CSE 5243 INTRO. TO DATA MINING

Word Embedding

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Source of slides

- Richard Socher's course in Stanford
- Tomas Mikolov's invited talk at the Deep Learning workshop in NIPS'13
- Dan Jurafsky's lecture about language modeling
- Tutorial at EMNLP'14: Embedding Methods for NLP
- Tutorial at ACL'14: New Directions in Vector Space Models of Meaning
- Manaal Faruqui's talk at NAACL'15: Retrofitting Word Vectors to Semantic Lexicons

How to let a computer understand meaning?

A cat sits on a mat.

#_$@^_&*^&_()_@_+@^=

Knowledge Representation

- Machine understandable representation of knowledge
- **Symbolic** solution, e.g., semantic lexicons like WordNet

hypernyms of 'panda' (is-a relation)

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```

synonym sets of 'good'

S: (adj) full, good
S: (adj) estimable, good, honorable, respectable
S: (adj) beneficial, good
S: (adj) good, just, upright
S: (adj) adept, expert, good, practiced, proficient, skillful
S: (adj) dear, good, near
S: (adj) good, right, ripe
...
S: (adv) well, good
S: (adv) thoroughly, soundly, good
S: (n) good, goodness
S: (n) commodity, trade good, good

Problems with this symbolic representation

- Great as resource but missing nuances
  - e.g. **synonyms**: adept, expert, good, practiced, proficient, skillful?
- Requires human labor to create and adapt
- Subjective, sometimes hard to reach agreement
- Missing new words (hard to keep up to date):

  wicked, badass, nifty, crack, ace, wizard, ninjia

Problems with this symbolic representation

- Words are distinctive atomic symbols
- In vector space terms, this is a vector with one 1 and a lot of zeroes. We call this the "one-hot" representation.

[0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]

Dimensionality: 20K (speech) – 50K (PTB) – 500K (big vocab) – 13M (Google 1T)

- No way to capture word similarity

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

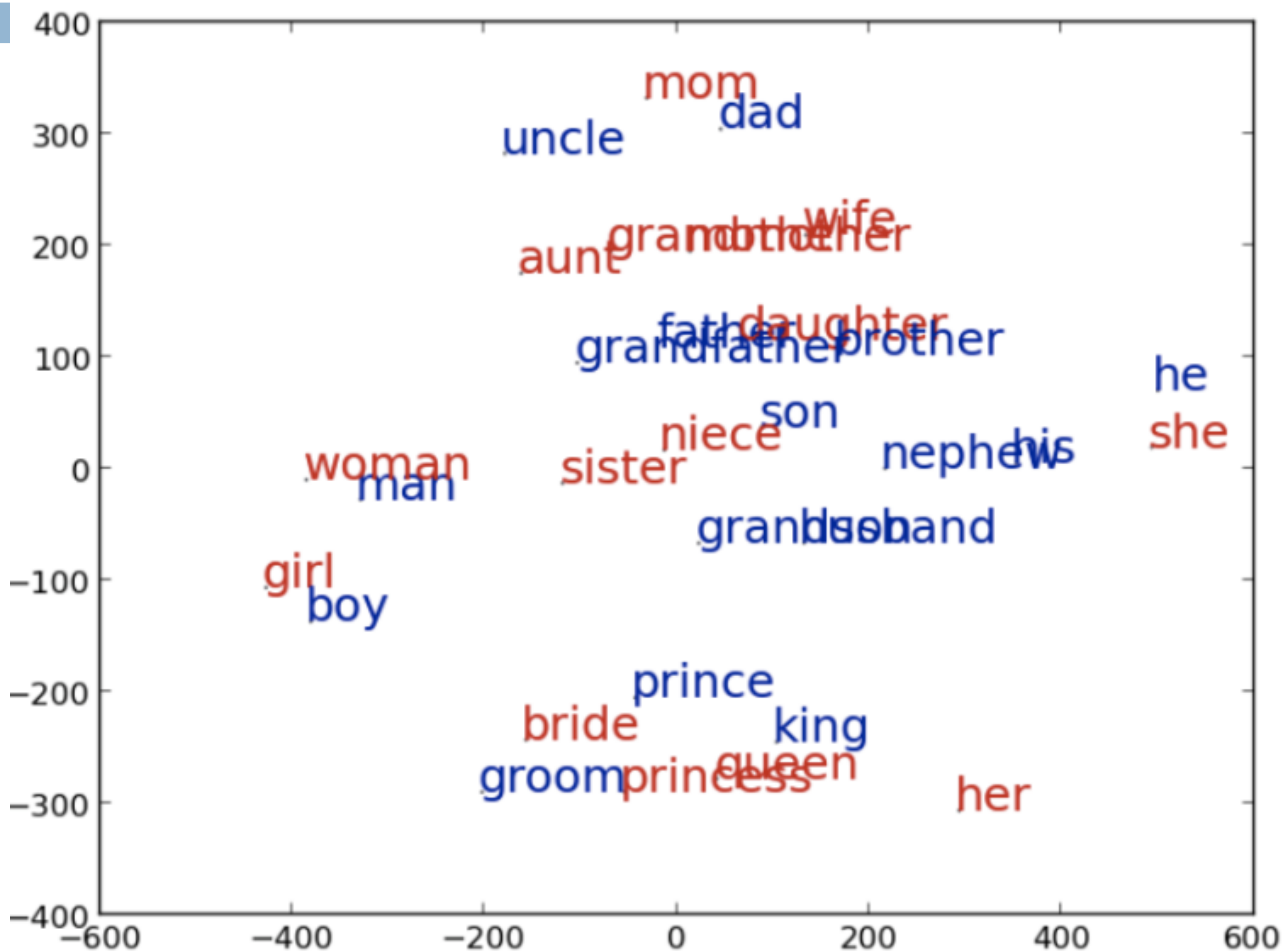
Is there another (probably better) way to represent the meaning of words? →

Statistical solution: word embedding

- Each word is represented as a dense vector
- Each dimension captures more information

$$linguistics = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$

(Expected) regularities in word vector space



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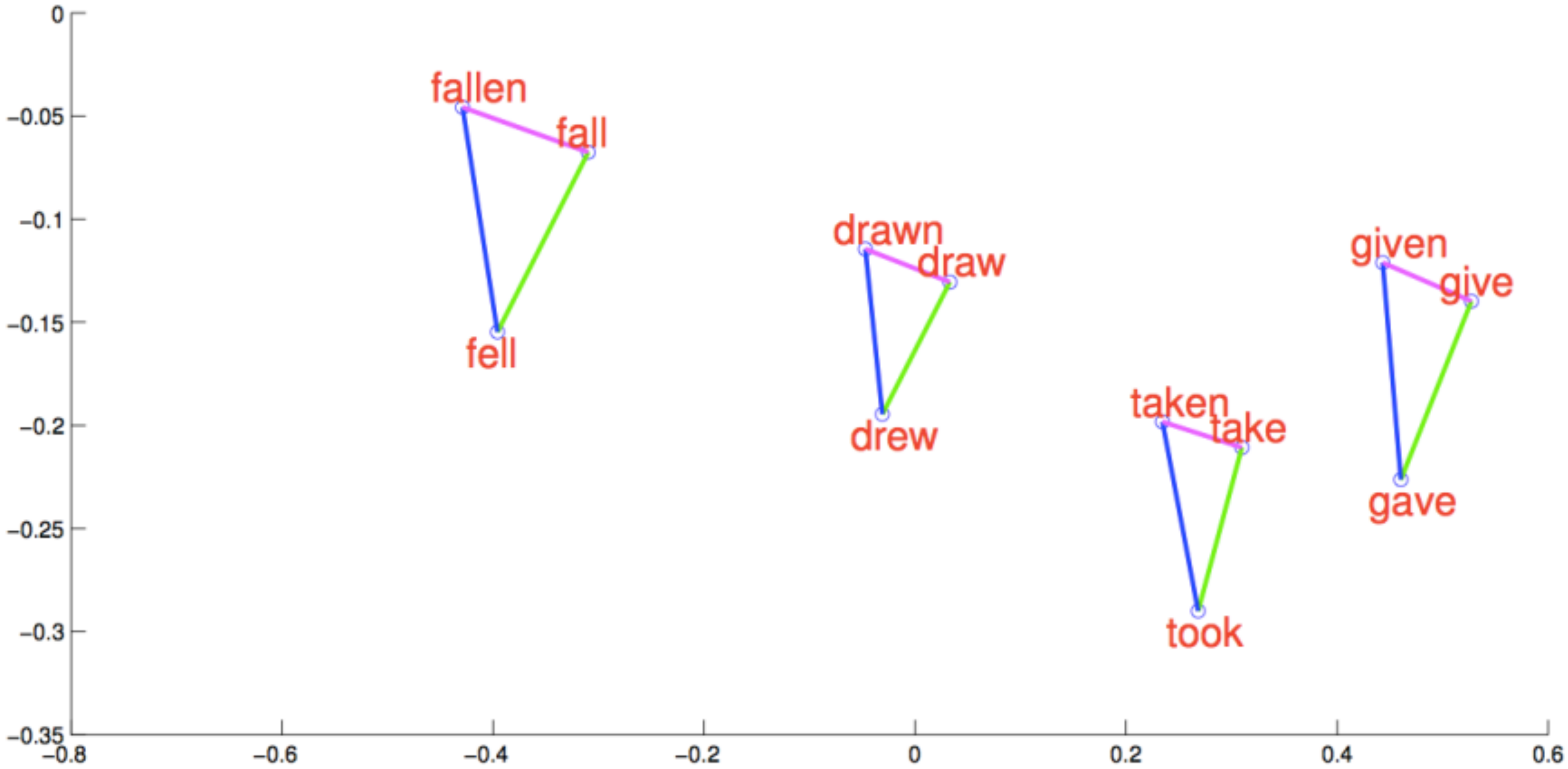
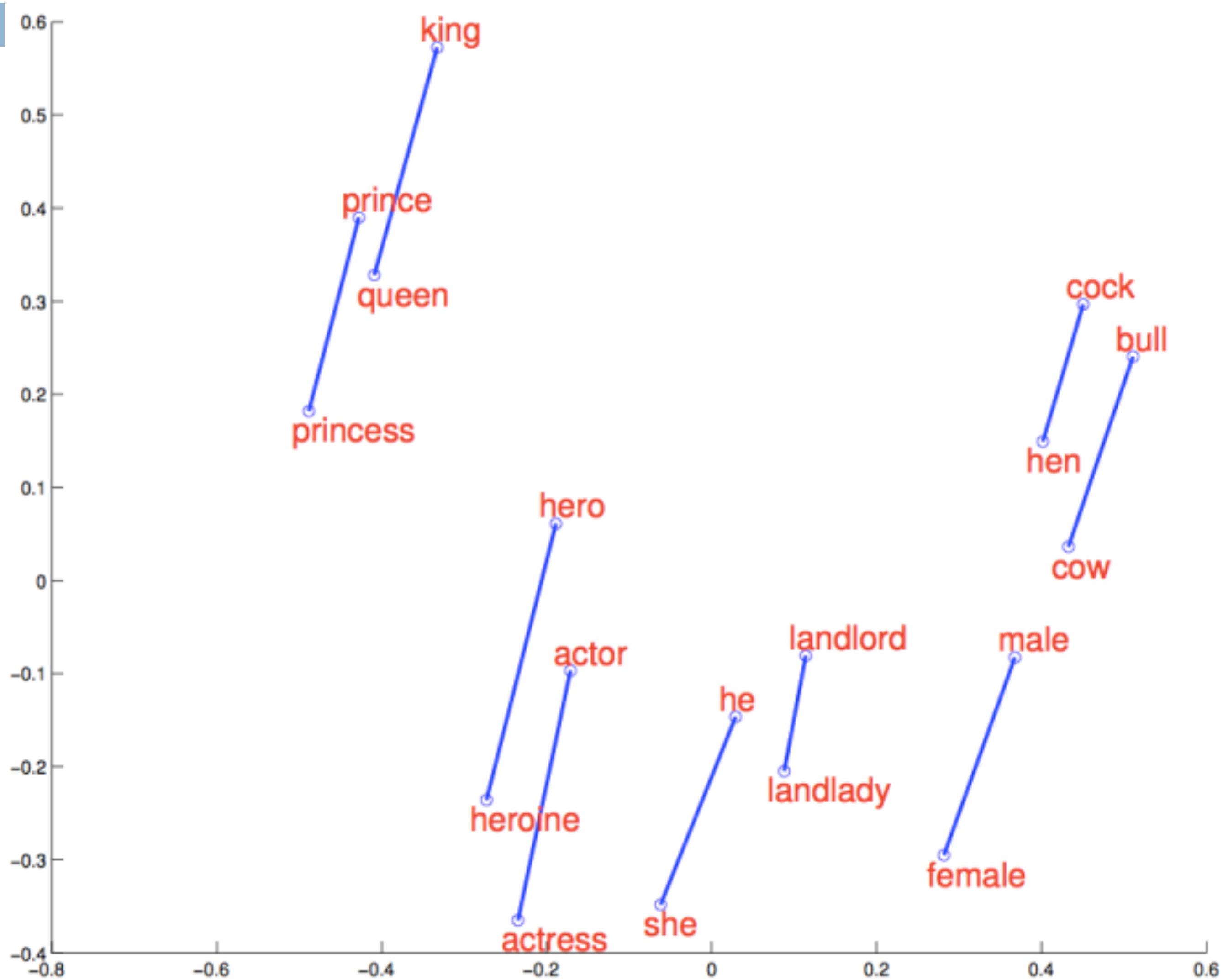


