Semantic parsing

Computational Linguistics

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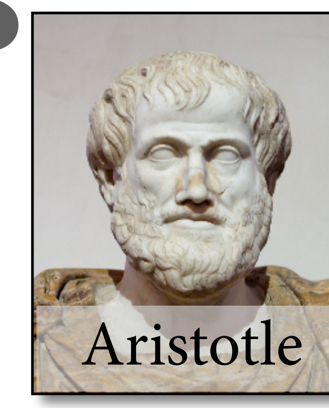
26 January 2018

Computing with meanings



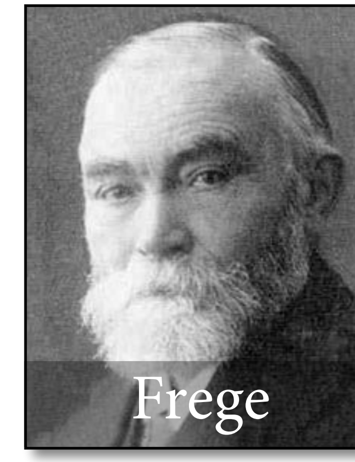
- Ancient problem: *inference.*
  - How can we tell whether a sentence follows from others?
  - Can we compute this automatically?

All men are mortal.

Socrates is a man.

Therefore, Socrates is mortal.

Formal meaning representations



- Modern approach to natural-language inference:
  - Compute *meaning representation* in some formal language (e.g. predicate logic)
  - so that it captures something relevant about the sentence's meaning (e.g. its *truth conditions*)
  - and then use reasoning tools for the formal language (e.g. a *theorem prover* for predicate logic)

All men are mortal.

Socrates is a man.

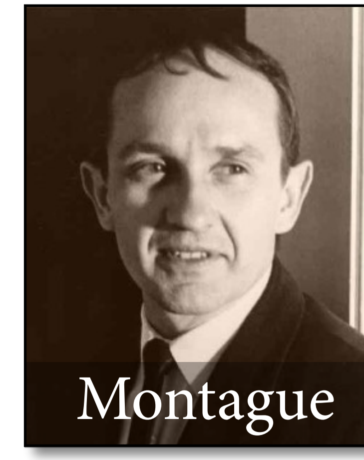
Therefore, Socrates is mortal.

$\forall x.\ \mathrm{man}(x) \rightarrow \mathrm{mortal}(x)$

$\mathrm{man}(s)$

$\mathrm{mortal}(s)$

Syntax-semantics interface



$S \rightarrow NP\ VP$	$\langle S \rangle = \langle NP \rangle(\langle VP \rangle)$
$VP \rightarrow V\ NP$	$\langle VP \rangle = \lambda y\ \langle NP \rangle(\langle V \rangle(y))$
$NP \rightarrow Det\ N$	$\langle NP \rangle = \langle Det \rangle(\langle N \rangle)$
$NP \rightarrow$ John	$\langle NP \rangle = \lambda P\ P(j^*)$
$V \rightarrow$ eats	$\langle V \rangle =$ eat'
$Det \rightarrow$ a	$\langle Det \rangle = \lambda P \lambda Q \exists x\ P(x) \wedge Q(x)$
$N \rightarrow$ sandwich	$\langle N \rangle =$ sw'

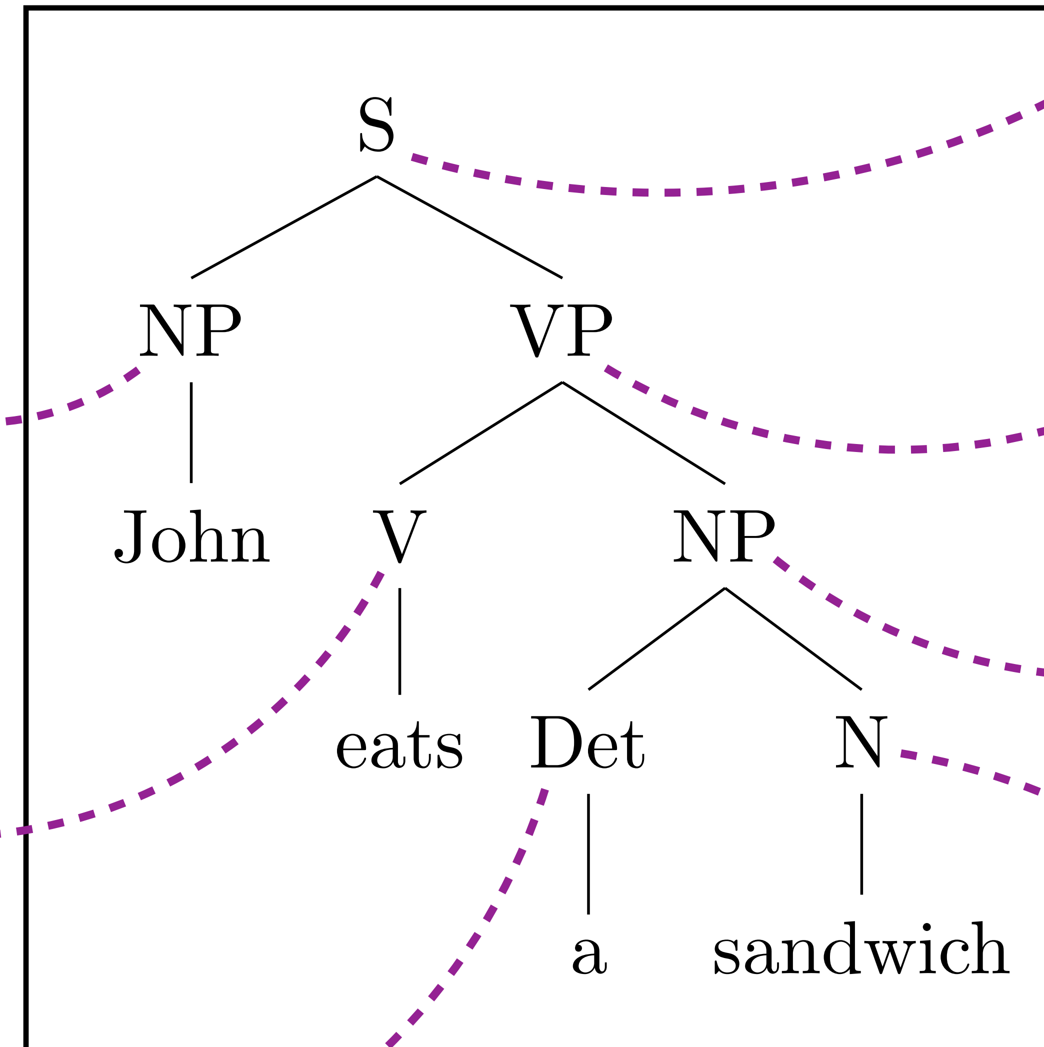
when you apply this syntax rule …

… construct λ-term for parent from λ-terms for children like this

Example

(λP P(j*)) (λy ∃x sw’(x) ∧eat’(y)(x))
$\rightarrow_\beta$ (λy ∃x sw’(x) ∧eat’(y)(x))(j*)
$\rightarrow_\beta$ ∃x sw’(x) ∧eat’(j*)(x)

λP P(j*)



λy (λQ∃x sw’(x) ∧ Q(x))(eat’(y))
$\rightarrow_\beta$ λy ∃x sw’(x) ∧eat’(y)(x)

(λPλQ∃x P(x) ∧ Q(x))(sw’)
$\rightarrow_\beta$ λQ∃x sw’(x) ∧ Q(x)

eat’

sw’

λPλQ∃x P(x) ∧ Q(x)

Semantic parsing

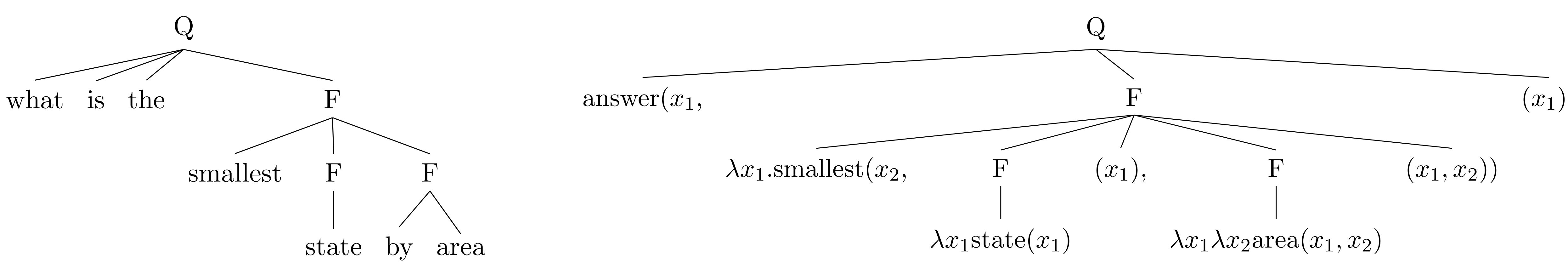
- Open issue in classical semantics construction: Where do we get large grammar that supports it?
- Current trend in CL is *semantic parsing*: learn mapping from sentence to formal meaning representation using statistical methods.
- E.g. from Geoquery corpus (880 sentences):

> What is the smallest state by area?
> `answer(x1, smallest(x2, state(x1), area(x1, x2)))`

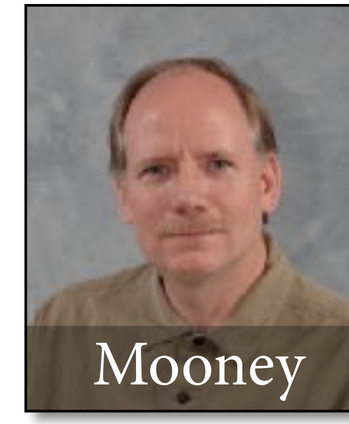
With synchronous grammars

- Use a synchronous grammar (≈ SFCG) to simultaneously generate strings and λ-expressions.

