CS11-747 Neural Networks for NLP

Models of Words

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Site

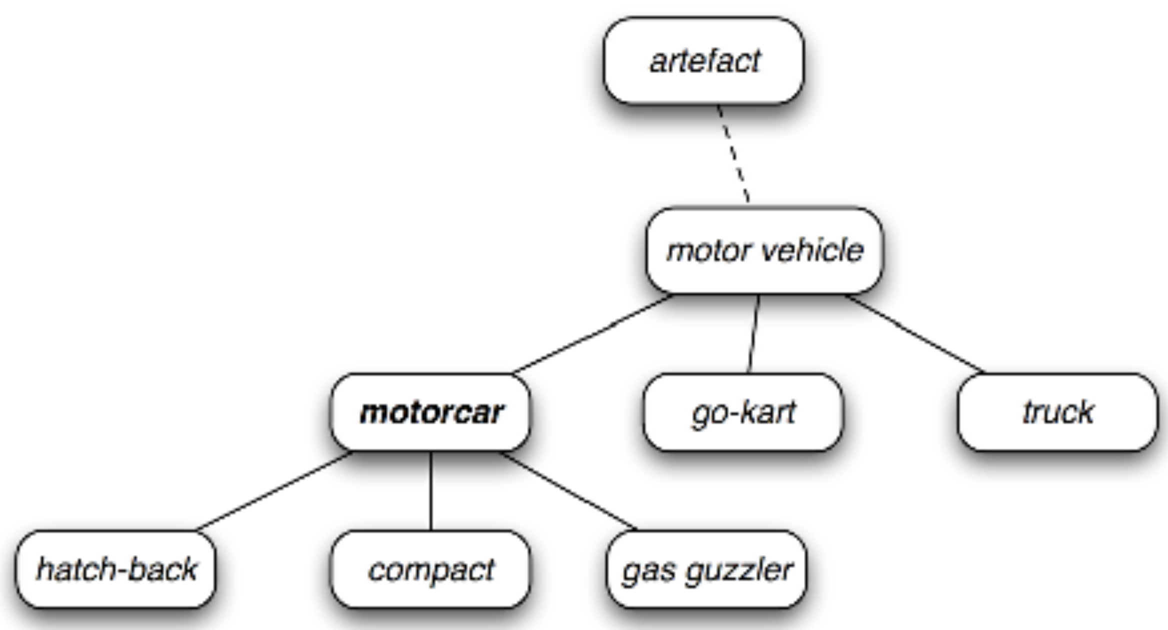
https://phontron.com/class/nn4nlp2017/

What do we want to know about words?

- Are they the same part of speech?
- Do they have the same conjugation?
- Do these two words mean the same thing?
- Do they have some semantic relation (is-a, part-of, went-to-school-at)?

A Manual Attempt: WordNet

- WordNet is a large database of words including parts of speech, semantic relations



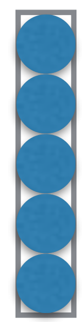
- Major effort to develop, projects in many languages.

- But can we do something similar, more complete, and without the effort?

Image Credit: NLTK

An Answer (?): Word Embeddings!

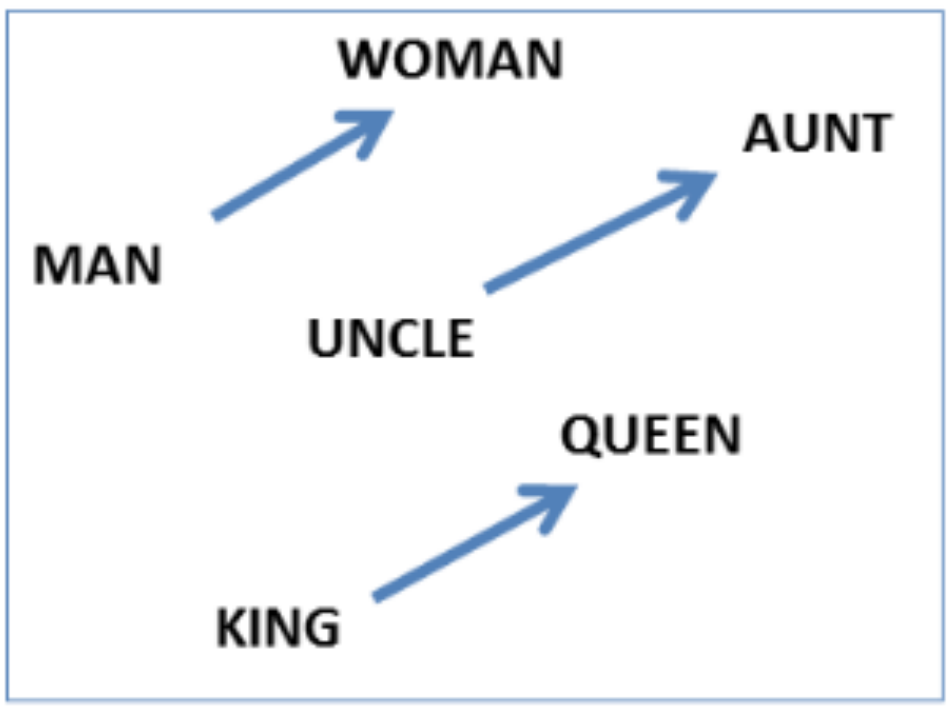
- A continuous vector representation of words

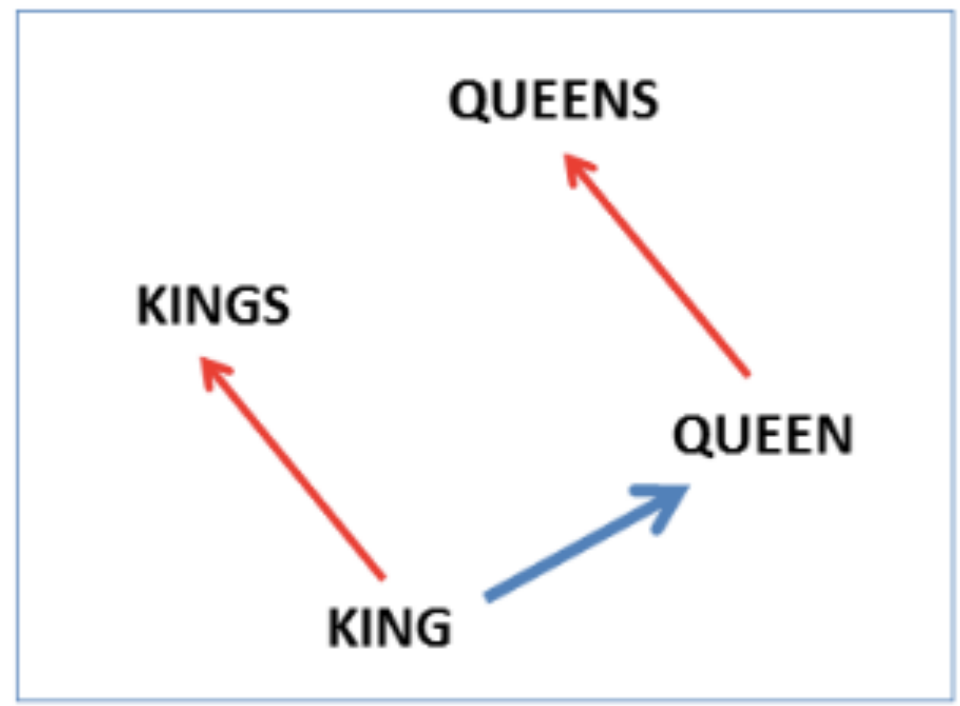


- Within the word embedding, these features of syntax and semantics may be included
  - Element 1 might be **more positive for nouns**
  - Element 2 might be **positive for animate objects**
  - Element 3 might have **no intuitive meaning whatsoever**

Word Embeddings are Cool!
(An Obligatory Slide)

- e.g. king-man+woman = queen (Mikolov et al. 2013)





- “What is the female equivalent of king?” is not easily accessible in many traditional resources

How to Train Word Embeddings?

