Raw Data

Word Embeddings

Cornell CS 5740: Natural Language Processing
Yoav Artzi, Spring 2023

Raw Data

- Raw text = human-created languge without any additional annotation
- A natural by-product of human use of language
- Abundant in text form for many domains and scenarios, but not for all
- How can learn without any annotation? What kind of representations can we get? How can we use them?
- Key idea: self-supervised learning

Raw Data

Self-supervised Learning

- Given: raw data without any annotation
- Formalize a prediction training objective that is using this data only
- Common approach: given one piece of the data, predict another
- The prediction task is often not interesting on its own
- But the learned representations are!
- Big advantage: can use as much data as you can find and have compute for
- In contrast, supervised learning relies on enriching the data with human annotations

Lexical Semantics

- Subfield of linguistics concerned with word meaning
- A very broad subfield
- We focus on common instantiations of it in contemporary NLP:
  - Word senses
  - Distributional semantics
  - Word2vec

Word Senses

Lemma and Wordform

- A **lemma** (or citation form)
  - Basic part of the word, same stem, rough semantics
- A **surface form** (or word form)
  - The word as it appears in text (i.e., the string)

Surface Form	Lemma
banks	bank
sung	sing
duermes	dormir

Word Senses

Lemma

- One lemma can have many meanings:
  - *…a **bank** can hold the investments in a custodial account…*
  - *…as agriculture burgeons on the east **bank** the river will shrink even more*
- **Sense** (or word sense)
  - A discrete representation of an aspect of a word’s meaning

Word Senses

Lemma

- One lemma can have many meanings:
  - *…a **bank**$_1$ can hold the investments in a custodial account…*
  - *…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

Word 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
- **Homographs**: same written form
  - Bank/bank, bat/bat
- **Homophones**: same spoken form
  - Write and right, piece and peace

Word Senses
Who Cares?

- Capturing such sense distinctions is important for many NLP problems
- Including very practical ones:
  - Information retrieval / question answering
    - bat care / how do I care for my bat?
  - Machine translation
    - bat: murciélago (animal) or bate (for baseball)
  - Text-to-speech
    - bass (stringed instrument) vs. bass (fish)

Word Senses

Who Cares?

- Can break common semantic expectations
- So an interesting test case for even the latest and largest model
- For example, GPT4V
  - *generate an image of a baseball player caring for his bat in the cave where he lives with all the other bats*

Word Senses

Zeugma

- A quick test to identify 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 Philadelphia?
- The conjunction sounds "weird"
  - Because we have two sense for *serve*

Sense and Word Relations

Synonyms

- Word that have the same meaning in some or all contexts.
  - filbert / hazelnut ; couch / sofa ; big / large
  - automobile / car ; vomit / throw up ; Water / H20
- 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.

Sense and Word Relations

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

Sense and Word Relations

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	could	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 a bit later!

Sense and Word Relations

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)

Hypernym	vehicle	fuirt	furniture
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…)
  - Various software support it

Category	Unique Strings
Noun	117798
Verb	11529
Adjective	22479
Adverb	4481

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

WordNet

Senses and Synsets

- 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

Lexical Machine Learning Problems

- Various ML problem have been studied extensively in NLP
- WordNet has been an important resource for building ML models
- Example: word-sense disambiguation
    - Given a word in context, what sense from an existing ontology (e.g., WordNet) is used

Distributional Semantics

The Distributional Hypothesis

You shall know a word by the company it keeps

- John Firth, 1957

Distributional Semantics

A bottle of Tesgüino is on the table.

Everybody likes tesgüino.

Tesgüino makes you drunk.

We make tesgüino out of corn.

Distributional Semantics

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
- …

Distributional Semantics

A bottle of Tesgüino is on the table.

Everybody likes tesgüino.

Tesgüino makes you drunk.

We make tesgüino out of corn.

