Semantic Analysis

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Contents

1.

Word sense disambiguation

Words have meanings

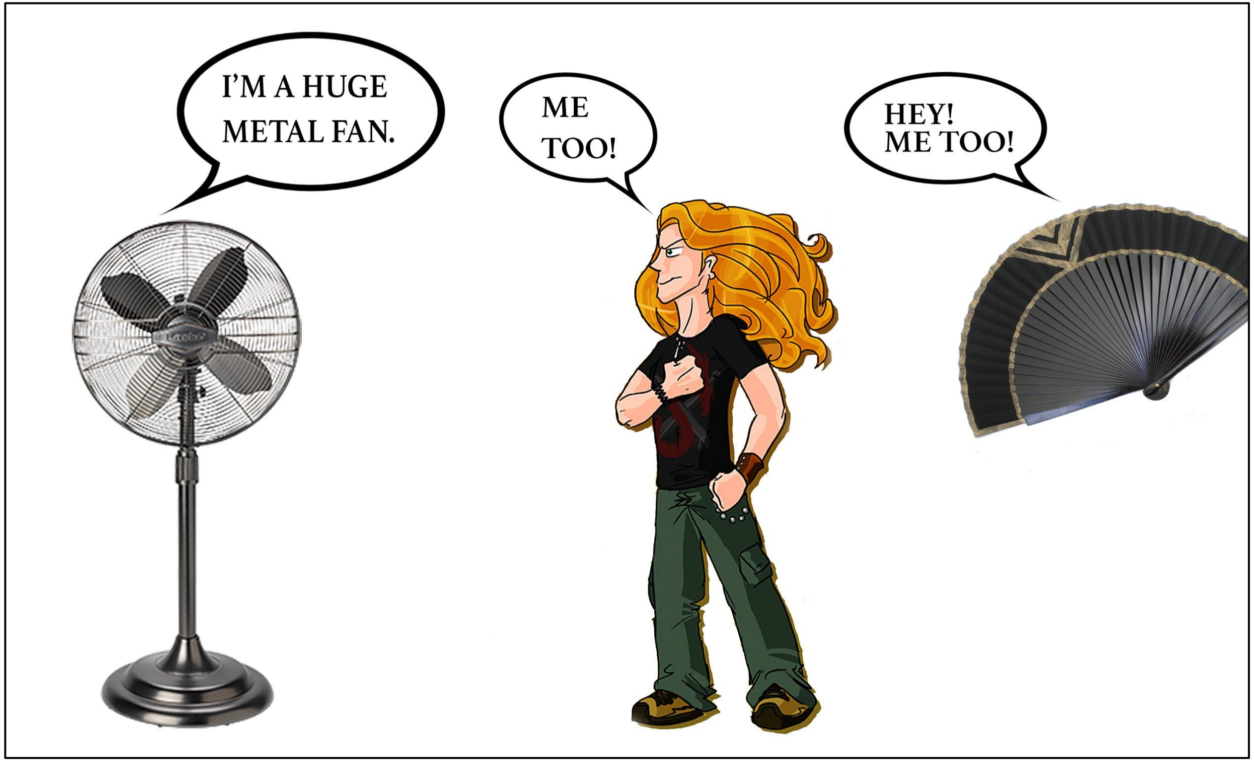


Image by Tetiana Turchyn

Words have meanings

Is it serious?

- ~40% of English words are polysemous
- most polysemous - verbs (~55% in WordNet)
- resources disagree
  - *“head”*, noun:
    - 11 meanings - Macmillan Dictionary
    - 16 meanings - Longman Dictionary
    - 33 meanings - WordNet
    - 34 meanings - Oxford Dictionary
- meanings overlap
  - *John works for the* ***newspaper*** *that you are reading.*

Is it just English?

... зробити так, щоби впала ***стіна****?*

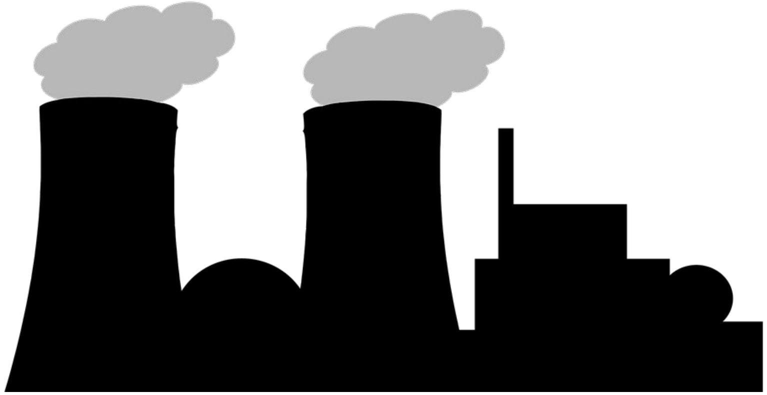
1. стіна будинку
2. стіна урвища
3. мур
4. те, що відокремлює, роз'єднує

Personal assistants

You: I need to buy a big **plant** for my mom. She likes gardening!

Siri: Hmm…

?



Information retrieval

Where is **Paris** now and what is she doing?

?

Sentiment analysis

Paris Hilton is very **rich**.

This area is **rich** in natural resources.

These comments are a bit **rich** coming from someone with no money worries.

Error correction

Animate or inanimate?

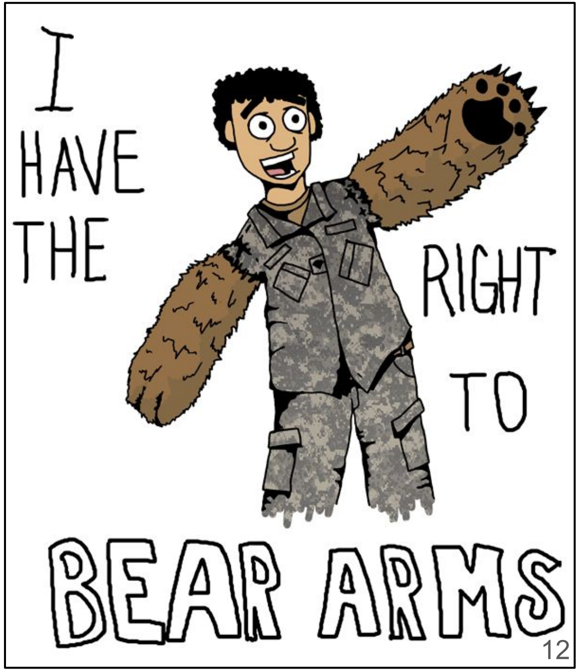
Then we have 2 laptop stands & 2 **mouses** left.

My cat catches **{mouses=>mice}** all the time.

Text mining

US **sells arms** to countries well-known for violating human rights.

Using recycled prosthesis, a hospital in Tanzania **sells arms** for around $500 each. There is also high demand for legs.



What is “sense”?

- senses = domains?
- senses = sentiments?
- senses = animate/inanimate?
- senses = jargon/standard?
- senses = countable/uncountable?
- senses = entities?
- senses = senses?

Dictionaries

bank (*plural* **banks**)

1. (*hydrology*) An edge of river, lake, or other watercourse. [quotations ▼]
2. (*nautical*, *hydrology*) An elevation, or rising ground, under the sea; a shallow area of shifting sand, gravel, mud, and so forth (for example, a sandbank or mudbank).

    the ***banks*** *of Newfoundland*

3. (*geography*) A slope of earth, sand, etc.; an embankment.
4. (*aviation*) The incline of an aircraft, especially during a turn.
5. (*rail transport*) An incline, a hill.

Example from en.wiktionary.org

Dictionaries

man[1] /mæn/ ●●● S1 W1 **noun** (*plural* **men** /men/)

1 **MALE PERSON** [countable] an adult male human → **woman**

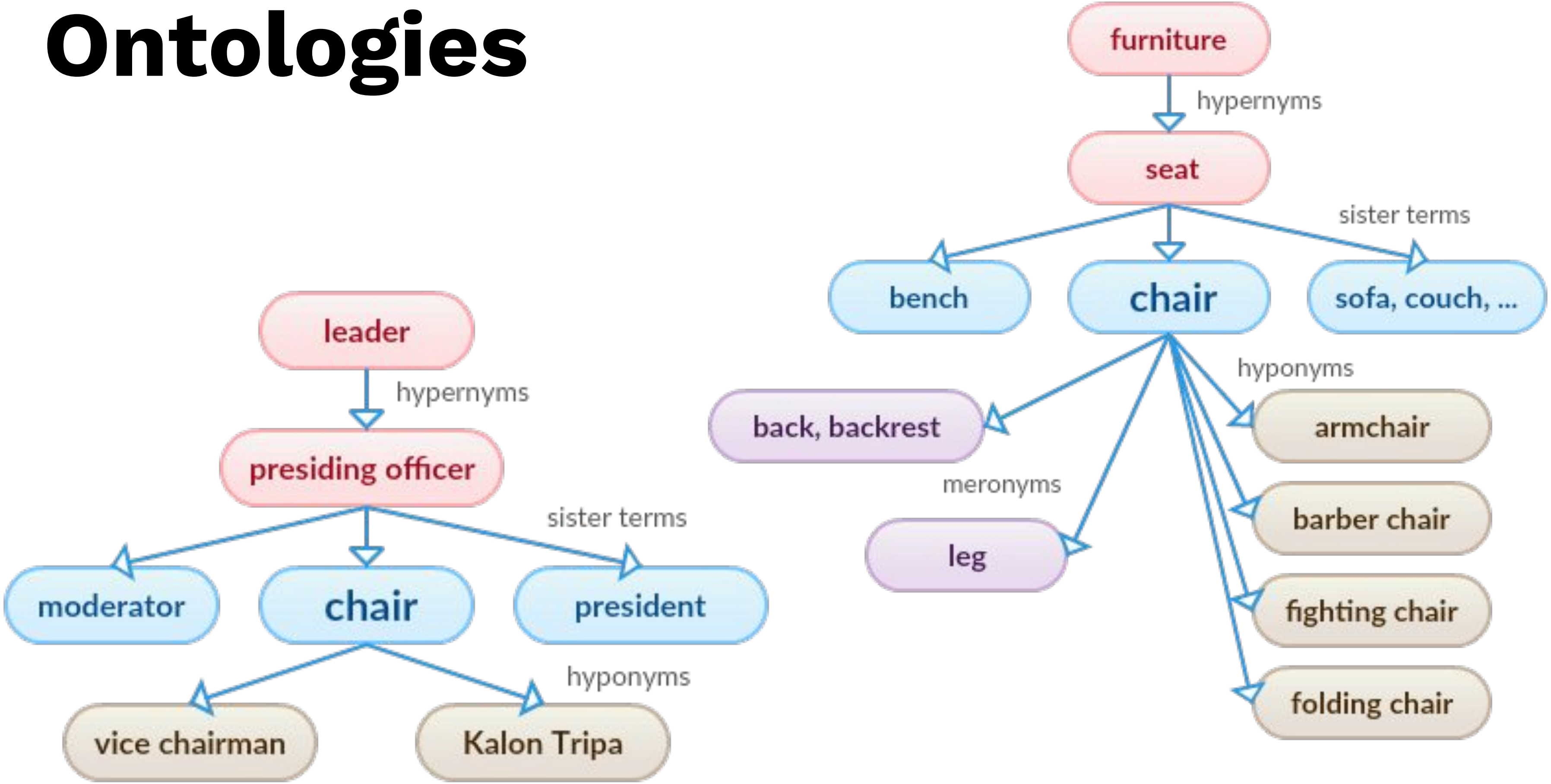
2 **STRONG/BRAVE** [countable usually singular] a man who has the qualities that people think a man should have, such as being brave, strong etc

3 **PERSON** [countable] a person, either male or female – used especially in formal situations or in the past

