Homework_5

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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.

Climbing

Using linear regression to track my climbing progress could be helpful and object. Climbing has several climbing grades depending on what type of climbing you do. I'll just speak about lead climbing which uses the Yosemite or YDS grading scale. The linear regression could use these independent variables: climbing frequency, training hours, rest days, body measurements, onsight difficulty. To onsight in sports climbing means to reach the top on the first try with little information or mistake.

The formula [1]:

$$\text{Climbing Difficulty} = \beta_0 + \beta_1(\text{Climbing Frequency}) + \beta_2(\text{Training Hours}) + \beta_3(\text{Rest Days}) + \beta_4(\text{Body Measurements}) + \beta_5(\text{Onsight Diff}$$

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.

The formula [2]:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where: - R^2 is the R-squared value - SS_{res} is the sum of squares of the residuals - SS_{tot} is the total sum of squares

Interpretations of results:

In this initial model, I did not select any independent variables or predictors; instead, I fed the entire dataset into the model to identify potential correlations. I examined the coefficients for indications of high correlations. My undergraduate professor humorously referred to the coefficient asterisks as "twinkle twinkle little stars"—the more stars, the stronger the correlation. I observed that both Ed and Ineq have two asterisks, indicating they are significantly correlated with crime rates.

The residual standard error is 209.1, which reflects the model's fitness. A lower residual standard error indicates a better fit. The multiple R-squared value is 0.8031, and the adjusted R-squared value is 0.7078. The F-statistic is 8.42. According to Dr. Sokol's lecture, R-squared values of 0.4 or 0.5 are considered quite good. The p-value of 3.539e-07 is lower than 0.05, indicating that the model is statistically significant.

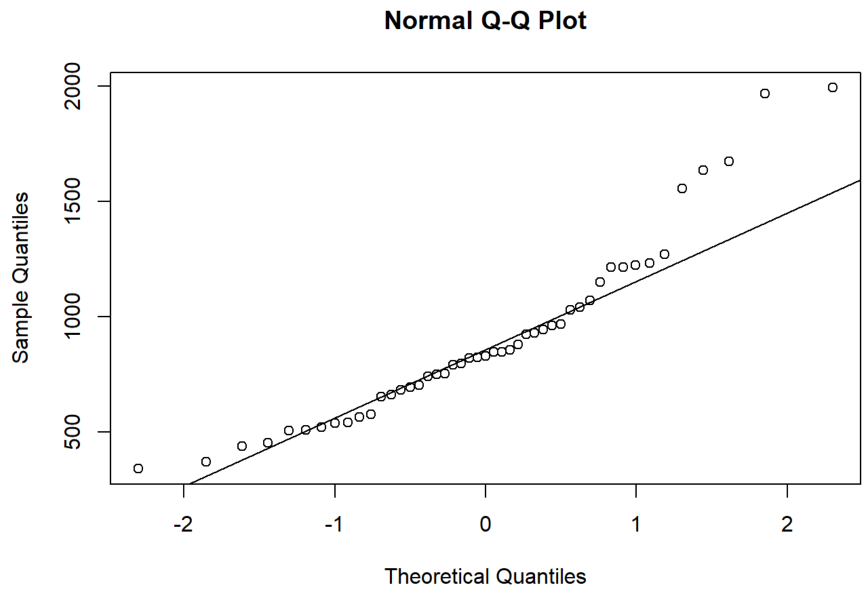
```r
# Remove all objects from the current workspace
rm(list = ls())

# Load necessary libraries
library(DAAG)

# Read the data from the specified file path into a data frame
uscrime <- read.table("C://Users//Clair//OneDrive//Documents//GitHub//omsa//ISYE 6501//Homework 5//uscrime.txt", stringsAsFa
ctors = FALSE, header = TRUE)

# Fit a linear model to the data with 'Crime' as the response variable and all other variables as predictors
lm_uscrime <- lm(Crime ~ ., data = uscrime)

# Display the linear model object
lm_uscrime
```

```
##
## Call:
## lm(formula = Crime ~ ., data = uscrime)
##
## 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
```

```r
# Display a summary of the linear model, including coefficients, R-squared, etc.
summary(lm_uscrime)
```

```
##
## Call:
## lm(formula = Crime ~ ., data = uscrime)
##
## 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) -5.984e+03  1.628e+03  -3.675 0.000893 ***
## M            8.783e+01  4.171e+01   2.106 0.043443 *
## So          -3.803e+00  1.488e+02  -0.026 0.979765
## Ed           1.883e+02  6.209e+01   3.033 0.004861 **
## Po1          1.928e+02  1.061e+02   1.817 0.078892 .
## Po2         -1.094e+02  1.175e+02  -0.931 0.358830
## LF          -6.638e+02  1.470e+03  -0.452 0.654654
## M.F          1.741e+01  2.035e+01   0.855 0.398995
## Pop         -7.330e-01  1.290e+00  -0.568 0.573845
## NW           4.204e+00  6.481e+00   0.649 0.521279
## U1          -5.827e+03  4.210e+03  -1.384 0.176238
## U2           1.678e+02  8.234e+01   2.038 0.050161 .
## Wealth       9.617e-02  1.037e-01   0.928 0.360754
## Ineq         7.067e+01  2.272e+01   3.111 0.003983 **
## Prob        -4.855e+03  2.272e+03  -2.137 0.040627 *
## Time        -3.479e+00  7.165e+00  -0.486 0.630708
## ---
## 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
```

```r
# Check the normality of the 'Crime' variable in the dataset using a Q-Q plot
qqnorm(uscrime$Crime)
qqline(uscrime$Crime)
```




```
# Calculate the total sum of squares (SST)
total_sum_squared_diff <- sum((uscrime$Crime - mean(uscrime$Crime))^2)
total_sum_squared_diff
```

