Practical Strategies for Model Verification

*Presentation is posted at www.statease.com/webinar.html

There are many attendees today! To avoid disrupting the Voice over Internet Protocol (VoIP) system, I will mute all. Please use the Questions feature on GotoWebinar. Feel free to email questions to stathelp@statease.com, which we will answer off-line.

-- Martin

Presented by Martin Bezener, PhD, Statistics
Stat-Ease, Inc., Minneapolis, MN
martin@statease.com

March 2015 Webinar
Hello!

Please click on the “raise hand” button if you can hear me!
Introduction

- Model confirmation is an important step in industrial experimentation.
- This step usually receives minimal (if any) attention in practice.
- Ignoring this step can result in a model that underperforms when used in future applications.
- This step is especially important in predictive modeling.
- Model confirmation gives the experimenter confidence that statistical results can be extrapolated to future work.
Agenda

Three major topics that will be discussed:

- **Part 1**: Model checking vs. confirmation
- **Part 2**: Some approaches to confirmation
- **Part 3**: Practical tips and tricks
Agenda

- Part 1: Model checking vs. confirmation
- Part 2: Some approaches to confirmation
- Part 3: Practical tips and tricks
Motivating Example

Typical Experimentation Sequence

1. Formulate Problem and Determine Goals
2. Design the Experiment (DOE)
3. Perform the Experiment
4. Analyze Data and Build Model
5. Check Model Assumptions
Motivating Example
The Situation

The Problem: An engineer wants to study a chemical reaction, in particular, the following three factors:

- **Time** (min): Low = 40, High = 50
- **Temperature** (deg. C): Low = 80, High = 90
- **Catalyst** (%): Low = 2, High = 3

The two response of interest are:

- **Conversion** (%)
- **Activity**

Knowledge of the relationship between the factors and the response will help him better control the chemical process.
Motivating Example
The Central Composite Design (CCD)

The design consists of **20 runs**:

- **6 Center** Points
- **8 Factorial** (or Cube) Points
- **6 Star** (or Axial) Points

12 runs were performed with one machine, 8 runs were performed using another machine. So there are **two blocks**.
### Motivating Example

**Data Analysis Results**

- We only analyze the response **Conversion** using the Design-Expert® 9 (DX9) software.
- A full quadratic model is fit to the data.
- Main effect **A** is included since **AC** is significant.
- Lack-of-fit p-value: 0.8574 – no problems here.
- **Question:** Are the statistical assumptions satisfied?

---

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block</td>
<td>64.53</td>
<td>1</td>
<td>64.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>2581.82</td>
<td>9</td>
<td>286.85</td>
<td>18.87</td>
<td>0.0001</td>
</tr>
<tr>
<td>A</td>
<td>14.44</td>
<td>1</td>
<td>14.44</td>
<td>0.66</td>
<td>0.2750</td>
</tr>
<tr>
<td>B</td>
<td>222.96</td>
<td>1</td>
<td>222.96</td>
<td>13.21</td>
<td>0.0054</td>
</tr>
<tr>
<td>C</td>
<td>525.64</td>
<td>1</td>
<td>525.64</td>
<td>31.15</td>
<td>0.0003</td>
</tr>
<tr>
<td>AB</td>
<td>36.13</td>
<td>1</td>
<td>36.13</td>
<td>2.14</td>
<td>0.1774</td>
</tr>
<tr>
<td>BC</td>
<td>120.12</td>
<td>1</td>
<td>120.12</td>
<td>7.12</td>
<td>0.0297</td>
</tr>
<tr>
<td>CI</td>
<td>51.76</td>
<td>1</td>
<td>51.76</td>
<td>3.07</td>
<td>0.1135</td>
</tr>
<tr>
<td>A2</td>
<td>119.19</td>
<td>1</td>
<td>119.19</td>
<td>7.06</td>
<td>0.0261</td>
</tr>
<tr>
<td>P</td>
<td>397.61</td>
<td>1</td>
<td>397.61</td>
<td>23.57</td>
<td>0.0009</td>
</tr>
<tr>
<td>Residual</td>
<td>151.85</td>
<td>9</td>
<td>16.87</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Pure Error** | 105.25 | 4 | 26.31
**Cor Total** | 2778.20 | 19

- Std. Dev. | 4.11 |
- Mean | 78.30 |
- C.V. % | 5.25 |
- Adj R-Squared | 0.8440 |
- Adj R-Squared | 0.8881 |
- Pred R-Squared | 0.7891 |
- PRESS | 572.20 |

---

©2015 Stat-Ease, Inc.

