Deep Neural Network Based Relation Extraction: An Overview

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Abstract Knowledge is a formal way of understanding the world, providing a human-level cognition and intelligence for the next-generation artificial intelligence (AI). One of the representations of knowledge is the structural relations between entities. An effective way to automatically acquire this important knowledge, called Relation Extraction (RE), a sub-task of information extraction, plays a vital role in Natural Language Processing (NLP). Its purpose is to identify semantic relations between entities from natural language text. To date, there are several studies for RE in previous works, which have documented these techniques based on Deep Neural Networks (DNNs) become a prevailing technique in this research. Especially, the supervised and distant supervision methods based on DNNs are the most popular and reliable solutions for RE. This article 1)introduces some general concepts, and further 2)gives a comprehensive overview of DNNs in RE from two points of view: supervised RE, which attempts to improve the standard RE systems, and distant supervision RE, which adopts DNNs to design the sentence encoder and the de-noise method. We further 3)cover some novel methods and describe some recent trends and discuss possible future research directions for this task.

Keywords Overview · Information Extraction · Relation Extraction · Neural Networks

1 Introduction

Artificial intelligence (AI) integrating knowledge is a hot topic in current research. It provides human thinking for artificial intelligence to solve complex tasks. One of the most important techniques for supporting this research is knowledge acquisition, also called relation extraction (RE). One aim of RE is to process the human language text, to find unknown relation facts from plain text, organizing unstructured information into structured information. A well-constructed and large-scale knowledge base can be useful for many downstream applications and empower knowledge-aware models with the ability of commonsense reasoning, thereby paving the way for AI.

RE built a large-scale knowledge base by extracting relation triples from raw text. For example, there is a sentence: "<e1>Jobs</e1> is the founder of <e2>Apple</e2>." It marks the entity "Jobs" and "Apple" by a pair of XML tags. From the sentence, the RE model can output a triple (Jobs, Apple, founded_by), which can be used for knowledge base construction.

Recently, RE has attracted extensive attention, but few researchers to report the review of DNN-based RE [27, 41]. While these articles have their emphasis, lacking a comprehensive, systematic introduction to DNN-based methods.

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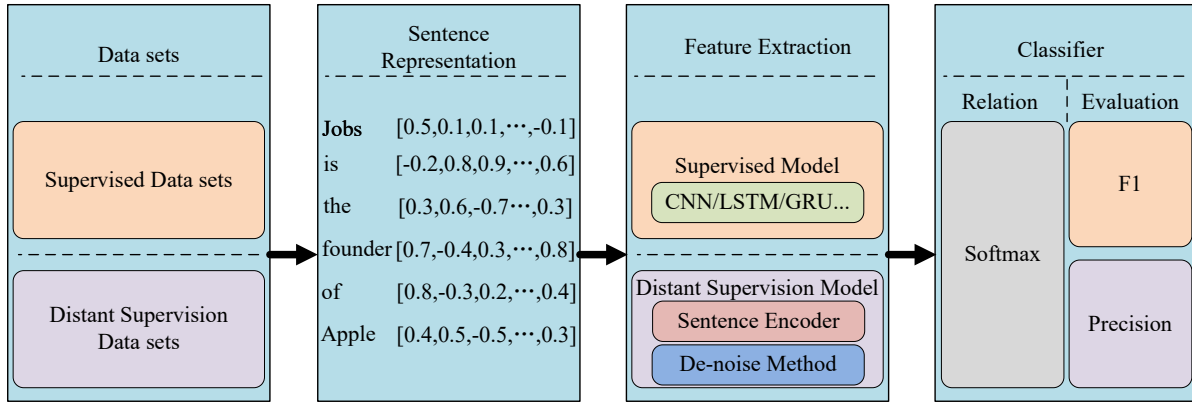E-mail: lgs@uestc.edu.cn

Fig. 1: The General Framework of DNN-based RE.

Consequently, this paper presents an extensive survey and gives a comprehensive introduction of RE to the prevalent DNN-based methods. To begin with, this paper introduces the premise of RE frameworks, including a general framework and some basic conceptions of RE. Second, a brief introduction of the traditional methods and the variation of DNN-based methods will be compared in detail. Third, the paper further provides an analysis of some problems and proposes future research directions.

2 Premise

2.1 General Framework

By conducting an extensive literature review, the framework of DNN-based RE methods can be summarized as four components, which are shown in Figure 1. The detailed description of these four components are as follows:

Data sets: The supervised data sets (SemEval 2010-task8 [20] and FewRel [17,14]) are often obtained by manual annotation with high accuracy and low noise, but small size. Instead, distant supervision data sets usually acquired by a physical alignment of entities between a corpus and a knowledge base (KB), which has a bigger size and high multi-domain applicability (e.g., Riedel et al. [48]), but low accuracy and high noise.

Sentence Representation: In NLP field, to understand human language for computers, words are usually represented as a series of real value vectors, such as word2vec and Glove methods. Meanwhile, the position embedding is introduced to better express the positional relation between words and the entity pair. Hence, the final representation of the words is the combination of the word vector and the position embedding, and the final sentence representation is composed of these word representations.

Feature extraction: In general, these DNN-based methods are fed with the sentence representation above. With the annotated data sets, these methods output a feature extractor by training. And this extractor can extract high-level features from sentence representation.

Classifier: With the high-level features and a predefined relation inventory, the classifier outputs the relation between the entity pair in the sentence, and then evaluates the result.

2.2 Basic Conception

In addition to the above general frameworks, the basic concepts of DNN-based RE system commonly used in these frameworks are as follows:

Neural Networks have been widely used in image processing, language processing, and other fields in recent years, with very remarkable results. Researches have designed many kinds of DNNs, including Convolutional Neural Networks (CNNs) [28], Recurrent Neural Networks (RNNs) [11], Recursive Neural Networks [55], and Graph Neural Networks (GNNs) [52]. Different kinds of DNNs have different characteristics and advantages in dealing with various language tasks. For example, the CNNs, with parallel processing ability, are adept at processing
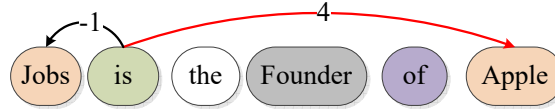
Fig. 2: The example of relative distance.

Table 1: The example sentence with position indicators.

Examples:	\<e1\>Jobs\</e1\> is the founder of \<e2\>Apple\</e2\>.
Indictors:	\<e1\>, \</e1\>, \<e2\>, \</e2\>

local and structural information. Instead, the RNNs, having advantages in dealing with a long text, can cope with time-series information by considering the factors before and after data input. Moreover, developed gradually in recent years, the GNNs, another kind of neural network, which can process data with a graphical structure. For example, the grammatical dependency parse tree, a general tool for the RE, is suitable for the GNNs. In addition to the above mentioned commonly used networks, there are also some other RNNs variant networks used in RE systems, such as LSTM (Long Short Term Memory network) [74,56,21], GRU (Gated Recurrent Unit) [9].

Word Embedding is a method used to represent words in NLP, leveraging uniform low dimensional, continuous, real-value vectors to represent language. One of the earlier forms was one-hot, which exits some problems like data sparsity, no meaning, dimensional disasters. To solve these problems, some scholars [35] proposed a new method called word2vec to overcome these disadvantages. In this way, all the word vectors are distributed, the dimensions of the vector can be arbitrary, generally in 50 to 100 dimensions, and the value of the element can be any real value. The greatest benefit of this approach is the semantic and contextual information of words can be captured, and the similarity of words can be calculated by simple addition and subtraction. Hence, word2vec is a common component in DNN-based RE. Aside from the word2vec method, some researchers also designed other methods [57,42].

