Semantic Role Labeling

车万翔
社会计算与信息检索研究中心
2017年春季学期

1. Introduction
2. State-of-the-art
3. Empirical evaluation and lessons learned
4. Problems and challenges
5. Conclusions

Tutorial Overview

1. Introduction
   - Problem definition and properties
   - Main Computational Resources and Systems
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Semantic Role Labeling: The Problem

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

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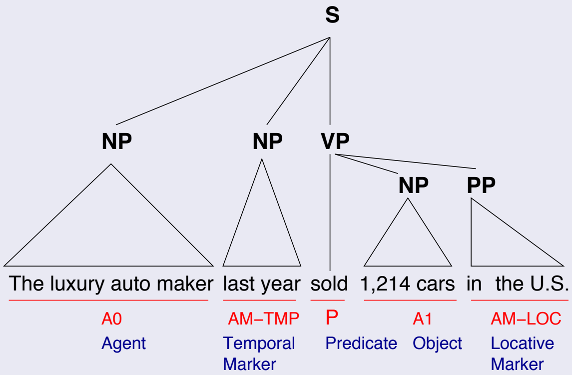
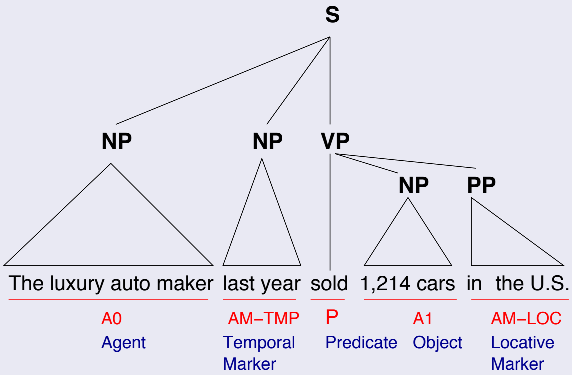


Semantic Role Labeling: The Problem

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



Semantic Role Labeling: The Problem

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

Example from (Yih & Toutanova, 2006)

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Semantic Role Labeling: The Problem

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$_{O}$ me$_{B-RECIP}$ this$_{B-TMP}$ morning$_{I}$.$_{O}$

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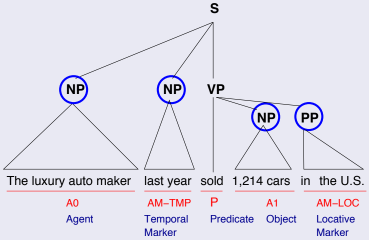
Semantic Role Labeling: The Problem

Linguistic nature of the problem

- Argument identification is strongly related to syntax



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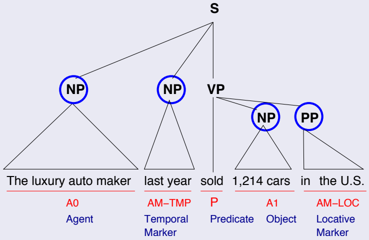

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Semantic Role Labeling: Applications

Is SRL really useful for NLP applications?

1. Information Extraction (Surdeanu et al., 2003; Frank et al., 2007)
2. Question & Answering (Narayanan and Harabagiu, 2004)
3. Automatic Summarization (Melli et al., 2005)
4. Coreference Resolution (Ponzetto and Strube, 2006)
5. Machine Translation (Boas, 2002; Giménez and Màrquez, 2007; Wu and Fung, 2009a;2009b)
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SRL: Computational Resources

From theory to computational resources

- Since (Fillmore, 1968), considerable linguistic research has been devoted to the nature of semantic roles
- Two broad families exist:
  1. Syntax-based approach : explaining the varied expression of verb arguments within syntactic positions : Levin (1993) verb classes ⟹ VerbNet (Kipper et al., 2000) ⟹ PropBank (Palmer et al., 2005) : Focused on verbs
  2. Situation-based approach (a word activates/invokes a frame of semantic knowledge that relates linguistic semantics to encyclopedic knowledge) : Frame semantics (Fillmore, 1976) ⟹ FrameNet (Fillmore et al., 2004) : Words with other POS can invoke frames too (e.g., nouns, adjectives)

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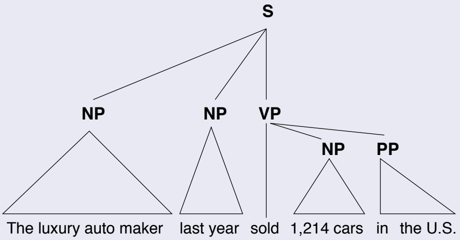
Semantic Role Labeling: Corpora

