

Statistical Data Analysis of US Economic Data

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libraries

```
library (psych)
```

```
## Warning: package 'psych' was built under R version 4.2.3
```

```
library (CCA)
```

```
## Warning: package 'CCA' was built under R version 4.2.3
```

```
## Loading required package: fda
```

```
## Warning: package 'fda' was built under R version 4.2.3
```

```
## Loading required package: splines
```

```
## Loading required package: fds
```

```
## Warning: package 'fds' was built under R version 4.2.3
```

```
## Loading required package: rainbow
```

```
## Warning: package 'rainbow' was built under R version 4.2.3
```

```
## Loading required package: MASS
```

```
## Loading required package: pcaPP
```

```
## Warning: package 'pcaPP' was built under R version 4.2.3
```

```
## Loading required package: RCurl
```

```
## Warning: package 'RCurl' was built under R version 4.2.3
```

```
## Loading required package: deSolve
```

```
## Warning: package 'deSolve' was built under R version 4.2.3
```

```
##  
## Attaching package: 'fda'
```

```
## The following object is masked from 'package:graphics':  
##  
##      matplot
```

```
## Loading required package: fields
```

```
## Warning: package 'fields' was built under R version 4.2.3
```

```
## Loading required package: spam
```

```
## Warning: package 'spam' was built under R version 4.2.3
```

```
## Spam version 2.9-1 (2022-08-07) is loaded.  
## Type 'help( Spam)' or 'demo( spam)' for a short introduction  
## and overview of this package.  
## Help for individual functions is also obtained by adding the  
## suffix '.spam' to the function name, e.g. 'help( chol.spam)'.
```

```
##  
## Attaching package: 'spam'
```

```
## The following objects are masked from 'package:base':  
##  
##      backsolve, forwardsolve
```

```
## Loading required package: viridis
```

```
## Warning: package 'viridis' was built under R version 4.2.3
```

```
## Loading required package: viridisLite
```

```
##  
## Try help(fields) to get started.
```

```
##  
## Attaching package: 'fields'
```

```
## The following object is masked from 'package:psych':  
##  
##      describe
```

```
library(scatterplot3d)
```

```
## Warning: package 'scatterplot3d' was built under R version 4.2.3
```

```
library(dplyr)
```

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

```
## The following object is masked from 'package:MASS':  
##  
##   select
```

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

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

loading the data

```
places = read.csv(file.choose(), header = T)  
#places
```

Summary statistics

```
summary(places)
```

```
##      Climate      HousingCost      HlthCare      Crime
## Length:329      Min.      :105.0      Min.      : 5159      Min.      : 43
## Class :character      1st Qu.:480.0      1st Qu.: 6760      1st Qu.: 583
## Mode  :character      Median :542.0      Median : 7877      Median : 833
##                                     Mean  :538.7      Mean   : 8347      Mean   :1186
##                                     3rd Qu.:592.0      3rd Qu.: 9015      3rd Qu.:1445
##                                     Max.   :910.0      Max.   :23640      Max.   :7850
##      Transp      Educ      Arts      Recreat      Econ
## Min.      : 308.0      Min.      :1145      Min.      :1701      Min.      : 52      Min.      : 300
## 1st Qu.: 707.0      1st Qu.:3141      1st Qu.:2619      1st Qu.: 778      1st Qu.:1316
## Median : 947.0      Median :4080      Median :2794      Median : 1871      Median :1670
## Mean   : 961.1      Mean   :4210      Mean   :2815      Mean   : 3151      Mean   :1846
## 3rd Qu.:1156.0      3rd Qu.:5205      3rd Qu.:3012      3rd Qu.: 3844      3rd Qu.:2176
## Max.    :2498.0      Max.    :8625      Max.    :3781      Max.    :56745      Max.    :4800
##      CaseNum      Long      Lat      Pop
## Min.      :3045      Min.      : 1      Min.      : -127.20      Min.      :25.65
## 1st Qu.:4842      1st Qu.: 83      1st Qu.: -96.69      1st Qu.:34.22
## Median :5384      Median :165      Median : -86.81      Median :39.65
## Mean   :5525      Mean   :165      Mean   : -90.18      Mean   :38.18
## 3rd Qu.:6113      3rd Qu.:247      3rd Qu.: -80.01      3rd Qu.:41.82
## Max.    :9980      Max.    :329      Max.    : -68.77      Max.    :48.88
##      StNum      X
## Min.      : 62820      Min.      : 1.00
## 1st Qu.: 132866      1st Qu.:11.00
## Median : 241617      Median :25.00
## Mean   : 522118      Mean   :25.64
## 3rd Qu.: 515259      3rd Qu.:39.00
## Max.    :8274961      Max.    :51.00
```

```
city_names = places[,1]
```

Data Transformation

```
data_log = places
data_log[,c(2,3,4,5,7,8,9)] = log(data_log[,c(2,3,4,5,7,8,9)])
```

Visualisation

1. Untransformed Data

```
par(mfrow=c(3,3))
places$Climate <- as.numeric(places$Climate)
```

```
## Warning: NAs introduced by coercion
```

```
places$Climate[is.na(places$Climate)] <- 0

hist(places$Climate, prob = TRUE, ylim = c(0, 0.005), main = NA, xlab = "Climate")
lines(density(places[,1]),col="red",lwd=2)

hist(places[,2],prob=TRUE,ylim = c(0,0.0003),main = NA,xlab = "Housing Cost")
lines(density(places[,2]),col="red",lwd=2)

hist(places[,3],prob=TRUE,ylim = c(0,0.0009),main = NA,xlab = "Health Care")
lines(density(places[,3]),col="red",lwd=2)

hist(places[,4],prob=TRUE,ylim = c(0,0.0015),main = NA,xlab = "Crime")
lines(density(places[,4]),col="red",lwd=2)

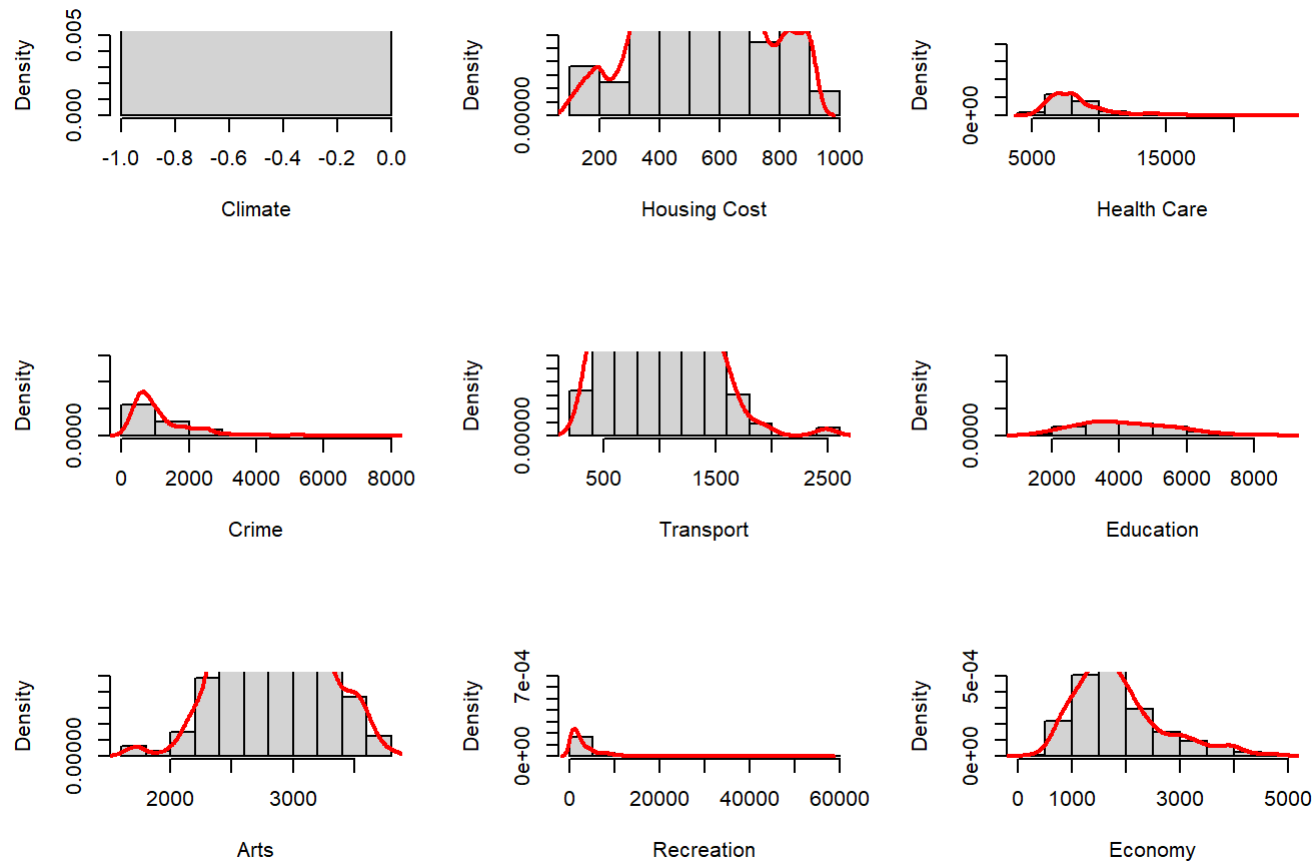
hist(places[,5],prob=TRUE,ylim = c(0,0.0003),main = NA,xlab = "Transport")
lines(density(places[,5]),col="red",lwd=2)

hist(places[,6],prob=TRUE,ylim = c(0,0.0015),main = NA,xlab = "Education")
lines(density(places[,6]),col="red",lwd=2)

hist(places[,7],prob=TRUE,ylim = c(0,0.00025),main = NA,xlab = "Arts")
lines(density(places[,7]),col="red",lwd=2)

hist(places[,8],prob=TRUE,ylim = c(0,0.0007),main = NA,xlab = "Recreation")
lines(density(places[,8]),col="red",lwd=2)

hist(places[,9],prob=TRUE,ylim = c(0,0.0005),main = NA,xlab = "Economy")
lines(density(places[,9]),col="red",lwd=2)
```



