Semantic Role Labeling. Generalizing Lexical Features using Selectional Preferences

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Talk Overview

The Problem

Semantic Role Labeling

SRL $\stackrel{def}{=}$ identify the *arguments* of a given proposition and assign them semantic labels describing the *roles* they play in the predicate (i.e., recognize predicate argument structures)

The Problem

IE point of view

SRL $\stackrel{def}{=}$ detecting basic event structures such as *who* did *what* to *whom*, *when* and *where*

[The luxury auto maker]$_{AGENT}$ [last year]$_{TEMP}$ sold$_{P}$ [1,214 cars]$_{OBJECT}$ [in the U.S.]$_{LOCATIVE}$

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Syntactic variations

$\overbrace{\text{Yesterday}}^{\text{TEMP}}$, $\overbrace{\text{Kristina}}^{\text{HITTER}}$ hit $\overbrace{\text{Scott}}^{\text{THING HIT}}$ $\overbrace{\text{with a baseball}}^{\text{INSTRUMENT}}$

- Scott was hit by Kristina yesterday with a baseball
- Yesterday, Scott was hit with a baseball by Kristina
- Yesterday Scott was hit by Kristina with a baseball
- Kristina hit Scott with a baseball yesterday

⇒ All of them share the same semantic representation:

hit(Kristina,Scott,yesterday,with a baseball)

Example from (Yih & Toutanova, 2006)

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Structural view

Mapping from input to output structures:

- **Input** is *text* (enriched with morpho-syntactic information)
- **Output** is a *sequence of labeled arguments*
- **Sequential** segmenting/labeling problem

" Mr. Smith sent the report to me this morning . "

[Mr. Smith]$_{AGENT}$ sent [the report]$_{OBJ}$ [to me]$_{RECIP}$ [this morning]$_{TMP}$.

Mr.$_{B-AGENT}$ Smith$_{I}$ sent the$_{B-OBJ}$ report$_{I}$ to$_{B-RECIP}$ me$_{I}$ this$_{B-TMP}$ morning$_{I}$.$_{O}$

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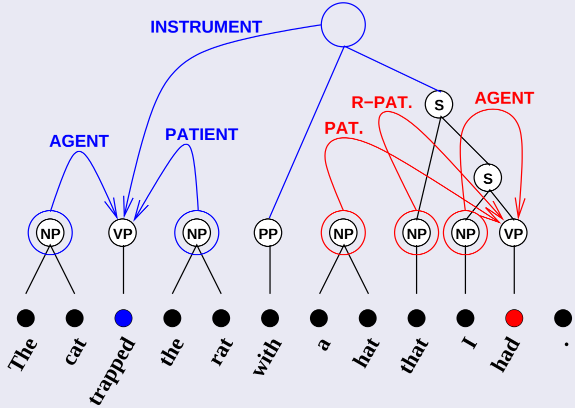

Output is a *hierarchy of labeled arguments*

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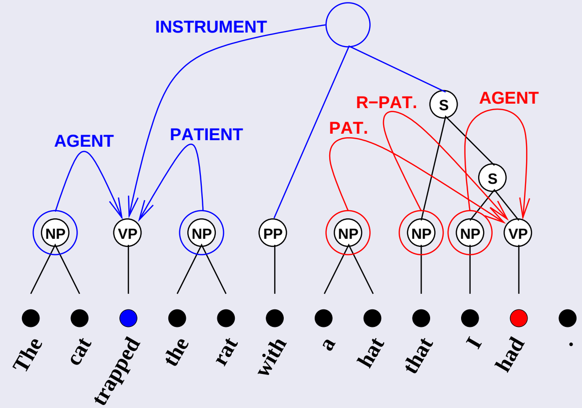

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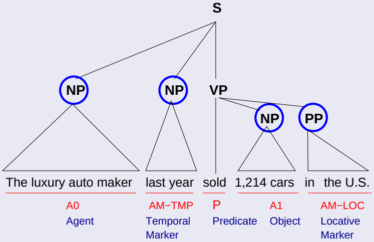
The Problem

Linguistic nature of the problem

- Argument identification is strongly related to syntax



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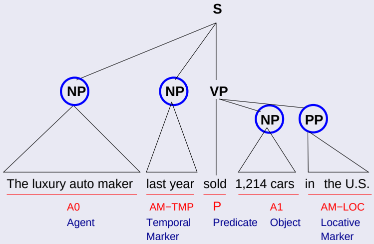

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SRL Systems Available

- ASSERT (Automatic Statistical SEmantic Role Tagger)
  http://cemantix.org/assert.html
- UIUC system demo
  http://l2r.cs.uiuc.edu/~cogcomp/srl-demo.php
- SwiRL: state-of-the-art system from CoNLL-2005
  http://www.surdeanu.name/mihai
- Shalmaneser: FrameNet-based system from SALSA project
  http://www.coli.uni-saarland.de/projects/salsa/shal/
- SEMAFOR: Probabilistic Frame(Net)-Semantic Parser
  http://www.ark.cs.cmu.edu/SEMAFOR/
- Brutus: A CCG-based Semantic Role Labeler
  http://www.ling.ohio-state.edu/~boxwell/software/brutus.html

