Text Analysis for Economics and Finance

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UPF, December 2020

Representing words as discrete symbols

- In the methods studied so far we have regarded words as discrete symbols: hotel vs. motel

Means one 1, the rest 0s

- Words can be represented by one-hot vectors

$$\begin{aligned} \text{motel} &= [0\,0\,0\,0\,0\,0\,0\,0\,1\,0\,0\,0\,0\,0\,0\,0] \\ \text{hotel} &= [0\,0\,0\,0\,1\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0] \end{aligned}$$

- Vector dimension = number of words in vocabulary (e.g. 500,000)

Problem with words as discrete symbols

- Example: in web search, if user searches for "Seattle motel", we would like to match documents containing "Seattle hotel"
- But:

$$\begin{aligned} \text{motel} &= [0\,0\,0\,0\,0\,0\,0\,0\,1\,0\,0\,0\,0\,0\,0] \\ \text{hotel} &= [0\,0\,0\,1\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0] \end{aligned}$$

- These two vectors are orthogonal
- There is no natural notion of similarity for one-hot vectors
- Solution:
  - Encode similarity in the vectors themselves

Representing words by their context

- Core idea: A word's meaning is given by the words that frequently appear close-by
  - *"You shall know a word by the company it keeps"* (J.R. Firth 1957)
  - One of the most successful ideas of modern statistical NLP
- When a word w appears in a text, its context is the set of words that appear nearby (within a fixed-size window)
- Use the many contexts of w to build up a representation of w

. . . government debt problems turning into	*banking*	*crises as happened in 2009 . . .*
. . . saying that Europe needs unified	*banking*	*regulation to replace the hodgepodge . . .*
. . . India has just given its	*banking*	*system a shot in the arm . . .*

These context words will represent **banking**

Word vectors

- We will build a dense vector for each word, chosen so that it is similar to vectors of words that appear in similar contexts

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

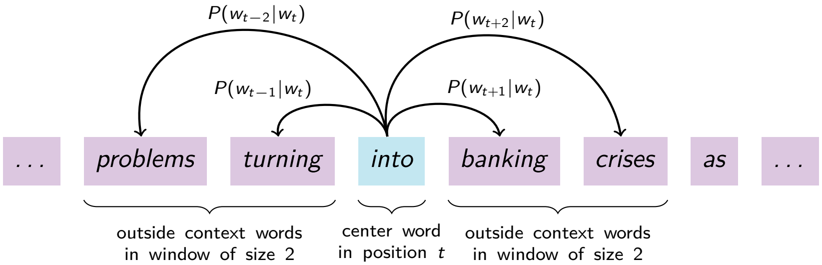
- Note: word vectors are sometimes called word embeddings or word representations

word2vec: overview

- word2vec (Mikolov et al. 2013) is a framework for learning word vectors
- Idea:
  - We have a large corpus of text
  - Every word in a fixed vocabulary is represented by a vector
  - Go through each position t in the text, which has a center word c and context ('outside') words o
  - Use the similarity of the word vectors for c and o to calculate the probability of o given c (or vice versa)
  - Keep adjusting the word vectors to maximize this probability

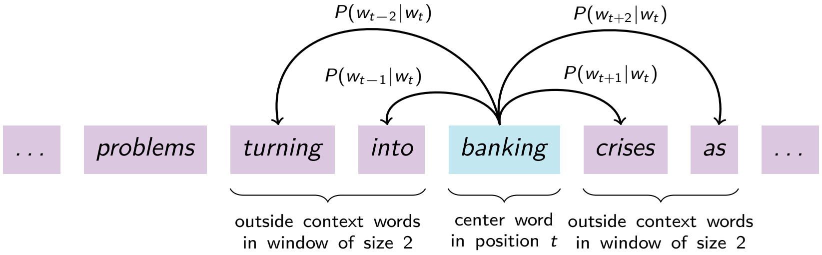
word2vec: overview

- Example windows and process for computing $P(w_{t+j}|w_t)$



word2vec: overview

- Example windows and process for computing $P(w_{t+j}|w_t)$



word2vec: objective function

- For each position $t = 1, \ldots, T$, predict context words within a window of fixed size m, given center word w_j

$$L(\theta) = \prod_{t=1}^{T} \prod_{-m \leq j \leq m} P\left(w_{t+j} \mid w_t; \theta\right)$$

  - θ is all the variables to be optimized

- The objective function $J(\theta)$ is the average negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{m \leq j \leq m} \log P\left(w_{t+j} \mid w_t; \theta\right)$$

