

All for One and One for All: A Universal Model for Various Information Extraction Tasks

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Abstract

The variety of information extraction tasks and the different data formats between tasks make it hard to share resources. This causes wastes to some extent and adds difficulties to build complex pipeline applications in real scenarios. Recent studies formulate IE tasks as a triplet extraction problem. However, such format does not support multi-span and n-ary extraction tasks, leading to weak versatility. To this end, we reorganize IE datasets into a unified format and propose a universal model for various IE tasks, namely Mirror. We regard IE tasks as a multi-span cyclic graph extraction problem, and devise a non-autoregressive graph decoding algorithm to extract all spans in a single step. Experiments on 22 datasets across 6 IE tasks show that our model has good compatibilities and achieves good performances under few-shot and zero-shot settings. The code, model weights and data will be publicly available at github.

1 Introduction

Information Extraction (IE) is a fundamental task in Natural Language Processing (NLP), which aims to extract structured information from unstructured text, such as Named Entity Recognition (NER), Relation Extraction (RE), Event Extraction (EE), etc. Each IE task is usually isolated, and it needs specific datasets and delicate models, which makes it difficult to build complex applications. It is a fascinating problem to combine different IE tasks into a whole, and make one model for universal IE tasks.

There are two ways to combine different IE tasks. The first is to utilize generative pretrained language models (PLMs) to generate the structured information directly. x, x and x structure the IE tasks as a sequence generation problem, and use T5 models to predict the structured information autoregressively. However, such methods cannot provide the exact positions of the structured information, which is

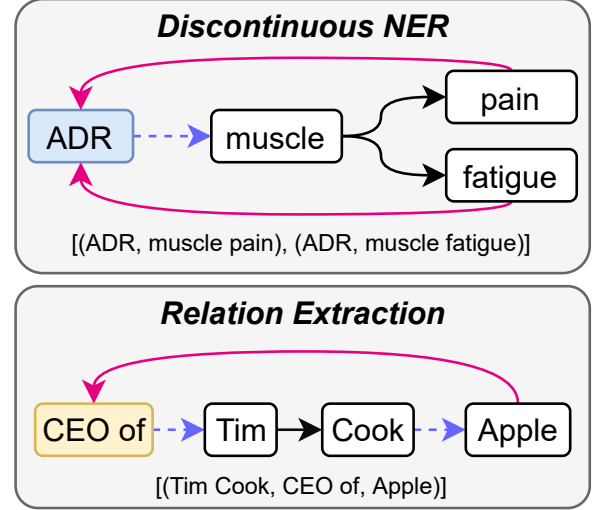


Figure 1: Multi-span cyclic graph for discontinuous NER and RE tasks (best viewed in color). The spans are connected by three types of edges, including *consecutive connections*, dotted *jump connections* and *tail-to-head connections*. ADR in discontinuous NER denotes the entity label of Adverse Drug Reaction.

important for some IE tasks, such as NER. Besides, the generation-based methods are usually slow, and it is difficult to train them on large-scale datasets. The second is to apply the extractive PLMs, which is way more faster to train and inference. UIE unifies the IE tasks into span spotting and associating problems. Based on this idea, x, x and x take the IE tasks into a triplet prediction problems, and propose different methods. However, such methods are not suitable for multi-span and n-ary IE tasks.

To extend the universal IE systems into more tasks, we propose a multi-task framework, namely Mirror, which can be applied on various IE tasks, including multi-span and n-ary extraction problems. We formulate IE tasks into a unified schema-guided multi-span graph, and regard labels as spans' leading tokens. We design three kind of connections and utilize the biaffine-style method to extract the structured information.