4 **PEOPLE** [uncountable] people as a group

Example from www.ldoceonline.com

Ontologies



Example of relations in WordNet

Wikipedia, Wikidata, DBpedia

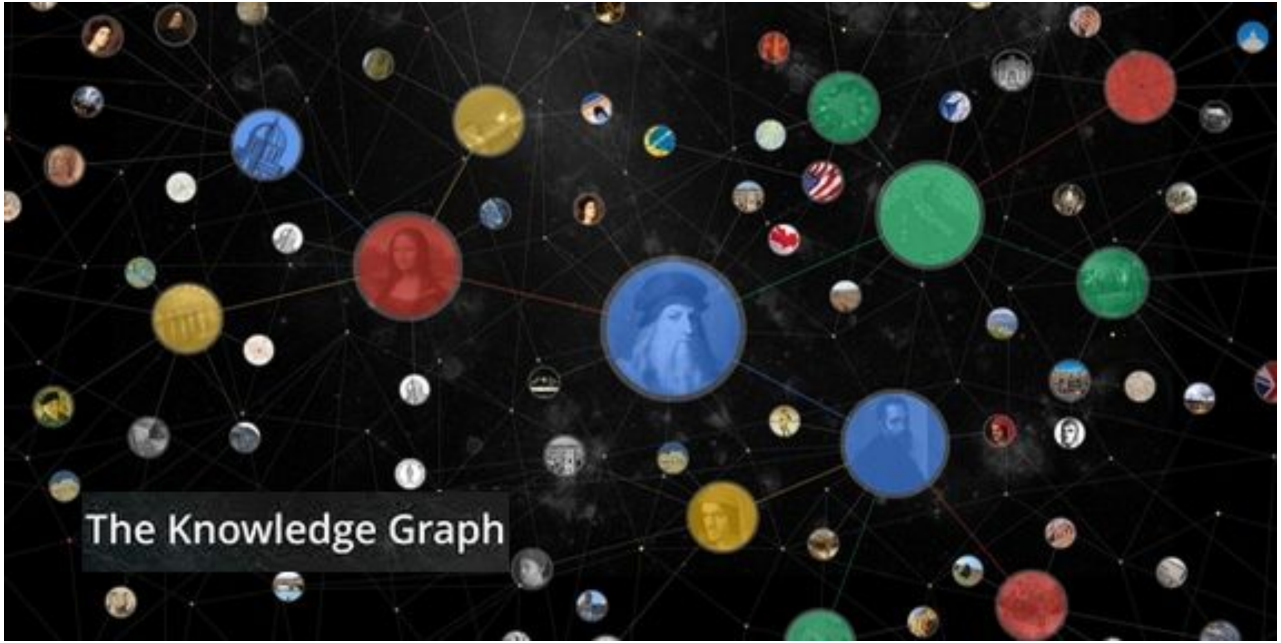
Finance [edit]

- Central bank
- Mutual savings bank
- Savings bank

Natural geography [edit]

- Bank (geography), a raised portion of seabed or sloping ground along the edge of a stream, river, or lake
- Ocean bank (topography)
- Ocean bank, a shallow area in a body of water
- Stream bank or riverbank, a terrain alongside the bed of a river, creek, or stream

Knowledge Graph

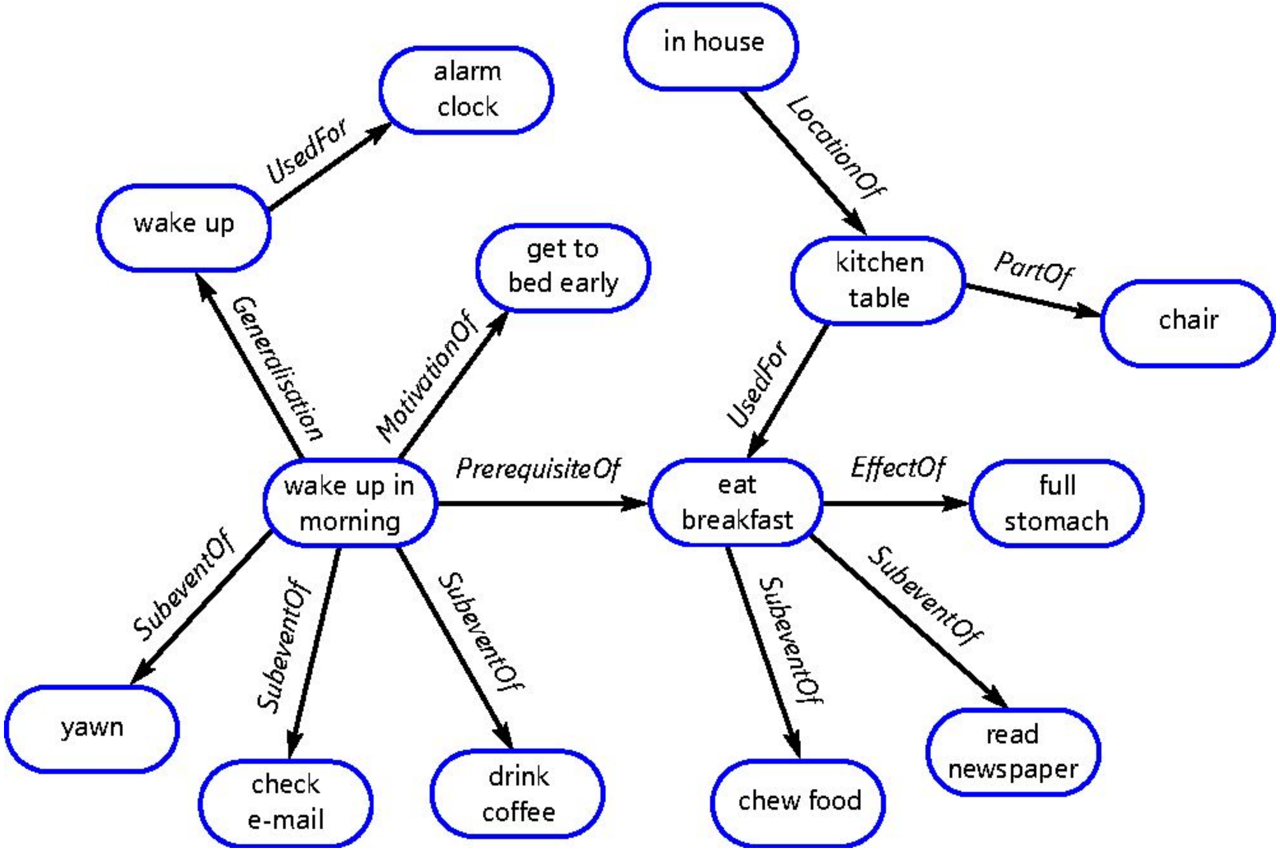


570 million entities

18 billion facts

Used in Google infoboxes, Google Assistant, and Google Home

ConceptNet



8 mln nodes

21 mln edges

83 languages

36 relation types

Represents human knowledge about the world.

Example from conceptnet.io

BabelNet

15.8 mln nodes

380 mln edges

284 languages

Noun

fan, mechanical fan, ventilator

A device for creating a current of air by movement of a surface or surfaces

ID: 00033599n | Concept

fan, rooter, sports fan

An enthusiastic devotee of sports

ID: 00033600n | Concept

Example from babelnet.org

Corpora: SemCor

<wf>The</wf>

<wf lemma="model" wnsn="3">model</wf>

<wf lemma="quite" wnsn="1">quite</wf>

<wf lemma="plainly" wnsn="1">plainly</wf>

<wf lemma="think" wnsn="1">thought</wf>

<wf lemma="person" wnsn="1">Michelangelo</wf>

<wf lemma="crazy" wnsn="1">crazy</wf>

<wf>;</wf>

http://web.eecs.umich.edu/~mihalcea/downloads.html

Corpora: Wikipedia

Beverly Johnson (born October 13, 1952) is an **[American|"United States"] [model|"Model (person)"]**, **[actress|"Actress"]**, **[singer|"Singer"]**, and **[businesswoman|"Businesswoman"]**.

https://en.wikipedia.org/wiki/Beverly_Johnson

How to determine the sense?

You shall know a word by the company it keeps.

John Rupert Firth, 1957

1. Lesk

With which sense **signature** does your **context** overlap the most?

```
function SIMPLIFIED LESK(word, sentence) returns best sense of word

 best-sense ← most frequent sense for word
 max-overlap ← 0
 context ← set of words in sentence
 for each sense in senses of word do
   signature ← set of words in the gloss and examples of sense
   overlap ← COMPUTEOVERLAP(signature, context)
   if overlap > max-overlap then
        max-overlap ← overlap
        best-sense ← sense
 end
 return(best-sense)
```

Lesk

Simon works at an industrial ***plant*** *as an engineer.*

- S: (n) **plant**, works, industrial plant (buildings for carrying on industrial labor) *"they built a large plant to manufacture automobiles"*
- S: (n) **plant**, flora, plant life ((botany) a living organism lacking the power of locomotion)
- S: (n) **plant** (an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience)
- S: (n) **plant** (something planted secretly for discovery by another) *"the police used a plant to trick the thieves"; "he claimed that the evidence against him was a plant"*

Example from WordNet

Lesk

- for context, use lemmas and filter stopwords
- for *signature* of each sense, use
  - examples
  - definitions
  - related terms
  - synonyms, hyponyms, hypernyms, holonyms, meronyms…
  - sentences from corpora, etc.

Lesk

How to compute overlap?

- number of overlapping words
- weighed by the number of occurrences
- weighed by $-\log(P(w))$
- weighed by IDF score: log(C(docs) / C(docs with word *i*))
- …

Important linguistic hypothesis

One sense per discourse!

I bought a ***plant*** *yesterday and put it in my small tank with some inch long baby cichlids.Lost 3 fish over night i never lose fish. i dont see any nibbles on the* ***plant*** *though.. any advice?*

Results

Pros:

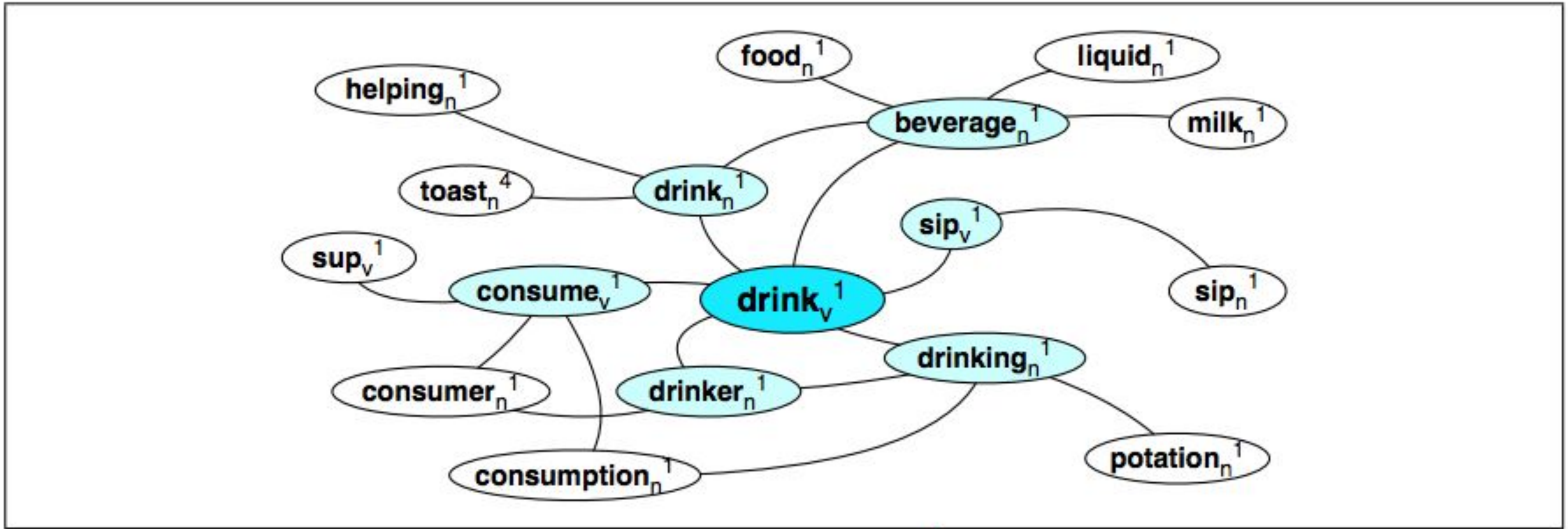
- good for partially annotating corpora
    - can be continued in a semi-supervised fashion
- links to the KB can be preserved
- unreasonably effective: The Unreasonable Effectiveness of Counting Words Near Other Words (2017)

Cons:

- some senses will be poorly covered

2. Graph-Based

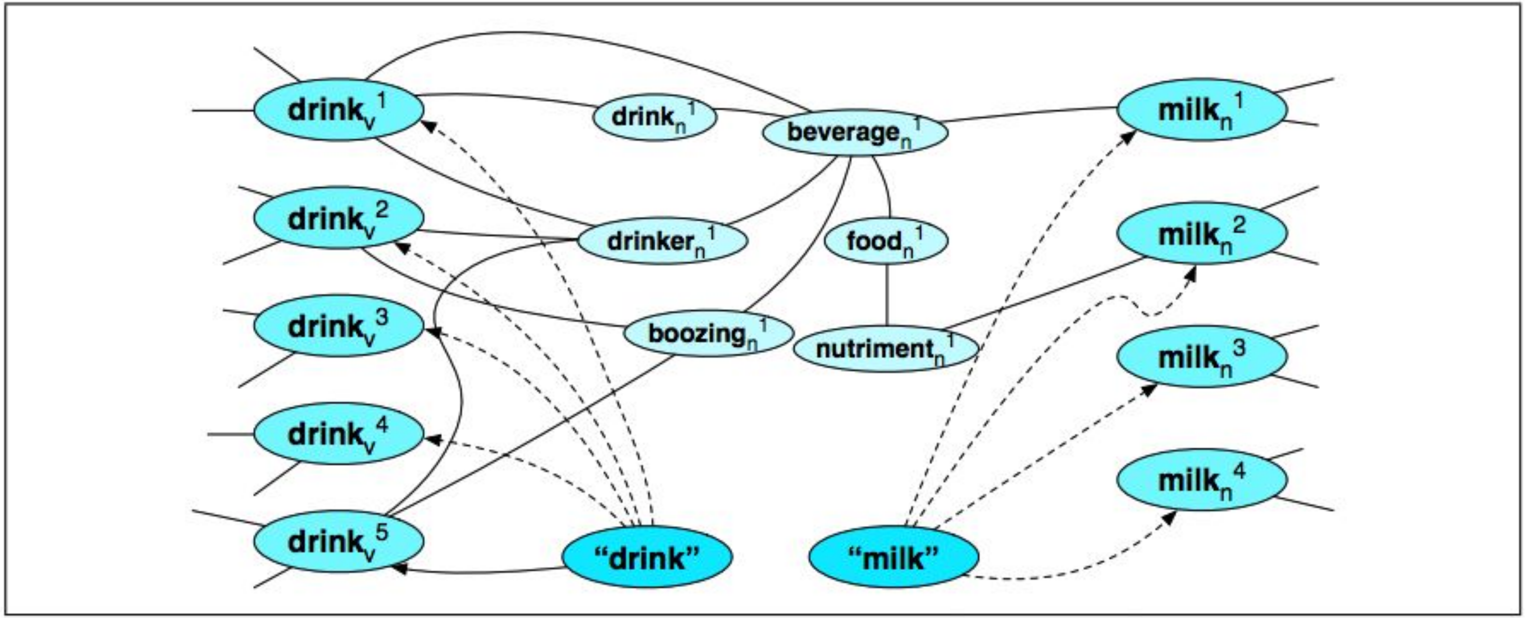
Which sense is the closest to context words?



Example from Navigli and Lapata (2010)

Graph-Based

Which sense of the context word to choose?



Example from Navigli and Lapata (2010)

Path similarity

Simon works at an industrial ***plant*** *as an* *engineer*.

```
>>> plant_1 = wn.synset('plant.n.01')
>>> plant_1.definition()
u'buildings for carrying on industrial labor'

>>> plant_2 = wn.synset('plant.n.02')
>>> plant_2.definition()
u'(botany) a living organism lacking the power of locomotion'

>>> engineer = wn.synset('engineer.n.01')
```

Path similarity

Simon works at an industrial ***plant*** *as an engineer.*

```
>>> plant_1 = wn.synset('plant.n.01')
>>> plant_1.definition()
u'buildings for carrying on industrial labor'

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>>> plant_2.definition()
u'(botany) a living organism lacking the power of locomotion'

>>> engineer = wn.synset('engineer.n.01')
>>> plant_1.path_similarity(engineer)
0.1111111111111111
>>> plant_2.path_similarity(engineer)
0.25
```
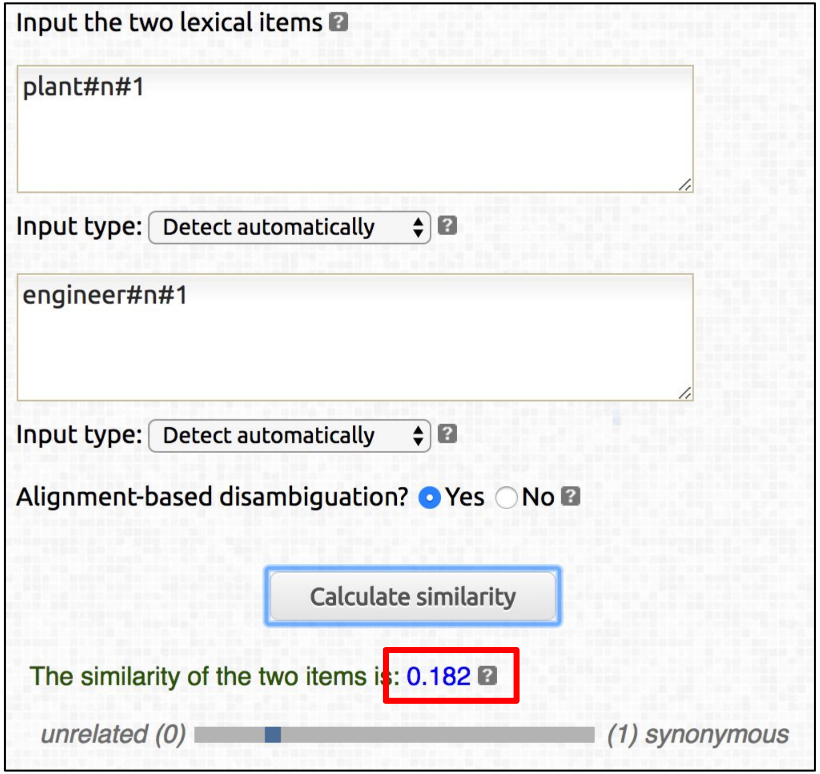
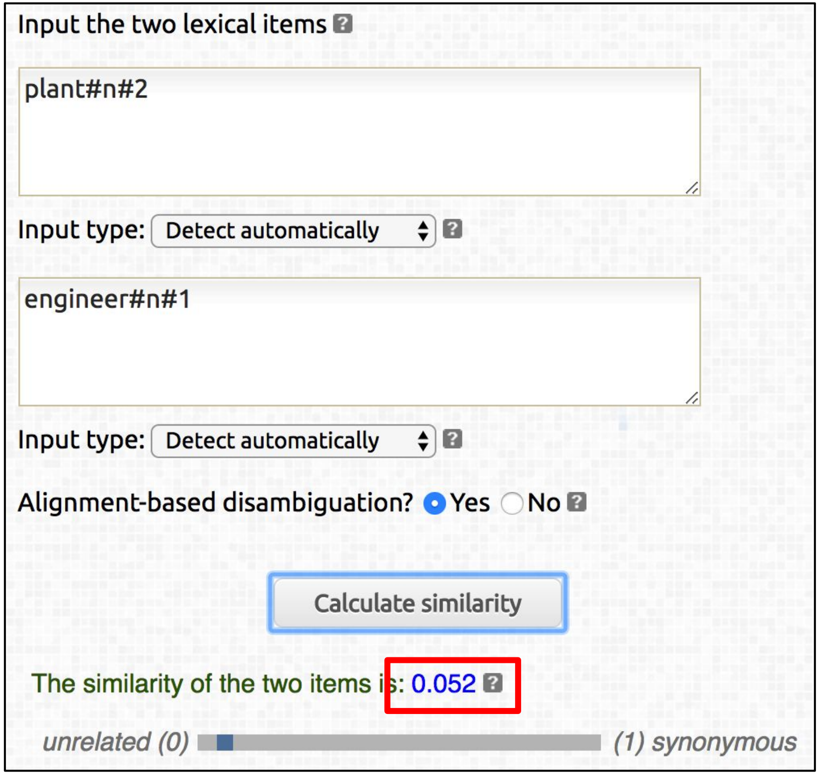

¯_(ツ)_/¯

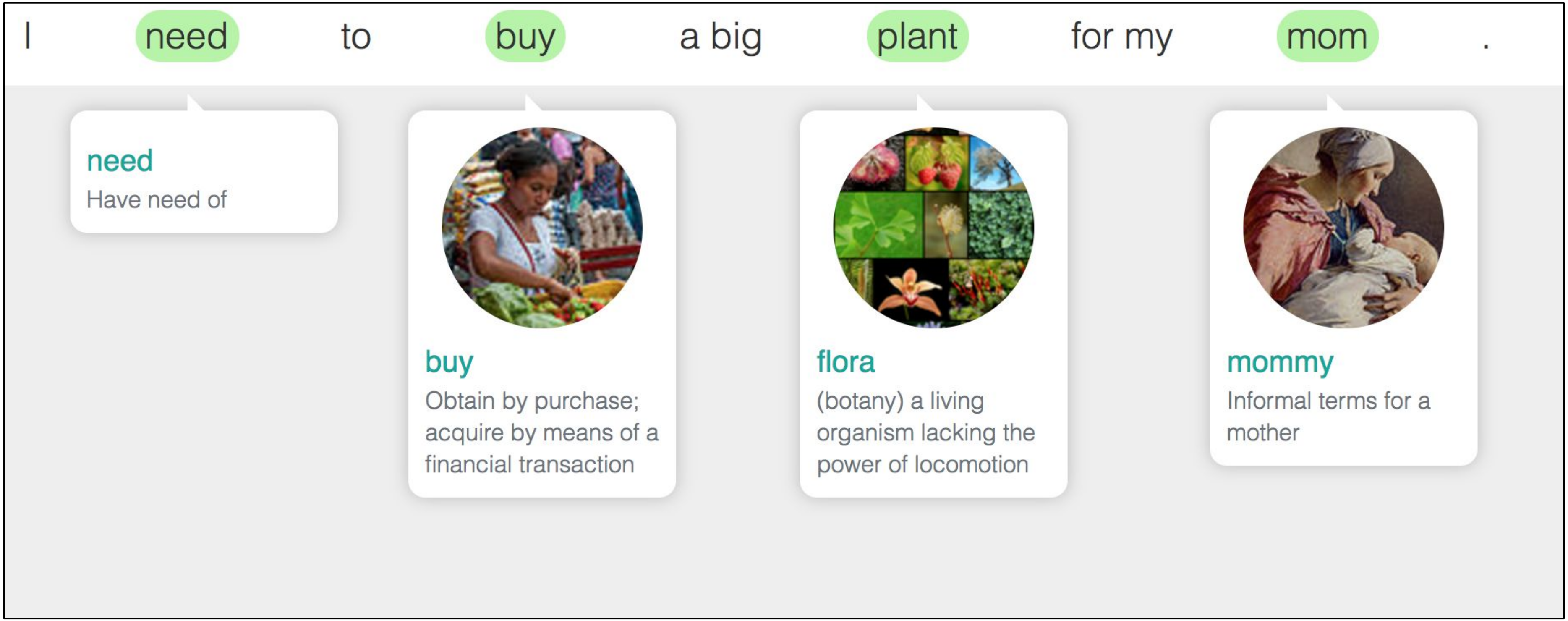
Align, Disambiguate, and Walk





Demo: http://lcl.uniroma1.it/adw/

Babelfy



Example from babelfy.org

Babelfy algorithm

- *[done once]* create semantic signatures for BabelNet concepts
  - assign weights to edges; higher weights in more densely connected areas

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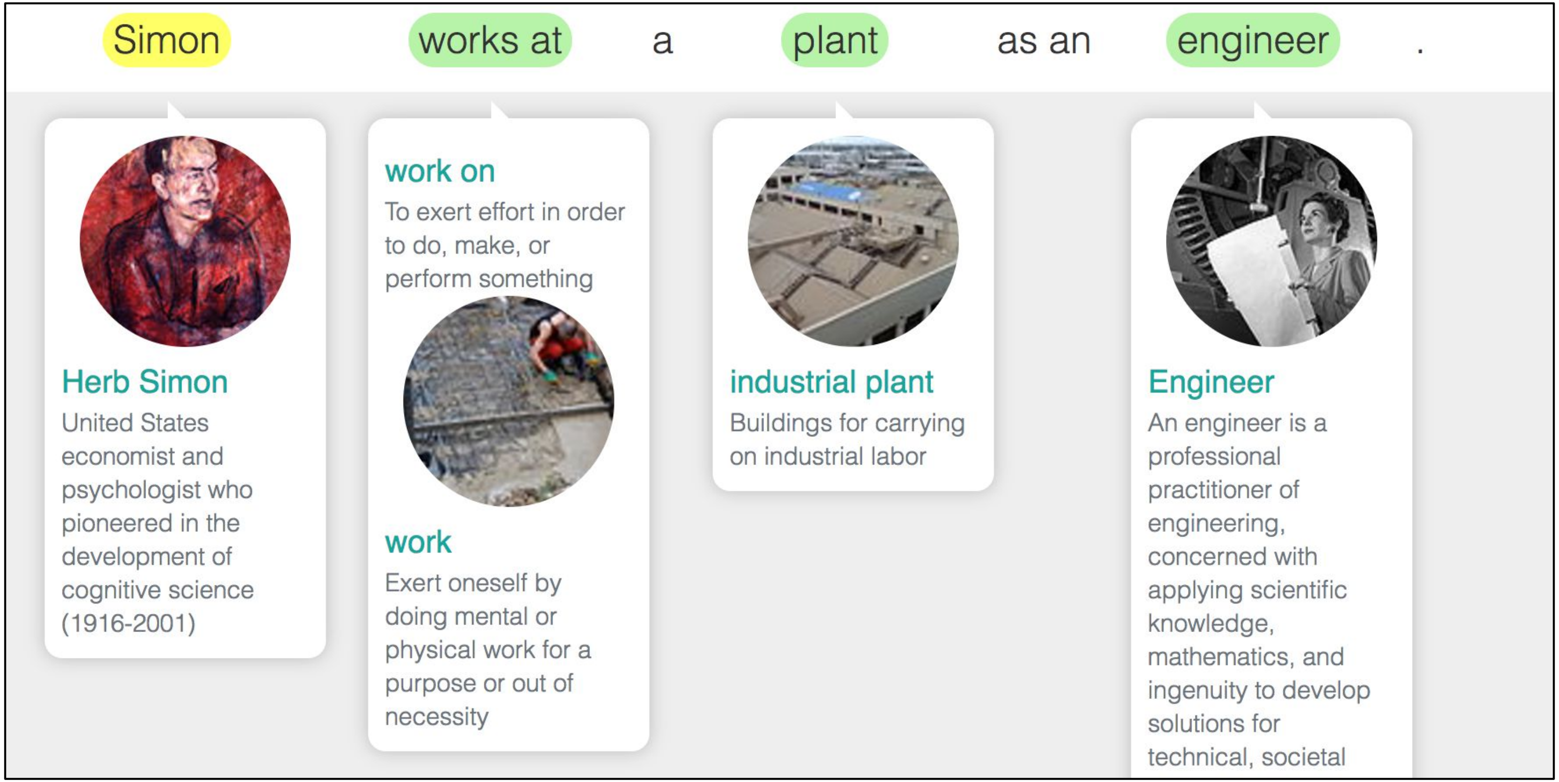
- extract all linkable fragments from the text
- list possible meanings for the fragments
- link the possible meanings of the fragments

