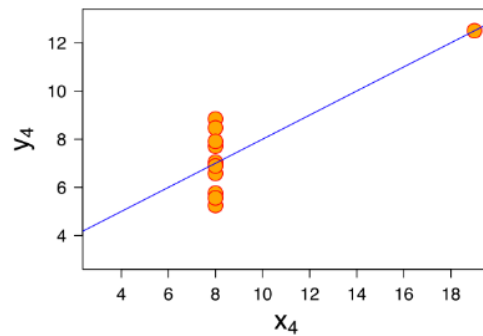
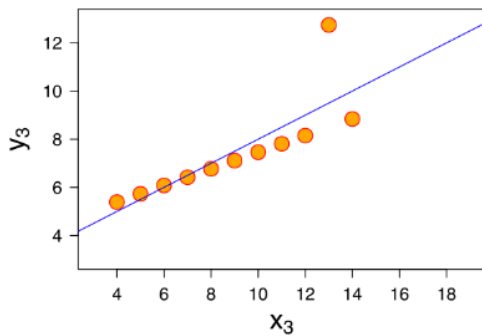
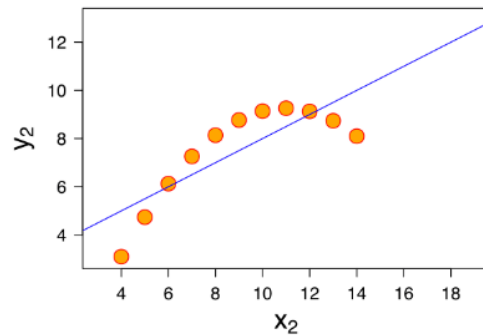
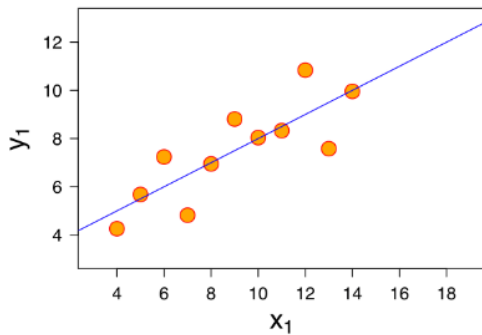


Session Agenda

- **Anscombe's Quartet**
- **Correlation**
 - **Pearson Product Moment**
 - **Testing hypotheses**
- **Simple Linear Regression**
 - **Basic Facts**
 - **Example**
 - **Coding in R**
- **Model Specification**
- **Confounding**
 - **ANOVA**
 - **Regression**
- **George E. P. Box Quote**
- **Review Problems**
- **Final Exam**

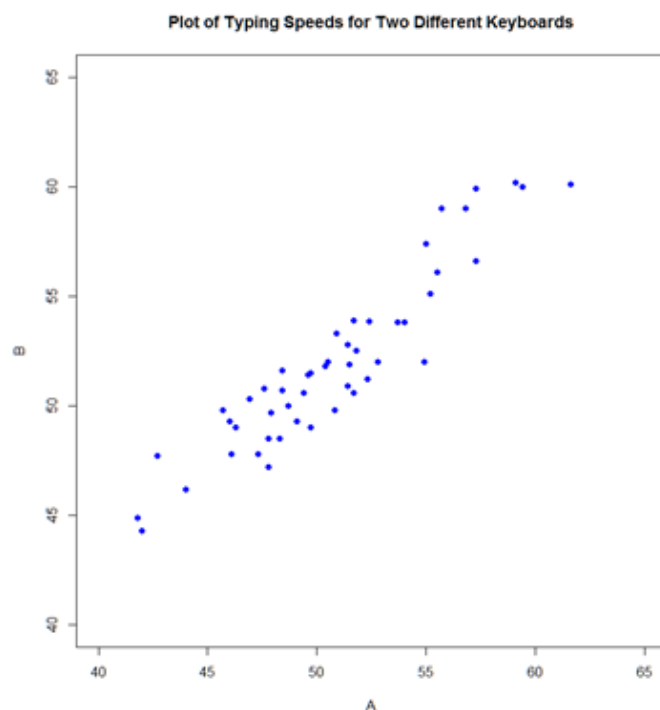
Anscombe's Quartet

Beware of relying only on simple descriptive statistics!



Property	Value	Accuracy
Mean of x	9	exact
Sample variance of x	11	exact
Mean of y	7.50	to 2 decimal places
Sample variance of y	4.125	plus/minus 0.003
Correlation between x and y	0.816	to 3 decimal places
Linear regression line	$y = 3.00 + 0.500x$	to 2 and 3 decimal places, respectively
Coefficient of determination of the linear regression	0.67	to 2 decimal places

Testing the Hypothesis of a Zero Correlation



```
> r <- cor(A,B)
> r
[1] 0.9325682
> n <- length(A)
> T <- r*sqrt((n-2)/(1-r^2))
> T
[1] 17.71045
> qt(0.95, n-2, lower.tail = TRUE)
[1] 1.677927
> pt(T, n-2, lower.tail = FALSE)
[1] 9.863848e-23
>
> cor.test(A, B, alternative = c("greater"), method = c("pearson"), conf.level = 0.95)
```

Pearson's product-moment correlation

```
data: A and B
t = 17.71, df = 47, p-value < 2.2e-16
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.8927321 1.0000000
sample estimates:
      cor
0.9325682
```

Simple Linear Regression Model

$$y = \beta_0 + \beta_1 x + \varepsilon$$

Where-

y	dependent variable,
x	independent variable,
β_0, β_1	unknown constants
ε	random error term.

The *method of least squares* is used to minimize the sum of squares:

$$S(\beta_0, \beta_1) = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

This provides a fitted equation:

$$\hat{y} = b_0 + b_1 x .$$

The differences between observed values for y and predicted values are called residuals. Residuals play an important role in diagnosing model adequacy or “model fit”.

A basic assumption of simple linear regression is that the random error term has a normal distribution with mean zero and constant variance for all observations. If investigation of the residuals reveals this is not true, the model must be changed.

Simple Linear Regression Estimators

Linear regression model estimators can be expressed in matrix terms. This is what the word “linear” denotes.