2. Transformed data

```
par(mfrow=c(3,3))
places$Climate <- as.numeric(places$Climate)
hist(places$Climate, prob = TRUE, ylim = c(0, 0.005), main = NA, xlab = "Climate")
lines(density(places$Climate), col = "blue", lwd = 2)

hist(data_log[,2],prob=TRUE,main = NA,xlab = "log(Housing Cost)")
lines(density(data_log[,2]),col="blue",lwd=2)

hist(data_log[,3],prob=TRUE,main = NA,ylim = c(0,1.4),xlab = "log(Health Care)")
lines(density(data_log[,3]),col="blue",lwd=2)

hist(data_log[,4],prob=TRUE,main = NA,ylim= c(0,3),xlab = "log(Crime)")
lines(density(data_log[,4]),col="blue",lwd=2)

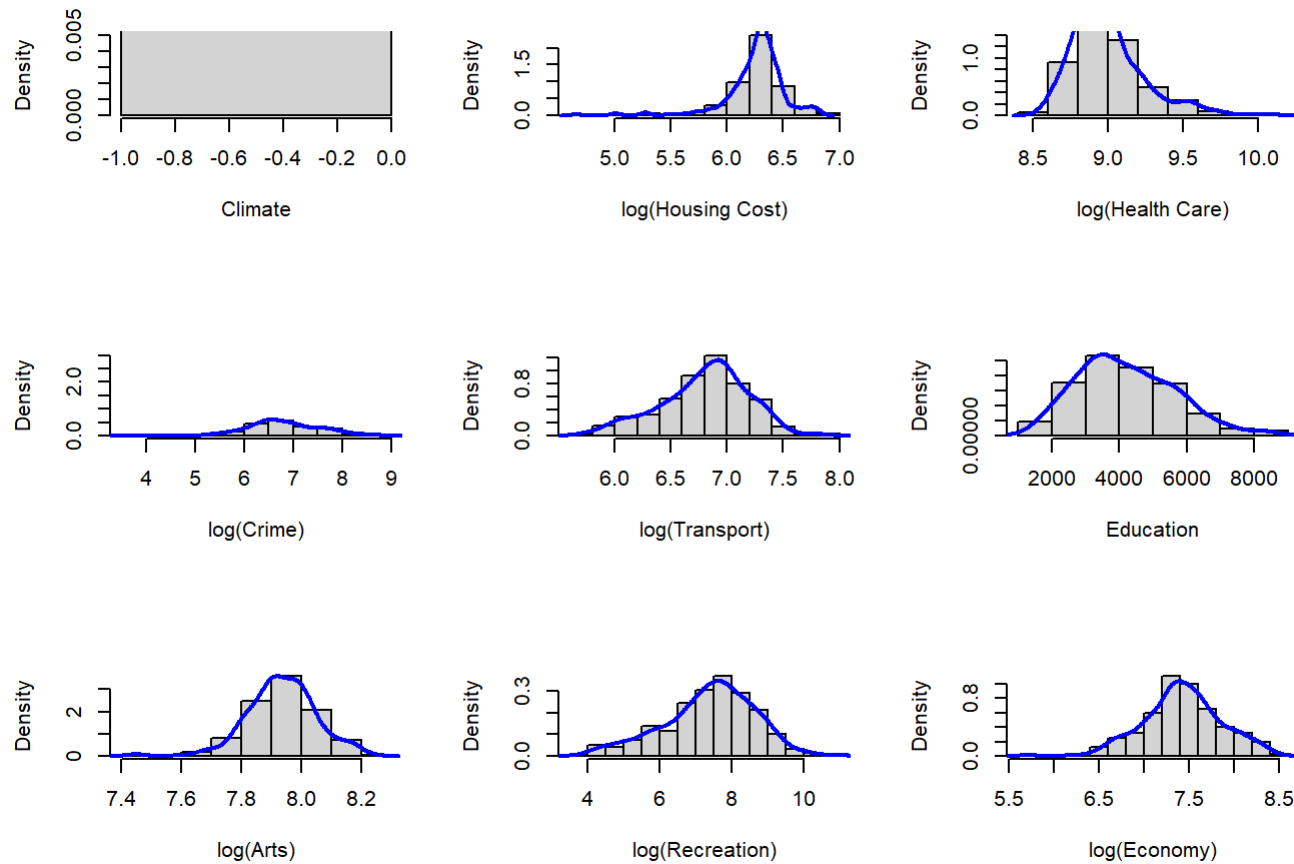
hist(data_log[,5],prob=TRUE,main = NA,xlab = "log(Transport)")
lines(density(data_log[,5]),col="blue",lwd=2)

hist(data_log[,6],prob=TRUE,main = NA,xlab = "Education")
lines(density(data_log[,6]),col="blue",lwd=2)

hist(data_log[,7],prob=TRUE,main = NA,xlab = "log(Arts)")
lines(density(data_log[,7]),col="blue",lwd=2)

hist(data_log[,8],prob=TRUE,main = NA,xlab = "log(Recreation)")
lines(density(data_log[,8]),col="blue",lwd=2)

hist(data_log[,9],prob=TRUE,main = NA,xlab = "log(Economy)")
lines(density(data_log[,9]),col="blue",lwd=2)
```

colnames and rownames for the log transformed data

```
colnames(data_log) = c("Climate", "HousingCost", "HlthCare", "Crime", "Transp", "Educ", "Arts", "Recreat", "Econ")
rownames(data_log) = city_names
```

Correlation matrix

```
data_log$Climate <- as.numeric(data_log$Climate)
```

```
## Warning: NAs introduced by coercion
```

```
data_log$Educ <- as.numeric(data_log$Educ)
```

```
data_log[is.na(data_log)] <- 0
```

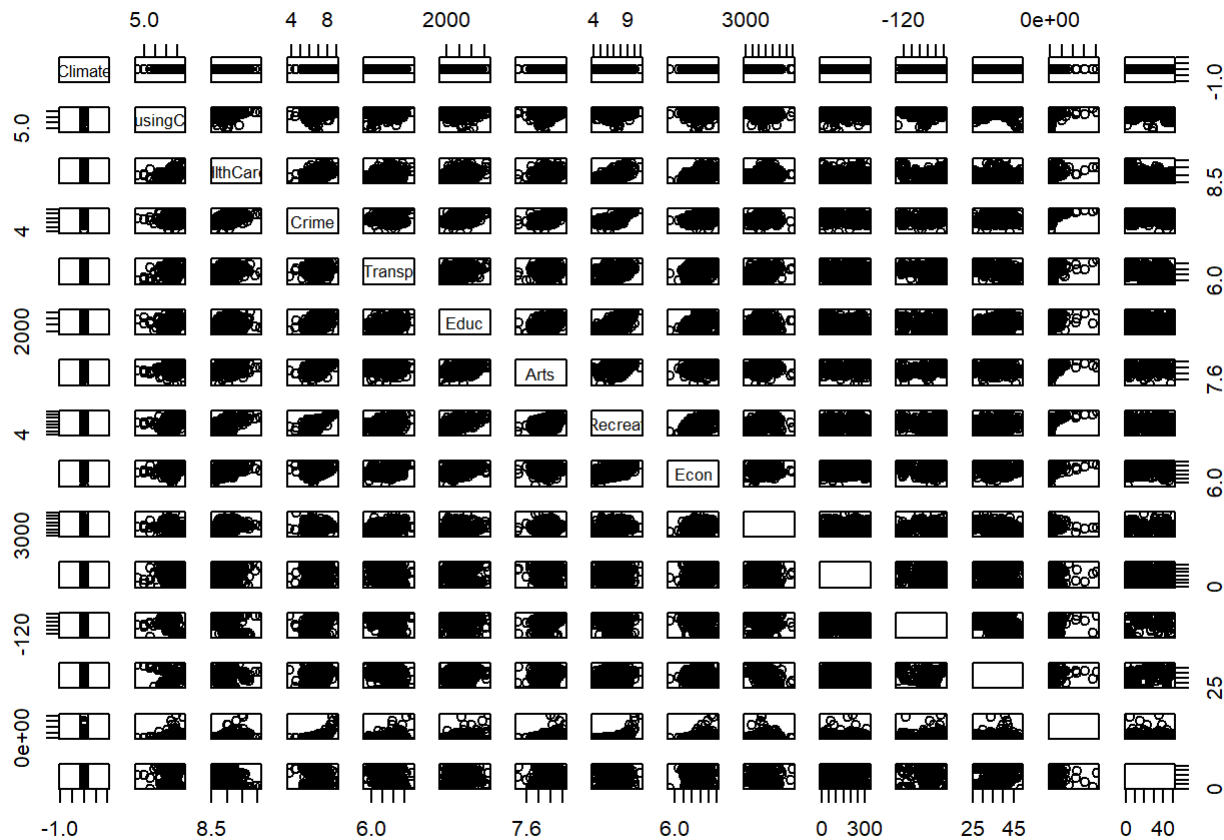
```
cor(data_log)
```

```
## Warning in cor(data_log): the standard deviation is zero
```

