Unsupervised Learning of Prototypical Fillers for Implicit Semantic Role Labeling

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Implicit Semantic Role Labeling (iSRL) — Motivation

“The answer isn’t price reductions.”, he said.

From the Penn Treebank / WSJ:2396:19:5
Implicit Semantic Role Labeling (iSRL) — Motivation

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From the Penn Treebank / WSJ:2396:19:5

Typically, different semantic roles are associated with the nominal predicate *price*:

1. seller (A0)
2. commodity, goods / price for what? (A1)
3. amount of the price, money (A2)
4. potential buyer (A3)
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However, none of these roles are present within the immediate syntactic context of the predicate, i.e. ⇒ they cannot be detected by traditional SRL.
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However, none of these roles are present within the immediate syntactic context of the predicate, i.e. ⇒ they cannot be detected by traditional SRL.
Probable Fillers for the A1/Commodity Role for \textit{price}

Stock \textit{price}?
Probable Fillers for the A1/Commodity Role for *price*

Oil *price*?
Probable Fillers for the A1/Commodity Role for price

Gold price?
Probable Fillers for the A1/Commodity Role for \textit{price}
Finding the Filler for the A1/Commodity Role for *price*

How can we detect the missing *implicit* role?
Finding Implicit Semantic Roles in the Context

Fortunately, some role fillers appear in the immediate (extra-sentential) context:

**Left context (1 sentence):**

“He questions whether that will be enough to stop Tandem’s first mainframe\textsubscript{A1} from taking on some of the functions that large organizations previously sought from Big Blue’s machines\textsubscript{A1}.

**Target sentence:**

“The answer isn’t price reductions.”, he said.
Previous Approaches to iSRL

The state-of-the-art in iSRL

1. integrates **supervised learning algorithms** which rely on costly **gold-annotated training data**:
   - Gerber and Chai (2012), Silberer & Frank (2012), Li et al. (2015)

2. proposes to **combine different scarce resources**:
   - Padó & Feizabadi (2015)

3. requires **language-specific** tools:
   - Laparra & Rigau (2013)
Idea of Unsupervised iSRL

Can we do (mostly) **unsupervised**, i.e. **without annotated training data**, hand-crafted features and **without manual feature engineering**?
Generating Prototypical Fillers

We train predicate-specific *prototypical fillers* for each frame element (role) individually:

\[
\vec{\text{protofiller}} = \frac{1}{N} \sum_{i=0}^{N} E(w_i)
\]  

- generated from large amounts of **explicit** SRL annotations in **automatically labeled** corpora.
- capturing the idiosyncratic **syntactic and semantic properties** of a role.
Generating a Role-Specific A1-Protofiller for the *price* Predicate

**Explicit SRL fillers:**
(from large corpora)

- [for gold]
- [energy]
- [of expensive cars]
- [crude oil]
- [land]...
- [of a ticket]

**Vector Average**

\[
\frac{1}{N} \sum_{i=0}^{N} E(w_i)
\]

**Role-specific proto-vector**

**Final aggregation:**

embedding function

**1st aggregation:**

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Unsupervised Learning of Prototypical Fillers for Implicit SRL
Identifying Implicit Roles

1. We collect a set of (parsed) candidate constituents and compute their vector representations. (by means of Eq. 1).

2. We then measure similarity between a trained protofiller $\vec{v}^p$ and a candidate constituent $\vec{v}^c$ by cosine similarity

$$\cos(\theta) = \frac{\vec{v}^p \cdot \vec{v}^c}{\|\vec{v}^p\| \|\vec{v}^c\|}$$

and predict a candidate as implicit role which maximizes the inner product with the protofiller.
Training Resources, Tools & Evaluation Data

SRL labelers:
- SEMAFOR / FrameNet-style parser (Das et al., 2014)
- MATE / PropBank/NomBank-style parser (Björkelund et al., 2009)

