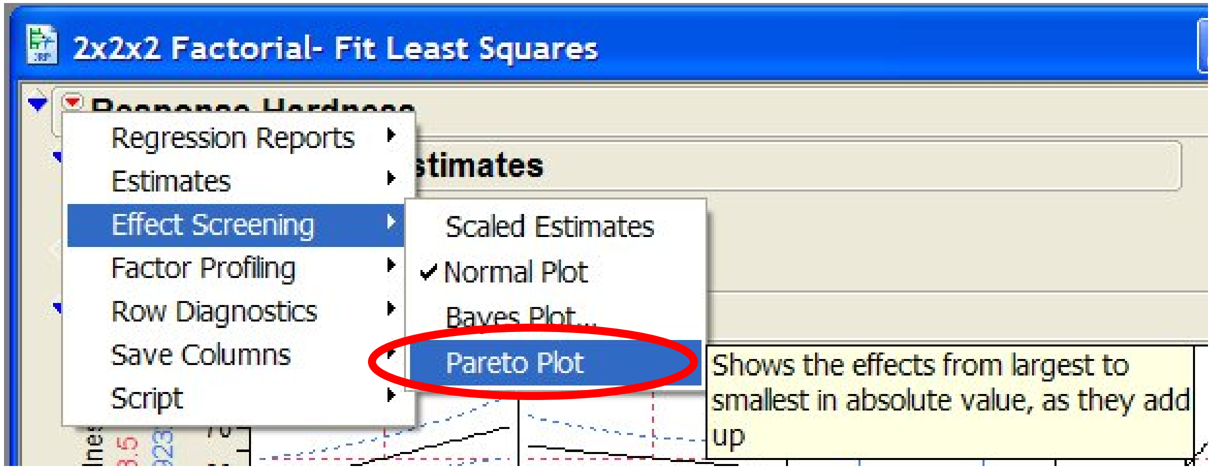
Pareto Plot

- Under the **Y Response Red Triangle**, select **Effect Screening>Pareto Plot**

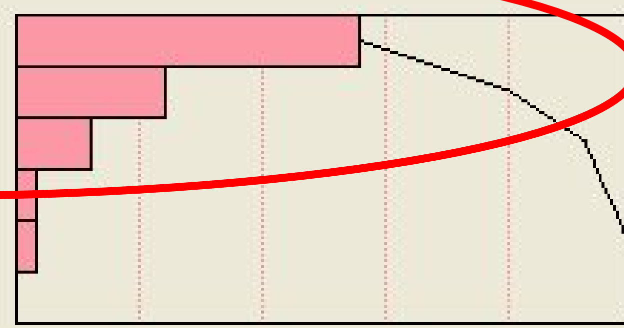


Pareto Plot

- The Pareto Plot shows that **Temperature, Time**, and the interaction of **Temperature and Oil** are the most significant model estimates.

Pareto Plot of Estimates

Term	Estimate
Temp(160,180)	11.50000
Temp*Oil[Brand A]	-5.00000
Time(5,15)	-2.50000
Oil[Brand A]	-0.75000
Temp*Time	0.75000
Time*Oil[Brand A]	0.00000

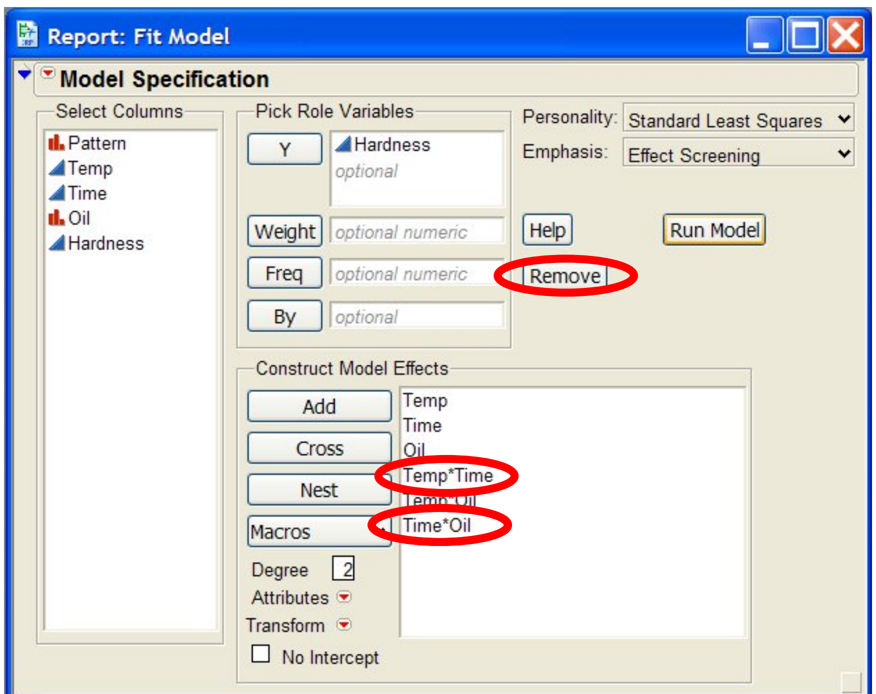


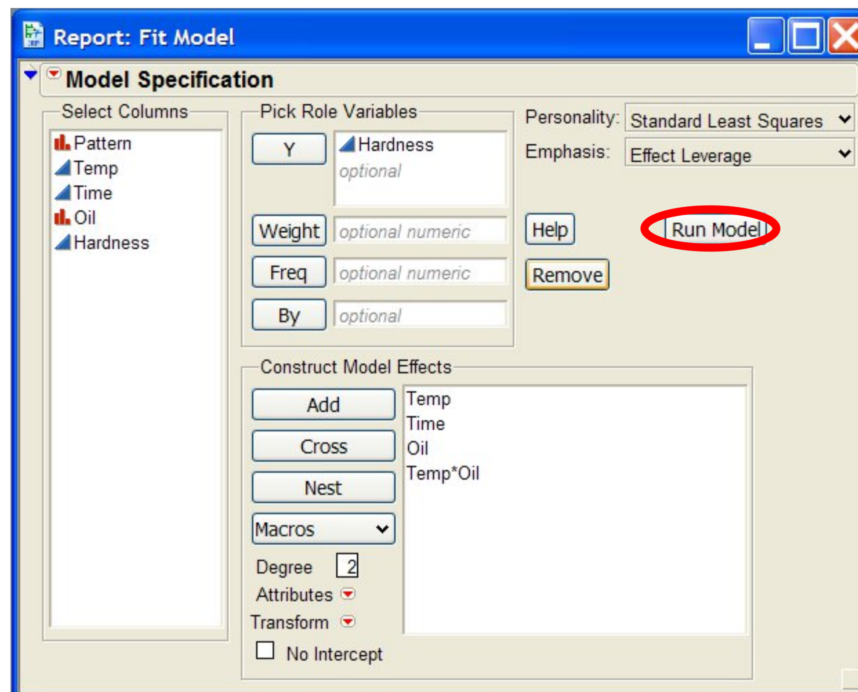
JMP Analysis *(Cont.)*

- Step 6: Reduce the Model to include the largest estimates.
- Note: If an interaction estimate is selected, then the interaction main factors must be included in the model.

JMP Analysis *(Cont.)*

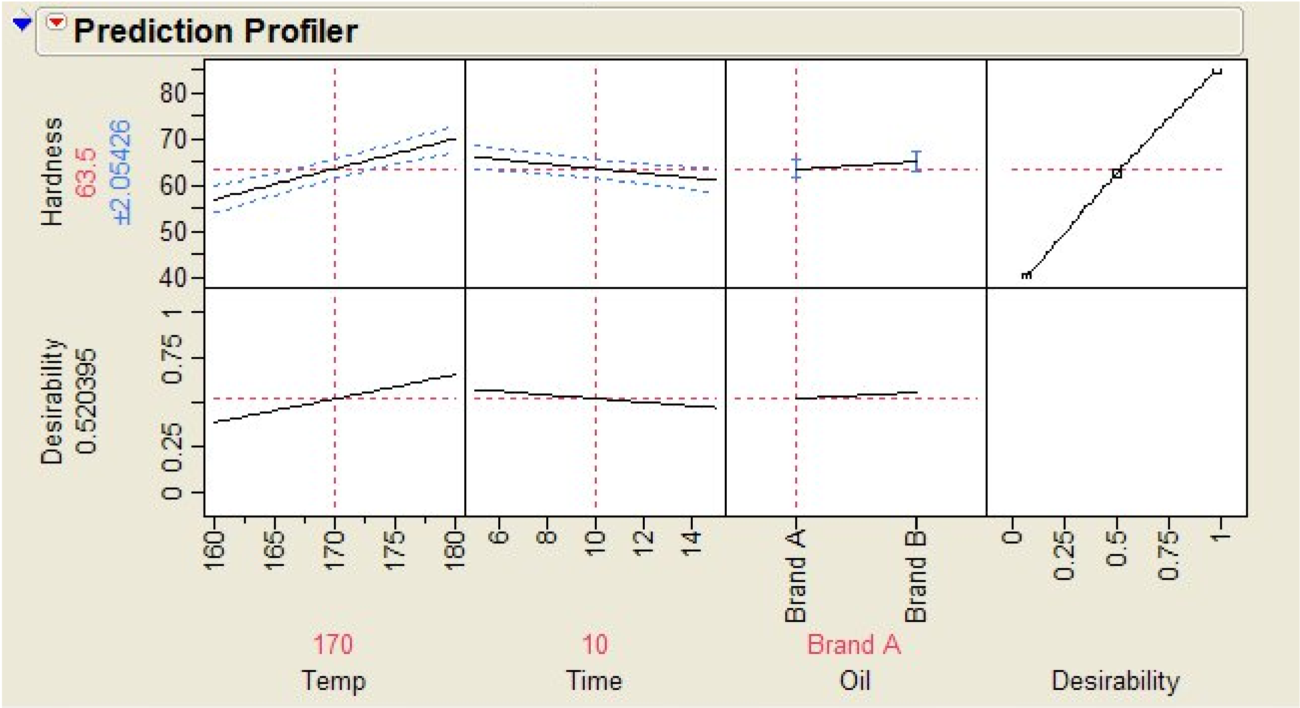
- Click-on the Fit Model Window from Analyze
- Click-on the non-significant estimates and then click-on **Remove**, and **Run Model.**





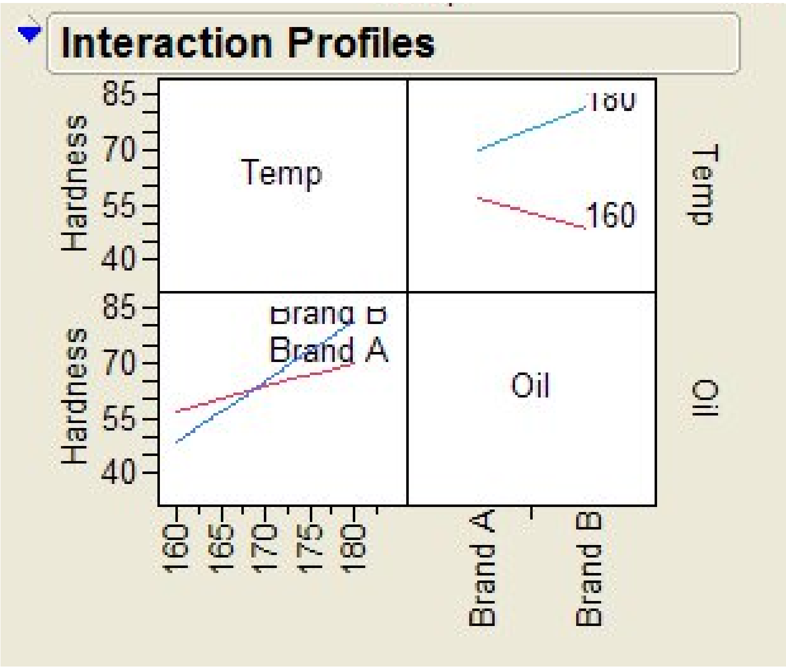
JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Profiler**



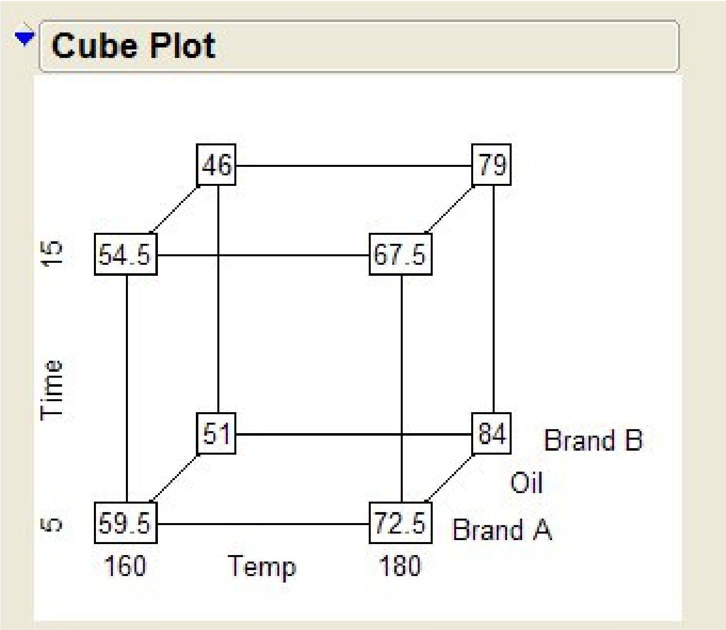
JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Interaction Plots**



JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Cube Plots**



JMP Analysis *(Cont.)*

- **Step 7: Construct a mathematical model.**

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64.25	0.456435	140.76	<.0001*
Temp(160,180)	11.5	0.456435	25.20	0.0001*
Time(5,15)	-2.5	0.456435	-5.48	0.0120*
Oil[Brand A]	-0.75	0.456435	-1.64	0.1989
Temp*Oil[Brand A]	-5	0.456435	-10.95	0.0016*

Model coefficients (coded) for Oil Brand A
Coded: Temp= -1,1 Time = -1,1

JMP Analysis *(Cont.)*

- **Step 7: Construct a mathematical model for Brand A.**

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64.25	0.456435	140.76	<.0001*
Temp(160,180)	11.5	0.456435	25.20	0.0001*
Time(5,15)	-2.5	0.456435	-5.48	0.0120*
Oil[Brand A]	-0.75	0.456435	-1.64	0.1989
Temp*Oil[Brand A]	-5	0.456435	-10.95	0.0016*

- Hardness = 64.25 + 11.50(Temp) – 2.5(Time)

  - 0.75 – 5.00 (Temp*Oil Type)

Where Temp=-1,1 Time=-1,1 For Brand A

JMP Analysis *(Cont.)*

- **Construct a mathematical model for Brand B. Change the sign on the coefficients that contain Oil Type**

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64.25	0.456435	140.76	<.0001*
Temp(160,180)	11.5	0.456435	25.20	0.0001*
Time(5,15)	-2.5	0.456435	-5.48	0.0120*
Oil Type[Brand A] B	+0.75	0.456435	-1.64	0.1989
Temp*Oil Type[Brand A] B	+5	0.456435	-10.95	0.0016*

