Natural Language Processing

Lecture 10: Semantic Role Labeling.

10/29/2021

COMS W4705
Yassine Benajiba

Word Meaning and Sentence Meaning

- So far we have discussed the meaning of individual words.
- Now: meaning of entire predicate-argument structures and sentences.
- What should the representations be?
- How do we compute predicate or sentence-level representations from word representations?
  - What is the role of syntax?

Approaches to Sentence Level Semantics

- Semantic Role Labeling (SRL) / Frame Semantic Parsing.
  - Target representation: PropBank predicate argument structures, FrameNet-style annotations.
- Full-sentence semantics
  - Target representations: Predicate-logic, Abstract Meaning Representation

Frame Semantics

(Fillmore, 1992)

- Long history in cognitive science, AI, ... **(Minksy 1974, Barsalou 1992)**
- A frame represents a situation, object, event providing background needed to understand a word ('cognitive schemata').
- Different words (of different part-of-speech) can evoke the same frame

Giving → {*donate.v, gift.n, give.v, hand over.v, treat.v, ...* }

- A pair of a word and a frame is called a lexical unit (LU).

Frame Elements

- Frames describe the interaction/relation between a set of frame-specific semantic roles called *Frame Elements* (FEs).

Giving: A Donor transfers a Theme from a Donor to a Recipient.

Core:

Donor *The person that begins in possession of the Theme and causes it to be in the possession of the Recipient*

Recipient *The entity that ends up in possession of the Theme.*

Theme *The object that changes ownership.*

Non-core:

The Means by which the Donor gives the Theme to the Recipient.

The Purpose for which the Donor gives the Theme to the Recipient.

⋮

FrameNet

(Baker et al, 1998)

- Lexical resource based on Frame Semantics: 13640 lexical units in 1087 frames.
- Example **annotations** illustrate how frame elements are realized linguistically.
  - Frames evoked by frame evoking elements (FEE).
  - Central interest: mapping from Grammatical Function (Subj, Obj, ...) to Frame Elements.

	Apple	wanted to	**donate**	a computer	to every school in the country .
POS	NNP	VVD TO	VB	DT NN	PRP DT NN IN DT NN .
FE	**Donor**		**FEE**	**Theme**	**Receipient**
GF	Subj			Obj	Dep-to
PT	NP			NP	PPto

http://framenet.icsi.berkeley.edu/

Valence Pattern

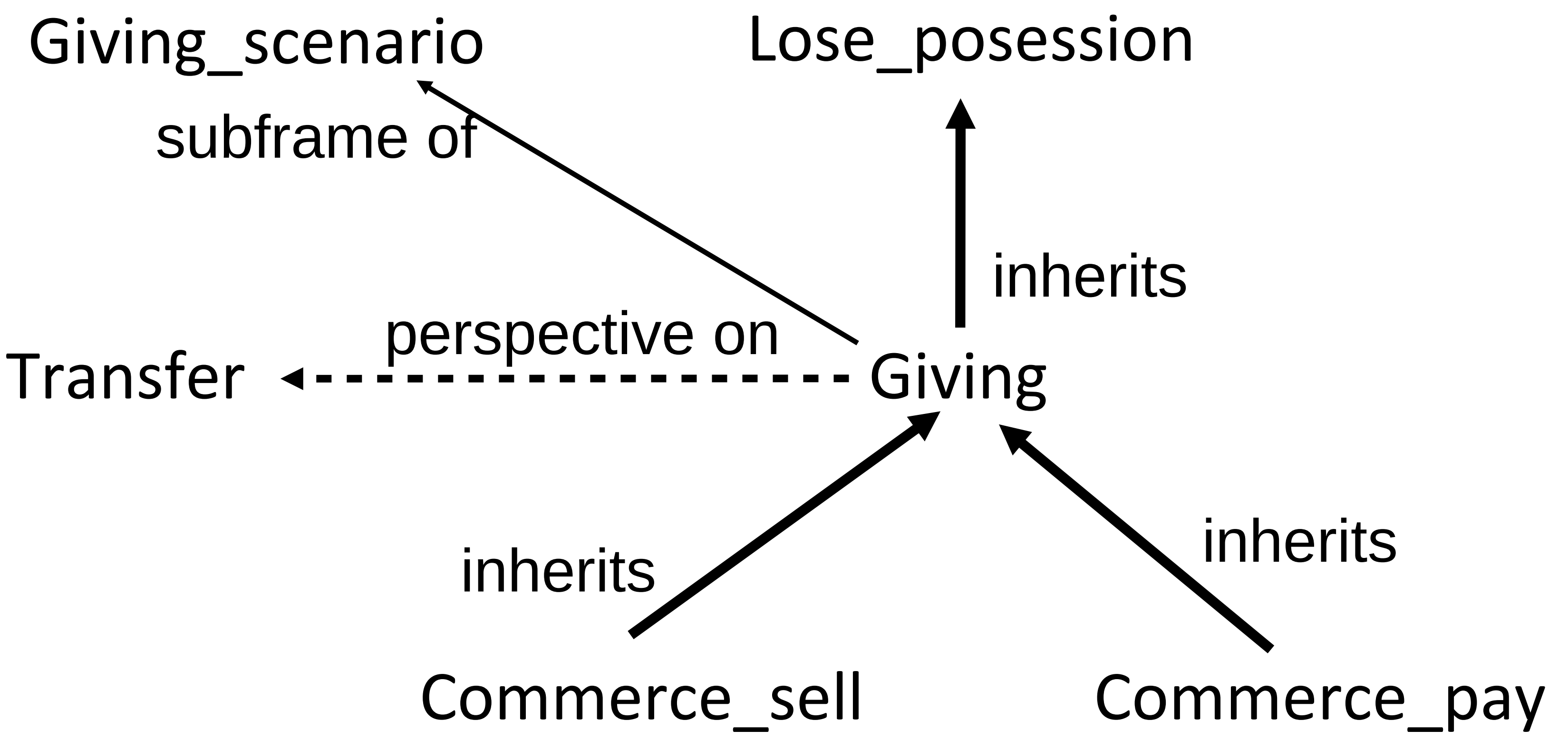
- Valence patterns (derived from annotated sentences) specify different ways grammatical roles (subject, object, ...) can be mapped to frame elements for a given lexical unit.

