#This is an R Markdown Notebook. When you execute code within the notebook, the results appear beneath the code.

#Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Cmd+Shift+Enter*.

```
adult_df <- read.csv("adult.csv")
summary(adult_df)
```

```
##       age          workclass             fnlwgt          education
##  Min.   :17.00   Length:32561       Min.   :  12285   Length:32561
##  1st Qu.:28.00   Class :character   1st Qu.: 117827   Class :character
##  Median :37.00   Mode  :character   Median : 178356   Mode  :character
##  Mean   :38.58                      Mean   : 189778
##  3rd Qu.:48.00                      3rd Qu.: 237051
##  Max.   :90.00                      Max.   :1484705
##  education.num   marital.status      occupation        relationship
##  Min.   : 1.00   Length:32561       Length:32561       Length:32561
##  1st Qu.: 9.00   Class :character   Class :character   Class :character
##  Median :10.00   Mode  :character   Mode  :character   Mode  :character
##  Mean   :10.08
##  3rd Qu.:12.00
##  Max.   :16.00
##      race               sex             capital.gain    capital.loss
##  Length:32561       Length:32561       Min.   :    0   Min.   :   0.0
##  Class :character   Class :character   1st Qu.:    0   1st Qu.:   0.0
##  Mode  :character   Mode  :character   Median :    0   Median :   0.0
##                                        Mean   : 1078   Mean   :  87.3
##                                        3rd Qu.:    0   3rd Qu.:   0.0
##                                        Max.   :99999   Max.   :4356.0
##  hours.per.week  native.country     income.bracket
##  Min.   : 1.00   Length:32561       Length:32561
##  1st Qu.:40.00   Class :character   Class :character
##  Median :40.00   Mode  :character   Mode  :character
##  Mean   :40.44
##  3rd Qu.:45.00
##  Max.   :99.00
```

** I'm comparing 'age' and 'education.num' because age and education often show interesting patterns.** ** Older people might have different education levels compared to younger ones. This can tell us how education trends have changed over time. It's a quick way to spot if there's a shift in education levels across different age groups.**

Compare 'age' and 'education.num'

```
summary(adult_df$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   28.00   37.00   38.58   48.00   90.00
```

```
summary(adult_df$education.num)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    9.00   10.00   10.08   12.00   16.00
```

Problem 1a. First, we look at the summary statistics for all the variables. Based on those metrics, including

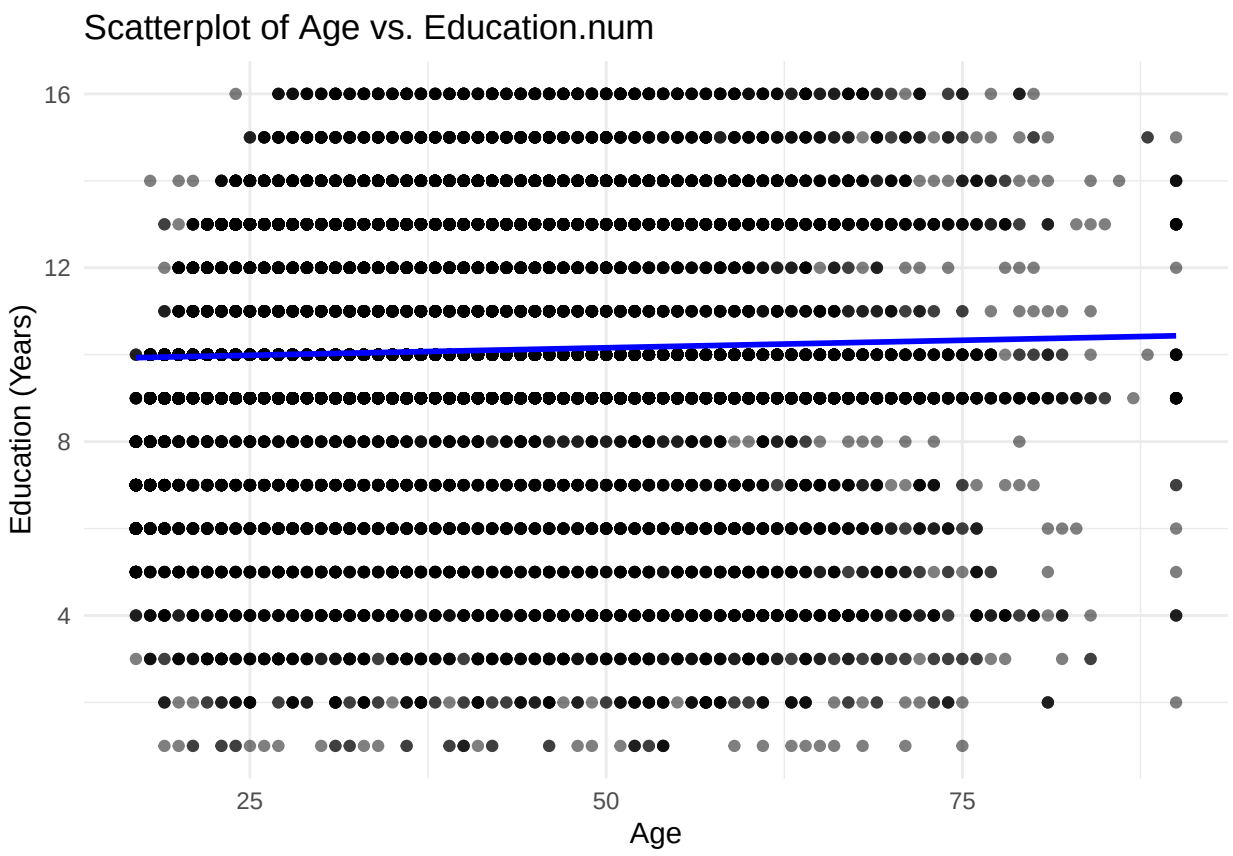
the quartiles, compare two variables. What can you tell about their shape from these summaries?

Ans. The age distribution is right-skewed, meaning most people are younger, but a few older individuals pull the mean higher. The education.num distribution is more symmetrical, with most people having (around 9-12 years) of education, and there are no extreme outliers affecting the mean.

