

Exploring_data01

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With the start of the College Football Season soon approaching here is a beginning of data analysis of NCAA Football statistics.

This dataset is a combination of data from collegefootballdata.com

```
library(tidyverse)

## — Attaching packages — tidyverse 1.3.1 —

## ✓ ggplot2 3.3.5      ✓ purrr 0.3.4
## ✓ tibble 3.1.3      ✓ dplyr 1.0.7
## ✓ tidyr 1.1.3       ✓ stringr 1.4.0
## ✓ readr 2.0.0       ✓ forcats 0.5.1

## — Conflicts — tidyverse_conflicts() —
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(ggplot2)
library(patchwork)

total_cfb <- read.csv('CFB2010_CFB2019.csv')

head(total_cfb[,c(1:9)])
```

	Year	team	conference	total.games	total.wins	total.losses
## 1	2010	Air Force	Mountain West	13	9	4
## 2	2010	Akron	Mid-American	12	1	11
## 3	2010	Alabama	SEC	13	10	3
## 4	2010	Arizona	Pac-10	13	7	6
## 5	2010	Arizona State	Pac-10	12	6	6
## 6	2010	Arkansas	SEC	13	10	3
##	firstDowns	fourthDownConversions	fourthDowns			
## 1	286	18	30			
## 2	175	5	12			
## 3	287	9	14			
## 4	308	9	18			
## 5	255	8	14			
## 6	291	9	19			

Here is a small look at what the dataframe looks like. This dataframe contains data from 2010 to 2019, 2020 data was not included as it was not a normal season.

The first Key Question that I would want to investigate is what is the most winningest conference, however number of conferences changed throughout the 2010s, this question had to be reframed with respect to starting with the College Football Playoff era starting in 2014.

Key Question: What conference is the most winningest in the College Football Playoff era?

```
era_playoff <- total_cfb %>% filter(Year %in% (2014:2019))

head(era_playoff[,c(1:9)])
```

##	Year	team	conference	total.games	total.wins	total.losses
## 1	2014	Air Force	Mountain West	13	10	3
## 2	2014	Akron	Mid-American	12	5	7
## 3	2014	Alabama	SEC	14	12	2
## 4	2014	Appalachian State	Sun Belt	12	7	5
## 5	2014	Arizona	Pac-12	14	10	4
## 6	2014	Arizona State	Pac-12	13	10	3

```
## firstDowns fourthDownConversions fourthDowns
## 1 287 20 28
## 2 259 7 21
## 3 340 10 13
## 4 283 14 23
## 5 346 16 26
## 6 301 10 23

conference_wins <- era_playoff %>% group_by(conference) %>%
  mutate(Sum_wins = sum(total.wins)) %>%
  select(conference, Sum_wins) %>% unique()

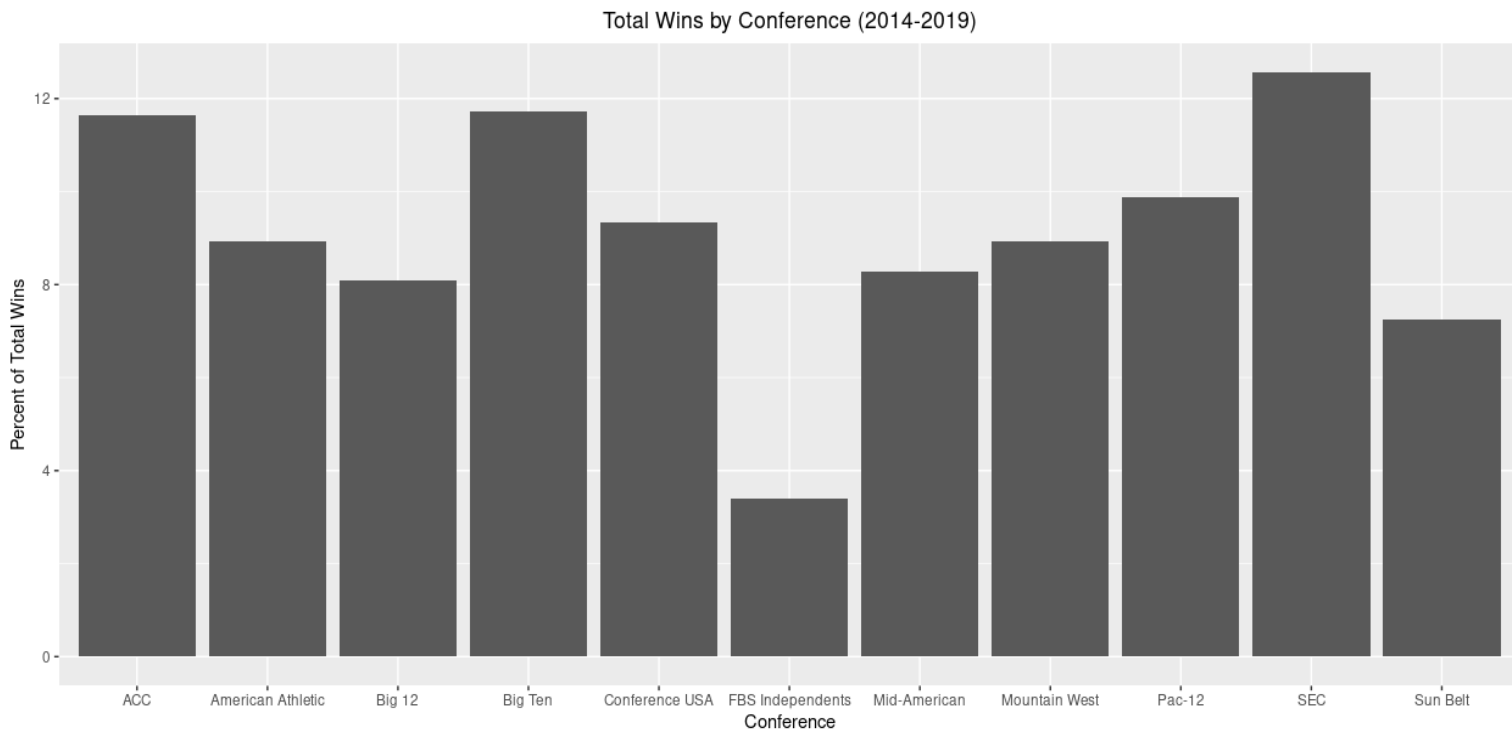
conference_wins$Percent_wins <- conference_wins$Sum_wins/sum(conference_wins$Sum_wins) *
100

conference_wins
```