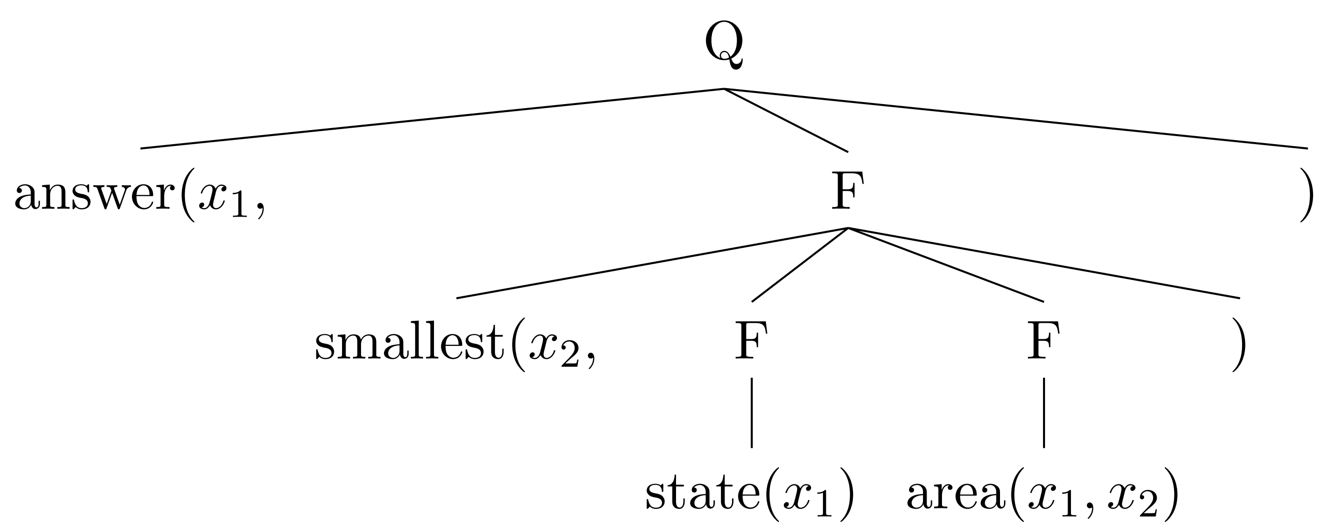
Q → what is the F	Q → answer(x_1, F(x_1))
F → smallest F F	F → λx_1 smallest(x_2, F(x_1), F(x_1, x_2))
F → state	F → λx_1 state(x_1)
F → by area	F → λx_1 λx_2 area(x_1, x_2)



Wong & Mooney

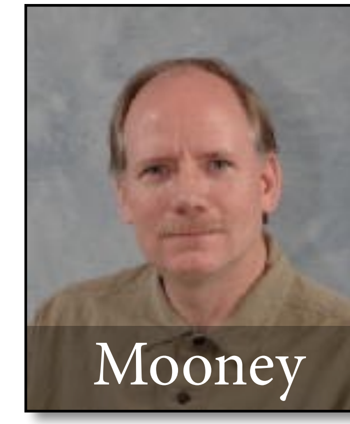


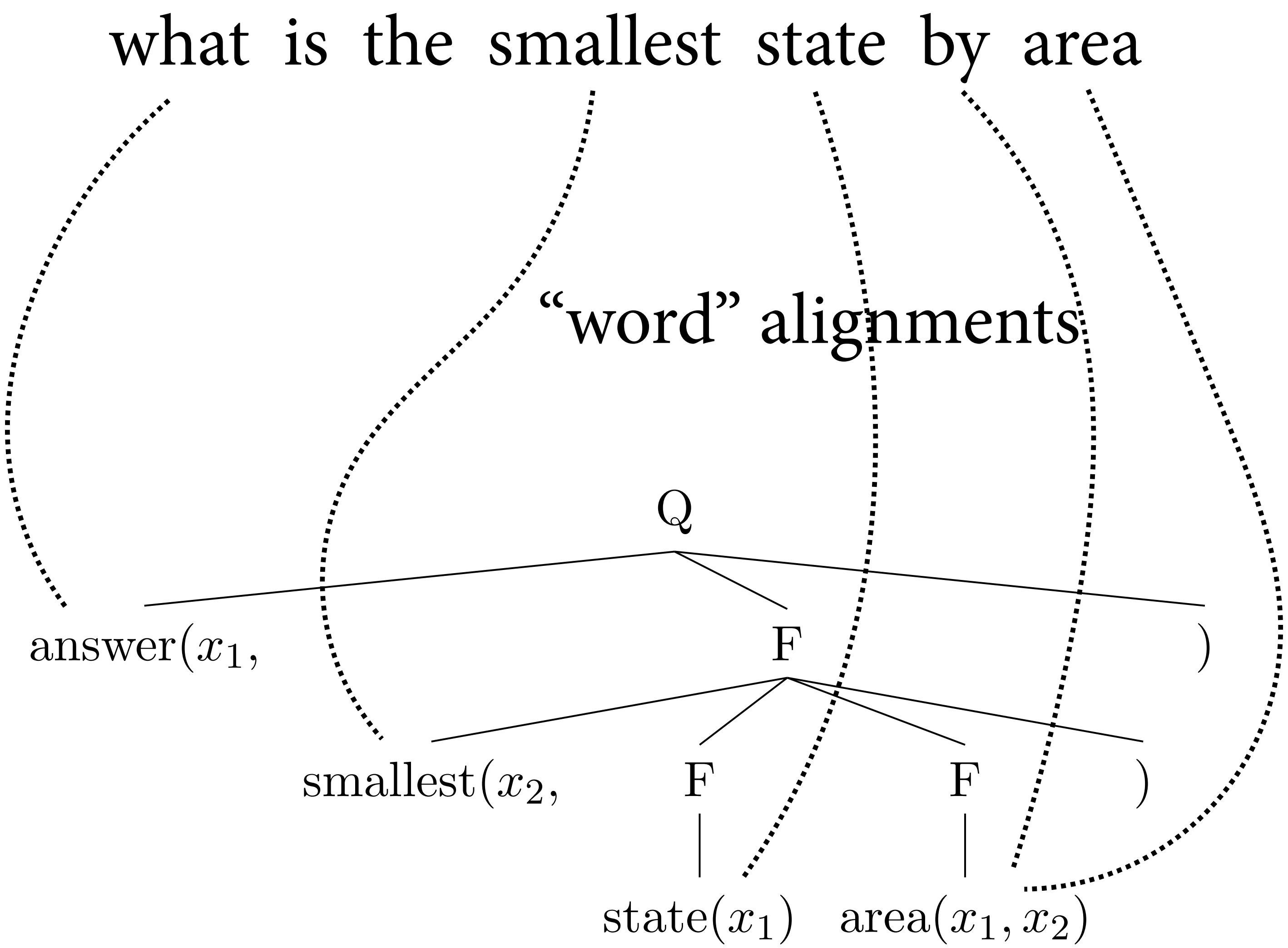
what is the smallest state by area



Assumptions:
- alignments between words and nodes
- unambiguous structure of meaning representation

Wong & Mooney





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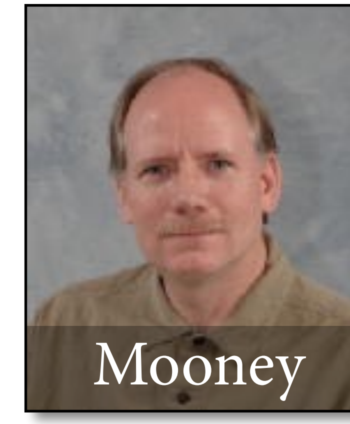