PropBank (Palmer et al., 2005)

- Annotation of all verbal predicates in WSJ (Penn Treebank)
- http://verbs.colorado.edu/∼mpalmer/projects/ace.html
- Add a semantic layer to the Syntactic Trees



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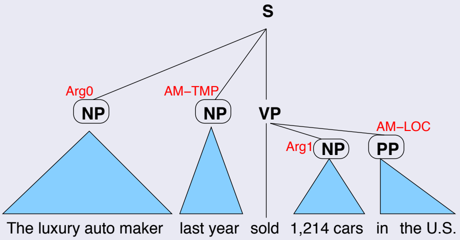

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- Theory neutral numeric core roles (Arg0, Arg1, etc.)
  - Interpretation of roles: verb-specific framesets
  - Arg0 and Arg1 usually correspond to prototypical Agent and Patient/Theme roles. Other arguments do not consistently generalize across verbs
  - 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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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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- NomBank Project: http://nlp.cs.nyu.edu/meyers/NomBank.html
- Annotation of the nominal predicates in WSJ–PennTreeBank

  IBM appointed John
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  IBM's appointment of John
  The appointment of John by IBM
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  [Her]$_{Arg0}$ gift of [a book]$_{Arg1}$ [to John]$_{Arg2}$

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Languages other than English

- Chinese PropBank
  http://verbs.colorado.edu/chinese/cpb/
- Korean PropBank
  http://www.ldc.upenn.edu/
- 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/
- Others are under development, e.g., Scandinavian and Baltic languages

Semantic Role Labeling: Corpora

Other extensions

- FrameNet for German (SALSA corpus), Spanish and Japanese
- OntoNotes corpus: TreeBank + PropBank + word senses + coreference annotation
  http://www.bbn.com/NLP/OntoNotes
- CoNLL–2008 shared task: joint representation for syntactic and semantic dependencies
  http://www.yr-bcn.es/conll2008/
- CoNLL–2009 shared task: extension to multiple languages (Catalan, Chinese, Czech, English, German, Japanese, Spanish)
  http://ufal.mff.cuni.cz/conll2009-st/

Semantic Role Labeling: Systems Available

Tools available online that produce SRL structures

- ASSERT (Automatic Statistical SEmantic Role Tagger)
  http://cemantix.org/assert
- UIUC system
  `http://l2r.cs.uiuc.edu/~cogcomp/srl-demo.php`
- SwiRL
  http://www.surdeanu.name/mihai
- Shalmaneser: FrameNet-based system from SALSA project
  http://www.coli.uni-saarland.de/projects/salsa/shal/

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- Feature engineering
- SRL systems in detail

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SRL: Step by Step

The Problem

- Given a sentence and a designated predicate p
- Every subsequence of words (not necessarily contiguous) is a potential argument of p
- Arguments can be discontinuous:
- SRL can be formalized as a mapping from word substrings to the set of argument labels plus 'non-argument'
- This is clearly impractical. We need to filter the set of candidates...

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Step 1: Select argument candidates

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- 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: Steps 1 + 2

