Taking uncertainty seriously

A Bayesian approach to word embedding bias estimation

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Boston, April Fools' Day

Presentation plan

- Bias in word embeddings
- WEAT and MAC methods
- Methodological problems
- Limitations of pre-averaging in bias detection methods
- Accounting for uncertainty with Bayesian approach

Word2vec

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...

Word2vec

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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.

Word2vec

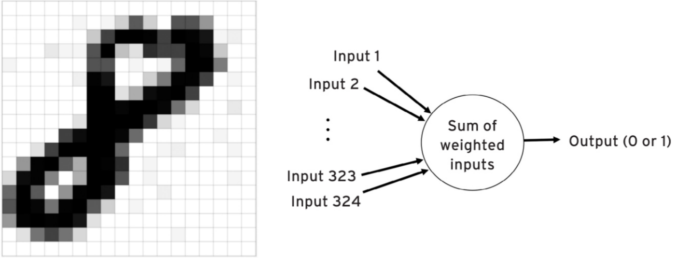
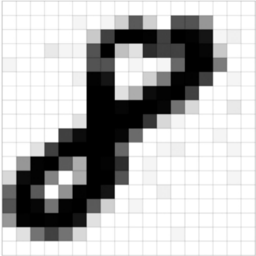


Illustration: M. Mitchell

Rosenblatt's perceptron

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

Word2vec



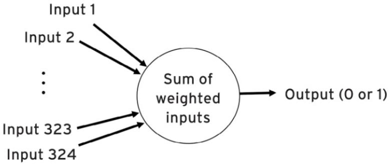


Illustration: M. Mitchell

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:

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

Word2vec

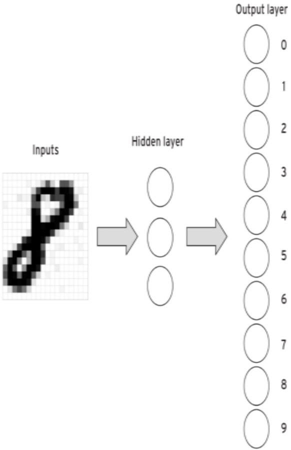


Illustration: M. Mitchell

- 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).

Word2vec

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)

Word2vec

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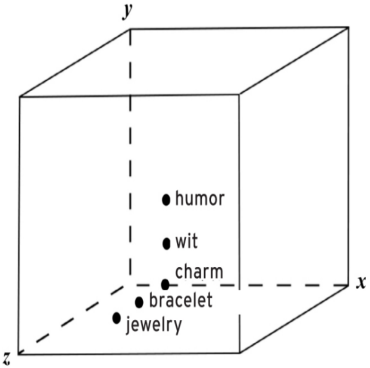
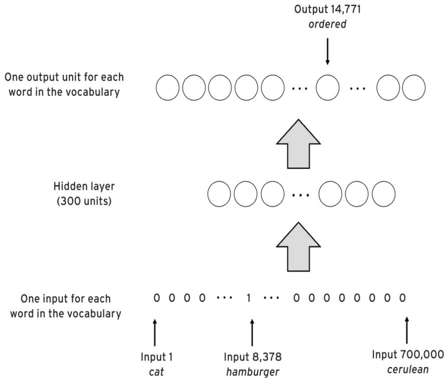


Illustration: M. Mitchell

Word2vec

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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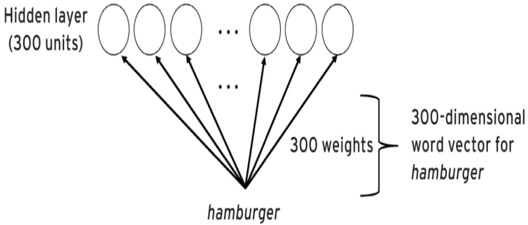

Illustration: M. Mitchell

Word2vec

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?

Word2vec

word	1	2	3	4	...
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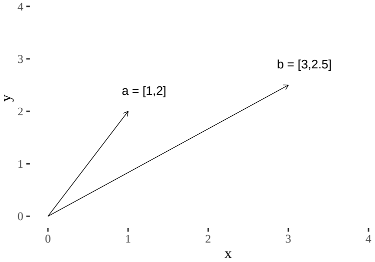
Question

How is this supposed to capture semantic relations?

General idea

Similarity in vector direction.

