Gathering Data

Throughout this post, a number of difference libraries will be used as outputs will include plots, maps, and

Loading Libraries

```
library(rvest) #Web-Scraping
library(tidyverse) #Data Cleaning and Plotting
library(janitor) #Data Cleaning
library(sf) #Manipulate Geographic Objects
library(httr) #Used to Download Excel File from Web
library(readxl) #Read in Excel Files
library(kableExtra) #Create HTML Tables
```

Getting the US Population by State in 1790

Data from the 1790 US Census will be gathered from Wikipedia and scraped using the `rvest` package. I from the webpage and then I guessed and checked until I found the table I was looking for (in this case w function converts the HTML table into a data frame and `clean_names()` from the `janitor` package wil

Finally, `stringr::str_remove_all()` will use regular expressions to remove the footnote notation "[convert the character variable with commas into a numeric.

```
us_pop_1790 <- read_html('https://en.wikipedia.org/wiki/1790_United_States_Census') %>%
  html_nodes("table") %>%
  .[[3]] %>%
  html_table() %>%
  clean_names() %>%
  filter(state_or_territory != 'Total') %>%
  transmute(
    state = state_or_territory,
    population_1790 = str_remove_all(total, '\\[.+\\]') %>%
      parse_number(),
    population_percent_1790 = population_1790/sum(population_1790)
  )
```

Getting US Population by State in 2019

A similar process will be used to get the population estimates for 2019 from Wikipedia. In this case there can be used rather than `html_nodes('table')` like in the above code block for 1790.

```
us_pop_2019 <- read_html('https://simple.wikipedia.org/wiki/List_of_U.S._states_by_population')
  html_node('table') %>%
  html_table() %>%
  clean_names() %>%
  filter(!is.na(estimated_population_per_electoral_vote_2019_note_2),
         !estimated_population_per_electoral_vote_2019_note_2 %in% c('', '—')
         rank_in_states_territories_2010 != '—') %>%
  transmute(
    state,
    population_2019 = parse_number(population_estimate_july_1_2019_2),
```

```
    population_percent_2019 = population_2019 / sum(population_2019)
    )
```

Getting # of Electoral Votes for Each State by Year

Finally, the table containing number of electoral votes by state by year will be extracted from Wikipedia. N selecting columns by number in the `dplyr::select()` and `dplyr::rename()` calls. Also, the use of replacement for `mutate_if`, `mutate_at`, and `mutate_all`. Here I tell the `mutate()` to take all variabl `readr::parse_number()` function to them keeping the names the same. We'll use this data set later c

```
electoral_votes <- read_html('https://en.wikipedia.org/wiki/United_States_Electoral_College')
  html_nodes("table") %>%
  .[[5]] %>%
  html_table(fill = T) %>%
  select(2, 4, 36) %>%
  filter(!Electionyear %in% c('Total', 'Electionyear', "State")) %>%
  rename(state = 1, electoral_votes_1792 = 2, electoral_votes_2020 = 3) %>%
  mutate(across(starts_with('electoral_votes'), parse_number))
```

Q1: Do states today represent smaller proportions of the populat Electoral College was formed?

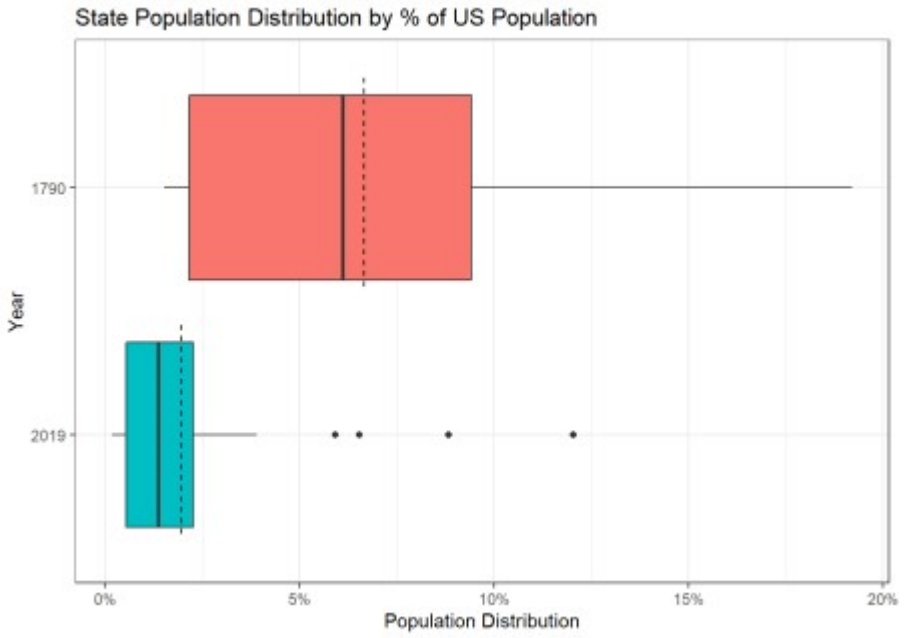
My hypothesis is that the electoral college has become less effective because we've added too many sm and that when the Electoral College was established the population distributions of states were more sim

