Cigarette Consumption and Unemployment

Celeste Guerrero 3/16/2021

Celeste Guerrero cbg928

```
# Introduction

# Installing necessary packages
library(readxl)
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



library(tidyverse)



## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.0.5     v stringr 1.4.0
## v tidyr   1.1.2     v forcats 0.5.0
## v readr   1.4.0

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

```r
library(ggplot2)
library(cluster)

#Importing data set 1
Cigarette <- read_excel("C:/Users/celes/Downloads/Cigarette.xlsx")
```

```
## New names:
## * `` -> ...1
```

```r
glimpse(Cigarette)
```

```
## Rows: 528
## Columns: 10
## $ ...1   <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 1...
## $ state  <chr> "AL", "AR", "AZ", "CA", "CO", "CT", "DE", "FL", "GA", "IA", ...
## $ year   <dbl> 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, ...
## $ cpi    <dbl> 1.076, 1.076, 1.076, 1.076, 1.076, 1.076, 1.076, 1.076, 1.07...
## $ pop    <dbl> 3973000, 2327000, 3184000, 26444000, 3209000, 3201000, 61800...
## $ packpc <dbl> 116.4863, 128.5346, 104.5226, 100.3630, 112.9635, 109.2784, ...
## $ income <dbl> 46014968, 26210736, 43956936, 447102816, 49466672, 60063368,...
## $ tax    <dbl> 32.50000, 37.00000, 31.00000, 26.00000, 31.00000, 42.00000, ...
## $ avgprs <dbl> 102.18167, 101.47500, 108.57875, 107.83734, 94.26666, 128.02...
## $ taxs   <dbl> 33.34834, 37.00000, 36.17042, 32.10400, 31.00000, 51.48333, ...
```

```r
# Import dataset 2
Produc1 <- read_excel("C:/Users/celes/Downloads/Produc1.xlsx")
```

```
## New names:
## * `` -> ...1
```

```r
glimpse(Produc1)
```

```
## Rows: 816
## Columns: 11
## $ ...1  <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18...
## $ state <chr> "AL", "AL", "AL", "AL", "AL", "AL", "AL", "AL", "AL", "AL", "...
## $ year  <dbl> 1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1...
## $ pcap  <dbl> 15032.67, 15501.94, 15972.41, 16406.26, 16762.67, 17316.26, 1...
## $ hwy   <dbl> 7325.80, 7525.94, 7765.42, 7907.66, 8025.52, 8158.23, 8228.19...
## $ water <dbl> 1655.68, 1721.02, 1764.75, 1742.41, 1734.85, 1752.27, 1799.74...
```

```
## $ util  <dbl> 6051.20, 6254.98, 6442.23, 6756.19, 7002.29, 7405.76, 7704.93...
## $ pc    <dbl> 35793.80, 37299.91, 38670.30, 40084.01, 42057.31, 43971.71, 5...
## $ gsp   <dbl> 28418, 29375, 31303, 33430, 33749, 33604, 35764, 37463, 39964...
## $ emp   <dbl> 1010.5, 1021.9, 1072.3, 1135.5, 1169.8, 1155.4, 1207.0, 1269....
## $ unemp <dbl> 4.7, 5.2, 4.7, 3.9, 5.5, 7.7, 6.8, 7.4, 6.3, 7.1, 8.8, 11.0, ...
```

```
#1 Tidying Data
# Wrangling data set 1 by filtering specific years
cigarette1 <- Cigarette %>%  filter(between(year,1985,1986))
cigarette1
```

```
## # A tibble: 96 x 10
##     ...1 state  year   cpi      pop packpc    income   tax avgprs  taxs
##    <dbl> <chr> <dbl> <dbl>    <dbl>  <dbl>     <dbl> <dbl>  <dbl> <dbl>
##  1     1 AL     1985  1.08  3973000   116.  46014968  32.5  102.   33.3
##  2     2 AR     1985  1.08  2327000   129.  26210736  37    101.   37
##  3     3 AZ     1985  1.08  3184000   105.  43956936  31    109.   36.2
##  4     4 CA     1985  1.08 26444000   100. 447102816  26    108.   32.1
##  5     5 CO     1985  1.08  3209000   113.  49466672  31     94.3  31
##  6     6 CT     1985  1.08  3201000   109.  60063368  42    128.   51.5
##  7     7 DE     1985  1.08   618000   144.   9927301  30    102.   30
##  8     8 FL     1985  1.08 11352000   122. 166919248  37    115.   42.5
##  9     9 GA     1985  1.08  5963000   127.  78364336  28     97.0  28.8
## 10    10 IA     1985  1.08  2830000   114.  37902896  34    102.   37.9
## # ... with 86 more rows
```

Updated: The data sets were obtained from te online databased of installed R packages, https://vincentarelbundock.github.io/Rdatasets/datasets.html. There are 528 observations across 10 variables focused on cigarette consumption in the United States between 1985-1995.The second data set represents the production data from the United States from 1970-1986. There are 816 observations across 11 variables. Both data sets were initially tidy, but some data wrangling was done beforehand to make the combination of data sets easier in #2. This topic was chosen because they had similar variables within similar time periods. In addition, the relationship between cigarette packs per capita and unemployment rate was further investigated.

