Practical Data Analysis with JMP[®]

Second Edition

Robert H. Carver

Student Solutions



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Practical Data Analysis with JMP®, Second Edition

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ISBN 978-1-61290-823-6

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July 2014

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Student Solutions to Application Scenarios

Scenario 1

Student answers will vary. Answers will depend on data set student selects to input into a new JMP data table

Scenario 2

Quantity of cement (component 1), expressed as kg in a m³ mixture. Quantity of Superplasticizer (component 5), expressed as kg in a m³ mixture. Quantity of Fine Aggregate (component 7), expressed as kg in a m³ mixture.

Scenario 3

Columns that need to be corrected: DMDMARTL, RIDEXPRG, BPQ150A

Scenario 4

NHANES does not contain experimental data because the experimenters are not manipulating any of the variables. The data was not obtained through a designed experiment but through observation.

Scenario 5

Open the **Military** table, and select **Rows** ►**Row** Selection ►Select **Randomly** and specify a sample size of **500**. Then choose **Tables** ►Subset.

Scenario 6

This data table contains monthly stock values and volume from the FTSE 100 index, from1 January 2003 through 1 December 2007. Data were collected by observation on

the first day of each month. The date column is ordinal because it is a chronological variable. Open, High, Low, Close, Volume, and change% are all Continuous columns containing numeric measurements. Open is the FTSE 100 index's opening price. High represents the high price for the day. Low is the low price for that day. Close is the closing price for that day. Volume is the number of shares exchanged during the day. change% is how much the index changed from open to close.

Scenario 7

This data table contains statistics from earthquakes recorded worldwide between August 20, 2009 and September 19, 2009. Data was collected by observation on the first day of each month. The date column is ordinal because it is a chronological variable. Latitude is a continuous variable indicating the latitudinal coordinate of where the earthquake took place. Longitude is also a continuous variable indicating the longitudinal coordinate of where the earthquake took place. Magnitude is a continuous measurement of how strong the earthquake was, while depth is a continuous variable describing how far from the surface the epicenter was. Time is an ordinal column describing when the earthquake took place. This data was found by observation.

Scenario 8

This table contains observational data from the WHO regarding tobacco use, cardiovascular disease and cancer rates. Code is a nominal variable uniquely identifying each nation. Country is a nominal variable that provides the name of the country relating to the data. Region is also a nominal variable indicating the region where the country is located in. TobaccoUse is a continuous variable observed describing the prevalence of tobacco use in that country. Female and Male are both continuous variables that were found observationally which describe the prevalence of tobacco use for both genders. CVmort is the mortality rate from cardiovascular disease for this country and CancerMort is the cancer mortality rate for this country. Both are continuous.

Scenario 10

The variables are Activity (travel, feed, social), Period (morning, noon, afternoon, evening), and Groups (numeric). The observational units were groups of dolphins. Activity and Period are nominal and Groups (# dolphins in each group) is continuous.

Scenario 11

The columns are as follows:

marst : marital status (nominal). Respondent's marital status, one of six levels

empstat: employment status (nominal). Respondent's employment status, one of five levels.

sleeping minutes spent sleeping each day (continuous).

telff minutes spent on the telephone with family and friends each day (continuous).

Scenario 11

This data table appears to contain demographic, economic, crime and other statistics for the 50 US states and the District of Columbia. The three specific variables are all continuous, and represent the following:

smoke is the percentage of the state population that smokes.

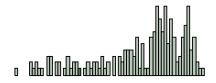
fed_spend is the per capita amount of federal spending in the state (dollars)

nuclear is the percentage of power coming from nuclear sources

Student Solutions to Application Scenarios

Scenario 1

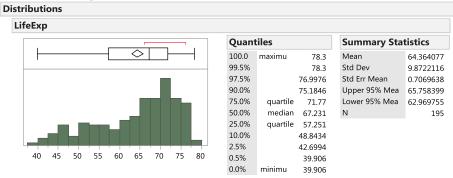
a.Using the grabber tool, click and drag upwards to increase the number of bars in the histogram. A second peak near 80 appears when as the number of bars increases, while the peak at 75 remains.



c.Scale can be manipulated in order to change the center, shape, and spread of a histogram, so it is important to carefully analyze and think critically about the choice of scale on an axis.



a. This histogram has a shape that is skewed to the left, has a mean of about 70, and a spread described by a range from 35 to 80. It has one peak

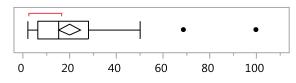


c. The standard deviation is 9.87 in the 1985 data compared to 10.4 in the 2010 data.

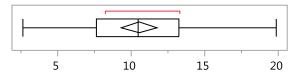
Scenario 3

a. The points furthest to the left and right indicate the minimum and maximum respectively. In each boxplot, the ends of the box represent the first and third quartiles, and the line within the box represents the median. The diamond shows the location of the mean. We see a handful of outlying points in the LifeSpan boxplot, but not in the TotalSleep plot.

LifeSpan



TotalSleep



c.99.5% of the species have a life span less than 100 years.

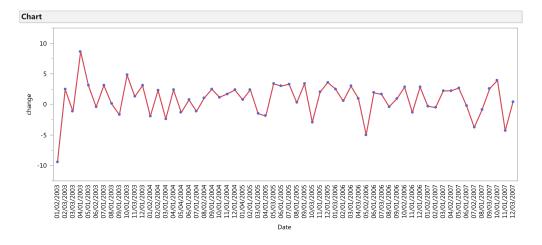
- e. The animals that get the most sleep tend to be relatively small animals and have low predation, exposure, and danger values.
- g. The animals that sleep in the most exposed locations are also the largest in terms of body weight. This may be because larger animals cannot hide as easily, or due to sheer size, they can sleep in exposed locations safely.

Scenario 4

a....Volume has a nearly symmetrical and normal distribution. It ranges from 1043.49 to 2115.33 with a median of 1726.22 and a mean of 1710.49.

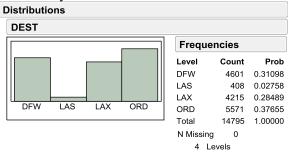
c.The FTSE declines approximately 25% of the time.

e. This line graph shows fluctuation without any obvious pattern. The monthly percentage change seems to vary at random from month to month, typically remaining approximately between -3% and +3%. There is no obvious growth over the five years, in contrast to the closing index value.



Scenario 5

a. The histogram has four bars. DFW, LAX, and ORD all have high with counts of over 4000 while LAS is low with only a count of around 400.

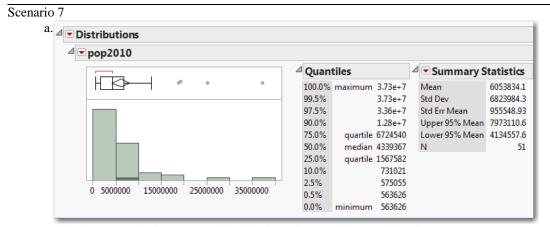


c.Because airlines attempt to schedule arrivals accurately, it is unlikely that very many flights would be extraordinarily early. However, given the many possible reasons for delays and the nature of travel, some flights can be exceptionally late. The practical minimum sets a lower bound for this variable, but there isn't a comparable upper bound. As such, a few flights with very long delays will tend to skew the data.

Scenario 6

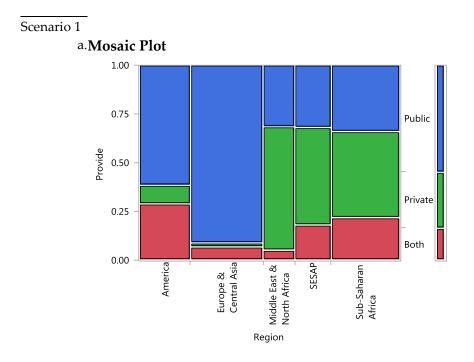
a.TobaccoUse is somewhat symmetrical with a mean of 24.77 and median of 25.6. It ranges from 4.3 to 51.8.

- c.CVMort has two peaks at around 150 and 400. It is skewed to the right. It has a mean of 355.5 and a median of 375. It ranges from 106 to 713.
- e.Europe & Central Asia and Sub-Saharan Africa have the highest count of countries in this data table. South Asia has the lowest count and America, East Asia & Pacific and Middle East & North Africa all fall in the middle.

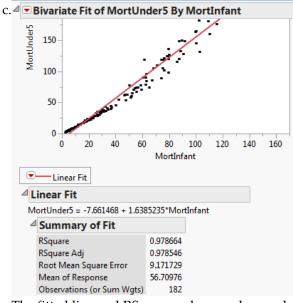


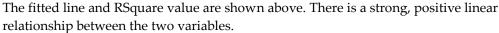
This is a strongly right-skewed distribution with 4 outliers (California, Texas, New York, and Florida). The mean population was 6,053,834 people and the median was just 4,339,367. States range from approximately 563,000 people in Wyoming to more than 37 million in California. The largest number of states have fewer than 5 million residents.

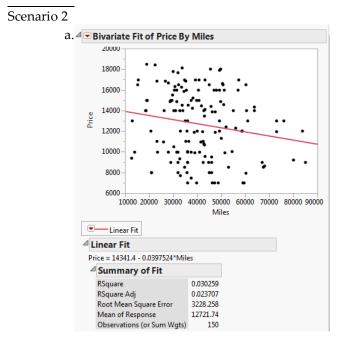
Student Solutions to Application Scenarios



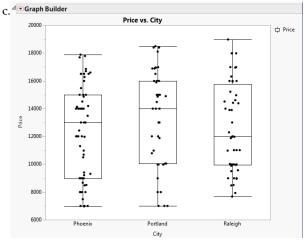
Public provision is most common by far in the Americas and Europe & Central Asia. Provide provision seems to be the norm in the rest of the world. Most areas have relatively few countries with both public and private, though such arrangements are fairly common (more than 25% of countries) in the Americas.



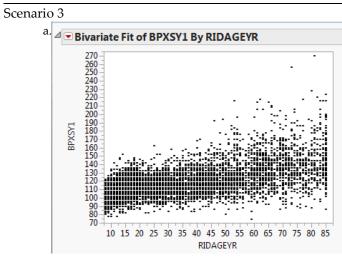




The plot, equation and Rsquare are shown above. The correlation coefficient is 0.17395. There is a weak negative relationship between mileage and price: the higher the mileage, the lower the price.

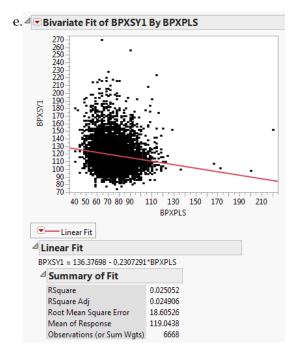


The distribution of price across the three cities seems to be fairly uniform. The box plot shows similar middle 50% with varying means. They also have very similar spreads.



As individuals get older, blood pressure increases.

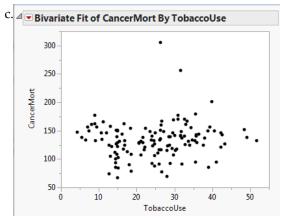
c.Men have a higher average systolic blood pressure. Both genders have similar shape, being skewed to the right. Women have a far greater range, spanning from 70 to 270 while men have readings from 80 to about 210.



It appears there is little evidence of a relationship between pulse and blood pressure, as the r squared statistic is .2, which is very low.

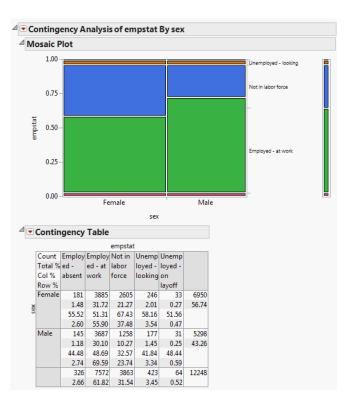
Scenario 4

a.Tobacco is most heavily used in Europe and Central Asia and to a lesser extent in East Asia and the Pacific. There is a moderate use in the Middle East and North Africa as well as the Americas while South Asia and Sub-Saharan Africa has the lowest tobacco use.



Here again, we find scant evidence of a relationship.





More males were employed (at work) than females while more females were not in the labor force. About the same amount of males and females were unemployed and looking or employed and absent.

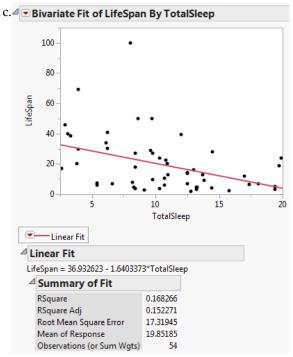
c.People employed had the lowest mean time spent sleeping. All employment statuses had nearly normal distributions with some like employed at work being more skewed to the right than others. Nearly all the spreads of employment categories ranged across the same amount of time.

Scenario 6

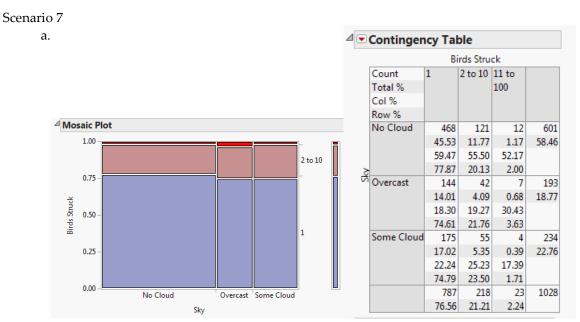
a.

Contin	igency	Table)			
		F	redatio	n		
Count Total %		2	3	4	5	
Col %						
Row %						
1	10	7	7	2	1	27
	16.13	11.29	11.29	3.23	1.61	43.55
	71.43	46.67	58.33	28.57	7.14	
	37.04	25.93	25.93	7.41	3.70	
2	2	7	2	0	2	13
	3.23	11.29	3.23	0.00	3.23	20.97
o	14.29	46.67	16.67	0.00	14.29	
S S S S S S S S S S S S S S S S S S S	15.38	53.85	15.38	0.00	15.38	
3	1	1	0	1	1	4
L.	1.61	1.61	0.00	1.61	1.61	6.45
	7.14	6.67	0.00	14.29	7.14	
	25.00	25.00	0.00	25.00	25.00	
4	1	0	0	3	1	5
	1.61	0.00	0.00	4.84	1.61	8.06
	7.14	0.00	0.00	42.86	7.14	
	20.00	0.00	0.00	60.00	20.00	
5	0	0	3	1	9	13
	0.00	0.00	4.84	1.61	14.52	20.97
	0.00	0.00	25.00		64.29	
	0.00	0.00	23.08	7.69	69.23	
	14	15	12	7	14	62
	22.58	24.19	19.35	11.29	22.58	

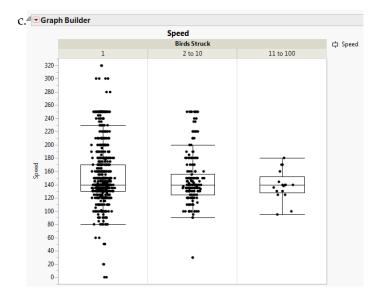
Animals with lower exposure values seem to have lower predation ratings. Conversely, creatures with higher exposure values also had higher predation ratings.



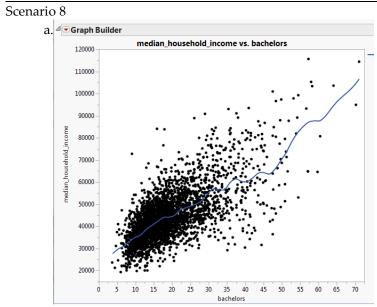
There seems to be evidence of a weak negative relationship between lifespan and total sleep. The Rsquare statistic is only 0.168.



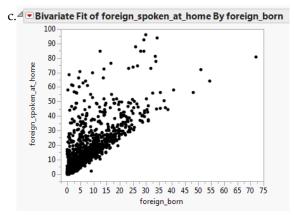
Neither the mosaic plot nor the contingency table show much evidence of large differences in number of birds struck across different sky conditions. Regardless of conditions, for example, it appears that about 75% of incidents involve a single bird.



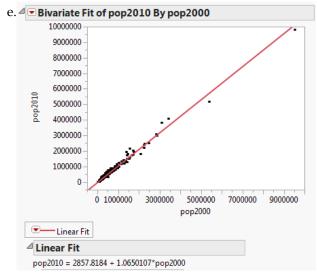
There are various ways to approach this question. One simple way is to explore the relationship using Graph Builder. In this graph we see that median speed is approximately the same regardless of the number of birds struck. However, single-bird incidents occur at a wide variety of speed; as the number of birds involved increases, the variability of speed decreases.



Using Graph Builder to investigate this relationship we find a positive but inconsistent relationship between income and percentage of population with a bachelor's degree. There is a clear upward pattern with a lot of scatter, indicating that a relationship exists but it is not very strong.



There are very few counties lying below the 45-degree diagonal line, indicating that the percentage of homes where a foreign language is spoken almost always exceeds the percentage of homes with a foreign-born member. This makes sense, assuming that homes with no foreign-born members would be less inclined to speak a foreign language.



The slope of the line is approximately 1.065, indicating that on average, the population of US counties grew by 6.5% from 2000 to 2010.