Differentiate the sum of squares for each parameter.

$$\frac{dS}{d\beta_0} = -2 \left[\sum y_i - \beta_0 n - \beta_1 \sum x_i \right]$$

$$\frac{dS}{d\beta_1} = -2 \left[\sum x_i y_i - \beta_0 \sum x_i - \beta_1 \sum x_i^2 \right]$$

Set equal to zero and form the Normal Equations:

$$\bar{y} = b_0 + b_1 \bar{x}$$

$$\sum x_i y_i / n = b_0 \bar{x} + b_1 \sum x_i^2 / n$$

Express in matrix algebra:

$$\begin{pmatrix} 1 & \bar{x} \\ \bar{x} & \sum x_i^2 / n \end{pmatrix} \begin{pmatrix} b_0 \\ b_1 \end{pmatrix} = \begin{pmatrix} \bar{y} \\ \sum x_i y_i / n \end{pmatrix}$$

Inverting and solving gives the estimators:

$$\begin{pmatrix} b_0 \\ b_1 \end{pmatrix} = \begin{pmatrix} 1 \\ (\sum x_i^2 / n) - \bar{x}^2 \end{pmatrix} \begin{pmatrix} \sum x_i^2 / n & -\bar{x} \\ -\bar{x} & 1 \end{pmatrix} \begin{pmatrix} \bar{y} \\ \sum x_i y_i / n \end{pmatrix}$$

Some Results

Fundamental Identity—

$$\sum (y - \bar{y})^2 = \sum (\hat{y} - \bar{y})^2 + \sum (y - \hat{y})^2 .$$

This states that the total variation about the mean of y equals the total variation of the predicted values of y about the mean of y plus the total variation of the residuals.

Coefficient of Determination—

$$r^2 = \frac{\text{explained variation}}{\text{total variation}} = \frac{\sum (\hat{y} - \bar{y})^2}{\sum (y - \bar{y})^2} .$$

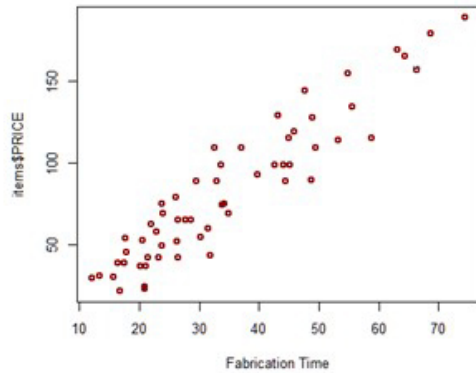
For a simple linear regression model, r^2 is the square of the Pearson Product Moment Correlation Coefficient. For a multiple linear regression model, the coefficient of multiple determination R^2 represents the proportion of variation of the dependent variable accounted for by the independent variables.

Variance of the Random Error Term—

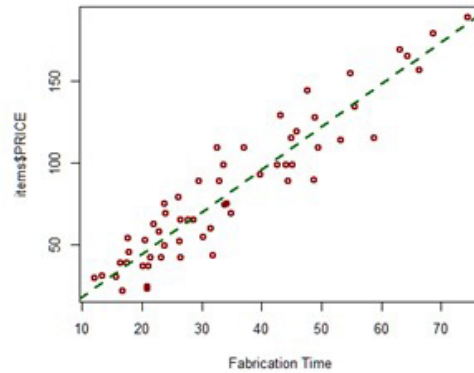
$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n e_i^2}{n-2} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n-2} .$$

Example of Simple Linear Regression

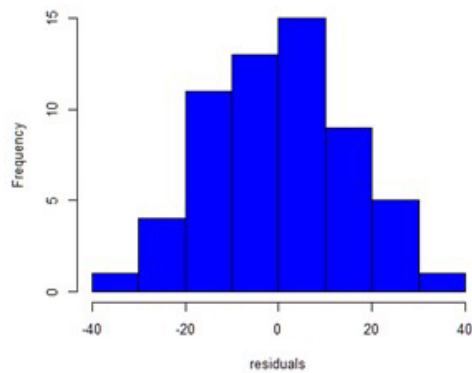
Item Price versus Fabrication Time



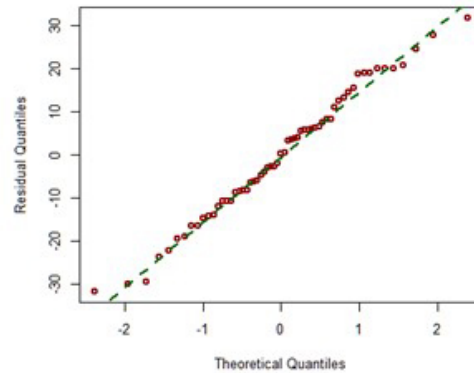
Regression of Price versus Time



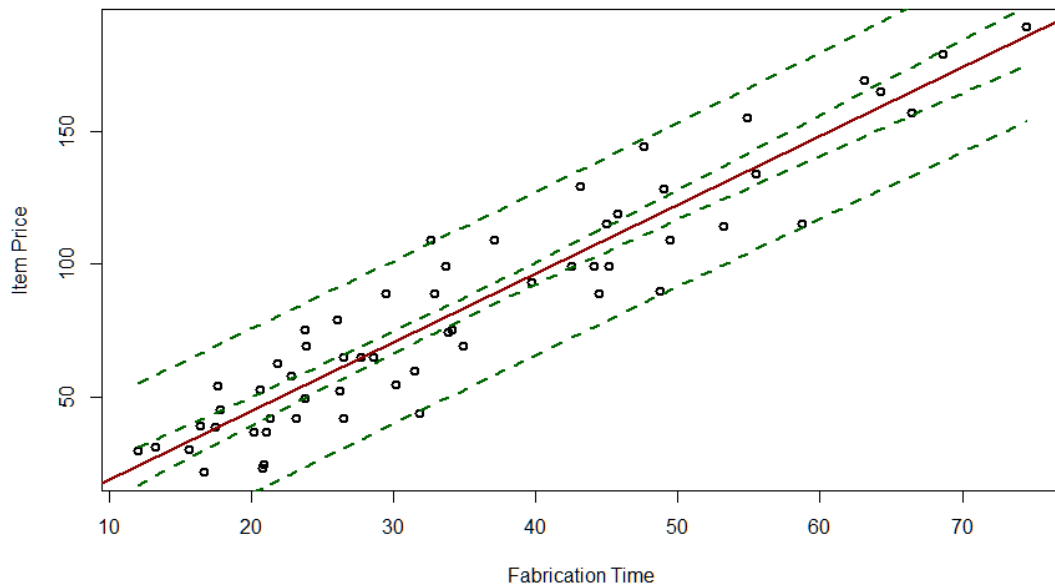
Histogram of residuals



Q-Q Plot of Residuals



Prediction and Confidence Limits



Linear Regression Example

```
> items <- read.csv(file.path("c:/R401/", "pricing.csv"), sep=",")
> require(moments)
> object <- lm(PRICE~TIME, items)
> summary(object)
```

