Cross-lingual Inference With a Chinese Entailment Graph

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Motivating Example

Previous work on Chinese Open Relation Extraction has been based on dependency parsers [3]. They have been less than satisfactory in delivering a comprehensive coverage of the rich set of relation patterns supported by the syntax of Chinese.

We also build our ORE method upon a SOTA dependency parser (specifically, DDParse [4]), but provide a much wider coverage of relations. Some patterns we additionally cover are exemplified below (in amber are subjects, in blue are predicates, in green are objects, in black are words irrelevant to relations):

- **A. PP Modifiers with DE Structures:**
  - Direct: 明晃晃的(left) Therapist(right) 父母的决定 (cause)
  - Ours: 明晃晃的(left) Therapist(right) 父母的决定 (cause)

- **B. Bounded Dependencies:**
  - Direct: 我（去-going）诊所（clinic） 打(take) 疫苗(vaccine).
  - Ours: 我（去-going）诊所（clinic） 打(take) 疫苗(vaccine).

- **C. Relative Clauses:**
  - Direct: 他(he) 解决了(solved) 困扰(puzzle) 大家(everyone) 的(de) 问题(problem)
  - Ours: 他(he) 解决了(solved) 困扰(puzzle) 大家(everyone) 的(de) 问题(problem)

- **E. Cope with Covert Objects:**
  - Direct: 设备(device) 是(is) 木头(wood) 做(made) 的(de).
  - Ours: 设备(device) 是(is) 木头(wood) 做(made) 的(de).

Chinese Open Relation Extraction

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Chinese Fine-Grained Entity Typing

- Purpose: entity type-pair for the subject and object of a predicate is used as the type of the predicate!
- Choice of type ontology: 1) sufficiently enough to disambiguate predicate context; 2) populous enough to host meaningful entailment subgraphs; 3) similar to English entailment graph to allow for alignment in the future.
- Method: we adapt an ultra-fine-grained entity typing dataset in Chinese (CFET) [5] to the FIGER ontology via label mapping (we refer to the resulting dataset as CFIGER); we train SOTA entity typing models on the CFIGER dataset, and use them to type the arguments of relations we retrieve from the Webhose corpus.

Experiments and Results

- For the construction of Chinese entailment graph, we use the Webhose Chinese News Corpus, containing ~314,000 articles and 5M sentences.
- We evaluate Chinese entailment graph against the Levy/Holt dataset through machine translation: Levy/Holt dataset consists of premise-hypothesis relation pairs, where each relation comes as a subject-predicate-object triple; we treat each triple as a short sentence and translate it into Chinese, then we re-parse each translated sentence back into a Chinese relation triple with our ORE method.
- We evaluate the cross-lingual complimentarity of Chinese and English [6] entailment graphs (EGc and EGc respectively) via an ensemble: for each Levy/Holt entry, we have the English entailment score from the original entry, and the Chinese entailment score from the entry's Chinese translation. We then ensemble the two scores by MAX, AVG or in lexicographic order, where the results are listed in the table below with the prefix "Ensemble": the SOTA English entailment graph built with the method of Contextual Link Prediction [7] is suffixed with "++".

<table>
<thead>
<tr>
<th>AUC (%)</th>
<th>dev</th>
<th>test</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT</td>
<td>5.5</td>
<td>3.2</td>
</tr>
<tr>
<td>Jia (2018)</td>
<td>0.9</td>
<td>2.4</td>
</tr>
<tr>
<td>DDPOR</td>
<td>9.8</td>
<td>5.9</td>
</tr>
<tr>
<td>EGc *</td>
<td>16.1</td>
<td>9.1</td>
</tr>
<tr>
<td>EGc++</td>
<td>20.7</td>
<td>16.5</td>
</tr>
<tr>
<td>EGc+++ (2021)</td>
<td>23.3</td>
<td>19.5</td>
</tr>
<tr>
<td>Ensemble En Zh</td>
<td>27.9 (γ: 0.5)</td>
<td>20.8</td>
</tr>
<tr>
<td>Ensemble Zh En</td>
<td>27.5 (γ: 0.5)</td>
<td>21.0</td>
</tr>
<tr>
<td>Ensemble MAX</td>
<td>29.8 (γ: 0.5)</td>
<td>21.6</td>
</tr>
<tr>
<td>Ensemble AVG</td>
<td>29.8 (γ: 0.3)</td>
<td>21.7</td>
</tr>
<tr>
<td>Ensemble++ AVG</td>
<td>31.2 (γ: 0.1)</td>
<td>24.0</td>
</tr>
<tr>
<td>EGc++-type *</td>
<td>11.1</td>
<td>7.0</td>
</tr>
</tbody>
</table>

Chinese entailment graphs built with our ORE method substantially outperforms other methods, and the ensemble of Chinese and English entailment graphs sets a new SOTA, with an 4.5 AUC point improvement upon previous best.

References