Classification EDA

2024-07-30

Set-Up

To run code set `eval = TRUE`, to not run code when knitting set `eval = FALSE`.

```
train <- read_csv("Data/train_class.csv")
```

```
## Rows: 2331 Columns: 126
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (2): winner, name
## dbl (124): id, total_votes, x0001e, x0002e, x0003e, x0005e, x0006e, x0007e, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
test <- read_csv("Data/test_class.csv")
```

```
## Rows: 780 Columns: 124
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (124): id, total_votes, x0001e, x0002e, x0003e, x0005e, x0006e, x0007e, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Takeaways

Summary

The most important takeaways are: - We need to deal with incomplete rows, as data on income/GDP is not available for every county - Like with the regression data, we need to deal with interaction effects within the data - May be a good idea to use log transformation on some data (e.g. `total_votes`) - As we can see in the graphs some of the data is skewed - E.g. Biden has a disproportional amount of votes in most urban counties compared to the bars

Feature Groups

After looking at the CSVs, I noticed that like with the regression project data, a lot of the features can be grouped together in as demographics. Each column represents the total population of each sub-demographic.For instance, there are several features that represent the total population of certain age ranges, income levels, etc. Furthermore, like with the regression project, we may need to check for interaction effects of these columns. Here are all of the columns that can be grouped together:

Columns	Demographic Category (in total pop.)
x0002E:x0003E	Represents total population of men and women respectively

Columns	Demographic Category (in total pop.)
x0005E:x0017E	Represents age range with each column being 5 year intervals
x0019E:x0024E*	Represents population above certain ages (e.g. > 18, > 21, etc.)
x0025E:x0031E**	Represents population above certain ages per gender (e.g. >18 men, > 18 women, etc.)
x0034E:x0057E	Racial and ethnicity demographics
x0058E:x0069E	Multiracial combination demographics
x0071E:x0075E	Demographics of Hispanic or Latino
x0076E:x0085E	Demographics of Non-Hispanic or Latino Races
x0087E:0089E	Citizens
C01_001E:C01_027E	Education levels of certain age groups (e.g. Bachelor's 18-24, High school graduates 25-34, etc.)
income_per_cap_2016:income_per_cap_2020	income per capita for county in year
gdp_2016:gdp_2020	GDP for the county in year

If this data is anything like the data in the regression project, then we'll need to account for interaction effects. Also I realized all of these columns are actually lower case in the dataset but was capitalized in the `col_descriptions.csv` file, so in the actual code just de-captalize the column names.

Note that some columns seem similar if not identical to other columns. for instance, `x0021E` and `x0024E`are both populations of 18 and over, however `x0021E` should be grouped within its category while `x0024E` appears to be the total of `x0026E` and `x0027E`. Perhaps these duplicates can be deleted to avoid linear dependency. Moreover, some categories may be unnecessary and all those columns can be dropped altogether. For instance, I don't see how `x0019E:x0024E` would be useful especially when we already have age data. It's possible it may be a powerful feature, but it's something worth considering in my opinion.

The education-related columsn are weird. We have age ranges of education as well as general age floors (e.g. we have the data of 25-34 year olds with bachelor's as well as how total population of those >25 with a bachelor's). Moreover, information regarding associate's and graduate/professional degrees is inconsistent. We only have that specific level of information for the population of those 25 and older, we don't know the information regarding other groups (e.g. we don't know how many 35-44 year olds specifically have an associate's, only high school or bachelor's).

Data regarding income and GDP is missing for some counties, so this **must** be accounted for. Some ways to deal with this include but are not limited to: - Somehow extrapolate data for incomplete rows - Drop those rows completely Also, it's possible these rows could have high interaction effects as well, so there's a chance we may only need one of these categories.

