

Sequencing Legal DNA

NLP for Law and Political Economy

6. Word Embeddings

Q&A Page

bit.ly/NLP-QA06

Outline

Word Embeddings

Bias in Language (Models)

Concepts

Applications

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where

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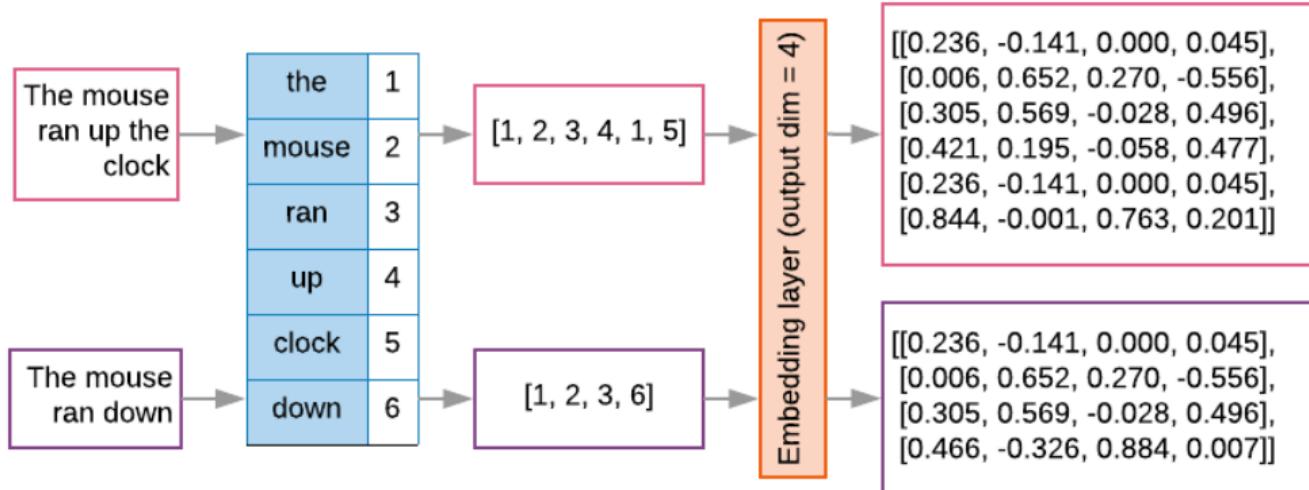
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- ▶ \mathbf{X} is flattened into an $L * n_E$ vector for input to the next layer.

Illustration



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 - ▶ rather than predicting some metadata (such as classifying topic labels) they predict the co-occurrence of neighboring words.
- ▶ “You shall know a word by the company it keeps”:
 - ▶ “He filled the **wampimuk**, passed it around and we all drunk some.”
 - ▶ “We found a little, hairy **wampimuk** sleeping behind the tree.”

Words and Contexts

A long line of NLP research aims to capture the distributional properties of words using a **word-context matrix M** :

- ▶ each row w represents a **word** (e.g. “income”), each column c represents a linguistic **context** in which words can occur (e.g. “corporate ___ tax”).
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 - ▶ A matrix entry $M_{[w,c]}$ quantifies the strength of association between a word and a context in a large corpus.
- ▶ each word (row) $M_{[w,:]}$ gives a distribution over contexts.
 - ▶ different definitions of contexts and different measures of association → different types of **word vectors**.
 - ▶ these vectors often have a **spatial interpretation** → geometric distances between word vectors reflect semantic distances between words.

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- ▶ Etc.

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- ▶ e.g. **counts**: $f_M(w, c) = \#(w, c)$, the number of times w appeared along with context c , or **document frequencies**: $f_M(w, c) = \frac{\#(w, c)}{n_D}$
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- ▶ Better: **Point-wise mutual information (PMI)**:

$$f_M(w, c) = \frac{\Pr(w, c)}{\Pr(w)\Pr(c)} = \frac{\frac{\#(w, c)}{n_D}}{\frac{\#(w)}{n_D} \frac{\#(c)}{n_D}} = \frac{n_D \#(w, c)}{\#(w)\#(c)}$$

where $\#(w)$ and $\#(c)$ are the corpus counts for w and c , respectively.

- ▶ as noted in Week 2, PMI assigns high value to rare word-context pairs → impose a minimum count threshold on (w, c) pairs; below the threshold, set to zero.

M is too high-dimensional

- ▶ M is $n_w \times n_c$
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- ▶ Going back to dimension reduction: can use singular value decomposition (SVD):
 - ▶ factorize $M \in \mathbb{R}^{n_w \times n_c}$ into a word matrix $W \in \mathbb{R}^{n_w \times n_E}$ and context matrix $C \in \mathbb{R}^{n_c \times n_E}$
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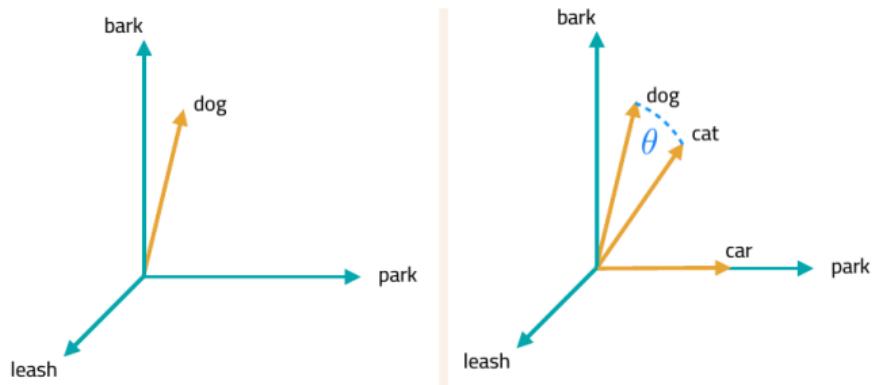
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- ▶ **similarity measures between rows of W approximate similarity measures between rows of M**

Word Similarity

- Once words are represented as vectors $\{v_1 = M_{[w_1,:]}, v_2 = M_{[w_2,:]}, \dots\}$, we can use linear algebra to understand the relationships between words:
 - Words that are geometrically close to each other are similar: e.g. “dog” and “cat”:



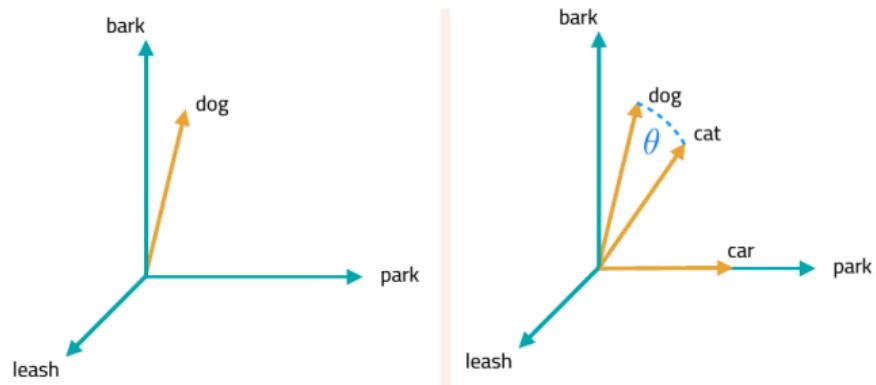
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- Thanks to linearity, can compute similarities between groups of words by averaging the groups.

