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Low-Resource Adaptation of Neural NLP Models

Thesis submitted for the degree of Philosophiae Doctor

Department of Informatics
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In memory of my father,  
I miss you everyday! You always encouraged me.
Abstract

Real-world applications of natural language processing (NLP) are challenging. NLP models rely heavily on supervised machine learning and require large amounts of annotated data. These resources are often based on language data available in large quantities, such as English newswire. However, in real-world applications of NLP, the textual resources vary across several dimensions, such as language, dialect, topic, and genre. It is challenging to find annotated data of sufficient amount and quality. The objective of this thesis is to investigate methods for dealing with such low-resource scenarios in information extraction and natural language understanding. To this end, we study distant supervision and sequential transfer learning in various low-resource settings. We develop and adapt neural NLP models to explore a number of research questions concerning NLP tasks with minimal or no training data. We first make use of sequential transfer learning in order to induce non-contextualized word embeddings to capture domain-specific semantics and benefit downstream tasks in NLP. We subsequently enhance these embeddings using a domain-specific knowledge resource and present a benchmark dataset for intrinsic and extrinsic evaluation of domain embeddings. In the information extraction field, we propose a hybrid model that combines a reinforcement learning algorithm with partial annotation learning to clean the noisy, distantly supervised data for low-resource named entity recognition in different domains and languages. In the next step following entity detection in the information extraction pipeline, we design a neural architecture with syntactic input representation to alleviate domain impact in low-resource relation extraction. Finally, we introduce a cross-lingual meta-learning framework that provides further improvements in low-resource cross-lingual natural language understanding tasks in various settings and languages.
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Farhad Nooralahzadeh
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Chapter 1

Introduction

1.1 Motivation

There is a growing interest in real-world applications of natural language processing (NLP) for extracting, summarizing, and analyzing textual data. While NLP methods have led to many breakthroughs in practical applications, most notably perhaps in machine translation, question answering, and natural language inference, it is still challenging to use NLP in many real-world scenarios. Since NLP relies heavily on supervised machine learning, the modeling of most NLP tasks requires large amounts of annotated data. These resources are often based on language data available in large quantities, such as English newswire. However, in NLP’s real-world applications, the textual resources may vary across several dimensions, such as language, dialect, topic, genre, etc. Considering the cross-product of these dimensions, it is difficult to find annotated data of sufficient amount and quality that spans all possible combinations and assists current advanced NLP techniques (Plank, 2016).

In general, NLP application scenarios, can be classified into three categories according to their data resources (Duong, 2017): (i) High- or Rich-resource settings, where a large amount of annotated data is available; (ii) Low-resource or Resource-poor ones, where there is limited annotated data; and (iii) Zero-resource settings, where there is no annotated data available in the target context. Off-the-shelf resource-intensive NLP techniques tend to perform poorly where annotated data are not readily available (i.e., low-resource and zero-resource settings). An immediate solution is to create annotated data representative of new target scenarios. However, collecting and annotating corpora for each new variety requires experts and is usually expensive. Therefore, it is necessary to find techniques that can relieve the problem of creating training sets. Our primary motivation in this thesis is based on the following argument in Plank (2016):

"If we embrace the variety of this heterogeneous data by combining it with proper algorithms, in addition to including text covariates/latent factors, we will not only produce more robust models, but will also enable adaptive language technology capable of addressing natural language variation."

NLP for low-resource settings has recently received much attention, with dedicated workshops on the topic (Haffari et al., 2018; Cherry et al., 2019). In general, most previous work associates the low resource property with the language dimension (King, 2015; Tsvetkov, 2016; Duong, 2017; Kann et al., 2019). In this work, we follow Plank (2016) and consider the low-resource setting as fundamentally multi-dimensional, spanning over all kinds of variability within
natural language, e.g., language, dialect, domain, genre. Therefore, the scope of this thesis is broader, and we explore how to adapt and improve the performance of NLP algorithms in a number of different low-resource settings, spanning across different domains, genres and languages and dealing with a number of central NLP tasks. We here make a distinction between domain, genre, and language. We call the variety aspect domain when the source dataset defers in terms of topic (chapters 3, 4, and 5). The term Topic is the general subject of a document and ranging from very broad to more detailed such as oil and gas, biomedical, and e-commerce. Furthermore, we use the term genre, where the source dataset covers non-topical text properties such as function, style, and text type in Chapter 6.

A number of approaches have been proposed to address the challenge of low-resource scenarios. They have significantly improved upon the state-of-the-art on a wide range of NLP tasks for various settings. In this thesis, we make use of adaptation techniques that fall into the following main paradigms: (i) Distant Supervision: A supervised learning paradigm where the training data is not manually annotated, but automatically generated using knowledge bases (KBs) and heuristics (Mintz et al., 2009) (ii) Transfer Learning: Techniques for leveraging data from additional domains, tasks or languages to train a model with better generalization properties (Ruder et al., 2019).

Real-world applications of NLP typically incorporate a number of more specialized, task-specific systems, e.g., pre-processing, various types of syntactic or semantic analysis, inference, etc. Here we focus mainly on NLP tasks from the areas of Information Extraction (specifically Named Entity Recognition and Relation Extraction) and Natural Language Understanding (more specifically Natural Language Inference and Question-Answering).

Before we delve into the theoretical and experimental study of our work, in the next few pages, we present our research questions and highlight some of our main contributions and, finally, provide a more detailed outline of the thesis.

1.2 Research Questions

At a high level of abstraction, we attempt to answer the following main research questions in this thesis:

RQ I. What is the impact of different input representations in neural low-resource NLP?

The vector representations of tokens instantiate the distributional hypothesis by learning representations of the meaning of words, called embeddings, directly from text corpora. These representations are crucial elements in the performance of downstream NLP systems and underlie the more powerful and more recent contextualized word representations. We here study input representations trained on data from specific domains using sequential transfer learning of word embeddings. Concretely, we attempt to answer the following research questions:
Research Questions

(i) Can word embedding models capture domain-specific semantic relations even when trained with a considerably smaller corpus size?

(ii) Are domain-specific input representations beneficial in downstream NLP tasks?

In order to address these questions, we study input representations trained on data from a low resource domain (Oil and Gas). We conduct intrinsic and extrinsic evaluations of both general and domain-specific embeddings. Further, we investigate the effect of domain-specific word embeddings in the input layer of a downstream sentence classification task in the same domain. Domain-specific embeddings are further studied in the context of the relation extraction task on data from an unrelated genre and domain: scientific literature from the NLP domain.

In many NLP tasks, syntactic information is viewed as useful, and a variety of new approaches incorporate syntactic information in their underlying models. Within the context of this thesis, we hypothesize that syntax may provide a level of abstraction that can be beneficial when there is little available labeled data. We pursue this line of research particularly for low-resource relation extraction, and we look at the following question:

(iii) What is the impact of syntactic dependency representations in low-resource neural relation extraction?

We design a neural architecture over dependency paths combined with domain-specific word embeddings to extract and classify semantic relations in a low-resource domain. We explore the use of different syntactic dependency representations in a neural model and compare various dependency schemes. We further compare with a syntax-agnostic approach and perform an error analysis to gain a better understanding of the results.

RQ II. How can we incorporate domain knowledge in low-resource NLP?

Technical domains often have knowledge resources that encode domain knowledge in a structured format. There is currently a line of research that tries to incorporate this knowledge encoded in domain resources in NLP systems. The domain knowledge can be leveraged either to provide weak supervision or to include additional information not available in text corpora to improve the model’s performance. Here, we explore this line of research in low-resource scenarios by addressing the following questions:

(i) How can we take advantage of existing domain-specific knowledge resources to enhance our models?

We investigate the impact of domain knowledge resources in enhancing embedding models. We augment the domain-specific model by providing vector representations for infrequent and unseen technical terms using a domain knowledge resource and evaluate its impact by intrinsic and extrinsic evaluations.
1. Introduction

Given the availability of domain-specific knowledge resources, distant supervision can be applied to generate automatically labeled training data in low-resource domains. In this thesis, we explore the use of distant supervision for low-resource Named Entity Recognition (NER) in various domains and languages. We here address the following question:

(ii) **How can we address the problem of low-resource NER using distantly supervised data?**

The outcome of distant supervision, however, is often noisy. To address this issue, we explore the following research question:

(iii) **How can we exploit a reinforcement learning approach to improve NER in low-resource scenarios?**

We present a system which addresses the problem of noisy, distantly supervised data using reinforcement learning and partial annotation learning.

**RQ III. How can we address the challenges of low-resource scenarios using transfer learning techniques?**

Transfer learning has yielded significant improvements in various NLP tasks. The most dominant practice of transfer learning is to pre-train embedding representations on a large unlabeled text corpus and then to transfer these representations to a supervised target task using labeled data. We explore this idea, namely sequential transfer learning of word embeddings, in the first research question (i.e., RQ I above).

Further, we consider the transfer of models between two linguistic variants such as genre and language, when little (i.e., low-resource) or no data (i.e., zero-resource) is available for a target genre or language. We study this challenging setup in two natural language understanding tasks using meta-learning. Accordingly, we investigate the following research questions:

(i) **Can meta-learning assist us in coping with low-resource settings in natural language understanding (NLU) tasks?**

(ii) **What is the impact of meta-learning on the performance of pre-trained language models in cross-lingual NLU tasks?**

We here explore the use of meta-learning to perform the zero-shot and few-shot cross-lingual and cross-genre transfer in two different natural language understanding tasks: natural language inference and question answering.

1.3 Structure of the Thesis

This thesis is a collection of case studies with the unifying objective of addressing low-resource settings in NLP and is structured as follows:
Chapter 2: Background

This chapter contains the background that is necessary to understand the contributions of the thesis as a whole. It gives an overview of a particular family of machine learning models that will be employed in the thesis, Deep Neural Networks (DNNs). In this chapter, we describe two paradigms that have been proposed to address low-resource NLP: Distant supervision and Transfer learning. The general NLP areas of Information Extraction (IE) and Natural Language Understanding (NLU) are briefly described in this chapter, whereas details regarding specific NLP tasks are delegated to subsequent chapters.

Chapter 3: Evaluation of Domain-specific Word Embeddings

In this chapter, we study input representations trained on data from a low resource domain (Oil and Gas) using sequential transfer learning of word embeddings. We conduct intrinsic and extrinsic evaluations of both general and domain-specific embeddings. We further adapt embedding enhancement methods to provide vector representations for infrequent and unseen terms.

Chapter 4: Named Entity Recognition in Low-Resource Domains

In this chapter, we explore the use of distant supervision for Named Entity Recognition (NER) in four low-resource scenarios. We apply distant supervision and present a system that addresses the problem of noisy, distantly supervised data in two ways. We study a reinforcement learning strategy with a neural network policy to identify false positive instances at the sentence level. We further adopt a technique of incomplete annotation to address the false negative cases. Finally, we evaluate the proposed hybrid model on various benchmark datasets.

Chapter 5: Low-Resource Relation Extraction

In this chapter, we focus on relation extraction in a low resource setting, namely scientific papers in NLP. We study the effect of varying input representations to a neural architecture, specifically Convolutional Neural Networks (CNN), to extract and classify semantic relations between entities in scientific papers. We investigate the effect of transfer learning using domain-specific word embeddings in the input layer and go on to provide an in-depth investigation of the influence of different syntactic dependency representations, which are used to produce dependency paths between the entities in the input to the system. We further compare our syntax-informed approach with a syntax-agnostic approach. In order to gain a better understanding of the results, we perform manual error analysis.
Chapter 6: Natural Language Understanding in Low-Resource Genres and Languages

In this chapter, we consider the transfer of models along two dimensions of variation, namely genre and language, when little or no data is available for a target genre or language, i.e. low-resource and zero-resource settings. We explore meta-learning to address this challenging setup, where, in addition to training a source model, another model learns to select which training instances are the most beneficial. We experiment using standard supervised, zero-shot cross-lingual, as well as few-shot cross-genre and cross-lingual settings for different natural language understanding tasks (natural language inference, question answering). We make use of an extensive experimental setup to investigate the effect of meta-learning in various low-resource scenarios. We apply our proposed cross-lingual meta-learning framework on various pre-trained language models for zero-shot and few-shot natural language inference and question answering tasks. We further conduct a comprehensive analysis to investigate the impact of typological sharing between languages in our framework.

Chapter 7: Conclusion and Future work

In this chapter, we describe our proposed methods and findings. Our main contributions are summarized, and we provide an outlook into future directions in this chapter.

1.4 Publications

The part of the work presented in this thesis has been presented in the following scientific articles:

1. Nooralahzadeh, Farhad; Øvrelid, Lilja and Lønning, Jan Tore (2018). "Evaluation of Domain-specific Word Embeddings using Knowledge Resources." In: Proceedings of the Eleventh International Conference on Language Resources and Evaluation, European Language Resources Association (ELRA).

2. Nooralahzadeh, Farhad; Øvrelid, Lilja and Lønning, Jan Tore (2018). "SIRIUS-LTG-UiO at SemEval-2018 Task 7: Convolutional Neural Networks with Shortest Dependency Paths for Semantic Relation Extraction and Classification in Scientific Papers." In: Proceedings of the 12th International Workshop on Semantic Evaluation. Association for Computational Linguistics.

3. Nooralahzadeh, Farhad and Øvrelid, Lilja (2018). "Syntactic Dependency Representations in Neural Relation Classification." In: Proceedings of the Workshop on the Relevance of Linguistic Structure in Neural Architectures for NLP. Association for Computational Linguistics.
4. Nooralahzadeh, Farhad; Lønning, Jan Tore and Øvrelid, Lilja (2019). "Reinforcement-based denoising of distantly supervised NER with partial annotation." In: *Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019). Association for Computational Linguistics*.

The following preprint is also discussed:

1. Nooralahzadeh, Farhad; Bekoulis, Giannis; Bjerva, Johannes; and Augenstein, Isabelle (2020). "Zero-shot cross-lingual transfer with meta learning." In: *CoRR* vol. abs/2003.02739.

Finally, while not directly related, the following article has also been completed over the course of the PhD:

1. Nooralahzadeh, Farhad and Øvrelid, Lilja (2018). "SIRIUS-LTG: An Entity Linking Approach to Fact Extraction and Verification." In: *Proceedings of the First Workshop on Fact Extraction and VERification (FEVER). Association for Computational Linguistics*.
Chapter 2

Background

This chapter contains the background that is necessary to understand the contributions of the thesis as a whole. We start by briefly discussing variation in textual data which is central to the thesis (Section 2.1). After that, we give an overview of a particular family of machine learning models that will be employed in the thesis, Deep Neural Networks (Section 2.2). We subsequently describe two machine learning paradigms that have been proposed to address low-resource NLP: Distant supervision in Section 2.3 and Transfer learning in Section 2.4. The general NLP areas of Information Extraction (IE) and Natural Language Understanding (NLU) are briefly described in Section 2.6 and 2.7, respectively. Whereas details regarding specific NLP tasks are delegated to subsequent chapters.

2.1 Dimensions of textual variation

The notion of *domain* is frequently used in low-resource NLP, although there is little common ground in what constitutes a domain (Plank, 2011). The term is usually used to refer to textual data of the same topic, genre, or source under the assumption that this common denominator will have some systematic impact on the vocabulary or linguistic aspects of the text. Various definitions of the term *domain* have been presented in previous research such as Lee (2002); Finkel and Manning (2009); Plank (2011); van der Wees et al. (2015); Plank (2016) and Aharoni and Goldberg (2020). Lee (2002) notes that the terms *genre, register, text type, domain, sub-language, and style* are often used differently in various communities or even interchangeably. Finkel and Manning (2009) further describe the meaning of domain as "It may refer to a topical domain or to distinctions that linguists might term mode (speech versus writing) or register (formal written prose versus SMS communications)". It is defined in Plank (2011) as a collection of texts from a certain coherent sort of discourse, and Aharoni and Goldberg (2020) define domains by implicit clusters of sentence representations provided by pre-trained language models (see Section 2.5.1.2). However, Plank (2016) argues that there are numerous other factors that should be taken into consideration, e.g., demographic factors, communicational purpose, sentence type, style, technology/medium, language, etc. She proposes to see a domain as a variety in a large dimensional variety space. In this view, most textual datasets are sub-spaces of this variety space. The dimensions in this space are fuzzy aspects such as language, dialect, topic, genre, social factors (age, gender, personality, etc.), including yet unknown aspects. "A domain forms a region in this space, with some members more prototypical than others" (Plank, 2016).
2. Background

In this thesis and as noted already in Chapter 1, we focus in particular on the textual varieties of domain, genre, and language. We call the variety aspect domain when datasets differ in terms of topic. Furthermore, we use the term genre where dataset differences are characterized by non-topical text properties such as function, style, and text type.

2.2 Deep Neural Networks in NLP

Natural Language Processing (NLP) involves the engineering of computational models and processes to solve practical problems in understanding human languages. Processing natural language text encompasses a number of syntactic, semantic, and discourse-level tasks (e.g., word segmentation, part-of-speech tagging, phrase chunking, parsing, word sense disambiguation, named entity recognition, semantic role labeling, semantic parsing, anaphora resolution). For a long time, NLP systems were based on traditional machine learning approaches, centered around algorithms such as Perceptrons, linear Support Vector Machines (SVM), and Logistic Regression trained on sparse hand-crafted features (Goldberg, 2017). These methods are known to have some challenges. Recently, the re-emergence of artificial neural networks (ANNs), also known as deep neural networks (DNNs), provides a way to develop highly automatic features and representations to handle complex interpretation tasks. These approaches, with the pioneering work of Collobert et al. (2011), have yielded impressive results for many different NLP tasks. In general, a neural network with many hidden layers is often referred to as a deep learning model. In the following sections, we will briefly introduce several DNN models that have been widely employed in NLP and that are central also in this thesis.

2.2.1 Deep Feed-Forward Networks

Deep Feed-Forward Networks, also known as Feed-Forward Neural Networks (FFNNs) or Multi-layer Perceptrons (MLPs), are the simplified version of DNNs (Goodfellow et al., 2016). They are the foundation of most deep learning models and consist of many layers, with the first layer taking the input and last layer providing outputs. The layers in the middle are known as hidden layers, and capture relations between the input and output. Figure 2.1 shows a typical structure of a feed-forward neural networks model.

The hidden layer is used to transform the input layer values into values in a higher-dimensional space so that we can learn more features automatically from the input. The transformation is done by a collection of perceptron nodes in the hidden layer using a non-linear function, known as an activation function. In such a model, information constantly flows from one layer to the next (i.e., input layer $\rightarrow$ hidden layers $\rightarrow$ output layer). Training of the FFNNs model in supervised learning is done by two steps: (i) Forward propagation of information from the input to the output layer through hidden layers and compute a loss function (i.e., training errors), and (ii) Backward propagation of loss from the
output to the input layer. The aim of backward propagation is to minimize the training error by measuring the margin of error of the output and then adjust the network parameters accordingly. We repeat both forward- and back-propagation to predict an output until the parameters of the model are calibrated.

2.2.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) (LeCun and Bengio, 1998; Krizhevsky et al., 2012) are a specialized kind of deep neural networks where convolution operations, derived from mathematics and signal processing, are applied to capture indicative local patterns from the data. The resulting local aspects are most informative for the prediction task at hand. In the field of NLP, The CNN’s feature functions (i.e., the convolution filters) are applied to extract high-level features from adjacent words or n-grams regardless of their position, while taking local ordering patterns into account (Goldberg, 2017). The CNN architecture consists of multiple convolutions and pooling layers. The convolution layers aim to extract useful local features from the input, which results in multiple feature maps. Then, a pooling layer is applied to one or multiple convolution layers to reduce the spatial size of feature maps. In the end, usually, a fully connected layer outputs the probability distribution over each target class.

Figure 2.2 presents the CNN architecture applied to a sentence classification.
2. Background

Figure 2.2: CNN architecture for a sentence classification task (Zhang and Wallace, 2017)

Figure 2.2: CNN architecture for a sentence classification task (Zhang and Wallace, 2017)

task and proposed by Kim (2014). For each sentence, words are represented as a vector in the input layer. Word vectors can be initialized randomly or fetched from pre-trained embeddings (see Section 2.5.1). The filter layer in Figure 2.2 includes three filter region sizes: 2, 3, and 4, each of which has two filters. This layer performs convolutions on the sentence matrix and generates (variable-length) feature maps. Subsequently, the 1-max pooling function performs pooling over each map (i.e., the largest number from each feature map is extracted). Thus a uni-variate feature vector is generated from all six maps, and a feature vector is formed by connecting these six features. Finally, the fully connected softmax layer receives this feature vector as input and uses it to classify the sentence as a binary classification task to output two possible output states (Zhang and Wallace, 2017). We could provide different characteristics or views
of a sentence in the input layer, referred to as a channel. For instance, in the sentence classification task, one channel will be the sequence of words, while another channel is the sequence of corresponding POS tags. It is common to apply a different set of filters to each channel, and then combine the multiple representations of input into a single vector.

The explained architecture in Figure 2.2 is just an example of CNNs (albeit a widely used architecture), and there are various designs where a different set of layers (i.e., filter, pooling, and fully connected layer) along with various hyper-parameters such as filter size, number of feature maps, activation function, pooling strategy, are employed.

CNN models have been effectively applied to position-invariant contextual features in various NLP tasks such as sentence and document classification. However, they have some challenges in maintaining sequential order and modeling long-distance dependencies, which is essential for many NLP tasks (Young et al., 2018). Recurrent Neural Networks and its variants are introduced as a suitable solution for such types of tasks, and we will now turn to these models in the next section.

2.2.3 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) (Rumelhart et al., 1986; Elman, 1990) are designed to process sequential information. The model is recurrent since it performs the same task for each input sequence element, such that the current step’s output is conditioned on the previous step. As shown in Figure 2.3, the input sequence is typically represented by a fixed-size vector of tokens and is passed sequentially (one by one) to a recurrent unit. The main power of the RNN is the ability to memorize the outputs of previous computation steps and utilize them in the current computation. This capability made the RNNs a preferred neural architecture in solving sequential NLP tasks such as language modeling, machine translation, named entity recognition, textual similarity, and text generation.

Some extensions of RNNs are introduced, such as Bidirectional RNN (Bi-RNNs) (Schuster and Paliwal, 1997), which can be seen as stacking two RNNs on top of each other, one going forward, the other one going backward over the sequence input (Figure 2.4). The Bi-RNNs are based on the idea that the output at a specific time step depends on the previous elements in the sequence, as well as future elements.

For a long sequence length, however, the vanilla RNN models suffer from the vanishing gradient problem (Hochreiter and Schmidhuber, 1997). This means that the gradient shrinks as it back propagates through time. If a gradient value becomes extremely small, it does not contribute to the learning process. The vanishing gradient causes the model to ignore long-term dependencies and, hence, hardly learn the dependencies between temporally distant sequences. In other words, the RNNs tend to focus on short term dependencies, which are often not desired. This limitation is mitigated by alternative network architectures like
2. Background

Figure 2.3: (left) Folded RNN with an input sequence and feedback loop. (right) Unfolded version of RNN through the time steps. The same RNN cell is applied in different time steps to the words in the sequence example. (Pilehvar and Camacho-Collados, 2020)

Figure 2.4: Bidirectional RNNs Model (Pilehvar and Camacho-Collados, 2020)

long short-term memory and gated recurrent unit networks, which are the most widely used RNN variants in NLP applications.

**Long Short-Term Memory Networks (LSTMs)** LSTMs (Hochreiter and Schmidhuber, 1997; Gers et al., 2000) are explicitly designed to cope with the vanishing gradients problem using a gating mechanism. In the vanilla RNNs, the repeating modules (i.e., the rectangle boxes in Figures 2.3 and 2.4) have a straightforward design, such as a single non-linearity. The structure of LSTMs
Deep Neural Networks in NLP

Figure 2.5: LSTM module structure at time step $t$ (Pilehvar and Camacho-Collados, 2020)

is not fundamentally different from the structure of RNNs, but the repeating module has a different setting. As shown in Figure 2.5, the repeating cell consists of four neural layers: the input gate, forget gate, cell state, and the output gate.

These layers are calculated according to the following formula (Goldberg, 2017):

$$
i_t = \sigma(x_t W^{xi} + h_{t-1} W^{hi})$$
$$f_t = \sigma(x_t W^{xf} + h_{t-1} W^{hf})$$
$$o_t = \sigma(x_t W^{xo} + h_{t-1} W^{ho})$$
$$\tilde{C}_t = \tanh(x_t W^{xc} + h_{t-1} W^{hc})$$
$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t$$
$$h_t = o_t \otimes \tanh(C_t)$$

Where $\otimes$ is element-wise multiplication, $h_t$ is the hidden state in time-step $t$ and $i, f, o$ are the input, forget and output gates, respectively. In the first step of the LSTM block, we decide what information should be retained or thrown away from the cell state (i.e., forget gate). For example, in the language model, the cell state might decide to remember the singular or plural information of the present subject in order to predict the correct verb tense in the next related states. While, if it sees a new subject, it will forget the information about the old subject. $\tilde{C}_t$ is called the candidate cell state and is computed based on the current input and the previous cell state. $C_t$ is the internal memory of the unit. It is a combination of the previous memory $C_{t-1}$ multiplied by the forget gate, and the newly computed cell state $\tilde{C}_t$, multiplied by the input gate. Given the memory $C_t$, the output hidden state $h_t$ is computed by multiplying the memory
2. Background

Figure 2.6: GRU module structure at time step $t$ (Pilehvar and Camacho-Collados, 2020)

with the output gate (i.e., a filtered version of the cell state). Intuitively, in the LSTM cell, we compute the $C$ and $h$ at time $t$ and output them to the next cell.

**Gated Recurrent Unit Networks (GRUs)** The GRUs, introduced by Cho et al. (2014), similar to LSTMs, follow the design of RNNs; however, each repeating block has a slightly simpler variant of the LSTM. GRU combines the forget gate and input gate into a single update gate. It incorporates two gates, the reset gate and the update gate, and manages the flow of information similar to LSTM without a memory unit (Figure 2.6). The formulation of the GRU module is as follows (Goldberg, 2017):

$$
\begin{align*}
    z_t &= \sigma(x_t W^{xz} + h_{t-1} W^{hz}) \\
    r_t &= \sigma(x_t W^{xr} + h_{t-1} W^{hr}) \\
    \tilde{h}_t &= \tanh(x_t W^{zh} + (r_t \otimes h_{t-1}) W^{h\tilde{h}}) \\
    h_t &= (1 - z_t) \otimes h_{t-1} +, z_t \otimes \tilde{h}_t
\end{align*}
$$

(2.2)

Because of this update, the final model is more straightforward than the standard LSTM and is also widely used in NLP.

### 2.2.4 Attention Mechanisms and Transformer

One of the common applications of RNN architectures is in *sequence-to-sequence* (seq2seq) models. Seq2seq models are DNNs that have been successfully
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Figure 2.7: The representation of the sequence to sequence (seq2seq) model - translating an input sequence A B C D into a target sequence X Y Z. Here, <eos> indicates the end of a sequence. The blue boxes at the left show the encoder, and the red boxes construct the decoder (Luong et al., 2015)

employed in NLP tasks like machine translation between multiple languages, text summarization, and language generation. The seq2seq model tries to transfer an input sequence to a new output sequence where the length of input and output may vary. The seq2seq model (Figure 2.7) normally has an encoder-decoder architecture, composed of:

- An encoder: It compiles the incoming sequence and captures the information into a context vector (i.e., sentence embedding vector) of a fixed length. This representation is assumed to be a good summary of the meaning of the whole source sequence.

- A decoder: It is initialized with the context vector to produce the output sequence. The early implementation of the seq2seq model used the last state of the encoder network as the initial decoder state.

Both the encoder and decoder are RNNs with LSTM or GRU units. The naive seq2seq model works fine for short sequences. However, in a long sequence, it becomes problematic when the encoder compresses the entire input into a fixed-sized context vector and transmits it into the decoder as the contextual information of the input. This problem is addressed by attention mechanisms proposed by Bahdanau et al. (2015) and Luong et al. (2015).

The attention mechanism (Figure 2.8) allows the decoder to refer back to the input sequence. Specifically, during decoding, it gives importance to specific parts of the input sequence instead of the entire sequence. Therefore, in the attention, all the intermediate outputs from the encoder state are considered, and we utilize them to generate the context vector from all states. It allows the
2. Background

Figure 2.8: The attention model proposed by Bahdanau et al. (2015). The decoder trying to generate the target word $y_t$ given a result of attention and encoder over the source sequence $X_1X_2 \ldots X_T$

model to focus on essential elements by giving weight to each element in the sequence.

Different ways of constructing attention mechanisms have been introduced, including global and local attention (Luong et al., 2015) and self-attention (Vaswani et al., 2017). Self-attention suggests implementing attention to words in the same sequence. For instance, while encoding a word in an input sentence, self-attention enables the encoder to look at other words in the input for clues that can further lead to a better encoding for the word. During decoding to produce a resulting sentence, it makes sense to provide appropriate attention to words that have already been produced. This type of attention mechanism has become widely used in a state-of-the-art encoder-decoder model called transformer.

The transformer model, shown in Figure 2.9, has many stacked layers in both encoder and decoder components. It considers self-attention in the encoder and decoder modules, as well as cross-attention between them. The proposed model is based entirely on an attention mechanism to capture the global relations between input and output, without including RNNs and CNNs. It incorporates other techniques in its encoder and decoder components such as residual connections (He et al., 2016), layer normalization (Ba et al., 2016), dropouts and positional encodings. The transformer becomes an essential component of pre-trained language models such as BERT and GPT (see Section 2.5.1.2).
Distant supervision has been proposed to deal with the lack of sufficient labeled data for training supervised machine learning methods by exploiting existing knowledge resources. Craven and Kumlien (1999) initiated this idea as a weak supervision method to populate a knowledge base in the biomedical domain. Subsequently, Mintz et al. (2009) generalized the initial idea for the relation extraction task and formulated the distant supervision assumption as follow:

"If two entities participate in a relation, any sentence that contains those two entities might express that relation." (Mintz et al., 2009, p. 1006)

The term distant is used by assuming that no explicit labeled data is provided, however knowledge resources (e.g., Wikipedia, Freebase) are available for automated labeling of training instances in text corpora. Distant supervision can be formally defined as follows (Smirnova and Cudré-Mauroux, 2018):

"Given a text corpus $C$ and a knowledge base $K$, distant supervision assigns relations from $K$ to sentences from $C$. More specifically, the
idea is to first collect those sentences from the corpus \( \mathcal{C} \) that contain entity pair \((e_1, e_2)\) where both \(e_1\) and \(e_2\) exist in the knowledge base \( \mathcal{K} \). If there exists one triple \((e_1, r, e_2)\) in the knowledge base, then the distant supervision set a label to the sentence as an instance of relation \(r\)." (Smirnova and Cudré-Mauroux, 2018, p. 106:4)

For example, the following sentence contains the entity pair (Steven Spielberg, Saving Private Ryan)

(2.3) [Steven Spielberg]'s film [Saving Private Ryan] is loosely based on the brothers' story.

Assuming the triple (Steven Spielberg, is director of, Saving Private Ryan) exists in the knowledge base, the textual sentence is labeled with the is director of relation label. It can be used as training data for subsequent relation extraction.

Distant supervision has been successfully applied to tasks like relation extraction (Riedel et al., 2010; Augenstein et al., 2014) and entity recognition (Fries et al., 2017; Shang et al., 2018b; Yang et al., 2018). We will return to this topic in Chapter 4 where we explore the use of distant supervision for named entity recognition in low-resource scenarios.

2.4 Transfer Learning

Humankind can learn new tasks faster and more efficiently if he/she has prior experience with similar tasks. For example, people who know how to ride a bike will likely manage to ride a motorcycle with little or no training. In short, we learn how to learn across tasks. This statement brings the following question: Is it possible to design a machine learning model with similar properties, learning new tasks by leveraging prior knowledge gained in other learning processes? Recently, this question is answered by transfer learning (Pan and Yang, 2010). Transfer learning makes use of knowledge acquired while solving one problem or more than one problem and applies it to a different but related problem/s. It refers to a set of methods that extend the learning mechanism by leveraging data from additional languages, domains, or tasks to train a model with better generalization properties. Transfer learning has yielded to a significant improvement in various NLP tasks (Chen and Moschitti, 2019; Devlin et al., 2019; Howard and Ruder, 2018; Peters et al., 2018) and this is due to the fact that NLP tasks share common knowledge about language, such as linguistic representation and structural similarity (Ruder et al., 2019). Moreover, languages have common typological features such as phonological, grammatical, and lexical properties (Dryer and Haspelmath, 2013).

Based on different scenarios that are mostly encountered in NLP systems, Pan and Yang (2010) and Ruder et al. (2019) proposed a taxonomy for transfer learning for the NLP field (Figure 2.10). Following the notation of Pan and Yang (2010) and Ruder et al. (2019), transfer learning is defined as follows:
Given a settings $S = \{D, T\}$ where, $D$ is a dataset that contains a feature space $\mathcal{X} = \{x_1, \ldots, x_n\}$ with a marginal probability distribution $P(\mathcal{X})$ over the feature space. On the other hand, a task $T = \{\mathcal{Y}, P(\mathcal{Y}), P(\mathcal{Y}|\mathcal{X})\}$ consists of a label space $\mathcal{Y}$, a prior distribution $P(\mathcal{Y})$, and a conditional probability distribution $P(\mathcal{Y}|\mathcal{X})$ which is usually learned using the training data consisting pairs of $x_i \in \mathcal{X}$ and $y_i \in \mathcal{Y}$. Having a source setting $S_s$ including $D_s$ and a corresponding source task $T_s$, as well as a target setting $S_t$ with $D_t$ and target task $T_t$, the aim of transfer learning is to perform the target task in order to learn the target $P_t(\mathcal{Y}_t|\mathcal{X}_t)$ in $D_t$ using the information provided by the elements in the source setting where $D_s \neq D_t$ or $T_s \neq T_t$. Typically, it is assumed that the target setting is either in low-resource or zero-resource mode.

According to the proposed taxonomy and notation, transfer learning involves the following scenarios:
2. Background

**Transductive transfer learning:** The source and target tasks are the same, whereas the source and target dataset vary. If the marginal probability distribution of source and target dataset are different $P_s(X_s) \neq P_t(X_t)$, when the datasets come from different domains or genres, the scenario is known as domain adaptation. If there is a discrepancy in the feature spaces of the source and target datasets $X_s \neq X_t$, for example, when the datasets are in two various languages, we refer to cross-lingual learning scenario in NLP. Cross-lingual learning can be viewed as an extreme case of adaptation (Plank, 2016).

**Inductive transfer learning:** The source and target tasks are different $T_s \neq T_t$, regardless of whether the source and target datasets are the same or not. In this case, if the tasks are learned simultaneously, the scenario is known as multi-task learning, while sequential transfer learning will be used if the learning process is performed sequentially. We want to stress that if in this category the variation on the source and target dataset is considered, both scenarios (i.e., multi-task learning and sequential transfer learning) can be applied to domain adaptation (i.e., $P_s(X_s) \neq P_t(X_t)$) and cross-lingual learning (i.e., $X_s \neq X_t$).

In the context of this thesis, we focus on sequential transfer learning.

### 2.5 Sequential Transfer Learning

Sequential transfer learning is defined as a setting where a learning process is carried out in sequence (Ruder et al., 2019). It can be useful when (i) the target task is in a low- or zero-resource setting, (ii) the source task is in a high-resource setting, and (iii) the objective is the adaptation of many target tasks. This learning approach consists of the two following steps (Ruder et al., 2019):

1. **Pre-training:** The general representation of the model is learnt on the source language, task, or domain.

2. **Adaptation:** The learned knowledge is transferred and adjusted to target languages, tasks, or domains. In other words, it involves copying the weights from a pre-trained network and tuning them on the targets.

The most dominant practice of sequential transfer learning is to pre-train embedding representations on a large unlabeled text corpus and then to transfer these representations to a supervised target task using labeled data. In the following section, we will give an overview of the pre-trained representations that are employed in this thesis.