- **Initialize randomly**, train jointly with the task
- Pre-train on a **supervised** task (e.g. POS tagging) and test on another, (e.g. parsing)
- Pre-train on an **unsupervised** task (e.g. `word2vec`)

Unsupervised Pre-training of Word Embeddings

(Summary of Goldberg 10.4)

Distributional vs. *Distributed* Representations

- **Distributional representations**
  - Words are similar if they appear in similar contexts (Harris 1954); distribution of words indicative of usage
  - In contrast: *non-distributional* representations created from lexical resources such as WordNet, etc.
- **Distributed representations**
  - Basically, something is represented by a vector of values, each representing activations
  - In contrast: *local* representations, where represented by a discrete symbol (one-hot vector)

Distributional Representations

(see Goldberg 10.4.1)

- Words appear in a context

<s>	<s>	<unk>	communications	pittsburgh	acquired	<unk>	&	co.
investment	managemen	inc.	a	pittsburgh	firm	that	runs	a
<s>	mr.	allen	's	pittsburgh	firm	advanced	investment	management
look	stupid	<unk>	former	pittsburgh	<unk>	second	<unk>	<unk>
through	the	university	of	pittsburgh	law	school	<s>	<s>
with	the	university	of	pittsburgh	<s>	<s>	<s>	<s>
<unk>	he	heads	the	pittsburgh	branch	of	the	committee
at	the	university	of	pittsburgh	earn	up	to	$

for	society	corp.	a	cleveland	bank	said	demand	for
as	washington	<unk>	r.i.	cleveland	<unk>	n.c.	minneapolis	and
<s>	<s>	<unk>	a	cleveland	merchant	bank	owns	about
new	stadiums	ranging	from	cleveland	to	san	antonio	and
<s>	the	philadelphia	and	cleveland	districts	for	example	reported
mcdonald	&	co.	in	cleveland	said	<unk>	's	unanticipated
<unk>	tumor	at	the	cleveland	clinic	in	N	<s>
at	mcdonald	&	co.	cleveland	<s>	<s>	<s>	<s>

(try it yourself w/ `kwic.py`)

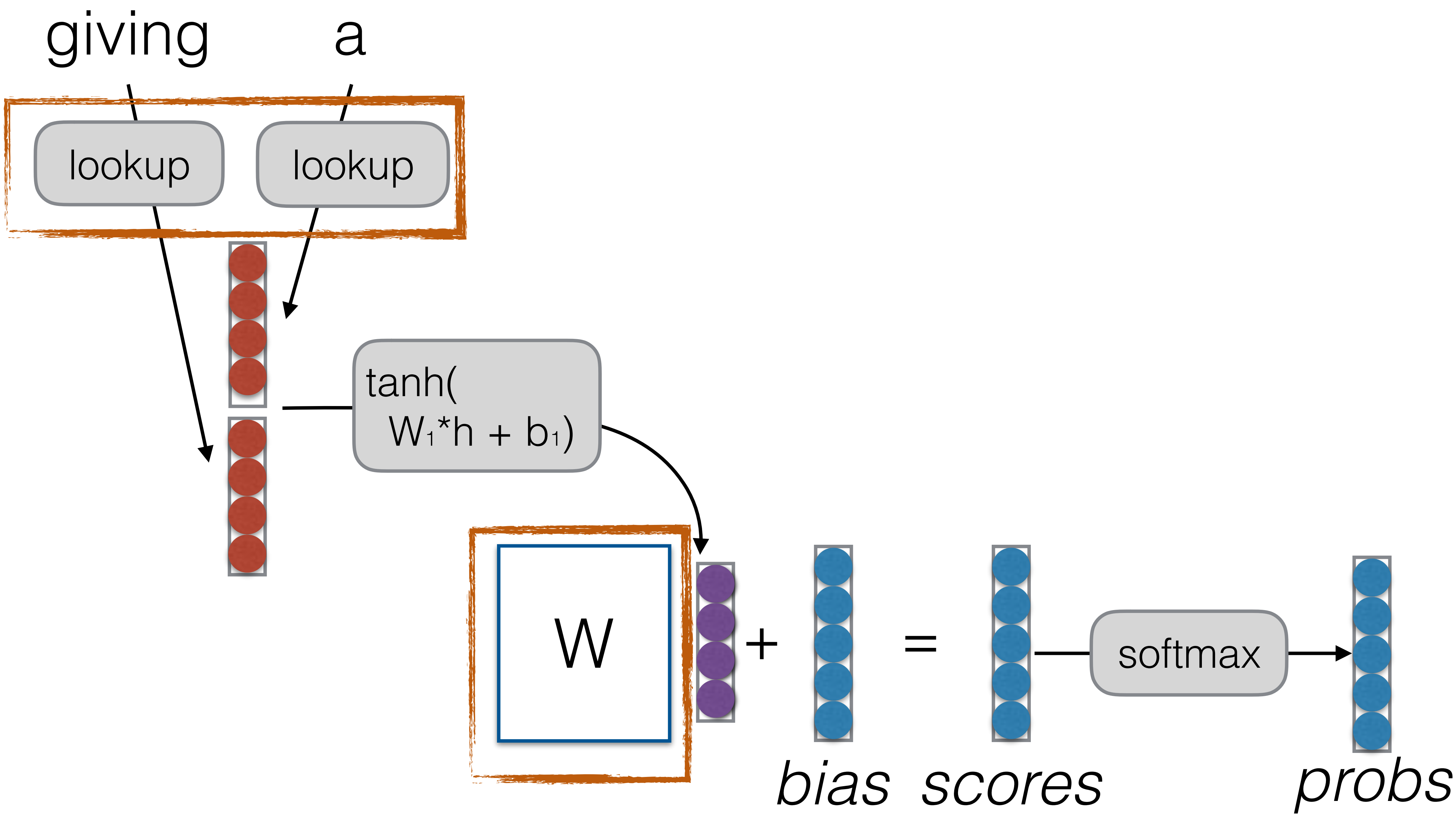
Count-based Methods

- Create a word-context count matrix
  - **Count** the number of co-occurrences of word/context, with rows as word, columns as contexts
  - Maybe **weight** with pointwise mutual information
  - Maybe **reduce dimensions** using SVD
- **Measure their closeness** using cosine similarity (or generalized Jaccard similarity, others)

Prediction-basd Methods
(See Goldberg 10.4.2)

- Instead, try to **predict** the words within a neural network
- Word embeddings are the byproduct

