

# 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

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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

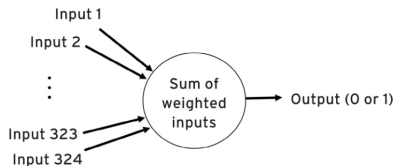
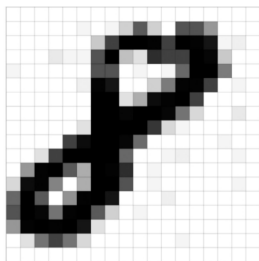


Illustration: M. Mitchell

## 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

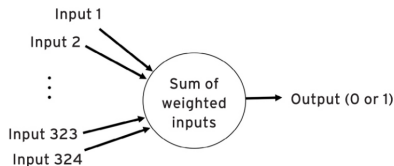
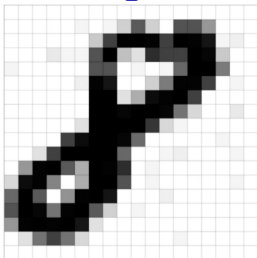


Illustration: M. Mitchell

## 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:

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

# Word embeddings

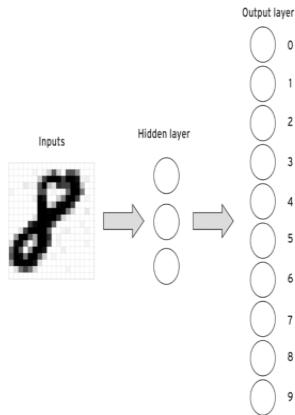


Illustration: M. Mitchell

- 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)

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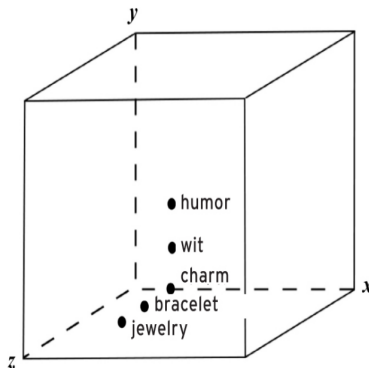


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# Word embeddings

## Google and Mikolov

*Efficient Estimation of Word Representation in Vector Space*, 2013

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

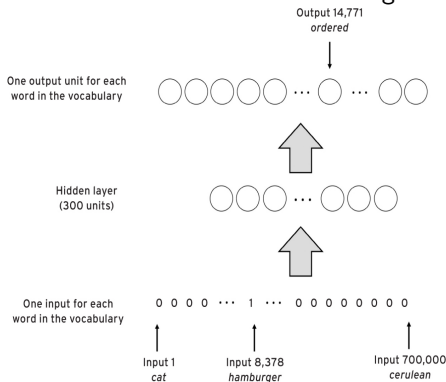


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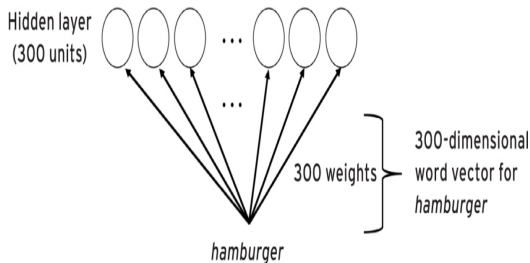


Illustration: M. Mitchell

# 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	...
woman	0.456	0.267	0.675	0.131	...
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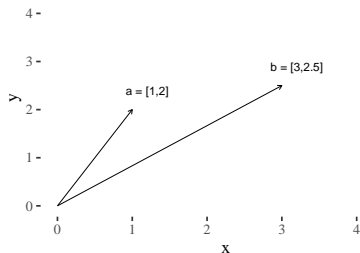
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How is this supposed to capture semantic relations?

## General idea

Similarity in vector direction.

