More Data, More Relations, More Context and More Openness:
A Review and Outlook for Relation Extraction

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Abstract

Relational facts are an important component of human knowledge, which are hidden in vast amounts of text. In order to extract these facts from text, people have been working on relation extraction (RE) for years. From early pattern matching to current neural networks, existing RE methods have achieved significant progress. Yet with explosion of Web text and emergence of new relations, human knowledge is increasing drastically, and we thus require "more" from RE: a more powerful RE system that can robustly utilize more data, efficiently learn more relations, easily handle more complicated context, and flexibly generalize to more open domains. In this paper, we look back at existing RE methods, analyze key challenges we are facing nowadays, and show promising directions towards more powerful RE. We hope our view can advance this field and inspire more efforts in the community.[1]

1 Introduction

Relational facts organize knowledge of the world in a triplet format. These structured facts act as an import role of human knowledge and are explicitly or implicitly hidden in the text. For example, "Steve Jobs co-founded Apple" indicates the fact (*Apple Inc.*, founded by, *Steve Jobs*), and we can also infer the fact (*USA*, contains, *New York*) from "Hamilton made its debut in New York, USA".

As these structured facts could benefit downstream applications, e.g, knowledge graph completion (Bordes et al., 2013; Wang et al., 2014), search engine (Xiong et al., 2017; Schlichtkrull et al., 2018) and question answering (Bordes et al., 2014; Dong et al., 2015), many efforts have been devoted

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[1]Most of the papers mentioned in this work are collected into the following paper list https://github.com/thunlp/NREPapers.

to researching **relation extraction (RE)**, which aims at extracting relational facts from plain text. More specifically, after identifying entity mentions (e.g., *USA* and *New York*) in text, the main goal of RE is to classify relations (e.g., contains) between these entity mentions from their context.

The pioneering explorations of RE lie in statistical approaches, such as pattern mining (Huffman, 1995; Califf and Mooney, 1997), feature-based methods (Kambhatla, 2004) and graphical models (Roth and Yih, 2002). Recently, with the development of deep learning, neural models have been widely adopted for RE (Zeng et al., 2014; Zhang et al., 2015) and achieved superior results. These RE methods have bridged the gap between unstructured text and structured knowledge, and shown their effectiveness on several public benchmarks.

Despite the success of existing RE methods, most of them still work in a simplified setting. These methods mainly focus on training models with **large amounts** of **human annotations** to classify two given entities **within one sentence** into **pre-defined relations**. However, the real world is much more complicated than this simple setting: (1) collecting high-quality human annotations is expensive and time-consuming, (2) many long-tail relations cannot provide large amounts of training examples, (3) most facts are expressed by long context consisting of multiple sentences, and moreover (4) using a pre-defined set to cover those relations with open-ended growth is difficult. Hence, to build an effective and robust RE system for real-world deployment, there are still some more complex scenarios to be further investigated.

In this paper, we review existing RE methods (Section 2) as well as latest RE explorations (Section 3) targeting more complex RE scenarios. Those feasible approaches leading to better RE abilities still require further efforts, and here we summarize them into four directions:

(1) **Utilizing More Data** (Section 3.1). Supervised RE methods heavily rely on expensive human annotations, while distant supervision (Mintz et al., 2009) introduces more auto-labeled data to alleviate this issue. Yet distant methods bring noise examples and just utilize single sentences mentioning entity pairs, which significantly weaken extraction performance. Designing schemas to obtain high-quality and high-coverage data to train robust RE models still remains a problem to be explored.

(2) **Performing More Efficient Learning** (Section 3.2). Lots of long-tail relations only contain a handful of training examples. However, it is hard for conventional RE methods to well generalize relation patterns from limited examples like humans. Therefore, developing efficient learning schemas to make better use of limited or few-shot examples is a potential research direction.

(3) **Handling More Complicated Context** (Section 3.3). Many relational facts are expressed in complicated context (e.g. multiple sentences or even documents), while most existing RE models focus on extracting intra-sentence relations. To cover those complex facts, it is valuable to investigate RE in more complicated context.

