

Lure your Black Belts into Learning Statistical Tools by using Practical Examples

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Overview

- Teaching statistical tools to reluctant Black Belt students can be a challenge
- One successful technique is to use examples that they can relate to, and to show that these tools can be applied outside their work lives as well
- Two such examples will be presented
 - Use Fit Model to determine market value of a house
 - Use Design of Experiments to optimize the golf drive



Practical Application of Statistical Modeling: Determining Market Value of a House

You want to sell your house. It has the following attributes:

- 2000 square feet
- 0.2 acre lot
- 2 years old
- 3 bedrooms
- 3 full bathrooms

What should your asking price be?







- Students are given the Excel file below with data. They are given 5 minutes to explore the data in Excel.
- Students are asked to provide listing prices based on their analyses. They typically use average \$/ft².
- Listing Prices:
 - \$
 - \$
 - **-** \$





Students Provided Same Data in JMP

🗱 JMP (SANDIA NAT	IONAL LABORAT	ORIES) - [Ho	use Data for	Summit Tuto	orial.JMP] - [House Data	for Summit T	utorial]
🛄 Eile Edit Tables	<u>R</u> ows <u>C</u> ols <u>D</u> C)E <u>A</u> nalyze	<u>G</u> raph T <u>o</u> ols	<u>V</u> iew <u>W</u> indo	w <u>H</u> elp			
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House Data for Sum	 Image: Second sec							
		SF	Lot	Age	BR	Bath	Price	Price/sf
	1	1373	0.13	7	4	3	204962.96	149.281107
	2	1377	0.2	1	2	3	279461.24	202.949339
	3	2696	0.21	1	2	3.75	432115.58	160.28026
	4	2743	0.2	11	3	2.75	291085.68	106.11946
	5	1128	0.19	14	5	3.25	163331.78	144.797677
	6	3721	0.16	5	3	2	417458.93	112.189984
	7	3372	0.05	19	4	2.5	291889.4	86.5626928
	8	1342	0.1	20	4	4	91196.94	67.9559911
Columns (8/0)	9	1317	0.23	17	3	3	118951.58	90.3201063
SF	10	2370	0.25	19	3	2.5	186523.51	78.701903
Lot	11	1645	0.18	9	5	4	277864.81	168.914778
Age	12	2306	0.08	0	4	2.75	339135.6	147.066609
a BR	13	1356	0.23	1	2	3.25	254317.26	187.549602
🚄 Bath	14	2421	0.08	20	3	3.75	176160.96	72.7637175
A Price	15	1801	0.17	11	4	3.75	245049.51	136.063026
A Price/sf 🖶	16	2195	0.19	17	2	3.5	195129.12	88.8970934
🚄 Bogus	17	2172	0.15	13	4	4	253373.93	116.654664
	18	2002	0.17	1	4	2.75	360202.51	179.921334
	19	1851	0.2	11	4	3.5	261394.12	141.217785
	20	2520	0.1	13	3	4	259948.18	103.15404
	21	2102	0.05	14	2	3.75	177637.02	84.5085728
	22	2533	0.08	11	3	3.25	285993.76	112.90713
	23	2983	0.11	0	4	2	442720.07	148.414371
Rows	24	3249	0.23	2	5	3	468637.93	144.240668
■ Rows All rows 30	25	1585	0.2	19	2	3.75	135501.42	85.4898549
Selected 0	26	1560	0.24	0	5	3	360846.46	231.311833
Excluded 0	27	3319	0.14	2	2	2.75	442828.35	133.422221
Hidden 0	28	3691	0.21	10	3	3.25	450724.35	122.114427
Labelled 0	29	1484	0.1	20	2	2	49746.35	33.5217992
	30	3619	0.11	17	5	2	338789.82	93.6142083



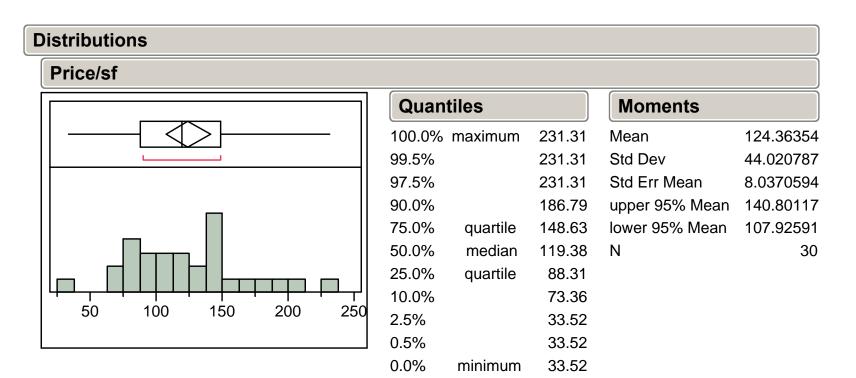
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Exercise: What Will Your Listing Price Be?

Based on Analysis of the distribution of Price/ft² :

Average = \$124.36/ft² Therefore, \$124.36/ft² x 2,000 ft² = \$248,720

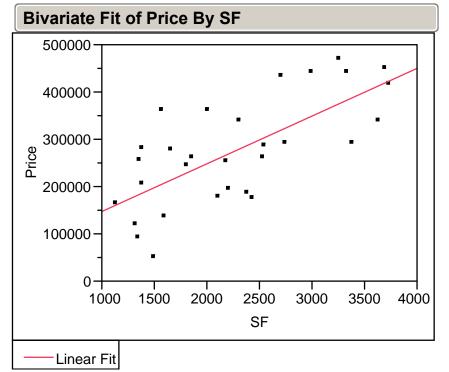




Students Analyze JMP Data

- More observant students might say there's a fixed price as well as a cost per square foot
- Perform a Fit Y by X for Price vs. ft²
- Add a Line Fit

Price = \$45,962 + \$101.34*ft² = \$248,642



F Ratio							
28.1954							
Prob > F							
<.0001*							
Parameter Estimates							
ob> t							
.3227							
.0001*							



Before Proceeding with the House Example, Teach Students Data Exploration using Cereal File

