Learning to Reason for Neural Question Answering

Jianfeng Gao

Joint work with Ming-Wei Chang, Jianshu Chen, Weizhu Chen, Kevin Duh, Yuqing Guo, Po-Sen Huang, Xiaodong Liu, and Yelong Shen.

Microsoft

MRQA workshop (ACL 2018)
Open-Domain Question Answering (QA)

**Text-QA**

**Will I qualify for OSAP if I’m new in Canada?**

**Selected Passages from Bing**

“Visit the OSAP website for application deadlines. To get OSAP, you have to be eligible. You can apply using an online form, or you can print off the application forms. If you submit a paper application, you must pay an application fee. The online application is free.”


“To be eligible to apply for financial assistance from the Ontario Student Assistance Program (OSAP), you must be a: 1 Canadian citizen; 2 Permanent resident; or 3 Protected person/convention refugee with a Protected Persons Status Document (PPSD).”


“You will not be eligible for a Canada-Ontario Integrated Student Loan, but can apply for a part-time loan through the Canada Student Loans program. There are also grants, bursaries and scholarships available for both full-time and part-time students.”


**Answer**

No. You won’t qualify.

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**Knowledge Base (KB)-QA**

**What is Obama’s citizenship?**

**Selected subgraph from Microsoft’s Satori**

**Answer**

USA
Question Answering (QA) on Knowledge Base

Large-scale knowledge graphs
- Properties of billions of entities
- Plus relations among them

An QA Example:

Question: what is Obama’s citizenship?
- Query parsing:
  (Obama, Citizenship, ?)
- Identify and infer over relevant subgraphs:
  (Obama, BornIn, Hawaii)
  (Hawaii, PartOf, USA)
- correlating semantically relevant relations:
  BornIn ~ Citizenship

Answer: USA
Reasoning over KG in symbolic vs neural spaces

Symbolic: comprehensible but not robust
- Development: writing/learning production rules
- Runtime: random walk in symbolic space
- E.g., PRA [Lao+ 11], MindNet [Richardson+ 98]

Neural: robust but not comprehensible
- Development: encoding knowledge in neural space
- Runtime: multi-turn querying in neural space (similar to nearest neighbor)
- E.g., ReasoNet [Shen+ 16], DistMult [Yang+ 15]

Hybrid: robust and comprehensible
- Development: learning policy π that maps states in neural space to actions in symbolic space via RL
- Runtime: graph walk in symbolic space guided by π
- E.g., M-Walk [Shen+ 18], DeepPath [Xiong+ 18], MINERVA [Das+ 18]
Symbolic approaches to QA

• Understand the question via **semantic parsing**
  • Input: what is Obama’s citizenship?
  • Output (LF): (Obama, Citizenship, ?)

• Collect relevant information via fuzzy **keyword matching**
  • (Obama, BornIn, Hawaii)
  • (Hawaii, PartOf, USA)
  • Needs to know that BornIn and Citizenship are semantically related

• Generate the answer via **reasoning**
  • (Obama, Citizenship, USA)

• **Challenges**
  • Paraphrasing in NL
  • Search complexity of a big KG

[Richardson+ 98; Berant+ 13; Yao+ 15; Bao+ 14; Yih+ 15; etc.]
Key Challenge in KB-QA: Language Mismatch (Paraphrasing)

- Lots of ways to ask the same question
  - “What was the date that Minnesota became a state?”
  - “Minnesota became a state on?”
  - “When was the state Minnesota created?”
  - “Minnesota's date it entered the union?”
  - “When was Minnesota established as a state?”
  - “What day did Minnesota officially become a state?”

