Semantic Role Labeling

Deep Processing Techniques for NLP
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Semantic Role Labeling

- Aka Thematic role labeling, shallow semantic parsing
- Form of predicate-argument extraction
- Task:
  - For each predicate in a sentence:
    - Identify which constituents are arguments of the predicate
    - Determine correct role for each argument
- 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?*
  - *S_A:…before Russia sold Alaska to the United States in 1867*

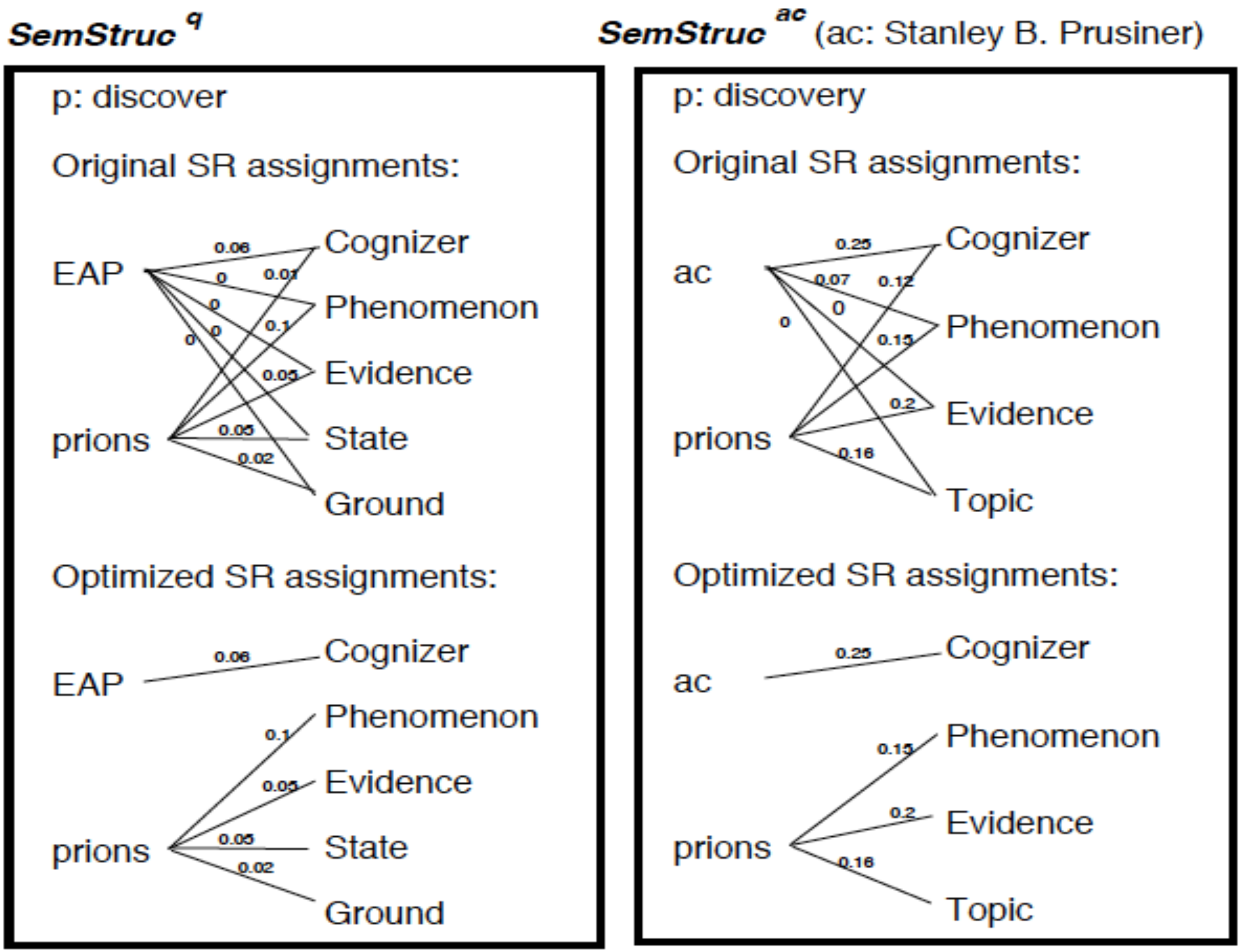
  - Learn surface text patterns?
    - Long distance relations, require huge # of patterns to find
  - Learn syntactic patterns?
    - Different lexical choice, different dependency structure

Semantic Roles & QA

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

Q: Who discovered prions?

