
TaylorFit

RESPONSE SURFACE ANALYSIS (RSA)



using
STEPWISE MULTIVARIATE POLYNOMIAL REGRESSION
(MPR)

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What is TaylorFit?

TaylorFit is a regression program that makes it easy to generate relatively simple equations to describe complex data. By “complex,” we mean data that have nonlinear relationships, including interactions among multiple variables. This even extends to describing processes that have the behavior known as “chaotic.”

The TaylorFit application works entirely client-side in your browser, so there's no need to download or install anything and no need to create an account. You can run the application simply by going to www.TaylorFit-RSA.com.

Examples of situations that can be modeled with TaylorFit can be found everywhere – in business, engineering, and the sciences. One simple way to think of its applicability is to envision any situation with numerical information that can be collected into a Table or spreadsheet with two or more columns of data, and with one column expected to depend upon the values in the other columns. Each row can be considered a distinct set of measurements repeated to form the set of rows. If the data in the rows were collected at fixed time intervals (e.g. daily or annual data), then the dataset is called a *time-series*. Some specific examples of datasets are:

- A company has a set of retail outlets. For each, they collected a dozen statistics that they think can predict the profitability. The statistics include each store's local market share, how long it has been there, how many years of experience the salespersons have, etc. The spreadsheet has data for each individual store in one row; the profitability of the store is in the first column, and the other statistics in other columns. They wish to predict the profitability in column one using the statistics in the other columns.
- Engineers would like a formula to predict the strength of concrete based on the recipe used to make it. They collect data on strength together with the pounds of water added per pound of cement, the amount of sand added, the amount of coarse aggregate, as well as the amount of several other additives.
- Agricultural scientists need to understand what affects the yield of a specific crop in their area. For example, they may have data from many farmers on the number of bushels of corn they produced per acre. Each farmer used different amounts of irrigation and fertilizer. The spreadsheet will have yield in one column, and irrigation and fertilizer amounts in others.
- Social scientists seek to develop a model to predict how an individual's income in a specific age bracket depends on a variety of socio-demographic factors. They collect income data, together with information on education level, the education level of individual's parents, the income of the parents, etc.
- *Time-series example:* A company has data on annual sales and advertising for a period of 54 years. Do sales in one year depend upon sales and advertising for previous years?

You can model any numerical data that can be collected into a Table or spreadsheet with two or more columns of data, where one column depends upon the others

TaylorFit Modeling approach

The type of models TaylorFit generates are called Multivariate Polynomial Regression (*MPR*) Models. These are extensions of the basic polynomial equations that are familiar from basic algebra, extended to multivariable data. A formal mathematical description of *MPR* is provided in a later chapter of this manual.

Consider the example above of agricultural crop yield (Y), which depends upon the amount of irrigation water (W) and fertilizer application (F). One of the best known approaches for this problem is Multilinear Regression (*MLR*). TaylorFit is an extension of *MLR* to include interactions and other nonlinearity. The *MLR* model for this case would be:

$$Y = a + b \cdot W + c \cdot F$$

This model has coefficients a , b , and c . The value of b indicates how much Y increases as W is increased. However, what if the effect of irrigation on yield depends upon how much fertilizer has been applied? This is an example of an *interaction*, and a *MLR* model cannot describe it. However, if we add a term $d \cdot W \cdot F$, the resulting model is capable of describing interactions:

$$Y = a + b \cdot W + c \cdot F + d \cdot W \cdot F$$

A further problem may be that yield increases with W and with F , but only up to a point. Then it saturates, or levels out. Plus, how fast yield saturates with irrigation may interact with fertilizer. The following model describes such a situation.

$$Y = 0.5 + 1.0 \cdot W + 1.0 \cdot W^2 + 0.2 \cdot F^2 - 3.5 \cdot W^2 \cdot F$$

If this looks complicated, consider that one should let the data determine the form and complexity of the model, not the other way around. If your data have such behaviors and you do not include them, then your model will be biased.

