

Linear Models Diagnostics

Prof Wells

STA 295: Stat Learning

February 6th, 2024

Outline

In today's class, we will...

- Discuss theoretical foundation for linear regression
- Perform inference for simple linear models
- Implement simple linear regression in R

Section 1

Problems with Linear Model

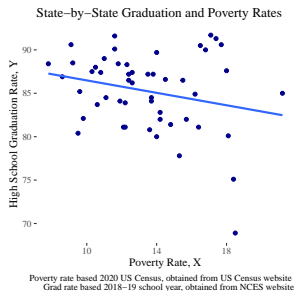
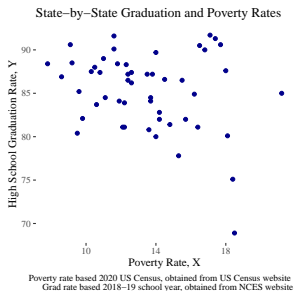
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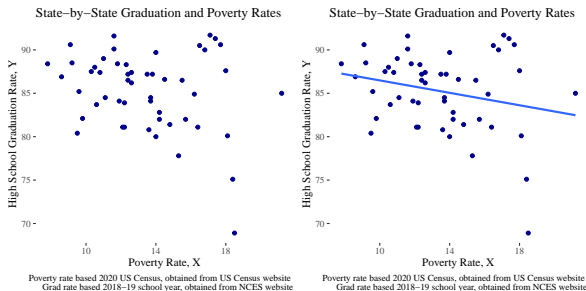
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However, if we want to make *predictions* or perform *statistical inference* we need to make sure key assumptions of randomness are met.

Common Problems

Most problems fall into 1 of 6 categories:

- ① Non-linearity of relationship between predictors and response
- ② Correlation of error terms
- ③ Non-constant variance in error
- ④ Outliers
- ⑤ High-leverage points
- ⑥ Collinearity of predictors

Non-linearity

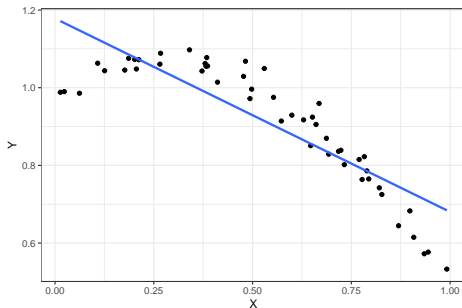
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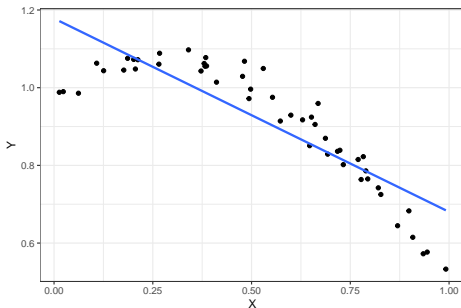
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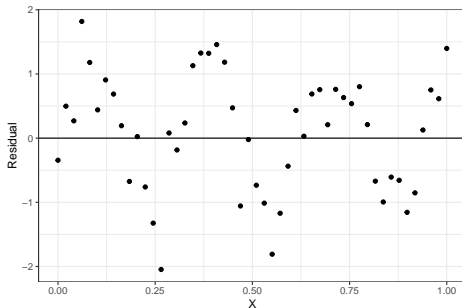
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But if this assumption is false, our model is likely to have high bias.

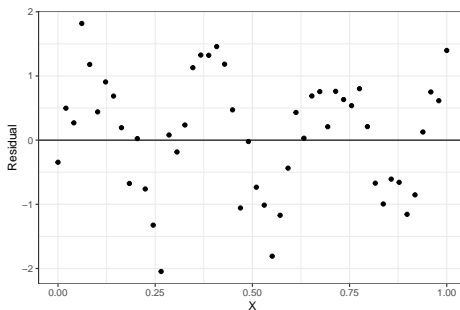
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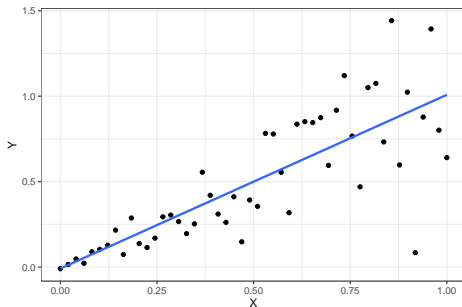