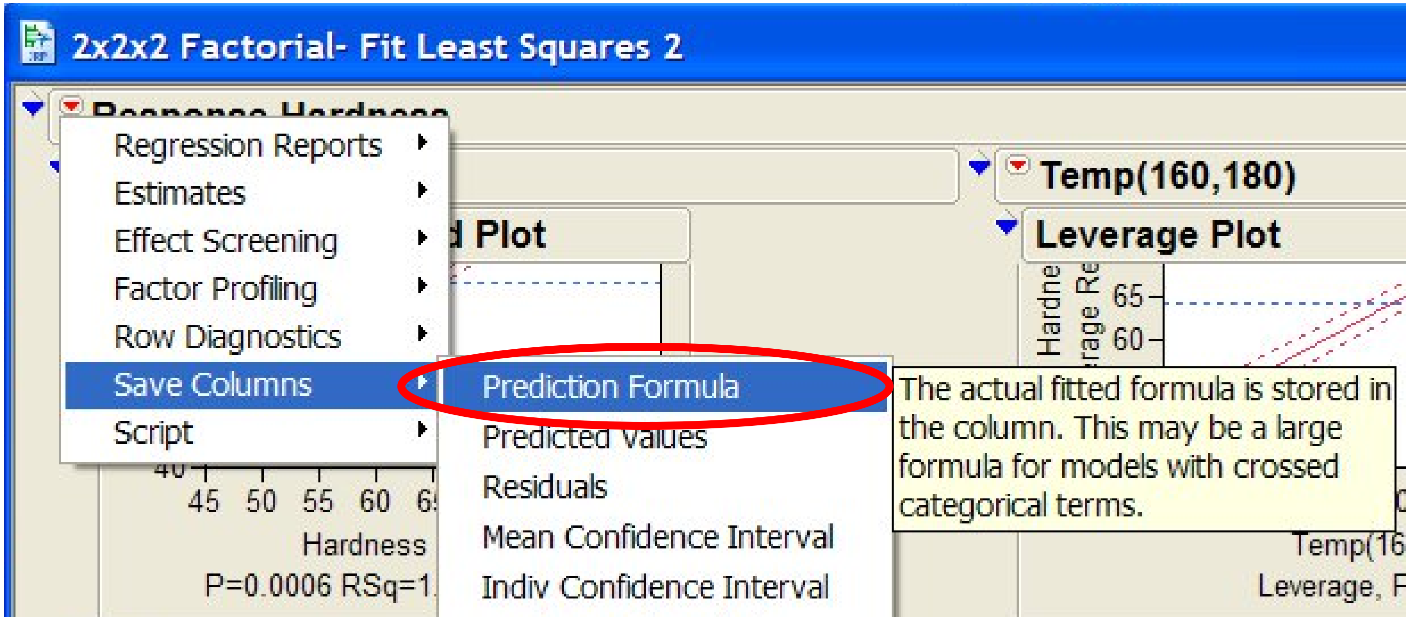
- Hardness = 64.25 + 11.50(Temp) – 2.5(Time) + 0.75 + 5.00 (Temp*Oil Type)

Where Temp=-1,1 Time=-1,1 For <u>Brand B</u>

Questions

- **Question 1:** What is the hardness when Temp = 1, Time=1 and Oil=Brand A?
- **Question 2:** What does that value represent?
- **Question 3:** What is the hardness when Temp = 1, Time=1 and Oil=Brand B?
- Check your answers using JMP.

JMP Analysis *(Cont.)*



- **Save Columns>Prediction Formula**

JMP Analysis *(Cont.)*

2x2x2 Factorial

2x2x2 Factorial
Design 2x2x2 Factorial
Screening
Model

Columns (7/0)
Pattern
Temp
Time
Oil
Hardness
Predicted Hardness

	Pattern	Temp	Time	Oil	Hardness	Predicted Hardness	Pred Formula Hardness
1	−−1	160	5	Brand A	60	59.5	59.5
2	+−1	180	5	Brand A	72	72.5	72.5
3	−+1	160	15	Brand A	54	54.5	54.5
4	++1	180	15	Brand A	68	67.5	67.5
5	−−2	160	5	Brand B	52	51	51
6	+−2	180	5	Brand B	83	84	84
7	−+2	160	15	Brand B	45	46	46
8	++2	180	15	Brand B	80	79	79

- **Maximum Hardness: Temp = 180, Time = 5, Oil Brand B**

Conclusions

- **Step 8**: Translate the mathematical model into process terms. Formulate conclusions and recommendations.
  - Conclusions: Temperature has the biggest effect on Hardness and will be a controlling factor in determining the hardness levels. Hardness can be maximized using Oil Type Brand B at Temp = 180°C and Time = 5 sec.
- **Step 9**: Replicate optimum conditions. Plan the next experiment or institutionalize the change.

Adding Center Points to 2^K Factorials

- There is always a risk in 2-level designs of missing a curvilinear relationship by only including two levels of the input variable.
- The addition of “Center Points” is an efficient way to test for curvature without adding a large number of experimental runs.

Example with Center Points

- A process engineer wants to improve the yield for two different die-castings. There are two inputs of interest: pressure and temperature. The engineer decides to conduct the experiment using a 2x2 design augmented with five center points to estimate experimental error and curvature.

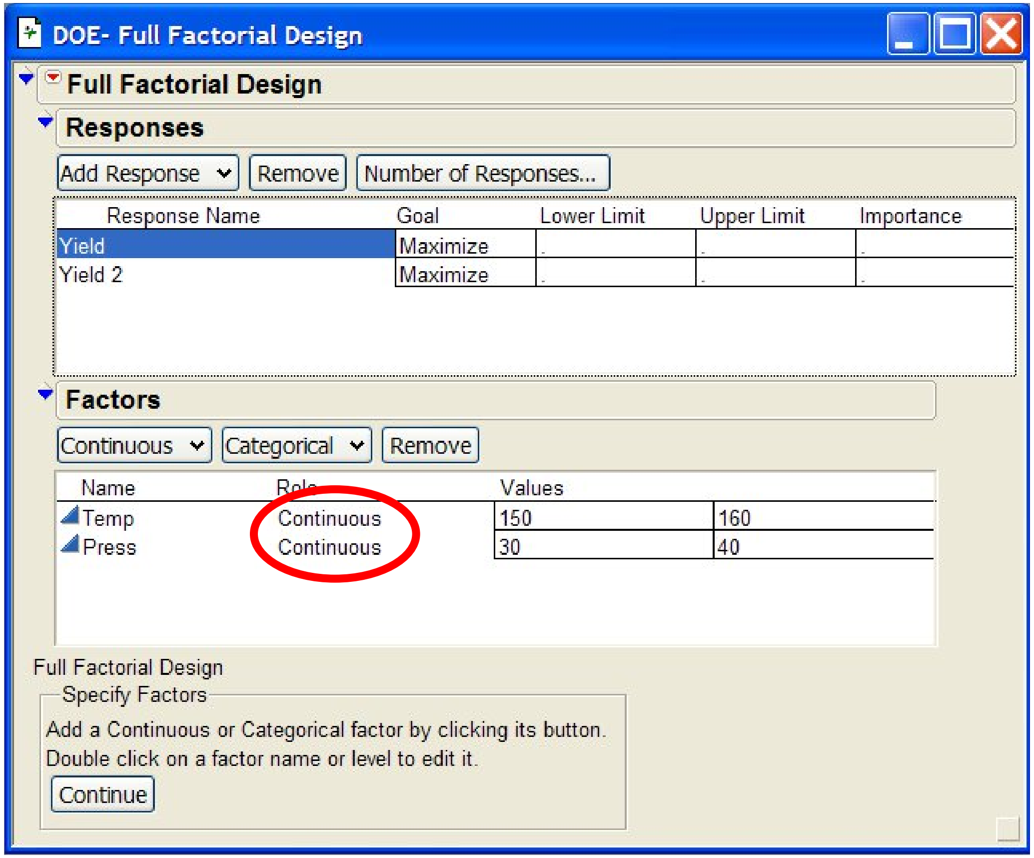
Example with Center Points

- State the problem: A process engineer wants to improve yield for two different die-castings. There are two inputs of interest: pressure and temperature.
- State the factors and levels of interest, and create a JMP experimental data sheet.
  - Temperature: 150, 160
  - Pressure: 30, 40

Design Matrix – Using JMP

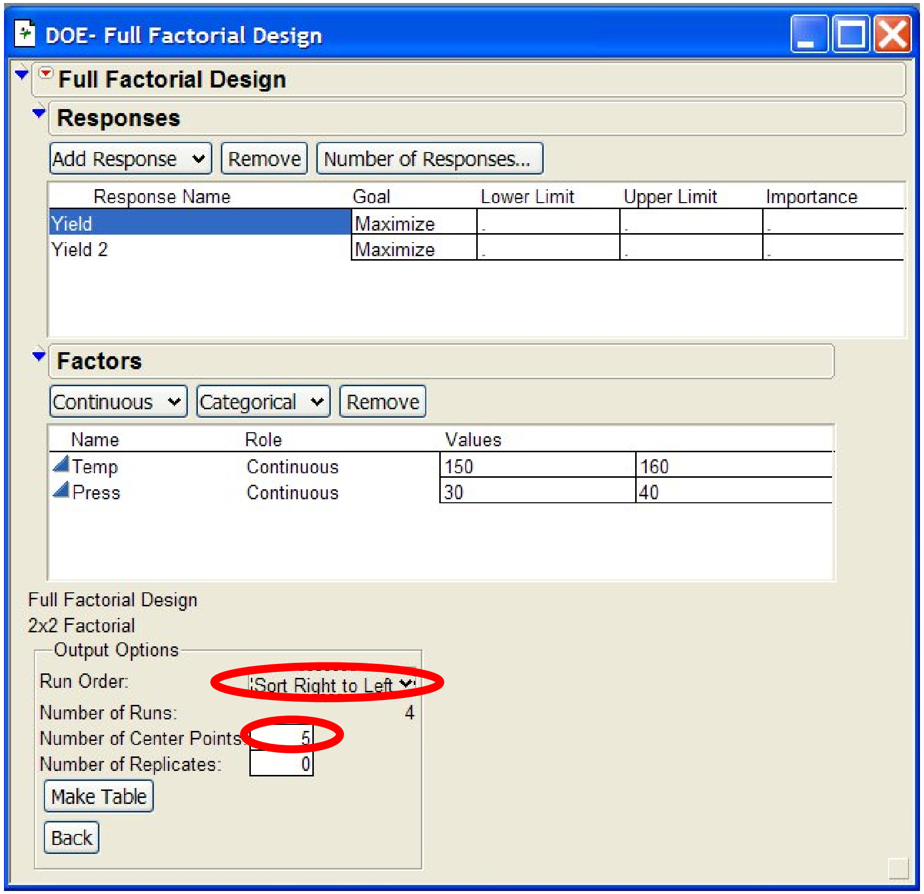
- **JMP>DOE>Classical>Full Factorial Design**

In order to insert center points into JMP, the variables are selected as continuous.



JMP DOE Design *(Cont.)*

- Change the **Number of Center Points** to *5.*
- Change **Randomize** to **Sort Right to Left** for teaching purposes.
- Select **Make Table**.



JMP DOE Design *(Cont.)*

2x2 Factorial

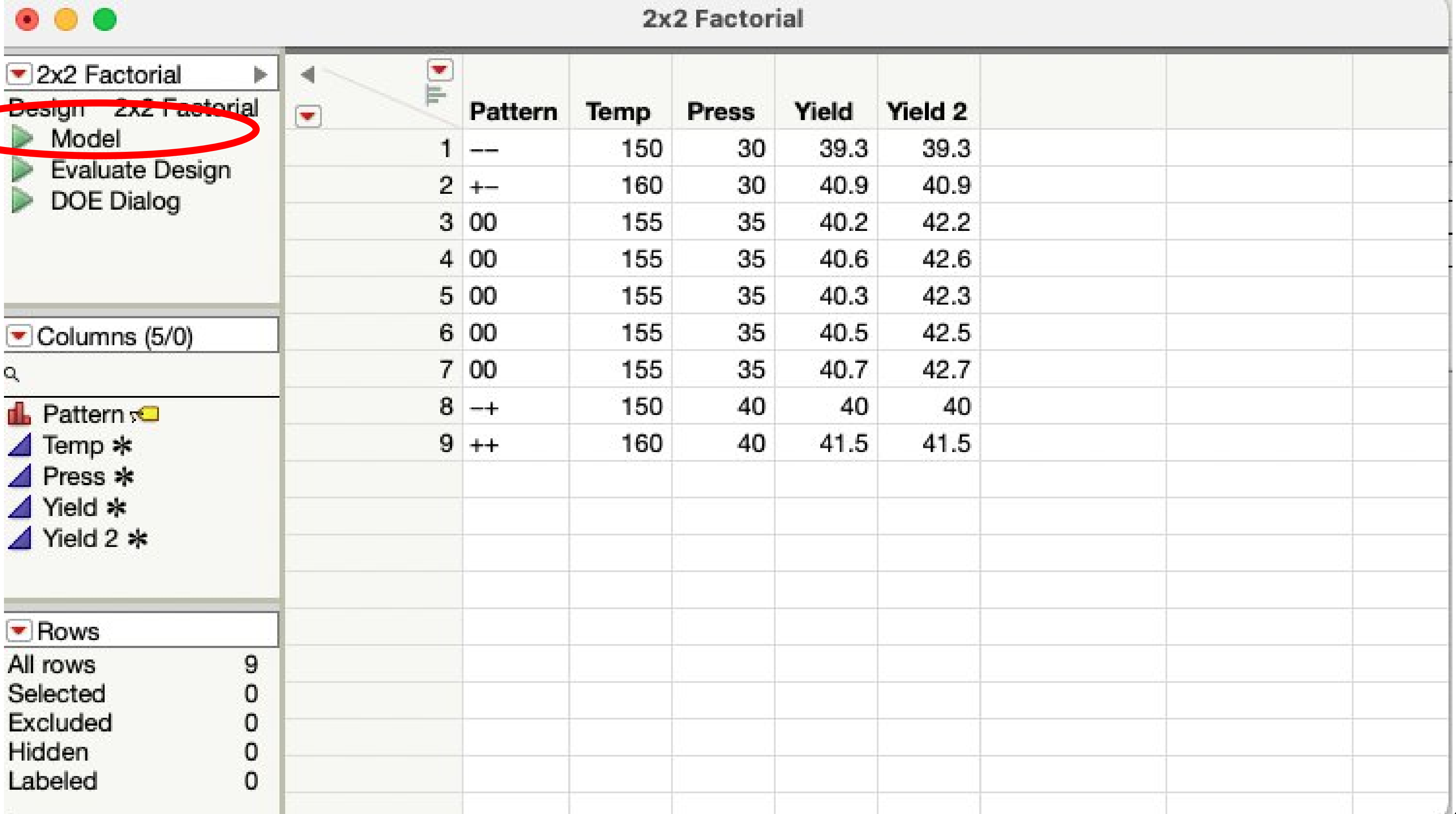
2x2 Factorial
Design 2x2 Factorial
Screening
Model