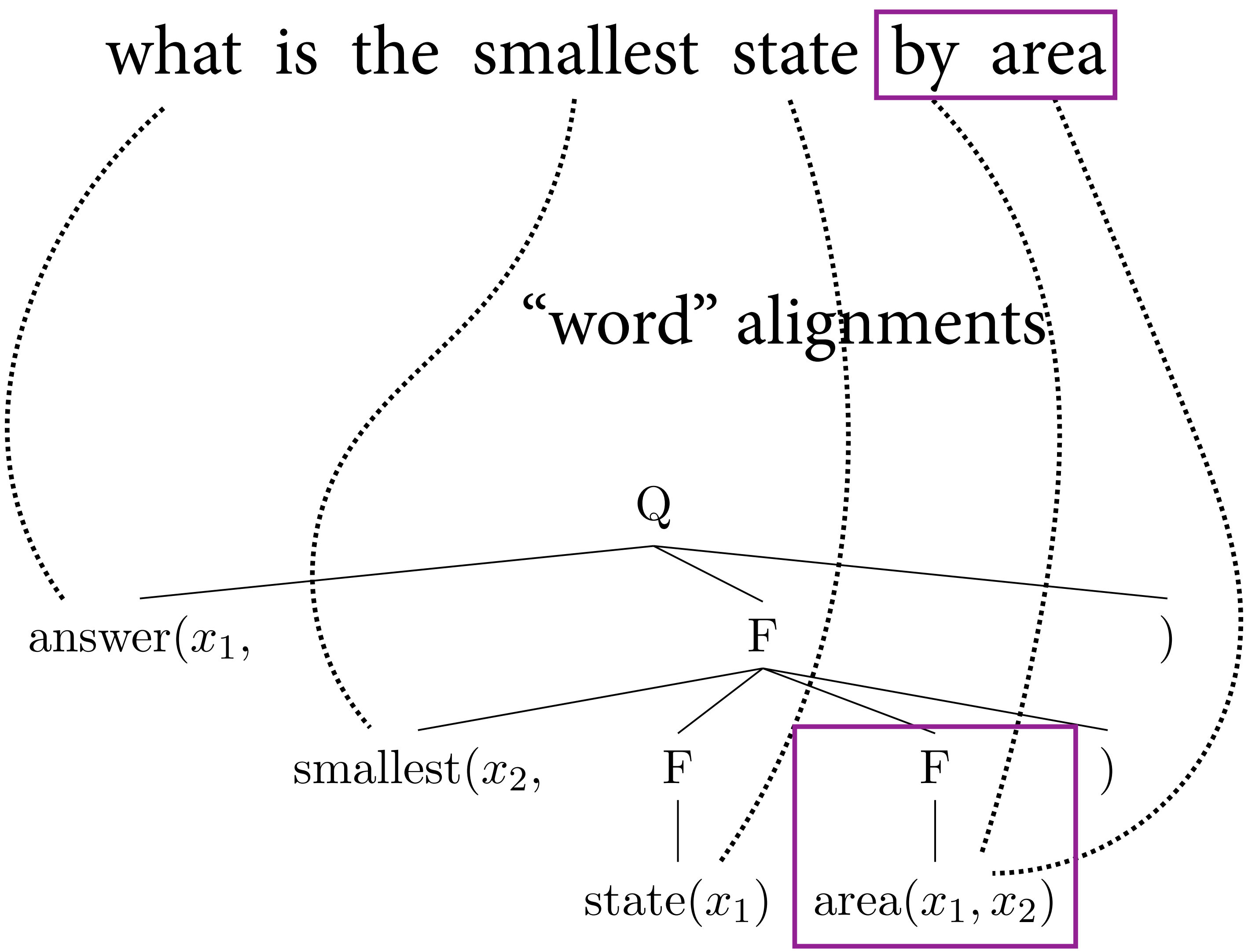

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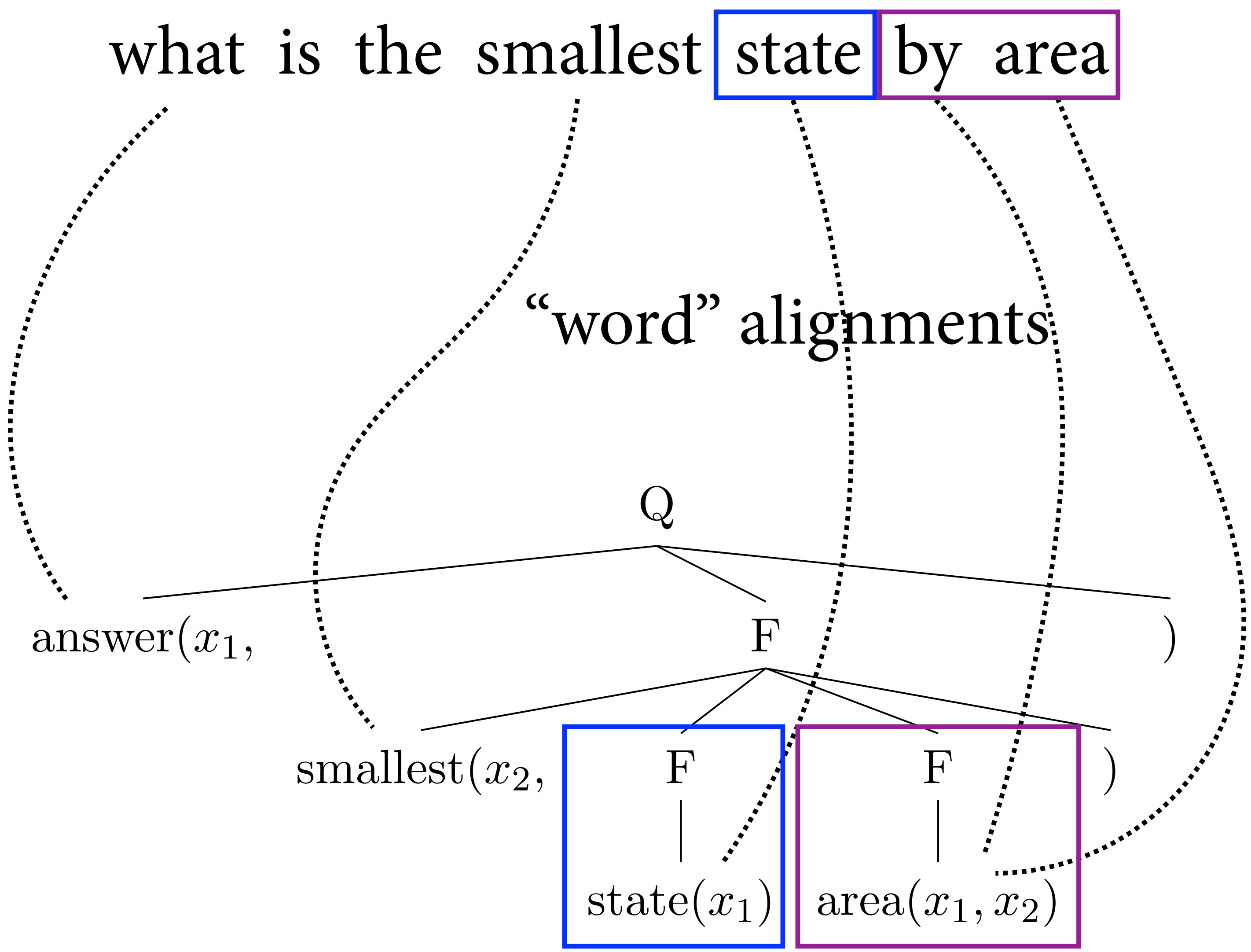

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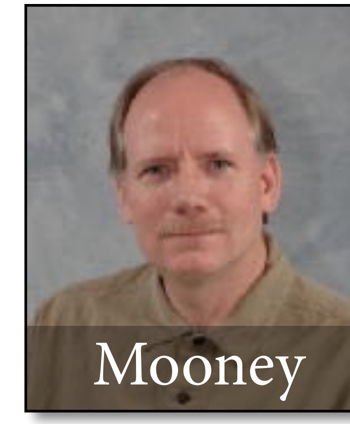

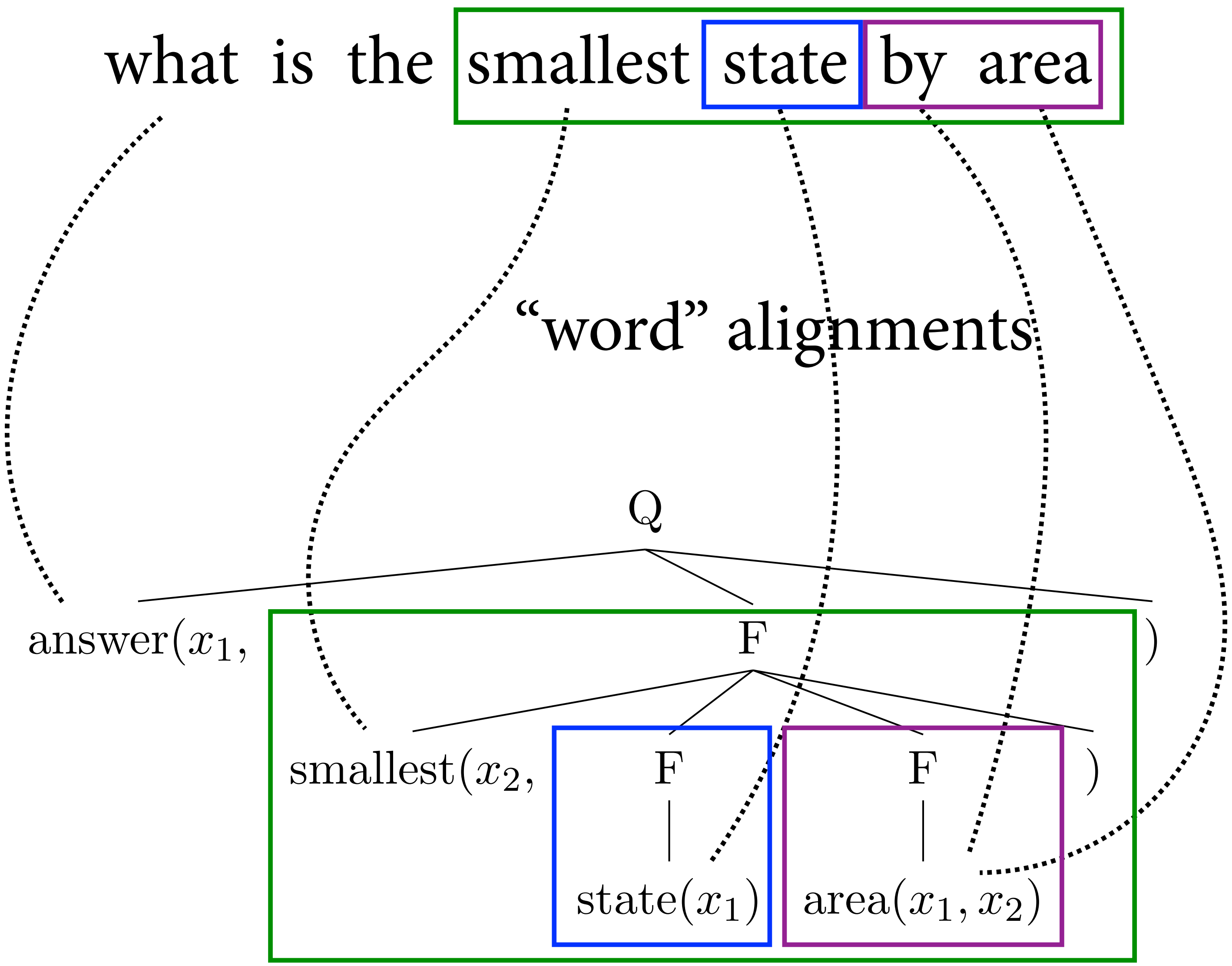

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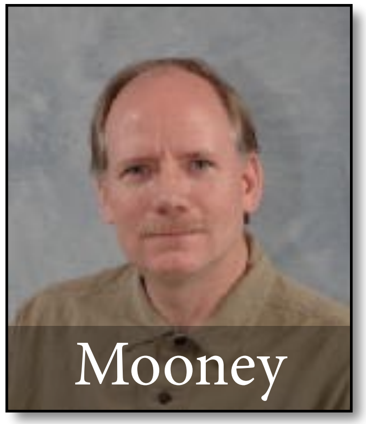

