Conceptual and methodological problems with bias detection and avoidance in natural language processing

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Preface

Test

Chapter 1

Introduction

state the general topic and give some background

Natural language processing (NLP) is a subfield of computer science that processes and analyzes language in text and speech with the use of modern programming methods. It has practical applications in everyday life as it concerns tasks such as email filters, smart assistants, search results, language translations, text analytics and so on. Models used to accomplish these tasks need a lot of data to learn from. This data originates from humans activities and historical recordings like texts, messages, speeches. It turns out that in the learning process these models can learn implicit biases that reflect harmful stereotypical thinking still present in modern societies. One can find methods that aim at identifying hidden biases and/or try to remove them by modifying the models explicitly. There are many different types of models in NLP depending on a task that they ought to solve. However all of them need as an input words represented as numerical values and this is accomplished with word embedding models. The biases seem to have their primary source in the way the words are assigned the numerical values.

review of the literature related to the topic

There is a bunch of literature available on the topic of bias detection and mitigation in NLP models. Bolukbasi2016Man focuses on gender biases that may be observable while investigating the representation of job occupations and gender in terms of their assigned numerical values. The authors apply cosine similarity measurement to investigate the phenomenon where jobs stereotypically associated with a given gender are in fact in the model situated closer to this gender.

Islam, Bryson, & Narayanan (2016) touches upon the topic of biases regarding race and gender. They apply knowledge from well-known psychological studies like Implicit Association Test to research the relation between human stereotypical thinking and model learnt biases to discover close relationship between these two. For the evaluation they use Word Embedding Association Test (WEAT) and the Word Embedding Factual Association Test (WEFAT).

manzini2019black proposes novel way of using a cosine similarity method to get the information on assumed resemblance between words. They investigate an approach that enables to measure the bias for a class (like gender, religion, race) and express the final result with only one averaged number.

define the terms and scope of the topic

It is worth noticing the general distinction of biases mentioned in Caliskan2017Semantics. They refer to the publication concerning Implicit Association Test Greenwald et al., 1998) where certain baseline of bias phenomenon was introduced. Namely it seems that humans naturally exhibit some biases and that not always bring social concern. One can imagine the intuitive associations between for example insects and flowers, and the feelings of pleasantness or unpleasantness. In general people would rather associate flowers with feeling pleasant than insects and this preference could be named a bias or prejudice in some direction. However this type of preference does not cause an uproar and it is rather morally neutral case. Unfortunately there are other biases and prejudices that directly influence the quality of other people's lives and therefore they should be taken care of.

One can find a bunch of various definitions trying to capture what bias and fairness actually are. With the choice of the definition, implications into the real-life applications may change as well as it was pointed out in Mehrabi2019Survey. They mark out that there exist different types of biases, the list if long but among others there are historical bias, representation bias, measurement bias. This indicates how complex the process itself is. Without the proper understanding and awareness of the problem, people are prone to unconsciously sustain this phenomenon.

In the article one can also find the distinction on different types of discrimination, some of them will be shortly described. It is worth first mentioning that protected attributes are those qualities, traits or characteristics that one cannot, according to the law, discriminated against. Direct discrimination refers to the situation when protected attributes of individuals explicitly result in non-favorable outcomes toward them. In contrast in indirect discrimination individuals appear to be treated equally but anyway they end up being treated unjustly due to the hidden effects of biases towards their protected attributes. Systemic discrimination takes place when policies, customs or behaviors that result from certain culture or organizational structure lead to discrimination against some groups of people. Finally, very common statistical discrimination refers to using average group statistics to judge person belonging to the group.

The topic of discrimination is entangled with another concept which is fairness. It is essential to grasp some concepts of fairness to take them into consideration while designing implementation of some machine learning model. In Mehrabi2019Survey one may notice that depending on the context and application different definitions may be applied.

outline the current situation The most popular methods focus on comparing the similarity between words from protected groups and those that are considered to be stereotypical or harmful in some way. One can find in this group methods such as euclidean distance, dot product or cosine similarity. There are also other ways to detect the effects of biases. For example through the investigation of the model performance on certain tasks that validate if the model returns some values independently on gender or race or not.

evaluate the current situation (advantages/ disadvantages) and identify the gap

In the currently used methods (like cosine similarity) the values of similarity are often aggregated in a way that may lead to false conclusions. For example due to the averaging of values and the lack of confidence interval information.

identify the importance of the proposed research One can find a number of articles on negative real-life implications resulting from the presence of unaddressed biases in the machine learning models.

state the research problem/ questions

In the paper we indicate how current methods used to detect biases in natural language models are limited in terms of confidence interval.

state the research aims and/or research objectives

Our research tries to answer the question of how to enhance the current way in which the bias detection is performed to make sure that it is methodologically valid.

state the hypotheses

Our hypothesis is that there can be greater understanding of data and bias implications when confidence interval and Bayesian method are applied to the methodology.
<!– **outline the order of information in the thesis** –>

outline the methodology

To discuss!