Position Embedding provides a uniform way for the RE model to be aware of word positions. In RE task, the CNN-based models are lack of judgment on the word location information. To address this issue, Zeng et al. [69] proposed the position feature (PF), which will be adopted in subsequent methods of using CNNs [39,51,60], RNNs [71,44,70], and mixed frameworks [47,72]. The PF is a combination of the relative distance between the other words around the labeled entities in the sentence. For instance, given labeled entities: "Jobs" and "Apple", in the sentence "Jobs is the founder of Apple", the relative distance of the word "*is*" to "*Jobs*" is -1, to "*Apple*" is 4. In this way, the distance of words around the entity words in the sentence can be clearly expressed. Furthermore, to make the model easy to understand the PF, the above two real values are mapped into a new vector space, namely the position embedding process. Normally the dimension of this vector is 5. The example is shown in Figure 2.

In addition to PE, some RNN-based methods also use position indicators (PI) to further enhance the representation of the entity pair. In SemEval 2010-task8, this data set uses four position indicators to indicate the entity pair in the sentence. The example is shown in Table 1.

Shortest Dependency Path (SDP) is a word-level de-noise method and derived from a grammatical dependency tree, which can mask irrelevant words influencing the relation of entities in a sentence. (The grammatical dependency tree can be obtained by the Stanford Parser[1]). Bunescu and Mooney [38] first used the SDP to design a kernel-based method to finish RE task, and then a lot of SDP-based models follow this work, such as SDP-LSTM [64], BRCNN [8], DesRC(BRCNN) [47] and Att-RCNN [15]. For instance, a sentence "\<e1\>People\</e1\>have been moving back into \<e2\>downtown\</e2\>." can be parsed to a SDP: "$[People]_{e_1} \rightarrow moving \rightarrow into \rightarrow [downtown]_{e_2}$". This example illustrates that the SDP captures the predicate-argument sequences. These sequences have great benefits for RE: firstly, this method compresses the information content of sentences. Secondly, it directly shows the dependency relations between each word. Finally, it provides a clearer relation direction between entities.

Table 2: The comparison of traditional methods and DNN-based methods.

Classifier	Feature Sets	F1
SVM	POS, stemming, syntactic patterns	60.1
SVM	word pair, words in between	72.5
SVM	POS, stemming, Syntactic patterns	74.8
MaxEnt	POS, morphological, noum compound, thesauri, Google n-grams, WordNet	77.6
SVM	POS, prefixes, morphological, WordNet, Dependency parse, Levin Classed, ProBank, FrameNet, NomLex-Plus, Google n-gram, paraphrases, TextRunner	82.2
RNN	POS, NER ,WordNet	77.6
MVRNN	POS, NER ,WordNet	82.4
CNN+softmax	Word pair, Words around word pair, WordNet	82.7

Some traditional classifiers, their feature sets and the F1-score for RE [69].

Table 3: The example of pattern "such Y as X".

Pattern	such Y as X
Corpus	... works by such authors as Herrick, Goldsmith, and Shakespeare.
Relation	Hyponym ("author", "Herrick"), Hyponym ("author", "Goldsmith"), Hyponym ("author", "Shakespeare")

3 Traditional Methods

3.1 Categories Of Methods

The existing RE approaches can be divided into **hand-built pattern methods, semi-supervised methods, supervised methods, unsupervised methods**, and **distant supervision methods.** In this paper, we refer to the five methods without DNNs as the traditional methods.

Hand-built pattern methods require the cooperation between domain experts and linguists to construct a knowledge set of patterns based on words, part of speeches, or semantics. With this linguistic knowledge and professional domain knowledge, RE can be realized by matching the preprocessed language fragment with the patterns. If they match, the statement can be said to have the relation of the corresponding pattern [19, 4]. Table 3 is an example of a pattern for hyponymy.

Semi-supervise methods are pattern-based method in essence. The typical method is a bootstrapping algorithm, and the representative model is DIPRE (Dual Iterative Pattern Relation Expansion) proposed by Brin [6]. The idea behind this method is first to find some seed tuples with high confidence, the bootstrapping algorithm extracts patterns with the tuples from a large number of an unlabeled corpus. And then these patterns can be used to extract

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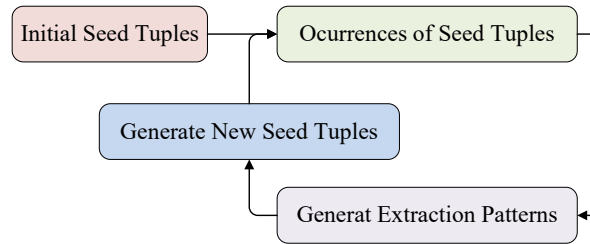[1] http://nlp.stanford.edu/software/lex-parser.shtml
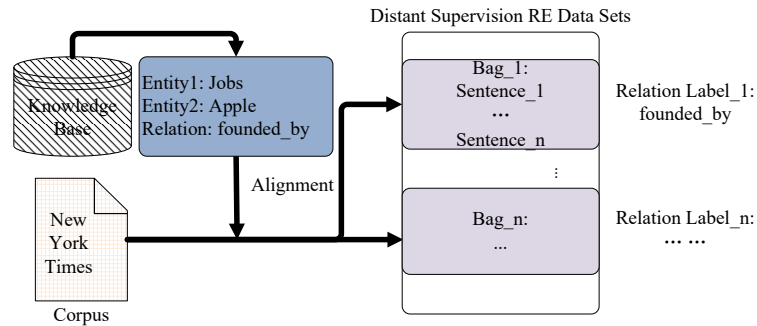
Fig. 3: The main idea of DIPRE.

Fig. 4: The process of distant supervision. The upper left of the figure is the knowledge base, and the lower left is the corpus source. After the text alignment process in the middle, the right side produces the packages corresponding to the knowledge base to represent various relationships, each package represents a relationship label and these packages contain several sentence instances.

new triples. This method looks like Figure 3. Some other representative models are: Snowball [1], KnowItAll [12], TextRunner [66]. There is also a recent method proposed by Phi[43].

Unsupervised methods adopt a bottom-up information extraction strategy based on the assumption: the context information of different entity pairs with the same semantic relation is relatively similar. An earlier unsupervised approach was proposed by Hasegawa et al. [18]. This extraction process can be divided into three steps: extracts an entity pair and its context, clusters the entity pair according to the context, and annotates the semantic relation of each class or describes the relation type.

Supervised methods consider RE as a multi-class classification problem. These approaches are classified into two types: feature-based and kernel-based [41]. In the feature-based methods [49, 25], each relation instance in the labeled data is used to train a classifier fed with subsequent new instances for classification. Generally, these features come from useful information (including lexical, syntactical, semantic) extracted from an instance context. Without a proper feature selection, a feature-based method is difficult to improve the performance. Compared with the feature-based methods, the kernel-based [38, 7] methods need rarely explicit linguistic preprocessing steps. But it depends more on the performance of the kernel function designed. The key step in this approach becomes how to design an effective kernel.

Distant Supervision methods are a kind of knowledge-based or weakly supervised method proposed by Mintz et al. [36]. All of these works are based on this assumption: If two entities participate in a relation, all sentences that mention these two entities can express that relation. In other words, any sentence that contains a pair of entities participating in a KB is likely to express that relation. In this way, distant supervision attempts to extract the relations between entities from the text by using a KB, such as Freebase, as the supervision source. When a sentence and a KB refer to the same entity pair, this method marks the sentence heuristically with the corresponding relation in the KB. For example, "Jobs is the founder of Apple.", in this sentence, the person "Jobs" and the organization "Apple" appear in Freebase, and Freebase has a triple (entity1: Jobs, entity2: Apple, relation: *founded_by*) corresponding to the mentioned entity pair. Therefore these entities express a relation *founded_by*. The process is shown in Figure 4.