Not every column groups are necessarily consecutively numbered. For instance, there does not exist `x0004E` or `x0032E`. Also, some columns are standalone features that can't be grouped into categories. Here are these columns:

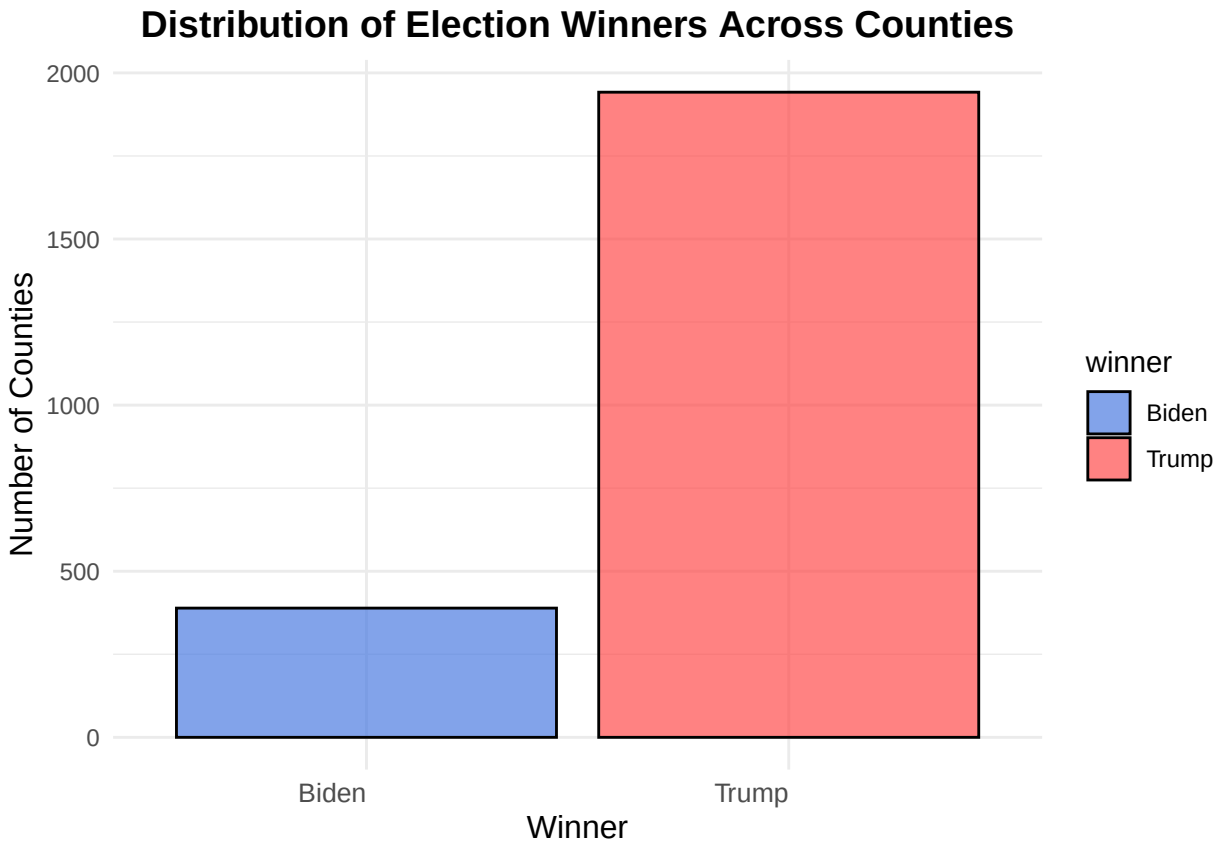
Columns | Column Dsecription (in total pop.)|
id | not a predictor |
winner | Biden or Trump |
total_votes | total votes |
name of county | not a predictor or in test set |
x0001E | Total population |
x0018E | Median age (years) |
x0033E | Duplicate of x0001E |
x0086E | Total housing units |
