Part II:
Algorithms and Applications

Speaker: Jeffrey Flanigan

Intro

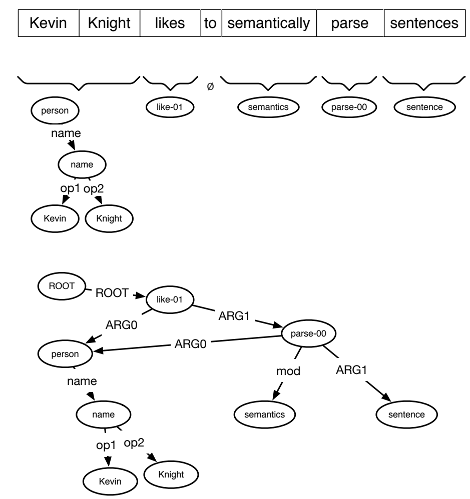
- You know how to annotate AMRs
- Now, we want to use them!
- To use AMRs, we need automatic **parsers**
- But first: **alignment**
- **Evaluation** (inter-annotator agreement, parser output)
- And also:
  - **Graph grammars** (like CFGs, but for graphs)
  - **Applications**

Alignment

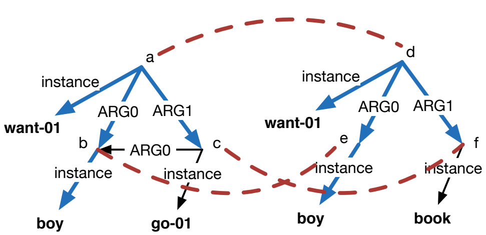
IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
   :ARG0 (o / organization
      :ARG0 (n / name
         :op1 "IAEA"))
   :ARG1 (t2 / thing
      :ARG1-of (p / propose-01
         :ARG0 (c / country
            :name (n2 / name
               :op1 "North"
               :op2 "Korea"))))
   :time (d / date-entity
         :month 11))
```

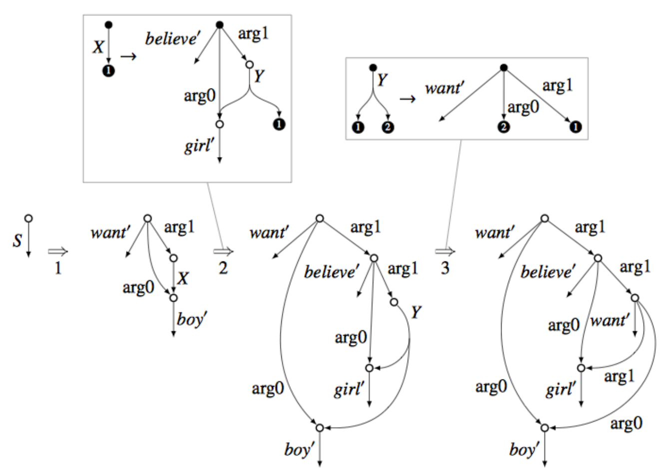
Parsing



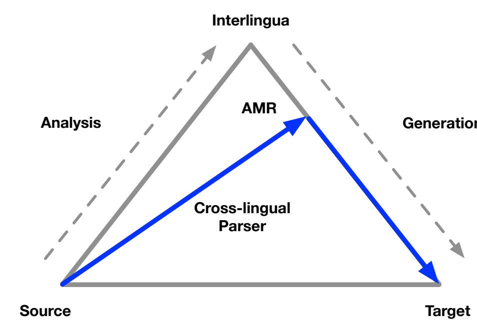
Evaluation



Graph grammars



Applications



Outline

- Alignment
- Parsing
- Evaluation
- Graph Grammars and Automata
- Applications

Alignment: Motivation

- AMR annotation has no explicit alignment to sentence
- Training data has whole sentence – AMR graph pairs
- For generalization performance, need fine-grained correspondence between words and pieces of AMR
- Alignments provide this correspondence

Need alignments to train parsers, etc

Alignment

The tour was a surprise offer made *by* North Korea *in* November.

```
(t / thing
     :ARG0-of (s / surprise-01)
     :ARG1-of (o / offer-01
          :ARG0 (c / country
               :name (n / name
                    :op1 "North"
                    :op2 "Korea"))
          :time (d / date-entity
                    :month 11))
     :domain (t2 / tour-01))
```

- Align concepts with words
- Can also align edges with function words

Alignment

- Alignment
  - Motivation
  - **JAMR's rule-based aligner**
  - ISI EM aligner
- Parsing
- Evaluation
- Graph Grammars and Automata
- Applications

JAMR Aligner (Flanigan et al, 2014)

- Aligns graph fragments to spans of words (edges not in fragments are unaligned)
- Uses a set of handcrafted rules
- Uses lemmatizer, string edit distance to match concepts with words
- Rules for: named entities, date entities, special concepts, negation, degrees, etc (15 total rules)

JAMR Aligner

For each rule

- Greedily align concepts in a depth first traversal of the AMR graph
- Rules are applied in a specified order

JAMR Aligner

IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :ARG0 (n / name
            :op1 "IAEA"))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 "North"
                    :op2 "Korea"))))
    :time (d / date-entity
            :month 11))
```

JAMR Aligner

Rule 1) Date entity

IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :ARG0 (n / name
            :op1 "IAEA"))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 "North"
                    :op2 "Korea"))))
    :time (d / date-entity
            :month 11))
```

JAMR Aligner

Rule 3) Named entity

IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :ARG0 (n / name
            :op1 "IAEA"))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 "North"
                    :op2 "Korea"))))
    :time (d / date-entity
            :month 11))
```

JAMR Aligner

Rule 5) Single concept (use lemma)

IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
     :ARG0 (o / organization
          :ARG0 (n / name
               :op1 "IAEA"))
     :ARG1 (t2 / thing
          :ARG1-of (p / propose-01
               :ARG0 (c / country
                    :name (n2 / name
                         :op1 "North"
                         :op2 "Korea"))))
     :time (d / date-entity
               :month 11))
```

JAMR Aligner

Rule 6) Fuzzy single concept (longest string prefix > 4)

IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
     :ARG0 (o / organization
          :ARG0 (n / name
               :op1 "IAEA"))
     :ARG1 (t2 / thing
          :ARG1-of (p / propose-01
               :ARG0 (c / country
                    :name (n2 / name
                         :op1 "North"
                         :op2 "Korea"))))
     :time (d / date-entity
               :month 11))
```

JAMR Aligner

Rule 10) person-of/thing-of

IAEA accepted North Korea ’s proposal in November.

```
(a / accept-01
     :ARG0 (o / organization
          :ARG0 (n / name
               :op1 “IAEA”))
     :ARG1 (t2 / thing
          :ARG1-of (p / propose-01
               :ARG0 (c / country
                    :name (n2 / name
                         :op1 “North”
                         :op2 “Korea”))))
     :time (d / date-entity
               :month 11))
```

JAMR Aligner

IAEA accepted North Korea ’s proposal in November.

```
(a / accept-01
     :ARG0 (o / organization
          :ARG0 (n / name
               :op1 “IAEA”))
     :ARG1 (t2 / thing
          :ARG1-of (p / propose-01
               :ARG0 (c / country
                    :name (n2 / name
                         :op1 “North”
                         :op2 “Korea”))))
     :time (d / date-entity
               :month 11))
```

JAMR Aligner

Evaluate on 200 hand-aligned sentences:

F_1: 90% Precision: 92% Recall: 89%

<u>Extracted concept table</u>

```
8       critical => (critical)
2       critical => (criticize-01)
1       critically => (critical)
1       criticised => (criticize-01)
14      criticism => (criticize-01)
30      criticized => (criticize-01)
1       critics => (critic)
4       critics => (person :ARG0-of (criticize-01))
5       crop => (crop)
5       crops => (crop)
3       cross => (cross)
15      cross => (cross-02)
3       cross => (cross-border)
2       cross => (cross-strait)
1       crossed => (cross-00)
2       crossing => (cross-02)
```

ISI Aligner (Pourdamghani et al, 2014)

- Aligns each concept or edge to at most one word
- Learns from data using EM
- Inspired by MT alignment models
- Basic idea: convert graph to linear string, use word alignment model

ISI Aligner

IAEA accepted North Korea ’s proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :name (n / name
            :op1 “IAEA”))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 “North”
                    :op2 “Korea”))))
    :time (d / date-entity
            :month 11))
```

ISI Aligner

IAEA accepted North Korea ’s proposal in November.

```
accept-01 :ARG0 organization :name name :op1
“IAEA” :ARG1 thing :ARG1-of propose-01 :ARG0
country :name name :op1 “North” :op2 “Korea” :time
date-entity :month 11
```

Linearize the AMR using a depth-first traversal

ISI Aligner

IAEA accepted North Korea proposal in November

```
accept organization name IAEA thing propose-01
country name North Korea :time date-entity 11
```

English: remove stop words

AMR: remove special concepts, relations that don't usually align, quotes, and sense tags

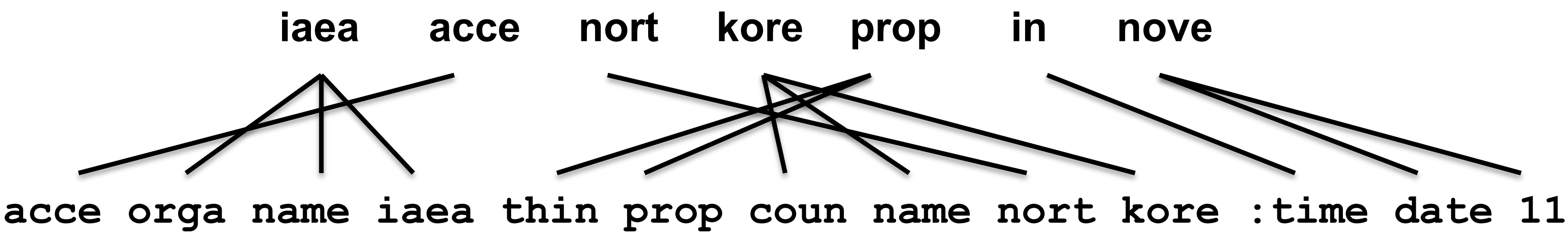
ISI Aligner

iaea acce nort kore prop in nove

```
acce orga name iaea thin prop coun name nort kore :time date 11
```

Both: Lowercase and stem to the first four letters

ISI Aligner



Run IBM alignment models with a symmetrization constraint, and project to AMR graph

Alignments are 1-to-many

Alignment: Summary

	JAMR aligner	**ISI aligner**
Alignment type	Graph fragment to span of words	Each concept or edge to at most one word
Aligns edges	No	Yes
Learned from data	No	Yes
Gold standard available	https://github.com/jflanigan/jamr	http://amr.isi.edu/research.html
F_1 score on concepts*	90% (spans)	89.8%
F_1 score on relations*	NA	49.3%

*JAMR and ISI not directly comparable, since different gold standard

In general, the desired type of alignment will depend on the application

Parsing

- Alignment
- **Parsing**
  - Graph-based parsing
    - Structured prediction
    - Concept identification
    - Relation identification
      - Maximum spanning connected graph algorithm (MSCG)
      - Graph determinism constraints using Lagrangian relaxation
    - Experiments
  - Transition-based parsing
  - Parsing using syntax-based MT
- Evaluation
- Graph Grammars and Automata
- Applications

Parsing

Kevin Knight likes to semantically parse sentences.

