# Project 1

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```
rm(list=ls())
```

## Set up the work space

Reduce the number of displayed digits.

```
options(
  digits = 4
)
```

This project analyzes the data set Grad_Admission. Variables description are as follows:

ID: Unique identification code for each student

GRE: GRE Scores (out of 340)

TOEFL: TOEFL Scores (out of 120)

Urate: University Rating (out of 5)

SOP: Statement of Purpose Strength (out of 5)

LOR: Letter of Recommendation Strength (out of 5)

CGPA: Undergraduate GPA (out of 4)

Chance:Chance of Admission (ranging from 0 to 100)

## 1. Load the data

```
Grad <- read.csv(
  file = "Grad_Admission.csv",
  header = TRUE
)
```

## 2. Print the dataset (Limit your print to include only the first and last ten observations)

```
head(Grad[,-1],10)
```

```
##    GRE TOEFL Urate SOP LOR CGPA Chance
## 1  337   118     4 4.5 4.5 3.86     92
## 2  324   107     4 4.0 4.5 3.55     76
## 3  316   104     3 3.0 3.5 3.20     72
```

```
## 4  322   110     3 3.5 2.5 3.47     80
## 5  314   103     2 2.0 3.0 3.28     65
## 6  330   115     5 4.5 3.0 3.74     90
## 7  321   109     3 3.0 4.0 3.28     75
## 8  308   101     2 3.0 4.0 3.16     68
## 9  302   102     1 2.0 1.5 3.20     50
## 10 323   108     3 3.5 3.0 3.44     45
```

```
tail(Grad,10)
```

```
##      ID GRE TOEFL Urate SOP LOR CGPA Chance
## 391 391 314   102     2 2.0 2.5 3.30     64
## 392 392 318   106     3 2.0 3.0 3.46     71
## 393 393 326   112     4 4.0 3.5 3.65     84
## 394 394 317   104     2 3.0 3.0 3.50     77
## 395 395 329   111     4 4.5 4.0 3.69     89
## 396 396 324   110     3 3.5 3.5 3.62     82
## 397 397 325   107     3 3.0 3.5 3.64     84
## 398 398 330   116     4 5.0 4.5 3.78     91
## 399 399 312   103     3 3.5 4.0 3.51     67
## 400 400 333   117     4 5.0 4.0 3.86     95
```

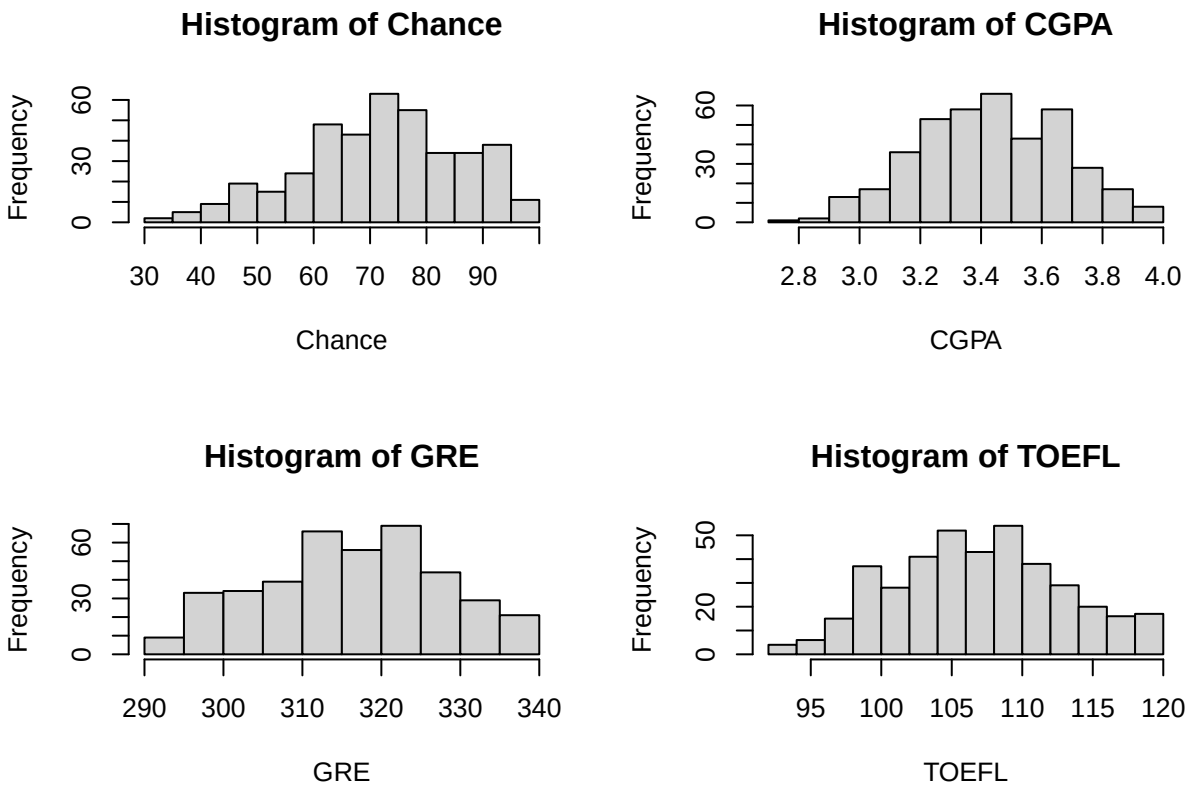
## 3. Print a table of the n/mean/standard deviation/min/max of three of the Features (GRE, TOEFL, CGPA).