Student Solutions to Application Scenarios

Scenario 1

				DMD	/ARTL				
Count	Marrie	Widow	Divorc	Separat	Never	Living	Refuse	Don't	
Total %	d	ed	ed	ed	Marrie	with	d	Know	
Col %					d	Partner			
Row %									
Mexican American	591	57	60	42	610	121	0	0	1481
	9.19	0.89	0.93	0.65	9.49	1.88	0.00	0.00	23.03
	22.57	13.26	13.36	26.58	26.38	26.54	0.00	0.00	
	39.91	3.85	4.05	2.84	41.19	8.17	0.00	0.00	
Other Hispanic	86	4	10	2	73	20	0	1	196
	1.34	0.06	0.16	0.03	1.14	0.31	0.00	0.02	3.05
	3.28	0.93	2.23	1.27	3.16	4.39	0.00	100.00	
	43.88	2.04	5.10	1.02	37.24	10.20	0.00	0.51	
Non-Hispanic White	1403	254	239	42	703	179	6	0	2826
	21.82	3.95	3.72	0.65	10.93	2.78	0.09	0.00	43.95
	53.59	59.07	53.23	26.58	30.41	39.25	100.00	0.00	
	49.65	8.99	8.46	1.49	24.88	6.33	0.21	0.00	
Non-Hispanic Black	426	102	122	66	824	116	0	0	1656
	6.63	1.59	1.90	1.03	12.81	1.80	0.00	0.00	25.75
	16.27	23.72	27.17	41.77	35.64	25.44	0.00	0.00	
	25.72	6.16	7.37	3.99	49.76	7.00	0.00	0.00	
Other	112	13	18	6	102	20	0	0	271
	1.74	0.20	0.28	0.09	1.59	0.31	0.00	0.00	4.21
	4.28	3.02	4.01	3.80	4.41	4.39	0.00	0.00	
	41.33	4.80	6.64	2.21	37.64	7.38	0.00	0.00	
	2618	430	449	158	2312	456	6	1	6430
	40.72	6.69	6.98	2.46	35.96	7.09	0.09	0.02	

NOTE: This contingency table provides the necessary information to respond to all parts:

a.*Pr(Mexican American)* =0.2303

c.Pr(Mexican American and Never Married) = 0.0949.

e.No. In part e we found that *Pr(Never Married | Mexican American)=* 0.4114. The marginal probability *Pr(Never Married) =* 0.3596. Because the probabilities are unequal, we find that the events are not independent.

Scenario 2

For all of the questions that follow, we can use this contingency table:

			Binge	e Freq		
	Count	At least	At least	At least	Never	
	Total %	once a	once a	once a		
	Col %	week	month	year		
	Row %					
¥	No	415	557	1071	1545	3588
de		10.92	14.65	28.18	40.65	94.40
0		85.57	94.73	95.03	96.50	
~		11.57	15.52	29.85	43.06	
	Yes	70	31	56	56	213
		1.84	0.82	1.47	1.47	5.60
		14.43	5.27	4.97	3.50	
		32.86	14.55	26.29	26.29	
		485	588	1127	1601	3801
		12.76	15.47	29.65	42.12	

a. $Pr(Binge \ at \ least \ once \ a \ week) = 0.1276.$

c.Pr(Accident) = 0.0560.

e.*Pr*(*Accident* | *binge at least once a week*) = 0.1443.

g.No. Comparing the results in parts a and f or parts c and e should lead to the conclusion that because the relevant marginal probabilities do not equal the corresponding conditionals, the events are not independent.

Scenario 3

NOTE: Different contingency tables are needed for different parts of this problem.

a.Pr(Not in labor force) =0.3154

Parts c and d rely on this				fullpart		
table:		Count	Full	NIU	Part	
table.		Total %	time	(Not in	time	
		Col %		univers		
		Row %		e)		
		Female	2925	2884	1141	6950
	ğ		23.88	23.55	9.32	56.74
	s		46.44	66.30	71.31	
			42.09	41.50	16.42	
		Male	3373	1466	459	5298
			27.54	11.97	3.75	43.26
			53.56	33.70	28.69	
			63.67	27.67	8.66	
			6298	4350	1600	12248
			51.42	35.52	13.06	

 $c.Pr(Part-time \ or \ female) = Pr(part-time) + Pr(female) - Pr(part-time \ and \ female) = 0.1306 + 0.5674 - 0.0932 = 0.6048$

e.	Frequencies		
	Level	Count	Prob
	Divorced	1683	0.13741
	Married - spouse absent	169	0.01380
	Married - spouse present	6085	0.49682
	Never married	2905	0.23718
	Separated	331	0.02702
	Widowed	1075	0.08777
	Total	12248	1.00000
	N Missing 20720		
	6 Levels		

The marital status column identifies three types of respondents who are not married: those who are divorced, never married, or widowed. To find the probability of selecting a person who is not married, we sum the probabilities of these three categories:

777 *Pr(Not Married)* =0.13741 + 0.23718 + 0.08777 = 0.46236.

This table can be used for Part f:

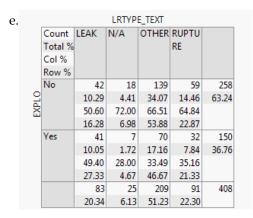
				empstat	t		
	Count	Employ	Employ	Not in	Unemp	Unemp	
	Total %	ed -	ed - at	labor	loyed -	loyed -	
	Col %	absent	work	force	looking	on	
	Row %					layoff	
	Divorced	44	1086	488	56	9	1683
		0.36	8.87	3.98	0.46	0.07	13.74
		13.50	14.34	12.63	13.24	14.06	
		2.61	64.53	29.00	3.33	0.53	
	Married - spouse absent	5	99	57	6	2	169
		0.04	0.81	0.47	0.05	0.02	1.38
		1.53	1.31	1.48	1.42	3.13	
		2.96	58.58	33.73	3.55	1.18	
	Married -	186	4107	1643	118	31	6085
marst	spouse present	1.52	33.53	13.41	0.96	0.25	49.68
Ë		57.06	54.24	42.53	27.90	48.44	
		3.06	67.49	27.00	1.94	0.51	
	Never married	70	1856	742	223	14	2905
		0.57	15.15	6.06	1.82	0.11	23.72
		21.47	24.51	19.21	52.72	21.88	
		2.41	63.89	25.54	7.68	0.48	
	Separated	10	214	90	12	5	331
		0.08	1.75	0.73	0.10	0.04	2.70
		3.07	2.83	2.33	2.84	7.81	
		3.02	64.65	27.19	3.63	1.51	
	Widowed	11	210	843	8	3	1075
		0.09	1.71	6.88	0.07	0.02	8.78
		3.37	2.77	21.82	1.89	4.69	
		1.02	19.53	78.42	0.74	0.28	
		326	7572	3863	423	64	12248
		2.66	61.82	31.54	3.45	0.52	

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Scenario 4

a.Pr(Central) = 0.2863

c.This problem is complicated by the fact that most cells in this column are blank and the remaining cells contain the label "Yes." There are 189 "Yes" values and 468 rows in all. Therefore Pr(Evacuation) = 189/468 = 0.4038.



 $Pr(Rupture \ or \ Explosion) = Pr(Rupture) + Pr(Explosion) - Pr(Rupture \ and \ Explosion) = 0.2230 + 0.3676 - 0.0784 = 0.5122.$

Scenario 5

a.Pr(Registered) = 0.6295

c.This table applies to questions c and d:

	S	subscript	tion_typ	e
	Count	Casual	Registe	
	Total %		red	
	Col %			
	Row %			
	Female	0	8634	8634
gender		0.00	24.31	24.31
der			24.31	
		0.00	100.00	
	Male	0	26876	26876
		0.00	75.69	75.69
			75.69	
		0.00	100.00	
		0	35510	35510
		0.00	100.00	

Pr(female who is registered) = 0.2431.

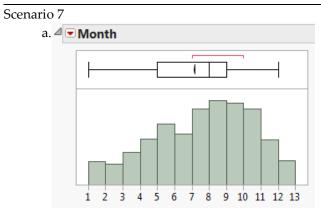
Note: The full contingency table is too large to reproduce effectively here. e.*Pr(began at South Station)* = 0.0477 = 2,636/ 55,230 trips.

g.Pr(start at South Station and end at Library) = 0.0013 = 72/55,230 trips.

Scenario 6

a.A Fit Y by X contingency table shows that 19 of the 1,000 women were smokers with premature babies. Hence, the probability is 0.019.

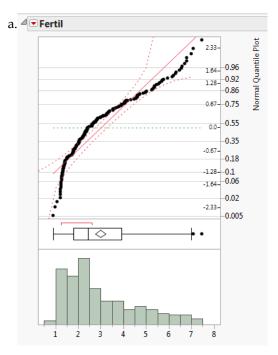
c.A Fit Y by X contingency table shows that 11 of the 1,000 women were smokers and mature moms. Hence, the probability is 0.011.



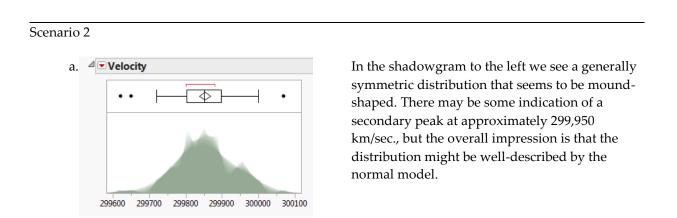
Birdstrikes occur most often July through October (months 7 through 10), and rather infrequently during December, January, and February. So, we would say that they do not occur with equal frequency through the year.

Student Solutions to Application Scenarios

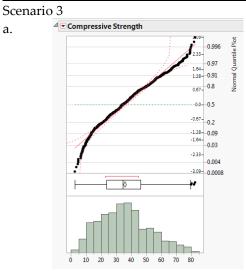
Scenario 1



The normal quantile plot appears to the left. The distribution is strongly skewed positively, and therefore the normal model is not suitable for this variable. c.Pr(X>5.5) = 1 - 0.9426 = 0.0574. In comparison, based on the reported quantiles, we find that more than 10% of the observed data lies above 5.5 children per woman.



c.The data set provides some support for the assumption. Michelson's various measurements of the speed of light seem to vary according to an approximate normal distribution.



This distribution shows mild skewness. The lower tail is truncated and therefore shorter and thicker than a normal distribution would be.

Scenario 4

- a. Student answers will vary. Most will likely choose the weekly change column corresponding to the Hang Seng market index, but others might select a different column (e.g. Tel Aviv or S&P). In these graphs, the points track most closely to the diagonal line.
- c. The mean and standard deviation of the changes in Hang Seng for the weeks observed are 1.102065 and 5.242892. For a normal distribution with that mean and standard deviation, Pr (X <0) =0.5832, or approximately 0.58.

Scenario 5

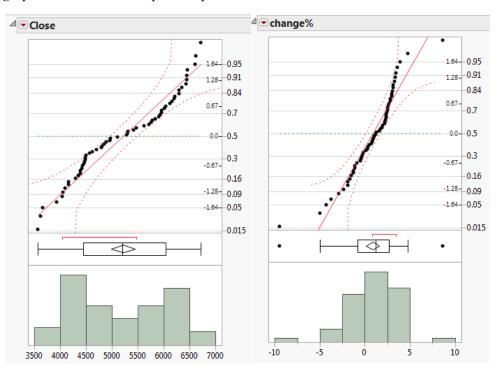
⊿ ■ sleeping ⊿ 💌 age 2 33-0.99 -0.99 1.64-1.28-1.64-0.67-0.7 0.67-0.7 0.0 - 0.0--0.67--0.67--1.28-0.08 -1.28- 0.08 -1.64 -2.33--2.33 -3.09- 0.0008 -3.09-0.0008 -0.000025 0.000025 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 0 150 300 450 600 750 900 1200 1500

Use these graphs to respond to all parts:

a. This histogram is mound-shaped with a single peak centered near 500 minutes. The large majority of respondents report between approximately 300 and 700 minutes of sleep per week.

c. The Age histogram is more skewed that the Sleeping histogram, with distinct secondary peaks in each tail. It appears to be centered near 40, but with the peaks in the tails it is difficult to generalize about the degree of dispersion. Again, the normal quantile plot casts doubts on using a normal model for this variable. The normal model seems to fit acceptably near the center of the distribution, but deviates quite dramatically in the tails.

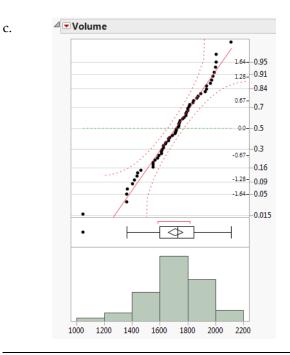
Scenario 6



These graphs can be used to respond to parts a and b.

a. Closing values appear to be symmetric and bimodal, with peaks between 4000-5000 and 6000-6500. The center of the distribution is close to 5000 and it ranges from approximately 3500 to 7000.

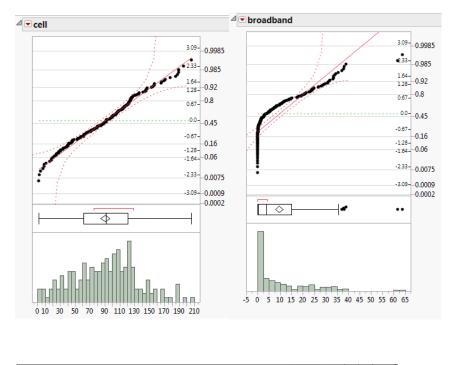
In contrast, the %change column is moderately symmetric with a single peak just above 0. Most of the distribution lies between -5 % and +5 %.

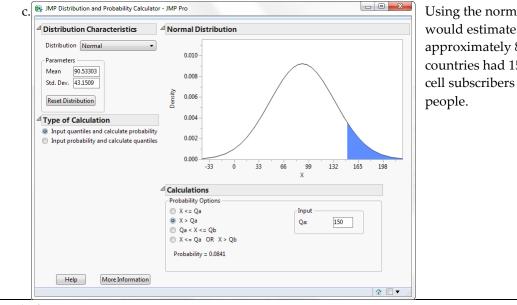


The volume column has a normal quantile plot that looks quite close to a normal distribution. It would be well described by a model ~N(1710.4911, 203.1369).

Scenario 7

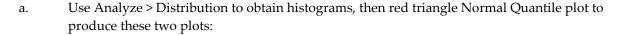
a.Here are the graphs, which very clearly show that the cell column is better modeled as normal than the broadband data. The broadband histogram is strongly skewed to the right and its probability plot does not track the diagonal line at all.

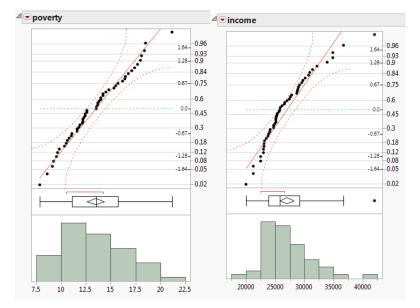




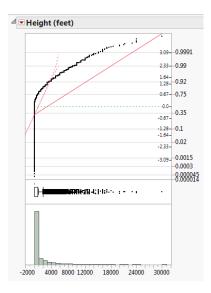
Using the normal model, we would estimate that approximately 8.4% of countries had 150 or more cell subscribers per 100

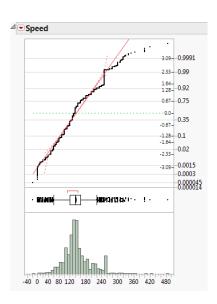
Scenario 8





Scenario 9





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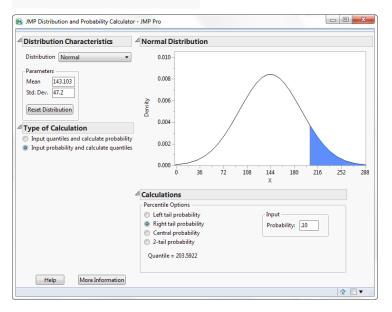
- a. The graphs above show that Height is very strongly skewed to the right with many outliers. Speed is more closely normal, through there is a second mode at approximately 250 mph.
- c.

4	Summary S	tatistics
	Mean	143.10305
	Std Dev	47.200664
	Std Err Mean	0.3107123
	Upper 95% Mean	143.71206
	Lower 95% Mean	142.49403
	N	23077

From the distribution platform, we find that the mean is 143.103 mph and the standard deviation is 47.2.

Placing these values into the normal distribution calculator, we can approximate that the 90th percentile of the normal distribution is 203.6 mph.

In this instance, the normal approximation comes reasonably close to the observed data.



Student Solutions to Application Scenarios

Scenario 1

a.Student answers will vary due to the operation of the random number generator.

c.The probability that a SRS of 250 households would include 25 or fewer homes without Internet service is 0.00031368.

Scenario 2

a. The proportion of countries in Sub-Saharan Africa is 0.24227.

[⊿] Frequencies				
Level		Count	Prob	
America			0.13333	⊿ ⊽ S
Europe & Centr			0.40000	Mear
Middle East & N SESAP	North Africa		0.13333	Std D
Sub-Saharan Af	rica	-	0.16667	Std Er
Total		-	1.00000	Upper
N Missing	0			Lower 9
5 Levels				N

Student answers will vary due to random sampling. Above we find the results of one random sample—only 5 of the 30 countries are in Sub-Saharan Africa (16.7%). The mean mortality rate in the sample is 29.82 (note that in this sample all 30 countries reported an infant mortality rate). In general students' results will not match the population values shown in parts a & b due to sampling variation.

