607 Lab 6 Project2

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```r
options(repos = c(CRAN = "https://cran.r-project.org"))
library(tidyr)
suppressPackageStartupMessages(library(dplyr))
library(readr)
library(ggplot2)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats   1.0.0     v stringr   1.5.1
## v lubridate 1.9.3     v tibble    3.2.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

Dataset 1: SAT scores in 2010

```r
url1<- "https://raw.githubusercontent.com/stormwhale/data-mines/refs/heads/main/SAT__College_Board__2010
df2<- read.csv(url1)
head(df2)
```

```
##      DBN                                    School.Name Number.of.Test.Takers
## 1 01M292 Henry Street School for International Studies                    31
## 2 01M448           University Neighborhood High School                    60
## 3 01M450                    East Side Community High School                    69
## 4 01M458                     SATELLITE ACADEMY FORSYTH ST                    26
## 5 01M509                                  CMSP HIGH SCHOOL                    NA
## 6 01M515             Lower East Side Preparatory High School                   154
##   Critical.Reading.Mean Mathematics.Mean Writing.Mean
## 1                   391              425          385
## 2                   394              419          387
## 3                   418              431          402
## 4                   385              370          378
## 5                    NA               NA           NA
## 6                   314              532          314
```

To tidy up and transform the data:

```
df2_tidy<- df2 %>%
  pivot_longer(cols = c('Critical.Reading.Mean', 'Mathematics.Mean', 'Writing.Mean'),
               names_to = 'Test_subjects',
               values_to = 'Average_scores',
               names_pattern ='(.*)\\.Mean')
df2_tidy<-rename(df2_tidy,c('Number_of_test_takers'='Number.of.Test.Takers', 'School_name'='School.Name

#drop NA schools
df2_tidy<- df2_tidy %>%
  subset(!is.na(Number_of_test_takers))

#check if any NA still exist:
any(sum(is.na(df2_tidy)))
```

```
## [1] FALSE
```

```
head(df2_tidy)
```

```
## # A tibble: 6 x 5
##   DBN    School_name          Number_of_test_takers Test_subjects Average_scores
##   <chr>  <chr>                                <int> <chr>                  <int>
## 1 01M292 "Henry Street Schoo~                    31 Critical.Rea~            391
## 2 01M292 "Henry Street Schoo~                    31 Mathematics              425
## 3 01M292 "Henry Street Schoo~                    31 Writing                  385
## 4 01M448 "University Neighbo~                    60 Critical.Rea~            394
## 5 01M448 "University Neighbo~                    60 Mathematics              419
## 6 01M448 "University Neighbo~                    60 Writing                  387
```

Analyzing the data

To get the top 10 schools ranked by total SAT scores:

```
top_total<-df2_tidy %>%
  group_by(School_name) %>%
  summarise(total_SAT_score= sum(Average_scores)) %>%
  slice_max(total_SAT_score, n= 10)

print(top_total)
```

```
## # A tibble: 10 x 2
##    School_name                                           total_SAT_score
##    <chr>                                                           <int>
##  1 "STUYVESANT HIGH SCHOOL "                                        2087
##  2 "BRONX HIGH SCHOOL OF SCIENCE "                                  1960
##  3 "STATEN ISLAND TECHNICAL HIGH SCHOOL "                           1928
##  4 "Townsend Harris High School at Queens College "                 1923
##  5 "HS of American Studies at Lehman College "                      1884
##  6 "QUEENS HS FOR SCIENCE YORK COL "                                1875
```

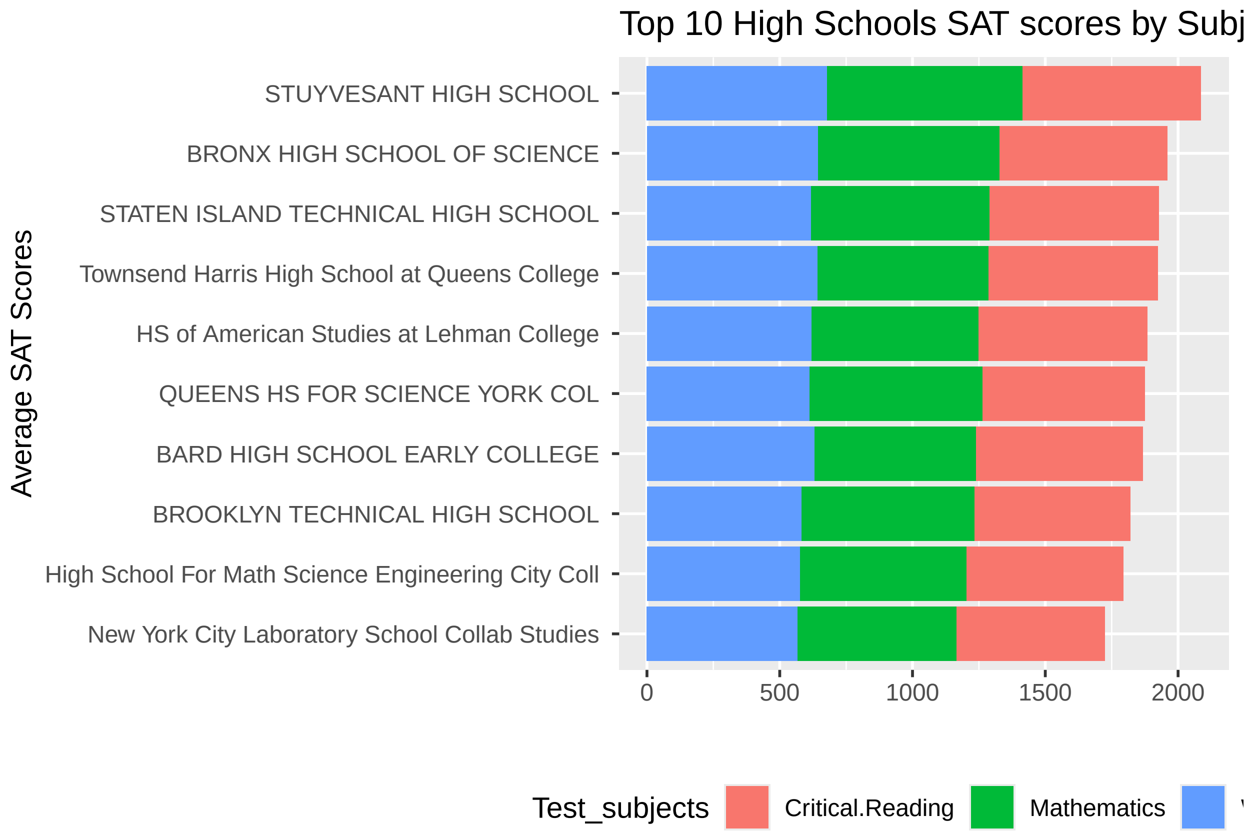
```
##  7 "BARD HIGH SCHOOL EARLY COLLEGE "                             1868
##  8 "BROOKLYN TECHNICAL HIGH SCHOOL "                             1821
##  9 "High School For Math Science Engineering City Coll "         1794
## 10 "New York City Laboratory School Collab Studies "             1725
```

Top 10 schools SAT SCOREs break down by each test subject

```r
top_sub <- df2_tidy %>%
  filter(School_name %in% top_total$School_name)
#To get the mean for each test subject from the top 10 schools:
top_sub_mean<- top_sub %>%
  group_by(Test_subjects) %>%
  summarise(Mean_score = mean(Average_scores))
print(top_sub_mean)
```

