## STAT 305: Beyond Chapter 4

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(Optional Reading)

#### **Model Diagnostics**

#### **Model Assumptions**

# Model Assumptions

- There are some assumptions in fitting a linear regression (either simple or multiple) to determine any possible relationship between response variable(s) and explanatory (experimental) variable(s). Some of them will be discussed in future chapters, and in this sub-section, we will discuss some assumptions relatd to residuals.
- The **Residals** are the difference between the observed data point and the fitted prediction:

$$e_i = y_i - \hat{y}_i$$

- ROPe: Residuals = Observed Predicted (using symbol  $e_i$ )
- Obviously, we would like our residuals to be small compared to the size of response values.

#### Assumptions in Linear Regression

## Model Assumptions

If a linear model makes sense, the residuals will

- have a constant (homogeneous) variance
- be approximately normally distributed (with a mean of zero), and
- be independent of one another.

The most useful graph for analyzing residuals is a **residual by predicted plot**. This is a graph of each residual value plotted against the corresponding predicted value.

- If the assumptions are met, the residuals will be randomly scattered around the center line of zero, with no obvious pattern. The residuals will look like an unstructured cloud of points, centered at zero
- This checks the constant (homogeneous) variance and independence of residuals.

#### **Assumptions in Linear Regression**

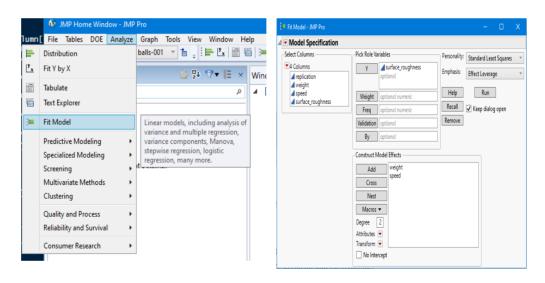
## Model Assumptions

#### Residual VS. predicted plot

## Residual plot

JMP: Analyze > Fit Model

then choose your response and explanatory variables and Run the model



After fiting a model, click on the red down arrow next to the model.

## **Assumptions in Linear Regression**

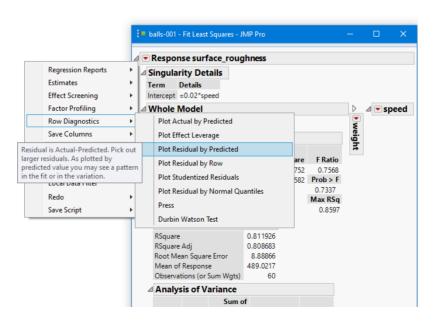
Model Assumptions

#### Residual VS. predicted plot

After fiting a model, click on the red down arrow next to the model

Residual plot

Row diagnostics> Plot residuals by predicated

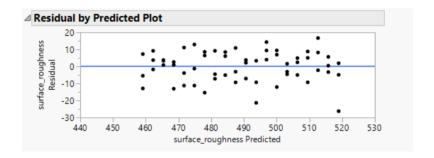


### **Assumptions in Linear Regression**

Model Assumptions Residual VS. predicted plot

Then you have **residuals**  $(e_i)$  on y axis and **predicted** values  $(\hat{y})$  on x axis

Residual plot



If there is a non-random pattern, the nature of the pattern can pinpoint potential issues with the model.

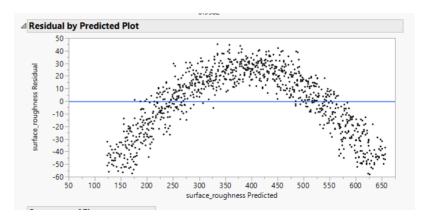
Model Assumptions

Residual plot

#### **Assumptions in Linear Regression**

#### Residual VS. predicted plot

For example, if curvature is present in the residuals, then it is likely that there is curvature in the relationship between the response and the predictor that is not explained by our model. A linear model does not adequately describe the relationship between the predictor and the response.



