

EK-BERT: An Enhanced K-BERT Model for Chinese Sentiment Analysis

Huan Bai, Daling Wang, Shi Feng, Yifei Zhang

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Introduction

- For Chinese sentiment analysis, historical stories and fables give rich connotations to words. Local attention can make the model focus on special areas.

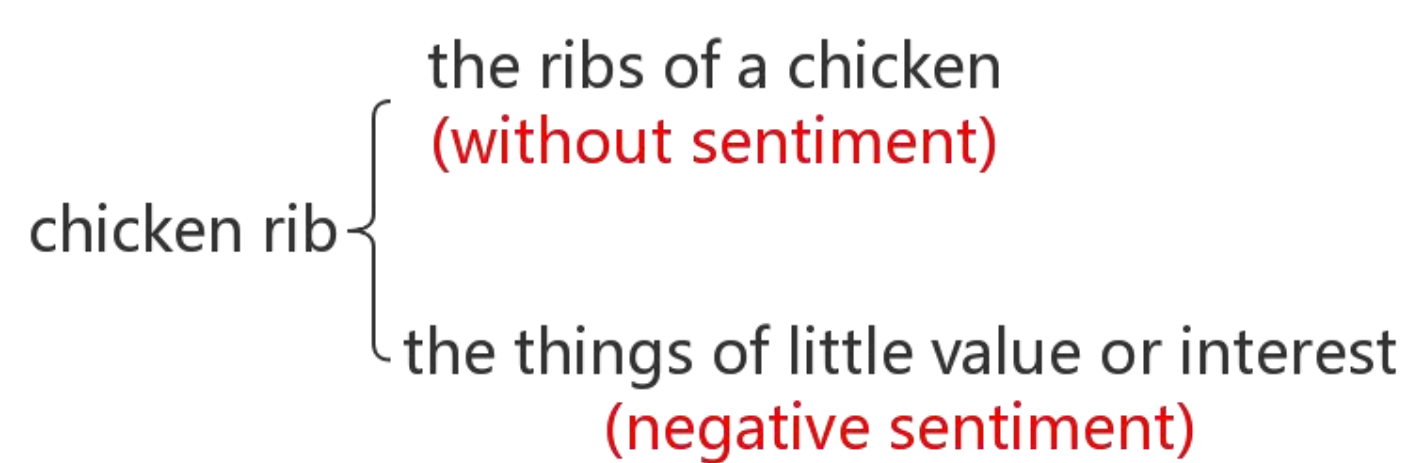


Fig.1 An example of polysemy in Chinese.

- We propose EK-BERT to improve the K-BERT model. EK-BERT uses sentiment knowledge graph to acquire domain knowledge, type-embedding to learn knowledge more effectively and local attention mechanism to improve the understanding ability of natural language.