Open Data File			<u>? ×</u>			
Look jn:	🗁 Sample Data	💽 📀 🔊 📼				
My Recent Documents Desktop My Documents	My Recent Documents Desktop My Documents My Computer CDrive (C:) Program Files SAS JMP7 Support Files English Sample Data UVD-RW Drive (D:) Support (D:) My Network Places	.jmp p mp age.jmp jmp .jmp jmp jmp	Birth Deat BirthDeatl Blood Pre: blsPriceDa Body Mea Boston Hc BoxCox.jr BpTime.jr Candy Ba Candy.jm Car Physic Car Poll.jr			
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🛄 Cereal		• 1	100% Bran	Nabisco	N	с	80	4	0.5	12
		× 2	100% Nat. Bran Oats & Honey	Quaker Oats	Q	с	230	5	9.0	:
		× 3	100% Nat. Low Fat Granola w raisins	Quaker Oats	Q	с	210	5	3.0	14
		• 4	All-Bran	Kelloggs	к	с	80	4	1.0	1
		• 5	All-Bran with Extra Fiber	Kelloggs	к	с	50	3	0.5	11
	Columns (18/0)	<u>~</u> 6	Almond Crunch w Raisins	Kelloggs	к	с	210	5	2.0	30
	Name (10/0)	+ 7	Apple Cinnamon Cheerios	General Mills	G	с	120	2	2.0	10
	🔥 Manufacturer 🐥	+ 8	Apple Jacks	Kelloggs	к	С	120	2	0.0	1:
	M fr	× 9	Banana Nut Crunch	Post	Р	С	250	5	6.0	24
	🔥 Hot/Cold	× 10	Basic 4	General Mills	G	С	200	4	3.0	3:
	🚄 Calories	♦ 11	Bran Buds	Kelloggs	к	С	80	3	0.5	2
	🚄 Protein	12	Bran Flakes	Post	Р	С	100	3	0.5	2
	A Fat	+ 13	Cap'n'Crunch	Quaker Oats	Q	с	110	1	1.5	2
	A Sodium	♦ 14	Cheerios	General Mills	G	с	110	3	2.0	2
Complex Carbos 🚽		+ 15	Cinnamon Toast Crunch	General Mills	G	С	130	1	3.5	2
Tot Carbo	+ 16	Cocoa Puffs	General Mills	G	с	120	1	1.0	1:	
	Sugars	17	Complete Oat Bran	Kelloggs	к	С	110	4	1.0	2
	🖉 Calories fr Fat	18	Complete Wheat Bran	Kelloggs	к	С	90	3	0.5	2
	🚄 Potassium	19	Corn Chex	General Mills	G	с	110	2	0.0	3
	al Enriched	♦ 20	Corn Flakes	Kelloggs	к	с	100	2	0.0	3
	Vt/serving	+ 21	Corn Pops	Kelloggs	к	с	120	1	0.0	1:
	/ cups/serv	× 22	Cracklin' Oat Bran	Kelloggs	к	С	190	4	6.0	17
	📕 Fiber Gr 🖶	23	Cream of Wheat (Instant)	Nabisco	N	Н	100	3	0.0	17
		◇ 24	Crispix	Kelloggs	к	с	110	2	0.0	2
		•🔁 25	Fiber One	General Mills	G	С	60	2	1.0	14
		+ 26	Franken Berry	General Mills	G	с	120	1	1.0	2
	Rows	+ 27	French Toast Crisp	General Mills	G	с	120	1	1.0	17
	All rows 76	+ 28	Froot Loops	Kelloggs	к	с	120	2	1.0	1:
	Selected 0	+ 29	Frosted Alphabits	Post	Р	с	130	3	1.5	2
	Excluded 0		Frosted Cheerios	General Mills	G	с	120	2	1.0	2
	Hidden 0		Frosted Flakes	Kelloggs	к	с	120	1	0.0	20
	Labelled 2		Frosted Mini-Wheats	Kelloggs	ĸ	c	200	6	2.0	
		× 33	Fruit & Fibre Dates, Walnuts, and Oa	Post	Р	С	210	4	3.0	2:
			Golden Crisp	Post	P	с	110	1	0.0	
			Golden Grahams	General Mills	G	c	120	1	1.0	28



A Few Setup Changes

- Rows \rightarrow Clear Row States
- File \rightarrow Preferences
 - Click Reports
 - » Change Graph Marker Size to medium.
 - Click Platforms
 - » Select Distribution. Under Options, select Stack.
 - Click OK.

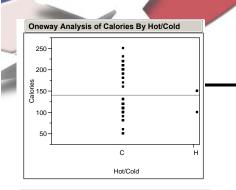


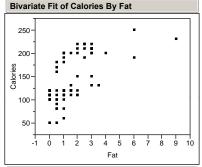
What Affects Calories?

Analyze \rightarrow Fit Y by X Select Calories for Y, those below for X

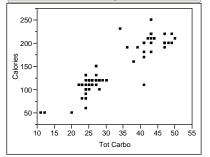
👬 JMP (SANDIA NATIUNAL LABURAT	'ORIES) - [Fit Y by X - Contextual] - [Fit Y by	y X - Contex							
🔝 Eile Edit Tables Rows Cols DO	OE <u>A</u> nalyze <u>G</u> raph T <u>o</u> ols <u>V</u> iew <u>W</u> indow <u>H</u>	<u>t</u> elp							
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Distribution of Y for each X. Modeling types determine analysis.									
-Select Columns	Cast Selected Columns into Roles	Action							
1. Name	Y, Response	ОК							
Manufacturer	optional	Cancel							
Hot/Cold									
Calories	X. Factor								
	X, Factor	Remove							
∠ Fat ∕ Sodium	_Fat	Recall							
		Help							
Complex Carbos	Block								
∠ Tot Carbo ∠ Sugars	Weight optional numeric								
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nt. Fiber Gr									
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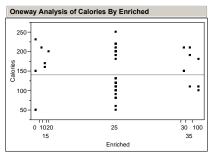


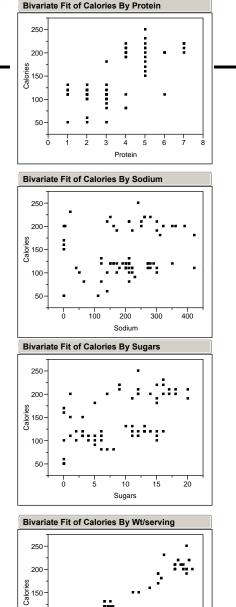




Bivariate Fit of Calories By Tot Carbo







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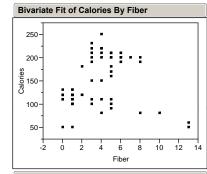
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Wt/serving

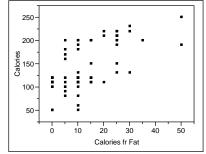
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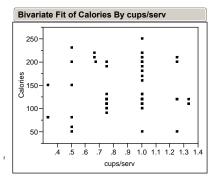
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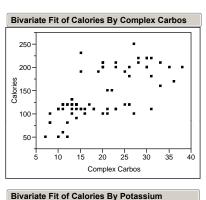
Fit Y by X Plots

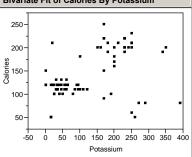


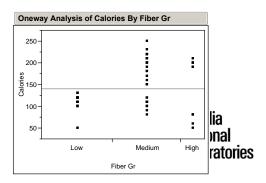
Bivariate Fit of Calories By Calories fr Fat