Scotty **said** the same words more loudly

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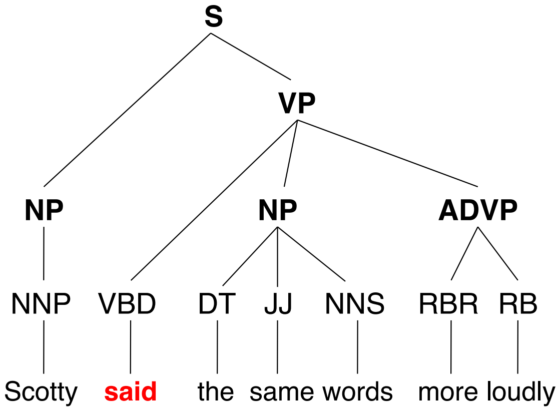
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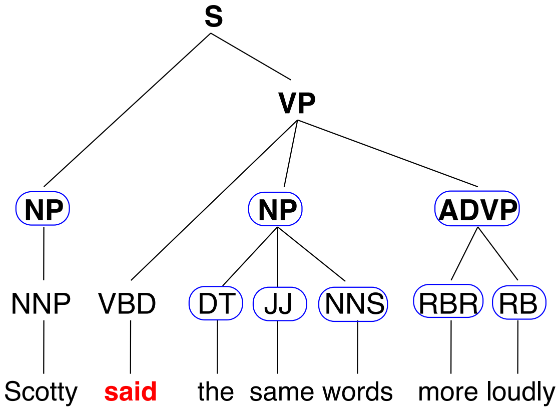
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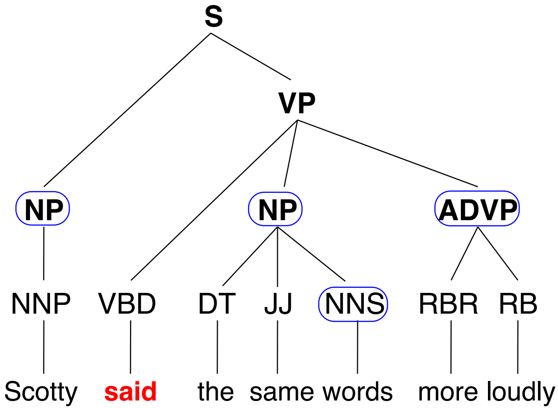
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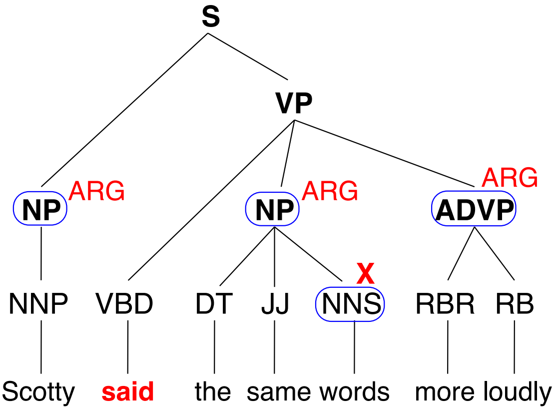
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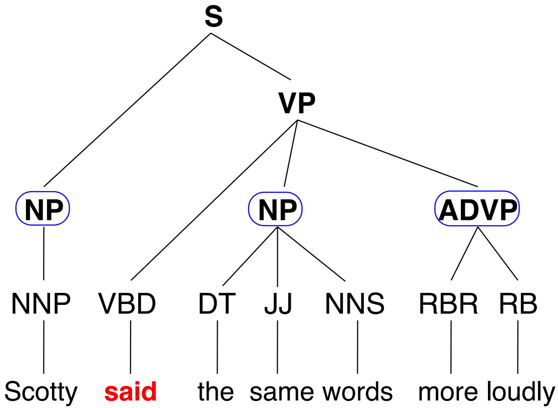
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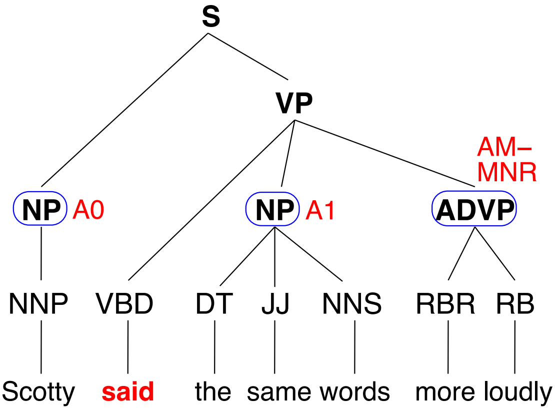
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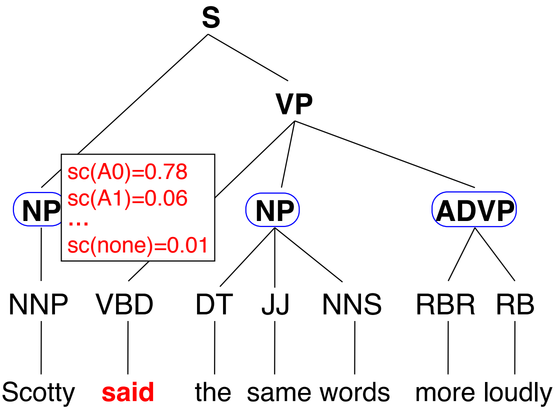
SRL: Motivating next step (joint scoring)



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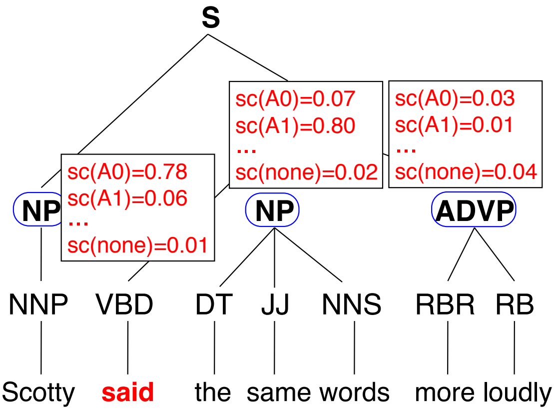

