Monte Carlo Presidency

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This is a mini-project for finding the distribution of electoral college votes.

Simulated polling data will be based on the 2024 election results proportions and taking a random n=1 sample for each state from standard normal distribution. That will then be transformed into a simulated proportion. The simulated sample sizes will be calculated by dividing the total vote count of each state by ten thousand.

Polling data where sample sizes of $n > 30$ for each state would be the appropriate methodology. In that case the CLT would apply to the mean of proportions for each state. That would give it a normal distribution for each state where a Monte Carlo simulation could be applied. Both Independence among states and dependence among states will be applied.

```
##        State Elec_votes   Trump  Harris REPUBLICANPERCENTAGE
## 1    Alabama          9 1462616  772412            0.6544061
## 2     Alaska          3  184458  140026            0.5684656
## 3    Arizona         11 1770242 1582860            0.5279416
## 4   Arkansas          6  759241  396905            0.6566999
## 5 California         54 6081697 9276179            0.3959986
## 6   Colorado         10 1377441 1728159            0.4435346
```

```
## # A tibble: 6 x 5
##   State      Elec_votes REPUBLICANPERCENTAGE simulated_sample_size
##   <chr>           <dbl>                <dbl>                 <dbl>
## 1 Alabama             9                0.654                   224
## 2 Alaska              3                0.568                    32
## 3 Arizona            11                0.528                   335
## 4 Arkansas            6                0.657                   116
## 5 California         54                0.396                  1536
## 6 Colorado           10                0.444                   311
##   simulated_proportion
##                  <dbl>
## 1                0.635
## 2                0.585
## 3                0.505
## 4                0.727
## 5                0.400
## 6                0.420
```

This is the simulated sample proportions from the results of the 2024 election and is statistical accurate in theory of what could happen in polling. In reality you would need to account for “dropout”, providing false information, unaccounted variable, etc.

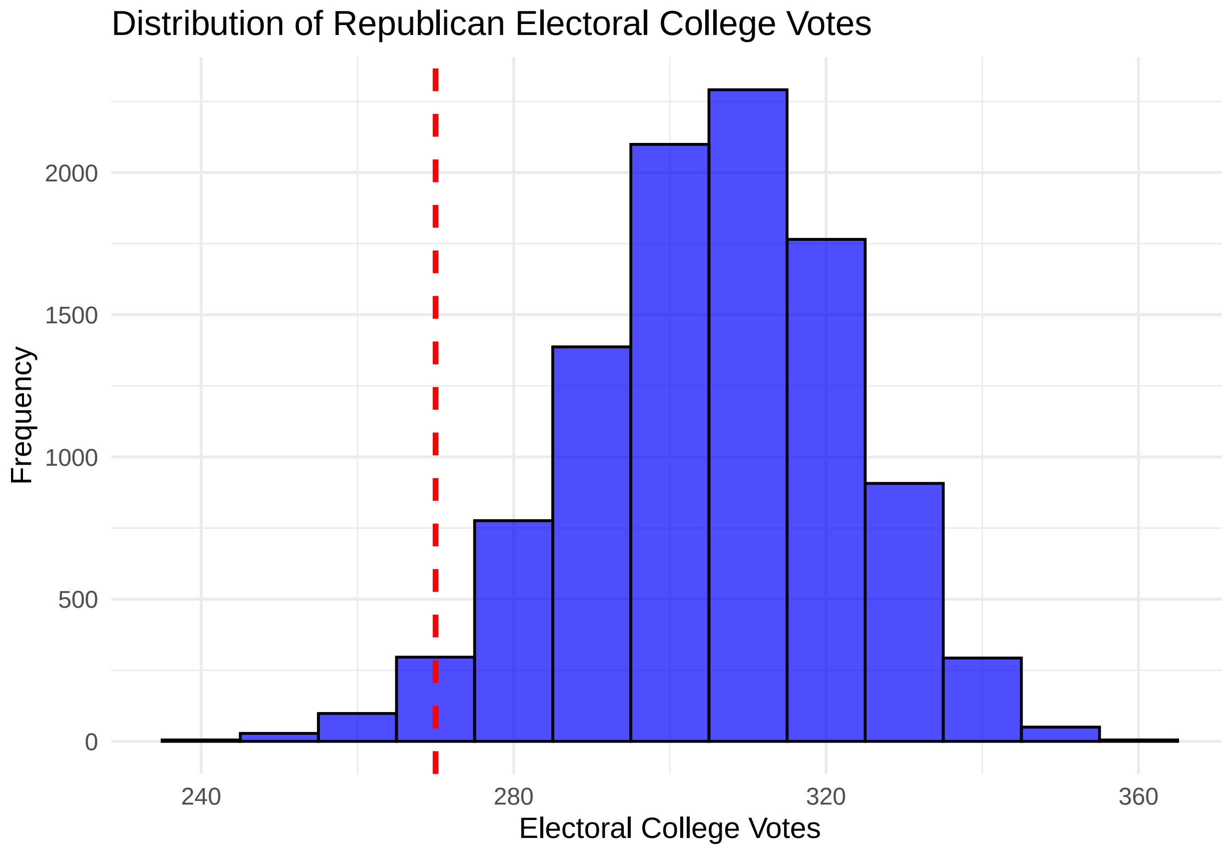
Dropout: In reality not everyone that is polled and says they are going to vote actually votes. This fact will need accounted for and if possibly modeled for.

