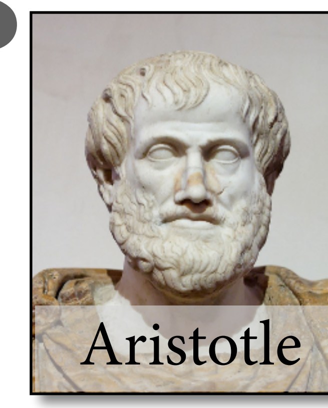
# Semantic parsing

Computational Linguistics

Alexander Koller

25 January 2019

# Computing with meanings




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

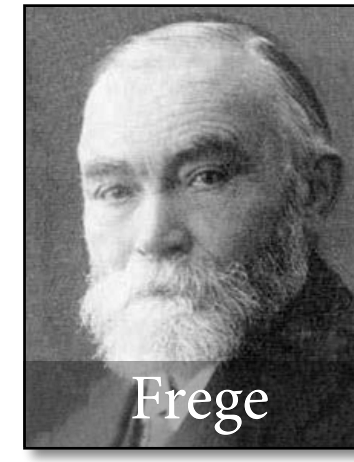
All men are mortal.

Socrates is a man.

---

Therefore, Socrates is mortal.

# Formal meaning representations


Frege

- Aristotle with more modern tools (ca. 2000):
  - 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.

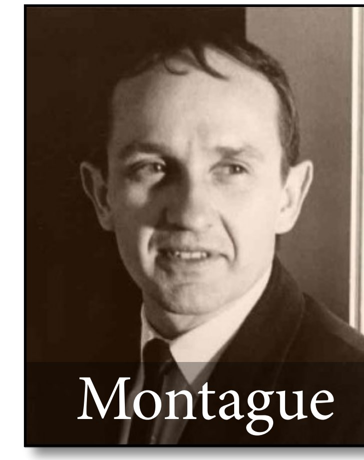
$\forall x.\ \mathrm{man}(x) \rightarrow \mathrm{mortal}(x)$

$\mathrm{man}(s)$

---

$\mathrm{mortal}(s)$

# Compositional semantics


Montague

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

when you apply this syntax rule …

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

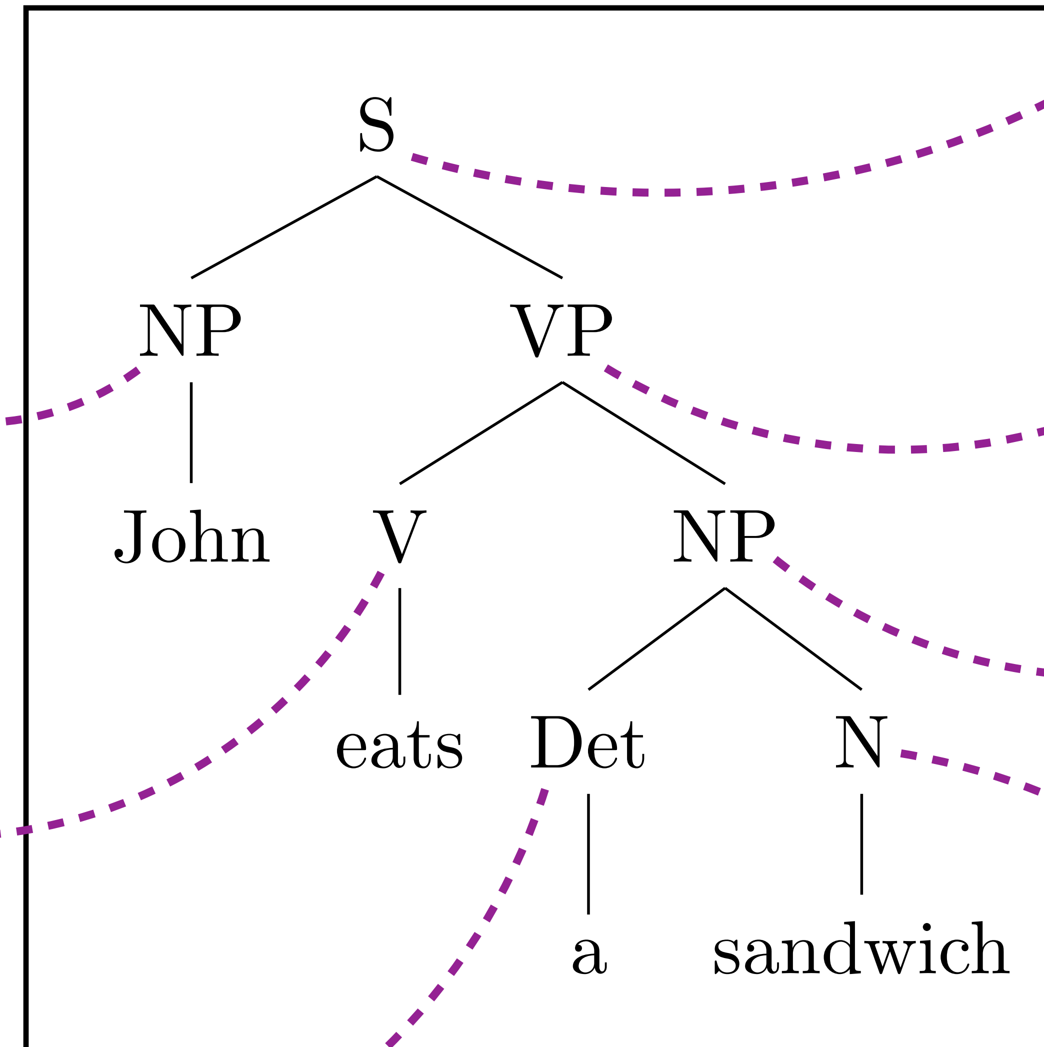
# Example

$(\lambda P\ P(j^*))\ (\lambda y\ \exists x\ sw'(x) \wedge eat'(y)(x))$

$\rightarrow_\beta (\lambda y\ \exists x\ sw'(x) \wedge eat'(y)(x))(j^*)$

$\rightarrow_\beta \exists x\ sw'(x) \wedge eat'(j^*)(x)$

$\lambda P\ P(j^*)$




$\lambda y\ \ (\lambda Q \exists x\ sw'(x) \wedge Q(x))(eat'(y))$

$\rightarrow_\beta \lambda y\ \exists x\ sw'(x) \wedge eat'(y)(x)$

$(\lambda P \lambda Q \exists x\ P(x) \wedge Q(x))(sw')$

$\rightarrow_\beta \lambda Q \exists x\ sw'(x) \wedge Q(x)$

$eat'$

$sw'$

$\lambda P \lambda Q \exists x\ P(x) \wedge Q(x)$

# Semantic parsing

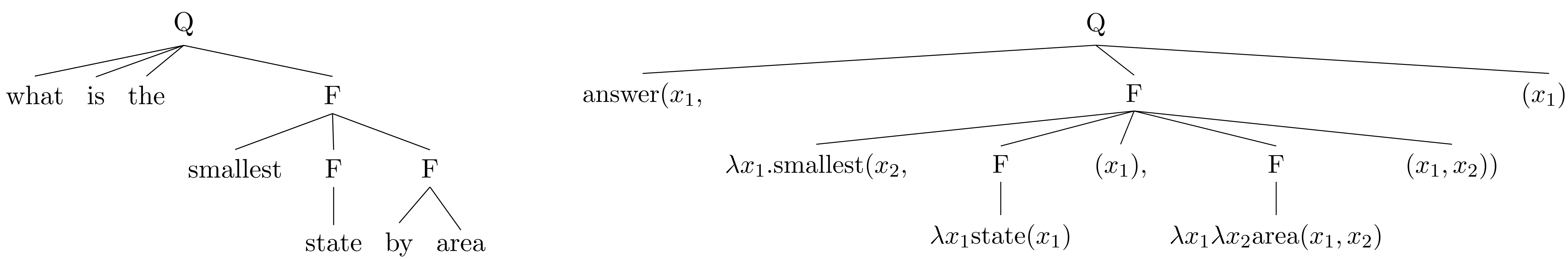
- Open issue in classical semantics construction: Where do we get large grammar that supports it?
- Current trend in CL is *semantic parsing*: learn mapping from sentence to formal meaning representation using statistical methods.
- E.g. from Geoquery corpus (880 sentences):

> What is the smallest state by area?
>
> answer($x_1$, smallest($x_2$, state($x_1$), area($x_1$, $x_2$)))

# With synchronous grammars

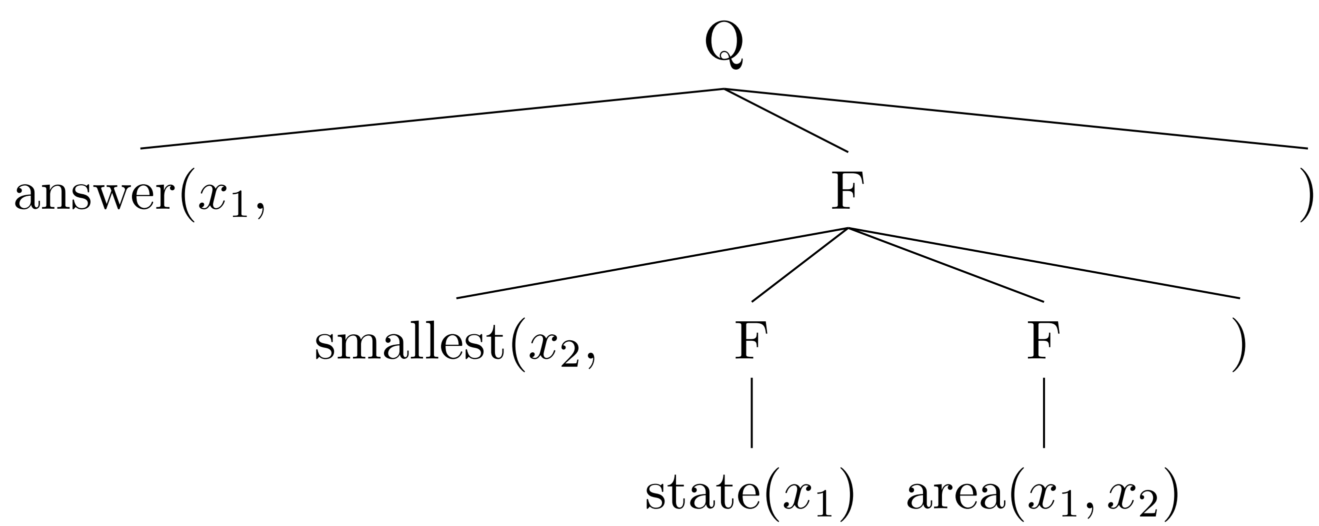
- Use a synchronous grammar (≈ SCFG) to simultaneously generate strings and λ-expressions.