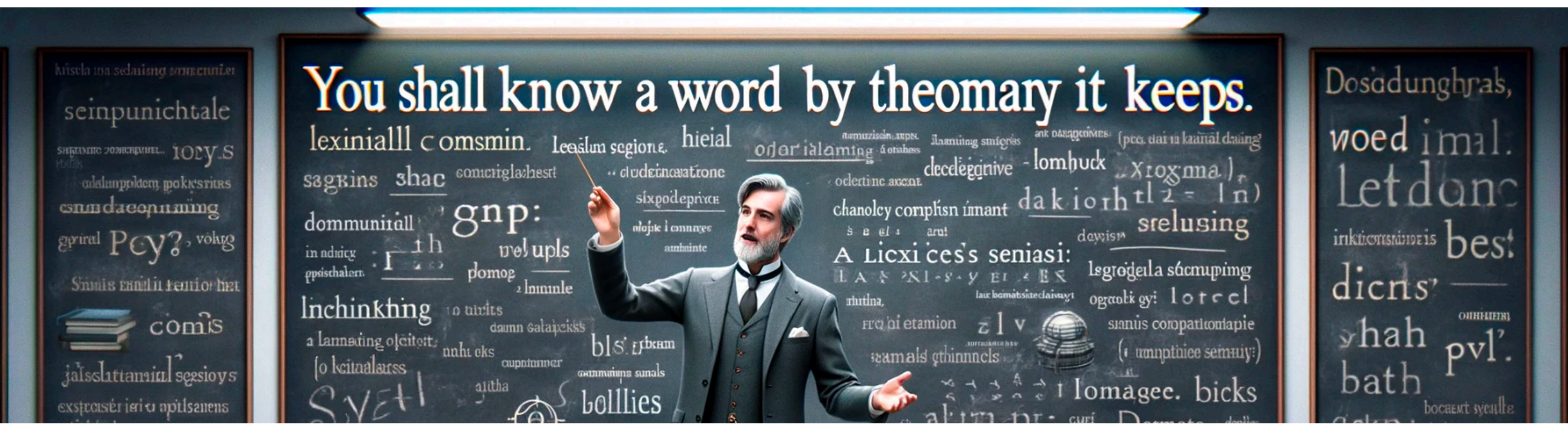
- Occurs before drunk
- Occurs after bottle
- Is the direct object of likes
- …

Similar to beer, wine, whiskey, …

Distributional Semantics

The Distributional Hypothesis

- Words that are used and occur in the same **<u>context</u>** tend to have similar meaning
- Similarity-based generalization: children can figure out how to **<u>use</u>** words by generalizing about their **<u>use</u>** from distributions of similar words
- The more semantically similar words are, the more distributionally similar they are
- But, what is the semantics of meaning? Hard question 😅, let's skip it!
- What is context? Informally: whatever you can get your hands on that makes sense!



Vector-space Models

- Words represented by vectors
    - Often called **embeddings**, especially when low-dimensional and dense
- In contrast to discrete class representation of word senses
- Sparse (high dimensional) vs. dense (low dimensional)

Sparse Representations

- Given a vocabulary of n words
- Let $f_i, i = 1 \dots n$ be a binary (or count) indictor for the presence (or count) of the i-th word in the vocabulary
- Represent a word w as, where f_i are computed in contexts of all uses of w:

$$w = (f_1, f_2, f_3, \dots, f_n)$$

- For example:

$$\text{Tsegüino} = (1,1,0,\dots)$$

corn drunk matrix

Measuring Similarity

$$\text{Tsegüino} = (1,1,0,\ldots)$$

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

- Similarity can be measured using vector distance measures
- 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 (completely identical)

Word2vec

- Widely-used method for learning word vectors from raw text
  - Another common method: GloVe
- Goal: good word embeddings
  - Embeddings are vectors in a low dimensional space
  - Similar words should be close to one another
- Key insight: self-supervised learning
- Two models:
  - Skip-gram (today)
  - CBOW (further reading: Mikolov et al. 2013)

Word2vec

The Skip-gram Model

- Given: corpus D of pairs (w, c) where w is a word and c is context
- Context can be a single neighboring word in a window of size k
  - But there are other common definitions
- Consider the probability parameterized by θ

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

- Objective: maximize the corpus probability

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

- How do we parametrize the probability distribution?