To check this I'll be comparing the distributions of State populations as a % of the Total US Population for that in the article for the 1790 state population, Maine is given its own row. However, Maine was a part of on "electing blocks" rather than states I will merge Maine into Massachusetts.

For this next code block, I join the two population data sets together and then all numeric variables summ into a long-form data frame. Finally, I extract the numeric year from the variable names and compare the from 1790 and 2019.

```
us_pop_2019 %>%
  left_join(
    us_pop_1790 %>%
      mutate(state = if_else(state == 'Maine', 'Massachusetts', state)) %>%
      group_by(state) %>%
      summarize(across(where(is.numeric), sum)),
    by = "state"
  ) %>%
  pivot_longer(
    cols = c(contains("percent")),
    names_to = "year",
    values_to = "population_dist"
  ) %>%
  mutate(year = str_extract(year, '\\d+') %>% as.integer) %>%
  ggplot(aes(x = fct_rev(factor(year)), y = population_dist,
             fill = factor(year))) +
    geom_boxplot() +
    labs(x = "Year", y = "Population Distribution",
         title = "State Population Distribution by % of US Population") +
    annotate('linerange', y = 1/nrow(us_pop_2019),
```

```
          xmin = .6, xmax = 1.45, lty = 2) +
annotate('linerange', y = 1/(nrow(us_pop_1790)-1),
          xmin = 1.6, xmax = 2.45, lty = 2) +
scale_y_continuous(label = scales::percent_format(accuracy = 1)) +
scale_fill_discrete(guide = F) +
coord_flip() +
theme_bw()
```



In the chart above we're looking at the distribution of states by the % of the total US population they make all states had the same amount. For example, there are 51 "voting bodies" that make up 100% of the US 2.0%. In 1790, the largest state made up 19.2% and the smallest state made up 1.5% of the total populat population and the smallest makes up 0.2% of the total population.

While some of this is due to having more states which means the same 100% is being cut into more piec smaller pieces of the population today than back is to compare the data to those expected values from be on average we'd expected each state to make up 6.7%. And when looking the distribution of the states in This is compared to the distribution in 2019 where 67% are below the expected amount of 2.0%.

When asking whether or not there are more small states in 2019 vs. 1790, I find that 28 of the 51 states (than the minimum state from 1790 [1.5%]. These 28 states make up 141 or 26% of the 538 electoral vote

So while there's not a large difference between actual and expected it does seem that we have a greater when the electoral college was first established based on the concentration that make up less than 1.5%

Q2. How could states be combined to ensure each "voting group threshold?

The fact that 55% of states have a % of 2019 US Population smaller than the smallest percentage in 179 be feasible. So for this exercise, **I'll combine states together in order to ensure that each group has**

Originally I had wanted to come up with a cool algorithm to find the optimal solution to ensure that each s location of the states being combined and the political culture of the states… but alas I couldn't figure out into account geography but completely ignoring how states usually vote. In my new construction the follo

