A Survey on Open Information Extraction from Rule-based Model to Large Language Model

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Abstract

Open Information Extraction (OpenIE) represents a crucial NLP task aimed at deriving structured information from unstructured text, unrestricted by relation type or domain. This survey paper provides an overview of OpenIE technologies spanning from 2007 to 2024, emphasizing a chronological perspective absent in prior surveys. It examines the evolution of task settings in OpenIE to align with the advances in recent technologies. The paper categorizes OpenIE approaches into rule-based, neural, and pre-trained large language models, discussing each within a chronological framework. Additionally, it highlights prevalent datasets and evaluation metrics currently in use. Building on this extensive review, the paper outlines potential future directions in terms of datasets, information sources, output formats, methodologies, and evaluation metrics.

1 Introduction

Open Information Extraction (OpenIE) aims to extract structured information from unstructured text sources (Niklaus et al., 2018), typically outputting relationships as triplets (arg_1, rel, arg_2). Unlike traditional IE, which relies on predefined categories to identify relationships, OpenIE operates without such constraints, as illustrated in Figure 1, enabling the extraction of diverse and unforeseen relations. This flexibility makes OpenIE especially valuable for rapidly evolving Natural Language Processing (NLP) tasks such as question answering, search engines, and knowledge graph completion (Han et al., 2020), as well as for handling large-scale and dynamic data sources like web data. Its capability to adapt to new contexts and extract a broader array of information without extensive manual input not only enhances scalability but also broadens the applicative horizon, placing OpenIE at the forefront of NLP research and attracting significant interest for its potential.

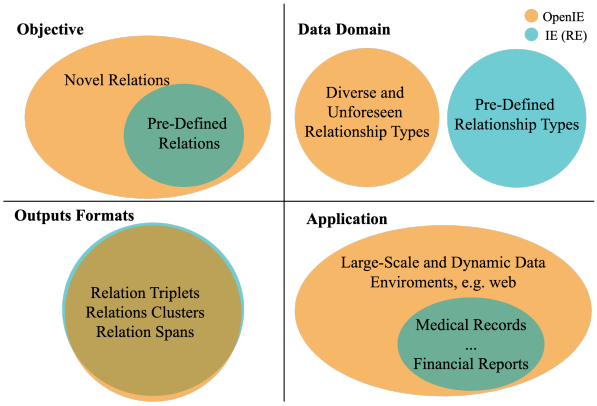

Figure 1: Comparison of OpenIE and traditional relation extraction.

Since its inception in 2007, the field of OpenIE has embodied the spirit of relentless innovation within NLP. Initially utilizing basic linguistic tools, OpenIE models have progressively integrated more complex syntactic and semantic features, while preserving the intuitive task of directly extracting relational triplets from text. The advent of neural models in 2019 marks a game-changer for OpenIE research, with systems employing Transformer-based architectures like BERT (Devlin et al., 2019) to significantly enhance feature extraction capabilities. To accommodate the technological shift, a variety of methodologies and task settings have evolved within diversified OpenIE approaches.

The emergence of Large Language Models (LLMs) in 2023 has marked another revolutionary phase, steering OpenIE toward a generative method of information extraction. The robust generalization abilities of these models not only advance the technical prowess of OpenIE systems but also facilitate a convergence of methodologies and task settings – revisiting the original, straightforward ***text*** $\rightarrow$ ***relational triplet*** format. This transition

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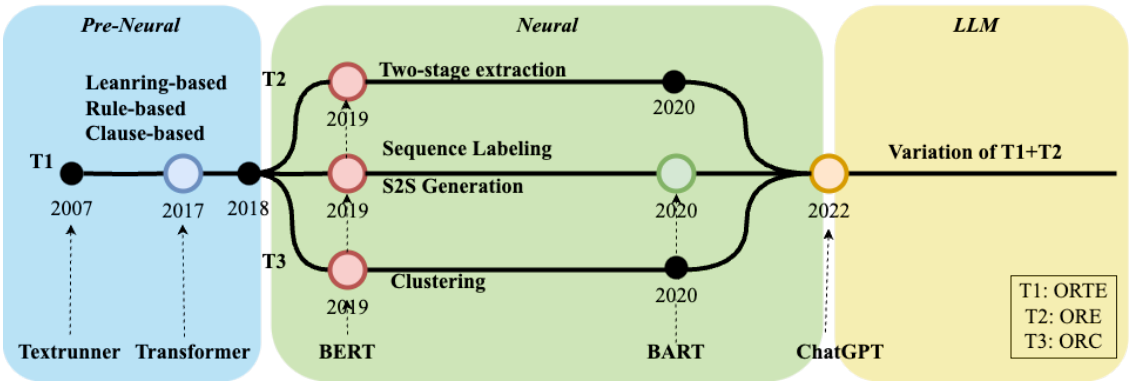

Figure 2: Chronological overview of Open IE methods.

also fosters potential integration with traditional IE tasks, pointing toward a promising future where extraction tasks are tackled through a unified, multi-task approach. With these advancements, OpenIE is poised not only to adapt to evolving technologies but also to influence the trajectory of other NLP downstream tasks.

The field of OpenIE has been marked by continuous innovation and evolution, yet there is a notable gap in the literature. Previous surveys largely focus on pre-LLM era models or limit their scope to methodological insights (Gamallo, 2014; Vo and Bagheri, 2018; Zouaq et al., 2017; Glauber and Claro, 2018; Niklaus et al., 2018; Zhou et al., 2022). Moreover, while recent studies (Xu et al., 2023b) delve into information extraction in the LLM era, they largely bypass OpenIE, concentrating instead on traditional IE tasks. This oversight highlights the urgent need for a comprehensive, chronological review that captures the full trajectory of OpenIE's development alongside advancements in broader NLP technologies. Undertaking such an in-depth exploration not only provide a macroscopic view of the field's historical progression but also illuminate future possibilities and opportunities within OpenIE, giving scholars and researchers a clearer roadmap for advancing this crucial area of study.

The remainder of this review paper is organized as follows. Section 2 details the primary OpenIE task setting and its variants. Section 3 and 4 cover popular datasets and evaluation metrics, respectively, followed by a chronological review of OpenIE models in Section 5, illustrated by Fig.2. The sources of information are thoroughly presented in Section 6.1, while Section 6.2 explores current limitations and future prospects of OpenIE.

2 Task Settings

We categorize OpenIE task settings into three groups: Open Relation Triplet Extraction (***ORTE***), Open Relation Span Extraction (***ORSE***) and Open relation clustering (***ORC***). ***ORTE*** is the classic task setting, while ***ORSE*** and ***ORC*** settings are variations developed to cater to diverse models with the advancement of NLP techniques. For all three task settings, the openness is shown in the absence of restraints on relation types. Figure 2 illustrates an overall review of the chronological development of task settings. Figure 3 depicts the workflow for each task setting.

ORTE Task: Text → Relational Triplet
Banko et al. (2007) initially defines open information extraction as an unsupervised task that automatically extracts $(entity_1, relation, entity_2)$ triplets from a vast corpus of unstructured web text, where $entity_1$, $entity_2$ and $relation$ consist of selected words from input sentences. This task setting, irrespective of the learning method or the forms of input and output, represents the most idealized configuration.

ORSE Task: Entities + Text → Relation Span
Different from the first setting, open relation span extraction finds relational spans according to previously extracted predicates and entities, aiming to partition complex tasks into easier ones to improve model performance. However, it should be clear that errors in entity extraction steps can accumulate in two-stage pipelines. See Open Relation Extraction (***ORSE***) in Fig.3 for an example.