Cosine similarity



Vectors

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

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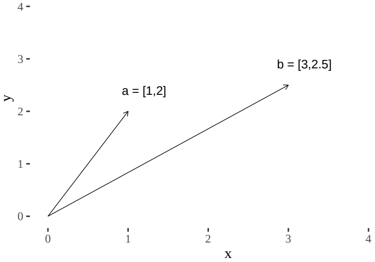

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Dot product

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

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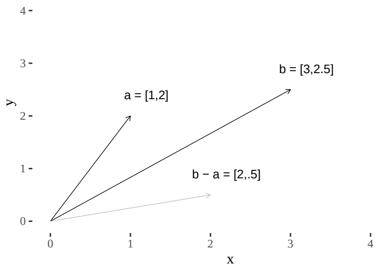

Vectors

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Vector difference

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

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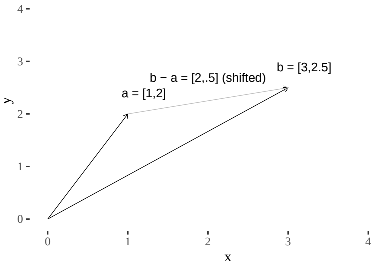

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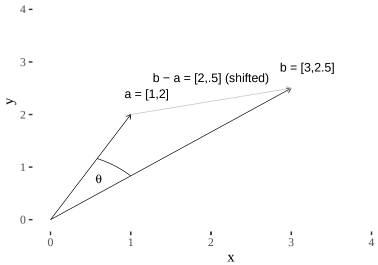
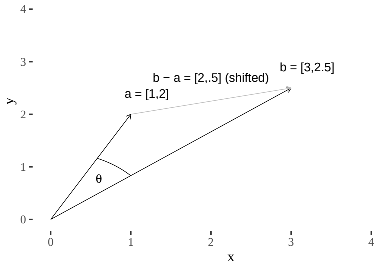


Angle

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

Cosine similarity



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Orthogonality

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

Cosine similarity & distance

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

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

- Geometric interpretation: direction (not length)
- cosineDistance $\in (0, 2)$
- Naive interpretation: proximity corresponds to semantic similarity

Cosine-based measures of bias

The worry

Word embeddings can learn implicit harmful biases

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Word embeddings can learn implicit harmful biases

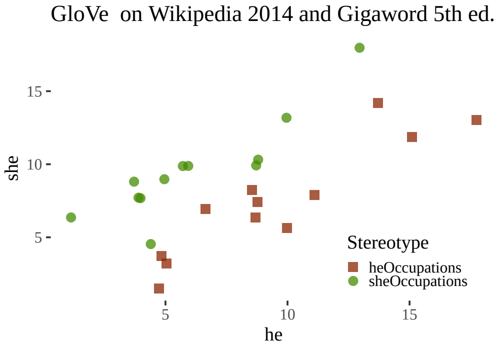
The basic intuition

Stereotypically connected words are cosine-close

Cosine-based measures of bias

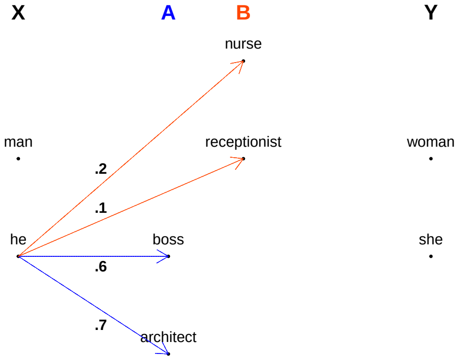
A visual example

- "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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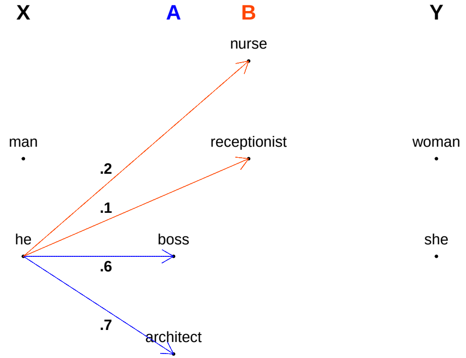


- $s_1 = s(he, A, B) = \frac{.6+.7}{2} - \frac{.2+.1}{2} = .65 - .15 = .5$
- $s_2 = s(man, A, B) = .3$,
  $s_3 = s(woman, A, B) = -.6$, $s_4 = s(she, A, B) = -.3$

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

Cosine-based measures of bias

Example: Word Embedding Association Test (WEAT)

