Taking uncertainty seriously

A Bayesian approach to word embedding bias estimation

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Boston, April Fools' Day

Presentation plan

- Word embeddings
- Cosine similarity
- Bias in word embeddings
- WEAT and MAC measures
- Methodological problems
- Bad consequences of pre-averaging
- Our Bayesian alternative

Word embeddings

Question

How to sensibly represent words with numbers?

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One-hot encoding

Well, you could use 30k binary vectors with a slot for each lexical unit...

Word embeddings

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How to sensibly represent words with numbers?

One-hot encoding

Well, you could use 30k binary vectors with a slot for each lexical unit...
...but this would be inefficient and wouldn't capture any relations between words.

Word embeddings

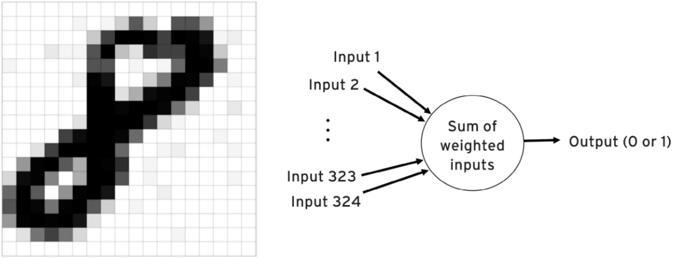
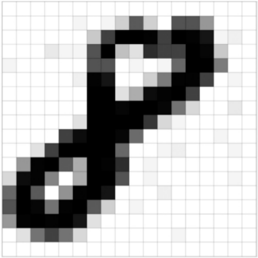


Illustration: M. Mitchell

Rosenblatt's perceptron

- Inputs (pixel intensities) with weights
- Nodes with activation levels from 0-1
- (Perhaps) 0-1 output based on a threshold

Word embeddings



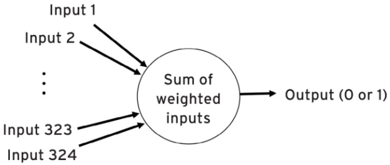


Illustration: M. Mitchell

Learning

- Start with random weights
- Test on a case:
  - If right, don't change weights.
  - If wrong, change weights a bit, with focus on the ones more responsible for the judgment:

$$w_j \leftarrow w_j = \overbrace{\eta}^{\text{learning rate}} \left(\underbrace{t}_{\text{correct output}} - \overbrace{y}^{\text{actual output}} \right) \underbrace{x_j}_{\text{actual input}}$$

Word embeddings

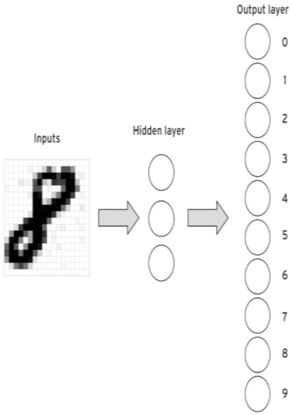


Illustration: M. Mitchell

- Each hidden unit takes a weighted sum of 324 inputs and passes on its activation level as input to outer layer units.
- Activation levels of outer layers are interpreted as network's levels of confidence in a classification problem.
- Learning: back-propagation (gradient descent: approximate the direction of steepest descent in the error surface w.r.t to weights, modify accordingly).

Word embeddings

Distributional semantics

- "You shall know a word by the company it keeps" (John Firth, 1957)
- "...the degree of semantic similarity between two linguistic expressions A and B is a function of the similarity of the linguistic contexts in which A and B can appear." (A. Lenci, 2008)

Word embeddings

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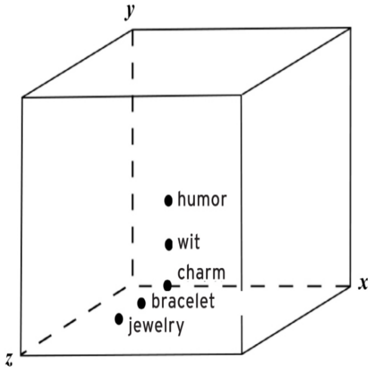

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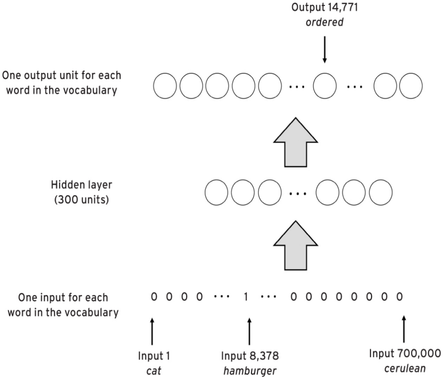
Word embeddings

Google and Mikolov

Efficient Estimation of Word Representation in Vector Space, 2013

Let's train a neural network and use vectors of weights!



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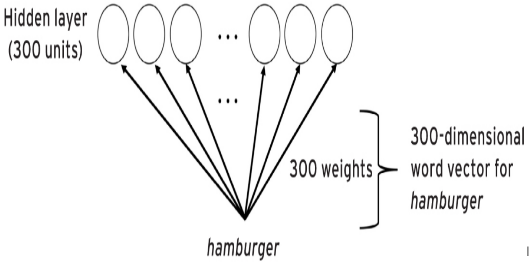

Illustration: M. Mitchell

Word embeddings

word	1	2	3	4	...
woman	0.456	0.267	0.675	0.131	...
man	0.451	0.897	0.472	0.088	...

Question

How is this supposed to capture semantic relations?