| | |
|---|---|
| Q → what is the F | Q → answer($x_1$, F($x_1$)) |
| F → smallest F F | F → λ$x_1$ smallest($x_2$, F($x_1$), F($x_1$, $x_2$)) |
| F → state | F → λ$x_1$ state($x_1$) |
| F → by area | F → λ$x_1$ λ$x_2$ area($x_1$, $x_2$) |



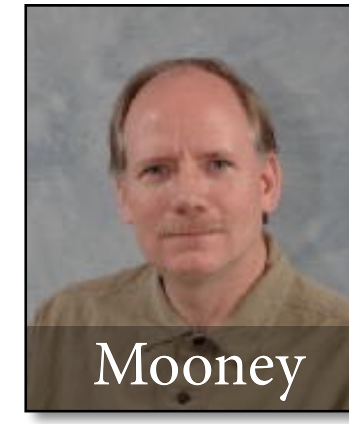
# Wong & Mooney

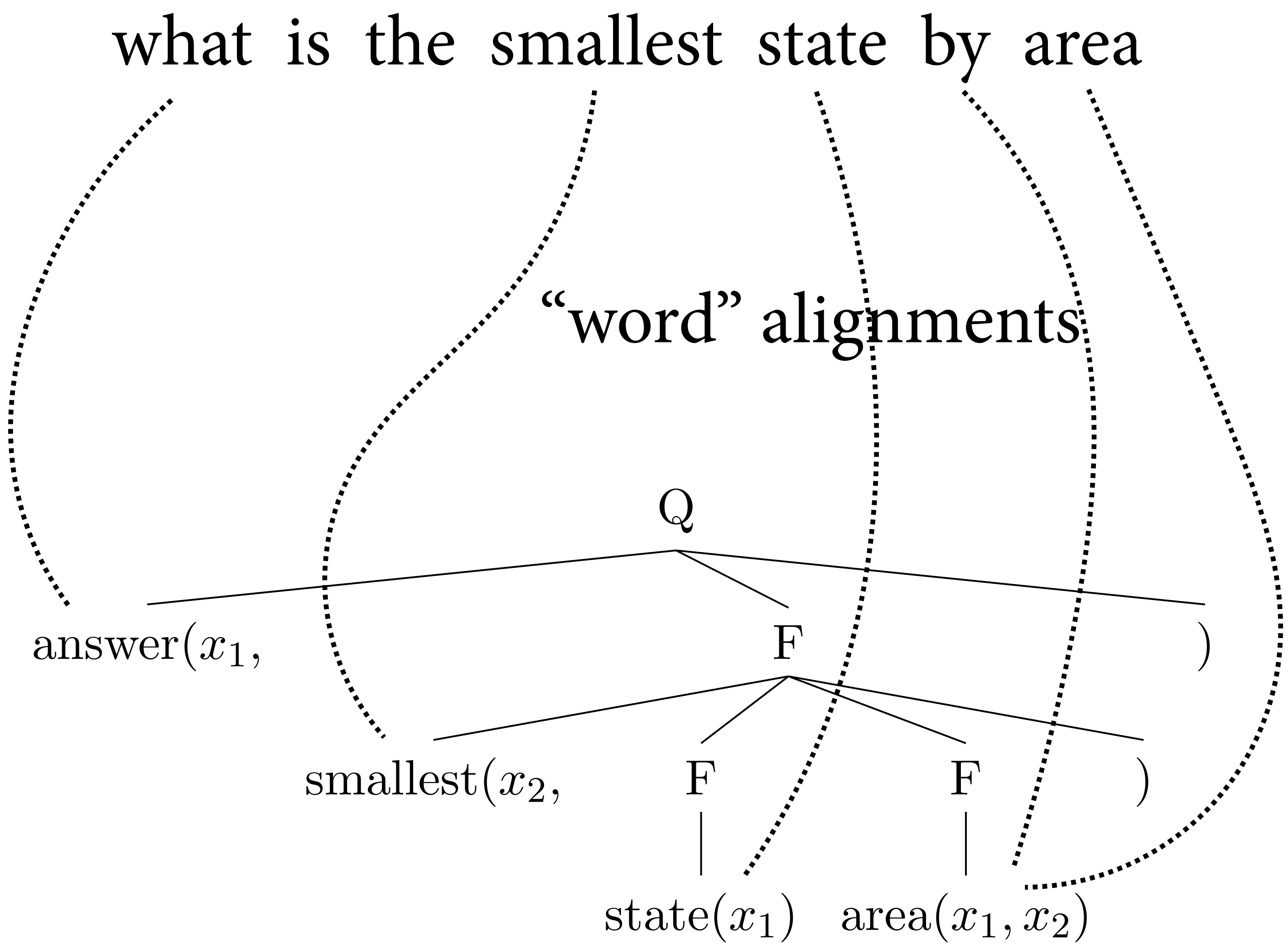

what is the smallest state by area




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

# Wong & Mooney

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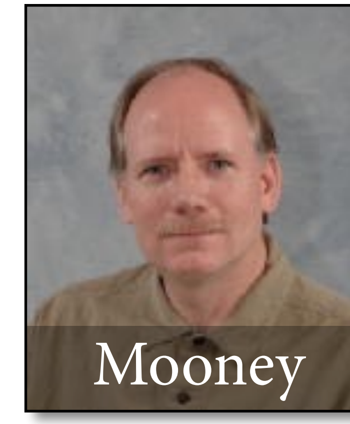


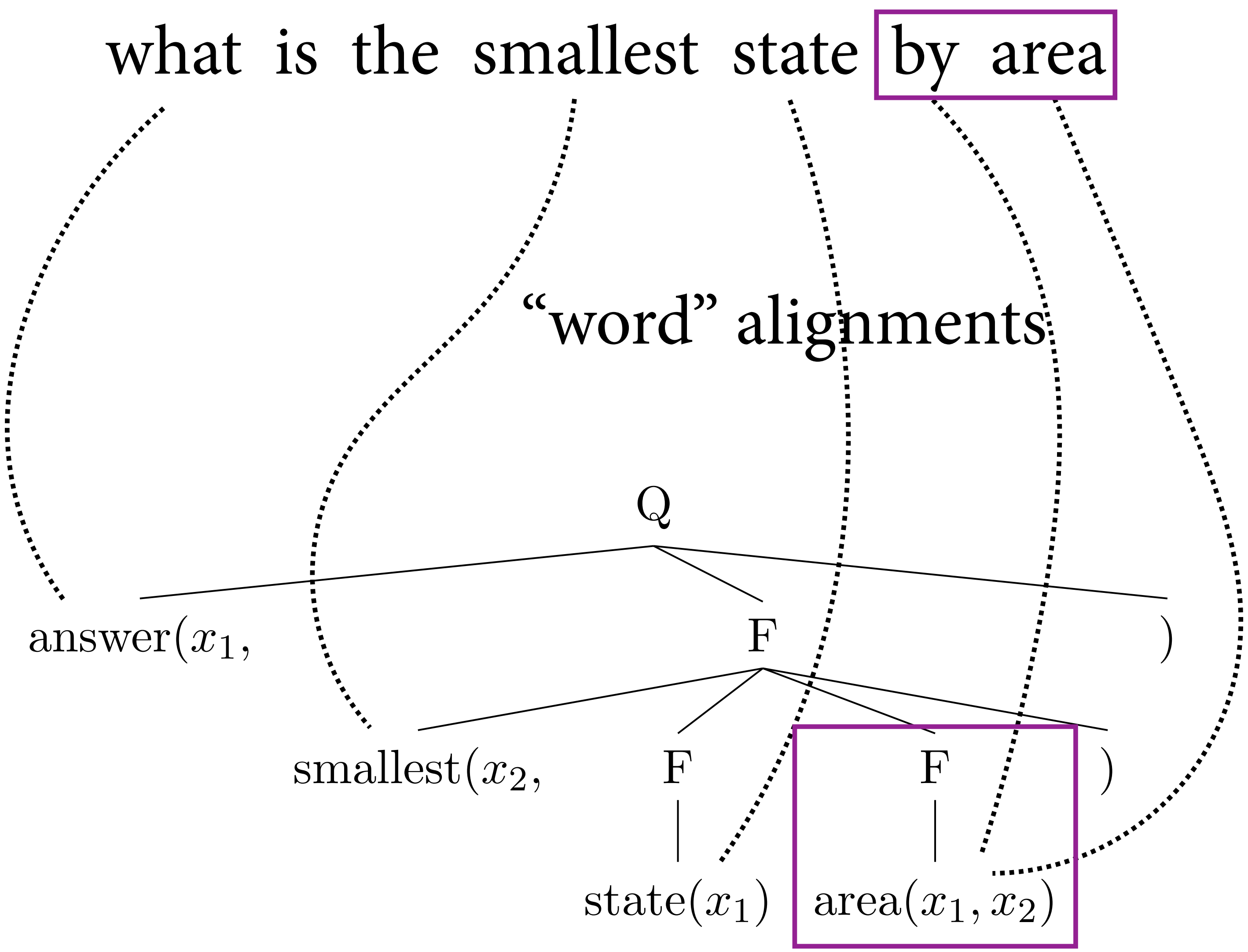


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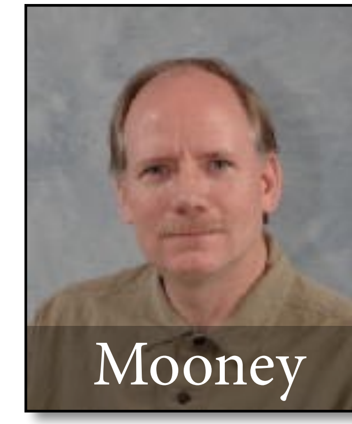