Call:
lm(formula = PRICE ~ TIME, data = items)

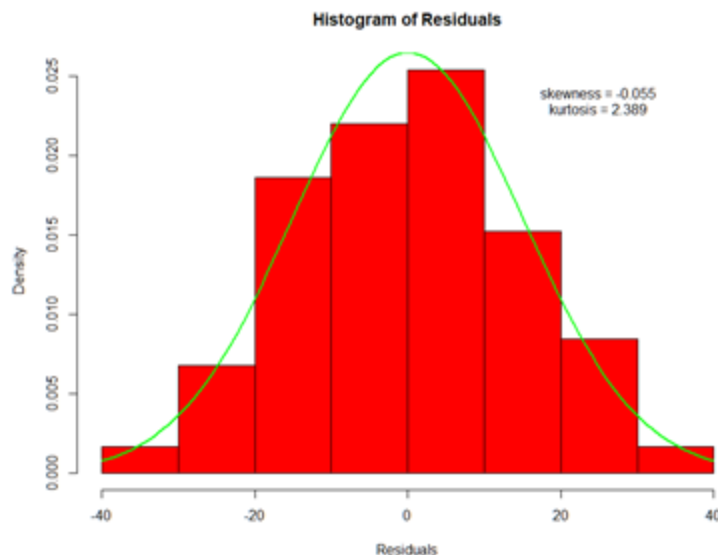
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.4467 4.8957 -1.521 0.134
TIME 2.5942 0.1287 20.154 <2e-16 ***

Residual standard error: 15.19 on 57 degrees of freedom
Multiple R-squared: 0.8769, Adjusted R-squared: 0.8748
F-statistic: 406.2 on 1 and 57 DF, p-value: <2.2e-16

```
> cbind(object$coefficients, confint(object, parm=c(1,2), level = 0.95))
```

		2.5 %	97.5 %
(Intercept)	-7.44667	-17.2502	2.3568
TIME	2.5942	2.3365	2.8520

```
> x <- seq(from = -40, to = 40, by = 1)
> hist(residuals, col = "red", freq = FALSE, xlab = "Residuals",
+ main = "Histogram of Residuals", xlim = c(-40, 40))
> curve(dnorm(x, mean = 0, sd = sd(residuals)), col = "green", lwd = 2, add = TRUE)
> text(x = 25, y = 0.024, paste("skewness =", round(skewness(residuals), digits = 3)))
> text(x = 25, y = 0.023, paste("kurtosis =", round(kurtosis(residuals), digits = 3)))
```



Bootstrap Applications

```
> # Percentile Bootstrap Example
> set.seed(123)
> alpha.boot <- numeric(0)
> beta.boot <- numeric(0)
> for(k in 1:1000){
+   x <- sample.int(59, size = 59, replace = TRUE)
+   result <- lm(PRICE[x]~ TIME[x], items)
+   alpha.boot[k] <- coef(result)[1]
+   beta.boot[k] <- coef(result)[2]
+ }
> alpha.coef <- quantile(alpha.boot, c(0.025, 0.975))
> beta.coef <- quantile(beta.boot, c(0.025, 0.975))
>
> c(mean(alpha.boot), mean(beta.boot))

      [1] -7.458544  2.593657

> boot.results <- cbind(original, rbind(alpha.coef, beta.coef))
> row.names(boot.results) <- c("(Intercept)", "TIME")
> boot.results
```

	original	2.5%	97.5%
(Intercept)	-7.446681	-15.320614	0.6434946
TIME	2.594250	2.354175	2.8200267

```
> # Bootstrap Using boot() and the bias-corrected and accelerated method
>
> bs <- function(formula, data, indices){
+   d <- data[indices,]
+   fit <- lm(formula, data = d)
+   return(coef(fit))
+ }
> library(boot)
> set.seed(123)
> results <- boot(data = items, statistic = bs, R = 1000, formula = PRICE~TIME)
>
> bca.intercept <- boot.ci(boot.out = results, type = "bca", index = 1)
> bca.slope <- boot.ci(boot.out = results, type = "bca", index = 2)
> bca.coef <- c(bca.intercept[2], bca.slope[2])
> bca.alpha <- c(bca.intercept$bca[4:5])
> bca.beta <- c(bca.slope$bca[4:5])
> comb.bca <- rbind(bca.intercept$bca[4:5], bca.slope$bca[4:5])
> colnames(comb.bca) <- c("2.5%", "97.5%")
> bca.estimates <- cbind(bca.coef, comb.bca)
> rownames(bca.estimates) <- c("(Intercept)", "TIME")
> bca.estimates
```

	bca.coef	2.5%	97.5%
(Intercept)	-7.446681	-15.745730	0.2645653
TIME	2.594250	2.346807	2.8087530

The bias-corrected and accelerated method is recommended for general use by Bradley Efron and Robert J. Tibshirani in *"An Introduction to the Bootstrap"* (CRC Press) Chapter 14 page 188.

Model Specification in Regression Analysis

Multiple linear regression relates a dependent variable to one or more independent variables.

