Generating Disambiguating Paraphrases for Structurally Ambiguous Sentences

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Introduction
How can we crowd-source data for adapting parsers to new domains?

- To some extent, **MTurk workers** can perform meaning- and form-oriented tasks such as annotating PP-attachment points, with some training (Snow et al., 2008; Jha et al., 2010)
- Gerdes (2013) and Zeldes (2016) also found that it was possible to obtain fairly high quality **class-sourced** annotations, where students only received a modest amount of training
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- In the current study, rather than annotating syntax, we use **natural language clarification questions**, simply asking Mturk workers to select the **right paraphrase** of a structurally ambiguous sentence
Big picture: Just ask people what ambiguous sentences mean.
Difference from previous studies

- Aiming (ultimately) for all structural ambiguities identifiable by an automatic parser, not confined to some specific constructions (Jha et al., 2010)
- AMT workers are making choices among paraphrases, not annotations, and no specific tutorial is needed
Methods
Generating disambiguating paraphrases: An illustration
Generating disambiguating paraphrases: An illustration

Top Parse

Stop.01 <TENSE>past, <MOOD>dcl
Mod Arg1 Arg0
With
He stopped Godzilla with the laser!
Rewrite
Realize

Next Parse

Stop.01 <TENSE>past, <MOOD>dcl
Mod Arg1 Arg0
Laser <NUM>sg
The
He stopped Godzilla with the laser!
Rewrite
Realize

Reversal

✗ He stopped Godzilla with the laser!
✓ With the laser, he stopped Godzilla!

Rewrite
Realize

Rewrite
Realize

Rewrite
Realize

Rewrite
Realize
Generating disambiguating paraphrases: An illustration

**Reversal**

✗ He stopped Godzilla with the laser
✓ With the laser, he stopped Godzilla

**Rewrite**

✓ Godzilla was stopped by him with the laser
Generating disambiguating paraphrases: An illustration

He stopped Godzilla with the laser

With the laser, he stopped Godzilla

He stopped Godzilla with the laser

Godzilla with the laser was stopped by him

Godzilla was stopped by him with the laser

Godzilla with the laser was stopped by him

He stopped Godzilla with the laser
Generating disambiguating paraphrases: An illustration

He stopped Godzilla with the laser!

With the laser, he stopped Godzilla!
Generating disambiguating paraphrases: An illustration

He stopped Godzilla with the laser

✓ Godzilla with the laser was stopped by him
1. Parse the input sentence with the OpenCCG parser to obtain its top 25 parses
2. Find a parse from the $n$-best parse list which is meaningfully distinct from the top parse:
Obtaining meaningfully distinct parses

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   - The symmetric difference cannot be empty, with neither set of dependencies a superset of the other
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3. If successful, this phase yields a \textit{top} and \textit{next} parse — the ones reflecting the \textbf{greatest uncertainty}
Two ways to obtain paraphrases

- **Paraphrases obtained from reverse realization** *(reversals)*
  - Able to generate paraphrases for ambiguities involving various constructions identifiable by an auto parser

- **Paraphrases obtained from logical form rewriting** *(rewrites)*
  - Triggered by specific syntactic constructions such as PP-attachment ambiguity and modifier scope ambiguity in coordination
Validating reverse realizations

Need to ensure paraphrases actually disambiguate intended meanings
Validating reverse realizations

Need to ensure paraphrases actually disambiguate intended meanings

1. **Realize** the *top* and *next* parse into a *n*-best realization list (*n*=25), using OpenCCG
2. Traverse the list to find a qualifying paraphrase, which has to
   - **be different** from the original sentence
   - **have different relative distance** among the words involving the ambiguity from the original sentence
Validating reverse realizations

Need to ensure paraphrases \textbf{actually disambiguate} intended meanings

1. \textbf{Realize} the \textit{top} and \textit{next} parse into a $n$-best realization list ($n=25$), using OpenCCG

2. Traverse the list to find a qualifying paraphrase, which has to
   \begin{itemize}
   \item be different from the original sentence
   \item have different relative distance among the words involving the ambiguity from the original sentence
   \end{itemize}

3. \textbf{Parse} each candidate paraphrase to make sure the most likely interpretation includes the dependencies from which it was generated
Two-sided paraphrases and one-sided paraphrases

- *Two-sided paraphrases*: Two paraphrases are obtained for the original sentence, one generated from the *top* parse, and one from the *next*

- *One-sided paraphrases*: Only one paraphrase is obtained for the original sentence
Rewritten logical forms are realized to obtain paraphrases which highlight the ambiguous part

- Passive and cleft rewrites for PP-attachment ambiguities
- Coordination rewrites for ambiguities in the scope of modiers with coordinated phrases
Passive rewrites: An example

I saw the girl with the telescope.