Model	TANL	UIE	DeepStruct	InstructUIE	USM	UniEX	RexUIE	Mirror
PLM #Params	T5-base 220M	T5-large 770M	GLM 10B	FlanT5 11B	RoBERTa large 372M	RoBERTa large 372M	DeBERTa-v3 large 434M	DeBERTa-v3 large 434M
Single-step	✓	✓	✓	✓	✓	✓	✗	✓
Indexing	✗	✗	✗	✗	✓	✓	✓	✓
NAR	✗	✗	✗	✗	✓	✓	✓	✓
Multi-span	✗	○	○	○	✗	✗	✗	✓
N-ary	✗	✗	✗	✗	✗	✗	✓	✓

Table 1: Comparisons with other systems. Single-step represents that the model predicts results in a single step. Indexing means whether the model could provide exact information positions. NAR denotes the non-autoregressive decoding strategy. Multi-span means the model supports multi-span extraction, e.g. the discontinuous named entity recognition task. N-ary denotes the ability of n-ary tuple extraction. ○ means the model supports the task theoretically, but the implementation is not available.

We conduct extensive experiments on 6 IE tasks, including NER, RE, EE, Aspect-based Sentiment Analysis (ABSA), multi-span discontinuous NER and n-ary hyper RE. Our Mirror shows good compatibility across different tasks and datasets, and achieves competitive results on few-shot settings. Besides, 434M Mirror outperforms FlanT5-11B InstructUIE in zero-shot NER tasks.

Our contributions are summarized as follows:

- We propose a multi-task framework, namely Mirror, which can be trained on various IE tasks, including multi-span and n-ary extraction problems.
- We conduct extensive experiments on x IE tasks, and the results show that our model achieves state-of-the-art performance on most of the tasks.

2 Related Work

2.1 Multi-task Information Extraction

Multi-task IE is a popular research topic in recent years. The main idea is to use a single model to perform multiple IE tasks. IE tasks could be formulated as different graph structures. Li et al. (2022) formulate flat, nested, and discontinuous NER tasks as a graph with next-neighboring and tail-to-head connections. Maximal cliques also have been used to flat & discontinuous NER tasks (Wang et al., 2021) and trigger-available & trigger-free event extractions (Zhu et al., 2022). DyGIE++ takes NER, RE and EE tasks as span graphs, and apply iterative propagation to enhance spans’ contextual representations (Wadden et al., 2019). OneIE uses the similar graph structures with global constraint features (Lin et al., 2020). In addition to explicit

graph-based multi-task IE systems, generative language models are also been widely used. Yan et al. (2021b) and Yan et al. (2021a) add special index tokens into BART (Lewis et al., 2020) vocabulary to help perform various NER and ABSA tasks and obtain explicit span positions. TANL (Paolini et al., 2021) apply T5 (Raffel et al., 2020) to generate texts with special enclosures as the predicted information. GenIE (Josifoski et al., 2022) and DeepStruct (Wang et al., 2022) share a similar idea to generate subject-relation-object triplets, and DeepStruct extends the model size to 10B with GLM as the backbone (Du et al., 2022).

2.2 Schema-guided Information Extraction

In schema-guided IE systems, schemas are input as an guidance signal to help the model extracting target information. UIE (Lu et al., 2022) categorize IE tasks into span spotting and associating elementary tasks and devise a linearized query language. Fei et al. (2022) introduces the hyper relation extraction task to represent complex IE tasks like EE, and utilize external parsing tools to enhance the text representations. InstructUIE (Wang et al., 2023) formulates schemas into instructions and uses FlanT5-11B (Chung et al., 2022) to performing multi-task instruction tuning. While the above methods use flexible generative language models, they cannot predict exact positions, which brings ambiguity when evaluating. Besides, large generative language models are usually slow to train and inference, and requires tons of computing resources. USM (Lou et al., 2023) and UniEX (Lu et al., 2023) utilize BERT-family models to extract triplets non-autoregressively. USM regards IE tasks into a unified schema matching task and use a label-text matching model to extract triplets.

UniEX inherits the idea and uses a triaffine module to predict hyper-dimensional links. Beyond triplets extraction, RexUIE (Liu et al., 2023) perform to extract n-ary tuples step-by-step. Although RexUIE supports n-ary extraction, it sacrifices the efficiency and requires more time when predicting results (one slot per step).

3 Mirror

Text text text

3.1 Multi-span Cyclic Graph

Text text text

3.2 Unified Data Interface

Text text text

3.3 Model Framework

Similar to ?, we apply consecutive span link prediction. Differently, we use a separate split matrix to represent skip-link.