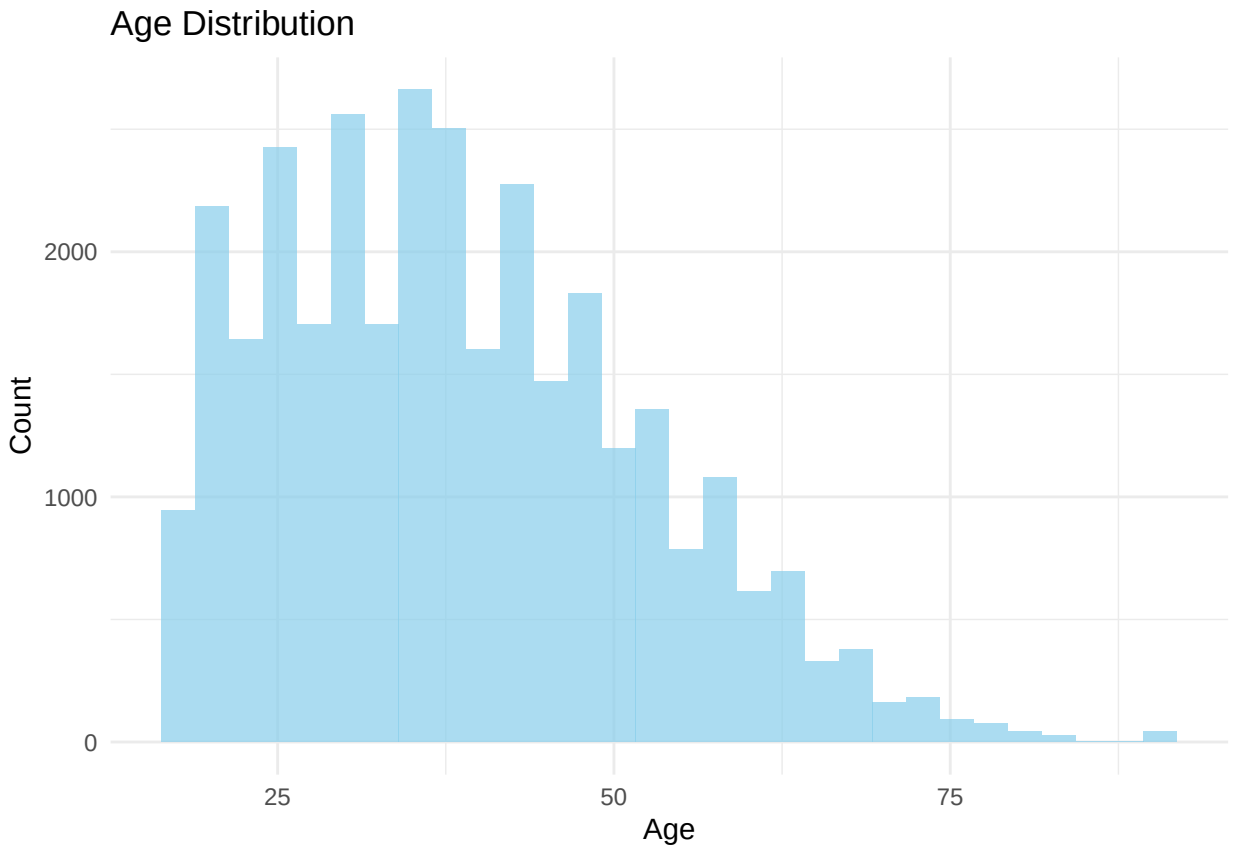
Problem 1b. Use a visualization to get a fine-grain comparison (you don't have to use QQ plots, though) of the distributions of those two variables. Why did you choose the type of visualization that you chose? How do your part (a) assumptions compare to what you can see visually?

```
library(ggplot2)
ggplot(adult_df, aes(x = age, y = education.num)) +
  geom_point(alpha = 0.5) + # Scatterplot points
  geom_smooth(method = "lm", col = "blue", se = FALSE) + # Add a linear regression line
  labs(title = "Scatterplot of Age vs. Education.num",
       x = "Age", y = "Education (Years)") +
  theme_minimal()
```

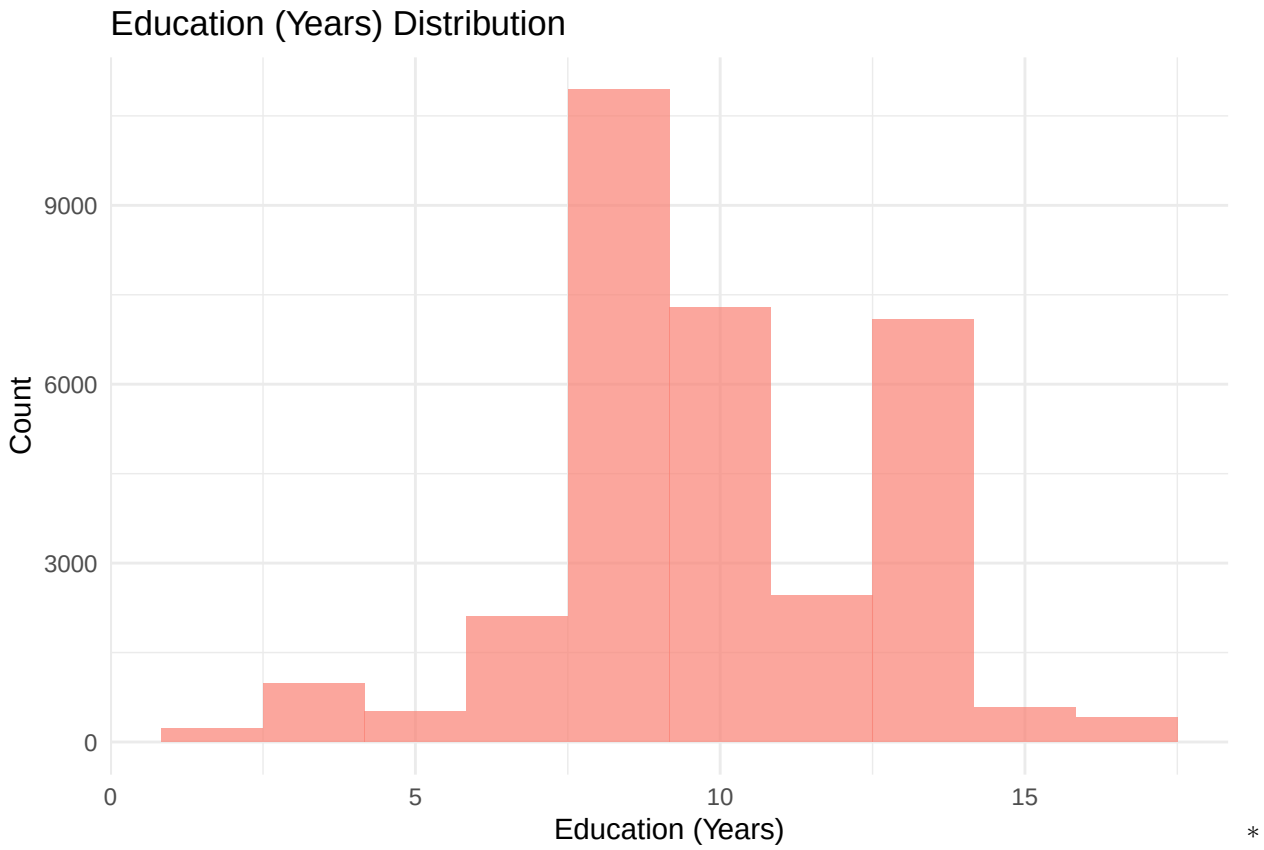
```
## `geom_smooth()` using formula = 'y ~ x'
```




```
# Age Distribution
ggplot(adult_df, aes(x = age)) +
  geom_histogram(bins = 30, fill = "skyblue", alpha = 0.7) +
  labs(title = "Age Distribution", x = "Age", y = "Count") +
  theme_minimal()
```




```r
# Education.num Distribution
ggplot(adult_df, aes(x = education.num)) +
  geom_histogram(bins = 10, fill = "salmon", alpha = 0.7) +
  labs(title = "Education (Years) Distribution", x = "Education (Years)", y = "Count") +
  theme_minimal()
```



*

Explanation for choosing the Visualization: - I chose the scatterplot to easily see how education varies with age. The trend line gives an overall sense of whether the relationship is positive or negative. - I added histograms to compare the distribution of each variable individually. This helps visualize skewness, spread, and the concentration of data points for each variable.