Corpora Resources

- (English) PropBank
  http://verbs.colorado.edu/∼mpalmer/projects/ace.html
- FrameNet
  http://framenet.icsi.berkeley.edu
- Korean PropBank
  http://www.ldc.upenn.edu/
- Chinese PropBank
  http://verbs.colorado.edu/chinese/cpb/
- AnCora corpus: Spanish and Catalan
  http://http://clic.ub.edu/ancora/
- Prague Dependency Treebank: Czech
  http://ufal.mff.cuni.cz/pdt2.0/
- Penn Arabic TreeBank: Arabic
  http://www.ircs.upenn.edu/arabic/

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- Syntax-based approach: explaining the varied expression of verb arguments within syntactic positions
- Annotation of all verbal predicates in WSJ (Penn Treebank)
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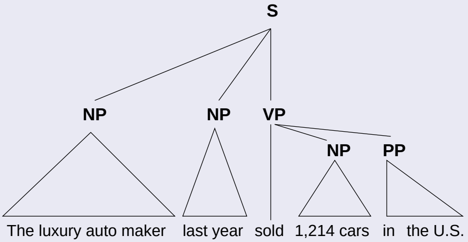
- Add a semantic layer to the Syntactic Trees



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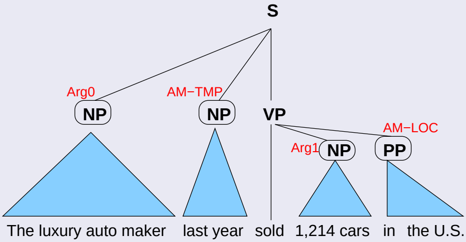

Corpora Resources

PropBank (Palmer et al., 2005)

- Theory neutral numbered core roles (Arg0, Arg1, etc.)
  - ⇒ Interpretation of roles: verb-specific framesets
  - ⇒ Arg0 and Arg1 usually correspond to prototypical Agent and Patient/Theme roles. Other arguments do not consistently generalize across verbs
  - ⇒ Different senses have different framesets
  - ⇒ Syntactic alternations that preserve meaning are kept toghether in a single frameset
- Closed set of 13 general labels for Adjuncts (e.g., Temporal, Manner, Location, etc.)

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Corpora Resources

PropBank: Frame files (Palmer et al., 2005)

- sell.01: commerce: seller
  Arg0="seller" (*agent*); Arg1="thing sold" (*theme*); Arg2="buyer" (*recipient*); Arg3="price paid"; Arg4="benefactive"
  [Al Brownstein]$_{Arg0}$ sold [it]$_{Arg1}$ [for \$60 a bottle]$_{Arg3}$
- sell.02: give up
  Arg0="entity selling out"
  [John]$_{Arg0}$ sold out
- sell.03: sell until none is/are left
  Arg0="seller"; Arg1="thing sold"; ...
  [The new Harry Potter]$_{Arg1}$ sold out [within 20 minutes]$_{ArgM-TMP}$

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Applications

Examples of applications of SRL (I)

- Information Extraction (Surdeanu et al., 2003)
- Question & Answering (Narayanan and Harabagiu, 2004; Frank et al., 2007; Shen and Lapata, 2007)
- Automatic Summarization (Melli et al., 2005)
- Coreference Resolution (Ponzetto and Strube, 2006)
- Text Categorization (Person et al., 2010)
- Opinion Expression Detection (Johansson and Moschitti, 2010)

Applications

Examples of applications of SRL (II)

- Machine Translation Evaluation
  (Giménez and Màrquez, 2007)
- Machine Translation
  (Boas, 2002; Wu and Fung, 2009a;2009b)
- Textual Entailment
  (Tatu & Moldovan, 2005; Burchardt et al., 2007)
- Modeling Early Language Acquisition (Connor et al., 2008;2009)
- Pictorial Communication Systems (Goldberg, et al., 2008)

Empirical Evaluation of SRL Systems

Evaluation Exercises

- Up to 10 evaluation exercises in the last 7 years
  - ⇒ CoNLL-2004/2005 shared tasks (Carreras & Màrquez, 2004; 2005)
  - ⇒ Senseval–3 (Litkowski, 2004)
  - ⇒ SemEval-2007 (Pradhan et al., 2007; Màrquez et al., 2007) (Baker et al., 2007; Litkowski & Hargraves, 2007)
  - ⇒ CoNLL-2008 shared task (Surdeanu et al., 2008)
  - ⇒ CoNLL-2009 shared task (Hajič et al., 2009)
  - ⇒ SemEval-2010 (Ruppenhofer et al., 2010)

Talk Overview

SRL Architecture: Step by Step

Step 1: Select argument candidates

- Given a sentence and a designated predicate
- Parse the sentence
- Identify candidates in tree constituents (filtering/pruning)
  - ⇒ Simple heuristic rules can be used, which maintain a high recall (Xue & Palmer, 2004)
- Key point: 95% of semantic arguments coincide with unique syntactic constituents in the gold parse tree (PropBank)
  - ⇒ Matching is still ∼90% when using automatic parsers

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Step 2: Local scoring of candidates

- Apply classifiers to assign confidence scores to argument candidates (all labels + 'non-argument')
- Candidates are treated independently of each other
- *Identification* and *Classification* may be performed separately
  - ⇒ Computational reasons but also modularity in feature engineering
- Many ML paradigms have been used: not big differences
- Features are more important

