Neural relation extraction: a survey

Mehmet AYDAR\textsuperscript{1,2}, Ozge BOZAL\textsuperscript{1,3,}\*, Furkan OZBAY\textsuperscript{1,4}
\begin{itemize}
\item \textsuperscript{1}AI Enablement Department, Huawei Turkey Research and Development Center, Istanbul, Turkey
\item \textsuperscript{2}Enterprise Architecture and Technology Innovation, Ford Otosan, Istanbul, Turkey
\item \textsuperscript{3}Department of Computational Science and Engineering, Bogazici University, Istanbul, Turkey
\item \textsuperscript{4}Department of Computer Engineering, Yildiz Technical University, Istanbul, Turkey
\end{itemize}

Abstract: Neural relation extraction discovers semantic relations between entities from unstructured text using deep learning methods. In this study, we present a comprehensive review of methods on neural network based relation extraction. We discuss advantageous and incompetent sides of existing studies and investigate additional research directions and improvement ideas in this field.

Key words: Neural relation extraction, distant supervision, deep learning

1. Introduction

Never-ending information generation and sharing on the Web provides us with abundant data, most of which constitute the unstructured text sources. To better make sense of and draw associations among those data, we, human beings, use relational facts among the subjects (entities) in the text. For a more comprehensive understanding of specific domains such as bioinformatics, finance, social networking etc., we need computers to process those information.

It is essential to represent the information delivered by the text in machine-readable format. One way to do that is to represent entities and their relations in so called triples, which indicate unambiguous facts about entities. A triple \((h, r, t)\) implies that entity \(h\) has relation \(r\) with another entity \(t\). Knowledge graphs (KG) such as FreeBase \cite{Freebase} and DBpedia \cite{DBpedia} are examples of such representations. They are directed and labeled graph structured data which aim to express such explicit semantics and relations of entities in triple form.

Relation extraction is a sub-task of natural language processing (NLP) which aims to discover relations \(r\) between entity pairs \(h\) and \(t\) given unstructured text data. Earlier work on relation extraction from text heavily relies on kernel based and feature based methods \cite{38}. However, recent research studies make use of data-driven deep learning methods eliminating conventional NLP approaches for relation extraction. Kumar \cite{30} explained how the conventional deep learning methods are integrated into relation extraction. Smirnova and Cudré-Mauroux \cite{47} reviewed relation extraction literature focusing on distant supervision. As the number of research studies on relation extraction increases, the need of a survey on current state-of-the-art of neural relation extraction methods arises.

This work provides a comprehensive and comparative review on the research field, focusing on the challenges together with improvement ideas. Section 2 explains various approaches for relation extraction. In section 3 neural relation extraction methods are classified in terms of data supervision and explained. Section 4

\*Correspondence: ozge.bozal@huawei.com
describes existing challenges in this field of research. In section 5, commonly used datasets in model assessment are evaluated. We discuss possible future research directions and improvement ideas in section 6 and we conclude our survey in section 7.

2. Relation extraction approaches

In this section, we categorize neural relation extraction methods regarding their assumptions on expressiveness of training instances about the relations.

2.1. Sentence-level relation extraction

In this approach, sentence-based annotated training data is used. Annotation contains sentence-triple alignment information, such that sentences in the training set are labeled with the triples. Once trained, the model’s objective is to predict new relations given new entity pairs. However, insufficient amount of training data is a major drawback as labeled data is not always available in real life scenarios. Table 1 shows total number of relations and sentences provided in common relation extraction datasets according to OpenNRE framework [20].

| Dataset            | #relations | #sentences  |
|--------------------|------------|-------------|
| SemEval-2010 Task 8| 9          | 6,647       |
| TACRED             | 42         | 21,784      |
| Wiki80             | 80         | 56,000      |

2.2. Bag-level relation extraction

Since labeling data in deep learning requires a lot of manual effort, external knowledge bases are used to enhance weakly labeled training set. Knowledge graphs contain information regarding the relations between the entities in the form of (head, relation, tail) triples. For creating distant supervision datasets such as NYT, entity pairs in a triple are aligned with sentences that contain head and tail entities in the natural text. In this approach, the sentences matched by an entity pair constitute a bag. For this reason these datasets are noisy. Besides that, they are imbalanced, that is, the instances are not evenly distributed across relations.

There are different selection methods to weigh the expressiveness of a bag’s instances. One might choose a maximum, average or attention selector which considers the most relevant instance, all instances or weighted average of all instances, respectively [26, 33, 45]. More details regarding this approach is given in section 3.2.

2.3. Document-level relation extraction

Sentence-level approach lacks in grasping entity pair relations across a document [41, 68], that is to say, it ignores relations which can be deduced only by understanding several sentences within a document. This can especially be vital for some domains such as drug-side effect relations in pharmaceutical documents [55]. The study of Quirk and Poon [41] is the first to address this problem in distantly supervised setups and proposes a document-level graph representation to extract more relations. DocRED [68] provides a benchmark dataset for document-level relation extraction which contains relations that can only be extracted from multiple sentences.
As of today, performance of document-level relation extraction methods fall behind the human performance when it comes to cross-sentence reasoning, therefore this approach needs more effort.

3. Types of relation extraction

3.1. Supervised relation extraction

Supervised neural relation extraction from text uses sentence-level relation extraction approach which requires labeled relation-specific training data. Many of the studies on this task rely on classifying entity pairs according to the particular relations they are assigned to. We list the results of existing methods in Table 2.