Babelfy algorithm

- *[done once]* create semantic signatures for BabelNet concepts
  - assign weights to edges; higher weights in more densely connected areas
- extract all linkable fragments from the text
- list possible meanings for the fragments
- link the possible meanings of the fragments
- extract a dense subgraph of this representation
  - connect meanings if they are in each other's signature
- select the best candidate meaning for each fragment

Babelfy



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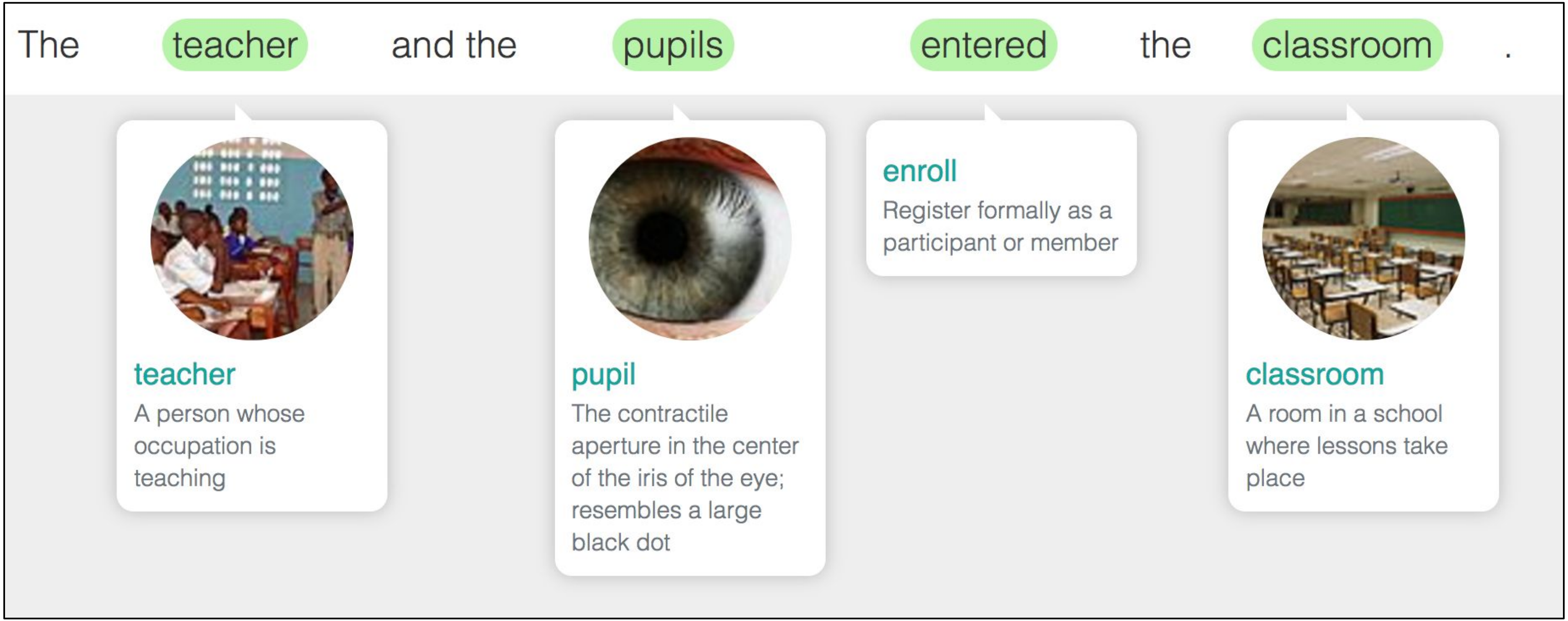

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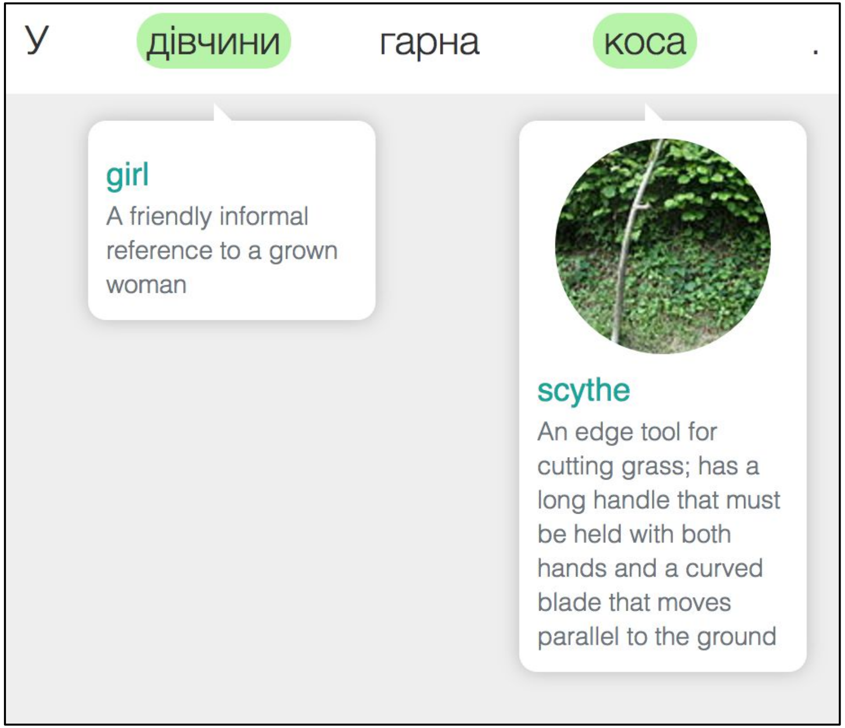

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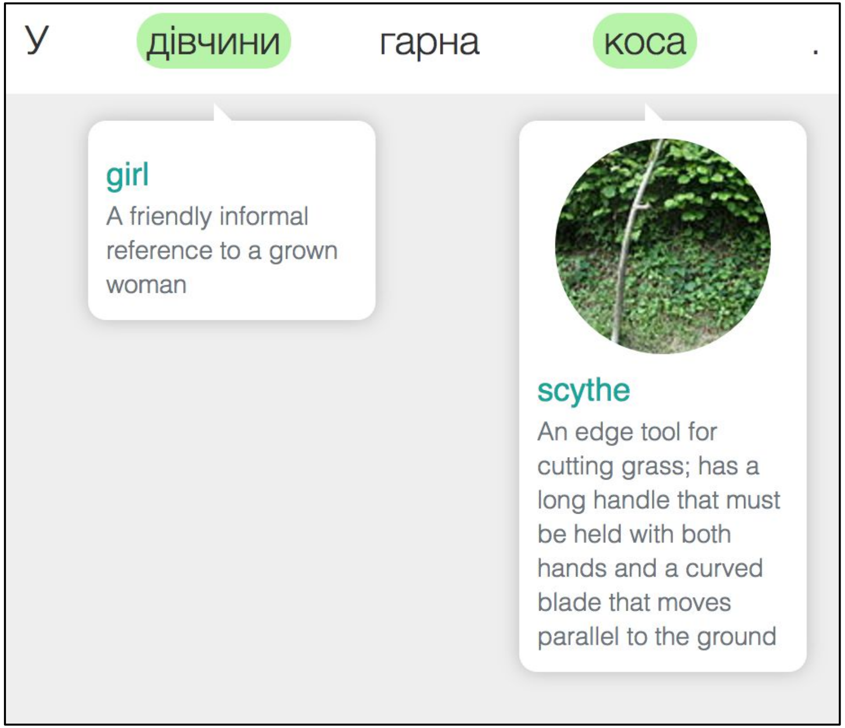

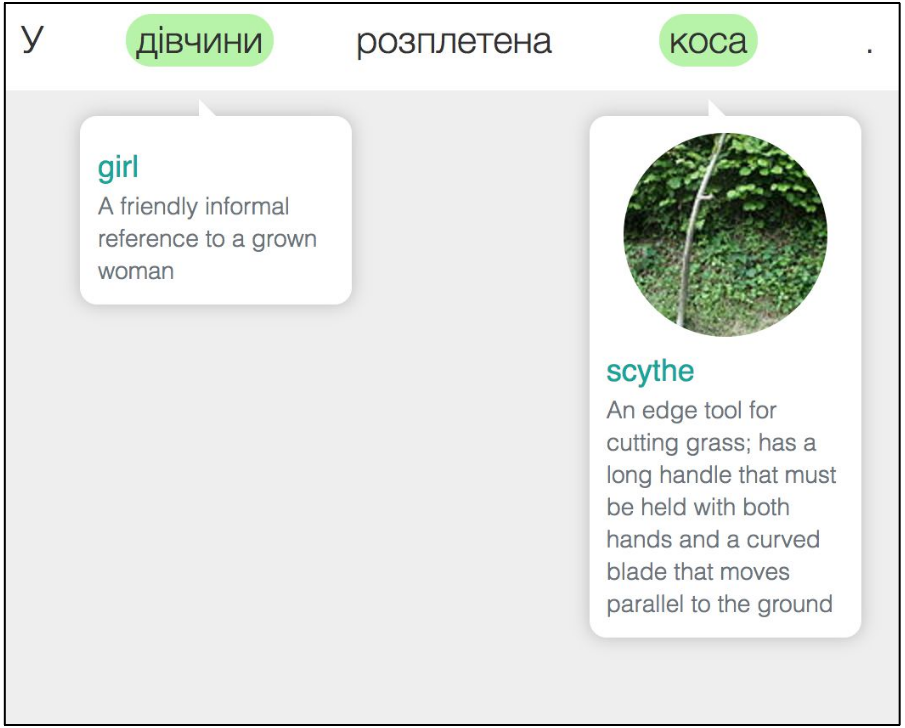

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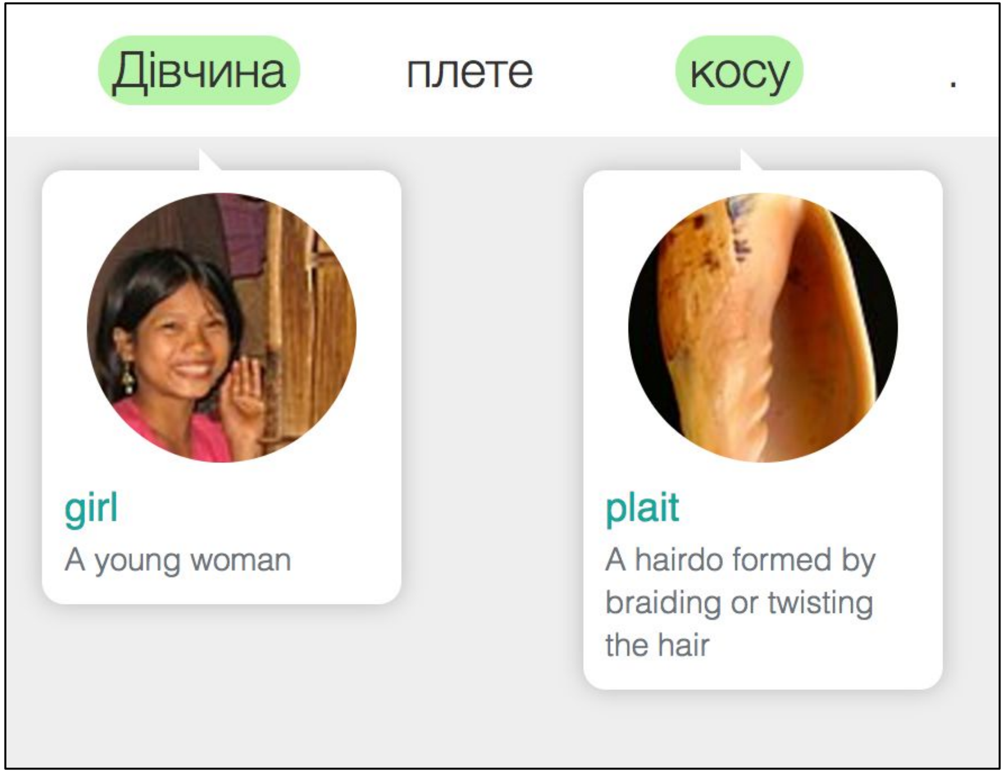