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- ▶ Word2Vec learns embedding vectors for the target word (“fox”) and context words (neighbors of “fox”) to distinguish true from false samples.

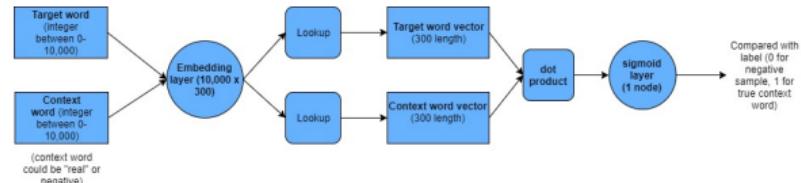
Word2Vec Negative Sampling Objective

The dataset is a collection of context pairs indexed by i :

- ▶ $y_i = 1$ means correct (it appeared in the corpus)
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- ▶ Both words are looked up in the same embedding matrix.
- ▶ The concatenated embeddings $[\mathbf{w}; \mathbf{c}]$ are input to a dense layer (no activation) then to sigmoid output:

$$\hat{y}(\mathbf{w}, \mathbf{c}) = \text{sigmoid}(([w; c] \cdot \omega_0) \cdot \omega_1)$$

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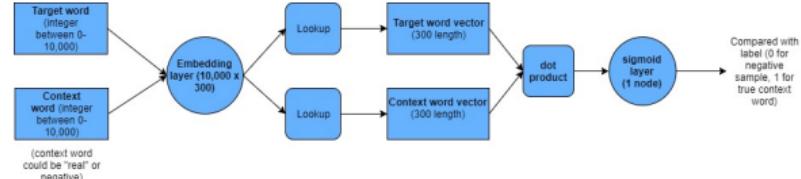
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- ▶ Word2Vec minimizes the binary cross-entropy

$$L(\theta) = - \sum_{i=1}^{n_D} [y_i \log \hat{y}_i(\mathbf{w}, \mathbf{c}; \theta) + [1 - y_i] \log(1 - \hat{y}_i(\mathbf{w}, \mathbf{c}; \theta))]$$



How does Word2Vec relate to the \mathbf{M} matrix?

- ▶ Word2Vec produces embedding matrices \mathbf{W} and \mathbf{C} .
 - ▶ generally, context embeddings are discarded after training.
- ▶ Levy and Goldberg (2014):
 - ▶ If we take $\tilde{\mathbf{M}} = \mathbf{W}\mathbf{C}'$, word2vec is equivalent to factorizing a matrix \mathbf{M} with items

$$\mathbf{M}_{[w,c]} = \text{PMI}(w, c) - \log a$$

where a is a constant calibrating the amount of negative sampling.

GloVe Embeddings

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Learn word vectors $\mathbf{w} = (w_1, \dots, w_i, \dots, w_{n_w})$, where $w_i \in (-1, 1)^{n_E}$, to solve

$$\min_{\mathbf{w}} \sum_{i,j} f(C_{ij}) \left(w_i^T w_j - \log(C_{ij}) \right)^2$$

where $f(\cdot)$ is weighting function to down-weight frequent words.

- ▶ Minimizes **squared difference** between:
 - ▶ **dot product of word vectors**, $w_i^T w_j$
 - ▶ **empirical co-occurrence**, $\log(C_{ij})$
[Arora et al (2016) put the PMI here instead of co-occurrence counts]
- ▶ Intuitively: words that co-occur should have high correlation (dot product)

Check for Understanding

1. What is the difference/connection between an embedding layer and a word embedding?
2. Why use PMI instead of co-occurrence frequencies when constructing the word association matrix?
3. What does negative sampling mean in general, and in the case of Word2Vec?
4. What are the main differences between Word2Vec and GloVe?

Word Embeddings Encode Linguistic Relations

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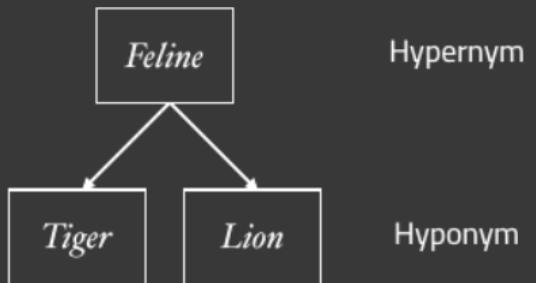
Synonymy



Antonymy



Hyponymy



Similarity vs. Relatedness (Budansky and Hirst, 2006)

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- ▶ Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

Most similar words to dog, depending on context window size

	2-word window	30-word window	
More paradigmatic	cat	<u>kennel</u>	
	horse	puppy	
	fox	pet	
	pet	bitch	
	rabbit	terrier	
	pig	rottweiler	
	animal	canine	
	mongrel	cat	
	sheep	bark	
	pigeon	alsatian	
		More syntagmatic	

- ▶ Small windows pick up substitutable words; large windows pick up topics.

Parts of Speech and Phrases

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- ▶ Can improve the quality of embeddings in these cases by attaching the POS to the word (e.g. “like:verb”, “like:prep”) before training.
- ▶ The default model only works by word, but “new york \neq “new” + “york”
 - ▶ can tokenize phrases together (see Week 2 lecture) before training.

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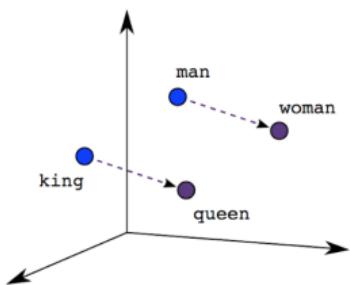
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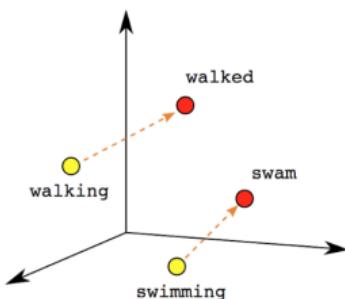
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- ▶ This is really important when we will use embeddings to analyze beliefs/attitudes.
 - ▶ And I don't see a solution to it.
- ▶ Relatedly, antonyms are often rated similarly, have to be careful with that.

Vector Directions \leftrightarrow Meaning

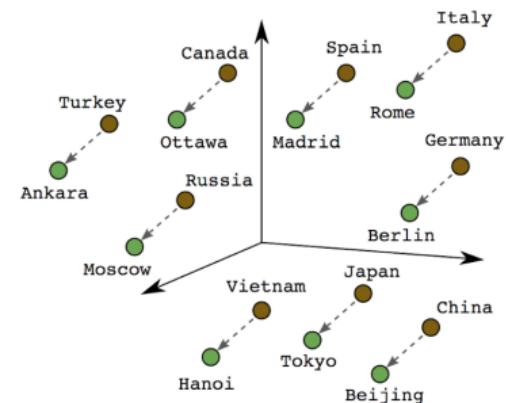
- Intriguingly, word2vec algebra can depict conceptual, analogical relationships between words:



Male-Female



Verb Tense



Country-Capital

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- More generally: The analogy $a_1 : b_1 :: a_2 : b_2$ can be solved (that is, find b_2 given a_1, b_1, a_2) by

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- Often works better with normalized vectors (so that one long vector doesn't wash out the others)

Word Embeddings for Analogies

$$\text{vec}(king) - \text{vec}(man) + \text{vec}(woman) \approx \text{vec}(queen)$$

- More generally: The analogy $a_1 : b_1 :: a_2 : b_2$ can be solved (that is, find b_2 given a_1, b_1, a_2) by

$$\arg \max_{b_2 \in V} \cos(b_2, a_2 - a_1 + b_1)$$

where V excludes (a_1, b_1, a_2) .