(4) **Orienting More Open Domains** (Section 3.4). New relations emerge every day from different domains in the real world, and thus it is hard to cover all of them by hand. However, conventional RE frameworks are generally designed for pre-defined relations. Therefore, how to automatically detect undefined relations in open domains remains an open problem.

Besides the introduction of promising directions, we also point out two key challenges for existing methods: (1) **learning from text or names** (Section 4.1) and (2) **datasets towards special interests** (Section 4.2). We hope that all these contents could encourage the community to make further exploration and breakthrough towards better RE.

2 Background and Existing Work

Information extraction (IE) aims at extracting structural information from unstructured text, which is an important field in natural language processing (NLP). Relation extraction (RE), as an important task in IE, particularly focuses on extracting relations between entities. A complete relation extraction system consists of a named entity recognizer to identify named entities (e.g., people, organizations, locations) from text, an entity linker to link enti-
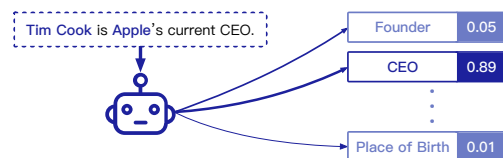

Figure 1: An example of RE. Given two entities and one sentence mentioning them, RE models classify the relation between them within a pre-defined relation set.

ties to existing knowledge graphs (KGs, necessary when using relation extraction for knowledge graph completion), and a relational classifier to determine relations between entities by given context.

Among these steps, identifying the relation is the most crucial and difficult task, since it requires models to well understand the semantics of the context. Hence, RE generally focuses on researching the classification part, which is also known as relation classification. As shown in Figure 1, a typical RE setting is that given a sentence with two marked entities, models need to classify the sentence into one of the pre-defined relations[2].

In this section, we introduce the development of RE methods following the typical supervised setting, from early pattern-based methods, statistical approaches, to recent neural models.

2.1 Pattern Extraction Models

The pioneering methods use sentence analysis tools to identify syntactic elements in text, then automatically construct pattern rules from these elements (Soderland et al., 1995; Kim and Moldovan, 1995; Huffman, 1995; Califf and Mooney, 1997). In order to extract patterns with better coverage and accuracy, later work involves larger corpora (Carlson et al., 2010), more formats of patterns (Nakashole et al., 2012; Jiang et al., 2017), and more efficient ways of extraction (Zheng et al., 2019). As automatically constructed patterns may have mistakes, most of the above methods require further examinations from human experts, which is the main limitation of pattern-based models.

2.2 Statistical Relation Extraction Models

As compared to using pattern rules, statistical methods bring better coverage and require less human efforts. Thus statistical relation extraction (SRE) has been extensively studied.

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[2]Sometimes there is a special class in the relation set indicating that the sentence does not express any pre-specified relation (usually named as N/A).

One typical SRE approach is **feature-based methods** (Kambhatla, 2004; Zhou et al., 2005; Jiang and Zhai, 2007; Nguyen et al., 2007), which design lexical, syntactic and semantic features for entity pairs and their corresponding context, and then input these features into relation classifiers.

Due to the wide use of support vector machines (SVM), **kernel-based methods** have been widely explored, which design kernel functions for SVM to measure the similarities between relation representations and textual instances (Culotta and Sorensen, 2004; Bunescu and Mooney, 2005; Zhao and Grishman, 2005; Mooney and Bunescu, 2006; Zhang et al., 2006b,a; Wang, 2008).

There are also some other statistical methods focusing on extracting and inferring the latent information hidden in the text. **Graphical methods** (Roth and Yih, 2002, 2004; Sarawagi and Cohen, 2005; Yu and Lam, 2010) abstract the dependencies between entities, text and relations in the form of directed acyclic graphs, and then use inference models to identify the correct relations.

Inspired by the success of **embedding models** in other NLP tasks (Mikolov et al., 2013a,b), there are also efforts in encoding text into low-dimensional semantic spaces and extracting relations from textual embeddings (Weston et al., 2013; Riedel et al., 2013; Gormley et al., 2015). Furthermore, Bordes et al. (2013), Wang et al. (2014) and Lin et al. (2015) utilize KG embeddings for RE.

