Neural Machine Translation with Source-Side Latent Graph Parsing

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Neural Machine Translation with Syntax

- Neural Machine Translation (NMT) has originally proposed as sequence-to-sequence mapping
- Explicitly incorporating syntax into NMT models is actively studied
  - Tree2seq (Eriguchi et al., 2016; +some)
  - Graph2seq (Bastings et al., 2017) ← EMNLP 2017
  - Seq2tree (Eriguchi et al., 2017; Aharoni et al., 2017; +some)

- Is it the best option to use existing syntactic parsers?
  - Is it possible to capture task- or domain-specific structures inherent in sentences?
What Does “Obliquely” Modify?

- PTB-based dependency parsers cannot capture domain-specific relations
  - The bigram “obliquely cross” appears several times in our MT training dataset

As a result, it was found that a path which crosses a sphere obliquely existed.

Reference: その結果、球内部を斜めに横切る行路の存在することが分かった。
What Does “Obliquely” Modify?

- Seq2seq models are sensitive to word order!
  - Google translation might not use in-domain data
  - SEQ is trained by using in-domain data!

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SEQ: その結果、球を横断する経路が斜めに存在することが分かった。
(As a result, it was found that a path which crosses a sphere existed obliquely.)

However... 😞
• Learning a graph-based dependency parser supervised by NMT

Input (source language)
Learning Latent Graphs for NMT

- Learning a graph-based dependency parser supervised by NMT

Input (source language) → Latent graph parser → Latent structure → Supervision (Treebank)
Learning a graph-based dependency parser supervised by NMT

Supervision (Parallel corpus)

Output (target language)

Neural machine translation

Latent structure

Latent graph parser

Input (source language)
Learning a graph-based dependency parser supervised by NMT

Supervision (Parallel corpus)

Output (target language)

Neural machine translation

Latent graph parser

Supervision (Treebank)

Latent structure

Input (source language)
Overview of Our Model Instantiation

- Two key components
  - Latent parser (Hashimoto et al., 2017) ← EMNLP 2017
  - Attention-based NMT (Luong et al., 2015)
Latent (Dependency) Graph Parser

- Representing sentences with weighted directed graphs
  - We use a multi-task parser in Hashimoto et al., (2017)

Example:
The parent of the word “C” is
- “A” \( (p = 0.1) \)
- “B” \( (p = 0.8) \)
- “ROOT” \( (p = 0.1) \)
For each word, aggregating the information about child-parent relations using the dependency scores

- The prob. values are directly used in NMT

In the case of “C”:

$$dep(C) = f \left( h(C), 0.8 \times h(A) + 0.1 \times h(B) + 0.1 \times h(\text{ROOT}) \right)$$
Attention to Dependency Composition

- Applying “attention” to the dep. composition vectors
  - Which dependency relations are important when outputting each target word?
- All the model parameters are jointly learned
Attention to Dependency Composition

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  - Which dependency relations are important when outputting each target word?
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Overall Objective Function

• Standard objective function to train NMT models
  – $D$: Training data
  – $(x, y)$: Source-target sentence pair

• By optimizing the NMT model, the parsing component is automatically learned end-to-end

\[
\frac{1}{|D|} \sum_{(x,y) \in D} \sum_{i=1}^{N_y} \log p(y_i | x, y_1, y_2, \ldots, y_{i-1})
\]
Speed-Up Model Training

- Sampling $K$ negative samples from the vocabulary
  - BlackOut \cite{Ji2016}, similar to NCE
  - Previously used in NMT \cite{Eriguchi2016, Eriguchi2017}
    - $K=\sim2500$
  - Enables to train NMT models on multi-core CPUs

Tips

- Sharing negative samples for each different sentence leads to cache-friendly training
  - Related: sharing negative samples for each mini-batch to accelerate GPU training \cite{Zoph2016}
Model Averaging (Recommended)

Tips

• Averaging the model parameters to improve generalization capacity
  – Save the model parameters after each epoch
  – Average the model parameters using the $T$ most recent sets of the model parameters

• Successfully used in some neural NLP models:
  – Tree-based RNN (Hashimoto et al., 2013)
  – LSTM language modeling (Merity et al., 2017)
Beam Search with Length Statistics

