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)

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where

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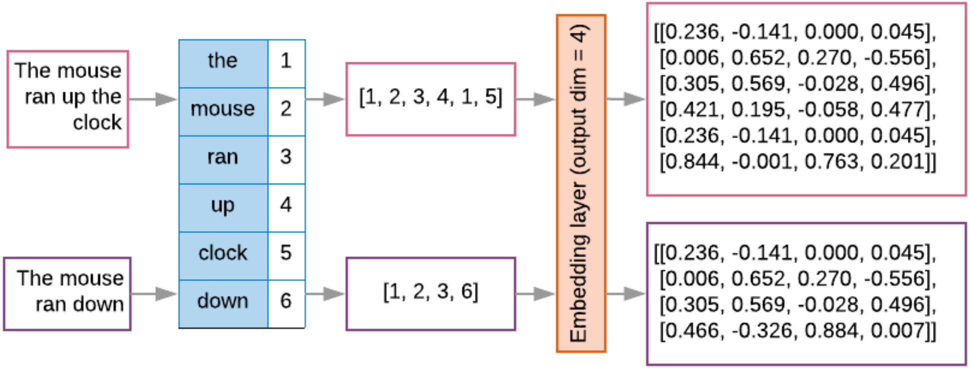
- $\boldsymbol{X}$ is flattened into an $L * n_E$ vector for input to the next layer.

Illustration



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  - rather than predicting some metadata (such as classifying topic labels) they predict the co-occurence 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

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- 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 $\boldsymbol{M}_{[w,c]}$ quantifies the strength of association between a word and a context in a large corpus.
- each word (row) $\boldsymbol{M}_{[w,:]}$ gives a distribution over contexts.
  - different definitions of contexts and different measures of association $\rightarrow$ different types of **word vectors**.
  - these vectors often have a **spatial interpretation** $\rightarrow$ geometric distances between word vectors reflect semantic distances between words.

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  - ...
- Etc.

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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 $\rightarrow$ impose a minimum count threshold on (w,c) pairs; below the threshold, set to zero.

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  - relatively low-dimensional ($n_E << n_w$, typically between 50 and 300)
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- **similarity measures between rows of $\boldsymbol{W}$ approximate similarity measures between rows of $\boldsymbol{M}$**

Word Similarity

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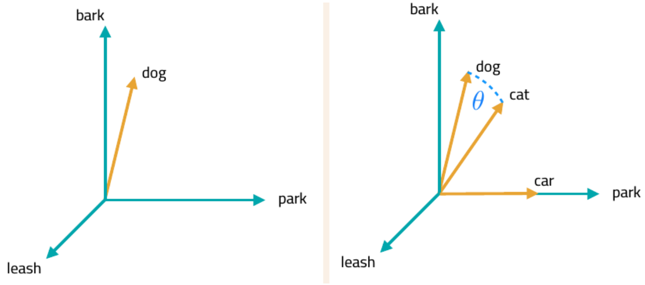
  - Words that are geometrically close to each other are similar: e.g. “dog” and “cat”:



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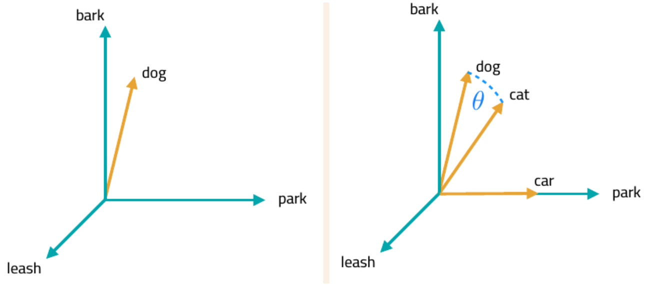

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- Thanks to linearity, can compute similarities between groups of words by averaging the groups.