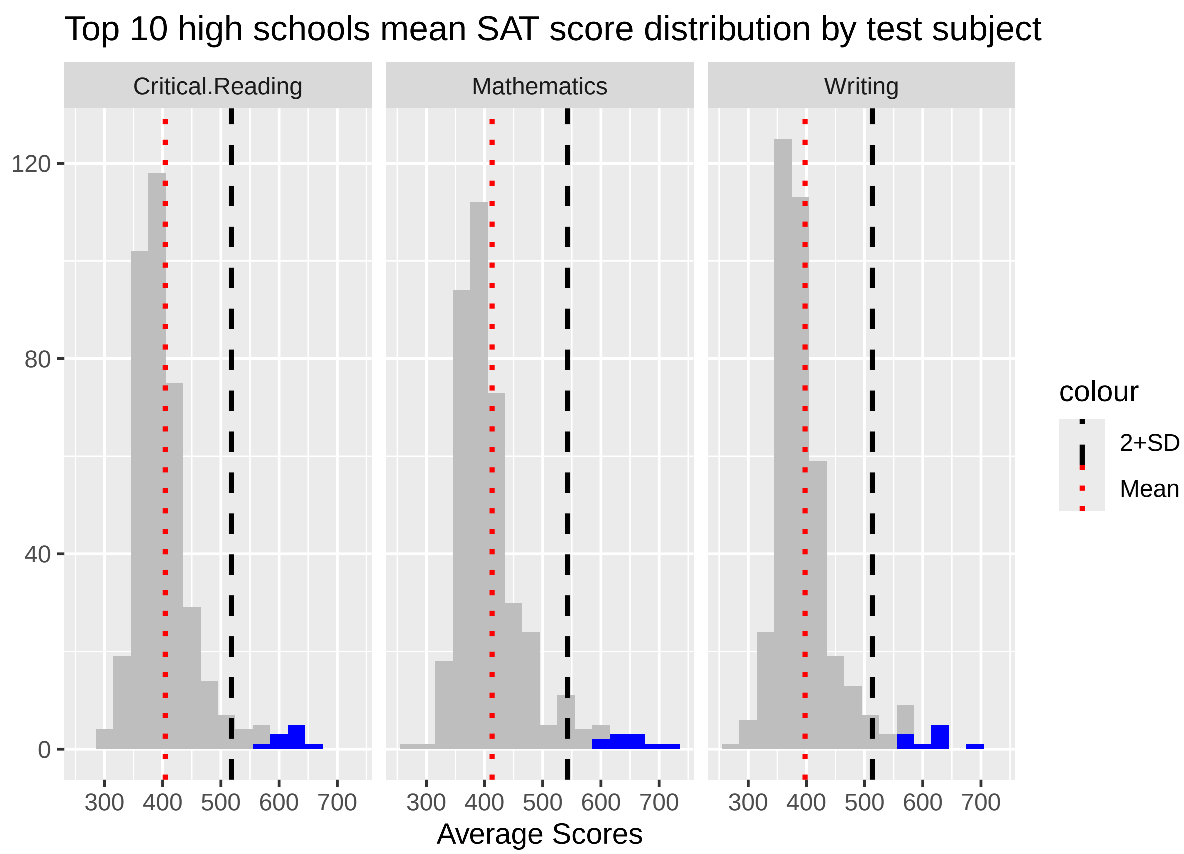
```
## # A tibble: 3 x 2
##   Test_subjects    Mean_score
##   <chr>                 <dbl>
## 1 Critical.Reading       620
## 2 Mathematics            650.
## 3 Writing                616.
```

```r
ggplot(top_sub, aes(x=reorder(School_name, Average_scores), y= Average_scores, fill=Test_subjects))+
  geom_bar(stat='identity') +
  coord_flip() +
  labs(title = 'Top 10 High Schools SAT scores by Subject', y='', x ='Average SAT Scores')+
  theme(legend.position = 'bottom')
```



To look at how far ahead the top 10 schools from the mean scores of other schools:

```
#To get the mean and standard deviation from all HS that took the SAT:
tot_stat<- df2_tidy %>%
  group_by(Test_subjects) %>%
  summarise(Mean_score= mean(Average_scores), SD=sd(Average_scores), '1+SD'=Mean_score+SD, '2+SD'=Mean_s

tot_stat_mean<- tot_stat$Mean_score
tot_stat_2sd<- tot_stat$`2+SD`

ggplot() +
  geom_histogram(data= df2_tidy, aes(x=Average_scores), fill='grey', binwidth=30)+
  geom_histogram(data= top_sub, aes(x=Average_scores), fill='blue', binwidth=30)+
    facet_wrap(~Test_subjects)+
  labs(title = 'Top 10 high schools mean SAT score distribution by test subject',
        y='',
        x='Average Scores') +
  geom_vline(data= tot_stat, aes(xintercept= tot_stat_mean, color ='Mean'), linetype='dotted', linewidtl
  geom_vline(data= tot_stat, aes(xintercept= tot_stat_2sd, color ='2+SD'), linetype='dashed', linewidth
  scale_color_manual(values= c('Mean'='red', '2+SD'='black'))
```

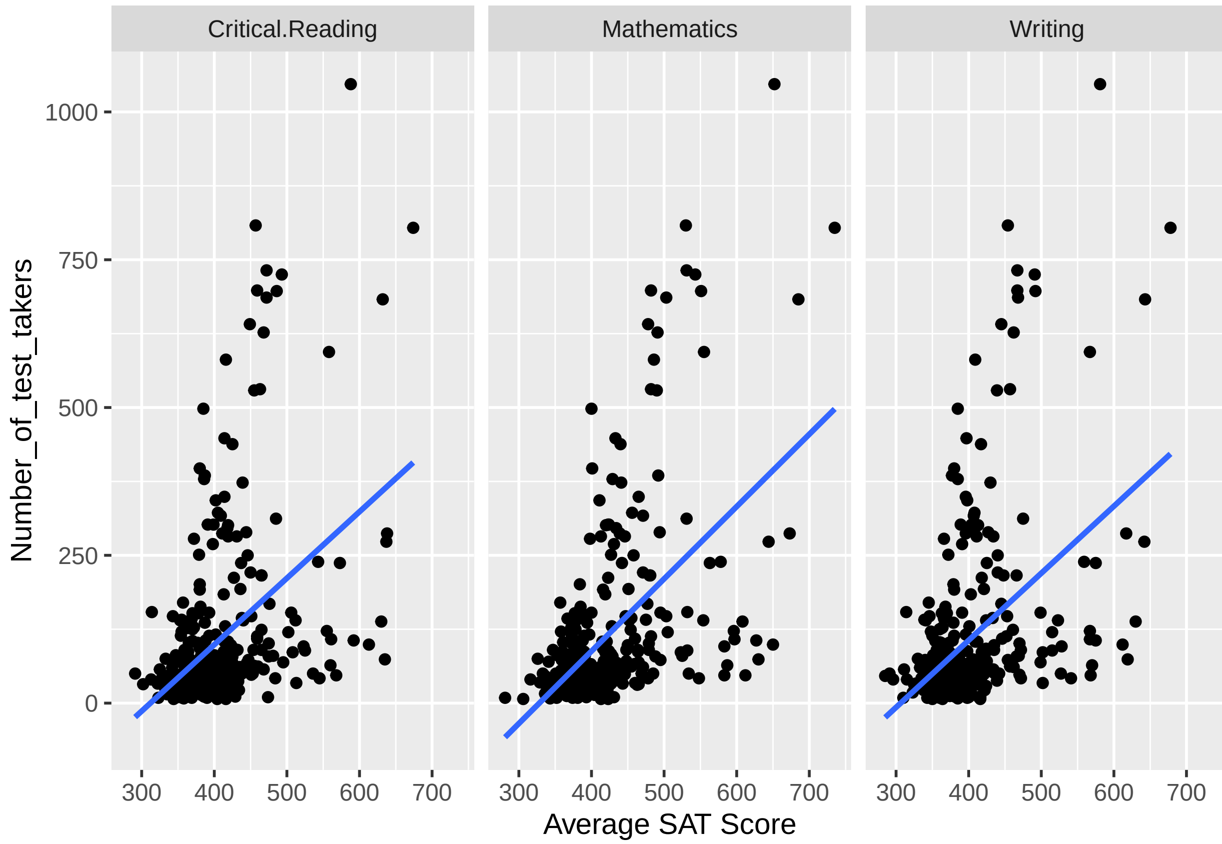


Conclusion: Top 10 High Schools are above 2 standard Deviation from the mean scores