- Combining the two existing methods
  - Statistics of input/output lengths (Eriguchi et al., 2016)
    - \( L_x \): input length, \( L_y \): output length
  - Length normalization (Cho et al., 2014)

\[
\frac{1}{L_y} \left( \sum_{i=1}^{L_y} \log p(y_i | x, y_1, \ldots, y_{i-1}) + \log p(L_y | L_x) \right)
\]

Only used when "EOS" appears
ASPEC En-Ja Corpus (Nakazawa et al., 2016)

- Training data
  - **Small** training dataset: 20,000 pairs
  - **Medium** training dataset: 100,000 pairs
  - **Large** training dataset: 1,346,946 pairs
- Development data: 1,790 pairs
- Test data: 1,812 pairs

- Evaluation metrics: **BLEU, RIBES** (, Perplexity)

- Our experiments are **word-based**, but it is interesting to consider dependency relations between sub-words
Experimental Settings (2)

• Latent parser: 100-dim. embeddings and LSTMs
  – Pre-trained word and character n-gram embeddings are used for initialization (Hashimoto et al., 2017)

• The parsing component can be further pre-trained
  – Training data: PTB WSJ
    • POS tagging: 38,219 sentences
    • Dependency parsing: 39,832 sentences
      – Stanford dependency
  – We follow Hashimoto et al. (2017) for pre-training
Experimental Settings (3)

- Optimization (details can be found in our paper)
  - SGD w/ momentum (w/ gradient clipping)
  - Globally randomized mini batch
  - Dropout, weight decay

- **Small** training dataset (output vocab. size: \(8,593\))
  - NMT’s embeddings and LSTMs: \(128\)dim

- **Medium** training dataset (output vocab. size: \(23,532\))
  - NMT’s embeddings and LSTMs: \(256\)dim

- **Large** training dataset (output vocab. size: \(65,680\))
  - NMT’s embeddings and LSTMs: \(512\)dim
Model Configurations

- **LGP-NMT**: Our proposed model
- **LGP-NMT+**: Our proposed model w/ pre-training

- **SEQ**
  - Attention-based seq2seq NMT by removing the dependency connections from LGP-NMT
- **UNI**
  - Using fixed uniform distributions for parent nodes
- **DEP** (similar to tree2seq)
  - Using dependency relations given by the pre-trained parser in LGP-NMT+
Small Dataset Results (on Dev. Data)

- **LGP-NMT** performs poorly
  - Too complex for such a small training dataset
- **LGP-NMT+** improves the scores
  - Small variance (it is good!)
- **DEP** performs the worst... :(

<table>
<thead>
<tr>
<th></th>
<th>BLEU</th>
<th>RIBES</th>
<th>Perplexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>LGP-NMT</td>
<td>14.31 ± 1.49</td>
<td>65.96 ± 1.86</td>
<td>41.13 ± 2.66</td>
</tr>
<tr>
<td>LGP-NMT+</td>
<td>16.81 ± 0.31</td>
<td>69.03 ± 0.28</td>
<td>38.33 ± 1.18</td>
</tr>
<tr>
<td>SEQ</td>
<td>15.37 ± 1.18</td>
<td>67.01 ± 1.55</td>
<td>38.12 ± 2.52</td>
</tr>
<tr>
<td>UNI</td>
<td>15.13 ± 1.67</td>
<td>66.95 ± 1.94</td>
<td>39.25 ± 2.98</td>
</tr>
<tr>
<td>DEP</td>
<td>13.34 ± 0.67</td>
<td>64.95 ± 0.75</td>
<td>43.89 ± 1.52</td>
</tr>
</tbody>
</table>

Average scores across 5 different runs
Does the size of the tagging/parsing datasets matter?