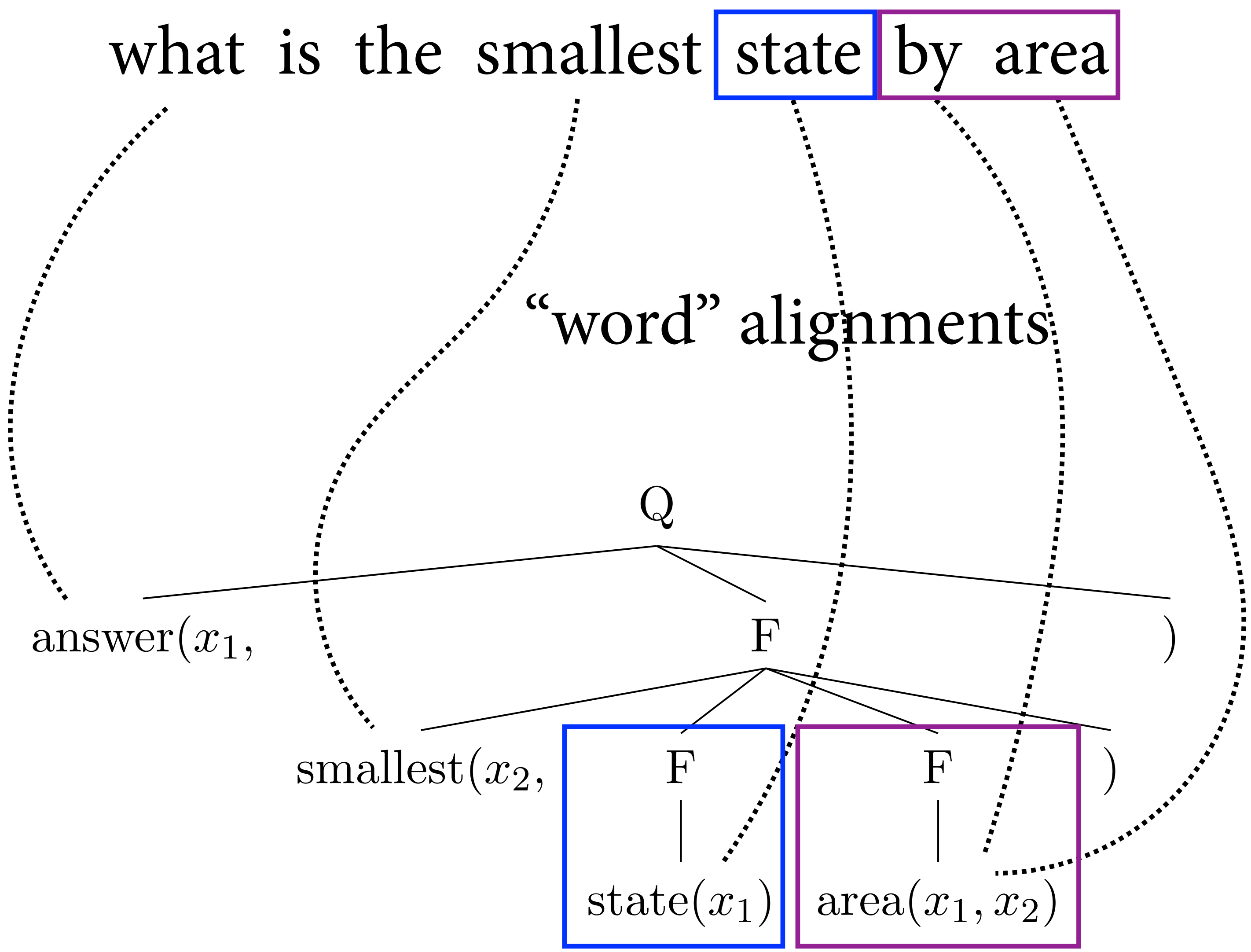


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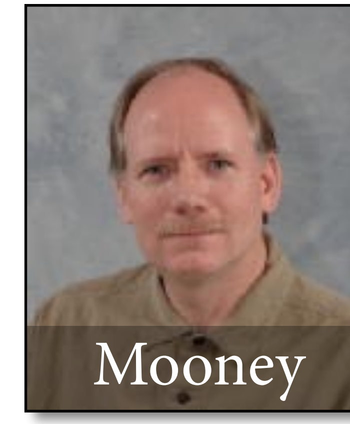


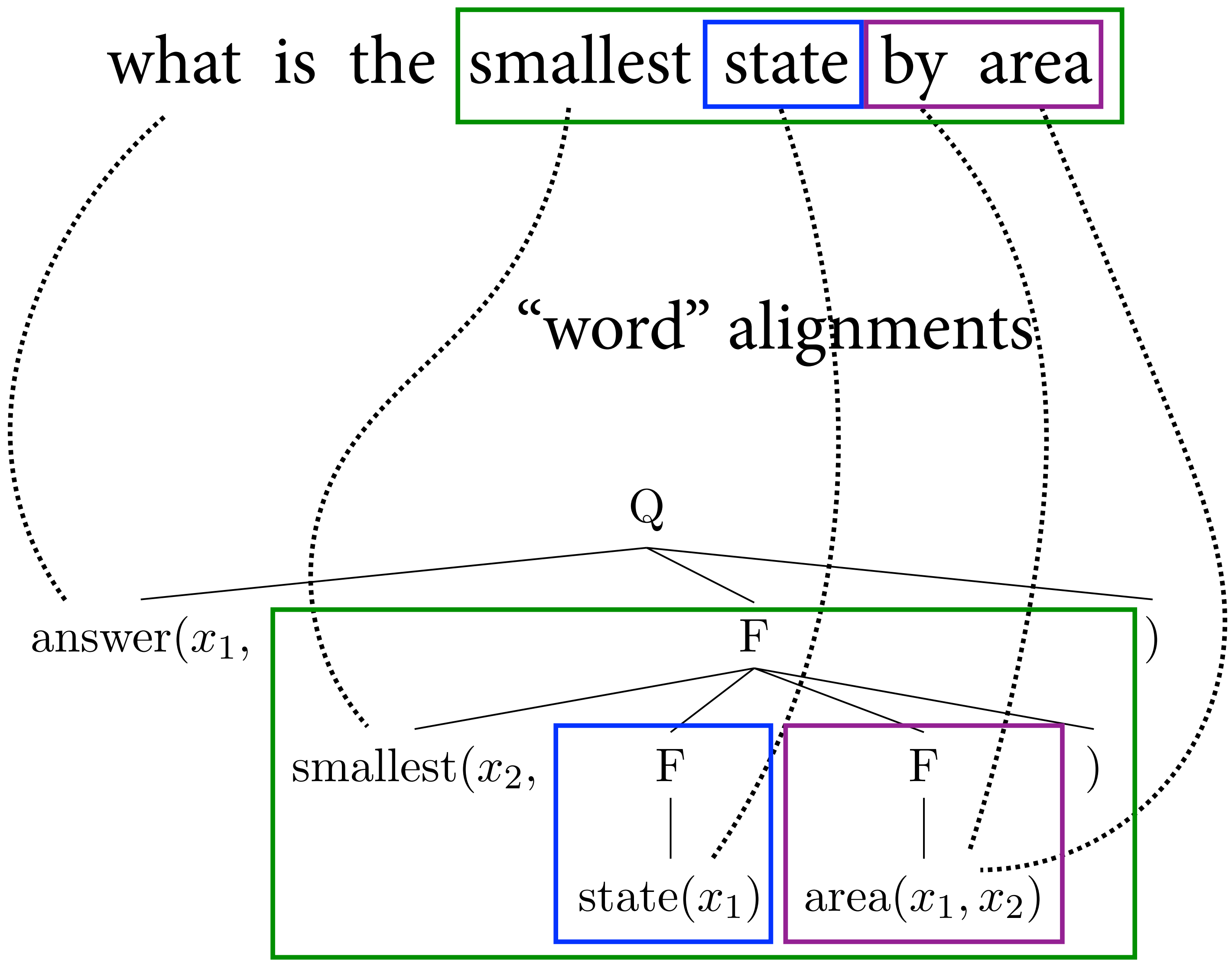


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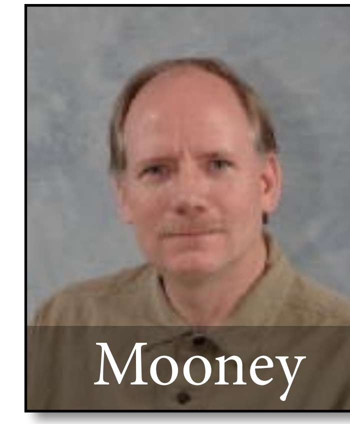