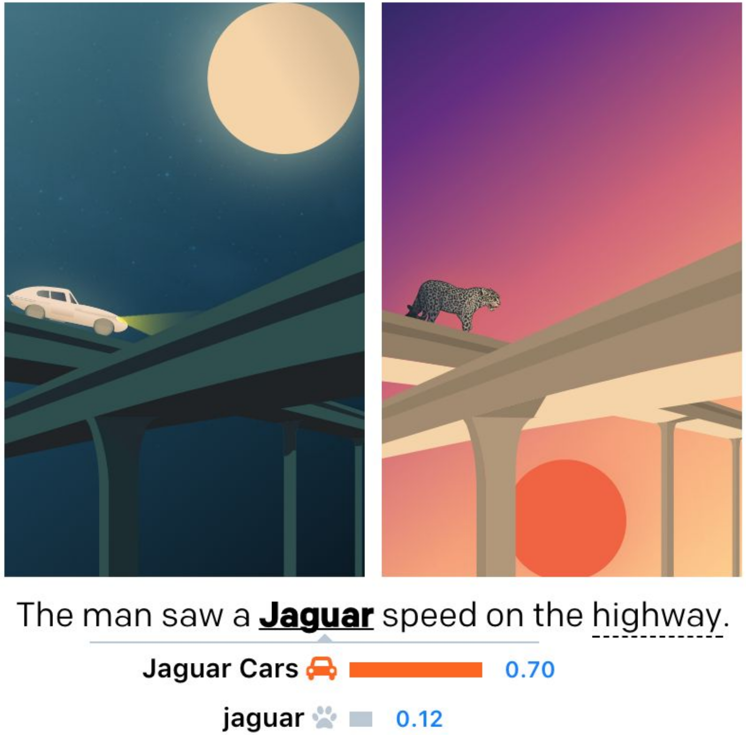
Example from babelfy.org

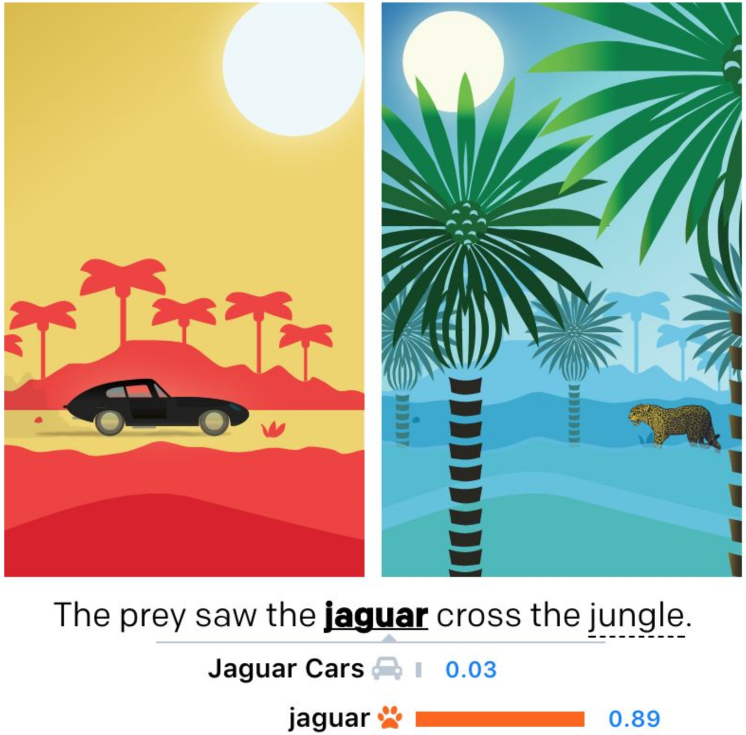
3. Classification

- For a specific word
  - *ngrams, syngrams, morphological features*
  - *overlap of current context with a predefined set of content words (extracted from a dictionary)*

- For a category

OpenAI: Type-based Neural Entity Disambiguation



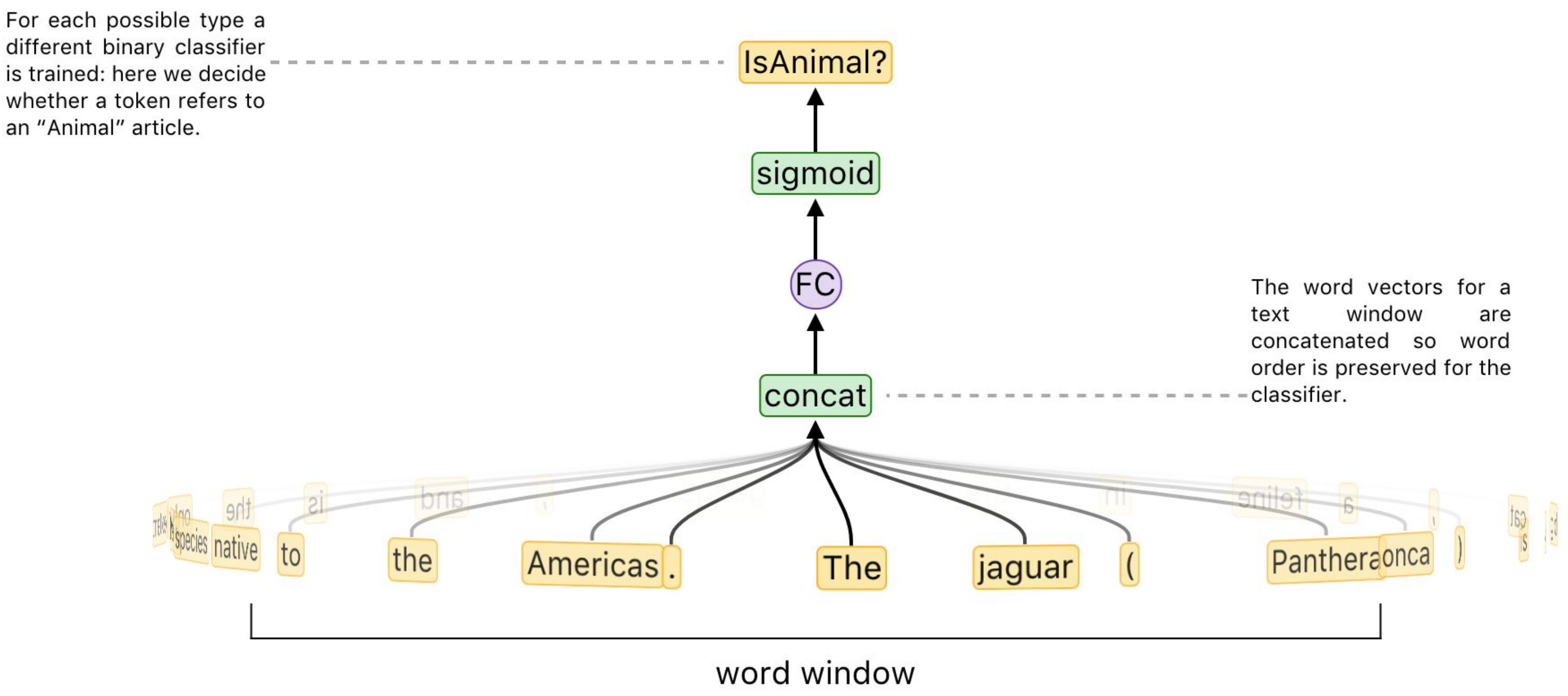


Example from blog.openai.com

OpenAI: Type-based Neural Entity Disambiguation

- Extract entities from Wikipedia
- Extract the set of categories for each entity from Wikipedia
- Pick a list of ~100 categories to be your “type” system
- Generate train data: word contexts mapped to 100-dimensional vectors
- Train: 400M tokens, bidirectional LSTM, F1 - 0.91

OpenAI: Type-based Neural Entity Disambiguation



Example from blog.openai.com

4. Word sense induction

Idea:

- for each word occurrence, compute a context vector
- cluster these context vectors
- map clusters to senses

Problem: how many clusters is enough?

Evaluation

- Intrinsic:
  - word similarity
  - word relatedness
  - analogy relations
  - synonym selection
- External:
  - sentiment analysis
  - textual entailment
  - question answering

2.

Semantic role labeling

Who did what to whom

The police officer detained the suspect at the crime scene.

detainer **detainee** **location**

The suspect was detained at the crime scene by the police officer.

detainee **location** **detainer**

This is the police officer who detained the suspect at the crime scene.

detainer **detainee** **location**

Who did what to whom

- Causer (agent/force)
- Instrument
- Result
- Patient
- Theme
- Source, path, goal/recipient, location
- Experiencer
- Stimulus
- Beneficiary
- Time, manner, reason...

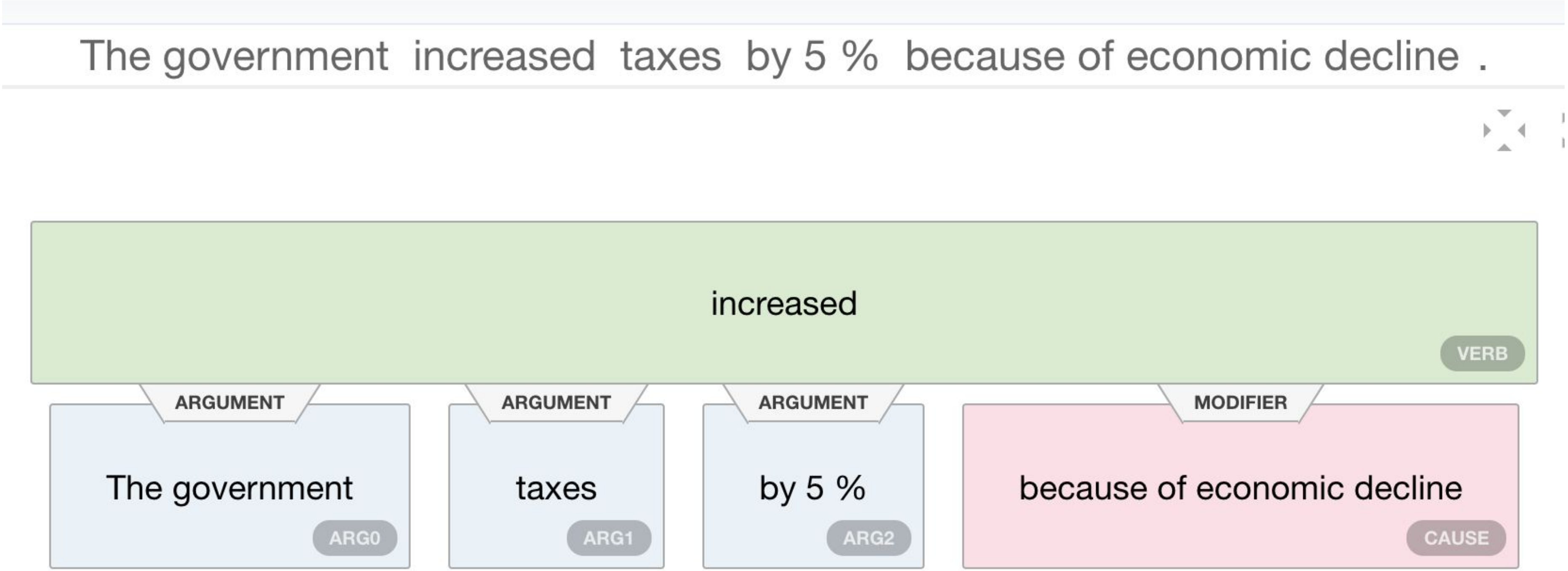
PropBank

- *increase.01 “go up incrementally”*
  - *Arg0: causer of increase*
  - *Arg1: thing increasing*
  - *Arg2: amount increased by*
  - *Arg3: start point*
  - *Arg4: end point*