- Need to map them to the predicate defined in KB
  - location.dated_location.date_founded
Scaling up semantic parsers

• Paraphrasing in NL
  • Introduce a paragraphing engine as pre-processor [Berant&Liang 14]
  • Using semantic similarity model (e.g., DSSM) for semantic matching [Yih+ 15]

• Search complexity of a big KG
  • Pruning (partial) paths using domain knowledge

• More details: IJCAI-2016 tutorial on “Deep Learning and Continuous Representations for Natural Language Processing” by Yih, He and Gao.
From symbolic to neural computation

Symbolic Space - human readable

Input: Q

Symbolic → Neural by Encoding (Q/D/Knowledge)

Reasoning: Question + KB → answer vector via multi-step inference, summarization, deduction etc.

Neural Space - Computationally efficient

Neural → Symbolic by Decoding (synthesizing answer)

Error(A, A*)

Output: A

Symbolic Space

- human readable

Symbolic → Neural by Encoding (Q/D/Knowledge)

Neural → Symbolic by Decoding (synthesizing answer)

From symbolic to neural computation
Case study: ReasoNet with Shared Memory

- **Shared memory** (M) encodes task-specific knowledge
  - **Long-term memory**: encode KB for answering all questions in QA on KB
  - **Short-term memory**: encode the passage(s) which contains the answer of a question in QA on Text

- **Working memory** (hidden state $S_t$) contains a description of the current state of the world in a reasoning process

- **Search controller** performs multi-step inference to update $S_t$ of a question using knowledge in shared memory
  - Input/output modules are task-specific

[Shen+ 16; Shen+ 17]
Joint learning of Shared Memory and Search Controller

Paths extracted from KG:
(John, BornIn, Hawaii)
(Hawaii, PartOf, USA)
(John, Citizenship, USA)
...

Training samples generated
(John, BornIn, ?)->(Hawaii)
(Hawaii, PartOf, ?)->(USA)
(John, Citizenship, ?)->(USA)
...

Embed KG to memory vectors

(John, Citizenship, ?)

(USA)
Joint learning of Shared Memory and Search Controller

Paths extracted from KG:
(John, BornIn, Hawaii)
(Hawaii, PartOf, USA)
(John, Citizenship, USA)
...

Training samples generated
(John, BornIn, ?)->(Hawaii)
(Hawaii, PartOf, ?)->(USA)
(John, Citizenship, ?)->(USA)
...
Shared Memory: long-term memory to store learned knowledge, like human brain

- Knowledge is learned via performing tasks, e.g., update memory to answer new questions
- New knowledge is *implicitly* stored in memory cells via gradient update
- Semantically relevant relations/entities can be compactly represented using similar vectors.
Search controller for KB QA

<table>
<thead>
<tr>
<th>Space</th>
<th>Inference Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbolic</td>
<td>$B \xrightarrow{\text{Grandfather}^{-1}} Z \xrightarrow{\text{Father}} Y \xrightarrow{\text{Father}} A \xrightarrow{\text{Relatives}} C$</td>
</tr>
<tr>
<td>Neural</td>
<td>$B \xrightarrow{\text{Relatives}}? \Rightarrow A \xrightarrow{\text{Relatives}} C$</td>
</tr>
</tbody>
</table>

[Shen+ 16]
M-Walk: Learning to Reason over Knowledge Graph

- **Graph Walking as a Markov Decision Process**
  - State: encode “traversed nodes + previous actions + initial query” using RNN
  - Action: choose an edge and move to the next node, or STOP
  - Reward: +1 if stop at a correct node, 0 otherwise
  - Learning to reason over KG = seeking an optimal policy $\pi$
Training with Monte Carlo Tree Search (MCTS)

- Address sparse reward by **running MCTS simulations to generate trajectories with more positive reward**
- Exploit that KG is given and MDP transitions are deterministic
- On each MCTS simulation, roll out a trajectory by selecting actions
  - Treat $\pi$ as a prior
  - Prefer actions with high value (i.e., $\frac{W(s,a)}{N(s,a)}$, where $N$ and $W$ are visit count and action reward estimated using value network)

(a) An example of MCTS path (in red) in M-Walk
Joint learning of $\pi_\theta$, $V_\theta$, and $Q_\theta$

(b) Iterative policy improvement in M-Walk
Experiments on NELL-995

• NELL-995 dataset:
  • 154,213 Triples
  • 75,492 unique entities
  • 200 unique relations.