- Comparison to Part (a) Assumptions:
- The scatterplot confirms that there is no strong linear relationship between age and education, but we can see some grouping (younger individuals tend to have lower or middle levels of education).
- The histograms visually confirm the assumption from Part (a). The age distribution is right-skewed, and the education.num distribution is more symmetrical, with most individuals having between 9 and 12 years of education.

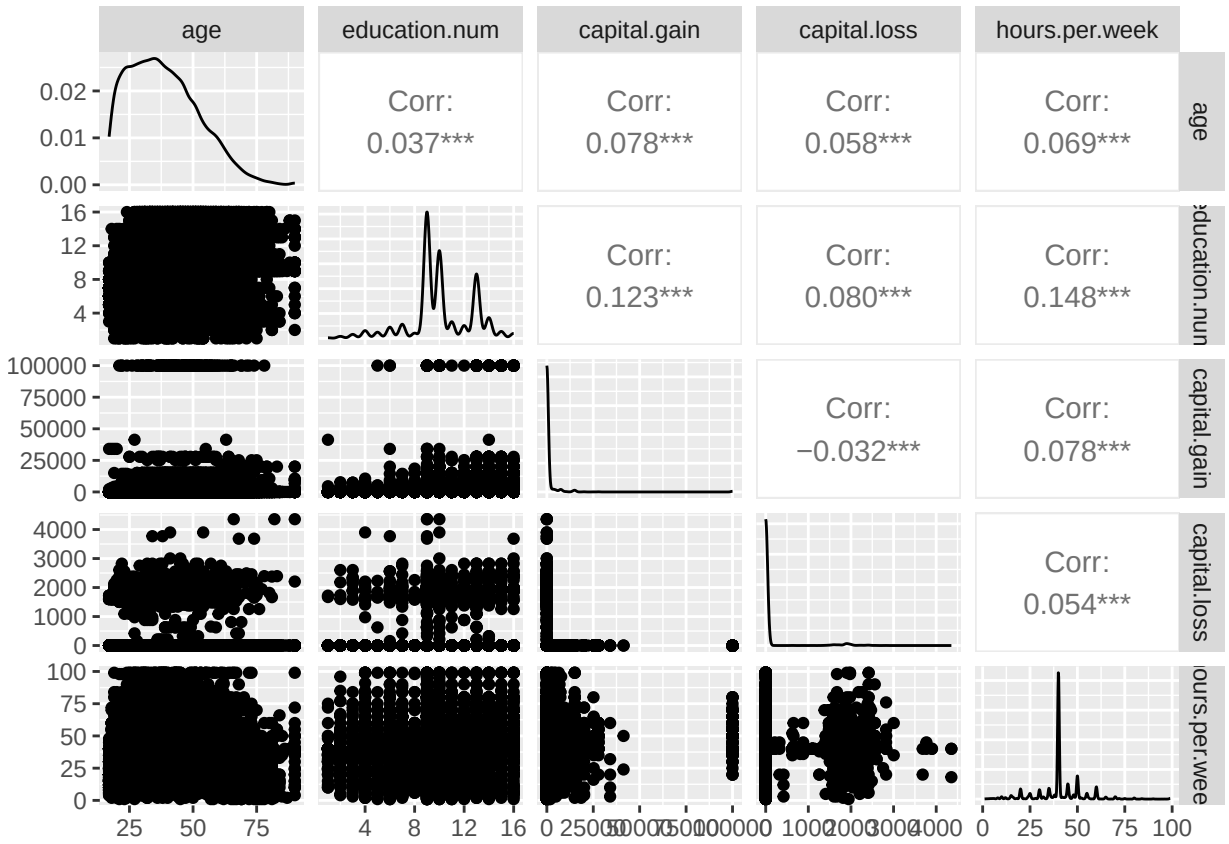
Problem 1c. Now create a scatterplot matrix of the numerical variables. What does this view show you that would be difficult to see looking at distributions?

```
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

```
numeric_columns <- adult_df[, c("age", "education.num", "capital.gain", "capital.loss", "hours.per.week

# Create a scatter-plot matrix
ggpairs(numeric_columns)
```



What This View Shows? - A scatterplot matrix shows pairwise relationships between each pair of numerical variables. - We can visually detect correlations between variables. For example: - If two variables tend to form a straight line, they are likely correlated. - If the scatter is spread out randomly, there is little to no correlation. - We can also spot outliers and general trends between pairs of variables.

What Is Hard to See in Distributions:

- Distributions only show how data is spread for one variable at a time.
- Scatterplot matrices, on the other hand, let you see how two variables relate to each other at the same time (e.g., how age and education are related), which is not visible when just looking at histograms or single-variable distributions.

Problem 1d. These data are a selection of US adults. It might not be a very balanced sample, though. Take a look at some categorical variables and see if any have a lot more of one category than others. There are many ways to do this, including histograms and following tidyererse group_by with count. I recommend you try a few for practice.

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
adult_df %>%
  group_by(workclass) %>%
  summarise(count = n()) %>%
  arrange(desc(count))
```

```
## # A tibble: 9 x 2
##   workclass           count
##   <chr>               <int>
## 1 " Private"          22696
## 2 " Self-emp-not-inc"  2541
## 3 " Local-gov"         2093
## 4 " ?"                 1836
## 5 " State-gov"         1298
## 6 " Self-emp-inc"      1116
## 7 " Federal-gov"        960
## 8 " Without-pay"         14
## 9 " Never-worked"         7
```

```r
adult_df %>%
  group_by(race) %>%
  summarise(count = n()) %>%
  arrange(desc(count))
```