Correlation between # of test takers and average SAT scores

```
ggplot(df2_tidy, aes(x= Average_scores, y=Number_of_test_takers))+
  geom_point() +
  facet_wrap(~Test_subjects) +
  geom_smooth(method='lm', se=FALSE) +
  labs(x= 'Average SAT Score')
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



There is a positive correlation between number of test takers and average SAT scores. The higher number of people from a school participating in the SAT, the average score is generally higher than the mean value. This is observed in all three test subjects.

Dataset 2: Unity Data - MTA Daily Ridership

Data Overview The dataset contains daily ridership and traffic data for various transportation modes in New York City during March 2020. The columns include:

- Date: The date of the record.
- Subways: Total estimated ridership and percentage of comparable pre-pandemic day.
- Buses: Total estimated ridership and percentage of comparable pre-pandemic day.
- LIRR (Long Island Rail Road): Total estimated ridership and percentage of comparable pre-pandemic day.
- Metro-North: Total estimated ridership and percentage of comparable pre-pandemic day.
- Access-A-Ride: Total scheduled trips and percentage of comparable pre-pandemic day.
- Bridges and Tunnels: Total traffic and percentage of comparable pre-pandemic day.
- Staten Island Railway: Total estimated ridership and percentage of comparable pre-pandemic day.

Initial Analysis:
- There is a noticeable decline in ridership across all transportation modes as the month progresses. - The percentage of ridership compared to pre-pandemic levels shows a significant decline. - Access-A-Ride: This services maintained higher percentages of pre-pandemic levels compared to other modes, indicating continued demand for these services despite the pandemic - Traffic through bridges and tunnels also decreased but not as drastically as public transportation ridership. This could suggest a shift towards private vehicle usege during the pandemic.

```r
url <- "https://raw.githubusercontent.com/Yedzinovich/Data-607/main/MTA_Daily_Ridership_Data.csv"

mta_data <- read_csv(url)
```

```
## Rows: 1671 Columns: 15
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): Date
## dbl (14): Subways: Total Estimated Ridership, Subways: % of Comparable Pre-P...
##
## 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.
```

```r
mta_data <- mta_data %>% mutate(Date = as.Date(Date, format = "%m/%d/%y"))

mta_data_long <- mta_data %>% pivot_longer(cols = -Date, names_to = "Metric", values_to = "Value")
head(mta_data_long)
```

```
## # A tibble: 6 x 3
##   Date       Metric                                      Value
##   <date>     <chr>                                       <dbl>
## 1 2020-03-01 Subways: Total Estimated Ridership        2212965
## 2 2020-03-01 Subways: % of Comparable Pre-Pandemic Day      97
## 3 2020-03-01 Buses: Total Estimated Ridership           984908
## 4 2020-03-01 Buses: % of Comparable Pre-Pandemic Day        99
## 5 2020-03-01 LIRR: Total Estimated Ridership             86790
## 6 2020-03-01 LIRR: % of Comparable Pre-Pandemic Day        100
```

```r
mta_data_long <- mta_data_long %>% separate(Metric, into = c("Transport_Mode", "Metric_Type"), sep = ":
head(mta_data_long)
```

```
## # A tibble: 6 x 4
##   Date       Transport_Mode Metric_Type                          Value
##   <date>     <chr>          <chr>                                <dbl>
## 1 2020-03-01 Subways        Total Estimated Ridership          2212965
## 2 2020-03-01 Subways        % of Comparable Pre-Pandemic Day        97
## 3 2020-03-01 Buses          Total Estimated Ridership           984908
## 4 2020-03-01 Buses          % of Comparable Pre-Pandemic Day        99
## 5 2020-03-01 LIRR           Total Estimated Ridership            86790
## 6 2020-03-01 LIRR           % of Comparable Pre-Pandemic Day       100
```

Now that we have the data in a long format, we can extract more comprehensive insights from it. Long format can help us to perform a variety of analyses that are more flexible and insightful compared to the original wide format.

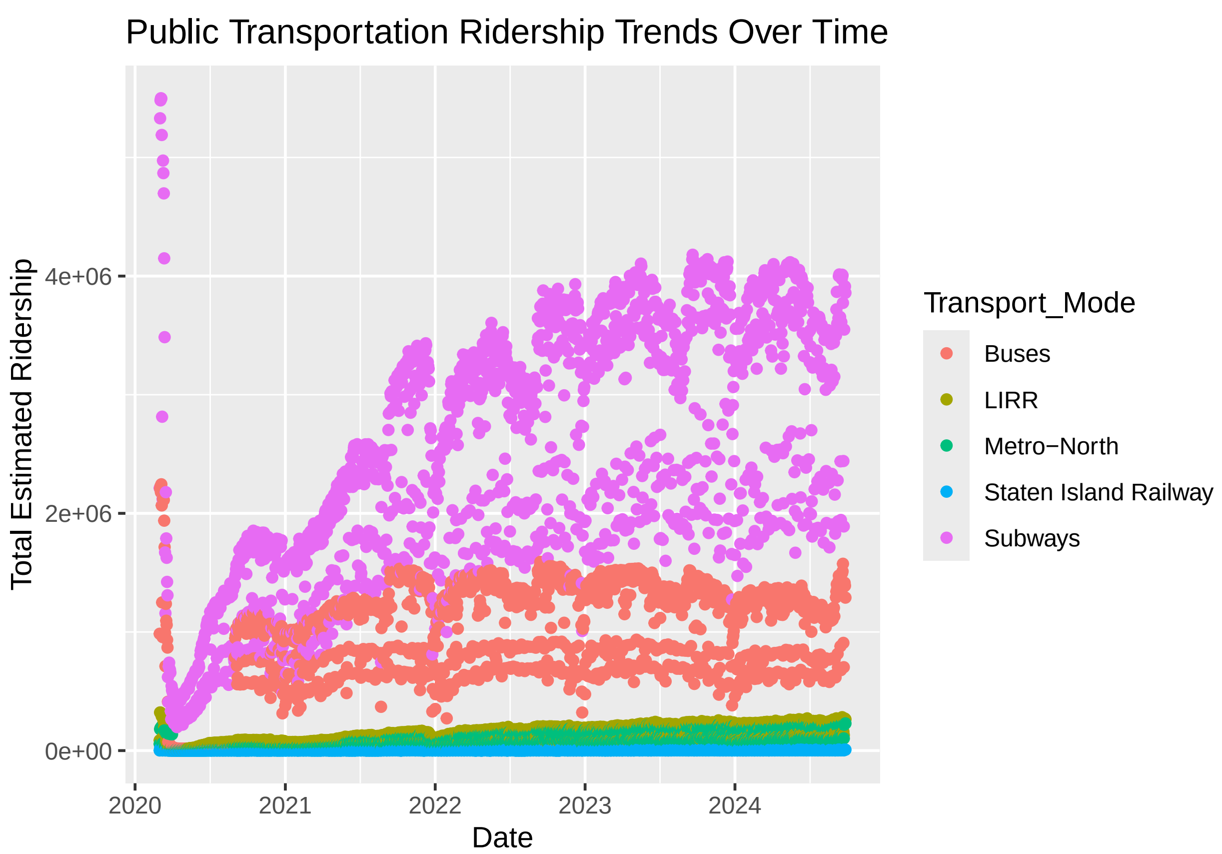
***What to know: - March 11, 2020, marks the start of the federal COVID-19 PHE declaration. - May 11, 2023, marks the end of the federal COVID-19 PHE declaration. Source:https://archive.cdc.gov/www_cdc_gov/coronavirus/2019-ncov/your-health/end-of-phe.html#:~:text=The%20federal%20COVID%2D19%20PHE,and%20testin

