Predicting the Ideological Position of Reddit Users

Dissertation

Targeted academic degree:
Master of Science (MSc)
in Applied Social Data Science

Department of Methodology
London School of Economics and Political Science

Candidate number: 52559
Supervisor: Blake Miller
Word count: 8611
August 2023

Abstract

Social networks are important platforms for political discussions, therefore being able to estimate the ideological position of users could be beneficial for understanding the sentiments of certain groups regarding specific social issues. The language that is being used can provide a lot of insight about the views of individuals, which makes textual data the most appropriate. Unlike other platforms, Reddit accommodates niche ideological communities in separate subforums, which equips us with additional information for understanding ideological positions. This research aims to answer whether there are differences in language based on ideological position, whether one can predict the ideological position of an individual based on the content they generate on social media, and, if so, what is the optimal way to do it.

Applying different forms of analysis to textual data from Reddit, we get the conclusion that there are distinct differences in the choice of words, properties of text and sentiment between various ideological communities. By estimating a variety of machine learning models, we find that the best results are achieved by using a neural network, with the second-best performance being that of an extreme gradient boosting regressor.

Key words: sentiment, ideological scaling, sentiment analysis, web scraping, social networks

Table of Contents

Introduction

Social media is undeniably one of the definitive technologies of the modern age, penetrating multiple spheres of human life and drastically affecting society, its outlook on life and the style of communication. With social media platforms gaining more and more popularity in the recent years, it reshapes discussions happening between individuals and social groups and replaces offline communications to a greater extent as time goes by. Consequently, we can view public discussions taking place on social media as a proxy for the current sentiments regarding corresponding events or subjects at a given moment in time. Taking this into account, researching social phenomena, sentiments of the public, behaviour of certain groups of the population becomes increasingly easier by using publicly available social media content.

Understanding political and social discussions happening on social media can be valuable and important for various reasons. Firstly, it could provide an insight into the sentiment of the public or certain groups regarding events, policies, and other phenomena which could be useful for policymakers or business managers considering introducing certain changes into the life of society. Secondly, it could help us to understand the demographics of adherents of certain political affiliations which could be relevant for research in political science, sociology, or psychology. Previous research has shown that certain populations of users in online political discussion groups contribute to political polarization, and those groups are identifiable through the language they use (Simchon et al., 2022). Gaining a deeper understanding of the matter could be useful in mitigating such undesirable activity. User profiling and predicting one's ideological position has also been named relevant for personalization and marketing (Preoţiuc-Pietro et al., 2017).

One of the most popular social media platforms used for political and social issues-oriented discussions is Reddit, with more than billion users as of 2022. Unlike other platforms, Reddit accommodates topical communities known as subreddits, which gives researchers additional information about certain users and allows to investigate the online behaviours of certain groups, or certain phenomena.

There have already been attempts made to study the differences in the content posted in communities of different political affiliations on Reddit and other platforms. For instance, Soliman et al. (2019) studied the differences between right-wing and left-wing communities on Reddit, while Hofmann et al. (2022) conducted an analysis of the whole political sphere represented on the platform. Conover et al. (2011) have attempted to predict the political leaning of Twitter users in the framework of left and right, reaching 91% accuracy. Preoţiuc-Pietro et al. (2017) took the idea further by categorising users into groups by extremity of their political position and examined the relationships between language and political views.

The main issue with previous related work is the focus on the left-right scale. There is great diversity within the left and the right ideologies, therefore it would make sense to consider political views in a different framework that would allow more diversity. Therefore, in this research we propose to switch focus from merely the left and right scale and to study political views in a two-dimensional framework to develop a more nuanced understanding of the matter.

Having elaborated on the ideas outlined above, the focus of this research is to develop a more complex framework through which we could study political affiliations of Reddit users. Similar to previous researchers, we are going to study the relationships between language used in the content posted online and the political views of the corresponding users. Then, we will attempt to answer whether it is possible to predict the ideological position of social media users in the developed framework, and if so, what is the optimal way of doing it. Our main source of data are the Reddit communities dedicated to political ideologies.

The paper is structured as follows. The first chapter elaborates on existing literature and related work. It features findings on the two key aspects of this research – differences in language depending on the political affiliation and prediction of political views of social media users. In the second chapter we will describe the methods, approaches to working with data and machine learning models that are going to be used. We will also provide some preliminary analysis of the data to gain a better understanding of it and to make some initial hypotheses on the possible outcomes of the research and implications of these findings. Finally, we will estimate the corresponding models and interpret the results. In the third chapter, we will compare our results to the findings in the past research papers and discuss the shortcomings of this work and the directions for future research.

Chapter 1. Previous findings and evidence

1.1.Evidence on differences in language in different political affiliations

Differences in ideological positions that different individuals adhere to can stem from various factors. There has been a prolonged interest in the determinants of the choice of political ideology by individuals, expressed in several past papers. Psychological traits, such as authoritarianism and religiosity were named as significant determinants of political ideology (Feldman and Johnson, 2014). Some claim that certain behavioural traits associated with specific gene combinations play a role in determining one's political affiliation (Settle et al., 2010). The authors state that some individuals are genetically inclined to be more novelty-seeking, and their ideological stance tends to be more liberal because of that. Similar ideas are expressed in many other works (Alford et al, 2005; Amodio et al., 2007; Smith et al., 2011). However, researchers admit that, even though genetic predisposition to certain behavioural traits appears to be crucial, the social environment, context and other factors are not to be dismissed and should be investigated further as possible determinants of political views.

Apart from trying to identify the main factors of political affiliation, researchers have made attempts to study the relationships between the ideological stances of individuals and their socio-economic and moral characteristics. For instance, Jonason (2014) found that political liberalism is correlated with extraversion and openness, while political conservatism is linked to lack of openness, psychopathy. However, surprisingly, conservatism was also found to be positively related to honesty, unlike political liberalism. In other works, being conservative was linked to a high need for certainty and security (Jost et al., 2003; Jost et al., 2009; Thorisdottir and Jost, 2011).

Another common finding is a happiness gap between liberals and conservatives, especially in the US (Taylor et al, 2006; Napier and Jost, 2008). While this could be possibly attributed to the differences in income, education, and other characteristics between them, researchers also find that liberal-leaning individuals are more prone to rumination, long discussions and complex answers to life questions, while conservatives' approaches to life's questions tend to be more "unsophisticated" (Kruglanski et al, 2006). Speaking of other characteristics, in the US, African Americans and Hispanics are more likely to be Democrats, and women are more likely to be Democrats than men. Furthermore, individuals with higher income tend to become less likely to support Democrats.

The discussion drives us to the conclusion that the determinants of one's political views are highly complex, there is likely an interplay between genetic, social, and demographic factors. However, there is undeniable evidence that individuals with liberal and conservative leanings indeed differ in their psychological traits and their way of thinking, which suggests that it is likely that the way they express themselves through language is also different.

