Automatic Semantic Role Labeling

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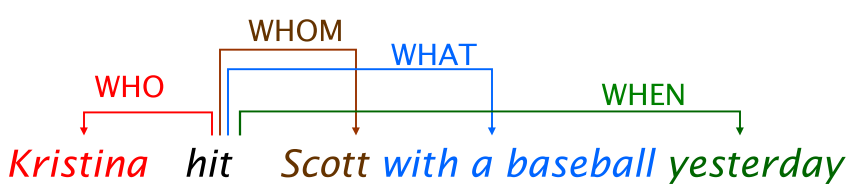
Natural Language Understanding
Question Answering



- Who hit Scott with a baseball?
- Whom did Kristina hit with a baseball?
- What did Kristina hit Scott with?
- When did Kristina hit Scott with a baseball?

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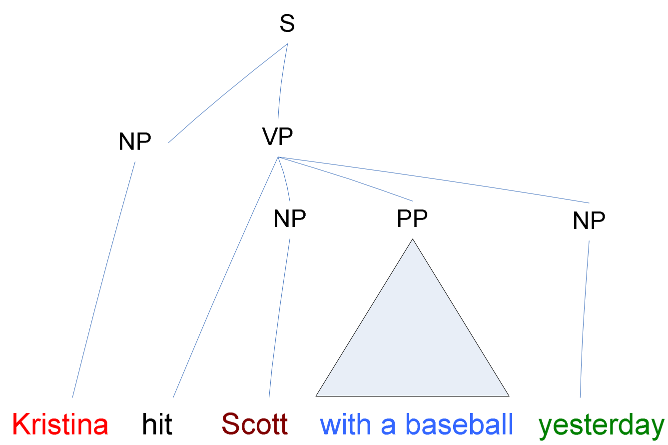
Syntactic Analysis (1/2)



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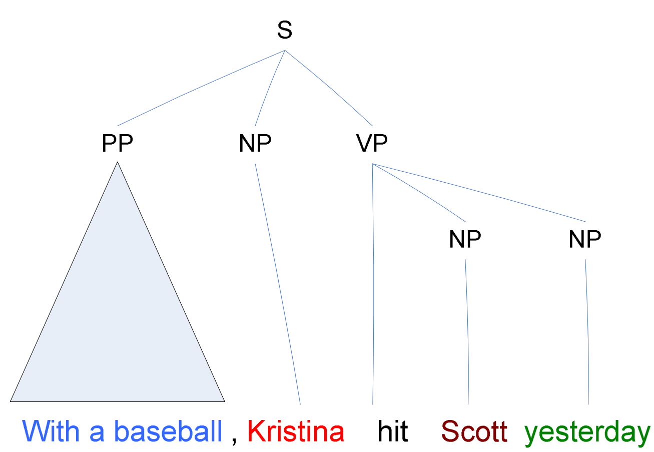
Syntactic Analysis (2/2)



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Syntactic Variations

Yesterday, *Kristina* hit *Scott* *with a baseball*

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*

Agent, hitter | Thing hit | Instrument | Temporal adjunct

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Semantic Role Labeling – *Giving Semantic Labels to Phrases*

- $[_{\text{AGENT}}$ John] **broke** $[_{\text{THEME}}$ the window]
- $[_{\text{THEME}}$ The window] **broke**
- $[_{\text{AGENT}}$Sotheby's] .. **offered** $[_{\text{RECIPIENT}}$ the Dorrance heirs] $[_{\text{THEME}}$ a money-back guarantee]
- $[_{\text{AGENT}}$ Sotheby's] **offered** $[_{\text{THEME}}$ a money-back guarantee] to $[_{\text{RECIPIENT}}$ the Dorrance heirs]
- $[_{\text{THEME}}$ a money-back guarantee] **offered** by $[_{\text{AGENT}}$ Sotheby's]
- $[_{\text{RECIPIENT}}$ the Dorrance heirs] will $[_{\text{ARM-NEG}}$ not] be **offered** $[_{\text{THEME}}$ a money-back guarantee]

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Why is SRL Important – *Applications*

- Question Answering
  - Q: When was Napoleon defeated?
  - Look for: [$_{\text{PATIENT}}$ Napoleon] [$_{\text{PRED}}$ **defeat-synset**] [$_{\text{ARGM-TMP}}$ *ANS*]
- Machine Translation

English (SVO)	Farsi (SOV)	
[$_{\text{AGENT}}$ The little boy]	[$_{\text{AGENT}}$ pesar koocholo]	boy-little
[$_{\text{PRED}}$ **kicked**]	[$_{\text{THEME}}$ toop germezi]	ball-red
[$_{\text{THEME}}$ the red ball]	[$_{\text{ARGM-MNR}}$ moqtam]	hard-adverb
[$_{\text{ARGM-MNR}}$ hard]	[$_{\text{PRED}}$ **zaad-e**]	hit-past

- Document Summarization
  - Predicates and Heads of Roles summarize content
- Information Extraction
  - SRL can be used to construct useful rules for IE

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Quick Overview

- Part I. Introduction
  - ✓ What is Semantic Role Labeling?
  - From manually created grammars to statistical approaches
    - Early Work
    - Corpora – FrameNet, PropBank, Chinese PropBank, NomBank
  - The relation between Semantic Role Labeling and other tasks
- Part II. General overview of SRL systems
  - System architectures
  - Machine learning models
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  - Details of top systems and interesting systems
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Moving toward Statistical Approaches

- Early work [Hirst 87] [Dolan, Richardson, Vanderwende, 93&98]
- Available corpora
  - FrameNet [Fillmore et al. 01]
    - http://framenet.icsi.berkeley.edu
  - PropBank [Palmer et al. 05]
    - http://www.cis.upenn.edu/~mpalmer/project_pages/ACE.htm
- Corpora in development
  - Chinese PropBank
    - http://www.cis.upenn.edu/~chinese/cpb/
  - NomBank
    - http://nlp.cs.nyu.edu/meyers/NomBank.html

Main Focus

Early Work [Hirst 87]

- Semantic Interpretation

  "The process of mapping a syntactically analyzed text of natural language to a representation of its meaning."
- *Absity* – semantic interpreter by Hirst
  - Based on manually created semantic rules
  - Input: *Nadia*$_{\textbf{subj}}$ *bought the book*$_{\textbf{obj}}$ *from a store in the mall.*
  - Output:

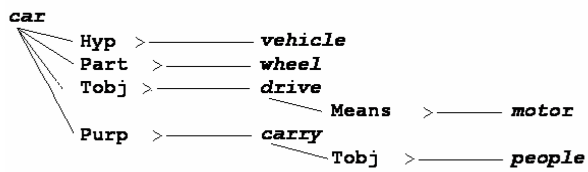
```
(a ?u
   (buy ?u
      (agent = (the ?x (person ?x
         (propername = "Nadia"))))
      (patient = (the ?y (book ?y)))
      (source = (a ?z (store ?z
         (location = (the ?w (mall ?w)))))))
```

Example taken from [Hirst 87]

Early Work [Dolan, Richardson, Vanderwende, 93 & 98]

- MindNet:
  - A graph of words labeled with semantic relations automatically acquired from on-line dictionaries and encyclopedias
  - MindNet identifies 24 labeled semantic relations based on manually created semantic rules
  - Relations are weighted based on vertex frequency

```
car :
"a vehicle with 3 or usu. 4 wheels and driven by a motor, esp. one
 one for carrying people"
```



http://research.microsoft.com/mnex

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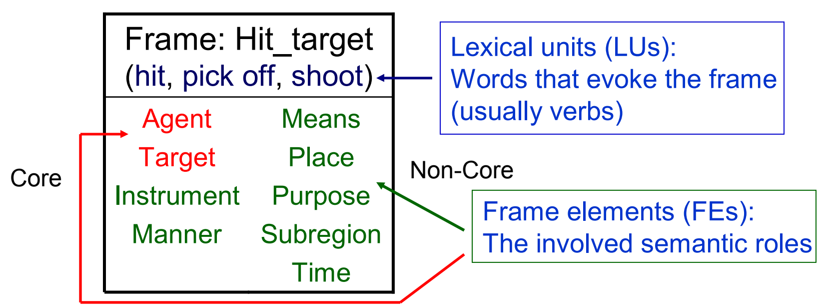
FrameNet [Fillmore et al. 01]

- Sentences from the British National Corpus (BNC)
- Annotated with *frame-specific* semantic roles
  - Various participants, props, and other conceptual roles



[$_{\text{Agent}}$ *Kristina*] ***hit*** [$_{\text{Target}}$ *Scott*] [$_{\text{Instrument}}$ *with a baseball*] [$_{\text{Time}}$ *yesterday*].

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FrameNet – Continued

- Methodology of constructing FrameNet
  - Define/discover/describe *frames*
  - Decide the participants (*frame elements*)
  - List *lexical units* that invoke the frame
  - Find example sentences in the corpus (BNC) and annotate them
- Corpora
  - FrameNet I – British National Corpus only
  - FrameNet II – LDC North American Newswire corpora
- Size
  - >8,900 lexical units, >625 frames, >135,000 sentences

http://framenet.icsi.berkeley.edu

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Proposition Bank (PropBank) [Palmer et al. 05]

- Transfer sentences to propositions
  - Kristina hit Scott → hit(Kristina,Scott)
- Penn TreeBank → PropBank
  - Add a semantic layer on Penn TreeBank
  - Define a set of semantic roles for each verb
  - Each verb's roles are numbered

…[**A0** the company] to … *offer* [**A1** a 15% to 20% stake] [**A2** to the public]
…[**A0** Sotheby's] … *offered* [**A2** the Dorrance heirs] [**A1** a money-back guarantee]
…[**A1** an amendment] *offered* [**A0** by Rep. Peter DeFazio] …
…[**A2** Subcontractors] will be *offered* [**A1** a settlement] …

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Proposition Bank (PropBank) Define the Set of Semantic Roles

- It's difficult to define a general set of semantic roles for all types of predicates (verbs).
- PropBank defines semantic roles for each verb and sense in the frame files.
- The (core) arguments are labeled by numbers.
  - A0 – Agent; A1 – Patient or Theme
  - Other arguments – no consistent generalizations
- Adjunct-like arguments – ***universal*** to all verbs
  - AM-LOC, TMP, EXT, CAU, DIR, PNC, ADV, MNR, NEG, MOD, DIS

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Proposition Bank (PropBank) Frame Files

- hit.01 "strike"
  - A0: agent, hitter; A1: thing hit; A2: instrument, thing hit by or with

  [$_{A0}$ *Kristina*] ***hit*** [$_{A1}$ *Scott*] [$_{A2}$ *with a baseball*] *yesterday*.

AM-TMP
Time

- look.02 "seeming"
  - A0: seemer; A1: seemed like; A2: seemed to

  [$_{A0}$ *It*] ***looked*** [$_{A2}$ *to her*] *like* [$_{A1}$ *he deserved this*].

- deserve.01 "deserve"
  - A0: deserving entity; A1: thing deserved; A2: in-exchange-for

  It looked to her like [$_{A0}$ *he*] ***deserved*** [$_{A1}$ *this*].

