Convolutional Spatial Attention Model for Reading Comprehension with Multiple-Choice Questions

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OUTLINE

• Introductions & Preliminaries

• Convolutional Spatial Attention Model (CSA)

• Experimental Results

• Quantitative Analysis

• Conclusions & Future Works
INTRODUCTION

• **Machine Reading Comprehension (MRC)** is to read and comprehend a given article and answer the questions based on it, which has become enormously popular in recent few years.

• **Type of MRC**
  - Cloze-style: CNN / Daily Mail [Hermann et al., 2015], CBT [Hill et al., 2015]
  - Span-extraction: SQuAD [Rajpurkar et al., 2016]
  - Choice selection: MCTest [Richardson et al., 2013], RACE [Lai et al., 2017]
  - Conversational MRC: CoQA [Reddy et al., 2018], QuAC [Choi et al., 2018]

• In this paper, we focus on solving the RC problem with multiple-choice questions
**INTRODUCTION**

- **RC with multiple-choice question**

- **Document**

- **Pre-requisites for answering the questions**

- **Question**

- **Candidates**

- **Answer**

Document:

James the Turtle was always getting in trouble. Sometimes he’d reach into the freezer and empty out all the food. Other times he’d sled on the deck and get a splinter. His aunt Jane tried as hard as she could to keep him out of trouble, but he was sneaky and got in to lots of trouble behind her back. One day, James thought he would go into town and see what kind of trouble he could get into. He went to the grocery store and pulled all the pudding off the shelves and ate two jars. Then he walked to the fast food restaurant and ordered 15 bags of fries. He didn't pay, and instead headed home. His aunt was waiting for him in his room. She told James that she loved him, but he would have to start acting like a well-behaved turtle. After about a month, and after getting into lots of trouble, James finally made up his mind to be a better turtle.

**Question:** What is the name of the trouble making turtle?

- A) Fries
- B) Pudding
- C) James
- D) Jane

**Answer:** C) James
INTRODUCTION

• RC with multiple-choice question
  • Document
  • Question
  • A natural question based on the documents
  • Candidates
  • Answer

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Answer: C) James
**INTRODUCTION**

- **RC with multiple-choice question**
  - **Document**
  - **Question**
  - **Candidates**
  - **Answer**

  - Choose the correct one as the answer

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**Answer:** C) James
**CSA Model**

• **Contributions**

  • Focus on modeling different semantic aspects of candidate answers
  
  • Propose **Convolutional Spatial Attention (CSA)** to simultaneously extract the attentions between various representations
  
  • Experimental results on RACE and SemEval 2018 Task 11 show that the proposed model achieves state-of-the-art performance.
CSA Model

- **Formal Definition of the Task**
  - Inputs: Document, Question, Candidate
  - Output: Candidate score of being the answer

- **Basic Components**
  - Embedding Layer
  - LSTM Layer
  - Enriched Representation Layer
  - Convolutional Spatial Attention Layer
  - Answer Layer
CSA Model

- Embedding Layer
  - GloVe Word Embedding [Pennington et al., 2013]
  - ELMo [Peters et al., 2018]
  - POS-tag Embedding
  - Exact Word Matching
  - Fuzzy Word Matching
- Concatenate all the features above
CSA Model

- LSTM Layer

  - Apply highway layer to better mix various types of embeddings
  - Place an ordinary Bi-LSTM layer after embedding to obtain contextual representation

\[
\tilde{H} = \sigma(2\text{-Highway}(E))
\]

\[
H = \text{Bi-LSTM}(\tilde{H})
\]
**CSA Model**

- **Enriched Representation Layer**
  - Using ‘enriched representation algorithm’ to get various attention-guided representations.
  - \( R_{CQ} \): question-aware candidate representation
  - \( R_{CP} \): passage-aware candidate representation
  - \( R_{QP} \): passage-aware question representation
  - \( R_{QQ} \): self-attended question representation
CSA Model

- Algorithm for Enriched Representation

- Two Key Points
  - Adopt symmetric attention mechanism [Huang et al., 2017]
  - Apply element-wise weight to the attention matrix

