

# UFO Sightings and Presidential Elections

Shelby Bearrows

Applied Computer Science  
University of Colorado  
Boulder, CO  
shbe4654@colorado.edu

Gurhar Khalsa

Applied Computer Science  
University of Colorado  
Boulder, CO  
gukh8079@colorado.edu

Sam Cramer

Applied Computer Science  
University of Colorado  
Boulder, CO  
sacr2234@colorado.edu

Kara Wolley

Applied Computer Science  
University of Colorado  
Boulder, CO  
wolley@colorado.edu

## ABSTRACT

This investigation aims to highlight trends over time and space in UFO sightings in the United States after 1976. This work also introduces new key insights on the relationship between UFO sightings and the two major political parties (republican and democratic) since 1976. Using data mining techniques, the resulting classification showed a 70% accuracy in predicting the political party. Additionally, we found that trends in how UFO sightings are described changed markedly around 1996. This timing coincided with a general explosion in sighting frequencies, the internet boom, as well as a pattern of more vague descriptions of sightings post 1996.

## INTRODUCTION

Recent scientific discoveries of Phosphine gas on Venus (Greaves et al.)<sup>6</sup> has re-invigorated one of the longest standing questions of human history, “Are we alone in the Universe”? This investigation aims to identify significant trends in UFO occurrence and shape and in sighting frequency as a function of geographical location to better understand advances in alien technology, or at least how human perception of aliens have changed over time. A secondary goal of this investigation is to explore potential relationships between presidential elections and reported UFO sightings. Presidential election data will shed light on the relationship between geographical region, UFO sighting frequency and UFO sighting description as a function of political party.

## RELATED WORK

To the authors’ knowledge, little work has been published on the relationship between UFO sightings and election information. Regarding UFO data analysis, prior work from the data source (National UFO Reporting Center, 2019)<sup>3</sup> also includes 166 references to additional analyses performed by individuals. Of these resources, most explored frequency of sightings by location (including per capita), word cloud analysis on the description attribute, shape of UFOs by time of year, sightings by shape and season, and shape frequencies. Perhaps the most explored question is whether sightings have increased over time, which some reported a possible correlation. An additional correlation between sightings and geographical region was reported (Adhokshaja, 2016)<sup>1</sup> using a chi-square analysis. While shape over time has been explored, the time variable was usually by week or month, rather than by decade for example (this could be interesting to explore).

Additional work has been done by a group of students from USC Viterbi school of engineering, using data scraped primarily from ufostracker.com. These students were able to conclude that “sci-fi movie releases correlated with an increase in sightings” and “that events like thunderstorms caused an uptick in reports” (Dawson, 2018)<sup>2</sup>. In addition, the data suggested higher frequencies of sightings during summer months. The authors used a word cloud to show similarity in words used to describe these sightings.

While others have explored some of the main questions regarding UFO sightings, merging our dataset with election data will likely add a new level of novelty to our work not present in the prior work.

## DATA SET

Two data sets were collected and compiled for use in this research. The primary data set consists of UFO sighting data published by the National UFO Reporting Center and spans almost a century (National UFO Reporting Center, 2019)<sup>3</sup>. Each entry includes date and location of the sighting, along with a description of the sighting that include the shape of the UFO and the duration of the sighting. This data set is approximately 28MB in size and contains 11 different attributes of UFO sightings. The secondary data set includes election data collected by the MIT Election Data and Science Lab (Tunguz, 2020)<sup>4</sup>. The dataset covers the complete voter breakdown in each county for every presidential election since 1976. It also includes information about each candidate that was on the ballot in each county like party affiliation and the number of votes they received in that county. The table is 4.5 MB and contains 11 different attributes for each entry. These datasets were joined into one table for easier analysis based on the city, state, and year. The attributes of the resulting table were:

- Date - Day when the sighting happened
- Time - Time the sighting occurred
- Last Election Year - most recent presidential election
- City - location of the sighting
- State - location of the sighting
- Shape - the shape of the UFO
- Duration (seconds) - length the sighting lasted
- Duration (hours) - length the sighting lasted in hours
- Comments - testimony from the witnesses
- Date Posted - when the sighting was reported publicly
- Latitude - latitude of sighting
- Longitude - longitude of sighting
- Candidate - who the winning candidate was in the city and state of the sighting
- Party - political part of the winning candidate in the city and state of the sighting
- Candidate Votes - number of votes for winning candidate in city and state of the sighting
- Total Votes - total votes cast in the city and state of the sighting.

## MAIN TECHNIQUES APPLIED

Data cleaning and integration was done prior to data analysis. The UFO dataset was especially 'dirty'. Reformatting of dates, state name and removal of random symbols (&, !, #) from the comments attribute was necessary. The US Elections dataset did not appear to need much cleaning. Data cleaning included correcting missing values, null handling and identifying erroneous data or outliers. Once these preliminary tasks were completed, the two data sets were integrated into a single table. Additionally, the two datasets were merged into one such that each row in the UFO election dataset coincides with the results of the closest past election. For example, a UFO sighting in Texas in 1979 coincides with the 1976 presidential election and the voting results for Texas during that election are listed alongside that UFO sighting. The reasoning behind this is that it captures what the voters and population were thinking and feeling during the four years between elections. The comments describing the UFO sightings had to be cleaned by removing all special characters and were stored in arrays split on the spaces in the descriptions to aid in further analysis.

After cleaning the data, our first analysis of the data involved some exploratory data analysis and visualization of the UFO data and election data. By grouping the data by election year and which political party was voted for in the city and state the UFO sighting was reported, we were able to group data into easily plottable groups. The first measurement we looked at was how many total sightings there were grouped by political party. Our first visualizations analyzed the change in UFO sighting frequency over time by party, how total votes changed over years by party, and how the average duration of a single UFO sighting changed over the years by party.

The main evaluation methods we used included scatter plots, bar charts, heatmaps, Apriori's algorithm, various classification techniques, word clouds, Pearson's correlation coefficient, lift and Student's t-test. Bar charts and scatter plots were used to compare UFO sightings over time and to quantify the change in reported description of the UFO sightings with regards to

time. Heatmaps were used to visualize geographic location of UFO sightings, weighted use of frequent descriptions, states and years. This highlighted where UFO sightings occur, not only geographically but also by the density of political parties. These explorations prompted classification using the comments attribute. Apriori's algorithm was used to quantify minimal support for frequent descriptors used in UFO sightings. Pearson's correlation coefficient and Lift were used to determine correlation between the UFO and election datasets. Student's t-test is used for a comparison of means between the datasets.

