http://tiny.cc/amrtutorial

The Logic of AMR

Practical, Unified, Graph-Based Sentence Semantics for NLP

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The Logic of AMR

Part I: The AMR Formalism (Tim & Nathan)

COFFEE BREAK

Part II: Algorithms and Applications (Jeff)

Introduction to the Abstract Meaning Representation (AMR)

http://tiny.cc/amrtutorial

If you are here early, go to the **AMR Editor** and try to log in:

http://tiny.cc/amreditor

Why does AMR matter now?

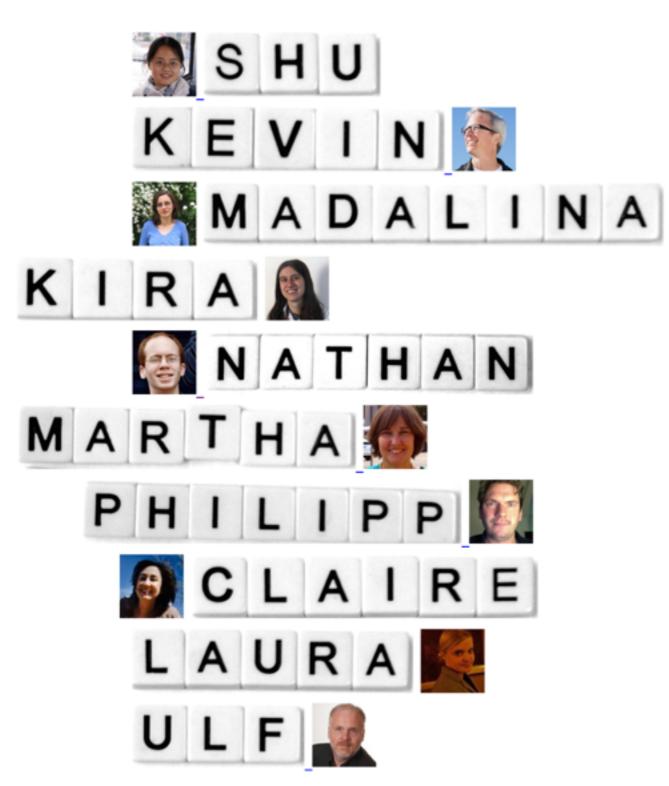
- AMR is a semantic representation aimed at largescale human annotation in order to build a giant semantics bank.
- We do a practical, replicable amount of abstraction (limited canonicalization).
- Capture many aspects of meaning in a single simple data structure.

Hasn't this been done before?

- Linguistics/CL have formalized semantics for a long time.
- A form of AMR has been around for a long time too (Langkilde and Knight 1998).
- It changed a lot since 1998 (add PropBank, etc.) and we actually built a corpus of AMRs.

Contemporary AMR

Banarescu et al.
 (2013) laid out the fundamentals of the annotation scheme we'll describe today.



Roadmap for Part I

- Fundamentals of the AMR representation
- Hands-on practice I: Representing basic examples
- Advanced topics and linguistic phenomena
- Comparison to other representations
- Hands-on practice II: Doing real, complex text

PENMAN notation

We use PENMAN notation (Bateman 1990).

 A way of representing a directed graph in a simple, tree-like form.

"The dog is eating a bone"

(e / eat-01

:ARG0 (d / dog)

:ARG1 (b / bone))



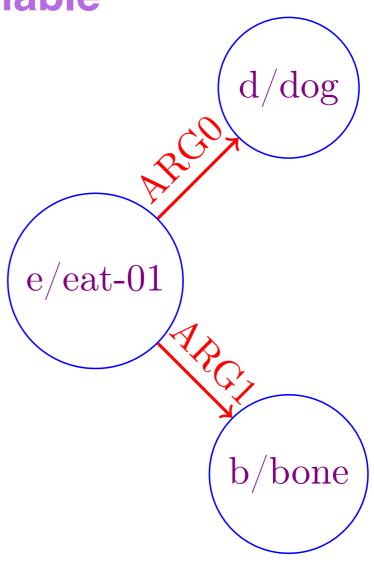
e/eat-01

b/bone

PENMAN notation

- The edges (ARG0 and ARG1) are relations
- Each node in the graph has a variable
- They are labeled with concepts
- d / dog means "d is an instance of dog"

```
"The dog is eating a bone"
(e / eat-01
:ARG0 (d / dog)
:ARG1 (b / bone))
```



PENMAN notation

• Concepts are technically edges (this matters in Part 2)

"The dog is eating a bone"

(e / eat-01

:ARG0 (d / dog)

:ARG1 (b / bone))

Reentrancy

 What if something is referenced multiple times?

 Notice how dog has two incoming roles now.

 To do this in PENMAN format, repeat the variable. We call this a reentrancy.

"The dog wants to eat the bone"

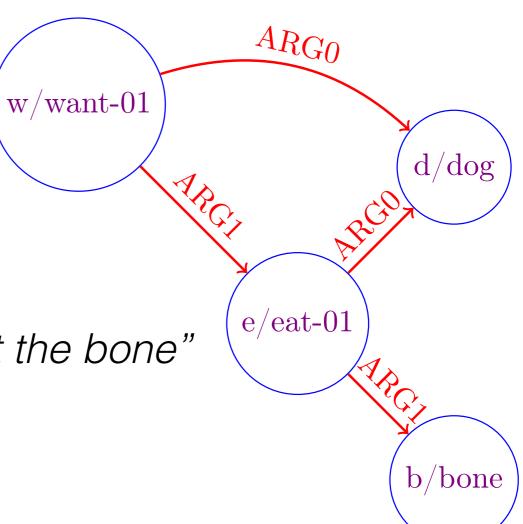
(want-01

:ARG0 (d / dog)

:ARG1 (e / eat-01

:ARG0 d

:ARG1 (b / bone)))



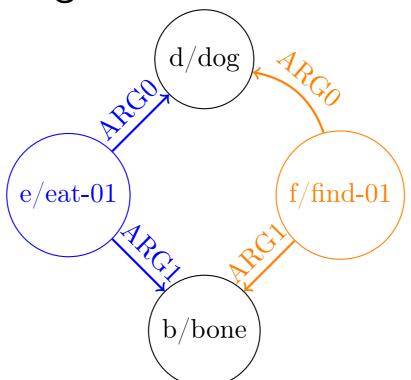
Reentrancy

It does not matter where the concept label goes.

"The dog wants to eat the bone"

```
(want-01 (want-01 :ARG0 (d / dog) :ARG1 (e /eat-01 :ARG1 (e /eat-01 :ARG0 (d / dog) :ARG1 (b / bone))) (want-01 :ARG1 (b / bone)))
```

What about "The dog ate the bone that he found"?



- How do we know what goes on top?
- How do we get these into the AMR format?

- We call "what goes on top" the focus.
- Conceptually, the main assertion.
- Linguistically, often the head.
 - For a sentence, usually the main verb.

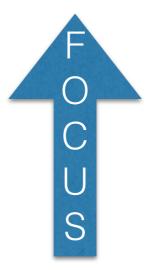
The man at the hotel



The dog ran



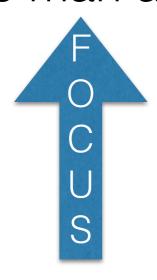
The hotel the man is at



The dog that ran



The man at the hotel



(m / man :location (h / hotel))

```
The dog ran
```

```
(r / ran-01 :ARG0 (d / dog))
```

```
(h / hotel
:??? (m / man))
```

```
(d / dog
:???? (r / ran-01))
```

The hotel the man is at

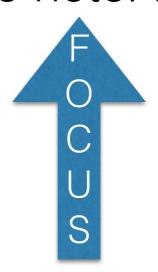


The dog that ran



The hotel the man is at

```
(h / hotel :location-of (m / man))
```

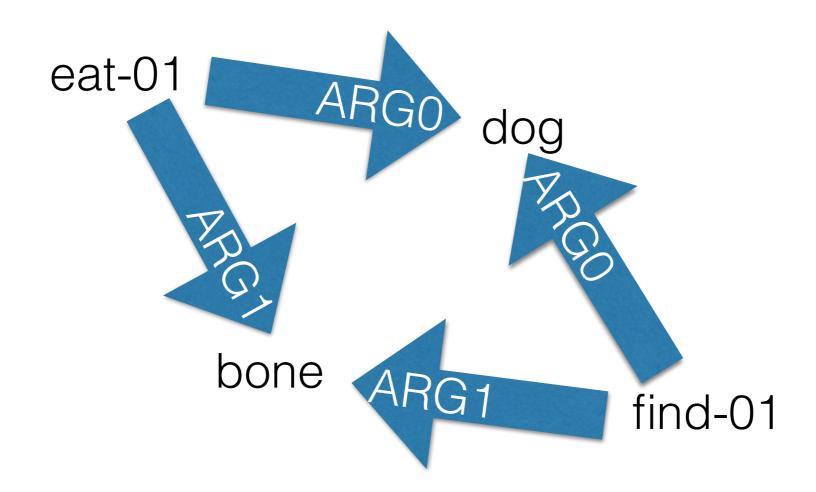


(d / dog :ARG0-of (r / ran-01)) The dog that ran



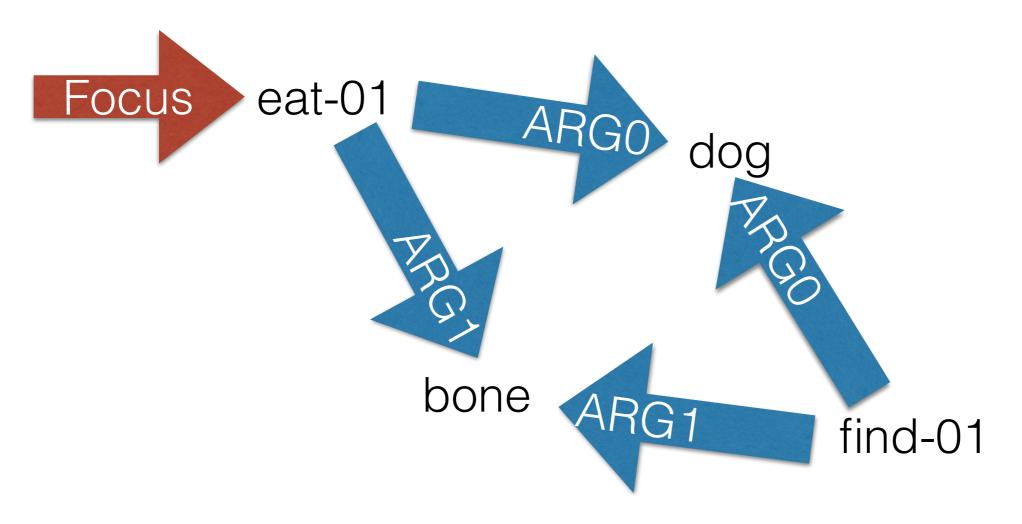
- This is a notational trick: X ARG0-of Y = Y ARG0 X
- Often used for relative clauses.
- These are equivalent for SMATCH scoring purposes too.

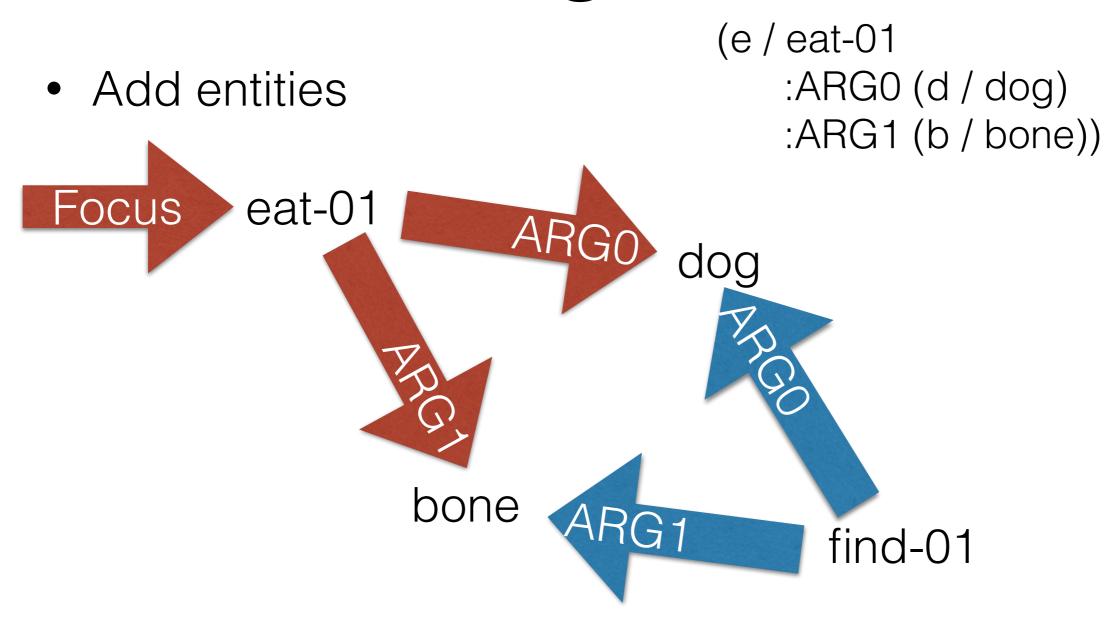
Imagine a graph for "The dog ate the bone that he found"



(e / eat-01 ...)

Find the focus

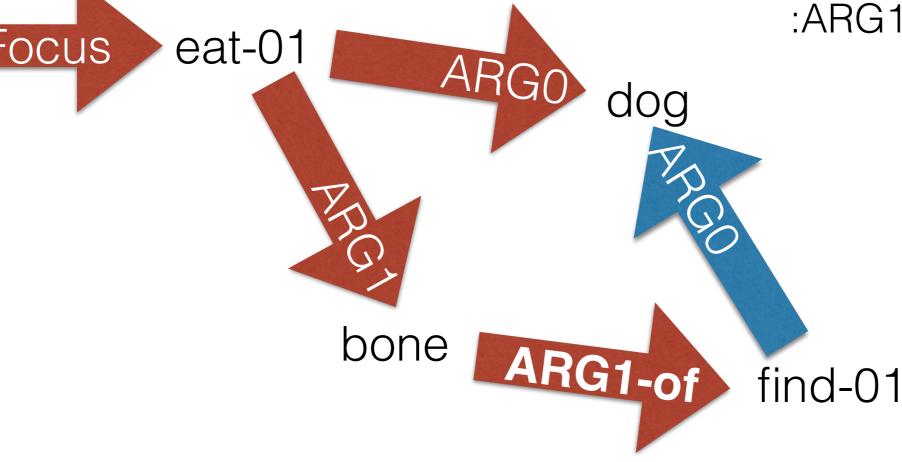


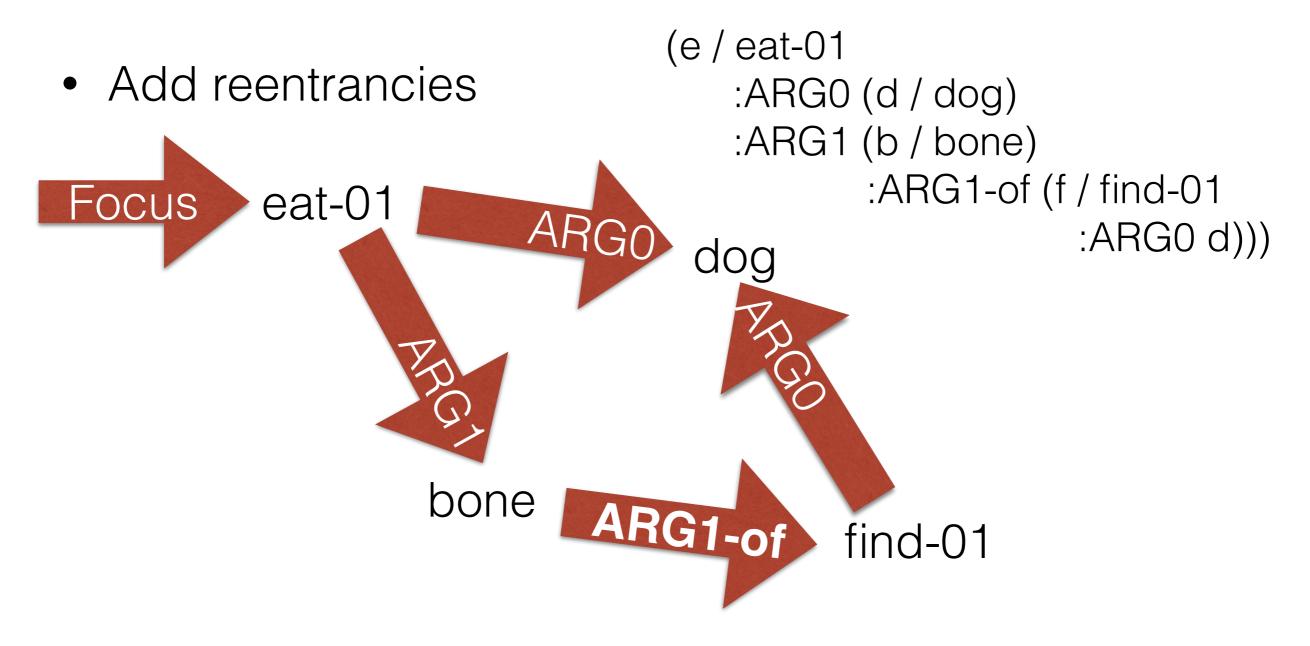


(e / eat-01

 Invert a relation if needed :ARG0 (d / dog) :ARG1 (b / bone

:ARG1-of (f / find-01))) eat-01





Constant

- Some relations, called constants, get no variable.
- The editor does this automatically for certain contexts.
- This happens for negation.

```
"The dog did not eat the bone"
(e /eat-01 :polarity -
:ARG0 (d / dog)
:ARG1 (b / bone))
```

Constant

- Some relations, called constants, get no variable.
- The editor does this automatically for certain contexts.

