Hasso Plattner Institut
IT Systems Engineering | Universität Potsdam

Sentence Annotation: Semantic Role Labeling

Question Anwering
Sebastian Oergel

Base

http://www.cs.rochester.edu/~gildea/

Daniel Gildea

Associate Professor
Computer Science
University of Rochester

http://www.stanford.edu/~jurafsky/

Daniel Jurafsky

Professor of Linguistics
Professor by Courtesy of Computer Science
Stanford University

Automatic Labeling of Semantic Roles

Agenda

- Frame Semantics
- Goals
- Approach
- Discussion

Hasso Plattner Institut

What are Semantic Roles?

Frame Semantics

- Linguistic theory
  - Knowledge of context → word can be (partially) understood

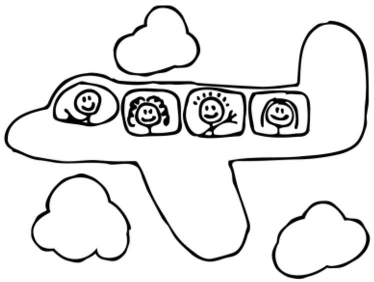
Jim flew his plane to Texas.

Alice destroys the item with a plane.

Frame Semantics

- Linguistic theory
  - Knowledge of context → word can be (partially) understood

Jim flew his plane to Texas.

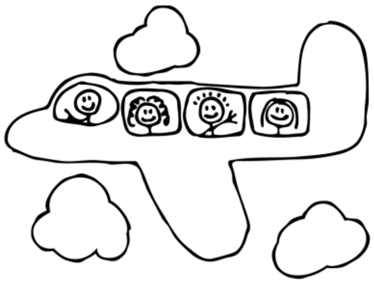


Alice destroys the item with a plane.

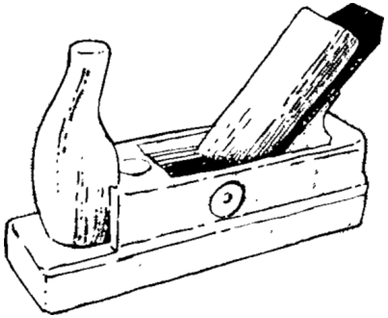
Frame Semantics

- Linguistic theory
  - Knowledge of context → word can be (partially) understood

Jim flew his plane to Texas.



Alice destroys the item with a plane.



Frame Semantics – Semantic Frames

- Semantic Frame: collection of facts that specify "characteristic features, attributes, and functions of a denotatum, and its characteristic interactions with things necessarily or typically associated with it" (Keith Alan, Natural Language Semantics)
- Target words invoke a semantic frame

Jim flew his plane to Texas.

Alice destroys the item with a plane.

Frame Semantics – Semantic Frames

- Semantic Frame: collection of facts that specify “characteristic features, attributes, and functions of a denotatum, and its characteristic interactions with things necessarily or typically associated with it” (Keith Alan, Natural Language Semantics)
- Target words invoke a semantic frame

Jim flew his plane to Texas.

Alice destroys the item with a plane.

Frame Semantics – Semantic Frames

- Semantic Frame: collection of facts that specify "characteristic features, attributes, and functions of a denotatum, and its characteristic interactions with things necessarily or typically associated with it" (Keith Alan, Natural Language Semantics)
- Target words invoke a semantic frame

Jim flew his plane to Texas.

Operate_vehicle

Alice destroys the item with a plane.

Frame Semantics – Semantic Frames

- Semantic Frame: collection of facts that specify "characteristic features, attributes, and functions of a denotatum, and its characteristic interactions with things necessarily or typically associated with it" (Keith Alan, Natural Language Semantics)
- Target words invoke a semantic frame

Jim flew his plane to Texas.

Operate_vehicle

Alice destroys the item with a plane.

Frame Semantics – Semantic Frames

- Semantic Frame: collection of facts that specify “characteristic features, attributes, and functions of a denotatum, and its characteristic interactions with things necessarily or typically associated with it” (Keith Alan, Natural Language Semantics)
- Target words invoke a semantic frame

Sentence	Frame
Jim flew his plane to Texas.	Operate_vehicle
Alice destroys the item with a plane.	Destroying

Frame Semantics – Semantic Roles

- Semantic Role: defined part of a Semantic frame
- Can be assigned to constituents of a sentence

Jim flew his plane to Texas.	Operate_vehicle
Alice destroys the item with a plane.	Destroying

Frame Semantics – Semantic Roles

- Semantic Role: defined part of a Semantic frame
- Can be assigned to constituents of a sentence

Jim flew his plane to Texas. — Operate_vehicle

Driver: Jim | Vehicle: his plane | Goal: to Texas.

Alice destroys the item with a plane. — Destroying

Frame Semantics – Semantic Roles

- Semantic Role: defined part of a Semantic frame
- Can be assigned to constituents of a sentence

Sentence	Frame
[Jim] flew [his plane] [to Texas.] Driver, Vehicle, Goal	Operate_vehicle
[Alice] destroys [the item] [with a plane.] Destroyer, Undergoer, Instrument	Destroying

Frame Semantics - Range

- Wide range possible

Abstract

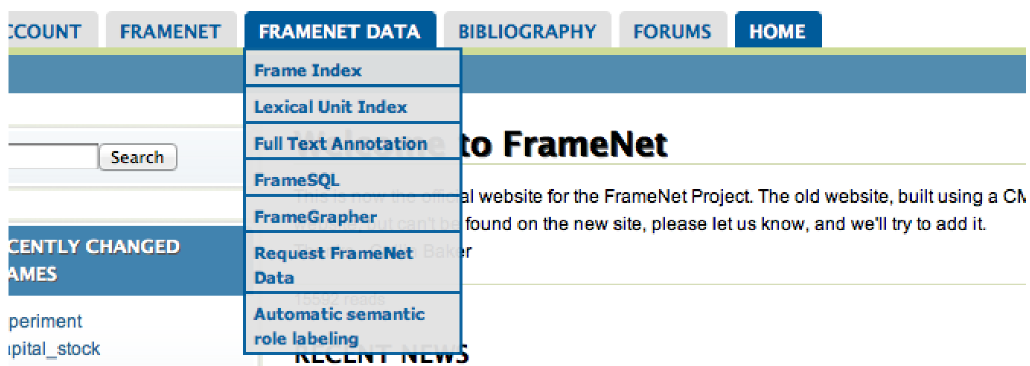
- Agent
- Patient
- Experiencer
- Source
- ...

Domain Specific

- Buyer
- Depart_Time
- Dest_Airport
- Winning_Team
- ...

Frame Semantics – FrameNet

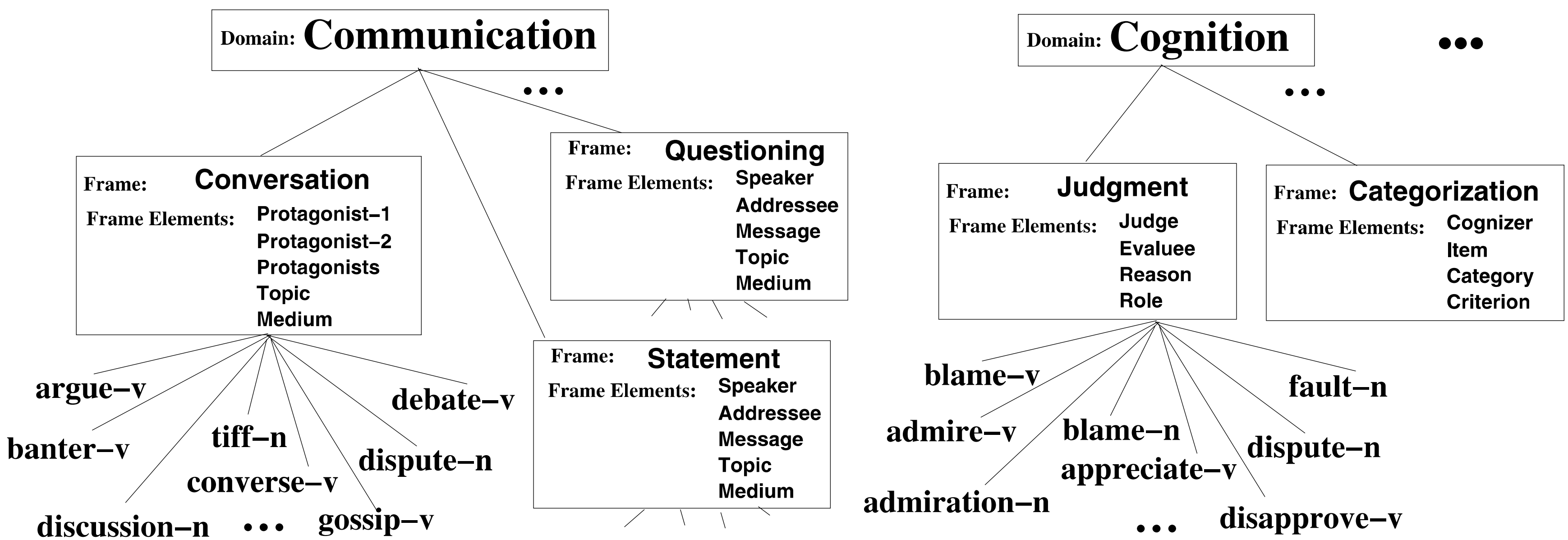
- Dictionary based on semantic frames
  - Uses British National Corpus
- Contains large set of:
  - Example sentences
  - Target words (“Lexical Units”)
  - Semantic frames (grouped in domains)
  - Associated roles (frame elements)
- Manually annotated



https://framenet.icsi.berkeley.edu

Frame Semantics – FrameNet

- Example



Goals

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Goals – Usage in QA

- How can semantic roles help in QA?

- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?

- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Cognizer New_idea

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: $\boxed{\text{Who}}$ invented the $\boxed{\text{first computer mouse?}}$

Cognizer New_idea

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?

- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Cognizer New_idea

New_idea Cognizer

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Cognizer New_idea

New_idea Cognizer

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Cognizer New_idea

New_idea Cognizer

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Royal Canadian Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

Goals – Usage in QA

Hasso Plattner Institut

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Q: Who invented the first computer mouse?

Cognizer New_idea

New_idea Cognizer

[...] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Roy Cognizer n Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 [...]