generated by PCA

(Expected) regularities in word vector space



generated by PCA

Q: How to generate word embedding?

A: Distributional semantics

Distributional semantics

- You can get a lot of value by representing a word by means of its neighbors (context)

"You shall know a word by the company it keeps"

(J. R. Firth 1957: 11)

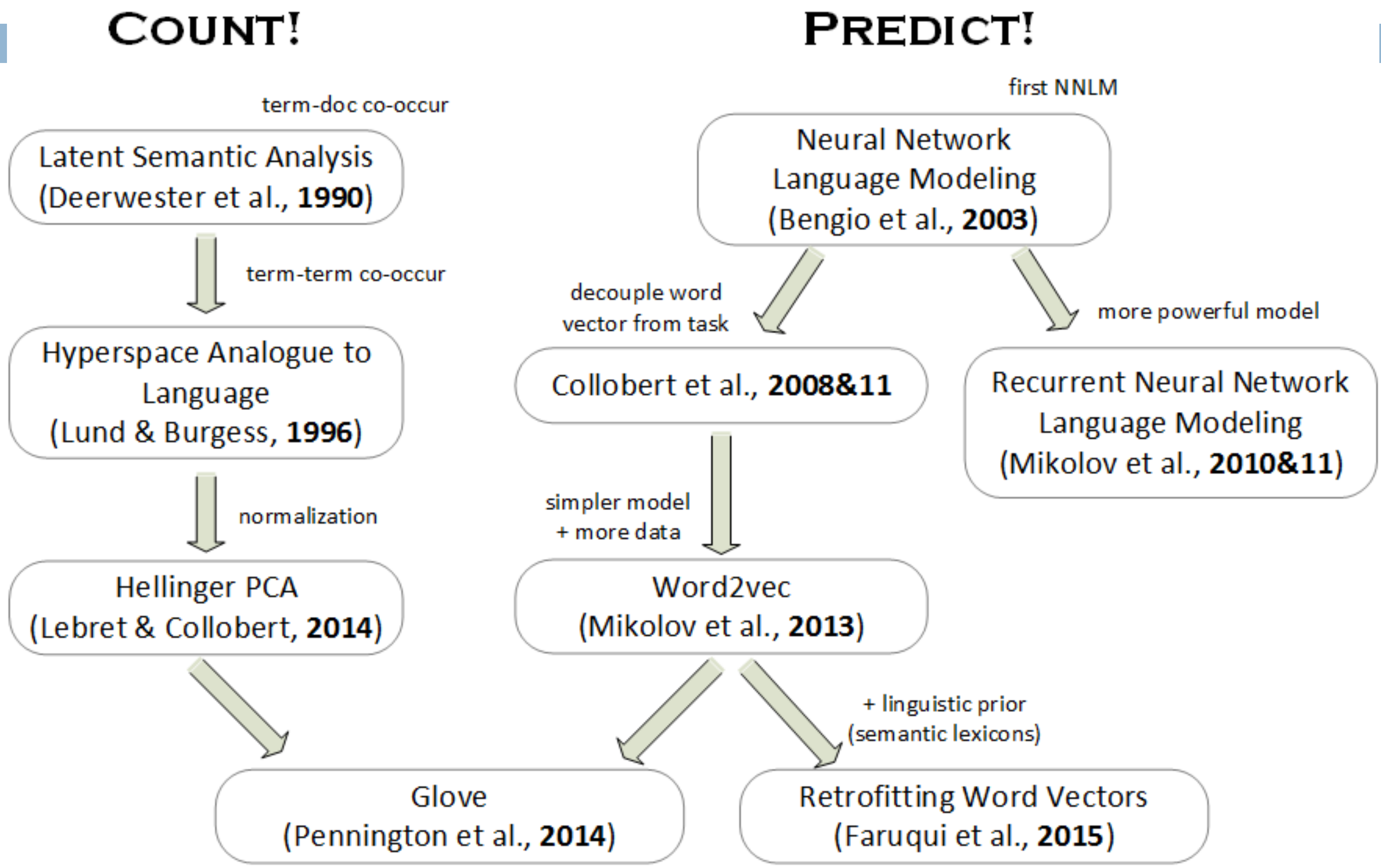
- One of the most successful ideas of modern statistical NLP

government debt problems turning into **banking** crises as has happened in

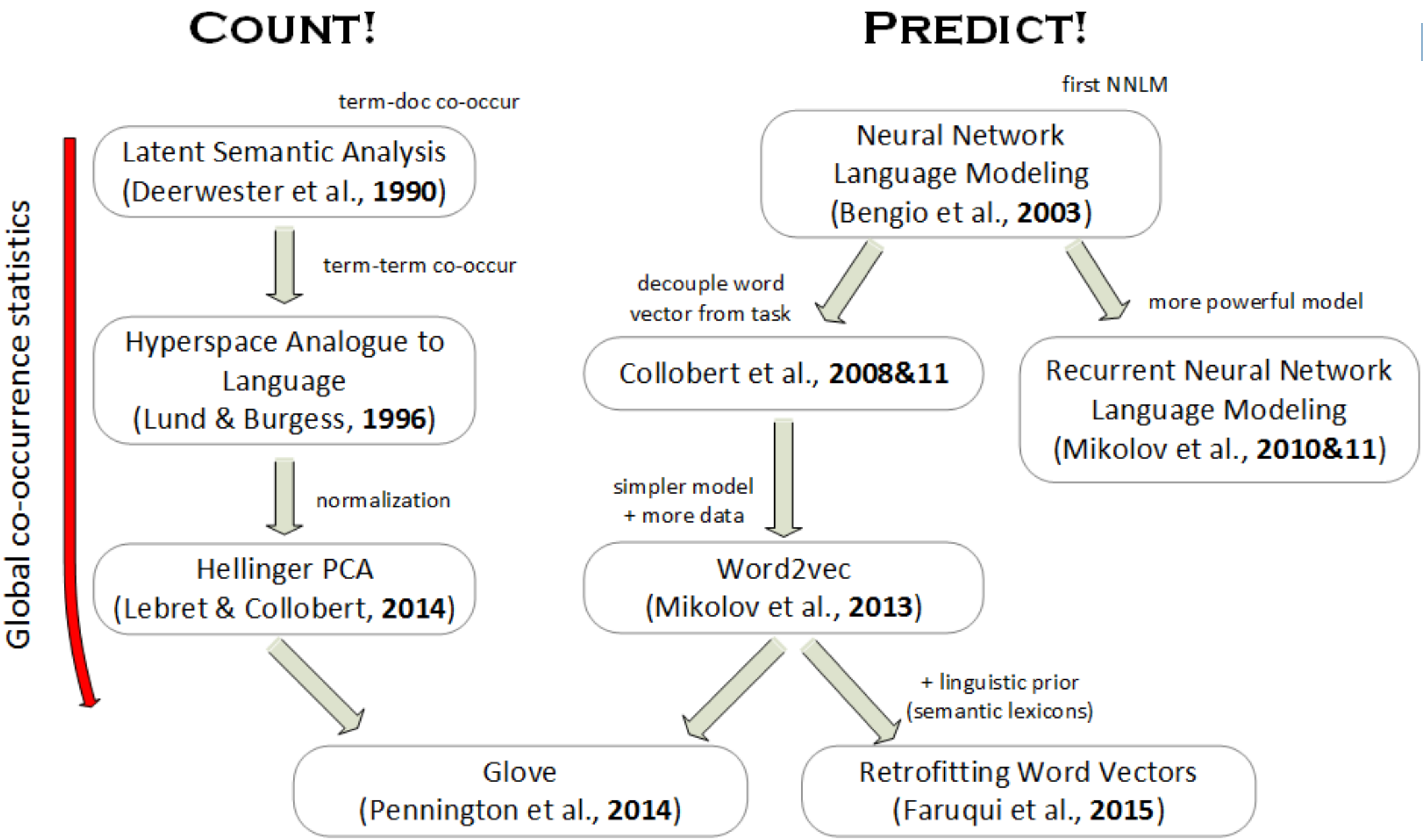
saying that Europe needs unified **banking** regulation to replace the hodgepodge