---

March 2015 Webinar
What are the assumptions that we must check?

- Residuals are Normally distributed.
- Residual variance is constant.
- Residuals are independent across the runs.
Check Residual Normality:

Residuals vs. Predicted

Externally Studentized Residuals

Normal % Probability

Design-Expert® Software Conversion
Color points by value of Conversion:
- 97.0
- 51.0

March 2015 Webinar

©2015 Stat-Ease, Inc.
Motivating Example
Model Checking

Check Residual Variance:

Residuals vs. Predicted

-6.00 -4.00 -2.00 0.00 2.00 4.00 6.00
97.0 51.0

Design-Expert® Software Conversion
Color points by value of Conversion:
-97.0
-51.0

Predicted
Externally Studentized Residuals

©2015 Stat-Ease, Inc.
Check Residual Autocorrelation:

![Residuals vs. Run plot]

- Design-Expert® Software
- Conversion
- Color points by value of Conversion:
  - 97.0
  - 51.0
Motivating Example
Model Checking

Check Model Accuracy:

- Design-Expert® Software
- Factor Coding: Actual
- Conversion (%)
  - Design points above predicted value
  - Design points below predicted value

- X1 = A: time
- X2 = B: temperature

- Actual Factor
- C: catalyst = 2

©2015 Stat-Ease, Inc.
Motivating Example
Model Checking

Check Model Accuracy:

- Design-Expert® Software
- Factor Coding: Actual
- Conversion (%)
  - ● Design points above predicted value
  - ● Design points below predicted value
- X1 = A: time
- X2 = B: temperature
- Actual Factor
  - C: catalyst = 2.5

©2015 Stat-Ease, Inc.

March 2015 Webinar
Motivating Example
Model Checking

Check Model Accuracy:

Predicted vs. Actual

Looks good, but...
Why is this not enough?

- The model will almost surely fit this particular data better than data collected from future replicates of the experiment.
- Therefore, assessing the goodness-of-fit of a model using only data that was used to build the model may produce over-optimistic results. Predictive accuracy of the model on new data will also generally be too optimistic.
- Model **confirmation** uses **new** data (data not used to build the model) to assess model adequacy.
- Model confirmation also gives the experimenter an idea of how well a model will predict future cases.
Model Checking vs. Confirmation

- Formulate Problem and Determine Goals
- Design the Experiment (DOE)
- Perform the Experiment
- Analyze Data and Build Model
- Check Model Assumptions
- Confirm (or Verify) the Model
**Goal**: Maximize Conversion

We’ll use the following limits during optimization:

- $40 < \text{Time} < 50$
- $80 < \text{Temp} < 90$
- $2 < \text{Catalyst} < 3$
Motivating Example
Optimization Solution

Design-Expert® Software
Factor Coding: Actual
Conversion (%)
- Design Points
  - 97.0
  - 51.0

X1 = A: time
X2 = B: temperature

Actual Factor
C: catalyst = 3

Solution:
- Time = 50
- Temp = 90
- Catalyst = 3

How do we know the solution is valid??

©2015 Stat-Ease, Inc.
Agenda

- **Part 1:** Model checking vs. confirmation
- **Part 2:** Some approaches to confirmation
  - No confirmation
  - Simple Confirmation
  - Concurrent Confirmation
- **Part 3:** Practical tips and tricks
Agenda

- **Part 1**: Model checking vs. confirmation
- **Part 2**: Some approaches to confirmation
  - No confirmation
  - Simple Confirmation
  - Concurrent Confirmation
- **Part 3**: Practical tips and tricks
No Confirmation

Do not confirm the model:

- The experimenter believes the model is valid and the result of it not being valid isn’t catastrophic.
- The work covers a non-critical process.
- The budget for experiments has been depleted.
- Physically not possible to run further experiments.
- The primary objective of the experiment is screening.