New_idea

Goals – Usage in QA

- How can semantic roles help in QA?
- ➔ analyze question ➔ analyze possible answer sentences ➔ find equalities between frames

Automatic Labeling of Semantic Roles

[…] The trackball was invented by Tom Cranston, Fred Longstaff and Kenyon Taylor working on the Roy Cognizer n Navy's DATAR project in 1952. Independently, Douglas Engelbart at the Stanford Research Institute invented the first computer mouse in 1963 […]

New_idea

Approach

Approach – Basic Idea

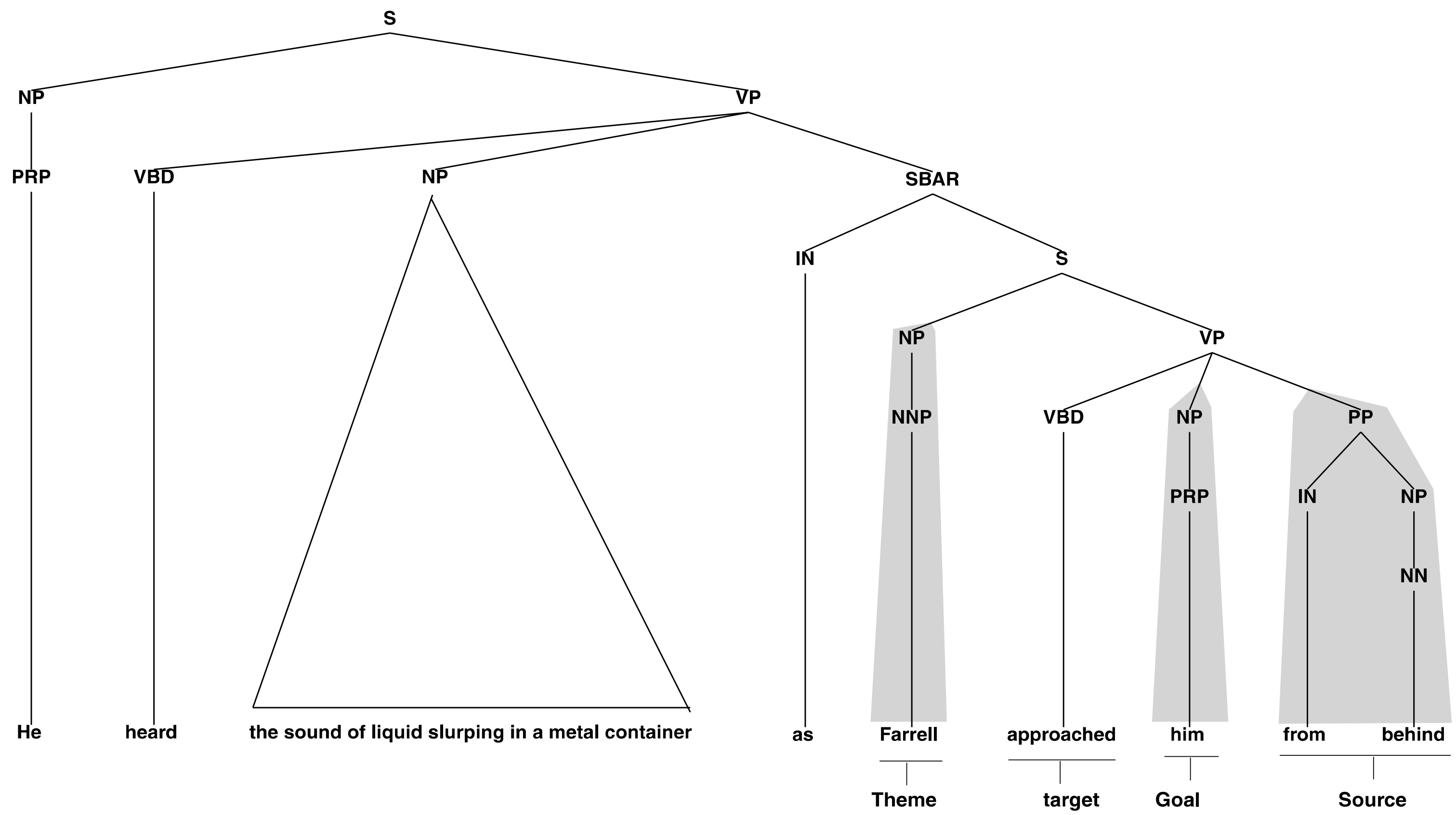
- Statistical classifier
  - Assigns roles based on probabilities
  - Probabilites calculated / derived from features

- FrameNet data
  - 10% for testing, 10% for tuning, 80% for training

- Given data:
  - Sentence / clause
  - Target word
  - Frame
  - (role boundaries)

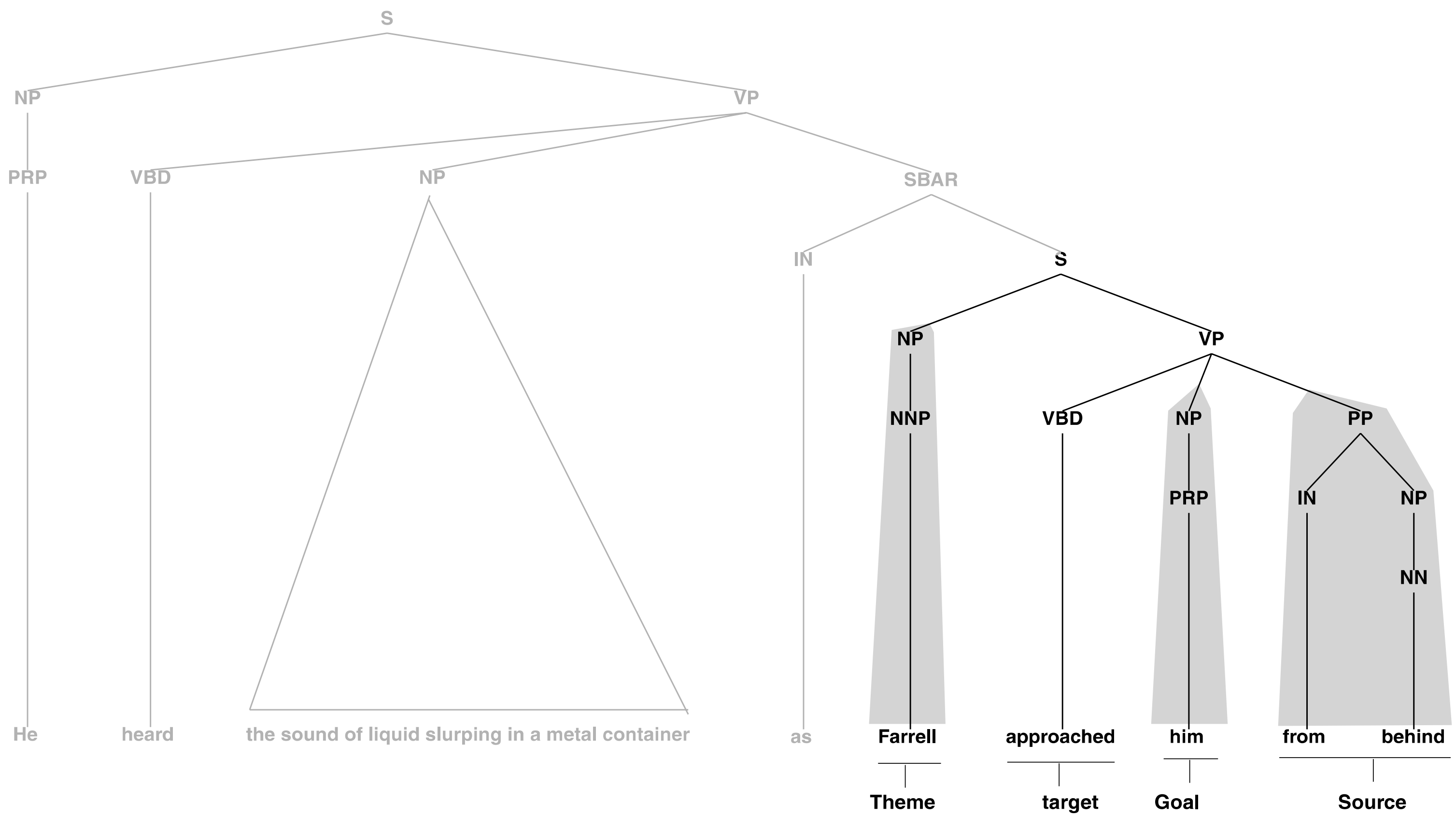
Approach – Features

- "Collins" Parser for generating a parse tree
- Used for the derivation of some features