ORC Task: Entities + Text→ Clustering without Explicit Relation Span or Label
Open relation clustering (***ORC***), also widely known as open relation extraction, clusters relation instances (h, t, s), where h and t denote head entity

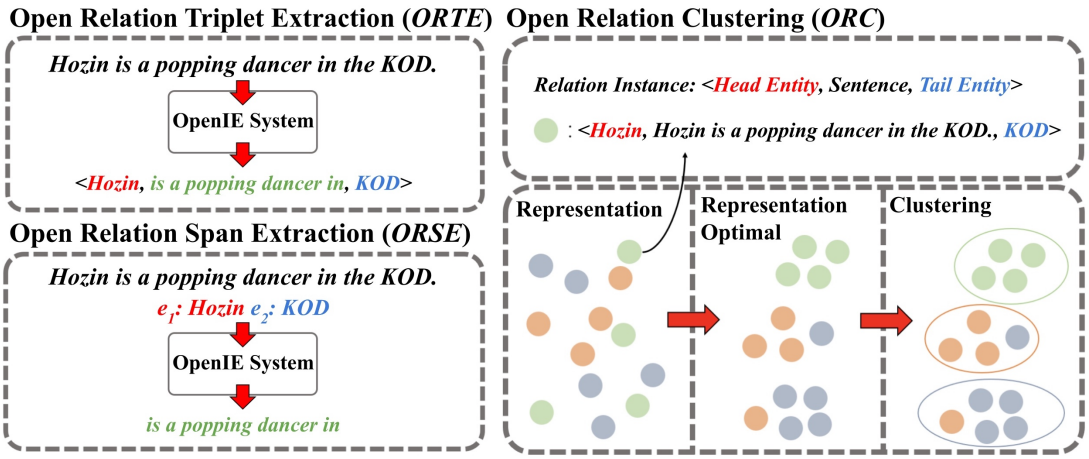

Figure 3: An overview of workflow processes in OpenIE task settings.

and tail entity respectively, and s denotes the sentence corresponding to two entities. Different from the ***ORTE***, ***ORC*** does not extract entities from text but uses the whole text to represent the relation between two entities. Clustering similar relations is a step forward in labeling specific relations to each relation instance. These task settings outlined above are distinctly characterized by era-specific traits and methodologies, further discussed in Section 5.

3 Datasets

Previous surveys (Niklaus et al., 2018; Ali et al., 2019) conclude with models of the first two generations and the datasets they used. We exclude those small-scale datasets and some seldom-used datasets. Table 1 lists some popular and promising OpenIE datasets grouped by their creating methods.

Question Answering (QA) derived datasets are converted from other crowd-sourced QA datasets. OIE2016 (Stanovsky and Dagan, 2016) is one of the most popular OpenIE benchmarks, which leverages QA-SRL (He et al., 2015) annotations. Additional datasets extend from OIE2016, such as AW-OIE (Stanovsky et al., 2018), Re-OIE2016 (Zhan and Zhao, 2020) and CaRB (Bhardwaj et al., 2019). LSOIE (Solawetz and Larson, 2021), is created by converting the QA-SRL 2.0 dataset (FitzGerald et al., 2018) to a large-scale OpenIE dataset, which claims to be 20 times larger than the next largest human-annotated OpenIE dataset.

Crowdsourced datasets are created from direct human annotation, including WiRe57 (Léchelle et al., 2019), SAOKE dataset (Sun et al., 2018), and BenchIE dataset (Gashteovski et al., 2021).

Knowledge Base (KB) derived datasets are established by aligning triplets in KBs with text in the corpus. Several works (Mintz et al., 2009; Yao et al., 2011) have aligned the New York Times corpus (Sandhaus, 2008) with Freebase (Bollacker et al., 2008) triplets, resulting in several variations of the same dataset, NYT-FB. Others are created by aligning relations of given entity pairs(ElSahar et al., 2018), such as TACRED(Zhang et al., 2017), FewRel (Han et al., 2018), T-REx (ElSahar et al., 2018), T-REx SPO and T-REx DS (Hu et al., 2020). COER (Jia et al., 2018), a large-scale Chinese KB dataset, is automatically created by an unsupervised open extractor.

Instruction-based datasets transform IE tasks into tasks requiring instruction-following, thus harnessing the capabilities of LLMs. Strategies include integrating existing IE datasets into a unified-format (Wang et al., 2023a; Lu et al., 2022), and deriving others from Wikidata and Wikipedia such as INSTRUCTOPENWIKI (Lu et al., 2023), INSTRUCTIE (Gui et al., 2023), and Wikidata-OIE (Wang et al., 2022b).

Overall, KB derived datasets are mostly used in open relation clustering task settings, illustrated in Section 5.4, whereas QA derived and crowd-sourced datasets are usually used in open relational triplet extraction (Section 5.2) and open relation span extraction task settings (Section 5.3). We provide more detailed descriptions in Appendix D.

4 Evaluation

Evaluation metrics for OpenIE models vary by task setting. In the open relational triplet and relation span extraction settings (Sections 5.2 and

Dataset	#Tuple	Domain
QA Derived		
OIE2016 (2016)	10,359	Wiki, Newswire
Re-OIE2016 (2020)	NR	Wiki, Newswire
CaRB (2019)	NR	Wiki, Newswire
AW-OIE (2018)	17,165	Wiki, Wikinews
LSOIE-wiki (2021)	56,662	Wiki, Wikinews
LSOIE-sci (2021)	97,550	Science
Crowdsourced		
WiRe57 (2019)	343	Wiki, Newswire
SAOKE^{zh} (2018)	NR	Baidu Baike
BenchIE^{en} (2021)	136,357	Wiki, Newswire
BenchIE^{de} (2021)	82,260	Wiki, Newswire
BenchIE^{zh} (2021)	5,318	Wiki, Newswire
KB Derived		
NYT-FB (2008; 2008; 2009; 2011)	39,000	NYT, Freebase
TACRED (2017)	119,474	TAC KBP
FewRel (2018)	70,000	Wiki, Wikidata
T-REx (2018)	11M	Wiki, Wikidata
COER^{zh} (2018)	1M	Baidu Baike, Chinese news
Instruction-Based		
INSTRUCTOPENWIKI (2023)	19M	Wiki, Wikidata
Wikidata-OIE (2022b)	27M	Wiki, Wikidata

Table 1: Statistics of popular OpenIE datasets. "NR" stands for "Not Reported". Non-English datasets are indicated with superscripts.

Task Setting	Evaluation Metrics
ORTE	Recall, AUC, F1
ORSE	F1
ORC	ARI, B^3, V-measure

Table 2: Core evaluation metrics of each task setting.

5.3), models are assessed using precision, recall, F1 score, and AUC, potentially employing various scoring functions. In the open relation clustering setting (Section 5.4), performance is evaluated using B^3 (Bagga and Baldwin, 1998), V-measure (Rosenberg and Hirschberg, 2007), and ARI (Hubert and Arabie, 1985).

In addition to standard metrics, various methods employ additional metrics, typically categorized into **token-level** and **fact-level** scorers. Token-level scorers focus on individual tokens to ensure precision and semantic accuracy, accommodating linguistic variability (Stanovsky and Dagan, 2016), enhancing conciseness (Léchelle et al., 2019), and adapting to complex model outputs like those from LLMs (Han et al., 2023). Fact-level scorers assess the informational faithfulness of extractions to ensure reliable knowledge extraction, validating semantic and information integrity (Sun et al., 2018; Gashteovski et al., 2021; Li et al., 2023a) to enhance OpenIE evaluations comprehensively. Further details are discussed in Appendix E.

