

Chapter 4

# SLR Model Assumptions

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This work is a derivative of 'Regression Methods' by Iain Pardoe, Laura Simon and Derek Young, used under CC BY-NC.

# Contents

1. Background
2. Residuals vs. Fits Plot
3. Residuals vs. Predictor Plot
4. Identifying Specific Problems Using Residual Plots
5. Residuals vs. Order Plot

# 1. Background

# 1. LINE Assumptions

- Linear Function: The mean of the response,  $E(Y_i)$ , at each value of the predictor,  $x_i$ , is a linear function of the  $x_i$ .
- Independent: The errors,  $\epsilon_i$ , are independent.
- Normally Distributed: The errors,  $\epsilon_i$ , at each value of the predictor,  $x_i$ , are normally distributed.
- Equal Variances: The errors,  $\epsilon_i$ , at each value of the predictor,  $x_i$ , have equal variances (denoted  $\sigma^2$ ).

## 2. Consequences of Violation

- All tests and intervals are very sensitive to even minor departures from independence.
- All tests and intervals are sensitive to moderate departures from equal variance.

## 2. Consequences of Violation

- The hypothesis tests and confidence intervals for  $\beta_0$  and  $\beta_1$  are fairly "robust" against departures from normality.
- Prediction intervals are quite sensitive to departures from normality.

## 2. Residuals vs. Fits Plot

# 1. Residuals vs. Fits Plot

- Scatter plot of residuals on the y axis and fitted values (estimated responses) on the x axis.
- The plot is used to detect non-linearity, unequal error variances, and outliers.



## 2. Data: Alcohol Arm

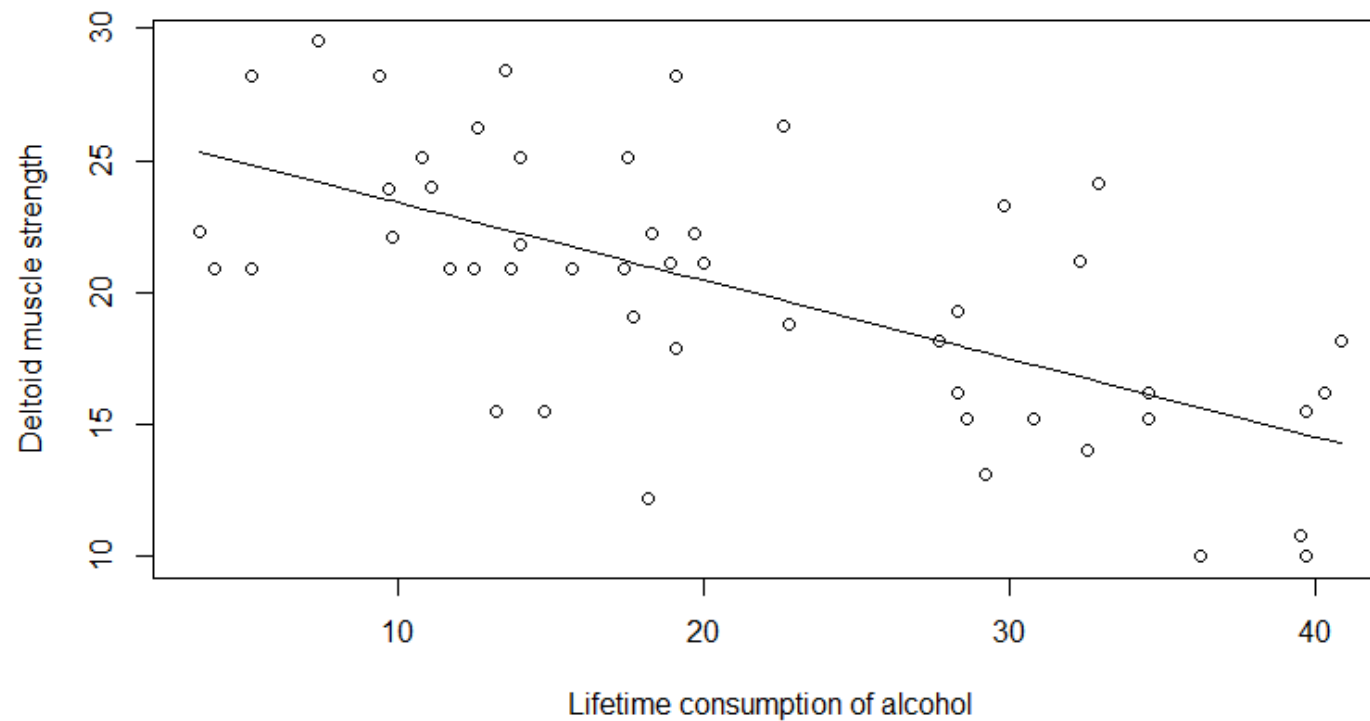
- Data: [Alcohol Arm](#)

```
alcoholarm <- read.table("alcoholarm.txt", header=T)
attach(alcoholarm)
model <- lm(strength ~ alcohol)
```

### 3. Regression Plot

```
plot(x=alcohol, y=strength,  
      xlab="Lifetime consumption of alcohol", ylab="Deltoid  
muscle strength",  
      panel.last = lines(sort(alcohol),  
fitted(model)[order(alcohol)]))
```