Valence pattern	**Example sentence**
(subj/**DONOR**) V (obj/**RECIPIENT**) (obj2/**THEME**)	*John gave Mary the book*
(subj/**DONOR**) V (obj/**THEME**) (dep-to/**RECIPIENT**)	*John gave the book to Mary*
(subj/**DONOR**) V (dep-of/**THEME**) (dep-to/**RECIPIENT**)	*John gave of his time to people like M.*
(subj/**DONOR**) V (dep-to/**RECIPIENT**)	*John gave to charity*

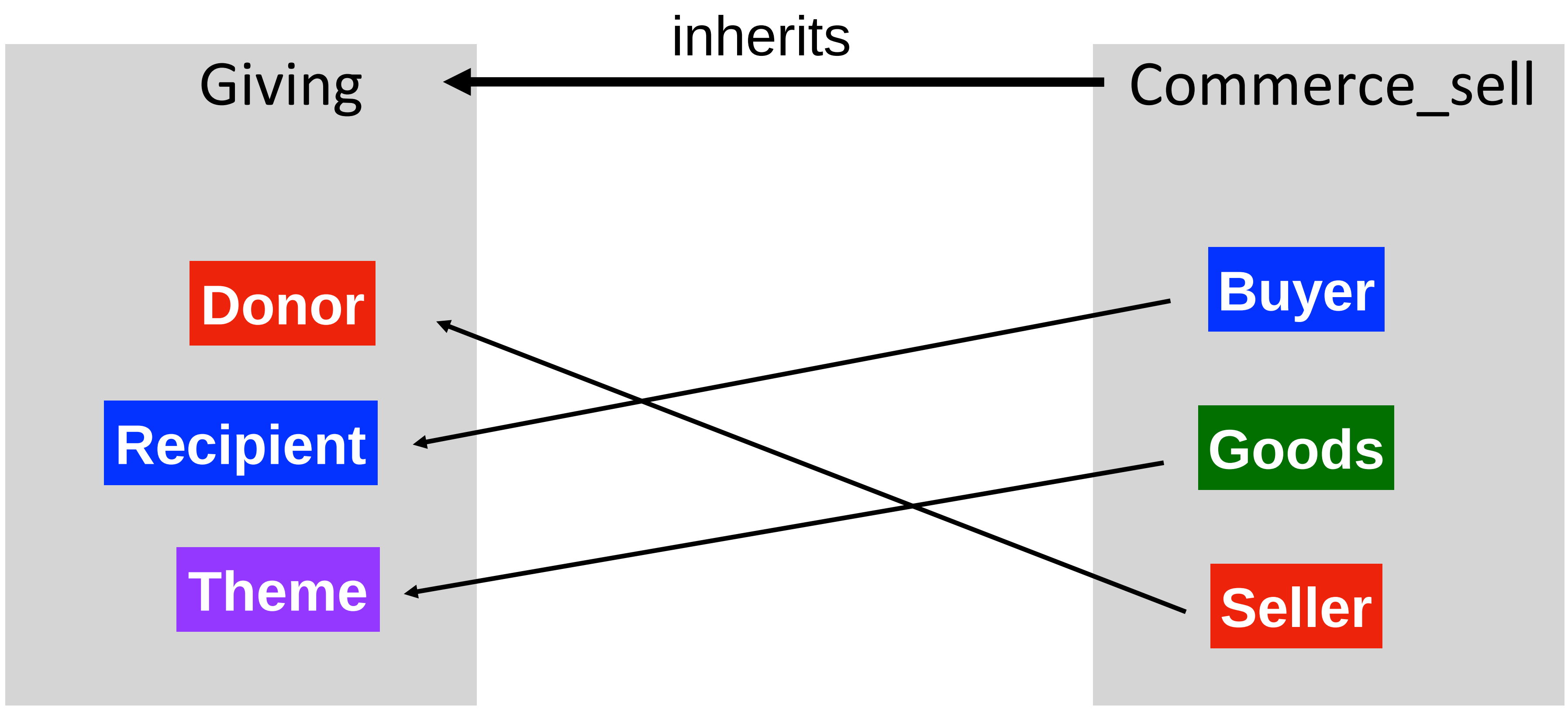
(Slide by Bob Coyne)

Frame-to-Frame Relations

- Frames are related via frame-to-frame relations.



Frame-Element Relations



PropBank

(Baker et al, 2005)

- Another corpus annotated with semantic roles, based on English Penn Treebank & OntoNotes 5.0. (~2m Words)
- Also available: Chinese, Hindi/Urdu, Arabic.
- Full-text annotation (only verbs).
- Numbered arguments (semantic roles).
  - Interpretation is specific to each verb.

Frameset for donate.01

Arg0: *giver*

Arg1: *thing given*

Arg2: *entity given to*

the company	donate d	over $35,000	to residents
Arg0	**rel**	Arg1	Arg2

Proto Roles

(Dowty 1991)

- Proto-Agent
  - Volitional involvement in event or state.
  - Sentience (and/or perception)
  - Causes an event or change of state in another participant
  - Movement (relative to position of another participant)
- Proto-Patient
  - Undergoes change of state
  - Causally affected by another participant
  - Stationary relative to movement of another participant

PropBank Roles

- Each frameset has numbered argument: Arg0, Arg1, Arg2,…
  - Arg0:PROTO-AGENT
  - Arg1:PROTO-PATIENT
  - Arg2: usually: benefactive, instrument, attribute, or end state
  - Arg3: usually: start point, benefactive, instrument, or attribute
  - Arg4 the end point (Arg2-Arg5 are not really that consistent, causes a problem for labeling)

PropBank FrameSets

- Different framesets correspond to different senses.

Frameset for tend.01, *care for*

Arg0: tender

Arg1: thing tended (to)

	John Arg0	tends **rel**	to the needs of his patrons Arg1

Frameset for tend.02, *have a tendency*

Arg0: theme

Arg2: attribute

	The cost, or premium Arg0	tends **rel**	to get fat in times of crisis Arg2

Another Example

Frameset for increase.01, *go up incrementally*

Arg0: causer of increase

Arg1: thing increasing

Arg2: amount increased by

Arg3: start point

Arg4: end point

[Arg$_0$ Big Fruit Co.] **increased** [Arg$_1$ the price of bananas]

[Arg$_1$ The price of bananas] was **increased** again [Arg$_0$ by Big Fruit Co.]