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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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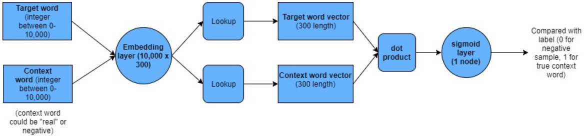

- Both words are looked up in the same embedding matrix.
- The concatened embeddings $[\boldsymbol{w}; \boldsymbol{c}]$ are input to a dense layer (no activation) then to sigmoid output:

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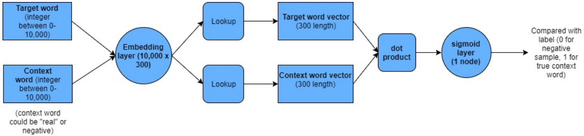

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- Word2Vec minimizes the binary cross-entropy

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

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

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

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

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

GloVe Embeddings

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

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

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,** $\log\left(C_{ij}\right)$
    [Arora et al (2016) put the PMI here instead of co-occurence 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-occurence 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?

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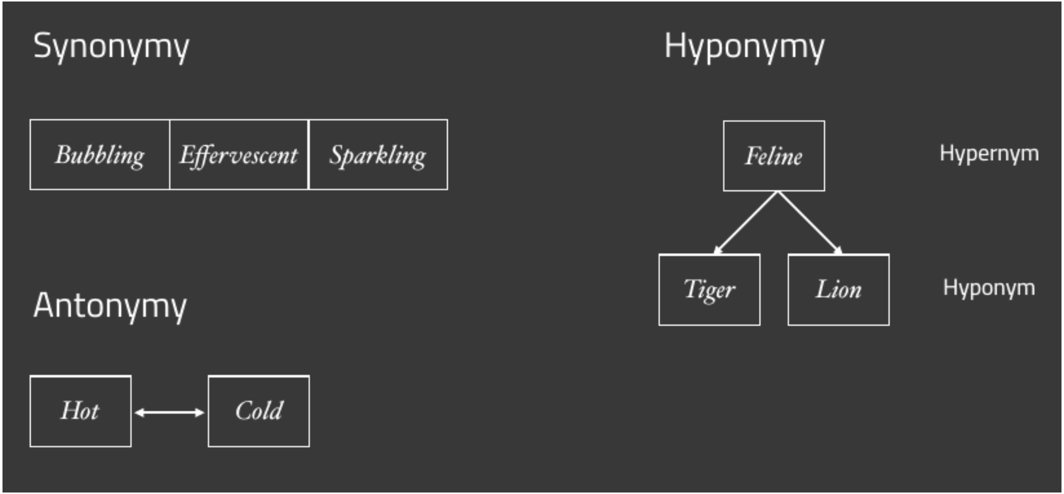

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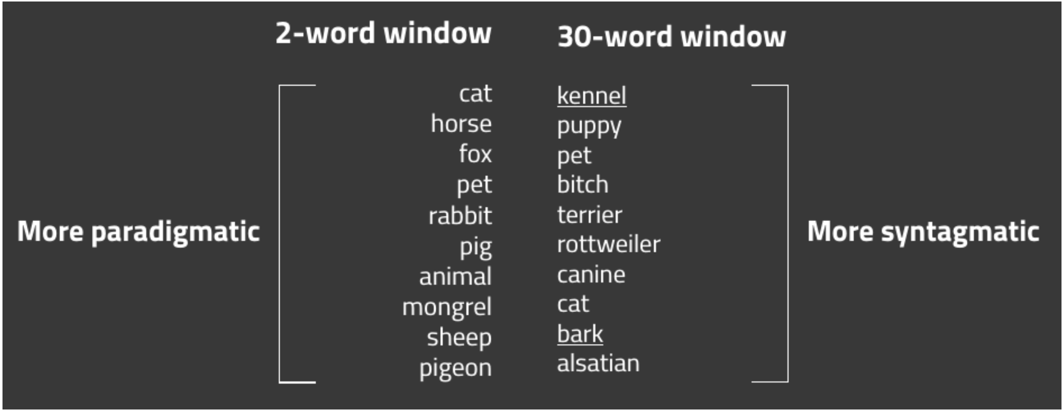
- Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