Proposition:
A sentence and a target verb

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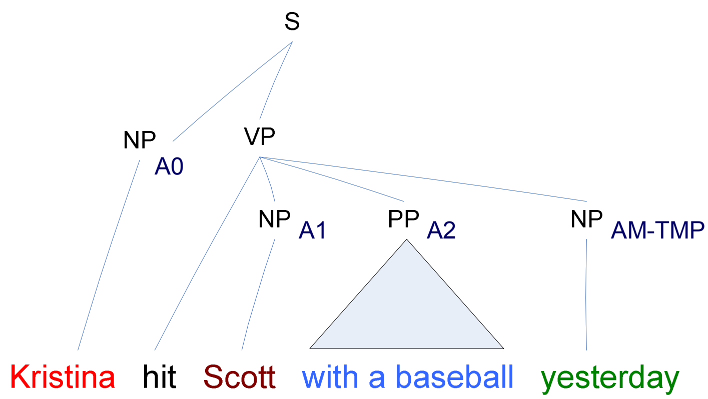
Proposition Bank (PropBank) Add a Semantic Layer



[$_{A0}$ *Kristina*] ***hit*** [$_{A1}$ *Scott*] [$_{A2}$ *with a baseball*] [$_{AM\text{-}TMP}$ *yesterday*].

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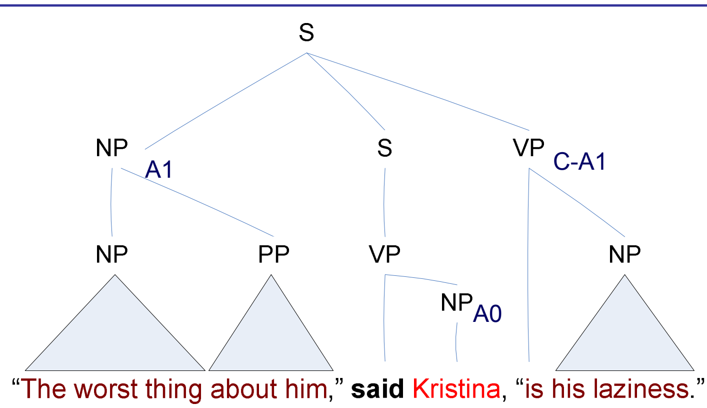
Proposition Bank (PropBank) Add a Semantic Layer – Continued



[$_{A1}$ *The worst thing about him*] ***said*** [$_{A0}$ *Kristina*] [$_{C\text{-}A1}$ *is his laziness*].

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Proposition Bank (PropBank) Final Notes

- Current release (Mar 4, 2005): Proposition Bank I
  - Verb Lexicon: 3,324 frame files
  - Annotation: ~113,000 propositions
    http://www.cis.upenn.edu/~mpalmer/project_pages/ACE.htm
- Alternative format: CoNLL-04,05 shared task
  - Represented in table format
  - Has been used as standard data set for the shared tasks on semantic role labeling
    http://www.lsi.upc.es/~srlconll/soft.html

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Corpora in Development

- Chinese PropBank http://www.cis.upenn.edu/~chinese/cpb/
  - Similar to PropBank, it adds a semantic layer on Penn Chinese Treebank
  - A pre-release version has 250K words and 10,364 sentences; ~55%
- NomBank http://nlp.cs.nyu.edu/meyers/NomBank.html
  - Label arguments that co-occur with nouns in PropBank
    [$_{A0}$ *Her*] [$_{REL}$ ***gift***] *of* [$_{A1}$ *a book*] [$_{A2}$ *to John*]
  - Current Release: Sep. 2005
    - 93,809 instances of nouns; 2,805 different words; ~80%
    - High frequency (>600) nouns have been completed

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Relation to Other Tasks

- Information extraction
- Semantic parsing for speech dialogues
- Deep semantic parsing
- Penn Treebank function tagging
- Predicting case markers
- Aspects of comparisons

	Coverage	**Depth of semantics**	**Direct application**
SRL	*Broad*	*Shallow*	*No*

Related Task: Information Extraction

- Example (HUB Event-99 evaluations, [Hirschman et al. 99])
  - A set of domain dependent *templettes*, summarizing information about events from multiple sentences

<MARKET_CHANGE_1>:=	
INSTRUMENT	London [gold]
AMOUNT_CHANGE	fell [$4.70] cents
CURRENT_VALUE	$308.45
DATE:	daily

Time for our daily market report from NASDAQ.
London gold fell $4.70 cents to $308.45.

- Many other task specifications: extracting information about products, relations among proteins, authors of books, etc.

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Information Extraction versus Semantic Role Labeling

Characteristic	**IE**	**SRL**
Coverage	narrow	broad
Depth of semantics	shallow	shallow
Directly connected to application	sometimes	no

- Approaches to task: diverse
  - Depends on the particular task and amount of available data
  - Hand written syntactic-semantic grammars compiled into FSA
  - Sequence labeling approaches (HMM, CRF, CMM)
  - Survey materials: *http://scottyih.org/IE-survey3.htm*
    [Appelt & Israel 99], [Muslea 99]

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Related Task: Speech Dialogs

- Spoken Language Understanding: *extract the semantics from an utterance*
- Must deal with uncertainly and disfluencies in speech input
- Example: task setup in a narrow flight reservations domain (ATIS evaluations, [Price 90])

```
<ShowFlight>
   <Flight>
     <DCity filler="City"> Seattle </DCity>
     <ACity filler="City"> Boston </ACity>
   </Flight>
</ShowFlight>
```

Sentence: *"Show me all flights from Seattle to Boston"*

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ATIS Parsing versus Semantic Role Labeling

Characteristic	**ATIS**	**SRL**
Coverage	narrow	broad
Depth of semantics	deeper	shallow
Directly connected to application	yes	no

- Approaches to ATIS parsing (overview in [Wang et al. 05]):
  - Simultaneous syntactic/semantic parsing [Miller et al. 96], knowledge-based approach [Ward 94, Dowding et al. 93]
  - Current best: small semantic grammar and a sequence labeling model (no full syntactic parsing information) **Error 3.8%** ([Wang et al. 06]).

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Related Task: Semantic Parsing for NL Interfaces to Databases

- Example: GeoQuery Domain (a domain of facts for US geography) [Zelle & Mooney 96]
  Sentence: *How many cities are there in the US?*
  Meaning Representation:
  answer(count(city(loc_2(countryid(usa)))))

- Characteristics:
  - A restricted domain for which we have a complete domain model
  - Sentences are usually short but could be ungrammatical
  - Syntax of target representation is more complex compared to the ATIS task
  - Need to represent quantifiers (the largest, the most populated, etc.)

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Semantic Parsing for NL Interfaces to Databases versus Semantic Role Labeling

Characteristic	**NL interfaces to DB**	**SRL**
Coverage	narrow	broad
Depth of semantics	deep	shallow
Directly connected to application	yes	no

- Approaches
  - Hand-built grammars [Androutsopoulos et al. 05] (overview)
  - Machine learning of symbolic grammars – e.g. [Zelle & Mooney 96]
  - Learned statistical syntactic/semantic grammar [Ge & Mooney 05] (supervised); [Zettlemoyer & Collins 05], [Wong & Mooney 06] (unsupervised)

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Related Task: Deep Parsing

- Hand-built broad-coverage grammars create simultaneous syntactic and semantic analyses
  - The Core Language Engine [Alshawi 92]
  - Lexical Functional Grammar LFG ([Bresnan 01], [Maxwell & Kaplan 93])
  - Head Driven Phrase Structure Grammar ([Pollard & Sag 94], [Copestake & Flickinger 00])
- Model more complex phenomena
  - Quantifiers, quantifier scope, not just verb semantics, anaphora, aspect, tense
- A set of analyses is possible for each sentence according to the grammar: need to disambiguate
- Until recently: no publicly available datasets or specifications for semantics
- Difficult to create and expand

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Deep Parsing versus Semantic Role Labeling

Characteristic	**Deep Parsing**	**SRL**
Coverage	broad	broad
Depth of semantics	deep	shallow
Directly connected to application	no	no

- Approach
  - Hand-build grammar (possibly expand automatically)
  - Treated as a parsing problem (joint syntactic and semantic disambiguation)
  - For LFG ([Riezler et al. 02])
  - For HPSG ([Toutanova et al. 04], [Miyao & Tsujii 05])

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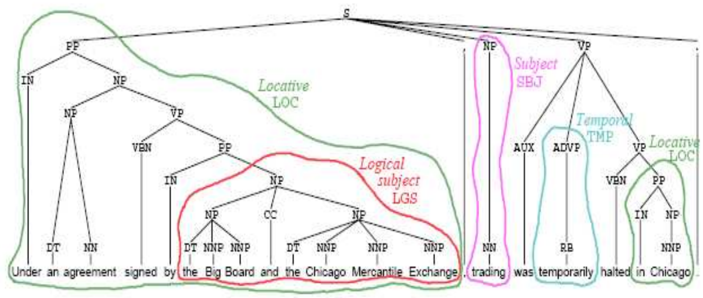
Related Task: Prediction of Function Tags

[Blaheta&Charniak 00]

The Penn Treebank contains annotation of function tags for some phrases: *subject, logical subject, adjuncts (temporal, locative, etc.)*



Slide from Don Blaheta 03 thesis defense

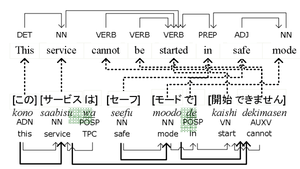
Prediction of Function Tags versus Semantic Role Labeling

Characteristic	**Predicting Function Tags**	**SRL**
Coverage	broad	broad
Depth of semantics	shallower	shallow
Directly connected to application	no	no

- Approach: a classifier based on voted perceptions and other ML techniques
  - Using rich syntactic information from Penn Treebank parse trees
  - Grammatical tags F1 96.4, other tags F1 83.8 [Blaheta 03]

Related Task: Predicting Case Markers

- Some languages have case markers
  - They indicate the syntactico-semantic relation between a phrase and the phrase it modifies
  - Needed for Machine Translation, foreign language learning



- In Japanese, case markers indicate e.g *subject, object, location.*
  - More similar to function tags than to semantic role labels
- Good news: no annotated data is required!
  - The case markers are part of the surface string

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Predicting Case Markers versus Semantic Role Labeling

Characteristic	**Predicting Case Markers**	**SRL**
Coverage	broad	broad
Depth of semantics	shallower	shallow
Directly connected to application	yes	no

- Approaches
  - Using content words from the target language only plus dependency information [Uchimoto et al. 02]
  - Using syntactic and word features from the source and target languages [Suzuki & Toutanova 06]; per case marker error using automatic parses: 8.4%

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Summary of Part I – Introduction

- What is Semantic Role Labeling?
- Corpora for Semantic Role Labeling
  - We will discuss mainly PropBank.
- Related tasks to SRL
  - Information extraction
  - Deep semantic parsing
  - Penn Treebank function tagging
  - Predicting case markers
- **Next part: overview of SRL systems**

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Part II: Overview of SRL Systems

- Definition of the SRL task
  - Evaluation measures
- General system architectures
- Machine learning models
  - Features & models
  - Performance gains from different techniques

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Development of SRL Systems

- Gildea & Jurafsky 2002
  - First statistical model on FrameNet
- 7+ papers in major conferences in 2003
- 19+ papers in major conferences 2004, 2005
- 3 shared tasks
  - Senseval 3 (FrameNet) – 8 teams participated
  - CoNLL 04 (PropBank) – 10 teams participated
  - CoNLL 05 (PropBank) – 19 teams participated

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Task Formulation

- Most general formulation: determine a labeling on (usually but not always contiguous) *substrings* (*phrases*) of the sentence *s,* given a predicate *p*

[$_{A0}$ The queen] **broke** [$_{A1}$ the window].