Approach

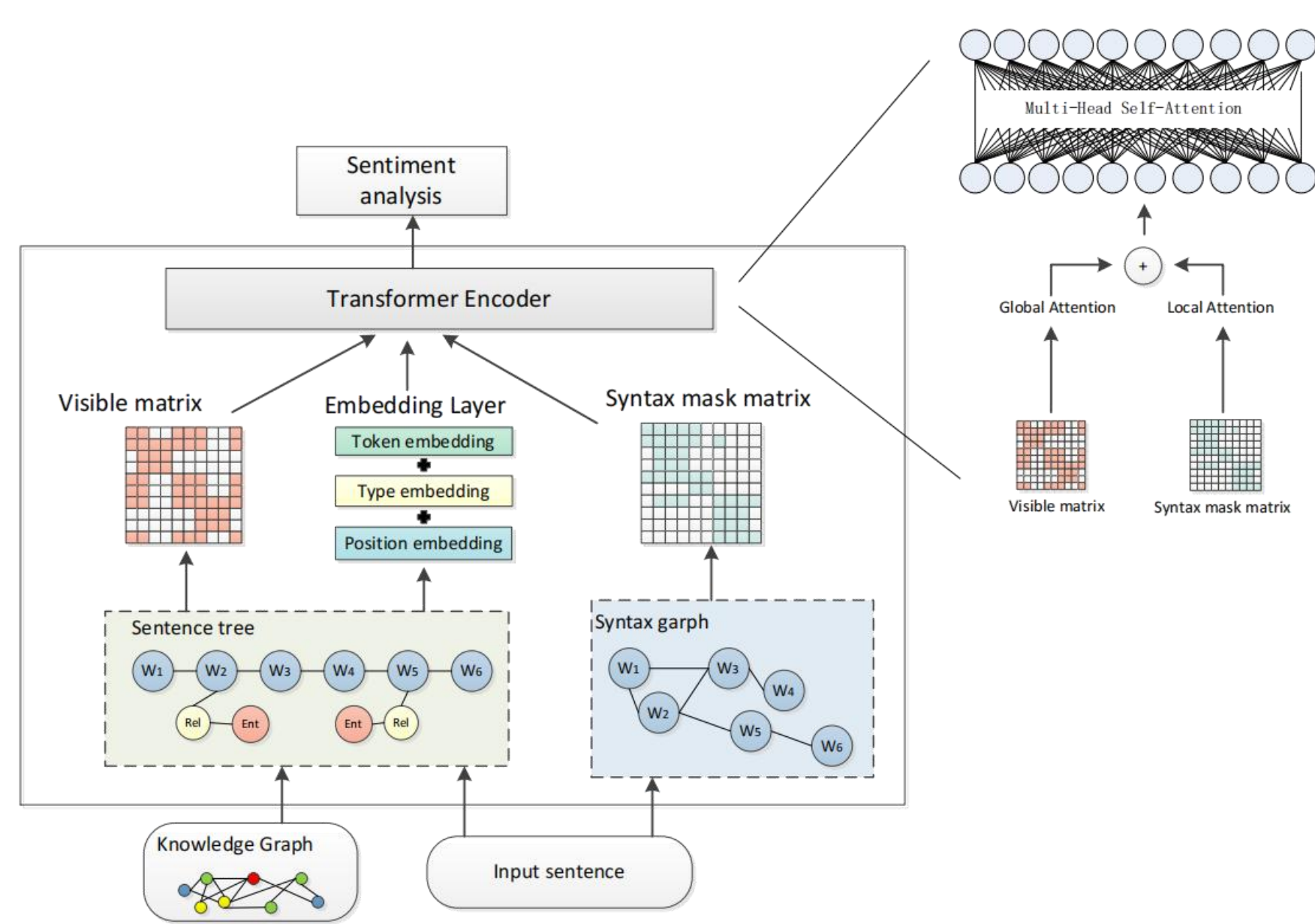


Fig.2 Overall structure of EK-BERT.

- Sentiment Knowledge Graph.** We combine four emotional dictionaries and reclassify these emotional words to get the last available sentiment word set. Then, we construct a sentiment knowledge graph using the sentiment word set and call it as Sen-Graph.

- Embedding Layer.** Inspired by CoLAKE, EK-BERT divides the input into two types: word and knowledge, and uses type embedding to distinguish ordinary text from knowledge. That is, the embedding layer of EK-BERT consists of token embedding, type embedding and position embedding.
- Local Attention.** We use SLA to modify attention mechanism of EK-BERT. By combining syntax-based local attention with global attention, the model pays more attention to syntactically related words. The syntactic structure of the input text is obtained by using Chinese syntactic analysis tool and treated as an undirected graph.

Result

- We compare the results of multiple models on two datasets and three graphs. EK-BERT does achieve better performance.

