

ISYE6501x Homework 5

Done By: Joel Quek

Question 8.1

Describe a situation or problem from your job, everyday life, current events, etc., for which a linear regression model would be appropriate. List some (up to 5) predictors that you might use.

I dabble in trading once in a while, and personally enjoy selling Bull Put Option Spreads on US Equities. My measure of success is when the options contracts expire Out Of The Money, which means I made the full premium as profit. When selling these Option Spreads there are many considerations, which I could use as predictors for my model. For example:

1. The Implied Volatility Percentile

2. The Delta Value of the Short Put Option

3. The Number of Days/Weeks to Expiration (A function of the Theta Value)

4. The overall trend of the market - Bullish, Bearish or Indifferent (Dummy variables would need to be used)

5. The Probability of being Out-Of-The-Money (Using Black-Scholes Formula)

Question 8.2

Using crime data from <http://www.statsci.org/data/general/uscrime.txt> (<http://www.statsci.org/data/general/uscrime.txt>) (file uscrime.txt, description at <http://www.statsci.org/data/general/uscrime.html> (<http://www.statsci.org/data/general/uscrime.html>)), use regression (a useful R function is lm or glm) to predict the observed crime rate in a city with the following data:

M = 14.0 So = 0 Ed = 10.0 Po1 = 12.0 Po2 = 15.5 LF = 0.640 M.F = 94.0 Pop = 150 NW = 1.1 U1 = 0.120 U2 = 3.6 Wealth = 3200 Ineq = 20.1 Prob = 0.04 Time = 39.0

Show your model (factors used and their coefficients), the software output, and the quality of fit.

Note that because there are only 47 data points and 15 predictors, you'll probably notice some overfitting. We'll see ways of dealing with this sort of problem later in the course.

1. Importing Dataset and Libraries

In [1]:

```
library(stats)
```

In [26]:

```
library(dplyr)
```

In [2]:

```
crime <- read.table("uscrime.txt", header=TRUE)
```

In [3]:

```
head(crime)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>
1	15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011	791
2	14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999	1635
3	14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401	24.3006	578
4	13.6	0	12.1	14.9	14.1	0.577	99.4	157	8.0	0.102	3.9	6730	16.7	0.015801	29.9012	1969
5	14.1	0	12.1	10.9	10.1	0.591	98.5	18	3.0	0.091	2.0	5780	17.4	0.041399	21.2998	1234
6	12.1	0	11.0	11.8	11.5	0.547	96.4	25	4.4	0.084	2.9	6890	12.6	0.034201	20.9995	682

In [4]:

```
summary(crime)
```

M		So		Ed		Po1	
Min.	:11.90	Min.	:0.0000	Min.	: 8.70	Min.	: 4.50
1st Qu.:	13.00	1st Qu.:	0.0000	1st Qu.:	9.75	1st Qu.:	6.25
Median	:13.60	Median	:0.0000	Median	:10.80	Median	: 7.80
Mean	:13.86	Mean	:0.3404	Mean	:10.56	Mean	: 8.50
3rd Qu.:	14.60	3rd Qu.:	1.0000	3rd Qu.:	11.45	3rd Qu.:	10.45
Max.	:17.70	Max.	:1.0000	Max.	:12.20	Max.	:16.60
Po2		LF		M.F		Pop	
Min.	: 4.100	Min.	:0.4800	Min.	: 93.40	Min.	: 3.00
1st Qu.:	5.850	1st Qu.:	0.5305	1st Qu.:	96.45	1st Qu.:	10.00
Median	: 7.300	Median	:0.5600	Median	: 97.70	Median	: 25.00
Mean	: 8.023	Mean	:0.5612	Mean	: 98.30	Mean	: 36.62
3rd Qu.:	9.700	3rd Qu.:	0.5930	3rd Qu.:	99.20	3rd Qu.:	41.50
Max.	:15.700	Max.	:0.6410	Max.	:107.10	Max.	:168.00
NW		U1		U2		Wealth	
Min.	: 0.20	Min.	:0.07000	Min.	:2.000	Min.	:2880
1st Qu.:	2.40	1st Qu.:	0.08050	1st Qu.:	2.750	1st Qu.:	4595
Median	: 7.60	Median	:0.09200	Median	:3.400	Median	:5370
Mean	:10.11	Mean	:0.09547	Mean	:3.398	Mean	:5254
3rd Qu.:	13.25	3rd Qu.:	0.10400	3rd Qu.:	3.850	3rd Qu.:	5915
Max.	:42.30	Max.	:0.14200	Max.	:5.800	Max.	:6890
Ineq		Prob		Time		Crime	
Min.	:12.60	Min.	:0.00690	Min.	:12.20	Min.	: 342.0
1st Qu.:	16.55	1st Qu.:	0.03270	1st Qu.:	21.60	1st Qu.:	658.5
Median	:17.60	Median	:0.04210	Median	:25.80	Median	: 831.0
Mean	:19.40	Mean	:0.04709	Mean	:26.60	Mean	: 905.1
3rd Qu.:	22.75	3rd Qu.:	0.05445	3rd Qu.:	30.45	3rd Qu.:	1057.5
Max.	:27.60	Max.	:0.11980	Max.	:44.00	Max.	:1993.0

In [5]:

```
names(crime)
```

'M' 'So' 'Ed' 'Po1' 'Po2' 'LF' 'M.F' 'Pop' 'NW' 'U1' 'U2' 'Wealth' 'Ineq' 'Prob' 'Time' 'Crime'

2. Linear Regression Model 1 (Unscaled Data)

In [6]:

```
model <- lm(Crime ~ M+So+Ed+Po1+Po2+LF+M.F+Pop+NW+U1+U2+Wealth+Ineq+Prob+Time, data=crime)
```

In [7]:

```
model
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = crime)

Coefficients:						
(Intercept)	M	So	Ed	Po1	Po2	
-5.984e+03	8.783e+01	-3.803e+00	1.883e+02	1.928e+02	-1.094e+02	
LF	M.F	Pop	NW	U1	U2	
-6.638e+02	1.741e+01	-7.330e-01	4.204e+00	-5.827e+03	1.678e+02	
Wealth	Ineq	Prob	Time			
9.617e-02	7.067e+01	-4.855e+03	-3.479e+00			

3. Linear Regression Model 2 (Scaled Data)

In [8]:

```
crime_scaled <- scale(crime[,1:15])
```

In [9]:

```
head(crime_scaled)
```

A matrix: 6 × 15 of type dbl

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ir
1	0.9886930	1.3770536	-1.3085099	-0.9085105	-0.8666988	-1.2667456	-1.12060499	-0.09500679	1.943738564	0.69510600	0.8313680	-1.3616094	1.67936
2	0.3521372	-0.7107373	0.6580587	0.6056737	0.5280852	0.5396568	0.98341752	-0.62033844	0.008483424	0.02950365	0.2393332	0.3276683	0.00000
3	0.2725678	1.3770536	-1.4872888	-1.3459415	-1.2958632	-0.6976051	-0.47582390	-0.48900552	1.146296747	-0.08143007	-0.1158877	-2.1492481	1.40364
4	-0.2048491	-0.7107373	1.3731746	2.1535064	2.1732150	0.3911854	0.37257228	3.16204944	-0.205464381	0.36230482	0.5945541	1.5298536	-0.67675
5	0.1929983	-0.7107373	1.3731746	0.8075649	0.7426673	0.7376187	0.06714965	-0.48900552	-0.691709391	-0.24783066	-1.6551781	0.5453053	-0.50130
6	-1.3983912	-0.7107373	0.3898903	1.1104017	1.2433590	-0.3511718	-0.64550313	-0.30513945	-0.555560788	-0.63609870	-0.5895155	1.6956723	-1.70442