```
summary(
  object = Grad[c(2,3,7)]
)
```

```
##       GRE          TOEFL          CGPA
##  Min.   :290   Min.   : 92   Min.   :2.72
##  1st Qu.:308   1st Qu.:103   1st Qu.:3.27
##  Median :317   Median :107   Median :3.44
##  Mean   :317   Mean   :107   Mean   :3.44
##  3rd Qu.:325   3rd Qu.:112   3rd Qu.:3.62
##  Max.   :340   Max.   :120   Max.   :3.97
```

## 4. Make histograms for “Chance”, “CGPA”, “GRE” and “TOEFL”

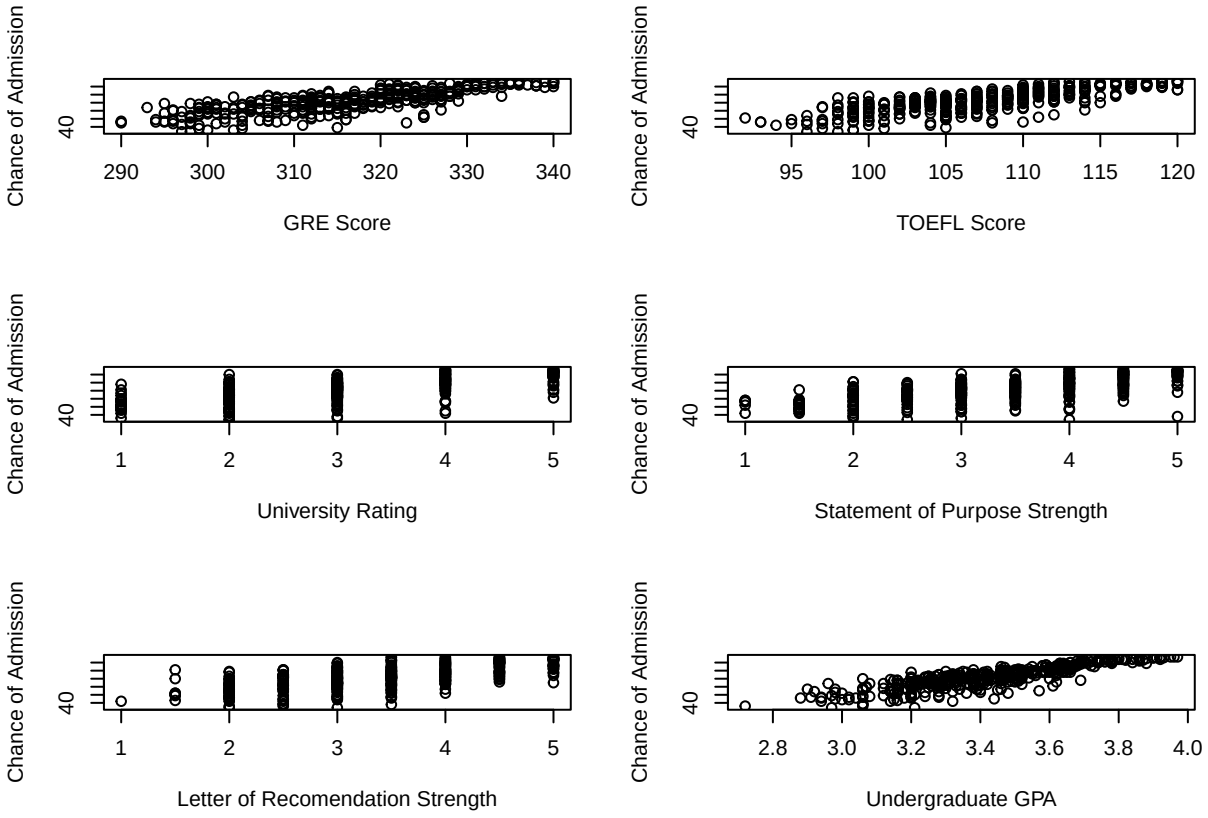
```
par(mfrow=c(2,2))
hist(Grad[,8],xlab = "Chance", main = "Histogram of Chance")
hist(Grad[,7],xlab = "CGPA", main = "Histogram of CGPA")
hist(Grad[,2],xlab = "GRE", main = "Histogram of GRE")
hist(Grad[,3],xlab = "TOEFL", main = "Histogram of TOEFL")
```




It seems that the probability distributions of Chance and CGPA are left skewed and they are not normal. The probability distributions of GRE and TOEFL are approximately normal.

## 5. Consider "Chance" as the response variable and print scatter plots of each of the other six variables against it.