↖ These words will represent *banking* ↗

History of word embedding



History of word embedding



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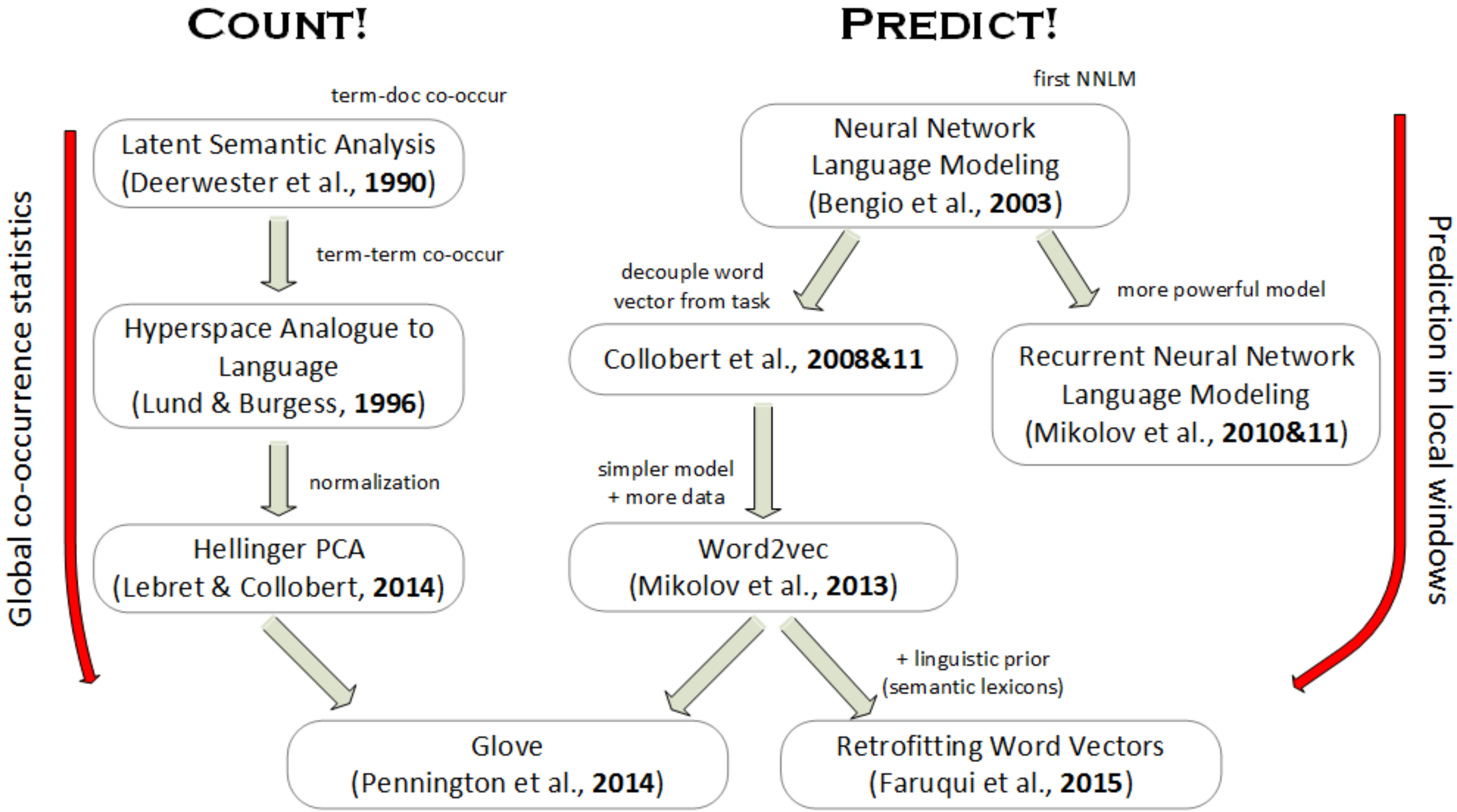

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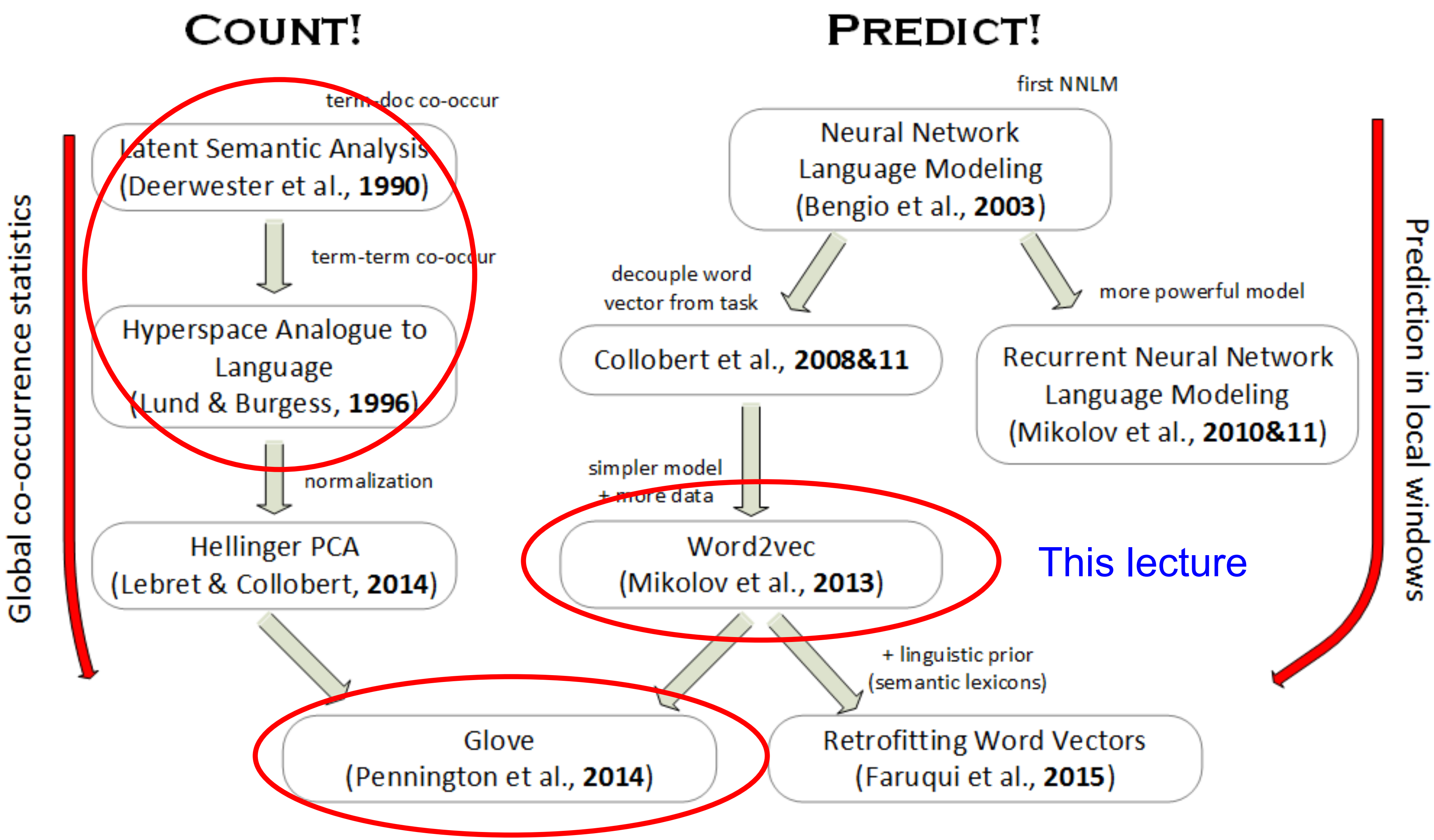