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

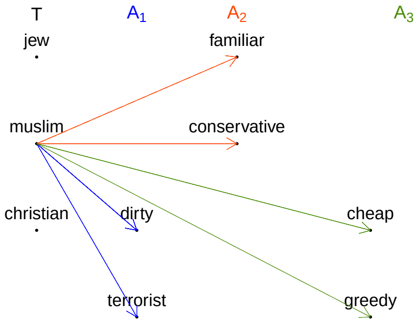
$$WEAT(A, B) = \frac{\mu\left(\{s(x, A, B)\}_{x \in X}\right) - \mu\left(\{s(y, A, B)\}_{y \in Y}\right)}{\sigma\left(\{s(w, A, B)\}_{w \in X \cup Y}\right)}$$

- 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

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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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No design considerations to sample size

- ETHAYARAJH IS YOUR criticizes WEAT uses Bernstein bounds and argues that we would need a bias specific dataset of size at least 11903 to claim that the system is biased (three times larger than WinoBias).

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ETHAYARAJH UNDERSTANDING shows 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

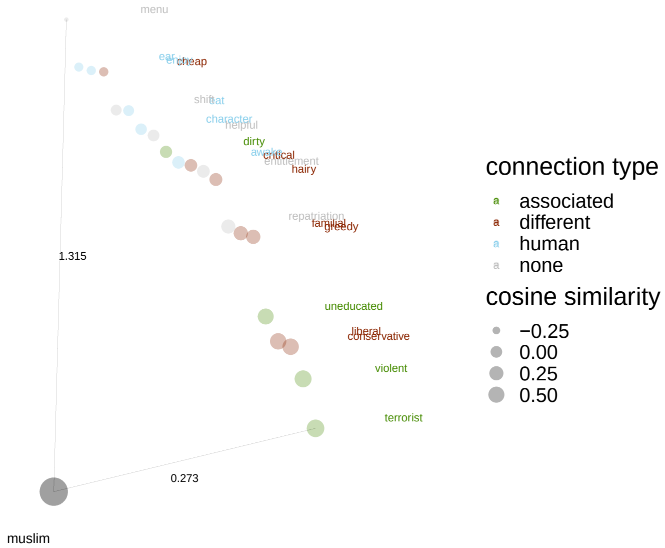
Some methodological problems

Outliers and surprisingly dissimilar words

We study those by visualizations and uncertainty estimates.

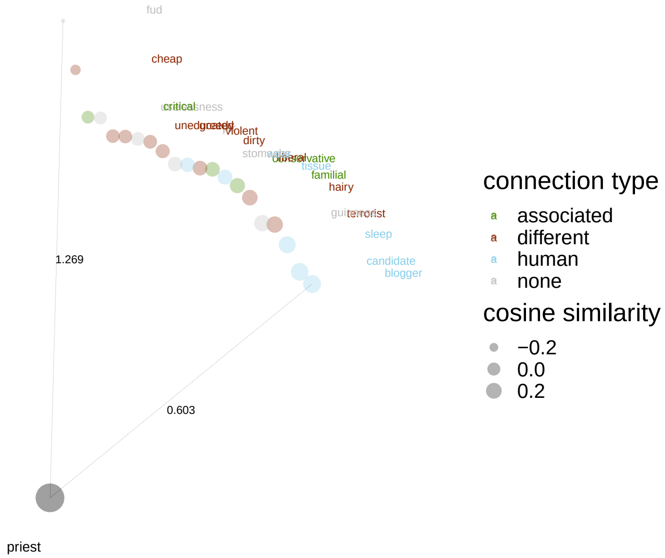
Some methodological problems

Distances for “muslim”



Some methodological problems

Distances for "priest"



Some methodological problems

No principled interpretation

Religion Debiasing	MAC (distance)
Biased	0.859
Hard Debiased	0.934
Soft Debiased ($\lambda = 0.2$)	0.894

- 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.

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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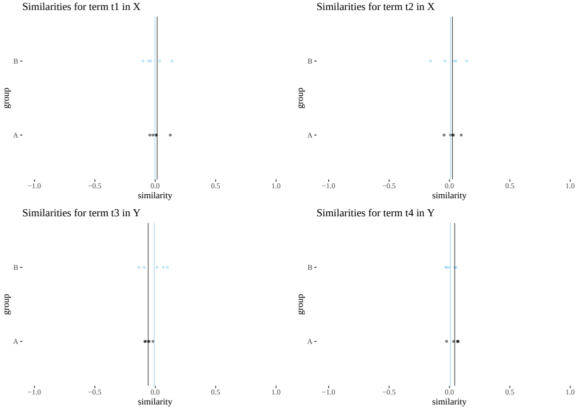
Our simulations

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!