Word2vec

The Skip-gram Model

- Objective: maximize the corpus probability

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

- Where:

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

- Let d be the dimensionality of the vectors, how many parameters do we have?

Word2vec

The Skip-gram Model

- Objective: maximize the corpus probability

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

- Where:

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

- Let d be the dimensionality of the vectors, how many parameters do we have?

$$d \times |V| + d \times |C|$$

Word2vec

The Skip-gram Model

- Objective: maximize the likelihood for the data (i.e., corpus)

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

- The log of the objective is:

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

- Any issue?

Word2vec

The Skip-gram Model

- Objective: maximize the likelihood for the data (i.e., corpus)

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

- The log of the objective is:

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

- Not tractable in practice
  - Sum over all context words — intractable
  - Approximate via negative sampling

Word2vec

Negative Sampling for Skip-gram

- **Negative sampling** is a general approach to approximate objectives that are intractable due to large internal sum
- Here: instantiated specifically for word2vec
- Consider a word-context pair (w, c)
- Let the binary probability that the pair (w, c) was observed:

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

- So the probability that it was not observed is

$$p(D = 0 \,|\, w, c) = 1 - p(D = 1 \,|\, w, c)$$

Word2vec

Negative Sampling for Skip-gram

- Let the probability that the pair (w, c) was observed:

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

- Parameterize this binary distribution as:

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

- New Learning objective:

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

- Basically: increase the probability of seen pairs, decrease of unseen ones

Word2vec

Negative Sampling for Skip-gram

- Let the probability that the pair (w, c) was observed:

$$p(D = 1 \mid w, c)$$

- Parameterize this binary distribution as:

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

- New Learning objective:

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

- Basically: increase the probability of seen pairs, decrease of unseen ones

- Unseen?! Need to get D'

Word2vec

Negative Sampling

- For a given l, the size of D' is l-times bigger than D
- Each context c is a word
- For each observed word-context pair, l samples are generated based on unigram distribution (i.e., the probability of each word in the data)

Word2vec

Negative Sampling for Skip-gram

- The new probabilistic model:

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

- Compare to the original model:

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

- Are they equivalent?

Word2vec

Negative Sampling for Skip-gram

- The new probabilistic model:

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

- Compare to the original model:

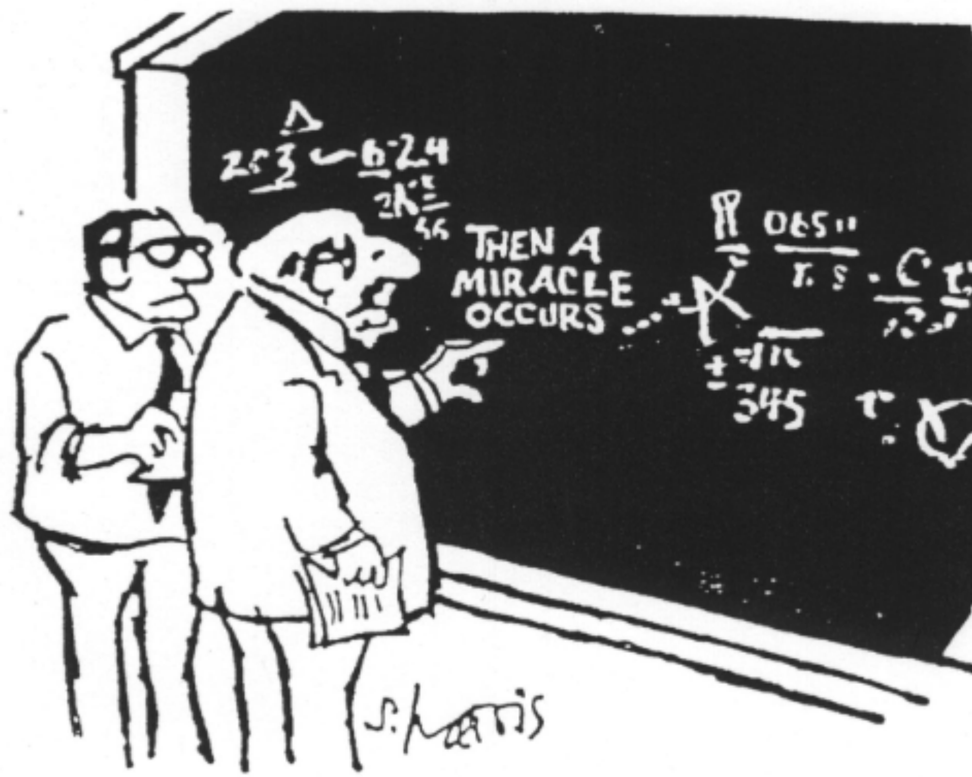
$$p(c \,|\, w; \theta) = \frac{e^{v_c \cdot v_w}}{\sum_{c' \in C} e^{v_{c'} \cdot v_w}}$$