3.2 Discussion

Although there are numerous ways to solve the problem of RE, this field has consistently shown that these methods exit various obstacles. The hand-built pattern and semi-supervised methods require the manual exhaustion of all the relation patterns, result in inevitable human errors. In the supervised method, a variety of mature NLP toolkits [34] provide technical support for these approaches, but both feature design and kernel design are still time-consuming and laborious. The clustering results generated by unsupervised methods are generally broad, and one of the main obstacles is to define an appropriate relation inventory. Moreover, this method has limited processing capacity for a low-frequency entity pair and also lacks a standard evaluation corpus or even unified evaluation criteria. The distant supervision can effectively label data for RE, yet suffers from the wrong label and low accuracy problem. In addition, all of these approaches have domain limitations, error propagation, and poor ability to learning underlying features.

To solve these problems, some scholars try to adopt DNN-based methods to improve the performance of RE. In fact, in other fields of NLP, DNNs have been widely applied, such as machine translation, sentiment analysis, automatic summarization, question answering, and information recommendation, and all of them have achieved state-of-the-art performance. To date, DNN-based RE methods have been used in supervised and distant supervision RE mentioned above. These DNN-based methods [33, 69, 64] can automatically learn features instead of manually designed features based on the various NLP toolkits. At the same time, most of them have completely surpassed the traditional methods in effect. Table 2 shows some comparison of traditional RE methods and the earlier DNN-based methods, which illustrates that DNN-based methods can obtain higher scores with fewer features.

Based on the five traditional methods mentioned above, DNN-based methods introduced in this paper mainly focus on supervised methods and distant supervision methods.

4 DNN-based Supervised RE

For the sake of simplicity and clarity, this paper further subdivides the methods using different DNNs as four types (e.g., **CNN, RNN or LSTM, Mix-structure**), of which the evolutionary process is shown in (a) in Figure 5. Although further subdivision is carried out, the advantages of high accuracy of DNN-based supervised methods are consistent with the traditional supervised methods, and they have been further improved. The architecture of the supervised methods is shown in (b) of Figure 5. To facilitate the analysis, the development process of each type of model set is divided into two stages: **The first stage (1st)** improves the ability of feature extraction; **The second stage (2nd)** improves the ability of semantic representation.

4.1 CNN-based

CNN-based models are a general model of RE, which have achieved excellent results. In these models, a part of them play a key role in the following RE tasks, especially some modules, such as CNN with multi filters [39], piecewise convolution [26], attention mechanism, PE [69]. In the following, this subsection will introduce these related models. Some comparisons are shown in Table 4.

The first stage: The first model using CNN on RE was proposed by Liu et al. [33]. With the synonym dictionary and any other lexical features, this model transforms the sentence into a series of word vectors, which is fed to a CNN and a softmax output layer to get a classification probability. This paper is just an attempt to adopt the CNN in this task. Better result as it has achieved, this method still depends on NLP toolkits, as well as barely considers the semantics, the model structure, the feature selection.

For improving the feature selection, Kim [26] introduced multiple filters and max-pooling modules for CNN, which is probably one of the earliest works in the text classification task. Based on this work, Kalchbrenneret et al. [24] described a dynamic CNN that uses a dynamic k max-pooling operator to pick up some features from the result of CNN. Both of the above two models [33, 24] achieve high performance on different tasks.

To finish this work with fewer NLP toolkits, Zeng et al. [69] creatively put forward the concept of PE between entities, and combined the lexical information of entities with the sentence-level features extracted by the CNN, and integrated these features into the network, achieving state-of-the-art on the task of SemEval-2010task8 at 2014. This model solves the cumbersome preprocessing problem in the task and avoids the error propagation problem to some extent. After this model, almost all CNN models use the PE method, and try to extract information with fewer

NLP toolkits, or even try to extract relations without using any information other than word embedding. However, this model uses a fixed-size-filter-CNN, which only focuses on the local features and ignores the global features.

Table 4: The comparison of CNN-based methods.

Stage	Author	Model name	Framework	Features set	Loss function	Optimization	F1
	Liu et al. [33]	-	fixed-size-filter-CNN	one-hot	-	-	-
	Zeng et al. [69]	-	fixed-size-filter-CNN	WE1+WA+WN+PE	Cross entropy	SGD	82.7
		-		WE1+WA+WN			69.7
	Nguyen et al. [39]	-	multi-sizes-filter-CNN +max-pooling	WE2+PE	-	SGD	82.8
1st	Santos et al. [51]	CR-CNN	fixed-size-filter-CNN +max-pooling	WE2+PE	Ranking lose	SGD	84.1
		-			Cross entropy		82.4
	Xu et al. [62]	depLCNN+NS	fixed-size-filter-CNN +max-pooling +Negative Sampling	WE1+WA+WN+SDP	Cross entropy	SGD	85.6
		-	fixed-size-filter-CNN +max-pooling	WE1+PE			83.7
2nd	Wang et al. [60]	-	fixed-size-filter-CNN +two-level-CNN +two-level-attention +max-pooling	WE2+PE+WA	Distance function	SGD	88
		Att-Pooling-CNN	fixed-size-filter-CNN +two-level-CNN +max-pooling	WE2+PE+WA			86.1

The WE1, WE2, WE3 remark refers to Word embedding proposed by Turian et al. [57], Mikolov et al. [35], Pennington et al. [42] respectively. The WA, WN, PE, PI remark refers to Word around nominals, WordNet, Position embedding, Position indicator. The SDP, GR, WN-SYN, Relative-DEP remark refers the shortest dependency path, grammar relation, hypernyms, relative-dependency. The F1 value is based on semeval2010-task8 [20]. This table lists the best result of the model and its variants,and subsequent tables follow this format.

To bring more structure information, Nguyen et al. [39] combined the concept of multiple-window size filters for RE based on Kim's [26] work. Compared with fixed-size-filter-CNN, this paper demonstrates that multi window sizes filters (multi-sizes-filter-CNN) can bring more structured information to the model. This would be an efficient way to improve the CNN architecture. Many subsequent models will use this technique as well. Meanwhile, this paper also shows that the word vectors pre-trained and changing dynamically with model training are helpful to improve the performance. But in fact, dynamic word vector is not often referenced. The model structure is shown in Figure 6. Besides, all the above models use the softmax module, which cannot eliminate the influence of other similar classes affecting the final classification results.

Santos et al. [51] improved the loss function instead of the softmax classifier. The Model's parameters are trained by minimizing a new ranking loss function (CR-CNN) over the training set, which can give a higher probability to the correct class and lower probability for the wrong classes. This new loss function improved this model and can be used in other classifiers.

The second stage: To learn more robust relation representations, Xu et al. [62] proposed a model through a CNN with the SDP (talked about it in Sec 2.2). The model, which mostly takes the subject to the object of a sentence as input, can remove the words that are not related to the relation discrimination, following high accuracy with simply negative samples. This is the first DNNs model to use the SDP, and this technic and its variants will be widely adopted in the subsequent models.