⇒ The girl with the telescope was seen by me.
Cleft rewrites: An example

I saw the girl with the telescope.

⇒ The girl with the telescope was what I saw.
The old men and women are becoming senile.

⇒ The old women and the old men are becoming senile
The old men and women are becoming senile.

⇒ The women and the old men are becoming senile
Experiment
Validation experiment

**Aim:** Examine the *quality of the crowd-sourced annotations* through disambiguating paraphrases

- Used AMT workers as our naive annotators
- For comparison, **hand annotated** 1,030 sentences as the optimal (‘gold’) annotations to measure the accuracy of the crowd-sourced annotations
Data preparation

Working assumption: Unannotated data available in large quantities, so can focus on most informative ambiguities
We selected the correct parse of the sentence by examining the dependency graphs of the input sentence:

- Annotated ‘top’ if the *top* parse was correct
- Annotated ‘next’ if the *next* parse was correct
- Annotated ‘neither’ if neither of them was more correct than the other one
Distribution of "top", "next" and "neither"
Collecting human judgments

- 5 judgments for each sentence were collected from AMT workers and the judgments of identical sentences were collapsed
- “Neither” cases were excluded from analysis
- Comprehension questions were asked to prevent random choosing
- Agreement levels among the AMT workers:
  
  **Majority** > 50% agreement
  **Strong Majority** > 75%
  **Unanimity** > 90%
Coverage vs. Accuracy: Higher accuracy (but lower coverage) with greater agreement
One-sided vs. Two-sided: Two-sided much more reliable

One and Two-sided Paraphrases

Accuracy (%)

Turker Agreement

One-sided  Two-sided

One-sided  65.2  59.1

Two-sided  71  87.2  79.9

Legend:
- Majority
- Strong
- Unanimity
Reversals vs. Rewrites: Reversals at least as accurate
Potential correction to current parser

Ratio of "next" parses correctly annotated

<table>
<thead>
<tr>
<th>Turker Agreement</th>
<th>Ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority</td>
<td>59.6</td>
</tr>
<tr>
<td>Strong Majority</td>
<td>68</td>
</tr>
<tr>
<td>Unanimity</td>
<td>74.6</td>
</tr>
</tbody>
</table>
Examined 43 sentences where unanimous AMT workers judgments did not agree with gold annotations and located the following reasons for error:

- Incompetent or broken realizations (29/43)
- Bad parses (11/43)
- Lack of context (3/43)
Preliminary parser retraining experiment

- Trained OpenCCG Parser with majority AMT worker annotations (along with original CCGbank data)
- Trained the parser separately in the two domains
- Evaluated the parser with 10-fold cross validation
Evaluation of retrained parser: an example

 Parses were considered correct if the *top* and *next* dependencies occur **in the same order** as in gold: e.g., for the sentence *I saw the girl with the telescope*, if (saw, with) is annotated as the correct dependency,

<table>
<thead>
<tr>
<th>n-best parses</th>
<th>Correct</th>
<th>Incorrect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>(saw, with)</td>
<td>...</td>
</tr>
<tr>
<td>3</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>4</td>
<td>...</td>
<td>(girl, with)</td>
</tr>
<tr>
<td>5</td>
<td>(girl, with)</td>
<td>...</td>
</tr>
<tr>
<td>6</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>(saw, with)</td>
</tr>
<tr>
<td>25</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
### Parser retraining results

<table>
<thead>
<tr>
<th></th>
<th>Dinosaur</th>
<th>Football</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train size</td>
<td>471</td>
<td>356</td>
</tr>
<tr>
<td>Eval size</td>
<td>291</td>
<td>226</td>
</tr>
<tr>
<td>Original acc.</td>
<td>0.701</td>
<td>0.668</td>
</tr>
<tr>
<td>Retrained acc.</td>
<td><strong>0.749</strong></td>
<td><strong>0.717</strong></td>
</tr>
<tr>
<td>Correction rate</td>
<td>0.243</td>
<td>0.32</td>
</tr>
</tbody>
</table>

