Unsupervised Learning of Prototypical Fillers for Implicit Semantic Role Labeling

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Implicit Semantic Role Labeling (iSRL) — Motivation

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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)
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Probable Fillers for the A1/Commodity Role for *price*

*Stock price?*

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Unsupervised Learning of Prototypical Fillers for Implicit SRL
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} 

\$\$\$ \ ???? 

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Finding the Filler for the A1/Commodity Role for \textit{price}

How can we detect the missing \textit{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 from taking on some of the functions that large organizations previously sought from Big Blue’s machines.

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)
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:

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

- 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 \textit{price} Predicate

\[
\text{Final aggregation:} \quad \text{embedding function} \quad \text{Vector Average} \\
\frac{1}{N} \sum_{i=0}^{N} \mathbb{E}(w_i)
\]

\[
\text{1st aggregation:} \\
w_1 \quad w_2 \quad w_1 \quad w_1 \quad w_2 \quad w_1 \quad w_2 \quad w_1
\]

Explicit SRL fillers: (from large corpora)

\begin{align*}
\text{[for gold]} & \quad \text{[energy]} & \quad \text{[of expensive cars]} & \quad \text{[crude oil]} & \quad \text{[land]} & \ldots & \quad \text{[of a ticket]} \\
A1 & \quad A1 & \quad A1 & \quad A1 & \quad A1 & \quad A1 & \quad A1
\end{align*}
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

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

(2)

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)
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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SemEval Task 10 – FrameNet iSRL (Linking Performance)

| Model Name                        | Type       | P  | R  | F1 |
|-----------------------------------|------------|----|----|----|
| Silberer and Frank (2012) M₁      | supervised | 30.8| 25.1| 27.7|
| Silberer and Frank (2012) M₁'     | supervised | 35.6| 20.1| 25.7|
| Gorinski et al. (2013) 4X         | supervised | 26.0| 24.0| 25.0|
| Gorinski et al. (2013) VEC        | unsupervised | 21.0| 18.0| 19.0|
| **Our approach: C&W embeddings**  | unsupervised | 27.2| 25.7| 26.4|

Our protofiller method

1. is competitive with supervised systems and particularly effective for same-sentence implicit roles (44.4% accuracy).
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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%)
   - is not restricted to *syntactic heads* (including *function words* is important!).
   - employs SRL-guided, *distributed representations* vs. mere context vectors.
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- **Similarity-based**:
  - implicit roles are found by means of distributional similarity
Summary

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

- **Idea**: prototypical role fillers
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- **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

|                | CLMET    | Gigaword |
|----------------|----------|----------|
| # explicit roles | 21.9M    | 264.0M   |
| # predicate instances | 9.5M | 122.5M   |
| # roles per predicate | 2.3¹ | 2.2      |
| # predicates per sentence | 7.6  | 4.2      |

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

¹FrameNet 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

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

| predicates: | B |  |  |  | Laparra & Rigau |  |  |  |  | Proto W2Vcbow |  |  |  |
|-------------|---|---|---|---|-----------------|---|---|---|---|-----------------|---|---|---|
|             | $F_1$ | $P$ | $R$ | $F_1$ | $P$ | $R$ | $F_1$ | $P$ | $R$ | $F_1$ | $P$ | $R$ | $F_1$ |
| sale        | 36.2 | 47.2 | **41.7** | **44.2** | 41.2 | 39.4 | 40.3 | 60.8 | 26.8 | 37.2 |
| price       | 15.4 | 36.0 | 32.6 | 34.2 | **53.3** | **53.3** | **53.3** | 21.8 | 36.6 | 27.3 |
| investor    | 9.8 | 36.8 | 40.0 | 38.4 | **43.0** | 39.5 | **41.2** | 24.1 | **57.2** | 33.9 |
| bid         | 32.3 | 23.8 | 19.2 | 21.3 | **52.9** | **51.0** | **52.0** | 40.0 | 41.5 | 40.7 |
| plan        | 38.5 | **78.6** | **55.0** | **64.7** | 40.7 | 40.7 | 40.7 | 44.3 | 51.0 | 47.4 |
| cost        | 34.8 | **61.1** | **64.7** | **62.9** | 56.1 | 50.2 | 53.0 | 49.9 | 29.3 | 36.9 |
| loss        | 52.6 | **83.3** | **83.3** | **83.3** | 68.4 | 63.5 | 65.8 | 54.7 | 63.8 | 58.9 |
| loan        | 18.2 | **42.9** | 33.3 | 37.5 | 25.0 | 20.0 | 22.2 | 33.2 | 44.2 | 37.9 |
| investment  | 0.0 | 40.0 | 25.0 | 30.8 | **47.6** | **35.7** | **40.8** | 39.2 | 34.3 | 36.6 |
| fund        | 0.0 | 14.3 | 16.7 | 15.4 | 66.7 | 33.3 | 44.4 | 75.0 | 25.0 | 37.5 |
| Overall     | **26.5** | **44.5** | **40.4** | **42.3** | **47.9** | **43.8** | **45.8** | 33.5 | 39.2 | 36.1 |
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

\[ \text{In the centre of this room} \] there was an upright beam,
\[ \text{which} \] had been placed \[ \text{at some period} \] as a support for the old worm-eaten baulk of timber which spanned the roof.