Although SRE has been widely studied, it still faces some challenges. Feature-based and kernel-based models require many efforts to design features or kernel functions. While graphical and embedding methods can predict relations without too much human intervention, they are still limited in model capacities. There are some surveys systematically introducing SRE models (Zelenko et al., 2003; Bach and Badaskar, 2007; Pawar et al., 2017). In this paper, we do not spend too much space for SRE and focus more on neural-based models.

2.3 Neural Relation Extraction Models

Neural relation extraction (NRE) models introduce neural networks to automatically extract semantic features from text. Compared with SRE models, NRE methods can effectively capture textual information and generalize to wider range of data.

Studies in NRE mainly focus on designing and utilizing various network architectures to capture the relational semantics within text, such as **recur-**
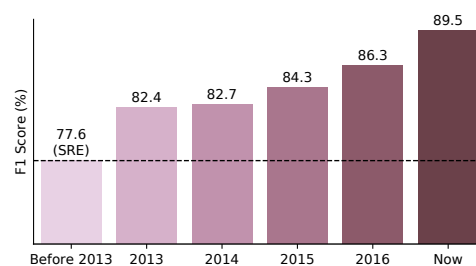

Figure 2: The performance of state-of-the-art RE models in different years on widely-used dataset SemEval-2010 Task 8. The adoption of neural models (since 2013) has brought great improvement in performance.

sive neural networks (Socher et al., 2012; Miwa and Bansal, 2016) that learn compositional representations for sentences recursively, **convolutional neural networks (CNNs)** (Liu et al., 2013; Zeng et al., 2014; Santos et al., 2015; Nguyen and Grishman, 2015b; Zeng et al., 2015; Huang and Wang, 2017) that effectively model local textual patterns, **recurrent neural networks (RNNs)** (Zhang and Wang, 2015; Nguyen and Grishman, 2015a; Vu et al., 2016; Zhang et al., 2015) that can better handle long sequential data, **graph neural networks (GNNs)** (Zhang et al., 2018; Zhu et al., 2019a) that build word/entity graphs for reasoning, and **attention-based neural networks** (Zhou et al., 2016; Wang et al., 2016; Xiao and Liu, 2016) that utilize attention mechanism to aggregate global relational information.

Different from SRE models, NRE mainly utilizes word embeddings and position embeddings instead of hand-craft features as inputs. **Word embeddings** (Turian et al., 2010; Mikolov et al., 2013b) are the most used input representations in NLP, which encode the semantic meaning of words into vectors. In order to capture the entity information in text, **position embeddings** (Zeng et al., 2014) are introduced to specify the relative distances between words and entities. Except for word embeddings and position embeddings, there are also other works integrating syntactic information into NRE models. Xu et al. (2015a) and Xu et al. (2015b) adopt CNNs and RNNs over **shortest dependency paths** respectively. Liu et al. (2015) propose a recursive neural network based on augmented dependency paths. Xu et al. (2016) and Cai et al. (2016) utilize deep RNNs to make further use of dependency paths. Besides, there are some efforts combining NRE with **universal schemas** (Verga et al., 2016; Verga and McCallum,
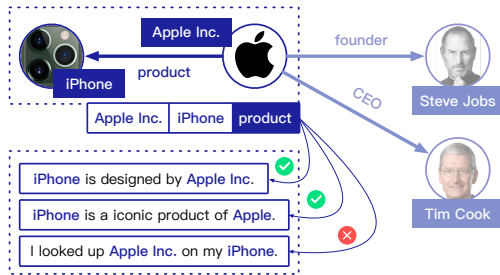
Figure 3: An example of distantly supervised relation extraction. With the fact (*Apple Inc.*, `product`, *iPhone*), DS finds all sentences mentioning the two entities and annotates them with the relation `product`, which inevitably brings noise labels.

Dataset	#Rel.	#Fact	#Inst.	N/A
NYT-10	53	377,980	694,491	79.43%
Wiki-Distant	454	605,877	1,108,288	47.61%

Table 1: Statistics for NYT-10 and Wiki-Distant. Four columns stand for numbers of relations, facts and instances, and proportions of N/A instances respectively.