```
par(mfrow=c(3,2))
plot(x = Grad$GRE, y = Grad$Chance, xlab="GRE Score", ylab="Chance of Admission")
plot(x = Grad$TOEFL, y = Grad$Chance, xlab="TOEFL Score", ylab="Chance of Admission")
plot(x = Grad$Urate, y = Grad$Chance, xlab="University Rating", ylab="Chance of Admission")
plot(x = Grad$SOP, y = Grad$Chance, xlab="Statement of Purpose Strength", ylab="Chance of Admission")
plot(x = Grad$LOR, y = Grad$Chance, xlab="Letter of Recomendation Strength", ylab="Chance of Admission")
plot(x = Grad$CGPA, y = Grad$Chance, xlab="Undergraduate GPA", ylab="Chance of Admission")
```




## 6. Draw your initial conclusions about the relationship between independent variables and the response variable based on the scatterplot.

There seems to be a strong positive linear relationship between Chance and the following features: GRE, TOEFL, and CGPA. The seems to be some relationship between SOP, LOR, Urate with respect to Chance. Since there are few possible rating options for those 3 features, it can be harder to tell if there is a relationship, but there seems to be a slight positive trend. These 3 features will not be useful by themselves, but can be useful to bolster a model that already contains GRE, TOEFL, or CGPA.

## 7. Confirm the validity of five major linear regression assumptions and comment on them.

