Large Language Models for Generative Information Extraction: A Survey

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Abstract

Information extraction (IE) aims to extract structural knowledge (such as entities, relations, and events) from plain natural language texts. Recently, generative Large Language Models (LLMs) have demonstrated remarkable capabilities in text understanding and generation, allowing for generalization across various domains and tasks. As a result, numerous works have been proposed to harness abilities of LLMs and offer viable solutions for IE tasks based on a generative paradigm. To conduct a comprehensive systematic review and exploration of LLM efforts for IE tasks, in this study, we survey the most recent advancements in this field. We first present an extensive overview by categorizing these works in terms of various IE subtasks and learning paradigms, then we empirically analyze the most advanced methods and discover the emerging trend of IE tasks with LLMs. Based on thorough review conducted, we identify several insights in technique and promising research directions that deserve further exploration in future studies. We maintain a public repository and consistently update related resources at: https://github.com/quqxui/Awesome-LLM4IE-Papers.

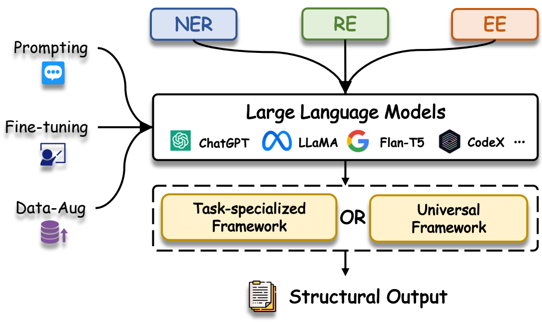

Figure 1: LLMs have been extensively explored for generative IE. These studies encompass various learning paradigms, diverse LLM architectures, and specialized frameworks designed for a single subtask, as well as universal frameworks capable of addressing multiple subtasks simultaneously.

1 Introduction

Information Extraction (IE) is a crucial domain in natural language processing that converts plain text into structured knowledge. IE serves as a foundational requirement for a wide range of downstream tasks, such as knowledge graph construction (Zhong et al., 2023), knowledge reasoning (Fu et al., 2019) and question answering (Srihari et al., 1999). Typical IE tasks consists of Named Entity Recognition (NER), Relation Extraction (RE) and Event Extraction (EE) (Wang et al., 2023c). Meanwhile, the emergence of large language models (LLMs) (e.g., GPT-4 (OpenAI, 2023a), Llama (Hugo et al., 2023)) has greatly promoted the development of natural language processing, due to their extraordinary capabilities in text understanding, generation, and generalization. Therefore, there has been a recent surge of interest in generative IE methods (Qi et al., 2023; Guo et al., 2023; Sainz et al., 2023) that adopt LLMs to generate structural information rather than extracting structural information from plain text. These methods prove to be more practical in real-world scenarios compared to discriminated methods (Chen et al., 2023a; Lou et al., 2023), as they efficiently handle schemas containing millions of entities without significant performance degradation (Josifoski et al., 2022).

On the one hand, LLMs have attracted significant attention from researchers in exploring their potential for various scenarios of IE tasks. In addition to excelling in individual IE tasks such as NER (Yuan et al., 2022), RE (Wan et al., 2023), and EE (Wang et al., 2023d), LLMs possess a remarkable ability to effectively model various IE tasks in a universal format. This is conducted by capturing inter-task dependencies with instructive prompts, and achieve consistent performance (Lu

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et al., 2022; Sainz et al., 2023). On the other hand, recent works have shown the outstanding generalization of LLMs to not only learn from IE training data through fine-tuning (Paolini et al., 2021), but also extract information in few-shot and even zero-shot scenarios relying solely on in-context examples or instructions (Wei et al., 2023; Wang et al., 2023d). For above two groups of research works: 1) the universal framework that encompasses multiple tasks (Zhao et al., 2023); 2) deficiency of training data scenarios, existing surveys (Nasar et al., 2021; Zhou et al., 2022a; Ye et al., 2022) do not fully explore them.

In this survey, we provide a comprehensive exploration of LLMs for generative IE. To achieve this, we categorize existing representative methods mainly using two taxonomies: (1) a taxonomy of numerous IE subtasks, which aims to classify the different types of information that can be extracted individually or uniformly using LLMs, and (2) a taxonomy of learning paradigms, which categorizes various novel approaches that utilize LLMs for generative IE. Furthermore, we also demonstrate studies that focus on specific domains and evaluate/analyze performance of LLMs for IE. Additionally, we compare performance of several representative methods across various settings to gain a deeper understanding of their potential and limitations, and provide insightful analysis on the challenges and future directions of employing LLMs for generative IE. To the best of our knowledge, this is the first survey on generative IE with LLMs.

The remaining part of this survey is organized as follows: We first introduce the definition of generative IE and target of all subtasks (Section 2). Then, in Section 3, we introduce representative models for each task and universal IE, and compare their performance. In Section 4, we summarize different learning paradigms of LLMs for IE. Additionally, we introduce works proposed for special domains in Section 5, and present recent studies that explore ability of LLMs on IE tasks in Section 6. Finally, we propose potential research directions for future studies in Section 7. In Appendix A and B, we provide a comprehensive summary of the most commonly used LLMs and dataset statistics, as reference for researchers.

2 Preliminaries of Generative IE

In this section, we provide the formula definition of generative IE and present the aim for each subtask. This generative IE survey primarily covers the tasks of NER, RE, and EE (Wang et al., 2023c; Sainz et al., 2023). The three types of IE tasks are formulated in a generative manner. Given an input text (e.g., sentence or document) with a sequence of n tokens $\mathcal{X} = [x_1, ..., x_n]$, a prompt $\mathcal{P}$, and the target extraction sequence $\mathcal{Y} = [y_1, ..., y_m]$, the objective is to maximize the conditional probability in an auto-regressive formulation:

$$p_\theta(\mathcal{Y}|\mathcal{X}, \mathcal{P}) = \prod_{i=1}^{m} p_\theta(y_i|\mathcal{X}, \mathcal{P}, y_{<i}), \qquad (1)$$

where θ donates the parameters of LLMs, which can be frozen or trainable. In the era of LLMs, several works have proposed appending extra prompts or instructions $\mathcal{P}$ to $\mathcal{X}$ in order to enhance the comprehensibility of the task for LLMs (Wang et al., 2023c). Even though the input text $\mathcal{X}$ remains the same, the target sequence varies for each task.:

- **Named Entity Recognition** (NER) includes two tasks: **Entity Identification** and **Entity Typing**. The former task is concerned with identifying spans of entities (e.g., 'Steve'), and the latter task focuses on assigning types to these identified entities (e.g., 'PERSON').