[$_{A1}$ By working hard], [$_{A0}$ he] **said**, [$_{C\text{-}A1}$ you can get exhausted].

- Every substring *c* can be represented by a set of word indices $c \subseteq \{1, 2, \ldots, m\}$
- More formally, a semantic role labeling is a mapping from the set of substrings of s to the label set ***L***. ***L*** includes all argument labels and NONE.

$$2^{\{1,2,\ldots,m\}} \mapsto L$$

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Subtasks

- Identification: $2^{\{1,2,\ldots,m\}} \mapsto \{NONE, ARG\}$
  - Very hard task: to separate the argument substrings from the rest in this exponentially sized set
  - Usually only 1 to 9 (avg. **2.7**) substrings have labels ARG and the rest have NONE for a predicate
- Classification: $2^{\{1,2,\ldots,m\}} \mapsto L \setminus \{NONE\}$
  - Given the set of substrings that have an *ARG* label, decide the exact semantic label
- Core argument semantic role labeling: (easier)
  - Label phrases with core argument labels only. The modifier arguments are assumed to have label NONE.

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Evaluation Measures

Correct: [$_{A0}$ The queen] **broke** [$_{A1}$ the window] [$_{AM-TMP}$ yesterday]
Guess: [$_{A0}$ The queen] broke the [$_{A1}$ window] [$_{AM-LOC}$ yesterday]

Correct	Guess
{The queen} →A0 {the window} →A1 {yesterday} ->AM-TMP all other → NONE	{The queen} →A0 {window} →A1 {yesterday} ->AM-LOC all other → NONE

- Precision ,Recall, F-Measure {*tp*=1,*fp*=2,*fn*=2} *p*=*r*=*f*=1/3
- Measures for subtasks
  - Identification (Precision, Recall, F-measure) {tp=2,fp=1,fn=1} *p*=*r*=*f*=2/3
  - Classification (Accuracy) acc = .5 (labeling of correctly identified phrases)
  - Core arguments (Precision, Recall, F-measure) {tp=1,fp=1,fn=1} *p*=*r*=*f*=1/2

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Part II: Overview of SRL Systems

- ✓ Definition of the SRL task
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Terminology: Local and Joint Models

- **Local models** decide the label of each substring independently of the labels of other substrings
- This can lead to inconsistencies
  - overlapping argument strings

    By [$_{A1}$ working [$_{A1}$ hard] , he] ***said*** *, you can achieve a lot.*
  - repeated arguments

    By [$_{A1}$ working] hard , [$_{A1}$ he] ***said*** *, you can achieve a lot.*
  - missing arguments

    [$_{A0}$ By working hard , he] **said** , [$_{A0}$ you can achieve a lot].

- **Joint models** take into account the dependencies among labels of different substrings

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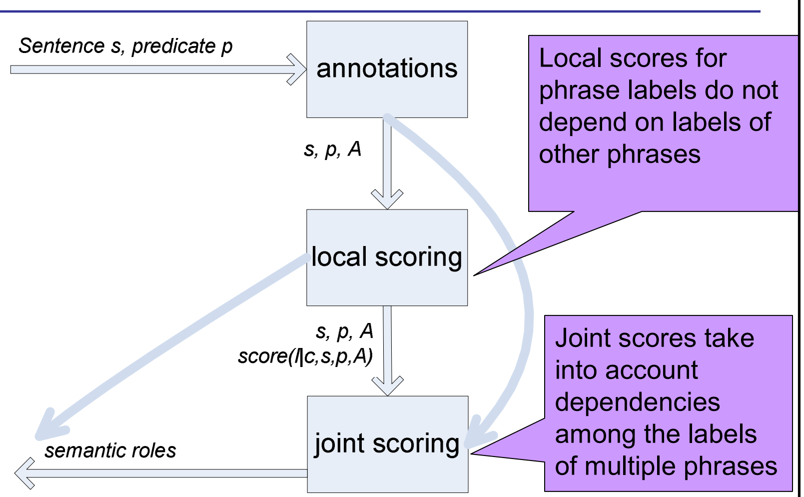
Basic Architecture of a Generic SRL System



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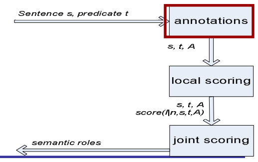
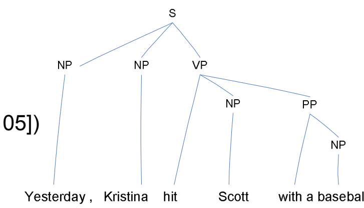


Annotations Used

- Syntactic Parsers
  - Collins', Charniak's (most systems)
    CCG parses
    ([Gildea & Hockenmaier 03],[Pradhan et al. 05])
    TAG parses ([Chen & Rambow 03])



- Shallow parsers
  [$_{NP}$Yesterday] , [$_{NP}$Kristina] [$_{VP}$hit] [$_{NP}$Scott] [$_{PP}$with] [$_{NP}$a baseball].

- Semantic ontologies (WordNet, automatically derived), and named entity classes
  (v) **hit** (cause to move by striking)
  WordNet hypernym
  propel, impel *(*cause to move forward with force*)*

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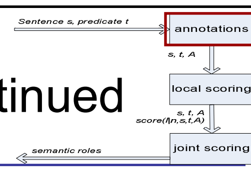

Annotations Used - Continued

Most commonly, substrings that have argument labels correspond to syntactic constituents

- In Propbank, an argument phrase corresponds to exactly one parse tree constituent in the correct parse tree for **95.7**% of the arguments;
  - when more than one constituent correspond to a single argument (**4.3**%), simple rules can join constituents together (in 80% of these cases, [Toutanova 05]);
- In Propbank, an argument phrase corresponds to exactly one parse tree constituent in Charniak's automatic parse tree for approx **90.0%** of the arguments.
  - Some cases (about 30% of the mismatches) are easily recoverable with simple rules that join constituents ([Toutanova 05])
- In FrameNet, an argument phrase corresponds to exactly one parse tree constituent in Collins' automatic parse tree for **87%** of the arguments.

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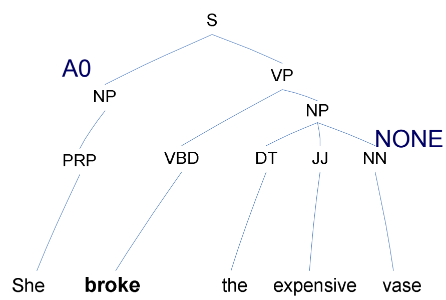
Labeling Parse Tree Nodes

- Given a parse tree *t*, label the nodes (phrases) in the tree with semantic labels
- To deal with discontiguous arguments
  - In a post-processing step, join some phrases using simple rules
  - Use a more powerful labeling scheme, i.e. C-A0 for continuation of A0



Another approach: labeling chunked sentences. Will not describe in this section.

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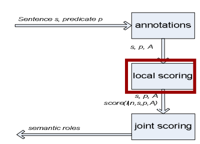
Local Scoring Models



- Notation: a constituent node c, a tree t, a predicate node p, feature map for a constituent $\Phi(c,t,p)$
- Target labels $l \in \{A0, \ldots, A5, AM_{LOC}, \ldots, NONE\}$

$Id(l) = NONE$ iff $l = NONE$

$Id(l) = ARG,$ otherwise

- Two (probabilistic) models
  - Identification model

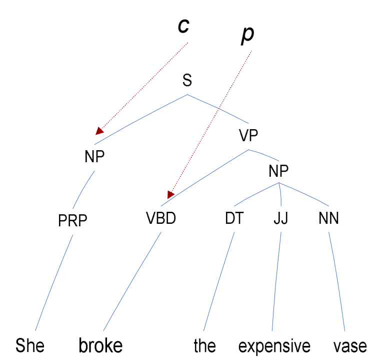
$$P(Id(l)|c,t,p) = P(Id(l)|\Phi(c,t,p))$$

  - Classification model

$$P(l|c,t,p) = P(l|Id(l),\Phi(c,t,p))$$

- Sometimes one model

$$P(l|c,t,p) = P(l|\Phi(c,t,p))$$



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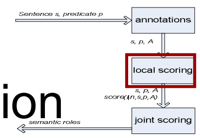
Why Split the Task into Identification and Classification



- Different features are helpful for each task
  - Syntactic features more helpful for identification, lexical features more helpful for classification
  - Example: the identity of the predicate, e.g. *p="hit"* is much more important for classification than for identification ([Pradhan et al. 04]):
    - Identification all features: 93.8 no predicate: 93.2
    - Classification all features: 91.0 no predicate: 82.4
  - Some features result in a performance decrease for one and an increase for the other task [Pradhan et al. 04]

- Splitting the task increases computational efficiency in training
  - In identification, every parse tree constituent is a candidate (linear in the size of the parse tree, avg. 40)
  - In classification, label a small number of candidates (avg. 2.7)

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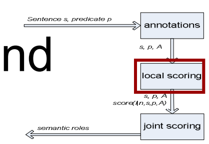
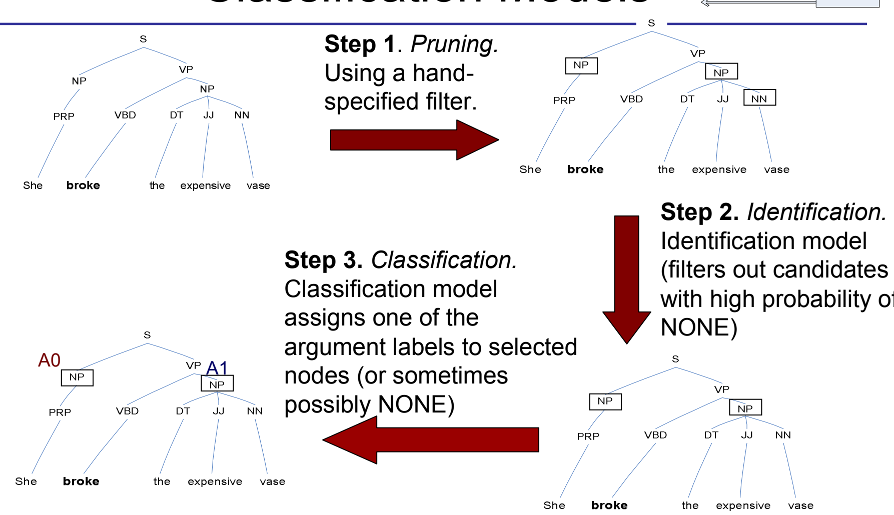
Combining Identification and Classification Models





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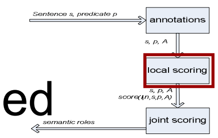
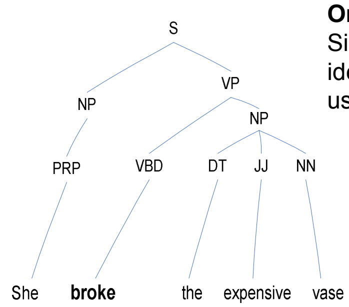
Combining Identification and Classification Models – Continued