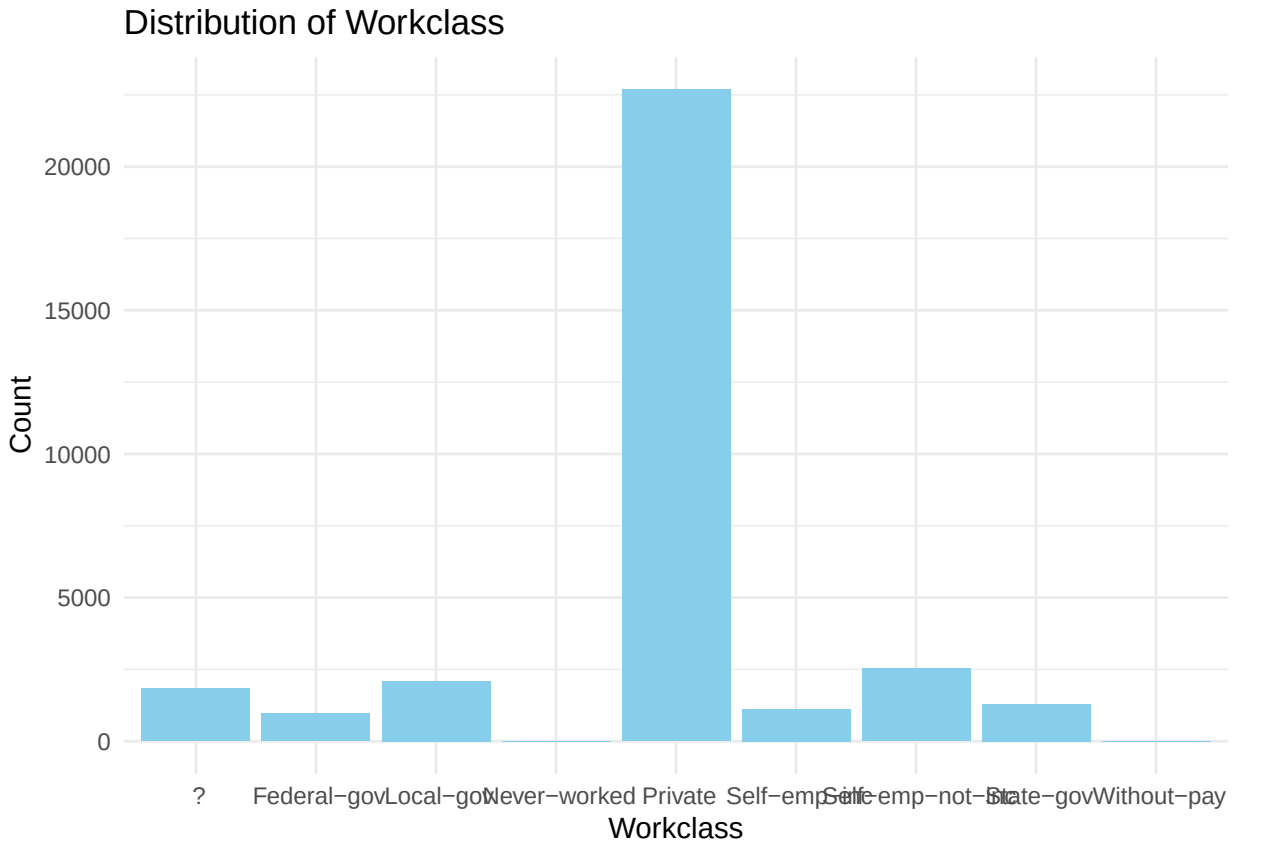
```
## # A tibble: 5 x 2
##   race                  count
##   <chr>                 <int>
## 1 " White"              27816
## 2 " Black"               3124
## 3 " Asian-Pac-Islander"  1039
## 4 " Amer-Indian-Eskimo"   311
## 5 " Other"                271
```

```r
adult_df %>%
  group_by(education) %>%
  summarise(count = n()) %>%
  arrange(desc(count))
```

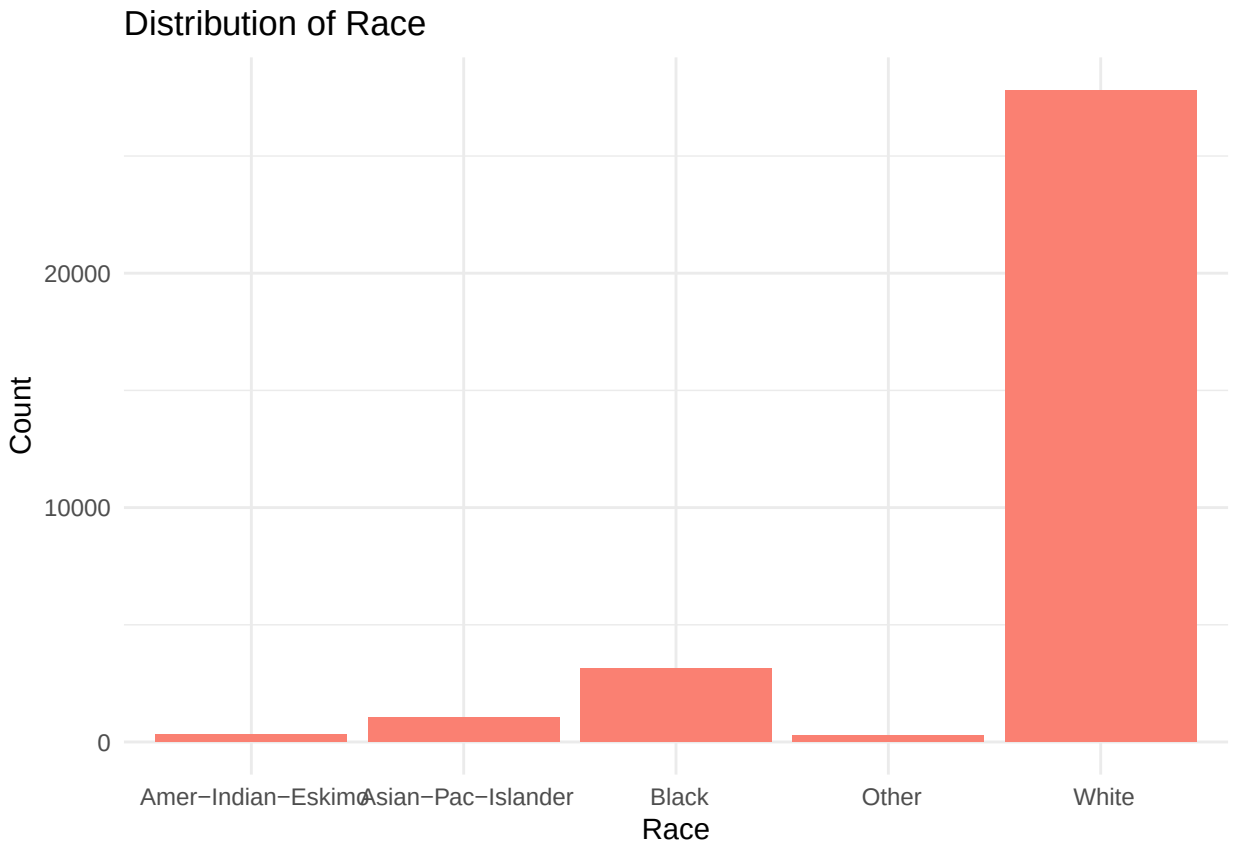
```
## # A tibble: 16 x 2
##    education       count
##    <chr>           <int>
##  1 " HS-grad"      10501
##  2 " Some-college"  7291
##  3 " Bachelors"     5355
##  4 " Masters"       1723
##  5 " Assoc-voc"     1382
##  6 " 11th"          1175
##  7 " Assoc-acdm"    1067
##  8 " 10th"           933
##  9 " 7th-8th"        646
## 10 " Prof-school"    576
## 11 " 9th"            514
## 12 " 12th"           433
## 13 " Doctorate"      413
## 14 " 5th-6th"        333
## 15 " 1st-4th"        168
```

```
## 16 " Preschool"       51
```