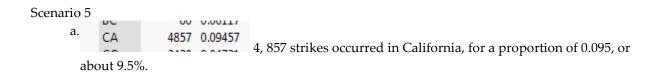
Scenario 3

- a.Student answers will vary. In general, the sampling distribution will be bell-shaped and symmetrical, centered very near 0.40 and ranging from about 0.35 to 0.45.
- c.Student answers will vary again. In general, the sampling distribution will be roughly bellshaped and possibly a little left skewed, centered very near 0.95. Compare to the distribution in part c, this distribution will be steep and range only from about 0.90 to 1.00.

e.In part c we notice that the population with a proportion of .95 generates samples with comparatively small standard errors. The risks associated with sampling variation tend to be smaller in more uniform populations.

Scenario 4

- a.Student responses will vary. In general, the sampling distribution will be bell-shaped and symmetrical, centered very near 15 with an overall standard error (std. deviation of the sample means) approximately equal to 0.10 and ranging from about 14.7 to 15.3.
- c.Student responses will again vary. In general, the sampling distribution will be bell-shaped and symmetrical, centered very near 15 with an overall standard error (std. deviation of the sample means) approximately equal to 0.40 and ranging from about 13.8 to 16.2.
- e. The results will be very similar to parts a and d though each student may have slightly different numerical results.



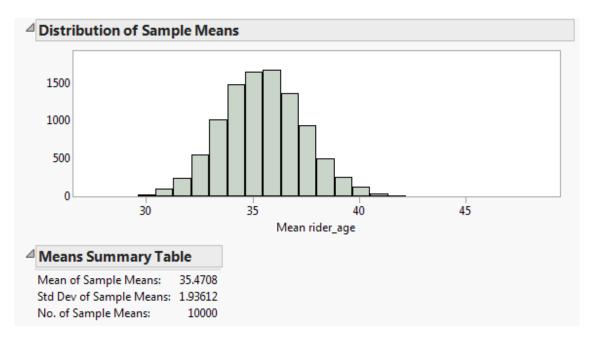
c.Each student will obtain a different SRS, so these answers will vary. In general they will differ from the values in parts a and b due to the chance variation associated with random sampling.

Scenario 6

a.	Summary S	tatistics
	Mean	35.456326
	Std Dev	10.999782
	Std Err Mean	0.0585974
	Upper 95% Mean	35.571178
	Lower 95% Mean	35.341473
	N	35238

c.Using the CLT, we'd expect the sampling distribution of the sample mean to approach an approximately normal distribution as the sample size, *n*, grows large. The mean of the distribution should be 35.46 years with a standard error equal to approximately 11/(sqrt(n)).

e.Here are the results of **one** such simulation, rescaled for clarity:



The sampling distribution is symmetric and unimodal, with a mean at 35.47 years and a standard error of 1.936. Note that in part c the CLT would have predicted a mean of 35.46 and a standard error of $11/\sqrt{50} = 1.56$

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Student Solutions to Application Scenarios

Scenario 1

a.⊿	a 💌 Confi	dence Ir	tervals	;		
	Level	Count	Prob	Lower CI	Upper CI	1-Alpha
	LEAK	93	0.20805	0.17299	0.248093	0.950
	N/A	28	0.06264	0.043691	0.089042	0.950
	OTHER	231	0.51678	0.470508	0.562763	0.950
	RUPTURE	95	0.21253	0.177135	0.252819	0.950
	Total	447				
	Note: Com	puted usir	ng score o	onfidence	intervals.	

Based on the analysis shown to the left, 95 of 447 disruptions with known causes were ruptures. The estimated confidence interval is from 0.177 to 0.253. We can be 95% confident that the true population proportion is somewhere between 0.177 and 0.253.

c.When we lower the confidence level the interval becomes narrower.

Scenario 2

a.Yes. We have a random sample of sufficient size to invoke the Central Limit Theorem.

2.4	Test P	Probabilit	ies			
	Level	Estim Pro	b Hypot	h Prob		
	No	0.1400	0 0	.18000		
	Yes	0.8600	0 0	.82000		
					Hypoth	
	Binom	ial Test	Level Tes	sted	Prob (p1)	p-Value
	Ha: Pro	ob(p < p1)	No		0.18000	0.0556

With a p-Value of 0.0556, this sample falls just short of statistical significance. Assuming that we are using the standard 5% significance level, the sample does not quite provide sufficient evidence to conclude that the rate is currently below 18%.

e.A larger sample with the very same proportion provides more precision in the confidence interval (i.e. a narrower interval) and enhances the statistical significance of the test result.

Scenario 3

a.Yes. We have a random sample of sufficient size to invoke the Central Limit Theorem.

c.We can be 99% confident that the population proportion is between 0.071 and 0.085. Both intervals are centered at the same value, but the 99% interval is wider than the 95% interval.

e. The lower the confidence level, the narrower the interval.

Scenario 4

a.Yes. We have a random sample of sufficient size to invoke the Central Limit Theorem.

Level	Estim Pr	ob Hypoth I	Prob	
No	0.872	40 0.9	0000	
Yes	0.127	60 0.1	0000	
Test		ChiSquare	DF	Prob>Chise
Likelih	ood Ratio	29.8532	1	<.0001
Pearso	n	32.1670	1	<.0001

(For this question, it is simplest to create a small summary table). Create a Because of the question's wording, a two-tailed test is most appropriate here. Based on this random sample, we can confidently conclude that it is *not* credible to conclude that 10% of the population binge drinks at least once per week. If anything, this sample suggests a higher population proportion.

Scenario 5

- a.It depends The total sample size is 189; because some events or combination of events are relatively rare, it may be the case that np < 5, in which case we should not interpret the inferential results.
- c.Although the observed relative frequency is 0.53, and thus greater than 0.5 the p-Value is 0.362 which is quite high enough that we can readily attribute the result to sampling error. In other words, a null hypothesis that the population proportion is 0.50 or less is still plausible, so we fail to reject the null.

a.

Δ	Cor	nfidence	Interva	als		
	Level	Count	Prob	Lower CI	Upper CI	1-Alpha
	No	63	0.50400	0.431141	0.57669	0.900
	Yes	62	0.49600	0.42331	0.568859	0.900
	Total	125				
	Note: C	omputed u	ising scor	e confiden	ce intervals.	

We can be 90% confident that the proportion of trading days on which McDonald's stock increases is somewhere between 0.423 and 0.569.

Scenario 7

a.Yes. We have very large samples, and can rely on the Central Limit Theorem.

c.The 99% confidence interval is (0.237 and 0..247). Like the prior interval, this interval is centered at 0.237, but is slightly wider.

Confidence Interv	/als				
Level	Count	Prob	Lower CI	Upper CI	1-Alpha
Divorced	7.782e+9	0.09030	0.090303	0.090306	0.950
Married - spouse absent	9.234e+8	0.01071	0.010714	0.010715	0.950
Married - spouse present	4.61e+10	0.53530	0.535293	0.5353	0.950
Never married	2.51e+10	0.29105	0.291049	0.291055	0.950
Separated	1.577e+9	0.01830	0.018298	0.018299	0.950
Widowed	4.682e+9	0.05433	0.054332	0.054335	0.950
Total	8.62e+10				
Note: Computed using sco	ore confide	ence inter	vals.		

When we apply the sampling weights, the point estimate changes from 23.7% to 29.1%, and the 95% confidence interval is approximately 29.1049% to 29.1055% -- it shrinks dramatically in width, and is considerably higher than before.

Scenario 8

a.It depends on which variables we examine. We have a random sample of sufficient size to invoke the Central Limit Theorem, but there is a considerable amount of missing data.

c.∠	Conf	idence Iı	nterval	5		
	Level	Count	Prob	Lower CI	Upper CI	1-Alpha
	0	6	0.00010	3.662e-5	0.000275	0.990
	1	51692	0.86476	0.861118	0.868324	0.990
	2 to 10	7583	0.12686	0.123392	0.130405	0.990
	11 to 100	481	0.00805	0.007159	0.009044	0.990
	Over 100	14	0.00023	0.000119	0.00046	0.990
	Total	59776				

We can be 99% confident that, out of all instances where there is a bird strike, a single bird is struck somewhere between 86.1% and 86.8% of the time. The 99% CI is slightly wider than the 95% CI.

Scenario 9

a.Yes. We have a random sample of sufficient size to invoke the Central Limit Theorem, but there is a considerable amount of missing data.

c.This question is most easily done by creating a small summary table.

4	Cor	nfidence	Interva	als		
	Level	Count	Prob	Lower CI	Upper CI	1-Alpha
	No	53094	0.96133	0.959685	0.962902	0.950
	Yes	2136	0.03867	0.037098	0.040315	0.950
	Total	55230				
	Note: Co	omputed u	ising scor	e confiden	ce intervals.	

We can be 95% confident that between 3.9% and 4% start at the library.

e. The smaller sample makes the interval wider, but has no effect on the center of the interval.

Student Solutions to Application Scenarios

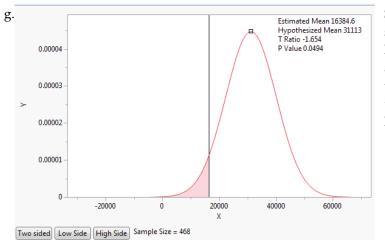
Scenario 1

a.Probably. These columns contain continuous data, and though both distributions are strongly right-skewed, both have a sufficiently large number of observations to rely on the Central Limit Theorem. The critical question is whether we can view this particular time period as representative of the overall process of pipeline disruptions; if we can regard it as random, then we can proceed to make inferences.

c.The 90% interval is –\$ 307,156 to \$ 2,979,847. We can be 90% certain that the mean damage cost lies between these two values.

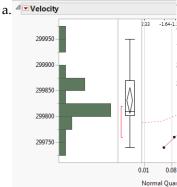
e.	🖉 💌 Confide	ence Inte	rvals		
	Parameter	Estimate	Lower CI	Upper CI	1-Alpha
	Mean	16384.57	-6646.48	39415.62	0.990
	Std Dev	192637.8	177593.4	210250.1	0.990

We can be 99% confident that the mean dollar cost of lost natural gas is between –\$6646.48 and \$39,415.62. NOTE: the distribution is so strongly right-skewed that we should be reluctant to draw conclusions from this sample, even with a sample size of 468.



Student answers will vary but should conclude that if the null hypothesis were that μ = approximately \$ 31,100 then we would reject the null in favor of the one-sided alternative hypothesis.

Scenario 2



Yes. We do not know the population σ so we will use the tdistribution. Because the sample is small (n = 20) we want to see if the sample data suggest that the population is roughly normal in shape. The histogram and normal quantile plots indicate mild skewness but no serious indication of non-normality.

c.From the confidence interval in part b we can see that Michelson would probably have (erroneously) concluded that the value 300,000 kps is not credible. The two-tailed hypothesis test yields a *P*-value < 0.0001 and a test statistic equal to -13.898; Michelson would have rejected a null hypothesis that the constant speed of light is 300,000 kps.

Scenario 3

a.Student answers will vary. On the one hand, because both measurements refer to the same child's height, we expect them to be quite similar. On the other hand, when a person stands the

spine may compress slightly, so that standing height measurements may be less than reclining measurements.

Scenario 4

- a.Yes. We do not know the population σ so we will use the t-distribution. Because the sample is so large (*n* = 1787) we can rely on the Central Limit Theorem to proceed.
- c.No. The interval is an estimate of the population *mean*, not the range of individual values. The interval provides an estimate of the location of the population mean acknowledging the uncertainty that arises from using a sample.
- e.If the true population mean actually = 10 minutes the power of this test would be approximately 0.996. In other words, if the reality were that the mean flight is delayed 10 minutes, this test would detect that the mean is less than 12 minutes.

Scenario 5

a.Yes. We do not know the population σ so we will use the t-distribution. Because the sample is so large (n = 1455) we can rely on the Central Limit Theorem to proceed.

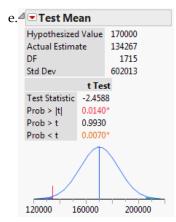
c. ▲ Confidence Intervals
 Parameter Estimate Lower
 Mean 34.0392 31.745.
 Std Dev 44.58922 43.025
 We can be 95% confident that the mean time from scheduled departure to wheels off is between 31.75 and 36.33 minutes.

Scenario 6

a. The speed column does seem to satisfy the conditions: it is moderately symmetric and the sample is very large (n = 23,077) so we can rely on the Central Limit Theorem to proceed. We do not know the population σ so we will use the t-distribution.

The Cost of Repairs column is a smaller sample (n = 1716) and very strongly skewed. Even with the CLT, we should proceed with caution.

c.At the 99% confidence level, we can be 99% confident that the mean flight speed at impact is between 142.3 and 143.9 MPH.



The test results indicate that the sample provides convincing evidence to reject the null hypothesis, yielding a very small P-value of just 0.007. The sample is, as noted, very right-skewed, but if anything that would overstate the population mean.

g.Student answers will vary, depending on which possible "True Mean" values they explore. It is useful to notice that the power of the test exceeds 90% for all true means below approximately \$127,000.

Scenario 7

a.Yes. We do not know the population σ so we will use the t-distribution. The sample is large enough (n = 1000; some mothers' gains are missing, n = 973) and the distributions are reasonably symmetric so we can rely on the Central Limit Theorem to proceed.

c.⊿	Confide	ence Inte	rvals		
	Parameter	Estimate	Lower CI	Upper CI	1-Alpha
	Mean	7.101	7.007368	7.194632	0.950
	Std Dev	1.50886	1.445507	1.578065	0.950

We can be 95% confident that the mean birthweight of infants in NC for the year 2004 was between 7 and 7.2 pounds.

Student Solutions to Application Scenarios

Scenario 1

a.

Test Probal	bilities		
Level	Estim Prob	Hypoth Pro	ь
CENTRAL	0.28632	0.2000	00
EASTERN	0.29915	0.2000	00
SOUTHERN	0.07479	0.2000	00
SOUTHWEST	0.09188	0.2000	00
WESTERN	0.24786	0.2000	00
Test	ChiSqua	e DF I	Prob>Chis
Likelihood Ra	tio 122.919	0 4	<.0001
Pearson	109.841	9 4	<.0001

Method: Fix hypothesized values, rescale omitted

c. ⊿ Tests

N	DF	-LogLike	RSquare (U)
425	4	2.4165731	0.0086
Test		ChiSquare	Prob>ChiSq
Test Likelihood R	atio	ChiSquare 4.833	Prob>ChiSq 0.3049

No. At the 0.05 level of significance we reject the null hypothesis of equal probabilities.

Based on this sample, we would conclude that the variables are independent. We do not have sufficient evidence to conclude that the two variables are not independent (assuming a significance level of 0.05).

a.

			Activity	,	
	Count Total %	Feed	Social	Travel	
	Col %				
	Row %				
	Afternoon	0	9	14	23
		0.00	4.76	7.41	12.17
		0.00	14.52	35.90	
		0.00	39.13	60.87	
	Evening	56	10	13	79
0		29.63	5.29	6.88	41.80
Period		63.64	16.13	33.33	
		70.89	12.66	16.46	
	Morning	28	38	6	72
		14.81	20.11	3.17	38.10
		31.82	61.29	15.38	
		38.89	52.78	8.33	
	Noon	4	5	6	15
		2.12	2.65	3.17	7.94
		4.55	8.06	15.38	
		26.67	33.33	40.00	
		88	62	39	189
		46.56	32.80	20.63	

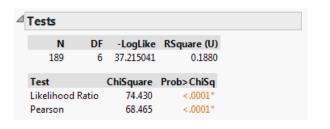
Scenario 3

a.	⊿	т	es	te
u.		т	es	te

Ν	DF	-LogLike	RSquare (U)
157	8	30.312288	0.1959
Test		ChiSquare	Prob>ChiSq
Likelihood R	atio	60.625	<.0001*
Pearson		54.842	<.0001*

c. ⊿ Tests

DF	-LogLike	RSquare (U)
4	25.704811	0.1016
	ChiSquare	Prob>ChiSq
atio	51.410	<.0001*
	37.010	<.0001*
	4	4 25.704811 ChiSquare atio 51.410



Because there are some cells with very small counts and expected counts, we should use caution making inferences from the ChiSquare test. However, we can note that the evidence points towards rejection of the null hypothesis of independence and we can also note (for example) that dolphins were regularly observed feeding in the morning and evening, but rarely if ever at other times.

No. At the 0.05 level of significance we reject that null hypothesis that Provider and Region are independent.

No. At the 0.05 level of significance we reject that null hypothesis that MatLeave90+ and Region are independent.

```
a. ⊿ Tests
```

10305				
N	DF	-LogLike	RSquare (U)	
6430	28	245.84627	0.0297	
Test		ChiSquare	Prob>ChiSq	
Likelihood F	Ratio	491.693	<.0001*	
Pearson		496.462	<.0001*	
Warning: 20% suspect.	6 of ce	lls have expe	cted count less	s than 5, ChiSquare

Scenario 5

a.

1 💌	Contingency Tabl	е		
		Acci	ident	
	Count Total % Col % Row %	No	Yes	
	At least once a week	415 10.92 11.57 85.57	70 1.84 32.86 14.43	485 12.76
Binge Freg	At least once a month		31 0.82	588 15.47
	At least once a year	1071 28.18 29.85 95.03	56 1.47 26.29 4.97	1127 29.65
	Never	1545 40.65 43.06 96.50	56 1.47 26.29 3.50	1601 42.12
		3588 94.40	213 5.60	3801
Te	sts			
	N DF -Log 3801 3 33.67		Square 0.0	
	elihood Ratio 67	iare Pr .353 .878	ob>Chi <.000 <.000	1*

Because there are a substantial proportion of cells with very small expected counts, we should use caution making inferences from the ChiSquare test. However, we can note that the evidence points toward rejecting the null hypothesis of independence. We might observe (for example) that married respondents were disproportionately non-Hispanic whites.

