Using Natural Language Relations between Answer Choices for Machine Comprehension

Rajkumar Pujari and Dan Goldwasser

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Intuition

When humans perform Reading Comprehension, we answer all the given questions consistently.

But, when we test Machine Comprehension, most computational settings consider each question or each choice in isolation.

Example

1. When were the eggs added to the pan to make the omelette?
   - When they turned on the stove
   - When the pan was the right temperature

2. Why did they use stove to cook omelette?
   - They didn't use the stove but a microwave
   - Because they needed to heat up the pan

Source: SemEval 2018 Task-11 dataset ([Ostermann et al. 2018])
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When humans perform Reading Comprehension, we answer all the given questions consistently.

But, when we test Machine Comprehension, most computational settings consider each question or each choice in isolation.

Example

1. *When were the eggs added to the pan to make the omelette?*
   - When they turned on the stove
   - When the pan was the right temperature ★

2. *Why did they use stove to cook omelette?*
   - They didn’t use the stove but a microwave
   - Because they needed to heat up the pan ★

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Similarly, in settings where multiple choices could be correct, we could use the relationships between choices.
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Example

- How can the military benefit from the existence of the CIA?
  1. They can use them as they wish
  2. The agency is keenly attentive to the military’s strategic and tactical requirements ★
  3. The CIA knows what intelligence the military requires and has the resources to obtain that intelligence ★

- $c_3$ entails $c_2 \implies$ flip $c_2$ from wrong to correct.

Source: MultiRC dataset ([Khashabi et al. 2018])
We propose a method to leverage entailment and contradiction relations between the answer choices to improve machine comprehension.
Abstract

1. We propose a method to leverage entailment and contradiction relations between the answer choices to improve machine comprehension.

2. We first perform Question Answering (QA) and “weakly-supervised” Natural Language Inference (NLI) relation detection separately. Then, we use the NLI relations to re-evaluate the answers.
We propose a method to leverage entailment and contradiction relations between the answer choices to improve machine comprehension.

We first perform Question Answering (QA) and “weakly-supervised” Natural Language Inference (NLI) relation detection separately. Then, we use the NLI relations to re-evaluate the answers.

We also propose a multitask learning model that learns both the tasks jointly.
Using NLI Relations for Machine Comprehension

Approach

\[(Q_1, c_1) \quad \text{Stand-alone QA System} \quad (Q_1, c_1) - \checkmark\]
\[(Q_1, c_2) - \times \quad (Q_1, c_3) - \checkmark\]
Approach

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Approach

Overview

Model

Results

Conclusion

Inputs

Models

Intermediate Output

Final Output
We use the TriAN-single model proposed by [Wang et al. 2018] for SemEval-2018 task-11 as our stand-alone QA system.

**Figure:** TriAN model architecture (figure adopted from [Wang et al. 2018])
Our NLI system was inspired from decomposable-attention model proposed by [Parikh et al. 2016]
NLI System

- Our NLI system was inspired from decomposable-attention model proposed by [Parikh et al. 2016]
- **Issue:** Choices are often short phrases. NLI relations among them exist only in the context of the given question.

**Example**

What do human children learn by playing games and sports?

1. Learn about the world 🌍
2. Learn to cheat
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What do human children learn by playing games and sports?

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**Resolution:** We modified the architecture proposed in [Parikh et al. 2016] to accommodate the question-choice pairs as opposed to sentence pairs in the original model.
We enforce consistency between the QA answers and the NLI relations at inference time.

1. \( c_i \) is true \& \( c_i \) entails \( c_j \) \( \Rightarrow \) \( c_j \) is true.

2. \( c_i \) is true \& \( c_i \) contradicts \( c_j \) \( \Rightarrow \) \( c_j \) is false.

We used Deep Relational Learning (DRaiL) framework proposed by [Zhang et al. 2016] for inference.
Inference

- We enforce consistency between the QA answers and the NLI relations at inference time.
- The answers and the relations are scored by the confidence scores from the QA and the NLI systems.

We used the following rules to enforce consistency:

1. $c_i$ is true & $c_i$ entails $c_j$ $\Rightarrow c_j$ is true.
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If the “SNLI-trained” NLI model predicted entailment with a confidence above a threshold and the gold labels of the ordered choice pair were true-true, the relation was labeled entailment, and similarly we generate data for contradiction.
The design of our joint model is motivated by the two objectives:

1. To leverage the benefit of multitask learning
2. To obtain a better representation for the question-choice pair for NLI detection
## MultiRC Results

<table>
<thead>
<tr>
<th>Method</th>
<th>$EM_0$</th>
<th>$EM_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stand-alone QA</td>
<td>18.15</td>
<td>52.99</td>
</tr>
<tr>
<td>QA + $NLIS_{NL}$</td>
<td>19.41</td>
<td>56.13</td>
</tr>
<tr>
<td>QA + $NLIM_{MultiRC}$</td>
<td>21.62</td>
<td>55.72</td>
</tr>
<tr>
<td>Joint Model</td>
<td>20.36</td>
<td>57.08</td>
</tr>
<tr>
<td>Human</td>
<td>56.56</td>
<td>83.84</td>
</tr>
</tbody>
</table>

**Table:** Summary of results on MultiRC dataset. $EM_0$ is the percentage of questions for which all the choices are correct. $EM_1$ is the percentage of questions for which at most one choice is wrong.
SemEval 2018 Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Dev</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stand-alone QA</td>
<td>83.20%</td>
<td>80.80%</td>
</tr>
<tr>
<td>Joint Model</td>
<td>85.40%</td>
<td>82.10%</td>
</tr>
</tbody>
</table>

Table: Accuracy of various models on SemEval’18 task-11 dataset
Error Analysis

- Identification of NLI relations is far from perfect.
- NLI system returns entailment when there is a high lexical overlap
- NLI system returns contradiction upon the presence of a strong negation word such as *not*.
We proposed a framework to use entailment and contradiction relations to improve Machine Comprehension.
Summary

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  1. I went shopping this extended weekend
  2. I ate a lot of junk food recently
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- Self-training results suggest the presence of other subtle relationships among choices.
- Consider:
  1. I went shopping this extended weekend
  2. I ate a lot of junk food recently

Text: *I snack when I shop*
Questions?
Daniel Khashabi, Snigdha Chaturvedi, Michael Roth, Shyam Upadhyay, and Dan Roth.

2018.
Looking beyond the surface: A challenge set for reading comprehension over multiple sentences.
In NAACL.

Simon Ostermann, Michael Roth, Ashutosh Modi, Stefan Thater, and Manfred Pinkal.

2018.

Ankur Parikh, Oscar Täckström, Dipanjan Das, and Jakob Uszkoreit.

2016.
A decomposable attention model for natural language inference.