3.1.1. Conventional neural models for relation extraction

Recent research studies focus on extracting relational features with neural networks instead of manual work [46, 50, 72]. Socher et al. [50] proposes a recurrent deep neural network model which admits a compositional vector representation of words and phrases on a parse tree. Each expression is represented by both a vector and a matrix, the former encodes semantic information of an expression and the latter encodes how much it influences the meaning of syntactically neighboring expressions.

In relation classification, drawing global features of relations within a sentence is a crucial task. Accordingly, Zeng et al. [72] utilize convolutional neural networks which can combine local features to obtain a globally representative one. To decrease effects of undesirable artificial classes of relations in prediction, Santos et al. [46] introduces a convolutional deep learning model that admits a pairwise ranking loss function and achieves better results than the former model.

TACRED is introduced by Zhang et al. [77], a relation extraction dataset created based on yearly TAC KBP evaluations. Proposed LSTM sequence model coupled with entity position-aware attention mechanism trained on TACRED outperforms the TAC KBP 2015 slot filling system.

In Zhang and Wang [75]’s work, it is claimed that RNN based relation extraction models excel CNN based models, for the reason that CNNs can only capture the local features, whereas RNNs are capable of learning long-distance dependency between entities.

An LSTM model proposed by Xu et al. [66] takes advantage of the shortest dependency path (SDP) between entities. They claim that the words along SDP are more informative. Dependency trees are directed graphs, therefore, there is the need of differentiating whether the first entity is related to the second entity or the relation implies the reverse direction. For this purpose, the SPD is divided into two sub-path, each is directed from the entity towards the ancestor node.

Uni-directional LSTM models lack in expressing the complete sequential information of the sentences. Zhang et al. [76] use bidirectional LSTM model (BLSTM) to better represent the sentences.

Meaningful information can be located anywhere in the sentence. Instead of using features from lexical sources such as dependency parsers and named entity recognizers, Zhou et al. [80] incorporate attention mechanism to BLSTM network to capture more informative parts of the sentence.

Pipeline approaches which first find the entities than match them with the appropriate relations are prone to error-propagation, namely, errors in the first part can’t be alleviated in the relation classification part. Recent models study extraction of entities together with their relations. Wei et al. [62] introduces a hierarchical tagging scheme that maximizes the likelihood of input data and the relational triples. Given a sentence, first it finds the subjects, then for each relation \( r \), it tags the appropriate objects, which can also be an empty set. This way, multiple triples can be extracted.
3.1.2. Pre-trained language models for relation extraction

Transfer learning is commonly used in deep learning to transfer existing knowledge of a model of a specific task to another similar or related task’s model. The former models are called pre-trained models and they save plenty of time and computational power. For NLP tasks there are several widely used pre-trained models such as BERT [11], Transformer-XL [9] and OpenAI’s GPT-2 [42].

Commonly preferred pre-trained language model in relation extraction studies, BERT, is an unsupervised transformer which is trained to predict the next sentence given a sequence of sentences, and also for masked language model. BERT’s model captures the contextual information of a word in a given sentence, along with the semantic relation of a sentence to the neighboring sentences in building the whole text. Wu and He [64] adjust the pre-trained BERT model to handle both sentence and its entities and they achieved better results on SemEval-2010 task 8 dataset than other conventional deep learning methods. Soares et al. [49] aim to build task agnostic, efficient relation representations from natural text using BERT. They achieved better results than previous models on SemEval-2010 task 8 and other models trained on TACRED. Zhao et al. [78] achieved the best result on SemEval-2010 task 8. They extract graph topological features on top of BERT embeddings. On the other hand, Wei et al. [62], which also utilizes BERT, achieved best results on the distantly supervised NYT dataset.

Table 2. States F1 scores of supervised relation classification approaches using Semeval 2010 Task-8 as input dataset.

|                     | SemEval 2010 |
|---------------------|--------------|
| CNN-based           |              |
| Zeng et al. [72]    | 82.7         |
| Nguyen and Grishman [37] | 82.8         |
| Santos et al. [46]  | 84.1         |
| Wang et al. [58]    | 88.0         |
| RNN-based           |              |
| Zhou et al. [80]    | 84.0         |
| Cai et al. [6]      | 86.3         |
| BERT-based          |              |
| Wei et al. [62]     | 87.5         |
| Soares et al. [49]  | 89.2         |
| Wu and He [64]      | 89.25        |
| Zhao et al. [78]    | 90.2         |

3.2. Relation extraction using distant supervision

Distant supervision aligns triples in a related knowledge graph with the sentences in input text, in order to automatically generate training data. Distant supervision assumes the responsibility to determine which sentence supports which relation and to what degree it expresses the relation of interest. In other words, distant supervision labels sentences with appropriate relations, and generates an error-prone training set consisting of possibly wrong labeled instances, which in turn is used to train relation extraction models.

Mintz et al. [36] is the first to use this technique. The assumption was that given a triple from the knowledge graph, all sentences that contain the head and tail entities of the triple express the corresponding relation. As a matter of fact, it causes wrong-labeling problem. For instance, consider a triple (Bill gates, Founder, Microsoft) from knowledge base and two sentences below:

‘‘Bill Gates is the co-founder of Microsoft.’’ and
‘‘The greatest mistake of Bill Gates cost Microsoft
It is clear that the first sentence expresses Founder relation, as the latter does not. Therefore, the training set including the second sentence is said to be noisy or wrongly labeled. Subsequent studies in distant supervision utilized the same trivial idea of triples in sentence alignment as the original paper. However, they differ in the machine learning models and feature encoders along with their approach to sentence labeling with appropriate relations and solving the wrong labeling problem caused by distant supervision. Reader can find the results of existing distantly supervised methods in Table 3.

