Analysis on the popular vote of the 2020 American federal election

Yena Joo, Woolim Kim, Guemin Kim

Nov 2, 2020

Predictions on the 2020 US Presidential Election based on the voter survey responses.

Code and data supporting this analysis is available at: https://github.com/Guemin/Problem_Set_3

Model

As the 2020 presidential election of the United States approaches, people across the world are interested in to which candidate the vote of the US citizens will be concentrated, either to Donald Trump or to Joe Biden. Since the election outcome will also affect our community in Canada, we are going to analyze and predict the winner of the popular vote in the 2020 American federal election.
Using the survey and census data obtained from Democracy Fund + UCLA Nationscape and IPUMS USA, we are going to predict the popular vote outcome of the election. To be more specific, we are going to use two logistic regression models, one for each candidate, and employ a post-stratification technique[1] with the models.
In the following sub-sections, we will describe the model specifics, the post-stratification calculation, and the result of the analysis.

Model specifics

As already mentioned, we will be using the logistic regression models and post-stratification technique with R software to predict the proportions of voters who will vote for either Donald Trump or Joe Biden. Specifically, we will create two models, each for proportions of voters for Trump or Biden, using 6 different variables(age_group, gender, race, education, household_income , and state)[2].

Since our response variables, vote_Trump and vote_Biden, are binary(either 'vote for' or 'not vote/not sure'), the logistic regression model is a suitable model to be used. Logistic regression is a mathematical model used to estimate the probability of an event occurring using binary data.
The logistic regression models we are using are:

$$log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 x_{age\ group} + \beta_2 x_{gender} + \beta_3 x_{race} + \beta_4 x_{education} + \beta_5 x_{household\ income} + \beta_6 x_{state}$$

[1]Post-stratification is a technique used in sample survey design to improve the quality of population estimates. In the post-stratification analysis, the population is partitioned into subgroups, and estimates are predicted within the subgroups. Then, the sum of the estimate times the respective population size in each group is calculated, and finally, it is divided by the sum of the total population size. Detailed procedures on post-stratification for our analysis will be shown in the following sub-sections.

[2]* age_group is divided into 4 different groups: "18-29 year olds", "30-44 year olds", "45-64 year olds", "65 years and older".
* gender indicates either "Male" or "Female".
* race is divided into 5 different categories: "White", "Black", "Native", "Asian", "Other".
* education is divided into 4 different categories: "Didn't graduate from high school", "High school graduate", "Some college or associate degree", "Bachelor's degree or higher".
* household income consists of 9 categories range from "Less than $14,999" to "$150,000 and over".
* state indicates abbreviated names of 52 states in the US.

Table 1: VIF models

model_trump_predictor	VIF	model_biden_predictor	VIF
age_group	1.210003	age_group	1.246368
gender	1.068826	gender	1.072452
race	1.240050	race	1.353103
education	1.477839	education	1.452881
household_income	1.555977	household_income	1.564889
state	1.468859	state	1.461147

where $log(\frac{p_i}{1-p_i})$ represents log odds in each model, and p_i is the proportion of voters who will vote for Donald trump or Joe Biden. Similarly, β_0 represents the intercept, and $\beta_1, \ldots, \beta_6$ indicate the slope parameters of the model. (Detailed descriptions on the x variables can be found in the footnote[3]).

model diagnostics

With the logistic regression models we created above, we are going to study diagnostics of the models. First, we need to keep in mind that logistic regressions are well performed under the following assumptions:
1. linearity between the log odds and the predictor variables
(independent variables should be linearly related to the log odds)
2. Binary logistic regression requires the response variable to be binary.
3. large sample size
4. multicollinearity among predictors is not too high
(predictor variables should be independent to each other)

In our models, we do not need to worry about the violation of the first assumption since all of our predictor variables are categorical; hence, categorization of the independent variables is not neccessary.
Similarly, since our reponse variables, vote_trump and vote_biden are binary, and the size of the survey data is large enough, we can confirm that the second and the thrid assumptions are also satisfied.
Now, we want to check if the multicollinearity among predictor variables is not too high. This can be done by calculating the variance inflation factor(VIF) for each predictor variable, which measures the amount of multicollinearity in a set of multiple regression variables; the bigger the VIF, the bigger the multicollinearity is. When the variance inflation factor is greater than 5, the corresponding predictor is said to be highly correlated with other predictors. Here are the values of variance inflation factors for predictors in each model:

As shown above, VIF values do not exceed 2 for both models for Trump and Biden, which suggest that there is no sign of multicollinearity among predictors. Therefore, it is safe to say that the last assumption is also satisfied.