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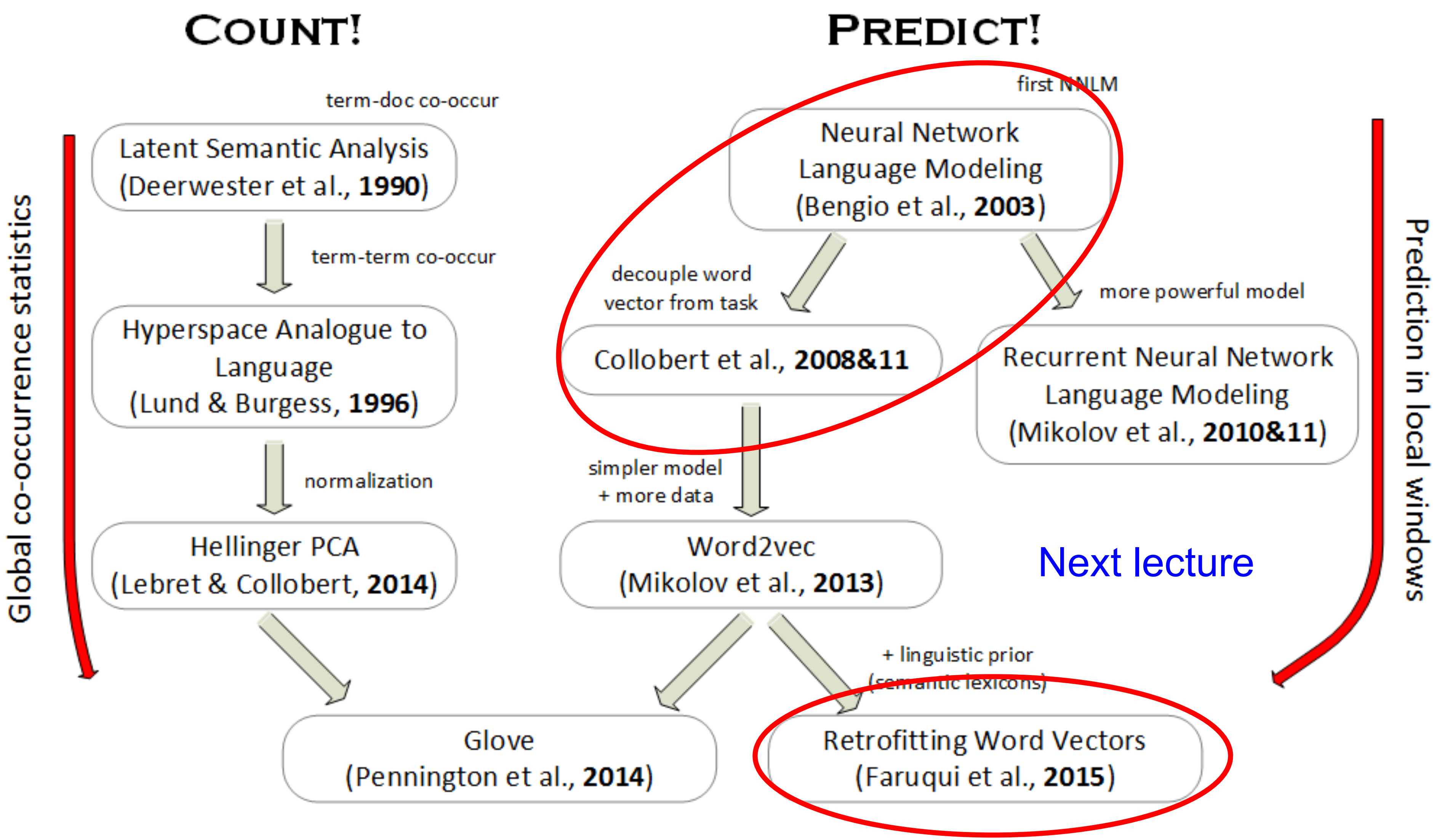


Count-based methods: Build global context matrix X

- Choice of context: Full document vs. Local window

- Full document:
  - Context = all the words in the same doc
  - Word-doc occurrence matrix

- Local window
  - Context = words within a certain distance
  - Word-word co-occurrence matrix

Word-doc occurrence matrix

Terms	Docs 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
data	1	1	0	0	2	0	0	0	0	0	1	2	1	1	1	0	1	0	0	0
examples	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
introduction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
mining	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
network	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1
package	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

- Word-doc occurrence matrix will give general topics, e.g., all sports words will have similar entries
- Lead to *Latent Semantic Analysis*

Word-word co-occurrence matrix

window size = 2

window size = 1

I am studying computer science in UCSB .

central word

- Window allows us to capture both syntactic and semantic information →

Word-word co-occurrence matrix: toy example

- Example corpus (window size=1):
  - I like deep learning.
  - I like NLP.
  - I enjoy flying.

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Problems with simple co-occurrence vectors

- Increase in size with vocabulary
- Very high dimensional: require a lot of storage
- Subsequent classification models have sparsity issues

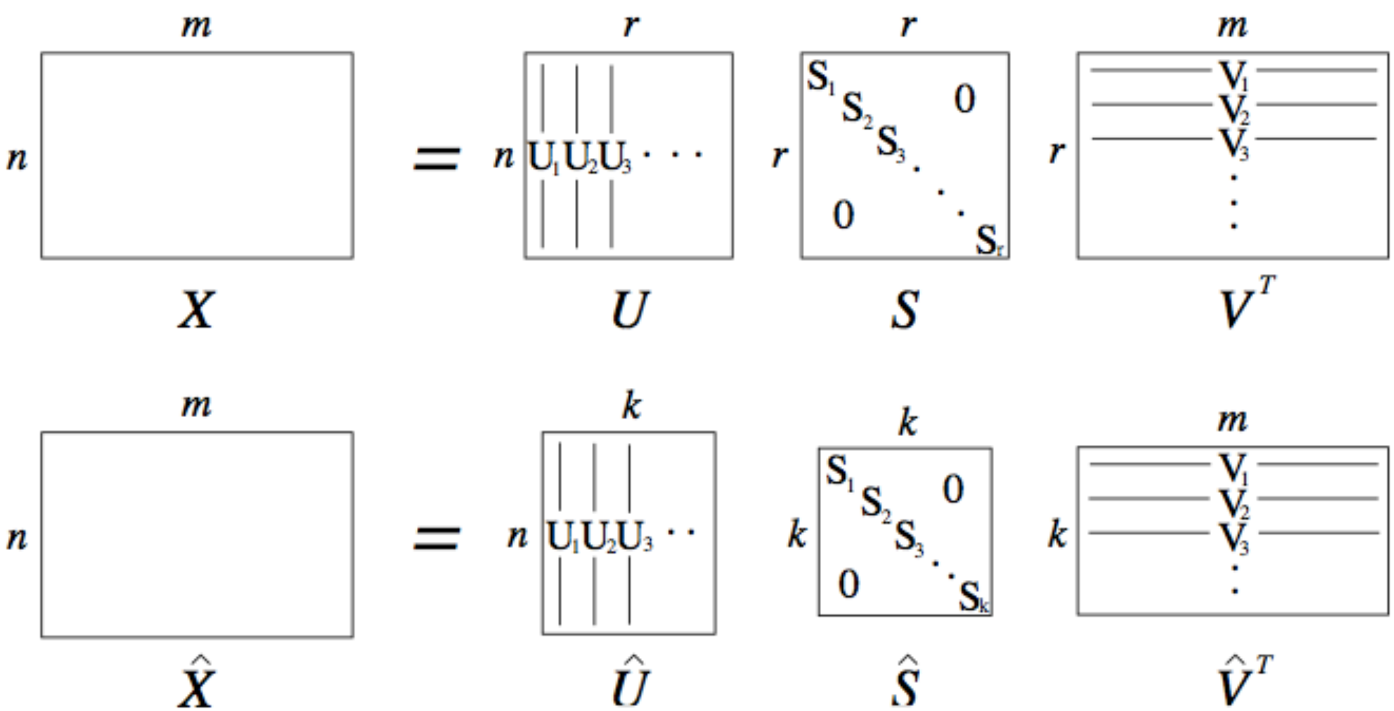
→ Models are less robust

Solution: Low-dimensional dense vectors

- Idea: store "most" of the important information in a fixed, small number of dimensions: a dense vector
- Usually around 25-1000 dimensions
- How to reduce the dimensionality?

Method 1: Dimensionality Reduction on X

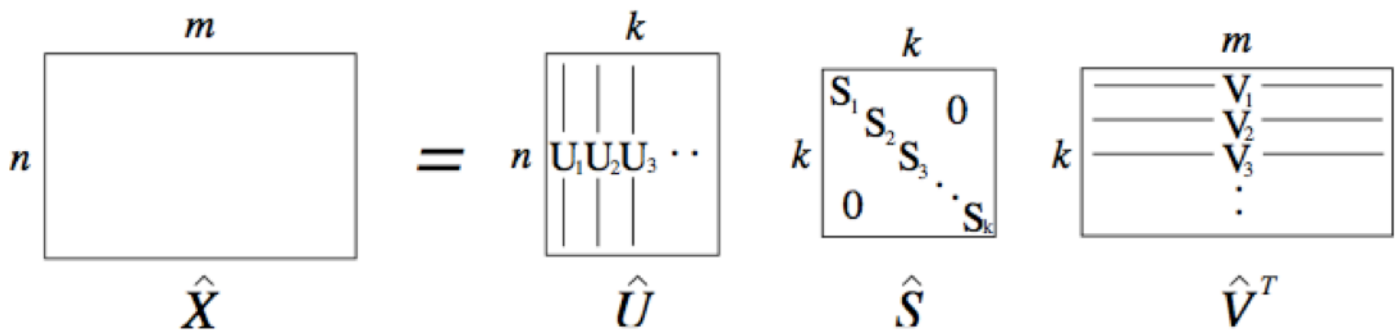
- Singular Value Decomposition (SVD) on X

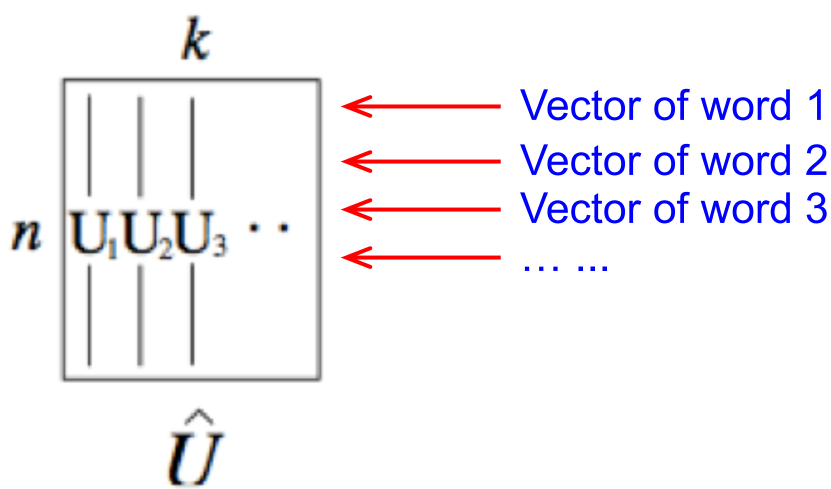


$\hat{X}$ is the best rank k approximation to X, in terms of least squares.