Unaccounted variables: could mean a lot of different things that will need to be tried and tested, such as subgroups, economic factors, and so much more that may not be accounted for .

Assumed Independence among States

This method creates a univariate normal distribution for all states with the simulated means and their variances.

```r
# Monte Carlo simulation
set.seed(1)
n_simulations <- 10000


simulation_results <- replicate(n_simulations, {
  simulated_values <- pmin(pmax(rnorm(nrow(sim_data), mean = sim_data$simulated_proportion,
                                      sd = sqrt(sim_data$variance)), 0), 1)

  total_electoral_votes <- sum(sim_data$Elec_votes[simulated_values > 0.5])

  return(total_electoral_votes)
})

simulation_df <- data.frame(total_electoral_votes = simulation_results)



ggplot(simulation_df, aes(x = total_electoral_votes)) +
  geom_histogram(binwidth = 10, fill = "blue", color = "black", alpha = 0.7) +
   geom_vline(xintercept = 270, color = "red", linetype = "dashed", size = 1) +
  labs(
    title = "Distribution of Republican Electoral College Votes",
    x = "Electoral College Votes",
    y = "Frequency"
  ) +
  theme_minimal()
```



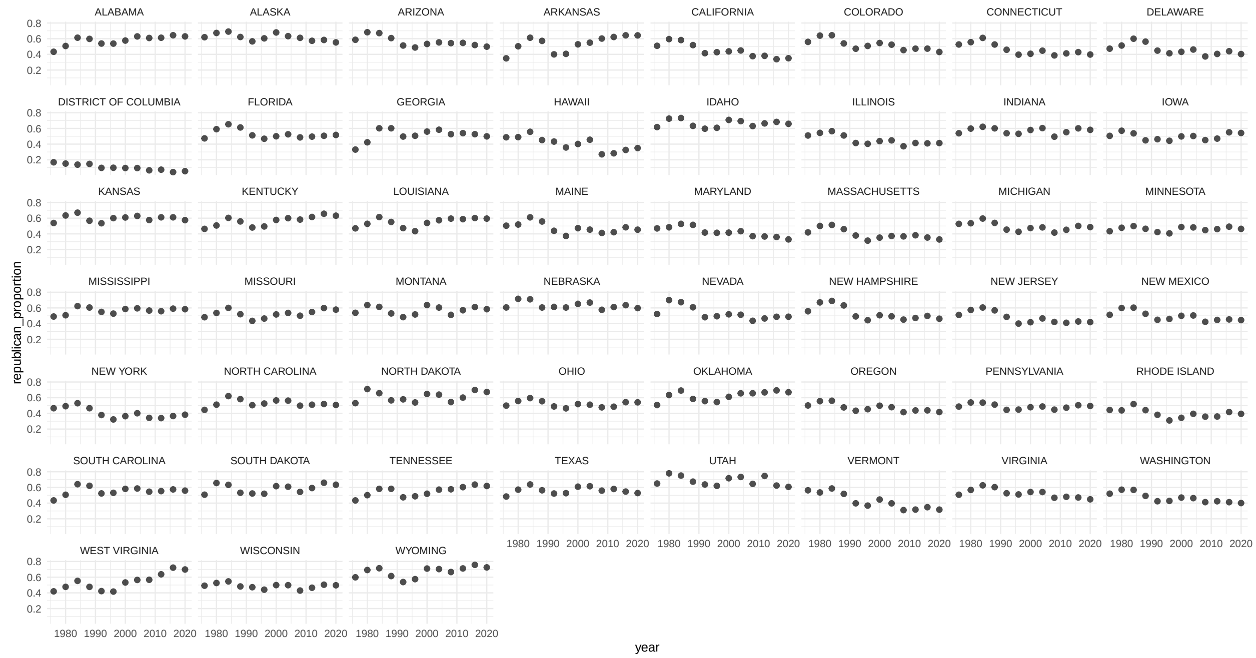

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   235.0   295.0   307.0   306.1   318.0   364.0
```