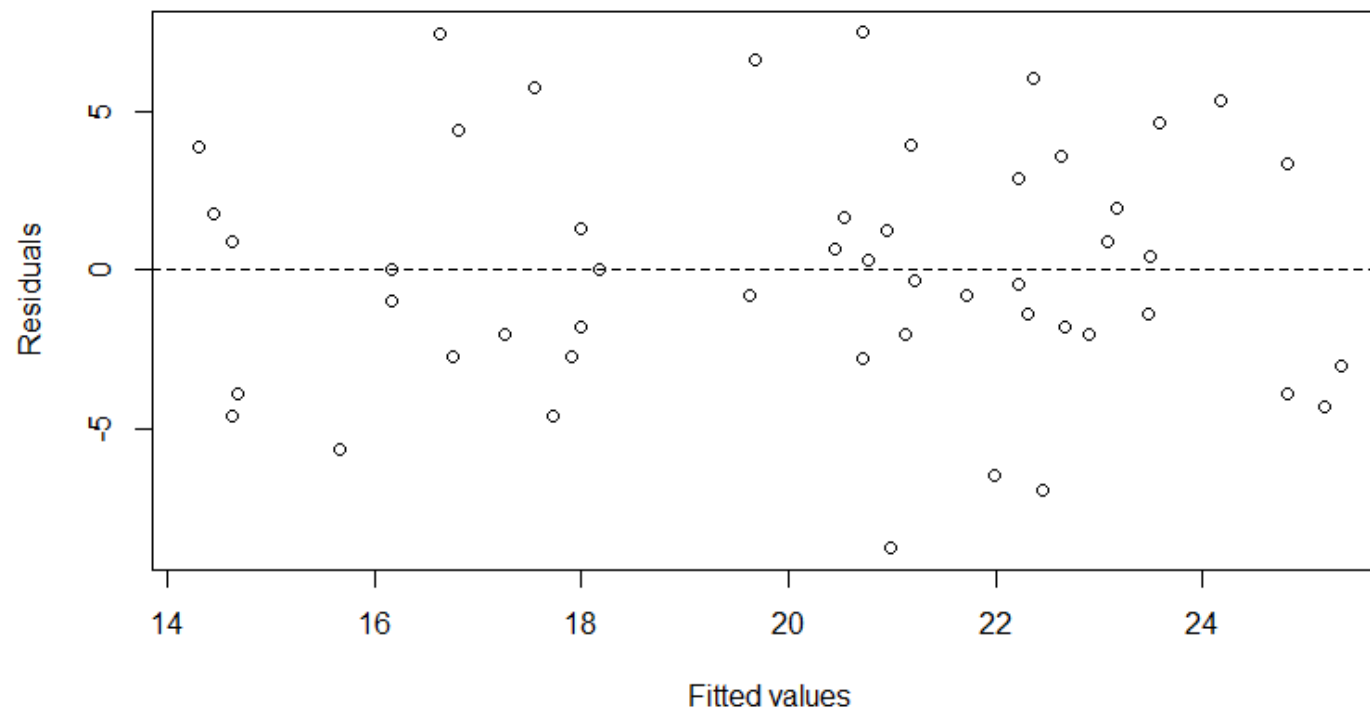
### 3. Regression Plot



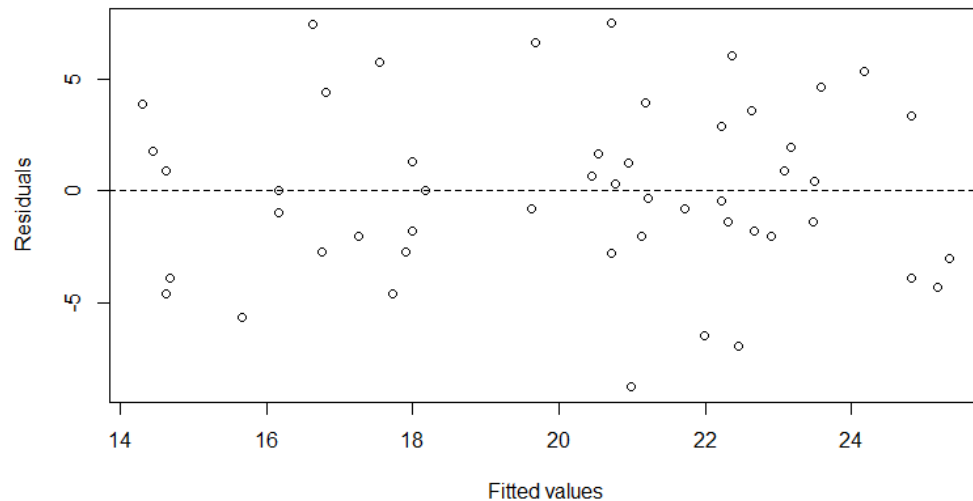
## 4. Residuals vs. Fits Plot

```
plot(x=fitted(model), y=residuals(model),  
     xlab="Fitted values", ylab="Residuals",  
     panel.last = abline(h=0, lty=2))
```

## 4. Residuals vs. Fits Plot

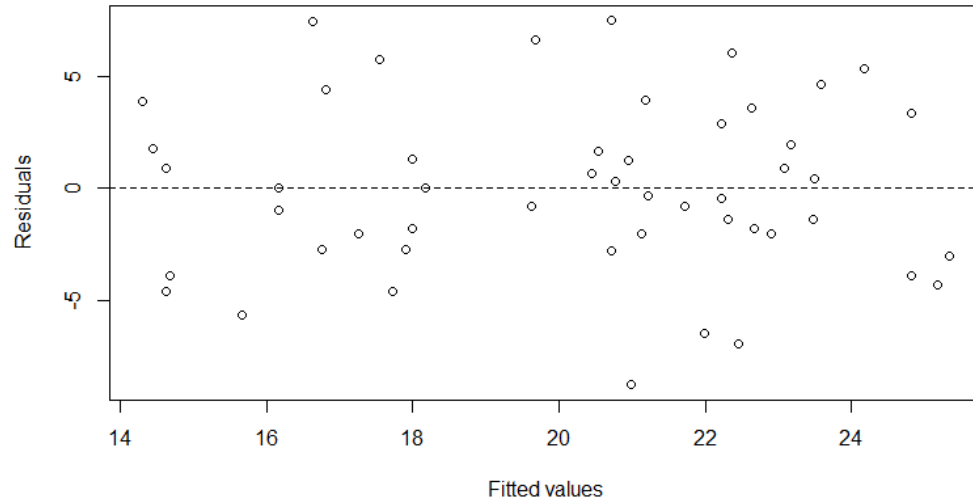


## 4. Residuals vs. Fits Plot



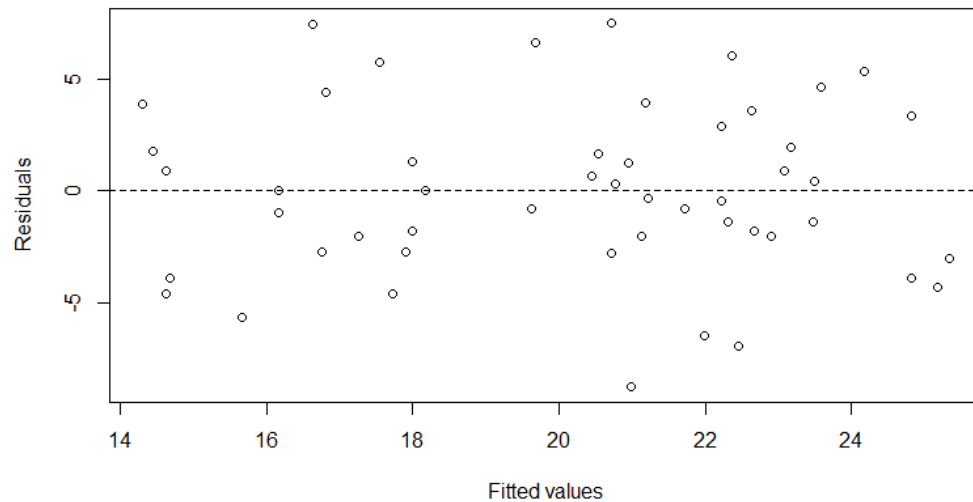
The residuals "bounce randomly" around the residual = 0 line. This suggests that the assumption that the relationship is linear is reasonable.

## 4. Residuals vs. Fits Plot



The residuals roughly form a "horizontal band" around the residual = 0 line. This suggests that the variances of the error terms are equal.

## 4. Residuals vs. Fits Plot



No one residual "stands out" from the basic random pattern of residuals. This suggests that there are no outliers.

