FBK @ IWSLT 2007

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FBK - Fondazione B. Kessler, Trento, Italy

Trento, 15 October 2007
Overview

• system architecture
• confusion network
• punctuation insertion
• improvement of lexicon
• use of multiple lexicons and language models
• system evaluation

Acknowledgments

• Hermes people: Marcello, Mauro, Roldano
• input from speech (word-graph or 1-best) or text

• pre and post processing (optional)
  – use of the SRILM toolkit
  – **CN extraction**: lattice-tool
  – **punctuation insertion**: hidden-ngram
  – case restoring: disambig

• **Moses** is a text/CN decoder

• rescoring of \(N\)-best translations (optional)
Step 1: take the ASR *word lattice*

- arcs are labeled with *words* and *acoustic and LM scores*
- arcs have start and end *timestamps*
- any path is a *transcription hypothesis*
Step 2: approximate the word lattice into a **Confusion Network**

- a CN is a linear word graph
- arcs are labeled with *words* or with the *empty word* (\(\epsilon\)-word)
- arcs are weighted with word *posterior probabilities*
- paths are a *superset* of those in the word lattice
- paths can have different lengths
- algorithm proposed by [Mangu, 2000]
  - exploit start and end timestamps of the lattice arcs
  - collapse/cluster close words
  - lattice-tool
**Step 3**: represent the CN as a *table*

<table>
<thead>
<tr>
<th>i,9</th>
<th>cannot,8</th>
<th>€,7</th>
<th>say,6</th>
<th>€,7</th>
<th>anything,8</th>
</tr>
</thead>
<tbody>
<tr>
<td>hi,1</td>
<td>can,1</td>
<td>€,1</td>
<td>said,2</td>
<td>any,3</td>
<td>thing,1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>says,1</td>
<td></td>
<td>things,1</td>
</tr>
</tbody>
</table>
Step 3: represent the CN as a table

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<tr>
<th>i.9</th>
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<th>ε.7</th>
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</tr>
</thead>
<tbody>
<tr>
<td>hi.1</td>
<td>can.1</td>
<td>not.3</td>
<td>said.2</td>
<td>any.3</td>
<td>thing.1</td>
</tr>
<tr>
<td>ε.1</td>
<td></td>
<td>ε.1</td>
<td>says.1</td>
<td>ε.1</td>
<td>things.1</td>
</tr>
</tbody>
</table>

Notes

- text is a trivial CN
- CN can be used for representing ambiguity of the input
  - transcription alternatives
  - punctuation
  - upper/lower case
The Problem

- *punctuation* improves *readability* and *comprehension* of texts
- *punctuation marks* are important clues for the translation process
- most ASR systems generate output *without* punctuation
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Our approach [Cattoni, Interspeech 2007]

- insert punctuation as a *pre-processing* step
- exploit *multiple* hypotheses of punctuation
- use *punctuated models* (i.e. trained on texts with punctuation)
- let the decoder choose the best punctuation (and translation)
Step 1: take the input \textit{not-punctuated CN}
Step 2: extract the not-punctuated *consensus decoding*

i cannot say anything at this point are there any comments
Step 3: compute the $N$-best hypotheses of punctuation (with hidden-ngram)

| NBEST_0  | -15.270 | i cannot say anything at this point . | are there any comments |
| NBEST_1  | -15.317 | i cannot say anything at this point . | are there any comments ? |
| NBEST_2  | -16.275 | i cannot say anything at this point ? | are there any comments ? |
| NBEST_3  | -16.322 | i cannot say anything at this point ? | are there any comments ? |
| NBEST_4  | -17.829 | i cannot say anything at this point are there any comments . |
| NBEST_5  | -18.284 | i cannot say anything at this point ? | are there any comments |
| NBEST_6  | -18.331 | i cannot say anything at this point are there any comments |
| NBEST_7  | -18.473 | i cannot say anything . at this point are there any comments |
| NBEST_8  | -18.521 | i cannot say anything . at this point are there any comments ? |
| NBEST_9  | -18.834 | i cannot say anything at this point . are there any comments . |
**Step 4:** compute the *punctuating CN* with *posterior probs* of multiple marks