"The dog ate **four** bones" (e /eat-01 :ARG0 (d / dog)

:ARG1 (b / bone :quant 4))

This happens for numbers.

(to create a concept starting with a nonalphabetic character, type "!" before the concept)

Constant

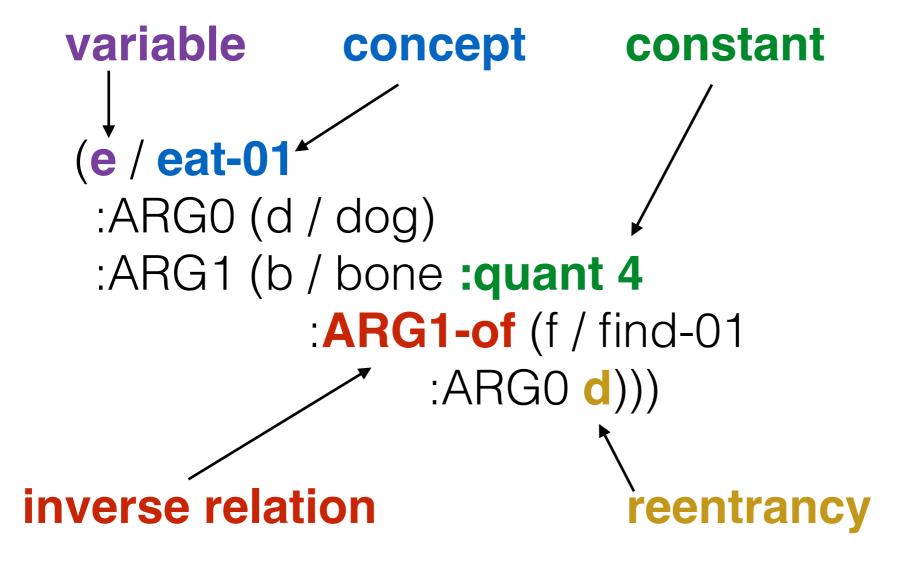
- Some relations, called constants, get no variable.
- The editor does this automatically for certain contexts.
- This happens for names

```
"Fido the dog"
(d / dog
:name (n / name :op1 "Fido"))
```

Concepts vs. Constants

- A concept is a type. For every concept node there will be ≥1 instance variable/node.
 - An instance can be mentioned multiple times.
 - Multiple instances of the same concept can be mentioned.
- Constants are singleton nodes: no variable, just a value. Specific non-core roles allow constant values.

 That's AMR notation! Let's review before discussing how we annotate AMRs.



PropBank Lexicon

- Predicates use the *PropBank* inventory.
- Each frame presents annotators with a list of senses.
- Each sense has
 its own definitions for its
 numbered (core)
 arguments

```
run-01 - "operate, proceed, operate or proceed"
```

- ARG0: operator
- · ARG1: machine, operation, procedure
- ARG2: employer
- ARG3: coworker
- ARG4: instrumental

Aliases: run (v), run (n), running (n) more

<u>run-02</u> - "walk quickly, a course or contest, run/jog, run for office"

- · ARG0: runner theme
- ARG1: course, race, distance location
- ARG2: opponent

Aliases: run (v), run (n), running (n) more

run-03 - "cost"

- ARG1: commodity
- · ARG2: price
- · ARG3: buyer

Aliases: run (v), running (n)

PropBank Lexicon

 We generalize across parts of speech and etymologically related words:

My fear of snakes	fear-01
I am fearful of snakes	fear-01
I fear snakes	fear-01
I'm afraid of snakes	fear-01

But we don't generalize over synonyms:

My fear of snakes	fear-01
I'm terrified of snakes	terrify-01
Snakes creep me out	creep_out-03

Stemming Concepts

Non-predicates don't have PropBank frames.
 They are simply stemmed.

All concepts drop plurality, articles, and tense.

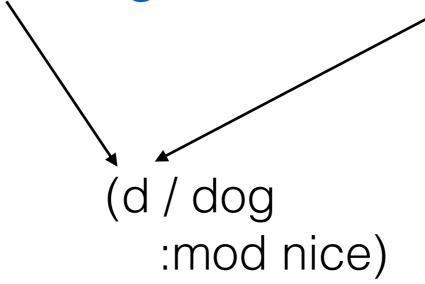
A cat eating
The cat eats
cats ate
the cats will eat

(c / cat) (e / eat-01)

Why drop articles?

 All mentions of a term go to the same variable, including pronouns and later nominal mentions.

I saw a nice dog and noticed he was eating a bone



Is "d" indefinite or definite?

• We do capture **demonstratives**:

This house

(h / house :mod (t / this))

Stemming Concepts

 Pronouns that do not have a coreferent nominal mention are made nominative and used as normal concepts.

```
The man saved himself He saved himself He saved me
```

```
(s / save-01 (s / save-01 (s / save-01 :ARG0 (m / man) :ARG0 (h / he) :ARG1 (i / i)) :ARG1 (i / i))
```

Why drop tense?

- English verbal tense doesn't generalize well cross-linguistically; not available for nominal predicates.
- Richer time representation might have required looking beyond a sentence.
- Keep a simple representation.

The man described the mission as a disaster.
The man's description of the mission: disaster.
As the man described it, the mission was a disaster.
The man described the mission as disastrous.

(d / describe-01

:ARG0 (m / man)

:ARG1 (m2 / mission)

:ARG2 (d / disaster))

Non-core Role Inventory

- If a semantic role is not in the core roles for a roleset, AMR provides an inventory of non-core roles
- These express things
 like :time, :manner, :part,
 :location, :frequency
- Inventory on handout, or in editor (the [roles] button)

run-01 - "operate, proceed, operate or proceed"

- ARG0: operator
- · ARG1: machine, operation, procedure
- · ARG2: employer
- ARG3: coworker
- ARG4: instrumental

- General semantic roles (incl. shortcuts): :accompanier ex :age of :compared-to ex :concession ex :condition ex :consist-of ex :cos :direction ex :domain ex :duration ex :employed-by ex :example :instrument ex :li ex :location ex :manner ex :meaning ex :med :name ex :ord ex :part ex :path ex :polarity ex :polite ex :poss :source ex :subevent ex :subset ex :superset ex :time ex :topic of the content of the c
- In quantities: :quant ex :unit ex :scale ex examples quantity
- In date-entity: :day :month :year :weekday :time :timezone @
 :year2 :decade :century :calendar ex :era ex :mod date-entity
- Ops: <u>:op1 :op2 :op3 :op4 :op5 :op6 :op7 :op8 :op9 :op1</u>
- In multi-sentence: :snt1 :snt2 :snt3 :snt4 :snt5 :snt6 :snt7

Non-core Role Inventory

 We use :mod for attribution, and :domain is the inverse of mod (:domain = :mod-of)

```
The yummy food
There is yummy food

(f / food
:mod (y / yummy))
```

```
The yumminess of the food
The food is yummy

(y / yummy
:domain (f / food))
```

seeing the yummy food seeing the food that is yummy

```
seeing that the food is yummy
```

```
(s / see-01
:ARG1 (f / food
:mod (y / yummy)))
```

```
(s / see-01
:ARG1 (y / yummy
:domain (f / food)))
```

Non-core Role Inventory

 This is also used for attribute/predicative demonstratives and nominals

```
This house

(h / house
:mod (t / this))

A monster truck the truck is a monster

(t / truck (m / monster
:mod (m / monster)) :domain (t / truck))
```

Non-core Roles: :op#

- Some relations need to have an ordered list of arguments, but don't have specific meanings for each entry.
- We use :op1, :op2, :op3, ... for these

:op# for coordination

We use this for coordination:

```
Apples and bananas (a / and :op1 (a2 / apple) :op2 (b / banana))
```

:op# for names

Barack Obama

```
(p / person
  :name (n / name
  :op1 "Barack"
  :op2 "Obama"))
```

Obama

```
(p / person
  :name (n / name
  :op1 "Obama"))
```

Named Entities

Barack Obama

 Entities with names get special treatment!

```
(p / person
```

- We assign a named entity type from our ontology.
- 70+ categories like person, criminal-organization, newspaper, city, food-dish, conference
- See your handout, or the [NE types] button in the editor

Named Entities

Barack Obama

```
(p / person :name (n / name
```

:op1 "Barack"

 Entities with names get special treatment! :op2 "Obama"))

- Each gets a :name relation to a name node
- That node gets :op# relations to the strings of their name as used in the sentence.

Named Entities

 If there is a more specific descriptor present in the sentence, we use that instead of the NE inventory.

a Kleenex

```
(p / product
  :name (n / name
  :op1 "Kleenex"))
```

a Kleenex tissue

```
(t / tissue
:name (n / name
:op1 "Kleenex"))
```

Wikification

 In a second pass of annotation, we add :wiki relations.

Barack Obama

http://en.wikipedia.org/wiki/Barack_Obama

Measurable Entities

 We also have special entity types we use for normalizable entities.

"Tuesday the 19th"

"five bucks"

```
(d / date-entity
```

:weekday (t / tuesday)

:day 19)

(m / monetary-quantity

:unit dollar

:quant 5)

Measurable Entities

 We also have special entity types we use for normalizable entities.

```
"$3 / gallon"
```

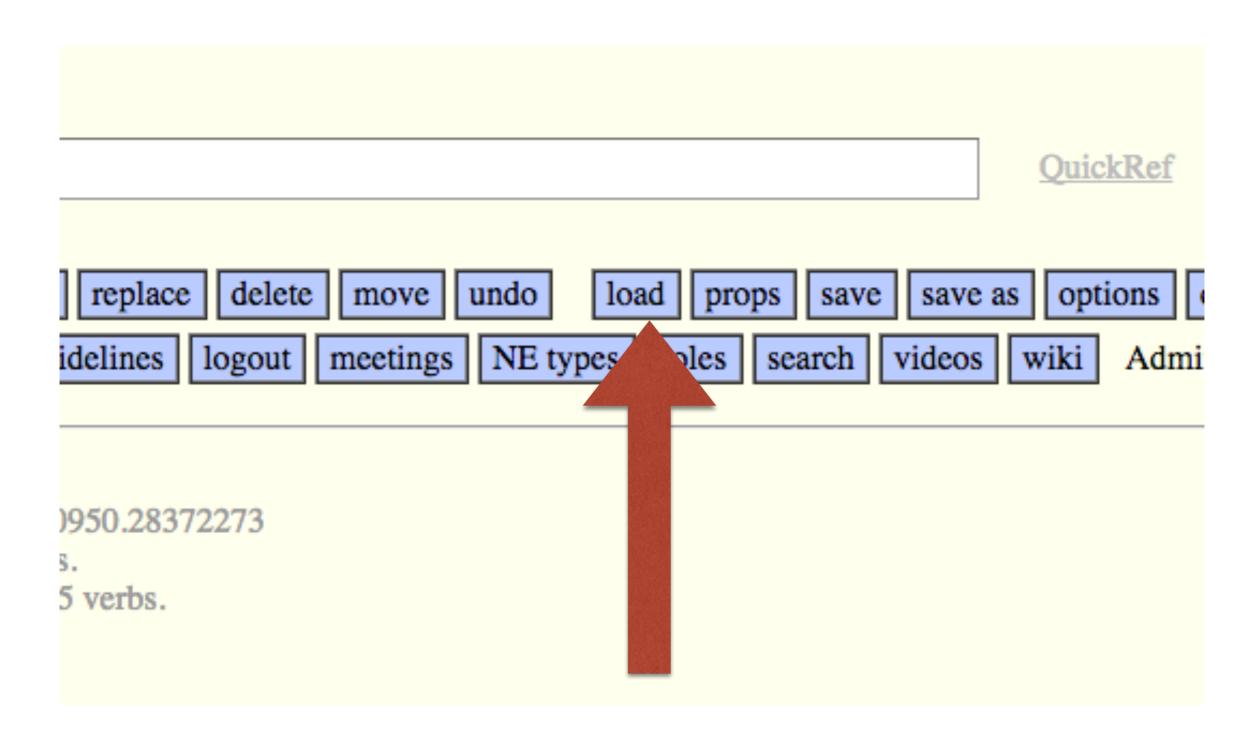
```
(r / rate-entity-91
     :ARG1 (m / monetary-quantity
          :unit dollar
     :quant 3)
     :ARG2 (v / volume-quantity
          :unit gallon
     :quant 1))
```

Hands-on Annotation!

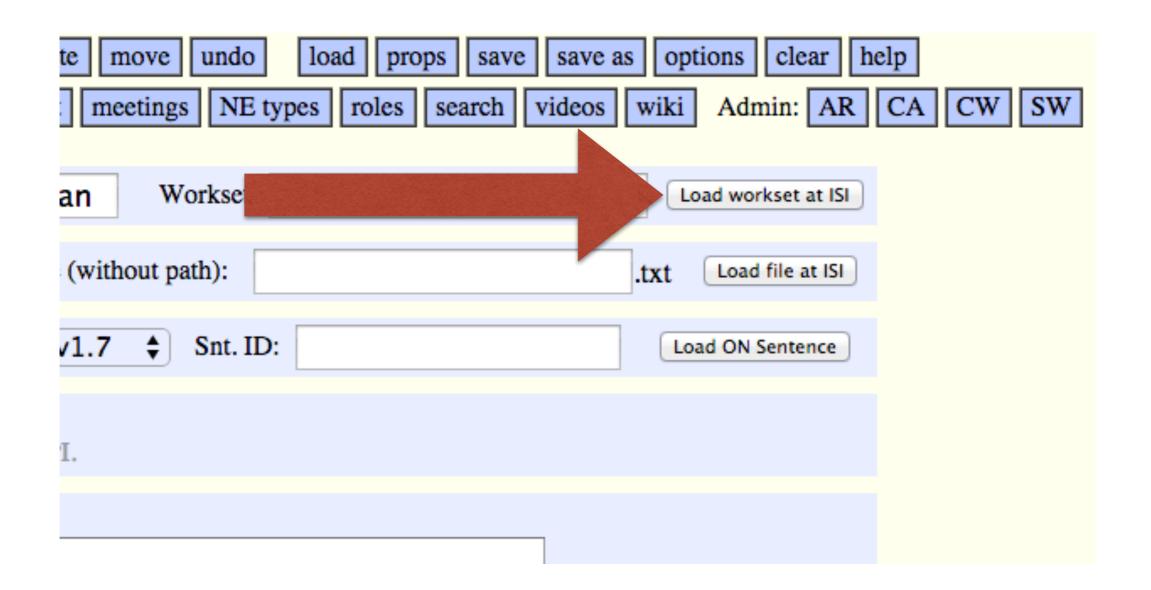
Go to the AMR Editor:

http://tiny.cc/amreditor

Load the Tutorial Sentences



Select "NAACL Tutorial"



It should look like this

Sentence: Tim likes to represent semantics abstractly			
npty AMR			
nter text command:			
ast command: Load next			
r select an action template: top add add-ne replace delete move undo exit			
Workset NAACL-tutorial-set 1/59 ocl_1008.1 (saved) Next: col_1008.2			
fore: check copy dict diff generate guidelines logout meetings NE types			
og: initialized empty AMR			
or role checking, loaded 128 roles and 11 non-roles			

Use "top <concept>" to make a top node

Sentence: Tim likes to represent semantics abstractly				
empty AMR				
Enter text command: top like				
Last command: Load next				
Or select an action template: top add add-ne replace delete move undo exit/load				
Workset NAACL-tutorial-set 1/59 ocl_1008.1 (saved) Next: col_1008.2 set				
More: check copy dict diff generate guidelines logout meetings NE types roles				
Log: initialized empty AMR				

For role checking, loaded 128 roles and 11 non-roles.

For OntoNotes frame availability check, loaded 6245 verbs.