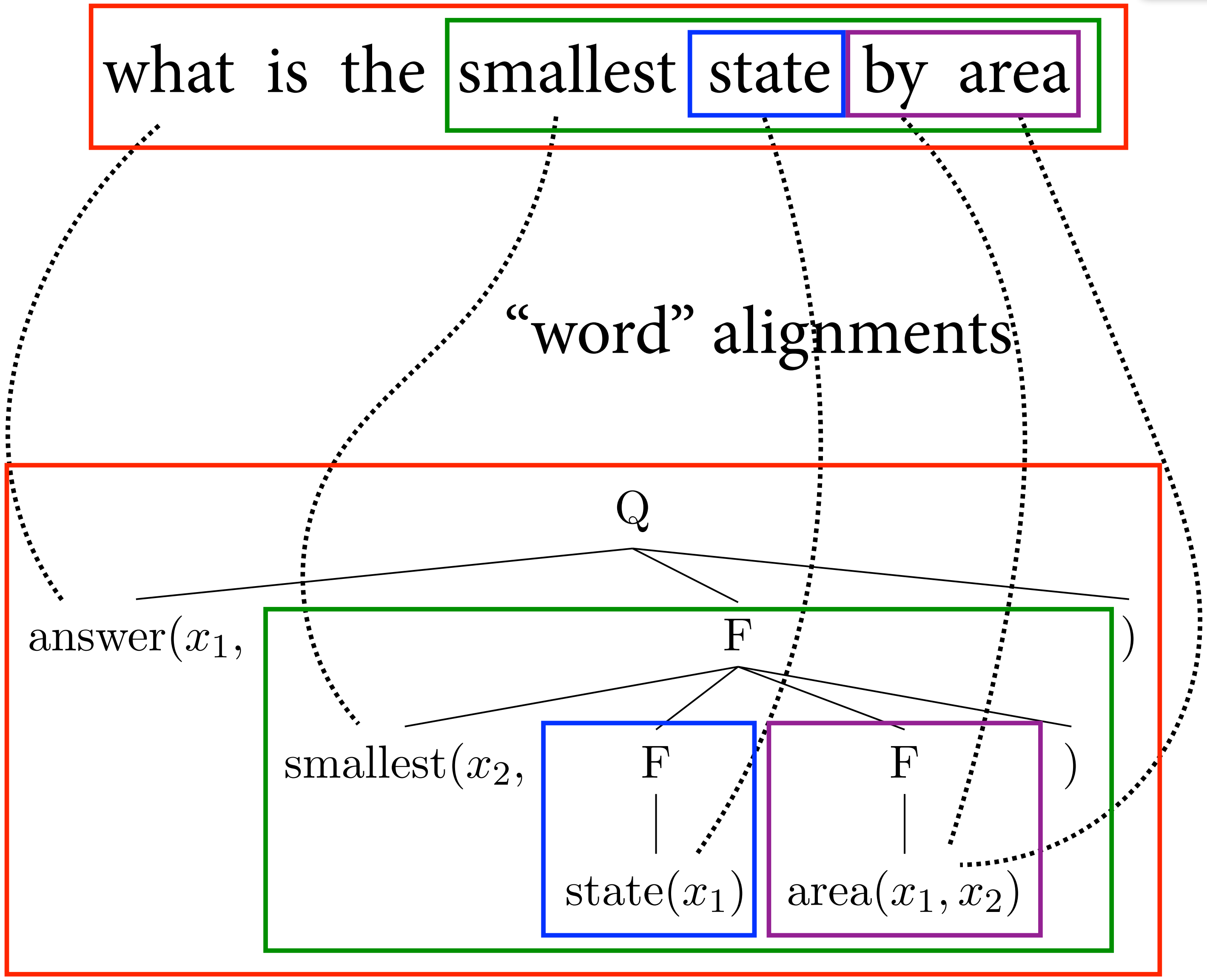

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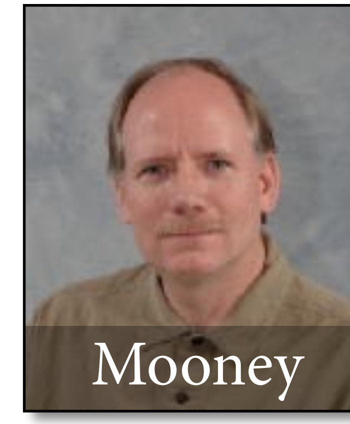
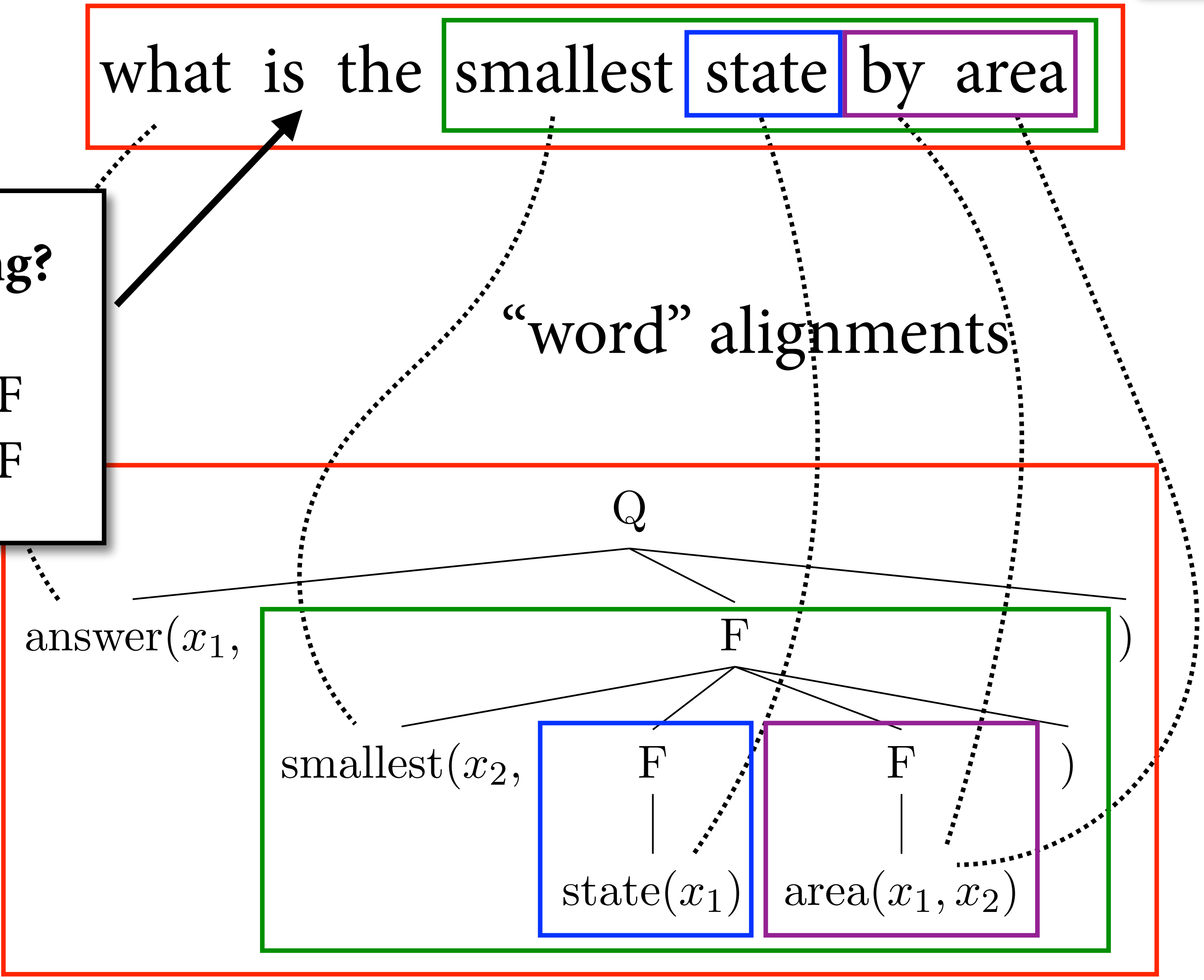




Where do unaligned words belong?

Q → what is the F | F → smallest F
Q → what F | F → is the smallest F

Assumptions:
- alignments between words and nodes
- unambiguous structure of meaning representation

Log-linear probability models

- Define probability of parse tree in terms of *features:*

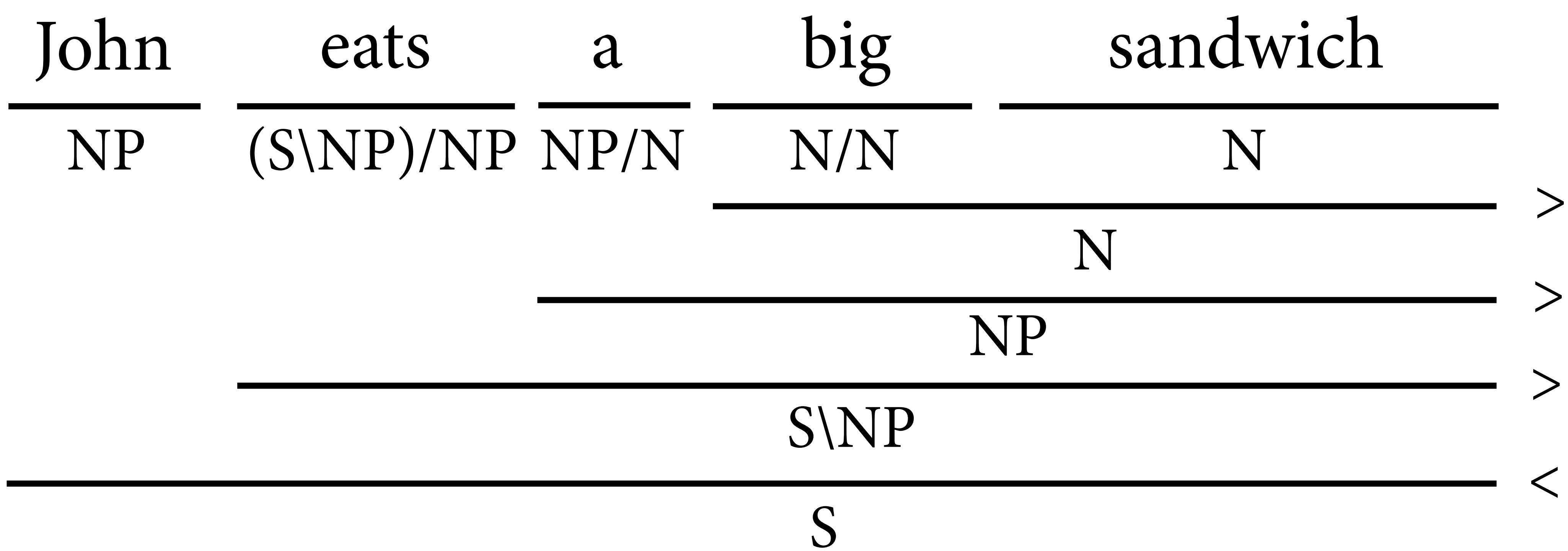
$$P(t \mid w) = \frac{e^{\theta \cdot f(t,w)}}{\sum_{t'} e^{\theta \cdot f(t',w)}}$$

  where $\theta \cdot f(t,w) = \theta_1 \cdot f_1(t,w) + \ldots + \theta_n \cdot f_n(t,w)$

- Features f(t,w) can capture arbitrary properties of t and w.
  - Here: Each feature counts uses of one grammar rule.

- Train weight vector θ from data.