# Cosine similarity

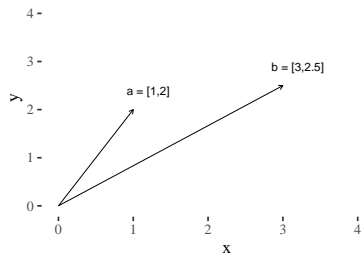


## Vectors

$$a = [1, 2]$$

$$b = [3, 2.5]$$

# Cosine similarity



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## Dot product

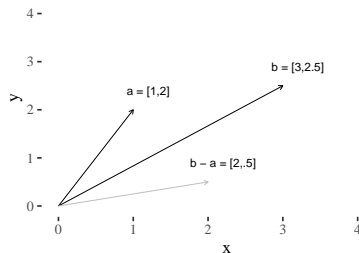
$$a \cdot b = a_1 b_1 + a_2 b_2$$

$$a \cdot a = a_1^2 + a_2^2$$

$$\|a\| = \sqrt{(a \cdot a)}$$



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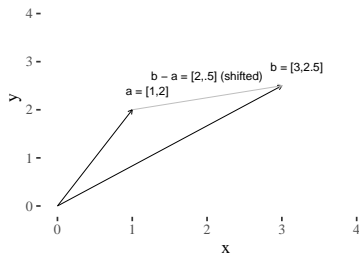
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## Vector difference

$$b - a = [b_1 - a_1, b_2 - a_2]$$

# Cosine similarity



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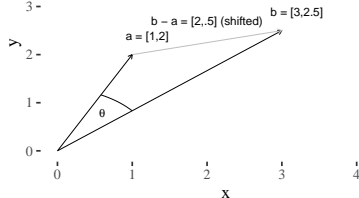
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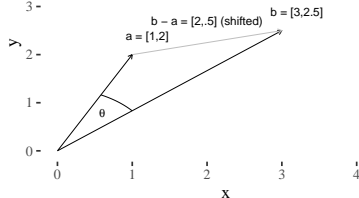
## Angle

$$\|b - a\|^2 = \|b\|^2 + \|a\|^2 - 2\|b\|\|a\| \cos \theta$$

$$b \cdot a = \|b\|\|a\| \cos \theta$$

$$\cos \theta = \frac{b \cdot a}{\|b\|\|a\|}$$

# Cosine similarity



## Angle

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$$b \cdot a = \|b\|\|a\| \cos \theta$$

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## Orthogonality

$$\cos(90^\circ) = 0$$

$$\frac{b \cdot a}{\|b\|\|a\|} = 0$$

$$b \cdot a = 0$$

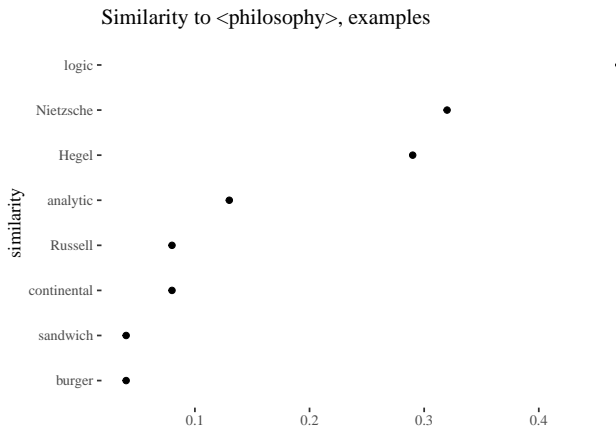
# Cosine similarity & distance

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

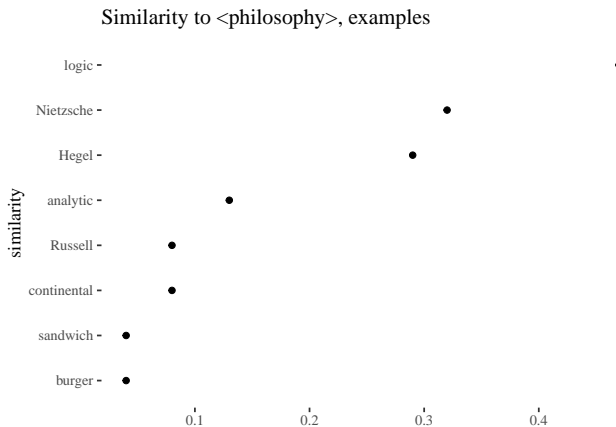
$$\text{cosineDistance}(A, B) = 1 - \text{cosineSimilarity}(A, B) \quad (\text{Distance})$$