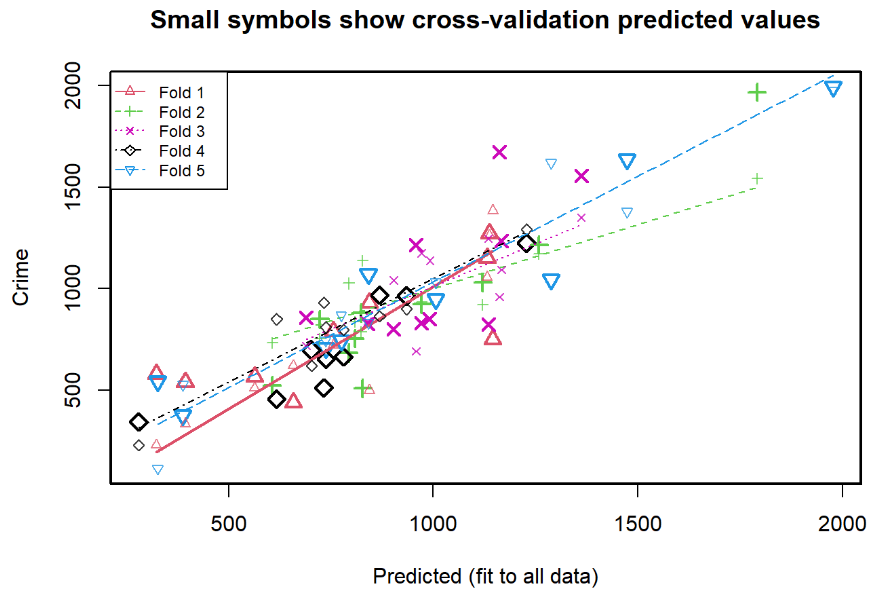
```
## [1] 6880928
```

```
# Calculate the sum of squares of the residuals (SSE)
sum_squared_residuals <- sum(residuals(lm_uscrime)^2)

# Calculate R-squared
r_squared <- 1 - (sum_squared_residuals / total_sum_squared_diff)
r_squared
```

```
## [1] 0.8030868
```

```
# Perform 5-fold cross-validation
set.seed(42)
cv_results <- cv.lm(uscrime, lm_uscrime, m = 5)
```

```
## Warning in cv.lm(uscrime, lm_uscrime, m = 5):
##
##  As there is >1 explanatory variable, cross-validation
##  predicted values for a fold are not a linear function
##  of corresponding overall predicted values.  Lines that
##  are shown for the different folds are approximate
```


