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Relation Extraction Method Based on Pre-trained LLM BERT

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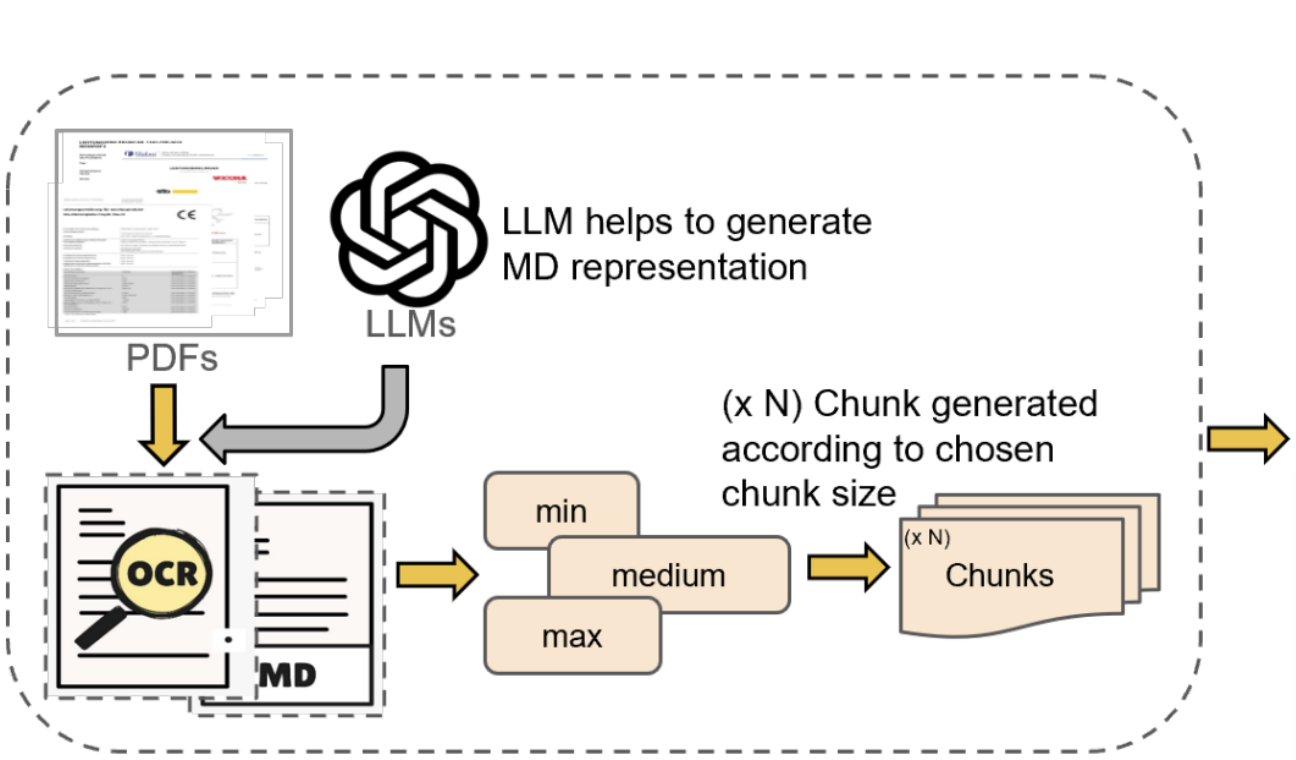
BERT