No. At the 0.05 level of significance we reject that null hypothesis that binge drinking regularity and involvement in car accidents are independent. Students who report binging at least once a week are far more likely to have been involved in an accident than other students.

1

a.

4	Test P	robabili	tie	s			
	Level	Estim Pr	ob	Hypoth	Prot	•	
	1	0.435	48	0.2	20000)	
	2	0.209	68	0.2	20000)	
	3	0.064	52	0.2	20000)	
	4	0.080	65	0.2	20000)	
	5	0.209	68	0.2	20000)	
	Test		Ch	iSquare	1	DF	Prob>Chisq
	Likelih	ood Ratio		26.3429		4	<.0001*
	Pearso	n		27.3548		4	<.0001*

Method: Fix hypothesized values, rescale omitted

c.

4	Tests			
	N DI	-LogLike	RSquare (U)	
	62 16	5 24.460914	0.2498	
	Test	ChiSquare	Prob>ChiSq	
	Likelihood Ratio	48.922	<.0001*	
	Pearson	47.678	<.0001*	
5	Warning: 20% of c suspect. Warning: Average			is than 5, ChiSquar niSquare suspect.

The Chi-Square goodness-of-fit test indicates that the five categories are not equally distributed across mammalian species. We reject the null hypothesis that all proportions are equal at 0.20.

The total sample size here leads to many cells with expected counts < 5, making the Chi-Square test unreliable. That said, the test results point in the direction of rejecting the null hypothesis.

Scenario 7

a.

Tests			
N	DF	-LogLike	RSquare (U)
12248	4	138.36581	0.0125
Test		ChiSquare	Prob>ChiSq
Likelihood l	Ratio	276.732	<.0001*
Pearson		272.293	<.0001*

According to the Chi-Square test the two variables are not independent. There is sufficient evidence to reject a null hypothesis that they are independent. c.

Tests			
Ν	DF	-LogLike	RSquare (U)
12248	20	644.81187	0.0584
Test		ChiSquare	Prob>ChiSq
Likelihood R	latio	1289.624	<.0001*
Pearson		1412.563	<.0001*

Scenario 8

a. 🖉	Test Probabilities
------	---------------------------

Level	Estim Pr	ob Hypoth	Prob	
female	0.503	00 0.	50000	
male	0.497	00 0.	50000	
Test		ChiSquare	DF	Prob>Chisq
Likelih	ood Ratio	0.0360	1	0.8495
Pearso	n	0.0360	1	0.8495

Method: Fix hypothesized values, rescale omitted

```
C. <sup>⊿</sup>Tests
```

N	DF	-LogLike	RSquare (U)
1000	2	2.9403290	0.0084
Test		ChiSquare	Prob>ChiSq
Likelihood	Ratio	5.881	0.0528
Pearson		9.584	0.0083*
Warning: 209 suspect.	% of ce	lls have expe	cted count les

According to the Chi-Square test the two variables are not independent. There is sufficient evidence to reject a null hypothesis that they are independent.

According to the Chi-Square test there is not sufficient evidence to reject a null hypothesis that mothers are equally likely to give birth to a male as a female baby.

We should be reluctant to draw inferences about this question because of the high number of cells with counts less than 5. That said, Pearson's test does indicate sufficient evidence to reject a null hypothesis that they are independent. It would be wise to obtain a larger sample before drawing a conclusion.

a.

Tests			
N	DF	-LogLike	RSquare (U)
1841	10	15.521620	0.0081
Test		ChiSquare	Prob>ChiSq
Likelihood	Ratio	31.043	0.0006*
Pearson		29.406	0.0011*
i curson		20,400	0.0011

According to the Chi-Square test the two variables are not independent. There is sufficient evidence to reject a null hypothesis that they are independent. The distribution of phase of flight is different at different airports.

c.

1	Tests			
	N	DF	-LogLike	RSquare (U)
	2104	4	21.884634	0.0203
	Test Likelihood I	Ratio	43.769	Prob>ChiSq <.0001*
	Pearson		41.135	<.0001*

According to the Chi-Square test the number of birds struck per incident does vary by airport. There is sufficient evidence to reject a null hypothesis that they are independent.

Student Solutions to Application Scenarios

Scenario 1

NOTE: Complete answers should note that we have continuous data, independent samples, and that the samples in each part of the question are large enough to rely on the Central Limit Theorem.

a.	⊿ t Test	We can be 95% confident that the mean
	Female-Male Assuming unequal variances Difference 0.71222 t Ratio 3.829386 Std Err Dif 0.18599 DF 5187.083 Upper CL Dif 1.07684 Prob > t 0.0001* Lower CL Dif 0.34761 Prob > t <.0001*	difference in Body Mass Index between men and women is between .34761 and 1.07684.
c.	✓ t Test Female-Male Assuming unequal variances Difference -3.5780 t Ratio Std Err Dif 0.4127 DF Upper CL Dif -2.7689 Prob > t Lower CL Dif -4.3871 Prob > t Confidence 0.95 Prob < t	We can be 95% confident that the mean difference in Diastolic Blood Pressure between men and women is between – 4.387 and –2.7689.

Scenario 2

a. We should first note that we have modest sample sizes (n= 35 and n=43) from strongly skewed distributions. Therefore, we should be reluctant to interpret the resulting interval at all. However, the reported 95% confidence interval is from -\$11,026,606 to +\$32,748,087.

a. ⊿t Test

= t lest					
RUPTURE-LEA	K				
Assuming une	equal varia	nces			
Difference	-97.68	t Ratio	-2.38845		
Std Err Dif	40.90	DF	144.3521		
Upper CL Dif	-16.85	Prob > t	0.0182*		
Lower CL Dif	-178.52	Prob > t	0.9909		
Confidence	0.95	Prob < t	0.0091*	-100 -50 () 50 100
Upper CL Dif Lower CL Dif	-16.85 -178.52	Prob > t Prob > t	0.0182* 0.9909	-100 -50 (0 50 100

We should first note that we have strongly skewed distributions but the sample sizes are reasonably large. Therefore, we can proceed to interpret the results of a t-test.

In this test, there is compelling evidence to suggest that it does not take longer to secure the area after a rupture than after a leak; to the contrary, leaks require more time.

				LINT	L_LENI		
			MeanA	bsDif	MeanAbs	Dif	
Level	Count	t Std Dev	/ to	Mean	to Medi	an	
LEAK	93	3 263657.6	5 16	8189.2	149673	3.5	
RUPTURE	95	5 399957.6	5 23	9527.7	210202	210202.5	
Test		F Ratio	DFNum	DFDen	p-Value		
O'Brien[.5]]	1.3173	1	186	0.2526		
Brown-For	rsythe	1.8915	1	186	0.1707		
Levene		3.3319	1	186	0.0696		
Bartlett		15.5717	1		<.0001*		
F Test 2-si	ded	2.3012	94	92	<.0001*		

In this case the different tests of homogeneity of variance lead to different conclusions. Using Levene's test, we would fail to reject the null hypothesis of equal variances; with F Test 2-sided, we would reject the null and conclude that the variances are unequal. Given the ambiguity, it is safer to conclude that the variances are unequal when conducting the tests of means (above).

Scenario 4

a. Student answers will differ. We have only 8 individuals without PD, and for the baseline pitch and jitter, the distributions appear bimodal with few observations in the "center"; shimmer may be normally distributed for non-PD observations. Among individuals with PD (*n* = 24) the distributions tend to be skewed. As such, with non-normal distributions and small samples, this sample does not satisfy the conditions for the use of the t-test.

c.

c.

Wilcoxon / Kruskal-Wallis Tests (Rank Sums) Expected Level Count Score Sum Score Score Mean (Mean-Mean0)/Std0 9.0625 -2.569 72,500 132.000 0 8 1 24 455.500 396.000 18,9792 2.569 2-Sample Test, Normal Approximation S Z Prob>|Z| 72.5 -2.56929 0.0102 ⁴ 1-way Test, ChiSquare Approximation ChiSquare DF Prob>ChiSq 6.7136 1 0.0096

Based on the Wilcoxon test (assuming a significance level of $\alpha = 0.05$) we reject the null hypothesis that the mean jitter measurement is equal for both groups. There is a statistically significant difference in this sample data.

Scenario 5

a.

Level	Co	unt	Std I		anAbsDif to Mean	MeanAbsDit to Mediar
American Airline	s Inc. 6	774	38.26	994	22.39524	20.42766
Skywest Airlines	inc. 7	179	40.35	580	22.00077	19.30185
Test	F Rati	D	FNum	DFDen	p-Value	
O'Brien[.5]	0.765	9	1	13951	0.3815	
Brown-Forsythe	3.526	3	1	13951	0.0604	
Levene	0.513	4	1	13951	0.4737	
Bartlett	19.598	9	1		<.0001*	
F Test 2-sided	1.112	0	7178	6773	<.0001*	

If we rely on Levene's test, we conclude that there is insufficient evidence to conclude that the variances are different; the F Test 2sided leads to the opposite conclusion. To be safe we'll use the t-test assuming unequal variances for the next question.

Scenario 6

a.

[⊿] t Test								
Male-Female								
Assuming une	equal varia	nces				\wedge		
Difference	-9.250	t Ratio	-4.90002			$/\Gamma$	$\langle \rangle$	
Std Err Dif	1.888	DF	19006.88				\backslash	
Upper CL Dif	-5.550	Prob > t	<.0001*	1				
Lower CL Dif	-12.950	Prob > t	1.0000	_ _				
Confidence	0.95	Prob < t	<.0001* -	-10	-5	0	5	10

Using just the 2003 data, we estimate with 95% confidence that females reported sleeping between 5.55 and 12.95 minutes more than males.

t Test								
Male-Female								
Assuming une	qual varia	nces				\wedge		
Difference	-4.2176	t Ratio	-4.28691				\backslash	
Std Err Dif	0.9838	DF	30524.88			·	$\langle \rangle$	
Upper CL Dif	-2.2893	Prob > t	<.0001*	1				
Lower CL Dif	-6.1460	Prob > t	1.0000					
Confidence	0.95	Prob < t	<.0001*	-4	-2	0	2	4

c.

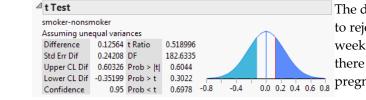
a.

smoker-nonsr	noker							
Assuming une	equal varia	nces				\wedge		
Difference	-0.31554	t Ratio	-2.35901		/		\backslash	
Std Err Dif	0.13376	DF	171.3247				$\langle \rangle$	
Upper CL Dif	-0.05151	Prob > t	0.0195*	1				
Lower CL Dif	-0.57957	Prob > t	0.9903	,,		_		>
Confidence	0.95	Prob < t	0.0097*	-0.4	-0.2	0.0	0.2	0

Combining all of the data from both years, we can conclude with 95% confidence that men spend, on average, 2.3 to 6.1 fewer minutes per day socializing than do women.

Comment: Smoking status is missing (NA) for one respondent—filter out that case in order to compare the means of smokers and non-smokers.

The data provide sufficient evidence to reject the hypothesis of equal birth weights, and conclude that smokers have lower birthweight babies than non-smokers.



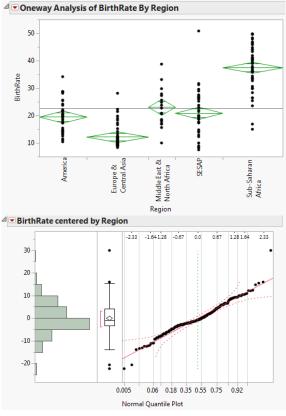
The data do not provide sufficient evidence to reject the hypothesis of equal number of weeks at delivery. We cannot conclude that there is any difference in the length of pregnancy between the two groups.

c.

Student Solutions to Application Scenarios

Scenario 1

a.

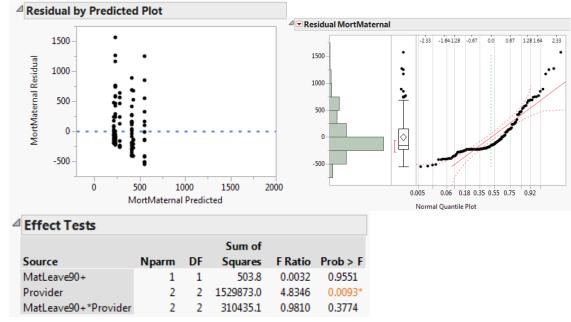


				MeanAbsDif	MeanAbsDif
Level		Count	Std Dev	to Mean	to Median
America		37	5.750668	4.543210	4.539414
Europe & Centra	l Asia	48	4.179637	2.996616	2.617055
Middle East & No	orth Africa	21	6.807553	5.290827	5.223986
SESAP		37	8.507616	6.439704	6.368328
Sub-Saharan Afri	ca	47	8.227619	6.410017	6.364044
Test	E D-Al-	DEN	DFDen	Prob > F	
O'Brien[.5]	2.7090	4	185	0.0316*	
Brown-Forsythe	5.2501	4	185	0.0005*	
Levene	5.0381	4	185	0.0007*	
Bartlett	6.5065	4		<.0001*	
[⊿] Welch's Te	st				
Welch Anova te		ns Equal, a	allowing S	td Devs Not Ea	ual

 F Ratio
 DFNum
 DFDen
 Prob > F

 90.9567
 4
 76.429
 <.0001*</td>

In this case we find that the regional variances are not equal but the residuals do appear to be approximately normal. According to Welch's test, the mean birthrate is not equal across the regions of the world. Strictly speaking we cannot rely on a formal test to determine which regions differ. Visual inspection of the means diamonds in the Oneway graph suggests that SubSaharan birth rates are unusually high, and that birth rates in Europe and Central Asia are unusually low.



We start by evaluating conditions. The Residual by Predicted Plot raises some question about the equality of variances, but it is not definitive. The residuals do not appear to be normally distributed, but we have reasonably large samples and can rely on the Central Limit Theorem.

We find no significant interaction term, and we do find a significant main effect associated with the Provider of benefits. It appears that countries with private provision of maternity benefits have significantly higher rates of maternal mortality.

Scenario 2

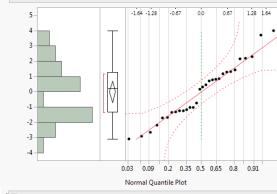
c.

a. We see no evidence that the ANOVA assumptions have been violated; variances across the three groups appear to be equal and residuals are approximately normal. The F Ratio of 4.6275

and corresponding P-value of 0.0187 indicate that we should reject the null hypothesis of equal means; there is compelling evidence that the different additives lead to different mean changes.

Levene

Bartlett



			MeanAbs	Dif M	eanAbsDif
Level	Count	Std Dev	to M	ean t	to Median
extra	10	1.590571	1.402	259	1.402259
regular	10	2.375603	1.863	848	1.863848
super	10	1.726470	1.430	697	1.369342
Test		F Ratio	DFNum	DFDen	Prob > F
O'Brien	[.5]	1.3218	2	27	0.2834
Brown-	Forsythe	0.6743	2	27	0.5179

2

2

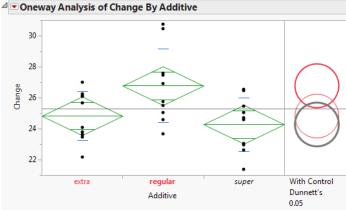
27

0.5015

0.4451

0.7081

0.8094



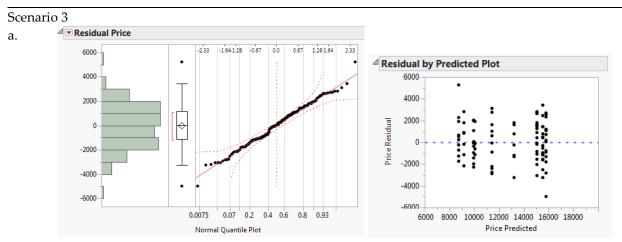
					-	
⊿	Anal	vsis	of V	arian	ce	

			Sum of			
	Source	DF	Squares	Mean Square	F Ratio	Prob > F
	Additive	2	34.41052	17.2053	4.6275	0.0187*
	Error	27	100.38696	3.7180		
	C. Total	29	134.79748			
1	Moone	for On		WD		

_	wean	s for One	way An	iova		
	Level	Number	Mean	Std Error	Lower 95%	Upper 95%
	extra	10	24.8237	0.60976	23.573	26.075
	regular	10	26.7721	0.60976	25.521	28.023
	super	10	24.2766	0.60976	23.025	25.528

Std Error uses a pooled estimate of error variance

c. We find that there is a significant improvement in insulation with the "super" additive—the temperature change is smallest with that additive. The company should switch from regular to super.



We start by evaluating conditions, and find no signs that the sample data violate the conditions for inference.

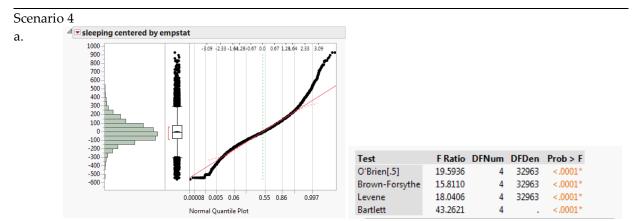
4	Effect Te	sts				
				Sum of		
	Source	Nparm	DF	Squares	F Ratio	Prob > F
	City	2	2	23253888.2	3.8819	0.0228*
	Model	2	2	1168074996	194.9929	<.0001*
	City*Model	4	4	34923934.8	2.9150	0.0235*

A review of the Effect Tests shows that we have a significant interaction effect as well as significant main effects. This tells us that prices vary by city and by model, and what's more the impact of model varies across the cities.