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TaylorFit gets its name from the Taylor Theorem, which proves that any functional relationship can be described by a polynomial series equation. The Taylor polynomial may have an infinite number of terms. However, it can also be proven that an arbitrary degree of accuracy can be achieved by truncating the Taylor polynomial to a finite number of terms. The models developed by *TaylorFit* can be viewed as truncated Taylor polynomials.

The previous equation is an example of a Multivariate Polynomial Regression (*MPR*) model. Things could be even more complicated. What if the behavior depended upon the *ratio* of two variables? This is a common situation. *MLR* cannot describe any such behaviors. Including negative exponents enables TaylorFit to test for the fit of ratios. This can make models more compact. For example, we could fit models that look like this:

$$Y = 0.5 + 1.0 \cdot W + 1.0 \cdot W^2 - 3.5 \cdot W^2 \cdot F + 2.5 \cdot W \cdot F^{-1} - 0.5 \cdot W^{-2} \cdot F$$

The problem with *MPR* models is that the number of possible terms may become very large, and it can be difficult to select which are important and which are not. *TaylorFit* solves this problem by using stepwise regression and cross-correlation. For more details explaining what *MPR* is, see the *MPR* Primer at <http://www.simetrica-llc.com/Products/MPR/modeling.html> or watch the 23-minute video at <https://www.youtube.com/watch?v=bLOXW5LR8-Y>.

How TaylorFit Works

TaylorFit uses a stepwise algorithm to select the best terms to include in the model, while keeping the model small by excluding terms that do not improve the fit. Fitting is done by least squares using the Singular Value Decomposition (SVD) method, which prevents roundoff problems (caused by multicollinearity) often found in multiple regression.

The user selects exponents that the program can use in generating candidate polynomial terms, as well as the possible number of multiplicands in each term. If the model to be fitted is a time series, the user can input the lags to be used in generating terms. These “fitting parameters” can all be changed during the fitting process. Candidate terms are picked one-at-a-time to be added to the current model if the added term improves the model. This allows the user to start with simpler models, and gradually increase model complexity until the fit can no longer be improved.

Goodness-of-Fit statistics

TaylorFit computes the coefficient for each term and a number of statistics used for building and evaluating the model. These include the following statistics associated with individual terms, either candidate terms or terms in the current model: the *t*-statistic, and the probability of erroneously concluding that the coefficient is not zero, $p(t)$. There are also a number of *Data* statistics: n_d , n_p , df , and *TSS*. Finally, there are the *Goodness-of-Fit (GoF)* statistics based on the overall fit of the model to the data. Any of the *GoF* statistics may be used as fitting criteria. These include:

<i>SSE</i> :	Sum of squares of the model errors (aka residuals)
<i>MSE</i> :	Mean square error; this is an estimate of the residuals sample variance
<i>Skew</i> :	A measure of skewness, or asymmetrical distribution of the residuals
<i>Excess Kurtosis</i> :	Kurtosis minus 3.0. This is a shape factor that describes a deviation of the residuals distribution relative to the “normal” distribution.
<i>RSQ</i> :	R^2 , the square of the multiple correlation coefficient
<i>Adj-RSQ</i> :	Adjusted R^2 – similar to R^2 , but with a penalty for model complexity (the number of terms)
<i>AIC</i> :	Akaike Information Criterion
<i>BIC</i> :	Bayesian Information Criterion
<i>Max Err </i> :	Maximum of the absolute values of the errors; used for minimax optimization
<i>F</i> :	The <i>F</i> -statistic; similar to the <i>t</i> -statistic for a term, but indicates the fit of the overall model, rather than of a particular term
$p(F)$:	The probability of <i>F</i> being this large or larger by chance

The formal mathematical definitions of these values are given in a chapter below.

Fitting parameters

The user begins by defining the fitting parameters. These include the set of exponents EXP , the maximum number of multiplicands in a single term (N_m), and (if the dataset is a time-series) the set of lags to consider $\{lag\}$. An intercept term is always considered, although the modeler does not have to select it into the current model. (In fact, the model will always initialize with only an intercept. If the modeler wishes, it may be removed.)