```
test_model <- lm(Chance~GRE+TOEFL+Urate+SOP+LOR+CGPA, data = Grad)
```

### 7.1. Existence

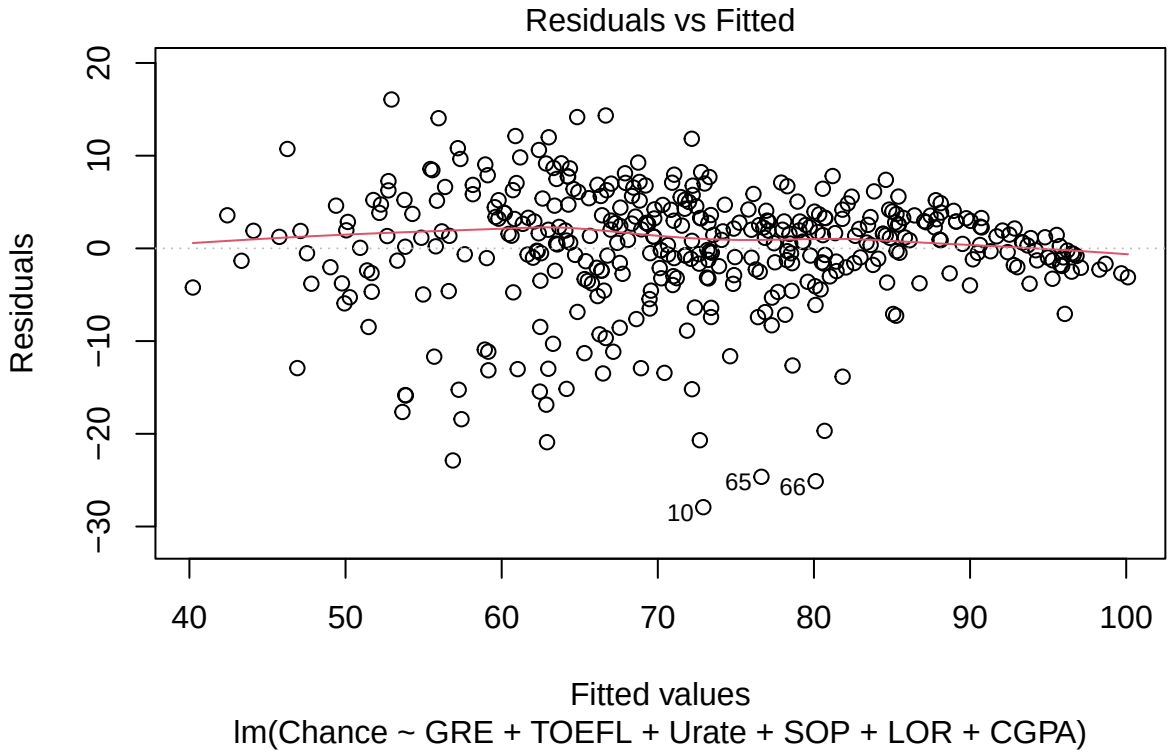
This assumption is always true for any regression model. Since a model can be made from the data, this assumption is true

### 7.2. Independence

Data is not a time-series. Each entry is independent of each other. Thus this assumption is true.

### 7.3. Linearity

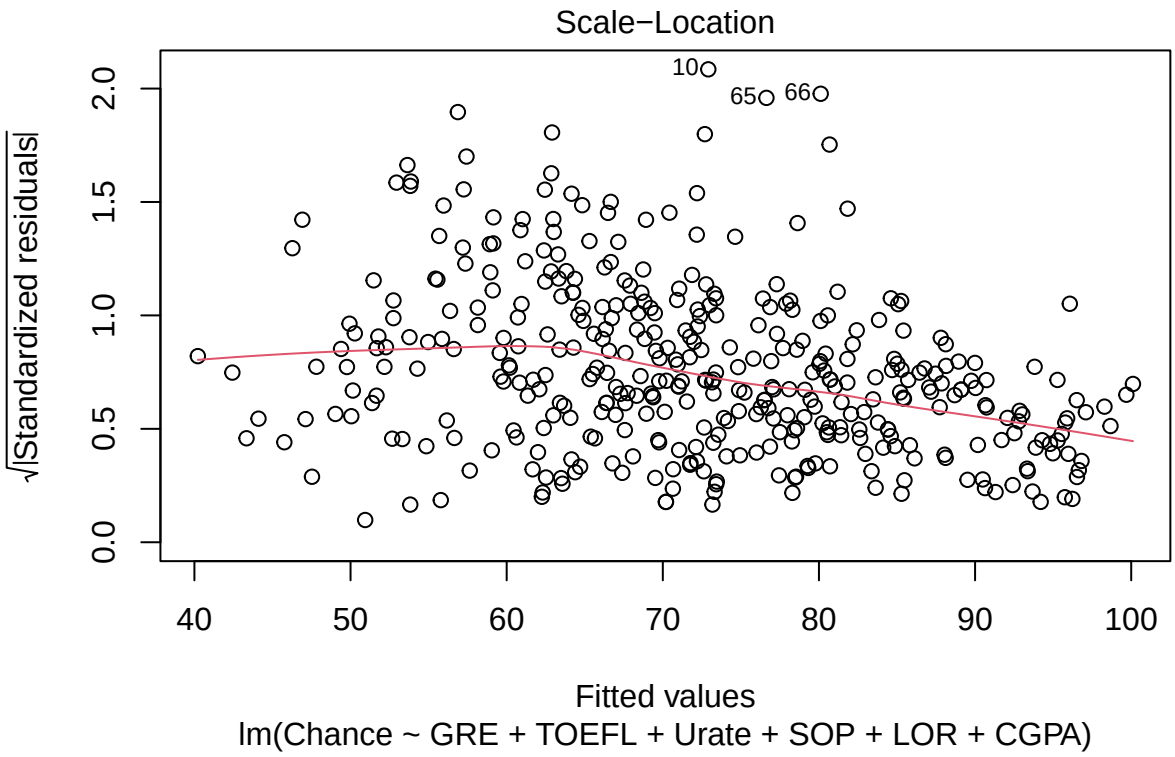
```
plot(test_model,1)
```




Residuals are around a horizontal line without distinct patterns. This indicates Linearity. This assumption holds true.

### 7.4. Homoscedasticity