						Least
Level						Sq Mean
Portland, Civic EX	А					15799.318
Raleigh, Civic EX	А					15531.000
Phoenix, Civic EX	А	В				15054.867
Portland,Corolla LE		В	С			13213.500
Phoenix, Corolla LE			С	D		11400.231
Raleigh,Corolla LE				D	Ε	10072.400
Raleigh, PT Cruiser				D	Ε	9937.800
Portland, PT Cruiser					Ε	9154.538
Phoenix, PT Cruiser					Ε	8735.944
Levels not connected	d b	v s	an	ne	let	ter are signif

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When we apply Tukey's HSD (output not shown fully here) we see the complexity of the interactions; we should not make statements about main effects but can use the connecting letters report to identify differences among the model-city combinations.

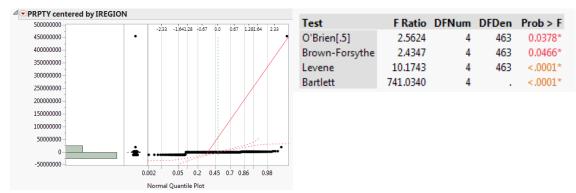


As usual we start by evaluating assumptions. We have a very large sample, so the Central Limit Theorem applies and we need not be concerned with normality (above we see the residuals are unimodal and symmetric, but depart from the normal model in the tails). We also see evidence that the variances are unequal. In practice, because of the very large sample it is not surprising that we find significant differences.

4	Welch's	Test			
١	Welch Anov	/a testing	Means Eq	ual, allowi	ng Std Devs Not Equal
	F Ratio	DFNum	DFDen	Prob > F	
	180.4634	4	1071.1	<.0001*	

Both Welch's test and the standard ANOVA results strongly indicate that there are significant differences in group means. There is no control group here. Tukey's HSD indicates that employed people at work get the least sleep and unemployed people who are looking report the most. All others are significantly different from those two groups, but indistinguishable from one another.

Scenario 5



As we can see from the output, the sample data seem to violate the assumptions of normality and equal variance. Each of the regional subsamples is large enough to rely on the Central Limit Theorem with respect to normality. Using Welch's test (below) we would conclude that the mean costs of property damage are not identical across the regions.

Welch's Test

a.

 Welch Anova testing Means Equal, allowing Std Devs Not Equal

 F Ratio
 DFNum
 DFDen
 Prob > F

 4.7168
 4
 157.95
 0.0013*

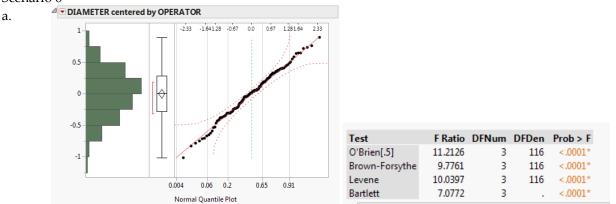
c. The distribution of residuals (not shown here) raises questions about normality and the usual tests indicate that the variances of the different disruption-type subgroups are unequal. According to Welch's test, there is at least one disruption type that differs from the others in terms of time required to make the area safe.

			MeanA	bsDif	MeanAbsDif			
Level	Coun	t Std Dev	/ to	Mean	to Median			
LEAK	9	3 344.4257	23	1.8180	188.2473			
N/A	2	4 59.0497	40	5.5347	42.2500			
OTHER	OTHER 226		8	7.8671	80.4513			
RUPTURE 9		4 193.1917	100	8.5523	97.7234			
Test		F Ratio	DFNum	DFDen	Prob > F			
O'Brien[.5]	7.8111	3	433	<.0001*			
Brown-Fo	rsythe	8.3345	3	433	<.0001*			
Levene		21.3279	3	433	<.0001*			
Bartlett		58.8941	3		<.0001*			
Durtrett	[⊿] Welch's Test							

<.0001*

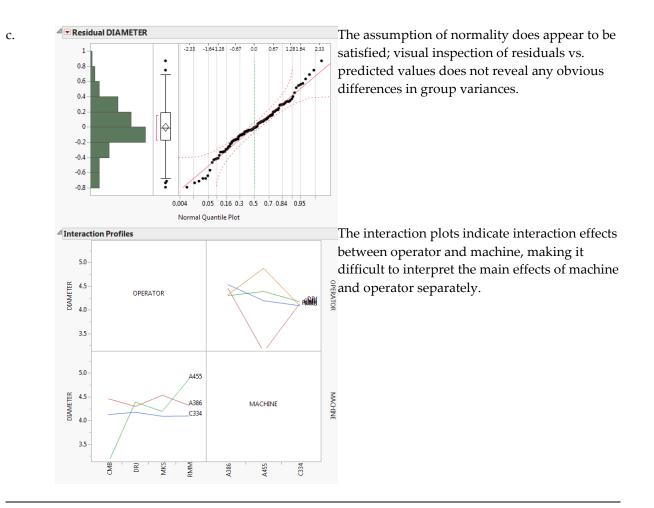
3 121.27

14.3506



We start by examining assumptions. The residuals appear to be normally distributed (the sample sizes are large enough to rely on the Central Limit Theorem in this case), but the subsamples appear not to share a common variance.

Both Welch's test and the conventional ANOVA find no significant differences among group means.



Scenario 7: NOTE-- Due to the large amount of output required in this problem, only a few selected results are shown.

a. We begin by checking the normality and equal variance assumptions. These are particularly important with such a small sample.

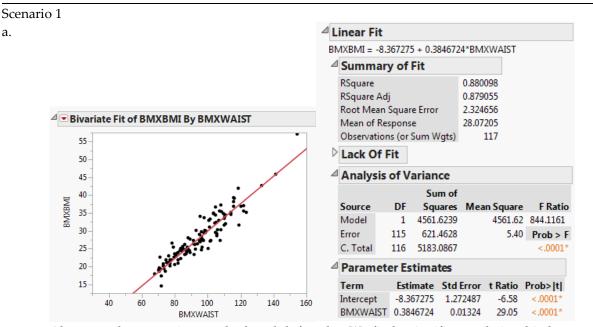
Among the three analyses, we find that there are unequal variances for the analysis of Yield by Popcorn type and Yield by batch.

The residuals in the analysis by Batch appear to be approximately normal, but the others do not. Due to the non-normality, we should use the Wilcoxon approach for the other two.

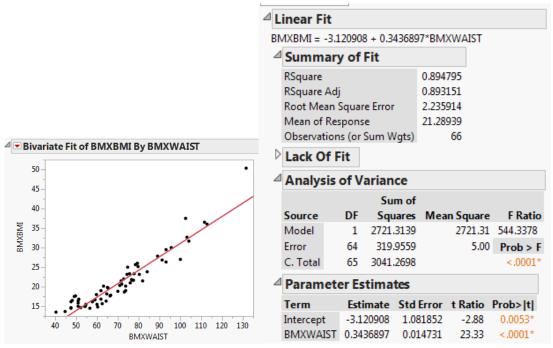
Yield vs. Batch satisfies normality, but not Equal Variance. Hence, we should consult Welch's test for Yield vs. batch.

There are no significant main effects on yield for either Popcorn or Oil Amt. However, the Welch's test result does indicate a significant effect of batch size (small batches improve yield).

Student Solutions to Application Scenarios



Above are the regression results for adult females. We find a significant relationship between waist circumference and BMI, with the waist measurement accounting for about 88% of the variation in BMI. Each addition centimeter of waist circumference is associated with an increase of 0.3847 in BMI.



If we restrict the analysis to females under the age of 17 we find a slightly stronger relationship between Waist and BMI. The estimated slope is slightly smaller than before (0.344 vs. 0.385) but otherwise the regression models are very similar.

F Ratio

<.0001*

30801.6 140.4231

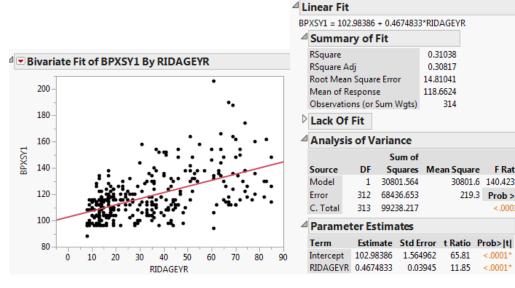
65.81

219.3 Prob > F

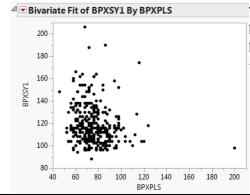
<.0001*

<.0001*

Scenario 2 a.



In this regression we find a weak ($R^2 = 0.31$) but highly significant positive relationship. Subjects who differ in age by 1 year tend to have, on average, systolic BP that is approximately 0.47 points higher per year. This is not a strong relationship because age accounts for less than one-third of the variation in systolic BP.

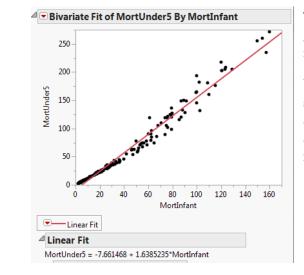


The scatterplot to the left shows little or no relationship between pulse and systolic BP. If anything, there may be a very weak negative relationship here, contrary to the suspicion expressed in the question.

Scenario 3

a.

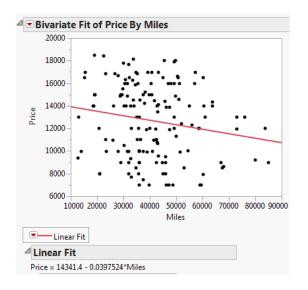
c.



The estimated equation is appears beneath the graph, with $R^2 = 0.979$ – indicating a very strong relationship and excellent fit.

Despite the strong summary statistics, the scatterplot very clearly indicates some doubt about the linear model: the points seem to bend around the line, suggesting that the relationship is not best described as a line.

Scenario 4

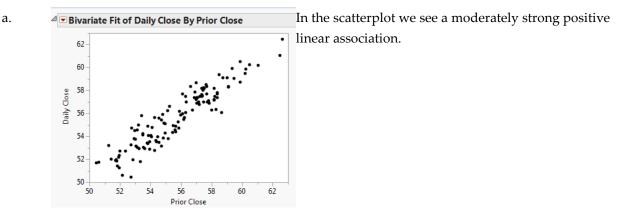


The equation appears beneath the graph, and $R^2 = 0.03$.

This regression shows there is a weak, significant negative relationship between mileage and price for used cars. The further a car has been driven, on average the lower the price (about 4 cents per mile, on average). However there is considerable scatter around the line.

Scenario 5

a.



Paramet	er Estima	ites			✓ Custom Test
Ferm ntercept		Std Error 1.775282		Prob> t 0.0041*	Random Walk
	0.9060521	0.031839	28.46	<.0001*	Parameter
					Intercept 0
					Prior Close 1
					= 1
					Value -0.093947855
					Std Error 0.031838543
					t Ratio -2.950758618
					Prob> t 0.0037964813
					SS 7.3790050123
					Sum of Squares 7.3790050123
					Numerator DF 1
					F Ratio 8.7069764218
					Prob > F 0.0037964813

Although the estimated slope of 0.906 might appear to be approximately 1, the custom test indicates a significant difference from 1 (p-value = .004). Moreover, we find that the Intercept is significantly different from 0.

Scenario 6

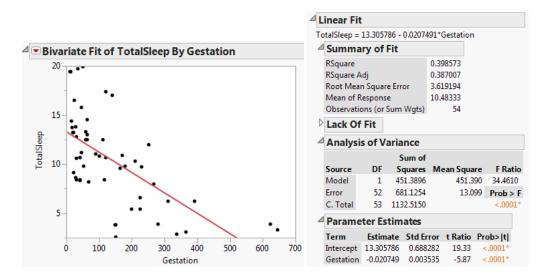
a.

Analys	is of Va	ariance			Custom Test
Source	DF	Sum of Squares	Mean Square	F Ratio	Parameter Intercept 0
Model	1	25657.718	25657.7	496.8029	Partb 1
Error C. Total	62 63	3202.032 28859.750	51.6	Prob > F <.0001*	= 0.61803 Value -0.008081357 Std Error 0.0273653631
Lack O	f Fit				t Ratio -0.295313357 Prob> t 0.7687412337
⁴ Parame	eter Est	timates			SS 4.5040178923
Term	Estima	te Std Erro	or t Ratio Pr	rob> t	Sum of Squares 4.50401789 Numerator DF
Intercept Partb	0.17850 0.60994			0.9363 <.0001*	F Ratio 0.08720997 Prob > F 0.76874123

Using the Haydn data we find a similar story to the one we saw with Mozart. We again find the Golden Mean model plausible.



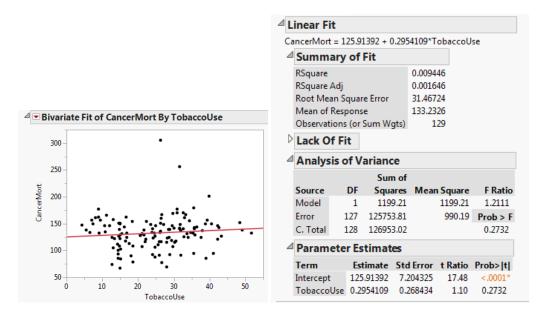
a.



Here we find a significant, but weak, negative relationship. On average, each additional day of gestation is associated with a reduction of 0.02 hours of sleep per night. Gestation accounts for only about 40% of the variation in total sleep, so it is a fair predictor of sleep hours.

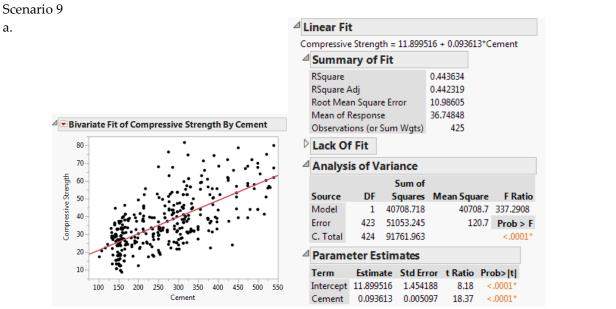
Scenario 8

a.



We find a non-significant relationship here – Tobacco Use is not a useful predictor of cancer deaths in a country.

c. The aggregate prevalence of tobacco use obscures the fine distinctions in the amount and length of tobacco use in individuals. We'd really want to look at data at the individual level in order to determine the degree to which increased tobacco use influences the risks of death from cancer or from cardiovascular disease.



This is a highly significant, but weak, positive relationship. For each additional kg of cement in the mixture, compressive strength increases on average by 0.09 megapascals.

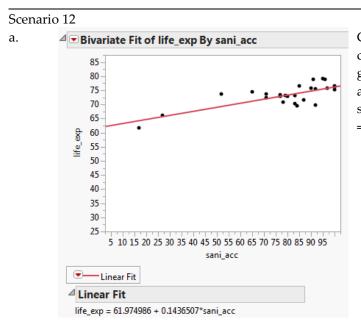
Scenario 10

a. There are slight differences, but when we round the major statistics we find that all four models are nearly identical: $Y_i = 3 + 0.5 X_i$. All R^2 (0.66) and p-values (0.0022 for the slope) are the same.

c. In the other three graphs, the points do not fall in a linear pattern at all. This illustrates a substantial risk in running a linear regression without first examining the data visually. (In JMP we *always* see a scatterplot of the points either prior to fitting a model or in conjunction with fitting a model).

Scenario 11

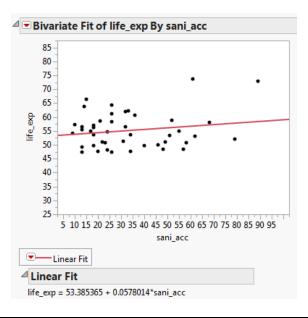
- a. The estimated equation is Price = 17625.688 0.054972*Miles. On average, the price declines approximately 5.5 cents per mile driven, and a car that had never been driving would have an asking price of \$ 17,625.69.
- c. The estimated equation is Price = 10659.169 0.0350164*Miles. Due to the large p-value for the slope, we cannot be confident that the true slope differs from 0, and hence should not venture an estimate of the price decline. The p-value for the intercept is significant , and we can estimate that a car that had never been driving would have an asking price of \$ 10,659.17.



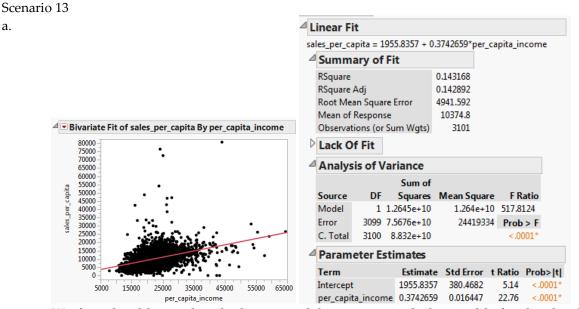
Countries in which higher percentages of citizens have access to sanitation have greater life expectancies. The equation appears beneath the fitted line plot. The slope is significant at the 0.0001 level, and $R^2 = 0.58$.



a.