```
(l / like-01
     :ARG0 (p / person
          :name (n / name
               :op1 "Kevin"
               :op2 "Knight"))
     :ARG1 (p2 / parse-00
          :ARG0 p
          :ARG1 (s / sentence)
          :mod (s2 / semantics)))
```

JAMR Overview (Flanigan et al, 2014)

Input

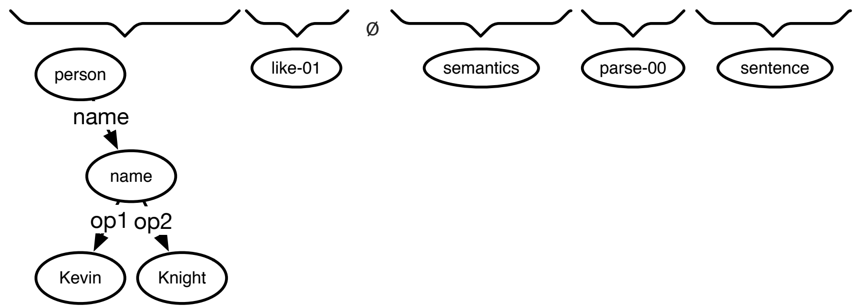
Kevin	Knight	likes	to	semantically	parse	sentences

JAMR Overview

Input

Kevin	Knight	likes	to	semantically	parse	sentences

Concept ID

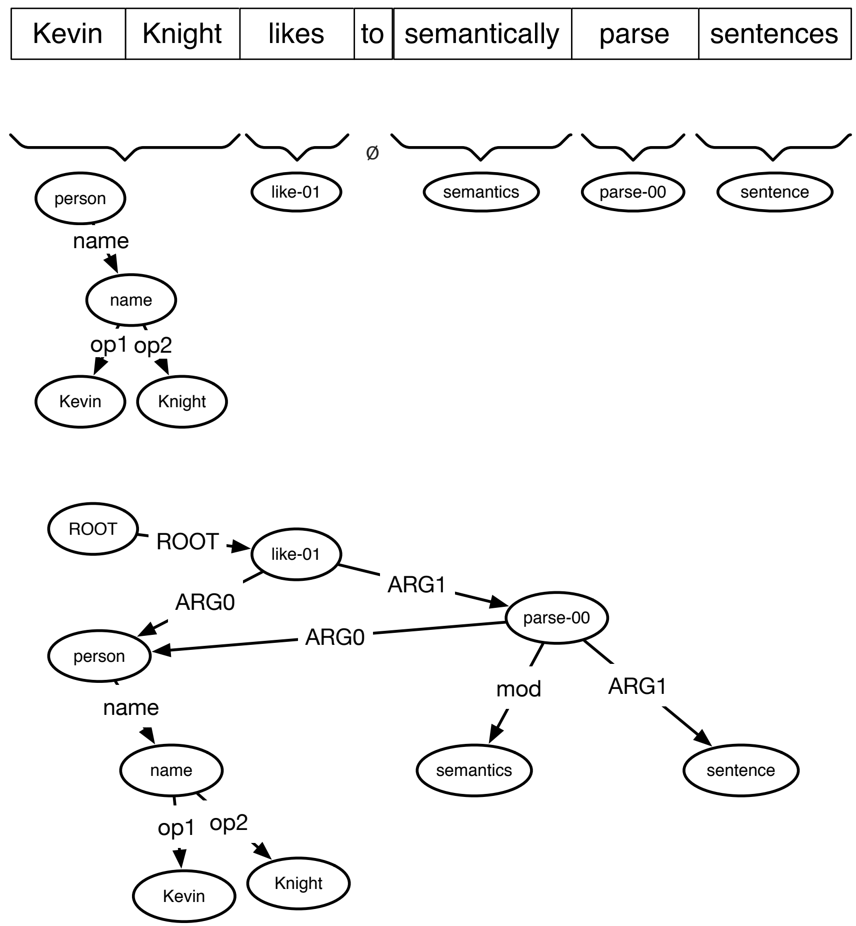


JAMR Overview

Input

Concept ID

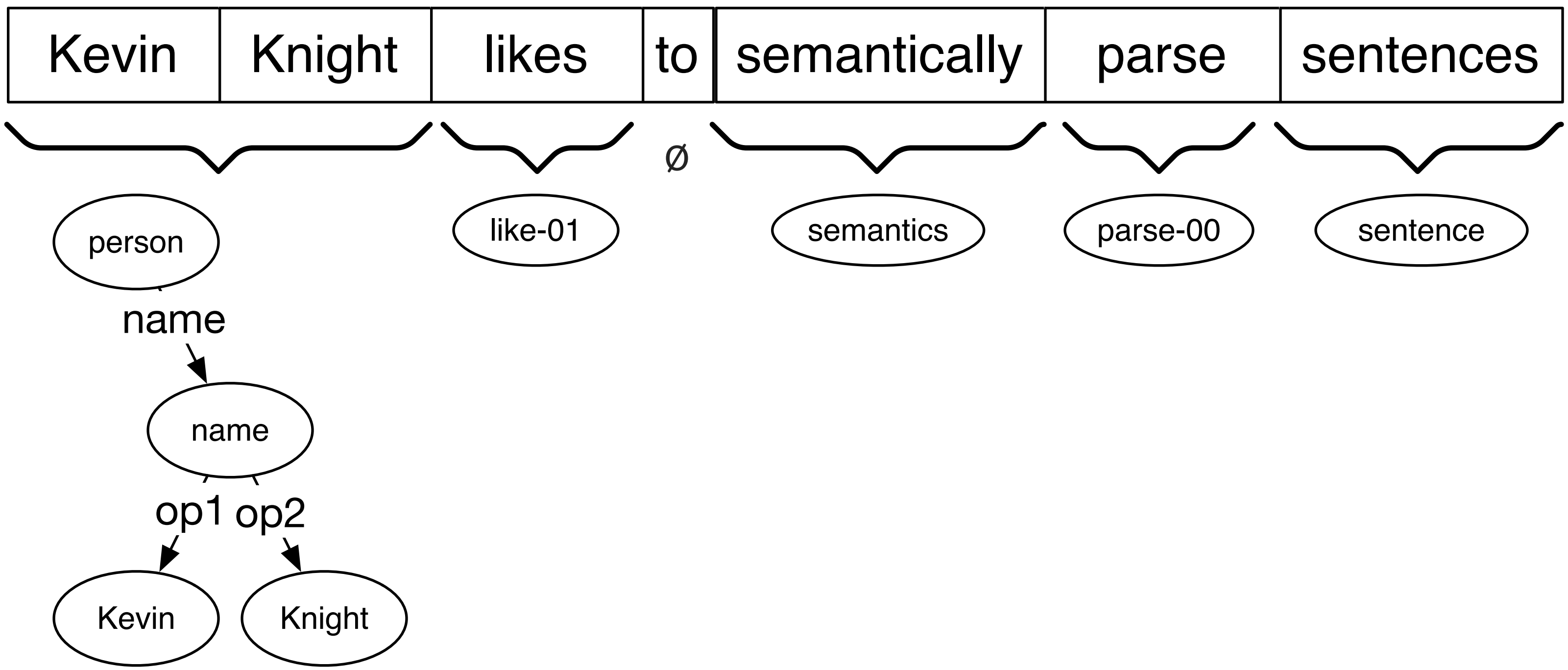
Relation ID



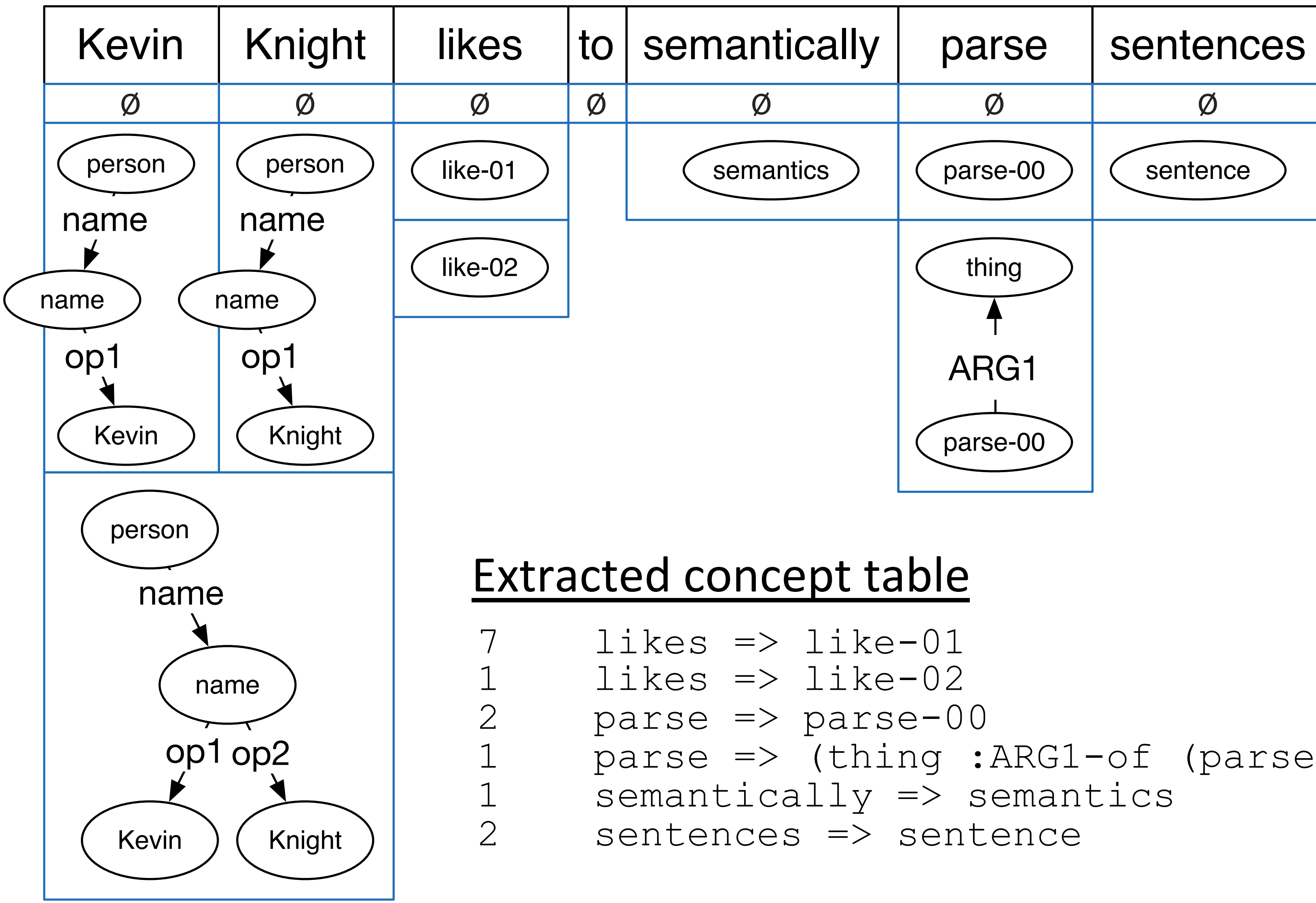
Concept Identification

Kevin	Knight	likes	to	semantically	parse	sentences

Concept Identification



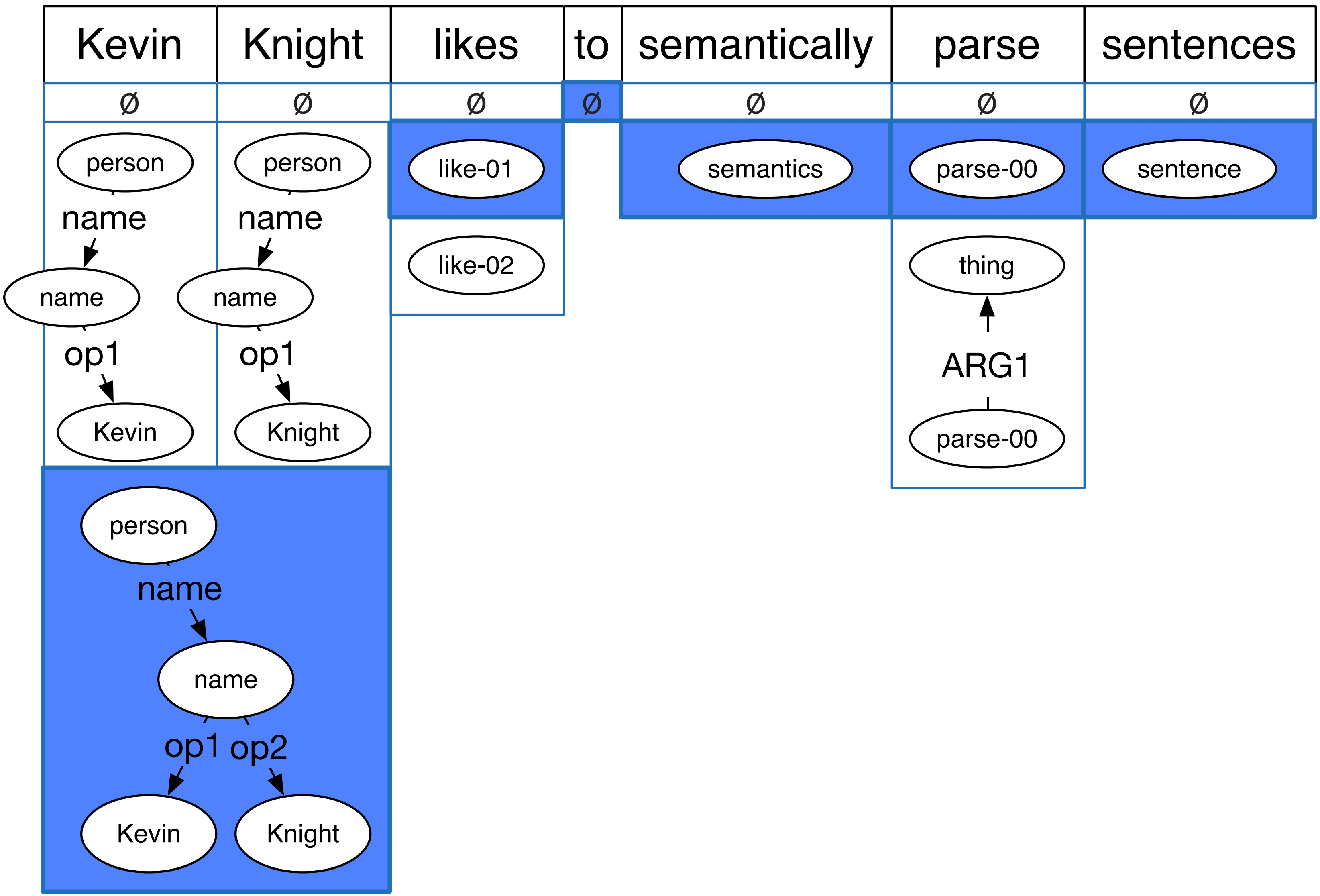
Concept Identification



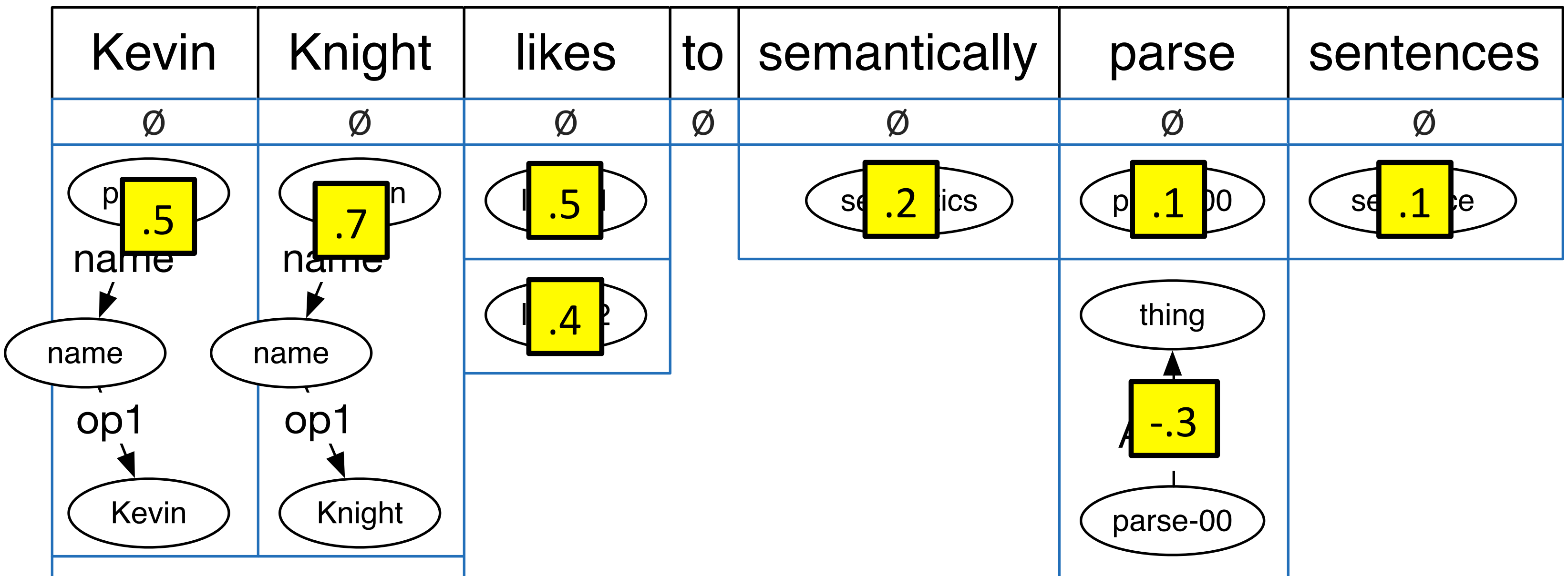
Extracted concept table

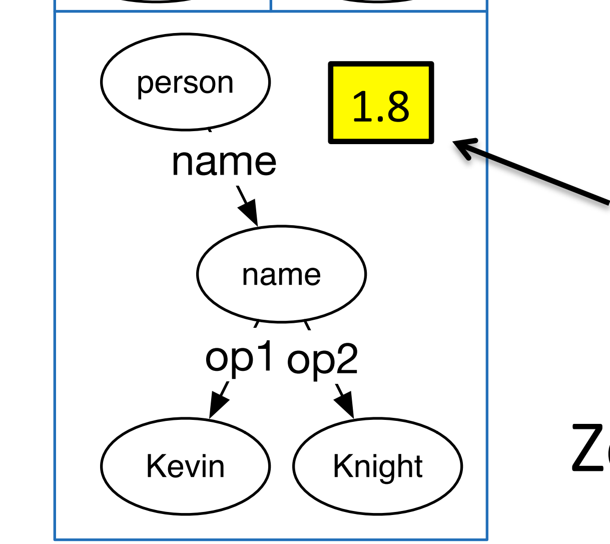
```
7     likes => like-01
1     likes => like-02
2     parse => parse-00
1     parse => (thing :ARG1-of (parse00))
1     semantically => semantics
2     sentences => sentence
```

Concept Identification



Concept Identification

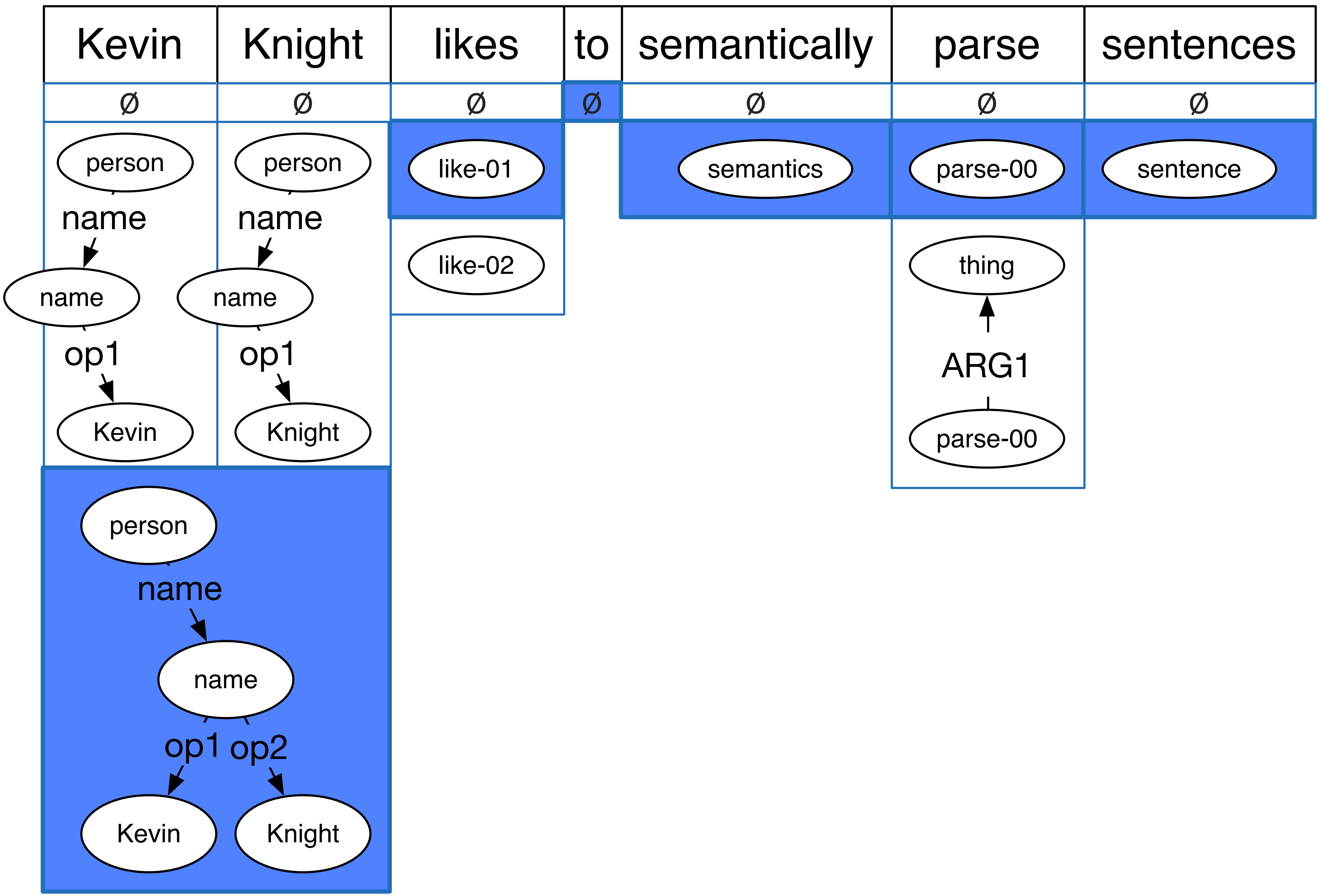




Local score = how much the model wants to include this fragment
= *model_weights · local_features*

Zeroth-order model

Concept Identification



Training

- AdaGrad structured perceptron

Learning rate

$$\theta_i^{t+1} = \theta_i^t - \frac{\eta}{\sqrt{\sum_{t'=1}^{t} g_i^{t'}}} g_i^t$$

Model weight component i at step t+1

Gradient

Training

- AdaGrad structured perceptron

Learning rate

$$\theta_i^{t+1} = \theta_i^t - \frac{\eta}{\sqrt{\sum_{t'=1}^{t} g_i^{t'}}} g_i^t$$

Model weight component i at step t+1

Gradient

$$g_i^t = feat_i(X_t, \hat{Y}_t) - feat_i(X_t, Y_t)$$

Input

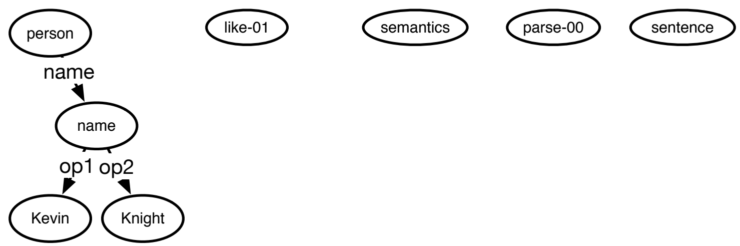
Predicted output

Gold output

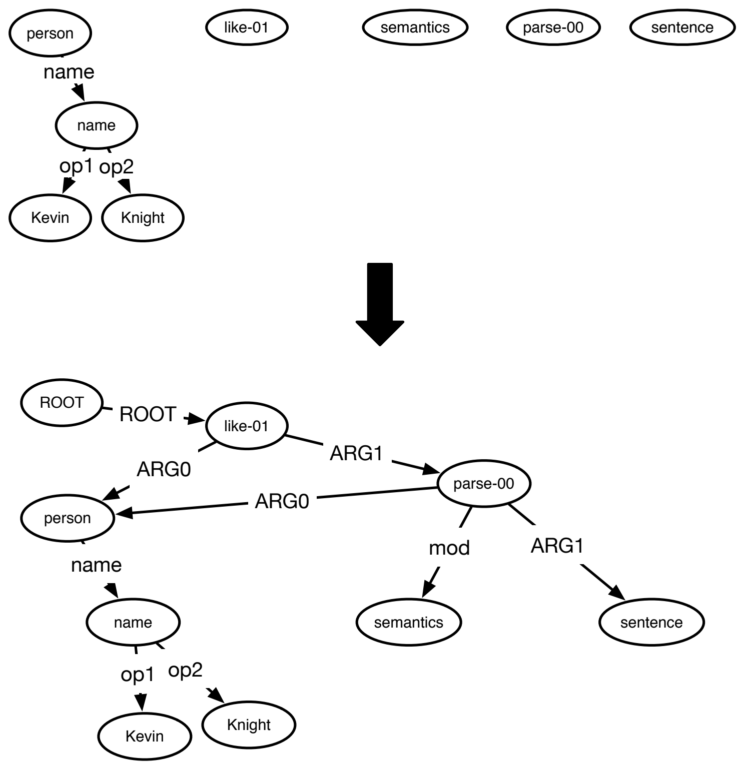
Relation Identification

- Evaluation
- Alignment
- Parsing
  - Graph-based parsing
    - Concept identification
    - **Relation identification**
      - Maximum spanning connected graph algorithm (MSCG)
      - Graph determinism constraints using Lagrangian relaxation
    - Experiments
  - Transition-based parsing
  - Parsing using syntax-based MT
- Graph Grammars and Automata
- Applications

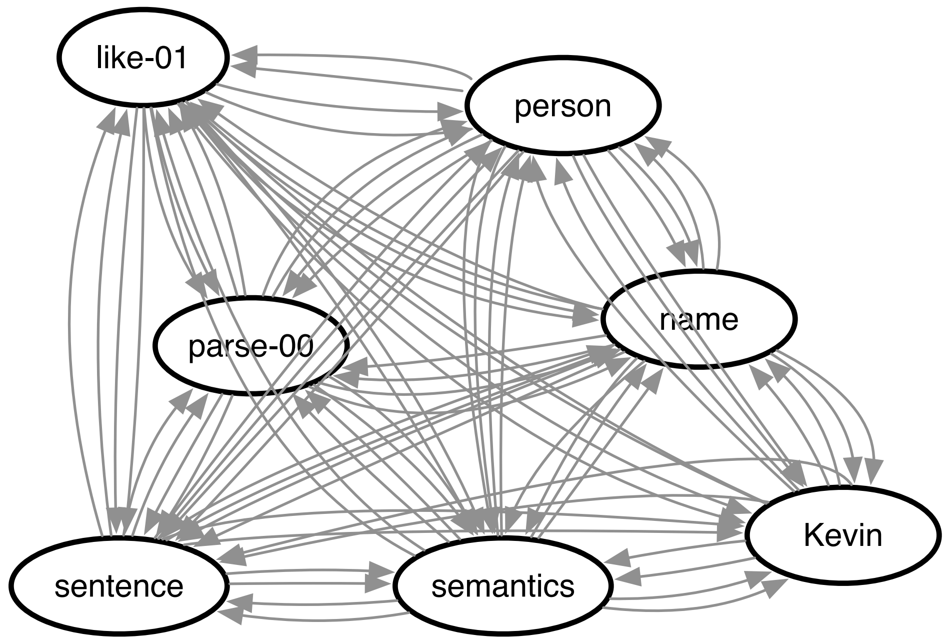
Relation Identification



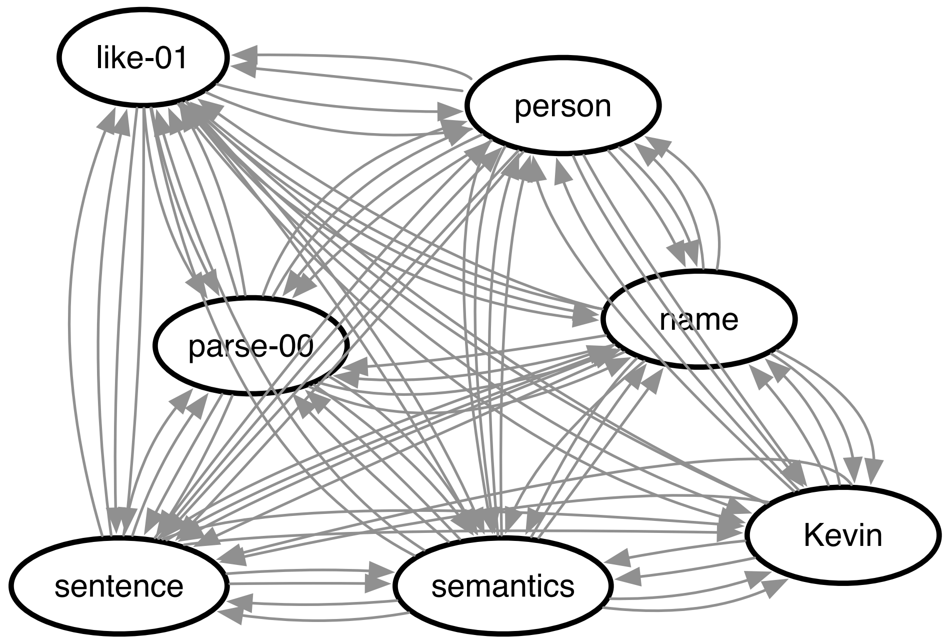
Relation Identification



Dense Graph

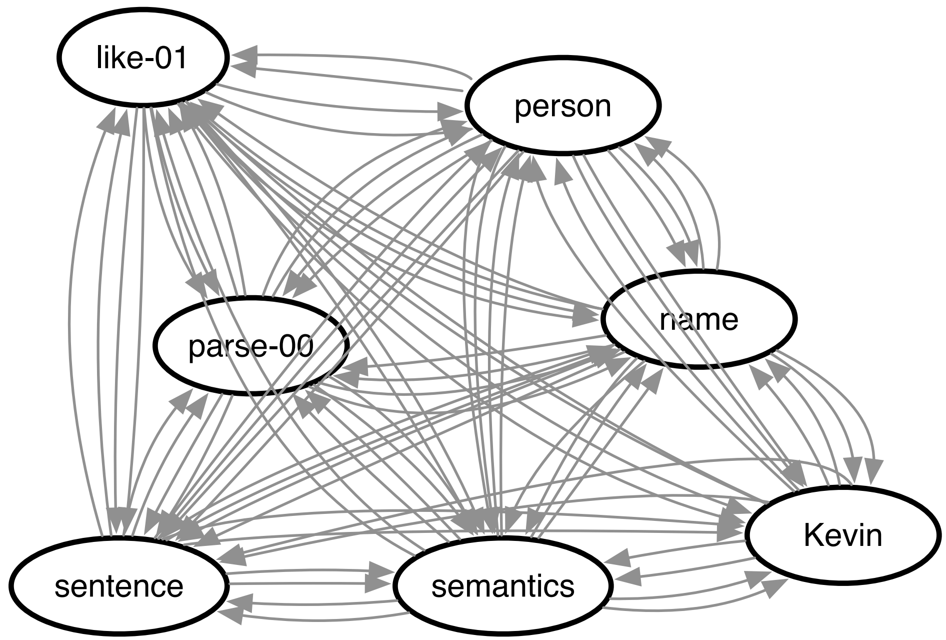


Dense Graph



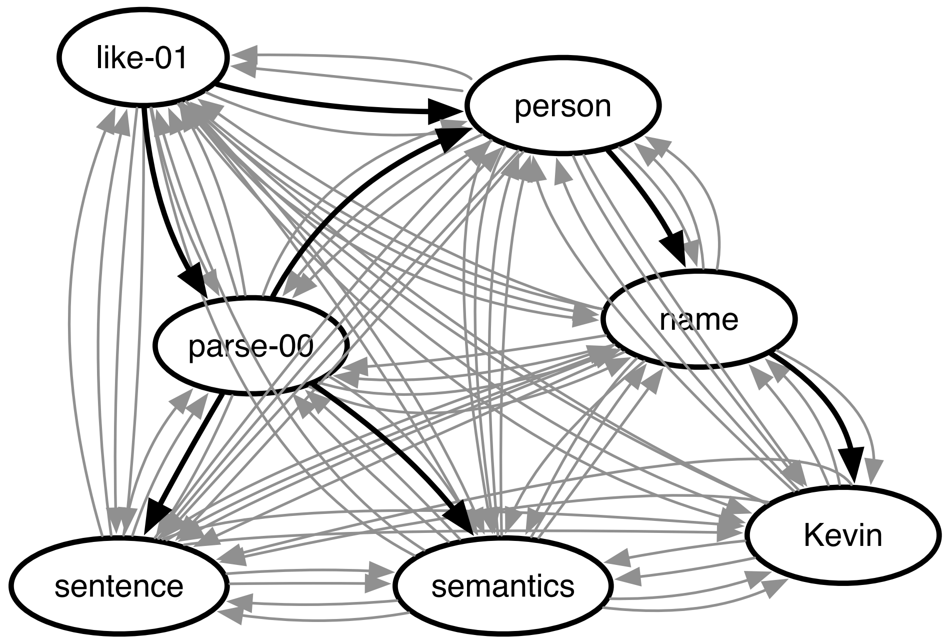
- All possible edges between all nodes
- Edges w/ weights

Dense Graph



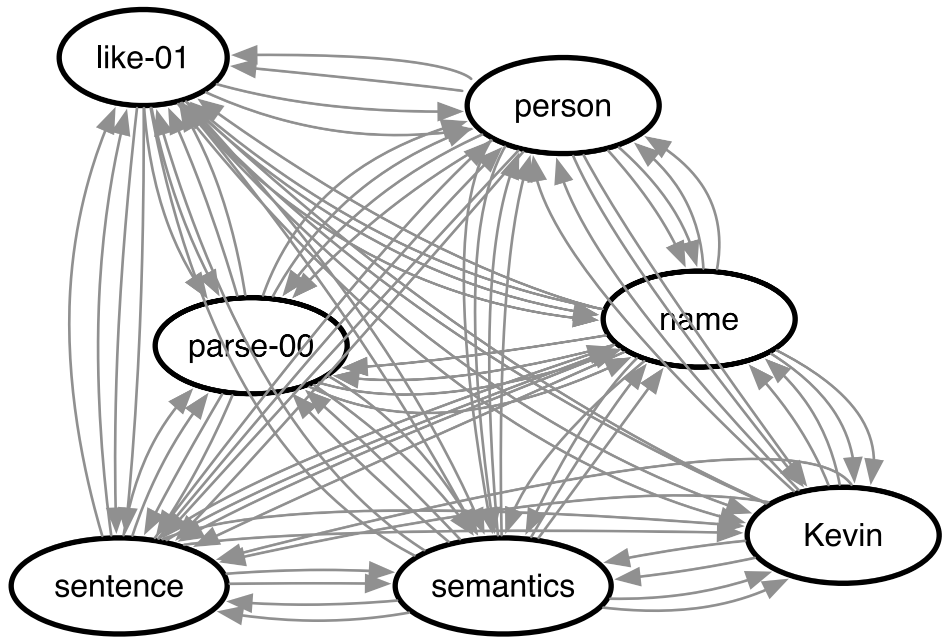
