

Semantic Role labeling

A little while ago and Now

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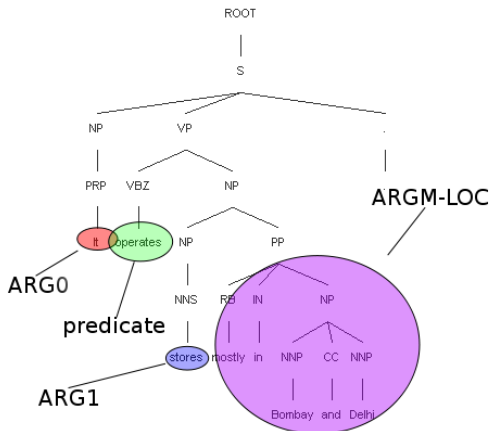
Outline

- 1 Introduction
- 2 Basics
- 3 State of the art
- 4 Conclusion and further work

What is SRL?

- Semantic Frames and relationships
- FrameNet, PropBank, etc.

Example of SRL.



Why SRL?

- Better Understanding
- Immediate Question Answering
- Sense disambiguation

Immediate and consistent question answering

- 1 [ARG0 Praveen] broke [ARG1 the window.]
- 2 [ARG1 The window] broke.

A sample question: *What* broke?

Example of why SRL

- 1 Chavi left the room.
- 2 Chavi left his brother all his belongings in his will.

In the first case:

ARG0: Entity Leaving

ARG1: Place Left

In the second case:

ARG0: Giver

ARG1: Thing given

ARG2: Beneficiary

How SRL's are done?

- Manually
 - FrameNet (Some verbs) (1998)
 - PropBank (More verbs) (2005)
 - NomBank (Nouns) (2007)

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- Automatically

Timeline

- **2002** : *Automatic Labeling of Semantic Roles* by David Gildea, Daniel Jurafsky.
- **2003** : *Semantic Role Labeling by Tagging Syntactic Chunks* by Kadri Hacioglu, Sameer Pradhan, Wayne Ward, James H. Martin, Daniel Jurafsky
- **2004** : *Pruning heuristics for Two Stage SRL systems* by Xue and Palmer
- **2004** : *Semantic role labeling via integer linear programming inference* by V Punyakanok, D Roth, W Yih, D Zimak
- **2005** : *Semantic Role Labeling: A sequence tagging problem* by Marquez, Pere Comas, and Catala

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How it all began?

The famous two layer architecture:

- 1 Recognize the boundaries of Arguments
 - 2 Label the arguments
- Used *Lattice organization* of probabilities with more specific probabilities on the top and the probabilities propagating down for estimation.
 - Introduced the primary set of features that were later used for machine learning.

Automatic Labeling of Semantic Roles by Gildea and Jurafsky.

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The holy grail I

Assumption A robust parsing of the sentence. Used the Collins's parser (1997).

The main features that they introduced were:

- **Phrase Type** : For example in a communication phrase:
 - **SPEAKER** is generally NP
 - **TOPIC** is generally PP
 - **MEDIUM** is generally PP
- **Governing Category** : *Only for NPs* Whether the phrase is governed by a S or by a VP.

The holy grail II

- **Parse Tree Path** : Path from the target word invoking that frame to the constituent invoking that frame.

Frequency	Path	Usual Description
14.2%	$VB \uparrow VP \downarrow PP$	PP argument/adjunct
11.8%	$VB \uparrow VP \uparrow S \downarrow NP$	Subject (ARG0/ARG1)
10.1%	$VB \uparrow VP \uparrow NP$	Object (ARG0/ARG1)
...		

- **Position** : Before the predicate or after it. To overcome errors due to incorrect parses.
- **Voice** : Active / Passive
- **Head Word** : Head words from the phrases taken as according to *Collin (1999)*

The holy grail III

- **Subcategorization** : *Only for Verbs* The structure of the node just above the verb in the parse of the sentence.
 - ① *He opened the door.* : **opened** has sub-category of $VP \rightarrow VB - NP$
 - ② *The door opened.* : **opened** has sub-category of $VP \rightarrow VB$
- **Frame Element Group** : *Only for Verbs* : The possible frames that might be present with a verb, and their probabilities.

Performance

- They used simple counting, splitting over features for identification, and linear interpolation of probabilities using difference features.
- Performance was marred by erroneous FrameNet annotations.
- 82% accuracy in identifying pre-segmented data.
- While simultaneously identifying segments and labeling them: 65% precision and 61% recall.