##	conference	Sum_wins	Percent_wins
##	<chr>	<int>	<dbl>
## 1	Mountain West	465	8.95
## 2	Mid-American	431	8.30
## 3	SEC	655	12.6
## 4	Sun Belt	360	6.93
## 5	Pac-12	515	9.92
## 6	FBS Independents	177	3.41
## 7	Big 12	422	8.13
## 8	ACC	606	11.7
## 9	American Athletic	465	8.95
## 10	Conference USA	486	9.36
## 11	Big Ten	611	11.8

```
p <- conference_wins %>% ggplot(mapping= aes(x = conference, y = Percent_wins)) +
  geom_bar(stat = 'identity') +
  labs(x = 'Conference', y = 'Percent of Total Wins', title = 'Total Wins by Conference
(2014-2019)') + theme(plot.title = element_text(hjust = 0.5))

plot(p)
```



This bar graph shows the Percent of total wins per conference from the start of the College Football Playoff in 2014. This graph shows that the SEC has the most wins. However, this graph is misleading as each conference does not have an equal number of teams.

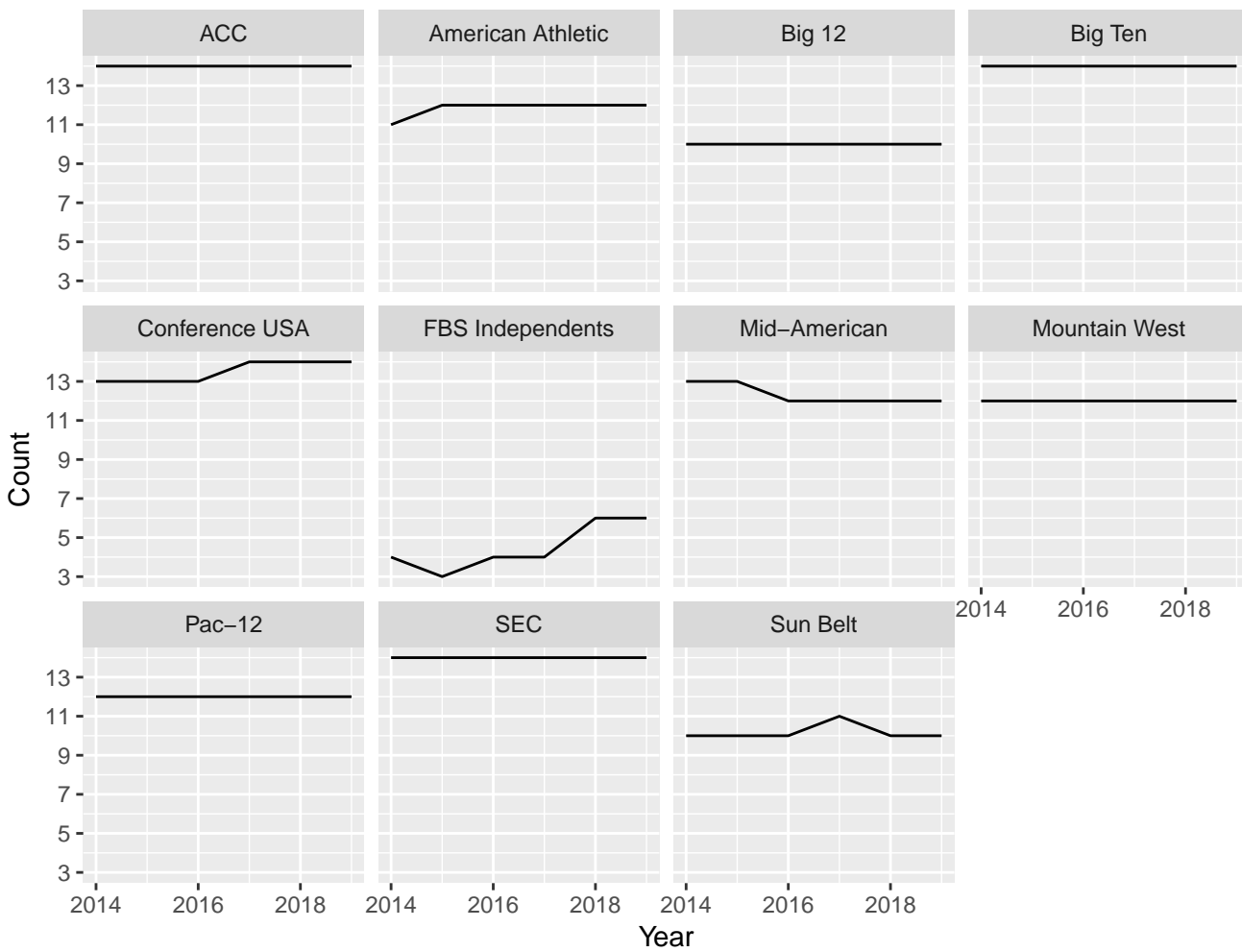
```
teams_per_conf <- era_playoff %>% count(Year,conference) %>% ggplot(mapping = aes(x =
Year , y = n)) +
  geom_line() +
  facet_wrap(~conference) +
  scale_y_continuous(breaks = c(3,5,7,9,11,13)) +
  labs(x = 'Year',
    y = 'Count',
    title = 'Number of Teams per Conference by Year') + theme(plot.title =
element_text(hjust = 0.5))
```

```
wins_per_conf <- era_playoff %>% select(Year, conference, total.wins) %>% ggplot(mapping
= aes(x = Year , y = total.wins)) +
  geom_bar(stat = 'identity') +
  facet_wrap(~conference) +
  labs(x = 'Year',
    y = 'Wins',
    title = 'Number of Wins per Conference by Year') + theme(plot.title =
element_text(hjust = 0.5))
```