There have been numerous attempts to study the differences in language through the lens of the social media and political communities online. For instance, Soliman et al. (2019) have conducted analysis of left-wing and right-wing political communities on Reddit using a dataset consisting of around 100 million observations and concluded that right-leaning communities are more likely to use derogatory, negative language, however left-wing communities tend to be biased towards news sources that reflect their point of view. Similar to some previously mentioned works, one of the main issues here is that only the left-right scale is being used which disregards nuances within the left and right. Adding to this point, the authors used rather popular communities ("politics", "SandersForPresident", "Conservative" and "The_Donald") which implies that there is great variety in the views of the followers that is not being accounted for.

Hofmann et al. (2022) conducted another large-scale research of the political sphere represented on Reddit; their data covered 600 discussion communities over a period of 12 years. This research is not focused on language used in ideological subreddits; however some findings could still be relevant; the authors find that within the Reddit political sphere Republican and Democrat subreddits within the network containing all subreddits form cohesive and distinct clusters, which could be viewed as evidence that the two do not share significant similarities and therefore are likely to differ in their online behaviours. One of the most significant advantages of this work is that the authors adopt a machine learning approach to identifying political subreddits, and as a result include a larger number of diverse discussion groups compared to authors that have resorted to hand-picking subreddits for their research.

There has been other language-related research on online political discussions. Simchon et al. (2022), using data from Reddit and Twitter, found that certain bad actors, known as "trolls", from several foreign countries are far more likely to use polarizing language than Americans, and such behaviour indeed creates more polarization in the corresponding communities. While this paper does not consider the notion of ideology directly, we can interpret its results as evidence that some populations on social media holding certain political beliefs are more likely to use certain words and patterns in speech compared to other users. It is possible that adherents of certain political ideologies tend to engage in similar behaviours, therefore it can be that in our research we discover that more polarizing language is used in some communities.

Analysis similar to those outlined above has also been done focusing on Twitter data. Alizadeh et al. (2019) studied the language and sentiment of political extremists compared to that of conventional liberal and conservative users and found that left-wing extremists use more language indicative of anxiety than liberal users, while users with right-wing extremist views use less of anxiety-related language compared to conservatives. In general, extremist users score higher in negative sentiment than users with a more moderate position on both sides of the spectrum. However, one of the key limitations of this study is that the data only includes non-violent extremist behaviour, which does not present a full picture.

To summarize this section, there is a significant body of literature addressing the differences in individuals of different political affiliation and the implications of that for their behaviour online, the language they use and their sentiment. Based on the discussion above we can claim there is evidence that individuals on different sides of the ideological spectrum presented online do differ in the way they behave and speak, however existing works mainly address the issue from the perspective of left and right or liberal and conservative, disregarding the diversity that likely exists within those communities. Another key issue is the lack of data on right-wing communities that tend to be banned on social media.

1.2. Findings on predicting the ideological position of social media users

Prediction of the political alignment of social media users is another widely studied subject in social media-related research. Common goals include predicting “social mood” and the sentiment of certain subpopulations regarding particular social issues and events (Hernandez-Suarez et al., 2017), characterising users of different political affiliations through text and predicting the ideological position of unlabelled or unseen users (Preoţiuc-Pietro et al., 2017). Predicting the political affiliation of users based on the textual content they post online comes from the assumption that the language individuals use to express themselves is linked to their demographic and psychological traits, such as age, gender, personality, socio-economic status. In the previous section we have elaborated on how political affiliation is largely correlated with these traits, so this assumption is justified.

Related research papers use different data sources, including Twitter, Facebook, and speeches of politicians, and different approaches to prediction, ranging from linear and logistic regression to more advanced machine learning methods. Most earlier works on the subject involve prediction of political affiliation on a single dimension, such as left and right or liberal and conservative. For instance, Conover et al. (2011) use manually annotated data on Twitter users engaged in discussions of American politics and implement a support vector machine (SVM) reaching 91% accuracy. The main rationale for the choice of model is that SVMs are known to be successful when working with sparse high-dimensional data. Another research implementing an SVM to predict political affiliation was done by Stobaugh and Murthy (2023), reaching an accuracy of 63%. However, here the main data source was the content of Venmo transactions. The researchers also evaluated a simple multilayer perceptron and a gradient boosted decision tree ensemble, however both were outperformed by the SVM.

Preoţiuc-Pietro et al. (2017) aimed to predict whether users lean liberal or conservative; they used a Twitter dataset of users self-reporting their political stance through surveys. Unlike Conover et al., they possessed additional data on how extreme the views of the users in the dataset were. The authors implemented a logistic regression model; the results have shown that the performance for users with more extreme views was higher compared to those with moderate views. Furthermore, the research demonstrated that using political words as features instead of Word2Vec clusters slightly improves the performance. As for the performance metrics, depending on the techniques and training data, accuracy varied from 57% to 97%.

Other works demonstrated that the approaches that were the most successful in predicting political affiliation on social media were SVMs and extreme gradient boosting (Ullah et al., 2021); nearest neighbour classifier (Chang et al., 2017); SVMs (Dahllöf, 2012). The algorithms that were also implemented but were not shown to be optimal were decision trees, naïve Bayes classifier, random forest and logistic regression.

In general, we see have evidence that the prediction of political affiliation based on text data posted by corresponding users is possible and rather high performance metrics can be reached if the corresponding data pre-processing is implemented and relevant models are used. However, one of the issues with previous related work is that the categories of political affiliation that are being predicted are rather limited. As mentioned earlier, often researchers resort to categorizing political views within one scale, which limits the diversity in political views that we take into account. It would be an improvement to predict the adherence of users to specific political ideologies, however it would be even more beneficial to instrumentalize political views as a continuous variable and consider them within more than one dimension. A similar idea was implemented in the work of Falck et al. (2020). The authors develop a framework of the “Sentiment Political Compass”, calculate the position of political newspapers within its axes and study the patterns and relationships in the data.

Since in our research political views are going to be represented in a continuous manner in two dimensions, the machine learning approaches for predictions found to be the most efficient in past papers will most likely will not be the same in our case. However, it will be relevant to compare the approaches and findings regarding continuous and categorical political views prediction. Given the complexity of the data and the relationships between the variables, it is anticipated that the best performing algorithm would be either SVM, or gradient boosting regressor, or the neural network approach. It is, however, crucial to notice that with the deep leaning approach we may encounter the high-dimension, low-sample size problem (HDLSS): making predictions based on text leads to using thousands of features, which, considering the number of parameters needed for the estimation of neural networks, can lead to poor performance and difficulties with model estimation in general.