- **Relation Extraction** (RE) may have different settings in different works. We categorize it using three terms following other works (Lu et al., 2022; Wang et al., 2023c): (1) **Relation Classification** refers to classifying the relation type between two given entities; (2) **Relation Triplet** refers to identifying the relation type and the corresponding head and tail entity spans; (3) **Relation Strict** refers to giving the correct relation type, the span, and the type of head and tail entity.

- **Event Extraction** (EE) can be divided into two subtasks (Wang et al., 2022a): (1) **Event Detection** (also known as Event Trigger Extraction in some works) aims to identify and classify the trigger word and type that most clearly represents the occurrence of an event. (2) **Event Arguments Extraction** aims to identify and classify arguments from the sentences that are specific roles in the events.

3 Information Extraction Tasks

In this section, we first present a comprehensive introduction to the relevant technologies for the subtasks of IE, including NER (§3.1), RE (§3.2), and

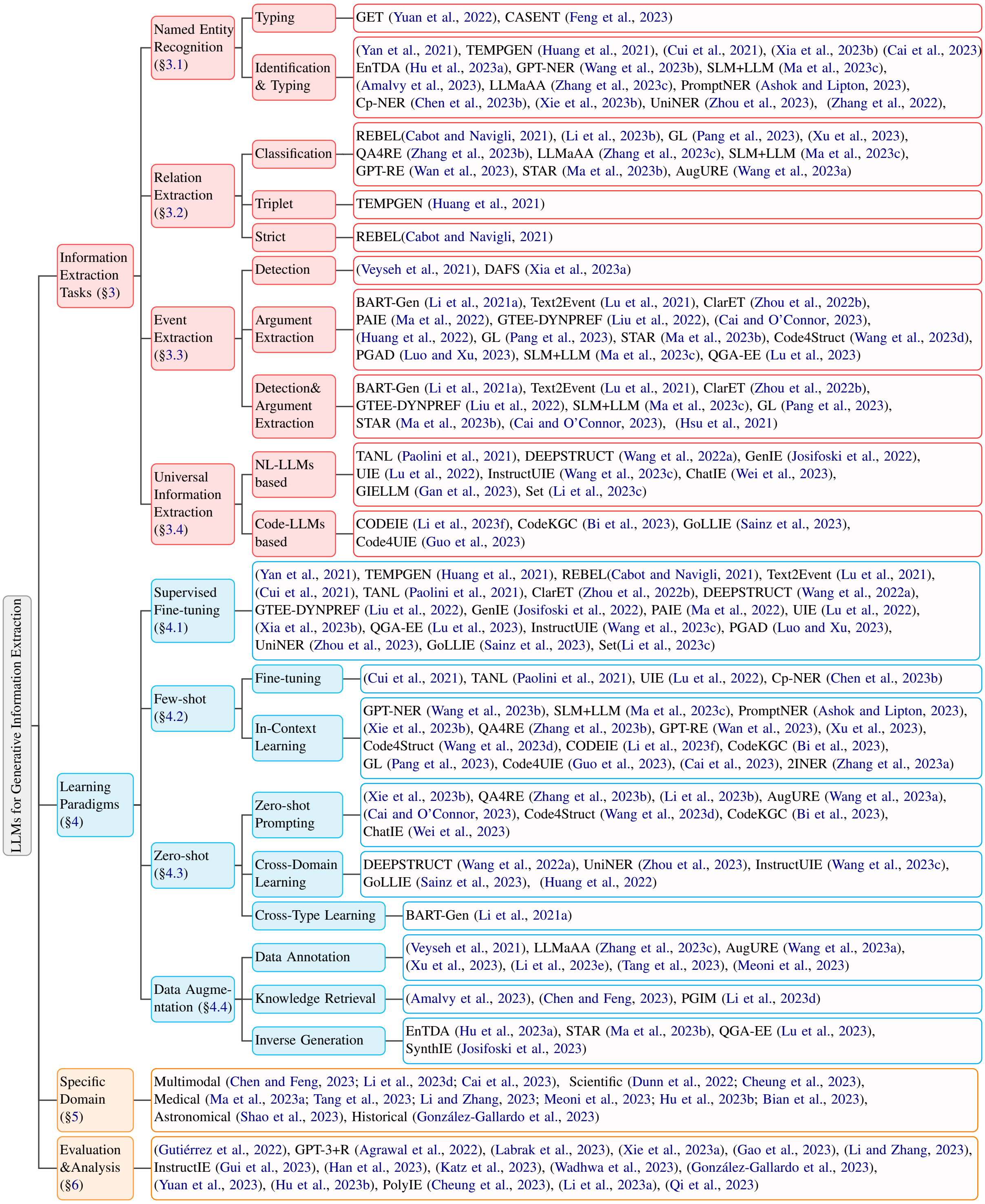

Figure 2: Taxonomy of research in generative IE using LLMs, which consists of tasks, learning paradigms, specific domain, and evaluation & analysis. The models within the sub-node of 'Specific Domain' node are divided by each domain. The display order of works in other leaf nodes is primarily organized chronologically.

EE (§3.3). We also conduct experimental analysis to evaluate the performance of various methods on representative datasets for three subtasks. Furthermore, we categorize universal frameworks into two formats: natural language (NL-LLMs based) and code language (Code-LLMs based), to discuss how they model the three distinct tasks using a unified paradigm (§3.4).