3.4 Pretraining

Text text text

4 Experiments

4.1 Experiment Setup

4.2 Datasets

4.3 Main Results

4.4 Few-shot Results

4.5 Zero-shot Results

4.6 Analysis on Training Strategies

4.7 Ablation Study

Limitations

Content input length and model compatibility. Multi-turn result modification. Laborious data cleaning and format unification.

Ethics Statement

All datasets are publicly available without further annotation, and the NLU tasks are traditional tasks in natural language processing communities. So there are no ethical issues.

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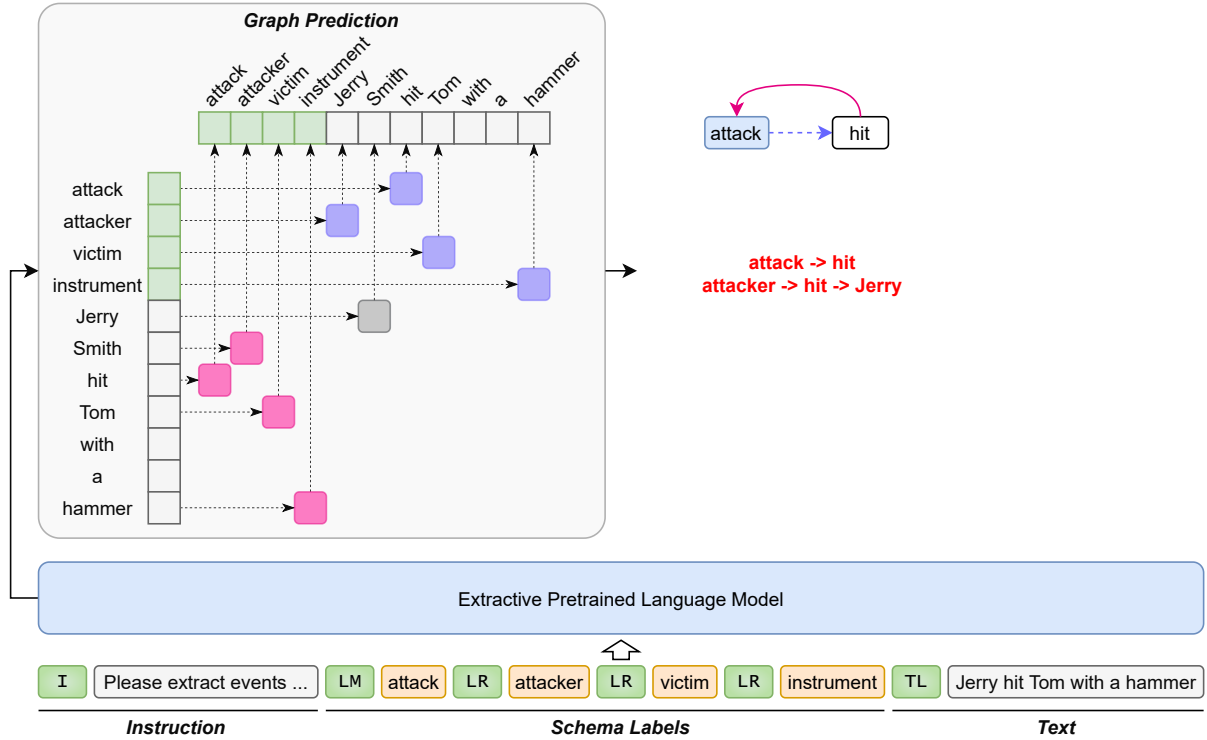


Figure 2: Model framework.