Not Recommended
Agenda

- **Part 1:** Model checking vs. confirmation
- **Part 2:** Some approaches to confirmation
  - No confirmation
  - Simple Confirmation
  - Concurrent Confirmation
- **Part 3:** Practical tips and tricks
Simple Confirmation
(Confirm with a Single Observation)

Run one observation at the optimal settings:

- The experimenter believes the model is valid.
- Being wrong is unacceptable.
- The budget and/or time is tight.
- The design doesn’t have blocks, or the block effects are small.

If the observation at the optimum is within the prediction interval, then the model has been confirmed. DX9 provides a fast and flexible way to perform model confirmation.
Simple Confirmation
Confirm with a Single Observation

Confirming results from the RSM Example:

94.02

94.02
Run several observations at the optimal settings:

- The experimenter believes the model is valid, but the risk of being wrong is unacceptable.
- The organization prefers data driven decisions rather than informed opinion.
- The budget and time allow multiple observations.
- The model has blocks.

If the average of “n” observations at the optimum is within the prediction interval, then the model has been confirmed.
Simple Confirmation
(Confirm with Multiple Observations)

Confirming results from the RSM Example using DX9:

Machine 1
(81.0, 85.3)

Machine 2
(97.2, 91.2)

88.68
Simple Confirmation
(Confirm with Multiple Observations)

What to do if there are problems?

- The model may be overfit and hence generalizes poorly to new data. Try to reduce the model. Also check to see if a transform is necessary using the Box-Cox plot.

- There may be outliers or other problematic model points in either the confirmation runs or the model-building runs. These points are not representative of the true underlying process, hence the discrepancy.

- The curse of “too much data.” Huge data sets may cause *practically irrelevant* effects and model irregularities to be detected. This is not usually an issue.
How does DX9 compute prediction intervals?

- One observation (n = 1):
  \[
  \hat{y} \pm \left( t_{\frac{\alpha}{2},df} \right) \left( s \sqrt{1 + x_0^T \left( X^T X \right)^{-1} x_0} \right)
  \]

- Many observations (n > 1):
  \[
  \hat{y} \pm \left( t_{\frac{\alpha}{2},df} \right) \left( s \sqrt{1 + x_0^T \left( X^T X \right)^{-1} x_0} \right)
  \]

- So as n increases, the width of the PI decreases.
**BIG** Question: How many confirmation runs at the optima?

The relationship between the probability of detecting an issue (if there actually is one) and the # of confirmation runs will look something like:
Simple Confirmation
(Confirm with Multiple Observations)

- Of course more is better!!
- Try to perform at the very least **two** confirmation runs at the optimal design point(s).
- The best “bang for your buck” is usually around 3 or 4 runs. Further confirmation runs will only give small, incremental improvements.
- Avoid excess confirmation runs. Those extra runs could be put to better use as model-building runs.
Agenda

- **Part 1:** Model checking vs. confirmation
- **Part 2:** Some approaches to confirmation
  - No confirmation
  - Simple Confirmation
  - Concurrent Confirmation
- **Part 3:** Practical tips and tricks
Concurrent Confirmation
Why?

Concurrent confirmation is used when it is not practical to perform confirmation after the DOE is complete:

- The DOE runs take a very long time and so will any follow-up confirmation experiments. (E.g. establishing a drug’s expiry date.)
- Time on the equipment for running for the DOE is expensive and/or time limited. (E.g. wind tunnel experiments.)
- You only have one shot at experimentation. (E.g. running a DOE on a production line.)
Concurrent confirmation is done by adding confirmation runs (aka verification runs) to the design plan.

- The verification runs are added to and randomized with the DOE runs.
- The verification runs are not used to estimate the model; only the DOE runs are used. The verification runs are essentially “held back”.
- The predicted values of the verification runs are compared to their observed values to confirm model predictions.
Drug Stability Characterization
Kinetic Study of Drug Product

How is it done?

- Store drug under varying conditions that test its stability to environmental factors; e.g. moisture, oxygen, etc.
- Takes a long time (e.g. months) to complete.

Why is it important?