3.1 Named Entity Recognition

Named Entity Recognition (NER) is a crucial component of IE and can be seen as a predecessor or

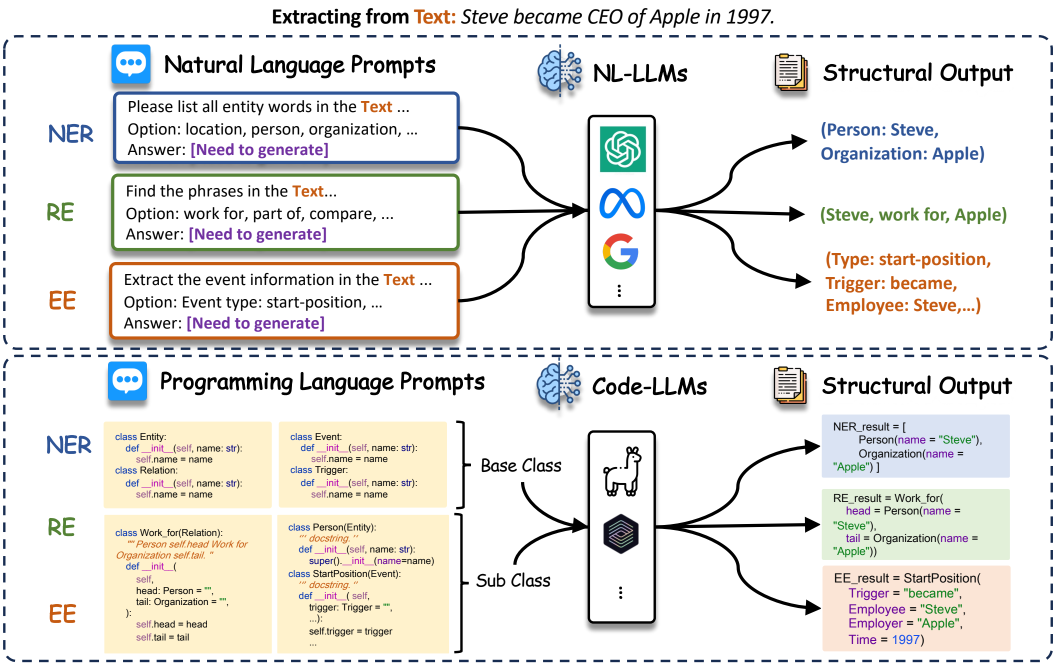

Figure 3: The comparison of prompts with NL-LLMs and Code-LLMs for Universal IE. This figure refers to InstructUIE (Wang et al., 2023c) and Code4UIE (Guo et al., 2023). Both NL and code-based methods attempt to construct a universal schema for various subtasks. However, they differ in terms of prompt format and the way they utilize the generation capabilities of LLMs. The Python subclass usually has docstrings for better explanation of the class to LLMs.

subtask of RE and EE. It is also a fundamental task in other Natural Language Processing (NLP) tasks, thus attracting significant attention from researchers to explore new possibilities in the era of LLMs. Xia et al. (2023b) introduces bias by allocating all probability mass to the observed sequence; this paper proposes a reranking-based approach within the Seq2Seq formulation that redistributes likelihood among candidate sequences using a contrastive loss, instead of augmenting data. Due to the gap between the sequence labeling nature of NER and text generation models like LLMs, GPT-NER (Wang et al., 2023b) introduces a transformation of NER into a generation task and proposes a self-verification strategy to rectify the mislabeling of NULL inputs as entities. Xie et al. (2023b) proposes a training-free self-improving framework that uses LLM to predict on the unlabeled corpus to obtain pseudo demonstrations, thereby enhancing the performance of LLM on zero-shot NER.

Tab. 1 shows the comparison of NER on five main datasets, which are obtained from their original papers. We can observe that: 1) the models in few-shot and zero-shot settings still have a huge performance gap with the models in SFT and DA settings. 2) Even though there is little difference between backbones, the performance varies greatly between methods under the ICL paradigm. For example, GPT-NER opens up at least a 6% F1 value gap with other methods on each dataset, and up to about 19% higher. 3) Compared to ICL, there are only minor differences in performance between models under the SFT paradigm, even though the parameters in their backbones can differ by up to a few hundred times.

3.2 Relation Extraction

RE also plays an important role in IE, which usually has different setups in different studies as mentioned in Section 2. To address the poor performance of LLMs on RE tasks due to the low incidence of RE in instruction-tuning datasets, as indicated in Gutiérrez et al. (2022), QA4RE (Zhang et al., 2023b) introduces a framework that enhances LLMs' performance by aligning RE tasks with QA tasks. GPT-RE (Wan et al., 2023) incorporates task-aware representations and enriching demonstrations with reasoning logic to improve the low relevance between entity and relation and the inability to explain input-label mappings. Due to the large number of predefined relation types and uncontrolled LLMs, Li et al. (2023e) proposes

Table 1: Comparison of Micro-F1 Values for Named Entity Recognition (Identification & Typing). † indicates that the model is discriminative. We demonstrate some universal and discriminative models for comparison. Learning Paradigms include Cross-Domain Learning (**CDL**), Zero-Shot Prompting (**ZS Pr**), In-Context Learning (**ICL**), Supervised Fine-Tuning (**SFT**), Data Augmentation (**DA**). **Uni. ?** denotes whether the model is universal. Details of backbones (§B) and datasets (§A) are presented in Appendix. The settings for all subsequent tables are consistent with this format.