Stages of regression analysis:

- 1. exploratory data analysis,**
- 2. model specification,**
- 3. estimation of the parameters of the model,**
- 4. diagnostic checking and validation,**
- 5. interpretation of the parameters.**

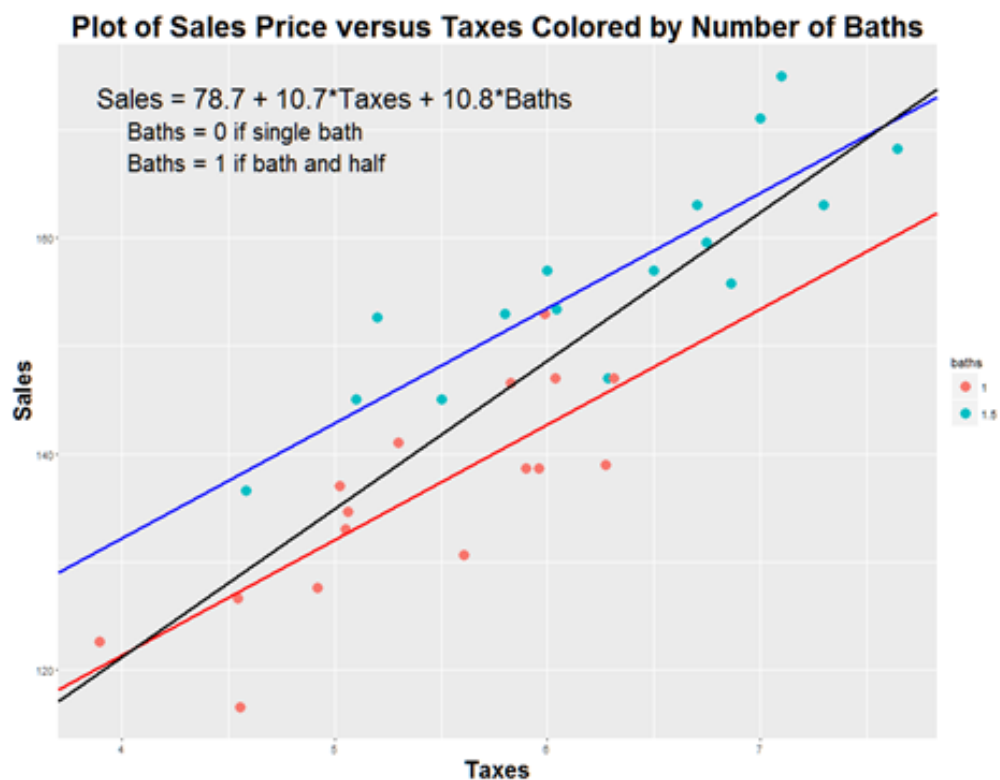
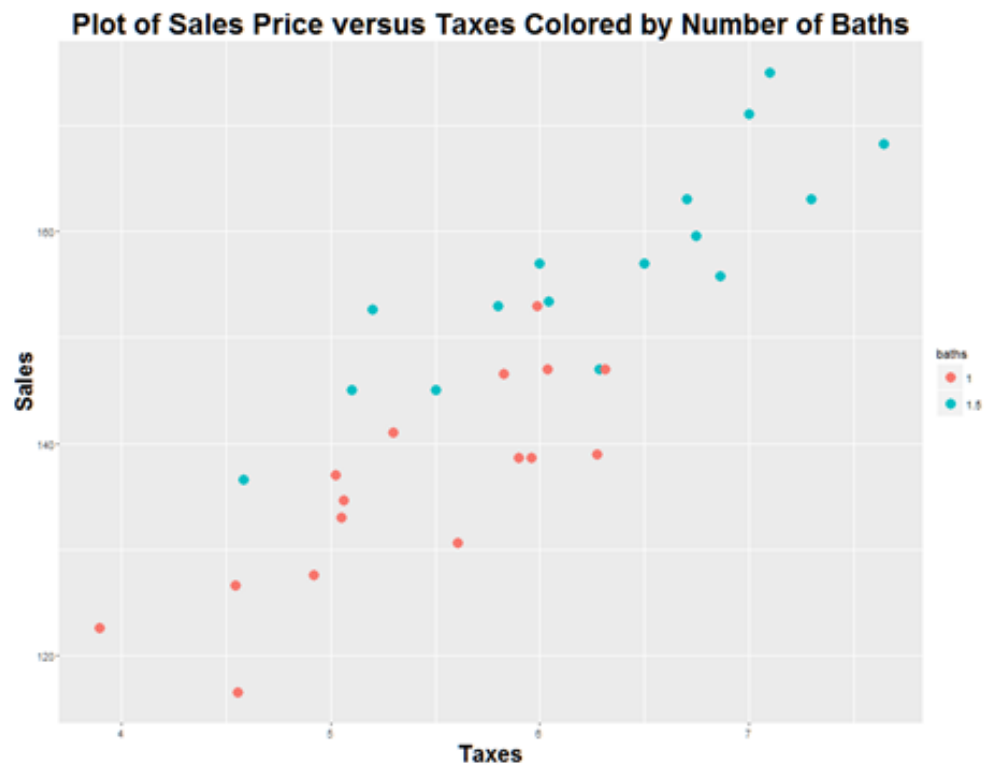
EDA, theoretical considerations and prior experience contribute to model specification.

Model Specification Questions:

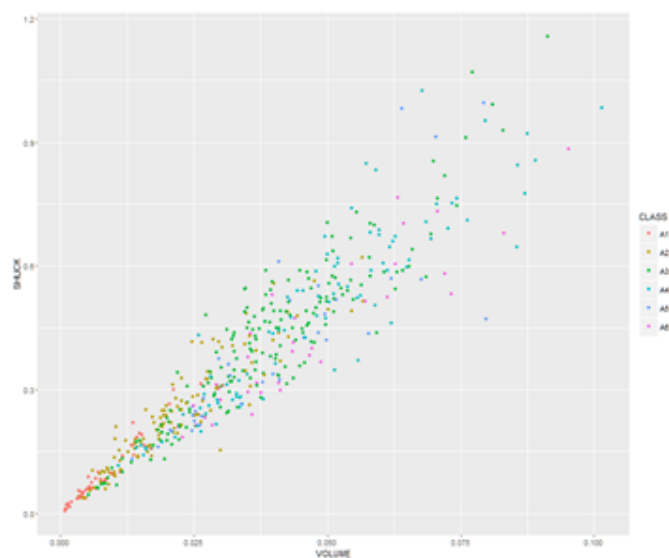
- Are the right independent variables included in the model?**
- Are unnecessary variables excluded from the model?**
- Are the variables expressed in proper functional form?**

Specification errors can lead to problems of estimation, interpretation and erroneous prediction.