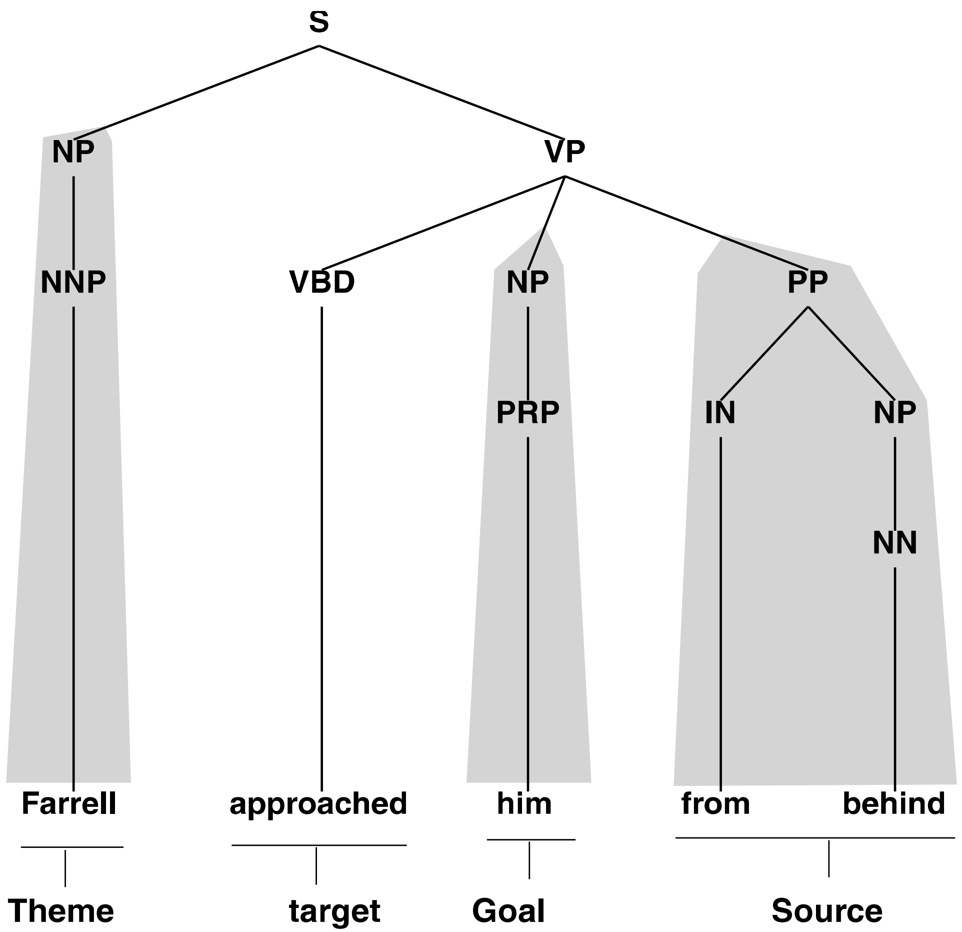


Approach – Features

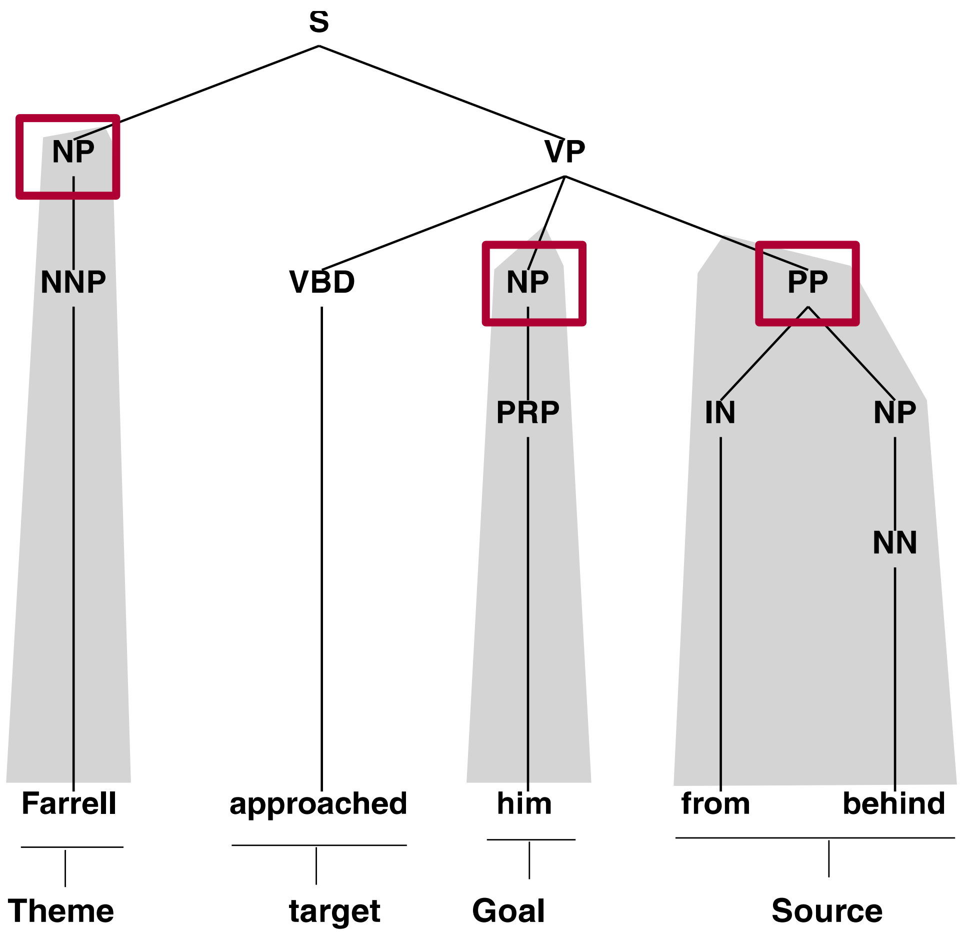
- "Collins" Parser for generating a parse tree
- Used for the derivation of some features