```
## [1] 0.0235
```

This simulation shows Trump winning Harris winning the presidency 2.35%.

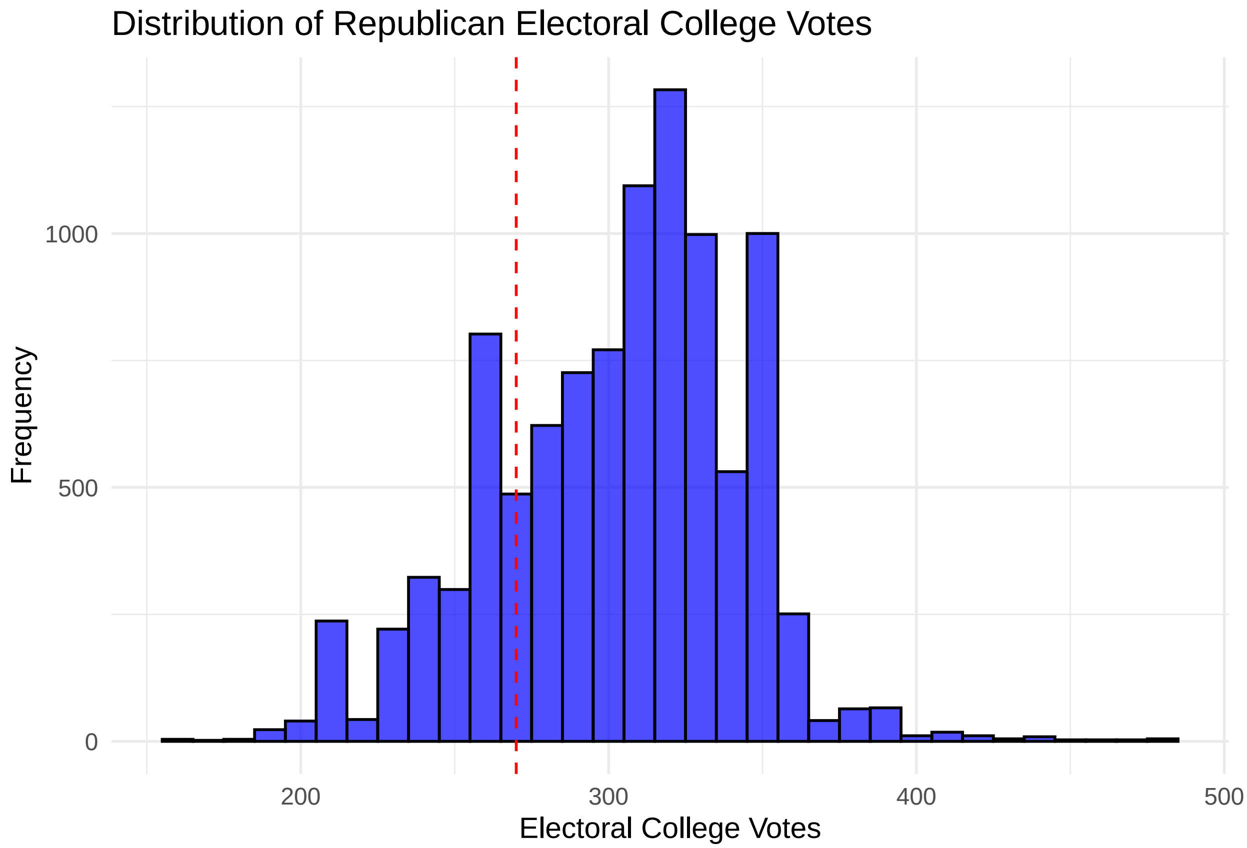
Assumed Dependence Among States

This method creates a multivariate normal distribution with the means of simulation proportion and a covariance matrix of past elections proportions. A Monte Carlo simulation is then conducted with this distribution.



Lets choose the past four elections for our covariance matrix

```r
# Monte Carlo simulation
library(MASS)

set.seed(1)
n_simulations <- 10000

simulation_results <- replicate(n_simulations, {
  # multivariate normal distribution
  simulated_proportions <- mvrnorm(1, mu = sim_data$simulated_proportion, Sigma = cov_matrix)

  simulated_proportions <- pmin(pmax(simulated_proportions, 0), 1)

  total_electoral_votes <- sum(sim_data$Elec_votes[simulated_proportions > 0.5])

  return(total_electoral_votes)
})

simulation_df <- data.frame(total_electoral_votes = simulation_results)


library(ggplot2)
ggplot(simulation_df, aes(x = total_electoral_votes)) +
  geom_histogram(binwidth = 10, fill = "blue", color = "black", alpha = 0.7) +
   geom_vline(xintercept = 270, color = "red", linetype = "dashed") +
  labs(
    title = "Distribution of Republican Electoral College Votes",
    x = "Electoral College Votes",
    y = "Frequency"
  ) +
  theme_minimal()
```




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   155.0   277.0   309.0   303.3   329.0   483.0
```

```
## [1] 0.2183
```

This simulation show Democrats winning 21.83%.

Conclusion

This method of prediction could prove useful but could b improved upon in many ways. * Improvements + Account for other political parties + Accounting for Demographics and other variables + Determine Independence of states and/or improve covariance matrix with more variables + Increase the number of simulations

- Testing and Evaluation
  - The only error that comes from this method happens during the survey process and possibly time since surveys will be cross sectional data.