Another way to improve semantic representation is attention mechanism. Wang et al. [60] used two levels of attention mechanism, called Multi-Level Attention CNNs which enables end to end learning from task-specific labeled data. This multiple attention mechanism can consider both the semantic information at the word level and the sentence level. This model rarely uses any other external semantic information at all. At first level attention, the model constructs an entity-based attention matrix at the input level, which is used to label the words related to the corresponding relation. At the second level, the mechanism is used again to capture more abstract high-level features to construct the final output matrix.
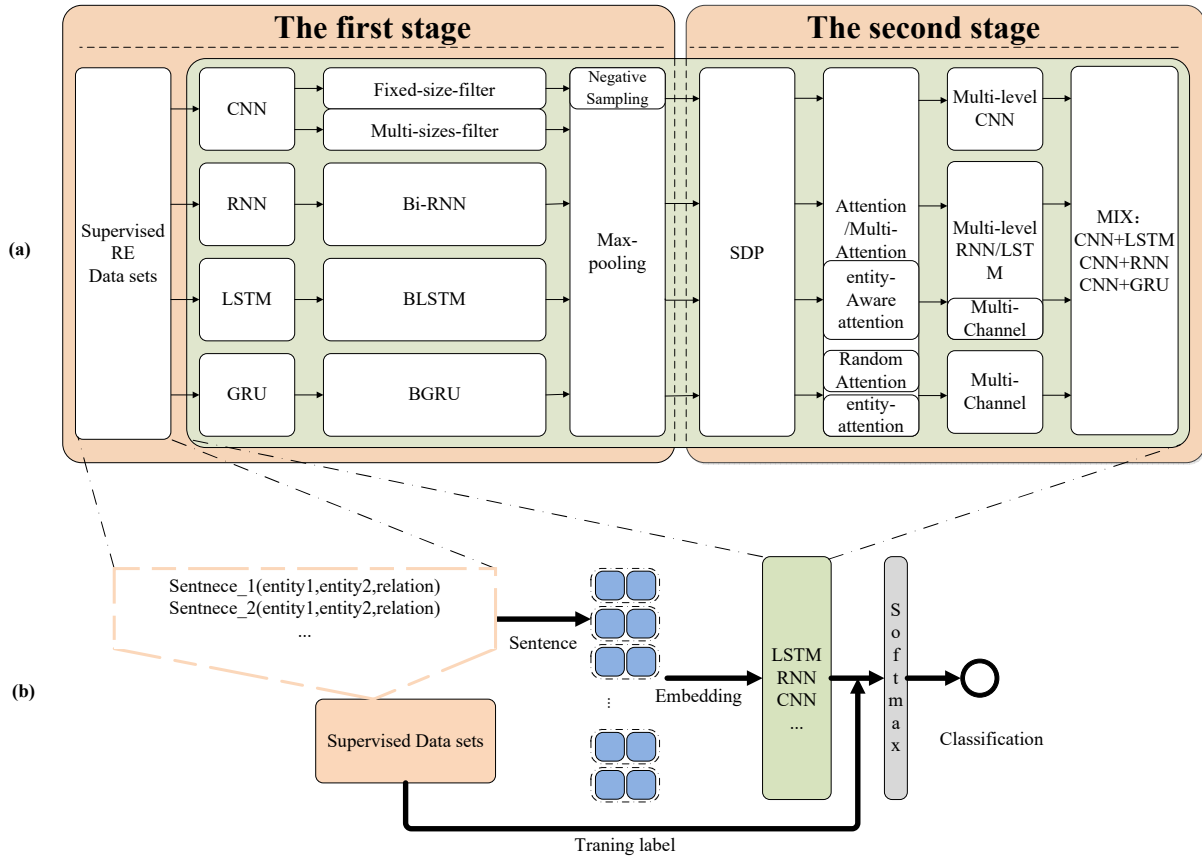
(a)

The first stage

Supervised RE Data sets

CNN → Fixed-size-filter / Multi-sizes-filter → Negative Sampling

RNN → Bi-RNN

LSTM → BLSTM

GRU → BGRU

Max-pooling

The second stage

SDP

Attention /Multi-Attention / entity-Aware attention / Random Attention entity-attention

Multi-level CNN

Multi-level RNN/LSTM → Multi-Channel

Multi-Channel

MIX: CNN+LSTM CNN+RNN CNN+GRU

(b)

Sentnece_1(entity1,entity2,relation)
Sentnece_2(entity1,entity2,relation)
...

Supervised Data sets

Sentence → Embedding → LSTM RNN CNN ... → Softmax → Classification

Traning label

Fig. 5: (a) and (b) are the evolutionary process and architecture of supervised methods respectively.

input sentence with marked entities

In the morning, the <e1>President</e1> traveled to <e2>Detroit</e2>

position embeddings matrix

table look-up

word embedding matrix

entity 1

entity 2

in
the
morning
the
president
traveled
to
detroit

Look-up tables | Convolutional layer with multiple window sizes for filters | Max pooling | Fully connected layer with dropout and softmax output
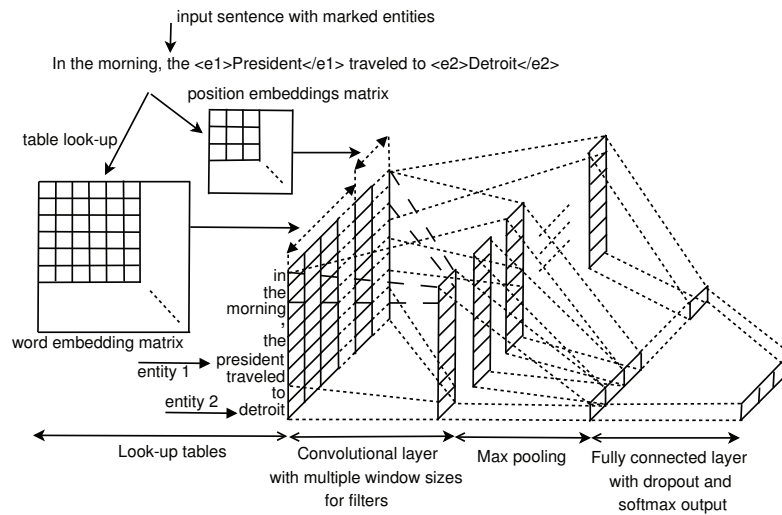
Fig. 6: The structure of model [39] with multi window filters.

4.2 RNN or LSTM based

Table 5: The comparison of RNN-based methods.

Stage	AUTHOR	model name	Framework	Features set	Loss function	Optimization	F1
1st	Zhang et al. [71]	RNN	Bi-RNN +max-pooling	WE1+PI	Cross entropy	SGD	80
				WE2+PI			82.5
	Zhang et al. [74]	BLSTM	BLSTM +max-pooling	WE3+PE+WN+NER +POS+WNSYN +Relative-DEP	-	-	84.3
				WE3+WA			82.7
2st	Xu et al. [64]	SDP-LSTM	SDP+LSTM	WE2+SDP	Cross entropy	SGD	82.4
				WE2+SDP+WA+POS+GR			83.7
	Zhou et al. [79]	Att-BLSTM	BLSTM +attention	WE3+PI	Negative-log-likelihood (Cross-Entropy)	AdaDelta	84
		BLSTM	BLSTM +max-pooling	WE3+WA	-	-	82.7
	Xu et al. [63]	DRNNs	multi-channel-rnn +max-pooling +augmentation	WE2+GR+POS +WN+SDP(augmentation)	Cross entropy	SGD	86.1
			multi-channel-rnn +max-pooling	WE2+GR+POS+WN+SDP			84.16
	Xiao et al. [61]	BLSTM+BLSTM	2-level-BLSTM +attention	WE2+WN+NER	Ranking lose function	AdaGrad	84.27
				WE2			83.9
	Qin et al. [44]	EAtt-BiGRU	Bi-GRU +entity-attention	WE2+PE	-	AdaDelta	84.7
		-	Bi-GRU +random-att				83.6
	Zhang et al. [70]	BiGUR-MCNN-ATT	BiGRU +multi-size-filter-cnn-attention	WE2+PE+SDP	-	AdaDelta	84.7
		BiGUR-Random-ATT	BiGRU +random-attention				84.2
	Lee et al. [29]	BLSTM+LET	BLSTM +Entity-aware-attention +Latent-Entity-Type	WE2+PE+LET	Cross entropy	AdaDelta	85.2
		-	BLSTM +Entity-aware-attention	WE2+PE			84.7

Symbols have the same meanings as Table. 4.

The general problems of CNNs in RE are that CNNs can not consider global features and time sequence information, especially for the long-distance dependency between entity pair. RNNs, LSMTs, and GRUs, the latest research methods for sequence modeling and problem transformation can alleviate these problems. In this section, this paper will introduce some RNN-based methods, of which the comparisons are shown in Table 5.