x2013_code | urban/rural code used by CDC with 1 being most urban 6 being most rural|

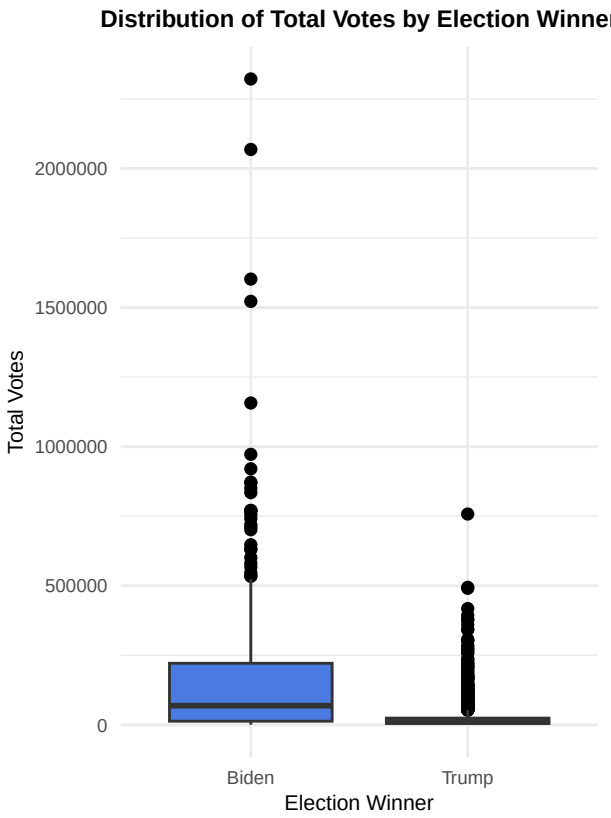
Correlation Matrix

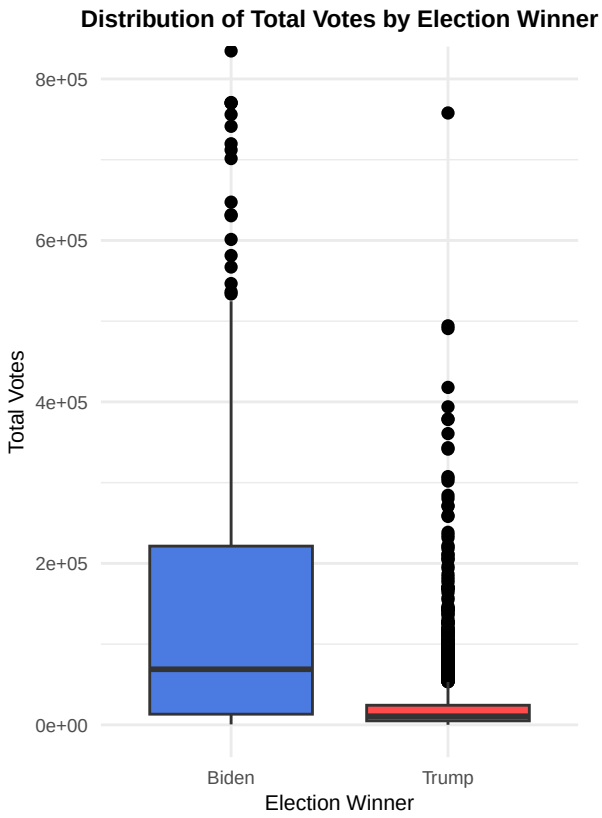
TODO: cells regarding income/GDP are NA because there is missing data, need to remake correlation matrix to account for this

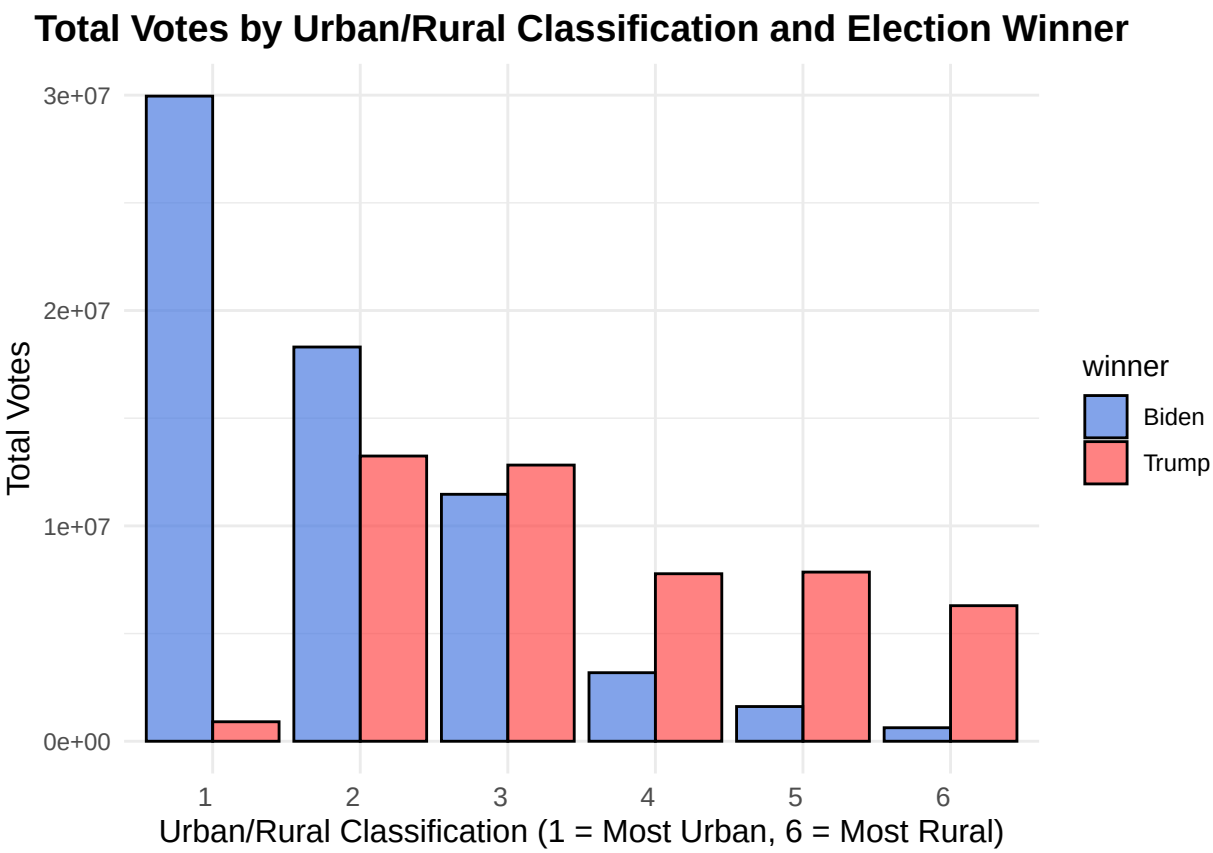
```
# First create correlation matrix to see which variables are highly correlated with each other
# Because there's so many features and so many cells (127^2 to be exact), I decided to save the matrix

cor_mx <-
  train %>%
    select_if(is.numeric) %>%
    cor()

write.csv(cor_mx, 'cor_mx.csv')
```

Graphs




Distribution of Total Votes by Election Winner
Total Votes
2000000
1500000
1000000
500000
0
Biden
Trump
Election Winner


Distribution of Total Votes by Election Winner
Total Votes
8e+05
6e+05
4e+05
2e+05
0e+00
Biden
Trump
Election Winner


Total Votes by Urban/Rural Classification and Election Winner
Total Votes
3e+07
2e+07
1e+07
0e+00
1
2
3
4
5
6
Urban/Rural Classification (1 = Most Urban, 6 = Most Rural)
winner
Biden
Trump