Word embeddings

word	1	2	3	4	...
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Question

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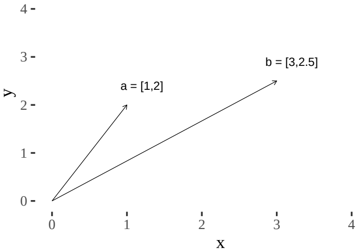
General idea

Similarity in vector direction.

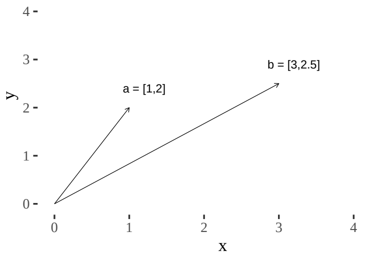
Cosine similarity



Vectors

$$a = [1, 2]$$
$$b = [3, 2.5]$$

Cosine similarity



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Dot product

$$a \cdot b = a_1 b_1 + a_2 b_2$$
$$a \cdot a = a_1^2 + a_2^2$$
$$\|a\| = \sqrt{(a \cdot a)}$$

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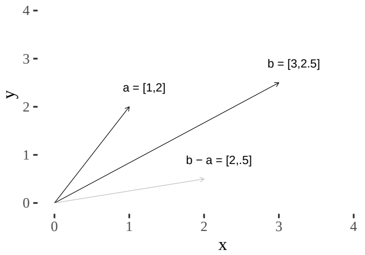

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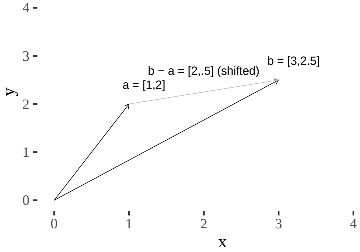

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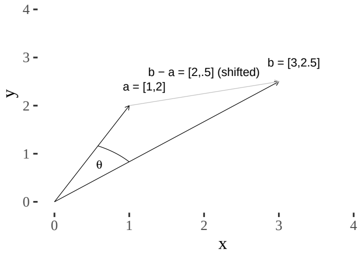
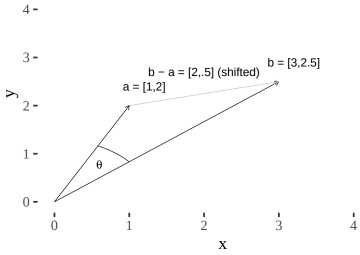


Angle

$$
\begin{aligned}
\|b-a\|^2 &= \|b\|^2 + \|a\|^2 - 2\|b\|\|a\|\cos\theta \\
b \cdot a &= \|b\|\|a\|\cos\theta \\
\cos\theta &= \frac{b \cdot a}{\|b\|\|a\|}
\end{aligned}
$$

Cosine similarity



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\end{aligned}
$$

Orthogonality

$$
\begin{aligned}
\cos(90^\circ) &= 0 \\
\frac{b \cdot a}{||b||||a||} &= 0 \\
b \cdot a &= 0
\end{aligned}
$$

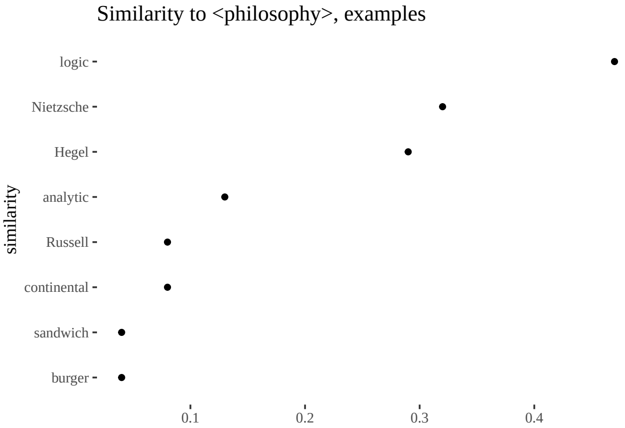
Cosine similarity & distance

$$\text{cosineSimilarity}(A, B) = \frac{A \cdot B}{\|A\| \, \|B\|} \tag{Sim}$$

$$\text{cosineDistance}(A, B) = 1 - \text{cosineSimilarity}(A, B) \tag{Distance}$$

- Naive interpretation: proximity corresponds to semantic similarity
- Geometric interpretation: direction $\cos \in (-1, 1)$
  - 1: maximally smilar
  - -1: opposites
  - 0: lack of similarity
- cosineDistance $\in (0, 2)$

Cosine similarity & distance



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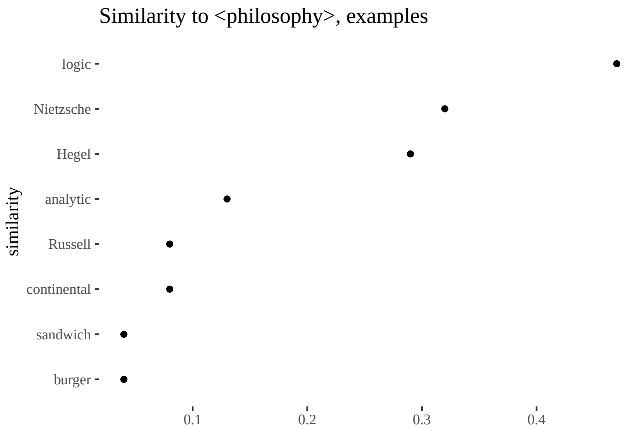


The only "jobs" in top-tens

- Man: robber (.55)
- Woman: policewoman (.6)

