Semantic Roles & Semantic Role Labeling

Ling571
Deep Processing Techniques for NLP
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Roadmap

- Semantic role labeling (SRL):
  - Motivation:
    - Between deep semantics and slot-filling
  - Thematic roles
  - Thematic role resources
    - PropBank, FrameNet
  - Automatic SRL approaches

Semantic Analysis

- Two extremes:
  - Full, deep compositional semantics
    - Creates full logical form
    - Links sentence meaning representation to logical world model representation
    - Powerful, expressive, AI-complete

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  - Full, deep compositional semantics
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    - Powerful, expressive, AI-complete
  - Domain-specific slot-filling:
    - Common in dialog systems, IE tasks
    - Narrowly targeted to domain/task
    - Often pattern-matching
    - Low cost, but lacks generality, richness, etc

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  - *Who* did *what* to *whom*, *where*, *when*, and *how*

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  - *Who* did *what* to *whom*, *where*, *when*, and *how*
- Intermediate level:
  - Shallower than full deep composition
  - Abstracts away (somewhat) from surface form
  - Captures general predicate-argument structure info
  - Balance generality and specificity

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- Yesterday Tom chased Jerry.
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- Same across all examples
- Roles: Chaser, ChasedThing, TimeOfChasing
  - Specific to verb “chase”
  - Aka “Deep roles”

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    - Not really, each event/role is specific
- Alternative: thematic roles

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  - Group verbs into classes based on shared patterns

Canonical Roles

Thematic Role	Example
AGENT	*The waiter* spilled the soup.
EXPERIENCER	*John* has a headache.
FORCE	*The wind* blows debris from the mall into our yards.
THEME	Only after Benjamin Franklin broke *the ice*...
RESULT	The French government has built a *regulation-size baseball diamond*...
CONTENT	Mona asked *"You met Mary Ann at a supermarket?"*
INSTRUMENT	He turned to poaching catfish, stunning them *with a shocking device*...
BENEFICIARY	Whenever Ann Callahan makes hotel reservations *for her boss*...
SOURCE	I flew in *from Boston*.
GOAL	I drove *to Portland*.

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  - Define roles specific to verbs/nouns: FrameNet

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    - Ex1: [$_{\text{Arg0}}$The group] agreed [$_{\text{Arg1}}$it wouldn't make an offer]

Propbank

- Resources:
  - Annotated sentences
    - Started w/Penn Treebank
    - Now: Google answerbank, SMS, webtext, etc
      - Also English and Arabic
  - Framesets:
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- http://verbs.colorado.edu/propbank
- Recent status:
  - 5940 verbs w/ 8121 framesets;
  - 1880 adjectives w/2210 framesets

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- FrameNet
  - [$_{ATTRIBUTE}$The price] of [$_{ITEM}$bananas] increased [$_{DIFF}$5%].
  - [$_{ATTRIBUTE}$The price] of [$_{ITEM}$bananas] rose [$_{DIFF}$5%].
  - There has been a [$_{DIFF}$5%] rise in [$_{ATTRIBUTE}$ the price] of [$_{ITEM}$ bananas].