```r
# Analysis #1
avg_ridership <- mta_data_long %>%
  filter(Metric_Type == "Total Estimated Ridership") %>%
```

```r
  group_by(Transport_Mode) %>%
  summarize(Average_Ridership = mean(Value, na.rm = TRUE))

print(avg_ridership)
```

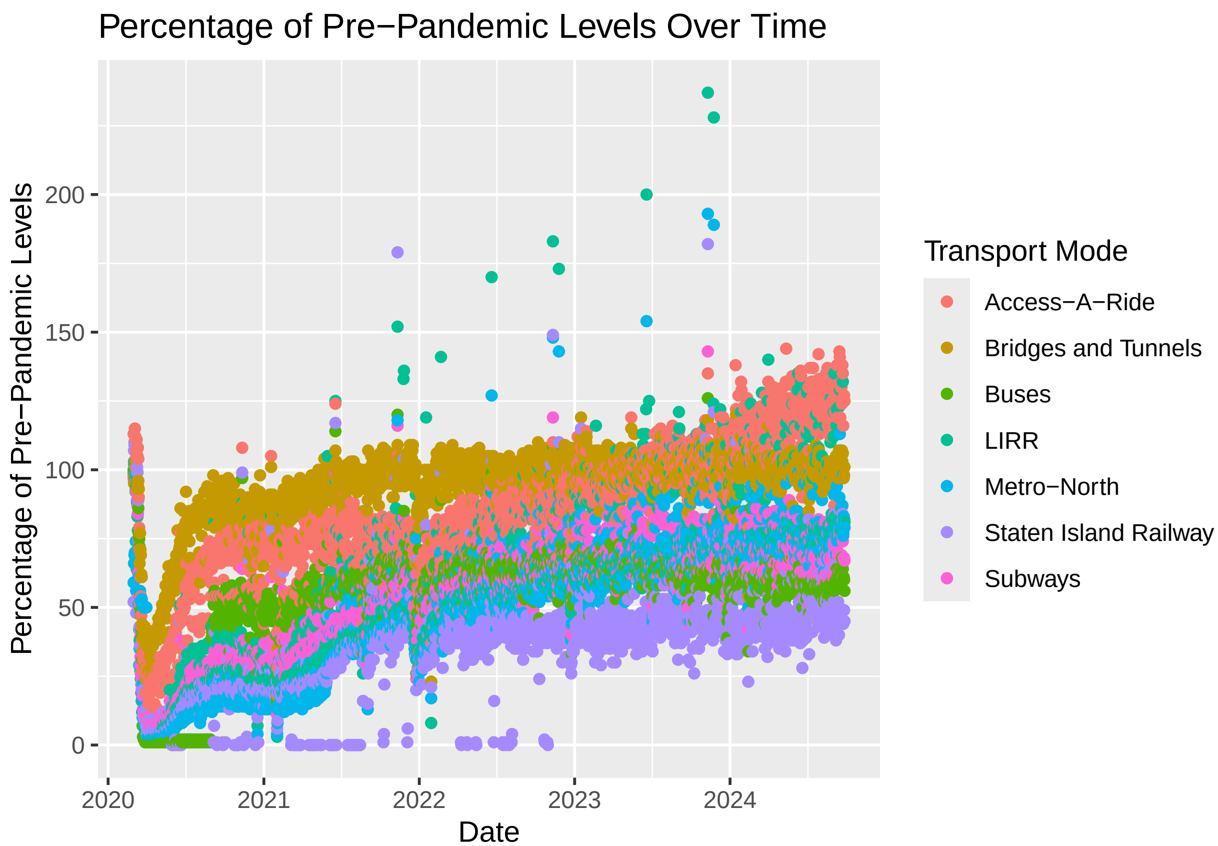
```
## # A tibble: 5 x 2
##   Transport_Mode        Average_Ridership
##   <chr>                             <dbl>
## 1 Buses                          1000673.
## 2 LIRR                            134099.
## 3 Metro-North                     113089.
## 4 Staten Island Railway             4382.
## 5 Subways                        2482768.
```

```r
# Analysis #2
ggplot(mta_data_long %>% filter(Metric_Type == "Total Estimated Ridership"), aes(x = Date, y = Value, c
  geom_point() +
  labs(title = "Public Transportation Ridership Trends Over Time", x = "Date", y = "Total Estimated Rid
```

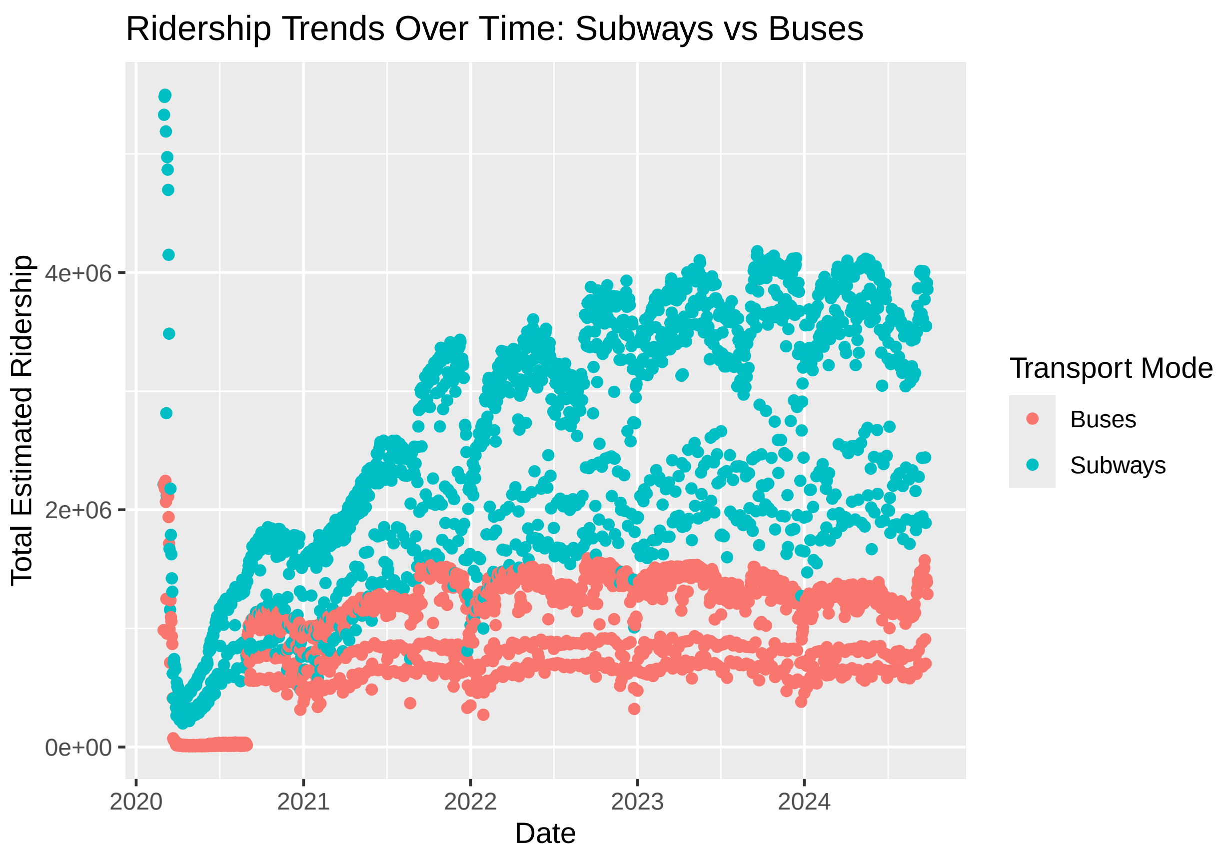