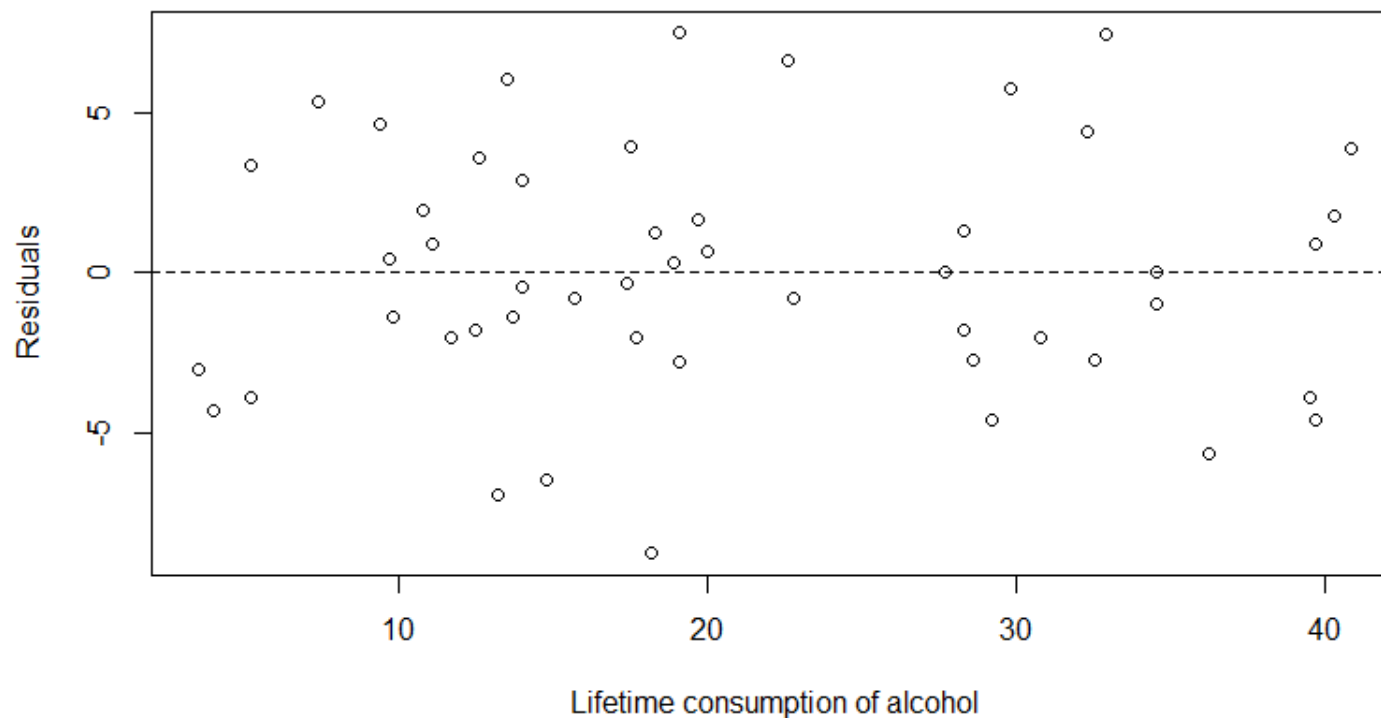


### 3. Residuals vs. Predictor Plot

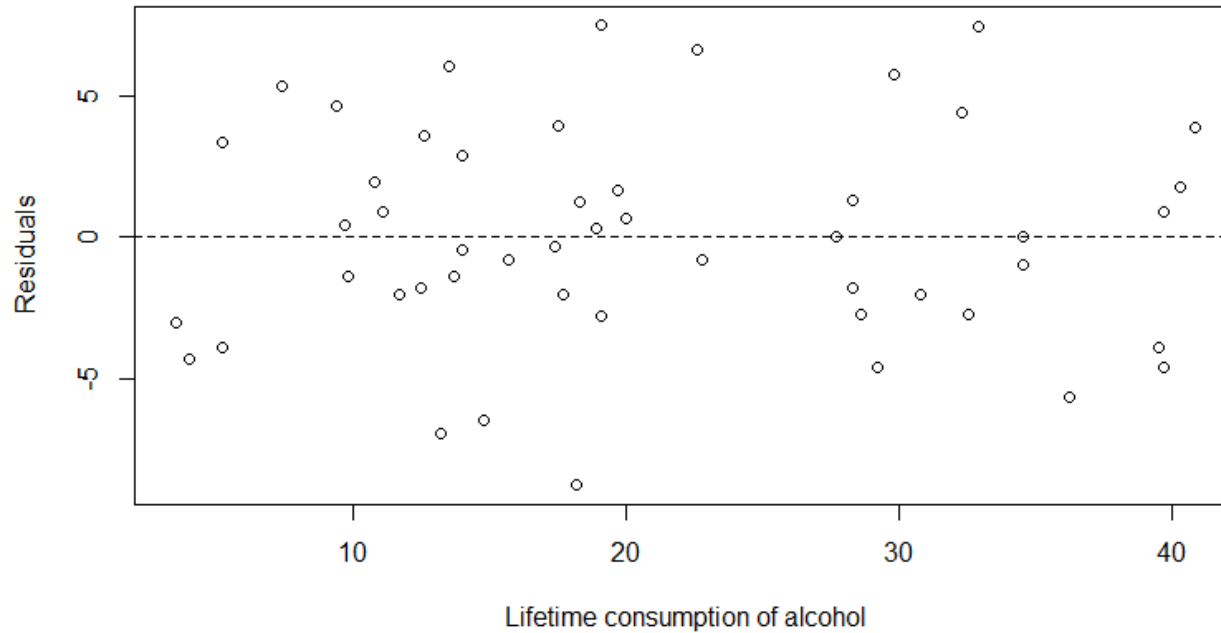
# 1. Residuals vs. Predictor Plot

```
plot(x=alcohol, y=residuals(model),  
     xlab="Lifetime consumption of alcohol", ylab="Residuals",  
     panel.last = abline(h=0, lty=2))
```

# 1. Residuals vs. Predictor Plot

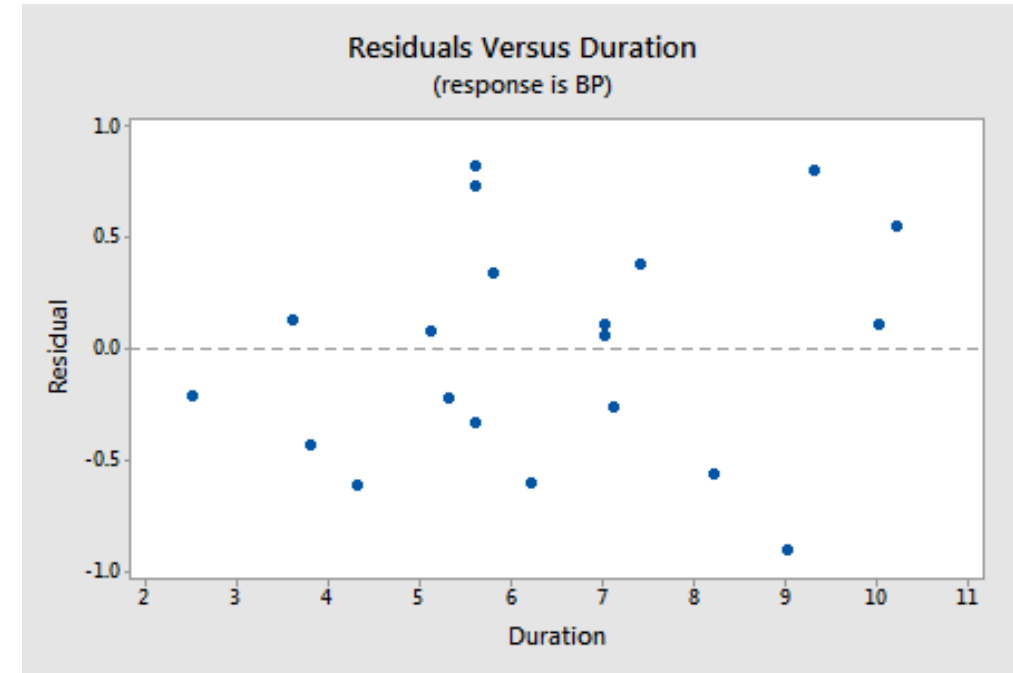
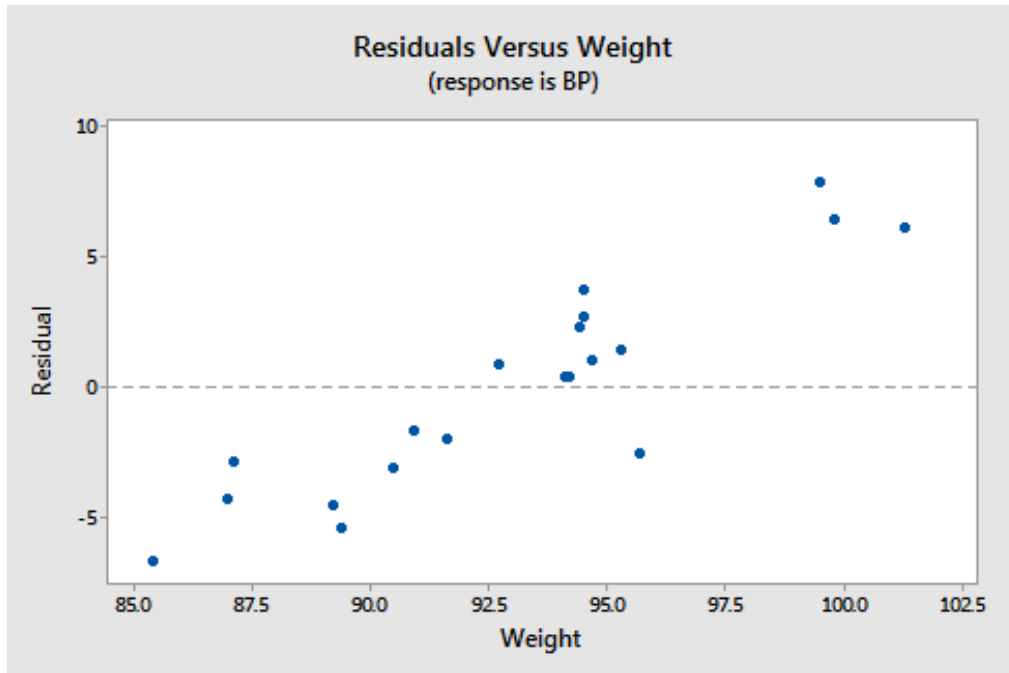