The first stage: For learning relations within a long context and considering the timing information, Zhang et al. [71] used a bi-directional RNN architecture to learn relations within a long context and to consider the timing information. RNN combines the output of each hidden state and then represents the feature at the sentence level. At the end of the model, it conducts a max-pooling operation to pick up a few trigger word features for prediction. Although max-pooling operation simplifies feature extraction, the effectiveness of these features remains to be discussed. Besides, the RNN model still has the problem of gradient explosion. To solve the problem of the gradient explosion, LSTM [21] is proposed by using the gate mechanism. Based on this, Xu et al. [64] proposed a model with LSTM (will be discussed in the 2nd stage)

With complete, sequential information about all words in the sentence is beneficial to RE, Zhang et al. [74] applied the bi-directional long short-term memory networks (BLSTM) to obtain the sentence level representation, and also use several lexical features. The experiment results show that using word embedding as input features alone is enough to achieve state-of-the-art results. This study documents the effectiveness of the BLSTM. Although the method improves the representation of sentence-level features, there are still two problems: a large number of external artificial features are used, and no effective feature filter mechanism.

The second stage: Based on the above problems, Xu et al. [64] proposed a new DNNs model called SDP-LSTM. This model leverages four types of information: Word vectors, POS tags, Grammatical relations, and Word-Net hypernyms, to construct four channels for this model to provide external information. And then, it concatenates the result of the four channels to the softmax layer for prediction. This model is a little more complex than Zhang et al. [71] by considering a lot of additional syntaxes and semantic information.
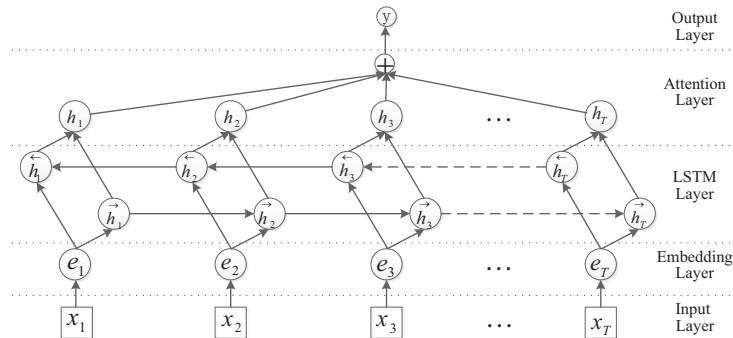
Fig. 7: The structure of the model [79], BLSTM with an attention mechanism.

Follow Xu et al. [64]'s work, to overcome the problem of the shallow architecture that can not represent the potential space in different network levels, Xu et al. [63] increased the neural network layers to tackle this challenge, with which this model captures the abstract features along the two sub-paths of SDP. Meanwhile, the small size of the semeval2010-task8 set and deeper neural networks may easily result in overfitting. Hence, the author augments the data set by adding the directivity of the data based on the original SDP, avoiding the overfitting problem.

The SDP can filter the input text but can not filter the extracted features. To tackle this issue, Zhou et al. [79] came up with the attention mechanism in BLSTM, which can automatically highlight the important features only with the raw text instead of any other NLP toolkits or lexical resources.

Similar to Zhou et al. [79]'s work, Xiao et al. [61] proposed a two-level BLSTM architecture with a two-level attention mechanism to extract a high-level representation of the raw sentence. Zhou et al. [79]'s work is a representative BLSTM model and the architecture is shown in Figure 7.

Although the attention mechanism can give more weight to the important features extracted by the model, Zhou et al [79]'s work just gives a random weight, which lacks the consideration of the prior knowledge. Therefore, the following works improved this model.

Fed with entity pair and sentence, EAtt-BiGRU proposed by Qin et al. [44] leveraged the entity pair as prior knowledge to form attention weight. Different from Zhou et al. [79]'s work, Eatt-BiGRU applies bi-directional GRU (BiGRU) instead of BLSTM to reduce computation, which helps in obtaining the representation of sentence and adopts a one-way GRU to extract prior knowledge of entity pair. With the representation and prior knowledge, this model can generate the corresponding attention weight adaptively. This work improves the random attention mechanism, but how to better integrate the prior knowledge needs further studying.

Zhang et al. [70] proposed another kind of attention mechanism based on the SDP, which is another prior knowledge. This model uses Bi-GRU to extract sentence-level features and uses attention weights extracted from multi-channel CNN to classify. Compared with other random or entity based attention mechanisms [79, 44], this model can construct a better attention weight using the SDP.

Further research was followed by Lee et al. [29] who proposed a mixed model with BLSTM, self-attention, entity-aware attention, and latent entity typing module, getting state-of-the-art without any high-level features. In general, the instance of the data set has no attribute of the entity type. However, the entity pair type is closely related to the relation classes. Previous works can only get word-level or sentence-level attention, but can not obtain the degree of correlation between entities and other related words. Hence, this model introduces the latent entity typing module, self-attention module, entity-aware attention module, which could give more prior knowledge.

4.3 Mix-structure based

In addition to the above two types of models, some scholars combined these models based on their respective characteristics, which can be beneficial to RE task. There exist two ways to merge these models: simply combination (**The first stage**) [72] and attention mechanism (**The second stage**) [15]. The comparison of them are shown in Table 6.

Table 6: The comparison of methods based on Mix neural networks.

Stage	Author	Model name	Framework	Features set	Loss function	Optimization	F1
1st	Zheng et al. [78]	MixCNN+CNN	multi-sizes-filter-CNN +fixed-size-filter-CNN +max-pooling	WE2+WA	Cross entropy	SGD	84.8
		MixCNN+LSTM	multi-sizes-filter-CNN +LSTM +max-pooling				83.8
	Zhang et al.[72]	BLSTM-CNN	BLSTM +fixed-size-filter-CNN +max-pooling	WE2+PI+PE	-	-	83.2
		BLSTM-CNN+PF		WE2+PE			81.9
		BLSTM-CNN+PI		WE2+PI			82.1
2nd	Cai et al. [8]	BRCNN	2level-LSTM +2level-fixed-size-filter-CNN +SDP(2direction)	WE2+POS+NER+SDP	Cross entropy	AdaDelta	86.3
				WE2+SDP			85.4
	Ren et al.[47]	DesRC(BRCNN)	BRCNN +fixed-size-filiter-CNN-description +attention	We2+PE+WN+SDP	-	SGD	87.4
		-	BRCNN +fixed-size-filter-CNN	We2+PE+SDP			84.7
	Guo et al.[15]	Att-RCNN	fixed-size-filter-CNN +max-pooling +Bi-GRU +attention	WE2+SDP	Pairwise logistic loss	SGD	86.6
		-	fixed-size-filter-CNN +max-pooling +Bi-GRU				85.1

[1] Table symbols have the same meanings as Table 4.

The first stage: To integrate RNN and CNN, Zheng et al. [78] proposed two neural networks based on CNN and LSTM (MixCNN+CNN and MixCNN+LSTM) framework by joint learning the entity semantic and relation pattern. In this model, the entity semantic properties can be reflected by their surrounding words, which can tackle the unknown words in entities (Out-of-vocabulary problem), and the relation pattern modeled by the sub-sentence between the given entities instead of the whole sentence. With the entity semantic and relation pattern, the performance of RE can be improved. This research sheds new light on merging these two modules, showing the complementarity of the two modules as well as the necessity of module integration.

Zhang et al. [72] introduced the BLSTM-CNN, without any lexical attention mechanism or NLP toolkits, just used three kinds of resources, word embedding, PE, PI, showing that simply merging BLSTM and CNNs can perform better than any other single models. However, the PE and PI, showing the words around the nominals, are same functions for RE which may result in overlap feeding.

The Second stage: Different from the above two works, Cai et al. [8] combined these two types of models depending on the SDP. To improve the model's sense of relation directivity, this model, called BRCNN, learned sentence features from the SDP on both positive and negative directions, which is beneficial for predicting the direction of the relation.

Following Cai et al. [8]'s work, Ren et al. [47] advanced a further work, a traditional CNN architecture with BRCNN [8], using two kinds of attention ('intra-cross') to combine the classification features that come from the original sentences and their corresponding descriptions. The description of an entity is from the external text, which can enrich the prior knowledge. Compared with different experiments and models, the result demonstrates that text descriptions can provide more features to model and replace WordNet to a certain extent in RE. In this line, this is the first RE method that uses entity description information. But the method of extracting description is too simple. As an external knowledge, description information should be closely related to the original sentence, therefore the selection of description should be more targeted.