Word Embeddings from Language Models

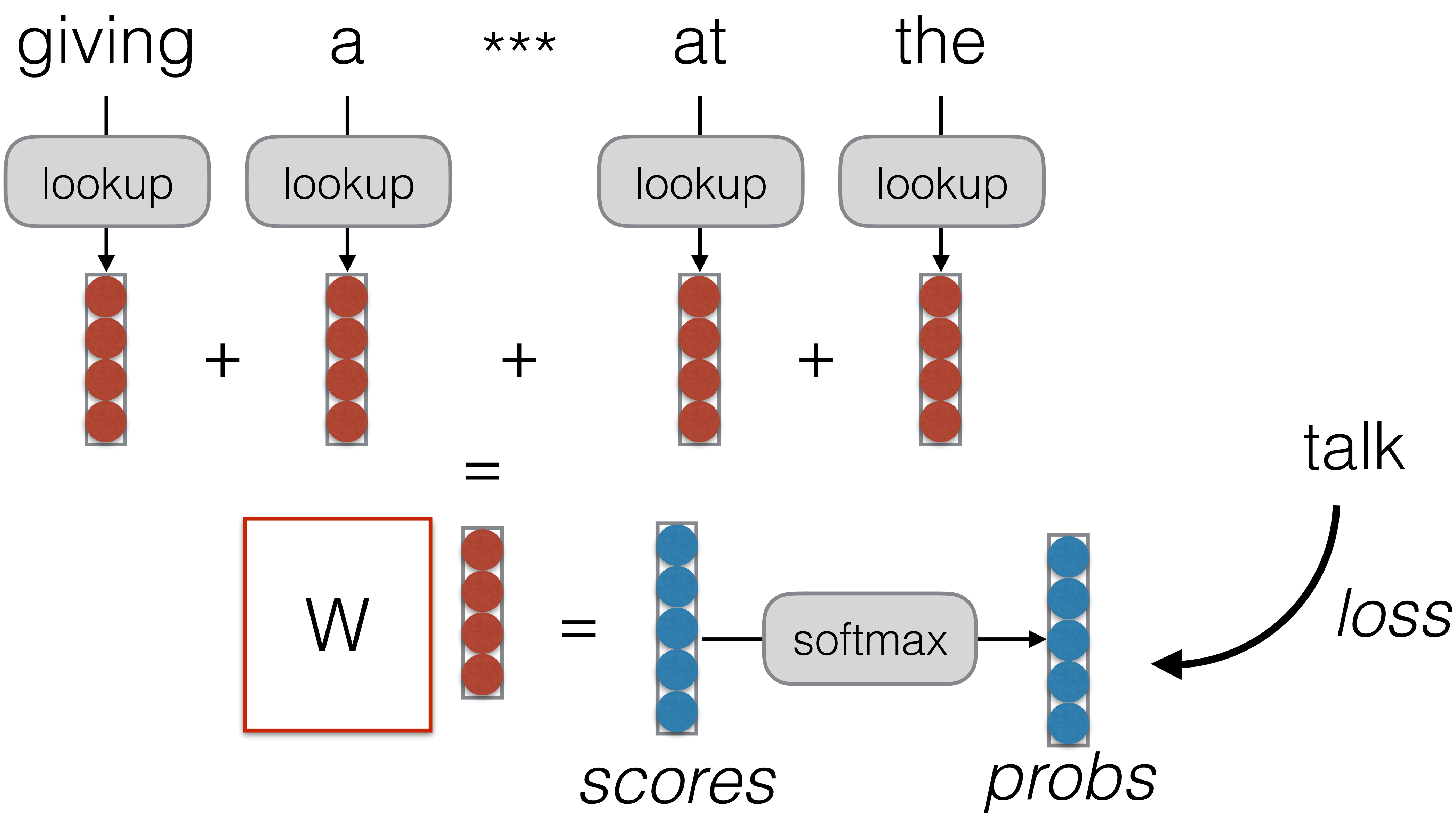


Context Window Methods

- If we don’t need to calculate the probability of the sentence, other methods possible!
- These can move **closer to the contexts used in count-based methods**
- These drive word2vec, etc.

CBOW
(Mikolov et al. 2013)

- Predict word based on sum of surrounding embeddings

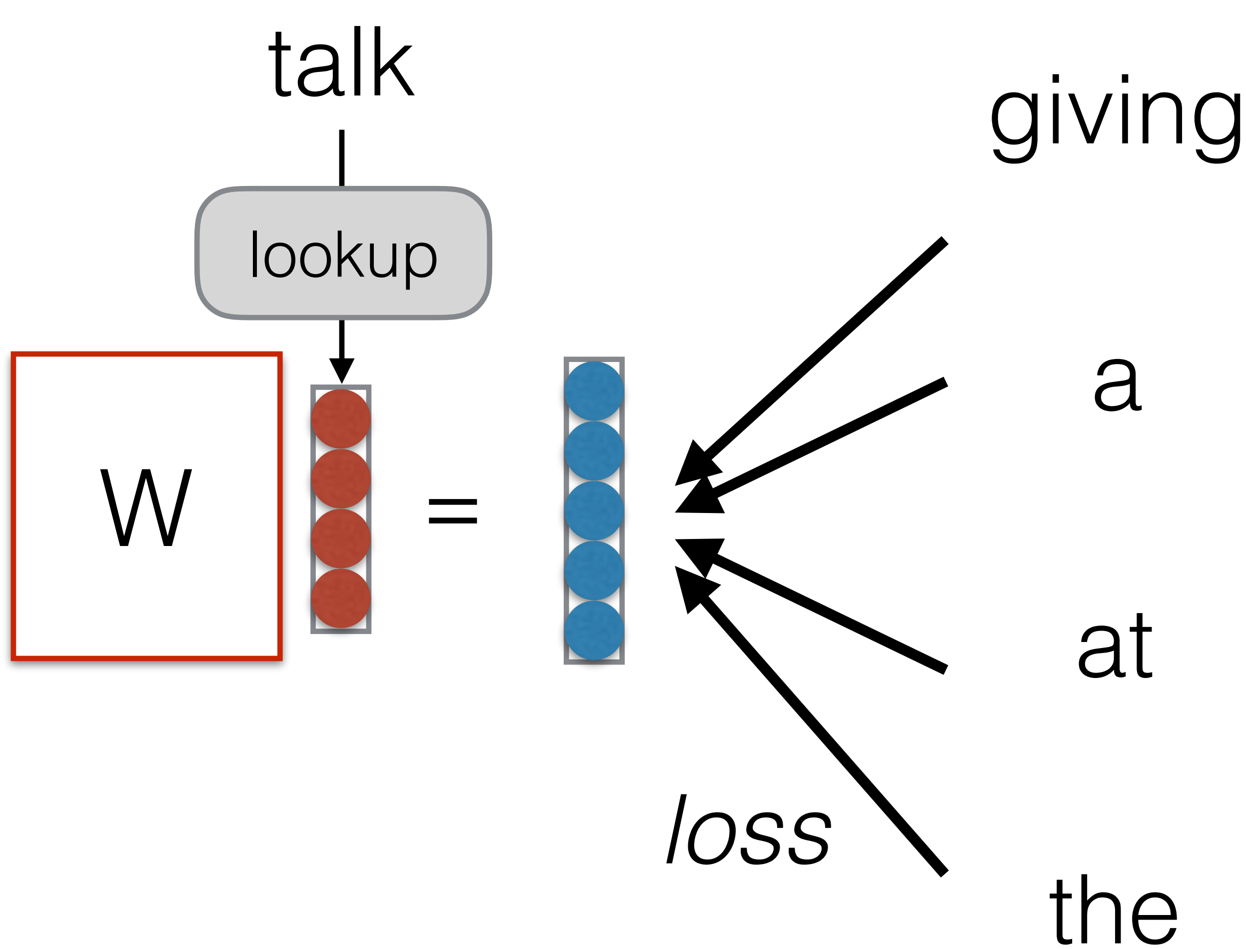


Let’s Try it Out!

`wordemb-cbow.py`

Skip-gram
(Mikolov et al. 2013)

- Predict each word in the context given the word



Let’s Try it Out!

`wordemb-skipgram.py`

Other Notes

- Strong connection between count-based methods and prediction-based methods (Levy and Goldberg 2014)
    - Skip-gram objective is equivalent to matrix factorization with PMI and discount for number of samples *k* (sampling covered next time)

$$M_{w,c} = \mathrm{PMI}(w, c) - \log(k)$$

- Other estimation methods: GloVe (Pennington et al. 2014), etc.

What Contexts?