Method 1: Dimensionality Reduction on X

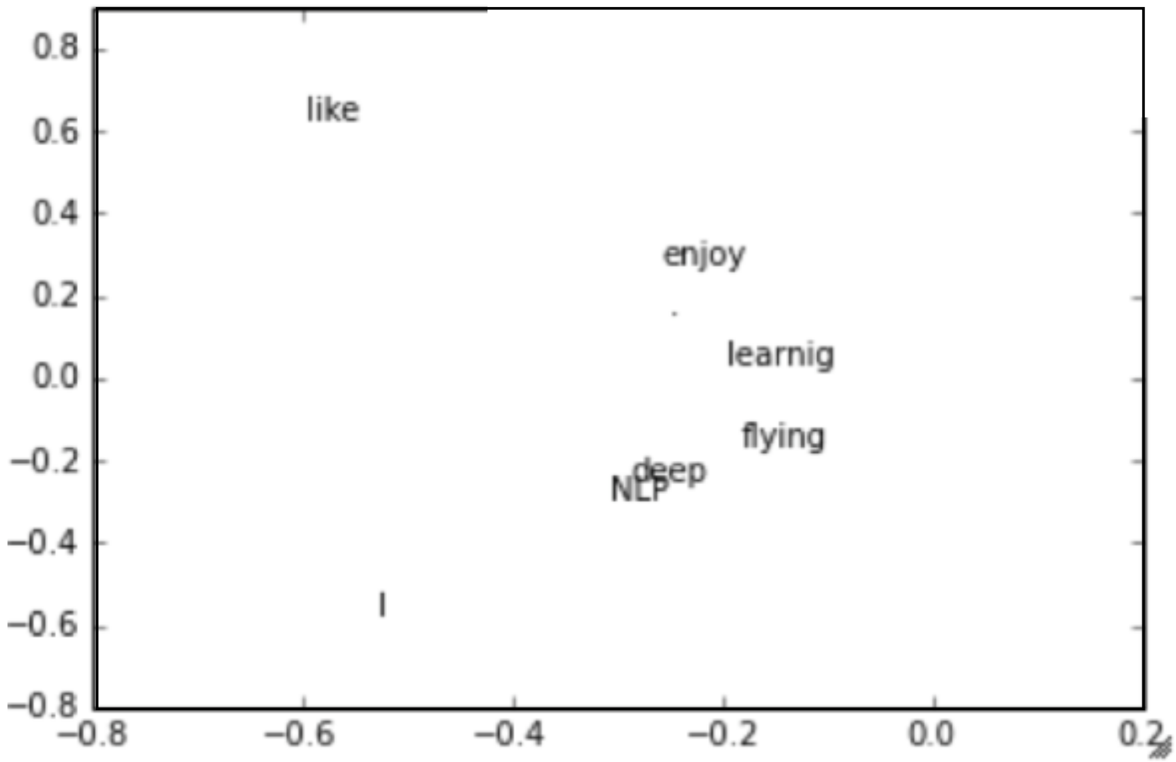
- Singular Value Decomposition (SVD) on X



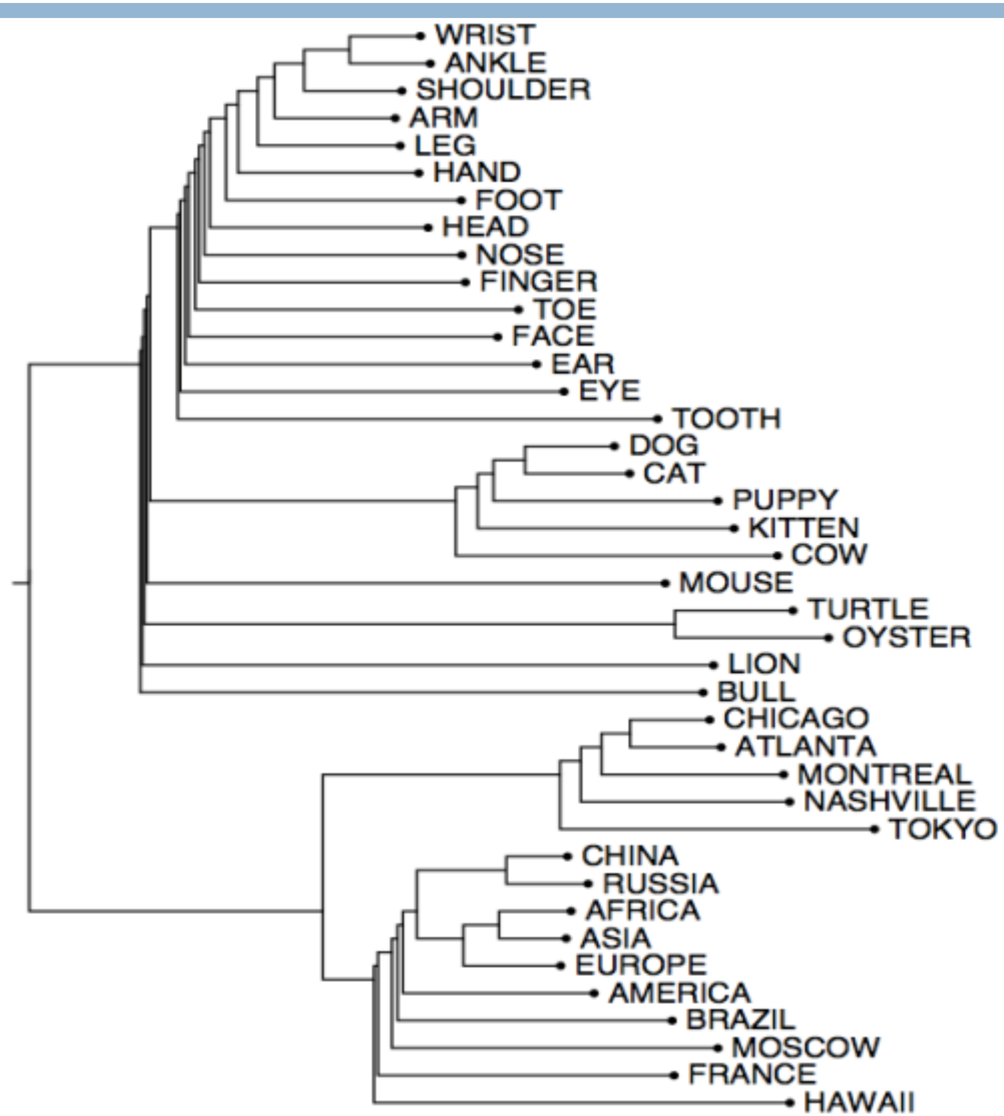


Simple SVD on X

- Corpus: I like deep learning. I like NLP. I enjoy flying.
- Print the first two columns of U corresponding to the 2 largest singular values

