**Data Exploration**

The team discussed a variety of different topics and subjects to consider for this project, we also looked at and read various topics on data exploration[[1]](#footnote-1). As we looked at the data available to us, we started shaping the discussion around our purpose. This gave us a more defined scope from which to focus. After sorting thru retail data, online sales and crises-specific major events, we opted for donation data focused on presidential election years.

Once we agreed on donation data, we focused on presidential elections and ways that the elections may be affected. This led us to narrow our focus on six specific states (AZ, FL, MI, NC, PA, and WI) and the counties therein. Historically, these states have been considered battleground and/or swing states, having a significant impact on the presidential election and electoral votes.

We set out to answer the following;

* Do presidential candidates influence how people donate?
* Can we predict who the president will be based on donation data?
* How much money is donated across candidates? States? Counties?
* Are donations affected by employment/unemployment?
* How do rural and urban neighborhoods affect voting?
* Does FL, MI, PA, NC, WI and AZ have a significant impact on elections?
* Do economics effect donations?
* How do major event effects on donations (9/11, real estate market crash, COVID) and/or presidential elections?
* Do demographics, such as age and education have an effect on these data?
* What significance does health information have?

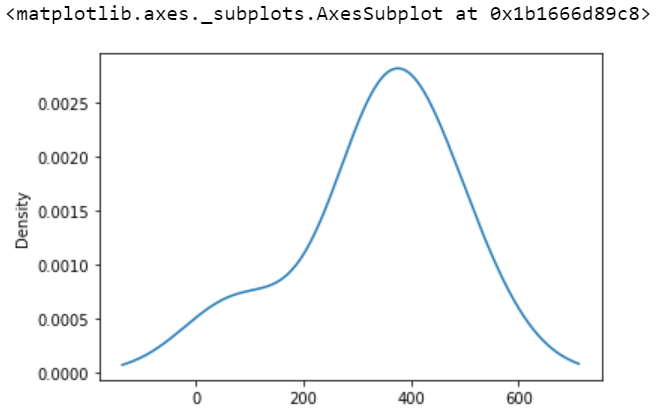
We explored the data and created several visualizations[[2]](#footnote-2), looking at different aspects of the data we sought to explore. We also did some value counts of the datasets to determine the best storage options and how to pull the recall the information to create our models, predictions and perform analysis. We have twelve tables for this analysis. Below is a list and graph with the information.

**Description Table Name Rows Columns**

1. Donors on selected states agg\_county\_donors 6,748 12
2. Voters on selected states agg\_county\_votes 2,020 14
3. Births and deaths birth\_death\_rate 305 6
4. Presidential candidates since 2000 candidates 141,375 17
5. Donations for presidential votes donations 14,954,054 21
6. Committee presidential donations donations 141,375 15
7. Educational levels by state education 3,283 47
8. Health information health\_metrics 3,193 507
9. County postal codes postal\_codes 52,889 5
10. Presidential votes on selected states pres\_votes\_6T 6,464 11
11. Donations for presidential votes six\_state\_donations 14,954,054 21
12. Unemployment rates unemployment 404 114

We created various charts and graphs while exploring the data.