```r
# Analysis #3
percentage_mta_data <- mta_data_long %>%
  filter(grepl("% of Comparable Pre-Pandemic Day", Metric_Type))

ggplot(percentage_mta_data, aes(x = Date, y = Value, color = Transport_Mode)) +
```

```r
  geom_point() +
  labs(title = "Percentage of Pre-Pandemic Levels Over Time",
       x = "Date",
       y = "Percentage of Pre-Pandemic Levels",
       color = "Transport Mode")
```




```r
# Analysis 4
pt_mta_ridership_data <- mta_data_long %>%
  filter(Metric_Type == "Total Estimated Ridership")

ggplot(pt_mta_ridership_data %>% filter(Transport_Mode %in% c("Subways", "Buses")),
       aes(x = Date, y = Value, color = Transport_Mode)) +
  geom_point() +
  labs(title = "Ridership Trends Over Time: Subways vs Buses",
       x = "Date",
       y = "Total Estimated Ridership",
       color = "Transport Mode")
```




```r
# Calculate the average ridership for each transport mode during the pandemic
avg_ridership_pandemic <- pt_mta_ridership_data %>%
  filter(Date >= as.Date("2020-03-01") & Date <= as.Date("2023-05-11")) %>%
  group_by(Transport_Mode) %>%
  summarize(Average_Ridership = mean(Value, na.rm = TRUE))

print(avg_ridership_pandemic)
```

```
## # A tibble: 5 x 2
##   Transport_Mode        Average_Ridership
##   <chr>                             <dbl>
## 1 Buses                           952938.
## 2 LIRR                            108023.
## 3 Metro-North                      88261.
## 4 Staten Island Railway             3890.
## 5 Subways                        2185483.
```

```r
# Analysis 5
pre_pandemic <- pt_mta_ridership_data %>%
  filter(Date >= as.Date("2020-03-01") & Date <= as.Date("2020-03-11"))
print(pre_pandemic)
```

```
## # A tibble: 55 x 4
##    Date       Transport_Mode        Metric_Type                  Value
##    <date>     <chr>                 <chr>                        <dbl>
```

```
##   1 2020-03-01 Subways              Total Estimated Ridership 2212965
##   2 2020-03-01 Buses                Total Estimated Ridership  984908
##   3 2020-03-01 LIRR                 Total Estimated Ridership   86790
##   4 2020-03-01 Metro-North          Total Estimated Ridership   55825
##   5 2020-03-01 Staten Island Railway Total Estimated Ridership    1636
##   6 2020-03-02 Subways              Total Estimated Ridership 5329915
##   7 2020-03-02 Buses                Total Estimated Ridership 2209066
##   8 2020-03-02 LIRR                 Total Estimated Ridership  321569
##   9 2020-03-02 Metro-North          Total Estimated Ridership  180701
##  10 2020-03-02 Staten Island Railway Total Estimated Ridership   17140
## # i 45 more rows
```

```r
post_pandemic <- pt_mta_ridership_data %>%
  filter(Date >= as.Date("2023-05-12") & Date <= as.Date("2024-10-10"))
print(post_pandemic)
```

```
## # A tibble: 2,520 x 4
##    Date       Transport_Mode        Metric_Type                 Value
##    <date>     <chr>                 <chr>                       <dbl>
##  1 2023-05-12 Subways               Total Estimated Ridership 3723192
##  2 2023-05-12 Buses                 Total Estimated Ridership 1436385
##  3 2023-05-12 LIRR                  Total Estimated Ridership  201367
##  4 2023-05-12 Metro-North           Total Estimated Ridership  185027
##  5 2023-05-12 Staten Island Railway Total Estimated Ridership    6629
##  6 2023-05-13 Subways               Total Estimated Ridership 2487178
##  7 2023-05-13 Buses                 Total Estimated Ridership  918257
##  8 2023-05-13 LIRR                  Total Estimated Ridership  113810
##  9 2023-05-13 Metro-North           Total Estimated Ridership  109940
## 10 2023-05-13 Staten Island Railway Total Estimated Ridership    1973
## # i 2,510 more rows
```

```r
avg_pre_pandemic <- pre_pandemic %>%
  group_by(Transport_Mode) %>%
  summarize(Average_Ridership_Pre = mean(Value, na.rm = TRUE))
print(avg_pre_pandemic)
```

```
## # A tibble: 5 x 2
##   Transport_Mode        Average_Ridership_Pre
##   <chr>                                 <dbl>
## 1 Buses                              1860634.
## 2 LIRR                                236933.
## 3 Metro-North                         154002.
## 4 Staten Island Railway                12476.
## 5 Subways                            4425676.
```

```r
avg_post_pandemic <- post_pandemic %>%
  group_by(Transport_Mode) %>%
  summarize(Average_Ridership_Post = mean(Value, na.rm = TRUE))
print(avg_post_pandemic)
```