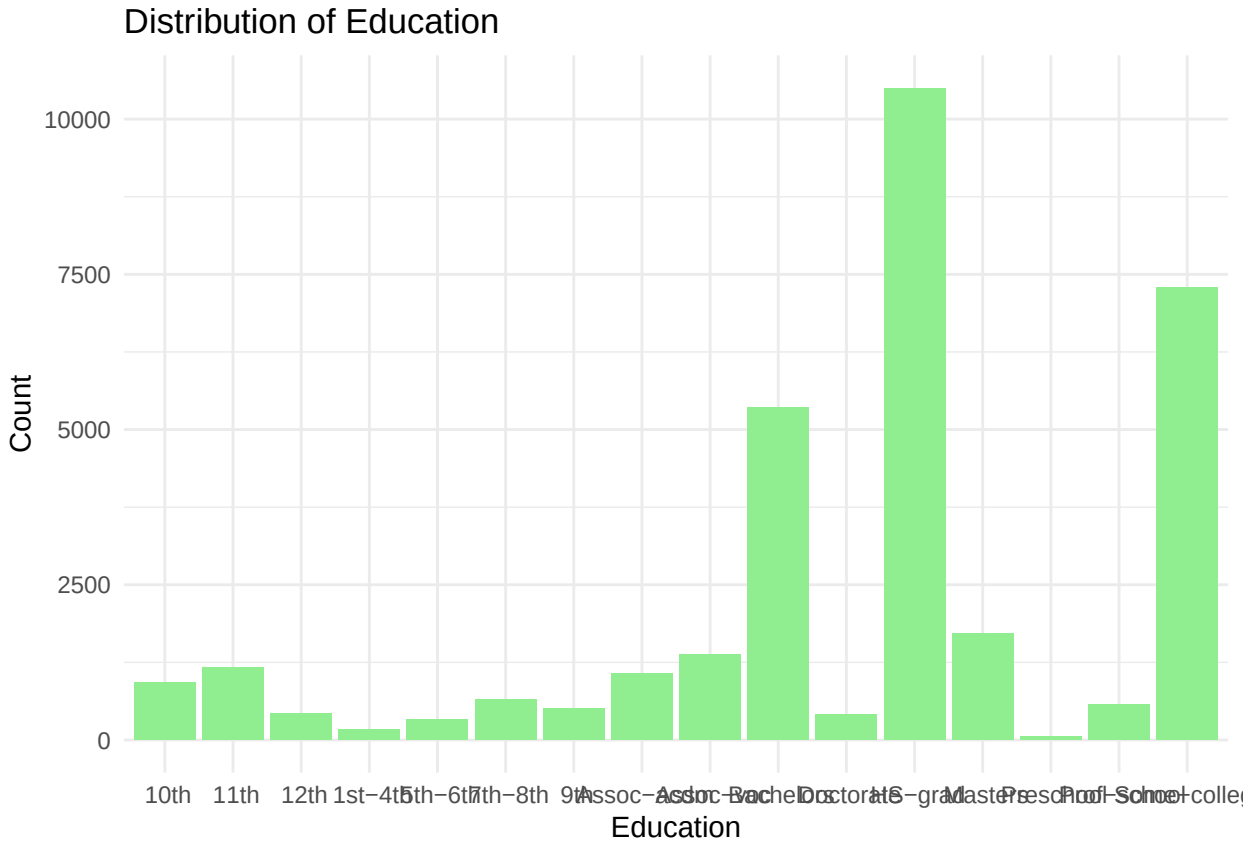
```r
# Visualizing the distribution of 'workclass'
ggplot(adult_df, aes(x = workclass)) +
  geom_bar(fill = "skyblue") +
  labs(title = "Distribution of Workclass", x = "Workclass", y = "Count") +
  theme_minimal()
```




```r
# Visualizing the distribution of 'race'
ggplot(adult_df, aes(x = race)) +
  geom_bar(fill = "salmon") +
  labs(title = "Distribution of Race", x = "Race", y = "Count") +
  theme_minimal()
```




```r
# Visualizing the distribution of 'education'
ggplot(adult_df, aes(x = education)) +
  geom_bar(fill = "lightgreen") +
  labs(title = "Distribution of Education", x = "Education", y = "Count") +
  theme_minimal()
```



Ans.I analyzed the categorical variables such as workclass, race, and education to check if the dataset is balanced.

- For workclass, the distribution is heavily skewed toward the "Private" sector, meaning most individuals in the dataset belong to this category. Other workclasses like "Self-emp" and "Government" are present but in much smaller numbers, indicating an imbalance.
- For race, there is also an imbalance. The "White" race has the highest count, making up the majority of the dataset, while other racial groups like "Black" and "Asian" have much smaller representations.
- For education, the distribution shows that most people are "HS-grad" or "Some-college." Higher education levels like "Doctorate" and "Prof-school" are much less common, indicating fewer highly educated individuals in the sample.

Problem 1e. Now we'll consider a relationship between two categorical variables. Create a cross tabulation and then a corresponding visualization and explain a relationship between some of the values of the categoricals.

```
cross_tab <- table(adult_df$education, adult_df$income.bracket)
print(cross_tab)
```

