Predicting Belief in Conspiracy Theories

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Abstract

The purpose of this project was to find the factors that correlate most strongly with a person believing or disbelieving in conspiracy theories, and if there are factors related strongly enough to create an effective regressor. To discover this, we took a dataset containing people's answers to questions regarding conspiracy theories[2], along with demographics and other information on the participants. We use various regression models on this dataset to find which traits most correlate to a belief in conspiracy theories.

Introduction

Are there some factors that correlate with a person believing or disbelieving in conspiracy theories? Some believe that only uneducated people, or overly educated people, have such beliefs, but do these impressions hold any water? (At the very least, among those who would complete an online survey?) For our project we will use online survey data about belief in conspiracy theories to find what factors most correlate to one believing or disbelieving in conspiracy theories. This question has been a topic of research for several decades and has only grown in importance over the past few years. As the COVID-19 pandemic has dragged on, more and more people have turned to QAnon and Facebook for answers, instead of science. Thus, identifying traits that lead to conspiracy theory belief remains an important topic.

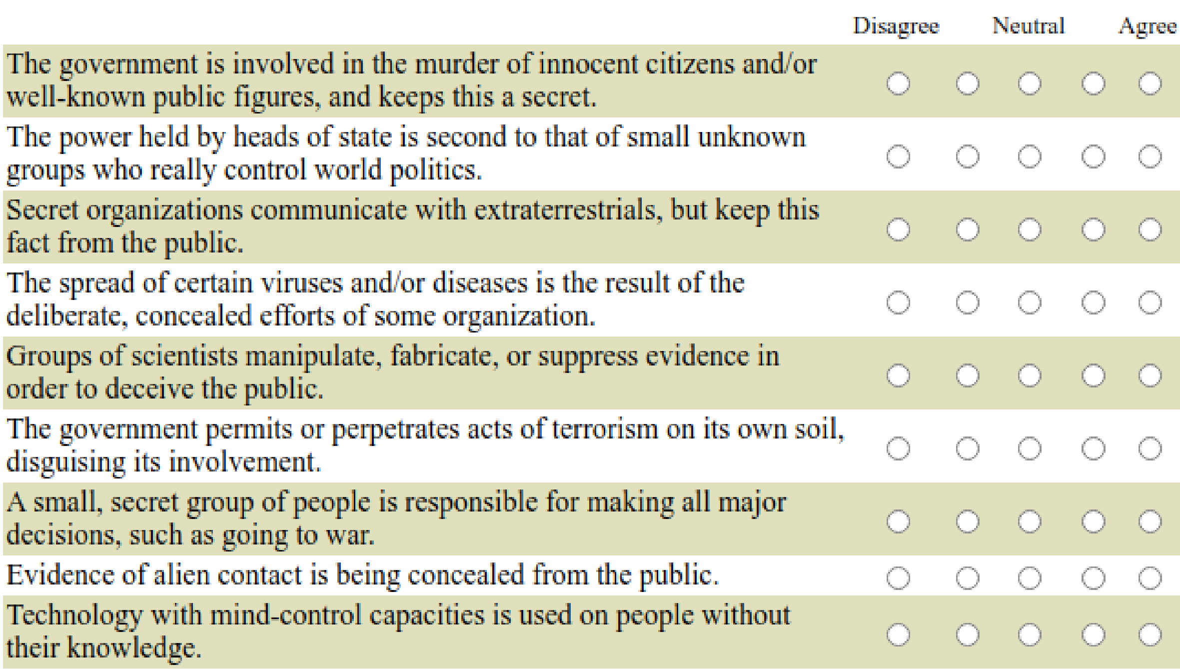
Previous studies focus on correlating certain traits to conspiracy theory belief. For example, research done by Natasha Galliford and Adrian Furnham in "Individual difference factors and beliefs in medical and political conspiracy theories"[2] attempted to find correlations between general traits. They used both demographic and psychological identifiers (age, race, sex, whether a person is introvered or extroverted, etc.) and correlated them with belief in political and medical conspiracy theories. Using step-wise regression, they concluded that religion and age tended to be big factors in whether one is more accepting of conspiracies. Another study, called, "Looking under the tinfoil hat: Clarifying the personological and psychopathological correlates of conspiracy beliefs" (Bowes et al., 2020), attempted to find correlation between extremely specific traits such as abnormal personality and psychological disorders and conspiracy theory belief. The authors used meta-regression to determine the strength of this correlation, and found that any personality trait that was correlated was usually weakly so.

