The impact of language models and loss functions on repair disfluency detection

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Outline

Detecting and correcting speech errors in fluent speech

Previous work on disfluency detection

Language models and reranker features

Loss functions

Experimental results

Conclusion
A typology of speech disfluencies

- **Filled pauses:**
  
  I think it’s *uh* refreshing to see the *uh* support . . .

- **Parentheticals**

  But you know I was reading the other day . . .

- **Repairs:**

  I want a flight to Boston *uh* I mean to Denver on Friday

- **Starts:**

  Why didn’t he why didn’t she stay at home?

A typology of speech disfluencies

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• **Restarts:**

  Why didn’t he *why didn’t she* stay at home?

Why treat restarts and repairs specially?

- Filled pauses are easy to recognise and remove from speech transcripts
- Modern NLP tools (e.g., parsers) handle parentheticals properly
- But restarts and repairs are often misanalysed by NLP tools

⇒ Detect and remove disfluencies before further processing

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I want a flight to Boston uh I mean to Denver on Friday.
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The structure of restarts and repairs

... and you get, uh, you can get a system...

- The Reparandum is *often not a syntactic phrase*
- The Interregnum is usually lexically and prosodically marked, but can be empty
- The Reparandum is often a "rough copy" of the Repair
  - Repairs are typically short
  - Repairs are not always copies
  - It's possible e.g. for there to be anaphoric dependencies into the reparandum

Shriberg 1994 “Preliminaries to a Theory of Speech Disfluencies”
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Machine-learning approaches to disfluency detection

... and you get uh you can get a system ...

- Train a classifier to predict whether each word is Edited or NotEdited
  - this approach classifies each word independently, but the classification should really be made over groups of words
- A very large number of features can be usefully deployed in such a system

Charniak and Johnson (2001), Zhang, Weng and Feng (2006)
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The “true” model of repairs (?)

...and you get, uh, you can get a system...

- Speaker generates intended “conceptual representation”
- Speaker incrementally generates syntax and phonology,
  ▶ recognizes that what is said doesn’t mean what was intended,
  ▶ “backs up”, i.e., partially deconstructs syntax and phonology, and
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Approximating the “true model”

I want a flight to Boston uh I mean to Denver on Friday

- Use Repair string as approximation to intended meaning
- Reparandum string is “rough copy” of Repair string
  - involves crossing (rather than nested) dependencies
- String with reparandum and interregnum excised is usually well-formed
  - after correcting the error, what's left should have high probability
    ⇒ use model of normal language to interpret ill-formed input
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The Noisy Channel Model

- Noisy channel models combine two different submodels.
- Channel model needs to generate *crossing dependencies*.
  \[ \Rightarrow \text{TAG transducer} \]

Johnson and Charniak (2004)
The Noisy Channel Model

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Reranking the Noisy Channel model

- Log probs from source model and channel model are \textit{reranker features}
- MaxEnt reranker can use \textit{additional features} as well

⇒ Best of both noisy channel and machine-learning approaches

- Johnson et al used a parser-based language model

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Johnson, Charniak and Lease (2004)
Other related work

- Schuler (2010) uses a Hierarchical Hidden Markov Model to simultaneously parse and perform disfluency detection
- Snover (2004) investigates the utility of lexical and prosodic cues for disfluency detection
- Kahn, Lease, Charniak, Johnson and Ostendorf (2005) integrated prosodic cues into the noisy-channel reranker to parse speech-recogniser output
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How does the language model affect performance?

- Is the size of the training corpus important?
  - $n$-gram KN language model trained on Google Web1T corpus ($\approx 10^{12}$ words)

- Is it important that the language model is trained on fluent language?
  - 4-gram KN language model trained on Gigaword corpus ($1.6 \times 10^9$ words)

- Is it important that the language model is trained on speech data?
  - 4-gram KN language model trained on Fischer corpus ($2.2 \times 10^7$ words)

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Additional reranker features

- Bigram language model and channel model \textit{log probabilities from noisy channel model}
- Log probabilities of other language models
- \textbf{CopyFlags}: \texttt{EDITED} flags surrounding a sequence of “copied” words (745 features)
- \textbf{WordsFlags}: \texttt{EDITED} flags surrounding specific lexical items (256,808 features)
- \textbf{SentenceEdgeFlags}: Distance of \texttt{EDITED} flags from the beginning or end of sentence (22 features)
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The unbalanced nature of the corpus

...I want a flight to Boston uh I mean to Denver on Friday...

- Reparandum
- Interregnum
- Repair

- Switchboard corpus annotates *reparandum, interregnum and repair*
- Trained on Switchboard files sw[23]*.dps (1.3M words)
- Punctuation and partial words ignored
- 31K repairs, average repair length 1.6 words
- Number of training words: *reparandum 50K (3.8%), interregnum 10K (0.8%), repair 53K (4%), too complicated 24K (1.8%)*
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Evaluate using f-score instead of accuracy

- Only around 5% words are \texttt{Edited} ⇒ trivial classifier that always predicts \texttt{NotEdited} scores 95% accuracy
- \textit{F-score} $f$ is geometric mean of precision and recall

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f = \frac{2c}{g + e}
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where $g$ and $e$ are number of gold and predicted \texttt{Edited} words, and $c$ is the number of correct \texttt{Edited} words

- Trivial classifier has 100% precision but 0% recall ⇒ f-score = 0
- Alternative measure: \textit{error rate} (= number of \texttt{Edited} word errors divided by number of true \texttt{Edited} words)

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- Alternative measure: error rate ($= \frac{\text{number of Edited word errors}}{\text{number of true Edited words}}$)

Modify classifier to optimise expected f-score

• A standard MaxEnt estimator optimises log-loss, which weights Edited \sim NotEdited errors equally

• We can modify the estimator so it optimises an approximate expected f-score instead

\[ \tilde{f} = \frac{2E_w[c]}{g + E_w[e]} \]

• \( \tilde{f} \) and its derivatives can be easily calculated

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Jansche (2005), Smith and Eisner (2006)
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- All partial words and punctuation were deleted from training, held-out and test
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<table>
<thead>
<tr>
<th>Model</th>
<th>F-score</th>
<th>log loss</th>
<th>expected f-score loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>NC (noisy channel, no reranking)</td>
<td>0.756</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NC + Switchboard</td>
<td>0.776</td>
<td>0.791</td>
<td></td>
</tr>
<tr>
<td>NC + Fisher</td>
<td>0.771</td>
<td>0.797</td>
<td></td>
</tr>
<tr>
<td>NC + Gigaword</td>
<td>0.777</td>
<td>0.797</td>
<td></td>
</tr>
<tr>
<td>NC + Web1T</td>
<td>0.781</td>
<td>0.798</td>
<td></td>
</tr>
<tr>
<td>NC + Reranker Feat.</td>
<td>0.824</td>
<td>0.827</td>
<td></td>
</tr>
<tr>
<td>NC + Reranker Feat. + Switchboard</td>
<td>0.827</td>
<td>0.828</td>
<td></td>
</tr>
<tr>
<td>NC + Reranker Feat. + Fisher</td>
<td>0.841</td>
<td>0.856</td>
<td></td>
</tr>
<tr>
<td>NC + Reranker Feat. + Gigaword</td>
<td>0.843</td>
<td>0.852</td>
<td></td>
</tr>
<tr>
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<td>0.843</td>
<td>0.850</td>
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<td>0.841</td>
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- One run on test corpus, NC + Reranker Feat. + All LM, expected f-score loss: 0.838
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  - Charniak and Johnson (2001) (Boosting classifier): 0.759
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