##	Climate	HousingCost	HlthCare	Crime	Transp
## Climate	1	NA	NA	NA	NA
## HousingCost	NA	1.00000000	0.27296448	0.150560853	0.22775093
## HlthCare	NA	0.27296448	1.00000000	0.431935493	0.13923425
## Crime	NA	0.15056085	0.43193549	1.000000000	0.18362455
## Transp	NA	0.22775093	0.13923425	0.183624550	1.00000000
## Educ	NA	0.03424105	0.32428769	0.447394137	0.27559314
## Arts	NA	0.07745819	0.20208781	0.464763552	0.05550755
## Recreat	NA	0.17268298	0.50850131	0.678128621	0.34646165
## Econ	NA	0.12060965	0.46069631	0.254036198	0.29212402
## <NA>	NA	-0.10429920	0.29032351	0.022621537	0.26817467
## <NA>	NA	0.09501600	0.09298513	0.003321376	0.03831948
## <NA>	NA	-0.11705350	-0.14638998	0.255328567	-0.24881019
## <NA>	NA	-0.05381434	0.20935822	0.149400615	-0.40815361
## <NA>	NA	0.20809655	0.34544939	0.594585830	0.34113491
## <NA>	NA	-0.06505669	-0.22173325	-0.080638875	-0.22292407
##	Educ	Arts	Recreat	Econ	<NA>
## Climate	NA	NA	NA	NA	NA
## HousingCost	0.03424105	0.07745819	0.17268298	0.12060965	-0.1042991959
## HlthCare	0.32428769	0.20208781	0.50850131	0.46069631	0.2903235124
## Crime	0.44739414	0.46476355	0.67812862	0.25403620	0.0226215370
## Transp	0.27559314	0.05550755	0.34646165	0.29212402	0.2681746726
## Educ	1.00000000	0.32230122	0.55233967	0.39390231	0.0592467535
## Arts	0.32230122	1.00000000	0.34789851	0.09300112	0.1154994504
## Recreat	0.55233967	0.34789851	1.00000000	0.49651912	0.1068522007
## Econ	0.39390231	0.09300112	0.49651912	1.00000000	0.1722302876
## <NA>	0.05924675	0.11549945	0.10685220	0.17223029	1.0000000000
## <NA>	-0.01130171	0.01554301	0.02753837	0.05853543	0.0096770315
## <NA>	-0.06147827	0.35253448	-0.03294129	-0.20169841	0.0005405777
## <NA>	0.22012207	0.08817433	0.11673024	0.02915801	-0.3974000570
## <NA>	0.40221425	0.33969890	0.56653959	0.34528737	0.0597583731
## <NA>	-0.01292504	0.12302572	-0.05281775	-0.08809709	-0.0766658507
##	<NA>	<NA>	<NA>	<NA>	<NA>
## Climate	NA	NA	NA	NA	NA
## HousingCost	0.095015998	-0.1170534964	-0.05381434	0.208096552	-0.06505669
## HlthCare	0.092985132	-0.1463899813	0.20935822	0.345449386	-0.22173325
## Crime	0.003321376	0.2553285672	0.14940062	0.594585830	-0.08063887
## Transp	0.038319477	-0.2488101862	-0.40815361	0.341134909	-0.22292407
## Educ	-0.011301715	-0.0614782729	0.22012207	0.402214251	-0.01292504

```
## Arts      0.015543006  0.3525344776  0.08817433  0.339698897  0.12302572
## Recreat   0.027538373 -0.0329412907  0.11673024  0.566539594 -0.05281775
## Econ      0.058535433 -0.2016984139  0.02915801  0.345287369 -0.08809709
## <NA>      0.009677032  0.0005405777 -0.39740006  0.059758373 -0.07666585
## <NA>      1.000000000 -0.1074371900  0.03843321  0.014569723  0.01094864
## <NA>     -0.107437190  1.00000000000  0.02150614  0.000803367  0.07537326
## <NA>      0.038433206  0.0215061428  1.00000000 -0.012937948  0.18525107
## <NA>      0.014569723  0.0008033670 -0.01293795  1.000000000 -0.03839843
## <NA>      0.010948639  0.0753732601  0.18525107 -0.038398426  1.00000000
```

```
pairs(data_log)
```



```
round(cor(data_log),digits = 4)
```

```
## Warning in cor(data_log): the standard deviation is zero
```

```
##           Climate HousingCost HlthCare   Crime  Transp    Educ   Arts Recreat
## Climate           1           NA         NA      NA      NA      NA      NA      NA
## HousingCost      NA      1.0000    0.2730  0.1506  0.2278  0.0342  0.0775  0.1727
## HlthCare         NA      0.2730    1.0000  0.4319  0.1392  0.3243  0.2021  0.5085
## Crime            NA      0.1506    0.4319  1.0000  0.1836  0.4474  0.4648  0.6781
## Transp           NA      0.2278    0.1392  0.1836  1.0000  0.2756  0.0555  0.3465
## Educ             NA      0.0342    0.3243  0.4474  0.2756  1.0000  0.3223  0.5523
## Arts             NA      0.0775    0.2021  0.4648  0.0555  0.3223  1.0000  0.3479
## Recreat          NA      0.1727    0.5085  0.6781  0.3465  0.5523  0.3479  1.0000
## Econ            NA      0.1206    0.4607  0.2540  0.2921  0.3939  0.0930  0.4965
## <NA>             NA     -0.1043    0.2903  0.0226  0.2682  0.0592  0.1155  0.1069
## <NA>             NA      0.0950    0.0930  0.0033  0.0383 -0.0113  0.0155  0.0275
## <NA>             NA     -0.1171   -0.1464  0.2553 -0.2488 -0.0615  0.3525 -0.0329
## <NA>             NA     -0.0538    0.2094  0.1494 -0.4082  0.2201  0.0882  0.1167
## <NA>             NA      0.2081    0.3454  0.5946  0.3411  0.4022  0.3397  0.5665
## <NA>             NA     -0.0651   -0.2217 -0.0806 -0.2229 -0.0129  0.1230 -0.0528
##           Econ    <NA>    <NA>    <NA>    <NA>    <NA>    <NA>
## Climate          NA      NA      NA      NA      NA      NA      NA
## HousingCost    0.1206 -0.1043  0.0950 -0.1171 -0.0538  0.2081 -0.0651
## HlthCare       0.4607  0.2903  0.0930 -0.1464  0.2094  0.3454 -0.2217
## Crime          0.2540  0.0226  0.0033  0.2553  0.1494  0.5946 -0.0806
## Transp         0.2921  0.2682  0.0383 -0.2488 -0.4082  0.3411 -0.2229
## Educ           0.3939  0.0592 -0.0113 -0.0615  0.2201  0.4022 -0.0129
## Arts           0.0930  0.1155  0.0155  0.3525  0.0882  0.3397  0.1230
## Recreat        0.4965  0.1069  0.0275 -0.0329  0.1167  0.5665 -0.0528
## Econ           1.0000  0.1722  0.0585 -0.2017  0.0292  0.3453 -0.0881
## <NA>            0.1722  1.0000  0.0097  0.0005 -0.3974  0.0598 -0.0767
## <NA>            0.0585  0.0097  1.0000 -0.1074  0.0384  0.0146  0.0109
## <NA>           -0.2017  0.0005 -0.1074  1.0000  0.0215  0.0008  0.0754
## <NA>            0.0292 -0.3974  0.0384  0.0215  1.0000 -0.0129  0.1853
## <NA>            0.3453  0.0598  0.0146  0.0008 -0.0129  1.0000 -0.0384
## <NA>           -0.0881 -0.0767  0.0109  0.0754  0.1853 -0.0384  1.0000
```

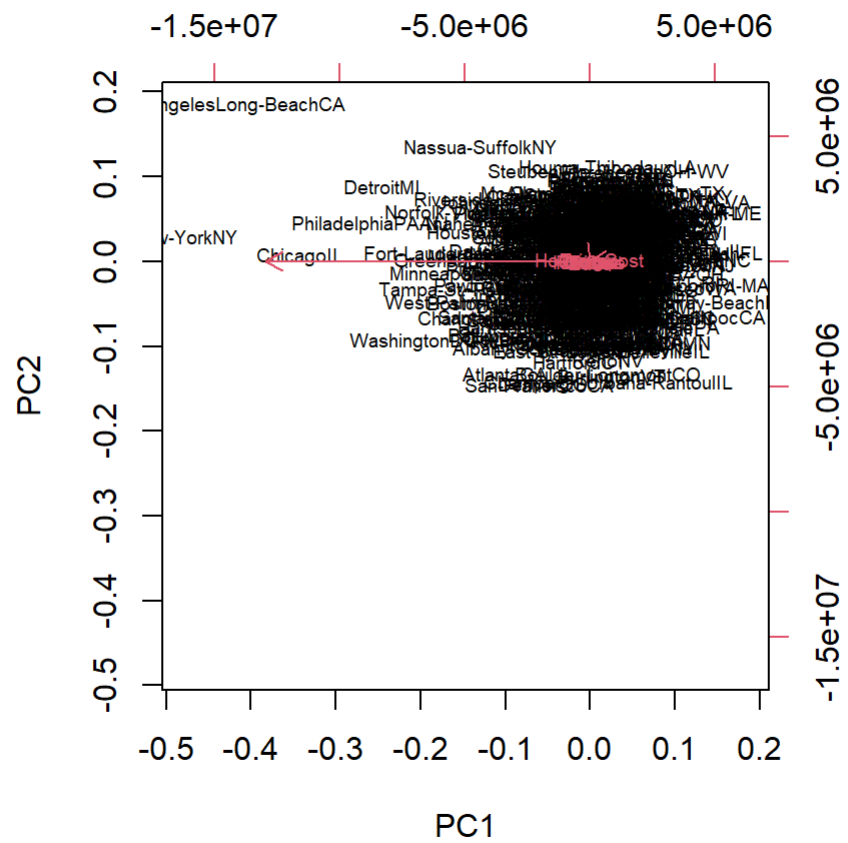
Principal Component Analysis

```
non_constant_columns <- apply(data_log, 2, var) != 0
data_log_filtered <- data_log[, non_constant_columns]

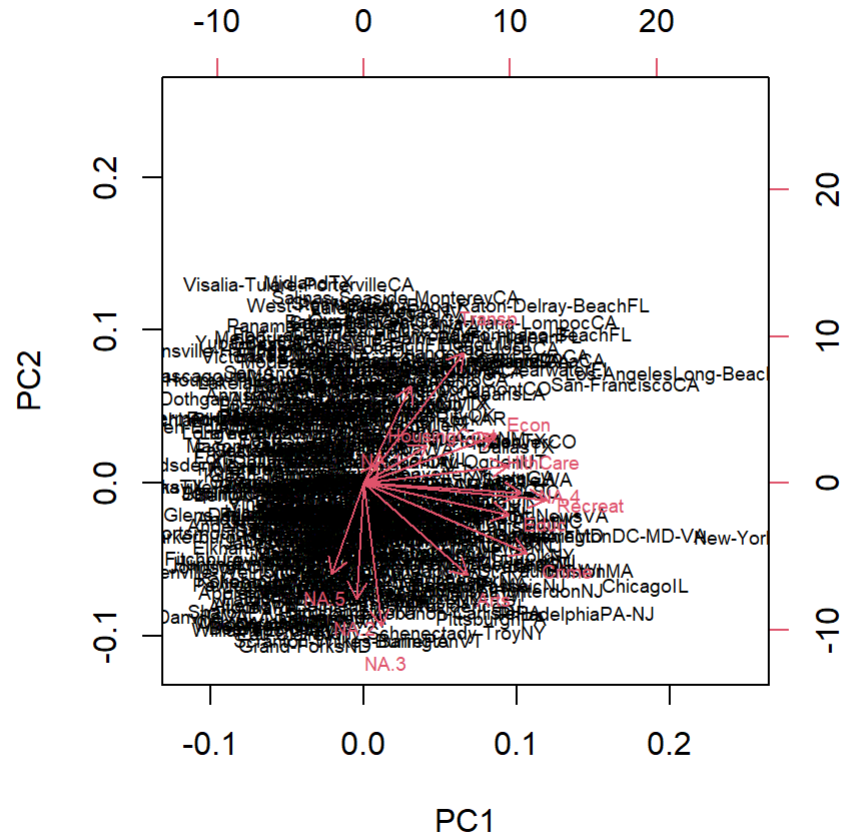
pca.data = prcomp(data_log,scale = F)
pca.dataScale <- prcomp(data_log_filtered, scale = TRUE) #with scaling

#biplots
biplot(pca.data, cex = 0.6)
```