3.2.1. Sentence-triple alignment

Four different frameworks exist for labeling sentences with appropriate relations, which are single-instance single-label (SISL), multi-instance single-label (MISL), single-instance multi-label (SIML) and multi-instance multi-label (MIML) learning. Regarding distant supervision, an instance refers to a sentence in the natural text and a label refers to a relation captured by the knowledge base. Single-instance models assume that a particular relation is derived from only one sentence, while multi-instance approach admits more than one sentence to represent a relation. Multi-instance learning is the bag-level distant supervision approach as explained in section 2.2. In single-label methods a particular sentence is relevant to only one relation, whereas in multi-label approach a sentence can express more than one relation. In this sense, MIML learning framework is more realistic, however, it is necessary to employ efficient ranking and denoising strategies.

Early methods used conventional NLP methods like dependency parsing and POS tagging for denoising strategies in distant supervision. Riedel et al. [45] assume multi-instance approach which is prone to producing noisy labels for training, in case none of the input sentences expresses the relation. Hoffmann et al. [26] and Surdeanu et al. [52] proposed (multi-instance, multi-label) learning to cover the overlapping triples problem. However, conventional NLP based methods suffer from propagation of errors generated by NLP tools.

Later studies have relied on deep learning methods to solve the wrong-labeling problem in distant supervision.

3.2.2. Solving wrong-labeling problem with deep learning methods

Distant supervision takes on the annotation burden, however it is obliged to wrong labeling problem. Multi-instance learning [12] aims to relieve problems caused by ambiguously-labeled training data. To denoise training instances of distant supervision, multi-instance learning has become the remedy in relation extraction studies [26, 45, 52, 71]. Riedel et al. [45] try to remedy wrong labeling with an undirected graphical model. Hoffmann et al. [26] focus on multi-instance learning with a probabilistic graphical model. Entity pairs in a corpus do not necessarily imply only one relation. In this direction, Surdeanu et al. [52] introduce a graphical model with latent variables, which can jointly model the entities and relations in multi-instance multi-label learning fashion.

First neural network model for multi-instance learning with distant supervision was proposed by Zeng et al. [71]. The method draws relational features with piece-wise convolutional neural network. The assumption is that, given a relation type, at least one of the input sentences that contain a specific entity pair, is informative, and it considers only the most expressive sentence in training and prediction. Obviously, this method neglects a large amount of data which might also be informative on that relation.

In Lin et al. [33]’s work, each sentence is ranked using the attention mechanism based on how well it represents a specific relation. Therefore, it suppresses the noisy ones rooted from distant supervision. To better extract the most appropriate relations, especially in ambiguous cases, Ji et al. [28] formulate entity descriptors
to include background information which operate on the instances weighted by sentence-level attention.

Relations are not individual tags, on the contrary, they are in semantic correlation with each other. To incorporate the rich information covered by relational correlations, Han et al. [22] apply a hierarchical attention on each bag of instances.

Another approach is accounting for the information covered by knowledge graphs. Han et al. [21] introduce a joint representation learning model for knowledge graph and text, the mutual guidance of which is fed back to the model under an attention mechanism to highlight the significant features of both. To benefit more from the knowledge graphs, Wang et al. [57] propose a novel distant supervision approach which refuse the hard labels imposed by regular distant supervision methods, rather, they train the relation classifier directly from KGs with soft labels.

Recent research papers [34, 44, 79] confirm that including high quality human annotation brings significant improvement in relation extraction by alleviating the noise. Zheng et al. [79] suggest a reinforcement learning based pattern extraction method to ease pattern-writing work for human experts. The pattern-instance pairs are subject to human annotation to be used in fusing the different labeling methods such as distant supervision and relational patterns.

Based on the complementarity and consistency properties of different languages, Lin et al. [32] combined mono-lingual and cross-lingual attention to take advantage of both language-specific features and the patterns that bear resemblance across languages. They aggregate sentence encodings with weighted attentions to further use in relation prediction. Sequel to this work, Wang et al. [59] investigate the effect of incorporating adversarial training in relation extraction. To alleviate possible incompetency in finding consistent patterns across different languages, this work defines a discriminator which can determine the language of each instance.

|               | NYT |
|---------------|-----|
| **Held-out**  |     |
| Jiang et al.  | 72.0|
| Lin et al.    | 72.2|
| Han et al.    | 71.0|
| Han et al.    | 81.6|
| **Manual**    |     |
| Zeng et al.   | 78.3|
| Ji et al.     | 81.3|
| Wang et al.   | 86.9|

3.2.3. Model extensions

Research studies on relation extraction with distant supervision are not limited to pure deep learning methods. Recent approaches extended their models by incorporating various NLP tools and machine learning methods.

Adversarial learning is used for training classifiers that are robust to both unmodified and perturbed samples. Essentially, it is widely used in supervised learning. Wu et al. [65] experiment the effects of using adversarial training in relation extraction with distant supervision on convolutional and recurrent neural network architectures and show that it can improve the performance of both. Redistribution of distantly supervised data can boost the performance of relation classifiers. Qin et al. [39] propose a denoising method for distant supervision relation extraction datasets, in cases where the true positives are more prevalent than the false
positives. Similar to generative adversarial networks, this method re-labels the positively labeled instances provided by distant supervision. Another approach is accounting for reinforcement learning to handle the noisy instances. Feng et al. [15] decompose the relation extraction problem into two tasks: instance selection and relation classification. Instance selector is a reinforcement learning agent which selects the most appropriate instance using the relation classifier’s weak supervision. To redistribute the distantly supervised data, Qin et al. [40] incorporate reinforcement learning, the policy of which is based on the mere classification performance.