- Often works better with normalized vectors (so that one long vector doesn't wash out the others)
- Levy and Goldberg (2014) recommend the following “CosMul” metric which tends to perform better:

$$\arg \max_{b_2 \in V} \frac{\cos(b_2, a_2) \cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$$

- requires normalized, non-negative vectors (can transform using $(x+1)/2$)
- ϵ is a small smoothing parameter.

Tokenizing for Word Embeddings

- ▶ drop capitalization
- ▶ punctuation is optional
- ▶ don't drop stopwords/function-words
- ▶ add special tokens for start of sentence and end of sentence
- ▶ for out-of-vocab words, substitute a special token or replace with part-of-speech tag

Can cluster word embeddings to produce topics

Cluster #	Top 10 Words
174	complicate, depend, crucial, illustrate, elusive, focus, important, straightforward, elide, critical
134	implausible, problematic, exaggeration, skeptical, ascribe, discredit, contradictory, weak, exaggerate, supportable
75	reverse, AFFIRM, affirm, vacate, reversed, REMANDED, forego, foregoing, forgoing, remands
70	importation, import, ecstasy, marihuana, illicit, opium, distilled, export, phencyclidine, narcotic
178	perverse, sensible, tempt, unlikely, unwise, anomalous, would, easy, costly, attractive
32	phrase, meaning, word, synonymous, language, interpret, noun, wording, verb, adjective
169	circumscribe, endow, unfettered, vest, unlimited, boundless, broad, constrain, exercise, unbounded
85	hundred, thousand, many, million, huge, massive, large, enormous, most, dozen
28	emphasis, bracket, alteration, citation, footnote, italic, ellipsis, ptcitation, idcitation, punctuation
138	logo, symbol, stylized, imprint, emblem, grille, prefix, lettering, suffix, crosshair
181	wilful, carelessness, recklessness, careless, intentional, willful, conscious, reckless, unintentional, wantonness
158	rigorous, demanding, heightened, reasonableness, rigid, heighten, objective, deferential, flexible, particular
55	agreement, contract, contractual, promise, novation, repudiate, guaranty, enforceable, novate, repurchase
197	summation, admonish, sidebar, prosecutor, admonishment, mistrial, curative, questioning, remark, recess
120	scrivener, typographical, reversible, plain, harmless, clerical, invited, clear, requiresthe, instructional
15	adjudicatory, adjudicative, adversarial, judicial, rulemaking, decisionmaking, administrative, meaningful, rulemake, agency

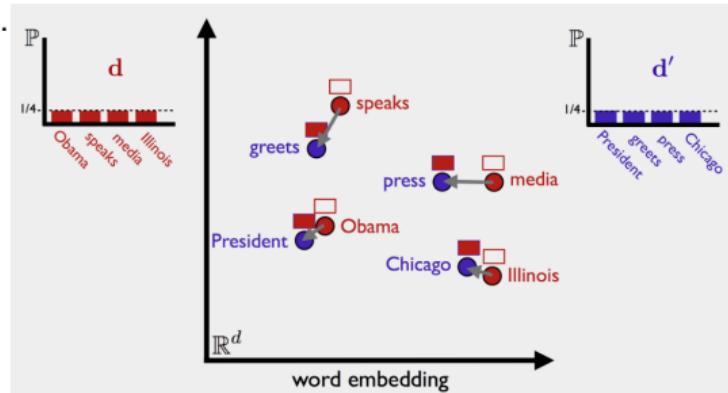
Clustered word embeddings in judicial opinions, from Ash and Nikolaus (2020)

Word Mover Distance

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- ▶ Word mover distance (Kusner, Sun, Kolkin, and Weinberger ICML 2015) between two texts is given by:
 - ▶ total amount of “mass” needed to move words from one side into the other
 - ▶ multiplied by the distance the words need to move
 - ▶ uses word embedding distance



Pre-trained word embeddings

- ▶ In many settings (e.g. a small corpus), better to use pre-trained embeddings.
- ▶ e.g., spaCy's GloVe embeddings:
 - ▶ one million vocabulary entries
 - ▶ 300-dimensional vectors
 - ▶ trained on the Common Crawl corpus
- ▶ Can initialize models with pre-trained embeddings, can fine-tune as needed.

“Enriching word vectors with subword information” (Bojanowski et al 2017)

- ▶ each word is represented as a bag of (hashed) character n-grams. (e.g., spicy = (spi, pic, icy)).
- ▶ learn embeddings for the character segments, and construct word embedding by summing over the segment embeddings

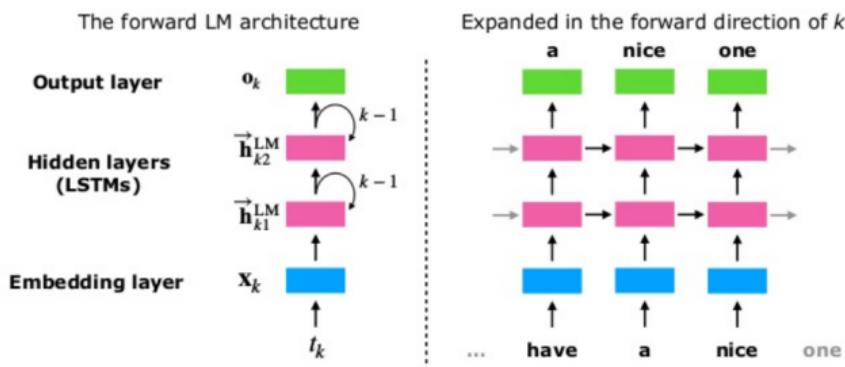
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- ▶ each word is represented as a bag of (hashed) character n-grams. (e.g., spicy = (spi, pic, icy)).
- ▶ learn embeddings for the character segments, and construct word embedding by summing over the segment embeddings
- ▶ competitive with word2vec in standard tasks; better in some languages.
- ▶ produces good embeddings for unseen words.

ELMo (Embeddings from Language Models)

- ▶ ELMo is a context-sensitive word embedding model that uses the output of a bidirectional LSTM:

With long short term memory (LSTM) network,
predicting the next words in both directions to build
biLMs



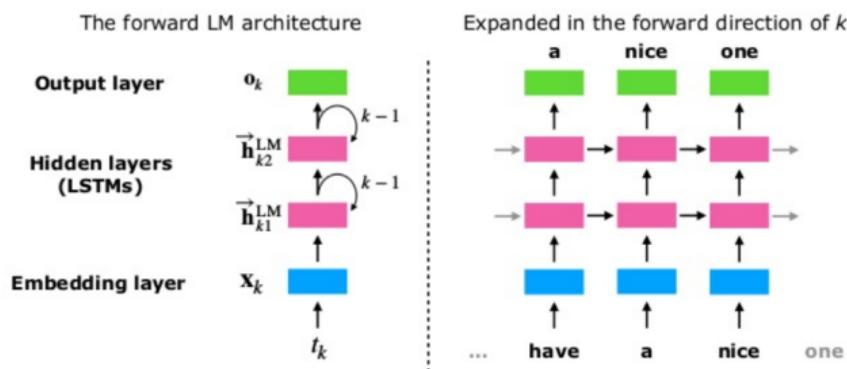
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- ▶ predict previous and next words in a sentence using a bidirectional LSTM.