- Context has a large effect!
- **Small context window:** more syntax-based embeddings
- **Large context window:** more semantics-based, topical embeddings
- **Context based on syntax:** more functional, w/ words with same inflection grouped

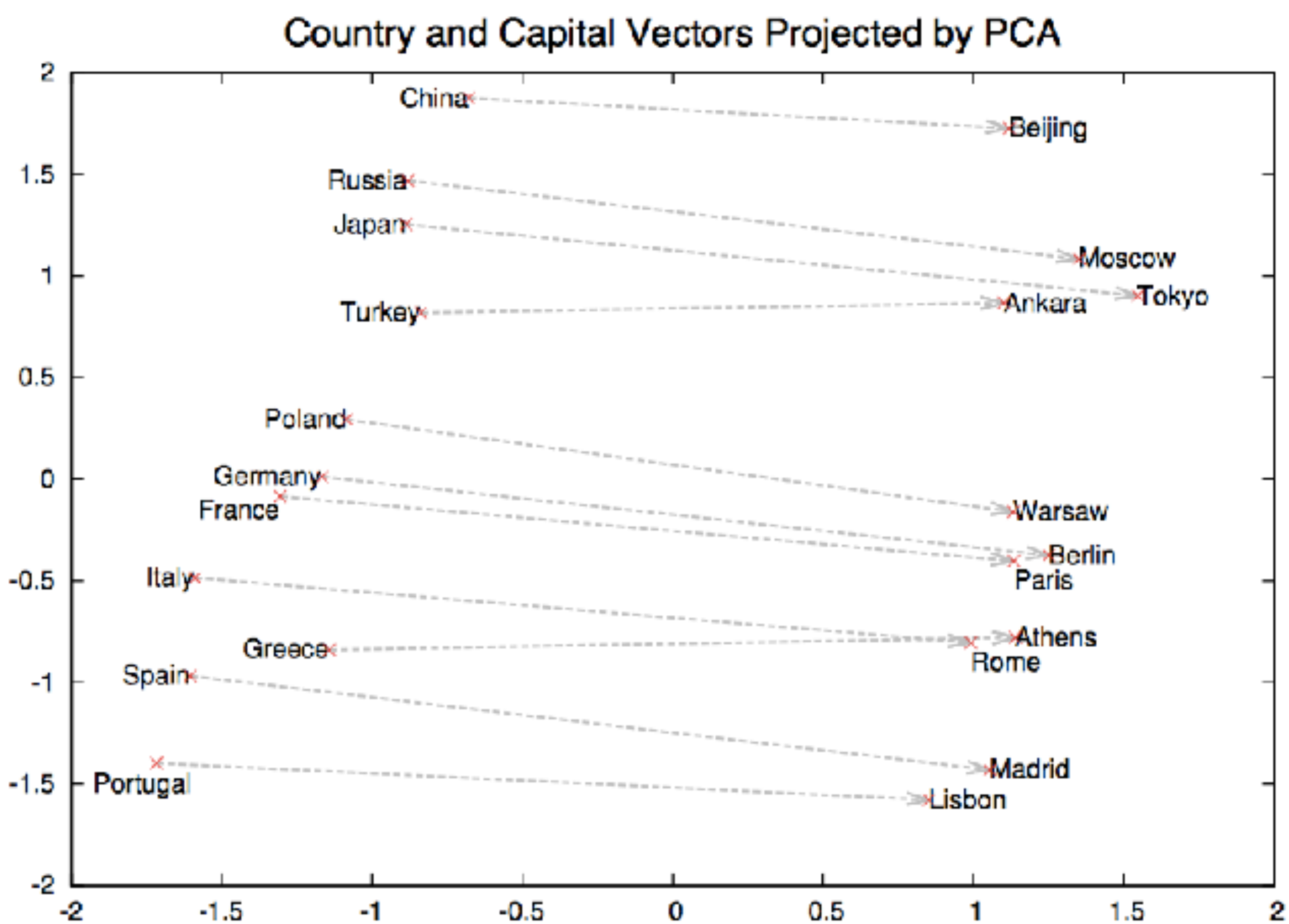
Evaluating Embeddings

Types of Evaluation

- Intrinsic vs. Extrinsic
  - **Intrinsic:** How good is it based on its features?
  - **Extrinsic:** How useful is it downstream?
- Qualitative vs. Quantitative
  - **Qualitative:** Examine the characteristics of examples.
  - **Quantitative:** Calculate statistics

Visualization of Embeddings

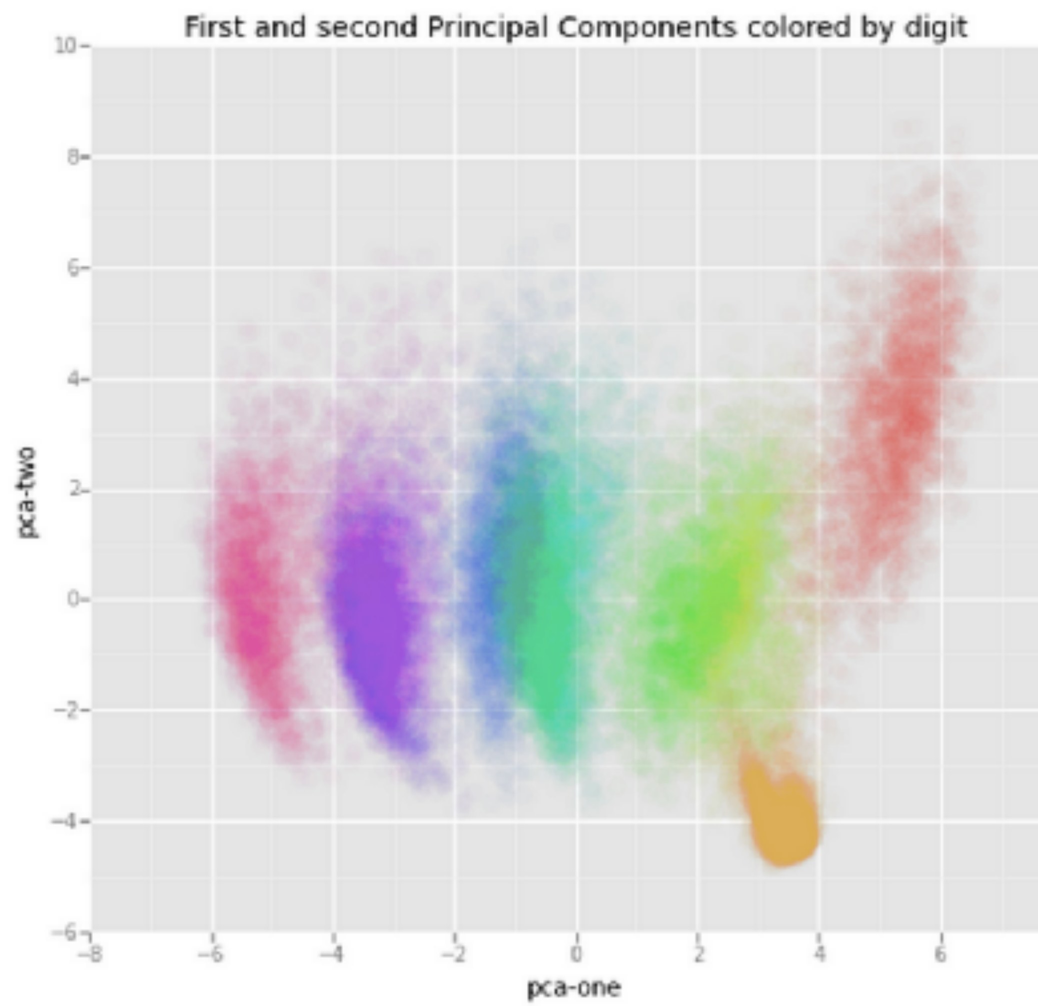
- Reduce high-dimensional embeddings into 2/3D for visualization (e.g. Mikolov et al. 2013)