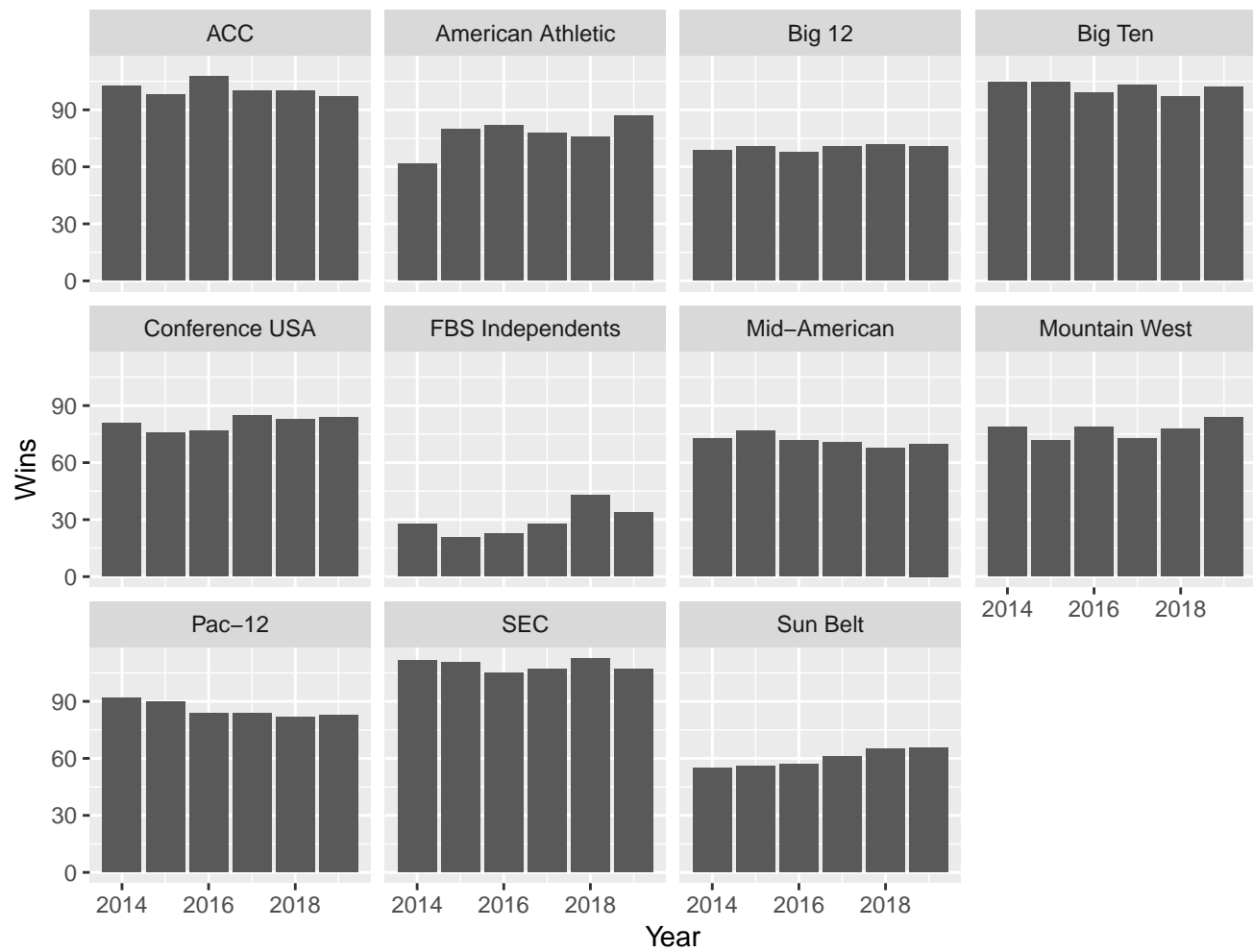
```
patch1 <- teams_per_conf + wins_per_conf
```

```
patch1
```

Number of Teams per Conference by Year



Number of Wins per Conference by Year



The graph above puts better context on the investigation of the winningest conference by viewing number of teams per conference by year alongside wins of each conference by year. Certain conferences such as the Big-12, Big-10, ACC, Pac-12, and the SEC usually known as the “Power-Five” had consistent number of team in their conference but showed slight variability in the number of wins per season. While conferences like Conference-USA and the Independents showed an increase in wins as the teams in the conference increased.