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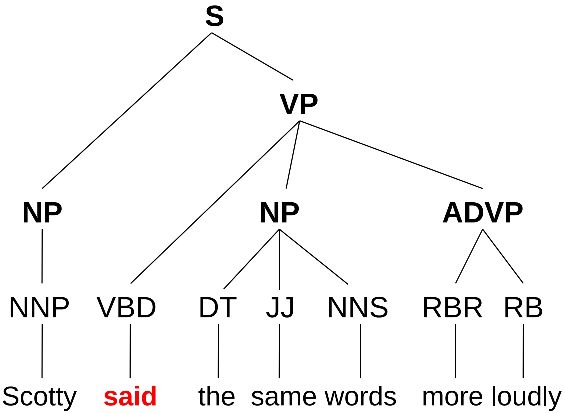
SRL Architecture: Steps 1 + 2

Scotty **said** the same words more loudly

SRL Architecture: Steps 1 + 2



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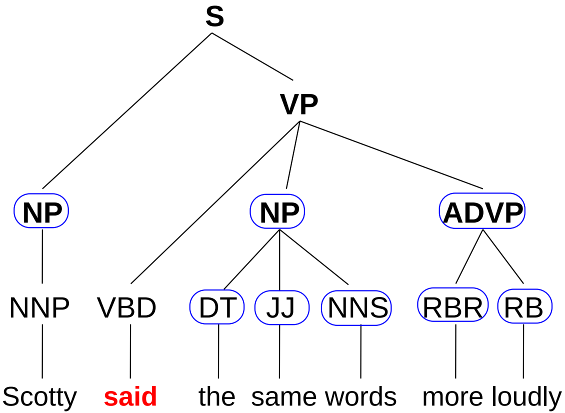

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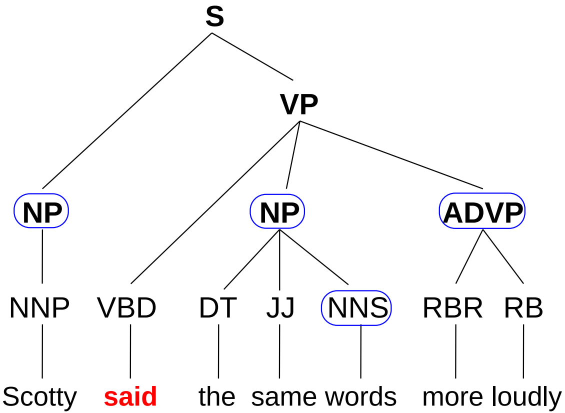

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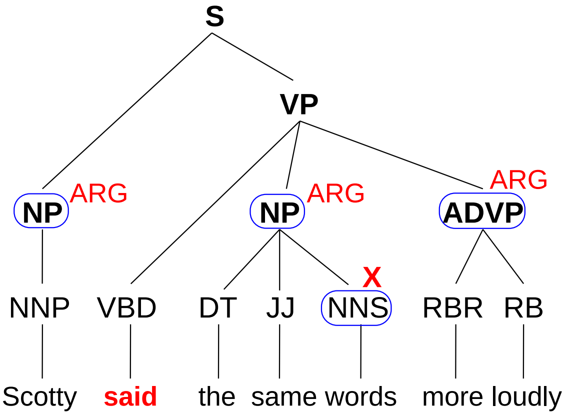

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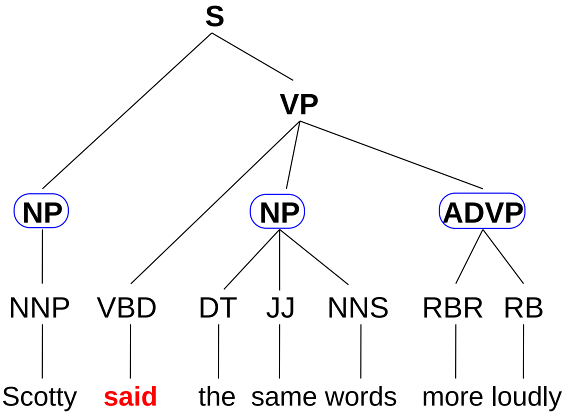

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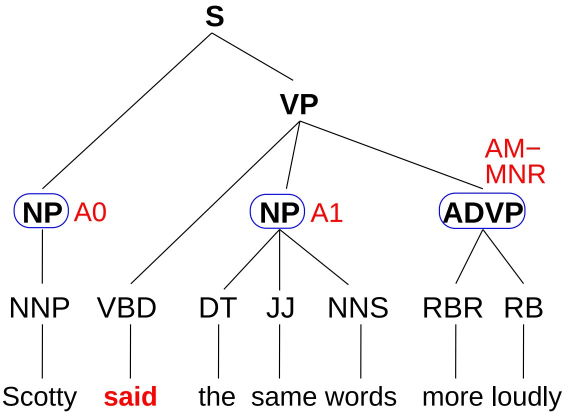
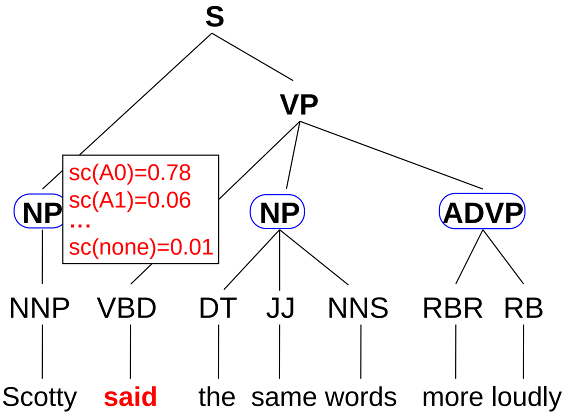


SRL Architecture: Motivating next step (joint scoring)