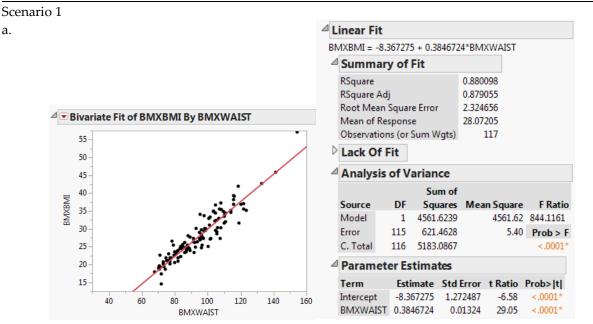
The equation appears beneath the fitted line plot. In this case, the estimated slope is not significant (p-value = 0.253) and R² = 0..03.



We first should note that the linear model is not particularly suitable for the cloud of points. There are a relatively small number of outlying points, but overall the trend is that higher per capita income is associated with higher retail spending. This makes logical sense because areas of higher incomes have residents who are in a position to

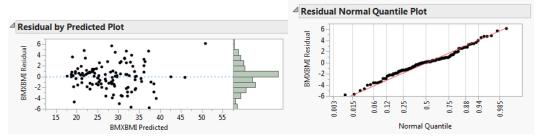
spend more, other things being equal. On average, each additional dollar in per capita income is associated with an increase of approximately 37 cents in spending. The estimated slope is highly significant, but the relationship is weak, with $R^2 = 0.14$.

Student Solutions to Application Scenarios



We first performed this regression in the previous chapter. Above are the regression results for adult females. We find a significant relationship between waist circumference and BMI, with the waist measurement accounting for about 88% of the variation in BMI. Each addition centimeter of waist circumference is associated with an increase of 0.3847 in BMI. When we save the residuals and check their normality, we find the normality assumption seems to be reasonable. The graph of residuals vs. predicted values suggests that the dispersion of

residuals increases as predicted values increase, though it is not an overly dramatic tendency. We can probably trust this model for predictions.



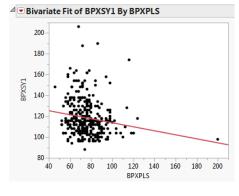
Looking at the fitted line graph, it appears that the mean BMI for women with 68 cm. waists is c. approximately18.

Scenario 2 ⁴ Residual Normal Quantile Plot 80 60 **BPXSY1** Residual 40 Residual by Predicted Plot 20 80 60 **BPXSY1** Residual 0 40 -20 20 --40 0 -20 0.003 0.015 0.06 0.12 0.25 5 8.0 0.94 985 -40 100 140 180 200 80 120 160 Normal Quantile RPXSV1 Pr dicted

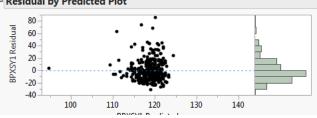
Once again we see the suggestion of heteroskedasticity on the left side of the graph. The residals are largely normal in shape, though somewhat right-skewed. We can probably use the model safely.

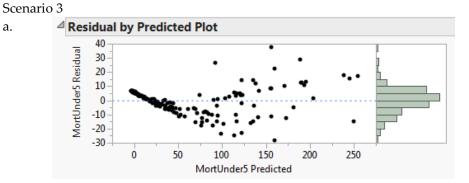


a.

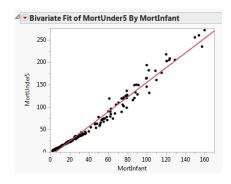


The scatterplot to the left shows little or no relationship between pulse and systolic BP. If anything, there may be a very weak negative relationship here, contrary to the suspicion expressed in the question. Residual by Predicted Plot





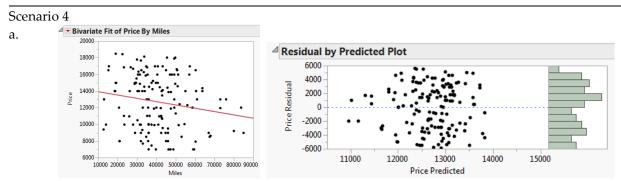
The residuals graphs cast doubt on both normality and constant variance.



a.

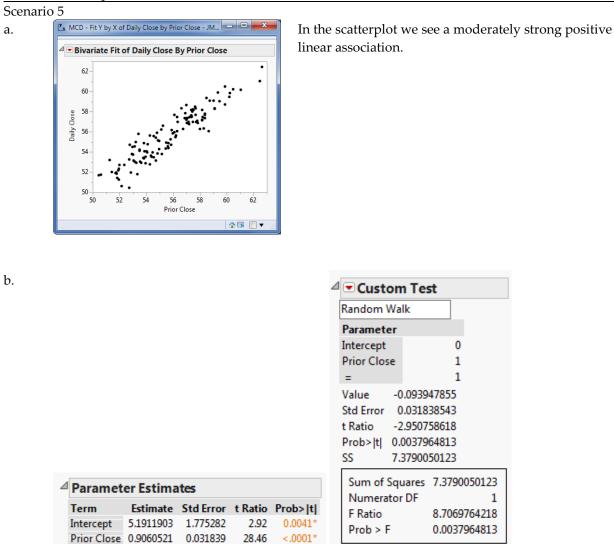
In Chapter 15 we noted that despite the strong summary statistics, the scatterplot very clearly indicates some doubt about the linear model: the points seem to bend around the line, suggesting that the relationship is not best described as a line.

The Residual by Predicted plot very clearly depicts both the non-linearity and the heteroskedasticity. Normality does not seem to present a serious problem.



(Note: it is wise to adjust the horizontal axis on the residual by predicted plot to more clearly see the pattern.) The residuals are not normally distributed, there may be a problem with constant variance on the left side of the graph. The sample size may be large enough to rely on the Central Limit Theorem.

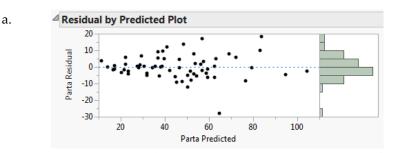
c. Student answers will vary. The prediction bands on this graph are quite wide, and even with rescaling the axes it is difficult to read predicted values of Y. A reasonable response would be that the price should fall between \$6200 to \$19,500.



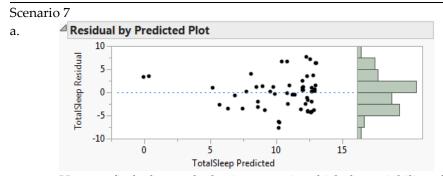
Although the estimated slope of 0.906 might appear to be approximately 1, the custom test indicates a significant difference from 1 (p-value = .004). Moreover, we find that the Intercept is significantly different from 0. Therefore, the Random Walk model does not

suit this set of data.

Scenario 6

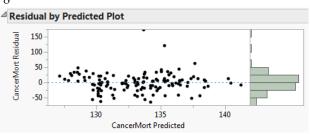


With the Haydn data, in the Residual vs. Partb plot we find a heteroskedastic pattern; the residual do deviate slightly from normality, but the distribution is single peaked, so inference is probably appropriate.



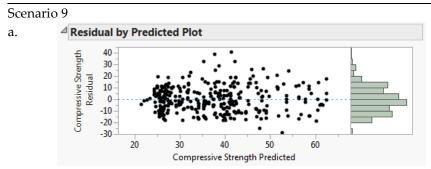
Here we find a heteroskedastic pattern in which the variability of residuals increases as the Gestation period lengthens. Normality is not ideal, but the sample size may be enough to rely on the CLT. Given the non-constant variance, we should be reluctant to interpret or use the results of the regression.

a.



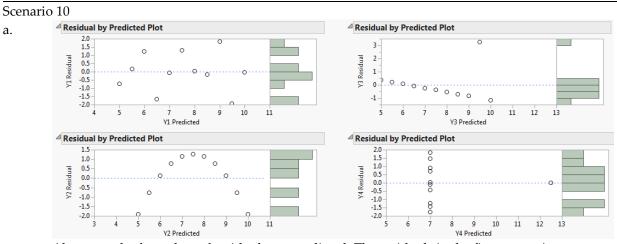
(Note: it is wise to adjust the horizontal axis on the residual by predicted plot to more clearly see the pattern.)

Recall that we find a non-significant relationship here – Tobacco Use is not a useful predictor of cancer deaths in a country. The residuals seem to show more variability in the middle range of tobacco use (non-constant variance), and residuals are nearly normal, with a long upper tail but large sample size. This model is not useful for inference.

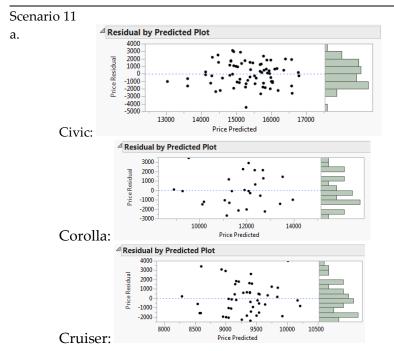


These residuals look good... the Residual vs. Cement plot shows an even scatter above and below the 0-line and the normal quantile plot shows that the residuals follow a nearly normal distribution except for the lower tail. In any case, we have a large sample, so the CLT applies. We can safely interpret the results.

This is a highly significant, but weak, positive relationship. For each additional kg of cement in the mixture, compressive strength increases on average by 0.005 megapascals.



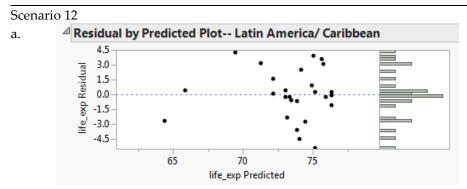
Above are the four plots of residuals vs. predicted. The residuals in the first regression are homoskedastic and approximately normal. The others indicate non-linearity and/or heteroskedasticity. Normality plots also indicate non-normal residuals in these small samples.



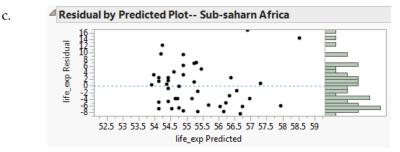
(Note: it is wise to adjust the horizontal axes on the residual by predicted plots to more clearly

see the pattern.)

Recall that we find a non-significant relationship for the Cruiser data. Each set of residuals would appear to have constant variance; the Civic data are most nearly normal, but normality is questionable for the others. Hence p-value estimates and confidence intervals may be inaccurate.

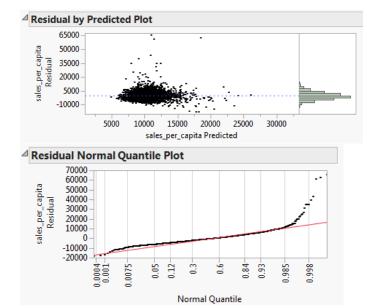


These residuals are unimodal and somewhat symmetric. With a small sample it is difficult to determine non-constant variance. No obvious violations, so inference is reasonable.



This is a non-significant relationship. The residuals seem to show constant variance, but a skewed and flat distribution. Inference is safe.

Scenario 13



This is a very large sample, so the skewness to the right side may not be a major issue. The residuals do not appear to have a purely random pattern with constant variance, so judgments based on confidence intervals and p-values may be questionable.

a.

Student Solutions to Application Scenarios

Scenario 1 Residual BMXBMI -233 -1.641.28 0.67 0.0 0.67 1.281.64 2.33 6 . Residual by Predicted Plot 4 6 2 4 **BMXBMI Residual** Ŷ 2 0 0 -2 -2 -4 -4 -6 0.002 0.05 0.2 0.45 0.7 0.86 0.98 20 35 40 45 50 15 25 30 55 Normal Quantile Plot BMXBMI Predicted

a.

The residual plots from this multiple regression model are very similar to those from the simple regression using Waist circumference as the only predictor (see those graphs below). We can use this set of data for estimation. The regression results themselves are shown below.

We find a strong relationship between BMI and the model, but this model is not much of an improvement over the previous model (shown again below). The intercept has changed dramatically, though in this model the intercept does not have much meaning. The effect size for the Waist measurement is almost equal to that of the single variable model, and the coefficient of height is not significant at the cusotmary .0.05 level. The height variable is not significant at the 0.05 level, though it is significant at the 0.10 level.

This set of Solutions for Students is a companion piece to the following SAS Press book: Carver, Robert. Practical Data Analysis with JMP®, Second Edition. Copyright © 2014, SAS Institute Inc., Cary, NC, USA. ALL RIGHTS RESERVED.

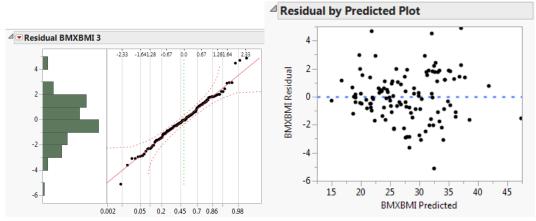
The two-variable model has a very small improvement in goodness of fit in comparison to the single-variable model.

4	Summa	ry of l	Fit						
	RSquare				0.883	615			
	RSquare A	dj			0.881	573			
	Root Mea	n Squar	e Error	r	2.300	333			
	Mean of R	lespons	e		28.07	205			
	Observatio	ons (or S	Sum W	/gts)		117			
4	Analysi	s of Va	arian	се					
			Su	m of					
	Source	DF	Squ	iares	Mea	n Squa	are	F Rat	tio
	Model	2	4579.	.8522		2289	.93	432.753	31
	Error	114	603	.2345		5	.29	Prob >	F
	C. Total	116	5183	.0867	Mean Square F Ratio 2289.93 432.7531				
4	Parame	ter Es	tima	tes					
	Term	Esti	mate	Std	Error	t Rati	io	Prob> t	L
	Intercept	0.814	1862	5.10	4596	0.1	.6	0.8736	
	BMXWAIS	T 0.385	52663	0.01	3105	29.4	0	<.0001	*
	BMXHT	-0.05	56898	0.03	80656	-1.8	36	0.0660	
	1		1						

In short, the addition of the height data does not improve the model in any material way.

We first performed this regression in Chapter 15. At that time we found a significant relationship between waist circumference and BMI, with the waist measurement accounting for about 88% of the variation in BMI. Each addition centimeter of waist circumference is associated with an increase of 0.3847 in BMI. When we saved the residuals and check their normality, we find the normality assumption seems to be reasonable. The graph of residuals vs. predicted values suggested that the dispersion of residuals increases as predicted values increase, though it is not an overly dramatic tendency. We can probably trust this model for predictions.

c. NOTE: The scenario question mistakenly asks for you to use the Write Circumference as a predictor. The question should ask for <u>thigh</u> circumference.

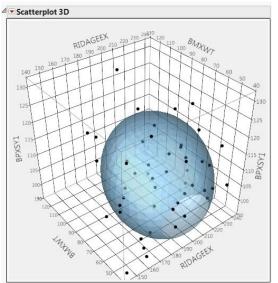


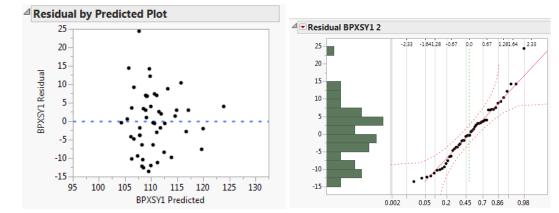
In the model using waist and thigh circumference (note typographical error in early printings of the book that this is refrered to as wrist cicumference), we find residuals that are approximtely normal and more heteroskedastic than our prior models. In this sense, the model is less attractive than the earlier ones. On the other hand, the goodness of fit is improved (Adj. RSquare; see below) now equals 0.92 and both slopes are statistically signifiant and make logical sense.

1	Summar	r of	Ci+						
	Summar	y 01	rit						
	RSquare				0.921	955			
	RSquare Adj	i			0.920	574			
	Root Mean	Squar	e Error		1.730	549			
	Mean of Res	spons	e		27.82224				
	Observation	is (or	Sum W	/gts)		116			
4	Analysis	of V	arian	се					
			Su	m of					
	Source	DF	Squ	iares	Mea	in Square	F Ratio		
	Model	2	3997.	7140		1998.86	667.4430		
	Error	113	338.	4122		2.99	Prob > F		
	C. Total	115	4336.	1262			<.0001*		
4	Paramet	er Es	tima	tes					
	Term Es		Estimate Std		Error	t Ratio	Prob> t		
	Intercept	-13.8	32162	1.24	46674	-11.09	<.0001*		
			0.2815128 0.01		14495 19.42				
	BMXWAIST	0.28	15128	0.01	4495	19.42	<.0001*		

c.

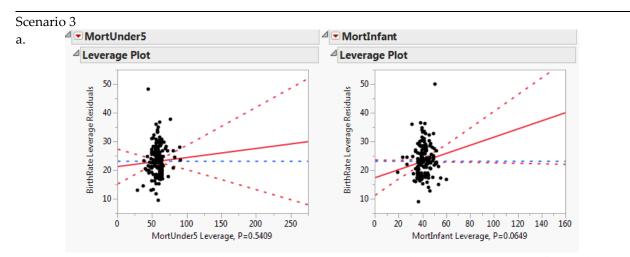
a. Student answers will vary. One rotated scatterplot is shown here (including a density ellipsoid). We see a weak tendency for systolic BP to increase both as age and weight increase.





Here again we find concerns about heteroskedasticity and normality; if we continue on to interpret the coefficient estimates, we see that the Diastolic BP adds little to the model. The estimated value is not significantly different from zero, and the adjusted R² is very nearly the same in the prior model using just 2 factors in the model. This model is no meaningful improvement over the prior one.