Our project examines both general identifiers (such as religion, race, and sex) and specific personality traits (such as is a person reserved, anxious, disorganized) as features for regression. We use linear and Random Forest regressors on our dataset to see which factors have a strong correlation to conspiracy theory belief. The dataset we use is taken from"Measuring belief in conspiracy theories: the generic conspiracist beliefs scale", a study that used the generic conspiracist beliefs scale (GCBS) score to quantify one's belief in conspiracy theories. The study also asked questions about demographic and personality traits, which we use to construct a design matrix. We use this dataset because it has an extensive amount of data, which we need to get a good estimator, and because all the data are available to the public. However, it is important to keep in mind that the data come from an internet survey. Thus, it is likely that not every person took it seriously, and some people likely lied. To account for this, we analyze the data to find people who may not have taken the survey seriously (more specifically, those who took little to no time to complete the survey, put the same answer for every question, or entered invalid responses).

To determine which features of our data contribute to general belief in conspiracy theories, we use three forms of regression. The first is an L_1-regularized regression (Lasso regression), our reasoning being that our design matrix has over 100 features and we do not wish to overfit. The other (and better) methods are ElasticNet and Random Forest regressors. Each of these is discussed in more detail later.

Dataset

Below is an illustration of some of the questions participants in the survey were asked about their beliefs:



	Disagree		Neutral		Agree
The government is involved in the murder of innocent citizens and/or well-known public figures, and keeps this a secret.					
The power held by heads of state is second to that of small unknown groups who really control world politics.					
Secret organizations communicate with extraterrestrials, but keep this fact from the public.					
The spread of certain viruses and/or diseases is the result of the deliberate, concealed efforts of some organization.					
Groups of scientists manipulate, fabricate, or suppress evidence in order to deceive the public.					
The government permits or perpetrates acts of terrorism on its own soil, disguising its involvement.					
A small, secret group of people is responsible for making all major decisions, such as going to war.					
Evidence of alien contact is being concealed from the public.					
Technology with mind-control capacities is used on people without their knowledge.					

The following table contains detailed descriptions of each feature of the dataset.

Label	Description
TIPI2	Question on whether the subject consider themselves critical and quarrelsome.
TIPI5	Question on whether the subject considers themselves open to new experiences and complex.
TIPI6	Question on whether the subject considers themselves reserved and quiet.
vocabulary_misclassification	All subjects were given a list of 16 words and asked if they knew what each word meant. 3 of the words were not real words. So this variable computes the misclassification rate of only these 3 words to find people who say they know the definition of a fake word. This helps us know which people are more likely to inflate their knowledge.
STEM	This is a binary variable saying whether or not the subject majored in STEM in college.
education_2	Binary variable saying whether the subject only has a high school education or some other level of education.
education_3	Binary variable saying whether the subject only has a University degree or some other level of education.
urban_3	The type of area that the subjects lived in as a child. This variable is a binary variable showing they either grew up in an urban environment or not.
gender_2	Binary variable saying whether a subject is female or not.
engnat_1	Binary variable saying whether a subject speaks English as their native language or not.
religion_2	Binary variable saying whether a subject is Atheist or not.
religion_3	Binary variable saying whether a subject is Buddhist or not.
religion_7	Binary variable saying whether a subject is a non-Catholic, non-LDS, non-Protestant Christian or not.
religion_12	Binary variable saying whether a subject is part of a religion that is not any major religion.
orientation_2	Binary variable saying whether a subject's sexual orientation is bisexual or not.
orientation_5	Binary variable saying whether a subject's sexual orientation is outside of heterosexual, homosexual, bisexual, and asexual.
voted_2	Binary variable saying whether the subject didn't vote in the last national election.
married_1	Binary variable saying whether the subject has never been married.

Data Cleaning and Feature Engineering

The survey includes many important features including (but not limited to) age, education, religion, major, and vocabulary comprehension. Most were categorized and one-hot encoded, but not all. Here we go over the changes we make to fields with text or categorical values.

GCB - General Conspiracy Belief

The first field we create is the GCB field, or "General Conspiracy Belief". The first 15 questions of the survey asked about level of belief in specific conspiracies on a 1-5 scale. The questions were in the form of statements, like the following example: "Groups of scientists manipulate, fabricate, or suppress evidence in order to deceive the public." The GCB is the average of these values for each person, as computed in the following code block, so 0.5 would indicate an average level of belief of 0.5 (or a response of 2.5 in the survey, which is on a scale from 1 to 5) in various conspiracies.

```
df['GCB'] = df[['Q'+str(i) for i in range(1, 16)]].mean(axis=1) / 5
```

This is used as the target "response" variable in our analysis. It simplifies the regression a lot to use an average of these answers rather than trying to have 15 different response variables.

