Zero-Resource Cross-Domain Named Entity Recognition

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Abstract

Existing models for cross-domain named entity recognition (NER) rely on numerous unlabeled corpus or labeled NER training data in target domains. However, collecting data for low-resource target domains is not only expensive but also time-consuming. Hence, we propose a cross-domain NER model that does not use any external resources. We first introduce Multi-Task Learning (MTL) by adding a new objective function to detect whether tokens are named entities or not. We then introduce a framework called Mixture of Entity Experts (MoEE) to improve the robustness for zero-resource domain adaptation. Finally, experimental results show that our model outperforms strong unsupervised cross-domain sequence labeling models, and the performance of our model is close to that of the state-of-the-art model which leverages extensive resources.

1 Introduction

Named entity recognition (NER) is a fundamental task in text understanding and information extraction. Recently, supervised learning approaches have shown their effectiveness in detecting named entities (Ma and Hovy, 2016; Chiu and Nichols, 2016; Winata et al., 2019). However, there is a vast performance drop for low-resource target domains when massive training data are absent. To solve this data scarcity issue, a straightforward idea is to utilize the NER knowledge learned from high-resource domains and then adapt it to low-resource domains, which is called cross-domain NER.

Due to the large variances in entity names across different domains, cross-domain NER has thus far been a challenging task. Most existing methods consider a supervised setting, leveraging labeled NER data for both the source and target domains (Yang et al., 2017; Lin and Lu, 2018). However, labeled data in target domains is not always available. Unsupervised domain adaptation naturally arises as a possible way to circumvent the usage of labeled NER data in target domains. However, the only existing method, proposed by Jia et al. (2019), requires an external unlabeled data corpus in both the source and target domains to conduct the unsupervised cross-domain NER task, and such resources are difficult to obtain, especially for low-resource target domains. Therefore, we consider unsupervised zero-resource cross-domain adaptation for NER which only utilizes the NER training samples in a single source domain.

To meet the challenge of zero-resource cross-domain adaptation, we first propose to conduct multi-task learning (MTL) by adding an objective function to detect whether tokens are named entities or not. This objective function helps the model to learn general representations of named entities and to distinguish named entities from sequences in target domains. Finally, experimental results show that our model outperforms the state-of-the-art model which leverages extensive resources.
2 Related Work

Most of the existing work on cross-domain NER has been to investigate the supervised setting, where both source and target domains have labeled data (Daume III, 2007; Obeidat et al., 2016; Yang et al., 2017; Lee et al., 2018). Yang et al. (2017) jointly trained models on the source and target domain with shared parameters. Lin and Lu (2018) added adaptation layers on top of existing models, and Wang et al. (2018) introduced label-aware feature representations for NER adaptation. However, no prior work has focused on the unsupervised setting of cross-domain NER, except for Jia et al. (2019). In Jia et al. (2019), however, external unlabeled data corpora resources in both the source and target domains are required to train language models for domain adaptations. This limitation has motivated us to develop a model that doesn’t need any external resources.

Tackling the low-resource scenario where there are zero or minimal existing resources has always been an interesting yet challenging task (Xie et al., 2018; Lee et al., 2019; Liu et al., 2019b,c; Liu and Fung, 2020). Instead of utilizing large amounts of bilingual resources, Liu et al. (2019a,b) only utilized a few word pairs for zero-shot cross-lingual dialogue systems. Unsupervised machine translation approaches (Lample et al., 2017; Artetxe et al., 2017; Liu et al., 2019c) have also been introduced to circumvent the need of parallel data. Bapna et al. (2017) and Shah et al. (2019) proposed to do cross-domain slot filling with minimal resources. To the best of our knowledge, we are the first to propose methods on cross-domain adaptation for NER with zero external resources.

3 Methodology

As illustrated in Fig. 1, our model combines a bi-directional LSTM and conditional random field (CRF) into a BiLSTM-CRF structure (Lample et al., 2016) with MTL and MoEE modules.

3.1 Multi-Task Learning

Due to the large variations of named entities across domains, unsupervised cross-domain NER models often suffer from an inability to recognize named entities. Hence, we propose to learn general representations of named entities and enhance the robustness for adaptation by adding an objective function to predict whether tokens are named entities or not, which is represented as Task1 in Fig. 1(a). To do so, based on the original named entity labels for each token in the training set, we create another label set, which represents whether tokens are named entities or not. Specifically, in this process, all non-entity tokens are consistent with the original labels, and other tokens belonging to different entity categories are classified as being in the same class representing the general named entity. Task2 in Fig. 1(a) represents the original NER task, which is to predict a concrete category for each token. Let us denote $X = [w_1, w_2, ..., w_n]$ as the input text sequence, and the MTL can be formulated as:

$$[h_1, h_2, ..., h_n] = \text{BiLSTM}([w_1, w_2, ..., w_n]),$$

$$[p^1_1, p^1_2, ..., p^1_n] = \text{CRF}_1([h_1, h_2, ..., h_n]),$$

$$[m_1, m_2, ..., m_n] = \text{MoEE}([h_1, h_2, ..., h_n]),$$

$$[p^2_1, p^2_2, ..., p^2_n] = \text{CRF}_2([m_1, m_2, ..., m_n]),$$

Figure 1: Model architecture (a) with multi-task learning and (b) with the Mixture of Entity Experts module.
where CRF$_1$ and CRF$_2$ denote the CRF layers for Task$_1$ and Task$_2$, respectively, and \([p_i^1, p_{i+1}^1, ..., p_n^1]\) and \([p_i^2, p_{i+1}^2, ..., p_n^2]\) represent the corresponding predictions.