Combinatory categorial grammar



Semantics in CCG

$$\frac{X: a}{Y/(Y\backslash X): \lambda P.P(a)}\;{>}\mathrm{T} \qquad \frac{X/Y: f \qquad Y/Z: g}{X/Z: \lambda x.f(g(x))}\;{>}\mathrm{B} \qquad \frac{X/Y: f \qquad Y\backslash Z: g}{X\backslash Z: \lambda x.f(g(x))}\;{>}\mathrm{Bx}$$

$$\frac{X: a}{Y\backslash(Y/X): \lambda P.P(a)}\;{<}\mathrm{T} \qquad \frac{Y\backslash Z: g \qquad X\backslash Y: f}{X\backslash Z: \lambda x.f(g(x))}\;{<}\mathrm{B} \qquad \frac{Y/Z: g \qquad X\backslash Y: f}{X/Z: \lambda x.f(g(x))}\;{<}\mathrm{Bx}$$

$$\dfrac{\dfrac{\dfrac{\dfrac{\text{John}}{NP: h^*}}{S/(S\backslash NP): \lambda P.P(h^*)}\;{>}\mathrm{T} \qquad \dfrac{\text{eats}}{(S\backslash NP)/NP: eat'}}{S/NP: \lambda x.(\lambda P.P(h^*))(eat'(x)) \Rightarrow_\beta \lambda x.eat'(x)(h^*)}\;{>}\mathrm{B} \qquad \dfrac{\text{a sandwich}}{NP: sw'}}{S: (\lambda x.eat'(x)(h^*))(sw') \Rightarrow_\beta eat'(sw')(h^*)}\;{>}$$

Zettlemoyer & Collins

GENLEX: build candidates for lexicon entries

Rules		Categories produced from logical form
Input Trigger	Output Category	$\arg\max(\lambda x.state(x) \wedge borders(x, texas), \lambda x.size(x))$
constant c	$NP : c$	$NP : texas$
arity one predicate p_1	$N : \lambda x.p_1(x)$	$N : \lambda x.state(x)$
arity one predicate p_1	$S\backslash NP : \lambda x.p_1(x)$	$S\backslash NP : \lambda x.state(x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(y, x)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(y, x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(x, y)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(x, y)$
arity one predicate p_1	$N/N : \lambda g.\lambda x.p_1(x) \wedge g(x)$	$N/N : \lambda g.\lambda x.state(x) \wedge g(x)$
literal with arity two predicate p_2 and constant second argument c	$N/N : \lambda g.\lambda x.p_2(x, c) \wedge g(x)$	$N/N : \lambda g.\lambda x.borders(x, texas) \wedge g(x)$
arity two predicate p_2	$(N\backslash N)/NP : \lambda x.\lambda g.\lambda y.p_2(x, y) \wedge g(x)$	$(N\backslash N)/NP : \lambda g.\lambda x.\lambda y.borders(x, y) \wedge g(x)$
an $\arg\max$ / $\min$ with second argument arity one function f	$NP/N : \lambda g.\arg\max / \min(g, \lambda x.f(x))$	$NP/N : \lambda g.\arg\max(g, \lambda x.size(x))$
an arity one numeric-ranged function f	$S/NP : \lambda x.f(x)$	$S/NP : \lambda x.size(x)$

Zettlemoyer & Collins

overall learning algorithm

Algorithm:

- For $t = 1 \dots T$

Step 1: (Lexical generation)

- For $i = 1 \dots n$:
  - Set $\lambda = \Lambda_0 \cup \text{GENLEX}(S_i, L_i)$.
  - Calculate $\pi = \text{PARSE}(S_i, L_i, \lambda, \bar{\theta}^{t-1})$.
  - Define λ_i to be the set of lexical entries in π.
- Set $\Lambda_t = \Lambda_0 \cup \bigcup_{i=1}^{n} \lambda_i$

Step 2: (Parameter Estimation)

- Set $\bar{\theta}^t = \text{ESTIMATE}(\Lambda_t, E, \bar{\theta}^{t-1})$

Evaluation results

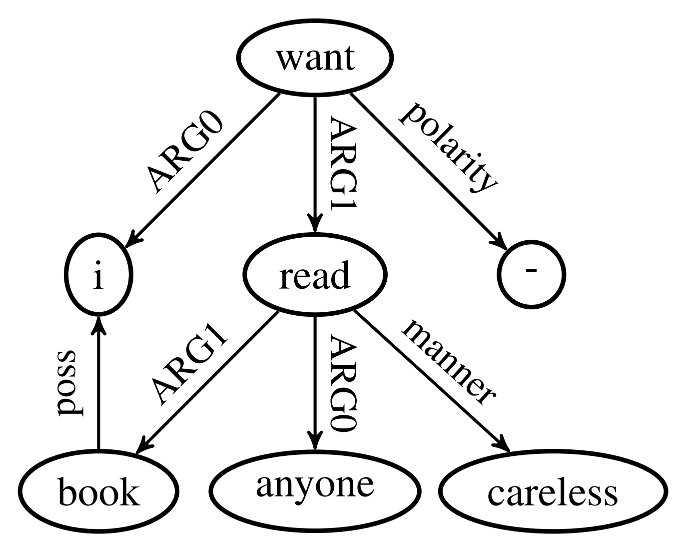
System	Variable Free			Lambda Calculus		
	Rec.	Pre.	F1	Rec.	Pre.	F1
Cross Validation Results						
KRISP	71.7	**93.3**	81.1	–	–	–
WASP	74.8	87.2	80.5	–	–	–
Lu08	81.5	89.3	**85.2**	–	–	–
λ-WASP	–	–	–	86.6	92.0	89.2
Independent Test Set						
ZC05	–	–	–	79.3	**96.3**	87.0
ZC07	–	–	–	86.1	91.6	88.8
UBL	81.4	89.4	**85.2**	85.0	94.1	**89.3**
UBL-s	**84.3**	85.2	84.7	**87.9**	88.5	88.2

(on Geoquery 880 corpus)

Abstract Meaning Representations

- Pros and cons of Geoquery:
  - semantic representations are trees — (too) easy
  - very small

- Since 2014, much larger corpora available:
~40k AMRs, graphs as semantic representations.



“I don’t want anyone to read my book carelessly.”

Dependency-style AMR parsing

"The boy wants to visit New York City."

JAMR; Flanigan et al. 2014

Dependency-style AMR parsing

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Concept Identification: determine atomic graph for each word.

JAMR; Flanigan et al. 2014

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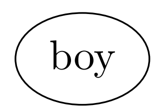

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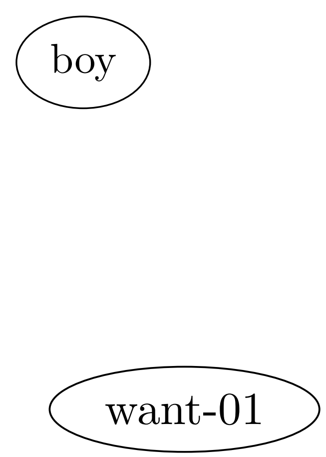

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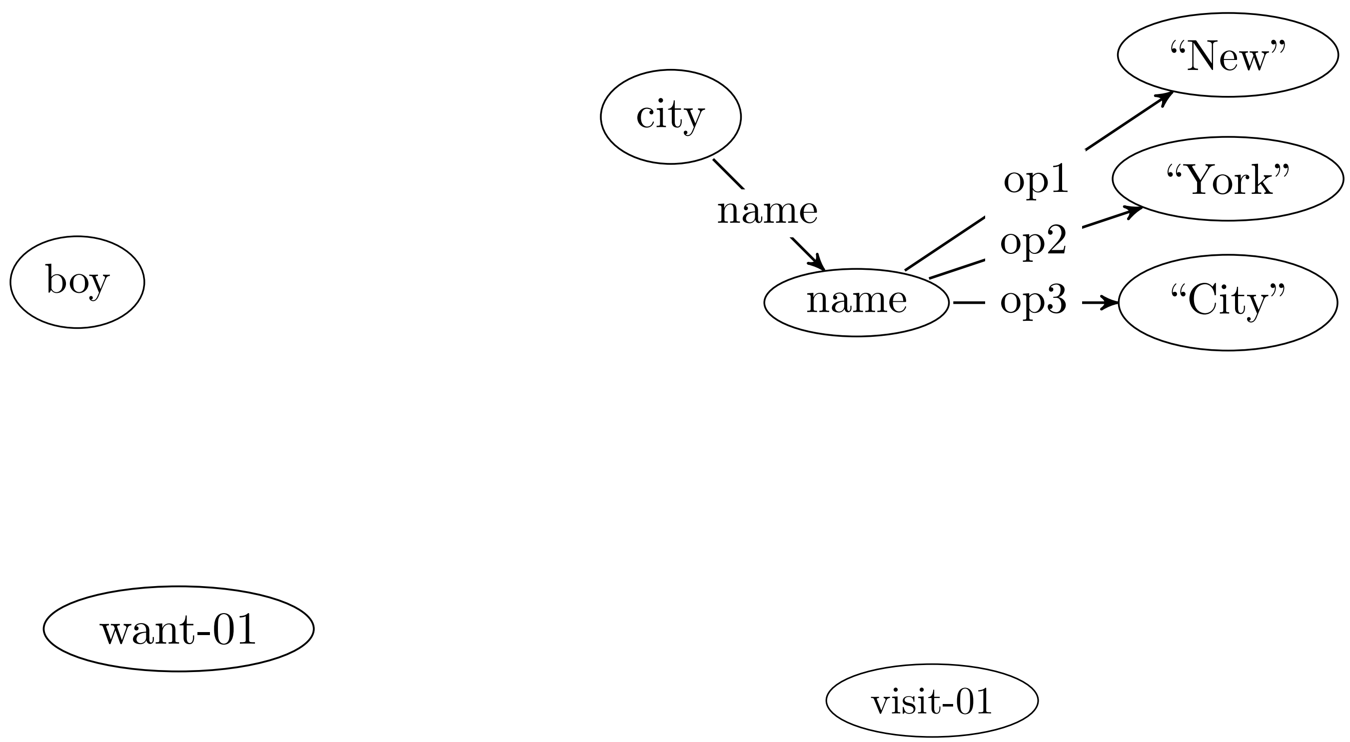