[Arg$_1$ The price of bananas] **increased** [Arg$_2$ 5%]

Observations:

Syntax and semantics do not map 1:1. Generalize away from syntactic variations.

PropBank senses are coarse

Semantic Role Labeling (SRL)

- Input: raw sentence.
- Goal: automatically produce PropBank or FrameNet-style annotations ("frame-semantic parsing").
- Applications:
  - Question Answering (Shen and Lapata 2007, Surdeanu et al. 2011)
  - Machine Translation (Liu and Gildea 2010, Lo et al. 2013)
  - Stock prediction, spoken dialog segmentation, ...
- How would you approach this problem?

Generic SRL Algorithm

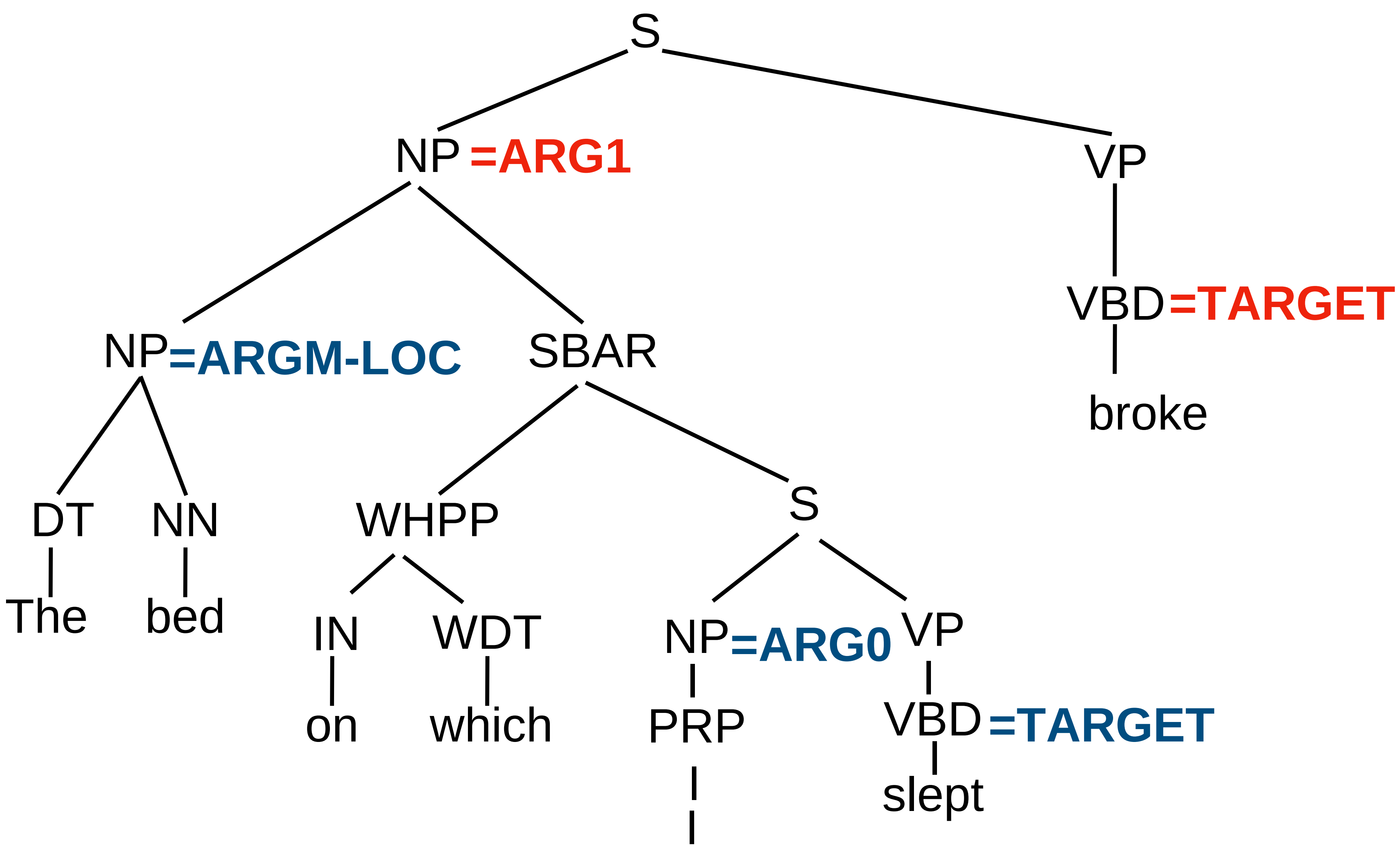
Algorithm outline:

- Parse the sentence (dependence or constituency parse)
- Detect all potential targets (predicates / frame evoking elements)
- For each predicate:
  - For each node in the parse tree use supervised ML classifiers to:
    1. identify if it is an argument.
    2. label the argument with a role.