For example, in the simplest case, if $EXP = \{1\}$ and $N_m = 1$, then *TaylorFit* will only create a MLR model. If $EXP = \{1, 2, 3\}$ and $N_m = 1$, then univariate polynomial terms up to degree 3 are considered. If $EXP = \{1, 2, 3\}$ and $N_m = 2$, then multivariate polynomial terms such as (from the example) $W \cdot F^2$ or $W^3 \cdot F^2$ are also considered. Once the set of exponents and lags and the maximum number of multiplicands are selected, *TaylorFit* generates all the possible terms and tests all the models consisting of the current model with each of the candidate terms not in the current model, one-at-a-time. It also tests the current model with each current term removed, one-at-a-time.

Stepwise regression

Stepwise regression consists of alternated addition and removal steps. In the **addition step**, candidate terms are tested to see if they improve the model and sorted based on the selected goodness-of-fit criterion. The user may then choose to add one of the terms into the current model; usually one that improves the fitting criteria or that has a probability $p(t)$ that meets the selection criteria (usually being less than 5%). In the **removal step**, the terms in the current model are tested one-at-a-time to see if the criterion can be improved by removing any single term. (Sometimes, a term that was significant early in the modeling process becomes insignificant at a later point and should be removed.) The addition and removal steps are alternated repeatedly until the model criterion cannot be improved by the addition or removal of any single term. At this point, the modeler may choose to extend the search by adding to the list of exponents, lags, or to increase N_m . Or, if the model is satisfactory, the user can stop at this point.

Data are expensive,
calculations are cheap.

Data Files

The data for *TaylorFit* will generally be in a tabular format, such as in an *Excel* spreadsheet, but saved as a "comma separated variable (CSV)" format. Each column in the table represents a variable, and each row is a single measurement or instance of all the variables. As a rule of thumb, there should be at least six to ten times as many rows as columns. But the more rows there are, the more complexity it may be possible to discover in the data.

TaylorFit can divide the datafile into up to three partitions. These are termed the "Fit", the "Cross", and the "Validation" sub-datasets, and each has a different purpose.

The **FIT sub-dataset** is used to compute statistics associated with individual terms, such as the term's coefficient, its t -statistic, and its probability $p(t)$. A model can be built using the *FIT* sub-dataset alone, although incorporating the others has important advantages.

The **CROSS sub-dataset** is used for a technique called **cross-validation**. In cross-validation, the model coefficients are still computed using the *FIT* dataset, but terms are chosen to add to the current model only if they improve the selected global model criterion for the *CROSS* dataset, and the $p(t)$ for the chosen term meets the chosen (usually 5%) significance level requirement. Cross validation is optional but is recommended whenever enough data are available. It helps eliminate problems such as overfitting or spurious correlation (discussed below).

The **VALIDATE sub-dataset** should be used only after the best model has been produced using the *FIT* and *CROSS* data and the model has been finalized for use in making predictions. Then, the model is used to compute the global statistics using the *VALIDATE* data. If the resulting statistics show the model is good, then the modeler's work is done. If not, the temptation to add or remove further terms should be avoided, unless additional data will be collected for further validation. Final validation should never be done using the same dataset as was used to generate the model.

The ALL dataset: This would be the dataset that the *FIT*, *CROSS*, and *VALIDATE* data sets were drawn from. This dataset will be used to update the model coefficients after the model is built and validated.

In some cases, the model is not intended for use in making predictions outside the dataset used to generate the model. For example, it may only be intended to discover correlations; i.e. to identify trends or functional relationships among variables. (In other words, to answer the question, "how does Y depend on X , Z , etc. in these data?") In such a case, validation is not necessary. However, it is always a good idea to use cross-validation, if possible.

If there are not enough data for final validation or for cross-validation, then the modeler should consider using more conservative fitting criteria. For example, the user might add terms only to the model only if the $p(t)$ or $p(F)$ is less than 1%, instead of 5% (i.e. $\alpha = 0.01$ instead of 0.05).

TaylorFit can generate a number of **output files** including a model description file and a data file. The data file contains the original data plus the model predictions and residual errors. The current model can be exported as code in *Javascript*, *Excel*, *C++*, *Matlab*, *Python* or *R* formats. The graphs can be downloaded as PNG files.