## KEY RESULTS

Preliminary data analysis was performed to explore data availability and initial responses to proposed research questions. A heatmap was created using the total number of UFO sightings by city in the lower in the United States. Figure 1 shows the change in UFO sightings by political party by election year. These results indicate that there was approximately a 3:2 ratio of UFO sightings in democratic states compared to republican states with over 20,000 sightings in democratic states and 12,500 in republican states. This is also reflected in the heatmap of UFO frequency by state as shown in Figure 2. It appears that California has been consistently reporting sightings since the 1990's, whereas other states such as Washington, and Arizona experience spikes in sighting frequencies over time (as shown by the intermittent green-yellow pixels of the heatmap).

Preliminary correlation analysis using Pearson's correlation coefficient showed positive and strong correlation between the increase in sightings and the increase in votes over time (Figure 3) however this was likely due to an increase in the population by 100 million people during that time. There was no correlation between duration of UFO sightings and time (years). Pearson's correlation coefficient analysis did not confirm a relationship between the UFO data other than positive correlation between the number of sightings and voter activity across the US. At this point, it became

apparent that for this analysis, the UFO sightings should be scaled due to the natural increase in population over time. For this reason, UFO sightings were derived as a percent of the total number of votes cast in the previous election.

Using the scaled UFO sightings, a heatmap was plotted by geographical location and political party (Figure 4). As shown in this figure, we believe that more sightings occur in coastal areas with some hotspots throughout the Midwest.

To begin our investigation regarding the relationship between UFO sightings and time, sightings were first plotted as a function of hour of day and month of year according to political party as shown in Figure 5. As anticipated, more UFOs were reported at night, between the hours of 5pm (hour 17) and 1am (hour 1). Interestingly, no UFO sightings were reported between May and September although we believe this is an error in the data collected not the presence of seasonality in UFO sightings. Figure 6 shows UFO sightings as a function of year since 1976. The data were best fit to an exponential trendline. Using this trendline, an estimated 18.2 million sightings should occur in the year 2020 across the United States. These data were then split by political party and again plotted by year (Figure 7). Using the scatter plot, no clear differences between republican and democratic parties were observed which prompted the use of a boxplot and a comparison of means test (Figure 8). This result appeared to show a difference in the mean number of reported UFO sightings between the democratic and republican parties since 1976 however the two-sided Student T Test resulted in a P value of 0.485 which indicates that this difference in means would occur by random chance almost 49% of the time.

The initial investigation on UFO sighting keyword descriptions resulted in somewhat inconclusive weights on the terms "light", "circle" and "triangle". Much of this was anticipated during the project ideation however new characteristics of "cigar" or "chevron" add novel keywords that can be used in Apriori and characterization techniques. Figure 9 shows that while some descriptions such as "light" or "triangle" appear frequent across states,

descriptors like “oval” and “formation” may be more frequent in areas like California. Hence some descriptions may be local to certain regions across the country.

The use of common characteristics for UFO sightings over time is shown in Figure 10. This figure shows that the descriptor “light” has been used somewhat consistently since the late 1990’s, whereas “circle”, “triangle”, and “fireball” may be terms used more frequently in recent years to describe UFO sightings. The characteristics of UFO sightings by election year between 1908 and 2012 reconfirms this trend through each election year as shown in Figure 11. In this plot, it appears that “disk”, “cylinder” and “diamond” were more commonly used to describe a UFO sighting up to the mid-90s. Following 1996 the description of “light” began to overwhelm the UFO sightings. This gave us a new avenue of exploration to probe for a pattern in the data.

From here, the shape attribute was grouped by similarity and again performing histogram and heatmap analysis we noticed that “circular” and “light” based shapes were predominant in the data (Figure 12). Moreover, the change in the mid-90s become more obvious when shapes were aggregated, and rather than using raw frequency in the visualization, the fraction of overall sightings in a year for a given shape was used as a measure of “heat” (Figure 13). This illustrated a shift from circular shapes to light-based shapes in the mid-90s.

This led to the application of classification algorithms to the data in order to determine if it was possible to predict whether a sighting was pre- or post-1996, solely on how it was described in the comments attribute. We hypothesized that there was a difference pre-1996 vs post-1996 descriptors that could lead to predictions with better than 50/50 odds.

In addition to previous text cleaning and preprocessing, stop words, or words which don’t heavily contribute to the meaning of a sentence, were removed from the comments attribute using the Natural Language Toolkit. Using TFIDF vectorization, the comments were transformed into vectors of numbers with

sklearn TfidfVectorizer. TFIDF is a useful vectorization technique for text since it produces vectors of numbers that are similar to one another if the text used to create them have relevant and similar words (Chaudhary 2020)<sup>8</sup>. In effect, the comments were transformed into vectors of numbers easily fed into machine learning algorithms. However, due to a class imbalance issue wherein our data contained roughly 28 times the amount of post 96 comments, it would prove challenging to construct a classification model yielding strong precision and recall. We opted for a shotgun approach using a variety of sklearn classification methods.

All classifiers used an 80/20 train/test split. All classifiers had exceptional accuracy in the 0.95 range. However not all had acceptable precision and recall from which to draw a meaningful conclusion. Four different classification techniques were applied.

Multinomial Naive Bayesian classification gave high accuracy, but the precision and recall were too low to indicate that the model wasn’t learning to just guess post-1996 virtually every time (Table 1). K-Nearest Neighbors Classification also gave high accuracy but mostly due to the fact that it always guessed post-1996 (Table 2). A Multilayer Perceptron Neural Network, however, was more fruitful. Network topology choices were largely based on trial and error, as is often the case with neural networks (Table 3). A network with a ten node hidden layer followed by two eight node hidden layers and another ten node layer gave best results. This model produced an f-score of about 0.57, after averaging pre- and post-1996 precision and recall scores. Precision and recall for pre-1996 comment predictions were still somewhat low, but these results indicated a difference between pre- and post-1996 comments. Linear Support Vector Classification probably produced the best results with ~0.47 precision for pre-1996 comments and the highest average precision of ~0.7, with an f-score of ~0.55 (Table 4). These results motivated Apriori association and word cloud analyses of pre- and post-1996 comments to shed more light on the apparent differences between these sets of descriptions as shown in Figure 14.