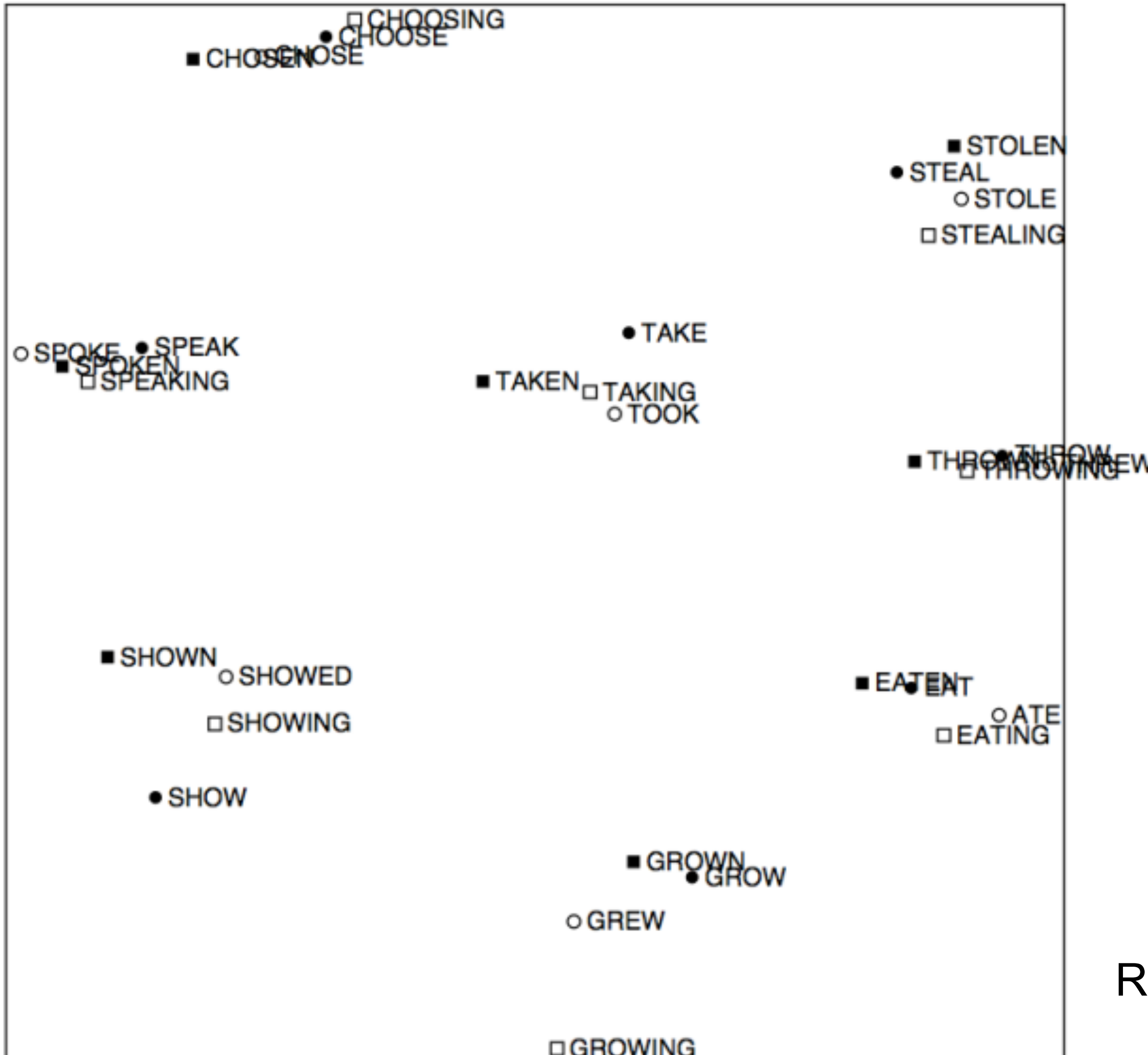


Interesting patterns emerge in the vectors



Rohde et al., 2005

Interesting patterns emerge in the vectors



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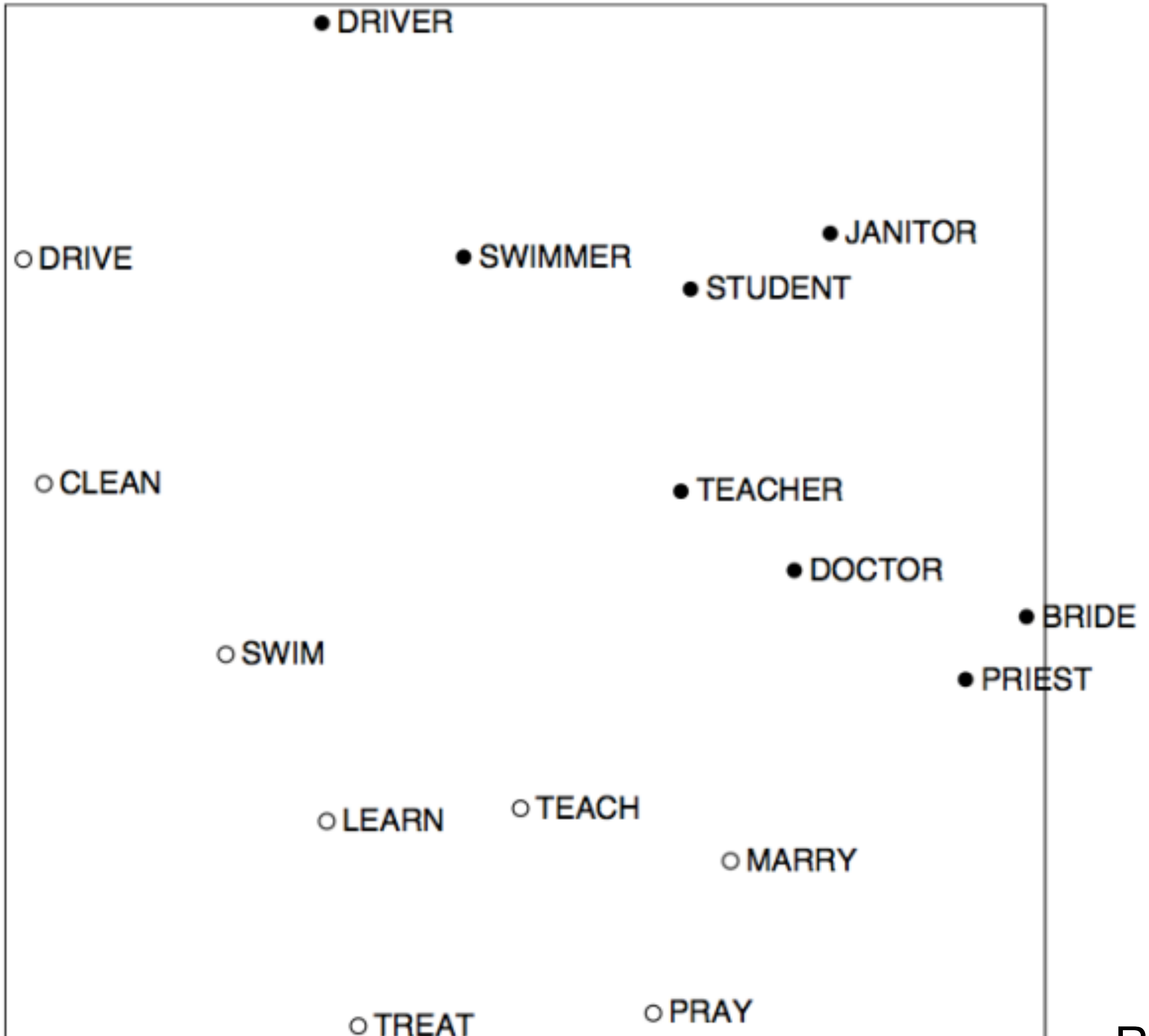


Rohde et al., 2005

Problems with SVD

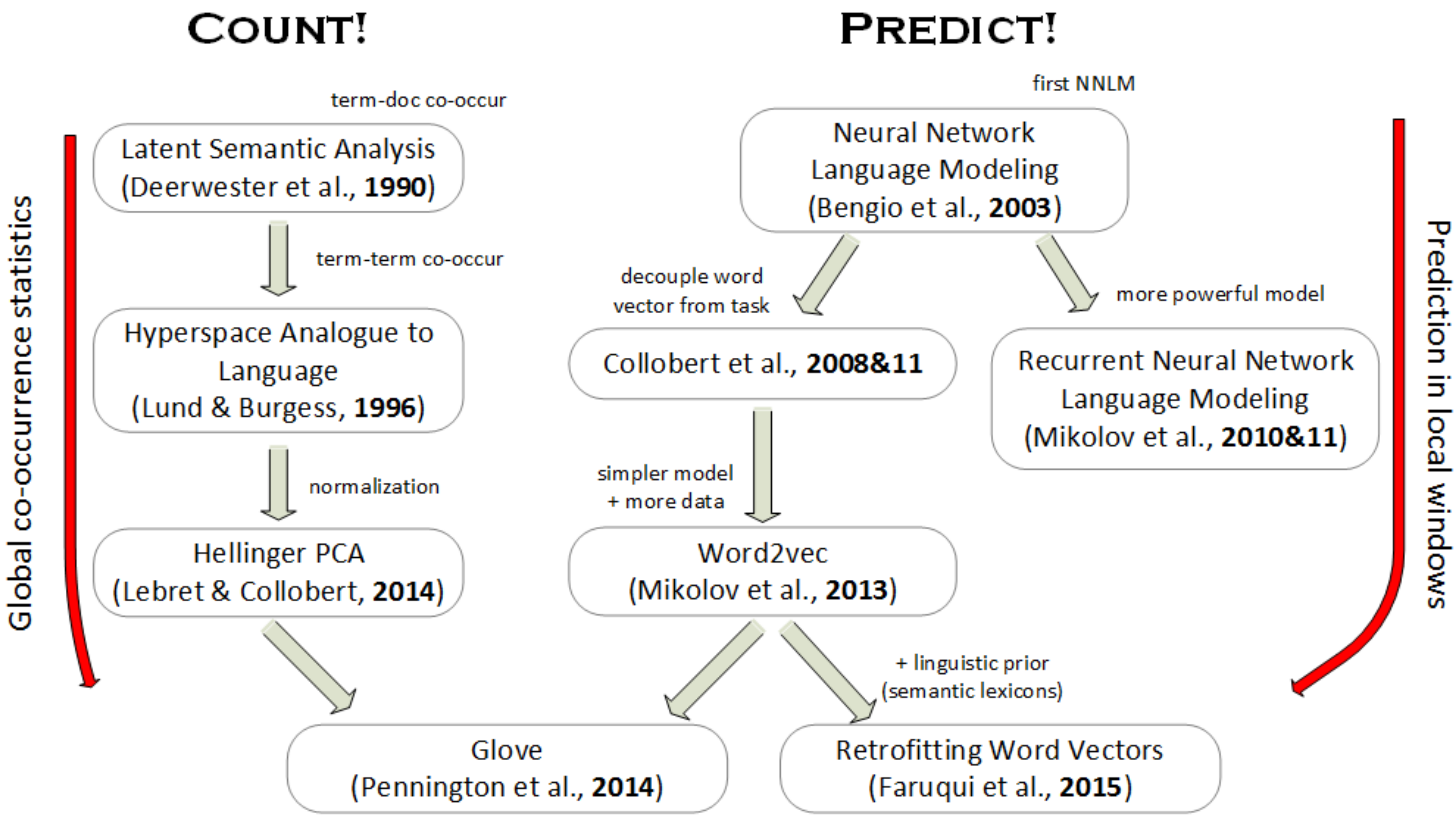
- Naive implementation: Computational cost scales quadratically for n x m matrix: $O(mn^2)$ when $n<m$

→ Bad for millions of words or documents

→ More efficient approximate solutions exist, though

- Hard to incorporate new words or documents
  - Changing a single entry has a global effect
  - Need to do it again…

Method 2: Directly learn low-dimensional word vectors



Main idea

- Instead of capturing global co-occurrence counts directly
- Sequentially scan local windows and do prediction
- Easily incorporate a new sentence/document or add a word to the vocabulary

Word2vec

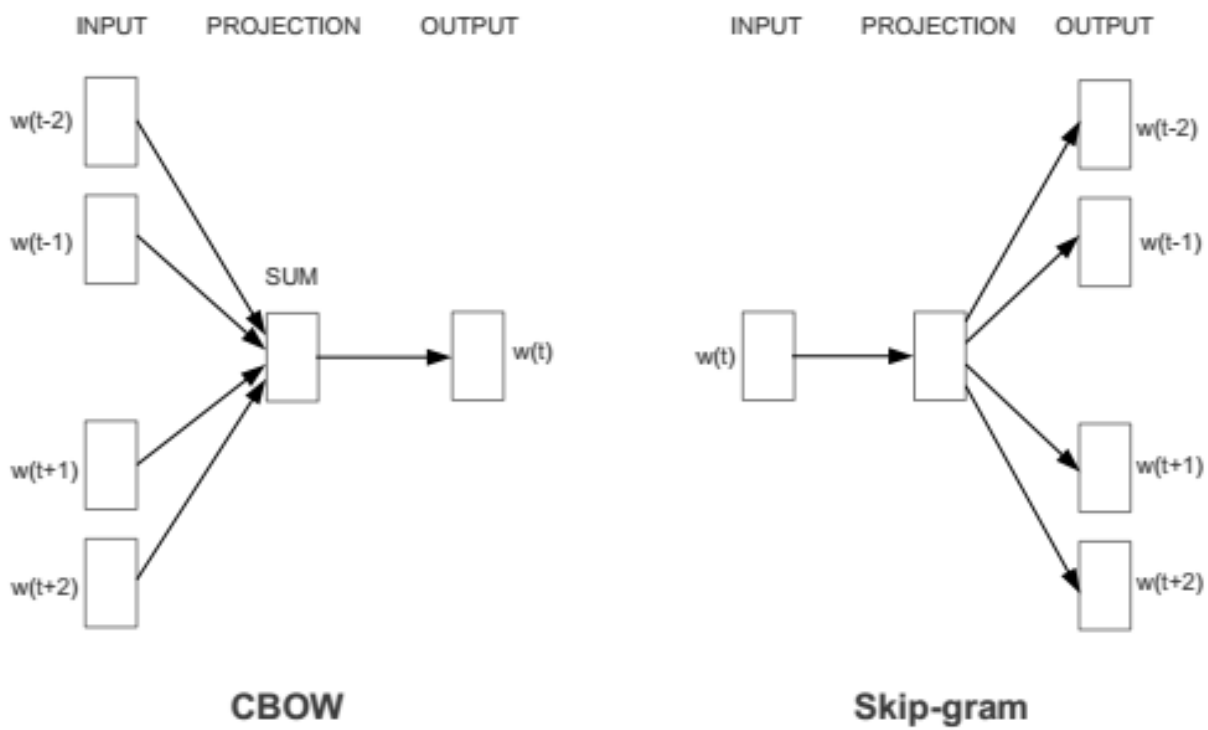
- The simplest NN-like model to learn word embedding