Chapter 2. Methodology and research

2.1. Descriptive statistics and preliminary conclusions from the data

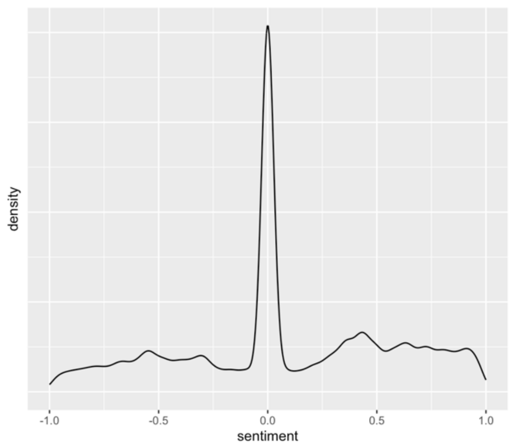
2.1.1. Dataset statistics and text complexity measures

To conduct our research, we will use posts and comments from Reddit communities, also known as subreddits, dedicated to political ideologies. The list of the corresponding communities was obtained with the help of the community “Reddit lists” that groups subreddits by topic or purpose. To gather the data, I used Pushshift Reddit API. Overall, I obtained 1083905 observations of posts and comments from 14 subreddits: "socialism”, "SocialDemocracy", "progressive", "Marxism", "LibertarianSocialism", "Libertarian", "Liberal", "labor", "GreenParty”, "Egalitarianism", "democrats", "Conservative”, "Anarcho_Capitalism", and "Anarchism". It is important to note that some ideological communities get banned on Reddit, therefore data on them is missing in this research.

For research purposes, it makes sense to include non-political content into the dataset so that the algorithms that we are going to estimate further in the research train on politically neutral data as well. Initially, it was planned to scrape non-political content posted by the same users as in the dataset of ideological communities, however due to API restrictions imposed by Reddit at the time this was not feasible. Instead, I decided to use comments from one of the most popular and active non-political community “AskReddit” dedicated to discussions on different topics. I used a publicly available dataset from Kaggle, containing 10 million observations. However, we will not use the whole dataset and will merely select a suitable number of observations to balance the political observations in our initial dataset. The “AskReddit” dataset features a column containing pre-analysed sentiment, the most common value in which is 0 (Figure 1). I believe this is beneficial, since if the comments are neutral from the sentiment point of view, they are more likely to be politically neutral as well, and therefore suitable for their purpose. However, we are still assuming that all the comments in this dataset are not related to politics, which is a shortcoming since this may not be 100% accurate in reality.

Figure 1. Distribution of the pre-analysed sentiment of comments from “AskReddit”

Source: plot obtained in R



In Table 1, I present some descriptive statistics and text complexity measures that are meant to help us conduct preliminary analysis of the data, infer potential issues with the dataset and make some conclusions and possibly predictions regarding the outcomes of our research. For each subreddit, I calculate the number of observations and the number of removed content units, treat the subset of the dataset dedicated to the given subreddit as a corpus, calculate the number of types, tokens, punctuation marks, symbols, URLs, tags, and emojis. Since our dataset is rather imbalanced, I divided the number of tokens, removed entries, punctuation marks, and other variables mentioned above by the number of observations to make the figures more comparable. Finally, I also calculated Flesch readability score (Flesch, 1948) and lexical diversity score as the Type-Token Ratio (TTR).

As we may see, the highest numbers of tokens and punctuation symbols (adjusted to the sample size) are observed in “r/Egalitarianism” which most likely indicates that on average this subreddit tends to have longer posts and comments. For “r/Marxism”, these are also rather high. The two subreddits that tend to use symbols (other than punctuation symbols, such as “$” or “%”) are “r/socialism” and “r/Libertarian”. This probably means that these communities discuss socio-economic statistics, money, spending and such more than others. The highest URL usage is observed in “r/socialism”, “r/Anarcho_Capitalism”, and “r/Marxism”, which likely refers to either posting links to news sources for discussion, or citing works of philosophers, political theorists, etc. Emojis do not appear to be commonly used, however the communities that used them the most are “r/SocialDemocracy” and “r/Liberal”. As for the removed posts, the subreddits with the highest removal rates were “r/Marxism”, “r/LibertarianSocialism”, and “r/Liberal”, with the one in “r/Marxism” being more than two times higher than in the other two.

Finally, as for the text complexity statistics, we can observe that the subreddits score roughly the same on both readability and lexical diversity. However, it can be noted that “r/socialism” has a noticeably lower readability score than the others, while “r/progressive” has scored the highest. In terms of lexical diversity, half of the subreddits score slightly higher than the other half (“r/socialism”, “r/progressive, “r/Liberal”, “r/labor”, “r/democrats”, “r/Conservative” and “r/Anarcho_Capitalism”). While some of these discrepancies can stem from the differences in moderation of a particular subreddit, or from the ideology and the political views of the members of the community, a more nuanced explanation can be achieved if the data on demographics of the subreddit members was available.

Table 1. Descriptive statistics and text complexity measures

Source: calculations performed in R

subreddit	n_documents	n_types	n_tokens (adjusted)	n_punct (adjusted)	n_symbols (adjusted)	n_urls (adjusted)	n_tags (adjusted)	n_emojis (adjusted)	n_removed (adjusted)	readability	lex_div
socialism	8466	2048	50.13	10.77	0.3	0.38	0.19	0.01	0.19	38.37	0.01
SocialDemocracy	112375	1927	50.66	6.17	0.11	0.12	0	0.05	0.03	48	0
progressive	5134	1682	15.47	2.18	0.02	0.02	0	0	0.12	64.83	0.01
Marxism	40805	3181	90.34	12.97	0.1	0.22	0	0	0.47	51.23	0
LibertarianSocialism	15335	1520	38.29	6.25	0.4	0.1	0	0.03	0.23	48.35	0
Libertarian	220918	1669	52.52	6.87	0.17	0.09	0	0.02	0.06	53.07	0
Liberal	17063	1812	22.81	3.19	0.09	0.05	0	0.04	0.21	63.57	0.01
labor	25030	1735	33.83	4.1	0.04	0.1	0	0.03	0.01	60.21	0.01
GreenParty	52057	1821	63.8	7.49	0.09	0.15	0	0	0	59.91	0
Egalitarianism	66412	1862	105.29	13.35	0.03	0.14	0.01	0	0.03	52.93	0
democrats	20641	1597	29.8	4.57	0.07	0.05	0	0.01	0.09	58.01	0.01
Conservative	37172	1467	17.65	2.21	0.11	0.06	0.01	0.02	0.06	51.11	0.01
Anarcho_Capitalism	51954	2028	40.67	6.45	0.12	0.26	0	0	0.02	52.12	0.01
Anarchism	410543	2299	68.06	8.81	0.04	0.13	0	0.01	0.06	50.4	0

2.1.2. Sentiment analysis

To deepen our analysis further, it makes sense to conduct sentiment analysis of the subreddits because the differences in the sentiment may reveal some differences existing between the ideologies. We are going to use two dictionaries, Lexicoder Sentiment Dictionary (LSD) and Moral Foundations Dictionary (MFD) to cover the sentiment analysis of our data from different perspectives and to make the conclusions more robust. LSD consists of four keys: negative, positive, and negative and positive preceded by a negation. However, none of the last two were detected in our corpus. MFD contains five groups: care, fairness, loyalty, authority, and sanctity, each divided into vice and virtue categories. For convenience, some prototypic words for each are shown in Table 2.