• Missing link prediction Task:
  • Predict the tail entity given the head entity and relation
  • i.e., Citizenship (Obama, ?) → USA

• Evaluation Metric:
  • Mean Average Precision (the higher the better)
# Missing Link Prediction Results

*Table 1. NELL-995 Link Prediction Performance Comparison using MAP scores.*

<table>
<thead>
<tr>
<th>Tasks</th>
<th>PRA</th>
</tr>
</thead>
<tbody>
<tr>
<td>athletePlaysForTeam</td>
<td>0.547</td>
</tr>
<tr>
<td>athletePlaysInLeague</td>
<td>0.841</td>
</tr>
<tr>
<td>athleteHomeStadium</td>
<td>0.859</td>
</tr>
<tr>
<td>athletePlaysSport</td>
<td>0.474</td>
</tr>
<tr>
<td>teamPlaySports</td>
<td>0.791</td>
</tr>
<tr>
<td>orgHeadquaterCity</td>
<td>0.811</td>
</tr>
<tr>
<td>worksFor</td>
<td>0.681</td>
</tr>
<tr>
<td>bornLocation</td>
<td>0.668</td>
</tr>
<tr>
<td>personLeadsOrg</td>
<td>0.700</td>
</tr>
<tr>
<td>orgHiredPerson</td>
<td>0.599</td>
</tr>
<tr>
<td>Overall</td>
<td>0.697</td>
</tr>
</tbody>
</table>

Path Ranking Algorithm: Symbolic Reasoning Approach
Missing Link Prediction Results

Table 1. NELL-995 Link Prediction Performance Comparison using MAP scores.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Path Ranking Algorithm (PRA)</th>
<th>TransE</th>
<th>TransR</th>
<th>ReasoNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>athletePlaysForTeam</td>
<td>0.547</td>
<td>0.627</td>
<td>0.673</td>
<td>0.789</td>
</tr>
<tr>
<td>athletePlaysInLeague</td>
<td>0.841</td>
<td>0.773</td>
<td>0.912</td>
<td>0.936</td>
</tr>
<tr>
<td>athleteHomeStadium</td>
<td>0.859</td>
<td>0.718</td>
<td>0.722</td>
<td>0.787</td>
</tr>
<tr>
<td>athletePlaysSport</td>
<td>0.474</td>
<td>0.876</td>
<td>0.963</td>
<td>0.969</td>
</tr>
<tr>
<td>teamPlaySports</td>
<td>0.791</td>
<td>0.761</td>
<td>0.814</td>
<td>0.833</td>
</tr>
<tr>
<td>orgHeadquarterCity</td>
<td>0.811</td>
<td>0.620</td>
<td>0.657</td>
<td>0.835</td>
</tr>
<tr>
<td>worksFor</td>
<td>0.681</td>
<td>0.677</td>
<td>0.692</td>
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<td>0.712</td>
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<td>0.836</td>
</tr>
<tr>
<td>personLeadsOrg</td>
<td>0.700</td>
<td>0.751</td>
<td>0.772</td>
<td>0.802</td>
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<tr>
<td>orgHiredPerson</td>
<td>0.599</td>
<td>0.719</td>
<td>0.737</td>
<td>0.768</td>
</tr>
<tr>
<td>Overall</td>
<td>0.697</td>
<td>0.723</td>
<td>0.775</td>
<td>0.817</td>
</tr>
</tbody>
</table>