Columns (5/0)
Pattern
Temp *
Press *
Yield *
Yield 2 *

	Pattern	Temp	Press	Yield	Yield 2
1	−−	150	30	39.3	39.3
2	+−	160	30	40.9	40.9
3	00	155	35	40.2	42.2
4	00	155	35	40.6	42.6
5	00	155	35	40.3	42.3
6	00	155	35	40.5	42.5
7	00	155	35	40.7	42.7
8	−+	150	40	40	40
9	++	160	40	41.5	41.5

Analysis With JMP *(Cont.)*

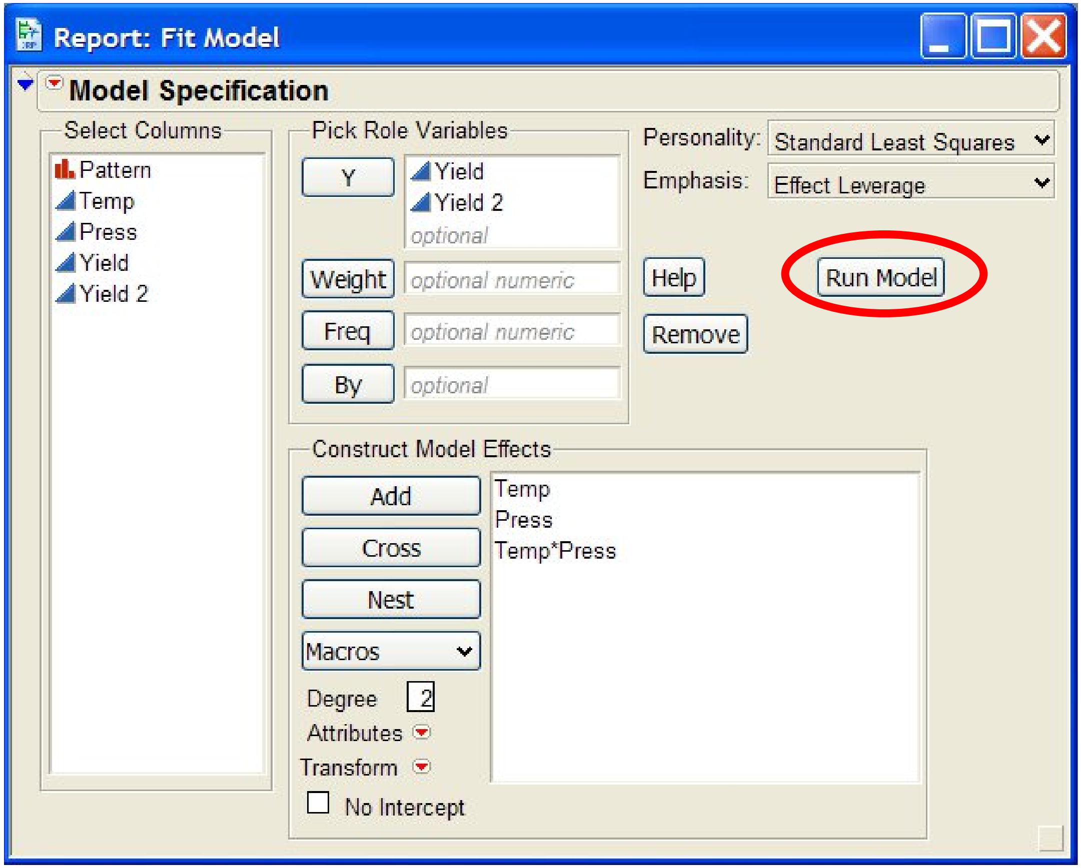
- From the **Model select the Green Triangle**



	Pattern	Temp	Press	Yield	Yield 2
1	−−	150	30	39.3	39.3
2	+−	160	30	40.9	40.9
3	00	155	35	40.2	42.2
4	00	155	35	40.6	42.6
5	00	155	35	40.3	42.3
6	00	155	35	40.5	42.5
7	00	155	35	40.7	42.7
8	−+	150	40	40	40
9	++	160	40	41.5	41.5

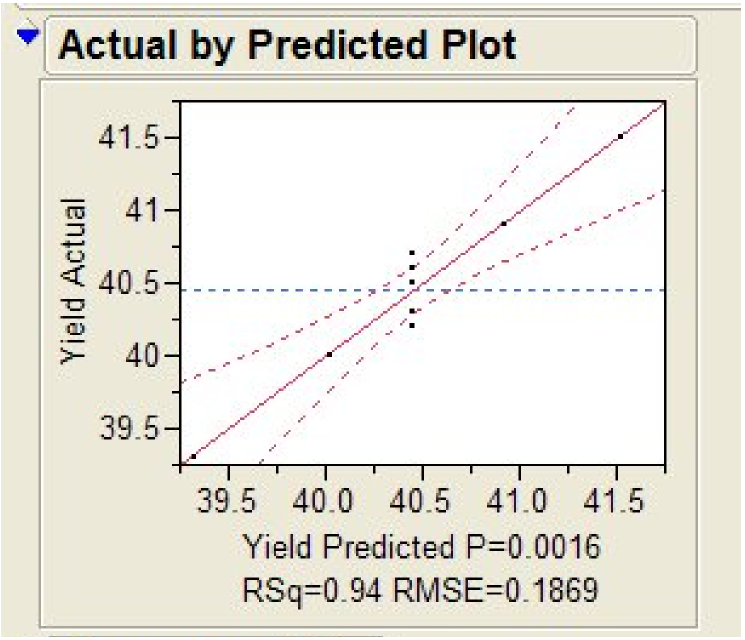
JMP Analysis *(Cont.)*

- Click **Run**

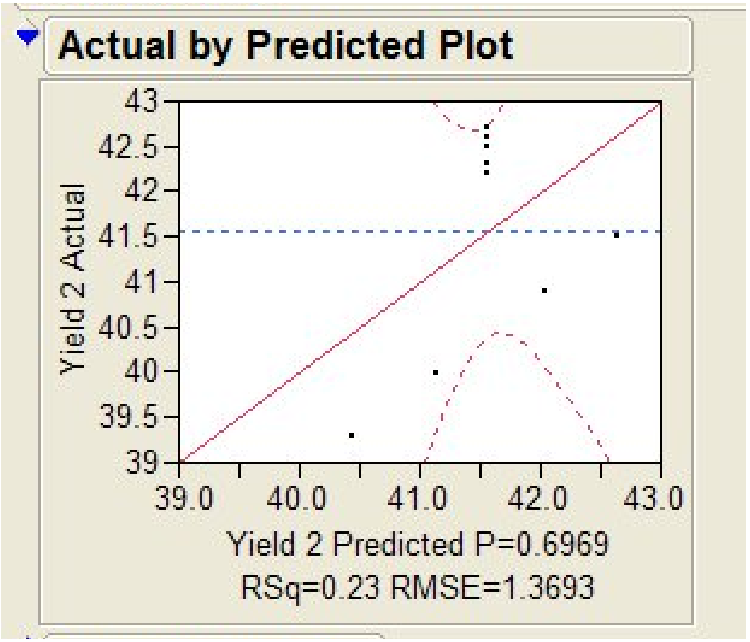


JMP Analysis *(Cont.)*

Yield



Yield 2



JMP Analysis *(Cont.)*

Yield

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	40.444444	0.062311	649.07	<.0001*
Temp(150,160)	0.775	0.093467	8.29	0.0004*
Press(30,40)	0.325	0.093467	3.48	0.0177*
Temp*Press	-0.025	0.093467	-0.27	0.7998

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Temp(150,160)	1	1	2.4025000	68.7520	0.0004*
Press(30,40)	1	1	0.4225000	12.0906	0.0177*
Temp*Press	1	1	0.0025000	0.0715	0.7998

Yield 2

Parameter Estimates

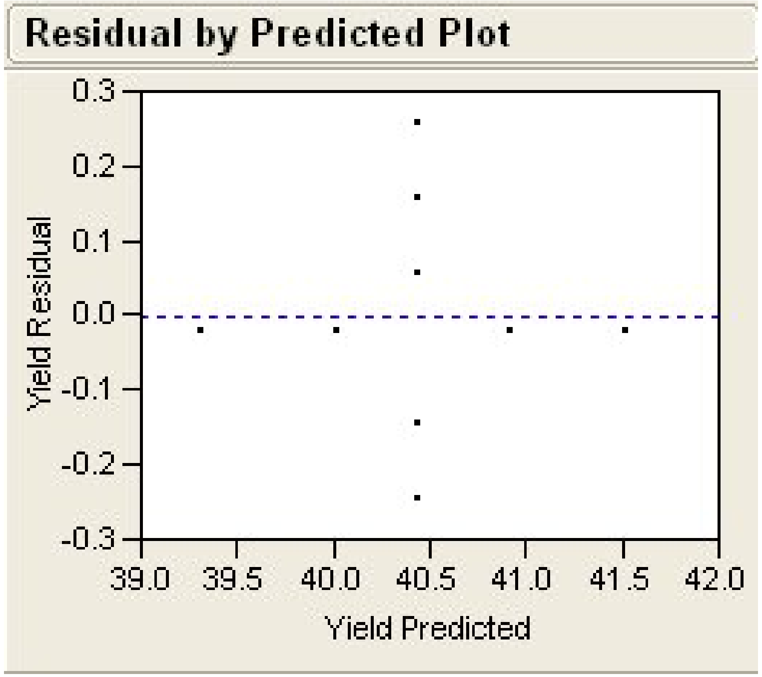
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	41.555556	0.456429	91.05	<.0001*
Temp(150,160)	0.775	0.684643	1.13	0.3090
Press(30,40)	0.325	0.684643	0.47	0.6550
Temp*Press	-0.025	0.684643	-0.04	0.9723

Effect Tests

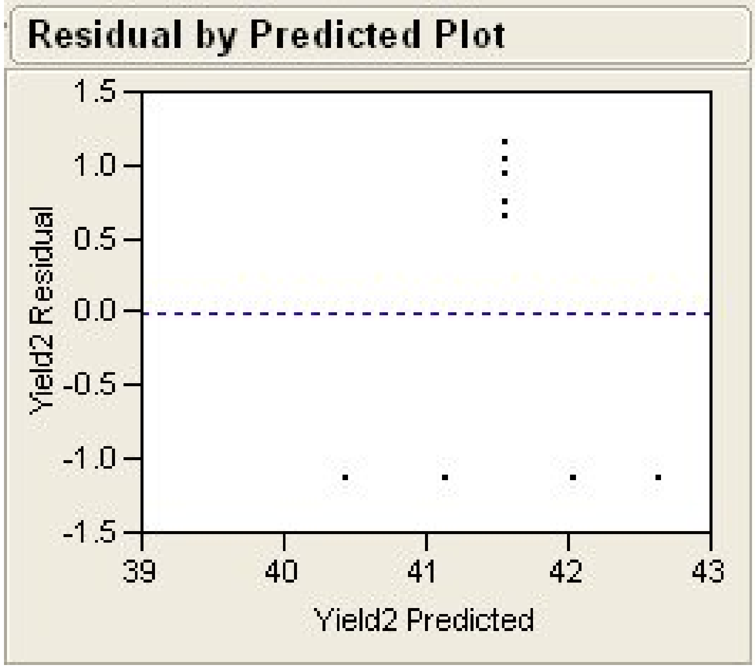
Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Temp(150,160)	1	1	2.4025000	1.2814	0.3090
Press(30,40)	1	1	0.4225000	0.2253	0.6550
Temp*Press	1	1	0.0025000	0.0013	0.9723

JMP Analysis *(Cont.)*

Yield

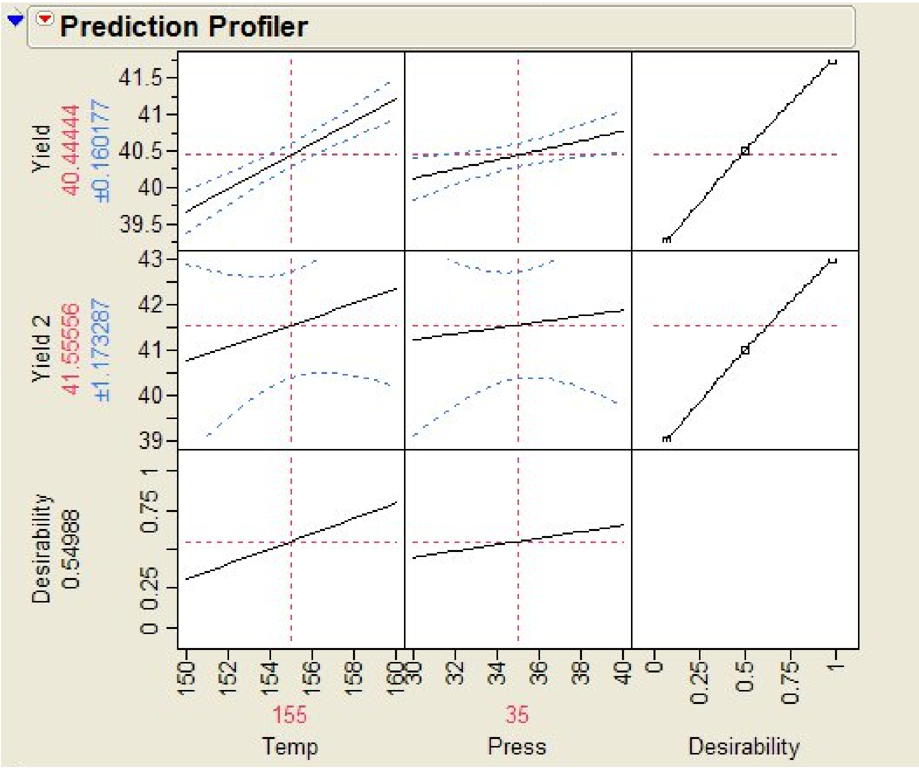


Yield 2



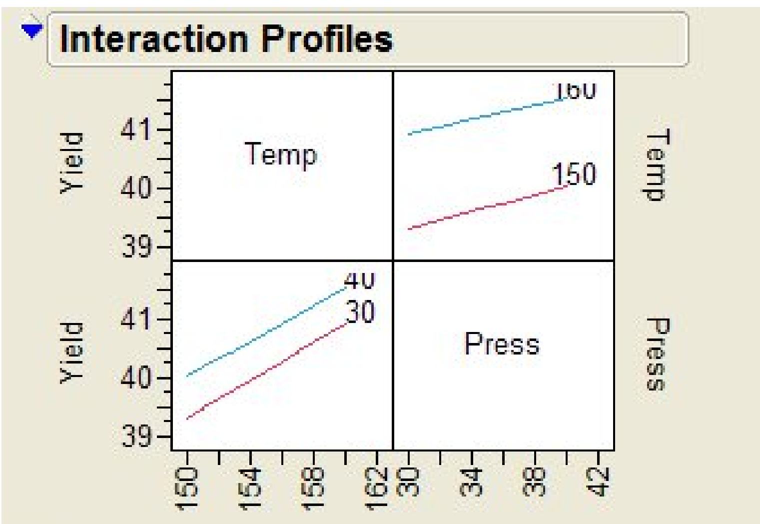
JMP Analysis *(Cont.)*

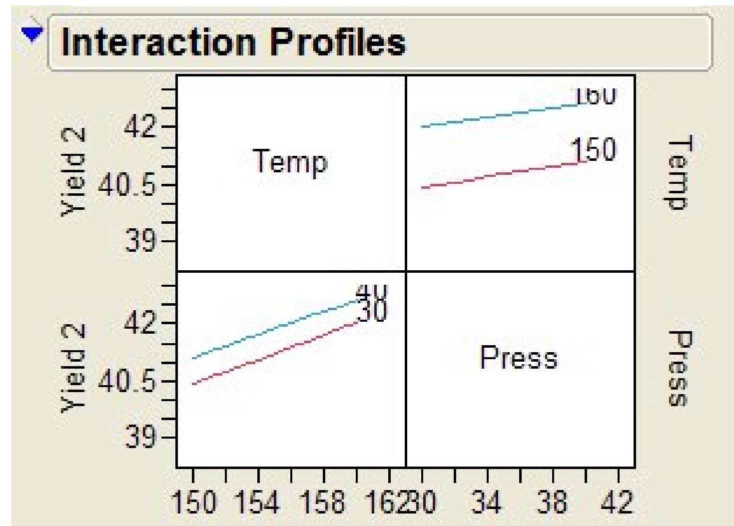
- From the **Response Yield Red Triangle,** select **Factor Profiling>Profiler**