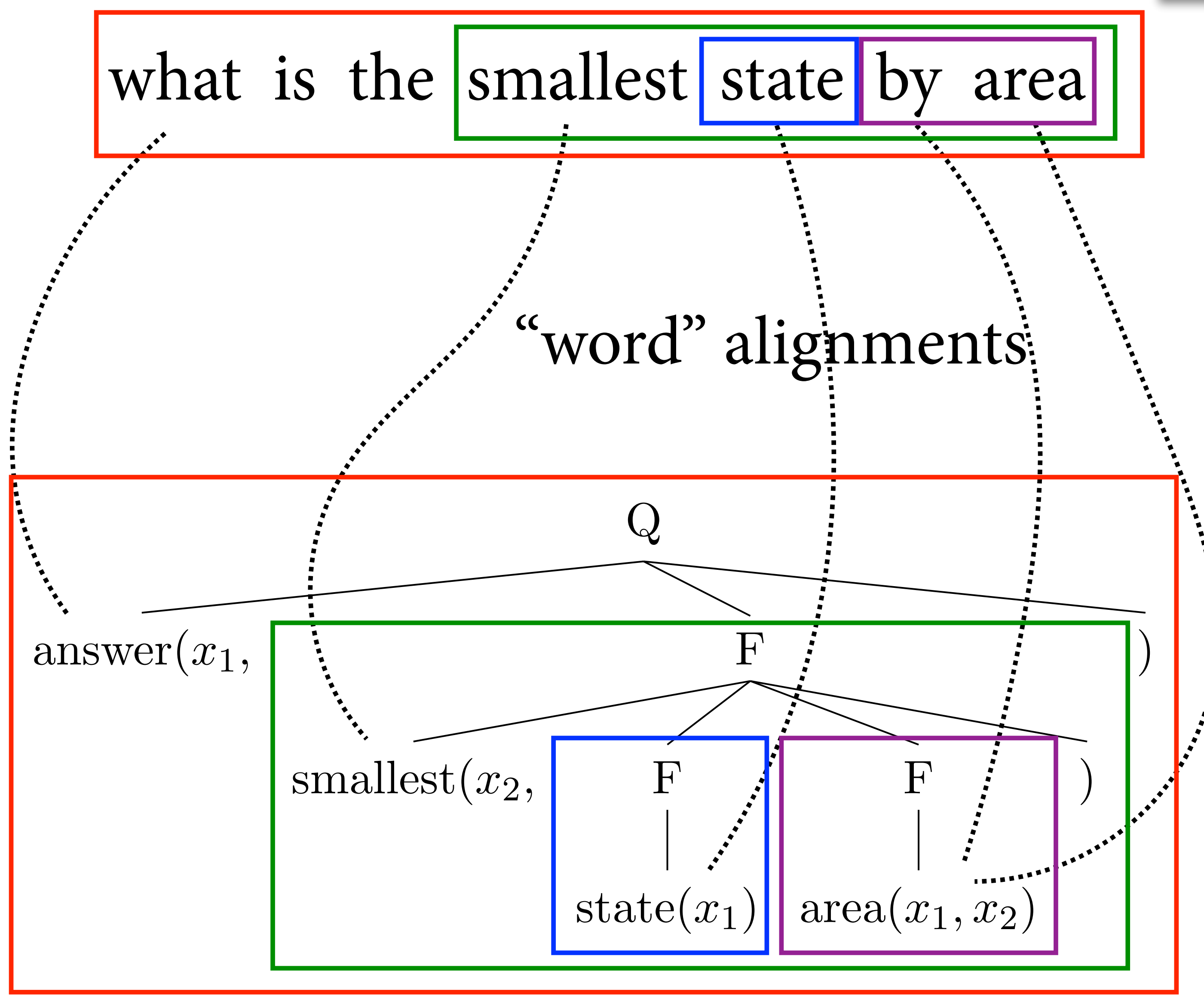


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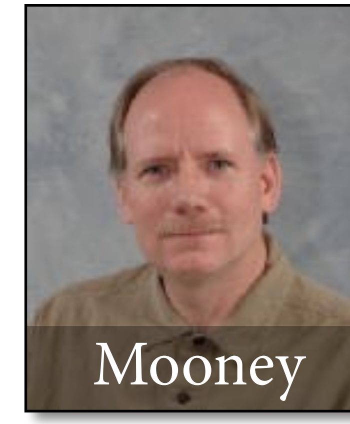
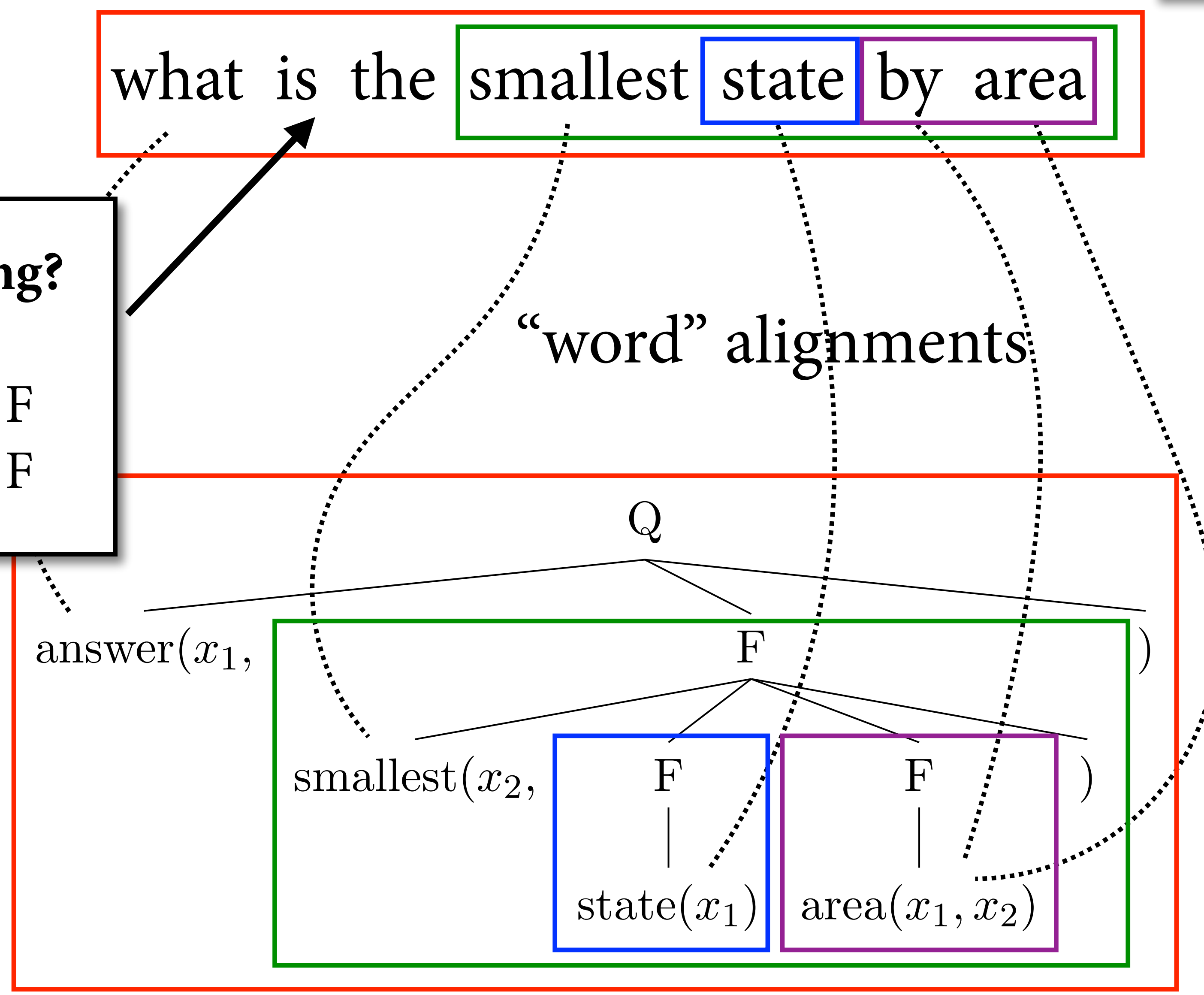



**Where do unaligned words belong?**

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




Assumptions:
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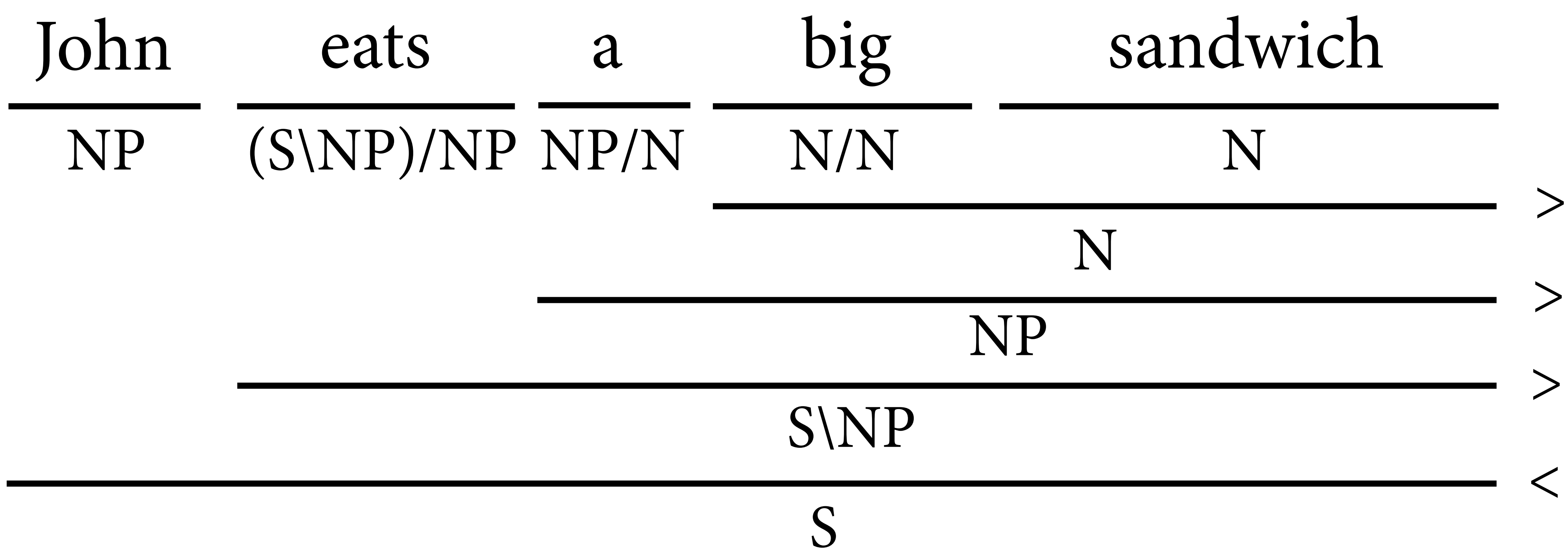
# Combinatory categorial grammar



# Semantics in CCG

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

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

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

# 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 $f$ | $S/NP : \lambda x.f(x)$ | $S/NP : \lambda x.size(x)$ |

# 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.

# 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 $\lambda_i$ to be the set of lexical entries in $\pi$.
- 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

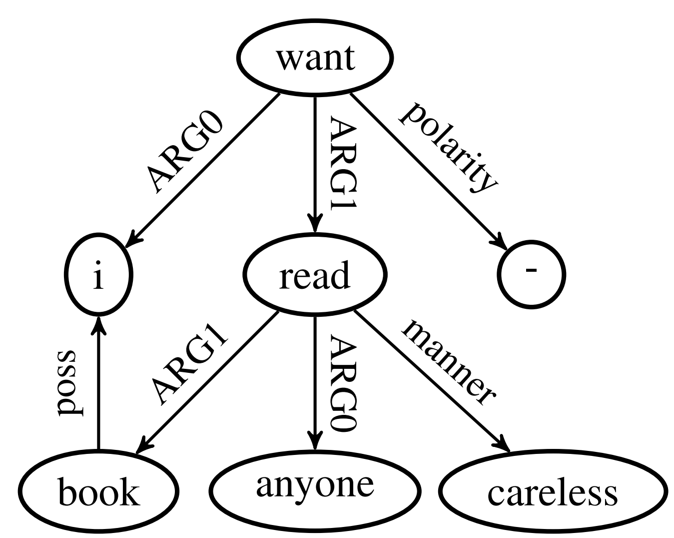
| System | Variable Free | | | Lambda Calculus | | |
|---|---|---|---|---|---|---|
| | Rec. | Pre. | F1 | Rec. | Pre. | F1 |
| Cross Validation Results | | | | | | |
| KRISP | 71.7 | **93.3** | 81.1 | – | – | – |
| WASP | 74.8 | 87.2 | 80.5 | – | – | – |
| Lu08 | 81.5 | 89.3 | **85.2** | – | – | – |
| $\lambda$-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

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“The boy wants to visit New York City.”