Approach – Features – Phrase type

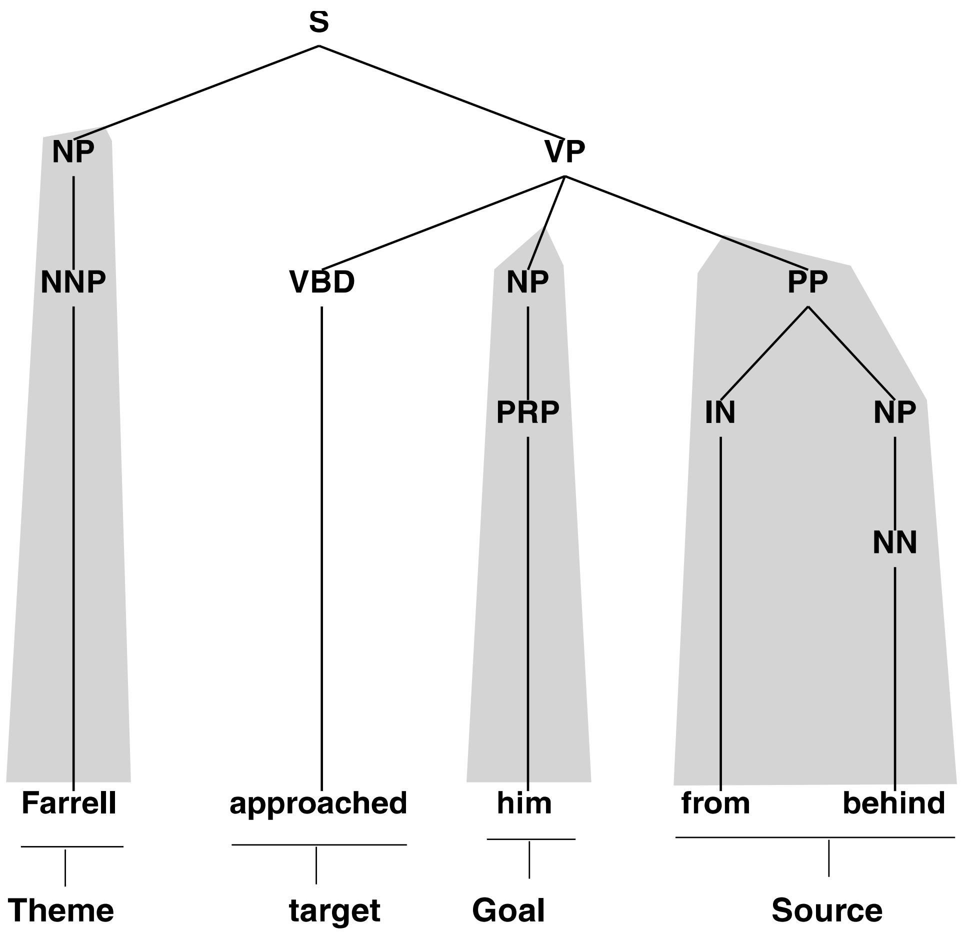


Approach – Features – Phrase type

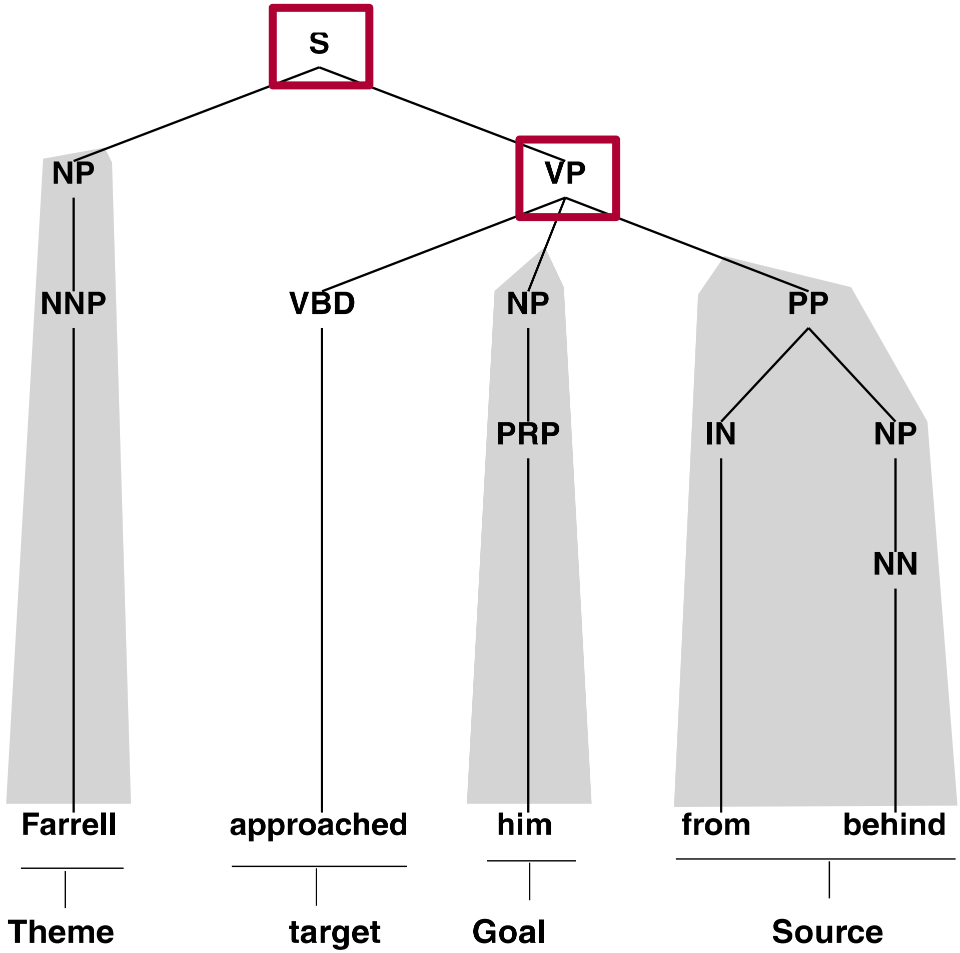


- "Farrell" → NP
- "him" → NP
- "from behind" → PP

Approach – Features – Governing Category

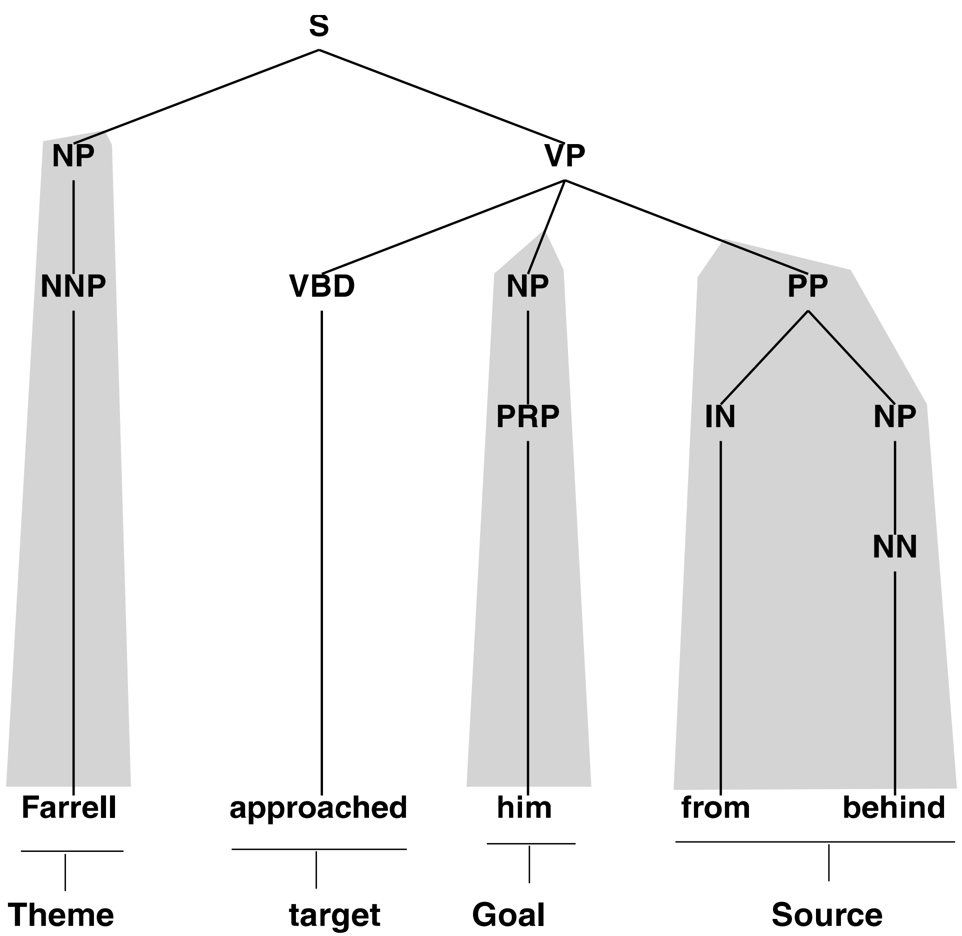


Approach – Features – Governing Category

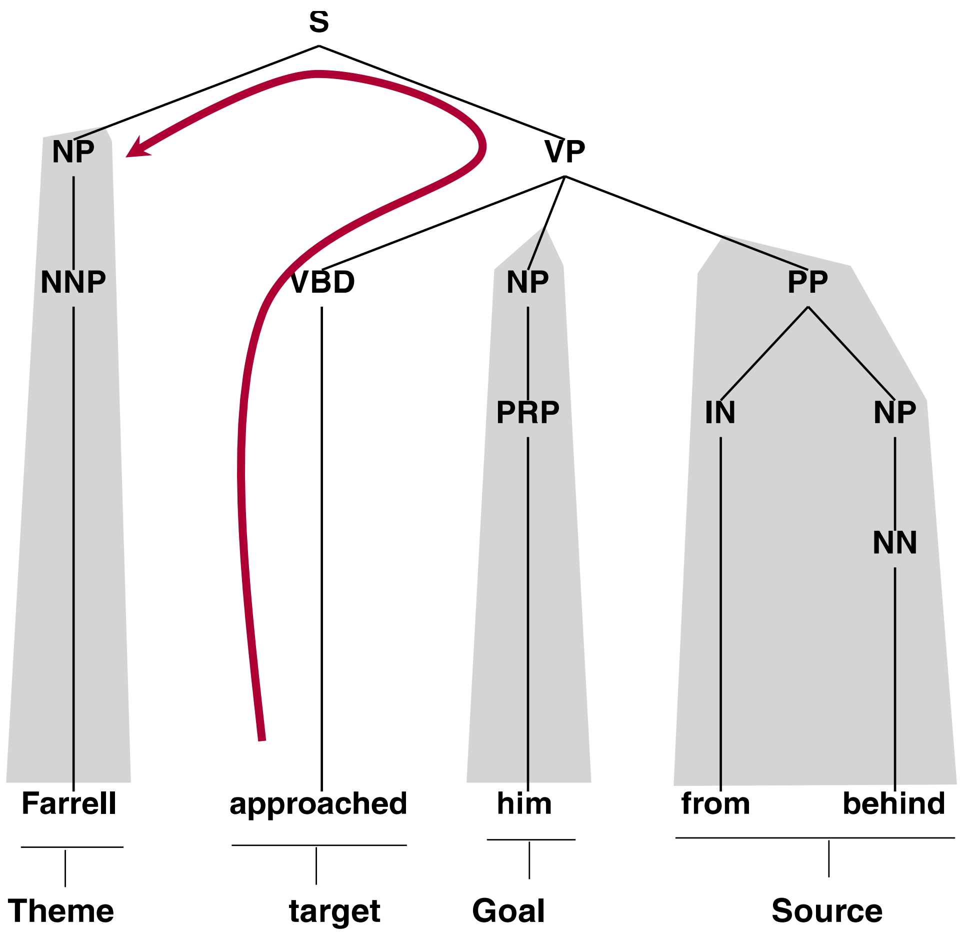


- "Farrell" → S
- "him" → VP
- "from behind" → *nothing*

Approach – Features – Parse Tree Path

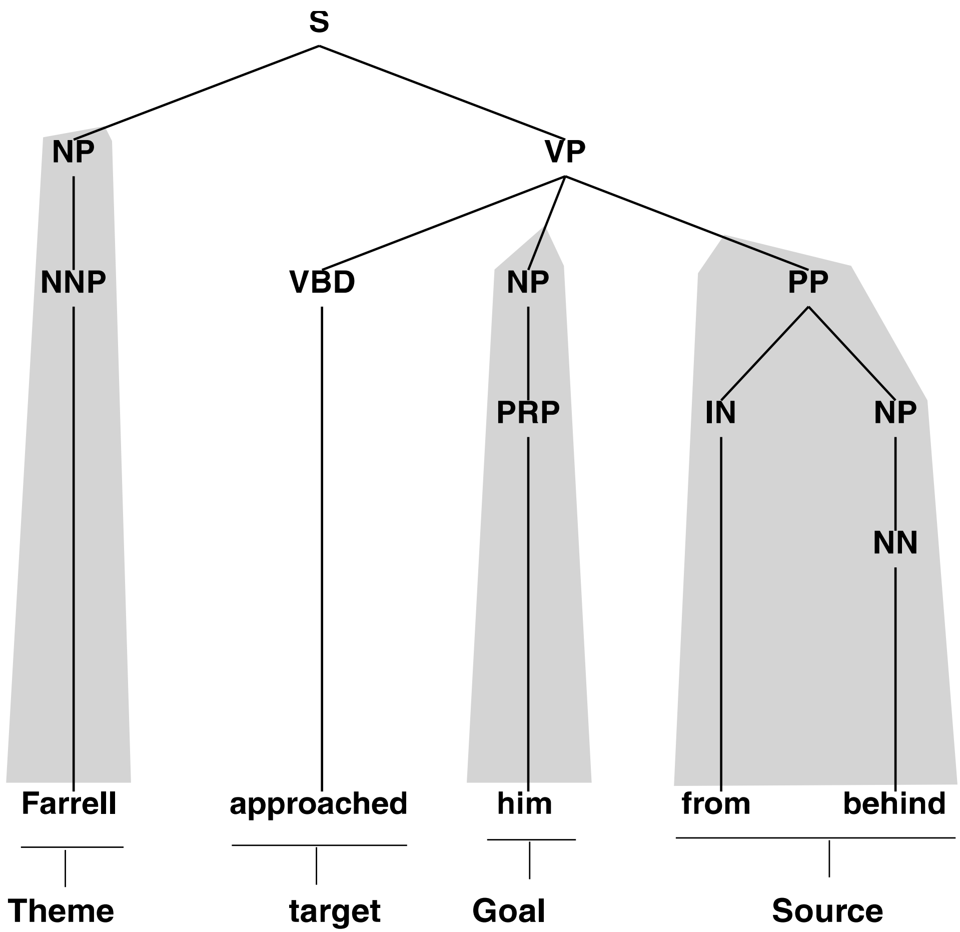


Approach – Features – Parse Tree Path

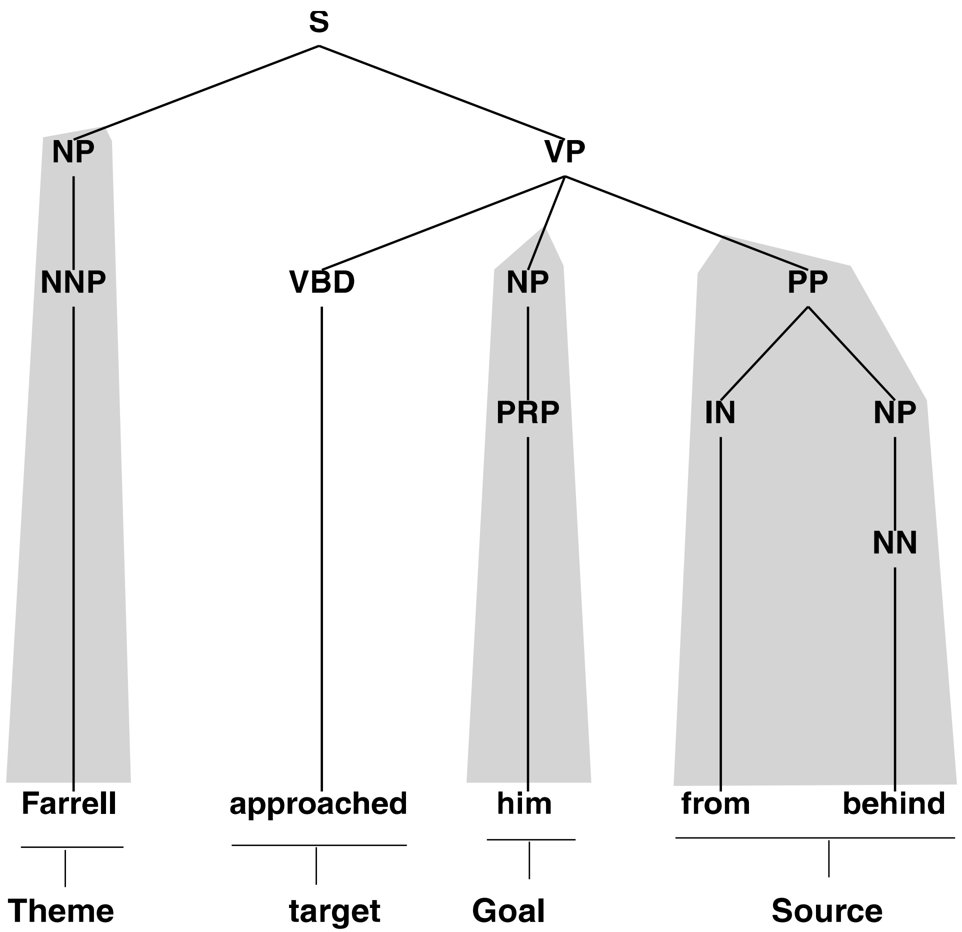


- "Farrell" → VBD↑VP↑S↓NP
- …
- …

Approach – Features – Position

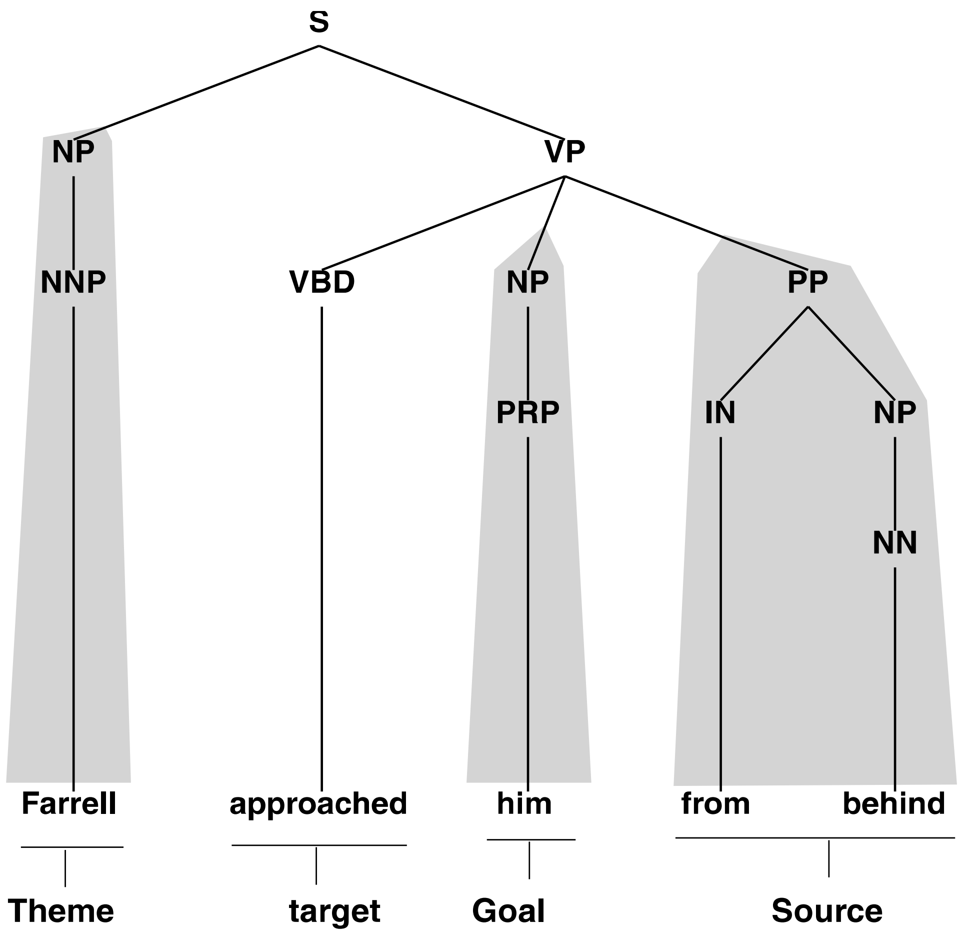


Approach – Features – Position

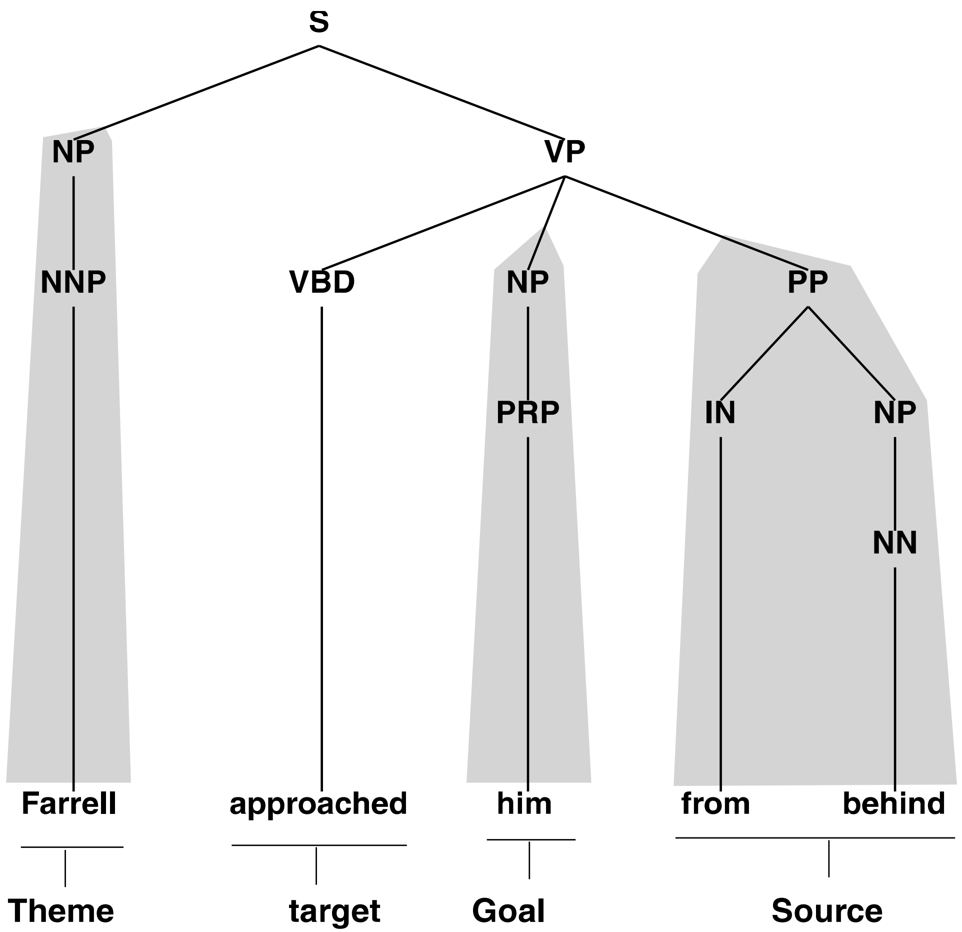


- "Farrell" → before
- "him" → behind
- "from behind" → behind

Approach – Features – Voice

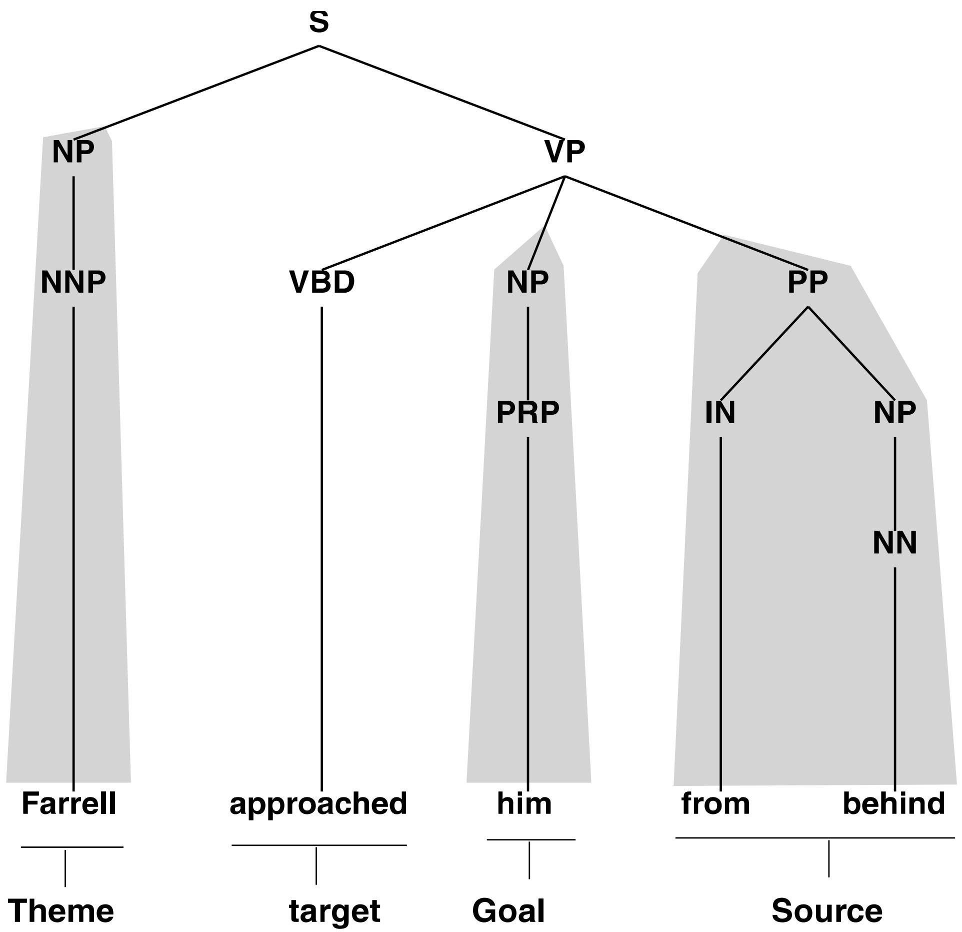


Approach – Features – Voice

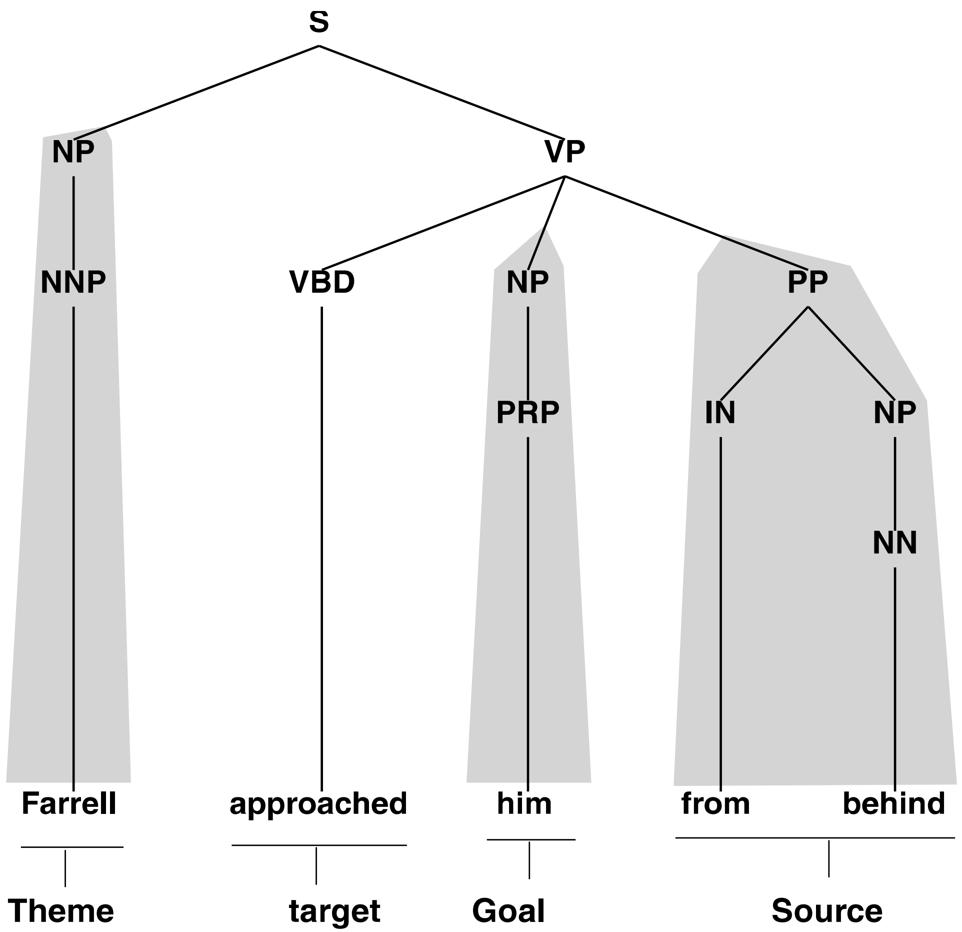


- "Farrell" → active
- "him" → active
- "from behind" → active

Approach – Features – Head Word



Approach – Features – Head Word



- "Farrell" → "Farrell"
- "him" → "him"
- "from behind" → "behind"

Approach – Probability Estimation

- Probabilities calculated based on features
- Probability:
- Calculation:

Approach – Probability Estimation

- Probabilities calculated based on features
- Probability: $P(r \mid h, pt, gov, position, voice, t)$
- Calculation:

Approach – Probability Estimation

- Probabilities calculated based on features
- Probability: $P(r \mid h, pt, gov, position, voice, t)$
- Calculation:

$$P(r \mid h, pt, gov, position, voice, t) = \frac{\#(r, h, pt, gov, position, voice,\ t)}{\#(h, pt, gov, position, voice,\ t)}$$

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs ("Farrell", NP, S, before, active,"approached")?

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs (“Farrell”, NP, S, before, active,”approached”)?