- Provides information needed to establish a drug’s expiry date.
- Used to establish manufacturing and packaging strategies to ensure the drug meets its expiry date.
Three factors affecting degradation rate:

- **Factor 1** $a_w$
  
  Water activity
  
  Expect rate to increase linearly with $a_w$.

- **Factor 2** $O_2$
  
  Expect rate to increase exponentially with increasing oxygen; use logarithmic scale, $\ln(O_2)$.

- **Factor 3** Temperature
  
  Expect Arrhenius relationship of rate to temperature; use inverse temperature, $(1/T)$.
Face Centered Design (FCD) with 15 Runs

- T
- $O_2$
- $a_w$
Drug Stability Characterization
FCD Augmented with Verification Runs

- points to determine Arrhenius relationship (4 runs)
- ▲ points to evaluate predictions from core design (4 runs)
### Drug Stability Characterization

**Augmented FCD (k % per week)**

<table>
<thead>
<tr>
<th>T °C</th>
<th>O₂ %</th>
<th>aₜ</th>
<th>0.05</th>
<th>0.20</th>
<th>0.35</th>
<th>0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>0.2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>50</td>
<td>0.2</td>
<td>□</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>△</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>△</td>
</tr>
<tr>
<td>60</td>
<td>0.2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>△</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>△</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>△</td>
</tr>
<tr>
<td>70</td>
<td>0.2</td>
<td>□</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
</tbody>
</table>

- ● Factorial points
- □ Axial and center points
- △ Arrhenius points
- △ aₜ = 0.50 points

**Timelines:**

- 2 wk, 4 wk, 8 wk, 16 wk
- 1 wk, 2 wk, 4 wk, 8 wk
- 3 day, 1 wk, 2 wk, 4 wk
- 1 day, 3 day, 1 wk, 2 wk

© 2015 Stat-Ease, Inc.
TDP Formation Rate
k (% per week)

k = 0.0961

k = 0.3403

(These two rates are circled on the next slide)
### TDP Degradation Rate

**Runs to Validate Arrhenius Model**

<table>
<thead>
<tr>
<th>1/T K</th>
<th>(\ln(O_2))</th>
<th>(a_w)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05</td>
<td>0.20</td>
</tr>
<tr>
<td>0.00319336</td>
<td>-1.60944</td>
<td>0.0240</td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td></td>
</tr>
<tr>
<td>0.00309454</td>
<td>-1.60944</td>
<td>0.0961</td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td>0.1515</td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td></td>
</tr>
<tr>
<td>0.00300165</td>
<td>-1.60944</td>
<td>0.4668</td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td></td>
</tr>
<tr>
<td>0.00291418</td>
<td>-1.60944</td>
<td>1.6955</td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td></td>
</tr>
</tbody>
</table>

©2015 Stat-Ease, Inc.
TDP Degradation Rate
Arrhenius Model is Valid!

Arrhenius Model Verification

\[ R_{adj}^2 = 0.9980 \]

\[ R_{adj}^2 = 0.9966 \]

0.2% O₂

\( a_w = 0.05 \)

\( a_w = 0.35 \)
# TDP Degradation Rate

**k (%) per week**

<table>
<thead>
<tr>
<th>1/T K</th>
<th>ln(O₂)</th>
<th>aₜₐₜₜ</th>
<th>0.05</th>
<th>0.20</th>
<th>0.35</th>
<th>0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00319336</td>
<td>-1.60944</td>
<td>0.0240</td>
<td>0.0511</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td>0.0355</td>
<td>0.0911</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td>0.0716</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.00309454</td>
<td>-1.60944</td>
<td>0.0961</td>
<td>0.1735</td>
<td>0.3403</td>
<td>0.5100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td>0.2157</td>
<td>0.3535</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td>0.4870</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.00300165</td>
<td>-1.60944</td>
<td>0.4668</td>
<td>1.4113</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td>0.9240</td>
<td>2.5575</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td>1.7318</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.00291418</td>
<td>-1.60944</td>
<td>1.6955</td>
<td>6.0500</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.69315</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.04452</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The verification runs are added to and randomized with the DOE runs.

The verification runs are not used to estimate the model; only the DOE runs are used.