Model	NYT-10	Wiki-Distant
PCNN-ONE	0.340	0.214
PCNN-ATT	0.349	0.222
BERT	0.458	0.361

Table 2: Area under the curve (AUC) of PCNN-ONE (Zeng et al., 2015), PCNN-ATT (Lin et al., 2016) and BERT (Devlin et al., 2019) on two datasets.

2016; Riedel et al., 2013). Recently, **Transformers** (Vaswani et al., 2017) and **pre-trained language models** (Devlin et al., 2019) have also been explored for NRE (Du et al., 2018; Verga et al., 2018; Wu and He, 2019; Baldini Soares et al., 2019) and have achieved new state-of-the-arts.

By concisely reviewing the above techniques, we are able to track the development of RE from pattern and statistical methods to neural models. Comparing the performance of state-of-the-art RE models in years (Figure 2), we can see the vast increase since the emergence of NRE, which demonstrates the power of neural methods.

3 "More" Directions for RE

Although the above-mentioned NRE models have achieved superior results on benchmarks, they are still far from solving the problem of RE. Most of these models utilize abundant human annotations and just aim at extracting pre-defined relations within single sentences. Hence, it is hard for them to work well in complex cases. In fact, there have been various works exploring feasible approaches that lead to better RE abilities on real-world scenarios. In this section, we summarize these exploratory efforts into four directions, and give our review and outlook about these directions.

3.1 Utilizing More Data

Supervised NRE models suffer from the lack of large-scale high-quality training data, since manually labeling data is time-consuming and human-intensive. To alleviate this issue, distant supervision (DS) assumption has been used to automatically label data by aligning existing KGs with plain text (Mintz et al., 2009; Nguyen and Moschitti, 2011; Min et al., 2013). As shown in Figure 3, for

any entity pair in KGs, sentences mentioning both the entities will be labeled with their corresponding relations in KGs. Large-scale training examples can be easily constructed by this heuristic scheme.

Although DS provides a feasible approach to utilize more data, this automatic labeling mechanism is inevitably accompanied by the wrong labeling problem. The reason is that not all sentences mentioning the two entities express their relations in KGs exactly. For example, we may mistakenly label "*Bill Gates* retired from *Microsoft*" with the relation `founder`, if (*Bill Gates*, `founder`, *Microsoft*) is a relational fact in KGs.

The existing methods to alleviate the noise problem can be divided into three major approaches:

(1) Some methods adopt multi-instance learning by combining sentences with same entity pairs and then **selecting informative instances** from them. Riedel et al. (2010); Hoffmann et al. (2011); Surdeanu et al. (2012) utilize graphical model to infer the informative sentences, while Zeng et al. (2015) use a simple heuristic selection strategy. Later on, Lin et al. (2016); Zhang et al. (2017); Han et al. (2018c); Li et al. (2020); Zhu et al. (2019c); Hu et al. (2019) design attention mechanisms to highlight informative instances for RE.

(2) **Incorporating extra context information** to denoise DS data has also been explored, such as incorporating KGs as external information to guide instance selection (Ji et al., 2017; Han et al., 2018b; Zhang et al., 2019a; Qu et al., 2019) and adopting multi-lingual corpora for the information consistency and complementarity (Verga et al., 2016; Lin et al., 2017; Wang et al., 2018).
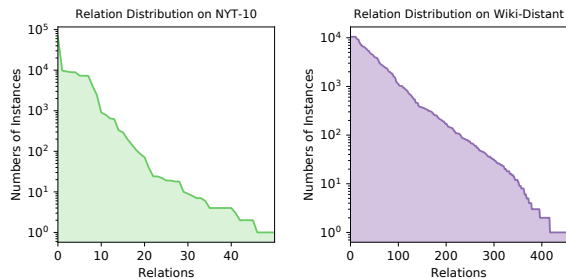
(3) Many methods tend to utilize **sophisticated**