JMP Analysis *(Cont.)*

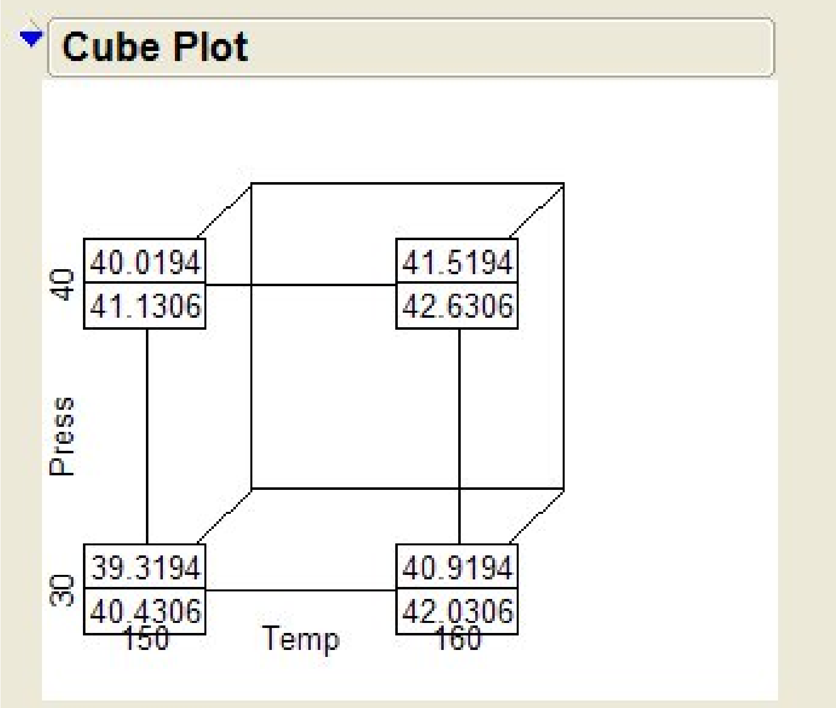
- From the **Response Yield Red Triangle**, select **Factor Profiling>Interaction Plots**





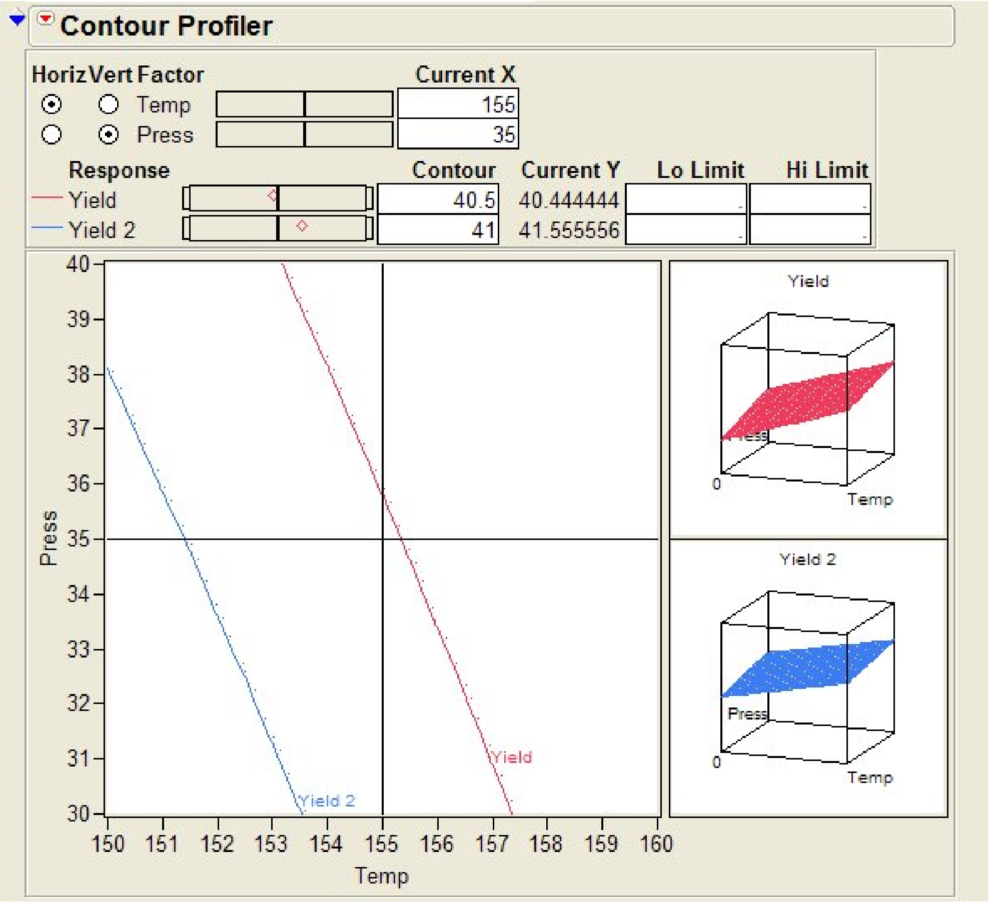
JMP Analysis *(Cont.)*

- From the **Response Yield Red Triangle**, select **Factor Profiling>Cube Plots**



JMP Analysis *(Cont.)*

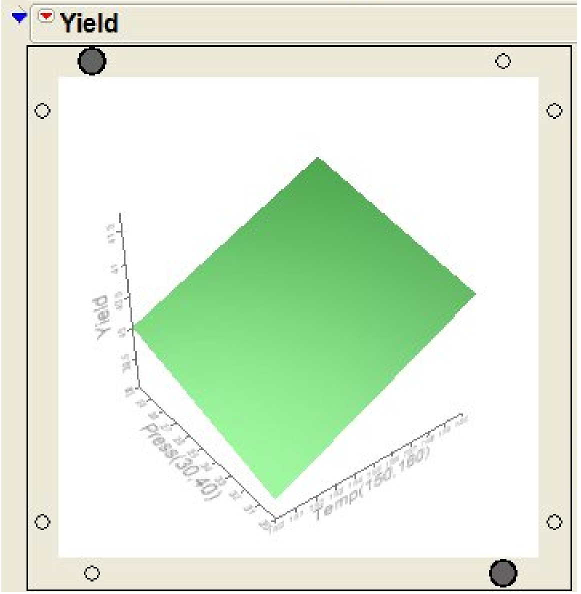
- From the **Response Yield Red Triangle**, select **Factor Profiling>Contour Profiler**



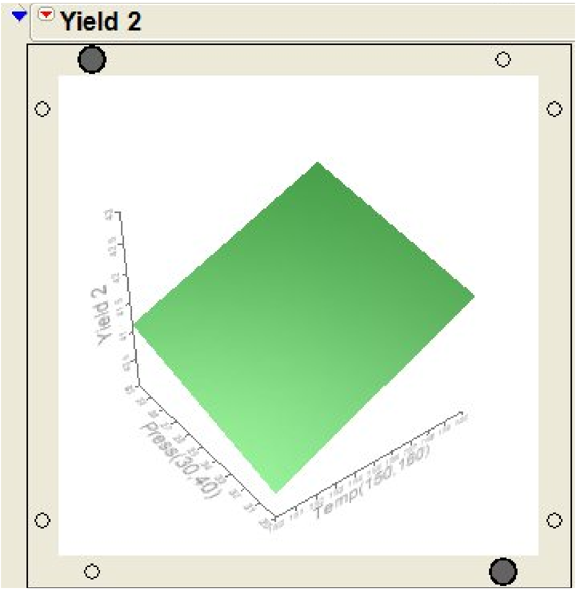
JMP Analysis *(Cont.)*

- From the **Response Yield Red Triangle**, select **Factor Profiling>Surface Profiler**

Yield



Yield 2



Mathematical Model

- State the mathematical model obtained. A simpler model is always preferable (Why?)
  - For the yield of product 1 we can reduce the model because the interaction is not significant.
  - For the yield of product 2 (yield 2), we haven't yet obtained a working model (no main effects or interactions are significant). At this point, we simply know that curvature exists.

- Product 1:

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	40.444444	0.062311	649.07	<.0001
Temp	0.775	0.093467	8.29	0.0004
Pressure	0.325	0.093467	3.48	0.0177
Temp *Pressure	-0.025	0.093467	-0.27	0.7998

$$Yield = 40.44 + .775*Temp + .325*Press$$

  - Note: The above equation is for coded variables only!

- Product 2:
  - Step 4 shows that Curvature is significant. Stop there!
  - Re-do the DOE. Change your level settings.

Conclusions

- Translate the mathematical model into process terms. Formulate conclusions and recommendations.
  - For product 1: To increase yield, set the current process to run at 160 degrees and 40 psi.
    - We also recommend a follow-up investigation to see if yield can be further improved at factor levels not tested in this experiment.
  - For product 2: Conduct additional experiments to model curvature.
- Replicate optimum conditions. Plan the next experiment or institutionalize the change.

Adding A Block To 2^K Factorials

- **Blocking Variable:** A factor in an experiment that has undesired influence as a source of variability is called a "block." A block can be a batch of material or a set of conditions likely to produce experimental runs that are more homogenous within the block (or batch) than between blocks.

Run	A	B	C	Block
1	-1	-1	-1	I
2	+1	-1	-1	I
3	-1	+1	-1	I
4	+1	+1	-1	I
5	-1	-1	+1	II
6	+1	-1	+1	II
7	-1	+1	+1	II
8	+1	+1	+1	II

Adding A Block To 2^K Factorials

- Suppose we wanted to run a 2x2x2 factorial. We would like to run the experiment under as homogeneous conditions as possible. But, we find that two batches of raw material are needed to run the entire experiment.

Run	A	B	C	Block
1	-1	-1	-1	I
2	+1	-1	-1	I
3	-1	+1	-1	I
4	+1	+1	-1	I
5	-1	-1	+1	II
6	+1	-1	+1	II
7	-1	+1	+1	II
8	+1	+1	+1	II

Adding A Block To 2^K Factorials

- It's easy to see that if we ran the first four runs with Batch 1 of raw material and the second four runs with Batch 2, we would completely "**confound**" Factor C. We could not distinguish between the effect due to Factor C and the effect of variation in the raw material.

Run	A	B	C	Block
1	-1	-1	-1	I
2	+1	-1	-1	I
3	-1	+1	-1	I
4	+1	+1	-1	I
5	-1	-1	+1	II
6	+1	-1	+1	II
7	-1	+1	+1	II
8	+1	+1	+1	II

Adding A Block To 2^K Factorials

- We must figure out a way to "spread" the raw material effect across the experiment so the differences in material batches are "seen" by all the main effects. Recall the expanded design matrix for a 2^3 factorial experiment showing all contrasts.

Adding A Block To 2^K Factorials

- In general, we make the assumption that "higher order interactions" are not significant (p-value > 0.05). Here we can use the contrast for the 3-way interactions to define our blocking variable. The new design would look like:

Run	A	B	C	A*B	A*C	B*C	A*B*C	Block
1	-1	-1	-1	1	1	1	-1	I
2	1	-1	-1	-1	-1	1	1	II
3	-1	1	-1	-1	1	-1	1	II
4	1	1	-1	1	-1	-1	-1	I
5	-1	-1	1	1	-1	-1	1	II
6	1	-1	1	-1	1	-1	-1	I
7	-1	1	1	-1	-1	1	-1	I
8	1	1	1	1	1	1	1	II

Adding A Block To 2^K Factorials

- We would run runs 1, 4, 6 and 7 with Batch 1 and runs 2, 3, 5 and 8 with Batch 2. This experiment would not allow us to test for the significance of the 3-way interaction, but it would allow us to investigate the main effects and 2-way interactions without worrying about confounding these effects with the Raw Material batch.

Note: In an actual experiment, you would randomize the runs within each Block. JMP will do that for you.

Run	A	B	C	Block
1	-1	-1	-1	I
2	1	-1	-1	II
3	-1	1	-1	II
4	1	1	-1	I
5	-1	-1	1	II
6	1	-1	1	I
7	-1	1	1	I
8	1	1	1	II

Run	A	B	C	Block
1	-1	-1	-1	I
4	1	1	-1	I
6	1	-1	1	I
7	-1	1	1	I
2	1	-1	-1	II
3	-1	1	-1	II
5	-1	-1	1	II
8	1	1	1	II

Lean Six Sigma

2^K Factorial Experiments

2^K Factorial Experiments

Objective: To develop a mathematical relationship between the significant factors and the response variable.

Deliverables: Y=f(x), Mathematical Model, DOE Report, Updated FMEA

2^K Factorial Experiments

Objective	Project Deliverables
DOE Planning	Experiment Planning Experiments
Screening Experiments (What are the significant factors?)	Fractional Factorial Experiments Reduced List of Input Variables
Y=f(x) (What is the mathematical relationship between the significant factors and the response variable?)	Mathematical Model 2^K Factorial Experiments Full Factorial Experiments Established Input Levels
Process Documentation	Updated Process FMEA DOE Report(s)

2^K Factorial Experiments Agenda

- Why do we need 2^K factorial experimentation?
- 2^K Standard Order Designs
  - Exercise:
    - Calculating main effects
    - Calculating interactions
  - 2^K Example (using JMP)
  - 2^K Exercises (using JMP)

2^K Factorial Experiments Agenda

- Adding Center Points
  - 2^K Example with center points (using JMP)
- Adding Blocking
  - 2^K Example with Blocking
- 2^K Vocabulary
- Steps for DOE Analysis

Juran 47.38

Why Use 2^K Factorial Experiments?

- The **GOAL** is to obtain a mathematical relationship which characterizes:
  - Y = f(x1, x2, x3, …)
- The mathematical relationship allows us to identify not only the *critical factors* but also the *best levels* for those factors.
- 2^K Factorial Experiments investigate multiple factors where each factor is studied at only two levels.

