# Semantic parsing with graph transformations

Ádám Kovács Kinga Gémes Gábor Recski

adaam.ko@gmail.com, kinga.andrea.gemes@gmail.com, recski@apollo.ai

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- Evaluation of our models on a machine comprehension task
- Integrating our model to a state-of-the-art system
- Results show some improvement on the task

**Text:** "Today we decided to paint the extra room in our house. Were going to have visitor coming next month so hopefully the painting ain't that smelly anymore. I made sure that the wall is clean and clear of all the nuisance. We already bought the pain and we decided the new wall pain is sky blue. My husband is putting newspaper on the floor to avoid any spill on our floor/carpet....."

Question: "Did anyone help him?"

1st answer: "It was the narrator and her husband"

2nd answer: "No, he worked alone."



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- The best two systems
  - HFL-RC
  - Yuanfudao
- MCScript
  - training and test data



Directed meaning graphs with 3 edge type

• type 0 edge



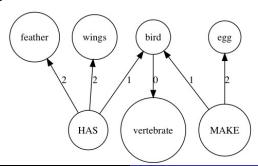
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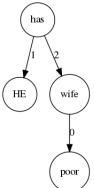


My poor wife!

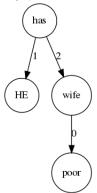


### I feel bad for my wife!

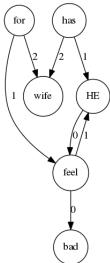
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#### Implementation

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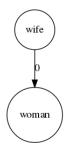
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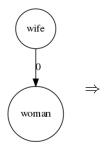
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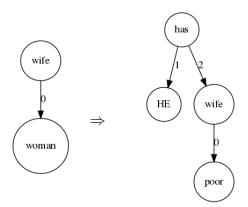
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- My poor wife! (G1)
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  - $\frac{|E(G_1)\cap E(G_2)|}{|E(G_2)|}$

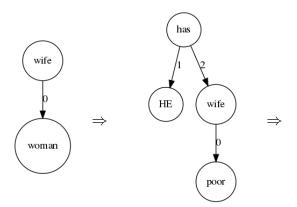
# Expanded graphs, the "expand" function

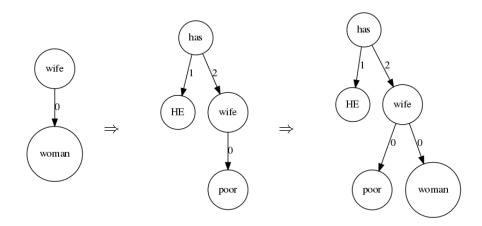






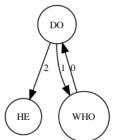




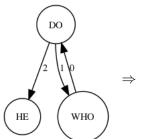


- Merged graph for all question-answer pair
- The "more" similar is the correct answer
- **68,3** accuracy score

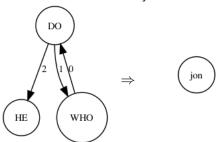
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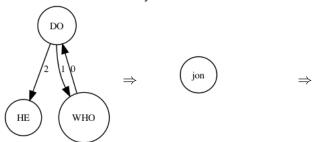
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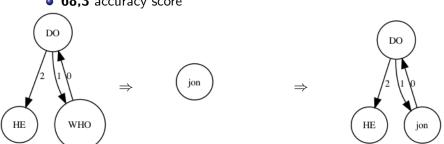
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## Yuanfudao system

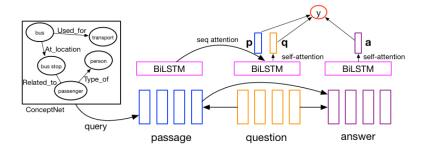


Figure: The structure of the system



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- 41ang similarity score calculated between words during the pre-processing
- New embedding layer for the 41ang similarities



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- New embedding layer for the 41ang similarities
- Expansion of the RNN layer, that the corresponding RNN gets the 41ang embedding's output

### Results

model	dev	test
TriAN, no ConceptNet	82.8%	80.2%
TriAN, with ConceptNet	82.7%	80.5%
TriAN, with 4lang	83.2%	80.9%
TriAN, with both	83.1%	80.8%

Table: Effect of 4lang and ConceptNet on results



### Results

model	dev	test
TriAN, no ConceptNet	83.7%	81.9%
TriAN, with ConceptNet	82.5%	80.3%
TriAN, with 4lang	84.2%	81.5%
TriAN, with both	83.4%	82.9%

Table: Effect of 41ang and ConceptNet on the pretrained models



### Results

pretrained, ensembled model	test
TriAN, no ConceptNet	82.95%
TriAN, with ConceptNet	83.697%
TriAN, with 4lang	82.8%
TriAN, with both	83.73%

Table: The effect of 41ang and ConceptNet on the pretrained and ensembled models





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### Thank you for your attention!

- Chen, Zhipeng et al. (2018). "HFL-RC System at SemEval-2018 Task 11: Hybrid Multi-Aspects Model for Commonsense Reading Comprehension". In: arXiv preprint arXiv:1803.05655.
- Kornai, András (2010). "The algebra of lexical semantics". In: Proceedings of the 11th Mathematics of Language Workshop. Ed. by Christian Ebert, Gerhard Jäger, and Jens Michaelis. LNAI 6149. Springer, pp. 174–199.
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- Wang, Liang et al. (2018). "Yuanfudao at SemEval-2018 Task 11: Three-way Attention and Relational Knowledge for Commonsense Machine Comprehension". In: arXiv preprint arXiv:1803.00191.