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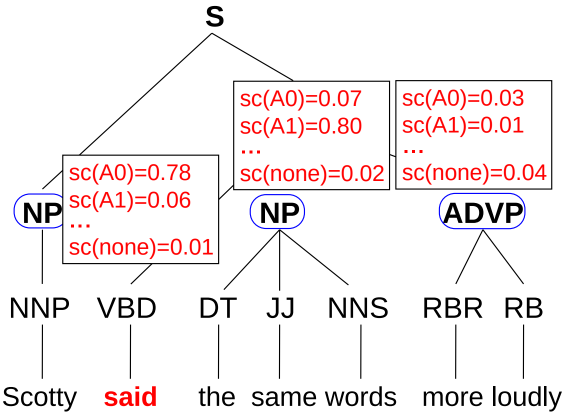

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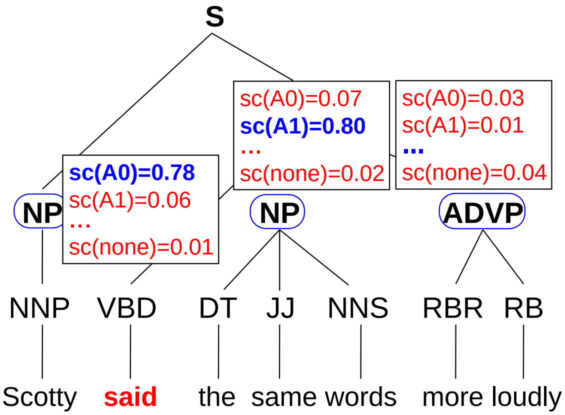

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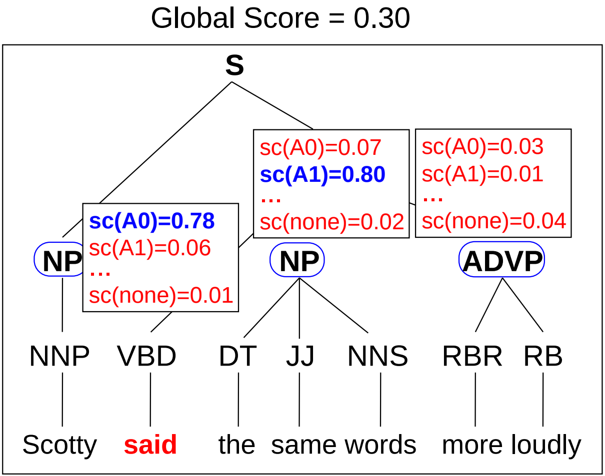

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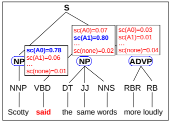
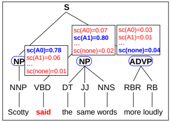
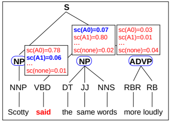


GS = 0.45

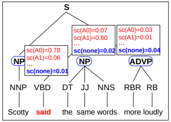


GS = 0.15



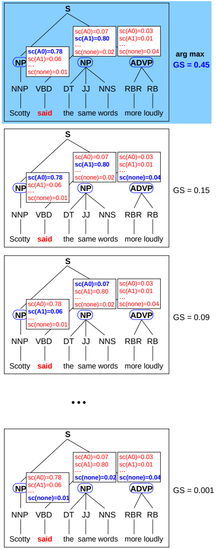
GS = 0.09

...



GS = 0.001

SRL Architecture: Motivating next step (joint scoring)



SRL Architecture: Step by Step

Step 3: Joint scoring — Paradigmatic examples

- Combine local predictions through ILP to find the best solution according to structural and linguistic constraints (Koomen et al., 2005; Punyakanok et al., 2008)

  −learning +features +search

- Re-ranking of several candidate solutions (Haghighi et al., 2005; Toutanova et al., 2008)

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- Global search integrating joint scoring: Tree CRFs (Cohn & Blunsom, 2005)

  +learning +/−features +/−search

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SRL Architecture: Step by Step

Step 4: Post-processing

- Application of a set of heuristic rules to:

  Correct frequent errors

  Enforce consistency in the solution

Joint System based on Reranking (Toutanova et al., 2008)

Architecture

- Use a probabilistic local SRL model to produce multiple (*n*-best) candidate solutions for the predicate structure
- Use a feature–rich reranking model to select the best solution among them

Main goal: is to build a rich model for joint scoring, which takes into account the dependencies among the labels of argument phrases

Joint System based on Reranking (Toutanova et al., 2008)

Local Steps

i. Parse the sentence and apply pruning (Xue & Palmer, 2004) to filter argument candidates for a given predicate p

ii. Apply a simple local scoring model trained with log-linear classifiers (MaxEnt): $P(label_i|node, p)$ probability distribution

iii. Consider a simple global scoring scheme assuming independence of local assignments:
$P_{LOCAL}(L|tree, p) = \prod_{node_i \in tree} P(label_i|node_i, p)$

iv. Use dynamic programming to find the n–most probable non-overlapping complete labelings for predicate p

Joint System based on Reranking (Toutanova et al., 2008)

Reranking Step

i. Consider a reranking model trained to select the best among the n–most probable complete labelings; again a log-linear model: $P_{JOINT}(L_i|tree, p)$

ii. Consider the following combination of local and joint scoring models: $log(P_{SRL}(L|tree, p)) =$