Why Use 2^K Factorial Experiments?

- 2^K Factorial Experiments allow us to investigate a large number of factors simultaneously in relatively few runs compared to full factorial designs.
- Finally, 2^K designs are used most frequently in industrial DOE applications because they are very easy to analyze and lend themselves well to sequential studies.

Types of 2^K Factorials

- **One observation per treatment combination**
  - **Usually low statistical power**
  - **Use Normal Quantile Plots or Pareto charts instead of F-tests**
  - **Can create full factorials by leaving unimportant factors out**

Types of 2^K Factorials

- More than one observation per treatment combination (known as repeats or replicates)
  - Better estimates of error
  - Better statistical power
  - Can still run reduced models
  - F-tests, normal plots and pareto charts can be used

Standard Order Of 2^K Designs

- **2^K factorials refer to <u>k</u> factors, each with 2 levels. A 2^2 factorial is a 2x2 factorial. This design has two factors with two levels and can be executed in only 2x2 or 4 runs. Likewise a 2^3 factorial has 3 factors, each with two levels. This experiment can be done 2x2x2 or 8 runs.**

Standard Order Of 2^K Designs *(Cont.)*

- The design matrix for 2^K factorials is usually shown in standard order. The low level of a factor is designated with "-" or –1 and the high level is designated with "+" or 1. An example of a design matrix follows.

2^2 Factorial

Temp	Conc
-1	-1
1	-1
-1	1
1	1

2^3 Factorial

Temp	Conc	Catalyst
-1	-1	-1
1	-1	-1
-1	1	-1
1	1	-1
-1	-1	1
1	-1	1
-1	1	1
1	1	1

Standard Order Of 2^K Designs Exercise

- **Create a 2^4 Factorial Design Matrix**
- **What are the minimum number of runs needed?**
- **Verify your results using JMP: JMP>DOE>Classical>Full Factorial Design**
- **Add two 2-level continuous factors and two 2-level categorical factors**

Standard Order Of 2^K Designs Exercise

Open JMP – new data table

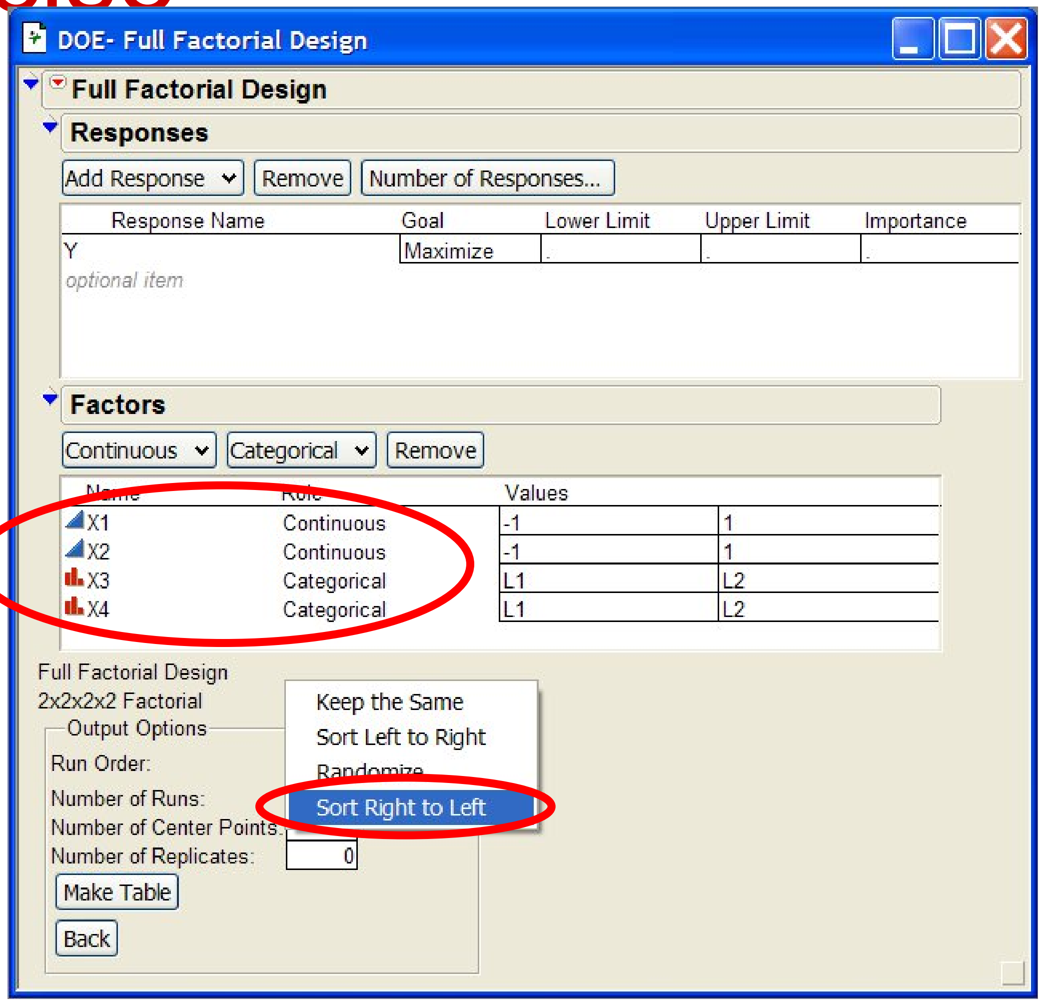
Click on DOE

Select Classical > Full Factorial Design

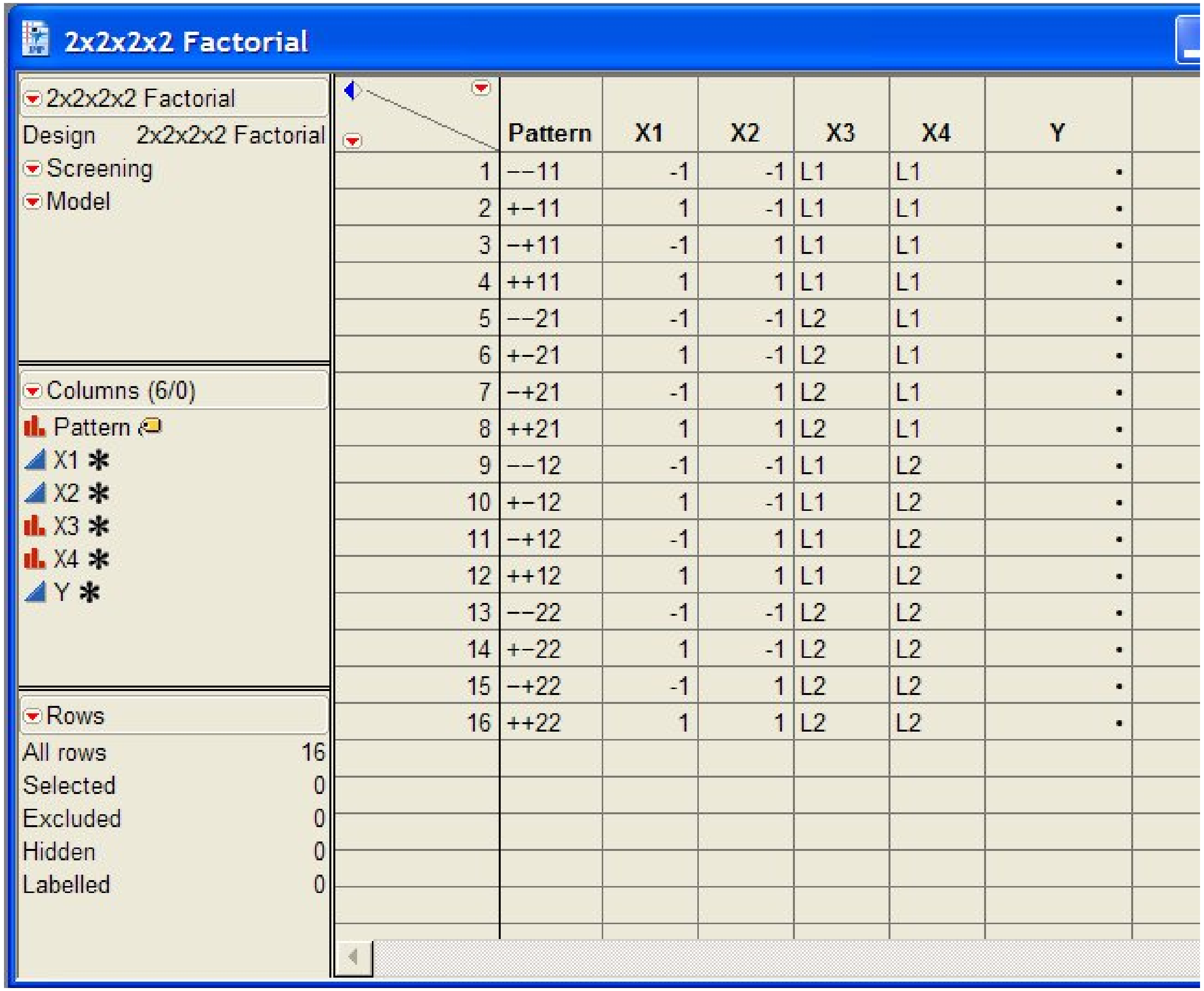
Y is response, Maximize

Select 2 continuous, 2 categorical variables, 2 levels each, click continue

Standard Order Of 2^K Designs Exercise



Standard Order Of 2^K Designs Exercise



	Pattern	X1	X2	X3	X4	Y
1	−−11	-1	-1	L1	L1	•
2	+−11	1	-1	L1	L1	•
3	−+11	-1	1	L1	L1	•
4	++11	1	1	L1	L1	•
5	−−21	-1	-1	L2	L1	•
6	+−21	1	-1	L2	L1	•
7	−+21	-1	1	L2	L1	•
8	++21	1	1	L2	L1	•
9	−−12	-1	-1	L1	L2	•
10	+−12	1	-1	L1	L2	•
11	−+12	-1	1	L1	L2	•
12	++12	1	1	L1	L2	•
13	−−22	-1	-1	L2	L2	•
14	+−22	1	-1	L2	L2	•
15	−+22	-1	1	L2	L2	•
16	++22	1	1	L2	L2	•

Exercise: Calculating Main Effects

Step 1: Problem Statement: A process engineer would like to determine the effect of Quench Temperature, Quench Time, and Quench Oil types on the hardness of a steel shaft. Goal: Maximize Hardness.

Step 2: The factors and levels:

- Quench Temp: 160° C (-1), 180° C (1)
- Quench Time (sec): 5 (-1), 15 (1)
- Quench Oil Type: Brand A (-1), Brand B (1)

Exercise: Calculating Main Effects

Step 3: The design matrix with the results column is as follows:

Temp	Time	Oil	Hardness
-1	-1	-1	60
1	-1	-1	72
-1	1	-1	54
1	1	-1	68
-1	-1	1	52
1	-1	1	83
-1	1	1	45
1	1	1	80

This is an example of 2^K Factorial Experiment with only one observation per treatment combination (experimental run).

Exercise: Calculating Main Effects

- Step 4: We will now calculate the effects of the experiment by hand. First, look at Temperature.
- We simply add the yields associated with (-1) and the yields associated with (1) and calculate the average (Sum/4). The “1’s” and “-1’s” in the temperature column are called the “contrast” for the main effect of temperature.

Exercise: Calculating Main Effects

Temp	Time	Oil	Hardness
-1	-1	-1	60
1	-1	-1	72
-1	1	-1	54
1	1	-1	68
-1	-1	1	52
1	-1	1	83
-1	1	1	45
1	1	1	80

$$TempMainEffect = \left(\frac{72+68+83+80}{4}\right) - \left(\frac{60+54+52+45}{4}\right)$$

$$= 75.75 - 52.75 = 23$$

Total -	-211
Total +	303
Sum	92
Avg Effect	23

The Hardness increases, on average, by 23 points as temperature moves from Low to High (160 to 180).

Exercise: Calculating Main Effects

- Now use the contrast for Time to calculate the effect Time has on Hardness.

$$TimeMainEffect = \left(\frac{54+68+45+80}{4}\right) - \left(\frac{60+72+52+83}{4}\right)$$

$$= 61.75 - 66.75 = -5$$

As the Time moves from 5 sec to 15 sec, the Hardness drops by 5 points on average.

Exercise: Calculating Main Effects

Temp	Time	Oil	Hardness
-1	-1	-1	60
1	-1	-1	72
-1	1	-1	54
1	1	-1	68
-1	-1	1	52
1	-1	1	83
-1	1	1	45
1	1	1	80

Total -	-211	-267	
Total +	303	247	
Sum	92	-20	
Avg Effect	23	-5	

Exercise: Calculating Main Effects

- Next use the contrast for Oil to calculate the effect Oil type has on Hardness.

Temp	Time	Oil	Hardness
-1	-1	-1	60
1	-1	-1	72
-1	1	-1	54
1	1	-1	68
-1	-1	1	52
1	-1	1	83
-1	1	1	45
1	1	1	80

-211	-267	
303	247	
92	-20	
23	-5	

Exercise: Calculating Main Effects

$$OilMainEffect = \left(\frac{\quad + \quad + \quad + \quad}{4}\right) - \left(\frac{\quad + \quad + \quad + \quad}{4}\right)$$

$$= \underline{\qquad\qquad} - \underline{\qquad\qquad} =$$

Interpretation: ______________________________________

Exercise: Calculating Interactions

- We have just finished calculating the Main Effects for this experiment. We've only investigated the independent effects of Temperature, Time and Oil Type. This is similar to conducting three 2-Sample T tests.
- The benefit of factorial experiments is that they provide the ability to assess "interactions" between factors. "Is there a particular combination of input settings that improve Hardness over and above the singular (main) effects?"

Exercise: Calculating Interactions

- The interaction contrast is derived by multiplying the columns to be represented.

Calculate the Interaction Contrasts below.