```
## # A tibble: 5 x 2
##   Transport_Mode        Average_Ridership_Post
```

```
##   <chr>                                  <dbl>
## 1 Buses                               1111202.
## 2 LIRR                                 194476.
## 3 Metro-North                          170578.
## 4 Staten Island Railway                  5523.
## 5 Subways                             3171124.
```

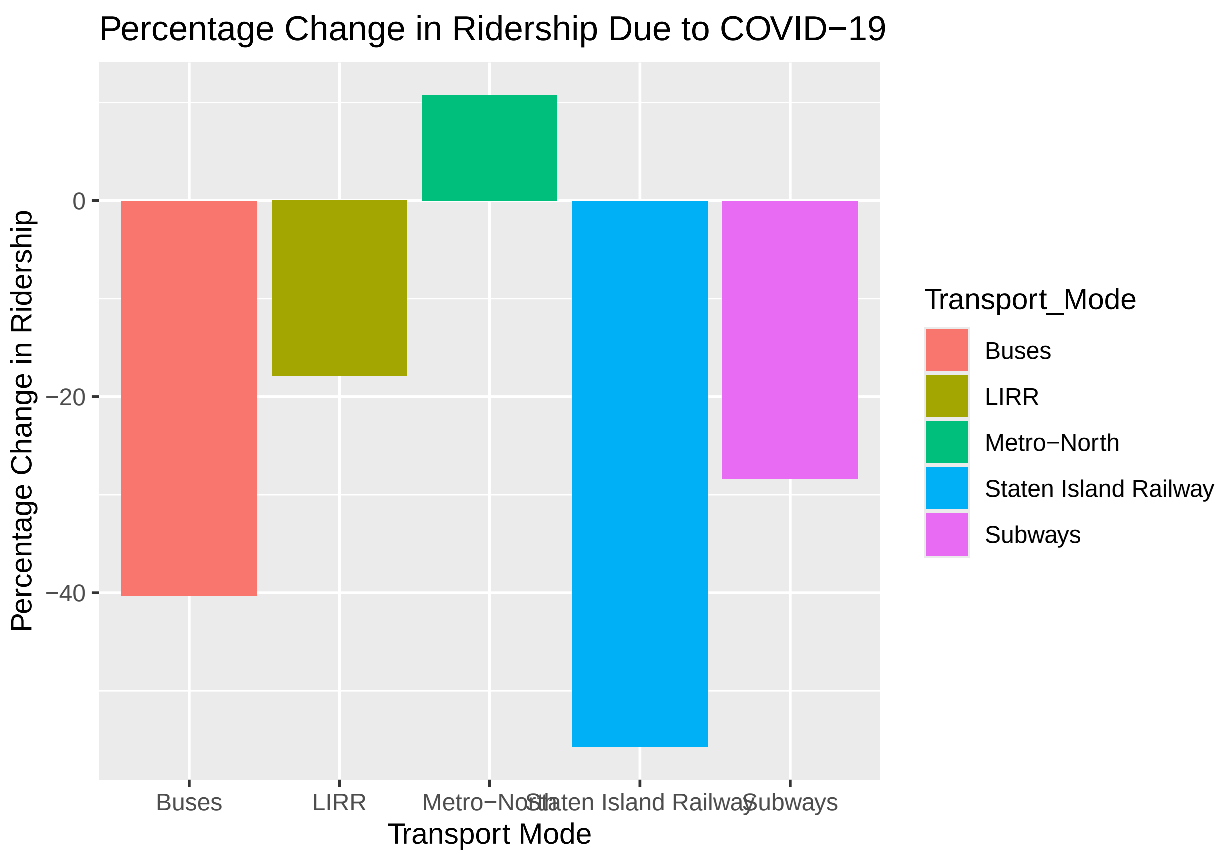
```r
avg_ridership <- merge(avg_pre_pandemic, avg_post_pandemic, by = "Transport_Mode")
print(avg_ridership)
```

```
##          Transport_Mode Average_Ridership_Pre Average_Ridership_Post
## 1                 Buses            1860634.45            1111202.327
## 2                  LIRR             236932.91             194476.022
## 3           Metro-North             154001.82             170578.192
## 4 Staten Island Railway              12476.09               5523.302
## 5               Subways            4425676.18            3171124.308
```

```r
avg_ridership <- avg_ridership %>%
  mutate(Percentage_Change = ((Average_Ridership_Post - Average_Ridership_Pre) / Average_Ridership_Pre)
print(avg_ridership)
```

```
##          Transport_Mode Average_Ridership_Pre Average_Ridership_Post
## 1                 Buses            1860634.45            1111202.327
## 2                  LIRR             236932.91             194476.022
## 3           Metro-North             154001.82             170578.192
## 4 Staten Island Railway              12476.09               5523.302
## 5               Subways            4425676.18            3171124.308
##   Percentage_Change
## 1         -40.27831
## 2         -17.91937
## 3          10.76375
## 4         -55.72891
## 5         -28.34712
```

```r
ggplot(avg_ridership, aes(x = Transport_Mode, y = Percentage_Change, fill = Transport_Mode)) +
  geom_bar(stat = "identity") +
  labs(title = "Percentage Change in Ridership Due to COVID-19",
       x = "Transport Mode",
       y = "Percentage Change in Ridership")
```



Analysis:

1- Analyze the average ridership for each transport mode. The data shows that subways have the most riders, with about 2.48 million people using them daily, much more than other types of transport. Buses come next, with around 1 million riders each day, making them very important. LIRR and Metro-North have fewer riders, with around 134,000 and 113,000 daily, since they serve commuters in specific regions. Staten Island Railway has the fewest riders, just over 4,000, likely because it covers a smaller area. Overall, subways and buses are the main ways people get around in the city.

2- Analyze how ridership for different transportation modes changes over time. This can help identify patterns, such as the impact of the COVID-19 pandemic on public transportation usage. As we can see, the chart shows public transportation ridership trends from 2020 to 2024, highlighting a sharp drop across all modes in early 2020 due to the COVID-19 pandemic, with subway ridership (in purple) experiencing the most significant decline. Ridership began recovering mid-2020, with buses showing a steadier recovery compared to the more volatile subway data. Regional transport modes like LIRR, Metro-North, and Staten Island Railway have consistently lower ridership. The chart reveals that, despite gradual recovery, ridership across all modes has not fully returned to pre-pandemic levels by 2024.

3- Analyze how the percentage of ridership compared to pre-pandemic levels changes over time for each transportation mode. The chart shows that public transportation usage dropped sharply during the pandemic but has been recovering at different rates across transport modes from 2020 to 2024. Bridges and tunnels saw the fastest recovery, exceeding 100% of pre-pandemic levels by 2021, indicating a shift towards car travel. Access-A-Ride and buses gradually returned to normal, nearing or slightly surpassing pre-pandemic levels by 2024. However, commuter services like the LIRR, Metro-North, and Staten Island Railway have been slower to recover, remaining below 100%, likely due to changes in work patterns. Subways are also recovering slowly, still below pre-pandemic levels by 2024.

4- Analyze the ridership trends between different transportation modes (subways vs buses) to see which modes were more resilient during the pandemic. The graph shows that both subway and bus ridership dropped sharply at the start of 2020 due to the pandemic. Subways saw a bigger drop than buses, but they have been recovering faster. By 2024, subway ridership has risen back to over 2 million, though it fluctuates more, while bus ridership has stayed steadier but remains below 2 million. Overall, subways have more riders than buses, but buses have a more stable number of users over time.

5- Analyze the impact of the COVID-19 pandemic on ridership by comparing pre-pandemic and post-pandemic data. The graph illustrates that most MTA transportation systems experienced a decline in ridership due to the COVID-19 pandemic, with Staten Island Railroad suffering the largest decrease, with over 50% fewer passengers. In contrast, Metro-North has seen an increase in ridership, likely due to people relocating from New York City during the pandemic and opting to commute using Metro-North.

Dataset 3: K-12 Schools diversity from 1994-2017 in all states

```r
url3<- "https://raw.githubusercontent.com/stormwhale/data-mines/refs/heads/main/school%20divers.csv"
df3<-read.csv(url3)
head(df3)
```

```
##   X.1 X  LEAID               LEA_NAME ST  d_Locale_Txt SCHOOL_YEAR       AIAN
## 1   1 1 100002 alabama youth services AL          <NA>   1994-1995 0.00000000
## 2   2 2 100005       albertville city AL  town-distant   1994-1995 0.00000000
## 3   3 3 100005       albertville city AL  town-distant   2016-2017 0.29373967
## 4   4 4 100006        marshall county AL rural-distant   1994-1995 0.10436857
## 5   5 5 100006        marshall county AL rural-distant   2016-2017 0.49235098
## 6   6 6 100007            hoover city AL    city-small   1994-1995 0.06518055
##       Asian      Black   Hispanic    White    Multi Total            diverse
## 1 0.5893910 71.7092338  0.1964637 27.50491       NA   509            Diverse
## 2 0.3207184  1.2828736  4.5221296 93.87428       NA  3118 Extremely undiverse
## 3 0.5507619  3.1944189 46.7413255 46.77804 2.441711  5447            Diverse
## 4 0.1341882  0.3727449  0.9094975 98.47920       NA  6707 Extremely undiverse
## 5 0.2989274  1.0726218 21.2941797 75.80447 1.037454  5687          Undiverse
## 6 1.6034415  6.0357189  0.5475166 91.74814       NA  7671 Extremely undiverse
##     variance         int_group
## 1         NA              <NA>
## 2         NA              <NA>
## 3 0.01155608 Highly integrated
## 4         NA              <NA>
## 5         NA              <NA>
## 6         NA              <NA>
```

Cleaning and tidying the dataset. The racial groups are already represented in percentage for each school. NA values are assumed to be 0. All percentage will be rounded to the nearest tenth value.