  - Minimizing objective function $\Leftrightarrow$ Maximizing predictive accuracy

word2vec: objective function

- We want to minimize the objective function

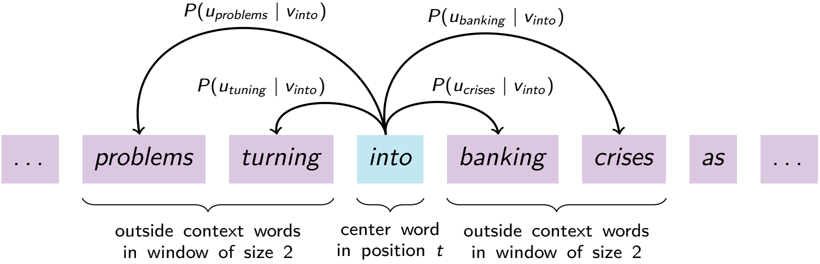
$$J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{m \leq j \leq m} \log P\left(w_{t+j} \mid w_t; \theta\right)$$

- Question: How to calculate $P\left(w_{t+j} \mid w_t; \theta\right)$
- Answer: We will use two vectors per word w:
  - v_w when w is a center word
  - u_w when w is a context word
- Then for a center word c and a context word o:

$$P(o \mid c) = \frac{\exp\left(u_o^T v_c\right)}{\sum_{w \in V} \exp\left(u_w^T v_c\right)}$$

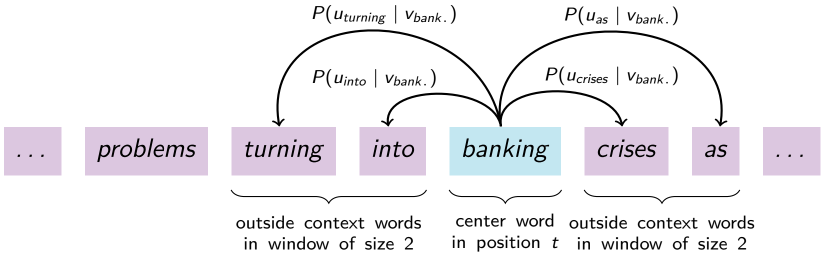
word2vec: overview with vectors

- Example windows and process for computing $P(w_{t+j} \mid w_t)$
- $P(u_{problems} \mid v_{into})$ is short for $P(problems|into, u_{problems}, v_{into}, \theta)$



word2vec: overview with vectors

- Example windows and process for computing $P(w_{t+j} \mid w_t)$



word2vec: prediction function

$$P(o \mid c) = \frac{\exp\left(u_o^T v_c\right)}{\sum_{w \in V} \exp\left(u_w^T v_c\right)}$$

- $u_o^T v_c$: dot product compares similarity of o and c. Larger dot product implies a larger probability
- $\sum_{w \in V} \exp\left(u_w^T v_c\right)$: after taking exponent, normalize over entire vocabulary
- This is an example of the softmax function $\mathbb{R}^n \to \mathbb{R}^n$
- The softmax function maps arbitrary values x_i to a probability distribution p_i
  - "max" because amplifies probability of largest x_i
  - "soft" because still assigns some probability to smaller x_i

To train the model: compute all vector gradients

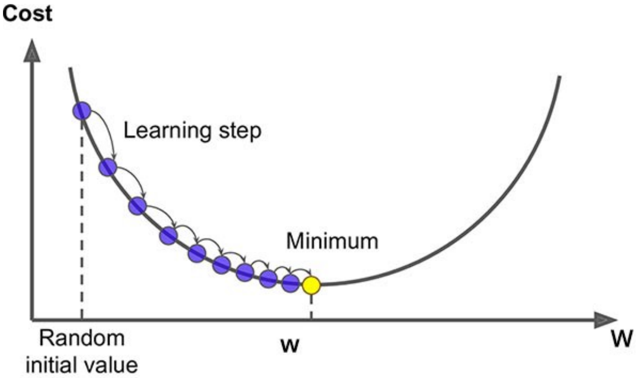
- Recall: θ represents all model parameters, in one long vector
- In our case with d-dimensional vectors and V-many words:

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ u_{aardvark} \\ u_a \\ \vdots \\ u_{zebra} \end{bmatrix} \in \mathbb{R}^{2dV}$$

- Recall: every word has two vectors
- We then optimize these parameters using stochastic gradient descent

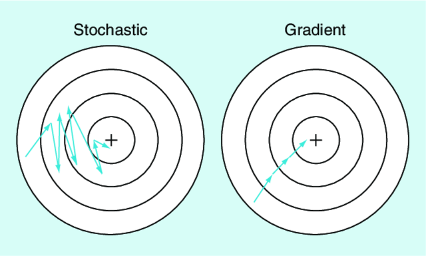
word2vec: gradient descent

- We have a cost function $J(\theta)$ we want to minimize
- Idea: for the current value of θ, calculate the gradient of $J(\theta)$, then take a small step in the direction of the negative gradient. Repeat.