One of our initial questions regarded the frequency of sightings in republican versus democratic states. We found that democratic states reported more UFOs than republican states. The difference in quality of UFO description pre- and post-1996 prompted an exploration in the difference in quality of descriptions in republican versus democratic states as well, using some of the same classification methods used to explore the difference between pre- and post-1996 comments. Pre-processing included removing objects in which a third-party candidate won that state during that time frame. The party category was more balanced than year. Again, an 80/20 train/test split was used. TFIDF vectorization was used again to transform the comments into vectors. Neural networks and support vector machines were used due to their relative success classifying on pre vs post 1996 comments, as well as random forest classification with bootstrap method.

A Multilayer Perceptron Neural Network with a ten node hidden layer followed by a twenty node hidden layer and another ten node layer proved best. Again, network topology was determined through trial and error. An F-score of about 0.57 was obtained with about 0.7 precision for democratic classification and 0.5 for republicans and about the same recall. While the accuracy was about 0.65, the results for precision and recall were successful. Support Vector Classification yielded 0.7 accuracy. With 0.7 precision and 0.8 recall for Democrats and 0.55 precision and 0.34 recall for Republicans. Average f-score was about 0.6 (Table 5).

The Random Forest Classification resulted in overfitting of the data in the initial pass, however, using the bootstrap method and increasing the number of trees helped overcome this overfitting. Results were similar to the Support Vector Machine, but with better Republican precision and worse Republican recall as shown in Table 6.

In addition to the classification methods, word clouds were used to visualize pre- and post-1996 descriptors (Figure 14)

To further investigate and substantiate our classification and word cloud results we looked for association rules in the comments attribute for pre-1996 and post-1996. The top 20 association rules, sorted by descending confidence, were selected. To visualize our association rules, we made graphs where the nodes size is mapped to the association rules support and the nodes color is mapped to the association rules lift. We see in pre-1996 that there are 7 nodes pointing to light while in post-1996 there is an increase in the number of association rules with light which can be seen as an increase in the number of incoming edges with light, which supports the word clouds of pre- and post-1996 comments (Figure 15).

A possible pattern emerged from these investigations. The internet became increasingly popular in the mid-90s, around the time that our data shows an explosion of sighting frequency. Moreover, the dominant words in the comments, (“light”, “object”, “sky”) as highlighted by the word cloud post 1996, are among the least meaningful descriptors. The Apriori association graph for post-1996 comments also has nearly twice as many paths leading to the word “light” than pre-1996. With a lot of activity around the node for the word “Sirius” as well. It is possible that more access to the internet made it easier to instantly report any small supposed discrepancy without as much forethought about whether what was seen was worth reporting. Moreover, there are popular conspiracy theories about aliens involving the star Sirius<sup>2,3</sup>. Robert Temple made pseudo-scientific claims about aliens and the star. What the data may be hinting to is a pattern of more noise and spread of misinformation post 96 due to the advent of the internet, and how it makes it easier to share both information and misinformation.

## APPLICATIONS

A potential avenue for exploring the spread of alien conspiracy theories online may have been hinted at by the analyses performed by this group. While that pattern may suggest misinformation spread, we also cannot definitively rule out the possibility of alien life

or visitation from our findings. More noise post 96 does not necessarily disprove alien existence.

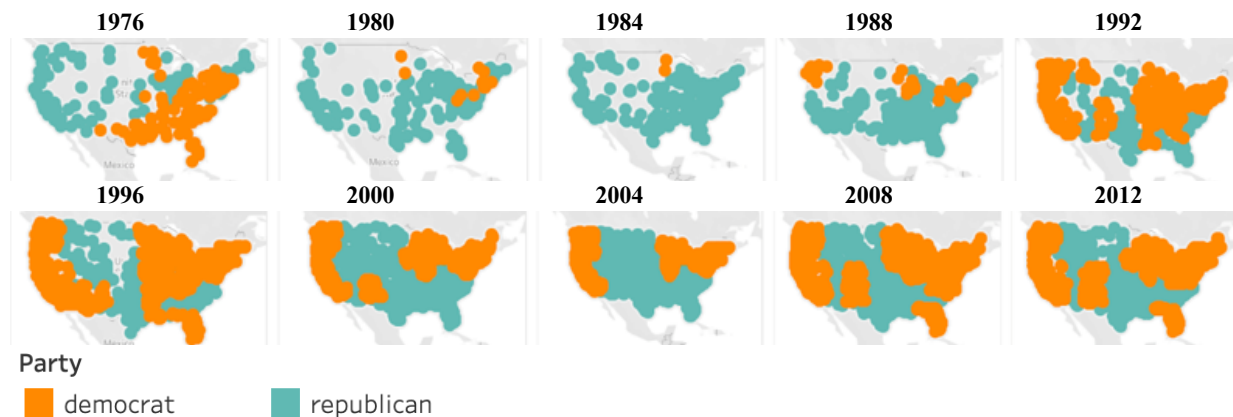
Although this work may have no direct positive impact on the general population, there has been recent renewed interest in discovering life on other planets. A recent research article published in Nature Astronomy found phosphine on Venus by using telescopes pointed at Venus' cloud decks (Greaves, 2020)<sup>6</sup>. The research group also published an article in Astrobiology the same day explaining that they believe there is no other biochemical pathway to producing phosphine than through living organisms (Bains, 2020)<sup>5</sup>. These articles made breaking, front page news at the New York Times. Now, researchers are scrambling to figure out if Venus could be an alien biosphere.

Discovering life on other planets could mean that there might be another habitable planet similar to earth which humans could inhabit when our sun eventually dies out. Finding life on planets so near to earth also means we may not have to travel very far to get there. Or, this could mean that aliens have existed in our solar system on Venus since the inception of life and have been meddling in our elections.