#### 2.5.1 Embedding Representations

The distributed vector representations of tokens, called *word embeddings*, are an essential component of neural methods for downstream NLP tasks. Word embeddings are vectors based on the distributional hypothesis meaning that
words appearing in a similar context have a similar meaning. In other words, they have learned representations of text where words with the same meaning have a similar representation. Learning useful word representations in a supervised setting with limited data is often difficult. Therefore, many unsupervised learning approaches have been proposed to take advantage of large amounts of unlabeled data that are readily available. It results in more useful word embeddings (Pennington et al., 2014; Mikolov et al., 2013a). However, the differences in the meaning of a word in varying contexts are lost when it is associated with a single representation. Static pre-trained embeddings are limited in two respects (Pilehvar and Camacho-Collados, 2020): (i) the role of context is ignored, and (ii) by providing the individual word vector representation, it is problematic to capture higher-order semantic phenomena, such as compositionality and long-term dependencies. To alleviate the limitations of static word embeddings and to deal with varying word context, pre-trained language models (Peters et al., 2018; Radford et al., 2018; Devlin et al., 2019; Yang et al., 2019; Conneau and Lample, 2019) are proposed and create context-sensitive word representations. The success of these approaches suggests that these representations capture highly transferable and task-agnostic properties of languages.

2.5.1.1 Static Word Embeddings

Word2vec, proposed by Mikolov et al. (2013a), is one of the most popular approaches in learning word representations from text inputs. It can effectively capture the semantics of words and is straightforwardly transferred into other downstream tasks. The proposed method consists of a single layer architecture based on the inner product between word vectors based on two different learning approaches as follows:

Continuous Bag-Of-Words (CBOW): Learns the embeddings by estimating the conditional probability of a particular word based on its context (i.e., surrounding words within a specified window size). Specifically, given a sequence of words, the model receives as input a window of $C$ context words and predicts the target word $w_t$ by minimizing the following objective (Rong, 2014):

$$E = -\frac{1}{|C|} \sum_{t=1}^{|W|} \log P(w_t|w_{t-C}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+C})$$

(2.4)

and

$$P(w_t|w_{t-C}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+C}) = \frac{\exp(u_t^Tv_c)}{\sum_{j=1}^{|V|} \exp(u_j^Tv_c)}$$

(2.5)

where $V$ is the vocabulary size, $v_c$ is the sum of the embeddings vector of the context words $w_{t-C}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+C}$, and $u$ is the embeddings vector of the target word.
2. Background

**Skip-gram:** Learns by predicting the surrounding words (context) given a current word. In other words, it minimizes the following objective (Rong, 2014):

\[
E = -\frac{1}{|C|} \sum_{t=1}^{|C|} \sum_{-C \leq j \leq C; j \neq 0} \log P(w_{t+j}|w_t) \tag{2.6}
\]

and

\[
P(w_{t+j}|w_t) = \frac{\exp(v_t^\top u_{t+j})}{\sum_i^{|V|} \exp(v_i^\top u_t)} \tag{2.7}
\]

where \( u \) and \( v \) are the current and context word embeddings, respectively.

Figure 2.11 depicts these two approaches of the word2vec model where the window size \( C = 2 \). In order to train the word2vec model, we provide many word-context pairs where the window size parameter characterizes the context, and the weights learned by the models make up the actual word vector representations. While the objective of both word2vec models is computationally expensive, the negative-sampling approach is presented as a more efficient way of deriving word embeddings. It means that for each positive pair (i.e., output word and context word), it samples \( k \) words \( w_j \) from the vocabulary and add it as a negative example \((w_o, w_j)\) to the \( W_{neg} \). The number of negative samples \( k \) is a parameter of the algorithm. To this effect, the following simplified training objective is capable of producing high-quality word embeddings:

\[
E = \log \sigma(u_{w_o}^\top v) - \sum_{w_j \in W_{neg}} \log \sigma(u_{w_j}^\top v) \tag{2.8}
\]

where \( u_{w_o} \) is the embeddings of output word (i.e., the positive sample), \( \sigma \) is the sigmoid function, \( W_{neg} \) is the set of negative samples and \( v \) in CBOW it is the mean of the embeddings vector of the context words \( w_{t-C}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+C} \), whereas, in the skip-gram model it is the input word embeddings.

### 2.5.1.2 Contextualized Word Representations

Before pre-trained language models, context-independent or static vectors as described in the previous section, were generally used for transfer learning in NLP tasks. A common practice was employing them as a look-up table to structure the input layer of deep neural models where it results in high training efforts to learn a target task. Considering the limitations of static word embeddings, recent work presents context-sensitive word representations using neural language models with two different transfer strategies (Devlin et al., 2019). The feature-based approach, such as ELMo (Embeddings from Language Models proposed by Peters et al. (2018)), uses task-specific architectures that include the pre-trained representations as additional features. In contrast, in the fine-tuning strategy such as GPT (Radford et al., 2018) and BERT (Devlin et al., 2019), the underlying network structure can be leveraged in the learning of a target task with simply fine-tuning all pre-trained parameters. These pre-trained language
models show that despite being trained with only a language modeling task, they provide highly transferable and task-agnostic features of the language (Liu et al., 2019a). ELMo creates contextualized representations derived from a 2-layer bidirectional LSTM. It is trained with a coupled language model (LM) objective on a large text corpus (Devlin et al., 2019). In contrast, BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) are bi-directional and uni-directional language models, respectively, based on the transformer architecture (Vaswani et al., 2017). They create a contextualized representation of each token by attending to different parts of the input sentence. Unlike GPT, BERT integrates the concept of masked language model in the pre-training phase, where the goal is to predict randomly masked
2. Background

Figure 2.13: Adaptation stage using GPT. (left) Transformer architecture. (right) Fine-tuning on different tasks. (Radford et al., 2018)

tokens given their captured context from both directions. It is also trained on a next sentence prediction task that further boosts the model’s performance. Figure 2.12 shows the differences in pre-training model architectures. It can be seen that BERT uses a bidirectional Transformer, while GPT employs a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right, and right-to-left LSTMs to generate features for downstream tasks. Among them, only BERT representations are jointly conditioned on both left and right context in all layers and it is deeply bidirectional (Devlin et al., 2019).

In the following section, we will discuss how GPT and BERT models are employed in the second step of sequential transfer learning, namely adaptation.

2.5.2 Adaptation

Adaptation is the second stage of sequential transfer learning, in which the representation is transferred to a new task. In prior works, only input word embeddings are transferred to the down-stream task, however with GPT and BERT, all parameters are transferred to initialize end-task model parameters. It involves updating the pre-trained representations (i.e., Fine-tuning).

Figure 2.13 depicts the adaptation stage using GPT and several input transformations to handle the inputs for different types of tasks. It can be seen that each task has a specific input transformation, and the discriminative fine-tuning step passes inputs through the GPT pre-trained model (i.e., transformer) to obtain the intermediate output. Then the transformer output is fed into an added softmax based linear output layer. BERT’s fine-tuning is similar to GPT, and for each task, it processes the task-specific inputs and outputs with the pre-trained BERT and performs fine-tuning of all the parameters end-to-end.
Figure 2.14: Sequential transfer learning using BERT. (left) Pre-training stage using transformer, (right) Fine-tuning stage where the same pre-trained model parameters are used to initialize the BERT model for various NLP tasks. During fine-tuning, all parameters are updated. By excluding the output layers, the same architectures are used in both stages of sequential transfer learning through BERT. (Devlin et al., 2019).

(Figure 2.14). It uses a sentence separator ([SEP]) and classifier token ([CLS]), in which their embeddings are learned during pre-training. For GPT, in contrast, these tokens are only introduced at fine-tuning time (Devlin et al., 2019). At the output level, as shown in Figure 2.15, for token level tasks such as sequence labeling and question answering, the token representations are fed into the final layer. For classification tasks (e.g., entailment and sentiment analysis), on the other hand, the representation of the classifier token ([CLS]) is fed into the output layer.

2.6 Information Extraction

Information extraction (IE) is the process of extracting desired knowledge in terms of names, entities, events, properties, and relations from a semi-structured or unstructured text by transforming them into a structured format. The structure is usually represented in the form of <subject, predicate, object> or <entity1, relation, entity2> triplets, known as facts. In this process, first, we have to define what constitutes a subject and object, then which type of relations should be considered. There are two paradigms of information extraction that have emerged recently (Nakashole, 2012):

- **Schema-based IE**: In this approach, the process of extracting information from various information sources is guided by an ontology. The ontology typically consists of two kinds of information views; those that make
2. Background

Figure 2.15: Fine-tuning in BERT for various NLP tasks (Devlin et al., 2019).

up the assertion-view and those that make up the taxonomy-view. The taxonomy-view represents a topology or taxonomy of the domain at hand and includes the definition of the concepts, attributes, and their inter-relationships. The assertion-view describes the attributes of instances (or individuals), the roles between instances, and other assertions about instances regarding their concept membership within the taxonomy-view. The concepts and relations in the ontology are generally hand-specified by either developers of the ontology or by domain experts. Therefore the major flaw in schema-based IE is the limited number of classes and relations that can be populated from sentences.

- **Schema-free IE**: This approach to IE aims to extract assertions from a large volume of textual data, avoiding the restriction to a pre-specified
vocabulary. It extracts all relations by learning a set of lexico-syntactic patterns in a supervised or unsupervised manner. While the schema-free IE answers the recall issue, it is highly susceptible to noise, due to the lack of tightly enforced semantics on relations and entities (Nakashole, 2012).

Traditionally, the process of information extraction can be divided into a series of tasks. It typically begins with lexical analysis like assigning part-of-speech and features to words and phrases through morphological analysis and dictionary. Then it continues by entity recognition to identify names and instances of particular concepts of interest. The syntactic analysis comes along in most solutions to identify the noun, verb phrases, and dependency structure. Finally, relation extraction and classification tasks are applied to construct the facts of interests. We can consider discourse analysis as a complementary step in the flow which resolves relations of co-reference and draws inferences from the document’s explicitly stated facts. Traditional IE systems are often based on a pipeline architecture where the tasks have been done sequentially using different task-specific patterns. The patterns are obtained using various statistical analysis and pattern recognition methods. Currently, most IE systems employ end-to-end neural networks by learning deep neural networks that map directly from the input to the output data naturally consumed and produced in IE tasks (e.g., Xu et al. (2015a), Gupta et al. (2016), Zheng et al. (2017), Zeng et al. (2018) and Cui et al. (2018)). Even though most IE neural systems work end-to-end, there has been interest in incorporating various linguistic categories (PoS-tags, dependencies) into them to improve the performance, such as Chiu and Nichols (2016), Xu et al. (2015b) and Nooralahzadeh et al. (2018).

Information Extraction has been explored under different areas such as Fact & Relation extraction, Knowledge base population and Unseen entity extraction.

- **Fact & Relation extraction.** This process generates structured data in the form of entity-relation triplets from natural language text documents. The conventional approach to fact extraction is to use pattern-based extraction and employ consistency constraint reasoning to provide proper facts. In schema-based IE approaches such as BOA (Gerber and Ngonga Ngomo, 2011), PORSPERA (Nakashole et al., 2011) , DARE (Xu et al., 2010), the patterns emerge by starting with a few seed facts from a knowledge base to bootstrap the extraction process. For example, BOA relies on distant supervision and existing facts from a knowledge base, in particular DBpedia. It applies a recursive procedure, starting with extracting triples from linked data, then extracting natural language patterns from sentences and constructing the facts in triplet format (i.e., RDF triples). In schema-free IE approaches (e.g., TextRunner (Yates et al., 2007), ReVerb (Fader et al., 2011; Mausam et al., 2012)) these patterns are constructed by leveraging linguistic structure, through syntactic and lexical rules. For instance, ReVerb extracts relations based on simple linguistic patterns (i.e., in terms of PoS-tags and noun phrase chunks). It extracts the facts by assuming that every relational phrase must be either
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a verb and a verb followed immediately by a preposition (e.g., located in), or a verb followed by nouns, adjectives, or adverbs ending in a preposition (e.g., has an atomic weight of) (Fader et al., 2011). ReVerb first looks for a matching relational phrase and then finds the arguments (i.e., \textit{entity}_1\textit{ and entity}_2) of the relationship. Although these systems have been widely used in a variety of fact and relation extraction approaches, most of them were built on hand-crafted patterns from syntactic parsing, which causes errors in propagation and compounding at each stage. To alleviate extraction errors, various deep neural-based approaches have recently been proposed (Stanovsky et al., 2018; Cui et al., 2018; Jiang et al., 2019; Zhang et al., 2017). For instance, Cui et al. (2018) applied a seq2seq framework to provide a schema-free IE system.

- **Knowledge Base Population (KBP).** Knowledge Base Population (KBP) is the task of taking an incomplete knowledge base, and a large corpus of text, and completing the incomplete elements of the knowledge base. That is, the model has to interpret the text and get the desired information out of it. Therefore in this task, we assume that we have prior but incomplete knowledge about the subject, and our aim is discovering its properties. Recent works like Lin et al. (2015) and Socher et al. (2013a), exploit knowledge embeddings to infer new relational facts.

- **Unseen entity extraction.** The previous areas rely on a common assumption in schema-based IE, namely the existence of a knowledge base that contains all entities and their types. However, during the extraction of facts from highly dynamic sources such as news, social media, and technical documents, new entities emerge that are not in the reference knowledge base. This area covers the problem of out-of knowledge base entities. Conventional named entity recognition tools have coarse-grained types and only deal with a limited set of entities such as a person, organization, and company. However, fine-grained methods (Ma et al., 2016; Mai et al., 2018; Dogan et al., 2019) consider up to 200 types. In contrast, the proposed tools in this area, like PEARL (Nakashole et al., 2013) and FINET (Del Corro et al., 2015), deal with thousands of types. They are semi-supervised systems that leverage a repository of many relational patterns. Subjects and objects of each pattern carry the type information. They categorize entity mentions by the most likely type according to the pattern repository. The type system is based on a partial or the entire WordNet (Miller, 1995) hierarchy.

In this thesis, we study two essential tasks in the area of Information Extraction, namely Named Entity Recognition (Chapter 4) and Relation Extraction (Chapter 5).
2.7 Natural Language Understanding

Understanding of natural language is an essential and general goal of NLP. Natural Language Understanding (NLU) comprises a wide range of diverse tasks, including, but not limited to, natural language inference, question answering, sentiment analysis, semantic similarity assessment, and document classification. In this thesis, we explore two central NLU tasks, including natural language inference and question answering (Chapter 6). We provide a brief description of these tasks in the following sections but go into details on related work in Chapter 6.

2.7.1 Natural Language Inference (NLI)

NLI is the task of predicting whether a hypothesis sentence is true (entailment), false (contradiction), or undetermined (neutral) given a premise sentence. NLI systems need some semantic understanding and models trained on entailment data can be applied to many other NLP tasks such as text summarization, paraphrase detection, and machine translation. The task of NLI, also known as textual entailment, is well-positioned to serve as a benchmark task for research on NLU (Williams et al., 2018).

2.7.2 Question Answering (QA)

The task of QA is often designed in the context of a reading comprehension task. This machine reading problem is formulated as extractive question answering, in which the answer is drawn from the original text (Eisenstein, 2019). In this context, given a context and a question, the QA task aims to identify the span answering the question in the context.
Chapter 3

Evaluation of Domain-specific Word Embeddings

In this chapter, we study input representations trained on data from a low resource domain (Oil and Gas) using sequential transfer learning of word embeddings (See Section 2.5 in Chapter 2). We conduct intrinsic and extrinsic evaluations of both general and domain-specific embeddings. We observe that constructing domain-specific word embeddings is worthwhile even with a considerably smaller corpus size. Although the intrinsic evaluation shows low performance in synonymy detection, an in-depth error analysis reveals the ability of these models to discover additional semantic relations such as hyponymy, co-hyponymy, and relatedness in the target domain. Extrinsic evaluation of the embedding models is provided by a domain-specific sentence classification task, which we solve using a convolutional neural network. We further adapt embedding enhancement methods to provide vector representations for infrequent and unseen terms. Experiments show that the adapted technique can provide improvements both in intrinsic and extrinsic evaluation.

3.1 Introduction

Domain-specific, technical vocabulary presents a challenge to NLP applications. Recently, word embedding models (See Section 3.3.2 in Chapter 2) have been shown to capture a range of semantic relations relevant to the interpretation of lexical items (Mikolov et al., 2013b) and furthermore provide useful input representations and transferable knowledge for a range of downstream tasks (Collobert et al., 2011). The majority of work dealing with intrinsic evaluation of word embeddings has focused on general domain embeddings and semantic relations between common and generic terms. However, it has been shown that embeddings differ from one domain to another due to lexical and semantic variation (Hamilton et al., 2016; Bollegala et al., 2015). Domain-specific terms are challenging for general domain embeddings since there are few statistical clues in the underlying corpora for these items (Bollegala et al., 2015; Pilehvar and Collier, 2016b). On the other hand, domain knowledge resources, where the meanings of words are represented by defining the various relationships among those words, provide valuable prior knowledge for many NLP tools. Many works show that the encoded knowledge available in lexical resources can be exploited to improve the semantic coherence or coverage of existing word vector representations (Faruqui et al., 2015; Pilehvar and Collier, 2017).

The following research questions related to the domain-specific data and model are investigated in this chapter:
3. Evaluation of Domain-specific Word Embeddings

RQ 3.1. Can word embedding models capture domain-specific semantic relations even when trained with a considerably smaller corpus size?

RQ 3.2. How can we take advantage of existing domain-specific knowledge resources to enhance the resulting models?

To answer these research questions, we train domain-specific embeddings and conduct a comprehensive study including a wide range of evaluation criteria against terminological resources, contrasting several general and domain-specific embedding models. We augment the domain-specific embeddings using a domain knowledge resource. We further adapt embedding enhancement methods to provide vector representations for infrequent and unseen terms by investigating the works of Pilehvar and Collier (2017) and Faruqui et al. (2015). We then go on to examine the contribution of these models in the performance of a downstream classification task.

3.2 Related Work

Despite the pervasive use of word embeddings in language technology, there is no agreement in the community on the best ways to evaluate these semantic representations of language\(^1\). There exist a variety of benchmarks that are widely employed to assess the quality of word representations and to compare different distributional semantic models. Existing evaluation methods can largely be separated into two categories: intrinsic evaluation and extrinsic evaluation.

3.2.1 Intrinsic Evaluation

Intrinsic evaluation methods attempt to directly quantify how well various kinds of linguistic regularities can be detected with a model-independent of its downstream applications (Baroni et al., 2014; Schnabel et al., 2015). Existing schemes in intrinsic evaluation fall into two major scenarios (Schnabel et al., 2015): Absolute intrinsic evaluation and Comparative intrinsic evaluation, which will be described in the following.

**Absolute intrinsic evaluation:** This type of evaluation directly tests for syntactic or semantic relationships between words (Schnabel et al., 2015) and analyzes the generic quality of embeddings (Yaghoobzadeh and Schütze, 2016). Since it is computationally inexpensive and leads to fast prototyping and development of vector models, it has been the topic of many evaluation challenges. Several datasets have been developed to this end. Table 3.1 shows a compilation of datasets employed for intrinsic evaluation of word embeddings, organized by the semantic relation. It involves tasks such as the following (Baroni et al., 2014; Schnabel et al., 2015):

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\(^1\)RepEval @ACL 2016, 2017, and 2019: Workshop on Evaluating Vector Space Representations for NLP

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| Task         | Dataset name | Dataset Inf. | Reference                      |
|-------------|--------------|--------------|--------------------------------|
| Semantic Relatedness | RG           | 65 word pairs | Rubenstein and Goodenough (1965) |
|              | MC-30        | 30 word pairs | Miller and Charles (1991)       |
|              | WordSim-353  | 353 word pairs | Finkelstein et al. (2001)      |
|              | YP-130       | 130 word pairs | Yang and Powers (2006)         |
|              | WS-Rel       | 252 word pairs | Agirre et al. (2009)           |
|              | WS-Sim       | 203 word pairs | Agirre et al. (2009)           |
|              | MTruk-287    | 287 word pairs | Radinsky et al. (2011)         |
|              | MTruk-771    | 771 word pairs | Halawi et al. (2012)           |
|              | MEN          | 300 word pairs | Bruni et al. (2012)            |
|              | Rare Word    | 2034 word pairs | Luong et al. (2013)           |
|              | Verb         | 144 word pairs | Baker et al. (2014)           |
|              | SimLex-999   | 999 word pairs | Hill et al. (2015)             |
| Synonym Detection | TOFEL        | 80 multi-choice questions (4 words) | Landauer and Dutnais (1997) |
| Categorization | AP           | 402 concepts, 21 categories | Almuhareb (2006) |
|              | ESSLLI       | 44 concepts, 6 categories | Baroni et al. (2008) |
|              | BATIING      | 83 concepts, 10 categories | Baroni and Lenci (2010) |
| Selectional Preference | UP           | 211 noun-verb pairs | Padó (2007) |
|              | MCRAE        | 100 noun-verb pairs | McRae et al. (1998) |
| Analogy      | AN           | 19.5 K analogy questions | Mikolov et al. (2013a) |
|              | ANSYN        | 10.5 K analogy questions | Mikolov et al. (2013a) |
|              | ANSEM        | 9 K analogy questions | Mikolov et al. (2013a) |
|              | BATS         | 99.2 analogy questions K | Gladkova et al. (2016) |
| Coherence or Outlier detection | Intrusion | 100 of 3+1 words | Schnabel et al. (2015) |
|              | 8-8-8        | 64 of 8+1 words | Camacho-Collados and Navigli (2016) |
| QVEC-CCA     | SEM-Matrix   | 4.2 K words with 41 features | Tsvetkov et al. (2015) |
|              | SYN-Matrix   | 10.8 K words with 45 features | Tsvetkov et al. (2016) |

Table 3.1: Absolute intrinsic evaluation datasets.
• **Semantic Relatedness:** Given a ground truth of human assigned proximity scores to word pairs such as \textit{money:dollar} \approx 8.42, \textit{tiger:mammal} \approx 6.85, the evaluation task aims to find the degree of correlation between the scores provided by the model and the human rating as a performance of the model. The cosine similarity of the corresponding vectors for word pairs provided by the model should be highly correlated with the gold standard (measured by Spearman or Pearson correlation).

• **Categorization:** Given a set of words, the system needs to group them into different semantic categories (e.g., \textit{helicopters} and \textit{motorcycles} should go to the \textit{vehicle} class, \textit{dogs} and \textit{elephants} into the \textit{mammal} class). By applying a clustering method to the corresponding vectors of all words in a dataset, the model’s performance is calculated concerning the purity of the outcome clusters concerning the human-judgment labels.

• **Synonym Detection:** The ability of the embedding model to find the correct synonym for a word is assessed. For example, for the target word \textit{levied} the list of options to choose are \textit{imposed} (correct one), \textit{believed}, \textit{requested} and \textit{correlated}. For each target word, its cosine similarities with synonym candidates are calculated, and the one with the highest score is selected. The model performance is the accuracy of the model prediction.

• **Selectional Preference:** The goal is to label a noun as a subject or object for a specific verb (e.g., people received a high average score as a subject of to eat, and a low score as an object of the same verb). Baroni et al. (2014) and Schnabel et al. (2015) followed the procedure of Baroni and Lenci (2010) to perform this task. First, for each verb in the dataset, the 20 nouns which are most strongly associated as subject or object are selected, then a \textit{prototype} vector is calculated as the average of these nouns is calculated. Therefore we will have a subject and object type prototype vector for each verb. The performance of the model will be the correlation degree (spearman) of the averaged human ratings for each type and the cosine scores between the target nouns vectors and the relevant prototype vectors of the verbs.

• **Analogy:** The analogy task asks the model to detect whether two pairs of words stand in the same relation. These relations fall into different types of linguistic relations, such as morphological and semantic relations. Having two word pairs \textit{A:B::C:D} where the \textit{D} is missing, the goal is to find the missing word in the relation: \textit{A} is to \textit{B} as \textit{C} is to \textit{D}, in which \textit{C}, \textit{D} are related by the same relation as \textit{A}, \textit{B}. For example, \textit{France : Paris :: Germany : Berlin}. Following the procedure proposed by Mikolov et al. (2013a), the first term vector in the first pair is subtracted from the second term vector, then the test term is added to the result (\textit{B-A+C}). Afterward, the nearest neighbor to the final vector is requested from the model. The performance of the model is measured as the proportion of the questions where the nearest neighbor suggested by the model is the correct answer (accuracy).
• **Coherence / Outlier Detection**: The goal is to assess whether the neighbor words in the embedding semantic space are mutually related. Therefore a good model should provide coherent neighborhoods for a target word. To tackle this task, groups of coherent words and intruder words are introduced, and the model should be able to spot the word that is an outlier and does not belong to the group of neighbor words. For example, among the following words: (a) *finally* (b) *eventually* (c) *immediately* (d) *put*, the query word is option (a), intruder is (d). Schnabel et al. (2015) presented this intrinsic evaluation as an intrusion task and evaluated the performance of the models by the precision metric. On the other hand, in Camacho-Collados and Navigli (2016), the task was introduced as outlier detection and solved as a clustering problem, in which each group of coherent words are clustered based on a compactness score and the intruder words are ranked by their positions (8 outlier positions: the 1st position has the lowest dissimilarity to the cluster and the 8th position has the highest dissimilarity). The model quality is measured by outlier position percentage and accuracy of the outlier detection.

• **QVEC and QVEC-CCA**: The basic hypothesis of QVEC is that dimensions in distributional vectors encode the linguistic features of words. It measures the quality of a model by how well the embedding correlates with a matrix of features from manually crafted lexical resources. For example, the target word *fish* is assigned to the following senses along with scores: *animal: 0.684, food: 0.157, competition: 0.0526, contact: 0.105*. Tsvetkov et al. (2015) introduced QVEC as a measure to quantify the linguistic regularities of an embedding model. For target words that are in the embedding model, it obtains an alignment between the word vector dimensions and the linguistic dimension in which it maximizes the correlation (Pearson correlation) between the aligned dimensions of the two matrices. The higher the correlation, the more salient the linguistic feature of the dimension. The QVEC-CCA (Tsvetkov et al., 2016) followed the same idea as QVEC. However, to measure the correlation between the embedding matrix and the linguistic matrix, it employs canonical correlation analysis (CCA (Hardoon et al., 2004)). CCA generates two basic vectors for the embedding and feature metrics such that the projections of these two metrics onto their basic vectors have a maximum correlation.

**Comparative intrinsic evaluation**: This type of evaluation is based on direct feedback from the user on the model outcome using a crowd-sourcing environment (e.g., Amazon Mechanical Turk). For each target word, each embedding model is questioned to provide the nearest neighbors at ranks $k \in \{1, 5, 50\}$. Then the human annotators select the most similar answer, and the model that has the majority votes is considered to be the winner. The dataset is called *Query Words* and includes 100 queries (Schnabel et al., 2015).
3. Evaluation of Domain-specific Word Embeddings

Table 3.2: Extrinsic evaluation tasks and datasets.

| Task                        | Data Set                                      | Dataset info. (Train/Dev/Test) | Evaluation Ref.   |
|-----------------------------|-----------------------------------------------|-------------------------------|-------------------|
| POS Tagging                 | Penn Treebank (Marcus et al., 1993)           | 958K, 34K, 58K                | Ghannay et al. (2016) |
|                             |                                               |                               | Chiu et al. (2016b) |
|                             |                                               |                               | Nayak et al. (2016) |
| Chunking                    | CoNLL 2000 (Tjong Kim Sang and Buchholz, 2000) | 191K, 21K, 47K                | Schnabel et al. (2015) |
|                             |                                               |                               | Chiu et al. (2016b) |
|                             |                                               |                               | Ghannay et al. (2016) |
|                             |                                               |                               | Nayak et al. (2016) |
| Named Entity Recognition    | CoNLL2003 (Tjong Kim Sang and De Meulder, 2003) | 205K, 52K, 47K                | Ghannay et al. (2016) |
|                             |                                               |                               | Chiu et al. (2016b) |
|                             |                                               |                               | Nayak et al. (2016) |
| Sentiment Analysis          | Stanford Sentiment Treebank (Socher et al., 2013b) | 8.5K, 1.1K, 2.2K              | Nayak et al. (2016) |
|                             | Movie Reviews (aclimdb) (Maas et al., 2011)   | 25K, -, 25K                   | Schnabel et al. (2015) |
| Question Classification     | TREC (Li and Roth, 2002)                      | 15.5k, -, 500                  | Nayak et al. (2016) |
| Natural Language Inference  | PPDB:Eng (Ganitkevitch et al., 2013a)         | 221.4M                         | Nayak et al. (2016) |

3.2.2 Extrinsic Evaluation

Given the widespread use of word embeddings as input representations in neural NLP systems, the quality of a word vector may also be assessed by performance in downstream tasks. This is done by measuring changes in performance metrics specific to the tasks by extrinsic evaluation. The downstream language technology tasks on which the quality of a word embedding has been examined, fall into syntactic (e.g., POS tagging, Chunking) and semantic (e.g., Named Entity Recognition, Sentiment Analysis) categories. However, by the definition of extrinsic evaluation, any downstream task could be considered as an evaluation method. Various downstream tasks and the related resources that are commonly used in the extrinsic evaluations of word embeddings are as follows (Table 3.2):

**Part-Of-Speech (POS) Tagging**  To identify the morpho-syntactic label of each word in the sentences. The evaluations are performed on the standard Penn treebank dataset (Marcus et al., 1993), using the neural method suggested by Collobert et al. (2011).

**Chunking**  The chunking is a syntactic sequence labeling task where the goal is to locate phrases in the text. The pre-trained embedding models are used as an input for a noun phrase chunking task similar to those employed by Turian et al. (2010) and Collobert et al. (2011) using the dataset of CONLL-2000 shared task (Tjong Kim Sang and Buchholz, 2000).

**Named Entity Recognition**  NER systems perform the task of detecting named entities in text (e.g., persons, locations and organization) as a sequence prediction
Intrinsic Evaluation Setup

Intrinsic evaluation of word embeddings has two main requirements. First, we require a query inventory as a gold standard, and second, a word embedding model that has been trained on a specific corpus. In this section, we describe how we build a domain-specific query inventory for the Oil and Gas domain by exploiting a domain-specific knowledge resource. Then, the domain-specific corpus and the training of the embedding models will be described. We then go on to clarify the evaluation methodology.

3.3.1 Domain-specific query inventory

As an intrinsic evaluation, we would like to assess the quality of representations independently of a specific NLP task. Currently, this type of evaluation is mostly done by testing the overall distance/similarity of words in the embedding space, i.e., it is based on viewing word representations as points and then computing full-space similarity. The assumption is that the high dimensional space is smooth and similar words are close to each other (Yaghoobzadeh and Schütze, 2016). Computational models that could capture similarity as distinct from the association have many applications in language technology such as ontology and dictionary creation, language correction tools, and machine
3. Evaluation of Domain-specific Word Embeddings

Figure 3.1: Term structure in the slb glossary.

translation. As described in detail above, for the general domain, there exists a wide range of gold standard resources for evaluating distributional semantic models in their ability to capture semantic relations of different types, for instance, Simlex-999 (Hill et al., 2015). WordSim-353 (Agirre et al., 2009) and MEN (Bruni et al., 2012) (See Table 3.1).

However, evaluating domain-specific embeddings by applying these gold standards will not provide an adequate picture of their quality since they do not share a common vocabulary and word meanings. The domain of oil and gas has received little previous work in NLP and there are no readily available resources. For this reason, we create a domain-specific gold standard using the Schlumberger oilfield glossary (slb).2 The slb is a reference that defines major oilfield activities and has been created by technical experts.

Figure 3.1 shows the structure of the term caprock in this glossary. Terms are described by their part of speech, their discipline (e.g., Geology, Well Completions), as well as a textual definition. Terms are linked to other terms in the glossary using semantic and lexical relations such as Synonyms, Antonyms, and Alternate forms. It provides a network of related terms that can be navigated through the glossary. In our example entry for instance, we find that the synonyms and alternate forms of caprock are seel and cap rock, respectively. (see Figure 3.1). Finally, if the term has an image that clarifies its definition, it will appear in the image section next to the definition part. All these elements in the

2http://www.glossary.oilfield.slb.com/
Intrinsic Evaluation Setup

| n-gram | #   | Noun | Verb | Adj. | Adv. | Pre-position |
|--------|-----|------|------|------|------|--------------|
| unigram | 1499 | 1261 | 98   | 189  | 1    | 2            |
| bigram  | 2569 | 2505 | 35   | 36   | 1    | 1            |
| trigram | 660  | 644  | 13   | 4    | 0    | 0            |
| >3      | 158  | 149  | 3    | 6    | 0    | 0            |
| All     | 4886 | 4559 | 138  | 246  | 2    | 3            |

Table 3.3: N-grams & Part of speech tags in the slb glossary.

term’s structure are located in the following tables inside a relational database:

**definitions:** All the main terms of the glossary are located in this table. They are defined by id, name, definition, term_type (verb, noun, adjective, adverb, preposition and transitive verb) as part of speech tags, postdate, and lastupdate. It is possible that one term has more than one definition if it has different part of speech tags, or if it is assigned to different disciplines or both. For example, the term dry gas has been assigned to the Geology and Well Completions disciplines and has different definitions in each discipline.

**disciplines:** There are 20 main categories that describe disciplines in the glossary (e.g., Drilling, Geology, Geophysics and Well Completion). Each term in the definitions table is assigned to one or more disciplines and its definition varies based on the assigned discipline.

**images:** To illustrate and clarify many definitions, high-quality and full-color photographs are assigned to the definition by image_name, image_caption and image_url.

**links:** The inter-glossary relations among the terms in the glossary are specified in this table. These relations are characterized with type taken from the following set: Synonym, Antonym, Alternative form and See. These relations form the basis of our intrinsic evaluation dataset.

We construct a domain query inventory by extracting all terms and their inter-glossary relations from the relational database. The terms are converted to lowercase and assigned n-gram type (i.e., a contiguous sequence of a word, unigram where n=1, bigram where n=2, trigram where n=3 and >3 where n>3). The glossary consists of 4,886 terms. Table 3.3 shows the distributions of terms in the glossary concerning their n-gram type and part of speech tags (one term may be assigned to more than one tag).

Following the symmetric nature of the Synonym, Antonym, and Alternative form relations, we infer a relationship if it is missing between terms. The final query inventory contains 878 synonym pairs, 284 antonym pairs and 934...
3. Evaluation of Domain-specific Word Embeddings

| Source                                      | Abbr. | Description                | Docs   | Sentences |
|---------------------------------------------|-------|----------------------------|--------|-----------|
| American Association of Petroleum Geologist | AAPG  | Scientific articles        | 3,382  | 72,243    |
| C&C Reservoirs-Digital Analogs              | CCR   | Field evaluation reports   | 1,140  | 244,017   |
| Elsevier                                    | ELS   | Scientific articles, magazines | 40,757 | 7,703,447 |
| Geological Society, London Memoirs          | GSL   | Scientific articles        | 152    | 32,352    |
| Norwegian Petroleum Directory               | NPD   | Norwegian Field info       | 514    | 49,426    |
| Tellus                                      | TELLUS| Basin info                 | 1,478  | 179,450   |
| Total                                       |       |                            | 47,423 | 8,280,935 |

Table 3.4: Sources of the Oil and Gas corpus.

alternative form pairs. We observe that the majority of terms in the query inventory are multi-word units (70%) and nouns (72%). This indicates that a large portion of the domain-specific vocabulary that we want to capture in our model consists of multi-word entities. Thus we need to take this into account during the training of embeddings.

3.3.2 Training of Word Embeddings

In order to train domain-specific embeddings, we need a domain-specific corpus. Therefore, we compile a corpus consisting of technical reports and scientific articles in the Oil and Gas domain. Table 3.4 shows detailed information about these sources. As we can see, the corpus covers several different genres with a majority taken from the genre of scientific articles. The corpus contains 47,423 documents and 8,280,935 sentences.

As can be seen from Table 3.4, the corpus contains different types of documents from various sources. Figure 3.2 depicts the distribution of sources in the domain corpora. We observe that most of the documents belong to Elsevier, and the other sources cover a small proportion of the documents. The

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3SIRIUS partners provided the sources for the corpus.
domain-specific dataset is preprocessed using the following steps:

1. Tokenization and lemmatization using Stanford-CoreNLP (Manning et al., 2014). English stop words and sentences with less than three words are removed from the corpus.

2. Shuffling: we randomly shuffle the text in the dataset. During the training of embedding models, the learning rate is linearly dropped as training progresses, text appearing early has a more significant effect on the model. Shuffling makes the effect of all text almost equivalent (Chiu et al., 2016a).

For training of the word embeddings, we exploit the available word2vec (see Section 3.3.2 in Chapter 2) implementation gensim (Řehůřek and Sojka, 2010). The elements that impact the performance of the model are the input corpus, model architecture, and the hyper-parameters. In many articles (Fares et al., 2017; Camacho-Collados and Pilehvar, 2018) lemmatizing, case-folding, and shuffling input during training the word2vec are recommended; we carried out our experiments with these settings as detailed above.