Click on "like" to select the right sense

about:blank
Current sentence: Tim likes to represent sen
OntoNotes 4.0 frames Generated by Ulf's script on-frame-xml2html.pl on We
Lemma: like (v)
Note: Frames file for 'like' based on survey of
like.01 - "affection"

New relation: <variable> :<role> <concept>

Sentence: Tim likes to represent semantics abstractly			
(1 / <u>like-01</u>)			
Enter text command:	l :arg1 represent		
Last command:	del r		
Or select an action ter	nplate: top add add-ne replace delete move undo exit/load props		
Workset NAACL-tutorial-set 1/59 col_1008.1 Save and load next Discard and load next Next: col_1008.1			
More: check copy	dict diff generate guidelines logout meetings NE types roles search		

Log: initialized empty AMR

For role checking, loaded 128 roles and 11 non-roles.

For OntoNotes frame availability check, loaded 6245 verbs.

Anything after the third element is made into a name

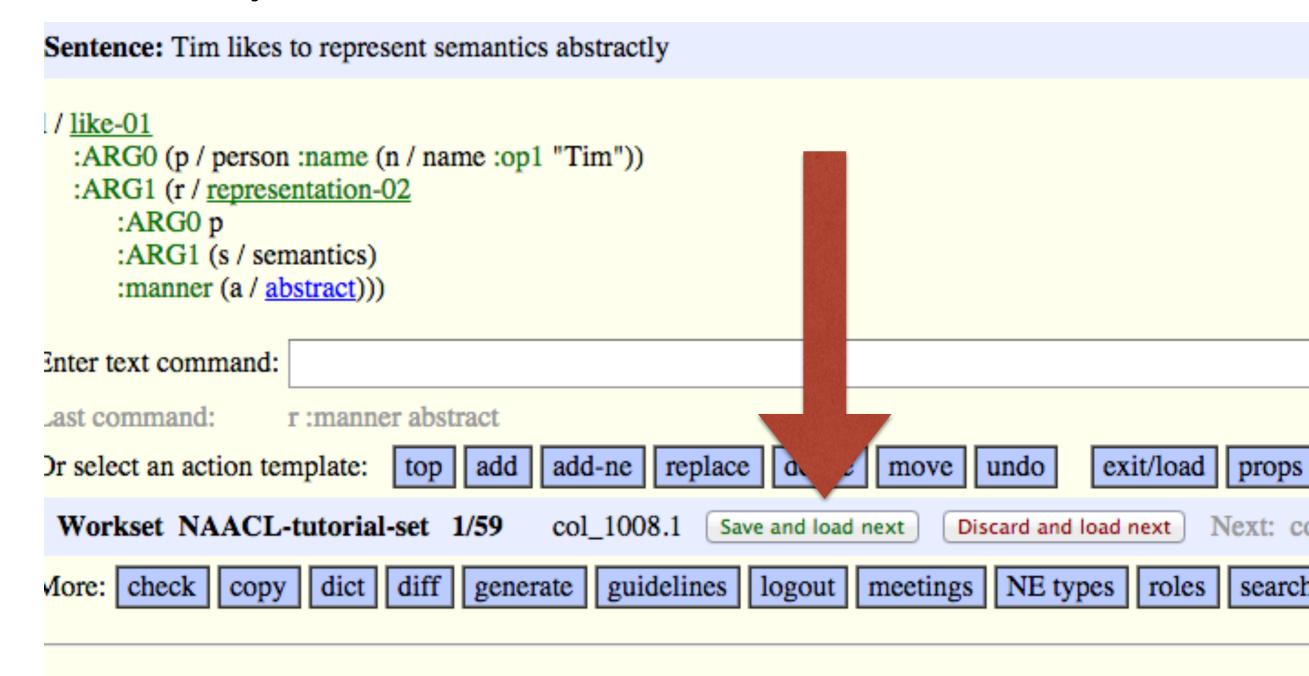
```
Search documents and file names for text emantics abstractly
1 / like-01
   :ARG1 (r / representation-02))
Enter text command: I :arg0 person Tim
                   replace concept at r with representation-02
Last command:
Or select an action template: top add add-ne replace delete move
 Workset NAACL-tutorial-set 1/59 col_1008.1 Save and load next
                                                                         Discard and
More: check | copy | dict | diff | generate | guidelines | logout | meetings
```

Make reentrancies with <variable> :<role> <variable>

```
Sentence: Tim likes to represent semantics abstractly
(1 / <u>like-01</u>
   :ARG0 (p / person :name (n / name :op1 "Tim"))
   :ARG1 (r / representation-02))
Enter text command: r :arg0 p
                   1 :arg0 person Tim
Last command:
                                           add-ne replace
Or select an action template:
                                                             delete
                                                                       move
                                                                               undo
 Workset NAACL-tutorial-set 1/59
                                           col_1008.1
                                                         Save and load next
                                                                             Discard and loa
                       dict | diff |
                                   generate | guidelines | logout | meetings |
```

I aga initialized assets: A MD

When you are done, use "Save and Load Next"



and initialized assets AND

Try the next sentence!

We will walk through it momentarily

Sentence: I hope Dumbledore likes my orange socks.
mpty AMR
Enter text command:
Last command: Save and load next
Or select an action template: top add add-ne replace delete move undo exit/load pro
Workset NAACL-tutorial-set 2/59 ocl_1008.2 (saved) Next: col_1008.3 sent. m
More: check copy dict diff generate guidelines logout meetings NE types roles se
og: initialized empty AMR
or role checking, loaded 128 roles and 11 non-roles.

or OntoNotes frame availability check, loaded 6245 verbs.



AMR Annotation: Special Topics

http://tiny.cc/amrtutorial

Congratulations!

You now know how to AMR simple sentences.

BUT: English is a wily opponent.

- Copulas, light verbs
- Prepositions
- Derivational morphology
- Relational nouns
- Coordination & clausal connectives
- Modality

- Non-declarative sentences
- Questions
- Comparisons
- Quantification
- Subsets
- Reification

Light semantics

- We try to eliminate purely grammatical words. E.g.:
 - copulas: I am happy

(h / happy :domain (i / i))

▶ light verbs: I'm taking a bath

(b / bathe-01 :ARG0 (i / i))

Heavy prepositions

- Most prepositions mark a (core or non-core) role. Some add crucial additional information meriting a concept:
 - at the school: :location (s / school)
 - next to the school:
 :location (n / next-to :op1 (s / school))
 - between the school and the house:
 :location (b / between :op1 (s / school)
 :op2 (h / house))
 - at the time of the war: :time (w / war)
 - after the war: :time (a / after :op1 (w / war))

Typical uses of inverse roles

- Relative clauses: someone who sifts thistles
- Derivational morphology
 - Participles: thistle-sifting person
 - Nominalizations: thistle sifter

Concept may be implicit

(p / person:ARG0-of (s / sift-01:ARG1 (t / thistle)))

Compositionality criterion

- We only "decompose" derivational morphology if a relative clause paraphrase is possible:
 - teacher = person who teaches

```
(p / person :ARG0-of (t / teach-01))
```

▶ professor ≠ person who professes

(p / professor)

Compositionality criterion

- Often core roles are available for modifiers:
 - math teacher / teacher of math= person who teaches math

```
(p / person :ARG0-of (t / teach-01 :ARG1 (m / math)))
```

▶ math professor ≠ person who professes math

```
(p / professor :mod (m / math))
```

Compositionality criterion

- Sometimes it is difficult to draw a line, but we do our best:
 - opinion = thing that is opined

```
(t / thing :ARG1-of (o / opine-01))
```

▶ profession ≠ thing that is professed

```
(p / profession)
```

Hallucinating relations

- Sometimes we have to "hallucinate" a relationship that the grammar underspecifies.
 - e.g., possessives and noun-noun compounds can express many different kinds of relations

Relational nouns

 Special predicates for individual—group and individual—individual relations:

```
He is a pilot for TWA
He is a TWA pilot

(h / have-org-role-91
:ARG0 (h2 / he)
:ARG1 (c / company
:name (n / name :op1 "TWA")) :ARG2 (f / father))
:ARG2 (p / pilot))
```

Coordination & Clausal Connectives

Example connectives	AMR treatment
and	and
or	or
but	contrast-01
because; due to; on account of	:cause
(in order) to; so (that)	:purpose
if	:condition
unless	<pre>:condition (:polarity -)</pre>
although; despite	:concession

Coordination

The most common patterns:

```
X, Y, and Z X, Y, or Z X but Y

(a / and (o / or (c / contrast-01 :op1 X :ARG1 X :op2 Y :op2 Y :op3 Z)
```

 "and", "or" take 2 or more conjuncts in sequence as :op#



```
(i / inspire-01
:ARG0 (c / cook-01
```

```
)
:ARG1 (p / person :name (n / name :op1 "Rachael" :op2 "Ray")))
```

Coordination: shared core args

We invited and then disinvited the students.

Coordination: shared non-core args

Yesterday we invited and then disinvited the students.

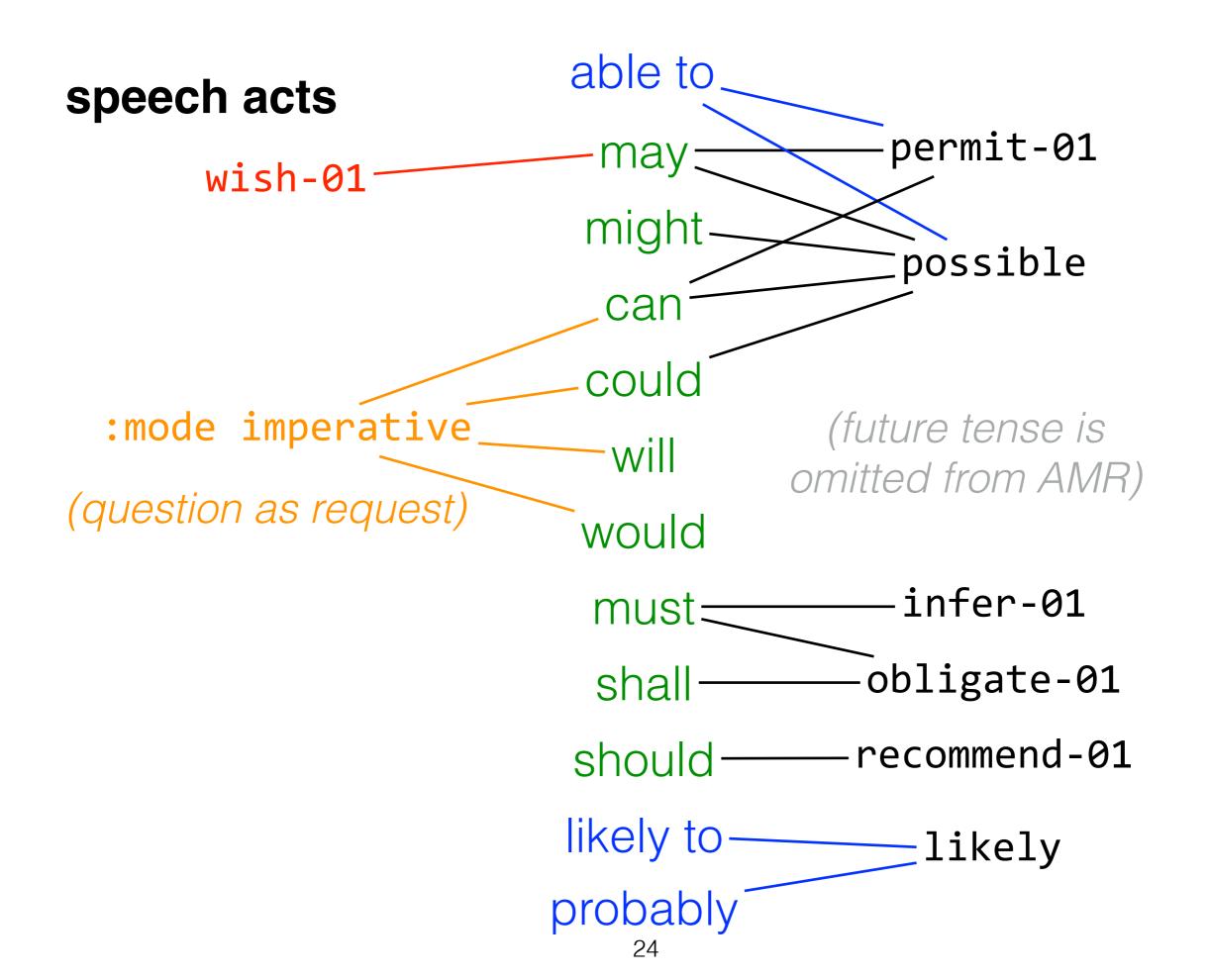
Coordination: copied predicates

We invited the students and then the professors.

Modal Concepts

You can leave.
 You may leave.
 It's all right for you to leave.

I can see Russia from my house!
 I'm able to see Russia from my house!



Sentence Types

Type	AMR treatment
indicative (declarative)	(default)
imperative (command)	:mode imperative (with you arg if implied subject)
interjection	:mode expressive
yes-no question	:mode interrogative
WH-question	amr-unknown
quotation without speech verb	(s / say-01 :ARG0 <speaker>)</speaker>
vocative	(s / say-01 :ARG2 <addressee>)</addressee>
polite ("please", etc.)	:polite +

Questions: yes-no

Are you worried?

```
(w / worry-01
   :ARG0 (y / you)
   :mode interrogative)
```

Questions: wh

Why worry? (What is the point of worrying?)

```
(w / worry-01
   :ARG0 (y / you)
   :purpose (a / amr-unknown))
```



What's the problem?

```
(p / problem
  :domain (a / amr-unknown))
```

Think of amr-unknown as an *in situ* question pronoun. Structurally, the AMR is the same as a declarative sentence.

How many peppers did Peter Piper pick?

Comparison

have-degree-91

ARG1: attribute

ARG2: domain, entity characterized by attribute

ARG3: degree itself ARG4: compared-to ARG5: consequence,

result of degree

- The treatment of comparative constructions is changing.
- Apples are redder than bananas.

old way:

new way:

Quantification

two apples

```
(a / apple
    :quant 2)
```

a lot of apples

```
(a / apple
    :quant (1 / lot))
```

All apples are fruit.

Only explicit quantifiers are included in the AMR.

Apples are fruit.

```
(f / fruit
  :domain (a / apple))
```

Sets

include-91 - "subset"

ARG1: subset (or member)

ARG2: superset

ARG3: relative size of subset

compared to superset

Special predicate include-91 for explicitly mentioned sets

• (late) 5 of the 12 donuts

42% of the donuts

Reification

be-located-at-91 -

"reification of :location"

ARG1: entity
ARG2: location

the man at the store

```
(m / man :location (s / store))
```

- What about: the man always at the store?
 - Need to "modify" the relation!
 - Solution: Convert ("reify") the relation w/ a special frame

```
(m / man
:ARG1-of (b / be-located-at-91
:ARG2 (s / store)
:time (a / always)))
```

Reification

be-located-at-91 -

"reification of :location"

ARG1: entity ARG2: location

- Reification also allows a relational predicate to be focused.
- The man is at the store.

```
(b / be-located-at-91
:ARG1 (m / man)
:ARG2 (s / store))
```

I think the man is at the store.

```
(t / think-01
:ARG0 (i / i)
:ARG1 (b / be-located-at-91
:ARG1 (m / man)
:ARG2 (s / store)))
```

Reification

be-located-at-91 -

"reification of :location"

ARG1: entity **ARG2:** location

- Every role has a designated reification—either a verb frame or a special -91 frame.
 - have-purpose-91, have-polarity-91, have-part-91, ...
 - have-topic-91 concern-02
- These slides are about semantics.

```
(c / concern-02
:ARG0 (s / slide :mod (t / this))
:ARG1 (s2 / semantics))
```

English is a wily opponent.