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



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

SRL Subtasks

- Argument identification:
  - The [San Francisco Examiner] issued [a special edition] [yesterday].
  - Which spans are arguments?
    - In general (96%), arguments are (gold) parse constituents
    - 90% arguments are aligned w/auto parse constituents
- Role labeling:
  - The [$_{\text{Arg0}}$San Francisco Examiner] issued [$_{\text{Arg1}}$a special edition] [$_{\text{ArgM-TMP}}$yesterday].

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

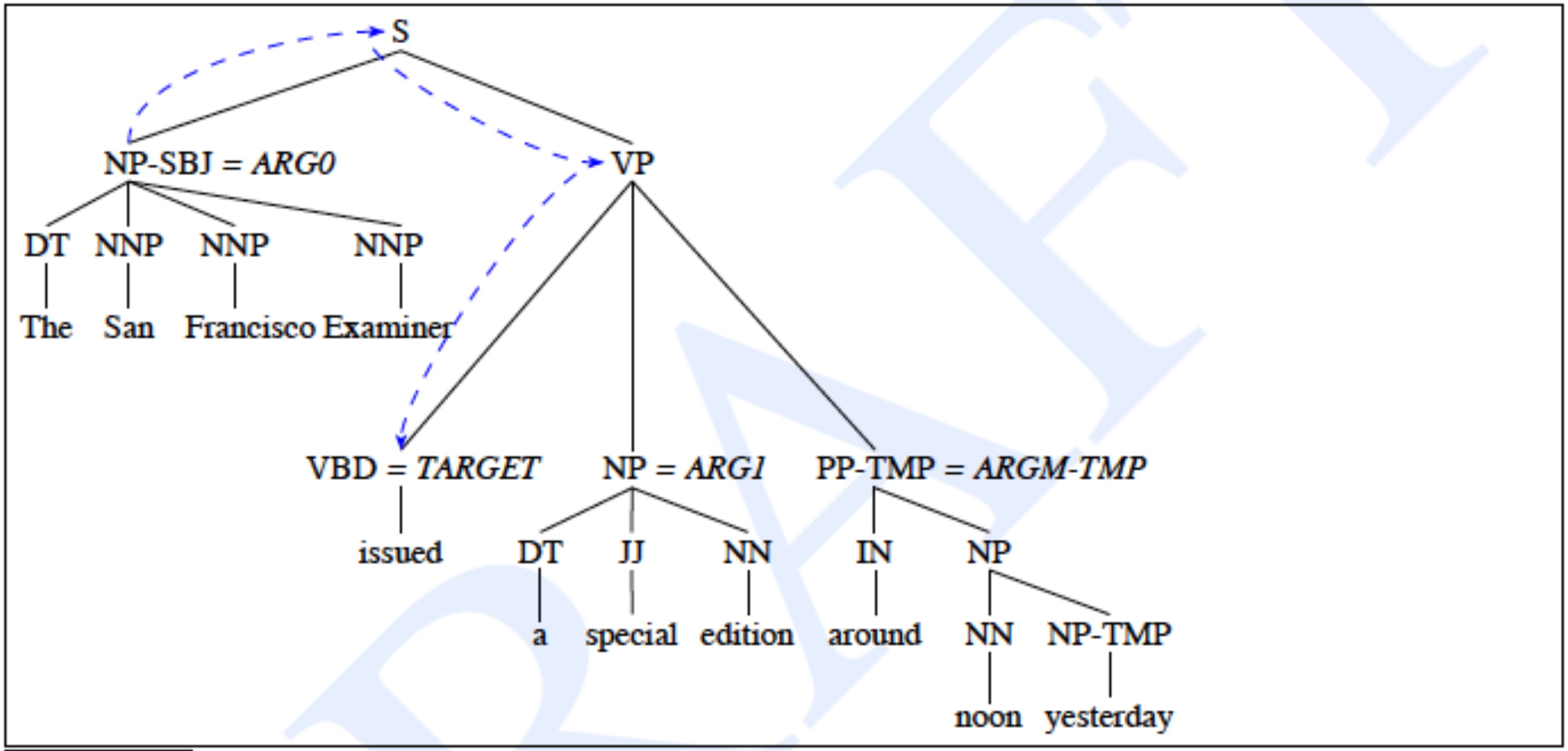


Figure 20.16 Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the path feature NP↑S↓VP↓VBD for ARG0, the NP-SBJ constituent *the San Francisco Examiner*.

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

Classification Features

- Gildea & Jurafsky, 2002 (foundational work)
  - Employed in most SRL systems
- Features:
  - specific to candidate constituent argument
  - for predicate generally
- Governing **predicate**:
  - Nearest governing predicate to the current node
    - Verbs usually (also adj, noun in FrameNet)
    - E.g. ‘issued’
  - Crucial: roles determined by predicate

SRL Features

- Constituent internal information:
  - Phrase type:
    - Parse node dominating this constituent
      - E.g. NP
    - 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

SRL Features

- Structural features:
  - Path: Sequence of parse nodes from const to pred
    - E.g. NP↑S↓VP↓VBD
      - Arrows indicate direction of traversal
    - Can capture grammatical relations
  - Linear position:
    - Binary: Is constituent **before** or **after** predicate
      - E.g. before
  - Voice:
    - Active or passive of clause where constituent appears
      - E.g. active (strongly influences other order, paths, etc)
  - Verb subcategorization

Other SRL Constraints

- Many other features employed in SRL
  - E.g. NER on constituents, neighboring words, path info
- Global Labeling constraints:
  - Non-overlapping arguments:
    - FrameNet, PropBank both require
  - No duplicate roles:
    - Labeling of constituents is not independent
      - Assignment to one constituent changes probabilities for others