- $K$: the number of sentences used for training

- **5,000~10,000** sentences seems to be sufficient
  - To avoid overfitting to different domain data

Such small training datasets can be available for ~50 languages as Universal Dependencies

<table>
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<th>$K$</th>
<th>BLEU</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>14.31±1.49</td>
<td>65.96±1.86</td>
<td>41.13±2.66</td>
</tr>
<tr>
<td>5,000</td>
<td>16.99±1.00</td>
<td>69.03±0.93</td>
<td>37.14±1.96</td>
</tr>
<tr>
<td>10,000</td>
<td>16.81±0.31</td>
<td>69.03±0.28</td>
<td>38.33±1.18</td>
</tr>
<tr>
<td>All</td>
<td>16.09±0.56</td>
<td>68.19±0.59</td>
<td>39.24±1.88</td>
</tr>
</tbody>
</table>
• SEQ is still strong

• **LGP-NMT+** slightly improves upon **LGP-NMT**
  – We need to inspect the translation results

• We focus on LGP-NMT and SEQ in the remaining part
  – UNI and DEP do not perform well

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<tr>
<td>LGP-NMT</td>
<td>28.70±0.27</td>
<td>77.51±0.13</td>
<td>12.10±0.16</td>
</tr>
<tr>
<td>LGP-NMT+</td>
<td>29.06±0.25</td>
<td>77.57±0.24</td>
<td>12.09±0.27</td>
</tr>
<tr>
<td>SEQ</td>
<td>28.60±0.24</td>
<td>77.39±0.15</td>
<td>12.15±0.12</td>
</tr>
<tr>
<td>UNI</td>
<td>28.25±0.35</td>
<td>77.13±0.20</td>
<td>12.37±0.08</td>
</tr>
<tr>
<td>DEP</td>
<td>26.83±0.38</td>
<td>76.05±0.22</td>
<td>13.33±0.23</td>
</tr>
</tbody>
</table>
LGP-NMT and LGP-NMT+ slightly improve upon SEQ
– What is missing in the state-of-the-art systems?
• BLEU scores do NOT tell us anything in detail :(

<table>
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<th>BLEU</th>
<th>RIBES</th>
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<tr>
<td>LGP-NMT</td>
<td>39.19</td>
<td>82.66</td>
</tr>
<tr>
<td>LGP-NMT+</td>
<td>39.42</td>
<td>82.83</td>
</tr>
<tr>
<td>SEQ</td>
<td>38.96</td>
<td>82.18</td>
</tr>
<tr>
<td>Ensemble of the above three models</td>
<td>41.18</td>
<td>83.40</td>
</tr>
<tr>
<td>Cromieres et al. (2016)</td>
<td>38.20</td>
<td>82.39</td>
</tr>
<tr>
<td>Neubig et al. (2015)</td>
<td>38.17</td>
<td>81.38</td>
</tr>
<tr>
<td>Eriguchi et al. (2016a)</td>
<td>36.95</td>
<td>82.45</td>
</tr>
<tr>
<td>Neubig and Duh (2014)</td>
<td>36.58</td>
<td>79.65</td>
</tr>
<tr>
<td>Zhu (2015)</td>
<td>36.21</td>
<td>80.91</td>
</tr>
<tr>
<td>Lee et al. (2015)</td>
<td>35.75</td>
<td>81.15</td>
</tr>
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</table>
Examples of Latent Graphs

• Learned by LGP-NMT

All the calculated electronic band structures are metallic.

• Learned by LGP-NMT+

Before

All the calculated electronic band structures are metallic.

After

All the calculated electronic band structures are metallic.
Example 1: Selectional Preference

- LGP-NMT captures the domain-specific relation
- The state-of-the-art seq2seq model fails to capture this relation (the distance is only 2!!)
  - Sensitive to word order... :(

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Example 2: Adjective or Adverb?

- Treebank-based pre-training is helpful
  - LGP-NMT+ alone recognizes the word “negatively” is an adverb

The androgen controls negatively ImRNA.
Reference: ImRNAはアンドロゲンにより負に調節される。

LGP-NMT+: アンドロゲンはImRNAを負に制御している。
(The androgen negatively controls ImRNA.)

Google trans: アンドロゲンは負のImRNAを制御する。
LGP-NMT: アンドロゲンは負のImRNAを制御する。
(The androgen controls negative ImRNA.)

SEQ: アンドロゲンは負のImRNAを負に制御する。
(The androgen negatively controls negative ImRNA.)
Summary

• This work proposes to learn \textbf{task-oriented latent graph structures} for neural machine translation
  – Treebank annotations provide information about basic structures and linguistic tags

• Future work
  – Applying the method to \textbf{other tasks}
  – Focusing on other issues like \textbf{PP attachments}