Key Question: What are the winningest Teams from 2010-2019?

After looking at the winningest conferences in the College Football Playoff era, looking at specific teams is the next step.

```
df_team_wins <- total_cfb %>% select(team | conference | total.wins)

total_team_wins <- df_team_wins %>% group_by(team) %>% mutate(Sum_team_wins =
sum(total.wins)) %>% select(team, Sum_team_wins) %>% arrange(Sum_team_wins) %
>% unique()

tail(total_team_wins)

## # A tibble: 6 × 2
## # Groups:   team [6]
##   team          Sum_team_wins
##   <chr>          <int>
## 1 LSU              103
## 2 Boise State      107
## 3 Oklahoma         109
## 4 Clemson          117
## 5 Ohio State       117
## 6 Alabama          124

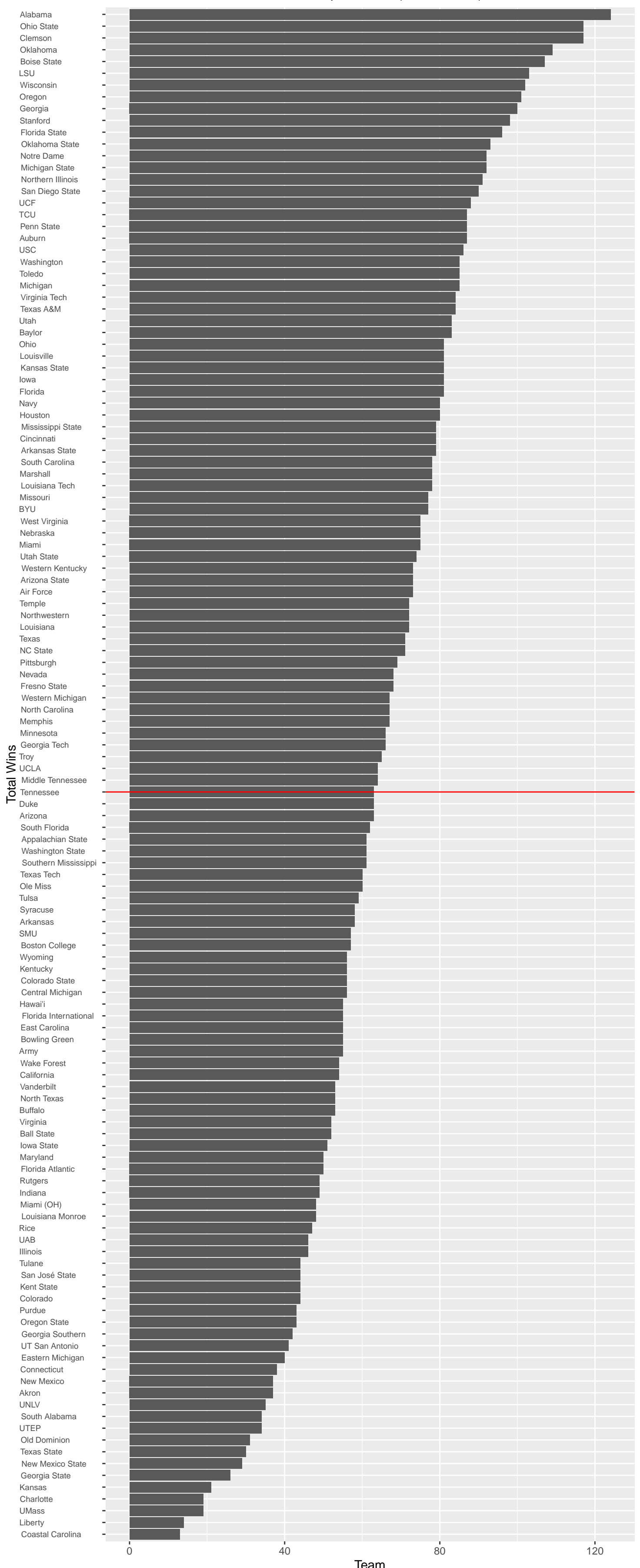
total_team_wins$team <- factor(total_team_wins$team, levels = total_team_wins
$team)

p <- total_team_wins %>% ggplot(mapping = aes(x = team, y = Sum_team_wins))+
  geom_bar(stat = 'Identity') +
  labs(x = 'Total Wins',
       y = 'Team',
       title = 'Total Wins per Team (2010-2019)') +

  theme(axis.text.y = element_text(size = 7, hjust = -0.05)) + coord_flip()
+
  geom_vline(aes(xintercept = median(Sum_team_wins)), color = 'red') +
  theme(plot.title = element_text(hjust = 0.5))

plot(p)
```

Total Wins per Team (2010–2019)



The graph above This graph shows how many games each team won, from the past decade (2010-2019).

The red line shows the median number of wins.

This shows the dominance of teams that are regulars in the College Football Playoffs such as Alabama, Ohio State, and Clemson. The graph also shows teams that commonly do not have a chance at to make the College Football Playoffs, such as Boise State, Toledo, and UCF as they dominate conferences that part of what is commonly referred to as “Group of 5”.