Model content

Prior to the modelings, we mutated variables in the survey data to create new variables that could be used in the analysis. Our response variables, vote_trump and vote_biden are also mutated from a variable named "vote_2020", which provides a name of a candidate that the respondent supports[4]. Also, the predictor variables, age_group, gender, race, education, household_income and state are mutated in the data cleaning process so that the categories in each variable in the survey data match with those in the census data.
Since only those who are 18 years old or older are eligible to vote, we removed the observations obtained

[3]* $x_{age\ group}$ represents one of the four age groups that the respondent is in.
* x_{gender} indicates the gender of the respondent(either "Male" or "Female").
* x_{race} indicates the race ethnicity of the respondent.
* $x_{education}$ indicates the education attainment of the respondent.
* $x_{household\ income}$ indicates the total pre-tax income of the respondent's household.
* x_{state} indicates the state in which the respondent is located.

[4]vote_trump is 1 when vote_2020 is "Donald Trump", and 0 otherwise; vote_biden is 1 when vote_2020 is "Joe Biden", and 0 otherwise.

from the respondents who are younger than 18 years old in the data cleaning process. Similarly, we removed the observations of respondents who answered "No, I am not eligible to vote" as vote_intention, since their responses to vote_trump and vote_biden will not count in the actual election. Also, we removed people who are "less than 1 year old" or "90 (90+ in 1980 and 1990)" since their responses are unrealistc or not necessary in our analysis.

Post-Stratification

- Any decisions that your group made should be explained and justified. (For example, are you looking at the proportion of people voting for Trump or Biden? why did you exclude sex in the cell split (practical explanations are acceptable)? etc.)

Using the log odds estimates, we are going to find vote_Trump and vote_Biden (the proportions of voters each for Donald Trump and Joe Biden) in every possible combinations of categories in our predictor variables, age_group, gender, race, education, household income, and state.

In order to estimate the proportions of voters for both Donald Trump and Joe Biden, we are going to perform a post-stratification analysis. In order to use this technique, we need to subdivide the population having similar characteristics into cells. Hence, we are going to create a total of 55,325 cells based on different age groups, gender, race-ethnicity, education attainment, household income, and state.
Using the logistic regression models presented in the previous sub-section, we will estimate the proportions of voters in each cell for each candidate. Then, we will weight each estimate within each cell by the respective population size of the cell, and sum those values, and divide that by the entire population size. This process can also be described by the expression:

$$\hat{y}^{ps} = \frac{\sum N_j * \hat{y_j}}{\sum N_j}$$

where $\hat{y_j}$ is the estimate of the probability of voting for either Trump or Biden in each cell, and N_j is the population size of the j^{th} cell based off demographics.

reason for Choice of the variables...

Results

Here you will include all results. This includes descriptive statistics, graphs, figures, tables, and model results. Please ensure that everything is well formatted and in a report style. You must also provide an explanation of the results in this section.

Please ensure that everything is well labelled. So if you have multiple histograms and plots, calling them Figure 1, 2, 3, etc. and referencing them as Figure 1, Figure 2, etc. in your report will be expected. The reader should not get lost in a sea of information. Make sure to have the results be clean, well formatted and digestible.

In the previous sub-sections, we have created the logistic regression models on proportions of voters voting for Donald Trump and Joe Biden with 6 different following variables: age_group, gender, race, education, household_income, and state. Based off the post-stratification analysis we made, our estimation of the proportion of voters voting for Donald Trump is <0.433> and Joe Biden to be <0.394>. From the result of our estimations, We can predict that Donald Trump is more likely to win the popular vote in the 2020 American federal election.

```
## # A tibble: 70 x 5
##    term                                    estimate std.error statistic  p.value
##    <chr>                                      <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept)                               -0.707    0.741     -0.954 3.40e- 1
##  2 as.factor(age_group)30-44 year olds        0.575    0.0950     6.05  1.43e- 9
##  3 as.factor(age_group)45-64 year olds        0.743    0.0940     7.91  2.59e-15
##  4 as.factor(age_group)65 years and older     0.782    0.108      7.25  4.10e-13
```