5 Methodologies

Research on OpenIE dates back to 2007, with the first generation of OpenIE models exemplified by TEXTRUNNER (Banko et al., 2007), WOE (Wu and Weld, 2010) and REVERB (Fader et al., 2011), which use shallow linguistic features such as part-of-speech (POS) tags and noun phrase (NP) chunk features. The second generation of OpenIE models, represented by OLLIE (Schmitz et al., 2012), ClausIE (Del Corro and Gemulla, 2013), SRL-IE (Christensen et al., 2010) and OPENIE4 (Mausam, 2016), incorporates deep linguistic features alongside shallow syntactic features. The third generation of OpenIE models, to be discussed in detail, benefits significantly from the advent of neural models such as Transformers (Vaswani et al., 2017), notably BERT (Devlin et al., 2019), and extensively employ pre-training models for feature extraction. The most recent, fourth-generation has emerged with the advancements in Large Language Models (LLMs), such as GPT models (OpenAI, 2024, 2023) and Llama 2 (Touvron et al., 2023), leading to generative IE methods. These innovations highlight a shift toward universal formats and multi-task models, indicating new trends in the future of OpenIE. In Fig.2, we present OpenIE methodologies in a chronological view and categorize them according to task settings instead of the approaches. More details about model implementation is provided in Appendix.B

5.1 Pre-neural Model Era

ORTE Task: Text → Relational Triplet

In the beginning, Open IE systems were developed to create a universal model capable of extracting relation triplets through shallow features, such as Part-of-Speech (POS) that do not have lexical information, for instance, characterizing a verb based on its context. Normally, traditional machine learning models, such as Naive Bayes (Rish et al., 2001) and Conditional Random Field (Sutton et al., 2012), are used to train on shallow features(Yates et al., 2007; Wu and Weld, 2010; Zhu et al., 2009). Using only lexical features will lead to problems of incoherent and uninformative relations. Therefore, lexical features and syntactic features are used to mitigate such problems (Schmitz et al., 2012; Qiu and Zhang, 2014; Mausam, 2016). Later, rule-based models take advantage of hand-written patterns and rules to match relations (Fader et al., 2011; Akbik and Löser, 2012). To extract relations in a fine-

	OpenIE System	OIE16		Re-OIE16		CaRB		FewRel			TACRED		
		F1	AUC	F1	AUC	F1	AUC	ARI	B^3	V	ARI	B^3	V
Pre-Neural (*ORTE*)	OLLIE (Schmitz et al., 2012)	38.6	20.2	49.5	31.3	41.1	22.4	-	-	-	-	-	-
	ClausIE (Del Corro and Gemulla, 2013)	58.0	36.4	64.2	46.4	44.9	22.4	-	-	-	-	-	-
Neural Era (*ORTE*)	OpenIE6 (Kolluru et al., 2020a)	-	-	-	-	52.7	33.7	-	-	-	-	-	-
	IMoJIE (Kolluru et al., 2020b)	-	-	-	-	53.5	33.3	-	-	-	-	-	-
Neural Era (*ORSE*)	Multi^{2}OIE (Ro et al., 2020)	-	-	83.9	74.6	52.3	32.6	-	-	-	-	-	-
	OIE@OIA (Wang et al., 2022e)	71.6	54.3	85.3	76.9	51.1	33.9	-	-	-	-	-	-
Neural Era (*ORC*)	SelfORE (Hu et al., 2020)	-	-	-	-	-	-	64.7	67.8	78.3	44.7	54.1	61.9
	MatchPrompt (Wang et al., 2022c)	-	-	-	-	-	-	66.5	72.3	82.2	75.3	83.0	84.5
LLM Era	IELM GPT-2_{XL} (Wang et al., 2022b)	-	-	35.0	-	22.7	-	-	-	-	-	-	-
	GPT-3.5-TURBO ICL (Ling et al., 2023)	65.1	-	67.9	-	52.1	-	-	-	-	-	-	-

Table 3: Performance of selected representative OpenIE models. Only report F1 scores for B^3 and V. Complete performance details in the Appendix A.

grained way, clause-based models determine the set of clauses and identify clause types before extracting relations (Del Corro and Gemulla, 2013; Schmidek and Barbosa, 2014; Angeli et al., 2015).

5.2 Neural Model Era: Open Relational Triplet Extraction

ORTE Task: Text → Relational Triplet

5.2.1 Labeling

RnnOIE (Stanovsky et al., 2018) is the first neural method, which formulates the OpenIE task as a sequence labeling problem. It uses a Bi-LSTM transducer to process input features, including word embeddings, part-of-speech tags, and indicated predicates. A Softmax classifier tags a BIO label for each token, after which triplets are constructed. Since one sentence usually contains more than one relation triplet, many approaches propose to avoid encoding and labeling the same input several times. OpenIE6 (Kolluru et al., 2020a) adopts a novel Iterative Grid Labeling (IGL) architecture to capture dependencies among extractions without re-encoding. MacroIE(Bowen et al., 2021) reformulates the OpenIE as finding maximal cliques from the graph. DetIE (Vasilkovsky et al., 2022) casts the task as a direct set prediction problem. SMiLe-OIE (Dong et al., 2022) improves the model in an information-source view, using GCNs and multi-view learning to incorporate constituency and dependency information and aggregating semantic features and syntactic features by concatenating BERT embedding and graph embeddings.

The sequence labeling paradigm is characterized by its efficiency, making it computationally advantageous for large-scale text processing. It yields readily interpretable output, as each token associates itself with a specific role, such as subject, relation, or object. A notable limitation of this approach is its lack of a holistic view, as it treats tokens in isolation, potentially failing to capture global context and complex relationships that extend beyond single tokens. Additionally, its output format may not adequately represent the nuanced variability of natural language.

5.2.2 Sequence to Sequence Generation

Cui et al. (2018) casts OpenIE as a sequence-to-sequence generation problem and proposes NeuralOIE, which is an encoder-decoder model generating tuples with placeholders as a sequence according to the given input sentence. To enlarge the vocabulary and reduce the proportion of generated unknown tokens, NeuralOIE uses the attention-based coping mechanism. Logician(Sun et al., 2018), based on attention-based sequence-to-sequence learning, transforms input sentences into structured facts. It employs a restricted copy mechanism to decide between copying information from input or selecting predefined keywords, enhancing reliability. IMoJIE(Kolluru et al., 2020b) is a generative OpenIE model that produces variable and diverse extractions for a sentence. It uses an iterative memory, implemented with a BERT encoder, to keep track of previous extractions. The model employs an LSTM decoder to generate extractions one word at a time until an "EndOfExtractions" token is reached.

The sequence generation paradigm focuses on generating sequences of text to represent extracted information, affording a more expressive and context-rich output. It excels in capturing global context and complex relationships, as it considers the broader contextual information in the text. This approach is adaptable to various languages and domains, rendering it versatile in a range of applications. Nevertheless, it entails complexity in training, potentially demanding larger datasets and longer training times. The generated sequences may also exhibit noise or ambiguities, necessitating

post-processing for refinement. The output format from sequence generation models can vary, which poses challenges for downstream applications requiring standardized output structures.