Major

We make several changes to the [college] "major" field. Here, survey respondents put in their major as a string; because this was a free response, we have hundreds of unique responses. Because there are so many majors (and so many major misspellings), we group the responses together in larger categories, namely STEM, Humanities, Business/Law, Arts, and Other. We understand that we are making the simplifying assumption that majors within the same sector to have similar correlations to a person's belief in conspiracies, but this loss in information is worth the time it saves us, as we no longer have to inspect each response. Because there were such varied responses, we initially assigned each major to a group manually. We then one-hot encoded these new variables to facilitate performance of classification. But in order to enable future expansion of the data used, we needed to implement a flexible major classification strategy that could sort new major strings robustly into the existing categories. We do this using Levenshtein edit distance, which is calculated using recursion to determine the difference between two strings in terms of how many primitive edits it takes to permute one into the other. The major category with the lowest Levenshtein distance to any newly observed response is taken to be the correct category for that response. Although this may result in some misclassified majors, using a natural language processing method to improve performance is outside the scope of this paper.

Below is the code detecting unassigned majors and using the Levenshtein function to categorize the majors accordingly.

```
unassigned = df[df["STEM"]+df["HUM"]+df["BUS"]+df["OTHER"]+df["ART"] == 0]
categories = ["STEM", "HUM", "BUS", "OTHER", "ART"]
score = dict()
for index,unknown_string in zip(unassigned.index,unassigned['major']):
    for category in categories:
        tf = open(f"{category}.txt", "r",newline='\n')
        majors = [i[:-2] for i in tf.readlines()]
        score[category] = min([levenshteinDistance(str(maj),str(unknown_string))\
```

```
        for maj in majors])
    min_key = min(score, key=score.get)
    df.loc[index,min_key] = 1
```

Vocabulary Knowledge and Vocabulary Misclassification

The survey we use includes questions in which the respondent identified the meaning of various vocabulary words. Correct answers for each question were recorded as 1s, and incorrect as 0s. We perform a simple averaging calculation to determine a person's approximate vocabulary knowledge (conceivably this works as a very rough proxy for general lexicographic knowledge). Omitted VCL__ questions are categorized into a separate variable "validity", since they were nonsense words included to prevent overconfident respondents from getting a perfect score. As illustrated in the code below, vocabulary questions 6, 9, and 12 were the nonsense words, and the rest of the questions are a true vocabulary knowledge test.

```
df['validity'] = df[['VCL6', 'VCL9', 'VCL12']].mean(axis=1)
knowledge = [1,2,3,4,5,7,8,10,11,13,14,15,16]
df['vocabulary_knowledge'] = df[['VCL' + str(i) for i in knowledge]].mean(axis=1)
```

Response Time

For further feature engineering, we examine the respondents who took the least amount of time and the most time to complete the survey, as well as the respondents who put the same answer for every question on belief in conspiracy theories. However, upon visual inspection of all of these edge cases, the demographic information seemed appropriately varied, and was completely filled out, implying that these rows should not be thrown out. We concluded that it is likely that the publishers of this survey data performed similar data cleaning and so any unfinished surveys or invalid responses would already be thrown out.

Methods

As mentioned in the introduction, the three methods we compare are L_1-regularized least-squares regression, ElasticNet regression, and a Random Forest ensemble of regression trees. We first use least-squares regression with L_1-regularization, hoping to remove any irrelevant features. We use $\alpha = 1 \times 10^{-3}$, which reduces the 100+ columns down to 20 columns with nonzero coefficients. We then run OLS without any regularization on the reduced set of columns simply so that the results table won't include features with coefficients of zero (and because, at the time of writing, statsmodels has not yet implemented the summary display for regularized regression models). The next methods we use are ElasticNet and Random Forest regression. In both cases we use a grid search across various hyperparameters, illustrated in Table 2 in the Results section, with 5-way cross validation, looking to maximize the classifier's R^2 value. With the Random Forests, we limited the possible tree parameters to preclude overfitting. In fact, by letting the max tree depth be 10, we found the tree to have an R^2 value of over .5, much higher than the .15-.2R^2 values found by the least-squares estimators. We concluded that the forest was likely very overfit, and so restricted ourselves to more conservative hyper parameters. Each Random Forest we tried used between 100 and 200 tree estimators, with the optimal Random Forest using 200 trees.

Results

Table 1 shows the coefficient of determination R^2 and correlation coefficients for different features for our initial attempt using L_1-regularization.