The problem with pre-averaging

Simple case: two pws, four terms



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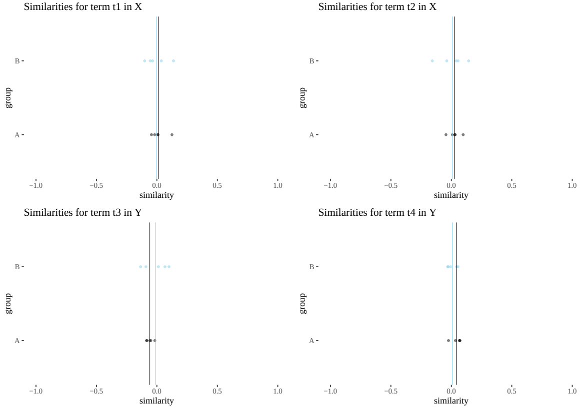
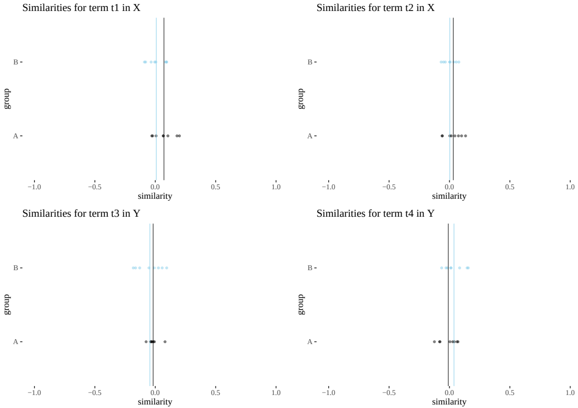


- Raw sd in data is 0.045
- The sd of means is 0.023
- The WEAT score is 1.825
- The largest effect size reported by Caliskan, Bryson, & Narayanan (2017) is 1.81!

The problem with pre-averaging on realistic set-up

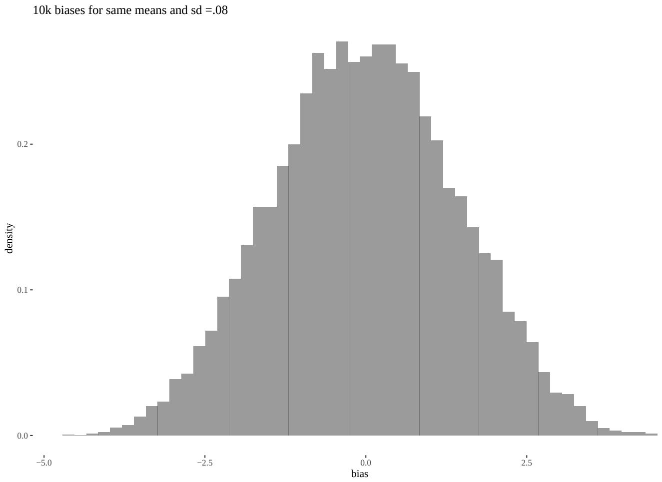
Simulation with realistic set-up (16 predicates)



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

The problem with pre-averaging on realistic set-up

10k simulations (same parameters)



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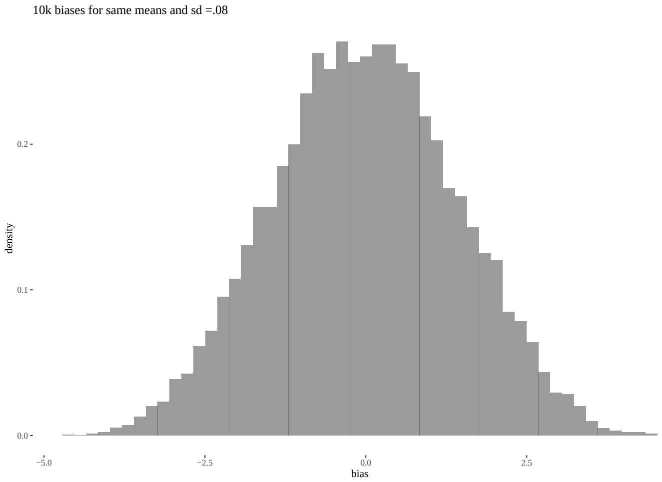
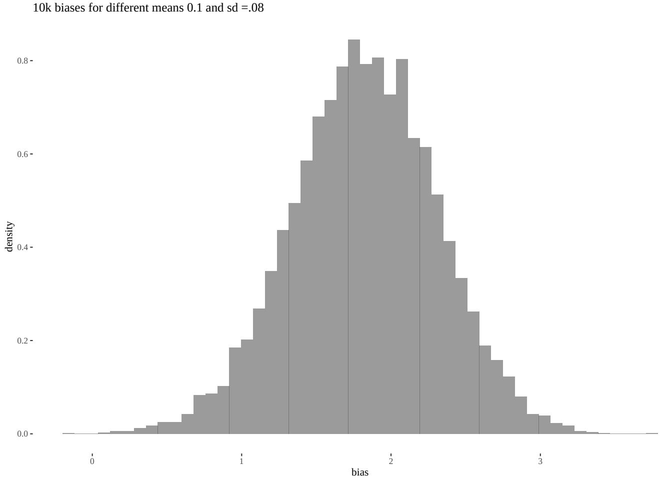