**Path Ranking Algorithm:** Symbolic Reasoning Approach

**Neural Reasoning Approaches**
### Missing Link Prediction Results

#### Table 1. NELL-995 Link Prediction Performance Comparison using MAP scores.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>ReinforceWalk</th>
<th>PG</th>
<th>A2C</th>
<th>MINERVA ³</th>
<th>DeepPath</th>
<th>PRA</th>
<th>TransE</th>
<th>TransR</th>
<th>ReasoNet</th>
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<tbody>
<tr>
<td>athletePlaysForTeam</td>
<td>0.831</td>
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<td>0.627</td>
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<td>0.955</td>
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<td>worksFor</td>
<td>0.786</td>
<td>0.758</td>
<td>0.758</td>
<td>0.752</td>
<td>0.711</td>
<td>0.681</td>
<td>0.677</td>
<td>0.692</td>
<td>0.769</td>
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<tr>
<td>bornLocation</td>
<td>0.786</td>
<td>0.767</td>
<td>0.766</td>
<td>0.782</td>
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<td>0.668</td>
<td>0.712</td>
<td>0.812</td>
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<tr>
<td>personLeadsOrg</td>
<td>0.821</td>
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<td>0.810</td>
<td>0.771</td>
<td>0.795</td>
<td>0.700</td>
<td>0.751</td>
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<tr>
<td>orgHiredPerson</td>
<td>0.843</td>
<td>0.832</td>
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<td>0.599</td>
<td>0.719</td>
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<td>0.768</td>
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<td>Overall</td>
<td><strong>0.876</strong></td>
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<td>0.817</td>
</tr>
</tbody>
</table>

- **Path Ranking Algorithm:** Neural Reasoning Approaches
- **Symbolic Reasoning Approach:** Reinforcement Symbolic + Neural Reasoning Approaches
- **Two variants of ReinforceWalk without MCTS**
What types of European groups were able to avoid the plague?

From Italy, the disease spread northwest across Europe, striking France, Spain, Portugal and England by June 1348, then turned and spread east through Germany and Scandinavia from 1348 to 1350. It was introduced in Norway in 1349 when a ship landed at Askøy, then spread to Björgvin (modern Bergen) and Iceland. Finally it spread to northwestern Russia in 1351. The plague was somewhat less common in parts of Europe that had smaller trade relations with their neighbours, including the Kingdom of Poland, the majority of the Basque Country, isolated parts of Belgium and the Netherlands, and isolated alpine villages throughout the continent.

A limited form of comprehension:
- No need for extra knowledge outside the paragraph
- No need for clarifying questions
- The answer must exist in the paragraph
- The answer must be a text span, not synthesized

- **Encoding**: map each text span to a semantic vector
- **Reasoning**: rank and re-rank semantic vectors
- **Decoding**: map the top-ranked vector to text
Neural MRC models...

Figure 1: BiDirectional Attention Flow Model  
(best viewed in color)

[Seo+ 16; Yu+ 18]
Will I qualify for OSAP if I’m new in Canada?

Selected Passages from Bing

“Visit the OSAP website for application deadlines. To get OSAP, you have to be eligible. You can apply using an online form, or you can print off the application forms. If you submit a paper application, you must pay an application fee. The online application is free.”

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“You will not be eligible for a Canada-Ontario Integrated Student Loan, but can apply for a part-time loan through the Canada Student Loans program. There are also grants, bursaries and scholarships available for both full-time and part-time students.”

Answer
No. You won’t qualify.

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail. Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall? gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail? graupel

Where do water droplets collide with ice crystals to form precipitation? within a cloud

Figure 1: Question-answer pairs for a sample passage in the SQuAD dataset. Each of the answers is a segment of text from the passage.
### Novice Task

<table>
<thead>
<tr>
<th>Rank</th>
<th>Model</th>
<th>Submission Date</th>
<th>Rouge-L</th>
<th>Bleu-1</th>
<th>F1</th>
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<td>8</td>
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<td>23.96</td>
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### Intermediate Task

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**MS MARCO**
Microsoft Machine Reading Comprehension Dataset

