End-to-end Event Factuality Identification via Hybrid Neural Networks

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- Event factuality identification (EFI) is a task to judge the factuality of events in texts.
- Previous research on EFI relied on annotated information, which cannot be applied to real world applications directly, and most studies only considered the default source AUTHOR.

Examples

1. Northbridge is a cool, calculating and clever criminal who could strike again.
2. If it rains tomorrow, I may stay at home.
3. He indicated that some assets might be sold off to service the debt.

Overall Framework

- Event: make, the current event.
- SIP: 1, whether the current event introduces a predicate to the source.
- Upper SIP: says, upper sip introduces the relevant source of the current event.
- Event related sources: Nations, event related source is introduced by the upper SIP.
- Speculative cue: 0, speculative cue that affect the factuality of the current event.
- Negative cue: 0, negative cue that affect the factuality of the current event.
- Sen: The United Nations says women and children make up about seventy-five percent of the Afghan population.
- SIP_Path: says comp make, the dependency path of upper SIP to the current event.
- SS_Path: says nsubj Nations, the dependency path of upper SIP to the event related sources.
- SC_Path: null, the dependency path of speculative cue to the current event.
- NC_Path: null, the dependency path of negative cue to the current event.

Training Objectives

- \( \ell = - \sum \lambda (\log(\Theta(y_{ij}))) \)

<table>
<thead>
<tr>
<th>Model</th>
<th>CT</th>
<th>UA</th>
<th>CP</th>
<th>PR</th>
<th>P0</th>
<th>Micro-F1</th>
<th>Macro-F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLSTM + At</td>
<td>64.61</td>
<td>41.48</td>
<td>20.79</td>
<td>21.86</td>
<td>18.96</td>
<td>40.27</td>
<td>29.44</td>
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<tr>
<td>CNN + BiLSTM</td>
<td>66.66</td>
<td>42.53</td>
<td>30.64</td>
<td>28.26</td>
<td>27.98</td>
<td>44.84</td>
<td>35.14</td>
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<tr>
<td>CNN + CNN</td>
<td>50.73</td>
<td>53.89</td>
<td>23.26</td>
<td>19.62</td>
<td>17.64</td>
<td>54.86</td>
<td>34.37</td>
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<tr>
<td>CNN + BiLSTM</td>
<td>61.14</td>
<td>53.82</td>
<td>25.18</td>
<td>22.43</td>
<td>18.89</td>
<td>57.23</td>
<td>37.53</td>
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<tr>
<td>CNN + BiLSTM + At</td>
<td>62.11</td>
<td>56.78</td>
<td>31.48</td>
<td>25.39</td>
<td>18.43</td>
<td>58.13</td>
<td>38.47</td>
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<tr>
<td>CNN + GCN_BiLSTM</td>
<td>65.10</td>
<td>59.48</td>
<td>35.53</td>
<td>25.33</td>
<td>24.71</td>
<td>58.87</td>
<td>42.01</td>
</tr>
</tbody>
</table>

- We propose an end-to-end model for event factuality identification, which identifies event factuality from raw texts without using annotated information.
- We introduce the event-related information, sentence and dependency paths to represent event factuality from different aspects and propose a hybrid model based on GCN and BiLSTM to learn semantic and syntactic features better.

This result shows that our CNN-based filtering model can effectively filter out the pseudo samples to improve the performance rapidly.
This result indicates that the use of GCN-based network to obtain semantic features is more effective in obtaining word-to-word connections.
The result shows that the combination of Dep and Baselongup (i.e., Baselongup+Dep) can further improve the performance and this indicates these two types are complementarity.

Conclusion

The NLP Lab, Soochow University