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- ▶ The task:
 - ▶ predict previous and next words in a sentence using a bidirectional LSTM.
- ▶ embeddings go through two hidden layers before the softmax output:
 - ▶ first layer learns syntax
 - ▶ second layer learns semantics



	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular <u>play</u> on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway <u>play</u> for Garson {...}	{...} they were actors who had been handed fat roles in a successful <u>play</u> , and had talent enough to fill the roles competently , with nice understatement .

Table 4: Nearest neighbors to “play” using GloVe and the context embeddings from a biLM.



ELMo can distinguish the word sense based on the context

- ▶ Pre-trained ELMo models are available from AllenNLP (allenlp.org/elmo)

Check for Understanding

1. How would it affect my word embeddings to use co-occurrence within paragraph, rather than within sentence?
2. How would it affect my embeddings to drop function words in a pre-processing step?
3. What is the black sheep problem in the context of word embeddings?
4. Think of a setting (and explain) where:
 - ▶ using pre-trained embeddings would not work.
 - ▶ using embeddings with subword information would help a lot
 - ▶ using elmo would work a lot better than glove.
 - ▶ you would care more about the first layer or the second layer from elmo.

Standard word embeddings (e.g. word2vec/glove) have a number of limitations:

- ▶ **polysemy**: you get one vector for multiple senses of a word
(e.g. “**glass** of water” vs “window **glass**”)

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- ▶ **n-grams**: does not produce embeddings for multi-word phrases

Scientists attending ACL work on **cutting edge** research in NLP

Petrichor: the earthy scent produced when rain falls on dry soil

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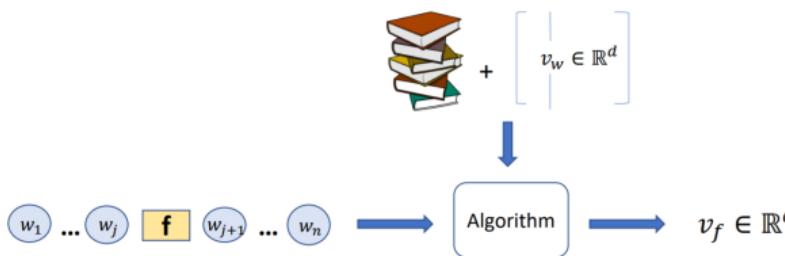
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- ▶ Goal of Khodak et al (2018): produce embeddings “a la carte” given a context:

Given: Text corpus and high quality
word embeddings trained on it



Input: A feature in context(s)

Output: Good quality embedding
for the feature

A la carte embeddings

- ▶ Given a target word f and its context c , define

$$v_f^{\text{avg}} = \frac{1}{|c|} \sum_{w \in c} v_w$$

the average vector for the words in the context.

- ▶ Arora et al (2018) prove that for vectors produced by a generative language model, there exists a matrix A such that

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$$v_f \approx A v_f^{\text{avg}}$$

- ▶ The “induction matrix” A can be learned with a least-squares (linear regression) objective

$$A^* = \arg \min_A \sum_w |v_w - A v_w^{\text{avg}}|_2^2$$

where w indexes over all the tokens in the corpus.

- ▶ empirically:

$$\text{cosine}(v_f, A^* v_f^{\text{avg}}) \geq 0.9$$

Using a la carte embeddings

- ▶ useful for producing embeddings for small corpora.
- ▶ e.g., Ash, Chen, and Ornaghi (2021), “Gender attitudes in the judiciary”:
 - ▶ could produce separate embeddings for each mention of a woman's name, project each of them on the family-to-career dimension.
 - ▶ → produce opinion-level measures of stereotypes.

Outline

Word Embeddings

Bias in Language (Models)

Concepts

Applications

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Bias in NLP Systems

Sentiment Analysis

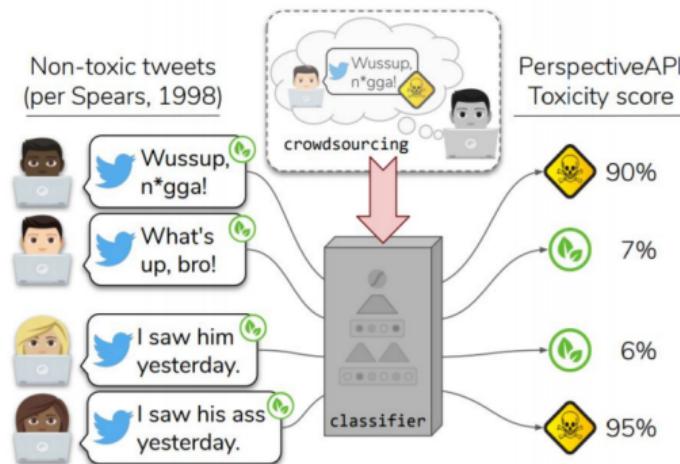
```
text_to_sentiment("Let's go get Italian food")
2.0429166109
text_to_sentiment("Let's go get Chinese food")
1.4094033658
text_to_sentiment("Let's go get Mexican food")
0.3880198556
```

```
text_to_sentiment("My name is Emily")
2.2286179365
text_to_sentiment("My name is Heather")
1.3976291151
text_to_sentiment("My name is Yvette")
0.9846380213
text_to_sentiment("My name is Shaniqua")
-0.4704813178
```

Is this sentiment model racist?

Bias in NLP Systems

Toxicity Detection



Within dataset proportions

Group	Acc.	% false identification		
		None	Offensive	Hate
AAE	94.3	1.1	46.3	0.8
White	87.5	7.9	9.0	3.8
Overall	91.4	2.9	17.9	2.3

Group	Acc.	% false identification		
		None	Abusive	Hateful
AAE	81.4	4.2	26.0	1.7
White	82.7	30.5	4.5	0.8
Overall	81.4	20.9	6.6	0.8

Is this toxicity detection model racist?

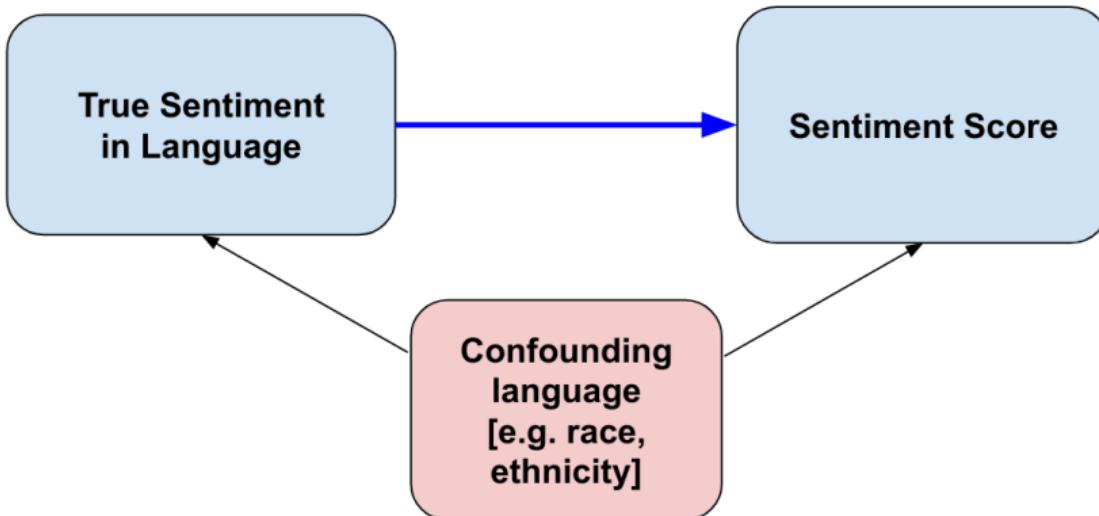
Source: Jacobs and Wallach slides.