Representative Model	Paradigm	Uni. ?	Backbone	ACE04	ACE05	CoNLL03	Onto. 5[1]	GENIA
DEEPSTRUCT (Wang et al., 2022a)	CDL		GLM-10B		28.1	44.4	42.5	47.2
(Xie et al., 2023b)	ZS Pr		Gpt-3.5-turbo		32.27	74.51		52.06
CODEIE (Li et al., 2023f)	ICL	√	Code-davinci-002	55.29	54.82	82.32		
Code4UIE (Guo et al., 2023)	ICL	√	Text-davinci-003	60.1	60.9	83.6		
PromptNER (Ashok and Lipton, 2023)	ICL		GPT-4			83.48		58.44
(Xie et al., 2023b)	ICL		Gpt-3.5-turbo		55.54	84.51		58.72
GPT-NER (Wang et al., 2023b)	ICL		Text-davinci-003	74.2	73.59	90.91	82.2	64.42
TANL (Paolini et al., 2021)	SFT	√	T5-base		84.9	91.7	89.8	76.4
(Cui et al., 2021)	SFT		Bart			92.55		
(Yan et al., 2021)	SFT		Bart-large	86.84	84.74	93.24	90.38	79.23
UIE (Lu et al., 2022)	SFT	√	T5-large	86.89	85.78	92.99		
DEEPSTRUCT (Wang et al., 2022a)	SFT	√	GLM-10B		86.9	93.0	87.8	80.8
(Xia et al., 2023b)	SFT		Bart-large	87.63	86.22	93.48	90.63	79.49
InstructUIE (Gui et al., 2023)	SFT	√	Flan-T5-11B		86.66	92.94	90.19	74.71
UniNER (Zhou et al., 2023)	SFT		LLaMA-7B	87.5	87.6		89.1	80.6
GoLLIE (Sainz et al., 2023)	SFT	√	Code-LLaMA-34B		89.6	93.1	84.6	
EnTDA (Hu et al., 2023a)	DA		T5-base	88.21	87.56	93.88	91.34	82.25
USM† (Lou et al., 2023)	SFT	√	Roberta-large	87.62	87.14	93.16		
RexUIE† (Liu et al., 2023)	SFT	√	DeBERTa-v3-large	87.25	87.23	93.67		
Mirror† (Zhu et al., 2023)	SFT	√	DeBERTa-v3-large	87.16	85.34	92.73		

to integrate LLM with a natural language inference module to generate relation triples, enhancing document-level relation datasets.

As shown in the Tab. 2 and 3, we statistically found that uni-ie models are generally biased towards solving harder Relation Strict problems due to learning the dependencies between multi-tasks (Paolini et al., 2021; Lu et al., 2022), while the task-specific methods solve more simple RE subtasks (e.g. Relation Classification). In addition, compared with NER, it can be found that the performance differences between models in RE are more obvious, indicating that the potential of LLM in RE task still has a great space to explore.

3.3 Event Extraction

Events can be defined as specific occurrences or incidents that happen in a given context. Recently, many studies (Lu et al., 2023) aim to understand events and capture their correlations by extracting event triggers and arguments using LLMs, which is essential for various reasoning tasks (Bhagavatula et al., 2020). ClarET (Zhou et al., 2022b) undergoes three pre-trained tasks to capture the correlation between events more efficiently and achieves SOTA on multiple downstream tasks. Code4Struct (Wang et al., 2023d) leverages LLMs' ability to translate text into code to tackle structured prediction tasks, using programming language features to introduce external knowledge and constraints through alignment between structure and code. Considering the interrelation between different arguments in the extended context, PGAD (Luo and Xu, 2023) employs a text diffusion model to create a variety of context-aware prompt representations, enhancing both sentence-level and document-level event argument extraction by identifying multiple role-specific argument span queries and coordinating them with the context.

We collect the experimental results from recent studies on the common EE dataset (i.e., ACE05 (Walker et al., 2006)), which is shown in Tab. 4. As can be seen from the results, the vast majority of current methods are based on the SFT paradigm, and the number of methods that use LLMs for either zero-shot or few-shot learning is small. In addition, generative methods outperform discriminative ones by a wide margin, especially in the metric of Argument Classification, indicating the great potential of generative LLMs for EE.

3.4 Universal Information Extraction

Different IE tasks are highly diversified, with different optimization objectives and task-specific

Table 2: Comparison of Micro-F1 Values for Relation Strict Extraction. † indicates that the model is discriminative.

Representative Model	Paradigm	Uni. ?	Backbone	NYT	ACE05	ADE	CoNLL04	SciERC
CodeKGC (Bi et al., 2023)	ZS Pr	√	Text-davinci-003			42.8	35.9	15.3
CODEIE (Li et al., 2023f)	ICL	√	Code-davinci-002	32.17	14.02		53.1	7.74
CodeKGC (Bi et al., 2023)	ICL	√	Text-davinci-003			64.6	49.8	24.0
Code4UIE (Guo et al., 2023)	ICL	√	Text-davinci-002	54.4	17.5	58.6	54.4	
REBEL (Cabot and Navigli, 2021)	SFT		Bart-large	91.96		82.21	75.35	
UIE (Lu et al., 2022)	SFT	√	T5-large		66.06		75.0	36.53
InstructUIE (Wang et al., 2023c)	SFT	√	Flan-T5-11B	90.47		82.31	78.48	45.15
GoLLIE (Sainz et al., 2023)	SFT	√	Code-LLaMA-34B		70.1			
USM† (Lou et al., 2023)	SFT	√	Roberta-large		67.88		78.84	37.36
RexUIE† (Liu et al., 2023)	SFT	√	DeBERTa-v3-large		64.87		78.39	38.37

Table 3: Comparison of Micro-F1 Values for Relation Classification.

Representative Model	Paradigm	Uni. ?	Backbone	TACRED	Re-TACRED	TACREV	SemEval
QA4RE (Zhang et al., 2023b)	ZS Pr		Text-davinci-003	59.4	61.2	59.4	43.3
SUMASK (Li et al., 2023b)	ZS Pr		Gpt-3.5-turbo-0301	79.6	73.8	75.1	
GPT-RE (Wan et al., 2023)	ICL		Text-davinci-003	72.15			91.9
(Xu et al., 2023)	ICL		Text-davinci-003	31.0	51.8	31.9	
REBEL (Cabot and Navigli, 2021)	SFT		Bart-large		90.36		
(Xu et al., 2023)	DA		Text-davinci-003	37.4	66.2	41.0	

schema, resulting in the need for isolated models to handle the complexity of a large amount of IE tasks, settings, and scenarios (Lu et al., 2022). As shown in Fig. 2, many works solely focus on a subtask of IE. However, recent advancements in LLMs have led to the proposal of a unified seq2seq framework in several studies (Wang et al., 2023c; Sainz et al., 2023). This framework aims to model all IE tasks, capturing the common abilities of IE and learning the dependencies across multiple tasks. The prompt format for Uni-IE can typically be divided into natural language-based LLMs (NL-LLMs) and code-based LLMs (code-LLMs), as illustrated in Fig. 3.