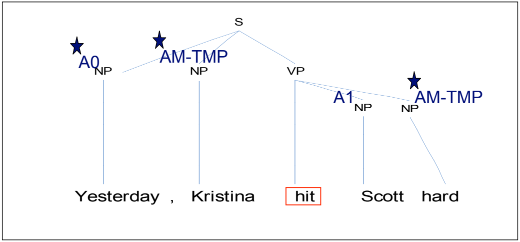
$$log(P_{JOINT}(L|tree, p)) + \lambda log(P_{LOCAL}(L|tree, p))$$

iii. Select the complete labeling ($L_i \in \{L_1, L_2, \ldots, L_n\}$) that maximizes the previous formula (reranking)

Joint System based on Reranking (Toutanova et al., 2008)

Features: joint scoring — slide from (Yih & Toutanova, 2006)

Joint Model Features



Repetition features: count of arguments with a given label c(AM-TMP)=2

Complete sequence syntactic-semantic features for the core arguments:

[NP_A0 hit NP_A1] , [NP_A0 VBD NP_A1] (backoff)

[NP_A0 hit] (left backoff)

[NP_ARG hit NP_ARG] (no specific labels)

[1 hit 1] (counts of left and right core arguments)

Joint System based on Reranking (Toutanova et al., 2008)

Enhancement by using multiple trees

- For top k trees from Charniak's parser, $t_1, t_2, \ldots, t_k$, find corresponding best SRL assignments $L_1, L_2, \ldots, L_k$ and choose the tree and assignment that maximize the score (approx. joint probability of tree and assignment)
  $score(L_i, t_i) = \alpha log(P(t_i)) + log(P_{SRL}(L_i|t_i))$
- Final Results (2nd best at CoNLL):
  WSJ-23: 78.45 (F_1), 79.54 (Prec.), 77.39 (Rec.)
  Brown: 67.71 (F_1), 70.24 (Prec.), 65.37 (Rec.)
  Bug-fixed post-evaluation: 80.32 F_1 (WSJ) 68.81 F_1 (Brown)
- Improvement due to the joint model: >2 F_1 points

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SRL Architecture

Exceptions to the standard architecture

- SRL as sequential tagging
  (Hacioglu et al., 2004; Màrquez et al., 2005; Surdeanu et al., 2007)
- Joint treatment of all predicates in the sentence
  (Carreras et al., 2004; Surdeanu et al., 2008)

SRL Architecture

Exceptions to the standard architecture

- Parsing variations for SRL
  - ⇒ Syntactic parser trained to predict argument candidates (Yi & Palmer, 2005)
  - ⇒ Joint parsing and SRL: semantic parsing (Musillo & Merlo, 2006; Merlo & Musillo, 2008)
  - ⇒ SRL based on dependency parsing (Johansson & Nugues, 2007)
  - ⇒ Systems from the CoNLL–2008 and 2009 shared tasks (Surdeanu et al., 2008; Hajič et al., 2009)
  - ⇒ CCG parser (Gildea and Hockenmaier, 2005; Boxwell et al., 2009)
  - ⇒ HPSG parsers with handcrafted grammars (Zhang et al., 2008; 2009)
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Feature Engineering

Features: local scoring (Gildea & Jurafsky, 2002)

- Highly influential for the SRL work. They characterize:

  i. The candidate argument (constituent) and its context: phrase type, head word, governing category of the constituent

  ii. The verb predicate and its context: lemma, voice, subcategorization pattern of the verb

  iii. The relation between the consituent and the predicate: position of the constituent with respect to the verb, category path between them.

Feature Engineering

Features: local scoring — extensions

- "Brute force" features. Applied to the constituent and possibly to parent and siblings:
  - ⇒ First and last words/POS in the constituent, bag-of-words, *n*-grams of POS, and sequence of top syntactic elements in the constituent.
- Linguistically–inspired features
  - ⇒ Content word, named entities (Surdeanu et al., 2003), syntactic frame (Xue & Palmer, 2004), path variations, semantic compatibility between constituent head and predicate (Zapirain et al., 2007; 2009), etc.
- Significant (and cumulative) increase in performance

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Feature Engineering

Features: joint scoring

- Richer features taking into account information from several arguments at a time
- Best example: when doing re-ranking one may codify patterns on the whole candidate argument structure (Hiaghighi et al., 2005; Toutanova et al., 2008)
- Good for capturing global preferences

Feature Engineering

Features: the Kernel approach

- Knowledge poor approach
- Let the kernel function to compute the similarity/differences between examples by considering all possible substructures as features
- Motivation: avoid intense knowledge engineering
- Potentially useful for rapid system development and working with under resourced languages
- Mostly variants of Collins' all-subtrees convolution kernel (Moschitti et al., 2008; Pighin & Moschitti, 2009; 2010)

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Talk Overview

1. Semantic Role Labeling
2. The Statistical Approach to SRL
3. Semantic Features for SRL
   - Joint work with **E. Agirre**, **M. Surdeanu** and **B. Zapirain**
4. Conclusions

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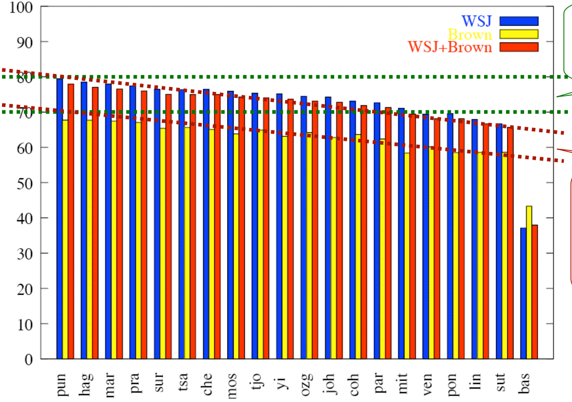
Results from CoNLL-2005 shared task