Chapter 2

Bayesian analysis of cosine-based bias

We start with loading the libraries needed for the analysis.

```
library(ggplot2)
library(ggthemes)
library(rethinking)
library(tidyverse)
library(ggpubr)
library(kableExtra)
library(dplyr)
library(ggExtra)
library(cowplot)
```

Chapter 3

Walkthrough with the religion dataset

We will use the choice of protected words and stereotypical predicates used in REF. This is a decent point of departure, not only we want to compare our method to that of REF, but also because this data format is fairly general (as contrasted, say, with a set up for binary stereotypes). Note also that the method we develop here can fairly easily be run for different stereotypization patterns. Let's start with explaining the method and its deployment using a dataset obtained for the religion-related protected words.

Let's load, clean a bit and inspect the head of the religion dataset we prepared. In order to obtain this dataset, we calculated the cosine distance between each protected word and each word from both the bias-related attribute groups, which were used in the original study, and to neutral and human control attributes which we added as control groups. For instance, for religion, the bias-related predicates (coming from the original study in REF) include muslim bias attributes, jew bias attributes, christian bias attributes (see a list in the APPENDIX).

We decided to add control groups in the form of two classes — neutral words and human-related words. Without a proper control group it is quite hard to compare the resulting cosine distances and decide on their significance in bias detection. We prepared approximately 300more or less neutral words to double-check the prima-facie neutral hypothesis that their cosine similarity to the protected words will oscillate around 0 (that is, the distances will be around 1). This provides us with a more reliable point of reference. Moreover, we added human attributes that are associated with people in general to investigate whether the smaller cosine distance between protected words and stereotypes can result simply from the fact that the stereotype predicates are associated with humans. For two control groups, we have randomly drawn 300 words that do

FIX later

Table 3.1: Head of the religion dataset.

protectedWord	wordToCompare	wordClass	cosineDistance	cosineSimilarity	connection
judaism	violent	muslim	0.7141939	0.2858061	different
judaism	terrorist	muslim	0.7461333	0.2538667	different
judaism	dirty	muslim	1.2002599	-0.2002599	different
judaism	uneducated	muslim	0.7885469	0.2114531	different
judaism	greedy	jewish	1.0026172	-0.0026172	associated
judaism	cheap	jewish	1.2323229	-0.2323229	associated

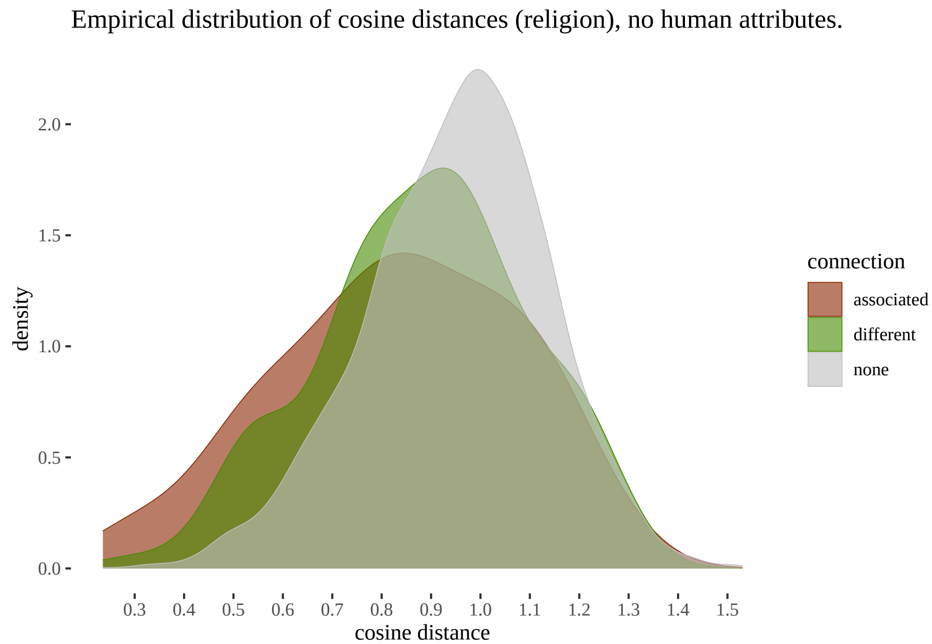
not express any property usually attributed to humans, and human attributes.

