Mapping between Compositional Semantic Representations and Lexical Semantic Resources: 
Towards Deep Accurate Semantic Parsing

Sergio Roa, Valia Kordoni and Yi Zhang

46th Annual Meeting of the ACL: HLT
Columbus, OH, USA
June 15-20 2008
Main ideas

- Rich compositional semantic representations as parser output.
  - Minimal Recursion Semantics (MRS) gives more fine-grained semantic representations.

- Shallow semantic parsers use lexical semantic resources for evaluation. (PropBank, VerbNet, FrameNet)

- Modelling of a probability distribution for the mapping between MRS and PropBank/VerbNet.
Main ideas

- Features are taken from Robust Minimal Recursion Semantics (RMRS) representation, used by the ERG English Resource Grammar (Head-Driven Phrase Structure formalism).
- Use of WordNet semantic network to reduce complexity of the model (define selectional restrictions).
- Use of the PropBank corpus for evaluation and VerbNet ↔ PropBank mapping.
RMRS representation

Some plans give advertisers discounts
PropBank semantic roles

- Some plans give advertisers discounts

  \([_{\text{Arg}_0 \text{Some plans}} \text{ give} \text{ }_{\text{Arg}_2 \text{advertisers}} \text{ }_{\text{Arg}_1 \text{discounts}}]\)
VerbNet thematic roles and classes

31 thematic roles, 237 top-level classes, and 194 new subclasses based on the classification by Levin.

**Class:** Give-13.1

**Parent:** –

**Themroles:** Agent Theme Recipient

**Selrestr:** [+animate or +organization] [+animate or +organization]

**Frame:**

<table>
<thead>
<tr>
<th>Name</th>
<th>Example</th>
<th>Syntax</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dative</td>
<td>Some plans give advertisers discounts</td>
<td>Agent V Recipient Theme</td>
</tr>
</tbody>
</table>
Bayesian network based mapping.

Other features: adjectives, prepositions (SEM-I classification), verbs, other SEM-I relations.

Example of SEM-I verb relations:

<table>
<thead>
<tr>
<th>Predicate</th>
<th>Synopsis</th>
</tr>
</thead>
<tbody>
<tr>
<td>_show_v_1_rel</td>
<td>ARG0 e ARG1 p ARG2 u [ ARG3 h ]</td>
</tr>
<tr>
<td>_show_v_1_rel</td>
<td>ARG0 e ARG1 p ARG2 x ARG3 x</td>
</tr>
<tr>
<td>_show_v_as_rel</td>
<td>ARG0 e ARG1 p ARG2 h</td>
</tr>
<tr>
<td>_show_v_up_rel</td>
<td>ARG0 e ARG1 p</td>
</tr>
</tbody>
</table>
Extraction of RMRS and SEM-I features

- Some plans give advertisers discounts

<table>
<thead>
<tr>
<th>SEM-I roles</th>
<th>Features</th>
<th>Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARG1</td>
<td>plan_n</td>
<td>plans</td>
</tr>
<tr>
<td>ARG2</td>
<td>discount_n</td>
<td>discounts</td>
</tr>
<tr>
<td>ARG3</td>
<td>generic_entity_rel</td>
<td>advertisers</td>
</tr>
</tbody>
</table>

- WordNet features (up to 5th level) may replace the nouns features.
Alignment between RMRS and lexical resources

- PropBank/VerbNet annotation: $[\text{Arg}_0(\text{Agent}) \text{ Some plans}] \text{ give } [\text{Arg}_2(\text{Recipient}) \text{ advertisers}] [\text{Arg}_1(\text{Theme}) \text{ discounts}]$

- Alignment process:

<table>
<thead>
<tr>
<th>SEM-I roles</th>
<th>Mapped roles</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARG1</td>
<td>Agent</td>
<td>$\text{plan}_n$</td>
</tr>
<tr>
<td>ARG2</td>
<td>Theme</td>
<td>$\text{discount}_n$</td>
</tr>
<tr>
<td>ARG3</td>
<td>Recipient</td>
<td>$\text{generic}<em>\text{entity}</em>\text{rel}$</td>
</tr>
</tbody>
</table>
Verb classes inference

A possible realisation of a bayesian network for semantic verb classes (following Sabine Schulte im Walde)

\[ P(\text{Food}) = P(\text{Food} \mid \text{Na}) = ? \]
A priori bayesian structure for VerbNet classes inference:

VerbNet class

wish−62

ARG1
living_thing_n

ARG2
propositional_m_rel

ARG3
null

Experimenter
living_thing_n

Theme
propositional_m_rel

ARGM
null

RMRS Features

Lexical type
v_cp_prop_le

PropBank/VerbNet Features
Learning and Inference

- **Learning phase:**
  - *Maximum Likelihood (ML)* for the a priori structure, generating conditional probability tables by using multinominal distributions.
  - *Structural Expectation Maximization (SEM)*. Iterative process when parameters and structures are updated based on the best network so far.

