Selected Projects of Huifen Zhou

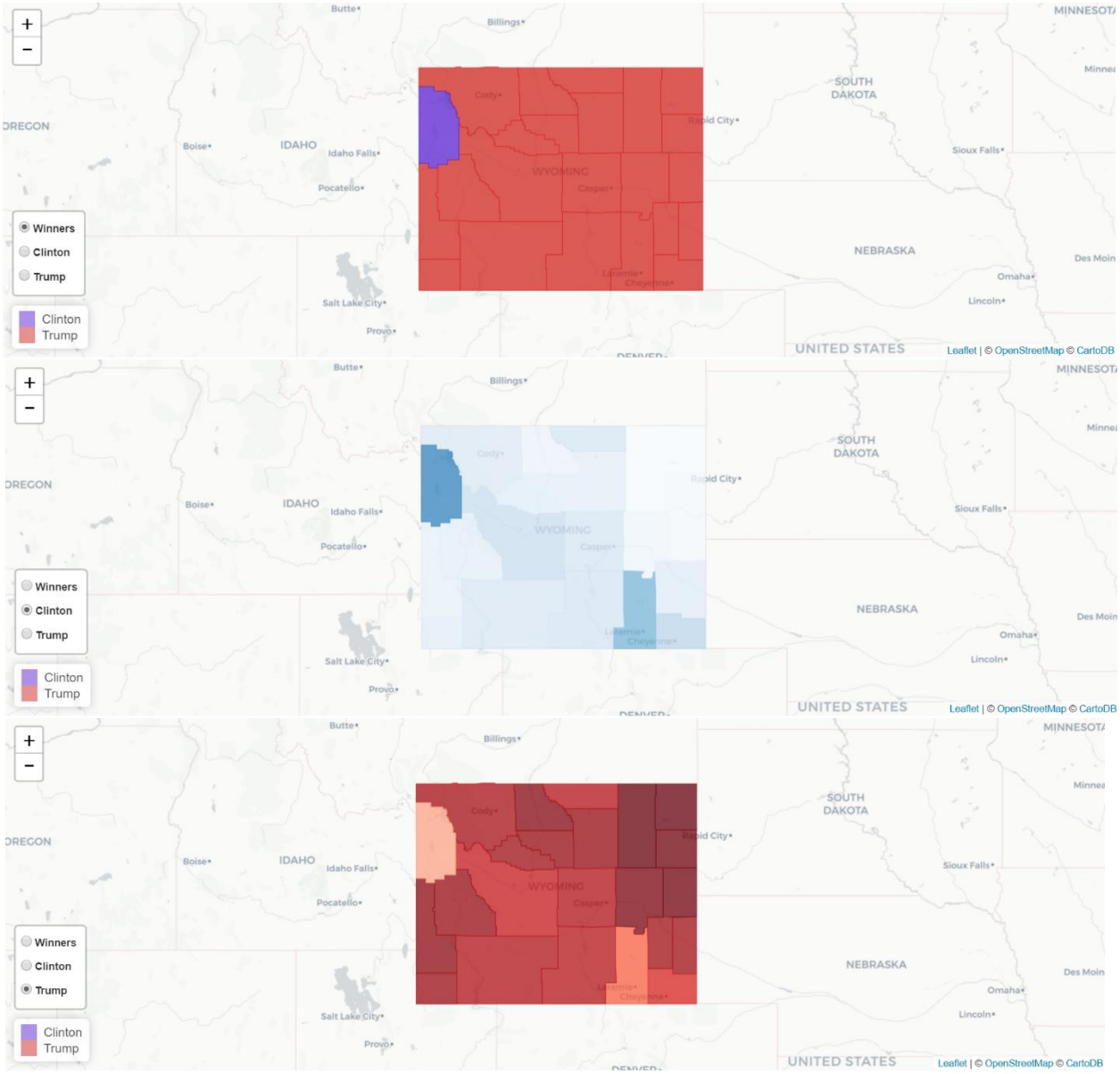
Email: Huifenzhou@gmail.com

Cell: 8143215101

Project 1

Election Map of Wyoming

The online map is available here: https://huifenzhou.shinyapps.io/project/



Code:

```
library("tmap")
library("leaflet")
library("chron")
library("rio")
```

```
library("scales")
library("shiny")
library("rsconnect")

#vote file

datafile <- "wy2016.xlsx"
wydata <- rio::import(datafile)
wydata <- wydata[,c("County", "Trump", "Clinton")]
#vote for Cand
wydata$Total <- wydata$Trump + wydata$Clinton
wydata$TrumpPct <- round(((wydata$Trump / wydata$Total)),3)
wydata$ClintonPct <- round(((wydata$Clinton / wydata$Total)),3)
#map file
usshapefile <- "cb_2014_us_county_5m/cb_2014_us_county_5m.shp"
wygeo <- read_shape(file=usshapefile)
wygeo <- wygeo[wygeo@data$STATEFP=="56",]

wygeo@data$NAME <- as.character(wygeo@data$NAME)
wygeo <- wygeo[order(wygeo@data$NAME),]
wydata <- wydata[order(wydata$County),]
wymap <- append_data(wygeo, wydata, key.shp = "NAME", key.data="County")

#wymap$winner <- ifelse (wydata$Clinton> wydata$Trump),ifelse(wydata$Trump> wydata$Clinton)
wymap$winner <- ifelse (wydata$Clinton> wydata$Trump ,'Clinton',ifelse(wydata$Trump>
wydata$Clinton,'Trump',NA))
minpct <- min(c(wymap$`ClintonPct`, wymap$`TrumpPct`))
maxpct <- max(c(wymap$`ClintonPct`, wymap$`TrumpPct`))
#palette
clintonPalette <- colorNumeric(palette = "Blues", domain = c(minpct, maxpct))
trumpPalette <- colorNumeric(palette = "Reds", domain = c(minpct, maxpct))
winnerPalette <- colorFactor(palette=c("#5c22d1","#d12522"), domain = wymap$winner)

wypopup <- paste0("County: ", wymap@data$NAME,
                  " Winner: ", wymap@data$winner,
                  ", Clinton: ", percent(wymap@data$`ClintonPct`),
                  ", Trump: ", percent(wymap@data$`TrumpPct`))
ui <- fluidPage(
  leafletOutput("map")
)

server <- function(input, output, session) {

  output$map <- renderLeaflet({


    leaflet(wymap) %>%
      addProviderTiles("CartoDB.Positron") %>%
      addPolygons(stroke=TRUE,
                  weight=1,
                  smoothFactor = 0.2,
```

```
            fillOpacity = .75,
            popup=wypopup,
            color= ~winnerPalette(wymap@data$winner),
            group="Winners"
    ) %>%
    addLegend(position="bottomleft", colors=c("#5c22d1", "#d12522"), labels=c("Clinton",
"Trump"))  %>%

    addPolygons(stroke=TRUE,
            weight=1,
            smoothFactor = 0.2,
            fillOpacity = .75,
            popup=wypopup,
            color= ~clintonPalette(wymap@data$`ClintonPct`),
            group="Clinton"
    ) %>%

    addPolygons(stroke=TRUE,
            weight=1,
            smoothFactor = 0.2,
            fillOpacity = .75,
            popup=wypopup,
            color= ~trumpPalette(wymap@data$`TrumpPct`),
            group="Trump"
    ) %>%

    addLayersControl(
      baseGroups=c("Winners", "Clinton", "Trump"),
      position = "bottomleft",
      options = layersControlOptions(collapsed = FALSE)
    )
  })
}

shinyApp(server = server, ui = ui)
```

Project 2
Analysis of Factors Affecting University Ranking

1. Introduction

University ranking plays a key role for students in determining which university to go. There are many factors affecting the ranking. It is important to identify the most important ones contributing to ranking. The findings could serve as a guide for university management and faculty members to improve their ranking. In this project, the best universities in the world and their geographical distribution are studied first by using R. Then regression models are developed to analyze variables used in rankings. It has been found that teaching, research, citations are the top 3 factors determining the ranking of a university.

2. DATA

A). Data source

https://www.kaggle.com/mylesoneill/world-university-rankings

B).Summary of Data

The dataset contains 13 variables named as below and has 2603 observations. The list as below

```
data.frame':                2603 obs. of  13 variables:
 $ world_rank           : chr  "1" "2" "3" "4" ...
 $ university_name      : chr  "Harvard University" "California Institute of Technology" "Massachusetts Institute
of Technology" "Stanford University" ...
 $ country              : chr  "United States of America" "United States of America" "United States of America" "Uni
ted States of America" ...
 $ teaching             : num  99.7 97.7 97.8 98.3 90.9 90.5 88.2 84.2 89.2 92.1 ...
 $ international        : chr  "72.4" "54.6" "82.3" "29.5" ...
 $ research             : num  98.7 98 91.4 98.1 95.4 94.1 93.9 99.3 94.5 89.7 ...
 $ citations            : num  98.8 99.9 99.9 99.2 99.9 94 95.1 97.8 88.3 91.5 ...
 $ income               : chr  "34.5" "83.7" "87.5" "64.3" ...
 $ total_score          : chr  "96.1" "96" "95.6" "94.3" ...
 $ num_students         : chr  "20,152" "2,243" "11,074" "15,596" ...
 $ student_staff_ratio  : num  8.9 6.9 9 7.8 8.4 11.8 11.6 16.4 11.7 4.4 ...
 $ international_students: chr  "25%" "27%" "33%" "22%" ...
 $ year                 : int  2011 2011 2011 2011 2011 2011 2011 2011 2011 2011 ...
```

C). Issues of Dataset

• Missing Value in the columns are shown on the list: world rank, income and total score.

