FinalReport

Jaime Valencia Lopez, Evan Silzle, and Sumukh Chanda

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R Markdown

Title: A Predictive Model of USA Presidential Election by States.

Link to the Github: https://github.com/JaimeVal24/STAT107_Final_Project

Abstract:

In this project, we aim to create a predictive model based on State data that aims to accurately predict the party that a state will vote for in the presidential electionbased on demographic data and past voting history. Our question is "Are we able to somewhat accurately predict a states voting tendency based on demographic data using logistic regression? If so, which variables are most important to the model?". **Conclusion to be done**

Introduction:

The purpose of this analysis is to find certain how certain characteristics in individuals, and how their demographic background impacts their voting tendencies. By creating a successful predictive model, one is able to act on these predictions, whether it is to change them or to ensure that they happen. Knowing which states have a chance of flipping to either political party is also extremely important, as it is in these states that presidential candidates have the hardest battles. Not only can this benefit politicians, but also the voters, as the model highlights what factors are more important to the way in which they vote, and will therefore force these politicians to address these factors. If we were to find that unemployment rate seems to be heavily associated with a voter voting for the Democratic party, the democratic party should aim to address their constituents and lower unemployment.

Data:

The data available is mostly demographic data relating to the 50 states, meaning that there are 50 observations (plus territories and overall USA data that will not be used). The data sets are as follows:

Demographic Data: (https://www.kff.org/state-health-policy-data/state-indicator/distribution-by-raceethnicity/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D)

Income Data: (https://hdpulse.nimhd.nih.gov/data-portal/social/table?age=001&age_options=ageall_1&demo=00011&demo_options=income_3&race=00&race_options=race_7&sex=0&sex_options=sexboth_1&socialtopic=030&socialtopic_options=social_6&statefips=00&statefips_options=area_states)

Unemployment Rates: (https://www.bls.gov/web/laus/laumstrk.htm)

Commuter Mode: (https://www.bts.gov/browse-statistical-products-and-data/state-transportation-statistics/commute-mode)

Gun Ownership: (https://worldpopulationreview.com/state-rankings/gun-ownership-by-state)

Covid Deaths: (https://catalog.data.gov/dataset/provisional-covid-19-death-counts-rates-and-percent-of-total-deaths-by-jurisdiction-of-res)

In order to clean and aggregate the data, we performed a few transformations. Most importantly, for the commuter mode data set, the rows were formatted as (State_Name_Commuter_Mode), where it was necessary to modify it so that the state became the row on its own and the commuter mode into a column for every state. All conversions were made so that we could have the data for each state.

The following are the variables for each of our observations:

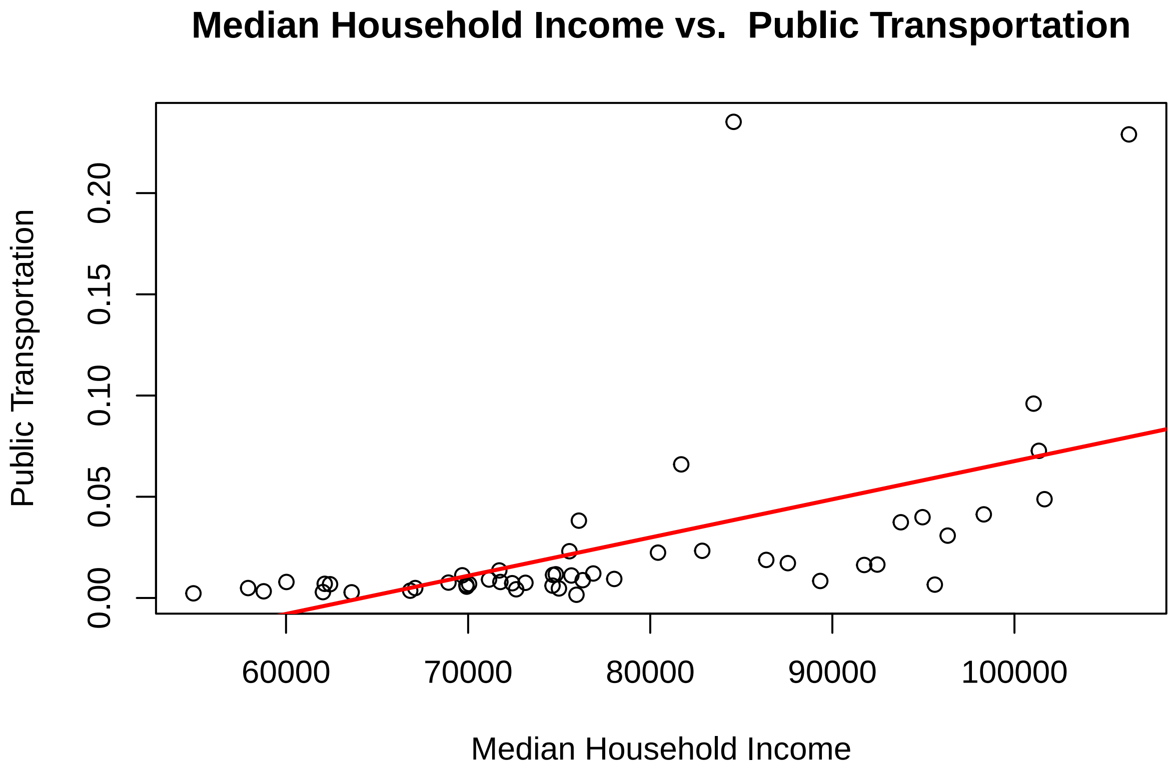
[1] "Location" "White"
[3] "Black" "Hispanic"
[5] "Asian" "American Indian or Alaska Native"
[7] "Native Hawaiian or Pacific Islander" "Multiple Races"
[9] "Total" "Bicycle"
[11] "Walked" "Taxi, motorcycle, or other"
[13] "Public transportation" "Worked at home"
[15] "Carpool" "Drove alone"
[17] "PercentageOfHouseholdsThatOwnGuns"