Edge weight = how much the model wants to include that edge in the output graph

Dense Graph



Output graph = max subgraph with constraints on well-formedness

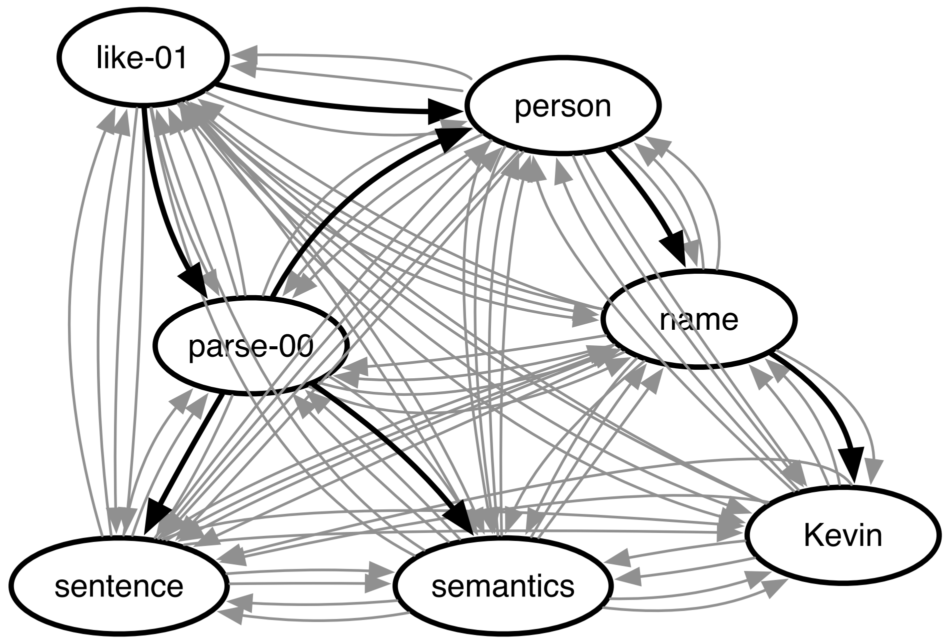
Dense Graph



$\mathbf{z}$ binary vector, indicates which edges are selected

ϕ real vector, contains the edge weights

Max Subgraph



Relation ID
optimization problem

$$\max_{\mathbf{z} \in G} \phi^T \mathbf{z}$$

Set of graphs satisfying the constraints

Output Graph Properties (Constraints)

- Preserving
- Simple
- Spanning (all nodes)
- Connected
- Deterministic

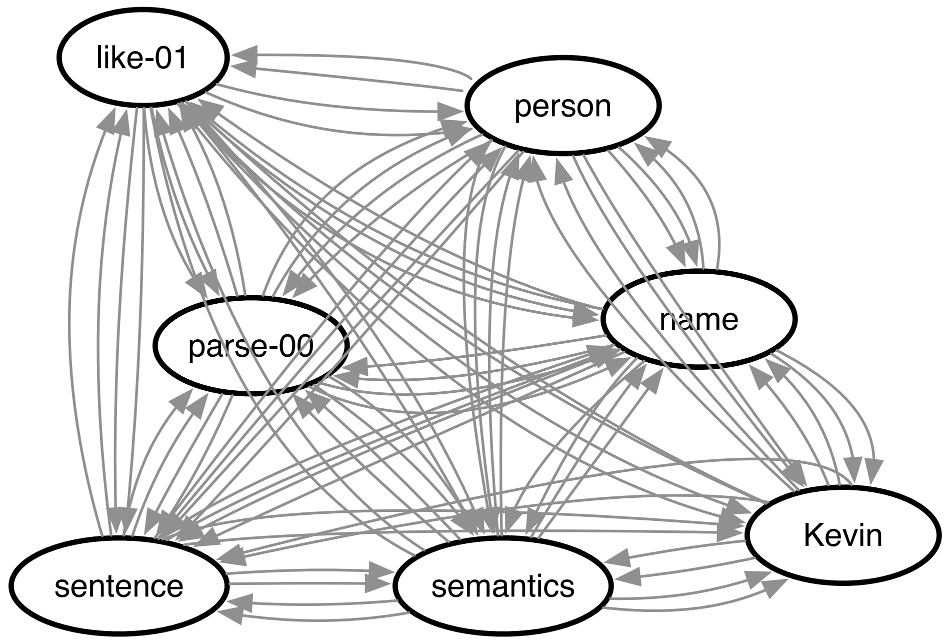
Output Graph Properties (Constraints)

- Preserving
- Simple
- Spanning (all nodes)
- Connected
- Deterministic

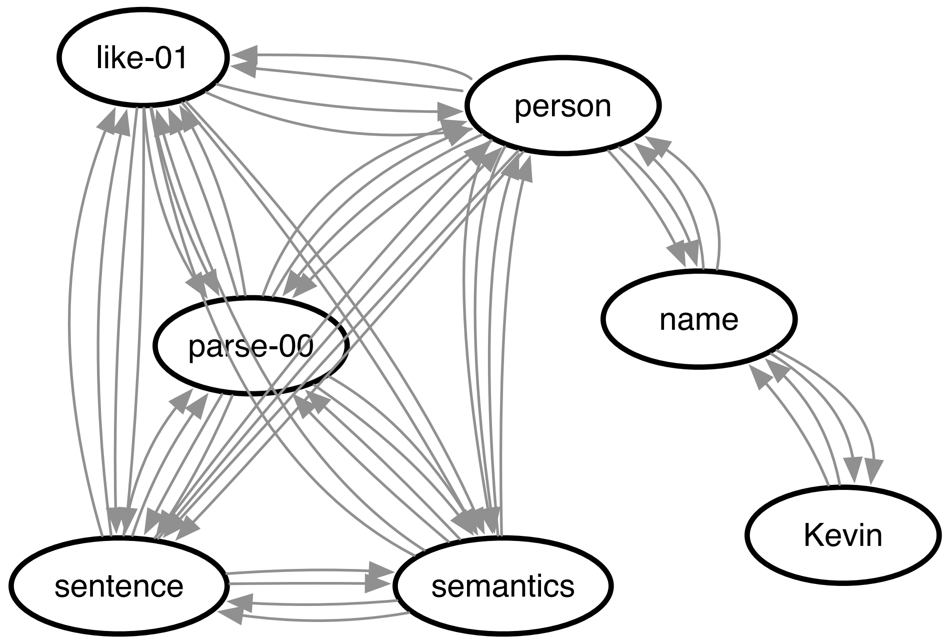
set $\mathcal{Z}$

set G

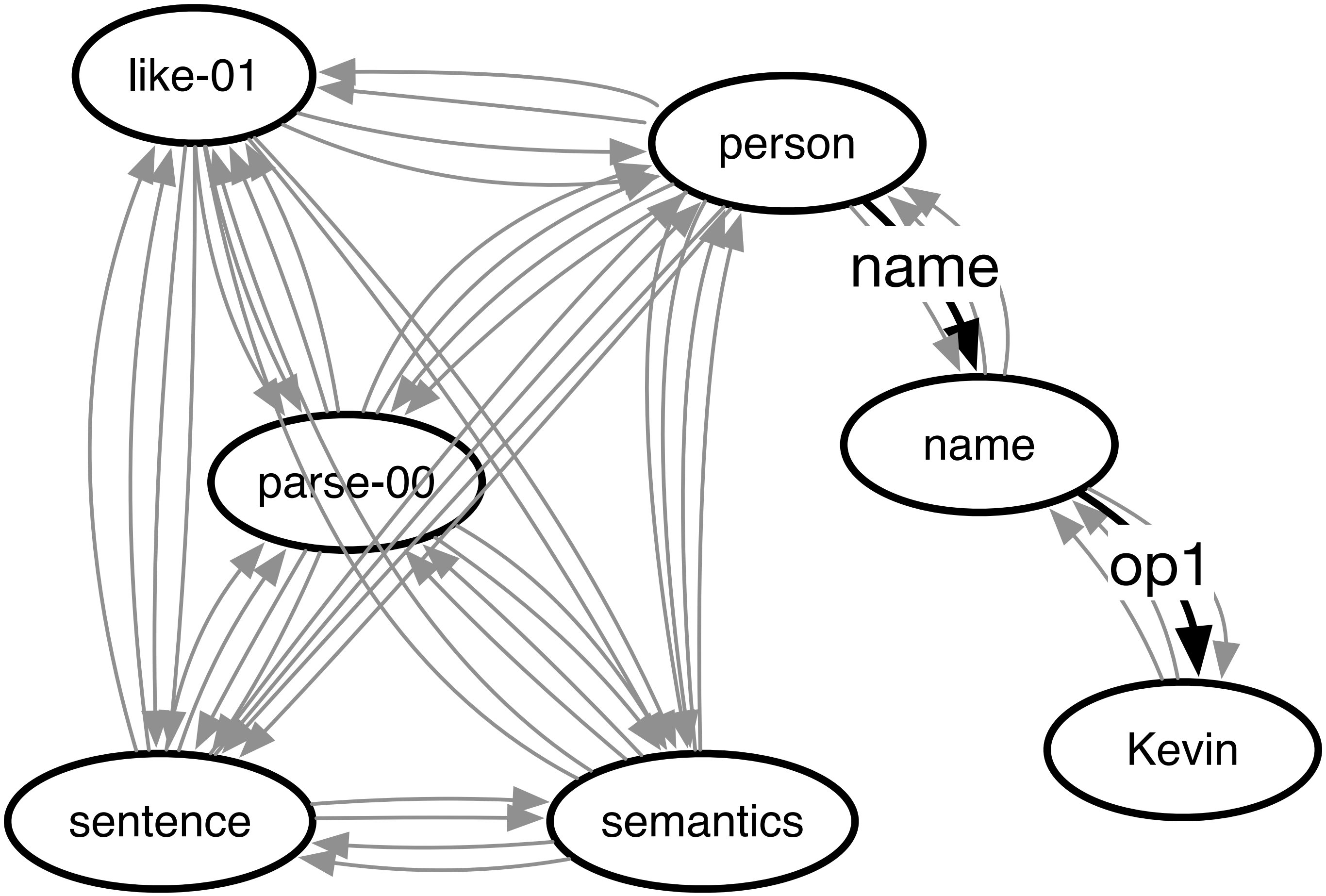
Dense Graph



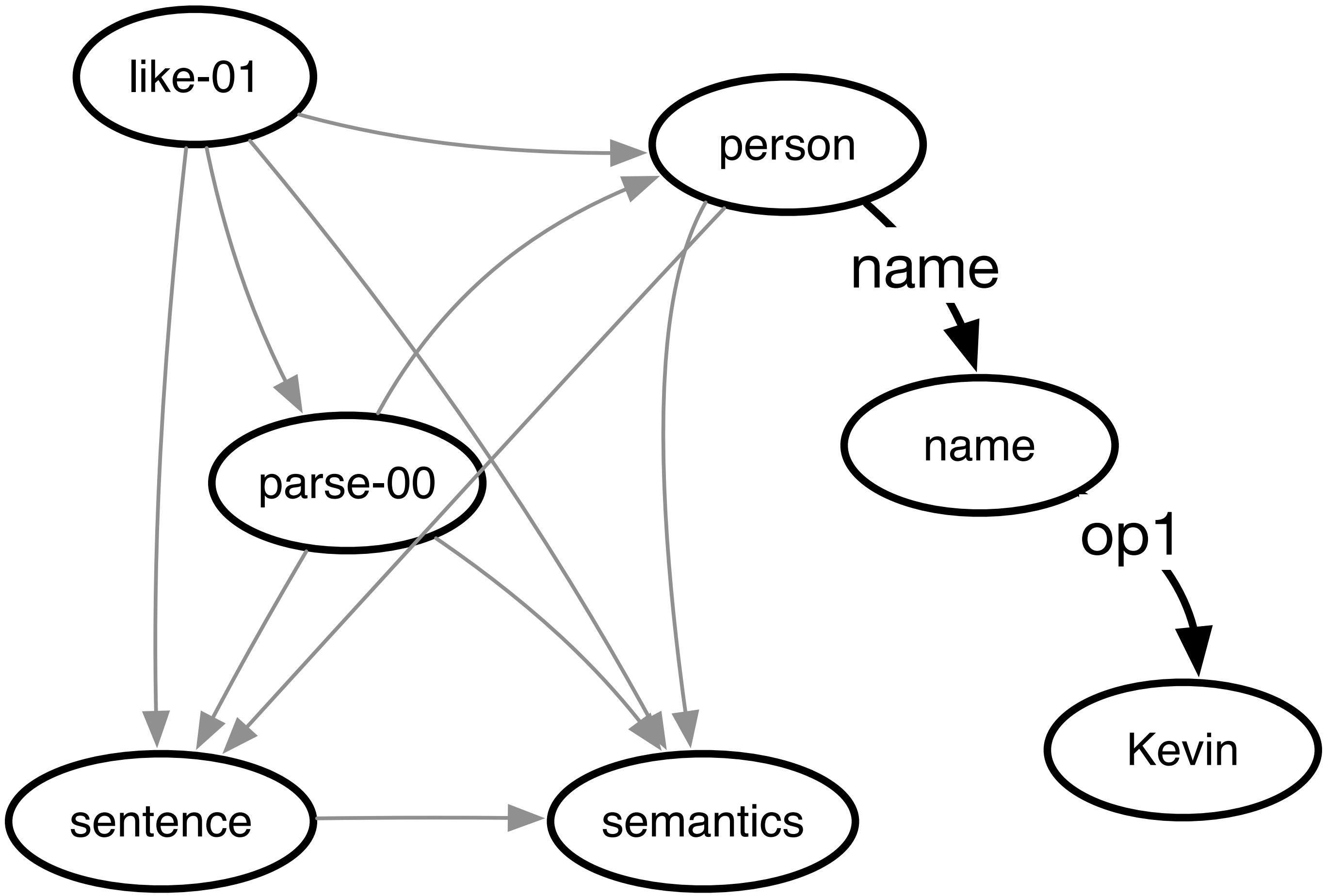
Reduced graph for clarity



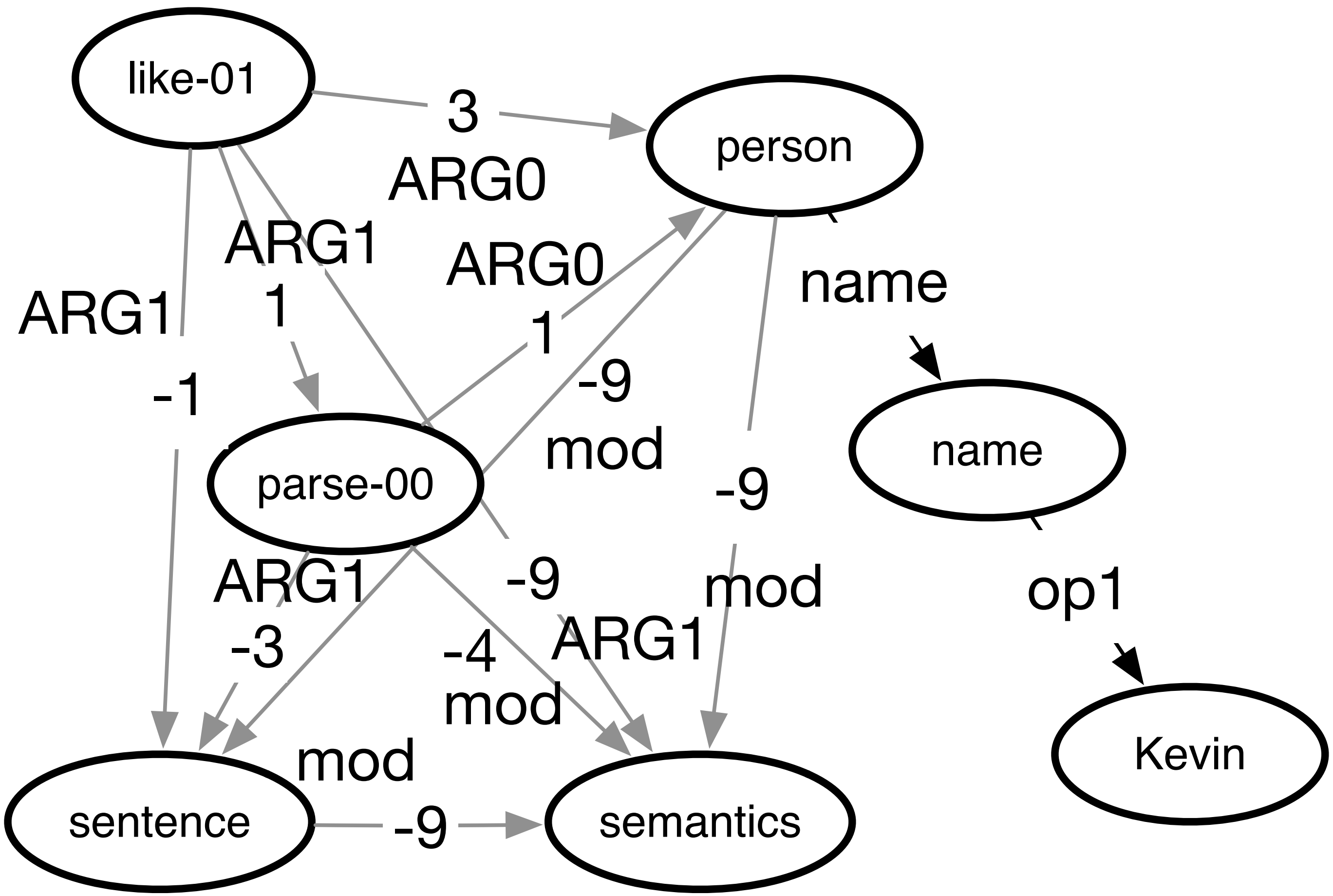
Constraint: Preserving



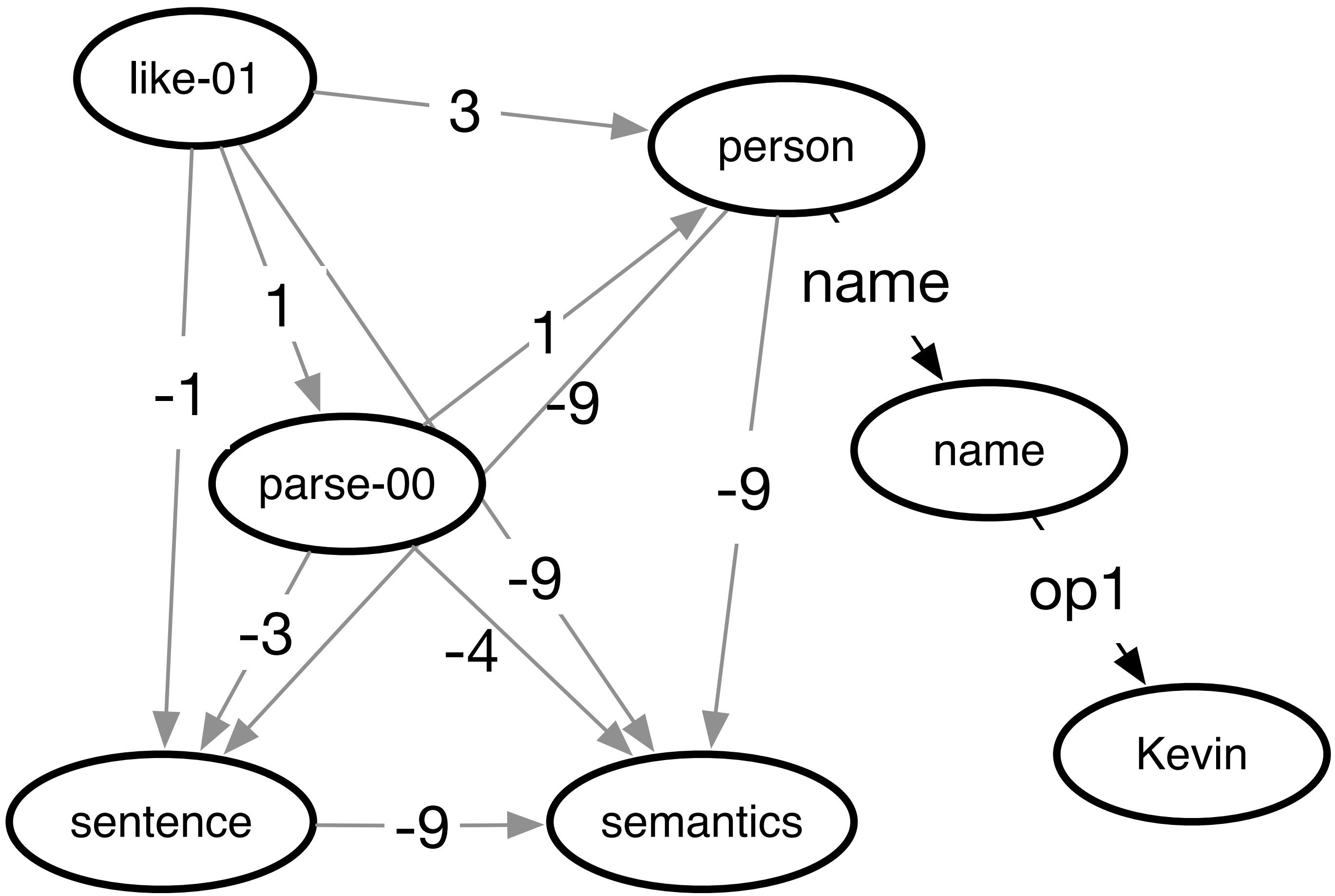
Constraint: Simple



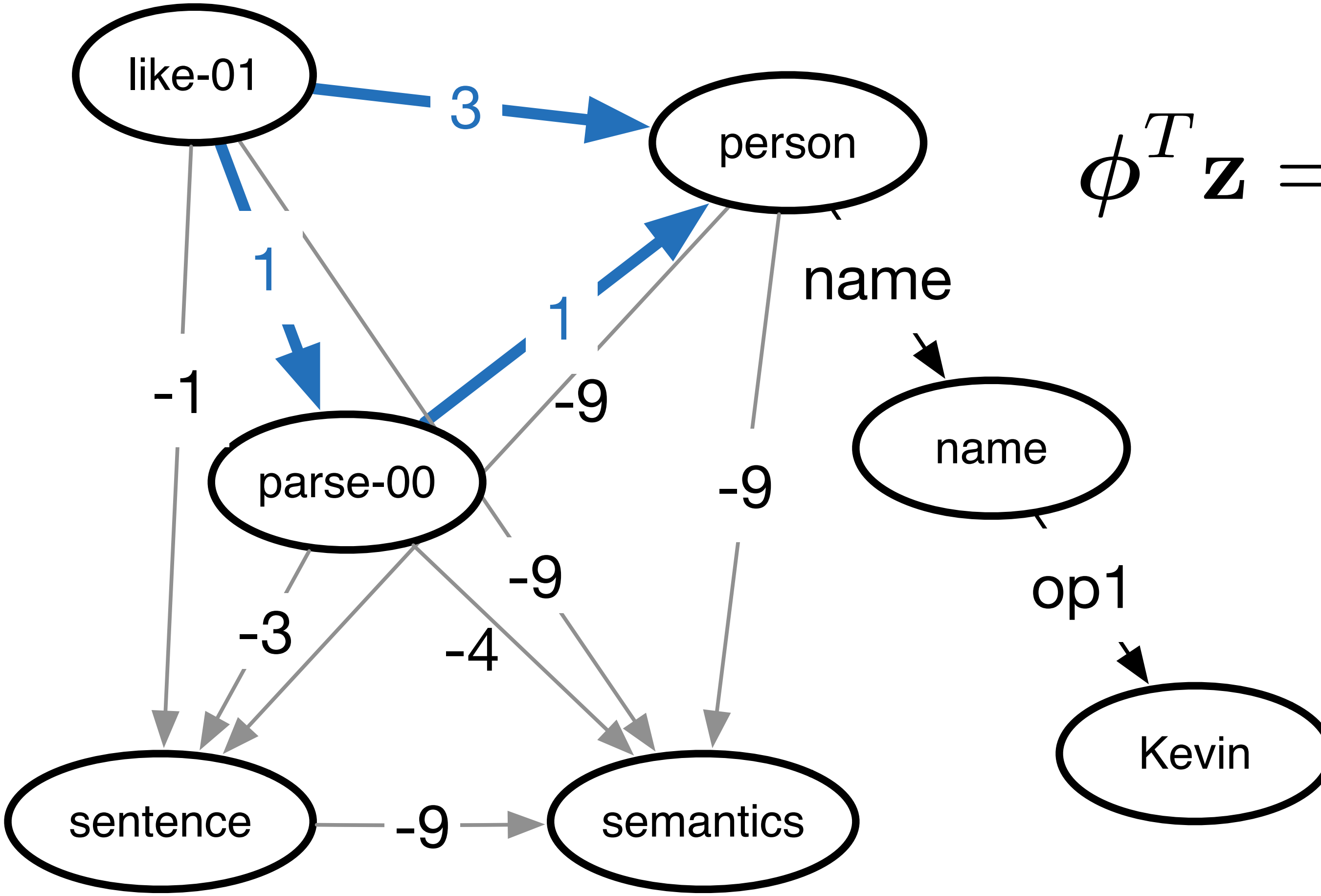
With Weights and Labels Shown



Maximum Weighted Subgraph

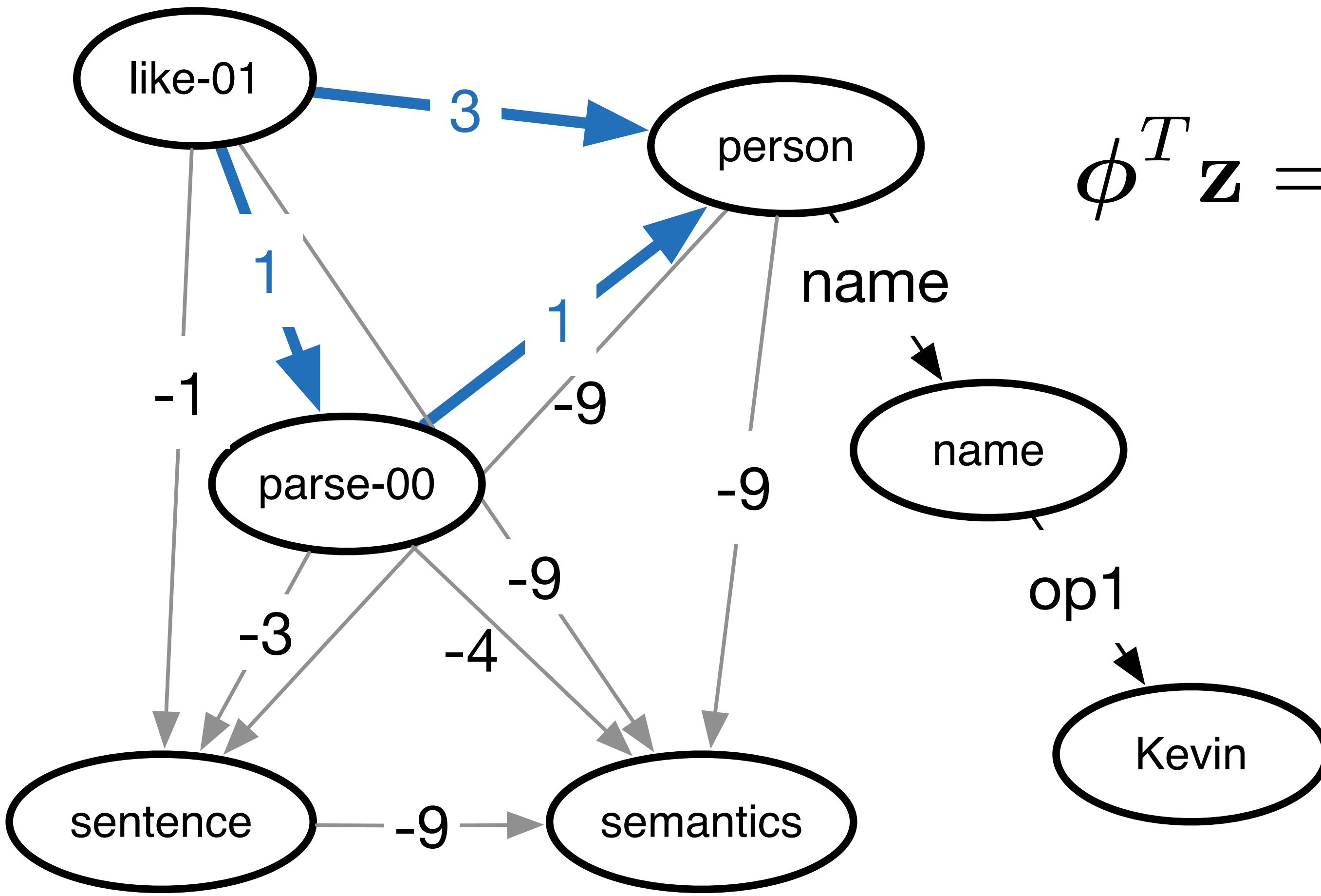


Maximum Weighted Subgraph



$$\phi^T \mathbf{z} = 5$$

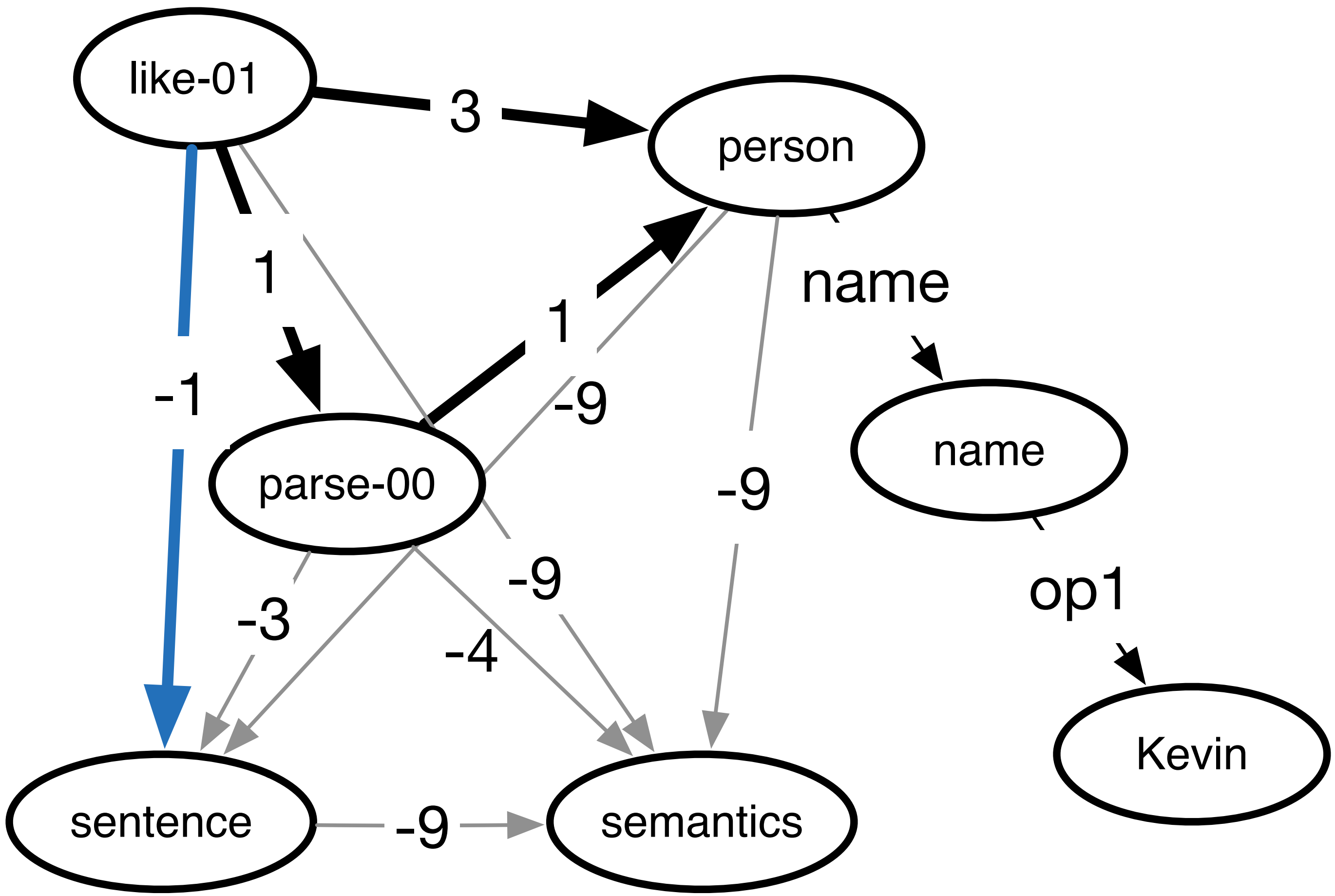
Maximum Weighted Subgraph



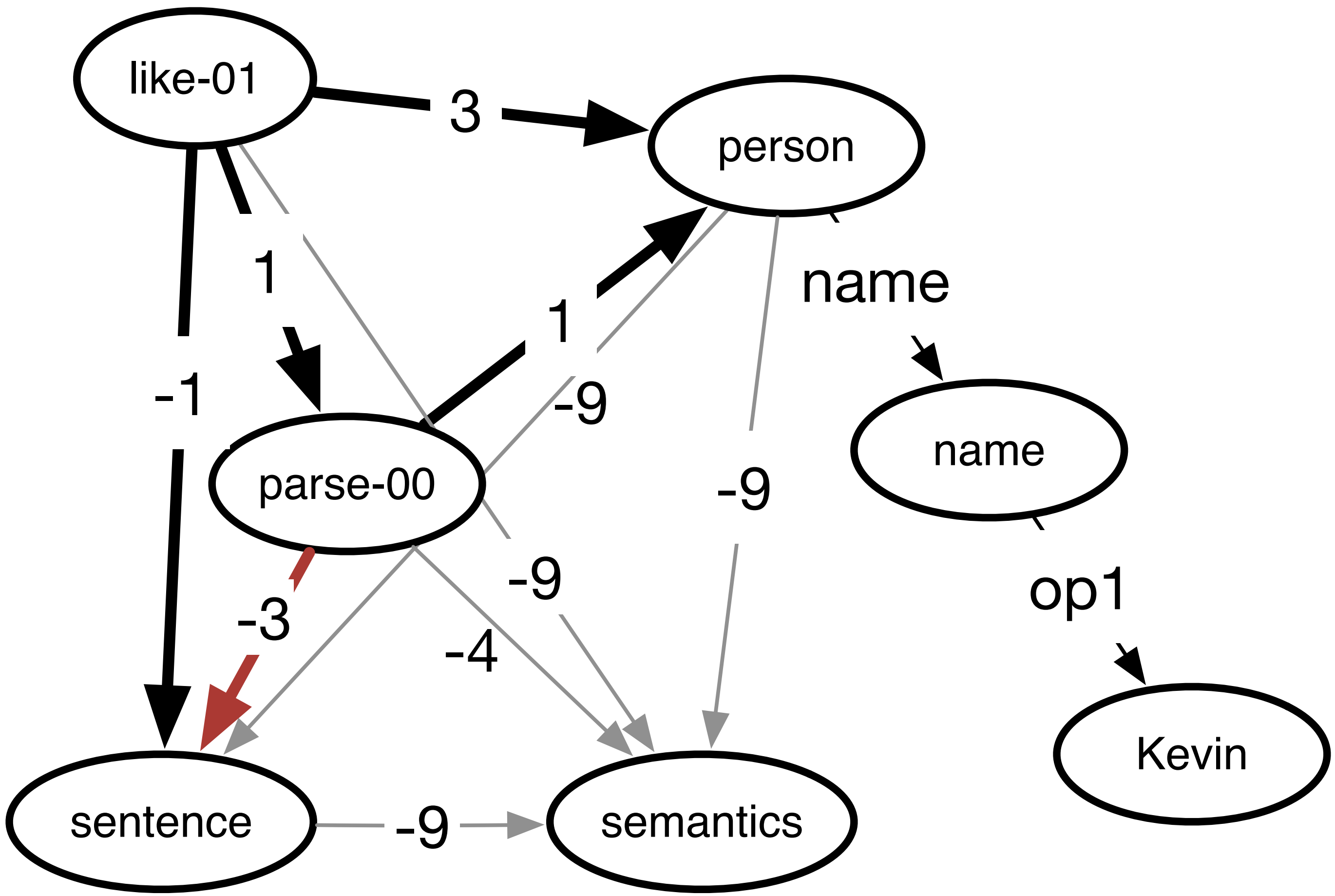
$$\phi^T \mathbf{z} = 5$$

Constraint: Graph must be connected

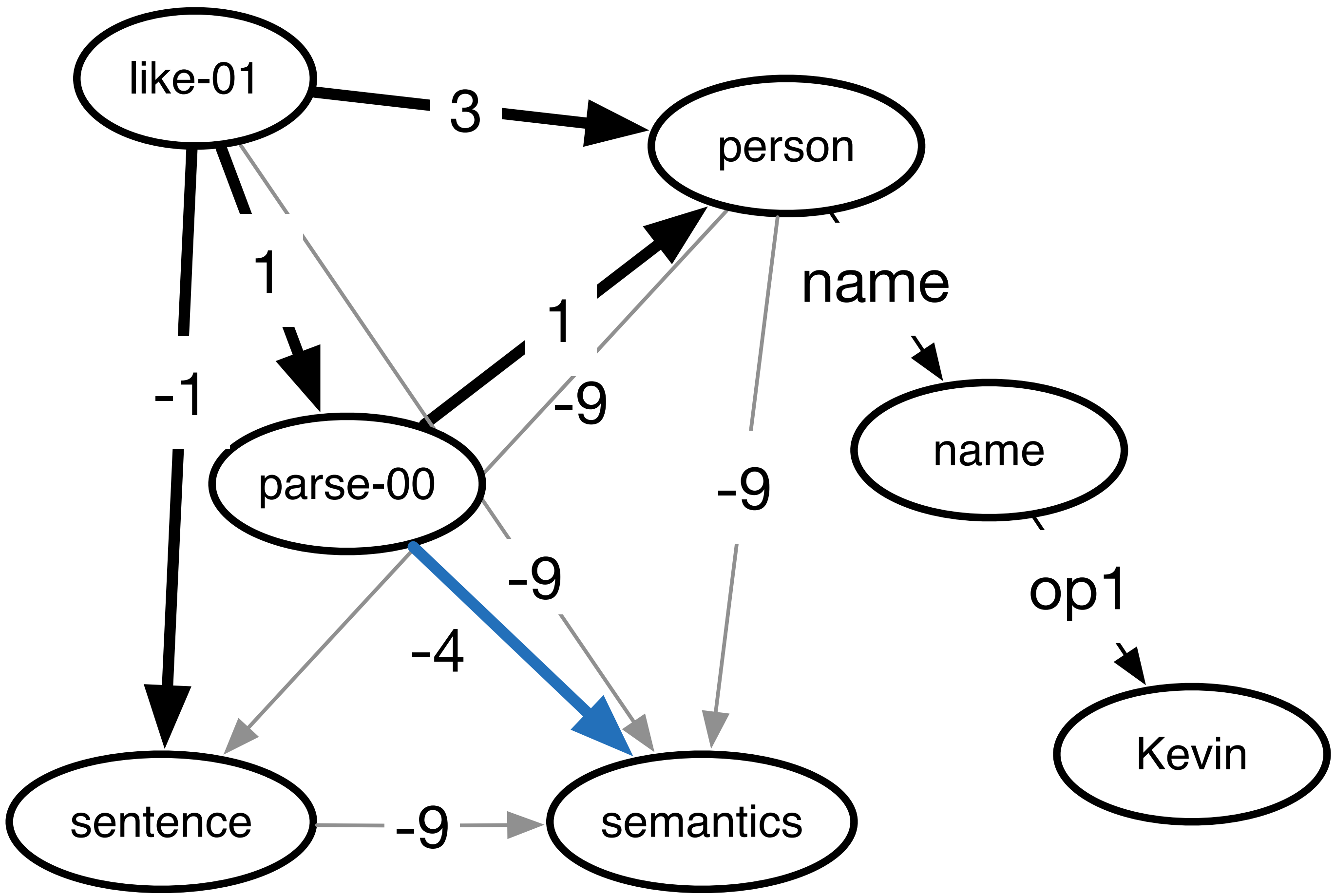
Maximum Spanning, Connected Subgraph (MSCG)



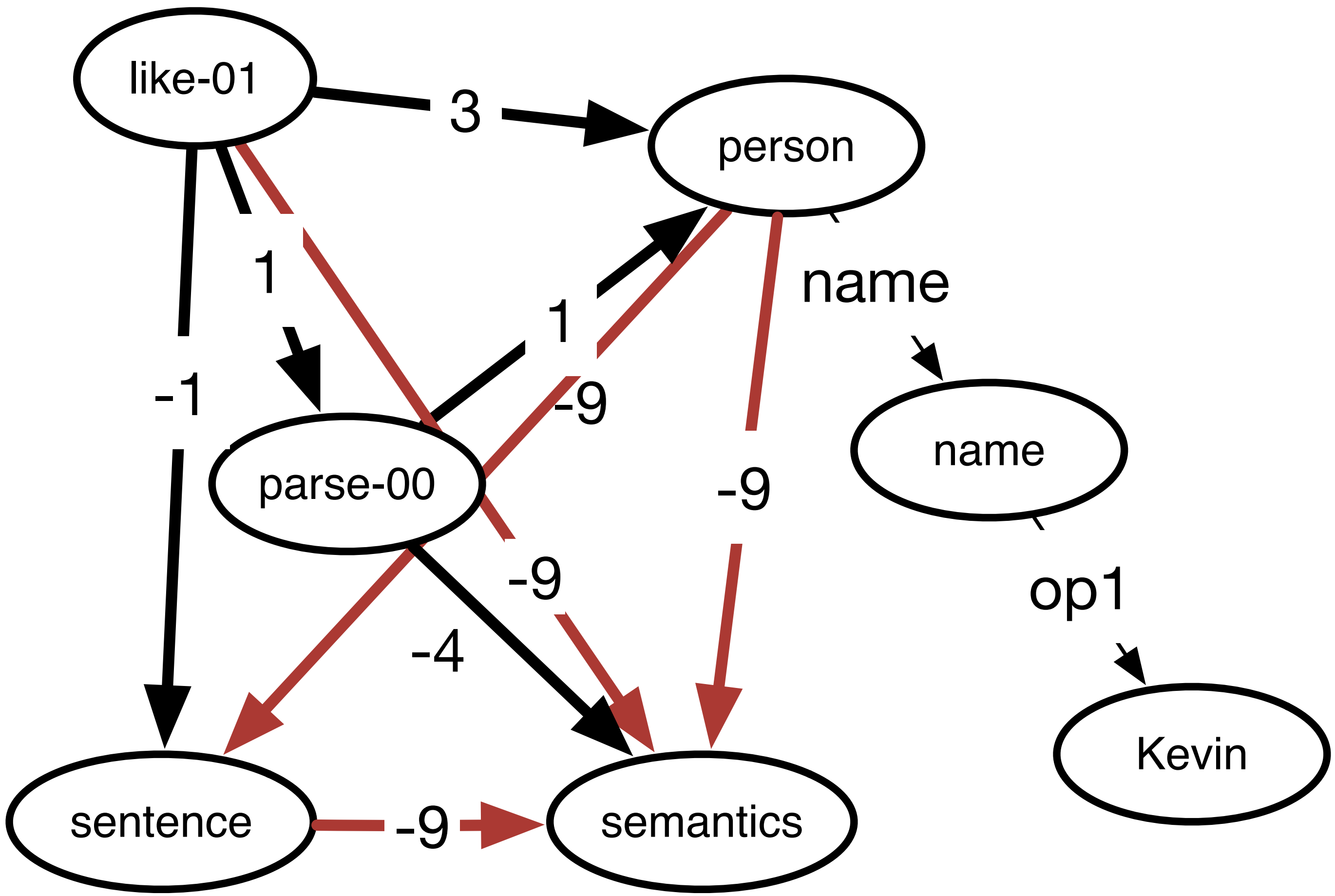
Maximum Spanning, Connected Subgraph (MSCG)



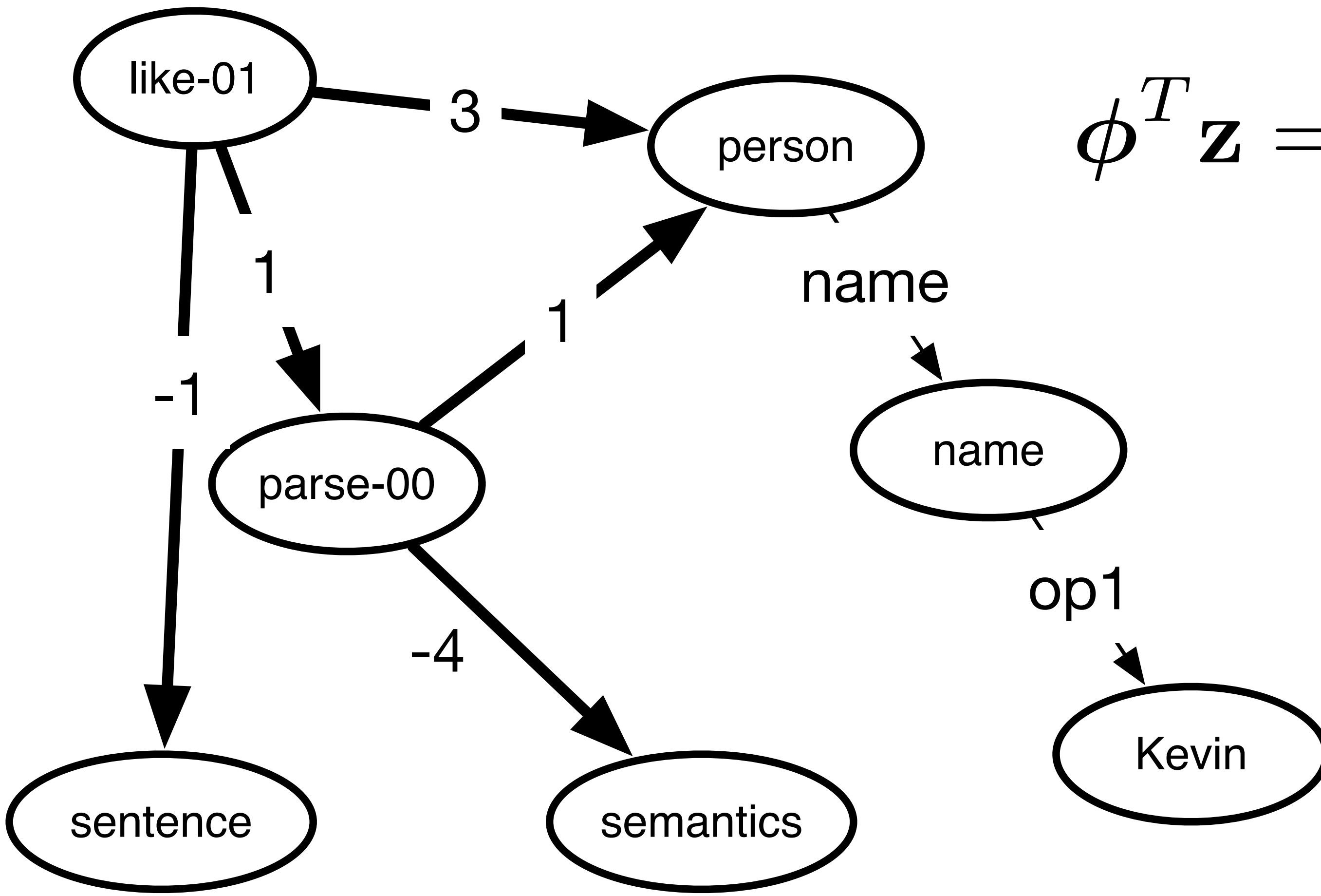
Maximum Spanning, Connected Subgraph (MSCG)



Maximum Spanning, Connected Subgraph (MSCG)

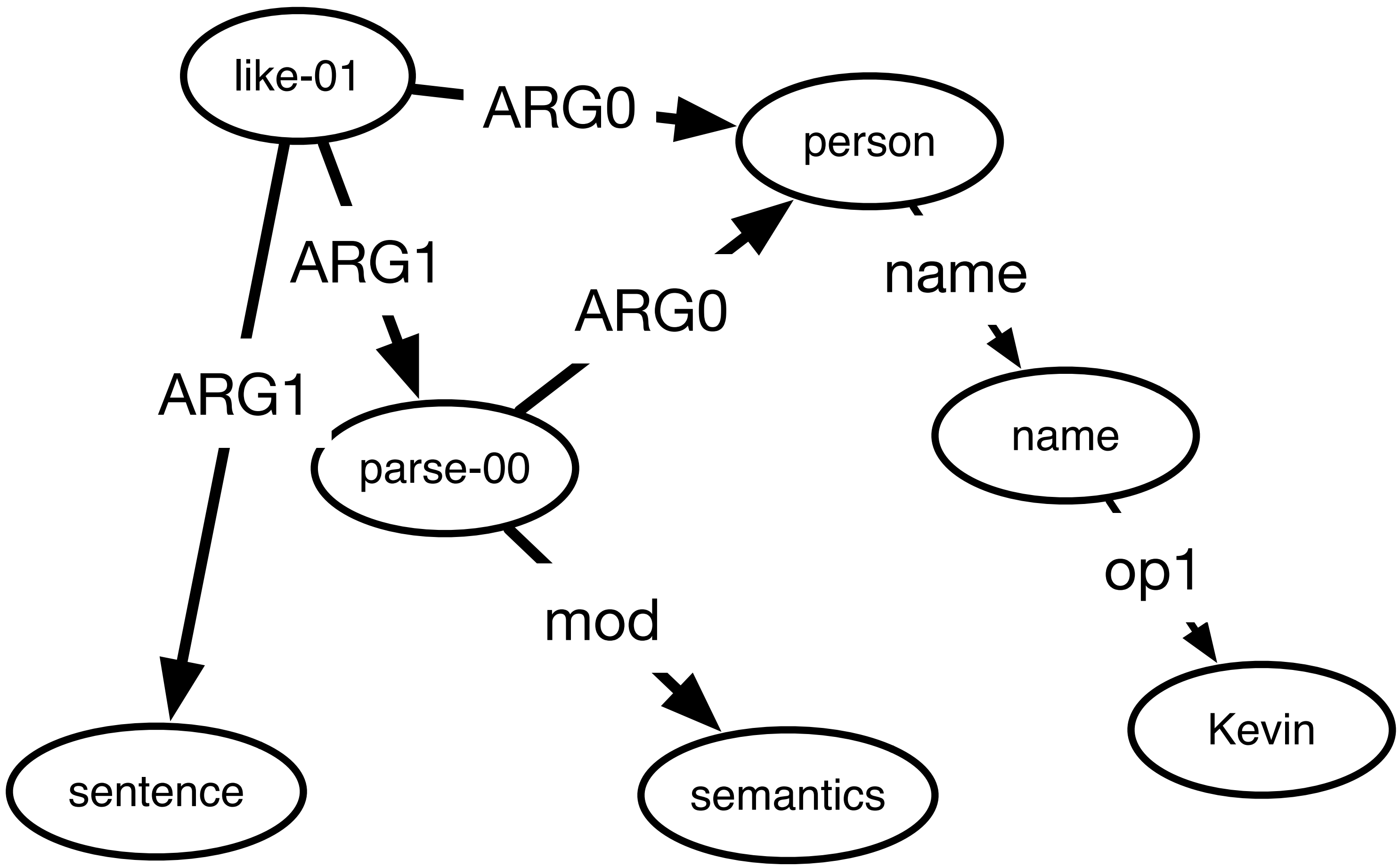


Maximum Spanning, Connected Subgraph (MSCG)



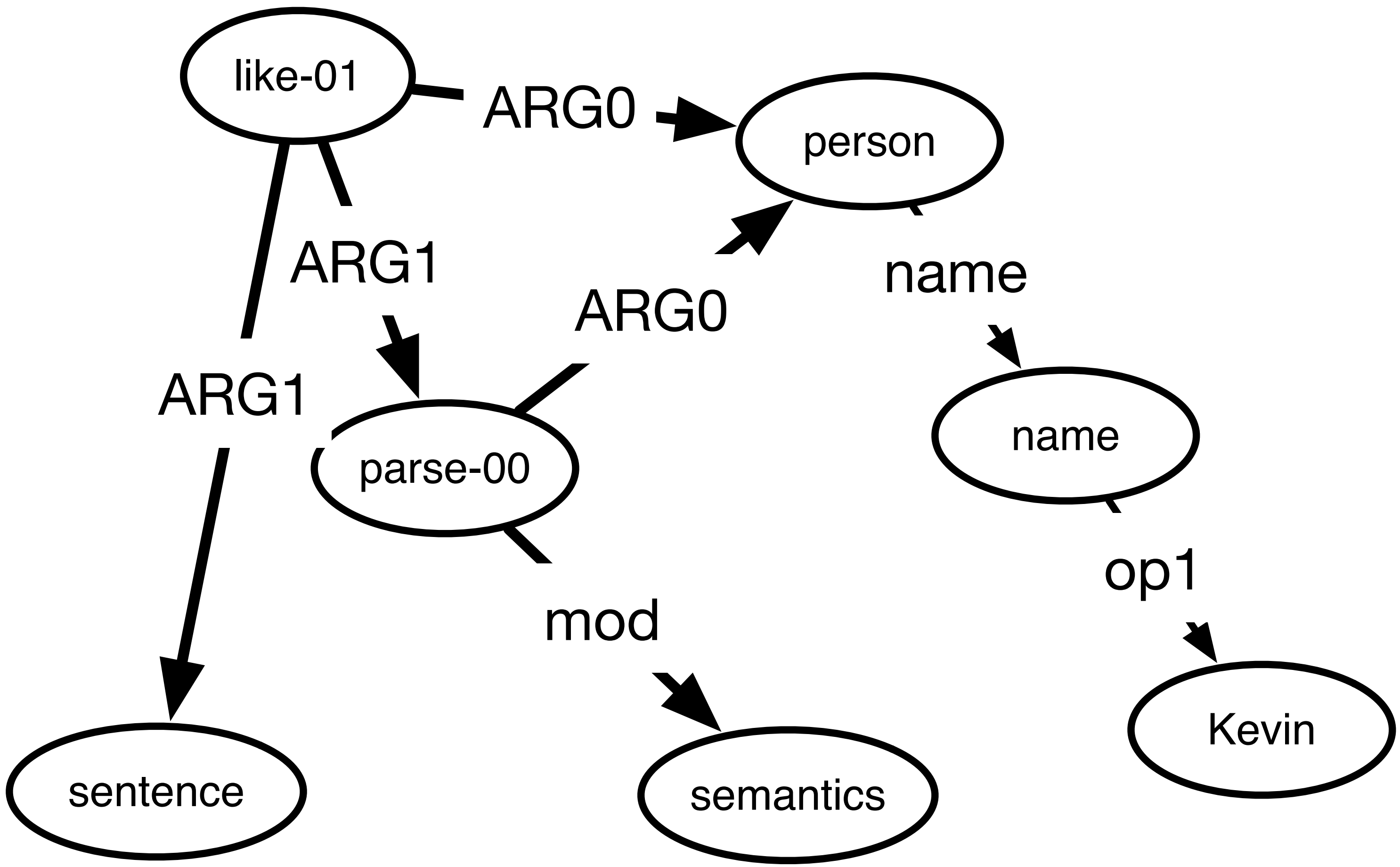
$$\phi^T \mathbf{z} = 0$$

Maximum Spanning, Connected Subgraph (MSCG)



Constraint: Graph must be deterministic

Determinism Constraints



Determinism Constraints

$$\mathbf{z}_{1 \xrightarrow{\text{ARG1}} 2} + \mathbf{z}_{1 \xrightarrow{\text{ARG1}} 3} + \ldots \leq 1$$

$$\mathbf{z}_{2 \xrightarrow{\text{ARG1}} 1} + \mathbf{z}_{2 \xrightarrow{\text{ARG1}} 3} + \ldots \leq 1$$

$$\vdots$$

Determinism Constraints

$$\mathbf{z}_{1 \xrightarrow{\text{ARG1}} 2} + \mathbf{z}_{1 \xrightarrow{\text{ARG1}} 3} + \ldots \leq 1$$

$$\mathbf{z}_{2 \xrightarrow{\text{ARG1}} 1} + \mathbf{z}_{2 \xrightarrow{\text{ARG1}} 3} + \ldots \leq 1$$

$$\vdots$$

$$A\mathbf{z} \leq b$$

Determinism Constraints

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

Preserving, simple, connected, spanning