Comparison with other modeling methods

There are many other ways to model data such as described above. Here are several that are most similar in their applicability, with a comparison.

Multilinear Regression (MLR)

As described above, MLR is a widely understood methodology. Since TaylorFit response surface analysis (RSA) with stepwise multivariate polynomial regression (MPR) is a natural extension of MLR, it is a good fit for researchers who have used MLR. By changing to RSA with MPR, they will gain the following advantages:

- More accurate models
- Reduced bias
- Ability to describe complex behaviors such as interactions and other kinds of nonlinearity

Data are expensive, calculations are cheap. Since there is a large body of research data that have been analyzed using MLR, we suggest that anyone who has used MLR in the past should consider re-analyzing their data using TaylorFit, to try to glean new knowledge from those data.

Artificial Neural Networks (ANNs)

ANNs are a powerful and increasingly popular modeling technique that is often described as a form of “artificial intelligence.” It can be thought of as having layers of functions as complex as MPR models between the multiple inputs (independent variables) and the output (the dependent variable).

ANNs typically have complex structures with a very large number of adjustable coefficients. This makes them susceptible to overfitting (also known as “memorizing the noise”). It also makes an ANN model difficult to communicate to others. You can’t write it down as a closed-form equation, like you can with a multivariate polynomial. It is common for researchers who produce ANN models to describe how well it worked. But they don’t print the form of the model for others to use. Because the ANN model cannot be easily expressed in mathematical form, it is difficult to perform standard kinds of analysis, such as computing derivatives for sensitivity analysis. You cannot provide the model to someone so they could compute it in the cell of a spreadsheet. Essentially, ANN models can provide predictions, but little other information about the behavior of the system being modeled. For these reasons, ANNs may be called “the blackest of the black box models.”

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Another characteristic of ANNs is that they may require a large number of iterative computations to obtain reasonable estimates of the model coefficients. ANNs iterate and converge more and more slowly and must be stopped by an arbitrary criterion. Since, as mentioned above, calculations are cheap, this is not a very serious problem. In fact, the computational intensity of ANNs is part of what inspired the development of TaylorFit. Once users were liberated from the constraint to keep the number of computations small, the large number of computations that may occur in TaylorFit were not perceived as a problem. Despite

this, TaylorFit tends to be computationally faster than ANNs, and it converges without an arbitrary stopping criterion.

To summarize the advantages of *TaylorFit* over ANNs:

- *TaylorFit* converges absolutely. That is, iterations ultimately reach a conclusion without an arbitrary stopping criterion.
- The *TaylorFit* S-RSA models are much easier to manipulate than ANNs. That is, they are relatively simple functional relationships (like MLR models), and so are easy to communicate and use in other programs such as spreadsheets, or to analyze, such as by differentiation or by graphical means.
- *TaylorFit* models are much more resistant to over-fitting than ANNs (especially if cross-validation is used), since every term in the model is forced to be statistically significant. It's common in ANNs for many of its coefficients to not be significant.
- *TaylorFit* models are parsimonious. This means they are compact and capture the behavior using a relatively small number of coefficients.

In short, *TaylorFit* RSA models are comparatively tractable, transparent, transferable, and simple – better!

Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is like, but different from, the response surface analysis with stepwise multivariate polynomial regression (*RSA-MPR*) that TaylorFit implements. *RSM* and *TaylorFit* both can produce multivariate polynomial models of data. The major difference is that *RSM* is a *Design of Experiment* methodology, in which the independent variables are fixed by the experimenter before conducting the experiment. On the other hand, TaylorFit is most appropriate for “natural experiments,” in which data are collected as they occur, without being selected by the experimenter. For example, data collected from the field are often of this type. But laboratory data in which variables are randomized may be of this sort.

In short, *Response Surface Methodology* is a Design-of-Experiment approach for developing data, while *Response Surface Analysis* is an approach for turning data into models. If the data have not been generated yet, and the experimenter can control the independent variables, and needs to know the best combination of independent variables to use, *RSM* is the way to go. If the data are “field” or “found” data, then TaylorFit S-RSA is the best way to explore and model the data.

TaylorFit RSA models are comparatively tractable, transparent, transferable, accurate and simple – better!