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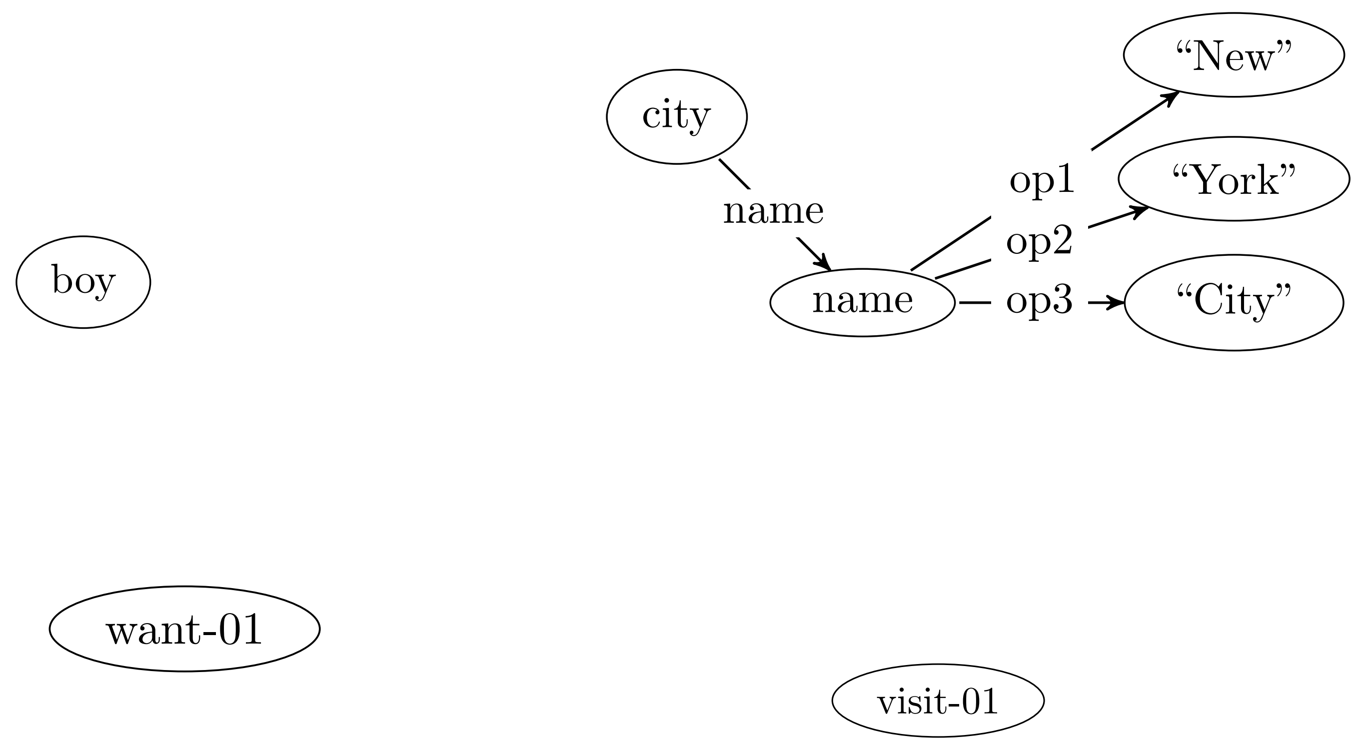

Concept Identification: determine atomic graph for each word.

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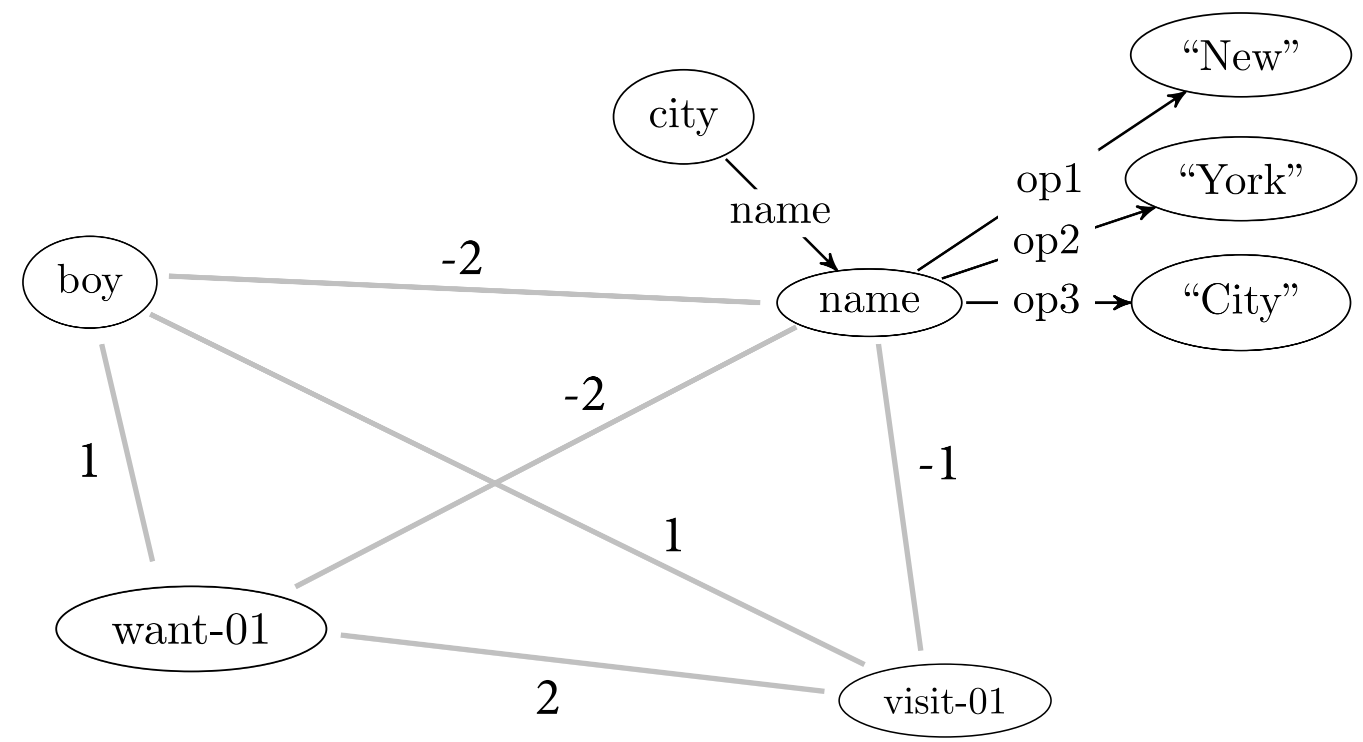

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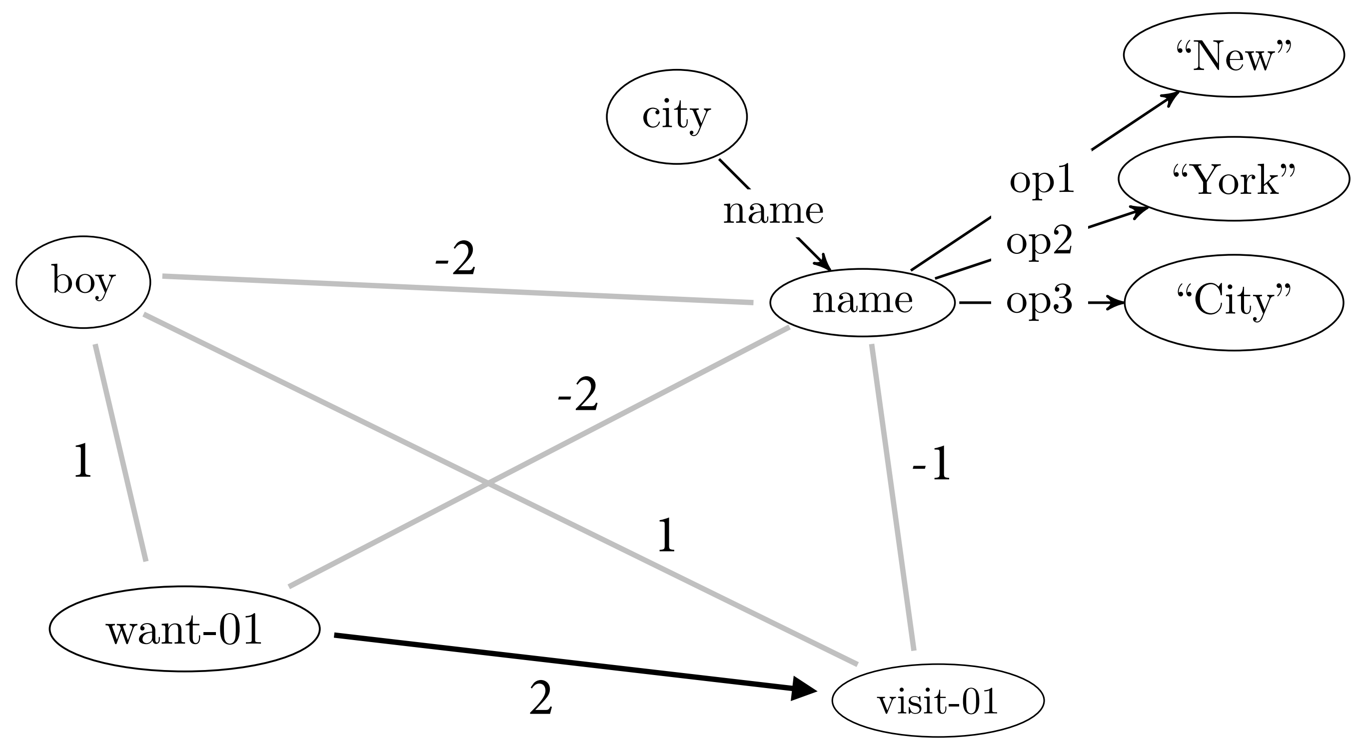

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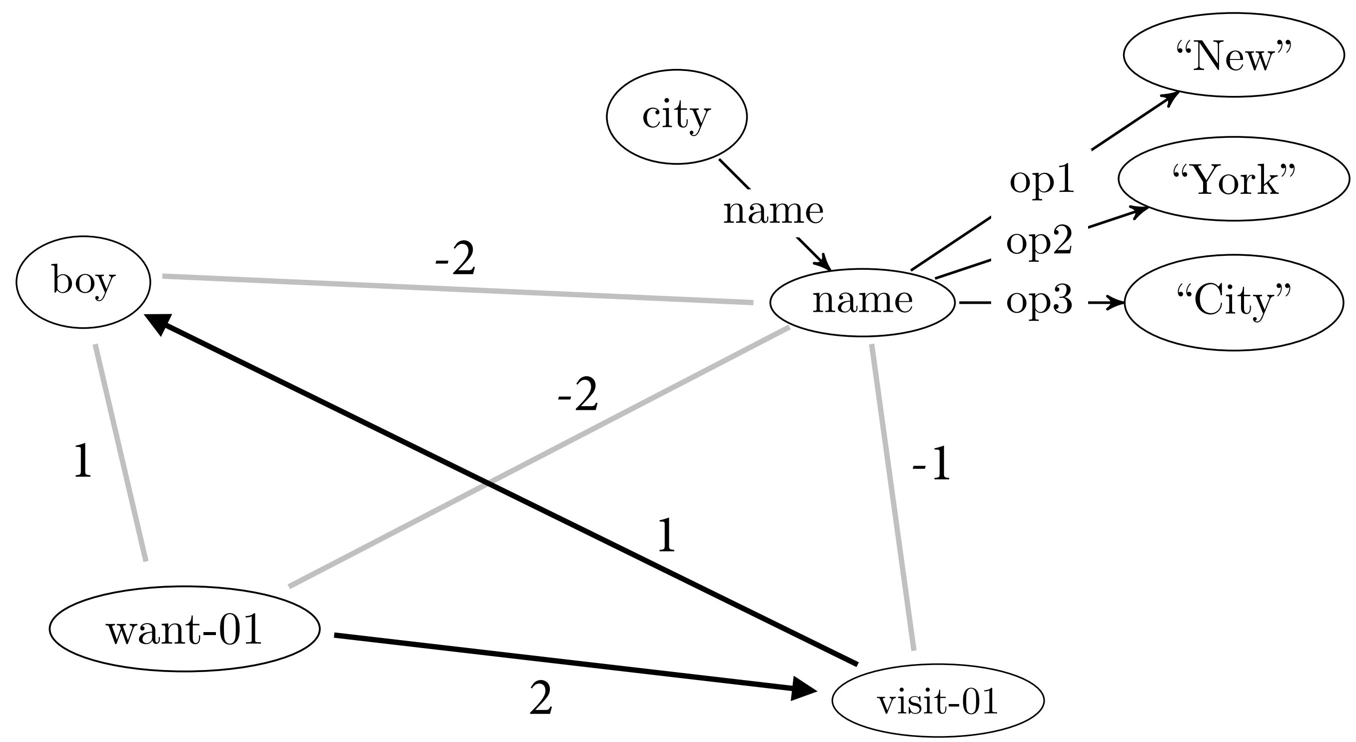