- Copulas, light verbs
- Prepositions
- Derivational morphology
- Relational nouns
- Coordination & clausal connectives
- Modality

- Non-declarative sentences
- Questions
- Comparisons
- Quantification
- Subsets
- Reification

Other Phenomena

- Many other patterns for specific phenomena are documented in the AMR Dictionary. E.g.:
 - We'll eat like kings → resemble-01
 - ► (Banarescu et al., 2013) → publication-91

AMR Dictionary

how

- :ARGx
 - How much does this cost? (cost-01 :ARG2 amr-unknown) Example
 - How did you solve the problem? (solve-01 :ARG2 amr-unknown) Example
- :degree
 - o How big was the dog that bit you? (big :degree amr-unknown :domain :dog) Example
 - o How beautiful you are. [= You are so beautiful.] (beautiful :degree so :domain you) Example
- :manner
 - How did you get him to help you? (get-04 :manner amr-unknown) Example
 - o The only thing that surprises me is how rapidly this is happening. (surprise-01 :ARGO (rapid :manner-of this)) Example
- :quant
 - o How tall are you? (tall :quant amr-unknown :domain you) Example
 - o How old is your father? (father :age amr-unknown :poss you) Example

however

- contrast-01 (most cases)
 - o John, however, stayed at home. (contrast-01 :ARG2 stay-01) Example
- · :concession
 - It started to rain; however, the game continued. (start-01 :ARG1 rain-01 :concession-of continue-01) Example

imperative @

- :mode imperative
 - ∘ Go home! (go-02 :mode imperative :ARGO you :destination home) Example
 - ∘ Let's go home. (go-02 :mode imperative :ARG0 we :destination home) Example
 - ∘ Come on folks!! (come-25 :mode imperative :ARG1 folk) Example
- :mode imperative :polite +
 - o Please close the door. (close-01 :mode imperative :polite +) Example
 - Could you close the door? (close-01 :mode imperative :polite +) <u>Example</u>

Further AMR Documentation

- Homepage: http://amr.isi.edu/
- Guidelines: https://github.com/amrisi/amr-guidelines/blob/master/amr.md
- Editor help pages, especially AMR Dictionary (http://www.isi.edu/~ulf/amr/lib/amr-dict.html)
- Editor release search (rs *query*) to check existing AMRs for a precedent

AMR Data

- Thus far: mostly made-up examples
- Real sentences tend to be longer, but AMRed using the same principles

control structure

subset → include-91

temporal connective

 We need to borrow 55% of the hammer price until we can get planning permission for restoration which will allow us to get a mortgage.

modal

 We need to borrow 55% of the hammer price until we can get planning permission for restoration which will allow us to get a mortgage.

deverbals → event predicates

We need to borrow 55% of the hammer price until we can get planning permission for restoration which will allow us to get a mortgage.

```
(n / need-01
:ARG0 (w / we)
:ARG1 (b / borrow-01
:ARG0 w
```

)

We need to borrow 55% of the hammer price until we can get planning permission for restoration which will allow us to get a mortgage.

```
(n / need-01

:ARG0 (w / we)

:ARG1 (b / borrow-01

:ARG0 w

:ARG1 (p / percentage-entity :value 55

:ARG1-of (i / include-91

:ARG2 (p2 / price

:mod (h / hammer))))
```

)

```
(n / need-01
   :ARG0 (w / we)
   :ARG1 (b / borrow-01
       :ARG0 w
       :ARG1 (p / percentage-entity :value 55
           :ARG1-of (i / include-91
               :ARG2 (p2 / price
                  :mod (h / hammer))))
       :time (u / until
           :op1 (p3 / possible
               :domain (g / get-01
                  :ARG0 w
                   :ARG1 (p4 / permit-01
                      :ARG1 (p5 / plan-01)
                      :purpose-of (r / restore-01)
                      :ARG0-of (a / allow-01
                          :ARG1 (m / mortgage-01
                              :ARG0 w))))))))
```

Datasets

AMR Bank: The Little Prince

LDC Releases

(novel—English translation) (news, discussion forums, ...)









= 15k AMRs

(with more to come!)

Datasets: Details

- AMR Bank (Release 1.4; http://amr.isi.edu/download/amr-bank-v1.4.txt)
- English translation of Le Petit Prince (The Little Prince), freely downloadable.
 1,500 AMRs
- AMR Public Release 1.0 (LDC2014T12): largest public release w/ 13,051 AMRs
- DEFT Release 3 (LDC2013E117): evaluation data in Flanigan et al. 2014, Wang et al. 2015.
- DEFT Release 4 (LDC2014E41): largest release w/ 18,779 AMRs total
- DEFT Release 5 (Sep. 2015) will include wikification, (pretty much) no directed cycles
- Small (100-AMR) sets of Czech and Chinese AMRs have been annotated.
- Vanderwende et al. (2015) data to appear: several languages, automatically converted from logical forms
- PropBank will soon all be converted to AMR style (mapping nominalizations to verbs, etc.) and re-released.

Working with AMR Data

- AMRs are stored in a plain text format (in Penman notation)
- Script for loading them into a Python data structure: https://github.com/nschneid/amr-hackathon/tree/master/src
 - Also accepts aligned AMRs from the ISI aligner

AMR *vs.*Other Formalisms

AMR Strengths

- abstracting away from morphological & syntactic variability
- predicate-argument structures
 - core + non-core roles
- named entities & values
- coreference (w/in sentence)
- modality

AMR Limitations

- no "deep" lexical semantics
 - fruit/berry, buy/sell, kill/die are formally unrelated
- no deep treatment of quantification & scope
- (almost) no information structure
- nothing across sentences in a discourse...yet

Design Decisions

- AMR annotations are not tied to individual words or any syntactic derivation
- Practicality for human annotators is primary
 - AMR makes no compromises for (current) algorithms
- Single structure rather than many layers
- Extensive documentation and tool support

Detailed Comparison

See "Other Formalisms" slides

Comparison - Semantic Roles

AMR: 70+ non-core roles, many verb-sense specific roles (up to 5 args/roleset, more than 10,000 rolesets)

FrameNet: large inventory of frame-specific roles

VerbNet: inventory of thematic roles

Groningen Meaning Bank: VerbNet inventory

Most others: small inventory of roles (agent, theme, etc.)

Comparison - Sense Lexicon

Groningen Meaning Bank: (automatic) WordNet synsets FrameNet/UCCA: Mark senses by frame/script, not lemma

AMR /PropBank: coarse-grained senses (get high ITA)

Prague Dependency TB: valency lexicon rolesets

Most others: undisambiguated concepts as predicates

Comparison - Entities

AMR: Rich named entity ontology (100+ types), wikification

GALE/Ontonotes Annotations: 29 types, 64 subtypes
Groningen Meaning Bank: 7 NE types
Domain-specific (ACE/UMLS/etc.): rich; not all entities

Others: no entity typing

Comparison - Alignment with text

Deepbank; Groningen Meaning Bank: Semantics linked up to a theory of its derivation from syntax (HPSG; CCG)

PropBank, Semantic Treebank: grounded in PTB Most others: Some link to words in sentence

AMR: No alignment to text (plan to release a few alignments)

Comparison - Logic/Scope/Entailments

Deepbank; Groningen Meaning Bank: Semantics grounds out in logical formalisms (DRT and MRS, respectively)

AMR entailment: linkage between its lexicon and VerbNet may allow rich decomposition

AMR scope: No scope of quantification

Comparison - Size and Quality

AMR: 18,779 sentences, goes beyond newswire, fully manual **Prague Dependency TB:** WSJ in Czech and English, manual

Deepbank; Groningen Meaning Bank: Large; automatic parses with human correction/feedback.

UCCA: fully manual, 160k tokens

Rich semantic systems with little affiliated data: TMR, LCS,

Part II: Algorithms and Applications

Speaker: Jeffrey Flanigan

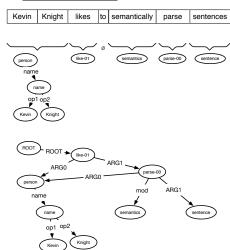
Intro

- 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

<u>Alignment</u>

IAEA accepted North Korea 's proposal in November.

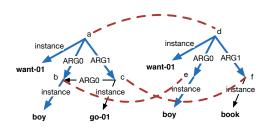
Parsing

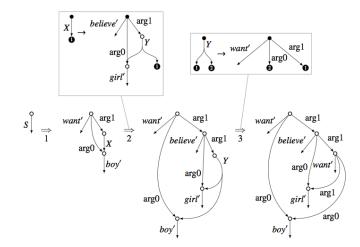


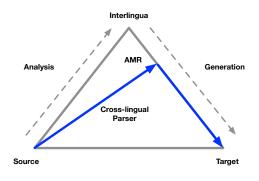
Evaluation

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.

- 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)

For each rule

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

Rule 1) Date entity

Rule 3) Named entity

Rule 5) Single concept (use lemma)

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

Rule 10) person-of/thing-of

Evaluate on 200 hand-aligned sentences:

F₁: 90% Precision: 92% Recall: 89%

Extracted concept table

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

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

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

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

iaea acce nort kore prop in nove

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

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.

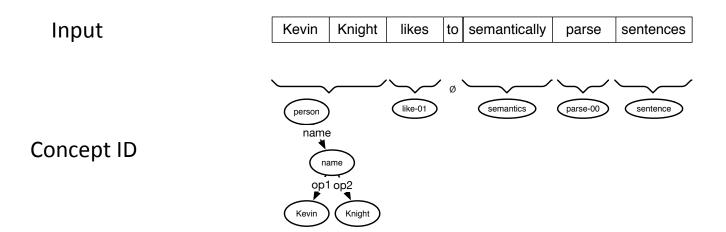


JAMR Overview (Flanigan et al, 2014)

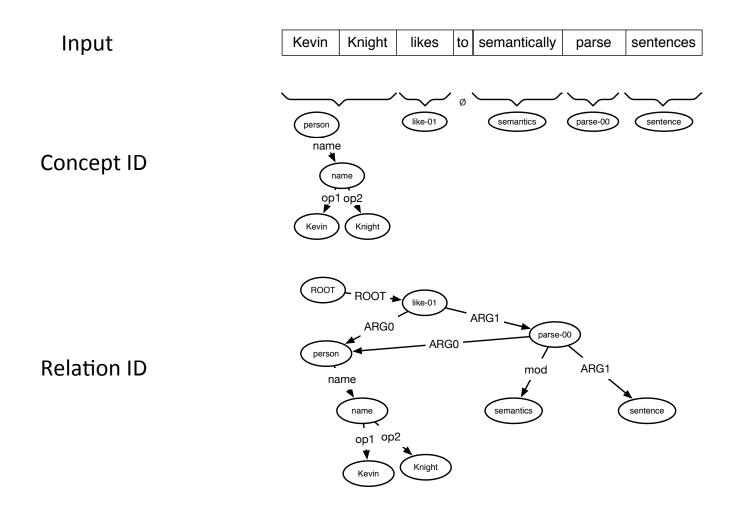
Input

Kevin Knight likes to	0	semantically	parse	sentences
-----------------------	---	--------------	-------	-----------

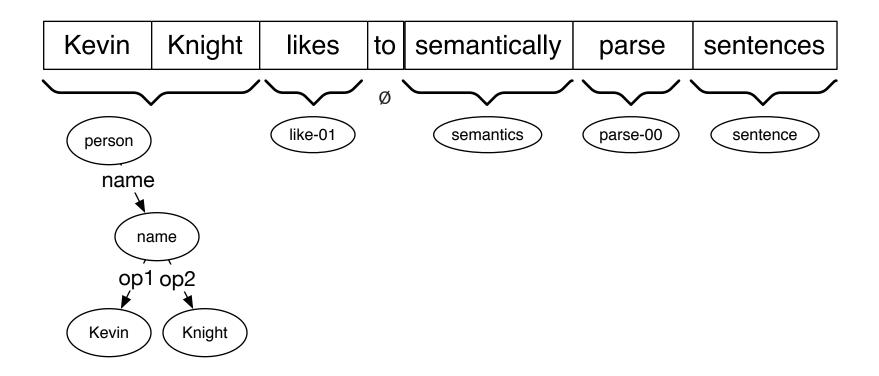
JAMR Overview

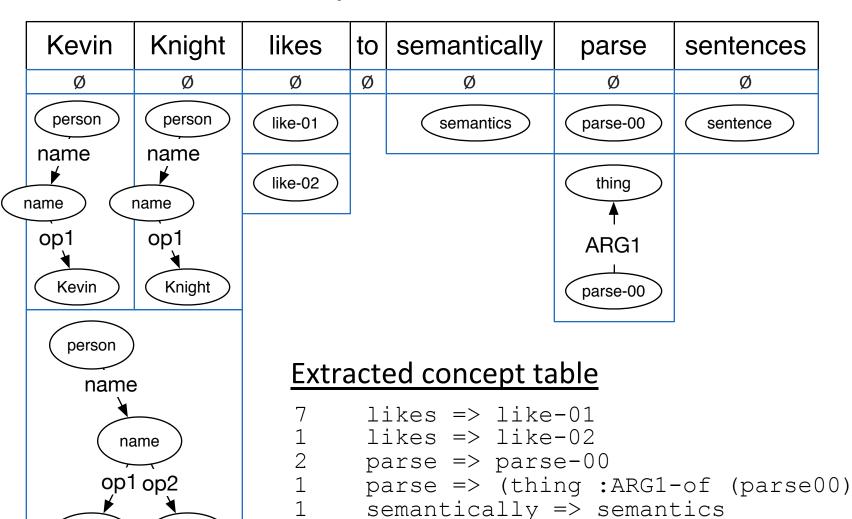


JAMR Overview



	Kevin	Knight	likes	to	semantically	parse	sentences
--	-------	--------	-------	----	--------------	-------	-----------

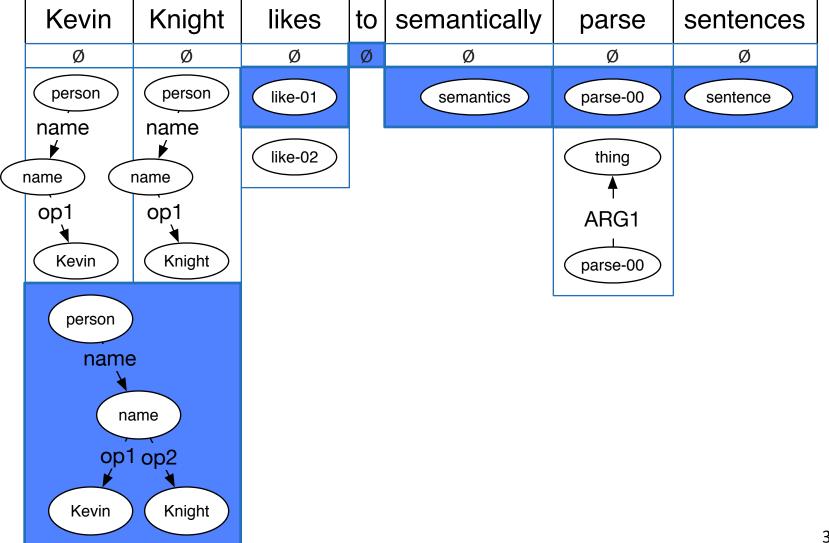


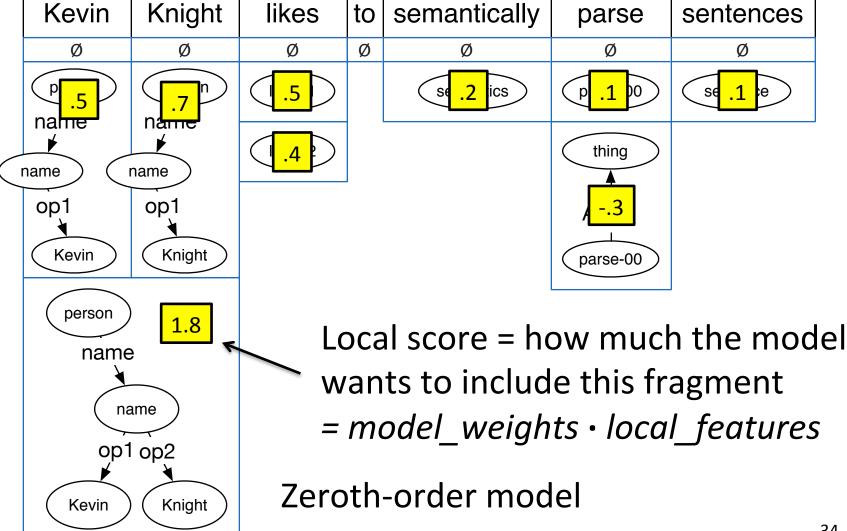


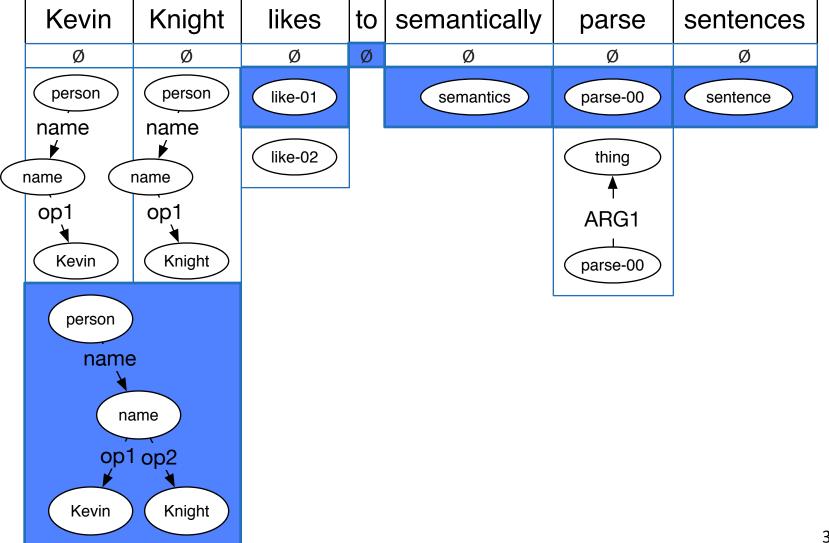
Kevin

Knight

sentences => sentence







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

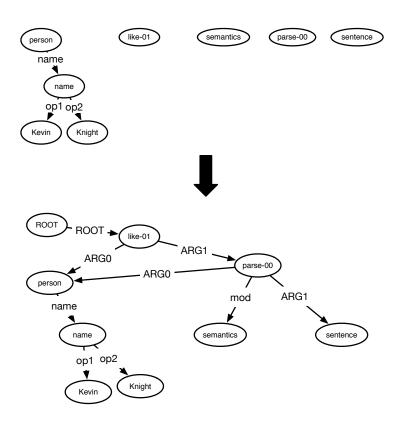
Relation Identification

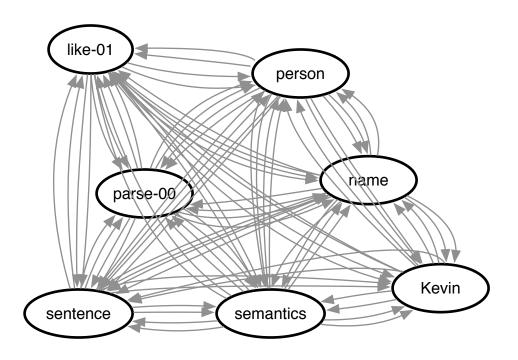
- Evaluation
- Alignment
- Parsing
 - Graph-based parsing
 - Concept identification
 - Relation identification
 - Maximum spanning connected graph algorithm (MSCG)
 - Graph determinism constraints using Lagrangian relaxation
 - Experiments
 - Transition-based parsing
 - Parsing using syntax-based MT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