[illegible]



```
biplot(pca.dataScale, cex = 0.6)
```

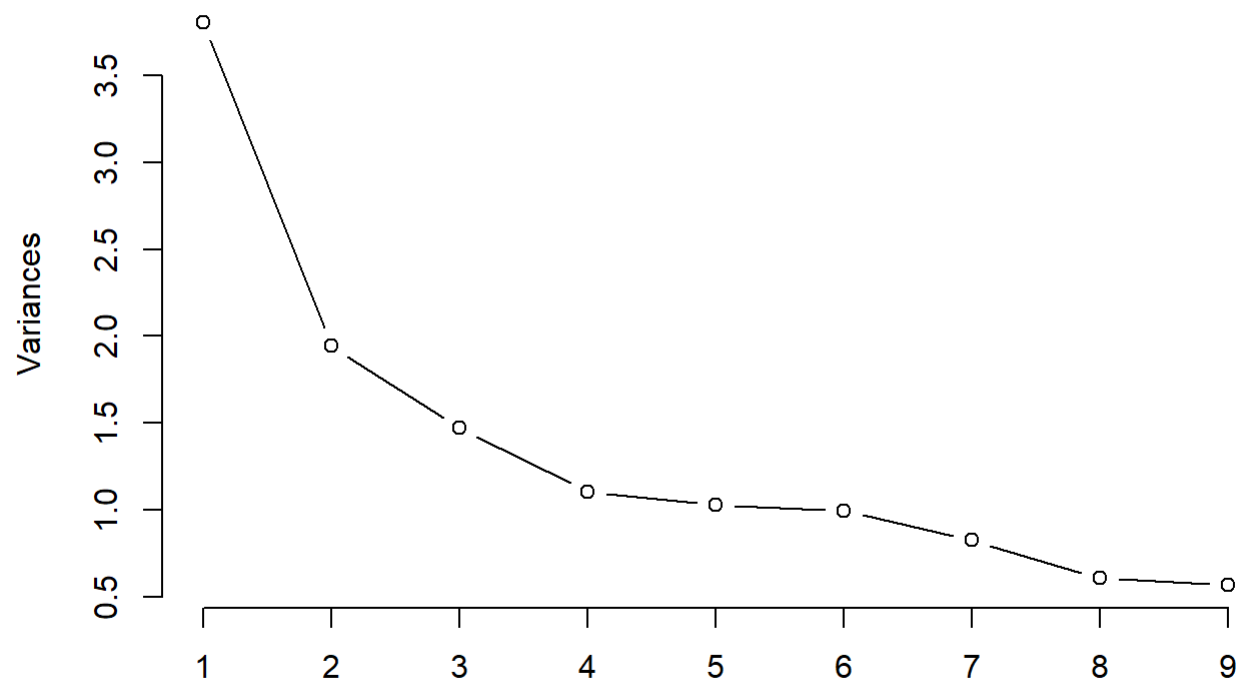



Number of PC's 1:"Elbow Rule"

```
clean_data <- data_log[complete.cases(data_log), ]
non_zero_sd_columns <- apply(clean_data, 2, sd) != 0
clean_data_filtered <- clean_data[, non_zero_sd_columns]

correlation_matrix <- cor(clean_data_filtered)
eig <- eigen(correlation_matrix)

screeplot(pca.dataScale, type="l", npcs = 9, main = NULL)
```



```
pve = rep(NA, dim(data_log)[2]) # proportion of variance explained
for(i in 1:9)
{
  pve[i] = print(sum(eig$values[1:i])/9)
}
```

```
## [1] 0.4226638
## [1] 0.6386353
## [1] 0.8020706
## [1] 0.9248888
## [1] 1.038863
## [1] 1.14956
## [1] 1.241133
## [1] 1.308513
## [1] 1.371401
```

```
eig$values
```

```
## [1] 3.8039745 1.9437429 1.4709181 1.1053639 1.0257636 0.9962754 0.8241574
## [8] 0.6064208 0.5659893 0.4610233 0.3918910 0.3442996 0.2389301 0.2212501
```

```
pve
```

```
## [1] 0.4226638 0.6386353 0.8020706 0.9248888 1.0388625 1.1495598 1.2411329
## [8] 1.3085130 1.3714007      NA      NA      NA      NA      NA
## [15]      NA
```

2: "Including PC's to explain 80% of total variation"

```
pca.variance <- eig$values
round(sum(pca.variance[1:5])/sum(pca.variance),digits=2) #82%
```

```
## [1] 0.67
```

```
round(sum(pca.variance[1:6])/sum(pca.variance),digits=2)
```

```
## [1] 0.74
```

3: "Kaiser rule"

```
round(pca.variance,digits=2)
```

```
## [1] 3.80 1.94 1.47 1.11 1.03 1.00 0.82 0.61 0.57 0.46 0.39 0.34 0.24 0.22
```

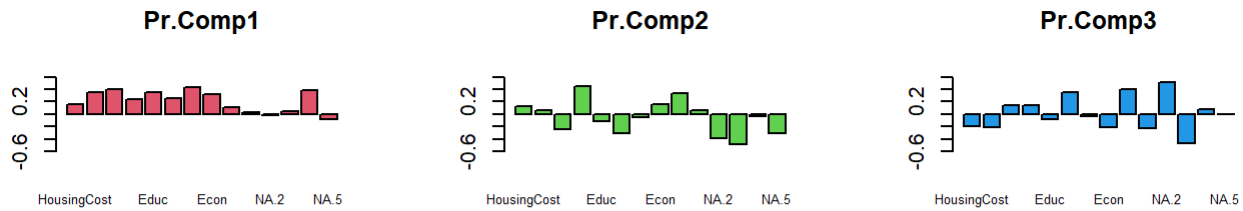
```
mean(pca.variance)
```

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

interpretation of PC's

```
par(mfrow=c(3,3))

barplot(pca.dataScale$rotation[,1],col=2,main='Pr.Comp1',
        ylim = c(-0.7,0.7),cex.names=0.6)
barplot(pca.dataScale$rotation[,2],col=3,main='Pr.Comp2',
        ylim = c(-0.7,0.7),cex.names=0.6)
barplot(pca.dataScale$rotation[,3],col=4,main='Pr.Comp3',
        ylim = c(-0.7,0.7),cex.names=0.6)
```



Correlation matrix of variables and PC's

```
cor_matrix <- pca.dataScale$rotation %*% diag(pca.dataScale$sdev)[, 1:9]
round(cor_matrix,digits=3)
```

##	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]
## HousingCost	0.298	0.176	-0.239	0.729	-0.048	0.053	-0.459	0.148	-0.121
## HlthCare	0.677	0.082	-0.252	-0.157	-0.201	0.443	-0.293	0.003	0.144
## Crime	0.768	-0.330	0.174	0.143	0.074	0.125	0.123	-0.165	0.158
## Transp	0.469	0.615	0.165	0.167	0.139	-0.302	0.161	0.168	-0.016
## Educ	0.681	-0.151	-0.105	-0.255	0.148	-0.225	0.191	0.414	-0.088
## Arts	0.489	-0.433	0.424	0.103	-0.223	-0.050	-0.064	0.347	-0.060
## Recreat	0.854	-0.079	-0.044	-0.051	0.069	-0.068	0.050	-0.121	0.034
## Econ	0.620	0.224	-0.254	-0.307	-0.025	-0.061	-0.100	-0.249	-0.542
## <NA>	0.223	0.458	0.479	-0.430	-0.382	0.110	-0.251	0.066	0.160
## NA.1	0.068	0.089	-0.278	0.224	-0.797	-0.028	0.467	-0.038	-0.033
## NA.2	-0.033	-0.543	0.625	0.130	-0.062	0.253	0.040	-0.116	-0.322
## NA.3	0.084	-0.674	-0.573	-0.174	0.007	0.132	-0.013	0.131	0.078
## NA.4	0.738	-0.046	0.095	0.194	0.117	-0.173	0.077	-0.324	0.242
## NA.5	-0.148	-0.429	-0.007	-0.094	-0.288	-0.710	-0.381	-0.137	0.058

PC scores

```
PC1PC2.scores <- round(pca.dataScale$x[,1:2],digits = 3)
row.names(PC1PC2.scores) <- NULL

PC1PC2.scores <- cbind.data.frame(city_names, PC1PC2.scores)
PC1.rank <- PC1PC2.scores[order(PC1PC2.scores[,2],decreasing = TRUE),c(1,2)]
PC1.rank
```

##	city_names	PC1
## 213	New-YorkNY	8.861
## 179	Los-AngelesLong-BeachCA	7.410
## 65	ChicagoIL	6.527
## 270	San-FranciscoCA	6.055
## 314	WashingtonDC-MD-VA	5.693
## 43	BostonMA	5.241
## 234	PhiladelphiaPA-NJ	4.935
## 26	BaltimoreMD	4.312
## 86	DetroitMI	4.057
## 269	San-DiegoCA	3.901
## 84	DenverCO	3.898
## 278	SeattleWA	3.788
## 218	OaklandCA	3.682
## 214	NewarkNJ	3.631
## 69	ClevelandOH	3.601
## 77	DallasTX	3.547
## 20	AtlantaGA	3.450
## 192	Miami-HialeahFL	3.430
## 262	St.-LouisMO-IL	3.404
## 11	Anaheim-Santa-AnaCA	3.367
## 271	San-JoseCA	3.286
## 135	HoustonTX	3.148
## 131	HartfordCT	3.133
## 207	Nassua-SuffolkNY	3.117
## 237	PittsburghPA	2.975
## 197	Minneapolis-St.-PaulMN-WI	2.865
## 34	Bergen-PassaicNJ	2.858
## 240	PortlandOR	2.858
## 133	HonoluluHI	2.821
## 290	StamfordCT	2.742
## 212	New-OrleansLA	2.693
## 217	NorwalkCT	2.564
## 210	New-Haven-MeridenCT	2.525
## 196	MilwaukeeWI	2.451
## 247	Raleigh-DurhamNC	2.450
## 256	RochesterNY	2.419
## 243	ProvidenceRI	2.345
## 193	Middlesex-SomersetHunterdonNJ	2.272

## 297	Tampa-St.-Petersburg-ClearwaterFL	2.246
## 48	Bridgeport-MilfordCT	2.236
## 67	CincinnatiOH-KY-IN	2.213
## 44	Boulder-LongmontCO	2.204
## 235	PhoenixAZ	2.186
## 5	AlbuquerqueNM	2.177
## 53	BuffaloNY	2.108
## 272	Santa-Barbara-Santa-Maria-LompocCA	2.073
## 252	Richmond-PetersburgVA	2.050
## 200	Monmouth-OceanNJ	2.003
## 318	West-Palm-Beach-Boca-Raton-Delray-BeachFL	1.972
## 258	SacramentoCA	1.869
## 15	Ann-ArborMI	1.866
## 266	Salt-Lake-City-OgdenUT	1.846
## 253	Riverside-San-BernardinoCA	1.753
## 153	Kansas-CityMO	1.748
## 302	TrentonNJ	1.738
## 216	Norfolk-Virginia-Beach-Newport-NewsVA	1.717
## 225	OrlandoFL	1.635
## 303	TusconAZ	1.608
## 108	Fort-Lauderdale-Hollywood-Pompano-BeachFL	1.606
## 273	Santa-CruzCA	1.572
## 191	MemphisTN-AR-MS	1.537
## 55	BurlingtonVT	1.532
## 294	SyracuseNY	1.532
## 138	IndianapolisIN	1.531
## 180	LouisvilleKY-IN	1.502
## 74	ColumbusOH	1.496
## 78	DanburyCT	1.466
## 185	MadisonWI	1.464
## 223	OmahaNE-IA	1.444
## 323	WilmingtonDE-NJ-MD	1.414
## 4	Albany-Schenectady-TroyNY	1.412
## 221	Oklahoma-CityOK	1.326
## 274	Santa-Rosa-PetalumaCA	1.278
## 250	RenoNV	1.238
## 287	SpringfieldIL	1.191
## 288	SpringfieldMA	1.187
## 114	Forth-ArlingtonTX	1.156

