Sequencing Legal DNA
NLP for Law and Political Economy

6. Word Embeddings

Q&A Page

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Outline

Word Embeddings

Bias in Language (Models)

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where

$$\underbrace{x_j}_{n_E \times 1} = \underbrace{\boldsymbol{E}}_{n_E \times n_w} \cdot \underbrace{w_j}_{n_w \times 1}$$

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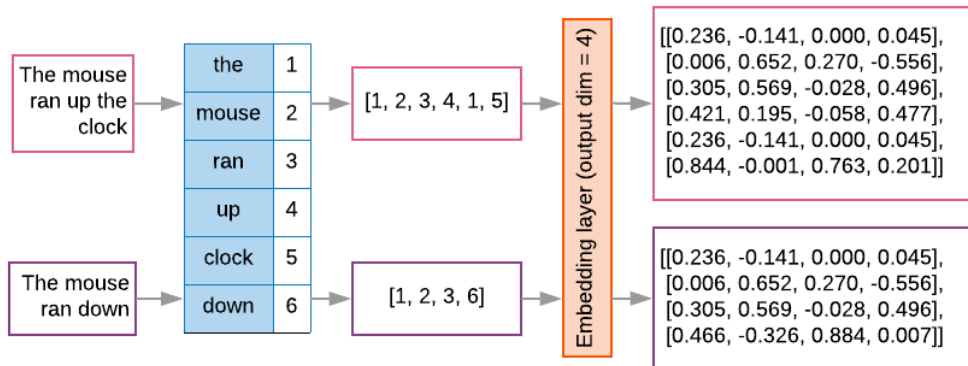
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  ▶ $\boldsymbol{E}$ is a matrix of word vectors. The column associated with the word at j is selected by the dot-product with one-hot vector w_j.
▶ $\boldsymbol{X}$ is flattened into an $L * n_E$ vector for input to the next layer.

Illustration

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- "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 $\rightarrow$ 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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- **M** is $n_w \times n_c$
    - if c is drawn from from the vocabulary of a reasonably large corpus, the associated word vectors $\{v_1 = M_{[w_1,:]}, v_2 = M_{[w_2,:]}, ...\}$ are too high-dimensional to be useful.

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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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- ▶ **similarity measures between rows of $\boldsymbol{W}$ approximate similarity measures between rows of $\boldsymbol{M}$**

Word Similarity

▶ Once words are represented as vectors $\{v_1 = \boldsymbol{M}_{[w_1,:]}, v_2 = \boldsymbol{M}_{[w_2,:]},...\}$, 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":
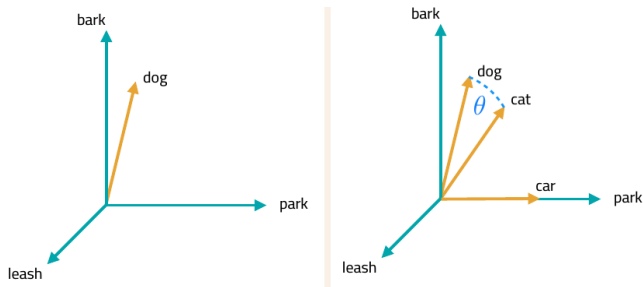
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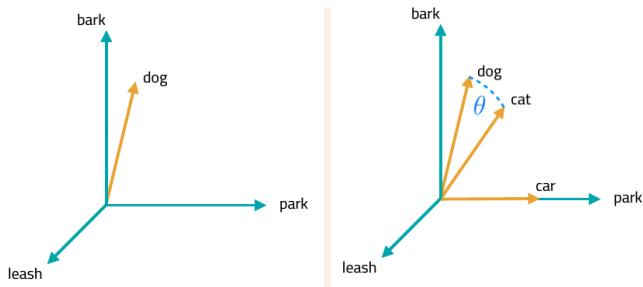
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- Thanks to linearity, can compute similarities between groups of words by averaging the groups.

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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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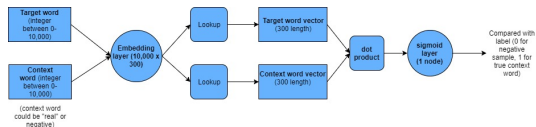
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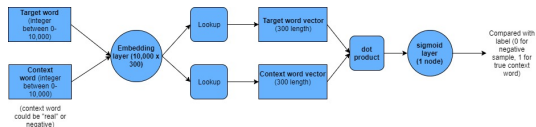
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▶ Word2Vec minimizes the binary cross-entropy

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

How does Word2Vec relate to the **M** matrix?