NLP “Bias” is statistical bias

- ▶ Sentiment scores that are trained on annotated datasets also learn from the correlated non-sentiment information.

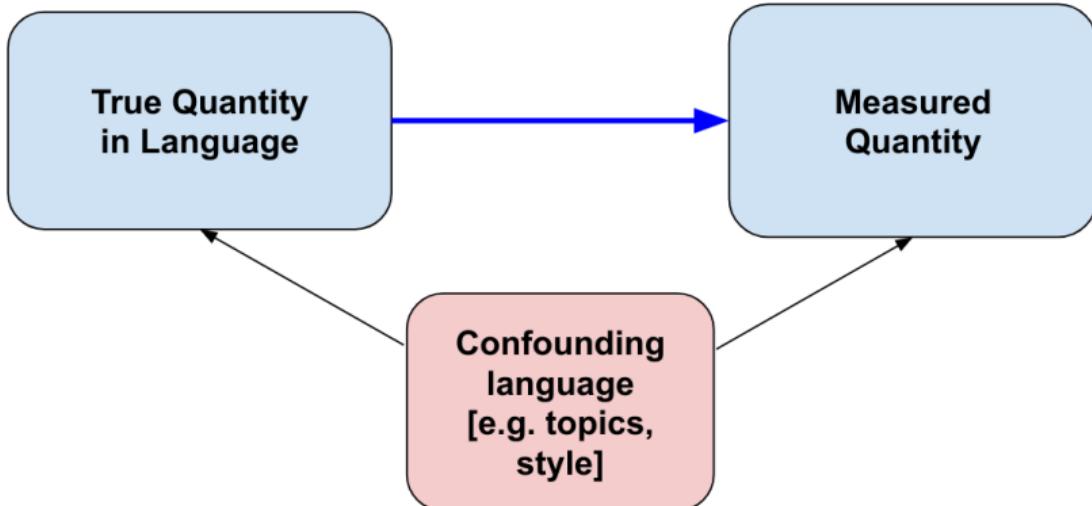
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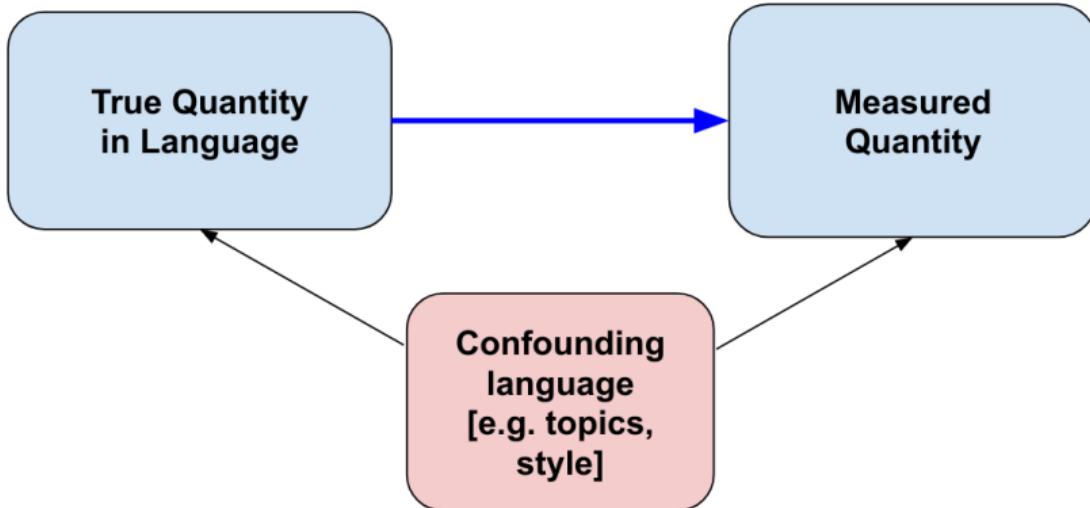
- ▶ Supervised sentiment models are confounded by correlated language factors.
 - ▶ e.g., in the training set maybe people complain about Mexican food more often than Italian food.

This is a universal problem



- ▶ supervised models (classifiers, regressors) learn features that are correlated with the label being annotated.
- ▶ unsupervised models (topic models, word embeddings) learn correlations between topics / contexts.

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- ▶ unsupervised models (topic models, word embeddings) learn correlations between topics / contexts.
- ▶ An important exception: dictionary methods (perhaps explaining why they are often used by economists). But they have other serious limitations.

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- ▶ Political partisanship → predicted probability being Democrat/Republican based on speeches.
confounders?
- ▶ Policy priorities → predicted probability of speeches/laws being about a particular policy topic.
confounders?

When is measurement confounding important?

- ▶ By itself, producing measurements that are biased by confounders might not be a problem.
- ▶ e.g.:
 - ▶ an NLP-based credit score that learns confounders → not a problem unless debtors learn about it and strategically alter their documents.
 - ▶ similarly with automated essay grading

