THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Diagnostics & Transformations 2

Lecture 18

STA 371G

Salaries of newly hired managers

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- Salary (response)
- Manager rating
- Years of experience
- Years since graduation
- Origin (internal or external hire)

Data issues

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Never run a regression without exploring and cleaning the data first!

The most common issues:

1. Outliers
2. Missing data
3. Multicollinearity
4. Assumption violations
5. High-leverage points

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Exploring the data: Outliers

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```
boxplot(manager$Salary, xlab='Salary', horizontal=T)
```

Exploring the data: Outliers

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

    Salary MngrRating YearsExp YrsSinceGrad   Origin
146    511        6.1        2            2 Internal

manager[manager$Salary<0,]

    Salary MngrRating YearsExp YrsSinceGrad   Origin
121    -66        5.7        1            2 Internal
```

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We can deal with outliers in two ways.

- If the result of **errors in the data**, we can try to correct or omit.
- If not, consider omitting, but report on them separately.

Exploring the data: Outliers

Let's omit the outliers by creating a new data set `mclean` that consists of the subset of the data where the salary is between $0 and $200,000.

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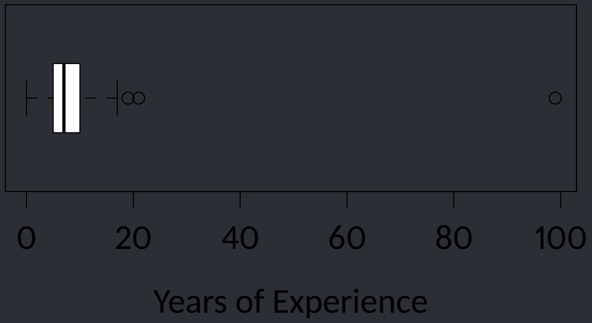

Exploring the data: Outliers

```
boxplot(mclean$YearsExp, xlab='Years of Experience',
  horizontal=T)
```



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```
mclean$YearsExp[mclean$YearsExp == 99] <- NA
```

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

```
    Salary MngrRating YearsExp YrsSinceGrad   Origin
103     75         NA        8            8 Internal
110     81         NA        9            9 External
124     73        5.9       NA            7 External
154     49        8.0        1            1     <NA>
```

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mclean[!complete.cases(mclean),]
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    Salary MngrRating YearsExp YrsSinceGrad   Origin
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154     49        8.0        1            1     <NA>
```

This isn't surprising—it is very common to have missing entries in your data.

Exploring the data: Missing entries

There are two ways of dealing with missing data:

- Omit the rows that have missing entries in it.

Omiting data is the easiest, but often not the best way, because you lose all the other information available in the same row.

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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.

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

mclean$YearsExp[is.na(mclean$YearsExp)] <-
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A smarter and more advanced way is to predict the missing data from the other data (using regression!).

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

We could also predict the missing entries, or treat the missing entries as a seperate level (e.g. "Unknown").

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- Making predictions for missing data based on available data reinforces the existing relationships between variables, so 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.

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Correlation between the response and the predictors is good, but correlation between the predictors is not!

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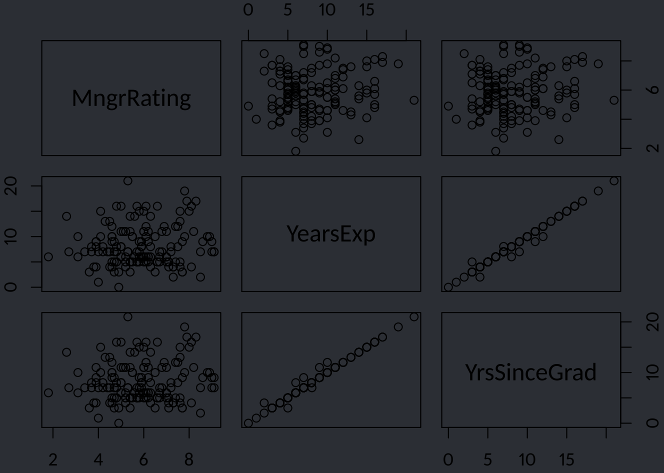
- Any conclusions based on the p-values, coefficients, and confidence intervals of the highly correlated variables will be unreliable.
- These statistics will not be stable: adding new data or predictors to the model could drastically change them.