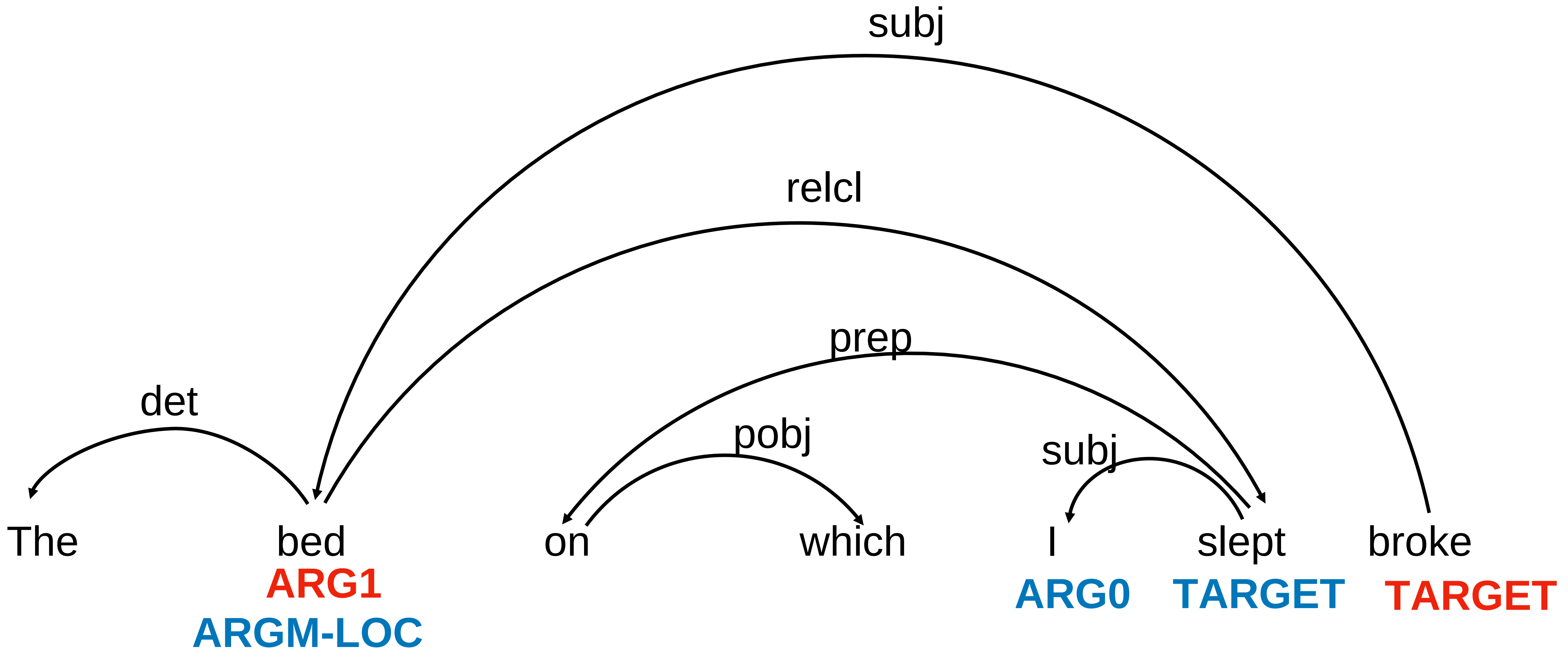
Choosing Targets

- For PropBank:
  - Choose all verbs.
- For FrameNet:
  - Choose all lexical items (verbs, nouns, adjectives) that are in the annotated FrameNet training data.

SRL Example


S
NP =ARG1
VP
VBD=TARGET
broke
NP=ARGM-LOC
SBAR
DT
NN
The
bed
WHPP
S
IN
WDT
on
which
NP=ARG0
VP
PRP
I
VBD =TARGET
slept

SRL Example


subj
relcl
prep
det
pobj
subj
The
bed
on
which
I
slept
broke
ARG1
ARGM-LOC
ARG0
TARGET
TARGET

Selectional Restrictions and Preferences

- Different semantic roles might have restrictions on the semantic type of arguments they can take.

*I want to **eat** **someplace nearby***

*I want to **eat** **Korean for lunch***

- **Food** FE (or ARG1) needs to be *edible*.
- But what about:

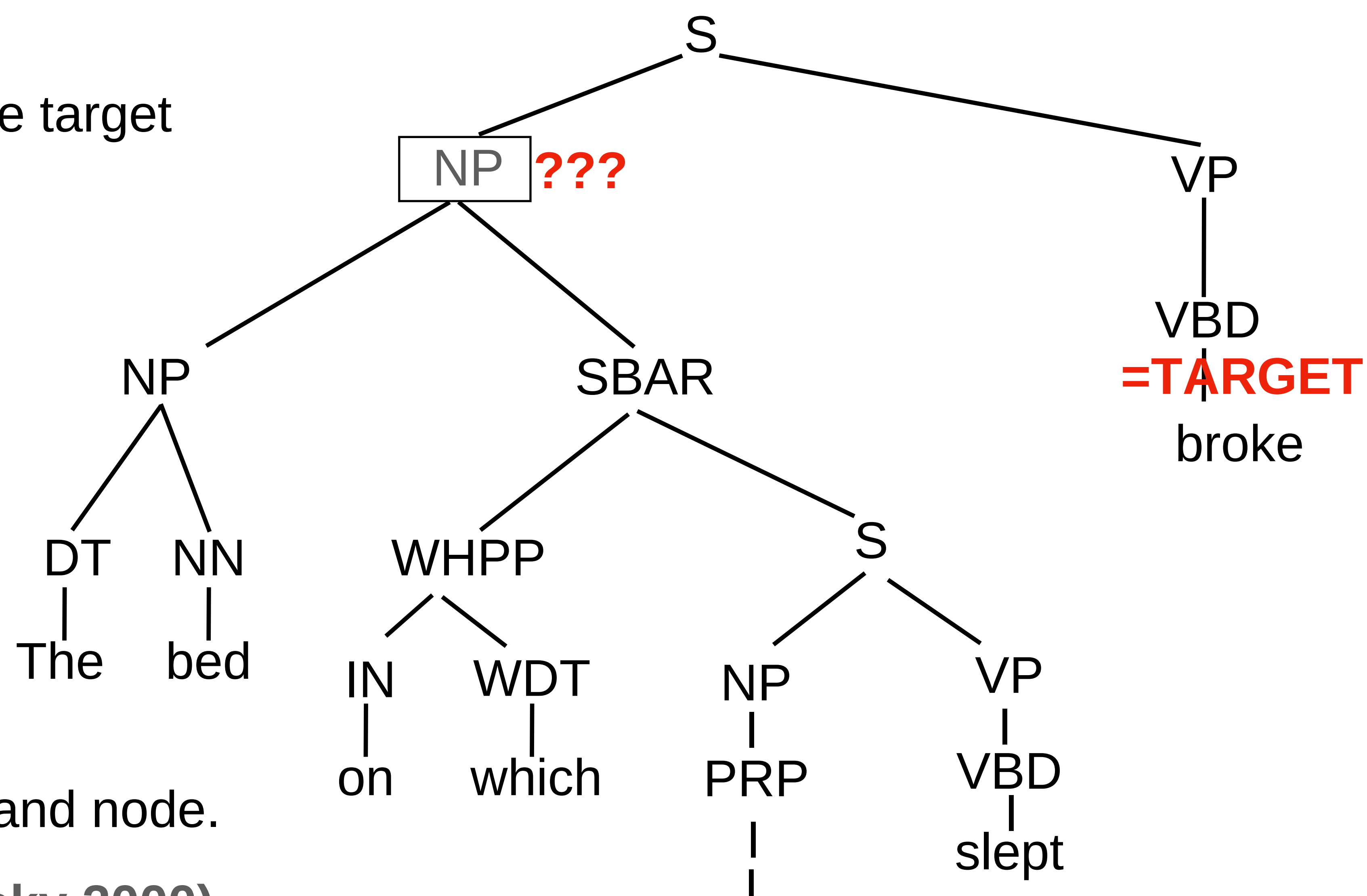
*...people realized you can't **eat** **gold for lunch** if you're hungry*

- How could you model these?

