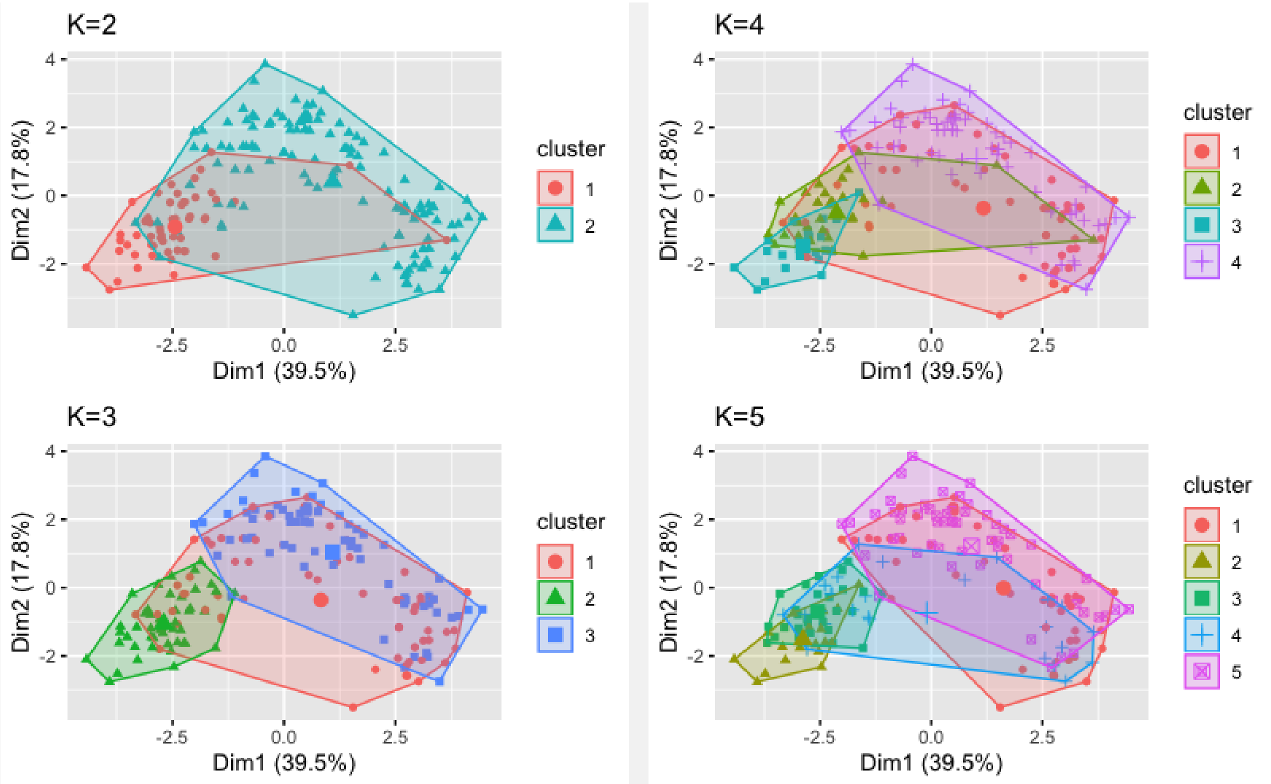
Adrian Sandoval-Vargas

CSI 5810 Assignment 4

Question 1

For this problem I used the language R. I wasn't sure were to find the wine dataset mentioned so I assumed and used the Wine Dataset found in the UCI Machine Learning database.