Because of the cost of controlled experimentation, *RSM* is usually limited to relatively small datasets, and the resulting polynomials are low-order polynomials. In fact, the references describing *RSM* never give examples of high-order polynomial models. *RSM* literature also does not give examples of models using exponents other than positive integers. Thus, the *RSM* approach does not evaluate the possibility of ratios or other negative exponent terms, or even higher-order polynomials. If the underlying response includes ratios or some other polynomial relationship, *RSM* will produce misspecified models. *TaylorFit* can fit data produced by *RSM*; however, it does not guide the user in choosing experimental conditions.

Quick Start for Developing a TaylorFit Model

The following is a brief summary of the seven steps for developing a *TaylorFit* Model:

1 – Data Wrangling

Before using *TaylorFit*, you should do some initial data conditioning or cleanup, also known as data wrangling. This involves checking for problems such as:

- Missing data
- Outliers
- Influential points

When complete, the data should be saved in a comma-separated-value (CSV) Table.

It may be necessary to make various transformations of the data, such as by differencing or taking logarithms. Although this can be done externally before producing the CSV file, *TaylorFit* has built-in functions to do this.

It is also a good idea to examine the data before beginning the modeling exercise, in order to become generally familiar with its behavior. This can be done by examining the numerical data itself, summary statistics of the data, or by performing some preliminary graphical analysis. *TaylorFit* can help with graphical analysis by making it easy to generate X-Y plots or histograms of the data.

2 – Starting TaylorFit

TaylorFit is launched from your web browser at www.TaylorFit-RSA.com. The Start Window shows several buttons, including: Import Data and Open Users' Manual (this document).

3 – Entering the data into TaylorFit

Start by selecting "Import Data." A file directory box will open where you can select a CSV file with your data. Choose the row numbers or percentages to be partitioned into the *FIT*, *CROSS* (for cross-validation), or (Final) *VALIDATE* datasets. These will all be from the same CSV file. For example, you may select 40% FIT, 40% CROSS, and 20% Validate. If you have very few data, you may select 100% FIT and 0% for the others. A fourth file containing *ALL* data should be maintained as well.

4 – Selecting Model Fitting Parameters

Once you select to import data or a project, you will note that the window displays three panes, each of which expands when you move the cursor over it: The *Data Pane* at the bottom left, the *Results Pane* at the top left, and the *Candidate Terms Table* at upper right. The *Results Pane* shows three items. From left to right it includes: The *Current Model Table*; the *Global Statistics Table*; and a *Residuals Plot* showing model residual errors versus predicted values of the dependent variable. At the upper right you will see a button for *Settings*.

During model building, the user can select the model fitting parameters, which are found after clicking the *Settings* button, and include the following pieces of information:

- The set of possible exponents, $EXP = \{e_1, e_2, \dots\}$
- The maximum number of multiplicands, N_m
- The set of possible lag values (if the dataset is a time-series), $LAGS = \{lag_1, lag_2, \dots\}$
- The goodness-of-fit criteria to be displayed in the Candidate Terms Table and used for cross-validation

Start with $EXP = \{1\}$ and $N_m = 1$, the default values.

If the dataset is a time-series, you must start by turning on the *Time Series* switch under the *Settings Button*. Then, set $LAG = \{1\}$ (this means you must click on the zero to turn it off). Later you may add to these fitting parameters. Once these are chosen (or the defaults used), the user can start building the model.

5 – Adding and Removing Terms

The model is built by alternately clicking on terms in the *Candidate Term Table* to add them to the *Current Model Table*, then clicking on any terms in the *Current Model Table* that may need to be removed. Terms are picked from the *Candidate Term Table* that have strong fitting criteria (such as the probability of the t -statistic, $p(t)$), and possibly that has meaning to the user. When a term in the *Candidate Term Table* is significant (i.e. $p(t) > \alpha$), then $p(t)$ will be highlighted in green.

After each term is added, the user should examine the terms in the *Current Model Table* to see if any should be removed based on their significance. For those terms, $p(t) < \alpha$, and $p(t)$ is highlighted in light red. Before adding new terms from the *Candidate Terms Table*, all non-significant terms should be removed from the *Current Model Table* by clicking on the X at the beginning of those terms.