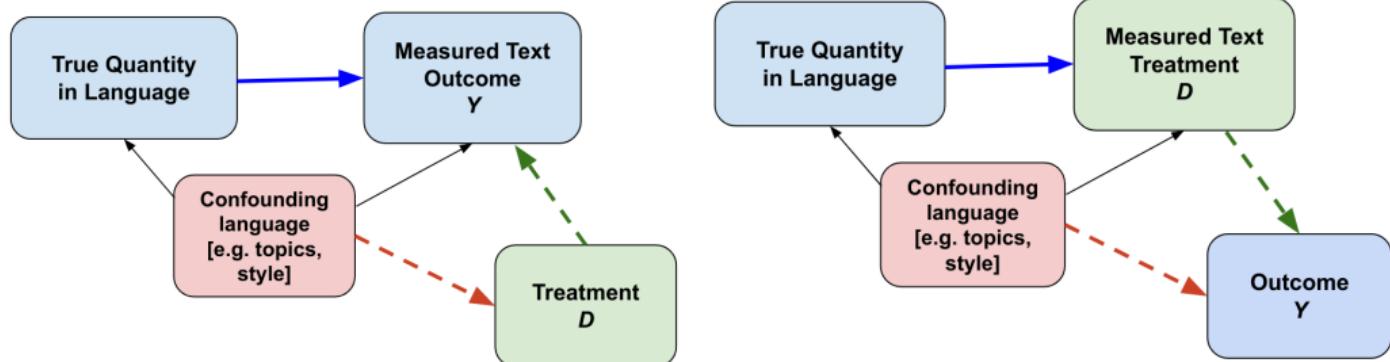
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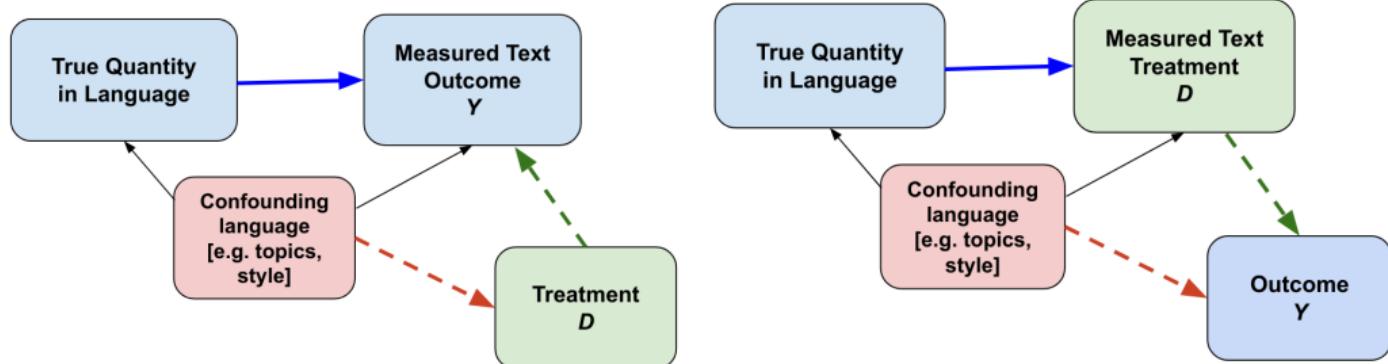
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 - ▶ but would matter a lot for summary statistics in a new domain
- ▶ even in domain, will matter for assessing the causal effect of a treatment, e.g. the electoral cycle:
 - ▶ elections might cause politicians to focus on social issues rather than economic issues,
 - ▶ if social/economic issues are confounded with partisanship, the resulting estimates are biased.

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 - ▶ e.g.: estimating the effect of politician speech sentiment on his/her reelection chances?

Steps for de-biasing

- ▶ Language features that are often confounded with an important quantity:
 - ▶ stopwords
 - ▶ person/organization/place names
- ▶ These can be dropped during pre-processing to reduce the influence of confounders in subsequent measurements.
- ▶ Can control for topic or style features or other potential confounders in regressions.

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 - ▶ Select a model and train it.
 - ▶ **Validate that the model is measuring what we want and that there are no clear confounders.**
4. Empirical analysis
 - ▶ Produce statistics or predictions with the trained model.
 - ▶ **Answer the research question.**

Implicit attitudes

"Attitudes that affect our understanding, actions, and decisions in an unconscious manner" (Kirwan institute, OSU)

Implicit attitudes

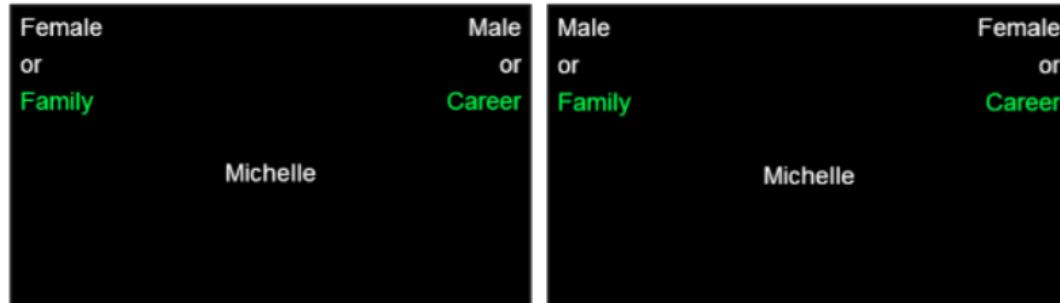
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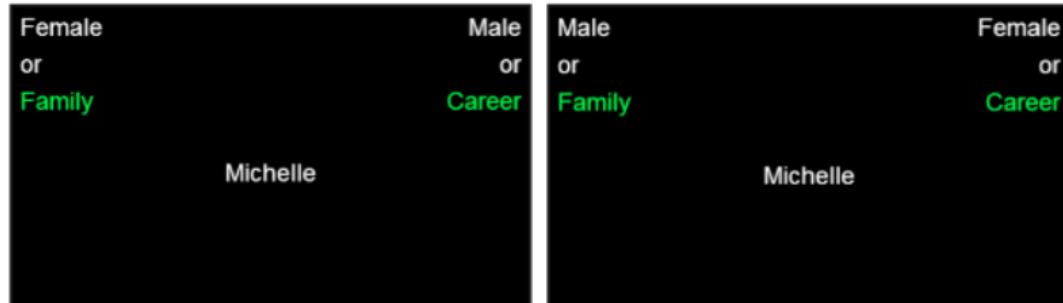


- ▶ Comparing reaction times across trials with different word pairs:
 - ▶ subjects tend to be slower and more error-prone in assignments against stereotype (e.g. "Michelle" goes to "Female or Career").

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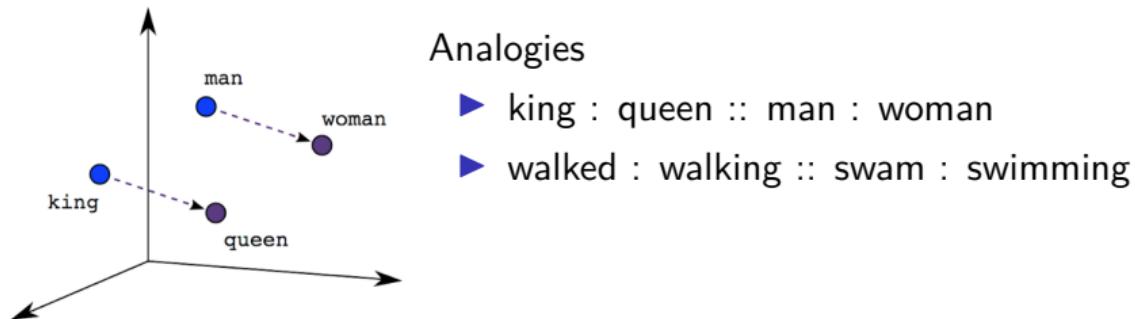


- ▶ Comparing reaction times across trials with different word pairs:
 - ▶ subjects tend to be slower and more error-prone in assignments against stereotype (e.g. "Michelle" goes to "Female or Career").
 - ▶ IAT score = difference in reaction time between stereotype-consistent and stereotype-inconsistent rounds.