```
#2 Join and Merge Data sets
cig_produc <- Produc1 %>%
  left_join(cigarette1, by="state")
head(cig_produc)
```

```
## # A tibble: 6 x 20
##   ...1.x state year.x   pcap   hwy water  util     pc   gsp   emp unemp ...1.y
##    <dbl> <chr>  <dbl>  <dbl> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1      1 AL      1970 15033. 7326. 1656. 6051. 35794. 28418 1010.   4.7      1
## 2      1 AL      1970 15033. 7326. 1656. 6051. 35794. 28418 1010.   4.7     49
## 3      2 AL      1971 15502. 7526. 1721. 6255. 37300. 29375 1022.   5.2      1
## 4      2 AL      1971 15502. 7526. 1721. 6255. 37300. 29375 1022.   5.2     49
## 5      3 AL      1972 15972. 7765. 1765. 6442. 38670. 31303 1072.   4.7      1
## 6      3 AL      1972 15972. 7765. 1765. 6442. 38670. 31303 1072.   4.7     49
## # ... with 8 more variables: year.y <dbl>, cpi <dbl>, pop <dbl>, packpc <dbl>,
## #   income <dbl>, tax <dbl>, avgprs <dbl>, taxs <dbl>
```

```
view(cig_produc)
```

Data set 1 and 2 were combined using a left join by state as pictured above. The join was appropriate because it allowed for further data wrangling in the following steps.

```
#3 Summary Statistics

#Selecting ideal variables from combined data set
cleancigprod <- cig_produc %>% select(state,year.x,year.y,unemp,pop,packpc) %>% arran
head(cleancigprod)
```

```
## # A tibble: 6 x 6
##   state year.x year.y unemp     pop packpc
##   <chr>  <dbl>  <dbl> <dbl>   <dbl>  <dbl>
## 1 AL      1970   1985   4.7 3973000   116.
## 2 AL      1970   1986   4.7 3992000   117.
## 3 AZ      1970   1985   4.4 3184000   105.
## 4 AZ      1970   1986   4.4 3309000   103.
## 5 AR      1970   1985   5   2327000   129.
## 6 AR      1970   1986   5   2332000   128.
```

The variables selected include state which includes most states of the U.S., year.x and year.y which correspond to produc and cigarette1, respectively. Unemp is the state unemployment rate, pop is the state population and packpc is the number of cigarette packs per capita.

```
# Observations based on same year across states
yearsim <- cleancigprod %>% mutate(Year = if_else(year.x == year.y, "Equal", "Not Equ
yearsim
```

```
## # A tibble: 96 x 7
##    state year.x year.y unemp      pop packpc Year
##    <chr>  <dbl>  <dbl> <dbl>    <dbl>  <dbl> <chr>
##  1 AL      1985   1985   8.9  3973000   116. Equal
##  2 AZ      1985   1985   6.5  3184000   105. Equal
##  3 AR      1985   1985   8.7  2327000   129. Equal
##  4 CA      1985   1985   7.2 26444000   100. Equal
##  5 CO      1985   1985   5.9  3209000   113. Equal
##  6 CT      1985   1985   4.9  3201000   109. Equal
##  7 DE      1985   1985   5.3   618000   144. Equal
##  8 FL      1985   1985   6   11352000   122. Equal
##  9 GA      1985   1985   6.5  5963000   127. Equal
## 10 ID      1985   1985   8     994000   103. Equal
## # ... with 86 more rows
```

```
#Clean data, removing extra variables, renamed
clean <- yearsim %>% select(-Year, -year.y) %>% rename("year"=year.x)
glimpse(clean) #final data set
```

```
## Rows: 96
## Columns: 5
## $ state  <chr> "AL", "AZ", "AR", "CA", "CO", "CT", "DE", "FL", "GA", "ID", ...
## $ year   <dbl> 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, 1985, ...
## $ unemp  <dbl> 8.9, 6.5, 8.7, 7.2, 5.9, 4.9, 5.3, 6.0, 6.5, 8.0, 9.0, 7.9, ...
## $ pop    <dbl> 3973000, 3184000, 2327000, 26444000, 3209000, 3201000, 61800...
## $ packpc <dbl> 116.4863, 104.5226, 128.5346, 100.3630, 112.9635, 109.2784, ...
```

The final data set has 96 observations across 5 different variables including state, year, unemployment rate, state population, and packs of cigarettes per capita.

```
# New variable representing packs of cigarettes consumed for each state population
clean1 <- clean %>% mutate(Packsperpop = packpc*pop)
clean1
```

```
## # A tibble: 96 x 6
##    state  year unemp      pop packpc Packsperpop
##    <chr> <dbl> <dbl>    <dbl>  <dbl>       <dbl>
##  1 AL     1985   8.9  3973000   116.  462800000.
##  2 AZ     1985   6.5  3184000   105.  332800001.
##  3 AR     1985   8.7  2327000   129.  299099995.
##  4 CA     1985   7.2 26444000   100. 2654000153.
```

```
##  5 CO     1985   5.9  3209000   113.  362499997.
##  6 CT     1985   4.9  3201000   109.  349800001.
##  7 DE     1985   5.3   618000   144.   88900002.
##  8 FL     1985   6   11352000   122. 1387000095.
##  9 GA     1985   6.5  5963000   127.  758700034.
## 10 ID     1985   8     994000   103.  102400004.
## # ... with 86 more rows
```

```
#Summary statistics overall
clean1 %>% summarize(mean(unemp), mean(pop), mean(packpc), mean(Packsperpop))
```

```
## # A tibble: 1 x 4
##   `mean(unemp)` `mean(pop)` `mean(packpc)` `mean(Packsperpop)`
##           <dbl>       <dbl>          <dbl>                <dbl>
## 1          7.00    4934031.           120.          584267715.
```

These summary statistics represent the overall mean of each variable regardless of state or year in the United States. Therefore, the average unemployment rate across the states between 1985-1986 was 6.99, the mean population was 4934031 people, the mean packs of cigarette consumption per capita was 120, and the mean packs of cigarettes across the population was 584267715.

