Evaluating Neural Machine Translation in English-Japanese Task
Zhongyuan Zhu

Overview (Abstract)
We evaluated Neural Machine Translation (NMT) models in English-Japanese translation task. Various network architectures with different recurrent units are tested. Additionally, we examine the effect of using pre-reordered data for the training. Our experiments show that even simple NMT models can produce better translations compared with all SMT baselines. For NMT models, recovering unknown words is another key to obtaining good translations. We describe a simple workaround to find missing translations with a back-off system. Surprisingly, performing pre-reordering on the training data hurts the model performance. We provide a qualitative analysis demonstrates specific error pattern in NMT translations which omits partial reordering on the training data hurts the model performance. We conducted a detailed qualitative analysis on a held-out development dataset.

Experimental details

- A comparison of two network architectures

- Visualization of the training process for different models

- Problem of unknown words

  Replacing unknown words in the target side with “unk” (Luong et al., 2015) works well with soft-attention models trained on pre-reordered data. However, for models trained on data of natural order, other sophisticated solutions are required.

  A simple workaround is to find the missing word in the translation result of a baseline system. As for the same target word, they usually share similar context even in different translations.

Evaluation results in English-Japanese task

<table>
<thead>
<tr>
<th>Model</th>
<th>BLEU</th>
<th>RIBES</th>
<th>HUMAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASELINE T2S SMT</td>
<td>33.44</td>
<td>0.758</td>
<td>30.00</td>
</tr>
<tr>
<td>Ensemble of 2 LSTM Search</td>
<td>33.38</td>
<td>0.800</td>
<td></td>
</tr>
<tr>
<td>+ UNK replacing (submitted system 1)</td>
<td>34.19</td>
<td>0.802</td>
<td>43.50</td>
</tr>
<tr>
<td>+ System combination</td>
<td>35.97</td>
<td>0.807</td>
<td></td>
</tr>
<tr>
<td>+ 3 pre-reordered ensembles (submitted system 2)</td>
<td>36.21</td>
<td>0.809</td>
<td>53.75</td>
</tr>
</tbody>
</table>

(For model comparison, we use SGD algorithm to optimize the network, details are presented in the paper)

Findings

- Soft-attention models outperform multi-layer encoder-decoder models
  - The evaluation of valid perplexity shows that soft-attention models outperform simple encoder-decoder models with a substantial margin.
  - This matches our expectation as the alignment between English and Japanese are far more complicated than English-French pair.

- Training models on pre-reordered data hurts the performance
  - Both the perplexity on valid data and automatic evaluation scores show that training soft-attention LSTM models on pre-reordered data degrades the performance.

- NMT models tend to make grammatically valid but incomplete translations
  - Input: this paper discusses some systematic uncertainties including casimir force, false force due to electric force, and various factors for irregular uncertainties due to patch field and detector noise.

    NMT result: ここでは、Casimir 力を考えたいくつかの系統的不確実性について論じた。

    Reference: Casimir 力や電気力による角の力、バッチ場や検出器 資料による不規則な不確実さの種々の要因を含め、幾つかの系統的不確実さを論じた。

Retrospection
We conducted a detailed qualitative analysis on a held-out development dataset. The existence of unknown words are found to drastically degrade the quality of translations. Even the missing word can be posteriorly recovered, some of the translations are still unnatural. In our experiments, we set vocabulary size to 80k and 40k for the input and output layer respectively. Increasing these numbers will significantly slow down the training. Overcoming this problem is expected to be the key of obtaining qualitative translations for NMT models.

Weblio Inc.