Other than the aforementioned methods utilizing adversarial networks and reinforcement learning, there are also other advanced training methods to overcome the drawbacks of distant supervision. For instance, Takamatsu et al. [53] utilize a generative model to predict the wrongly labeled patterns in distant supervision.

Unlike studies regarding sentence-level denoising, Liu et al. [35] adopt entity pair-level denoising approach and derive soft labels for each entity pair bag, which are subject to change during training. Different from the above studies, the noise-tolerant model introduced by Huang and Wang [27] utilize deep residual learning [24]. Zeng et al. [73] incorporate path relations from text corpus, namely, they build a model which can handle relations that can be driven from several sentences.

3.3. Relation extraction using few-shot approach
Few-shot learning is a learning method, in which in contrast to regular deep learning methods the amount of available training data is small. The assumption is that reliable algorithms can be built to achieve competitive performance to the models trained with abundant data. We list some studies related to few-shot learning for relation extraction in Table 4. For the purpose of experimenting few-shot learning algorithms for relation extraction, Han et al. [23] provide the “FewRel” dataset. Prototypical networks [48], which admit prototypes rather than classes, are used in few-shot learning scenarios for relation extraction [17]. The model proposed by Soares et al. [49] outperforms human accuracy on few-shot relation matching. Ye and Ling [69] introduce an aggregation network model and a matching mechanism which is multi-level.

Table 4. Accuracy scores of few-shot relation classification methods with the best performing configuration on FewRel dataset.

| Best configuration | FewRel   |
|-------------------|----------|
| Soares et al. [49]| 5 Way 1 Shot | 88.9 |
| Gao et al. [17]   | 5 Way 10 Shot | 92.06 |
| Ye and Ling [69]  | 5 Way 5 Shot  | 92.66 |

4. Challenges of relation extraction
Challenges in neural relation extraction regarding available data and existing contextual and structural approaches are presented in this section.

4.1. Overlapping triples
An entity (SingleEntityOverlap) or even an entity pair (EntityPairOverlap) may imply more than one relation in a sentence. Most studies identify entities before the relation classification which assumes that each entity pair is assigned to a single relation (see section 3.1). Zeng et al. [74] propose an end-to-end model which considers
relation extraction to be a triple generation problem and applies a copy mechanism to cope with overlapping triples. Another approach proposed by Takanobu et al. [54] admits a hierarchy of high-level relation indicator detection to mine the relations in a sentence and low-level entity mention extraction to match these relation to the corresponding entities. GraphRel, introduced by Fu et al. [16] is a graph convolutional network based neural model that jointly learns entities and relations. It excels the former methods in solving the overlapping triples problem by incorporating the regional and sequential dependency features of words. Unlike the aforementioned methods, Wei et al. [62] offer a new formulation for learning relational triples that first identifies subjects, then the relations with a BERT-based subject tagger module, and finally identifies the objects with a relation-specific object module.

4.2. Noise in distant supervision

Relation extraction needs large amount of annotated data. To handle this problem, recent studies incorporate distant supervision which brings its own drawbacks. Distant supervision faces the problem of wrong labeled sentences troubling the training due to the excessive amount of noise. Related studies try to remedy this problem by sentence-level attention [33], hierarchical attention [22], multi-lingual knowledge extraction [32], joint extraction with knowledge graphs [21] or introducing human annotation to relation extraction [34, 44, 79]. Detailed information on these methods is given in section 3.2.2.

4.3. Few-shot instances

Few-shot based modelling is especially challenging for NLP tasks, since text data is noisy and human annotators tend to be mistaken in language-specific tasks [17]. Han et al. [23] investigate few-shot learning for relation extraction and provide a dataset for this specific task. Gao et al. [18] improve the former dataset by addressing domain adaptation issues and “none-of-the-above” case which adds extra class to the model. Prototypical networks which assume classification models built on prototypes rather than class labels enable the classifier to identify new classes when only few instances are present for each of those [17, 48].

5. Datasets and evaluation

5.1. Datasets

SemEval 2010 Task-8 Dataset [25] contains 2717 sentences, which do not overlap with the 8000 training instances from the version that was released on March 5, 2010 and the instances from SemEval 2007 Task-4. The dataset has 9 distinct relation type.

NYT Dataset (NYT10) [45], was created by aligning relations in Freebase with the sentences in the New York Times Annotated Corpus. Training and test set is generated by splitting the dataset by specific years. Numerous previous work used NYT dataset for relation extraction tasks, however they leverage the dataset as their option.

FewRel [18] is a supervised dataset created to be used in relation classification methods which utilize few-shot approaches. Large set of sentences were first assigned to relations via distant supervision, next, they were annotated by human experts for denoising. The dataset contains 100 relations, each of which has 700 instances.

Wiki80 is created based on FewRel dataset for few-shot relation extraction tasks, however it is not recognized as a benchmark. It consists of 56,000 samples of 80 distinct relations. The samples are gathered from Wikidata and Wikipedia.
TACRED is the crowd-annotated TAC Relation Extraction Dataset developed by The Stanford NLP Group [77]. TACRED contains 106,264 samples and 41 relation types with “no_relation” label to indicate that there is no relation between entities.