```
# Summary statistics based on state between 1985-1986
clean1 %>% group_by(state) %>%summarize(mean(pop), mean(unemp), mean(packpc), mean(Pa
```

```
## # A tibble: 48 x 8
##    state `mean(pop)` `mean(unemp)` `mean(packpc)` `mean(Packsperp~ `sd(pop)`
##  * <chr>       <dbl>         <dbl>          <dbl>            <dbl>     <dbl>
##  1 AL        3982500          9.35          117.        465249997.    13435.
##  2 AR        2329500          8.7           128.        298399996.     3536.
##  3 AZ        3246500          6.7           104.        337299997.    88388.
##  4 CA       26775000          6.95           98.4      2633050093.   468105.
##  5 CO        3223500          6.65          111.        358099995.    20506.
##  6 CT        3212500          4.35          108.        347000002.    16263.
##  7 DE         623000          4.8           142.         88650000.     7071.
##  8 FL       11510500          5.85          121.       1397250064.   224153.
##  9 GA        6024000          6.2           127.        764450012.    86267.
## 10 IA        2811000          7.5           111.        311400003.    26870.
## # ... with 38 more rows, and 2 more variables: `sd(unemp)` <dbl>,
## #   `sd(packpc)` <dbl>
```

Updated: The summary statistics represent the mean and standard deviation of the numeric variables, state population, unemployment rate, and cigarette packs per capita as shown above, but grouped by state from 1985-1986. For Texas, the mean and standard deviation of state population was 16419000 +/- 203646.753 people. The mean unemployment rate is 7.95 +/- 1.34350288 (as a percent) for Texas.

```
#Summary Statistics cont
clean1 %>% group_by(year) %>% summarize(mean(pop), mean(unemp), mean(packpc), mean(Pa
```

```
## # A tibble: 2 x 5
##    year `mean(pop)` `mean(unemp)` `mean(packpc)` `mean(Packsperpop)`
## * <dbl>       <dbl>         <dbl>          <dbl>               <dbl>
## 1  1985    4911271.          7.07           122.          588497924.
## 2  1986    4956792.          6.93           119.          580037505.
```

These summary statistics describe the means of state population, unemployment rate, packs of cigarettes per capita, and packs of cigarettes per population grouped by the years 1985-1986. They give an idea of the changes that occurred in the U.S. over the years despite state specificity.

```
 # Correlation Matrix, filtered out non numeric variables
cigproduc1 <- as.data.frame(clean1) %>% select(-state, -year)
head(cigproduc1)
```

```
##   unemp      pop   packpc Packsperpop
## 1   8.9  3973000 116.4863   4.628e+08
## 2   6.5  3184000 104.5226   3.328e+08
## 3   8.7  2327000 128.5346   2.991e+08
## 4   7.2 26444000 100.3630   2.654e+09
## 5   5.9  3209000 112.9635   3.625e+08
## 6   4.9  3201000 109.2784   3.498e+08
```

```
# Correlation matrix
library(corrplot)
```

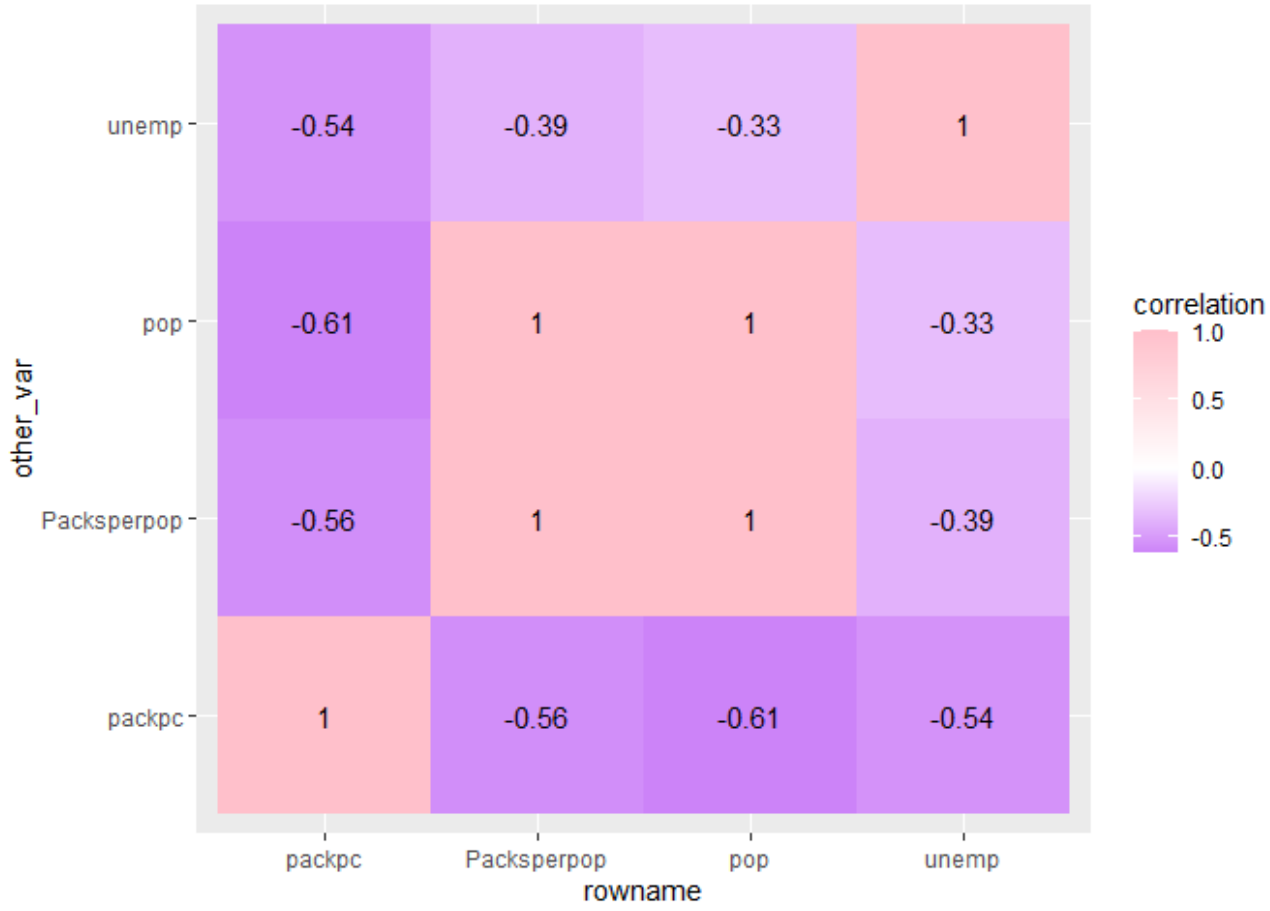
```
## Warning: package 'corrplot' was built under R version 4.0.4
```