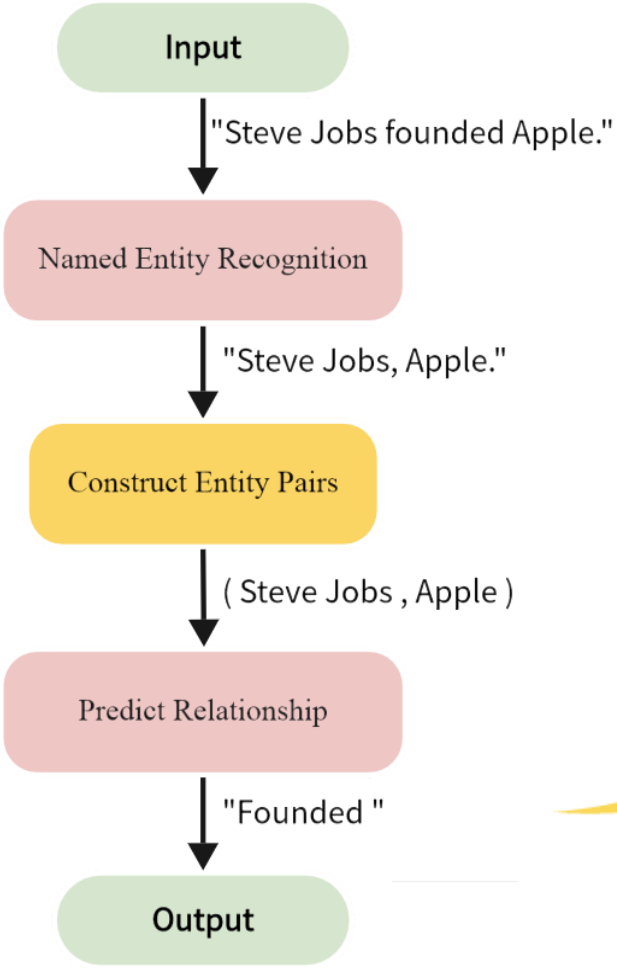
Introduction



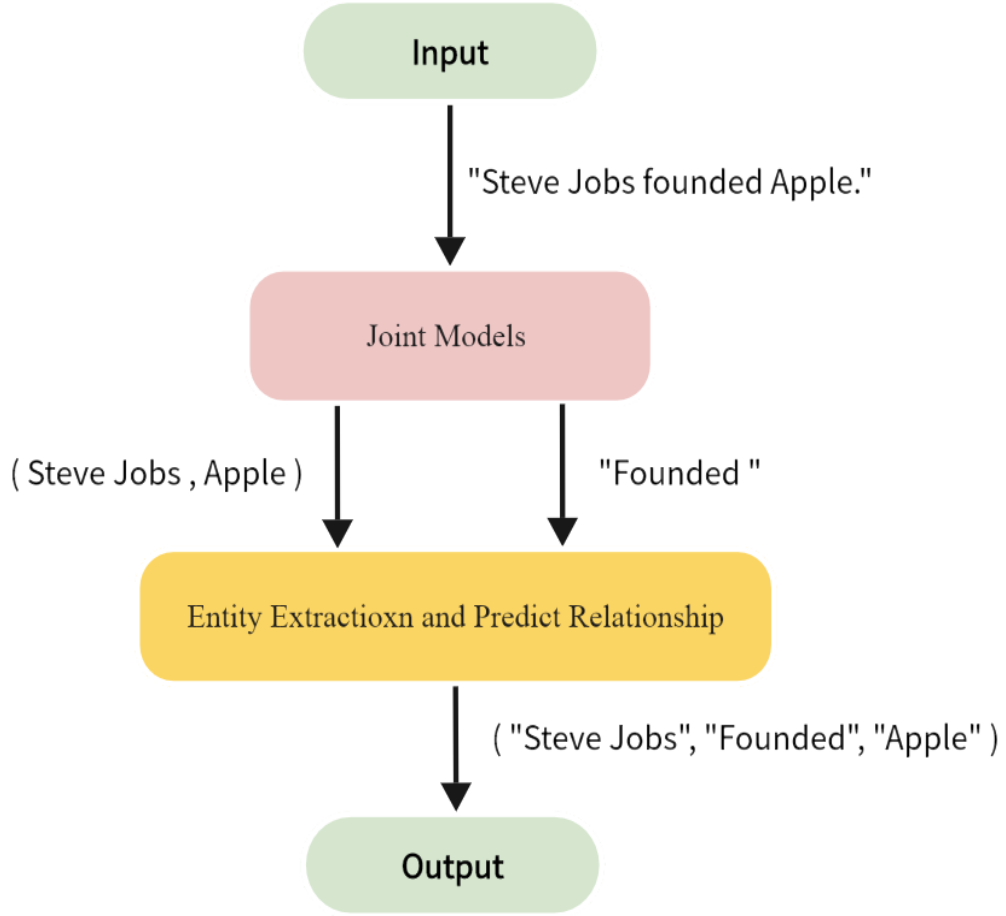
Named Entity Recognition

Relation Extraction

Introduction

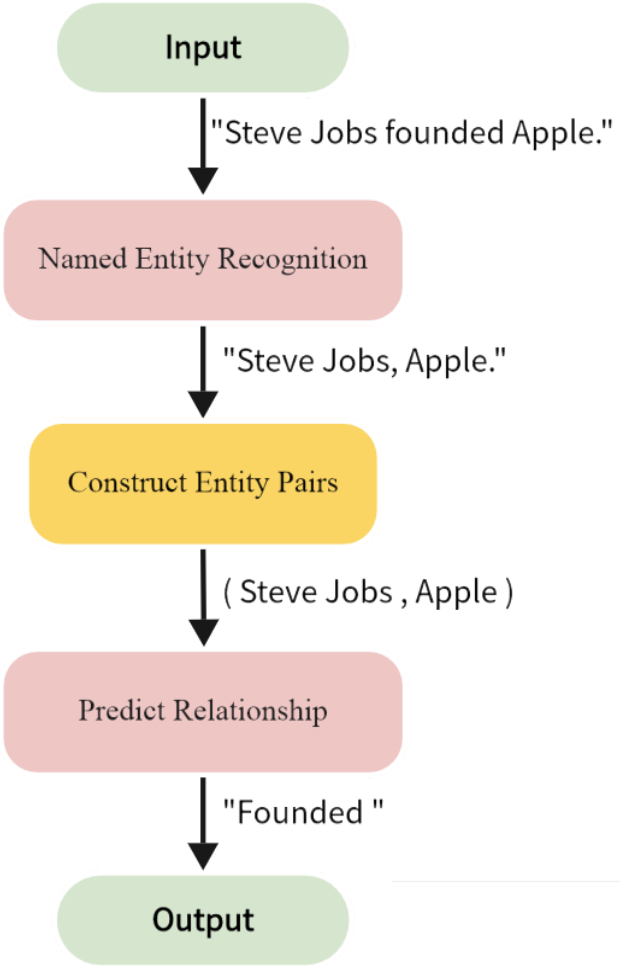


Pipeline-Based Methods

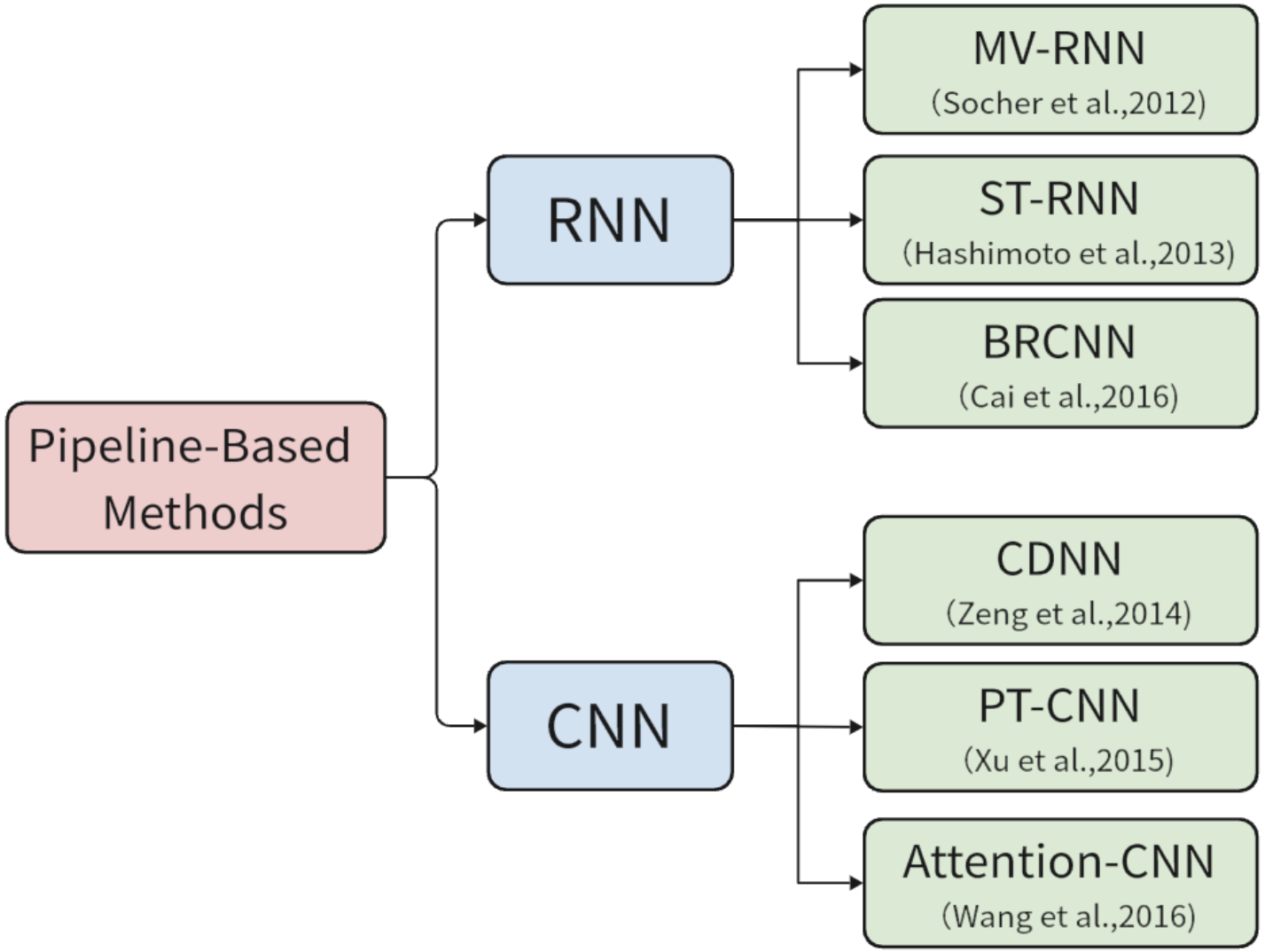