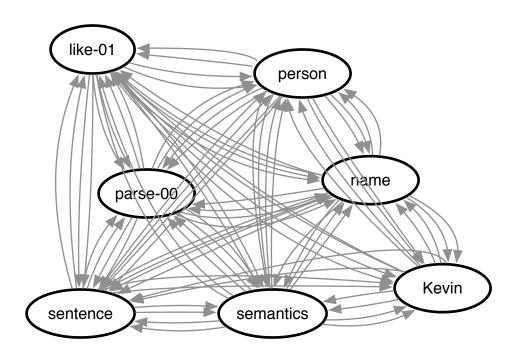
Relation Identification



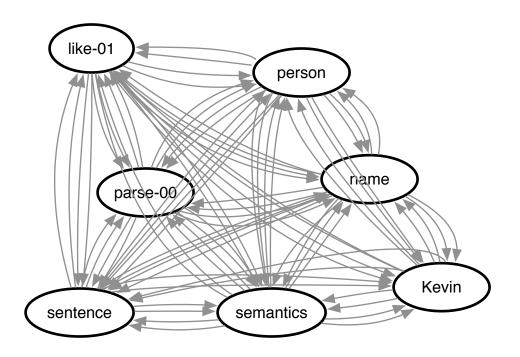
Relation Identification



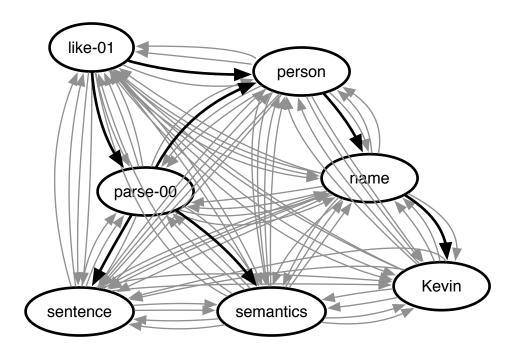




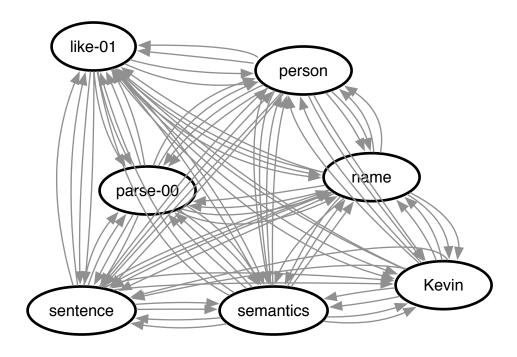
- All possible edges between all nodes
- Edges w/ weights



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

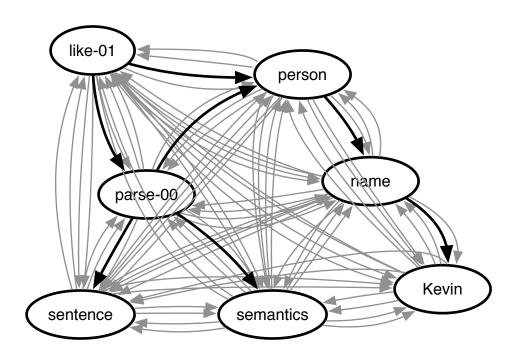


Output graph = max subgraph with constraints on well-formedness



- **Z** binary vector, indicates which edges are selected
- ϕ real vector, contains the edge weights

Max Subgraph



Relation ID optimization problem

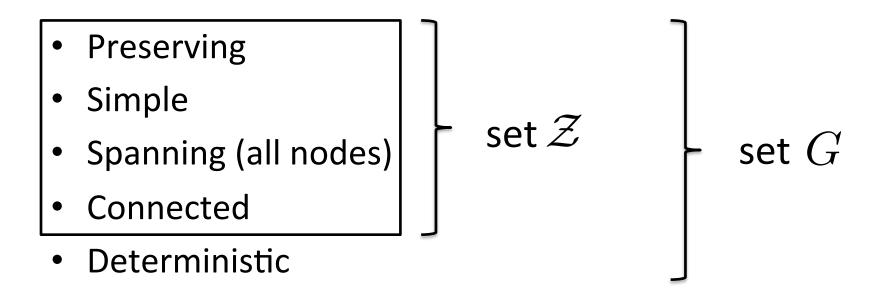
 $\max_{\mathbf{z} \in G} \phi^T \mathbf{z}$

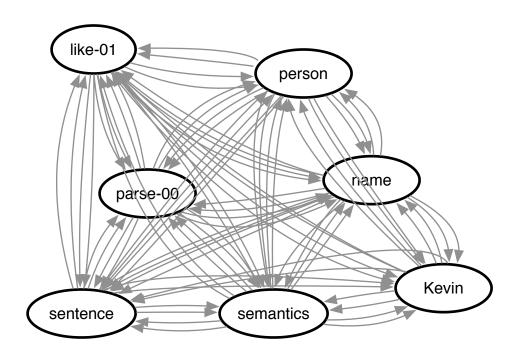
Set of graphs satisfying the constraints

Output Graph Properties (Constraints)

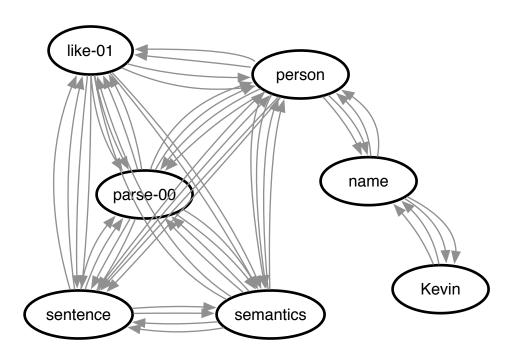
- Preserving
- Simple
- Spanning (all nodes)
- Connected
- Deterministic

Output Graph Properties (Constraints)

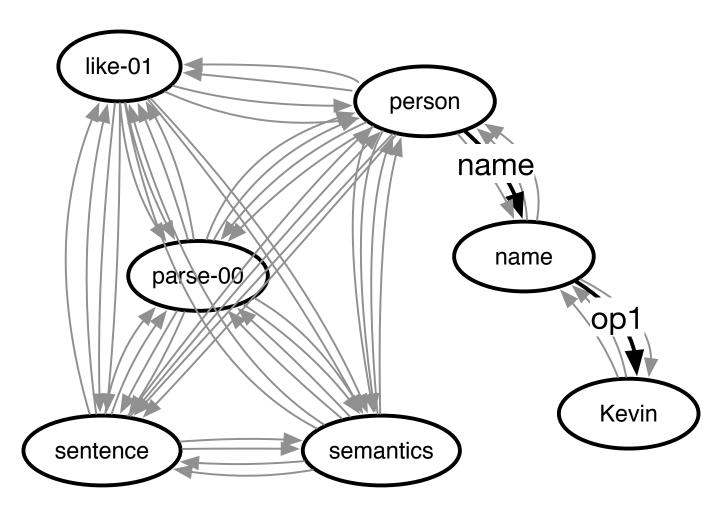




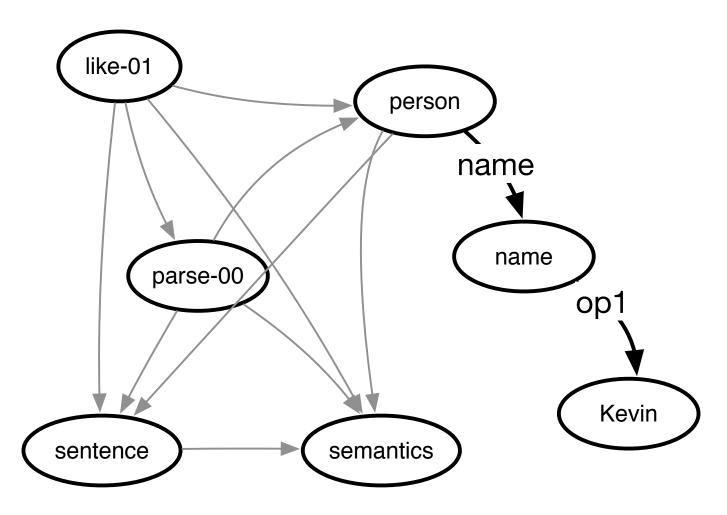
Reduced graph for clarity



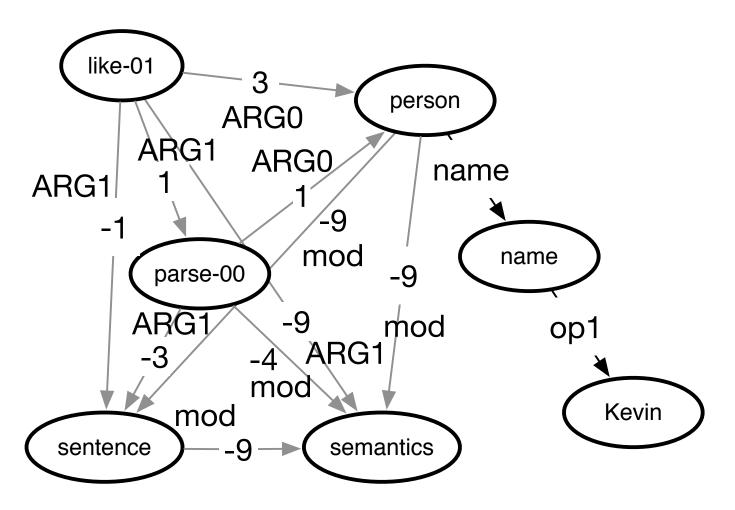
Constraint: Preserving



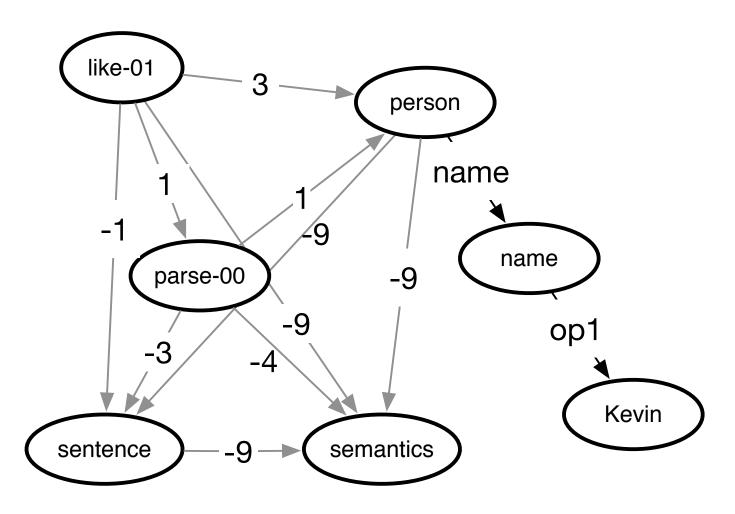
Constraint: Simple



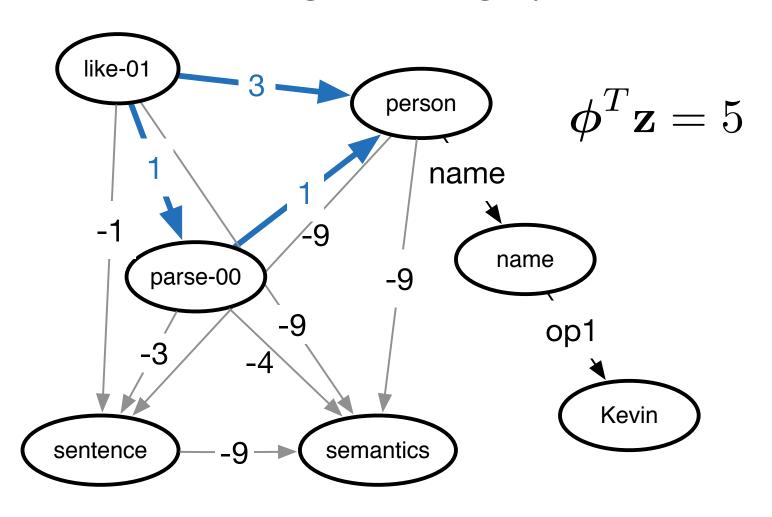
With Weights and Labels Shown



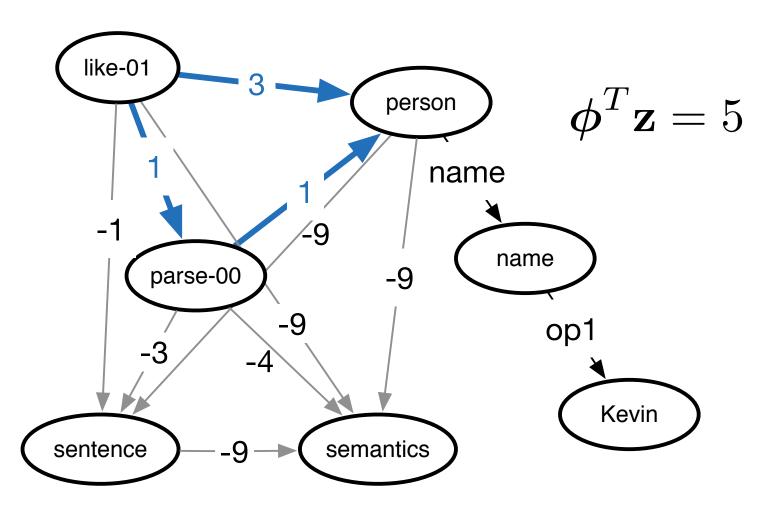
Maximum Weighted Subgraph



Maximum Weighted Subgraph

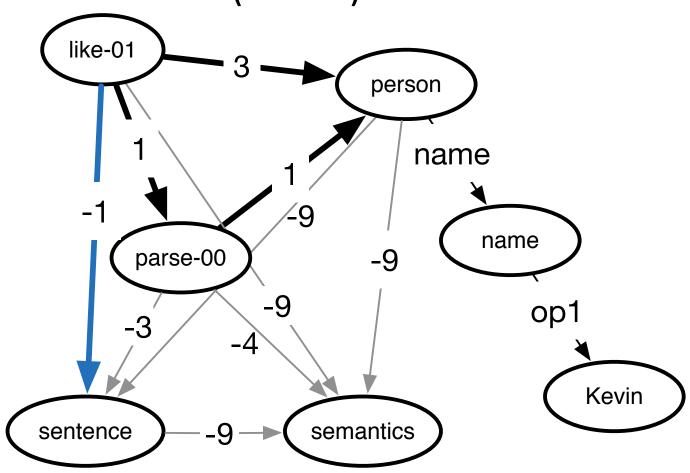


Maximum Weighted Subgraph

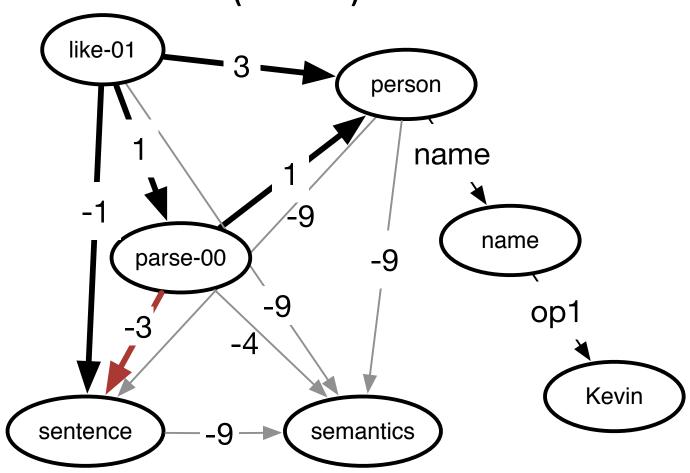


Constraint: Graph must be connected

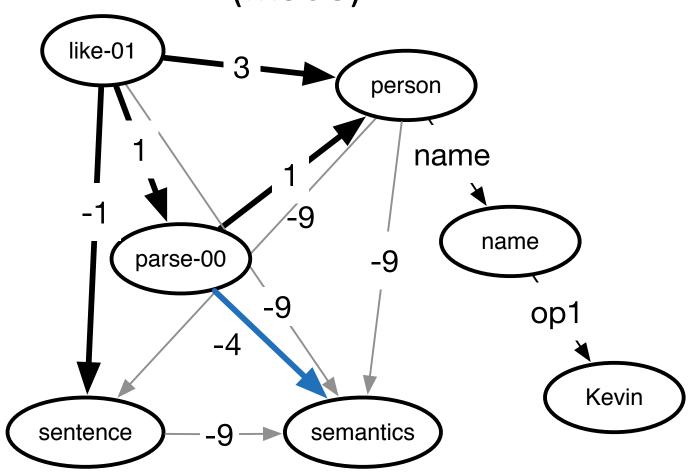
Maximum Spanning, Connected Subgraph (MSCG)