Features

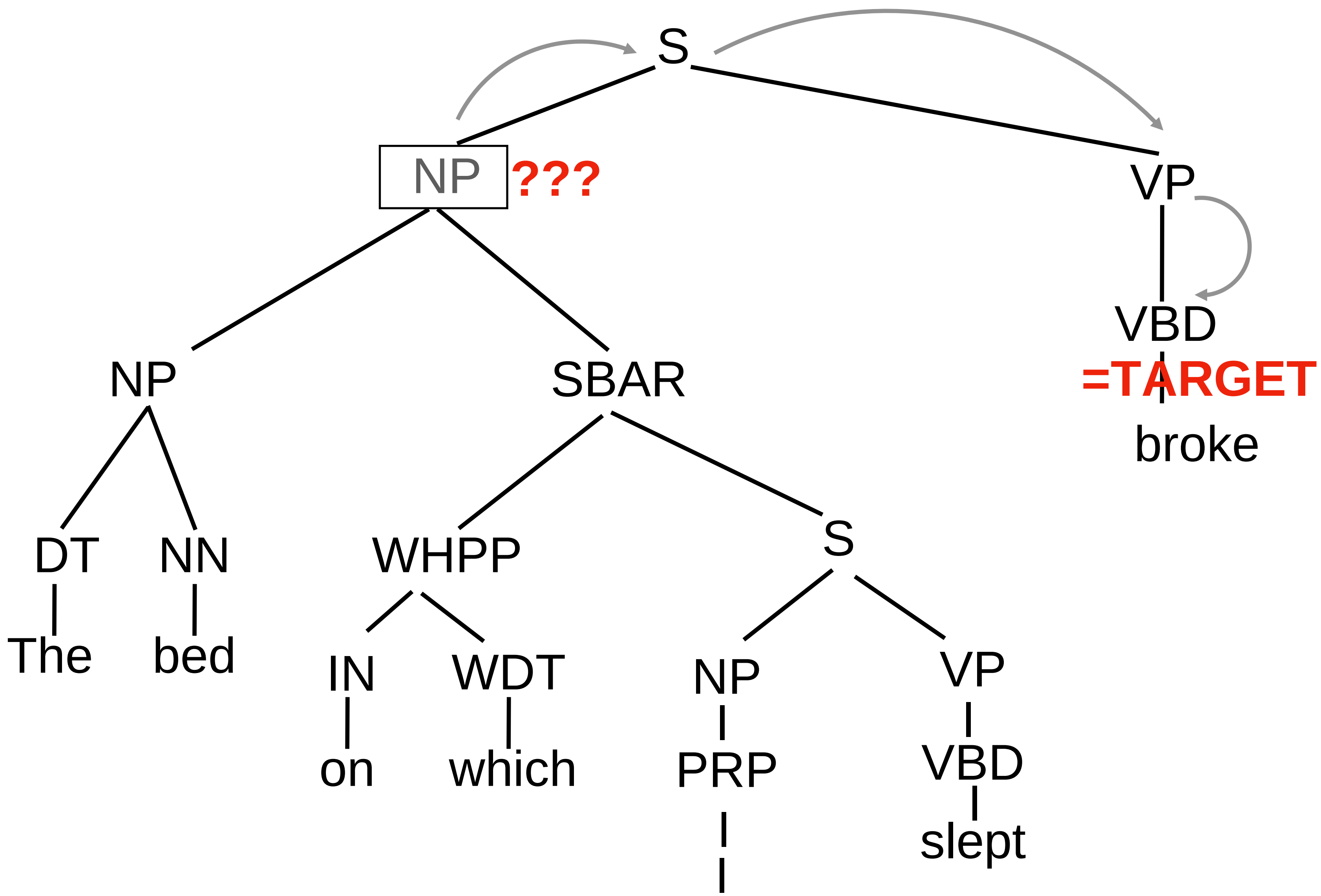
What features should we use for argument detection and labeling?

- target predicate: broke
- headword (+POS): *bed NN*
- phrase type: NP
- linear position: before or after the target
- argument structure of the verb. "NP broke"
- target voice: active
- possibly semantic features (named entity class, WordNet synsets of head word, ...)
- first and last word of constituent and their POS.
- Parse tree path between target and node.