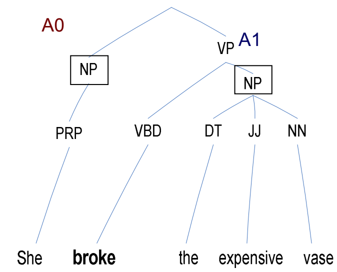
$P(l|c,t,p) = P_{ID}(Id(l)|\Phi(c,t,p)) * P_{CLS}(l|Id(l),\Phi(c,t,p))$

or

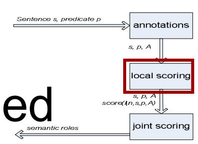
$P(l|c,t,p) = P(l|\Phi(c,t,p))$



One Step. Simultaneously identify and classify using $P(l|c,t,p)$

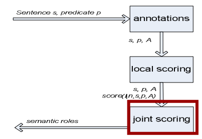


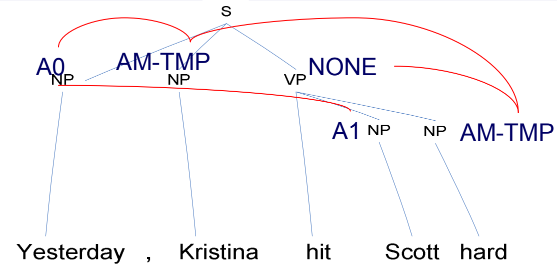
Combining Identification and Classification Models – Continued



- [Gildea&Jurafsky 02]
  - **Identification** + **Classification** for local scoring experiments
  - **One Step** for joint scoring experiments
- [Xue&Palmer 04] and [Punyakanok et al. 04, 05]
  - **Pruning** + **Identification** + **Classification**
- [Pradhan et al. 04] and [Toutanova et al. 05]
  - **One Step**

Joint Scoring Models





- These models have scores for a whole labeling of a tree (not just individual labels)
  - Encode some dependencies among the labels of different nodes

$$P_{JOINT}(l_1, \ldots, l_n | n, t, p) \neq \prod_i P(l_i | n_i, t, p)$$

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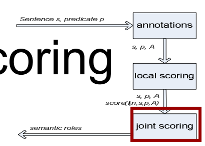
Combining Local and Joint Scoring Models



- Tight integration of local and joint scoring in a single probabilistic model and exact search [Cohn&Blunsom 05] [Màrquez et al. 05],[Thompson et al. 03]
  - When the joint model makes strong independence assumptions
- Re-ranking or approximate search to find the labeling which maximizes a combination of local and a joint score [Gildea&Jurafsky 02] [Pradhan et al. 04] [Toutanova et al. 05]
  - Usually exponential search required to find the exact maximizer
- Exact search for best assignment by local model satisfying hard joint constraints
  - Using Integer Linear Programming [Punyakanok et al 04,05] (worst case NP-hard)
- More details later

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Part II: Overview of SRL Systems

- ✓ Definition of the SRL task
  - ✓ Evaluation measures
- ✓ General system architectures
- Machine learning models
  - Features & models
    - For Local Scoring
    - For Joint Scoring
  - Performance gains from different techniques

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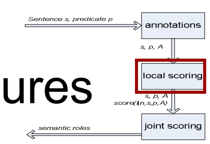
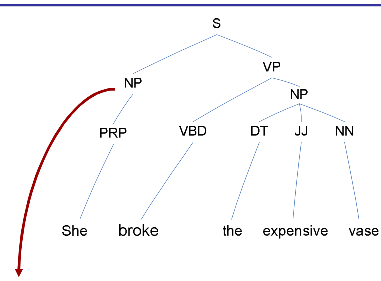
Gildea & Jurafsky (2002) Features



- Key early work
  - Future systems use these features as a baseline
- Constituent Independent
  - Target predicate (lemma)
  - Voice
  - Subcategorization
- Constituent Specific
  - Path
  - Position (*left, right*)
  - Phrase Type
  - Governing Category (*S* or *VP*)
  - Head Word



Target	*broke*
Voice	*active*
Subcategorization	*VP→VBD NP*
Path	*VBD↑VP↑S↓NP*
Position	*left*
Phrase Type	*NP*
Gov Cat	*S*
Head Word	*She*

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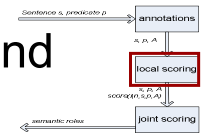
Evaluation using Correct and Automatic Parses

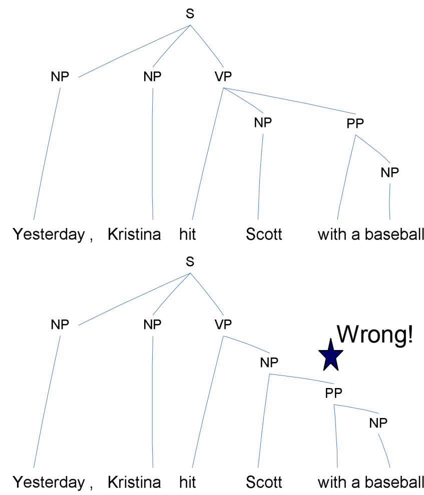


For a correct parse, 95.7% of arguments correspond to a single constituent and their boundaries are easy to consider

For an automatic parse (Charniak's parser), about 90% of the arguments correspond to a single constituent;

- the arguments for which the parser made a bracketing error are difficult to get

- additionally, attachment errors and labeling errors make the task much harder



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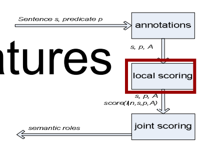
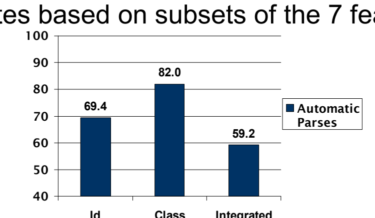
Performance with Baseline Features using the G&J Model

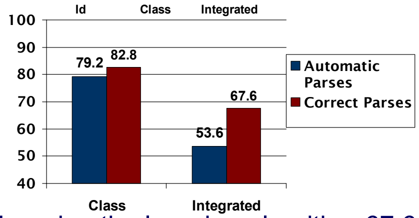


- **Machine learning algorithm:** interpolation of relative frequency estimates based on subsets of the 7 features introduced earlier

FrameNet Results



Propbank Results



Just by changing the learning algorithm 67.6 → **80.8** using SVMs [Pradhan et al. 04]),

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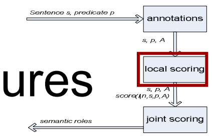
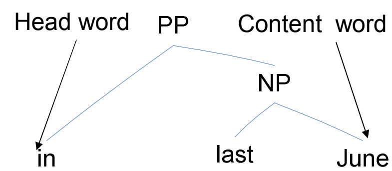
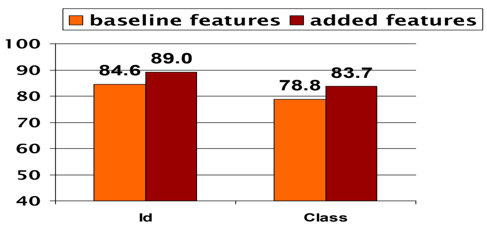
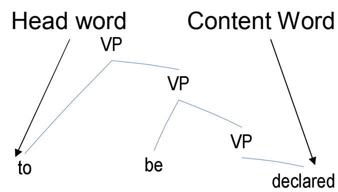
Surdeanu et al. (2003) Features



- Content Word (different from head word)
- Head Word and Content Word POS tags
- NE labels (Organization, Location, etc.)

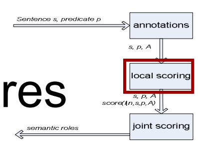




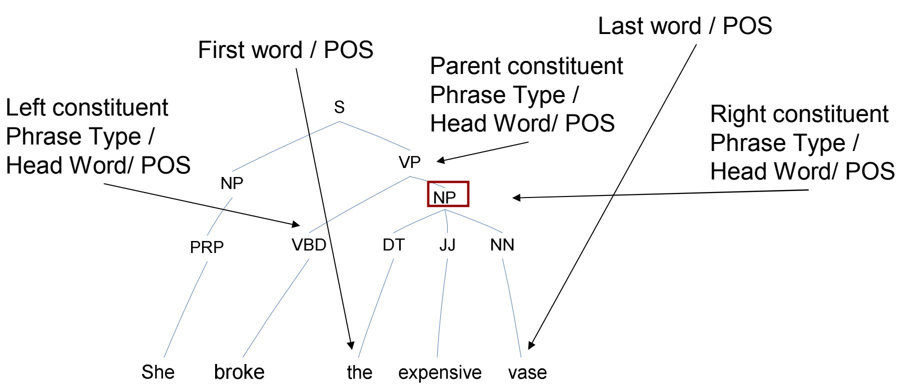


Gains from the new features using correct parses; **28%** error reduction for Identification and **23%** error reduction for Classification

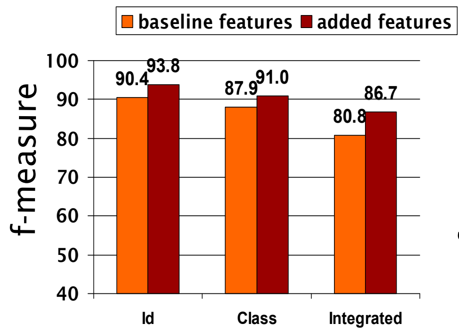
Pradhan et al. (2004) Features



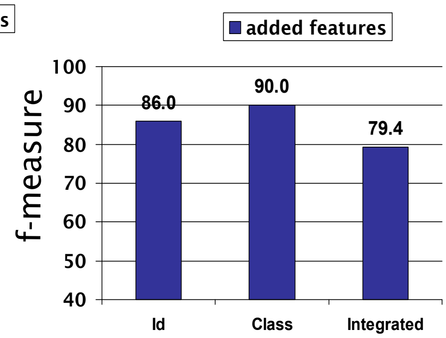
- More structural/lexical context (**31%** error reduction from baseline due to these + Surdeanu et al. features)



Pradhan et al. (2004) Results



Results on correct parse trees

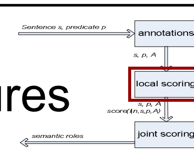


Results on automatic parse trees

Baseline results higher than Gildea and Jurafsky's due to a different classifier - SVM

These are the highest numbers on Propbank version July 2002

Xue & Palmer (2004) Features

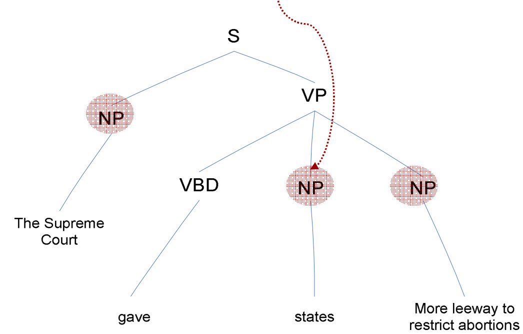


- Added explicit feature conjunctions in a MaxEnt model, e.g. predicate + phrase type
- Syntactic frame feature (**helps a lot**)
- Head of PP Parent (**helps a lot**)
  - If the parent of a constituent is a PP, the identity of the preposition (feature good for PropBank Feb 04)

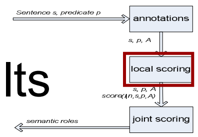
np_give_NP_np

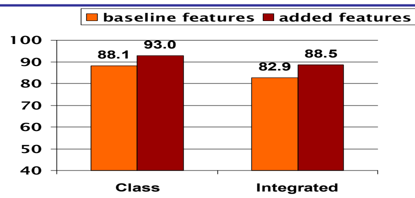
np_give_CURR_np

np_v_NP_np



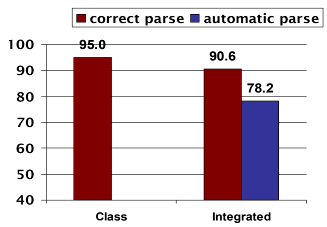
Xue & Palmer (2004) Results



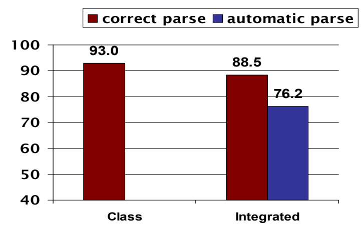


All Arguments Correct Parse

A newer version of Propbank – February 2004



Core Arguments



All Arguments

Results not better than [Pradhan et al. 04], but comparable.