- Alaska & Oregon
- Arkansas & Mississippi

- Connecticut & Rhode Island
- Washington DC, Delaware, and West Virginia
- Hawaii & Nevada
- Iowa & Nebraska
- Idaho, Montana, North Dakota, South Dakota, and Wyoming
- Kansas & Oklahoma
- New Hampshire, Maine, and Vermont
- New Mexico & Utah

```
new_groupings <- us_pop_2019 %>%
  mutate(
    state = if_else(state == 'D.C.', 'District of Columbia', state),
    new_grouping = case_when(
      state %in% c('New Hampshire', 'Maine', 'Vermont') ~ 'NH/ME/VT',
      state %in% c('Rhode Island', 'Connecticut') ~ 'CT/RI',
      state %in% c('West Virginia', 'Delaware', 'District of Columbia') ~
        'DC/DE/WV',
      state %in% c('Alaska', 'Oregon') ~ 'AK/OR',
      state %in% c('Utah', 'New Mexico') ~ 'NM/UT',
      state %in% c('Hawaii', 'Nevada') ~ 'HI/NV',
      state %in% c('Idaho', 'Montana', 'North Dakota',
                   'South Dakota', 'Wyoming') ~ 'ID/MT/ND/SD/WY',
      state %in% c('Iowa', 'Nebraska') ~ 'IA/NE',
      state %in% c('Arkansas', 'Mississippi') ~ 'AR/MS',
      state %in% c('Oklahoma', 'Kansas') ~ 'KS/OK',
      TRUE ~ state
    )
  )
```

To display this brave new world, I will construct a map that shows my new compressed electoral map and
The first step is adding the electoral votes into the data frame constructed in the last code block:

```
new_groupings <- new_groupings %>%
  left_join(
    electoral_votes %>%
      transmute(state = if_else(state == 'D.C.', 'District of Columbia', stat
                electoral_votes_2020),
    by = "state"
  )
```

Next, I need a mechanism to assign a number of electoral votes to my compressed map. Normally, there
members of Congress, the 100 Senators, and 3 additional electoral votes for Washington DC. Since I'm r
maintain the 2 votes per group represented by the Senate allocation and the population allocation from th
this relationship I'm building a quick and dirty linear regression model to predict the population componen

```
electorial_vote_model <- lm(electoral_votes_2020-2 ~ population_2019,
                            data = new_groupings)

electorial_vote_model
##
## Call:
## lm(formula = electoral_votes_2020 - 2 ~ population_2019, data = new_groupi
##
```

```
## Coefficients:
##     (Intercept)  population_2019
##     0.094428506      0.000001313
```

This model shows that there is 1.313 electoral votes per 1 million people.

To visualize what this new electoral map will look map, I will use the `sf` package. While I'm not very famil I've tinkered around with the format before and have found it very compatible with tidy principles.

The first step is getting a shape file. For the United States, I will leverage the `usa_sf` function from the `a` feature. The "laea" represents the projection.

```
usa <-  albersusa::usa_sf("laea") %>% select(name, geometry)

knitr::kable(head(usa))
```

name	geometry
Arizona	MULTIPOLYGON (((-1111066 -8…
Arkansas	MULTIPOLYGON (((557903.1 -1…
California	MULTIPOLYGON (((-1853480 -9…
Colorado	MULTIPOLYGON (((-613452.9 -…
Connecticut	MULTIPOLYGON (((2226838 519…
District of Columbia	MULTIPOLYGON (((1960720 -41…

What makes the magic of the `sf` class is that the shape information is contained in the geometry column, data frame. So for the next step, I'll join the "state groupings" information to this shape file data using the column from the groupings data.

Next, I summarize the data to "combined state groupings" level where I get the sums of the population an parts of this summarize statement are:

- `st_union` which will combine geographic areas from the shape file into new shapes. If you wante boundaries then `st_combine` would be used instead.
- Creating a better label for the combined state names by using `paste` in the summarize with the `cc` aggregation.
- The final mutate step uses the `predict` function to apply the regression model to compute the ne state that wasn't combined retained its original number of votes.

Afterwards, the new data set looks like:

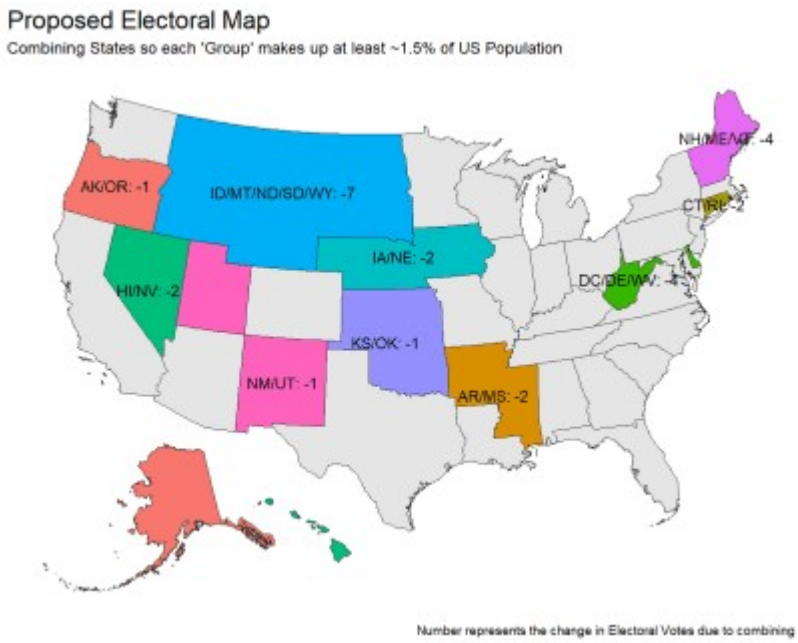
```
new_usa <- usa %>%
  left_join(new_groupings %>%
              transmute(state,
                        new_grouping,
                        population_2019,
                        electoral_votes_2020
                        ),
            by = c("name" = "state")
  ) %>%
  group_by(new_grouping) %>%
  summarize(
    geom = st_union(geometry),
```

```
    population_2019 = sum(population_2019),
    electoral_votes = sum(electoral_votes_2020),
    states = paste(name, collapse = '/')
  ) %>%
  mutate(
    new_ev = if_else(
      states == new_grouping,
      electoral_votes,
      ceiling(predict(electorial_vote_model, newdata = .) + 2)
    ),
    lbl = if_else(new_grouping == states, NA_character_,
                  paste0(new_grouping, ": ", new_ev - electoral_votes)))

knitr::kable(head(new_usa))
```

new_grouping	geom	population_2019	electoral_votes	states
AK/OR	MULTIPOLYGON (((-1899337 -2…	4949282	10	Oregon/Alaska
Alabama	MULTIPOLYGON (((1145349 -15…	4903185	9	Alabama
AR/MS	MULTIPOLYGON (((1052956 -15…	5993974	12	Arkansas/Mississipp
Arizona	MULTIPOLYGON (((-1111066 -8…	7278717	11	Arizona
California	MULTIPOLYGON (((-1853480 -9…	39512223	55	California
Colorado	MULTIPOLYGON (((-613452.9 -…	5758736	9	Colorado

Now we're ready to plot the map. Plotting `sf` geometries work within the `ggplot` paradigm where `geom_` handle the overlays for the given groups. `coord_sf` changes the coordinate system of the plot. And ever

```
new_usa %>%
ggplot() +
  geom_sf(color = "#2b2b2b", size=0.125, aes(fill = lbl)) +
  geom_sf_text(aes(label = lbl), check_overlap = T, size = 3) +
  coord_sf(crs = st_crs("+proj=laea +lat_0=45 +lon_0=-100 +x_0=0 +y_0=0 +a=63
+units=m +no_defs"), datum = NA) +
  scale_fill_discrete(guide = F, na.value = "grey90") +
  labs(title = "Proposed Electoral Map",
       subtitle = "Combining States so each 'Group' makes up at least ~1.5% o
       caption = "Number represents the change in Electoral Votes due to comb
  ggthemes::theme_map() +
  theme(
    plot.title = element_text(size = 14)
  )
```



The states in gray remained unchanged and the filled in states represent our new groupings. The states t
an “electoral grouping” with a newly assigned number of electoral votes. Since the electoral vote model w
electoral votes comes primarily from the loss of the two senate votes for each combined state.

For example, NH/ME/VT originally would have had 11 electoral votes and under the new system will have
combined states 2 senate votes.

Under the normal electoral college there were 538 votes and under this new system that number is reduc

Now that we have our new electoral college, would it have made a difference in 2016?

Q3: Would this new system have impacted the results of the 2016

The 2016 election results between Donald Trump and Hillary Clinton is provided in great detail from the F
to find the number of votes by state in an easily consumable way where I wouldn’t have to recode all the
took some complicated data manipulation.

Since the FEC data comes from an Excel file, I first need to download the file from the FEC website. I’ll u
to a temporary file and then will use `read_excel` from `readxl` to read in the file.