- Are they equivalent?
  - Not really, at least as far as we know — it's an approximation

Word2vec

The Skip-gram Model

- Optimized for word-context pairs
- To get word embedding, take the vectors 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

Word2vec

Visualizations

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

Word2vec

The Skip-gram Context

Scientists from Australia **discover** star with a telescope

- Consider a skip-gram context with $n = 2$

[Levy and Goldberg 2014]

Word2vec

The Skip-gram Context

Scientists from Australia **discover** star with a telescope

- Consider a skip-gram context with $n = 2$

Word2vec

The Skip-gram Context

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

- Consider 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?

Dependency Structures

A Linguistic Detour

- A structural formalism of sentence structure
- Will provide a framework to think beyond adjacency contexts
  - More generally: it is model of sentence structure
- Dependency structure shows which words depend on (modify or are arguments of) which other words
- Numerous methods developed to recover them (but we won’t cover them 😢)

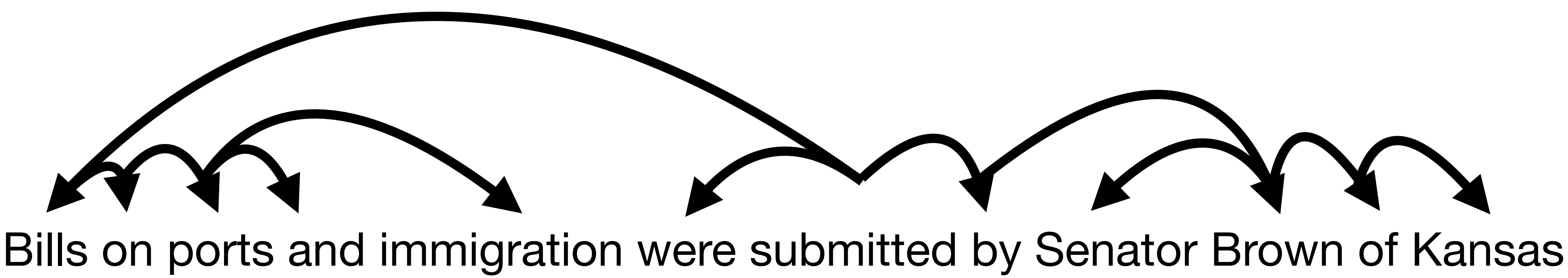
Dependency Structures

- A syntactic structure that consists of:
  - Lexical items (words)