Figure 4: Relation distributions (log-scale) on the training part of DS datasets NYT-10 and Wiki-Distant, suggesting that real-world relation distributions suffer from the long-tail problem.
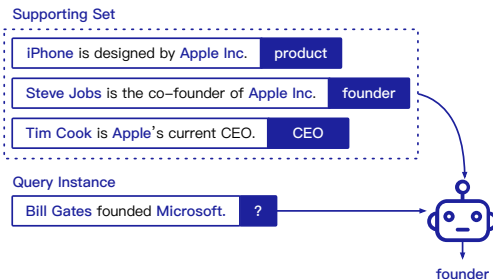

Figure 5: An example of few-shot RE. Give a few instances for new relation types, few-shot RE models classify query sentences into one of the given relations.

mechanisms and training strategies to enhance distantly supervised NRE models. Vu et al. (2016); Beltagy et al. (2019) combine different architectures and training strategies to construct hybrid frameworks. Liu et al. (2017) incorporate a soft-label scheme by changing unconfident labels during training. Furthermore, reinforcement learning (Feng et al., 2018; Zeng et al., 2018) and adversarial training (Wu et al., 2017; Wang et al., 2018; Han et al., 2018a) have also been adopted in DS.

The researchers have formed a consensus that utilizing more data is a potential way towards more powerful RE models, and there still remains some open problems worth exploring:

(1) Existing DS methods focus on **denoising auto-labeled instances** and it is certainly meaningful to follow this research direction. Besides, current DS schemes are still similar to the original one in (Mintz et al., 2009), which just covers the case that the entity pairs are mentioned in the same sentences. To achieve better coverage and less noise, **exploring better DS schemes** for auto-labeling data is also valuable.

(2) Inspired by recent work in adopting pre-trained language models (Zhang et al., 2019b; Wu and He, 2019; Baldini Soares et al., 2019) and active learning (Zheng et al., 2019) for RE, to **perform unsupervised or semi-supervised learning** for utilizing large-scale unlabeled data as well as using knowledge from KGs and introducing human experts in the loop is also promising.

Besides addressing existing approaches and future directions, we also propose a new DS dataset to advance this field, which will be released once the paper is published. The most used benchmark for DS, NYT-10 (Riedel et al., 2010), suffers from small amount of relations, limited relation domains and extreme long-tail relation performance. To alleviate these drawbacks, we utilize Wikipedia and Wikidata (Vrandečić and Krötzsch, 2014) to construct **Wiki-Distant** in the same way as Riedel et al. (2010). As demonstrated in Table 1, Wiki-Distant covers more relations and possesses more instances, with a more reasonable N/A proportion. Comparison results of state-of-the-art models on these two datasets[3] are shown in Table 2, indicating that Wiki-Distant is more challenging and there is a long way to resolve distantly supervised RE.

3.2 Performing More Efficient Learning

Real-world relation distributions are long-tail: Only the common relations obtain sufficient training instances and most relations have very limited relational facts and corresponding sentences. We can see the long-tail relation distributions on two DS datasets from Figure 4, where many relations even have less than 10 training instances. This phenomenon calls for models that can learn long-tail relations more efficiently. Few-shot learning, which focuses on grasping tasks with only a few training examples, is a good fit for this need.

To advance this field, Han et al. (2018d) first built a large-scale few-shot relation extraction dataset (FewRel). This benchmark takes the N-way K-shot setting, where models are given N random-sampled new relations, along with K training examples for each relation. With limited information, RE models are required to classify query instances into given relations (Figure 5).

The general idea of few-shot models is to train good representations of instances or learn ways of fast adaptation from existing large-scale data, and then transfer to new tasks. There are mainly two ways for handling few-shot learning: (1) **Metric learning** learns a semantic metric on existing

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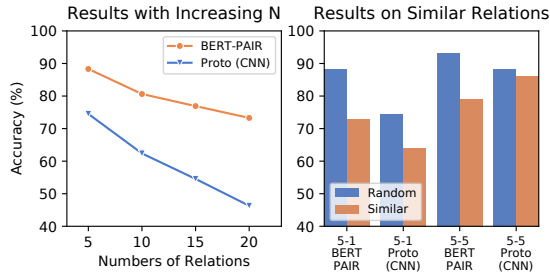[3] Due to the large size, we do not use any denoise mechanism for BERT, which still achieves the best results.