---

**Algorithm 1** Enriched Representation.

**Input:**
- Time-Distributed representation $X_1$
- Time-Distributed representation $X_2$

**Initialize:**
- Random weight matrix $W_1 \in \mathbb{R}^{h \times h_{att}}$
- Random weight matrix $W_2 \in \mathbb{R}^{h \times h_{att}}$
- Diagonal weight matrix $D \in \mathbb{R}^{h_{att} \times h_{att}}$
- All-one weight matrix $W \in \mathbb{R}^{[X_1] \times [X_2]}$

**Output:** $X_2$-aware $X_1$ representation $Y$

1. Calculate attention matrix $M' \in \mathbb{R}^{[X_1] \times [X_2]}$:
   $$M' = f(W_1X_1^T) \cdot D \cdot f(W_2X_2^T)$$
2. Apply element-wise weight: $M = M' \odot W$
3. Apply softmax function to the last dimension of $M$:
   $$M_{att} = softmax(M)$$
4. Calculate raw representation $Y' \in \mathbb{R}^{[X_2] \times h}$:
   $$Y' = M_{att}^T \cdot X_1$$
5. Concatenate raw representation $Y'$ and raw input $X_1$, then apply Bi-LSTM:
   $$Y = \text{Bi-LSTM}([X_1; Y'])$$
6. **return** $Y$
• Convolutional Spatial Attention Layer

• Candidate information is important

• We calculate dot attentions between three candidate representations and two question representations

• Concatenate 2*3=6 attention matrices, forming an attention cuboid $M$ with shape [6, candidate_len, question_len]
**CSA Model**

- **Convolutional Spatial Attention Layer**
  
  - The resulting matching cuboid $M$ can be seen as a 2D-image with 6-channels.
  
  - We use Convolution-MaxPooling operation to dynamically extract high-level features with kernel size 5, 10, 15.

\[
\begin{align*}
O_1 &= \text{Max-Pooling}_{1 \times 3}\{CNN_{1 \times 5}(M)\} \\
O_2 &= \text{Max-Pooling}_{1 \times 2}\{CNN_{1 \times 10}(M)\} \\
O_3 &= \text{Max-Pooling}_{1 \times 1}\{CNN_{1 \times 15}(M)\}
\end{align*}
\]
**CSA Model**

- **Answer Layer**
  - Concatenate all three feature vectors
  - Pass through a fully-connected layer to get a scalar score

\[
s_i = w^T \cdot [O_1; O_2; O_3]
\]

\[
Pr(A|P, Q, C) = \text{softmax}([s_1; \ldots; s_N])
\]

- Prediction: choose the candidate that has the largest score as the answer
EXPERIMENTS

• **Dataset**
  
  • RACE: English examinations of Chinese middle and high school students. (4 candidate selections)
  
  • SemEval 2018 Task 11: Machine Comprehension using Commonsense Knowledge (2 candidate selections)

• **Hyper-parameters**
  
  • Passage/Question/Candidate max length: 300 / 20 / 10
  
  • Word Embedding: 200-dim
  
  • Bi-LSTM hidden size: 250-dim
  
  • ELMo: 1024-dim

• **Implementation**: Keras + TensorFlow
EXPERIMENTS

• Results on RACE

• Shows state-of-the-art performance, especially on RACE-H (high school)