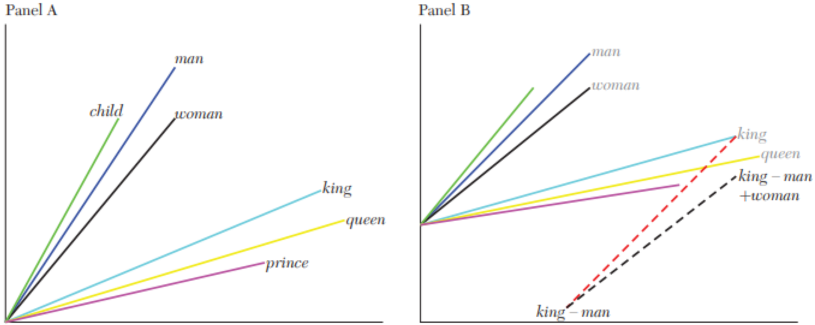
word2vec: stochastic gradient descent

- Problem: $J(\theta)$ is a function of all windows in the corpus
  - $\nabla_\theta J(\theta)$ may be very expensive to compute
- You would wait a very long time before making a single update. A very bad idea for pretty much all neural nets
- Solution: stochastic gradient descent (SGD)
  - Repeatedly sample windows, and update after each one



word2vec: applications

- Once the vectors are constructed, they can be used to represent relations between words



Garg, Schiebinger, Jurafsky, and Zou (2018)

- Goal: develop a systematic framework to analyze word embeddings trained over a century of text data to identify historical patterns of bias and stereotype changes in the US
- Motivation: in word-embedding models, words are assigned to a high-dimensional vector in a way that they capture relationships not found through simple co-occurrence analysis
- Idea: exploit differences in Euclidean distance between ethnic-gender terms and professions-stereotypes words to quantify historical trends
- Main findings: the embedding captures societal shifts and sheds light on how specific adjectives and occupations became more closely associated with certain populations over time

GSJZ (2018): data

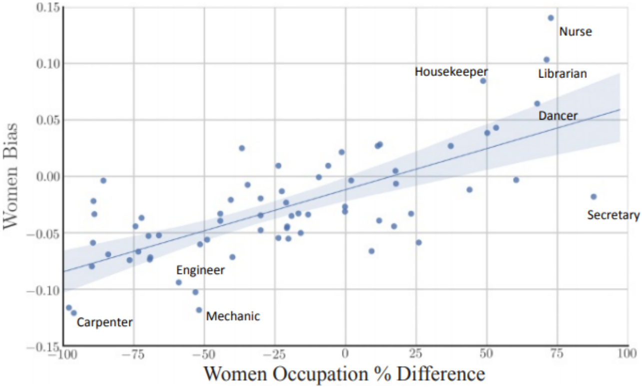
- Word embeddings:
  - word2vec embeddings trained on the Google News dataset
  - Nine decade-specific embeddings trained on text from the Corpus of Historical American English
- Word lists:
  - Gender: *he, she, son, daughter, male, female, boy, girl, etc.*
  - Ethnicty: *harris, ruiz, cho, thompson, gomez, lin, etc.*
  - Occupations: *janitor, teacher, shoemaker, scientist, carpenter, etc.*
  - Adjectives: *headstrong, inventive, enterprising, poised, moody, etc.*

GSJZ (2018): methodology

- Measure the strength of association between occupations or adjectives (neutral words) and a gender or ethnicity
    1. Compute the average vector representation of a gender or ethnic group
    2. Calculate the average Euclidean distance between the representative vector and each vector in a list of neutral words
    3. Use the difference of the average distance between gender or ethnicity pairs as a measure of embedding bias
- e.g. the occupational embedding bias for women
    1. Compute average embedding distance between words *she, female* and occupational words *teacher, lawyer*. Repeat for words he, male
    2. Compute the difference in average distances between group pair