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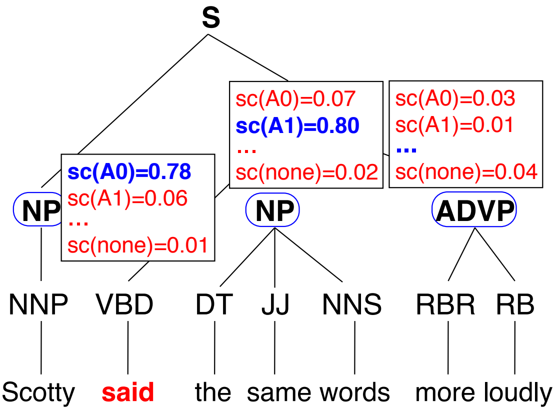

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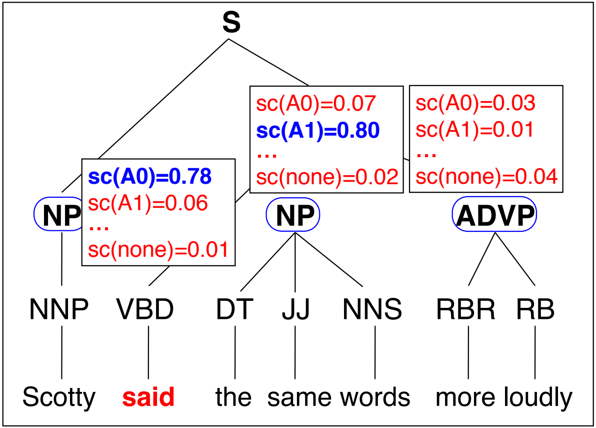
Global Score = 0.30



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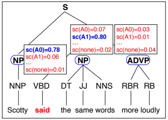
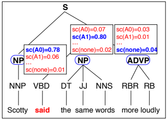
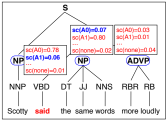


GS = 0.45

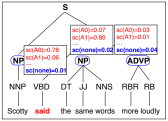


GS = 0.15



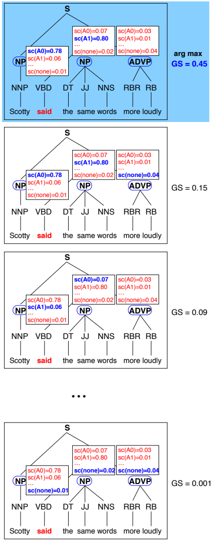
GS = 0.09

...



GS = 0.001

SRL: Motivating next step (joint scoring)



SRL: 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 +dependencies +search
- Re-ranking of several candidate solutions
  (Haghighi et al., 2005; Toutanova et al., 2008)
  +learning +dependencies −search
- Global search integrating joint scoring: Tree CRFs
  (Cohn & Blunsom, 2005)
  +learning +/−dependencies +/−search

SRL: Step by Step

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  +learning +/–dependencies +/–search

SRL: Step by Step

Step 4: Post-processing

- Application of a set of heuristic rules to:

  Correct frequent errors

  Enforce consistency in the solution

Tutorial Overview

1 Introduction

2 State-of-the-art
- Architecture
- Feature engineering
- SRL systems in detail

3 Empirical evaluation and lessons learned

4 Problems and challenges

5 Conclusions

SRL: Feature Engineering

Features: local scoring (Gildea & Jurafsky, 2002)

- Highly influential for the SRL work.
  They characterize:
  1. The candidate argument (constituent) and its context: phrase type, head word, governing category of the constituent
  2. The verb predicate and its context: lemma, voice, subcategorization pattern of the verb
  3. The relation between the consituent and the predicate: position of the constituent with respect to the verb, category path between them.

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SRL: 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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Generalized Inference – ILP (Koomen et al., 2005; Punyakanok et al., 2008)

Inference

- The output of the argument classifier often violates some constraints, especially when the sentence is long
- Finding the best legitimate output is formalized as an optimization problem and solved via Integer Linear Programming (Roth & Yih, 2004)
- Input formed by:
  - The probability estimation (by the argument classifier)
  - Structural and linguistic constraints
- Allows incorporating expressive constraints (non-sequential) on the variables (the arguments types)

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Integer Linear Programming Inference

- For each candidate argument a_i $(1 \leq i \leq n)$,
  Set up a Boolean variable: $a_{i,t}$ indicating whether a_i is classified as argument type t
- Goal is to maximize: $\sum_i \mathrm{score}(a_i = t) \cdot a_{i,t}$
  Subject to the (linear) constraints
- If $\mathrm{score}(a_i = t) = P(a_i = t)$, the objective is to find the assignment that maximizes the expected number of arguments that are correct and satisfies the constraints