Cosine-based measures of bias

The worry

Word embeddings can learn implicit harmful biases

Cosine-based measures of bias

The worry

Word embeddings can learn implicit harmful biases

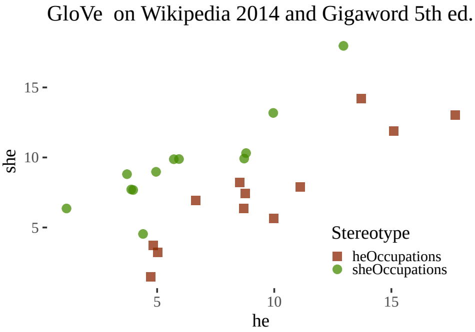
The basic intuition

Stereotypically connected words are cosine-close

Cosine-based measures of bias

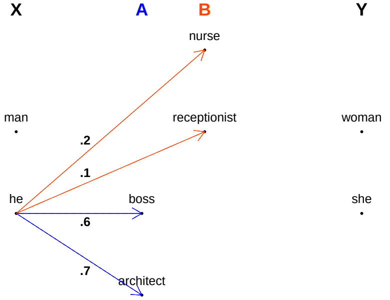
A visual example

- "feminine" occupations: "homemaker," "nurse," "receptionist," "librarian," etc.
- "masculine" occupations: "maestro," "captain," "architect," "boss," etc.



Cosine-based measures of bias

Example: Word Embedding Association Test (WEAT)



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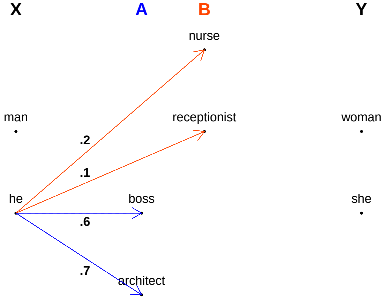


- $s_1 = s(he, A, B) = \frac{.6+.7}{2} - \frac{.2+.1}{2} = .65 - .15 = .5$
- $s_2 = s(man, A, B) = .3,$
  $s_3 = s(woman, A, B) = -.6, s_4 = s(she, A, B) = -.3$

$$\text{WEAT}(A, B) = \frac{(s_1+s_2)/2 - (s_3+s_4)/2}{sd(\{s_1, s_2, s_3, s_4\})} \approx 1.93$$

Cosine-based measures of bias

Example: Word Embedding Association Test (WEAT)

$$s(t, A, B) = \frac{\sum_{a \in A} f(t, a)}{|A|} - \frac{\sum_{b \in B} f(t, b)}{|B|}$$

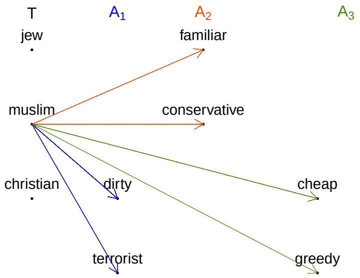
$$WEAT(A, B) = \frac{\mu\left(\{s(x, A, B)\}_{x \in X}\right) - \mu\left(\{s(y, A, B)\}_{y \in Y}\right)}{\sigma\left(\{s(w, A, B)\}_{w \in X \cup Y}\right)}$$

- t is a term, A, B are sets of stereotype attribute words, X, Y are protected group words
- For instance, X might be a set of male names, Y a set of female names, A might contain stereotypically male-related career words, and B stereotypically female-related family words
- s-values are used as datapoints in statistical significance tests

(Caliskan, Bryson, & Narayanan, 2017) with extensions in (Lauscher & Glavas, 2019) and applications in (Garg, Schiebinger, Jurafsky, & Zou, 2018)

Cosine-based measures of bias

Our main target: Mean Average Cosine Similarity (MAC)



$$s_1 = s(muslim, A_1) = \frac{cos(muslim, dirty) + cos(muslim, terrorist)}{2}$$

$$s_2 = s(muslim, A_2) = \frac{cos(muslim, familiar) + cos(muslim, conservative)}{2}$$

$$\vdots$$

$$MAC(T, A) = \text{mean}(\{s_i | i \in 1, \ldots, k\})$$

Cosine-based measures of bias

Our main target: Mean Average Cosine Similarity (MAC)

$$S(t_i, A_j) = \frac{1}{|A_j|} \sum_{a \in A_j} \cos(t, a)$$

$$MAC(T, A) = \frac{1}{|T|\,|A|} \sum_{t_i \in T} \sum_{A_j \in A} S(t_i, A_j)$$

- $T = \{t_1, \ldots, t_k\}$ is a class of protected words
- each $A_j \in A$ is a set of attributes stereotypically associated with a protected word
- The t-tests they employ are run on average cosines used to calculate MAC

(Manzini, Lim, Tsvetkov, & Black, 2019)

Cosine-based measures of bias

Our main target: Mean Average Cosine Similarity (MAC)

Table 2: A few rows from the religion dataset

protectedWord	wordToCompare	cosineDistance	cosineSimilarity
jew	greedy	0.6947042	0.3052958
rabbi	greedy	1.0306175	-0.0306175
rabbi	conservative	0.7175887	0.2824113
christian	uneducated	0.5081939	0.4918061
christianity	cheap	1.2816164	-0.2816164
muslim	terrorist	0.2726106	0.7273894

Cosine-based measures of bias

General challenges

- Gender-direction: insufficient indicator of bias (Gonen & Goldberg, 2019)
- Use of analogies: unreliable (Nissim, Noord, & Goot, 2020)
- High sensitivity to irrelevant factors (Zhang, Sneyd, & Stevenson, 2020)

Some methodological problems

Word list choice is unprincipled

- We run with it for comparison.