The *Current Model Table* shows each term of the model as a separate row, along with its term statistics. For example, consider the following *Current Model Table* for a model developed to correlate automobile fuel economy (MPG) with factors such as model year (YR), engine power (HP), vehicle acceleration (A), foreign versus domestic origin (OR), and vehicle weight (WT):

Term	t	p(t)
-14669	-3.2965	0.00107
+189.78(YR)	3.2328	0.00133
+0.12702(HP ⁻¹)(YR ²)	8.2729	2.2204e-15
-0.00841(A ²)(OR ⁻¹)	-4.6039	5.6403e-6
-0.01119(WT)	-7.2173	2.8465e-12
+8.4562e-5(WT ²)(YR ⁻¹)	5.3777	1.3114e-7
+3.7800e+5(YR ⁻¹)	3.3657	8.4017e-4
-0.81175(YR ²)	-3.1490	0.00177

Representing this model in the usual algebraic notation gives:

$$MPG = -14669 + 1.8978 \cdot YR + 0.12702 \frac{YR^2}{HP} - 0.00841 \frac{A^2}{OR} - 0.01119 \cdot WT \\ + 8.4562 \cdot 10^{-5} \cdot \frac{WT^2}{YR} + 3.7800 \cdot 10^5 \frac{1}{YR} - 0.81175 \cdot YR^2$$

The last term in this model, for example, is a quadratic term in model year. The associated *t*-statistic is -3.15, which has an associated two-tailed probability of 0.00177 (0.177%).

This addition/removal cycle ends when adding or removing any single term cannot improve the model with respect to the selected goodness-of-fit criterion. In other words, until there are no terms highlighted in red in the *Current Model Table* or highlighted in green in the *Candidate Term Table*.

6 – Changing Fitting Parameters

At the end of each addition/removal cycle, the user may change the fitting parameters by one of these changes:

- Increasing the maximum number of multiplicands (N_m). E.g. try $N_m = 2$
- Adding new exponents to the exponent set. E.g. try $EXP = \{1, 2, -1\}$
- Adding additional lags to the lag set (if the data are a time-series). E.g. try $LAGS = \{1, 2, 3\}$

Start by clicking the up arrow next to “*Max Multiplicands*” once so that 2 shows in the associated field. This enables *TaylorFit* to test for more terms consisting of one-at-a-time or two-at-a-time independent variables multiplied together.

Repeat Step 5 (addition/removal cycle) until the model cannot be improved. Then return to settings and click the (+) next to “*Exponents*.” Use this to add exponents 2 (and the 3, -1, 4, etc. later). Repeat Step 5 again. Increment *Max Multiplicands* and add to *Exponents* repeatedly until the model new terms are not found after such an increment, then stop.

7 – Ending the Modeling Development/Validation

If the fitting parameters are changed as described above, and an addition/removal cycle does not result in new terms that could improve the model, then the user should stop model building, and perform the following steps:

- (1) Check the Goodness-of-Fit statistics for the VALIDATE sub-dataset and verify that the model performance is good. The checks should also be done by a graphical examination of residuals.
- (2) (Optional) Re-fit the model with the same terms but using ALL the data. Repeat the *GoF* and residuals checks. This step will optimize the model using all the data, which should improve its performance when used with new data.

Caution: Do not add or remove any terms once this is done, unless you plan to obtain new data for another iteration of final validation.

- (3) Save the model for future use or dissemination and for analysis and evaluation.

8 – Model Analysis and Evaluation

Once you are satisfied with your model, you can use it for prediction or forecasting, or to reveal system behavior using graphical analysis and sensitivity analysis.

In the **Results** pane, you can click on the “Export to Code” button to generate a code version of the current model in *Javascript*, *Excel*, *C++*, *Matlab*, *Python* or *R* formats. You can copy and paste from the export popup into your programs.

Try clicking the dropdown arrow in the data area by the column labeled “Residual.” You can select several options, including the display of graphical plots such as histograms, cumulative frequency distribution and, using “XY Plot,” a graph of the residuals versus any other column in the data file. *TaylorFit* also has options for computing model sensitivity for each data column. This will be described in chapter Step 8 below.