5.3 Neural Model Era: Two-Stage Open Relation Extraction

ORSE Task: Entities + Text → Relation Span

Taking advantage of the remarkable representation capability of PLMs such as BERT, many researchers refine the model architecture into two stages to achieve more effective extractions. Multi^{2}OIE (Ro et al., 2020) is a two-stage labeling method. Its first stage is to label all predicates upon BERT-embedded hidden states instead of locating predicates with syntactic features. The second stage is to extract the arguments associated with each identified predicate by using a multi-head attention mechanism. GEN2OIE (Kolluru et al., 2022) extends to a generative paradigm operating in two stages, generating all possible relational predicates and relation triplet sequentially. QuORE (Yang et al., 2022) is a framework to extract relations and detect non-existent relationships based on the argument-context queries generated in the first stage.

Some researchers in this modularized setting are exploring various intermediate representations to enhance the performance of the pipeline. OIE@OIA (Wang et al., 2022e) is an adaptable OpenIE system that employs the methodology of Open Information eXpression (OIX) by parsing sentences into Open Information Annotation (OIA) Graphs. It consists of two components: an OIA generator that converts sentences into OIA graphs and a set of adaptors, each designed for a specific OpenIE task, allowing for efficient and versatile information extraction. By using different intermediate representations, Chunk-OIE (Dong et al., 2023) introduces the Chunk sequence (SaC) as an intermediate representation layer while Yu et al. (2022) introduce directed acyclic graph (DAG) as a minimalist intermediate expression.

5.4 Neural Model Era: Open Relation Clustering

ORC Task: Entities + Text→ Clustering without Explicit Relation Span or Label

Representation by Defined Features. Early clustering methods represent relation instances in feature space with the help of explicit features from various types of information. Ru et al. (2017) compares the contributions of different sequential patterns, syntactic information and the combination of the above to the representation of relation instances, which are clustered by a hierarchical clustering algorithm (Zhao et al., 2005). The result shows that sequential patterns and syntactic information are both beneficial to relation representation. With more fine-grind features, Lechevrel et al. (2017) select core dependency phrases to capture the semantics of the relations between entities. Since different relations in one sentence can be viewed as noises when clustering a certain relation, Elsahar et al. (2017) propose a more resilient approach based on the shortest dependency path instead of directly cutting irrelevant information in sentences.

With the development of pre-trained language models, contextualized semantics can be better represented. Before the clustering step, recent clustering-based approaches tend to optimize relation representations with different supervision signals instead of manually extracting features based on different rules.

Semantic Representation by PLM–unsupervised learning. Unlike the above OpenIE systems that follow Banko et al. (2007) to use unsupervised learning methods, RSN (Wu et al., 2019) exploits existing labeled data and relational facts in knowledge bases during training. To narrow the representation gap between pre-defined relations and novel relations, RSN learns a relational similarity matrix that can transfer relation knowledge from supervised data to unsupervised data. Wang et al. (2022c) and (Genest et al., 2022) introduce a similar unsupervised prompt-based algorithm, MatchPrompt, which clusters sentences by leveraging representations from masked relation tokens within a prompt template. Its superb performance against traditional unsupervised methods indicates that fully leveraging the semantic expressive power of pre-trained models is very important. IRLC(Wang et al., 2022d) presents a robust solution for relation representation that employs data augmentation to create additional examples.

Semantic Representation by PLM–semi-supervised learning. Without taking advantage of labeled datasets, SelfORE (Hu et al., 2020) proposes a self-supervised learning method for learning better feature representations for clustering. SelfORE is composed of three sections: (1) encode relation instances by leveraging BERT (Devlin et al., 2019) to obtain relation representations;

(2) apply adaptive clustering based on updated relation representations from (1) to assign each instance to a cluster with high confidence. In this way, pseudo labels are generated. (3) pseudo labels from (2) are used as supervision signals to train the relation classifier and update the encoder in (1). Repeat (2). As mentioned above high-dimensional vectors need to be clustered in a more complex way; Zhao et al. (2021) argue that such high-dimensional vectors contain too much irrelevant information for relation clustering, such as complex linguistic information. They propose a relation-oriented model based on SelfORE with a similar unsupervised training part and a modified supervised part. Duan et al. (2022) also make use of the distance between labeled data with every cluster center as soft pseudo labels. (Zhao et al., 2023) have proposed a method of active learning, which allows the model to identify and present difficult data for manual annotation during the clustering process. This method not only reduces the amount of data that needs to be labeled but also achieves better experimental results.

Hierarchical Information. Apart from labeled data, knowledge bases also benefit OpenIE by generating positive and negative instances. Datasets generated from distant supervision bring in spurious correlations (Roth et al., 2013; Jiang et al., 2018; Chen et al., 2021a). Fangchao et al. (2021) conduct interventions derived by KB to entities and context separately to avoid spurious correlations of them to relation types. OHRE (Zhang et al., 2021a) proposes a top-down hierarchy expansion algorithm to cluster and label relation instances based on the distance between the KB hierarchical structure. In this way, clusters of existing relations are labeled clearly, and novel relations can be labeled as children relations of existing relation labels.

5.5 Large Language Models Era

ORTE Task: Text → Relational Triplet

The recent evolution and emergence of Large Language Models (LLMs), such as GPT-4 (OpenAI, 2024), ChatGPT (OpenAI, 2023), and Llama 2 (Touvron et al., 2023), have significantly advanced the field of NLP. Their remarkable capabilities in text understanding, generation, and generalization have led to a surge of interest in generative IE methods (Qi et al., 2023b; Xu et al., 2023b). Recent studies have employed LLMs for OpenIE tasks by transforming input text through specific instructions or schemas. This approach facilitates tasks such as triplet extraction and relation classification under the structured language generation framework. It allows for a versatile task configuration where diverse forms of input text can be processed to generate structured relational triplets uniformly.

Zero-Shot. Wang et al. (2022b) propose IELM, a benchmark for assessing the zero-shot performance of GPT-2 (Radford et al., 2019) by encoding entity pairs in the input and extracting relations associated with each entity pair. On large-scale evaluation on various OpenIE benchmark tasks, research has shown that the zero-shot performance of leading LLMs, such as ChatGPT, still falls short of the state-of-the-art supervised methods (Han et al., 2023; Qi et al., 2023b), specifically on more challenging tasks (Li et al., 2023a). This shortfall is partly because LLMs struggle to distinguish irrelevant context from long-tail target types and relevant relations (Ling et al., 2023; Han et al., 2023).

Fine-Tuning and Few-Shot. Consequently, efforts have been made to fine-tune pre-trained LLMs or employ in-context learning prompting strategies to utilize and enhance the instruction-following ability of LLMs. For example, Lu et al. (2023) addresses open-world information extraction, including unrestricted entity and relation detection, as an instruction-following generative task, and develops PIVOINE, a fine-tuned information extraction LLM that generates comprehensive entity profiles in JSON format. To minimize the need for extensive fine-tuning of LLMs, Ling et al. (2023) proposes various in-context learning strategies for performing relation triplet generation to improve the instruction-following ability of LLMs, and introduces an uncertainty quantification module to increase the confidence in the generated answers. Qi et al. (2023a) proposes an approach of constructing a consistent reasoning environment by mitigating the distributional discrepancy between test samples and LLMs. This strategy aims to improve the few-shot reasoning capability of LLMs on specific OpenIE tasks.

UIE and Applications. Besides reviewing the work that utilizes LLMs to address OpenIE, we then broaden our scope to 1. introduce some emerging trends and paradigms in universal information extraction (UIE), 2. exploration of how LLMs are applied to general IE tasks, and 3. the integration of LLMs in IE system pipelines in Appendix C.

We believe that this broader perspective provides readers with a comprehensive understanding of cur-

rent trends and future directions in OpenIE and generic IE in the LLM era, enhancing their understanding of the field's evolving dynamics, with the impact further discussed in Section 6.2.