- 95% of the scores are in range -2.763, 2.698
- 21.38% of the absolute values are above 1.81

The problem with pre-averaging on realistic set-up

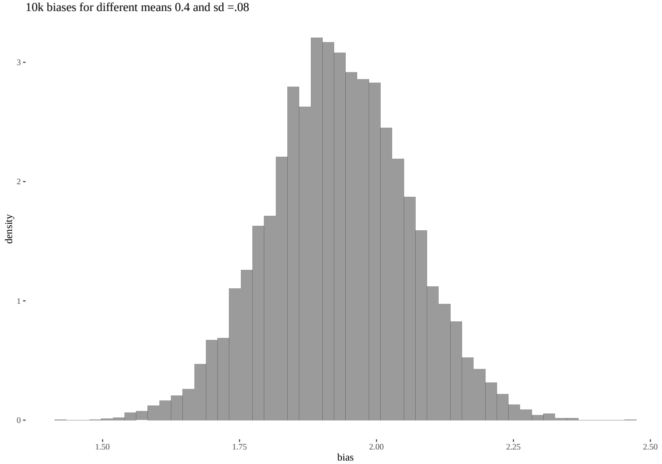
10k simulations with mean similarity 0.1



- 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 simulations with mean similarity 0.4



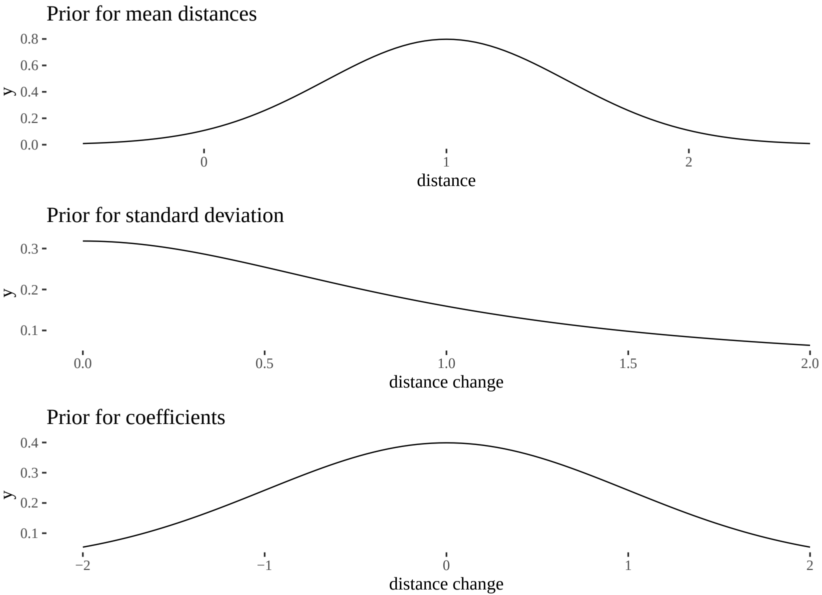
- 95% of the scores are in range 1.679, 2.185
- 82.9% of the absolute values are above 1.81