ACE-2005 Multilingual Training Corpus is created for English, Chinese and Arabic languages [56] for the 2005 Automatic Content Extraction (ACE) technology evaluation. The datasets consist of various types of annotated data for entities, relations and events.

WebNLG [19] is another dataset generated for NLP methods. Zeng et al. [74] adapted this dataset for relation extraction tasks. The processed dataset contains 246 relation types, 5019 training, 703 test and 500 validation instances.

5.2. Evaluation
For supervised relation classification tasks the standard precision, recall and F-measure are used for evaluation. Authors usually provide the precision-recall curves for their classification results. For distantly supervised relation extraction models, held-out and/or manual evaluation is conducted. The labels of aligned text with a knowledge base are not gold. For this reason, only the relational facts coming from the knowledge base are considered to be true for the test set in held-out evaluation, newly predicted relations are treated as false. Since this assumption does not express the reality, some work (see Table 4) conduct manual evaluation which requires human effort. In few-shot learning, there are configurations in the form of \( m \) way \( n \) shot, \( m \) representing the number of relations (classes), and \( n \) representing labeled instance number per relation, in this case, sentences. The models are tested on different configuration of data and accuracy results of models on test set are stated.

6. Discussion to solve common difficulties
Neural relation extraction heavily makes use of the research on both deep learning and the semantic web. In this section, we discuss possible research directions regarding relation extraction.

6.1. Question generation and question answering
Neural question generation from text is an emerging research field [13, 31, 63, 70, 81]. Question-answering on the knowledge graph is also a well-studied research topic [43]. Joint use of these studies on question generation from text and question answering on knowledge bases can help to discover missing relations between entities. Appropriate questions can be generated from each sentence using neural question generation methods. Each question is asked to the knowledge graph using question-answering methods that work on the knowledge base. If the system gets a response, then the response can be added to the natural text. Furthermore, a new triple can be generated based on the question and the response, which is appended to the existing triples in the knowledge base. As a result, the training data provides more insights in deep learning methods, as both the natural text and the knowledge graph is enhanced using question generation and question answering methods.

6.2. Possible solutions to improve results of attention mechanism
In relation extraction, attention mechanism usually works best with sentences ranked according to how well they match a specific relation. A similarity metric is involved in matching the relation with the sentence. In this regard, various similarity methods can be explored. Based on the results of the relation extraction, importance weights can be refined, until the algorithm comes up with optimum results.
Another possible approach for improvement is to run event detection algorithms on each of the sentences, paragraphs or documents, and make use of the events in sentence encoding and attention mechanism. Once the sentence’s event is determined, event type-specific triples can be given a higher ranking to be aligned with the sentence. Event detection from a knowledge graph is also an emerging research area [60, 61].

6.3. Multilingual bi-text mining in machine translation

One possible research field that can be integrated with distant supervision is machine translation using neural network models. Machine translation models require a comprehensive training corpus which comprises aligned sentences in different languages. Consequently, sentence alignment is significant in machine translation.

Google’s Universal Sentence Encoder (USE) [7] embeds sentences into vectors by maintaining the context of the whole sentence, with a pre-trained model available for public use. An extension to USE which supports multilingual sentence encoding has also been published [67]. Facebook also published a similar multilingual sentence encoding study called Laser [1]. These studies make “bi-text mining” possible, which captures similarity scores of sentences even if they are in different languages and matches sentences having close similarity scores.

Triples used in distant supervision can also be converted to sentences using natural language generation (NLG). Several studies exist for generating natural text from triples [5, 8, 14, 51, 82]. Once triples are converted to natural text, the problem reduces to bi-text mining, where pre-trained models such as USE and Laser can be utilized. It is also possible to align knowledge bases and natural text in different languages using NLG and a multilingual sentence encoding tool. Since most of the general-purpose knowledge bases have more content in English, being able to align them with sentences in different languages can lead to tremendous improvement in distant supervision.

6.4. Paraphrasing

Another improvement in distant supervision can be achieved by expressing sentences in the natural text with different words. Several paraphrased version of a sentence could be encoded into a vector space along with the original sentence. This can help to capture latent words and can result in a higher similarity score with related triples from knowledge bases. One possible drawback of this approach could be that while producing abundant data, it simultaneously increases the number of false positives. The remedy could be extending the model with reinforcement learning or adversarial learning. As stated in section 3.2.3, such methods give promising results in noise filtering.

6.5. Possible solutions for document-level relation extraction

As stated in section 2.3, current methods on document-level relation extraction give poor results comparing to human performance. Enhancing the knowledge base and natural text can be relevant in this scenario, as it assists in finding hidden relation using neural relation prediction methods on the knowledge graph. Besides, external ontologies can be used to enhance the natural text, as ontologies include vocabularies and rule-sets. Locality-sensitive hashing (LSH) methods [3, 10] could also be adopted to quickly determine which ontology aligns well with the input sentence, paragraph or document.

6.6. Integration with few-shot relation extraction

Modern methods on neural relation extraction filter out instances that do not have a sufficient amount of training data. As stated in section 3.3, few-shot relation extraction is suitable with small amount of training samples.
In real scenarios, eliminating instances might not be desired. As a result, a joint method of neural relation extraction using distant supervision with a few-shot relation extraction algorithm might be more suitable for real-life scenarios.

7. Conclusion
In this survey, we summarized neural relation extraction methods in terms of their approaches and data supervision and datasets for this task. In addition, we explained common challenges and discussed possible remedies to them.