```
## corrplot 0.84 loaded
```

```
cor1 <- cigproduc1 %>% select_if(is.numeric) %>%
cor(cigproduc1, use = "pairwise.complete.obs")
cor1
```

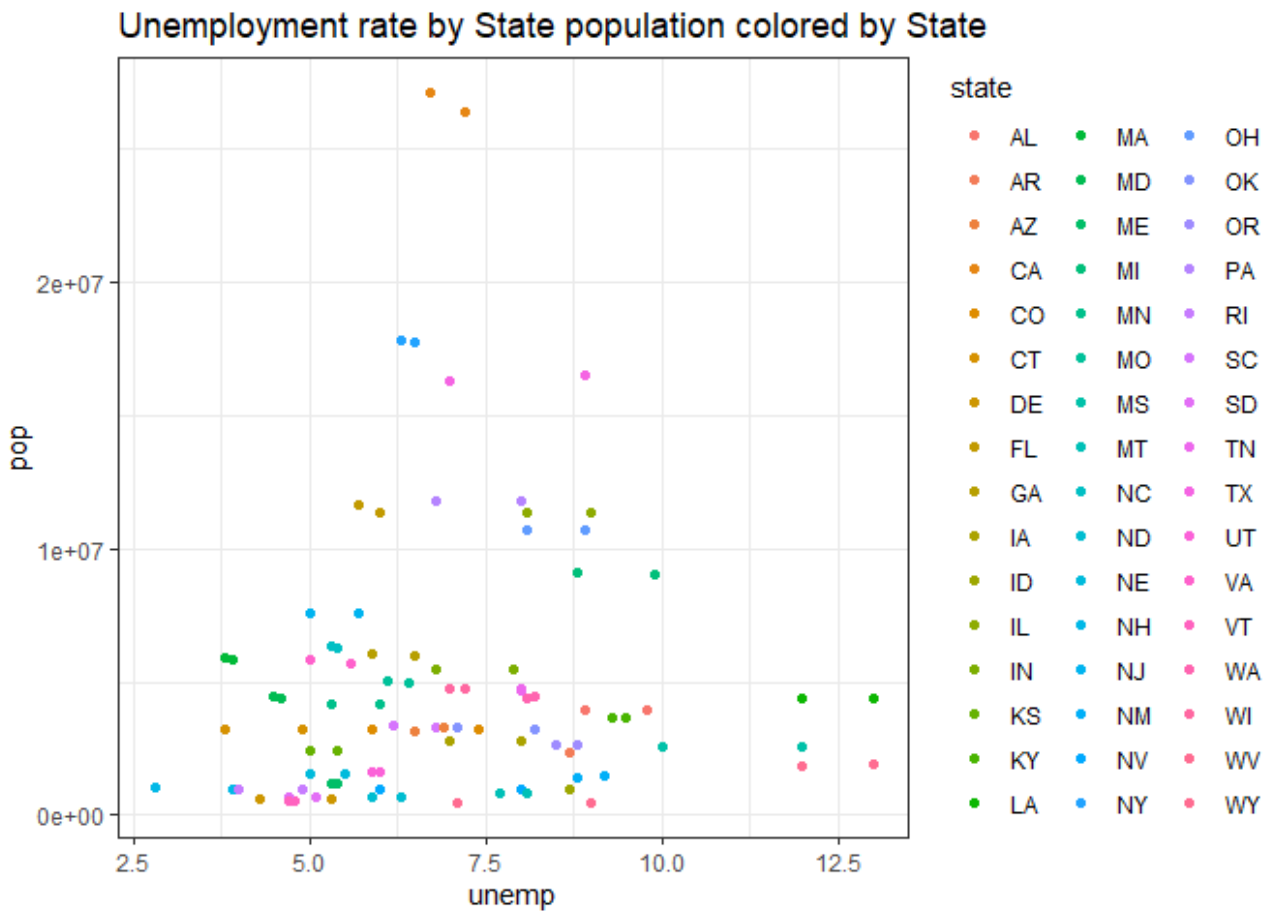
```
##                   unemp         pop      packpc Packsperpop
## unemp        1.00000000  0.06553684 -0.11096026  0.07544039
## pop          0.06553684  1.00000000 -0.09259659  0.98707655
## packpc      -0.11096026 -0.09259659  1.00000000  0.01168794
## Packsperpop  0.07544039  0.98707655  0.01168794  1.00000000
```