We employ the phrase model of gensim, which automatically detects common phrases (multi-word expressions). The phrases are collocations (frequently co-occurring tokens), and we consider bigrams and trigrams in this extraction process. The phrase model has two main parameters:

1. min.count: During training, all words and phrases with total count lower than this number are ignored.

2. threshold: Represents a threshold for forming the phrases (higher means fewer phrases).

A phrase of words $a$ and $b$ is extracted if:

$$\frac{(\text{count}(a,b) - \text{min.count}) \times N}{\text{count}(a) \times \text{count}(b)} > \text{threshold}$$

(3.1)

Here N is the total vocabulary size and $\text{count}(a,b)$ is the total number of times where word $a$ and $b$ co-occur as a multi-word expression in the corpus. We set the $\text{min.count}$ equal to 5 and the $\text{threshold}$ equal to 200 and 100 for bigrams and trigrams, respectively (these values were determined empirically). We further proceed with the domain-specific model generation by creating two sets of embeddings, employing both the CBOW and the Skip-gram architectures (see Section 3.3.2 in Chapter 2) with default settings. In the initial evaluation step, we compare the outcomes of these two models to determine the better architecture.

Embedding models consist of several parameters that can be tuned. We now go on to compare different settings for the hyperparameters, while keeping all other settings constant. It has been claimed in previous works that optimizations of hyper parameters and certain system choices constitute the leading causes
3. Evaluation of Domain-specific Word Embeddings

of differences in performance rather than the algorithms themselves (Levy et al., 2015). Here we investigate the impact of various system design choices in the evaluation of domain-specific embeddings across the following parameters 4:

- **Vector size** \((dim)\): The dimensionality of the learned dense vector is determined by the vector size parameter. \((dim \in 50, 100, 200, 300, 400, 500, 600)\)

- **Context window size** \((win)\): The range of words included in the context of a target word is determined by the window size parameter. For instance, a size of 3, takes three words before and after a target word and injects into the training model as context words. \((win \in 2, 3, 5, 10, 15, 20)\).

- **Negative sampling size** \((neg)\): The idea of word2vec is to maximize the similarity between the word vectors, which appear close together (in the context of each other), and minimize the similarity of words that do not. However, this process includes an expensive computation to calculate the similarity between the target word and all other context words in the corpus. Negative sampling is one of the ways of addressing this problem, by simply selecting a couple of contexts at random and calculating the similarity of target word to randomly chosen negative words. \((neg \in 3, 5, 10, 15)\) (See section 3.3.2 in Chapter 2).

- **Frequency cut off** \((min.count)\): Words with a total frequency lower than the \(min.count\) will be ignored from the corpus. This results in fewer words in the vocabulary of the model. \((min.count \in 2, 3, 5, 10)\).

- **n-most-similar**: The parameter \(n\) for top \(n\)-most-similar as output is fixed at the value 5 (the maximum number of terms that are involved in each relation set in the query inventory).

We evaluate these different system design settings based on our intrinsic benchmark. We train different embedding models by varying values of one hyper-parameter and keeping others as default. After that, we perform evaluations over the domain-specific query inventory.

### 3.3.3 Evaluation measures

For evaluation, we assume that for each term in the inventory, an embedding model should be able to propose similar words which are related semantically as either **synonym**, **alternative form** or **antonym**. We will measure this by looking at a target word and its relation set in the query inventory, for instance, its synonyms and top \(n\)-most similar words predicted by the embeddings model. If the synonym of the target word is in the \(n\)-most-similar words, we will count it as a true positive. Otherwise, the target word and its synonym will be considered as a false negative, and the target word and the predicted word by the model will be counted as a false positive. Since these relations are symmetric, the pairs \((t_i, t_j)\) and \((t_j, t_i)\) are considered equivalent in the evaluation. We calculate the

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4 Default values are in bold.
### Intrinsic Evaluation Experiments

| Model     | Synonymy | Antonymy | Alt. form |
|-----------|----------|----------|-----------|
|           | $A$  | $R$  | $P$   | $A$  | $R$  | $P$   | $A$  | $R$  | $P$   |
| Skip-gram | 9.8 | 8.0 | 2.2   | 46.4 | 41.3 | 9.3   | 12.1 | 10.4 | 2.4   |
| CBOW      | 12.7 | 10.2 | 2.7   | 55.3 | 49.2 | 11.1  | 12.8 | 11.0 | 2.6   |

Table 3.5: Evaluation results for different architectures.

**accuracy** ($A$) as the number of target words for which the model provides at least one correct prediction, the **recall** ($R$) as the number of correctly predicted word pairs over all word pairs (i.e., the sum of true positives and false negatives) and **precision** ($P$) as the number of correctly predicted word pairs over all predicted word pairs (i.e., the sum of true positives and false positives) for each relation category.

### 3.4 Intrinsic Evaluation Experiments

In the following, we present experiments that evaluate the domain-specific word embedding models intrinsically. We first present tuning experiments and then present an experimental comparison between domain-specific and general domain embedding models.

#### 3.4.1 Model architecture: Skip-gram vs. CBOW

First, we compare the models obtained using the different word2vec architectures (CBOW and Skip-gram) with default values for hyper-parameters i.e. $\text{dim} = 100$, $\text{win} = 5$, $\text{min.count} = 5$ and $\text{neg} = 5$. Table 3.5 presents the results for the two architectures broken down by semantic relation from the query inventory. The results show that the embedding models have higher scores for **antonymy** prediction than **synonymy**, see Table 3.5. This result is consistent with previous studies such as Plas and Tiedemann (2006) and Leeuwenberg et al. (2016) in which they reported that using distributional similarity some word categories like antonyms, (co)hyponyms or hypernyms show up more often than synonyms. In general, we find that the CBOW based model shows better results than the Skip-gram in all semantic relation tasks.

#### 3.4.2 Hyper-parameter tuning

We go on to explore the impact of each hyper-parameter on the detection of semantic relations. We observe that the performance of the embedding models can be notably improved over the default hyper-parameters, but like the findings in other studies (Gladkova et al., 2016; Chiu et al., 2016a), the effects of different configurations are diverse and sometimes they are contradictory. For example,
3. Evaluation of Domain-specific Word Embeddings

| dim | Synonymy | Antonymy | Alt. form |
|-----|----------|----------|-----------|
|     | A        | R        | P        | A        | R        | P        | A        | R        | P        |
| 50  | 12.7     | 10.2     | 2.7      | 48.2     | 42.9     | 9.6      | 11.4     | 9.8      | 2.3      |
| 100 | 12.7     | 10.2     | 2.7      | 55.4     | 49.2     | 11.1     | 12.9     | 11.0     | 2.6      |
| 200 | 14.7     | 12.4     | 3.3      | 55.4     | 49.2     | 11.1     | 14.3     | 12.3     | 2.9      |
| 300 | 15.7 **13.1** | 3.5      | 55.4     | 49.2     | 11.1     | 13.6     | 11.7     | 2.7      |          |
| 400 | 15.7 **13.1** | 3.5      | 57.1     | **50.8** | **11.4** | 13.6     | 11.7     | 2.7      |          |
| 500 | 14.7     | 12.4     | 3.3      | 53.6     | 47.6     | 10.7     | **15.0** | **12.9** | **3.0**  |          |
| 600 | 14.7     | 12.4     | 3.3      | 51.8     | 46.0     | 10.4     | 12.9     | 11.0     | 2.6      |          |
| 700 | 14.7     | 12.4     | 3.3      | 53.6     | 47.6     | 10.7     | 13.6     | 11.7     | 2.7      |          |

Table 3.6: Evaluation results for different vector size (default=100).

| win | Synonymy | Antonymy | Alt. form |
|-----|----------|----------|-----------|
|     | A        | R        | P        | A        | R        | P        | A        | R        | P        |
| 2   | 12.7     | 10.2     | 2.7      | 55.4     | 49.2     | 11.1     | **13.6** | **12.3** | **2.9**  |
| 3   | **13.7** | **12.4** | **3.3**  | 48.2     | 42.9     | 9.6      | 11.4     | 9.8      | 2.3      |
| 5   | 12.7     | 10.2     | 2.7      | 55.4     | 49.2     | 11.1     | 12.9     | 11.0     | 2.6      |
| 10  | 13.1     | 10.9     | 2.9      | 53.6     | 47.6     | 10.7     | **13.6** | **12.3** | **2.9**  |
| 15  | 12.7     | 10.2     | 2.7      | **67.1** | **50.8** | **11.4** | 12.9     | 11.0     | 2.6      |
| 20  | 12.7     | 10.2     | 2.7      | 53.6     | 47.6     | 10.7     | 12.1     | 10.4     | 2.4      |

Table 3.7: Evaluation results for different context window size (default=5).

different relation categories benefit from different context window sizes, and we find that the model with larger context windows tends to capture the *antonymy* relation while a model with smaller windows, better captures *synonymy* relation of the words. We also observe that negative sampling and frequency cut-off parameters have different impacts on the three relation categories.

**Vector size (dim)** The effect of vector size on the trained models is quite similar in all tasks (Table 3.6). We observe a large improvement in all evaluations when the dimensionality is increased. However, the improvement peaks at 400 for the *synonymy* and *antonymy* predictions and 500 for *alternative form*.

**Context window size (win)** Table 3.7 depicts the impact of window size per evaluation task. We find that the embedding model can benefit from low window size ($w=3$) for the *synonymy* task while in *antonymy* and *alternative* form tasks the model performance fluctuates between lower and higher window sizes.
Intrinsic Evaluation Experiments

| neg | Synonymy | Antonymy | Alt. form |
|-----|----------|----------|-----------|
|     | A  | R  | P  | A  | R  | P  | A  | R  | P  |
| 3   | 12.7| 10.2| 2.7| 53.6| 47.6| 10.7| 12.1| 10.4| 2.4|
| 5   | 12.7| 10.2| 2.7| 55.4| 49.2| 11.1| 12.9| 11.0| 2.6|
| 10  | 12.7| 10.2| 2.7| 55.4| 49.2| 11.1| 13.0| 11.7| 2.7|
| 15  | 12.7| 10.2| 2.7| 51.8| 46.0| 10.4| 13.6| 12.3| 2.9|

Table 3.8: Evaluation results for different number of negative samples (default=5).

| min.count | Synonymy | Antonymy | Alt. form |
|------------|----------|----------|-----------|
|            | A  | R  | P  | A  | R  | P  | A  | R  | P  |
| 2          | 12.4| 9.9 | 2.7| 54.4| 48.4| 10.9| 13.0| 11.8| 2.7|
| 3          | 12.6| 10.1| 2.7| 56.1| 50.0| 11.2| 13.2| 12.0| 2.8|
| 5          | 12.7| 10.2| 2.7| 55.4| 49.2| 11.1| 12.9| 11.0| 2.6|
| 10         | **13.1**| **10.4**| **2.8**| 54.7| 48.3| 10.9| 13.0| 11.8| 2.7|

Table 3.9: Evaluation results for different value for frequency cut off (default=5).

**Negative sampling (neg)**  Unlike the practical recommendation in Levy et al. (2015) who state that the skip-gram model prefers many negative samples, the CBOW model shows the contradictory result with respect to this parameter in our evaluation benchmarks. Table 3.8 presents that the results remain constant regardless of the negative sampling number in the synonym prediction task. On the other hand, we find that the performance correlates with an increase of this parameter in alternative form detection. For the antonym task, performance reaches a peak on neg equal to 5 and 10 before dropping.

**Frequency cut off (min.count)**  The impact of excluding words that are less frequent in response to variation of the min.count parameter is summarized in Table 3.9. This parameter shows a different impact compared to the other parameters. While, ignoring more words has a positive effect in synonymy detection, improvement halts at min.count = 3 for antonymy and alternative form relations.

Since the context window size (win), negative sampling (neg) and frequency cut off (min.count) parameters showed inconsistent results among the relations, we selected the CBOW model with vector size (dim) equal to 400 and we fixed the other parameters to their defaults i.e. win = 5, min.count = 5 and neg = 5. This configuration, hereinafter referred to as OilGas.d400, showed the overall best performance during the tuning experiments.
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![Table 3.10: General domain and domain-specific embedding models.](image)

| Model          | Coverage          | dim |
|----------------|-------------------|-----|
| Google News    | 26% (100B, 3M)    | 300 |
| Wiki+Giga      | 23% (6B, 400K)    | 300 |
| OilGas.d400    | 31% (108M, 330K)  | 400 |
| enwiki         | 29% (1.8B, 2M)    | 400 |
| enwiki+OilGas  | 31% (1.9B, 2.3M)  | 400 |

3.4.3 Comparative evaluation

In order to compare the domain-specific embeddings with general domain embeddings, we select two widely used pre-trained embedding models: Wiki+Giga \(^5\) and GoogleNews \(^6\) to see how they perform in our evaluation benchmark. The pre-trained models were chosen to have similar settings to our models. The input data in the Wiki+Giga has been tokenized and lowercased with the Stanford tokenizer, whereas the GoogleNews model is trained on a part of the Google News dataset and it contains both words and phrases. The phrases are obtained using the same approach, as described in Section 3.3.2. The words are not lemmatized in both models, and GoogleNews also contains capitalized words.

The results of the comparative evaluation of the domain-specific and pre-trained models are summarized in Table 3.11. Since the words in the vocabularies of both pre-trained models are not in lemma form, we consider the surface form of terms for the evaluation. We also report the proportion of query terms that are covered by the vocabulary of each model as coverage. We find that despite the large input and vocabulary size in both GoogleNews and Wiki+Giga models, they have less coverage than the domain-specific model. We further observe that (see Tables 3.10 and 3.11) despite the considerably smaller training data set, the OilGas.d400 performs better across all the tasks.

It is clear that, this comparison is somewhat unfair due to differences in pre-processing and hyperparameter tuning. Therefore, to investigate the impact of these differences, we apply the same pre-processing steps and hyperparameters to train the CBOW model over the English Wikipedia dump (20 September 2016), here dubbed enwiki. Furthermore, we conduct a similar experiment with a data set consisting of both the general and domain-specific corpora (enwiki+OilGas). However, these approaches do not show further improvements in our evaluation benchmark, as reported in Table 3.11. Surprisingly, the mixing of Wikipedia and OilGas does not increase the coverage rate. It can be attributed to the fact that the phrase extraction method (Section 3.3.2) is not able to capture the missing multi-word expressions. In many cases in the mixed corpus (enwiki+OilGas)

\(^5\)https://nlp.stanford.edu/projects/glove/

\(^6\)https://code.google.com/archive/p/word2vec/
the relative increase in the frequency of tokens individually is higher than the relative increase of co-occurring tokens (e.g., the relative increase of the word 'source' and the word 'rock' in the enwiki+OILGAS is larger than the relative increase of the word 'source rock' compared to the OILGAS corpus).

### 3.5 Manual Analysis

The results in Section 3.4.3 show that the domain-specific model provides better results than general domain models for a domain-specific benchmark. However, we also observe that performance is low for all three tasks, in particular for the synonymy detection task. In this section, we explore the reasons behind these low scores and gain insight into the domain-specific model predictions, in particular the synonymy detection, through an in-depth error analysis.

As noted above, the primary cause of low performance is due to out of vocabulary (OOV) terms in the query inventory. As shown in Table 3.10 the model vocabulary contains only 31% of the evaluation dataset. We find that the majority of terms that participate in synonymy relations are not included in the word embeddings model, this is in particular the case for multiword items. The majority of these terms either do not occur or have a frequency lower than the cut off threshold in the domain dataset. Excluding the OOV terms from the evaluation tasks has some impact on the model performance for synonymy detection, recall (R) is 29%, and precision (P) is 6.5%. Still, these scores are low, we therefore examine the model predictions closer.

We randomly choose 100 terms from the reference inventory, which are also in the model vocabulary, and we manually categorize their 10-most-similar words provided in the word embeddings. The manual analysis was performed by two domain experts as well as the author.

In this section, we are inspired by the work of Leeuwenberg et al. (2016), where the authors categorized the result of embeddings for a synonym extraction task in the following categories (The categories with * are added by us).
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- **Spelling Variant**: The prediction is an abbreviation or there are differences between prediction and target word because of hyphenation.

- **Alternative or derived form**: The prediction is an alternative or derived form of the target word.

- **Reference-Synonyms**: The prediction is a synonym of the target word in the oilfield glossary.

- **Human-judged Synonyms**: The prediction is judged as true by the expert (but is not present in the glossary).

- **Antonyms**: The prediction is an antonym of a target term.

- **Hypernyms**: The prediction is a more general category of the target term.

- **Hyponyms**: The prediction is a more specific type of the target term.

- **Co-Hyponyms**: The prediction and target term share a common hypernym.

- **Holonyms**: The prediction denotes a whole whose part is denoted by the target term.

- **Meronyms**: The prediction is a part of the target term.

- **Related**: The prediction is semantically related to target.

- **Unrelated/Unknown**: The prediction and target terms are semantically unrelated.

3.5.1 Annotation tools

For manual analysis, the domain experts are asked to categorize the randomly selected terms (Section 3.5) and their 10-most-similar words provided by the domain-specific embedding model. We implement a live web application using React.js and the Firebase platform. Figures 3.3, 3.4 and 3.5 depict screenshots of the annotation environment. The annotator can log in to the annotation environment using the first screen (Figure 3.3). Then, the annotator selects the discipline that he/she wants to annotate (Figure 3.4). In the annotation interface (Figure 3.5), we provide the target words according to their discipline in the Schlumberger oilfield glossary. Each annotation page contains a target word at the top and the 10-most-similar words provided by the model in the grid (predicted words). The annotators should consider a target word and a predicted word as a pair and select one of the target categories. Each category is denoted by its abbreviation in the page (e.g., "Synonyms" as "SYN"). In each annotation page, there are 10-word pairs. Using "Next" and "Back", the annotators can navigate through the pages. In the end, they will find a "Submit" button.

7http://obscure-tor-63439.herokuapp.com/
Survey App

Figure 3.3: Annotation interface (1): login and annotation guideline.

Figure 3.4: Annotation interface (2): disciplines and years of experience.
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Figure 3.5: Annotation interface (3): target and prediction word pairs and relations.
Manual Analysis

Figure 3.6: Agreements/Disagreements categories among annotators. Each column shows the number of pairs in which there is an agreement among the annotators. It also shows the category that has been assigned by one of the annotators in case of disagreement. (e.g., in alternative or derived form (ALT), all annotators agree on 13 instances, while there is a disagreement in one instance and one of the annotators selects the spelling variant (SPL)).

button to send the results. Using this tool, the annotators assign each pair, i.e., target and predicted word to one of the categories. We also allow annotators to leave empty the assignment if they do not have sufficient knowledge about the relation between the terms. In order to encourage inter-annotator consistency, we provide a general annotation guideline (Figure 3.3).

3.5.2 Results and discussion

We receive annotation results for 240-word pairs (24 target words) from the domain experts in the geology discipline. We report the inter-annotator agreement as a proportion of agreement. For this task, we do not use the
3. Evaluation of Domain-specific Word Embeddings

Kappa statistic as the chance of agreement for the task is very low due to implicit similarity among the categories. We observe that in 175 cases, we have a majority agreement among three annotators. Moreover, all the annotators agree in 72 cases. By this observation, the inter-annotator agreement for the task is \( \frac{175}{240} = 0.729 \).

To explore the disagreements of annotators in more detail, we extract the instances for which the two annotators determine the same category, whereas the third annotator selects another category, and we report it as a confusion matrix.

Figure 3.6 shows the resulting confusion matrix. In general, we find that the annotators disagree in terms of similar categories. For example the hyponyms are annotated as meronyms, related, synonyms and co-hyponyms. The categories with the highest number of disagreements are hyponyms, hypernyms, related and synonyms. The annotators agree mostly on alternative or derived form and unrelated categories. For further analysis, we consider the majority vote among the annotators as a final category for the word pairs.

Table 3.12 shows the result of this analysis. We count the number of each category that has been considered as an error in the synonym extraction task. It means that a word is predicted as 10-most-similar words (i.e., 1\(^{st}\):10\(^{th}\)) by the model and is considered as a false positive. However, the prediction and target word are assigned to a specific category during the manual annotation process.

In general, the result of this analysis shows that the model predictions are semantically meaningful in a majority of cases, and all categories except the Unrelated/Unknown represent some type of morphosyntactic or semantic relation between terms. Less than 20\% of the errors are assigned to the Unrelated/Unknown category. This reveals that if we consider the count of human-judged synonyms as true positives, the actual scores for precision and recall will be considerably higher than those reported in the evaluation section. Moreover, the embeddings model proposes more synonyms that are not in the reference, even though the reference is provided by the manual procedure. The most frequent error type falls in the related category.

The hyponym and co-hyponym relations are another frequent error type that were also reported in previous studies (Plas and Tiedemann, 2006; Leeuwenberg et al., 2016). The morphosyntactic type of relations such as Alternative forms, spelling variant cover another type of errors. The error analysis further reveals several meaningful relation types such as Hypernyms, Meronyms, and Holonyms that are useful in many downstream applications.

3.6 Embedding Enrichment Using a Knowledge Resource

Even though the word embeddings capture important semantic relations in the domain, the first experiment shows that the domain-specific technical vocabulary has many elements that are generally disregarded by the distributional representation techniques. In other words, they still fall short of providing domain-specific representations for many terms. These approaches rely on the
Embedding Enrichment Using a Knowledge Resource

| Category                        | Example [target→ prediction]                                      | $1^{st}$:$10^{th}$ $(\%)$ |
|--------------------------------|--------------------------------------------------------------------|-----------------------------|
| 1. Spelling Variant            | borehole → bore-hole                                              | 2.4                         |
| 2. Alternative or derived form | acidizing → acidization                                            | 3.2                         |
| 3. Reference-Synonyms          | filter cake → mud cake                                            | 2.8                         |
| 4. Human-judged Synonyms       | seismometer → seismograph                                         | 8.4                         |
| 5. Antonyms                    | transgressive → regressive                                        | 0.9                         |
| 6. Hypernyms                   | acidizing → stimulation                                           | 1.3                         |
| 7. Hyponyms                    | EOR → In-situ combustion                                          | 9.3                         |
| 8. Co-Hyponyms                 | EOR → MEOR                                                        | 13.1                        |
| 9. Holonyms                    | shoe → wellbore                                                   | 1.1                         |
| 10. Meronyms                   | rig → wellhead                                                    | 2.8                         |
| 11. Related                    | Kirchhoff migration → NMO correlation                             | 35.2                        |
| 12. Unrelated/Unknown          | backflow → sediment-laden                                         | 19.5                        |

Table 3.12: Manual analysis results for the 10-most-similar words.

statistics derived from textual input; therefore, they are incapable of providing representations for words that are not seen frequently in the training process. Furthermore, they do not include the valuable information that is accommodated in domain knowledge resources such as semantic lexicons and glossaries. In this section, we address these issues by applying a set of techniques that exploit prior domain knowledge in enhancing the embedding models and induce representations for OOV terms. We then go on to evaluate the impact of the refinement methods over an unseen terminological resource.

3.6.1 Related Work

Although word embedding techniques have drawn significant interest in the field, they are not well equipped to deal with unseen and infrequent words, nor do they consider word relations found in knowledge resources. Improving the quality of embedding models has been an active area of research for the past few years. Based on the way they view the problem, these techniques can be classified into two main branches: (1) Improving word vectors using lexical resources, (2) Learning representations for rare words.

In the first line of techniques, researchers work on leveraging semantic knowledge resources such as WordNet (Miller, 1995), PPPD (Ganitkevitch et al., 2013b), and FrameNet (Baker et al., 1998) as a relational semantics to improve the outcome of distributional semantics. Such semantic knowledge can provide the sense of the word, its relation with other words, such as synonyms, antonyms, hypernymy, and meronymy. The question is how to design new distributional semantic algorithms to leverage relational semantics and generate high-quality word embeddings given the availability of morphological, syntactic, and semantic knowledge. In Yu and Dredze (2014), and Fried and Duh (2015), it was shown that the quality of word vectors could be improved by using
semantic knowledge from lexicons. In both works, they propose a new training objective that incorporates the word2vec language model objective and prior knowledge from semantic resources. These models use constraints among words as a regularization term on the learning objective during training. However, the proposed models are built on a specific distributional semantic technique i.e., word2vec. Similarly, Faruqui et al. (2015) and Pilehvar and Collier (2016a) proposed a refinement method as a post-processing step which exploits knowledge from the semantic network to apply to existing pre-trained embeddings. These approaches are general in that they can be readily applied to any set of word representations and any semantic network and they are not limited to particular methods for constructing vectors.

The Zipfian distribution (Zipf, 1972) is a characteristic of words in natural language, where some words are frequent, but most are rare. Learning representations for words in the "long tail" of this distribution is challenging for word embedding techniques since their learning methods require many occurrences of each word to generalize well. The second branch of related work includes methods that produce representations for words that were not encountered frequently during the training of the embeddings models. Botha and Blunsom (2014) and Soricut and Och (2015) have proposed methods that incorporate morphological information into word representations. They focus on morphologically complex rare words and tried to derive representations of words from morphemes using different composition functions. In another framework for the training of word embeddings, known as fasttext, Bojanowski et al. (2017) improved the representation of words by taking into account subword information. The proposed approach incorporates character n-grams into the skip-gram model. It can construct a vector for a word from its character n-grams, even if a word does not appear in the training corpus. However, these techniques are incapable of deriving representations for words for which no sub-word information might be available in the training corpus, such as infrequent domain-specific terms.

To expand the vocabulary of the embedding model not only for morphological variation but also for unseen and infrequent domain-specific words, the approach proposed by Pilehvar and Collier (2017) exploits the knowledge encoded in lexical resources and induce vector representation for terms which either have low frequencies or are non-existent in domain corpora. Here, we employ the techniques of Pilehvar and Collier (2017) and Faruqui et al. (2015), since they can be applied to vectors obtained from any word vector training method as a post-processing step. In the following sections, these approaches are described further, and their impacts in our study are subsequently evaluated.

### 3.6.2 Embeddings for infrequent terms

To induce embeddings for rare and unseen words, Pilehvar and Collier (2017) recommend a technique that expands the vocabulary of pre-trained embedding models. The technique leverages knowledge encoded in external lexical resources that provides better coverage of rare words or comprises domain-specific terminologies. It assumes that there is a pre-trained word embedding model $W$.
and a lexical resource $S = (V, E)$ in a graph structure, where $V$ is a set of nodes that correspond to words and $E$ is a set of semantic relations among the words. To produce an embedding for an infrequent word $w_r$ that does not exist in the vocabulary of $W$, but is covered by $S$, the following phases are implemented:

I. Word Semantic Landmarks Extraction A set of landmarks for word $w_r$ are the most semantically similar words, which can be extracted from $S$. As shown in Figure 3.7, it is achieved by viewing $S$ as a semantic network and analyzing its structure. The semantic landmarks for word $w_r$ are extracted by using the Personalized PageRank (Haveliwala, 2003) algorithm, here dubbed PPR. The PPR provides promising results in many NLP tasks such as Word Sense Disambiguation (Agirre and Soroa, 2009), Named entity linking (Nooralahzadeh et al., 2016) and Word sense similarity (Pilehvar andNavigli, 2015). The PPR is a modified version of PageRank (Brin and Page, 1998) algorithm. PageRank is a method for ranking the nodes in a graph according to their relative structural importance. The main idea of PageRank is that whenever a link from node $i$ to node $j$ exists in a graph, a vote from node $i$ to node $j$ is produced, and hence the rank of node $j$ increases. Besides, the strength of the vote from $i$ to $j$ also depends on the rank of node $i$: the more important node $i$ is, the more strength its votes will have. Moreover, PageRank can also be viewed as the result of a random walk process, where the final rank of node $i$ represents the probability of a random walk over the graph ending in node $i$, for sufficiently many steps.

Let $S$ be a graph derived from external lexical resources, with $n$ nodes $\{w_1, \ldots, w_n\}$ and $d_i$ be the outdegree of node $i$; let $P_{n \times n}$ be a transition probability matrix, where $P_{i,j}$ denotes the probability of shifting from node $i$ to node $j$. The $P_{i,j}$ is equal to the inverse of $d_i$ if there is a semantic link from $i$
3. Evaluation of Domain-specific Word Embeddings

to \( j \) and zero otherwise. Therefore, to calculate PageRank vector \( x^T \) over \( S \) for each node \( i \), the power method can be used as follows:

\[
x^{(t)T} = \alpha x^{(t-1)T} P + (1 - \alpha) v
\]  \hspace{1cm} (3.2)

In equation 3.2, \( v \) is the \( n \times 1 \) column vector in which the prior importance of each node is assigned to the cell corresponding to each node and \( \alpha \) is the damping factor, a scalar value between 0 and 1. In the traditional PageRank, the vector \( v \) is a stochastic normalized vector whose element values are all \( \frac{1}{n} \), thus assigning equal probabilities to all nodes in the graph in case of random jumps. However, in PPR, a modified version of \( v \) is used. PageRank is calculated by applying an iterative algorithm that computes the equation successively until convergence below a given threshold is achieved, or, more typically, until a fixed number of iterations are executed. Once \( x^T \) is calculated for a word \( i \) in the semantic lexicon, we can obtain a list of most similar words to the \( w_i \), i.e., semantic landmarks for word \( i \), by sorting the \( x^T \) according to their probabilities.

II. Embedding Induction: Let \( L_i \) be a sorted list of semantic landmarks for word \( i \) and \( q(x) \) be an embedding of word \( x \) in the space of \( W \). The induced embedding for \( w_i \) in the same semantic space can be provided using the following equation:

\[
\hat{q}(w_i) = \theta q(w_i) + \frac{1}{|L_i|} \sum_{j=1}^{|L_i|} e^{-i} q(l_{j,i})
\]  \hspace{1cm} (3.3)

where \( l_{j,i} \) is the \( j^{th} \) word in \( L_i \) and \( q(w_i) \) is the observed embedding of word \( w_i \) in \( W \). Here the intuition is to calculate a new embedding for \( w_i \) by the weighted average of its semantic landmarks. The exponential weighting provides more importance to the top words in the semantic landmarks since these are more representative for word \( i \). The parameter \( \theta \) adjusts the contribution of the initial embeddings \( q(w_i) \) in the final embeddings. To induce embeddings for unseen words, \( \theta \) is set to zero.

In another work, Faruqui et al. (2015) proposed the retrofitting method as a post-processing step to apply to existing pre-trained embeddings. The goal is to refine word vector representations to capture relatedness suggested by semantic lexicons while preserving their similarity to the corresponding embeddings. The objective of the retrofitting method is to minimize the following:

\[
\Psi(Q) = \sum_{i=1}^{n} \left[ \alpha_i ||q_i - \hat{q}_i||^2 + \sum_{(i,j) \in E} \beta_{ij} ||q_i - q_j||^2 \right]
\]  \hspace{1cm} (3.4)

where \( \hat{q} \in \hat{Q} \) is the observed vector representation for each term in the semantic lexicon and \( q \in Q \) is the corresponding retrofitted vector.

The method aims to learn \( Q \) such that the \( q \) is close to its counterparts in \( \hat{Q} \) (i.e., \( \hat{q} \)) and to adjacent nodes in the semantic lexicon under a distance metric. Figure 3.8 depicts an example graph with such connections; white nodes are
Embedding Enrichment Using a Knowledge Resource

Figure 3.8: Graph with links between related words showing the observed (grey) and the inferred (white) word vectors. (Faruqui et al., 2015).

labeled with the retrofitted vectors \( q \), shaded nodes are labeled with the observed ones \( \hat{q} \). \( E \) is the set of relations among the terms in the semantic lexicon. \( \alpha \) and \( \beta \) correspond to the relative weights of the relation type. Since \( \Psi \) is convex in \( Q \), an efficient iterative updating method is used to solve the objective function. Retrofitted embeddings \( Q \) are initialized to be equal to the observed ones \( \hat{Q} \). Then by taking the first derivative of \( \Psi \) with respect to \( q_i \) the following online update is used for ten iterations to reach convergence:

\[
q_i = \frac{\sum_{j: (i,j) \in E} \beta_{ij} q_j + \alpha_i \hat{q}_i}{\sum_{j: (i,j) \in E} \beta_{ij} + \alpha_i} \tag{3.5}
\]

The formula in the Eq. 3.5 computes a new embedding for a term \( i \), which is in the pre-trained model and has relations of interest in the semantic lexicon, whereas its neighbors should be part of the pre-trained model. To provide an embedding for OOV words, we extend \( \hat{Q} \) in each iteration by adding the terms that are in the semantic lexicon and connect to the terms that are in \( \hat{Q} \) via relations of interest. Since there is no initial vector for these type of words in the observed model, \( \alpha \) is set to zero, and the online update formula for the OOV terms will be as follows:

\[
q_i = \frac{\sum_{j: (i,j) \in E} \beta_{ij} q_j}{\sum_{j: (i,j) \in E} \beta_{ij}} \tag{3.6}
\]

### 3.6.3 Additional domain-specific query inventory

We use another domain-related glossary to perform a quantitative comparison of domain-specific word embeddings before and after the inducing and retrofitting process. We create a test query inventory using the same approach as explained
3. Evaluation of Domain-specific Word Embeddings

Figure 3.9: Term structure in the Geoscience Vocabularies (GeoSci) data set.

in Section 3.3.1 over the Geoscience Vocabularies data set, here dubbed GeoSci. GeoSci was developed by the IUGS (CGI Commission for the Management and Application of Geoscience Information). GeoSci covers the domain of geology and describes geological features, geological time, mineral occurrences, and mining-related features. Figure 3.9 shows the structure of the term carbonate mud in this domain-specific resource. Each term is defined as a resource under geosciml name-space with a specific URI. Resources are linked to other resources with syntactically and semantically aligned relations such as Abbreviated label, Synonym, Broader and Narrower.

We construct a test query inventory by extracting all terms and their inter-glossary relations from the RDF files. Table 3.13 shows the distributions of terms in the glossary with respect to their n-gram and participated relations. The test set consists of 1,753 terms. It contains 196 synonym pairs, 1,639 broader pairs, 1,584 narrower pairs and 986 abbreviated label pairs. Like the slb glossary, the majority of terms are multi-word units (63%).

---

8 http://resource.geosciml.org/
9 Uniform Resource Identifier
10 GeoSic vocabulary specifies this relation as Alternative label.
Table 3.13: N-grams and Relations in the Geoscience Vocabularies (GeoSci) data set.

| n-grams | #  | Synonymy | Broader | Narrower | Abbr. label |
|---------|----|----------|---------|----------|-------------|
| unigram | 651| 110      | 588     | 387      | 730         |
| bigram  | 598| 45       | 550     | 737      | 201         |
| trigram | 328| 28       | 326     | 305      | 47          |
| >3      | 176| 13       | 175     | 155      | 8           |
| All     | 1753| 196     | 1639    | 1584     | 986         |

3.6.4 Experiments and Evaluation

We use the structure of the slb glossary as prior domain knowledge to enrich the OilGas.d400 embeddings model that was selected as the best embedding model following our experiments in Section 3.4. To enrich the pre-trained embeddings, we employ the two techniques that are described in Section 3.6.2 as follows:

**Inducing embeddings for unseen words:** We create the semantic graph $G = (V, E)$ using the slb glossary, where $V$ is the set of slb terms and $E$ is the set of edges that denote semantic relationships i.e., *synonymy*, *antonymy* and *alternative form* among terms in $V$. For each term in $V$, we extract semantic landmarks using the PPR algorithm by using Eq. 3.2. We set the damping factor $\alpha$ to its default value (0.85), and the personalize vector $v$ is a one-hot initialization vector in which 1.0 is assigned to the cell corresponding to the term. We choose top $n = 10$ most similar words according to their probability in $x(t)$ as a semantic landmark for each word. We induce new embeddings for observed terms in the OilGas.d400 embedding model by exploiting the Eq. 3.3 and setting $\theta$ to 1.0 and for OOV to zero (".induced#10").

**Retrofitting Word Vectors to Semantic Lexicons** Experiments in Faruqui et al. (2015) showed that including all semantic relations in the retrofitting process has a better impact than having only one of them. We, therefore, consider connections of a word to its synonyms, alternative forms, and antonyms. Moreover, similar to the origin, all $\alpha_i$ are set to 1 and $\beta_{ij}$ to be $\text{degree}(i)^{-1}$. The Eq. 3.6 is used to retrofit the OilGas.d400 model by employing the structure of the semantic lexicon (".retrofitted"). To induce word vectors for OOV terms, we carry out the retrofitting process with Eq. 3.6 (".retrofitted+OOV").