Concept Identification: determine atomic graph for each word.

JAMR; Flanigan et al. 2014

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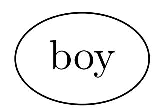


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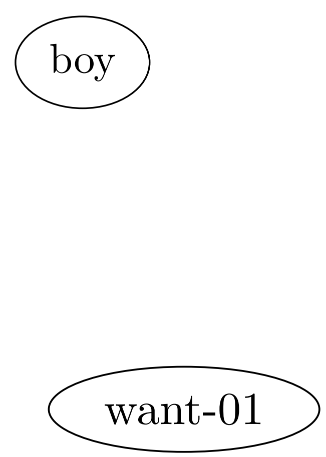


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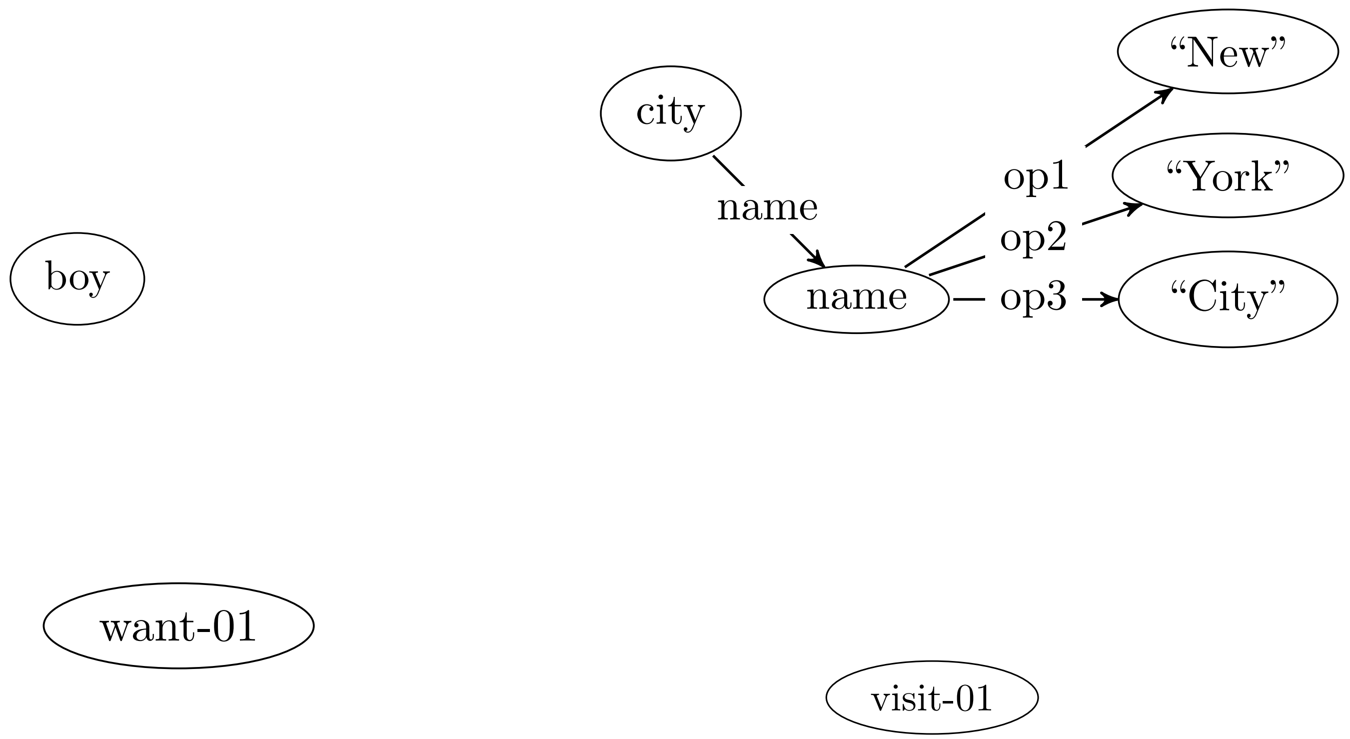


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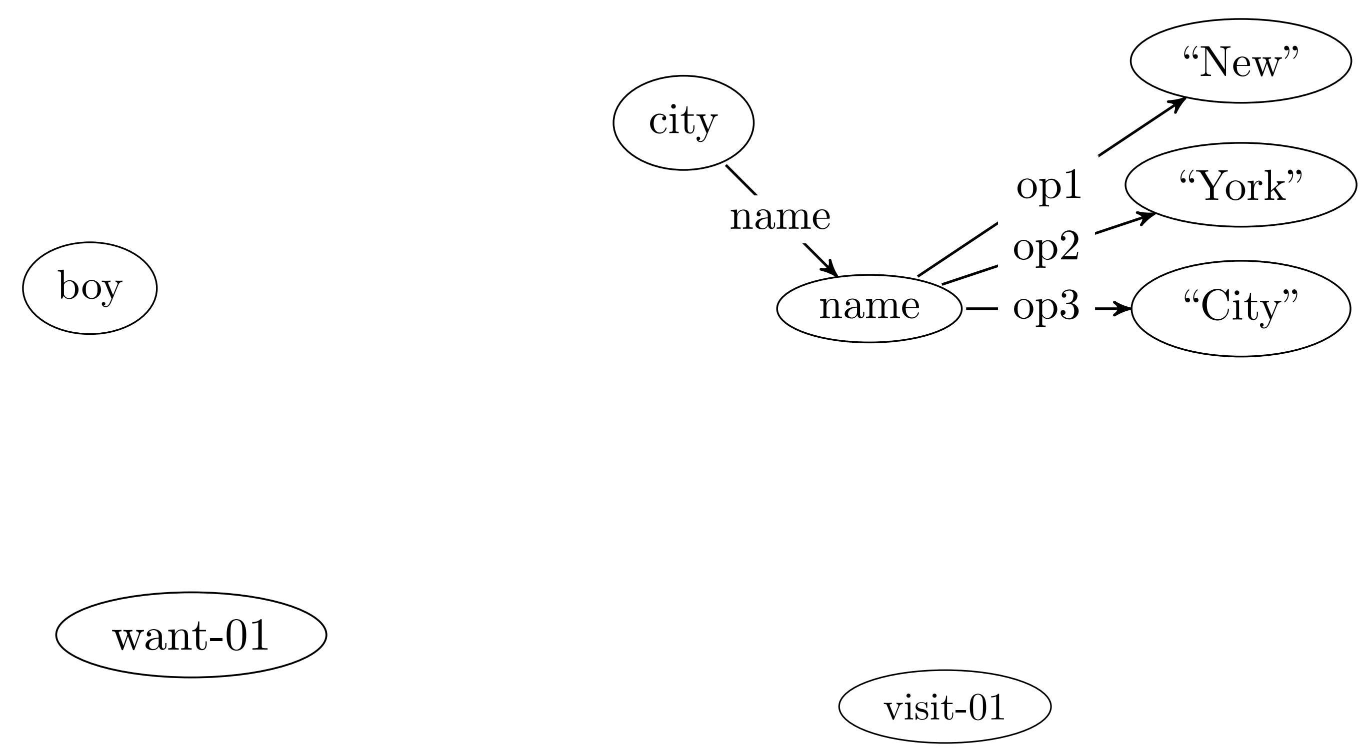


Concept Identification: determine atomic graph for each word.

Relation Identification: add all edges with positive weight; then repeatedly add least negative edge that connects subgraphs.

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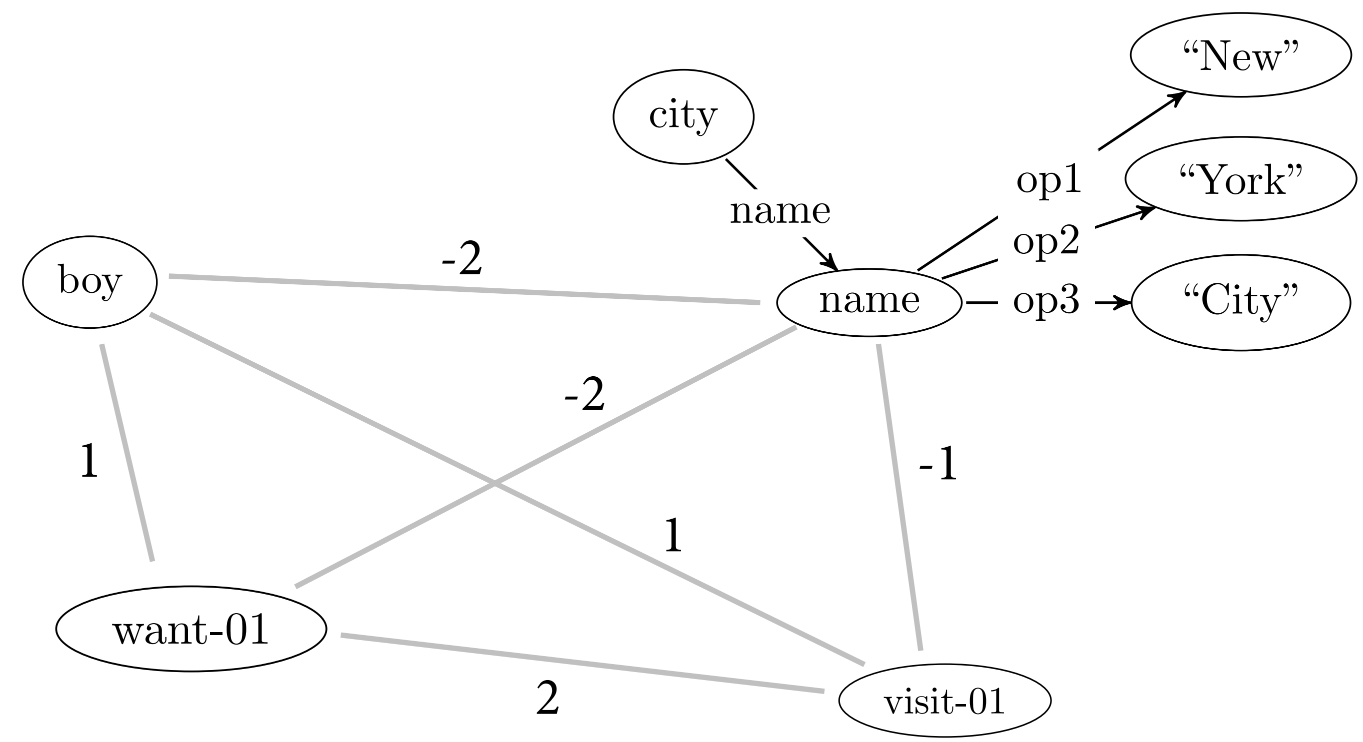