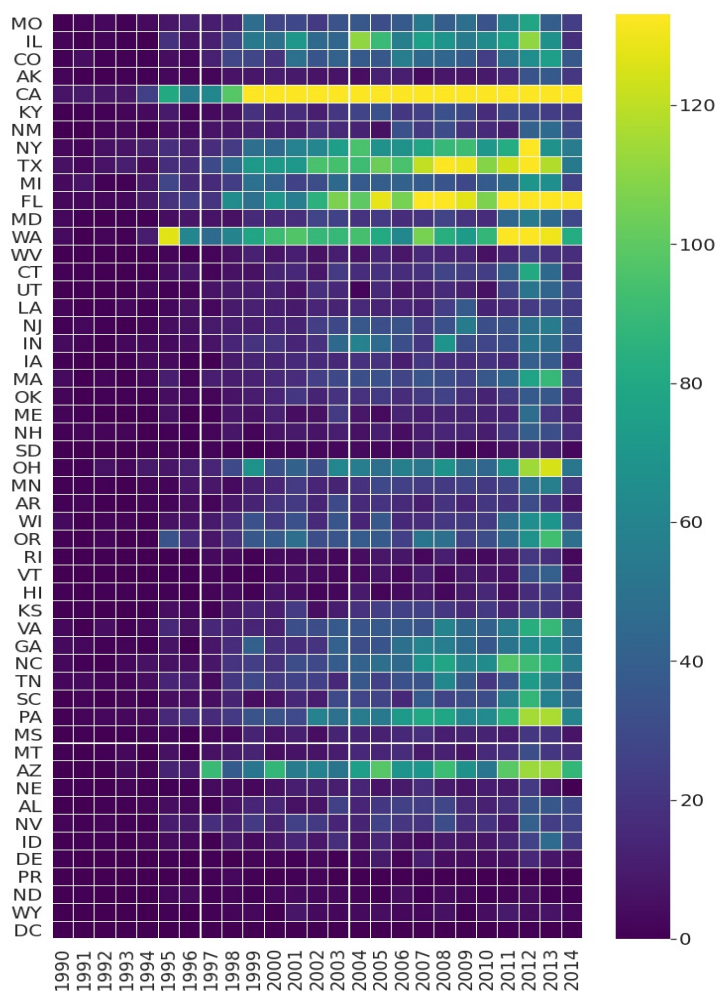
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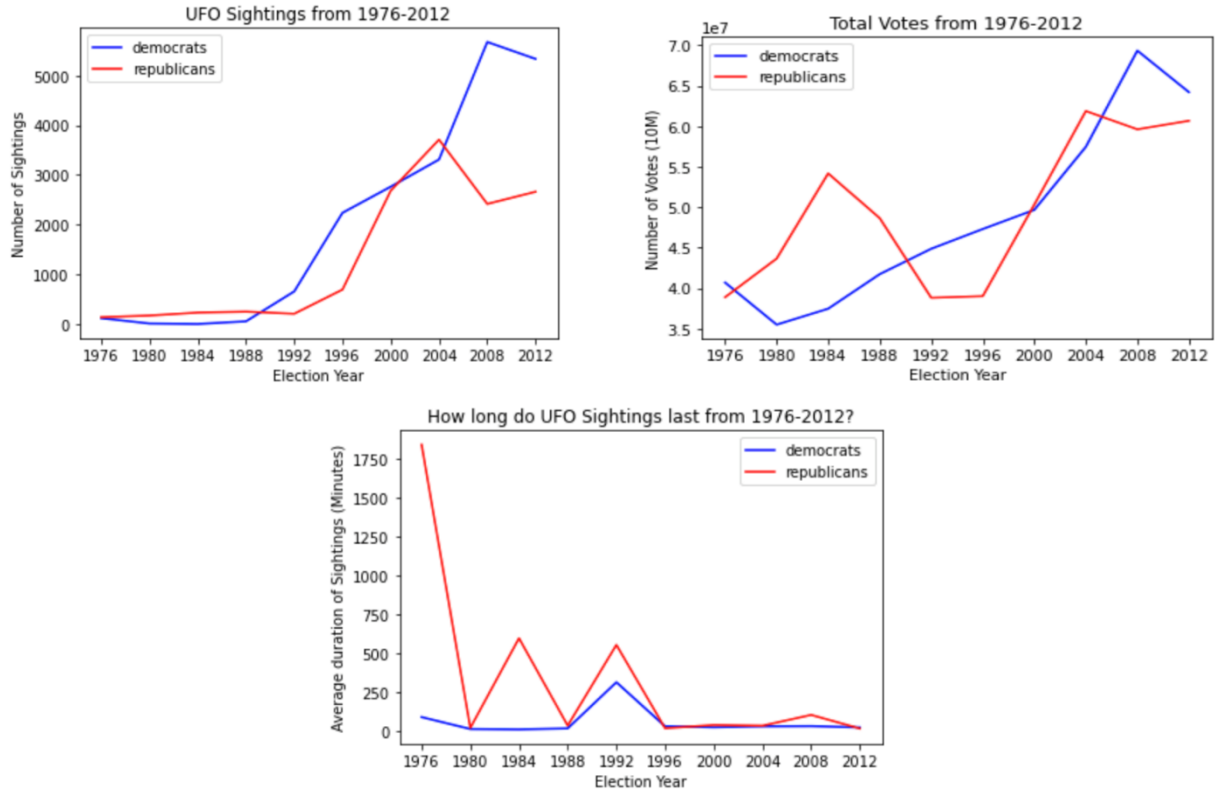
## Appendix A: Figures



**Figure 1: UFO sightings across the United States during election years between 1976 and 2014 as a function of political party.**