Joint Learning-Based Methods

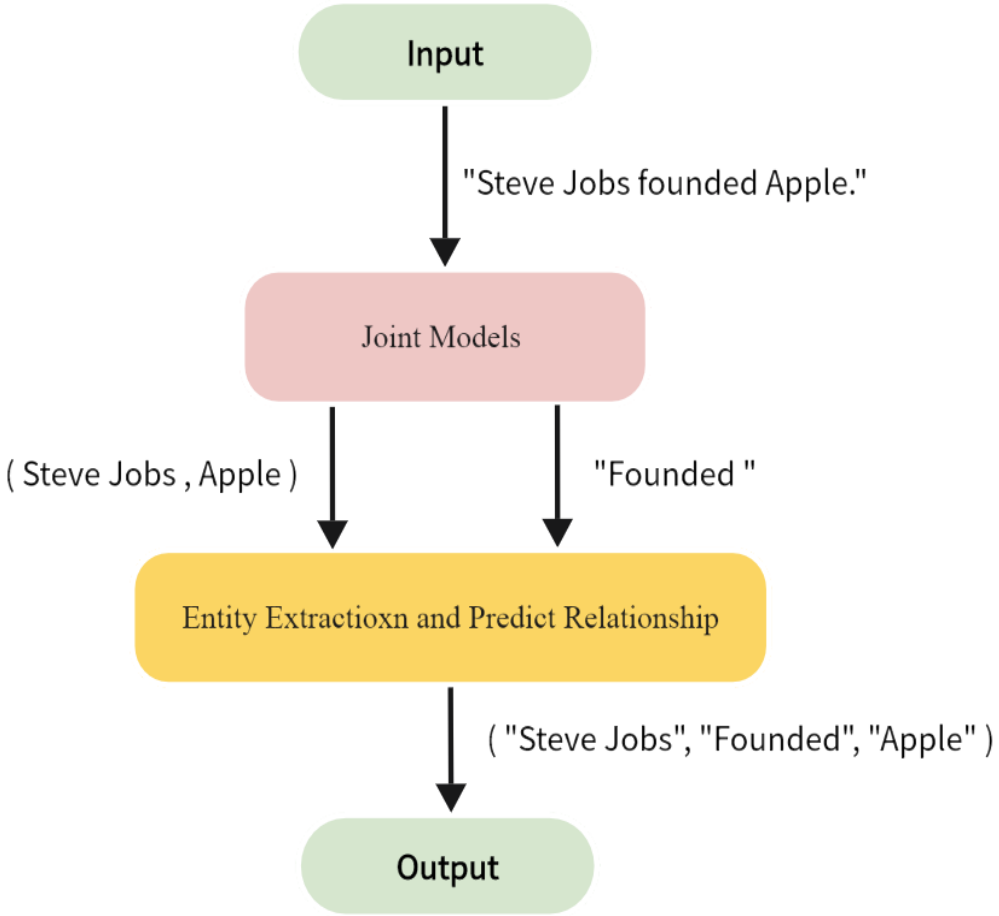
Related Work: Pipeline-Based Methods



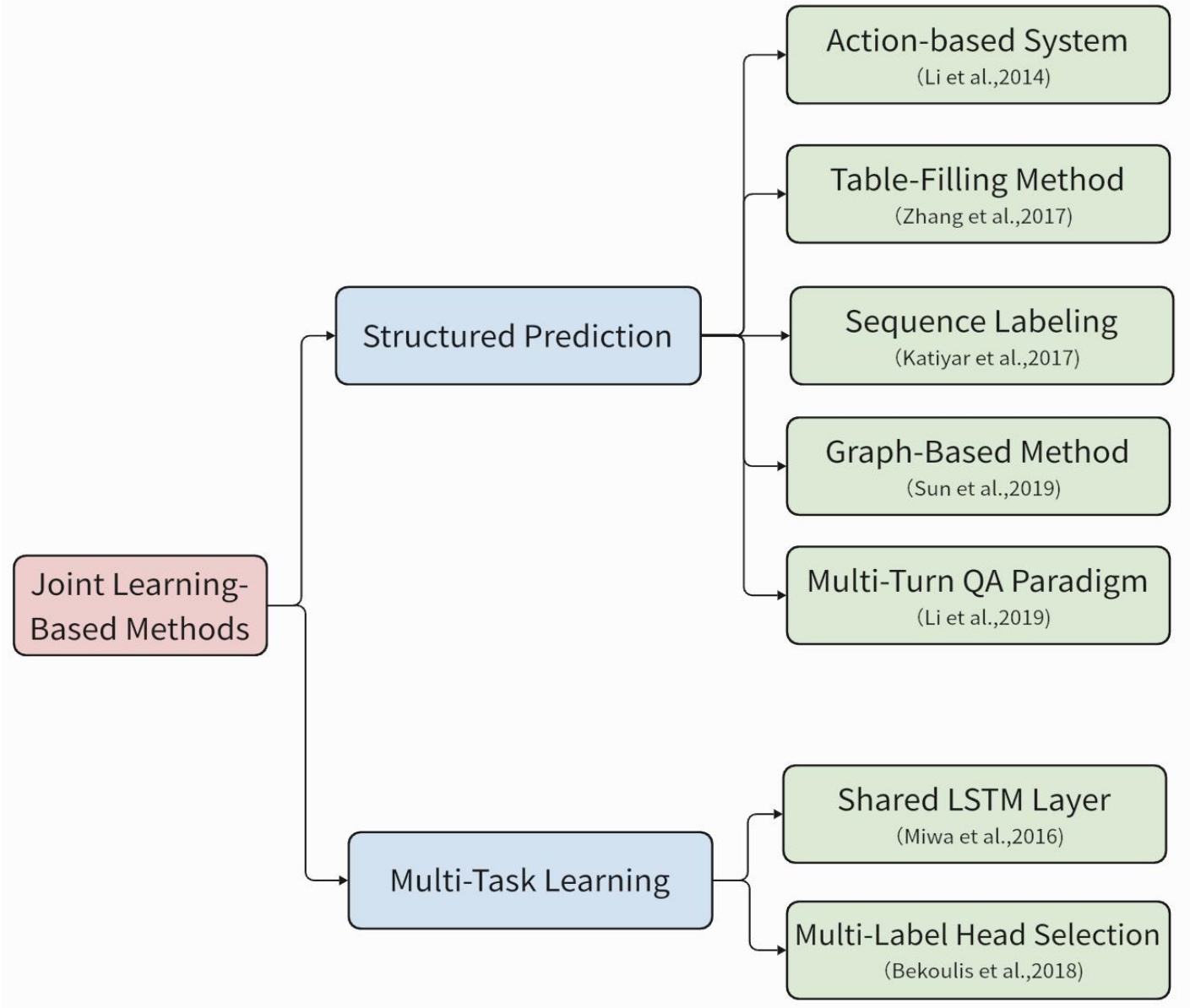
Pipeline-Based Methods



Related Work: Joint Learning-Based Methods



Joint Learning-Based Methods



Task Analysis