# 1. Residuals vs. Predictor Plot



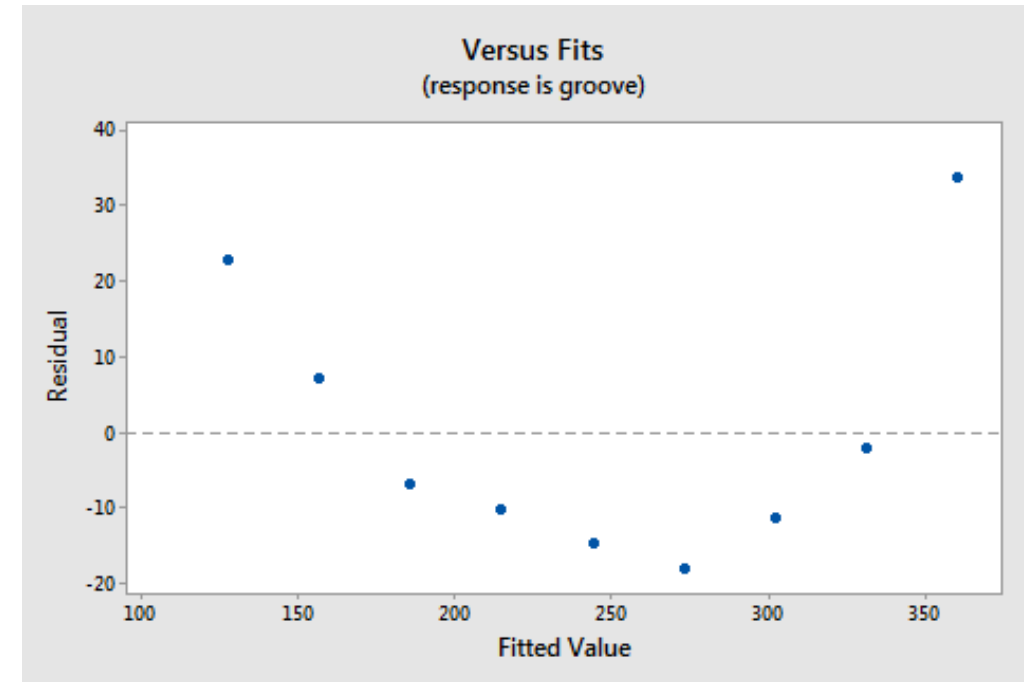
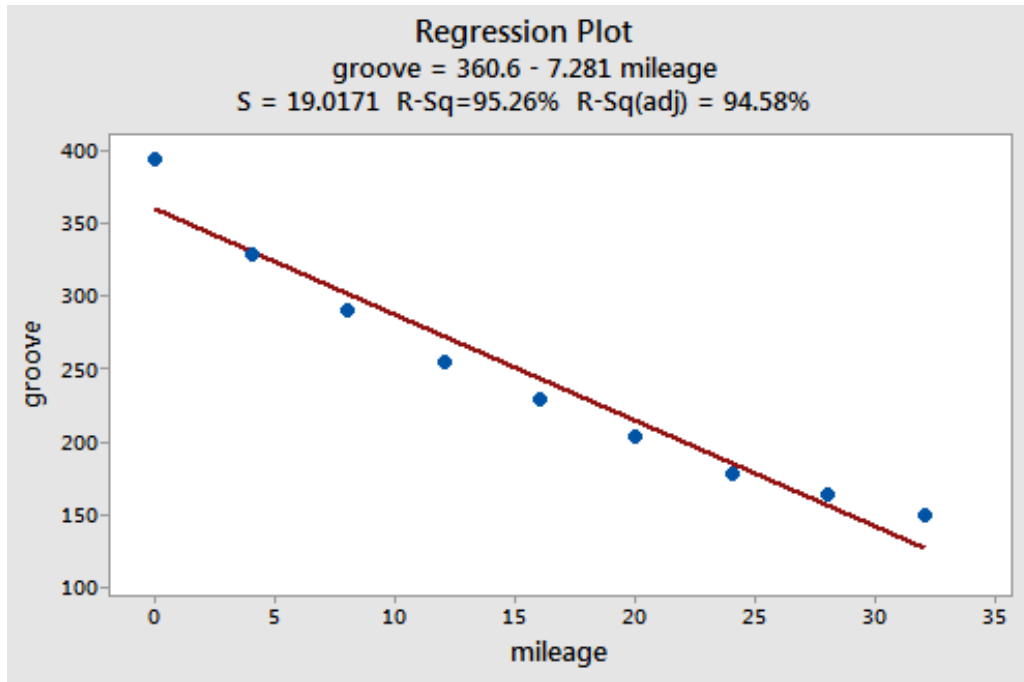
For this example, the residuals vs. predictor plot is just a mirror image of the residuals vs. fits plot. The residuals vs. predictor plot offers no new information.