Small symbols show cross-validation predicted values
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Crime
500
1000
1500
2000
Predicted (fit to all data)

```
##
## fold 1
## Observations in test set: 9
##                    1        3       17       18        19        22         36
## Predicted   755.03222 322.2615 393.3633 843.8072 1145.7379  657.2092 1137.61711
## cvpred      719.48189 227.3811 334.2928 497.4904 1384.9349  620.1834 1261.61602
## Crime       791.00000 578.0000 539.0000 929.0000  750.0000  439.0000 1272.00000
## CV residual  71.51811 350.6189 204.7072 431.5096 -634.9349 -181.1834   10.38398
##                   38         40
## Predicted   562.6934 1131.45326
## cvpred      509.0826 1057.08701
## Crime       566.0000 1151.00000
## CV residual  56.9174   93.91299
##
## Sum of squares = 804290.7    Mean square = 89365.64    n = 9
##
## fold 2
## Observations in test set: 10
##                    4         6        12        25         28        32
## Predicted   1791.3619  792.9301 722.04080  605.8824 1258.48423 807.81667
## cvpred      1542.8663 1025.6864 752.84607  733.1797 1170.10415 836.60938
## Crime       1969.0000  682.0000 849.00000  523.0000 1216.00000 754.00000
## CV residual  426.1337 -343.6864  96.15393 -210.1797   45.89585 -82.60938
##                   34        41        44        46
## Predicted   971.45581 823.74192 1120.8227  827.3543
## cvpred      934.62797 786.74042  919.1066 1137.6778
## Crime       923.00000 880.00000 1030.0000  508.0000
## CV residual -11.62797  93.25958  110.8934 -629.6778
##
## Sum of squares = 779686.2    Mean square = 77968.62    n = 10
##
## fold 3
## Observations in test set: 10
##                    5         8        9        11        15        23
## Predicted   1166.6840 1361.7468 688.8682 1161.3291  903.3541  957.9918
## cvpred      1092.1924 1349.7715 717.0401  958.3058 1040.2775  690.2073
## Crime       1234.0000 1555.0000 856.0000 1674.0000  798.0000 1216.0000
## CV residual  141.8076  205.2285 138.9599  715.6942 -242.2775  525.7927
##                   37       39        43        47
## Predicted    971.1513 839.2864 1134.4172  991.7629
## cvpred      1174.2195 838.1895 1246.7022 1138.2873
## Crime        831.0000 826.0000  823.0000  849.0000
## CV residual -343.2195 -12.1895 -423.7022 -289.2873
##
## Sum of squares = 1310071    Mean square = 131007.1    n = 10
##
## fold 4
## Observations in test set: 9
##                    7        13        14         20       24       27
## Predicted   934.16366  732.6412  780.0401 1227.83873 868.9805 279.4772
## cvpred      898.53488  929.2776  797.4106 1290.40739 863.7702 227.4408
## Crime       963.00000  511.0000  664.0000 1225.00000 968.0000 342.0000
## CV residual  64.46512 -418.2776 -133.4106  -65.40739 104.2298 114.5592
##                   30        35        45
## Predicted   702.69454  737.7888  616.8983
## cvpred      618.72406  808.0845  848.6350
## Crime       696.00000  653.0000  455.0000
## CV residual  77.27594 -155.0845 -393.6350
##
## Sum of squares = 410147.4    Mean square = 45571.93    n = 9
##
## fold 5
## Observations in test set: 9
##                    2        10         16        21         26        29
## Predicted   1473.6764 736.50802 1005.65694  774.8506 1977.37067 1287.3917
## cvpred      1379.5108 743.27567 1031.35676  867.6315 1975.12567 1619.8299
## Crime       1635.0000 705.00000  946.00000  742.0000 1993.00000 1043.0000
## CV residual  255.4892 -38.27567  -85.35676 -125.6315   17.87433 -576.8299
##                   31        33       42
## Predicted    388.0334  840.9992 326.3324
## cvpred       525.4791  830.6871 112.9800
## Crime        373.0000 1072.0000 542.0000
## CV residual -152.4791  241.3129 429.0200
##
## Sum of squares = 688401.1    Mean square = 76489.01    n = 9
##
## Overall (Sum over all 9 folds)
```

```
##       ms
## 84948.87
```

```
cv_results
```

```
##       M So   Ed  Po1  Po2    LF   M.F Pop   NW    U1  U2 Wealth Ineq     Prob
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 12 13.4  0 10.8  7.5  7.1 0.595  97.2  47  5.9 0.083 3.1   5800 17.2 0.031201