    - 436 times

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs (“Farrell”, NP, S, before, active,”approached”)?
    - 436 times
    - How often does this combination have the role “Theme”?
      - 387 times

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs (“Farrell”, NP, S, before, active,”approached”)?
    - 436 times
    - How often does this combination have the role “Theme”?
      - 387 times
    - How often does this combination have the role “Vehicle”?
      - 8 times

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs ("Farrell", NP, S, before, active,"approached")?
    - 436 times
    - How often does this combination have the role "Theme"?
      - 387 times
    - How often does this combination have the role "Vehicle"?
      - 8 times

$$P(\text{"}Theme\text{"} \mid \text{"}Farrell\text{"}, NP, S, before, active, \text{"}approached\text{"}) \approx 89\%$$

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs (“Farrell”, NP, S, before, active,”approached”)?
    - 436 times
    - How often does this combination have the role “Theme”?
      - 387 times
    - How often does this combination have the role “Vehicle”?
      - 8 times

$$P(\text{"}Theme\text{"} \mid \text{"}Farrell\text{"}, NP, S, before, active, \text{"}approached\text{"}) \approx 89\%$$

$$P(\text{"}Vehicle\text{"} \mid \text{"}Farrell\text{"}, NP, S, before, active, \text{"}approached\text{"}) \approx 2\%$$

Approach – Probability Estimation

$$P(r \mid h, pt, gov, position, voice, t)$$

- Example:
  - How often occurs ("Farrell", NP, S, before, active,"approached")?
    - 436 times
    - How often does this combination have the role "Theme"?
      - 387 times
    - How often does this combination have the role "Vehicle"?
      - 8 times

$$P(\underline{"Theme"} \mid "Farrell", NP, S, before, active, "approached") \approx 89\%$$

$$P("Vehicle" \mid "Farrell", NP, S, before, active, "approached") \approx 2\%$$