describe once the words are selected

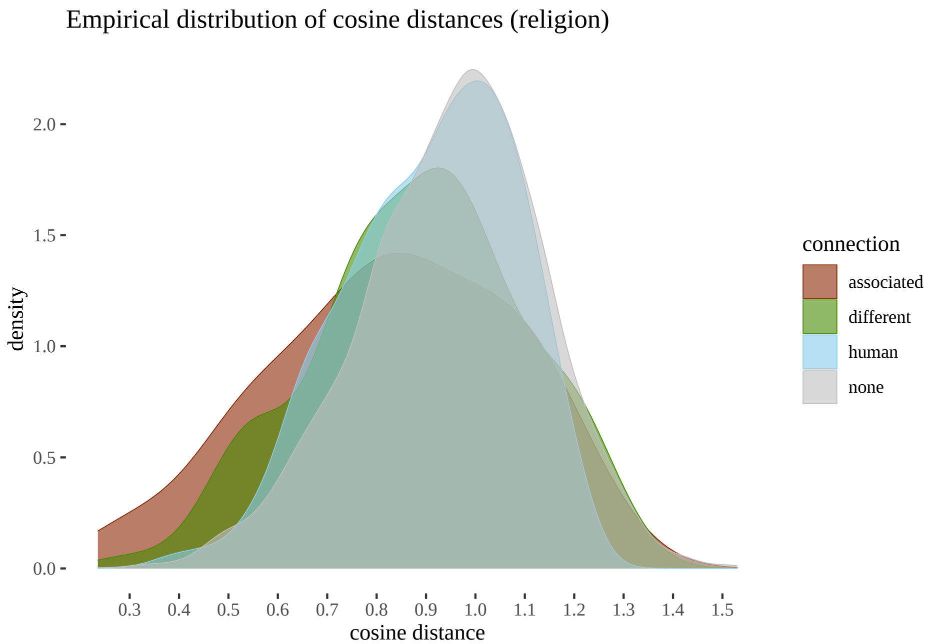
```
religion <- read.csv("../datasets/religionReddit.csv")[-1]
colnames(religion) <- c("protectedWord","wordToCompare","wordClass",
                        "cosineDistance","cosineSimilarity","connection")
levels(religion$wordClass) <- c("christian","human","jewish","muslim","neutral")
head(religion)  %>%  kable(format = "latex",booktabs=T,
                      linesep = "",  escape = FALSE,
                      caption = "Head of the religion dataset.") %>%
                      kable_styling(latex_options=c("scale_down"))
```

The `protectedWord` column contains words from a protected class that (in a perfect world according to the assumptions of the orignal study) should not be associated with harmful stereotypes. `wordToCompare` contains attributes, including stereotypes and control group words. For each row we compute the cosine distances between a given protected word and a given attribute word. `wordClass` tells us which class an attribute is supposed to be stereotypically associated with, that is, whether the word from `wordToCompare` is associated stereotypically with jews, christians or muslims, or whether it belongs to a control group. `cosineDistance` is simply a calculation of the cosine distance between protected word and atrribute. `cosineSimilarity` contains the result of substracting cosine distance from 1. `connection` contains information about the relation type between a protected word and an attribute. If the attribute is e.g. a harmful jewish stereotype and the protected word is also from the judaism group, the connection has value `associated`. If the attribute is still stereotypically jewish, but the protected word comes from another religion, the connection is labelled as `different`. If the attribute belongs to a neutral group then the connection is labelled as `none` and if an attribute belongs to the `human` class, then the connection is labelled as `human`.

First let's take a look at the empirical distribution of distances by the connection type, initially ignoring the human control class for now.



The first impression is that while there is a shift for associated words towards smaller cosine distances as compared to the neutral words, slightly surprisingly a slightly weaker shift in the same direction is visible for attributes associated with different stereotypes. Moreover, the empirical distributions overlap to alarge extent and the means grouped by connection type do not seem too far from each other. In fact, as there is a lot of variety in the consine distances (as we will soon see), abd we need to gauge the uncertaintly involved, and to look more carefully at individual protected words to get a better idea of how the cosine distance distribution changes for different attribute groups and different protected classes. Now, let's add the human attributes to the picture:



Notice that the distribution for `human` (even though we did our best not to include in it any stereotype-related atributes) is left-skewed, with much overlap with `associated` and `different`, which illustrates the need to take being associated with humans as an important predictor.

Our focus lies in `connection` as a predictor. Morever, later on we'll be interested in looking at the protected words separately, and at protected words split by connection. For technical reasons it is useful to represent these factors as integer vectors.

```
religion$con <- as.integer(religion$connection)
religion$pw <- as.integer(religion$protectedWord)
religion$pwFactor <- factor(paste0(religion$protectedWord, religion$connection))
religion$pwIndex <- as.integer(religion$pwFactor)
```

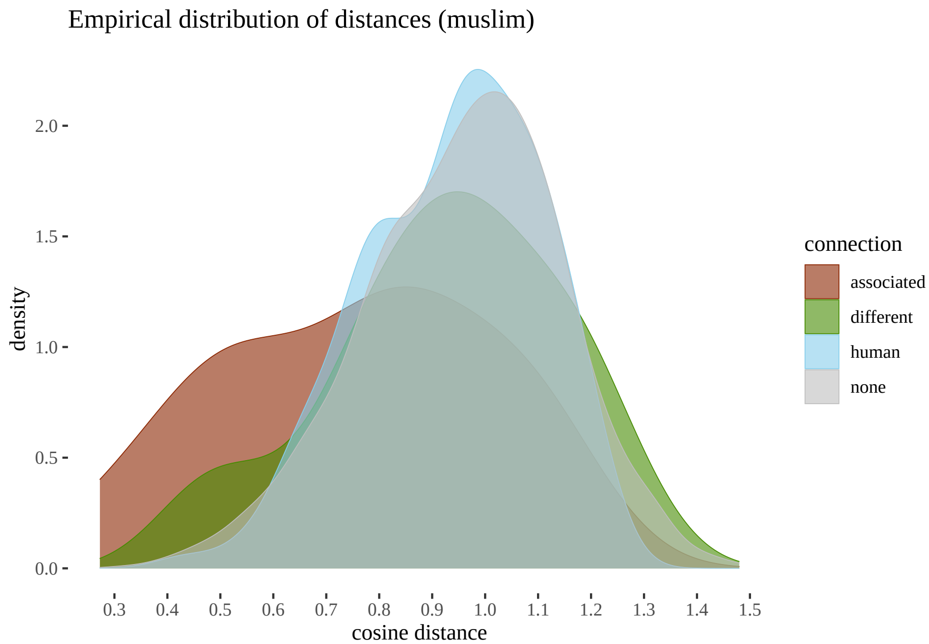
A short script, `cleanDataset` to make this faster, so equivalently:

```
source("../functions/cleanDataset.R")
religion <- read.csv("../datasets/religionReddit.csv")[-1]
religion <- cleanDataset(religion,c("christian","human","jewish","muslim","neutral"))
```

