Question Answering by Reasoning Across Documents with Graph Convolutional Networks

UNIVERSITY OF AMSTERDAM

THE UNIVERSITY of EDINBURGH

Nicola De Cao[1,2], Wilker Aziz[2], and Ivan Titov[1,2]

[1]University of Edinburgh, [2]University of Amsterdam

Key Ideas

- We do **reading comprehension** on **multiple documents**
- We frame it as an **inference problem on a graph:**
    - mentions of entities are **nodes**
    - **edges** encode relations between different mentions
- **Graph convolutional networks** performs multi-step reasoning
- Our method is scalable and compact, and it achieves **state-of-the-art** results on WikiHop (Welbl et al., 2018)

Introduction

Data:

- Set of **<documents, question>** pairs
- Automatically constructed from a text corpus (*Wikipedia*) and a knowledge base (*Wikidata*)
- Questions are constructed to encourage **reasoning across documents**

Task:

- multiple choice from a set of **candidate answers** (C)

Approach:

1. explicitly **build a graph** of useful mentions from supporting documents (S) used for reasoning steps
2. **graph convolutional networks (GCN)** are applied to these graphs allowing for information propagation
3. **candidates are scored** through an MLP conditioned on a question representation and a pooling operation

```
Thorildsplan is a small park in Kristineberg in
 Stockholm, named in 1925 after the writer [..]

    Stockholm is the capital of Sweden
     and the most populous city in [..]

query: country Thorildsplan
candidates: {Denmark, Finland, Sweden, Italy, ...}
answer: Sweden
```

Figure 1. A sample from WikiHop.

Building the Graph

Nodes are **mentions** from all supporting documents and are connected with different edge-types/relations:

- Mentions within the **same document** (DOC-BASED)
- Exact matches **across documents** (MATCH)
- **Coreferences** — using an external system (COREF)
- The complement graph (COMPLEMENT)

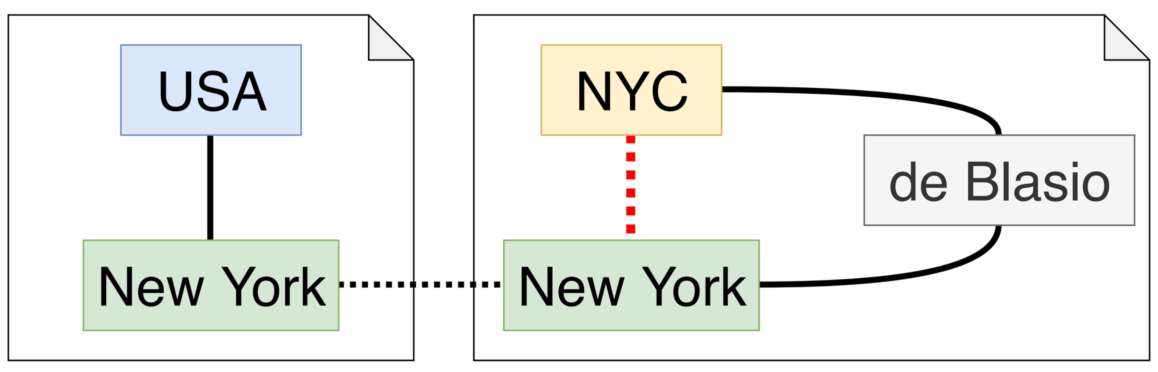

Figure 2. Two supporting documents.

Node embeddings are initialised using ELMo (Peters et al., 2018), a pre-trained language model, and a question representation.

NOTE: **no further readers are applied to the text!**

Processing the Graph

Entity Relational Graph Convolutional Network

Gated version of **relational-GCNs** (Schlichtkrull et al., 2018).

$$\mathbf{u}_i^{(\ell)} = f_s(\mathbf{h}_i^{(\ell)}) + \frac{1}{|N_i|}\sum_{j\in N_i}\sum_{r\in R_{ij}} f_r(\mathbf{h}_j^{(\ell)})$$

} The update vector ($\mathbf{u}$) of a node is a function of its neighbours (N) conditioned on the relations between them

$$\mathbf{a}_i^{(\ell)} = \sigma\left(f_a\left([\mathbf{u}_i^{(\ell)}, \mathbf{h}_i^{(\ell)}]\right)\right)$$

} attention gate

$$\mathbf{h}_i^{(\ell+1)} = \phi(\mathbf{u}_i^{(\ell)}) \odot \mathbf{a}_i^{(\ell)} + \mathbf{h}_i^{(\ell)} \odot (1 - \mathbf{a}_i^{(\ell)})$$