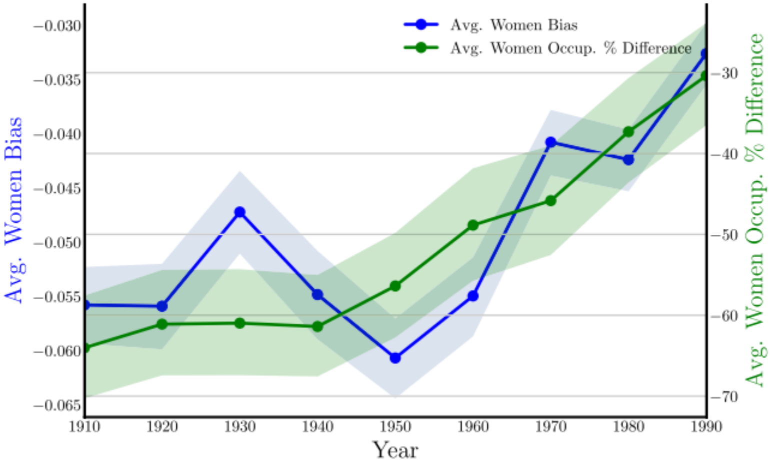
$$\text{relative norm distance } = \sum_{v_m \in M} \|v_m - v_1\|_2 - \|v_m - v_2\|_2$$

GSJZ (2018): gender bias snapshot validation



- Occupation difference as the relative percentage of women in each occupation using data from the Integrated Public Use Microdata Series

GSJZ (2018): gender bias historical validation

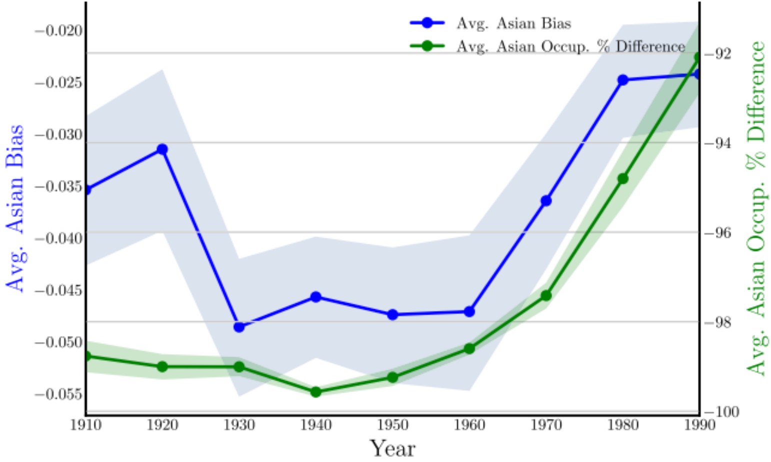


GSJZ (2018): ethnic bias historical validation

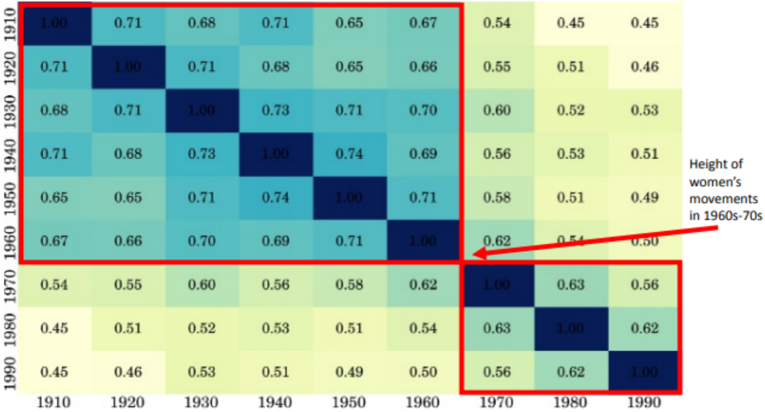
Table 1. The top 10 occupations most closely associated with each ethnic group in the Google News embedding

Hispanic	Asian	White
Housekeeper	Professor	Smith
Mason	Official	Blacksmith
Artist	Secretary	Surveyor
Janitor	Conductor	Sheriff
Dancer	Physicist	Weaver
Mechanic	Scientist	Administrator
Photographer	Chemist	Mason
Baker	Tailor	Statistician
Cashier	Accountant	Clergy
Driver	Engineer	Photographer

GSJZ (2018): ethnic bias historical validation



GSJZ (2018): quantifying gender stereotypes



- Pearson correlation in embedding bias scores for adjectives over time

GSJZ (2018): quantifying gender stereotypes

Table 2. Top adjectives associated with women in 1910, 1950, and 1990 by relative norm difference in the COHA embedding