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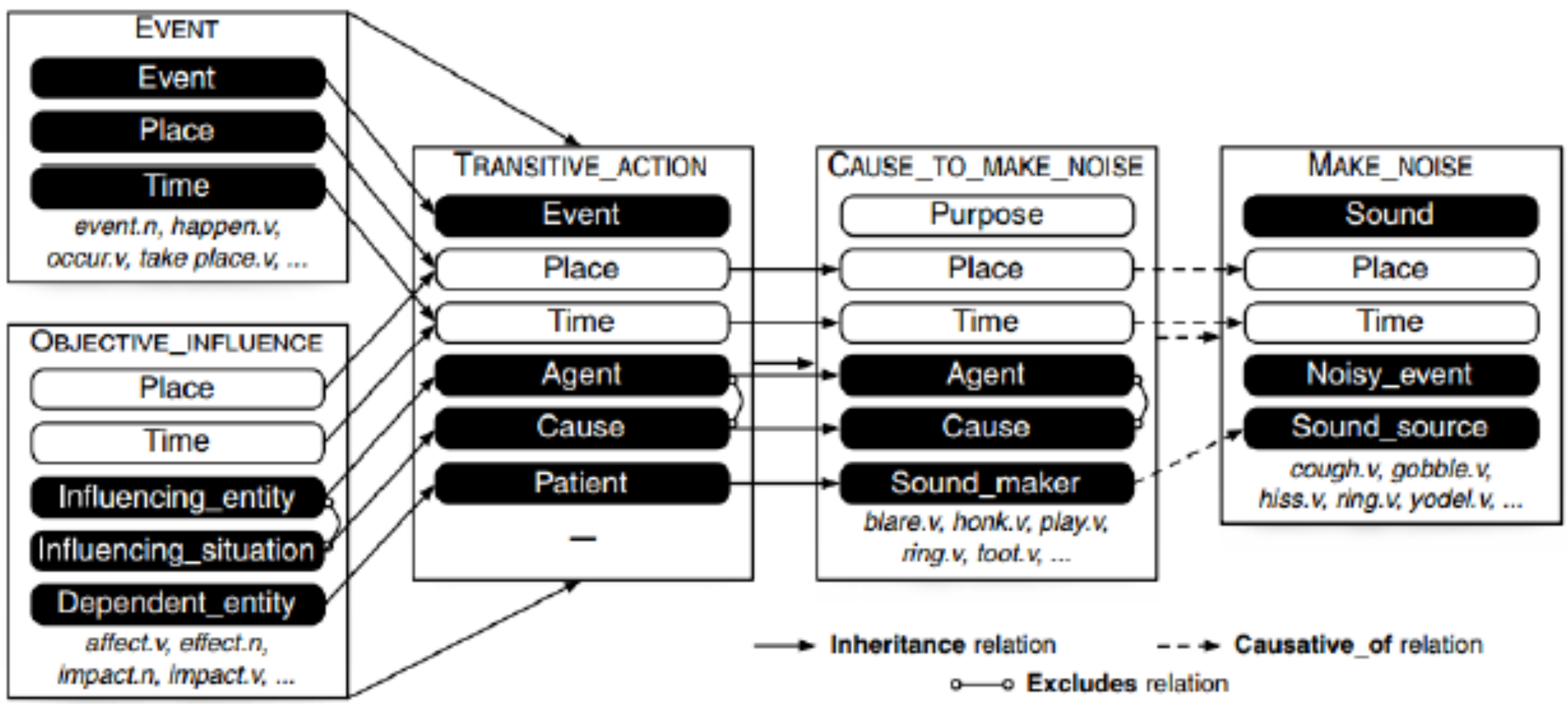
  - Core, non-core roles
  - Relationships b/t frames, frame elements
    - Add causative: cause_change_position_on_scale

Change of position on scale

VERBS:	dwindle	move	soar	escalation	shift
advance	edge	mushroom	swell	explosion	tumble
climb	explode	plummet	swing	fall	
decline	fall	reach	triple	fluctuation	**ADVERBS:**
decrease	fluctuate	rise	tumble	gain	increasingly
diminish	gain	rocket		growth	
dip	grow	shift	**NOUNS:**	hike	
double	increase	skyrocket	decline	increase	
drop	jump	slide	decrease	rise	

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an ITEM changes its position on the scale.
FINAL_STATE	A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
FINAL_VALUE	The position on the scale where the ITEM ends up.
INITIAL_STATE	A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
INITIAL_VALUE	The initial position on the scale from which the ITEM moves away.
ITEM	The entity that has a position on the scale.
VALUE_RANGE	A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

FrameNet Inheritance



FrameNet

- Current status:
  - 1190 frames
  - 12000+ lexical units (mostly verbs, nouns)
  - Annotations over:
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- Under active development
- Still only ~6K verbs, limited coverage

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- Task:
  - For each predicate in a sentence:
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- Both PropBank, FrameNet used as targets
- Potentially useful for many NLU tasks:
  - Demonstrated usefulness in Q&A, IE

SRL in QA

- Intuition:
  - Surface forms obscure Q&A patterns
  - *Q: What year did the U.S. buy Alaska?*
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  - Learn syntactic patterns?
    - Different lexical choice, different dependency structure

Semantic Roles & QA

- Approach:
  - Perform semantic role labeling
    - FrameNet
  - Perform structural and semantic role matching
  - Use role matching to select answer