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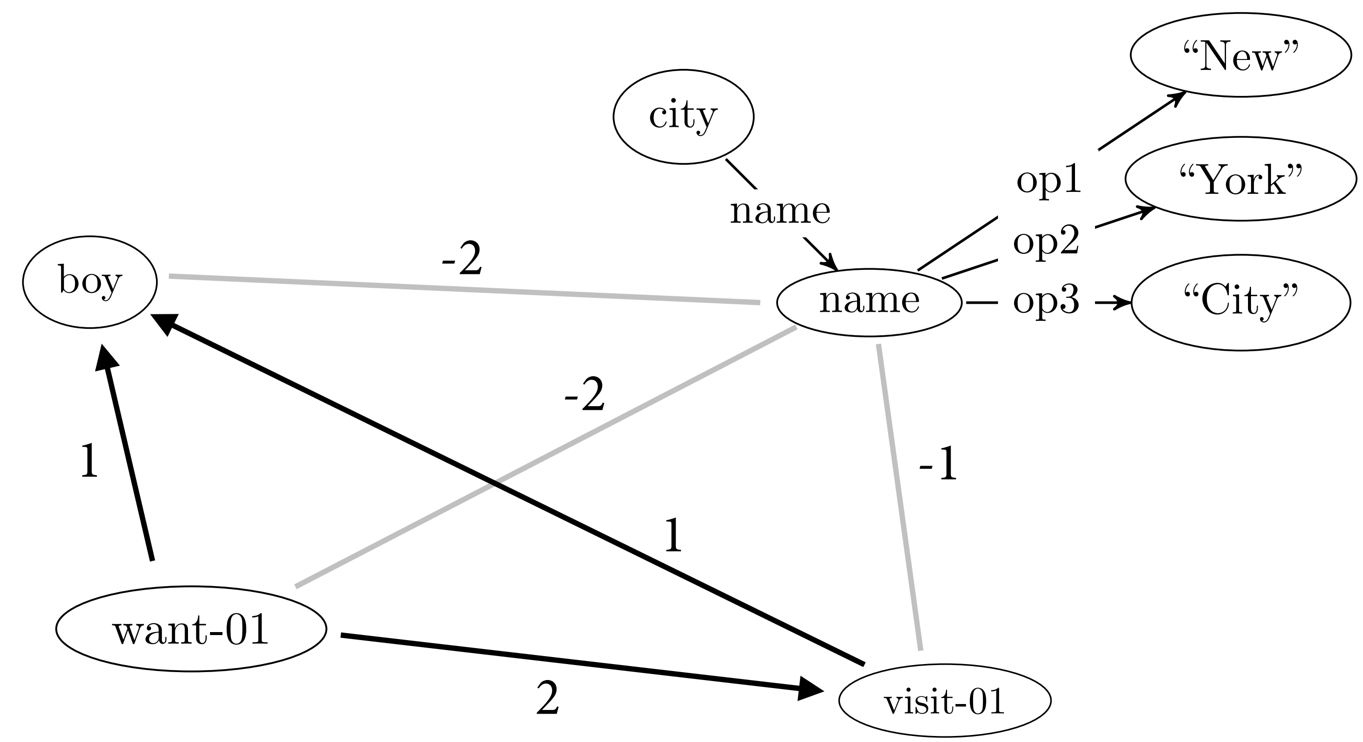

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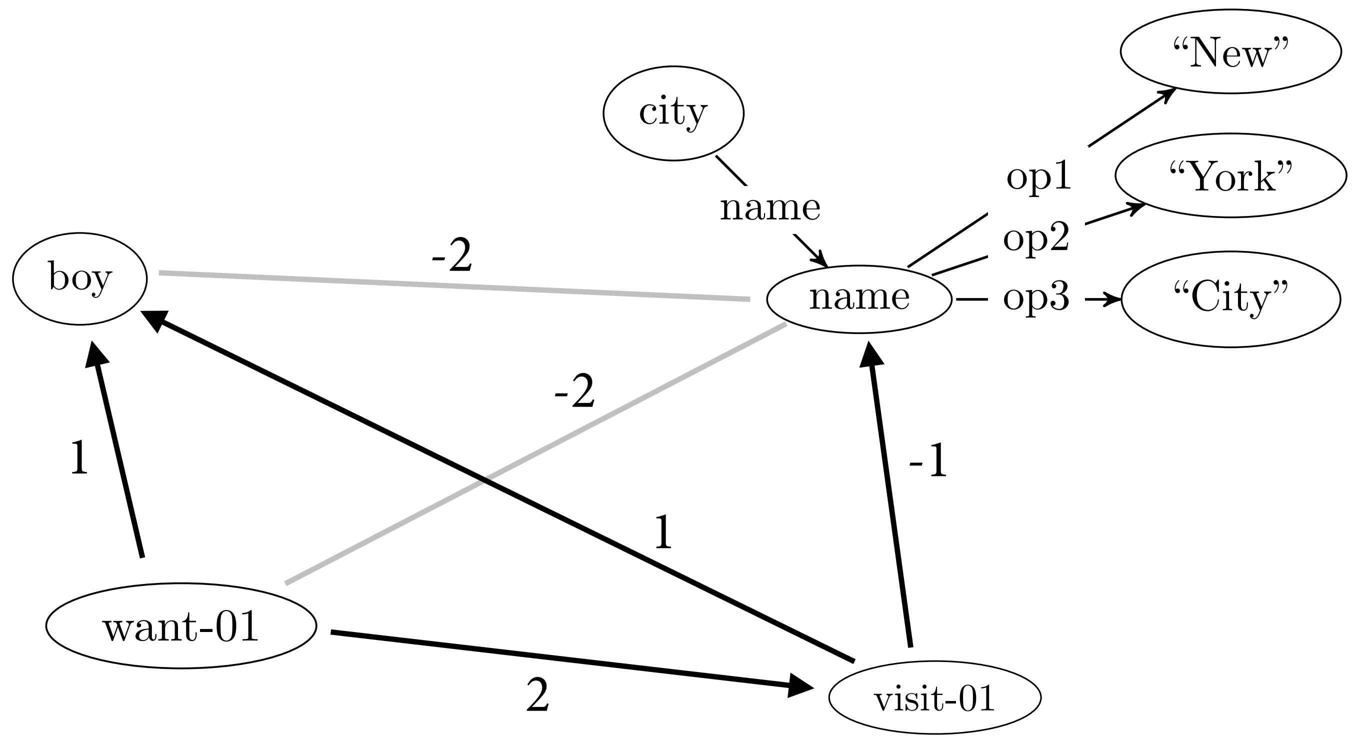

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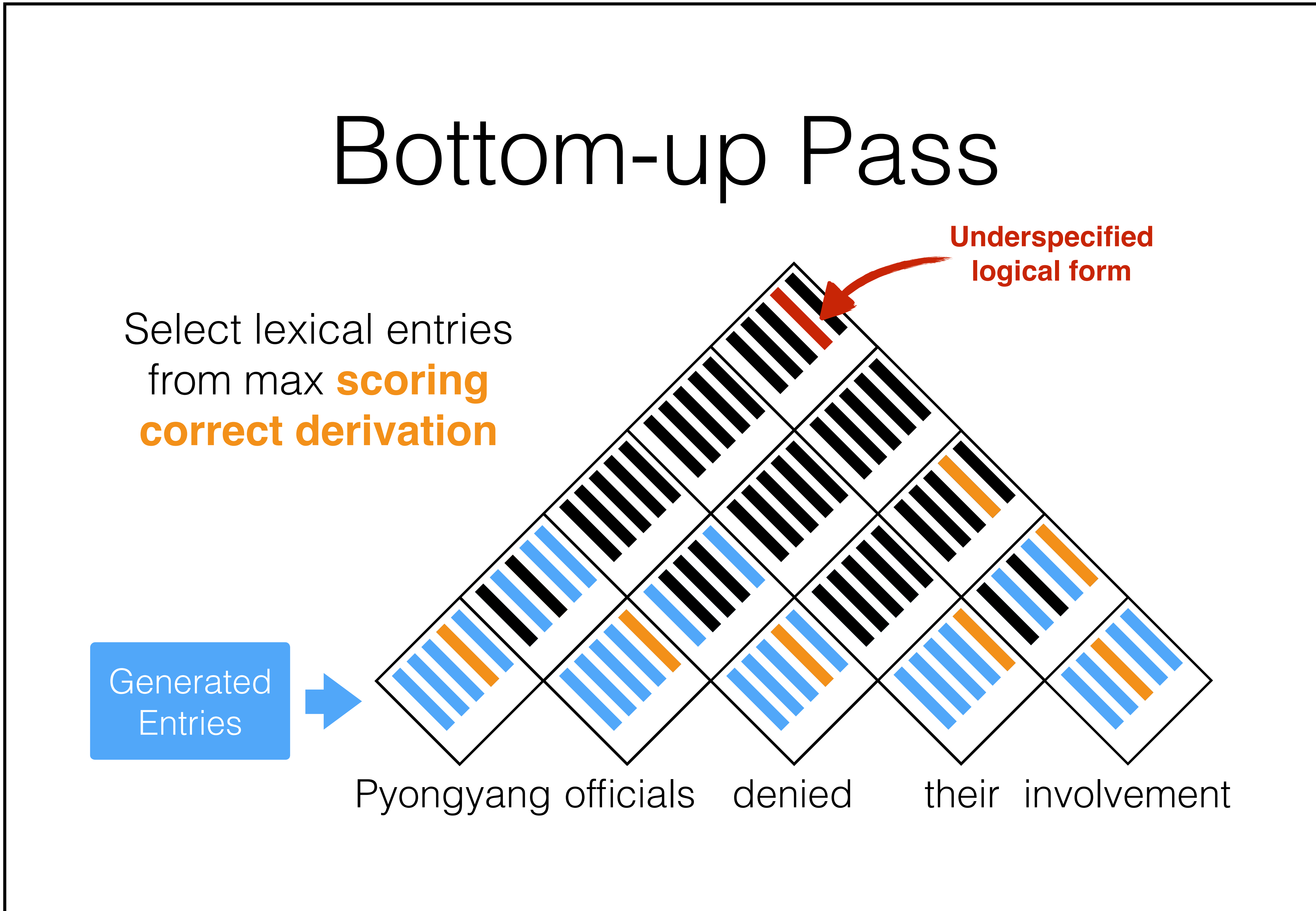