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

# Cosine similarity & distance



# Cosine similarity & distance



## 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



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## The worry

Word embeddings can learn implicit harmful biases

## The basic intuition

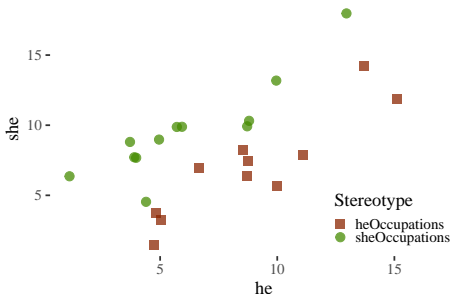
Stereotypically connected words are cosine-close

# Cosine-based measures of bias

## A visual example

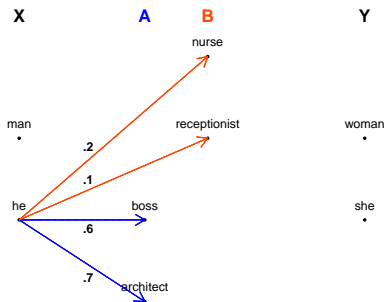
- “feminine” occupations: “homemaker,” “nurse,” “receptionist,” “librarian,” etc.
- “masculine” occupations: “maestro,” “captain,” “architect,” “boss,” etc.

GloVe on Wikipedia 2014 and Gigaword 5th ed.



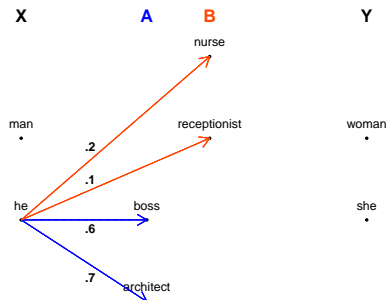
# Cosine-based measures of bias

## Example: Word Embedding Association Test (WEAT)



# Cosine-based measures of bias

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

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

# Cosine-based measures of bias

## Example: Word Embedding Association Test (WEAT)

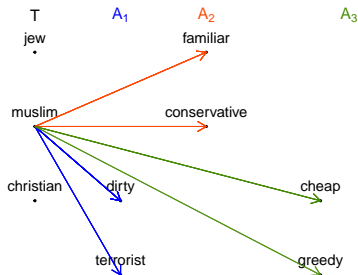
$$s(t, A, B) = \frac{\sum_{a \in A} f(t, a)}{|A|} - \frac{\sum_{b \in B} f(t, b)}{|B|}$$
$$WEAT(A, B) = \frac{\mu(\{s(x, A, B)\}_{x \in X}) - \mu(\{s(y, A, B)\}_{y \in Y})}{\sigma(\{s(w, A, B)\}_{w \in X \cup Y})}$$

- $t$  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)



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

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

⋮

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

# Cosine-based measures of bias

Our main target: Mean Average Cosine Similarity (MAC)

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

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

- $T = \{t_1, \dots, t_k\}$  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)

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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