\[
i_1 \text{ cannot } 1 \text{ say } 1 \text{ anything } 1 \epsilon_{.9} \text{ at } 1 \text{ this } 1 \text{ point } 1 \epsilon_{.2} \text{ are } 1 \text{ there } 1 \text{ any } 1 \text{ comments } 1 \epsilon_{.6} \\
\]

\[
\text{.1} \quad \text{.7} \quad \text{.3} \quad \text{.1}
\]
Step 5: *merge* the input CN and the punctuating CN

\[
\begin{align*}
&\text{i}._9 & \text{cannot}._8 & \epsilon._1 & \text{not}._3 & \text{say}._6 & \epsilon._7 & \text{anything}._8 & \text{at}._9 & \text{this}._8 & \text{point}._7 & \text{are}._1 & \text{there}._8 & \epsilon._8 & \text{any}._7 & \text{comments}._7 \\
&\text{hi}._1 & \text{can}._1 & \epsilon._1 & \text{not}._3 & \text{say}._1 & \epsilon._7 & \text{thing}._1 & \epsilon._1 & \text{these}._1 & \text{points}._1 & \text{a}._1 & \text{air}._1 & \text{new}._1 & \text{comment}._2 \\
&\text{pint}._1 & \epsilon._1 & \text{cannot}._1 & \text{say}._1 & \text{anything}._1 & \text{at}._1 & \text{this}._1 & \text{point}._1 & \text{are}._1 & \text{there}._1 & \text{any}._1 & \text{comments}._1 \\
\end{align*}
\]
Step 6: get the final *punctuated CN*
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Notes

• this approach works with any speech input (1-best and CN) without punctuation and with partially punctuated input
Step 6: get the final *punctuated CN*

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<th>$\epsilon$.7</th>
<th>are1</th>
<th>there.8</th>
<th>$\epsilon$.8</th>
<th>any.7</th>
<th>comments.7</th>
<th>$\gamma$.6</th>
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<tbody>
<tr>
<td>hi.1</td>
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<td>$\epsilon$.1</td>
<td>thing.1</td>
<td>$\gamma$.1</td>
<td>these.1</td>
<td>those.1</td>
<td>punt.1</td>
<td>$\gamma$.1</td>
<td>the.1</td>
<td>a.1</td>
<td>new.1</td>
<td>a.1</td>
<td>commit.1</td>
</tr>
</tbody>
</table>

Notes
- this approach works with any speech input (1-best and CN) without punctuation and with partially punctuated input
- one system (with punctuated models) translates any input (text and speech)
Which is the better approach to add punctuation marks?
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- in the *source* as a *pre-processing* step
Which is the better approach to add punctuation marks?

- in the *source* as a *pre-processing* step
- in the *target* as a *post-processing* step
  - translate with not-punctuated models
  - add punctuation to the best translation (with hidden-ngram)
Which is the better approach to add punctuation marks?

- in the source as a pre-processing step
- in the target as a post-processing step
  - translate with not-punctuated models
  - add punctuation to the best translation (with hidden-ngram)

- evaluation
  - task: eval set 2006, TC-STAR English-to-Spanish
  - training data: FTE transcriptions of EPPS (36Mw English, 38Mw Spanish)
  - verbatim input (w/o punctuation), case-insensitive

<table>
<thead>
<tr>
<th>approach</th>
<th>BLEU</th>
<th>NIST</th>
<th>WER</th>
<th>PER</th>
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<tbody>
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<td>source</td>
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Do multiple punctuation hypotheses help to improve translation quality?
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- evaluation
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<th>input</th>
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Do multiple punctuation hypotheses help to improve translation quality?