# 1. Residuals vs. Predictor Plot

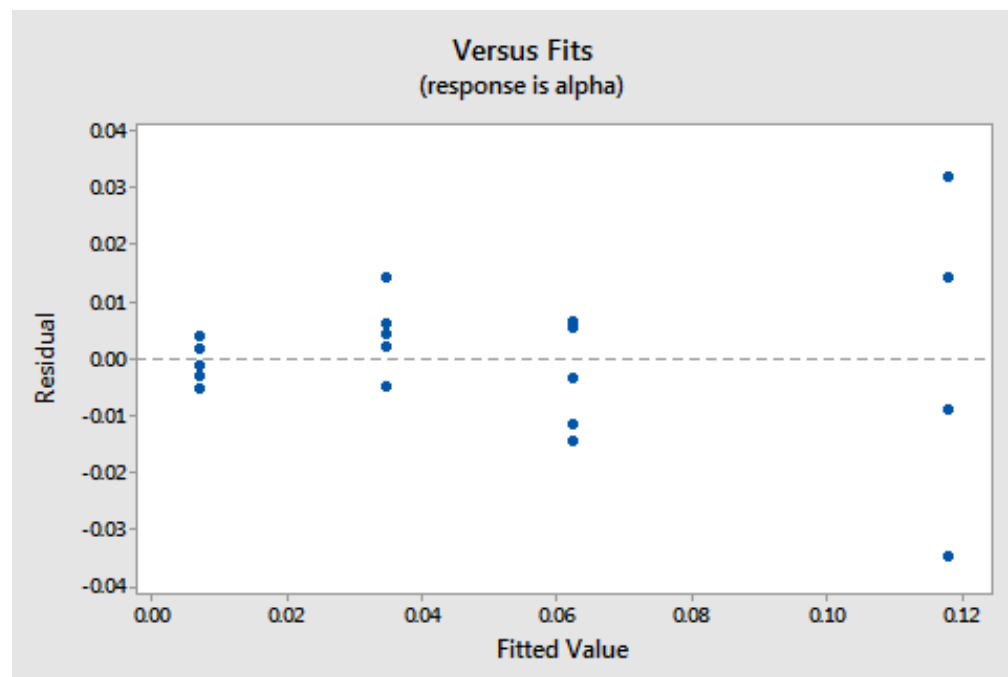
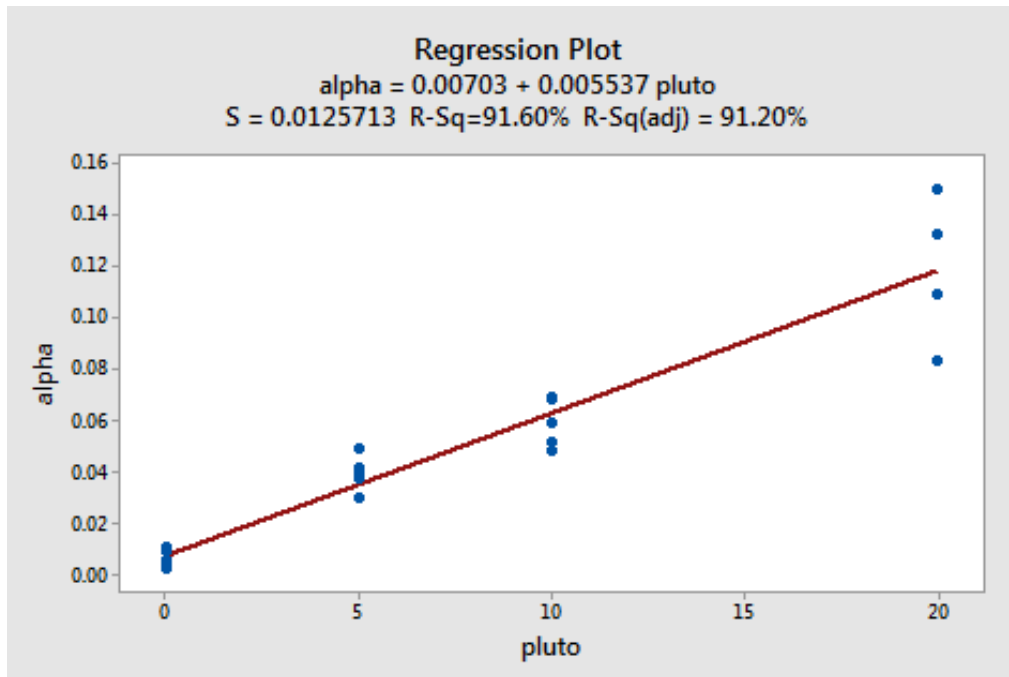


## 4. Identifying Specific Problems Using Residual Plots

# 1. How does a non-linear regression function show up on a residual vs. fits plot?

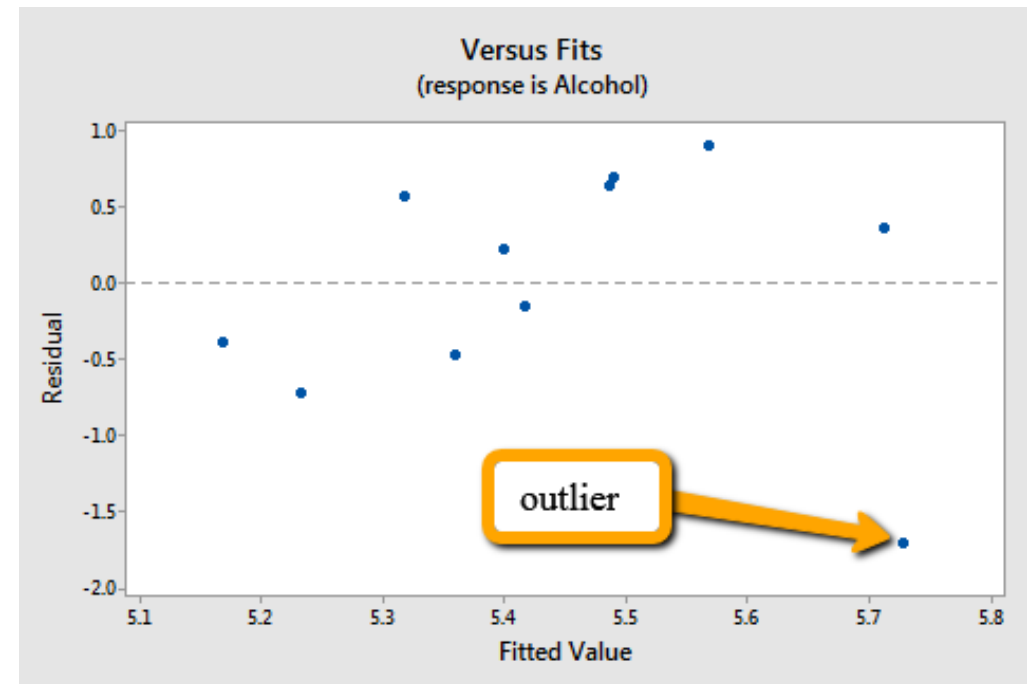
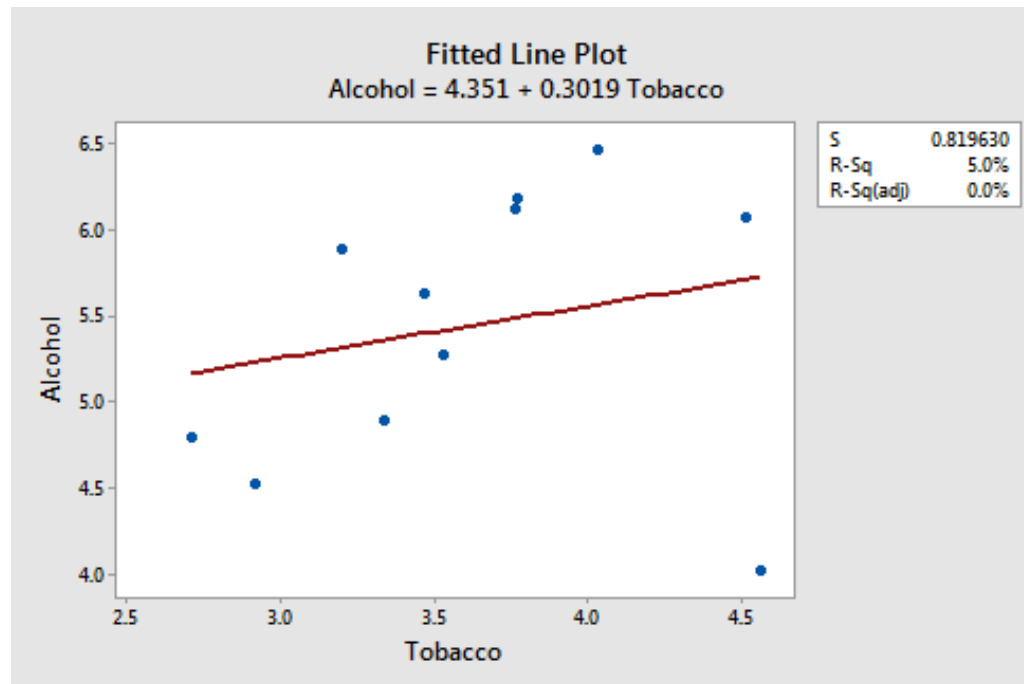