## 206	NashvilleTN	1.146
## 142	JacksonvilleFL	1.134
## 162	Lake-CountyIL	1.093
## 62	Charlotte-Gastonia-Rock-HillNC-SC	1.088
## 130	Harrisburg-Lebanon-CarlislePA	1.081
## 300	ToledoOH	1.076
## 63	CharlottesvilleVA	1.057
## 59	Champaign-Urbana-RantoulIL	1.048
## 60	CharlestonSC	1.038
## 295	TacomaWA	0.949
## 97	Eugene-SpringfieldOR	0.943
## 126	Greensboro-Winston-Salem-High-PointNC	0.941
## 168	Las-VegasNV	0.933
## 145	Jersey-CityNJ	0.920
## 268	San-AntonioTX	0.911
## 81	Dayton-SpringfieldOH	0.910
## 239	PortlandME	0.870
## 21	Atlantic-CityNJ	0.854
## 2	AkronOH	0.845
## 173	Lexington-FayetteKY	0.834
## 308	Vallejo-Fairfield-NapaCA	0.824
## 38	BirminghamAL	0.795
## 224	Orange-CountyNY	0.783
## 72	ColumbiaSC	0.781
## 165	Lansing-East-LansingMI	0.758
## 304	TulsaOK	0.754
## 265	Salinas-Seaside-MontereyCA	0.752
## 209	New-BritainCT	0.716
## 12	AnchorageAK	0.715
## 264	Salem-GloucesterMA	0.708
## 119	Gary-HammondIN	0.696
## 150	KalamazooMI	0.659
## 276	SavannahGA	0.654
## 115	FresnoCA	0.621
## 227	Oxnard-VenturaCA	0.584
## 118	Galveston-Texas-CityTX	0.582
## 141	JacksonMS	0.563
## 211	New-London-NorwichCT-RI	0.554
## 152	Kansas-CityKS	0.548

## 154	KenoshaWI	0.513
## 148	JolietIL	0.481
## 194	MiddletownCT	0.463
## 85	Des-MoinesIA	0.417
## 170	Lawrence-HaverhillMA-NH	0.393
## 117	GainesvilleFL	0.385
## 70	Colorado-SpringsCO	0.355
## 175	LincolnNE	0.330
## 282	ShreveportLA	0.323
## 176	Little-RockNorth-Little-RockAR	0.317
## 127	Greenville-SpartanburgSC	0.259
## 263	SalemOR	0.241
## 122	Grand-RapidsMI	0.235
## 285	South-Bend-MishawakaIN	0.215
## 24	AustinTX	0.196
## 82	Daytona-BeachFL	0.194
## 320	WichitaKS	0.194
## 139	Iowa-CityIA	0.181
## 325	WorcesterMA	0.155
## 198	MobileAL	0.145
## 156	KnoxvilleTN	0.119
## 41	Bloomington-NormalIL	0.099
## 182	LubbockTX	0.088
## 107	Fort-Collins-LovelandCO	0.080
## 23	Aurora-ElginIL	0.077
## 50	BrocktonMA	0.030
## 296	TallahasseeFL	0.013
## 35	BillingsMT	-0.001
## 113	Fort-WayneIN	-0.016
## 275	SarasotaFL	-0.033
## 27	BangorME	-0.040
## 324	WilmingtonNC	-0.047
## 158	La-CrosseWI	-0.052
## 160	LafayetteLA	-0.053
## 231	Pawtucket-Woonsocket-AttleboroRI-MA	-0.057
## 42	Boise-CityID	-0.072
## 301	TopekaKS	-0.075
## 181	LowellMA-NH	-0.076
## 80	Davenport-Rock-Island-MolineIA-IL	-0.152

## 71	ColumbiaMO	-0.169
## 286	SpokaneWA	-0.182
## 104	FlintMI	-0.195
## 259	Saginaw-Bay-City-MidlandMI	-0.211
## 190	Melbourne-Titusville-Palm-BayFL	-0.220
## 232	PensacolaFL	-0.224
## 311	Vineland-Millville-BridgetonNJ	-0.231
## 109	Fort-MyersFL	-0.235
## 37	BinghamptonNY	-0.254
## 328	Youngstown-WarrenOH	-0.254
## 129	Hamilton-MiddletownOH	-0.260
## 18	AshevilleNC	-0.271
## 246	RacineWI	-0.273
## 205	NashuaNH	-0.277
## 99	Fall-RiverMA-RI	-0.299
## 254	RoanokeVA	-0.319
## 110	Fort-PierceFL	-0.334
## 316	Waterloo-Cedar-FallsIA	-0.356
## 90	East-St.-Louis-BellevilleIL	-0.359
## 249	ReddingCA	-0.364
## 233	PeoriaIL	-0.400
## 66	ChicoCA	-0.408
## 25	BakersfieldCA	-0.410
## 8	AltonGranite-CityIL	-0.419
## 28	Baton-RougeLA	-0.432
## 159	LafayetteIN	-0.436
## 61	CharlestonWV	-0.477
## 293	StocktonCA	-0.487
## 277	Scranton-Wilkes-BarrePA	-0.502
## 32	BellinghamWA	-0.554
## 167	Las-CrucesNM	-0.556
## 178	Lorain-ElyriaOH	-0.587
## 98	EvansvilleIN-KY	-0.590
## 203	MuncieIN	-0.591
## 248	ReadingPA	-0.593
## 169	LawrenceKS	-0.594
## 125	Green-BayWI	-0.607
## 75	Corpus-ChristiTX	-0.608
## 96	EriePA	-0.621

## 242	PoughkeepsieNY	-0.637
## 215	Niagara-FallsNY	-0.658
## 58	Cedar-RapidsIA	-0.662
## 10	AmarilloTX	-0.682
## 52	Bryan-College-StationTX	-0.692
## 164	LancasterPA	-0.707
## 92	El-PasoTX	-0.724
## 289	SpringfieldMO	-0.743
## 204	MuskegonMI	-0.748
## 89	DuluthMN-WI	-0.781
## 315	MaterburyCT	-0.792
## 7	AllentownBethlehemPA-NJ	-0.824
## 219	OcalaFL	-0.826
## 309	VancouverWA	-0.828
## 183	LynchburgVA	-0.838
## 255	RochesterMN	-0.845
## 146	Johnson-City-Kingsport-BristolTN-VA	-0.875
## 244	Provo-OremUT	-0.879
## 17	Appleton-Oshkosh-NeenahWI	-0.882
## 128	HagerstownMD	-0.922
## 106	FlorenceSC	-0.940
## 100	Fargo-MoorheadND-MN	-0.948
## 30	Beaumont-Port-ArthurTX	-0.958
## 245	PuebloCO	-0.991
## 174	LimaOH	-1.008
## 283	Sioux-CityIA-NE	-1.014
## 40	BloomingtonIN	-1.015
## 49	BristolCT	-1.017
## 257	RockfordIL	-1.020
## 22	AugustaGA-SC	-1.021
## 101	FayettevilleNC	-1.030
## 284	Sioux-FallsSD	-1.036
## 140	JacksonMI	-1.060
## 186	ManchesterNH	-1.090
## 291	State-CollegePA	-1.098
## 189	MedfordOR	-1.138
## 305	TuscaloosaAL	-1.141
## 238	PittsfieldMA	-1.145
## 208	New-BedsfordMA	-1.163

## 222	OlympiaWA	-1.185
## 123	Great-FallsMT	-1.204
## 307	Utica-RomeNY	-1.232
## 326	YakimaWA	-1.250
## 195	MidlandTX	-1.269
## 29	Battle-CreekMI	-1.281
## 163	Lakeland-Winter-HavenFL	-1.284
## 172	Lewiston-AuburnME	-1.300
## 56	CantonOH	-1.325
## 94	ElmiraNY	-1.334
## 121	Grand-ForksND	-1.337
## 73	ColumbusGA-AL	-1.368
## 202	MontgomeryAL	-1.368
## 144	Janesville-BeloitWI	-1.371
## 136	Huntington-AshlandWV-KY-OH	-1.383
## 161	Lake-CharlesLA	-1.383
## 313	WacoTX	-1.384
## 306	TylerTX	-1.386
## 19	AthensGA	-1.390
## 124	GreeleyCO	-1.402
## 241	Portsmouth-Dover-RochesterNH-ME	-1.415
## 64	ChattanoogaTN-GA	-1.437
## 102	Fayetteville-SprindaleAR	-1.444
## 46	BrazoriaTX	-1.456
## 137	HuntsvilleAL	-1.480
## 57	CasperWY	-1.481
## 312	Visalia-Tulare-PortervilleCA	-1.491
## 184	MaconWarner-RobbinsGA	-1.495
## 298	Terre-HauteIN	-1.500
## 39	BismarckND	-1.526
## 83	DecaturIL	-1.545
## 1	AbileneTX	-1.591
## 91	Eau-ClaireWI	-1.609
## 321	Wichita-FallsTX	-1.625
## 201	MonroeLA	-1.629
## 36	Biloxi-GulfportMS	-1.639
## 45	BradentonFL	-1.646
## 228	Panama-CityFL	-1.658
## 199	ModestoCA	-1.665

## 317	WausauWI	-1.672
## 88	DubuqueIA	-1.673
## 327	YorkPA	-1.679
## 171	LawtonOK	-1.731
## 47	BremertonWA	-1.734
## 260	St.-CloudMN	-1.744
## 267	San-AngeloTX	-1.813
## 31	Beaver-CountyPA	-1.836
## 143	JacksonvilleNC	-1.891
## 76	CumberlandMD-WV	-1.892
## 187	MansfieldOH	-1.907
## 155	Kileen-TempleTX	-1.968
## 151	KankakeeIL	-1.972
## 95	EnidOK	-1.973
## 112	Fort-Walton-BeachFL	-1.984
## 220	OdessaTX	-2.018
## 261	St.-JosephMO	-2.046
## 147	JohnstownPA	-2.105
## 226	OwensboroKY	-2.125
## 177	Longview-MarshallTX	-2.127
## 132	HickoryNC	-2.183
## 251	Richland-Kinnewick-PascoWA	-2.188
## 111	Fort-SmithAR-OK	-2.198
## 103	Fitchburg-LeominsterMA	-2.207
## 280	SheboyganWI	-2.214
## 93	Elkhart-GoshenIN	-2.221
## 319	WheelingWV-OH	-2.235
## 6	AlexandriaLA	-2.268
## 33	Benton-HarborMI	-2.279
## 3	AlbanyGA	-2.363
## 229	Parkerburg-MariettaWV-OH	-2.417
## 322	WilliamsportPA	-2.487
## 134	Houma-ThibodauxLA	-2.512
## 16	AnnistonAL	-2.519
## 9	AltoonaPA	-2.542
## 68	Clarksville-HopkinsvilleTN-KY	-2.585
## 329	Yuba-CityCA	-2.643
## 105	FlorenceAL	-2.684
## 13	AndersonIN	-2.690