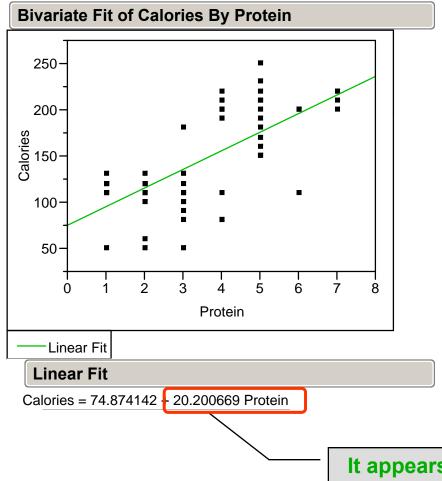








Look Closer at Protein Right-click title bar – Fit Line



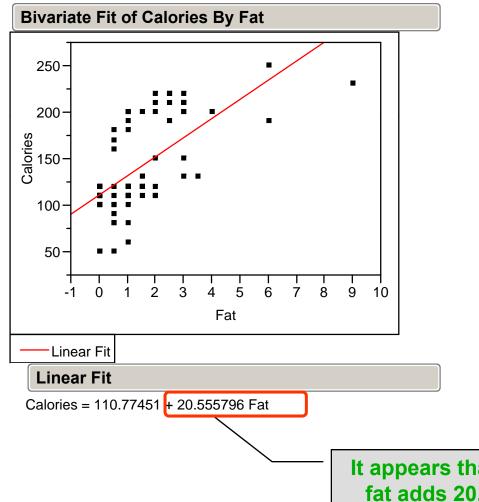
y of F	it						
			0.495	772			
RSquare Adj							
Root Mean Square Error							
Mean of Response							
s (or S	Sum W	/gts)		76			
of Va	arian	се					
DF	Sum	of Sq	uares	Me	ean S	quare	F Ratio
1		915	09.03		91	509.0	72.7589
74		930	69.92		1	257.7	Prob > F
75		1845	78.95				<.0001*
er Es	timat	tes					
Est	imate	Std	Error	t F	Ratio	Prob>	t
74.87	4142	8.70)5646	8	3.60	<.0001	*
20.20	0669	2.36	8223	8	3.53	<.0001	*
	j Square sponse s (or S of V a DF 1 74 75 er Es Est 74.87	Square Error sponse s (or Sum W of Varian DF Sum 1 74 75 er Estimate 74.874142	j Square Error sponse s (or Sum Wgts) of Variance DF Sum of Sq 1 915 74 930 75 1845 er Estimates Estimate Std 74.874142 8.70	0.495 j 0.488 Square Error 35.46 sponse 140.5 s (or Sum Wgts) of Variance DF Sum of Squares 1 91509.03 74 93069.92 75 184578.95 er Estimates	0.495772 j 0.488958 Square Error 35.46409 sponse 140.5263 s (or Sum Wgts) 76 of Variance DF Sum of Squares Me 1 91509.03 74 93069.92 75 184578.95 er Estimates Estimate Std Error t R 74.874142 8.705646 8	0.495772 j 0.488958 Square Error 35.46409 sponse 140.5263 s (or Sum Wgts) 76 of Variance 76 DF Sum of Squares Mean S 1 91509.03 91 74 93069.92 1 75 184578.95 1 er Estimates Estimate Std Error t Ratio 74.874142 8.705646 8.60	0.495772 j 0.488958 Square Error 35.46409 sponse 140.5263 s (or Sum Wgts) 76 of Variance 76 DF Sum of Squares Mean Square 1 91509.03 91509.0 74 93069.92 1257.7 75 184578.95 76 er Estimates Estimate Std Error t Ratio 74.874142 8.705646 8.60 <.0001

It appears that each g of protein adds 20.2 calories





Look Closer at Fat Right-click title bar – Fit Line



Summa	Summary of Fit								
RSquare	RSquare								
RSquare A	().409	425						
Root Mean	Root Mean Square Error								
Mean of Re	esponse)		140.5	263				
Observation	Observations (or Sum Wgts)								
Analysis of Variance									
Source	DF	Sum	of Squa	ares	Mean S	Square	F Ratio		
Model	1		7702	4.73	77	024.7	52.9949		
Error	74		10755	4.22	1	453.4	Prob > F		
C. Total	75		18457	8.95			<.0001*		
Paramet	Parameter Estimates								
Term	Est	imate	Std E	rror	t Ratio	Prob>			
Intercept	110.7	7451	5.985	571	18.51	<.0001	*		
Fat	20.55	5796	2.82	369	7.28	<.0001	*		

It appears that each g of fat adds 20.6 calories



Analyze → Fit Model Calories in Y, all below that in X

File Edit Tables Rows Cols DOE Analyze Graph Tools View Window Help Windows ▲ ● ● ● ● ● ● ● ● ● ● ● ● ● ● ● ● ● ●
JMP Starter Model Specification Select Columns Pick Role Variables Pick Role Variables Personality: Stepwise Manufacturer Mfr Hot/Cold Optional Numeric Protein Freq Fat
JMP Starter Image: Cereal Image: Cereal Select Columns Pick Role Variables Image: Select Columns Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Personality: Stepwise Image: Personality: Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Personality: Stepwise Image: Select Columns Image: Pick Role Variables Image: Pick Role Variables Image: Pick
Select Columns Pick Role Variables Personality: Stepwise Personality: Stepwise It Model It
Image: Name Y Calories Image: Calories Image: Name Help Image: Protein Freq optional Numeric Image: Fat Image: Name Remove
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Select Personality → Stepwise, Run Model Change Direction to Mixed

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🗢 Stepwise Fit							
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Intercept Protein	140.8	1	-	71.476	0.0000		
Fat	Ő	1		53.200	0.0000		
Fat Sodium	0	1	7229.601	2.983	0.0884		
Fiber	0	1	6803.278	2.800	0.0985		
Fiber Complex Carbos Tot Carbo Sugars Calories fr Fat Potassium Enriched(0&10&15&20&25&30&35-100)	0	1		59.033	0.0000		
Tot Carbo	0		151698.7	341.229	0.0000		
Sugars Calories fr Fat	0	1	48260.7 83468.88	25.925 60.519	0.0000		
Calories fr Fat	0		36211.09	17.868	0.0000		
Enriched(0&10&15&20&25&30&35-100)	ő	1		0.758	0.3867		
Enriched(0&10&15&20&25-30&35)	0		7358.154	1.498	0.2304		
Enriched(0-10815820825)	0	3	9011.016	1.218	0.3097		
Enriched(10815820-25)	0	4	17304.63	1.815	0.1356		
Enriched(10-15820)	0		18137.96	1.508	0.1988		
Enriched(15-20)	0	6		1.300 1.002	0.2689		
Enriched(30-35) Vt/serving	0	3	7478.154 166749.4	1.002	0.3972		
Enriched(0&10&15&20&25-30&35) Enriched(0-10&15&20&25) Enriched(10&15&20-25) Enriched(10-15&20) Enriched(15-20) Enriched(30-35) Vt/serving cups/serv	0	1	2503.25	1.006	0.3192		
Fiber Gr{ Low-High& Medium}	0	1		26.273	0.0000		
Fiber Gr{High- Medium}	0	2	50823.59	13.723	0.0000		

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- You already changed direction to Mixed.
- Change "Prob to Enter" and "Prob to Leave" to 0.100

4
F

Click Step and Watch Factors Get Added to the Model

🛼 JMP - [Cereal- Fit	itepwise]		
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Cereal	✓ Stepwise Fit		
Fit Model	Response: Calories		
	Stepwise Regression Control		
	Prob to Enter 0.050 Enter All		
	Direction: Mixed 🗸 Remove All		
	Rules: Combine V		
	Go Stop Step Make Model		
	1 rows not used due to excluded rows or	nissing values.	
	Current Estimates		
	SSE DFE MSE RSquare R	quare Adj Cp AlC	
	2361.5019 69 34.224666 0.9872	0.9862 13.857241 270.7174	
	Lock Entered Parameter	Estimate nDF SS "FRatio" "Prob≽F"	
		-5.2762836 1 0 0.000 1.0000	
	 Protein Fat 	0 1 108.0134 3.259 0.0754 7.29376175 1 5262.903 153.775 0.0000	
	Sodium	0 1 7.077795 0.204 0.6526	
	Fiber	-3.6657725 1 5463.813 159.645 0.0000	
	Complex Carbos	0 1 0.061301 0.002 0.9666	
	☐ ✓ Tot Carbo ☐ ☐ Sugars	0.69015019 1 211.2171 6.171 0.0154	
		0 1 0.061301 0.002 0.9666	
	Calories fr Fat	0 1 47.93983 1.409 0.2393 0 1 44.55929 1.308 0.2568	
	Potassium Enriched{0&10&15&20&25&30&35-		
	Enriched (0&10&15&20&25&30&35)	0 2 48.87546 0.708 0.4963	
	Enriched{0-10&15&20&25}	0 3 53.50218 0.510 0.6768	
	Enriched{10&15&20-25}	0 4 97.28987 0.698 0.5959	
	Enriched{10-15&20}	0 5 102.9973 0.584 0.7123	
	Enriched(15-20)	0 6 103.0703 0.479 0.8213	
	Enriched(30-35)	0 3 107.5512 1.050 0.3765 3.00809054 1 6234.103 182.152 0.0000	
	VM/serving	3.00809054 1 6234.103 182.152 0.0000 11.0815235 1 335.1154 9.792 0.0026	
	Fiber Gr{ Low-High& Medium}	0 1 6.129258 0.177 0.6753	
	Fiber Gr{High- Medium}	0 2 164.2459 2.504 0.0894	Sandia
	✓ Step History		National Stational Stationae Stat
	. Step matory		Laborat