Results on WSJ and Brown Tests



F_1: 70% ~ 80%
Small differences

Every system suffers from cross-domain test (~10%)

Results from CoNLL-2005 shared task

Reasons for the low generalization ability

- The training corpus is not representative and large enough (and it will never be)
- Taggers and syntactic parsers also experience a significant drop in performance
- The main loss in performance takes place in role classification, not identification — semantic explanation (Pradhan et al., 2008)

Semantic Features for SRL

Motivation

- Most current systems capture semantics through lexicalized features on the predicate and the head word of the argument to be classified
- But lexical features are sparse and generalize badly

  [JFK]$_{Patient}$ *was_assassinated* [in Dallas]$_{LOC}$

  [JFK]$_{Patient}$ *was_assassinated* [in November]$_{TMP}$
- [in Texas]$_{???}$, [in autumn]$_{???}$

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Semantic Features for SRL

Motivation

Selectional Preferences and distributional similarity techniques should help us to classify arguments with low–frequency or unknown head words

[Dallas $\approx$ Texas]$_{Location}$, [November $\approx$ autumn]$_{Temporal}$

Previous Work

Selectional Preferences

- Modeling semantic preferences that predicates impose on their arguments
- Long tradition of automatic acquisition of selectional preferences (SPs) from corpora. WordNet–based and distributional models of SPs
  (Resnik, 1993; Pantel and Lin, 2000; Brockmann and Lapata, 2003)
  (Erk 2007; Erk et al., 2011; etc.)
  - ⇒ e.g., estimate plausibility of triples:
    (verb, argument, head-word)
  - ⇒ useful for syntactic-semantic disambiguation

Previous Work

SPs applied to Semantic Role Labeling

- (Gildea and Jurafsky, 2002) – FrameNet
  - ⇒ First researchers to apply selectional preferences to SRL
  - ⇒ Distributional clustering and WordNet-based techniques to generalize argument heads
  - ⇒ Slight improvement in role classification (NP arguments)
- Zapirain et al. (2009; 2010) – PropBank
  - ⇒ Show that selectional preferences can improve semantic role classification in a state-of-the-art SRL system

Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

Two types of selectional preferences (SP)

i. **verb**–*role*: list of heads of NP arguments of the predicate **verb** that are labeled with the role *role*

```
write-Arg0:  Angrist anyone baker ball bank Barlow Bates ...
write-Arg1:  abstract act analysis article asset bill book ...
write-Arg2:  bank commander hundred jaguar Kemp member ...
write-AM-LOC: paper space ...

...
```

ii. **prep**–*role*: list of nominal heads of PP arguments with preposition **prep** that are labeled with the role *role*

```
from-Arg2:  academy account acquisition activity ad ...
from-Arg3:  activity advertising agenda airport ...
from-Arg4:  europe Golenbock system Vizcaya west
from-AM-TMP: april august beginning bell day dec.  half ...
from-AM-LOC: agency area asia body bureau orlando ...

...
```

Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

SP models: $SP_{sim}(p, r, w)$ plausibility score

- Discriminative approach: given a new argument of a predicate p, we compare its head (w) to the selectional preference of each possible role label r, i.e., we want to find the role with the selectional preference that fits the head best
- We compute the compatibility scores using two different methods
  - ⇒ WordNet based —using (Resnik, 1993)
  - ⇒ Based on distributional similarity —a la Erk (2007)

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Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

WordNet SP models

- Resnik formula (1993) is used to precalculate a weighted list of relevant synsets for the lists of words contained in the SPs

SP **write**–*Arg0*: Angrist anyone baker ball bank Barlow Bates ...

n#00002086 5.875 **life form** organism being living thing "any living entity"
n#00001740 5.737 **entity** something "anything having existence (living or nonliving)"
n#00009457 4.782 **object** physical object "a physical (tangible and visible) entity;"
n#00004123 4.351 **person** individual someone somebody mortal human soul "a human being;"
...

SP **write**–*Arg1*: abstract act analysis article asset bill book ...

n#00019671 7.956 **communication** "something that is communicated between people or groups"
n#04949838 4.257 **message** content subject matter substance "what a communication that ..."
n#00018916 3.848 **relation** "an abstraction belonging to or characteristic of two entities"
n#00013018 3.574 **abstraction** "a concept formed by extracting common features from examples"
...

Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

WordNet SP models

- At test time, for a new argument of the predicate **write** with head word book:
  - $\Rightarrow$ consider $S = \{$`<book>`$\} \cup$ “all its hypernyms in WordNet” (for all senses of book)
  - $\Rightarrow$ $SP_{Res}(\textbf{write}, Arg1, book)$ returns the sum of the weights of the sysnsets in S matching the synsets in the list corresponding to the SP **write**–*Arg1*

Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

Distributional SP models: based on Erk's (2007) setting

JFK was assassinated [in Texas]$_{???}$

SP **in**–*TMP*: *November, century, month*

SP **in**–*LOC*: *Dallas, railway, city*

$$SP_{sim}(p, r, w) = \sum_{w_i \in Seen(p,r)} sim(w, w_i) \cdot weight(p, r, w_i)$$

$$\begin{aligned} SP(in, TMP, Texas) = \; & sim(Texas, November) \cdot weight(in, TMP, November) + \\ & sim(Texas, century) \cdot weight(in, TMP, century) + \\ & sim(Texas, month) \cdot weight(in, TMP, month) \end{aligned}$$