• The column of the world_rank has unclear data such as 201-300.

• Some columns' type should be numeric but they are character variables such as total_score, num_students..

3. Using R

A) SQL

1. Top1 University from 2011 to 2016

Table 2 shows the top 1 university from 2011 to 2016. It can be learned that in 2011 Harvard University is the top 1 university. From 2012 to 2016 the California Institute of Technology is the top 1 university for 5 years.

	worldRank	university_name	country	year
1	1	Harvard University	United States of America	2011
2	1	California Institute of Technology	United States of America	2012
3	1	California Institute of Technology	United States of America	2013
4	1	California Institute of Technology	United States of America	2014
5	1	California Institute of Technology	United States of America	2015
6	1	California Institute of Technology	United States of America	2016

Table 2. Top 1 University in the world from 2011 to 2016

2. Ranking of University of Cincinnati

I'd like to learn more about my own university. The highest ranking is 190th in 2011 while from 2012 to 2106 the ranking is not available as shown in Table 3 below.

	world_rank	university_name	total_score	year
1	190	University of Cincinnati	46.9	2011
2	NA	University of Cincinnati	NA	2012
3	NA	University of Cincinnati	NA	2013
4	NA	University of Cincinnati	NA	2014
5	NA	University of Cincinnati	NA	2015
6	NA	University of Cincinnati	NA	2016

Table 3. University of Cincinnati's Rank from 2011 to 2016

B) Plot

1. The Ranking Trend of Duke, Harvard and Princeton University.

I just show 3 universities which I am interested in.

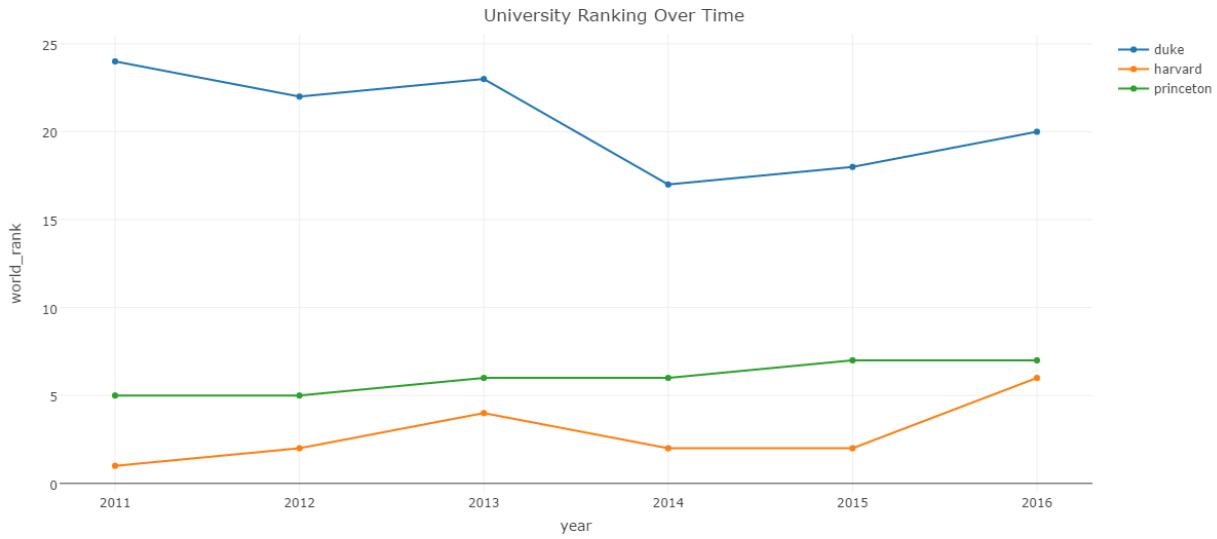


Figure 1. 3 Universities' Ranking Trend

Figure 1 shows the trend of the ranking of these 3 different universities.

The Harvard University is the best one in 2011, and its ranking changed year by year and down to No.6 in 2016.

The ranking of Princeton University is stable, which is always in the range of No.5 to No.7.

The Duke University has a gradual improvement over time, from No.24 in 2011 to No.20 in 2016.

2. The Top 10 Countries by the Number of Universities (Top 200 Universities)

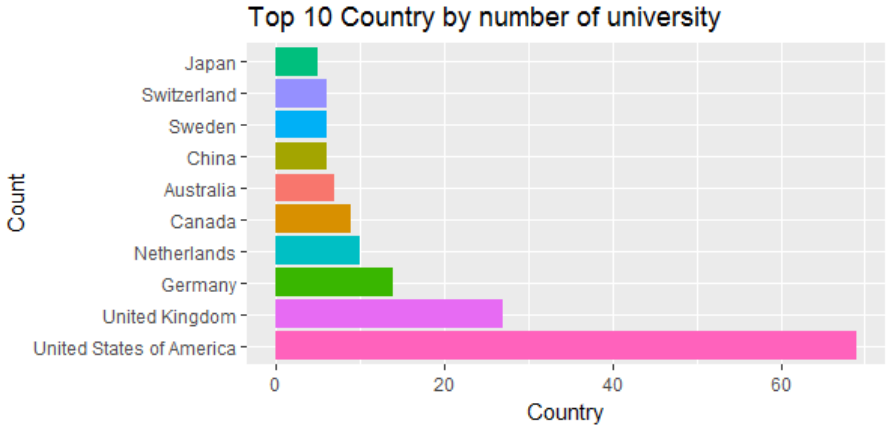


Figure 2. TOP 10 countries by number of top 200 universities

From the Figure 2, it can be learned that the USA has the most of top 200 universities and the number is near 70 universities. The UK is the No.2 country which has over than 20 universities. And other top 200 universities belong to Germany, Netherlands, Canada, Australia, China, Sweden, Switzerland and Japan. To make the results more visually clear, the map of the geographical distribution density of these countries is generated.

3. Mapping of Top 10 Counties by the Number of Top 200 Universities

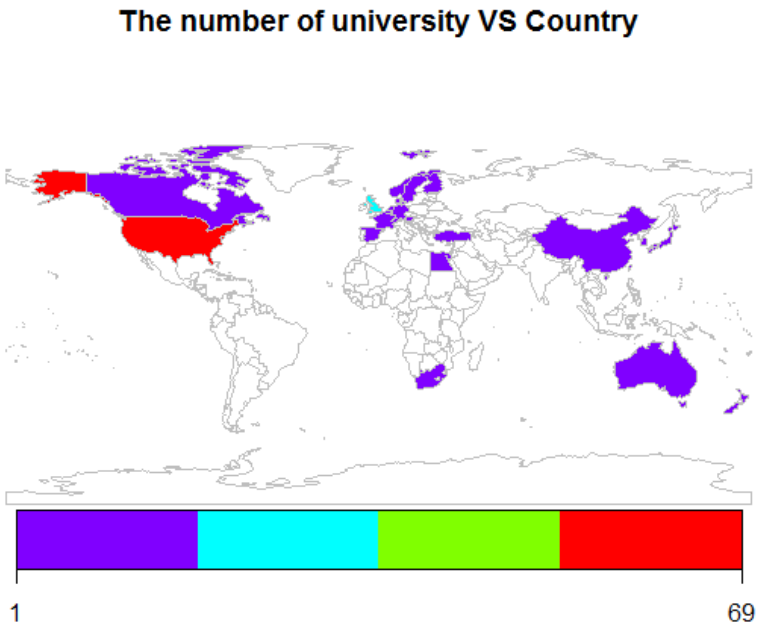


Figure 3. The Top 200 Universities' distribution

From Figure 3, it is obvious that United States has the most universities of top 200. The United Kingdom is the second country. And other universities are distributed in Canada, China, Austria, Japan and other European countries.

4. Regression

Section 1. Introduction of Data Set and Purpose of Project

a) Introduction of Data Set

To get the ranking of a university, we use scores to evaluate it. To get the scores, certain factors are used. Here I propose to use the total score as the dependent variable; teaching, research, citations and other variables as independent variables.

This study provides top 100 universities as observation in 2016. I want to find the relationship between dependent variables and independent variables.

b) Data Clean

As I mentioned in the data part, some variables should be numeric variables but instead they are character variables. Then the first step is to change the variable type.

I dropped observations which contain the missing value. Then 99 observations will be used to do the linear regression.

Section 2. Data Analysis

a) Correlation between independent variables

From table 1 in appendix, we know that there is a strong positive correlation between *teaching* and *research* (0.87), and between *international* and *international students* (0.82). As we know, *teaching* and research are the important factors to a university. However, the score of *international* depends on *international_stud.* Maybe the international will contain *internation_stud* and the P-value of the correlation between *internation_stud* and international is 0.000. We conclude that they have significant relationship. So in my first model, I prefer to drop the variable *internation_stud.*

b) Regression Analysis for Model one

To determine the best predictive model for total score, I choose the model as below:

Total_score= β_0+ β_1(teaching) + β_2(international) + β_3(research) + β_4(citations) + β_5(income) + β_6 (num_students) + β_7(student_staff_ratio)+εi

Based on the output in table 2, Appendix, the model's P-value is very small and R^2 is very large, 0.9999. However, the variable num_students' P-value is pretty large (0.473). So I will do model selection in next step.

c) Model Selection

I use the stepwise selection in R in order to figure out a better fitted model. Based on the output in table 3 in appendix, I dropped the variable num_students. Then I will do the regression again by using the selected variables.