Approach – Probability Estimation

- Problem: features not always available (0 occurences)
  - Esp. head word: very specific
- $P(r \mid h, pt, gov, position, voice, t)$ might be too strict

Approach – Probability Estimation

- Problem: features not always available (0 occurences)
  - Esp. head word: very specific
- $P(r \mid h, pt, gov, position, voice, t)$ might be too strict

- Solution:
  - Subset
    of probabilities
  - Different
    combinations

Approach – Probability Estimation

- Problem: features not always available (0 occurences)
  - Esp. head word: very specific
- $P(r \mid h, pt, gov, position, voice, t)$ might be too strict

- Solution:
  - Subset of probabilities
  - Different combinations

Distribution	Coverage	Accuracy	Performance
$P(r \mid t)$	100.0%	40.9%	40.9%
$P(r \mid pt, t)$	92.5	60.1	55.6
$P(r \mid pt, gov, t)$	92.0	66.6	61.3
$P(r \mid pt, position, voice)$	98.8	57.1	56.4
$P(r \mid pt, position, voice, t)$	90.8	70.1	63.7
$P(r \mid h)$	80.3	73.6	59.1
$P(r \mid h, t)$	56.0	86.6	48.5
$P(r \mid h, pt, t)$	50.1	87.4	43.8

Approach – Probability Estimation

- Idea: combine distributions
  - Linear interpolation

$$
\begin{aligned}
P(r \mid constituent) \quad = \quad & \lambda_1 P(r \mid t) + \lambda_2 P(r \mid pt, t) \\
& + \lambda_3 P(r \mid pt, gov, t) + \lambda_4 P(r \mid pt, position, voice) \\
& + \lambda_5 P(r \mid pt, position, voice, t) + \lambda_6 P(r \mid h) \\
& + \lambda_7 P(r \mid h, t) + \lambda_8 P(r \mid h, pt, t)
\end{aligned}
$$

Approach – Probability Estimation

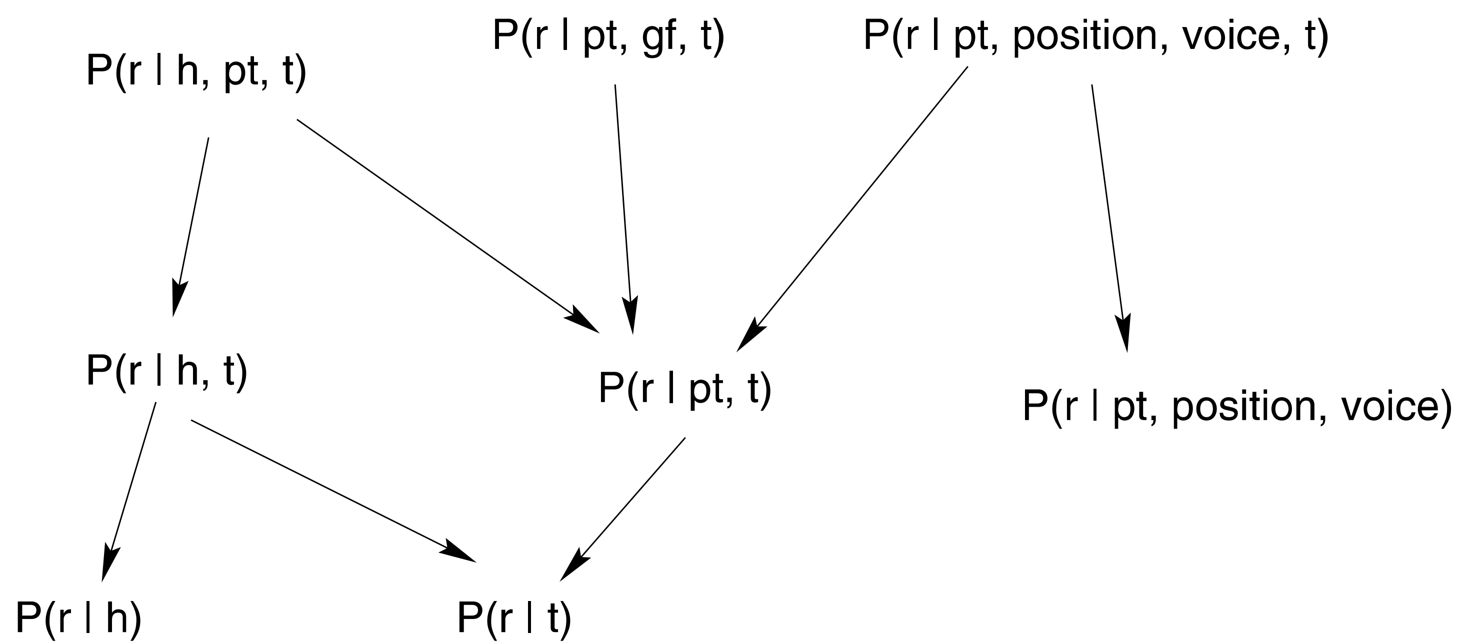
- Idea: combine distributions
  - Linear interpolation

$$
\begin{aligned}
P(r \mid constituent) \quad = \quad & \lambda_1 P(r \mid t) + \lambda_2 P(r \mid pt, t) \\
& + \lambda_3 P(r \mid pt, gov, t) + \lambda_4 P(r \mid pt, position, voice) \\
& + \lambda_5 P(r \mid pt, position, voice, t) + \lambda_6 P(r \mid h) \\
& + \lambda_7 P(r \mid h, t) + \lambda_8 P(r \mid h, pt, t)
\end{aligned}
$$

