CS5740: Natural Language Processing

Lexical Semantics

Instructor: Yoav Artzi

Slides adapted from Dan Jurafsky, Chris Manning, Slav Petrov, Dipanjan Das, and David Weiss

Overview

- Word sense disambiguation (WSD)
  - Wordnet
- Semantic role labeling (SRL)
- Continuous representations

Lemma and Wordform

- A lemma (or citation form)
  - Basic part of the word, same stem, rough semantics
- A wordform
  - The "inflected" word as it appears in text

Wordform	Lemma
banks	bank
sung	sing
duermes	dormir

Word Senses

- One lemma can have many meanings:

Sense 1:
  - `…a` **`bank`**$_1$ `can hold the investments in a custodial account…`

Sense 2:
  - `"…as agriculture burgeons on the east` **`bank`**$_2$ `the river will shrink even more"`

- **Sense** (or **word sense**)
  - – A discrete representation of an aspect of a word's meaning.
- The lemma **bank** here has two senses

Homonymy

Homonyms: words that share a form but have unrelated, distinct meanings:

bank$_1$: financial institution, bank$_2$: sloping land

bat$_1$: club for hitting a ball, bat$_2$: nocturnal flying mammal

1. Homographs (bank/bank, bat/bat)
2. Homophones:
    1. Write and right
    2. Piece and peace

Homonymy in NLP

- Information retrieval
  - “`bat care`”
- Machine Translation
  - `bat`: murciélago (animal) or bate (for baseball)
- Text-to-Speech
  - `bass` (stringed instrument) vs. `bass` (fish)

Quick Test for Multi Sense Words

- Zeugma
  - When a word applies to two others in different senses

```
Which flights serve breakfast?
Does Lufthansa serve Philadelphia?
```

Does Lufthansa serve breakfast and San Jose?

- The conjunction sounds “weird”
  - So we have two senses for *serve*

Synonyms

- Word that have the same meaning in some or all contexts.
  - filbert / hazelnut
  - couch / sofa
  - big / large
  - automobile / car
  - vomit / throw up
  - Water / H_20
- Two words are synonyms if …
  - … they can be substituted for each other
- Very few (if any) examples of perfect synonymy
  - Often have different notions of politeness, slang, etc.

Synonyms

- Perfect synonymy is rare
- Consider the words **big** and **large**
- Are they synonyms?
  - *How big is that plane?*
  - *Would I be flying on a large or small plane?*
- How about here:
  - *Miss Nelson became a kind of big sister to Benjamin.*
  - *Miss Nelson became a kind of large sister to Benjamin.*
- Why?
  - big has a sense that means being older, or grown up
  - large lacks this sense
- Synonymous relations are defined between senses

Antonyms

- Senses that are opposites with respect to one feature of meaning
- Otherwise, they are very similar!

`dark`	`short`	`fast`	`rise`	`hot`	`up`	`in`
`light`	`long`	`slow`	`fall`	`cold`	`down`	`out`

- Antonyms can
  - Define a binary opposition: **`in/out`**
  - Be at the opposite ends of a scale: **`fast/slow`**
  - Be reversives: **`rise/fall`**
- Very tricky to handle with some representations – remember for later!

Hyponymy and Hypernymy

- One sense is a **hyponym/subordinate** of another if the first sense is more specific, denoting a subclass of the other
  - ***car*** is a hyponym of *vehicle*
  - *mango* is a hyponym of *fruit*
- Conversely **hypernym/superordinate** (“hyper is super”)
  - *vehicle* is a hypernym of *car*
  - *fruit* is a hypernym of *mango*
- Usually transitive
  - (A hypo B and B hypo C entails A hypo C)

Superordinate/hyper	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

WordNet

- A hierarchically organized lexical database
- On-line thesaurus + aspects of a dictionary
    - Word senses and sense relations
    - Some other languages available (Arabic, Finnish, German, Portuguese…)

Category	Unique Strings
Noun	117,798
Verb	11,529
Adjective	22,479
Adverb	4,481

WordNet

WordNet Search - 3.1
- [WordNet home page] - [Glossary] - [Help]