Figure 6: Few-shot RE results with (A) increasing N and (B) similar relations. The left figure shows the accuracy (%) of two models in N-way 1-shot RE. In the right figure, "random" stands for the standard few-shot setting and "similar" stands for evaluating with selected similar relations.
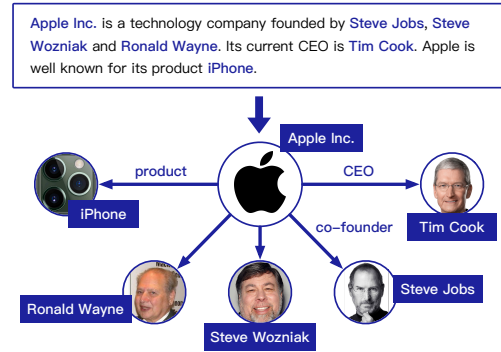

Figure 7: An example of document-level RE. Given a paragraph with several sentences and multiple entities, models are required to extract all possible relations between these entities expressed in the document.

data and classifies queries by comparing them with training examples (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Baldini Soares et al., 2019). While most metric learning models perform distance measurement on sentence-level representation, Ye and Ling (2019); Gao et al. (2019) utilize token-level attention for finer-grained comparison. (2) **Meta-learning**, also known as "learning to learn", aims at grasping the way of parameter initialization and optimization through the experience gained on the meta-train data (Ravi and Larochelle, 2017; Finn et al., 2017; Mishra et al., 2018).

Researchers have made great progress in few-shot RE. However, there remain many challenges that are important for its applications and have not yet been discussed. Gao et al. (2019) propose two problems worth further investigation:

(1) **Few-shot domain adaptation** studies how few-shot models can transfer across domains . It is argued that in the real-world application, the test domains are typically lacking annotations and could differ vastly from the training domains. Thus, it is crucial to evaluate the transferabilities of few-shot models across domains.

(2) **Few-shot none-of-the-above detection** is about detecting query instances that do not belong to any of the sampled N relations. In the N-way K-shot setting, it is assumed that all queries express one of the given relations. However, the real case is that most sentences are not related to the relations of our interest. Conventional few-shot models cannot well handle this problem due to the difficulty to form a good representation for the none-of-the-above (NOTA) relation. Therefore, it is crucial to study how to identify NOTA instances.

(3) Besides the above challenges, it is also impor-

tant to see that, the existing **evaluation protocol** may over-estimate the progress we made on few-shot RE. Unlike conventional RE tasks, few-shot RE randomly samples N relations for each evaluation episode; in this setting, the number of relations is usually very small (5 or 10) and it is very likely to sample N distinct relations and thus reduce to a very easy classification task.

We carry out two simple experiments to show the problems (Figure 6): (A) We evaluate few-shot models with increasing N and the performance drops drastically with larger relation numbers. Considering that the real-world case contains much more relations, it shows that existing models are still far from being applied. (B) Instead of randomly sampling N relations, we hand-pick 5 relations similar in semantics and evaluate few-shot RE models on them. It is no surprise to observe a sharp decrease in the results, which suggests that existing few-shot models may overfit simple textual cues between relations instead of really understanding the semantics of the context. More details about the experiments are in Appendix A.

3.3 Handling More Complicated Context

As shown in Figure 7, one document generally mentions many entities exhibiting complex cross-sentence relations. Most existing methods focus on intra-sentence RE and thus are inadequate for collectively identifying these relational facts expressed in a long paragraph. In fact, most relational facts can only be extracted from complicated context like documents rather than single sentences (Yao et al., 2019), which should not be neglected.

There are already some works proposed to extract relations across multiple sentences:

(1) **Syntactic methods** (Wick et al., 2006; Gerber and Chai, 2010; Swampillai and Stevenson, 2011; Yoshikawa et al., 2011; Quirk and Poon, 2017) rely on textual features extracted from various syntactic structures, such as coreference annotations, dependency parsing trees and discourse relations, to connect sentences in documents.