Correlated errors lead to underestimates of residual standard error

- This produces incorrectly narrow confidence intervals, as well incorrectly small p-values
- It also leads to models with higher variance

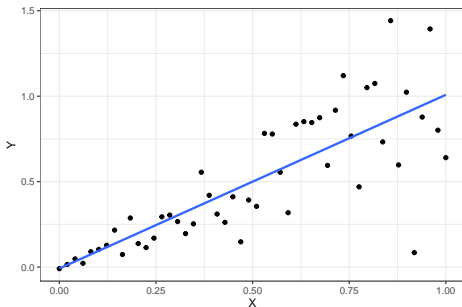
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Estimates for regression coefficients (β_0, β_1) are still *unbiased*; However, estimated standard errors SE are incorrect

- Confidence intervals and hypothesis tests should not be trusted
- There are other estimates for β_0 and β_1 that are still unbiased, but have lower variance (and hence, have lower test MSE)

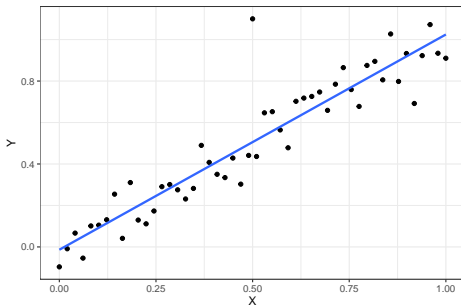
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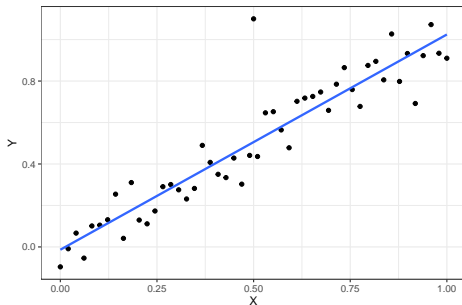
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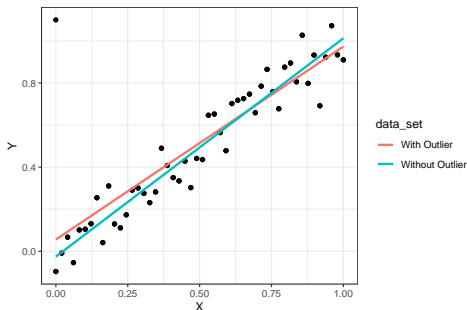
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- Presence of outliers decrease estimated R^2 and RSE compared to similar data set without outliers.

High Leverage points

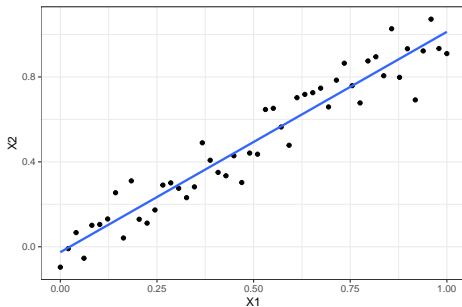
Outliers which have extreme values for **both** predictors and response are called high-leverage points



- Outliers can cause noticeable changes in the parameter estimates, and can lead to less accurate models

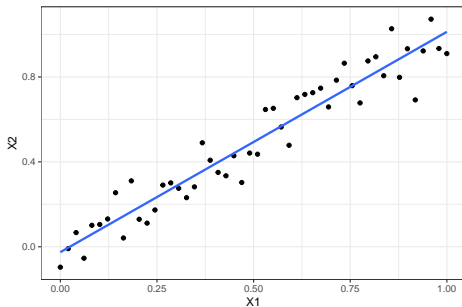
Collinearity

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Collinearity produces high variance in estimates for β .

- We'll talk more about this next week.