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Determinism constraints

Solve using Lagrangian relaxation

Lagrangian Relaxation Tutorial

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Lagrangian Relaxation Tutorial

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Easy (know how to solve)

Lagrangian Relaxation Tutorial

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Easy

But this makes it hard

Lagrangian Relaxation Tutorial

Easy

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

But this makes it hard

Problem #1

Hard

Lagrangian Relaxation Tutorial

Easy

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Problem #1

Hard

But this makes it hard

$$\lambda^T(\mathbf{b} - A\mathbf{z})$$

Lagrange multipliers ≥ 0

Lagrangian Relaxation Tutorial

Easy

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Problem #1

Hard 

But this makes it hard

$$\max_{\mathbf{z} \in \mathcal{Z}} \phi^T \mathbf{z} + \lambda^T (\mathbf{b} - A\mathbf{z})$$

Add to original objective

Lagrangian Relaxation Tutorial

$$\max_{\mathbf{z}\in\mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Easy

Problem #1

Hard

But this makes it hard

$$\min_{\lambda\geq 0} \max_{\mathbf{z}\in\mathcal{Z}} \phi^T \mathbf{z} + \lambda^T(\mathbf{b} - A\mathbf{z})$$

Minimize over λ

Lagrangian Relaxation Tutorial

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$

s.t. $\mathbf{z}$ satisfies $A\mathbf{z} \leq b$

Easy

Problem #1
Hard

But this makes it hard

$$\approx$$

$$\min_{\lambda \geq 0} \max_{\mathbf{z} \in \mathcal{Z}} \phi^T \mathbf{z} + \lambda^T (\mathbf{b} - A\mathbf{z})$$

Problem #2
Easy

Not always equivalent, as we shall see

Solving Problem #2

- Problem #2 (aka "Lagrange Dual"):

$$\min_{\lambda \geq 0} \max_{\mathbf{z} \in \mathcal{Z}} \phi^T \mathbf{z} + \lambda^T (\mathbf{b} - A\mathbf{z})$$

- For a given λ, the max can be solved using algorithm given before (preprocessing + MSCG)
- To minimize over lambda
  – Use subgradient descent

Solving Problem #2

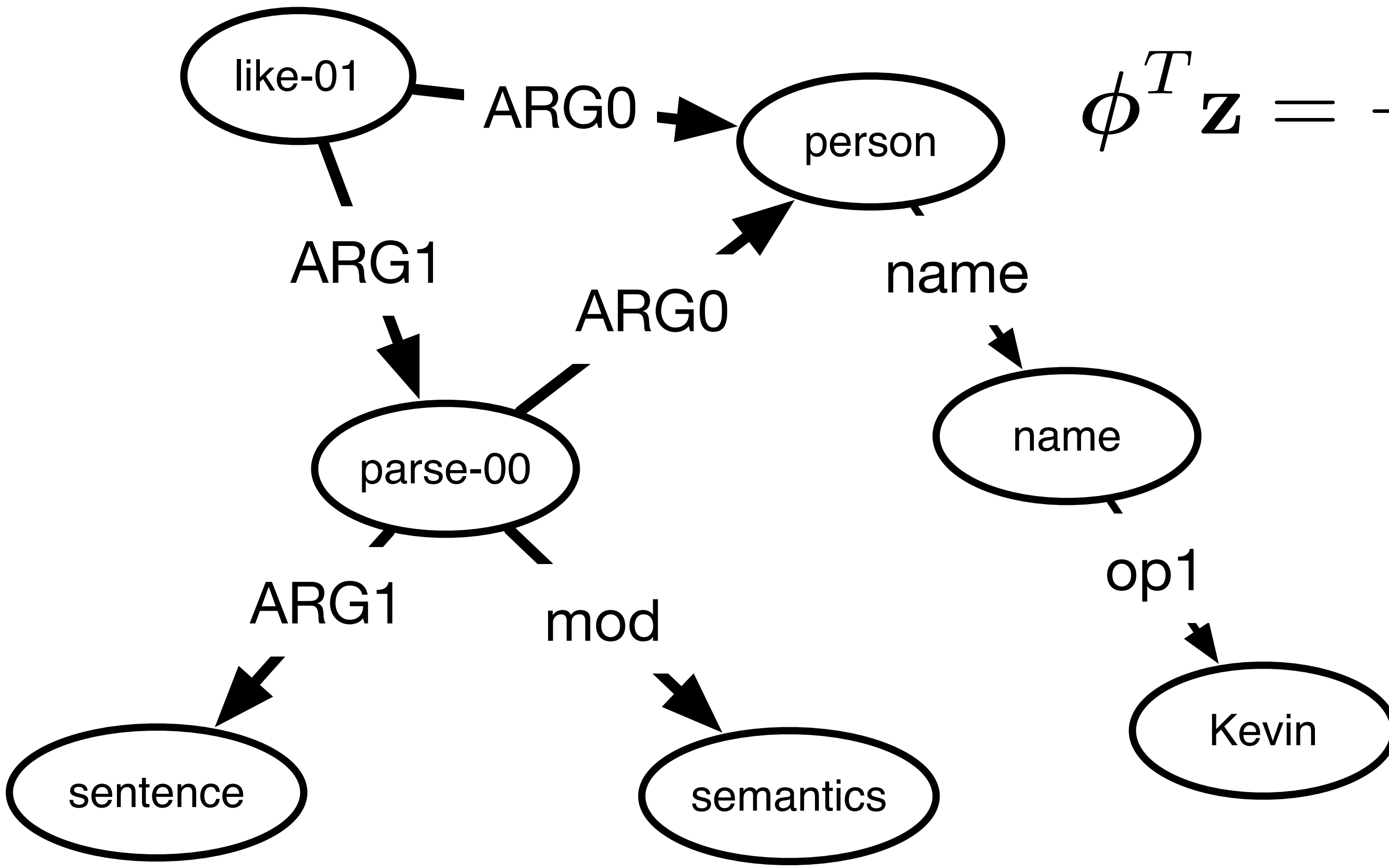
- Problem #2 (aka "Lagrange Dual"):

$$\min_{\lambda \geq 0} \max_{\mathbf{z} \in \mathcal{Z}} \phi^T \mathbf{z} + \lambda^T (\mathbf{b} - A\mathbf{z})$$

- For a given λ, the max can be solved using algorithm given before (preprocessing + MSCG)
- To minimize over lambda
  – Use subgradient descent

If constraints are not satisfied at minimum, then Problem #1 ≠ Problem #2

After subgradient descent



$$\phi^T \mathbf{z} = -2$$

Summary: Output Graph Properties

- Maximum weight
- Preserving
- Simple
- Spanning (all nodes)
- Connected
- Deterministic

Features & Training

- Features
  - Edge bias
  - Edge label