Table 2. Prototypic words for MFD

Source: Moral Foundations Dictionary for Linguistic Analyses 2.0 (Frimer et al., 2019)

Valence	Foundation				
	Care	Fairness	Loyalty	Authority	Sanctity
Virtue	kindness compassion nurture empathy	fairness equality justice rights	loyal team player patriot fidelity	authority obey respect tradition	purity sanctity sacred wholesome
Vice	suffer cruel hurt harm	cheat fraud unfair injustice	betray treason disloyal traitor	subversion disobey disrespect chaos	impurity depravity degradation unnatural

The sentiment scores adjusted for the number of observations for each subreddit are presented in Table 3. First thing to notice is that the scores for negative and positive sentiment tend to be comparable, which indicates that if a subreddit tends to use emotional language, it is likely to reflect emotions of different kinds. However, some subreddits feature a high discrepancy in positive and negative sentiment (the difference between "positive" and "negative" is shown in the "delta" column). We observe that "r/Egalitarianism" and "r/SocialDemocracy" feature a higher positive sentiment, while "r/Conservative" shows a more negative sentiment on average. This can be possibly because conservatives are focused on criticizing the change happening in the society, while others aspire for positive change and celebrate achievements that are being made. Furthermore, previous research has found that right-leaning subreddits, "r/Conservative" included, are more likely to use negative language (Soliman et al., 2019).

As for the other types of sentiment, the subreddits featuring a higher proportion of care-virtue are "r/labor" and "r/SocialDemocracy". "r/Egalitarianism" has a significantly higher share in fairness-virtue compared to other communities, which is self-explanatory from the nature of this ideology. The subreddits that feature a high score in loyalty-virtue are "r/Anarchism", "r/GreenParty", and "r/SocialDemocracy". This is rather surprising, since this sentiment mainly refers to issues of patriotism, loyalty to a social group, which is not characteristic of the ideologies in question. However, in this context this sentiment may refer to seeing the greater good of society or a social group that one belongs to as a goal, hence the loyalty aspect. Surprisingly, "r/Libertarian" shows a relatively high score for authority-virtue, given the view on the government in this ideology. Other types of analysis need to be conducted to make more robust conclusions from this data.

Table 3.1. Sentiment analysis results

Source: calculations performed in R

subreddit	positive	negative	delta	care virtue	care vice	fairness virtue	fairness vice	loyalty virtue	loyalty vice
Anarchism	0.4	0.45	-0.05	0.06	0.07	0.03	0.02	0.13	0
Anarcho_Capitalism	0.38	0.37	0.01	0.1	0.03	0.03	0.01	0.03	0
Conservative	0.25	0.39	-0.14	0.07	0.07	0.03	0.03	0.06	0
democrats	0.37	0.31	0.06	0.06	0.04	0.03	0.03	0.02	0
Egalitarianism	0.48	0.3	0.18	0.07	0.1	0.12	0.06	0.05	0
GreenParty	0.48	0.31	0.17	0.09	0.05	0.06	0.01	0.13	0
labor	0.34	0.36	-0.02	0.13	0.06	0.03	0.02	0.12	0
Liberal	0.28	0.31	-0.03	0.03	0.05	0.01	0.01	0.06	0
Libertarian	0.44	0.37	0.07	0.1	0.04	0.02	0.02	0.07	0
LibertarianSocialism	0.35	0.3	0.05	0.04	0.05	0.02	0	0.06	0
Marxism	0.27	0.23	0.04	0.08	0.02	0.04	0.01	0.07	0
progressive	0.32	0.42	-0.1	0.08	0.08	0.04	0	0.05	0.02
SocialDemocracy	0.51	0.32	0.19	0.13	0.02	0.06	0.02	0.16	0
socialism	0.32	0.3	0.02	0.07	0.05	0.02	0.05	0.07	0

subreddit	authority virtue	authority vice	sanctity virtue	sanctity vice
Anarchism	0.05	0.04	0.08	0.1
Anarcho_Capitalism	0.07	0.03	0.07	0.05
Conservative	0.09	0.01	0.04	0.03
democrats	0.07	0	0.07	0.06
Egalitarianism	0.06	0	0.02	0.04
GreenParty	0.02	0	0.02	0.05
labor	0.04	0.01	0.05	0.06
Liberal	0.08	0.01	0.01	0.07
Libertarian	0.12	0.01	0.01	0.08
LibertarianSocialism	0.05	0.03	0.03	0.08
Marxism	0.08	0.04	0.04	0
progressive	0.06	0.01	0.03	0.09
SocialDemocracy	0.06	0.02	0.06	0.02
socialism	0.07	0.01	0.01	0.01

To study the sentiment patterns further, I have included a correlation matrix for the sentiment variables (Table 3.2.). The strongest associations appear to be the following: 0.66 correlation coefficient between negative and sanctity-vice, 0.6 between positive and fairness-virtue, and -0.46 between loyalty-virtue and authority-virtue. One would anticipate negative and positive sentiments from different dictionaries to be correlated with each other, however the question is why with some the correlation is stronger than others. Examining all words in LSD is not feasible, therefore we cannot infer whether some groups from MFD are more or less represented in LSD. However, this may be due to the fact that the positive or negative language in a given subreddit mostly refers to sanctity, or fairness, or another group. Finally, it makes sense that loyalty-virtue and authority-virtue are correlated because in a political context loyalty refers to patriotism or loyalty to the nation or traditions, which most likely involves respecting the government, past and present authority figures.

Table 3.2. Correlation matrix for sentiment scores

Source: calculations performed in R

	negative	**positive**	**care.virtue**	**care.vice**	**fairness.virtue**	**fairness.vice**	**loyalty.virtue**	**loyalty.vice**	**authority.virtue**	**authority.vice**	**sanctity.virtue**	**sanctity.vice**
negative	1	0.02	0.12	0.42	-0.2	-0.15	0.12	0.41	0.02	0.07	0.35	0.66
positive	0.02	1	0.43	-0.01	0.6	0.2	0.45	-0.18	-0.3	-0.21	0.09	0.09
care.virtue	0.12	0.43	1	-0.29	0.22	0	0.5	0.01	-0.1	-0.05	0.25	-0.27
care.vice	0.42	-0.01	-0.29	1	0.43	0.39	-0.14	0.35	-0.21	-0.38	-0.22	0.37
fairness.virtue	-0.2	0.6	0.22	0.43	1	0.49	0.13	0.01	-0.32	-0.3	-0.05	-0.26
fairness.vice	-0.15	0.2	0	0.39	0.49	1	-0.1	-0.34	0.14	-0.43	-0.14	-0.42
loyalty.virtue	0.12	0.45	0.5	-0.14	0.13	-0.1	1	-0.19	-0.46	0.16	0.15	-0.05
loyalty.vice	0.41	-0.18	0.01	0.35	0.01	-0.34	-0.19	1	-0.07	-0.12	-0.1	0.35
authority.virtue	0.02	-0.3	-0.1	-0.21	-0.32	0.14	-0.46	-0.07	1	0.03	-0.23	-0.1
authority.vice	0.07	-0.21	-0.05	-0.38	-0.3	-0.43	0.16	-0.12	0.03	1	0.46	0.01
sanctity.virtue	0.35	0.09	0.25	-0.22	-0.05	-0.14	0.15	-0.1	-0.23	0.46	1	0.11
sanctity.vice	0.66	0.09	-0.27	0.37	-0.26	-0.42	-0.05	0.35	-0.1	0.01	0.11	1

2.1.3. Keyness analysis

Let us proceed to analyse the results presented in Table 4. While in most cases the key words detected for each subreddit make sense given the nature of its ideology, some require further analysis. It appears that most key words are related to either the issues discussed by the modern adherents of a given ideology (“transphobia”, “homophobia” in “r/socialism”; “fossil”, “fuels”, “CO2” in “r/GreenParty), or politicians or groups of people they oppose (“right-wingers”, “anti-capitalist” in “r/socialism”; “bourgeois” in “r/Marxism”; “DeSantis” in “r/Liberal”), or the proponents and tenets of the ideology (“Marx”, “Lenin”, “state”, “capital” in “r/Marxism”; “feminism”, “equality” in “r/Egalitarianism”).