- Word2Vec produces embedding matrices **W** and **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 **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,** $\log\left(C_{ij}\right)$
▶ Intuitively: words that co-occur should have high correlation (dot product)

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Similarity vs. Relatedness (Budansky and Hirst, 2006)
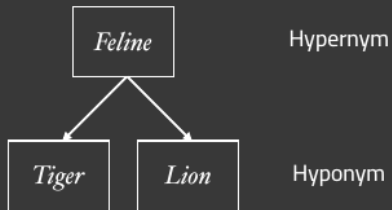
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▶ Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

Most similar words to dog, depending on context window size

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

▶ 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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- ▶ This is really important when we will use embeddings to anayze 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 ↔ Meaning

▶ Intriguingly, word2vec algebra can depict conceptual, analogical relationships between words:
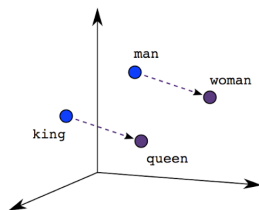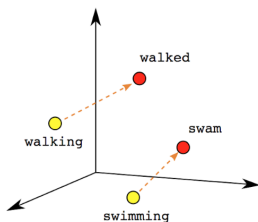
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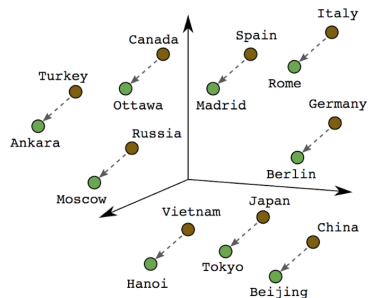
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▶ More generally: The analogy $a_1 : b_1 :: a_2 : b_2$ can be solved (that is, find b_2 given a_1, b_1, a_2) by

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▶ 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

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
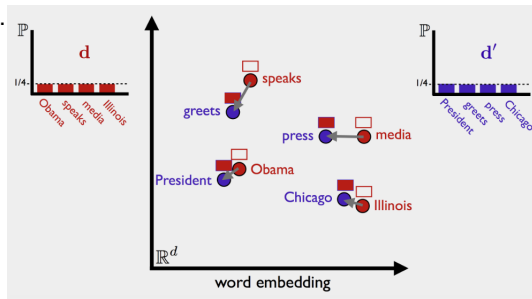
Pre-trained word embeddings

- 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

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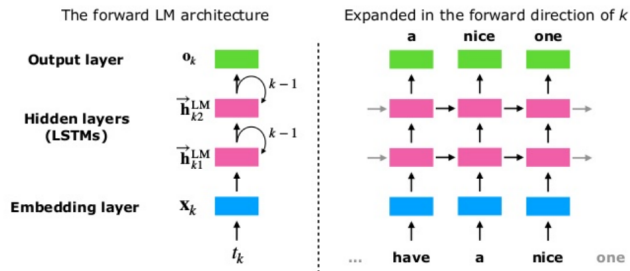
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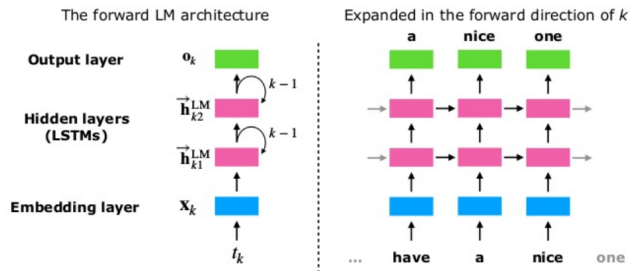
▶ The task:
  ▶ predict previous and next words in a sentence using a birectional LSTM.
▶ embeddings go through two hidden layers before the softmax output:
  ▶ first layer learns syntax
  ▶ second layer learns semantics

	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 <u>play</u> .
	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 .

GloVe mostly learns sport-related context

ELMo can distinguish the word sense based on the context

Table 4: Nearest neighbors to "play" using GloVe and the context embedding from a biLM.

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

Outline

Bias in NLP Systems
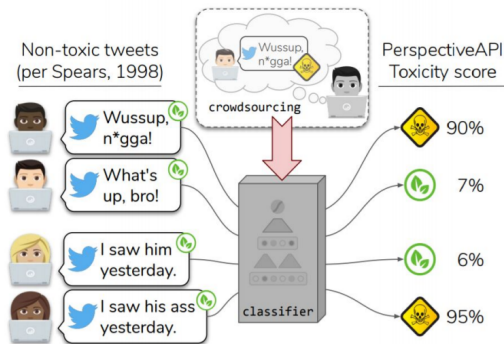
Within dataset proportions				
			% false identification	
DWMW17 Group	Acc.	None	Offensive	Hate
AAE	94.3	1.1	**46.3**	0.8
White	87.5	**7.9**	9.0	**3.8**
Overall	91.4	2.9	17.9	2.3
			% false identification	
FDCL18 Group	Acc.	None	Abusive	Hateful
AAE	81.4	4.2	**26.0**	**1.7**
White	82.7	**30.5**	4.5	0.8
Overall	81.4	20.9	6.6	0.8

What outcomes do we care about?
Jacobs and Wallach (2019)

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

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   What outcomes do we care about? ↔ What would we like to measure?