1910	1950	1990
Charming	Delicate	Maternal
Placid	Sweet	Morbid
Delicate	Charming	Artificial
Passionate	Transparent	Physical
Sweet	Placid	Caring
Dreamy	Childish	Emotional
Indulgent	Soft	Protective
Playful	Colorless	Attractive
Mellow	Tasteless	Soft
Sentimental	Agreeable	Tidy

GSJZ (2018): quantifying ethnic stereotypes

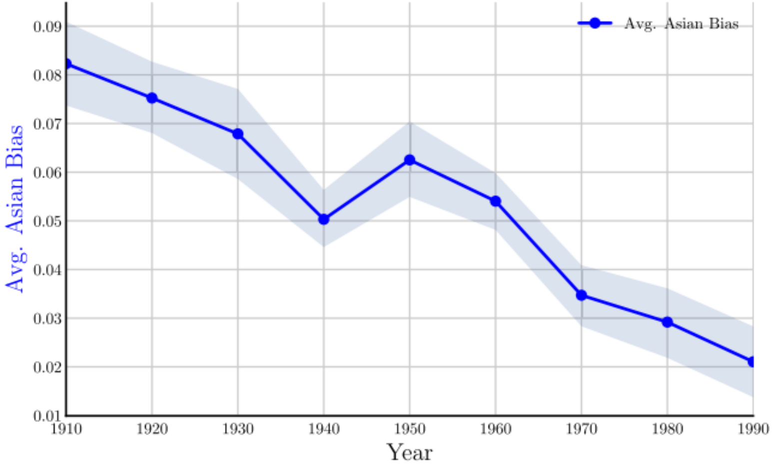
- Pearson correlation in embedding Asian bias scores for adjectives

GSJZ (2018): quantifying ethnic stereotypes

Table 3. Top Asian (vs. White) adjectives in 1910, 1950, and 1990 by relative norm difference in the COHA embedding

1910	1950	1990
Irresponsible	Disorganized	Inhibited
Envious	Outrageous	Passive
Barbaric	Pompous	Dissolute
Aggressive	Unstable	Haughty
Transparent	Effeminate	Complacent
Monstrous	Unprincipled	Forceful
Hateful	Venomous	Fixed
Cruel	Disobedient	Active
Greedy	Predatory	Sensitive
Bizarre	Boisterous	Hearty

GSJZ (2018): quantifying ethnic stereotypes



- Asian bias score over time for words related to outsiders in COHA data

Kozlowski, Taddy and Evans (2019): geometry of culture

- Motivation
  - If text represents culture, can we construct cultural dimensions of class from the dimension of word embedding vectors?
  - Has the meaning of these dimensions changed over the XXth century?
- Class as the systematic and hierarchical distinction of people and groups in social standing. Dimension-specific nuances:
  - **Money:** easy to convert into various forms of power → affluence
  - **Education:** determines the labor market position → education
  - **Status:** based on authority and social position → status
  - **Cultivated taste:** based on the culture consumed → cultivation
  - **Gender:** misogynistic or patriarchal hierarchies → gender
  - **Race:** reflected in post-colonial, structural racism → race

KTE (2019): the cultural dimensions of class

- These dimensions can be represented through semantic contrasts
  - **Affluence:** rich vs poor, wealthy vs impoverished, luxury vs cheap
  - **Education:** educated vs uneducated, knowledgeable vs ignorant
  - **Status:** acclaimed vs modest, eminent vs mundane
  - **Cultivation:** civil vs uncivil, cultured vs uncultured
  - **Gender:** masculine vs feminine, he vs she, male vs female
  - **Race:** black vs white, African vs European
- Main idea: words that are opposites semantically will display systematic differences in their vector representation

KTE (2019): the cultural dimensions of class

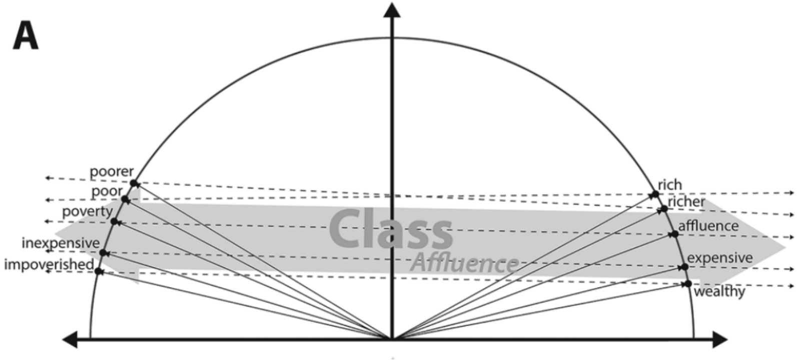
- Intuition: solving an analogy is equivalent to projecting a word vector onto a specific dimension

$$\overrightarrow{\text{king}} + \overrightarrow{\text{woman}} - \overrightarrow{\text{man}} \approx \overrightarrow{\text{queen}}$$