  - 79.5% performance

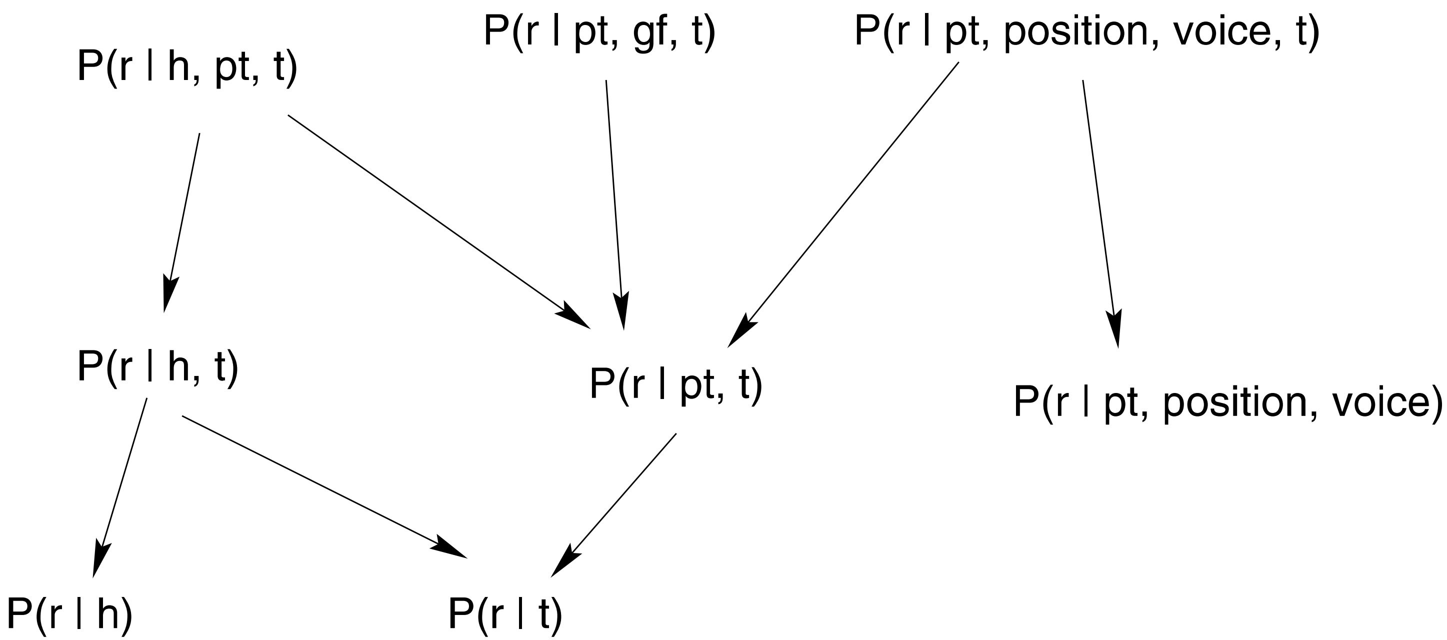
Approach – Probability Estimation

- Idea: combine distributions
  - "Backoff"



Approach – Probability Estimation

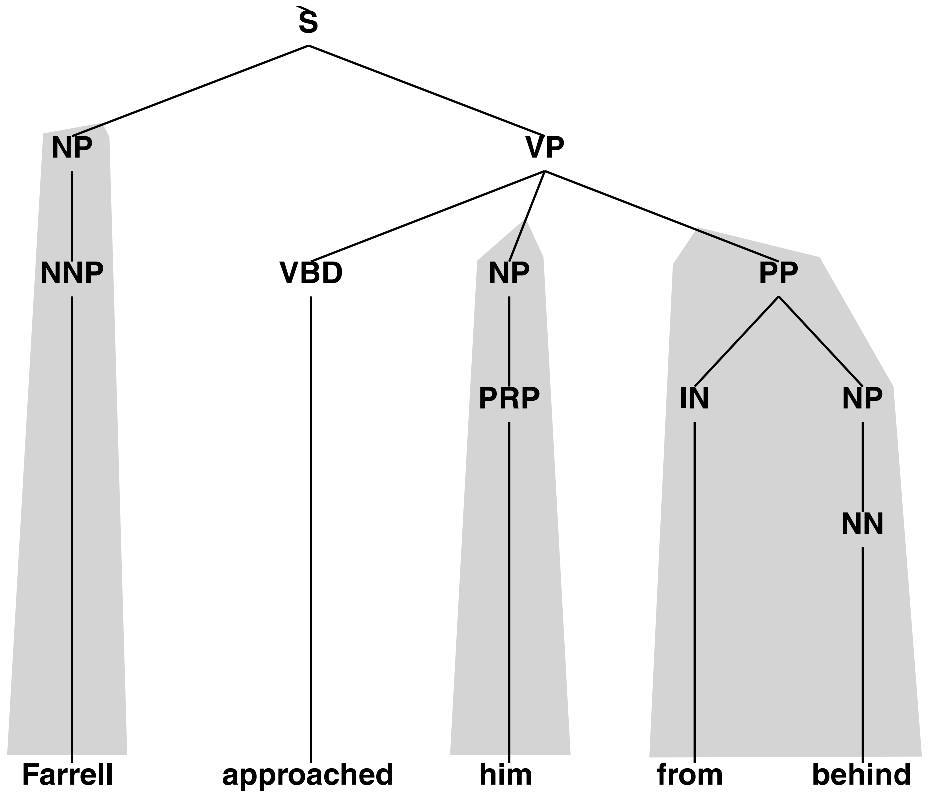
- Idea: combine distributions
  - "Backoff"



  - 80.4% performance

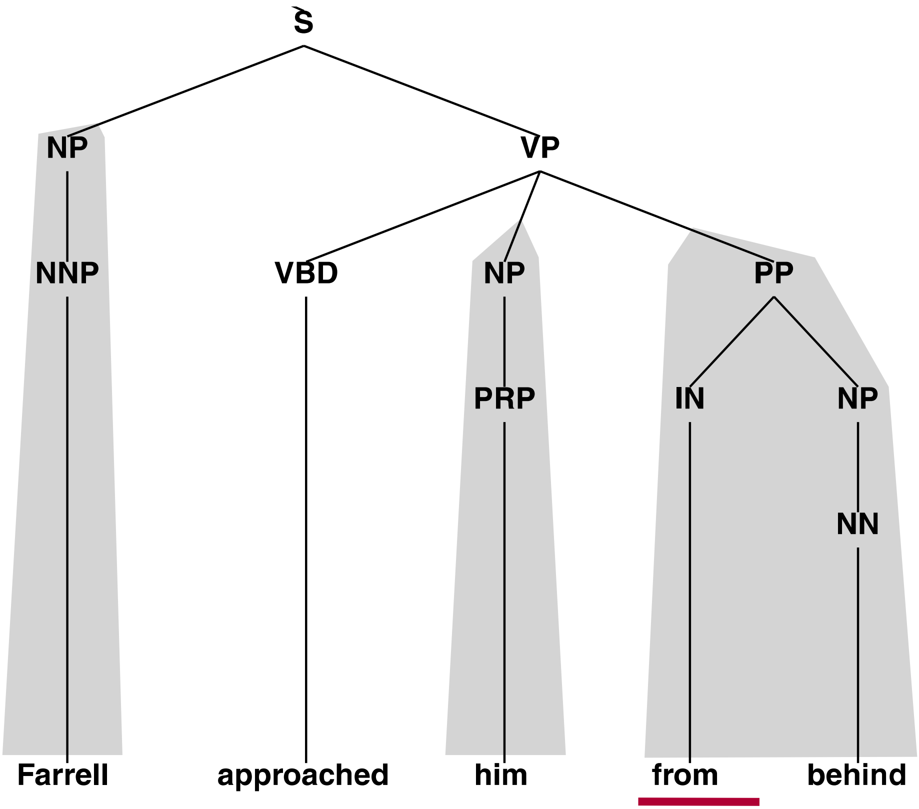
Optional: Boundaries

- Additional step before the automatic labeling
- Similar techniques as described before
  - Here: no differentiation among multiple roles → is parse constituent a role or not?
  - Threshold for probability required



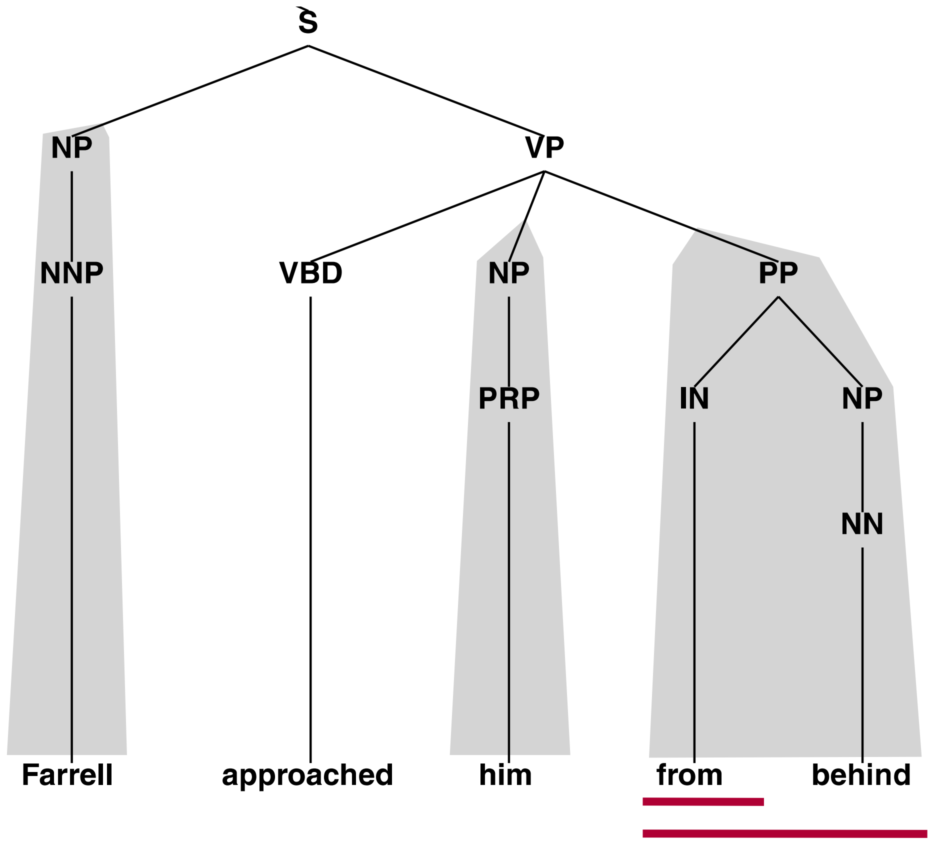
Optional: Boundaries

- Additional step before the automatic labeling
- Similar techniques as described before
  - Here: no differentiation among multiple roles → is parse constituent a role or not?
  - Threshold for probability required