Before data manipulation, but after filtering to just Trump and Clinton, the data looks like.

```
GET("https://www.fec.gov/documents/1890/federalelections2016.xlsx",
    write_disk(tf <- tempfile(fileext = ".xlsx")))
results2016 <- read_excel(tf, sheet = '2016 Pres General Results') %>%
  clean_names() %>%
  filter(last_name %in% c('Trump', 'Clinton')) %>%
  select(state, state_abbreviation, last_name, general_results)

knitr::kable(head(results2016, 5))
```

state	state_abbreviation	last_name	general_results
Alabama	AL	Trump	1318255
Alabama	AL	Clinton	729547
Alaska	AK	Trump	163387

state	state_abbreviation	last_name	general_results
Alaska	AK	Clinton	116454
Arizona	AZ	Trump	1252401

There was a small data quirk with New York state where because the same candidate can appear on mul rows (Clinton appears 4 times and Trump 3). Therefore a first group-by is done to make the data 2 rows p electoral votes are added back and allocated to the winning candidate (technically this is wrong since Nel but its close enough for this exercise).

Then the data is aggregated to the new electoral groupings from the prior section and our “new” electoral candidate.

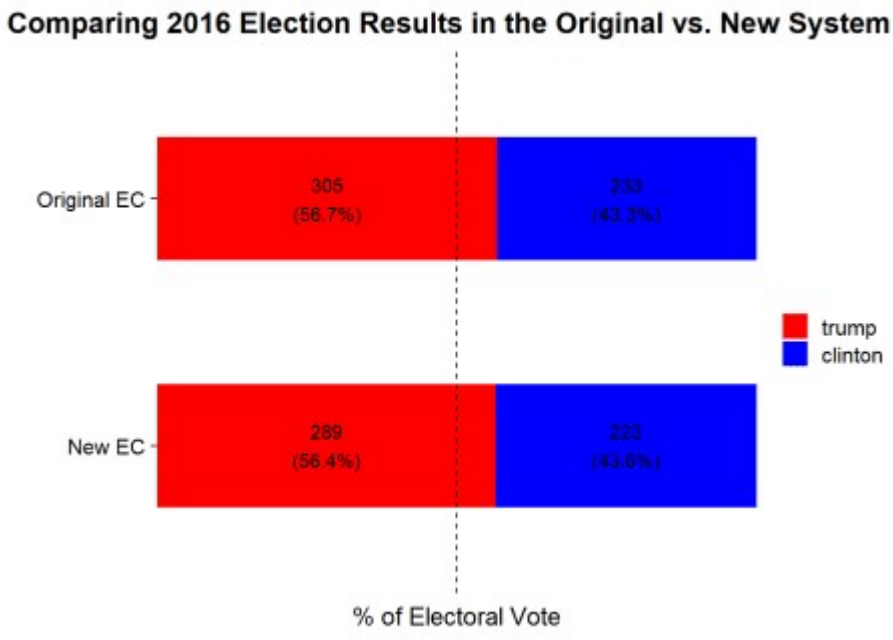
```
results2016 <- results2016 %>%
  group_by(state, state_abbreviation, last_name) %>%
  summarize(general_results = sum(general_results, na.rm = T),
            .groups = 'drop') %>%
  pivot_wider(
    names_from = "last_name",
    values_from = "general_results"
  ) %>%
  left_join(
    new_groupings %>%
      select(state, new_grouping, electoral_votes_2020, population_2019),
    by = "state"
  ) %>%
  mutate(trump_ev = (Trump > Clinton)*electoral_votes_2020,
         clinton_ev = (Clinton > Trump)*electoral_votes_2020
  ) %>%
  group_by(new_grouping) %>%
  summarize(across(where(is.numeric), sum, na.rm = T),
            states = paste(state, collapse = '/')) %>%
  mutate(new_ev = if_else(
              states == new_grouping,
              electoral_votes_2020,
              ceiling(predict(electorial_vote_model, newdata = .) + 2)
            )) %>%
  mutate(
    new_trump_ev = if_else(Trump > Clinton, new_ev, 0),
    new_clinton_ev = if_else(Trump < Clinton, new_ev, 0)
  )

knitr::kable(head(results2016, 5))
```

new_grouping	Clinton	Trump	electoral_votes_2020	population_2019	trump_ev	clinton_ev	states
AK/OR	1118560	945790	10	4949282	3	7	Alaska
Alabama	729547	1318255	9	4903185	9	0	Alabar
AR/MS	865625	1385586	12	5993974	12	0	Arkans
Arizona	1161167	1252401	11	7278717	11	0	Arizon
California	8753792	4483814	55	39512223	0	55	Califor

