A Joint Many-Task Model: Growing a Neural Network for Multiple NLP Tasks

Overview: A Single Deep Model to Handle Different Types of NLP Tasks

Deep Learning for Natural Language Processing (NLP):
A recent trend is developing more and more complex models for single or a few related tasks
Many NLP tasks are related to each other. Why not developing a single model which can handle many different tasks?

Model: Handling More Complex Tasks in Successively Deeper Layers

The core ideas are:
- handling different tasks in different layers of multi-layer bi-LSTMs (or any types of bi-directional recurrent neural networks),
- connecting word representations and output from word-level tasks directly to higher layers
- preventing the model from forgetting the information learned for low-level tasks (successive regularization).

Interested in an extension of this model?
"Neural Machine Translation with Source-Side Latent Graph Parsing" Hashimoto and Tsuruoka, EMNLP 2017

Results: State-of-the-Art Results with a Single Model

Table 1: Test set results for the five tasks. In the relatedness task, the lower scores are better.

<table>
<thead>
<tr>
<th>Task</th>
<th>Single</th>
<th>JMT-all</th>
<th>JMT-ASB</th>
<th>JMT-ASD</th>
<th>JMT-DEL</th>
<th>JMT-TED</th>
<th>JMT-TCD</th>
<th>JMT-TEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A ◁ POS</td>
<td>97.45</td>
<td>97.55</td>
<td>97.52</td>
<td>97.54</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>JMT-all</td>
</tr>
<tr>
<td>B ◁ Chunking</td>
<td>95.02</td>
<td>95.77</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>JMT-all</td>
</tr>
<tr>
<td>C ◁ Dependency UAS</td>
<td>95.35</td>
<td>94.67</td>
<td>n/a</td>
<td>n/a</td>
<td>93.53</td>
<td>93.57</td>
<td>93.62</td>
<td>91.69</td>
</tr>
<tr>
<td>C ◁ Dependency LAS</td>
<td>91.42</td>
<td>92.90</td>
<td>92.92</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>93.62</td>
</tr>
<tr>
<td>D ◁ Relational</td>
<td>0.237</td>
<td>0.233</td>
<td>0.238</td>
<td>0.251</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>JMT-all</td>
</tr>
<tr>
<td>E ◁ Entailment</td>
<td>81.8</td>
<td>86.2</td>
<td>n/a</td>
<td>n/a</td>
<td>86.8</td>
<td>82.4</td>
<td>93.57</td>
<td>93.62</td>
</tr>
</tbody>
</table>

Table 7: Effectiveness of the Shortcut Connections (SC) and the Label Embeddings (LE).

Table 8: Effectiveness of using different layers for different tasks.

Different word similarity should be Captured in different tasks

Key insight:
Simple linear transformation can derive different meanings from the shared word embeddings

Hashimoto and Tsuruoka, EMNLP 2017

What is close to “standing”? (Table 15 in Supplemental Material)

Table 10: Effects of the order of training.

Table 11: Effects of depth for the single tasks.

Table 9: Effectiveness of the Successive Regularization (SR) and the Vertical Connections (VC).