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Benchmarking Knowledge-Enhanced Commonsense Question Answering via Knowledge-to-Text Transformation Ning Bian, Xianpei Han, Bo Chen, Le Sun Institute of Software, Chinese Academy of Sciences, Beijing, China

1. Introduction

Commonsense Question Answering (CQA): Answering questions whose answers rely on commonsense knowledge.

Try to Answer Three Important Questions:

Q1: How far can we get by exploiting external knowledge for CQA?

Q2: How much potential of knowledge has been exploited in current CQA models?

Q3: Which are the most promising directions for future CQA?

2. Knowledge-to-Text CQA Model



Answer to Q1: By incorporating golden external knowledge, CQA can be significantly improved and can achieve close-to-human performance.

3. Benchmarking Experiments

Answer to Q2: The potential of knowledge is still far from being fully exploited by current knowledgeenhanced CQA methods:

1) Current knowledge-enhanced CQA methods only exploit knowledge to a limited extent.

2) Despite the effectiveness of our method, there is still great potential in generating accurate question-relevant knowledge descriptions.

3) The commonsense knowledge embedded in current pretrained language models is still not enough for CQA.

| i l | | | | | |
|-----|------------|----------|-----------|---------------|------------|
| | Models | WSC | HellaSWAG | SOCIAL IQa | ← |
| _ ' | BERT | 66.0 | 42.3 | 66.2 | Accuracies |
| | +Knowledge | 68.1 | 44.2 | 68.8 | on other |
| | RoBERTa | 81.4 | 82.5 | 74.3 | COA |
| n | +Knowledge | 82.5 | 83.0 | 75.0 | datasets |
| | ALBERT | 84.9 | 86.1 | 77.2 | aatabetb |
| | +Knowledge | 87.0 | 86.9 | 77.8 | |
| | Human | 92.1 | 94.5 | 86.9 | |
| X | KLNet Ro | BERTa | ALBERT | 1 | |
| | 88.0 | <u> </u> | 88.0 | T7 1 1 | |

| Model | Knowledge Source | BERT | XLNet | RoBERTa | ALBERT | |
|---------------------------|-------------------------|------------------|------------------|---------------|---------------|----------------------------|
| Human | | 88.9 | 88.9 | 88.9 | 88.9 | Knowledge-to-text |
| Golden Knowledge | Human Explanations | 81.1 | 85.1 | 84.7 | 83.7 | transformation is |
| Knowledge-to-Text | | | | effective and | | |
| Template-based | ConceptNet | 67.9 | 77.5 | 78.1 | 81.1 | robust for |
| Paraphrasing-based | ConceptNet | 67.2 | 74.9 | 77.8 | 79.3 | knowledge- |
| Retrieval-based | ConceptNet | 65.0 | 75.0 | 77.1 | 79.4 | enhanced CQA. |
| Full | ConceptNet | 70.4 | 80.3 | 80.8 | 83.3 | |
| Best Knowledge-enhanced | ConcentNet | 69.0 | 79.3 | 80.8 | (No available | \leftarrow Accuracies on |
| System with Different PLM | Conceptivet | (Ma et al. 2019) | (Lv et al. 2019) | (KEDGN) | model so far) | |
| Base Model | No knowledge | 63.6 | 68.9 | 76.2 | 78.6 | CommonsenseQA |

4. Conclusions (Answer to Q3)

(1) Context-sensitive knowledge selection is critical for knowledge-enhanced CQA. (2) The knowledge-text heterogeneity is a critical bottleneck for exploiting the information from both knowledge and text.

(3) It is valuable to incorporate more commonsense in pretrained language models.

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