Table 3.14 shows the performance of the model in the test dataset as well as the induced and retrofitted models with two different configurations. We observe that the inducing algorithm has negative impacts on the *synonymy* and *abbreviated label* relation. It seems that with a small semantic lexicon, the inducing algorithm provides noisy semantic landmarks for each term, which leads the induced embeddings vector to be close to non-related terms. However, the retrofitting
3. Evaluation of Domain-specific Word Embeddings

| Model                     | Synonymy | Antonymy | Alt. form |
|---------------------------|----------|----------|-----------|
|                           | A        | R        | P         | A        | R        | P         | A        | R        | P         |
| OilGas                    | 25.5     | 15.5     | 5.1       | 12.5     | 5.0      | 2.7       | 4.7      | 4.4      | 0.9       | 2.4      | 2.3      | 0.5       |
| OilGas.induced#10         | 11.0     | 6.7      | 2.2       | 12.5     | 5.0      | 2.7       | 4.7      | 4.4      | 0.9       | 2.0      | 2.0      | 0.4       |
| OilGas.retrofitted        | 27.4     | 16.7     | 5.5       | 12.5     | 5.0      | 2.7       | 4.7      | 4.4      | 0.9       | 2.2      | 2.2      | 0.4       |
| OilGas.retrofitted+OOV    | 30.2     | 18.4     | 6.1       | 12.5     | 5.0      | 2.7       | 4.7      | 4.4      | 0.9       | 2.4      | 2.3      | 0.5       |

Table 3.14: Evaluation over the GeoSci knowledge resource.

| Model                     | Synonymy | Antonymy | Alt. form |
|---------------------------|----------|----------|-----------|
|                           | A        | R        | P         | A        | R        | P         | A        | R        | P         |
| OilGas.retrofitted        | 55.0     | 47.3     | 12.4      | 87.3     | 82.2     | 18.5      | 32.6     | 29.1     | 6.8       |
| OilGas.retrofitted+OOV    | 94.6     | 90.7     | 25.3      | 98.5     | 97.6     | 24.1      | 96.2     | 94.7     | 21.7      |

Table 3.15: Evaluation in the slb data set (learning data set).

process provides an improvement in the synonymy relation. The improvement is highest when we consider the adapted version (retrofitted+OOV). Interestingly the inducing and retrofitted models have no impact in the narrower and broader relationships. This can be attributed to the fact that the employed semantic lexicon does not include these kinds of associations to lead the retrofitting process. In the abbreviated label relation, there is a slightly negative effect when we apply the original retrofitting process. Expectedly, the applied retrofitting process encourages the terms in semantic lexicons to have similar vector representations with respect to their semantic and morphosyntactic relations (i.e., synonymy, antonymy and Alternative forms). The improvement is biggest for retrofitted models when they are assessed in the query inventory generated from the input semantic lexicons. Covering OOV terms by using Eq.3.6, empowers the model to provide high performance in each relation benchmark (Table 3.15).

3.7 Extrinsic Evaluation

While the intrinsic evaluation attempts to interpret the encoding content of an embedding model in terms of lexical-semantic relations, extrinsic evaluation investigates the contribution of an embedding model to the performance of a specific downstream task (Section 3.2.2). In this section, we investigate the influence of our domain-specific model in a domain related classification task.

3.7.1 Classification Data Set

The task of the exploration department in the Oil and Gas industry is to find exploitable deposits of hydrocarbons (oil or gas). Geo-scientists in the exploration
Extrinsic Evaluation

| Property               | Label | # Sentences |
|------------------------|-------|-------------|
| Lithology_Main         | \(L_M\) | 1,193       |
| DepEnv_Main            | \(D_M\) | 483         |
| Facies                 | F     | 387         |
| DepEnv_Sub             | \(D_S\) | 298         |
| Lithology_RockType     | \(L_R\) | 191         |
| BasinType              | B     | 49          |
| DepEnv_General         | \(D_G\) | 38          |

Table 3.16: Classification data set.

department model the subsurface geography by classifying rock layers according to multiple stratigraphic hierarchies using information from a wide range of different sources. The quality of the analysis depends on the availability and the ease of access to the relevant data. Previous technical studies, reports, and surveys are crucial resources in this process.

We were granted access to a dataset of 1,348 sentences from exploration textual documents, which are then manually labeled with various geological type properties by domain experts. Example 3.7 shows a sentence from the data set along with its assigned set of properties.

(3.7) *Submarine fans and deltaic/estuarine facies of the San Juan Formation were deposited during the Maastrichtian regression, which gave way during the Paleocene-Eocene to black marine shales and carbonates of the Vidoño Formation and the shelfal and pro-delta shales of the Caratas Formation.*

Properties: Lithology_RockType \((L_R)\), Lithology_Main \((L_M)\), DepEnv_Sub \((D_S)\), DepEnv_General \((D_G)\)

The resulting data set contains 1,348 sentences in which experts assigned each sentence to 7 different properties. The sentences are pre-processed using the same approach, as described in Section 3.3.2. Table 3.16 depicts the properties and number of sentences for each. It is clear that the data set is unbalanced regarding the properties, and the downstream task is a multi-label classification task.

### 3.7.2 Multi-label Classification Model

We use a slight variant of the *Convolutional Neural Networks* (CNNs) architecture (see Section 2.2.2 in Chapter 2) that is proposed by Kim (2014) for sentence classification tasks. We keep the value of hyperparameters equal to the ones that are reported in the original work, however we update the dimension of the embedding layer according to the dimension of the domain-specific embedding
3. Evaluation of Domain-specific Word Embeddings

| Model                        | $D_S$ | $L_M$ | B   | $D_G$ | F   | $D_M$ | $L_R$ |
|------------------------------|-------|-------|-----|-------|-----|-------|-------|
|                              | $F_1$ | $F_1$ | $F_1$ | $F_1$ | $F_1$ | $F_1$ | $F_1$ |
| CNN.rand                     | 28.9  | 90.6  | 0.0  | 0.0   | 63.0 | 57.1  | 68.2  |
| CNN.domain                   | 51.1  | 91.4  | 23.9 | 11.3  | 71.1 | 66.3  | 65.8  |
| CNN.multi.rand               | 38.0  | 91.4  | 7.3  | 5.0   | 63.9 | 58.6  | 69.9  |
| CNN.multi.enwiki             | 43.9  | 90.5  | 11.3 | 0.0   | 61.1 | 61.4  | 57.8  |
| CNN.multi.domain             | 56.2  | 92.2  | 33.8 | 15.0  | 71.7 | 69.4  | 72.5  |
| CNN.multi.retrofitted+OOV    | 64.0  | 91.3  | 11.3 | 0.0   | 67.6 | 68.8  | 72.2  |
| CNN.multi.domain & retrofitted+OOV | **68.2** | **92.8** | 32.0 | 9.4   | **73.4** | **73.5** | 71.1  |
| CNN.multi.retrofitted+OOV&domain | 53.4  | 92.6  | 20.9 | 10.0  | 71.8 | 67.0  | 70.7  |

Table 3.17: Results of the classification task with various configurations.

model. Furthermore, since the architecture aims to assign a single label to each sentence, we update the activation function to sigmoid at the output layer. The sigmoid is a non-linear function, is defined as $\sigma(x) = \frac{1}{1+e^{-x}}$ and produces a probability for each of the potential properties. During training, these probabilities are used to compute the error, while during testing, we round each of the probabilities to 0 or 1 depending upon a set threshold (0.5).

### 3.7.3 Extrinsic evaluation experiments

Like Kim (2014), we run experiments with several variants of the model to investigate the importance of domain-specific input as follows:

- **CNN.rand:** As a baseline model, all words in the embedding layer are randomly initialized and updated in the training process.

- **CNN.domain:** The embedding layer is initialized with a domain-specific model and fine-tuned for the target task.

- **CNN.multi.rand:** There are two embedding layers as a ‘channel’ in the CNN architecture. Both channels are initialized randomly, and only one of them is updated during training while the other remains static.

- **CNN.multi.domain:** Same as before, but the channels are initialized with domain-specific vectors.

- **CNN.multi.enwiki:** The channels consider the general domain word vectors from section 3.4.3 using the English Wikipedia data.

To deal with the effects of an unbalanced dataset and guarantee that each fold in 5-fold cross-validation will have the proportion of the same classes during training and testing, we apply the stratification of multi-label data proposed by Sechidis.
et al. (2011). The stratification is a sampling method that takes into account
the existence of disjoint labels within a dataset and provides samples where the
proportion of these labels is maintained. Sechidis et al. (2011) introduce an
iterative stratification method that distributes samples based on how desirable a
given label is in each fold, tackling the problem of lack of rare label evidence in
folds.

Results of the classification task with various CNN configurations are
presented in the first section of Table 3.17. In general, the multi-channel
model performs better than the single-channel setting. The results suggest that
having a significant amount of sentences per property helps the CNN model to
classify better. The baseline model does not perform well on its own. The use
of the pre-trained embeddings model helps the model in property assignment.
Particularly, domain-specific embeddings provide higher performance gain in
the task-at-hand when it is used in both channels. We further investigate the
influence of the refined word embedding models in our classification task.

- **CNN.multi.retrofitted+OOV**: We used the retrofitted domain embed-
dings including the OOV vectors for two channels. One channel is static
and the other is non-static.

- **CNN.multi.domain&retrofitted+OOV**: First channel is initialized
with original domain-specific embeddings with static mode and the second
makes use of the retrofitted embeddings with a non-static mode.

- **CNN.multi.retrofitted+OOV&domain**: Same as previous setting,
but the channels swap their input.

In these experiments, because of having many multi-words as OOV terms in
the model, we replaced tokens in the sentences with their bigram and trigram
forms if their combination occurs in the model vocabulary (e.g., \textit{fracture porosity}
is replaced by \textit{fracture\_porosity} as an input unit). The experiment (second
section of Table 3.17) shows that the enhanced embedding models provide better
input representations for classes with a sufficient number of instances.

### 3.8 Summary

This chapter contains research and experiments on the evaluation of word
embedding models trained on a low-resource domain, namely the Oil and Gas
domain. The first research question is whether constructing domain-specific
word embeddings is beneficial even with limited input data. This question is
answered by conducting intrinsic and extrinsic evaluations of both general and
domain-specific embeddings. The empirical evaluation shows that even though
the distributional models have low performance in domain-specific synonymy
detection, an in-depth manual error analysis reveals the striking ability of the
embedding models to discover other semantic relations such as (co)hyponymy,
hypernymy, and relatedness. Furthermore, we observe that domain-specific
3. Evaluation of Domain-specific Word Embeddings

trained embeddings perform better compare to the general domain embeddings trained on much larger input data.

The second research question investigates the impact of existing domain knowledge resource on enhancing the embedding models. We augment the domain-specific model by providing vector representations for infrequent and unseen technical terms using a domain knowledge resource. Experiments show the importance of dealing with rare words in an embedding model in both intrinsic and extrinsic evaluation.

To summarize, we make the following contributions in this chapter:

(i) We create a domain-specific evaluation dataset: a corpus and a query inventory for the oil and gas domain,

(ii) We train and release the domain-specific embeddings for the oil and gas domain ¹¹,

(iii) We conduct intrinsic evaluation including a manual analysis by domain experts,

(iv) We inject domain knowledge into domain embeddings and show that it produces advancements in the intrinsic and extrinsic evaluation.

¹¹Link to the domain-specific model: http://vectors.nlpl.eu/repository/11/75.zip.
Chapter 4

Named Entity Recognition in Low-Resource Domains

Named Entity Recognition (NER) is an important task in the information extraction pipeline as stated in Section 2.6 of Chapter 2. Existing NER systems rely on large amounts of human-labeled data for supervision. However, obtaining large-scale annotated data in low-resource scenarios is challenging, particularly in specific domains like health-care, e-commerce, and so on. Given the availability of domain specific knowledge resources (e.g., ontologies, dictionaries), distant supervision has become a solution to generate automatically labeled training data to reduce human effort, as explained in Section 2.3 of Chapter 2. The outcome of distant supervision for NER is often noisy however. False positive and false negative instances are the main issues that reduce performance on this kind of auto-generated data.

In this chapter, we explore the use of distant supervision for NER in four low-resource scenarios. We present a system which addresses the problem of noisy data in two ways. We study a reinforcement learning strategy with a neural network policy to identify false positive instances at the sentence level. We further adopt a technique of incomplete annotation to address the false negative cases. The proposed hybrid model achieves competitive performance on benchmark datasets.

4.1 Introduction

Named Entity Recognition (NER) is one of the primary tasks in information extraction pipelines. Traditional studies apply statistical techniques such as Hidden Markov Models (HMM) and Conditional Random Fields (CRF) using large amounts of features and extra resources (Ratinov and Roth, 2009; Passos et al., 2014). In recent years, deep learning approaches achieve state-of-the-art results in the task without any feature engineering (Ma and Hovy, 2016; Lample et al., 2016). Most of these works assume that there is a certain amount of annotated sentences in the training phase. However, the availability of large amounts of labeled data is problematic, particularly in specific domains. In the low-resource setting, where the amount of data and the knowledge of the domain are insufficient for traditional approaches, distant supervision (see Section 2.3 in Chapter 2) is proposed by Mintz et al. (2009) to address the challenge of obtaining training data for new domains using existing knowledge resources (dictionaries, ontologies). It has previously been successfully applied to tasks like relation extraction (Riedel et al., 2010; Augenstein et al., 2014) and entity recognition (Fries et al., 2017; Shang et al., 2018b; Yang et al., 2018). To create
training data in a NER task, it identifies entity mentions if they exist in the knowledge base (e.g., domain-specific dictionary, glossary, ontology) and assigns the corresponding type according to the knowledge base.

However, distant supervision approaches encounter two main limitations. First, due to limited coverage of the knowledge resources, unmatched tokens result in False Negatives (FNs). Second, since simple string matching is employed to detect entity mentions, ambiguity in the knowledge resource may lead to False Positives (FPs). For the FN problem, Tsuboi et al. (2008) incorporate partial annotations into CRFs and propose a parameter estimation method for CRFs using partially annotated corpora (here-in after referred to as Partial-CRF). In order to reduce the negative impact of FPs for relation extraction, Qin et al. (2018) propose a deep reinforcement learning (RL) agent where the agent’s goal is to decide whether to remove or keep the distantly supervised instance.

In this chapter, we combine the Partial-CRF approach with the RL approach to clean the noisy, distantly supervised data for NER. More specifically, we explore the following research questions:

**RQ 4.1.** How can we address the problem of low-resource NER using distantly supervised data?

**RQ 4.2.** How can we exploit a reinforcement learning approach to improve NER in low-resource scenarios?

**RQ 4.3.** Is the proposed solution beneficial for different low-resource scenarios?

### 4.2 Background

In the following sections, we will describe the background of NER and models that have been proposed for the NER task.

#### 4.2.1 Named Entity Recognition

The term *Named Entity* was introduced in 1996 at the 6th Message Understanding Conference (MUC), as *unique identifiers* of entities (organizations, persons, locations), times (dates, times), and quantities (monetary values, percentages) (Chinchor, 1998). Most of the annotation datasets for the NER task contain these types of named entities, though with important variations. Example 4.1 shows an example of named entities in the widely used CoNLL shared task (Tjong Kim Sang and De Meulder, 2003) dataset.

(4.1) *Adams* and *Platt* are both injured and will miss *England’s* . . .

At first glance, it seems that only proper names (e.g., Adams, Platt, England) can be considered as named entities. However, depending on the application, it can be useful to recognize some other linguistic categories as named entities such as pronouns (e.g., it, who, she, he) or nominal mentions (e.g., the girl, mother, the company). Furthermore, the definition can vary depending on the
genre and domain (e.g., Health care, Technical review, e-commerce). As an example, 4.2 depicts another type of named entities in the bio-medical domain from BioCreative V CDR task corpus (Li et al., 2016). Here we see that domain specific tags, such as Chemical and Disease, are used to label named entity mentions.

\[(4.2) \text{Selegiline-induced postural hypotension in Parkinson's disease}\]

The NER task, or the more general entity mention detection task, is the first step and an essential component of the information extraction pipeline. It involves detecting the boundaries of the phrases that correspond to entities and determining their entity types. Intuitively, given a sentence of words \( W : w_1w_2...w_n \), NER assigns a sequence of tags \( y : y_1y_2...y_n \) from a predefined set of categories \( y_i \in \Phi, |\Phi| = k \).

A single named entity can span several tokens within a sentence. Therefore, sentences are usually represented in specific sequence labeling schemes in NER datasets. The two most popular ones are the following schemes:

- **BIO**: It stands for Beginning, Inside and Outside (of a text segment). If the token is the beginning of a named entity, it will be labeled as B-<type of NE>, if it is inside a named entity, but not the first token within the token, it will be labeled I-<type of NE>, and if it is not a part of a named entity, it will be labeled as O.

- **BIOES**: Similar but more detailed than BIO, BIOES encodes the beginning, the inside, and last token of multi-token chunks while differentiating them from unit-length chunks. It encodes a singleton entity as S-<type of NE> and explicitly marks the end token of multi-word named entities as E-<type of NE>.

Table 4.1 shows an example sentence that is annotated in both of the BIO and BIOES labeling schemes.

### 4.2.2 Neural NER models

Recently, deep neural models have been employed in the NER task and reached state-of-the-art results on many NER datasets. They benefit from continuous vector representations and semantic composition through nonlinear processing to discover useful representations and underlying factors from input data (see Section 2.2 in Chapter 2). Existing models are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Their architecture (Figure 4.1) usually consists of three main components (Li et al., 2020) as follows:

- **Distributed representations for input**: Distributed representations, as described in Section 2.5.1 of Chapter 2, present each word or character
Table 4.1: Example sentence from CoNLL03 in BIO and BIOES annotation schemes.

by a low dimensional dense vector where each dimension comprises a latent feature. Word-level distributed representations are considered inputs to the NER models. This representation is typically pre-trained over a large collection of text through unsupervised algorithms and captures the syntactic and semantic properties of its elements. The input layer can be either frozen or fine-tuned during the training phase. The pre-trained word embeddings that are used widely in English NER models are Google Word2vec ¹, Stanford GloVe ², Facebook fastText ³ and SENA ⁴. Several NER models incorporate character-based word representations besides the word representations as an input layer. This representation is learned using an end-to-end neural model. It enables the NER model

¹https://code.google.com/archive/p/word2vec/
²http://nlp.stanford.edu/projects/glove/
³https://fasttext.cc/docs/en/english-vectors.html
⁴https://ronan.collobert.com/senna/
Background

Figure 4.1: General Architecture in the Deep Neural NER in the BIO labeling (Li et al., 2020).

to learn the representations for unseen words and to share information of morpheme-level regularities. In addition to word- and character-level representations, some NER models include other syntactical, context, morphological, and lexical features into the input layer such as POS tags, word shape, dependency roles, word positions, and gazetteers. However, incorporating these types of features may affect the generality of the NER models.

- **Context encoder**: The second module of neural NER models is devoted to capturing the contextual dependency from the input representations. The widely-used contextual encoders are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (see Section 2.2 of Chapter 2 for more details). Lately, pre-trained language models, as explained in Section 2.5.1.2 of Chapter 2, such as ELMO (Peters et al., 2018) and BERT (Devlin et al., 2019), are used as context encoders and provide a pre-trained deep representation model from unlabeled text. It is empirically verified that the pre-trained model can be fine-tuned with one additional layer for various downstream tasks, including NER, and enhance their performance.

- **Tag decoder**: As a last part of the NER model, it takes the output of
the context encoder and predicts a sequence of labels corresponding to the input sequence. A Conditional Random Fields (CRFs) framework (Lafferty et al., 2001) is the most common choice for the tag decoder step. Most of the state-of-the-art NER models employ CRFs to capture inter-dependency among the labels and show that CRFs can provide higher tagging accuracy in general. A Multi-Layer Perceptron and Softmax based decoder is another type of design choice for the tag decoder step in some NER models. It casts the sequence labeling task as a multi-class classification problem. In this arrangement, the label for each token is independently predicted without taking into account the adjacent label.

4.2.3 BiLSTM-CRF framework

BiLSTM-CRF (Figure 4.2) is a commonly used neural framework that is exploited for NER. In the following, we introduce the components of the BiLSTM-CRF architecture employed in our work.

BiLSTMs Encoder. Bidirectional Recurrent Neural Networks (Bi-RNNs) (Schuster and Paliwal, 1997) combines an RNN network (see Section 2.2.3 in Chapter 2) which moves forward through time, beginning from the start of the sequence representation, along with another RNN that moves backward, starting from the end of the sequence and is trained using all available input information in the past and future of a specific time frame.

The BiLSTM context encoder employs a Long Short Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) instead of RNN. LSTM, as described in
Section 2.2.3 in Chapter 2, is a special kind of RNN, capable of learning long-term dependencies. This network architecture can efficiently solve the long-term dependencies problem by introducing a gating mechanism and a memory cell.

**Character- and World level encoding.** The character-level BiLSTM networks process characters of word input and learn character-level features while training. Learning character-level embeddings has the advantage of learning representations specific to the task and domain at hand. It has been shown that this type of representation is useful for morphologically rich languages, and handles the out-of-vocabulary problem for some downstream tasks such as part-of-speech tagging and language modeling (Ling et al., 2015). The randomly initialized embedding vector corresponding to each character in the input word is passed through the BiLSTM network in a forward and backward fashion. The forward and backward outputs from the BiLSTM are concatenated to form a character-level encoding for each word. As shown in Figure 4.3, this character-level encoding is then concatenated with word embeddings from a word embeddings lookup-table and given to another BiLSTM network as a final context encoder layer. Let $X : x_1 x_2 \ldots x_n$ be a word-level input representation, where $x_i$ is the embedding vector for the $i$th word and its character-level input is $C : c_{0,-} c_{1,1} c_{1,2} c_{1,3} c_{1,-} \ldots c_{i,j} \ldots c_{n,-}$, where $c_{i,j}$ is the dense vector of the $j$th character in word $w_i$ and $c_{i,-}$ is the representation for a space character after $w_i$. The first BiLSTM encoder layer will receive a dense vector corresponding to each character. Formally, an LSTM cell will compute the current hidden state $h_t$ based on the current vector $c_t$, the previous hidden state $h_{t-1}$ and the previous cell state $s_{t-1}$, however we will only consider $h_t$ at word boundaries, namely space characters or $c_{i,-}$ (see the implementation of LSTM in Section 2.2.3 of Chapter 2). If $\vec{h}_{c_{i,-}}$ is the output of the forward character-level LSTM at $c_{i,-}$ and $\vec{h}_{c_{i,-}}$ is the output of the backward character-level LSTM at $c_{i,-}$, the character-level encoding result for the $i$th word is:

$$h_i^c = \vec{h}_{c_{i,-}} \oplus \vec{h}_{c_{i,-}} \quad (4.3)$$

Subsequently, the character-level encoding output for $i$th word is concatenated to its word embedding vector and is fed into the second BiLSTMs network. $\vec{h}_i$ as the output of the forward word-level LSTM at the $i$th word and the output of backward word-level LSTM $\vec{h}_i$ are concatenated and provide the word-level encoding representation $h_i$ for a word $i$:

$$h_i = \vec{h}_i \oplus \vec{h}_i \quad (4.4)$$

**CRF** In sequence labeling tasks, the dependencies between adjacent labels should be taken into account. Particularly in NER, the characteristics of tagging schemes (e.g. BIO, BIOES) impose various hard constraints such as (Lample et al., 2016):
4. Named Entity Recognition in Low-Resource Domains

Figure 4.3: Character- and word-level BiLSTM encoding of NER model in the BIO labeling (Liu et al., 2018a).

- The first word in a sentence should be annotated with a label that begins with B- or O, not I- in the BIO scheme.
- The label I-ORG cannot come after B-LOC or any other tag that is not LOC.
- The possible tag that can take place after B-ORG is either I-ORG or O in the BIO scheme.

In order to guarantee that the output label sequence is valid, we jointly decode a chain of labels. CRF, as a discriminative type of sequence-based model, considers the dependencies between labels in neighborhoods and defines a conditional probability distribution over a label sequence. It learns the dependency among labels automatically based on the annotated samples during the training process. The CRF layer comes on top of the last layer (i.e, word-level BiLSTM) to model the dependencies across output tags and locate the best tag sequence by maximizing the log-probability in the following equation:

$$
\log(p(y|W)) = \log \frac{e^{s(W,y)}}{\sum_{y' \in Y} e^{s(W,y')}}
$$

(4.5)

where

$$
s(W, y) = \sum_{i=1}^{n} P_{t, y_i} + \sum_{i=1}^{n} T_{y_i, y_{i+1}}
$$

(4.6)
Where $W: w_1 w_2 \ldots w_n$ is an input sequence, $y: y_1 y_2 \ldots y_n$ is an annotated tag sequence and $Y$ is all possible tag sequences of the sentence. CRF takes $P$ as an emission score matrix which is a $k \times n$ output tensor of a linear encoder applied to the last BiLSTM layer where $P_{i,j}$ corresponds to the score of the $j^{th}$ tag of the $i^{th}$ word in a sentence. $T$ is a $(k + 2) \times (k + 2)$ transition tensor which represents the transition probability from the $i^{th}$ tag to the $j^{th}$ tag. Two additional tags $<\text{BOS}>$ and $<\text{EOS}>$ are added at the start and end of a sequence, respectively. The transition matrix is randomly initialized and is learned by the CRF during the training phase. For training, we encourage the model to produce a valid sequence of output labels by defining the loss function as the negative log likelihood of the current sequence tag $y$:

$$
\mathcal{L} = -\log(p(y|W)) = \log\left(\sum_{y' \in Y} e^{s(W,y')}\right) - s(W,y) \quad (4.7)
$$

While testing or decoding, the goal is to determine the best label sequence $y^*$ that maximizes the likelihood conditioned on the input sentence $W$ and learnt model parameters $\Theta$ (e.g, $T$ and $P$):

$$
y^* = \arg \max_{y \in Y} p(y|W; \Theta) \quad (4.8)
$$

Since we model only bi-gram interactions (i.e, two adjacent labels) in the CRF model, both Eq. 4.7 and Eq. 4.8 can be computed by adopting the Viterbi algorithm.

### 4.2.4 Reinforcement Learning

Reinforcement learning (RL) differs from supervised and unsupervised learning in that the goal is to learn a set of actions without relying on a labeled training dataset to maximize a predefined reward function. The learning process is based on the finite Markov Decision Process (MDP) framework where the RL model consists of various key elements: In a given state $(s_t)$ of a stochastic environment, an agent as a learner and decision maker tries to find an optimal action $(a_t)$ in order to maximize the expected rewards $(r_t)$, by following a policy $(\pi)$. More specifically, at each time step $t = \{0, 1, 2, \ldots, T\}$, the agent receives a state $s_t \in S$ as representation of the environment, and following the policy, the agent performs an action $(a_t \in A)$. The RL model aims to maximize the following objective function (Sutton et al., 1998):

$$
\max_{\theta} E_{\tau \sim \pi_\theta(\tau)} \left[ \sum_{t} r(s_t, a_t) \right] \quad (4.9)
$$

Where $r(s_t, a_t)$ is a reward in time step $t$, $\tau$ is a sequence of states, actions, and rewards known as a trajectory, and $\pi_\theta(\tau)$ is the joint probability of a sequence of actions that can be formulated in MDP as:

$$
\pi_\theta(\tau) = \pi_\theta(s_1, a_1, \ldots, s_T, a_T) = p(s_1) \prod_{t=1}^{T} \pi_\theta(a_t|s_t)p(s_{t+1}|s_t, a_t) \quad (4.10)
$$
\( \pi_\theta(a_t|s_t) \) is a policy that tells the agent how to act from a particular state, and \( p(s_{t+1}|s_t, a_t) \) known as the model in RL, is a transition function that predicts the next state after taking action.

The most successful RL techniques employ a neural network in conjunction with RL. Neural models enable the RL model to deal with unstructured environments, learn complex functions, solve complicated problems in an end-to-end fashion, or predict actions in unseen states. Policy Gradient introduced by Sutton et al. (1999) is one of the RL algorithms that focuses on the policy. The policy is learned by directly differentiating the objective function in Eq. 4.9 as follows:

\[
J(\theta) = E_{\tau \sim \pi_\theta(\tau)} \left[ \sum_{t=1}^{T} r(s_t, a_t) \right] = E_{\tau \sim \pi_\theta(\tau)} [r(\tau)] = \int \pi_\theta(\tau) r(\tau) d\tau
\]

Since:

\[
\nabla_\theta f(x) = f(x) \frac{\nabla_\theta f(x)}{f(x)} = f(x) \nabla_\theta \log f(x)
\]

Then:

\[
\nabla_\theta J(\theta) = \int \nabla_\theta \log \pi_\theta(\tau) r(\tau) d\tau = \int \pi_\theta(\tau) \nabla_\theta \log \pi_\theta(\tau) r(\tau) d\tau = E_{\tau \sim \pi_\theta(\tau)} [\nabla_\theta \log \pi_\theta(\tau) r(\tau)]
\]

Considering Eq. 4.10:

\[
\log \pi_\theta(\tau) = \log p(s_1) + \sum_{t=1}^{T} \log \pi_\theta (a_t|s_t) + \log p(s_{t+1}|s_t, a_t)
\]

\[
\nabla_\theta J(\theta) = E_{\tau \sim \pi_\theta(\tau)} \left[ \left( \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta (a_t|s_t) \right) \left( \sum_{t=1}^{T} r(s_t, a_t) \right) \right]
\]

Since:

\[
J(\theta) = E_{\tau \sim \pi_\theta(\tau)} \left[ \sum_{t=1}^{T} r(s_t, a_t) \right] \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t} r(s_{i,t}, a_{i,t})
\]

Then:

\[
\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left( \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta (a_{i,t}|s_{i,t}) \right) \left( \sum_{t=1}^{T} r(s_{i,t}, a_{i,t}) \right) \tag{4.11}
\]

Eq. 4.11 computes how likely the trajectory is under the current policy. If the results of the trajectory lead to a high positive reward, it will increase the likelihood. On the other hand, it will decrease the likelihood of a policy if it outputs a high negative reward. In short, keep what has positive effects and throw out what does not. REINFORCE (Williams, 1992) is known as the
Low-Resource NER

Algorithm 1: REINFORCE (Williams, 1992).

1 Initialize $\theta$ at random
2 for $\text{Generate } \{\tau^i\}$, following $\pi_\theta$ do
3 for $t = 1 \text{ to } T - 1$ do
4 $\nabla_\theta J(\theta) \approx \sum_i \left( \sum_t \nabla_\theta \log \pi_\theta (a_{i,t}|s_{i,t}) \right) \left( \sum_t r(s_{i,t}, a_{i,t}) \right)$
5 $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$
6 Return $\theta$

Monte-Carlo policy gradient, which uses Monte Carlo rollout to compute the rewards (see Algorithm 1). The agent collects a trajectory $\tau$ of one episode using its current policy and updates the policy parameter using the $\tau$. Since one full trajectory must be completed to construct a sample space, REINFORCE updates the policy network parameters (weights) in the direction of the gradient (see line 5 of Algorithm 1).

4.3 Low-Resource NER

The task of NER has been widely studied in the last decade and is usually formulated as a sequence labeling problem. Using neural techniques, many studies report state-of-the-art results on this task (Lample et al., 2016; Ma and Hovy, 2016). These studies utilize character and/or word embeddings to encode sentence-level features automatically. Recently, the use of contextualized word representation (Peters et al., 2018; Akbik et al., 2018) significantly improves the state-of-the-art results in many sequence labeling tasks and specifically also in the NER benchmark.

In the supervised paradigm, NER suffers from a lack of large-scale labeled training data when moving to a new domain or new language. To alleviate the reliance on human annotated data, distant supervision is proposed by Mintz et al. (2009), to generate annotated data by heuristically aligning text to an existing domain-specific knowledge resource. It is widely used for relation extraction (Mintz et al., 2009; Riedel et al., 2010; Augenstein et al., 2014) and lately it has attracted attention also for NER (Ren et al., 2015; Fries et al., 2017; Shang et al., 2018b; Yang et al., 2018). In this section, we look more closely at previous works that utilize the data generated by distant supervision in relation extraction and NER tasks and address the challenges of noisy generated data.

Feng et al. (2018) propose a model for sentence level relation classification in noisy sentences that are collected via distant supervision. The model contains a relation classifier and an instance selector. The instance selector filters out the low-quality sentences by using reinforcement learning and provides the selected sentences for the relation classifier. They adopt REINFORCE in the instance
filtering step. The relation classifier predicts the relation at the sentence level and produces rewards as a weak supervision signal to the filtering module. The two modules are trained jointly to optimize their objective functions. In the relation classification module, a convolutional architecture determines the relation class for entity pairs in a given sentence. The instance selector is the agent that follows a feed-forward neural policy network to distill the training data for the relation classifier. At the same time, it refines its policy function using the feedback from the relation classifier. The reward is calculated based on the prediction probabilities in the CNN model when the selection of all training sentences is finished.

Qin et al. (2018) also explore deep reinforcement learning as a false positive removal tool for distantly supervised relation extraction. The policy-based agents are learned for each relation type, and they aim to determine and remove the false positive cases from auto-generated labeled data. In contrast to Feng et al. (2018), the reward is intuitively reflected by the performance change of the relation classifier. They design the policy agent in a supervised fashion and use a pre-trained policy network in the RL module. Here, we adapt their approach to the NER task. Unlike Qin et al. (2018), we learn the policy agent in an unsupervised manner, where the parameters are learned by interaction with the environment.

Yang et al. (2018) make use of reinforcement learning to tackle false positives in distantly supervised NER. Similar to our work, Yang et al. (2018) address the noisy automatic annotation in NER, by using partial annotation learning and reinforcement learning. However, unlike our approach, they train the NER model and reinforcement learning model jointly, calculating the reward based on the loss of the NER model. In contrast, we employ the RL module as a pre-processing/filtering step, incorporating the previous state to satisfy a Markov decision process (MDP). Yang et al. (2018) evaluate only on a Chinese dataset, whereas we apply our model also to English datasets. Furthermore, after running their code, we observe that to reach the reported results in their paper on the e-commerce dataset, the model needs more than 500 epochs and the reinforcement learning component removes all the distantly annotated sentences after some epochs. This means that after some epochs, the code in reality only applies the baseline NER model on the annotation dataset and ignores the RL module since there are no distantly annotated sentences. Their two datasets are included in our experiment in order to compare to their results.

Shang et al. (2018b) present the AutoNER model, which employs a new type of tagging scheme (dubbed Tie or Break) rather than the common ones (i.e., BIO, BIOES). The model does not have a final CRF layer but still achieves state-of-the-art unsupervised F1 scores on several benchmark datasets. Instead of predicting the label of each token, they propose predicting whether two adjacent tokens are tied (i.e., Tie) in the same entity mention or not (i.e., Break). They find that even when the boundaries of an entity mention are mismatched by distant supervision, most of its inner ties are not affected, and thus more robust to noise.
Accordingly, they design a neural architecture (AutoNER), that identifies all possible entity spans by detecting such ties and then predicts the entity type for each span. Crucially, they employ a set of high-quality phrases in distant supervision, using a phrase mining technique, AutoPhrase (Shang et al., 2018a), to reduce the false-negative labels. The AutoPhrase framework leverages available high-quality phrases in general knowledge bases such as Wikipedia and Freebase for distant supervision to avoid additional manual labeling effort. Therefore, it independently creates samples of positive labels from general knowledge and negative labels from the given domain corpora and trains several classifiers. Then, it aggregates the predictions of the classifiers to reduce the noise from negative labels. In the first phase, AutoPhrase establishes the set of phrase candidates that contains all n-grams considering a threshold based on the raw frequency of the n-grams. Given a phrase candidate, the quality of the phrase is estimated by some statistical features such as point-wise mutual information, point-wise KL divergence, and inverse document frequency. Finally, it finds a complete semantic unit in some given context by using part-of-speech-guided phrasal segmentation. AutoPhrase can support any languages as long as a general knowledge base of the language is available, while benefiting from, but not requiring a POS tagger (Shang et al., 2018a).

### 4.4 Model

In this section, we present the proposed model, which copes with the problems in distantly supervised NER. We implement Partial-CRF together with a performance-driven, policy-based reinforcement learning method to detect FNs and FPs in distantly supervised NER. We here combine techniques that have been shown to be useful in previous work (Yang et al., 2018). In our architecture, as shown in Figure 4.4, we first apply partial annotation learning (PA) using the annotation dataset (A) and distantly labeled data (D). Then, we apply reinforcement learning (RL) to clean FPs from the noisy dataset (D). Our RL agent is rewarded based on the change in the NER’s performance and is modeled as a Markov Decision Process (MDP).