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The form of the definition is suspicious

- Ethayarajh, Duvenaud, & Hirst (2019) show that if there are two target words only WEAT is always maximal in one direction.
- We show the problem runs deeper and stems from pre-averaging, and we statistically gauge the uncertainty that arises from raw sample sizes.

Some methodological problems

No word class distinction and no control group

We make the subclasses clear, add human neutral predicates and neutral predicates for control. We used L2-Reddit corpus and GoogleNews (we present the results for Reddit for brevity).

Table 3: Rows from extended religion dataset.

protectedWord	wordToCompare	wordClass	cosineDistance	cosineSimilarity	connection
torah	hairy	jewish	1.170	-0.170	associated
christian	dirty	muslim	0.949	0.051	different
judaism	cheap	jewish	1.232	-0.232	associated
christianity	familial	christian	0.645	0.355	associated
mosque	approve	neutral	0.995	0.005	none
imam	carry	human	0.993	0.007	human
mosque	merging	neutral	0.868	0.132	none
muslim	nationalized	neutral	0.870	0.130	none

Some methodological problems

Our neutral words (examples, full list size = 242)

liquor, pow, ballpark, glitchy, billy, dallas, rip, called, outlooks, viet, floater, rattlesnake, exports, peruvian, recursion, shortfall, corrected, amicable, solutions, diagnostic, patently, flops, approx, percents, lox, catapults, hamburger, engulfed, households, north, snubbed, playtest

Our human-related words (examples, full list size = 27)

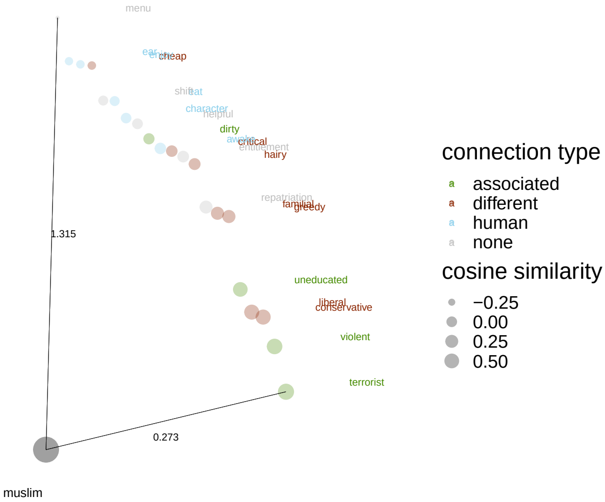
wear, walk, visitor, toy, tissue, throw, talk, speak, sleep, eye, enjoy, blogger, character, candidate, breakfast, supper, dinner, eat, drink, carry, run, cast, ask, awake, ear, nose, lunch

Some methodological problems

Outliers and surprisingly dissimilar words

We study those by visualizations and uncertainty estimates.

Some methodological problems



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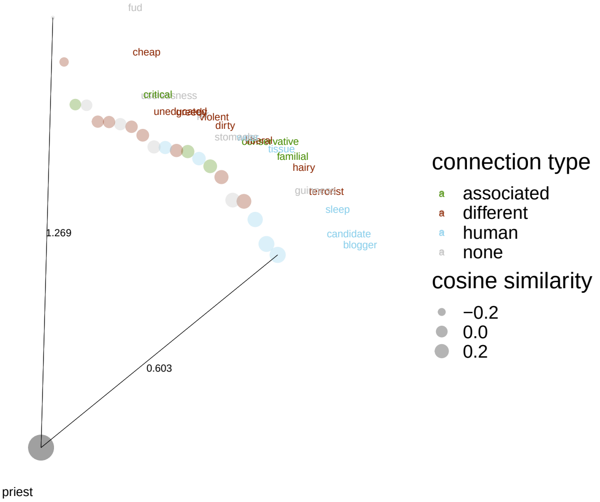

Some methodological problems

No principled interpretation

Category	Biased	Hard Debiased	Diff
Religion	0.859	0.934	0.141
Race	0.892	0.925	0.108
Gender	0.623	0.700	0.377

- What values are sufficient for the presence of bias and what differences are sign of real improvement?
- Low p-values are not high effect indicators!
- We compare HPDIs.

Some methodological problems

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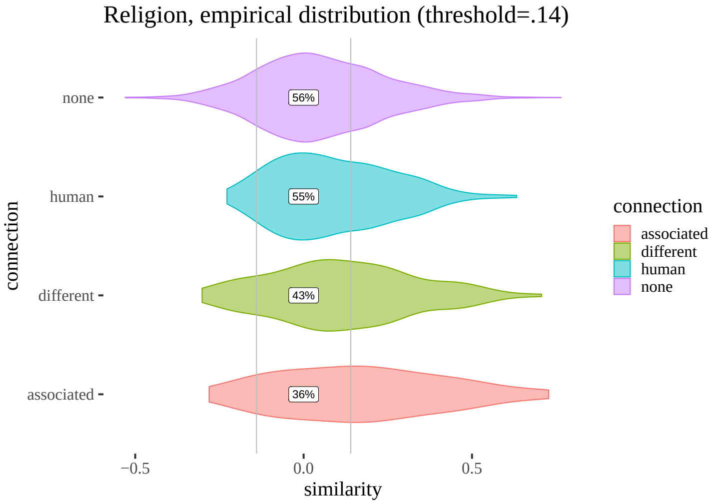