Some of the non-straightforward examples include the following. The community “r/progressive” has a lot of words associated with teeth (“dental”, “dentists”, etc.); keywords in context analysis has shown that this community has a lot of discussions on health insurance, and posts about teeth-related issues are particularly common. Many of the libertarian socialism subreddit keywords are associated with Chomsky and Srebrenica massacre. It appears that discussing Chomsky, posting content featuring him is rather common in this subreddit, and there was a controversy regarding his views on the massacre, which explains the obtained results. Both abovementioned communities are small relative to the others, so focusing on certain topics and people could lead to such distortions in keywords. Another unconventional example is “autism” in “r/democrats”. In context analysis shows that it comes either from posts about Republican politicians claiming vaccines cause autism, or from posts about autism diagnosis and awareness. Lastly, a lot of keywords related to veganism and animals in the “r/Anarchism” have to do with the fact that many members of this anarchist community believe that both human and non-human life should not be subject to oppression, therefore they tend to switch to veganism.

Table 4. Keyness analysis results

Source: calculations performed in R

AskReddit	socialism	SocialDemocracy	progressive	Marxism	LibertarianSocialism	Libertarian	Liberal
AskReddit	right-wingers	social	dental	Marx	Chomsky	submission	meatball
question	transphobia	democracy	dentist	state	massacre	Idaho	meatballs
post	anti-capitalist	housing	payed	*и* (and)	Rojava	Oregon	DeSantis
please	homophobia	democratic	smith	bourgeois	Bosnian	libertarian	Ron
rule	socialism	socdem	elementary	*это* (this)	atrocities	statement	Italian
r	non-socialists	third	filings	capital	guardian	raiders	president
got	participating	modern	molars	*Гегель* (Hegel)	mutualism	government	midterms
title	reactionaries	orthodox	teeth	Lenin	Minsk	raiding	refugees
friend	sectarianism	zoning	cleaning	*в* (in)	Parecon	hot	Ron's
message	socialism's	socialist	spelled	Marx's	Srebrenica	balloon	sex-ed

labor	GreenParty	Egalitarianism	democrats	Conservative	Anarcho_Capitalism	Anarchism
salary	green	women	autism	presidential	climate	vegan
temple	party	men	borrowers	WordPress	foreskin	animal
week	greens	feminism	Jimmy	pathway	medical	animals
hours	fossil	equality	Trump	woke	necessity	meat
deduct	unrelated	power	repayment	Asbury	Greta	products
EEOC	fuels	male	surgery	revival	penile	nature
PTO	rural	black	undergraduate	Dahl	UTI	live
strike	mastodon	feminists	Carter	Ukraine	allow	straight

smear	CO2	disparity	diagnosis	Biden	decision	traits
truckers	labour	subjective	intentions	scrambles	entitled	animalistic

2.2. Methodological approach

2.2.1. Political compass framework and ideological scaling

As elaborated in the previous chapter, one of the key shortcomings of previous works related to the topic of this research is that political views were considered in a limited fashion, e.g., either grouped in several categories or merely on a scale of left and right. Both approaches fail to consider a large share of diversity that exists within left and right, and within ideological groups. We aim to address this issue by examining political views in a continuous manner in two dimensions instead of one to introduce more nuance and diversity into one's ideological position. To do so, we propose to utilize the concepts of political compass and ideological scaling.

The political compass is a framework that aims to measure, examine, or represent political views using two axes. There are various past approaches to the concept (Bryson and McDill, 1969; Christie and Meltzer, 1970; The Political Compass, 2001; Gindler, 2021), however we decided to stick to the left-right and authoritarian-liberal axes approach, since it has been implemented in some recent papers related to the topic (Falck et al., 2018; Falck et al., 2020) and is widely used on Reddit to categorize the political opinion of users. For these reasons, we believe this approach would be the most accessible and appropriate.

Since the leaning of the ideologies in our sample in terms of left-right and authoritarian-liberal axes is either known or can be estimated based on available knowledge, we believe that it would be appropriate to implement a supervised approach to ideological scaling. We are going to use the wordscores (Laver et al., 2003) approach to do so. This method utilises reference texts with assigned ideological scores to estimate the model that scales texts on one dimension; this model can be then used to calculate the ideological scores for "virgin" texts without a score. We will implement the approach twice, for both the left-right and the authoritarian-liberal scale.

One of the main challenges here is to assign ideological scores to reference texts. The assignment of certain ideologies to either side of each spectrum is not always obvious, and ranking the ideological position of subreddits objectively is rather challenging. Utilising a binary approach, e.g., labelling left as -1 and right as 1, appears to be inherently flawed. Certain subreddits in our sample are going to be more extreme on the left or the liberal scale than the others, for instance, we would expect anarchism-related ideologies to rank much higher in liberalism than conventional liberal-leaning communities. Therefore, apart from simply categorizing ideologies in terms of left-right and authoritarian-liberal, we will also rank the extremity of their position in 3 categories – mild (1/3), moderate (2/3) or extreme (1). The "reference" category, e.g., the non-political subreddit is going to be labelled as 0 in both axes.

To assess the quality of the ideological scaling, I have calculated average scores on both axes for each subreddit, which is shown in Table 4. As we may see, the scores mostly make sense, however, are imperfect: anarchism and Marxism are the furthest on the left, anarcho-capitalism, conservatism, and libertarianism are on the right, while other communities, that are left-leaning, are also on the left. However, "r/Conservative" is quite close to 0, while "r/AskReddit" is not at 0. As for the authoritarian-liberal scale, the communities furthest on the liberal scale are anarchism, libertarian socialism, libertarianism, and anarcho-capitalism, which is reasonable given the nature of these ideologies; nonetheless, we would anticipate some of them, especially anarchist communities, to be further down the scale. As we may also notice, there are no subreddits that have a positive score on this scale, however conservatism is the closest to 0.