(2) Zeng et al. (2017); Christopoulou et al. (2018) build inter-sentence entity graphs, which can utilize **multi-hop paths between entities** for inferring the correct relations.

(3) Peng et al. (2017); Song et al. (2018); Zhu et al. (2019b) employ **graph-structured neural networks** to model cross-sentence dependencies for relation extraction, which bring in memory and reasoning abilities.

To advance this field, some document-level RE datasets have been proposed. Quirk and Poon (2017); Peng et al. (2017) build datasets by DS. Li et al. (2016); Peng et al. (2017) propose datasets for specific domains. Yao et al. (2019) construct a general document-level RE dataset annotated by crowdsourcing workers, suitable for evaluating general-purpose document-level RE systems.

Although there are some efforts investing into extracting relations from complicated context (e.g., documents), the current RE models for this challenge are still crude and straightforward. Followings are some directions worth further investigation:

(1) Extracting relations from complicated context is a challenging task requiring **reading, memorizing and reasoning** for discovering relational facts across multiple sentences. Most of current RE models are still very weak in these abilities.

(2) Besides documents, **more forms of context** is also worth exploring, such as extracting relational facts across documents, or understanding relational information based on heterogeneous data.

(3) Inspired by Narasimhan et al. (2016), which utilizes search engines for acquiring external information, **automatically searching and analysing context for RE** may help RE models identify relational facts with more coverage and become practical for daily scenarios.

3.4 Orienting More Open Domains

Most RE systems work within pre-specified relation sets designed by human experts. However, our world undergoes open-ended growth of relations and it is not possible to handle all these emerging
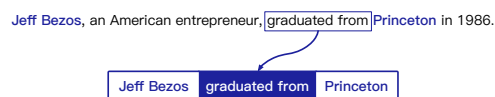

Figure 8: An example of open information extraction, which extracts relation arguments (entities) and phrases without relying on any pre-defined relation types.
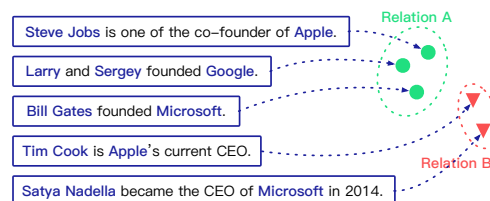

Figure 9: An example of clustering-based relation discovery, which identifying potential relation types by clustering unlabeled relational instances.

relation types only by humans. Thus, we need RE systems that do not rely on pre-defined relation schemas and can work in open scenarios.

There are already some explorations in handling open relations: (1) **Open information extraction (Open IE)**, as shown in Figure 8, extracts relation phrases and arguments (entities) from text (Banko et al., 2007; Fader et al., 2011; Mausam et al., 2012; Del Corro and Gemulla, 2013; Angeli et al., 2015; Stanovsky and Dagan, 2016; Mausam, 2016; Cui et al., 2018). Open IE does not rely on specific relation types and thus can handle all kinds of relational facts. (2) **Relation discovery**, as shown in Figure 9, aims at discovering unseen relation types from unsupervised data. Yao et al. (2011); Marcheggiani and Titov (2016) propose to use generative models and treat these relations as latent variables, while Shinyama and Sekine (2006); El-sahar et al. (2017); Wu et al. (2019) cast relation discovery as a clustering task.

Though relation extraction in open domains has been widely studied, there are still lots of unsolved research questions remained to be answered:

(1) **Canonicalizing relation phrases and arguments** in Open IE is crucial for downstream tasks (Niklaus et al., 2018). If not canonicalized, the extracted relational facts could be redundant and ambiguous. For example, Open IE may extract two triples (*Barack Obama*, `was born in`, *Honolulu*) and (*Obama*, `place of birth`, *Honolulu*) indicating an identical fact. Thus, normalizing extracted results will largely benefit the applications of Open IE. There are already some preliminary works in this area (Galárraga et al., 2014;

Vashishth et al., 2018) and more efforts are needed.