Temp(T)	Time (S)	Oil (O)	T*S	T*O	S*O	T*S*O	Hardness
-1	-1	-1					60
1	-1	-1					72
-1	1	-1					54
1	1	-1					68
-1	-1	1					52
1	-1	1					83
-1	1	1					45
1	1	1					80

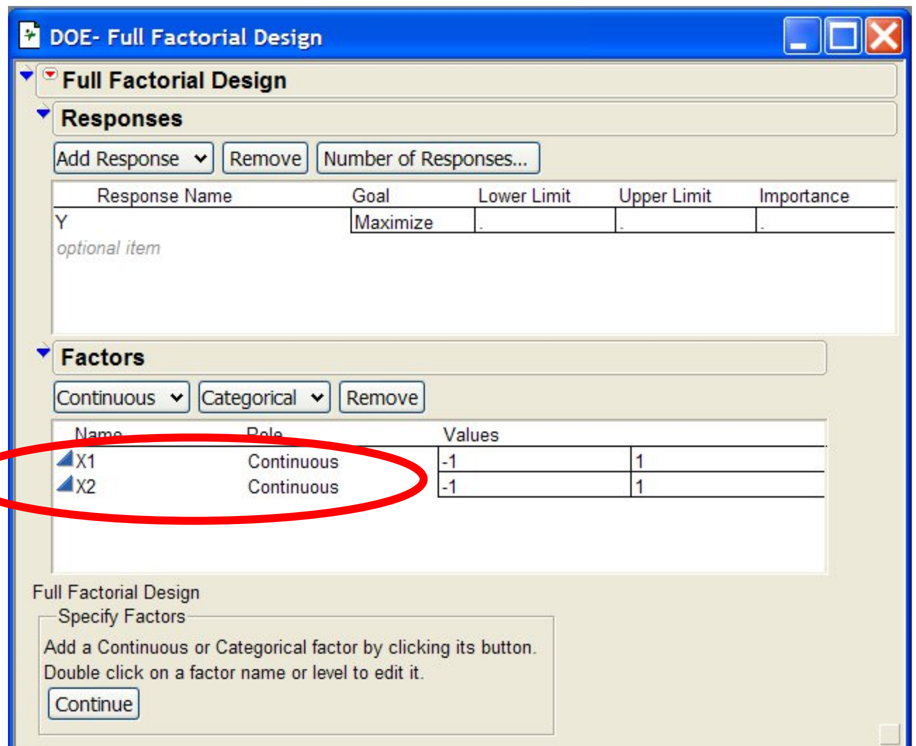
Exercise: Calculating Interactions

	-1	-1	-1	1	1	1	-1	60
	1	-1	-1	-1	-1	1	1	72
	-1	1	-1	-1	1	-1	1	54
	1	1	-1	1	-1	-1	-1	68
	-1	-1	1	1	-1	-1	1	52
	1	-1	1	-1	1	-1	-1	83
	-1	1	1	-1	-1	1	-1	45
	1	1	1	1	1	1	1	80
Total -	-211	-267						
Total +	303	247						
Sum	92	-20						
Effect	23	-5	1.5	1.5	10	0	0.5	
Estimate	11.5	-2.5	0.75	0.75	5	0	0.25	

- Verify the “Contrast” for each interaction using JMP.

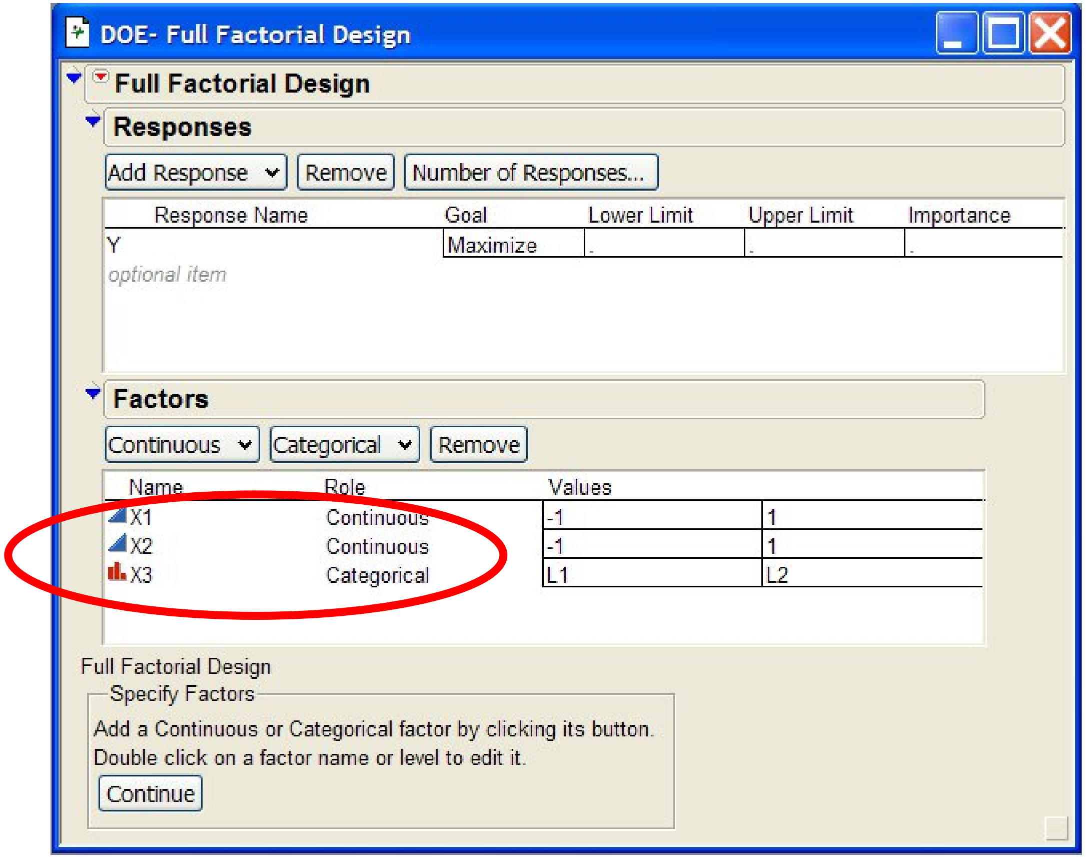
Design Matrix – Using JMP

- JMP> DOE > Classical > Full Factorial Design
  - **Continuous>2 Level**
    - Repeat the previous step (**Continuous>2 Level**)



Design Matrix – Using JMP

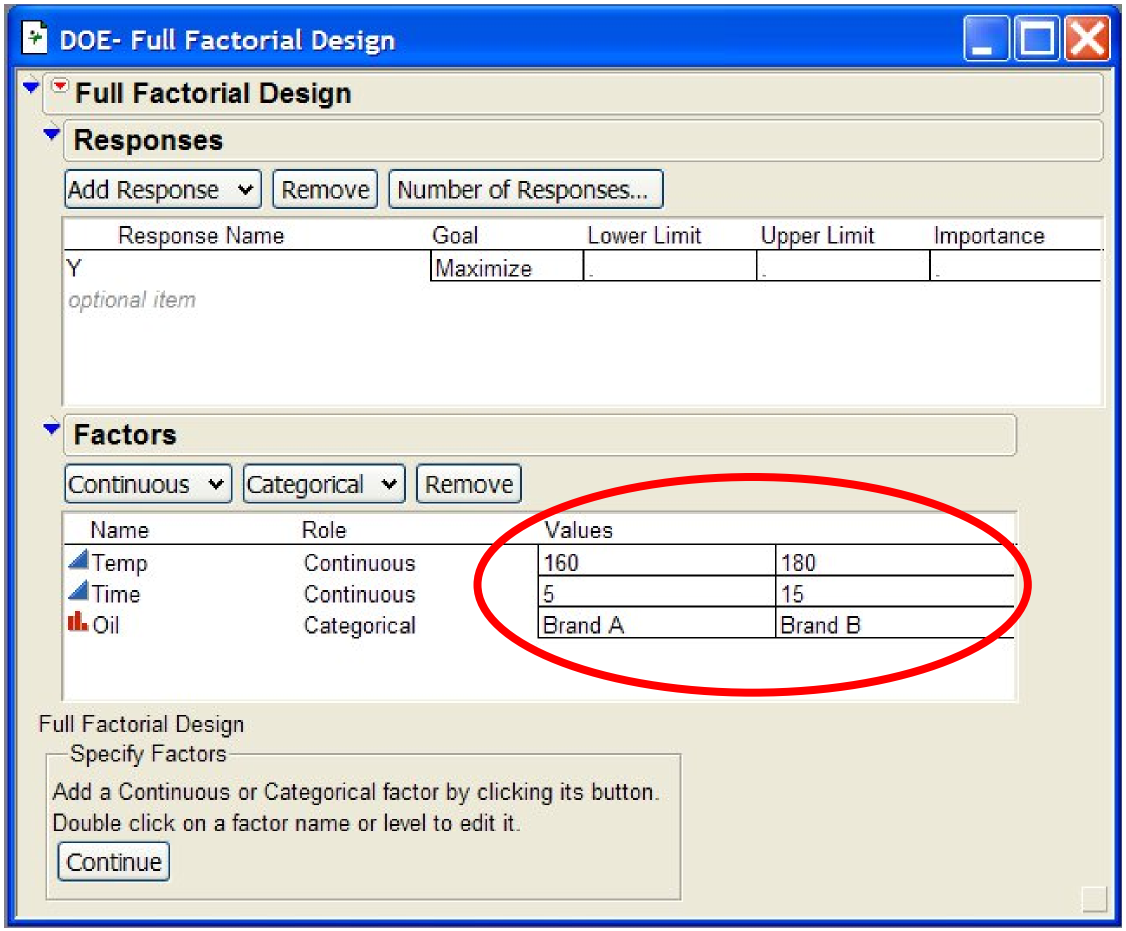
- JMP > DOE > Classical > Full Factorial Design
  - **Categorical>2 Level**



JMP DOE Design *(Cont.)*

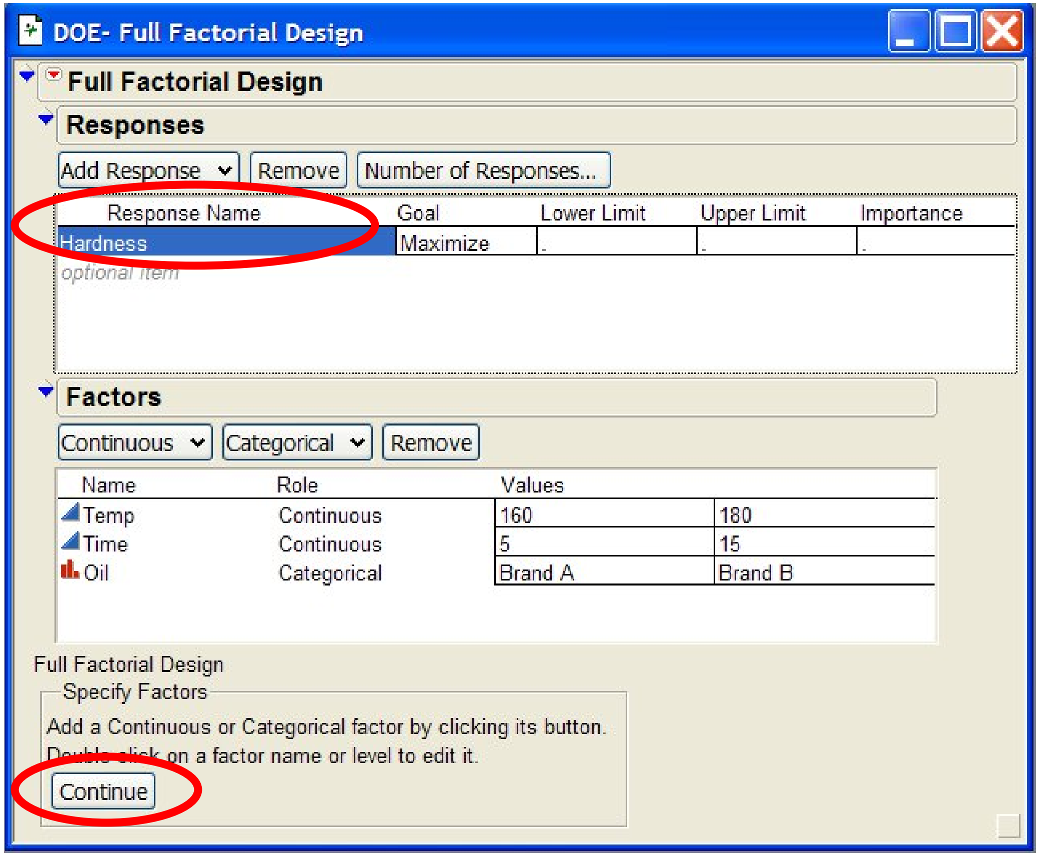
- Double-click in the Name Column to change X1, X2 and X3 to Temp, Time and Oil.
  - Quench Temp: 160° C (-1), 180° C (1)
  - Quench Time (sec): 5 (-1), 15 (1)
  - Quench Oil: Brand A (L1), Brand B (L2)
- Double-click in the Values Column to change the Temp row to 160 and 180, the Time row to 5 and 15, and the Oil row to Brand A and Brand B.

JMP DOE Design *(Cont.)*



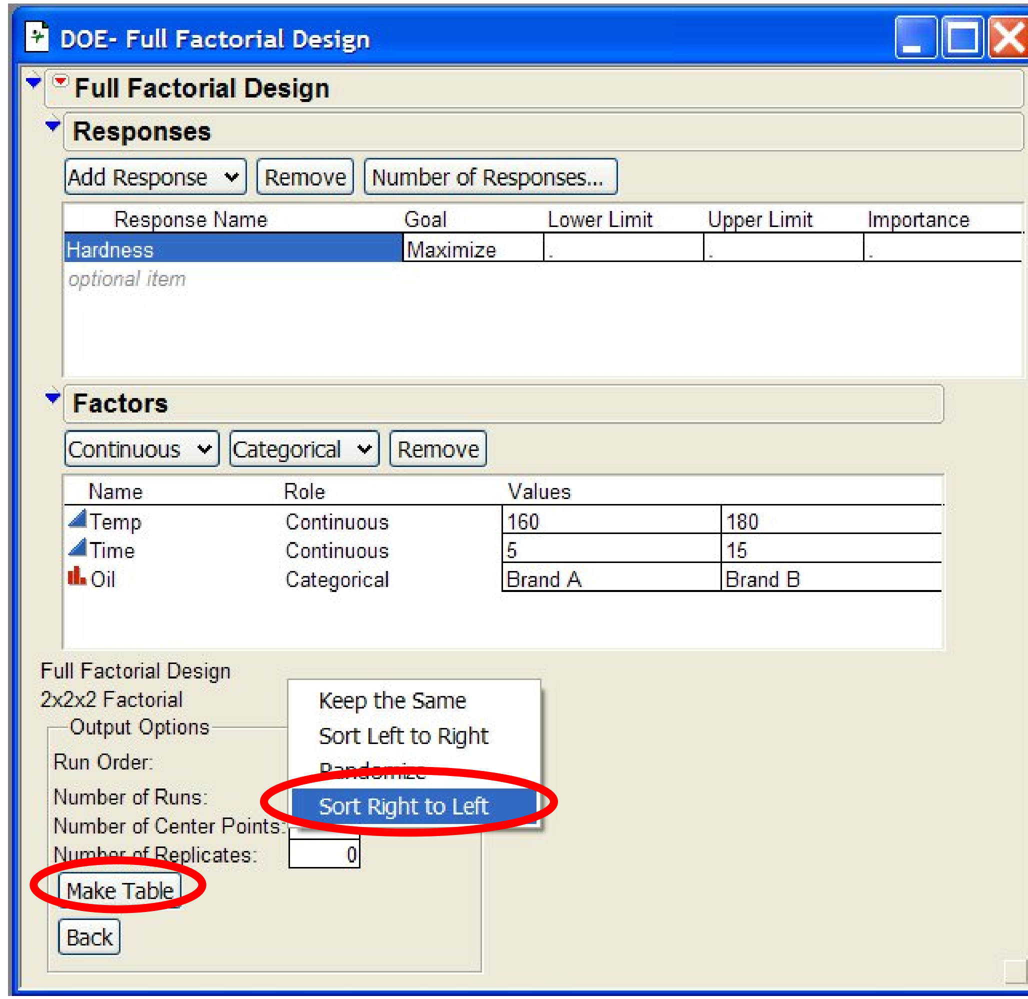
Design Matrix – Using JMP

- Enter the Response column heading.
- Enter *Hardness* as the Response Name.
- Select **Continue.**