The predicted values of the verification runs are compared to their observed values to confirm model predictions.
TDP Degradation Rate
ANOVA from FCD *(without validation runs)*

Transform: Natural log

ANOVA for Response Surface Linear Model

Analysis of variance table [Partial sum of squares - Type III]

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F Value</th>
<th>p-value Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>27.59</td>
<td>3</td>
<td>9.20</td>
<td>847.40</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>A-aw</td>
<td>2.37</td>
<td>1</td>
<td>2.37</td>
<td>218.38</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>B-ln(O2)</td>
<td>0.11</td>
<td>1</td>
<td>0.11</td>
<td>10.36</td>
<td>0.0082</td>
</tr>
<tr>
<td>C-1/T</td>
<td>25.10</td>
<td>1</td>
<td>25.10</td>
<td>2313.46</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Residual</td>
<td>0.12</td>
<td>11</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cor Total</td>
<td>27.71</td>
<td>14</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Std. Dev. 0.10  R-Squared 0.9957
Mean -1.64 Adj R-Squared 0.9945
C.V. % 6.36 Pred R-Squared 0.9918
PRESS 0.23 Adeq Precision 80.940
Looking at the verification runs on the diagnostic plots we see they fall in line with DOE runs.

Model is confirmed!
Confirmation Strategies Summary

Confirming model predictions:

- **No confirmation**
  - Not a recommended strategy.

- **Simple confirmation**
  - Single observation is better than no confirmation.
  - Multiple observations is better yet.

- **Concurrent confirmation**
  - A great strategy when it isn’t practical to follow-up a completed DOE with additional observations.
Agenda

- **Part 1**: Model checking vs. confirmation
- **Part 2**: Some approaches to confirmation
- **Part 3**: Practical tips and tricks
Pitfall: Avoid using $R^2$ as a way of “confirming” your model!

- $R^2$ cannot decrease when adding terms to a model, even if the terms are completely independent of the response.
- Hence, $R^2$ will always suggest choosing a larger model – danger of over-fitting!!
- Some processes naturally produce noisy, hard-to-measure responses. Even great models can have low $R^2$.
- Predicted $R^2$ is a better option. It gives some degree of model confirmation.
Tip: Always use subject matter knowledge!

- If subject-matter knowledge doesn’t suggest that a model should work in practice, reconsider your model!
- Model confirmation may suggest that a model is adequate or inadequate, but it doesn’t tell you why that’s the case.
Tip: When in doubt, choose the smaller model!

- Confirmation runs point to evidence of an over or under-fit model.

- When several models appear to fit the data well, and are confirmed with future runs, it’s usually (but not always) better to select the simpler model.
Tip: Focus on confirmation techniques that use external data!

- Predicted $R^2$ and PRESS statistic give an idea of how well a model will predict future responses.

- Use confirmation runs to verify the predicted response(s) at locations of interest (e.g. minima or maxima) in the design space.

- Future versions of Design-Expert will likely include new techniques for out-of-sample confirmation.
Tip: How to handle blocks?

- Perform the confirmation runs at many different blocks – assuming you can repeat at the same blocks used in the model!! Block effects will average out in the confirmation runs.

- If you can only perform one confirmation run, look at the ANOVA and choose the block with the lowest effect. Run the confirmation run at that block – again, assuming you actually can repeat a run at the block.

- Not much can be done if a block is not repeatable (e.g. year).
How to Get Help

- In Stat-Ease software press for Screen Tips, view reports in annotated mode, look for context-sensitive Help (right-click) or search the main Help system.
- Explore the Stat-Ease Experiment Design Forum http://forum.statease.com (read only).
- E-mail stathelp@statease.com for answers from Stat-Ease’s staff of statistical consultants.
- Call 612.378.9449 and ask for “statistical help.”
Support for DOE

- The triannual *Stat-Teaser* newsletter (if you don’t opt out)
- Bi-Monthly *DOE FAQ Alert* e-mail (if you don’t opt out)
  - Subscribe at: [www.statease.com/doealertreg.html](http://www.statease.com/doealertreg.html).
- StatsMadeEasy blog at [www.statsmadeeasy.net](http://www.statsmadeeasy.net).
Thank you all for joining us today!

As a reminder, this presentation is posted at:
www.statease.com/webinar.html
References