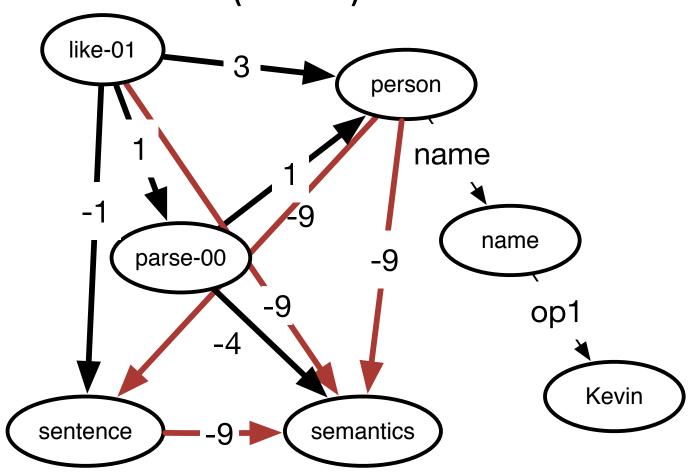
Maximum Spanning, Connected Subgraph (MSCG)



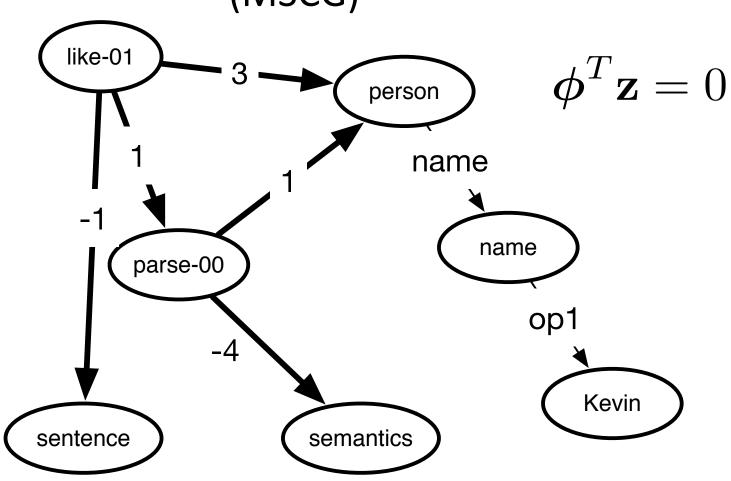
Maximum Spanning, Connected Subgraph (MSCG)



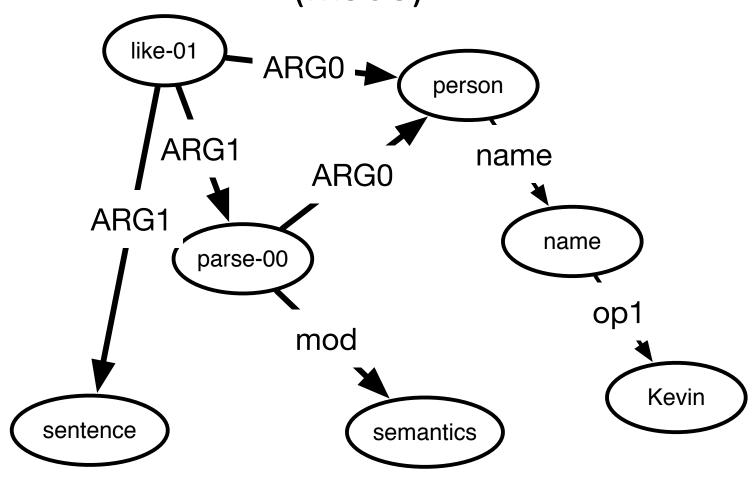
Maximum Spanning, Connected Subgraph (MSCG)



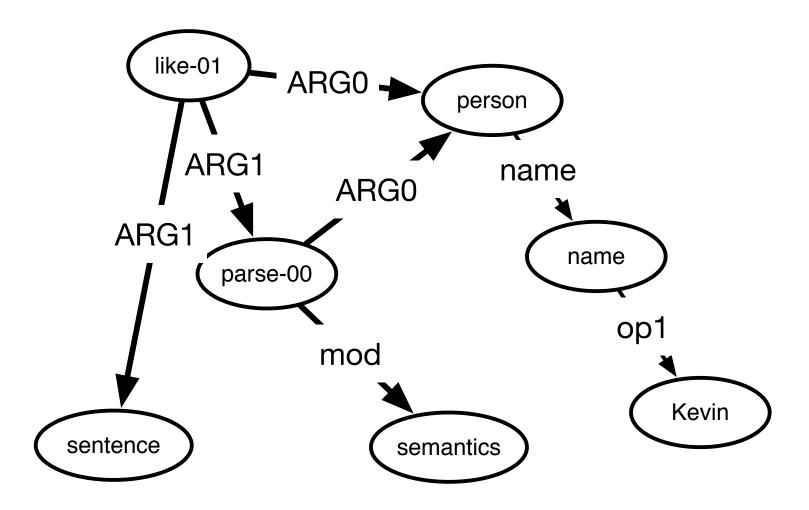
Maximum Spanning, Connected Subgraph (MSCG)



Maximum Spanning, Connected Subgraph (MSCG)



Constraint: Graph must be deterministic



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

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

$$\vdots$$

$$\mathbf{z}_{1 \xrightarrow{ARG1} 2} + \mathbf{z}_{1 \xrightarrow{ARG1} 3} + \dots \leq 1$$
 $\mathbf{z}_{2 \xrightarrow{ARG1} 1} + \mathbf{z}_{2 \xrightarrow{ARG1} 3} + \dots \leq 1$
 \vdots
 $A\mathbf{z} < b$

$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$
 Preserving, simple, connected, spanning s.t. \mathbf{z} satisfies $A\mathbf{z} \leq b$ Determinism constraints

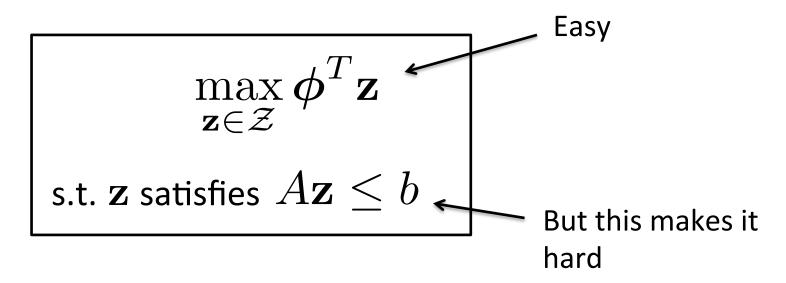
Solve using Lagrangian relaxation

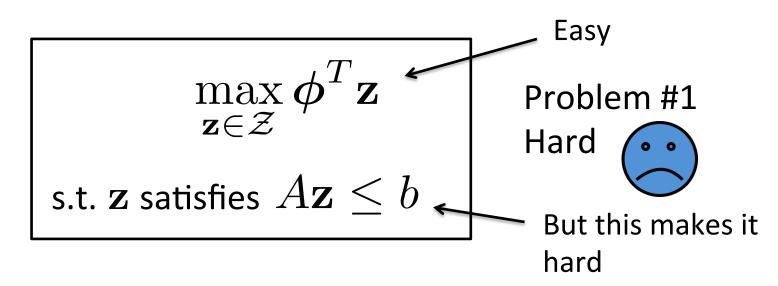
$$\max_{\mathbf{z} \in \mathcal{Z}} \boldsymbol{\phi}^T \mathbf{z}$$
 s.t. \mathbf{z} satisfies $A\mathbf{z} \leq b$

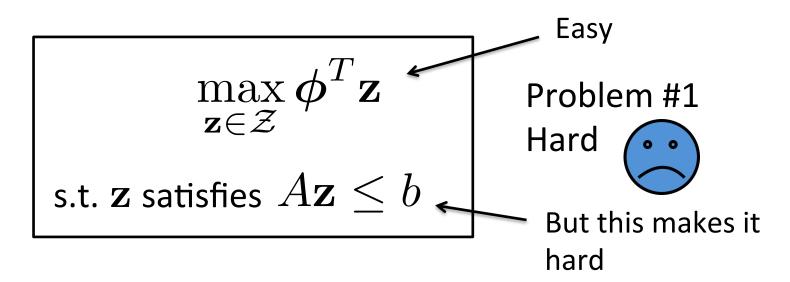
 $\max_{\mathbf{z} \in \mathcal{Z}} oldsymbol{\phi}^T \mathbf{z}$

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

Easy (know how to solve)

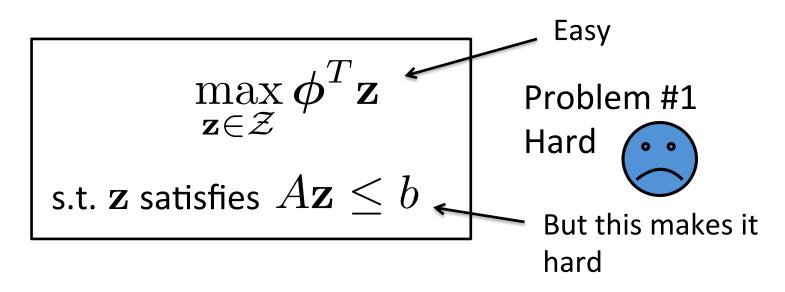






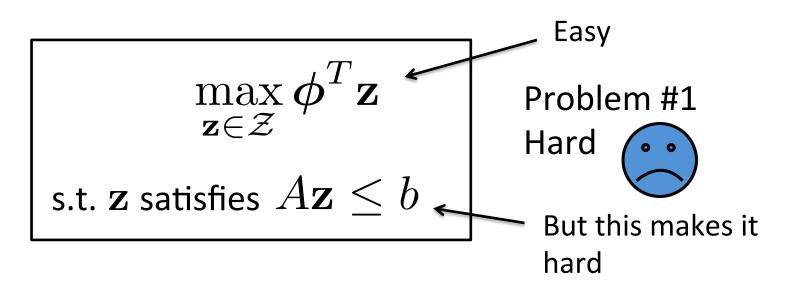
$$\lambda^T(\mathbf{b} - A\mathbf{z})$$

Lagrange multipliers ≥ 0



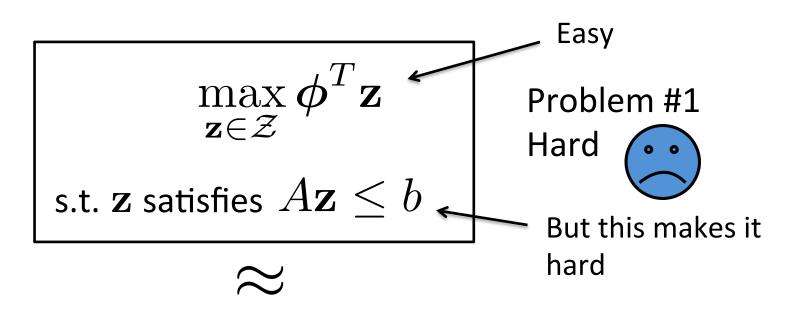
$$\max_{\mathbf{z}\in\mathcal{Z}}\phi^T\mathbf{z} + \lambda^T(\mathbf{b} - A\mathbf{z})$$

Add to original objective



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

Minimize over λ



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

Problem #2
Easy

Not always equivalent, as we shall see

Solving Problem #2

Problem #2 (aka "Lagrange Dual"):

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

- 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

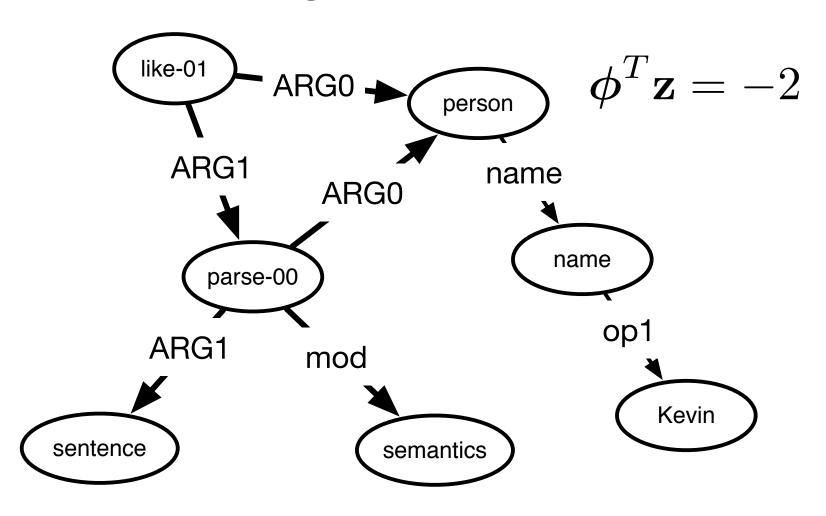
• Problem #2 (aka "Lagrange Dual"):

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

- 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



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

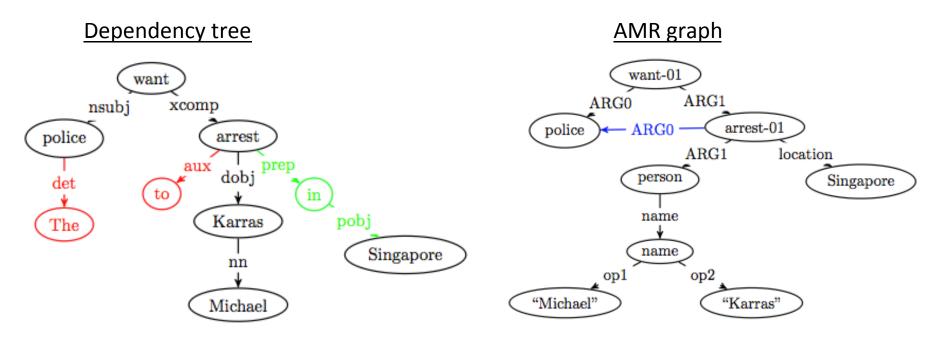
Experiments

	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)

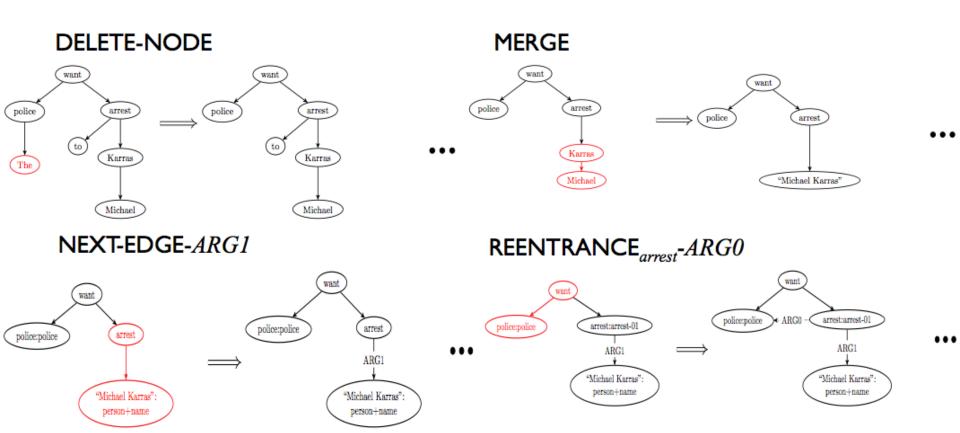
- Convert dependency tree into AMR graph
- Motivation: only a few difference between syntactic dependencies and AMR



Transition-based AMR Parsing

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

Transition-based AMR Parsing



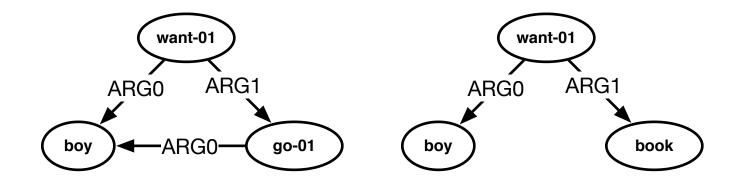
AMR Parsing using Syntax-based MT (Pust et al, 2015)