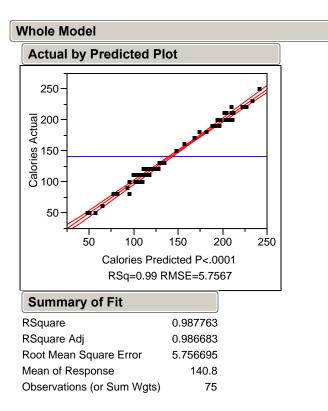
Click Make Model

ereal- Fit Stepwise		
Stepped Model		
Model Specificat	tion	
Select Columns	Pick Role Variables	Personality: Standard Least Squares 🐱
IL Name IL Manufacturer IL Mfr	Y A Calories optional	Emphasis: Effect Leverage 🗸
II. Hot/Cold ▲ Calories ▲ Protein ▲ Fat ▲ Sodium	Weight optional numeric Freq optional numeric By optional	Help Run Model Recall Remove
Fiber Complex Carbos Tot Carbo	Construct Model Effects	
Sugars Calories fr Fat Potassium Enriched Wt/serving	Cross Fat Fiber Tot Carbo Wt/serving cups/serv	
dups/serv ∎Fiber Gr	Degree 2 Attributes • Transform •	
	No Intercept	





Click Run Model



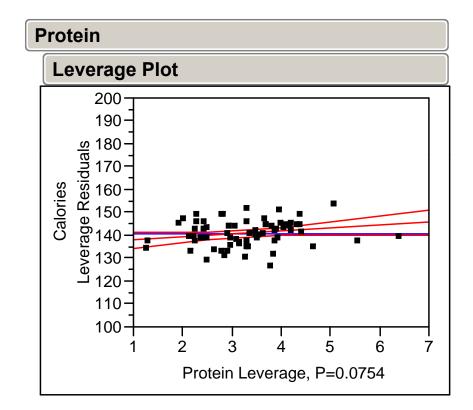
Analysis	of Variance)			
Source	DF Sum of	Squares M	lean Squ	Jare	F Ratio
Model	6 18	81898.51	3031	16.4 91	4.8112
Error	68	2253.49	3	33.1 P	rob > F
C. Total	74 18	34152.00		<	.0001*
Lack Of F	it				
Source	DF Sum	of Squares	Mean	Square	F Ratic
Lack Of Fit	65	2253.4886	3	4.6691	
Pure Error	3	0.0000		0.0000	Prob > F
Total Error	68	2253.4886			
					Max RSq
					1.0000
Paramete	r Estimates	5			
Term	Estimate	Std Error	t Ratio	Prob>	t
Intercept	-4.230658	3.478264	-1.22	0.2281	
Protein	1.3019557	0.721158	1.81	0.0754	
Fat	7.414865	0.582652	12.73	<.0001*	
Fiber	-3.874463	0.308004	-12.58	<.0001*	
Tot Carbo	0.8724868	0.291431	2.99	0.0038*	
Wt/serving	2.755463	0.260157	10.59	<.0001*	
cups/serv	10.097625	3.527139	2.86	0.0056*	
Residual	by Predicte	ed Plot			
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na	***				
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Å I		•	• • • •	.	
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Calories Residua 		-			
			•		
-15-	-				
+	50 100	, , , , , , , , , , , , , , , , , , , 			

Calories Predicted

andia ational ıboratories

What is the Effect of Protein Now?

Parameter Estimates						
Term	Estimate	Std Error	t Ratio	Prob> t		
Intercept	-4.230658	3.478264	-1.22	0.2281		
Protein	1.3019557	0.721158	1.81	0.0754		
Fat	7.414865	0.582652	12.73	<.0001*		
Fiber	-3.874463	0.308004	-12.58	<.0001*		
Tot Carbo	0.8724868	0.291431	2.99	0.0038*		
Wt/serving	2.755463	0.260157	10.59	<.0001*		
cups/serv	10.097625	3.527139	2.86	0.0056*		



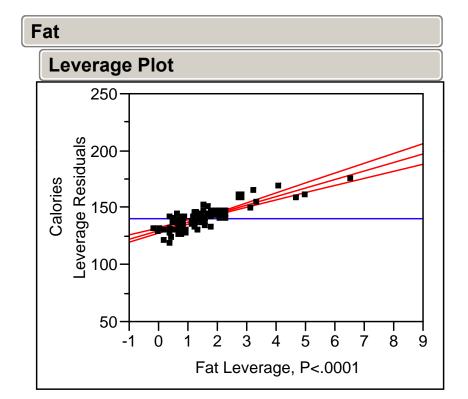
Recall that it was 20.2 calories per g when we just looked at calories vs. protein. Nutritionists tell us that the real number is 4 calories per g of protein.





What is the Effect of Fat Now?

Parameter Estimates						
Term	Estimate	Std Error	t Ratio	Prob> t		
Intercept	-4.230658	3.478264	-1.22	0.2281		
Protein	1.3019557	0.721158	1.81	0.0754		
Fat	7.414865	0.582652	12.73	<.0001*		
Fiber	-3.874463	0.308004	-12.58	<.0001*		
Tot Carbo	0.8724868	0.291431	2.99	0.0038*		
Wt/serving	2.755463	0.260157	10.59	<.0001*		
cups/serv	10.097625	3.527139	2.86	0.0056*		



Recall that it was **20.6 calories per g** when we just looked at calories vs. fat. Nutritionists tell us that the real number is 9 calories per g of fat.





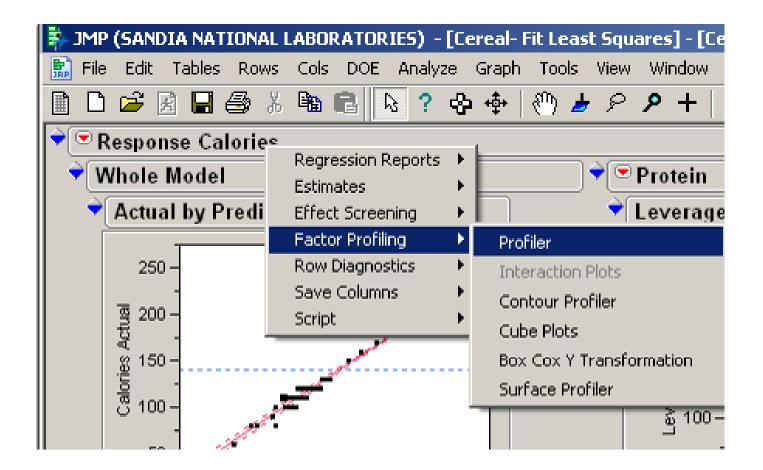
The Model is Revealing

Calories per gram	Individual Fit Y by X	Fit Model	Nutritionists ¹
Protein	20.2	1.3	4
Fat	20.6	7.4	9

¹ http://www.nutristrategy.com/nutrition/calories.htm



Right-click Response Calories title bar Select Factor Profiling → Profiler

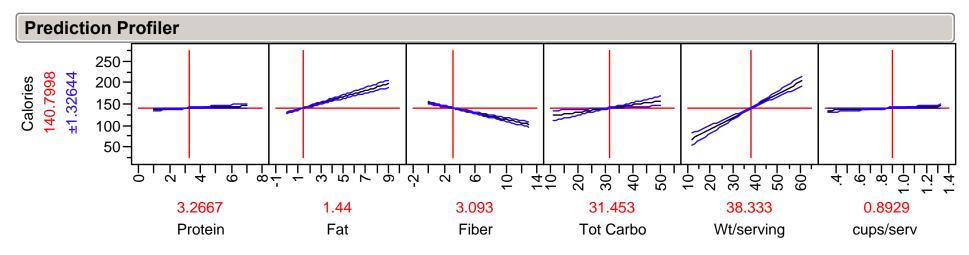






Try moving the vertical lines.