## 13 12.8  0 11.3  6.7  6.0 0.624  97.2  28  1.0 0.077 2.5   5070 20.6 0.045302
## 14 13.5  0 11.7  6.2  6.1 0.595  98.6  22  4.6 0.077 2.7   5290 19.0 0.053200
## 15 15.2  1  8.7  5.7  5.3 0.530  98.6  30  7.2 0.092 4.3   4050 26.4 0.069100
## 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
## 17 14.3  0 11.0  6.6  6.3 0.537  97.7  10  0.6 0.114 3.5   4870 16.6 0.076299
## 18 13.5  1 10.4 12.3 11.5 0.537  97.8  31 17.0 0.089 3.4   6310 16.5 0.119804
## 19 13.0  0 11.6 12.8 12.8 0.536  93.4  51  2.4 0.078 3.4   6270 13.5 0.019099
## 20 12.5  0 10.8 11.3 10.5 0.567  98.5  78  9.4 0.130 5.8   6260 16.6 0.034801
## 21 12.6  0 10.8  7.4  6.7 0.602  98.4  34  1.2 0.102 3.3   5570 19.5 0.022800
## 22 15.7  1  8.9  4.7  4.4 0.512  96.2  22 42.3 0.097 3.4   2880 27.6 0.089502
## 23 13.2  0  9.6  8.7  8.3 0.564  95.3  43  9.2 0.083 3.2   5130 22.7 0.030700
## 24 13.1  0 11.6  7.8  7.3 0.574 103.8   7  3.6 0.142 4.2   5400 17.6 0.041598
## 25 13.0  0 11.6  6.3  5.7 0.641  98.4  14  2.6 0.070 2.1   4860 19.6 0.069197
## 26 13.1  0 12.1 16.0 14.3 0.631 107.1   3  7.7 0.102 4.1   6740 15.2 0.041698
## 27 13.5  0 10.9  6.9  7.1 0.540  96.5   6  0.4 0.080 2.2   5640 13.9 0.036099
## 28 15.2  0 11.2  8.2  7.6 0.571 101.8  10  7.9 0.103 2.8   5370 21.5 0.038201
## 29 11.9  0 10.7 16.6 15.7 0.521  93.8 168  8.9 0.092 3.6   6370 15.4 0.023400
## 30 16.6  1  8.9  5.8  5.4 0.521  97.3  46 25.4 0.072 2.6   3960 23.7 0.075298
## 31 14.0  0  9.3  5.5  5.4 0.535 104.5   6  2.0 0.135 4.0   4530 20.0 0.041999
## 32 12.5  0 10.9  9.0  8.1 0.586  96.4  97  8.2 0.105 4.3   6170 16.3 0.042698
## 33 14.7  1 10.4  6.3  6.4 0.560  97.2  23  9.5 0.076 2.4   4620 23.3 0.049499
## 34 12.6  0 11.8  9.7  9.7 0.542  99.0  18  2.1 0.102 3.5   5890 16.6 0.040799
## 35 12.3  0 10.2  9.7  8.7 0.526  94.8 113  7.6 0.124 5.0   5720 15.8 0.020700
## 36 15.0  0 10.0 10.9  9.8 0.531  96.4   9  2.4 0.087 3.8   5590 15.3 0.006900
## 37 17.7  1  8.7  5.8  5.6 0.638  97.4  24 34.9 0.076 2.8   3820 25.4 0.045198
## 38 13.3  0 10.4  5.1  4.7 0.599 102.4   7  4.0 0.099 2.7   4250 22.5 0.053998
## 39 14.9  1  8.8  6.1  5.4 0.515  95.3  36 16.5 0.086 3.5   3950 25.1 0.047099
## 40 14.5  1 10.4  8.2  7.4 0.560  98.1  96 12.6 0.088 3.1   4880 22.8 0.038801
## 41 14.8  0 12.2  7.2  6.6 0.601  99.8   9  1.9 0.084 2.0   5900 14.4 0.025100
## 42 14.1  0 10.9  5.6  5.4 0.523  96.8   4  0.2 0.107 3.7   4890 17.0 0.088904
## 43 16.2  1  9.9  7.5  7.0 0.522  99.6  40 20.8 0.073 2.7   4960 22.4 0.054902
## 44 13.6  0 12.1  9.5  9.6 0.574 101.2  29  3.6 0.111 3.7   6220 16.2 0.028100
## 45 13.9  1  8.8  4.6  4.1 0.480  96.8  19  4.9 0.135 5.3   4570 24.9 0.056202
## 46 12.6  0 10.4 10.6  9.7 0.599  98.9  40  2.4 0.078 2.5   5930 17.1 0.046598
## 47 13.0  0 12.1  9.0  9.1 0.623 104.9   3  2.2 0.113 4.0   5880 16.0 0.052802
##       Time Crime Predicted    cvpred fold
## 1  26.2011   791  755.0322  719.4819    1
## 2  25.2999  1635 1473.6764 1379.5108    5
## 3  24.3006   578  322.2615  227.3811    1
## 4  29.9012  1969 1791.3619 1542.8663    2
## 5  21.2998  1234 1166.6840 1092.1924    3
## 6  20.9995   682  792.9301 1025.6864    2
## 7  20.6993   963  934.1637  898.5349    4
## 8  24.5988  1555 1361.7468 1349.7715    3
## 9  29.4001   856  688.8682  717.0401    3
## 10 19.5994   705  736.5080  743.2757    5
## 11 41.6000  1674 1161.3291  958.3058    3
## 12 34.2984   849  722.0408  752.8461    2
## 13 36.2993   511  732.6412  929.2776    4
## 14 21.5010   664  780.0401  797.4106    4
## 15 22.7008   798  903.3541 1040.2775    3
## 16 26.0991   946 1005.6569 1031.3568    5
## 17 19.1002   539  393.3633  334.2928    1
## 18 18.1996   929  843.8072  497.4904    1
## 19 24.9008   750 1145.7379 1384.9349    1
## 20 26.4010  1225 1227.8387 1290.4074    4
## 21 37.5998   742  774.8506  867.6315    5
## 22 37.0994   439  657.2092  620.1834    1
## 23 25.1989  1216  957.9918  690.2073    3
## 24 17.6000   968  868.9805  863.7702    4
## 25 21.9003   523  605.8824  733.1797    2
## 26 22.1005  1993 1977.3707 1975.1257    5
## 27 28.4999   342  279.4772  227.4408    4
## 28 25.8006  1216 1258.4842 1170.1042    2
```

```
## 29 36.7009  1043 1287.3917 1619.8299    5
## 30 28.3011   696  702.6945  618.7241    4
## 31 21.7998   373  388.0334  525.4791    5
## 32 30.9014   754  807.8167  836.6094    2
## 33 25.5005  1072  840.9992  830.6871    5
## 34 21.6997   923  971.4558  934.6280    2
## 35 37.4011   653  737.7888  808.0845    4
## 36 44.0004  1272 1137.6171 1261.6160    1
## 37 31.6995   831  971.1513 1174.2195    3
## 38 16.6999   566  562.6934  509.0826    1
## 39 27.3004   826  839.2864  838.1895    3
## 40 29.3004  1151 1131.4533 1057.0870    1
## 41 30.0001   880  823.7419  786.7404    2
## 42 12.1996   542  326.3324  112.9800    5
## 43 31.9989   823 1134.4172 1246.7022    3
## 44 30.0001  1030 1120.8227  919.1066    2
## 45 32.5996   455  616.8983  848.6350    4
## 46 16.6999   508  827.3543 1137.6778    2
## 47 16.0997   849  991.7629 1138.2873    3
```