6 Discussion

This section reviews the diverse sources of information used by OpenIE models and discusses current limitations and future prospects, offering a comprehensive overview of the field's evolving trajectory.

6.1 Source of information

In this section, we provide an overview of the information sources utilized by OpenIE models.

Input-based information refers to features explicitly or implicitly present in the input unstructured text. Early OpenIE models extensively utilized explicit information such as ***shallow syntactic information***, including part of speech (POS) tags and noun-phrase (NP) chunks (Banko et al., 2007; Wu and Weld, 2010; Fader et al., 2011). Although this approach is reliable, it does not capture all relation types (Stanovsky et al., 2018), leading to the increasing use of ***deep dependency information***, which reveals word dependencies within sentences (Vo and Bagheri, 2018; Elsahar et al., 2017). Subsequent OpenIE models have emphasized the use of ***semantic information*** to grasp literal meanings and linguistic structures, thereby enhancing the expression of relations despite the risk of over-specificity (Vashishth et al., 2018; Wu et al., 2018). Recent models, including pre-trained language models, combine syntactic and semantic information to improve accuracy (Hwang and Lee, 2020; Ni et al., 2021). Further details are available in Appendix F.1.

External information supplements OpenIE systems to enhance model performance. Early systems employ ***expert rules***, including heuristic rules that integrate domain knowledge and assist in error tracing and resolution, based on syntactic analyses such as POS-tagging (Chiticariu et al., 2013; Fader et al., 2011). Following this, the integration of ***hierarchical information*** from knowledge bases (KBs) has advanced knowledge representation learning. This integration provides structured hierarchies and detailed factual knowledge, which support more organized relation extraction and data augmentation (Xie et al., 2016; Zhang et al., 2021a; Fangchao et al., 2021). More recently, with the development of LLMs, the ***pre-trained knowledge*** within these models is utilized, encapsulating extensive relational data (Jiang et al., 2020; Petroni et al., 2020) and enabling efficient retrieval with well-designed instructions. Further details in Appendix F.2.

6.2 Future Directions

Chronologically, IE systems increasingly employ diverse information sources and approaches, and now begin to converge on utilizing universal formats for various tasks (UIE). This shift is driven by advances in NLP techniques, especially pre-training models that enhance text extraction, and by increased computing power over the last two decades that enables more complex models. Recently, the exceptional language understanding and generalization capabilities of LLMs are promoting a shift towards UIE, broadening applications across different domains. More details are in Appendix C.

OpenIE datasets are growing but remain small relative to web information. Currently, these datasets are mostly confined to sources like Wiki, Newswire, NYT, and Freebase, with limited multilingual and multi-source corpus. Future expansions should include more languages and broader sources. Additionally, there is a need for synthesized datasets to improve both quality and quantity in OpenIE, as discussed in Appendix D. This could facilitate the creation of cross-domain datasets and integration of existing datasets and tasks.

Overly-specific relation output and the lack of a **standard form for OpenIE output** continue to challenge current models. Over-specificity in OpenIE arises from metrics focusing on token rather than semantic similarity, leading to verbose and incomplete outputs, while in ORC, sentences containing multiple relations introduce noise, complicating clustering and downstream tasks. Furthermore, the absence of standardized outputs hinders model comparison and canonicalization. Future research should focus on developing semantic-level evaluation metrics for OpenIE and establishing output standards tailored to downstream task requirements, alongside exploring text purification strategies for ORC to isolate distinct relations.

Despite advances, most current LLM-based UIE systems focus on traditional IE tasks and often overlook OpenIE, a complex challenge within the IE spectrum. LLMs are inherently suited for OpenIE due to their extensive pre-trained knowledge, unlike smaller models that require extensive training to learn relational information. The **primary challenge of LLMs** lies not in extracting relational

information but in accurately interpreting and following task-specific instructions.

Limitations

Our survey primarily concentrates on the chronological evolution of OpenIE technologies and their alignment with significant milestones in NLP development. Consequently, we have not covered multi-domain and multi-lingual datasets or methodologies extensively. While we do address some non-English datasets, specifically Mandarin, and briefly mention multilingual models in Appendix B and model applications across various domains in Appendix C.3, these discussions are not the focal point of our analysis. This limitation is intentional in order to maintain a clear focus on the historical progression of the field rather than the breadth of dataset diversity or the adaptability of methodologies across languages and domains.

Another potential limitation is our survey's emphasis on the macro aspects of the OpenIE field rather than detailed, micro-level analysis of specific methodologies. As outlined in Section 1, many existing surveys already cover methodologies and models from the pre-LLM era, and we felt that redundant elaboration on these would not add significant value. Post-LLM, despite substantial research leveraging LLMs for traditional IE tasks, there is still a scarcity of studies specifically applying LLMs to OpenIE tasks. This scarcity has constrained our ability to conduct an in-depth survey focused exclusively on LLM methodologies within OpenIE. Nonetheless, from the existing work on LLMs in traditional IE and UIE, detailed in Appendix C, we observe emerging trends that warrant a macro-level analysis. Our approach of integrating and reviewing the field through a historical lens is essential to provide a comprehensive view, enabling a clearer understanding of the task and aiding in the development of a more defined future roadmap.

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A Table of OpenIE Models

The performances of up-to-date open IE models are summarized in Table 4. The models are categorized the same as that in Section 5 into five groups. For models of pre-neural (***ORTE***), neural era (***ORTE***), neural era (***ORSE***), and LLM era, the F1 scores and accuracy on OIE16, Re-OIE16, and CaRB datasets are reported. For models of neural era (***ORC***), the ARI, F1 scores for B^3, and F1 scores for V-measure on FewRel and TACRED datasets are reported.

B Open IE Methodologies in Details

B.1 Open Relation Triplet Extraction

B.1.1 Labeling

OpenIE6 (Kolluru et al., 2020a) adopts a novel Iterative Grid Labeling (IGL) architecture, with which OpenIE is modeled as a 2-D grid labeling problem. Each extraction corresponds to one row in the grid. Iterative assignments of labels assist the model in capturing dependencies among extractions without re-encoding.

Owing to the outstanding performance of PLMs, many researchers extend the sequence labeling task to other problems. MacroIE(Bowen et al., 2021) reformulates the OpenIE as a non-parametric process of finding maximal cliques from the graph. It uses a non-autoregressive framework to mitigate the issue of enforced order and error accumulation during extraction. DetIE (Vasilkovsky et al., 2022) casts the task to a direct set prediction problem. This encoder-only model extracts a predefined number of possible triplets (proposals) by generating multiple labeled sequences in parallel, and its order-agnostic loss based on bipartite matching ensures the predictions are unique.

B.2 Open Relation Span Extraction

GEN2OIE (Kolluru et al., 2022) extends to a generative paradigm operating in two stages. It first generates all possible relations from input sentences. Then, it produces extractions for each generated relation. This generative approach allows for overlapping relations and multiple extractions with the same relation.

Jia et al. (2022) propose a hybrid neural network model (HNN4ORT) for open relation tagging. The model employs the Ordered Neurons LSTM (Shen et al., 2019) to encode potential syntactic information for capturing associations among arguments and relations. It also adopts a novel Dual Aware Mechanism, integrating Local-aware Attention and Global-aware Convolution. QuORE (Yang et al., 2022) is a framework to extract single/multi-span relations and detect non-existent relationships, given an argument tuple and its context. The model uses a manually defined template to map the argument tuple into a query. It concatenates and encodes the query together with the context to generate sequence embedding, with which this framework dynamically determines a sub-module (Single-span Extraction or Query-based Sequence Labeling) to label the potential relation(s) in the context.