Which factors could you change in order to reduce calories?







You want to sell your house. It has the following features:

- 2000 square feet
- 0.2 acre lot
- 2 years old
- 3 bedrooms
- 3 full bathrooms





- Your real estate agent pulls up the set of data for recent home sales in your zip code, and tells you the average selling price was \$124.36 per square foot.
- Your real estate agent breaks out the calculator and tells you your home is worth \$124.36/ft² x 2,000 ft² = \$248,720.
- Your real estate agent tells you to list your house for \$260,000. "That leaves a little room for negotiating," they explain.
- You're just about to sign the listing paperwork, but you remember the modeling you just learned using cereal data





- Create a model for home price, including only significant factors.
- Determine the value of your home based on the model.
- Capture the students' listing prices on the board.
- Are these much different than what your real estate agent recommended?

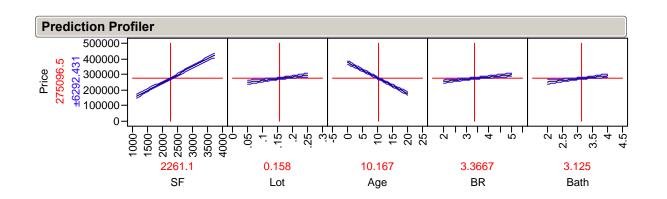


Solutions

Create a model for home price, including only significant factors.

Parameter Estimates						
Term	Estimate	Std Error	t Ratio	Prob> t		
Intercept	3242.1849	28037.38	0.12	0.9089		
SF	100.26837	4.377378	22.91	<.0001*		
Lot	228519.2	55577.05	4.11	0.0004*		
Age	-9954.605	456.565	-21.80	<.0001*		
BR	14362.019	2925.965	4.91	<.0001*		
Bath	19803.935	5364.676	3.69	0.0011*		

Prediction Expression







- Which factors are statistically significant?
- What are the coefficients for these factors?
- In particular, what is the coefficient for \$/square foot?





Determine the value of your home based on the model.

3242.18 + 100.27 * (2000) + 228519.20 * (0.2) - 9954.60 * (2) + 14362.02 * (3) + 19803.93 * (3) = 100.27 * (2000) + 228519.20 * (0.2) - 9954.60 * (2) + 14362.02 * (3) + 19803.93 * (3) = 100.27 * (2000) + 228519.20 * (0.2) - 9954.60 * (2) + 14362.02 * (3) + 19803.93 * (3) = 100.27 * (2000) + 228519.20 * (0.2) - 9954.60 * (2) + 14362.02 * (3) + 19803.93 * (3) = 100.27 * (2000) + 228519.20 * (2000) + 228519.20 * (2) + 100.27 * (2000) + 228519.20 * (2) + 100.27 * (2) +

\$332,075

Should you listen to your real estate agent and list your house for \$260,000?





A Different Approach

- Three types of variables
 - Continuous
 - » Time
 - » Distance
 - Ordinal
 - » Character data with an order (poor, fair, good, better, best)
 - » Numerical data with unequal spacing (4 = strongly agree, 3 = agree, 2 = disagree, 1 = strongly disagree)
 - Nominal
 - » Character data with no specific order (green, blue, yellow)
 - » Numerical data with no specific order (NASCAR car #)
- Should BR and Bath be treated as continuous variables?
- What if we had treated them as Ordinal Variables?





Treating BR and Bath as Ordinal

• If Time Permits, change BR and Bath to Ordinal and redo the analysis

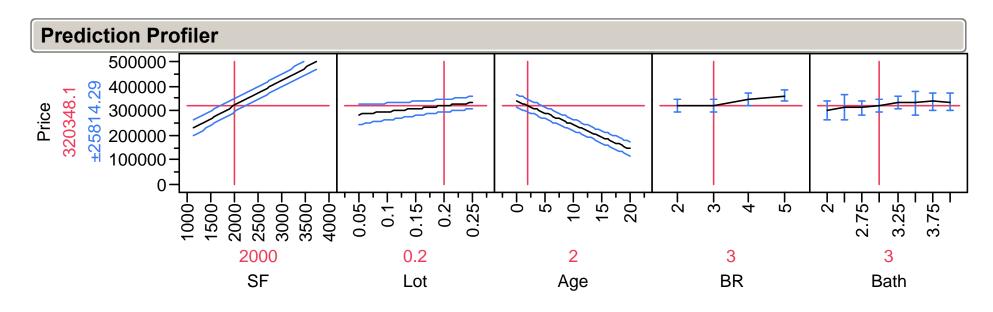
● House Data for Sum	◆ ♥				
]		SF	Lot	Age	BR
:	1	1373	0.13	7	4
	2	1377	0.2	1	2
	3	2696	0.21	1	2
	4	2743	0.2	11	3
	5	1128	0.19	14	5
	6	3721	0.16	5	3
	7	3372	0.05	19	4
	8	1342	0.1	20	4
Columns (7/1)	9	1317	0.23	17	3
🚄 SF	10	2370	0.25	19	3
🚄 Lot	11	1645	0.18	9	5
Age	12	2306	0.08	0	4
	13	1356	0.23	1	2
✓ Continuous	14	2421	0.08	20	3
Ordinal	15	1801	0.17	11	4
Nominal	16	2195	0.19	17	2
	47	0470	0.45	40	4

💌 Columns (7/0)	
🚄 SF	
🚄 Lot	
🚄 Age	
📲 BR	
🛁 Bath	
🚄 Price	
🥒 Price/sf 🖶	





Use Prediction Profiler

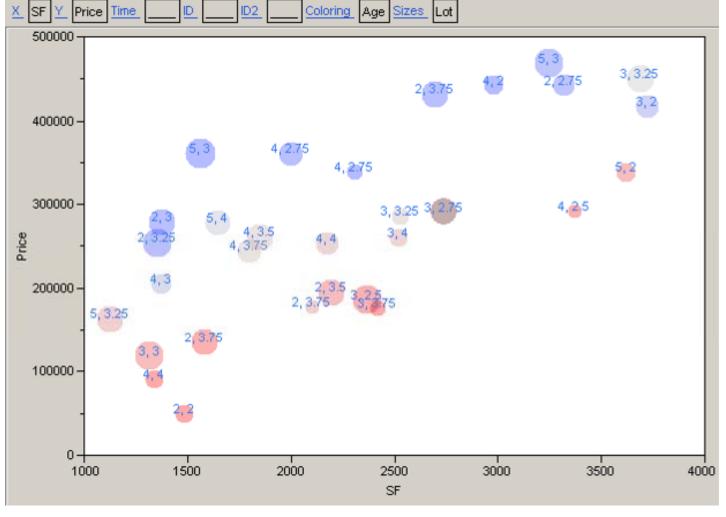


What is the predicted price now?



One More Tip: Visually Display your Data!

How many dimensions are shown in this single graph?







Practical Application of Design of Experiments: Optimize the Golf Drive

Simple Golf Example

- We want to increase the distance of our golf drive
- We suspect changing distance from the ball and right hand position may be factors
- How would you approach increasing drive distance by varying these factors?