For now, let's focus on five protected words related to islam ("imam", "islam", "mosque", "muslim", and "quran"). The word list associates with islam four stereotypical attributes ("violent", "terrorist", "uneducated" and "dirty"). First, we select and plot the empirical distributions for these protected words.

```
library(tidyverse)
muslimWords <- c("imam","islam","mosque","muslim","quran")
muslim <- religion %>% filter(protectedWord %in% muslimWords)
```

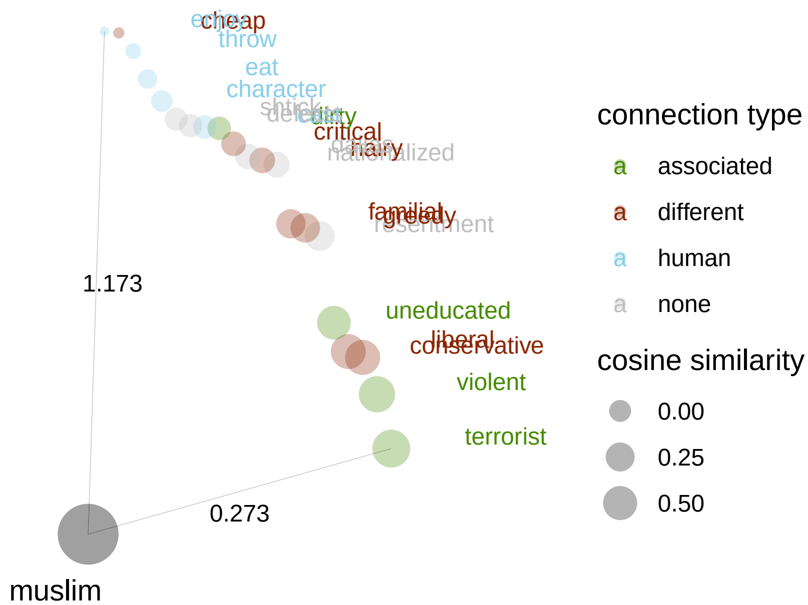
```
ggplot(muslim, aes(x =  cosineDistance, fill = connection, color = connection))+
  geom_density(alpha=0.6,size = .2)+
  scale_fill_manual(values = c("orangered4","chartreuse4", "skyblue", "gray"))+
  scale_x_continuous(breaks = seq(0.3,1.5, by = 0.1))+xlab("cosine distance")+
  scale_color_manual(values = c("orangered4","chartreuse4","skyblue","gray"))+
  theme_tufte()+ggtitle("Empirical distribution of distances (muslim)")
```



Once we focus on words related to islam, the associated bias seems to be stronger than in the whole dataset. This is a step towards illustrating that the distribution of bias is uneven.

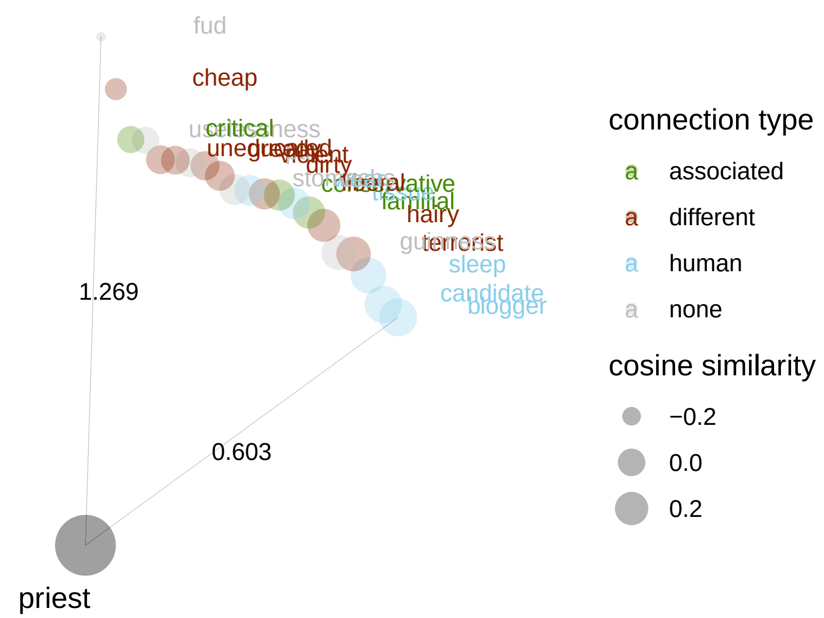
Now, say we want to look at a single protected word. Since the dataset also contains comparison multiple control neutral and human attributes, we randomly select only 5 from `none` and 5 from `human` control groups of those for the visualisation purposes.

```
library(tidyverse)
muslimClass <- muslim %>% filter(protectedWord == "muslim")
neutralSample <- sample_n(filter(muslimClass,connection == "none"), 5)
humanSample <- sample_n(filter(muslimClass,connection == "human"), 5)
muslimVis <- muslimClass %>% filter(connection != "none" & connection !="human")
muslimVis <- rbind(muslimVis,neutralSample,humanSample)

#we plug in our visualisation script
source("../functions/visualisationTools.R")
#two arguments: dataset and protected word
visualiseProtected(muslimVis,"muslim")
```