Guo et al. [15] proposed a novel Att-RCNN model to extract text features. This model leverages GRU units instead of LSTM units, which has a higher speed in computing convergence and uses CNNs to extract high-level

features. Meanwhile, the two-level attention mechanism is similar to [60]. The special part of this model is the introduction of a new de-noise method, which can get a continuous fragment of the original text, based on the SDP [64].

5 DNN-based Distant Supervision RE

Table 7: The comparison of DNN-based distant supervision methods.

Type	Author	Model name	Framework	Features set	De-noise method	Loss function	Optimization
En	Zeng et al. [68]	PCNN	multi-fixed-size-filter-CNN +piecewise-max-pooling	WE2+PE	Multi-instance Learning	Cross entropy	Adadelta
	Lin et al. [32]	PCNN+ATT	multi-fixed-size-filter-CNN +piecewise-max-pooling +cross-sentence-max-pooling	WE2+PE	Selective attention	cross entropy	SGD
	Jiang et al. [23]	MIMLCNN	multi-fixed-size-filter-CNN +piecewise-max-pooling +ross-sentence-max-pooling	WE2+PE	Output multi label	Cross entropy	Adadelta
Re	Yang et al. [65]	BiGRU+2ATT	BiGRU +word-level-attention +sentence-level-attention	WE2+PE	Sentence-level-attention	Cross entropy	Adam
	Lin et al. [31]	MNRE	multi-fixed-size-filter-CNN +max-pooling +mono-lingual attention +cross-lingual attention	WE1+PE	Mono-lingual (Sentence-level- attention)	-	SGD
	Banerjee et al. [3]	MEM	multi-channel-BLSTM	WE3+DP+POS	Co-occurrence statistics	Cross entropy	-
	Du et al. [10]	MLSSA	BLSTM +word-level-attention +sentence-level-attention	WE2+PE	Sentence-level-attention	-	Adam
Ex	Ji et al. [22]	APCNNs+D	multi-fixed-size-filter-CNN +piecewise max-pooling +fixed-size-filiter-CNN-description +sentence-level-attention	WE2+PE	Sentence-level-attention	Cross entropy	Adadelta
	Wang et al. [59]	LFDS	multi-fixed-size-filter-CNN +piecewise max-pooling +word-level-attention	WE2+PE	KG Embedding	Margin loss	-
	Vashishth et al. [58]	RESIDE	GCN +Bi-GRU +word-level-attention +senten-level-attention	WE3+PE+DP	-	-	-
Pl	Qin et al. [46]	RL	fixed-size-filter-CNN +Reinforcement learning	WE2	Reinforcement Learning	-	-
	Qin et al. [45]	DSAGN	fixed-size-filter-CNN +GAN	WE2+PE	DSGAN	-	-

[1] Table symbols have the same meanings as Table 4. In addition, the En, Re, Ex, Pl remark refers to sentence encoder, Enhanced representation, External knowledge, Plug-and-play component.

In the supervised method of RE, the insufficient training corpus puzzles the further development of RE despite of their excellent results. This paper introduced the conception of distant supervision in section 3, which can alleviate these above problems. To solve this problem, Mintz et al. [36] proposed distant supervision, which is strongly based on an assumption that plays an important role in the selection of training examples. To date, this assumption has evolved into **Three assumptions**. Meanwhile, distant supervision methods are composed of two research directions: **Sentence Encoder** is to optimize the model and the performance of RE; **De-noise Algorithm** is to de-noise and improve the quality of the data sets. The architecture of DNN-based distant supervision is shown in (b) of Figure 8. This section presents some related works and summarizes the evolution of this approach (shown in (a) of Figure 8). Hence, the rest of this chapter will follow these three points. In addiction, different from the supervised method, this table does not include evaluation indicators in distant supervised methods. Because most of these methods in Table 7 is just an approximate measure of precision.

5.1 Three Assumptions

To solve the insufficient training samples problem, in 2009, Stanford University Professor Mintz et al. [36] proposed RE method of distant supervision at ACL conference. This method rarely needs manual annotation and generates
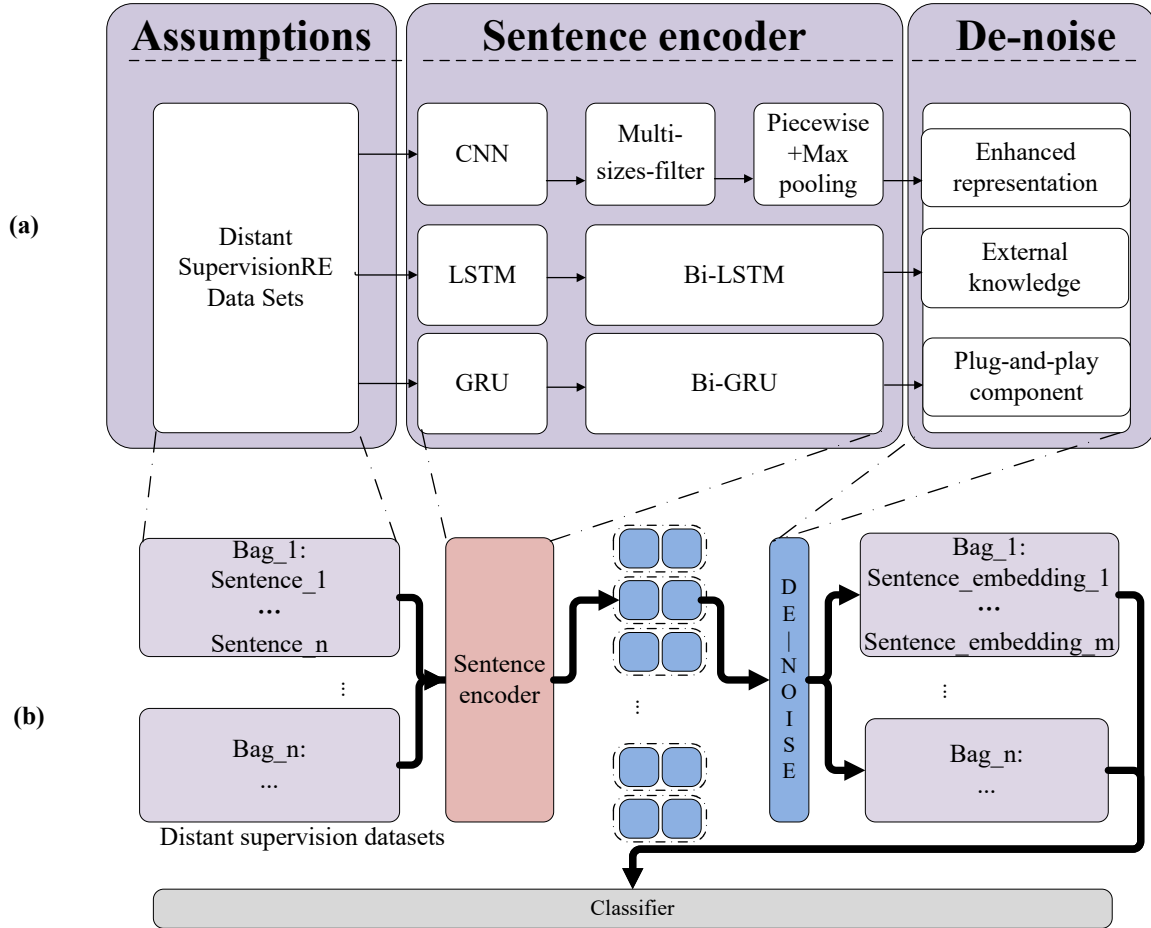
Fig. 8: (a) and (b) are the evolutionary process and architecture of DNN-based distant supervision methods. The sub-figure (b) also shows the relationship between sentence encoder and de-noise method. The sentence encoder is responsible for encoding the sentence bag in the distant supervision data set into vectors, while the de-noise algorithm is responsible for selecting the sentences in each bag that can correctly represent the relationship.

large-scale training data sets (talked about that in section 3). The large-scale training data sets are from these assumptions:

Assumption 1: *If two entities participate in a relation, all sentences that mention these two entities express that relation.*

Assumption 2: *If two entities participate in a relation, at least one sentence that mentions these two entities might express that relation.*

Assumption 3: *A relation holding between two entities can be either expressed explicitly or inferred implicitly from all sentences that mention these two entities.*

The first assumption [36] physically aligns the texts with a KB and trains a classifier heuristically using the existing triples in the KB. Riedel et al. [48] thought the first assumption is too strong resulting in the wrong label problem (noisy problem), and then proposed the second assumption, called: "one sentence from one bag". It leads to more accurate results. The third assumption [23] can consider more sentence features (will be introduced in the next subsection).