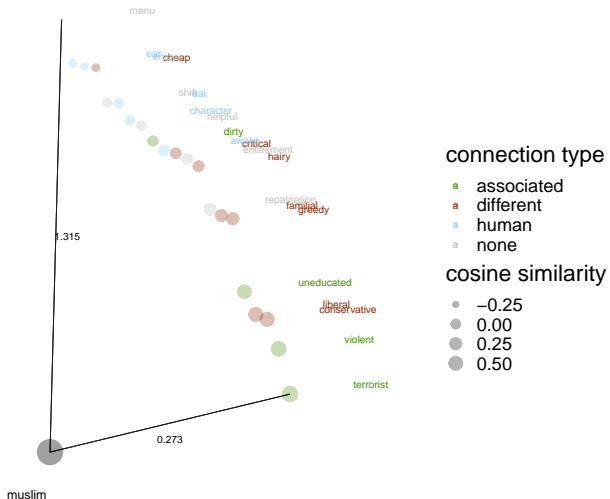
# Some methodological problems

## Outliers and surprisingly dissimilar words

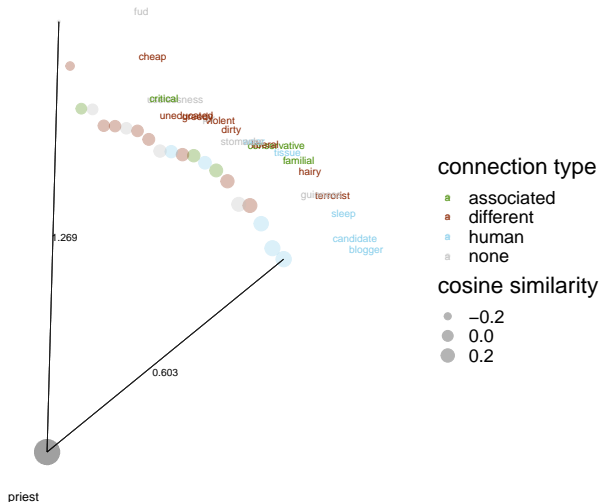
We study those by visualizations and uncertainty estimates.



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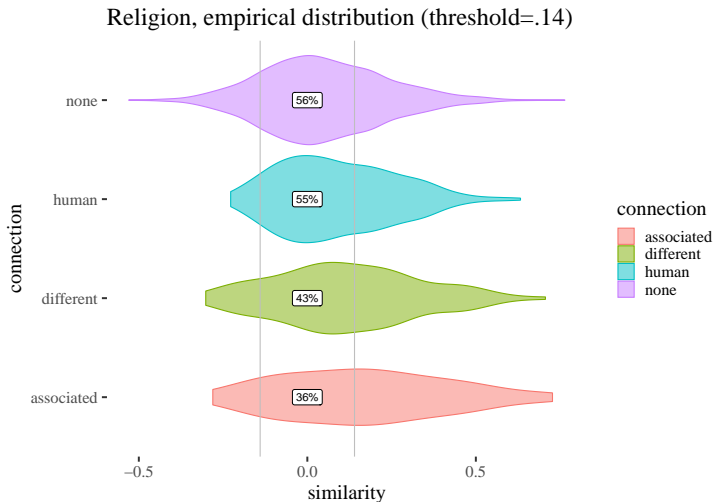
## No principled interpretation

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.

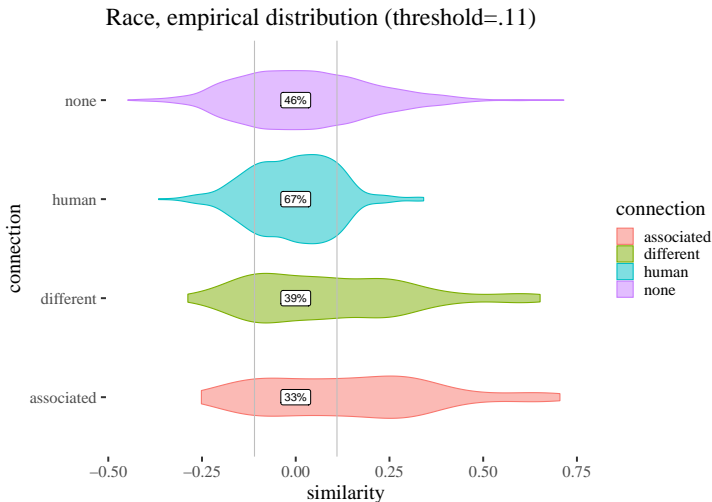
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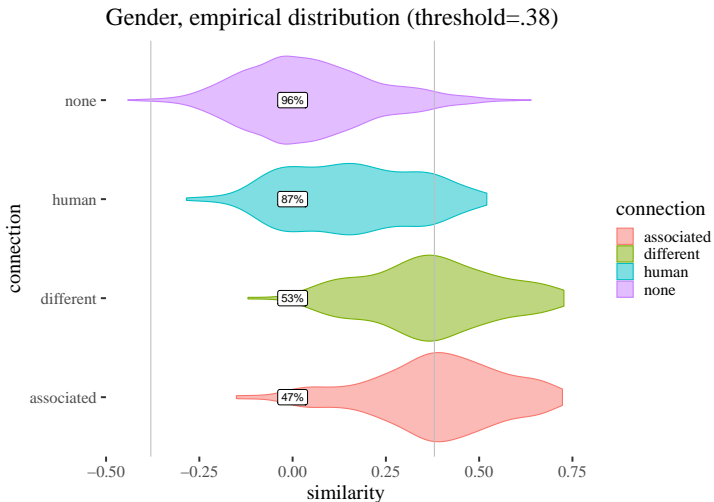
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## Key conceptual issues