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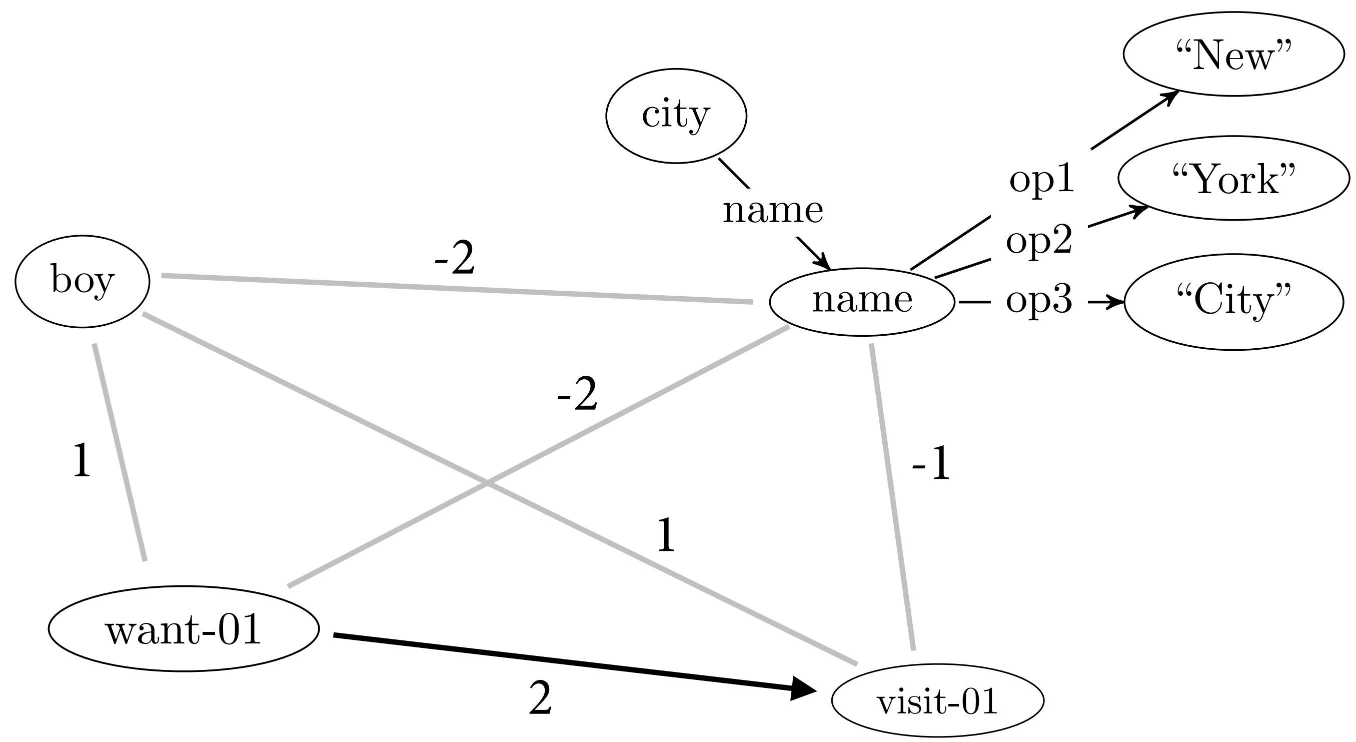


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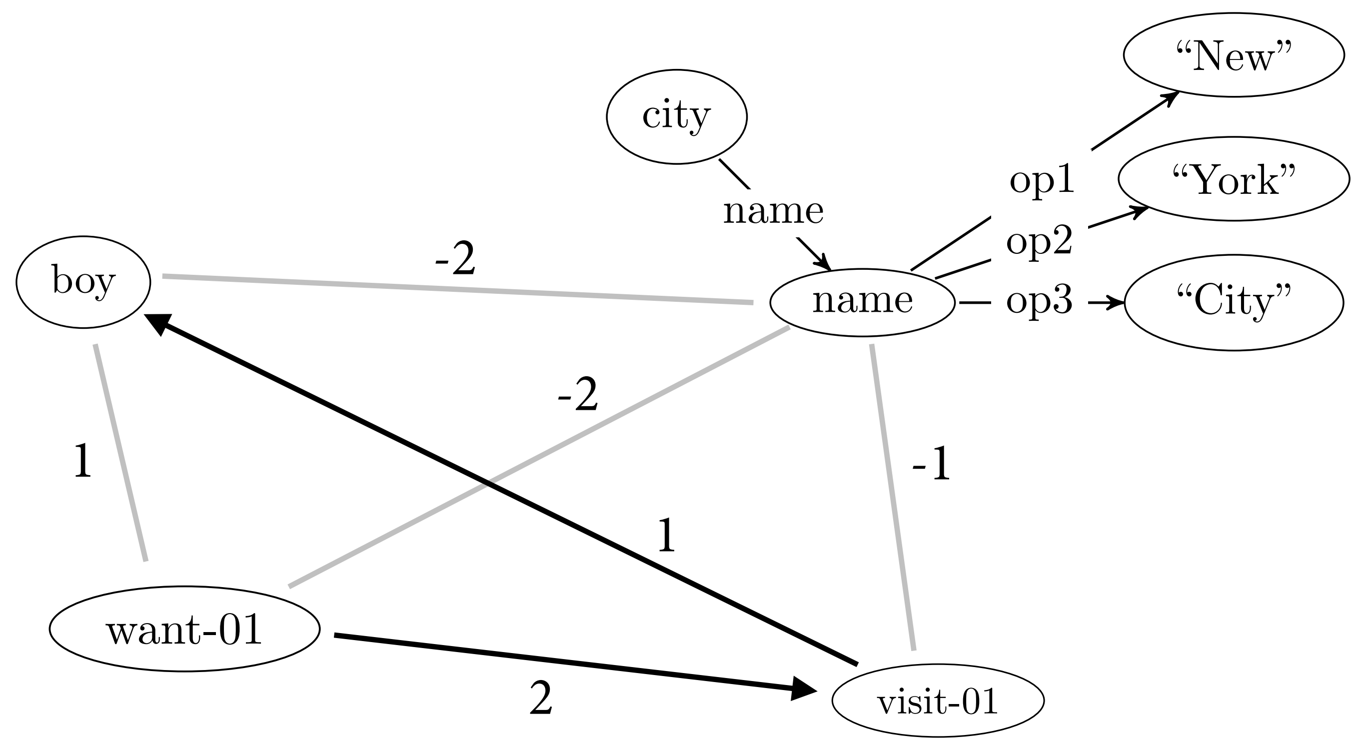


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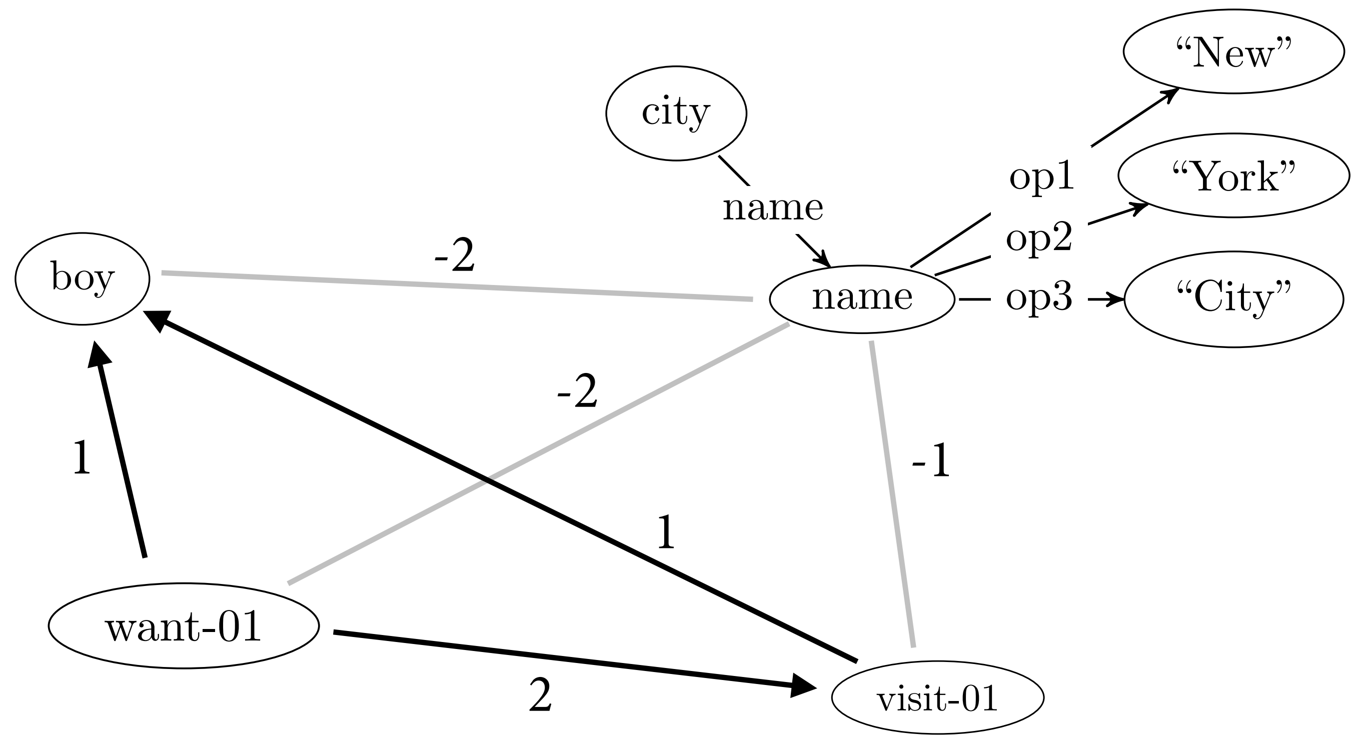