NL-LLMs. NL-based methods unify all IE tasks in a universal natural language schema. For instance, UIE (Lu et al., 2022) proposes a unified text-to-structure generation framework that encodes extraction structures, and captures common IE abilities through a structured extraction language. InstructUIE (Wang et al., 2023c) enhances UIE by constructing expert-written instructions for fine-tuning LLMs to consistently model different IE tasks and capture the inter-task dependency. Additionally, ChatIE (Wei et al., 2023) explores the use of LLMs like GPT3 (Brown et al., 2020) and ChatGPT (OpenAI, 2023b) in zero-shot prompting, transforming the task into a multi-turn question-answering problem.

Code-LLMs. On the other hand, Code-based methods unify IE tasks by generating code with a universal programming schema (Wang et al., 2023d). Code4UIE (Guo et al., 2023) proposes a universal retrieval-augmented code generation framework, which leverages Python classes to define schemas and uses in-context learning to generate codes that extract structural knowledge from texts. Besides, CodeKGC (Bi et al., 2023) leverages the structural knowledge inherent in code and employs schema-aware prompts and rationale-enhanced generation to improve performance. To enable LLMs to adhere to guidelines out-of-the-box, GoLLIE (Sainz et al., 2023) is proposed to enhance zero-shot performance on unseen IE tasks by fine-tuning LLMs to align with annotation guidelines.

In general, NL-LLMs are trained on a wide range of text and can understand and generate human language, which allows the prompts and instructions to be more concise and easier to design. However, NL-LLMs may struggle to produce unnatural outputs due to the distinct syntax and structure of IE tasks (Bi et al., 2023), which differs from the training data. Code, being a formalized language, possesses the inherent capability to accurately represent knowledge across diverse schema, which makes it more suitable for structural prediction (Guo et al., 2023). But code-based methods often require a substantial amount of text to define a Python class (see Fig. 3), which in turn limits the sample size of the context. Through experimental

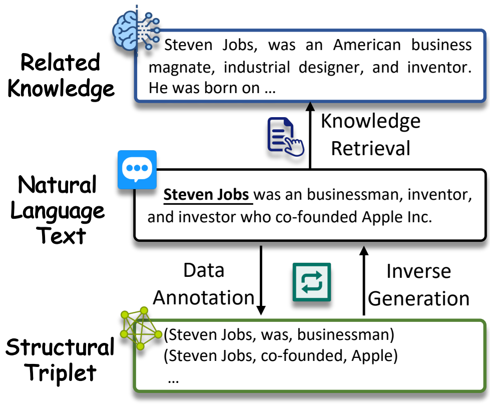

Figure 4: Comparison of different data augmentation methods.

comparison in Tab. 1, 2, and 4, we can observe that uni-IE models with SFT setting outperform task-specific models in the NER, RE, and EE tasks for most datasets.

4 Learning Paradigms

In this section, we categorize methods based on their learning paradigms, including **Supervised Fine-tuning** (§4.1, refers to further training LLMs on IE tasks using labeled data), **Few-shot** (§4.2, refers to the generalization from a small number of labeled examples by training or in-context learning), **Zero-shot** (§4.3, refers to generating answer without any training examples for the specific IE tasks), and **Data Augmentation** (§4.4, refers to enhancing information by applying various transformations to the existing data using LLMs), to highlight the commonly used approaches for adapting LLMs to IE.

4.1 Supervised Fine-tuning

Entering all training data to fine-tune LLMs is the most common and promising method, which allows the model to capture the underlying structural patterns in the data, and generalize well to unseen IE tasks. For example, Deepstruct (Wang et al., 2022a) introduces structure pre-training on a collection of task-agnostic corpora to enhance the structural understanding of language models. UniNER (Zhou et al., 2023) explores targeted distillation and mission-focused instruction tuning to train student models for broad applications, such as NER. GIELLM (Gan et al., 2023) fine-tunes LLMs using mixed datasets, which are collected to utilize the mutual reinforcement effect to enhance performance on multiple tasks.

4.2 Few-shot

Few-shot learning has access to only a limited number of labeled examples, leading to challenges like overfitting and difficulty in capturing complex relationships (Huang et al., 2020). Fortunately, scaling up the parameters of LLMs gives them amazing generalization capabilities compared to small pre-trained models, allowing them to achieve excellent performance in few-shot settings (Li and Zhang, 2023; Ashok and Lipton, 2023). TANL, UIE, and cp-NER propose innovative approaches (e.g., Translation between Augmented Natural Languages framework (Paolini et al., 2021), text-to-structure generation framework (Lu et al., 2022), Collaborative Domain-Prefix Tuning (Chen et al., 2023b)), which achieve state-of-the-art performance and demonstrate effectiveness in few-shot fine-tuning. Despite the success of LLMs, they face challenges in training-free IE because of the difference between sequence labeling and text-generation models (Gutiérrez et al., 2022). To overcome these limitations, GPT-NER (Wang et al., 2023b) introduces a self-verification strategy, while GPT-RE (Wan et al., 2023) enhances task-aware representations and incorporates reasoning logic into enriched demonstrations. These approaches demonstrate how to effectively leverage the capabilities of GPT for in-context learning. CODEIE (Li et al., 2023f) and CodeKGC (Bi et al., 2023) show that converting IE tasks into code generation tasks with code-style prompts and in-context examples leads to superior performance compared to NL-LLMs. This is because code-style prompts provide a more effective representation of structured output, enabling them to effectively handle the complex dependencies in natural language.