Table 1: Lasso Regression Results.

Dep. Variable:	GCB	**R-squared:**	0.135
Model:	OLS	**Adj. R-squared:**	0.129
Method:	Least Squares	**F-statistic:**	24.15
Date:	Wed, 01 Dec 2021	**Prob (F-statistic):**	8.15e-67
Time:	17:11:36	**Log-Likelihood:**	573.41
No. Observations:	2495	**AIC:**	-1113.
Df Residuals:	2478	**BIC:**	-1014.
Df Model:	16		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
TIPI1	0.0046	0.003	1.817	0.069	-0.000	0.010
TIPI2	0.0130	0.002	5.968	0.000	0.009	0.017
TIPI5	0.0038	0.003	1.321	0.187	-0.002	0.009
TIPI6	0.0003	0.003	0.101	0.919	-0.005	0.005
TIPI7	0.0013	0.002	0.541	0.589	-0.003	0.006
vocabulary_misclassification	0.0707	0.017	4.045	0.000	0.036	0.105
OTHER	0.0228	0.008	2.699	0.007	0.006	0.039
education_2	0.0301	0.008	3.637	0.000	0.014	0.046
urban_3	0.0237	0.008	2.890	0.004	0.008	0.040
gender_2	0.0229	0.008	2.880	0.004	0.007	0.039
religion_2	-0.0756	0.009	-8.253	0.000	-0.094	-0.058
religion_3	0.0864	0.028	3.092	0.002	0.032	0.141
religion_7	0.0639	0.014	4.449	0.000	0.036	0.092
religion_12	0.1034	0.013	8.256	0.000	0.079	0.128
orientation_5	0.0438	0.017	2.591	0.010	0.011	0.077
voted_2	0.0208	0.009	2.434	0.015	0.004	0.038
const	0.4135	0.028	14.870	0.000	0.359	0.468

Omnibus:	76.163	**Durbin-Watson:**	1.910
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	40.646
Skew:	0.123	**Prob(JB):**	1.49e-09
Kurtosis:	2.425	**Cond. No.**	80.3

None of our features seems to be strongly correlated with GCB, and we only account for about 13.5% of the variance in beliefs with these features. Among what we do find, however, the strongest predictors of belief in conspiracy theories seem to be religion (in particular marking 'other' as one's choice of religion), age, and low knowledge of the given vocabulary words, as determined by the engineered features "vocabulary knowledge" and "vocabulary_misclassification".

We achieve better results using a grid search on the scikit-learn implementations of ElasticNet and RandomForestRegressor. As Table 2 illustrates, we achieve the best results (R^2 = .2297) using a Random Forest. Note that the Random Forest listed here is not the best (in terms of R^2) Random Forest that we were able to generate, but it is the best that has hyper parameters that don't lend themselves to overfitting.

Table 2: Best Estimators and Results.

Model	Best Hyperparameters	R^2
sklearn ElasticNet	$\alpha = .001$, `l1_ratio` = .4842	.1811
sklearn RandomForestRegressor	`max_depth` = 5, `min_samples_leaf` = 6	.2297

In Table 3, we see which features are most important in the Random Forest. Note that a high Gini importance indicates that a feature is important in determining whether or not a person believes in conspiracy theories, but that feature is not necessarily positively correlated (it could be negatively correlated). For example, the way the least-squares regression interpreted these features, religion_2, vocabulary_knowledge, and TIPI10 were negatively correlated with GCB, and religion_12 and age were positively correlated with GCB.

Table 3: Feature Importance.

Feature	Meaning	Gini Importance
`religion_2`	Atheist	.2040
`vocabulary_knowledge`	% of words marked correctly	.1749
`religion_12`	"Other" Religion	.1218
`age`	Years Old	.0664
`TIPI10`	Conventional, Uncreative Personality	.0566

These results indicate that among the group of people that was surveyed, there are a number of features which are definitely correlated with belief in conspiracy theories. It is possible that these features are also correlated with conspiracy belief in the population in general. However, it is important to note that

1. our R^2 values indicate that our model accounts for very little of the variance in belief in conspiracy beliefs and
2. since this was an online volunteer survey, we have no reason to believe that the respondents are representative of society or any general group.

With these things in mind, we note that the strongest predictors of belief in conspiracy theories seem to be religion (in particular marking 'other' or 'atheist' as one's choice of religion), low knowledge of the given vocabulary words, and age. The two most important quantitative variables are the engineered vocabulary score features and age; Figure 1 is a heatmap of General Conspiracy Belief in relation to a person's age and vocabulary score. Although we do see a concentration of higher GCB in the lower age/lower vocab score area, there is no strong correlation immediately apparent. This matches up with the low predictive power of our various regressors - correlations do exist, but are not strong.