(2) The **not applicable (N/A) relation** has been hardly addressed in relation discovery. In previous work, it is usually assumed that the sentence always expresses a relation between the two entities (Marcheggiani and Titov, 2016). However, in the real-world scenario, a large proportion of entity pairs appearing in a sentence do not have a relation, and ignoring them or using simple heuristics to get rid of them may lead to poor results. Thus, it would be of interest to study how to handle these N/A instances in relation discovery.

4   Other Challenges

In this section, we analyze two key challenges faced by RE models, address them with experiments and show their significance in the research and development of RE systems[4].

4.1   Learning from Text or Names

In the process of RE, both entity names and their context provide useful information for classification. **Entity names** provide typing information (e.g., we can easily tell *JFK International Airport* is an airport) and help to narrow down the range of possible relations; In the training process, entity embeddings may also be formed to help relation classification (like in the link prediction task of KG). On the other hand, relations can usually be extracted from the semantics of **text** around entity pairs. In some cases, relations can only be inferred implicitly by reasoning over the context.

Since there are two sources of information, it is interesting to study how much each of them contributes to the RE performance. Therefore, we design three different settings for the experiments: (1) **normal** setting, where both names and text are taken as inputs; (2) **masked-entity** (ME) setting, where entity names are replaced with a special token; (3) **only-entity** (OE) setting, where only names of the two entities are provided.

Results from Table 3 show that compared to the normal setting, models suffer a huge performance drop in both the ME and OE settings. Besides, it is surprising to see that in some cases, only using entity names outperforms only using text with entities masked. It suggests that (1) both entity names and text provide crucial information for RE, and

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[4]For more details about these experiments, please refer to our open-source toolkit `https://github.com/thunlp/OpenNRE`.

Benchmark	Normal	ME	OE
Wiki80 (Acc)	0.861	0.734	0.763
TACRED (F-1)	0.666	0.554	0.412
NYT-10 (AUC)	0.349	0.216	0.185
Wiki-Distant (AUC)	0.222	0.145	0.173

Table 3: Results of state-of-the-arts models on the normal setting, masked-entity (ME) setting and only-entity (OE) setting. We report accuracies of BERT on Wiki80, F-1 scores of BERT on TACRED and AUC of PCNN-ATT on NYT-10 and Wiki-Distant. All models are from the OpenNRE package (Han et al., 2019).

(2) for some existing state-of-the-art models and benchmarks, entity names contribute even more.

The observation is contrary to human intuition: we classify the relations between given entities mainly from the text description, yet models learn more from their names. To make real progress in understanding how language expresses relational facts, this problem should be further investigated and more efforts are needed.

4.2   RE Datasets towards Special Interests

There are already many datasets that benefit RE research: For supervised RE, there are MUC (Grishman and Sundheim, 1996), ACE-2005 (Ntroduction, 2005), SemEval-2010 Task 8 (Hendrickx et al., 2009), KBP37 (Zhang and Wang, 2015) and TACRED (Zhang et al., 2017); and we have NYT-10 (Riedel et al., 2010), FewRel (Han et al., 2018d) and DocRED (Yao et al., 2019) for distant supervision, few-shot and document-level RE respectively.

However, there are barely datasets targeting special problems of interest. For example, RE across sentences (e.g., two entities are mentioned in two different sentences) is an important problem, yet there is no specific datasets that can help researchers study it. Though existing document-level RE datasets contain instances of this case, it is hard to analyze the exact performance gain towards this specific aspect. Usually, researchers (1) use hand-crafted sub-sets of general datasets or (2) carry out case studies to show the effectiveness of their models in specific problems, which is lacking of convincing and quantitative analysis. Therefore, to further study these problems of great importance in the development of RE, it is necessary for the community to construct well-recognized, well-designed and fine-grained datasets towards special interests.

5 Conclusion

In this paper, we give a comprehensive and detailed review on the development of relation extraction models, generalize four promising directions leading to more powerful RE systems (utilizing more data, performing more efficient learning, handling more complicated context and orienting more open domains), and further investigate two key challenges faced by existing RE models. We thoroughly survey the previous RE literature as well as supporting our points with statistics and experiments. Through this paper, we hope to demonstrate the progress and problems in existing RE research and encourage more efforts in this area.

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