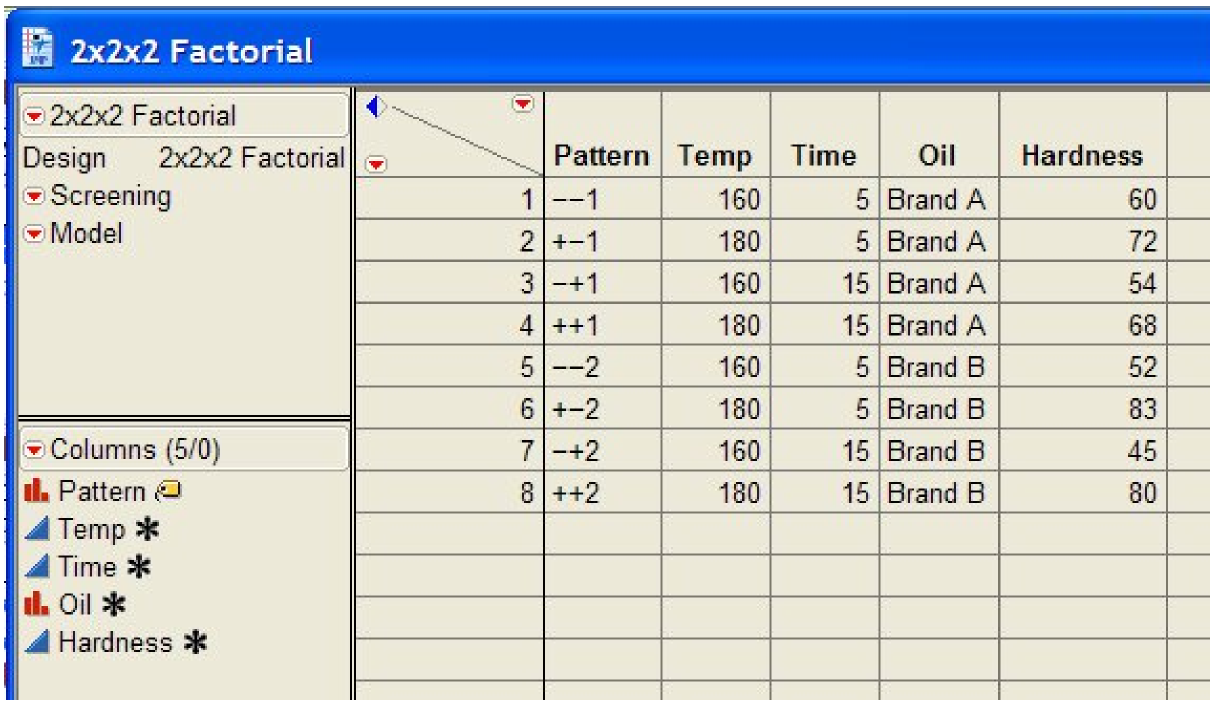
JMP DOE Design *(Cont.)*

- Number of Replicates = Number of Additional Replicates
- For this example, there are no additional replicates.
- Change **Randomize** to **Sort Right to Left** for teaching purposes.
- Click **Make Table.**



JMP DOE Design *(Cont.)*

- Use the table to enter in the Y-values.



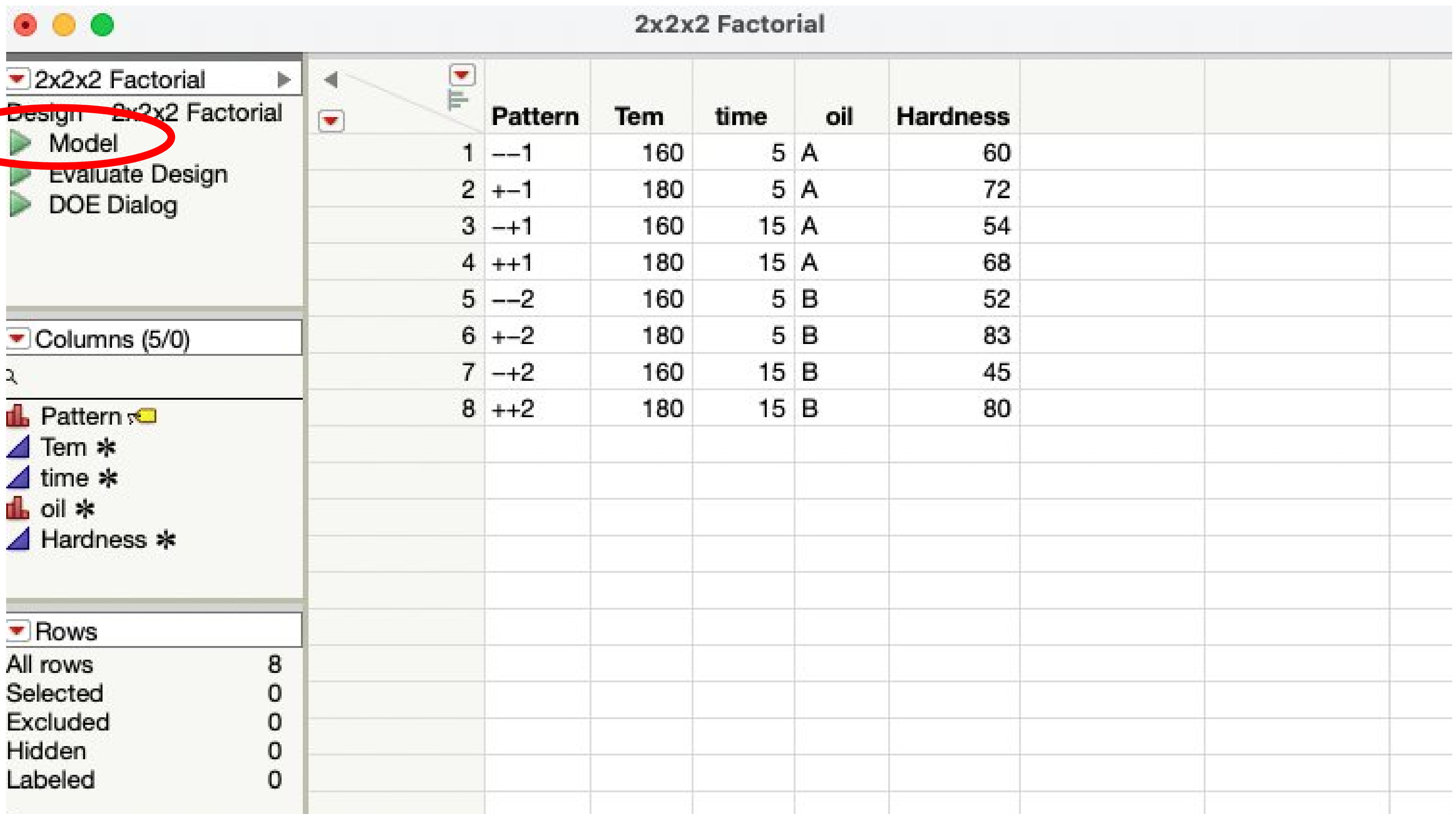
	Pattern	Temp	Time	Oil	Hardness
1	−−1	160	5	Brand A	60
2	+−1	180	5	Brand A	72
3	−+1	160	15	Brand A	54
4	++1	180	15	Brand A	68
5	−−2	160	5	Brand B	52
6	+−2	180	5	Brand B	83
7	−+2	160	15	Brand B	45
8	++2	180	15	Brand B	80

Analysis With JMP

- This experiment only has one observation per treatment combination. Therefore, we can't analyze the "full factorial" using the ANOVA procedure until we learn a few analysis tricks.
- When there is only one observation per treatment combination, we use the Normal Probability Plot or Pareto Chart to interpret which effects are likely to be significant.
- If a factor or its interaction is insignificant (the null hypothesis, effect = 0, is true), then we expect to see the effects normally distributed around a mean of zero. Any outlying effect is considered significant.

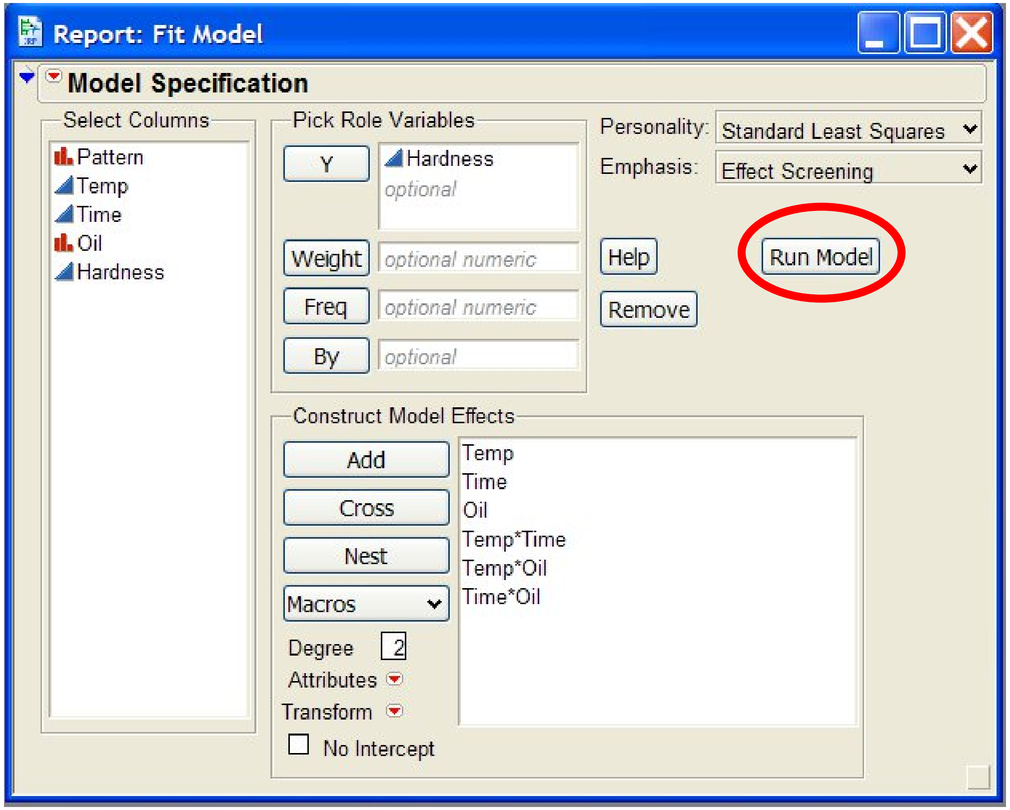
Analysis With JMP *(Cont.)*

Step 4: From the **Model**, select the **Green Triangle**



JMP Analysis *(Cont.)*

- Click **Run**



JMP Analysis *(Cont.)*

JMP Output (Use Red Triangle under Response)>
Regression Report>summary of Fit
Regression Report> Analysis of Variance

Summary of Fit

RSquare	0.99962
RSquare Adj	0.997343
Root Mean Square Error	0.707107
Mean of Response	64.25
Observations (or Sum Wgts)	8

Analysis of Variance

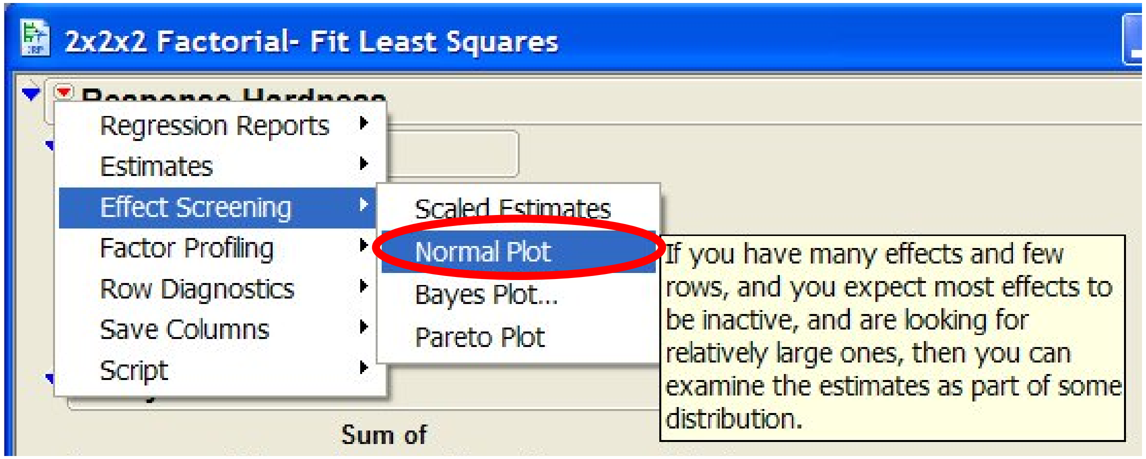
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	1317.0000	219.500	439.0000
Error	1	0.5000	0.500	Prob > F
C. Total	7	1317.5000		0.0365*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64.25	0.25	257.00	0.0025*
Temp(160,180)	11.5	0.25	46.00	0.0138*
Time(5,15)	-2.5	0.25	-10.00	0.0635
Oil[Brand A]	-0.75	0.25	-3.00	0.2048
Temp*Time	0.75	0.25	3.00	0.2048
Temp*Oil[Brand A]	-5	0.25	-20.00	0.0318*
Time*Oil[Brand A]	0	0.25	0.00	1.0000

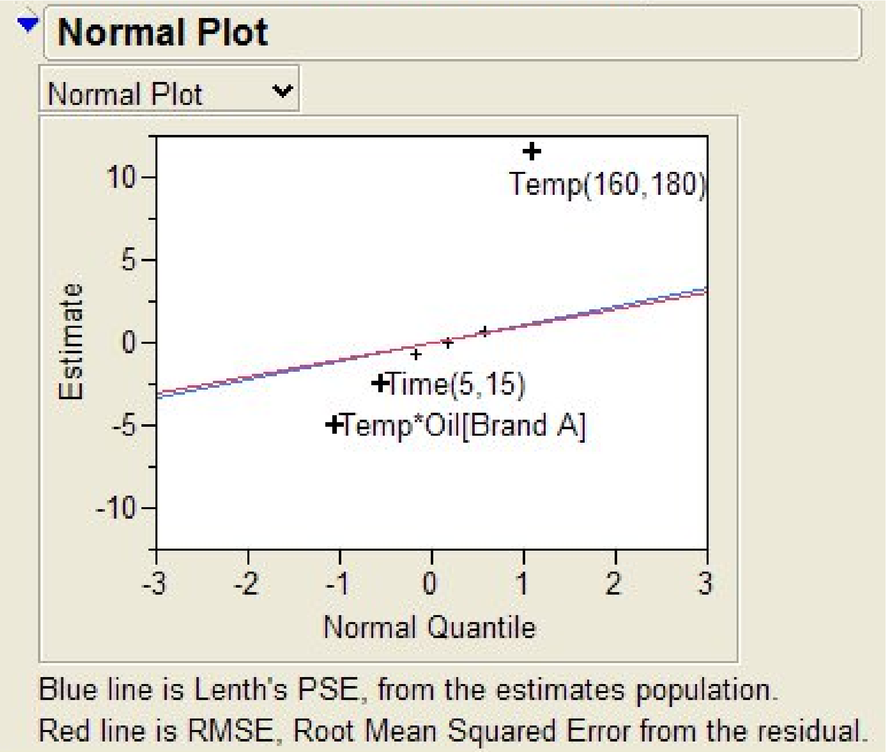
JMP Analysis *(Cont.)*

- Step 5: Identify the most significant Model Effects or **Estimates** by looking at the Normal Plot and Pareto Plot of the Estimates.