Model by stepwise:

Total_score= β_0+ β_1(teaching) + β_2(international) + β_3(research) + β_4(citations) + β_5(income) + β_6 (student_staff_ratio)+εi

Section3: Analysis of the Best Regression Equations

After analyzing the Pearson Correlation test and model selection, I dropped two variables named num_students and internation_stud. I used the regression analysis to figure out which one to be excluded from our equation. Below is the best regression equation for total score from those 6 selected :

total_score =-0.15 + 0.305(teaching)+ 0.075(international)+ 0.297(research)+ 0.301(citations)+ 0.024 (income) + 0.004(student_staff_ratio)

From the output in table 4, Appendix, it can be learned that R^2 is 0.9999. Since the multiple coefficient of determination (R squared) is close to 1, it presents a very good fit. The Variance Inflation Factors (VIF) values look reasonable since they are all under 10 (table 5, Appendix), which means there is no multicollinearity between the 6 variables.

In addition, I tested the assumption of multiple regression for the selected equation above. The first test of normal distribution for the error, showed by Figure 1a and b in Appendix, indicates the equation above is in fact a normal distribution with minimal outliers. The second assumption is to test the independence of the error. I used the Durbin-Watson (DW) Statistic to prove that there is no serial correlation and thus to prove the independence of the error. Using R we found the DW is equal to 2.201324 (table 6 in Appendix), which is close to 2 proving that the null hypothesis ($\rho\epsilon,\varepsilon$-1=0) is reasonable. Therefore, the two assumptions are met.

Using the given Analysis of Variance (ANOVA) Table by R, we used the F test to evaluate the best regression equation for weight from those 6 selected variables. The hypothesis test is:

$$H_0: \beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=0 \ VS \ H_1: \text{at least one of the } \beta_i \text{ is not equal to zero.}$$

The F value is determined by the mean squared of regression divided by the mean squared of error. Since the computed value of F=2.204e+05 and the P-Value is < 2.2e-16 (Table 4), we reject the null hypothesis and conclude that the regression is significant at a level of 0.05. What's more, all the six variables are significant. Finally, we tested the Graphical Analysis of Residuals (residuals against fitted values) shown in Figure 1 c. We found that residual model against the fitted values is constant. This indicates the model is reasonable.

Section 4: Conclusion and Recommendation

From my analysis utilizing multiple methods of data processing technique, I have determined that the best acceptable models are applicable to the data. The best model includes factors such as teaching, international, research, citations, income, student_staff_ratio. And teaching, research, citations contribute much more than other factors to the ranking of a university. Based on the findings, if a university want to improve its' ranking, the management should pay more attention to teaching quality, research production and publication's citation.

5.Conclusion

a). United States has the most top universities and owns the top 1 university from 2011 to 2016.

b). The ranking of University of Cincinnati is on the list of top 200 universities in 2011 only.

c). The regression model developed here is reasonable. Based on this model, the most important factors affecting a university's ranking are teaching, research and citation.

6. Appendix:

Table 1

	teaching	international	research	citations	income	num_students	student_staff_ratio	international_students
teaching	1.00	-0.05	0.87	0.27	0.05	-0.09	-0.38	0.08
international	-0.05	1.00	0.09	0.11	-0.07	-0.24	0.16	0.82
research	0.87	0.09	1.00	0.21	0.16	0.01	-0.18	0.16
citations	0.27	0.11	0.21	1.00	-0.18	-0.23	-0.32	0.13
income	0.05	-0.07	0.16	-0.18	1.00	-0.01	0.02	-0.07
num_students	-0.09	-0.24	0.01	-0.23	-0.01	1.00	0.31	-0.32
student_staff_ratio	-0.38	0.16	-0.18	-0.32	0.02	0.31	1.00	-0.01
international_students	0.08	0.82	0.16	0.13	-0.07	-0.32	-0.01	1.00

n= 99

P

	teaching	international	research	citations	income	num_students	student_staff_ratio	international_students
teaching		0.6535	0.0000	0.0073	0.6237	0.3838	0.0001	0.4260
international	0.6535		0.3971	0.2806	0.5166	0.0153	0.1182	0.0000
research	0.0000	0.3971		0.0383	0.1110	0.9303	0.0820	0.1114
citations	0.0073	0.2806	0.0383		0.0680	0.0218	0.0013	0.1838
income	0.6237	0.5166	0.1110	0.0680		0.9106	0.8226	0.5039
num_students	0.3838	0.0153	0.9303	0.0218	0.9106		0.0019	0.0011
student_staff_ratio	0.0001	0.1182	0.0820	0.0013	0.8226	0.0019		0.8925
international_students	0.4260	0.0000	0.1114	0.1838	0.5039	0.0011	0.8925	

>

Table 2

Call:

```
lm(formula = total_score ~ teaching + international + research +
    citations + income + num_students + student_staff_ratio,
    data = d1)
```

Residuals:

```
     Min       1Q   Median       3Q      Max
-0.17288 -0.04856 -0.01263  0.03405  0.60981
```

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.228e-01	1.040e-01	-1.181	0.241	
teaching	3.045e-01	1.471e-03	207.038	< 2e-16	***
international	7.480e-02	5.299e-04	141.157	< 2e-16	***
research	2.970e-01	1.324e-03	224.404	< 2e-16	***
citations	3.010e-01	9.081e-04	331.510	< 2e-16	***
income	2.389e-02	4.050e-04	58.975	< 2e-16	***
num_students	-6.095e-07	8.452e-07	-0.721	0.473	
student_staff_ratio	4.677e-03	1.074e-03	4.353	3.51e-05	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09122 on 91 degrees of freedom

Multiple R-squared: 0.9999, Adjusted R-squared: 0.9999

F-statistic: 1.879e+05 on 7 and 91 DF, p-value: < 2.2e-16

Table 3

Stepwise Model Path

Analysis of Deviance Table

Initial Model:

total_score ~ teaching + international + research + citations +

income + num_students + student_staff_ratio

Final Model:

total_score ~ teaching + international + research + citations +

income + student_staff_ratio

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1				91	0.7572080	-466.4505
2	- num_students	1	0.004326731	92	0.7615347	-467.8864

Table 4

Call:

lm(formula = total_score ~ teaching + international + research +

citations + income + student_staff_ratio, data = d1)

Residuals:

Min	1Q	Median	3Q	Max
-0.16422	-0.04674	-0.01225	0.03599	0.60756

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.1501202	0.0966341	-1.553	0.124	
teaching	0.3046112	0.0014524	209.724	< 2e-16	***
international	0.0749299	0.0004986	150.273	< 2e-16	***
research	0.2968649	0.0012964	228.985	< 2e-16	***
citations	0.3011255	0.0008981	335.276	< 2e-16	***
income	0.0239218	0.0004012	59.624	< 2e-16	***
student_staff_ratio	0.0044759	0.0010350	4.324	3.87e-05	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09098 on 92 degrees of freedom

Multiple R-squared: 0.9999, Adjusted R-squared: 0.9999

F-statistic: 2.204e+05 on 6 and 92 DF, p-value: < 2.2e-16

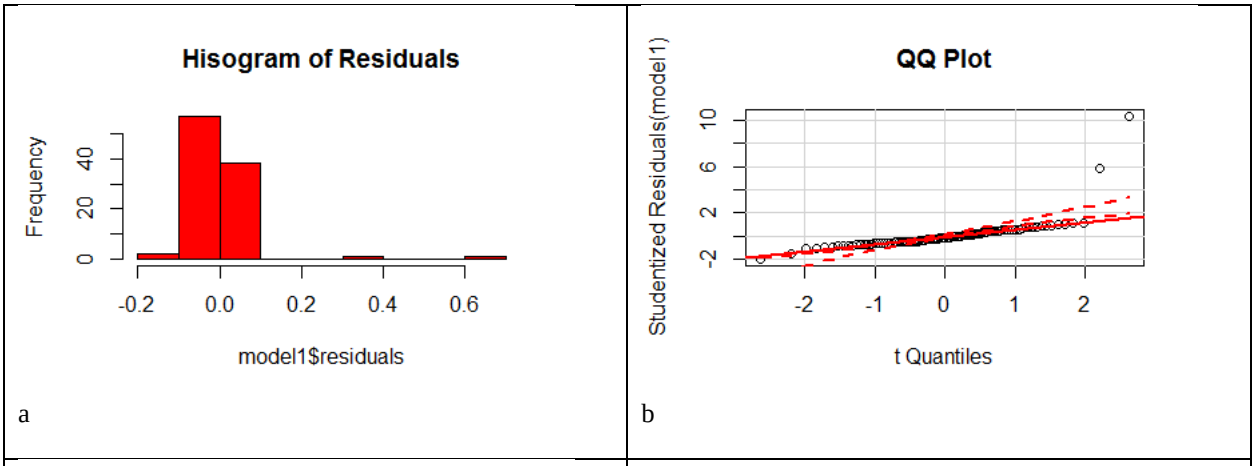
Table 5

teaching	international	research	citations	income	student_staff_ratio
5.542051	1.119002	5.120617	1.228735	1.125707	1.411789