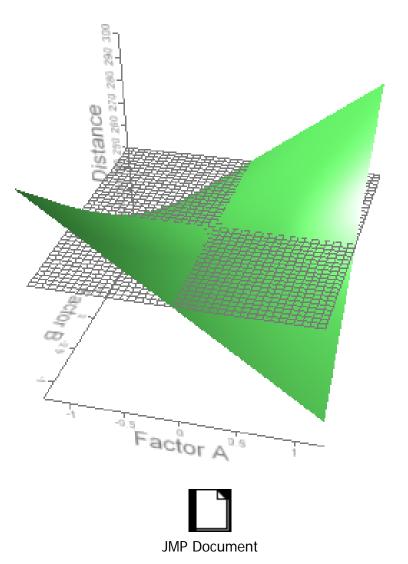


Traditional Approach

- Vary one factor at a time
- Look for changes
- Experimenters call this an OFAT experiment (One Factor At a Time)
- Problems with Traditional Approach
 - Does not catch interactions
 - Requires multiple experiments (one for each factor)







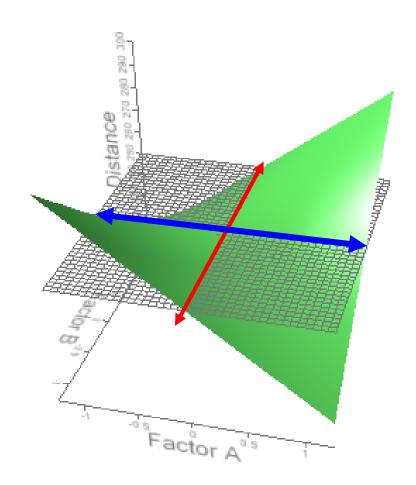




The Traditional Approach

- Vary "distance from ball" in one experiment (blue line)
- Vary "right hand position" in another experiment (red line)

• Our conclusion would incorrectly be, "Neither factor affects distance."





- A Designed Experiment would Change Both Factors Simultaneously
- Example: 2-factor, 2-level Full Factorial
 - There are 2 factors at two levels, or 2² combinations

●	Distance from ball	Right hand
1	Close	Weak
2	Close	Strong
3	Far	Weak
4	Far	Strong





- I've taken various golf lessons throughout the past 10 years
- Once I learned DOE, I quickly realized I was a victim of the OFAT approach to experimental design during these lessons
- Some of the factors instructors typically vary:
 - Right Hand Position (Weak to Strong)
 - Stance Width
 - Distance to Ball (Reach)
 - Ball Forward / Backward in Stance





A Better Way

- As instructors identified the "optimum" for a particular factor, they found that I had to readjust the other factors as well, to compensate for the change in the one factor.
- This told me that I had *interactions* present.
- This was a great opportunity to apply DOE.
- Disclaimer: I am not very good at golf. Sample video:







- Used Custom Design Response Surface Methodology (RSM)
- Three Replicates and Four Center Points
- Results in 80 runs (80 balls)







Four Factors at Three Levels Each

- Right Hand
 - » Weak
 - » Neutral
 - » Strong
- Stance Width
 - » Narrow
 - » Normal
 - » Wide

- Distance to Ball
 - » Close
 - » Middle
 - » Far
- Ball in Stance
 - » Back
 - » Middle
 - » Forward







Right Hand Settings



Weak



Neutral

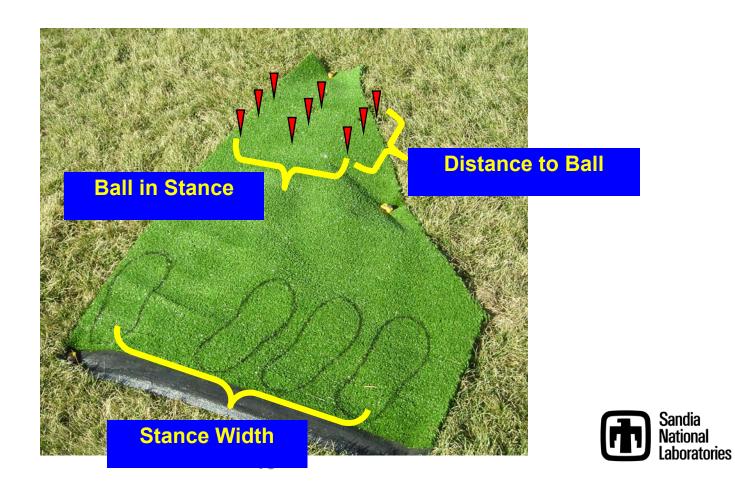


Strong



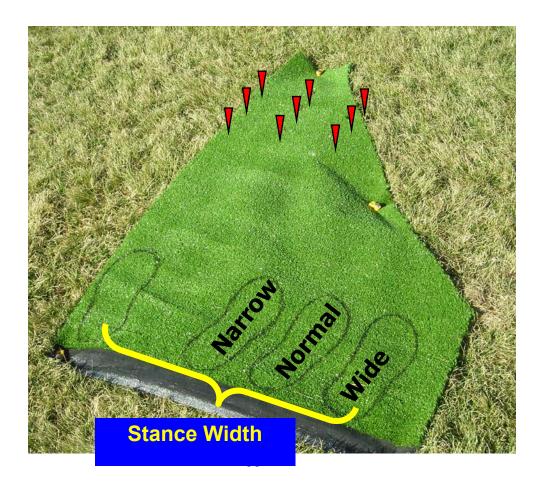


Used a mat as a template





Stance Width







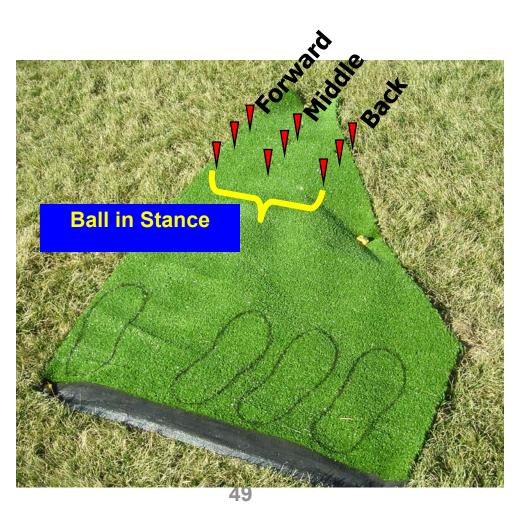
Distance to Ball







Ball in Stance







Experiment Details

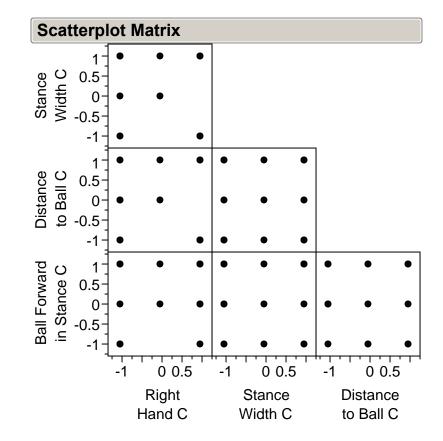
Settings for the First 20 Balls

Ball	Right Hand	Stance Width	Distance to Ball	Ball in Stance
1	Neutral	Normal	Middle	Middle
2	Neutral	Normal	Middle	Middle
3	Neutral	Normal	Middle	Middle
4	Neutral	Wide	Far	Forward
5	Neutral	Normal	Middle	Middle
6	Weak	Narrow	Middle	Back
7	Weak	Wide	Far	Back
8	Strong	Wide	Far	Middle
9	Weak	Wide	Close	Middle
10	Strong	Narrow	Far	Forward
11	Weak	Normal	Close	Back
12	Strong	Narrow	Far	Forward
13	Weak	Narrow	Far	Middle
14	Strong	Wide	Far	Middle
15	Neutral	Normal	Middle	Middle
16	Weak	Wide	Middle	Forward
17	Strong	Narrow	Close	Middle
18	Weak	Wide	Far	Back
19	Weak	Normal	Far	Forward
20	Weak	Wide	Middle	Forward