Table 5. Average left-right and authoritarian-liberal scores for each subreddit

Source: calculations performed in R

subreddit	left_right_mean	auth_lib_mean
Anarchism	-0.56	-0.65
Anarcho_Capitalism	0.16	-0.51
Conservative	0.08	-0.04
Egalitarianism	-0.33	-0.45
GreenParty	-0.28	-0.33
Liberal	-0.24	-0.42
Libertarian	0.14	-0.5
LibertarianSocialism	-0.39	-0.52
Marxism	-0.46	-0.48
SocialDemocracy	-0.23	-0.49
askreddit	-0.11	-0.22
democrats	-0.24	-0.4
labor	-0.27	-0.4
progressive	-0.19	-0.37
socialism	-0.3	-0.32

2.2.2. Data pre-processing

Before our dataset is used for model estimation, steps involving data cleaning, removal of some features, and data transformation need to be undertaken. As was demonstrated in Table 1, a substantial number of submissions were removed; to not distort our data, we exclude all such observations. After transforming the dataset into a corpus format and removing punctuation, numbers, URLs, symbols, separators, and stopwords, more than 100000 features were obtained. Model estimations of such volume are not feasible within our resources, therefore by setting minimum term frequency to 100 and minimum document frequency to 3, the number of features was reduced to 3257. We then resort to term frequency-inverse document frequency (TF-IDF), a measure that weights the importance of a word within a document and calculate it for the features in our corpus.

Finally, we have shown that the subreddits in the dataset are rather imbalanced; to address the issue, we randomly gather an equal number of observations from each subreddit equal to the smallest number of observations from a subreddit. Overall, we obtain a dataset with 67455 observations. One of the issues here is that our approach to balancing the dataset is flawed; ideally, we need to balance left, right, liberal and authoritarian communities, however, since we cannot infer the actual leaning of some communities and some sides of the political spectrum are not represented (such as the far-right communities banned on Reddit), we decided to resort to the approach above for the lack of a better alternative to at least achieve a diverse dataset that would make models more robust.

2.3. Model estimation and interpretation of results

Models appropriate for regression will be used given the continuous nature of our target – scores of the left-right and authoritarian-liberal axes. One of the key issues is that most machine learning algorithms are not capable of predicting two at the same time, therefore in most cases we will have to resort to assuming that they are uncorrelated and predicting them separately. The correlation coefficient between the two scores in our dataset is 0.36, meaning right-wing and authoritarian views are moderately positively correlated (source: calculations performed in R). This is not a strong correlation, so making the assumption outlined above is not a major flaw, however it should not be dismissed when discussing the results.

We will implement various approaches: multiple linear regression, regularization techniques – ridge, lasso and elastic net regressions, tree-based methods – decision tree, random forest regressor, gradient boosting regressor (GBR), extreme gradient boosting

(XGBoost), and artificial neural networks. In case of neural networks, we will attempt predicting axes both together and separately, since this type of algorithms allows for this.

An attempt was made to estimate a Support Vector Regression (SVR), however with the very large number of features and relatively large sample size the estimation time was too high even without performing a grid search, which was not feasible with the available computational resources.

As was anticipated in Chapter 1, the performance of some neural networks on the full dataset was hindered because of the HDLSS problem. With the neural networks predicting axes separately losses of 0.1258 and 0.1844 were achieved for the left-right and authoritarian-liberal axes correspondingly, and these values could not be lowered after various experiments with the architecture and parameters. To be specific, we implemented neural networks with blocks consisting of a one-dimensional convolution layer, a deep layer, and a dropout layer. Models consisting of one, two and three of such blocks were experimented with. We used the stochastic gradient descent optimizer and a rectified linear unit (ReLU) as the activation function. The parameters that we experimented with were the following: the learning rate, the dropout rate, the number of nodes in deep layers, the number of filters and the kernel size in the one-dimensional convolution layers. The final architecture of the model is shown in Appendix 2. The chosen dropout rate was 0.2, the learning rate 0.01, and the model was trained for 20 epochs. The first convolution layer has 16 filters and a kernel size of 8; the corresponding figures for the second convolution layers are 8 and 4. Dense layers have 200 and 100 nodes respectively.

Therefore, there were two approaches to mitigate the issue: either to increase the number of observations at the expense of a balanced dataset, or to perform some type of feature selection to reduce the number of parameters to be estimated and minimize overfitting – both were attempted. Our computational resources failed at the first one since handling a dataset with over several thousand features and tens of thousands of rows turned out to be too large. Therefore, we resorted to feature selection. Given the number of features in our dataset and the computational intensity of neural networks, traditional methods, such as backward and forward selection were not feasible, therefore we resorted to selecting a subset of variables based on their correlation coefficient with the target. The correlation coefficients were rather low: the highest correlation coefficients by absolute value were -0.1418 and 0.1363 for left-right and authoritarian-liberal correspondingly. We experimented by setting different thresholds for the minimum absolute value of the correlation coefficient, however losses lower than outlined above could not be achieved.

Surprisingly, much better results were achieved with a neural network that predicts both axes simultaneously. An architecture similar to the one outlined above was used, and different values for the dropout rate and the learning rate were experimented with. Without any further model and data modifications, a loss of 0.0329 was achieved. We attempted to perform feature selection in the same manner as above to possibly improve performance further, however higher values of loss were obtained.

The results are shown in Table 6, represented by the mean squared error as the loss value. For the models predicting axes separately, we calculate the average loss outputted for predicting the left-right and authoritarian-liberal axes. As we may see, the best result was achieved for the neural network predicting axes together. Likely an improvement over the other neural network was achieved due to the incorporation of the relationship between the two axes. The second-best performing algorithm is the XGBoost, however it is important to note that lasso, elastic net and the tree-based methods were performing on roughly the same level.

Table 6. Loss values of the estimated machine learning models

Source: estimations performed in Python

Model	**Test MSE**
Linear regression	2.3722e+20
Ridge regression	0.1709
Lasso regression	0.0505
Elastic Net regression	0.0505
Decision tree	0.0509
Random forest	0.0507
Gradient boosting regressor	0.0498
XGBoost	0.0494
Neural network (separate axes)	0.1551
Neural network (non-separate axes)	0.0329

Chapter 3. Correspondence with previous works and implications for future research

3.1. Comparison of our research and conclusions to previous findings

Let us proceed to compare the ideas, findings and conclusions outlined in Chapter 1 to our results presented in Chapter 2. First, we concluded from the analysis of the content from the Reddit communities in our dataset that there are indeed differences in the sentiment and the key words identifying each community, e.g., we did not observe general language related to political issues in every subreddit. To elaborate, we observed that in most left-leaning subreddits the positive sentiment outweighs the negative, however we cannot fully confirm the previous findings that right-leaning subreddits are more likely to use negative language since there are several right-leaning communities in our sample in which the positive sentiment prevails, while in “r/progressive” the sentiment tends to be more negative.

One of the previous papers stated that right-wing communities are more likely to use derogatory language; while this is not quite likely to be inferred from our results since we focused on keyness and sentiment analysis, we can see that one of the key words in “r/Conservative” is “woke”, which can be regarded as an instance of this. However, it is the only example, and nothing similar is observed in other right-wing communities in our sample. Another past work has concluded that individuals with extreme views on the left are more likely to use anxiety-related words than their counterparts on the right. Our analysis again differs in nature, and no anxiety-related language is observed in the key words, however we clearly see that many of the left-wing subreddits’ key words are dedicated to social issues, rights of marginalized group, which could involve words indicative of anxiety.

