Generating FrameNets of various granularities: The FrameNet Transformer

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FrameNet offers additional structure and detail, making it attractive for information-access tasks.
Pros and Cons of Using FrameNet

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- Detail and richness
- Word senses grouped into Frames
- Several types of frame relations
- Parallel to frame relations, FE relations

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- Many units are exemplified by relatively few annotated training instances (e.g. Kaisser & Webber 2007).
- Distinctions often too fine-grained (Burchardt et al. 2009) to allow robust shallow semantic parsing.
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Coarsening FrameNet

- We address the problems of data sparsity and too fine distinctions by coarsening FrameNet with the FN transformer tool.

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- Parameters
  - selection of frames that receive annotations
  - selection of frames that disappear
  - stop frames (e.g. Event, Entity,...)
Choosing suitable relations

- Good candidates
  - **PERSPECTIVE ON** (Hiring $\rightarrow$ Employment start $\leftarrow$ Get a job)
  - **SUBFRAME** (Criminal process $\rightarrow$ Arrest, Arraignment, ...)
  - **CAUSATIVE OF** (Killing $\rightarrow$ Death)
  - **INCHOATIVE OF** (Death $\rightarrow$ Dead or alive)

- Less reliable
  - **USING** (Communication $\rightarrow$ Volubility)
  - **INHERITANCE** (Transitive action $\rightarrow$ Cause to end)
Crime scenario after 1 iteration of frame-based merging
Crime scenario after 2nd iteration of frame-based merging
Lemma-based mode

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- Mostly they are involved in polysemy between 2 known senses but in some cases a lemma belongs to 9 different frames.
- These 1316 lemmas have a total of 2587 pairs of senses that could potentially be merged.
Lemma-based mode II

- Two cases
  - one LU’s frame is ancestor of the other LU’s frame (530 potential pairs to merge)
  - neither LU’s frame is an ancestor for the other: create a new LU in a third frame, reflecting the broader semantic range covered by the combination.
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- user selects the types of relations to cross on the path from source to target LUs
The FN Transformer

- Java 1.6
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  - path to FrameNet data release
  - path to an output directory
  - logfile to be created

output is a format-compliant FrameNet release (xml files)
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Evaluation

- A baseline evaluation consists in confirming that we do obtain the expected improved **accuracy** of frame-semantic parsers trained on the modified data.
- In a further step, we perform a task-based evaluation to check whether we improve parsing accuracy at the cost of losing **relevant information**.
Parsing accuracy: setup

- Compare the performance of the Shalmaneser semantic parser (Erk & Padó 2006) in two settings:
  - Baseline: FrameNet release 1.3.
  - Coarsened: modified FrameNets created by our transformer
- Data: subset of lemmas that were affected by the transformation
- 10-fold cross-validation setting
  - frame assignment
  - argument recognition
  - argument labeling
## Parsing accuracy

<table>
<thead>
<tr>
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<th>task</th>
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Table: Performance of Shalmaneser on FN release 1.3 and on transformations (10-fold cross-validation)
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Preservation of relevant information - RTE

- Ensure that better parser performance is not achieved at the cost of losing relevant information
- Evaluate our coarsened FrameNet versions in the context of the entailment recognition (RTE) task
- Entailment recognition is the task of determining whether a text \( T \) entails a hypothesis \( H \) in a common sense way.
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Entailment recognition is the task of determining whether a text $T$ entails a hypothesis $H$ in a common sense way.

(3) $T$: An avalanche has struck a popular skiing resort in Austria, killing at least 11 people.
$H$: Humans died in an avalanche.
Frame semantic information in the RTE task

- Techniques for judging entailment include measuring lexical overlap, shallow syntactic parsing, and the use of WordNet relations.
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- Another kind of approach consists in using shallow semantic representations that abstract away from semantically irrelevant variations.

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Assessing the contribution of frame semantics to RTE

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- **Key assumption**: the more of the semantics of the hypothesis can be embedded into the text, the more likely it is that an entailment relation holds between text and hypothesis.
- Extracting frame-based statistical information from the positive and negative examples of the annotated corpus, respectively, and measuring the overlap of frame structures between text and hypothesis in an entailment pair.

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Frame label overlap

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<td>0.4585</td>
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**Table:** Average frame label overlap on entailment pairs in three versions of the Fate corpus
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Visual diff

Becoming_a_member

Inchoative_of

Membership

Using

Using

Exclude_member