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

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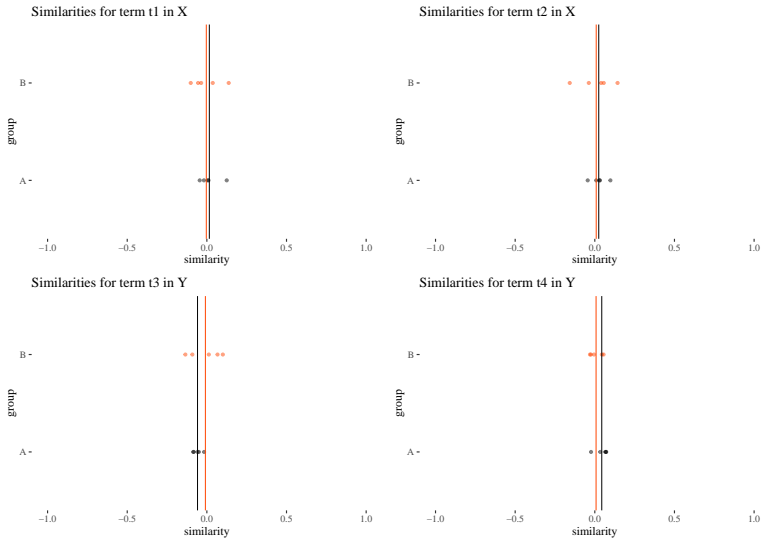
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## Our simulations

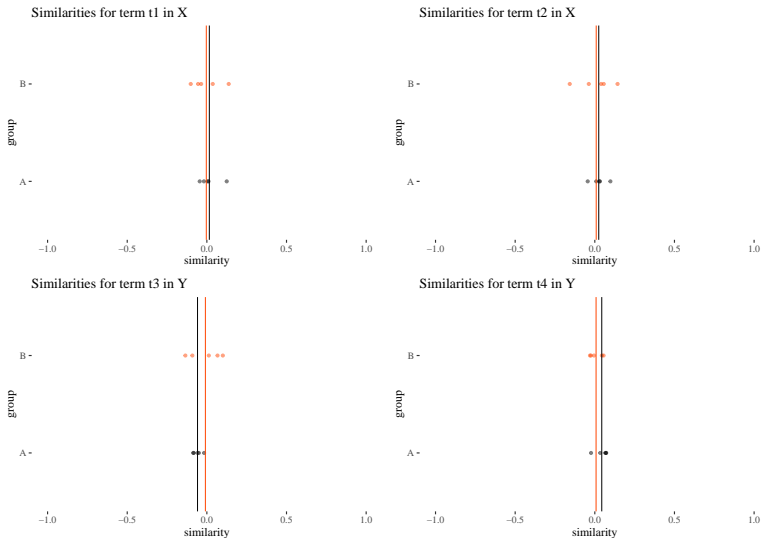
Suppose all similarities for two classes are randomly drawn from the same distribution,  $\text{Normal}(\mu = 0, \sigma = .08)$ , you still can get a really high WEAT!