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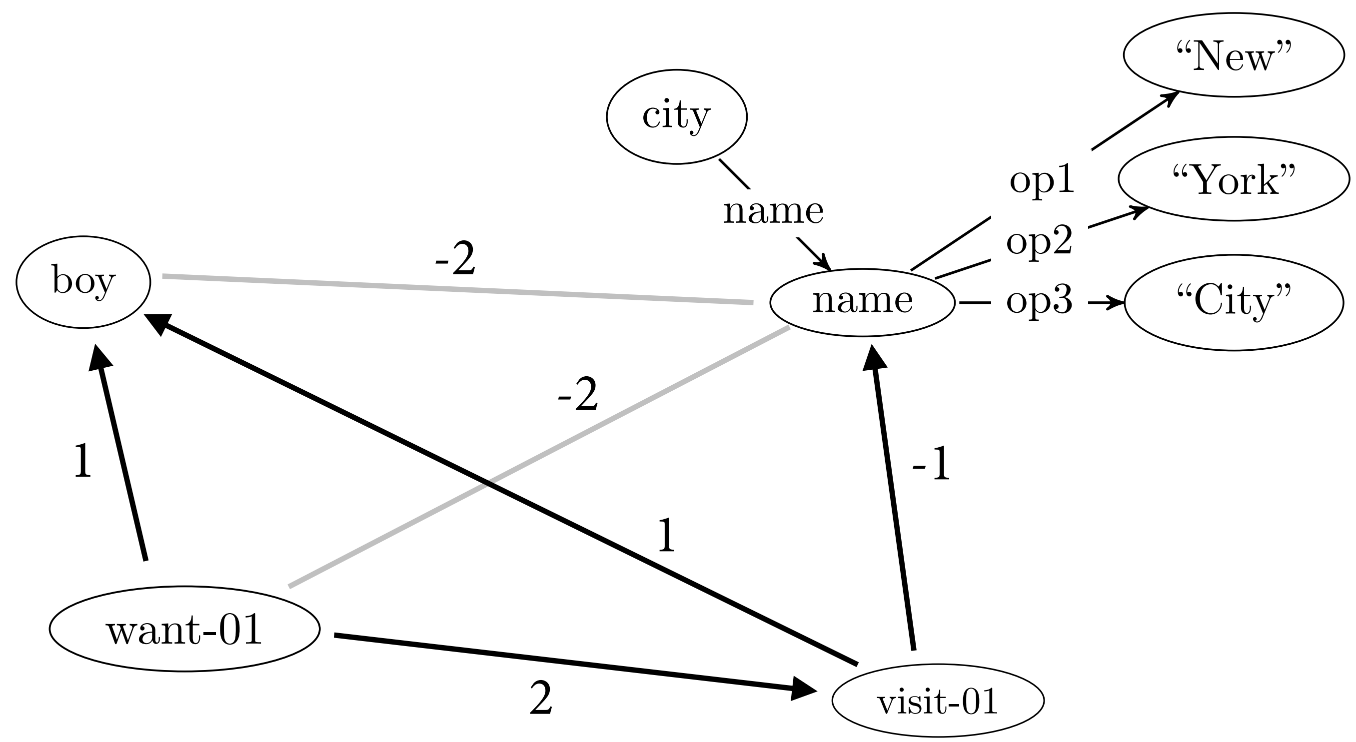


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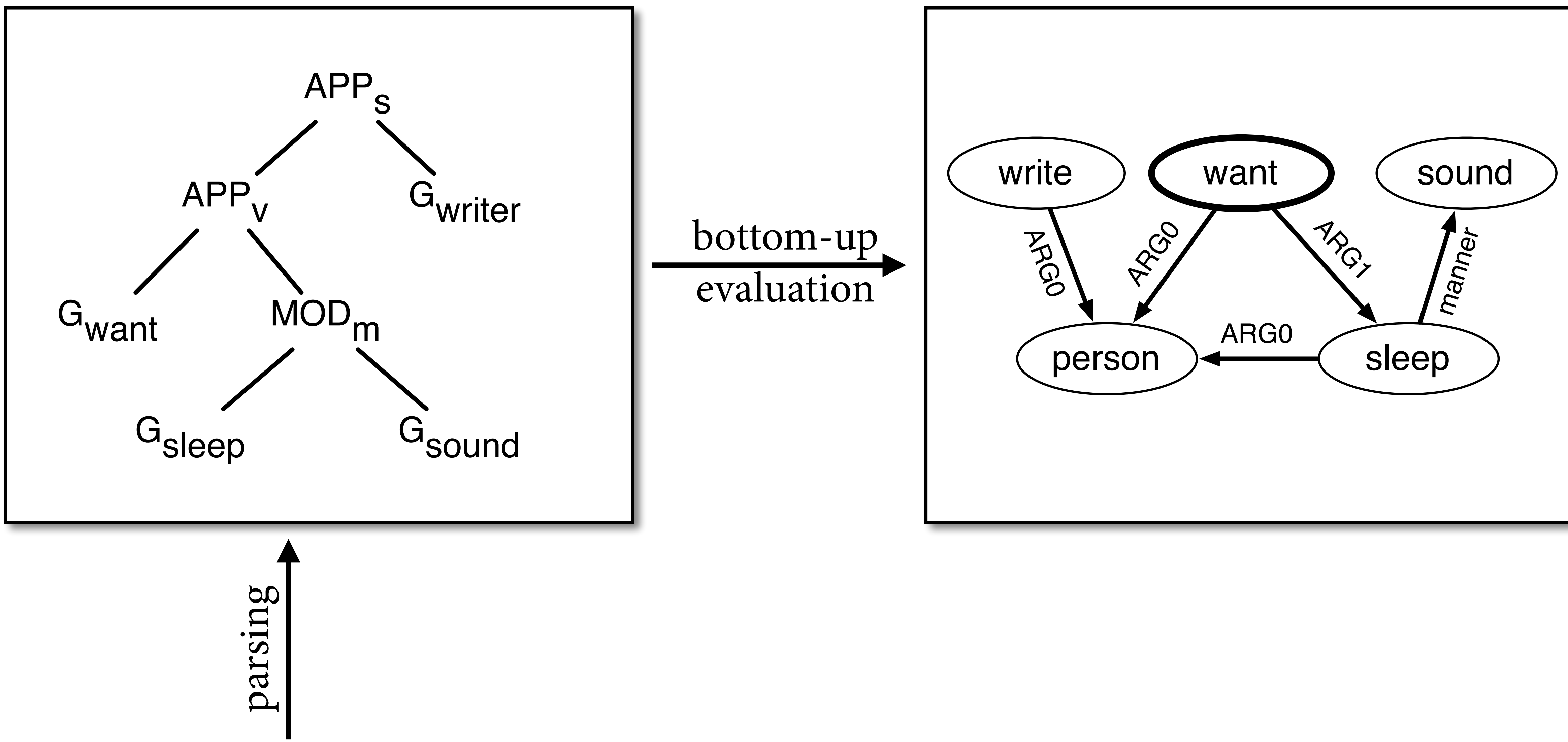
# Issues with JAMR

- JAMR can draw edge between any two nodes; syntactic structure of sentence used only indirectly.
- Semantic representations for words don't know anything about their semantic arguments.
- Edges for control verbs added arbitrarily, not because linguistic principle of control discovered.
- No notion of compositionality!

# Compositional AMR Parsing

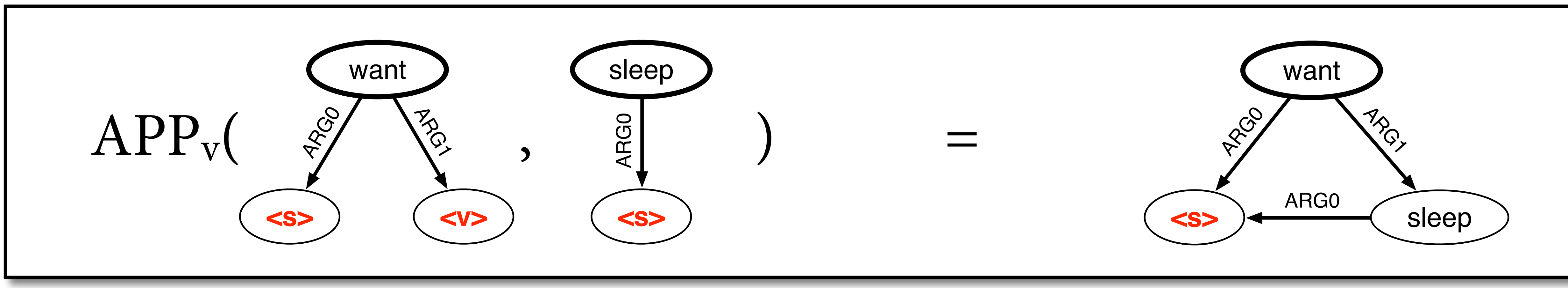


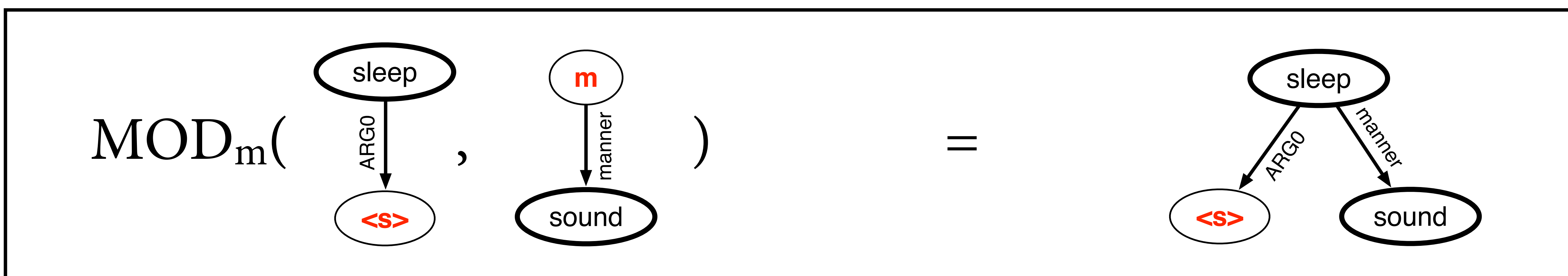

"The writer wants to sleep soundly."