## 236	Pine-BluffAR	-2.693
## 310	VictoriaTX	-2.722
## 14	AndersonSC	-2.800
## 166	LaredoTX	-2.807
## 157	KokomoIN	-2.816
## 188	McAllen-Edinburg-MissionTX	-2.881
## 54	BurlingtonNC	-2.907
## 292	Steubenville-WeirtonOH-WV	-3.076
## 279	SharonPA	-3.081
## 120	Glens-FallsNY	-3.225
## 51	Brownsville-HarlingtonTX	-3.236
## 281	Sherman-DenisonTX	-3.237
## 149	JoplinMO	-3.298
## 230	PascagoulaMS	-3.488
## 299	TexarkanaTX-TexarkanaAR	-3.596
## 87	DothganAL	-3.618
## 79	DanvilleVA	-3.730
## 116	GadsdenAL	-4.142

```
PC2.rank <- PC1PC2.scores[order(PC1PC2.scores[,3],decreasing = TRUE),c(1,3)]
PC2.rank
```

##		city_names	PC2
## 195		MidlandTX	3.336
## 312	Visalia-Tulare-PortervilleCA		3.306
## 265	Salinas-Seaside-MontereyCA		3.061
## 293		StocktonCA	2.996
## 318	West-Palm-Beach-Boca-Raton-Delray-BeachFL		2.922
## 160		LafayetteLA	2.896
## 115		FresnoCA	2.875
## 168		Las-VegasNV	2.822
## 227		Oxnard-VenturaCA	2.704
## 25		BakersfieldCA	2.692
## 272	Santa-Barbara-Santa-Maria-LompocCA		2.640
## 228		Panama-CityFL	2.595
## 303		TusconAZ	2.590
## 110		Fort-PierceFL	2.548
## 192		Miami-HialeahFL	2.452
## 108	Fort-Lauderdale-Hollywood-Pompano-BeachFL		2.436
## 190	Melbourne-Titusville-Palm-BayFL		2.391
## 220		OdessaTX	2.326
## 133		HonoluluHI	2.320
## 329		Yuba-CityCA	2.313
## 82		Daytona-BeachFL	2.282
## 275		SarasotaFL	2.270
## 271		San-JoseCA	2.249
## 45		BradentonFL	2.243
## 225		OrlandoFL	2.185
## 51	Brownsville-HarlingtonTX		2.184
## 161		Lake-CharlesLA	2.132
## 219		OcalaFL	2.128
## 310		VictoriaTX	2.109
## 269		San-DiegoCA	2.076
## 253	Riverside-San-BernardinoCA		2.054
## 11	Anaheim-Santa-AnaCA		2.050
## 199		ModestoCA	2.033
## 308	Vallejo-Fairfield-NapaCA		2.026
## 218		OaklandCA	2.023
## 28		Baton-RougeLA	2.002
## 109		Fort-MyersFL	1.930
## 235		PhoenixAZ	1.925

## 273	Santa-CruzCA	1.914
## 232	PensacolaFL	1.907
## 274	Santa-Rosa-PetalumaCA	1.873
## 297	Tampa-St.-Petersburg-ClearwaterFL	1.873
## 70	Colorado-SpringsCO	1.868
## 267	San-AngeloTX	1.822
## 179	Los-AngelesLong-BeachCA	1.805
## 230	PascagoulaMS	1.768
## 134	Houma-ThibodauxLA	1.736
## 258	SacramentoCA	1.734
## 249	ReddingCA	1.698
## 163	Lakeland-Winter-HavenFL	1.691
## 12	AnchorageAK	1.677
## 270	San-FranciscoCA	1.654
## 276	SavannahGA	1.638
## 137	HuntsvilleAL	1.626
## 107	Fort-Collins-Lover=landCO	1.625
## 75	Corpus-ChristiTX	1.619
## 167	Las-CrucesNM	1.592
## 44	Boulder-LongmontCO	1.551
## 296	TallahasseeFL	1.546
## 212	New-OrleansLA	1.495
## 16	AnnistonAL	1.493
## 171	LawtonOK	1.493
## 182	LubbockTX	1.435
## 201	MonroeLA	1.399
## 87	DothganAL	1.391
## 1	AbileneTX	1.352
## 198	MobileAL	1.352
## 118	Galveston-Texas-CityTX	1.313
## 114	Forth-ArlingtonTX	1.306
## 92	El-PasoTX	1.295
## 250	RenoNV	1.289
## 21	Atlantic-CityNJ	1.282
## 36	Biloxi-GulfportMS	1.272
## 66	ChicoCA	1.249
## 245	PuebloCO	1.227
## 52	Bryan-College-StationTX	1.192
## 305	TuscaloosaAL	1.163

## 321	Wichita-FallsTX	1.151
## 30	Beaumont-Port-ArthurTX	1.132
## 282	ShreveportLA	1.119
## 221	Oklahoma-CityOK	1.109
## 281	Sherman-DenisonTX	1.102
## 176	Little-RockNorth-Little-RockAR	1.094
## 112	Fort-Walton-BeachFL	1.086
## 251	Richland-Kinnewick-PascoWA	1.066
## 236	Pine-BluffAR	1.064
## 95	EnidOK	1.028
## 142	JacksonvilleFL	0.993
## 313	WacoTX	0.976
## 202	MontgomeryAL	0.941
## 117	GainesvilleFL	0.934
## 304	TulsaOK	0.926
## 188	McAllen-Edinburg-MissionTX	0.923
## 3	AlbanyGA	0.921
## 166	LaredoTX	0.858
## 268	San-AntonioTX	0.854
## 46	BrazoriaTX	0.850
## 177	Longview-MarshallTX	0.826
## 24	AustinTX	0.781
## 324	WilmingtonNC	0.748
## 90	East-St.-Louis-BellevilleIL	0.737
## 320	WichitaKS	0.732
## 5	AlbuquerqueNM	0.728
## 135	HoustonTX	0.719
## 84	DenverCO	0.712
## 184	MaconWarner-RobbinsGA	0.642
## 289	SpringfieldMO	0.630
## 19	AthensGA	0.626
## 77	DallasTX	0.616
## 295	TacomawA	0.592
## 42	Boise-CityID	0.571
## 143	JacksonvilleNC	0.561
## 124	GreeleyCO	0.554
## 102	Fayetteville-SprindaleAR	0.545
## 261	St.-JosephMO	0.524
## 326	YakimaWA	0.500

## 111	Fort-SmithAR-OK	0.448
## 306	TylerTX	0.407
## 10	AmarilloTX	0.398
## 169	LawrenceKS	0.382
## 162	Lake-CountyIL	0.372
## 73	ColumbusGA-AL	0.369
## 266	Salt-Lake-City-OgdenUT	0.343
## 38	BirminghamAL	0.342
## 57	CasperWY	0.340
## 116	GadsdenAL	0.321
## 6	AlexandriaLA	0.315
## 47	BremertonWA	0.284
## 105	FlorenceAL	0.262
## 309	VancouverWA	0.183
## 173	Lexington-FayetteKY	0.150
## 71	ColumbiaMO	0.136
## 20	AtlantaGA	0.113
## 155	Kileen-TempleTX	0.113
## 204	MuskegonMI	0.100
## 301	TopekaKS	0.095
## 278	SeattleWA	0.086
## 23	Aurora-ElginIL	0.065
## 50	BrocktonMA	0.055
## 152	Kansas-CityKS	0.053
## 151	KankakeeIL	0.049
## 226	OwensboroKY	0.045
## 98	EvansvilleIN-KY	0.035
## 85	Des-MoinesIA	0.020
## 60	CharlestonSC	-0.017
## 208	New-BedsfordMA	-0.022
## 323	WilmingtonDE-NJ-MD	-0.043
## 299	TexarkanaTX-TexarkanaAR	-0.045
## 189	MedfordOR	-0.048
## 191	MemphisTN-AR-MS	-0.052
## 64	ChattanoogaTN-GA	-0.054
## 233	PeoriaIL	-0.067
## 68	Clarksville-HopkinsvilleTN-KY	-0.075
## 22	AugustaGA-SC	-0.086
## 222	OlympiaWA	-0.116

## 153	Kansas-CityMO	-0.118
## 62	Charlotte-Gastonia-Rock-HillNC-SC	-0.126
## 170	Lawrence-HaverhillMA-NH	-0.130
## 48	Bridgeport-MilfordCT	-0.138
## 72	ColumbiaSC	-0.150
## 141	JacksonMS	-0.154
## 33	Benton-HarborMI	-0.168
## 149	JoplinMO	-0.169
## 54	BurlingtonNC	-0.179
## 257	RockfordIL	-0.205
## 206	NashvilleTN	-0.221
## 287	SpringfieldIL	-0.228
## 240	PortlandOR	-0.233
## 32	BellinghamWA	-0.234
## 104	FlintMI	-0.251
## 83	DecaturIL	-0.290
## 290	StamfordCT	-0.293
## 285	South-Bend-MishawakaIN	-0.320
## 311	Vineland-Millville-BridgetonNJ	-0.340
## 181	LowellMA-NH	-0.382
## 244	Provo-OremUT	-0.386
## 40	BloomingtonIN	-0.394
## 59	Champaign-Urbana-RantoulIL	-0.399
## 35	BillingsMT	-0.430
## 138	IndianapolisIN	-0.435
## 99	Fall-RiverMA-RI	-0.436
## 211	New-London-NorwichCT-RI	-0.437
## 101	FayettevilleNC	-0.443
## 132	HickoryNC	-0.477
## 283	Sioux-CityIA-NE	-0.477
## 8	AltonGranite-CityIL	-0.478
## 263	SalemOR	-0.479
## 200	Monmouth-OceanNJ	-0.491
## 180	LouisvilleKY-IN	-0.493
## 41	Bloomington-NormalIL	-0.498
## 187	MansfieldOH	-0.500
## 120	Glens-FallsNY	-0.502
## 97	Eugene-SpringfieldOR	-0.505
## 58	Cedar-RapidsIA	-0.523

## 156	KnoxvilleTN	-0.531
## 80	Davenport-Rock-Island-MolineIA-IL	-0.534
## 254	RoanokeVA	-0.536
## 123	Great-FallsMT	-0.547
## 217	NorwalkCT	-0.551
## 29	Battle-CreekMI	-0.553
## 216	Norfolk-Virginia-Beach-Newport-NewsVA	-0.555
## 315	MaterburyCT	-0.564
## 106	FlorenceSC	-0.568
## 13	AndersonIN	-0.572
## 150	KalamazooMI	-0.572
## 209	New-BritainCT	-0.580
## 140	JacksonMI	-0.588
## 139	Iowa-CityIA	-0.592
## 127	Greenville-SpartanburgSC	-0.602
## 194	MiddletownCT	-0.640
## 126	Greensboro-Winston-Salem-High-PointNC	-0.650
## 119	Gary-HammondIN	-0.651
## 122	Grand-RapidsMI	-0.652
## 242	PoughkeepsieNY	-0.664
## 14	AndersonSC	-0.676
## 262	St.-LouisMO-IL	-0.682
## 298	Terre-HauteIN	-0.692
## 145	Jersey-CityNJ	-0.697
## 148	JolietIL	-0.705
## 129	Hamilton-MiddletownOH	-0.752
## 223	OmahaNE-IA	-0.752
## 175	LincolnNE	-0.757
## 286	SpokaneWA	-0.764
## 302	TrentonNJ	-0.776
## 49	BristolCT	-0.792
## 259	Saginaw-Bay-City-MidlandMI	-0.797
## 241	Portsmouth-Dover-RochesterNH-ME	-0.799
## 316	Waterloo-Cedar-FallsIA	-0.809
## 239	PortlandME	-0.816
## 78	DanburyCT	-0.824
## 26	BaltimoreMD	-0.852
## 247	Raleigh-DurhamNC	-0.854
## 174	LimaOH	-0.866