```
plot(test_model, 3)
```



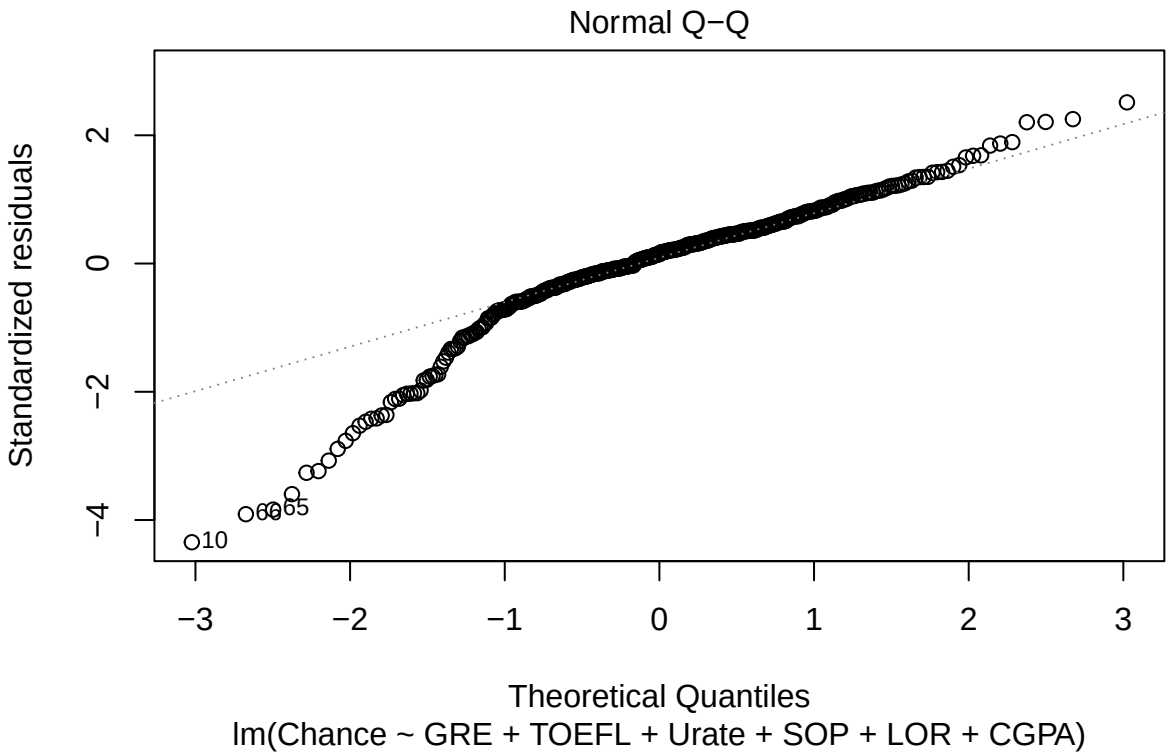

```
lmtest::bptest(test_model)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  test_model
## BP = 20, df = 6, p-value = 0.003
```

While there seems to be less variance where Chance of Admission increases, the Breusch-Pagan Test at $\alpha = 0.05$ passes. This confirms the Homoscedasticity assumption.

### 7.5.

```
plot(test_model, 2)
```




```
sresid <- MASS::studres(test_model) #using MASS package function to transform data easily
shapiro.test(sresid)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  sresid
## W = 0.92, p-value = 9e-14
```

Most of the points fall along the reference line In the QQ plot. The left endpoints do deviate, suggesting the distribution is left-skewed. The model passes the Shapiro-Wilk test at $\alpha = 0.05$. This confirms the Normality assumption of the model.

## 8. Choose the best three independent variables based on your immediate insight into the relationship and list them.

The best three independent variables based on the scatter plots in section 5 are GRE, TOEFL, CGPA. The model is $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + E$ Y: Chance X1: GRE X2: TOEFL X3: CGPA E: Error

## 9. Build up a table, including the correlation between all independent variables and the response variable.

```
model_corr_matrix <- cor(Grad[,-1],use = "pairwise.complete.obs")
model_corr_matrix
```

```
##           GRE  TOEFL  Urate    SOP    LOR   CGPA Chance
## GRE    1.0000 0.8360 0.6690 0.6128 0.5576 0.8332 0.8026
## TOEFL  0.8360 1.0000 0.6956 0.6580 0.5677 0.8283 0.7916
## Urate  0.6690 0.6956 1.0000 0.7345 0.6601 0.7469 0.7113
## SOP    0.6128 0.6580 0.7345 1.0000 0.7296 0.7184 0.6757
## LOR    0.5576 0.5677 0.6601 0.7296 1.0000 0.6702 0.6699
## CGPA   0.8332 0.8283 0.7469 0.7184 0.6702 1.0000 0.8734
## Chance 0.8026 0.7916 0.7113 0.6757 0.6699 0.8734 1.0000
```

All the features have a positive correlation with admission chance. It can be deduced that it will be worth testing all of these features in the model coefficient they all display correlation with the response variable. The relationship between correlation coefficient and slope is that their signs match. When Correlation coefficient is positive, slope is positive, and when it is negative, slope is negative.

# 10. Report the result of hypothesis testing for the correlation coefficient of each independent variable. $\alpha = 0.05$

## 10.1. GRE vs Chance