Interpretations of results:

In this improved model, I selected a subset of predictors (M, Ed, Po1, U2, Ineq, Prob) from the full list. I also conducted a cross-validation test to ensure the model’s quality. Regarding the coefficients, Ed, Po1, and Ineq are the most significant, while M is significant, and U2 and Prob are less significant. Overall, this new model demonstrates stronger correlations and coefficients compared to the initial model. The residual standard error is 200.7, which is similar to the original model’s score. The multiple R-squared value is 0.7659, slightly better than the original model’s 0.8031, and the adjusted R-squared value is 0.7307, which is higher than the original model’s 0.7078. According to Dr. Sokol’s lecture, R-squared values of 0.4 or 0.5 are considered quite good. The p-value of 3.418e-11 is lower than 0.05 (and 3.539e-07 from the first model), indicating that this model is statistically significant and more significant than the first model.

```
# Remove all objects from the current workspace
rm(list = ls())

# Load necessary libraries
library(DAAG)

# Read the data from the specified file path into a data frame
uscrime <- read.table("C://Users//Clair//OneDrive//Documents//GitHub//omsa//ISYE 6501//Homework 5//uscrime.txt", stringsAsFa
ctors = FALSE, header = TRUE)

# Fit a linear model to the data with 'Crime' as the response variable and selected predictors
lm_uscrime_2 <- lm(Crime ~ M + Ed + Po1 + U2 + Ineq + Prob, data = uscrime)

# Display the linear model object
lm_uscrime_2
```

```
##
## Call:
## lm(formula = Crime ~ M + Ed + Po1 + U2 + Ineq + Prob, data = uscrime)
##
## Coefficients:
## (Intercept)            M           Ed          Po1           U2         Ineq
##    -5040.50       105.02       196.47       115.02        89.37        67.65
##        Prob
##    -3801.84
```

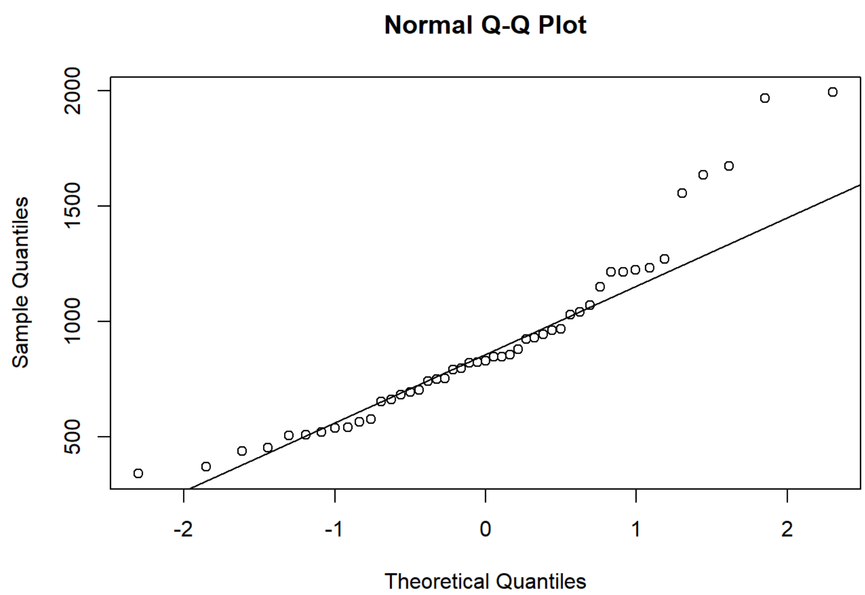
```
# Display a summary of the linear model, including coefficients, R-squared, etc.
summary(lm_uscrime_2)
```

```
##
## Call:
## lm(formula = Crime ~ M + Ed + Po1 + U2 + Ineq + Prob, data = uscrime)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -470.68  -78.41  -19.68  133.12  556.23
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5040.50     899.84  -5.602 1.72e-06 ***
## M             105.02      33.30   3.154  0.00305 **
## Ed            196.47      44.75   4.390 8.07e-05 ***
## Po1           115.02      13.75   8.363 2.56e-10 ***
## U2             89.37      40.91   2.185  0.03483 *
## Ineq           67.65      13.94   4.855 1.88e-05 ***
## Prob        -3801.84    1528.10  -2.488  0.01711 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 200.7 on 40 degrees of freedom
## Multiple R-squared:  0.7659, Adjusted R-squared:  0.7307
## F-statistic: 21.81 on 6 and 40 DF,  p-value: 3.418e-11
```

```
# Create a new data frame with a test point for prediction
test_point <- data.frame(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)

# Use the linear model to predict the 'Crime' value for the test point
pred_model_2 <- predict(lm_uscrime_2, test_point)
pred_model_2
```

```
##        1
## 1304.245
```

```
# Check the normality of the 'Crime' variable in the dataset using a Q-Q plot
qqnorm(uscrime$Crime)
qqline(uscrime$Crime)
```




```
# Calculate the total sum of squares (SST)
total_sum_squared_diff <- sum((uscrime$Crime - mean(uscrime$Crime))^2)
total_sum_squared_diff
```