This shows that as there is conference realignment there is an opportunity to restructure the conferences to make them more equal in size and talent to give more teams an opportunity at the playoff.

```
rank_teams <- total_team_wins %>% mutate(Decade_Rank =  
  case_when(Sum_team_wins >= 64 ~ 'Above_team_med  
an',  
            Sum_team_wins < 64 ~ 'Below_team_med  
ian'))  
  
total_cfb <- merge(x = total_cfb , y = rank_teams %>% select(team,Sum_team_wi  
ns, Decade_Rank), by = 'team')  
  
total_cfb <-total_cfb%>% select(Year,team,conference:tacklesForLoss,Sum_team_  
wins,Decade_Rank,conferenceGames.games:location.longitude) %>% arrange(Year)  
  
group_A <- total_cfb %>% filter(Decade_Rank == 'Above_team_median') %>% arran  
ge(desc(Sum_team_wins),Year)  
  
group_B <- total_cfb %>% filter(Decade_Rank == 'Below_team_median') %>% arran  
ge(desc(Sum_team_wins),Year)
```

Two new dataframes have been created. The teams will be split into two groups Group A , and Group B. Group A are the teams above the median line in the previous figure, and Group B are the teams below the median line the in the previous figure.

Key Question: What is the difference in the variability of wins per year between the top of Group A to the bottom of Group A? What is the difference in the variability of wins per year between Group A and Group B?


```

plot_group_A_top <- group_A[c(1:200),] %>% ggplot(mapping = aes(x= Year, y =
total.wins)) + geom_line() +
  scale_x_continuous(breaks = seq(2010,2019,2)) +
