THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Diagnostics & Transformations 2

Lecture 13

STA 371G

Newly hired manager salaries

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- Salary (response)
- Manager Rating
- Years of Experience
- NUmber of years since graduation
- Origin (internal or external hire)

Data issues

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- Missing data
- Multicollinearity
- Violation of LINE assumptions

It is almost always necessary to explore and clean the data before doing the modeling

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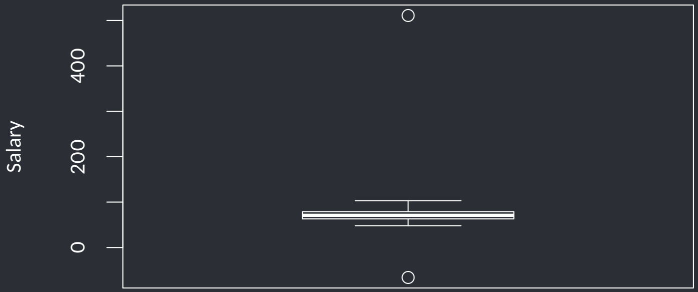
```
boxplot(manager$Salary, ylab='Salary')
```



There is a negative entry, and a very large one. We need to investigate these.

Exploring the data: Outliers

```
manager[manager$Salary>200,]

# A tibble: 1 5
  Salary MngrRating YearsExp YrsSinceGrad   Origin
   <int>      <dbl>    <int>        <int>    <chr>
1    511        6.1        2            2 Internal

manager[manager$Salary<0,]

# A tibble: 1 5
  Salary MngrRating YearsExp YrsSinceGrad   Origin
   <int>      <dbl>    <int>        <int>    <chr>
1    -66        5.7        1            2 Internal
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   <int>      <dbl>    <int>        <int>    <chr>
1    -66        5.7        1            2 Internal
```

These are probably just incorrect entries.
Try to correct the data whenever you can. If not possible, we will omit them.

Exploring the data: Outliers

```
mclean <- manager[manager$Salary>0 & manager$Salary<200,]
```

Exploring the data: Outliers

```r
mclean <- manager[manager$Salary>0 & manager$Salary<200,]
```

Select the subset of the data where the salary is between 0 and 200K.

Exploring the data: Outliers

```
boxplot(mclean$YearsExp, ylab='Years of Experience')
```

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mclean$YearsExp[mclean$YearsExp==99] <- NA
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Now, what? We have missing entries our data!

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Great.

Exploring the data: Missing entries

Let’s see if we have other missing data.

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```
mclean[!complete.cases(mclean),]
```

```
# A tibble: 4 5
  Salary MngrRating YearsExp YrsSinceGrad   Origin
   <int>      <dbl>    <int>        <int>    <chr>
1     75         NA        8            8 Internal
2     81         NA        9            9 External
3     73        5.9       NA            7 External
4     49        8.0        1            1     <NA>
```

Exploring the data: Missing entries

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mclean[!complete.cases(mclean),]
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1     75         NA        8            8 Internal
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4     49        8.0        1            1     <NA>
```

This should not come a surprise, because it is very common to have missing entries in your data.
*If you are not seeing the last entry, it is because na.strings is set to NA (it should be empty in RStudio, and na.strings=" should be used while in read.csv command).

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Let's try to fill in some estimates.

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The simplest way would be to use the averages in the respective columns.

```
average_MngrRating <- mean(mclean$MngrRating, na.rm=TRUE)
mclean$MngrRating[is.na(mclean$MngrRating)] <- average_MngrRating

average_YearsExp <- mean(mclean$YearsExp, na.rm=TRUE)
mclean$YearsExp[is.na(mclean$YearsExp)] <- average_YearsExp
```

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average_MngrRating <- mean(mclean$MngrRating, na.rm=TRUE)
mclean$MngrRating[is.na(mclean$MngrRating)] <- average_MngrRating

