Predicting Belief in Conspiracy Theories

Calix Barrus, Laren Edwards, Dallan Olsen, Elijah Cox

December 1, 2021

Abstract

The purpose of this project was to find what factors most correlate with a person believing or disbelieving in conspiracy theories, and if there are factors related strongly enough to create an effective classifier/regressor. To discover this we took a dataset that scored peoples' belief of conspiracy theories based on their answers to certain questions. The dataset also included demographics and other information on the subjects which we used with a linear regression model 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" 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. They 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 will look at 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 will then use linear regression on our dataset to see which factors have a strong correlation to conspiracy theory belief. The dataset we used was taken from"Measuring belief in conspiracy theories: the generic conspiracist beliefs scale." It was 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 will use to look for correlations. We used this dataset because it had an extensive amount of data, which we needed to get a good estimator, and because all the data was available to the public. However, it is important to keep in mind that the data came 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 analyzed the data to find people who may not have taken the survey seriously (took little to no time to complete the survey, put the same answer for every question, entered invalid responses, etc.). We then ended with a clean dataset that we were able to analyze. As part of our analysis, we found which traits correlated most with conspiracy theory belief. This is done by performing an L1 regularization on the data to find which traits had the strongest correlation. We then ran a linear regression on these traits to find exactly how they were correlated to conspiracy theory belief. ## 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 made in the fields. ### GCB - General Conspiracy Belief The first field we created was 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, so 2.5 would indicate an average level of belief of 2.5 in various conspiracies.