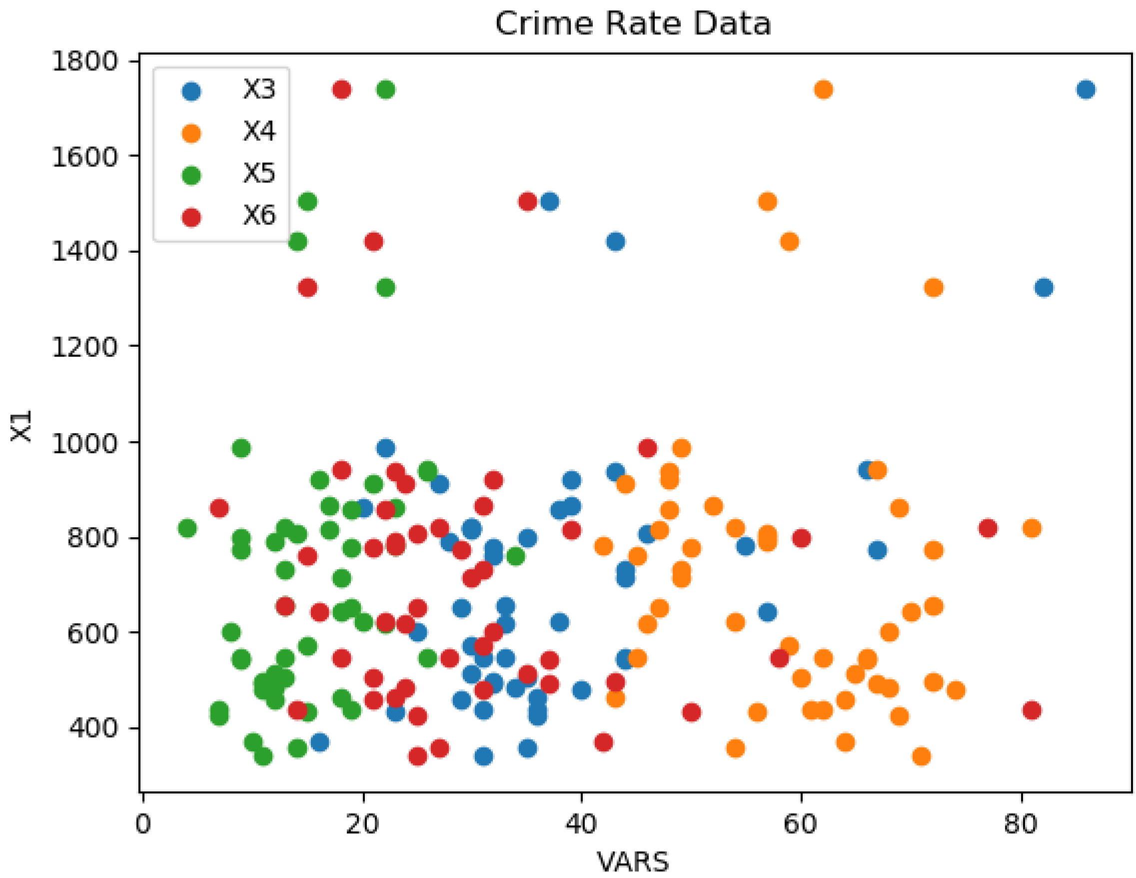
Figures of K-means clustering on Wine Dataset.

The SSE and Rand Index are as follows:

	K2	K3	K4	K5
SSE	4543801.2	2370742.3	1331953.8	916424.2
Rand Index	0.6702850	0.7186568	0.7002476	0.7164984

Question 2

Since X1 is our target values, then we do not need X2. Data:



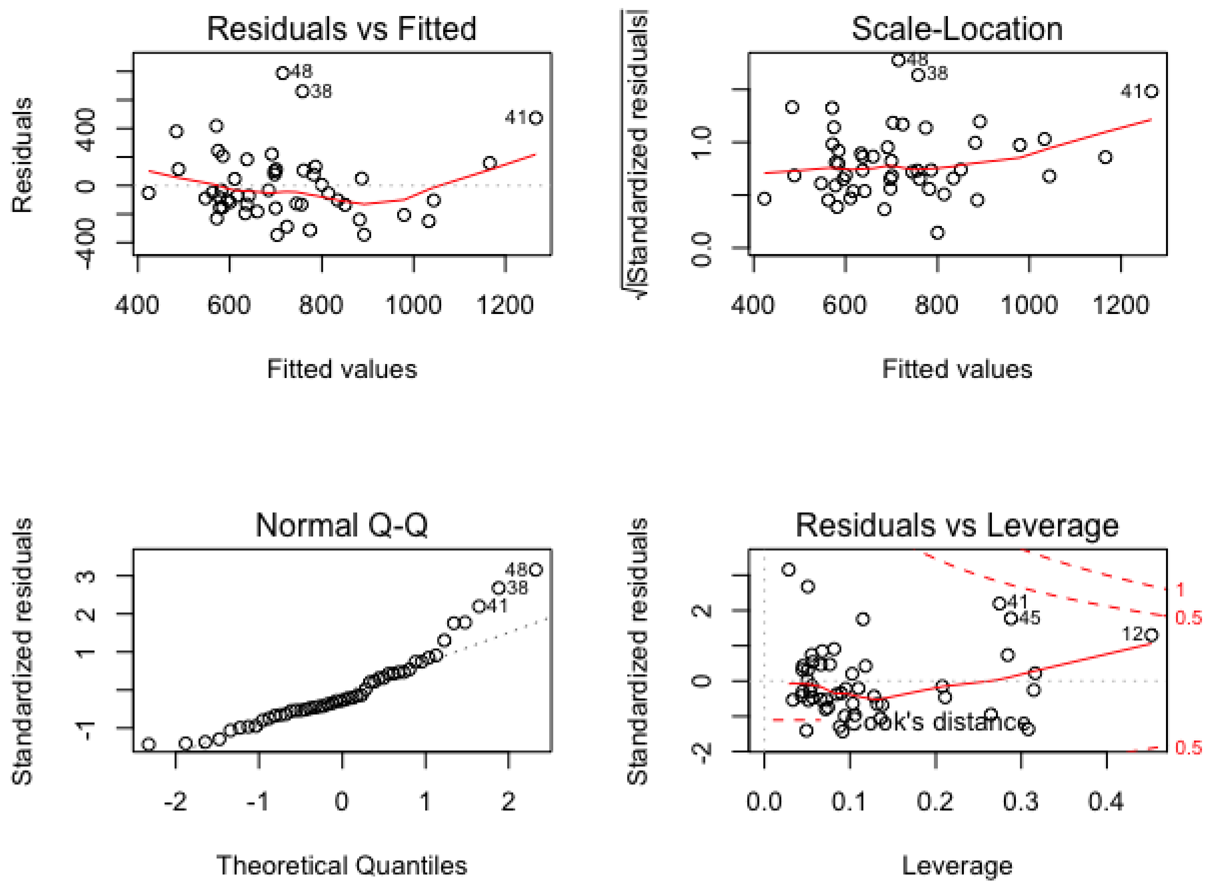
After building the linear model and reading the summary:

```
target = CrimeRate$X1
vars = as.matrix(CrimeRate[,3:7])
lm1 <- lm(target ~ vars)
summary(lm1)
```

We obtain:

	Estimate	Std.Error	tvalue	Pr(>abs(t))
(Intercept)	489.649	472.366	1.037	0.305592
varsX3	10.981	3.078	3.568	0.000884
varsX4	-6.088	6.544	-0.930	0.357219
varsX5	5.480	10.053	0.545	0.588428
varsX6	0.377	4.417	0.085	0.932367
varsX7	5.500	13.754	0.400	0.691150

This model gives us something like:



Using are Intercept and Betas 'Estimates' from our table above. This model gives us:

```
X1 = 489.65 + (10.98 * X3) - (6.09 * X4) + (5.48 * X5) + (0.38 * X6) +
(5.50 * X7)
```

With a Multiple R-squared of: 0.3336 which translates to 33% accuracy. Which is not what we want.

So lets do gradient descent on each attribute(X3, X4, X5, X6, X7)

X3:

```
data = pd.read_excel("CrimeRate.xlsx")
X3 = data['X3']
N = 50
alpha = 1.3
w = np.random.randn(50)
l_rate = 15
result = []
loss = 0
for t in range(5):
    y_pred = X3.dot(w)
    loss = np.square(y_pred - Y)
    if t % 10 == 0:
```

```
        print("t: " + str(t) +" loss " + str(loss))
        result.append(loss)
    grad_y_pred = 2.0 * (y_pred - Y)
    grad_w = X3.T.dot(grad_y_pred)
    w -= l_rate * grad_w

print(w)
```

X3:

Learning Rate 15 yields: a weight of 8.056

Learning Rate 10 yields: a weight of 8.163

Similarly we can do the same with the other attributes.