[18] "GunOwnership_NumOfGunLicenses_num_2022" "data_as_of"
[20] "Group" "data_period_start"
[22] "data_period_end" "COVID_deaths"
[24] "COVID_pct_of_total" "pct_change_wk"
[26] "pct_diff_wk" "crude_COVID_rate"
[28] "aa_COVID_rate" "crude_COVID_rate_ann"
[30] "aa_COVID_rate_ann" "footnote"
[32] "end_date" "Unemployment.Rate.August.2025"
[34] "Median.Household.Income" "Voting.Results.2016"
[36] "Voting.Results.2020" "Voting.Results.2024"
[38] "Electoral.College.Votes"

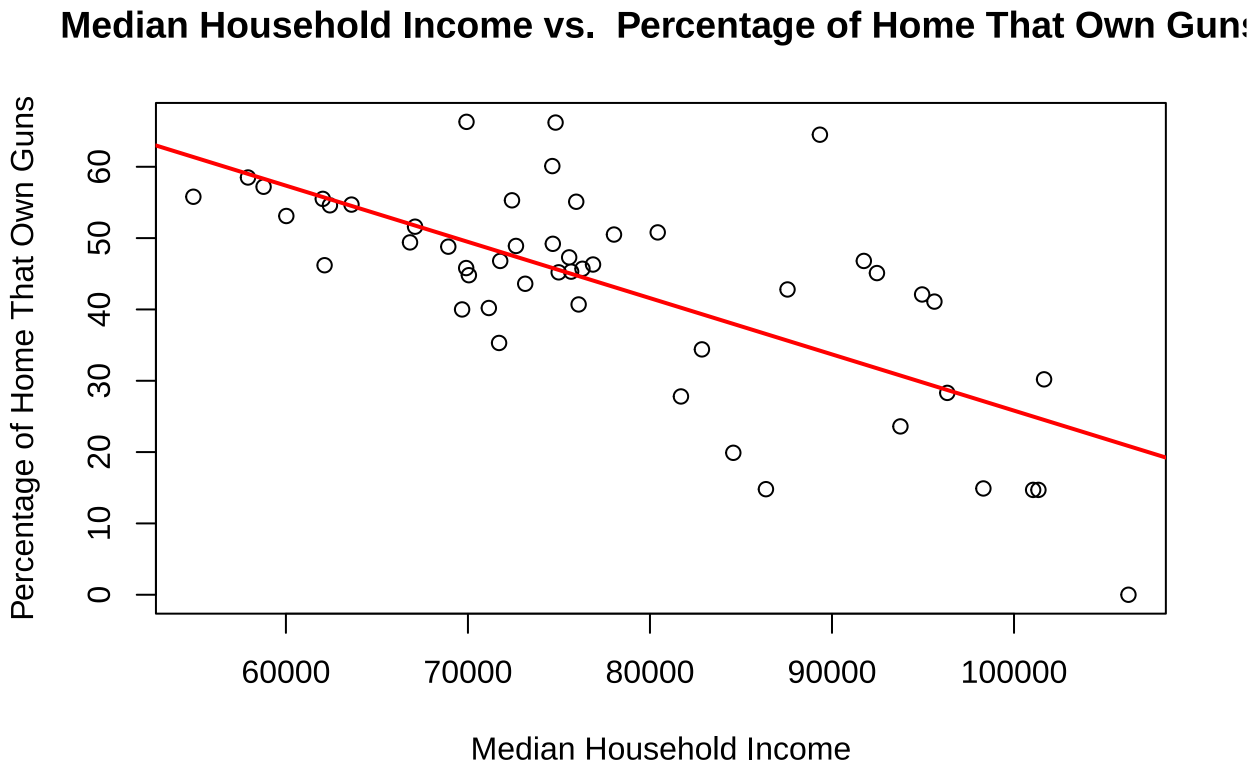
Data cleaning consisted of removing columns that were not necessary and could not be used for our future model. This included dates, fully empty columns, etc. We then replaced NA values in numerical columns with 0, as it will allow for the data set to be more manageable when it comes to implementing our model. Lastly, we turned the character columns of voting results from 2016, 2020 and 2024 into factor values.