Detailed Functions of TaylorFit

The following chapters expand on the previous summary of the steps for using TaylorFit. Despite the broad functionality, the program maintains an easy-to-use interface. It is common to be able to generate well-developed models from data in just ten or twenty minutes.

Step 1 – Data Wrangling

Before using *TaylorFit*, you should do some initial data conditioning or cleanup, also known as data wrangling. This must be done before entering the data into TaylorFit, using spreadsheets or other programs.

Data cleanup involves checking for problems such as:

- Missing data
- Outliers
- Influential points

Here are the steps for preparing a data file in more detail. This assumes you are using a spreadsheet program or something similar.

- a) Form a flat file structure; that is, the data should be in the form of a rectangular table, each column representing a different variable, each row a different set of measurements of those variables. If the data is a time-series, each row is a successive measurement taken at equally spaced time intervals. Time itself should not be one of the columns, or, if it is, that column should be disabled using the *Ignore Column* function within *TaylorFit*.

Always LOOK AT YOUR
DATA!

- b) The first row in the file may have text to indicate names or acronyms corresponding to the variables in the respective columns. The acronyms must start with an alphabetic character, or else *TaylorFit* will assume they are numerical data. If acronyms are not provided, TaylorFit will use default names X_0, X_1, \dots for non-time-series models. For time-series models, the default names will be $X_0 \text{ lag}_1, X_1 \text{ lag}_1, \dots, X_0 \text{ lag}_2, X_1 \text{ lag}_2, \dots$ (indicating variable₀ lag₁, variable₁ lag₁, variable₀ lag₂, variable₁ lag₂, etc.)
- c) The first column will be the dependent variable, although this is not required. The designation can be changed within *TaylorFit*. The other columns will be independent (causative) variables.
- d) Graphically examine the data, looking for any anomalies. Watch for outliers and influential points; these may appear as points that stand apart from the others. Graphical examination can include:
- i) Plot the dependent variable versus each independent variable (X-Y plots).
 - ii) Plot each independent variable versus each other, looking for strong correlations
 - iii) Examine the each variable using histogram, cumulative frequency distribution, quantile-quantile (QQ) plot, or autocorrelation plot.
 - iv) If the dataset is a *time series*, plot each column versus time
- This step can also be done within *TaylorFit* as described in Step 3.
- e) Look for any missing data. Missing data can be treated by one of the following:
- i) Remove the row or column containing the missing data. This may be your choice if there are many missing data points in the corresponding row or column.

(If the dataset is a time-series, the row cannot be removed as you will then no longer have a continuous sequence of data.)

- ii) Fill in missing data; one way to fill in missing data is to use the mean of the column. If it is a time-series, you could linearly interpolate between the previous and next values. However, you should avoid this approach if there are too many missing values. In such a case it may be better to remove that column.
- f) If there are enough data, you should plan to divide the data into two or three similar sub-datasets. This will be done in Step 3, but you should plan for it at the start. You should ensure that each sub-dataset is “comparable” in range, distribution, etc. In other words, they should “look” similar using graphical examination.

The three sub-datasets are designated:

- i) FIT: Used to compute the coefficients and *t*-statistics of the terms of the model;
- ii) CROSS: Used to compute global statistics for cross-validation;
- iii) (FINAL) VALIDATE: Used only after the best model has been built using the FIT and CROSS sub-datasets to see if the model is capable of making good predictions when used with an independent dataset. Often data are scarce. It may be necessary to do without a separate VALIDATE dataset, or to use a single dataset for all three purposes. However, in this case the resulting model should be used with extreme caution for making predictions. Without validation, the model may be used to express *correlation* among the variables. That is, the model can show relationships between the variables. But predicting the outcome of the dependent variable using new measurements of the independent variables is risky and not scientifically valid.

In addition, there is the dataset we will refer to as “ALL”: This refers to the complete dataset incorporating all of the data in the FIT, CROSS and VALIDATE datasets combined.