```r
df3_tidy<- df3 %>%
  mutate_all(~replace(., is.na(.), 0)) %>%
  pivot_longer(cols = AIAN:Multi,
               names_to = 'Ethnicity',
               values_to = 'Student_percentage') %>%
  mutate(Student_percentage=round(as.numeric(Student_percentage),1))

head(df3_tidy)
```

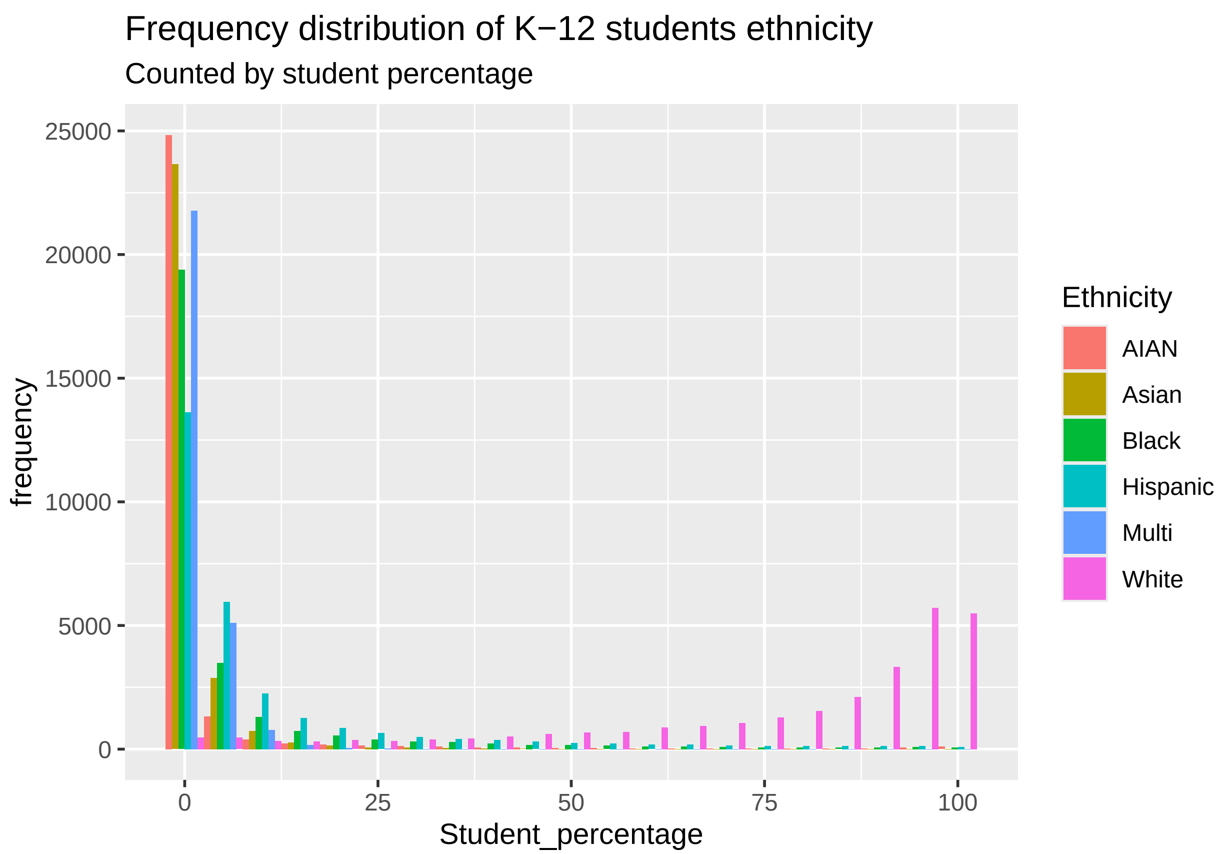
```
## # A tibble: 6 x 13
##     X.1     X  LEAID LEA_NAME       ST    d_Locale_Txt SCHOOL_YEAR Total diverse
##   <dbl> <dbl>  <dbl> <chr>          <chr> <chr>        <chr>       <dbl> <chr>
## 1     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## 2     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## 3     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## 4     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## 5     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## 6     1     1 100002 alabama youth~ AL    0            1994-1995     509 Diverse
## # i 4 more variables: variance <dbl>, int_group <chr>, Ethnicity <chr>,
## #   Student_percentage <dbl>
```

Data analysis:

1) Overall ethnicity distribution of K-12 students:

Asian and AIAN groups seem to be the most under integrated among different schools. (See plot below)

```r
ggplot(df3_tidy, aes(x=Student_percentage, fill=Ethnicity)) +
  geom_histogram(binwidth = 5, position='dodge') +
  labs(y='frequency',
       title = 'Frequency distribution of K-12 students ethnicity',
       subtitle = 'Counted by student percentage')
```



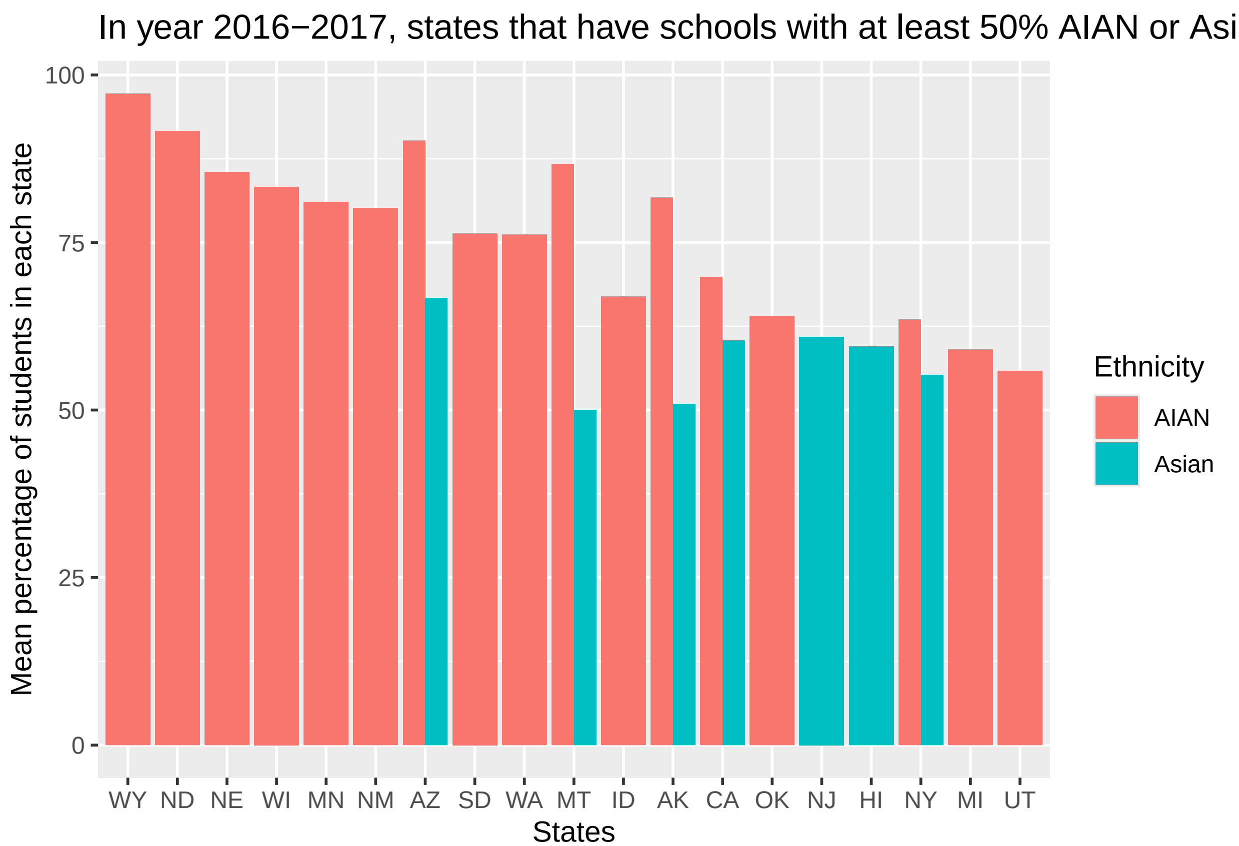
In 2016-2017, which states have schools that integrated at least 50% Asian and AIAN students?