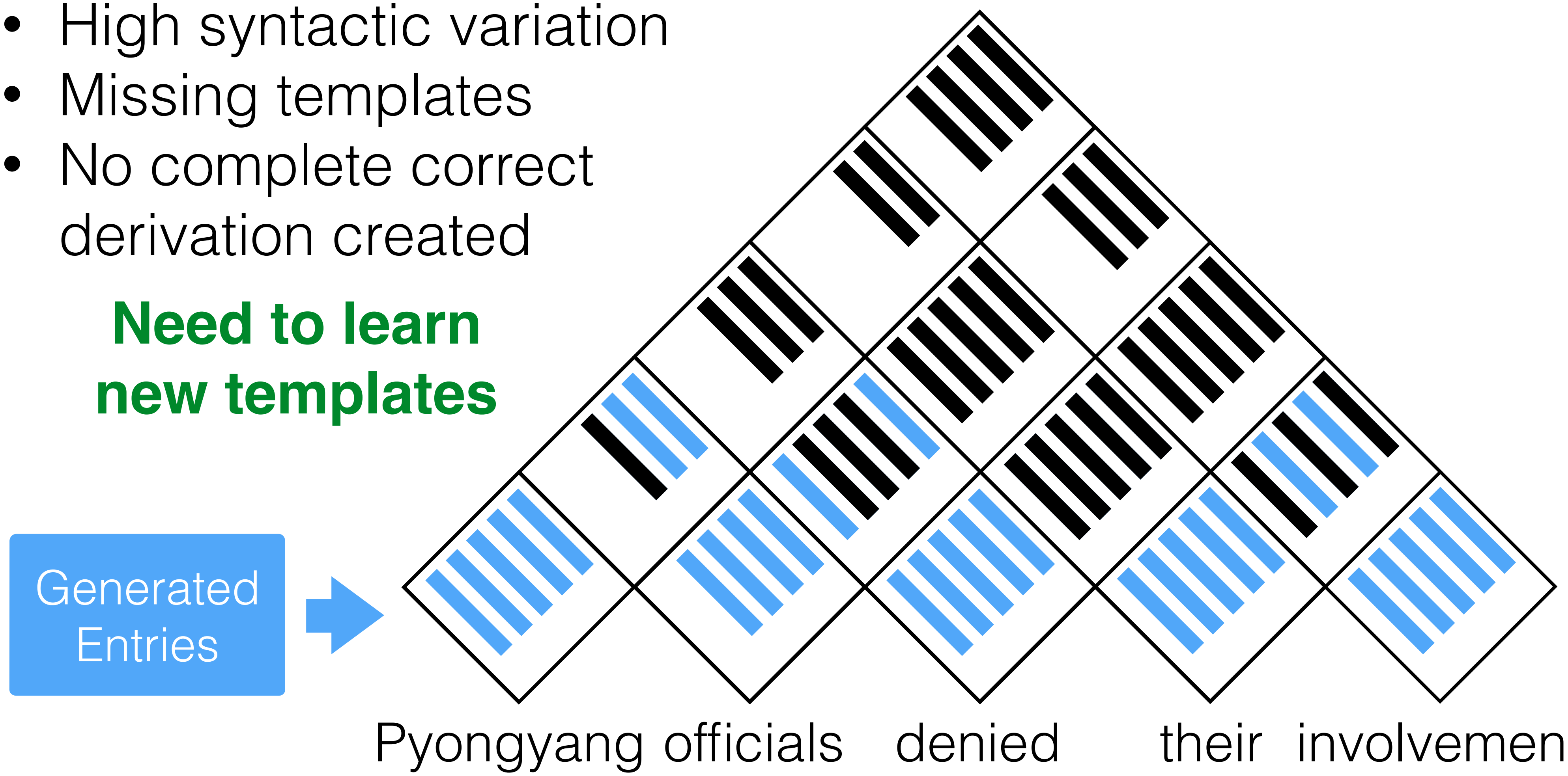
(slide by Yoav Artzi)

CCG-based AMR parsing

Common Failure

- High syntactic variation
- Missing templates
- No complete correct derivation created

Need to learn new templates



(this happens in 40% of training data)

(slide by Yoav Artzi)

CCG-based AMR parsing

Splitting CCG Categories

Given a CCG category $C : h$:

1. Split logical form h to f and g s.t.:

$$f(g) = h \text{ or } \lambda x.f(g(x)) = h$$

2. Infer syntax from logical form type

$$NP_{[nb]} : \lambda i.\text{involve-01}(i) \wedge \text{ARG1}(i, \mathcal{R}(\text{ID}))$$

$$NP_{[x]}/N_{[x]} : \lambda f.\lambda i.f(i) \wedge \text{ARG1}(i, \mathcal{R}(\text{ID}))$$
$$N_{[nb]} : \lambda i.\text{involve-01}(i)$$

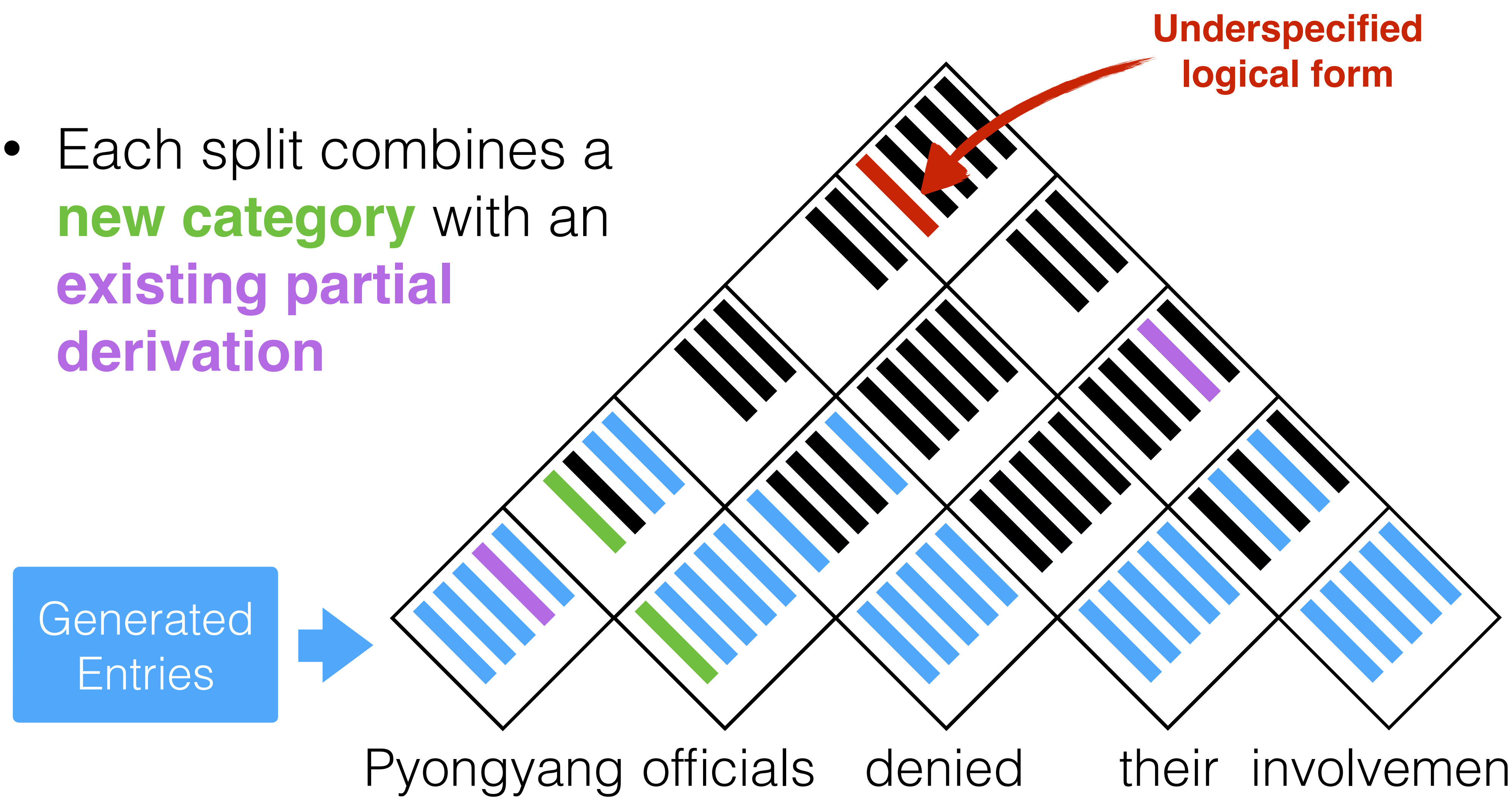
$$NP_{[pl]} : \mathcal{R}(\text{ID})$$
$$NP_{[nb]} \backslash NP : \lambda x.\lambda i.\text{involve-01}(i) \wedge \text{ARG1}(i, x)$$

(slide by Yoav Artzi)

CCG-based AMR parsing

Top-down Pass

- Each split combines a **new category** with an **existing partial derivation**



(slide by Yoav Artzi)

Results

	P	R	F1
JAMR (fixed)	67.8	59.2	63.2
Our approach	66.8	65.7	66.3
Pre-release corpus results			
JAMR (Flanigan et al., 2014)	52.0	66.0	58.0
JAMR (fixed)	66.8	58.3	62.3
Wang et al. (2015)	64.0	62.0	63.0

Table 1: Test SMATCH results.

(Artzi et al. 2015)

Conclusion

- Challenge in compositional semantic construction: Where do we get large-scale grammars?

- Semantic parsing: Learn such grammars from corpora with semantic annotations.
  - GeoQuery: small corpus of trees
  - AMRBank: new hotness

- Very active research topic right now.