TMP	when?
LOC	where?
DIR	where to/from?
MNR	how?
PRP/CAU	why?
REC	
ADV	miscellaneous

- ***The government*** *increased* ***taxes*** *by* ***5%****.*
- ***Taxes*** *increased.*

Semantic role labelling: AllenNLP



Parsed by https://demo.allennlp.org/

FrameNet

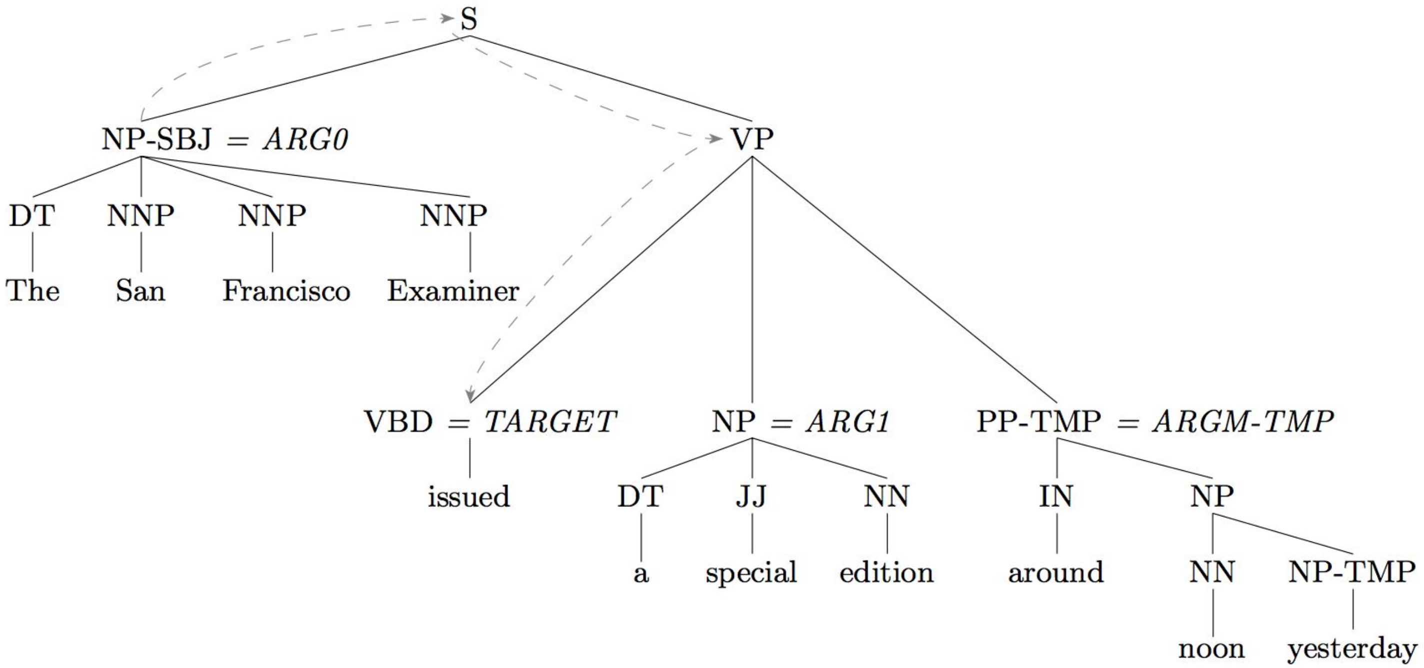
- Abandonment**:**
  - *abandon, abandoned, abandonment, leave, forget*
- An ***Agent*** leaves behind a ***Theme*** effectively rendering it no longer within their control or as one's property...
- examples:
  - ***Carolyn*** *<u>abandoned</u>* ***her car*** *and jumped on a bus.*
  - *<u>Abandonment</u> of* ***a child*** *is considered to be a serious crime in many jurisdictions.*
  - *Perhaps* ***he*** *<u>left</u>* ***the key*** *in the ignition.*

Basic SRL algorithm

- parse the sentence
- find all predicates *(mapped to PropBank or FrameNet)*
- for each predicate in the sentence
    - for each node in the parse tree
        - assign the semantic role (if any) for the predicate

Logistic regression, SVM, Perceptron, CRF, etc.

Basic SRL example



What features would you use?

Image from Jurafsky, Martin (2017)

Basic SRL features

- predicate
  - lemma, POS, active/passive voice, etc.
  - syntactic frame
    - e.g., VP → VBD NP PP
- node
  - label
  - headword lemma, headword POS, etc.
  - linear position, distance to predicate
- path from the constituent to the predicate
  - e.g., NP↑S↓VP↓VBD
- more: ngrams, dependencies, etc.

Basic SRL notes

- Evaluation:
  - precision, recall, f-measure
- Also possible two steps:
  - identification
    - to prune unlikely constituents
    - to avoid nested constituents
  - classification
- To avoid two ARG0s:
  - return probability distribution of classes for nodes
  - do reranking

3.

Textual entailment

Textual entailment

We say that text *T* entails hypothesis *H* (i.e., $T \Rightarrow H$) if the meaning of *H* can be inferred from the meaning of *T*, *as would typically be interpreted by people*.

- **Positive TE** (text entails hypothesis):
  - *A girl swings high in the air.*
  - *A girl is on a swing.*
- **Negative TE** (text contradicts hypothesis):
  - *A girl swings high in the air.*
  - *A girl is laying in the pool.*
- **Non-TE** (text does not entail nor contradict):
  - *A girl swings high in the air.*
  - *A girl is looking for her mother.*

Textual entailment

Text: The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008.

Hyp 1: BMI acquired an American company.
Hyp 2: BMI bought employee-owned LexCorp for $3.4Bn.
Hyp 3: BMI is an employee-owned concern.

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- NER: *LexCorp, BMI, $2Bn*
- WordNet: *purchase (n.) => purchase (v.), acquire, buy*
- Knowledge base: *Houston-based => American*
- Syntactic analysis + semantic role labeling / semantic parsing

Textual entailment

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Hyp 1: BMI acquired an American company.
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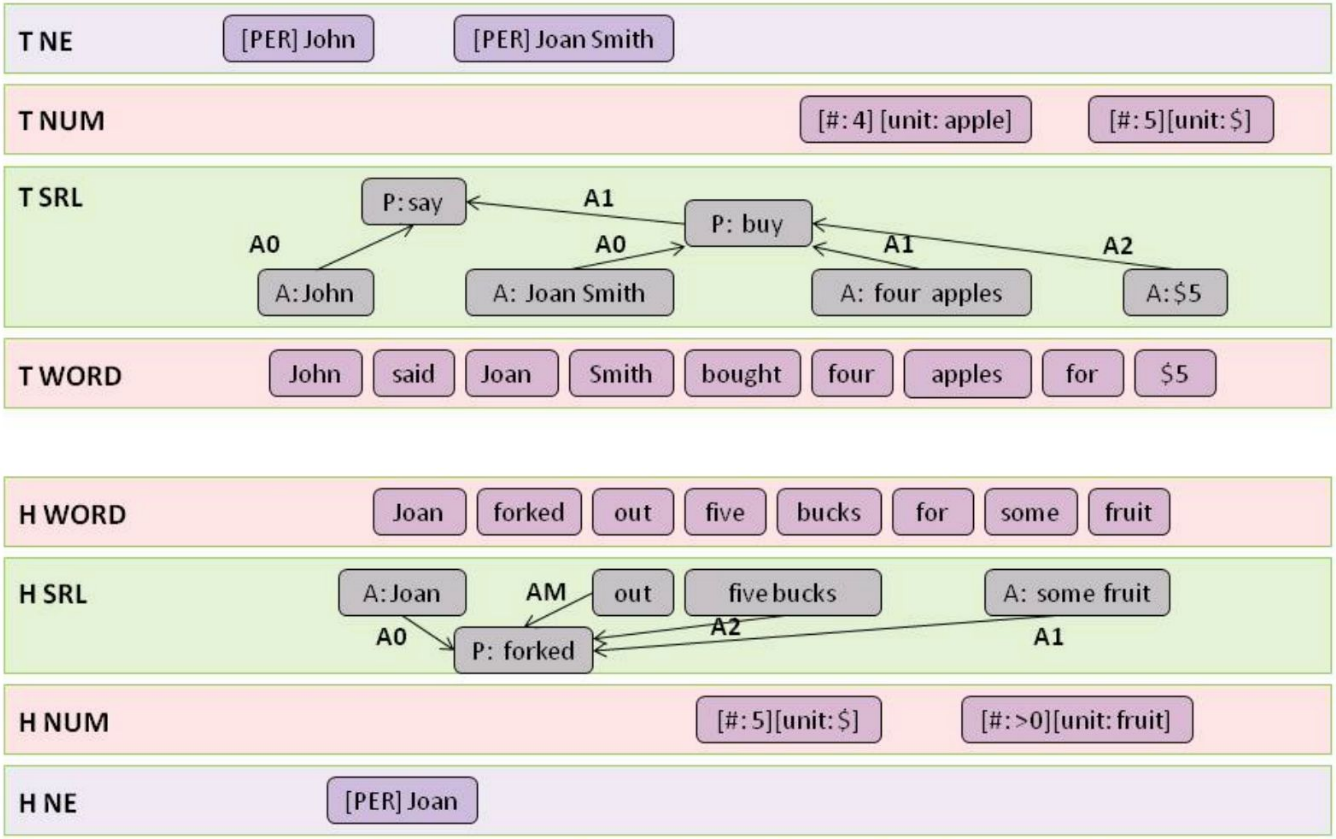
- Normalization of quantities: *\$2Bn => 2,000,000,000*
- Fuzzy match of NE: *BMI => Business Machine Inc.*
- Coreference resolution
- Scope of negation

Textual entailment pipeline

- Text and hypothesis preprocessing
- Align syntactic/semantic representations of *T* and *H*
  - only a small portion of *T* is relevant to *H*
- Features: compare the constituents
  - match of NEs and numerical measures
  - lexico-semantic relations (synonyms, antonyms, hypernyms, meronyms, entailment)
  - word similarity
  - noun-verb relations (*"is a winner"* => *"won"*)
  - idioms (*"kick the bucket"* => *"die"*)
  - paraphrases (*"has been unable to"* => *"could not"*)
  - syntactic mapping (active => passive)

Textual entailment pipeline



Textual entailment: TEASE

- Extract entailment paraphrases from web using a dependency parser
  - both lexical and grammatical
- Apply iteratively to transform *T* to *H*

X write *Y*	*X* who write *Y* *X* publish *Y* *X* compose *Y* read *Y* by *X* *Y* attributed to *X* perform *Y* by *X* *X* writer of *Y* selected *Y* of *X*	*X* produce *Y* *X* pen *Y* *X* create *Y* *X*'s *Y* *X* complete *Y* *X* book of *Y* *X* say in *Y* *X* work include *Y*

4.

Semantic parsing

Meaning representation formalisms

- abstract meaning representation
- typed lambda-calculus expressions
- combinatory categorial grammar
- minimal recursion semantics
- universal conceptual cognitive annotation
- ... (a hundred more formalisms)

Meaning representation formalisms

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Abstract meaning representation

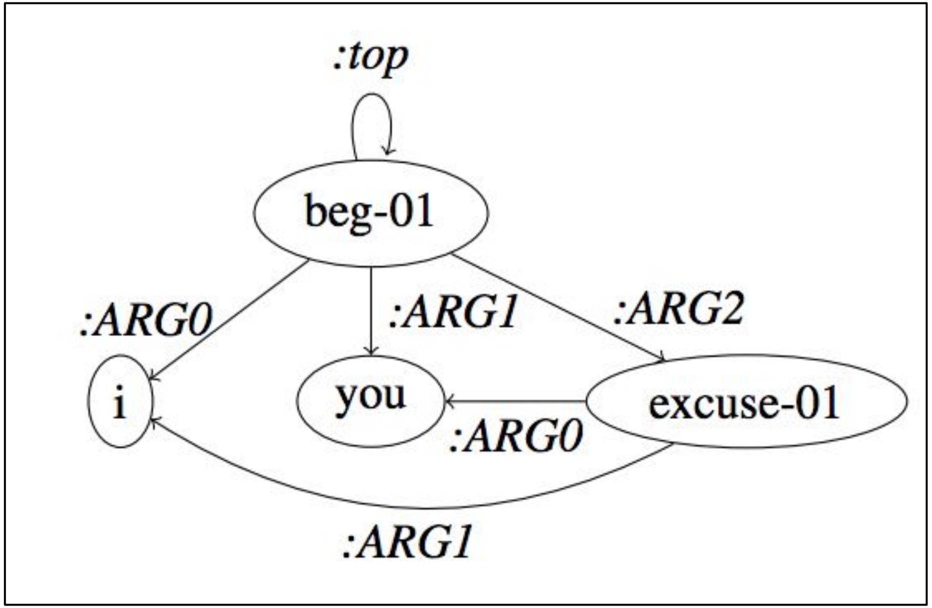
What is AMR?