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

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

Major

The last field that we made large changes to was the "major" field. Here, survey respondents would put in their major as a string. Because this was a free response, we had hundreds of unique responses for major. Because there are so many majors (and so many major misspellings), we decided to group the responses together in larger categories. We used STEM, Humanities, Business/Law, Arts, and Other as our categories. Logically, this makes sense because we expect majors within the same sector to have similar correlations to a person's belief in conspiracies. 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. In order to enable future expansion of the data used, we implemented a flexible major classification strategy that can sort new major strings robustly into the existing categories. This strategy uses a Levenshtein edit distance to find the category with the most similar major in it. This is calculated with a function that uses recursion to determine the difference between two strings in terms of how many primitive edits it takes to permute one into the other. On testing, this strategy worked quite well and proved to be reliable in categorizing new majors. 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 majo
    min_key = min(score, key=score.get)
    df.loc[index,min_key] = 1
```

vocabulary_knowledge, vocabulary_misclassification

The survey we used included 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 did 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 were categorized into a slightly separate variable, since they were nonsense words included to provide general validity.

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

Time feature engineered

For further feature engineering, we looked at 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

To analyze our data we tried to use OLS with regularization, and Random Forest Regression. We first used OLS with L_1-regularization to see if how many of the 100+ columns in our cleaned data were irrelevant. After cutting the 100+ columns down to the 20 columns with nonzero coefficients, we ran OLS without any regularization on the reduced set of columns. In addition to trying L1 regularization, on the entire data set we did a grid search of hyper parameters for Elastic Net regression, as well as a grid search of hyper parameters for Random Forests. In both cases we used grid search 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 OLS estimators. We concluded that the forest was likely very overfit, and so restricted ourselves to more conservative hyper parameters.

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Results

For our initial attempt using L_1-regularization, the figure below shows the coefficient of determination R^2 and correlation coefficients for different features.

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

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

None of our features seems to be strongly correlated with GCB, and we only account for about 13.9% of the variance in beliefs with these features. Among what we did find, however, the strongest predictors of belief in conspiracy theories seem to be religion (in particular marking 'other' as one's choice of religion), low knowledge of the given vocabulary words, and age. The engineered features "vocabulary knowledge" and "vocabulary_misclassification" determine this.

We got better results using a grid search on the sklearn implementations of ElasticNet and RandomForestRegressor. As can be seen in the below table, we got our best results using a random

forest with an R^2 of .2297, much better than the .139 than plain OLS. 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.

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

In the next table, we see which features were most impactful 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). The way the OLS regression interpreted these features, religion_2, vocabulary_knowledge, and TIPI10 were negatively correlated, and religion_12 and age were positively correlated.

Column	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

By analyzing this data we found that among the group of people that was surveyed, there are a number of features which are definitely correlated with belief in conspiracy theories. These features are definitely correlated among the group of survey respondents, and it is possible that these features could also be very gently 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 variation of 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. None of our features seems to be strongly correlated with GCB, and we only account for about 13.9% of the variance in beliefs with these features. Among what we did find, however, the strongest predictors of belief in conspiracy theories seem to be religion (in particular marking 'other' as one's choice of religion), low knowledge of the given vocabulary words, and age. The engineered features "vocabulary knowledge" and "vocabulary_misclassification" indicate the knowledge of vocab words, and age is a quasi-continuous variable. The following figure 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.
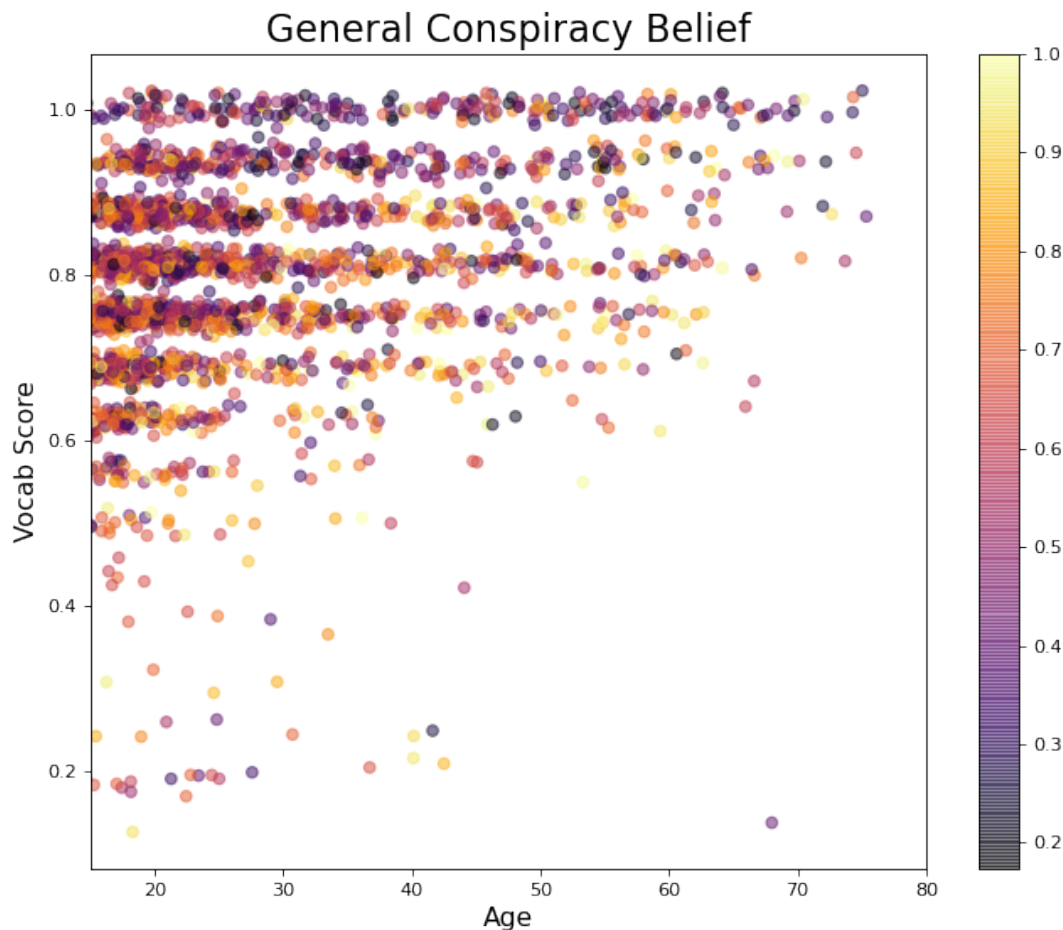
Ethical Implications

It is important to remember that, although we have found traits with positive and negative correlation to conspiracy theory belief, our model has a very low R^2 score. That means that our model 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 again, it should not be used to make absolute assumptions. 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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