MSMARCO V2.1 is now available. Start experimenting today!
Multi-step reasoning: example

<table>
<thead>
<tr>
<th>Query</th>
<th>Who was the #2 pick in the 2011 NFL Draft?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passage</td>
<td>Manning was the #1 selection of the 1998 NFL draft, while Newton was picked first in 2011. The matchup also pits the top two picks of the 2011 draft against each other: Newton for Carolina and Von Miller for Denver.</td>
</tr>
<tr>
<td>Answer</td>
<td>Von Miller</td>
</tr>
</tbody>
</table>

- **Step 1:**
  - **Extract:** Manning is #1 pick of 1998
  - **Infer:** Manning is NOT the answer

- **Step 2:**
  - **Extract:** Newton is #1 pick of 2011
  - **Infer:** Newton is NOT the answer

- **Step 3:**
  - **Extract:** Newton and Von Miller are top 2 picks of 2011
  - **Infer:** Von Miller is the #2 pick of 2011
ReasoNet: learn to stop reading

With Q in mind, read Doc repeatedly, each time focusing on different parts of doc until a satisfied answer is formed:

1. Given a set of docs in memory: \( M \)
2. Start with query: \( S \)
3. Identify info in \( M \) that is related to \( S \): \( X = f_a(S, M) \)
4. Update internal state: \( S = RNN(S, X) \)
5. Whether a satisfied answer \( O \) can be formed based on \( S \): \( f_{tc}(S) \)
6. If so, stop and output answer \( O = f_o(S) \); otherwise return to 3.

The step size is determined dynamically based on the complexity of the problem using reinforcement learning.

[Shen+ 17]
ReasoNet: learn to stop reading

Query: Who was the #2 pick in the 2011 NFL Draft?

Passage: Manning was the #1 selection of the 1998 NFL draft, while Newton was picked first in 2011. The matchup also pits the top two picks of the 2011 draft against each other: Newton for Carolina and Von Miller for Denver.

Answer: Von Miller

Step | Termination Probability | Prob. Answer
---|---|---
1 | 0.001 | 0.392
**Query**  
Who was the #2 pick in the 2011 NFL Draft?

**Passage**  
Manning was the #1 selection of the 1998 NFL draft, while Newton was picked first in 2011. The matchup also pits the top two picks of the 2011 draft against each other: Newton for Carolina and Von Miller for Denver.

**Answer**  
Von Miller

**Step**  
<table>
<thead>
<tr>
<th>Step</th>
<th>Termination Probability</th>
<th>Prob. Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.001</td>
<td>0.392</td>
</tr>
<tr>
<td>2</td>
<td>0.675</td>
<td>0.649</td>
</tr>
</tbody>
</table>

*S: Manning is #1 pick of 1998, but this is unlikely the answer.*
ReasoNet: learn to stop reading

Query  Who was the #2 pick in the 2011 NFL Draft?

Passage  Manning was the #1 selection of the 1998 NFL draft, while Newton was picked first in 2011. The matchup also pits the top two picks of the 2011 draft against each other: Newton for Carolina and Von Miller for Denver.

Answer  Von Miller

Rank-1  Manning is #1 pick of 1998, Newton is #1 pick of 2011, but neither is the answer.

<table>
<thead>
<tr>
<th>Step</th>
<th>Termination Probability $f_{tc}$</th>
<th>Prob. Answer $f_{o}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.001</td>
<td>0.392</td>
</tr>
<tr>
<td>2</td>
<td>0.675</td>
<td>0.649</td>
</tr>
<tr>
<td>3</td>
<td>0.939</td>
<td>0.865</td>
</tr>
</tbody>
</table>
Stochastic Answer Net

• Training uses *stochastic prediction dropout* on the answer module

• Reasoning employs all the outputs of multiple-step reasoning via voting

• Differs from ReasoNet
  • Easy to train, BP vs. policy gradient
  • Better performance, i.e., best documented MRC model on the SQuAD leaderboard as of Dec. 19, 2017

Figure 1: Illustration of “stochastic prediction dropout” in the answer module during training. At each reasoning step $t$, the model combines memory (bottom row) with hidden states $s_{t-1}$ to generate a prediction (multinomial distribution). Here, there are three steps and three predictions, but one prediction is dropped and the final result is an average of the remaining distributions.