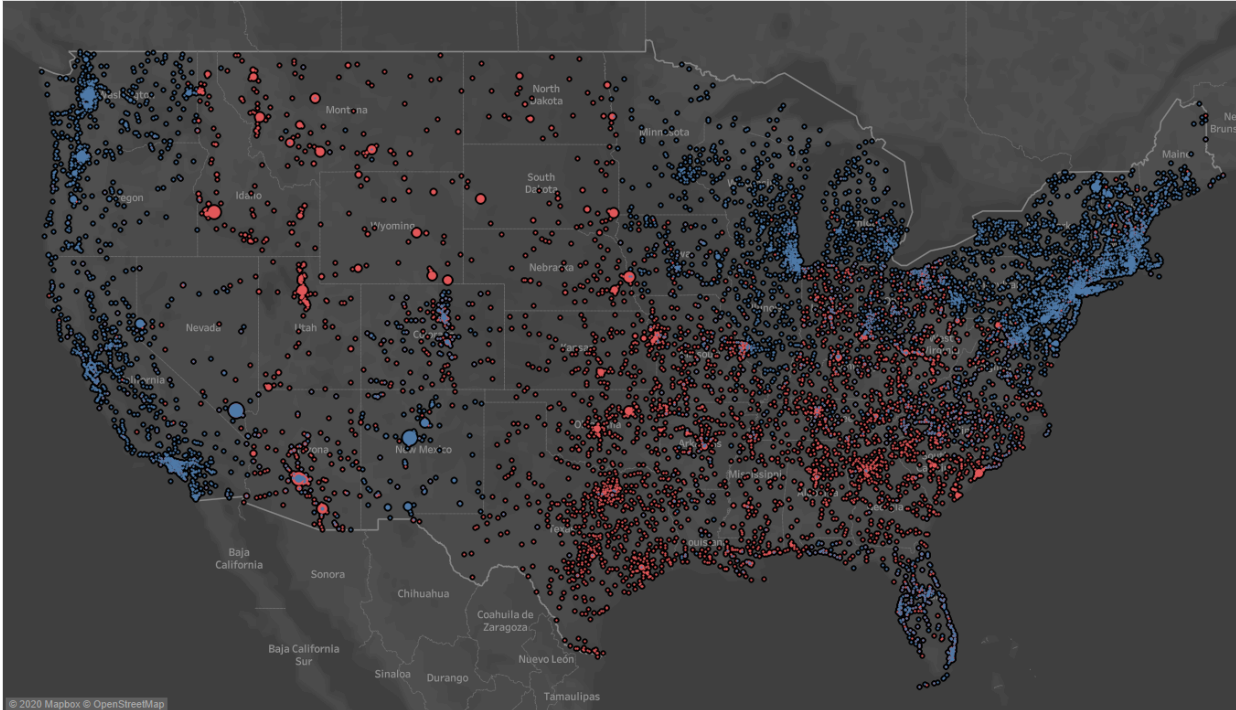
**Figure 2: Heatmap of UFO sightings by year in each state.**



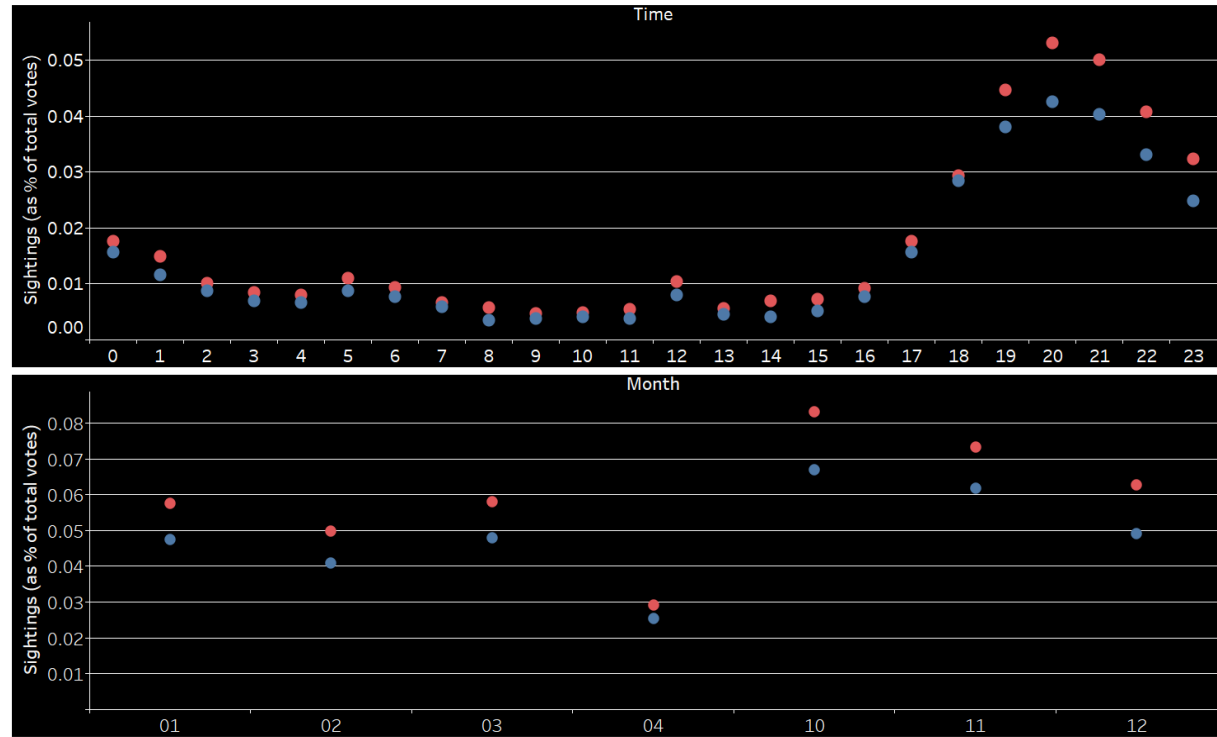
	election_years	dem_votes_year	rep_votes_year	dem_ufo_sightings	rep_ufo_sightings	dem_time_year	rep_time_year
election_years	1.000000	0.923465	0.695396	0.935860	0.843115	-0.125038	-0.608772
dem_votes_year	0.923465	1.000000	0.694626	0.975797	0.809245	-0.120176	-0.366542
rep_votes_year	0.695396	0.694626	1.000000	0.687736	0.781332	-0.483529	-0.446459
dem_ufo_sightings	0.935860	0.975797	0.687736	1.000000	0.826678	-0.228438	-0.438671
rep_ufo_sightings	0.843115	0.809245	0.781332	0.826678	1.000000	-0.299684	-0.448843
dem_time_year	-0.125038	-0.120176	-0.483529	-0.228438	-0.299684	1.000000	0.336700
rep_time_year	-0.608772	-0.366542	-0.446459	-0.438671	-0.448843	0.336700	1.000000

Figure 3: UFO sightings by year (top left), total votes by year (top right) and duration of UFO sighting by year (center).





**Figure 4:** UFO sightings in the United States since 1976. The number of UFO sightings is scaled to the total number of votes cast in the previous election. Color indicates political party for the previous election year while the size of the marker indicates UFO sightings.



**Figure 5:** UFO sightings by hour of the day (top) and month of year (bottom) in the United States since 1976. Color indicates political party for previous election (blue is democratic, red is republican). Number of sightings is as a percent of the number of sightings per total number of votes in the previous election year.