Word to search for: bass [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **bass** (the lowest part of the musical range)
- S: (n) **bass**, bass part (the lowest part in polyphonic music)
- S: (n) **bass**, basso (an adult male singer with the lowest voice)
- S: (n) sea bass, **bass** (the lean flesh of a saltwater fish of the family Serranidae)
- S: (n) freshwater bass, **bass** (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- S: (n) **bass**, bass voice, basso (the lowest adult male singing voice)
- S: (n) **bass** (the member with the lowest range of a family of musical instruments)
- S: (n) **bass** (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Adjective

- S: (adj) **bass**, deep (having or denoting a low vocal or instrumental range) *"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"*

http://wordnetweb.princeton.edu/perl/webwn

WordNet

- S: (n) **bass**, basso (an adult male singer with the lowest voice)
  - *direct hypernym* / ***inherited hypernym*** / *sister term*
    - S: (n) singer, vocalist, vocalizer, vocaliser (a person who sings)
      - S: (n) musician, instrumentalist, player (someone who plays a musical instrument (as a profession))
        - S: (n) performer, performing artist (an entertainer who performs a dramatic or musical work for an audience)
          - S: (n) entertainer (a person who tries to please or amuse)
            - S: (n) person, individual, someone, somebody, mortal, soul (a human being) *"there was too much for one person to do"*
              - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                - S: (n) living thing, animate thing (a living (or once living) entity)
                  - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                    - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                      - S: (n) physical entity (an entity that has physical existence)
                        - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

http://wordnetweb.princeton.edu/perl/webwn

Senses and Synsets in WordNet

- Each word in WordNet has at least one sense
- Each sense has a gloss (textual description)
- The **synset** (synonym set), the set of near-synonyms, is a set of senses with a shared gloss
- Example: chump as a noun with the gloss:

  "a person who is gullible and easy to take advantage of"
- This sense of "chump" is shared with 9 words:

  chump^{1}, **fool**^{2}, **gull**^{1}, **mark**^{9}, **patsy**^{1}, **fall guy**^{1}, **sucker**^{1}, **soft touch**^{1}, **mug**^{2}
- All these senses have the same gloss → they form a synset

WordNet Noun Relations

Relation	Also called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Member Meronym	Has-Member	From groups to their members	$faculty^2 \rightarrow professor^1$
Has-Instance		From concepts to instances of the concept	$composer^1 \rightarrow Bach^1$
Instance		From instances to their concepts	$Austen^1 \rightarrow author^1$
Member Holonym	Member-Of	From members to their groups	$copilot^1 \rightarrow crew^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7 \rightarrow meal^1$
Antonym		Opposites	$leader^1 \rightarrow follower^1$

WordNet 3.0

- Where it is:
  - http://wordnetweb.princeton.edu/perl/webwn
- Libraries
  - Python:
    - NLTK
  - Java:
    - JWNL, extJWNL
  - And more:
    - https://wordnet.princeton.edu/wordnet/related-projects/

Word Sense Disambiguation

I play **bass** in a Jazz band

musical_instrument

She was grilling a **bass** on the stove top

freshwater_fish

Supervised WSD

- Given: a lexicon (e.g., WordNet) and a word in a sentence
- Goal: classify the sense of the word
- Linear model:

$$p(\text{sense} \mid \text{word}, \text{context}) \propto e^{\theta \cdot \phi(\text{sense}, \text{word}, \text{context})}$$

Feature function looking at the sense, word, and context

Supervised WSD

- Given: a lexicon (e.g., WordNet) and a word in a sentence
- Goal: classify the sense of the word
- Linear model:

$$p(\text{sense} \mid \text{word}, \text{context}) = \frac{e^{\theta \cdot \phi(\text{sense},\text{word},\text{context})}}{\sum_{s'} e^{\theta \cdot \phi(s',\text{word},\text{context})}}$$

Summing over all senses for the word (e.g., from WordNet)

Unsupervised WSD

- Goal: induce the senses of each word and classify in context

1. For each word in context, compute some features
2. Cluster each instance using a clustering algorithm
3. Cluster labels are word senses

More reading: Section 20.10 of J&M

Semantic Roles

- Some word senses (a.k.a. predicates) represent events
- Events have participants that have specific roles (as arguments)
- Predicate-argument structure at the type level can be stored in a lexicon