To acquire abundant training instances, the latest studies make use of distant supervision. However, it brings noise to data which greatly affects the training of relation extraction models. In addition, there are no explicit negative samples, since the data itself have wrong annotations due to ill-alignment of the unstructured text and the knowledge graph. For that reason, instead of sentence-level approaches in supervised relation extraction, multi-instance approaches are developed for relation extraction with distant supervision. Also, few-shot learning for relation extraction is a research area that has still room for improvement. Supervised approaches are not to be abandoned. Indeed, incorporating pre-trained language models in supervised relation extraction make significant improvements in comparison to using conventional deep learning methods. Instead of treating entity recognition and relation extraction separately as in pipeline approaches, later studies adopt end-to-end approaches jointly extracting the entities and relations, which tend to better handle problems associated with overlapping triples and long-tail relations.

References
[1] Artetxe, M. and Schwenk, H. (2019). Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics, 7:597–610.
[2] Auer, S., Bizer, C., Kobilarov, G., Lehmann, J., Cyganiak, R., and Ives, Z. (2007). Dbpedia: A nucleus for a web of open data. In The semantic web, pages 722–735. Springer.
[3] Aydar, M. and Ayvaz, S. (2019). An improved method of locality-sensitive hashing for scalable instance matching. Knowledge and Information Systems, 58(2):275–294.
[4] Bollacker, K., Evans, C., Paritosh, P., Sturge, T., and Taylor, J. (2008). Freebase: a collaboratively created graph database for structuring human knowledge. In Proceedings of the 2008 ACM SIGMOD international conference on Management of data, pages 1247–1250. AcM.
[5] Bouayad-Agha, N., Casamayaor, G., and Wanner, L. (2014). Natural language generation in the context of the semantic web. Semantic Web, 5(6):493–513.
[6] Cai, R., Zhang, X., and Wang, H. (2016). Bidirectional recurrent convolutional neural network for relation classification. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 756–765.
[7] Cer, D., Yang, Y., Kong, S.-y., Hua, N., Limtiaco, N., John, R. S., Constant, N., Guajardo-Cespedes, M., Yuan, S., Tar, C., et al. (2018). Universal sentence encoder. arXiv preprint arXiv:1803.11175.
[8] Cui, W., Zhou, M., Zhao, R., and Norouzi, N. (2019). KB-NLG: From knowledge base to natural language generation. In Proceedings of the 2019 Workshop on Widening NLP, pages 80–82, Florence, Italy. Association for Computational Linguistics.
[9] Dai, Z., Yang, Z., Yang, Y., Carbonell, J. G., Le, Q. V., and Salakhutdinov, R. (2019). Transformer-xl: Attentive language models beyond a fixed-length context. CoRR, abs/1901.02860.
[10] Datar, M., Immorlica, N., Indyk, P., and Mirrokni, V. S. (2004). Locality-sensitive hashing scheme based on p-stable distributions. In Proceedings of the twentieth annual symposium on Computational geometry, pages 253–262. ACM.
[11] Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

[12] Dietterich, T. G., Lathrop, R. H., and Lozano-Pérez, T. (1997). Solving the multiple instance problem with axis-parallel rectangles. Artificial intelligence, 89(1-2):31–71.

[13] Du, X., Shao, J., and Cardie, C. (2017). Learning to ask: Neural question generation for reading comprehension. arXiv preprint arXiv:1705.00106.

[14] Duma, D. and Klein, E. (2013). Generating natural language from linked data: Unsupervised template extraction. In Proceedings of the 10th International Conference on Computational Semantics (IWCS 2013)–Long Papers, pages 83–94.

[15] Feng, J., Huang, M., Zhao, L., Yang, Y., and Zhu, X. (2018). Reinforcement learning for relation classification from noisy data. In Thirty-Second AAAI Conference on Artificial Intelligence.

[16] Fu, T.-J., Li, P.-H., and Ma, W.-Y. (2019). Graphrel: Modeling text as relational graphs for joint entity and relation extraction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1409–1418.

[17] Gardent, C., Shimorina, A., Narayan, S., and Perez-Beltrachini, L. (2017). The WebNLG challenge: Generating text from RDF data. In Proceedings of the 10th International Conference on Natural Language Generation, pages 124–133, Santiago de Compostela, Spain. Association for Computational Linguistics.

[18] Han, X., Gao, T., Yao, Y., Ye, D., Liu, Z., and Sun, M. (2019). Opennre: An open and extensible toolkit for neural relation extraction. arXiv preprint arXiv:1909.13078.

[19] Han, X., Liu, Z., and Sun, M. (2018a). Neural knowledge acquisition via mutual attention between knowledge graph and text. In Thirty-Second AAAI Conference on Artificial Intelligence.

[20] Han, X., Yu, P., Liu, Z., Sun, M., and Li, P. (2018b). Hierarchical relation extraction with coarse-to-fine grained attention. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2236–2245.

[21] Han, X., Zhu, H., Yu, P., Wang, Z., Yao, Y., Liu, Z., and Sun, M. (2018c). Fewrel: A large-scale supervised few-shot relation classification dataset with state-of-the-art evaluation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4803–4809.

[22] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778.

[23] Hendrickx, I., Kim, S. N., Kozareva, Z., Nakov, P., Ó Séaghdha, D., Padó, S., Pennacchiotti, M., Romano, L., and Szpakowicz, S. (2009). SemEval-2010 task 8: Multi-way classification of semantic relations between pairs of nominals. In Proceedings of the Workshop on Semantic Evaluations: Recent Achievements and Future Directions, pages 94–99. Association for Computational Linguistics.