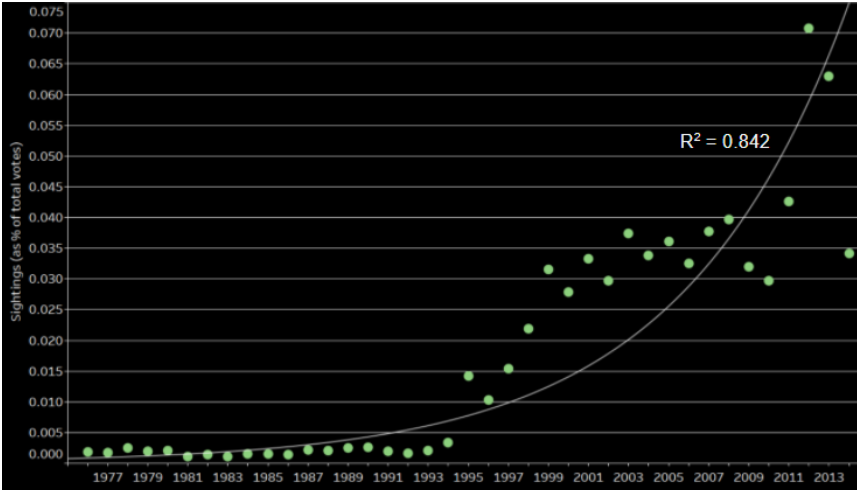


Figure 6: UFO sightings in the United States since 1976.

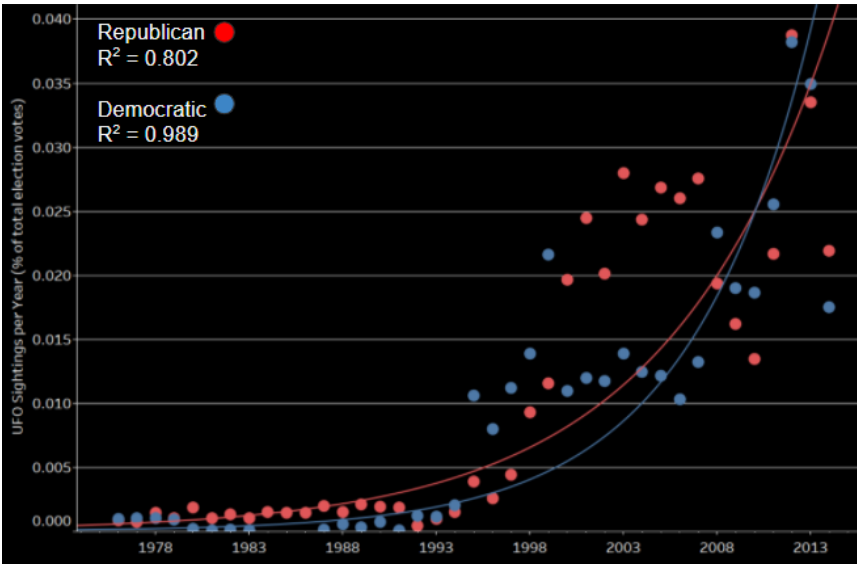
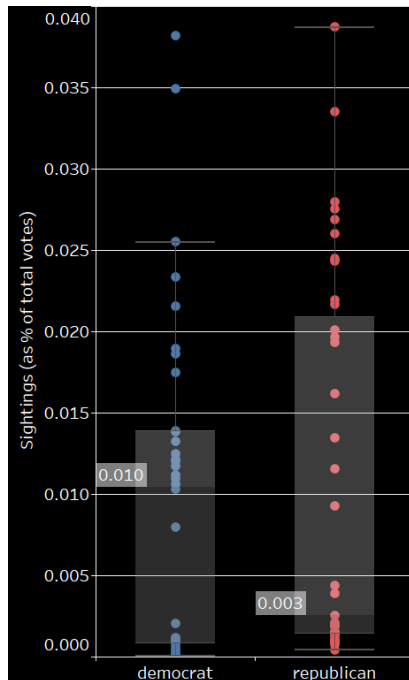
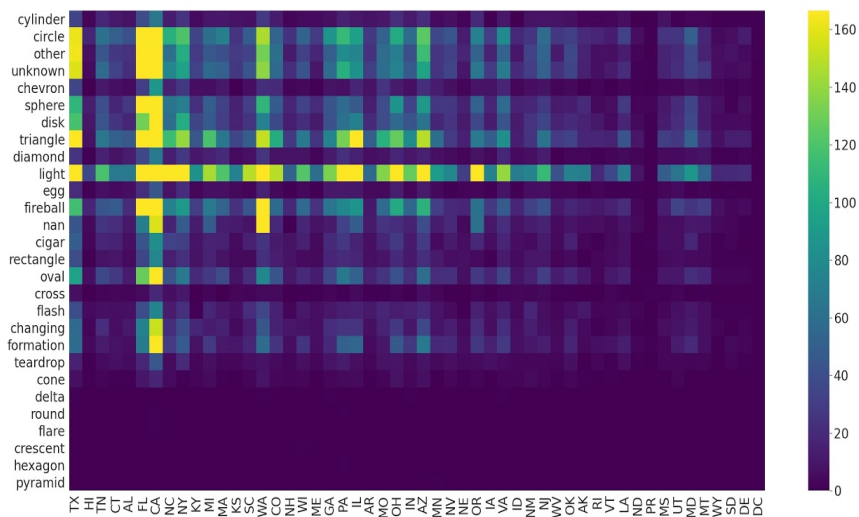


Figure 7: UFO sightings in the United States since 1976. Color indicates political party for previous election (blue is democratic, red is republican). Number of sightings is as a percent of the number of sightings per total number of votes in the previous election year.