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



```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
```

Exploring the data: Multicollinearity

One way to see if two variables are collinear is to check the correlation between the two:

```
cor(mclean$YearsExp, mclean$YrsSinceGrad)

[1] 0.9947616
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cor(mclean$YearsExp, mclean$YrsSinceGrad)

[1] 0.9947616
```

Any correlation ≥ 0.95 is definitely a problem, but smaller correlations could be problematic too.

Exploring the data: Multicollinearity

A better way to check multicollinearity is using Variance Inflation Factors (VIF).

- Remember: If we have multicollinearity, we will have large standard errors (i.e. high variance) in our estimators.
- The VIF is

$$\text{VIF}(\beta_j) = \frac{\text{Variance of } \beta_j \text{ in multiple regression}}{\text{Variance of } \beta_j \text{ if } X_j \text{ is the only predictor}}$$

- It is a measure of how much more uncertain we are about β_j, once we've included the other predictors.

Exploring the data: Multicollinearity

```r
library(car)
vif(model)

  MngrRating      YearsExp YrsSinceGrad        Origin
    1.136002     95.954255    97.011260      1.540448
```

Predictors with VIF > 5 indicate multicollinearity.

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Remember: Multicollinearity could exist between more than two predictors (this is why there are only $n - 1$ dummy variables for a categorical variable with n values).

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Drop any predictor that has VIF > 5.

Remember: Multicollinearity could exist between more than two predictors (this is why there are only $n - 1$ dummy variables for a categorical variable with n values).

```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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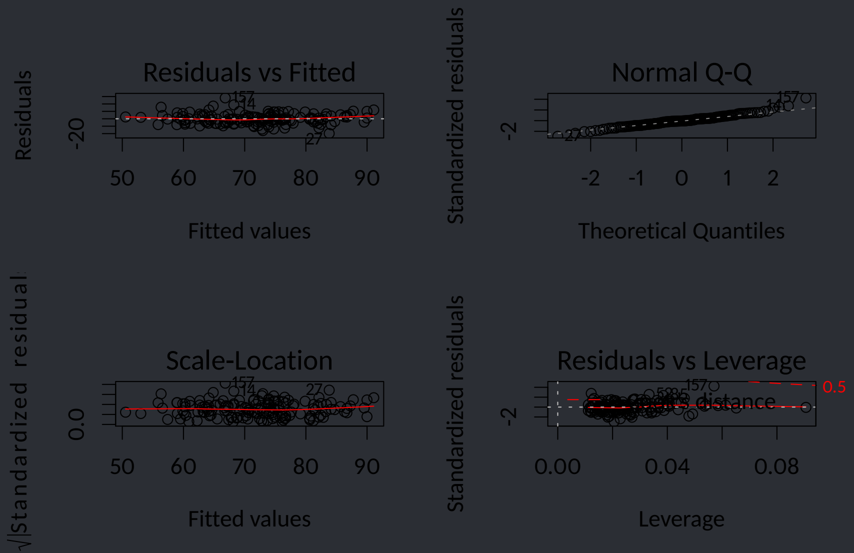
```r
plot(model2)
```



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Outliers among the residuals

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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       157
18.76901 -19.81152  17.14133  15.66079  28.18007
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```

These cases are not predicted well by the model.

Outliers among the residuals

Let's look at row 157:

```
manager[157,]

    Salary MngrRating YearsExp YrsSinceGrad   Origin
157     95          4        1            1 Internal
```

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

Outliers among the residuals

Let’s look at row 157:

```
manager[157,]

    Salary MngrRating YearsExp YrsSinceGrad   Origin
157     95          4        1            1 Internal
```

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

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

Influential cases

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- The Residuals vs Leverage plot tells about influential cases.
- A **high-leverage case** is one that has an unusual combination of predictor values.
- An **influential case** is a high-leverage case that also has a high residual: it could change your β values significantly when excluded from your analysis, i.e., it does not follow the overall trend.
- Look for the cases on the upper/lower right corners (beyond the dashed curves).