- evaluation
  - verbatim (w/o punctuation), 1-best, and CN
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Create a phrase-pair lexicon

- take a case-sensitive parallel corpus
- word-align the corpus in direct and inverse directions (GIZA++)
- combine both word-alignments in one symmetric way:
  - grow-diag-final, union, and intersection
- extract phrase pairs from a symmetrized word-alignment
- add single word translation from direct alignment
- score phrase pairs according to word and phrase frequencies
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Ideas for improving the lexicon:

- use case-insensitive corpus for word-alignment, but case-sensitive extraction
Create a phrase-pair lexicon

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Ideas for improving the lexicon:

- use *case-insensitive* corpus for word-alignment, but case-sensitive extraction
- extract phrase pairs separately from more symmetrized word-alignments, concatenate them and compute their scores
How much improvement do we get?
How much improvement do we get?

- evaluation
  - task: IWSLT Chinese-to-English, 2006 eval set
  - training data: BTEC and dev sets (’03-’05)
  - weight optimization on 2006 dev set
  - verbatim input, case-sensitive

<table>
<thead>
<tr>
<th>symmetrization</th>
<th>text for word-alignment</th>
<th># phrase pairs</th>
<th>BLEU</th>
<th>NIST</th>
</tr>
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<tbody>
<tr>
<td>grow-diag-final</td>
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<tr>
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<tr>
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<td>5.2M</td>
<td>22.71</td>
<td>6.31</td>
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</tbody>
</table>
• multiple training corpora
  – non-homogeneous data (size, domain)
  – small corpus for domain adaptation
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• **one TM and one LM**
  – concatenation of all corpora
  – corpus characteristics are (too?) smoothed
• **multiple training corpora**
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• **one TM and one LM**
  – concatenation of all corpora
  – corpus characteristics are smoothed

• **multiple TMs and multiple LMs**
  – **advantages**
    * more specialized models, more flexibility
    * easy combination/selection of models
    * effective (for TMs)
  – **drawbacks**
    * complexity of the model
How much improvement do we get?
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• evaluation
  – task: IWSLT Italian-to-English, second half of 2007 dev set
  – training data:
    † baseline: BTEC, Named Entities, MultiWordNet and dev sets (’03-’06):
      3.8M phrase pairs, 362K 4-grams
    † EU Proceedings (39M phrase pairs, 16M 4-grams)
    † Google Web 1T (336M 5-grams)
  – weight optimization on the first half of 2007 devset
  – verbatim input repunctuated with CN, case-insensitive

<table>
<thead>
<tr>
<th>TM_1,LM_1</th>
<th>TM_2,LM_2</th>
<th>LM_3</th>
<th>OOV</th>
<th>BLEU</th>
<th>NIST</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td></td>
<td>-</td>
<td>1.68</td>
<td>28.70</td>
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<tr>
<th>TM&lt;sub&gt;1&lt;/sub&gt;,LM&lt;sub&gt;1&lt;/sub&gt;</th>
<th>TM&lt;sub&gt;2&lt;/sub&gt;,LM&lt;sub&gt;2&lt;/sub&gt;</th>
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Multiple TMs and LMs

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<tr>
<th>( \text{TM}_1, \text{LM}_1 )</th>
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<tr>
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<td>0.28</td>
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1-best vs. Confusion Networks
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<table>
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<tr>
<th>task</th>
<th>input</th>
<th>BLEU</th>
</tr>
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<tbody>
<tr>
<td>IE, ASR</td>
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<td>41.51</td>
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<tr>
<td></td>
<td>cn</td>
<td>42.29*</td>
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</tbody>
</table>

* primary run

- CN outperforms 1-best
### 1-best vs. Confusion Networks

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* primary run

- CN outperforms 1-best
- no inspection on CN for JE
Multiple TMs and LMs
### Multiple TMs and LMs

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<tr>
<td>IE, clean</td>
<td>baseline</td>
<td>baseline</td>
<td>43.41</td>
</tr>
<tr>
<td></td>
<td>+EP</td>
<td>+EP+web</td>
<td>44.32*</td>
</tr>
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</table>