Visualization:

We want to explore the relationships between some of our variables, and see if they ar correlated. If there are correlations between different variables in our data then we can start to gain a clearer idea of how they might influence voting.



From the plot above we can see the relationship between the median household income and the rate of using public transportation to get to work. From the line of best fit we can tell that there is a relationship between the two variables. The states with higher median household income see higher rates of their workforce using public transportation to work. One thing that sticks out are the two high outliers at the top. New York has a median household income of 84,578 and a public transportation rate of 0.2352, and D.C. has a median household income of 106,287 and a public transportation rate of 0.2290.



When comparing the median household income of a state to the percentage of homes that own guns, we see a very clear trend that indicates that states with a higher median income own less guns, and vice versa.

Next, we can look at the ethnic breakdown of each election, split by states that went red in each election and states that went blue. We can see that for every election the Democrats had less of a proportion of their votes from white voters, and more of a proportion of their votes from minority races. Additionally, although the ethnic breakdowns of each election differ greatly for democratic states vs republican states, the breakdowns barely differ when comparing different years.

We can compare the average gun ownership percentage, pandemic COVID-19 rate, unemployment rate, and median household income for states that went blue and red in the 2024 election. We can see that states that voted Republican in 2024 have a much higher average gun ownership rate and average COVID-19 rate during the pandemic, and democratic states have a slightly higher average unemployment rate and average median household income.

Lastly, we can create box plots to understand the distribution of the data sets through their median, spread, and overall range. They highlight the central tendency, variability, and possible outliers and will give us more insight into our specific data and the validity of it as we are able to identify any skewed distributions. These specific ones are just a few of all of the box plots we can create for each variable introduced.

Analysis:

Our modeling strategy focused on constructing a logistic regression model that maximized predictive accuracy while maintaining interpretability. To validate our results, we employed a cross-validation technique by randomly splitting our 50-state dataset into a training set (75%) and a testing set (25%). This separation ensured that the model was trained on roughly 37 states and then evaluated on 13 “unseen” states, preventing the model from simply memorizing the data and ensuring it could generalize to new observations.

Variable Selection (LASSO Regression)

Our initial dataset contained over 25 potential predictor variables, ranging from transportation methods to racial demographics. To determine which variables were most relevant without succumbing to overfitting, we implemented *LASSO (Least Absolute Shrinkage and Selection Operator) Regression.* LASSO is a regularization technique that improves model accuracy by applying a penalty to the regression coefficients. It mathematically shrinks the coefficients of less important variables to exactly zero, effectively removing them from the model and leaving only the most impactful predictors.

Crucially, before running the selection process, we removed the 2016 and 2020 election results from the dataset. While past voting behavior is the strongest predictor of future voting, including it would have overshadowed the demographic trends we aimed to study. The goal of our project is to understand what variables are most important in the way a state will vote; if we were to have used 2016 and 2020 election results, we could have very possibly arrived at a model with 100% accuracy. However, it would not have given us any insight unto what demographic variables are most important