Inspired by OIA, Chunk-OIE (Dong et al., 2023) introduces the concept of Sentence as Chunk sequence (SaC) as an intermediate representation layer, utilizing chunking to divide sentences into related non-overlapping phrases. Yu et al. (2022) introduce directed acyclic graph (DAG) as a minimalist expression of open fact in order to reduce the extraction complexity and improves the generalization behavior. They propose DragonIE which leverages the sequential priors to reduce the complexity of function space (edge number and type) in the previous graph-based model from quadratic to linear, while avoiding auto-regressive extraction in sequence-based models.

B.3 Open Relation Clustering

Lechevrel et al. (2017) select core dependency phrases to capture the semantics of the relations between entities. The design rules are based on the length of the dependency phrase in the dependency path, which sometimes contains more than one dependency phrase that uses all terms and brings in irrelevant information. Each relation instance is clustered on the basis of the semantics of core dependency phrases. Finally, clusters are named by the core dependency phrase most similar to the center vector of the cluster.

Instead of directly cutting less irrelevant information, Elsahar et al. (2017) propose a more resilient approach based on the shortest dependency path. The model generates representations of relation instances by assigning a higher weight to word embedding of terms in the dependency path and then reduces feature dimensions by PCA (Shen, 2009). Although the model ignores noisy terms in the dependency path, re-weighting is a forward-looking idea resembling the subsequent attention mechanism.

The key idea of Fangchao et al. (2021) is based

	OpenIE System	OIE16		Re-OIE16		CaRB		FewRel			TACRED		
		F1	AUC	F1	AUC	F1	AUC	ARI	B^3	V	ARI	B^3	V
Pre-Neural (*ORTE*)	OLLIE (Schmitz et al., 2012)	38.6	20.2	49.5	31.3	41.1	22.4	-	-	-	-	-	-
	ClausIE (Del Corro and Gemulla, 2013)	58.0	36.4	64.2	46.4	44.9	22.4	-	-	-	-	-	-
	OPENIE4 (Mausam, 2016)	58.8	40.8	68.3	50.9	51.6	29.5	-	-	-	-	-	-
	PropS (Stanovsky and Dagan, 2016)	54.4	32.0	64.2	43.3	31.9	12.6	-	-	-	-	-	-
Neural Era (*ORTE*)	RnnOIE (Stanovsky et al., 2018)	62.0	48.0	-	-	49.0	26.1	-	-	-	-	-	-
	OpenIE6 (Kolluru et al., 2020a)	-	-	-	-	52.7	33.7	-	-	-	-	-	-
	SpanOIE (Zhan and Zhao, 2020)	69.4	49.1	77.0	65.8	48.5	-	-	-	-	-	-	-
	IMoJIE (Kolluru et al., 2020b)	-	-	-	-	53.5	33.3	-	-	-	-	-	-
	MacroIE (Bowen et al., 2021)	-	-	-	-	54.8	36.3	-	-	-	-	-	-
	DetIE$_{LSOIE}$ (Vasilkovsky et al., 2022)	-	-	-	-	43.0	27.2	-	-	-	-	-	-
	DetIE$_{IMoJIE}$ (Vasilkovsky et al., 2022)	-	-	-	-	52.1	36.7	-	-	-	-	-	-
	SMiLe-OIE (Dong et al., 2022)	-	-	-	-	53.8	34.9	-	-	-	-	-	-
Neural Era (*ORSE*)	Multi^{2}OIE (Ro et al., 2020)	-	-	83.9	74.6	52.3	32.6	-	-	-	-	-	-
	GEN2OIE (Kolluru et al., 2022)	-	-	-	-	54.4	32.3	-	-	-	-	-	-
	GEN2OIE (label-rescore)	-	-	-	-	54.5	38.9	-	-	-	-	-	-
	OIE@OIA (Wang et al., 2022e)	71.6	54.3	85.3	76.9	51.1	33.9	-	-	-	-	-	-
	DragonIE (Yu et al., 2022)	-	-	-	-	55.1	36.4	-	-	-	-	-	-
	ChunkOIE(SaC-OIA-SP) (Dong et al., 2023)	-	-	-	-	53.6	35.5	-	-	-	-	-	-
	ChunkOIE(SaC-CoNLL)	-	-	-	-	53.2	34.7	-	-	-	-	-	-
Neural Era (*ORC*)	RSN (Wu et al., 2019)	-	-	-	-	-	-	45.3	58.9	70.8	45.9	63.1	64.3
	RSN-CV (Wu et al., 2019)	-	-	-	-	-	-	54.2	63.8	72.4	-	-	-
	SelfORE (Hu et al., 2020)	-	-	-	-	-	-	64.7	67.8	78.3	44.7	54.1	61.9
	RSN-BERT (Zhao et al., 2021)	-	-	-	-	-	-	53.2	70.9	78.1	75.6	83.4	85.9
	RoCORE (Zhao et al., 2021)	-	-	-	-	-	-	70.9	79.6	86	81.2	86	88.8
	OHRE (Zhang et al., 2021b)	-	-	-	-	-	-	64.2	70.5	76.7	-	-	-
	MatchPrompt (Wang et al., 2022c)	-	-	-	-	-	-	66.5	72.3	82.2	75.3	83.0	84.5
	PromptORE (Genest et al., 2022)	-	-	-	-	-	-	43.4	48.8	71.8	-	-	-
	CaPL (Duan et al., 2022)	-	-	-	-	-	-	79.4	81.9	88.9	82.9	87.3	89.8
	ASCORE (Zhao et al., 2023)	-	-	-	-	-	-	67.6	73.5	83.5	78.1	78	83.1
LLM Era	IELM GPT-2$_{XL}$ (Wang et al., 2022b)	-	-	35.0	-	22.7	-	-	-	-	-	-	-
	GPT-3.5-TURBO ICL (Ling et al., 2023)	65.1	-	67.9	-	52.1	-	-	-	-	-	-	-
	ChatGPT n-shot (Qi et al., 2023a)	-	-	-	-	55.3	-	-	-	-	-	-	-

Table 4: Performance of OpenIE models. Only report F1 scores for B^3 and V.

on blocking backdoor paths from a causal view (Pearl, 2000). The intervened context is generated by a generative PLM, while entities are intervened by placing them with three-level hierarchical entities in KB. Model parameters are optimized by those intervened instances via contrastive learning. The learned model encodes each instance into its representations, before using clustering algorithms.

B.4 Neural Model Era: Other Settings

Translation. Wang et al. (2021) cast information extraction tasks into a text-to-triplet translation problem. They introduce DEEPEX, a framework that translates NP-chunked sentences to relational triplets in a zero-shot setting. This translation process consists of two steps: generating a set of candidate triplets and ranking them.

Multilingual. MILIE (Kotnis et al., 2022) is an integrated model of a rule-based system and a neural system, which extracts triplet slots iteratively from simple to complex, conditioning on preceding extractions. The iterative nature guarantees the model to perform well in a multilingual setting. Multi^{2}OIE (Ro et al., 2020) also has a multilingual version based on multilingual-BERT, which makes it able to deal with various languages. Differently, LOREM (Harting et al., 2020) trains two types of models, language-individual models, and language-consistent models and incorporates multilingual, aligned word embeddings to enhance model performance.

C LLMs for IE in general

In Section 5.5, we begin by reviewing the work that utilizes LLMs to address OpenIE. Here, we 1). broaden our scope to introduce some emerging trends and paradigms in universal information extraction. For an in-depth exploration of how LLMs are applied to closed relation extraction and other IE tasks, we refer readers to the survey by Xu et al. (2023b) for comprehensive details. Moreover, we 2). further expand our discussion to explore research that integrates LLMs into IE system pipelines, beyond merely using them for direct IE task solution. We 3). also includes an discussion of current trends in IE dataset using LLMs that shed light on the future of datasets on openIE.