```
#Correlation heat map
cor(cor1, use = "pairwise.complete.obs") %>%
  # Save as a data frame
  as.data.frame %>%
  # Convert row names to an explicit variable
  rownames_to_column %>%
  # Pivot so that all correlations appear in the same column
  pivot_longer(-1, names_to = "other_var", values_to = "correlation") %>%
  ggplot(aes(rowname, other_var, fill=correlation)) +
  # Heatmap with geom_tile
  geom_tile() +
  # Change the scale to make the middle appear neutral
  scale_fill_gradient2(low="purple",mid="white",high="pink") +
  # Overlay values
  geom_text(aes(label = round(correlation,2)), color = "black", size = 4)
```



Updated: Based on the heat map, there is little to no correlation between the numeric variables in the data frame. The closest correlation is between state unemployment rate and state population with a factor of -0.33 and this will be looked into further. The 'year' variable was removed from the correlation matrix because it is discrete as opposed to continuous.

```
# Visualizations
# Plot of unemployment rate and state population colored by state
ggplot(data=clean, mapping = aes(x = unemp, y = pop)) +
  geom_point(aes(color = state)) +
  theme_bw() + ggtitle("Unemployment rate by State population colored by State")
```



The visualization above represents the state unemployment rate by the state population colored by the different states. It appears there is no correlation as shown by the matrix, but it shows some interesting findings. States with the highest unemployment rates have low state population while states with high population have the average overall unemployment rate.

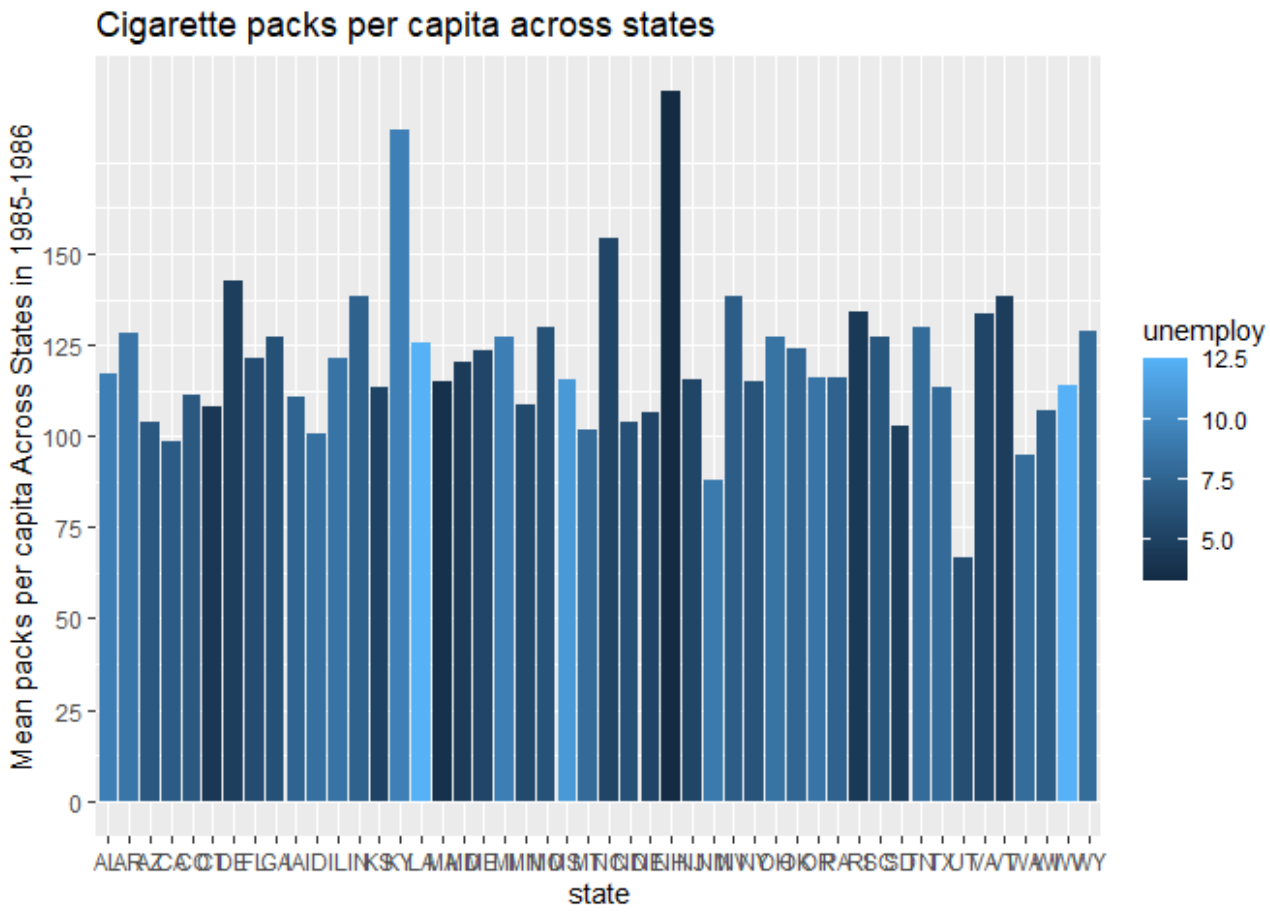
```
# Visualization
clean2 <- clean %>%
  group_by(state) %>%
  select(state, packpc, unemp, year) %>%
  summarise(packs = mean(packpc), unemploy = mean(unemp))
clean2
```