Table 2: Comparison of predicted estimate between Trump and Biden

total_predict_trump	total_predict_biden
0.4334444	0.3944298

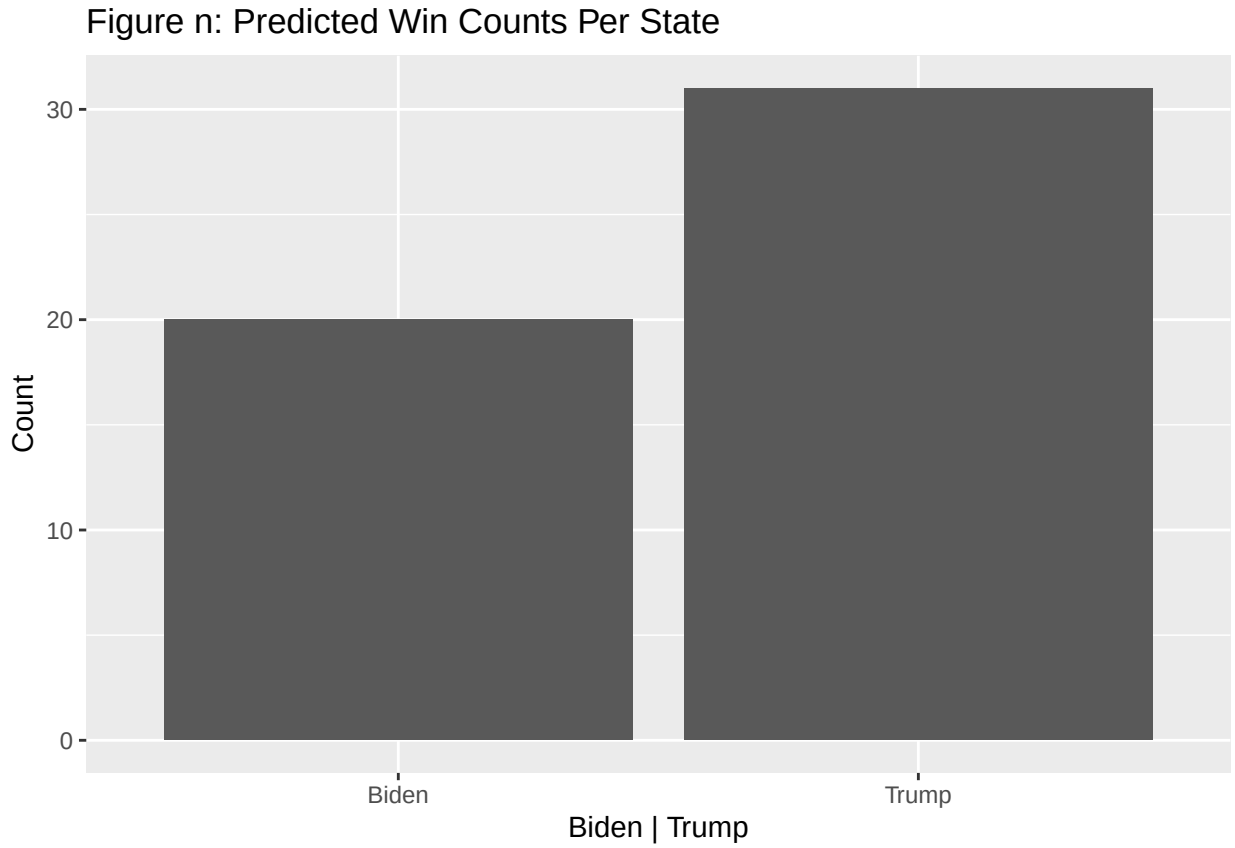
```
##  5 as.factor(gender)Male                     0.422    0.0612     6.90  5.25e-12
##  6 as.factor(race)Black                     -1.42     0.209     -6.79  1.12e-11
##  7 as.factor(race)Native                     0.483    0.285      1.70  8.99e- 2
##  8 as.factor(race)Other                     -0.132    0.200     -0.661 5.08e- 1
##  9 as.factor(race)White                      0.589    0.160      3.68  2.37e- 4
## 10 as.factor(education)Didn't graduate fr~    0.357    0.119      3.01  2.61e- 3
## # ... with 60 more rows
```

```
## # A tibble: 70 x 5
##    term                                estimate std.error statistic    p.value
##    <chr>                                  <dbl>     <dbl>     <dbl>      <dbl>
##  1 (Intercept)                         -0.418      0.839    -0.498     6.18e-1
##  2 as.factor(age_group)30-44 year olds -0.200      0.0856   -2.34      1.93e-2
##  3 as.factor(age_group)45-64 year olds -0.287      0.0855   -3.35      8.01e-4
##  4 as.factor(age_group)65 years and old~ -0.125    0.101    -1.24      2.14e-1
##  5 as.factor(gender)Male               -0.302      0.0592   -5.11      3.27e-7
##  6 as.factor(race)Black                 0.999      0.166     6.03      1.67e-9
##  7 as.factor(race)Native               -0.442      0.278    -1.59      1.12e-1
##  8 as.factor(race)Other                 0.00339    0.173     0.0196    9.84e-1
##  9 as.factor(race)White                -0.449      0.143    -3.14      1.66e-3
## 10 as.factor(education)Didn't graduate ~ -0.667    0.114    -5.86      4.61e-9
## # ... with 60 more rows
```