Section 2

Diagnostic Plots

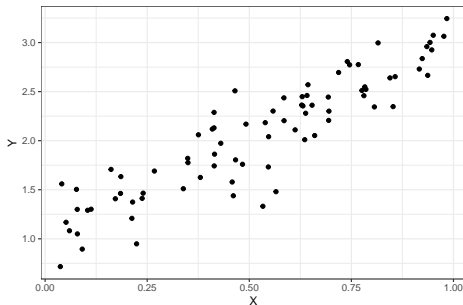
A Valid Model

Let's begin by creating a valid linear model to use as a baseline:

$$Y = 1 + 2X + \epsilon \quad \epsilon \sim N(0, 0.25)$$

```
set.seed(700)
X <- runif(80, 0, 1)
e <- rnorm(80, 0, .25)
Y <- 1 + 2*X + e
my_data <- data.frame(X,Y)

ggplot(my_data, aes(x = X , y = Y)) + geom_point()
```



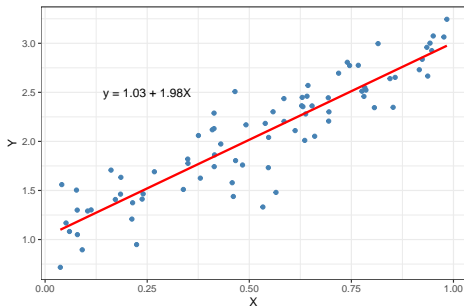
Linear Model

```
my_mod<-lm(Y ~ X, data = my_data)
my_mod$coefficients
```

```
## (Intercept)          X
##    1.025947    1.981375
```

```
summary(my_mod)$r.sq
```

```
## [1] 0.8275073
```



Model Diagnostics

Goal: Create graphics to assess how well data fits modeling assumptions.

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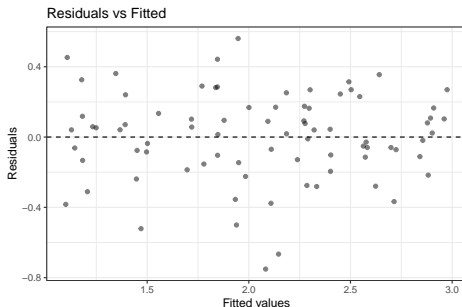
Goal: Create graphics to assess how well data fits modeling assumptions.

The trade-off:

- The base R `plot` function can be used to quickly create all diagnostic plots necessary
 - But we then are restricted to `plot` aesthetics
- Alternatively, we can use the `ggglm` function in the package of the same name, created and maintained by Reed alum, Grayson White.
 - Provides the same diagnostic plots as `plot`, but with `ggplot2` appearances and customization.

Residual Plot

```
library(ggglm)  
ggplot(data = my_mod) +stat_fitted_resid()
```

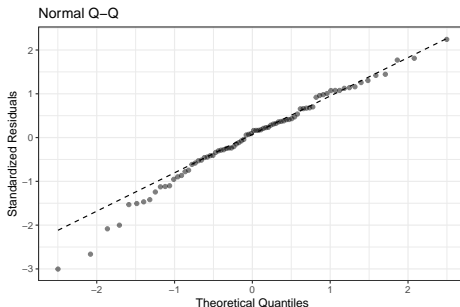


What is represented along the horizontal axis? Why?

What should we look for?

QQ Plot

```
library(ggglm)  
ggplot(data = my_mod) +stat_normal_qq()
```

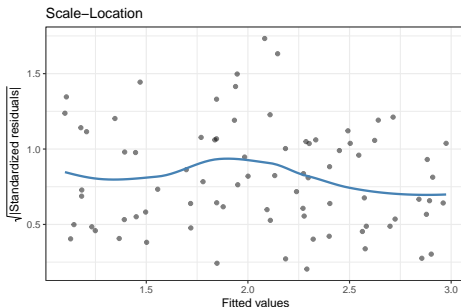


What is represented along the horizontal and vertical axes? Why?

What should we look for?

Scale-Location Plot

```
library(ggplot)  
ggplot(data = my_mod) +stat_scale_location()
```

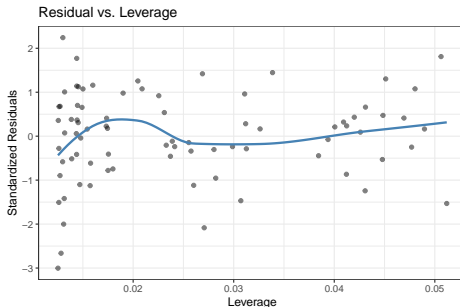


What is represented along the vertical axes? Why?

What should we look for?

Leverage Plot

```
library(ggglm)  
ggplot(data = my_mod) +stat_resid_leverage()
```



What is represented along the horizontal and vertical axes? Why?

What should we look for?

Plot Quartet

```
library(ggglm)  
ggglm(my_mod)
```