Algorithm 2 describes the overall training procedure for our model, and in the following sections, we detail the various components of our model.
4. Named Entity Recognition in Low-Resource Domains

4.4.1 Baseline NER model

Our baseline model is a BiLSTM-CRF architecture (Lample et al., 2016; Habibi et al., 2017), which is described in Section 4.2.3. The first layer takes character embeddings for each word sequence and then merges the output vector with the word embedding vector to feed into a second BiLSTM layer. We modify the top element (CRF layer) of the baseline model as follows.

4.4.2 Partial-CRF layer (PA)

As mentioned above, FN instances constitute a common problem in distantly annotated datasets. It is caused by limited coverage of the knowledge base resource when some of the entity mentions are not found in the resource and followingly labeled as non-entities ('O'). We follow Tsuboi et al. (2008) and treat the result of distant supervision as a partially annotated dataset where non-entity text spans are annotated as any possible tag. Figure 4.5 illustrates the annotation of distantly supervised examples using the BIOES labeling scheme that we employ.
Figure 4.5: Annotation of the distantly labeled example in Partial-CRF based on the BIOES labeling. The words with green tags are found in the dictionary and assigned to the corresponding entity types, and the ones that are not found in the dictionary are assigned to all possible tags (yellow).

Let $Y_L$ denote all the possible tag sequences for a distantly supervised sentence $W$. Then, the conditional probability of the subset $Y_L$ given $W$ is:

$$p(Y_L|W) = \sum_{y \in Y_L} p(y|W)$$  \hspace{1cm} (4.12)

Extending the original equation of the CRF layer (Eq. 4.5) provides the log-probability for the distantly supervised instance:

$$\log(p(Y_L|W)) = \log \frac{\sum_{y \in Y_L} e^{s(W,y)}}{\sum_{y' \in Y} e^{s(W,y')}}$$  \hspace{1cm} (4.13)

Using partial annotation learning, non-entity text spans are annotated as any possible tag. It gives a chance for non-entity text spans to be considered and scored properly in the updated version of CRF (Partial-CRF) and become a part of the most optimal tag sequence.

4.4.3 Reinforcement Learning (RL)

The RL agent is designed to determine whether the distantly supervised instance is a true positive or not. There are two main components in RL: (i) the environment, and (ii) the policy-based agent. Following Qin et al. (2018), we model the environment as a Markov Decision Process (MDP), where we add information from the previous state to the current state. The policy-based agent is formulated based on the Policy Gradient Algorithm (Sutton et al., 1999), as explained in Section 4.2.4, where we update the policy model by computing the reward after finishing the selection process for the whole training set. Algorithm 3 presents additional details of the RL strategy in our NER model. The following subsections describe the elements of the RL agent.
Algorithm 3: Reinforcement learning Algorithm to clean FPs on D.

Input: Training dataset ($A_{train}$) + Distantly Labeled Data ($D$),
Pre-train NER+PA on $A_{train} + D$, Validation dataset ($A_{val}$)

1. Initialize $\theta$ in policy network
2. Initialize $s^*$ as all-zero vector with the same dimension of $s_j$
3. for epoch $i = 0 \rightarrow N$ do
4. for instance $d_j \in D$ do
5. Provide $s_j$ using NER+PA model $\tilde{s}_j = \text{concatenation}(s_j, s^*)$
6. Randomly sample $a_j \sim \pi(a; \theta, \tilde{s}_j)$; compute $p_j = \pi(a; \theta, \tilde{s}_j)$, save $(a_j, p_j)$
7. if $a_j == 0$ then
8. save $\tilde{s}_j$ into $\Psi_i$
9. Recompute the $s^*$ as an average of $\forall \tilde{s}_j \in \Psi_i$
10. $D_i = D - (\forall d_j; j \in \Psi_i)$
11. Train NER+PA on $A_{train} + D_i$
12. Calculate $F^i_1$ on $A_{val}$ and save $F^i_1$ and $\Psi_i$
13. $r_i = F^i_1 - F^{i-1}_1$
14. Find $\Omega_i, \Omega_{i-1}$ (Eq. 4.15)
15. Update Policy network (Eq. 4.14)
16. Update $D = D - (\forall d_j; j \in \Psi_N)$
17. Re-train NER+PA on $A + D$

4.4.3.1 State

The RL agent interacts with the environment to decide about instances at the sentence level. A central component of the environment is the current and previous state in the selection process. The state $S_i$ in step $i$ represents the current instances as well as their label sequences. Following Yang et al. (2018) the state vector $S_i$ includes:

- The vector representation of instances before the Partial-CRF layer, where we concatenate the outputs of the first and last nodes in the BiLSTM layer of the base NER model.

- The label sequence scores calculated by the linear encoder before the Partial-CRF model. (i.e, $P_{i,j}$ in Eq. 4.6).

If a word is annotated with a specific label, the score will be the corresponding value of the label. Otherwise, the score will be the mean of all possible word labels in the linear encoder. These two vectors are concatenated to represent the current state. To satisfy the MDP, the average vector of the removed instances
in the earlier step $i-1$ is concatenated to the current state and represents the
state for the RL agent.

4.4.3.2 Reward

The NER model will achieve improved performance if the RL agent filters out
the FP instances from the noisy dataset. Accordingly, the RL agent will receive
a positive reward; otherwise, the agent will receive a negative reward. Following
Qin et al. (2018), we model the reward as a change of the NER performance;
particularly, we adapt the $F_1$ score to calculate the reward as the difference
between $F_1$ scores of the adjacent epochs (i.e., $r_i = F_1^i - F_1^{i-1}$).

4.4.3.3 Policy Network

The policy network $\pi(a_j; \theta, s_j)$ is a feed forward network with two fully-connected
hidden layers. It receives the state vector for each distantly supervised instance
and then determines whether the instance is a false positive or not. The $\pi$ as a
classifier with parameter $\theta$ decides an action $a_j \in \{1, 0\}$ for each $s_j \in S_j$. The
loss function for the policy network is formulated based on the policy gradient
method and the REINFORCE algorithm (Section 4.2.4). Since we calculate the
reward as a difference between $F_1$ scores in two contiguous epochs, the agent will
be compensated for a set of actions that has a direct impact on the performance
of the NER model in the current epoch. In other words, the different parts of
the removed instances in each epoch are the reason for the change in $F_1$ scores.
Accordingly, the policy will update using the following gradient:

$$
\theta = \theta + \alpha \left[ \sum_{a_j, s_j \in \Omega_i} \log \pi(a_j|S_j; \theta) r_i 
+ \sum_{a_j, s_j \in \Omega_{i-1}} \log \pi(a_j|S_j; \theta)(-r_i) \right]
$$

(4.14)

According to Qin et al. (2018), assuming $\Psi_i$ is removed in epoch $i$ :

$$
\Omega_i = \Psi_i - (\Psi_i \cap \Psi_{i-1}) \\
\Omega_{i-1} = \Psi_{i-1} - (\Psi_i \cap \Psi_{i-1})
$$

(4.15)

This means that if there is an increase in $F_1$ at the current epoch $i$, we will
assign a positive reward to the instances that have been removed in epoch $i$ and
not in epoch $i-1$ and negative reward to the instances that have been removed
in epoch $i-1$ and not in the current epoch.

4.5 Experiments

We perform experiments on four benchmark datasets to compare our method to
similar techniques and investigate the impact of the number of available annotated
sentences for our approach. In this section, we describe the experimental setup
and various components of the model.
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### Table 4.2: Overview of datasets in our experiments.

| Name     | Domain                  | Entity Types             | Size (Train/Dev./Test) | Dictionary Size | # Raw Sent. |
|----------|-------------------------|--------------------------|------------------------|-----------------|-------------|
| BC5CDR   | Bio-Medical             | Disease, Chemical        | 4,560/4,581/4,797      | 322,882         | 20,217      |
| LaptopReview | Technical Reviews     | Aspect terms             | 2,445/609/800         | 13,457          | 15,000      |
| EC       | E-commerce (Chinese)    | Brand, Product Model, Material Specification | 1,200/400/800 | 927 | 2,500 |
| NEWS     | news (Chinese)          | Person                   | 3,000/3,328/3,186     | 71,664          | 3,722       |

#### 4.5.1 Datasets

Our approach requires an annotated dataset, a knowledge resource, and a corpus of raw text. We rely on the resources used by Shang et al. (2018b) and Yang et al. (2018) for English and Chinese, respectively, as well as their train-test splits. As is shown in Table 4.2, these datasets are from several different domains (biomedical, e-commerce, technical reviews, and news) as well as two different languages. For all datasets, the distant supervision is performed on the raw data to create a distantly annotated dataset using the knowledge resource (i.e., dictionary). The annotation is based on the BIOES labeling scheme. Below we briefly describe the datasets.

**BC5CDR.** This dataset is from BioCreative V Chemical Disease Relation task (Li et al., 2016) and contains 12,852 Disease and 15,935 Chemical entity mentions in 1,500 articles. Example 4.16 shows an annotated sentence in this dataset with the BIOES tags. The BC5CDR is already partitioned randomly into a training, a development and a test set (500 articles each). The related dictionary is constructed from the MeSH database and the CTD chemical and Disease vocabularies and contains 322,882 Disease and Chemical entities. As raw text, we use a corpus consisting of 20,217 sentences that is provided in Shang et al. (2018b) and extracted from PubMed papers.

(4.16) Selegiline - induced postural hypotension in Parkinson

s disease :
S-Chemical O O B-Disease E-Disease O B-Disease I-Disease

**LaptopReview.** The LaptopReview dataset contains laptop aspect terms taken from the SemEval 2014 Challenge, Task 4 Subtask 1 (Pontiki et al., 2014). The 3,845 review sentences are annotated with 3,012 AspectTerm mentions (e.g., disk

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6https://www.nlm.nih.gov/mesh/download_mesh.html
7http://ctdbase.org/downloads/
Experiments

We extract 15,000 sentences from the Amazon laptop review dataset as raw text. Wang et al. (2011) designed this dataset for aspect-based sentiment analysis. Thanks to Shang et al. (2018b), they provide a dictionary of 13,457 computer terms crawled from a public website. An example sentence from the training in the BIOES tags is shown in example 4.17.

\[(4.17) \quad I \quad love \quad the \quad operating \quad system \quad and \quad the \quad preloaded \quad software .\]

\[O \quad O \quad O \quad B-\text{AspectTerm} \quad E-\text{AspectTerm} \quad O \quad O \quad B-\text{AspectTerm} \quad E-\text{AspectTerm} \quad O \quad O \quad\]

EC. The EC dataset is a Chinese dataset from the e-commerce domain. We choose this dataset in order to compare our results to the approach by Yang et al. (2018). There are 5 entity types: Brand, Product, Model, Material and Specification on user queries. An example sentence of the EC dataset is represented in example 4.18. This corpus contains 1,200 training instances, 400 in development set, and 800 in the test set. Yang et al. (2018) provide a small dictionary of 927 entries and 2,500 sentences as raw text.

\[(4.18) \quad 我\quad要\quad买\quad一\quad台\quad游\quad戏\quad本\quad。\quad\]

\[O \quad O \quad O \quad O \quad O \quad B-\text{Product} \quad I-\text{Product} \quad E-\text{Product} \quad O \quad O \quad\]

\['I\ want\ to\ buy\ a\ gaming\ computer.'\]

NEWS. The NEWS dataset is another Chinese dataset from the news domain and is annotated with Person type (PER) and provided by Yang et al. (2018), as shown by the sentence taken from this dataset in example 4.19. The NEWS dataset contains 3,000 sentences for training, 3,328 for development, and 3,186 for testing. Yang et al. (2018) apply distant supervision to raw data, and obtain 3,722 annotated sentences. The dataset and raw text are taken from the MSRA corpus (Levow, 2006).

\[(4.19) \quad 巫\quad昌\quad桢\quad、\quad罗\quad涵\quad先\quad委\quad员\quad…\quad\]

\[B-\text{PER} \quad I-\text{PER} \quad E-\text{PER} \quad O \quad B-\text{PER} \quad I-\text{PER} \quad E-\text{PER} \quad O \quad O \quad…\quad\]

\['Committee\ members\ Wu\ Changzhen\ and\ Luo\ Hanxian\ …'\]

4.5.2 Pre-trained Embeddings

The pre-trained embeddings have been used as initialization for the embedding layer of the LSTM layers of the BiLSTM model described in Section 4.4. Standard pre-trained GloVe 100-dimensional word vectors are employed for the LaptopReview dataset. In our experiments on the EC dataset, we use the 100-dimensional Chinese character embeddings provided by Yang et al. (2018), which is trained on one million sentences of user-generated text. For the biomedical

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8http://times.cs.uiuc.edu/~wang296/Data/

9https://www.computerhope.com/jargon.htm
dataset, we use pre-trained 200-dimensional word vectors trained on PubMed abstracts, all PubMed Central (PMC) articles, and English Wikipedia (Pyysalo et al., 2013). We here employ an embedding model that is domain-specific since we observe that this type of model provides an improvement in our previously studied domain-specific downstream task (see Chapter 3). In addition, Wang et al. (2019c) show that the domain-specific embeddings are beneficial for tagging performance on the BC5CDR dataset.

4.5.3 Evaluation

We report the performance of the model on the test set as the micro-averaged precision, recall, and $F_1$ score. According to CoNLL-2003 (Tjong Kim Sang and De Meulder, 2003), a predicted entity is counted as a true positive if both the entity boundary and entity type is the same as the ground-truth (i.e., exact match). To alleviate the randomness of the scores, the mean of five different runs are reported.

4.5.4 Model Variants

We use slightly different variants of our model for English and Chinese. For English we follow Liu et al. (2018b) in leveraging a language model to extract character-level knowledge. We keep the parameters in the model the same as in the original work. In order to compare to state-of-the-art models, we follow the same approach during training (i.e., by merging the training and development data as a training set in BC5CDR and randomly selecting 20% from the training set as the development set in LaptopReview). For the Chinese EC dataset, we only use character-based LSTM and CRF layers and discard the word-based LSTM and language model. For a fair comparison, the model parameters are set to be the same as in Yang et al. (2018), as well as the batch size, optimizer, and learning rate for RL module. We use 100 epochs in RL and initialize the average vector of the removed sentences as an all-zero vector.

4.5.5 High-Quality Phrases

Considering all non-entity spans (i.e., 'O' type) as a potential entity, provides noise in the Partial-CRF process. To address this issue, we use a set of quality multi-word and single-word phrases, provided by Shang et al. (2018b) and obtained using their AutoPhrase method (Shang et al., 2018a). Note that this resource is available only for the English datasets; therefore, it is not included in the experiments on the Chinese datasets. When using these phrases, we assign all possible tags only for the token spans that are matched with this extended list. In our model, we treat high-quality phrases as potential entities, and we assign all possible entity types in the annotation of distantly supervised sentences. For example, in Figure 4.5, we could only find the word 'leprosy' in this list, therefore, in annotation, we assign all possible tags to this token, and the other non-entity tokens remain as 'O'.
### Experiments

| Model Variant | Data       | Pr. | Re.   | F1   |
|---------------|------------|-----|-------|------|
| NER+PA        | BC5CDR     | 85.82 | 88.58 | 87.18 |
| NER+PA        | Laptop Review | 91.28 | 87.07 | 89.13 |
| NER+PA+RL     | Laptop Review | 87.00 | 89.04 | 88.01 |
| NER+PA+RL     | Laptop Review | 92.05 | 87.91 | 89.93 |

Table 4.3: Result with different setting of the distantly supervised NER model. *indicates that we use the list of high-quality phrases along with the dictionary to annotate raw text. The PA and RL denote the use of partial annotation learning and reinforcement-based components, respectively.

| Model                                 | Data       | Pr.   | Re.   | F1   |
|---------------------------------------|------------|-------|-------|------|
| Liu et al. (2018b) *                  | BC5CDR     | 88.84 | 85.16 | 86.96 |
| Wang et al. (2019c)                   | BC5CDR     | 89.10 | 88.47 | 88.78 |
| Beltagy et al. (2019)**               | BC5CDR     | 88.47 | 88.78 | 88.94 |
| NER+PA+RL (This work)                 | BC5CDR     | 92.05 | 87.91 | 89.93 |

Table 4.4: NER models comparison. *: is the base NER model in our approach and results are reported by Wang et al. (2019c). **: They use Pretrained Contextualized Embeddings for Scientific Text (SciBERT) with an in-domain vocabulary (SciVocab) in Ma and Hovy (2016) for NER.
4. Named Entity Recognition in Low-Resource Domains

4.6 Performance Comparison

We investigate the impact of the different components of the model (Table 4.3) in the two English datasets via ablation experiments, where we contrast the use of partial annotation learning (PA) (see Section 4.4.2) and the reinforcement-based component (RL) (see Section 4.4.3), with and without the high-quality phrases (the high-quality phrases (●) are available only for the English datasets).

The experiments confirm the efficiency of the PA and RL modules in resolving FN and FP issues in the distantly labeled datasets. We observe that compared with NER+PA+RL, NER+PA+RL● obtains absolute improvements of +1.92 and +0.44 F1 points on the BC5CDR and LaptopReview datasets, respectively. Overall, our final system (NER+PA+RL●) achieves an improvement of +2.75 and +11.85 F1 on the BC5CDR and LaptopReview respectively over the baseline system NER+PA. The results also corroborate Shang et al. (2018b), showing that incorporating high-quality phrases always leads to a boost in precision and, subsequently, F1 scores.

Table 4.4 depicts the comparison of our model to the previous NER models. We observe that our final system, the NER+PA+RL model with high-quality phrases, achieves higher F1 scores on the different datasets compared to the other models. In order to compare to the RL based approach in Yang et al. (2018), we run the model without high-quality phrases on the Chinese EC and NEWS dataset. Our design provides higher F1 scores than Yang et al. (2018), where it boosts the reported F1 score with +2.11 and +0.82 points on the EC and NEWS datasets, respectively. These experiments show that the different design of the RL module leads to improved results.

Following this work, there are some new studies on the BC5CDR and LaptopReview datasets such as Beltagy et al. (2019) and Liu et al. (2020). These approaches generally rely on the use of large, pre-trained language models. Beltagy et al. (2019) achieve 90.01% F1 score in the BC5CDR by fine-tuning SciBERT and Liu et al. (2020) report 82.80% F1 score in the LaptopReview using ELMO (Peters et al., 2018) trained on the corresponding dataset.

4.7 Size of Gold Dataset

In all the previous experiments, we take advantage of the availability of an annotated dataset. However, one of the challenges in domain-specific NER is the availability of gold supervision data. We here examine the performance of our proposed model under settings using different sizes of human-annotated data. In order to conduct this examination with our final method, we focus on the English datasets because of the availability of high-quality phrases. We proportionally select sub-samples x% ∈ [2, 10, 20, 30, 40, 50, 60, 70, 80, 100] from the training data of the BC5CDR and LaptopReview (with random sampling). Figures 4.6 and 4.8 show the performances of the models trained on the selected sentences. The X-axis is the corresponding proportions (x%) of the human-annotated dataset, while the Y-axis is the F1 scores on the testing set. We observe that
the performance of all models (including baselines) improves as more training instances become available. However, as shown in Figures 4.6 and 4.8, the final method (NER+PA+RL) achieves a performance of 83.18 and 63.50 with only 2% of the annotated dataset in the BC5CDR and LaptopReview, respectively. Whereas the base NER model requires almost 45% of the ground truth sentences to reach the same performance. This indicates that with a small set of human annotated data, our model can deliver a relatively good performance.

We further carry out experiments on the BC5CDR and LaptopReview test sets, where our model is trained exclusively on distantly annotated data. We report the outcome together with the scores of the other state-of-the-art unsupervised methods in Table 4.5, where we also compare to simple dictionary matching. It is clear that the model of Shang et al. (2018b) (AutoNER) is still the best performing NER method on the BC5CDR and LaptopReview datasets in an unsupervised setup. However, if we compare the performance of our model (NER+PA+RL in Figure 4.6) with AutoNER trained with both gold training and distantly labeled sentences in the BC5CDR dataset (i.e., AutoNER-GOLD+DistantSupervision in Figure 4.7 taken from Shang et al. (2018b)), we observe that our method provides slightly higher performance (F1 score) compared to the AutoNER system \(^{10}\) in a similar training scenario (i.e., training with both human annotated and distantly labeled sentences). Furthermore, comparing the performance of our model on the LaptopReview dataset (NER+PA+RL in Figure 4.8) with AutoNER (i.e., AutoNER-GOLD+DistantSupervision in Figure 4.9 taken from Shang et al. (2018b)) shows that both systems have quite similar results (i.e., F1 scores) on this dataset. It is also worth noting that the approach proposed by Fries et al. (2017) utilizes extra human effort to design regular expressions and requires

\(^{10}\)The absolute F1 score is not reported in the original work. Therefore, we compare our result with the corresponding F1 in Figure 4.7.
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specialized hand-tuning.

4.8 Summary

This chapter presents an approach to alleviate the critical shortcoming of auto-generated data in low-resource NER. We propose a performance-driven, policy-based reinforcement learning module that removes the sentences with FPs, whereas the adapted Partial-CRF layer deals with FNs. We examine the impact of each component in ablation experiments. We also found that the proposed model and methodology lead to competitive results on four benchmark datasets from different domains and languages in a supervised setting.

To summarize, the contribution of our model is three-fold. Concretely, we:

(i) combine the Partial-CRF approach with performance-driven, policy-based reinforcement learning to clean the noisy, distantly supervised data for low-resource NER in a pre-processing step;

(ii) formulate the reward function in RL based on the change in the performance of the NER module where the policy of RL is trained in an unsupervised manner by interaction with the environment;

(iii) show that our approach can boost the neural NER system’s performance on four datasets from different domains and for two different languages (English and Chinese).
Figure 4.6: Performance of the different configuration of our model trained on various sizes of annotated dataset in the BC5CDR. F1 Score on Test vs, the percentage of human annotated sentences.

Figure 4.7: Test F1 score vs. the number of distantly supervised sentences in the BC5CDR dataset. The supervised benchmarks with 86.96 F1 score, is LM-LSTM-CRF (Liu et al., 2018b) trained with all human-annotate sentences (NER in our experiment). AutoNER-DistantSupervision is the AutoNER model (Shang et al., 2018b) trained on the selected sentences from distantly labeled data. AutoNER-Gold+DistantSupervision is the AutoNER model trained on both human-annotated and selected distantly labeled sentences.
4. Named Entity Recognition in Low-Resource Domains

Figure 4.8: Performance of the different configuration of our model trained on various sizes of annotated dataset in the LaptopReview. F1 Score on Test vs. the percentage of human annotated sentences.

Figure 4.9: Test F1 score vs. the number of distantly supervised sentences in the LaptopReview dataset. The supervised benchmarks with the scores of 74.55 is the score of the winner system in the SemEval2014 Challenge Task 4 Subtask 1 (Pontiki et al., 2014). AutoNER-DistantSupervision is the AutoNER model (Shang et al., 2018b) trained on the selected sentences from distantly labeled data. AutoNER-Gold+DistantSupervision is the AutoNER model trained on both human-annotated and selected distantly labeled sentences.
Chapter 5

Low-Resource Relation Extraction

Relation extraction is the next step following entity detection in the information extraction pipeline, where semantic relationships are extracted from an input text. Extracted relationships usually occur between two or more named entities (see Section 4.2 in Chapter 4) and are classified based on a set of predefined semantic categories. Relation extraction allows us to acquire structured knowledge from unstructured text as explained in Section 2.6 of Chapter 2. In this chapter, we focus on relation extraction in a low resource setting, namely the genre and domain of scientific papers in NLP. We study the effect of varying input representations to a neural architecture, specifically CNN (see Section 2.2.2 of Chapter 2), to extract and classify semantic relations between entities in scientific papers. We investigate the effect of transfer learning using domain-specific word embeddings in the input layer and go on to provide an in-depth investigation of the influence of different syntactic dependency representations which are used to produce dependency paths between the entities in the input to the system. We compare the widely used CoNLL, Stanford Basic, and Universal Dependencies schemes and further compare them with a syntax-agnostic approach. In order to gain a better understanding of the results, we perform manual error analysis.

5.1 Introduction

Over the past years, natural language technology has been used increasingly in computational research for humanities and sciences. It provides an intelligent way for search engines to access scientific literature, and it enables the search engines to respond to complex queries such as *Which papers address a problem using a specific method*, or *What materials or resources have been utilized for a specific problem in the articles?* One of the critical elements of this type of technology is relation extraction and classification.

The neural advances in the NLP field, as explained in Section 2.2 of Chapter 2, challenge long-held assumptions regarding system architectures. The classical NLP systems, where components of increasing complexity are combined in a pipeline architecture, are being challenged by end-to-end architectures trained on distributed word representations to directly produce different types of analyses traditionally assigned to downstream tasks. Syntactic parsing has been viewed as a crucial component for many tasks aimed at extracting various aspects of meaning from text, but recent work challenges many of these assumptions. For the task of semantic role labeling, for instance, systems that make little or no use of syntactic information, have achieved state-of-the-art results (Marcheggiani et al., 2017). For tasks where syntactic information is still viewed as useful, a variety of new methods for the incorporation of syntactic information have been
employed, such as recursive models over parse trees (Ebrahimi and Dou, 2015; Socher et al., 2013c), tree-structured attention mechanisms (Kokkinos and Potamianos, 2017), multi-task learning (Wu et al., 2017), or the use of various types of syntactically aware input representations, such as embeddings over syntactic dependency paths (Xu et al., 2015b).

In this chapter, we continue this line of work and present a system based on a CNN architecture over the shortest dependency paths combined with domain-specific word embeddings to extract and classify semantic relations in scientific papers. We investigate the use of different syntactic dependency representations in a neural relation classification task and compare the widely used CoNLL, Stanford Basic, and Universal Dependencies schemes. We further compare with a syntax-agnostic approach and perform an error analysis to gain a better understanding of the results. Accordingly, the contributions of this chapter lie in investigating the following research questions:

RQ 5.1. Are domain-specific input representations beneficial for relation extraction task?

RQ 5.2. What is the impact of syntactic dependency representations in low-resource neural relation extraction?

RQ 5.3. Which kind of syntactic dependency representation is most beneficial for neural relation extraction and classification?

5.2 Previous Work

Relation extraction and classification can be defined as follows: given a sentence where entities are manually annotated, we aim to identify the pairs of entities that are instances of the semantic relations of interest and classify them based on a pre-defined set of relation types. Different approaches have been applied to solve the task of relation extraction and classification in previous work. The traditional studies mainly focus on feature-based methods. Almost all systems submitted to SemEval 2010 task 8 \(^1\) (Hendrickx et al., 2010), used either Maximum Entropy or Support Vector Machine classifiers. These systems made use of contextual, lexical, and syntactic features combined with richer linguistic and background knowledge such as WordNet and FrameNet (Hendrickx et al., 2010; Rink and Harabagiu, 2010).

The re-emergence of neural networks provides a way to develop highly automatic features and representations to handle complex interpretation tasks. These approaches have yielded impressive results for many different NLP tasks. In the relation classification task, the use of deep neural networks has been investigated in several studies (Socher et al., 2012; Lin et al., 2016; Zhou et al., 2016). There are three widely used deep neural networks (DNNs) architectures (see Section 2.2 of Chapter 2 for more details) used for relation extraction:

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\(^1\)SemEval 2010 task 8: Multi-Way Classification of Semantic Relations Between Pairs of Nominals
Convolutional neural networks (CNNs), Recurrent neural networks (RNNs), and hybrid models which combine these two types of models. Recently, pre-trained language model, as explained in Section 2.5.1.2 of Chapter 2, such as BERT (Devlin et al., 2019) is used for several tasks in scientific text. For example, SciBERT (Beltagy et al., 2019) leverages BERT on a large multi-domain corpus of scientific publications to improve performance on downstream scientific NLP tasks. Subsequently, Wang et al. (2019a) and Jiang et al. (2020) employed BERT and SciBERT for the scientific relation classification task.

In previous work, CNNs have been effectively applied to extract lexical and sentence level features for relation classification (Zhang and Wang, 2015; Lee et al., 2017; Nguyen and Grishman, 2015). Sentences or the context between two target entities are used as input for the CNNs. Such representations suffer from irrelevant sub-sequences or clauses when target entities occur far from each other, or there are other target entities in the same sentence. To avoid negative effects from irrelevant chunks or clauses and capture the relation between two entities, the researchers proposed methods that can embed syntactic tree features within a neural architecture. The shortest dependency path (sdp) between two entities is frequently used for relation classification. The sdp between two entities in the dependency graph captures a condensed representation of the information required to assert a relationship between two entities (Bunescu and Mooney, 2005). Xu et al. (2015a), Liu et al. (2015) and Xu et al. (2015b) employ DNNs such as CNNs and RNNs to learn more robust and effective relation representations from the sdp between two entities. Their experiments on the SemEval 2010 relation classification data set show that sdp can be a valuable resource for relation classification by covering highly relevant information of target relations.

Dependency representations have by now become widely used representations for syntactic analysis, often motivated by their usefulness in downstream applications. There is currently a wide range of different types of dependency representations in use, which vary mainly in terms of choices concerning syntactic head status. Some previous studies have examined the effects of these choices in various downstream applications (Miyao et al., 2008; Elming et al., 2013). Most recently, two Shared Tasks on Extrinsic Parser Evaluation (Oepen et al., 2017; Fares et al., 2018) were aimed at providing better estimates of the relative utility of different types of dependency representations and syntactic parsers for downstream applications. However, the downstream systems in this previous work have been limited to traditional (non-neural) systems, and there is still a need for a better understanding of the contribution of syntactic information in neural downstream systems.

5.3 SemEval 2018 Task 7

In this chapter, we employ the data sets released for the SemEval 2018 task 7 (Gábor et al., 2018), which encode relation instances between scientific concepts. The relations belong to a set of semantic categories that are related to the science
domain, and their instances are frequently used in abstracts and introductions of scientific articles. The shared task provides systematic evaluation steps that are essential for complete information extraction from scientific text. The concepts represent domain entities specific to the scientific discipline of Natural Language Processing (NLP). The task consists of three sub-tasks, where the first two sub-tasks are dedicated to the classification of relation instances, and the last one is devoted to the full task of extracting the relation instances, as well as classifying them. Our system participated in this task and ranked third (out of 28) participants in the overall evaluation.

The data that is provided in the task is extracted from the abstract section of scientific papers from the ACL Anthology corpus (Gábor et al., 2016). Each sub-task makes available 350 annotated abstracts and 150 abstracts as training and test data, respectively. The training and test data sets contain pre-annotated domain entities. Furthermore, the relation instances along with their directionality, are provided in both the training and the test data sets of the classification sub-tasks. The test data provided for the extraction sub-task, on the other hand, does not contain the relation instances. Below, we will describe the sub-tasks in more detail.

5.3.1 Relation classification scenario

The task of relation classification on this data set is to predict the semantic relation between a given pair of entities within the abstract of a scientific paper. The semantic relation set contains five asymmetric relations (USAGE, RESULT, MODEL-FEATURE, PART_WHOLE, TOPIC) and one symmetric relation (COMPARE). Each abstract in the training dataset contains pairs of entities that are assigned to one of these six relations. Table 5.1 shows the semantic relation typology of the six major relation types and their definitions, along with some example entity pairs.

There are two sub-tasks in this relation classification scenario: classification on clean data and classification on noisy data.

Sub-task 1.1: Relation classification on clean data: The entities and corresponding relations have been manually annotated in the training and test dataset. The test dataset contains the unlabeled relation instances, and the task is to predict the label for each entity pair. For example in the text snippet in example 5.1, the relation instance holds between two entity identifiers, i.e., (P05-1057.3, P05-1057.4) and the relation label should be predicted as : USAGE (P05-1057.3, P05-1057.4).

(5.1) <entity id='P05-1057.3'> All knowledge sources </entity> are treated as <entity id='P05-1057.4'> feature functions </entity>

Sub-task 1.2: Relation classification on noisy data: In sub-task 1.2 the entities have been automatically annotated based on a combination of terminology extraction (Saffron Knowledge Extraction Framework (Bordea et al., 2013)) and
| Relation Type     | Explanation                                                                 | Example          |
|-------------------|-----------------------------------------------------------------------------|------------------|
| USAGE             | Methods, tasks, and data are linked by usage relations.                     |                  |
| used by           | ARG1: method, system ARG2: other method                                      | approach - model |
| used_for_task     | ARG1: method, system ARG2: task                                              | approach - parsing|
| used_on_data      | ARG1: method applied to ARG2: data                                           | MT system - Japanese|
| task_on_data      | ARG1: task performed on ARG2: data                                           | parse - sentence |
| RESULT            | An entity affects or yields a result.                                        |                  |
| affects           | ARG1: specific property of data ARG2: results                               | order - performance|
| problem           | ARG1: phenomenon is a problem in a ARG2: field/task                          | ambiguity - sentence|
| yields            | ARG1: experiment/method ARG2: result                                         | parser - performance|
| MODEL             | An entity is a analytic characteristic or abstract model of another entity.  |                  |
| char              | ARG1: observed characteristics of an observed ARG2: entity                   | order - constituents|
| model             | ARG1: abstract representation of an ARG2: observed entity                    | interpretation - utterance|
| tag               | ARG1: tag/meta-information associated to an ARG2: entity                     | categories - words|
| PART_WHOLE        | Entities are in a part-whole relationship.                                   |                  |
| composed_of       | ARG1: database/resource ARG2: data                                           | ontology - concepts|
| datasource        | ARG1: information extracted from ARG2: kind of data                         | knowledge - domain|
| phenomenon        | ARG1: : entity, a phenomenon found in ARG2: context                         | expressions - text|
| TOPIC             | This category relates a scientific work with its topic.                     |                  |
| propose           | ARG1: : paper/author presents ARG2: an idea                                   | paper - method   |
| study             | ARG1: analysis of a ARG2: phenomenon                                         | research - speech|
| COMPARISON        | An entity is compared to another entity.                                     |                  |
| compare           | ARG1: result, experiment compared to ARG2: result, experiment                | result, standard|

Table 5.1: Semantic relation typology and the coarse relations from a finer grained ones that are used in annotation process (Source: Gábor et al. (2018)).
available ontological resources such as WordNet (Miller, 1995) and BabelNet (Navigli and Ponzetto, 2012). Therefore, the dataset contains a fair amount of noise (verbs, irrelevant words). The terms include high-level terms (e.g. algorithm, paper, method) and are not always full NPs. The example sentence in 5.2 shows an instance from the test dataset for this sub-task, where we observe the noisy entity assignments which incorrectly predicts an entity label for challenging.

(5.2) Morphological <entity id='N06-1042.14'> ambiguity </entity> (e.g. lives = live+s or life+s) is a <entity id='N06-1042.15'> challenging </entity> <entity id='N06-1042.16'> problem </entity> for agglutinative <entity id='N06-1042.17'> languages </entity>

The relation instance in example 5.2 is \((N06-1042.14, N06-1042.17)\) and the task is to predict the label as: MODEL-FEATURE \((N06-1042.14, N06-1042.17)\).

5.3.2 Relation extraction and classification scenario

Given an abstract and pre-annotated entities, the goal of the extraction and classification task is: 1) To find entity pairs that are in a relation 2) To predict the relation label (as in the classification sub-tasks) and its direction. The training data contains manually annotated entities and labeled semantic relations that hold between these along with the directionality of the relation. The dataset is identical to the one provided for sub-task 1.1. In the test dataset, only abstracts and annotated entities are given, and participants are asked to predict the entity pairs, their relation types, and the direction of the relations. For instance, in the following sentence in example 5.3, the entity pairs \((H01-1001.5, H01-1001.7, \text{REVERSE})\) and \((H01-1001.9, H01-1001.10)\) should be identified and classified with the USAGE label.

(5.3) Traditional <entity id='H01-1001.5'> information retrieval </entity> use a <entity id='H01-1001.6'> histogram </entity> of <entity id='H01-1001.7'> keywords </entity> as the <entity id='H01-1001.8'> document representation </entity> but <entity id='H01-1001.9'>oral communication</entity> may offer additional <entity id='H01-1001.10'> indices </entity> such as the time and place of the rejoinder and the attendance.

5.4 Evaluation Metrics

Following the SemEval 2018 task 7 (Gábor et al., 2018), each sub-task is evaluated differently. For sub-tasks 1.1 and 1.2, which are classification tasks, the following evaluation metrics are used:

- **Relation class-wise:** Precision, recall, and F1-measure \((\beta=1)\) for each semantic relation label.