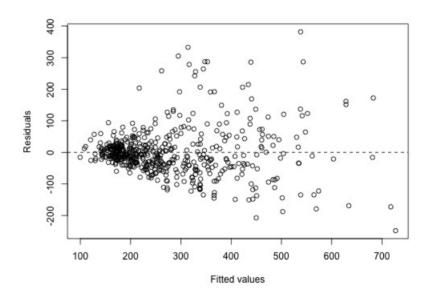
#### **Assumptions in Linear Regression**

Model Assumptions

#### Residual VS. predicted plot

Megaphone shaped pattern: variability of  $e_i$  increases or decreases as  $\hat{y}_i$  increases.

#### Residual plot



This indicates non-constant (not homogeneous) variance.

## Assumptions in Linear Regression

## Model Assumptions

Residual plot

#### Normality

#### Normality of residuals

- In addition to the residual versus predicted plot, there are other residual plots we can use to check regression assumptions.
- A histogram of residuals and a normal probability plot (QQ-plot) of residuals can be used to evaluate whether our residuals are approximately normally distributed.
  - However, unless the residuals are far from normal or have an obvious pattern, we generally don't need to be overly concerned about normality.
- Note that we check the residuals for normality. We don't need to check for normality of the raw data. Our response and predictor variables do not need to be normally distributed in order to fit a linear regression model.

### **Assumptions in Linear Regression**

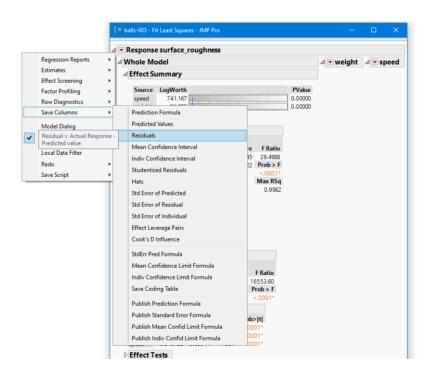
Model Assumptions Normality of residuals

To draw the histogram of the residuals, first save residuals of the model.

Residual plot

Save Culumns> Residuals

**Normality** 



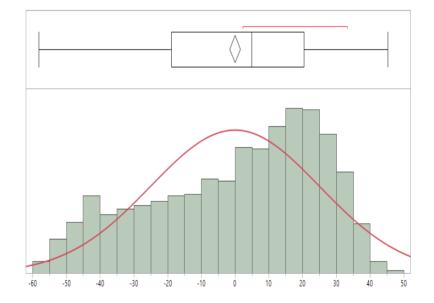
#### **Assumptions in Linear Regression**

Model Assumptions Normality of residuals

Then draw a histogram of the residuals (review the JMP toturial for histograms)

Residual plot

**Normality** 



It seems the residuals are not normaly distributed in this example.

Model Assumptions

Residual plot

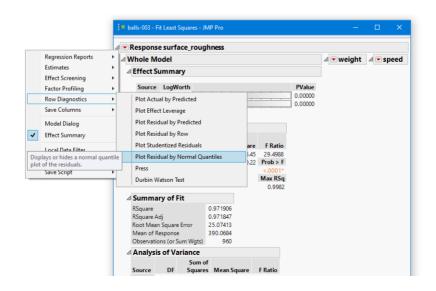
Normality

#### **Assumptions in Linear Regression**

#### Normality of residuals

As the instructions on the JMP toturials (and also HW #3), you can draw **Normal QQ-plot** to evaluate if the residuals meet the assumptions of normaly distributed.

Row Diagnostics> Plot Residual by Normal Quantile



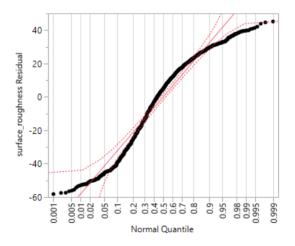
Assumptions in Linear Regression

Model Assumptions Normality of residuals

Plotting Normal QQ-plot of the same example

Residual plot

**Normality** 



- Again, the QQ-plot also confirms that the assumption of Normal distribution of residuals is violated to some extend in this example.
- More examination is required to fix the issue or to find the problem.