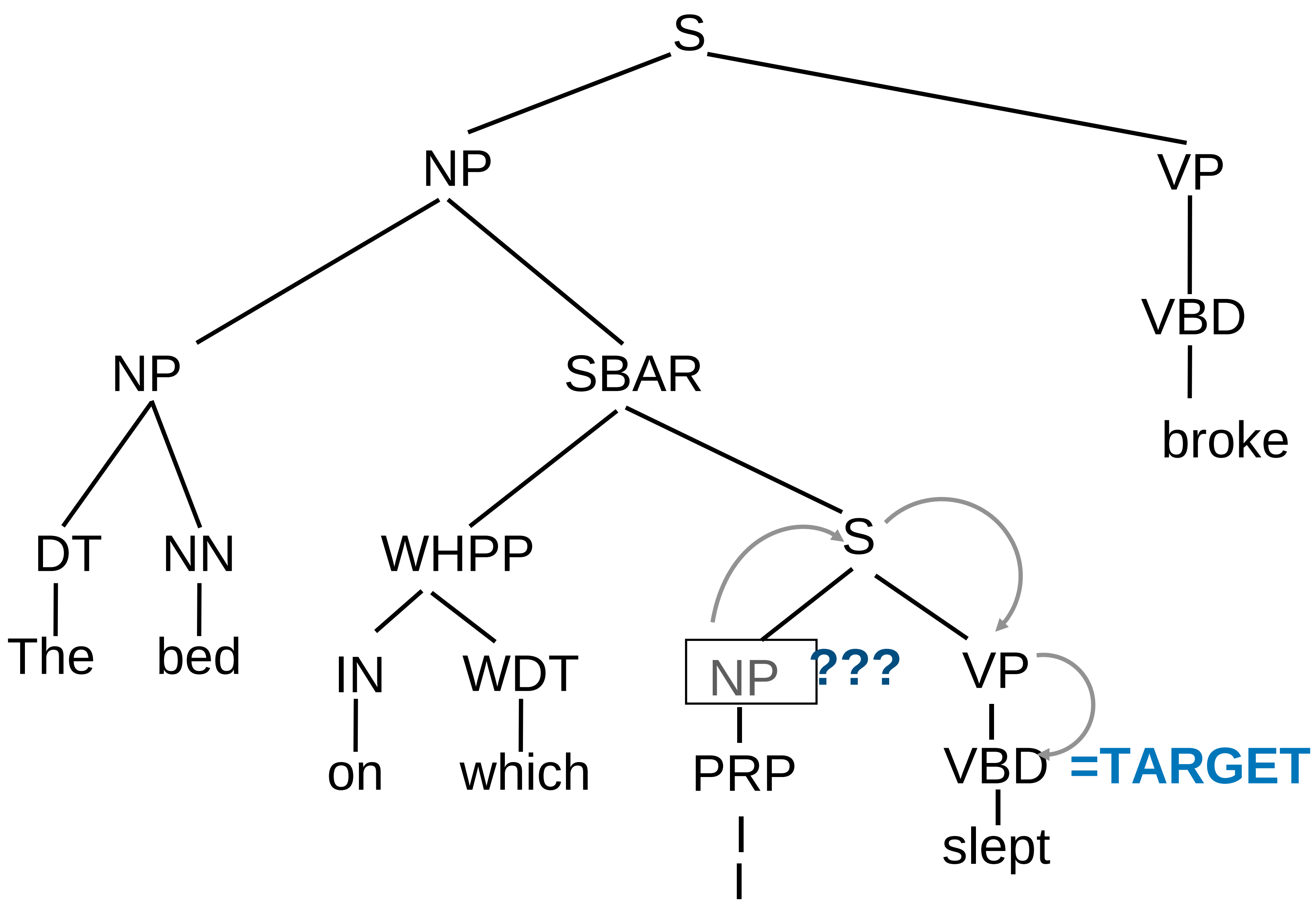
(Features used in Gildea & Jurafsky 2000)