Table 6

```
> durbinWatsonTest(model1)
 lag Autocorrelation D-W Statistic p-value
   1      -0.1044311       2.201324   0.324
 Alternative hypothesis: rho != 0
```

Fig 1



Code:

R Code

```
library(RSQLite)
library(RODBC)
odbcDataSources(type = c("all", "user", "system"))

#Create connection
db <- odbcConnect("Example", uid = "", pwd = "")
#Query a database (select statement)
UniversityRank <- sqlQuery(db, "SELECT * FROM WorldUniversityRanking.dbo.timesData")
sqlBasic <- sqlQuery(db, "SELECT
```

```
    world_rank
   ,university_name
   ,country
   ,teaching
   ,international
   ,research
   ,citations
   ,income
   ,total_score
   ,num_students
   ,student_staff_ratio
   ,international_students
   ,female_male_ratio
   ,year
   from WorldUniversityRanking.dbo.timesData")

library(dplyr)

# the summary of the obs
sqlsummary<-sqlQuery(db," Select Count(*) AS TotabObs, Avg(total_score) AS Avgscore
        From WorldUniversityRanking.dbo.timesData")
sqlsummary

#List the top 1 Universities from 2011 to 2016 */
TOP1<-sqlQuery(db,"select *
    from ( select ROW_NUMBER() over(partition by year order by world_rank ASC ) worldRank,
    university_name,country,year
    from WorldUniversityRanking.dbo.timesData
    where world_rank<201) a
    where worldRank<2")
TOP1
```

```
# rank of UC
UC<-sqlQuery(db," Select world_rank,university_name,total_score,year
        From WorldUniversityRanking.dbo.timesData
        where university_name like '%Cincinnati'")
UC

##Plot
library(ggplot2) # Data visualization
library(readr) # CSV file I/O, e.g. the read_csv function
library(dplyr)
library(plotly)
univer<-read.csv("C:/6045 R&SAS/final/data/timesData.csv",stringsAsFactors=FALSE,header=T);
str(univer)
#take Duke,Harvard,Princeton University as an example to show the change of rank
duke<-"Duke University"
duke.university<-univer[univer$university_name==duke,]

Harvard<-"Harvard University"
Harvard.University<-univer[univer$university_name==Harvard,]

Princeton<-"Princeton University"
Princeton.University<-univer[univer$university_name==Princeton,]

total <- rbind(duke.university,Harvard.University,Princeton.University)

str(total)
#converting world_rank

# converting world_rank in times to numeric

duke.university[,1]=as.numeric(duke.university$world_rank)
Harvard.University[,1]=as.numeric(Harvard.University$world_rank)
```

```
Princeton.University[,1]=as.numeric(Princeton.University$world_rank)
#https://plot.ly/r/line-and-scatter/
#Plotting rankings of the top 3 universities over the years
library(magrittr)
plot_ly(data= duke.university, x= ~year, y = ~world_rank,name ='duke', type='scatter', mode='lines+markers')%>%
  add_trace(data = Harvard.University,name= 'harvard')%>%
  add_trace(data=Princeton.University,name = 'princeton')%>%
  layout(title = 'University Ranking Over Time')

#read the data for the year of 2011
uni<-univer[univer$year==2011,]

# country VS university count
country_VS_uni<-uni %>%
  na.omit() %>%
  group_by(country)%>%
  summarize(count = n())

# List top 10 country
top_10_country <- country_VS_uni %>%
  arrange(desc(count)) %>%
  head(10)
top_10_country

# Plot top 10 country as per university count
ggplot(top_10_country,
       aes(x=reorder(country, -count), y=count, fill=country)) +
  geom_bar(stat="identity") +
  coord_flip() +
  theme(legend.position="none") +
  labs(x="Count",y="Country") +
  ggtitle("Top 10 Country by number of university ")
```

```
#mapping
library(rworldmap)
gtdMap <- joinCountryData2Map( country_VS_uni, nameJoinColumn="country", joinCode="NAME" )
mapParams <- mapCountryData(gtdMap,
                            nameColumnToPlot="count",
                            catMethod="fixedWidth",
                            numCats=4,colourPalette="rainbow",
                            mapTitle="The number of university VS Country")

#Regression
#due to the 2016 has the less missing value
uni_2016 <- univer[univer$year==2016,]
uni2016 <- uni_2016[1:100,4:12]
str(uni2016)
#output data
getwd()
library(RODBC)
write.csv(d, file = "C:/6045 R&SAS/final/data/tdclean2.csv", row.names = F, quote = F)
write.table(uni2016, file = 'C:/6045 R&SAS/final/data/tdclean.txt',quote = F)

#from the output, then it can be learned that some variable need to be cleaned.
#clean data
uni2016$international <- as.numeric(as.character(uni2016$international))
uni2016$income <- sub('-','0',uni2016$income)
uni2016$income <- as.numeric(as.character(uni2016$income))
uni2016$total_score <- as.numeric(as.character(uni2016$total_score))
uni2016$num_students <- gsub(',',",uni2016$num_students)
uni2016$num_students <- as.numeric(as.character(uni2016$num_students))
uni2016$international_students <- as.numeric(as.character(gsub('%',",uni2016$international_students)))/100
str(uni2016)
d1 <- na.omit(uni2016)
```

```
d1
summary(d1)

#Correlation
cor(d1[,c(1:5,7:9)],method="pearson")
#http://www.statmethods.net/stats/regression.html
#regression
model<- lm(total_score~., d1)
print(summary(model))

# Stepwise Regression
library(MASS)
model<- lm(total_score~teaching + international + research + citations +
        income + num_students +student_staff_ratio,d1)
print(summary(model))

#stepwise selection
step <- stepAIC(model, direction="both")
step$anova # display results


#Finnal Model
model1<-lm(total_score ~ teaching + international + research + citations +
        income + student_staff_ratio,d1)
print(summary(model1))

#Evaluate Collinearity
library(car)
vif(model1) # variance inflation factors

# Test for Autocorrelated Errors
library(lmtest)
```

```
durbinWatsonTest(model1)


#residual diagoues

#QQ plot

outlierTest(model1)# Bonferonni p-value for most extreme obs

qqPlot(model1, main="QQ Plot")

qqnorm(model1$residuals)


#Constant Variance

ncvTest(model1)

spreadLevelPlot(model1,main="Residual Plot",ylab="Residual")


plot(model1$fitted.values,model1$residuals,main="Fitted Value vs Residuals",xlab="Fitted Values",ylab="Residuals",col="red")


av.Plots(model1)

cutoff <- 4/((nrow(mtcars)-length(model1$coefficients)-2))

plot(model1, which=4, cook.levels=cutoff)


#diagouse

windows()

layout(matrix(c(1,2,3,4), 2, 2, byrow = TRUE))

qqnorm(model1$residuals)

plot(model1$fitted.values,model1$residuals,main="Fitted Value vs Residuals",xlab="Fitted Values",ylab="Residuals",col="red")

hist(model1$residuals,col="red",main = "Hisogram of Residuals")

plot(uni2016$total_score[1:99],model1$residuals,main="Observations vs Residuals",xlab="Observations",ylab="Residuals",col="blue")
```

SAS:

```
PROC IMPORT DATAFILE = 'C:/6045 R&SAS/final/data/tdclean2.xls' DBMS=XLS OUT = uni20163;

RUN;

PROC PRINT DATA = uni20163;
```

```
TITLE 'Regression Data for University Rank 2016';
RUN;
PROC CONTENTS  data=uni20163;
run;
```

Project 3

Multivariate Statistical Analysis of Crime Data in United States

(0) Definition of each crime

Murder is the unlawful killing of another human without justification or valid excuse, especially the unlawful killing of another human being with malice aforethought. This state of mind may, depending upon the jurisdiction, distinguish murder from other forms of unlawful homicide, such as manslaughter. Manslaughter is a killing committed in the absence of malice, brought about by reasonable provocation, or diminished capacity. Involuntary manslaughter, where it is recognized, is a killing that lacks all but the most attenuated guilty intent, recklessness.

Rape is a type of sexual assault usually involving sexual intercourse or other forms of sexual penetration carried out against a person without that person's consent. The act may be carried out by physical force, coercion, abuse of authority, or against a person who is incapable of giving valid consent, such as one who is unconscious, incapacitated, has an intellectual disability or is below the legal age of consent. The term rape is sometimes used interchangeably with the term sexual assault.

Robbery is the crime of taking or attempting to take anything of value by force, threat of force or by putting the victim in fear. According to common law, robbery is defined as taking the property of another, with the intent to permanently deprive the person of that property, by means of force or fear; that is to say, it is a larceny or theft accomplished by an assault. Precise definitions of the offence may vary between jurisdictions. Robbery is differentiated from other forms of theft (such as burglary, shoplifting or car theft) by its inherently violent nature (a violent crime); whereas many lesser forms of theft are punished as misdemeanors, robbery is always a felony in jurisdictions that distinguish between the two.

