INTRODUCTION

Relation extraction has been widely used for finding unknown relational facts from plain text. Most existing methods focus on exploiting mono-lingual data for relation extraction, ignoring massive information from the texts in various languages.

1. Consistency. A relational fact is usually expressed with certain patterns in various languages, and the correspondence of these patterns among languages is substantially consistent.

<table>
<thead>
<tr>
<th>Relation</th>
<th>City in</th>
</tr>
</thead>
<tbody>
<tr>
<td>English</td>
<td>New York is a city in the northeastern United States.</td>
</tr>
<tr>
<td>Chinese</td>
<td>纽约是美国东海岸的东部分支港口, 是美国第一大城市及第一大港。 (New York is in the United States New York and on the Atlantic coast of the southeast Atlantic, is the largest city and largest port in the United States.)</td>
</tr>
</tbody>
</table>

Fig 1: An example of Chinese sentences and English sentence about the fact (New York, CityOf, United States)

1. Complementarity. The texts in different languages can be complementary to each other, especially from those resource-rich languages to resource-poor languages.

In this paper, we introduce a multi-lingual neural relation extraction (MNRE) framework, which employs mono-lingual attention to utilize the information within mono-lingual texts and further proposes cross-lingual attention to consider the information consistency and complementarity among cross-lingual texts.

METHOD

The MNRE framework contains two main components:

1. Sentence Encoder. Given a sentence and two target entities, we employ CNN to encode relation patterns in the sentence into a distributed representation.

2. Multi-lingual Attention. We apply mono-lingual and cross-lingual attentions to capture those informative sentences with accurate relation patterns.

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Fig 2: Overall architecture of our multi-lingual attention which contains two languages including English and Chinese

Experiments

1. Effectiveness of Consistency

Fig 3: Aggregated precision/recall curves of CNN-En, CNN-Zh, CNN+joint, CNN+share, and MNRE.

Discuss: MNRE model can successfully improve multi-lingual relation extraction by considering pattern consistency among languages. In the study case, MNRE can identify the second and fourth sentences that unambiguously express the relation PlaceOfBirth with higher attention.

<table>
<thead>
<tr>
<th>MNRE</th>
<th>Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1. Barzun is a commune in the Pyrénées-Atlantiques department in the Nouvelle-Aquitaine region of south-western France.</td>
</tr>
<tr>
<td>High</td>
<td>2. Barzun was born in Créteil, France.</td>
</tr>
</tbody>
</table>

Discuss: by jointly training with multi-lingual attention, both Chinese and English relation extractors are beneficial from those sentences from the other language.

2. Effectiveness of Complementarity

Fig 4: An example of our multi-lingual attention.

Fig 5: Aggregate precision/recall curves of CNN-En, CNN-Zh, MNRE-En and MNRE-Zh.

Discuss: by jointly training with multi-lingual attention, both Chinese and English relation extractors are beneficial from those sentences from the other language.

CONCLUSION

In this paper, we introduce a neural relation extraction framework with multi-lingual attention to consider pattern consistency and complementarity among multiple languages. We evaluate our framework on multi-lingual relation extraction task, and the results show that our framework can effectively model relation patterns among languages and achieve state-of-the-art results.