The LASSO algorithm identified three distinct variables as the strongest drivers of the 2024 vote: 1. *Percentage of Households that Own Guns* (Cultural) - This variable seems to represent a more cultural aspect of the population. We hypothesized that a higher percentage of households that own guns will result in a higher likely likelihood that the state will vote Republican. 2. *Median Household Income* (Economic) - This variable represent the economic aspect of the state's population. We hypothesized that a higher median household income will result in higher likelihood of the state voting Democrat. (States with higher) 3. *African American COVID Death Rate* (Regional/Health) - This variable provides a much harder to understand relationship. While it seems to represent a regional or health aspect of the state, it being chosen and how it will affect the models decision is a harder to theorize. While it is true that demograph data on the race makeup of a state can theoretically provide significance to the model, there also exists a variable in our dataset "black" that specifically targets the percentage of the state that is made up by an African American / Black population. What this variable seems to target. on the other hand is, more specifically, the number of African American individuals that unfortunately died from the COVID virus. We can hypothesize that this relates not only to the proportion of black population in a state (which appears to be higher on the southern republican states), but also to the degree of COVID prevention and medical care provided to these individuals.

Model Refinement (Bayesian Logistic Regression)

We used these three selected variables to fit our final *Bayesian Logistic Regression* model. We chose the Bayesian approach (`bayesglm`) over standard logistic regression due to the small size of our dataset ($n = 50$). Standard logistic regression often becomes unstable with small samples, especially when predictors are very strong (a problem known as "complete separation"), leading to infinite coefficients and unreliable standard errors. Bayesian logistic regression solves this by applying a prior distribution that acts as a stabilizer, gently pulling coefficients towards realistic values and ensuring the math remains robust.

Results and Interpretation

The Champion Model achieved a **92.3% accuracy** on the test data, correctly classifying the voting outcome for **12 out of the 13 states** in the testing set.

Table 1: Champion Model Results (Bayesian Logistic Regression)

Predictor Variable	Coefficient	P-Value	Significance
(Intercept)	3.845	0.575	
Gun Ownership (%)	-0.119	**0.027**	*
Median Household Income	$5.12e^{-5}$	0.356	
AA COVID Death Rate	-0.012	0.160	
Test Set Accuracy	*92.3%*	**(12/13 Correct)*	

As seen in Table 1, Gun Ownership was the primary driver of the model and the only statistically significant variable at the $\alpha = 0.05$ level ($p = 0.027$). The coefficient for gun ownership is negative (-0.119), indicating a strong inverse relationship with voting Democrat. Specifically, the odds ratio suggests that for every 1% increase in a state's gun ownership, the odds of that state voting Democrat decrease by approximately 11.2%. This magnitude identifies cultural identity as a massive divider in the current political landscape.

While Median Household Income ($p = 0.356$) and AA COVID Death Rate ($p = 0.160$) yielded p-values above the traditional 0.05 threshold, their inclusion was essential for the model's predictive power. In small datasets, variables that overlap (multicollinearity) often split the statistical "credit," causing their individual p-values to rise. However, without these variables, the model lacks the nuance to identify "swing" states. Income helps distinguish wealthy suburban areas (which may lean Democrat despite moderate gun ownership), while COVID rates likely help identify specific regional voting patterns in the South.

Comparison with Alternative Models

To confirm the necessity of our three-variable approach, we tested simpler models using traditional Forward Selection methods, which prioritized single variables like Income or Commuting methods.

Table 2: Comparison Model Results (Income Only)

Predictor Variable	Coefficient	P-Value	Accuracy
(Intercept)	−15.88	0.001	
Median Household Income	0.0002	0.001	
Test Set Accuracy	*76.9%*	*(10/13 Correct)*	

As shown in Table 2, a model relying solely on *Median Household Income* was statistically significant ($p < 0.01$) but failed to capture the full picture. This "Money Only" model achieved an accuracy of only *76.9%* on the test data. The drop in accuracy from 92.3% to 76.9% demonstrates that economic factors alone are insufficient to explain the 2024 election. The "Culture" variable (Guns) and "Regional" variable (COVID) provided the critical context needed to correctly predict the final 15% of states.

Contributions:

Jaime Valencia Lopez: Wrote 21_DataProcessing.Rmd (merged the first four datasets and added the descriptions), 22_DataCleaning.Rmd (all code and descriptions), 01_funct_DataCleaning.R, FinalReport (excluding vizualizations) and README.md.

Evan Silzle: Wrote 02_func_PLots.r, Helped contribute to data cleaning process by merging a set of simple data sets manually, loading and cleaning them, then merging them with the main data set, as well as some cleaning of the merged data frame. Created and analyzed comparative data visualizations using loops and functions: two scatterplots, six related pie charts, and four related bar graphs.

Sumukh Chanda: Helped contribute to the idea and worked on the data visualization models.