  scale_y_continuous(breaks=seq(1,17,3)) + facet_wrap(~team) +
  labs(x = 'Year', y = 'Wins', title = 'Top of Group A',) +
  theme(plot.title = element_text(hjust = 0.5))

plot_group_A_bottom <- (group_A %>% arrange((Sum_team_wins),Year))[c(1:200),]
%>% ggplot(mapping = aes(x= Year, y = total.wins)) + geom_line() +
  scale_x_continuous(breaks = seq(2010,2019,2)) +
  scale_y_continuous(breaks=seq(1,17,3)) + facet_wrap(~team) +
  labs(x = 'Year', y = 'Wins', title = 'Bottom of Group A',) +
  theme(plot.title = element_text(hjust = 0.5))

plot_group_B_top <- group_B[c(1:116),] %>% ggplot(mapping = aes(x= Year, y =
total.wins)) + geom_line(aes(group=team)) +
  scale_x_continuous(breaks = seq(2010,2019,2)) +
  scale_y_continuous(breaks=seq(1,17,2)) + facet_wrap(~team) +
  labs(x = 'Year', y = 'Wins', title = 'Top of Group B',) +
  theme(plot.title = element_text(hjust = 0.5))

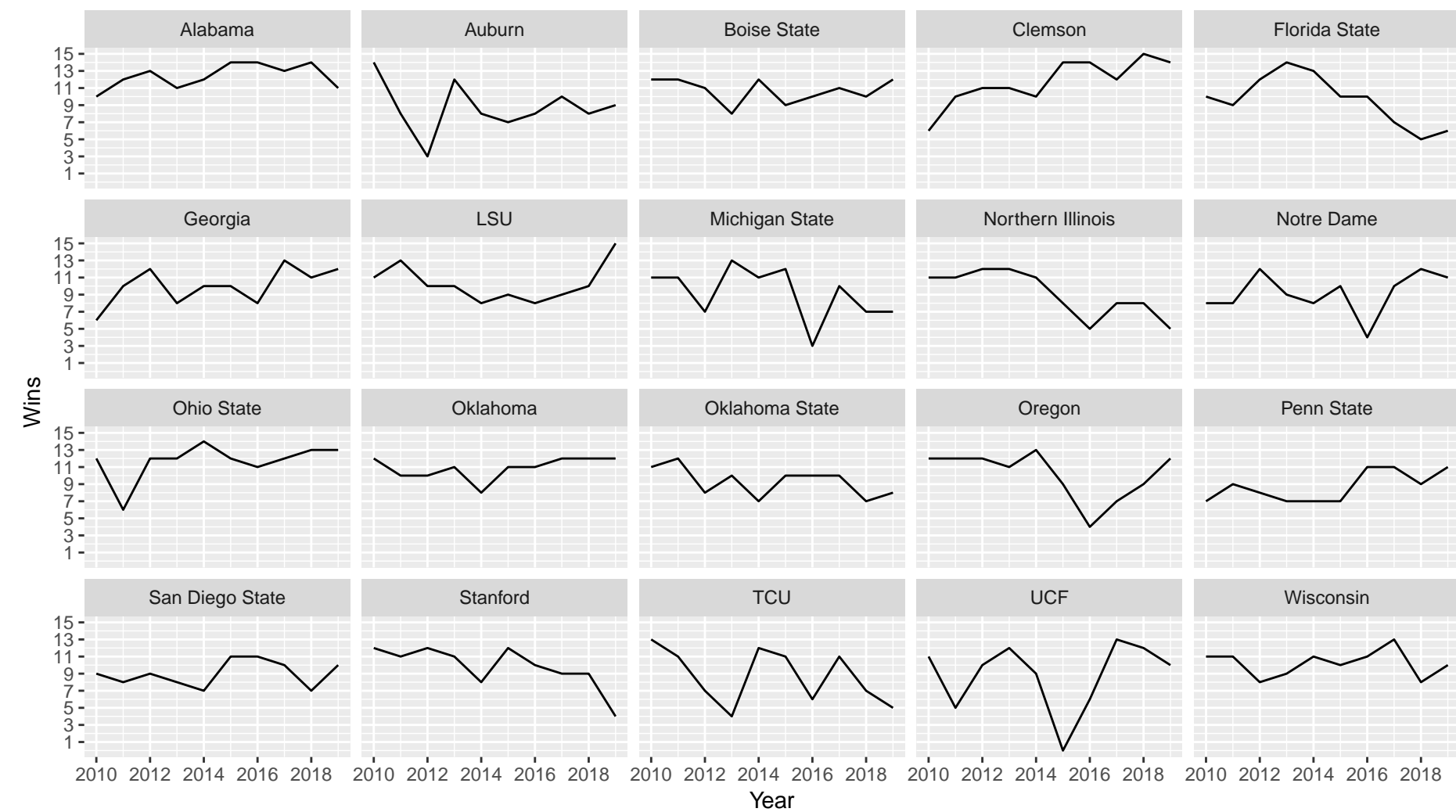
plot_group_B_bottom <-(group_B %>% arrange((Sum_team_wins),Year))[c(1:85),] %
>% ggplot(mapping = aes(x= Year, y = total.wins)) + geom_line() +
  scale_x_continuous(breaks = seq(2010,2019,2)) +
  scale_y_continuous(breaks=seq(1,17,2)) + facet_wrap(~team) +
  labs(x = 'Year', y = 'Wins', title = 'Bottom of Group B ',) +
  theme(plot.title = element_text(hjust = 0.5))

group_patch <-plot_group_A_top + plot_group_A_bottom + plot_group_B_top + plo
t_group_B_bottom + plot_layout(widths=1)

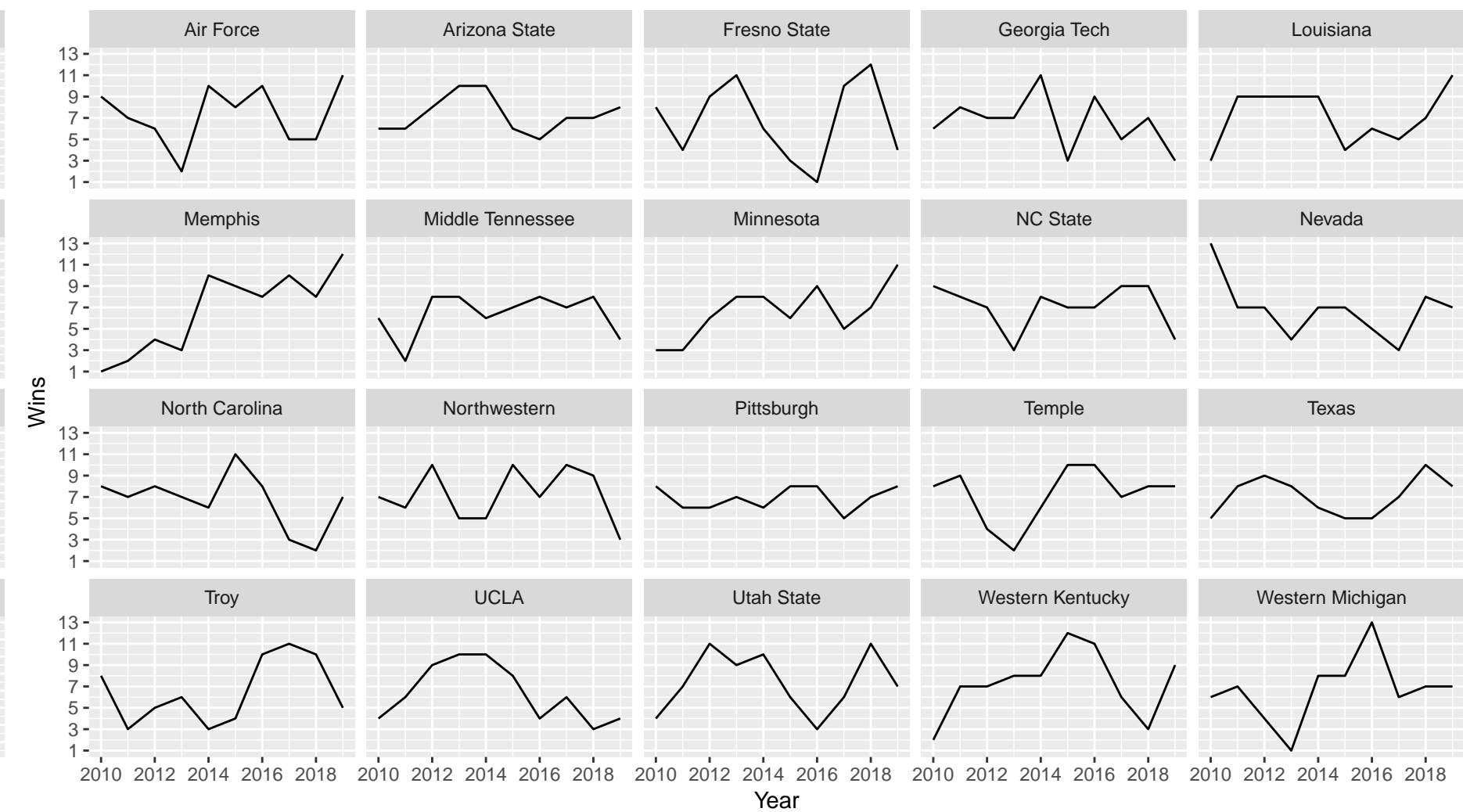
group_patch