In [10]:

```
crime_scaled <- data.frame(crime_scaled)
```

In [11]:

```
head(crime_scaled)
```

A data.frame: 6 × 15

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	
1	0.9886930	1.3770536	-1.3085099	-0.9085105	-0.8666988	-1.2667456	-1.12060499	-0.09500679	1.943738564	0.69510600	0.8313680	-1.3616094	1.67
2	0.3521372	-0.7107373	0.6580587	0.6056737	0.5280852	0.5396568	0.98341752	-0.62033844	0.008483424	0.02950365	0.2393332	0.3276683	0.00
3	0.2725678	1.3770536	-1.4872888	-1.3459415	-1.2958632	-0.6976051	-0.47582390	-0.48900552	1.146296747	-0.08143007	-0.1158877	-2.1492481	1.40
4	-0.2048491	-0.7107373	1.3731746	2.1535064	2.1732150	0.3911854	0.37257228	3.16204944	-0.205464381	0.36230482	0.5945541	1.5298536	-0.67
5	0.1929983	-0.7107373	1.3731746	0.8075649	0.7426673	0.7376187	0.06714965	-0.48900552	-0.691709391	-0.24783066	-1.6551781	0.5453053	-0.50
6	-1.3983912	-0.7107373	0.3898903	1.1104017	1.2433590	-0.3511718	-0.64550313	-0.30513945	-0.555560788	-0.63609870	-0.5895155	1.6956723	-1.70

In [12]:

```
model12 <- lm(crime$Crime ~., data=crime_scaled)
```

In [13]:

```
model12
```

Call:
lm(formula = crime\$Crime ~ ., data = crime_scaled)

Coefficients:						
(Intercept)	M	So	Ed	Po1	Po2	
905.085	110.382	-1.822	210.678	572.995	-305.958	
LF	M.F	Pop	NW	U1	U2	
-26.826	51.293	-27.906	43.234	-105.056	141.714	
Wealth	Ineq	Prob	Time			
92.792	281.954	-110.394	-24.655			

In [27]:

summary(model2)

Call:

lm(formula = crime\$Crime ~ ., data = crime_scaled)

Residuals:

Min	1Q	Median	3Q	Max
-395.74	-98.09	-6.69	112.99	512.67

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	905.085	30.495	29.680	< 2e-16 ***
M	110.382	52.424	2.106	0.04344 *
So	-1.822	71.250	-0.026	0.97977
Ed	210.678	69.458	3.033	0.00486 **
Po1	572.995	315.347	1.817	0.07889 .
Po2	-305.958	328.483	-0.931	0.35883
LF	-26.826	59.394	-0.452	0.65465
M.F	51.293	59.977	0.855	0.39900
Pop	-27.906	49.095	-0.568	0.57385
NW	43.234	66.642	0.649	0.52128
U1	-105.056	75.906	-1.384	0.17624
U2	141.714	69.536	2.038	0.05016 .
Wealth	92.792	100.028	0.928	0.36075
Ineq	281.954	90.630	3.111	0.00398 **
Prob	-110.394	51.667	-2.137	0.04063 *
Time	-24.655	50.780	-0.486	0.63071

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 209.1 on 31 degrees of freedom

Multiple R-squared: 0.8031, Adjusted R-squared: 0.7078

F-statistic: 8.429 on 15 and 31 DF, p-value: 3.539e-07

4. Evaluation of Models

P-Values of Coefficients

A low P-value (< 0.05) means that the coefficient is likely not to equal zero. A high P-value (> 0.05) means that we cannot conclude that the explanatory variable affects the dependent variable

Source: <https://feliperego.github.io/blog/2015/10/23/Interpreting-Model-Output-In-R> (<https://feliperego.github.io/blog/2015/10/23/Interpreting-Model-Output-In-R>)

I will remove coefficients with P-Value greater than 0.05 later

- so
- po1
- po2
- LF
- M.F.
- Pop
- NW
- U1
- U2
- wealth
- time

Train-Test Split Accuracy Test

Source: <http://www.sthda.com/english/articles/40-regression-analysis/165-linear-regression-essentials-in-r/> (<http://www.sthda.com/english/articles/40-regression-analysis/165-linear-regression-essentials-in-r/>)

Source: <https://www.statology.org/train-test-split-r/> (<https://www.statology.org/train-test-split-r/>)

Test on Model 1 (Unscaled Data)

In [15]:

library(caTools)