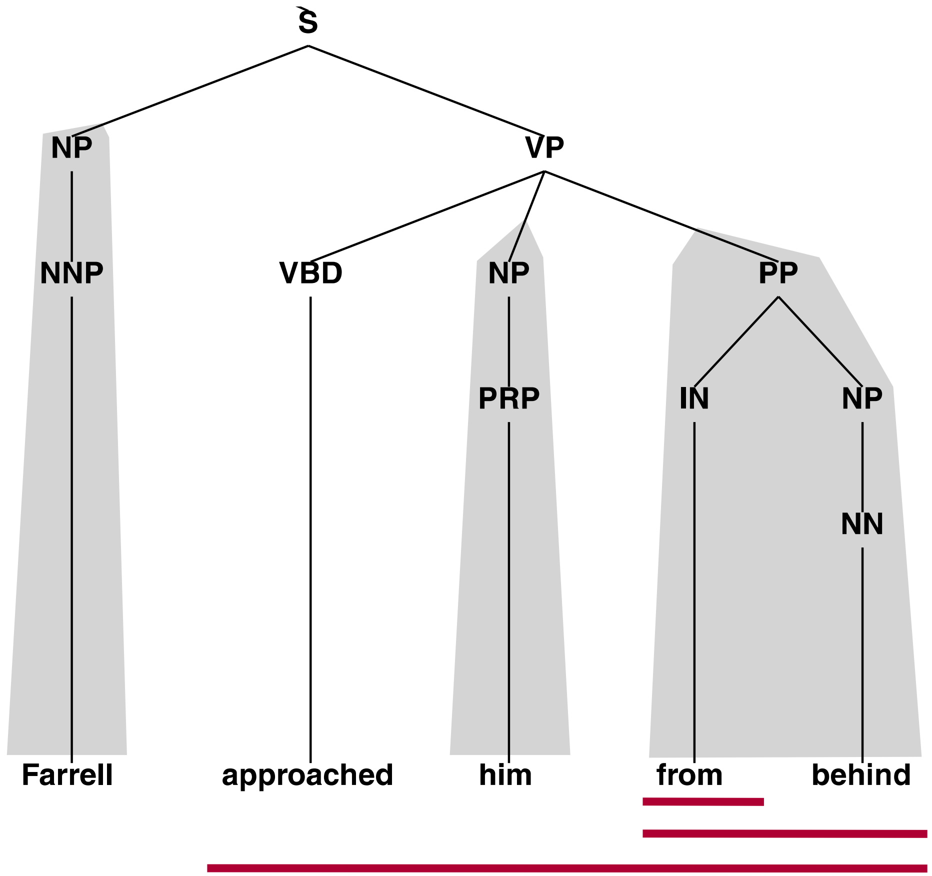
Optional: Boundaries

- Additional step before the automatic labeling
- Similar techniques as described before
  - Here: no differentiation among multiple roles → is parse constituent a role or not?
  - Threshold for probability required



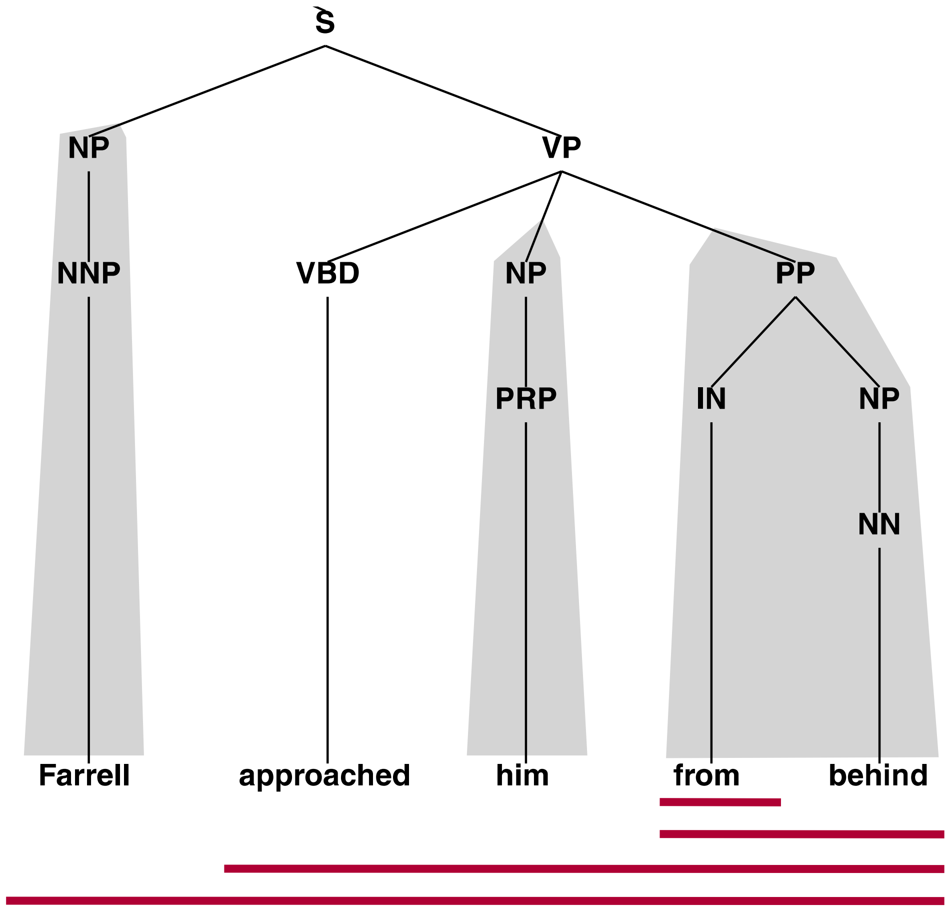
Optional: Boundaries

- Additional step before the automatic labeling
- Similar techniques as described before
  - Here: no differentiation among multiple roles → is parse constituent a role or not?
  - Threshold for probability required

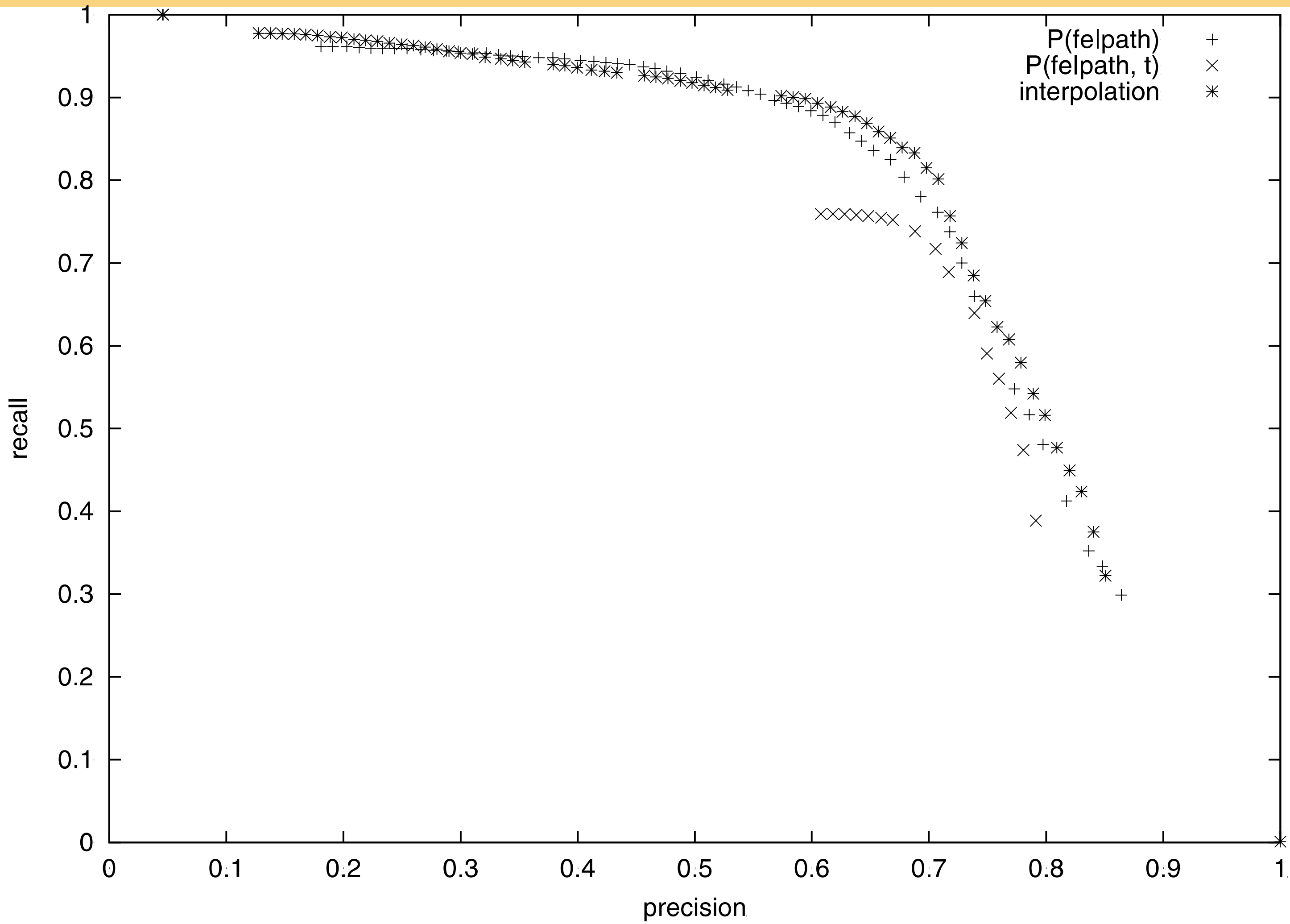


Optional: Boundaries

- Additional step before the automatic labeling
- Similar techniques as described before
  - Here: no differentiation among multiple roles → is parse constituent a role or not?
  - Threshold for probability required



Boundaries – Precision / Recall



For different recognition thresholds

Discussion

- With given boundaries → relatively high performance
  - Interpolation of different probability distributions combinations makes sense
- Without boundaries → much lower performance
- Still some tasks open
  - Mostly disambiguation

Discussion

- With given boundaries → relatively high performance
  - Interpolation of different probability distributions combinations makes sense
- Without boundaries → much lower performance
- Still some tasks open
  - Mostly disambiguation

- Integration into QA system
  - Input: Question + Possible answer sentences (→ disambiguation for frame required)
  - Connection to FrameNet

References

- Daniel Gildea, Danied Jurafsky, Automatic Labeling of Semantic Roles, Journal of Computational Linguistics, 2002

- Michael Collins, Head-Driven Statistical Models for Natural Language Parsing, Ph.D. dissertation, University of Pennsylvania, Philadelphia, 1999