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Towards Robust Semantic Role Labeling I

The pioneers in using SVMs in SRL task. The paper talks about the performance of *ASSERT* on various corpus of data.

- 1 PropBank Wall Street Journal corpus.
- 2 PropBank Brown Corpus data.

The task is the same, but using SVMs.

- *Why SVMs?* **Multidimensional Data** : A huge classification problem.
- *Which SVMs?* **One v/s All, Binary Classifiers** : Used a Sigmoid function to map distance to probability.
- *Only SVMs?* **Problem of Independence** : This means that all nodes in the parse tree have a class (which can be NULL), independent of what are the classes of its neighbors.

Towards Robust Semantic Role Labeling II

- **Viterbi Search** : So another model is made, similar to the Markov models
 - **States** : n -best hypothesis ARGs from the SVMs.
 - **State probabilities** : Tri-grams of possible classes sequences (trained along with the SVMs)
 - **Observation Probabilities** : Function of probabilities obtained from the SMVs
 - **Search** : Is constrained such that no two overlapping nodes are given a NON-NULL label.

Robustness I

- The performance:

Parse	Task	Prec(%)	Rec (%)	Accuracy (%)
<i>TreeBank</i>	Id.	97.5	96.1	-
	Class.	-	-	93.0
	Both	91.8	90.5	-
<i>Auto¹</i>	Id.	87.8	84.1	-
	Class.	-	-	92.0
	Both	81.7	78.4	-

- Performance on Brown Corpus was more difficult because the problem is fundamentally harder to solve for heterogeneous data.
- Parsing is **not** a problem any more.

Robustness II

- More general features needed for classification, while Identification is robust.
- More diverse training and testing data.

¹Charniak parser was used for parsing

Importance of Parsing and Inference in SRL I

Pioneers in attempting to use Linear Programming and Inference in Semantic Role Labeling task. The paper talks about the effect of using features from complete Parsers \forall / \exists shallow parsers for SRL.

- 1 Used the Charniak parser's top five parses.
- 2 Used the Collin's parser full parse tree.
- 3 Used inference and pruning stage.
- 4 *Identification without Parsing* Two classifiers.

Importance of Parsing and Inference in SRL II

Design of the Inference engine:

- Constrains were designed:
 - 1 Arguments cannot overlap
 - 2 If there exists a $R\text{-arg}^2$ then a parent arg must be present.
 - 3 Given the predicate, some frames are illegal: *stalk* only takes A0 or A1....

Importance of Parsing and Inference in SRL III

- A linear program was made for the constraints:

$$u^* = \operatorname{argmax}_{u \in \{0,1\}^d} p \cdot u$$

Constraints: $C_1 \cdot u \geq b_1$ and $C_2 \cdot u = b_2$ With p as a cost vector.
 Then the classes

$$\hat{c}^{1:M} = \operatorname{argmax}_{c^{1:M} \in C} \sum_{i=1}^M \operatorname{score}(S^i = c^i)$$

are the same as:

$$\hat{c}^{1:M} = \operatorname{argmax}_{u_{ic} \in \{0,1\}; \forall i \in [1, M]; c \in C} \sum_{i=1}^M \sum_{c \in C} p_{ic} u_{ic}$$

Importance of Parsing and Inference in SRL IV

Where p_{ic} is the probability of constituent S^i being of class c^i
and

Subject to

$$\sum_{c \in C} u_{ic} = 1 \forall i \in [1, M]$$

, that is each segment gets only one class.

- **Note:** Solving a Integer Linear Program is in general NP-hard, but in practice its competitively fast.

²Reference Argument

Necessity of Full parsing

- Full Parsing greatly enhances the identification of Constituent boundaries.
- Joint inference with multiple probabilities considered from more than one source improves performance.

	Full	Parsing	Shallow	Parsing
<i>Parse</i>	Prec.	Rec	Prec.	Rec
<i>Gold</i>	86.22	87.40	75.34	74.28
<i>Auto</i>	77.09	75.51	75.48	67.13

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When the hurly-burly's done . . .

- **Future of Parsing**

- Importance ascertained
- State-of-the-art Accuracy ascertained

- **Semantic Role Labeling**

- Need for another breakthrough?
- More experimentation :
 - Combining SVMs with the Inferences as constrains in Viterbi Search.
 - Performing SVMs on parses from various parsers.

References

- *Importance of Parsing and Inference in SRL (2006)* by Punyakanok, Roth and Yih
- *Towards Robust Semantic Role Labeling (2006)* by Pradhan, Ward and Martin
- *Automatic Labeling of Semantic Roles (2002)* by Gildea and Jurafsky

Thank you

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