4.3 Zero-shot

The main challenges in zero-shot learning lie in enabling the model to effectively generalize for tasks and domains that it has not been trained on, as well as aligning the pre-trained paradigm of LLMs. Due to the large amount of knowledge embedded within, LLMs show impressive abilities in zero-shot scenarios of unseen tasks (Kojima et al., 2022; Wei et al., 2023). To achieve zero-shot cross-domain generalization of LLMs in IE tasks, several works have been proposed (Wang et al., 2022a; Sainz et al., 2023; Zhou et al., 2023; Wang et al., 2023c). These works offer a universal framework for modeling various IE tasks and domains, and introduce in-

Table 4: Comparison of Micro-F1 Values for Event Extraction on ACE05. Evaluation tasks include: Trigger Identification (Trg-I), Trigger Classification (Trg-C), Argument Identification (Arg-I), and Argument Classification (Arg-C). [†] indicates that the model is discriminative.

Representative Model	**Paradigm**	**Uni. ?**	**Backbone**	**Trg-I**	**Trg-C**	**Arg-I**	**Arg-C**
Code4Struct (Wang et al., 2023d)	ZS Pr		Code-davinci-002			50.6	36.0
Code4UIE (Guo et al., 2023)	ICL	√	Gpt-3.5-turbo-16k		37.4		21.3
Code4Struct (Wang et al., 2023d)	ICL		Code-davinci-002			62.1	58.5
TANL (Paolini et al., 2021)	SFT	√	T5-base	72.9	68.4	50.1	47.6
Text2Event (Lu et al., 2021)	SFT		T5-large		71.9		53.8
BART-Gen (Li et al., 2021a)	SFT		Bart-large			69.9	66.7
UIE (Lu et al., 2022)	SFT	√	T5-large		73.36		54.79
GTEE-DYNPREF (Liu et al., 2022)	SFT		Bart-large		72.6		55.8
DEEPSTRUCT (Wang et al., 2022a)	SFT	√	GLM-10B	73.5	69.8	59.4	56.2
PAIE (Ma et al., 2022)	SFT		Bart-large			75.7	72.7
PGAD (Luo and Xu, 2023)	SFT		Bart-base			74.1	70.5
QGA-EE (Lu et al., 2023)	SFT		T5-large			75.0	72.8
InstructUIE (Wang et al., 2023c)	SFT	√	Flan-T5-11B		77.13		72.94
GoLLIE (Sainz et al., 2023)	SFT	√	Code-LLaMA-34B		71.9		68.6
USM[†] (Lou et al., 2023)	SFT	√	Roberta-large		72.41		55.83
RexUIE[†] (Liu et al., 2023)	SFT	√	DeBERTa-v3-large		75.17		59.15
Mirror[†] (Zhu et al., 2023)	SFT	√	DeBERTa-v3-large		74.44		55.88

novative training prompts (e.g., instruction (Wang et al., 2023c) and guidelines (Sainz et al., 2023)) for learning and capturing the inter-task dependencies of known tasks and generalizing them to unseen tasks and domains. In terms of cross-type generalization, BART-Gen (Li et al., 2021a) proposes a document-level neural model, by formulating EE task as conditional generation, resulting in better performance and excellent portability on unseen event types.

On the other hand, In order to improve the ability of LLMs under zero shot prompts (no need for further fine-tuning on IE tasks), QA4RE (Zhang et al., 2023b) and ChatIE (Wei et al., 2023) propose to improve the performance of LLMs (like FLAN-T5 (Chung et al., 2022) and GPT (OpenAI, 2023a)) on zero-shot IE tasks, with transforming IE into a multi-turn question-answering problem for aligning IE tasks with QA tasks. (Li et al., 2023b) integrates the chain-of-thought approach and proposes the summarize-and-ask prompting to solve the challenge of ensuring the reliability of outputs from black box LLMs (Ma et al., 2023c; Wang et al., 2023c).

4.4 Data Augmentation

Data augmentation involves generating meaningful and diverse data to effectively enhance the training examples or information, while avoiding the introduction of unrealistic, misleading, and offset patterns. Recent powerful LLMs also demonstrate remarkable performance in data generation tasks (Whitehouse et al., 2023), which has attracted the attention of many researchers using LLMs to generate synthetic data for IE. It can be roughly divided into three strategies as shown in Fig. 4.

Data Annotation. This strategy directly generates labeled data using LLMs. For instance, Zhang et al. (2023c) proposes LLMaAA to improve accuracy and data efficiency by employing LLMs as annotators within an active learning loop, thereby optimizing both the annotation and training processes. AugURE (Wang et al., 2023a) employs within-sentence pairs augmentation and cross-sentence pairs extraction to enhance the diversity of positive pairs for unsupervised RE, and introduces margin loss for sentence pairs.

Knowledge Retrieval. This strategy retrieves relevant knowledge from LLMs for IE. PGIM (Li et al., 2023d) presents a two-stage framework for Multimodal NER, which leverages ChatGPT as an implicit knowledge base to heuristically retrieve auxiliary knowledge for more efficient entity prediction. Amalvy et al. (2023) proposes to improve NER on long documents by generating a synthetic context retrieval training dataset, and training a neural context retriever.

Inverse Generation. This strategy prompts LLMs to produce natural text or questions based on the structural data provided as input, aligning with the training paradigm of LLMs. For example, SynthIE (Josifoski et al., 2023) shows that LLMs can create high-quality synthetic data for complex tasks by reversing the task direction. They used this approach to create a large dataset for closed information extraction and trained new models that outperformed previous benchmarks. This demonstrates the potential of using LLMs for generating synthetic data for various complex tasks. Rather than relying on ground-truth targets, which limits their generalizability and scalability, STAR (Ma et al., 2023b) generates structures from valid triggers and arguments, then generates passages with LLMs.

Overall, these strategies have their own advantages and disadvantages. While data annotation can directly meet task requirements, the ability of LLMs for structured generation still needs improvement. Knowledge retrieval can provide additional information about entities and relations, but it suffers from the hallucination problem and introduces noise. Inverse generation is aligned with the QA paradigm of LLMs. However, it requires structural data and there exists a gap between the generated pairs and the domain that needs to be addressed.