# The problem with pre-averaging

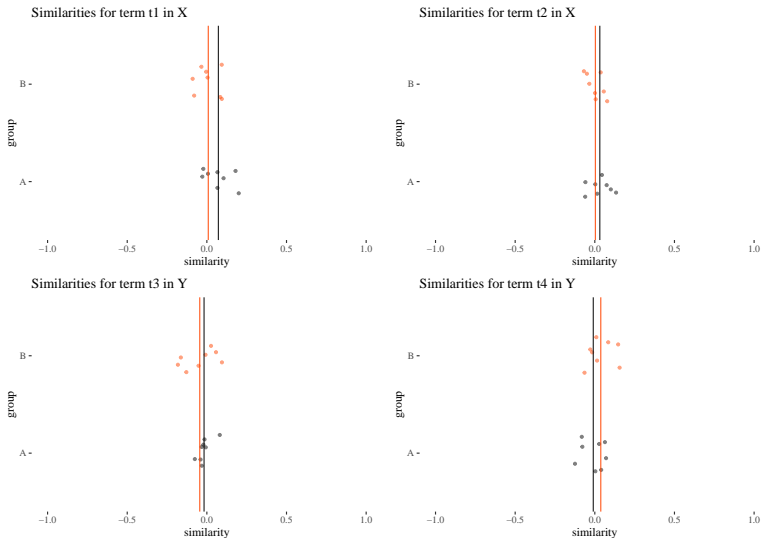


# The problem with pre-averaging



- 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!

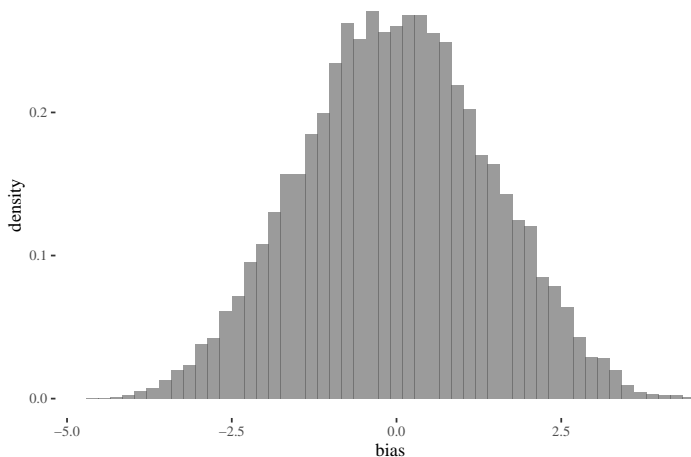
# The problem with pre-averaging on realistic set-up



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

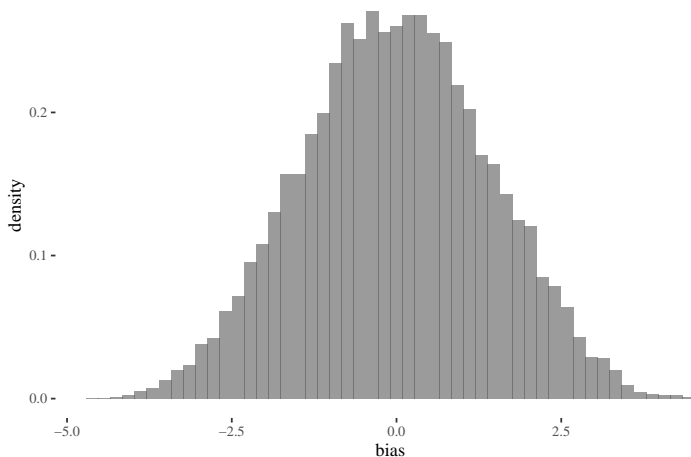
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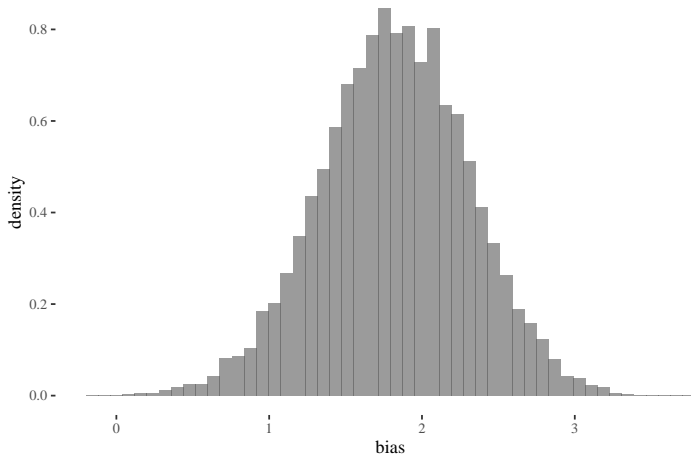
10k biases for same means and sd = .08