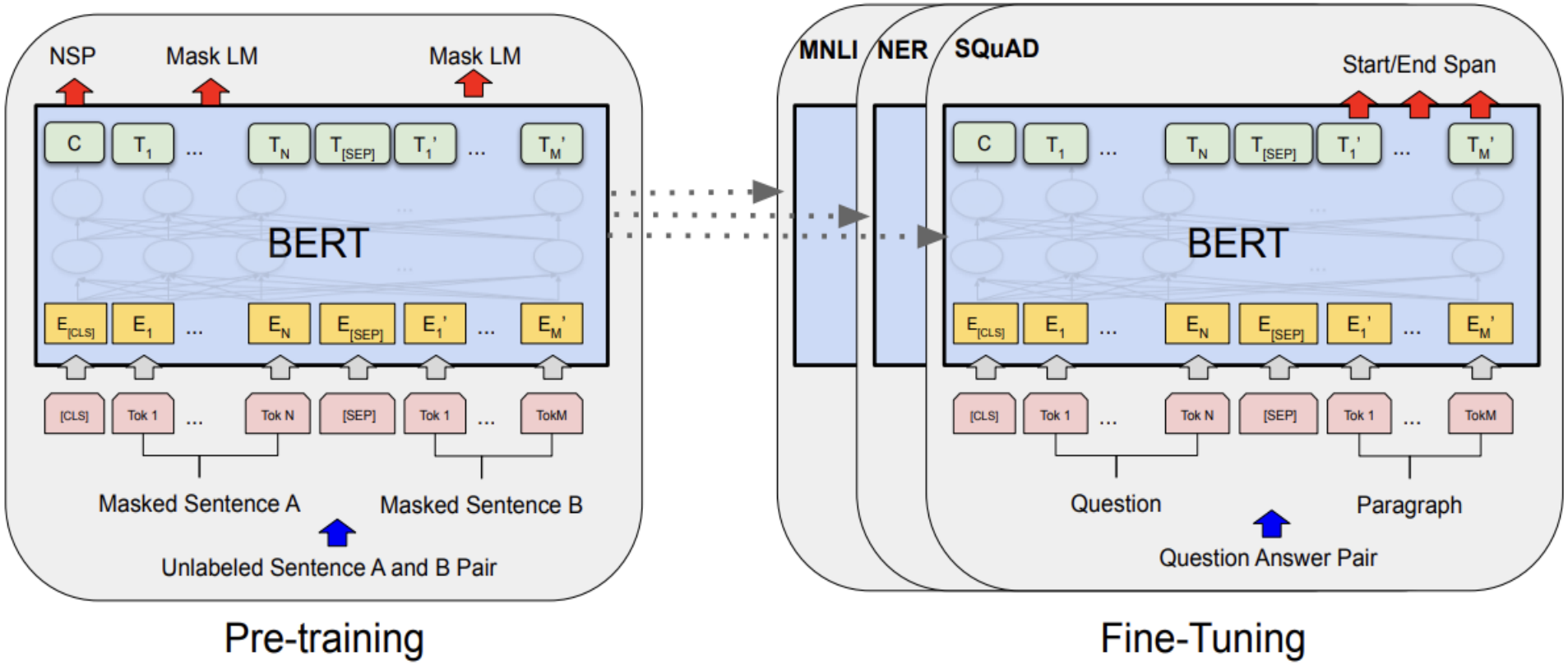
- **Objective:**
  Identify and classify different types of medical relationships from medical text in Chinese.

- **There are 10 relationship categories:**
  Clinical Manifestation, Drug Treatment, Synonym,Etiology,Complication, Pathological Subtype, Laboratory Test, Adjuvant Treatment, Related, and Imaging Test.

Example	
ID	2437
sentence	Food poisoning @ Fever may be caused by extragastrointestinal infection or overlapping infection.
(h)	Food Poisoning
(t)	stress ulcer
(r)	Etiology