Assault is an attempt to initiate harmful or offensive contact with a person, or a threat to do so.[1]It is distinct from battery, which refers to the actual achievement of such contact. An assault is carried out by a threat of bodily harm coupled with an apparent, present ability to cause the harm. It is both a crime and a tort and, therefore, may result in either criminal and/or civil liability. Generally, the common law definition is the same in criminal and tort law. There is, however, an additional criminal law category of assault consisting of an attempted but unsuccessful battery. The term is often confused with battery, which involves physical contact. The specific meaning of assault varies between countries, but can refer to an act that causes another to apprehend immediate and personal violence, or in the more limited sense of a threat of violence caused by an immediate show of force. Assault in many US jurisdictions and Scotland is defined more broadly still as any intentional physical contact with another person without their consent; but in England and Wales and in most other common law jurisdictions in the world, this is defined instead as battery. Some jurisdictions have incorporated the definition of civil assault into the definition of the crime making it a criminal assault intentionally to cause another person to apprehend a harmful or offensive contact.

Burglary (also called breaking and entering and sometimes housebreaking) is an unlawful entry into a building or other location for the purposes of committing an offence. Usually that offence is theft, but most jurisdictions include others within the ambit of burglary.

Larceny is a crime involving the unlawful taking of the personal property of another person or business. It was an offence under the common law of England and became an offence in jurisdictions which incorporated the common law of England into their own law.

Car theft or grand theft auto is the criminal act of stealing or attempting to steal any motor vehicle, usually an automobile.

Note: These definitions are quoted from Wikipedia.

(a) Principal analysis

Based on the summary of the data, this dataset contains 50 obs. and 7 variables. And the mean and standard deviation of this dataset are shown as below.

From the table Eigenvalues of the covariance Matrix and scree plot, it can be learned that the first two components can be used to explain the total variance, and they contribute more than 95 % of the total variance. Then the first two principal components can be used to explain the original data. Then no more than 4% of the total variance are contributed by the subsequent components.

The first two eigenvectors of the covariance matrix are

e_1^T =[0.000864, 0.008773, 0.056993, 0.059196, 0.465346, 0.872863, 0.121384]

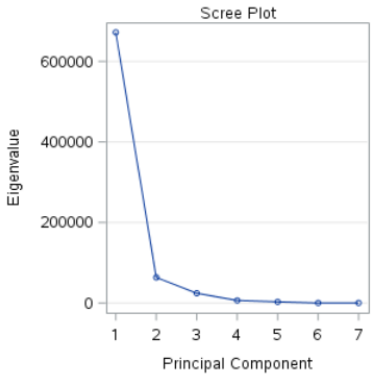
e_2^T =[[0.007077, 0.011477, 0.165921, 0.174243, 0.774439, -.481781, 0.331752]

The first component contains the variables of larceny (0.872863), burglary (0.465346) and maybe the auto (0.121384) because it shows very large eigen values for these three variables. Within the first component, all the other crimes also have small positive loading. The second component has a high positive loading on burglary (0.774439) and auto (0.331752), and high negative loading on larceny (-.481781). But the other variables' loadings are small and positive. The second component can be interpreted as "type of crimes" component.

Simple Statistics

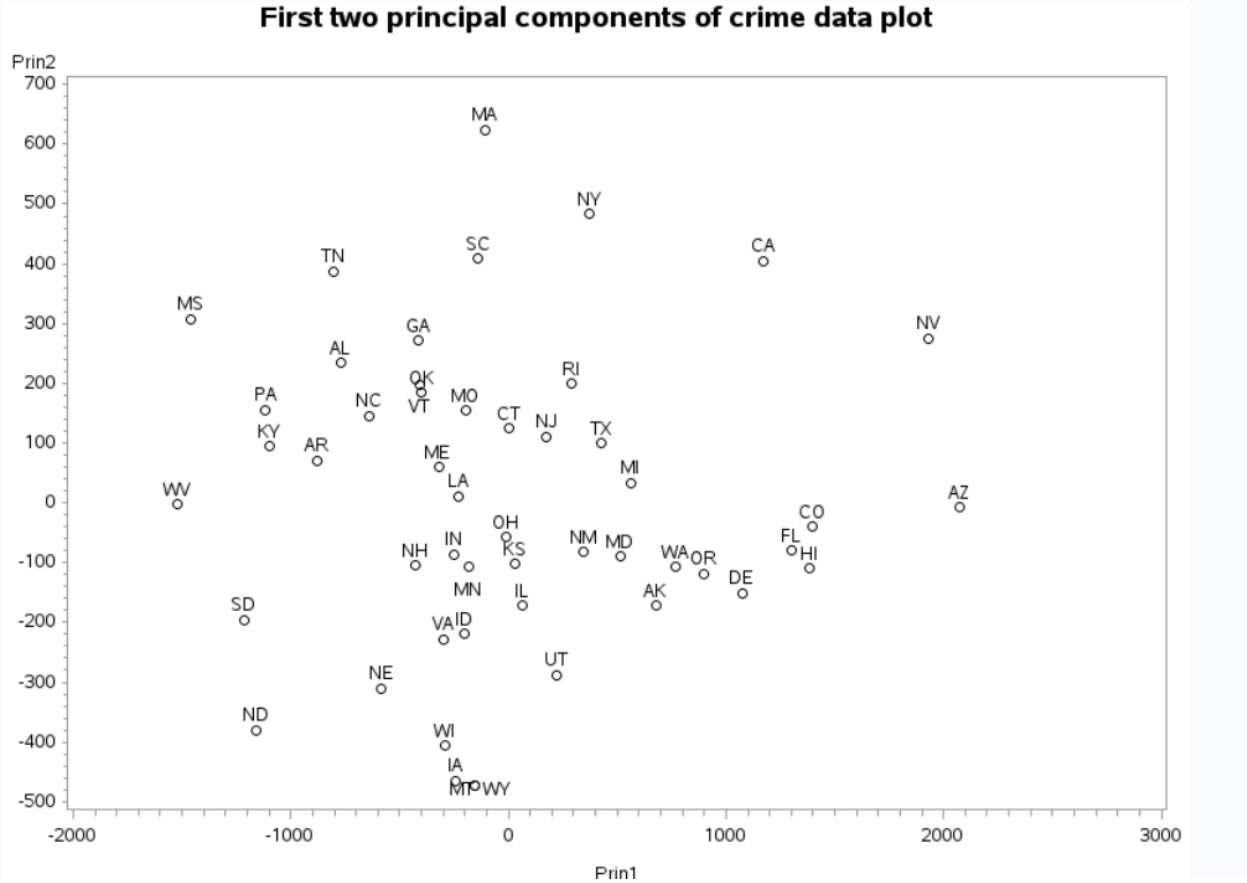
	murder	rape	robbery	assault	burglary	larceny	auto
Mean	7.444000000	25.73400000	124.0920000	211.3000000	1291.904000	2671.288000	377.5260000
StD	3.866768941	10.75962995	88.3485672	100.2530492	432.455711	725.908707	193.3944175

Eigenvalues of the Covariance Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	672099.938	608440.269	0.8736	0.8736
2	63659.669	39443.589	0.0827	0.9563
3	24216.080	17902.616	0.0315	0.9878
4	6313.464	3295.814	0.0082	0.9960
5	3017.650	2980.468	0.0039	0.9999
6	37.183	31.510	0.0000	1.0000
7	5.673		0.0000	1.0000



Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
murder	0.000864	0.007077	-.007375	0.022236	0.005032	0.184911	0.982437
rape	0.008773	0.011477	-.010400	0.051813	-.005986	0.981012	-.185953
robbery	0.056993	0.165921	0.110301	0.457211	0.864522	-.022240	-.011008
assault	0.059196	0.174243	-.150513	0.849046	-.468663	-.053603	-.009165
burglary	0.465346	0.774439	-.345505	-.253581	-.001246	-.003897	-.002102
larceny	0.872863	-.481781	0.059703	0.049105	0.001277	-.003608	0.002712
auto	0.121384	0.331752	0.917649	-.013601	-.181365	0.005253	0.004640

The plot of the first two principal components shows the first two PCs for the 50 states. It can be learned that the states with large number of crime due to burglary, larceny and maybe auto on the right hands side (NV, AZ) for the first PC. For the second PC, MA may have the highest chance of burglary and auto theft, and lowest chance of larceny.



(b) Factor Analysis

Based on the principal component analysis and the likelihood ratio test result, the number of factors should be m=2. From the table Factor Pattern, it can be learned that factor 1 shows the all crimes. That's because all kinds crimes load a large positive value. The factor 2shows that property crimes have the positive loading but violent crimes have the negative loading.

The communalities $h_j^2, j = 1 \ldots 7$, measure the part of variance of each variable that can be assigned to the common factors.