Finally to visualize the difference in electoral votes between the actual 2016 results and our new 2016 res

to get the data back into a tidy format with the proper labeling. The plot is a simple stacked barplot.

```
results2016 %>%
  summarize(across(contains(c("trump_ev", "clinton_ev")), sum)) %>%
  pivot_longer(cols = everything(),
               names_to = 'variable',
               values_to = 'electoral_votes') %>%
  group_by(str_detect(variable, 'new')) %>%
  mutate(
    percents = electoral_votes/sum(electoral_votes),
    old_v_new = if_else(str_detect(variable, 'new'), 'New EC', 'Original EC')
    candidate = case_when(
       str_detect(variable, 'trump') ~ "trump",
       str_detect(variable, 'clinton') ~ 'clinton',
       TRUE ~ 'total'
     ),
    lbl = paste0(electoral_votes,
                 '\n(',
                 scales::percent(percents, accuracy = .1) ,')')
  ) %>%
   ggplot(aes(y = old_v_new, x = percents, fill = candidate)) +
    geom_col(width = .5) +
    geom_text(aes(label = lbl), position = position_stack(vjust = .5)) +
    geom_vline(xintercept = .5, lty = 2) +
    scale_x_continuous(label = scales::percent, expand = c(0,0)) +
    scale_fill_manual(values = c('clinton' = 'blue', 'trump' = 'red')) +
    guides(fill = guide_legend(reverse = T)) +
    labs(x = "% of Electoral Vote",
         y = "",
         title = "Comparing 2016 Election Results in the Original vs. New Sys
         fill = "") +
    cowplot::theme_cowplot() +
    theme(
      plot.title.position = 'plot',
      axis.line = element_blank(),
      axis.ticks.x = element_blank(),
      axis.text.x = element_blank()
    )
```



With the new electoral grouping system the net change in percentage of electoral votes was only 0.3%, s

What Actually Changed in the New System?

The final question would be **how did the electoral votes change between the old system and the nev** into the table format which will only have rows for groupings where the number of electoral votes is differe symbols.

```
tbl_dt <- results2016 %>%
  filter(trump_ev != new_trump_ev | clinton_ev != new_clinton_ev) %>%
  transmute(
    new_grouping,
    clinton_delta = (new_clinton_ev - clinton_ev),
    trump_delta = (new_trump_ev - trump_ev),
    clinton_lbl = paste0(
      if_else(clinton_delta > 0, "+", ""),
      clinton_delta
    ),
    trump_lbl = paste0(
      if_else(trump_delta > 0, "+", ""),
      trump_delta
    )
  ) %>%
  select(new_grouping, clinton_lbl, trump_lbl)
```

To complete the table visualization I'm using the `kableExtra` package. The `kable_paper` argument is the cell background to either red or green if the label constructed above is non-zero and white otherwise with `kableExtra` and while I'm happy that I was able to get this to be how I wanted, I found certain parts

```
tbl_dt %>%
  kbl(align = c('l', 'c', 'c'),
      col.names = c('', 'Clinton', 'Trump'),
      caption = "Election 2016: Candidate's Change in Electoral Votes") %>%
  kable_paper(full_width = F) %>%
  column_spec(2, color = 'white', background = case_when(
```

```
  str_detect(tbl_dt$clinton_lbl, "\\+") ~ 'green',
  str_detect(tbl_dt$clinton_lbl, "\\-") ~ 'red',
  TRUE ~ 'white'
  )
) %>%
column_spec(3, color = 'white', background = case_when(
  str_detect(tbl_dt$trump_lbl, "\\+") ~ 'green',
  str_detect(tbl_dt$trump_lbl, "\\-") ~ 'red',
  TRUE ~ 'white'
  )
)
```

Table 1: Election 2016: Candidate's Change in Electoral Votes

	Clinton	Trump
AK/OR	+2	-3
AR/MS	0	-2
CT/RI	-2	0
DC/DE/WV	+1	-5
HI/NV	-2	0
IA/NE	0	-2
ID/MT/ND/SD/WY	0	-7
KS/OK	0	-1
NH/ME/VT	-4	0
NM/UT	-5	+4

In most cases, votes were lost due to the combining of smaller states into these groupings but in a few in won the popular vote. For example, in the Alaska/Oregon there were originally 10 electoral votes (3 from Clinton). The grouping lost vote in the combining and then the combined Oregon/Alaska went to Clinton c (+2 from the initial 7) and Trump loses the 3 he had from Alaska.

Wrapping Up

Back at the beginning of this analysis I hypothesized that the Electoral College had become more over-w during the early days of the electoral college. Based on comparing the % of the US Population of states f not massively.