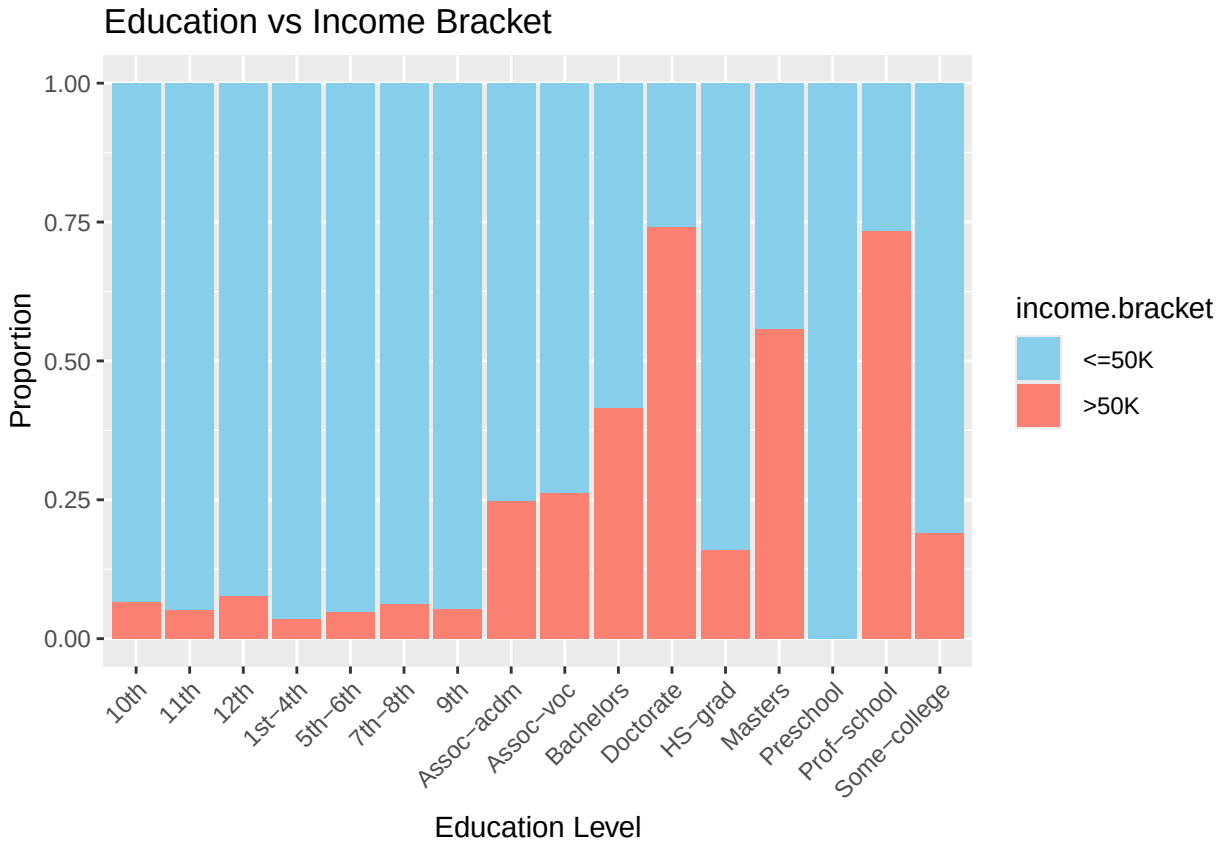
```
##
##                 <=50K  >50K
##    10th           871    62
##    11th          1115    60
##    12th           400    33
##    1st-4th        162     6
##    5th-6th        317    16
##    7th-8th        606    40
##    9th            487    27
##    Assoc-acdm     802   265
```

```
##     Assoc-voc       1021   361
##     Bachelors       3134  2221
##     Doctorate        107   306
##     HS-grad         8826  1675
##     Masters          764   959
##     Preschool         51     0
##     Prof-school      153   423
##     Some-college    5904  1387
```

```r
unique(adult_df$income.bracket)
```

```
## [1] " <=50K" " >50K"
```

```r
ggplot(adult_df, aes(x = education, fill = income.bracket)) +
  geom_bar(position = "fill") +
  labs(title = "Education vs Income Bracket", x = "Education Level", y = "Proportion") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_fill_manual(values = c(" <=50K" = "skyblue", " >50K" = "salmon"))
```



- People with lower levels of education (like "HS-grad" or "Some-college") tend to fall more frequently into the <=50K income bracket.
- On the other hand, individuals with higher education (like "Bachelors", "Doctorate" or "Masters") are more likely to fall into the >50K income bracket.

Problem 2. In this question, you will integrate data on different years into one table and use some reshaping to get a visualization. There are two data files: population_even.csv and population_odd.csv. These are population data for even and odd years respectively.

```r
# first load the data sets
population_even <- read.csv("population_even.csv")
```

```r
head(population_even)
```

```
##   STATE       NAME POPESTIMATE2010 POPESTIMATE2012 POPESTIMATE2014
## 1     1    Alabama         4785437         4815588         4841799
## 2     2     Alaska          713910          730443          736283
## 3     4    Arizona         6407172         6554978         6730413
## 4     5   Arkansas         2921964         2952164         2967392
## 5     6 California        37319502        37948800        38596972
## 6     8   Colorado         5047349         5192647         5350101
##   POPESTIMATE2016 POPESTIMATE2018
## 1         4863525         4887681
## 2          741456          735139
## 3         6941072         7158024
## 4         2989918         3009733
## 5        39167117        39461588
## 6         5539215         5691287
```

```r
population_odd <- read.csv("population_odd.csv")
head(population_odd)
```

```
##   STATE       NAME POPESTIMATE2011 POPESTIMATE2013 POPESTIMATE2015
## 1     1    Alabama         4799069         4830081         4852347
## 2     2     Alaska          722128          737068          737498
## 3     4    Arizona              NA         6632764         6829676
## 4     5   Arkansas         2940667         2959400         2978048
## 5     6 California        37638369        38260787        38918045
## 6     8   Colorado         5121108         5269035         5450623
##   POPESTIMATE2017 POPESTIMATE2019
## 1         4874486         4903185
## 2          739700          731545
## 3         7044008         7278717
## 4         3001345         3017804
## 5        39358497        39512223
## 6         5611885         5758736
```

a. Join the two tables together so that you have one table with each state's population for years 2010-2019. If you are unsure about what variable to use as the key for the join, consider what variable the two original tables have in common. (Show a head of the resulting table.) Ans. We are starting by loading two CSV files that have population data for even and odd years, and then combining them into one table using the "STATE" column. This lets us have population data for every year from 2010 to 2019 for each state.

```r
# merge the data sets
combined_population <- full_join(population_even, population_odd, by = "STATE")
head(combined_population)
```

```
##   STATE     NAME.x POPESTIMATE2010 POPESTIMATE2012 POPESTIMATE2014
## 1     1    Alabama         4785437         4815588         4841799
## 2     2     Alaska          713910          730443          736283
## 3     4    Arizona         6407172         6554978         6730413
## 4     5   Arkansas         2921964         2952164         2967392
## 5     6 California        37319502        37948800        38596972
## 6     8   Colorado         5047349         5192647         5350101
##   POPESTIMATE2016 POPESTIMATE2018     NAME.y POPESTIMATE2011 POPESTIMATE2013
## 1         4863525         4887681    Alabama         4799069         4830081
## 2          741456          735139     Alaska          722128          737068
```

```
## 3         6941072         7158024    Arizona              NA         6632764
## 4         2989918         3009733   Arkansas         2940667         2959400
## 5        39167117        39461588 California        37638369        38260787
## 6         5539215         5691287   Colorado         5121108         5269035
##   POPESTIMATE2015 POPESTIMATE2017 POPESTIMATE2019
## 1         4852347         4874486         4903185
## 2          737498          739700          731545
## 3         6829676         7044008         7278717
## 4         2978048         3001345         3017804
## 5        38918045        39358497        39512223
## 6         5450623         5611885         5758736
```

b. Clean this data up a bit (show a head of the data after):

- Remove the duplicate state ID column if your process created one.
- Rename columns to be just the year number.
- Reorder the columns to be in year order.