[24] Hoffmann, R., Zhang, C., Ling, X., Zettlemoyer, L., and Weld, D. S. (2011). Knowledge-based weak supervision for information extraction of overlapping relations. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 541–550, Portland, Oregon, USA. Association for Computational Linguistics.

[25] Huang, Y. and Wang, W. Y. (2017). Deep residual learning for weakly-supervised relation extraction. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1803–1807.

[26] Ji, G., Liu, K., He, S., and Zhao, J. (2017). Distant supervision for relation extraction with sentence-level attention and entity descriptions. In Thirty-First AAAI Conference on Artificial Intelligence.
[29] Jiang, X., Wang, Q., Li, P., and Wang, B. (2016). Relation extraction with multi-instance multi-label convolutional neural networks. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pages 1471–1480.

[30] Kumar, S. (2017). A survey of deep learning methods for relation extraction. arXiv preprint arXiv:1705.03645.

[31] Kupiec, J. M. (1996). Method for extracting from a text corpus answers to questions stated in natural language by using linguistic analysis and hypothesis generation. US Patent 5,519,608.

[32] Lin, Y., Liu, Z., and Sun, M. (2017). Neural relation extraction with multi-lingual attention. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2124–2133.

[33] Liu, A., Soderland, S., Bragg, J., Lin, C. H., Ling, X., and Weld, D. S. (2016). Effective crowd annotation for relation extraction. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 897–906.

[34] Liu, T., Wang, K., Chang, B., and Sui, Z. (2017). A soft-label method for noise-tolerant distantly supervised relation extraction. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1790–1795.

[35] Mintz, M., Bills, S., Snow, R., and Jurafsky, D. (2009). Distant supervision for relation extraction without labeled data. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2-Volume 2, pages 1003–1011. Association for Computational Linguistics.

[36] Nguyen, T. H. and Grishman, R. (2015). Relation extraction: Perspective from convolutional neural networks. In Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing, pages 39–48, Denver, Colorado. Association for Computational Linguistics.

[37] Pawar, S., Palshikar, G. K., and Bhattacharyya, P. (2017). Relation extraction: A survey. arXiv preprint arXiv:1712.05191.

[38] Qin, P., Xu, W., and Wang, W. Y. (2018a). Dsgan: generative adversarial training for distant supervision relation extraction. arXiv preprint arXiv:1805.09929.

[39] Qin, P., Xu, W., and Wang, W. Y. (2018b). Robust distant supervision relation extraction via deep reinforcement learning. arXiv preprint arXiv:1805.09927.

[40] Quirk, C. and Poon, H. (2017). Distant supervision for relation extraction beyond the sentence boundary. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 1171–1182.

[41] Radford, A., Wu, J., Child, R., Lu, D., Amodei, D., and Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI Blog, 1(8).

[42] Rajpurkar, P., Zhang, J., Lopyrev, K., and Liang, P. (2016). Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250.

[43] Ratner, A. J., De Sa, C. M., Wu, S., Selsam, D., and Ré, C. (2016). Data programming: Creating large training sets, quickly. In Advances in neural information processing systems, pages 3567–3575.

[44] Riedel, S., Yao, L., and McCallum, A. (2010). Modeling relations and their mentions without labeled text. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pages 148–163. Springer.

[45] Santos, C. N. d., Xiang, B., and Zhou, B. (2015). Classifying relations by ranking with convolutional neural networks. arXiv preprint arXiv:1504.06580.

[46] Smirnova, A. and Cudré-Mauroux, P. (2018). Relation extraction using distant supervision: A survey. ACM Computing Surveys (CSUR), 51(5):106.
[48] Snell, J., Swersky, K., and Zemel, R. (2017). Prototypical networks for few-shot learning. In Advances in Neural Information Processing Systems, pages 4077–4087.

[49] Soares, L. B., FitzGerald, N., Ling, J., and Kwiatkowski, T. (2019). Matching the blanks: Distributional similarity for relation learning. arXiv preprint arXiv:1906.03158.

[50] Socher, R., Huval, B., Manning, C. D., and Ng, A. Y. (2012). Semantic compositionality through recursive matrix-vector spaces. In Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural processing, pages 1201–1211. Association for Computational Linguistics.

[51] Sun, X. and Mellish, C. (2006). Domain independent sentence generation from rdf representations for the semantic web. In Combined Workshop on Language-Enabled Educational Technology and Development and Evaluation of Robust Spoken Dialogue Systems, European Conference on AI, Riva del Garda, Italy.

[52] Surdeanu, M., Tilshirani, J., Nallapati, R., and Manning, C. D. (2012). Multi-instance multi-label learning for relation extraction. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 455–465, Jeju Island, Korea. Association for Computational Linguistics.

[53] Takamatsu, S., Sato, I., and Nakagawa, H. (2012). Reducing wrong labels in distant supervision for relation extraction. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1, pages 721–729. Association for Computational Linguistics.

[54] Takanobu, R., Zhang, T., Liu, J., and Huang, M. (2019). A hierarchical framework for relation extraction with reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 7072–7079.

[55] Verga, P., Strubell, E., and McCallum, A. (2018). Simultaneously self-attending to all mentions for full-abstract biological relation extraction. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 872–884, New Orleans, Louisiana. Association for Computational Linguistics.

[56] Walker, C., Strassel, S., Medero, J., and Maeda, K. (2005). Ace 2005 multilingual training corpus-linguistic data consortium. URL: https://catalog.ldc.upenn.edu/LDC2006T06.