Bills on ports and immigration were submitted by Senator Brown of Kansas

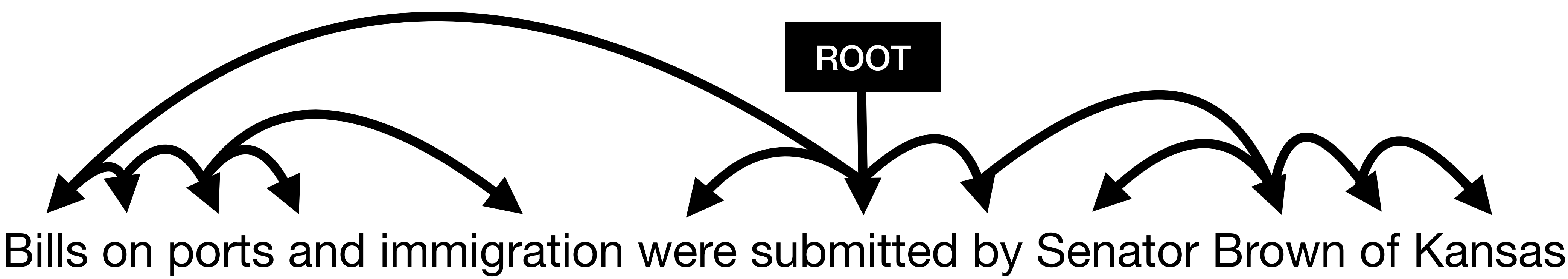
Dependency Structures

- A syntactic structure that consists of:
  - Lexical items (words)
  - Binary asymmetric relations → dependencies
    - Arrow usually from **head** to **modifier**



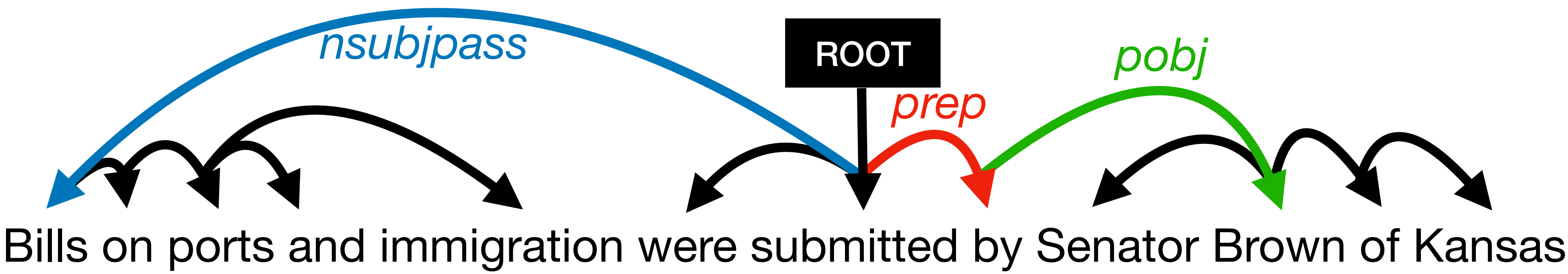
Dependency Structures

- A syntactic structure that consists of:
  - Lexical items (words)
  - Binary asymmetric relations → dependencies
- Dependencies form a tree with a standard root node



Dependency Structures

- A syntactic structure that consists of:
  - Lexical items (words)
  - Binary asymmetric relations → dependencies
- Dependencies form a tree with a standard root node
- Dependencies are typed with names of grammatical relations



Word2vec

Structured Contexts

- Dependency structures allow us to consider notions of adjacency beyond just neighboring words in the text
- Because we can look at the dependency structure connectivity
- These edges can connect words at arbitrary distances
  - If they have a syntactic relation between them