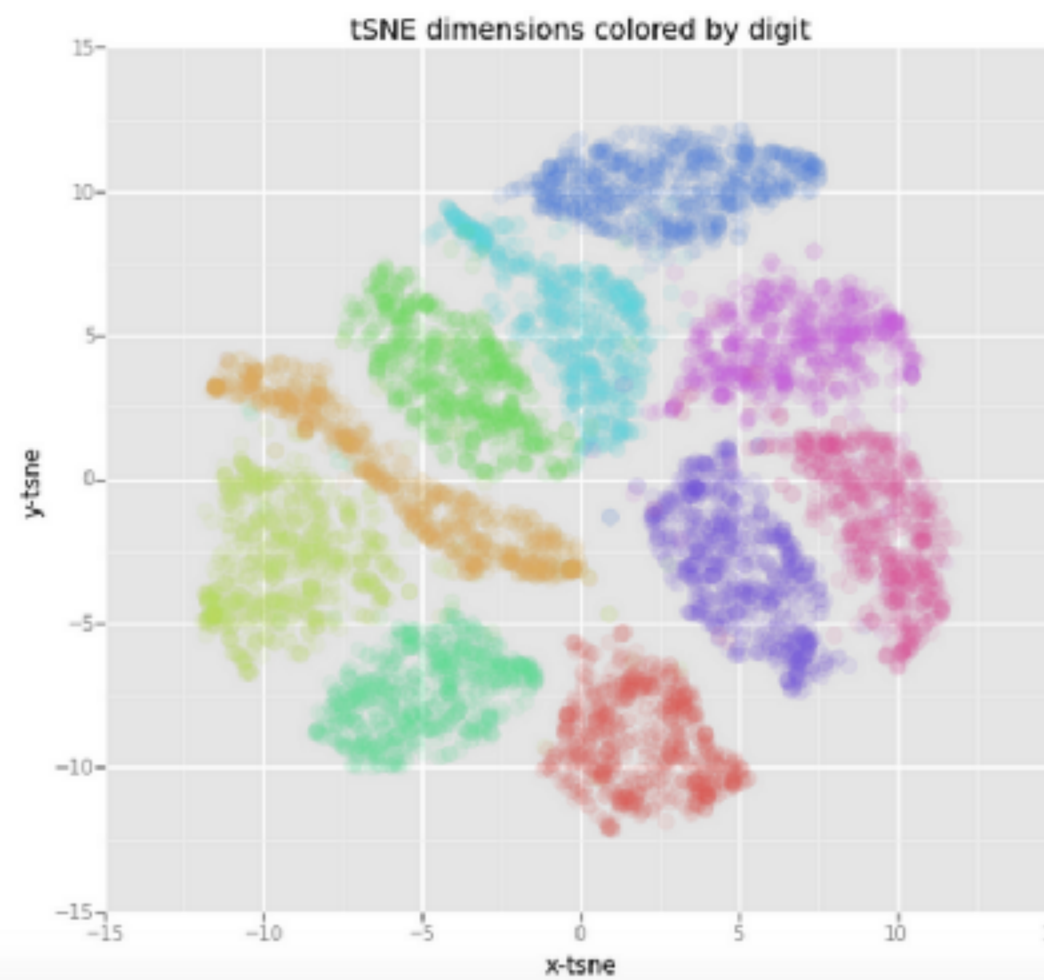


Non-linear Projection

- Non-linear projections group things that are close in high-dimensional space
- e.g. SNE/t-SNE (van der Maaten and Hinton 2008) group things that give each other a high probability according to a Gaussian

PCA





t-SNE

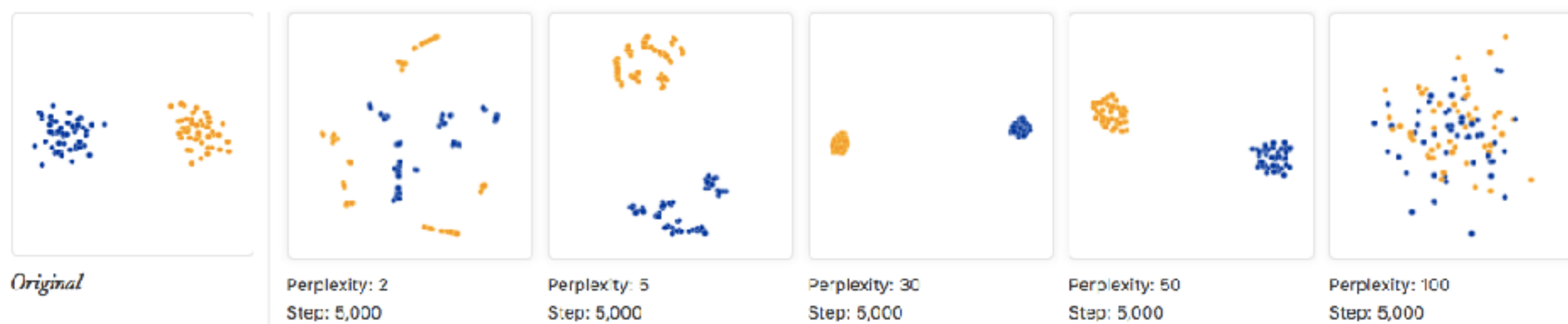
(Image credit: Derksen 2016)

Let’s Try it Out!

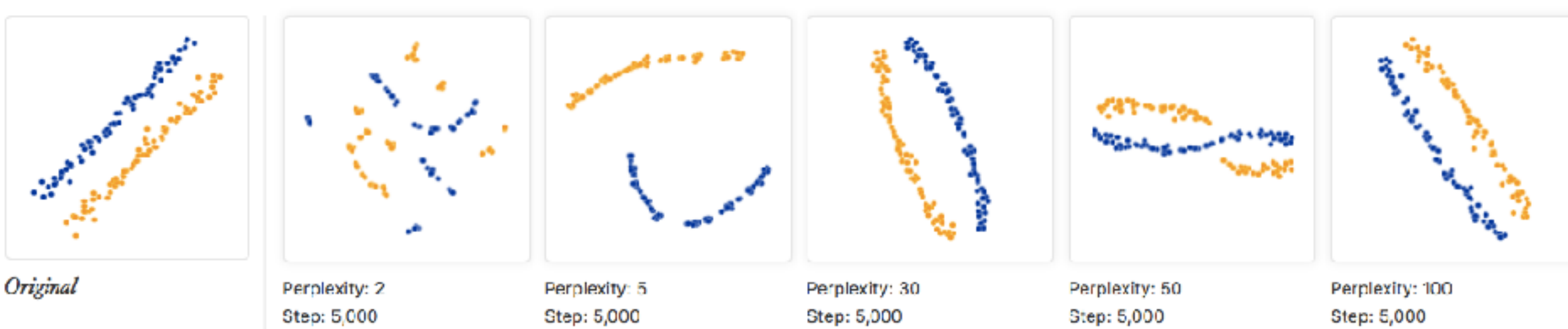
`wordemb-vis-tsne.py`

t-SNE Visualization can be Misleading! (Wattenberg et al. 2016)

- Settings matter



- Linear correlations cannot be interpreted



Intrinsic Evaluation of Embeddings

(categorization from Schnabel et al 2015)

- **Relatedness:** The correlation btw. embedding cosine similarity and human eval of similarity?
- **Analogy:** Find x for "*a is to b, as x is to y*".
- **Categorization:** Create clusters based on the embeddings, and measure purity of clusters.
- **Selectional Preference:** Determine whether a noun is a typical argument of a verb.

Extrinsic Evaluation: Using Word Embeddings in Systems

- **Initialize** w/ the embeddings
- **Concatenate** pre-trained embeddings with learned embeddings
- Latter has the potential to provide better generalization, but

How Do I Choose Embeddings?

- No one-size-fits-all embedding (Schnabel et al 2015)

	relatedness						categorization			sel. prefs		analogy			
	rg	ws	wss	wsr	men	toefl	ap	esslli	batt.	up	mcrae	an	ansyn	ansem	average
CBOW	**74.0**	**64.0**	**71.5**	**56.5**	**70.7**	66.7	**65.9**	**70.5**	**85.2**	24.1	13.9	**52.2**	**47.8**	**57.6**	**58.6**
GloVe	63.7	54.8	65.8	49.6	64.6	**69.4**	64.1	65.9	77.8	27.0	**18.4**	42.2	44.2	39.7	53.4
TSCCA	57.8	54.4	64.7	43.3	56.7	58.3	57.5	**70.5**	64.2	**31.0**	14.				
C&W	48.1	49.8	60.7	40.1	57.5	66.7	60.6	61.4	80.2	28.3	16.				
H-PCA	19.8	32.9	43.6	15.1	21.3	54.2	34.1	50.0	42.0	-2.5	3.				
Rand. Proj.	17.1	19.5	24.9	16.1	11.3	51.4	21.9	38.6	29.6	-8.5	1.				

Table 1: Results on absolute intrinsic evaluation. The best result for each
The second row contains the names of the corresponding datasets.

	dev	test	p-value
Baseline	94.18	93.78	0.000
Rand. Proj.	94.33	93.90	0.006
GloVe	94.28	93.93	0.015
H-PCA	94.48	93.96	0.029
C&W	**94.53**	**94.12**	
CBOW	94.32	93.93	0.012
TSCCA	**94.53**	94.09	0.357

Table 4: F1 chunking results using different word embeddings as features. The p-values are with respect to the best performing method.