[57] Wang, G., Zhang, W., Wang, R., Zhou, Y., Chen, X., Zhang, W., Zhu, H., and Chen, H. (2018a). Label-free distant supervision for relation extraction via knowledge graph embedding. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2246–2255.

[58] Wang, L., Cao, Z., De Melo, G., and Liu, Z. (2016). Relation classification via multi-level attention cnns. In Proceedings of the 54th annual meeting of the Association for Computational Linguistics (volume 1: long papers), pages 1298–1307.

[59] Wang, X., Han, X., Lin, Y., Liu, Z., and Sun, M. (2018b). Adversarial multi-lingual neural relation extraction. In Proceedings of the 27th International Conference on Computational Linguistics, pages 1156–1166.

[60] Wang, X., Han, X., Liu, Z., Sun, M., and Li, P. (2019a). Adversarial training for weakly supervised event detection. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 998–1008.

[61] Wang, X., Wang, Z., Han, X., Liu, Z., Li, J., Li, P., Sun, M., Zhou, J., and Ren, X. (2019b). HMEAE: Hierarchical modular event argument extraction. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5781–5787, Hong Kong, China. Association for Computational Linguistics.

[62] Wei, Z., Su, J., Wang, Y., Tian, Y., and Chang, Y. (2019). A novel hierarchical binary tagging framework for joint extraction of entities and relations. arXiv preprint arXiv:1909.03227.

[63] Wolfe, J. H. (1976). Automatic question generation from text—an aid to independent study. In ACM SIGCUE Outlook, volume 10, pages 104–112. ACM.

[64] Wu, S. and He, Y. (2019). Enriching pre-trained language model with entity information for relation classification. arXiv preprint arXiv:1905.08284.
[65] Wu, Y., Bamman, D., and Russell, S. (2017). Adversarial training for relation extraction. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1778–1783.

[66] Xu, Y., Mou, L., Li, G., Chen, Y., Peng, H., and Jin, Z. (2015). Classifying relations via long short term memory networks along shortest dependency paths. In proceedings of the 2015 conference on empirical methods in natural language processing, pages 1785–1794.

[67] Yang, Y., Cer, D., Ahmad, A., Guo, M., Law, J., Constant, N., Abrego, G. H., Yuan, S., Tar, C., Sung, Y.-H., et al. (2019). Multilingual universal sentence encoder for semantic retrieval. arXiv preprint arXiv:1907.04307.

[68] Yao, Y., Ye, D., Li, P., Han, X., Lin, Y., Liu, Z., Liu, Z., Huang, L., Zhou, J., and Sun, M. (2019). Docred: A large-scale document-level relation extraction dataset. arXiv preprint arXiv:1906.06127.

[69] Ye, Z.-X. and Ling, Z.-H. (2019). Multi-level matching and aggregation network for few-shot relation classification. arXiv preprint arXiv:1906.06678.

[70] Yuan, X., Wang, T., Gulcehre, C., Sordoni, A., Bachman, P., Subramanian, S., Zhang, S., and Trischler, A. (2017). Machine comprehension by text-to-text neural question generation. arXiv preprint arXiv:1705.02012.

[71] Zeng, D., Liu, K., Chen, Y., and Zhao, J. (2015). Distant supervision for relation extraction via piecewise convolutional neural networks. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1753–1762.

[72] Zeng, D., Liu, K., Lai, S., Zhou, G., Zhao, J., et al. (2014). Relation classification via convolutional deep neural network.

[73] Zeng, W., Lin, Y., Liu, Z., and Sun, M. (2017). Incorporating relation paths in neural relation extraction. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1768–1777.

[74] Zeng, X., Zeng, D., He, S., Liu, K., Zhao, J., et al. (2018). Extracting relational facts by an end-to-end neural model with copy mechanism.

[75] Zhang, D. and Wang, D. (2015). Relation classification via recurrent neural network. arXiv preprint arXiv:1508.01006.

[76] Zhang, S., Zheng, D., Hu, X., and Yang, M. (2015). Bidirectional long short-term memory networks for relation classification. In Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation, pages 73–78, Shanghai, China.

[77] Zhang, Y., Zhong, V., Chen, D., Angeli, G., and Manning, C. D. (2017). Position-aware attention and supervised data improve slot filling. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 35–45.

[78] Zhao, Y., Wan, H., Gao, J., and Lin, Y. (2019). Improving relation classification by entity pair graph. In Asian Conference on Machine Learning, pages 1156–1171.

[79] Zheng, S., Han, X., Lin, Y., Yu, P., Chen, L., Huang, L., Liu, Z., and Xu, W. (2019). Diag-nre: A neural pattern diagnosis framework for distantly supervised neural relation extraction. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1419–1429.

[80] Zhou, P., Shi, W., Tian, J., Qi, Z., Li, B., Hao, H., and Xu, B. (2016). Attention-based bidirectional long short-term memory networks for relation classification. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 207–212.

[81] Zhou, Q., Yang, N., Wei, F., Tan, C., Bao, H., and Zhou, M. (2017). Neural question generation from text: A preliminary study. In National CCF Conference on Natural Language Processing and Chinese Computing, pages 662–671. Springer.

[82] Zhu, Y., Wan, J., Zhou, Z., Chen, L., Qiu, L., Zhang, W., Jiang, X., and Yu, Y. (2019). Triple-to-text: Converting RDF triples into high-quality natural languages via optimizing an inverse KL divergence. CoRR, abs/1906.01965.