Table 1. Results of various models on Chinese sentiment analysis task. We use the abbreviations "HN", "CN", and "Sen" to represent the HowNet, CN-DBpedia, and Sen-Graph knowledge graphs respectively.

| Model\Datasets | Chinese_metaphor | | Book_excerpt | |
|--------------------|------------------|---------------|---------------|---------------|
| | Acc | F1 | Acc | F1 |
| BERT | 87.24% | 88.74% | 87.90% | 87.77% |
| RoBERTa | 88.12% | 89.47% | 87.50% | 87.26% |
| ERNIE | 87.02% | 88.86% | 85.69% | 85.28% |
| K-BERT(HN) | 86.47% | 87.76% | 89.30% | 59.33% |
| K-BERT(CN) | 86.25% | 87.90% | 89.60% | 89.28% |
| K-BERT(HN+Sen) | 87.90% | 88.96% | 90.10% | 90.03% |
| K-BERT(CN+Sen) | 87.02% | 88.54% | 89.60% | 89.52% |
| EK-BERT(HN+Sen) | 88.12% | 89.72% | 90.80% | 90.89% |
| EK-BERT(CN+Sen) | 87.35% | 88.78% | 90.80% | 90.78% |
| EK-BERT(HN+CN+Sen) | 87.46% | 89.10% | 89.50% | 89.45% |

Conclusion

- EK-BERT achieves better performance results than baseline models on Chinese sentiment analysis task and does not require retraining.
- In future work, we will further investigate the influence of sentiment knowledge on other PLMs.