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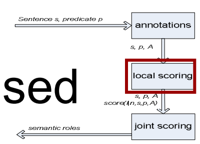
Machine Learning Models Used



- Back-off lattice-based relative frequency models ([Gildea&Jurafsky 02], [Gildea& Palmer 02])
- Decision trees ([Surdeanu et al. 03])
- Support Vector Machines ([Pradhan et al. 04])
- Log-linear models ([Xue&Palmer 04][Toutanova et al. 05])
- SNoW ([Punyakanok et al. 04,05])
- AdaBoost, TBL, CRFs, …

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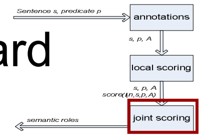
Joint Scoring: Enforcing Hard Constraints



- Constraint 1: Argument phrases do not overlap

  *By [A1 working [A1 hard] , he] **said** , you can achieve a lot.*
  - Pradhan et al. (04) – greedy search for a best set of non-overlapping arguments
  - Toutanova et al. (05) – exact search for the best set of non-overlapping arguments (dynamic programming, linear in the size of the tree)
  - Punyakanok et al. (05) – exact search for best non-overlapping arguments using integer linear programming
- Other constraints ([Punyakanok et al. 04, 05])
  - no repeated core arguments (good heuristic)
  - phrases do not overlap the predicate
  - (*more later*)

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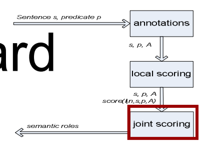
Gains from Enforcing Hard Constraints



- Argument phrases do not overlap
  - Pradhan et al. (04) good gains for a baseline system: 80.8 → 81.6 correct parses
  - Toutanova et al. (05) a small gain from non-overlapping for a model with many features 88.3 → 88.4 correct parses
- Other hard constraints (no repeating core arguments, set of labeled arguments allowable, etc.)
  - Punyakanok et al. (04) evaluation of this aspect only when using chunked sentences (not full parsing) 87.1 → 88.1 correct parses 67.1 → 68.2 automatic parses

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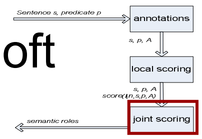
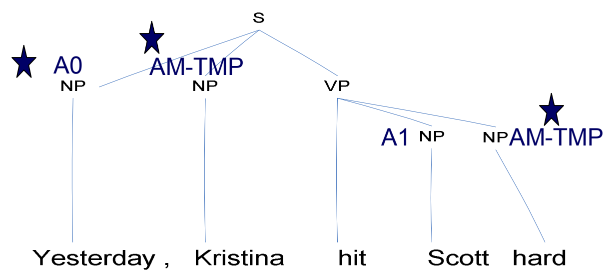
Joint Scoring: Integrating Soft Preferences





- There are many statistical tendencies for the sequence of roles and their syntactic realizations
  - When both are before the verb, AM-TMP is usually before A0
  - Usually, there aren't multiple temporal modifiers
  - Many others which can be learned automatically

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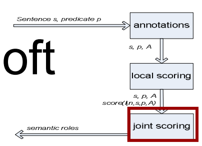
Joint Scoring: Integrating Soft Preferences



- Gildea and Jurafsky (02) – a smoothed relative frequency estimate of the probability of frame element multi-sets:

  $$P(\{A0, AM_{TMP}, A1, AM_{TMP}\}|hit)$$

  - Gains relative to local model 59.2 → 62.9 FrameNet automatic parses

- Pradhan et al. (04) – a language model on argument label sequences (with the predicate included)

  $$P(A0, AM_{TMP}, hit, A1, AM_{TMP})$$

  - Small gains relative to local model for a baseline system 88.0 → 88.9 on core arguments PropBank correct parses

- Toutanova et al. (05) – a joint model based on CRFs with a rich set of joint features of the sequence of labeled arguments (*more later)*
  - Gains relative to local model on PropBank correct parses 88.4 → 91.2 (24% error reduction); gains on automatic parses 78.2 → 80.0

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Combining Annotations and Combining Systems

- Punyakanok et al. (05) combine information from systems trained on top *n* parse trees produced by Charniak's parser and Collins' parser.
  - Effectively constituents from all trees can be selected as arguments
  - Constraints for non-overlap and other constraints are enforced through ILP
  - Gains 74.8 → 77.3 on automatic parses (CoNLL 05 dev set)
- Haghighi et al. (05) combine top *n* Charniak parse trees
  - This is achieved in a Bayesian way: sum over the parse trees approximated by max
  - Gains 79.7 → 80.3 on automatic parses (CoNLL 05 test set)
- Pradhan et al. (05) combine different syntactic views
  - Charniak syntactic parse, Combinatory Categorial Grammar parse
  - Gains 77.0 → 78.0 on automatic parses (CoNLL 05 dev set)
- Other systems in CoNLL 2005
- *More later on all of these*

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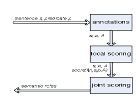
Summary of Part II – System Overview



- Introduced SRL system architecture:
  - *annotations, local scoring, joint scoring*
- Described major features helpful to the task
  - showed that large gains can be achieved by improving the features
- Described methods for local scoring, combining i*dentification* and *classification* models
- Described methods for joint scoring
  - gains from incorporating *hard* constraints
  - gains from incorporating *soft* preferences
- Introduced the concept of combining systems and annotations
  - significant gains possible
- **Next part**: more details on the systems in CoNLL 2005

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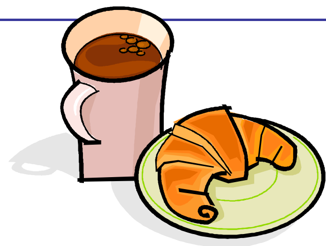

Break!!

[$_{A0}$ We] [$_{AM\text{-}MOD}$ will] see [$_{A1}$ you] [$_{AM\text{-}TMP}$ after the break].

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Quick Overview

- Part I. Introduction
  - ✓ What is Semantic Role Labeling?
  - ✓ From manually created grammars to statistical approaches
    - Early Work
    - Corpora – FrameNet, PropBank, Chinese PropBank, NomBank
  - ✓ The relation between Semantic Role Labeling and other tasks
- ✓ Part II. General overview of SRL systems
  - ✓ System architectures
  - ✓ Machine learning models
- Part III. CoNLL-05 shared task on SRL
  - Details of top systems and interesting systems
  - Analysis of the results
  - Research directions on improving SRL systems
- Part IV. Applications of SRL

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Part III: CoNLL-05 Shared Task on SRL

- Details of top systems and interesting systems
  - Introduce the top 4 systems
  - Describe 3 spotlight systems
- Analysis of the overall results
  - General performance
  - System properties
  - Per argument performance
- Directions for improving SRL systems

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Details of CoNLL-05 Systems

- Top performing systems
  - #3 Màrquez et al. (Technical University of Catalonia)
  - #4 Pradhan et al. (University of Colorado at Boulder)
  - #1 Punyakanok et al. (U. of Illinois at Urbana-Champaign)
  - #2 Haghighi et al. (Stanford University)

  Kristina's system
  Scott's system
- Spotlight systems
  - Yi & Palmer – *integrating syntactic and semantic parsing*
  - Cohn & Blunsorn – *SRL with Tree CRFs*
  - Carreras – *system combination*

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SRL as Sequential Tagging [Màrquez et al.]

- A conceptually simple but competitive system
- SRL is treated as a flat sequential labeling problem represented in the BIO format.
- System architecture
  - Pre-processing (sequentialization)
    - FP_{CHA}: full-parse, based on Charniak's parser
    - PP_{UPC}: partial-parse, based on UPC chunker & clauser
  - Learning using AdaBoost
  - Greedy combination of two systems

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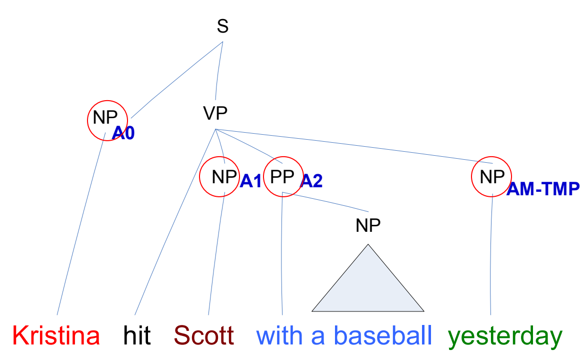
Sequentialization – Full Parse
[Màrquez et al.] – Continued

- Explore the sentence regions defined by the clause boundaries.
- The top-most constituents in the regions are selected as tokens.
- Equivalent to [Xue&Palmer 04] pruning process on full parse trees

Kristina	B-A0
hit	O
Scott	B-A1
with a baseball	B-A2
yesterday	B-AM-TMP



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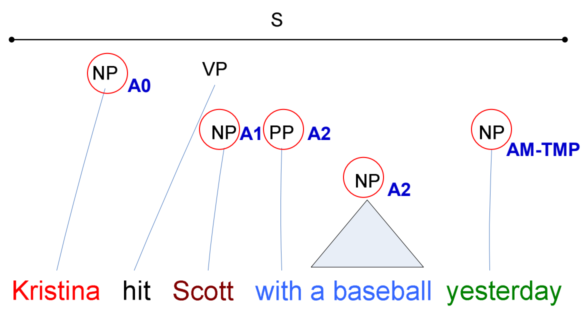
Sequentialization – Partial Parse

[Màrquez et al.] – Continued

- Only clauses and base chunks are available.
- Chunks within the same clause are selected as tokens.

Kristina	B-A0
hit	O
Scott	B-A1
with	B-A2
a Baseball	I-A2
yesterday	B-AM-TMP



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Greedy Combination

[Màrquez et al.] – Continued

- Join the maximum number of arguments from the output of both systems
  - More impact on Recall
- Different performance on different labels
  - FP_{CHA}: better for A0 and A1; PP_{UPC}: better for A2-A4
- Combining rule
  1. Adding arguments A0 and A1 from FP_{CHA}
  2. Adding arguments A2, A3, and A4 from PP_{UPC}
  3. Repeat Step 1&2 for other arguments
  - *Drop overlapping/embedding arguments*

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Results
[Màrquez et al.] – Continued

- Overall results on development set

	F_1	Prec.	Rec.
PP_{UPC}	73.57	76.86	70.55
FP_{CHA}	75.75	78.08	73.54
Combined	76.93	78.39	75.53

- Final results on test sets
  - WSJ-23 (2416 sentences)
    - 77.97 (F_1), 79.55 (Prec.), 76.45 (Rec.)
  - Brown (426 sentences; cross-domain test)
    - 67.42 (F_1), 70.79 (Prec.), 64.35 (Rec.)

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Semantic Role Chunking Combining Complementary Syntactic Views [Pradhan et al.]