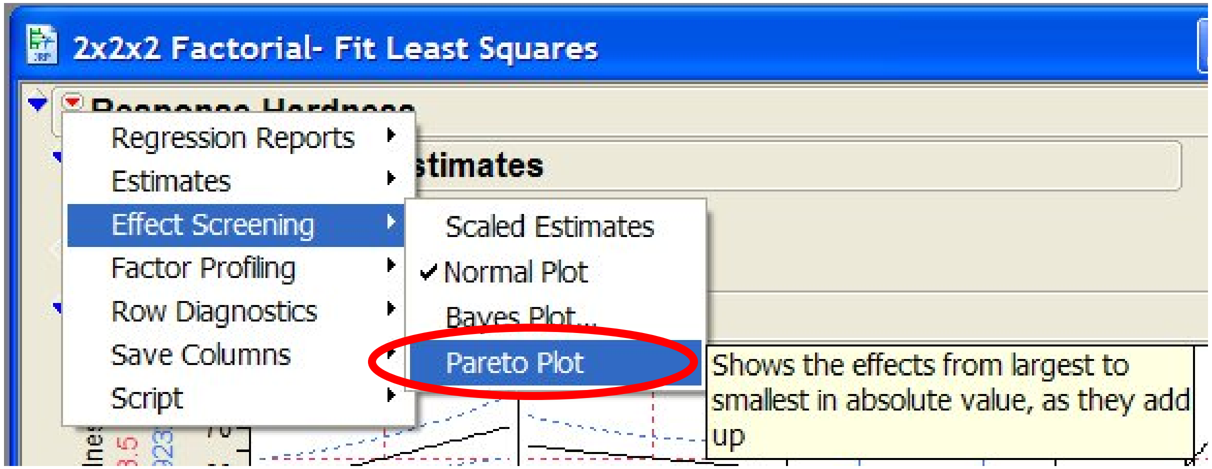
Normal Plot

- The Normal Plot shows that **Temperature, Time**, and the interaction of **Temperature and Oil** are the most significant model estimates.



Pareto Plot

- Under the **Y Response Red Triangle**, select **Effect Screening>Pareto Plot**

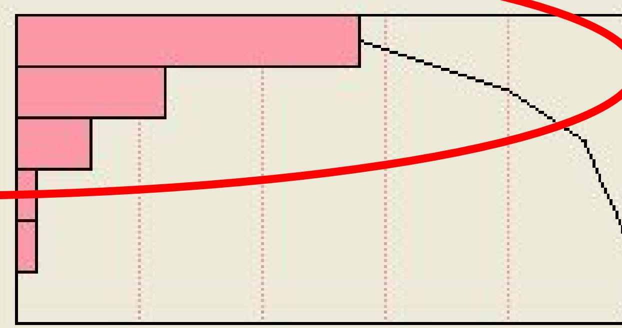


Pareto Plot

- The Pareto Plot shows that **Temperature, Time**, and the interaction of **Temperature and Oil** are the most significant model estimates.

Pareto Plot of Estimates

Term	Estimate
Temp(160,180)	11.50000
Temp*Oil[Brand A]	-5.00000
Time(5,15)	-2.50000
Oil[Brand A]	-0.75000
Temp*Time	0.75000
Time*Oil[Brand A]	0.00000

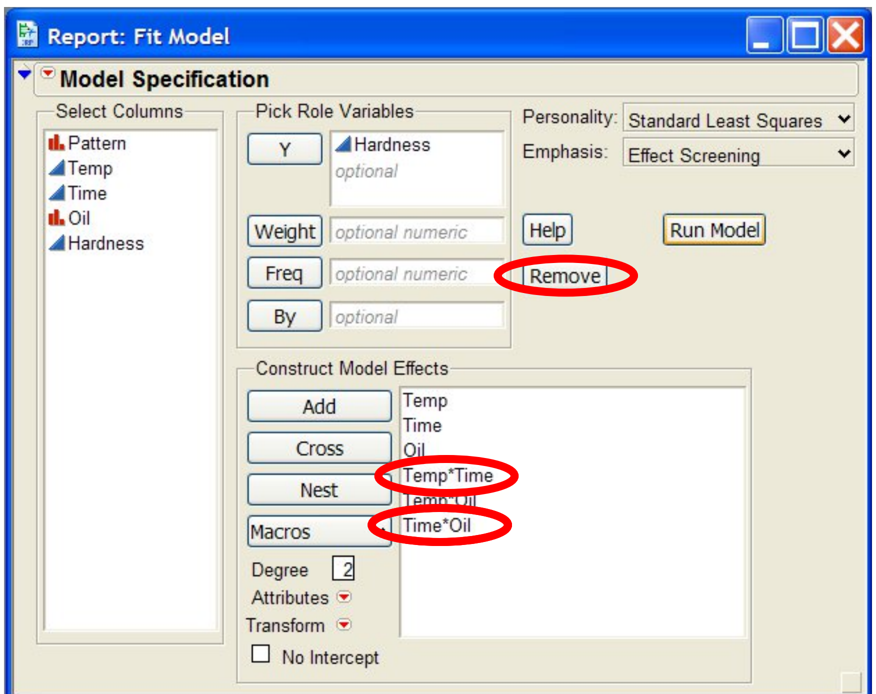


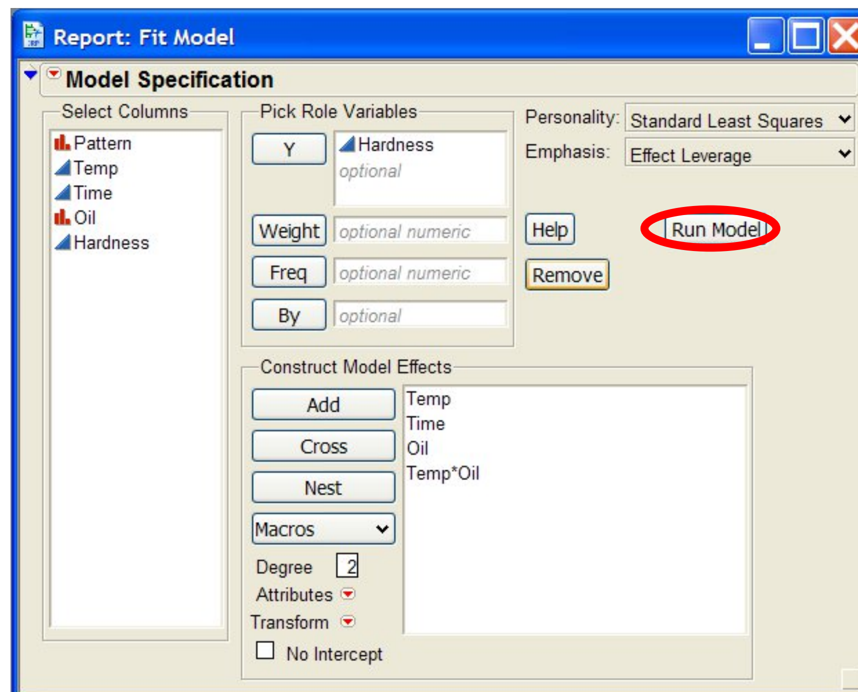
JMP Analysis *(Cont.)*

- Step 6: Reduce the Model to include the largest estimates.
- Note: If an interaction estimate is selected, then the interaction main factors must be included in the model.

JMP Analysis *(Cont.)*

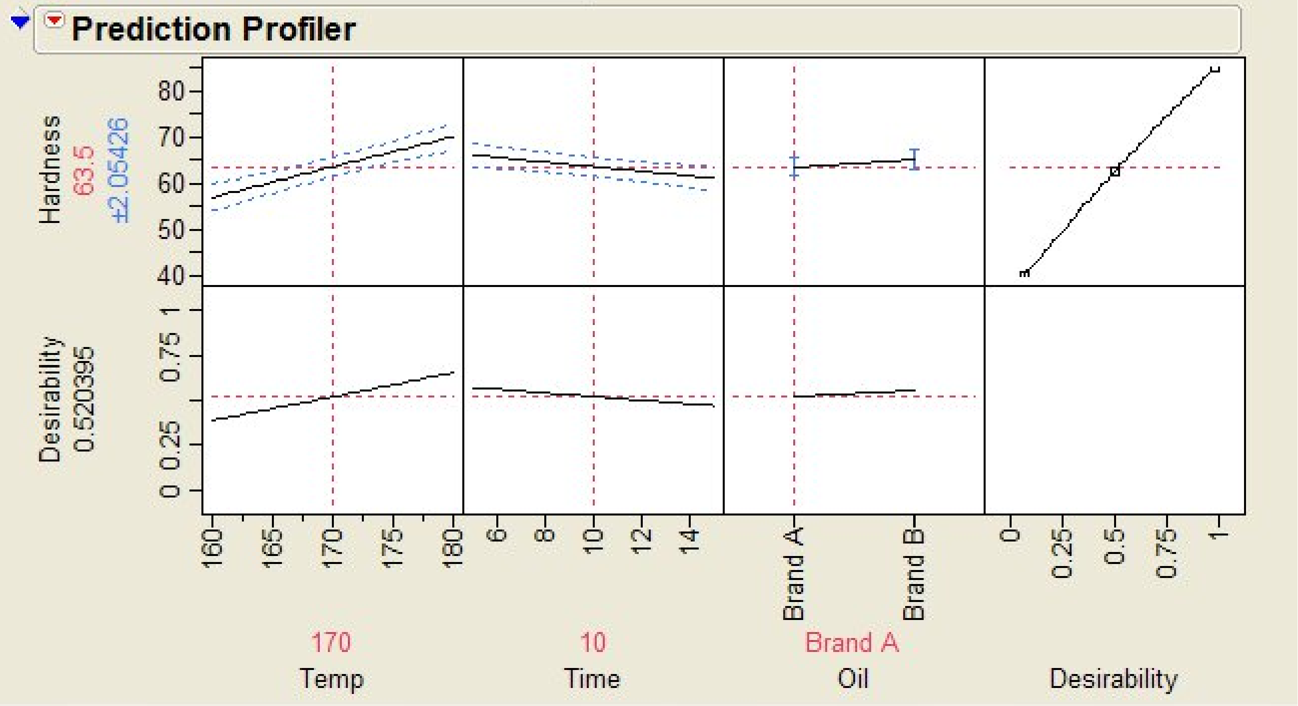
- Click-on the Fit Model Window from Analyze
- Click-on the non-significant estimates and then click-on **Remove**, and **Run Model.**





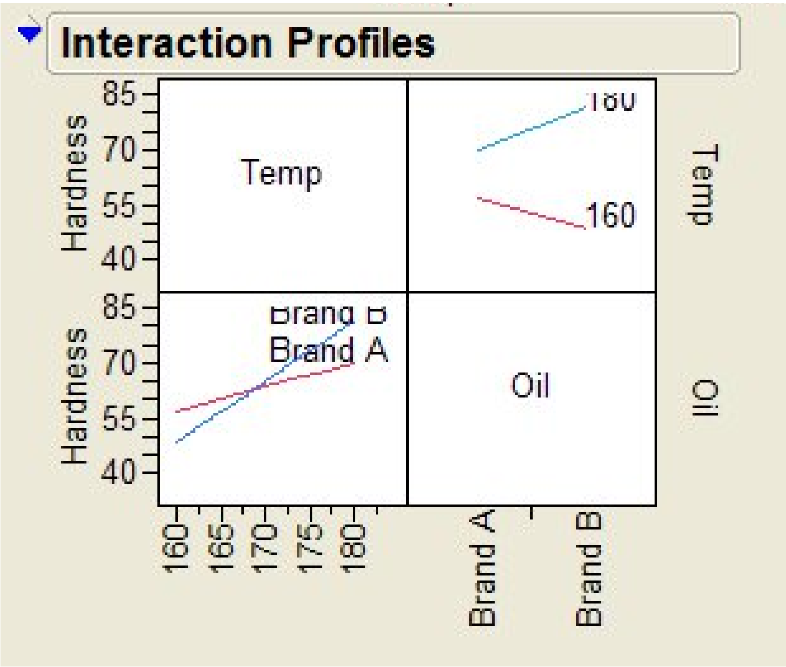
JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Profiler**



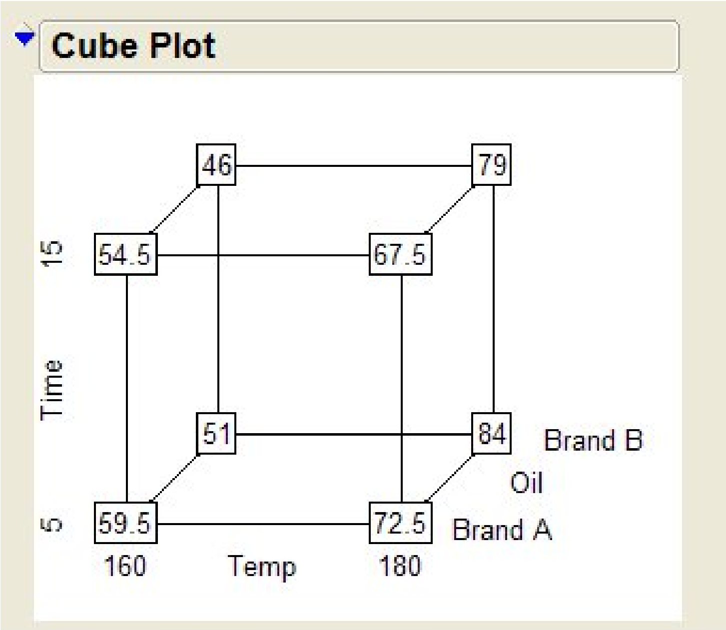
JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Interaction Plots**



JMP Analysis *(Cont.)*

- From the **Response Y Red Triangle**, select **Factor Profiling>Cube Plots**



JMP Analysis *(Cont.)*

- **Step 7: Construct a mathematical model.**

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64.25	0.456435	140.76	<.0001*
Temp(160,180)	11.5	0.456435	25.20	0.0001*
Time(5,15)	-2.5	0.456435	-5.48	0.0120*
Oil[Brand A]	-0.75	0.456435	-1.64	0.1989
Temp*Oil[Brand A]	-5	0.456435	-10.95	0.0016*

Model coefficients (coded) for Oil Brand A
Coded: Temp= -1,1 Time = -1,1