Supplement

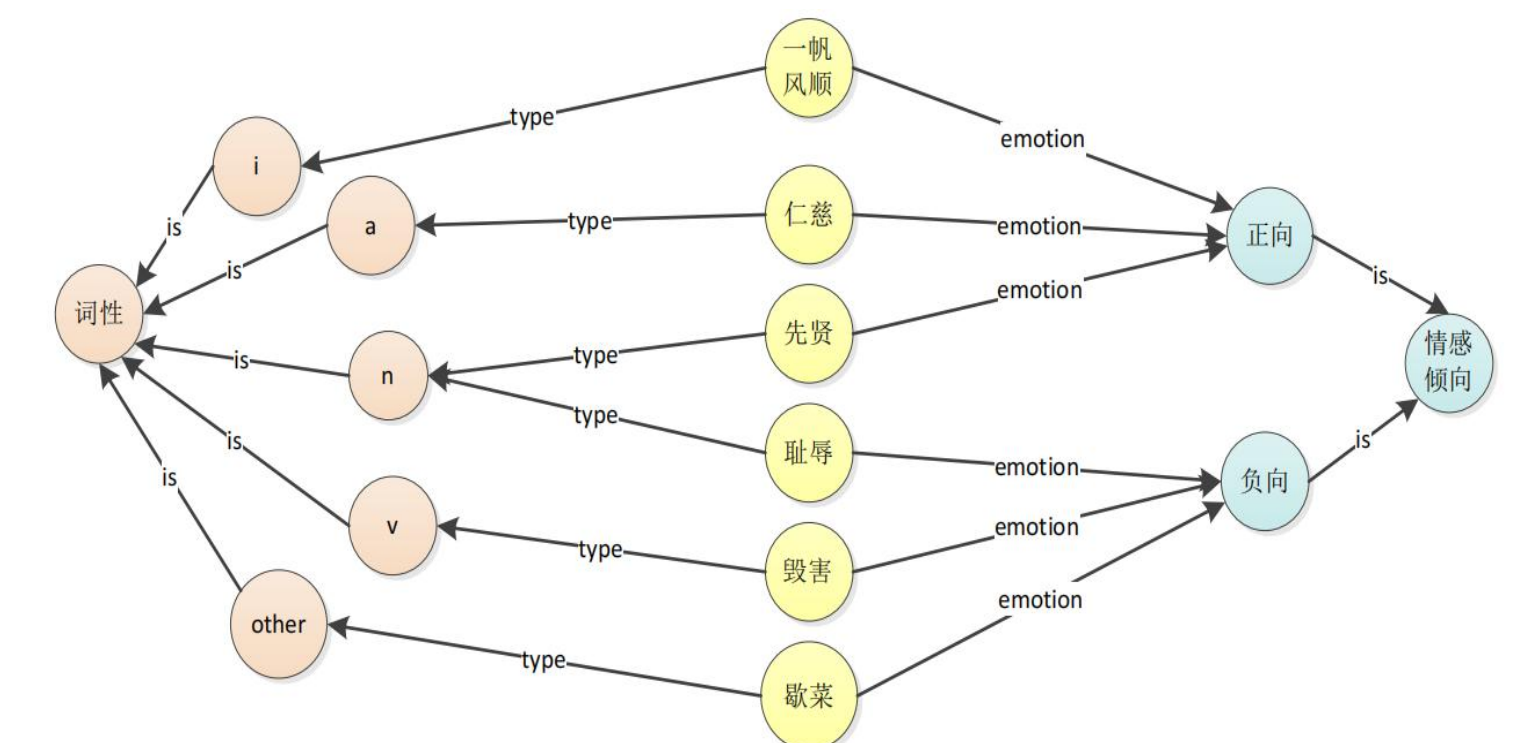


Fig.1 Part of sentiment knowledge graph Sen-Graph.

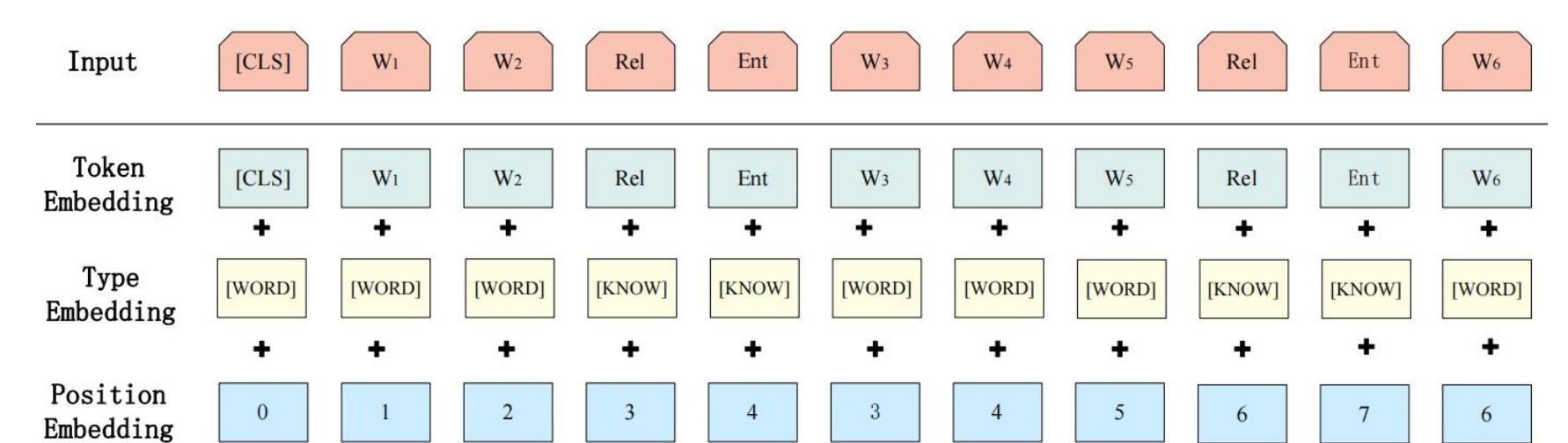


Fig.2 Embedding Layer of EK-BERT.