Parse Tree Path



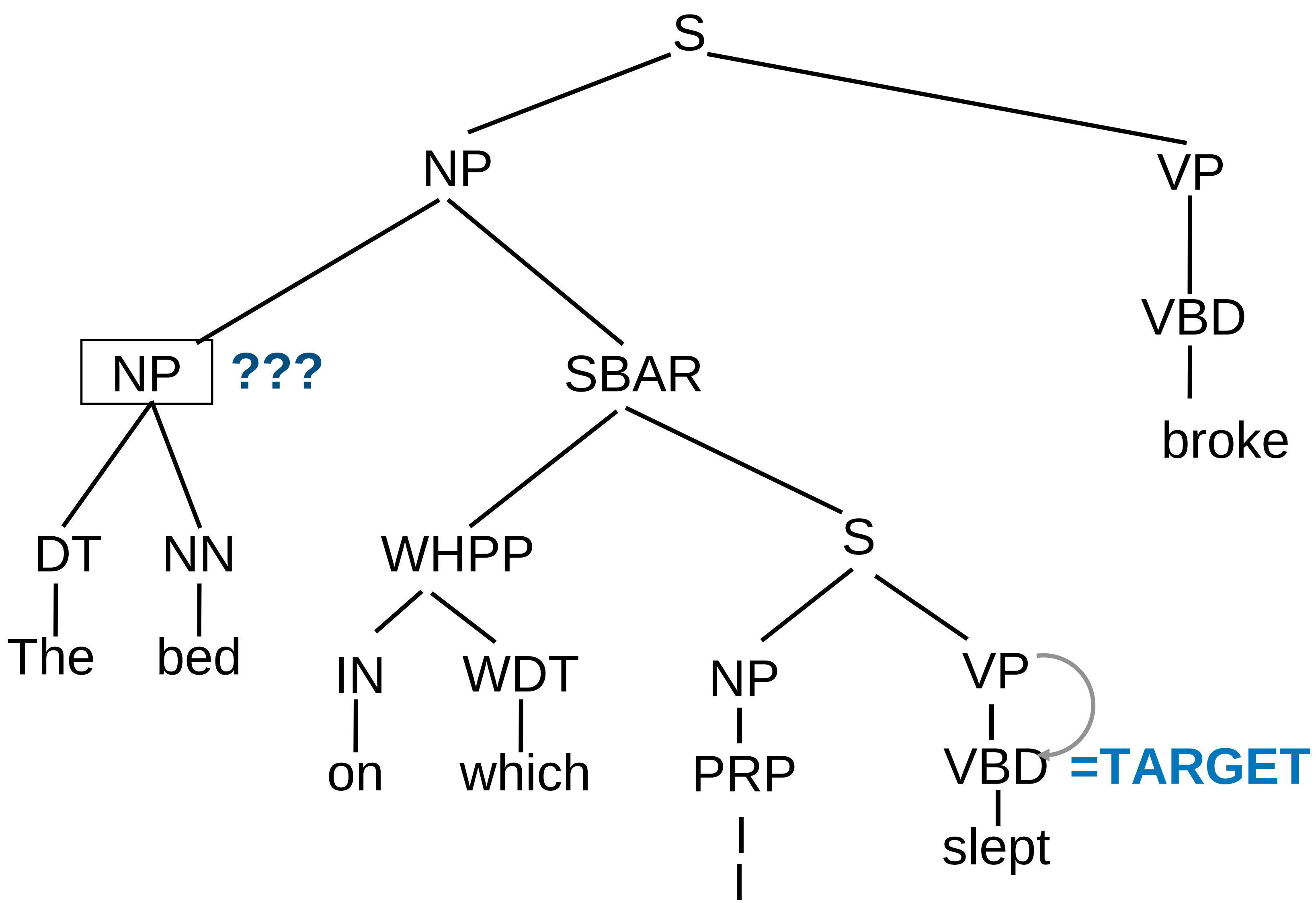
NP↑S↓VP↓VBD

Parse Tree Path



NP↑S↓VP↓VBD

Parse Tree Path



NP↑NP↓SBAR↓S↓VP↓VBD

Frequent Path Features

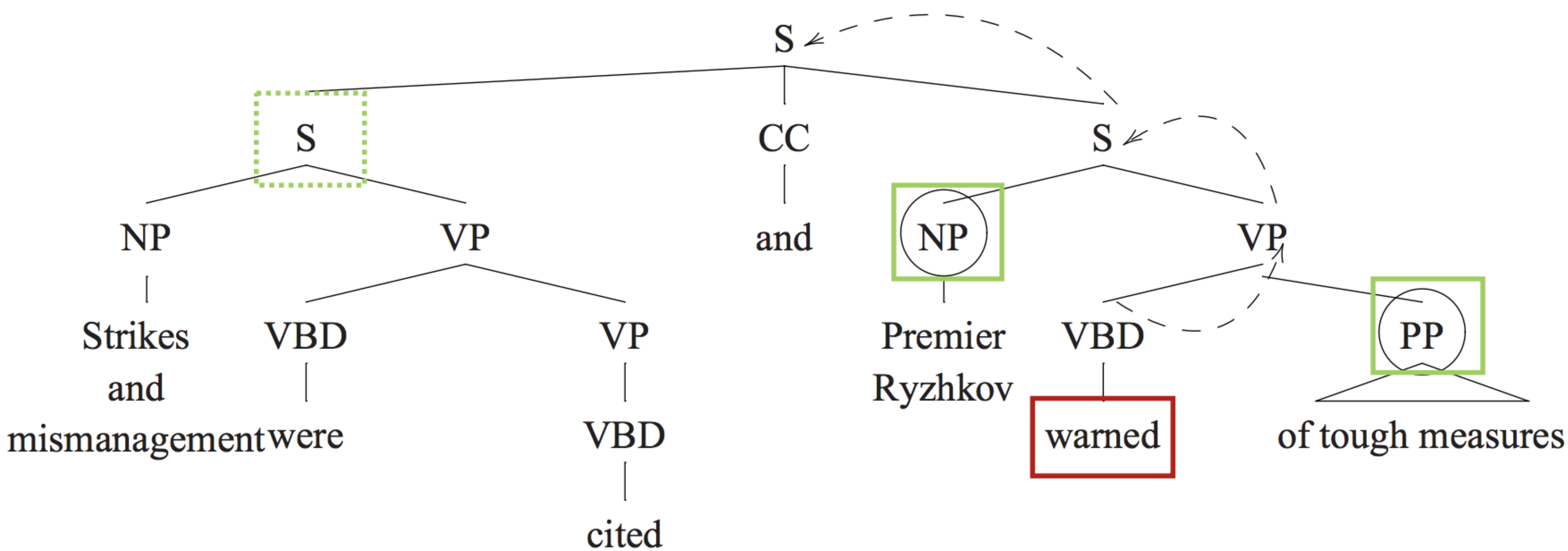
Frequency	Path	Description
14.2%	VB↑VP↓PP	PP argument/adjunct
11.8	VB↑VP↑S↓NP	subject
10.1	VB↑VP↓NP	object
7.9	VB↑VP↑VP↑S↓NP	subject (embedded VP)
4.1	VB↑VP↓ADVP	adverbial adjunct
3.0	NN↑NP↑NP↓PP	prepositional complement of noun
1.7	VB↑VP↓PRT	adverbial particle
1.6	VB↑VP↑VP↑VP↑S↓NP	subject (embedded VP)
14.2		no matching parse constituent
31.4	Other	

(from Palmer, Gildea, Xiu, 2010, SRL book)

Candidate Pruning

(Xue and Palmer 2004)

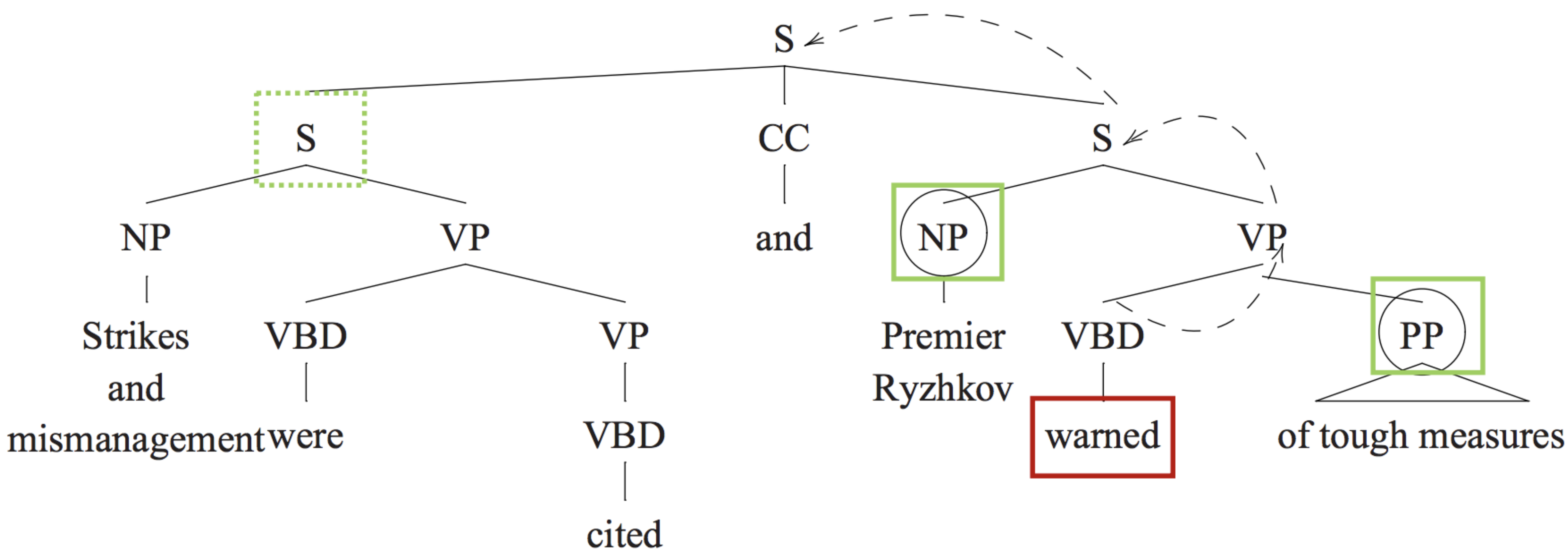
- Algorithm looks at one target at a time. Very few phrases can possibly be arguments.
- Difficult for classifiers to learn: Few positive samples (phrases that are arguments), few positive samples.
- Syntax should tell us *something* about possible arguments.