- individuals with household_income "less than $14,999" are more likely to vote for Biden over Trump (due to Biden's election promises for lower income people?)
- state: **idk**
  Using the estimate proportion grouped by states, ...

```
## [1] 31
```

```
## [1] 20
```



Under the assumption that whoever gets a higher expected proportion for each state wins in that state, Trump is expected to win in 31 states, and Biden is expected to win in 20 states. Both Figure x and Figure y show that Donald Trump has a higher possibility to win the election.

Discussion

Here you will summarize the previous sections and discuss conclusions drawn from the results. Make sure to elaborate and connect your analysis to the goal of the study.

Using the survey and census data obtained from Democracy Fund + UCLA Nationscape and IPUMS USA, we have predicted the popular vote outcome of the 2020 president election in USA. Logistic Regression is used to predict who is more likely to be elected for the 2020 presidential election. Explanatory variables used for the logistic regression model are age_group, gender, race, education, household_income, and state. Then, $\hat{y}^{ps}$ is measured using post-stratification technique to estimate the proportion of voters in favor of voting for each candidate.
- By using the post stratification, we created 55,325 cells based on the 6 variables that was used in the model, and found the probability of voting estimates for each cells. - Then we grouped each cell estimates into states and predicted who is expected to have more - The result shows that estimate value for proportion of voters voting for Joe Biden is 39.4% and Donald Trump 43.34%. Also Trump is ahead of Biden by 21 counts in estimate for each state. - *discuss about the result*

To conclude, based off the estimated proportion of voters in favor of voting for Donald Trump being 0.4334 (43.34%) and expected to win 31 states, we predict that Trump will win the 2020 president election. (. . . . .)

Weaknesses

Here we discuss weaknesses of the study, data, analysis, etc. You can also discuss areas for improvement. 1. Weakness: Some variables could not be included in the generalized logistic model because either census data or survey data did not include the particular variables. If there is an important variable that could have affected the vote outcome, there might exist an omitted variable bias. (The omitted variables should be correlated with the dependent variable and with the explanatory variables included in the model).

- the Census data used in the analysis is 2018 data, so it might not reflect the most accurate vote outcome. 2020 data is more suitable to analyze more accurate results. Also, people who were underage in 2016, hence not included in the estimate would have the right to vote in 2020.

Next Steps

Here you discuss subsequent work to be done after this report. This can include next steps in terms of statistical analysis (perhaps there is a more efficient algorithm available, or perhaps there is a caveat in the data that would allow for some new technique). Future steps should also be specified in terms of the study setting (eg. including a follow-up survey on something, or a subsequent study that would complement the conclusions of your report).

- With the 2020 census data, we could estimate the proportion of voting for each candidate by state and estimate the winner of each state which would make a more reasonable and realistic prediction of the election.

- Create visualization of the results to view the groups of the voting estimates at once.

- In our future analysis, we can try to analyze the multilevel regression models using Bayes coding techniques.