## 74	ColumbusOH	-0.872
## 246	RacineWI	-0.875
## 314	WashingtonDC-MD-VA	-0.883
## 213	New-YorkNY	-0.885
## 229	Parkerburg-MariettaWV-OH	-0.893
## 264	Salem-GloucesterMA	-0.899
## 252	Richmond-PetersburgVA	-0.902
## 67	CincinnatiOH-KY-IN	-0.917
## 2	AkronOH	-0.918
## 255	RochesterMN	-0.920
## 224	Orange-CountyNY	-0.958
## 144	Janesville-BeloitWI	-0.967
## 215	Niagara-FallsNY	-0.969
## 88	DubuqueIA	-0.974
## 18	AshevilleNC	-0.983
## 131	HartfordCT	-0.987
## 214	NewarkNJ	-1.006
## 203	MuncieIN	-1.035
## 93	Elkhart-GoshenIN	-1.049
## 113	Fort-WayneIN	-1.096
## 186	ManchesterNH	-1.127
## 183	LynchburgVA	-1.140
## 81	Dayton-SpringfieldOH	-1.146
## 300	ToledoOH	-1.152
## 205	NashuaNH	-1.153
## 56	CantonOH	-1.162
## 154	KenoshaWI	-1.174
## 128	HagerstownMD	-1.180
## 207	Nassua-SuffolkNY	-1.185
## 165	Lansing-East-LansingMI	-1.186
## 288	SpringfieldMA	-1.202
## 172	Lewiston-AuburnME	-1.249
## 103	Fitchburg-LeominsterMA	-1.259
## 86	DetroitMI	-1.271
## 15	Ann-ArborMI	-1.295
## 328	Youngstown-WarrenOH	-1.301
## 159	LafayetteIN	-1.307
## 210	New-Haven-MeridenCT	-1.315
## 136	Huntington-AshlandWV-KY-OH	-1.350

## 69	ClevelandOH	-1.353
## 238	PittsfieldMA	-1.388
## 146	Johnson-City-Kingsport-BristolTN-VA	-1.396
## 43	BostonMA	-1.422
## 61	CharlestonWV	-1.441
## 292	Steubenville-WeirtonOH-WV	-1.448
## 197	Minneapolis-St.-PaulMN-WI	-1.467
## 63	CharlottesvilleVA	-1.530
## 125	Green-BayWI	-1.531
## 96	EriePA	-1.538
## 248	ReadingPA	-1.548
## 256	RochesterNY	-1.573
## 157	KokomoIN	-1.592
## 284	Sioux-FallsSD	-1.606
## 178	Lorain-ElyriaOH	-1.615
## 158	La-CrosseWI	-1.645
## 280	SheboyganWI	-1.648
## 231	Pawtucket-Woonsocket-AttleboroRI-MA	-1.660
## 53	BuffaloNY	-1.684
## 34	Bergen-PassaicNJ	-1.701
## 94	ElmiraNY	-1.710
## 260	St.-CloudMN	-1.710
## 65	ChicagoIL	-1.715
## 291	State-CollegePA	-1.740
## 193	Middlesex-SomersetHunterdonNJ	-1.752
## 327	YorkPA	-1.760
## 196	MilwaukeeWI	-1.818
## 17	Appleton-Oshkosh-NeenahWI	-1.820
## 39	BismarckND	-1.854
## 307	Utica-RomeNY	-1.857
## 27	BangorME	-1.866
## 185	MadisonWI	-1.881
## 325	WorcesterMA	-1.910
## 100	Fargo-MoorheadND-MN	-1.928
## 294	SyracuseNY	-1.968
## 7	AllentownBethlehemPA-NJ	-1.992
## 243	ProvidenceRI	-2.005
## 9	AltoonaPA	-2.026
## 279	SharonPA	-2.104

```
## 37                BinghamtonNY -2.117
## 130            Harrisburg-Lebanon-CarlislePA -2.150
## 234            PhiladelphiaPA-NJ -2.171
## 79                DanvilleVA -2.193
## 164            LancasterPA -2.205
## 89                DuluthMN-WI -2.259
## 237            PittsburghPA -2.262
## 76            CumberlandMD-WV -2.264
## 317                WausauWI -2.299
## 147            JohnstownPA -2.301
## 319            WheelingWV-OH -2.355
## 31            Beaver-CountyPA -2.399
## 322            WilliamsportPA -2.433
## 91                Eau-ClaireWI -2.476
## 4                Albany-Schenectady-TroyNY -2.494
## 277            Scranton-Wilkes-BarrePA -2.591
## 55                BurlingtonVT -2.613
## 121            Grand-ForksND -2.669
```

Factor Analysis

```
non_zero_var <- apply(data_log, 2, var) != 0
data_log_filtered <- data_log[, non_zero_var]
fa.data <- factanal(data_log_filtered, 3, rotation = "none")
fa.data
```



```
##
## Call:
## factanal(x = data_log_filtered, factors = 3, rotation = "none")
##
## Uniquenesses:
## HousingCost      HlthCare      Crime      Transp      Educ      Arts
##      0.922      0.582      0.247      0.542      0.588      0.629
##      Recreat      Econ      <NA>      NA.1      NA.2      NA.3
##      0.264      0.600      0.797      0.983      0.451      0.005
##      NA.4      NA.5
##      0.510      0.928
##
## Loadings:
##      Factor1 Factor2 Factor3
## HousingCost 0.232      -0.147
## HlthCare    0.560  0.212 -0.245
## Crime       0.802  0.154  0.292
## Transp      0.434 -0.408 -0.322
## Educ        0.590  0.223 -0.122
## Arts        0.461      0.387
## Recreat     0.844  0.121
## Econ        0.510      -0.373
## <NA>        0.195 -0.397
## NA.1        0.122
## NA.2        0.739
## NA.3        0.997
## NA.4        0.700
## NA.5       -0.125  0.185  0.147
##
##      Factor1 Factor2 Factor3
## SS loadings 3.278  1.500  1.174
## Proportion Var 0.234  0.107  0.084
## Cumulative Var 0.234  0.341  0.425
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 231.32 on 52 degrees of freedom.
## The p-value is 1.83e-24
```

```
fa.dataRot = factanal(data_log_filtered, 3, rotation = "varimax")  
fa.dataRot
```

```
##
## Call:
## factanal(x = data_log_filtered, factors = 3, rotation = "varimax")
##
## Uniquenesses:
## HousingCost    HlthCare    Crime    Transp    Educ    Arts
##      0.922      0.582      0.247      0.542      0.588      0.629
##      Recreat      Econ      <NA>      NA.1      NA.2      NA.3
##      0.264      0.600      0.797      0.983      0.451      0.005
##      NA.4      NA.5
##      0.510      0.928
##
## Loadings:
##           Factor1 Factor2 Factor3
## HousingCost 0.202  0.144  0.130
## HlthCare    0.587           0.272
## Crime       0.824           -0.269
## Transp      0.289  0.568  0.228
## Educ        0.623           0.153
## Arts        0.483           -0.369
## Recreat     0.839  0.144  0.104
## Econ        0.482  0.187  0.364
## <NA>         0.444
## NA.1         0.127
## NA.2         -0.152 -0.721
## NA.3        0.275 -0.938  0.199
## NA.4        0.669  0.205
## NA.5         -0.238 -0.106
##
##           Factor1 Factor2 Factor3
## SS loadings  3.247  1.600  1.105
## Proportion Var 0.232  0.114  0.079
## Cumulative Var 0.232  0.346  0.425
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 231.32 on 52 degrees of freedom.
## The p-value is 1.83e-24
```

```
fa.dataRot = factanal(data_log_filtered, 4, rotation = "varimax")  
fa.dataRot
```

```
##
## Call:
## factanal(x = data_log_filtered, factors = 4, rotation = "varimax")
##
## Uniquenesses:
## HousingCost    HlthCare    Crime    Transp    Educ    Arts
##      0.897      0.005      0.257      0.501      0.557      0.626
##      Recreat      Econ      <NA>      NA.1      NA.2      NA.3
##      0.266      0.616      0.688      0.981      0.411      0.005
##      NA.4      NA.5
##      0.494      0.888
##
## Loadings:
##      Factor1 Factor2 Factor3 Factor4
## HousingCost 0.176 -0.107 0.225 -0.100
## HlthCare    0.375      0.919
## Crime       0.769      0.181 0.344
## Transp      0.407 -0.496      -0.295
## Educ        0.643 0.113      -0.109
## Arts        0.436      0.421
## Recreat     0.828      0.215
## Econ        0.460      0.298 -0.278
## <NA>        -0.435 0.345
## NA.1        -0.104
## NA.2        -0.113 0.755
## NA.3        0.150 0.981
## NA.4        0.690 -0.125 0.108
## NA.5        0.219 -0.241
##
##      Factor1 Factor2 Factor3 Factor4
## SS loadings 2.930 1.507 1.289 1.083
## Proportion Var 0.209 0.108 0.092 0.077
## Cumulative Var 0.209 0.317 0.409 0.486
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 130.3 on 41 degrees of freedom.
## The p-value is 3.13e-11
```

```
fa.dataRot = factanal(data_log_filtered, 2, rotation = "varimax")  
fa.dataRot
```

```
##
## Call:
## factanal(x = data_log_filtered, factors = 2, rotation = "varimax")
##
## Uniquenesses:
## HousingCost    HlthCare    Crime    Transp    Educ    Arts
##      0.926      0.670      0.344      0.345      0.611      0.749
##      Recreat      Econ      <NA>      NA.1      NA.2      NA.3
##      0.259      0.701      0.855      0.997      0.877      0.617
##      NA.4      NA.5
##      0.519      0.921
##
## Loadings:
##           Factor1 Factor2
## HousingCost 0.202  0.184
## HlthCare    0.570
## Crime       0.806
## Transp      0.291  0.755
## Educ        0.621
## Arts        0.480 -0.144
## Recreat     0.851  0.134
## Econ        0.484  0.255
## <NA>         0.372
## NA.1
## NA.2         -0.343
## NA.3        0.209 -0.582
## NA.4        0.673  0.169
## NA.5         -0.276
##
##           Factor1 Factor2
## SS loadings   3.185  1.425
## Proportion Var 0.228  0.102
## Cumulative Var 0.228  0.329
##
## Test of the hypothesis that 2 factors are sufficient.
## The chi square statistic is 430.63 on 64 degrees of freedom.
## The p-value is 9.29e-56
```

```
fa.dataRot = factanal(data_log_filtered, 1, rotation = "varimax")  
fa.dataRot
```



```
##
## Call:
## factanal(x = data_log_filtered, factors = 1, rotation = "varimax")
##
## Uniquenesses:
## HousingCost    HlthCare    Crime    Transp    Educ    Arts
##      0.950      0.657      0.416      0.860      0.614      0.806
##      Recreat      Econ      <NA>      NA.1      NA.2      NA.3
##      0.240      0.718      0.980      0.998      1.000      0.986
##      NA.4      NA.5
##      0.534      0.991
##
## Loadings:
##           Factor1
## HousingCost 0.224
## HlthCare    0.585
## Crime       0.764
## Transp      0.375
## Educ        0.621
## Arts        0.440
## Recreat     0.872
## Econ        0.531
## <NA>        0.143
## NA.1
## NA.2
## NA.3        0.120
## NA.4        0.683
## NA.5
##
##           Factor1
## SS loadings  3.249
## Proportion Var 0.232
##
## Test of the hypothesis that 1 factor is sufficient.
## The chi square statistic is 636.54 on 77 degrees of freedom.
## The p-value is 5.74e-89
```