- **Global:** Macro-average and Micro-average F1 scores evaluated for every distinct relation label.
For sub-task 2, evaluation is conducted for each step (i.e., Extraction and Classification). The quality of the extraction step is evaluated based on the standard measures of Precision, Recall, and F1, where the label and directionality of the relations are ignored in the calculation. In the classification step, the same evaluation metrics as sub-task 1.1 and 1.2 are employed. However, only correctly connected entities with correct directions (when relevant) and labels are considered as a correct instance. Here, we report the official scores of each experiment’s task, i.e., for the classification tasks, we report Macro-average F1, and we report the F1 score for the extraction task.

5.5 System Design

In this section, we describe the various components of our system. We introduce the input data’s specifics in terms of pre-processing, label encoding, and word embeddings and further introduce the architecture of our CNN system for relation extraction and classification.

5.5.1 Dataset preparation

For each relation instance, in the training data set, the sentence containing the participant entities is considered as a text representation of the relation instance. Therefore, if two relations appear in one sentence, they will have the same text representation. Sentence and token boundaries are detected using the Stanford CoreNLP tool (Manning et al., 2014). Since most of the entities are multi-word units, in order to obtain a precise dependency path between entities, we replace the participant entities in the relation instance with their codes prior to parsing. The example sentence in 5.4 below is thus transformed to (5.5).²

(5.4) All knowledge sources are treated as feature functions.

(5.5) All P05_1057_3 are treated as P05_1057_4.

Given an encoded sentence, we obtain the shortest dependency path connecting two target entities for each relation instance using a syntactic parser, see below.

For syntactic parsing, we employ the parser described in Bohnet and Nivre (2012), a transition-based parser that performs joint PoS-tagging and parsing. We train the parser on the standard training sections 02-21 of the Wall Street Journal (WSJ) portion of the Penn Treebank (Marcus et al., 1993). The constituency-based treebank is converted to dependencies using two different conversion tools: (i) the pennconverter software³ (Johansson and Nugues, 2007), which produces the CoNLL dependencies⁴, and (ii) the Stanford parser using:

²Preliminary results showed that this replacement technique improved results for relation extraction classification.
³http://nlp.cs.lth.se/software/treebank-converter/
⁴The pennconverter tool is run using the rightBranching=false flag.
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either the option to produce basic dependencies \(^5\) or its default option which is Universal Dependencies v1.3\(^6\). The parser achieves a labeled accuracy score of 91.23 when trained on the CoNLL08 representation, 91.31 for the Stanford basic model, and 90.81 for the UD representation, when evaluated against the standard evaluation set (section 23) of the WSJ. We acknowledge that these results are not strictly speaking state-of-the-art parse results for English. However, the parser is straightforward to use and re-train with the different dependency representations. We also compare to another widely used parser, namely the pre-trained parsing model for English included in the Stanford CoreNLP toolkit (Manning et al., 2014), which outputs Universal Dependencies only. However, it was clearly outperformed by our version of the Bohnet and Nivre (2012) parser in the initial development experiments.

Based on the dependency graphs output by the parser, we extract the shortest dependency path connecting two entities. The path records the direction of arc traversal using left and right arrows (i.e., ← and →) as well as the dependency relation of the traversed arcs and the predicates involved, following Xu et al. (2015a). The entity codes in the final path are replaced with the corresponding word tokens at the end of the pre-processing step. For the sentence in (5.4) and the two entities knowledge sources and feature functions we thus extract the path in (5.6) below.

(5.6) knowledge sources ← SBJ ← are → VC → treated → ADV → as → PMOD →
feature functions

Since the related entity pairs and the relation types are provided for the full dataset, we extend the dataset for sub-task 1.1 and 2 by extracting the related entities and their corresponding sdp from the sub-task 1.2 dataset. In order to train a model for sub-task 2, we also augment the dataset by extracting NONE relation instances (see Section 5.5.2), from the corresponding dataset. Table 5.2 shows the number of instances for each relation class. As we can see, the class distribution is clearly unbalanced.

5.5.2 Label encoding

The classification sub-tasks contain five asymmetric and one symmetric classes (see Section 5.3.1). The relation instances, along with their directionality, are provided in both the training and the test data sets. For these sub-tasks, we therefore use the same labels in our system. For sub-task 2, which combines the extraction and classification tasks, however, we construct an extra set of relation types. First, we collect every pair of entities within a single sentence that are not included in the annotated relation set. To minimize the noise, we retain only the entity pairs which are not further away than 6 tokens. From these

\(^5\) The Stanford parser is run using the -basic flag to produce the basic version of Stanford dependencies.

\(^6\) Note, however, that the Stanford converter does not produce UD PoS-tags, but outputs native PTB tags.
entity pairs, we generate negative instances with the *NONE* class and extract the corresponding *sdp*. Second, to preserve the directionality in the asymmetric relations, we add the \( \neg \) symbol to the instances with reverse directionality (e.g., *USAGE*(e1,e2,*REVERSE*) becomes \( \neg USAGE(e1,e2) \)). The final label set for sub-task 2 thus consists of 12 relations.

### 5.5.3 Word embeddings

In our system, following the sequential transfer learning of word embeddings (see Section 2.5.1 in Chapter 2), two different sets of pre-trained word embeddings are used for initialization. One is the 300-d pre-trained embeddings provided by the NLPL repository \(^7\) (Fares et al., 2017), trained on English Wikipedia data with word2vec (Mikolov et al., 2013a), here dubbed wiki-w2v. In Chapter 3, we saw that domain-specific embeddings perform better compared to the general domain embeddings trained on much larger input data. Therefore, we train a second set of domain-specific embeddings on the ACL Anthology corpus. We obtain the XML versions of 22,878 articles from ACL Anthology \(^8\). After extracting the raw texts, for training of the 300-d word embeddings (acl-w2v), we exploit the available word2vec (Mikolov et al., 2013a) implementation *gensim* (Řehůřek and Sojka, 2010) for training.

### 5.5.4 Classification Model

At the time of the SemEval task, the dominant approaches in relation extraction using the shortest dependency path as an input representation generally involve a CNN architecture. We design our system based on a CNN architecture similar to the one used for sentence classification by Kim (2014) (see Section 2.2.2 in

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| Relation     | Sub-task 1.1 & 2 | Sub-task 1.2 | Reverse False | Reverse True | Total |
|--------------|------------------|--------------|---------------|--------------|-------|
| USAGE        | 483              | 464          | 615           | 332          | 947   |
| MODEL-FEATURE| 326              | 172          | 346           | 152          | 498   |
| RESULT       | 72               | 121          | 135           | 58           | 193   |
| TOPIC        | 18               | 240          | 235           | 23           | 258   |
| PART_WHOLE   | 233              | 192          | 273           | 152          | 425   |
| COMPARE      | 95               | 41           | 136           | -            | 136   |
| NONE         | 2315             | -            | 2315          | -            | 2315  |

Table 5.2: Number of instances for each relation in the final dataset.
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Chapter 2 and also employed for sentence classification in Chapter 3). Figure 5.1 provides an overview of the proposed model. It consists of 4 main layers as follows:

1. **Look-up Table and Embedding layer**: In the first step, the model takes the shortest dependency path (i.e., the words, dependency edge directions, and dependency labels) between entity pairs as input and maps it into a feature vector using a look-up table operation. Each element of the dependency path (i.e., word, dependency label, and arrow) is transformed into an embedding layer by looking up the embedding matrix $M \in \mathbb{R}^{d \times V}$, where $d$ is the dimension of the CNN embedding layer, and $V$ is the size of the vocabulary. Each column in the embedding matrix can be initialized randomly or with pre-trained embeddings. The dependency labels and edge directions are always initialized randomly and fine-tuned during model training.

2. **Convolutional Layer**: The next layer performs convolutions with ReLU activation over the embeddings using multiple filter sizes, and extracts feature maps.

3. **Max pooling Layer**: By applying the $\text{max}$ operator, the most effective local features are generated from each feature map.

4. **Fully connected Layer**: Finally, the higher-level syntactic features are fed to a fully connected $\text{softmax}$ layer, which outputs the probability distribution over each relation.
5.6 Initial Experiments

In an initial round of experimentation, we assess the influence of different word embedding models for our task. Specifically, we contrast the use of general domain embeddings with domain-specific word embeddings. We also assess the use of a two-channel architecture (see Section 2.2.2 in Chapter 2) for the incorporation of pre-trained word embeddings in our model.

5.6.1 Model settings

In the initial experiments, we keep the value of the model hyper-parameters equal to the ones that are reported by Kim (2014), i.e., 128 filters for each window size, a dropout rate of $\rho = 0.5$ and $l_2$ regularization of 3. To deal with the effects of class imbalance, we weight the cost by the ratio of class instances. Thus each observation receives a weight, depending on the class it belongs to. The effect of the minority class observations is thereby increased simply by a higher weight of these instances and is decreased for majority class observations. Furthermore, to guarantee that each fold in $n$-fold cross-validation will have the same distribution of classes during training, development, and test, we apply the stratification technique proposed by Sechidis et al. (2011). We use the development set to detect when overfitting starts during the training of our model; using early stopping, training is then stopped before convergence to avoid overfitting (Prechelt, 2012). As described above, the official evaluation metric is the macro-averaged F1-score. Therefore we implement early-stopping with patience= 20 (i.e., the number of epochs to wait before early stop if no progress on the development set) based on the macro-F1 score in the development set.

5.6.2 Model variants

We run experiments with several variants of the model. In particular, we here contrast the use of pre-trained (general vs. domain-specific) and randomly initialized word embeddings in the input layer, and the use of one or two channels (see Section 2.2.2 in Chapter 2). Specifically, we compare the following model variants:

- **cnn.rand**: A baseline model, where all elements in the embedding layer are randomly initialized and updated in the training process.

- **cnn.wiki-w2v**: The embedding layer is initialized with the pre-trained Wikipedia word embeddings and fine-tuned for the target task.

- **cnn.acl-w2v**: The embedding layer is initialized with the pre-trained ACL Anthology word embeddings and fine-tuned for the target task.

- **cnn.multi.rand**: There are two embedding layers as a 'channel' in the CNN architecture. Both channels are initialized randomly, and only one of them is updated during training while the other remains static.
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| Model                  | Sub-task 1.1 | Sub-task 1.2 | Sub-task 2 Ext. | Sub-task 2 Class. |
|------------------------|--------------|--------------|-----------------|-------------------|
| cnn.rand               | 68.86        | 73.47        | 72.33           | 54.62             |
| cnn.wiki-w2v           | 70.14        | 74.20        | 72.50           | 54.20             |
| cnn.acl-w2v            | 72.74        | 75.69        | 72.74           | 57.56             |
| cnn.multi.rand         | 68.30        | 74.11        | 72.56           | 55.16             |
| cnn.multi/wiki-w2v     | 68.07        | 75.01        | 72.59           | 55.30             |
| cnn.multi.acl-w2v      | 72.85        | 75.83        | 72.63           | 55.45             |
| cnn.multi/wiki-w2v.rand| 69.85        | 75.58        | 72.70           | 56.69             |
| cnn.multi.acl-w2v.rand | **73.06**    | **76.36**    | 72.05           | 56.99             |

Table 5.3: F1.(avg. in 5-fold) scores for different model setting during training.

- **cnn.multi.wiki-w2v**: Same as before, but the channels are initialized with Wikipedia embedding vectors.

- **cnn.multi.acl-w2v**: The two channels are initialized with ACL embedding vectors.

- **cnn.multi.wiki-w2v.rand**: First, the channel is initialized with Wikipedia embeddings in static mode and the second initialized randomly with a non-static mode.

- **cnn.multi.acl-w2v.rand**: Same as previous setting, but the first channel makes use of ACL embeddings.

### 5.6.3 Results

During development, we first investigated the performance of different model variants (see Section 5.6.1) using the Universal Dependency representation output by the Stanford CoreNLP toolkit; by running 5-fold cross-validation. The data set is split into five folds. In the first iteration, the first fold is used to test the model, and the rest is used to train the model (i.e., three folds for training and one fold for development set to perform early stopping). In the second iteration, the second fold is used as the testing set, while the rest serve as the training set. This process is repeated until each fold of the five folds has been used as the testing set. The experiments (Table 5.3) show that the multi-channel mode performs better only in the classification sub-tasks compared to the single-channel setting. The use of the pre-trained embeddings helps the model in class assignments. Notably, the domain-specific embeddings (i.e., acl-w2v) provide higher performance gains when used in the model.
Initial Experiments

| Representation                  | cnn.multi.acl-w2v.rand | cnn.acl-w2v        |
|--------------------------------|------------------------|--------------------|
|                                | 1.1                    | 1.2                |
| Stanford Basic                 | 74.16                  | 77.70              |
| CoNLL08                        | 72.65                  | 76.83              |
| UD v1.3                        | 69.55                  | 76.60              |
| UD (Stanford CoreNLP)          | 73.06                  | 76.36              |
|                                | Ext.                   | 72.91              |
|                                | Class.                 | 58.11              |
|                                |                        | 74.26              |
|                                |                        | 60.31              |
|                                |                        | 71.09              |
|                                |                        | 54.53              |
|                                |                        | 72.74              |
|                                |                        | 57.56              |

Table 5.4: F1.(avg. in 5-fold) scores for different dependency representation during training.

Further, we experiment with the selected configuration for each task using different dependency representations to produce the shortest paths between entities. Table 5.4 presents the F1-score of each dependency representation for each sub-task via 5-fold cross-validation on the training data. In the evaluation period, we re-run 5-fold cross-validation using the selected model for each sub-task. However, in this setting we use four folds as training and one fold as a development set, and we apply the output model to the evaluation dataset. The results indicate that the Stanford Basic scheme performs best in the classification subtask, whereas the CoNLL representation provides the highest result in the full extraction task.

The comparison of different syntactic representations is potentially problematic; however, given that the default hyper-parameters may favor one of the representations simply by chance. Ideally, the hyper-parameters should be tuned for each dependency representation in turn to enable a fair comparison. In the next sections, we apply Bayesian Optimization to tune our hyper-parameters and provide an analysis of the influence of syntax and various syntactic dependency representations in our system.

5.6.4 Participating systems and results in SemEval 2018

The SemEval 2018 task attracted 32 participants. The subtask 1.1, subtask 1.2, and subtask 2 received around 28, 19, and 11 participants, respectively. The DNNs methods, including CNNs and LSTMs were widely used by the participating teams. Only five teams applied non-neural approaches such as Support Vector Machines (SVM) (Gábor et al., 2018).

We select the first (1st) and second (2nd) best performing models on the development datasets as well as the majority vote (mv) of 5 models for the final submission. The overall results of our system, as evaluated on the SemEval 2018 shared task dataset are shown in Table 5.5.
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| Sub-task | 1st Ext. | 1st Class. | 2nd Ext. | 2nd Class. | mv Ext. | Class. |
|----------|----------|------------|----------|------------|---------|--------|
| 1.1      | -        | 72.1       | -        | 74.7       | -       | 76.7   |
| 1.2      | -        | 83.2       | -        | 82.9       | -       | 80.1   |
| 2        | 37.4     | 33.6       | 36.5     | 28.8       | 35.6    | 28.3   |

Table 5.5: Official evaluation results of the submitted runs on the test set.

|       | 1.1 Ext. | 1.1 Class. | 1.2 Ext. | 1.2 Class. | 2 Ext. | Class. |
|-------|---------|------------|---------|------------|--------|--------|
| Baseline (Gábor et al., 2018) | 34.4 | 53.5 | 26.8 | 12.6 | |
| ETH-DS3Lab (Rotsztejn et al., 2018) | 81.7 | 90.4 | 48.8 | 49.3 | |
| UWNLP (Luan et al., 2018) | 78.9 | - | 50 | 39.1 | |
| Talla (Pratap et al., 2018) | 74.2 | 84.8 | - | - | |
| SIRIUS-LTG-UiO (Our system) | 76.7 | 83.2 | 37.4 | 33.6 | |
| Entity-Aware BERT$_{sp}$ (Wang et al., 2019a) | 81.4 | - | - | - | |
| MRC-SciBERT (Jiang et al., 2020) | 80.5 | - | - | - | |

Table 5.6: Results on SemEval Task 2018 Task 7 (Gábor et al., 2018).

Our system ranks third in all three sub-tasks of the shared task (Gábor et al., 2018). We compare our system to the baseline and the winning systems in Table 5.6. We also report the most recent works on the SemEval 2018 dataset, Wang et al. (2019a) and Jiang et al. (2020), where the pre-trained transformers such as BERT (Devlin et al., 2019) and SciBERT (Beltagy et al., 2019) have been exploited in the relation classification task.

5.7 Syntactic Dependency Representations

In this section, we further examine the use of syntactic representations as input to our neural relation classification system. We hypothesize that the shortest dependency path as a syntactic input representation provides an abstraction that is somehow domain independent. Therefore, the use of this type of structure may lessen domain effects in low-resource settings. We quantify the influence of syntactic information by comparing to a syntax-agnostic approach and further compare different syntactic dependency representations that are used to generate embeddings over dependency paths.
5.7.1 Dependency representations

Figure 5.2 illustrates the three different dependency representations we compare: the so-called CoNLL-style dependencies (Johansson and Nugues, 2007) which were used for the 2007, 2008, and 2009 shared tasks of the Conference on Natural Language Learning (CoNLL), the Stanford ‘basic’ dependencies (SB) (de Marneffe et al., 2006) and the Universal Dependencies (v1.3) (UD; McDonald et al. (2013); de Marneffe et al. (2014); Nivre et al. (2016)). We see that the analyses differ both in terms of their choices of heads vs. dependents and the inventory of dependency types. Where CoNLL analyses tend to view functional words as heads (e.g., the auxiliary verb *are*), the Stanford scheme capitalizes more on content words as heads (e.g., the main verb *treated*). UD takes the tendency to select contentful heads one step further, analyzing the prepositional complement *functions* as a head, with the preposition *as* itself as a dependent case marker. This is in contrast to the CoNLL and Stanford scheme, where the preposition is head.
5. Low-Resource Relation Extraction

| Relation          | best F1 (in 5-fold) |
|-------------------|---------------------|
|                   | without sdp | with sdp | Diff.  |
| USAGE             | 60.34       | 80.24    | + 19.90 |
| MODEL-FEATURE     | 48.89       | 70.00    | + 21.11 |
| PART_WHOLE        | 29.51       | 70.27    | +40.76  |
| TOPIC             | 45.80       | 91.26    | +45.46  |
| RESULT            | 54.35       | 81.58    | +27.23  |
| COMPARE           | 20.00       | 61.82    | +41.82  |
| macro-averaged    | 50.10       | 76.10    | +26.00  |

Table 5.7: Effect of using the shortest dependency path on each relation type in sub-task 1.1 (see Section 5.3.1).

5.7.2 Experiments

We run all the experiments with the multi-channel setting described above\(^9\) in which the first channel is initialized with the pre-trained ACL embeddings in static mode (i.e., it is not updated during training) and the second channel is initialized randomly and is fine-tuned during training (non-static mode). The macro F1-score is measured by 5-fold cross-validation and, once again, to deal with the effects of class imbalance, we weight the cost by the ratio of class instances; thus, each observation receives a weight, depending on the class it belongs to.

5.7.3 Assessing the effect of syntactic information

To evaluate the effects of syntactic information in general for the relation classification task, we compare the model’s performance with and without the dependency paths. In the syntax-agnostic setup, a sentence that contains the participant entities is used as input for the CNN. In addition to the word embeddings, to specify the position of each entity pair, we also use position embeddings for all words in the sentence. The position embeddings encode the relative distances of each word to the entity mentions. We here keep the value of hyper-parameters equal to the ones used in the initial experiments. To provide the shortest dependency path (sdp) for the syntax-aware version we compare to, we use our parser with Stanford dependencies, as described above. Table 5.7 shows the effect of using syntactic information through the shortest dependency path for each relation type. We find that the effect of syntactic structure varies between the different relation types. However, the sdp

\(^9\)As we recall, our initial rounds of experiments show that the multi-channel model works better than the single-channel model.
Table 5.8: Hyper parameter optimization results for each model with different representation. The max pooling strategy consistently performs better in all model variations. We also report the default value for each hyper parameter.

| Sub-task | Repr. | Filter size | Feature maps | Activation func. | L2 Reg. | Learning rate | Dropout Prob. |
|----------|-------|-------------|--------------|------------------|---------|---------------|---------------|
| 1.1 CoNLL | 4-5   | 1000        | Softplus     | 1.15e+01         | 1.13e-03| 1             |
| 1.1 SB    | 4-5   | 806         | Sigmoid      | 8.13e-02         | 1.79e-03| 0.87          |
| 1.1 UD v1.3 | 5    | 716         | Softplus     | 1.66e+00         | 9.63e-04| 1             |
| 2 CoNLL   | 3-4-5 | 667         | ReLU         | 4.96e+00         | 1.26e-03| 0.88          |
| 2 SB      | 6-7   | 339         | Sigmoid      | 1.00e-04         | 6.96e-04| 0.48          |
| 2 UD v1.3 | 3-4-5 | 549         | Iden         | 5.22e-01         | 5.09e-04| 0.81          |
| Default values | 3-4-5 | 128 | ReLU | 3 | 1e-3 | 0.5 |

Table 5.9: Performance of each model with optimized hyper parameters for different representation. In optimized column we evaluate each model with the optimal value for each hyper parameter, given in Table 5.8. In default column, the default value for each hyper parameter is used.

| Sub-task | Repr. | F1.(avg. in 5-fold) |
|----------|-------|---------------------|
| 1.1 CoNLL | 72.65 | 74.49 |
| 1.1 SB    | 74.16 | **75.05** |
| 1.1 UD v1.3 | 69.55 | 69.57 |
| 2 CoNLL   | 60.31 | 60.54 |
| 2 SB      | 58.11 | **61.18** |
| 2 UD v1.3 | 54.53 | 56.80 |

Table 5.9: Performance of each model with optimized hyper parameters for different representation. In optimized column we evaluate each model with the optimal value for each hyper parameter, given in Table 5.8. In default column, the default value for each hyper parameter is used.

information has a clear positive impact on all the relation types, ranging from improvements of 20 to 45 percentage points depending on the specific relation. This can be attributed to the fact that the context-based representations suffer from irrelevant sub-sequences or clauses when target entities occur far from each other, or there are other target entities in the same sentence. The sdp between two entities in the dependency graph captures a condensed representation of the information required to assert a relationship between two entities (Bunescu and Mooney, 2005).
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5.7.4 Comparison of different dependency representations

To assess model performance with various syntactic dependency representations, we create a \textit{sdp} for each training example using the different parse models and exploit them as input to both the relation extraction and classification model. With the use of default parameters, there is a risk that these favor one of the representations simply by chance. In order to perform a fair comparison between the different dependency representations, we make use of Bayesian optimization (Brochu et al., 2010) in order to locate optimal hyper-parameters for each of the dependency representations. We construct a Bayesian optimization procedure using a Gaussian process with 100 iterations and Expected Improvement (EI) for its acquisition functions. We set the objective function to maximize the macro F1 score over 5-fold cross-validation on the training set. Here we investigate the impact of various system design choices with the following parameters\textsuperscript{10}:

- \textit{Filter region size:} $\in \{3, 4, 5, 6, 7, 8, 9, 3-4, 4-5, 5-6, 6-7, 7-8, 8-9, 3-4-5, 4-5-6, 5-6-7, 6-7-8, 7-8-9\}$
- \textit{Number of feature maps for each filter region size:} $\in \{10 : 1000\}$
- \textit{Activation function:} $\in \{\text{Sigmoid, ReLU, Tanh, Softplus, Iden}\}$.
- \textit{Pooling strategy:} $\in \{\text{max, avg}\}$.
- \textit{L2 regularization:} $\in \{1e-4 : 1e+2\}$.
- \textit{Learning rate:} $\in \{1e-6 : 1e-2\}$.
- \textit{Dropout probability} \textsuperscript{11}: $\in \{0.1 : 1\}$.

Table 5.8 presents the optimal values for each configuration using different dependency representations. We see that the optimized parameter settings vary for the different representations, showing the importance of tuning for these types of comparisons. The results (Table 5.9) furthermore show that the \textit{sdps} based on the Stanford Basic (SB) representation provide the best performance for both subtasks following hyperparameter tuning, followed by the CoNLL08 representation. We also observe that for the extraction subtask (subtask 2), the best representation changes following tuning of the system. It can be seen that the results for the UD representation are consistently quite a bit lower than the two others. This is perhaps somewhat surprising given the fact that downstream usefulness is one of the motivations behind this dependency framework.

5.8 Error Analysis

Our results show that the best performing dependency framework in our system is the Stanford Basic scheme and furthermore that the widely used Universal

\textsuperscript{10} Default values are \{3-4-5, 128, ReLU, max, 3, 1e-3, 0.5\}

\textsuperscript{11} The probability that each element is kept, in which 1 implies that none of the nodes are dropped out
Dependencies scheme consistently provides somewhat lower results in both relation classification and full extraction. To gain a better understanding of the reasons behind these differences in performance, we perform error analysis.

Table 5.10 presents the effect of each parser representation in the classification task, broken down by relation type. Firstly, we note that in general, the results differ between the different relation types, where the TOPIC relation has the highest score (90.57 F1 with the SB representation). In contrast, the most infrequent COMPARE relation has the lowest F-score (66.67 F1 with SB). We further observe that the UD-based model falls behind the others on most of the relation types (i.e., COMPARE, MODEL-FEATURE, PART_WHOLE, TOPICS).

To explore these differences in more detail, we manually inspect the instances for which the CoNLL/SB-based models correctly predict the relation type in 5-fold trials, whereas the UD-based model has an incorrect prediction. Table 5.11 shows some of these examples for the classification sub-task, marking the entities and the gold class of each instance and also showing the sdp from each representation. We observe that the UD paths are generally shorter. A striking similarity between most of the instances is the fact that one of the entities resides within a prepositional phrase. Whereas the SB and CoNLL paths explicitly represent the preposition in the path, the UD representation does not. Clearly, the difference between, for instance, the USAGE and PART_WHOLE relation may be indicated by the presence of a specific preposition (X for Y vs. X of Y). This is also interesting since this particular syntactic choice has been shown in previous work to have a negative effect on intrinsic parsing results for English (Schwartz et al., 2012).

We go on to examine the errors in the full extraction sub-task (task 2, see Section 5.3.2) where the system trained using UD-based paths has an incorrect prediction, whereas the two other systems (CoNLL-based and SB-based) do not. We note that here as well the exclusion of the preposition from the path in the

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Table 5.10: Effect of using the different parser representation on each relation type in sub-task 1.1 (see Section 5.3.1).

| Relation       | Freq. | CoNLL | SB   | UD   |
|---------------|-------|-------|------|------|
| USAGE         | 947   | 76.84 | 82.39| 77.56|
| MODEL-FEATURE | 498   | 68.27 | 68.54| 66.36|
| PART_WHOLE    | 425   | 75.32 | 71.28| 67.11|
| TOPIC         | 258   | 89.32 | 90.57| 87.62|
| RESULT        | 193   | 82.35 | 81.69| 82.86|
| COMPARE       | 136   | 66.67 | 66.67| 54.24|
| macro-averaged|       | 76.94 | 77.57| 72.83|

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### 5. Low-Resource Relation Extraction

In the process we also provide a formal definition of parsing motivated by an informal notion due to Lang.

| Table 5.1: The examples for which the CoNLL/SB-based models in the classification sub-task correctly predict the relation type in 5-fold trials, whereas the UD based model has an incorrect prediction. |
| --- |
| Arabic in English, and the output summary is English. |

| Table 5.12: The examples for which the CoNLL/SB-based models in the extraction sub-task correctly predict the relation type in 5-fold trials, whereas the UD based model has an incorrect prediction. |
| --- |
| Arabic in English, and the output summary is English. |

| Sentence 2 |
| --- |
| We consider the case of multi-document summarization, where the input documents are in Arabic, and the output summary is in English. |

| Sentence 3 |
| --- |
| However, for grammar formalisms which use more fine-grained grammatical categories, for example tag and ccg, tagging accuracy is much lower. |

| Sentence 4 |
| --- |
| This paper describes a practical "black-box" methodology for automatic evaluation of question-answering NL systems in spoken dialogue. |

| Sentence 5 |
| --- |
| We describe a practical "black-box" methodology for automatic evaluation of question-answering NL systems in spoken dialogue.
UD representation is problematic. A high proportion of the errors contain an entity that resides within a prepositional phrase, as exemplified by the sentences in Table 5.11. We also observe some parse errors in the UD parse. Sentence 4 in Table 5.12, for instance, gives an example where the UD parser incorrectly assigns the embedded verb (use) of a relative clause status as a main verb with two modifier dependents, rather than recognizing that the relative clause (which use more fine-grained grammatical categories) depends on the entity fine-grained grammatical categories. We also find another difference between the representations which shows up in the errors, namely the combination of the aforementioned UD treatment of prepositions as dependent case markers and the copula construction, e.g., for Sentence 5 in Table 5.12, where the CoNLL and SB parsers assign head status to the copula verb are in combination with the PP complement in Arabic, whereas the UD parser assigns head status to Arabic of which the documents is a subject dependent.

5.9 Summary

This chapter presents a CNN model over the shortest dependency paths between entity pairs for relation extraction and classification in scientific text. We examine several variants of this architecture for the proposed model. The experiments demonstrate the effectiveness of domain-specific word embeddings for all sub-tasks as well as sensitivity to the specific dependency representation employed in the input layer. We compared three widely used dependency representations (CoNLL, Stanford Basic, and Universal Dependencies) and find that representation matters and that certain choices have clear consequences in downstream processing. Our experiments also underline the importance of performing hyperparameter tuning when comparing different input representations.

To summarize, the following contributions are made in this chapter:

(i) We evaluate the effect of syntax in a neural relation extraction and classification system,

(ii) We study the impact of domain-specific embeddings,

(iii) We assess the effect of varying the syntactic input representations, and

(iv) We perform a manual error analysis that helps understand the most important aspects of syntactic representation for these tasks.
Chapter 6
Natural Language Understanding in Low-Resource Genres and Languages

Learning what to share between tasks (i.e., transfer learning as explained in 2.3 of Chapter 2) has been a topic of great importance recently, as strategic sharing of knowledge has been shown to improve the performance of downstream tasks. In multilingual applications, sharing knowledge between languages is important when considering that most languages in the world suffer from being under-resourced. In this chapter, consider the transfer of models along two dimensions of variation (see Section 2.4 in chapter 2), namely genre and language, when little or no data is available for a target genre or language. These scenarios are known as low-resource and zero-resource settings. We show that this challenging setup can be approached using meta-learning, where, in addition to training a source model, another model learns to select which training instances are the most beneficial. We experiment using standard supervised, zero-shot cross-lingual, as well as few-shot cross-genre and cross-lingual settings for different natural language understanding tasks (natural language inference, question answering). Our extensive experimental setup demonstrates the consistent effectiveness of meta-learning in various low-resource scenarios. We improve the performance of pre-trained language models for zero-shot and few-shot NLI and QA tasks on two NLI datasets (i.e., MultiNLI and XNLI), and on the MLQA dataset. We further conduct a comprehensive analysis, which indicates that the correlation of typological features between languages can further explain when parameters sharing learned via meta-learning is beneficial.

6.1 Introduction

There are more than 7000 languages spoken in the world, over 90 of which have more than 10 million native speakers each (Eberhard et al., 2019). Despite this, very few languages have proper linguistic resources when it comes to natural language understanding tasks. Although there is a growing awareness in the field, as evidenced by the release of datasets such as XNLI (Conneau et al., 2018), most NLP research still only considers English (Bender, 2019). While one solution to this issue is to collect annotated data for all languages, this process is both too time consuming and expensive to be feasible. Additionally, it is not trivial to train a model for a task in a particular language (e.g., English) and apply it directly to another language where only limited training data is available (i.e., low-resource languages). Therefore, it is essential to investigate strategies that
allow us to use a large amount of training data available for English for the benefit of other languages.

Meta-learning has recently been shown to be beneficial for several machine learning tasks (Koch et al., 2015; Vinyals et al., 2016; Santoro et al., 2016; Finn et al., 2017; Ravi and Larochelle, 2017; Nichol et al., 2018). In the case of NLP, recent work has also shown the benefits of this sharing between tasks and domains (Dou et al., 2019; Gu et al., 2018; Qian and Yu, 2019). Although meta-learning for cross-lingual transfer has been investigated in the context of machine translation (Gu et al., 2018), in this chapter, we attempt to study the meta-learning effect for natural language understanding tasks. We investigate cross-lingual meta-learning using two challenging evaluation setups, namely:

(i) **Few-shot learning**: where only a limited amount of training data is available for the target domain or genre.

(ii) **Zero-shot learning**: where no training data is available for the target domain or genre.

Specifically, in Section 6.7, we evaluate the performance of our model on two natural language understanding tasks, as follows:

- Natural Language Inference (NLI) by experimenting on the MultiNLI (cross-genre setup) and the XNLI (cross-lingual setup) datasets (Conneau et al., 2018).

- Question Answering (QA) on the MLQA as a multilingual question answering dataset (Lewis et al., 2020).

Accordingly, we investigate the following research questions in this chapter:

**RQ 6.1.** Can meta-learning assist us in coping with low-resource settings in natural language understanding (NLU) tasks?

**RQ 6.2.** What is the impact of meta-learning on the performance of pre-trained language models such as BERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019) and XLM-RoBERTa (Conneau et al., 2020) in cross-lingual NLU tasks?  

**RQ 6.3.** Can meta-learning provide a model- and task-agnostic framework in low-resource NLU tasks?

**RQ 6.4.** Are typological commonalities among languages beneficial for the performance of cross-lingual meta-learning?

---

1 At the time of writing, these are the top performing models in cross-lingual NLU benchmarks.
6.2 Natural Language Understanding (NLU)

Understanding of natural language is an essential and challenging goal of NLP. Natural language understanding comprises a wide range of diverse tasks, including, but not limited to, natural language inference, question answering, sentiment analysis, semantic similarity assessment, and document classification. In this thesis, we explore the use of transfer learning by leveraging meta-learning to perform various NLU tasks, including natural language inference and question answering. We provide a brief description of these tasks in the following sections.

6.2.1 Natural Language Inference (NLI)

NLI is the task of predicting whether a hypothesis sentence is true (entailment), false (contradiction), or undetermined (neutral) given a premise sentence. NLI systems need some semantic understanding and models trained on entailment data can be applied to many other NLP tasks such as text summarization, paraphrase detection, and machine translation. The task of NLI, also known as textual entailment, is well-positioned to serve as a benchmark task for research on NLU (Williams et al., 2018). Here, we present some of the datasets that have been provided for NLI tasks and are exploited in this chapter.

MultiNLI The Multi-Genre Natural Language Inference (MultiNLI) corpus has 433k sentence pairs annotated with textual entailment information (Williams et al., 2018). It covers a range of different genres of spoken and written text and offers an explicit setting for cross-genre evaluation. The NLI premise sentences are derived from 10 different resources to cover a maximally broad range of genres of American English, such as: facetoface, telephone, verbatim, state, government, fiction, letters, 9/11, travel and oup. All of the genres appear in the test and development sets, but only five are included in the training set (See Table 6.1, which presents the statistics for the MultiNLI dataset by genre). Table 6.2 depicts randomly chosen examples from the MultiNLI dataset, shown with their genre labels, and both the selected gold labels.