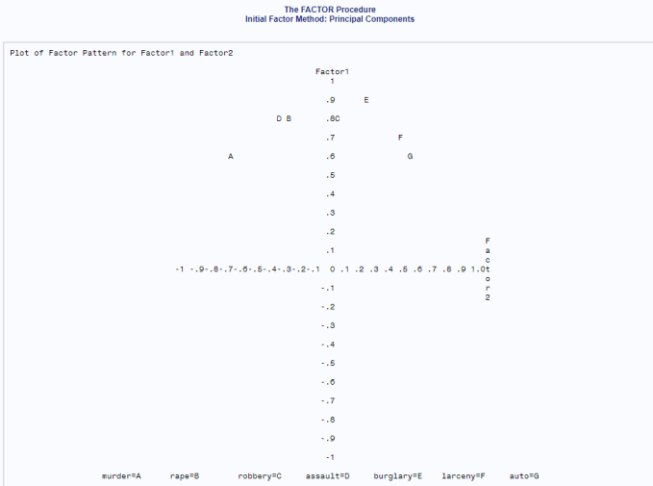
The estimated communalities are obtained

The $\widehat{h_j^2}^T = [0.86139693,0.80265644,0.65035880,0.79360069,0.84844347,0.72600469,0.67122032]$.

Factor Pattern		
	Factor1	Factor2
murder	0.60913	-0.70026
rape	0.87584	-0.18858
robbery	0.80508	0.04702
assault	0.80462	-0.38234
burglary	0.89287	0.22631
larceny	0.72492	0.44777
auto	0.59878	0.55918

Final Communality Estimates: Total = 5.353681						
murder	rape	robbery	assault	burglary	larceny	auto
0.86139693	0.80265644	0.65035880	0.79360069	0.84844347	0.72600469	0.67122032

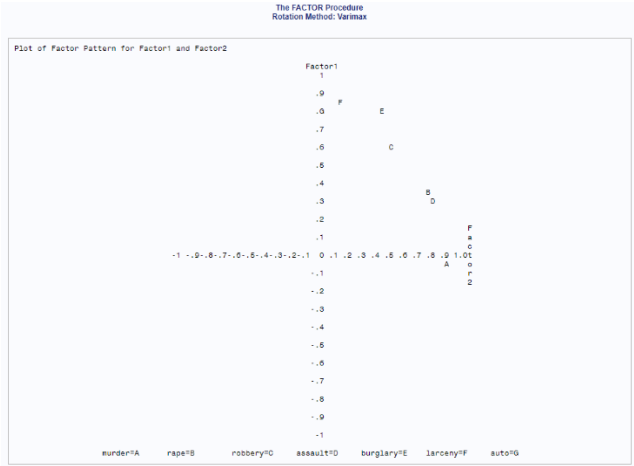
The Factor Procedure shows that some variables such as murder, auto are not clear in factor 1 or factor 2. Then the method of rotation is used.



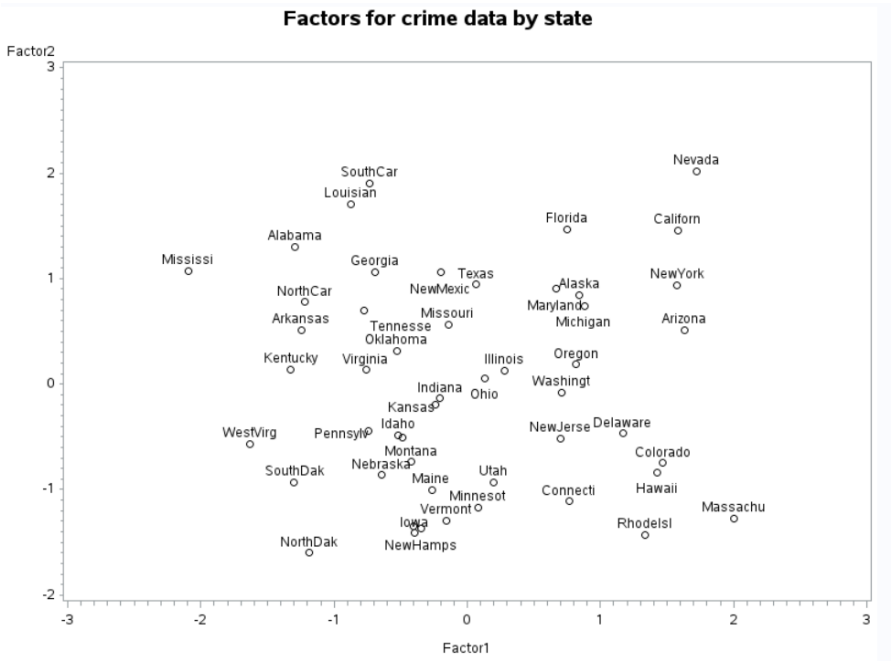
Rotation of factor loading

The Rotated Factor Pattern shows that larceny, auto theft and burglary have the large value of loading in factor 1 which means factor 1 represents property crimes. For factor 2, murder, assault and rape have the large value of loading. That means factor 2 represents violent crimes. The Factor Procedure plot also shows the same results to that. However, robbery isn't clear in both factor 1 and factor 2.

Rotated Factor Pattern		
	Factor1	Factor2
larceny	0.83310	0.17873
auto	0.81921	0.01100
burglary	0.80099	0.45481
robbery	0.61351	0.52341
murder	-0.04522	0.92701
assault	0.31595	0.83293
rape	0.50148	0.74241

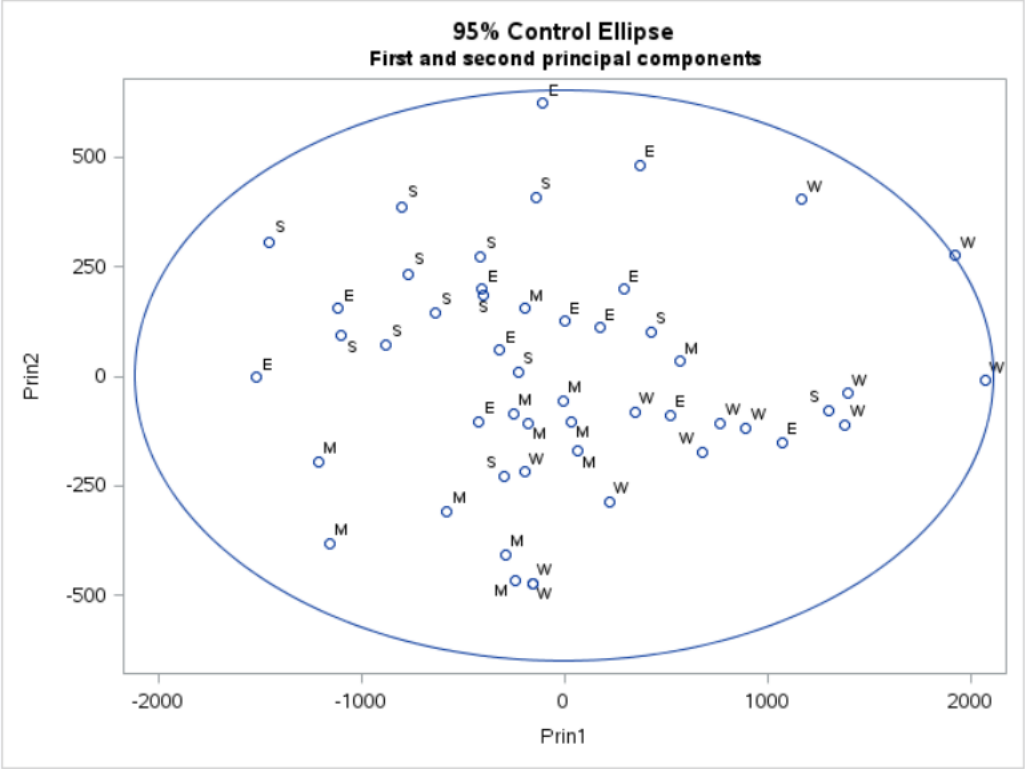


The plot of Factors for crime data shows that Nevada has high overall crimes, North Dakota has low crimes, Massachusetts has high property crimes but low violent crimes and Mississippi has high violent crimes but low property crimes.