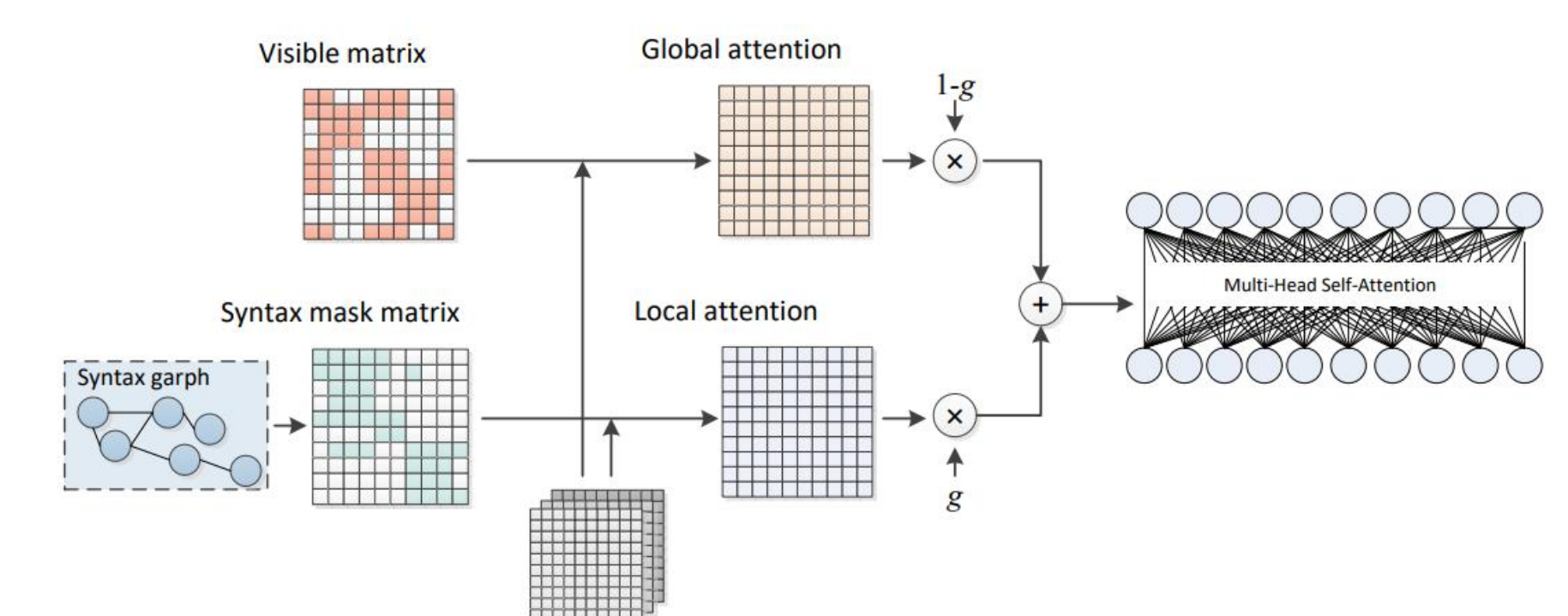


Fig.3 The attention mechanism of EK-BERT.

Table 1. Results of ablation experiments. We use the abbreviations "HN", "CN", and "Sen" to represent the HowNet, CN-DBpedia, and Sen-Graph knowledge graphs respectively. Moreover, we use "-x" to represent the EK-BERT model without x.

| Model\Datasets | Chinese_metaphor | | Book_excerpt | |
|------------------|------------------|---------------|---------------|---------------|
| | Acc | F1 | Acc | F1 |
| EK-BERT(HN+Sen) | 88.12% | 89.72% | 90.80% | 90.89% |
| -Local attention | 86.25% | 87.92% | 90.40% | 90.30% |
| -Type embedding | 87.93% | 86.50% | 90.90% | 90.91% |
| -Sen | 87.02% | 88.50% | 88.80% | 88.93% |
| EK-BERT(HN+Sen) | 87.35% | 88.78% | 90.80% | 90.78% |
| -Local attention | 86.03% | 87.63% | 89.40% | 89.31% |
| -Type embedding | 85.59% | 87.37% | 89.30% | 89.46% |
| -Sen | 86.25% | 88.13% | 89.70% | 89.56% |