- Skip-gram: given the central word, predict surrounding words

- Continuous Bag-of-words (CBOW): given the surrounding words, predict the central word

$$\text{I}\ \overbrace{\text{am studying computer science in}}^{\text{window size = 2}}\ \text{UCSB .}$$

central word



Skip-gram

- Given the central word, predict surrounding words in a window of size c

- Objective function: Maximize the log probability of the surrounding words given the current central word:

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} \sum_{-c\leq j\leq c, j\neq 0} \log p(w_{t+j} | w_t)$$

Skip-gram

- Given the central word I, predict a surrounding word O

- Softmax: the simplest formulation for $p(O \mid I)$:

$$p(O \mid I) = \frac{\exp({v'_O}^T v_I)}{\sum_{w \in V} \exp({v'_w}^T v_I)}$$

- *v* and *v'* are the "input" and "output" vectors of words (each word has two vectors!)
- *V* is the whole vocabulary

Derivation of gradients

$$\log p(O \mid I) = v'^{T}_{O} v_I - \log\left(\sum_{w} \exp(v'^{T}_{w} v_I)\right)$$

Try to derive it by yourself!

1. Note that all *v*s are vectors
2. The chain rule is your good friend

$$\frac{\partial \log p(O \mid I)}{\partial v'_O} = v_I$$

$$\frac{\partial \log p(O \mid I)}{\partial v_I} = v'_O - \sum_{w} p(w \mid I) v'_w$$

Skip-gram naive implementation: step by step

Input: a text corpus, dimensionality k

Output: two k-dimensional vectors for each word

- Convert the corpus into a single string of words
- A single epoch: scan from the first word to the last word, for each window with central word I:
  - For each context word O, compute $\frac{\partial \log p(O \mid I)}{\partial v_I}$ and $\frac{\partial \log p(O \mid I)}{\partial v'_O}$
  - Update v_I and v'_O using stochastic gradient ascent
- Repeat the above step

Problem of the naive implementation

- With large vocabularies this objective function is not scalable and would train too slowly! → Why?

- Solutions: Approximate the normalization or

- Just sample a few negative words (not in context) to contrast with the positive word (in context)

- Will talk about them in the next lecture

Linguistic regularities in word vector space

- The resulting distributed representations of words contain surprisingly a lot of syntactic and semantic information

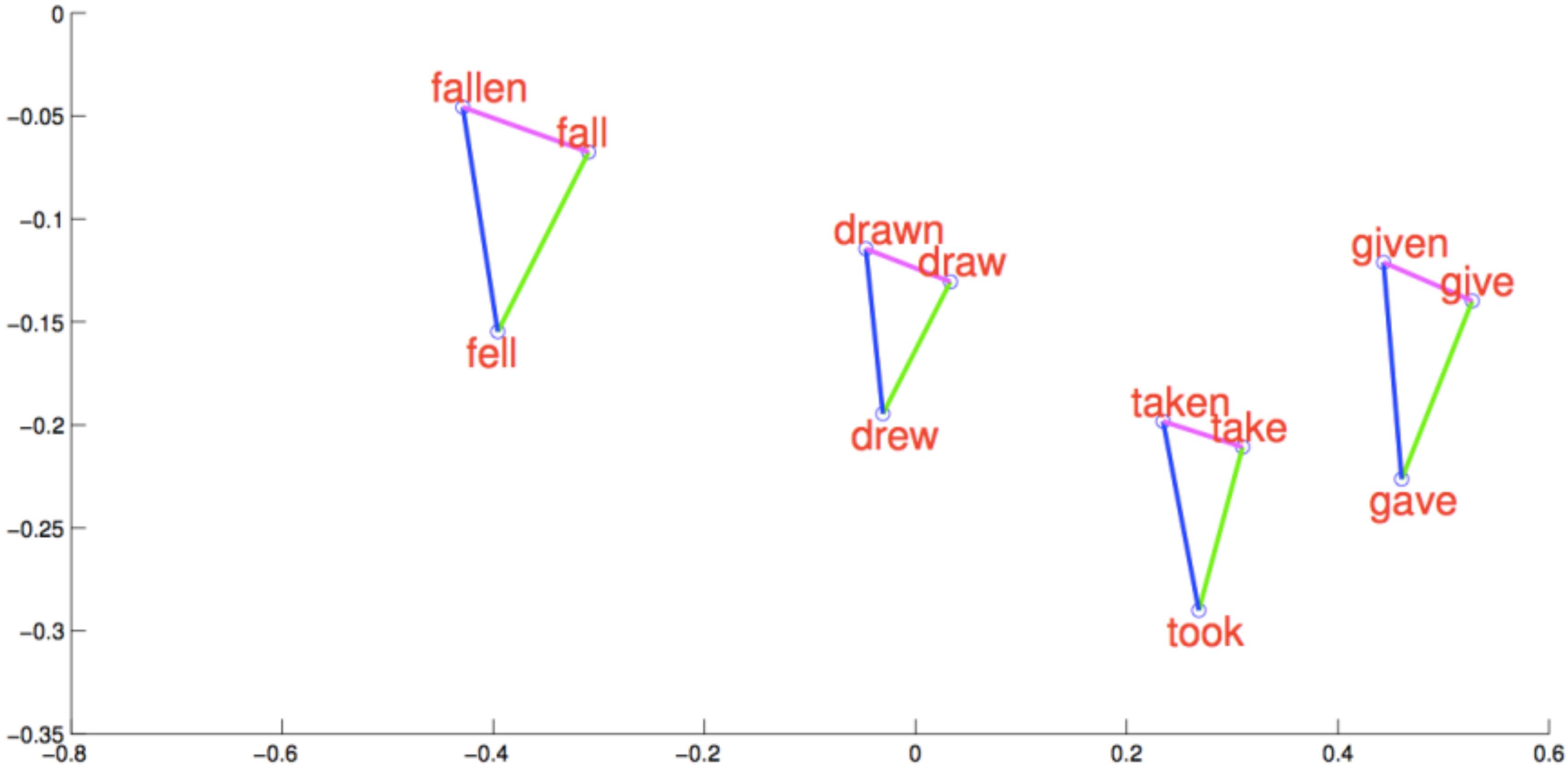
- There are multiple degrees of similarity among words:
  - **KING** is similar to **QUEEN** as **MAN** is similar to **WOMAN**
  - **KING** is similar to **KINGS** as **MAN** is similar to **MEN**

- Simple vector operations with the word vectors provide very intuitive results
  - $V_{KING} - V_{QUEEN} \approx V_{MAN} - V_{WOMAN}$
  - $V_{KING} - V_{KINGS} \approx V_{MAN} - V_{MEN}$

Linguistic regularities in word vector space

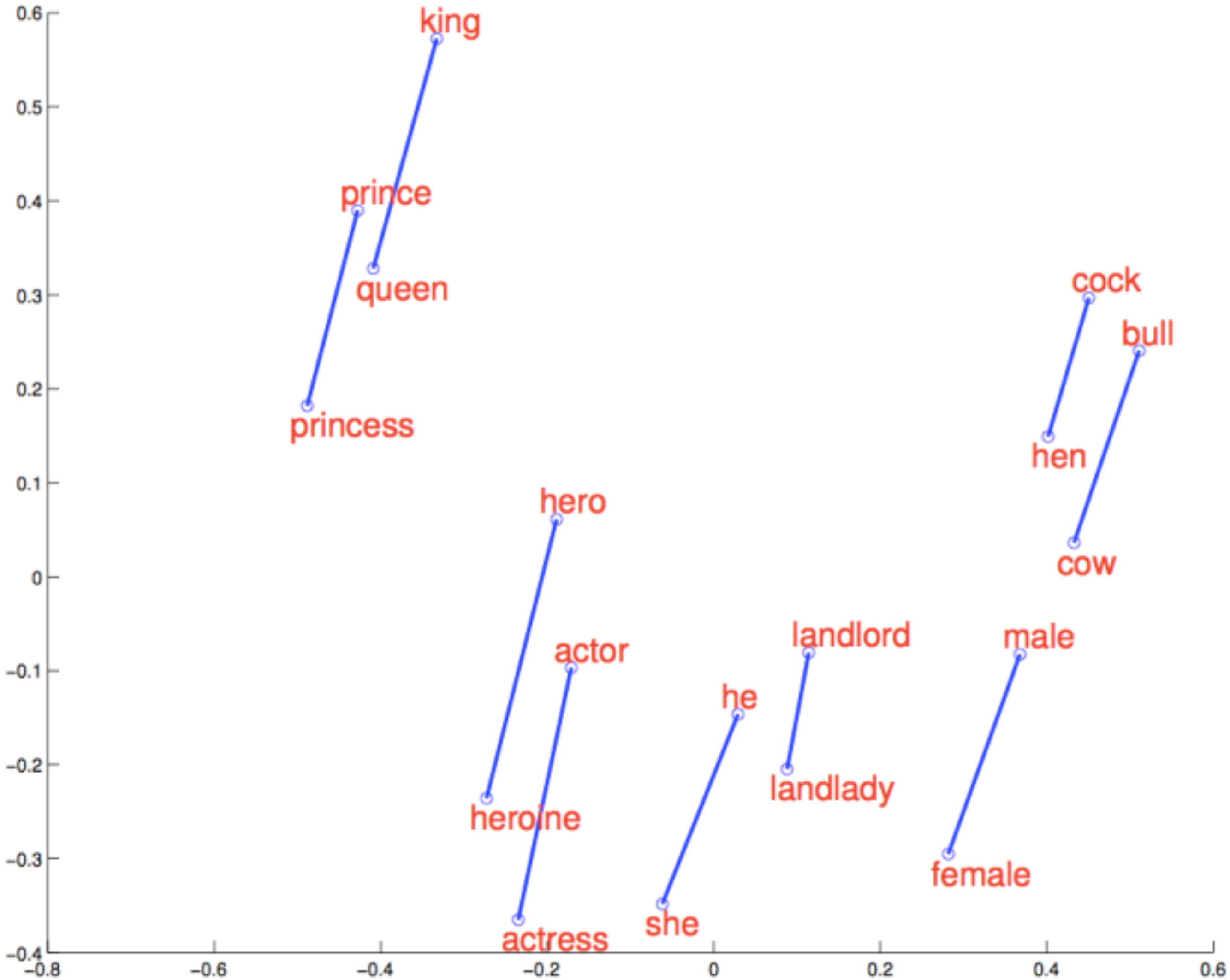
Expression	*Nearest token*
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadiens - Montreal + Toronto	Toronto Maple Leafs