  - Head concept, tail concept, head word, tail word
  - Dependency path (dependency edge labels and POS on the shortest path between any two words in the span)
  - Various distance features
  - Within fragment edge indicator
  - Various conjunctions of above features

- Weights trained using AdaGrad structured perceptron

Experiments

- Alignment
- Parsing
  - Graph-based parsing
    - Concept identification
    - Relation identification
      - Maximum spanning connected graph algorithm (MSCG)
      - Graph determinism constraints using Lagrangian relaxation
    - **Experiments**
  - Transition-based parsing
  - Parsing using syntax-based MT
- Evaluation
- Graph Grammars and Automata
- Applications

Experiments

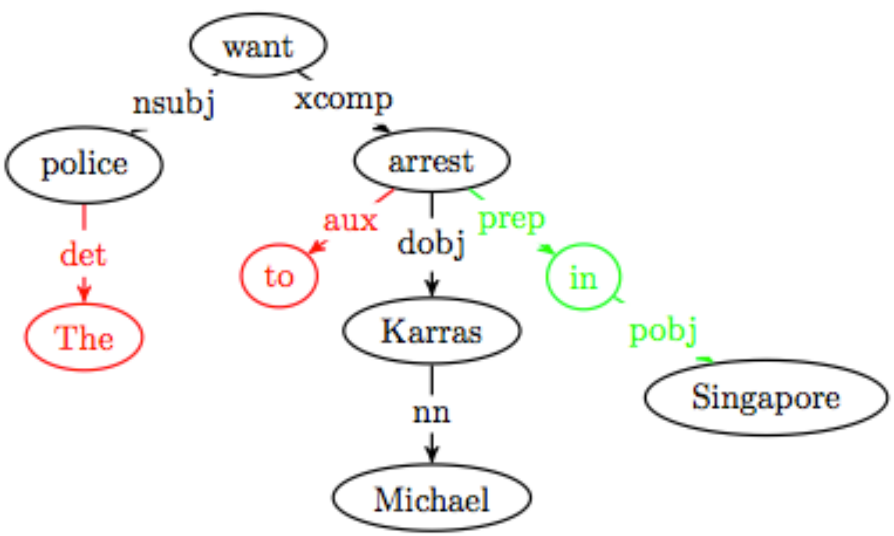
	ACL 2014	Now
Full System (gold concepts)	80% Smatch	81% Smatch
Full System	58% Smatch	62% Smatch

- Data: LDC2013E117
  - 4,000 training instances
  - 2,000 test
  - 2,000 dev

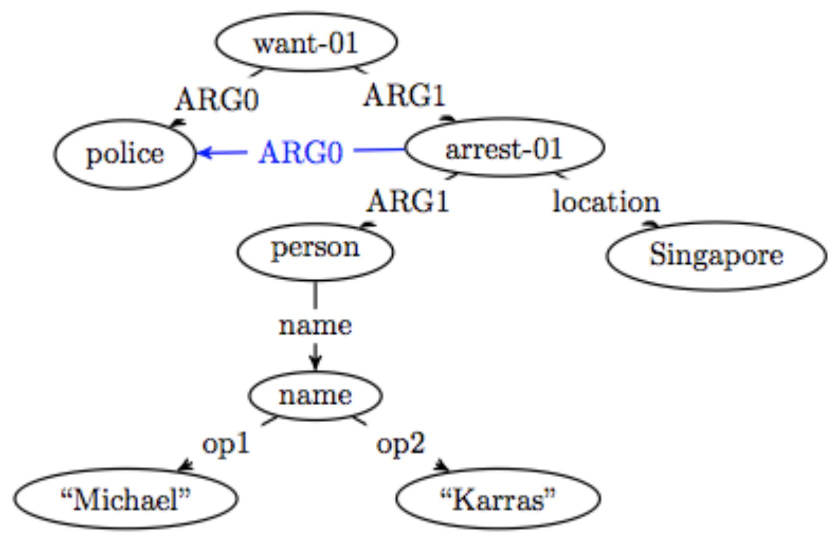
Transition-based AMR Parsing (Wang et al, NAACL 2015)

- Convert dependency tree into AMR graph
- Motivation: only a few difference between syntactic dependencies and AMR

<u>Dependency tree</u>



<u>AMR graph</u>

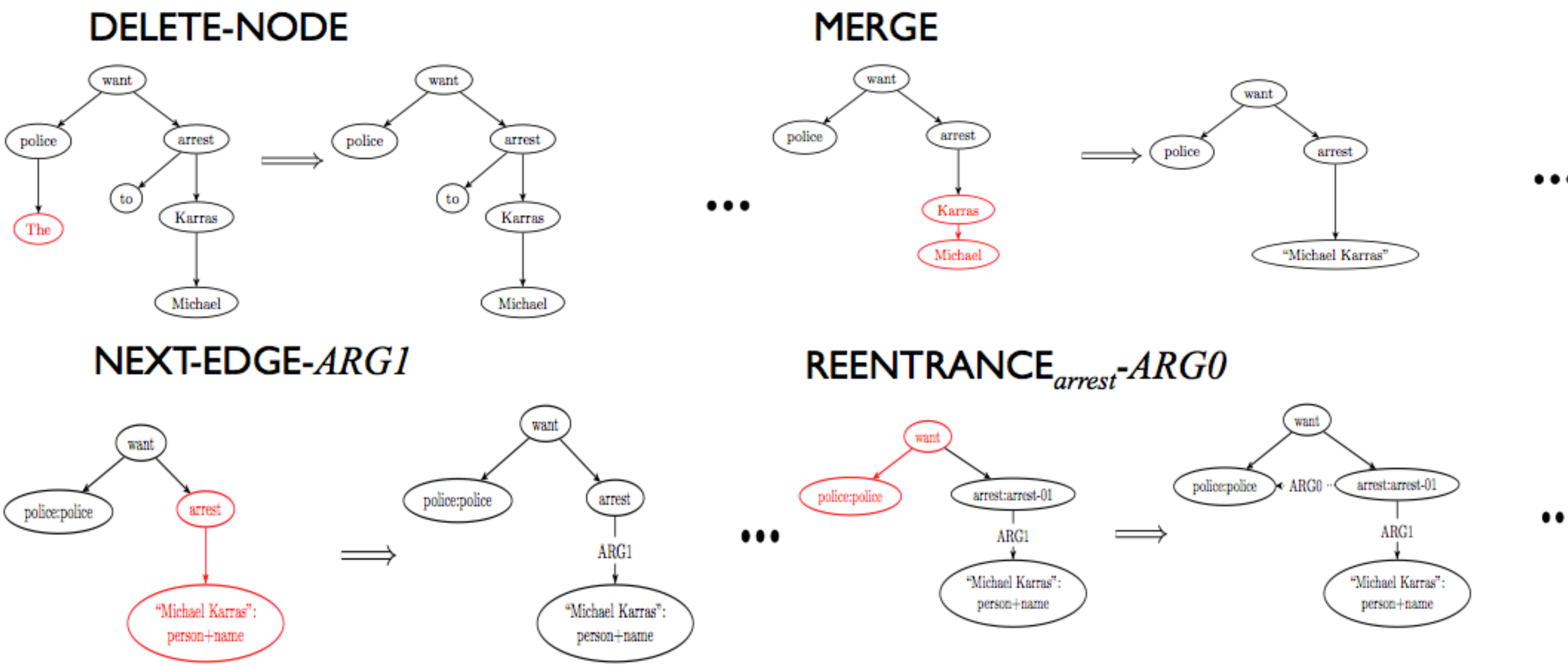


(graphic thanks to Chuan Wang)

Transition-based AMR Parsing

- Actions applied to graph in post-order traversal
- Parser actions
  - **NEXT-EDGE-l_r** (attach edge and move to next word)
  - **SWAP-l_r** (swap nodes and attach with edge)
  - **REATTACH$_k$-l_r** (delete edge and reattach to already processed node)
  - **REPLACE-HEAD** (replace node with another node)
  - **REENTRANCE$_k$-l_r** (attach edge to already processed node)
  - **MERGE** (merge two nodes)
  - **NEXT-NODE-l_c** (label with concept and move to next word)
  - **DELETE-NODE** (deletes a word)

Transition-based AMR Parsing



(graphic thanks to Chuan Wang)

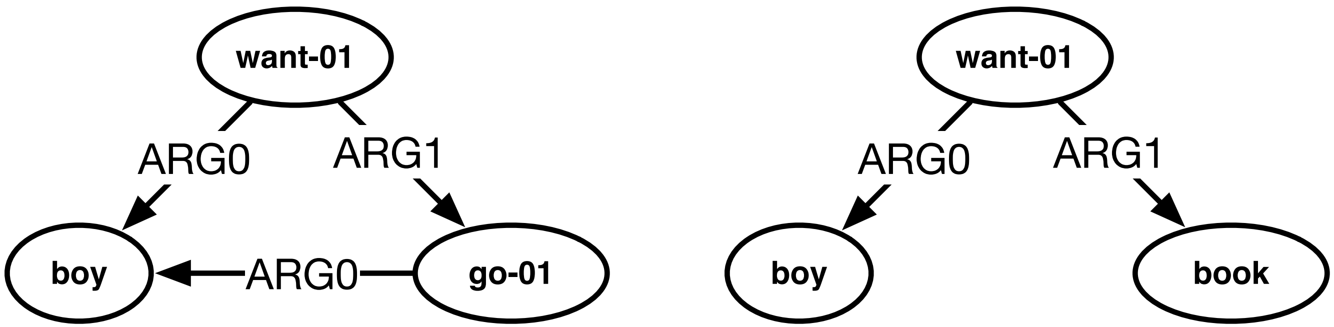
AMR Parsing using Syntax-based MT (Pust et al, 2015)

- Idea: already have sophisticated string-to-tree syntactic MT systems. Use them for AMR parsing
- Approach: convert AMR graphs into trees suitable for training string-to-tree MT systems
- Important features:
  - Language model on the linearized AMR
  - Semantic categories built using WordNet
- Large performance gains JAMR (7 smatch points)

Evaluation

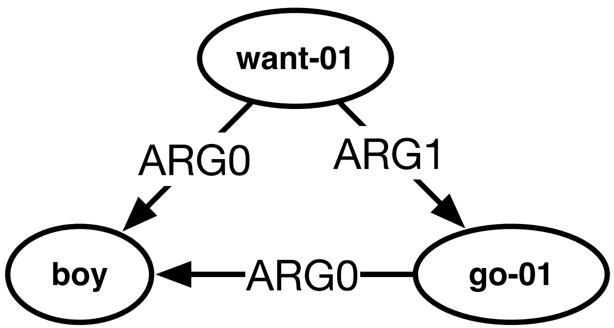
- Alignment
- Parsing
- **Evaluation**
- Graph Grammars and Automata
- Applications

Evaluation: Smatch (Cai & Knight, 2013)

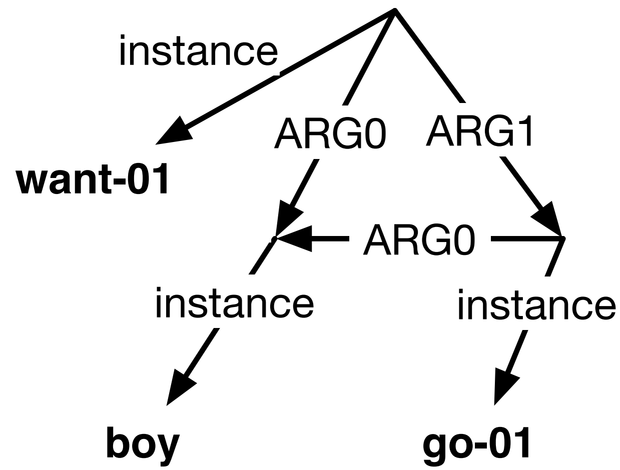


Want a number which indicates the similarity between two graphs

Evaluation: Smatch

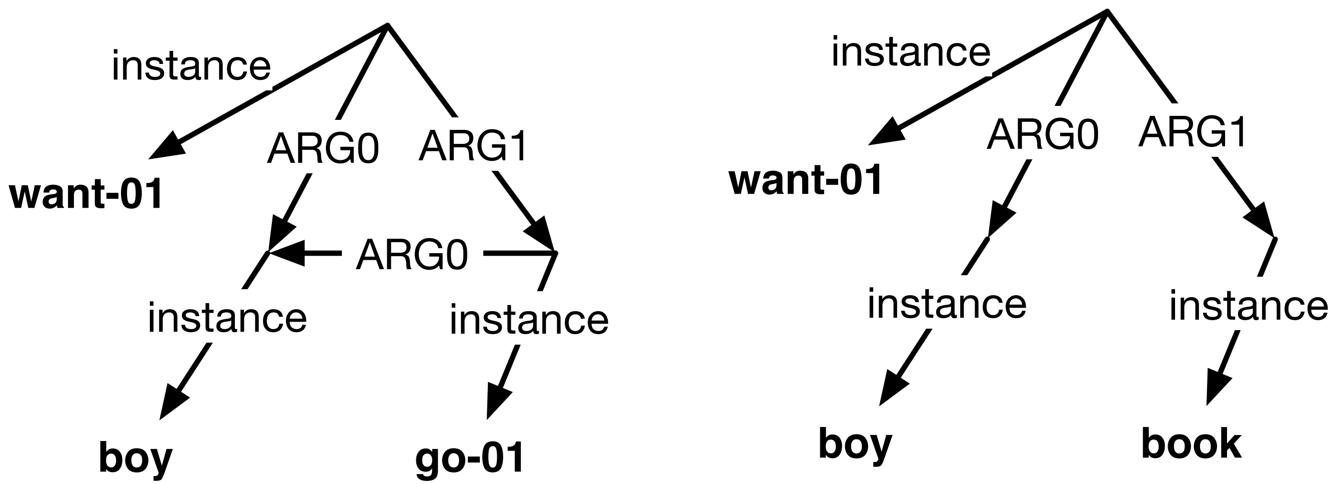