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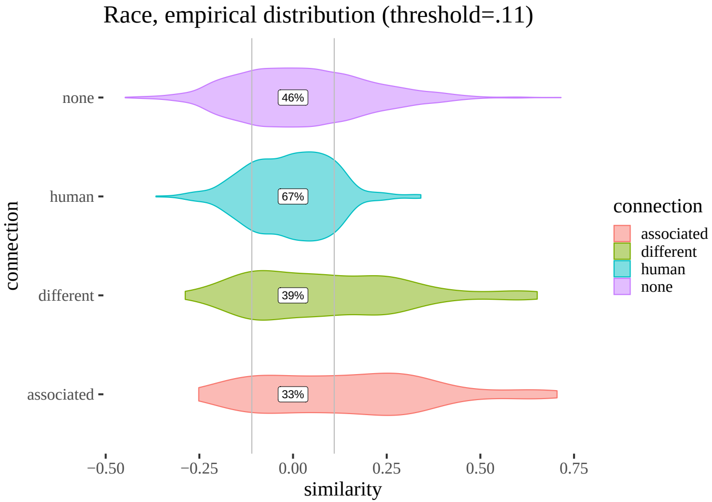

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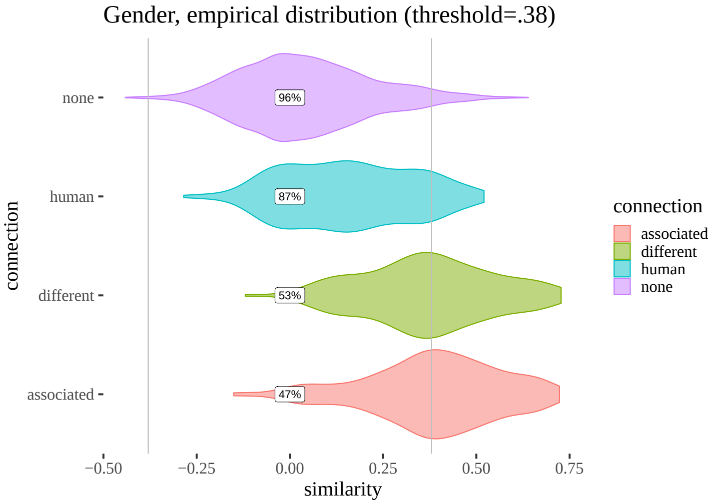

The problem with pre-averaging

Key conceptual issues

- It throws away information about sample sizes
- It ignores variation in the raw data, which leads to false confidence

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Our simulations

Suppose all similarities for two classes are randomly drawn from the same distribution, Normal($\mu = 0, \sigma = .08$), you still can get a really high WEAT!

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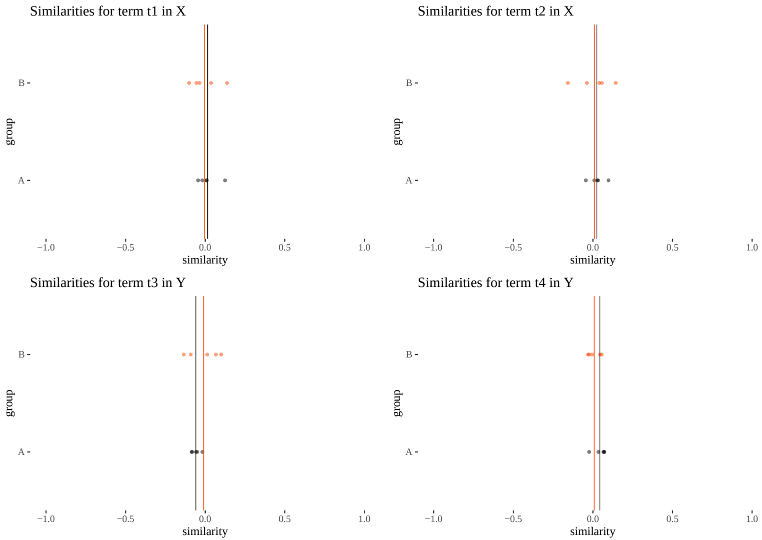

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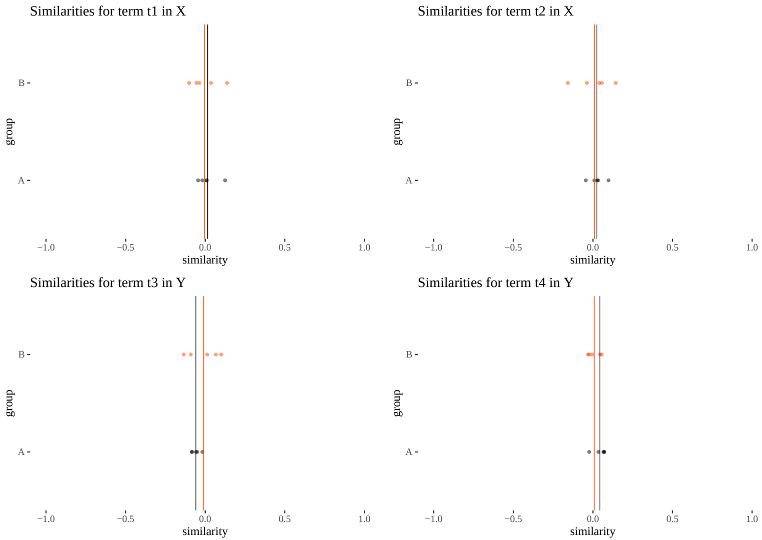
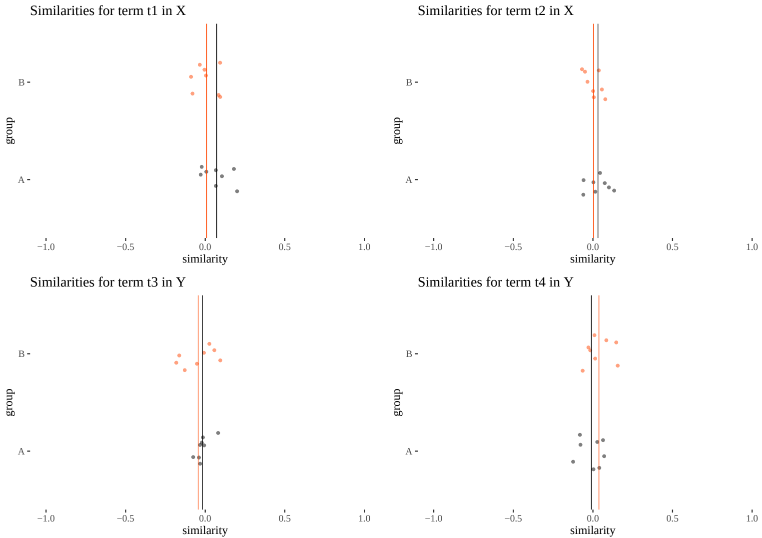