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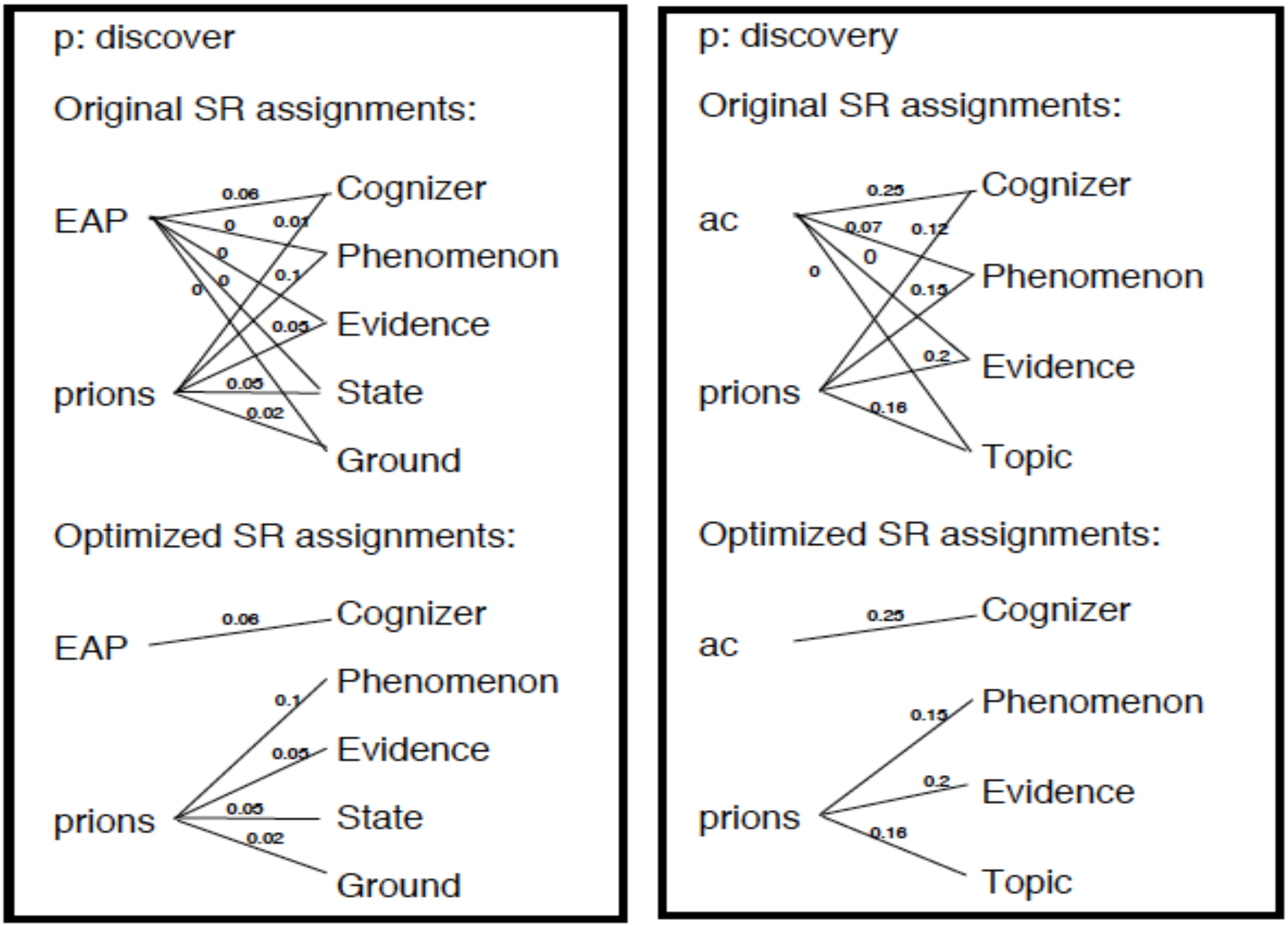
  - Compare resulting semantic structures
  - Select highest ranked

Q: Who discovered prions?

S: 1997: Stanley B. Prusiner, United States, discovery of prions, ...