- Observation: the performance of an SRL system depends heavily on the syntactic ***view***
  - Syntactic parse trees generated by full parsers
    - Charniak's, Collins', …
  - Partial syntactic analysis by chunker, clauser, etc.
- Usage of syntactic information
  - Features (e.g., path, syntactic frame, etc.)
  - Argument candidates (mostly the constituents)
- Strategy to reduce the impact of incorrect syntactic info.
  - Build individual SRL systems based on different syntactic parse trees (Charniak's and Collins')
  - Use the predictions as additional features
  - Build a final SRL system in the sequential tagging representation

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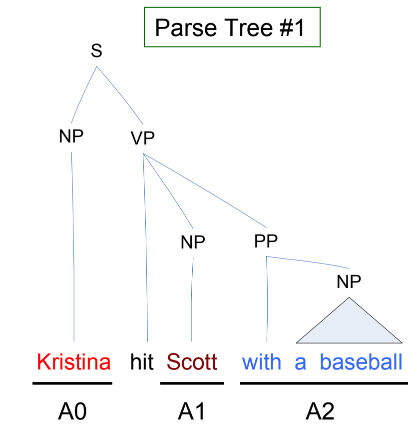
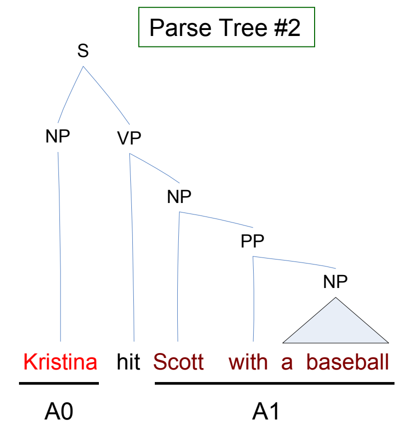
Constituent Views

[Pradhan et al.] – Continued





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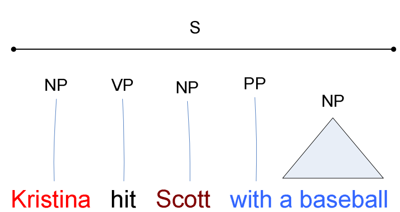
Chunk View

[Pradhan et al.] – Continued

- Sequentialization using base chunks [Hacioglu&Ward 03]
- Chunker: *Yamcha* [Kudo&Matsumoto 01]
  - http://chasen.org/~taku/software/yamcha/



Chunks	True Label	Pred #1	Pred #2
Kristina	B-A0	B-A0	B-A0
hit	O	O	O
Scott	B-A1	B-A1	B-A1
with	B-A2	B-A2	I-A1
a Baseball	I-A2	I-A2	I-A2

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Algorithm

[Pradhan et al.] – Continued

- Generate features from Charniak's and Collins' parse trees
- Add a few features from one to the other, and construct two SRL systems
- Represent the output as semantic BIO tags, and use them as features
- Generate the final semantic role label set using a phrase-based chunking paradigm

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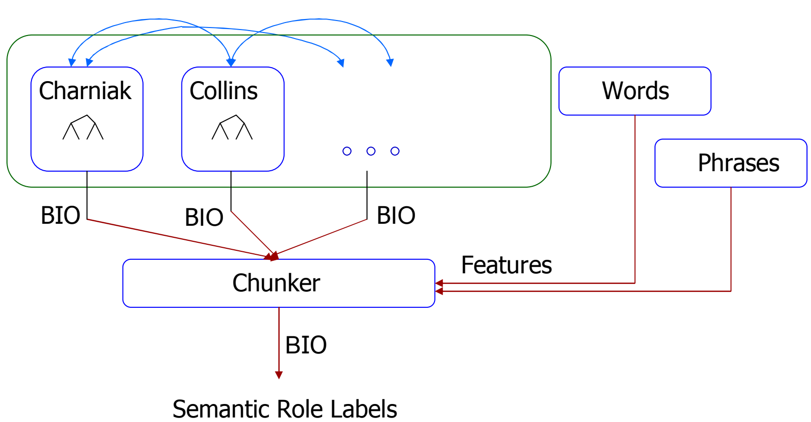
Architecture

[Pradhan et al.] – Continued



Slide from Pradhan et al. (CoNLL 2005)

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Results
[Pradhan et al.] – Continued

- Overall results on development set

System	F_1	Prec	Rec
Charniak	77	80	75
Collins	76	79	74
Combined	78	81	76

- Performance (F_1) on Test sets
  - Submitted system: WSJ-23 77.4, Brown 67.1
  - Bug-fixed system: WSJ-23 78.6, Brown 68.4

➢ Software: ASSERT (Automatic Statistical SEmantic Role Tagger)
http://oak.colorado.edu/assert

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Generalized Inference [Punyakanok et al.]

- The output of the argument classifier often violates some constraints, especially when the sentence is long.
- Use the integer linear programming inference procedure [Roth&Yih 04]
  - Input: the local scores (by the argument classifier), and structural and linguistic constraints
  - Output: the best legitimate global predictions
  - Formulated as an optimization problem and solved via Integer Linear Programming.
  - Allows incorporating expressive (non-sequential) constraints on the variables (the arguments types).

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Integer Linear Programming Inference

[Punyakanok et al.] – Continued

- For each argument a_i and label t
  - Set up a Boolean variable: $a_{i,t} \in \{0,1\}$
    - indicating if a_i is classified as t
- Goal is to maximize
  - $\sum_i \text{score}(a_i = t)\, a_{i,t}$
  - Subject to the (linear) constraints
    - Any Boolean constraint can be encoded this way.
- If score($a_i = t$) = P($a_i = t$), then the objective is
  - Find the assignment that maximizes the expected number of arguments that are correct
  - Subject to the constraints.

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Examples of Constraints

[Punyakanok et al.] – Continued

Any Boolean rule can be encoded as a set of linear constraints.

- No duplicate argument classes

  $\sum_{a \in \text{PotArg}} x_{\{a = A0\}} \leq 1$

- C-ARG

  If there is a C-*arg* phrase, there is an *arg* before it

  $\forall a' \in \text{PotArg}$,

  $\sum_{(a \in \text{PotArg}) \wedge (a \text{ is before } a')} x_{\{a = A0\}} \geq x_{\{a' = \text{C-A0}\}}$

- Many other possible constraints:
  - No overlapping or embedding
  - If the verb is of type A, no argument of type B
    - ***hit*** can take only A0-A2 but **NOT** A3-A5
  - Relations between number of arguments

Joint inference can be used also to combine different SRL Systems.

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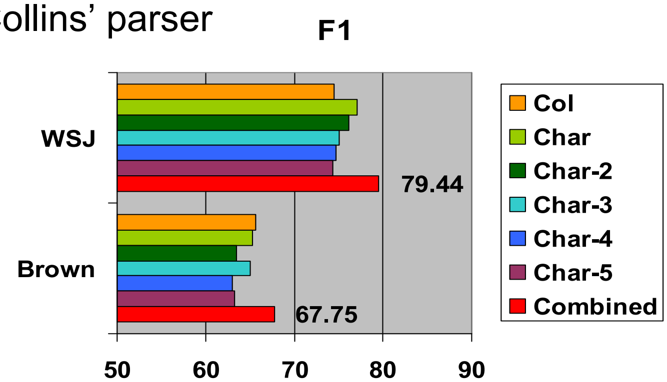
Results
[Punyakanok et al.] – Continued

- Char: Charniak's parser (5-best trees)
- Col: Collins' parser



Online Demo: http://l2r.cs.uiuc.edu/~cogcomp/srl-demo.php

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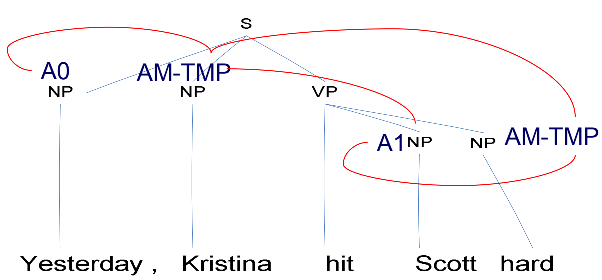
A Joint Model for SRL [Haghighi et al.]

- The main idea is to build a rich model for joint scoring, which takes into account the dependencies among the *labels* of argument phrases.

One possible labeling suggested by local models



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Joint Discriminative Reranking

[Haghighi et al.] – Continued

- For computational reasons: start with local scoring model with strong independence assumptions

$$P(labels|tree) = \prod_{node_i \in tree} P(labels_i|node_i)$$

- Find top N non-overlapping assignments for local model using a simple dynamic program [Toutanova et al. 05]
- Select the best assignment among top N using a joint log-linear model [Collins 00]
- The resulting probability of a complete labeling *L* of the tree for a predicate *p* is given by:

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

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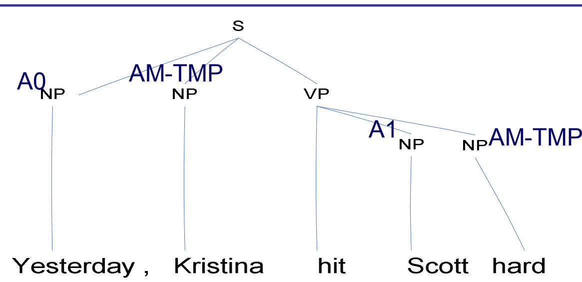
Joint Model Features

[Haghighi et al.] – Continued



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)

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Using Multiple Trees

[Haghighi et al.] – Continued

- Using the best Charniak's parse, on development set
  - Local Model: 74.52(F_1); Joint Model: 76.71(F_1)
- Further enhanced by using Top K trees
  - For top *k* trees from Charniak's parser $t_1, t_2, \cdots, t_k$ find corresponding best SRL assignments $L_1, \cdots, L_k$ 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:
  - 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: WSJ-23 80.32 (F_1) Brown 68.81 (F_1)

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Details of CoNLL-05 Systems

- ✓ Top performing systems
  - ✓ Màrquez et al. (Technical University of Catalonia)
  - ✓ Pradhan et al. (University of Colorado at Boulder)
  - ✓ Punyakanok et al. (U. of Illinois at Urbana-Champaign)
  - ✓ Haghighi et al. (Stanford University)
- Spotlight systems
  - Yi & Palmer – *integrating syntactic and semantic parsing*
  - Cohn & Blunsom – *SRL with Tree CRFs*
  - Carreras – *system combination*

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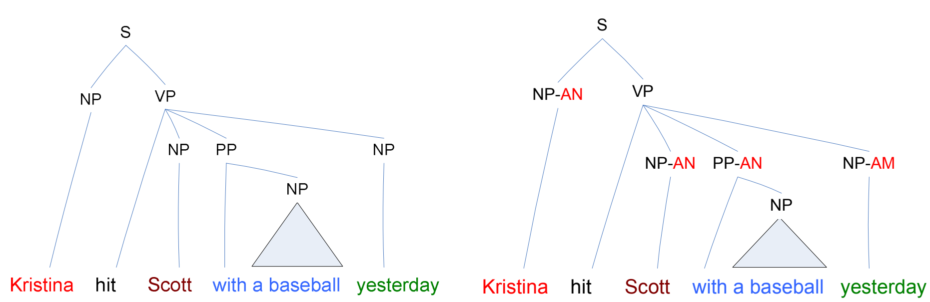
The Integration of Syntactic Parsing and Semantic Role Labeling [Yi & Palmer]

- The bottleneck of the SRL task: parsing
  - With [Xue&Palmer 04] pruning, given different parsers: 12%~18% arguments are lost (Development Set: WSJ-22)
- What do we want from syntactic parsing?
  - Correct constituent boundaries
  - Correct tree structures: expressing the dependency between the target verb and its arguments (e.g., the *path* feature)
- The proposed approach:
  - Combine syntactic parsing & argument identification (different cut of the task)
    - Train a new parser on the training data created by merging the Penn Treebank & the PropBank (sec 02-21)

Slide from Yi&Palmer (CoNLL 2005) 95

Data Preparation & Base Parser
[Yi & Palmer] – Continued

- Data preparation steps
  - Strip off the Penn Treebank function tags
  - 2 types of sub-labels to represent the PropBank arguments
    - AN: core arguments
    - AM: adjunct-like arguments
- Train new maximum-entropy parsers [Ratnaparkhi 99]



Based on Yi&Palmer's slides (CoNLL 2005) 96

Results & Discussion

[Yi & Palmer] – Continued

- Overall results on development set

	F_1	Prec.	Rec.
AN-parser	67.28	71.31	63.68
AM-parser	69.31	74.09	65.11
Charniak	69.98	76.31	64.62
Combined	72.73	75.70	69.99

- Final F_1 – WSJ-23: 75.17, Brown: 63.14
- Worse than using Charniak's directly
  - Because of weaker base parser?
- Hurt both parsing and argument identification?