Canonical Correlation Analysis

```
# One group -> Arts and Health Care
```

```
X= data_log_filtered[,c(3,7)]  
Y= data_log_filtered[,-c(3,7)]  
cor(X)
```

```
##           Crime   Recreat  
## Crime   1.0000000 0.6781286  
## Recreat 0.6781286 1.0000000
```

```
cor(Y)
```

##	HousingCost	HlthCare	Transp	Educ	Arts
## HousingCost	1.00000000	0.27296448	0.22775093	0.03424105	0.07745819
## HlthCare	0.27296448	1.00000000	0.13923425	0.32428769	0.20208781
## Transp	0.22775093	0.13923425	1.00000000	0.27559314	0.05550755
## Educ	0.03424105	0.32428769	0.27559314	1.00000000	0.32230122
## Arts	0.07745819	0.20208781	0.05550755	0.32230122	1.00000000
## Econ	0.12060965	0.46069631	0.29212402	0.39390231	0.09300112
## <NA>	-0.10429920	0.29032351	0.26817467	0.05924675	0.11549945
## NA.1	0.09501600	0.09298513	0.03831948	-0.01130171	0.01554301
## NA.2	-0.11705350	-0.14638998	-0.24881019	-0.06147827	0.35253448
## NA.3	-0.05381434	0.20935822	-0.40815361	0.22012207	0.08817433
## NA.4	0.20809655	0.34544939	0.34113491	0.40221425	0.33969890
## NA.5	-0.06505669	-0.22173325	-0.22292407	-0.01292504	0.12302572
##	Econ	<NA>	NA.1	NA.2	NA.3
## HousingCost	0.12060965	-0.1042991959	0.095015998	-0.1170534964	-0.05381434
## HlthCare	0.46069631	0.2903235124	0.092985132	-0.1463899813	0.20935822
## Transp	0.29212402	0.2681746726	0.038319477	-0.2488101862	-0.40815361
## Educ	0.39390231	0.0592467535	-0.011301715	-0.0614782729	0.22012207
## Arts	0.09300112	0.1154994504	0.015543006	0.3525344776	0.08817433
## Econ	1.00000000	0.1722302876	0.058535433	-0.2016984139	0.02915801
## <NA>	0.17223029	1.0000000000	0.009677032	0.0005405777	-0.39740006
## NA.1	0.05853543	0.0096770315	1.000000000	-0.1074371900	0.03843321
## NA.2	-0.20169841	0.0005405777	-0.107437190	1.0000000000	0.02150614
## NA.3	0.02915801	-0.3974000570	0.038433206	0.0215061428	1.00000000
## NA.4	0.34528737	0.0597583731	0.014569723	0.0008033670	-0.01293795
## NA.5	-0.08809709	-0.0766658507	0.010948639	0.0753732601	0.18525107
##	NA.4	NA.5			
## HousingCost	0.208096552	-0.06505669			
## HlthCare	0.345449386	-0.22173325			
## Transp	0.341134909	-0.22292407			
## Educ	0.402214251	-0.01292504			
## Arts	0.339698897	0.12302572			
## Econ	0.345287369	-0.08809709			
## <NA>	0.059758373	-0.07666585			
## NA.1	0.014569723	0.01094864			
## NA.2	0.000803367	0.07537326			
## NA.3	-0.012937948	0.18525107			

```
## NA.4      1.000000000 -0.03839843
## NA.5     -0.038398426  1.000000000
```

```
cor(X,Y)
```

```
##      HousingCost HlthCare   Transp      Educ      Arts      Econ
## Crime    0.1505609 0.4319355 0.1836245 0.4473941 0.4647636 0.2540362
## Recreat  0.1726830 0.5085013 0.3464617 0.5523397 0.3478985 0.4965191
##      <NA>      NA.1      NA.2      NA.3      NA.4      NA.5
## Crime    0.02262154 0.003321376 0.25532857 0.1494006 0.5945858 -0.08063887
## Recreat  0.10685220 0.027538373 -0.03294129 0.1167302 0.5665396 -0.05281775
```

```
cca.almanac = cc(X,Y)
cca.almanac$cor # 2 canonical Correlations
```

```
## [1] 0.7932054 0.4774861
```

The CCA analysis indicates two canonical correlations: 0.793 and 0.477. These values represent the strength of the relationship between the two sets of variables (X and Y) in a reduced-dimensional space. A higher canonical correlation suggests a stronger relationship between the sets of variables.

```
cca.almanac$xcoef; cca.almanac$ycoef
```

```
##      [,1]      [,2]
## Crime -0.7444834  1.6866868
## Recreat -0.4320033 -0.9941881
```

```
##           [,1]      [,2]
## HousingCost  1.042019e-01  2.580476e-02
## HlthCare    -1.575696e+00  2.203967e-01
## Transp      -4.386140e-01 -6.006368e-01
## Educ        -1.842730e-04 -1.056164e-04
## Arts        -1.451181e+00  1.189129e+00
## Econ        -2.098991e-01 -1.265259e+00
## <NA>         1.196040e-04 -1.129163e-04
## NA.1         6.299739e-05  2.775650e-04
## NA.2        -1.526817e-02  3.780540e-02
## NA.3        -8.645051e-03 -2.578585e-04
## NA.4        -4.777664e-07  3.709736e-07
## NA.5        -9.772853e-05 -1.456368e-02
```

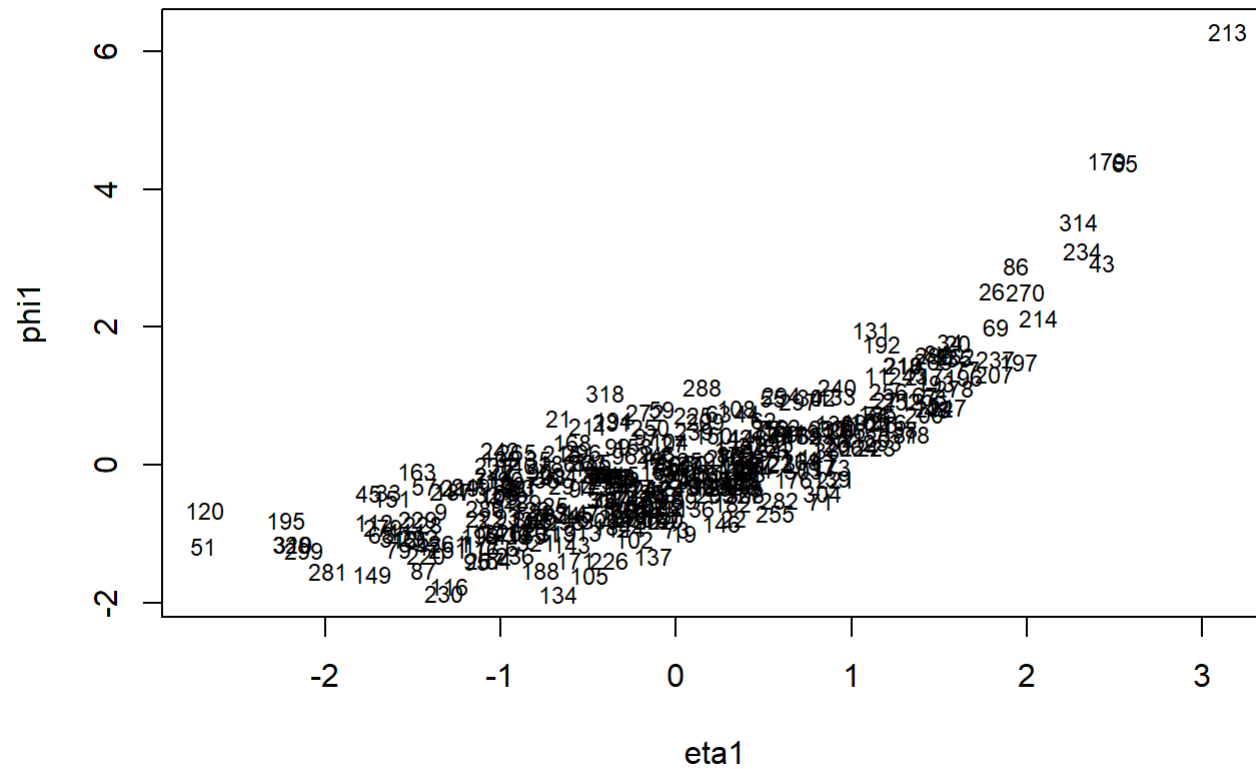
The coefficient for the first canonical variable (x_1) is -0.744 for Crime and -0.432 for Recreat. This indicates that Crime has a stronger influence on the first canonical variable compared to Recreat. In other words, a higher value of the first canonical variable indicates higher Crime and lower Recreat.

The coefficient for HousingCost is 0.104 for y_1 and 0.026 for y_2 . This means that HousingCost has a small positive influence on both the first and second canonical variables.

Similarly, the coefficients for HlthCare, Transp, Educ, Arts, and Econ indicate their contributions to the first and second canonical variables.

```
plot(-cca.almanac$scores$xscores[,1], -cca.almanac$scores$yscores[,1],
     type="n", xlab="eta1", ylab="phi1")

text(x = -cca.almanac$scores$xscores[,1], y = -cca.almanac$scores$yscores[,1],
     labels = row.names(places), cex=.75)
```



This graph verifies the correlation.

```
plot(-cca.almanac$scores$xscores[,2], -cca.almanac$scores$yscores[,2],
     type="n", xlab="eta2", ylab="phi2")

text(x = -cca.almanac$scores$xscores[,2], y = -cca.almanac$scores$yscores[,2],
     labels = row.names(places), cex=.75)
```