(Groschwitz et al., ACL 2018)

# AM algebra

Two operations for combining s-graphs:
Apply (= head + complement), Modify (= head + modifier).




APP and MOD can be expressed in terms of rename, forget, merge.

(Groschwitz et al., IWCS 2017; inspired by Copestake et al. 2001)

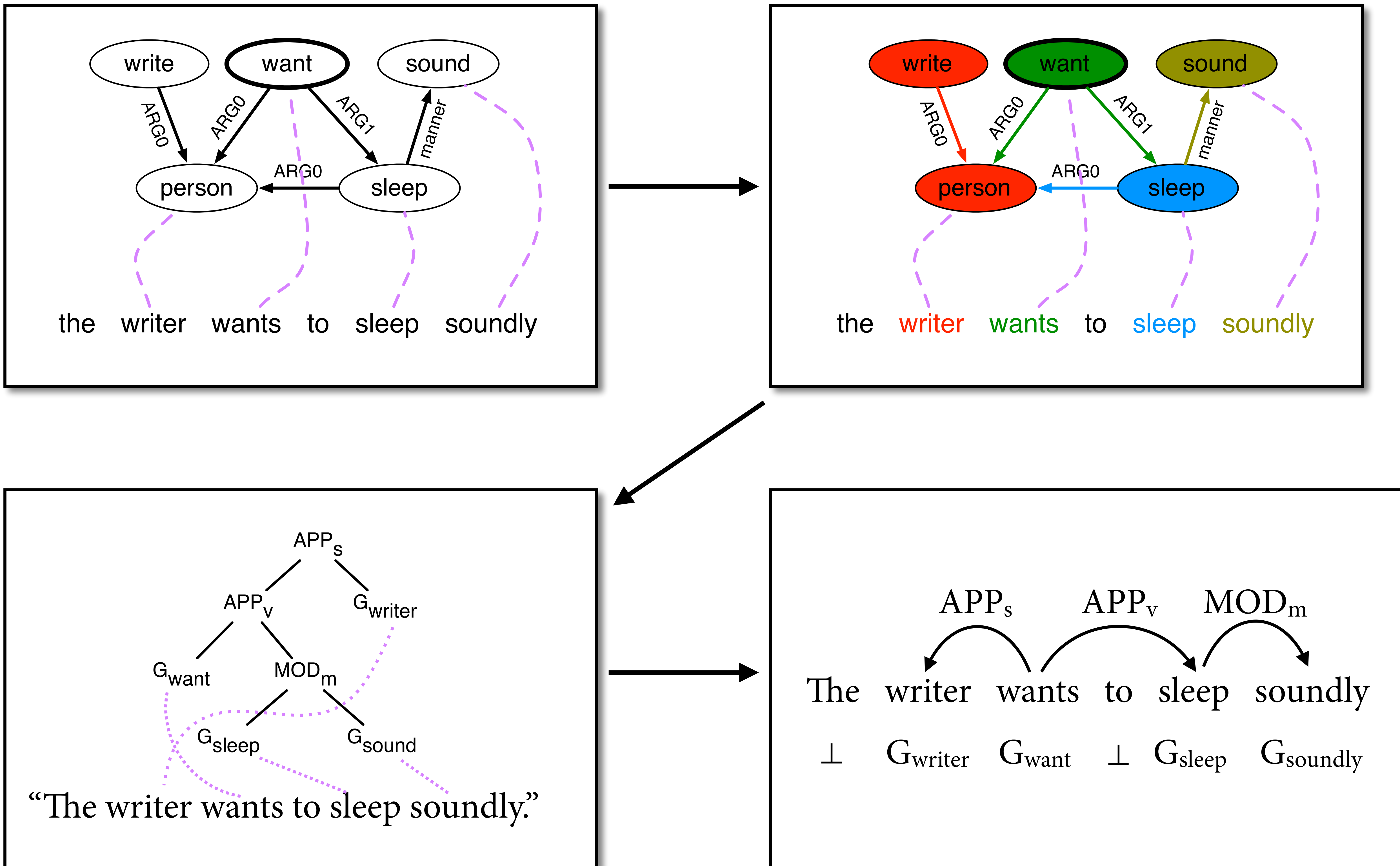
# Approach

- Convert (string, graph) training data into (string, supertags + dependencies) training data.

- Train neural supertagger + dependency parser to assign scores to supertags + dependencies.
  - easier than predicting the whole graph; compositional!

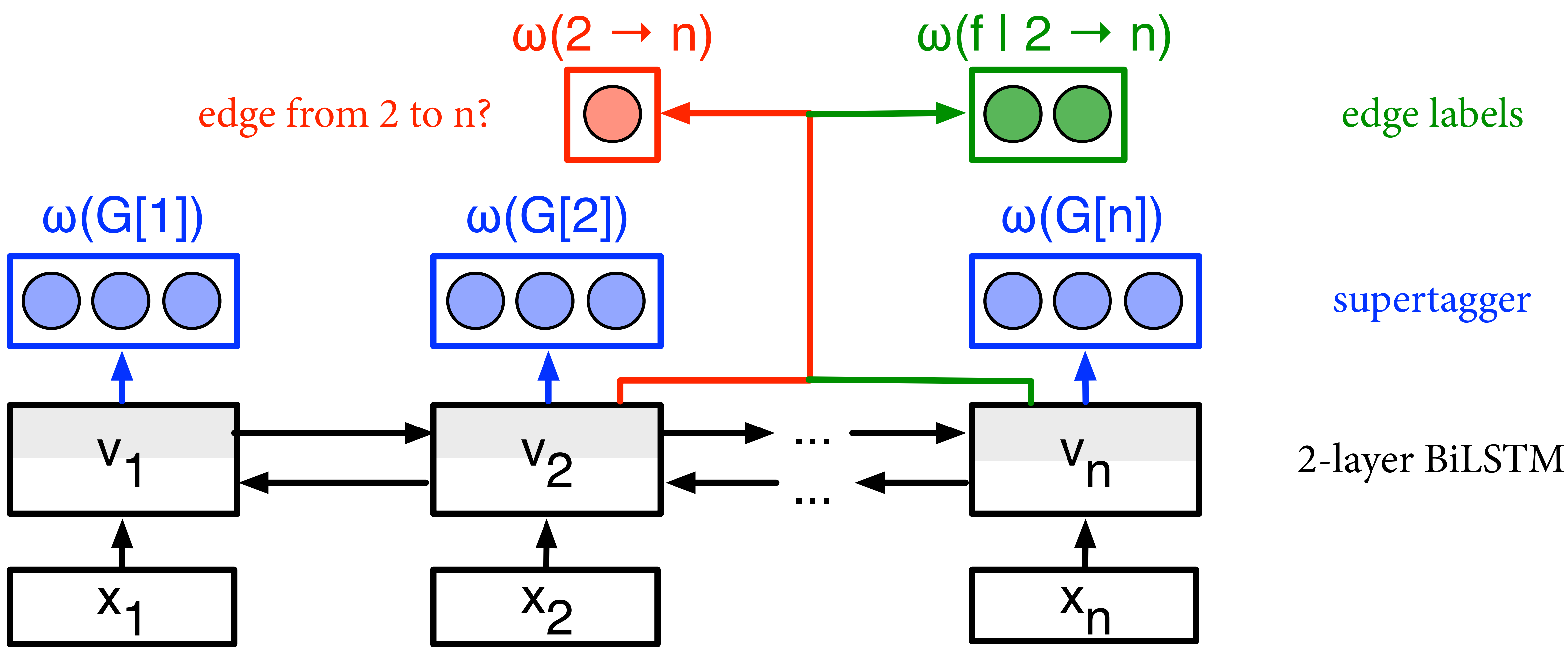
- At evaluation time, compute highest-scoring well-typed dependency tree.
  - well-typedness requirement makes this NP-complete
  - solve approximately with CKY-style parsing algorithm

# Converting training data




(Groschwitz et al., ACL 2018)

# Neural model




$\omega(2 \rightarrow n) = \log P(\text{edge from } 2 \rightarrow n \mid \mathbf{x})$ is *score* for this edge.
Analogously for supertags and edge labels.

(cf. Lewis et al. 2014; Kiperwasser & Goldberg 2016)

# Evaluation

- Train and test on LDC2015E86 and LDC2017T10 AMRBank corpora.
- Baselines (both type-unaware):
  - fixed-tree decoder that chooses best supertags and edge labels while ignoring type requirements
  - JAMR-style: remove all unlabeled nodes from elementary s-graphs, then use dependency model to predict edges

# Results

| Model | 2015 | 2017 |
|---|---|---|
| Ours | | |
| local edge + projective decoder | 70.2±0.3 | **71.0**±0.5 |
| local edge + fixed-tree decoder | 69.4±0.6 | 70.2±0.5 |
| K&G edge + projective decoder | 68.6±0.7 | 69.4±0.4 |
| K&G edge + fixed-tree decoder | 69.6±0.4 | 69.9±0.2 |
| Baselines | | |
| fixed-tree (type-unaware) | 26.0±0.6 | 27.9±0.6 |
| JAMR-style | 66.1 | 66.2 |
| Previous work | | |
| CAMR (Wang et al., 2015) | 66.5 | - |
| JAMR (Flanigan et al., 2016) | 67 | - |
| Damonte et al. (2017) | 64 | - |
| van Noord and Bos (2017b)* | 68.5 | **71.0** |
| Foland and Martin (2017) | **70.7** | - |
| Buys and Blunsom (2017) | - | 61.9 |

*) uses 100k additional sentences of silver data

# 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.