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SRL with Tree CRFs [Cohn & Blunsom]

- A different joint model – apply tree CRFs
  - Generate the full parse tree using Collins' parser
  - Prune the tree using [Xue&Palmer 04]
  - Label each remaining constituent the **semantic role** or **None**
  - Learn the CRFs model
- Efficient CRF inference methods exist for trees
  - Maximum Likelihood Training: sum-product algorithm
  - Finding the best in Testing: max-product algorithm

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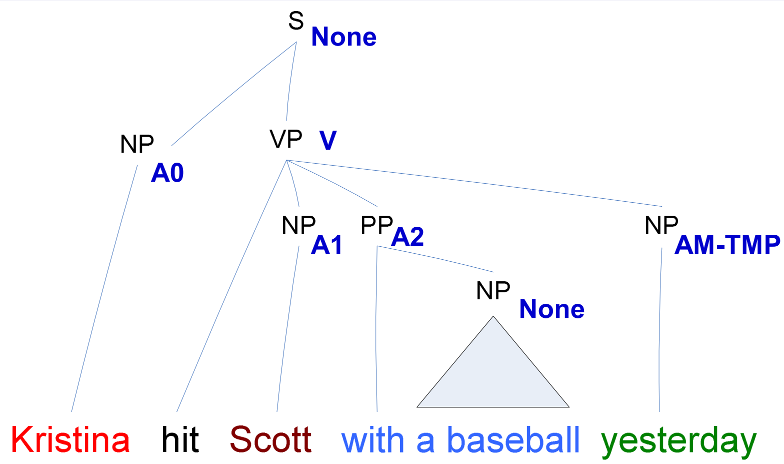
Tree Labeling

[Cohn & Blunsom] – Continued



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Model and Results

[Cohn & Blunsom] – Continued

- Definition of CRFs $p(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp \sum_{c \in C} \sum_k \lambda_k f_k(c, \mathbf{y}_c, \mathbf{x})$
- Maximum log-likelihood training
  $E_{\tilde{p}(\mathbf{x},\mathbf{y})}[f_k] - E_{p(\mathbf{x},\mathbf{y})}[f_k] = 0$
  - Use sum-product to calculate marginal $E_{p(\mathbf{x},\mathbf{y})}[f_k]$
- Inference
  - Use max-product to find the best labeling
- Results: Final F_1 – WSJ-23: 73.10, Brown: 63.63
- Findings [Cohn&Blunsom CoNLL-05 slides]:
  - CRFs improved over maxent classifier (+1%)
  - Charniak parses more useful (+3%)
  - Very few inconsistent ancestor/dependent labelings
  - Quite a number of duplicate argument predictions

Data from Cohn&Blunsom's slide (CoNLL 2005)

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System Combination [Carreras et al.]

- How much can we gain from combining different participating systems at argument level?
  - Each system proposes arguments, scored according to overall F_1 on development
  - The final score for an argument is the sum of scores given by systems
- Greedy Selection
  - Repeat, until no more arguments in the candidate list
    - Select argument candidate with the best score
    - Removing overlapping arguments from candidate list

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Results & Discussion
[Carreras et al.] – Continued

WSJ-23	F_1	Prec.	Rec.
punyakanok+haghighi+pradhan	80.21	79.10	81.36
punyakanok	79.44	82.28	76.78

Brown	F_1	Prec.	Rec.
haghighi+marquez+pradhan+tsai	69.74	69.40	70.10
punyakanok	67.75	73.38	62.93

- The greedy method of combing systems increases recall but sacrifices precision.
- The gain on F_1 is not huge.

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Part III: CoNLL-05 Shared Task on SRL

- ✓ Details of top systems and interesting systems
  - ✓ Introduce the top 4 systems
  - ✓ Describe 3 spotlight systems
- Analysis of the overall results
  - General performance
  - System properties
  - Per argument performance
- Directions for improving SRL systems

Results on WSJ and Brown Tests

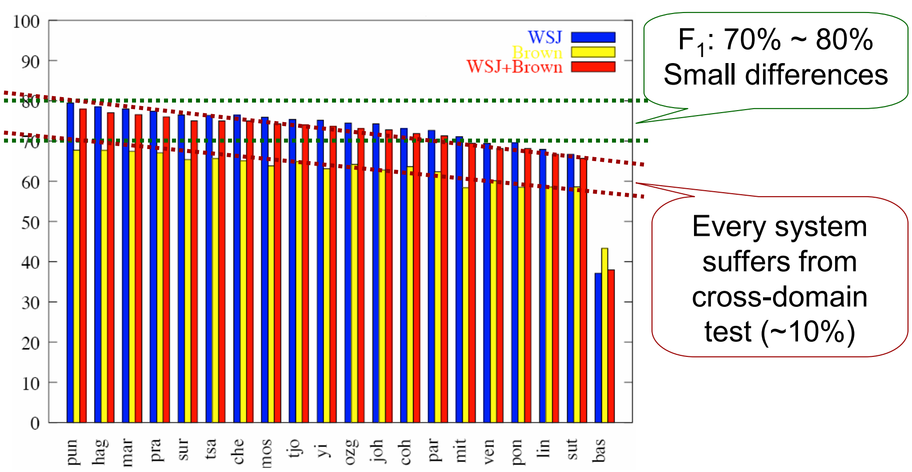

Figure from Carreras&Màrquez's slide (CoNLL 2005)

System Properties

- Learning Methods
  - SNoW, MaxEnt, AdaBoost, SVM, CRFs, etc.
  - ➢ *The choice of learning algorithms is less important.*
- Features
  - All teams implement more or less the standard features with some variations.
  - *A must-do for building a good system!*
  - *A clear feature study and more feature engineering will be helpful.*

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System Properties – Continued

- Syntactic Information
  - Charniak's parser, Collins' parser, clauser, chunker, etc.
  - Top systems use Charniak's parser or some mixture
  - ➢ *Quality of syntactic information is very important!*
- System/Information Combination
  - 8 teams implement some level of combination
  - Greedy, Re-ranking, Stacking, ILP inference
  - ➢ *Combination of systems or syntactic information is a good strategy to reduce the influence of incorrect syntactic information!*

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Per Argument Performance

CoNLL-05 Results on WSJ-Test

- Core Arguments (Freq. ~70%)

	Best F_1	Freq.
A0	88.31	25.58%
A1	79.91	35.36%
A2	70.26	8.26%
A3	65.26	1.39%
A4	77.25	1.09%

- Adjuncts (Freq. ~30%)

	Best F_1	Freq.
TMP	78.21	6.86%
ADV	59.73	3.46%
DIS	80.45	2.05%
MNR	59.22	2.67%
LOC	60.99	2.48%
MOD	98.47	3.83%
CAU	64.62	0.50%
NEG	98.91	1.36%

Arguments that need to be improved

Data from Carreras&Màrquez's slides (CoNLL 2005) 107

Groups of Verbs in WSJ-Test

- By their frequencies in WSJ-Train

	0	1-20	21-100	101-500	501-1000
Verbs	34	418	359	149	18
Props	37	568	1098	1896	765
Args.	70	1049	2066	3559	1450

- CoNLL-05 Results on WSJ-Test – Core Arguments

	0	1-20	21-100	101-500	501-1000
Args. %	0.9	12.8	25.2	43.4	17.7
Best F_1	73.38	76.05	80.43	81.70	80.31

Arguments of low-frequency verbs need to be improved

Data from Carreras&Màrquez's slides (CoNLL 2005) 108

Part III: CoNLL-05 Shared Task on SRL

- ✓ Details of top systems and interesting systems
  - ✓ Introduce the top 4 systems
  - ✓ Describe 3 spotlight systems
- ✓ Analysis of the overall results
  - ✓ General performance
  - ✓ System properties
  - ✓ Per argument performance
- Directions for improving SRL systems

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Directions for Improving SRL

- Better feature engineering
  - Maybe the most important issue in practice
- Joint modeling/inference
  - How to improve current approaches?
- Fine-tuned learning components
  - Can a more complicated system help?
- Cross domain robustness
  - Challenge to applying SRL systems

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Better Feature Engineering

Gildea&Jurafsky '02
- Target predicate
- Voice
- Subcategorization
- Path
- Position (left, right)
- Phrase Type
- Governing Category
- Head Word

Surdeanu et al '03
- Content Word
- Head Word POS
- Content Word POS
- Named Entity

Xue&Palmer '04
- Feature conjunctions
- Syntactic frame
- Head of PP Parent

Pradhan et al '04
- Phrase Type / Head Word / POS of Left/Right/Parent constituent
- First/Last word/POS

- Individual feature contribution is not clear
  - Every set of features provide some improvement, but…
  - Different system, different corpus, different usage

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Joint Model/Inference

- Unless pure local model reaches prefect results, joint model/inference often can improve the performance
- Greedy rules
  - ✓ Fast & Effective
  - × With no clear objective function
  - × Often increase recall by sacrificing precision
- Integer linear programming inference [Roth&Yih 04]
  - ✓ With clear objective function
  - ✓ Can represent fairly general *hard* constraints
  - × More expensive to integrate *soft (statistical)* constraints
- Joint Model [Toutanova et al. 05] [Cohn&Blunsom 05]
  - ✓ Capture statistical and hard constraints directly from the data
  - × Need re-ranking to avoid complexity problems [Toutanova et al. 05]
  - × Capture only local dependency [Cohn&Blunsom 05]

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Fine-tuned Learning Components

- Separate core arguments and adjuncts
  - Adjuncts are independent of the target verb
  - Performance may be enhanced with specific features
    - *Pradhan et al. (2005) did feature selection for each argument type*
- Train systems for different (groups of) verbs
  - Verbs (or senses) may have very different role sets
  - Example: stay.01(remain) vs. look.02 (seeming)

[$_{A1}$ Consumer confidence] **stayed** [$_{A3}$ strong] in October.

[$_{A0}$ The demand] **looked** [$_{A1}$ strong] in October.