Sentence => a *rooted*, *directed*, *acyclic* graph, where:

- nodes are concepts
- edges are semantic relations
- function words are omitted

I *beg you to excuse* ***me***.

same node



AMR nodes

AMR nodes are concepts that can be:

- a PropBank or FrameNet frame (“beg-01”)
- a word (“you”, “boy”)
- a special keyword (“person”, “organization”, “date-entity”, “volume-quantity”, “temporal-quantity”, etc.)

AMR pros and cons

AMR handles:

- semantic roles
- entity types
- coreference
- modality
- polarity
- wikification

AMR doesn't handle:

- tense
- definiteness
- plurality

AMR notation

AMR uses PENMAN notation, where each node is assigned a variable:

```
(b / beg-01
    :ARG0 (i / i)
    :ARG1 (y / you)
    :ARG2 (e / excuse-01
              :ARG0 y
              :ARG1 i))
```

*I beg you to excuse **me**.*

same node

AMR examples: frames

The boy <u>desires</u> the girl to believe him.
The boy <u>wants</u> the girl to believe him.
The boy <u>desires</u> to be believed by the girl.
The boy <u>has a desire</u> to be believed by the girl.
The boy's <u>desire is</u> for the girl to believe him.
The boy <u>is desirous of</u> the girl believing him.

```
(w / desire-01
   :ARG0 (b / boy)
   :ARG1 (b2 / believe-01
            :ARG0 (g / girl)
            :ARG1 b))
```

AMR examples: polarity

The soldier <u>was not afraid of</u> dying.
The soldier <u>was not afraid to</u> die.
The soldier <u>did not fear</u> death.

```
(f / fear-01
    :polarity "-"
    :ARG0 (s / soldier)
    :ARG1 (d / die-01
            :ARG1 s))
```

AMR examples: modality

The boy <u>must</u> not go.
<u>It is obligatory that</u> the boy not go.

```
(o / obligate-01
   :ARG2 (g / go-02
            :ARG0 (b / boy)
            :polarity -))
```

AMR examples: unknown variables

Which state borders with Kansas?

```
(b / border-01
    :ARG0 (s / state
              :name (n / name :op1 (a / amr-unknown)))
    :ARG1 (s2 / state
              :name (n2 / name :op1 “Kansas”)))
```

AMR examples: unknown variables

Does Texas border with Kansas?

```
(b / border-01
    :ARG0 (s / state
             :name (n / name :op1 “Texas”))
    :ARG1 (s2 / state
             :name (n2 / name :op1 “Kansas”))
    :polarity (a / amr-unknown))
```

14,000 people fled their homes at the weekend after a tsunami warning was issued, the UN said on its web site.

```
(s / say-01
    :ARG0 (o / organization
             :name (n / name :op1 "UN"))
    :ARG1 (f / flee-01
             :ARG0 (p / person :quant 14000)
             :ARG1 (h / home :poss p)
             :time (w / weekend)
             :time (a2 / after
                        :op1 (w2 / warn-01
                                 :ARG1 (t / tsunami))))
    :medium (s2 / site
                :poss o
                :mod (w3 / web)))
```

AMR data

AMR Banks in PENMAN format:

- 1.K sentences from *The Little Prince* :)
- 59K sentences of newswire, discussion forum and other web logs, television transcripts
- 7K sentences of Bio AMR (cancer-related PubMed articles)

The Little Prince in AMR

You become responsible , forever , for what you have tamed .

```
(b / become-01
    :ARG1 (y / you)
    :ARG2 (r / responsible-03
               :ARG0 y
               :ARG1 (t2 / thing
                          :ARG1-of (t / tame-01
                                         :ARG0 y))
               :extent (f / forever)))
```

AMR parsing

Parsing algorithms:

- graph-based
- transition-based
- ~~rule-based~~
- ~~seq2seq-based~~

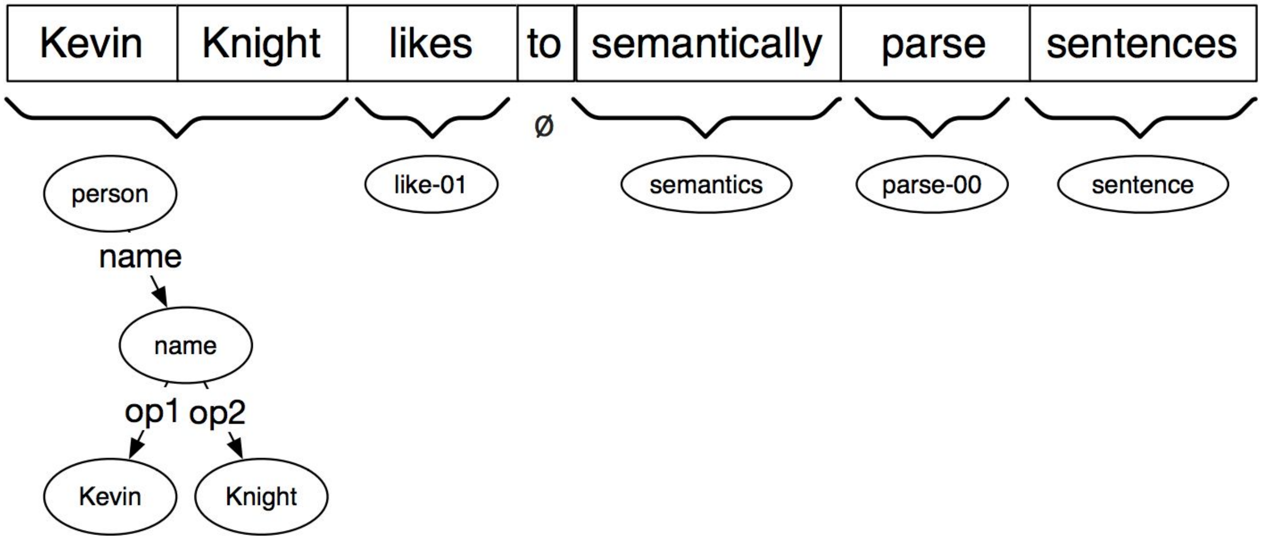
What is needed:

- POS tagging
- NER
- syntactic parsing
- coreference resolution

Graph-based AMR parsing

JAMR parser:

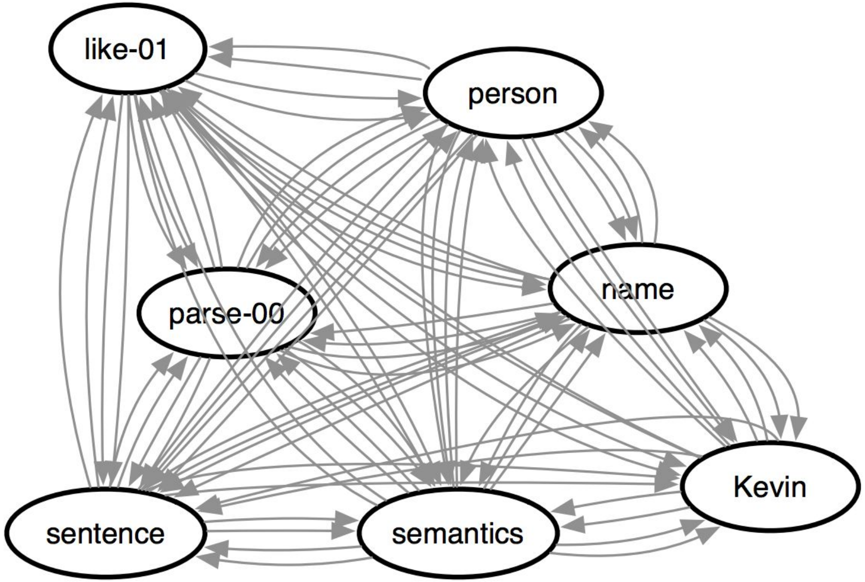
- identify concepts
- identify relations between concepts



Graph-based AMR parsing

JAMR parser:

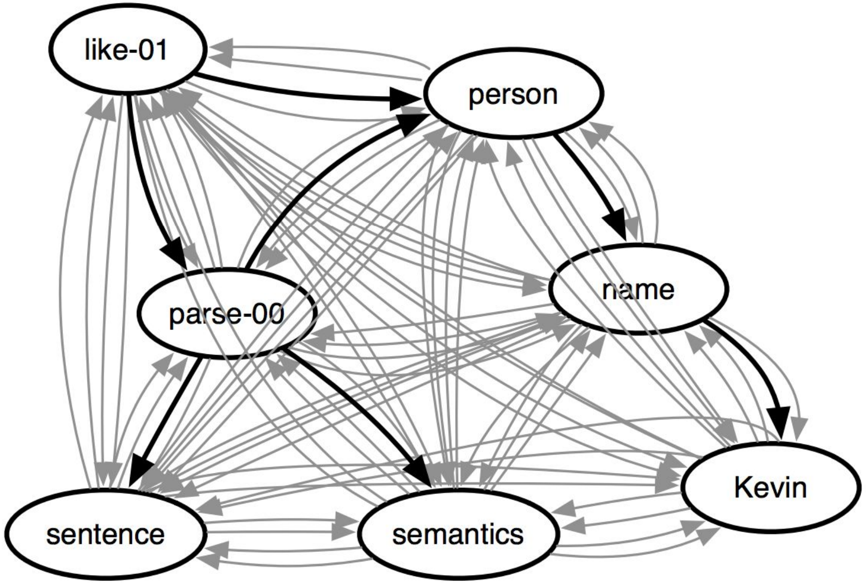
- identify concepts
- identify relations between concepts



Graph-based AMR parsing

JAMR parser:

- identify concepts
- identify relations between concepts

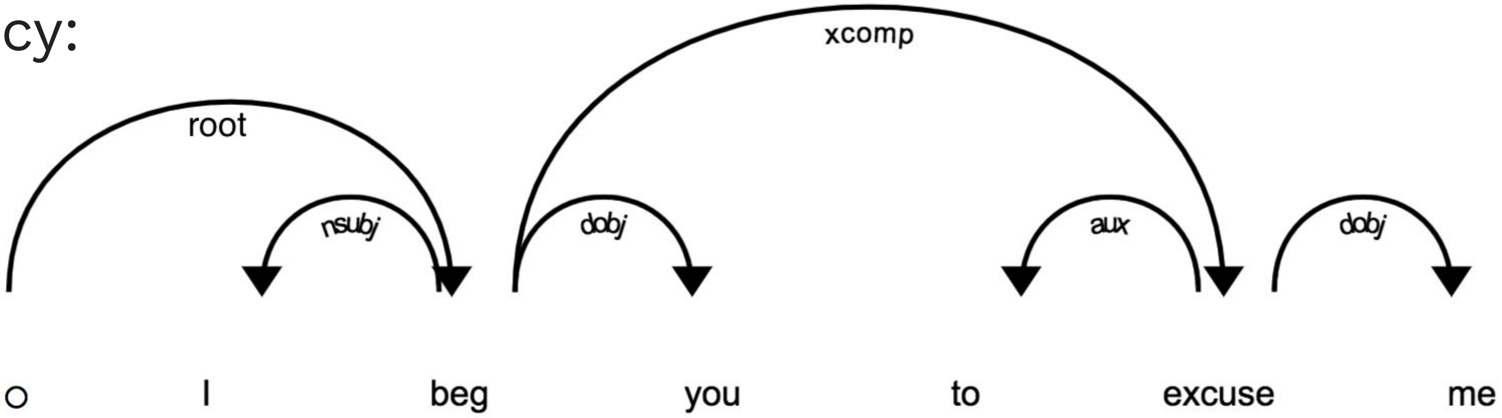


Transition-based AMR parsing

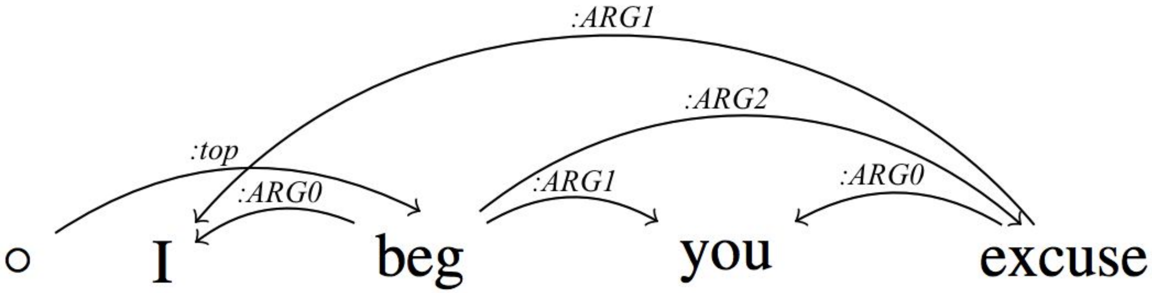
AMR graphs look similar to dependency parse trees, don’t they?

