Question Answering with Subgraph Embeddings

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(presented by Karel Ha)

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Open-domain question answering

Definition (Open QA)

the task to automatically answer questions asked in natural language **on any topic** or **in any domain**

Nowadays: lookup in large scale structured knowledge bases (KBs)

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A lot of human supervision: lexicons, grammars, KB schema ...

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- ability to answer more complicated questions (indirect answers)
- more sophisticated inferences

Freebase

the knowledge base of general facts

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Database of 14 million triplets:

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“What is the `predicate` of the `type2 subject`? (`object`)”

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Turned automatically into questions-answer pairs for training:
"What is the predicate of the type2 subject? (object)"
"What is the nationality of the person barack_obama? (united_states)"

WebQuestions

the dataset of 5810 QA pairs built from Freebase

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Questions from:

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One Freebase entity identified in each (natural) question using string matching:
"What degrees did Barack Obama get? (`bachelor_of_arts`, `juris_doctor`)"

ClueWeb Extractions

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- (subject, "text string", object)
- "Where barack_obama was allegedly bear in? (hawaii)"

Paraphrases

There are issues with automagically generated questions:

- semi-automatic wording
- rigid syntax
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⇒ pairs of question **paraphrases**:

- from WikiAnswers (users have option to tag rephrasings of questions)
- 2 million distinct questions
- 350,000 paraphrase clusters

Scoring function

Let us have a question q and a candidate answer a.
Goal: to learn the scoring function

$$S(q, a) = f(q)^\top g(a)$$

So that: high score if a is the correct answer; low score otherwise

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- vectors $\varphi(q) \in \mathbb{N}_0^N$ indicates how many times each word occurs in the question
- $\psi(a) \in \mathbb{N}_0^N$ is the vector representation of the answer (next slide)

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- $f(q) = \mathbf{W}\varphi(q)$ and $g(a) = \mathbf{W}\psi(a)$ are embeddings into $\mathbb{R}^k$

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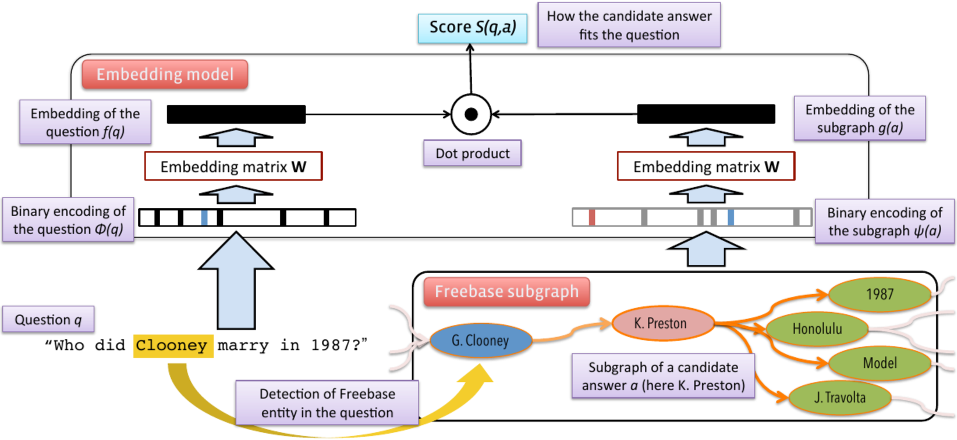
  - C entities connected to the answer entity via D relations: either $(3 + C + D)$-of-N_S or $(4 + C + D)$-of-N_S coded vector

Overview


Score S(q,a)
How the candidate answer fits the question
Embedding model
Embedding of the question f(q)
Dot product
Embedding of the subgraph g(a)
Embedding matrix W
Embedding matrix W
Binary encoding of the question Φ(q)
Binary encoding of the subgraph ψ(a)
Freebase subgraph
Question q
"Who did Clooney marry in 1987?"
G. Clooney
K. Preston
1987
Honolulu
Model
J. Travolta
Subgraph of a candidate answer a (here K. Preston)
Detection of Freebase entity in the question

Training and Ranking Loss Function

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So that: the score of a question paired with a correct answer is greater than with any incorrect answer $\overline{a}$ by at least m.

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- optimization:
  - stochastic gradient descent
  - multi-threaded
  - columns of **W** are inside the unit ball: $\forall i : ||\mathbf{W}_{*,i}|| \leq 1$

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- negative samples taken from different paraphrase clusters

Inference

The trained model predicts the answer by

$$\widehat{a} = \arg\max_{a' \in \mathcal{A}(q)} S(q, a')$$

where $\mathcal{A}_q$ is the candidate answer set for each question, chosen as:

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  - rank KB's relations using $S(q, a)$
  - top 10 relations $\Rightarrow$ only 2-hop paths containing them
  - 1-hop triplets weighted by value 1.5

Multiple answers

"Who are David Beckham's children?" $\Rightarrow$ a whole set of answers, all on the path:

(david_beckham, people.person.children, *)

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Vector representing multiple answers is the average of sub-answers:

$$\psi_{all}(a') = \frac{1}{|a'|} \sum_{a'_j \in a'} \psi(a'_j)$$

Results on the WebQuestions test set

Method	P@1 (%)	F1 (Berant)	F1 (Yao)
Baselines			
(Berant et al., 2013)	–	31.4	–
(Bordes et al., 2014b)	31.3	29.7	31.8
(Yao and Van Durme, 2014)	–	33.0	42.0
(Berant and Liang, 2014)	–	39.9	43.0
Our approach			
Subgraph & $\mathcal{A}(q) = C_2$	**40.4**	39.2	43.2
Ensemble with (Berant & Liang, 14)	–	**41.8**	**45.7**
Variants			
Without multiple predictions	**40.4**	31.3	34.2
Subgraph & $\mathcal{A}(q) =$ All 2-hops	38.0	37.1	41.4
Subgraph & $\mathcal{A}(q) = C_1$	34.0	32.6	35.1
Path & $\mathcal{A}(q) = C_2$	36.2	35.3	38.5
Single Entity & $\mathcal{A}(q) = C_1$	25.8	16.0	17.8

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- low-dimension embeddings
- exploiting richer structure of the answers, which is provided by their local neighborhood in the KB graph
- training for question paraphrasing task at the same time
- promising performance on the WebQuestions benchmark

Thank you!

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Time for human Question Answering!