SemStruc ^{q} ***SemStruc*** ^{ac} (ac: Stanley B. Prusiner)



Summary

- FrameNet and QA:
  - FrameNet still limited (coverage/annotations)
  - Bigger problem is lack of alignment b/t Q & A frames
- Even if limited,
  - Substantially improves where applicable
  - Useful in conjunction with other QA strategies
  - Soft role assignment, matching key to effectiveness

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Semantic Role Complexities

- Discontinuous arguments:
  - [$_{Arg1}$The pearls], [$_{Arg0}$ she] said, [$_{C\text{-}Arg1}$ are fake].
- Arguments can include referents/pronouns:
  - [$_{Arg0}$The pearls], [$_{R\text{-}Arg0}$ that] are [$_{Arg1}$ fake]

SRL over Parse Tree

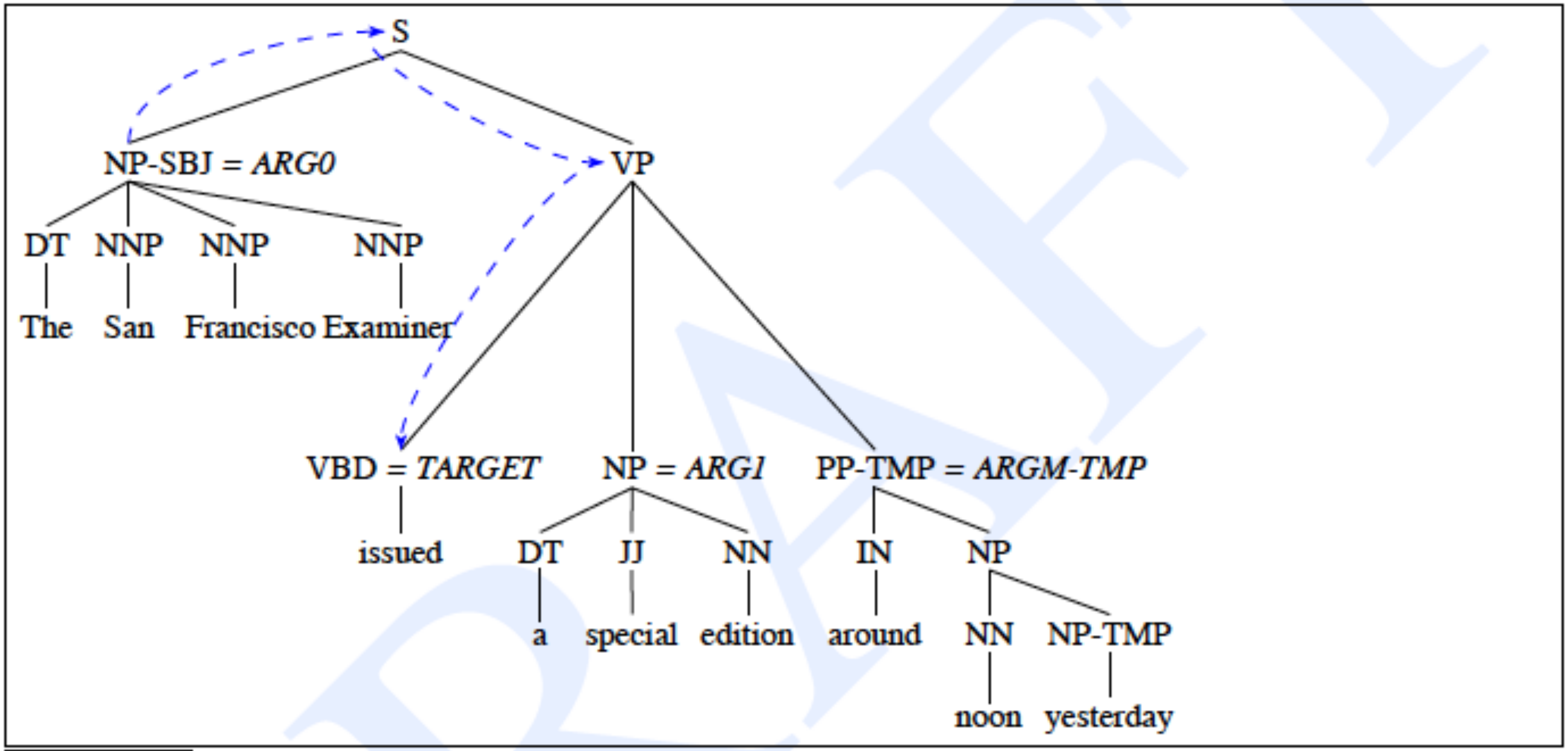

Figure 20.16 Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the path feature NP↑S↓VP↓VBD for ARG0, the NP-SBJ constituent *the San Francisco Examiner*.