5 Specific Domain

It is non-ignorable that LLMs have tremendous potential for extracting information from some specific domains, such as mulitmodal (Chen and Feng, 2023; Li et al., 2023d), medical (Tang et al., 2023; Ma et al., 2023a) and scientific (Dunn et al., 2022; Cheung et al., 2023) information. For example:

Multimodal. Chen and Feng (2023) introduces a conditional prompt distillation method that enhances a model's reasoning ability by combining text-image pairs with chain-of-thought knowledge from LLMs, significantly improving performance in multimodal NER and multimodal RE.

Medical. Tang et al. (2023) explores the potential of LLMs in the field of clinical text mining and proposes a novel training approach, which leverages synthetic data, to enhance performance and address privacy issues.

Scientific. Dunn et al. (2022) presents a sequence-to-sequence approach by using GPT-3 for joint NER and RE from complex scientific text, demonstrating its effectiveness in extracting complex scientific knowledge in materials chemistry.

6 Evaluation & Analysis

Despite the great success of LLMs in various natural language processing tasks, their performance in the field of information extraction is still questionable (Han et al., 2023). To alleviate this problem, recent research has explored the capabilities of LLMs with respect to the major subtasks of IE (i.e., NER (Xie et al., 2023a; Li and Zhang, 2023), RE (Wadhwa et al., 2023; Yuan et al., 2023), and EE (Gao et al., 2023)). Considering the superior reasoning capabilities of LLMs, Xie et al. (2023a) proposes four reasoning strategies for NER, which are designed to simulate ChatGPT's potential on zero-shot NER. Wadhwa et al. (2023) explores the use of LLMs for RE and finds that few-shot prompting with GPT-3 achieves near SOTA performance, while Flan-T5 can be improved with chain-of-thought style explanations generated via GPT-3. For EE tasks, Gao et al. (2023) shows that ChatGPT still struggles with it due to the need for complex instructions and a lack of robustness.

Along this line, some researchers perform a more comprehensive analysis of LLMs by evaluating multiple IE subtasks simultaneously. Li et al. (2023a) evaluates ChatGPT's overall ability on IE, including performance, explainability, calibration, and faithfulness. They find that ChatGPT mostly performs worse than BERT-based models in the standard IE setting, but excellently in the OpenIE setting. Furthermore, Han et al. (2023) introduces a soft-matching strategy for a more precise evaluation and identifies "unannotated spans" as the predominant error type, highlighting potential issues with data annotation quality.

7 Future Directions

The development of integrating LLMs for generative IE systems is still in its early stages, and there are numerous opportunities for improvement.

Universal IE. Previous generative IE methods and benchmarks are often tailored for specific domains or tasks, limiting their generalizability (Yuan et al., 2022). Although some unified methods (Lu et al., 2022) using LLMs have been proposed recently, they still suffer from certain limitations (e.g., long context input, and misalignment of structured output). Therefore, further development of universal IE frameworks that can adapt flexibly to different domains and tasks is a promising research direction (such as integrating the insights of task-specific models to assist in constructing universal models).

Low-Resource IE. The generative IE system with LLMs still encounters challenges in resource-limited scenarios (Li et al., 2023a). Based on our summary, there is a need for further exploration of in-context learning of LLMs, particularly in terms of improving the selection of examples. Future research should prioritize the development of robust cross-domain learning techniques (Wang et al., 2023c), such as domain adaptation or multi-task learning, to leverage knowledge from resource-rich domains. Additionally, efficient data annotation strategies with LLMs should also be explored.

Prompt Design for IE. Designing effective instructions is considered to have a significant impact on the performance of LLMs (Qiao et al., 2022; Yin et al., 2023). One aspect of prompt design is to build input and output pairs that can better align with the pre-training stage of LLMs (e.g., code generation) (Guo et al., 2023). Another aspect is optimizing the prompt for better model understanding and reasoning (e.g., Chain-of-Thought) (Li et al., 2023b), by encouraging LLMs to make logical inferences or explainable generation. Additionally, researchers can explore interactive prompt design (such as multi-turn QA) (Zhang et al., 2023b), where LLMs can iteratively refine or provide feedback on the generated extractions automatically.

Open IE. The Open IE setting presents greater challenges for IE models, as they do not provide any candidate label set and rely solely on the models' ability to comprehend the task. LLMs, with their knowledge and understanding abilities, have significant advantages in some Open IE tasks (Zhou et al., 2023). However, there are still instances of poor performance in more challenging tasks (Qi et al., 2023; Li et al., 2023a), which require further exploration by researchers.

8 Conclusion

In this survey, we focus on reviewing existing studies that utilize LLMs for various generative IE tasks. We first introduce the subtasks of IE and discuss some universal frameworks aiming to unify all IE tasks. Additional theoretical and experimental analysis provides insightful exploration for these methods. Then we delve into different learning paradigms that apply LLMs for IE and demonstrate their potential for extracting information in specific domains. We also introduce some studies for evaluation purposes. Finally, we analyze the current challenges and present potential future directions. We hope this survey can provide a valuable resource for researchers to explore more efficient utilization of LLMs for IE.

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A Benchmarks

As shown in Tab. 5, we compiled a comprehensive collection of benchmarks covering various domains and tasks, to provide researchers with a valuable resource that they can query and reference as needed.

B Backbones

We briefly describe some backbones that are commonly used in the field of generative information extraction, which is shown in Tab. 6

Table 5: Detailed datasets statistics. ∗ denotes the dataset is multimodal. The data in the table is partially referenced from InstructUIE (Gui et al., 2023).