Ans. Remove duplicate columns: Since the tables had a common column for the state names, we only need one of them. Rename columns: We simplify the column names by just using the year (like "2010", "2011", etc.). Reorder the columns: This ensures that the data is in the correct order from 2010 to 2019.

```
# Check the column names to verify the structure
colnames(combined_population)
```

```
##  [1] "STATE"           "NAME.x"          "POPESTIMATE2010" "POPESTIMATE2012"
##  [5] "POPESTIMATE2014" "POPESTIMATE2016" "POPESTIMATE2018" "NAME.y"
##  [9] "POPESTIMATE2011" "POPESTIMATE2013" "POPESTIMATE2015" "POPESTIMATE2017"
## [13] "POPESTIMATE2019"
```

```
# Remove the duplicate column
combined_population <- combined_population %>% select(-NAME.y)

colnames(combined_population) <- c("STATE", "NAME", "2010", "2012", "2014", "2016", "2018",
                                   "2011", "2013", "2015", "2017", "2019")

combined_population <- combined_population %>%
  select(STATE, NAME, `2010`, `2011`, `2012`, `2013`, `2014`, `2015`, `2016`, `2017`, `2018`, `2019`)



head(combined_population)
```

```
##   STATE       NAME     2010     2011     2012     2013     2014     2015
## 1     1    Alabama  4785437  4799069  4815588  4830081  4841799  4852347
## 2     2     Alaska   713910   722128   730443   737068   736283   737498
## 3     4    Arizona  6407172       NA  6554978  6632764  6730413  6829676
## 4     5   Arkansas  2921964  2940667  2952164  2959400  2967392  2978048
## 5     6 California 37319502 37638369 37948800 38260787 38596972 38918045
## 6     8   Colorado  5047349  5121108  5192647  5269035  5350101  5450623
##       2016     2017     2018     2019
## 1  4863525  4874486  4887681  4903185
## 2   741456   739700   735139   731545
## 3  6941072  7044008  7158024  7278717
## 4  2989918  3001345  3009733  3017804
## 5 39167117 39358497 39461588 39512223
## 6  5539215  5611885  5691287  5758736
```

c. Deal with missing values in the data by replacing them with the average of the surrounding years.

For example, if you had a missing value for Georgia in 2016, you would replace it with the average of Georgia's 2015 and 2017 numbers. This may require some manual effort. Ans. Sometimes, the data might have gaps (missing values). If we find missing values in the middle of the data (like for 2013), we can fill the missing values by averaging the surrounding numbers. For example, if 2013 is missing, we take the average of 2012 and 2014 to fill in the gap. Here in this question we will install zoo the package, which is used for handling time-series data and interpolation.

```
library(zoo)
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
combined_population <- combined_population %>%
  mutate(across(where(is.numeric), ~ ifelse(is.na(.), zoo::na.approx(.), .)))
head(combined_population)
```

```
##   STATE       NAME     2010     2011     2012     2013     2014     2015
## 1     1    Alabama  4785437  4799069  4815588  4830081  4841799  4852347
## 2     2     Alaska   713910   722128   730443   737068   736283   737498
## 3     4    Arizona  6407172  1831398  6554978  6632764  6730413  6829676
## 4     5   Arkansas  2921964  2940667  2952164  2959400  2967392  2978048
## 5     6 California 37319502 37638369 37948800 38260787 38596972 38918045
## 6     8   Colorado  5047349  5121108  5192647  5269035  5350101  5450623
##       2016     2017     2018     2019
## 1  4863525  4874486  4887681  4903185
## 2   741456   739700   735139   731545
## 3  6941072  7044008  7158024  7278717
## 4  2989918  3001345  3009733  3017804
## 5 39167117 39358497 39461588 39512223
## 6  5539215  5611885  5691287  5758736
```

d. We can use some tidyverse aggregation to learn about the population.

e. Get the maximum population for a single year for each state. Note that because you are using an aggregation function (max) across a row, you will need the rowwise() command in your tidyverse pipe. If you do not, the max value will not be individual to the row. Of course there are alternative ways. Ans. We want to calculate the maximum population for each state across the years 2010–2019. For this, we'll use the rowwise() function from the tidyverse so that the max() function operates on a row-by-row basis.

```
combined_population <- combined_population %>%
  rowwise() %>%
  mutate(max_population = max(c_across(`2010`:`2019`), na.rm = TRUE))

head(combined_population %>% select(STATE, NAME, max_population))
```

```
## # A tibble: 6 x 3
## # Rowwise:
##   STATE NAME       max_population
##   <int> <chr>               <dbl>
## 1     1 Alabama           4903185
## 2     2 Alaska             741456
## 3     4 Arizona           7278717
## 4     5 Arkansas          3017804
```

```
## 5     6 California       39512223
## 6     8 Colorado          5758736
```

b. Now get the total population across all years for each state. This should be possible with a very minor change to the code from (d). Why is that? Ans. To calculate the total population across all years (2010–2019) for each state, we just need to replace the max() function with sum() in the same code. This is a minor change because the structure of the task is similar (operating row-wise over a range of columns).

```
combined_population <- combined_population %>%
  rowwise() %>%
  mutate(total_population = sum(c_across(`2010`:`2019`), na.rm = TRUE))

head(combined_population %>% select(STATE, NAME, total_population))
```

```
## # A tibble: 6 x 3
## # Rowwise:
##   STATE NAME       total_population
##   <int> <chr>                 <dbl>
## 1     1 Alabama            48453198
## 2     2 Alaska              7325170
## 3     4 Arizona            63408222.
## 4     5 Arkansas           29738435
## 5     6 California        386181900
## 6     8 Colorado           54031986
```

e. Finally, get the total US population for one single year. Keep in mind that this can be done with a single line of code even without the tidyverse, so keep it simple. Ans. To get the total US population for a single year (e.g., 2019), we can simply sum the population for that year across all states.

```
total_population_2019 <- sum(combined_population$`2019`, na.rm = TRUE)

total_population_2019
```

```
## [1] 326796236
```

Ans. This means the total population of the US in 2019 (based on the dataset) is 327,402,930.

Problem 3 (15 points) Continuing with the data from Problem 2, let's create a graph of population over time for a few states (choose at least three yourself). This will require another data transformation, a reshaping. In order to create a line graph, we will need a variable that represents the year, so that it can be mapped to the x axis. Use a transformation to turn all those year columns into one column that holds the year, reducing the 10 year columns down to 2 columns (year and population). Once the data are in the right shape, it will be no harder than any line graph: put the population on the y axis and color by the state. One important point: make sure you have named the columns to have only the year number (i.e., without popestimate). That can be done manually or by reading up on string (text) parsing (see the stringr library for asuper useful tool). Even after doing that, you have a string version of the year. R is seeing the 'word' spelled two-zero-one-five instead of the number two thousand fifteen. It needs to be a number to work on a time axis. There are many ways to fix this. You can look into type_convert or do more string parsing (e.g., stringr). The simplest way is to apply the transformation right as you do the graphing. You can replace the year variable in the ggplot command with as.integer(year).