Most similar words to dog, depending on context window size



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

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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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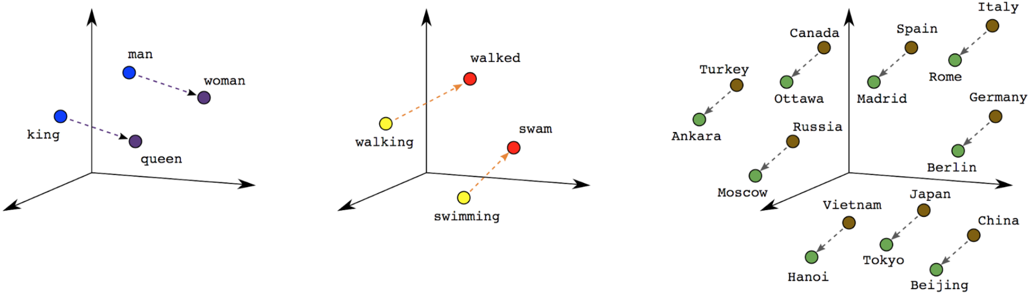
  - And I don't see a solution to it.
- Relatedly, antonyms are often rated similarly, have to be careful with that.

Vector Directions $\leftrightarrow$ Meaning

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



Male-Female   Verb Tense   Country-Capital

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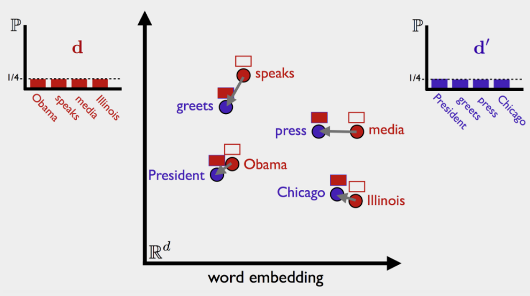
- Word mover distance (Kusner, Sun, Kolkin, and Weinberger ICML 2015) between two texts is given by:
  - total amount of "mass" needed to move words from one side into the other
  - multiplied by the distance the words need to move
  - uses word embedding distance



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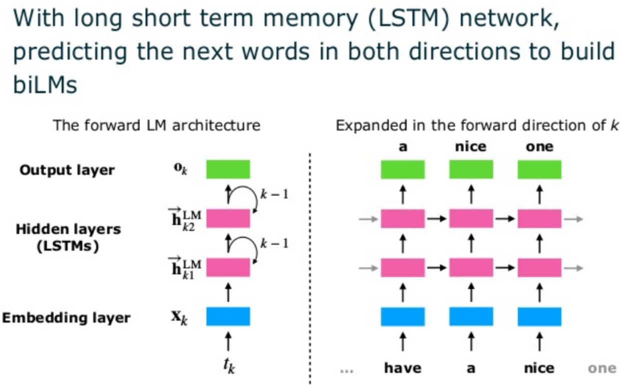
- each word is represented as a bag of (hashed) character n-grams. (e.g., spicy = (spi, pic, icy)).
- learn embeddings for the character segments, and construct word embedding by summing over the segment embeddings
- competitive with word2vec in standard tasks; better in some languages.
- produces good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

ELMo (Embedings from Language Models)

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



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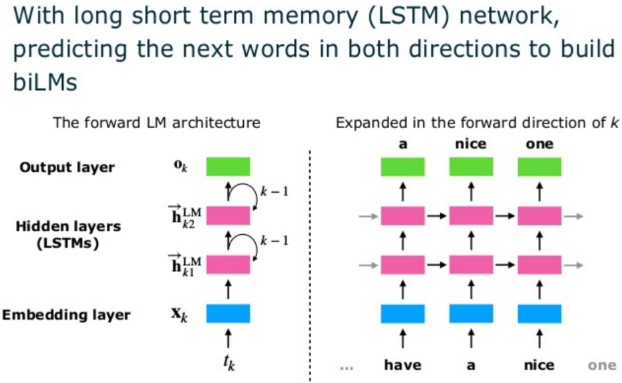


- The task:
  - predict previous and next words in a sentence using a birectional LSTM.
- embeddings go through two hidden layers before the softmax output:
  - first layer learns syntax
  - second layer learns semantics

GloVe mostly learns *sport*-related context

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play 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 play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , 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 (allennlp.org/elmo)

Check for Understanding

1. How would it affect my word embeddings to use co-occurence within paragraph, rather than within sentence?
2. How would it 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.

