Using Word Posterior in Lattice Translation

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Motivation - Common approaches

- Serial approach:
  - + simple and fast - propagates errors from ASR

- Semi-coupled approach:
  - n-best: + simple - redundancy, time-consuming
  - lattice: + full searched space - time-consuming
  - confusion network: + simplified lattice, efficient - loss of grammar

- Integrated approach:
  - + theoretically promising - bad performance on non-simple corpora
Word Posterior Probabilities

- Motivation
  - One should maximize word posterior probabilities to minimize WER (Mangu00)
  - Confusion networks (Bertoldi05):
    * word posterior probabilities
    * lattice simplification

- Our approach
  - Word posterior probabilities over a lattice
  - Take advantage of techniques in confidence measures (Sanchis04)
**Word Posterior Probabilities: Forward-Backward**

- being $w$ the hypothesized word, $s$ the start node and $e$ the end node:

$$P([w, s, e] \mid \vec{x}_1^T) = \frac{1}{P(\vec{x}_1^T)} \sum_{f_1^J \in G:\exists[w', s', e']:w' = w, s' = s, e' = e} P(f_1^J, \vec{x}_1^T)$$ (1)
• maximum of the frame time posterior probability (Wessel01)

\[
P_t(w \mid \vec{x}_1^T) = \sum_{t \in [s', e']} P([w, s', e'] \mid \vec{x}_1^T) \tag{2}
\]

\[
P([w, s, e] \mid \vec{x}_1^T) = \max_{s \leq t \leq e} P_t(w \mid \vec{x}_1^T) \tag{3}
\]
Translation System

• Log-linear model:
  – Word posterior probabilities
  – GIATI:
    ✴ Joint probability model
    ✴ N-grams of bilingual pairs
    ✴ 5-gram (w/o cutting off)
    ✴ integrated lattice search
    ✴ monotonous search
  – Output word penalty
  – Output language model (5-gram)
Translation System

• Reordering:
  – Serial, 1BEST approach
  – Monotonization of the output
  – Translate with moses from monotonized to regular word order
  – Models: reordering table and output language model
  – Monotonous search
Preprocess and postprocess

- Preprocess:
  - Case and punctuation were removed from training
  - Sentence splitting at sentence boundaries (., ?!)
  - Lattice pruning

- Postprocess:
  - Punctuation and case restoration: IWSLT06 method using SRILM
  - Capitalization after punctuation marks
## Corpus Statistics

<table>
<thead>
<tr>
<th></th>
<th>Sentences</th>
<th>Running words</th>
<th>OOV words</th>
<th>Vocabulary</th>
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Effect of adding features to the baseline model

• Primary run: 16.13 BLEU

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<th>dev4 NIST</th>
<th>dev5a BLEU</th>
<th>dev5a NIST</th>
<th>dev5b BLEU</th>
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<th>test NIST</th>
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<td>14.34</td>
<td>4.37</td>
<td>23.22</td>
<td>5.86</td>
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</tbody>
</table>

• WP, output word insertion penalty
• OL, output language model
• RM, reordering model
Effect of adding dev corpus to the training corpus

- Primary run: 16.13 BLEU

<table>
<thead>
<tr>
<th></th>
<th>w/o dev</th>
<th></th>
<th>with dev</th>
<th></th>
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<tbody>
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<td>BLEU</td>
<td>NIST</td>
<td>BLEU</td>
<td>NIST</td>
</tr>
<tr>
<td>baseline</td>
<td>22.80</td>
<td>5.49</td>
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<td>+WP</td>
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<td>+WP+OL+RM</td>
<td>23.22</td>
<td>5.86</td>
<td>31.21</td>
<td>6.77</td>
</tr>
</tbody>
</table>

- WP, output word insertion penalty
- OL, output language model
- RM, reordering model
## Results for different input conditions

<table>
<thead>
<tr>
<th></th>
<th>dev4</th>
<th>dev5a</th>
<th>dev5b</th>
<th>test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLEU</td>
<td>NIST</td>
<td>BLEU</td>
<td>NIST</td>
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<td>1BEST</td>
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<td>LAT</td>
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<td>6.95</td>
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<td>GER</td>
<td>34.11</td>
<td>7.02</td>
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<td>CLEAN</td>
<td>38.98</td>
<td>7.81</td>
<td>32.86</td>
<td>7.18</td>
</tr>
</tbody>
</table>

- **LAT**, lattice with word posterior probabilities
- **GER**, using the sentence from the lattice with less word error rate
Conclusions

- Word Posterior approach
  - Results not conclusive
  - Small differences between 1BEST and CLEAN scores
  - Some improvements were achieved
  - Needs work on pruning

- Adding devset to training matters
Future Work

- Comparison with n-best, confidence measures, lattice with acoustic scores
- Add additional state-of-the-art confidence features
- Add translation features
- Features based on multiple lattices
- Lattice reduction
Thank you for your attention!

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References