Task	Dataset	Domain	#Class	#Train	#Val	#Test
NER	ACE04 (Doddington et al., 2004)	News	7	6202	745	812
	ACE05 (Walker et al., 2006)	News	7	7299	971	1060
	BC5CDR (Li et al., 2016)	Biomedical	2	4560	4581	4797
	Broad Twitter Corpus (Derczynski et al., 2016)	Social Media	3	6338	1001	2000
	CADEC (Karimi et al., 2015)	Biomedical	1	5340	1097	1160
	CoNLL03 (Sang and De Meulder, 2003)	News	4	14041	3250	3453
	CoNLLpp (Wang et al., 2019)	News	4	14041	3250	3453
	CrossNER-AI (Liu et al., 2021)	Artificial Intelligence	14	100	350	431
	CrossNER-Literature (Liu et al., 2021)	Literary	12	100	400	416
	CrossNER-Music (Liu et al., 2021)	Musical	13	100	380	465
	CrossNER-Politics (Liu et al., 2021)	Political	9	199	540	650
	CrossNER-Science (Liu et al., 2021)	Scientific	17	200	450	543
	FabNER (Kumar and Starly, 2022)	Scientific	12	9435	2182	2064
	Few-NERD (Ding et al., 2021)	General	66	131767	18824	37468
	FindVehicle (Guan et al., 2023)	Traffic	21	21565	20777	20777
	GENIA (Kim et al., 2003)	Biomedical	5	15023	1669	1854
	HarveyNER (Chen et al., 2022)	Social Media	4	3967	1301	1303
	MIT-Movie (Liu et al., 2013)	Social Media	12	9774	2442	2442
	MIT-Restaurant (Liu et al., 2013)	Social Media	8	7659	1520	1520
	MultiNERD (Tedeschi and Navigli, 2022)	Wikipedia	16	134144	10000	10000
	NCBI (Doğan et al., 2014)	Biomedical	4	5432	923	940
	OntoNotes 5.0 (Pradhan et al., 2013b)	General	18	59924	8528	8262
	ShARe13 (Pradhan et al., 2013a)	Biomedical	1	8508	12050	9009
	ShARe14 (Mowery et al., 2014)	Biomedical	1	17404	1360	15850
	SNAP* (Lu et al., 2018)	Social Media	4	4290	1432	1459
	TTC (Rijhwani and Preotiuc-Pietro, 2020)	Social Meida	3	10000	500	1500
	Tweebank-NER (Jiang et al., 2022)	Social Media	4	1639	710	1201
	Twitter2015* (Zhang et al., 2018)	Social Media	4	4000	1000	3357
	Twitter2017* (Lu et al., 2018)	Social Media	4	3373	723	723
	TwitterNER7 (Ushio et al., 2022)	Social Media	7	7111	886	576
	WikiDiverse* (Wang et al., 2022b)	News	13	6312	755	757
	WNUT2017 (Derczynski et al., 2017)	Social Media	6	3394	1009	1287
RE	ACE05 (Walker et al., 2006)	News	7	10051	2420	2050
	ADE (Gurulingappa et al., 2012)	Biomedical	1	3417	427	428
	CoNLL04 (Roth and Yih, 2004)	News	5	922	231	288
	DocRED (Yao et al., 2019)	Wikipedia	96	3008	300	700
	MNRE* (Zheng et al., 2021)	Social Media	23	12247	1624	1614
	NYT (Riedel et al., 2010)	News	24	56196	5000	5000
	Re-TACRED (Stoica et al., 2021)	News	40	58465	19584	13418
	SciERC (Luan et al., 2018)	Scientific	7	1366	187	397
	SemEval2010 (Hendrickx et al., 2010)	General	19	6507	1493	2717
	TACRED (Zhang et al., 2017)	News	42	68124	22631	15509
	TACREV (Alt et al., 2020)	News	42	68124	22631	15509
EE	ACE05 (Walker et al., 2006)	News	33/22	17172	923	832
	CASIE (Satyapanich et al., 2020)	Cybersecurity	5/26	11189	1778	3208
	GENIA11 (Kim et al., 2011)	Biomedical	9/11	8730	1091	1092
	GENIA13 (Kim et al., 2013)	Biomedical	13/7	4000	500	500
	PHEE (Sun et al., 2022)	Biomedical	2/16	2898	961	968
	RAMS (Ebner et al., 2020)	News	139/65	7329	924	871
	WikiEvents (Li et al., 2021b)	Wikipedia	50/59	5262	378	492

Table 6: The common backbones for generative information extraction. We mark the commonly used base and large versions for better reference.

Series	Model	Size	Base Model	Open Source	Instruction Tuning	RLHF
BART	BART	140M (base), 400M (large)	-	√	-	-
T5	T5 (Raffel et al., 2020)	60M, 220M (base), 770M (large), 3B, 11B	-	√	-	-
	mT5 (Xue et al., 2021)	300M, 580M (base), 1.2B (large), 3.7B, 13B	-	√	-	-
	Flan-T5 (Chung et al., 2022)	80M, 250M (base), 780M (large), 3B, 11B	T5	√	√	-
GLM	GLM (Du et al., 2022)	110M (base), 335M (large), 410M, 515M, 2B, 10B	-	√	-	-
LLaMA	LLaMA (Touvron et al., 2023)	7B, 13B, 33B, 65B	-	√	-	-
	Code-LLaMA (Roziere et al., 2023)	7B, 13B, 34B	-	√	-	-
	Alpaca (Taori et al., 2023)	7B, 13B	LLaMA	√	√	-
	Vicuna (Chiang et al., 2023)	7B, 13B	LLaMA	√	√	-
	LLaMA2 (Hugo et al., 2023)	7B, 13B, 70B	-	√	-	-
GPT	GPT-2 (Radford et al., 2019)	117M, 345M, 762M, 1.5B	-	√	-	-
	GPT-3 (Brown et al., 2020)	175B	-	-	-	-
	GPT-J (Wang, 2021)	6B	GPT-3	√	-	-
	Code-davinci-002 (Ouyang et al., 2022)	-	GPT-3	-	√	-
	Text-davinci-002 (Ouyang et al., 2022)	-	GPT-3	-	√	-
	Text-davinci-003 (Ouyang et al., 2022)	-	GPT-3	-	√	√
	GPT-3.5-turbo (OpenAI, 2023b)	-	-	-	√	√
	Gpt-3.5-turbo-16k (OpenAI, 2023b)	-	-	-	√	√
	GPT-4 (OpenAI, 2023a)	-	-	-	√	√