The measurement process

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
...

construct ⟫⟫ **operationalization** ⟫⟫ **measurement**

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e.g., representational harms from NLP systems [Barocas et al. 2017]

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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

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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" (Kirnan institute, OSU)

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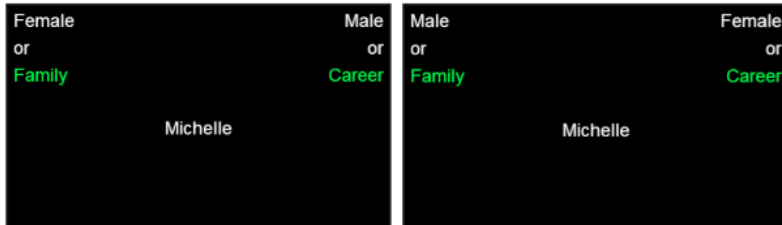
▶ Comparing reaction times across trials with different word pairs:
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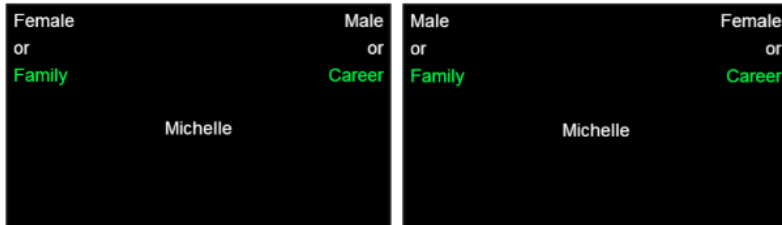
▶ Comparing reaction times across trials with different word pairs:
  ▶ subjects tend to be slower and more error-prone in assignments against stereotype (e.g. "Michelle" goes to "Female or Career").
  ▶ IAT score = difference in reaction time between stereotype-consistent and stereotype-inconsistent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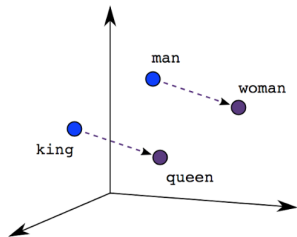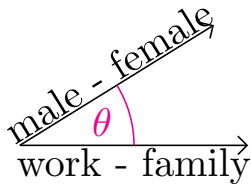
Analogies
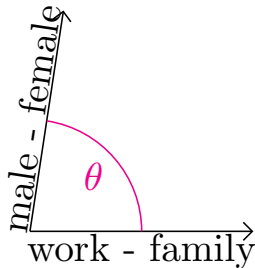- king : queen :: man : woman
- walked : walking :: swam : swimming
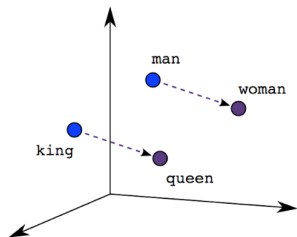
Analogies

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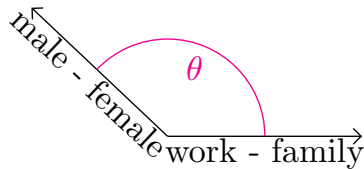- he : physician :: she : nurse

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
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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?

De-Biasing Word Embeddings

De-Biasing Word Embeddings

- Bolukbasi et al (NIPS 2016):
  - "Geometrically, **gender bias is first shown to be captured by a direction in the word embedding**."

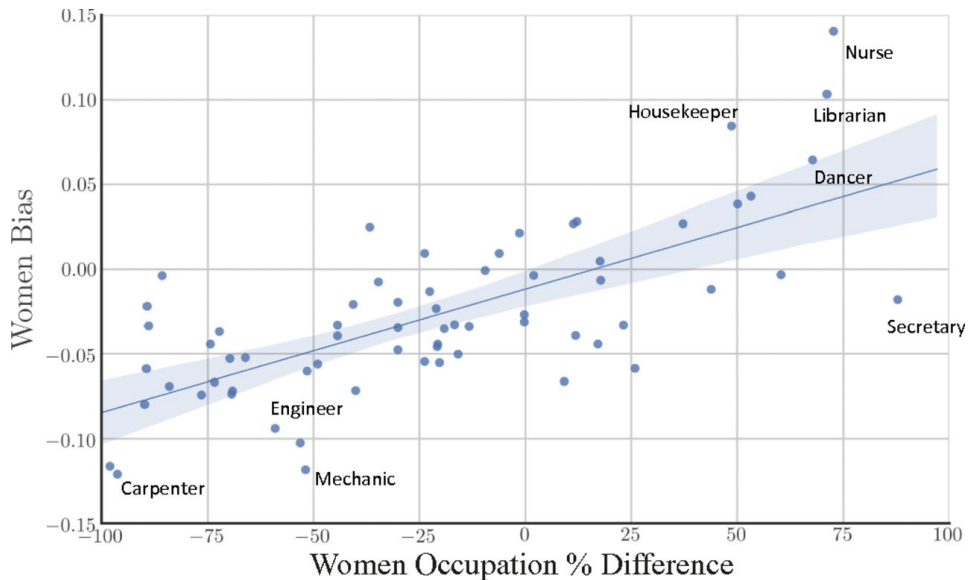# De-Biasing Word Embeddings

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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..."*