Transition-based AMR parsing

Dependency:



AMR:



Transition-based AMR parsing

CAMR parser - transform a dependency parse tree into AMR

- traverse the dependency tree
- at each node/edge, collect features and classify action
  - merge nodes
  - swap nodes
  - delete a node
  - replace node
  - re-enter a node
  - attach edge
  - delete edge and re-attach to a new node
  - label with concept

Transition-based AMR parsing

CAMR parser setup:

- σ - a buffer with not yet processed nodes
  - σ_0 - top of σ
- β - a buffer with not yet processed edges attached to σ_0
- G - span graph that stores the partial parses
  - initialised as a dependency tree

Transition-based AMR parsing

Actions:

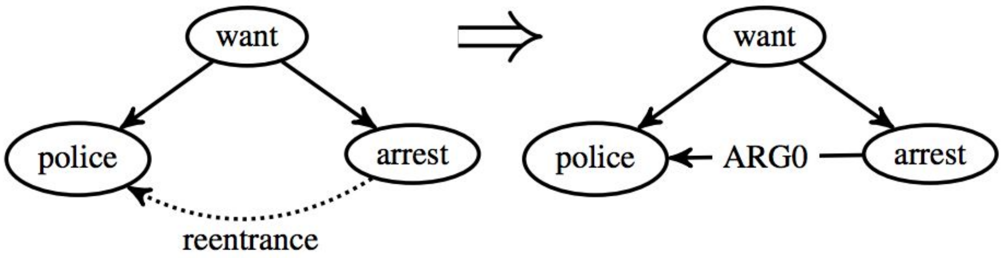
- NEXT-EDGE-l_r - attach edge *(σ0, β0)* and move to next node
- SWAP-l_r - swap nodes and attach with edge
- REATTACH$_k$-l_r - delete edge and reattach to already processed node
- REPLACE-HEAD - replace node with another node
- REENTRANCE$_k$-l_r - attach edge to already processed node
- MERGE - merge two nodes
- NEXT-NODE-l_c - label with concept and move to next word
- DELETE-NODE - delete a word

Transition-based AMR parsing

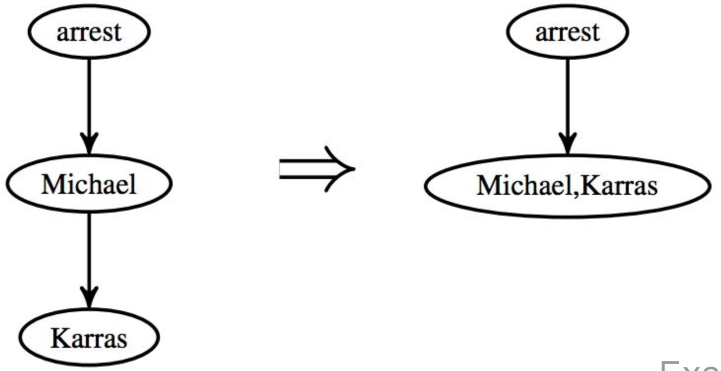
Action	Current state $\Rightarrow$ Result state	Assign labels	Precondition
NEXT EDGE-l_r	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\sigma_0\|\sigma', \beta', G')$	$\delta[(\sigma_0, \beta_0) \rightarrow l_r]$	β is not empty
SWAP-l_r	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\sigma_0\|\beta_0\|\sigma', \beta', G')$	$\delta[(\beta_0, \sigma_0) \rightarrow l_r]$	
REATTACH$_k$-l_r	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\sigma_0\|\sigma', \beta', G')$	$\delta[(k, \beta_0) \rightarrow l_r]$	
REPLACE HEAD	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\beta_0\|\sigma', \beta = CH(\beta_0, G'), G')$	NONE	
REENTRANCE$_k$-l_r	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\sigma_0\|\sigma', \beta_0\|\beta', G')$	$\delta[(k, \beta_0) \rightarrow l_r]$	
MERGE	$(\sigma_0\|\sigma', \beta_0\|\beta', G) \Rightarrow (\tilde{\sigma}\|\sigma', \beta', G')$	NONE	
NEXT NODE-l_c	$(\sigma_0\|\sigma_1\|\sigma', [], G) \Rightarrow (\sigma_1\|\sigma', \beta = CH(\sigma_1, G'), G')$	$\gamma[\sigma_0 \rightarrow l_c]$	β is empty
DELETE NODE	$(\sigma_0\|\sigma_1\|\sigma', [], G) \Rightarrow (\sigma_1\|\sigma', \beta = CH(\sigma_1, G'), G')$	NONE	

AMR: transition-based parsing

REENTRANCE$_k$-l_r



MERGE



Example from Wang et al (2015)

AMR evaluation: smatch

```
(w / want-01
   :ARG0 (b / boy)
   :ARG1 (b2 / believe-01
             :ARG0 (g / girl)
             :ARG1 b))
```

```
instance(w, want-01)           /* w is an instance of wanting */
instance(b, boy)               /* b is an instance of boy */
instance(b2, believe-01)       /* b2 is an instance of believing */
instance(g, girl)              /* g is an instance of girl */
ARG0(w, b)                     /* b is the wanter in w */
ARG1(w, b2)                    /* b2 is the wantee in w */
ARG0(b2, g)                    /* g is the believer in b2 */
ARG1(b2, b)                    /* b is the believee in b2 */
```

AMR evaluation: smatch

- F1 smatch (up to 70%)
  - graph-based > transition-based

- Speed
  - graph-based < transition-based

Application of AMR

- natural language generation (SemEval shared task, 2017)
- information extraction (Rao et al., 2017)
- entity linking (Pan et al., 2015)
- text summarization (Liu et al., 2015; Takase et al., 2016, Dohare et al., 2017, Liao et al., 2018)
- question answering (Jurczyk and Choi, 2015)
- machine comprehension (Sachan and Xing, 2016)

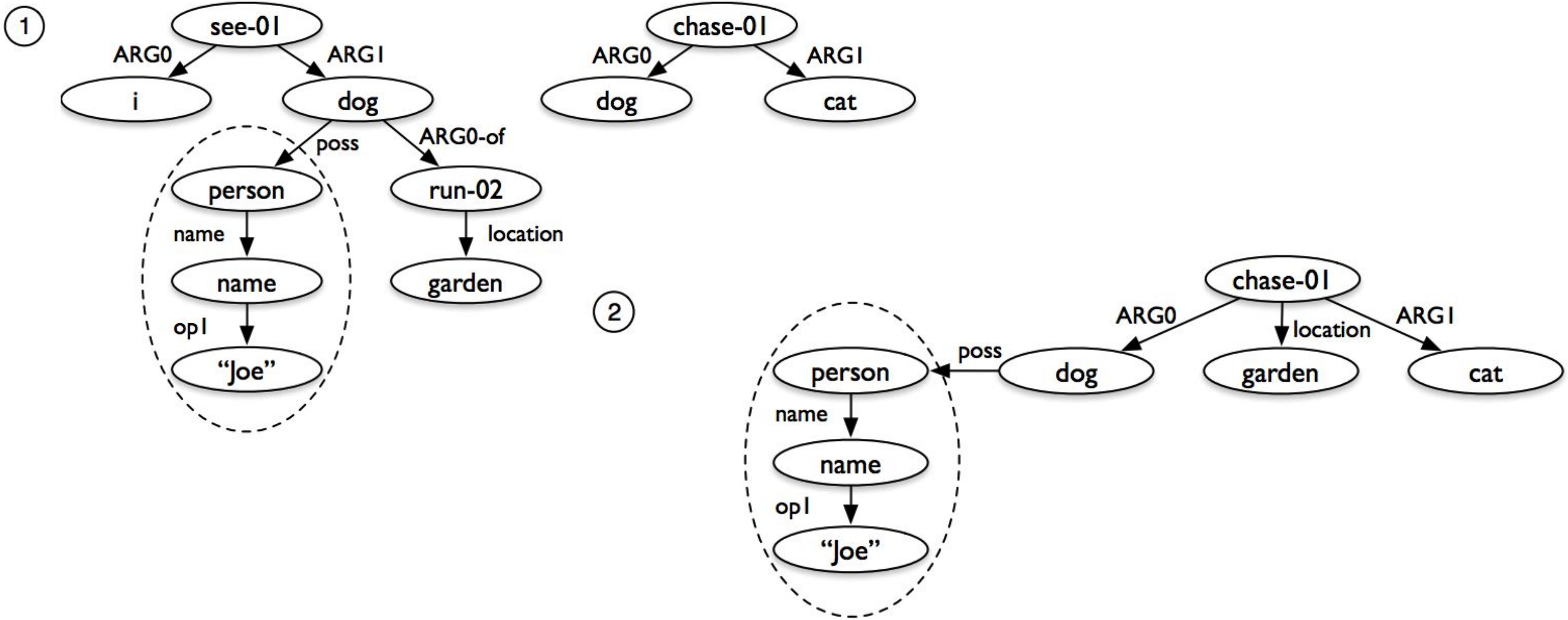
Abstractive text summarization

Idea:

- sentences in the document → AMR graphs
- AMR graphs → summary graph
- summary graph → summary sentences

Sentence A: I saw Joe's dog, which was running in the garden.

Sentence B: The dog was chasing a cat.



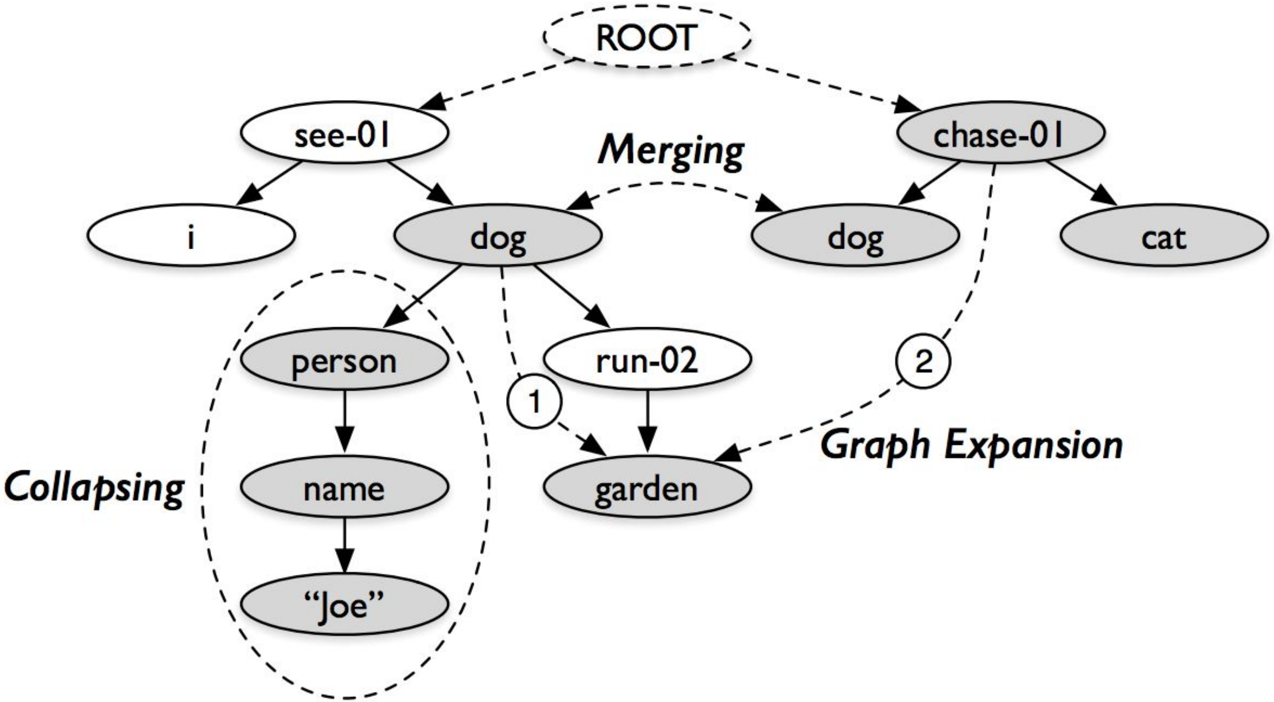
3 Summary: Joe's dog was chasing a cat in the garden.

Example from Liu et al (2015)

Abstractive text summarization

How to build a summary graph:

- build a document-level AMR
- predict the most meaningful subgraph



Sentence A: I saw Joe's dog, which was running in the garden.

Sentence B: The dog was chasing a cat.

Example from Liu et al (2015)

Abstractive text summarization

How to build a summary graph:

- build a document-level AMR
- predict the most meaningful subgraph
    - predict nodes
    - predict edges
    - ensure the result is a valid graph

Training data

- texts and their summaries parsed into AMRs

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