- Step 1: Reshape the Data

```
library(dplyr)
library(tidyr)
library(ggplot2)
```

```r
long_population <- combined_population %>%
  pivot_longer(cols = "2010":"2019", names_to = "year", values_to = "population")

# Convert 'year' column to numeric type to be used in plotting
long_population$year <- as.integer(long_population$year)

head(long_population)
```

```
## # A tibble: 6 x 6
##   STATE NAME    max_population total_population  year population
##   <int> <chr>            <dbl>            <dbl> <int>      <dbl>
## 1     1 Alabama        4903185         48453198  2010    4785437
## 2     1 Alabama        4903185         48453198  2011    4799069
## 3     1 Alabama        4903185         48453198  2012    4815588
## 4     1 Alabama        4903185         48453198  2013    4830081
## 5     1 Alabama        4903185         48453198  2014    4841799
## 6     1 Alabama        4903185         48453198  2015    4852347
```

- Step 2: Filter for a few states
- Choosing three states that we want to plot. For example, let's use Alabama, California, and New York.

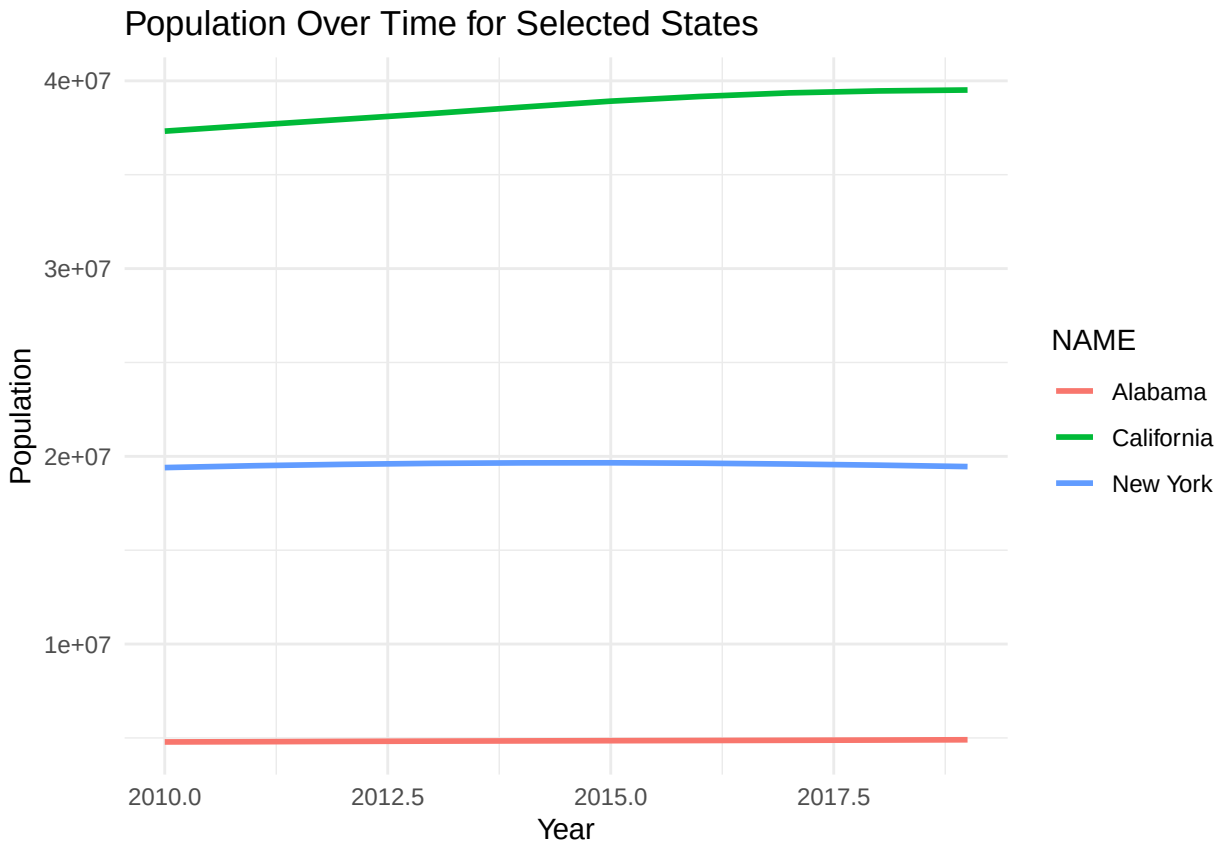
```r
states_to_plot <- long_population %>%
  filter(NAME %in% c("Alabama", "California", "New York"))

head(states_to_plot)
```

```
## # A tibble: 6 x 6
##   STATE NAME    max_population total_population  year population
##   <int> <chr>            <dbl>            <dbl> <int>      <dbl>
## 1     1 Alabama        4903185         48453198  2010    4785437
## 2     1 Alabama        4903185         48453198  2011    4799069
## 3     1 Alabama        4903185         48453198  2012    4815588
## 4     1 Alabama        4903185         48453198  2013    4830081
## 5     1 Alabama        4903185         48453198  2014    4841799
## 6     1 Alabama        4903185         48453198  2015    4852347
```

- Step 3: Create the line graph

```r
ggplot(states_to_plot, aes(x = year, y = population, color = NAME)) +
  geom_line(linewidth = 1) +  # Replacing size with linewidth
  labs(title = "Population Over Time for Selected States",
       x = "Year",
       y = "Population") +
  theme_minimal()
```



Problem 4 - Short Answer Questions

a. Two Ways Data Can Be Dirty and Solutions

1. Missing Data: Some entries may have missing values, like a customer's age or purchase amount. Solution: Use imputation to fill in missing values (e.g., average for numerical data or the most common category for categorical data).
2. Inconsistent Data: Data might have inconsistencies, like different spellings for the same product ("milk" vs "Milk"). Solution: Standardize the data by converting everything to a uniform format, such as lowercase for text or consistent units for numerical data.

b. Data Mining Functionalities for These Questions

1. Grouping Customers by Similar Purchases: Functionality: Clustering. Clustering algorithms like k-means can group customers who buy similar items into five different segments.
2. Predicting if a Customer Will Buy Milk: Functionality: Classification. A classification model like logistic regression or decision trees can predict if a customer will buy milk based on their purchase history.
3. Finding Sets of Products Bought Together: Functionality: Association Rule Mining. Techniques like Apriori or FP-Growth can identify sets of products frequently purchased together (e.g., market basket analysis).

c. Is This a Data Mining Task?

1. Organizing Customers by Education Level: Not data mining. This is just a data organization task, not a discovery of patterns or insights.
2. Computing Total Sales of a Company: Not data mining. This is basic calculation or aggregation, not an analytical task involving pattern discovery.

3. Sorting Students by ID Number: Not data mining. Sorting is a simple data manipulation task, not an exploration or modeling activity.
4. Predicting Outcomes of Dice Tosses: Not data mining. Dice tosses are random and can't be predicted based on past patterns.
5. Predicting Future Stock Prices: Data mining. This involves using historical data to forecast future trends, which is a typical use of data mining models.