Embeddings:
- SENNA word embeddings (Collobert et al., 2011)
- Dependency-based word embeddings (Levy and Goldberg, 2014)
- Google News vectors (Mikolov et al., 2013)
- Custom trained embeddings (skip-gram and CBOW with word2vec)
Training Resources, Tools & Evaluation Data

Evaluation sets:
- Augmented NomBank data (Gerber and Chai, 2010)
- SemEval 2010 Task 10 on FrameNet-style iSRL (Ruppenhofer et al., 2010)
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- Augmented **NomBank** data (Gerber and Chai, 2010)
- **SemEval 2010 Task 10 on FrameNet-style iSRL** (Ruppenhofer et al., 2010)
### Introduction

**Approach**

**Evaluation**

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SemEval Task 10 – FrameNet iSRL (Linking Performance)

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Type</th>
<th>$P$</th>
<th>$R$</th>
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</tr>
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<tbody>
<tr>
<td>Silberer and Frank (2012) $M_1$</td>
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<td>25.1</td>
<td>27.7</td>
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**Our approach**: C&W embeddings

unsupervised 27.2 25.7 26.4

---

Our protofiller method

- is competitive with supervised systems and particularly effective for **same-sentence** implicit roles (44.4% accuracy).
# Introduction

## Approach

### Evaluation

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1. is competitive with supervised systems and particularly effective for **same-sentence** implicit roles (44.4% accuracy).
2. outperforms a very similar vector-based strategy (VEC, >7%)
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1. is competitive with supervised systems and particularly effective for **same-sentence** implicit roles (44.4% accuracy).
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<th>F&lt;sub&gt;1&lt;/sub&gt;</th>
</tr>
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Our protofiller method

1. is competitive with supervised systems and particularly effective for **same-sentence** implicit roles (44.4% accuracy).
2. outperforms a very similar vector-based strategy (VEC, >7%)
   - is not restricted to syntactic heads (including function words is important!).
   - employs SRL-guided, distributed representations vs. mere context vectors.
We have described an **unsupervised** approach to implicit semantic role labeling.
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**Idea: prototypical role fillers**
- induced from large amounts of explicit SRL annotations
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- **Idea**: prototypical role fillers
  - induced from large amounts of explicit SRL annotations

- **Similarity-based**:
  - implicit roles are found by means of distributional similarity
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- **Idea**: prototypical role fillers
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- **Similarity-based**:
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- **Knowledge-poor**:
  - no manual gold annotations required
  - mainly language-independent
  - builds a strong baseline for knowledge-poor iSRL (NomBank)
Introduction

We have described an **unsupervised** approach to implicit semantic role labeling.

- **Idea:** prototypical role fillers
  - induced from large amounts of explicit SRL annotations

- **Similarity-based:**
  - implicit roles are found by means of distributional similarity

- **Knowledge-poor:**
  - no manual gold annotations required
  - mainly language-independent
  - builds a strong baseline for knowledge-poor iSRL (NomBank)

- **Competitive:**
  - with supervised systems on a standard evaluation set
Thank you!

The protofillers are available at:

www.acoli.informatik.uni-frankfurt.de/resources
Backup Slides
# Explicit Fillers for Training Protofillers

<table>
<thead>
<tr>
<th></th>
<th>CLMET</th>
<th>Gigaword</th>
</tr>
</thead>
<tbody>
<tr>
<td># explicit roles</td>
<td>21.9M</td>
<td>264.0M</td>
</tr>
<tr>
<td># predicate instances</td>
<td>9.5M</td>
<td>122.5M</td>
</tr>
<tr>
<td># roles per predicate</td>
<td>2.3&lt;sup&gt;1&lt;/sup&gt;</td>
<td>2.2</td>
</tr>
<tr>
<td># predicates per sentence</td>
<td>7.6</td>
<td>4.2</td>
</tr>
</tbody>
</table>

Statistics on the number of explicit fillers used for training protofillers.