• Incorporating ELMo yields another significant improvements

<table>
<thead>
<tr>
<th>Model</th>
<th>RACE-M</th>
<th>RACE-H</th>
<th>RACE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sliding Window (Lai et al. 2017)</td>
<td>37.3</td>
<td>30.4</td>
<td>32.2</td>
</tr>
<tr>
<td>Stanford AR (Lai et al. 2017)</td>
<td>44.2</td>
<td>43.0</td>
<td>43.3</td>
</tr>
<tr>
<td>GA Reader (Lai et al. 2017)</td>
<td>43.7</td>
<td>44.2</td>
<td>44.1</td>
</tr>
<tr>
<td>ElimiNet (Parikh et al. 2018)</td>
<td>N/A</td>
<td>N/A</td>
<td>44.5</td>
</tr>
<tr>
<td>Hierarchical Attention Flow (Zhu et al. 2018)</td>
<td>45.0</td>
<td>46.4</td>
<td>46.0</td>
</tr>
<tr>
<td>Dynamic Fusion Network (Xu et al. 2017)</td>
<td>51.5</td>
<td>45.7</td>
<td>47.4</td>
</tr>
<tr>
<td>CSA Model (single model)</td>
<td>51.0</td>
<td>47.3</td>
<td>48.4</td>
</tr>
<tr>
<td>CSA Model + ELMo (single model)</td>
<td><strong>52.2</strong></td>
<td><strong>50.3</strong></td>
<td><strong>50.9</strong></td>
</tr>
<tr>
<td>GA Reader (6-ensemble)</td>
<td>-</td>
<td>-</td>
<td>45.9</td>
</tr>
<tr>
<td>ElimiNet (6-ensemble)</td>
<td>-</td>
<td>-</td>
<td>46.5</td>
</tr>
<tr>
<td>GA + ElimiNet (12-ensemble)</td>
<td>-</td>
<td>-</td>
<td>47.2</td>
</tr>
<tr>
<td>Dynamic Fusion Network (9-ensemble)</td>
<td>55.6</td>
<td>49.4</td>
<td>51.2</td>
</tr>
<tr>
<td>CSA Model (7-ensemble)</td>
<td>55.2</td>
<td>52.4</td>
<td>53.2</td>
</tr>
<tr>
<td>CSA Model + ELMo (9-ensemble)</td>
<td><strong>56.8</strong></td>
<td><strong>54.8</strong></td>
<td><strong>55.0</strong></td>
</tr>
</tbody>
</table>
EXPERIMENTS

• Results on SemEval 2018

  • Baselines are the top two teams in SemEval 2018 Task 11.
  
  • CSA model shows marginal but consistent improvements on single/ensemble settings.
  
  • With the help of ELMo, there is another boost in performance.

<table>
<thead>
<tr>
<th>Model</th>
<th>Dev</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMA (Chen et al. 2018)</td>
<td>84.48</td>
<td>80.94</td>
</tr>
<tr>
<td>TriAN (Wang 2018)</td>
<td>83.84</td>
<td>81.94</td>
</tr>
<tr>
<td>CSA Model (single model)</td>
<td>83.63</td>
<td>82.20</td>
</tr>
<tr>
<td>CSA Model + ELMo (single model)</td>
<td>83.84</td>
<td>83.27</td>
</tr>
<tr>
<td>TriAN (ensemble)</td>
<td>85.27</td>
<td>83.95</td>
</tr>
<tr>
<td>HMA (ensemble)</td>
<td>86.46</td>
<td>84.13</td>
</tr>
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<td>CSA Model (ensemble)</td>
<td>84.05</td>
<td>84.34</td>
</tr>
<tr>
<td>CSA Model + ELMo (ensemble)</td>
<td>85.05</td>
<td>85.23</td>
</tr>
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</table>
Ablation Study

- Ablation Results on RACE

  - w/o attention weight: do not apply element-wise weight on attention
  - w/o enriched repr: only use LSTM outputs
  - w/o CSA: using two fully connected layer to achieve dimensionality reduction of the 3D-attention

- Importance: CSA > enriched repr > att weight

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<td>CSA Model</td>
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<td>48.18</td>
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<td>w/o enriched representation</td>
<td>47.52</td>
</tr>
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<td>w/o convolutional spatial attention</td>
<td>47.30</td>
</tr>
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<td>50.89</td>
</tr>
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<td>w/o attention weight</td>
<td>49.49</td>
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<td>w/o enriched representation</td>
<td>49.78</td>
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<td>w/o convolutional spatial attention</td>
<td>48.47</td>
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**Analysis**

- **Quantitative Analysis on Different Type of Questions (on RACE data)**
  - `[+]` CSA model is good at handling ‘how’ and ‘why’ questions, which needs comprehensive reasoning on the document
  - `[-]` On the contrary, CSA model shows inferior performance on ‘who’, ‘when’, ‘where’ questions
  - Further efforts should be made on balancing the word-level attention and highly abstracted attention.
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CONCLUSIONS & FUTURE WORK

• Conclusion
  
  • Propose Convolutional Spatial Attention model for RC with multiple-choice questions
  
  • The proposed model done well on hard problems types, such as ‘how’ and ‘why’
  
  • Experimental results show significant improvements on RACE and SemEval 2018 datasets
  
• Future Work
  
  • Integrate CSA model into BERT
  
  • Further exploiting the relations between the document, question, and candidates


REFERENCES


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THANK YOU!

ENJOY YOUR TIME IN HAWAII!

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