Basic SRL Approach

- Generally exploit supervised machine learning
- Parse sentence (dependency/constituent)
  - For each predicate in parse:
    - For each node in parse:
      - Create a feature vector representation
      - Classify node as semantic role (or none)
- Much design in terms of features for classification

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- Governing **predicate**:
  - Nearest governing predicate to the current node
    - Verbs usually (also adj, noun in FrameNet)
    - E.g. ‘issued’
  - Crucial: roles determined by predicate

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    - Different roles tend to surface as different phrase types
  - Head word:
      - E.g. Examiner
      - Words associated w/specific roles – e.g. pronouns as agents
  - POS of head word:
      - E.g. NNP

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      - E.g. active (strongly influences other order, paths, etc)
  - Verb subcategorization

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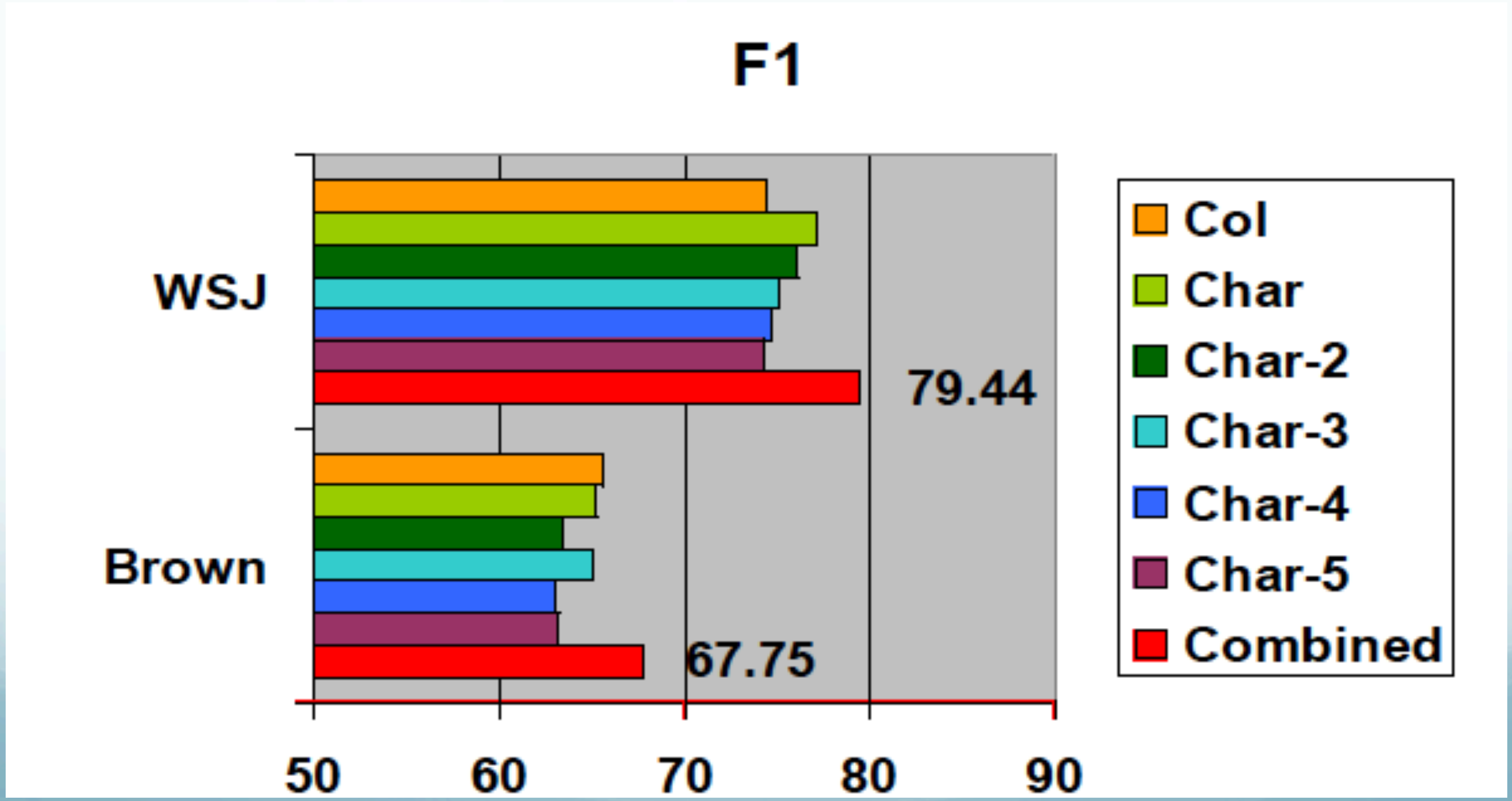
  - However, hard to effectively exploit global constraints
- Alternative approaches
  - Classification + reranking
  - Joint modeling
  - Integer Linear Programming (ILP)
    - Allows implementation of global constraints over system