Visualization of regularities in word vector space



generated by PCA

Visualization of regularities in word vector space



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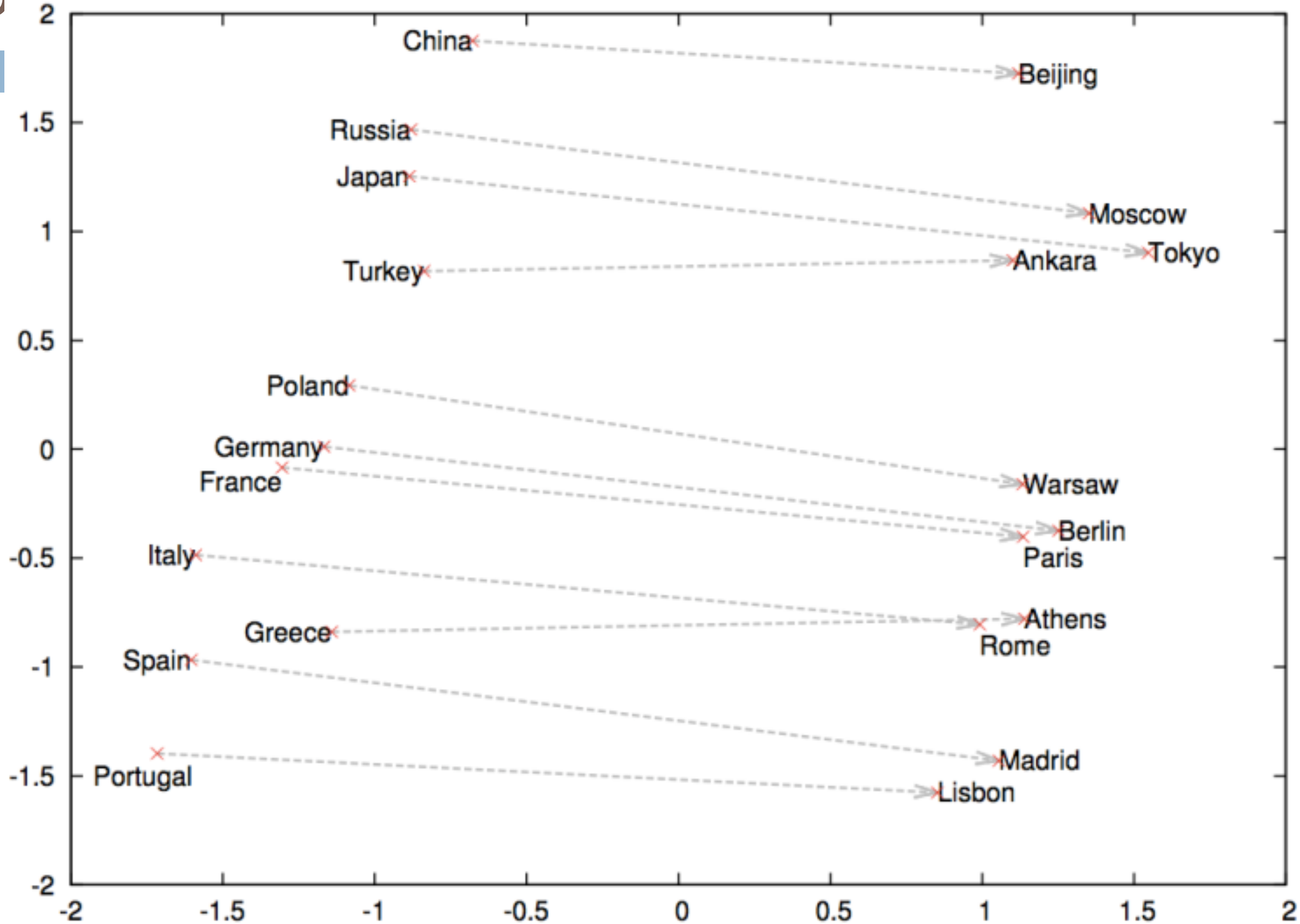
Visualization of regularities in word vector space



generated by PCA

Count based vs. prediction based

Count

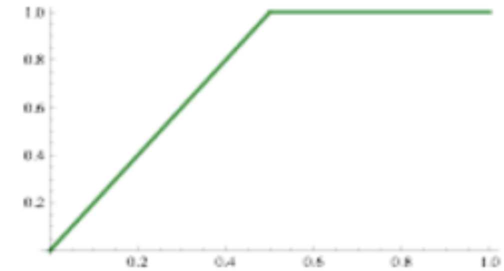
- Efficient usage of global statistics
- Primarily used to capture word similarity

Prediction

- Inefficient usage of global statistics
- Improved performance on other tasks
- Can capture richer relations between words

Combining the two worlds: GloVe (EMNLP'14)

$$J = \frac{1}{2}\sum_{ij} f(P_{ij})\left(w_i \cdot \tilde{w}_j - \log P_{ij}\right)^2 \qquad f \sim$$



- P_{ij} is the number of co-occurrences of word i and word j
- f is just a weighting function
- Fast training: $\sim O(|C|^{0.8})$, $|C|$ is the corpus size
- Scalable to huge corpora (840 billion words)

Glove results

Nearest words to
frog:

1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus

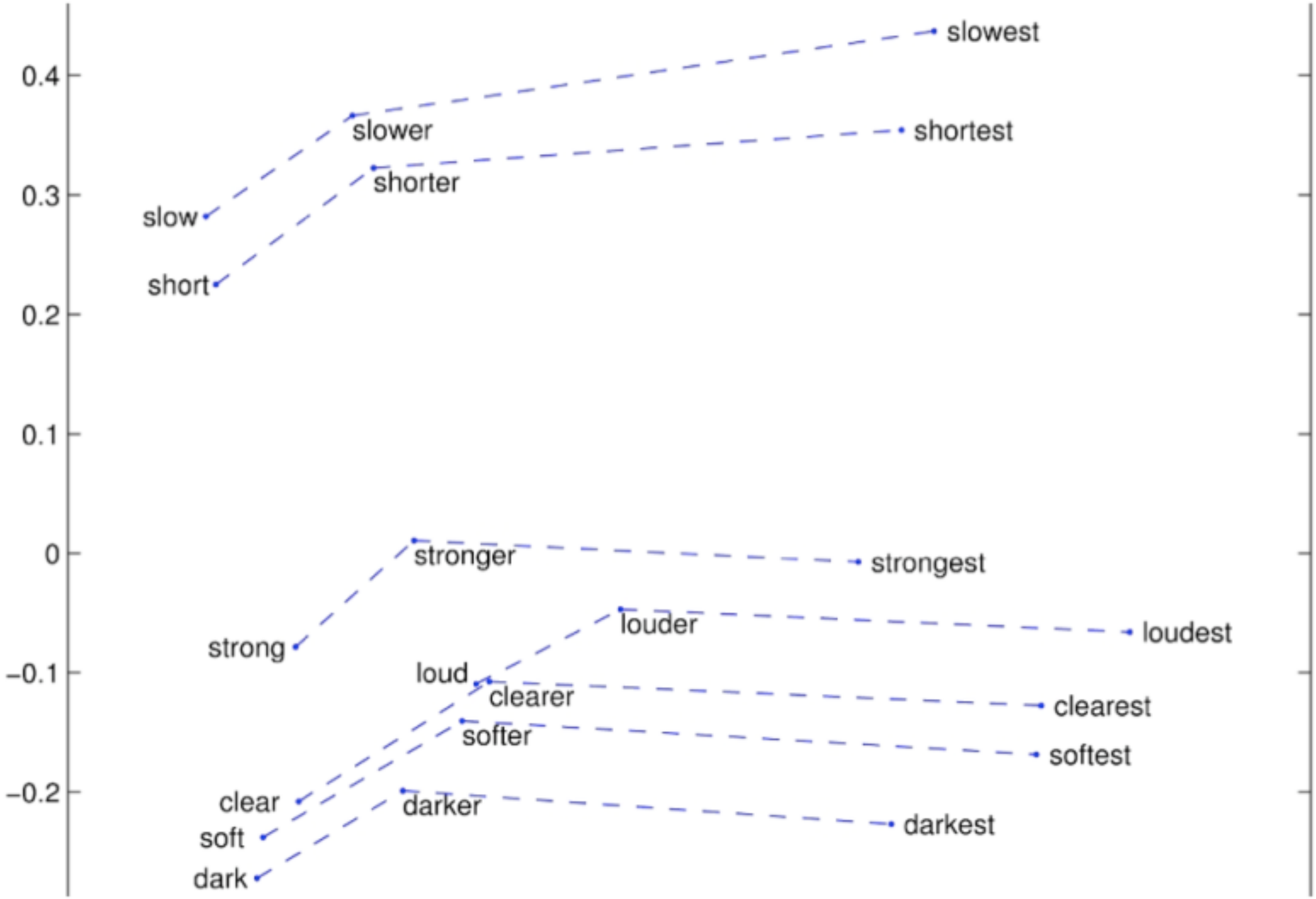
litoria

leptodactylidae

rana

eleutherodactylus

Glove results



Resources

- Word2vec: https://code.google.com/p/word2vec/
  - including codes, training/testing sets and pre-trained vectors

- Glove: http://nlp.stanford.edu/projects/glove/
  - including codes, training/testing sets and pre-trained vectors

- Dimensionality reduction:
  - Tapkee for C++: http://jmlr.org/papers/v14/lisitsyn13a.html
  - Scikit-learn for Python: http://scikit-learn.org/stable/