T Value	0.701
Two Sided P Value	48.542%

**Figure 8: UFO sightings in the United States since 1976 by political party. Color indicates political party for previous election (blue is democratic, red is republican). Number of sightings is as a percent of the number of sightings per total number of votes in the previous election year.**



**Figure 9: Heatmap of UFO sighting keyword by state.**

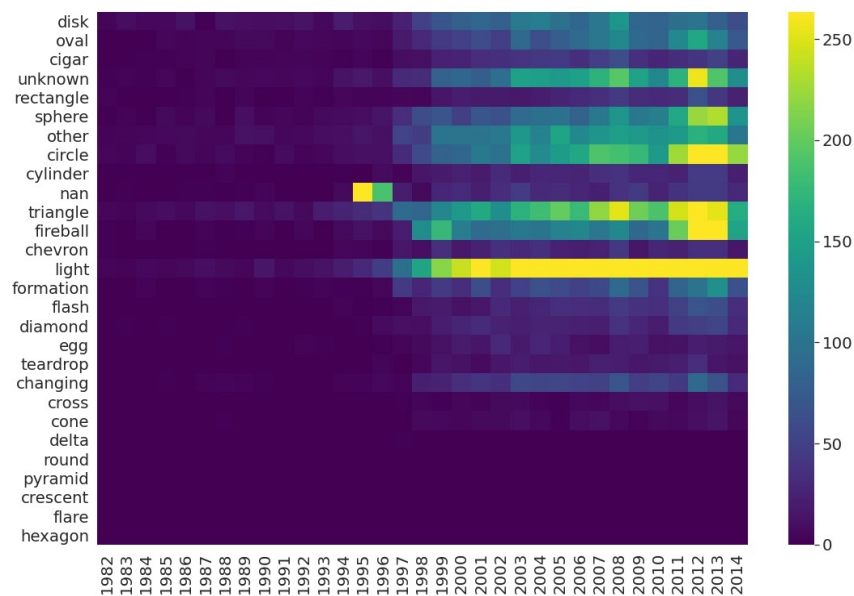


Figure 10: Heatmap of UFO sighting keyword by year.

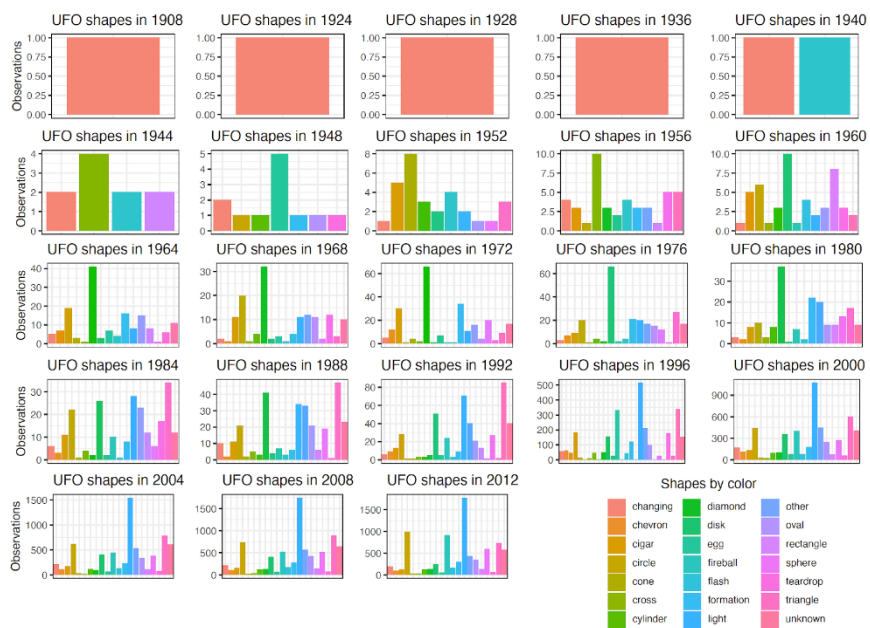


Figure 11: Changes in description of UFO sightings for each election year between 1908 and 2012. Bars are colored by shape.

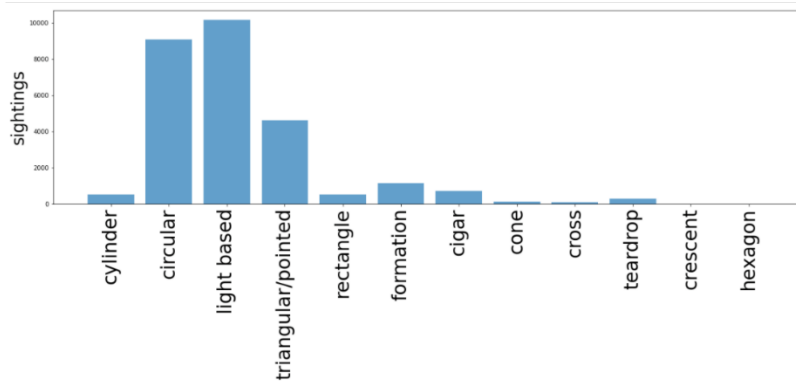


Figure 12: Histogram of sightings by shape with aggregated attributes.

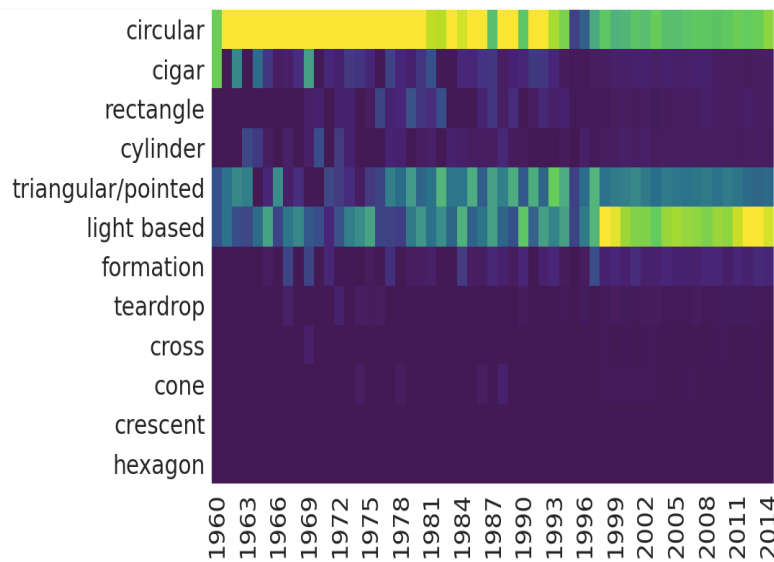


Figure 13: Heatmap of aggregated shapes by year with heat representing the fraction of sightings in that year taken by that shape rather than just raw frequency. Illustrates the change in the mid/late 90s from circular shapes being predominant to light based shapes.