- **Inference**: Markov Chain Monte Carlo (MCMC) inference engine (sampling process considering the evidence).
Learning algorithm

- Algorithm for training Bayesian Networks for inference of lexical semantic roles

procedure $Train (Model)$

1: for all Verbs do
2:   for all Sentences and Parsings which include the current verb do
3:     Initialize vertices of the network with SEM-I labels and features.
4:     Initialize vertices with the corresponding VerbNet class.
5:     Initialize edges connecting corresponding features.
6:     Append the current features as evidence for the network.
7:   end for
8: Start Training Model for the current Verb, where Model is ML or SEM.
9: end for
### Results for inference of mapped roles

10370 sentences of the PropBank corpus successfully parsed using the ERG grammar.

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Nr. iter.</th>
<th>Mode</th>
<th>WordNet feature</th>
<th>Verb classes</th>
<th>Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>PropBank with VerbNet features</td>
<td>1000</td>
<td>ML</td>
<td></td>
<td></td>
<td>78.41</td>
</tr>
<tr>
<td></td>
<td>10000</td>
<td>ML</td>
<td></td>
<td></td>
<td>84.48</td>
</tr>
<tr>
<td></td>
<td>10000</td>
<td>ML</td>
<td></td>
<td>×</td>
<td>87.92</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>ML</td>
<td>×</td>
<td></td>
<td>84.74</td>
</tr>
<tr>
<td></td>
<td>10000</td>
<td>ML</td>
<td>×</td>
<td></td>
<td>86.79</td>
</tr>
<tr>
<td></td>
<td>10000</td>
<td>ML</td>
<td>×</td>
<td>×</td>
<td>87.76</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>SEM</td>
<td></td>
<td></td>
<td>84.25</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>SEM</td>
<td>×</td>
<td></td>
<td>87.26</td>
</tr>
<tr>
<td>PropBank with PropBank features</td>
<td>1000</td>
<td>ML</td>
<td></td>
<td></td>
<td>87.46</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>ML</td>
<td>×</td>
<td></td>
<td>75.70</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>SEM</td>
<td></td>
<td></td>
<td>90.27</td>
</tr>
</tbody>
</table>
The inference of a VerbNet class can help disambiguate the parsing.

Regardless of whether [Theme you] hike from lodge to lodge or stay\textsubscript{ LODGE-46 } [Location \textit{in one place}] and take day trips, there are plenty of choices.

Using ERG, an incorrect mapping for the verb \textit{stay} to the VerbNet class \texttt{EXIST-47.1-1} with the (falsely) favored parse where the PP \textit{“in one place”} is treated as an adjunct/modifier is derived.
Discussion

- Reliable mapping between MRSs structures and lexical semantic resources.
- Potential improvement of the parse disambiguation task by using verb semantic information.
- Enrichment of shallow semantic information with compositional semantic structures can eventually be helpful for applications like question answering.
The End...

Thanks for your attention!
Results of alignment

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Nr of parsings</th>
<th>Parsability</th>
<th>Alignment %</th>
</tr>
</thead>
<tbody>
<tr>
<td>PropBank with VerbNet features</td>
<td>10</td>
<td>25.67%</td>
<td>80.65%</td>
</tr>
<tr>
<td>PropBank with PropBank features</td>
<td>25</td>
<td>26.54%</td>
<td>84.15%</td>
</tr>
</tbody>
</table>
Pseudocode alignment

Algorithm for the alignment of SEM-I and PropBank (VerbNet) labels

```
procedure AlignRMRSPropBankLabels (Sentence, Parsing)
1: for all Verbs at the current Sentence and Parsing do
2:     for all SEM-I argument role labels do
3:         for all PropBank (VerbNet) argument role labels do
4:             if All the words in current SEM-I argument are found in PropBank argument then
5:                 Map SEM-I and PropBank (VerbNet) roles.
6:                 Do not allow more mappings for these labels.
7:             end if
8:         end for
9:     end for
10:    end for
11:    Obtain the VerbNet semantic class for the current verb.
12:    Obtain the leaf lexical type for the current verb.
end for
```