- 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)

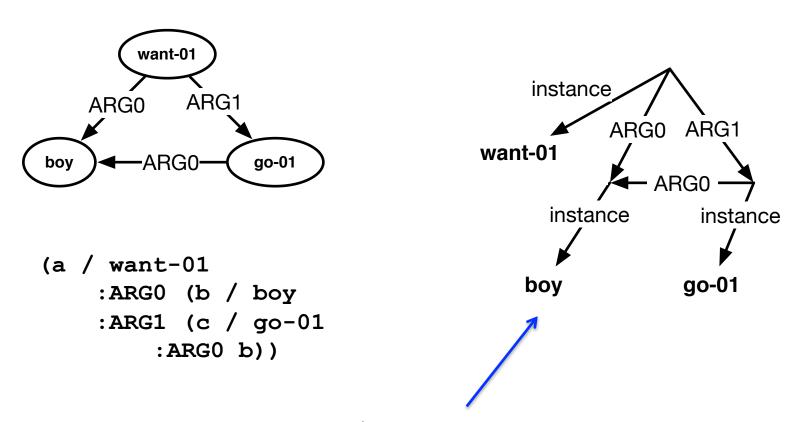
Evaluation

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

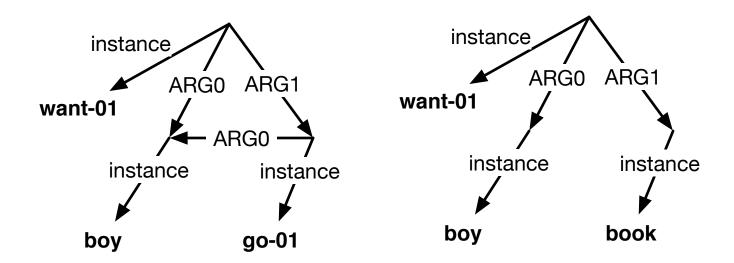
Evaluation: Smatch (Cai & Knight, 2013)

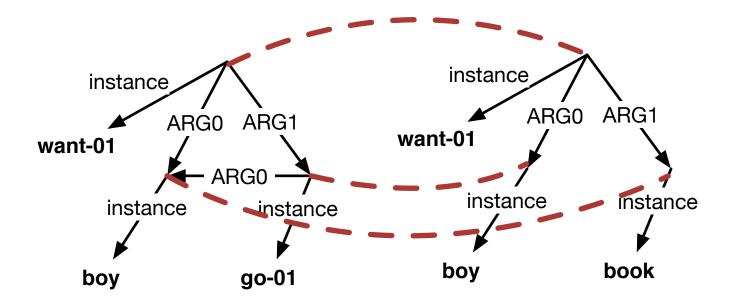


Want a number which indicates the similarity between two graphs

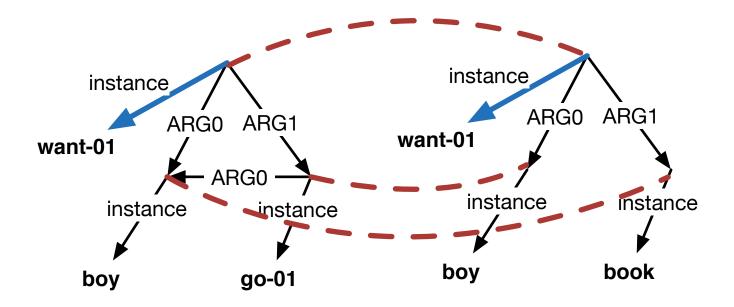


AMR graph w/ explicit instance edges

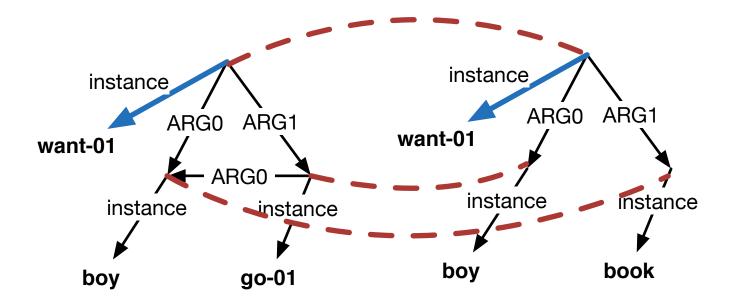




Consider an alignment between the nodes

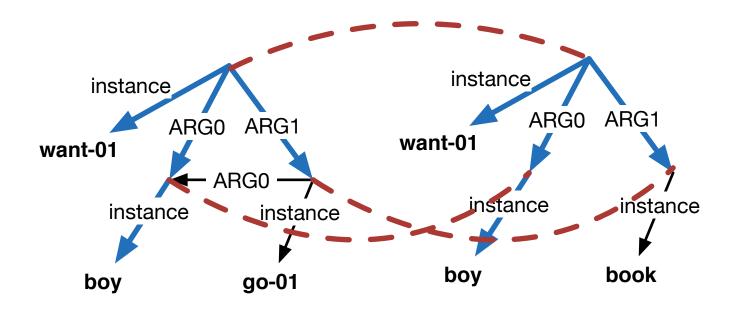


f-score =
$$F_1$$
 of identical matching edges
= 2 Match/(Total₁ + Total₂)
= 2 / (6 + 5) = .18



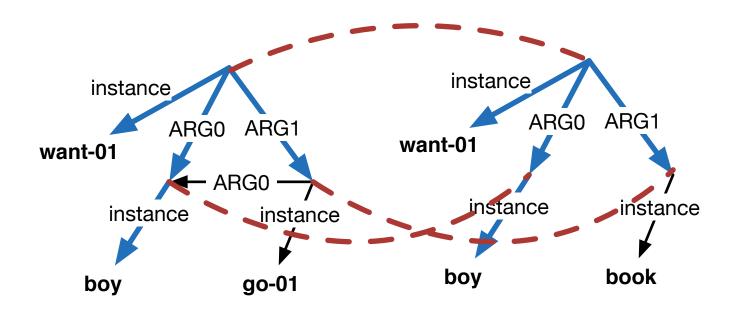
Smatch score = maximum f-score over all possible alignments

NP hard => approximate inference to find highest scoring alignment



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

Highest scoring alignment



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

Grammar

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

<u>Grammar</u>

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

Example derivation S

<u>Grammar</u>

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

Example derivation

S

$$\Rightarrow_1 NP VP$$

<u>Grammar</u>

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

Example derivation

S

 $\Rightarrow_1 NP VP$

 $\Rightarrow_3 NP V NP$

<u>Grammar</u>

- 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

<u>Grammar</u>

- 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

 $\Rightarrow_3 NP V NP$

 $\Rightarrow_{\Delta} NP like NP$

 \Rightarrow_6 NP like ice cream

<u>Grammar</u>

- 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

 $\Rightarrow_3 NP V NP$

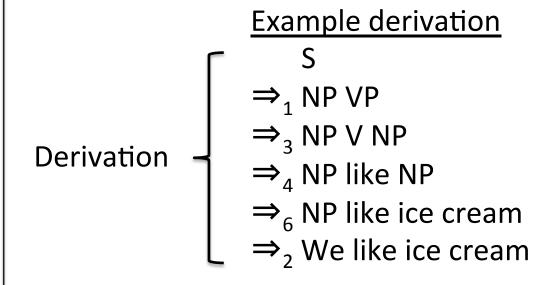
 \Rightarrow_{Δ} NP like NP

 \Rightarrow_6 NP like ice cream

 \Rightarrow_2 We like ice cream

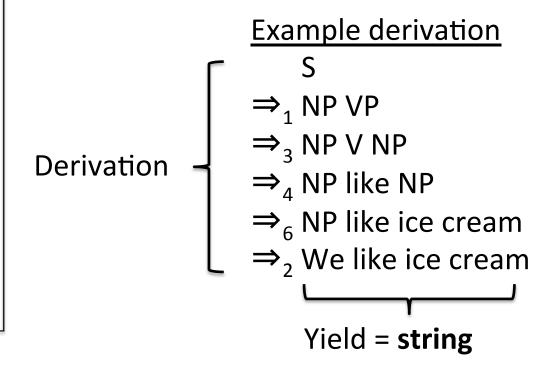
<u>Grammar</u>

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



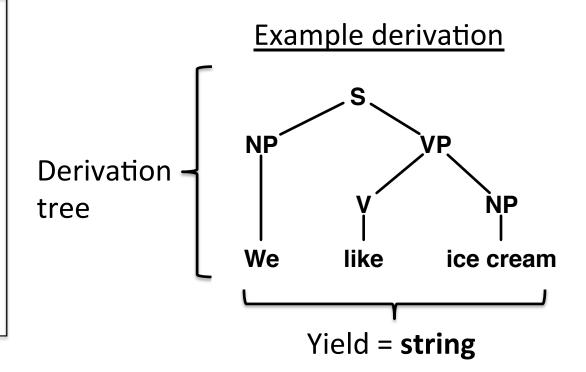
<u>Grammar</u>

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

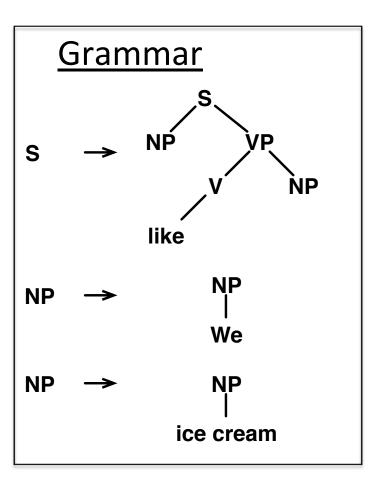


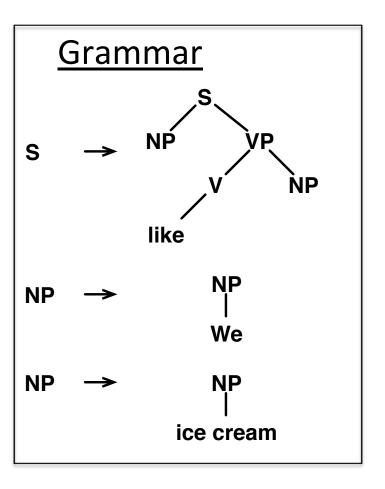
<u>Grammar</u>

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



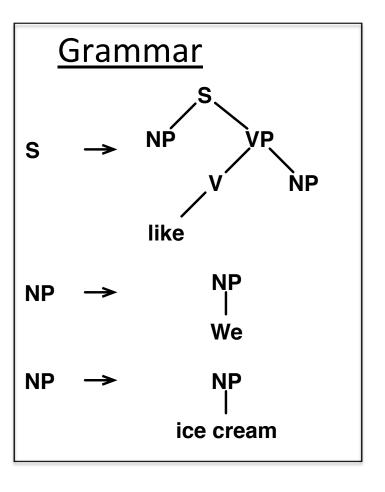
Language over strings (yield), and trees (derivations)