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

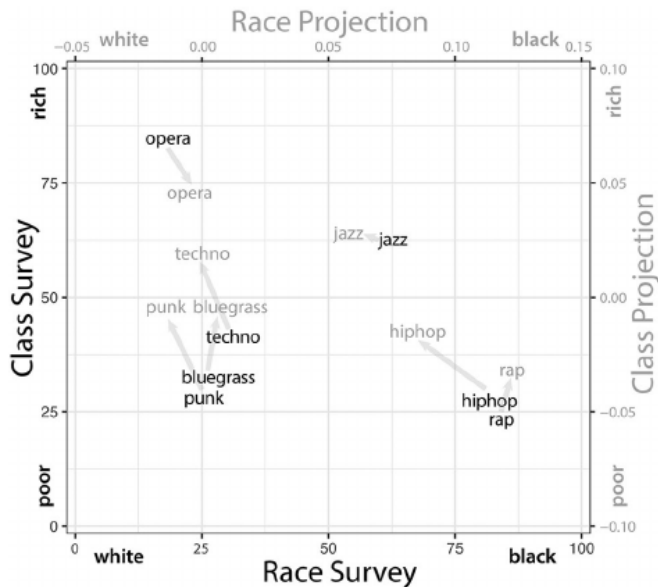Women's occupation relative percentage vs. embedding bias in Google News vectors.
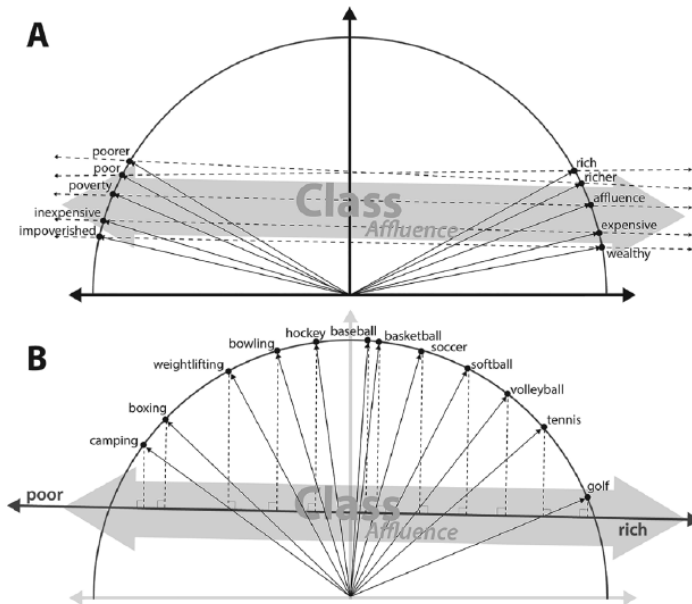
Figure 3. Projection of Music Genres onto Race and Class Dimensions of the Google News Word Embedding (Gray) and Average Survey Ratings for Race and Class Associations (Black)
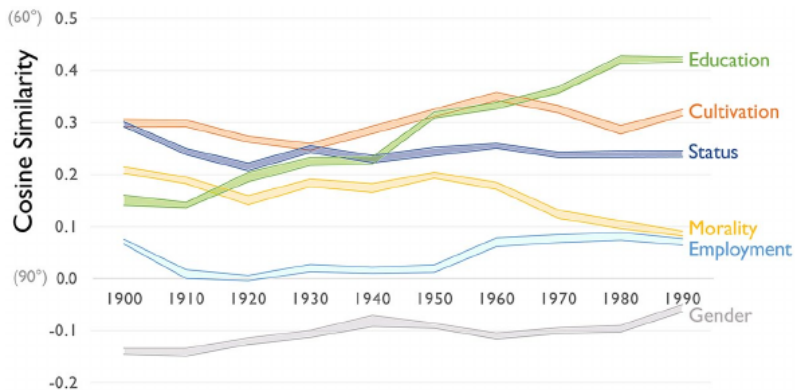
Time Series Analysis of Affluence

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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- ▶ Does language matter?
  - ▶ Djourelova (2020): style change from "illegal" to "undocumented" immigrant softened attitudes toward immigration.
  - ▶ what about slanted law? on judges, lawyers, law students, etc.