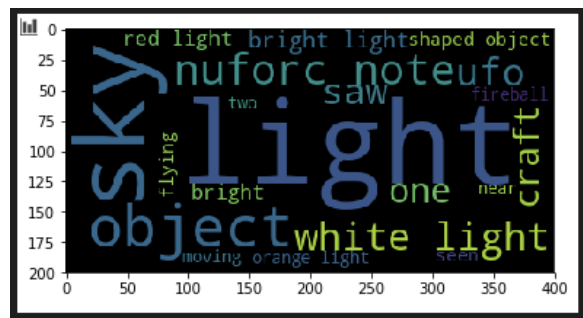
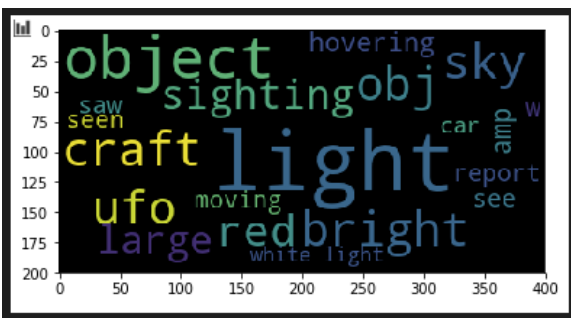
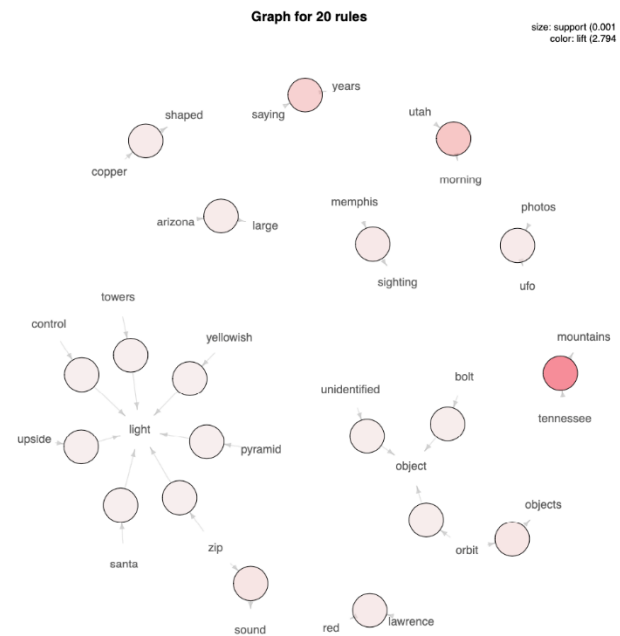
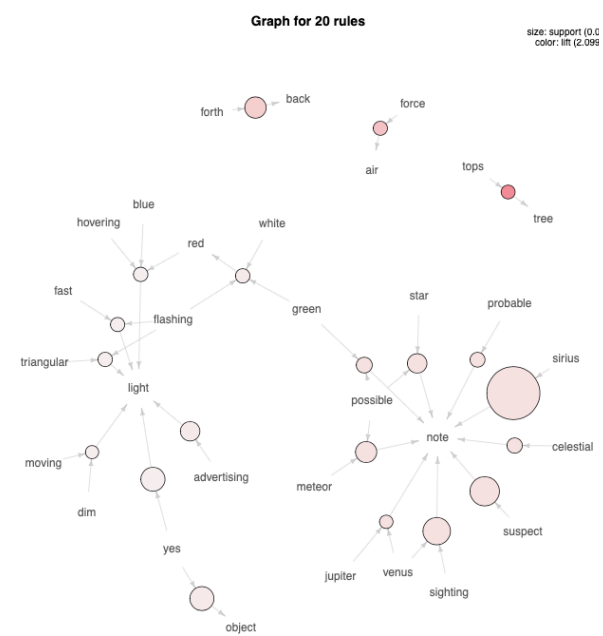


Figure 14: Word cloud for UFO descriptors pre-1996 (left) and post-1996 (right).

## Pre-1996



## Post-1996



**Figure 15: Apriori Association rules for pre- and post-1996 in the number of UFO sightings.**

## Appendix B: Tables

**Table 1: Multinomial Bayesian Classification report for UFO descriptors used pre-1996 and those used post-1996.**

	Precision	Recall	F-Score	Support
Post-1996	0.97	1.00	0.99	4458
Pre-1996	1.00	0.01	0.01	136
Accuracy			0.97	4594
Macro average	0.99	0.50	0.50	4594
Weighted average	0.97	0.97	0.96	4594

**Table 2: K-Nearest Neighbors Classification report for UFO descriptors used pre-1996 and those used post-1996.**

	Precision	Recall	F-Score	Support
Post-1996	0.97	1.00	0.98	4458
Pre-1996	0.00	0.00	0.00	136
Accuracy			0.97	4594
Macro average	0.49	0.50	0.49	4594
Weighted average	0.94	0.97	0.96	4594

**Table 3: Multilayer Perceptron Neural Network report for UFO descriptors used pre-1996 and those used post-1996.**

	Precision	Recall	F-Score	Support
Post-1996	0.97	0.98	0.98	4458
Pre-1996	0.16	0.13	0.14	136
Accuracy			0.95	4594
Macro average	0.56	0.56	0.56	4594
Weighted average	0.95	0.95	0.95	4594

**Table 1: Support Vector Classification report for UFO descriptors used pre-1996 and those used post-1996.**

	Precision	Recall	F-Score	Support
Post-1996	0.97	1	0.99	4458
Pre-1996	0.56	0.07	0.3	436
Accuracy			0.97	4594
Macro average	0.76	0.54	0.56	4594
Weighted average	0.96	0.97	0.96	4594

**Table 5: Support Vector Classification report for Democratic versus Republican UFO descriptors.**

	Precision	Recall	F-Score	Support
Democrat	0.72	0.88	0.79	3069
Republican	0.54	0.29	0.38	1456
Accuracy			0.69	4525
Macro average	0.63	0.59	0.59	4525
Weighted average	0.66	0.69	0.66	4525

**Table 6: Random Forest Classification report for Democratic versus Republican UFO descriptors.**

	Precision	Recall	F-Score	Support
Democrat	0.71	0.96	0.82	3069
Republican	0.67	0.18	0.29	1456
Accuracy			0.71	4525
Macro average	0.69	0.57	0.55	4525
Weighted average	0.70	0.71	0.65	4525