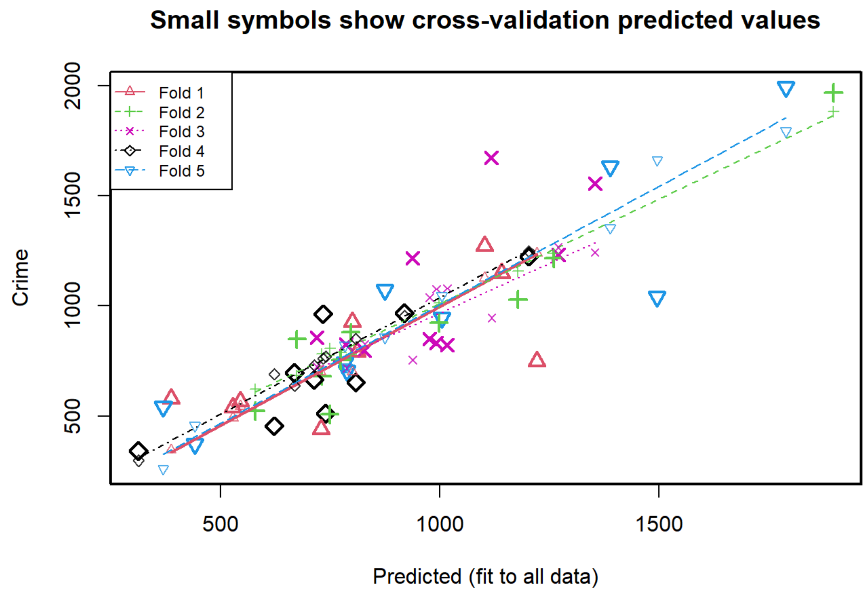
```
## [1] 6880928
```

```
# Calculate the sum of squares of the residuals (SSE)
sum_squared_residuals_2 <- sum(residuals(lm_uscrime_2)^2)

# Calculate R-squared
r_squared_2 <- 1 - (sum_squared_residuals_2 / total_sum_squared_diff)
r_squared_2
```

```
## [1] 0.7658663
```

```
# Perform 5-fold cross-validation
set.seed(42)
cv_results_2 <- cv.lm(uscrime, lm_uscrime_2, m = 5)
```

```
## Warning in cv.lm(uscrime, lm_uscrime_2, m = 5):
##
##  As there is >1 explanatory variable, cross-validation
##  predicted values for a fold are not a linear function
##  of corresponding overall predicted values.  Lines that
##  are shown for the different folds are approximate
```