- Be aware, and use the best one for the task

When are Pre-trained Embeddings Useful?

- Basically, when training data is insufficient
- **Very useful:** tagging, parsing, text classification
- **Less useful:** machine translation
- **Basically not useful:** language modeling

Improving Embeddings

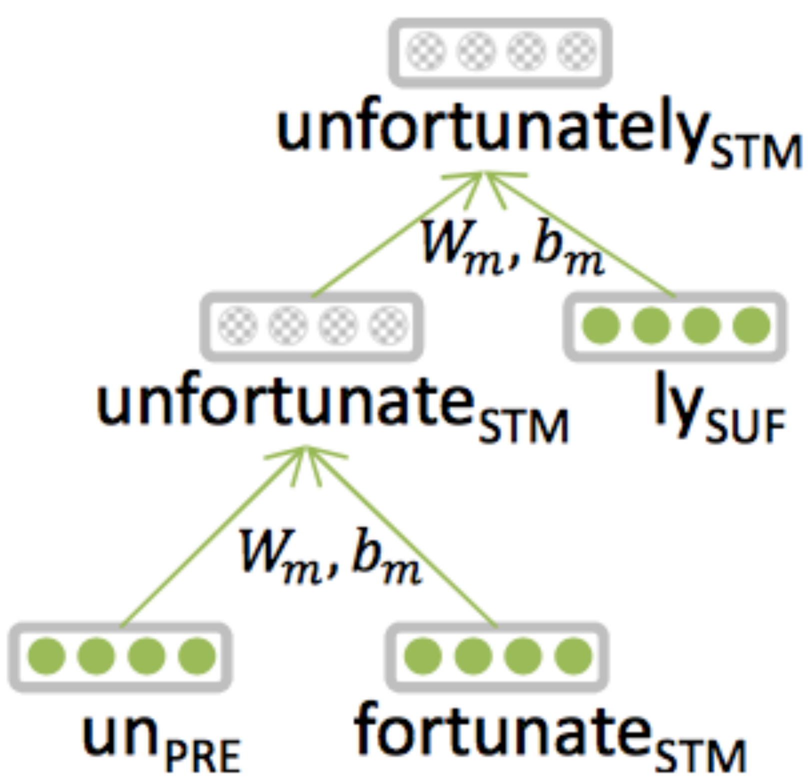
Limitations of Embeddings

- Sensitive to **superficial differences** (dog/dogs)
- **Insensitive to context** (financial bank, bank of a river)
- **Not necessarily coordinated** with knowledge or across languages
- **Not interpretable**
- Can **encode bias** (encode stereotypical gender roles, racial biases)

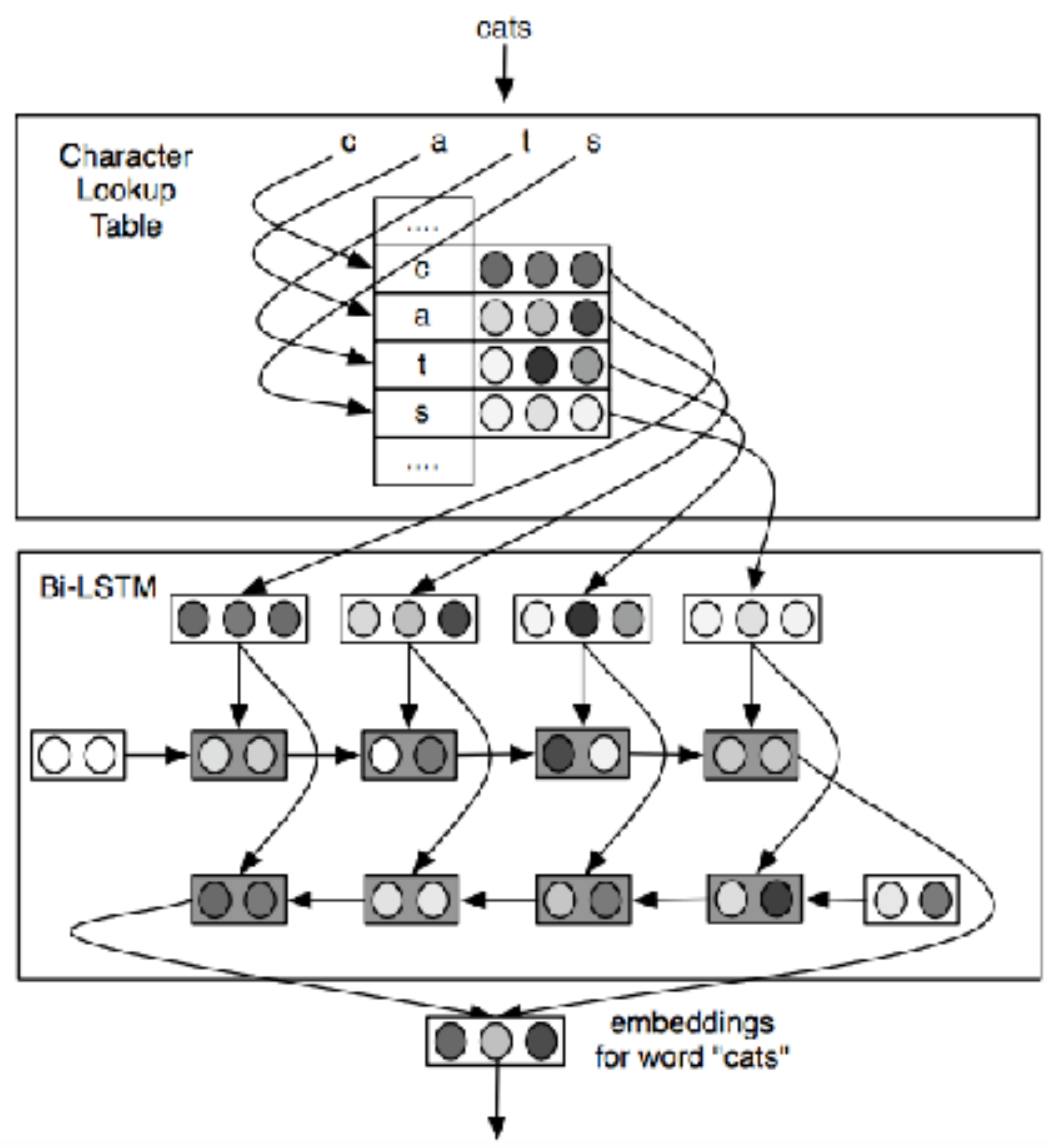
Sub-word Embeddings (1)

- Can capture sub-word regularities

<u>Morpheme-based (Luong et al. 2013)</u>



<u>Character-based (Ling et al. 2015)</u>



Sub-word Embeddings (2)