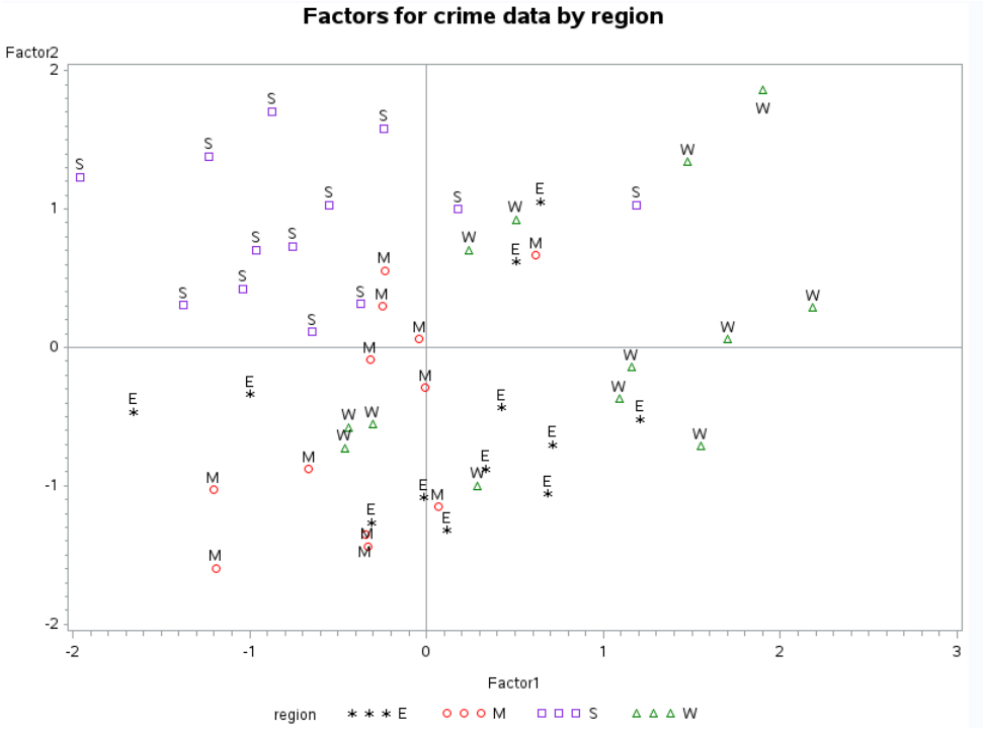
(c) Plot data by Region

1. PCA plot



The 95% control ellipse shows that all the data are controlled. Except 2 points of east region which have large value in PC2 and 2 points of west region which have large value in PC1. The region' plot of principal components shows that the states which locate in south region have positive value in principal 2 but negative value in principal 1. Only one state has negative value in PC2 and 2 states have positive value in PC1. And two points which belongs to west region show that they have larger chance in larceny, burglary and auto theft. West region's states have a positive and large value in PC 1 but some of them have positive value in PC2 and some of them have negative value in PC2.Most states of east region are around middle area. But there are 2 east states have extremely large value in PC2. Most states in middle region have negative value in PC1 and PC2. But they are more separate than south region.

2. Factors plot



Most of these points, stars, squares and triangles are in the middle of the plot and closes to its own region. The south region states locate the left upper area which means the positive loading of factor 2(violent crime) and negative loading of factor 1(property crime) and only one point locates in upper middle area. Most east region states' points in the bottom of the plot but there are 2 points locate in the upper side. Almost all west region's states have positive loading in factor 1 except 2 states have negative loading in factor 1. But some of them are have positive loading in factor2, some have negative loading in factor 2. That's means west region has a large chance in property crimes. For the middle region, most of the states' loading in the negative factor1 and facotr2, which means they have low chance of crimes.

(d) Characteristics of the regions with respect to the variables/ factors

Based on the explanation of(c), it indicates south region has more violent crimes than property crimes. Most east region states have a high loading in factor 1(property crime) but one or two points show that they have lower crimes both in property crimes and violent crimes. Most west region states are in the right side of vertical line which means west region has a large chance in property crimes. 2 points of west region has a large loading in both factor 1 and 2, which means they have all kinds of crimes. The middle region's states are distributed around 0 which means they have "average" chance of crimes. But most of these middle region's states' loading are negative in factor 1(property crimes) and factor 2 (violent crimes). That means middle region has low property crimes and violent crimes.

(e) Discriminant analysis

Based on the result of test of homogeneity, the P-value of Chi-square test is less than 0.001 which is smaller than significant level at 0.05. That result indicates that these variables have unequal variance.

From the table as below, the apparent error rate (APER) can be obtained : $APER = \frac{n_{1m}+n_{2m}+n_{3m}+n_{4m}}{n_1+n_2+n_3+n_4} = \frac{0}{50} = 0$, This result shows that there is no misclassification in this case.

The DISCRIM Procedure
Test of Homogeneity of Within Covariance Matrices

Chi-Square	DF	Pr > ChiSq
165.655758	84	<.0001

The DISCRIM Procedure
Classification Summary for Calibration Data: WORK.CRIME
Resubstitution Summary using Quadratic Discriminant Function

Number of Observations and Percent Classified into region

From region	E	M	S	W	Total
E	12 100.00	0 0.00	0 0.00	0 0.00	12 100.00
M	0 0.00	12 100.00	0 0.00	0 0.00	12 100.00
S	0 0.00	0 0.00	13 100.00	0 0.00	13 100.00
W	0 0.00	0 0.00	0 0.00	13 100.00	13 100.00
Total	12 24.00	12 24.00	13 26.00	13 26.00	50 100.00
Priors	0.25	0.25	0.25	0.25	

Error Count Estimates for region

	E	M	S	W	Total
Rate	0.0000	0.0000	0.0000	0.0000	0.0000
Priors	0.2500	0.2500	0.2500	0.2500	

Then using two factors to do the discriminant analysis. The results are shown as below. The P-value of Chi-square is 0.2874 which is bigger than the significant level 0.05. Then the pooled covariance matrices can be used in discriminant analysis. The $APER = \frac{n_{1m}+n_{2m}+n_{3m}+n_{4m}}{n_1+n_2+n_3+n_4} = \frac{3+7+2+6}{50} = 0.36$.

The DISCRIM Procedure
Test of Homogeneity of Within Covariance Matrices

Chi-Square	DF	Pr > ChiSq
10.831424	9	0.2874

The DISCRIM Procedure
Classification Summary for Calibration Data: WORK.FF
Resubstitution Summary using Linear Discriminant Function

Number of Observations and Percent Classified into region

From region	E	M	S	W	Total
E	6 50.00	4 33.33	0 0.00	2 16.67	12 100.00
M	1 8.33	7 58.33	1 8.33	3 25.00	12 100.00
S	0 0.00	0 0.00	12 92.31	1 7.69	13 100.00
W	2 15.38	3 23.08	1 7.69	7 53.85	13 100.00
Total	9 18.00	14 28.00	14 28.00	13 26.00	50 100.00
Priors	0.25	0.25	0.25	0.25	

Error Count Estimates for region

	E	M	S	W	Total
Rate	0.5000	0.4167	0.0769	0.4615	0.3638
Priors	0.2500	0.2500	0.2500	0.2500	

Then using two principal components to do the discriminant analysis. The results are shown as below. The P-value of Chi-square is 0.0922which is bigger than the significant level 0.05. Then the pooled covariance matrices can be used in discriminant analysis. The $APER = \frac{n_{1m}+n_{2m}+n_{3m}+n_{4m}}{n_1+n_2+n_3+n_4} = \frac{3+5+6+5}{50} = 0.38$.

The DISCRIM Procedure
Test of Homogeneity of Within Covariance Matrices

Chi-Square	DF	Pr > ChiSq
14.954463	9	0.0922

Error Count Estimates for region					
	E	M	S	W	Total
Rate	0.6667	0.2500	0.3846	0.2308	0.3830
Priors	0.2500	0.2500	0.2500	0.2500	

The DISCRIM Procedure
Classification Summary for Calibration Data: WORK.AA
Resubstitution Summary using Quadratic Discriminant Function

Number of Observations and Percent Classified into region					
From region	E	M	S	W	Total
E	4 33.33	1 8.33	5 41.67	2 16.67	12 100.00
M	0 0.00	9 75.00	1 8.33	2 16.67	12 100.00
S	2 15.38	2 15.38	8 61.54	1 7.69	13 100.00
W	1 7.69	2 15.38	0 0.00	10 76.92	13 100.00
Total	7 14.00	14 28.00	14 28.00	15 30.00	50 100.00
Priors	0.25	0.25	0.25	0.25	

(f) Multivariate analysis of variance on region to variables and factors

Based on the results of variables which are shown as below, all test's P-value are less than 0.001 which are less than significant level at 0.05. The null hypothesis can be rejected. Then it can be concluded that these variables are not same in two different regions.

The GLM Procedure
Multivariate Analysis of Variance

Characteristic Roots and Vectors of: E Inverse * H, where H = Type III SSCP Matrix for region, E = Error SSCP Matrix								
		Characteristic Vector V'EV=1						
Characteristic Root	Percent	murder	rape	robbery	assault	burglary	larceny	auto
2.65110276	58.77	0.05871936	0.00794771	-0.00220498	0.00025858	0.00007934	-0.00002066	-0.00025870
1.49262362	33.09	-0.01111281	0.01696452	-0.00073937	-0.00070447	-0.00029115	0.00031129	-0.00001050
0.36736422	8.14	-0.00836249	-0.00321187	-0.00115988	0.00051791	0.00053353	-0.00014669	0.00043647
0.00000000	0.00	0.02493941	0.00145434	-0.00106718	-0.00001854	-0.00040262	0.00007993	0.00095045
0.00000000	0.00	-0.01748393	-0.00803047	-0.00016067	0.00229827	-0.00030042	0.00011700	0.00000000
0.00000000	0.00	0.01467732	-0.00389938	0.00160226	0.00013934	-0.00018752	0.00010093	0.00000000
0.00000000	0.00	0.03609437	-0.02074866	-0.00043601	-0.00009189	0.00001085	0.00023868	0.00000000

MANOVA Test Criteria and F Approximations for the Hypothesis of No Overall region Effect H = Type III SSCP Matrix for region E = Error SSCP Matrix S=3 M=1.5 N=19					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.08035909	7.73	21	115.41	<.0001
Pillai's Trace	1.59359239	6.80	21	126	<.0001
Hotelling-Lawley Trace	4.51109061	8.38	21	77.224	<.0001
Roy's Greatest Root	2.65110276	15.91	7	42	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Based on the results of factors which are shown as below, all test's P-value are less than 0.001 which are less than significant level at 0.05. The null hypothesis can be rejected. Then it can be concluded that the 2 factors (property crimes and violent crimes) are not same in two different regions.