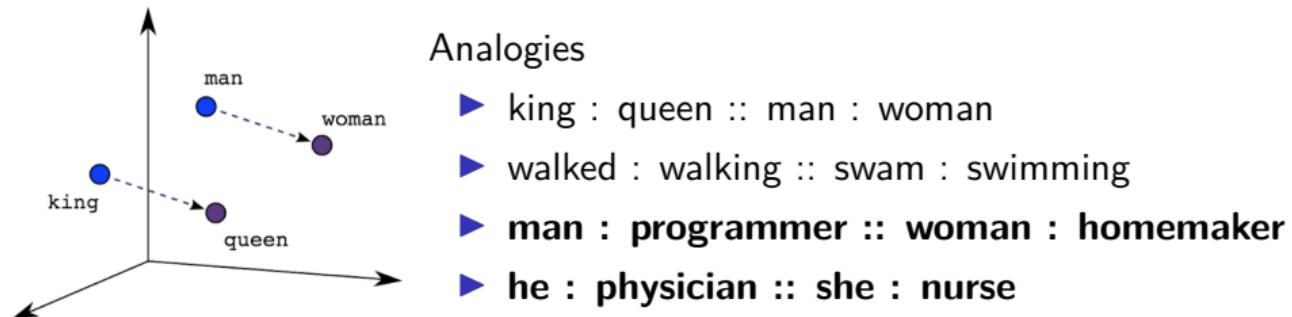
Caliskan, Bryson, and Narayanan (*Science* 2017)

- ▶ “We replicated a spectrum of known biases, as measured by the Implicit Association Test, using a widely used, purely statistical machine-learning model trained on a standard corpus of text from the World Wide Web. . . ”

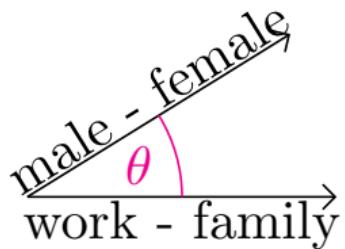
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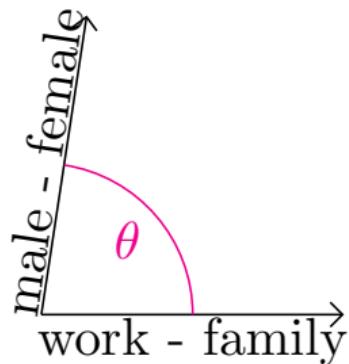
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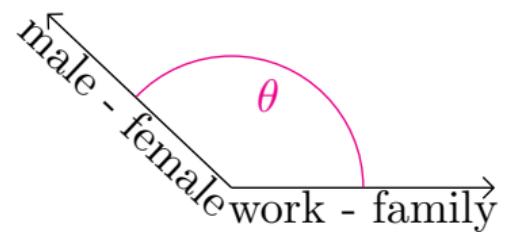
Measuring Gender Stereotypes using Cosine Similarity



(a)



(b)



(c)

Example Stimuli

- ▶ Targets:
 - ▶ **Flowers:** aster, clover, hyacinth, marigold, poppy, azalea, crocus, iris, orchid, rose, bluebell, daffodil, lilac, pansy, tulip, buttercup, daisy, lily, peony, violet, carnation, gladiola, magnolia, petunia, zinnia.
 - ▶ **Insects:** ant, caterpillar, flea, locust, spider, bedbug, centipede, fly, maggot, tarantula, bee, cockroach, gnat, mosquito, termite, beetle, cricket, hornet, moth, wasp, blackfly, dragonfly, horsefly, roach, weevil.

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- ▶ Attributes:
 - ▶ **Pleasant:** caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest, lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation.
 - ▶ **Unpleasant:** abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred, pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison.

Results

- ▶ Pleasant vs. Unpleasant?
 - ▶ Flowers vs. Insects
 - ▶ Musical instruments vs. weapons.

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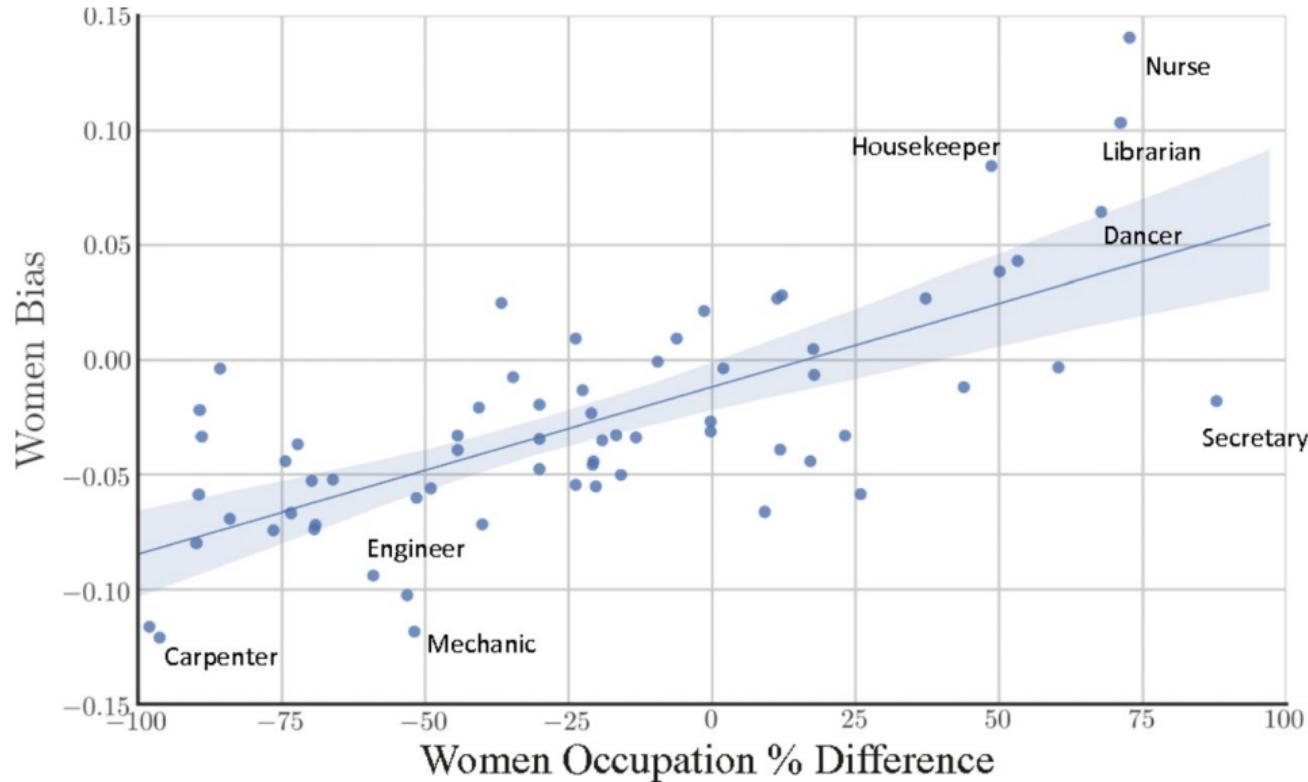
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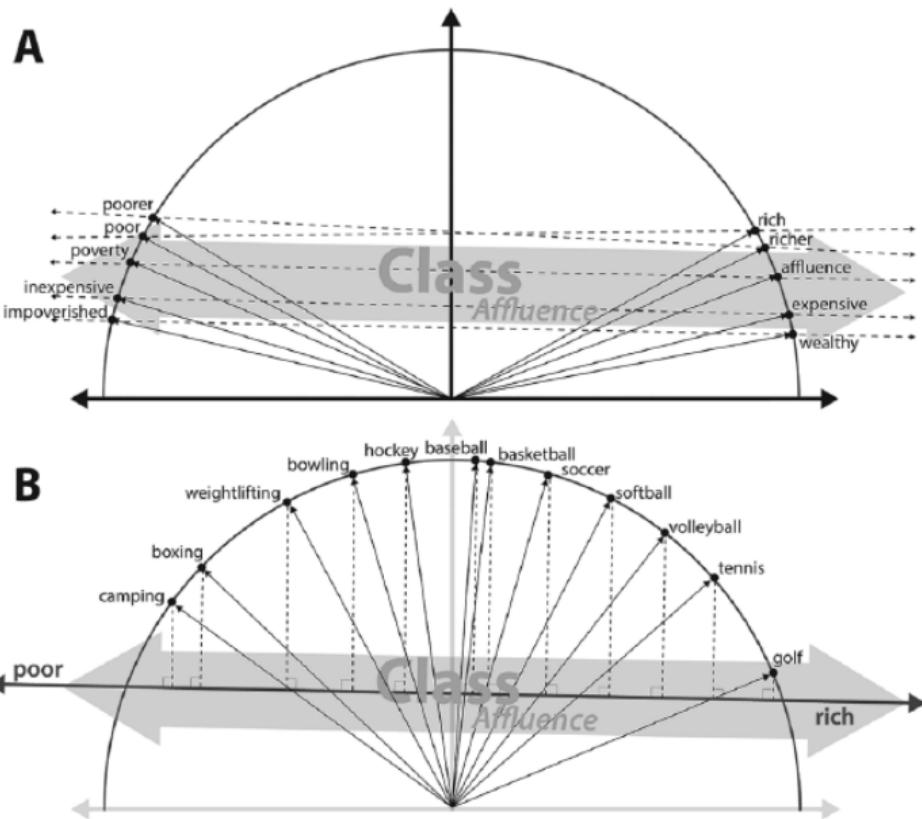
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 - ▶ Musical instruments vs. weapons.
 - ▶ European-American names vs. African-American names
- ▶ Male names vs. Female names:
 - ▶ Career words (e.g. professional, corporation, ...) vs. family words (e.g. home, children, ...)
 - ▶ Math/science words vs arts words