Pruning Heuristic

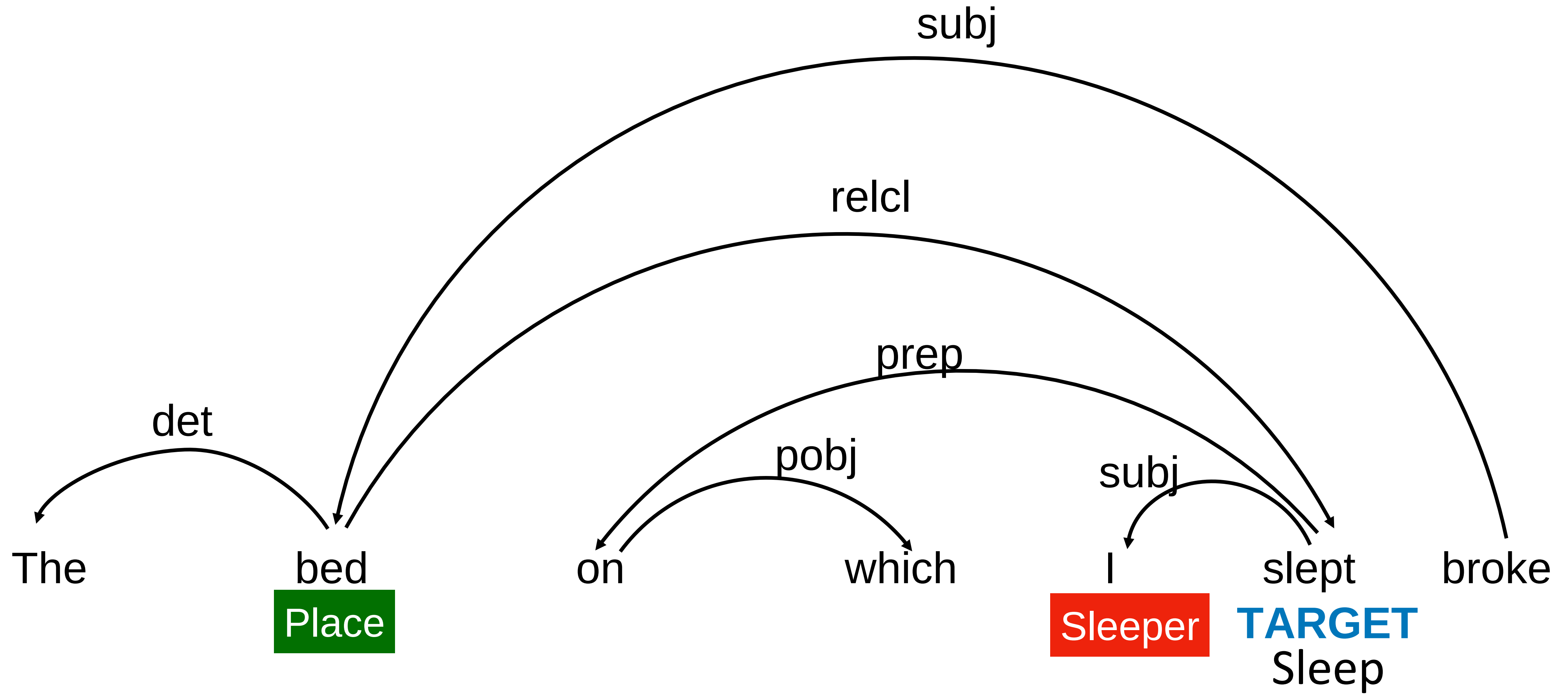
(Xue and Palmer 2004)

- Add sisters of the predicate, then aunts, then great-aunts, etc.
  - Ignore nodes in the subtrees of the selected nodes.
  - Ignore anything in coordinated structures.



FrameNet Parsing

- Slightly more complex: Need to decide on the frame first, then use frame-specific classifiers for the semantic roles.



Frame Semantic Parsing Systems

<table>
<tr><th></th><th colspan="2">FrameNet I</th><th colspan="2">SemEval 2007; FrameNet 1.3</th></tr>
<tr><th></th><th>Gildea & Jurafsky 2002</th><th>Thompson et al. 2003</th><th>Johansson & Nugues 2007</th><th>“SEMAFOR” Das et al. 2010, 2012</th></tr>
<tr><td>Argument Classification</td><td>P(fe|features)</td><td rowspan="3">generative prob. model</td><td>SVM</td><td rowspan="2">log-linear + dual decomp.</td></tr>
<tr><td>Argument Identification</td><td>P(arg|features)</td><td>heuristics+ SVM</td></tr>
<tr><td>Frame Selection</td><td>✗</td><td>SVM</td><td>log-linear</td></tr>
<tr><td>Target Identification</td><td>✗</td><td>✗</td><td>heuristics</td><td>heuristics</td></tr>
<tr><td>Input Syntactic representation</td><td colspan="2">Constituency</td><td colspan="2">Dependency</td></tr>
</table>

More recent work uses Neural Networks (e.g. Swayamdipta et al. 2017**)**

Features used in FrameNet Parsing

	G&J	J&N	SEMAFOR
Syntactic Representation	**PS** **Collins**	**DepMST**	**DepMST**
Target Dependency Labels and Words		✓	✓
Target parent word / POS		✓	✓
Target word/ POS	✓	✓	✓
Voice (for verb targets)	✓	✓	✓
Relative Position (before/after/on)	✓	✓	✓

Global Inference

- So far, classifier just decided on one argument at a time.
  - But there are interactions between arguments!
    - FEs may not overlap.
      - Labeling one constituent as ARG0 should increase the probability of another constituent to be ARG1.
    - Some argument combinations are impossible.
  - Solutions: Beam Search (Das et al. 2010/2014),
    Dual Decomposition (Des et al. 2010/2014), DP algorithm (Täckström et al. 2015)

Acknowledgments

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