In [31]:

```
head(crime)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>
1	15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011	791
2	14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999	1635
3	14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401	24.3006	578
4	13.6	0	12.1	14.9	14.1	0.577	99.4	157	8.0	0.102	3.9	6730	16.7	0.015801	29.9012	1969
5	14.1	0	12.1	10.9	10.1	0.591	98.5	18	3.0	0.091	2.0	5780	17.4	0.041399	21.2998	1234
6	12.1	0	11.0	11.8	11.5	0.547	96.4	25	4.4	0.084	2.9	6890	12.6	0.034201	20.9995	682

In [17]:

```
set.seed(123)
#use 70% of dataset as training set and 30% as test set
split = sample.split(crime$Crime, SplitRatio = 0.7)
train  = subset(crime, split == TRUE)
test   = subset(crime, split == FALSE)
```

In [32]:

```
head(train)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>
1	15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011	791
3	14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401	24.3006	578
6	12.1	0	11.0	11.8	11.5	0.547	96.4	25	4.4	0.084	2.9	6890	12.6	0.034201	20.9995	682
7	12.7	1	11.1	8.2	7.9	0.519	98.2	4	13.9	0.097	3.8	6200	16.8	0.042100	20.6993	963
9	15.7	1	9.0	6.5	6.2	0.553	95.5	39	28.6	0.081	2.8	4210	23.9	0.071697	29.4001	856
10	14.0	0	11.8	7.1	6.8	0.632	102.9	7	1.5	0.100	2.4	5260	17.4	0.044498	19.5994	705

In [19]:

```
names(train)
```

'M' · 'So' · 'Ed' · 'Po1' · 'Po2' · 'LF' · 'M.F' · 'Pop' · 'NW' · 'U1' · 'U2' · 'Wealth' · 'Ineq' · 'Prob' · 'Time' · 'Crime'

In [33]:

```
head(test)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>
2	14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999	1635
4	13.6	0	12.1	14.9	14.1	0.577	99.4	157	8.0	0.102	3.9	6730	16.7	0.015801	29.9012	1969
5	14.1	0	12.1	10.9	10.1	0.591	98.5	18	3.0	0.091	2.0	5780	17.4	0.041399	21.2998	1234
8	13.1	1	10.9	11.5	10.9	0.542	96.9	50	17.9	0.079	3.5	4720	20.6	0.040099	24.5988	1555
11	12.4	0	10.5	12.1	11.6	0.580	96.6	101	10.6	0.077	3.5	6570	17.0	0.016201	41.6000	1674
16	14.2	1	8.8	8.1	7.7	0.497	95.6	33	32.1	0.116	4.7	4270	24.7	0.052099	26.0991	946

In [21]:

```
names(test)
```

'M' · 'So' · 'Ed' · 'Po1' · 'Po2' · 'LF' · 'M.F' · 'Pop' · 'NW' · 'U1' · 'U2' · 'Wealth' · 'Ineq' · 'Prob' · 'Time' · 'Crime'

In [34]:

```
# Train Model using Unscaled Data
model <- lm(Crime ~ M+So+Ed+Po1+Po2+LF+M.F+Pop+Nw+U1+U2+Wealth+Ineq+Prob+Time, data=train)
```

In [35]:

```
model
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = train)

Coefficients:

(Intercept)	M	So	Ed	Po1	Po2
-3.094e+03	1.218e+02	6.252e+01	1.158e+02	1.505e+02	-7.226e+01
LF	M.F	Pop	NW	U1	U2
1.427e+03	-1.846e+01	-2.043e+00	6.782e+00	1.492e+03	6.862e+01
Wealth	Ineq	Prob	Time		
7.033e-02	4.973e+01	-4.958e+03	-4.693e+00		