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

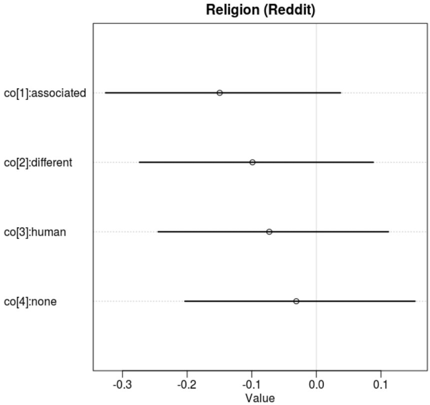


Bayesian model architecture

```
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

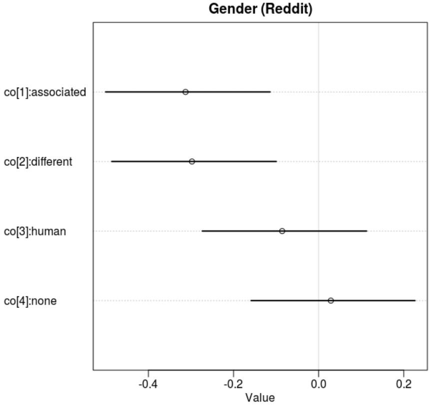
Religion with 89%-compatibility intervals (HPDI)



- 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

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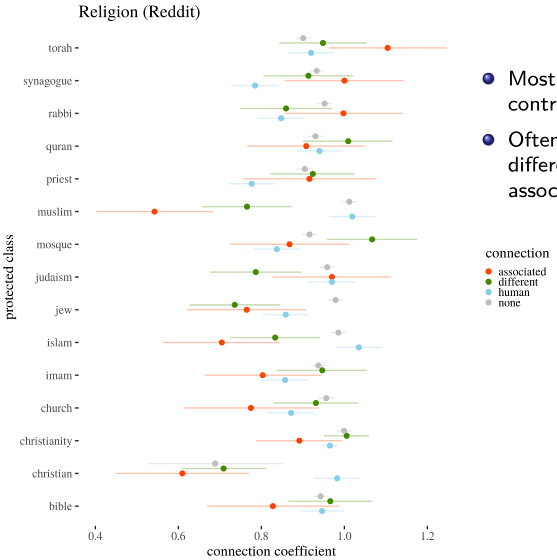
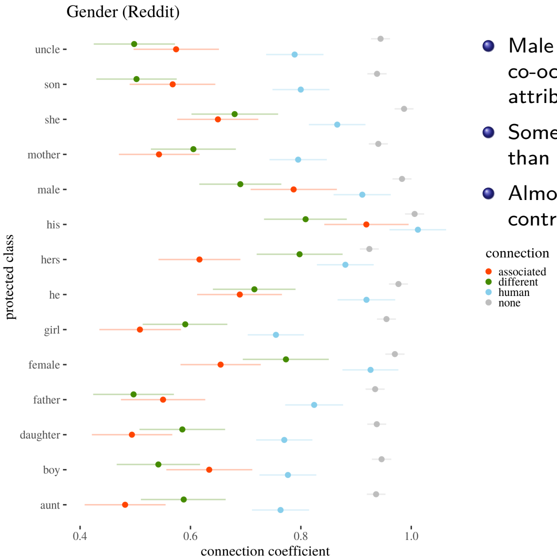
Word-level coefficients



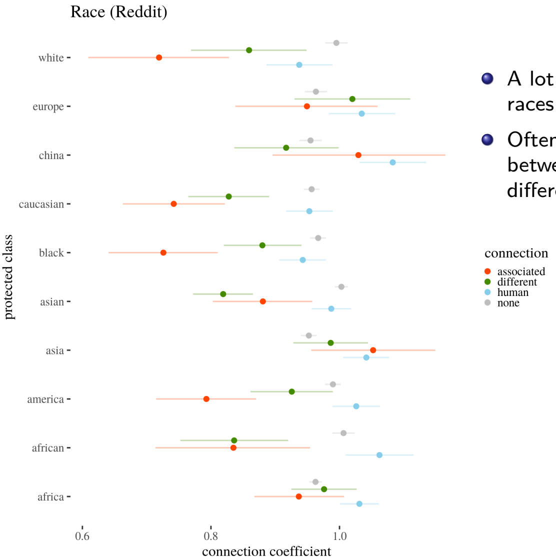
- Most intervals overlap with control groups
- Often not too much difference between associated and different

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

- Bias in word embeddings
- WEAT and MAC methods
- Methodological problems
- Limitations of pre-averaging in bias detection methods
- Accounting for uncertainty with Bayesian approach

Further work

- Including contrasts in Bayesian calculation
- Performance cross-validation in comparison to other methods (regular linear regression, KNN, . . .)
- Downstream tasks and connection with intrinsic evaluation
- Testing data from the original Implicit Association Test (IAT)
- Applying uncertainty to WEAT and better word lists
- Looking at other similarity measures

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