```
cor.test(Grad$GRE, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$GRE and Grad$Chance
## t = 27, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.7647 0.8350
## sample estimates:
##    cor
## 0.8026
```

## 10.2.TOEFL vs Chance

```
cor.test(Grad$TOEFL, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$TOEFL and Grad$Chance
## t = 26, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.7519 0.8256
## sample estimates:
##    cor
## 0.7916
```

## 10.3. Urate vs Chance

```
cor.test(Grad$Urate, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$Urate and Grad$Chance
## t = 20, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.6592 0.7565
## sample estimates:
##    cor
## 0.7113
```

### 10.4. SOP vs Chance

```
cor.test(Grad$SOP, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$SOP and Grad$Chance
## t = 18, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.6187 0.7257
## sample estimates:
##    cor
## 0.6757
```

### 10.5. LOR vs Chance

```
cor.test(Grad$LOR, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$LOR and Grad$Chance
## t = 18, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.6120 0.7206
## sample estimates:
##    cor
## 0.6699
```

### 10.6. CGPA vs Chance

```
cor.test(Grad$CGPA, Grad$Chance, method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  Grad$CGPA and Grad$Chance
## t = 36, df = 398, p-value <2e-16
## alternative hypothesis: true correlation is not equal to 0
```

```
## 95 percent confidence interval:
##  0.8479 0.8948
## sample estimates:
##    cor
## 0.8734
```

# 11. Build up the univariate models

## 11.1. Chance regression on GRE

```
lm_1 <- lm(
  formula = Chance ~ GRE,
  data = Grad
)
anova(lm_1)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## GRE         1  52273   52273     721 <2e-16 ***
## Residuals 398  28873      73
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_1)
```

```
##
## Call:
## lm(formula = Chance ~ GRE, data = Grad)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -33.61  -4.60   0.41   5.64  18.34
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -243.6084    11.7814   -20.7   <2e-16 ***
## GRE            0.9976     0.0372    26.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.52 on 398 degrees of freedom
## Multiple R-squared:  0.644,  Adjusted R-squared:  0.643
## F-statistic:  721 on 1 and 398 DF,  p-value: <2e-16
```

The model is: $Chance = -243.608 + 0.9976 * GRE + E$

## 11.2. Chance regression on TOEFL

```
lm_2 <- lm(
  formula = Chance ~ TOEFL,
  data = Grad
)
```

```
anova(lm_2)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## TOEFL       1  50848   50848     668 <2e-16 ***
## Residuals 398  30298      76
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_2)
```

```
##
## Call:
## lm(formula = Chance ~ TOEFL, data = Grad)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -31.25  -5.13   1.33   5.45  21.07
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -127.340      7.742   -16.4   <2e-16 ***
## TOEFL          1.860      0.072    25.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.73 on 398 degrees of freedom
## Multiple R-squared:  0.627,  Adjusted R-squared:  0.626
## F-statistic:  668 on 1 and 398 DF,  p-value: <2e-16
```

The model is : $Chance = -127.34 + 1.8599 * TOEFL + E$

### 11.3. Chance regression on Urate

```
lm_3 <- lm(
  formula = Chance ~ Urate,
  data = Grad
)
anova(lm_3)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## Urate       1  41050   41050     407 <2e-16 ***
## Residuals 398  40096     101
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_3)
```

```
##
## Call:
## lm(formula = Chance ~ Urate, data = Grad)
```

```
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -38.53  -4.56   1.47   6.34  27.21
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   45.054      1.446    31.1   <2e-16 ***
## Urate          8.868      0.439    20.2   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10 on 398 degrees of freedom
## Multiple R-squared:  0.506,  Adjusted R-squared:  0.505
## F-statistic:  407 on 1 and 398 DF,  p-value: <2e-16
```

The model is : $Chance = 45.054 + 8.868 * Urate + E$

## 11.4. Chance regression on SOP

```
lm_4 <- lm(
  formula = Chance ~ SOP,
  data = Grad
)
anova(lm_4)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## SOP         1  37053   37053     334 <2e-16 ***
## Residuals 398  44094     111
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_4)
```