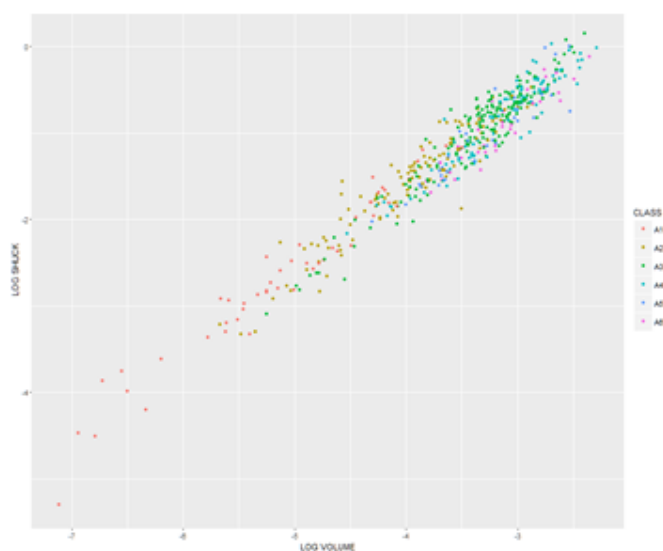
Model Specification and Dummy Variables



Transformations



$$Shuck \cong k * Volume$$



$$\log(Shuck) \cong c + m * \log(Volume)$$

<http://kenbenoit.net/assets/courses/ME104/logmodels2.pdf>

Abalone Regression Analysis

```
> model <- lm(L_SHUCK ~ L_VOLUME + CLASS + TYPE, data = mydata)
> summary(model)
```

Call:

```
lm(formula = L_SHUCK ~ L_VOLUME + CLASS + TYPE, data = mydata)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.270634	-0.054287	0.000159	0.055986	0.309718

Coefficients:

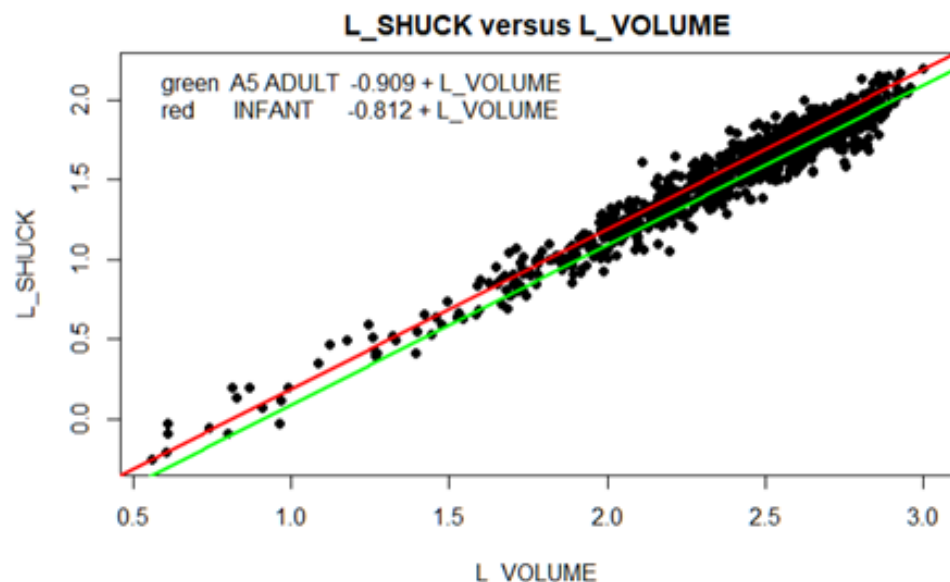
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.817512	0.019040	-42.936	<2e-16 ***
L_VOLUME	0.999303	0.010262	97.377	<2e-16 ***
CLASSA2	-0.018005	0.011005	-1.636	0.102124
CLASSA3	-0.047310	0.012474	-3.793	0.000158 ***
CLASSA4	-0.075782	0.014056	-5.391	8.67e-08 ***
CLASSA5	-0.117119	0.014131	-8.288	3.56e-16 ***
TYPEADULT	0.021093	0.007688	2.744	0.006180 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08297 on 1029 degrees of freedom

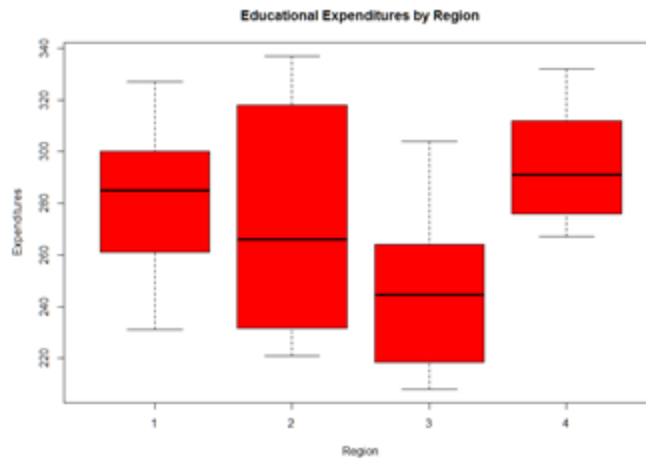
Multiple R-squared: 0.9504, Adjusted R-squared: 0.9501

F-statistic: 3287 on 6 and 1029 DF, p-value: <2.2e-16



Model Specification

Annual educational expenditure data are collected each of the fifty states. The states are grouped according to geographic region. It is of interest to find if regional differences can be detected. The initial analysis is a one-way ANOVA of Y = Per capita expenditure on education versus region (1, 2, 3, 4).