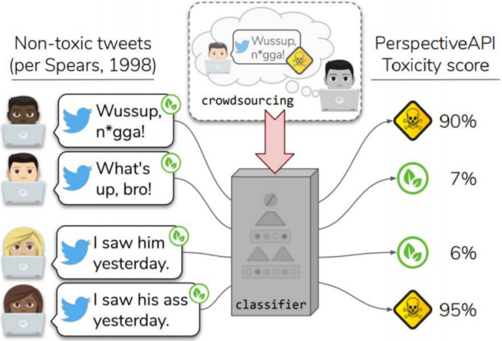
Outline

Word Embeddings

Bias in Language (Models)

Bias in NLP Systems

Toxicity Detection



Within dataset proportions

DWMW17

		% false identification		
Group	Acc.	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

FDCL18

		% false identification		
Group	Acc.	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

What outcomes do we care about?

Jacobs and Wallach (2019)

- Prosocial behavior
- Fairness
- Creditworthiness
- Teacher quality
- Risk to society
- Toxic language
- Healthy communities

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What outcomes do we care about? $\leftrightarrow$ **What would we like to measure?**

The measurement process

Jacobs et al (2020)

Creditworthiness

Teacher quality

Risk to society

Toxic language

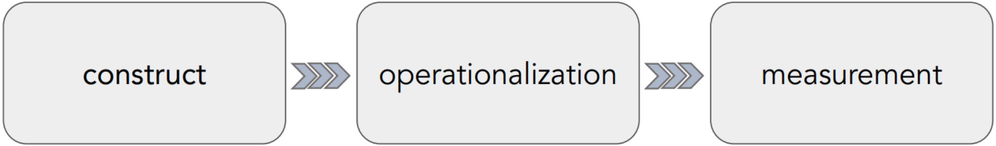
Healthy communities

Prosocial behavior

Fairness

...

Credit scores
Value-added assessment scores
Recidivism risk
Toxicity score
Health score
(Not) banned behavior
Fairness
Individual fairness
Group fairness
...



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- Quality of service
  - performance differences between text about or by different groups
- Public participation
  - diminishing of participation in public discourse or democratic processes

Research Objectives

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4. Empirical analysis
   - Produce statistics or predictions with the trained model.
   - **Answer the research question.**

Implicit attitudes

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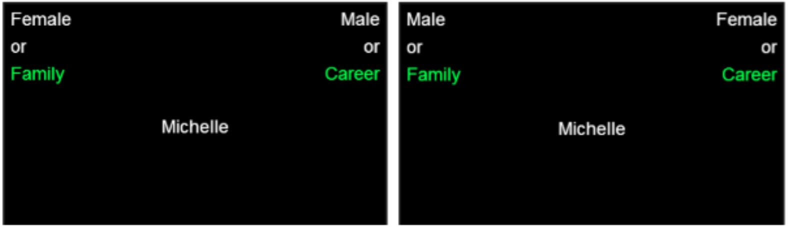

- Comparing reaction times across trials with different word pairs:
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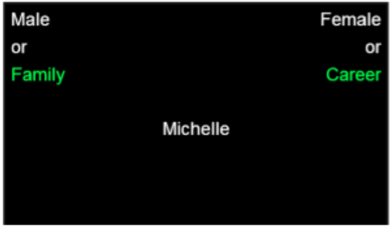