- 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

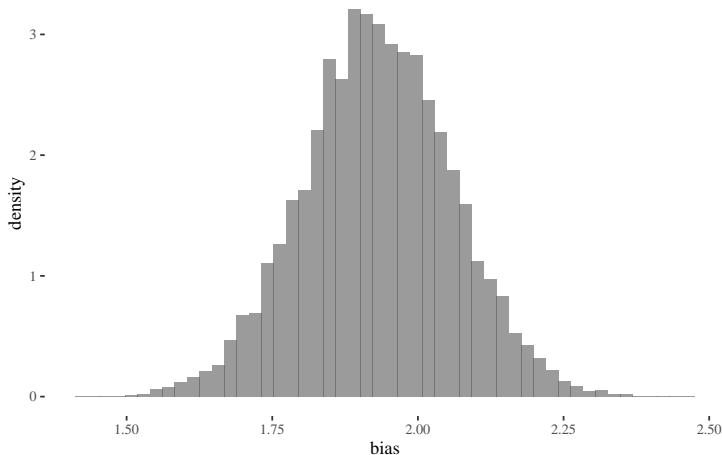
10k biases for different means 0.1 and  $sd = .08$



- 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

10k biases for different means 0.4 and  $sd = .08$



- 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

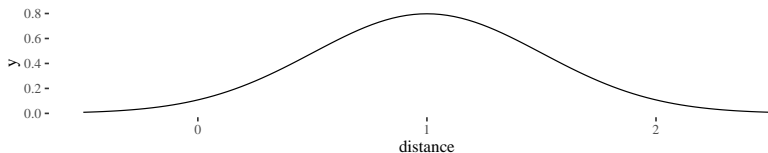
- Direct impact of sample sizes
- Straightforward interpretation in terms of posterior probabilities
- Freedom to choose granularity level
- More honest risk assessment and decision making