### 3.2 Mixture of Entity Experts

Traditional NER models make predictions based on the features of the tokens and the context. Due to the confusion among different entity categories, NER models could easily overfit to the source domain entities and lose generalization ability to the target domain. Therefore, we introduce an MoEE framework, as depicted in Fig. 1(b). It combines representations generated by experts to produce the final prediction.

Each entity category acts as an entity expert, which consists of a linear layer. Note that we consider the non-entity as a special entity category. The expert gate consists of a linear layer followed by a softmax layer, which generates the confidence distribution over entity experts. We use the gold labels in Task$_2$ to supervise the training of the expert gate. Finally, the meta-expert feature incorporates features from all experts based on the confidences generated by experts to produce the final prediction.

During training, we optimize for Task$_1$ and Task$_2$ with cross-entropy losses \(L_{\text{task}1}\) and \(L_{\text{task}2}\), respectively, as we detail below:

\[
L_{\text{task}1} = \sum_{j=1}^{J} \sum_{k=1}^{Y_j} - \log (p_{jk}^1 \cdot (y_{jk}^1)^T),
\]

\[
L_{\text{task}2} = \sum_{j=1}^{J} \sum_{k=1}^{Y_j} - \log (p_{jk}^2 \cdot (y_{jk}^2)^T),
\]

where \(J\) and \(Y_j\) denote the number of training data and the length of the tokens for each training sample, respectively; \(p_{jk}\) and \(y_{jk}\) denote the predictions and labels for each token, respectively; and the superscripts of \(p_{jk}\) and \(y_{jk}\) represent the tasks.

### 4 Experiments

#### 4.1 Dataset

We take the CoNLL-2003 English NER data (Tjong Kim Sang and De Meulder, 2003) containing 15.0K/3.5K/3.7K samples for the training/validation/test sets as our source domain. We take the dataset containing 2K sentences from SciTech News provided by Jia et al. (2019) as our target domain. The datasets in the source and target domains contain the same four types of entities, namely, PER (person), LOC (location), ORG (organization), and MISC (miscellaneous).

#### 4.2 Experimental Setup

**Embeddings** We test our approaches on the FastText word embeddings (Bojanowski et al., 2017) and the pre-trained model BERT (Devlin et al., 2019). Entity names in the target domain are likely to be out-of-vocabulary (OOV) words because they don’t usually exist in the source domain training set. FastText word embeddings are able to leverage the subword information and avoid the OOV problem, and BERT can solve this problem by using the BPE encoding. We try both freeze and unfreeze settings for FastText embeddings in the training. And for the BERT model, we add different modules (e.g., MoEE) on top to do fine-tuning.

**Baselines** Since we are the first to conduct zero-resource cross-domain NER, we compare our approach with strong unsupervised cross-domain sequence labeling models under minimal resources. **Concept Tagger** was proposed by Bapna et al. (2017) to utilize entity descriptions for unsupervised cross-domain utterance slot filling, and **Robust Sequence Tagger** (Shah et al., 2019) was introduced to combined both entity descriptions
and a few examples from each entity category for the same unsupervised task. In addition, we also compare our approach with the following baselines BiLSTM-CRF (Lample et al., 2016), BiLSTM-CRF w/ MTL, and BiLSTM-CRF w/ MoEE, as well as with the state-of-the-art model of the unsupervised cross-domain NER from Jia et al. (2019) which utilizes a large corpus in both the source and target domains.

4.3 Results & Discussion

From Table 1, our model combined with MTL and the MoEE outperforms the strong baselines Concept Tagger and Robust Sequence Tagger on all the embedding settings that we test. We conjecture that these two baselines, which utilize slot descriptions or slot examples, are suitable for limited slot names in the slot filling task, while they fail to cope with wide variances of entity names in the NER task across different domains, while our model is more robust to the domain variations. MTL helps our model recognize named entities in the target domain, while the MoEE adds information from different entity experts, which are expected to learn the “PER” and “ORG” expert representations based on the hidden state of “Drudge”, which contains the information of this token and its context, and then combine the expert representations for the prediction.

Figure 2: Confidence scores on different entity experts from the expert gate. “O” denotes non-entity expert.

In this paper, we propose a zero-resource cross-domain framework for the named entity recognition task, which consists of multi-task learning and Mixture of Entity Experts modules. The former learns the general representations of named entities to cope with the model’s inability to recognize named entities, while the latter learns to combine the representations of different entity experts, which are based on the BiLSTM hidden states. Experimental results show that our model outperforms strong cross-domain sequence tagging models, and the performance is close to that of the state-of-the-art model that utilizes extensive resources.
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