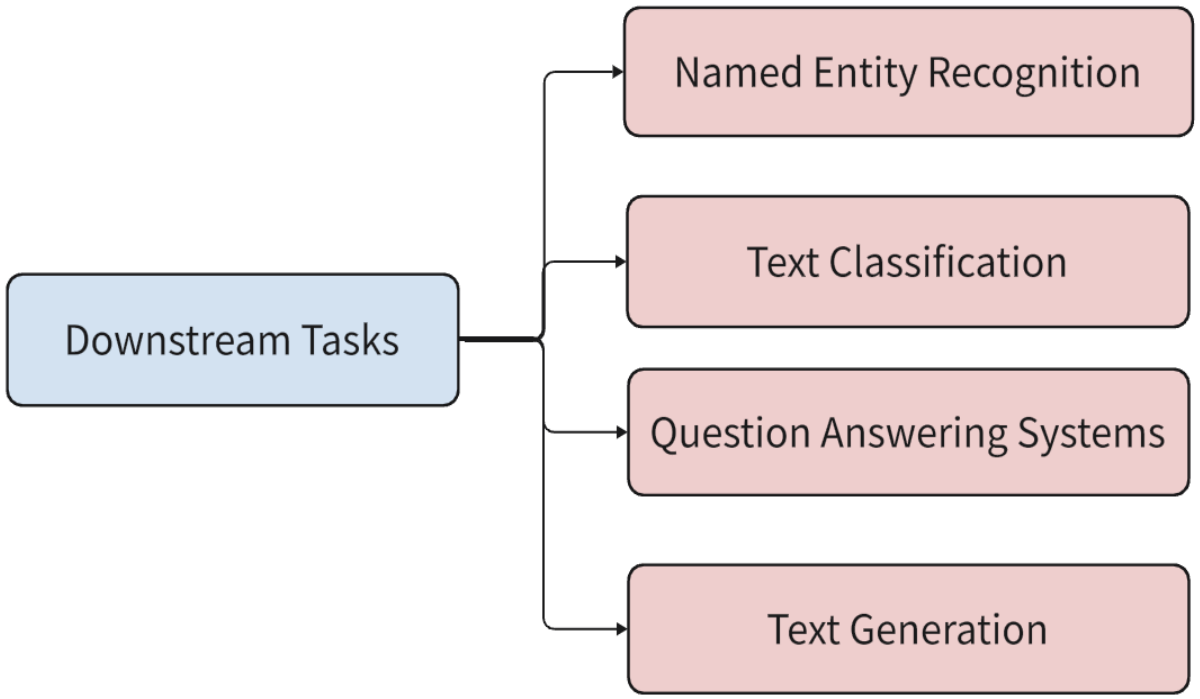
Table 1: Data Example. Each piece of data includes: Sentence, Head Entity (h), Tail Entity (t),and Relationship (r).

Method Description: Pre-trained LLM BERT

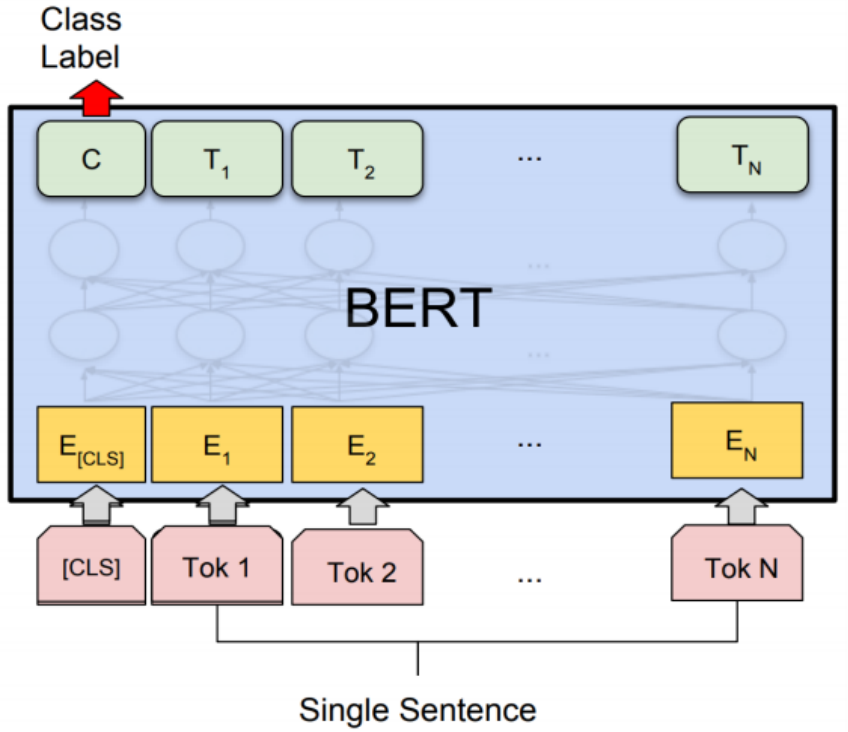


Overall pre-training and fine-tuning procedures for BERT.