```
> result <- aov(Y~region, data=schools)
> summary(result)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
region	3	17469	5823	5.454	0.00271 **
Residuals	46	49111	1068		

```
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> aggregate(Y~region, data = schools, mean)
```

region	Y
1	280.6667
2	273.8333
3	246.8125
4	294.5385

```
> TukeyHSD(result)
```

Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = Y ~ region, data = schools)

```
$region
```

	diff	lwr	upr	p adj
2-1	-6.833333	-45.23834	31.571669	0.9643719
3-1	-33.854167	-70.14348	2.435150	0.0754499
4-1	13.871795	-23.89485	51.638443	0.7619900
3-2	-27.020833	-60.28054	6.238875	0.1482733
4-2	20.705128	-14.16052	55.570776	0.3982160
4-3	47.725962	15.20545	80.246473	0.0016539

Model Development

Now consider the analysis if covariates are included in a multiple linear regression analysis. They are:

X1 = Per capita income

X2 = Number of residents per thousand under 18 years of age

X3 = Number of residents per thousand living in urban areas

Revised analysis includes both continuous and categorical predictors.

```
> rs <- lm(Y~X1+X2+X3+region, data=schools)
> summary(rs)
```

Call:

```
lm(formula = Y ~ X1 + X2 + X3 + region, data = schools)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-58.324	-18.336	-2.848	19.900	66.752

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-44.48314	112.25760	-0.396	0.69387
X1	0.03518	0.01071	3.285	0.00203 **
X2	0.43372	0.27782	1.561	0.12582
X3	0.02158	0.04000	0.539	0.59243
region2	-9.26738	12.50284	-0.741	0.46259
region3	-11.07212	12.50480	-0.885	0.38085
region4	10.30383	13.04614	0.790	0.43398

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 26.91 on 43 degrees of freedom

Multiple R-squared: 0.5324, Adjusted R-squared: 0.4672

F-statistic: 8.161 on 6 and 43 DF, p-value: 6.463e-06

Region is no longer a predictive factor. X1 emerges.

Subsequent Analysis