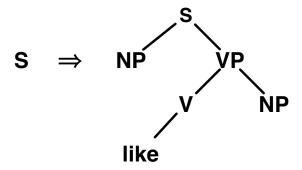


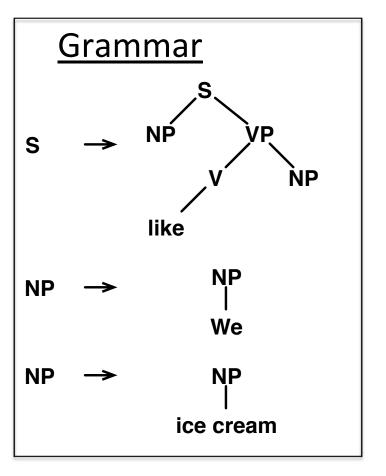
Example derivation

S

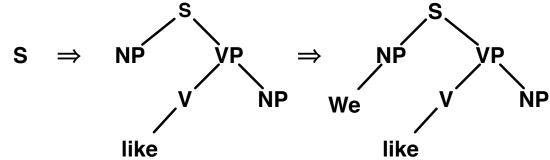


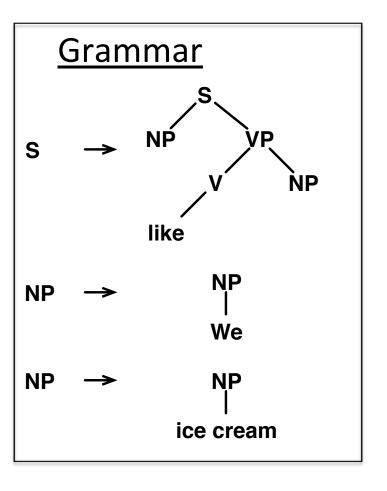
Example derivation



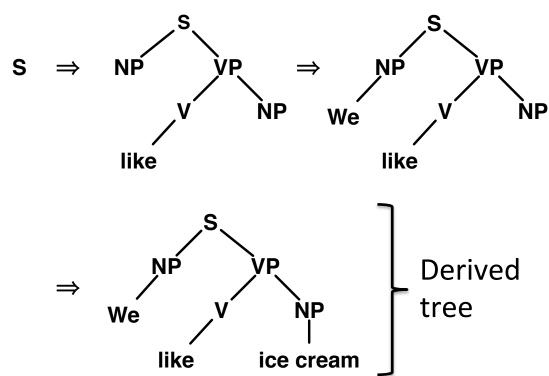


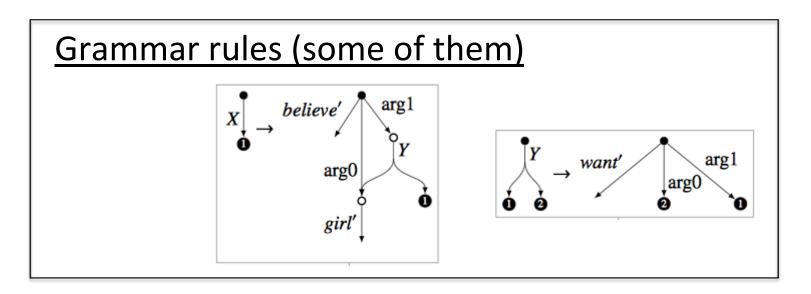
Example derivation

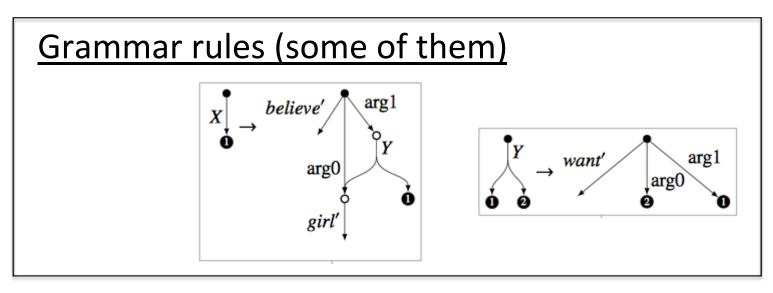


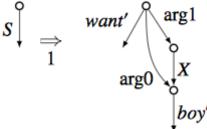


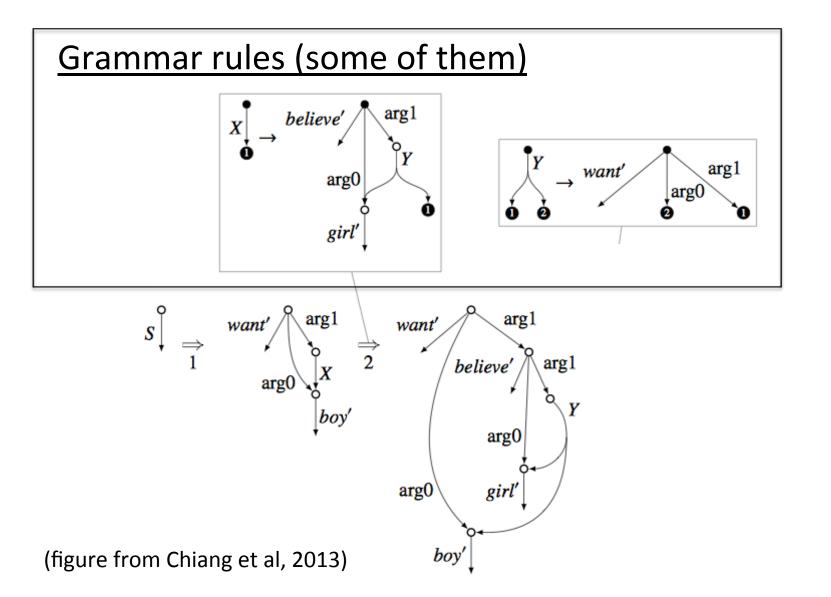
Example derivation

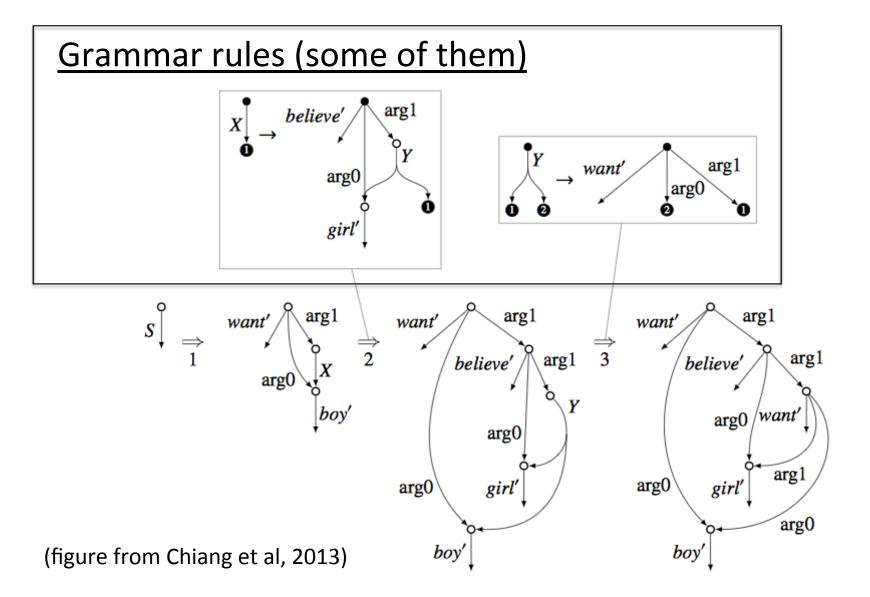




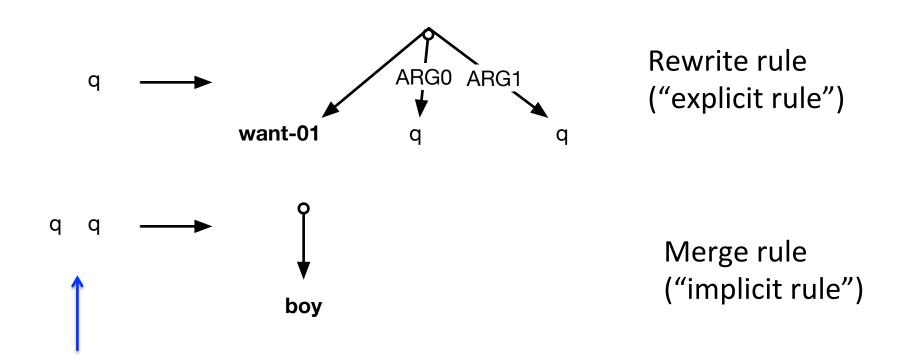




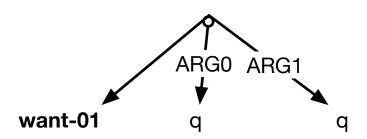


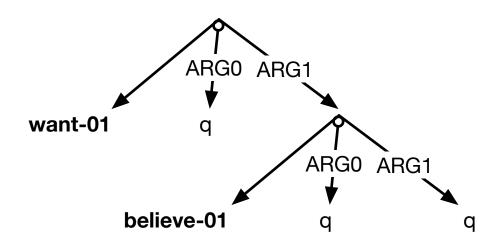


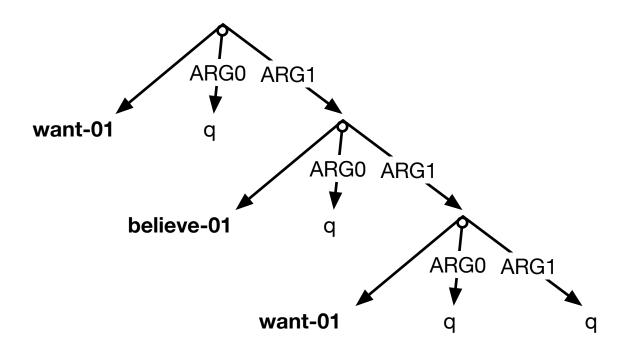
(Kamimura and Slutzki, 1981. Quernheim and Knight, 2012)

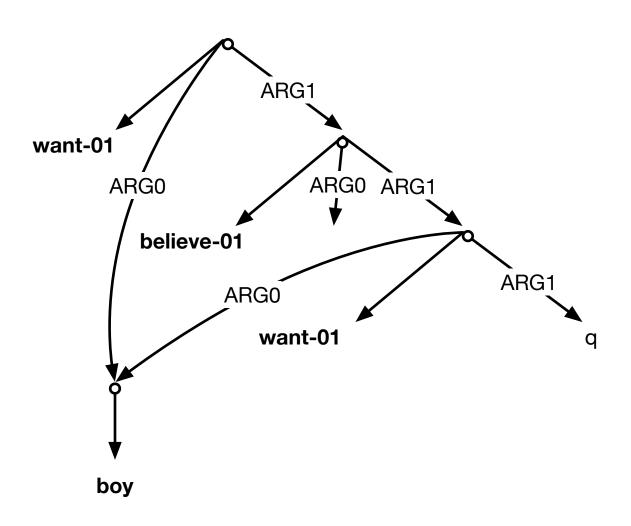


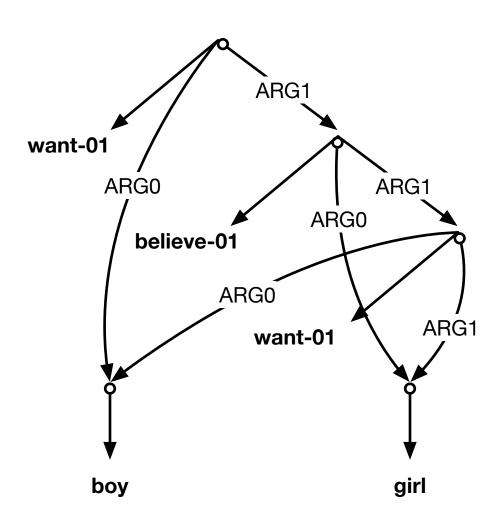
Two or more states can merge rule











Extensions

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

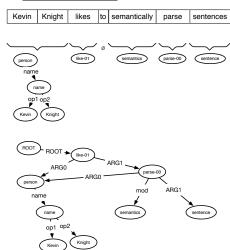
Recent/Ongoing work

- 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.

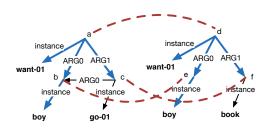
Parsing

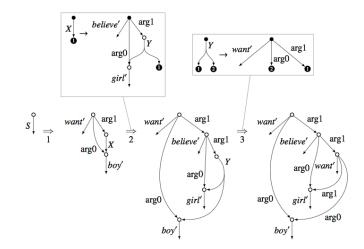


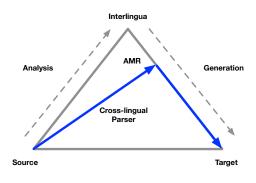
Evaluation

Graph grammars

Applications





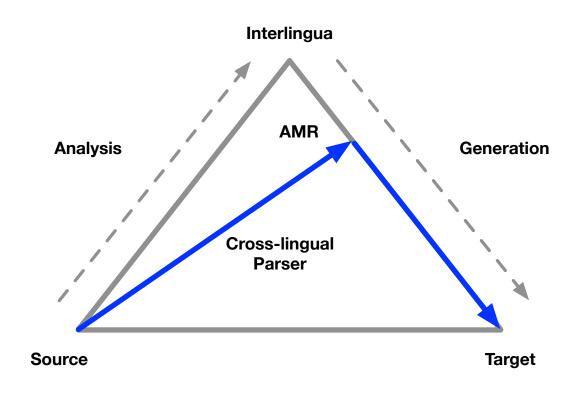


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Applications

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

Machine Translation



Summarization (Liu et al, NAACL 2015)

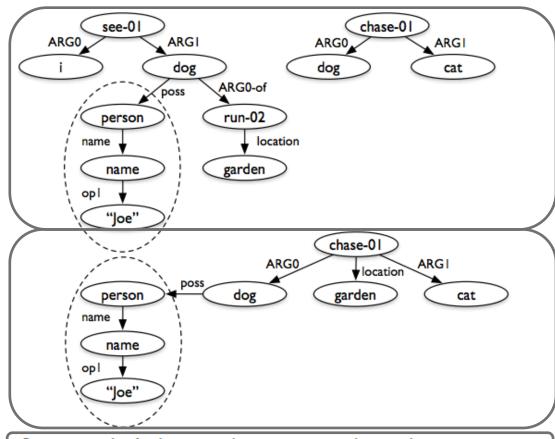
Document Sentences (input)

Document AMRs (run parser)

Summary AMR (select nodes and edges)

Summary (generate)

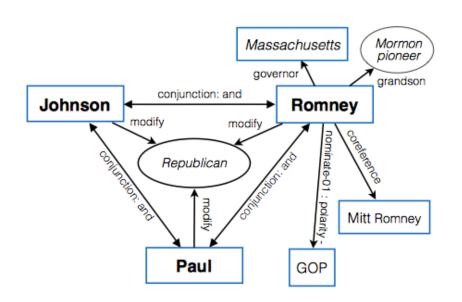
Sentence A: I saw Joe's dog, which was running in the garden. Sentence B: The dog was chasing a cat.



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 AMRannotated corpus"
- Naomi Saphra and Adam Lopez. "AMRICA: an AMR Inspector for Crosslanguage 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))
```

Thanks to: Miguel Ballesteros, David Chaing, Shay Cohen, Chris Dyer, Kevin Knight, Lingpeng Kong, Fei Liu, Noah Smith, Sam Thomson, and Chuan Wang

The Zen of AMR







One graph to rule them all.

One graph to rule them all.

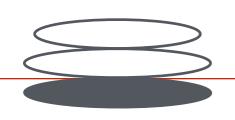
Defragmented semantics in (basically) a rooted DAG.

One graph to rule them all.

Defragmented semantics in (basically) a rooted DAG.

AMR is not in the derivation business.





Deep is better than shallow. (Paraphrases should have the same AMR.)

...but practicality (for annotation) beats purity.

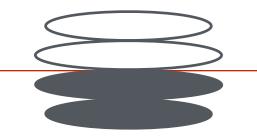
Theodore is in love with his computer's operating system.

Theodore loves his computer's operating system.

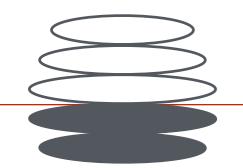
The operating system of Theodore's computer is loved by him.

Theodore adores the operating system in his computer.

Theodore is romantically involved with his operating system.

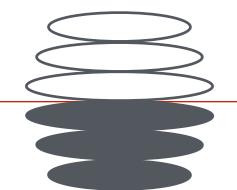


It doesn't have to be an interlingua, so long as it is more logical than English.



There should be one and preferably only one obvious way to AMR it.

AMR is a canonical form.



The annotator experience matters.

AMR Editor nathans

Written by Ulf Hermjakob, USC/ISI Version 1.7.4z11 December 10, 2014

undo del o3

Sentence: According to Ginsburg, we have an obligation to provide others with contraception

```
(s / say-01)
   :ARG0 (p / person :wiki "Ruth Bader Ginsburg" :name (n / name :op1 "Ginsburg"))
   :ARG1 (o / obligate-01
       :ARG1 (w / we)
       :ARG2 (p2 / <u>provide-01</u>
           :ARG0 w
           :ARG1 (c / contra provide-01
                                ARG0: provider
           :ARG2 (p3 / perso ARG1: thing provided
                                ARG2: entity provided for (benefactive)
```

Enter text command: p3 : mod other

how

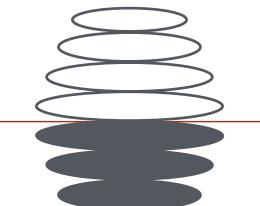
- :ARGx
 - How much does this cost? (cost-01 :ARG2 amr-unknown) Example
 - How did you solve the problem? (solve-01 :ARG2 amr-unknown) Example
- :degree
 - How big was the dog that bit you? (big :degree amr-unknown :domain :dog) Example
 - o How beautiful you are. [= You are so beautiful.] (beautiful :degree so :domain you) Example
- :manner
 - How did you get him to help you? (get-04 :manner amr-unknown) Example
 - o The only thing that surprises me is how rapidly this is happening. (surprise-01 :ARGO (rapid :manner-of this)) Example
- :quant
 - o How tall are you? (tall :quant amr-unknown :domain you) Example
 - How old is your father? (father :age amr-unknown :poss you) Example

however

- contrast-01 (most cases)
 - ∘ John, however, stayed at home. (contrast-01 :ARG2 stay-01) Example
- · :concession
 - o It started to rain; however, the game continued. (start-01 :ARG1 rain-01 :concession-of continue-01) Example

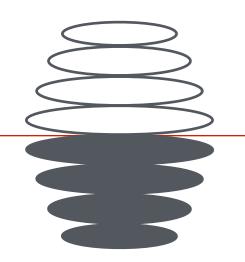
imperative @

- :mode imperative
 - ∘ Go home! (go-02 :mode imperative :ARGO you :destination home) Example
 - ∘ Let's go home. (go-02 :mode imperative :ARG0 we :destination home) Example
 - o Come on folks!! (come-25 :mode imperative :ARG1 folk) Example
- :mode imperative :polite +
 - o Please close the door. (close-01 :mode imperative :polite +) Example
 - o Could you close the door? (close-01 :mode imperative :polite +) Example



Morphosyntactic sugar is considered unhealthy.

He made a thoughtless political decision.



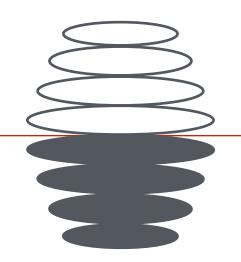
Verbs (events) are better than nouns (plain concepts).

Adjectives are better than adverbs.

Adjective frames are better than :mod.

Core roles are better than non-core roles.

Anything is better than :prep-X!



Verbs (events) are better than nouns (plain concepts).

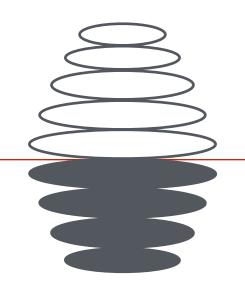
(Except when the meaning is noncompositional.)

Adjectives are better than adverbs.

Adjective frames are better than :mod.

Core roles are better than non-core roles.

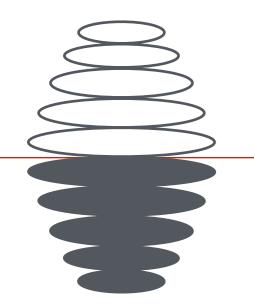
Anything is better than :prep-X!



Occasionally you need to hallucinate to fill in the gaps.

```
(g / government-organization
:ARG0-of (g2 / govern-01
:ARG1 (...China...)))
```

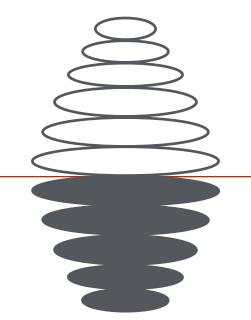
the Chinese government the government of China



A government is a government - organization that governs.

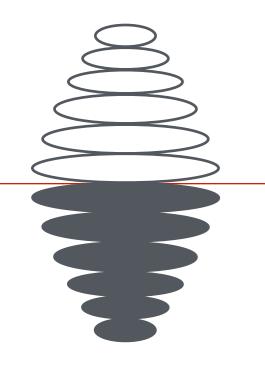
```
(g / government-organization
:ARG0-of (g2 / govern-01)
:mod (f / federal))
```

the federal government



The sentence is a starting point. It should not be a straightjacket.

In the future, AMR will pay better attention to cross-sentence/discourse phenomena.



AMR does not compromise for algorithmic expedience. (Algorithms will have to catch up!)

http://amr.isi.edu

AMR Bibliography

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AMR Editor Command Line

Editing

Adding stuff

- Start the AMR: top concept
- Attach a new concept under a variable v: v : REL concept
- Attach a new NE under a variable: v : REL type Parts Of Name
- Add a new relation between two existing variables: v :REL v2

Changing stuff

- Move a variable under another one: v :REL v2-
- Change the relation between two variables: v : NEWREL v2-
- Select a PropBank frame: Add as a plain concept, click on the blue link, then click on the frame you want to add a sense number (the link in the AMR will turn green). (If you know the sense number in advance you can enter it as the concept name.)
- Rename a concept: rc v new-concept
- Delete the primary occurrence of a variable and everything under it that is not used elsewhere: del v
- Delete dummy nodes (unused suggestions from preprocessor): dd
- Undo last action: u
- Save changes: save
- Save and continue to the next sentence; click the button

Documentation

- Open the list of non-core roles and special frames: roles
- Open the list of entity types: types
- Open the AMR Dictionary: dict
- Open the AMR Guidelines: guidelines
- Search all release AMRs: rs query