Generalized Inference – ILP (Koomen et al., 2005; Punyakanok et al., 2008)

Constraints: examples

- No duplicate argument classes: $\sum_{i=1}^{n} a_{i,Arg0} \leq 1$
- On discontinuous arguments (C-ARG)
  $\forall j (1 \leq j \leq n), \sum_{i=1}^{j-1} a_{i,Arg0} \geq a_{j,C-Arg0}$
- On reference arguments (R-ARG)
  $\forall j (1 \leq j \leq n), \sum_{i \neq j} a_{i,Arg0} \geq a_{j,R-Arg0}$
- Many other possible constraints:
  - Unique labels
  - No overlapping or embedding
  - Relations between number of arguments; order constraints
  - If verb is of type A, no argument of type B
- ILP inference can be used to combine different SRL systems

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  [The deregulation]$_{Arg1}$ of railroads and trucking companies [that]$_{R-Arg1}$ began [in 1980]$_{AM-TMP}$ enabled ...

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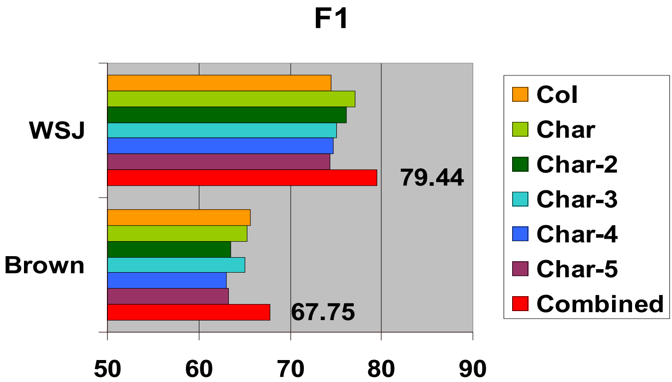

- Inference with many parsers improves results ~ 2.6 F_1 points
- Best results at CoNLL-2005 shared task (Carreras & Màrquez, 2005)

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4. Problems and challenges
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Empirical Evaluation of SRL Systems

Evaluation Exercises

- Up to 9 evaluation exercises in the last 5 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)

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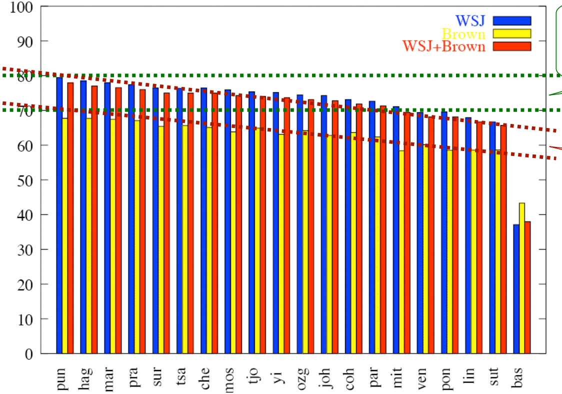
Domain Dependence

- All statistical ML systems suffer from domain dependence
- How large is this dependence in the case of SRL?
- CoNLL-2005 evaluation: out-of-domain test corpus (Brown) $\Longrightarrow \sim$10 F_1 point drop in performance
- Similar evaluations at CoNLL-2008/2009 shared tasks

Domain Dependence: CoNLL-2005

Results on WSJ and Brown Tests



F_1: 70% ~ 80%
Small differences

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

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Impact of Syntactic Processing in SRL

- SRL results strongly depend on syntax (bottleneck)
- Gold vs. automatic parses: ∼90% vs. ∼80% F_1
- Drop in performance occurs in identifying argument boundaries

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SRL in Applications

Examples of applications of SRL

- Information Extraction (Surdeanu et al., 2003)
- Question & Answering (Narayanan and Harabagiu, 2004; Frank et al., 2007)
- Automatic Summarization (Melli et al., 2005)
- Coreference Resolution (Ponzetto and Strube, 2006)
- See (Yih & Toutanova, 2006) tutorial for a discussion on all previous works

SRL in Applications

Other applications of SRL

- 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)
- ...
- We will concentrate on Machine Translation

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General Conclusions

- SRL is an important problem in NLP with strong connections to applications requiring some degree of semantic interpretation
- It is a very active topic of research, which has generated an important body of work in the last 6 years
- Some news are good but...
- SRL still has to face important challenges before we see systems in real open-domain applications
- Good opportunities for future research on the topic