We believe this broader perspective provides readers with a comprehensive understanding of current trends and future directions in OpenIE and generic IE in the LLM era, enhancing their grasp of the field's evolving dynamics.

C.1 Universal Information Extraction

Recent advancements and the robust generalization capabilities of LLMs have led to the exploration

of universal frameworks designed to tackle all IE tasks (UIE). These frameworks aim to harness the shared capabilities inherent in IE, while also uncovering and learning from the dependencies that exist between various tasks (Xu et al., 2023b). This approach marks a significant shift from focusing on isolated subtasks such as OpenIE to a more integrated methodology that seeks to understand a more integrated and comprehensive understanding of the domain.

Natural Language-Based Schema. A prevailing trend in developing universal IE frameworks is to establish a unified, structured natural language schema for diverse subtasks, designed for schema-prompting LLMs. For instance, Wang et al. (2022a) introduce DeepStruct, which reformulates various IE tasks as triplet generation tasks, using generalized task-specific prefixes in prompts and pretraining LLMs to comprehend text structures. Lu et al. (2022) propose UIE, encoding different extraction structures uniformly through a structured extraction language and adaptively generating specific extractions with a schema-based prompt strategy. Similarly, Lou et al. (2023) present USM, encoding different schemas and input texts together to enable structuring and conceptualizing, aiming for a single model that addresses all tasks. Building on UIE and USM, Wang et al. (2023a) introduce InstructUIE, which models various IE tasks uniformly with descriptive natural language instructions for instruction tuning, exploiting inter-task dependencies.

Code-Based Schema. Despite their empirical success, natural language-based approaches face challenges in generating outputs for IE tasks due to the distinct syntax and structure that differ from the training data of LLMs (Bi et al., 2024). In response to these limitations and leveraging recent advancements in Code-LLMs (Chen et al., 2021b), researchers have begun to utilize Code-LLMs for structure generation tasks (Wang et al., 2022f), as code, a formalized language, adeptly describes structural knowledge across various schemas universally (Guo et al., 2023b). For instance, Li et al. (2023d) present CodeIE, which translates structured prediction tasks such as NER and RE into code generation, employing Python functions to create task-specific schemas and using few-shot learning to instruct Code-LLMs. Guo et al. (2023b) introduce Code4UIE, utilizing Python classes to define task-specific schemas for diverse structural knowledge universally. Similarly, Sainz et al. (2023) propose GoLLIE, which employs Python classes to encode IE tasks and, in addition, integrates task-specific guidelines as docstrings, enhancing the robustness of fine-tuned Code-LLMs to schemas not encountered during training.

C.2 Role of LLMs in IE System

In addition to directly addressing IE tasks, LLMs have shown utility as specific components within IE system pipelines, including data synthesis for IE model training and knowledge retrieval for downstream IE tasks.

Data Synthesis. A prominent application of LLMs in IE systems is the synthesis of high-quality training data, as data curation through human annotation is time-consuming and labor-intensive. One approach employs LLMs as annotators within a learning loop (Zhang et al., 2023a), while another strategy involves using LLMs to inversely generate natural language text from structured data inputs (Josifoski et al., 2023; Ma et al., 2023), thereby producing large-scale, high-quality training data for IE tasks.

Knowledge Retrieval. Another research direction exploits the capability of LLMs, developed through pre-training, as implicit knowledge bases to generate or retrieve relevant context for downstream IE tasks. For instance, Li et al. (2023b, 2024) employ LLMs to generate auxiliary knowledge improving multimodal IE tasks. Amalvy et al. (2023) demonstrate that pre-trained LLMs possess inherent knowledge of the datasets they work on, and use these models to generate a context retrieval dataset, enhancing NER performance on long documents.

C.3 IE in Different Domains

The development of Information Extraction (IE) has seen significant advancements across various domains, including Multimodal IE, Medical Information Extraction, and the application of Code Models for IE tasks. These developments have been particularly enhanced by the integration of Large Language Models (LLMs), which have improved downstream task performance through their use in model architecture and as tools for annotation and training guidance.

Medical Information Extraction has greatly benefited from the use of LLMs as efficient tools for annotation, as highlighted in research by Goel et al. (2023); Meoni et al. (2023). These applications enhance data quality and contribute to the

overall improvement of model performance.

Multimodal IE tasks, such as Multimodal Named Entity Recognition (MNER) and Multimodal Relation Extraction (MRE), have advanced through frameworks that capitalize on the capabilities of LLMs in IE. Cai et al. (2023) propsed to use in-context learning (ICL) ability in ChatGPT to help Few-Shot MNER by employing in-context learning to convert visual data into text and select relevant examples for effective entity recognition. Li et al. (2023c) tackles MNER on social media by efficient usage of generated knowledge and improved generalization, which utilizes ChatGPT as an implicit knowledge base for generating auxiliary knowledge to aid entity prediction. Chen and Feng (2023) distill the reasoning ability of LLMs by using "chain of thought" (CoT) to elicit reasoning capability from LLMs across multiple dimensions to improve MNER and MRE.

Code generative LLMs have found application in performing IE tasks such as Universal Information Extraction (UIE) (Li et al., 2023d; Guo et al., 2023a), Event Structure Prediction (Wang et al., 2023b), and Generative Knowledge Graph (Bi et al., 2024), where researchers convert the structured output in the form of code instead of natural language, and utilize generative LLMs of code (Code-LLMs) by designing code-style prompts and formulating these IE tasks as code generation tasks.

Leveraging LLMs across different domains has not only broadened the scope of IE applications but also significantly improved the effectiveness and efficiency of extraction tasks.

D Datasets

Question Answering (QA) derived datasets are converted from other crowdsourced QA datasets. OIE2016 (Stanovsky and Dagan, 2016) is one of the most popular OpenIE benchmarks, which leverages QA-SRL (He et al., 2015) annotations. AW-OIE (Stanovsky et al., 2018) extends the OIE2016 training set with extractions from QAMR dataset (Michael et al., 2017). The OIE2016 and AW-OIE datasets are the first datasets used for supervised OpenIE. However, because of its coarse-grained generation method, OIE2016 has some problematic annotations and extractions. On the basis of OIE2016, Re-OIE2016 (Zhan and Zhao, 2020) and CaRB (Bhardwaj et al., 2019) re-annotate part of the dataset. LSOIE (Solawetz and Larson, 2021) is created by converting QA-SRL 2.0 dataset (FitzGerald et al., 2018) to a large-scale OpenIE dataset, which claims 20 times larger than the next largest human-annotated OpenIE dataset.

Crowdsourced datasets are created from direct human annotation, including WiRe57 (Léchelle et al., 2019), SAOKE dataset (Sun et al., 2018), and BenchIE dataset (Gashteovski et al., 2021). WiRe57 is created based on a small corpus containing 57 sentences from 5 documents by two annotators following a pipeline. SAOKE dataset is generated from Baidu Baike, a free online Chinese encyclopedia, like Wikipedia, containing a single/multi-span relation and binary/polyadic arguments in a tuple. It is built in a predefined format, which assures its completeness, accurateness, atomicity, and compactness.