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Task	Datasets	TANL	UIE	DeepStruct	InstructUIE	USM	UniEX	RexUIE	Mirror
NER	ACE04	-	86.89	-	-	87.62	87.12	87.25	87.63
	ACE05	84.90	85.78	86.9	86.66	87.14	87.02	87.23	86.81
	CoNLL03	91.70	92.99	93	92.94	93.16	92.65	93.67	92.83
RE	ACE05	63.70	66.06	66.8	-	67.88	66.06	64.87	66.70
	CoNLL04	71.40	75.00	78.3	78.48	78.84	73.40	78.39	71.48
	NYT	-	93.54	93.3	90.47	94.07	-	94.55	91.66
	SciERC	-	36.53	-	45.15	37.36	38.00	38.37	36.08
Event	ACE05-Tgg	68.40	73.36	69.8	77.13	72.41	74.08	75.17	69.95
	ACE05-Arg	47.60	54.79	56.2	72.94	55.83	53.92	59.15	48.12
	CASIE-Tgg	-	69.33	-	67.80	71.73	71.46	73.01	69.19
	CASIE-Arg	-	61.30	-	63.53	63.26	62.91	63.87	55.09
ABSA	14-res	-	74.52	-	-	77.26	74.77	77.46	77.20
	14-lap	-	63.88	-	-	65.51	65.23	66.41	62.84
	15-res	-	67.15	-	-	69.86	68.58	70.84	68.82
	16-res	-	75.07	-	-	78.25	76.02	77.20	75.53

Table 2: Main results.

	P	R	F1
<i>Discontinuous NER: CADEC</i>			
BART-NER	70.08	<u>71.21</u>	70.64
W2NER	<u>74.09</u>	72.35	73.21
Mirror	74.83	67.88	<u>71.19</u>
<i>N-ary Tuples: HyperRED</i>			
CubeRE	66.39	67.12	66.75
RexUIE	-	-	75.20
Mirror	70.88	64.05	<u>67.29</u>

Table 3: Results on multi-span and n-ary information extraction tasks. The best results are in **bold**, and the second best results are underlined.

	Model	1-shot	5-shot	10-shot	Avg.
NER CoNLL03	UIE	57.53	75.32	79.12	70.66
	USM	71.11	<u>83.25</u>	<u>84.58</u>	79.65
	RexUIE	86.57	89.63	90.82	89.07
	Mirror	<u>77.50</u>	82.73	84.48	<u>81.57</u>
RE CoNLL04	UIE	34.88	51.64	58.98	48.50
	USM	<u>36.17</u>	<u>53.20</u>	<u>60.99</u>	<u>50.12</u>
	RexUIE	43.80	54.90	61.68	53.46
	Mirror	34.66	52.23	58.68	48.52
Event Trigger ACE05	UIE	42.37	53.07	54.35	49.93
	USM	40.86	55.61	58.79	51.75
	RexUIE	56.95	64.12	65.41	62.16
	Mirror	<u>49.50</u>	65.61	<u>60.68</u>	<u>58.60</u>
Event Arg ACE05	UIE	14.56	31.20	35.19	26.98
	USM	19.01	36.69	<u>42.48</u>	32.73
	RexUIE	30.43	<u>41.04</u>	45.14	38.87
	Mirror	<u>23.46</u>	48.32	41.90	<u>37.89</u>
ABSA 16res	UIE	23.04	42.67	53.28	39.66
	USM	30.81	<u>52.06</u>	58.29	47.05
	RexUIE	<u>37.70</u>	49.84	<u>60.56</u>	<u>49.37</u>
	Mirror	67.06	73.51	68.70	69.76

Table 4: Few-shot results. The best results are in **bold**, and the second best results are underlined.

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Model	Movie	Restaurant	AI	Literature	Music	Politics	Science	Avg.
Davinci	0.84	2.94	2.97	9.87	13.83	18.42	10.04	8.42
ChatGPT	<u>41.00</u>	37.76	54.40	<u>54.07</u>	61.24	<u>59.12</u>	63.00	52.94
USM	37.73	14.73	28.18	56.00	44.93	36.10	44.09	37.39
InstructUIE	63.00	<u>20.99</u>	49.00	47.21	53.61	48.15	49.30	47.32
Mirror	40.96	20.02	<u>51.13</u>	44.80	<u>60.63</u>	61.19	<u>53.65</u>	<u>47.48</u>
Upper Bound	85.94	83.30	65.72	67.93	78.25	75.92	70.96	75.43

Table 5: Zero-shot NER results. The best results are in **bold**, and the second best results are underlined. The upper bound is the Mirror performance where these zero-shot NER training sets are included in the pretraining phase.

A Dataset Statistics

test

This is a section in the appendix.