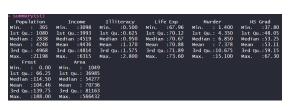
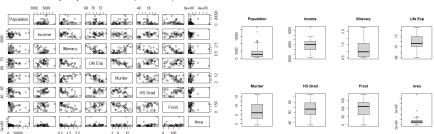
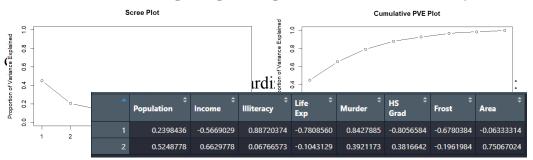
2. PCA on State Statistics:

a. The dataset has 8 columns and 50 rows. I started off by identifying if any correlation exists between the columns using a pair plot. From the pairplot, we can see that there is some correlation or relationship among some columns as we see some linear trends. For example, we see a linear trend between income and HS grad, Illiteracy and life expectancy, etc. After doing the summary() function we can see the unit of measurements of these columns differ a lot, hence scaling will be needed moving forward. From the boxplots, we see that population, area, and income have a few outliers.



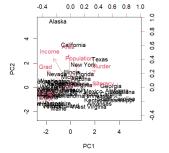


- b. Yes, as discussed above standardizing the variables will be a good idea as we can see by results of summary() our columns have different ranges
- c. After plotting the scree and cumulative pve plot, we can see that we should use 5 components indicated by the elbow shape, and insignificant gain afterwards. Hence, 5 pc helps us explain around 95% variability.



- ii. Cumulative percentage of the total variability by the two component: > cumsum(pve) [1:2]
- [1] 0.4498619 0.6538519 iii. Scores on the two components & bi plot:

> pca.fit\$rotation[,1:2] PC1 PC1
Population 0.12642809 0.41087417
Income -0.29882991 0.51897884
Illiteracy 0.46766917 0.05296872
Life Exp -0.41161037 -0.08165611
Murder 0.44425672 0.30694934
HS Grad -0.42468442 0.29876662
Frost -0.35741244 -0.15358409
Area -0.03338461 0.58762446



iv. Interpretation of results: we can clearly see that PC1 is more correlated with Illiteracy, life expectancy, murder, HS grad, frost,

while PC2 is more correlated with population, income, area. Furthermore, a southern component is illiteracy and murder as we see alot of southern states pointed in that direction on the biplot. Hence, southern states scored better on PC1 than PC2.