```
##
## Call:
## lm(formula = Chance ~ SOP, data = Grad)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -49.75  -5.39   1.82   7.04  22.39
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   39.894      1.856    21.5   <2e-16 ***
## SOP            9.571      0.523    18.3   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.5 on 398 degrees of freedom
## Multiple R-squared:  0.457,  Adjusted R-squared:  0.455
## F-statistic:  334 on 1 and 398 DF,  p-value: <2e-16
```

The model is : $Chance = 39.894 + 9.571 * SOP + E$

## 11.5. Chance regression on LOR

```
lm_5 <- lm(
  formula = Chance ~ LOR,
  data = Grad
)
anova(lm_5)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## LOR         1  36414   36414     324 <2e-16 ***
## Residuals 398  44732     112
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_5)
```

```
##
## Call:
## lm(formula = Chance ~ LOR, data = Grad)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -34.94  -6.26   0.06   7.39  29.33
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   35.726      2.107    16.9   <2e-16 ***
## LOR           10.633      0.591    18.0   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.6 on 398 degrees of freedom
## Multiple R-squared:  0.449,  Adjusted R-squared:  0.447
## F-statistic:  324 on 1 and 398 DF,  p-value: <2e-16
```

The model is : $Chance = 35.726 + 10.633 * LOR + E$

## 11.6. Chance Regression on CGPA

```
lm_6 <- lm(
  formula = Chance ~ CGPA,
  data = Grad
)
anova(lm_6)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## CGPA        1  61898   61898    1280 <2e-16 ***
```

```
## Residuals 398  19248      48
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(lm_6)
```

```
##
## Call:
## lm(formula = Chance ~ CGPA, data = Grad)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.460  -2.959   0.973   4.180  18.076
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -107.22       5.03   -21.3   <2e-16 ***
## CGPA           52.23       1.46    35.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.95 on 398 degrees of freedom
## Multiple R-squared:  0.763,  Adjusted R-squared:  0.762
## F-statistic: 1.28e+03 on 1 and 398 DF,  p-value: <2e-16
```

The model is : $Chance = -107.22 + 52.23 * CGPA + E$

# 12. Report the ANOVA table for two variables with the highest R-square value? What conclusion is achievable looking at these tables?

## 12.1. ANOVA for CGPA model

```
anova(lm_6)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## CGPA        1  61898   61898    1280 <2e-16 ***
## Residuals 398  19248      48
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 12.2. ANOVA for GRE model

```
anova(lm_1)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## GRE         1  52273   52273     721 <2e-16 ***
## Residuals 398  28873      73
```

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

Both of these variables are significant by themselves. But the CGPA has much less error than the GRE model. This means that CGPA explains more of the variance in Chance than GRE.

## 13. Build up a model, including all six variables available in the dataset.

```
full_model <- lm(Chance~GRE+TOEFL+Urate+SOP+LOR+CGPA, data = Grad)
anova(full_model)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value  Pr(>F)
## GRE         1  52273   52273  1258.2 < 2e-16 ***
## TOEFL       1   3921    3921    94.4 < 2e-16 ***
## Urate       1   2370    2370    57.0 3.0e-13 ***
## SOP         1    757     757    18.2 2.5e-05 ***
## LOR         1   1574    1574    37.9 1.9e-09 ***
## CGPA        1   3923    3923    94.4 < 2e-16 ***
## Residuals 393  16328      42
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(full_model)
```

```
##
## Call:
## lm(formula = Chance ~ GRE + TOEFL + Urate + SOP + LOR + CGPA,
##     data = Grad)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.915  -2.381   0.935   3.577  16.057
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -141.4185    11.5420  -12.25  < 2e-16 ***
## GRE            0.2270     0.0578    3.93   0.0001 ***
## TOEFL          0.2762     0.1099    2.51   0.0124 *
## Urate          0.5995     0.4821    1.24   0.2144
## SOP           -0.2000     0.5604   -0.36   0.7213
## LOR            2.2784     0.5598    4.07  5.7e-05 ***
## CGPA          30.0138     3.0886    9.72  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.45 on 393 degrees of freedom
## Multiple R-squared:  0.799,  Adjusted R-squared:  0.796
## F-statistic:  260 on 6 and 393 DF,  p-value: <2e-16
```

The model is : $Chance = -141.4185 + 0.2270 * GRE + 0.2762 * TOEFL + 0.5995 * Urate - 0.2 * SOP +$

$2.2784 * LOR + 30.0138 * CGPA + E$ Urate and SOP are not Significant at $\alpha = 0.05$