[Liu+ 18]
<table>
<thead>
<tr>
<th>Answer Module</th>
<th>EM</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard 1-step</td>
<td>75.139</td>
<td>83.367</td>
</tr>
<tr>
<td>Fixed 5-step with Memory Network (prediction from final step)</td>
<td>75.033</td>
<td>83.327</td>
</tr>
<tr>
<td>Fixed 5-step with Memory Network (prediction averaged from all steps)</td>
<td>75.256</td>
<td>83.215</td>
</tr>
<tr>
<td>Dynamic steps (max 5) with ReasoNet</td>
<td>75.355</td>
<td>83.360</td>
</tr>
<tr>
<td>Stochastic Answer Network (SAN ), Fixed 5-step</td>
<td><strong>76.235</strong></td>
<td><strong>84.056</strong></td>
</tr>
</tbody>
</table>

Table 1: SQuAD devset results

<table>
<thead>
<tr>
<th>Single Model</th>
<th>ROUGE</th>
<th>BLEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>ReasoNet++(Shen et al., 2017)</td>
<td>38.01</td>
<td>38.62</td>
</tr>
<tr>
<td>V-Net(Wang et al., 2018)</td>
<td>45.65</td>
<td>-</td>
</tr>
<tr>
<td>Standard 1-step in Table 1</td>
<td>42.30</td>
<td>42.39</td>
</tr>
<tr>
<td>SAN</td>
<td><strong>46.14</strong></td>
<td><strong>43.85</strong></td>
</tr>
</tbody>
</table>

Table 7: MS MARCO devset results.

<table>
<thead>
<tr>
<th>Single model:</th>
<th>AddSent</th>
<th>AddOneSent</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR (Rajpurkar et al., 2016)</td>
<td>23.2</td>
<td>30.3</td>
</tr>
<tr>
<td>SEDT (Liu et al., 2017a)</td>
<td>33.9</td>
<td>44.8</td>
</tr>
<tr>
<td>BiDAF (Seo et al., 2016)</td>
<td>34.3</td>
<td>45.7</td>
</tr>
<tr>
<td>jNet (Zhang et al., 2017)</td>
<td>37.9</td>
<td>47.0</td>
</tr>
<tr>
<td>ReasoNet(Shen et al., 2017)</td>
<td>39.4</td>
<td>50.3</td>
</tr>
<tr>
<td>RaSoR(Lee et al., 2016)</td>
<td>39.5</td>
<td>49.5</td>
</tr>
<tr>
<td>Mnemonic(Hu et al., 2017)</td>
<td><strong>46.6</strong></td>
<td>56.0</td>
</tr>
<tr>
<td>QANet(Yu et al., 2018)</td>
<td>45.2</td>
<td>55.7</td>
</tr>
<tr>
<td>Standard 1-step in Table 1</td>
<td>45.4</td>
<td>55.8</td>
</tr>
<tr>
<td>SAN</td>
<td><strong>46.6</strong></td>
<td><strong>56.5</strong></td>
</tr>
</tbody>
</table>

Table 5: Test performance on the adversarial SQuAD dataset in F1 score.
Conclusion

• Neural approaches to QA = encoding + reasoning + decoding

• Learning to reason for KB QA
  • Symbolic: comprehensible but not robust
  • Neural: robust but not comprehensible
  • Hybrid: robust and comprehensible

• Learning to reason for Text QA / MRC
  • Need better tasks / datasets! – MS MARCO?
  • ReasoNet: Learning when to step via RL
  • SAN: stochastic prediction dropout