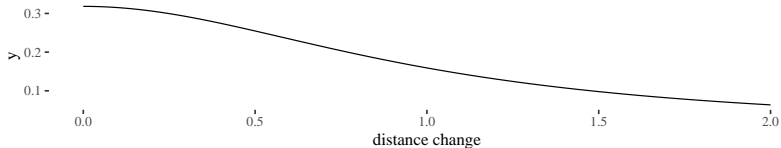
# Bayesian model

## Choosing priors

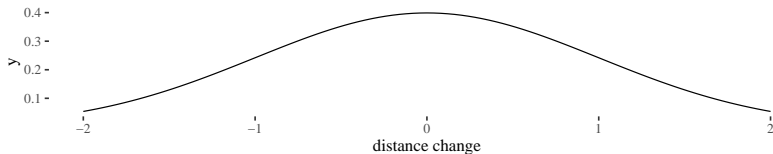
Prior for mean distances



Prior for standard deviation



Prior for coefficients

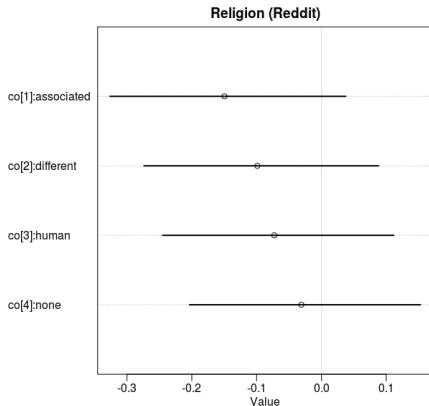


# Bayesian model architecture

```
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

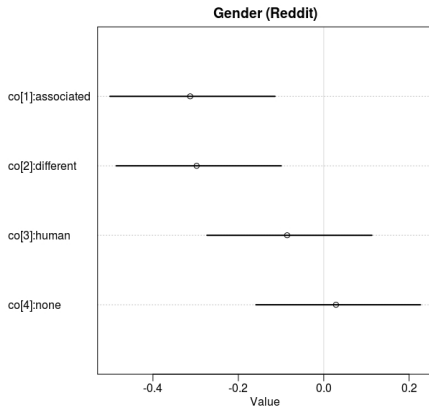
## Religion with 89%-compatibility intervals (HPDI)



- 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)

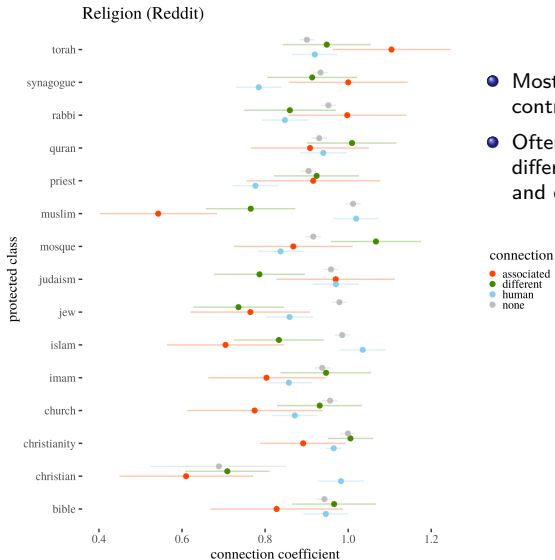


- Associated and different are away from 0
- But they were supposed to be opposites and are very close to each other (co-occurrence?)
- Differences between classes are still relatively small

# Bayesian model architecture

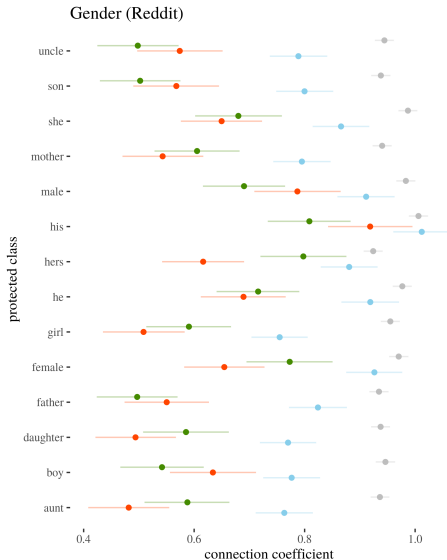
```
library(rethinking)
options(buildtools.check = function(action) TRUE )
religionCoefs <- ulam(
  alist(
    cosineDistance ~ dnorm(mu,sigma),
    mu <- m[pw] + co[con],
    m[pw] ~ dnorm(1,.5),
    co[con] ~ dnorm(0,.5),
    sigma ~ dcauchy(0,1)
  ),
  data = religion,
  chains=2 , iter=8000 , warmup=1000,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

# Word-level coefficients



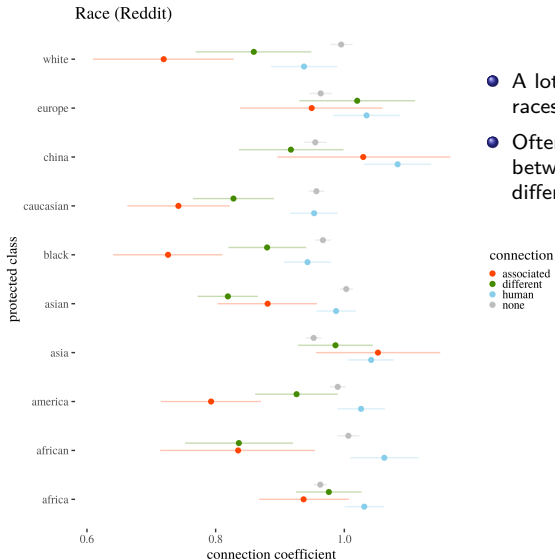
- Most intervals overlap with control groups
- Often not too much difference between associated and different

# 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!

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- 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

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## Summary

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Please remember about the feedback!

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