Word2vec

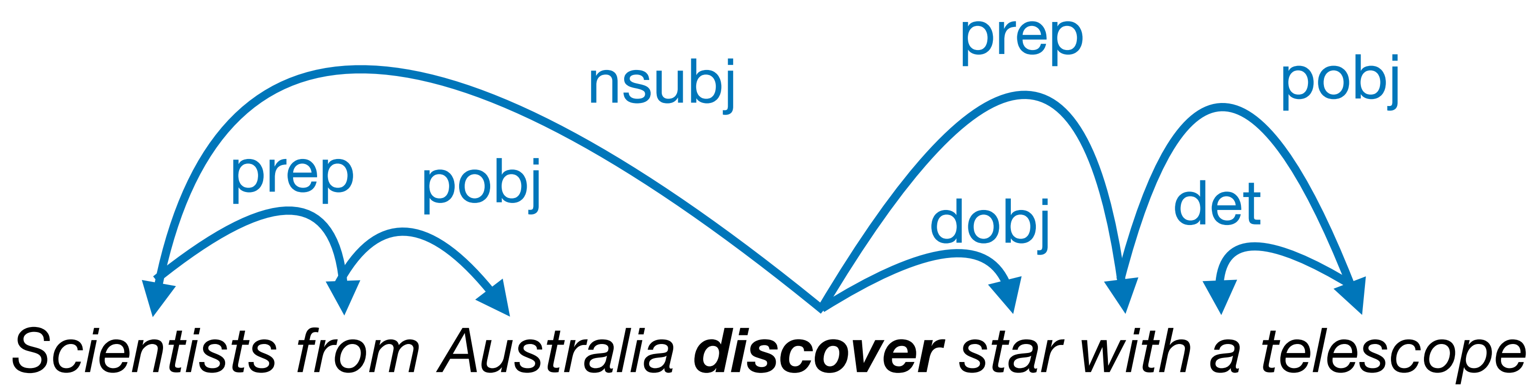
Dependency Contexts

Scientists from Australia ***discover*** *star with a telescope*

[Levy and Goldberg 2014]

Word2vec

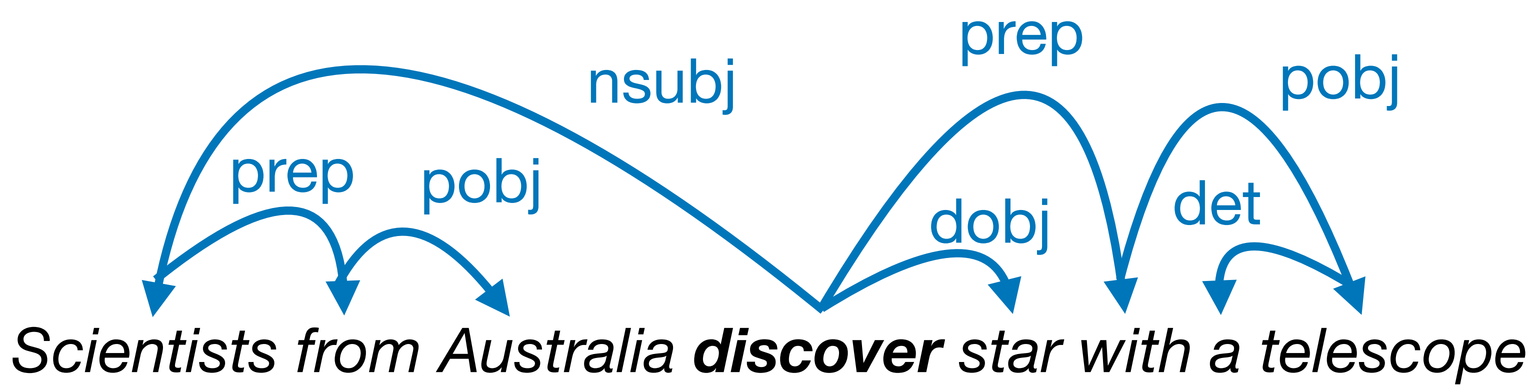
Dependency Contexts



[Levy and Goldberg 2014]