```
df3_2017<- df3_tidy %>%
  filter(SCHOOL_YEAR=='2016-2017') %>%
  filter((Ethnicity =='Asian' | Ethnicity == 'AIAN') & Student_percentage >= 50) %>%
  group_by(ST, Ethnicity) %>%
  summarize(mean_percentage = mean(Student_percentage), .groups = 'drop') %>%
  arrange(desc(mean_percentage))

print(df3_2017)
```

```
## # A tibble: 24 x 3
##    ST    Ethnicity mean_percentage
##    <chr> <chr>               <dbl>
##  1 WY    AIAN                 97.2
##  2 ND    AIAN                 91.6
##  3 AZ    AIAN                 90.2
##  4 MT    AIAN                 86.7
##  5 NE    AIAN                 85.5
##  6 WI    AIAN                 83.3
##  7 AK    AIAN                 81.7
##  8 MN    AIAN                 81.0
##  9 NM    AIAN                 80.1
## 10 SD    AIAN                 76.4
```

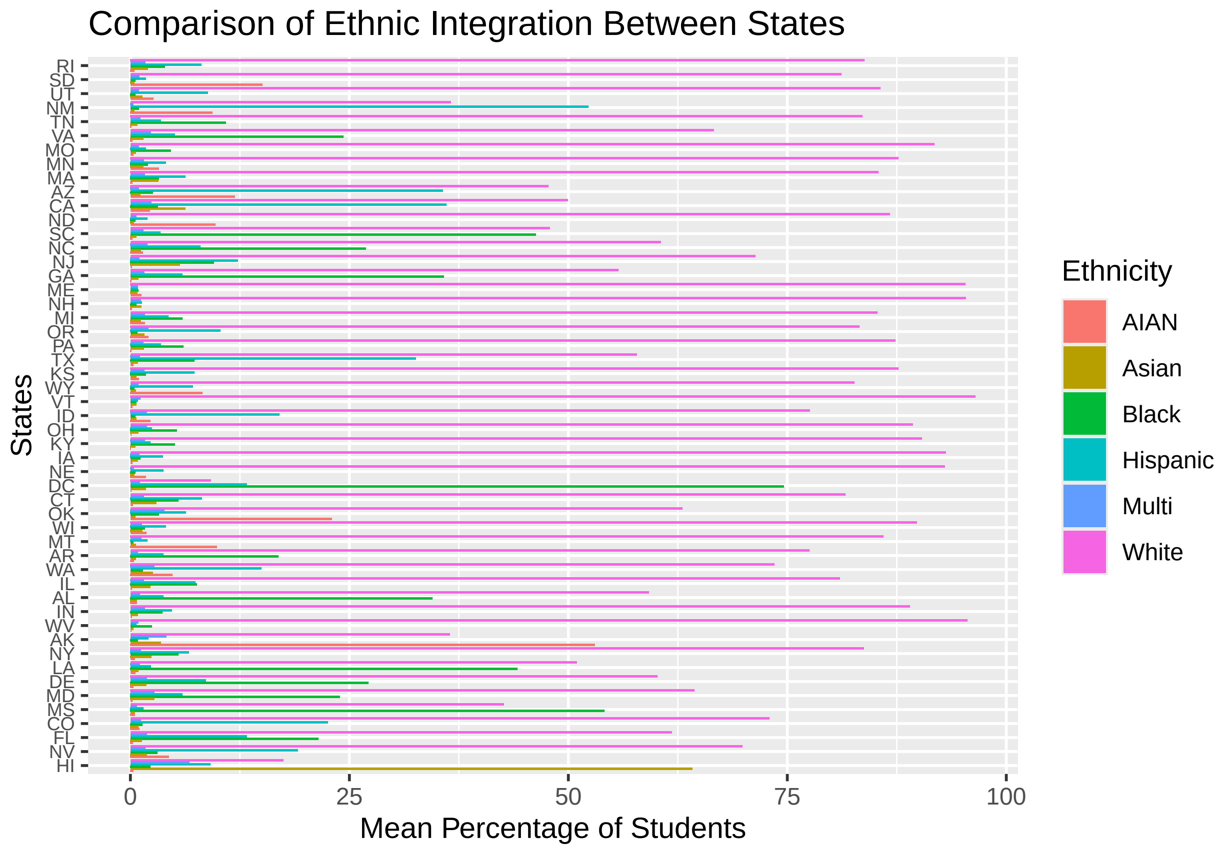
```
## # i 14 more rows
```

```
ggplot(df3_2017, aes(x=reorder(ST, -mean_percentage), y=mean_percentage, fill= Ethnicity)) +
  geom_bar(stat='identity', position = 'dodge') +
  labs(title = 'In year 2016-2017, states that have schools with at least 50% AIAN or Asian',
       x='States',
       y='Mean percentage of students in each state')
```



2) - Between State Comparisons, compare the integration levels of different ethnic groups between states to see which states are more integrated.

```
df3_state_comparison <- df3_tidy %>%
  group_by(ST, Ethnicity) %>%
  summarize(mean_percentage = mean(Student_percentage), .groups = 'drop') %>%
  arrange(desc(mean_percentage))

ggplot(df3_state_comparison, aes(x=reorder(ST, -mean_percentage), y=mean_percentage, fill=Ethnicity)) +
  geom_bar(stat='identity', position='dodge') +
  labs(title = 'Comparison of Ethnic Integration Between States',
       x='States',
       y='Mean Percentage of Students') +
  coord_flip() +
  theme(axis.text.y= element_text(size = 7))
```



Analysis 1: Overall distribution of ethnicity The graph depicts the mean percentage of students in U.S. states during the 2016-2017 school year, with at least 50% of either American Indian and Alaska Native or Asian students integrated into schools. Wyoming, North Dakota, and Nebraska have the highest proportions of AIAN students, approaching or at 100%. In contrast, states like Arizona, California, and New Jersey show substantial integration of Asian students. States like South Dakota, Washington, and Idaho present a more balanced distribution between AIAN and Asian student populations. Overall, the chart highlights significant regional differences in ethnic integration within school systems, particularly for AIAN and Asian students

Analysis 2: Between State Comparison The graph compares the ethnic integration of students in various states, showing the mean percentage of different racial groups in schools. White students make up the largest proportion of students in most states, often exceeding 50% and even approaching 100% in several. Hispanic, Black, and Asian students are represented at lower percentages across states, with some variation. AIAN students and students of multiple races have smaller but noticeable percentages in some states. The chart highlights significant racial differences in student populations across states, with White students being the most dominant group.