Multiple Downstream Tasks of BERT

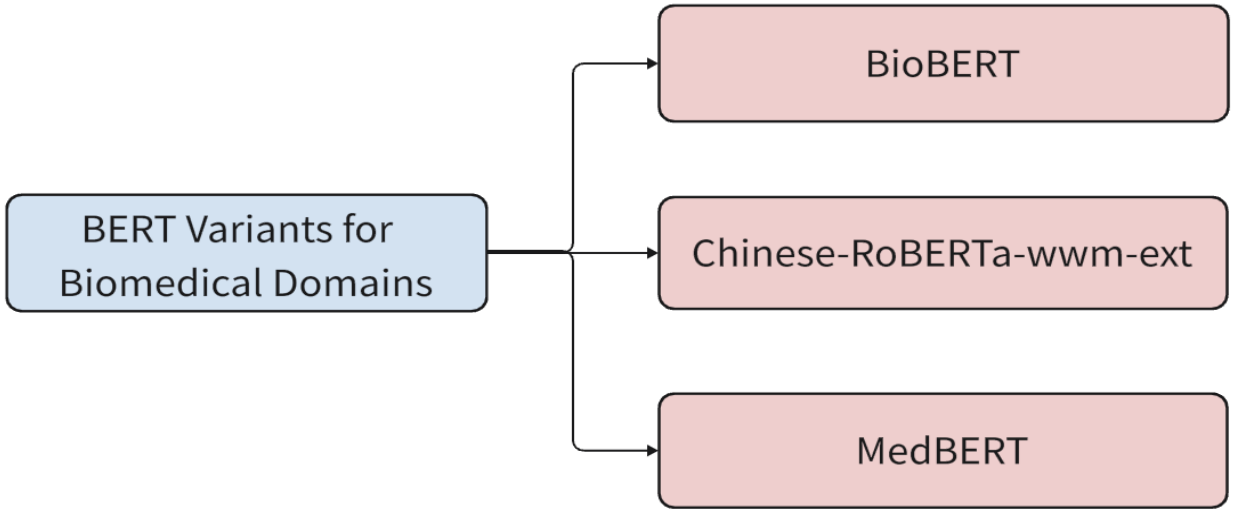


The four main categories of BERT's downstream tasks

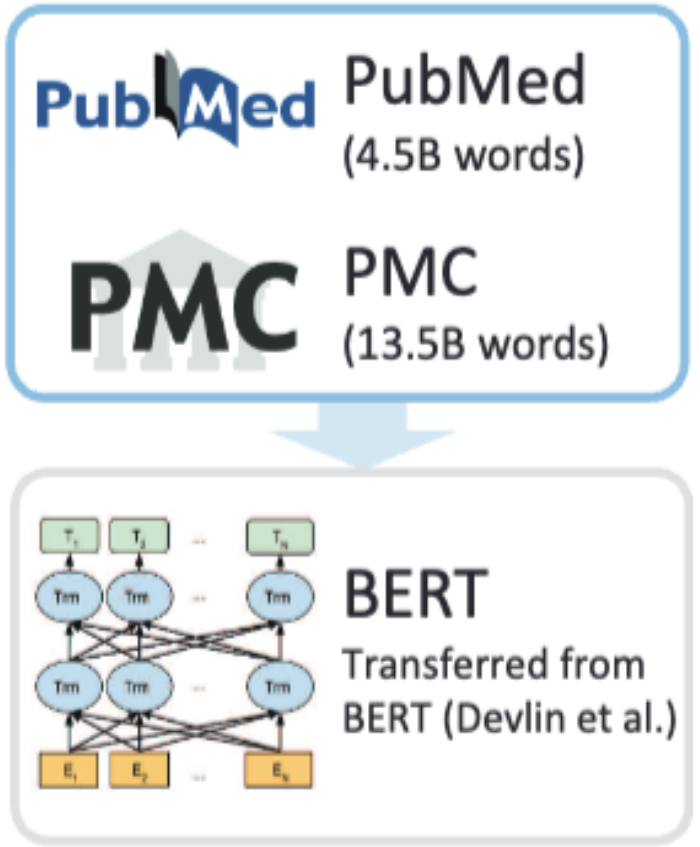


Text Classification

BERT Variants for Different Domains

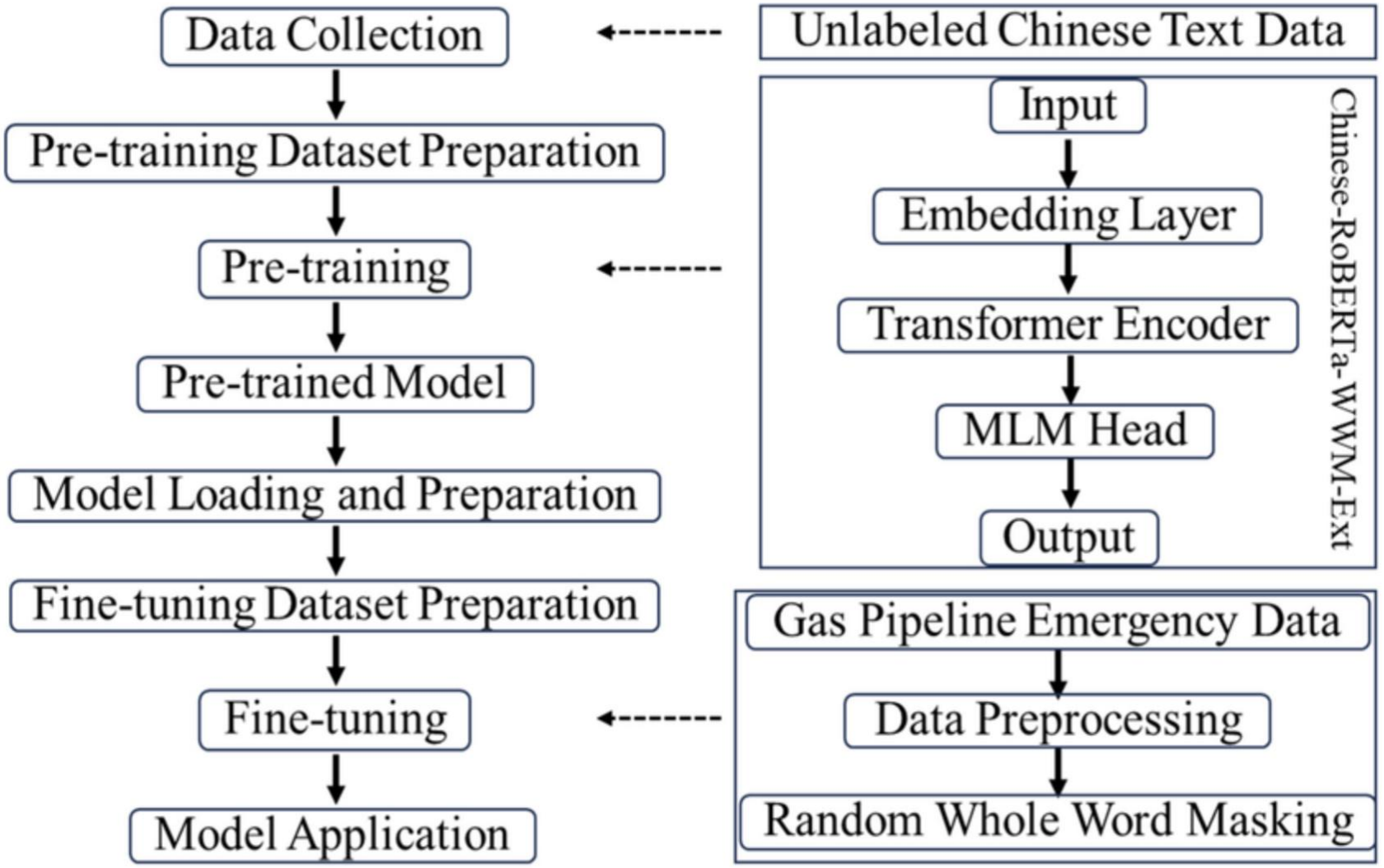


Three variants of BERT in the field of biomedicine



Flowchart

Chinese-RoBERTa-wwm-ext



Encoding schemes and Enhancement Strategy

Method	Pattern
Basic1	*[CLS] {h} [SEP] sentence [SEP] {t}*
Basic2	*[CLS] {h} [SEP] {t} [SEP] sentence*
QA	*[CLS] What is the relationship between {h} and {t}? [SEP] sentence*
Entity1[1]	*[CLS] s1 [E1] {h} [/E1] s2 [E2] {t} [/E2] s3 [SEP]*
Entity2[2]	*[CLS] s1 [Entity1] {h} [/Entity1] s2 [Entity2] {t} [/Entity2] s3 [SEP]*

Encoding schemes.
s1/2/3 denote sentence segments around entity spans.
1.Entity1 is Entity_marked1
2.Entity2 is Entity_marked2

- **We apply weak sample augmentation and weighted cross-entropy：**

$$\mathcal{L} = -\frac{1}{N}\sum_{n=1}^{N}\sum_{c=1}^{C}\omega_c\, y_c^{(n)} \log p_c^{(n)}$$

with class weights w emphasizing hard categories.

Results:Pretrained Model Comparison

- Scores of Chinese-RoBERTa-wwm-ext with Different Text Encoding Methods.

Model	BioBERT[1]	Chinese-RoBERTa[2]	MedBERT[3]
Macro-P	46.00%	**90.93%**	89.79%
Macro-R	36.30%	**90.20%**	88.70%
Macro-F1	30.80%	**90.24%**	88.80%
Micro-F1	46.28%	**90.46%**	89.25%

1.BioBERT : Entity_marked1
2.Chinese-RoBERTa : Entity_marked2
3.MedBERT : QA

Chinese-RoBERTa-wwm-ext achieved the highest score across all indicators.

Results:Encoding Strategy Impact

- Chinese-RoBERTa-wwm-ext performance under encoding variants.

	Macro-P	Macro-R	Macro-F1	Micro-F1
Basic1	88.94%	88.60%	86.71%	89.01%
Basic2	89.33%	88.00%	88.09%	88.46%
QA	89.23%	86.80%	87.06%	89.25%
Entity1[1]	88.34%	87.30%	87.60%	87.81%
Entity2[2]	**90.72%**	**90.20%**	**90.24%**	**90.46%**