5.2 Classical Sentence Encoder

In this section, this article focus on several classic models of the sentence encoder, including PCNN (Piecewise CNN), max-pooling, multi-instance learning (MIL), attention mechanism.

PCNN+MIL: Inspired by Zeng et al. [69], Zeng et al. [68] used the PCNN with MIL, which divides the sentence into 3 segments based on the positions of two entities, to extract the relevant features automatically from a sentence and to get the important structural information. And then, they use MIL to train the model with the highest confidence level instance to reduce the noise (used one sentence from one bag). This model outperforms several competitive baselines but ignores other instances in the bag.

PCNN+Att(Attention): Use "one sentence from one bag" will lose a lot of useful information in the bag. Different from the above method, in Lin et al. [32]'s work, they use the weight of the attention mechanism to flag all instances in one bag, and then applied the vector weighted sum of all the sentences to represent a bag. Hence, this model can identify important instances from noisy sentences, as well as utilizes all the information in the bag to optimize the performance. As a special case of the MIL, this model can effectively reduce the influence of wrong labeled instances.

MIMLCNN: The same purpose as above, Jiang et al. [23] proposed a multi-instance multi-label CNN for distant supervision. The author introduced a new assumption (assumption 3 mentioned in section 5.1): This work leverages CNN to extract features from a single sentence and then aggregates all sentence representations into an entity-pair-level representation by cross-sentence max-pooling. In this way, the model can merge features from different sentences, not one sentence from one bag. Meanwhile, the multi-relation pattern between entity pairs can be considered. Hence, for a given entity pair, the model can predict multiple relations simultaneously.

5.3 De-noise Methods

This paper summaries three main ways to deal with the noise reduction of distant supervision data: the first is to make full use of the word-level and sentence-level features of the instances in the bag (**enhanced representation**); the second is to introduce the **external knowledge**; while the third is to construct a **plug-and-play** component.

Enhanced representation: Yang et al. [65] and Du et al. [10]'s work are similar, both of them use two different kinds of attention mechanism (two-level) to extract features. The first one is used to present the sentence, which looks like [79], and alleviates the distractions of irrelevant words. The second one is like [32], leveraging attention mechanism to choose the weight of the sentence with the highest probability.

Different from Yang et al. [65] and Du et al.[10]'s work, Lin et al. [31] introduced a novel attention model considering multi-lingual corpus, which is also base on [32]. This work proposed mono-lingual attention and a cross-lingual attention mechanism to leverage diverse information hidden in the data of different languages, and the experimental results show that this work can effectively model relation patterns among different languages. However, if each language builds a cross attention matrix, it doesn't seem realistic.

In addition to using attention mechanisms, there are also ideas for incorporating more information to enhance the model. Banerjee et al. [3] proposed a simple co-occurrence based strategy method for calculating the highest confidence in distant supervision bag, which uses the most frequent samples in the bag as the training label of the package. This is also a way to enhance the presentation.

External knowledge: Only with the entity pair and the context, the extracted features is not enough to represent the sentence, which may result in low accuracy. In recent years, with the word vectors and knowledge graphs, additional background information has been introduced, which improves the description accuracy of relation vectors [22,59,58].

In Ji et al. [22]'s work, they continue to use the classic PCNN model to get sentence feature vectors. But in the data source processing step, this work introduces the conception of the relation vector from the knowledge graph $r = e_1 - e_2$ to present the relation, and then, combines these two kinds of vectors to a new vector by concatenation. With the new vector, this model generates an attention weight vector to weight sum all of the sentence feature vectors as the bag's features. Meanwhile, to get additional background information, a description for entities from Freebase and Wikipedia pages is introduced to improve the entity representations. The experimental results show that this method can provide more background knowledge to entities.

Following Ji et al. [22]'s work, Wang et al. [59] also introduce the concept of the relation vector of the knowledge graph $r = e_1 - e_2$ to present the relation. But this model is different from the above, it leverages the label data from the sentence itself, which means that all the labels of the training data are determined by sentence and aligned entity pairs. In the end, the sentences can be classified into a diverse group by the types of the aligned entities in the knowledge graph, and form a sentence pattern. Hence, this method also alleviates the wrong label problem and can make full use of the training corpus produced by distant supervision.
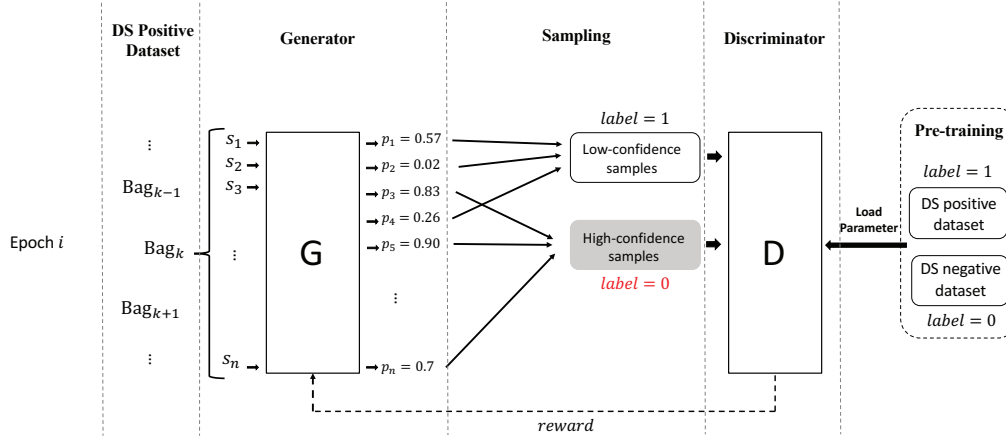
Fig. 9: The structure of model DSGAN [45].

Since not all entities have description information, the above two methods may not apply to all entities, but some side information describing entities type or entity relations can be utilized. In Vashishth et al. [58]'s work, they consider some relevant and additional side information of KB, such as entity type and relation alias, and employs GCN to encode syntactic information from text. The entity type information, in this method, is embedded into an embedding to represent various entity types. And the relation alias come from some NLP toolkits (Stanford Open IE [2]) or Paraphrase database (PPDB [40]). This kind of description can also be seen as a knowledge, which can improve the performance of RE model.

Plug-and-play component: Either the "enhanced representation" or the "external knowledge" methods mentioned above is to improve RE model itself, which is not universal. Hence, to directly construct a method as a plug-and-play component in distant supervision to reduce the noise of data sets must be a new insight.

Qin et al. [46,45] offered two approaches to constructing this plug-and-play component: One is the reinforcement learning framework for distant supervision [46] to solve false-positive case problem. The author argues that those wrong label sentences must be filtered by a hard decision, not by a soft weight of attention. In this way, this model can generate less noise training data sets which can be used in any previous state-of-the-art model. The second is DSGAN, using the idea of GAN to obtain a generator to classify the positive and negative samples in a bag from distant supervision. This is a kind of adversarial learning strategy, which can detect true-positive samples from the noisy distant supervision data sets. To some extent, these two methods can also alleviate the wrong label problem and form a new high-confidence training data sets. With this new data sets, some recent state-of-the-art models can achieve further improvement in the experiment. Hence, both of the "reinforcement learning framework" and DSGAN can be seen as a plug-and-play component in distant supervision. The structure of DSGAN is shown in Figure 9.