- **Bag of character n-grams** used to represent word (Bojanowski et al. 2017)

where

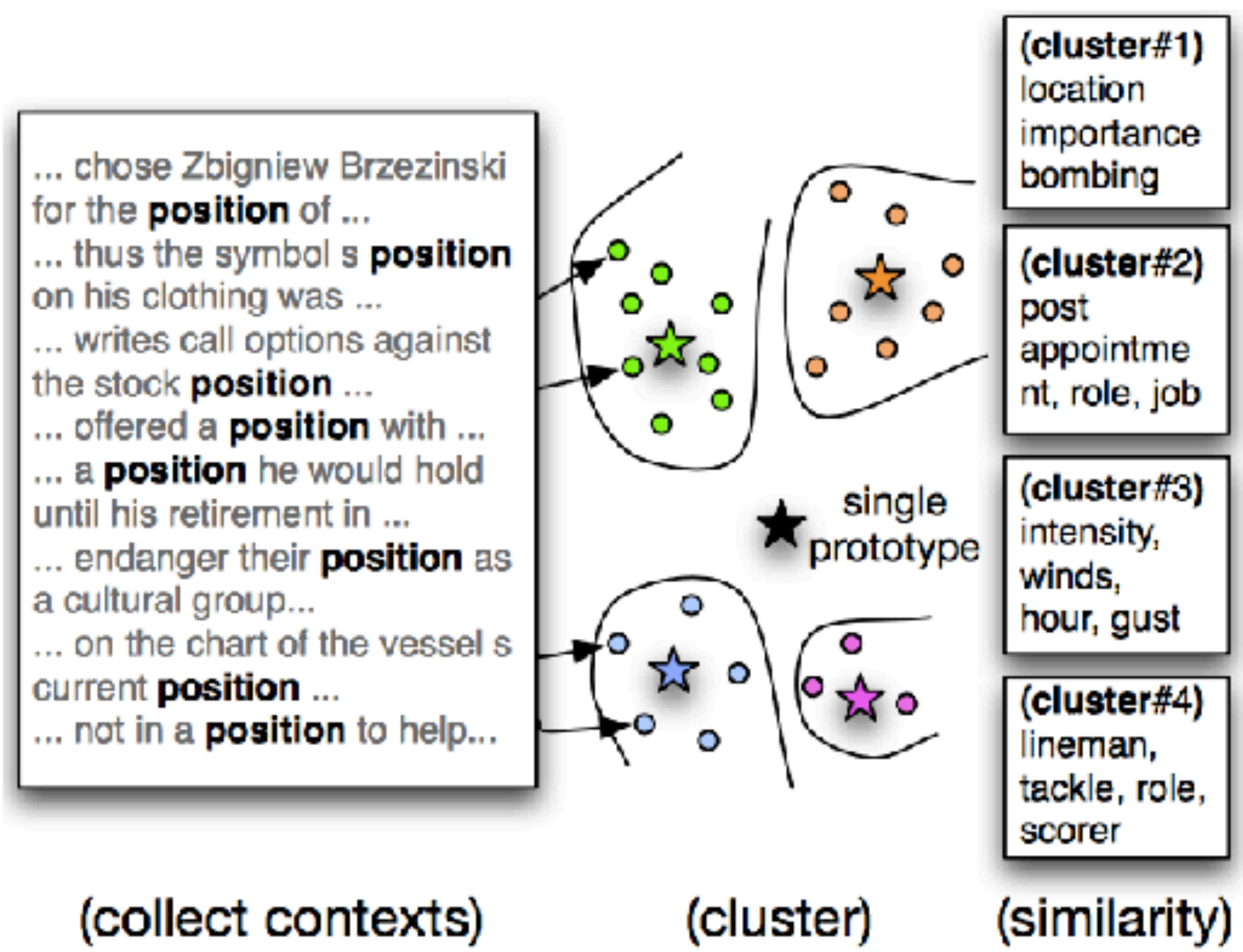
<wh, whe, her, ere, re>

- Use n-grams from 3-6 plus word itself

- Used in the “fasttext” toolkit

Multi-prototype Embeddings

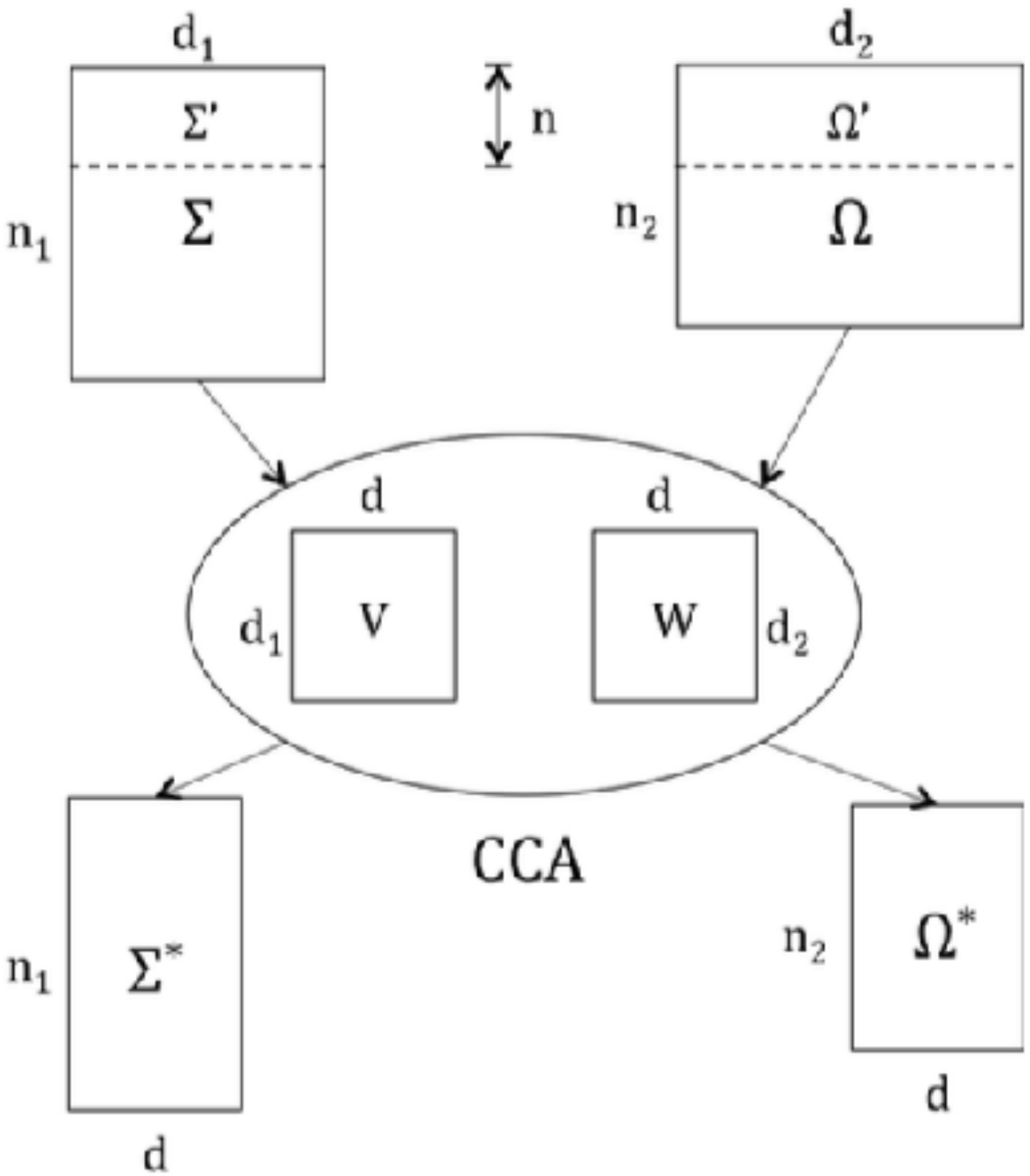
- Simple idea, words with multiple meanings should have different embeddings (Reisinger and Mooney 2010)