XNLI The Cross-lingual Natural Language Inference (XNLI) dataset (Conneau et al., 2018) consists of 5000 test data and 2500 development hypothesis-premise pairs with their textual entailment labels for English. The pairs are annotated and translated, by employing professional translators, into 14 languages French (fr), Spanish (es), German (de), Greek (el), Bulgarian (bg), Russian (ru), Turkish (tr), Arabic (ar), Vietnamese (vi), Thai (th), Chinese (zh), Hindi (hi), Swahili (sw) and Urdu (ur). XNLI provides a multilingual benchmark to evaluate how to perform inference in low-resource languages such as Swahili or Urdu, in which only training data for the high-resource language English is available from MultiNLI. Some examples from the XNLI corpus are shown in Table 6.3.
6. Natural Language Understanding in Low-Resource Genres and Languages

| Genre          | #Examples |
|----------------|-----------|
|                | Train     | Dev.  | Test |
| Fiction        | 77,348    | 2,000 | 2,000|
| Government     | 77,350    | 2,000 | 2,000|
| Slate          | 77,306    | 2,000 | 2,000|
| Telephone      | 83,348    | 2,000 | 2,000|
| Travel         | 77,350    | 2,000 | 2,000|
| 9/11           | 0         | 2,000 | 2,000|
| Face-to-face   | 0         | 2,000 | 2,000|
| Letters        | 0         | 2,000 | 2,000|
| OUP            | 0         | 2,000 | 2,000|
| Verbatim       | 0         | 2,000 | 2,000|
| MultiNLI Overall | 392,702 | 20,000| 20,000|

Table 6.1: Statistics for the MultiNLI corpus by genre. The first five genres represent in the training, development and test sets, and the remaining five represent in the development and test set (Williams et al., 2018).

| Premise | Label | Hypothesis |
|---------|-------|------------|
| Fiction |       |            |
| The Old One always comforted Ca’daan, except today. | neutral | Ca’daan knew the Old One very well. |
| Letters |       |            |
| Your gift is appreciated by each and every student who will benefit from your generosity. | neutral | Hundreds of students will benefit from your generosity. |
| Telephone |       |            |
| yes now you know if if everybody like in August when everybody’s on vacation or something we can dress a little more casual or | contradiction | August is a black out month for vacations in the company. |
| 9/11    |       |            |
| At the other end of Pennsylvania Avenue, people began to line up for a White House tour. | entailment | People formed a line at the end of Pennsylvania Avenue. |

Table 6.2: Examples from the MultiNLI corpus, shown with their genre and selected gold labels (Williams et al., 2018).
Natural Language Understanding (NLU)

Table 6.3: Examples (premise and hypothesis) from various languages and genres from the XNLI corpus (Conneau et al., 2018).

| Language | Premise / Hypothesis                                                                 | Genre          | Label       |
|----------|--------------------------------------------------------------------------------------|----------------|-------------|
| English  | You don’t have to stay there. You can leave.                                         | Face-To-Face   | Entailment  |
| French   | La figure 4 montre la courbe d’offre des services de partage de travaux.             | Government     | Entailment  |
| Spanish  | Y se estremeció con el recuerdo. El pensamiento sobre el acontecimiento hizo su estremecimiento. | Fiction        | Entailment  |
| German   | Während der Depression war es die ärmste Gegend, kurz vor dem Hungertod. Die Weltwirtschaftskrise dauerte mehr als zehn Jahre an. | Travel         | Neutral     |
| Swahili  | Ni silaha ya plastiki ya moja kwa moja inayopiga risasi. Inadumu zaidi kikilicho silaha ya chuma. | Telephone      | Neutral     |
| Russian  | И мы занимаемся этим уже на протяжении 85 лет. Мы только начали заниматься этим.      | Letters        | Contradiction|
| Chinese  | 让我告诉你。美国人最终如何看待作为独立顾问的表现。美国人完全不知道你是独立律师。 | Slate          | Contradiction|
| Arabic   | لا يمكنك توقع أن تكون قادرة على فهم مسائل إنتاج. لا يمكنك توقع نعمة أو بدأ.        | Nine-Eleven    | Contradiction|

Figure 6.1: QA instances in the MLQA dataset. Answers shown as highlighted spans in contexts. Contexts shorten for clarity with "]...[" (Lewis et al., 2020).

| Dataset | English (en) | Arabic (ar) | German (de) | Spanish (es) | Hindi (hi) | Vietnamese (vi) | Chinese (zh) |
|---------|--------------|-------------|-------------|--------------|-----------|----------------|--------------|
| Dev     | 1148         | 517         | 512         | 500          | 507       | 507            | 507          |
| Test    | 11590        | 5335        | 4517        | 5253         | 4918      | 4918           | 4918         |

Table 6.4: Overview of the number of QA instances in the development and test portions of the MLQA dataset across the different languages.
6. Natural Language Understanding in Low-Resource Genres and Languages

6.2.2 Question Answering (QA)

The task of QA is often designed in the context of a reading comprehension task. This machine reading problem is formulated as extractive question answering, in which the answer is drawn from the original text (Eisenstein, 2019). In this context, given a context and a question, the QA task aims to identify the span answering the question in the context. We study the QA task using the following two datasets:

**SQuAD**  Stanford Question Answering Dataset (SQuAD v1.1), provided by Rajpurkar et al. (2016), is a reading comprehension dataset and contains 107,785 question-answer pairs obtained from 536 English Wikipedia articles.

**MLQA**  Lewis et al. (2020) introduce a Multilingual Question Answering dataset (called MLQA) containing QA instances in 7 languages, namely English (en), Arabic (ar), German (de), Spanish (es), Hindi (hi), Vietnamese (vi) and Simplified Chinese (zh). Figure 6.1 shows some examples from the MLQA dataset. MLQA is split into development and test splits, with detailed numbers in Table 6.4. Recently, it has been used in many benchmarks for the evaluation of cross-lingual transfer learning, e.g., Hu et al. (2020a) and Liang et al. (2020).

6.3 NLU Models

We perform experiments on a variety of models that have been proposed for NLU tasks, including Enhanced Sequential Inference Model (ESIM), Bidirectional Encoder Representations from Transformers (BERT), Cross-Lingual Language Model (XLM) and XLM on RoBERTa (XLM-RoBERTa). These models have become competitive baselines on NLI and QA tasks. In the following sections, we will briefly describe the models.

**ESIM**  Enhanced Sequential Inference Model (ESIM), proposed by Chen et al. (2017), is commonly used for textual entailment problems. ESIM employs LSTMs with attention to create a rich representation, capturing the relationship between premise and hypothesis sentences. It introduces local inference modeling, which models the inference relationship between premise and hypothesis after the two fragments have been aligned locally. Figure 6.2 shows the architecture of the ESIM model. It consists of three layers. The input encoding layer, which is the first layer, uses BiLSTM to provide a contextual representation of each word element in the input premise and hypothesis. Then, the local inference modeling collects information to perform local inference between words and phrases in the second layer. This layer computes a form of soft attention computed between the words in the two sentences to model their interactions. The softmax function is applied to transfer the attention weights computed between each word in the premise and the hypothesis to a probability distribution. The inference between sentence pairs is modeled by concatenation of the encoded and conditioned
representations of words, their difference, and component-wise product. The last layer is devoted to inference composition to perform composition and aggregation over local inference output and to make the global judgment. Since the previous layer introduces a lot of new dimensions, the outputs from inference modeling are first passed through a mapping function $F$ consisting of a simple feed-forward layer with ReLU activation to control the model’s complexity. Then, the second BiLSTM layer provides two new vectors. To merge these two vectors, average and max pooling operations are applied, and the results are concatenated in a final representation to predict the probabilities of the classes associated to the input sentences. The prediction step contains a two-layer perceptron $G$ with tanh and softmax activation functions.

Figure 6.2: Architecture of the ESIM model (Chen et al., 2017).
6. Natural Language Understanding in Low-Resource Genres and Languages

Figure 6.3: Modified Masked Language Model and Translation Language Model in XLM (Conneau and Lample, 2019).

**BERT** The Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) is designed to pretrain deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers (see Section 2.5.1.2 in Chapter 2). In our study, we employ the original English BERT model (En-BERT) and Multilingual BERT (Multi-BERT) models. Like the original English BERT model, Multi-BERT is a 12 layer transformer, but instead of being trained only on monolingual English data with an English-derived vocabulary, it is trained on the Wikipedia pages of 104 languages with a shared word piece vocabulary.

**XLM** XLM, proposed by Conneau and Lample (2019), uses a similar pre-training objective as Multi-BERT with a larger model, a more extensive shared vocabulary, and leverages both monolingual and parallel data. XLM modifies BERT in the following way: First, instead of using word or characters as the input of the model, it uses Byte-Pair Encoding (BPE), introduced by Sennrich et al. (2016), that splits the input into the most common sub-words across all languages, thereby increasing the shared vocabulary between languages. This setting is denoted as Masked Language Modeling (MLM). Second, the Translation Language Modeling (TLM) modifies the BERT architecture as follows: (i) It extends the masked language model to pairs of parallel sentences. Unlike BERT, each training sample consists of the same text in two languages. Therefore, the model can use the context from one language to predict tokens in the other, as different words are randomly masked words in each language, and (ii) The
model is also informed about the language ID and the order of the tokens (i.e., the Positional Encoding) in each language as input metadata. It helps the model learn the relationship between related tokens in different languages. The complete XLM model is trained by both MLM and TLM and alternating between them (Figure 6.3). We make use of a variant of the XLM-15 that is trained with MLM + TLM on the 15 XNLI languages.

**XLM-RoBERTa (XML-R)** Robustly Optimized BERT Pre-training Approach (RoBERTa) (Liu et al., 2019b) has the same architecture as BERT, but uses SentencePiece (Kudo and Richardson, 2018) as a tokenizer. It modifies key hyperparameters, removing the next-sentence pretraining objective and training with much larger mini-batches and learning rates. XLM-RoBERTa (XML-R) is a RoBERTa-version of XLM trained based on a much larger multilingual corpus (i.e., more than two terabytes of publicly available CommonCrawl data in 100 different languages) and has become the new state-of-the-art on cross-lingual benchmarks (Hu et al., 2020a). The biggest update that XLM-R offers over the original is a significantly increased amount of training data. XLM-R$_{base}$ with 125M parameters and XLM-R$_{large}$ with 355M parameters are the variations of XLM-R that are trained on 2.5 TB of CommonCrawl data in 100 languages and have been used in our work.

### 6.4 Model-Agnostic Meta-Learning (MAML)

Meta-learning, or learning to learn, can be seen as an instance of sequential transfer learning (see Section 2.5 of Chapter 2). It trains a high-level model sequentially based on the sub-models that are typically optimized (Ruder et al., 2019). Meta-learning tries to tackle the problem of fast adaptation to a handful of new training data instances. It discovers the structure among multiple tasks such that learning new tasks can be done quickly. In NLP, this has been done by repeatedly simulating the learning process on low-resource tasks using various high-resource tasks (Gu et al., 2018). There are several ways of performing meta-learning:

(i) **Metric-based:** It aims to learn similarities between feature representations of instances from different training sets given a similarity metric. The idea is to learn a metric space and then use it to compare low-resource testing to high-resource training samples. The representative works in this category include Siamese Network (Koch et al., 2015), Matching Network (Vinyals et al., 2016), and Relation Network (Sung et al., 2018).

(ii) **Model-based:** The idea is to use an additional meta-learner to learn and to update the original learner with a few training examples. The focus has been on adapting models that learn fast (e.g., memory networks) for meta-learning (Santoro et al., 2016). Ravi and Larochelle (2017) introduce an LSTM-based meta-learner to learn the optimization algorithm used to train the original network.
6. Natural Language Understanding in Low-Resource Genres and Languages

(iii) Optimization-based: The optimization algorithm itself is designed in a way that favors fast adaption (Finn et al., 2017; Nichol et al., 2018). The optimization-based methods introduce no additional architectures nor parameters. They can find good initialization parameters of the model using a small training set and adapt to new tasks quickly.

In this chapter, we focus on optimization-based methods due to their superiority in several tasks (e.g., computer vision (Finn et al., 2017)) over the above-mentioned meta-learning architectures. They achieved stat-of-the-art performance by directly optimizing the gradient towards a proper parameters initialization and fine-tuning on low-resource scenarios. We investigate the idea of meta-learning for transferring knowledge in a cross-genre and cross-lingual setting for natural language understanding, particularly for NLI and QA tasks. Specifically, we exploit the usage of Model Agnostic Meta-Learning (MAML), which uses gradient descent and achieves a good generalization for a variety of tasks (Finn et al., 2017). MAML can quickly adapt to new target tasks by using only a few instances at test time, assuming that these new target tasks are drawn from the same distribution.

Formally, MAML (see Figure 6.4) is applied in supervised learning step-by-step as follows (Finn et al., 2017):

\[
\theta'_{t+1} = \theta'_{t} - \alpha \nabla_{\theta} \mathcal{L}_{T_{t}}(\theta'_{t})
\]

\[
\theta_{t+1} = \theta - \alpha \nabla_{\theta} \mathcal{L}_{T_{t}}(\theta'_{t+1})
\]

Figure 6.4: Model Agnostic Meta-Learning (MAML) in supervised learning.
Model-Agnostic Meta-Learning (MAML)

Figure 6.5: Example of applying Model Agnostic Meta-Learning (MAML) in supervised learning.

1. Let us assume that there is a model $M$ with parameters $\theta$ and a distribution $p(\mathcal{T})$ over tasks.

2. We sample a batch of tasks $\mathcal{T}_i$ from the distribution $p(\mathcal{T})$. Let us say we sample $n$ tasks as $\{\mathcal{T}_1, \ldots, \mathcal{T}_n\}$.

3. In the inner loop, for each task $\mathcal{T}_i$ in tasks $\mathcal{T}$, we prepare the support set (i.e., $D_i^{train}$) and query set (i.e., $D_i^{test}$). The parameters $\theta$ is updated using one or a few iterations of gradient descent steps on the training examples in the support set (i.e., $D_i^{train}$) of task $\mathcal{T}_i$. For example, for one gradient update,

$$\theta_i' = \theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}(M_{\theta})$$ (6.1)
where $\alpha$ is the step size, the $M_{\theta}$ is the learned model from the neural network and $L_{T_i}$ is the loss on the specific task $T_i$.

4. The parameters of the model $\theta$ are trained to optimize the performance of $M_{\theta'}$ on the unseen test examples (i.e., $D_{i_{test}}$) across tasks $p(T)$. The meta-learning objective is:

$$\min_{\theta} \sum_{T_i \sim p(T)} L_{T_i}(M_{\theta'}(\theta)) = \min_{\theta} \sum_{T_i \sim p(T)} L_{T_i}(M_{\theta - \alpha \nabla_{\theta} L_{T_i}(\theta)})$$ (6.2)

The MAML algorithm aims to optimize the model parameters via a small number of gradient steps on a new task, which we refer to as the meta-update. The meta-update across all involved tasks is performed for the $\theta$ parameters of the model using stochastic gradient descent (SGD) as:

$$\theta \leftarrow \theta - \beta \sum_{T_i \sim p(T)} \nabla_{\theta'} L_{T_i}(M_{\theta'})$$ (6.3)

where $\beta$ is the meta-update step size.

5. We repeat step 2 to 4 for $N$ number of iterations as outer-loop.

6. The final parameters $\theta$ is the optimal parameters that can be used to initialize the model $M$ in a new task.

The meta-update step in MAML (Eq. 6.3) involves a gradient through a gradient which can be both computationally and memory intensive. A modified version of MAML ignores the second derivative (Finn et al., 2017), resulting in a simplified and cheaper implementation, known as First-Order MAML (FOMAML):

$$\theta \leftarrow \theta - \beta \sum_{T_i \sim p(T)} \nabla_{\theta'} L_{T_i}(M_{\theta'})$$ (6.4)

We further illustrate MAML with a simple example, shown in Figure 6.5. We here have two image classification tasks: One training task (Task 1), to label images as a cat, lamb, or pig, and another task, to label images as a dog, shark, or lion. The aim is to train a neural network model $M$ towards parameters that can adapt quickly and with few examples to a novel classification task (i.e., to label images as a duck, dolphin, or hen). First, we randomly initialize our model parameters $\theta$. We train our model on Task 1 using the train set and minimize the loss using gradient descent and find the optimal parameters $\theta_1'$ (see Eq. 6.1). Similarly, for Task 2, we start with a randomly initialized model parameters $\theta$ and minimize the loss by finding the optimal parameters $\theta_2'$ using gradient descent. In the next step, we perform meta-optimization in each task’s test set by minimizing the loss in the test set. We calculate the losses (i.e., $L_{T_1}(M_{\theta_1'})$ and $L_{T_2}(M_{\theta_2'})$) by taking the gradient with respect to our optimal parameters calculated in the previous step $\theta_1'$ and $\theta_2'$. Then, we update the original parameters $\theta$ using the test sets of Tasks 1 and 2 (see Eq. 6.3). During
meta-training, the MAML learns the optimal initialization parameters that allow the model $M$ to adapt quickly and efficiently to a new few-shot task with new, unseen classes (i.e., Task 3).

6.5 Related Work

This chapter’s primary motivation is the low availability of labeled training datasets for most of the different text genres and languages. To alleviate this issue, several methods, including so-called few-shot learning approaches, have been proposed. Few-shot learning methods have initially been introduced within the area of image classification (Vinyals et al., 2016; Ravi and Larochelle, 2017; Finn et al., 2017), but have recently also been applied to NLP tasks such as relation extraction (Han et al., 2018), text classification (Yu et al., 2018) and machine translation (Gu et al., 2018). Specifically, in NLP, these few-shot learning approaches include either: (i) the transformation of the problem into a different task (e.g., relation extraction is transformed to question answering (Abdou et al., 2019; Levy et al., 2017)); or (ii) meta-learning (Andrychowicz et al., 2016; Finn et al., 2017).

6.5.1 Meta-Learning

Meta-learning has recently received much attention from the NLP community. It has been applied to the task of machine translation (Gu et al., 2018), where they propose to use meta-learning for improving the machine translation performance for low-resource languages by learning to adapt to target languages based on multilingual high-resource languages. They show that the use of meta-learning significantly outperforms the multilingual, transfer learning-based approach proposed by Zoph et al. (2016) and enables them to train a competitive neural machine translation system with only a fraction of training examples. However, in the proposed framework, they include 18 high-resource languages as auxiliary languages and five diverse low-resource languages as target languages. In this chapter, we assume access to only English as a high-resource language.

For the task of dialogue generation, Qian and Yu (2019) address domain adaptation using meta-learning. They introduce an end-to-end trainable dialog system that learns from multiple resource-rich tasks and is adapted to new domains with minimal training samples using meta-learning. Model-agnostic meta-learning (MAML) (Finn et al., 2017) is applied to the dialog domain and adapts a dialog system model using multiple resource-rich single domain dialog datasets. They show that the meta-learning enables the model to learn general features across multiple tasks and is capable of learning a competitive dialog system on a new domain with only a few training examples in an efficient manner.

Dou et al. (2019) explore model-agnostic meta-learning (MAML) and variants thereof for low-resource NLU tasks in the GLUE dataset (Wang et al., 2018). They consider different high-resource NLU tasks such as MultiNLI (Williams et al., 2018) and QNLI (Rajpurkar et al., 2016) as auxiliary tasks to learn
meta-parameters using MAML. Then, they fine-tune the low-resource tasks using the adapted parameters from the meta-learning phase. They demonstrate the effectiveness of model-agnostic meta-learning in NLU tasks and show that the learned representations can be adapted to new tasks effectively.

Obamuyide and Vlachos (2019) show that framing relation classification as an instance of meta-learning improves the performance of supervised relation classification models, even with limited supervision at training time. They apply model-agnostic meta-learning to explicitly learn model parameters initialization for enhanced predictive performance across all relations with limited supervision in relation classification.

Recently, model-agnostic meta-learning has been applied to the task of Natural Language Generation (NLG) (Mi et al., 2019). They formulate the problem from a meta-learning perspective and propose a generalized optimization-based approach. They show that the meta-learning based approach significantly outperforms other training procedures since it adapts fast and well to new low-resource settings.

All the works mentioned above on meta-learning in NLP assume that there are multiple high-resource tasks or languages, which are then adapted to new target tasks or languages with a handful of training samples. However, in a cross-lingual NLI and QA setting, the available high-resource language is usually only English.

6.5.2 Cross-Lingual NLU

Cross-lingual learning has a fairly short history in NLP, and has mainly been restricted to traditional NLP tasks, such as PoS tagging and parsing. In contrast to these tasks, which have seen much cross-lingual attention (Plank et al., 2016; Bjerva, 2017; de Lhoneux et al., 2018), there has been relatively little work on cross-lingual NLU, partly due to a lack of benchmark datasets. Existing work has mainly been focused on NLI (Agić and Schluter, 2018; Conneau et al., 2018), and to a lesser degree on RE (Faruqui and Kumar, 2015; Verga et al., 2016) and QA (Lewis et al., 2020; Abdou et al., 2019). Previous research generally reports that cross-lingual learning is challenging and that it is hard to beat a machine translation baseline (e.g., Conneau et al. (2018)). Such a baseline is (for instance) suggested by Faruqui and Kumar (2015), where the text in the target language is automatically translated to English. For many language pairs, a machine translation model may be available, which can be used to obtain data in the target language. To evaluate the impact of using such data, in much of previous research work, the English training data is translated into the target language using a machine translation system. Then, the model is fine-tuned on the translated data and evaluated on the test set of target languages and reported as a TRANSLATE-TRAIN baseline. Alternatively, after fine-tuning the model on the English training data, a TRANSLATE-TEST baseline is introduced by evaluating the model on the test data that is translated from the target language to English using the machine translation system.
In this chapter, we show that our meta-learning based framework can achieve competitive performance compared to a machine translation baseline (for XNLI), and propose a method that requires no training instances for the target task in the target language.

### 6.6 Cross-Lingual Meta-Learning

The underlying idea of using MAML in NLP tasks (Gu et al., 2018; Dou et al., 2019; Qian and Yu, 2019) is to employ a set of high-resource auxiliary tasks or languages to find an optimal initialization from which learning a target task or language can be done using only a small number of training instances. In a cross-lingual setting (i.e., XNLI, MLQA), where only an English dataset is available as a high-resource language, and a small number of instances are available for other languages, the training procedure for MAML requires some non-trivial changes. For this purpose, we introduce a cross-lingual meta-learning framework (X-MAML), which uses the following training steps (a more formal description of the proposed model X-MAML is given in Algorithm 4):

1. Pre-training on the high-resource language $h$ (i.e., English): Given all the training samples in the high-resource language $h$, we first train the model $\mathcal{M}$ on $h$ to initialize the model parameters $\theta$.

2. Meta-learning using low-resource languages $L$: This step consists of choosing one or more auxiliary languages $A$ from the low-resource set $L$. Using the development set of each auxiliary language in $A$, we construct a randomly sampled batch of tasks $\mathcal{T}_i$. Then, we update the model parameters using $K$ data points of $\mathcal{T}_i (D_i^{\text{train}})$ by one gradient descent step (see Eq. (6.1)). After this step, we can calculate the loss value using $Q$ examples ($D_i^{\text{test}}$) in each task. It should be noted that the $K$ data points used for training ($D_i^{\text{train}}$) are different from the $Q$ data points used for constructing $D_i^{\text{test}}$. We sum up the loss values from all tasks to minimize the meta-objective function and to perform a meta-update using Eq. (6.3). This step is performed in multiple iterations.

3. Zero-shot or few-shot learning on the target languages $\{L \setminus A\}$: In the last step of X-MAML, we first initialize the model parameters with those learned during meta-learning. We then continue by evaluating the model on the test set of the target languages (i.e., zero-shot learning) or fine-tuning the model parameters with standard supervised learning using the development set of target languages and evaluate on the test set (i.e., few-shot learning).

### 6.7 Experiments

In this section, we address our research questions (i.e., RQ 6.1 and RQ 6.2 are explored across Sections 6.7.2, 6.7.3 and 6.7.4, and RQ 6.3 is addressed in
Algorithm 4: X-MAML.

**Input:** high-resource language \( h \), set of low-resource languages \( L \), Model \( M \), step size \( \alpha \) and learning rate \( \beta \)

1. Pre-train \( M \) on \( h \) and provide initial model parameters \( \theta \)
2. Select one or more languages from \( L \) as a set of auxiliary languages \( A \)

while not done do

for \( l \in A \) do

Sample batches of tasks \( T_i \) using the development set of the auxiliary language \( l \)

for each \( T_i \) do

Sample \( K \) data-points to form \( D_{\text{train}}^i \) \( = \{ (X_k, Y_k) \}_{k=1}^K \in T_i \)

Sample \( Q \) data-points to form \( D_{\text{test}}^i \) \( = \{ (X_q, Y_q) \}_{q=1}^Q \in T_i \) for meta-update

Compute \( \nabla_\theta L_{T_i}^i (M_\theta) \) on \( D_{\text{train}}^i \)

Compute adapted parameters with gradient descent:

\[ \theta' = \theta - \alpha \nabla_\theta L_{T_i}^i (M_\theta) \]

Compute \( L_{T_i}^i (M_{\theta'}) \) using \( D_{\text{test}}^i \)

Update \( \theta \leftarrow \theta - \beta \nabla_\theta \sum_i L_{T_i}^i (M_{\theta'}) \)

End for

End for

Perform either (i) zero-shot or (ii) few-shot learning on \( \{ L \setminus A \} \) using meta-learned parameters \( \theta \)

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Section 6.7.4) by conducting a set of experiments. We perform experiments on the MultiNLI, XNLI, and MLQA datasets using different NLU models, as explained in Section 6.3. We report results for few-shot as well as zero-shot cross-genre and cross-lingual learning. To examine the model- and task-agnostic features of X-MAML, we conduct experiments with various models for both tasks.

### 6.7.1 Experimental Setup:

We implement X-MAML using the higher library. We use the Adam optimizer (Kingma and Ba, 2014) with a batch size of 32 for both zero-shot and few-shot learning. We fix the step size \( \alpha \) and learning rate \( \beta \) to \( 1 \times 10^{-4} \) and \( 1 \times 10^{-5} \), respectively. We experimented using \([10, 20, 30, 50, 100, 200, 300] \) meta-learning iterations in X-MAML. However, 100 iterations led to the best results in our experiments. We sample two sets of 16 data points from the batch to construct \( D_{\text{train}}^i \) and \( D_{\text{test}}^i \) (i.e., The sample sizes \( K \) and \( Q \) in X-MAML are equal to 16 for each dataset). We report results for each experiment by averaging the performance over ten different runs (i.e., various random seeds). An evaluation of

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2=https://github.com/facebookresearch/higher
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NLI benchmarks is performed reporting accuracy on the respective test sets. For the evaluation of the QA dataset, we use the F1 score following the multilingual evaluation script available with the MLQA data.

**Baselines:** In order to evaluate the impact of meta-learning on various scenarios, we create our baseline for each scenario. We create: (i) zero-shot baselines: directly evaluate the model on the test set of the target languages and genres (for each task), and (ii) few-shot baselines: fine-tune the model on the development set and evaluate on the test set of the low-resource languages and genres.

### 6.7.2 Few-Shot Cross-Genre NLI

To verify our learning routine more generally and to address the research question RQ 6.1, we define $\mathcal{T}_i$ as an NLI task in each genre. We exploit MAML, in its original setting (see Section 6.4), to investigate whether meta-learning encourages the model to learn a good initialization for all target genres, which can then be fine-tuned with limited supervision for each genre’s development instances (2000 examples) to achieve a good performance on its test set. In MultiNLI, which is a cross-genre dataset, we employ the Enhanced Sequential Inference Model (ESIM), as explained in Section 6.3. We train ESIM on the MultiNLI training set to provide initial model parameters $\theta$. We evaluate the pre-trained model on the English test set of XNLI (since the MultiNLI test set is not publicly available) to set the baseline for this scenario. Since MultiNLI is already split into genres, we use each genre as a task within MAML. We then include either the training set (5 genres) or the development set (10 genres) during meta-learning (similar to Step 2 in Section 6.6). In the last phase (similar to Step 3 in X-MAML), we first initialize the model parameters with those learned by MAML. We then continue to fine-tune the model using the development set of MultiNLI and report the accuracy on the English test set of XNLI. We proportionally select sub-samples $x = [1\%, 2\%, 3\%, 5\%, 10\%, 20\%, 50\%, 100\%]$ from the training data (with random sampling). The results obtained by training on the corresponding proportions ($x\%$) of the MultiNLI dataset using ESIM (as the learner model $\mathcal{M}$) are shown in Table 6.5.

We observe that for both settings (i.e., MAML on training (5 tasks) and on development (10 tasks)), the performances of all models (including baselines) improve as more training instances become available. However, as demonstrated by our experimental study, the effectiveness of MAML is larger when only limited training data is available (improving by 12% in accuracy when 2% of the data is available on the development set).

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3https://github.com/facebookresearch/MLQA
Table 6.5: Test accuracies with different settings of MAML on MultiNLI. x%: the percentage of training samples. Baseline: The test accuracy of trained ESIM using x% of training data. MAML: The test accuracy of ESIM after meta-learning, where $T_{Train}$: 5 tasks are defined in MAML using the training set, and $T_{Dev}$: 10 tasks are included in MAML using the development set. Bold font indicates best results for the various proportions of the used training data.

### 6.7.3 Zero- and Few-Shot Cross-Lingual NLI

We now aim to answer the questions RQ 6.1 and RQ 6.2 and proceed to investigate zero- and few-shot X-MAML for the cross-lingual NLI task. In XNLI, which is a cross-lingual dataset, we employ the PyTorch version of BERT \(^4\) (Devlin et al., 2019) as the underlying model \(M\) (see Section 6.3). However, since our proposed meta-learning method is model-agnostic, it can easily be extended to any other architecture. Following our X-MAML framework, we first study the impact of meta-learning with one low-resource language to serve as an auxiliary language. We evaluate the performance of a cross-lingual NLI model on the set of languages provided in the XNLI dataset. In the following sections, we study the effect of X-MAML on the performance of the En-BERT and Multi-BERT models (see Section 6.3) for the cross-lingual NLI task.

#### 6.7.3.1 Zero-Shot Learning

In this set of experiments, we employ the proposed framework (i.e., X-MAML) within a zero-shot setup, in which we do not fine-tune after the meta-learning step.

**Zero-shot X-MAML with Multi-BERT** As the first training step (i.e., pre-training on a high-resource language, see Step 1 in Section 6.6 for more

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\(^4\)https://github.com/huggingface/transformers
Table 6.6: Accuracy results on the XNLI test set for zero- and few-shot X-MAML. Columns indicate the target languages. The models of Devlin et al. (2019) and Wu and Dredze (2019) are also Multi-BERT models. For our Multi-BERT baseline model for (i) zero-shot learning, we evaluate the pre-trained model on the test set of the target language; and for (ii) few-shot learning, we fine-tune the model on the development set and evaluate on the test set of the target language. The avg column indicates row-wise average accuracy. We also report the average (AVG) and maximum (MAX) performance by using one auxiliary language for each target language.

$(l_1, l_2) \rightarrow X$ are the most beneficial auxiliary languages for X-MAML in improving the test accuracy of each target language $X$. In TRANSLATE-TEST (Devlin et al., 2019), the target language test data is translated to English and then the model is fine-tuned on English. In TRANSLATE-TRAIN (Wu and Dredze, 2019), the English training data is translated to the target language and the model is fine-tuned using the translated data.
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![Figure 6.6: Differences in performance in terms of accuracy scores on the test set for zero-shot X-MAML on XNLI using the Multi-BERT model. Rows correspond to target and columns to auxiliary languages used in X-MAML. Numbers on the off-diagonal indicate performance differences between X-MAML and the baseline model in the same row. The coloring scheme indicates the differences in performance (e.g., blue for large improvement).](image)

information) in X-MAML for XNLI, we fine-tune Multi-BERT on the MultiNLI dataset (English) to obtain the initial model parameters $\theta$ for each experiment. We go on to apply the second and third steps of X-MAML in the zero-shot scenario. We report the impact of meta-learning for each target language as a difference in accuracy with and without meta-learning on top of the baseline model (Multi-BERT) on the test set (Figure 6.6). Each column corresponds to the performance of Multi-BERT after meta-learning with a single auxiliary language, and evaluation on the target language of the XNLI test set. In general, we observe that our zero-shot approach with X-MAML outperforms the baseline model without MAML and results reported by Devlin et al. (2019). This way, we improve the performance of Multi-BERT in zero-shot cross-lingual NLI. We
observe the largest difference in performance when transferring from Urdu (ur) as an auxiliary language to Hindi (hi) as a target (e.g., +3.6% in accuracy). We also detect strong gains when transferring from Urdu (ur), Russian (ru), and Bulgarian (bg) as auxiliary languages in X-MAML.

Furthermore, Hindi (hi) is the most effective auxiliary language and provides the highest average accuracy in the zero-shot setting. Table 6.7 shows the average accuracy over ten runs of X-MAML on the XNLI dataset using Multi-BERT as the base model. Each column corresponds to the performance of the Multi-BERT system after meta-learning with a single auxiliary language, and evaluation on the target language of the XNLI test set. The auxiliary language is not included during the evaluation phase. Results of the Multi-BERT model without X-MAML (baseline) are also reported.

In Table 6.6, we include the original baseline performances reported in Devlin et al. (2019)⁵ and Wu and Dredze (2019). We report the average and maximum performance by using one auxiliary language for each target language. We also report the performance of X-MAML by also using Hindi (which is the most

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⁵https://github.com/google-research/bert/blob/master/multilingual.md
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effective auxiliary language for the zero-shot setting, as shown in Figure 6.6). We once again, suspect that this may be because of the typological similarities between Hindi (hi) and other languages.

Now we conduct the zero-shot X-MAML using two auxiliary languages (see Step 3 in Section 6.6). The results (Table 6.6) show that X-MAML using two auxiliary languages obtains the largest benefit in the zero-shot experiments. It improves our internal Multi-BERT baseline by +3.65% points in terms of average accuracy \(^6\) on the zero-shot scenario. We report the most beneficial pair of auxiliary languages for the zero-shot X-MAML in improving the test accuracy of each target language in Table 6.6.

We further experiment with regular training of the model using an auxiliary language, instead of performing meta-learning (step 2 in Section 6.6), followed by zero-shot learning on the target languages. In other words, we apply all steps of X-MAML as explained in Section 6.6, however instead of step 2, we perform regular supervised learning using the development set of the auxiliary language. We evaluate the final model on the test sets of the target languages. From this experiment, we observe that meta-learning has a strongly positive effect on predictive performance (see Figure 6.7). Comparing the results in Figure 6.6 and Figure 6.7 shows that we have similar trends of the improvements, however using meta-learning boost performance on all languages in the XNLI dataset up to 3.6%, while the largest improvement without meta-learning is 2.5%.

**Zero-shot X-MAML with En-BERT** Similar to the previous section, as the first training step (i.e., pre-training on a high-resource language, see Step 1 in Section 6.6 for more information) in X-MAML for XNLI, we fine-tune En-BERT on the MultiNLI dataset (English) to obtain the initial model parameters \(\theta\) for each experiment. Then, we apply the second and third steps of X-MAML in the zero-shot scenario. Figure 6.8 and Table 6.8 depict the results of this experiment.

We observe an improvement in accuracy by performing X-MAML on cross-lingual NLI using En-BERT (see Figure 6.8). We further note that English as an auxiliary shows negative impact (i.e., decreasing performance) in most of the cases. In the reverse setting, using any other language as an auxiliary does not lead to improvement on the English test dataset. The experiments show that the target languages such as Spanish (es), French (fr) and German (de) obtain the largest gains (i.e., improvements up to +9.3% points in terms of average accuracy), while languages such as Thai (th), Swahili (sw) and Vietnamese (vi) get the lowest gains in X-MAML on the cross-lingual NLI using En-BERT. This can possibly be attributed to the fact that the performance of En-BERT depends directly on word piece overlap, as denoted by Pires et al. (2019). For the exact accuracy scores, we refer to Table 6.8.

\(^6\)We consider only the best auxiliary languages for each target language, and then take the average.
Figure 6.7: Differences in performance in terms of accuracy scores on the test set for the zero-shot case using training (without meta-learning) on XNLI with the Multi-BERT model. Rows correspond to target and columns to auxiliary languages used in X-MAML. Numbers on the off-diagonal indicate performance differences between training on the auxiliary languages (without meta-learning) and the baseline model in the same row. The coloring scheme indicates the differences in performance (e.g., blue for large improvement).

6.7.3.2 Few-Shot Learning

For few-shot learning, following the steps in X-MAML, we perform fine-tuning on the development set (2.5k instances) of the target languages, and then evaluate on the test set (Step 3 in Section 6.6). We employ Multi-BERT as the underlying model $M$ in this scenario. Detailed ablation results are presented in Table 6.9 and Figure 6.9.

Overall, these results demonstrate that we have a positive impact on most of the low-resource target languages. However, the improvements in the few-shot X-MAML are lower compared to the zero-shot setting (i.e., improvements up to +0.61% points in terms of average accuracy for few-shot X-MAML on XNLI...
Figure 6.8: Differences in performance in terms of accuracy scores on the test set for zero-shot X-MAML on XNLI using the En-BERT (English) model. Rows correspond to target and columns to auxiliary languages used in X-MAML. Numbers on the off-diagonal indicate performance differences between X-MAML and the baseline model in the same row. The coloring scheme indicates the differences in performance (e.g., blue for large improvement).