## 2. How does non-constant error variance show up on a residual vs. fits plot?

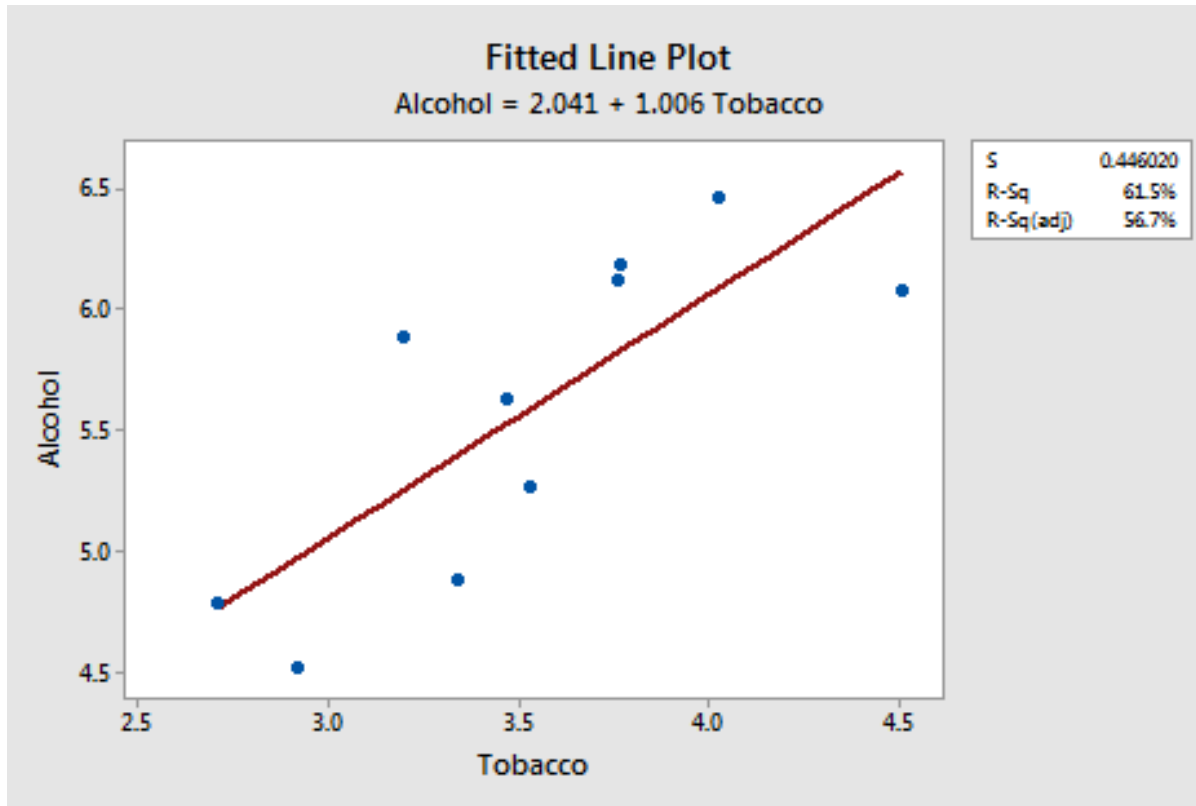




### 3. How does an outlier show up on a residual vs. fits plot?

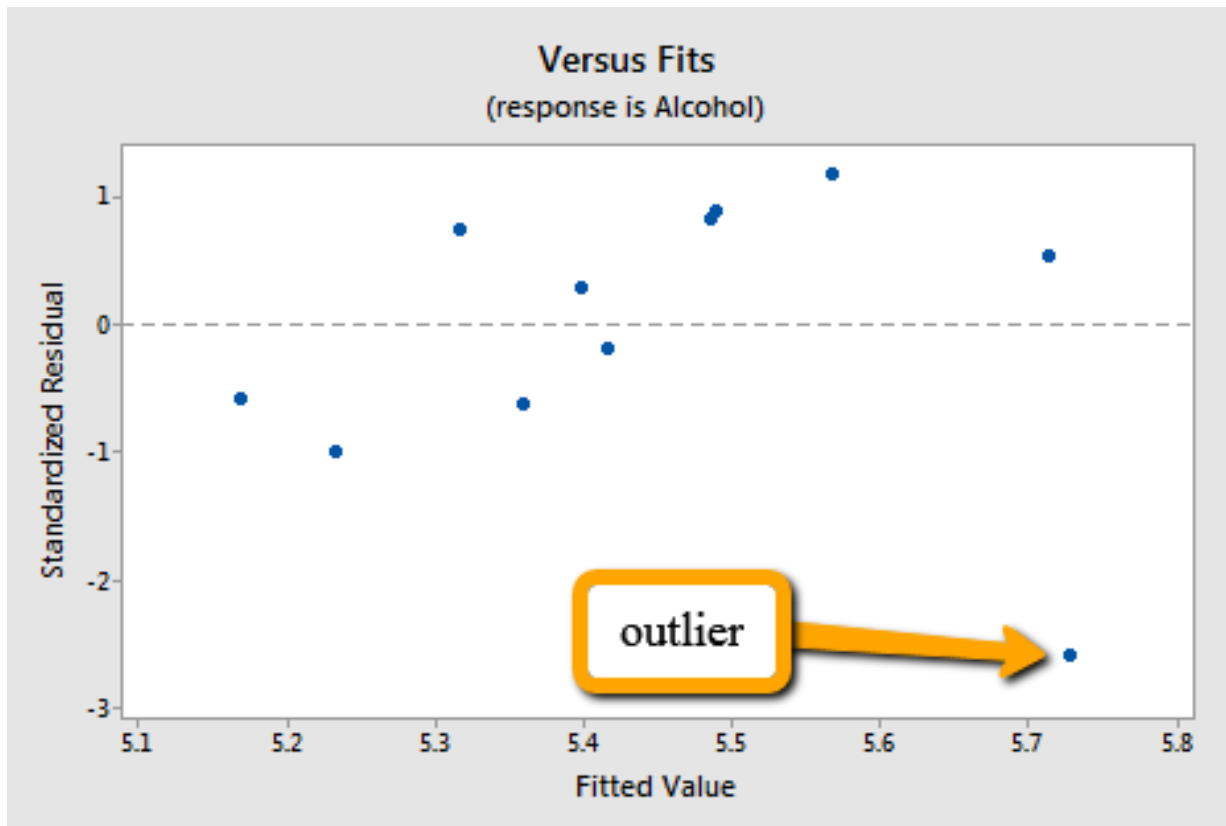


### 3. How does an outlier show up on a residual vs. fits plot?



The  $r^2$  value has jumped from 5% ("no-relationship") to 61.5% ("moderate relationship").