Sematic Roles

- PropBank: a semantic role lexicon

run.01 (operate)
    ARG0 (operator)
    ARG1 (machine/operation)
    ARG2 (employer)
    ARG3 (co-worker)
    ARG4 (instrument)

Frame

Semantic roles

Sematic Roles

- PropBank: a semantic role lexicon

run.01 (operate)
ARG0 (operator)
ARG1 (machine/operation)
ARG2 (employer)
ARG3 (co-worker)
ARG4 (instrument)

run.02 (walk quickly)
ARG0 (runner)
ARG1 (course/race)
ARG2 (opponent)

Also: FrameNet, an alternative role lexicon

http://propbank.github.io/

Semantic Role Labeling

- Task: given a sentence, disambiguate predicate frames and annotate semantic roles

Mr. Stromach wants to resume a more influential role in **running** the company.

ARG0

ARG1

II. Role labeling

run.01

I. Frame identification

Role Identification

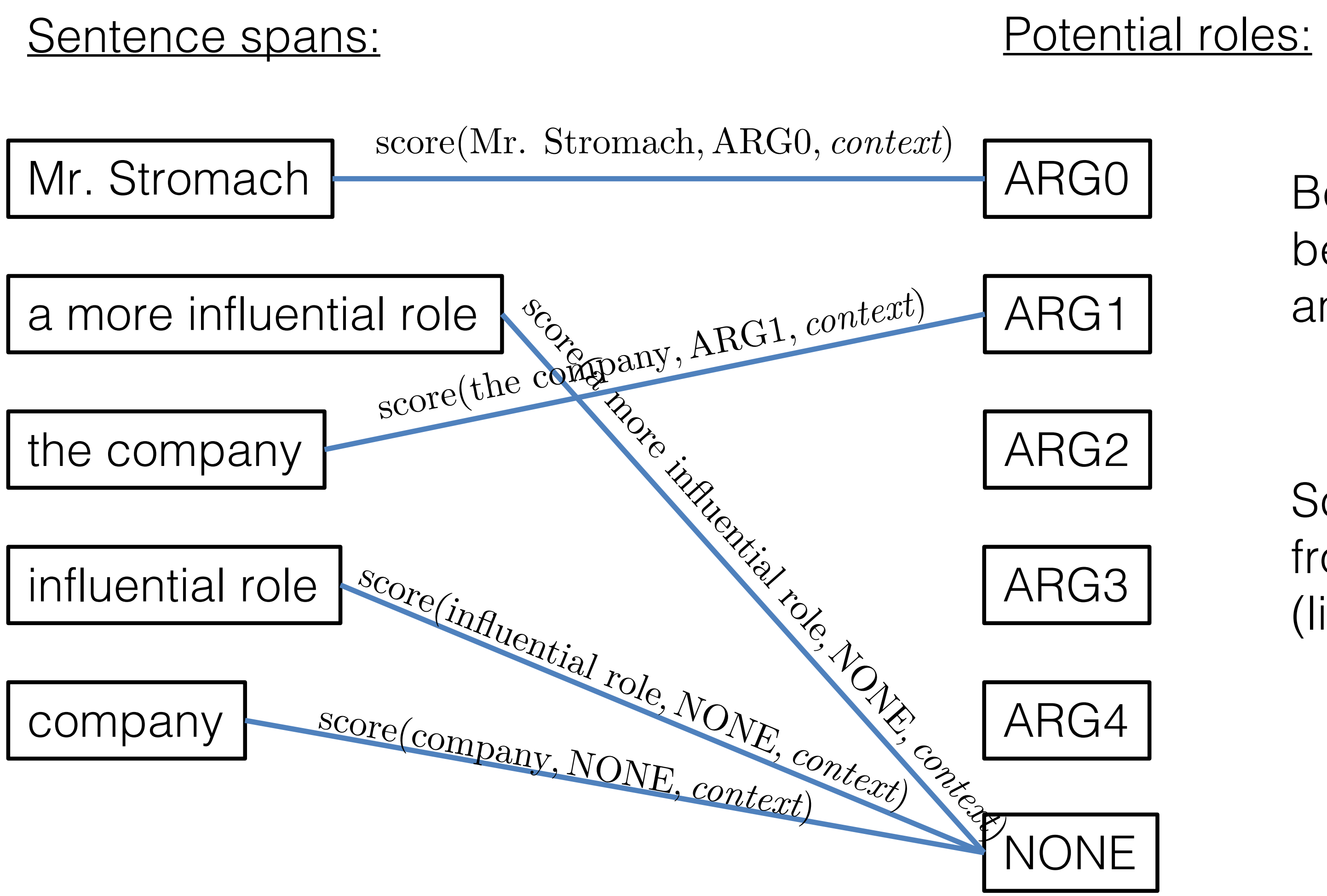
- Classification models similar to WSD

Mr. Stromach wants to resume a more influential role in **running** the company.

run.01

I. Frame identification

Role Labeling



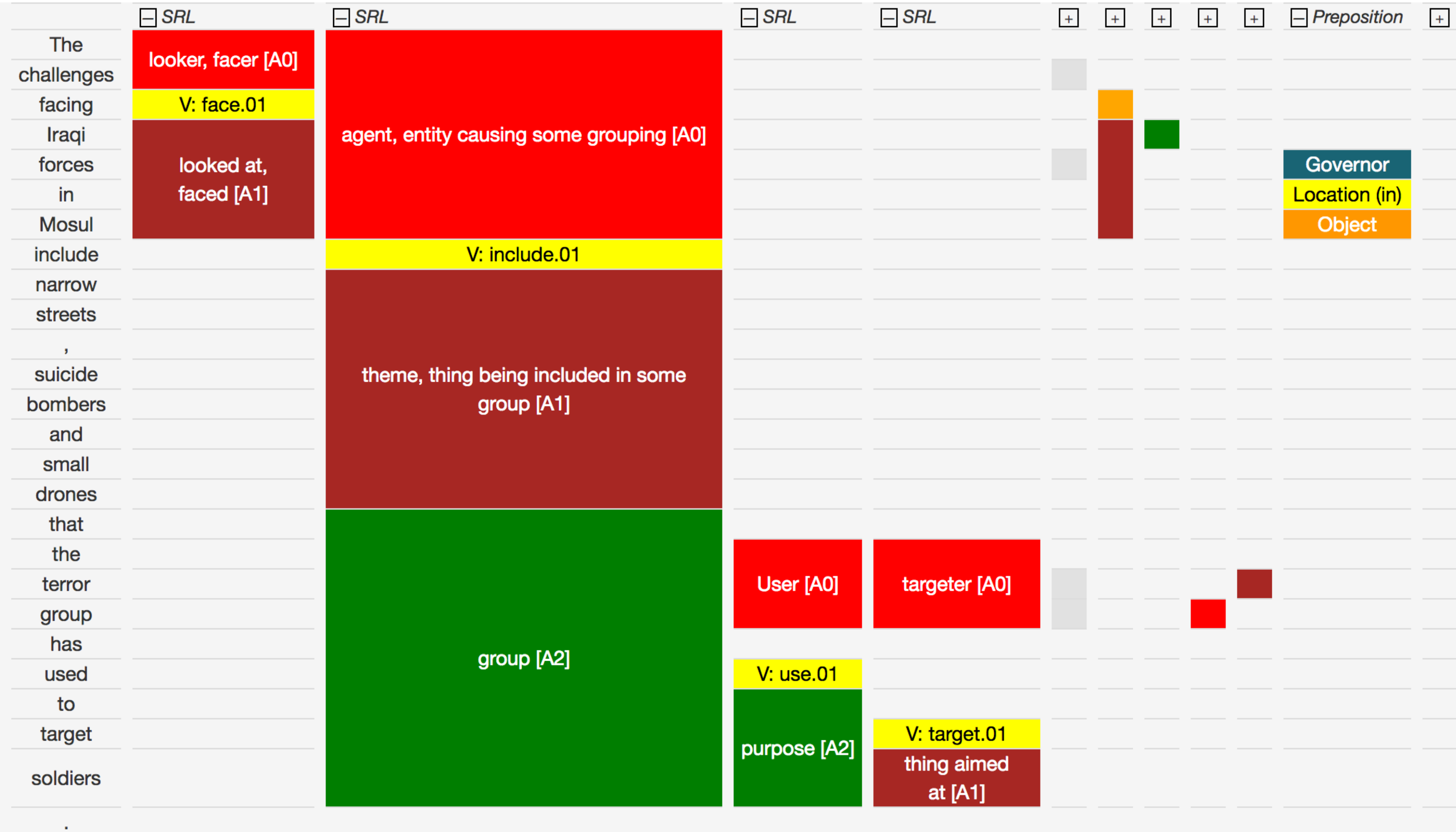
Best matching between spans and roles

Score can come from any classifier (linear, SVM, NN)