What do we learn from this?

Garg, Schiebinger, Jurafsky, and Zou (PNAS 2018)



Women's occupation relative percentage vs. embedding bias in Google News vectors.



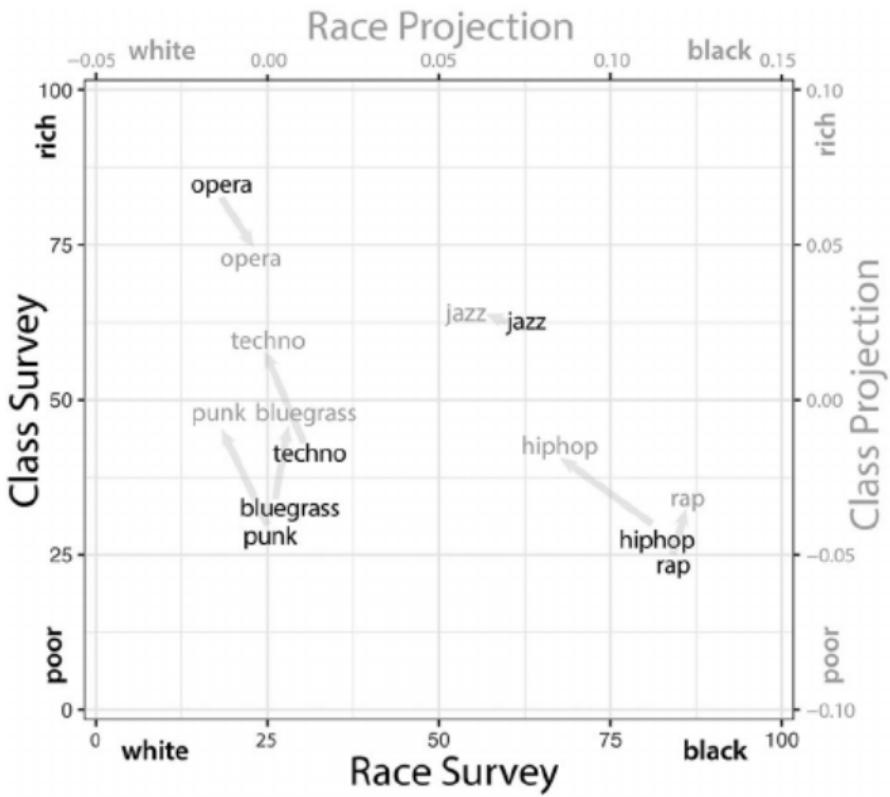


Figure 3. Projection of Music Genres onto Race and Class Dimensions of the Google News Word Embedding (Gray) and Average Survey Ratings for Race and Class Associations (Black)

Time Series Analysis of Affluence

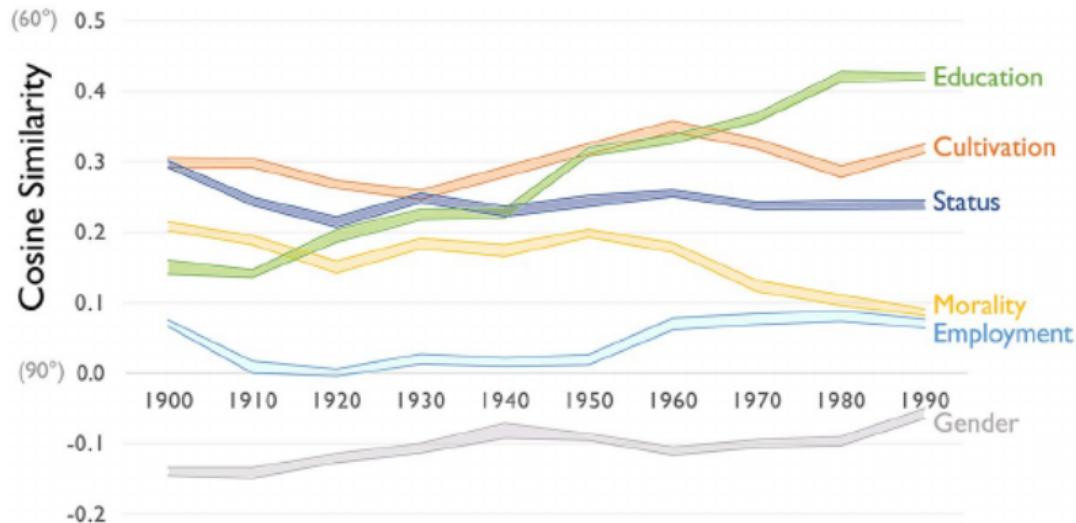


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

"Among the 10 nouns most highly projecting on the affluence dimension in the first decade of the twentieth century are "fragrance," "perfume," "jewels," and "gems," ..."

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- ▶ But: Gonen and Goldberg (2019):
 - ▶ *“... we argue that this removal is superficial. While the bias is indeed substantially reduced according to the provided bias definition, the actual effect is mostly hiding the bias, not removing it. The gender bias information is still reflected in the distances between ‘gender-neutralized’ words in the debiased embeddings, and can be recovered from them...”*
- ▶ Project idea: use double machine learning to de-bias word embeddings.

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- ▶ Does language matter?
 - ▶ Djourelova (2020): style change from “illegal” to “undocumented” immigrant softened attitudes toward immigration.