```

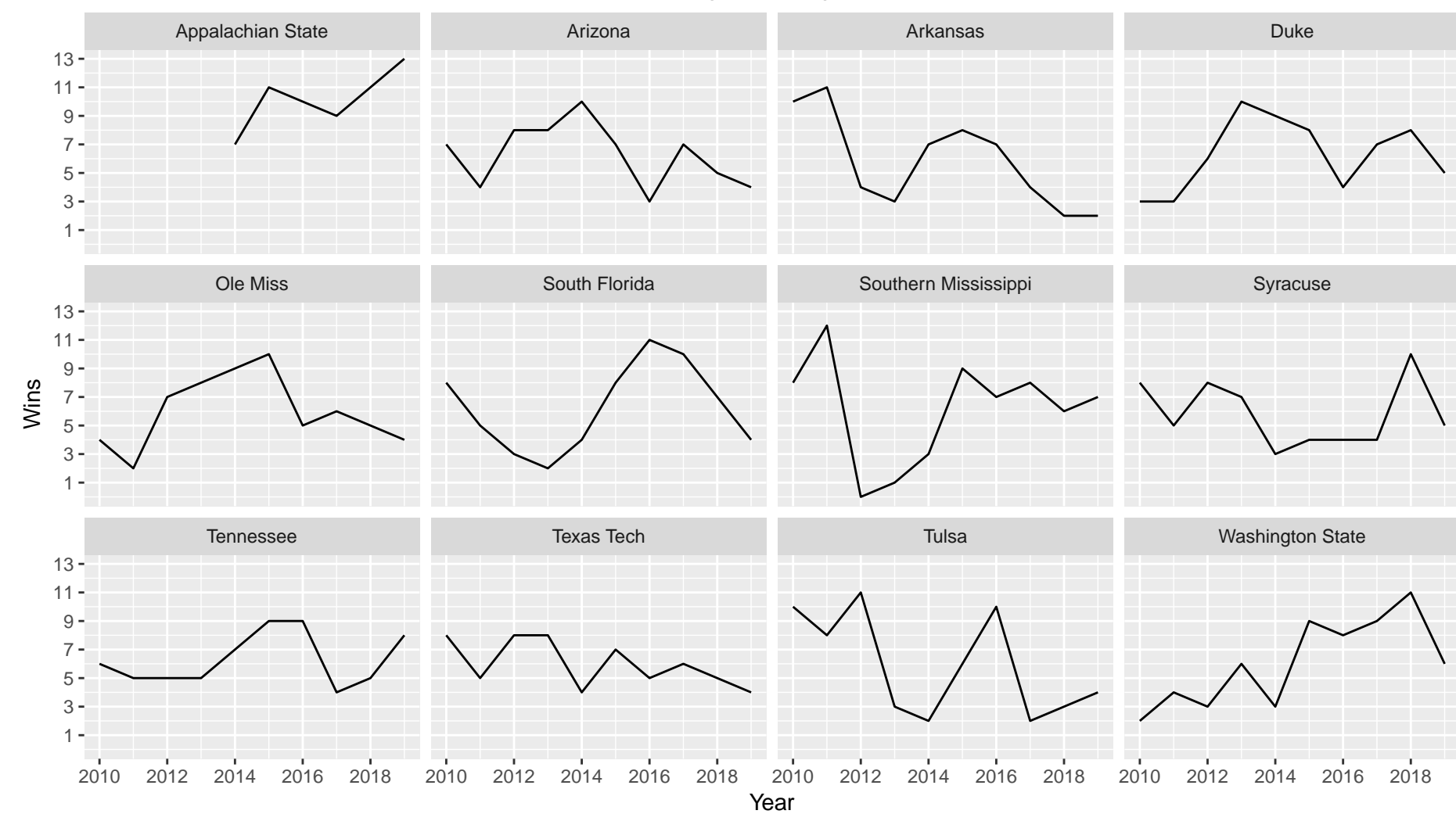
Top of Group A



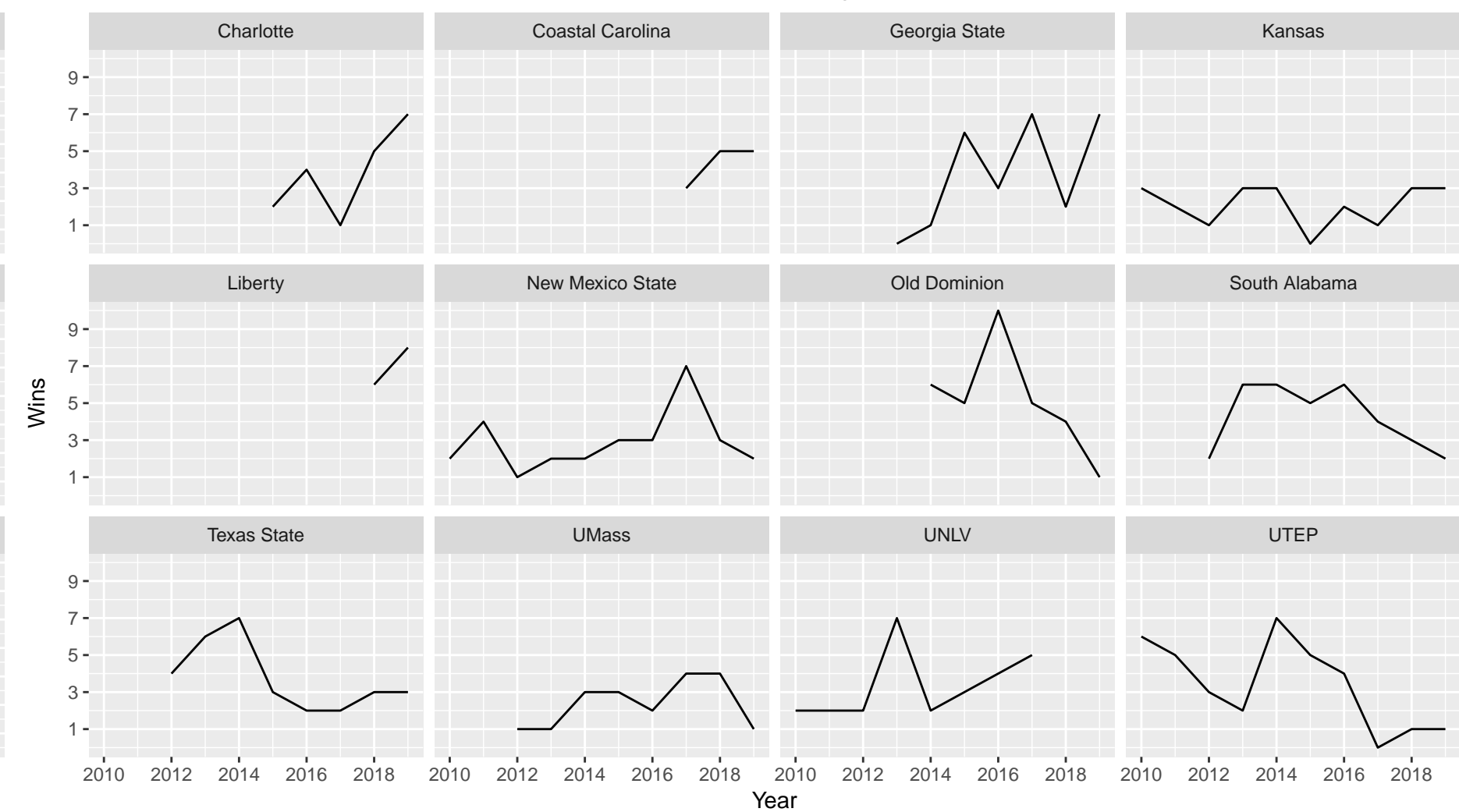
Bottom of Group A



Top of Group B



Bottom of Group B



The Graph above show the number of wins per year for the Top and Bottom of each Group. The two graphs show an interesting picture of College Football. The variability in wins per year in Group B is more dramatic than Group A. An example would be Arizona which in 2011 had 4 wins and in 2016 had 3 wins but in 2014 hit their decade win high of 10 wins. Another example, South Florida had an increase of wins from 2013 to 2016 with 11 wins. But then preceded to decrease in wins since ending 2019 with 4 wins. While the team at the top of Group A: Alabama, had been very consistent with wins. The variability in wins increases from the top of Group A to the bottom of Group B. This shows the consistency of the best programs in college football such as Alabama, Ohio State, and Clemson.

Patterns to look at:

“V” shaped Recovery: Ohio State, Oklahoma, Michigan State, Notre Dame, and UCF.

Ohio State and Oklahoma show similar trajectories in that they had a significant drop in wins for a year, 2011 for Ohio State and 2014 for Oklahoma, but since those years both programs have had consistent wins per season.

The quick ‘V’ shaped recovery is shown in Michigan State, Notre Dame, and UCF. The most dramatic ‘v’ shaped recovery was UCF which had 9 wins in 2014, 0 wins in 2015, 13 in 2017. The will be further exploring of the data to see if the stats show possible reasons for the ‘V’ shaped recovery.

Plateau

A plateau of more than two years is shown in Oklahoma State and Penn State. A reason for this plateau is not known from the data present but will be investigated in the future.

Yo-yo

Looking at both TCU and Northwestern throughout the decade there is no consistency just up-down-up-down pattern.

Quick Peak and Steep Fall