- We can compare our prediction and the result of the actual 2020 president election.
  (something about comparing with the actual election results and do a post-hoc analysis (or at least a survey) of how to better improve estimation in future elections.)

References

1. Survey data: https://www.voterstudygroup.org/downloads?key=9337162e-e5ef-49d7-96fd-48a5c5dba31c
2. Census data: https://usa.ipums.org/usa-action/extract_requests/summary?
3. Post-Stratification technique: https://www.microsoft.com/en-us/research/wp-content/uploads/2016/04/forecasting-with-nonrepresentative-polls.pdf
4. Logit Regression Assumptions source 1: https://rpubs.com/guptadeepak/logit-assumptions
5. Logit Regression Assumptions source 2: https://www.statisticssolutions.com/wp-content/uploads/wp-post-to-pdf-enhanced-cache/1/assumptions-of-logistic-regression.pdf
6. Variance Inflation Factor(VIF): https://www.statisticshowto.com/variance-inflation-factor/
7. Tables side by side: https://bookdown.org/yihui/rmarkdown-cookbook/kable.html

#Appendix

state	predict_trump2	state	predict_biden2
AK	0.6178175	AK	0.2121776
AL	0.5294578	AL	0.3429311
AR	0.5690489	AR	0.2163157
AZ	0.4970620	AZ	0.3532261
CA	0.3500102	CA	0.4605909
CO	0.4748248	CO	0.3723088
CT	0.2840064	CT	0.5343268
DC	0.2715509	DC	0.7314580
DE	0.3901171	DE	0.5308874
FL	0.4677497	FL	0.3841190
GA	0.4716816	GA	0.3827232
HI	0.3371692	HI	0.5260513
IA	0.4501696	IA	0.3894466
ID	0.6617140	ID	0.2276048
IL	0.4152228	IL	0.3984838
IN	0.4497127	IN	0.3483643
KS	0.5724607	KS	0.2903427
KY	0.4997506	KY	0.4122667
LA	0.4574786	LA	0.4197140
MA	0.2894075	MA	0.5138926
MD	0.3519287	MD	0.4938823
ME	0.4062306	ME	0.4861133
MI	0.4074363	MI	0.4562030
MN	0.4807777	MN	0.4625594
MO	0.4489350	MO	0.3787824
MS	0.4849136	MS	0.3758363
MT	0.5407824	MT	0.3513251
NC	0.4647314	NC	0.4126773
ND	0.5234047	ND	0.1747900
NE	0.4228730	NE	0.3367801
NH	0.4164238	NH	0.4753414
NJ	0.4045109	NJ	0.4240766
NM	0.2288712	NM	0.5074545
NV	0.5159548	NV	0.3375036
NY	0.3888962	NY	0.4355101
OH	0.4457807	OH	0.3743578
OK	0.4921180	OK	0.2217403
OR	0.4084833	OR	0.4259771
PA	0.4706141	PA	0.3096477
RI	0.3574909	RI	0.4515775
SC	0.5061444	SC	0.2786692
SD	0.5185028	SD	0.3387865
TN	0.5126872	TN	0.2784533
TX	0.5087421	TX	0.3048833
UT	0.4055765	UT	0.2632457
VA	0.3846518	VA	0.4476426
VT	0.1026603	VT	0.7455384
WA	0.3766525	WA	0.4615358
WI	0.3970139	WI	0.4124047
WV	0.5386586	WV	0.3194931
WY	0.1878584	WY	0.2659662

Table 3: Figure n

household_income	predict_trump	household_income	predict_biden
$100,000 to $149,999	0.4788905	$100,000 to $149,999	0.3644576
$15,000 to $24,999	0.3819243	$15,000 to $24,999	0.4089684
$150,000 and over	0.5013108	$150,000 and over	0.3746106
$25,000 to $34,999	0.3917869	$25,000 to $34,999	0.3918452
$35,000 to $44,999	0.4036812	$35,000 to $44,999	0.4117412
$45,000 to $54,999	0.4363749	$45,000 to $54,999	0.3898337
$55,000 to $74,999	0.4219549	$55,000 to $74,999	0.4162607
$75,000 to $99,999	0.4191757	$75,000 to $99,999	0.4305907
Less than $14,999	0.3219549	Less than $14,999	0.3930797