* primary run
# Multiple TMs and LMs

<table>
<thead>
<tr>
<th>task</th>
<th>TMs</th>
<th>LMs</th>
<th>BLEU</th>
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<tbody>
<tr>
<td>IE, clean</td>
<td>baseline</td>
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<tr>
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<td>+EP</td>
<td>+EP+web</td>
<td>44.32*</td>
</tr>
<tr>
<td>IE, ASR, CN</td>
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<td>+EP</td>
<td>+EP+web</td>
<td>41.51*</td>
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</table>

* primary run
## Multiple TMs and LMs

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<tr>
<td>CE, clean</td>
<td>baseline + LDC</td>
<td>baseline + web</td>
<td>35.08</td>
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<td>34.72*</td>
</tr>
</tbody>
</table>

* primary run

- additional TMs improves performance (+0.77 BLEU)
- Google Web LM severely affects performance on CE (-1.14 BLEU)
Future work

- punctuation insertion in other languages (Chinese, Japanese)
- use of *caseing* CN to for case restoring
Future work

- punctuation insertion in other languages (Chinese, Japanese)
- use of *caseing* CN to for case restoring
- automatic way of selecting corpora
Future work

- punctuation insertion in other languages (Chinese, Japanese)
- use of *caseing* CN to for case restoring

- automatic way of selecting corpora

- further inspection on the use of Google Web corpus
Thank you!
Chinese-to English

- word-alignment on ci texts, grow-diag-final + union + inter
- case sensitive models
- distortion models: distance-based and orientation-bidirectional-fe
- (stack size, translation option limit, reordering limit) = (2000, 50, 7)
- BTEC and dev sets ('03-'07) (TM₁: 5.9M phrase pairs, LM₁: 39K 6-grams)  
  LDC: (TM₂: 27M phrase pairs)  
  Google Web (LM₂: 336M 5-grams)
- 5 official runs
Japanese-to English

- word-alignment on ci texts, grow-diag-final + union + inter
- case sensitive models
- distortion models: distance-based and orientation-bidirectional-fe
- (stack size, translation option limit, reordering limit) = (2000, 50, 7)
- BTEC and dev sets (’03-’07) (TM₁: 9.1M phrase pairs, LM₁: 39K 6-grams)
  Reuters: (TM₂, 176K phrase pairs)
- 6 official runs
Italian-to English

- word-alignment on ci texts, grow-diag-final + union
- case insensitive TMs and LMs and case restoring
- distortion models: distance-based
- (stack size, translation option limit, reordering limit) = (200, 20, 6)
- BTEC NE, MWN, dev sets ('03-'07) (TM$_1$: 3.8M phrase pairs, LM$_1$: 362K 4-grams)
  EU Proceedings: (TM$_2$: 39M phrase pairs, LM$_2$: 16M 4-grams)
  Google Web (LM$_3$: 336M 5-grams)
- rescoring with 5K-best translations
- case-restoring with a 4-gram LM
- 12 official runs
• **Toolkit for SMT:**
  – translation of both text and CN inputs
  – incremental pre-fetching of translation options
  – handling multiple lexicons and LMs
  – handling of huge LMs and LexMs (up to Giga words)
  – on-demand and on-disk access to LMs and LexMs
  – factored translation model (surface forms, lemma, POS, word classes, ...)

• **Multi-stack DP-based decoder:**
  – theories stored according to the coverage size
  – synchronous on the coverage size

• **Beam search:**
  – deletion of less promising partial translations:
    – histogram and threshold pruning

• **Distortion limit:** reduction of possible alignments

• **Lexicon pruning:** limit the amount of translation options per span
• log-linear statistical model

• features of the first pass
  – (multiple) language models
  – direct and inverted word- and phrase-based (multiple) lexicons
  – word and phrase penalties
  – reordering model: distance-based and lexicalized (CE, JE)

• (additional) features of the second pass (IE)
  – direct and inverse IBM Model 1 lexicon scores
  – weighted sum of $n$-grams relative frequencies ($n = 1, \ldots, 4$) in $N$-best list
  – the reciprocal of the rank
  – counts of hypothesis duplicates
  – $n$-gram posterior probabilities in $N$-best list [Zens, 2006]
  – sentence length posterior probabilities [Zens, 2006]