SRL

- http://cogcomp.org/page/demo_view/srl

- Example: The challenges facing Iraqi forces in Mosul include narrow streets, suicide bombers and small drones that the terror group has used to target soldiers.



http://cogcomp.org/page/demo_view/srl

Word Similarity

- Task: given two words, predict how similar they are

The Distributional Hypothesis:

You shall know a word by the company it keeps

(John Firth, 1957)

Word Similarity

A bottle of Tesgüino is on the table.
Everybody likes tesgüino.
Tesgüino makes you drunk.
We make tesgüino out of corn.

- Occurs before *drunk*
- Occurs after *bottle*
- Is the direct object of *likes*
- *…*

Similar to beer, wine, whiskey, …

Jurafsky and Martin, 20.7

Word Similarity

- Given a vocabulary of n words
- Represent a word w as:

$$\vec{w} = (f_1, f_2, f_3, \ldots, f_n)$$

Binary (or count) features indicating the presence of the i^{th} word in the vocabulary in the word's context

- For example:

$$\overrightarrow{\text{Tsegüino}} = (1, 1, 0, \ldots)$$

corn drunk matrix

Word Similarity

$$\vec{\text{Tsegüino}} = (1, 1, 0, \dots)$$
$$\vec{\text{beer}} = (0, 1, 0, \dots)$$

- Similarity can be measured using vector distance metrics
- For example, cosine similarity:

$$\text{similarity}(w, u) = \frac{w \cdot u}{\|w\| \|u\|} = \frac{\sum_{i=1}^{n} w_i u_i}{\sqrt{\sum_{i=1}^{n} w_i^2} \sqrt{\sum_{i=1}^{n} u_i^2}}$$

which gives values between -1 (completely different), 0 (orthogonal), and 1 (the same)

Vector-space Models

- Words represented by vectors
- In contrast to the discrete class representation of word senses
- Common methods (and packages): Word2Vec, GloVe

Word2Vec

- Method (and open-source package) for learning word vectors from raw text
- Widely used across academia/industry
  - Another common package: GloVe
- Goal: good word embeddings
  - Embeddings are vectors in a low dimensional space
  - Similar words should be close to one another
- Two models:
  - Skip-gram (today)
  - CBOW (further reading: Mikolov et al. 2013)

The Skip-Gram Model

- Given: Corpus D of pairs (w, c) where w is a word and c is context
- Context may be a single neighboring word (in window of size k)
  - Later: different definition
- Consider the parameterized probability

$$p(c|w;\theta)$$

- Goal: maximize the corpus probability

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(c|w;\theta)$$

- The important thing: how we parametrize the probability distribution

The Skip-Gram Model

- Goal: maximize the corpus probability

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(c|w;\theta)$$

where:

$$p(c|w;\theta) = \frac{e^{v_c \cdot v_w}}{\sum_{c' \in C} e^{v_{c'} \cdot v_w}}$$

if d is the dimensionality of the vectors, we have $d \times |V| + d \times |C|$ parameters

The Skip-Gram Model

- Goal: maximize the corpus probability

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(c|w;\theta)$$

- The log of the objective is:

$$\arg\max_{\theta} \sum_{(w,c)\in D} (\log e^{v_c \cdot v_w} - \log \sum_{c'} e^{v_{c'} \cdot v_w})$$

- Not tractable in practice
  - Sum over all context – intractable
  - Approximated via negative sampling

Negative Sampling for Skip-Gram

- Efficient way of deriving word embeddings
- Consider a word-context pair (w, c)
- Let the probability that this pair was observed:

$$p(D = 1|w, c)$$

- The probability that it was not observed is:

$$1 - p(D = 1|w, c)$$

Negative Sampling

- Parameterization:

$$p(D=1|w,c) = \frac{1}{1+e^{-v_c \cdot v_w}}$$

- New learning objective:

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(D=1|w,c) \prod_{(w,c)\in D'} p(D=0|w,c)$$

- Need to get *D'*

Negative Sampling

- For a given **k**, the size of **D'** is **k**-times bigger than **D**
- Each context **c** is a word
- For each observed word-context pair, **k** samples are generated based on unigram distribution

Negative Sampling

- New learning objective:

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(D=1|w,c) \prod_{(w,c)\in D'} p(D=0|w,c)$$

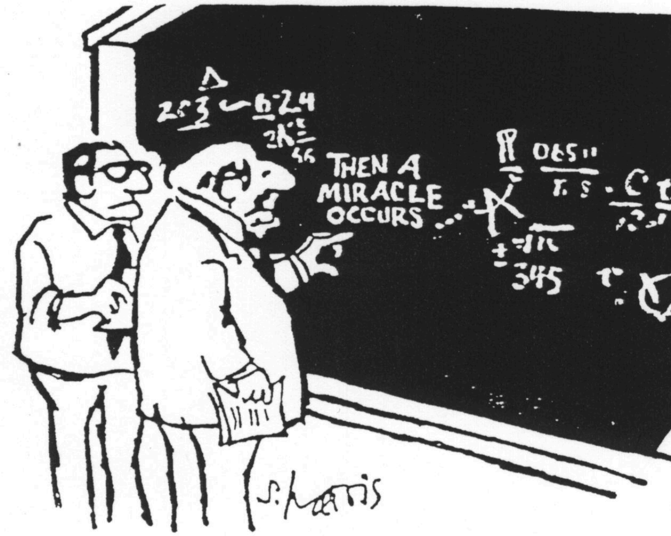
- Original learning objective:

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(c|w;\theta)$$

- How does the new objective approximate the original one?

The Skip-Gram Model

- Optimized for word-context pairs
- To get word embedding, take the vectors of the words v_w
- But why does it work?
- Intuitively: words that share many contexts will be similar
- Formal:
  - *Neural Word Embedding as Implicit Matrix Factorization / Levy and Goldberg 2014*
  - A Latent Variable Model Approach to PMI-based Word Embeddings / *Arora et al. 2016*



I think you should be a little more specific, here in Step 2

Word Galaxy

- Word Galaxy
  - http://anthonygarvan.github.io/wordgalaxy/
- Embeddings for word substitution
  - http://ghostweather.com/files/word2vecpride/