State-of-the-Art

- Best system from CoNLL shared task (PropBank)
  - ILP-based system (Punyakanok)



FrameNet Parsing

- (Das et al., 2014)
- Identify targets that evoke frames
  - ~ 79.2% F-measures
- Classify targets into frames
  - 61% for exact match
- Identify arguments
  - ~ 50%

SRL Challenges

- Open issues:
  - SRL degrades significantly across domains
    - E.g. WSJ → Brown: Drops > 12% F-measure
  - SRL depends heavily on effectiveness of other NLP
    - E.g. POS tagging, parsing, etc
    - Errors can accumulate
  - Coverage/generalization remains challenging
    - Resource coverage still gappy (FrameNet, PropBank)
- Publicly available implementations:
  - Shalmaneser, SEMAFOR

Lexical Semantics

What is a plant?

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plant**s and animals in the rainforest that we have not yet discovered.

The Paulus company was founded in 1938. Since those days the product range has been the subject of constant expansions and is brought up continuously to correspond with the state of the art. We're engineering, manufacturing, and commissioning world-wide ready-to-run **plants** packed with our comprehensive know-how.

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  - Internal meaning structure of words
    - Basic internal units combine for meaning

Terminology

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    - **Lemma**: citation form; infinitive in inflection
      - Sing: sing, sings, sang, sung,…
- **Lexicon**: finite list of lexemes

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- Why?
  - Problem for applications: TTS, ASR transcription, IR

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- Polysemy
  - Multiple RELATED senses
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  - Big issue in lexicography
    - # of senses, relations among senses, differentiation
    - E.g. serve breakfast, serve Philadelphia, serve time

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    - Register:
      - social factors: e.g. politeness, formality

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  - Organize as ontology/taxonomy

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  - Synonymy: in synset
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WordNet

The noun "bass" has 8 senses in WordNet.

1. bass^1 - (the lowest part of the musical range)
2. bass^2, bass part^1 - (the lowest part in polyphonic music)
3. bass^3, basso^1 - (an adult male singer with the lowest voice)
4. sea bass^1, bass^4 - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass^1, bass^5 - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass^6, bass voice^1, basso^2 - (the lowest adult male singing voice)
7. bass^7 - (the member with the lowest range of a family of musical instruments)
8. bass^8 - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

The adjective "bass" has 1 sense in WordNet.

1. bass^1, deep^6 - (having or denoting a low vocal or instrumental range) *"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"*

Noun WordNet Relations

Relation	Also Called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Instance Hypernym	Instance	From instances to their concepts	$Austen^1 \rightarrow author^1$
Instance Hyponym	Has-Instance	From concepts to concept instances	$composer^1 \rightarrow Bach^1$
Member Meronym	Has-Member	From groups to their members	$faculty^2 \rightarrow professor^1$
Member Holonym	Member-Of	From members to their groups	$copilot^1 \rightarrow crew^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7 \rightarrow meal^1$
Substance Meronym		From substances to their subparts	$water^1 \rightarrow oxygen^1$
Substance Holonym		From parts of substances to wholes	$gin^1 \rightarrow martini^1$
Antonym		Semantic opposition between lemmas	$leader^1 \Longleftrightarrow follower^1$
Derivationally Related Form		Lemmas w/same morphological root	$destruction^1 \Longleftrightarrow destroy^1$

WordNet Taxonomy

```
Sense 3
bass, basso --
(an adult male singer with the lowest voice)
=> singer, vocalist, vocalizer, vocaliser
   => musician, instrumentalist, player
      => performer, performing artist
         => entertainer
            => person, individual, someone...
               => organism, being
                  => living thing, animate thing,
                     => whole, unit
                        => object, physical object
                           => physical entity
                              => entity
               => causal agent, cause, causal agency
                  => physical entity
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```

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  - Associate with WordNet synset (and hyponyms)

Primitive Decompositions

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