

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.

Relation	City in
English	1. New York is a city in the northeastern United States .
Chinese	1. 纽约 位于美国纽约州东南部大西洋沿岸, 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 .) 2. 纽约 是美国人口最多的城市. (New York is the most populous city in the United States)

Fig1: 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.

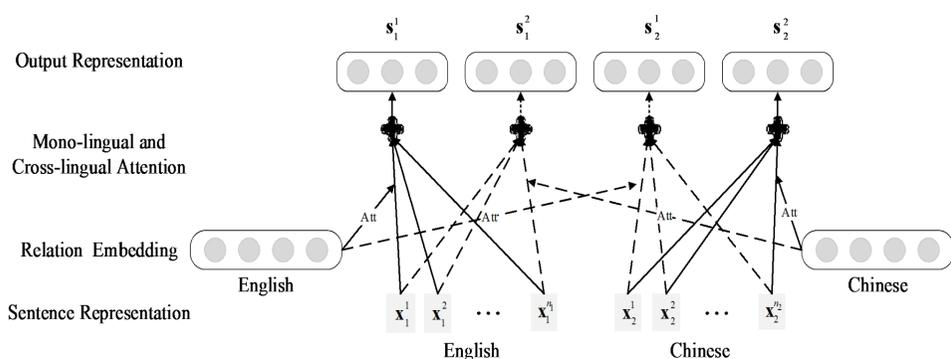


Fig2: Overall architecture of our multi-lingual attention which contains two languages including English and Chinese

Experiments

1. Effectiveness of Consistency

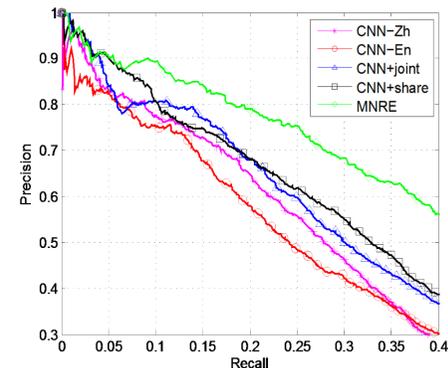


Fig3: Aggregated precision/recall curves of CNN-En, CNN-Zh, CNN+joint, CNN+share, and MNRE.

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

MNRE	Sentence
Low	1. Barzun is a commune in the Pyrénées-Atlantiques department in the Nouvelle-Aquitaine region of south-western France .
High	2. Barzun was born in Créteil , France
Low	3. 作为从 法国 移民到美国来的顶尖知识分子, 巴尔赞 与莱昂内尔·特里林、德怀特·麦克唐纳等人一道, 在冷战时期积极参与美国的公共知识生活...(As a top intellectual immigrating from France to the United States, Barzun , together with Lionel Trilling and Dwight Macdonald, actively participated in public knowledge life in the United States during the cold war ...)
High	4. 巴尔赞 于1907年出生于 法国 一个知识分子家庭, 1920年赴美. (Barzun was born in a French intellectual family in 1907 and went to America in 1920.)

Fig4: An example of our multi-lingual attention.

2. Effectiveness of Complementarity

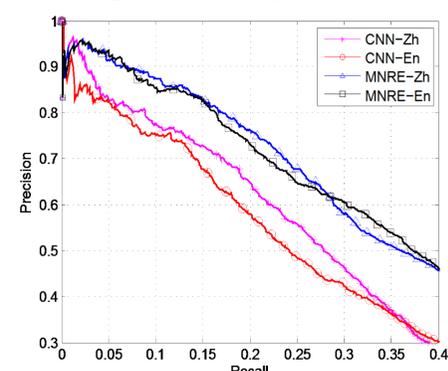


Fig5: Aggregate precision/recall curves of CNN-En, CNN-Zh, MNRE-En and MNRE-Zh.

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.