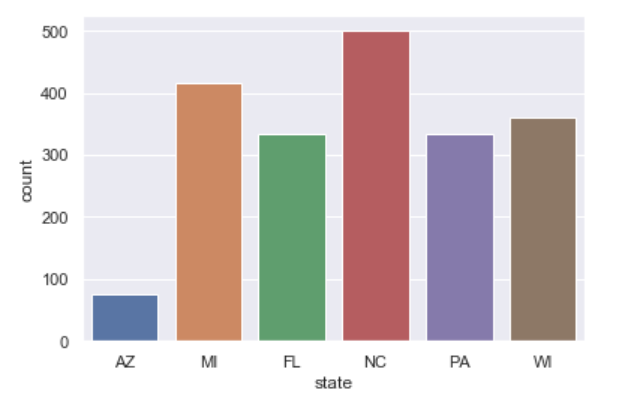
**Total Votes graph**



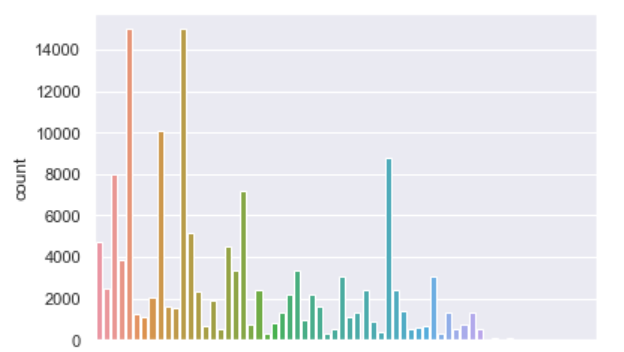
We used several steps out of the 15-step data exploration method[[3]](#footnote-3) to describe our process. We also obtained data exploration information from Medium[[4]](#footnote-4)

**1. Unique value counts: examples of votes by county and candidates by state**

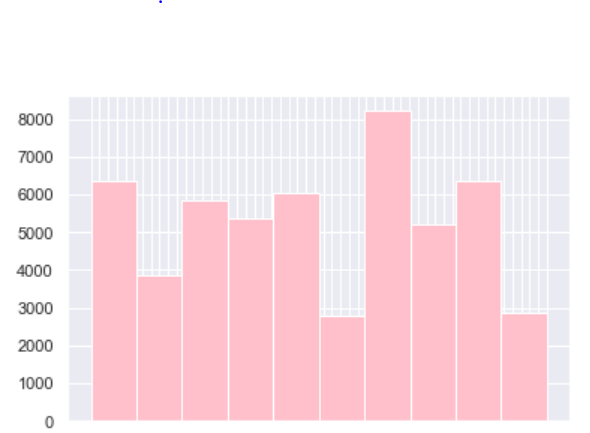
**Aggregated County Votes by State = 2,020**



**Candidates by State = 141,375**



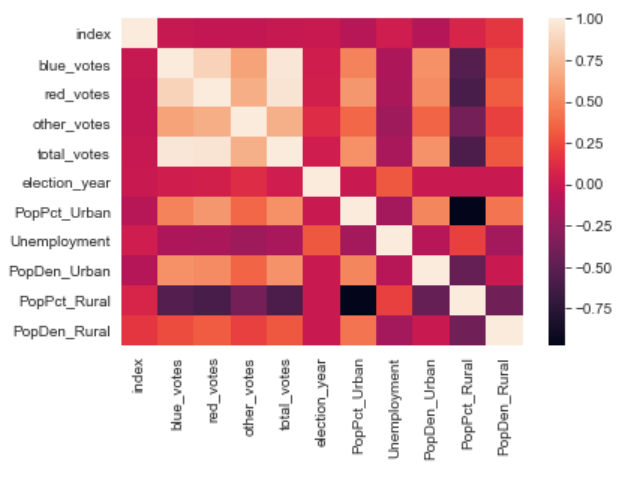
**2. Frequency Count**

**Histogram of Postal Codes by State**

**3. Correlation**

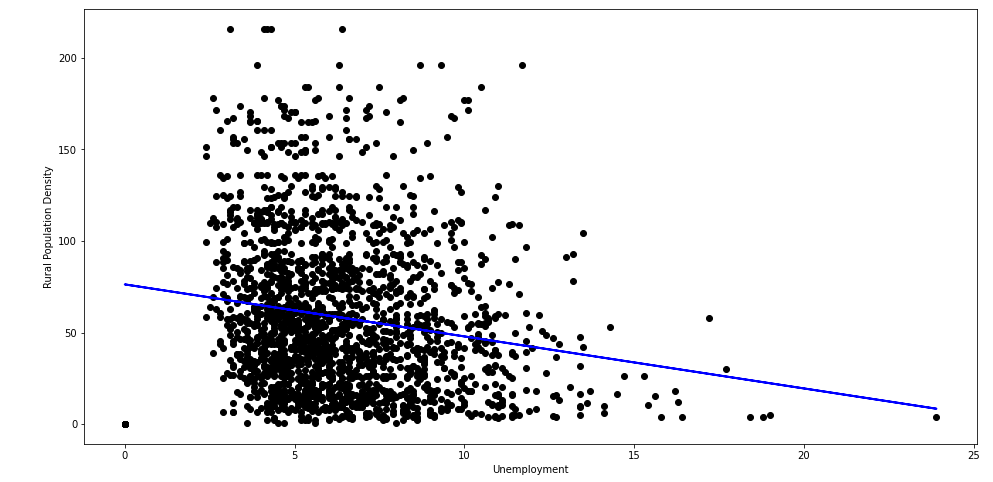
When it comes to analyzing numeric values, some basic information such as minimum, maximum and variance are very useful. Variance gives a good indication how the values are spread.