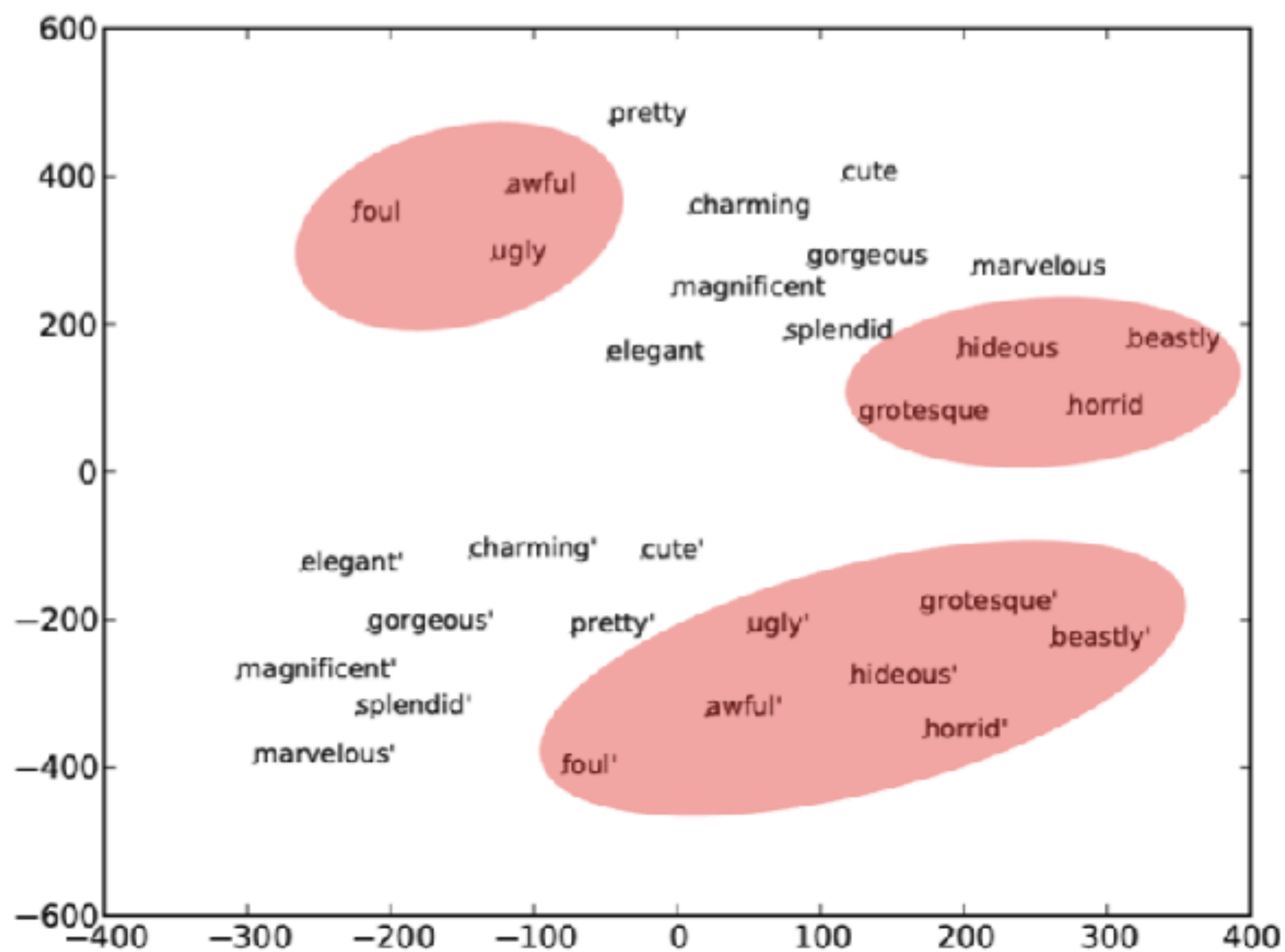


- Non-parametric estimation (Neelakantan et al. 2014) also possible

Multilingual Coordination of Embeddings (Faruqui et al. 2014)

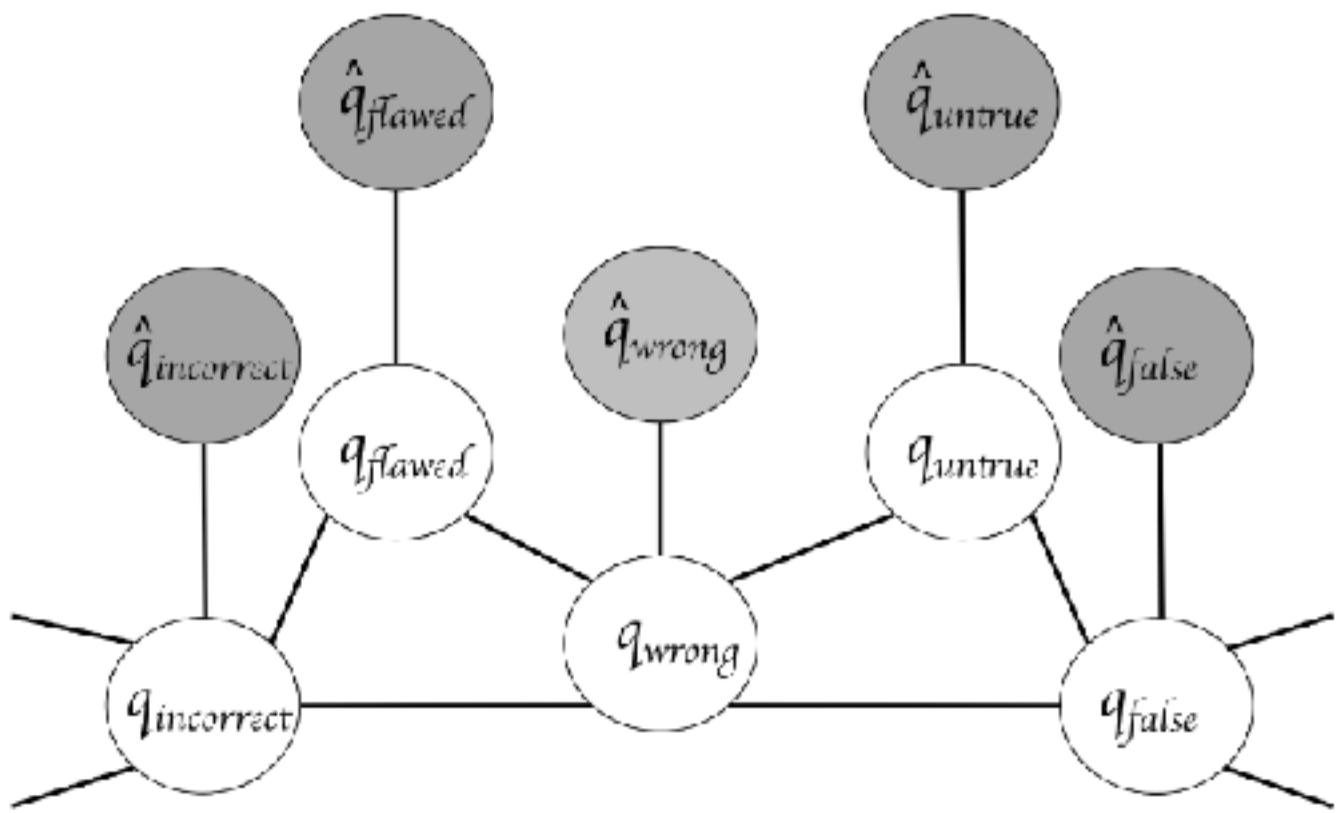
- We have word embeddings in two languages, and want them to match





Retrofitting of Embeddings to Existing Lexicons

- We have an existing lexicon like WordNet, and would like our vectors to match (Faruqui et al. 2015)



Sparse Embeddings

- Each dimension of a word embedding is not interpretable
- Solution: add a sparsity constraint to increase the information content of non-zero dimensions for each word (e.g. Murphy et al. 2012)

Model	Top 5 Words (per dimension)
SVD_{300}	well, long, if, year, watch
	plan, engine, e, rock, very
	get, no, features, music, via
	features, by, links, free, down
	works, sound, video, building, section
$NNSE_{1000}$	inhibitor, inhibitors, antagonists, receptors, inhibition
	bristol, thames, southampton, brighton, poole
	delhi, india, bombay, chennai, madras
	pundits, forecasters, proponents, commentators, observers
	nosy, averse, leery, unsympathetic, snotty

De-biasing Word Embeddings (Bolukbasi et al. 2016)

- Word embeddings reflect bias in statistics

Extreme *she*	**Extreme *he***
1. homemaker	1. maestro
2. nurse	2. skipper
3. receptionist	3. protege
4. librarian	4. philosopher
5. socialite	5. captain
6. hairdresser	6. architect
7. nanny	7. financier
8. bookkeeper	8. warrior
9. stylist	9. broadcaster
10. housekeeper	10. magician

Gender stereotype *she-he* analogies

sewing-carpentry	registered nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	lovely-brilliant

Gender appropriate *she-he* analogies

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

- Identify pairs to "neutralize", find the direction of the trait to neutralize, and ensure that they are neutral in that direction

Questions?