Note that the distance between the grey point and the other points is proportional to cosine distance, the non-grey point size is proportional to cosine similarity to the protected word, and color groups by the connection type. So for `muslim` it seems that the stereotypes coming from the word list are fairly well visible. To give you some taste of how uneven the dataset is, compare this to what happens with `priest`.

```
library(tidyverse)
priestClass <- religion %>% filter(protectedWord == "priest")
neutralSample <- sample_n(filter(priestClass,connection == "none"), 5)
humanSample <- sample_n(filter(priestClass,connection == "human"), 5)
priestVis <- priestClass %>% filter(connection != "none" & connection !="human")
priestVis <- rbind(priestVis,neutralSample,humanSample)

#we plug in our visualisation script
source("../functions/visualisationTools.R")
#two arguments: dataset and protected word
visualiseProtected(priestVis,"priest")
```



Here you can see that some human attributes are closer than stereotype attributes, and that there is no clear reason to claim that `associated` attributes are closer than `different` or `human` attributes. This, again, illustrates the need of case-by-case analysis with control groups.

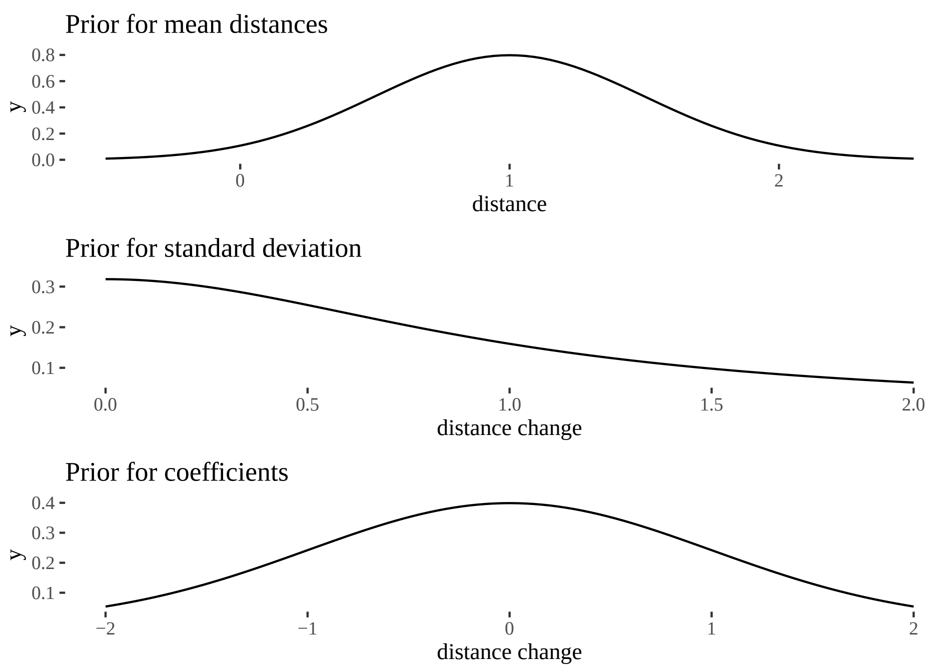
The general idea now is that the word lists provided in different pieces of research are just samples of attributes associates with various stereotypes and should be treated as such: the uncertaintly involved and the sample sizes should have clear impact on our estimates.

We will now think of cosine distance as the output variable, and will build a few bayesian models to compare. First, we just build a baseline model which estimates cosine distance to the attributes separately for each protected word. The underlying idea is that different protected words migh in general have different relations to all the attributes and this relations should be our point of departure.

Here is the intution behind the mathematical Bayesian model involved. Our outcome variable is `cosine difference`, which we take to me normally distributed around the predicted mean for a given protected word (that is, we assume the residuals are normally distributed). The simplest model specification is:

$$cosineDistance_i \sim dnorm(\mu_i, \sigma) \tag{3.1}$$
$$\mu_i = m_{pw} \tag{3.2}$$
$$m_{pw} \; dnorm(1, .5) \tag{3.3}$$
$$\sigma \sim dcauchy(0, 1) \tag{3.4}$$

That is, we assume the estimated means might be different for diferent protected words and our prior for the mean and the overal standard deviation are normal with mean 1 and sd=.5 and half-cauchy with parameters `0,1`. Further on we'll also estimate additional impact the connection type may have. For this impact we take a slightly skeptical prior centered around 0 distributed normally with sd = 1. These are fairly weak and slightly skeptical regularizing priors, which can be illustrated as follows:



Now we can define and compile the baseline model. Its parameters will have a posterior distribution obtained using either Hamiltionian Monte Carlo methods (STAN) available through the `rethinking` package.

```
library(rethinking)
options(buildtools.check = function(action) TRUE )
religionBaseline <- ulam(
  alist(
    cosineDistance ~ dnorm(mu,sigma),
    mu <- m[pw],
    m[pw] ~ dnorm(1,.5),
    sigma ~ dcauchy(0,1)
  ),
  data = religion,
  chains=2 , iter=4000 , warmup=1000,
  start= list(mu = 1, co = 0, sigma= .3),
  log_lik = TRUE, cores=4
)
#saving
#saveRDS(religionBaseline,
```

```
#file = "cosineAnalysis/models/religionBaseline.rds")
```

The only reason we need it is the evaluation of connection as a predictor. Does including it in o the model improve the situation? To investigate this, let's now build a model according to the following specification:

$$cosineDistance_i \sim dnorm(\mu_i, \sigma) \tag{3.5}$$
$$\mu_i = m_{pw} + co_{con} \tag{3.6}$$
$$m_{pw}\ dnorm(1, .5) \tag{3.7}$$
$$co_{con}\ dnorm(0, 1) \tag{3.8}$$
$$\sigma \sim dcauchy(0, 1) \tag{3.9}$$

The idea now is that each connection type comes with its own coefficient *co* that has impact on mean distances for protected words taken separately.

```
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
)
```

First, let's see if this model is really better in terms of the Widely Acceptable Information Criterion (WAIC):

```
#the calculation requires models which are large, we prepared the table
#compareBaseline <- print(round(compare(religionBaseline, religionCoefs)), 3)
compareBaseline <- readRDS("../datasets/compareBaseline.rds")
compareBaseline
```

```
##                   WAIC SE dWAIC dSE pWAIC weight
## religionCoefs    -2328 93     0  NA    20      1
## religionBaseline -2283 95    45  17    16      0
```

Clearly, it should be given weight 1 as compared to the baseline model. So far, we've learned that the connection type actually has predictive value. Let's take a look at the coefficient estimates:

```
##              mean        sd       5.5%      94.5%    n_eff    Rhat4
## co[1] -0.14956420 0.1151675 -0.3261650 0.03741930 294.2033 1.001449
## co[2] -0.09880543 0.1145024 -0.2736985 0.08813271 291.5044 1.001564
## co[3] -0.07282752 0.1133894 -0.2447778 0.11158986 287.7820 1.001627
## co[4] -0.03103179 0.1131420 -0.2034442 0.15268770 286.8283 1.001606
```

Let's plot them together with their highest posterior density invervals, for the three topic groups.

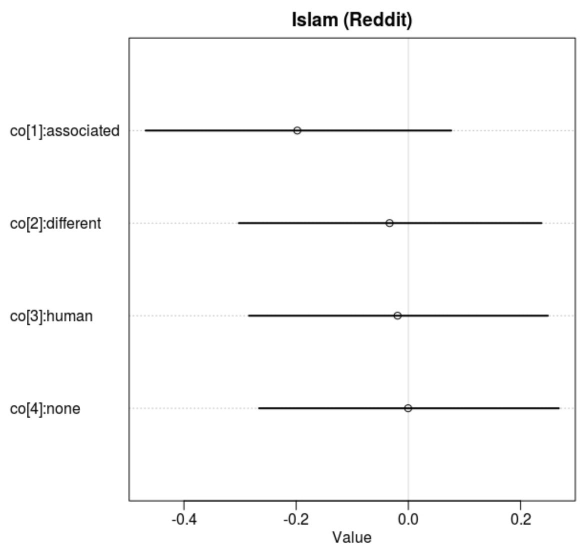
What should strike us is that while the mean estimates of the coefficients indeed do differ a bit, usually the highest posterior density invervals all include zero, and so we do not have strong reasons to say that, say, as far as the whole religion dataset is involved, being associated indeed is connected with lower cosine distance. A second striking observation is that the estimated impact for associated stereotypes is quite often not too different from the estimated impact of attributes associated with different stereotypes, and both are sometimes not too far from the estimated impact for simply human attributes. In general, once the uncertainty involved is taken seriously by using control groups and statistical uncertainty estimation that does not dispose of pointwise data, the picture which focuses only on differences between means of means is too simplistic.