In [36]:

```
summary(model)
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = train)

Residuals:

Min	1Q	Median	3Q	Max
-287.128	-65.042	-4.796	103.893	298.405

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-3.094e+03	1.892e+03	-1.636	0.1214
M	1.218e+02	5.851e+01	2.082	0.0538
So	6.252e+01	1.670e+02	0.374	0.7131
Ed	1.158e+02	9.058e+01	1.278	0.2193
Po1	1.505e+02	1.359e+02	1.107	0.2845
Po2	-7.226e+01	1.376e+02	-0.525	0.6068
LF	1.427e+03	2.346e+03	0.608	0.5515
M.F	-1.846e+01	2.848e+01	-0.648	0.5260
Pop	-2.043e+00	1.748e+00	-1.169	0.2595
NW	6.782e+00	8.065e+00	0.841	0.4128
U1	1.492e+03	5.299e+03	0.282	0.7819
U2	6.862e+01	1.052e+02	0.652	0.5235
Wealth	7.033e-02	1.300e-01	0.541	0.5958
Ineq	4.973e+01	2.408e+01	2.065	0.0555
Prob	-4.958e+03	2.484e+03	-1.996	0.0632
Time	-4.694e+00	8.425e+00	-0.557	0.5852

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 186.3 on 16 degrees of freedom
Multiple R-squared: 0.6955, Adjusted R-squared: 0.41
F-statistic: 2.436 on 15 and 16 DF, p-value: 0.04361

In [44]:

```
pred <- predict(model, test)
```

In [45]:

```
pred
```

2: 1307.43637908047 4: 1413.86347241968 5: 1183.18623573892 8: 1173.29695832952 11: 911.744484497506 16: 1117.75858148835 20: 1077.31969386968 21: 752.574620263444 22: 832.68523190931 24: 870.408783693826 26: 1599.58579046693 31: 439.77242807706 32: 713.3862501965 34: 817.194137524441 37: 1364.52664269435

In [46]:

```
model %>% predict(test)
```

2: 1307.43637908047 4: 1413.86347241968 5: 1183.18623573892 8: 1173.29695832952 11: 911.744484497506 16: 1117.75858148835 20: 1077.31969386968 21: 752.574620263444 22: 832.68523190931 24: 870.408783693826 26: 1599.58579046693 31: 439.77242807706 32: 713.3862501965 34: 817.194137524441 37: 1364.52664269435

<https://www.statology.org/error-in-evalpredvars-data-env-object-not-found/#:~:text=This%20error%20occurs%20when%20you,used%20to%20fit%20the%20model>
(<https://www.statology.org/error-in-evalpredvars-data-env-object-not-found/#:~:text=This%20error%20occurs%20when%20you,used%20to%20fit%20the%20model>).

In [47]:

```
sum(pred == test[,16]) / nrow(test) # Incorrect to use this as it is not a classification model
```

0

In [49]:

```
# Calculate Sum of Squared Error For Predictions
sum((pred-test[,16])^2)
```

1817449.95771349

In [84]:

```
# Calculate Root Mean Squared Error For Predictions
sqrt((sum((pred-test[,16])^2)/nrow(test)))
```

348.085234553597

Test on Model 2 (Scaled Data)

In [56]:

```
crime_scaled <- crime
```

In [57]:

```
crime_scaled[,1:15]<-scale(crime_scaled[,1:15])
```

In [58]:

```
head(crime_scaled)
```

Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Cr
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<
5099	-0.9085105	-0.8666988	-1.2667456	-1.12060499	-0.09500679	1.943738564	0.69510600	0.8313680	-1.3616094	1.6793638	1.6497631	-0.05599367	
0587	0.6056737	0.5280852	0.5396568	0.98341752	-0.62033844	0.008483424	0.02950365	0.2393332	0.3276683	0.0000000	-0.7693365	-0.18315796	
2888	-1.3459415	-1.2958632	-0.6976051	-0.47582390	-0.48900552	1.146296747	-0.08143007	-0.1158877	-2.1492481	1.4036474	1.5969416	-0.32416470	
1746	2.1535064	2.1732150	0.3911854	0.37257228	3.16204944	-0.205464381	0.36230482	0.5945541	1.5298536	-0.6767585	-1.3761895	0.46611085	
1746	0.8075649	0.7426673	0.7376187	0.06714965	-0.48900552	-0.691709391	-0.24783066	-1.6551781	0.5453053	-0.5013026	-0.2503580	-0.74759413	
8903	1.1104017	1.2433590	-0.3511718	-0.64550313	-0.30513945	-0.555560788	-0.63609870	-0.5895155	1.6956723	-1.7044289	-0.5669349	-0.78996812	

In [59]:

```
set.seed(123)
#use 70% of dataset as training set and 30% as test set
scale_split = sample.split(crime_scaled$Crime, SplitRatio = 0.7)
scale_train = subset(crime_scaled, split == TRUE)
scale_test = subset(crime_scaled, split == FALSE)
```

In [61]:

```
head(scale_train)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	
1	0.9886930	1.3770536	-1.3085099	-0.9085105	-0.86669885	-1.2667456	-1.12060499	-0.09500679	1.9437386	0.69510600	0.8313680	-1.361609422	1
3	0.2725678	1.3770536	-1.4872888	-1.3459415	-1.29586316	-0.6976051	-0.47582390	-0.48900552	1.1462967	-0.08143007	-0.1158877	-2.149248102	1
6	-1.3983912	-0.7107373	0.3898903	1.1104017	1.24335901	-0.3511718	-0.64550313	-0.30513945	-0.5555608	-0.63609870	-0.5895155	1.695672300	-1
7	-0.9209743	1.3770536	0.4792798	-0.1009456	-0.04413392	-1.0440385	-0.03465789	-0.85673768	0.3683047	0.08497051	0.4761471	0.980579287	-0
9	1.4661099	1.3770536	-1.3978993	-0.6729708	-0.65211669	-0.2027004	-0.95092575	0.06259271	1.7978651	-0.80249928	-0.7079224	-1.081790417	1
10	0.1134288	-0.7107373	1.1050061	-0.4710795	-0.43753454	1.7521735	1.56032692	-0.77793793	-0.8375829	0.25137110	-1.1815502	0.006394603	-0

In [62]:

```
head(scale_test)
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	
2	0.3521372	-0.7107373	0.65805874	0.6056737	0.5280852	0.5396568	0.98341752	-0.62033844	0.008483424	0.02950365	0.2393332	0.3276683	0.
4	-0.2048491	-0.7107373	1.37317459	2.1535064	2.1732150	0.3911854	0.37257228	3.16204944	-0.205464381	0.36230482	0.5945541	1.5298536	-0.
5	0.1929983	-0.7107373	1.37317459	0.8075649	0.7426673	0.7376187	0.06714965	-0.48900552	-0.691709391	-0.24783066	-1.6551781	0.5453053	-0.
8	-0.6026964	1.3770536	0.30050081	1.0094561	1.0287769	-0.4748980	-0.47582390	0.35152511	0.757300739	-0.91343301	0.1209263	-0.5532434	0.
11	-1.1596827	-0.7107373	-0.05705712	1.2113474	1.2791227	0.4654211	-0.57763144	1.69112082	0.047383024	-1.02436673	0.1209263	1.3640350	-0.
16	0.2725678	1.3770536	-1.57667830	-0.1345942	-0.1156613	-1.5884338	-0.91698990	-0.09500679	2.138236568	1.13884089	1.5418097	-1.0196084	1.

In [63]:

```
# Train Model using Unscaled Data
model_scaled <- lm(Crime ~ M+So+Ed+Po1+Po2+LF+M.F+Pop+NW+U1+U2+Wealth+Ineq+Prob+Time, data=scale_train)
```

In [64]:

```
model_scaled
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = scale_train)

Coefficients:

(Intercept)	M	So	Ed	Po1	Po2
869.21	153.08	29.94	129.55	447.23	-202.06
LF	M.F	Pop	NW	U1	U2
57.67	-54.40	-77.78	69.74	26.90	57.96
Wealth	Ineq	Prob	Time		
67.86	198.41	-112.73	-33.26		