Small symbols show cross-validation predicted values
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Crime
500
1000
1500
2000
500
1000
1500
Predicted (fit to all data)

```
##
## fold 1
## Observations in test set: 9
##                     1        3       17       18        19        22        36
## Predicted   810.825487 386.1368 527.3659 800.0046 1220.6767  728.3110 1101.7167
## cvpred      785.364736 345.3417 492.2016 700.5751 1240.2916  701.5126 1127.3318
## Crime       791.000000 578.0000 539.0000 929.0000  750.0000  439.0000 1272.0000
## CV residual   5.635264 232.6583  46.7984 228.4249 -490.2916 -262.5126  144.6682
##                   38         40
## Predicted   544.37325 1140.79061
## cvpred      544.69903 1168.21107
## Crime       566.00000 1151.00000
## CV residual  21.30097  -17.21107
##
## Sum of squares = 439507.2    Mean square = 48834.14    n = 9
##
## fold 2
## Observations in test set: 10
##                     4         6       12        25         28        32
## Predicted   1897.18657 730.26589 673.3766 579.06379 1259.00338 773.68402
## cvpred      1882.73805 781.75573 684.3525 621.37453 1238.31917 788.03429
## Crime       1969.00000 682.00000 849.0000 523.00000 1216.00000 754.00000
## CV residual   86.26195 -99.75573 164.6475 -98.37453  -22.31917 -34.03429
##                   34       41        44        46
## Predicted    997.54981 796.4198 1177.5973  748.4256
## cvpred      1013.92532 778.0437 1159.3155  807.6968
## Crime        923.00000 880.0000 1030.0000  508.0000
## CV residual  -90.92532 101.9563 -129.3155 -299.6968
##
## Sum of squares = 181038.4    Mean square = 18103.83    n = 10
##
## fold 3
## Observations in test set: 10
##                     5         8        9        11        15        23
## Predicted   1269.84196 1353.5532 718.7568 1117.7702 828.34178  937.5703
## cvpred      1266.79544 1243.1763 723.5331  946.1309 826.28548  754.2511
## Crime       1234.00000 1555.0000 856.0000 1674.0000 798.00000 1216.0000
## CV residual  -32.79544  311.8237 132.4669  727.8691 -28.28548  461.7489
##                   37       39        43        47
## Predicted    991.5623 786.6949 1016.5503  976.4397
## cvpred      1076.5799 717.0989 1079.7748 1038.3321
## Crime        831.0000 826.0000  823.0000  849.0000
## CV residual -245.5799 108.9011 -256.7748 -189.3321
##
## Sum of squares = 1033612    Mean square = 103361.1    n = 10
##
## fold 4
## Observations in test set: 9
##                   7        13        14        20        24        27
## Predicted   733.3799  739.3727 713.56395 1202.9607 919.39117 312.20470
## cvpred      759.9655  770.2015 730.05546 1247.8616 953.72478 297.19321
## Crime       963.0000  511.0000 664.00000 1225.0000 968.00000 342.00000
## CV residual 203.0345 -259.2015 -66.05546  -22.8616  14.27522  44.80679
##                   30        35        45
## Predicted   668.01610  808.0296  621.8592
## cvpred      638.87118  850.6961  690.6802
## Crime       696.00000  653.0000  455.0000
## CV residual  57.12882 -197.6961 -235.6802
##
## Sum of squares = 213398.5    Mean square = 23710.94    n = 9
##
## fold 5
## Observations in test set: 9
##                    2        10        16        21        26        29
## Predicted   1387.8082 787.27124 1004.3984 783.27334 1789.1406 1495.4856
## cvpred      1355.7097 723.66781 1046.8197 819.71145 1794.6456 1663.6272
## Crime       1635.0000 705.00000  946.0000 742.00000 1993.0000 1043.0000
## CV residual  279.2903 -18.66781 -100.8197 -77.71145  198.3544 -620.6272
##                  31        33       42
## Predicted   440.4394  873.8469 368.7031
## cvpred      456.5736  857.7052 260.9211
## Crime       373.0000 1072.0000 542.0000
## CV residual -83.5736  214.2948 281.0789
##
## Sum of squares = 650990    Mean square = 72332.23    n = 9
##
## Overall (Sum over all 9 folds)
```

```
##       ms
## 53586.08
```

```
cv_results_2
```

```
##       M So   Ed  Po1  Po2    LF   M.F Pop   NW    U1  U2 Wealth Ineq     Prob
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 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
## 12 13.4  0 10.8  7.5  7.1 0.595  97.2  47  5.9 0.083 3.1   5800 17.2 0.031201
## 13 12.8  0 11.3  6.7  6.0 0.624  97.2  28  1.0 0.077 2.5   5070 20.6 0.045302
## 14 13.5  0 11.7  6.2  6.1 0.595  98.6  22  4.6 0.077 2.7   5290 19.0 0.053200
## 15 15.2  1  8.7  5.7  5.3 0.530  98.6  30  7.2 0.092 4.3   4050 26.4 0.069100
## 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
## 17 14.3  0 11.0  6.6  6.3 0.537  97.7  10  0.6 0.114 3.5   4870 16.6 0.076299
## 18 13.5  1 10.4 12.3 11.5 0.537  97.8  31 17.0 0.089 3.4   6310 16.5 0.119804
## 19 13.0  0 11.6 12.8 12.8 0.536  93.4  51  2.4 0.078 3.4   6270 13.5 0.019099
## 20 12.5  0 10.8 11.3 10.5 0.567  98.5  78  9.4 0.130 5.8   6260 16.6 0.034801
## 21 12.6  0 10.8  7.4  6.7 0.602  98.4  34  1.2 0.102 3.3   5570 19.5 0.022800
## 22 15.7  1  8.9  4.7  4.4 0.512  96.2  22 42.3 0.097 3.4   2880 27.6 0.089502
## 23 13.2  0  9.6  8.7  8.3 0.564  95.3  43  9.2 0.083 3.2   5130 22.7 0.030700
## 24 13.1  0 11.6  7.8  7.3 