```
(a / want-01
     :ARG0 (b / boy
     :ARG1 (c / go-01
          :ARG0 b))
```

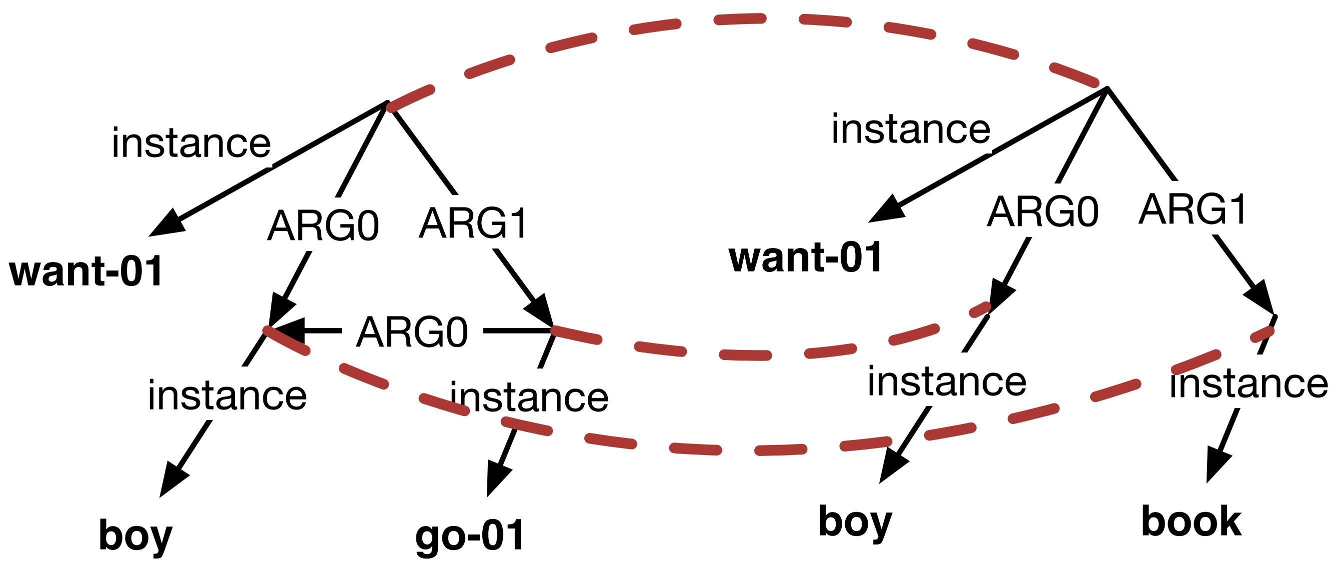


AMR graph w/ explicit instance edges

Evaluation: Smatch

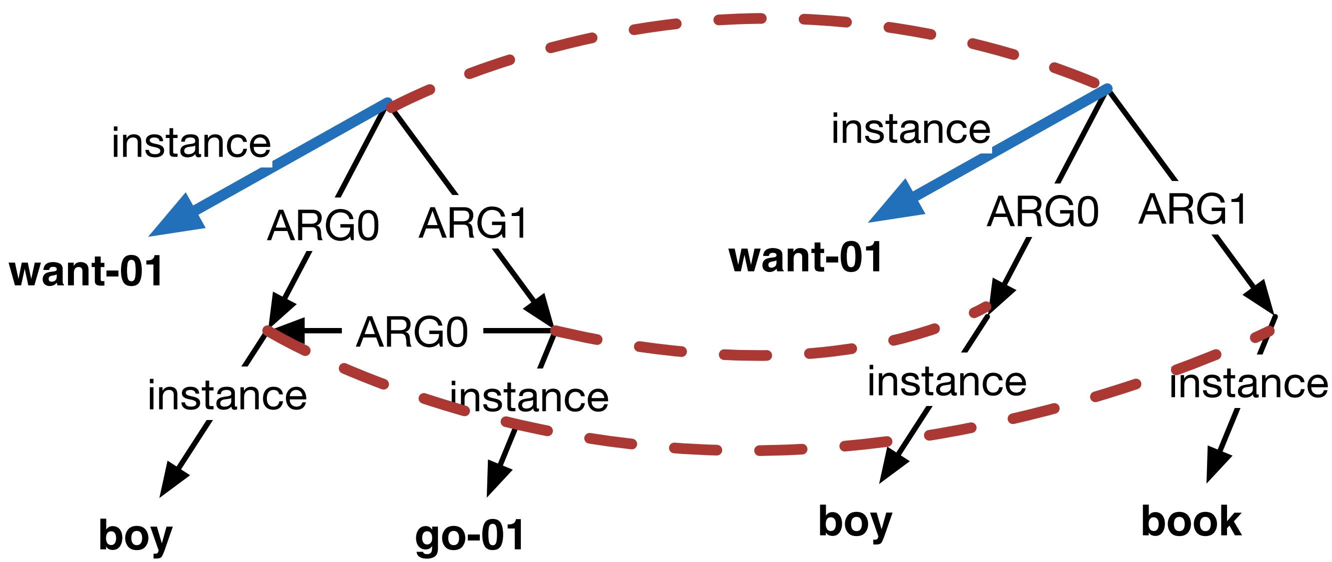


Evaluation: Smatch



Consider an alignment between the nodes

Evaluation: Smatch

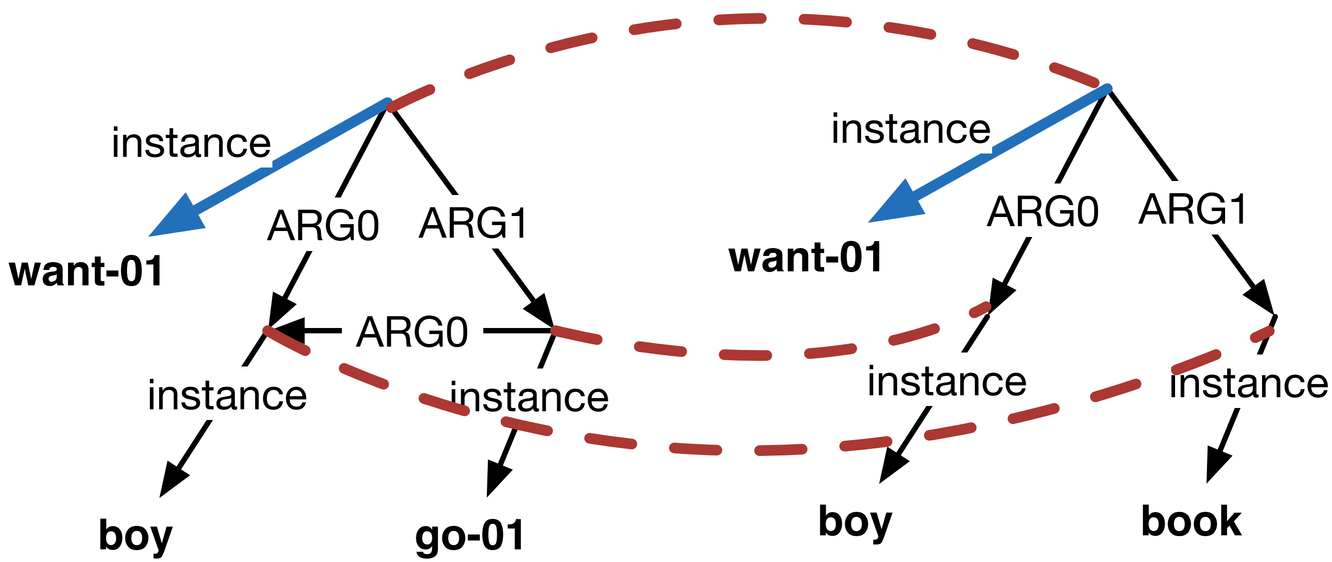


f-score = F_1 of identical matching edges

= 2 Match/(Total_1 + Total_2)

= 2 / (6 + 5) = .18

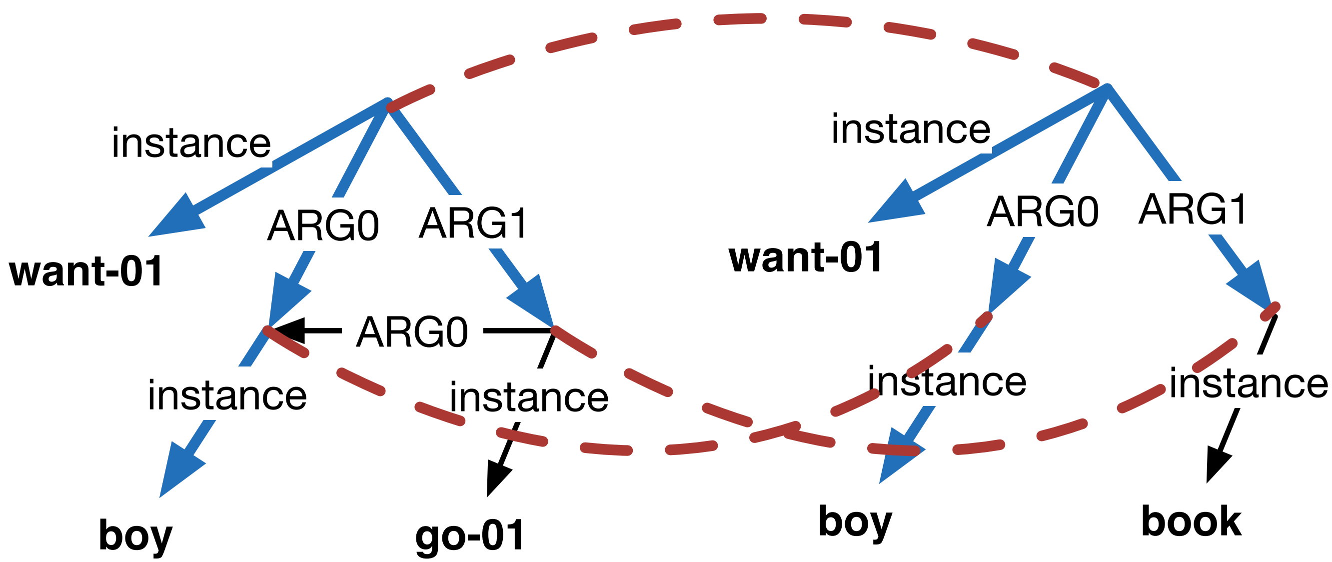
Evaluation: Smatch



Smatch score = maximum f-score over all possible alignments

NP hard => approximate inference to find highest scoring alignment

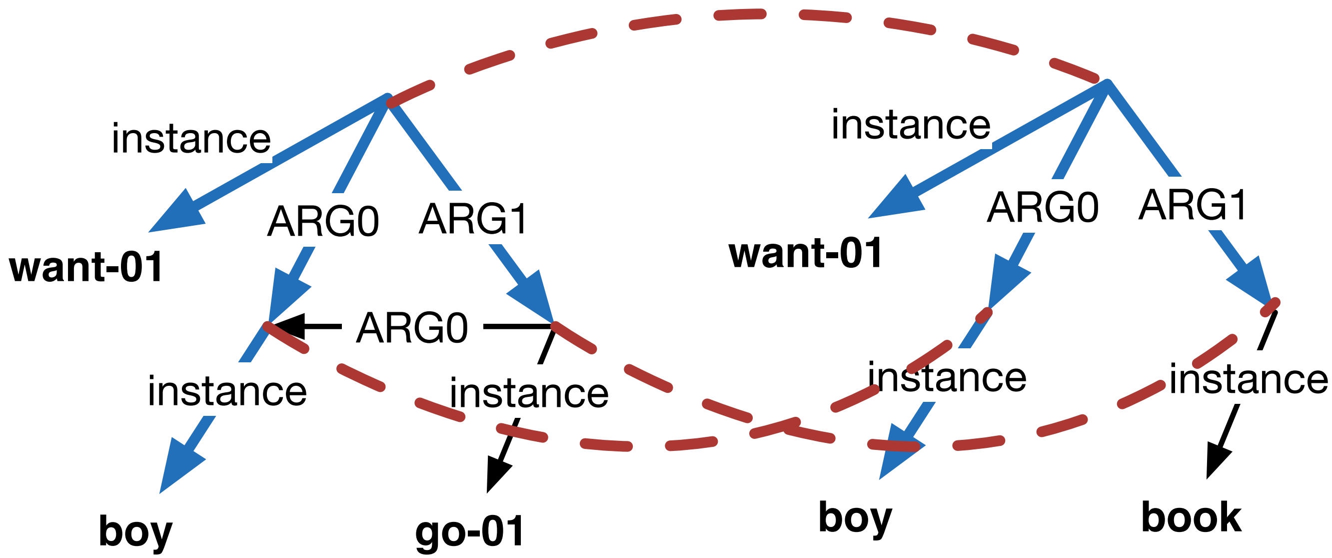
Evaluation: Smatch



Smatch score = 8 / (6 + 5) = .73

Highest scoring alignment

Evaluation: Smatch



Multi-lingual version of Smatch: AMRICA demo by Naomi Saphra at NAACL 2015

Roadmap

- Alignment
- Parsing
- Evaluation
- **Graph Grammars and Automata**
  - Background: CFGs and tree substitution grammars
  - Hyperedge Replacement Grammars (HRGs)
  - Directed Acyclic Graph (DAG) Automata
- Applications

Motivation for Graph Grammars

- String and tree grammars, automata, transducers, etc widely used in NLP applications
  - Phrase structure parsers, syntactic MT systems
- Semantics (like AMR) is represented as graphs

We would like grammars, automata, transducers, etc over graphs

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

S

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

S

$\Rightarrow_1$ NP VP

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

S

$\Rightarrow_1$ NP VP

$\Rightarrow_3$ NP V NP

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

S

$\Rightarrow_1$ NP VP

$\Rightarrow_3$ NP V NP

$\Rightarrow_4$ NP like NP

Context Free Grammar (CFG)

<u>Grammar</u>

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

<u>Example derivation</u>

S

$\Rightarrow_1$ NP VP

$\Rightarrow_3$ NP V NP

$\Rightarrow_4$ NP like NP

$\Rightarrow_6$ NP like ice cream

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

S
$\Rightarrow_1$ NP VP
$\Rightarrow_3$ NP V NP
$\Rightarrow_4$ NP like NP
$\Rightarrow_6$ NP like ice cream
$\Rightarrow_2$ We like ice cream

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Derivation

Example derivation

$$\left\{\begin{array}{l} \quad S \\ \Rightarrow_1 \text{NP VP} \\ \Rightarrow_3 \text{NP V NP} \\ \Rightarrow_4 \text{NP like NP} \\ \Rightarrow_6 \text{NP like ice cream} \\ \Rightarrow_2 \text{We like ice cream} \end{array}\right.$$

Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

Derivation

S

$\Rightarrow_1$ NP VP

$\Rightarrow_3$ NP V NP

$\Rightarrow_4$ NP like NP

$\Rightarrow_6$ NP like ice cream

$\Rightarrow_2$ We like ice cream

Yield = **string**

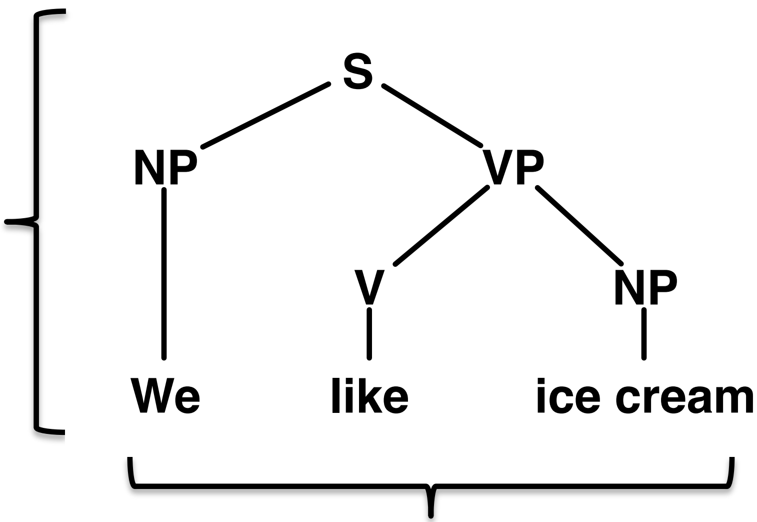
Context Free Grammar (CFG)