Using the Multi-BERT model. Target languages such as Hindi (hi), Russian (ru), Thai (th), Arabic (ar) and Greek (el) benefit from X-MAML with Multi-BERT. At the same time, the few-shot X-MAML with Multi-BERT provides negative impacts for French (fr), Turkish (tr) and Urdu (ur) as target languages.

In Table 6.6, we compare X-MAML results with one and two auxiliary languages to the external and internal baselines. We detect that using two auxiliary languages in the meta-learning step (Step 2 in Section 6.6) leads to similar conclusions as before (i.e., using two auxiliary languages leads the largest benefits in the few-shot X-MAML with Multi-BERT).

In contrast to the zero-shot X-MAML with Multi-BERT, we observe that Swahili (sw) acts as the overall most effective auxiliary language for meta-learning.
Table 6.8: The performance in terms of average test accuracy for the zero-shot setting over 10 runs of X-MAML on the XNLI dataset using En-BERT (monolingual), as base model. Each column corresponds to the performance of the En-BERT system after meta-learning with a single auxiliary language, and evaluation on the target language of the XNLI test set. The auxiliary language is not included during the evaluation phase. Results of the En-BERT model without X-MAML (baseline) are also reported.

|     | ar | bg | de | el | en | es | fr | hi | ru | sw | th | tr | ur | vi | zh | baseline |
|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|----------|
| ar  | -  | 39.09 | 37.32 | 40.90 | 34.48 | 36.49 | 36.65 | 39.24 | 39.10 | 38.09 | 35.48 | 38.36 | 39.79 | 37.46 | 37.03 | 34.47    |
| bg  | 42.33 | -  | 38.29 | 41.92 | 35.17 | 37.55 | 37.58 | 40.04 | 38.93 | 38.32 | 36.37 | 38.42 | 41.70 | 39.90 | 37.31 | 35.23    |
| de  | 41.88 | 42.77 | -  | 41.59 | 37.68 | 46.41 | 46.83 | 40.90 | 42.70 | 44.89 | 39.42 | 45.70 | 41.05 | 45.03 | 40.30 | 38.52    |
| el  | 40.08 | 38.50 | 38.70 | -  | 35.18 | 37.65 | 37.80 | 40.15 | 39.72 | 39.42 | 35.91 | 39.82 | 41.06 | 38.73 | 37.99 | 35.15    |
| en  | 81.95 | 81.87 | 81.89 | 82.22 | -  | 53.18 | 45.79 | 47.56 | 51.10 | 44.69 | 52.04 | 46.30 | 50.83 | 45.87 | -       | 43.95    |
| es  | 47.41 | 47.64 | 53.24 | 46.59 | 42.86 | -  | 53.18 | 45.79 | 47.56 | 51.10 | 44.69 | 52.04 | 46.30 | 50.83 | 45.87 | -       | 43.95    |
| fr  | 45.55 | 46.40 | 49.81 | 48.81 | 40.08 | 49.92 | -  | 44.14 | 46.30 | 48.05 | 42.13 | 48.54 | 44.24 | 48.67 | 43.58 | -       | 41.04    |
| hi  | 39.61 | 38.91 | 36.91 | 39.32 | 34.46 | 36.87 | 36.78 | -  | 39.08 | 37.14 | 35.88 | 37.15 | 39.98 | 37.20 | 37.40 | -       | 34.69    |
| ru  | 41.87 | 38.73 | 39.10 | 41.98 | 35.08 | 38.02 | 38.13 | 40.73 | -  | 38.89 | 36.11 | 39.51 | 41.12 | 38.54 | 37.69 | -       | 35.09    |
| sw  | 39.05 | 37.55 | 40.07 | 39.00 | 36.41 | 40.33 | 39.85 | 38.45 | 37.57 | -  | 37.26 | 42.01 | 38.82 | 42.70 | 38.72 | -       | 37.96    |
| th  | 36.16 | 35.41 | 36.46 | 36.17 | 35.63 | 36.43 | 36.42 | 35.64 | 35.43 | 36.74 | -  | 36.91 | 36.05 | 36.63 | 36.67 | -       | 35.73    |
| tr  | 39.33 | 37.62 | 41.44 | 39.42 | 37.34 | 42.07 | 41.26 | 38.83 | 37.63 | 44.12 | 38.23 | -  | 38.97 | 43.42 | 39.86 | -       | 38.84    |
| ur  | 36.85 | 38.46 | 36.27 | 39.55 | 34.16 | 35.72 | 35.63 | 39.09 | 38.64 | 36.80 | 35.33 | 36.94 | -  | 36.91 | 36.85 | -       | 33.93    |
| vi  | 41.85 | 39.35 | 42.97 | 41.62 | 38.53 | 43.85 | 42.52 | 40.53 | 39.38 | 45.46 | 39.89 | 45.11 | 41.63 | -  | 41.84 | -       | 40.72    |
| zh  | 37.21 | 36.09 | 37.18 | 36.68 | 34.48 | 36.33 | 36.55 | 35.25 | 36.16 | 37.73 | 36.64 | 37.70 | 35.99 | 37.66 | -  | 34.63    |

with Multi-BERT in the few-shot learning setting (see results in the few-shot learning section in Table 6.6).

Moving on, in Table 6.6 we report results from Devlin et al. (2019) that use machine translation at test time (TRANSLATE-TEST) and results from Wu and Dredze (2019) that use machine translation at training time (TRANSLATE-TRAIN), where they have been shown to be strong baselines in previous work. In TRANSLATE-TRAIN, the English training data is translated to the target language, and the model is fine-tuned using the translated data. While in TRANSLATE-TEST, the target language test data is translated into English, and then the model is fine-tuned on the translated version.

Note that, using X-MAML, we can alleviate the machine translation step (TRANSLATE-TEST) from the target language into English. The results in Table 6.6 also indicate that X-MAML boosts Multi-BERT performance on XNLI. It is worthwhile mentioning that Multi-BERT in the TRANSLATE-TRAIN setup outperforms our few-shot X-MAML. However, we only use 2k development examples from the target languages, whereas work mentioned above, 433k translated sentences are used for fine-tuning.

### 6.7.4 Zero-Shot Cross-Lingual QA

Here, we attempt to answer our research questions RQ 6.2 and 6.3 in the cross-lingual QA. To understand whether our framework is model- and task-agnostic
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Figure 6.9: Differences in performance in terms of accuracy scores on the test set for few-shot X-MAML on XNLI using the Multi-BERT model. Rows correspond to target and columns to auxiliary languages used in X-MAML. Numbers on the off-diagonal indicate performance differences between X-MAML and the baseline model in the same row. The coloring scheme indicates the differences in performance (e.g., blue for large improvement).

and can apply to other tasks and models besides NLI and BERT, we conduct additional experiments for the question answering task. We investigate the impact of X-MAML on other pre-trained language models, namely XLM and XLM-RoBERTa (XLM-R) (see Section 6.3). We use these models as the base model M in X-MAML for our QA experiments. We employ the XLM-15 version of XLM, XLM-R_{base} and XLM-R_{large} versions of XLM-R (see Section 6.3). The SQuAD v1.1 training data (see Section 6.2.2) is used in the pre-training step of X-MAML (see Step 1 in Section 6.6). We use the cross-lingual development and test splits provided in the MLQA dataset (Table 6.4) for meta-learning and evaluation steps, respectively. We use a similar approach for cross-lingual QA on the MLQA dataset.

Table 6.10 shows the results of zero-shot X-MAML for the MLQA dataset. We
Table 6.9: The performance in terms of average test accuracy for the few-shot setting over 10 runs of X-MAML on the XNLI dataset using MultiBERT (multilingual BERT), as base model. Each column corresponds to the performance of the Multi-BERT system after meta-learning with a single auxiliary language, and evaluation on the target language of the XNLI test set. The auxiliary language is not included during the evaluation phase. Results of the Multi-BERT model without X-MAML (baseline) are also reported.

| Auxiliary language | ar | bg | de | el | en | es | fr | hi | ru | sw | th | tr | ur | vi | zh |
|--------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| ar                 | 67.84 | 67.73 | 67.62 | 67.84 | 67.80 | 67.85 | 67.87 | 67.86 | 67.87 | 67.82 | 67.80 | 67.86 | 67.82 | 67.81 | 67.86 |
| bg                 | 71.79 | 71.76 | 71.80 | 71.72 | 71.80 | 71.74 | 71.94 | 71.78 | 71.78 | 71.77 | 71.74 | 71.79 | 71.72 | 71.79 | 71.92 |
| de                 | 73.36 | 73.23 | 73.37 | 73.30 | 73.30 | 73.33 | 73.46 | 73.27 | 73.34 | 73.38 | 73.32 | 73.37 | 73.34 | 73.43 | 73.25 |
| el                 | 69.95 | 69.98 | 69.97 | 69.94 | 69.99 | 69.91 | 69.93 | 69.95 | 69.98 | 70.03 | 70.02 | 69.94 | 69.95 | 70.03 | 69.54 |
| en                 | 82.24 | 82.21 | 82.13 | 82.22 | 82.15 | 82.27 | 82.24 | 82.19 | 82.39 | 82.25 | 82.14 | 82.20 | 81.94 | 82.20 | 82.14 |
| es                 | 76.07 | 76.12 | 76.14 | 76.02 | 76.06 | 76.18 | 76.14 | 75.94 | 75.91 | 76.10 | 75.79 | 76.09 | 75.79 | 75.79 | 75.91 |
| fr                 | 75.32 | 75.23 | 75.16 | 75.24 | 75.23 | 75.18 | 75.19 | 75.22 | 75.31 | 75.28 | 75.19 | 75.28 | 75.28 | 75.28 | 75.39 |
| hi                 | 64.95 | 64.82 | 64.89 | 64.64 | 64.63 | 64.90 | 64.87 | 64.94 | 64.73 | 64.84 | 64.79 | 64.83 | 64.87 | 64.79 | 64.37 |
| ru                 | 71.19 | 71.27 | 71.17 | 71.33 | 71.19 | 71.33 | 71.28 | 71.31 | 71.94 | 71.45 | 71.18 | 71.39 | 70.84 | 71.29 | 71.38 |
| sw                 | 58.14 | 58.23 | 57.95 | 57.99 | 57.53 | 57.97 | 57.94 | 58.10 | 58.04 | 58.00 | 58.22 | 58.08 | 58.01 | 58.09 | 57.82 |
| th                 | 61.59 | 61.64 | 61.57 | 61.71 | 61.40 | 61.51 | 61.51 | 61.68 | 61.54 | 61.50 | 61.58 | 61.41 | 61.56 | 61.74 | 61.18 |
| tr                 | 64.74 | 64.79 | 64.69 | 64.82 | 64.59 | 64.82 | 64.76 | 64.83 | 64.70 | 64.89 | 64.92 | - | 64.74 | 64.73 | 64.66 |
| ur                 | 63.67 | 63.58 | 63.69 | 63.63 | 63.55 | 63.63 | 63.68 | 63.61 | 63.72 | 63.63 | 63.81 | - | 63.67 | 63.69 | 63.71 |
| vi                 | 73.51 | 73.52 | 73.46 | 73.35 | 73.36 | 73.29 | 73.39 | 73.31 | 73.51 | 73.38 | 73.39 | 73.41 | 73.42 | - | 73.41 |
| zh                 | 74.04 | 73.97 | 74.02 | 74.02 | 73.74 | 74.01 | 74.02 | 74.10 | 74.11 | 73.99 | 74.01 | 74.21 | 74.06 | 73.95 | - | 73.93 |

The baseline values are provided by training each base model on the SQuAD v1.1 train set (see Step 1 in Section 6.6) and evaluating on the test set of MLQA. In Table 6.10, we consider only the best auxiliary languages for each target language, and then compute the average F1 score.

We observe that all of the target languages benefit from at least one of the auxiliary languages by adapting the models using X-MAML, highlighting the benefits of this method. We find that: (i) our zero-shot results with X-MAML improve on those without meta-learning (i.e., baselines); (ii) performing X-MAML with two auxiliary languages provides the largest gains for the models in cross-lingual QA. Overall, zero-shot learning models with X-MAML outperform both internal and external baselines. The improvement is +1.04%, +0.89% and +1.47% in average F1 score compared to XLM-15, XLM-R Base and XLM-R Large, respectively.

6.8 Discussion and Analysis

Somewhat surprisingly, we find that cross-lingual transfer with meta-learning yields improved results even when languages strongly differ (i.e., in terms of language family) from one another. For instance, for zero-shot meta-learning on XNLI, we observe gains for almost all auxiliary languages, except for Swahili (sw).
## 6. Natural Language Understanding in Low-Resource Genres and Languages

| Model            | Model | en | ar  | de  | es  | hi  | vi  | zh  | avg |
|------------------|-------|----|-----|-----|-----|-----|-----|-----|-----|
| XLM              |       | 69.80 | 48.95 | 52.64 | 58.15 | 46.67 | 48.46 | 42.64 | 52.47 |
| X-MAML           | (One aux. lang.) | l → X | 69.39 | 48.45 | 53.04 | 57.68 | 46.90 | 49.79 | 44.36 | 52.80 |
|                  | (Two aux. lang.) | (l₁, l₂) → X | 68.88 | 49.76 | 53.18 | 58.00 | 48.43 | 50.86 | 45.44 | 53.51 |
| XLM-R base       | Liang et al. (2020) |       | 80.1 | 56.4 | 62.1 | 67.9 | 60.5 | 67.1 | 61.1 | 65.1 |
|                  | Our baseline |       | 80.38 | 57.23 | 63.08 | 67.91 | 61.46 | 67.14 | 62.73 | 65.70 |
| X-MAML           | (One aux. lang.) | l → X | 80.19 | 57.97 | 63.57 | 67.46 | 61.70 | 67.97 | 64.91 | 66.12 |
|                  | (Two aux. lang.) | (l₁, l₂) → X | 80.31 | 58.14 | 64.07 | 68.08 | 62.67 | 68.82 | 64.06 | 66.59 |
| XLM-R large      | Hu et al. (2020a) |       | 83.5 | 66.6 | 70.1 | 74.1 | 70.6 | 74 | 62.1 | 71.6 |
|                  | Our baseline |       | 83.95 | 66.09 | 70.62 | 74.59 | 70.64 | 74.13 | 69.80 | 72.83 |
| X-MAML           | (One aux. lang.) | l → X | 84.31 | 66.61 | 70.84 | 74.32 | 70.94 | 74.84 | 70.74 | 73.23 |
|                  | (Two aux. lang.) | (l₁, l₂) → X | 84.60 | 66.95 | 71.00 | 74.62 | 70.93 | 74.73 | 70.29 | 74.30 |

Table 6.10: F1 scores (average over 10 runs) on the MLQA test set using zero-shot X-MAML. Columns indicate the target languages. The avg column indicates row-wise average F1 score. We also report the most beneficial auxiliary language/s for X-MAML in improving the test F1 of each target language.

This indicates that the meta-parameters learned with X-MAML are sufficiently language agnostic, as we otherwise would not expect to see any benefits in transferring from, e.g., Russian (ru) to Hindi (hi) (one of the strongest results in Figure 6.6). This is dependent on having access to a pre-trained multilingual model such as BERT; however, using monolingual BERT (En-BERT) yields overwhelmingly positive gains in some target/auxiliary settings (see results in Figure 6.8). For few-shot learning when we only have access to a handful of training instances, our findings are similar, as almost all combinations of auxiliary and target languages lead to improvements when using Multi-BERT (Figure 6.9). Therefore, we try to shed light on the behavior of our proposed model and answer our last research question (i.e., RQ 6.4) in the following section.

### 6.8.1 Typological Correlations

In order to better explain our results for cross-lingual zero-shot and few-shot learning, we investigate typological features, and their overlap between target and auxiliary languages. We evaluate on the World Atlas of Language Structure (WALS, Dryer and Haspelmath (2013)), which is the largest openly
available typological database. It comprises approximately 200 linguistic features with annotations for more than 2500 languages, which have been made by expert typologists through the study of grammars and field work. We draw inspiration from previous works (Bjerva and Augenstein, 2018a; Bjerva and Augenstein, 2018b) that attempt to predict typological features based on language representations learned under various NLP tasks. Similarly, we experiment with the two following conditions:

(i) We attempt to predict typological features based on the mutual gain/loss in performance using X-MAML.

(ii) We investigate whether sharing between two typologically similar languages is beneficial for performance using X-MAML.

We train one simple logistic regression classifier per condition above, for each WALS feature. In the first condition (i), the task is to predict the exact WALS feature value of a language, given the change in accuracy in combination with other languages. In the second condition (ii), the task is to predict whether a main and auxiliary language have the same WALS feature value, given the change in accuracy when the two languages are used in X-MAML. We compare with two simple baselines, one based on always predicting the most frequent feature value in the training set, and one based on predicting feature values with respect to the distribution of feature values in the training set. We then investigate whether any features could be consistently predicted above baseline levels, given different test-training splits. We apply a simple paired t-test to compare our model predictions to the baselines. As we are running a large number of tests (one per WALS feature), we apply Bonferroni correction, changing our cut-off p-value from $p = 0.05$ to $p = 0.00025$.

We first investigate a few-shot X-MAML, when using Multi-BERT, as reported in Table 6.9. We find that languages sharing the feature value for WALS feature 67A The Future Tense are beneficial to each other. This feature encodes whether or not a language has an inflectional marking of the future tense, and can be considered to be a morphosyntactic feature. We next look at zero-shot X-MAML with Multi-BERT, as reported in Table 6.7. For this case, we find that languages sharing a feature value for the WALS feature 25A Locus of Marking: Whole-language Typology typically help each other. This feature describes whether the morphosyntactic marking in a language is on the syntactic heads or dependents of a phrase. For example, English (en), German (de), Russian (ru), and Chinese (zh) are ‘dependent-marking’ in this feature. Moreover, if we look at the results in Figure 6.6, they have the largest mutual gains from each other during the zero-shot X-MAML, as shown in Figure 6.10. In both cases, we thus find that languages with similar morphosyntactic properties can be beneficial to one another when using X-MAML.
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Figure 6.10: The mutual gains among English (en), German (de), Russian (ru), and Chinese (zh) languages in zero-shot X-MAML with Multi-BERT. Rows correspond to target and columns to auxiliary languages used in X-MAML. Numbers indicate performance differences between X-MAML and the baseline model in the same row. The coloring scheme indicates the differences in performance (e.g., blue for large improvement).

6.9 Summary

In this chapter, we show that meta-learning allows us to leverage training data from auxiliary languages and genres, to perform the zero-shot and few-shot cross-lingual and cross-genre transfer. We achieve competitive performance compared to a machine translation baseline (for XNLI), and propose a method that requires no training instances for the target task in the target language. Experiments with different models show that our method is model agnostic, and can be used to extend any pre-existing model. We evaluated this on two challenging NLU tasks (NLI and QA), and on a total of 15 languages. We can improve the performance of strong baseline models for (i) zero-shot XNLI, and (ii) zero-shot QA on the MLQA dataset. Furthermore, we show in a typological analysis that languages which share certain morphosyntactic features tend to benefit from this type of transfer.

To summarize, the contribution of this chapter (detailed in Section 6.6) is four-fold. Concretely, we:

(i) exploit the use of meta-learning methods for two different natural language understanding tasks (i.e., NLI, QA);

(ii) evaluate the performance of the proposed architecture on various scenarios: cross-genre, cross-lingual, standard supervised, and zero-shot, across a total
of 15 languages (i.e., 15 languages in XNLI and 7 languages in MLQA);

(iii) observe consistent improvements of our cross-lingual meta-learning architecture (X-MAML) over the previous models on various cross-lingual benchmarks (i.e., improving the Multilingual BERT model by $+3.65\%$ and $+1.04\%$ points in terms of average accuracy on zero-shot and few-shot XNLI, respectively, and boosting the XLM-R_{large} by $+1.47\%$ in terms of average F$_1$ score on zero-shot QA);

(iv) perform an error analysis, which reveals that typological commonalities between languages can partially explain the cross-lingual trends.
Chapter 7

Conclusion and Future work

This thesis investigates methods for dealing with low-resource scenarios in information extraction and natural language understanding tasks. To this end, we study distant supervision and sequential transfer learning in various low-resource settings. We develop and analyze models to explore three essential questions concerning NLP tasks with minimal or no training data which cut across several of the chapters in this thesis (see Table 7.1 for an overview that maps the general research questions to individual chapters and sub-questions):

RQ I. What is the impact of different input representations in neural low-resource NLP?

RQ II. How can we incorporate domain knowledge in low-resource NLP?

RQ III. How can we address challenges of low-resource scenarios using transfer learning techniques?

During the course of this thesis we have made contributions in low-resource NLP in four different areas: domain-specific embeddings (Chapter 3), named entity recognition (Chapter 4), relation extraction and classification (Chapter 5), and cross-genre and cross-lingual natural language understanding (Chapter 6). In the following, we describe our proposed methods and findings (Section 7.1). Our main contributions are summarized in Section 7.2, and we provide an outlook into future directions in Section 7.3.

7.1 Proposed Methods and Findings

Previous research shows that automatically learning transferable representations in terms of word embeddings boosts NLP models’ performance in various downstream tasks. The following research question addresses a central challenge that needs to be answered for embeddings in a technical domain:

• RQ 3.1. Can word embedding models capture domain-specific semantic relations even when trained with a considerably smaller corpus size?

To answer this question, we here focus on a new and relatively unexplored technical domain: the oil and gas domain, train domain-specific embeddings on this technical low-resource domain. We further construct a domain-specific evaluation dataset, including a corpus and a query inventory for the oil and gas domain (Section 3.3.1). We evaluate, in Sections 3.4 and 3.7, the effectiveness of domain-specific models using intrinsic and extrinsic evaluations. In Section 3.4, empirical intrinsic evaluations reveal that domain-specific trained embeddings perform better than general domain embeddings trained on much larger input...
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| Question                                                                 | Chapter | Sub-Question |
|--------------------------------------------------------------------------|---------|--------------|
| RQ I: What is the impact of different input representations in neural low-resource NLP? | Chapter 3 | RQ 3.1       |
|                                                                           |         | RQ 5.1       |
|                                                                           |         | RQ 5.2       |
|                                                                           |         | RQ 5.3       |
| RQ II: How can we incorporate domain knowledge in low-resource NLP?      | Chapter 3 | RQ 3.2       |
|                                                                           |         | RQ 4.1       |
|                                                                           |         | RQ 4.2       |
| RQ III: How can we address challenges of low-resource scenarios using transfer learning techniques? | Chapter 3 | RQ 3.1       |
|                                                                           |         | RQ 5.1       |
|                                                                           |         | RQ 5.2       |
|                                                                           | Chapter 5 | RQ 6.1       |
|                                                                           |         | RQ 6.2       |
|                                                                           | Chapter 6 | RQ 6.1       |
|                                                                           |         | RQ 6.2       |

Table 7.1: Overview of the research questions and related chapters.

Furthermore, in Section 3.5, the in-depth manual analysis shows the ability of the domain model to discover semantic relations such as (co)hyponymy, hypernymy, and relatedness, giving insight into these models beyond the intrinsic evaluation dataset.

In our target domain, in addition to text, there exists a domain-specific knowledge resource (i.e., Schlumberger oilfield glossary) created by domain experts to facilitate information processing. We here pose the following research question:

- **RQ 3.2. How can we take advantage of existing domain-specific knowledge resources to enhance the resulting models?**

We enhance, in Section 3.6, the domain embeddings by incorporating domain knowledge from the oilfield glossary and constructing embedding representations for infrequent technical terms. We find that the domain embeddings and their enhanced versions can be useful resources to support a downstream domain-specific NLP task (Section 3.7.3). The results on a multi-label domain-specific sentence classification task show that the enhanced domain embeddings provide higher performance and aid the model in label assignment.

NER is a central task in NLP and one that often requires domain-specific, annotated data. In Chapter 4, we focus on the named entity recognition task in several low-resource domains. We here pose the following research questions:

- **RQ 4.1. How can we address the problem of low-resource NER using distantly supervised data?**
• **RQ 4.2.** *How can we exploit a reinforcement learning approach to improve NER in low-resource scenarios?*

We introduce a framework to address the common challenges of distantly supervised datasets for low-resource NER. The main concerns in distantly supervised NER are false positive and false negative instances. Our framework combines a neural NER model with a partial-CRF layer and a policy-based reinforcement learning component (Section 4.4). The partial-CRF component (PA in Section 4.4.2) is designed to deal with the false negatives, while the reinforcement-based module (RL in Section 4.4.3) handles the false positives instances. We quantify, in Section 4.6, the impact of each component in our proposed framework. We further in Section 4.7, investigate the performance of our model under settings using different sizes of human-annotated data. The ablation studies determine the efficiency of the partial-CRF and policy reinforcement modules in fixing the problems in the distantly annotated NER datasets. Overall, our final system, a combination of NER, PA, and RL, achieves an improvement of +2.75 and +11.85 F1 on the BC5CDR and LaptopReview respectively over the baseline system. Furthermore, we observe that our model can deliver relatively good performance with a small set of gold data. Our final method achieves a performance of 83.18 and 63.50 with only 2% of the annotated dataset in the BC5CDR and LaptopReview domains, respectively. In contrast, the base NER model requires almost 45% of the ground truth sentences to reach the same performance.

In Section 4.6, we aim to answer:

• **RQ 4.3.** *Is the proposed solution beneficial for different low-resource scenarios?*

We evaluate our model across four diverse datasets from different domains (i.e., biomedical, e-commerce, technical reviews, and news) and languages (English and Chinese). Experimental results show that our approach can boost the performance of the neural NER system in resource-poor settings and achieve higher F1 scores on the different datasets compared to previous work.\(^1\)

Another central IE task is relation extraction. In Chapter 5, we introduce an adapted neural framework incorporating domain-specific embeddings and syntactic structure to address low-resource relation extraction tasks in the SemEval 2018 task 7. Our framework is based on a CNN architecture over the shortest dependency paths between entity pairs for relation extraction and classification in scientific text (Section 5.5). The framework leverages knowledge from both domain-specific embeddings and syntactic representations to help the low-resource relation extraction task. It ranks third in all three sub-tasks of the SemEval 2018 task. With this, we attempt to answer the following questions:

• **RQ 5.1.** *Are domain-specific input representations beneficial for relation extraction task?*

\(^1\) At the time of publishing the results were state-of-the-art.
• **RQ 5.2.** What is the impact of syntactic dependency representations in low-resource neural relation extraction?

We first, in Section 5.6.1, investigate the utility of domain-specific word embeddings to our neural relation extraction model. The sensitivity analysis study confirms, what we already found in Chapter 3, the positive impact of domain-specific embeddings by providing higher performance gains when used in our model. By inspecting the performance of the model with and without the dependency paths in Section 5.7.3, we affirm the influence of syntactic structure compared to a syntax-agnostic approach in this setting. We find that the effect of syntactic structure varies between different relation types. However, the syntactic representation has a clear positive impact on all the relation types, ranging from improvements of 20 to 45 percentage points depending on the specific relation. We further ask the following question:

• **RQ 5.3** Which kind of syntactic dependency representation is most beneficial for neural relation extraction and classification?

Thus, in Section 5.7.4, we examine the influence of incorporating various dependency representations in our neural model. We contrast the use of three input representations for our relation extraction model employing the widely used CoNLL, Stanford Basic (SB), and Universal Dependencies (UD) schemes. We compare the effectiveness of specific inputs to our neural relation extraction model by inspecting the effect of various syntactic representations. Furthermore, we observe that the widely used Universal Dependencies scheme consistently provides somewhat lower results in both relation classification and extraction tasks. We, therefore, opted for manual inspection of a set of incorrect predictions provided by the Universal Dependencies-based model, which are correctly predicted by the two other systems (CoNLL and Stanford Basic-based models). Overall, our results and analysis show that the particular choice of syntactic representation has clear consequences in downstream processing. We observe that the UD paths are generally shorter, and the entities often reside within a prepositional phrase. Whereas the SB and CoNLL paths explicitly represent the preposition in the path, the UD representation does not. We note that the system benefits from the explicit inclusion of prepositions in the path, and that the UD treatment of prepositions as dependent case markers, as well as the copula construction, is problematic in our system design.

There are several other dimensions of variation for natural language texts, as discussed in Section 2.1 in Chapter 2. In Chapter 6 we go on to study low-resource settings in cross-genre and cross-lingual natural language understanding tasks. We explore the use of meta-learning by leveraging training data from an auxiliary genre or language, to perform the zero-shot and few-shot cross-lingual and cross-genre transfer in two different natural language understanding (NLU) tasks: natural language inference (NLI) and question answering (QA). We here attempt to answer the following questions:

• **RQ 6.1.** Can meta-learning assist us in coping with low-resource settings in natural language understanding (NLU) tasks?
RQ 6.2. *What is the impact of meta-learning on the performance of pre-trained language models such as BERT, XLM, and XLM-RoBERTa in cross-lingual NLU tasks?*

RQ 6.3. *Can meta-learning provide a model- and task-agnostic framework in low-resource NLU tasks?*

We propose, in Section 6.6, a cross-lingual meta-learning framework for low-resource NLU tasks. We evaluate our framework on various scenarios, including cross-genre and cross-lingual NLI in zero- and few-shot settings across 15 languages (Section 6.7.3). We further, in Section 6.7.4, investigate the model- and task-agnostic properties of our proposed framework by conducting experiments for the cross-lingual QA task. The experiments show that our cross-lingual meta-learning architecture (X-MAML) consistently improves the strong baseline models. It improves the multilingual BERT by +3.65 and +1.04 percentage points in terms of average accuracy on zero-shot and few-shot XNLI, respectively. Furthermore, it boosts the XLM-RoBERTa by +1.47 percentage points in terms of the average F1 score on zero-shot QA. In Section 6.8, we aim to answer:

RQ 6.4. *Are typological commonalities among languages beneficial for the performance of cross-lingual meta-learning?*

Thus, we conduct an error analysis to explore the impact of typological sharing between languages in our framework. We evaluate on the World Atlas of Language Structure (WALS) as the largest openly available typological database. We attempt to predict typological features based on the mutual gain/loss in performance using our meta-learning framework. We further investigate whether the target and auxiliary languages have the same WALS feature value, given the change in accuracy when the two languages are used in cross-lingual meta-learning. This indicates that languages with similar morphosyntactic properties can be beneficial to one another in our meta-learning framework. For instance, we observe that languages sharing a feature value for the WALS feature 25A *Locus of Marking: Whole-language Typology* typically help each other in zero-shot cross-lingual meta-learning with Multi-BERT.

### 7.2 Contributions

We here summarize the main contributions of the thesis:

(i) Make use of sequential transfer learning in terms of non-contextualized word embeddings to address the problem of low-resource domains in downstream tasks in NLP (see Chapters 3, 4 and 5).

(ii) Enhance domain-specific embeddings using a domain-specific knowledge resource and present a benchmark dataset for intrinsic and extrinsic evaluation of domain embeddings (Chapter 3).
7. Conclusion and Future work

(iii) Propose a hybrid model that combines a reinforcement learning algorithm with partial annotation learning to clean the noisy, distantly supervised data for low-resource NER in different domains and languages (see Chapter 4).

(iv) Design a neural architecture with syntactic input representation to alleviate domain impact in low-resource relation extraction (see Chapter 5).

(v) Introduce a cross-lingual meta-learning framework that provides further improvements in low-resource cross-lingual NLU tasks in various settings and languages (see Chapter 6).

7.3 Future directions

Even though the proposed methods achieve competitive performance compared to previous work in the respective low-resource NLP tasks, there are several potential avenues for future research. In the following, we will look into some of the future research directions that can alleviate some of the limitations of the proposed methods and low-resource NLP in general.

Sequential transfer learning through pre-trained word embeddings has brought significant improvements for many low-resource NLP tasks. The pre-trained word embeddings that we employed in chapters 3, 4 and 5 provide a single static representation for each word and have limitations that are already discussed in Section 2.5.1 of Chapter 2. The immediate idea for improving the proposed models in this thesis is to exploit the use of contextualized embeddings such as BERT, ELMo, and GPT. Some domain-specific versions of BERT are available, which are trained or fine-tuned on in-domain text, including SciBERT (Beltagy et al., 2019), BioBERT (Lee et al., 2020) and ClinicalBERT (Alsentzer et al., 2019) and can be used in low-resource NER and relation extraction tasks on some of the target domains. However, there is still a need to train the contextualized embedding models in other domains. This remains a challenge since it requires large amounts of training data.

Even though the contextualized embeddings handle rare words implicitly using techniques such as byte-pair encoding and WordPiece embeddings, they still struggle with small corpora and with providing good representations for unseen words (Schick and Schütze, 2020). In chapter 3, we incorporate a knowledge resource to augment the trained non-contextual embeddings by providing vector representations for infrequent and unseen technical terms. However, the proposed solution is limited in two respects: (i) the target word must appear in the knowledge resource, and (ii) its neighbors must be part of the vocabulary of the embeddings model. One way to overcome this limitation and improve embeddings of uncommon words is to jointly incorporate surface-form and context information directly from the textual content as described in Schick and Schütze (2019b) and Schick and Schütze (2019a). The former combines an embedding based on n-grams with an embedding obtained from averaging over all context words. Whereas, the latter introduces an attentive mimicking model that computes an
embedding by giving access not only to a word’s surface form, but also to all available contexts. The attentive mimicking model learns to attend to the most informative and reliable contexts.

The pre-trained language models can be further enhanced by leveraging knowledge accumulated by humans in terms of knowledge resources such as WordNet (Miller, 1995), ConceptNet (Speer et al., 2017), FrameNet (Baker et al., 1998), DBpedia (Lehmann et al., 2015). Work on incorporating knowledge resources into pre-trained language models has shown some promise on several NLP tasks (Zhang et al., 2020; Peters et al., 2019; Wang et al., 2019b; Zhang et al., 2019). It would also be interesting to investigate the impact of jointly applying both of these research directions, i.e., surface-context information and knowledge-representations, on pre-trained language models.

A limitation of work in this thesis is the use of conventional neural architectures such as CNNs and BiLSTM in low-resource named entity recognition and relation extraction tasks, respectively. Transformer-based models such as BERT, GPT, XLM, and XLM-RoBERTa, which are proposed as one system for all tasks, might be more appropriate on low-resource NLP settings. Adapting the transformer-based model (see Section 2.5.2 in Chapter 2) by the task specific fine-tuning, mitigates the need for having task-specific models and it transfers a pre-trained language model directly to a target task through minimal modifications, usually by modifying the last layer. (Pilehvar and Camacho-Collados, 2020).

For low-resource NER, we envision numerous directions for future research. For instance, we deal with false positive instances at the sentence level via a reinforcement model. However, our method still has some challenges, and the false positive problem is still a bottleneck for the performance. We want to modify our approach to treat false positives at the entity type level, rather than treating these at the sentence level. Moreover, we can expand our work to other types of reinforcement learning techniques such as imitation learning. It has been shown that the algorithmic expert in imitation learning allows direct policy learning. At the same time, the learned policies transfer successfully between domains and languages, improving the performance of low-resource NLP tasks (Du and Ji, 2019; Liu et al., 2018c).

Another limitation is the use of supervised learning algorithms throughout. The current neural models in chapters 4 and 5 require a set of training examples to provide good generalization. Future work can be to extend the study to improve the performance of the models in an unsupervised fashion.

We believe that there is room for further improvement in low-resource relation extraction, as presented in Chapter 5. A limitation of this work is that we cannot say that syntactic representations are more helpful in a resource-poor setting than in a resource-rich. This is an interesting future direction. Another possible area of improvement would be to extend the study to neural dependency parsers. Graph-based neural dependency parser has been shown to provide more accurate parses (Dozat et al., 2017; Kiperwasser and Goldberg, 2016; Song et al., 2019). Moreover, we can study the problem of relation extraction in resource-poor settings by open information extraction (Open IE) techniques. Although the idea of Open IE has been investigated in many recent works (Cui et al., 2018;
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Stanovsky and Dagan, 2016; Gao et al., 2020; Wu et al., 2019; Han et al., 2019; Hu et al., 2020b), there are still a lot of open research questions. Most Open IE approaches focus on the English language and general domains, leaving aside other settings. The applicability and transferability of previously proposed Open IE approaches to other languages and domains will be an interesting direction for future work.

In this thesis, we study the impact of typology sharing among languages in our cross-lingual meta-learning framework. It would be interesting to investigate how NLP and linguistic typology can interact and benefit from each other in low-resource scenarios and extend our work to other cross-lingual NLP tasks and more languages.

Overall, the real world applications of NLP models are still challenging, and our contribution has been a step on the way, but there is more to do. We hope that our research in this thesis serves as a stepping stone for future research and inspires others to study open research questions in the area of low-resource NLP.
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