Similar to Ullah et al. (2021), in our prediction problem extreme gradient boosting was one of the best-performing algorithms. However, unlike in numerous works that found SVM to be the optimal model, in our research that was not the case, and the deep learning approach was found to be the best instead. In general, similar to other authors, by implementing different algorithms and optimizing parameters, we were able to achieve a significant improvement in performance compared to initially estimated models, such as linear and ridge regression, therefore we believe predicting political views based on textual content posted online is possible and should be explored further.

3.2. Discussion of methods and limitations of this research

Our methodology has several limitations that were outlined at corresponding stages of this research. In this section, let us explicitly state them and elaborate on their implications and the possible ways to address them. First, the dataset used for data analysis and the estimation of models is not exhaustive and does not represent all the diversity that exists in the political spectrum. Many right-wing communities, such as “r/new_right”, “r/The_Donald”, “r/altright” and “r/alternativeright”, get banned on Reddit for violating content policy, which limits our ability to retrieve up-to-date data on the content posted by individuals adhering to these views. Furthermore, we should admit that the list of ideological subreddits, obtained through the community “Reddit lists” may not be exhaustive as the authors may not be aware of every single political community on the platform.

Furthermore, after the calculation of wordscores, there was not enough diversity in the authoritarian-liberal scale, e.g., there were no communities with an average score on this scale above 0. This could be because authoritarian-leaning communities are underrepresented in the sample, or because online communities would not be showing signs of authoritarian behaviour. In other words, it is impossible to have an online community advocating for extreme authoritarian views, e.g., any form of totalitarianism, or even a community advocating for the establishment of any substantially authoritarian regimes. Either way, this is an issue since our models were exposed to a limited range of values, which distorts the model parameters by making them biased and deteriorates performance.

Adding to the previous point, in this case it was rather challenging to make the dataset used for model training truly balanced. To balance the dataset, we selected the same number of observations from each subreddit, however, as follows from average left-right and authoritarian-liberal scores, in reality our data is biased towards left- and liberal-leaning communities.

Another point to address is that it was assumed that the observations from the non-political subreddit “r/AskReddit”, included into the dataset to provide a “reference” group for the models so that some non-political words do not get erroneously selected as a key word for an ideological subreddit or as a significant predictor of a political leaning, were all not related to politics. To alleviate this issue, one would have to go through the observations and filter out the ones related to politics manually, which was not feasible in the scope of this research.

Furthermore, we inexplicitly assumed that the content posted in the Reddit communities in our sample dedicated to the corresponding political ideologies represents the language and the mode of expression of adherents of these ideologies. In reality, the way the ideology was devised in the beginning, or the way it is expressed in communities other than Reddit can be very different, so our research lacks "ground truth" on what each ideology constitutes. However, we may simply regard our research as an attempt to predict ideology only in the context of Reddit and the way it is expressed there.

The last limitation regarding the dataset is that our data is inherently biased towards individuals who post on Reddit, which may make our conclusions not generalizable to the users of other platforms and people in general. To deal with this limitation, one will need to gather similar data from other social media platforms or forums and obtain ideological scores for the observations.

As for the limitations regarding model estimation and selection, the key issues stem from the lack of computational resources. Firstly, we did not try certain models that could have performed well on our data based on previous works, such as SVR. Secondly, larger grids of parameters could have been tried. Finally, a more robust procedure of feature selection could have been attempted for the neural networks, as well as for the other algorithms.

Conclusion

In the first chapter, examined the differences in political views in individuals, the reasons for such disparities and the variability in thought patterns and language used that stem from that. We then elaborated on the differences in the language of individuals leaning towards different sides of the political spectrum that were discovered in the past works using different methods and social media platforms. Finally, we reviewed the existing attempts to instrumentalize political views of individuals expressed online and to predict them using machine learning methods.

In the second chapter, we conducted our own data analysis focusing on keyness and sentiment analysis. We then tried to predict political views using various machine learning approach. While similar research has been done, previous papers focused on analysis from slightly different perspectives, which indicates our research managed to look at political social media data from a different angle. The most crucial point is, however, that in our research we attempted to inrtumentalize political views in a continuous two-axes manner compared to previous works that presented political views either as categories or on the scale of left and right. Finally, we compared our findings to previous works.

Possible directions for further research could be the following. First, similar research should be carried out using more powerful computational resources since many of the shortcomings of this work stem from the lack of such. Improving the data input, e.g., using a larger and a more balanced dataset that would better represent the political spectrum is also a possibility. Furthermore, other machine learning approaches that were not implemented in this paper should be attempted, for instance, other neural network architectures. Finally, for robustness of conclusions similar research should be conducted on other social media platforms to eliminate the bias for Reddit since other social media users could represent other demographics and express their political beliefs and ideology differently. Consequently, it is highly likely that the conclusions from language analysis and optimal machine learning approaches for prediction would be different as well.

References

1. Alford, J. R., Funk, C. L., & Hibbing, J. R. (2008). Beyond liberals and conservatives to political genotypes and phenotypes. Perspectives on Politics, 6(2), 321-328.
2. Alizadeh, M., Weber, I., Cioffi-Revilla, C., Fortunato, S., & Macy, M. (2019). Psychology and morality of political extremists: evidence from Twitter language analysis of alt-right and Antifa. EPJ Data Science, 8(1), 1-35.
3. Amodio, D. M., Jost, J. T., Master, S. L., & Yee, C. M. (2007). Neurocognitive correlates of liberalism and conservatism. Nature neuroscience, 10(10), 1246-1247.
4. Biessmann, F., Lehmann, P., Kirsch, D., & Schelter, S. (2016). Predicting political party affiliation from text. PolText, 14(14), 2016.
5. Bryson, M., & McDill, W. (1968). The political spectrum: A bi-dimensional approach. Rampart Journal of Individualist Thought, 4(2), 19-26.
6. Chang, C. C., Chiu, S. I., & Hsu, K. W. (2017, January). Predicting political affiliation of posts on Facebook. In Proceedings of the 11th International Conference on Ubiquitous Information Management and Communication (pp. 1-8).
7. Christie, S., & Meltzer, A. (1970). Floodgates of Anarchy. PM Press.
8. Conover, M. D., Gonçalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011, October). Predicting the political alignment of twitter users. In 2011 IEEE third international conference on privacy, security, risk and trust and 2011 IEEE third international conference on social computing (pp. 192-199). IEEE.
9. Dahllöf, M. (2012). Automatic prediction of gender, political affiliation, and age in Swedish politicians from the wording of their speeches—A comparative study of classifiability. Literary and linguistic computing, 27(2), 139-153.
10. Datareportal (2023). Social Media Statistics. Retrieved June 15th, https://datareportal.com/social-media-users.
11. Falck, F., Marstaller, J., Stoehr, N., Maucher, S., Ren, J., Thalhammer, A., ... & Studer, R. (2020). Measuring proximity between newspapers and political parties: the sentiment political compass. Policy & internet, 12(3), 367-399.
12. Falck, F., Marstaller, J., Stoehr, N., Maucher, S., Ren, J., Thalhammer, A., ... & Studer, R. (2018). Sentiment political compass: a data-driven analysis of online newspapers regarding political orientation. In The Internet, Policy & Politics Conference (No. 3).