average_YearsExp <- mean(mclean$YearsExp, na.rm=TRUE)
mclean$YearsExp[is.na(mclean$YearsExp)] <- average_YearsExp
```

A smarter and more advanced way is to predict, e.g., what the Manager Rating would be for a person with $75K salary, 8 years of experience and who is an internal hire.

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This removes all the rows that contain missing entries (only the Origin column has missing entries in this case.)

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There are also ways of predicting the missing entries in a categorical variable.

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There are also ways of predicting the missing entries in a categorical variable.

Or we could have treated the missing entries as a seperate level (e.g. "Unknown").

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- Making predictions for missing data based on available data enforces the already existing relationships between variables, therefore impacts the standard error.
- If a lot of data is missing (e.g. more than 5%) for a particular variable, you may have to discard the whole column.

Exploring the data: Multicollinearity

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Exploring the data: Multicollinearity

In multiple regression models, multicollinearity exists whenever two or more of the predictors in a regression model are moderately or highly correlated.

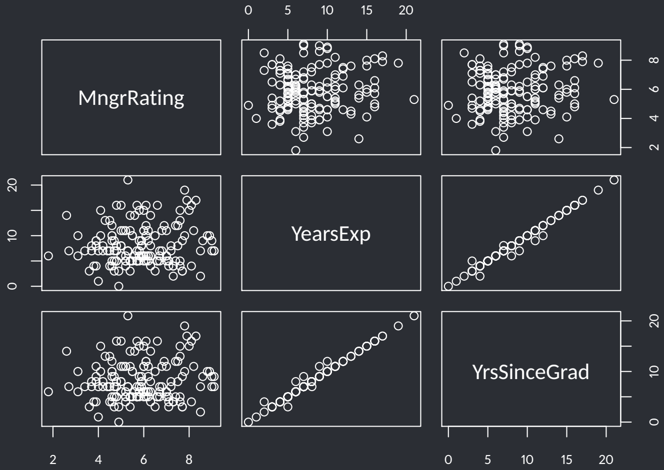
It is a problem, because:

- Any conclusions based on the p-values, coeffients and confidence intervals of the highly correlated variables will be unreliable.
- These statistics will not be stable: adding new data or predictors to the model could drastically change them.

```r
model<- lm(Salary ~ MngrRating + YearsExp
                  + YrsSinceGrad + Origin, data=mclean)
summary(model)
```

```

Call:
lm(formula = Salary ~ MngrRating + YearsExp + YrsSinceGrad + 
    Origin, data = mclean)

Residuals:
     Min       1Q   Median       3Q      Max 
-19.7766  -4.2842  -0.2906   3.3266  28.2773 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     54.1521     2.6071  20.771  < 2e-16 ***
MngrRating       4.5147     0.3997  11.296  < 2e-16 ***
YearsExp        -1.5262     1.3790  -1.107 0.270203    
YrsSinceGrad     0.7692     1.3833   0.556 0.578976    
OriginInternal  -4.7314     1.3878  -3.409 0.000838 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.838 on 149 degrees of freedom
Multiple R-squared:  0.6065,Adjusted R-squared:  0.596 
F-statistic: 57.42 on 4 and 149 DF,  p-value: < 2.2e-16
```

```r
pairs(~ MngrRating+YearsExp+YrsSinceGrad, data=mclean)
```



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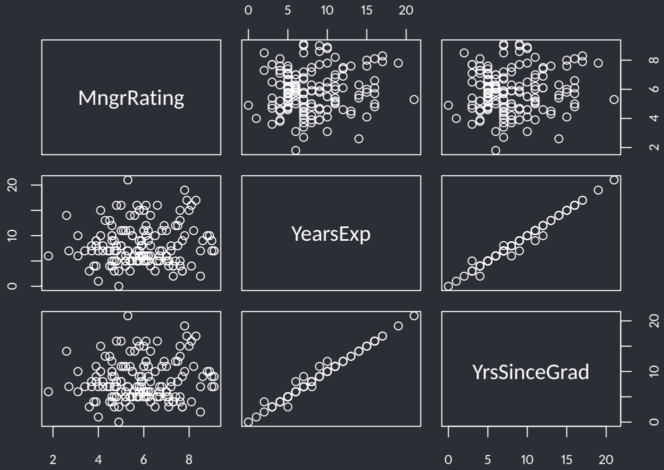

Exploring the data: Multicollinearity

If you check the correlation between the two:

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cor(mclean$YearsExp,mclean$YrsSinceGrad)

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A better way to check multicollinearity:

```
library(car)
vif(model)

MngrRating     YearsExp YrsSinceGrad       Origin
  1.136002    95.954255    97.011260     1.540448
```

Drop one of the predictors that has a VIF higher than 5.

Exploring the data: Multicollinearity

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```

Drop one of the predictors that has a VIF higher than 5.

Remember: Multicollinearity could exist between more than two predictors (e.g. having seperate columns with binary values for Spring, Summer, Autumn, Winter).