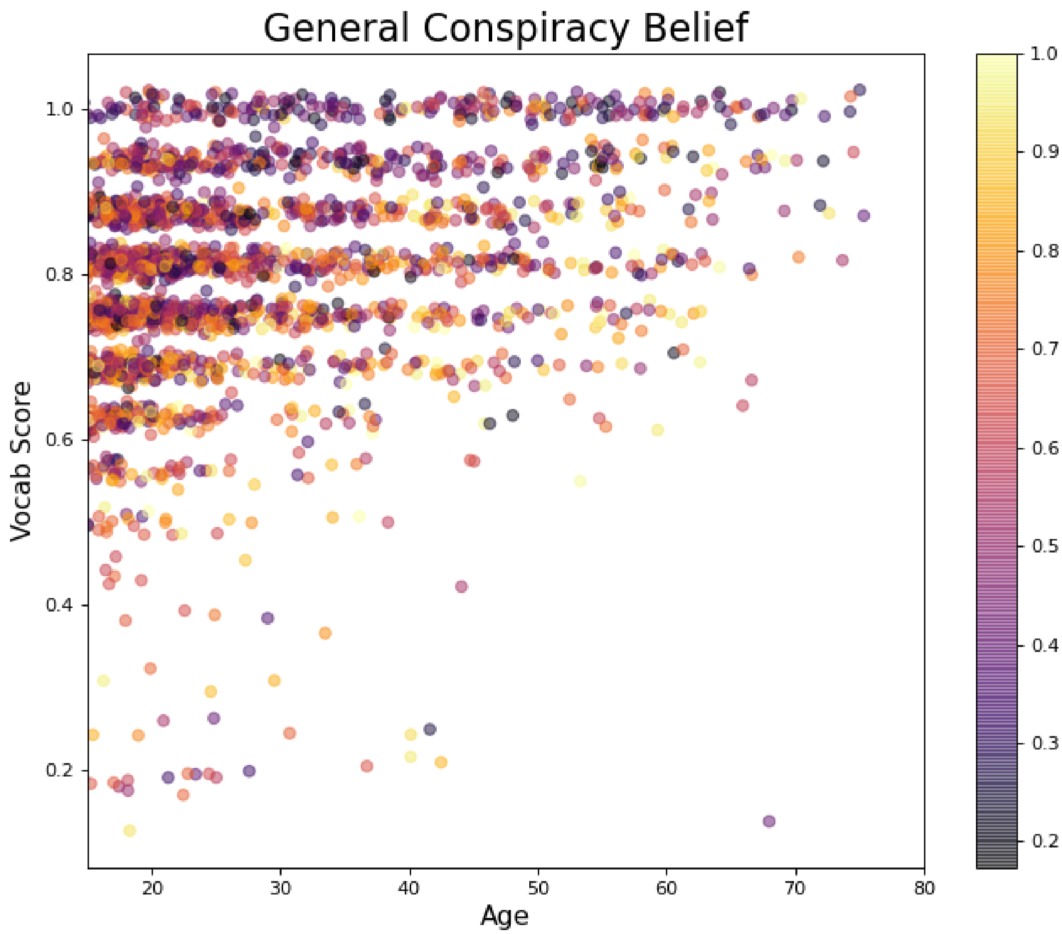


Figure 1: Heatmap of the most Gini-important quantitative features.

Ethical Implications

It is important to remember that, although we have found traits with positive and negative correlation to conspiracy theory belief, our model has a low R^2 score, so it does not account for a lot of the variance in the data. Thus, just because someone may have many of the traits that correlate with conspiracy theory belief, that does not mean they do believe in conspiracy theories. Human beings are diverse and multi-faceted in their beliefs. Thus, absolute assumptions should not be made from the data above. Instead, the data above should be used as merely a soft guide to indicate that a person may believe conspiracy theories. This could be useful in anticipating a group's beliefs prior to giving them information about controversial topics, or in determining the issues most important to a group of people. But it should not be relied on for any important decisions.

Additionally, it is important that predictions from this model not be used to discriminate against individuals or disqualify them from anything, such as jobs or political offices. High correlations are good leads for other questions of research, such as "why is belief in conspiracy highly correlated with ____?" Understanding the causes behind the trends could help us answer questions about nature vs. nurture, psychology, and other topics in the field of study.

References

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