13. Feldman, S., & Johnston, C. (2014). Understanding the determinants of political ideology: Implications of structural complexity. Political Psychology, 35(3), 337-358.
14. Flesch, R. (1948). A new readability yardstick. Journal of applied psychology, 32(3), 221.
15. Frimer, J. A., Boghrati, R., Haidt, J., Graham, J., & Dehgani, M. (2019). Moral Foundations Dictionary for Linguistic Analyses 2.0. Unpublished manuscript.
16. Gindler, A. (2021). The Theory of the Political Spectrum. Journal of Libertarian Studies, 24(2).
17. Guimaraes, A., Balalau, O., Terolli, E., & Weikum, G. (2019, July). Analyzing the traits and anomalies of political discussions on reddit. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 13, pp. 205-213).
18. Hernandez-Suarez, A., Sanchez-Perez, G., Martinez-Hernandez, V., Perez-Meana, H., Toscano-Medina, K., Nakano, M., & Sanchez, V. (2017, April). Predicting political mood tendencies based on Twitter data. In 2017 5th International Workshop on Biometrics and Forensics (IWBF) (pp. 1-6). IEEE.
19. Hiaeshutter-Rice, D., & Hawkins, I. (2022). The language of extremism on social media: An examination of posts, comments, and themes on Reddit. Frontiers in Political Science, 4, 43.
20. Hofmann, V., Schütze, H., & Pierrehumbert, J. B. (2022, May). The Reddit Politosphere: A Large-Scale Text and Network Resource of Online Political Discourse. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 16, pp. 1259-1267).
21. Jonason, P. K. (2014). Personality and politics. Personality and Individual Differences, 71, 181-184.
22. Jost, J. T., Federico, C. M., & Napier, J. L. (2009). Political ideology: Its structure, functions, and elective affinities. AnnualReview of Psychology, 60(1), 307–337.
23. Jost, J. T., Glaser, J., Kruglanski, A. W., & Sulloway, F. J. (2003). Political conservatism as motivated social cognition. Psychological Bulletin, 129(3), 339–375
24. Kruglanski, A.W., Pierro, A., Mannetti, L., & DeGrada, E. (2006). Groups as epistemic providers: Need for closure and the unfolding of group-centrism. Psychological Review, 113, 84–100.
25. Laver, M., Benoit, K., & Garry, J. (2003). Extracting policy positions from political texts using words as data. American political science review, 97(2), 311-331.

26. Makazhanov, A., & Rafiei, D. (2013, August). Predicting political preference of Twitter users. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (pp. 298-305).
27. Napier, J. L., & Jost, J. T. (2008). Why are conservatives happier than liberals?. Psychological Science, 19(6), 565-572.
28. Preoţiuc-Pietro, D., Liu, Y., Hopkins, D., & Ungar, L. (2017, July). Beyond binary labels: political ideology prediction of twitter users. In Proceedings of the 55th annual meeting of the association for computational linguistics (volume 1: long papers) (pp. 729-740).
29. Pushshift Reddit API Documentation. Retrieved June 1st, https://github.com/pushshift/api.
30. Settle, J. E., Dawes, C. T., Christakis, N. A., & Fowler, J. H. (2010). Friendships moderate an association between a dopamine gene variant and political ideology. The Journal of Politics, 72(4), 1189-1198.
31. Simchon, A., Brady, W. J., & Van Bavel, J. J. (2022). Troll and divide: The language of online polarization. PNAS nexus, 1(1), pgac019.
32. Smith, K. B., Oxley, D. R., Hibbing, M. V., Alford, J. R., & Hibbing, J. R. (2011). Linking genetics and political attitudes: Reconceptualizing political ideology. Political Psychology, 32(3), 369-397.
33. Soliman, A., Hafer, J., & Lemmerich, F. (2019, September). A characterization of political communities on reddit. In Proceedings of the 30th ACM conference on hypertext and Social Media (pp. 259-263).
34. Statista (2022). Reddit - Statistics & Facts. Retrieved June 15th, https://www.statista.com/topics/5672/reddit/#topicOverview.
35. Stobaugh, B., & Murthy, D. (2023). Predicting Gender and Political Affiliation Using Mobile Payment Data. arXiv preprint arXiv:2302.08026.
36. Taylor, P., Funk, C., & Craighill, P. (2006). Are we happy yet? Retrieved August 19, 2007, from the Pew Research Center Web site: http:// pewresearch.org/assets/social/pdf/AreWeHappyYet.pdf
37. Ten Million Reddit Answers – Kaggle Dataset. Retrieved June 15th, https://www.kaggle.com/datasets/pavellexyr/ten-million-reddit-answers?select=ten-million-reddit-answers.csv.
38. The Political Compass, https://www.politicalcompass.org/. Retrieved July 9th, 2023.

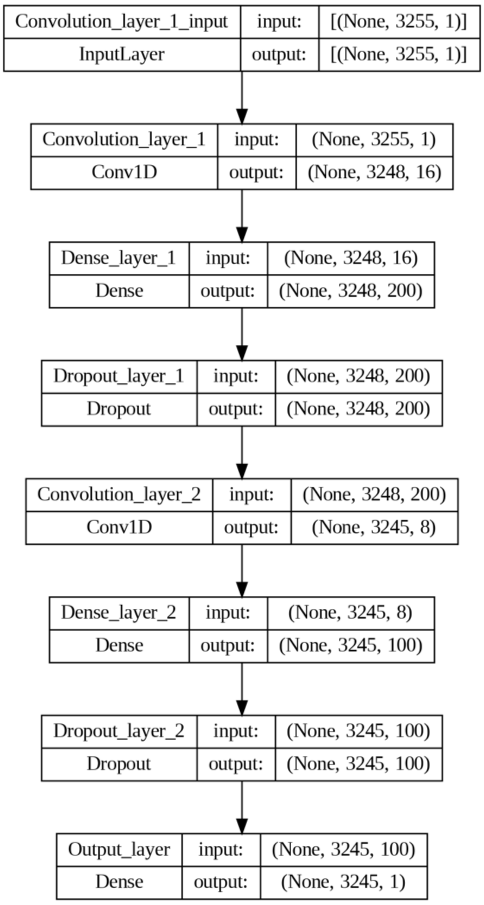
39. Thorisdottir, H., & Jost, J. T. (2011). Motivated closed-mindedness mediates the effect of threat on political conservatism. Political Psychology, 32(5), 785–811.
40. Ullah, H., Ahmad, B., Sana, I., Sattar, A., Khan, A., Akbar, S., & Asghar, M. Z. (2021). Comparative study for machine learning classifier recommendation to predict political affiliation based on online reviews. CAAI Transactions on Intelligence Technology, 6(3), 251-264.
41. Young, L. & Soroka, S. (2012). Affective News: The Automated Coding of Sentiment in Political Texts]. doi:10.1080/10584609.2012.671234. Political Communication, 29(2), 205–231.

Annexes

Appendix 1. GitHub repository links

https://github.com/mariaadshead/dissertation_code

Appendix 2. Neural network architecture*



*For the neural network predicting axes together the number of outputs is equal to 2.