```r
model2<- lm(Salary ~ MngrRating + YearsExp
                  + Origin, data=mclean)
summary(model2)
```

```
Call:
lm(formula = Salary ~ MngrRating + YearsExp + Origin, data = mclean)

Residuals:
     Min       1Q   Median       3Q      Max 
-19.8115  -4.3474  -0.3964   3.3358  28.1801 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     54.1080     2.5999  20.812  < 2e-16 ***
MngrRating       4.5309     0.3977  11.394  < 2e-16 ***
YearsExp        -0.7651     0.1687  -4.534 1.18e-05 ***
OriginInternal  -4.6467     1.3762  -3.376 0.000935 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.823 on 150 degrees of freedom
Multiple R-squared:  0.6057,Adjusted R-squared:  0.5978 
F-statistic: 76.82 on 3 and 150 DF,  p-value: < 2.2e-16
```

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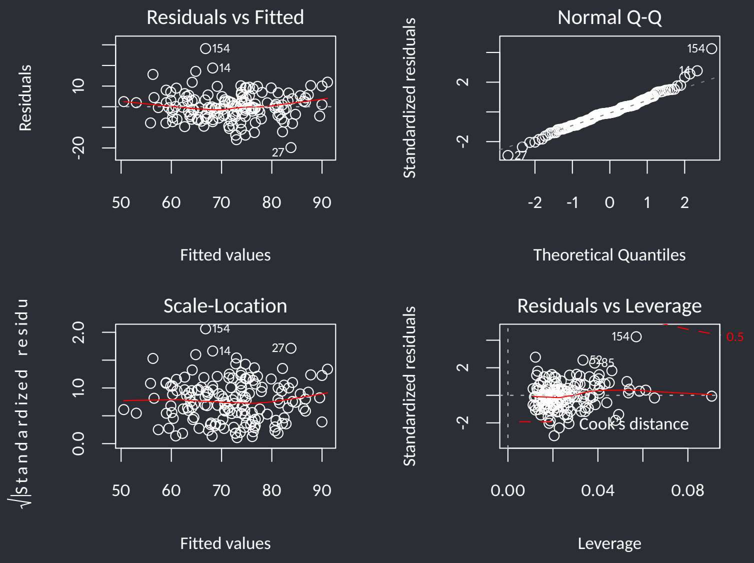
- Look for a horizontal red line in the Residuals-Fitted plot for linearity.
- Look for a horizontal red line in the Scale-Location plot for equal variance.
- Look for a straight line in the Normal Q-Q plot for normality.

```r
par(mfrow=c(2,2)) # Change the panel layout to 2 x 2
plot(model2)
```




```r
par(mfrow=c(1,1)) # Change back to 1 x 1
```

Outliers among the residuals

The data with index 154 seems to be hanging out by itself. It is worth investigating.

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We can display the indices of all of the outliers among the residuals.

```
boxplot(resid(model2))$out
```

```
      14        27        52        85       154 
18.76901 -19.81152  17.14133  15.66079  28.18007 
```

Outliers among the residuals

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We can display the indices of all of the outliers among the residuals.

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Basically, the model is not able to explain these cases very well.

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```

Basically, the model is not able to explain these cases very well. Let's also see them on the

plot.

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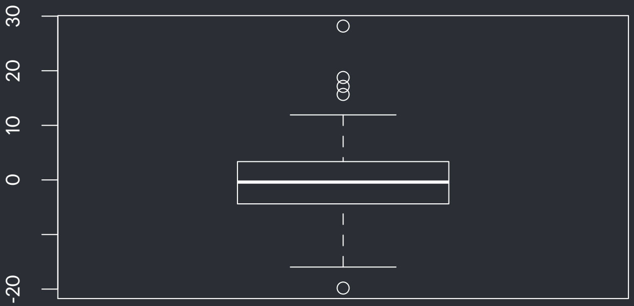

Outliers among the residuals

```
  mclean[154,] # 154th row and all columns
```

```
# A tibble: 1 5
  Salary MngrRating YearsExp YrsSinceGrad   Origin
   <int>      <dbl>    <dbl>        <int>    <chr>
1     95          4        1            1 Internal
```

Someone with only 1 year of experience and poor rating is hired as manager at $95K!

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1     95          4        1            1 Internal
```

Someone with only 1 year of experience and poor rating is hired as manager at $95K!

If you decide that this is an anomaly (e.g. CEO's son promoted!) that you don't want to include in your analysis, omit that row and report it in your conclusions.

Influential cases

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Look for the cases on the upper/lower right corners (beyond the dashed curves).