The Design Space





Sample of Some of the "Extreme" Set-ups







Experiment Location

Albuquerque International Balloon Fiesta Park Very heavy rough (little or no roll)







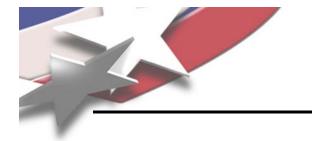
The Methodology

- Number 80 balls
- Hit balls in randomized order
- Track ball location using GPS
 - GPS receiver on laptop
 - Accurate to within 5 feet
- Convert GPS coordinates to distance and angle







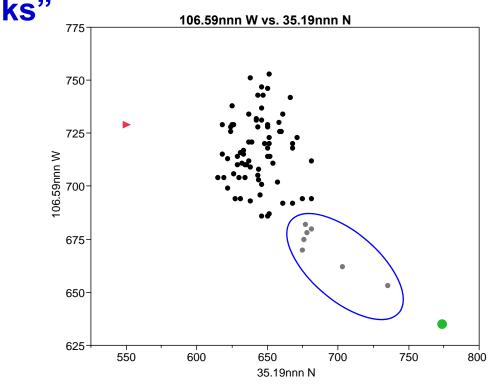


- Complete shanks were rerun at the end (still random)
- These were expected ... DOEs should start by pushing variables to the extremes
- For example, hitting a ball with a narrow stance, far reach, and the ball back in your stance is tough to do for an amateur like me





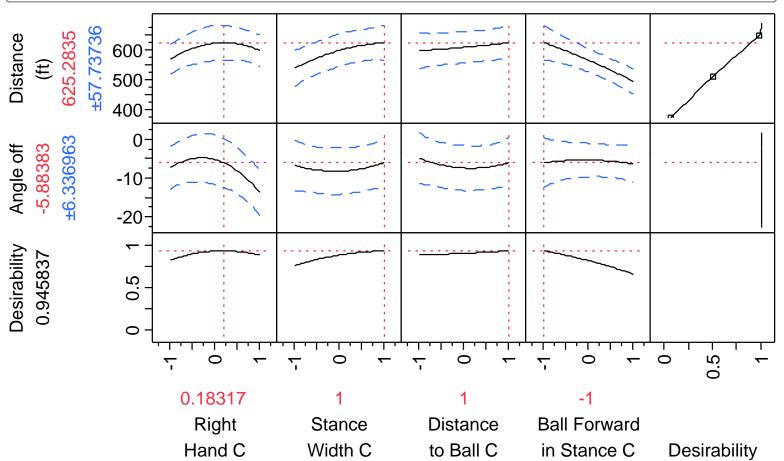
- Even after Re-hitting Shanks, there were Still Some Outliers
- I Excluded These because they were "Semishanks"





Results (Excluding Seven Outliers)

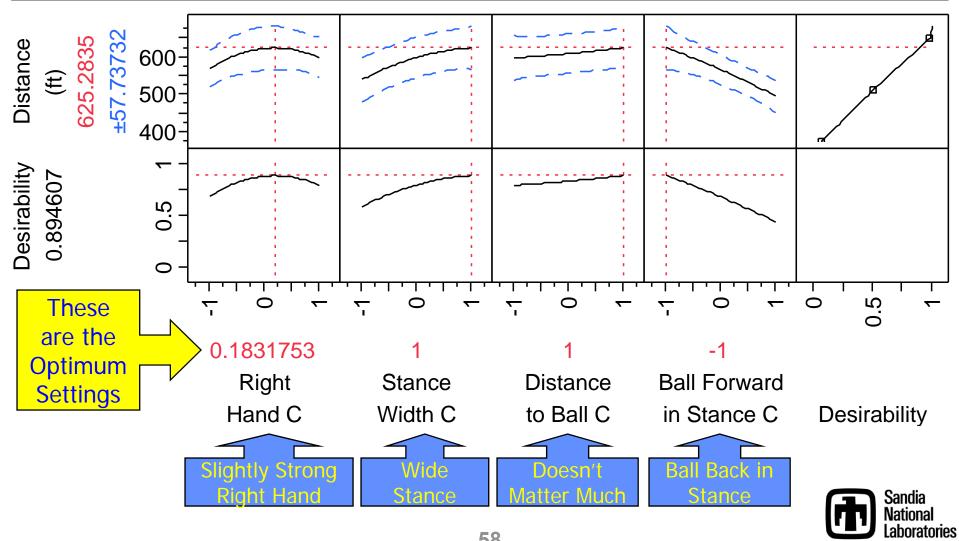
Prediction Profiler





Taking a Closer Look

Prediction Profiler





Optimum Settings for Me

Right Hand = 0.18

- » Weak = -1
- » Neutral = 0
- » Strong = 1

Stance Width = 1

- » Narrow = -1
- » Normal = 0
- » Wide = 1

Distance to Ball = 1

- » Close = -1
- » Middle = 0
- » Far = 1

Ball in Stance = -1

- » Back = -1
- » Middle = 0
- » Forward = 1





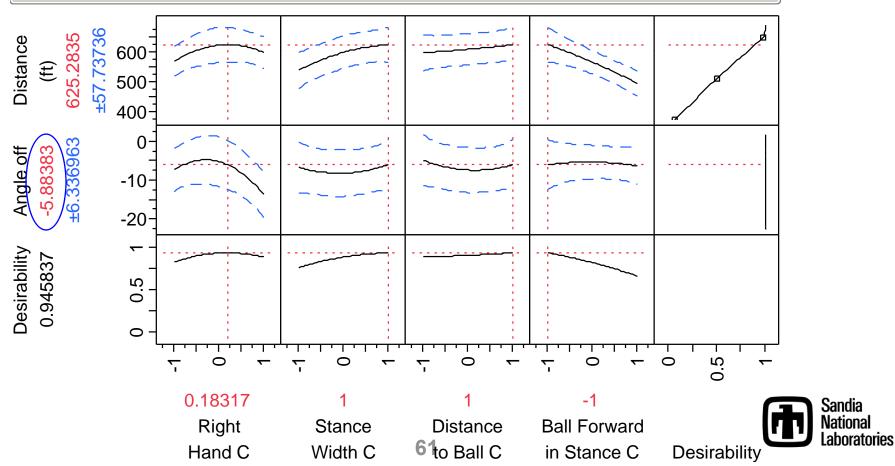
- In addition to learning what settings are optimum, I also learned what angle I can expect the ball to fly
- My GPS data allowed me to calculate angle data (in addition to distance data)





• An "Aha!" moment for me: I need to align my feet 6 degrees left of my target

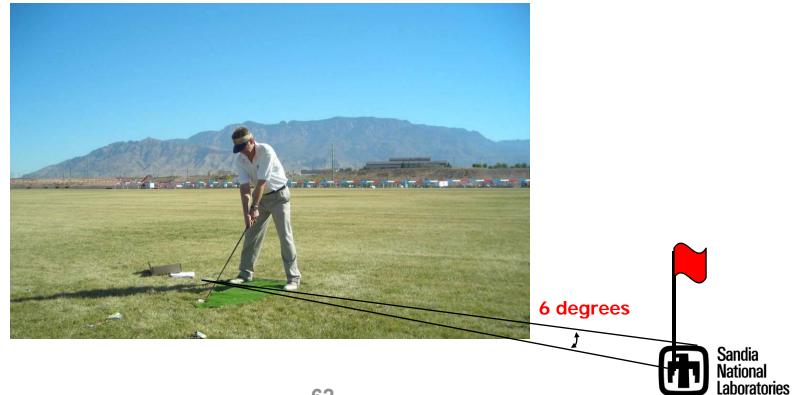






What about Angle?