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Cross Domain Robustness

- The performance of SRL systems drops significantly when applied on a different corpus
  - ~10% F_1 from WSJ to Brown
  - The performance of all the syntactic taggers and parsers drops significantly
    - All trained on WSJ
- May not build a robust system without data
  - Semi-supervised learning
  - Active learning

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Summary of Part III:
CoNLL-05 Shared Task on SRL

- Described the details of top performing SRL systems
  - Implement generally all *standard* features
  - Use good syntactic information – Charniak's parser & more
  - Deploy system/information combination schemes
  - Achieve ~80% F_1 on WSJ, ~70% F_1 on Brown
- Introduced some interesting systems
  - Train syntactic parser and argument identifier together
  - Apply Tree CRFs model
  - Investigate the performance of a large system combination

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Summary of Part III:
CoNLL-05 Shared Task on SRL – Continued

- Analyzed the results of the CoNLL-05 systems
  - General performance
    - Performance on WSJ is between 70% and 80%
    - The differences among systems are small
    - Every system suffers from cross-domain test; ~10% F_1 drop on Brown corpus
  - Per argument performance
    - Core arguments A1 and A2 and some frequent adjunct arguments need to be improved
    - Arguments of low-frequency verbs need to be improved

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Summary of Part III:
CoNLL-05 Shared Task on SRL – Continued

- Directions for improving SRL systems
  - Perform careful feature study
  - Design better features
  - Enhance current joint model/inference techniques
  - Separate models for different argument sets
  - Improve cross domain robustness
- **Next part**: Applications of SRL systems

Quick Overview

Part IV: Applications

- Information Extraction
  - Reduce development time
- Summarization
  - Sentence matching
- Question Answering
  - Understand questions better
- Textual Entailment
  - Deeper semantic representation

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SRL in Information Extraction
[Surdeanu et al. 03]

- Information Extraction (HUB Event-99 evaluations, [Hirschman et al 99])
  - A set of domain dependent *templettes*, summarizing information about events from multiple sentences

<MARKET_CHANGE_1>:=	
INSTRUMENT	London [gold]
AMOUNT_CHANGE	fell [$4.70] cents
CURRENT_VALUE	$308.45
DATE:	daily

Time for our daily market report from NASDAQ.
London gold fell $4.70 cents to $308.45.

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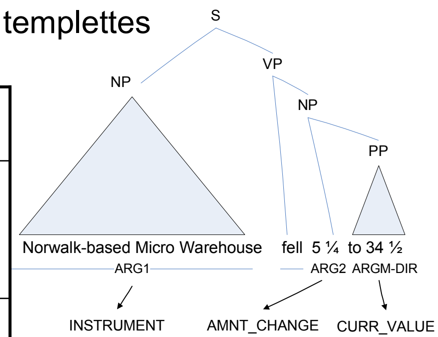
SRL in Information Extraction

[Surdeanu et al. 03]-Continued

- Find predicate argument relations and map resulting structures into templettes via hand-written simple rules

ARG1 and MARKET_CHANGE_VERB => INSTRUMENT
ARG2 and (MONEY or PERCENT or QAUNTITY) and MARKET_CHANGE_VERB => AMOUNT_CHANGE
(ARG4 or ARGM_DIR) and NUMBER and MARKET_CHANGE_VERB=> CURRENT_VALUE



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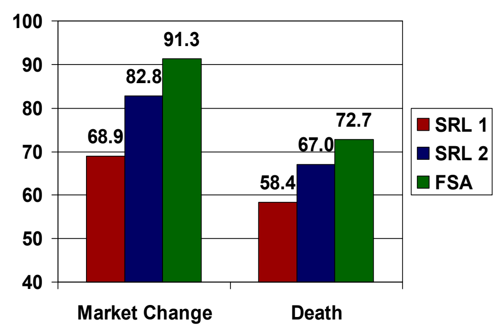
SRL in Information Extraction

[Surdeanu et al. 03]-Continued

- Results
  - SRL 1
    - Identification 71.9
    - Classification 78.9
  - SRL 2
    - Identification 89.0
    - Classification 83.7
  - FSA is a traditional finite state approach



Better SRL leads to significantly better IE performance.

The FSA approach does better but requires intensive human effort (10 person days).

The systems using SRL require 2 hours of human effort.

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SRL in Summarization (SQUASH, [Melli et al. 05] SFU)

- The task is to generate a 250-word summary from multiple documents
  - Given a specified topic and level of detail (specific, general)

Title: American Tobacco Companies Overseas

Narrative: In the early 1990's, American tobacco companies tried to expand their business overseas. What did these companies do or try to do and where? How did their parent companies fare?

Granularity: specific

- The system uses SRL extensively for:
  - Estimating a significance score for a sentence
    - which entities participate in which semantic relations
  - Estimating sentence similarity
    - which entities participating in which *semantic relations* are contained in two sentences

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SRL in Summarization (SQUASH, [Melli et al. 05]-Continued)

- It is not possible to remove just the SRL component from the system since SRL is used throughout
- Improving the SRL system improves Summarization performance (ROUGE-2 scores on the development set)
  - Naïve SRL **0.0699**
  - ASSERT SRL **0.0731**
- This is a pretty large improvement considering the impact of other successful features
  - Bias toward the first sentences 0.0714 → 0.0738
- The overall placement of an earlier version of SQUASH was 7th out of 25 systems in DUC 2005

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SRL in Question Answering
[Narayanan & Harabagiu 04]

- Parsing Questions

Q: What kind of materials were stolen from the Russian navy?

PAS(Q): What [A1 kind of nuclear materials] were [Predicate:stolen] [A2 from the Russian Navy]?

- Parsing Answers

A(Q): Russia's Pacific Fleet has also fallen prey to nuclear theft; in 1/96, approximately 7 kg of HEU was reportedly stolen from a naval base in Sovetskaya Gavan.

PAS(A(Q)): [A1(P1) Russia's Pacific Fleet] has [AM-DIS(P1) also] [P1: fallen] [A1(P1) prey to nuclear theft]; [AM-TMP(P2) in 1/96], [A1(P2) approximately 7 kg of HEU] was [AM-ADV(P2) reportedly] [P2: stolen] [A2(P2) from a naval base] [A3(P2) in Sovetskawa Gavan]

- Result: exact answer= *"approximately 7 kg of HEU"*

Slide from Harabagiu and Narayanan (HLT 2004)

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SRL in Question Answering
[Narayanan & Harabagiu 04]-Continued

- Parsing Questions

Q: What kind of materials were stolen from the Russian navy?

FS(Q): What [GOODS kind of nuclear materials] were [Target-Predicate stolen] [VICTIM from the Russian Navy]?

- Parsing Answers

A(Q): Russia's Pacific Fleet has also fallen prey to nuclear theft; in 1/96, approximately 7 kg of HEU was reportedly stolen from a naval base in Sovetskaya Gavan.

FS(A(Q)): [VICTIM(P1) Russia's Pacific Fleet] has also fallen prey to [GOODS(P1) nuclear] [Target-Predicate(P1) theft]; in 1/96, [GOODS(P2) approximately 7 kg of HEU] was reportedly [Target-Predicate (P2) stolen] [VICTIM (P2) from a naval base] [SOURCE(P2) in Sovetskawa Gavan]

- Result: exact answer= *"approximately 7 kg of HEU"*

Slide from Harabagiu and Narayanan (HLT 2004)

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SRL in Question Answering

[Narayanan & Harabagiu 04]-Continued

- Evaluation of gains due to predicate-argument information.

Structure Used	Percent of Questions
Answer Hierarchy	12%
PropBank analyses	32%
FrameNet analyses	19%

Percent of questions for which the correct answer type was identified through using each structure.

- **Question:** What is the additional value compared to matching based on syntactic analyses?

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SRL in Textual Entailment

[Braz et al. 05]

- Does a given text *S* entail a given sentence *T*
  - *S: The bombers had not managed to enter the building*
  - *T: The bombers entered the building*
- Evaluating entailment by matching predicate argument structure
  - *S1: [$_{ARG0}$The bombers] had [$_{ARGM_NEG}$not] managed to [$_{PRED}$enter] [$_{ARG1}$ the building]*
  - *T1: [$_{ARG0}$The bombers] [$_{PRED}$entered] [$_{ARG1}$ the building]*

S does not entail *T* because they do not have the same set of arguments

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SRL in Textual Entailment

[Braz et al. 05]-Continued

- SRL forms the basis of the algorithm for deciding entailment.
- It is also extensively used in *rewrite rules* which preserve semantic equivalence.
- Not possible to isolate the effect of SRL and unknown whether a syntactic parse approach can do similarly well.
- Results on the PASCAL RTE challenge 2005
  - Word based baseline: **54.7**
  - System using SRL and syntactic parsing: **65.9**
- The system placed 4^{th} out of 28 runs by 16 teams in the PASCAL RTE Challenge

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Summary of Part IV: Applications

- Information Extraction
  - SRL has advantages in development time; good SRL $\rightarrow$ good IE
  - FSA systems are still about 10% better.
- Summarization
  - Sophisticated sentence matching using SRL
  - Improving SRL improves summarization.
- Question Answering
  - Having more complex semantic structures increases the number of questions that can be handled about 3 times.
- Textual Entailment
  - SRL enables complex inferences which are not allowed using surface representations.
- **Action item**: evaluate contributions of SRL vs. syntactic parsing
  - None of the systems performs a careful comparison

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Conclusions

- Semantic Role Labeling is relatively new but has attracted a lot of interest
- Large corpora with annotated data are available
  - FrameNet, PropBank
- It provides a novel *broad-coverage* level of semantic interpretation
  - Shallower than some alternatives (Deep Parsing for limited and broad domains)
  - Deeper than others (Penn Treebank analyses with function tags)
- Tasks which profit from Penn Treebank syntactic analyses should profit from this semantic layer

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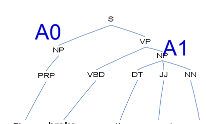
Conclusions
Current State of the Art systems



- Achieve about **80%** per-argument F-measure (**60%** whole propositions correct)
  - Performance is respectable but still there is a lot of room for improvement
  - Inter-annotator agreement is **99%** for *all* nodes given *gold-standard* syntactic parses (chance agreement is **88%**); not comparable to system results
- Build on the strength of statistical parsing models
  - Perform poorly when the syntactic parsers do so
- Use syntactic information extensively
- Have mechanisms for increasing robustness to parser error
- Use powerful machine learning techniques
- Model dependencies among argument labels

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Conclusions
Directions for Improving SRL

- Increase robustness to syntactic parser error
- Find ways to collect additional knowledge
  - Use unlabeled data
  - Share information across verbs
  - Can applications create more data for SRL automatically?
- Improve the statistical models
  - Other features, other dependencies
- Improve search/inference procedures

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Conclusions
Major Challenges

- Need to connect SRL to natural language applications
  - Study the additional value of semantic labels compared to surface representations and syntactic analyses
  - Apply SRL to other applications
    - More Information Extraction applications
    - ATIS labeling and NL interfaces to databases
  - Have we defined the corpora well?
    - Validate the annotation standards through application domains
  - What level of accuracy is needed in order for SRL to be useful?

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Final Remarks

- Semantic Role Labeling is an exciting area of research!
  - Progress is fast
  - There is still room for large contributions
- Provides robust broad-coverage semantic representations
- Easy integration with applications (Information Extraction, Question Answering, Summarization, Textual Entailment)
  - Good results in tasks
- Tools available online that produce SRL structures
  - ASSERT (Automatic Statistical SEmantic Role Tagger) http://oak.colorado.edu/assert
  - UIUC system (http://l2r.cs.uiuc.edu/~cogcomp/srl-demo.php)

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