But this doesn't mean important differences for some protected words are not there. For one thing, if you start with a word list that is very uneven, the actually not so bad status of some of the protected words might mask a pretty bad situation in which some other protected words are. For comparison, let's see what a model focused on words related to islam tells us.

```
#this is how we build the model
religion <- read.csv("cosineAnalysis/datasets/religionReddit.csv")[-1]
colnames(religion) <- c("protectedWord","wordToCompare","wordClass",
                        "cosineDistance","cosineSimilarity","connection")
levels(religion$wordClass) <- c("christian","human","jewish","muslim","neutral")
muslimWords <- c("imam","islam","mosque","muslim","quran")
muslim <- religion %>% filter(protectedWord %in% muslimWords)
muslim$protectedWord <- droplevels(muslim$protectedWord)
muslim$pw <- as.integer(muslim$protectedWord)
muslim$con <- as.integer(muslim$connection)
muslim$pwFactor <- factor(paste0(muslim$protectedWord, muslim$connection))
muslim$pwIndex <- as.integer(muslim$pwFactor)

islamCoefs <- 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 = muslim,
  chains=2 , iter=10000 , warmup=1000, cores = 4,
  log_lik = TRUE
)
```

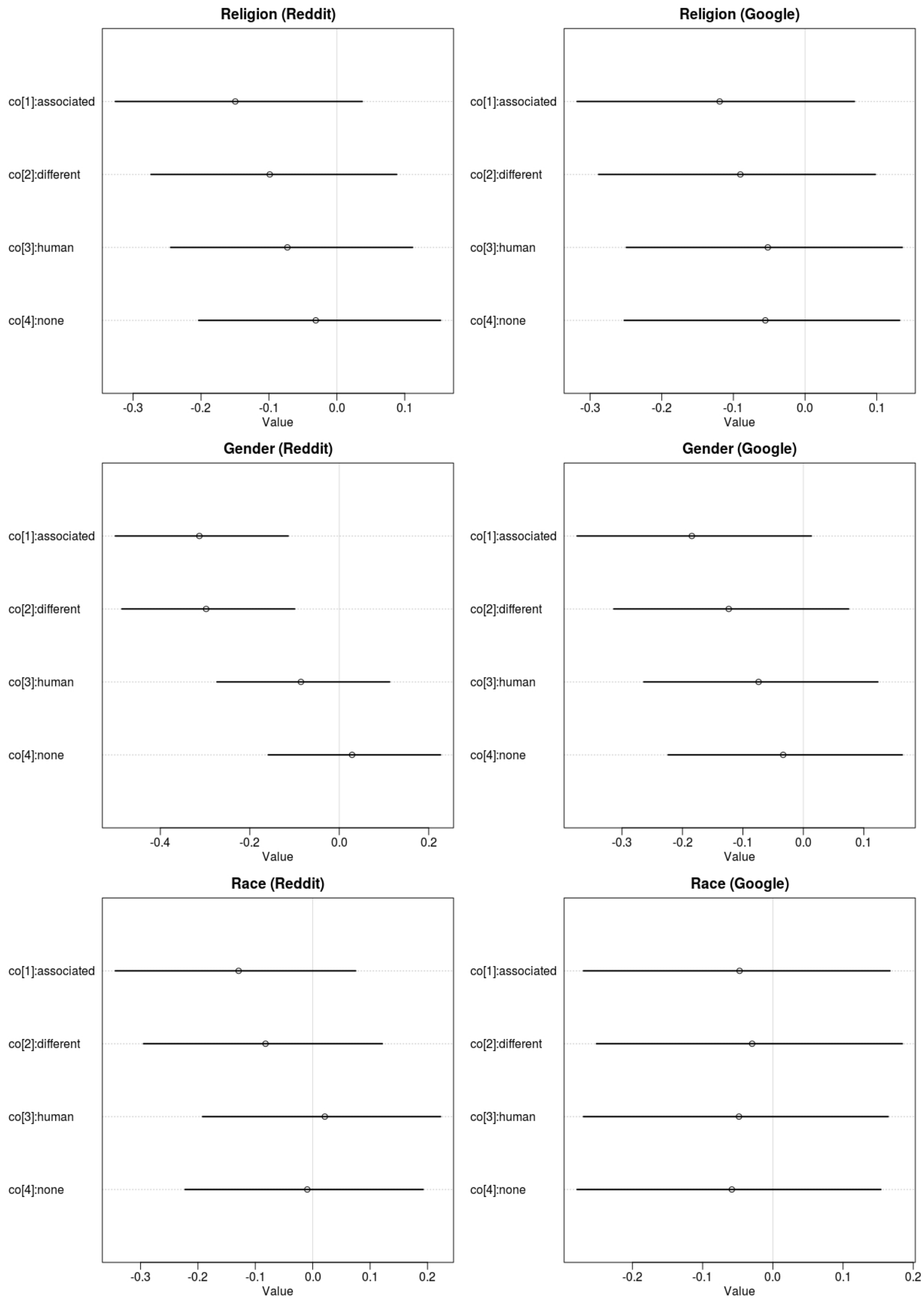
Let's take a look at the coefficients:

```
##                mean        sd       5.5%      94.5%    n_eff    Rhat4
## co[1] -0.1979930035 0.1708785 -0.4682696 0.07634977 1789.894 1.003445
## co[2] -0.0334215769 0.1687587 -0.3021954 0.23720938 1738.720 1.003575
## co[3] -0.0192492753 0.1675754 -0.2840596 0.24860974 1732.907 1.003755
## co[4] -0.0003911363 0.1670610 -0.2661047 0.26815172 1723.758 1.003837
```



While muslim words were unusual in the sense that the disparity between associated attributes and others is stronger, the evidence is still not conclusive. This is because the variation even within islam-related words is large enough (and sample sizes sufficiently small) for all the highest posterior density invervals to still include zeros.