- Comparing reaction times across trials with different word pairs:
  - subjects tend to be slower and more error-prone in assignments against stereotype (e.g. "Michelle" goes to "Female or Career").
  - IAT score = difference in reaction time between stereotype-consistent and stereotype-inconsistent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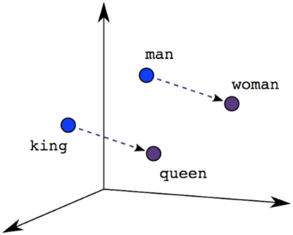

Analogies

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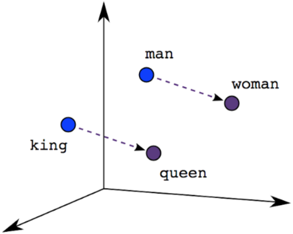
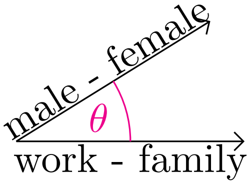


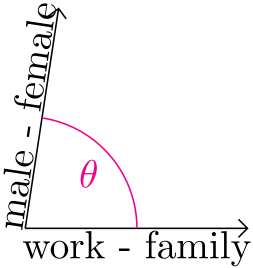
Analogies

- king : queen :: man : woman
- walked : walking :: swam : swimming
- **man : programmer :: woman : homemaker**
- **he : physician :: she : nurse**

Measuring Gender Stereotypes using Cosine Similarity



(a)



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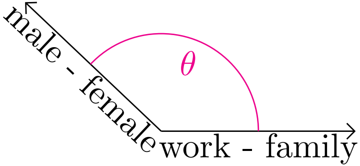

(c)

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
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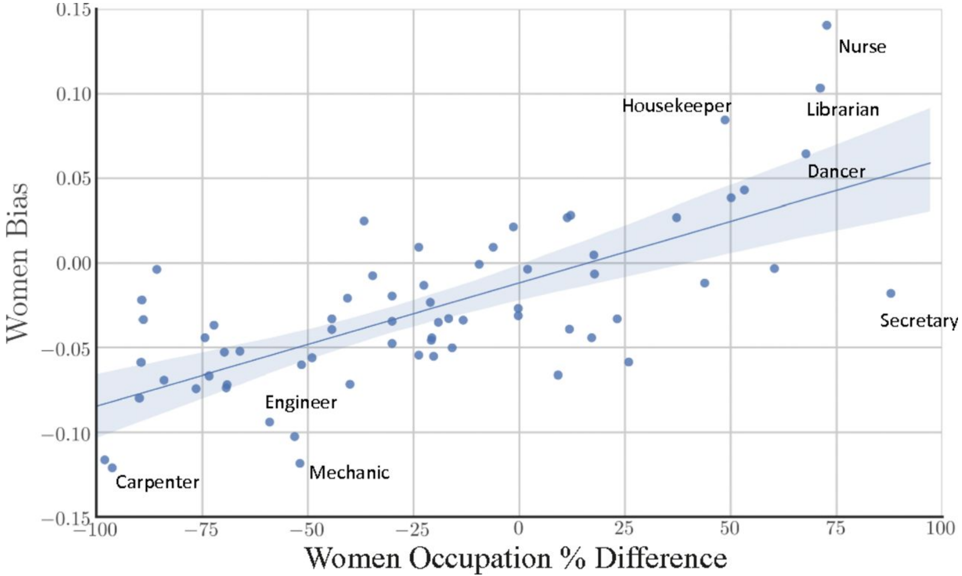
- Male names vs. Female names:
  - Career words (e.g. professional, corporation, ...) vs. family words (e.g. home, children, ...)
  - Math/science words vs arts words