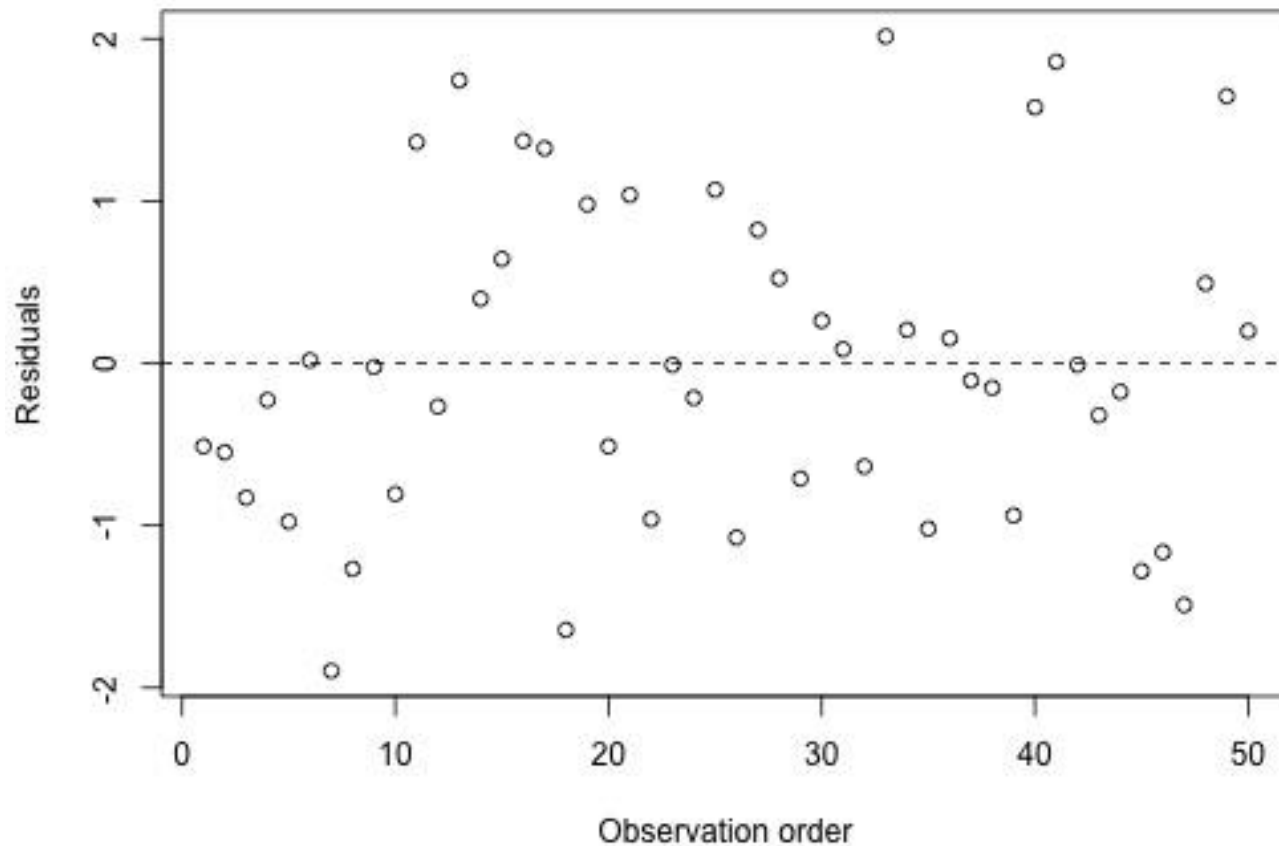
### 3. How does an outlier show up on a residual vs. fits plot?



We can make the residuals "unitless" by dividing them by their standard deviation. In this way we create what are called "standardized residuals."