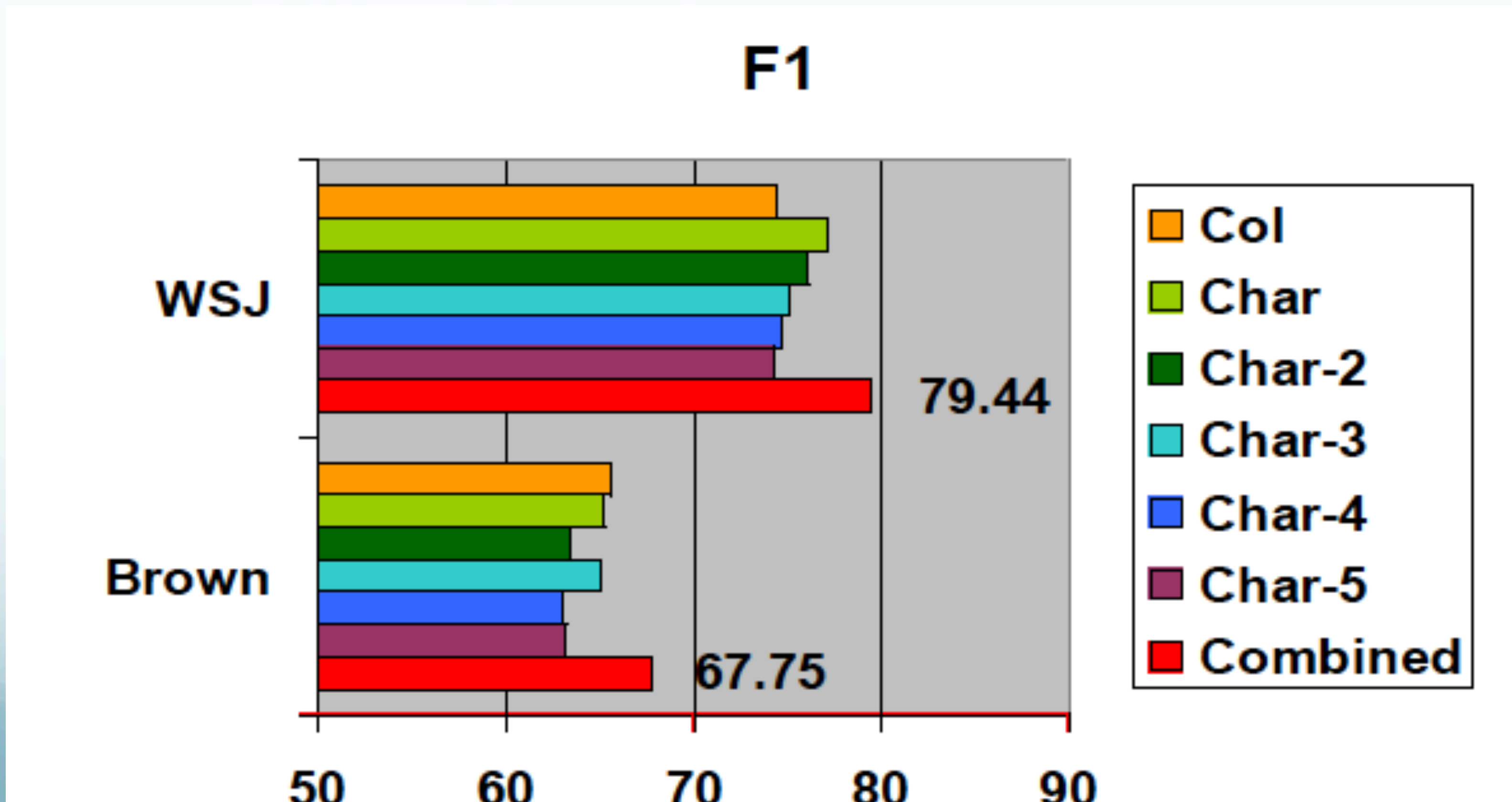
Classification Approaches

- Many SRL systems use standard classifiers
  - E.g. MaxEnt, SVM
  - 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-measure
- 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

Summary

- Computational Semantics:
  - Deep compositional models yielding full logical form
  - Semantic role labeling capturing who did what to whom
  - Lexical semantics, representing word senses, relations

Computational Models of Discourse

Roadmap

- Discourse
  - Motivation
  - Dimensions of Discourse
  - Coherence & Cohesion
  - Coreference

What is a Discourse?

- Discourse is:
  - Extended span of text
  - Spoken or Written
  - One or more participants
  - Language in Use
  - Goals of participants
    - Processes to produce and interpret

Why Discourse?

- Understanding depends on context
  - Referring expressions: it, that, the screen
  - Word sense: plant
  - Intention: Do you have the time?
- Applications: Discourse in NLP
  - Question-Answering
  - Information Retrieval
  - Summarization
  - Spoken Dialogue
  - Automatic Essay Grading

Reference Resolution

U: Where is A Bug's Life playing in Summit?
S: A Bug's Life is playing at the Summit theater.
U: When is it playing there?
S: It's playing at 2pm, 5pm, and 8pm.
U: I'd like 1 adult and 2 children for the first show.
How much would that cost?

- Knowledge sources:
  - Domain knowledge
  - Discourse knowledge
  - World knowledge

From Carpenter and Chu-Carroll, Tutorial on Spoken Dialogue Systems, ACL '99

Coherence

- *First Union Corp. is continuing to wrestle with severe problems. According to industry insiders at PW, their president, John R. Georgius, is planning to announce his retirement tomorrow.*
- Summary*:*
- *First Union President John R. Georgius is planning to announce his retirement tomorrow.*

- Inter-sentence coherence relations:
  - Second sentence: main concept (nucleus)
  - First sentence: subsidiary, background

Different Parameters of Discourse

- Number of participants
  - Multiple participants -> Dialogue
- Modality
  - Spoken vs Written
- Goals
  - Transactional (message passing) vs Interactional (relations,attitudes)
  - Cooperative task-oriented rational interaction

Coherence Relations

- John hid Bill's car keys. He was drunk.
- ?? John hid Bill's car keys. He likes spinach.

- Why odd?
  - No obvious relation between sentences
    - Readers often try to construct relations
- How are first two related?
  - Explanation/cause
- Utterances should have meaningful connection
  - Establish through **coherence relations**