In [65]:

```
summary(model_scaled)
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = scale_train)

Residuals:

Min	1Q	Median	3Q	Max
-287.128	-65.042	-4.796	103.893	298.405

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	869.21	40.72	21.345	3.5e-13 ***
M	153.08	73.54	2.082	0.0538 .
So	29.94	80.01	0.374	0.7131
Ed	129.55	101.34	1.278	0.2193
Po1	447.23	403.82	1.107	0.2845
Po2	-202.06	384.86	-0.525	0.6068
LF	57.67	94.80	0.608	0.5515
M.F	-54.40	83.91	-0.648	0.5260
Pop	-77.78	66.53	-1.169	0.2595
NW	69.74	82.93	0.841	0.4128
U1	26.90	95.53	0.282	0.7819
U2	57.96	88.86	0.652	0.5235
Wealth	67.86	125.39	0.541	0.5958
Ineq	198.41	96.08	2.065	0.0555 .
Prob	-112.73	56.47	-1.996	0.0632 .
Time	-33.26	59.71	-0.557	0.5852

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 186.3 on 16 degrees of freedom
Multiple R-squared: 0.6955, Adjusted R-squared: 0.41
F-statistic: 2.436 on 15 and 16 DF, p-value: 0.04361

In [68]:

```
scale_pred <- predict(model_scaled, scale_test)
```


In [69]:

```
scale_pred
```

2: 1307.43637908046 4: 1413.86347241967 5: 1183.18623573892 8: 1173.29695832952 11: 911.744484497504 16: 1117.75858148834 20: 1077.31969386968 21: 752.574620263441 22: 832.685231909299 24: 870.408783693821 26: 1599.58579046693 31: 439.772428077062 32: 713.386250196495 34: 817.194137524438 37: 1364.52664269433

In [67]:

```
# Calculate R Squared Error For Predictions
sum((scale_pred-scale_test[,16])^2)
```

1817449.95771349

In [85]:

```
# Calculate Root Mean Squared Error For Predictions
sqrt((sum((scale_pred-scale_test[,16])^2)/nrow(test)))
```

348.085234553597

The unscaled data also had a *RMSE* score of 348.085234553597

5. Predictions

M = 14.0 So = 0 Ed = 10.0 Po1 = 12.0 Po2 = 15.5 LF = 0.640 M.F = 94.0 Pop = 150 NW = 1.1 U1 = 0.120 U2 = 3.6 Wealth = 3200 Ineq = 20.1 Prob = 0.04 Time = 39.0

In [71]:

```
x <- c(14.0, 0, 10.0, 12.0, 15.5, 0.640, 94.0, 150, 1.1, 0.120, 3.6, 3200, 20.1, 0.04, 39.0)
```

In [73]:

```
x<-list("M" = 14.0, "So" = 0, "Ed" = 10.0, "Po1" = 12.0, "Po2" = 15.5, "LF" = 0.640, "M.F" = 94.0, "Pop" = 150, "NW" = 1.1, "U1" = 0.120,
```

In [76]:

```
crime_pred_scaled <- predict(model_scaled, x)
```

In [77]:

```
crime_pred_scaled
```

1: 209924.369411726

In [78]:

```
crime_pred<-predict(model,x)
```

In [79]:

```
crime_pred
```

1: 603.326307807169

The Model Coefficients

In [80]:

```
model
```

Call:
lm(formula = Crime ~ M + So + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time, data = train)

Coefficients:

(Intercept)	M	So	Ed	Po1	Po2
-3.094e+03	1.218e+02	6.252e+01	1.158e+02	1.505e+02	-7.226e+01
LF	M.F	Pop	NW	U1	U2
1.427e+03	-1.846e+01	-2.043e+00	6.782e+00	1.492e+03	6.862e+01
Wealth	Ineq	Prob	Time		
7.033e-02	4.973e+01	-4.958e+03	-4.693e+00		

Prediction of Crime Level

I have to use the unscaled model to predict because the required input is unscaled.

The predicted crime level is 603.326.

The Quality of Fit

The *RMSE* of the Model is 348.085234553597

In [82]:

```
sd(crime$Crime)
```

386.762697146186

In [83]:

```
summary(crime$Crime)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
342.0	658.5	831.0	905.1	1057.5	1993.0

The RMSE is similar to the data Standard Deviation, and the value of the RMSE is close to the minimum value of the data, which is a good sign. To make the fit better, I can also remove the coefficients with high P-Values.