- Raw sd in data is 0.072, the sd of means is 0.037
- The WEAT score is 1.825, the largest effect size reported by Caliskan, Bryson, & Narayanan (2017) is 1.81!

The problem with pre-averaging on realistic set-up



Raw sd: 0.082, sd of means: 0.031, WEAT: 2.337.

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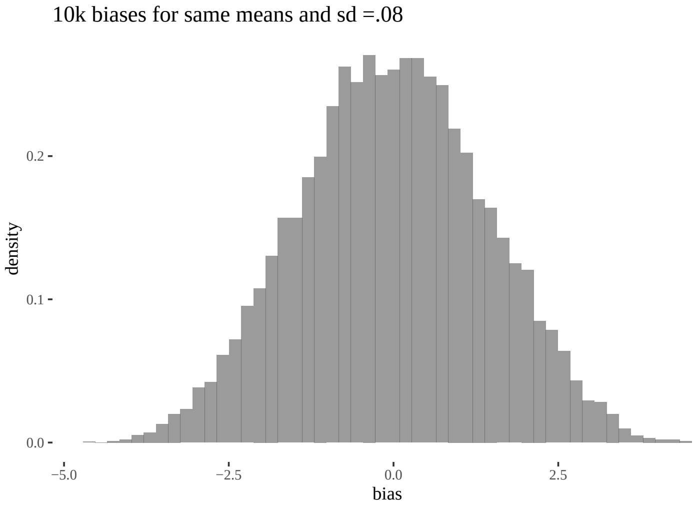

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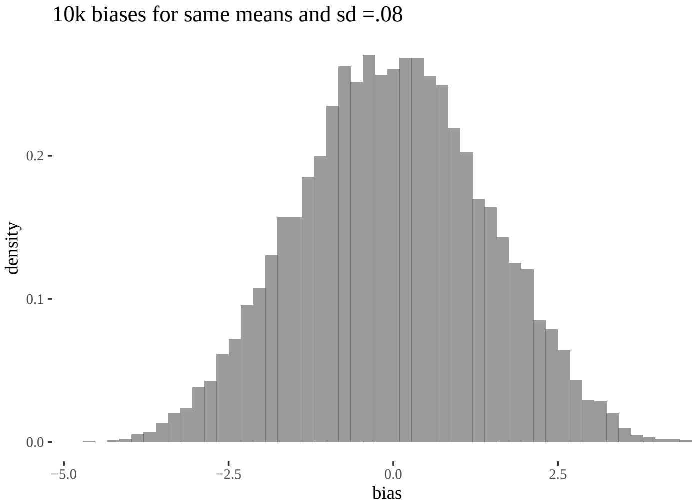
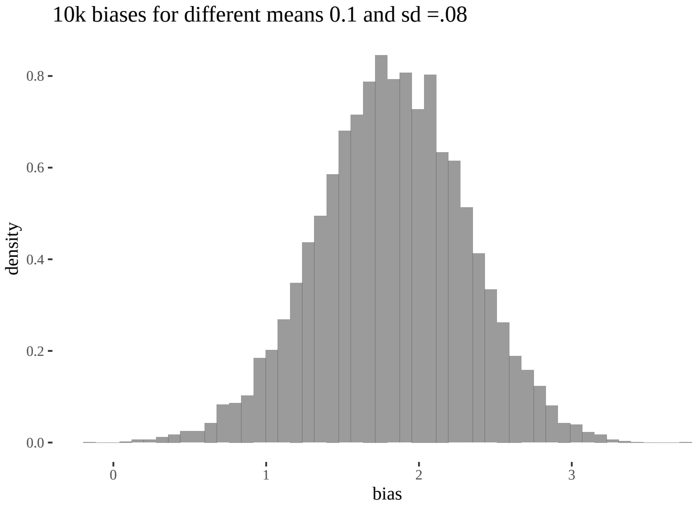