A Quick peak and fall can be seen with North Carolina, and Georgia State, which both within the decade had a jump of 4 wins or more in a year and then never reached that level of wins in the following years.

Note: The graph showing the Bottom of Group B shows teams with missing data such as Idaho, which left the FBS to go to the FCS and teams such as Coastal Carolina which moved from FCS to FBS.

Looking to the future of College Football:

Key Question: How would all 4 graphs above look for 2020-2029?

With the advent of NIL deals, imminent conference restructuring, and possible College Football expansion the future of College Football is exciting but uncertain.

If 'super' conferences with over 20 teams, visualizing the winningest conference would cease to be useful. With NIL deals, and teams gaining more exposure through a playoff expansion this may help teams to maintain consistency in recruiting and allow for more rapid increase in wins, like the 'v' shaped recovery exhibited in the last graph. However, the increased accessibility of the transfer portal may cause teams to have Quick peaks and fall as their best player leave for more consistent winning programs. With the changes to College Football a graph such as the third image for 2020-2029 could show teams more equal in wins or will exacerbate the inequality and increase the gap between the teams at the top of 'Group A' and the teams at the bottom of 'Group A'.

The patterns exhibited in the fourth image are due to the nature of college football, with consistent roster turnover and would not be fixed with conference restructuring. I would like to compare these patterns with a 10-year period of the NFL.

Part of the future exploration of this data set will be looking at what the future the College Football may look like.

Here I will save the new data frame for Exploring_data02.

```
write.csv(total_cfb, 'CFB_Total.csv', row.names = FALSE)
```