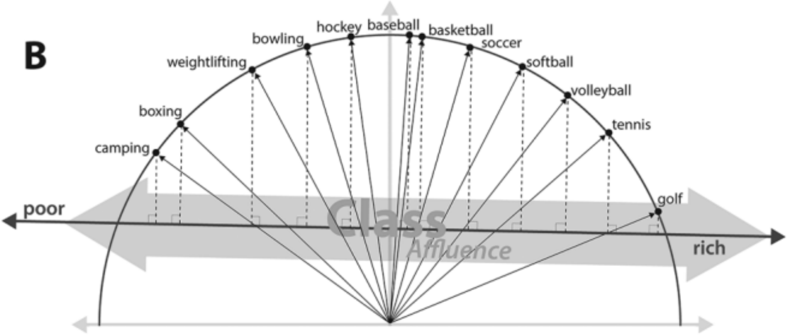
- The projection of the word vector for king onto a gender dimension captured by $\overrightarrow{\text{woman}} - \overrightarrow{\text{man}}$ yields the word vector for queen
- Collate lists of antonyms similar to $\overrightarrow{\text{woman}} - \overrightarrow{\text{man}}$ for the different dimensions of class, i.e. $\overrightarrow{\text{rich}} - \overrightarrow{\text{poor}}$
- Project words onto dimension-specific antonym lists to identify the cultural associations embedded in the word

$$\overrightarrow{\text{hockey}} + \overrightarrow{\text{rich}} - \overrightarrow{\text{poor}} \approx \overrightarrow{\text{lacrosse}}$$

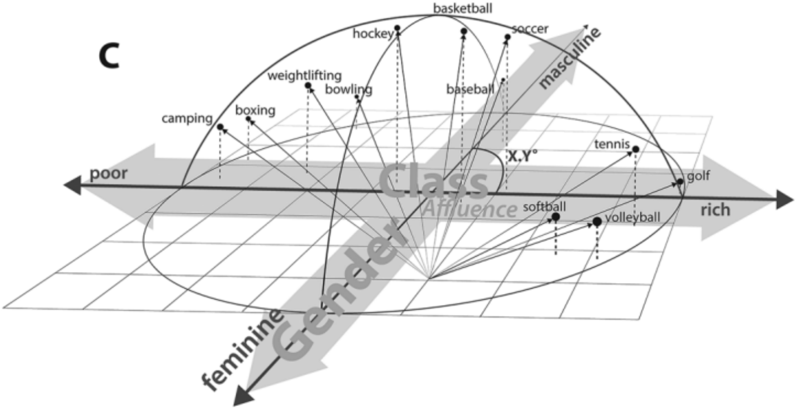
KTE (2019): the cultural dimensions of class



KTE (2019): the cultural dimensions of class



KTE (2019): the cultural dimensions of class



KTE (2019): data and methods

- Use three pre-trained word embedding models:
  - Google Ngrams US
  - Google News embeddings
  - GloVe embeddings
- Trained via Google Ngram corpus
  - 6% of all books ever published
  - Only look at 5-grams
  - Divide corpus by decades
  - Keep only words that appear $>$ 25 times
- Antonym lists compiled from five thesauri

KTE (2019): data

Table D1. Word Pairs Used to Construct Affluence, Gender, and Race Dimensions for Amazon Mechanical Turk Survey Validation

Affluence		Gender	Race
rich-poor	precious-cheap	man-woman	black-white
richer-poorer	priceless-worthless	men-women	blacks-whites
richest-poorest	privileged-underprivileged	he-she	Black-White
affluence-poverty		him-her	Blacks-Whites
affluent-destitute	propertied-bankrupt	his-her	African-European
advantaged-needy	prosperous-unprosperous	his-hers	African-Caucasian
wealthy-impoverished	developed-underdeveloped	boy-girl	Afro-Anglo
costly-economical		boys-girls	
exorbitant-impecunious	solvency-insolvency	male-female	
expensive-inexpensive	successful-unsuccessful	masculine-feminine	
exquisite-ruined	sumptuous-plain		
extravagant-necessitous	swanky-basic		
flush-skint	thriving-disadvantaged		
invaluable-cheap	upscale-squalid		
lavish-economical	valuable-valueless		
luxuriant-penurious	classy-beggarly		
luxurious-threadbare	ritzy-ramshackle		
luxury-cheap	opulence-indigence		
moneyed-unmonied	solvent-insolvent		
opulent-indigent	moneyed-moneyless		
plush-threadbare	rich-penniless		
luxuriant-penurious	affluence-penury		
	posh-plain		
	opulence-indigence		