• I need to align my feet 6 degrees left of my target





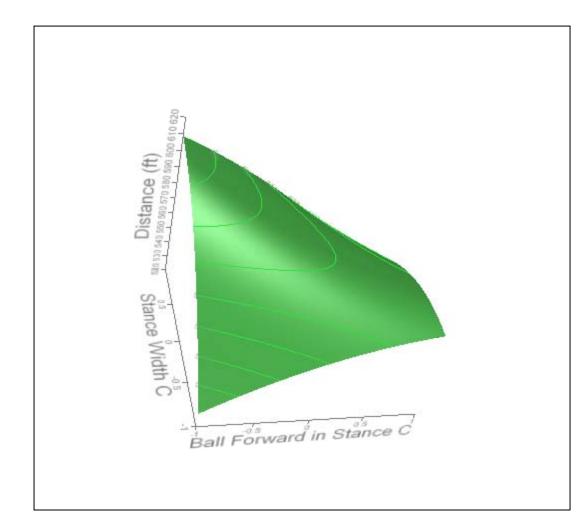
Significance of Factors

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	 Prob> t
(Stance Width C-0.06849)*(Ball Forward in Stance C-0.0274)	-32.43008	8.918967	-3.64	0.0006*
Right Hand C	19.589935	6.777577	2.89	0.0054*
(Distance to Ball C-0.06849)*(Ball Forward in Stance C-0.0274)	-21.70966	8.918967	-2.43	0.0180*
(Right Hand C+0.09589)*(Right Hand C+0.09589)	-39.36472	20.65248	-1.91	0.0616
Distance to Ball C	-11.25945	6.898557	-1.63	0.1081
Ball Forward in Stance C	-11.23923	7.502341	-1.50	0.1395
(Right Hand C+0.09589)*(Ball Forward in Stance C-0.0274)	-11.39382	7.689659	-1.48	0.1438
(Right Hand C+0.09589)*(Stance Width C-0.06849)	-8.365868	7.098898	-1.18	0.2434
(Stance Width C-0.06849)*(Stance Width C-0.06849)	-17.24583	16.56152	-1.04	0.3020
Stance Width C	6.2352511	7.008115	0.89	0.3773
(Ball Forward in Stance C-0.0274)*(Ball Forward in Stance C-0.0274)	-6.127163	12.53297	-0.49	0.6268
(Stance Width C-0.06849)*(Distance to Ball C-0.06849)	3.1510016	7.715673	0.41	0.6845
(Right Hand C+0.09589)*(Distance to Ball C-0.06849)	-1.645035	6.956826	-0.24	0.8139
(Distance to Ball C-0.06849)*(Distance to Ball C-0.06849)	1.9091748	17.52639	0.11	0.9136



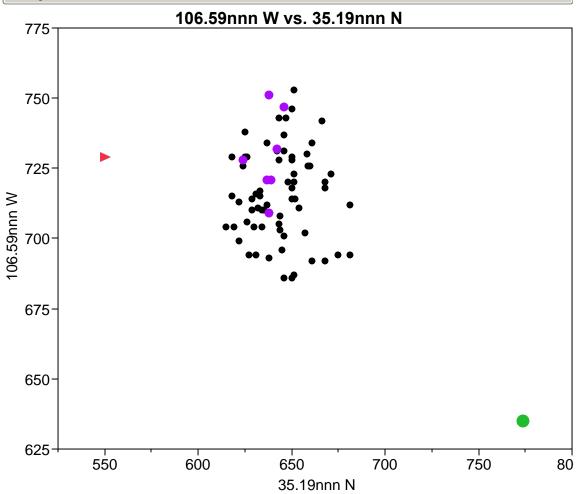






Use Data Filter to see Various Combinations such as Back & Wide

Graph Builder









- Unfortunately, access to Balloon Fiesta Park is a paperwork nightmare
- The true test is on the golf course
- I've been playing golf with my brother for 15 years and have never beat him
- With this new set-up, I tied him (missed a birdie putt on 18 or I would have beat him)
- I played my very next round in Phoenix. I strive for 6 pars, and only accomplish that about half the time. I had 11 pars that day!





Other Applications of DOE

- Design of New Equipment, such as a new putter
 - What Factors are significant with respect to minimizing putt variation?
 - » Moment of Inertia?
 - » Center of Gravity?
 - » Shaft Length?
- Comparing Existing Equipment
 - Is a hybrid better than an iron?
 - Which driver loft angle, shaft material, and shaft length are best for me?





Conclusion

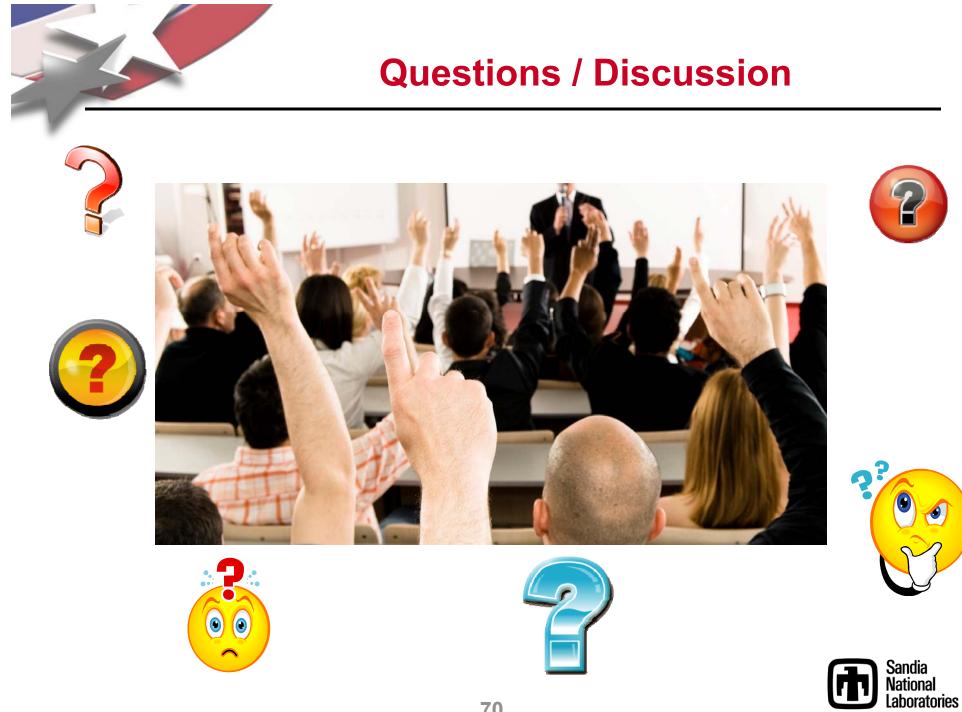
- This portion of the presentation wasn't about showing you how I improved my game; it was about showing you how DOE can be used even on the most obscure processes
- Design of Experiments was used to Optimize the Set-up
 - Right Hand Position (Weak to Strong)
 - Stance Width
 - Distance to Ball (Reach)
 - Ball Forward / Backward in Stance
- The Interaction between *Ball in Stance* and *Stance Width* would have never been detected by varying only one of these at a time!
- A well-designed experiment can give us much more information at a fraction of the cost of multiple experiments



Student Feedback on Using Practical Examples

- "Great new ways to simply look at existing data"
- "Tools and modeling should be added to BB training"
- "Make it (statistical modeling) mandatory for BB certification"
- "The examples were great. They really held my interest much more than boring technical examples."







"... all models are wrong; the practical question is how wrong do they have to be to not be useful ..."

George Box and Norman Draper, Empirical Model Building and Response Surfaces, John Wiley, 1987, pg. 74