So, it seems, taking a closer look does seem to make a difference. The question is, what happens if we do take a close look at the level of protected words?


Religion (Reddit)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.3 -0.2 -0.1 0.0 0.1
Value
Religion (Google)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.3 -0.2 -0.1 0.0 0.1
Value
Gender (Reddit)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.4 -0.2 0.0 0.2
Value
Gender (Google)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.3 -0.2 -0.1 0.0 0.1
Value
Race (Reddit)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.3 -0.2 -0.1 0.0 0.1 0.2
Value
Race (Google)
co[1]:associated
co[2]:different
co[3]:human
co[4]:none
-0.2 -0.1 0.0 0.1 0.2
Value

Chapter 4

Protected-word level analysis

Let's turn then to data analysis that takes a look at protected words separately. This time for each combination of a protected word and a connection status we will have a separate mean cosine distance estimate, each coming with its own highest posterior density interval. This means we will use indices that are result from all such combinations (and then we will split them up in the model precis to build visualisation, feel free to look at the `visualiseStats.R` script for details).

```
options(buildtools.check = function(action) TRUE ) #removes install pop-up request
religion$pwFactor <- factor(paste0(religion$protectedWord, "-", religion$connection))
religion$pwIndex <- as.integer(religion$pwFactor)

religionSeparate <- ulam(
  alist(
    cosineDistance ~ dnorm(mu,sigma),
    mu <- c[pwIndex],
    c[pwIndex] ~ dnorm(1,.5),
    sigma ~ dcauchy(0,1)
  ),
  data = religion,
  chains=2 , iter=10000 , warmup=1000,
  start=list(no = 1, a = 0, d = 0, sigma= .3), log_lik =  TRUE
)
```

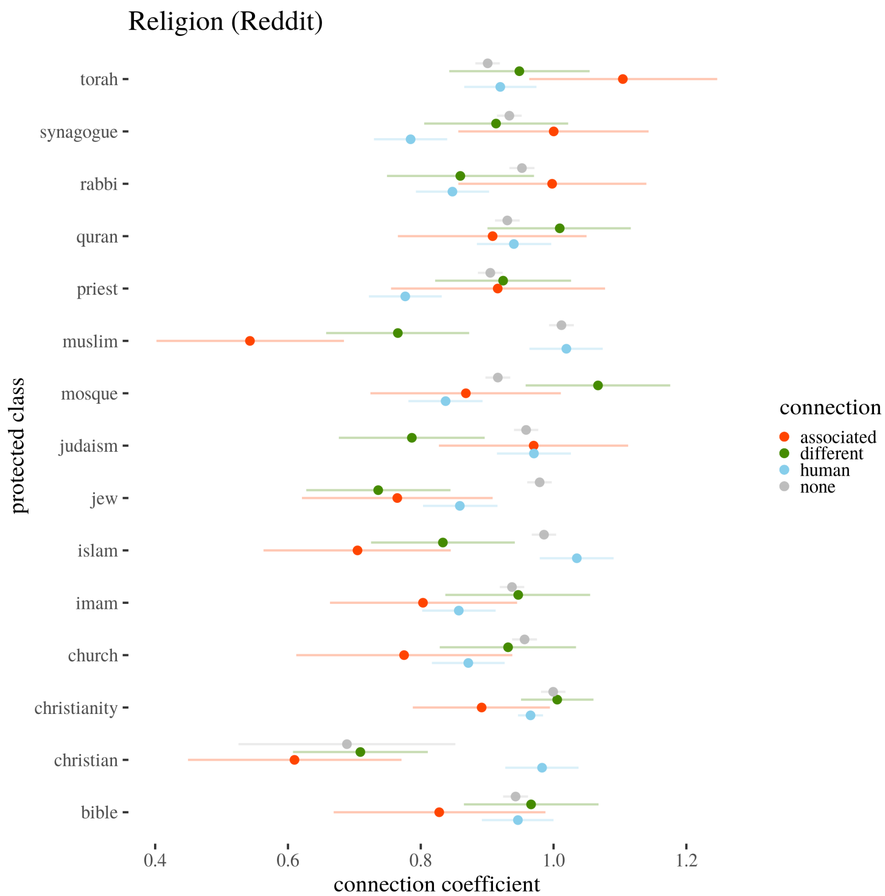
Let's see if the individualized model does better than the previous models in light of WAIC which does add penalty for the number of parameters.

```
compareBaselineCoefsSeparate<- readRDS("../datasets/compareBaselineCoefsSeparate.rds")
compareBaselineCoefsSeparate
```

```
##                   WAIC SE dWAIC dSE pWAIC weight
## religionSeparate -2400 93     0  NA    60      1
```

```
## religionCoefs    -2328 93    72  29    20      0
## religionBaseline -2283 95   117  37    16      0
```

Great, it seems that we do want to prefer this model, despite its relative complication. Now, what does it tell us about the protected words? Let's visualise the predicted means together with 89% highest posterior density intervals.



Islam, A. C., Bryson, J. J., & Narayanan, A. (2016). Semantics derived automatically from language corpora necessarily contain human biases. *CoRR*, *abs/1608.07187*. Retrieved from http://arxiv.org/abs/1608.07187