Δ	Summa								
	RSquare				0.19	4144			
	RSquare A	dj			0.14	1589			
	Root Mea	n Square	e Erro	or	8.37	9746			
	Mean of R	esponse	2		11	0.56			
	Observatio	ons (or S	Sum	Wgts)		50			
⊿	Analysi	s of Va	aria	nce					
RS RS RS M O O O O O O S G M B Err C. C O T 4 In RI B			S	um of					
	Source	DF	quares	Me	an Squa	ire	F Rat	io	
	Model	3	77	8.1931		259.3	98	3.694	1
	Error	46	323	0.1269		70.2	20	Prob >	F
	C. Total	49	400	8.3200				0.018	3*
Δ	Parame	ter Es	tim	ates					
	Term	Estim	ate	Std E	rror	t Ratio	Р	rob> t	
	Intercept	95.121	093	13.24	218	7.18		<.0001*	
	RIDAGEEX	-0.041	445	0.041	.677	-0.99		0.3252	
	BMXWT	0.2206	758	0.068	3708	3.21		0.0024*	
	BPXDI1	0.149	581	0.142	639	1.05		0.2998	



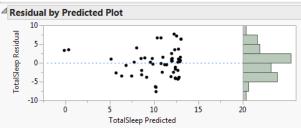
The leverage plots immediately suggest a problem with collinearity, which is confirmed by the very high VIFs in the table of parameter estimates (below):

Parameter Estimates												
Term	Estimate	Std Error	t Ratio	Prob> t	VIF							
Intercept	13.286898	0.702092	18.92	<.0001*								
MortMaternal	0.0074981	0.002851	2.63	0.0093*	7.4325523							
MortUnder5	0.0316232	0.051616	0.61	0.5409	61.071947							
MortInfant	0.1418103	0.076308	1.86	0.0649	48.623078							

This model should not be used or interpreted.

Scenario 4





When we estimate a simple linear model using gestation as the factor, we find a heteroskedastic pattern in which the variability of residuals diminishes as the Gestation period lengthens. Normality is not ideal, but the sample size is large enough to rely on the CLT. Given the non-constant variance, we should be reluctant to interpret or use the results of the regression.

c.

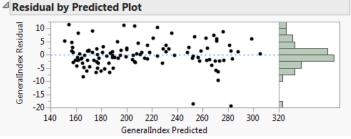
4	Parame	ter Estim	ates			
	Term	Estimate	Std Error	t Ratio	Prob> t	VIF
	Intercept	13.988263	0.766827	18.24	<.0001*	
	Gestation	-0.029326	0.005706	-5.14	<.0001*	2.6878834
	BrainWt	0.0019058	0.001645	1.16	0.2522	11.122211
	BodyWt	-0.000415	0.001454	-0.29	0.7767	8.1620725

This model is not an improvement over the prior two. We still see heteroskedasticity in the plot of residuals vs. fitted values (not shown here). We see evidence of collinearity in the large VIF for BrainWt, and only the Gestation variable is statistically significant.

a. *Correlations*

	GeneralIndex Ba	sicGoods C	apGoods Inte	ermedGoods Co	Durables	NonDur	
GeneralIndex	1.0000	0.9932	0.9634	0.9716	0.9801	0.9254	0.9598
BasicGoods	0.9932	1.0000	0.9524	0.9675	0.9651	0.9237	0.9415
CapGoods	0.9634	0.9524	1.0000	0.9277	0.9119	0.8884	0.8850
IntermedGoods	0.9716	0.9675	0.9277	1.0000	0.9241	0.9060	0.8952
Consumer	0.9801	0.9651	0.9119	0.9241	1.0000	0.9021	0.9918
Durables	0.9254	0.9237	0.8884	0.9060	0.9021	1.0000	0.8396
NonDur	0.9598	0.9415	0.8850	0.8952	0.9918	0.8396	1.0000

In the correlation matrix we find that the Basic Goods index is most highly correlated with the General Index. The simple model that estimates monthly values of the General IIP from the Basic Goods IIP provides an excellent goodness of fit and the sample is large enough to invoke the CLT. However, we do see some evidence of non-linearity in the plot of residuals vs. fitted values (below):



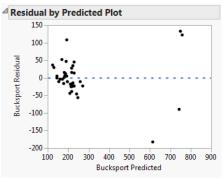
Given the R² value of nearly 0.99, the non-linearity may not be a major problem. The estimation results are as follows:

Δ	Paramete	er Estima	tes		
	Term	Estimate	Std Error	t Ratio	Prob> t
	Intercept	-45.42024	2.919964	-15.56	<.0001*
	BasicGoods	1.3979391	0.015697	89.06	<.0001*

An increase of 1 in the Basic Goods index will be accompanied on average by an increase of approximately 1.4 in the General Index.

c. See discussion in part (b) above. It is not surprising that these index variables are all highly correlated because they all measure different aspects of the fundamental production activity within the Indian economy, and all reflect the general level of economic activity.

a. Student models will vary. Here is one plausible result using the Enfield and Orono columns:

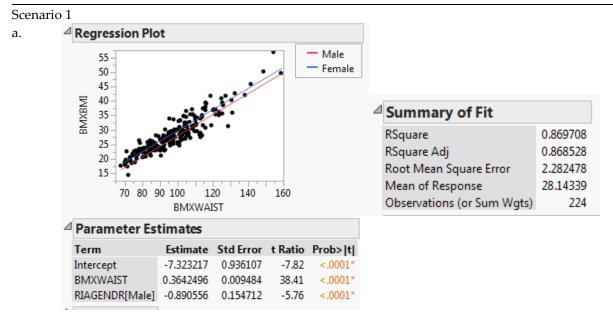


The residuals appear to have a non-constant variance,

which raises a problem with using this model for prediction or estimation. The model adjusted R² is approximately 0.9 which indicates a very good fit. Both variables are statistically significant and we see no real evidence of collinearity.

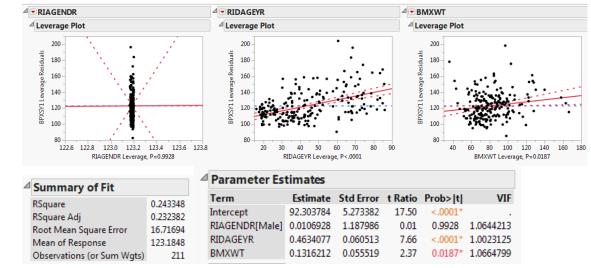
4	Parame	eter Estin	nates			
	Term	Estimate	Std Error	t Ratio	Prob> t	VIF
	Intercept	-136.672	81.02309	-1.69	0.1001	
	Enfield	1.1770766	0.332625	3.54	0.0011*	1.1065036
	Orono	0.6331057	0.034694	18.25	<.0001*	1.1065036

Student Solutions to Application Scenarios

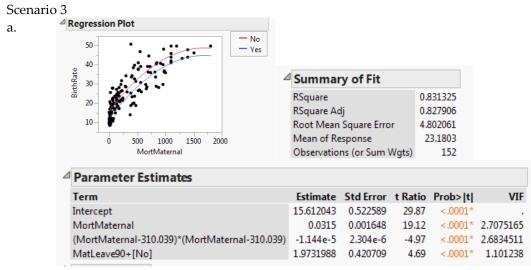


The key results are shown above. Compared to the model using waist circumference only, this model has a slightly higher adjusted RSquare and smaller Root Mean Square Error. Both variables are statistically significant. The residuals vs. fits graph is quite similar in both models, and this model makes logical sense.

Scenario 2

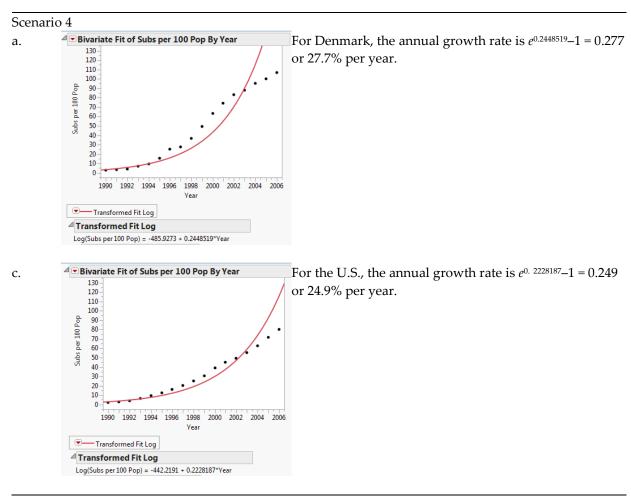


The leverage plots indicate collinearity problems. We see that the model has rather poor fit, and only the Gender variable is not statistically significant.

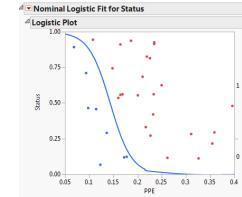


This model fits the data rather well, and all coefficients are significant. We find that other things equal higher rates of maternal mortality are associated with higher birthrates, and that after controlling for differences in maternal mortality, countries that do not offer lengthy maternity leaves have higher birthrates than countries with longer leaves. Residuals appear to be normally distributed with equal variances.

a.



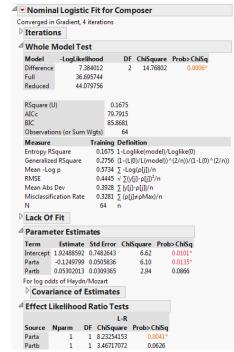
a.



The logistic regression results appear to the left. The regressor, PPE, is statistically significant and we see that patients with Parkinson's Disease have significantly lower PPE values than patients without PD. In the Logistic Plot, the dark markers are patients with PD; we see that the estimated curve distinguishes between PD and non-PD patients.

Whole N	/lodel Te	st					
Model	-LogLike	lihood	. I	OF ChiS	quare	Prob>C	hiSq
Difference	9.	17137(5	1 18.	34275	<.0	001*
Full	8.	823349	9				
Reduced	17.	99472	5				
RSquare (U)		0.509				
AICc			22.060	-			
BIC			24.578	-			
Observatio	ns (or Sum	n Wgts) 3.	2			
Measure		Trai	ining De	finition			
Entropy RS	quare	0.	5097 1-L	oglike(m	odel)/l	Loglike(0)	
Generalized	d RSquare	0.	6461 (1-	(L(0)/L(m	odel))	^(2/n))/(1	-L(0
Mean -Log	р	0.	2757 ∑ -	Log(p[j])	'n		
RMSE				(y[i]-p[i]			
Mean Abs	Dev			([i]-p[i]]/			
Misclassific	ation Rate			p[j]≠pMa			
N			32 n	011 011			
Lack Of	Fit						
Daramot	ter Estin						
raranie		Idito					
Term	Estimate			•		•	
ntercept	6.46989978	2.70	81092	5.71		0.0169*	
ntercept PPE	6.46989978 -45.284036	2.70	81092	•		•	
ntercept PPE or log odd	6.46989978 -45.284036 ls of 0/1	2.70 17.	81092 22916	5.71		0.0169*	
ntercept PPE or log odd	6.46989978 -45.284036	2.70 17.	81092 22916	5.71		0.0169*	
intercept PPE or log odd Covari	6.46989978 -45.284036 ls of 0/1	2.70 17. Estin	81092 22916 nates	5.71 6.91		0.0169*	
intercept PPE or log odd Covari	6.46989978 -45.284036 Is of 0/1 ance of	2.70 17. Estin	81092 22916 nates	5.71 6.91 s		0.0169*	
intercept of PPE or log odd Covari	6.46989978 -45.284036 Is of 0/1 ance of kelihoo o	2.70 17. Estin	81092 22916 nates io Test L-F	5.71 6.91 s		0.0169*	

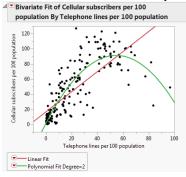
a.



The results are to the left. We find that the whole model is significant with a rather poor fit, as measured by U. Other things being equal, the longer Part a is the lower the odds that it was composed by Haydn. Conversely, the longer Part b is (holding Part a constant) the higher the odds that it was composed by Haydn.

Scenario 7

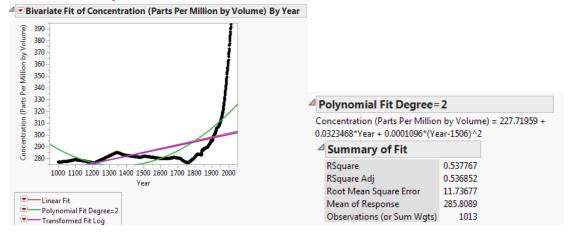
a. Here are the results for the quadratic and linear fits:



Linear Fit	t						Polynom	ial Fit	Degree=	2				
Cellular subs	cribers	per 100 pop	ulation = 17.425	75 +		Cellular subscribers per 100 population = 17.232324 +					324 +			
L.3272881*Te	elephon	e lines per 1	00 population				1.9558382*T							
⊿ Summa	arv of	Fit							· · ·	100 population-2	21.7652)^2			
	- C		0.581146				⊿ Summa	ary of	Fit					
RSquare							RSquare			0.75143				
RSquare A			0.578965				RSquare A	٨dj		0.748827				
Root Mea	in Squar	e Error	23.92515				Root Mea	n Squar	e Error	18.47915				
Mean of F	Respons	e	46.15928				Mean of I	Respons	e	46.15928				
Observati	ons (or	Sum Wgts)	194				Observati	ons (or	Sum Wgts)	194				
Lack Of	f Fit						Lack Of	Fit						
⊿ Analysi	is of V	ariance					Analysis of Variance							
-		Sum of							Sum of					
c	DE		N	C.DMa			Source	DF		Mean Square	F Ratio			
Source	DF		Mean Square	F Ratio			Model	2	197168.00		288.6972			
Model	1	152487.19	152487	266.3937			Error	191	65222.47		Prob > F			
Error	192	109903.27	572	Prob > F			C. Total	193	262390.46		<.0001*			
C. Total	193	262390.46		<.0001*			⊿ Parame	eter Es	timates					
⊿ Parame	eter Es	timates					Term				Estimate	Std Error	t Ratio	Prob> t
-				C. 15			Intercept				17.232324	1.899833	9.07	<.0001*
Term				e Std Error					per 100 pop		1.9558382	0.083454	23.44	<.0001*
Intercept			17.425		7.08	<.0001*	(Telephor	ne lines	per 100 pop	oulation-21.7652)	^2 -0.030063	0.002628	-11.44	<.0001*
Telephon	e lines p	er 100 popu	lation 1.327288	0.081321	16.32	<.0001*								

We can see that the quadratic model has better goodness of fit statistics, and graphically it is clear the parabolic model fits the observed points better than the linear model.

a. Here are the results for the linear, quadratic and log-linear fits: The linear and log-linear are nearly indistinguishable. None of the models fit particularly well, which visual inspection makes clear. The quadratic model has the best fit of the three, but it is weak.



Student Solutions to Application Scenarios

Scenario 1

a.

Model Comparison												
Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
- 🗸		 Winters Method (Additive) 	101	45.37764	711.39900	719.33217	0.942	705.399	0.999994		3.132245	5.846902
		 Winters Method (Additive) 	104	50.177156	735.50239	743.52087	0.940	729.50239	0.000006		3.315726	6.109066

As shown above, using a 6-month season (top row) is a minor improvement over the 3-month season. The variance, MAPE, and MAE are smaller with this model than the earlier model, and RSquare is very slightly higher.

c.

Model Comparison

Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
		 Winters Method (Additive) 	101	45.37764	711.39900	719.33217	0.942	705.399	0.999661		3.132245	5.846902
		- ARI(2, 1)	107	42.046266	727.42716	735.52860	0.954	721.42716	0.000331		2.825473	5.258672
-		 Winters Method (Additive) 	104	50.177156	735.50239	743.52087	0.940	729.50239	0.000006		3.315726	6.109066
		- ARI(1, 1)	108	46.320348	736.88434	742.28530	0.949	732.88434	0.000003		2.877901	5.367753
-		— AR(1)	109	99.891165	830.57245	835.99151	0.878	826.57245	0.000000		4.290917	7.913439

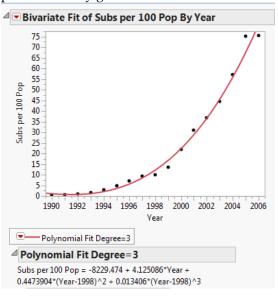
As shown above, the AR(2,1) model is an improvement as indicated by all measures of fit.

Scenario 2

a. Student answers will vary. Responses should note that Durables show a marked upward trend with likely seasonal component. Below are summary results for several reasonable approaches. Among the methods available through the Time Series platform, Linear Exponential Smoothing outperforms the others according to the measures we have studied. The adjusted RSquare statistics for the regression-based models are inferior to all but the AR(1) model, as follows: Linear, (.854), Quadratic (.855), LogLinear (.867).

Model Co	lodel Comparison											
Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
		 Winters Method (Additive) 	104	528.09261	989.97456	997.99305	0.873	983.97456	0.995917		5.876557	18.367321
		 Linear (Holt) Exponential Smoothing 	107	519.71387	1000.9686	1006.3513	0.875	996.96864	0.004082		5.741653	17.872988
		- ARI(1, 1)	108	597.81201	1017.5667	1022.9677	0.870	1013.5667	0.000001		5.840147	18.695112
▼ 🗸		- AR(1)	109	689.3022	1044.5854	1050.0045	0.832	1040.5854	0.000000		6.783594	21.001116

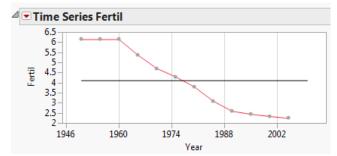
- a. This is an annual series and therefore there can be no seasonal component.
- c. Student answers will vary. For the Malaysia data, a 3rd degree polynomial (cubic) model provides a very good fit:



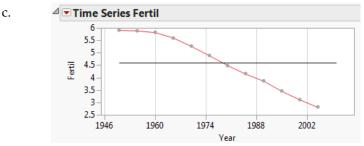
e. These countries are all best approximated by different models. Effective time-series modeling requires the use of a variety of approaches.