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$$\begin{aligned} SP(in, LOC, Texas) \; = \; & sim(Texas, Dallas) \cdot freq(in, LOC, Dallas) + \\ & sim(Texas, railway) \cdot freq(in, LOC, railway) + \\ & sim(Texas, city) \cdot freq(in, LOC, city) \end{aligned}$$

SP(in,LOC,Texas) > SP(in,TMP,Texas)

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SP(in,LOC,Texas) > SP(in,TMP,Texas)

Selectional Preferences for SRL (Zapirain et al., 2009; 2010)

Distributional SP models: various instantiations for *sim*

- Using Padó and Lapata's software (2007) for computing distributional similarity measures
  - ⇒ Run on the British National Corpus
  - ⇒ Optimal parameterization as described in the paper
  - ⇒ Jaccard, cosine and Lin's similarity measures: sim_{Jac}, sim_{cos} and sim_{Lin}
- Using the already available Lin's thesaurus (Lin, 1998)
  - ⇒ Direct and second order similarity: sim^{th}_{Lin}, sim^{th2}_{Jac} and sim^{th2}_{cos}
  - ⇒ Average of both directions similarity

Evaluation of SPs in isolation (Zapirain et al., 2009; 2010)

Setting: Assign role labels to argument head words based solely on SP scores

⇒ For each head word (w), select the role (r) of the predicate or preposition (p) which fits best the head word: $R_{sim}(p, w) = \arg\max_{r \in Roles(p)} SP_{sim}(p, r, w)$

⇒ SPs based on (p, r, w) triples from CoNLL-2005 data

⇒ In-domain (WSJ) and out-of-domain (Brown) test sets CoNLL-2005

⇒ Lexical baseline model: for a test pair (p, w), assign the role under which the head (w) occurred most often in the training data given the predicate (p)

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Evaluation of SPs in isolation

(Zapirain et al., 2009; 2010)

	WSJ-test			Brown		
	prec.	rec.	F_1	prec.	rec.	F_1
lexical	**82.98**	43.77	57.31	**68.47**	**13.60**	22.69
SP_{Res}	63.47	53.24	57.91	55.12	44.15	49.03
$SP_{sim_{Jac}}$	61.83	61.40	61.61	55.42	53.45	54.42
$SP_{sim_{cos}}$	64.67	64.22	64.44	56.56	54.54	55.53
$SP_{sim^{th2}_{Jac}}$	70.82	**70.33**	**70.57**	62.37	**60.15**	**61.24**
$SP_{sim^{th2}_{cos}}$	70.28	69.80	70.04	62.36	60.14	61.23

⇒ Lexical features have a high precision but very low recall

⇒ SPs are able to effectively generalize lexical features

⇒ SPs based on distributional similarity are better

⇒ Second-order similarity variants (Lin) attain the best results

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SPs in a SRL System (Zapirain et al., 2009; 2010)

- *SwiRL* system for SRL (Surdeanu et al., 2007)
  - ⇒ System from CoNLL-2005 shared task (PropBank)
  - ⇒ Standard architecture (ML based on AdaBoost and SVMs)
  - ⇒ Best results from single (non-combined) systems at CoNLL-2005
- Simple approach: extending *SwiRL* features with SP predictions
  - ⇒ We train several extended *SwiRL-SP*$_i$ models, one per selectional preferences model SP_i
  - ⇒ For each example (p, w) of *SwiRL-SP*$_i$, we add a single new feature whose value is the predicted role label $R_i(p, w)$

SPs in a SRL System

(Zapirain et al., 2009; 2010)

Results

	WSJ-test			Brown		
	Core	Adj	All	Core	Adj	All
SwiRL	93.25	81.31	90.83	84.42	57.76	79.52
SwiRL+SP_{Res}	93.17	81.08	90.76	84.52	59.24	79.86
SwiRL+$SP_{sim_{Jac}}$	93.37	80.30	90.86	84.43	59.54	79.83
SwiRL+$SP_{sim_{cos}}$	93.33	80.92	90.87	85.14	60.16	80.50
SwiRL+$SP_{sim^{th2}_{Jac}}$	93.03	82.75	90.95	85.62	59.63	80.75
SwiRL+$SP_{sim^{th2}_{cos}}$	93.78	80.56	91.23	84.95	61.01	80.48

$\Rightarrow$ Slight improvements, especially noticeable on Brown corpus

$\Rightarrow$ Weak signal of a single feature?