1.Entity1 is Entity_marked1
2.Entity2 is Entity_marked2

The model achieved the highest overall score by using Entity_marked2 .

Results:Class Enhancement Effects

- Chinese-RoBERTa-wwm-ext respectively utilized weighted Loss and sample augmentation to improve the scores.

	Regular Loss	Weighted Loss	Variation
Macro-P	88.02%	89.62%	+1.60%
Macro-R	88.1%	88.60%	+1.70%
Macro-F1	87.01%	88.71%	+1.70%
Micro-F1	86.90%	89.01%	+2.11%
F1 Range	26.29%	18.01%	-8.28%

Weighted Loss.

	Weighted Loss	Weighted+Aug	Variation
Macro-P	89.62%	90.93%	+1.31%
Macro-R	88.6%	90.20%	+1.60%
Macro-F1	88.71%	90.24%	+1.53%
Micro-F1	89.01%	90.46%	+1.45%
F1 Range	18.01%	9.45%	-8.56%

Sample Augmentation

We further enhanced the model's performance on the weakly classified categories, and achieved significant improvements in overall accuracy and robustness.

Conclusion

- The experimental results show that the model based on Chinese-RoBERT a-wwm-ext ***performs exceptionally well*** in the relation classification task.
- Compared with other pre-trained models, our method has increased the ***Micro-F1 value by 44.18% and 1.21%*** respectively, verifying the significance of ***domain-specific optimization and entity marking methods*** in this task.
- We also effectively alleviated the problem of difficult categories through the ***category enhancement strategy***, further improving the model's performance in categories that are difficult to distinguish.
- This research provides a method for extracting relationships in ***Chinese medical texts***, and it has high practical application value.

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This project referred to a total of 34 references. Due to space constraints, we will not list them all in this presentation. For the full list, please refer to the report.

Acknowledgments

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