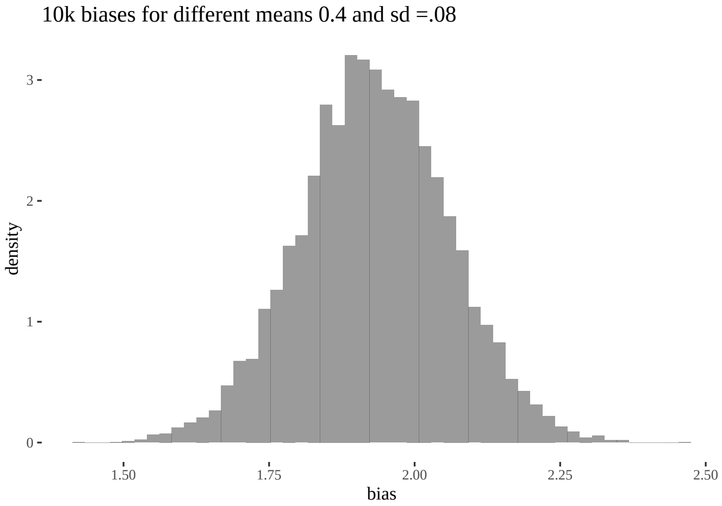
- 95% of the scores are in range -2.763, 2.698
- 21.38% of the absolute values are above 1.81

The problem with pre-averaging on realistic set-up



- 95% of the scores are in range 0.851, 2.764
- 51.3% of the absolute values are above 1.81

The problem with pre-averaging on realistic set-up



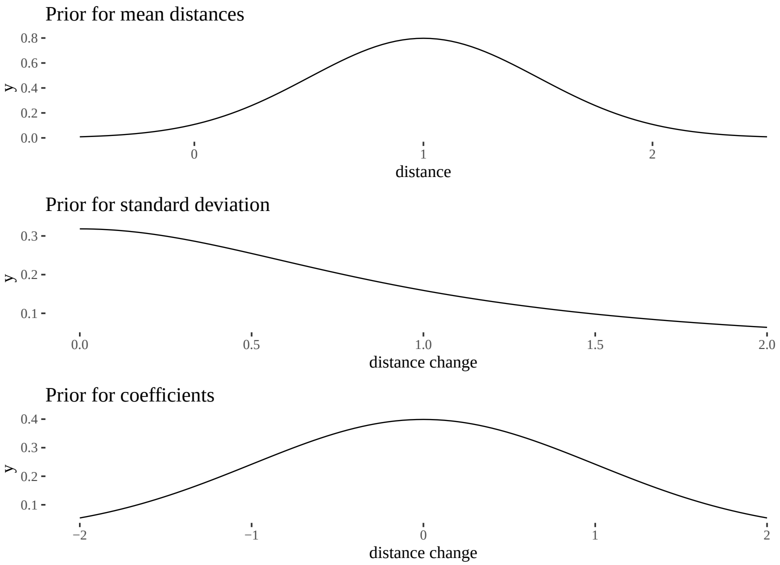
- 95% of the scores are in range 1.679, 2.185
- 82.9% of the absolute values are above 1.81

Advantages of the Bayesian way

- Direct impact of sample sizes
- Straightforward interpretation in terms of posterior probabilities
- Freedom to choose granularity level
- More honest risk assessment and decision making

Bayesian model

Choosing priors

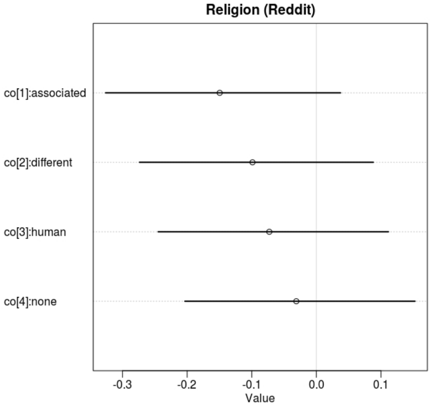


Bayesian model architecture

```r
library(rethinking)
options(buildtools.check = function(action) TRUE )
religionCoefs <- ulam(
  alist(
    cosineDistance ~ dnorm(mu,sigma),
    mu <- m + co[con],
    m ~ dnorm(1,.5),
    co[con] ~ dnorm(0,.5),
    sigma ~ dcauchy(0,1)
  ),
  data = religion,
  chains=2 , iter=8000 , warmup=1000,
  log_lik = TRUE
)
```

Dataset-level coefficients

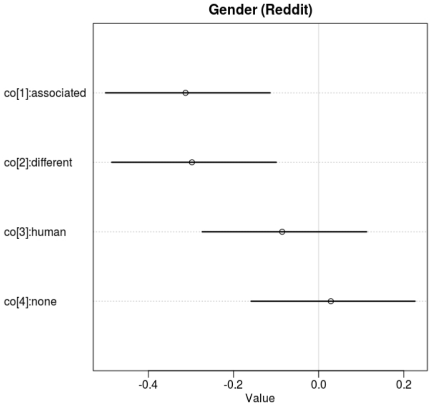
Religion with 89%-compatibility intervals (HPDI)



- All HPDIs overlap with 0
- Differences between classes are relatively small
- Coefficients for Race are similar

Dataset-level coefficients

Gender with 89%-compatibility intervals (HPDI)

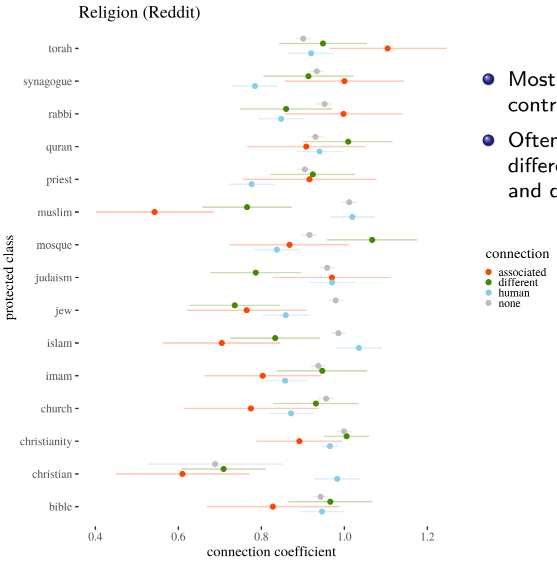


- Associated and different are away from 0
- But they were supposed to be opposites and are very close to each other (co-occurrence?)
- Differences between classes are still relatively small