SPs in a SRL System (Zapirain et al., 2009; 2010)

- Simple combinations of the individual $SwiRL{+}SP_i$ classifiers worked quite well (majority voting)
- We also trained a meta-classifier to combine the $SwiRL{+}SP_i$ classifiers and the stand-alone SP_i models:
  - ⇒ Binary classification approach:
    "is a proposed role correct or not?"
  - ⇒ Features are based on the predictions of base SP_i and $SwiRL{+}SP_i$ models
  - ⇒ Trained with a SVM with a quadratic polynomial kernel

SPs in a SRL System

(Zapirain et al., 2009; 2010)

Results (II)

	WSJ-test			Brown		
	Core	Adj	All	Core	Adj	All
SwiRL	93.25	81.31	90.83	84.42	57.76	79.52
$+SP_{sim^{th2}_{cos}}$	93.78	80.56	91.23	84.95	61.01	80.48
Meta	**94.37**	**83.40**	**92.12**	**86.20**	**63.40**	**81.91**

- Statistically significant improvements (99%) for both core and adjunct arguments, both in domain and out of domain

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SPs in a SRL System (Zapirain et al., 2009; 2010)

Output analysis

- Manual inspection of 50 cases in which the meta classifier corrects SwiRL:
  - ⇒ Usually cases with low frequency verbs or argument heads
  - ⇒ In ∼58% of the cases, syntax does not disambiguate, seems to suggest a wrong role label or it is confusing SwiRL because it is incorrect. However, most of the SP predictions are correct.
  - ⇒ ∼30% of the cases: unclear source of the SwiRL error but still several SP models suggest the correct role
  - ⇒ ∼12% of the cases: chance effect

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SPs in a SRL System (Zapirain et al., 2009; 2010)

Output analysis: example 1

		Several	JJ	(S1(S(NP*
		traders	NNS	*)
		could	MD	(VP*
		be	VB	(VP*
		seen	VBN	(VP*
		shaking	VBG	(S(VP*
		their	PRP$	(NP*
		heads	NNS	*)))
		when	WRB	(SBAR(WHADVP*)
A1	A0	the	DT	(S(NP*
A1	A0	**news**	NN	*)
	(P)	**flashed**	VBD	(VP*))))))
		.	.	*))

SPs in a SRL System

(Zapirain et al., 2009; 2010)

Output analysis: example 2

		Italian	NNP	(S1(S(NP*
		President	NNP	*
		Francesco	NNP	*
		Cossiga	NNP	*)
	(P)	**promised**	VBD	(VP*
A2	A1	a	DT	(NP(NP*
A2	A1	quick	JJ	*
A2	A1	**investigation**	NN	*)
A2	A1	into	IN	(PP*
A2	A1	whether	IN	(SBAR*
A2	A1	Olivetti	NNP	(S(NP*)
A2	A1	broke	VBD	(VP*
A2	A1	Cocom	NNP	(NP*
A2	A1	rules	NNS	*)))))))
		.	.	*))

SPs in a SRL System (Zapirain et al., 2009; 2010)

Output analysis: example 3

		Annual	JJ	(S(NP*
		payments	NNS	*)
		will	MD	(VP*
		more	RBR	(VP(ADVP*
		than	IN	*)
	(P)	double	VB	*
A3	TMP	**from**	IN	(PP*
A3	TMP	a	DT	(NP*
A3	TMP	**year**	NN	*
A3	TMP	ago	RB	*))
		to	TO	(PP*
		about	RB	(NP(QP*
		$240	CD	*
		million	CD	*)))
		...		

SPs in a SRL System (Zapirain et al., 2009; 2010)

Output analysis: example 4

			Procter	NNP	(S1(S(NP*
			&	CC	*
			Gamble	NNP	*
			Co.	NNP	*)
			plans	VBZ	(VP*
			to	TO	(S(VP*
			begin	VB	(VP*
		(P)	**testing**	VBG	(S(VP*
			next	JJ	(NP*
			month	NN	*)))
A1	A0		a	DT	(NP(NP*
A1	A0		superco.	JJ	*
A1	A0		**detergent**	NN	*)
A1	A0		that	WDT	(SBAR(WHNP*)
			...		
A1	A0		washload	NN	(NP*))))))))))))
			.	.	*))

Talk Overview

Summary

i. SRL is an important problem in NLP, strongly related to applications requiring some degree of semantic interpretation

ii. It is an active topic of research, which has generated an important body of work in the last 8 years
$\Rightarrow$ techniques, resources, applications

Some news are good but...

$\Rightarrow$ SRL still has to resolve important problems before we see a spread usage in real open-domain applications

$\Rightarrow$ A jump is needed from the laboratory conditions to the real world.

Summary

i. SRL is an important problem in NLP, strongly related to applications requiring some degree of semantic interpretation

ii. It is an active topic of research, which has generated an important body of work in the last 8 years
$\Rightarrow$ techniques, resources, applications

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$\Rightarrow$ A jump is needed from the laboratory conditions to the real world.

Remarks

i. Generalization to new predicates/out-of-domain corpora is a weak point of statistical SRL systems

⇒ System portability must be improved (e.g., domain adaptation, appropriate role sets, lexical semantic generalization, etc.)

ii. System complexity is increasing at a higher scale than performance

⇒ SRL systems have to be more efficient for massive text processing

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Remarks

iii. SRL Systems for languages other than English should be developed and made available to the NLP community

iv. Reducing the cost of producing semantically annotated corpora for under resourced languages (e.g., making use of semi-supervised learning, projections from corpora in other languages, etc.)

Some Research Lines

i. Unsupervised and semi-supervised approaches to SRL

ii. SRL adapted to other languages types, genres, etc. (e.g., tweets, MT output, etc.)

iii. SRL applied to assess semantic similarity (e.g., MT evaluation)

Some Research Lines

iv. Investigate learning architectures that take advantage of the joint resolution of several syntactic–semantic levels (esp. parsing–SRL, but also WSD, NEs, coreference, etc.)

v. SemEval-2010 task #10: "Linking Events and their Participants in Discourse" (cross-sentence links between argument structures: null instantiation linking)

Semantic Role Labeling. Generalizing Lexical Features using Selectional Preferences

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