```
> rs <- lm(Y~X1, data=schools)
> summary(rs)
```

Call:
lm(formula = Y ~ X1, data = schools)

Residuals:

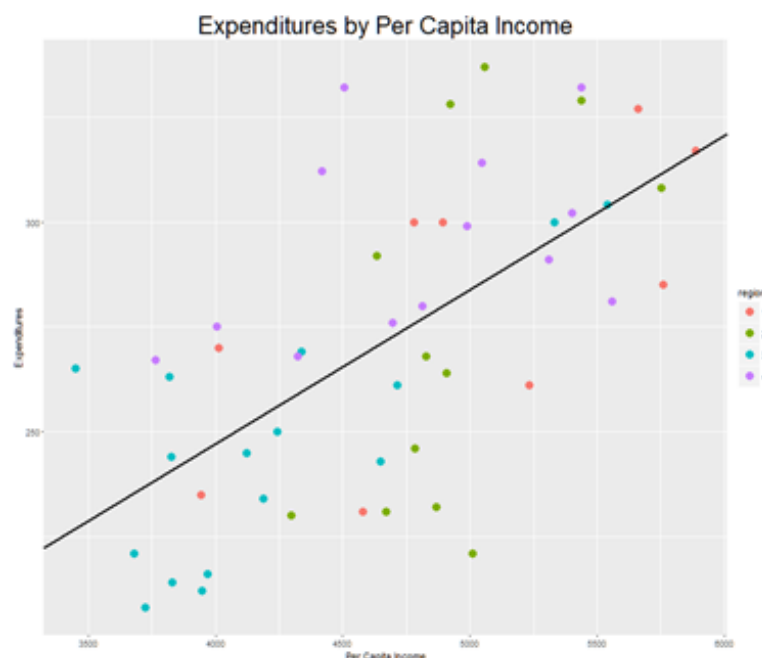
Min	1Q	Median	3Q	Max
-63.340	-25.969	0.338	22.230	66.333

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.001e+02	3.026e+01	3.309	0.00178 **
X1	3.676e-02	6.419e-03	5.726	6.55e-07 ***

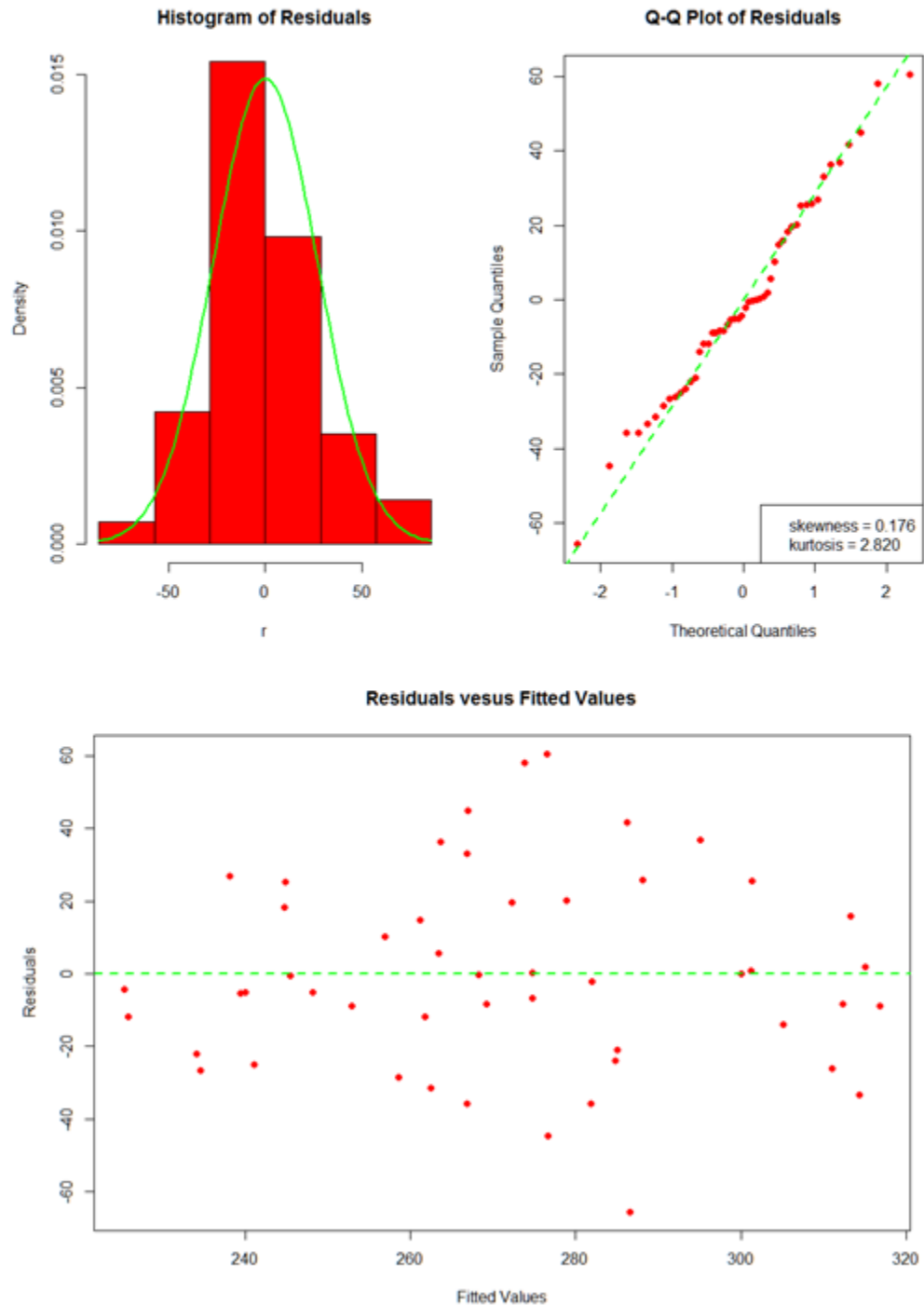
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.71 on 48 degrees of freedom
Multiple R-squared: 0.4059, Adjusted R-squared: 0.3935
F-statistic: 32.79 on 1 and 48 DF, p-value: 6.552e-07



Subsequent regression analysis on X1, X2 and X3 indicates X1 and X2 should be retained as predictors in a multiple linear regression model.

Model Diagnostics (X1 and X2 predictors)



Essentially, all
models are wrong,
but some are
useful.

George E.P. Box

meetville.com

George Edward Pelham Box FRS

(18 October 1919 – 28 March 2013) was a statistician, who worked in the areas of [quality control](#), [time-series analysis](#), [design of experiments](#), and [Bayesian inference](#). He has been called "one of the great statistical minds of the 20th century".

- **Statistics, as a science, is not algorithmic or deterministic. Data are rarely perfect. Judgment is necessary in the application of statistical methods to arrive at valid, useful conclusions.**
- **A model for data must be discarded or revised if it does not adequately fit the data and is misleading. This may lead to insights and progress.**
- **When faced with judgment calls, make the choice that best facilitates understanding the world as it is. It is fine to consider alternative models in the process of drawing conclusions.**

Selected Review Problems

Use Bayes' Theorem to find the indicated probability with the following table.

	Approve of mayor	Do not approve of mayor
Republican	8	17
Democrat	18	13
Independent	7	37

One of the 100 test subjects is selected at random. Given that the person selected approves of the mayor, what is the probability they vote Democrat?

$$\frac{18/100}{(18/31)(31/100) + (8/25)(25/100) + (7/44)(44/100)} = 18/33 = 0.545$$

Suppose there are three married couples: A, B and C: couple A, both partners approve of the mayor, couple B, both partners no not approve of the mayor, and couple C, one partner approves of the mayor and the other partner does not approve of the mayor.

Pick one couple at random and partner at random. If the selected partner does not approve of the mayor, what is the probability the other partner approves of the mayor?

Solution by enumeration: Couple A is out of consideration. Only couples B and C could result in the initial selection mentioned. However only couple C has an unselected partner who approves of the mayor. Thus, based on the stated sampling condition, there are three ways the first partner could be picked. Couple B partner 1, Couple B partner 2 or Couple C partner 1 (partner 2 has the opposite opinion). Thus the conditional probability is 1 out of 3 possibilities or 1/3.

By Bayes theorem: $(1/2)(1/3) / (0(1/3) + 1(1/3) + (1/2)(1/3)) = (1/2) / (1 + 1/2) = 1/3$.

Solve the problem.

- 6) True or False: In a hypothesis test, an increase in α will cause a decrease in the power of the test provided the sample size is kept fixed.

A) True

B) False

- 7) True or False: In a hypothesis test regarding a population mean, the probability of a type II error, β , depends on the true value of the population mean.

A) False

B) True

(6) is False and (7) is true.

The systolic blood pressures of the patients at a hospital are normally distributed with a mean of 138 mm Hg and a standard deviation of 13.5 mm Hg. Find the two blood pressures having these properties: The mean is midway between them and 90% of all blood pressures are between them.

We are looking for an interval that is symmetric with the mean in the middle. To have 90% of the blood pressures between them, 95% of the readings must be to the left of the upper bound, and 5% to the left of the lower bound.

```
> qnorm(0.95, 138, 13.5, lower.tail = TRUE)
[1] 160.2055
> qnorm(0.05, 138, 13.5, lower.tail = TRUE)
[1] 115.7945
```

Construct the indicated confidence interval for the difference between population proportions $p_1 - p_2$. Assume that the samples are independent and that they have been randomly selected.

$x_1 = 15$, $n_1 = 50$ and $x_2 = 23$, $n_2 = 60$; Construct a 90% confidence interval for the difference between population proportions $p_1 - p_2$.

A) $-0.232 < p_1 - p_2 < 0.065$

B) $0.477 < p_1 - p_2 < 0.122$

C) $0.123 < p_1 - p_2 < 0.477$

D) $0.151 < p_1 - p_2 < 0.449$

```
> x <- c(15, 35)
> y <- c(23, 37)
> M <- rbind(x, y)
> prop.test(M, alternative = c("two.sided"), conf.level = 0.90, correct = FALSE)
```

2-sample test for equality of proportions without continuity correction

```
data: M
X-squared = 0.8376, df = 1, p-value = 0.3601
alternative hypothesis: two.sided
90 percent confidence interval:
-0.23173354 0.06506688
sample estimates:
prop 1 prop 2
0.3000000 0.3833333
```

A researcher was interested in comparing the amount of time spent watching television by women and by men. Independent simple random samples of 14 women and 17 men were selected, and each person was asked how many hours he or she had watched television during the previous week. Assume the population variances are equal so that the sample variances can be pooled.

	Women	Men
Sample average	11.4 hr	16.8 hr
Standard deviation	4.1 hr	4.7 hr
Sample size	14	17

Use a 0.05 significance level to test the claim that the mean amount of time spent watching television by women is smaller than the mean amount of time spent watching television by men. Use the tradition method of hypothesis testing.

For this problem, a one-sided test is required. The alternative will be framed as a positive.