```
## # A tibble: 48 x 3
##    state packs unemploy
##  * <chr> <dbl>    <dbl>
##  1 AL    117.      9.35
##  2 AR    128.      8.7
##  3 AZ    104.      6.7
##  4 CA     98.4     6.95
##  5 CO    111.      6.65
##  6 CT    108.      4.35
```

```
##  7 DE    142.      4.8
##  8 FL    121.      5.85
##  9 GA    127.      6.2
## 10 IA    111.      7.5
## # ... with 38 more rows
```

```
ggplot(clean2, aes(x = state, y = packs)) + geom_bar(stat = "summary", fun = mean, ae
```

```
## No summary function supplied, defaulting to `mean_se()`
```



Updated: Based on the visualization above, some states had a higher mean of the packs of cigarette consumption than others. The state with the highest mean of cigarette packs per capita had a low unemployment rate based on the color of the bar. The state with the lowest mean of cigarette packs per capita has a relatively low unemployment rate as well.

```
# Perform k-means/PAM cluster/PCA
pca <- clean %>%
  # Remove categorical variables
  select(-state) %>%
  # Scale to 0 mean and unit variance (standardize)
```

```
  scale() %>%
  prcomp()
names(pca)
```

```
## [1] "sdev"     "rotation" "center"   "scale"    "x"
```

```
pca #visualize pca results
```

```
## Standard deviations (1, .., p=4):
## [1] 1.0893182 1.0169429 0.9670865 0.9186711
##
## Rotation (n x k) = (4 x 4):
##               PC1        PC2         PC3        PC4
## year    0.1857235 -0.8692674 -0.07338439 -0.4522120
## unemp   0.5321400  0.4264017 -0.51725197 -0.5171644
## pop     0.5126958  0.1368137  0.82680445 -0.1865996
## packpc -0.6476703  0.2093748  0.20846947 -0.7023004
```

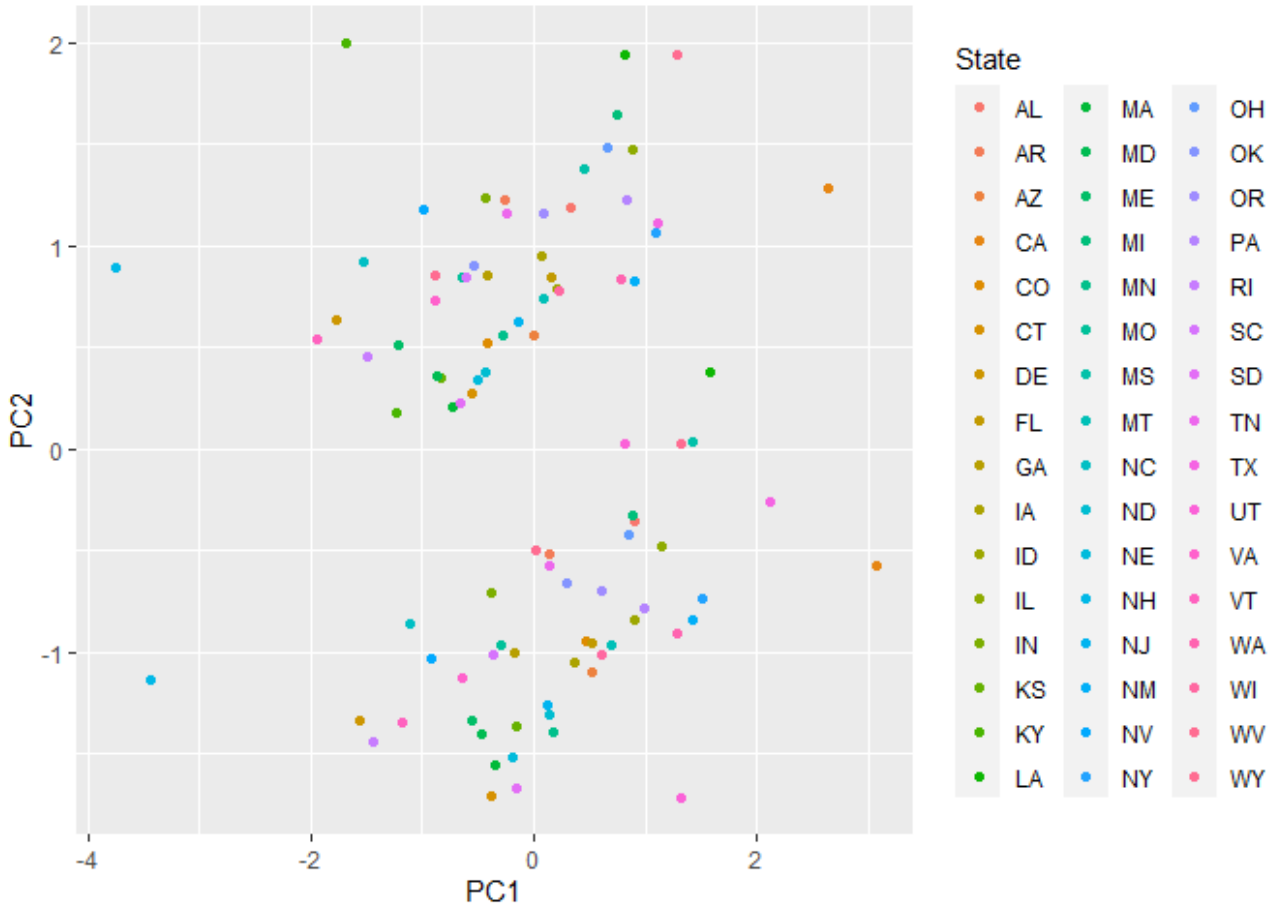
```
head(pca$x) #View rotated data
```