<sup>1</sup>FrameNet specifies 9.7 frame elements per lexical frame (including non-core roles): https://framenet.icsi.berkeley.edu/fndrupal/current_status.
### Statistics on Implicit Gold Arguments and Candidate Phrases

<table>
<thead>
<tr>
<th></th>
<th>SemEval</th>
<th>NomBank</th>
</tr>
</thead>
<tbody>
<tr>
<td># predicate instances</td>
<td></td>
<td></td>
</tr>
<tr>
<td>in training set</td>
<td>1,370</td>
<td>816</td>
</tr>
<tr>
<td>in test set</td>
<td>1,703</td>
<td>437</td>
</tr>
<tr>
<td># implicit arguments</td>
<td></td>
<td></td>
</tr>
<tr>
<td>in training set</td>
<td>245</td>
<td>650</td>
</tr>
<tr>
<td>in test set</td>
<td>259</td>
<td>246</td>
</tr>
<tr>
<td># of candidate phrases (in test set) per predicate instance</td>
<td>27.6</td>
<td>52.2</td>
</tr>
<tr>
<td>proportion of single tokens</td>
<td>63.4%</td>
<td>47.9%</td>
</tr>
<tr>
<td>proportion of phrases</td>
<td>36.6%</td>
<td>52.1%</td>
</tr>
<tr>
<td>∅ token length of candidate phrase (in test set)</td>
<td>5.8</td>
<td>7.1</td>
</tr>
</tbody>
</table>
NomBank iSRL Data Set (Gerber & Chai, 2010)
The 10 NomBank Predicates in Protofiller Space
### Gerber & Chai 2010 Data – NomBank iSRL

<table>
<thead>
<tr>
<th>predicates:</th>
<th>Gerber &amp; Chai</th>
<th>Laparra &amp; Rigau</th>
<th>Proto W2Vcbow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$F_1$</td>
<td>$P$</td>
<td>$R$</td>
</tr>
<tr>
<td>sale</td>
<td>36.2</td>
<td>47.2</td>
<td><strong>41.7</strong></td>
</tr>
<tr>
<td>price</td>
<td>15.4</td>
<td>36.0</td>
<td>32.6</td>
</tr>
<tr>
<td>investor</td>
<td>9.8</td>
<td>36.8</td>
<td>40.0</td>
</tr>
<tr>
<td>bid</td>
<td>32.3</td>
<td>23.8</td>
<td>19.2</td>
</tr>
<tr>
<td>plan</td>
<td>38.5</td>
<td><strong>78.6</strong></td>
<td><strong>55.0</strong></td>
</tr>
<tr>
<td>cost</td>
<td>34.8</td>
<td><strong>61.1</strong></td>
<td><strong>64.7</strong></td>
</tr>
<tr>
<td>loss</td>
<td>52.6</td>
<td><strong>83.3</strong></td>
<td><strong>83.3</strong></td>
</tr>
<tr>
<td>loan</td>
<td>18.2</td>
<td><strong>42.9</strong></td>
<td>33.3</td>
</tr>
<tr>
<td>investment</td>
<td>0.0</td>
<td>40.0</td>
<td>25.0</td>
</tr>
<tr>
<td>fund</td>
<td>0.0</td>
<td>14.3</td>
<td>16.7</td>
</tr>
<tr>
<td>Overall</td>
<td>26.5</td>
<td>44.5</td>
<td>40.4</td>
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</tbody>
</table>
Generalization over Explicit Fillers

1. We generalize over labeled filler instances of the PLACING frame, e.g.,
   - placed on the middle picture, planted on the top of the church, hung over the river, laid on the table, etc.

2. exploiting their syntactic (here: prepositional) and semantic properties (inanimate, spacial NPs)

3. capturing a composed meaning

4. approximating the correct implicit role

\[
\begin{align*}
\text{[GOAL/NI In the centre of this room]} & \text{ there was an upright beam,} \\
\text{[THEME which] had been placed [TIME at some period]} & \text{ as a support for the old worm-eaten baulk of timber which spanned the roof.}
\end{align*}
\]