Improved Neural Relation Detection for Knowledge Base Question Answering

Mo Yu, Wenpeng Yin, Kazi Saidul Hasan, Cicero dos Santos,
Bing Xiang, Bowen Zhou
AI Foundations, IBM Research, USA Center for Information and
Language Processing, LMU Munich ‡IBM Watson, USA

Motivation

Relation information can revise the entity-linking error (ex.homonymy entity, actor Jack and writer Jack).

Different Granularity in KB Relations

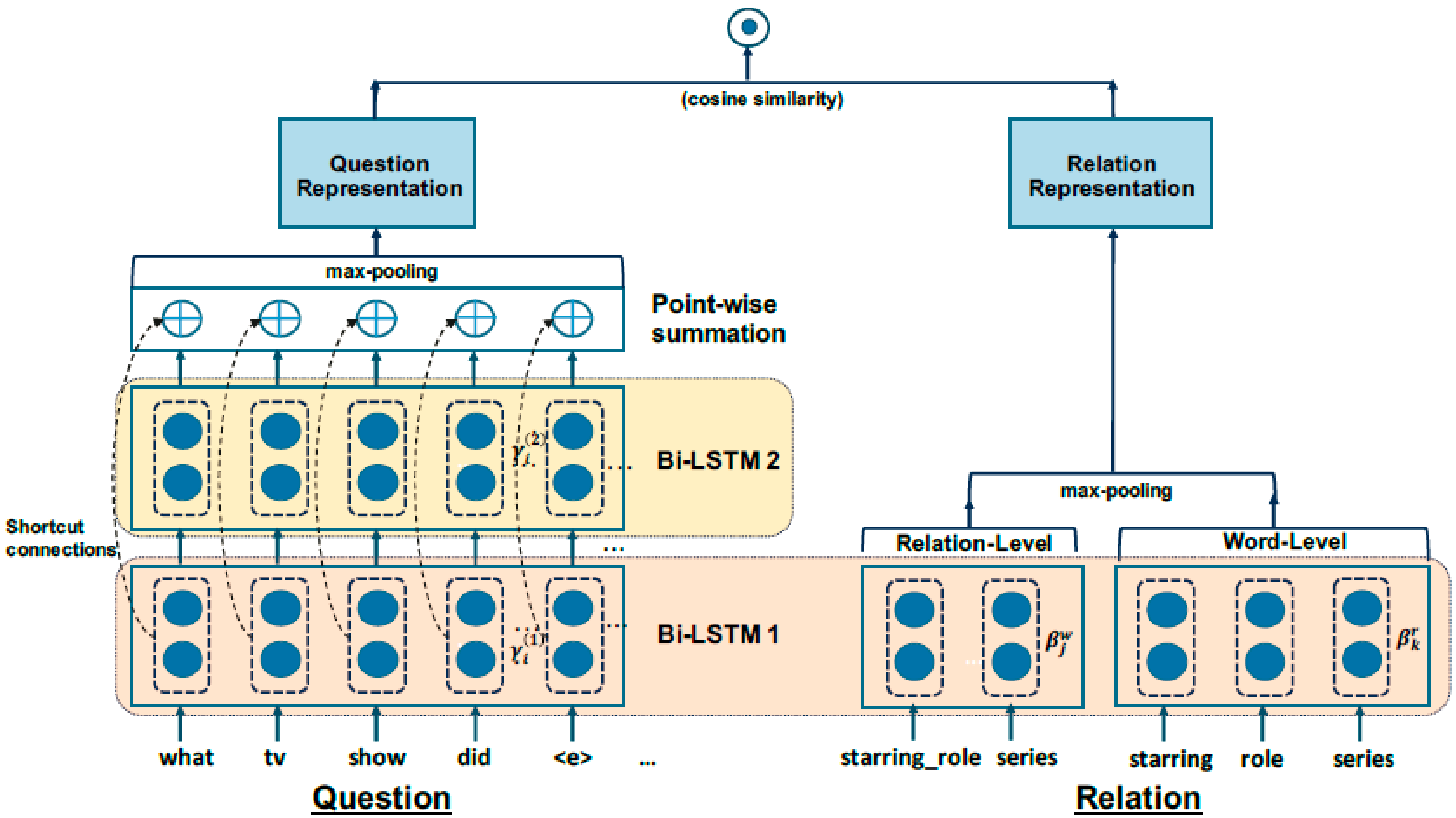
Relation Name as a Single Token (Relation Level): this method can learn the relation representation better, but it is weak to unseen relations.

Relation as Word Sequence (word-level): this method can represent unseen relations.

KB Relation Level

	Relation Token
relation-level	episodes_written
word-level	episodes
	written

Model (HR-BiLSTM)



2-layer BiLSTM+residusal network +max pooling + hierarchical matching score

KBQA Enhanced by Relation Detection

1. Entity Re-Ranking: 对于候选实体，会先有个$s_{linker}(e;q)$实体链接得分。然后，对与每个候选相连的relation带入HR-BiLSTM进行评分，得到s_{rel}。最终，对于每一个实体都有一个s_{rerank}评分。

   $$s_{rerank}(e;q) = \alpha \cdot \cdot \cdot_{linker}(e;q) + (1-\alpha) \cdot \max_{r \in R_q^l \cap R_e} S_{rel}(r;q).$$

   我们选取K'<K个实体根据s_{rerank}评分。
2. Relation Detection: 选取好候选实体后，对每个候选实体的相连relation带入HR-BiLSTM中计算评分。得到s_{rel}(r;e,q)。
3. Query Generation: 选取最终的实体和关系。

   $$s(\hat{e},\hat{r};q) = \max_{e \in EL'_{K'}(q), r \in R_e} (\beta \cdot s_{\text{rerank}}(e;q) + (1-\beta) \cdot s_{\text{rel}}(r;e,q)),$$

4. Constraint Detection: 计算问题q与关系链上实体相邻实体的相似度评分，将高分的相邻实体和实体关系加入到query中。

Experiments

Model	Relation Input Views	Accuracy SimpleQuestions	WebQSP
AMPCNN (Yin et al., 2016)	words	91.3	-
BiCNN (Yih et al., 2015)	char-3-gram	90.0	77.74
BiLSTM w/ words	words	91.2	79.32
BiLSTM w/ relation names	rel_names	88.9	78.96
Hier-Res-BiLSTM (HR-BiLSTM)	words + rel_names	**93.3**	**82.53**
w/o rel_name	words	91.3	81.69
w/o rel_words	rel_names	88.8	79.68
w/o residual learning (weighted sum on two layers)	words + rel_names	92.5	80.65
replacing residual with attention (Parikh et al., 2016)	words + rel_names	92.6	81.38
single-layer BiLSTM question encoder	words + rel_names	92.8	78.41
replacing BiLSTM with CNN (HR-CNN)	words + rel_names	92.9	79.08

Experiments

System	Accuracy	
	SQ	**WQ**
STAGG	72.8	**63.9**
AMPCNN (Yin et al., 2016)	*76.4*	-
Baseline: Our Method w/ baseline relation detector	75.1	60.0
Our Method	**77.0**	63.0
w/o entity re-ranking	74.9	60.6
w/o constraints	-	58.0
Our Method (multi-detectors)	**78.7**	**63.9**