```
##               PC1       PC2          PC3        PC4
## [1,]  0.325903225 1.1892717 -0.593308102  0.1438493
## [2,]  0.001908984 0.5580009 -0.243207990  1.1674353
## [3,] -0.260529951 1.2241881 -0.690010436 -0.1484244
## [4,]  2.636495110 1.2810980  3.295803791  0.2851758
## [5,] -0.408500687 0.5197990 -0.006624566  1.0339214
## [6,] -0.551377178 0.2782596  0.203885567  1.4053811
```

```
pca_data <- data.frame(pca$x, State = clean$state) #Groups by State added in
head(pca_data)
```

```
##            PC1       PC2          PC3        PC4 State
## 1  0.325903225 1.1892717 -0.593308102  0.1438493    AL
## 2  0.001908984 0.5580009 -0.243207990  1.1674353    AZ
## 3 -0.260529951 1.2241881 -0.690010436 -0.1484244    AR
## 4  2.636495110 1.2810980  3.295803791  0.2851758    CA
## 5 -0.408500687 0.5197990 -0.006624566  1.0339214    CO
## 6 -0.551377178 0.2782596  0.203885567  1.4053811    CT
```

```
# Visualization of PCA
ggplot(pca_data, aes(x = PC1, y = PC2, color = State)) +
  geom_point()
```



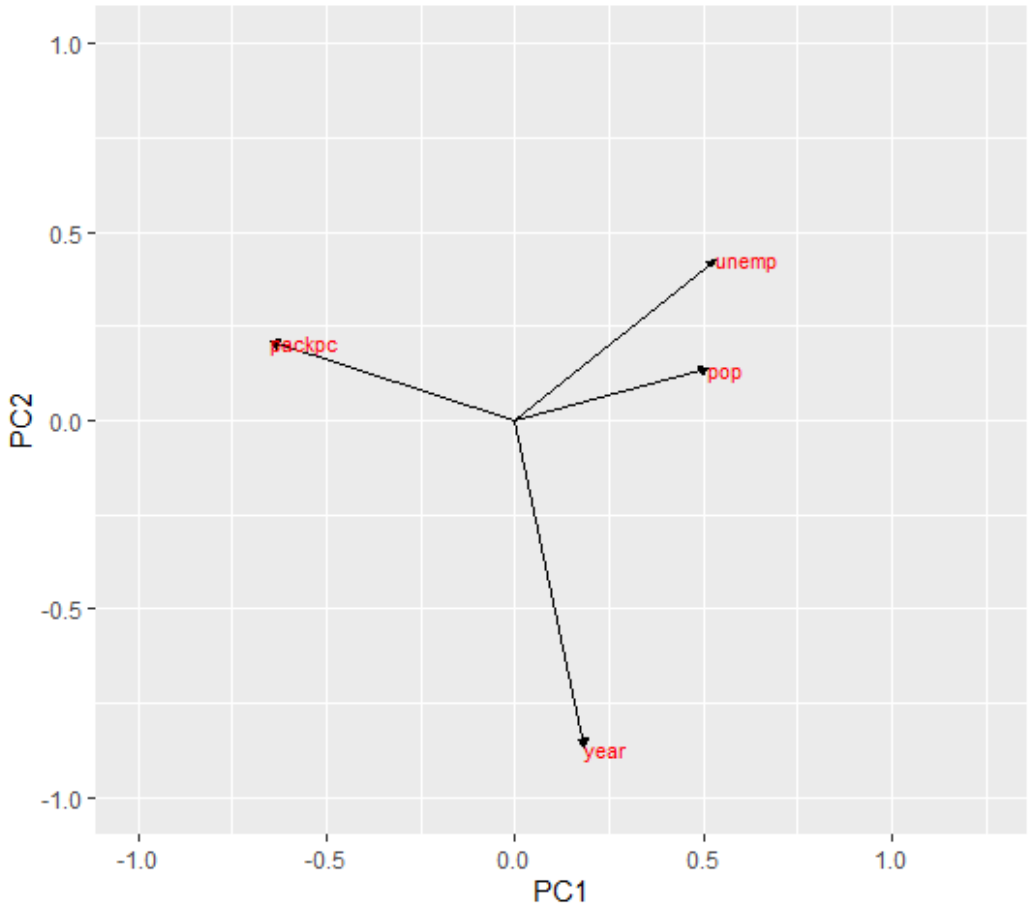
There appears to be two clusters of states that are most similar based on the PCA plot above.