Word2vec

Dependency Contexts

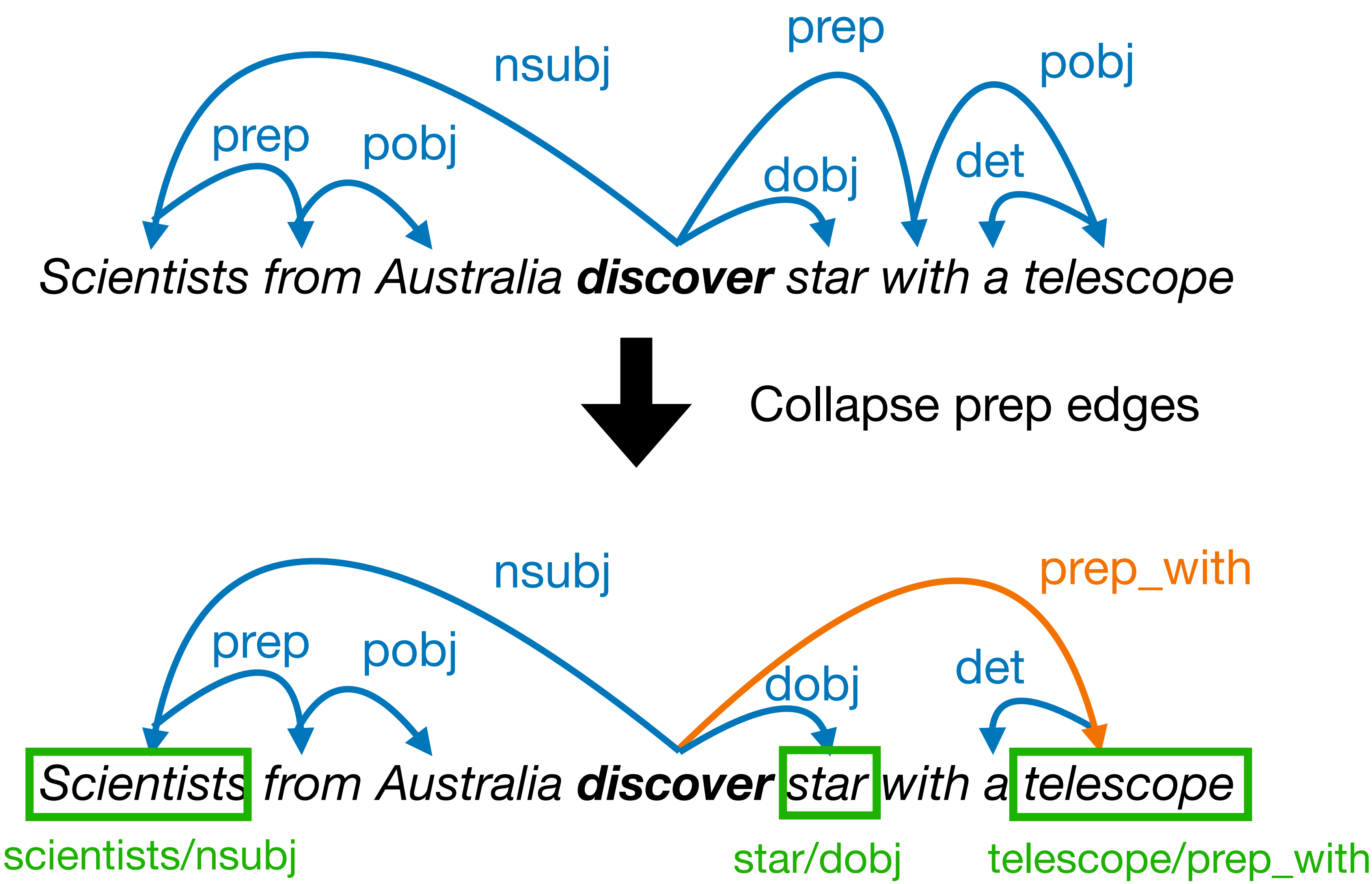


Collapse prep edges

[Levy and Goldberg 2014]