} the new node embedding

Candidates scoring

We use the final node embeddings ($\mathbf{h}^{(L)}$) and the question representation ($\mathbf{q}$) to **predict a distribution over candidates.**

$$P(c \mid q, C_q, S_q) \propto \exp\left(\max_{i\in M_c} f_o([\mathbf{q}, \mathbf{h}_i^{(L)}])\right)$$

} A **max-pooling** operation among the mentions (M_c) of the same candidate (c)

Results

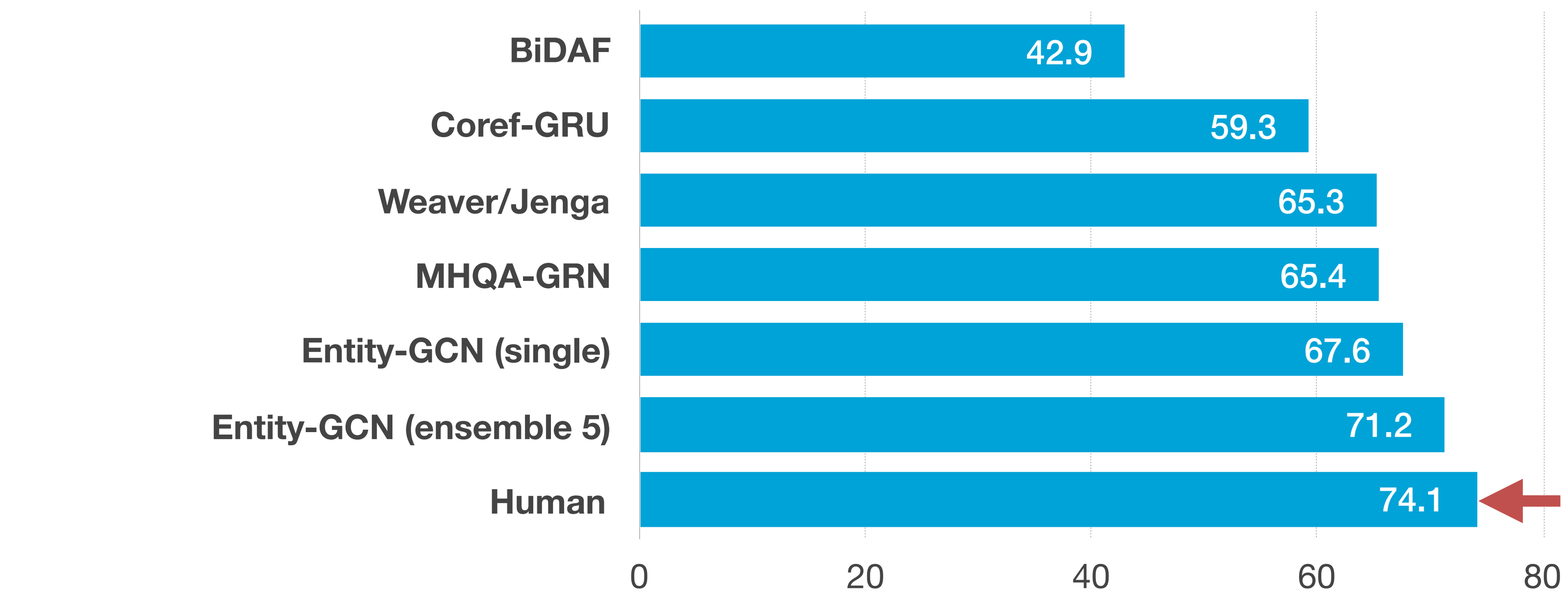

Figure 1. Accuracy on WikiHop closed test set.

Entity-GCN is at least **5 times faster to train than BiDAF**

NOTE: ensemble models add negligible overhead since embeddings are computed only once!

Ablation study

Model	
Full (ensemble)	**68.5**
Full (single)	**65.1±0.11**
GloVe w/o R-GCN	51.2
GloVe w/ R-GCN	59.2
No relation type	62.7
No DOC-BASED	62.9
No MATCH	64.3
No COREF	64.8
No COMPLEMENT	64.1
Induced edges	61.5

Figure 2. Accuracy on WikiHop validation set.

R-GCN is useful

Relations are important

DOC-BASED relations are the most significant

Learning to **predict edges** is hard and an open problem

Contact Information

Nicola De Cao

Ph.D. Candidate at University of Amsterdam

nicola.decao@gmail.com

https://nicola-decao.github.io

https://twitter.com/nicola_decao

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