X4:

Learning Rate 15 yields: a weight of 5.34

Learning Rate 10 yields: a weight of 4.415

X5:

Learning Rate 10 yields: a weight of 2.201

Learning Rate 15 yields: a weight of 1.458

X6:

Learning Rate 15 yields: a weight of 4.192

Learning Rate 10 yields: a weight of 5.995

X7:

Learning Rate 10 yields: a weight of 8.794

Learning Rate 15 yields: a weight of 6.597

This results in a new model of

```
X1 = 489.65 + (8.056 * X3) + (5.34 * X4) + (1.458* X5) + (4.192 * X6) +
(6.597 * X7)
```

Question 3

Decomposition of minimum support threshold of 30%:

Item	Frequency	Support %
A	5	50%

Item	Frequency	Support %
B	7	70%
C	5	50%
D	9	90%
E	6	60%

Threshold of the combinations of the TID:

Item	Frequency	Support %
AB	3	30%
~~AC~~	~~2~~	~~20%~~
AD	4	40%
AE	4	40%
BC	3	30%
BD	6	60%
BE	4	40%
CD	4	40%
~~CE~~	~~2~~	~~20%~~
DE	6	60%

Since AC and CE are below 30% we can remove.

Now that we have our singular and 2 combinations above the 30% threshold we can look into the three items that have an occurance of 30%:

Item	Frequency	Support %
~~ABD~~	~~2~~	~~20%~~
~~ABE~~	~~2~~	~~20%~~
ADE	4	40%
~~BCD~~	~~2~~	~~20%~~
~~BCE~~	~~1~~	~~10%~~
BDE	3	30%

Again removing the items that below 30% gives us:

Item	Frequency	Support %

Item	Frequency	Support %
ADE	4	40%
BDE	3	30%

So ADE and BDE are the most frequent subsets that are at par or greater than 30%.

Question 4

Note: I conducted the SVD example and got exact results as in lecture notes, but when I did them with the HW Term Document Matrix, the result are different from the lectures notes. I proceeeded with my calculations

i.

SVD of F: (rounded to 3 decimals)

F = 2.163 * [0.44 -0.296 -0.569 0.577 -0.246] * [0.749 0.28 0.204 0.447 0.325 0.121] +

1.594 * [0.129 -0.331 0.587 0. -0.727] * [-0.286 -0.528 -0.186 0.626 0.22 0.406] +

1.275 * [0.476 -0.511 0.368 0. 0.614] * [-0.28 0.749 -0.447 0.204 -0.121 0.325]+

1.0 * [0.703 0.351 -0.155 -0.577 -0.16] * [-0. 0. 0.577 0. -0.577 0.577] +

0.394 * [0.263 0.647 0.415 0.577 0.087] * [0.528 -0.286 -0.626 -0.186 -0.406 0.22]

ii & iii

Our top two singular values are: 2.163 and 1.594

2.163 * [0.44 -0.296 -0.569 0.577 -0.246] * [0.749 0.28 0.204 0.447 0.325 0.121] +

1.594 * [0.129 -0.331 0.587 0. -0.727] * [-0.286 -0.528 -0.186 0.626 0.22 0.406]

```
k = s[0] * np.matmul(np.reshape(U[0], (5,1)),np.reshape(VT[0], (1,6)))
k = k + s[1] * np.matmul(np.reshape(U[1], (5,1)),np.reshape(VT[1], (1,6)))
```

yields us the following matrix (rounded to 3 decimals):

	D1	D2	D3	D4	D5	D6
K1	0.654	0.157	0.156	0.554	0.355	0.199
K2	-0.328	0.1	-0.032	-0.617	-0.324	-0.292
K3	-1.19	-0.839	-0.425	0.035	-0.195	0.23
K4	0.935	0.349	0.254	0.558	0.406	0.152
K5	-0.067	0.464	0.107	-0.963	-0.428	-0.535

approximation of V^t:

	D1	D2	D3	D4	D5	D6
K1	-1.62	-0.60	-0.44	-0.97	-0.70	-0.26
K2	-0.46	-0.84	-0.30	1.00	0.35	0.65

approximation of U:

K1	-0.95	-0.48
K2	-0.28	-0.52
K3	-1.04	-0.81
K4	-1.51	0.56
K5	-0.56	1.03

iv

Similarity Matrix:

1	0	0.5	0.40824829	0
0	1	0.70710678	0	0
0.5	0.70710678	1	0.40824829	0
0.40824829	0	0.40824829	1	0.40824829
0	0	0	0.40824829	1