**Correlation Heat Map**



We looked at the relationship between different aspects of the data, to determine whether the correlation was positive or negative. This example shows a negative correlation.

**Correlation: Rural Population w/Unemployment**



**Data Analysis**

Our team used a variety or tools and tables to analyze the data.

* Jupyter Notebook

This has been our main form of data analysis. We read in the tables from our SQL and Cloud connections to write simple to complex coding, focused on understanding and displaying the necessary data. To measure presidential data, we’ve pulled in donation and voter information, along with unemployment, education and demographics. We have discovered that these pieces of information have been useful in helping us transform and mold the data into information that is useful for looking at presidential elections.

* Spreadsheets

Everyone on the team participated in data gathering and located information to assist in our project. This information was located online, using data from the FEC, Kaggle and the Census Bureau. These data were analyzed and saved as CSV files that were uploaded to GitHub, PostgreSQL PGAdmin and Google Cloud for easy access and data sharing.

* Google Cloud

We place large dataset and bucketed information onto this platform. This allows to perform the ETL and join tables.

* PG Admin

We used PGAdmin to perform SQL queries and analyze datasets, as well as review table details.

**Feature Engineering**

Feature engineering, als0 know as data preparation was done during the first two weeks of the project. The team rallied together to select all of the necessary types of data from various online options. We took various tables and processed the data in Jupyter Notebook and Google Cloud. This gave us a better understanding of each data element, along with what information we need to group, focus on and what we needed to remove. Then, we sorted thru the data and optimized it for our project. We believe, from the data, that looking at previous voter information, coupled with donation info and demographics might provide insights on our main focus which is donations affecting presidential elections in swing states. We’re testing to see if there is a correlation between the money people donate and who is elected.

**Decision-making Process**

After discussing this project with our instructor and teacher’s assistants, we determined that we had to do more research to make sure we had enough data elements, feature and information to use a predictive model for our project. Our advisors thought that we should use some classification and regression models to see what more we can learn these data. This led us to work on supervised and unsupervised machine learning models.

Following this process, we realize that we still have some information and interest in using a predictive model. We ran a neural network on the data and the results were .98 in the deep learning model. This led us to believe that the model is likely overfitting.[[5]](#footnote-5) We will look at other portions of the data to determine the next steps.

**Peer Review**

In order to verify the steps and assist one another in our code, we reviewed the various notebooks and provided updates and enhancement to the info. All of our updates are tracked in GitHub.

***Presentation Slide Deck*** [*https://docs.google.com/presentation/d/1ijhyfkdBBYox\_7o6rQUraLtBufkcBuDwIpVaxm5wSqs/edit?usp=sharing*](https://docs.google.com/presentation/d/1ijhyfkdBBYox_7o6rQUraLtBufkcBuDwIpVaxm5wSqs/edit?usp=sharing)

1. Toward Data Science: 15 Steps to Data Exploration <https://towardsdatascience.com/15-data-exploration-techniques-to-go-from-data-to-insights-93f66e6805df> [↑](#footnote-ref-1)
2. <https://www.sisense.com/glossary/data-exploration/> [↑](#footnote-ref-2)
3. Towards Data Science: “An Extensive Step by Step Guide to Exploratory Data Analysis” <https://towardsdatascience.com/an-extensive-guide-to-exploratory-data-analysis-ddd99a03199e> [↑](#footnote-ref-3)
4. Medium: “Data Exploration” <https://medium.com/@abhinavr8/data-preparation-and-exploration-5e09b92cf00e> [↑](#footnote-ref-4)
5. Recognising Traffic Signs With 98% Accuracy Using Deep Learning <https://towardsdatascience.com/recognizing-traffic-signs-with-over-98-accuracy-using-deep-learning-86737aedc2ab> [↑](#footnote-ref-5)