KTE (2019): data

Table D3. Word Pairs Used to Construct Class Dimensions (Along with Affluence and Gender in Table D1)

Cultivation	Employment	Education	Status	Morality
cultivated-uncultivated	employer-employee	educated-uneducated	prestigious-unprestigious	good-evil
cultured-uncultured	employers-employees	learned-unlearned	honorable-dishonorable	moral-immoral
civilized-uncivilized	owner-worker	knowledgeable-ignorant	esteemed-lowly	good-bad
courteous-discourteous	owners-worker	trained-untrained	influential-uninfluential	honest-dishonest
proper-improper	industrialist-laborer	taught-untaught	reputable-disreputable	virtuous-sinful
polite-rude	industrialists-laborers	literate-illiterate	distinguished-commonplace	virtue-vice
cordial-uncordial	proprietor-employee	schooled-unschooled	eminent-mundane	righteous-wicked
formal-informal	proprietors-employees	tutored-untutored	illustrious-humble	chaste-transgressive
courtly-uncourtly	capitalist-proletarian	lettered-unlettered	renowned-prosaic	principled-unprincipled
urbane-boorish	capitalists-proletariat		acclaimed-modest	unquestionable-questionable
polished-unpolished	manager-staff		dignitary-commoner	noble-nefarious
refined-unrefined	managers-staff		venerable-unpretentious	uncorrupt-corrupt
civility-incivility	director-employee		exalted-ordinary	scrupulous-unscrupulous
civil-uncivil	directors-employees		estimable-lowly	altruistic-selfish
urbanity-boorishness	boss-worker		prominent-common	chivalrous-knavish
politesse-rudeness	bosses-workers			honest-crooked
edified-loutish	foreman-laborer			commendable-reprehensible
mannerly-unmannerly	foremen-laborers			pure-impure
polished-gruff	supervisor-staff			dignified-undignified
gracious-ungracious	superintendent-staff			holy-unholy
obliging-unobliging				valiant-fiendish
cultured-uncultured				upstanding-villainous
genteel-ungenteel				guiltless-guilty
mannered-unmannered				decent-indecent
polite-blunt				chaste-unsavory
				righteous-odious
				ethical-unethical

KTE (2019): methods

- For each class dimension, calculate the following:

$$\frac{\sum_p^{|P|} \overrightarrow{p_1} - \overrightarrow{p_2}}{|P|}$$

- p are all antonym couples in set P of relevant words by context
- The projection of a word vector onto a dimension is computed using cosine similarity

KTE (2019): methods

Validation

- Use two surveys
  - **Modern Survey:** rate 59 words on different dimensions (class, race, gender)
  - ***Historical* Survey:** rate 360 words on 20 semantic dimensions (good/bad, soft/hard, ...)
- Example:
  - On a scale from 0 (very working class) to 100 (very upper class), how would you rate a steak?

Table B3. Percentage of Statistically Significant ($p < .01$) Survey Differences Correctly Classified in Google News Word Embedding Model

	Sports	Food	Music	Occupations	Vehicles	Clothes	Names	All Domains
Gender	87.9%	88.2%	72.2%	93.6%	82.4%	74.4%	95.2%	84.8%
Class	96.3%	93.8%	88.9%	60.9%	94.1%	90.0%	77.3%	75.3%
Race	90.0%	68.8%	100%	51.5%	87.5%	55.0%	94.7%	69.1%

KTE (2019): methods

Validation

Table B1. List of Words Rated in Cultural Associations Survey

Occupations	Clothing	Sports	Music Genres	Vehicles	Food	First Names
Banker	Blouse	Baseball	Bluegrass	Bicycle	Beer	Aaliyah
Carpenter	Briefcase	Basketball	Hip hop	Limousine	Cheesecake	Amy
Doctor	Dress	Boxing	Jazz	Minivan	Hamburger	Connor
Engineer	Necklace	Golf	Opera	Motorcycle	Pastry	Jake
Hairdresser	Pants	Hockey	Punk	Skateboard	Salad	Jamal
Journalist	Shirt	Soccer	Rap	SUV	Steak	Molly
Lawyer	Shorts	Softball	Techno	Truck	Wine	Shanice[a]
Nanny	Socks	Tennis				Tyrone
Nurse	Suit	Volleyball				
Plumber	Tuxedo					
Scientist						