Scenario 4

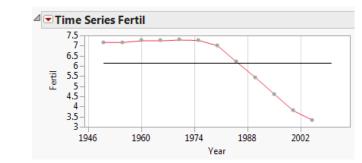
a. The fertility rate in Brazil has declined following an S-shaped curve:



An AR(1,1) model fits modertately well, with relatively high RSquare (0.969), low variance (0.077) and MAPE and MAE of 5.35% and 0.20 respectively.



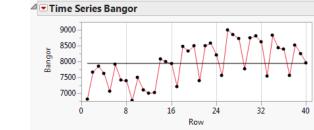
India's decline is very regular, especially since 1960. Linear Exponential Smoothing (Holt's method) and AR(1,1) models both fit extremely well.



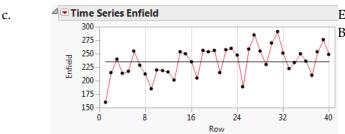
e.

Saudi Arabia's decline is very regular, especially since 1980. Linear Exponential Smoothing (Holt's method) and AR(1,1) models both fit extremely well.

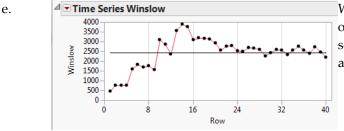
a.



Bangor: For this series, an AR(4,1) works moderately well. The strong seasonal element here suggests that points are correlated with the observation 4 quarters earlier.



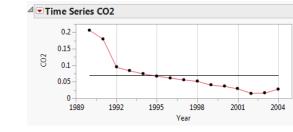
Enfield: This pattern is much like the one in Bangor; Once again an AR(4,1) model fits well.



Winslow: Here we see the dramatic change occurring roughly half-way through the time series. Simple exponential smoothing provides are reasonably good model.

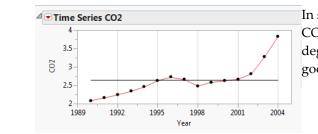
Scenario 6

a.

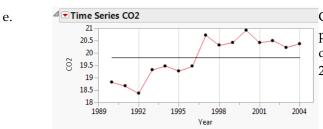


CO2 emissions in Afghanistan have fallen since the series began, and have leveled off (with minor increases) in most recent years.

For this series, a log-linear model fits quite well (Rsqr =0.905). The other time series methods do not fit quite as well, though an AR(1,1) provides a good fit.



In sharp contrast to the prior two graphs, China's CO2 emissions have been rapidly rising. A 3rd-degree polynomial (cubic) provides a moderately good fit, as does AR(1,1).



CO2 emissions in the US rose for much of the period and seem to have leveled off, presenting a quite different pattern from the prior 4 nations. A 2nd degree polynomial fits best.



The series to the left (expanded for clarity) would be poorly described with any type of linear trend model because it exhibits several changes of direction. Because we have just 6 months of data, we should not use Winter's

Scenario 8

c.

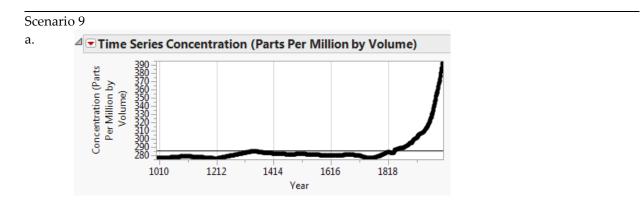
a. ⊿

Correlations										
	NIK225	FTSE	SP500 H	angSeng	IGBM	TA100				
NIK225	1.0000	0.9674	0.9812	0.9688	0.9379	0.9506				
FTSE	0.9674	1.0000	0.9810	0.9770	0.9795	0.9305				
SP500	0.9812	0.9810	1.0000	0.9652	0.9637	0.9498				
HangSeng	0.9688	0.9770	0.9652	1.0000	0.9731	0.9468				
IGBM	0.9379	0.9795	0.9637	0.9731	1.0000	0.9281				
TA100	0.9506	0.9305	0.9498	0.9468	0.9281	1.0000				

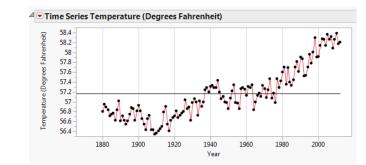
There are 1 missing values. The correlations are estimated by REML method.

The Nikkei225 has the highest correlation with the S&P500 (0.9812) and the FTSE100 is close behind with r = 0.9810)

c. Yes. Both markets are engaged in competition in the same global markets, and move very closely together as indicatd by their very high correlation.



This is a non-stationary annual series with a curvilinear trend since approximately 1800. We saw in the previous chapter that a quadratic trend model fit to a degree, but this pattern is probably better modeled as an autoregressive process.



This non-stationary annual series shows considerable variability. A trend model won't capture the year-to year oscillations, but an autoregressive model will.

Looking at the summary of 4 different AR models (below) it appears that the AR(2,1) model performs best. The estimates using that model are shown below the Model Comparison table.

c.

Model Comparison

Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
		- ARI(2, 1)	129			-76.10509	0.890	-90.7535	0.977823		0.245075	0.140145
		- ARI(1, 1)	130	0.0322389	-76.70080	-70.93519					0.254696	0.145682
		— AR(2)	130	0.0322338	-74.01722	-65.34617	0.876	-80.01722	0.004559		0.257463	0.147277
		— AR(1)	131	0.03416	-67.47918	-61.69849	0.869	-71.47918	0.000173		0.261399	0.149573

2013	58.272704408
2014	58.257001165
2015	58.262675668
2016	58.28208585

2017 58.290882083

Student Solutions to Application Scenarios

Scenario 1 a. Pattern 1 --1 2 --1 3 +-1 4 -+2 5 --2The first 5 rows are shown to the left.

c. Assuming we follow the example presented in the chapter, we now have 50 experimental runs, the first 10 of which are assigned to team member #1. Each team member will perform 10 of the 16 possible runs, with each member having a slightly different pattern assigned randomly.

Scenario 2

- a. There will be 32 runs in a Resolution IV, full-factorial design.
- c. [NOTE: The question should read: "Briefly explain what happens when we move from a **two**-factor screening design to a five-factor design."]

In a two-factor screening design there would be just four runs (2^2) and the five-factor model has $2^5 = 32$ runs.

Scenario	3	_	_			
a.		Pattern	Gender	TestCondition	Interruptions	
	1	212	Male	AwakeFirst	Interrupted	
	2	112	Female	AwakeFirst	Interrupted	
	3	111	Female	AwakeFirst	Fullnight	
	4	112	Female	AwakeFirst	Interrupted	
	5	212	Male	AwakeFirst	Interrupted	

The first five rows of the data table, including Patterns, are shown above.

With 72 subjects, the prediction profiler shows that the variance ranges from approximately c. 0.042 to approximately 0.056. With 144 subjects, the corresponding variance range is reduced by half, ranging from approximately 0.021 to 0.028.

Scenario 4

Categorical factors: type of incentive, timing of incentive, survey mode, guarantee vs. lottery. a. Continuous factors: Duration of survey, number of contacts made, and amount of money offered.

[some students might classify "burden" of survey as categorical.]

Assuming that we use minimal number of factor levels described in b, and two factor levels for c. the continuous factors, we would have four dichotomous categorical factors and three continuous factors. This would, then, require $2 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 = 2^7 = 128$ runs.

Scenario	5								
a.	. Here are the first five rows of the table:								
	Pattern ImpactModifier Thermal Stabilizer AntiUV								
	1	413	MBS	PdBaCd	10				
	2	331	ABS	BaCd	3				
	3	233	CPE	BaCd	10				
	4	421	MBS	Pb	3				
	5	411	MBS	PdBaCd	3				

The full-factorial design has 528 runs and the fractional custom design has 35. In the initial c. design, the Anti-UV additive is tested at levels of 3, 5 and 10 with each of the three tested in one-third of the runs. In the revised design, the levels are 3, 6.5, and 10. The profiler for the custom design reveals substantial interactions among the three factors; the fractional design can detect these, but the loss of resolution in this design could be costly.

Scenario 6

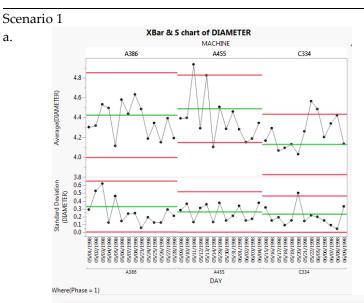
a.

	This table has	572,072 rows.	Here are the	first five:
--	----------------	---------------	--------------	-------------

	Pattern	Subject	Call to Action	Promotion	Salutation	Closing
1	12231	Crayola	Because	Prodcut	User	Crayola
2	12232	Crayola	Because	Prodcut	User	Education
3	22122	Help	Because	None	Greetings	Education
4	21312	Help	As Crayola	Amazon	Hi	Education
5	22231	Help	Because	Prodcut	User	Crayola

c. In the full factorial design, every combination of all levels the five factors (2 x 3 x 2 x 3 x 2 = 72) is tested whereas in the reduced custom design, far fewer are tested because interactions are limited to two factors at a time.

Student Solutions to Application Scenarios



DIAMETER Limit Summaries

a.

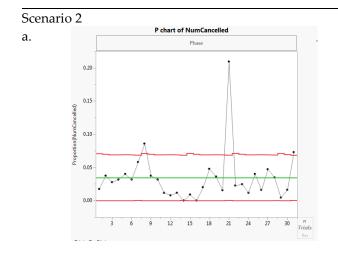
Points plotted	MACHINE	LCL	Avg	UCL	Limits Sigma	Sample Size
Average	A386	3.998813	4.42727	4.855727	Standard Deviation	6
Average	A455	4.150375	4.490839	4.831304	Standard Deviation	6
Average	C334	3.825622	4.130796	4.43597	Standard Deviation	6
Standard Deviation	A386	0.010107	0.332878	0.655649	Standard Deviation	6
Standard Deviation	A455	0.008032	0.264515	0.520998	Standard Deviation	6
Standard Deviation	C334	0.007199	0.237097	0.466995	Standard Deviation	6

As we can see in the graphs above, Machine C334 may have an unstable standard deviation and machine A455 shows two sample means beyond the control limits. These machines should be inspected closely for possible adjustment.

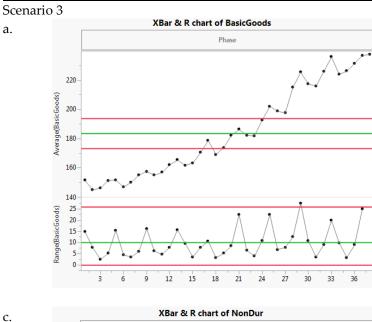
c.

Capability Individual Detailed Reports Value Portion 3.9 Below LSL 4.4 Above USL Specification % Actua Lower Spec Limit 2.5000 2.5000 Spec Target Upper Spec Limit 4.9 Total Outside 5 0000 Long Term Sigma wer CI Upper CI Index L CP 0.687 0.600 0.774 CP 0.577 0.482 0.671 CPM CPL 0.652 0.572 0.737 Mean 0.671 0.482 LSL CPU 0.797 0.679 0.914 Target USL Siam 3.5 4.5 5 Portion PPM Perce 0 Below LSL 4.1823 41823.187 3.230 Sigma = 0.2427 Above USL 0.8415 8415.2303 3.890 Total Outside 5.0238 50238.418 3.143

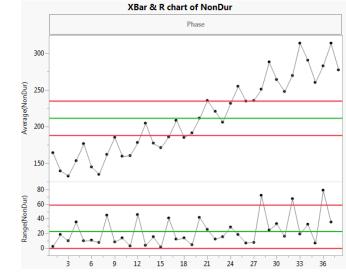
This capability analysis shows that 5% of the observations lie outside the capability limits, indicating that the process is capable of producing tubing that is within .5 mm of 4.4.



This process is out of control at three points. Because a day with 0 cancellations is desirable, we should not be concerned about dates with values below the LCL. However, the chart shows 3 date well above the UCL.



Production of basic goods has been rising steadily over time, which is a good thing. This is not a process designed for a constant target, but rather one of continuous growth.

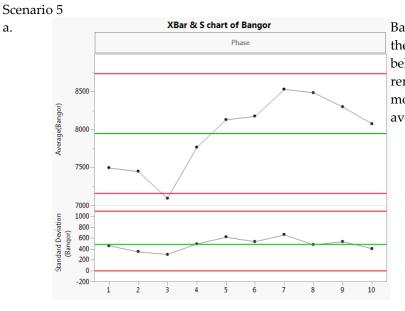


Once again we see a steady pattern of growth, with clear seasonal variation. In contrast to the control chart for Basic Goods, the one for NonDurables may exhibit a more linear upward trend, and substantial growth in variability (the R Chart) in the most recent years.

Because the need for basic goods probably follows the growth in population we might expect steady growth akin to population trends.

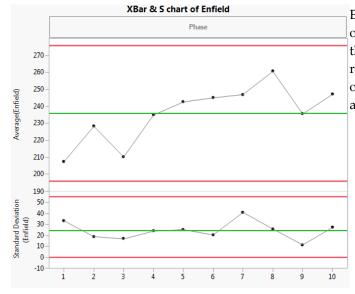
Scenario 4

a. In most regions except for the Southwest the standard deviations are sufficiently unstable that we should not interpret the Xbar charts. In the Southwest, the standard deviations have been steadily increasing but the limited data (only five sample mean) indicates increasing mean times to restore the area to safety, but still within control limits.

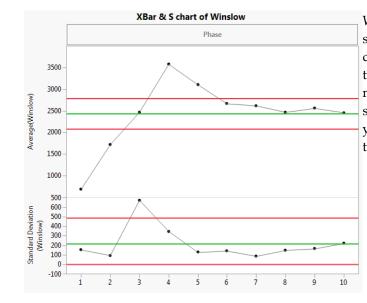


c.

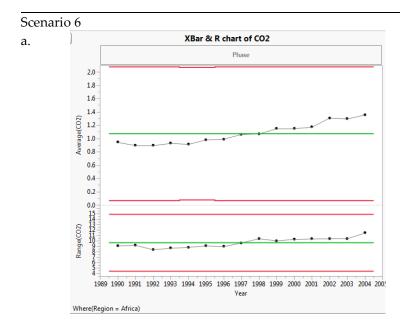
Bangor: The S chart is stable; early in the study period there was one year below the LCL. Otherwise Bangor has remained within limits, though the 6 most recent years have been above average.



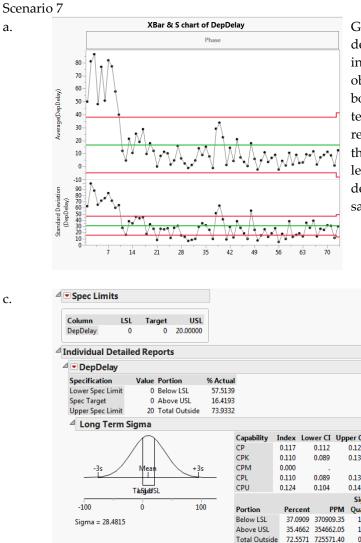
Enfield: This pattern is much like the one in Bangor. The S chart is stable throughout. Otherwise Enfield has remained within limits, though the 5 of the 6 most recent years have been above average



Winslow: In year 3 the S chart (not shown) shows the sample standard deviation above the UCL; otherwise the standard deviations are moderately stable. The Xbar chart shows a process out of control until year 6, after which the process seems to be in control.



Emissions in most regions are relatively stable In Africa (shown to the left), both the ranges and means have been steadily rising over the 15year period.



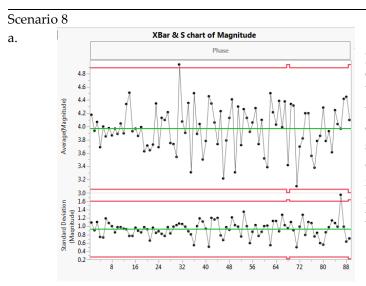
Given the instability in the standard deviations, we should be reluctant to interpret the Xbar chart. However, we might observe that for roughly the first 10 samples both the standard deviations and means tended to be substantially higher than for the remainder of the period. It would appear that there was a fundamental process change leading to shorter and more predictable departure delays sometime around the 10th sample.

Lower CI Upper CI 0.122 0.130 0.130 0.145 Sigma Quality 1.829 1.873 0.901

We need to use the Data Filter to select only the weekday flights. In the Capability analysis, the critical capability limit here is the USL, which we set at 20 minutes; the other values may be set to zero

We see that 16% of the flights exceeded delays of more than 20 minutes. Therefore the current process is not capable of meeting the goal.

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It appears that the variability of the process standard deviation has increased over time, with one recent S above the UCL. Nearly all of the sample means are within the control limits; early in the observation period (roughly the first 15 samples) the mean magnitudes remained quite close to 4.0. Since that time, the fluctuations in mean magnitude have increased even as the mean appears to have remained stable.