Grammar

1) S -> NP VP
2) NP -> We
3) VP -> V NP
4) V -> want
5) V -> like
6) NP -> ice cream

Example derivation

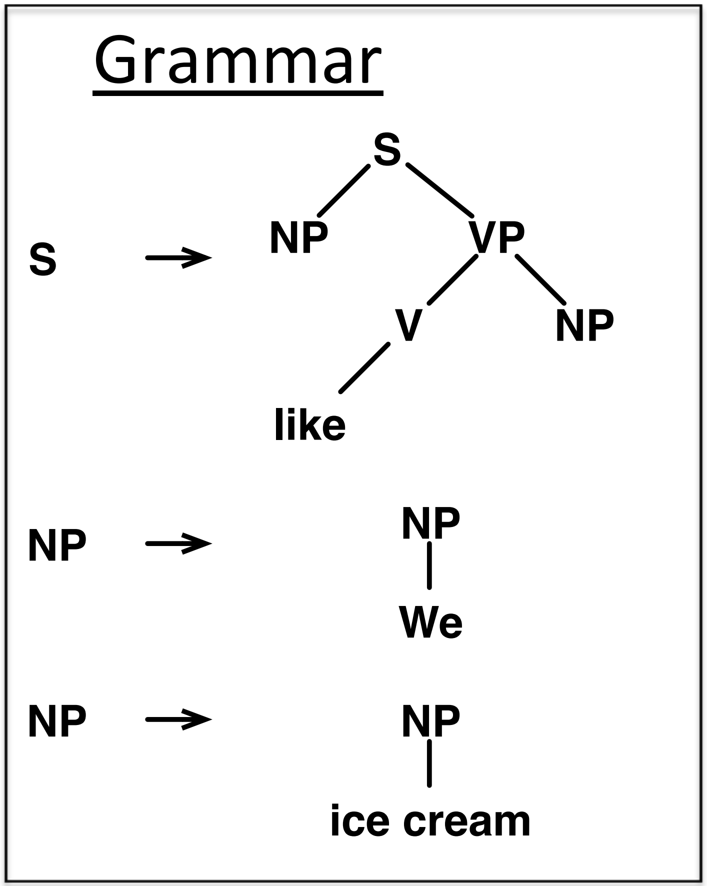
Derivation tree



Yield = **string**

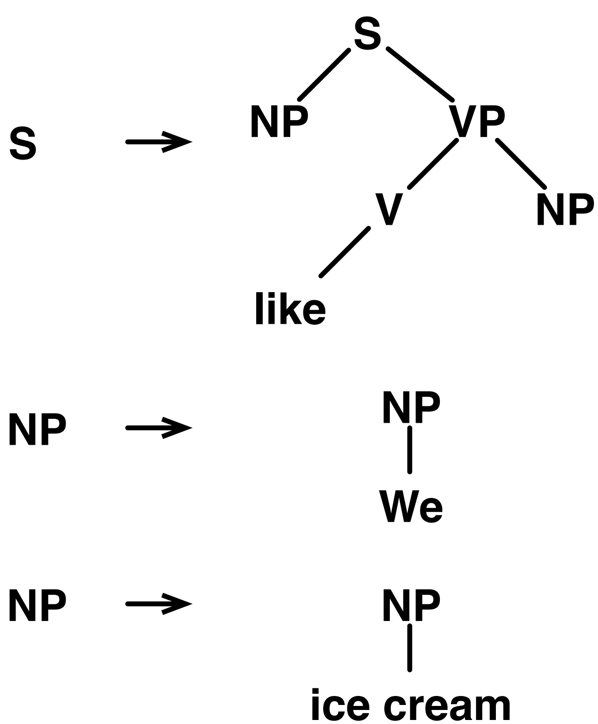
Language over strings (yield), and trees (derivations)

Tree Substitution Grammar (TSG)



Tree Substitution Grammar (TSG)

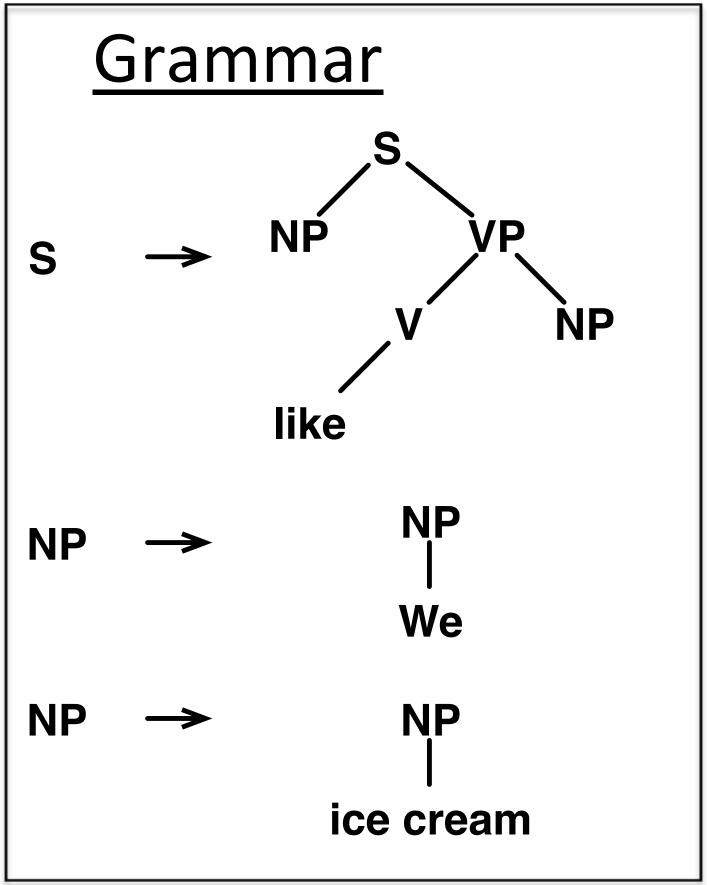
Grammar

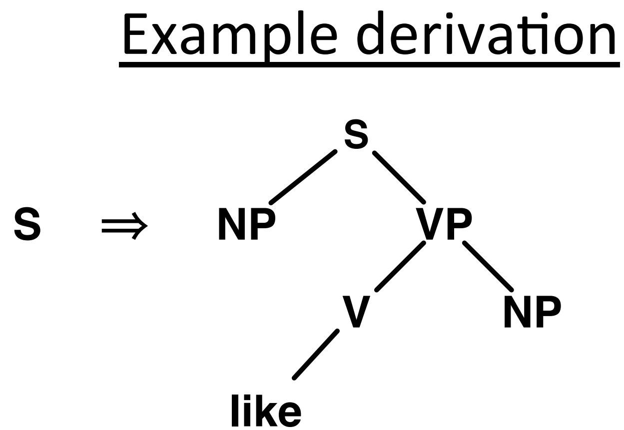


Example derivation

S

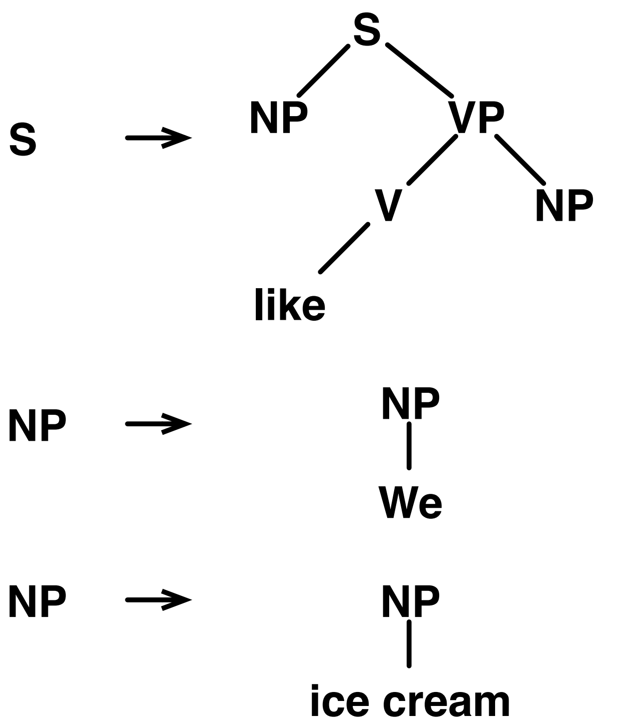
Tree Substitution Grammar (TSG)



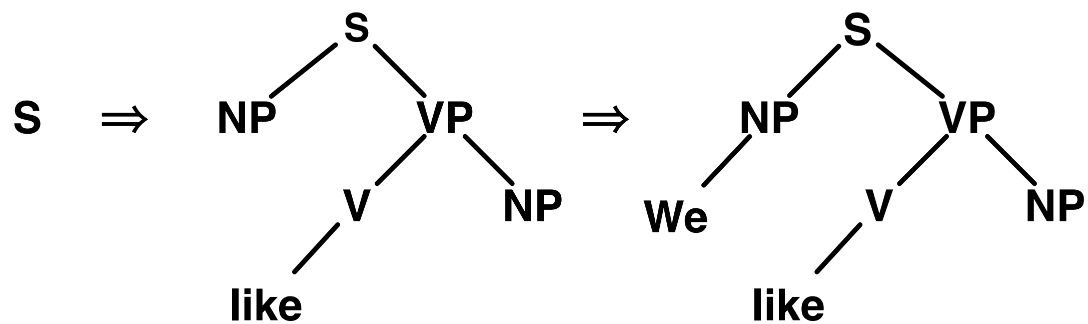


Tree Substitution Grammar (TSG)

Grammar

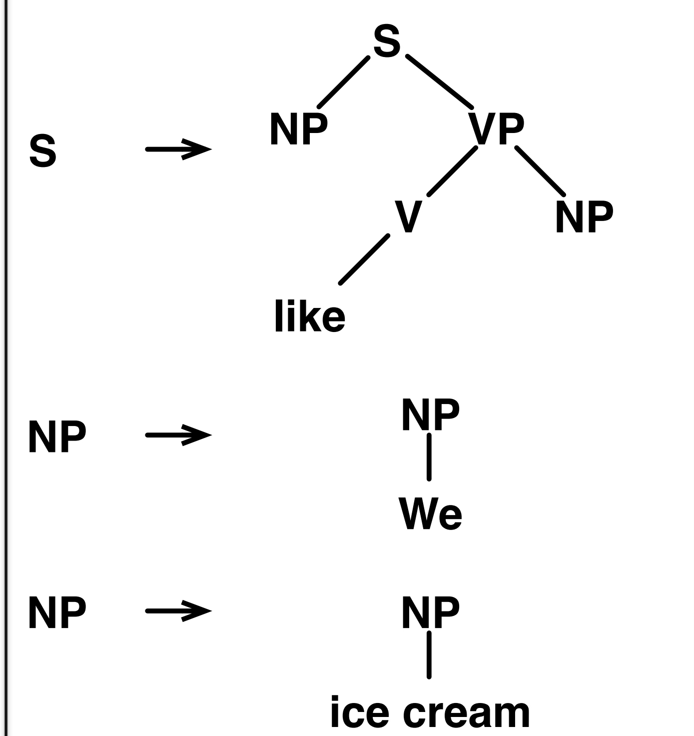


Example derivation

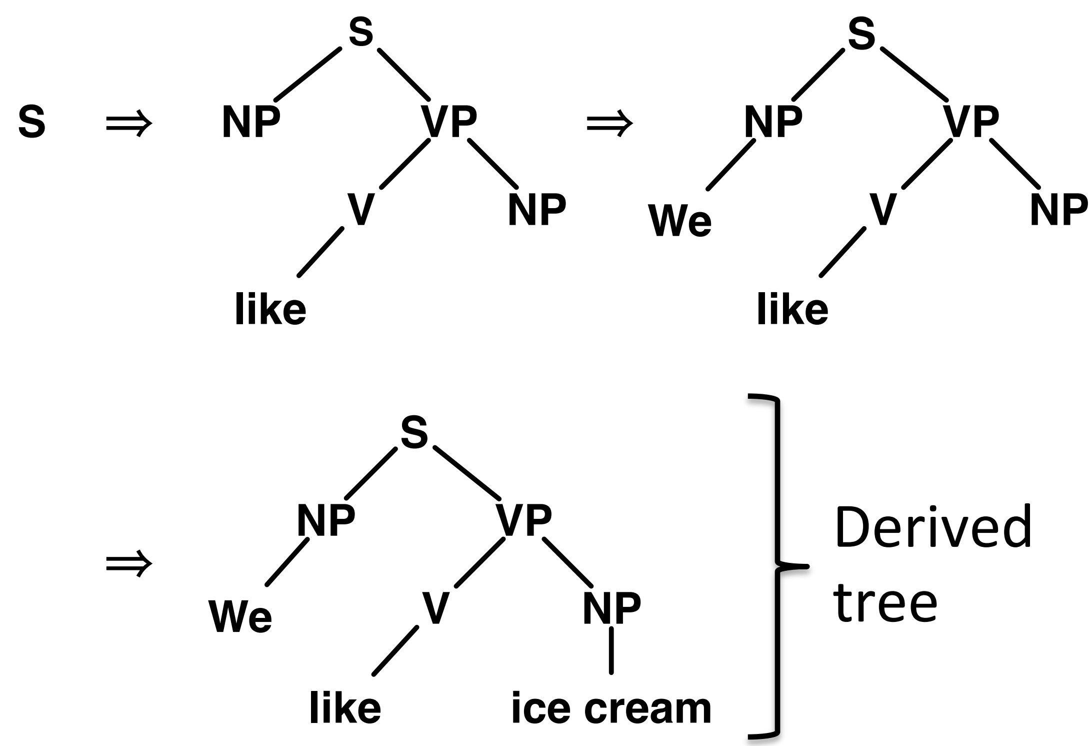


Tree Substitution Grammar (TSG)

Grammar

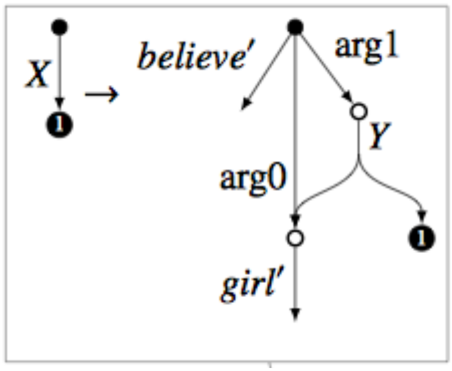


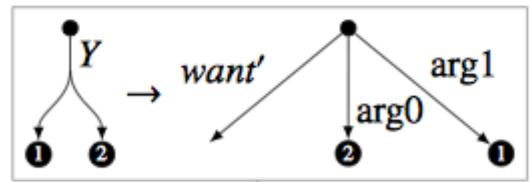
Example derivation



Hyperedge Replacement Grammar (HRG)

Grammar rules (some of them)

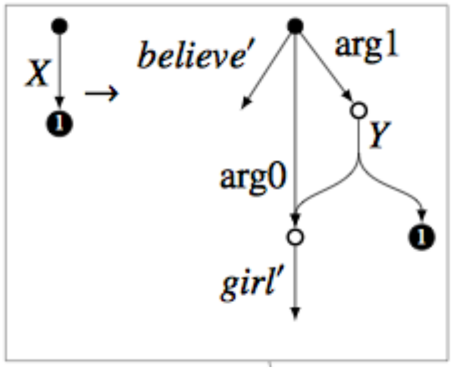


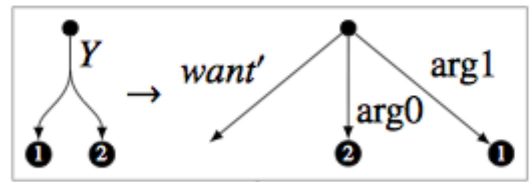


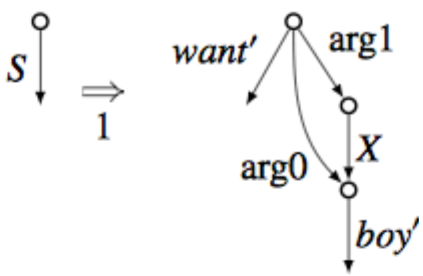
(figure from Chiang et al, 2013)

Hyperedge Replacement Grammar (HRG)

Grammar rules (some of them)



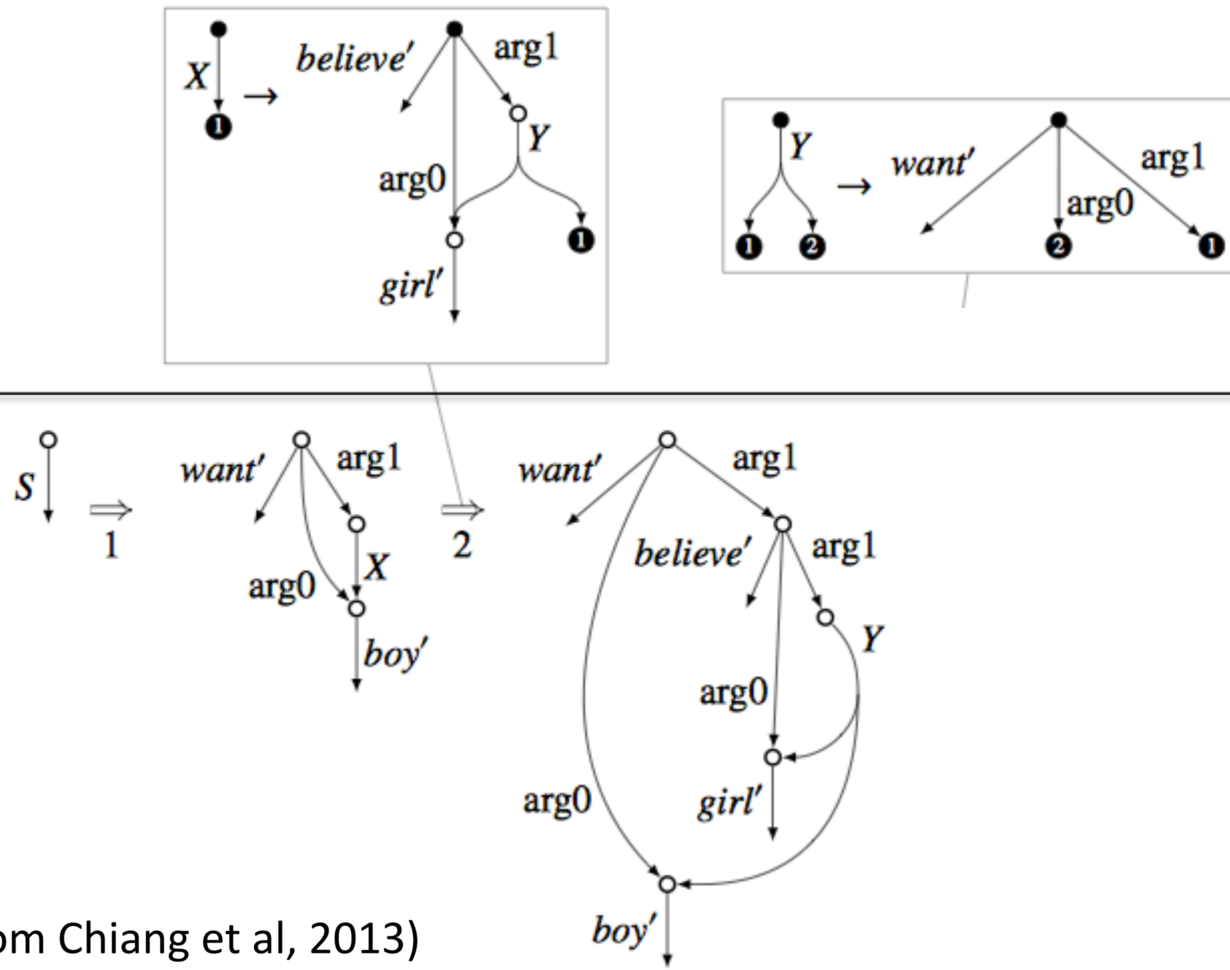




(figure from Chiang et al, 2013)

Hyperedge Replacement Grammar (HRG)

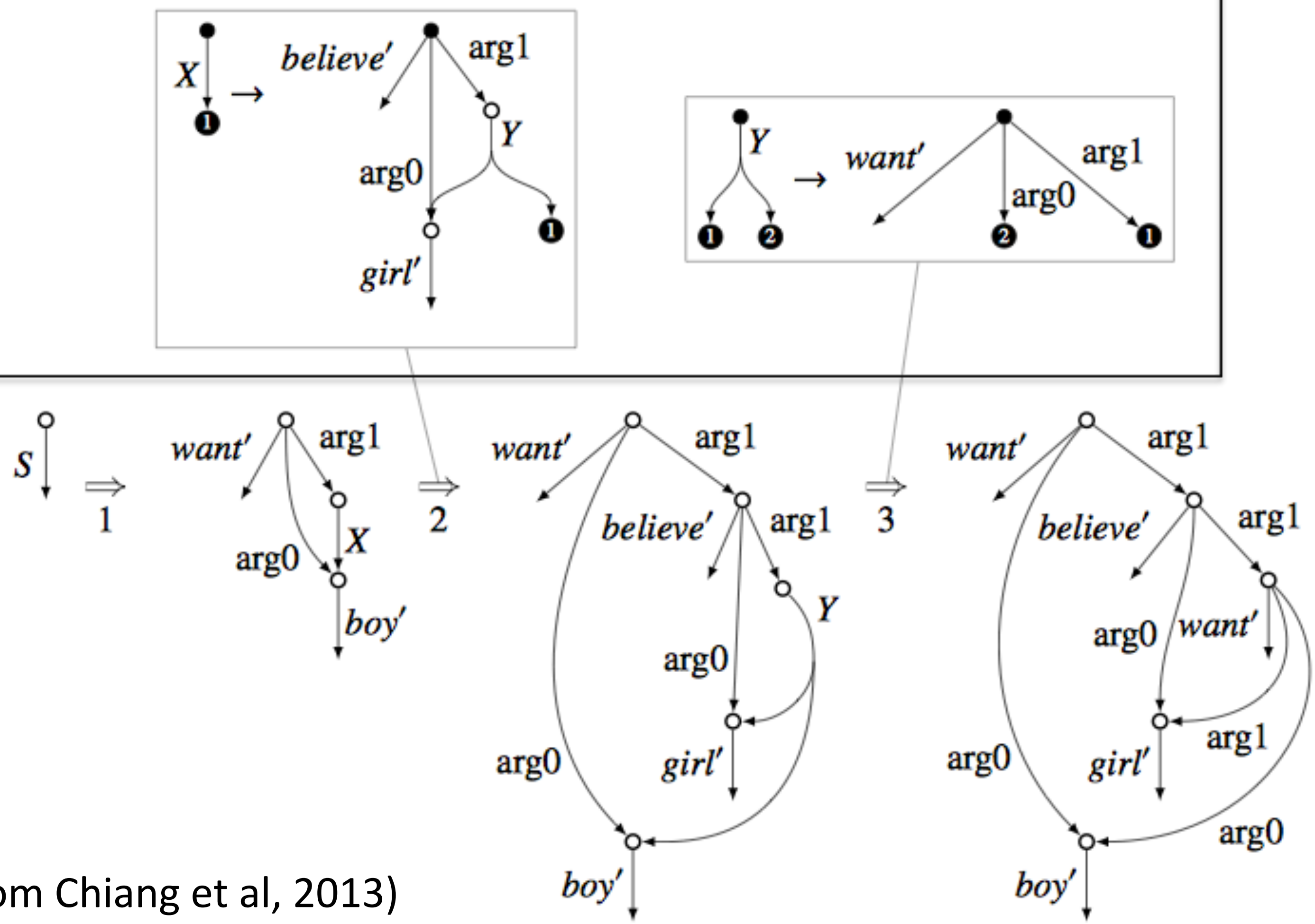
Grammar rules (some of them)



(figure from Chiang et al, 2013)

Hyperedge Replacement Grammar (HRG)

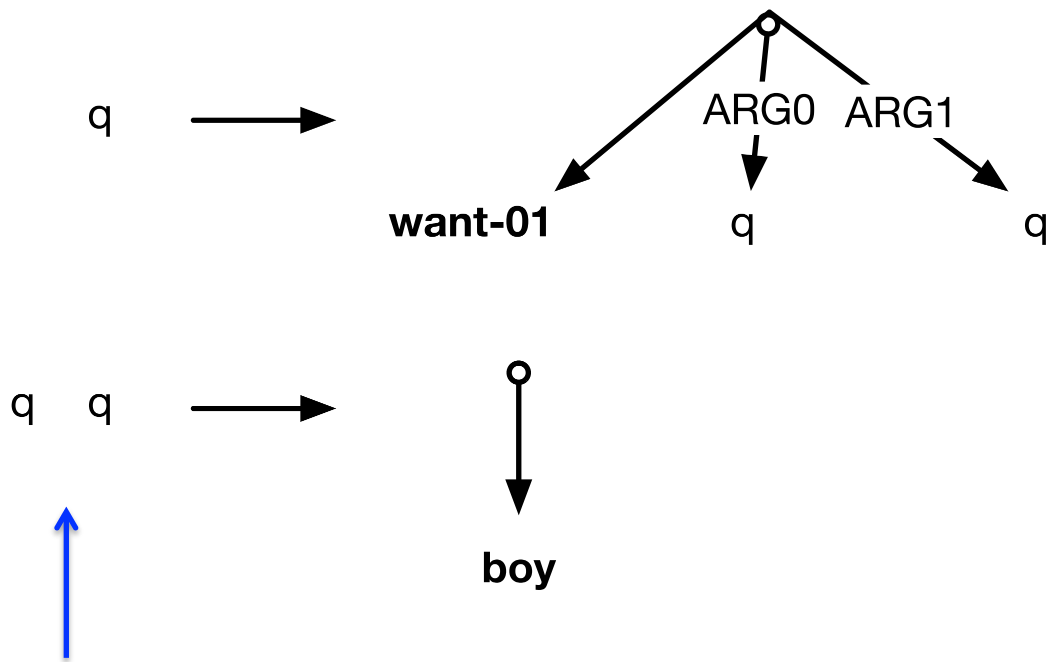
Grammar rules (some of them)



(figure from Chiang et al, 2013)

DAG Automata

(Kamimura and Slutzki, 1981. Quernheim and Knight, 2012)

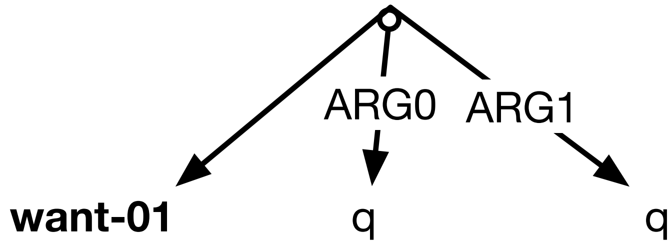


Rewrite rule
(“explicit rule”)

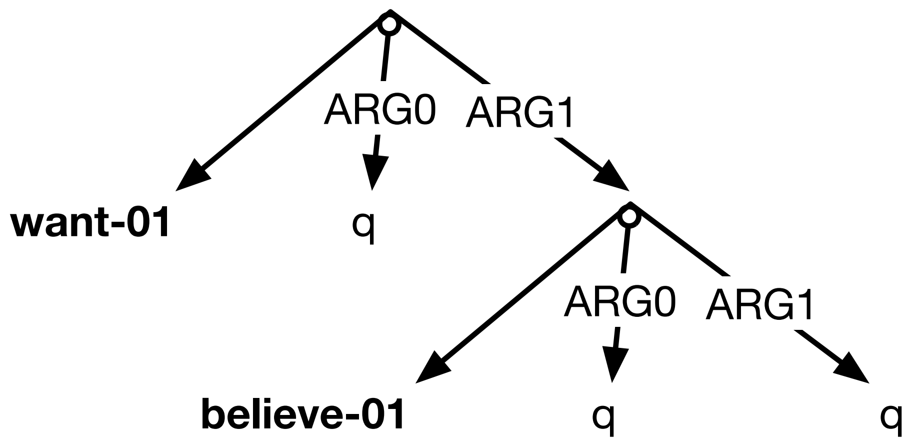
Merge rule
(“implicit rule”)

Two or more states can merge rule

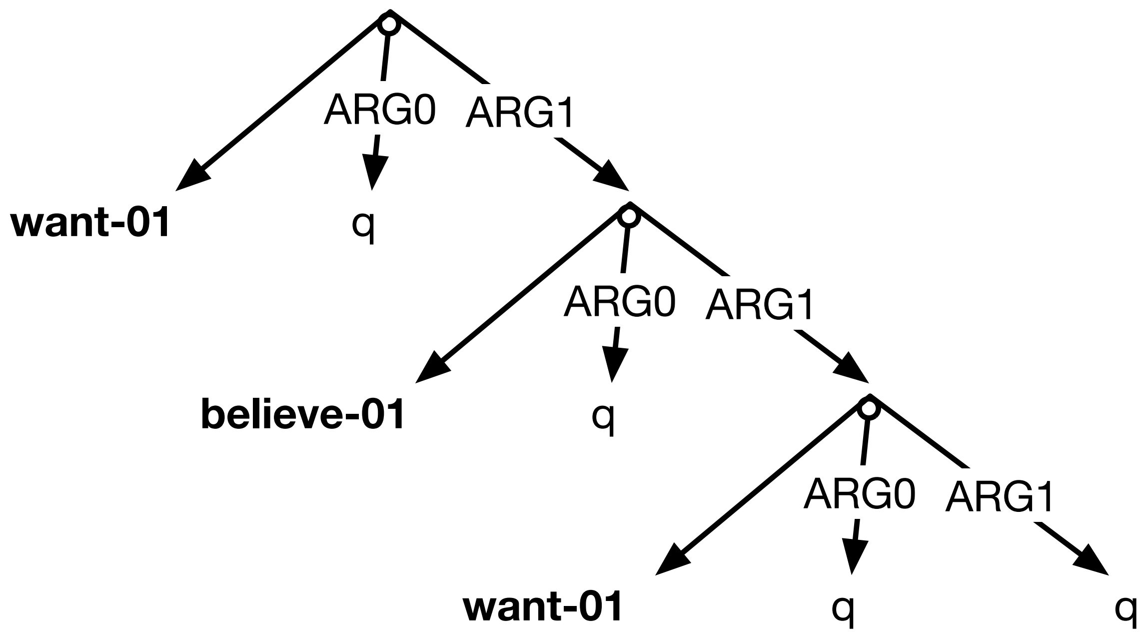
DAG Automata



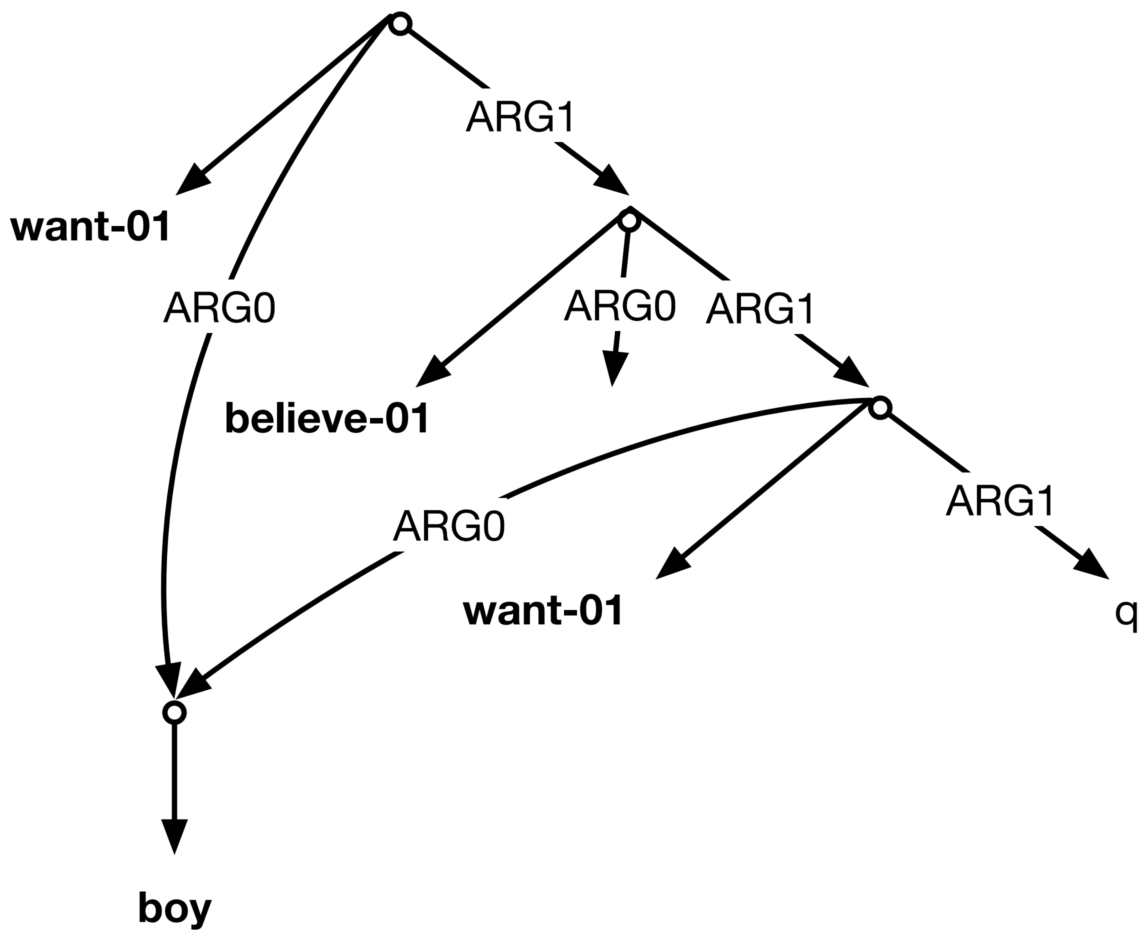
DAG Automata



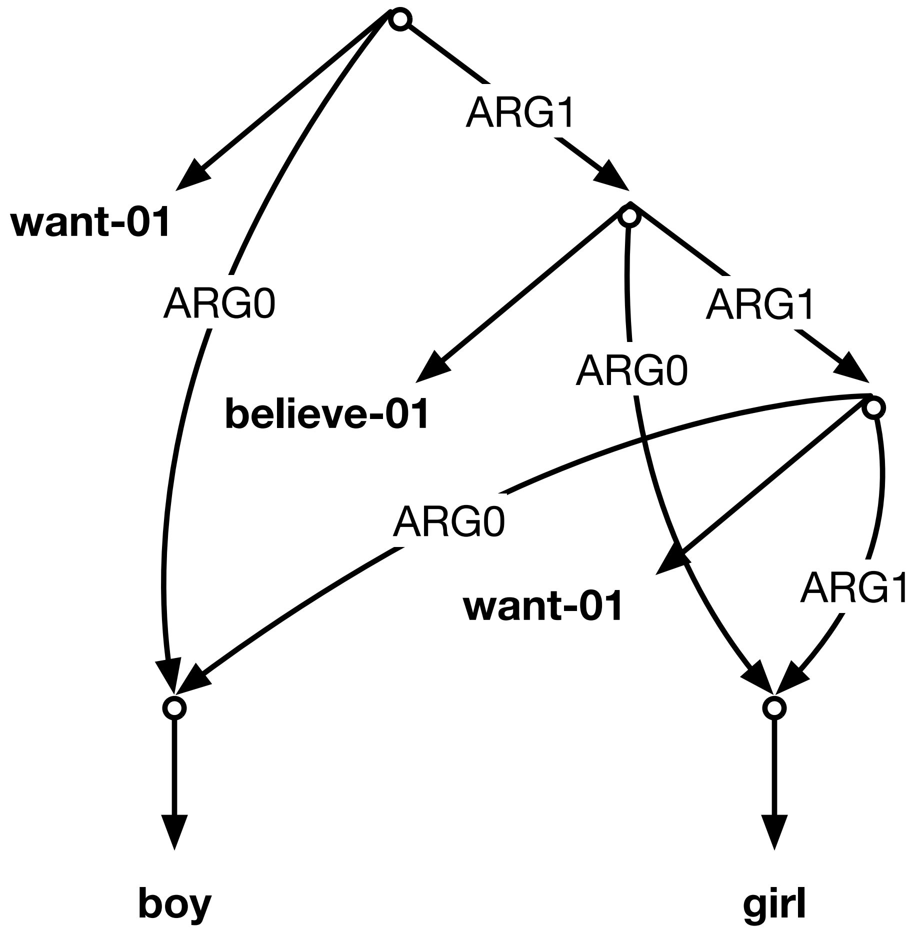
DAG Automata



DAG Automata



DAG Automata



Extensions

- Weighted and probabilistic grammars
- Synchronous grammars and transducers
  - Useful for building parsers, generators, and MT systems

Recent/Ongoing work

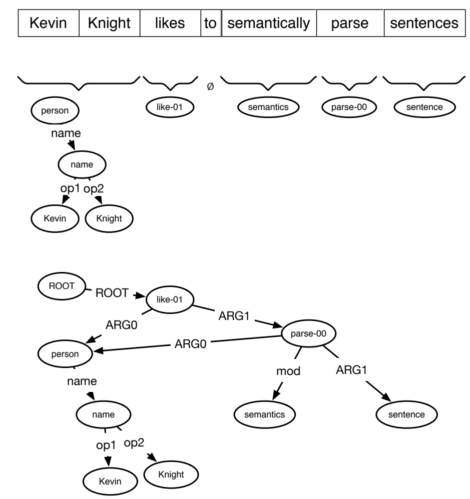
- Improved parsing algorithms (Chiang et al, 2013)
- Applications to parsing and generation (Braune et al, 2014) and MT (Jones et al, 2012)
- Implementations
  - Hyperedge replacement grammars: **Bolinas** (Chiang et al, 2013; Jones et al, 2012)
  - DAG automata: **DAGGER** (Quernheim & Knight, 2012)

Alignment

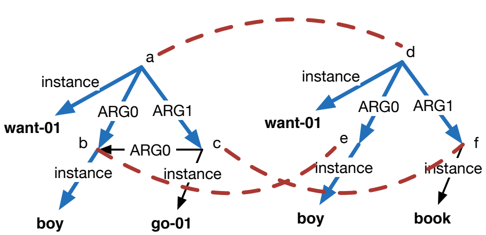
IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :ARG0 (n / name
            :op1 "IAEA"))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 "North"
                    :op2 "Korea")))))
    :time (d / date-entity
        :month 11))
```