Bayesian model architecture

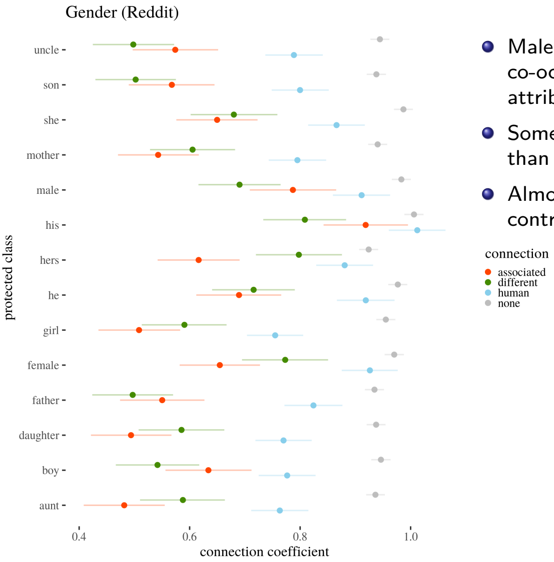
```
library(rethinking)
options(buildtools.check = function(action) TRUE )
religionCoefs <- ulam(
  alist(
    cosineDistance ~ dnorm(mu,sigma),
    mu <- m[pw] + co[con],
    m[pw] ~ dnorm(1,.5),
    co[con] ~ dnorm(0,.5),
    sigma ~ dcauchy(0,1)
  ),
  data = religion,
  chains=2 , iter=8000 , warmup=1000,
  log_lik = TRUE
)
```

Word-level coefficients



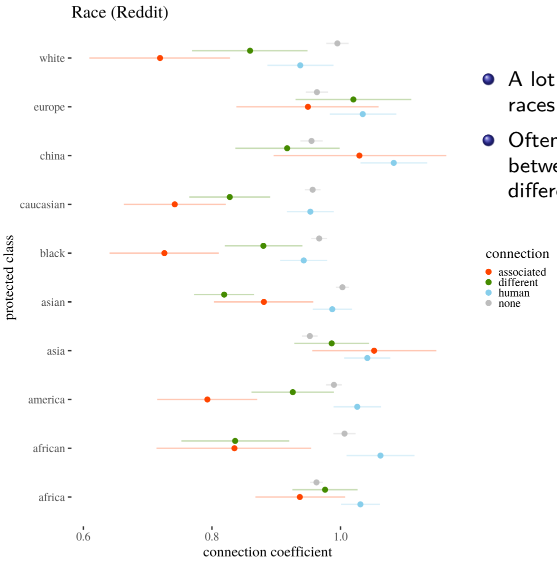
- Most intervals overlap with control groups
- Often not too much difference between associated and different

Word-level coefficients



- Male attributes: strong co-occurrence with female attributes
- Sometimes different is closer than associated
- Almost no overlap with control groups

Word-level coefficients



- A lot of variation between races
- Often not much difference between associated and different

Thank you!

Summary

Thank you!

Summary

- The existing measures of bias by pre-averaging oversimplify the picture and lead to false confidence

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- Our simulation results show that the mainstream interpretations are too hasty

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Summary

- The existing measures of bias by pre-averaging oversimplify the picture and lead to false confidence
- Our simulation results show that the mainstream interpretations are too hasty
- Bayesian analysis with proper control groups suggests that:
  - The word lists in use are too short
  - Associated and different groups behave similarly, which undermines the semantic interpretation of cosine similarity
  - Analysis at different levels of generality shows that there is more variety than one may initially think

Thank you!

Please remember about the feedback!

https://bit.ly/3uu8nYZ

References

Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, *356*(6334), 183–186. https://doi.org/10.1126/science.aal4230

Ethayarajh, K. (2020). *Is your classifier actually biased? Measuring fairness under uncertainty with bernstein bounds*.

Ethayarajh, K., Duvenaud, D., & Hirst, G. (2019). Understanding undesirable word embedding associations. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 1696–1705.

Garg, N., Schiebinger, L., Jurafsky, D., & Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644. https://doi.org/10.1073/pnas.1720347115

Gonen, H., & Goldberg, Y. (2019). Lipstick on a pig: Debiasing methods cover up systematic gender biases in word embeddings but do not remove them. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 609–614. Minneapolis, Minnesota: Association for Computational Linguistics. https://doi.org/10.18653/v1/N19-1061

Lauscher, A., & Glavas, G. (2019). Are we consistently biased? Multidimensional analysis of biases in distributional word vectors. *CoRR*, *abs/1904.11783*. Retrieved from http://arxiv.org/abs/1904.11783

Manzini, T., Lim, Y. C., Tsvetkov, Y., & Black, A. W. (2019). *Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings*. Retrieved from http://arxiv.org/abs/1904.04047

Nissim, M., Noord, R. van, & Goot, R. van der. (2020). Fair is better than sensational: Man is to doctor as woman is to doctor. *Computational Linguistics*, *46*(2), 487–497. https://doi.org/10.1162/coli_a_00379

Zhang, H., Sneyd, A., & Stevenson, M. (2020). *Robustness and reliability of gender bias assessment in word embeddings: The role of base pairs*. Retrieved from http://arxiv.org/abs/2010.02847