Knowledge Base (KB) derived datasets are established by aligning triplets in KBs with text in the corpus. Several works (Mintz et al., 2009; Yao et al., 2011) have aligned the New York Times corpus (Sandhaus, 2008) with Freebase (Bollacker et al., 2008) triplets, resulting in several variations of the same dataset, NYT-FB. FewRel (Han et al., 2018) is created by aligning relations of given entity pairs in Wikipedia sentences with distant supervision, and then filtered by human annotators. ElSahar et al. (2018) propose a pipeline to align Wikipedia corpus with Wikidata (Vrandečić, 2012) and generate T-REx. By filtering triplets and selecting sentences, Hu et al. (2020) create T-REx SPO and T-REx DS. In addition, COER (Jia et al., 2018), a large-scale Chinese knowledge base dataset, is automatically created by an unsupervised open extractor from diverse and heterogeneous web text, including encyclopedia and news. Overall, KB derived datasets are mostly used in open relation clustering task setting, illustrated in Section 5.4, whereas QA derived and crowdsourced datasets are usually used in open relational triplet extraction (Section 5.2) and open relation span extraction task settings (Section 5.3).

Instruction-based datasets transform IE tasks into tasks requiring instruction-following, thus harnessing the capabilities of LLMs. One strategy involves integrating various existing IE datasets into a unified-format benchmark dataset with specifically designed instructions (Wang et al., 2023a; Lu et al., 2022). Alternatively, instruction-based IE datasets such as INSTRUCTOPENWIKI (Lu et al., 2023) and INSTRUCTIE (Gui et al., 2023), or structured IE datasets like Wikidata-OIE (Wang et al., 2022b)—derived from Wikidata and

Wikipedia—are created. The first method primarily focuses on ClosedIE tasks, while the second offers more flexibility in generating OpenIE datasets (Lu et al., 2023; Wang et al., 2022b).

Synthesized datasets using LLMs on IE expands significantly compared to previous ones in both the size of the datasets and data qualities. While the methodologies for synthesizing these datasets have been extensively explored within the domain of closed Information Extraction (ClosedIE) (Zhang et al., 2023b; Xu et al., 2023a), where researchers claims the proposed methods can be adapted for OpenIE setting (Josifoski et al., 2023), there remains a notable gap in the literature regarding comprehensive studies on synthesized datasets for OpenIE.

E Evaluation

Token-level Scorers. To allow some flexibility (e.g., omissions of prepositions or auxiliaries), if automated extraction of the model and the gold triplet agree on the grammatical head of all of their elements (predicate and arguments), OIE2016 (Stanovsky and Dagan, 2016) takes it as matched. Léchelle et al. (2019) penalize the verbosity of automated extractions as well as the omission of parts of a gold triplet by computing precision and recall at token-level in WiRe57. Their precision is the proportion of extracted words that are found in the gold triplet, while recall is the proportion of reference words found in extractions. To improve token-level scorers, CaRB (Bhardwaj et al., 2019) computes precision and recall pairwise by creating an all-pair matching table, with each column as extracted triplet and each row as gold triplet. When assessing LLM extracted spans, Han et al. (2023) report the ratio of invalid responses, which include incorrect formats and content not aligned with task-specific prompts. As generative models, LLMs aim to mimic human-like responses and often generate longer text than the gold standard annotations.

Fact-level Scorers. SAOKE (Sun et al., 2018) measures to what extent gold triplets and extracted triplets imply the same facts and then calculates precision and recall. BenchIE (Gashteovski et al., 2021) introduces *fact synset*: a set of all possible extractions (i.e., different surface forms) for a given fact type (e.g., VP-mediated facts) that are instances of the same fact. It takes the informational equivalence of extractions into account by exactly matching extracted triplets with the gold fact synsets. In assessing outputs from LLMs, Li et al. (2023a) have ChatGPT provide justifications for its predictions and use domain expert annotation to verify their faithfulness relative to the input.

F Source of Information

Section 6.1 provides a brief overview of the sources of information utilized in OpenIE models. This section offers a detailed discussion of each specific information source.

F.1 Input-based Information

Shallow syntactic information such as part of speech (POS) tags and noun-phrase (NP) chunks abstract input sentences into patterns. It is pervasively used in the early work of OpenIE as an essential model feature (Banko et al., 2007; Wu and Weld, 2010; Fader et al., 2011). In rule-based models, those patterns directly determine whether the input text contains certain relations or not (Xavier et al., 2013; A and A, 2013). Shallow syntactic information is reliable because there is a clear relationship between the relation type and the syntactic information in English (Banko et al., 2007). However, merely using shallow syntactic information can not discover all relation types. Subsequent work uses shallow syntactic information as part of the input and incorporates additional features to enhance the model performance (Stanovsky et al., 2018).

Deep dependency information shows the dependency between words in a sentence, which can be used directly to find relations (Vo and Bagheri, 2018). But because dependency analysis is more complex and time-consuming than shallow syntactic analysis, such information source was not popular in early OpenIE studies. It was the second generation of OpenIE models that brought dependency parsing to great attention. Right now, dependency information is still used as part of the model input, though with less popularity and sometimes not directly. Elsahar et al. (2017) make use of the dependency path to give higher weight to words between two named entities, in which way the model only uses dependency information as a supplement and relies more on the semantic meaning to extract information.

Semantic information captures not only linguistic structures of sentences but literal meanings of phrases, which can express more diverse and fitting relations compared to syntactic patterns. How-

ever, semantic information can also be too specific and hence lead to the canonicalizing problem (Galárraga et al., 2014; Vashishth et al., 2018; Wu et al., 2018). The second generation of OpenIE models has tried to use semantic information via semantic role labeling, for example EXAMPLAR (Mesquita et al., 2013), or via dependency parsing, for instance OLLIE (Schmitz et al., 2012). There were also attempts to use WordNet output to comprise semantic information (Liu and Yang, 2012). The third generation of OpenIE models typically use the word and sentence representations obtained from pre-trained language models (Kolluru et al., 2020b; Hwang and Lee, 2020; Xinwei and Hui, 2020). These representations contain both syntactic and semantic information (Jawahar et al., 2019). Meanwhile, some OpenIE models use word embeddings from word embedders such as GloVe, ELMo, and Word2Vec to capture semantic information (Ni et al., 2021).

F.2 External Knowledge

Expert rules are knowledge imported in the form of heuristic rules. It is easy for rule-based OpenIE systems to incorporate domain knowledge as well as to trace and fix errors (Chiticariu et al., 2013). Heuristic rules can be employed to avoid incoherent extractions (Fader et al., 2011). For example, verb words between two entities are likely to be the relation. Thus, to alleviate incoherence, a rule can be defined: *If there are multiple possible matches for a single verb, the shortest possible match is chosen.* Based on patterns generated from POS-tagging, dependency parse, and other syntactic analyses, different rules can be created.

Hierarchical information that implicitly exists in languages, which can be explicitly exhibited by knowledge bases, benefits knowledge representation learning (Wang et al., 2014; Lin et al., 2015; Hu et al., 2015; Xie et al., 2016). In addition, KBs contain fine-grained factual knowledge that provides background information and hierarchical structures needed for relation extraction. Compared to traditional clustering, KB can provide hierarchical information that helps represent and cluster relations in a more organized way (Zhang et al., 2021a) and hierarchical factual knowledge for data augmentation (Fangchao et al., 2021).

Pre-trained knowledge of language models, particularly LLMs, exhibit substantial potential to encapsulate relational knowledge (Jiang et al., 2020; Petroni et al., 2020). Unlike smaller models, which require learning from input and external knowledge in a bottom-up manner, LLMs hold extensive, ready-to-use knowledge from pre-training. Consequently, recent efforts aim to direct LLMs to concentrate solely on pertinent knowledge for specific IE tasks.