To summarize, distant supervision adopts various methods to get an excellent result. However, no matter to improve the model or to de-noise the data set, they only add something extra burden to the basic model instead of solving insufficient training corpus problem (We compare the characteristics of supervision and distant supervision methods in Table 8). And of course, some researchers are considering other solutions, and we'll talk about those methods later.

6 Other DNN-based RE

All the above RE methods are to extract one relation of the entity pair. An entity pair may have multiple relations in a sentence. To address this issue, Zhang et al. [73] came up with a RE approach based on capsule networks with an attention mechanism, which can output multi-relations of one entity pair. To some extent, this method can consider more detailed features. In addition, joint extraction methods [30,67,77,37], known as end-to-end extraction, is also a new sight. Unlike the methods discussed earlier, the joint extraction method integrates NER and RE into one model, which can output the relation and the entity pair together. In general, although the joint extraction method

Table 8: The comparison of supervised methods and distant supervision methods.

Item	Features	Supervision	Distant Supervision
Data sets	Annotate mode Accuracy of labeled data Noise Data Size	Manually annotated High accuracy Low noise Small	Distant alignment KB Low accuracy High noise Large
Applicability	Model portability Cross-domain applicability	Low Low	High High
Accuracy of prediction	-	High	Low

Table 9: The comparison of data sets.

Data set	Relations	Data Amount (words/language)
SemEval-2010 Task8	18	10717
ACE04	24	350K
NYT+Freebase	53	695059
FewRel	100	70000

Table 10: Some examples from SemEval 2010-task8.

Example1:	<e1>People</e1>have been moving back into <e2>downtown</e2>.
Relation:	Entity-Destination(e1,e2).
Example2:	Cieply's <e1>story</e1>makes a compelling <e2>point</e2>about modern-day studio economics.
Relation:	Message-Topic(e1,e2).

reduces the possibility of error propagation. compared with other methods, its accuracy and usability still have a large room for further improvement.

7 Data Sets

Variety of data sets exits for different methods, common data sets are SemEval 2010-task8 [20], ACE series 2003-2005, NYT+Freebase [48]. The SemEval 2010-task8 and ACE series are commonly used for supervised learning classification tasks, while the NYT+Freebase for distant supervision methods. Table 9 shows the comparison of 4 representative data sets. The following is a brief introduction to these data sets.

SemEval 2010-task8 [20] was released in 2010, as an improvement on the Semeval 2007-task4, it provides a standard testbed for evaluating various methods of RE. This data set is used widely for evaluation, which contains 9 directional relations and an additional 'other' relation, resulting in 19 relation classes in total. Most of the supervised methods discussed in this article use the same data set. The relations are as follows:

- Cause-Effect: An event or object leads to an effect. (those cancers were caused by radiation exposures)
- Component-Whole: An object is a component of a larger whole. (my apartment has a large kitchen)
- Content-Container: An object is physically stored in a delineated area of space, the container. (Earth is located in the Milky Way)
- Entity-Destination: An entity is moving towards a destination. (the boy went to bed)
- Entity-Origin: An entity is coming or is derived from an origin, e.g., position or material. (letters from foreign countries)
- Message-Topic: An act of communication, written or spoken, is about a topic. (the lecture was about semantics)
- Member-Collection: A member forms a nonfunctional part of a collection. (there are many trees in the forest)
- Instrument-Agency: An agent uses an instrument. (phone operator)
- Product-Agency: A producer causes a product to exist. (a factory manufactures suits)
- Other: If none of the above nine relations appears to be suitable.

Table 11: An introduction to ACE data sets.

Corpus	Data Amount (words/language)	Tasks	Languages
ACE03	100K training 50K evaluation	entities relations	Chinese English Arabic
ACE04	300K training 50K evaluation	entities relations events	Chinese English Arabic
ACE05	750K training 150K evaluation	entities relations events	Chinese English Arabic

This data set contains 10717 labeled data, of which 8000 are used for training and the remaining 2717 for testing. The nominals of the sentences in the data set are marked by XML tags. Table 10 shows an example of labeled sentences.

ACE2003-2005 Series come from LDC (Linguistic Data consortium), consisting of various types of annotated for entities and relations. In three different years of the corpus (ACE 2003, 2004, 2005), the ACE tasks are more complex than SemEval 2010-task8. The corpus can be divided into broadcast news, newswire and telephone conversations, including the complete set of English, Arabic, Chinese training data. So the annotated entities in this corpus are pronoun words or other irregular words. In addition to the task of RE, they can also be applied in the following five tasks: Entity Detection and Recognition (EDR), Entity Mention Detection (EMD), EDR Co-reference, Relation Mention Detection (RMD), and Relation Detection and Recognition (RDR) of given reference entities. This data set is typically used in supervised models. Table 11 shows the introduction of ACE data sets.

NYT+Freebase means New York times + Freebase, which is a common way to generate data sets in distant supervision. The distant supervision method produces data sets by extracting relations through the heuristic alignment of text and entities in the KB (talked about that in section 3). As a result, in this way, distant supervision can create large-scale training data automatically. This process is shown in Figure 4. The most widely used data set was generated by Riedel [48], which has 522611 training sentences and 172448 test sentences, labeled by 53 candidate relations in Freebase, and an extra-label of NA (nearly 80% of the sentences in the training data are labeled as NA).

Other Data sets include SemEval2017-task10 [5], SemEval2018-task7 [13], TACRED [76], KBP37 [71], DDIExtraction2011 [54], DDIExtraction2013 [53], FewRel [17], FewRel2 [14].

8 Conclusions

This article begins by laying out the general framework and some basic concepts, focusing on DNNs methods of full supervision and distant supervision, as well as some novel methods. In general, despite its long success, RE methods still have several problems as follows:

Transfer learning: Presently, most RE models are explored in predefined relation inventory and suffered from the insufficient data set. Nevertheless, world knowledge is growing fast and the number of relations is not stagnant. How to keep the model continuously receiving new training samples and make full use of other related corpus is very worthy of exploration. It is noted that no one has done this work yet.

Relationship Reasoning: It is a very forward-looking work to obtain the relation directly from the existing corpus in the real world. Without the relation category in advance, using background knowledge to obtain the relation by reasoning is an exciting way to solve the problem. Several attempts ([22], [59], [47]) have been made to use a knowledge graph or introduce entity description information to RE. However, how to correlate the introduced information and further improve the reasoning mechanism still needs further studying.

Relationship Framework: Another problem is the diversity of relation inventory in data sets (out-of-vocabulary problem). Different data sets have different definitions of relation inventories, making the training model of each data set limited in domain adaptability. If the industry can construct a framework with a unified description of all kinds of relations and make RE have a hierarchical structure, then it may have a better multi-domain adaptation. Predecessors have done a lot of work on the definition of relation inventories, but no agreement has been reached ([20]).

Cross-sentence RE: Moreover, cross-sentence RE is likewise one significant field. The current RE task mainly focuses on processing the entity pair relation in intra-sentence. In the actual situation, most entities in the text represent the relation between each other by multi sentences. Current models may not be able to handle such tasks directly. Especially, distant supervision generates a large scale of document-level corpora, which can only be solved by a cross-sentence RE technique. some researchers [50,16,75] proposed a series of novel methods to obtain the entity relation across sentences. These studies offer some important insights into cross-sentence RE.

Others: In addition to these fields of research, several problems in the existing methods also need solving, one is the problem of error propagation in supervised methods, and the other is the problem of the wrong label in distant supervision. Especially for the latter one, if the wrong label problem can be well solved, a large amount of effective sample data will be obtained, which will make an important contribution to this field.

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