## 14. Remove all non-significant variables from the model and rebuild the model.

```
best_model <- lm(Chance~GRE+TOEFL+LOR+CGPA, data = Grad)
anova(best_model)
```

```
## Analysis of Variance Table
##
## Response: Chance
##            Df Sum Sq Mean Sq F value Pr(>F)
## GRE         1  52273   52273  1259.6 <2e-16 ***
## TOEFL       1   3921    3921    94.5 <2e-16 ***
## LOR         1   4090    4090    98.6 <2e-16 ***
## CGPA        1   4469    4469   107.7 <2e-16 ***
## Residuals 395  16392      41
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(best_model)
```

```
##
## Call:
## lm(formula = Chance ~ GRE + TOEFL + LOR + CGPA, data = Grad)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -27.969  -2.288   0.932   3.651  16.170
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -146.2511    10.5731  -13.83  < 2e-16 ***
## GRE            0.2311     0.0576    4.01  7.2e-05 ***
## TOEFL          0.2929     0.1076    2.72   0.0068 **
## LOR            2.3960     0.4839    4.95  1.1e-06 ***
## CGPA          30.7403     2.9622   10.38  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.44 on 395 degrees of freedom
## Multiple R-squared:  0.798,  Adjusted R-squared:  0.796
## F-statistic:  390 on 4 and 395 DF,  p-value: <2e-16
```

The model is : $Chance = -146.2511 + 0.2311 * GRE + 0.2929 * TOEFL + 2.3960 * LOR + 30.7403 * CGPA + E$

The is not much of a difference of between the anova tables outside of there being less variables. Also mean square error is lower in the model from section 14.

## 15. Build up confidence bands and prediction bands for all records.

```
test_df = Grad[, c(2:7)]
conf_bands <- predict(best_model, newdata = test_df, interval = "confidence")
```

```
write.csv(conf_bands,"confidenceBands.csv")
head(conf_bands, 10)
```

```
##      fit   lwr   upr
## 1  95.64 94.30 96.98
## 2  79.88 78.59 81.17
## 3  64.00 62.59 65.41
## 4  73.05 71.79 74.30
## 5  64.51 63.57 65.44
## 6  85.86 84.30 87.42
## 7  70.28 68.63 71.93
## 8  61.24 59.66 62.83
## 9  55.39 53.72 57.05
## 10 72.97 71.97 73.97
```

```
pred_bands <- predict(best_model, newdata = test_df, interval = "prediction")
write.csv(pred_bands,"predictionBands.csv")
head(pred_bands, 10)
```

```
##      fit   lwr    upr
## 1  95.64 82.90 108.37
## 2  79.88 67.15  92.61
## 3  64.00 51.26  76.74
## 4  73.05 60.32  85.78
## 5  64.51 51.81  77.21
## 6  85.86 73.10  98.62
## 7  70.28 57.51  83.05
## 8  61.24 48.48  74.00
## 9  55.39 42.61  68.16
## 10 72.97 60.26  85.67
```

## 16. Write the appropriate equation to predict the admission chance with variables included in final model from section 14.

$Chance = -146.2511 + 0.2311 * GRE + 0.2929 * TOEFL + 2.3960 * LOR + 30.7403 * CGPA$

The Intercept has no meaning in this case. With 0 for GRE, TOEFL, LOR, CGPA, one would have a negative 146 chance of admission. This number is outside the valid range of chance thus no meaningful information can be gathered from it.

The meaning of the slope is that for every 1 point increase in GRE, admission chance increases by 0.2311. For every 1 point increase in TOEFL, admission chance increases by 0.2929. For every 1 point increase in LOR, admission chance increases by 2.3960. For every 1 point in CGPA, admission chance increases by 30.7403.

## 17. What conclusion can you arrive at from this exploration in terms of the suitability of descriptive statistics and regression in data exploration? What is the recommendation that you would provide future data explorations to include as a result necessarily?

Exploratory Data Analysis is a necessary step before developing models for a data set. Descriptive statistics of the data set and Visualizations made from them along with basic regression were able to paint a picture of the data. It allows for deduction of which type of model to train and which features will have the most

weight. Future data explorations should scale the data to lie between 0 and 1. Along with data scaling, more models should be explored. There are more powerful linear regression models. Such models include Batch Gradient Descent, Stochastic Gradient Descent, Ridge Regression, Lasso Regression, ElasticNet regression. Polynomial and interaction feature transformation can be used as well to increase the number of features in the model potentially increasing accuracy. A train/test split of the data set should also be utilized in order to prevent over fitting of such models.