KTE (2019): methods

Validation

Table 1. Pearson Correlations between Survey Estimates and Word Embedding Estimates for Gender, Class, and Race Associations

	Class (Affluence)	Gender	Race
Google Ngrams *word2vec* Embedding[†]	.53	.76	.27
Google News *word2vec* Embedding	.58	.88	.75
Common Crawl *GloVe* Embedding	.57	.90	.44

KTE (2019): methods

Validation

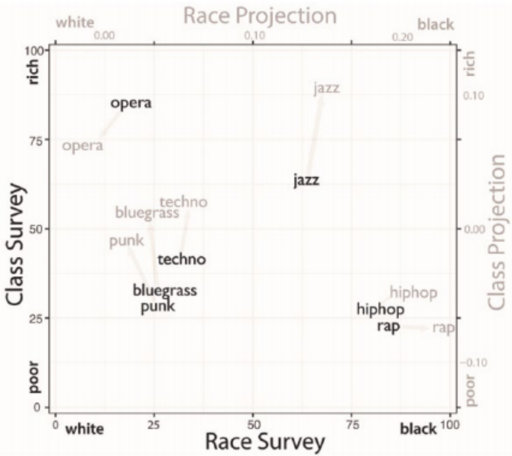


Figure 3. Projection of Music Genres onto Race and Class Dimensions of the Google News Word Embedding (Gray) and Average Survey Ratings for Race and Class Associations (Black)

KTE (2019): results

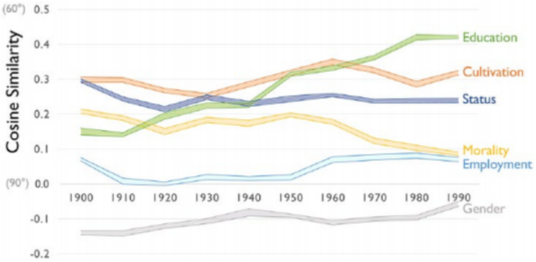


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

- Education has become more synonymous with **affluence**
  - Crucial for a competitive labor market → **signaling**
  - Mediated by cultivation: when controlled, negligible correlation

KTE (2019): results

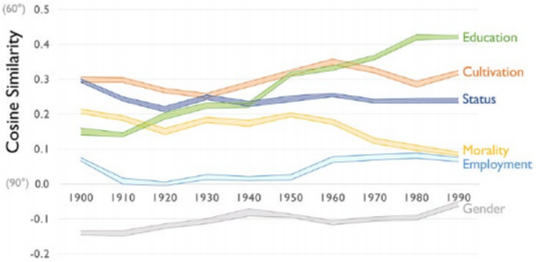


Figure 5. Cosine Similarity between the Affluence Dimension and Six Other Cultural Dimensions of Class by Decade; 1900 to 1999 Google Ngrams Corpus
Note: Bands represent 90 percent bootstrapped confidence intervals produced by subsampling.

- Gender: positive association between femininity and **affluence**
  - Veblen's idea of women as vessels for men's *vicarious consumption*
  - Words strongly projected include *fragance, jewel, gem, perfume*

KTE (2019): results

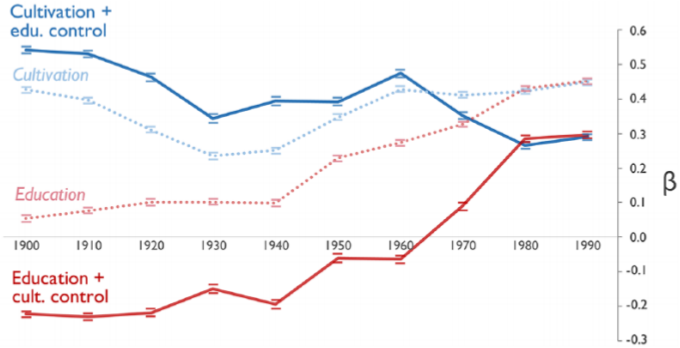


Figure 6. Standardized Coefficients from OLS Regression Models in Which Word Projections on Cultivation and Education Dimensions Predict Projection on the Affluence Dimension; 1900 to 1999 Google Ngrams Corpus

Note: A separate OLS regression model is fit for each decade; N = 50,000 most common words in each decade.