Structured Contexts

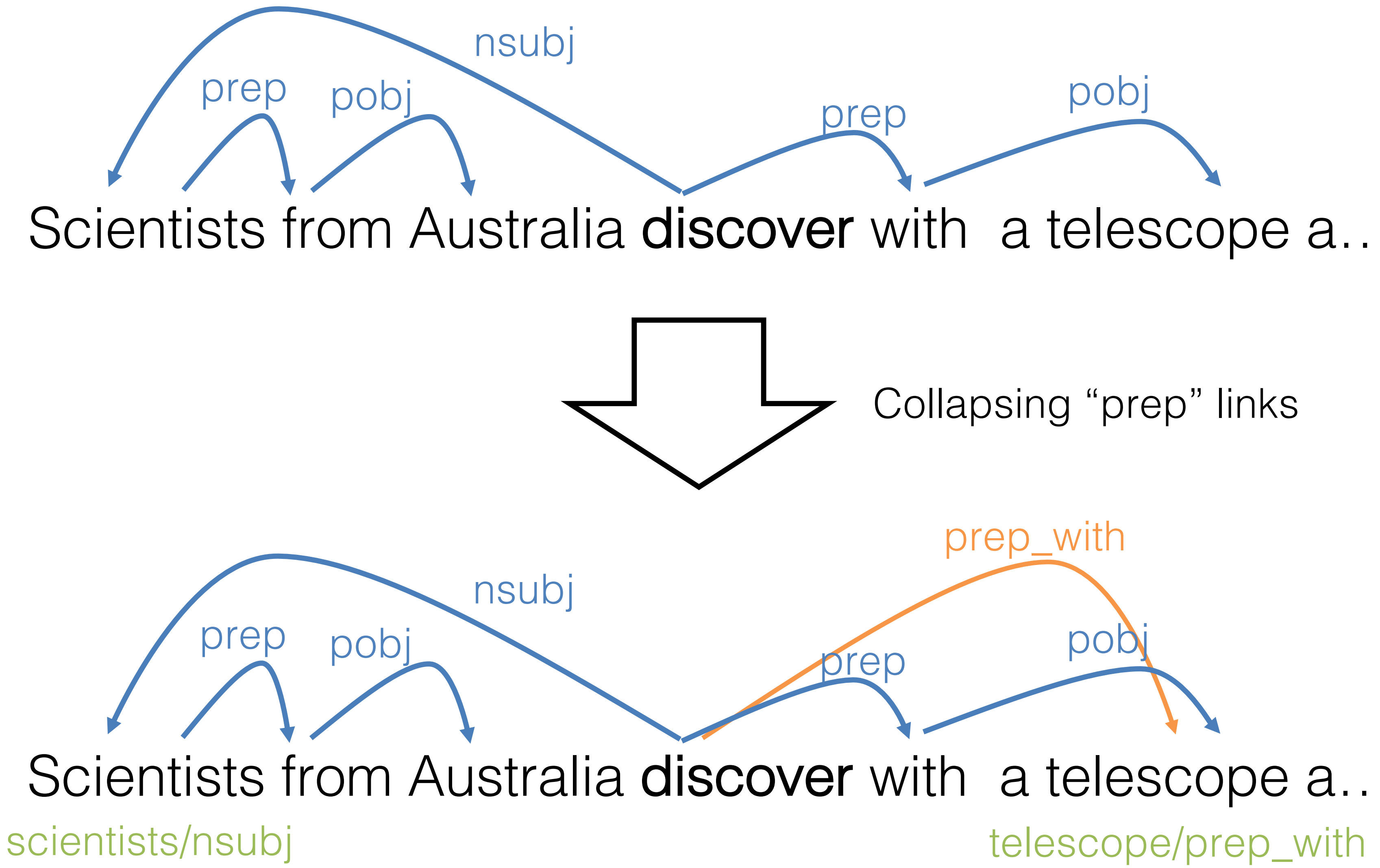
Scientists $\boxed{\text{from}}$ $\boxed{\text{Australia}}$ **discover** $\boxed{\text{with}}$ $\boxed{\text{a}}$ telescope a…

Skip-Gram context with n=2

- Just looking at neighboring words, often doesn't capture arguments and modifiers
- Maybe just a bigger window?
- Can we use anything except adjacency to get context?

Levy and Goldberg 2014

Structured Contexts



Levy and Goldberg 2014

Structured Context

Target Word	BoW5	BoW2	Deps
batman	nightwing aquaman catwoman superman manhunter	superman superboy aquaman catwoman batgirl	superman superboy supergirl catwoman aquaman
hogwarts	dumbledore hallows half-blood malfoy snape	evernight sunnydale garderobe blandings collinwood	sunnydale collinwood calarts greendale millfield
turing	nondeterministic non-deterministic computability deterministic finite-state	non-deterministic finite-state nondeterministic buchi primality	pauling hotelling heting lessing hamming
florida	gainesville fla jacksonville tampa lauderdale	fla alabama gainesville tallahassee texas	texas louisiana georgia california carolina
object-oriented	aspect-oriented smalltalk event-driven prolog domain-specific	aspect-oriented event-driven objective-c dataflow 4gl	event-driven domain-specific rule-based data-driven human-centered
dancing	singing dance dances dancers tap-dancing	singing dance dances breakdancing clowning	singing rapping breakdancing miming busking

Table 1: Target words and their 5 most similar words, as induced by different embeddings.

Levy and Goldberg 2014

Word Embeddings vs. Sparse Vectors

- Count vectors: sparse and large
- Embedded vectors: small dense
- One advantage: dimensionality
- More contested advantage: better generalization
  - See Levy et al. 2015 (Improving Distributional Similarity with Lessons Learned from Word Embeddings) for detailed analysis

Applications

- Word vectors are often input to various end applications
  - Parsing, co-reference resolution, named-entity recognition, semantic role labeling, etc.
- Input to sentence models, including recurrent and recursive architectures