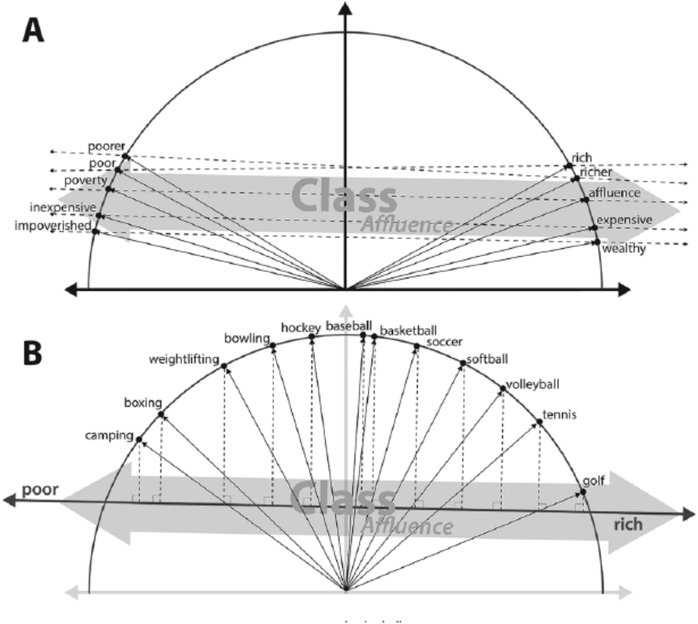
What do we learn from this?

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



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

Kozlowski, Evans, and Taddy (ASR 2019)



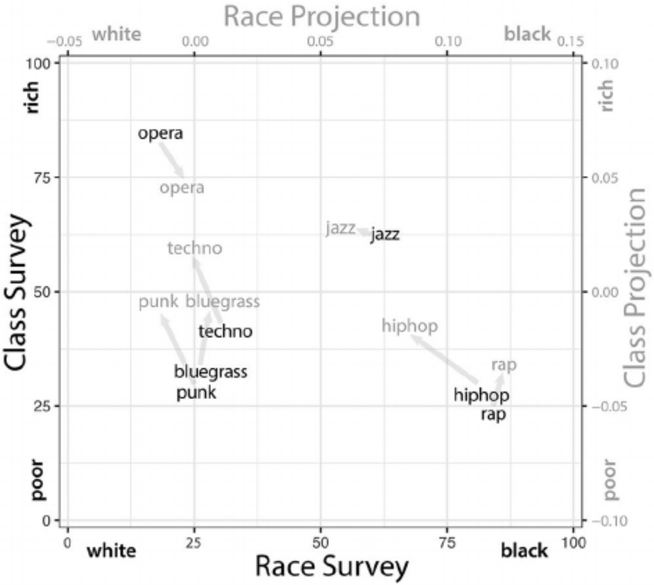


Figure 3. Projection of Music Genres onto Race and Class Dimensions of the Google News Word Embedding (Gray) and Average Survey Ratings for Race and Class Associations (Black)

Time Series Analysis of Affluence

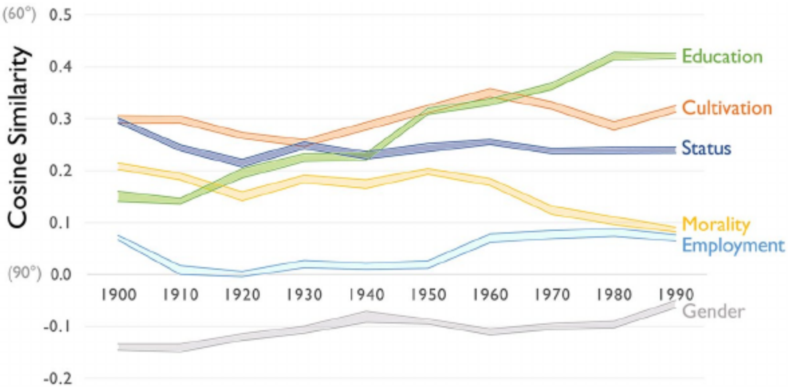


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

"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..."***

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- In what domains is this relevant?
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- Does language matter?
  - Djourelova (2020): style change from "illegal" to "undocumented" immigrant softened attitudes toward immigration.