0.574 103.8   7  3.6 0.142 4.2   5400 17.6 0.041598
## 25 13.0  0 11.6  6.3  5.7 0.641  98.4  14  2.6 0.070 2.1   4860 19.6 0.069197
## 26 13.1  0 12.1 16.0 14.3 0.631 107.1   3  7.7 0.102 4.1   6740 15.2 0.041698
## 27 13.5  0 10.9  6.9  7.1 0.540  96.5   6  0.4 0.080 2.2   5640 13.9 0.036099
## 28 15.2  0 11.2  8.2  7.6 0.571 101.8  10  7.9 0.103 2.8   5370 21.5 0.038201
## 29 11.9  0 10.7 16.6 15.7 0.521  93.8 168  8.9 0.092 3.6   6370 15.4 0.023400
## 30 16.6  1  8.9  5.8  5.4 0.521  97.3  46 25.4 0.072 2.6   3960 23.7 0.075298
## 31 14.0  0  9.3  5.5  5.4 0.535 104.5   6  2.0 0.135 4.0   4530 20.0 0.041999
## 32 12.5  0 10.9  9.0  8.1 0.586  96.4  97  8.2 0.105 4.3   6170 16.3 0.042698
## 33 14.7  1 10.4  6.3  6.4 0.560  97.2  23  9.5 0.076 2.4   4620 23.3 0.049499
## 34 12.6  0 11.8  9.7  9.7 0.542  99.0  18  2.1 0.102 3.5   5890 16.6 0.040799
## 35 12.3  0 10.2  9.7  8.7 0.526  94.8 113  7.6 0.124 5.0   5720 15.8 0.020700
## 36 15.0  0 10.0 10.9  9.8 0.531  96.4   9  2.4 0.087 3.8   5590 15.3 0.006900
## 37 17.7  1  8.7  5.8  5.6 0.638  97.4  24 34.9 0.076 2.8   3820 25.4 0.045198
## 38 13.3  0 10.4  5.1  4.7 0.599 102.4   7  4.0 0.099 2.7   4250 22.5 0.053998
## 39 14.9  1  8.8  6.1  5.4 0.515  95.3  36 16.5 0.086 3.5   3950 25.1 0.047099
## 40 14.5  1 10.4  8.2  7.4 0.560  98.1  96 12.6 0.088 3.1   4880 22.8 0.038801
## 41 14.8  0 12.2  7.2  6.6 0.601  99.8   9  1.9 0.084 2.0   5900 14.4 0.025100
## 42 14.1  0 10.9  5.6  5.4 0.523  96.8   4  0.2 0.107 3.7   4890 17.0 0.088904
## 43 16.2  1  9.9  7.5  7.0 0.522  99.6  40 20.8 0.073 2.7   4960 22.4 0.054902
## 44 13.6  0 12.1  9.5  9.6 0.574 101.2  29  3.6 0.111 3.7   6220 16.2 0.028100
## 45 13.9  1  8.8  4.6  4.1 0.480  96.8  19  4.9 0.135 5.3   4570 24.9 0.056202
## 46 12.6  0 10.4 10.6  9.7 0.599  98.9  40  2.4 0.078 2.5   5930 17.1 0.046598
## 47 13.0  0 12.1  9.0  9.1 0.623 104.9   3  2.2 0.113 4.0   5880 16.0 0.052802
##       Time Crime Predicted    cvpred fold
## 1  26.2011   791  810.8255  785.3647    1
## 2  25.2999  1635 1387.8082 1355.7097    5
## 3  24.3006   578  386.1368  345.3417    1
## 4  29.9012  1969 1897.1866 1882.7381    2
## 5  21.2998  1234 1269.8420 1266.7954    3
## 6  20.9995   682  730.2659  781.7557    2
## 7  20.6993   963  733.3799  759.9655    4
## 8  24.5988  1555 1353.5532 1243.1763    3
## 9  29.4001   856  718.7568  723.5331    3
## 10 19.5994   705  787.2712  723.6678    5
## 11 41.6000  1674 1117.7702  946.1309    3
## 12 34.2984   849  673.3766  684.3525    2
## 13 36.2993   511  739.3727  770.2015    4
## 14 21.5010   664  713.5639  730.0555    4
## 15 22.7008   798  828.3418  826.2855    3
## 16 26.0991   946 1004.3984 1046.8197    5
## 17 19.1002   539  527.3659  492.2016    1
## 18 18.1996   929  800.0046  700.5751    1
## 19 24.9008   750 1220.6767 1240.2916    1
## 20 26.4010  1225 1202.9607 1247.8616    4
## 21 37.5998   742  783.2733  819.7114    5
## 22 37.0994   439  728.3110  701.5126    1
## 23 25.1989  1216  937.5703  754.2511    3
## 24 17.6000   968  919.3912  953.7248    4
## 25 21.9003   523  579.0638  621.3745    2
## 26 22.1005  1993 1789.1406 1794.6456    5
## 27 28.4999   342  312.2047  297.1932    4
## 28 25.8006  1216 1259.0034 1238.3192    2
```

```
## 29 36.7009  1043 1495.4856 1663.6272    5
## 30 28.3011   696  668.0161  638.8712    4
## 31 21.7998   373  440.4394  456.5736    5
## 32 30.9014   754  773.6840  788.0343    2
## 33 25.5005  1072  873.8469  857.7052    5
## 34 21.6997   923  997.5498 1013.9253    2
## 35 37.4011   653  808.0296  850.6961    4
## 36 44.0004  1272 1101.7167 1127.3318    1
## 37 31.6995   831  991.5623 1076.5799    3
## 38 16.6999   566  544.3733  544.6990    1
## 39 27.3004   826  786.6949  717.0989    3
## 40 29.3004  1151 1140.7906 1168.2111    1
## 41 30.0001   880  796.4198  778.0437    2
## 42 12.1996   542  368.7031  260.9211    5
## 43 31.9989   823 1016.5503 1079.7748    3
## 44 30.0001  1030 1177.5973 1159.3155    2
## 45 32.5996   455  621.8592  690.6802    4
## 46 16.6999   508  748.4256  807.6968    2
## 47 16.0997   849  976.4397 1038.3321    3
```

References:

[1] “Microsoft CoPilot. Accessed 2024-9-22. Prompt: ‘climbing frequency, training hours, rest days, body measurements, onsight difficulty are independent variables to my climbing difficulty (dependency variable) write my linear regression formula in markeddown sytnax’ Generated using https://copilot.microsoft.com/ (https://copilot.microsoft.com/).”

[2] “Microsoft CoPilot. Accessed 2024-9-23. Prompt: ‘r squared formula in markeddown syntax’ Generated using https://copilot.microsoft.com/ (https://copilot.microsoft.com/).”

[3] How to Interpret Significance Codes in R? (2022, January 1). GeeksforGeeks. https://www.geeksforgeeks.org/how-to-interpret-significance-codes-in-r/ (https://www.geeksforgeeks.org/how-to-interpret-significance-codes-in-r/)

[4] Zach. (2021, May 11). How to Interpret Residual Standard Error. Statology. https://www.statology.org/how-to-interpret-residual-standard-error/ (https://www.statology.org/how-to-interpret-residual-standard-error/)