Appendix:

Code:

```
data crime;
 input state $1-15 murder rape robbery assault burglary larceny auto state $ region $;
 cards;
 Alabama         14.2 25.2 96.8 278.3 1135.5 1881.9 280.7 AL S
 Alaska          10.8 51.6 96.8 284.0 1331.7 3369.8 753.3 AK W
 Arizona          9.5 34.2 138.2 312.3 2346.1 4467.4 439.5 AZ W
 Arkansas         8.8 27.6 83.2 203.4 972.6 1862.1 183.4 AR S
 California      11.5 49.4 287.0 358.0 2139.4 3499.8 663.5 CA W
 Colorado         6.3 42.0 170.7 292.9 1935.2 3903.2 477.1 CO W
 Connecticut      4.2 16.8 129.5 131.8 1346.0 2620.7 593.2 CT E
 Delaware         6.0 24.9 157.0 194.2 1682.6 3678.4 467.0 DE E
 Florida         10.2 39.6 187.9 449.1 1859.9 3840.5 351.4 FL S
 Georgia          11.7 31.1 140.5 256.5 1351.1 2170.2 297.9 GA S
 Hawaii           7.2 25.5 128.0 64.1 1911.5 3920.4 489.4 HI W
 Idaho           5.5 19.4 39.6 172.5 1050.8 2599.6 237.6 ID W
 Illinois        9.9 21.8 211.3 209.0 1085.0 2828.5 528.6 IL M
 Indiana          7.4 26.5 123.2 153.5 1086.2 2498.7 377.4 IN M
 Iowa            2.3 10.6 41.2 89.8 812.5 2685.1 219.9 IA M
 Kansas           6.6 22.0 100.7 180.5 1270.4 2739.3 244.3 KS M
 Kentucky         10.1 19.1 81.1 123.3 872.2 1662.1 245.4 KY S
 Louisiana        15.5 30.9 142.9 335.5 1165.5 2469.9 337.7 LA S
 Maine           2.4 13.5 38.7 170.0 1253.1 2350.7 246.9 ME E
 Maryland         8.0 34.8 292.1 358.9 1400.0 3177.7 428.5 MD E
 Massachusetts    3.1 20.8 169.1 231.6 1532.2 2311.3 1140.1 MA E
 Michigan         9.3 38.9 261.9 274.6 1522.7 3159.0 545.5 MI M
 Minnesota        2.7 19.5 85.9 85.8 1134.7 2559.3 343.1 MN M
 Mississippi      14.3 19.6 65.7 189.1 915.6 1239.9 144.4 MS S
 Missouri         9.6 28.3 189.0 233.5 1318.3 2424.2 378.4 MO M
 Montana          5.4 16.7 39.2 156.8 804.9 2773.2 309.2 MT W
 Nebraska         3.9 18.1 64.7 112.7 760.0 2316.1 249.1 NE M
 Nevada          15.8 49.1 323.1 355.0 2453.1 4212.6 559.2 NV W
 New Hampshire    3.2 10.7 23.2 76.0 1041.7 2343.9 293.4 NH E
 New Jersey       5.6 21.0 180.4 185.1 1435.8 2774.5 511.5 NJ E
 New Mexico       8.8 39.1 109.6 343.4 1418.7 3008.6 259.5 NM W
 New York         10.7 29.4 472.6 319.1 1728.0 2782.0 745.8 NY E
 North Carolina   10.6 17.0 61.3 318.3 1154.1 2037.8 192.1 NC S
 North Dakota     0.9 9.0 13.3 43.8 446.1 1843.0 144.7 ND M
 Ohio            7.8 27.3 190.5 181.1 1216.0 2696.8 400.4 OH M
 Oklahoma         8.6 29.2 73.8 205.0 1288.2 2228.1 326.8 OK S
 Oregon          4.9 39.9 124.1 286.9 1636.4 3506.1 388.9 OR W
 Pennsylvania     5.6 19.0 130.3 128.0 877.5 1624.1 333.2 PA E
 Rhode Island     3.6 10.5 86.5 201.0 1489.5 2844.1 791.4 RI E
 South Carolina   11.9 33.0 105.9 485.3 1613.6 2342.4 245.1 SC S
 South Dakota     2.0 13.5 17.9 155.7 570.5 1704.4 147.5 SD M
 Tennessee        10.1 29.7 145.8 203.9 1259.7 1776.5 314.0 TN S
```

```
Texas          13.3 33.8 152.4 208.2 1603.1 2988.7 397.6 TX S
Utah           3.5 20.3 68.8 147.3 1171.6 3004.6 334.5 UT W
Vermont        1.4 15.9 30.8 101.2 1348.2 2201.0 265.2 VT E
Virginia       9.0 23.3 92.1 165.7 986.2 2521.2 226.7 VA S
Washington     4.3 39.6 106.2 224.8 1605.6 3386.9 360.3 WA W
West Virginia  6.0 13.2 42.2 90.9 597.4 1341.7 163.3 WV E
Wisconsin      2.8 12.9 52.2 63.7 846.9 2614.2 220.7 WI M
Wyoming        5.4 21.9 39.7 173.9 811.6 2772.2 282.0 WY W
;



*principle analysis;
proc princomp data=crime cov out=aa outstat=aa_stat;
var  murder rape robbery assault burglary larceny auto;
run;
proc score data=crime score=aa_stat out=FScore;
var   murder rape robbery assault burglary larceny auto;
run;


GOPTIONS RESET=ALL;
proc corr data=aa;        *the principal components are uncorrelated/independent;
 var prin1-prin7;
run;
SYMBOL1 pointlabel=('#state')V=circle C=black I=none;
TITLE1 "Crime Rates per 100,000 Population by State";
TITLE2 "Plot of the First Two Principal Components";;
proc gplot;
 title 'PLOT OF the First Two PRINCIPAL COMPONENTS';
 plot prin2*prin1;
* symbol1 v=1 c=red;
run;

**pcs for crime data by region;
SYMBOL1 pointlabel=('#region')V=star C=black I=none;
SYMBOL2 pointlabel=('#region')V=circle C=red I=none;
SYMBOL3 pointlabel=('#region')V=square C=blueviolet I=none;
SYMBOL4 pointlabel=('#region')V=triangle C=green I=none;
title "95% Control Ellipse";
title2 "First and second principal components";
proc sgplot data=aa  noautolegend;
   scater x=prin1 y=prin2/datalabel=region;
   ellipse x=prin1 y=prin2/alpha=0.05;          /* default is ALPHA=0.05 */
run;
```

```
proc gplot;
title 'Principals for crime data by region';
 plot prin2*prin1=REGION/href=0 vref=0;
run;
quit;

title "95% Prediction Ellipse";
title2 "First and second principal components";
proc sgplot data=aa  noautolegend;
   scater x=prin1 y=prin2/datalabel=state;
   ellipse x=prin1 y=prin2/alpha=0.05;          /* default is ALPHA=0.05 */
run;
*factor analysis;
proc factor data=crime  ;
var murder rape robbery assault burglary larceny auto ;
run;

proc factor data=crime rotate=v reorder n=2 out=ff outstat=ff_1 plot;
 var murder rape robbery assault burglary larceny auto  ;
run;

proc factor data=crime rotate=v reorder method=ml heywood n=2  ;
var murder rape robbery assault burglary larceny auto ;
run;

proc score data=crime score=ff_1 out=FScore;
var  murder rape robbery assault burglary larceny auto;
run;
proc print data=FScore;
run;
proc corr data=ff;
run;


proc gplot;
title 'PLOT OF FACTORS FOR CRIME DATA';
 plot factor2*factor1=state;
run;
 **********LANBLE REGION******;
SYMBOL1 pointlabel=('#region')V=star C=black I=none;
SYMBOL2 pointlabel=('#region')V=circle C=red I=none;
SYMBOL3 pointlabel=('#region')V=square C=blueviolet I=none;
SYMBOL4 pointlabel=('#region')V=triangle C=green I=none;
proc gplot;
title 'Factors for crime data by region';
 plot factor2*factor1=REGION/href=0 vref=0;
```

```
run;

******discriminant analysis*****;
proc stepdisc data=crime ;
 *this will test the equality of the variance covariance matrices;
 class region;
 var  murder rape robbery assault burglary larceny auto ;
run;


proc discrim data=crime method=normal  pool=test slpool=0.05;*wcov short;
 *this will test the equality of the variance covariance matrices;
 class region;
 var  murder rape robbery assault burglary larceny auto ;
run;

proc discrim data=crime pool=yes out=out outd=outd;
 *we will pool in this example if though it is INappropriate;
 class region;
 var  murder rape robbery assault burglary larceny auto ;
* priors  'E'=0.25 'M'=0.25  'S'=0.25 'W'=0.25;
run;

proc discrim data=ff pool=test wcov short ;
 class region;
 var factor2 factor1;
run;


proc discrim data=aa pool=test wcov short ;
 class region;
 var prin1 prin2;
run;

proc discrim data=aa pool=test wcov short ;
 class region;
 var prin1 prin2;
run;
***MANOVA**;
proc glm data=crime;
class region;
model murder rape robbery assault burglary larceny auto= region/ss3;
manova h=_all_/printe;
means region;
run;
```