- MacNemars chi-square test shows a **significant improvement** in the dinosaur domain ($p = 0.02$)
- No significant improvement on football data due to the smaller data size
- The retrained parsers **do not differ significantly from the original parser** ($p > 0.05$ for both) on the CCGbank development set
Conclusions
Conclusions and future work

- It is possible to obtain **accurate crowd-sourced judgments** from naive annotators **with no instruction** — pointing the way towards collecting parser training data on a **massive scale**
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- It is possible to obtain accurate crowd-sourced judgments from naive annotators with no instruction — pointing the way towards collecting parser training data on a massive scale
- The preliminary parsing experiment already suggests that automatic parsers can be retrained to achieve better parsing accuracy
- In the future, we plan to experiment with parser adaptation with multiple parsers and larger data sets
- We also plan to experiment with generating paraphrases with sentence splitting and simplification (Siddharthan, 2006; Siddharthan, 2011)
We thank James Curran, Eric Fosler-Lussier, the OSU Clippers Group and the anonymous reviewers for helpful comments and discussion. This work was supported in part by NSF grant 1319318.
Thank you!
Incompetent realizations

Realization ok, but fails to reliably capture the different meaning in the parses

Usually involved just adding or deleting punctuation
Incompetent realizations: An example

The teeth were adapted to **crush** bivalves, gastropods and other **animals** **with** a shell or exoskeleton.

(animals, with): Same as the original sentence

(crush, with): The teeth were adapted to **crush** bivalves, gastropods and other **animals**, **with** a shell or exoskeleton.
• Inappropriate heavy NP shift
• Long adverbials moved between verbs and their (other) complements
• Wrong modifier-modificand word order
• Wrong position of the particle for phrasal verbs
• Wrong preposition-complement position
They are thought to have gone extinct during the Triassic-Jurassic extinction event.

(gone, during): They are thought to have gone during the Triassic-Jurassic extinction event extinct.

(thought, during): They are thought during the Triassic-Jurassic extinction event to have gone extinct.
Bad parses

Although one parse is better than the other one for the disputed dependency, the rest of both parses are so broken that the realization cannot reliably capture the meaning difference

- Parsing *in* as a conjunction
- Bad parse in general
Coming off a disappointing 2-10 season in 2009 Maryland returns to a bowl game to face East Carolina.

(returns, to): Coming off a disappointing 2-10 season in 2009 returns to a bowl game to face East Carolina Maryland.

(Coming, to): Coming off a disappointing 2-10 season to a bowl game to face East Carolina in 2009 Maryland returns.
Coming off a disappointing 2-10 season in 2009 Maryland returns to a bowl game to face East Carolina.
Coming off a disappointing 2-10 season in 2009 Maryland returns to a bowl game to face East Carolina.
Lack of context

Turkers fail to choose the correct parse because of lack of context
Michigan’s backup center, Gerald Ford, expressed a desire to attend the fair while in Chicago.

(attend, while): Michigan’s backup center, Gerald Ford, expressed a desire to attend while in Chicago the fair.

(expressed, while): Michigan’s backup center, Gerald Ford, expressed while in Chicago a desire to attend the fair.
Regression analysis

A regression analysis to determine the factors affecting AMT workers choices:

<table>
<thead>
<tr>
<th></th>
<th>One-sided</th>
<th>Two-sided</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maj</td>
<td>S. Maj</td>
</tr>
<tr>
<td>parse</td>
<td>-0.03</td>
<td>-0.05</td>
</tr>
<tr>
<td>bleu</td>
<td>3.05*</td>
<td>4.38**</td>
</tr>
<tr>
<td>rlz.glb</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

AMT workers tend to choose:

- the paraphrases similar to the original sentence
- the paraphrases with higher fluency scores
Regression analysis for coverage and accuracy trade-off
Distribution of test data

Proportion of paraphrase types

- Reversal: 70.2%
- Passive: 11.9%
- Cleft: 13.3%
- Coordination: 4.6%
1. We collected 6,335 sentences from *Prehistoric Reptiles* and 7,779 from *Big 10 Conference Football*

2. After parsing the sentences and filtering sentences too short or too long, 5,063 sentences were found to be ambiguous

3. Valid paraphrases were generated for 3,605 sentences

4. 515 sentences from each domain were selected for validation experiment