## 5. Residuals vs. Order Plot

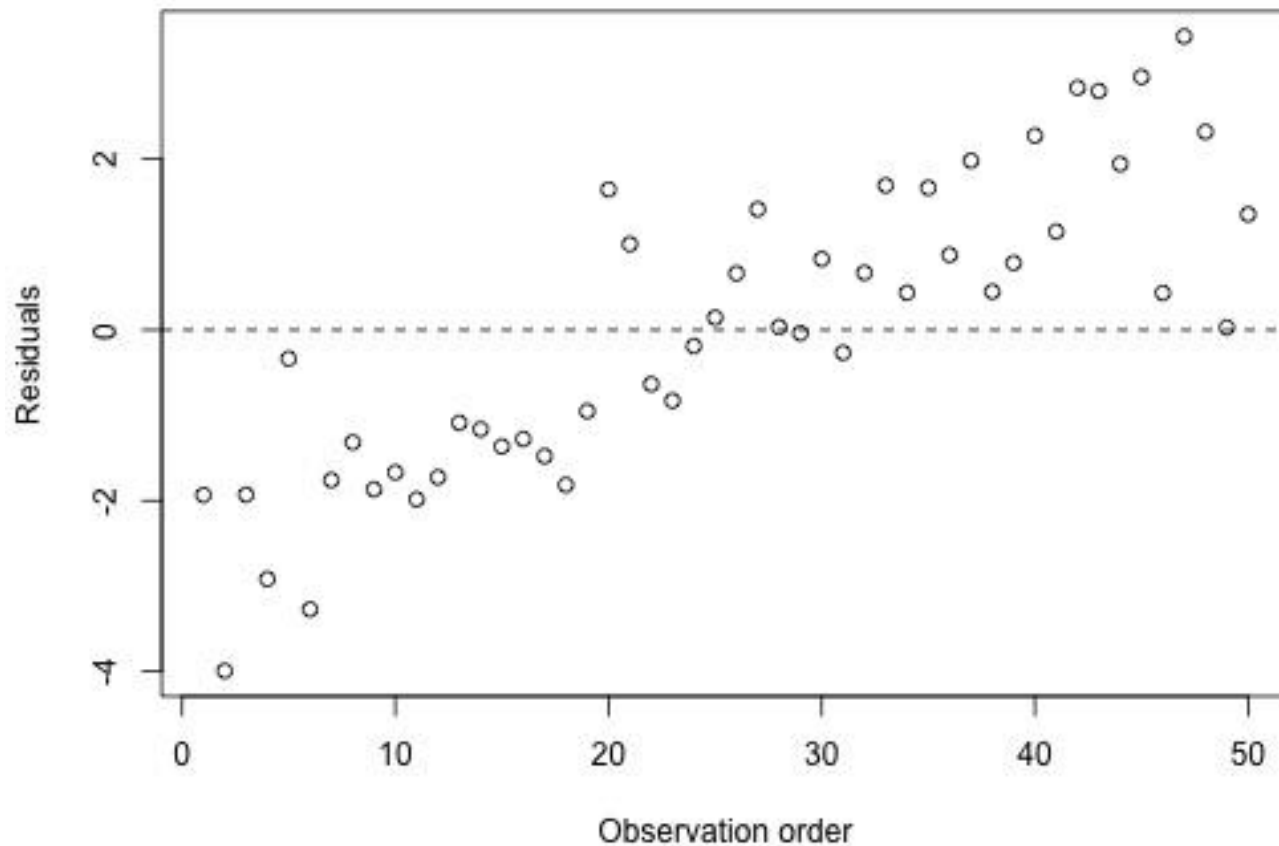
# 1. Residuals vs. Order Plot



# 1. Residuals vs. Order Plot

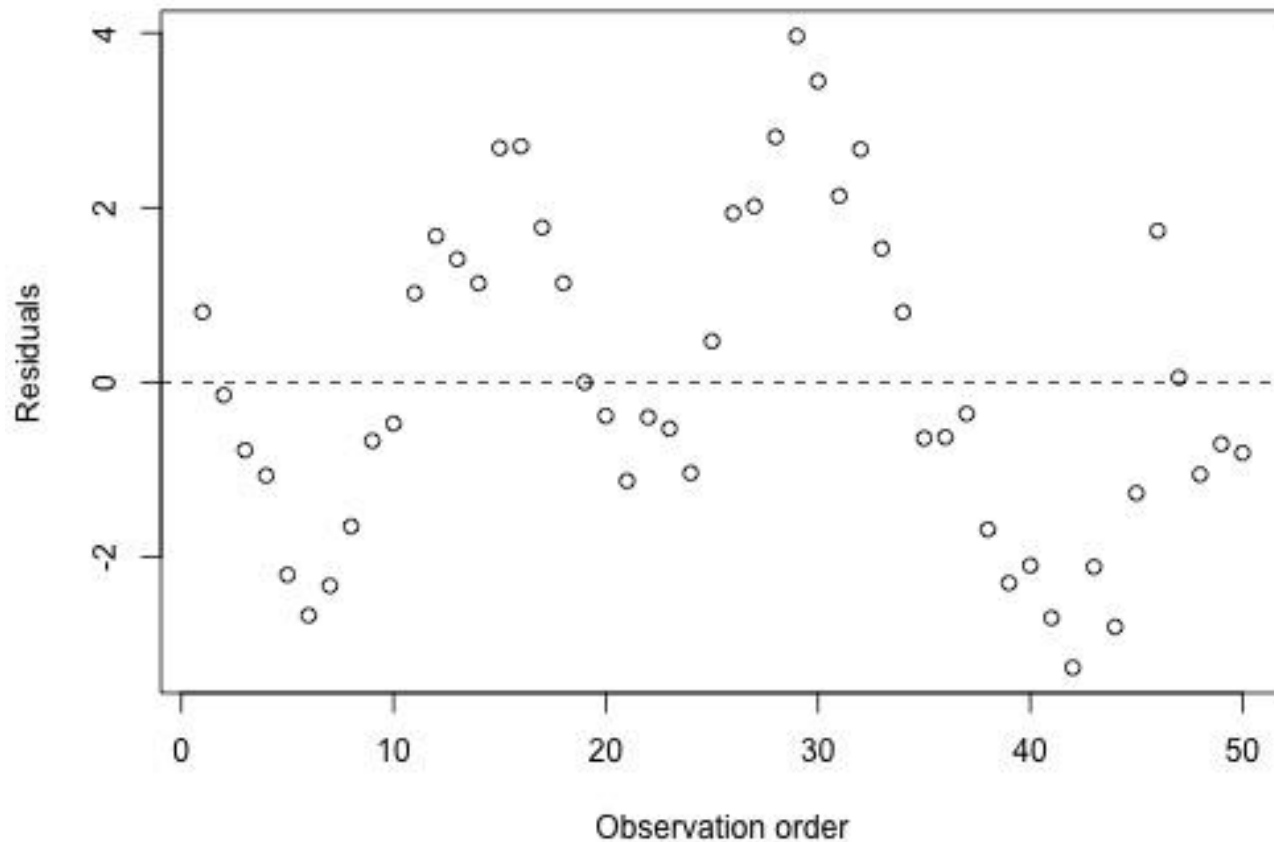
- A way of detecting a particular form of non-independence of the error terms, namely serial correlation.
- If the data are obtained in time (or space) sequence, a residuals vs. order plot helps to see if there is any correlation between the error terms that are near each other in the sequence.
- **The plot is only appropriate if you know the order in which the data were collected!**

## 2. A time trend



It might be a good idea to add the predictor "time" to the model.

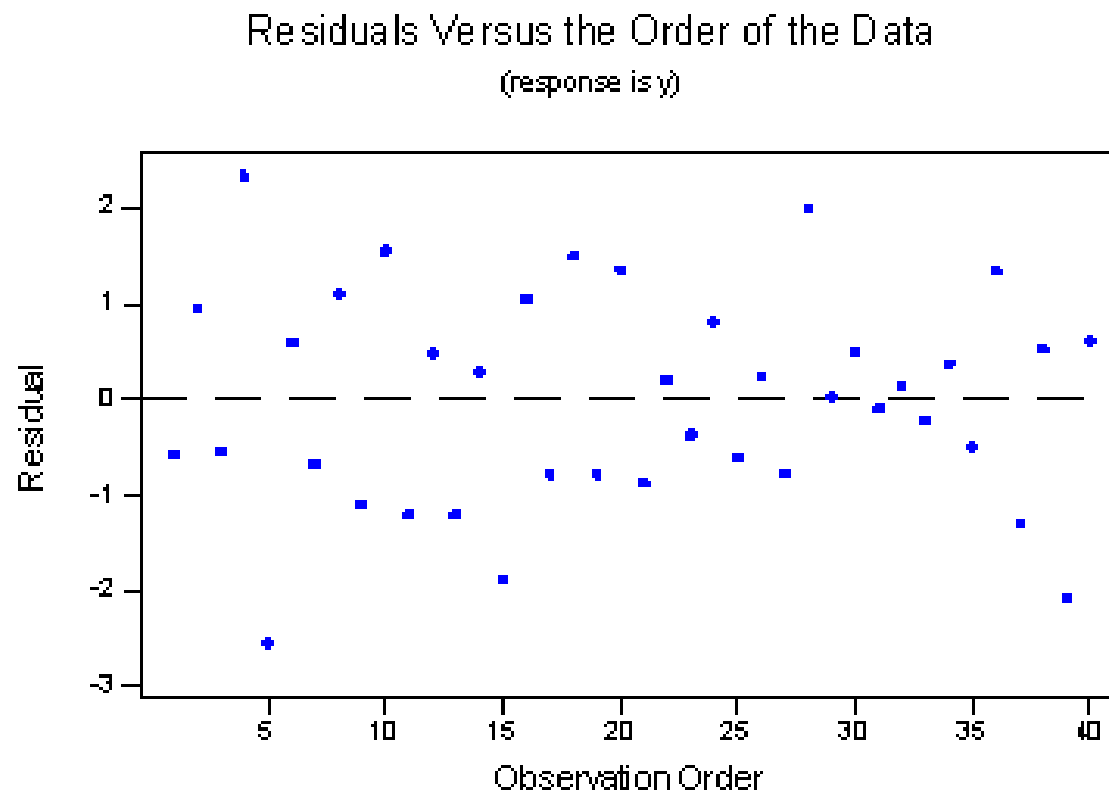
### 3. Positive serial correlation



Time series modeling is more more appropriate than linear regression in this case.



## 4. Negative serial correlation



Time series modeling is more more appropriate than linear regression in this case.

## 5. Checking LINE Assumptions

- Linear Function → Residuals vs. Fits Plot
- Independent → Residuals vs. Order Plot
- Normally Distributed → ?
- Equal Variances → Residuals vs. Fits Plot

Next

# Chapter 5

## SLR Model Assumptions II