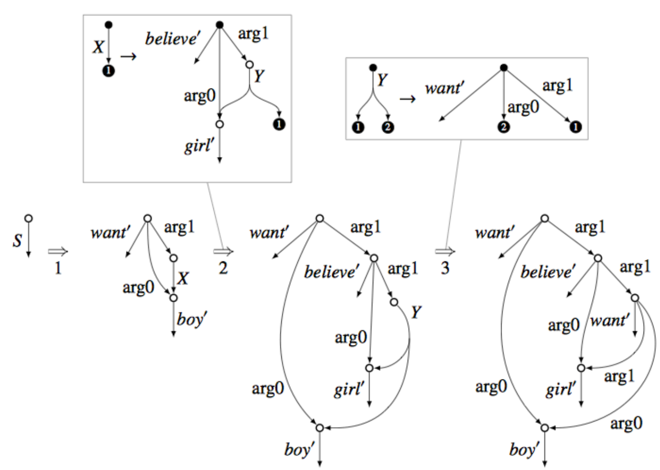
Parsing



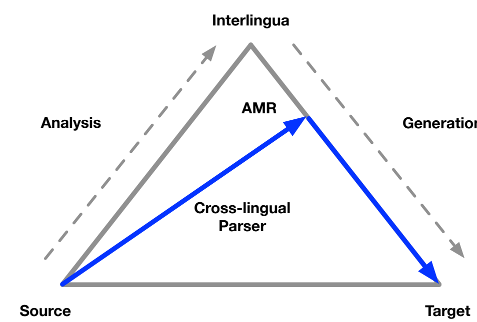
Evaluation



Graph grammars



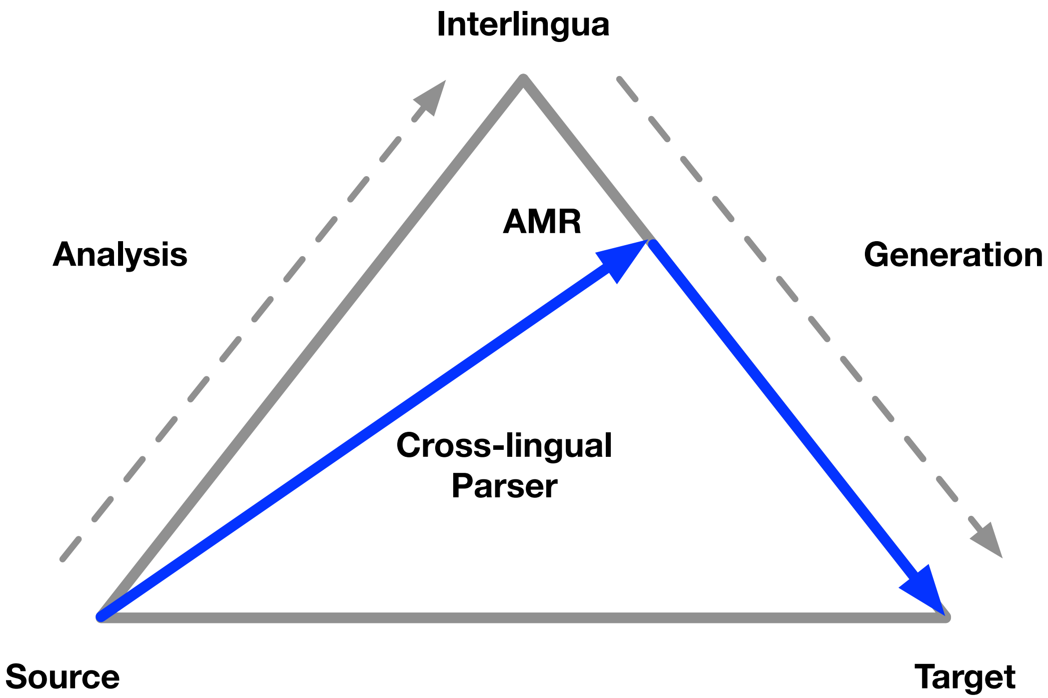
Applications



Applications

- Alignment
- Parsing
- Evaluation
- Graph Grammars and Automata
- **Applications**
  - MT, Summarization, Entity linking

Machine Translation

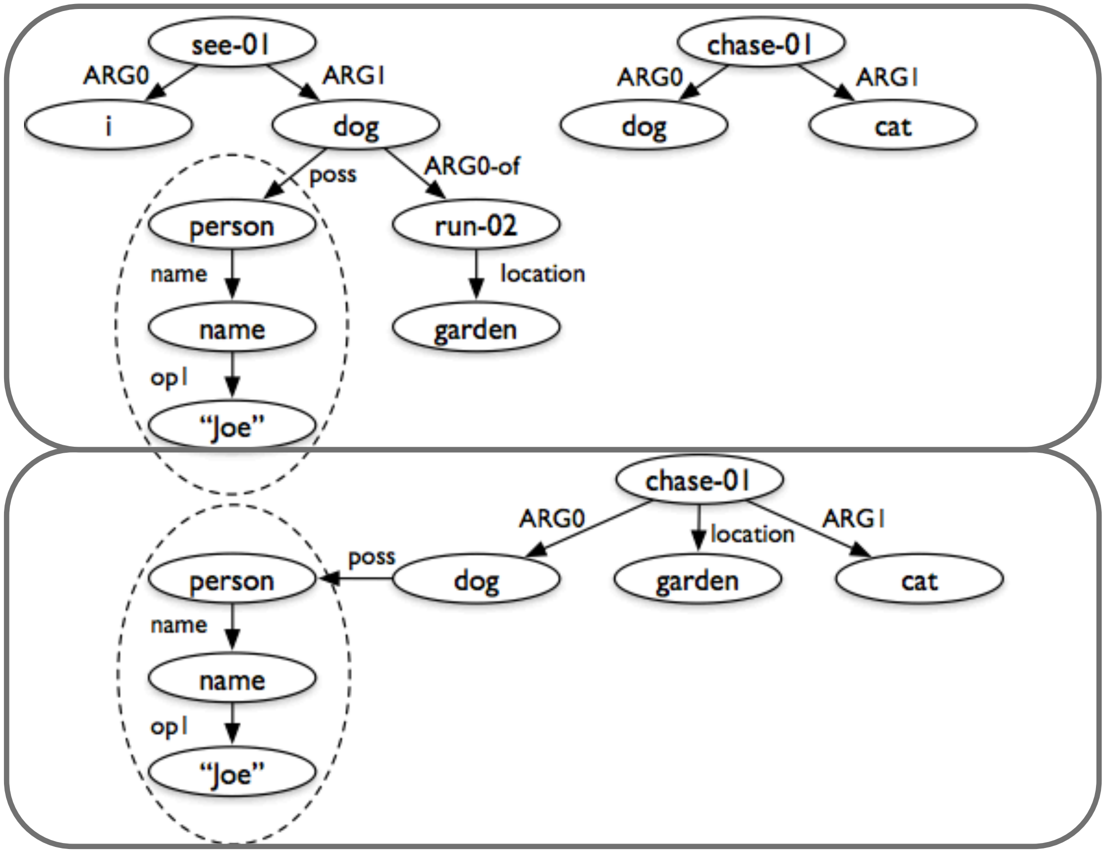


Summarization (Liu et al, NAACL 2015)

Document Sentences (input)

Sentence A: I saw Joe's dog, which was running in the garden.
Sentence B: The dog was chasing a cat.

Document AMRs (run parser)



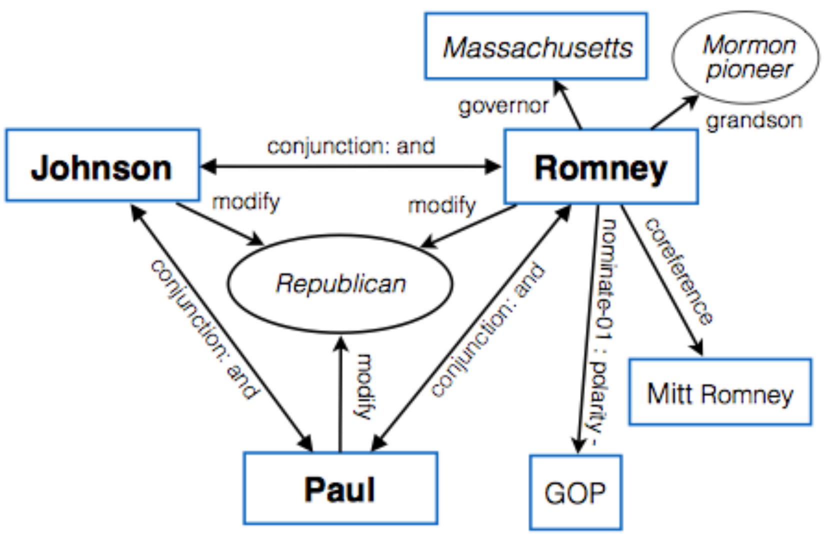
Summary AMR (select nodes and edges)

Summary (generate)

Summary: Joe's dog was chasing a cat in the garden.

Unsupervised Entity Linking with AMR (Pan et al, NAACL 2015)

- Link entity mentions in text to knowledge base
- Look at context to disambiguate mention
- Uses AMR graphs as context to build knowledge networks:



AMR context performs much better than SRL context for unsupervised entity linking

AMR at NAACL 2015

- Talks
  - Fei Liu, Jeffrey Flanigan, Sam Thomson, Norman Sadeh, Noah A. Smith. "*Toward Abstractive Summarization Using Semantic Representations*"
  - Xiaoman Pan, Taylor Cassidy, Ulf Hermjakob, Heng Ji, Kevin Knight. "*Unsupervised Entity Linking with Abstract Meaning Representation*
- Posters
  - Chuan Wang, Nianwen Xue, Sameer Pradhan. "*A Transition-based Algorithm for AMR Parsing*"
- Demonstrations
  - Lucy Vanderwende, Arul Menezes and Chris Quirk. "*An AMR parser for English, French, German, Spanish and Japanese and a new AMR-annotated corpus*"
  - Naomi Saphra and Adam Lopez. "*AMRICA: an AMR Inspector for Cross-language Alignments*"

Resources

- **AMR website**: http://amr.isi.edu
- **JAMR**: https://github.com/jflanigan/jamr
- **Transition-based parser**:

https://github.com/Juicechuan/AMRParsing/

- **Bolinas toolkit**:

http://www.isi.edu/publications/licensed-sw/bolinas/

- **DAGGER tookit**:

http://www.ims.uni-stuttgart.de/~daniel/dagger

```
(t / thank-01
      :ARG1 (y / you))
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