Improving open domain question answering with Knowledge Base and Wikipedia graph

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ABSTRACT

A clear and well-documented LaTeX document is presented as an

KEYWORDS

neural networks

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1 INTRODUCTION

Input

- Dataset:(question, answer) pair.
- Knowledge Base:(entity, relation, entity) triple. Knowledge Base is a multi-relational graphs, each edge has a label and direction associated with it. Each node in the graph is an entity.
- Wikipedia graph[1]:(text, text) pair. Wikipedia graph is constructed by Hyperlinks and within-document links, Each node in the graph is an article.

Output representation of all the retrieved passage, as the input to a reader model to extract answer.

Goal To better embed the retrieved passage, which based on Wikipedia graph, with Knowledge Base knowledge.

Method Fuse Knowledge Base knowledge into Wikipedia graph to formulate (P_a, relation, P_b) triple.

(1) identify the relations between two passage node
Assuming that :
$rSet_{(a,b)}$: the set of relation between P_a and P_b, initialized empty
(P_a, P_b) exits in Wikipedia graph.
P_a contains n entities($e_{a1}, ..., e_{an}$) ,
P_b contains m entities($e_{b1}, ..., e_{bm}$)
If (e_{ai}, r, e_{bj})(1<=i,j<=n) exits in Knowledge Base, add r into $rSet_{(a,b)}$. Finally, $rSet_{a,b} = (r_1 ..., r_k)$

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(2) corperate identified relations into passage node embedding

$$\alpha_{r_i} = sorce(h_a, e_{ai}, r_i, q)$$

$$h_{inter-b} = FNN(h_a, \sum_{i=1}^{k} \alpha_{r_i} * ri)$$

$h_{inter-b}$ is the intermediate representation of passage b. α_{r_i} is the relation score.
Suppose that h_b is link by $[h_{a1}, ..., h_{at}]$,then update h_b by

$$h_b = GCN(h_b, \sum_{1}^{t} h_{inter-b})$$

(3) answer extraction
We adopt Multi-passage BERT [7] as our reader model,which use Shared normalization[2], specifically to process passages independently, but compute the span probability across spans in all passages in every mini-batch.Globally normalizing answer scores across all passages of the same question enables to find better answers by utilizing more passages.
Denote the passage score as $Pr(P_i|Q, P)$,which reranks all retrieved passages

$$Pr(P_i|Q, P) = softmax(h_i^{\mathrm{T}} W)$$

W is a trainable parameter.
The score of an answer span from passage P_i will be

$$Pr(a|Q, P) = Pr(P_i|Q, P)P_s(a_s|Q, P)P_e(a_e|Q, P).$$

Some details remain specific

(1) how to get the representation of relation.
In GRAFT-Nets[5], they average word vectors to compute a relation vector from the surface form of the relation.
In PullNet[4] ,embedding of relations are pretrained ,and can be looked up from an embedding table.
In [3] ,they only consider the most frequent 100 relations, and pretrain their embedding.
[8] tokenize the relation ,and then encode it by a shared LSTM with the question .
In [6],it handles multi-relational graphs representation where each edge has a label and direction associated with it, and jointly embeds both nodes and relations in a relational graph.

(2) the representaion of question
In GRAFT-Nets[5], the question representation is updated as $h_q = FFN(\sum_{v \in S_q} h_v)$, where S_q denotes the seed entities mentioned in the question.
In PullNet[4]and [8] , the question representation is accquired by a LSTM.
In [3] ,the question is not directly encoded,but with passage jointly by BERT.

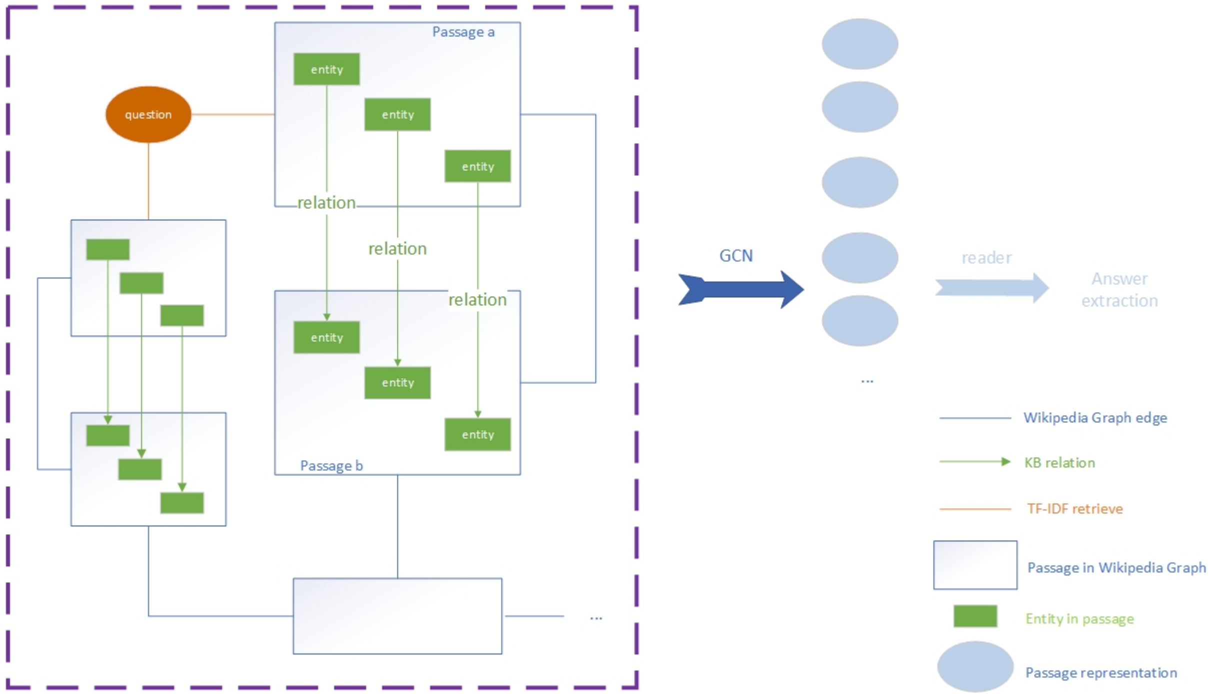

Figure 1: A diagram of approach

(3) how to score relation attention
Most work take the dot product between the embedding of relation and question.Considering the different framework here,we reformulate the score as:

$$\alpha_{r_i} = sorce(h_a, e_{ai}, r_i, q)$$

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