```
pca$rotation
```

```
##                PC1        PC2         PC3        PC4
## year    0.1857235 -0.8692674 -0.07338439 -0.4522120
## unemp   0.5321400  0.4264017 -0.51725197 -0.5171644
## pop     0.5126958  0.1368137  0.82680445 -0.1865996
## packpc -0.6476703  0.2093748  0.20846947 -0.7023004
```

```
rotation_data <- data.frame(
  pca$rotation,
  variable = row.names(pca$rotation))
arrow_style <- arrow(length = unit(0.05, "inches"), type = "closed")
```

```
 # Visual of the contribution of variables to PC
ggplot(rotation_data) +
  geom_segment(aes(xend = PC1, yend = PC2), x = 0, y = 0, arrow = arrow_style) +
  geom_text(aes(x = PC1, y = PC2, label = variable), hjust = 0, size = 3, color = "re
  xlim(-1., 1.25) +
  ylim(-1., 1.) +
  coord_fixed()
```



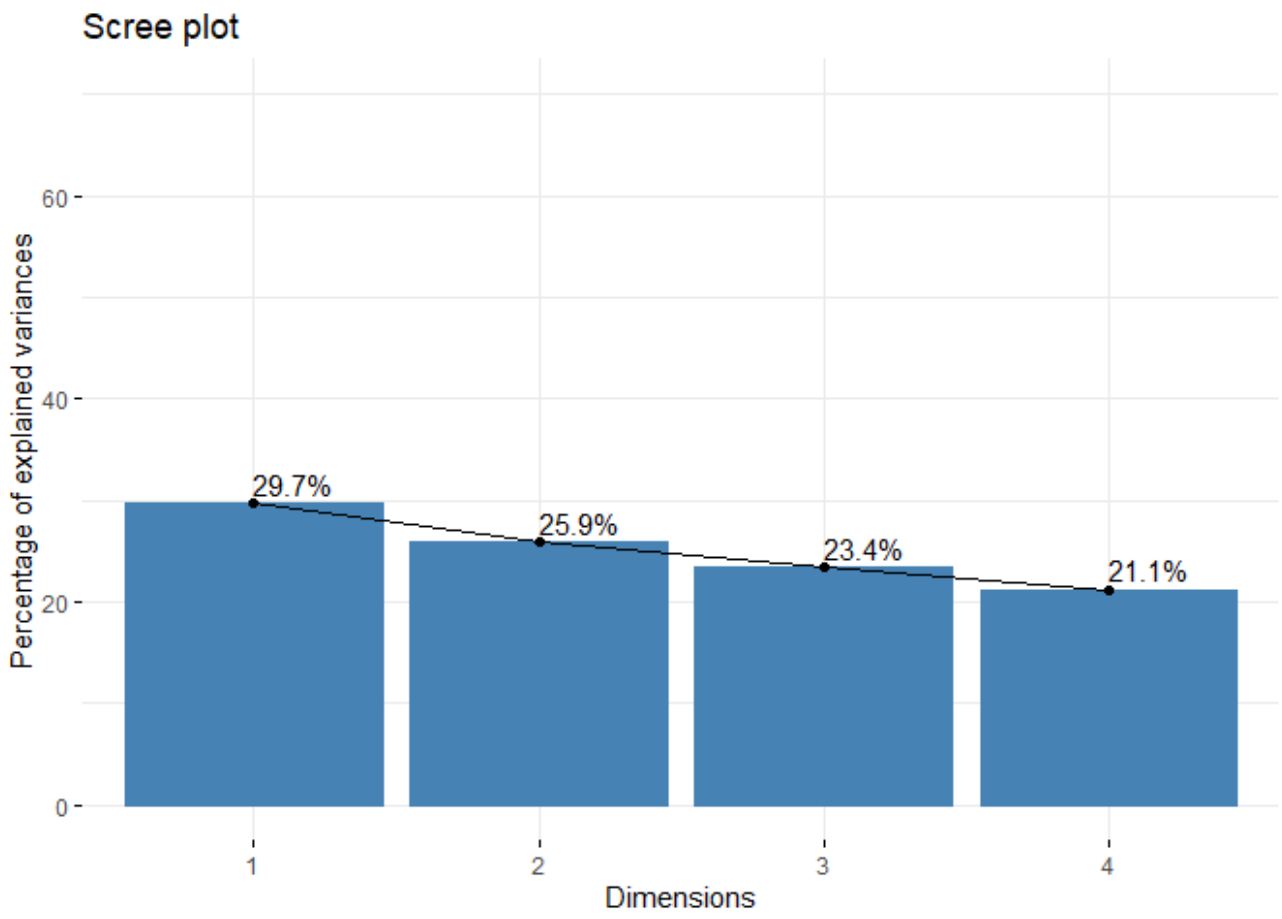
The variables year, unemp and pop influence PC1 more strongly. The variable packpc influences PC2 more strongly based on the above figure. Again, based on the loading plot there is a small angle between unemployment rate and state population which signifies a more positive correlation as opposed to the others.

```
#Scree plot
library(tidyverse)
library(cluster)
library(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 4.0.4
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve
```

```
fviz_eig(pca, addlabels = TRUE, ylim = c(0, 70))
```



Based on the scree plot, PCA is not the best fit for the data as there is no steep curve with a plateau seen.