Word2vec

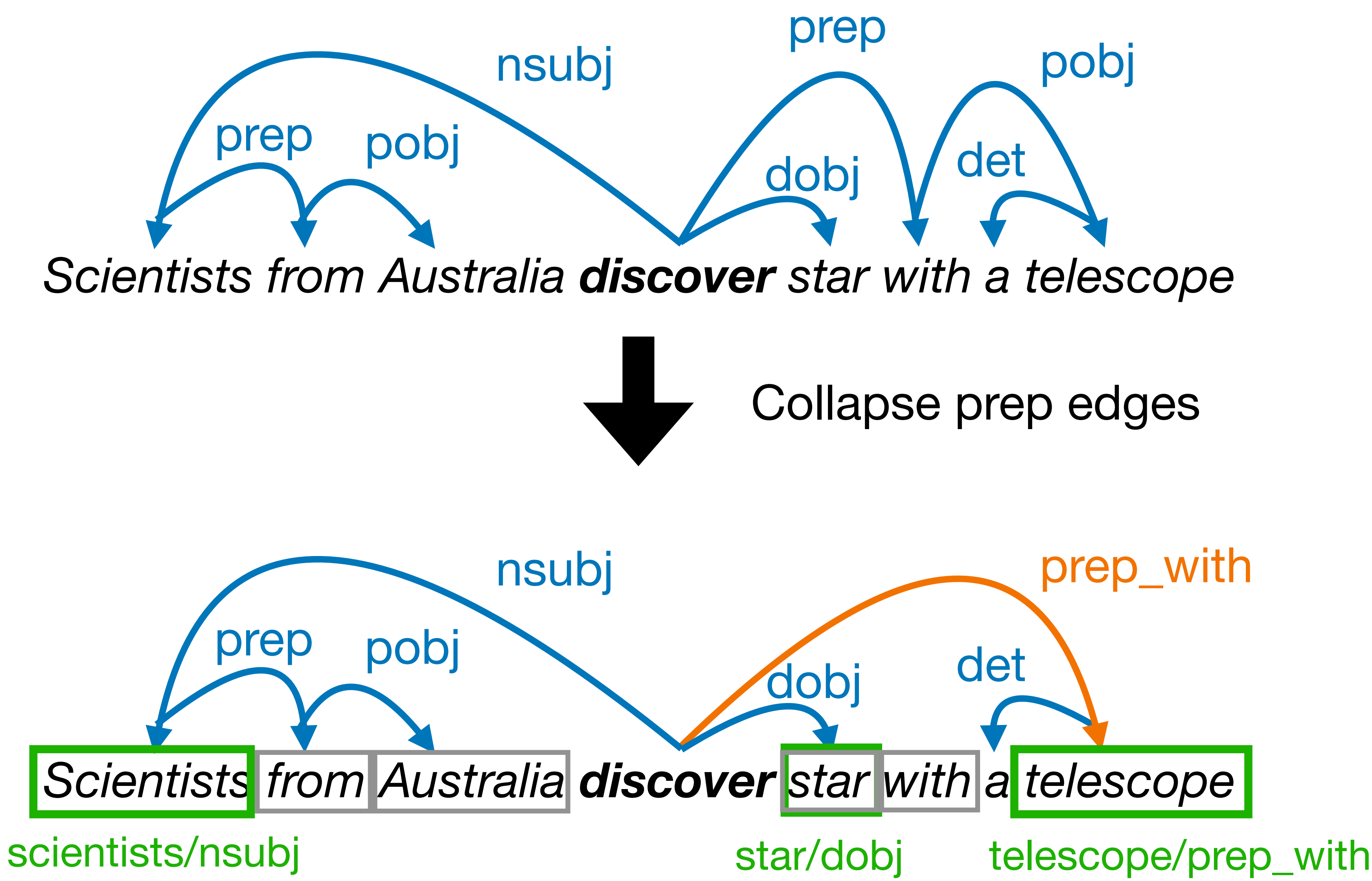
Dependency Contexts



[Levy and Goldberg 2014]

Word2vec

Dependency Contexts



[Levy and Goldberg 2014]

Word2vec

Dependency Contexts

- What is learned?
- What is the cost?

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

How to Use Them?

- Word embeddings are often input to models of various end applications
- They provide lexical information beyond the annotated task datasets, which is often small
- Often kept fixed (i.e., not fine tuned), while the task network is trained
- Can also be input to sentence embedding models