```
> s1.2 <- 4.1^2
> s2.2 <- 4.7^2
> n1 <- 14
> n2 <- 17
> pool <- sqrt((s1.2*(n1-1)+s2.2*(n2-1))/(n1+n2-2))
> den <- pool*sqrt(1/n1+1/n2)
> x1 <- 11.4
> x2 <- 16.8
> t <- (x2-x1)/den
> t
[1] 3.369099
> pt(t,29,lower.tail=FALSE)
[1] 0.001073162
> qt(0.95,29,lower.tail=TRUE)
[1] 1.699127
```

Use the given data to find the equation of the regression line. Round the final values to three significant digits, if necessary.

15)
$$\begin{array}{c|cccc} x & 6 & 8 & 20 & 28 & 36 \\ \hline y & 2 & 4 & 13 & 20 & 30 \end{array}$$

A) $\hat{y} = -2.79 + 0.897x$
 C) $\hat{y} = -3.79 + 0.801x$

B) $\hat{y} = -2.79 + 0.950x$
 D) $\hat{y} = -3.79 + 0.897x$

```
> x <- c(6, 8, 20, 28, 36)
> y <- c(2, 4, 13, 20, 30)
> lm(y~x)
```

Call: `lm(formula = y ~ x)`

Coefficients:

(Intercept) x
 -3.7900 0.8975

16) For the data below, determine the value of the linear correlation coefficient r between y and x^2 .

x	1.2	2.7	4.4	6.6	9.5
y	1.6	4.7	9.9	24.5	39.0

A) 0.913 B) 0.990 C) 0.873 D) 0.985

```
> x <- c(1.2, 2.7, 4.4, 6.6, 9.5)
> y <- c(1.6, 4.7, 9.9, 24.5, 39.0)
> x <- x^2
> cor(x, y, method = c("pearson"))
[1] 0.9902759
```

18) In studying the occurrence of genetic characteristics, the following sample data were obtained. At the 0.05 significance level, test the claim that the characteristics occur with the same frequency.

Characteristic	A	B	C	D	E	F
Frequency	28	30	45	48	38	39

This is a Chi-square goodness-of-fit test. The counts are expected to be equal under the null hypothesis. This expectation is 38 which needed to be compared against the observed counts.

```
> obs <- c(28, 30, 45, 48, 38, 39)
> ec <- rep(sum(obs)/6, times = 6)
> diff <- sum((obs - ec)^2/ec)
> diff
[1] 8.263158
> pchisq(diff, df = 5, lower.tail = FALSE)
[1] 0.1423164
> qchisq(0.95, df = 5, lower.tail = TRUE)
[1] 11.0705
```

20) Fill in the missing entries in the following partially completed one-way ANOVA table.

Source	df	SS	MS=SS/df	F-statistic
Treatment	3			11.16
Error		13.72	0.686	
Total				

Error degrees of freedom = $13.72/0.686 = 20$. Total degrees of freedom = $3 + 20 = 23$

Treatment MS = $11.16(0.686) = 7.656$. Treatment SS = $7.656(3) = 22.97$

Total SS = $13.72 + 22.97 = 36.69$

Some Sync Session Learning Points

- Essentially all models are wrong, but some are useful.
- It is perfectly proper to use both classical and robust methods routinely and only worry when they differ enough to matter.
- The Pearson Correlation Coefficient is intended to measure the association between two normally distributed random variables.
- Simple linear regression involves estimating two parameters in the equation and the variance of the error term.
- In simple linear regression, r^2 equals the square of the Pearson Correlation Coefficient.
- r^2 is the ratio of explained variation to total variation.
- Linear regression requires the normal equations to be amenable to linear algebra. It must be possible to isolate the coefficients.
- Multiple linear regression is not limited to straight line relationships. Polynomials may qualify.
- Model specification involves answering three questions:
 - Are the right variables included?
 - Are unnecessary variables excluded?
 - Are the variables in proper functional form?

Final Exam Topics

- **Probability**
 - Calculations using probability
 - Bayes' Theorem
 - Means and variances for probability distributions
- **Hypothesis Testing**
 - Type I and Type II Errors
 - Correlation
 - t tests
 - one sample
 - two sample
- **Confidence Interval Construction**
- **One-way AOV**
 - F test
 - p-values
- **Linear Regression**






The test is two hours, proctored, with open book and open notes. There are ten multiple choice or true/false questions. No preview of the exam is available. Review questions are available in module ten. Excel, R or any comparable calculator application may be used. The course site, WileyPlus, electronic files, hardcopy and e-readers for kindles may be used. Cloud storage of files is allowed.

Only one computer screen is allowed. Portable devices such as kindles and iPads are not allowed unless special arrangements are made. No navigation from the testing site to the internet for browsing is allowed.

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No leaving seat
No talking
Webcam, speakers, and microphone must remain on throughout the test.
The proctor must be able to see you for the duration of the test.

Additional Rules
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All resources located on the test taker's personal computer are permitted. Students may access any printed materials, text books, printed notes, personal computer files and the Canvas course site which includes use of WileyPlus. Documents can be in any format such as .pdf, .docx or .html.	
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Final Exam and Proctoring

☰ ▾ Week 10: Course Wrap-Up



CTEC Reminder



Week 10 Overview



Discussions (close Sunday 8 pm CST):



Only one comment is needed this week.



What have you learned? How will you apply it?



Proctored Final Exam



Practice Problems for Final with Solutions



Final Exam

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