You should determine the percentages or row numbers from the data file that you plan to use for the FIT, CROSS and VALIDATE sub-datasets. You will provide this information to *TaylorFit* in Step 3 when you upload the data. For example, you might choose to use the first 40% of the rows for the FIT data, the next 40% for the CROSS data, and the last 20% for the VALIDATE data. The proportions are a matter of judgement, subject to having enough data in each sub-dataset for fitting and validation.

How many data are enough? A rule of thumb is that each sub-dataset, and especially the FIT and CROSS sub-datasets, should have at least six to ten times as many rows as columns. It may be possible to have fewer rows than this, but in such a case avoid having a final model that uses all the columns. In other words, the number of independent variables actually used in the final model should be less than one-sixth as many rows as in the FIT dataset. (Note that with step-wise fitting, it is possible that some columns may turn out to not contribute significantly to the prediction capability of the model, and thus may not appear in the final result.)

Is it ever OK to use the same data for fitting and validation? Sometimes: If the cause-and-effect relations are well-established, and if the model will not be used for making predictions and you are looking only to identify the strength and geometry of the relationships. However, this must be done with caution.

- g) If you have a single dataset is that is large enough to form two or three sub-datasets as just described, you should graphically and statistically examine each sub-dataset to ensure that they are similar to each other. If not, and the dataset is not a time-series, you can shuffle the data in one of two ways:
- i) Random shuffle: For example, in *Excel*, follow these steps:
 - create an additional column and use the `RAND()` function to enter random numbers.
 - sort the rows by the random number column
 - delete the random number column and then save the data into a CSV file.
 - ii) Stratified sampling: Suppose it is found that one of the sub-datasets differed from the others substantially in one of the variables. Again, if you are using *Excel*, perform these steps:
 - sort the dataset by the variable of concern
 - create a new column and enter the repeating sequence 1, 2, 3, 1, 2, 3, ...
 - sort on the column with the repeating sequence
 - delete the column with the 1-2-3 sequence and save the CSV file.

When you load the stratified dataset into *TaylorFit* you can use the first 33% of the data for the *FIT* data; the second third for the *CROSS* data, and the remainder for the *VALIDATE* data.

When complete, you should save the entire dataset in a single comma-separated-value (CSV) Table.

Step 2 – Start TaylorFit

TaylorFit is run within a web browser from the website www.TaylorFit-RSA.com. The *Start Window* shows several buttons including:

- *Import FIT Data* allows the user to begin to import data, starting with the *FIT* file. The user will subsequently be able to input *CROSS* and *VALIDATE* datasets.
- *Import Project* allows the user to import the data, fitting parameters, and current model that was previously saved
- *Open Users' Manual* opens this manual as a PDF in a separate browser tab
- *Simetrica LLC* opens a new tab at a site with additional information
- *AutoMPG* downloads an example CSV file with data describing automobile fuel economy and variables that could explain and predict the fuel economy
- *Lydia Pinkham* downloads an example *time-series* data file describing a business application
- *Give Us Feedback* opens an online form for contacting us with questions and providing suggestions

The subsequent steps below assume that the user is beginning a new project. The use of the import project button allows the user to pick up where she/he left off on a previous modeling effort.

Step 3 – Manipulating Data in TaylorFit

To get started, simply click on the *Import Data* button. A file directory box opens that allows the user to select the CSV data file.

Importing Data

Once you have selected and open a datafile, a *Data Partition* dialogue box opens as shown below that allows you to partition the data between the *FIT*, *CROSS* and *VALIDATE* sub-datasets. You can select the partitions by percentage of the datafile or by selecting non-overlapping row numbers.

Data Partition				
Fit	38	%	Rows	1 - 150
Cross	38	%	Rows	151 - 300
Validate	24	%	Rows	301 - 393
<input type="button" value="Import"/>				

If there are not enough data available for separate sub-datasets, the user can proceed with just a *FIT* sub-dataset. However, if there are not enough data for a separate final validation, then extreme caution is needed if the model is to be used for predicting outcomes of new cases. Predictions with an un-validated model may not be considered scientifically valid. On the other hand, correlations and analytical dependencies revealed by the model can be considered scientifically valid.

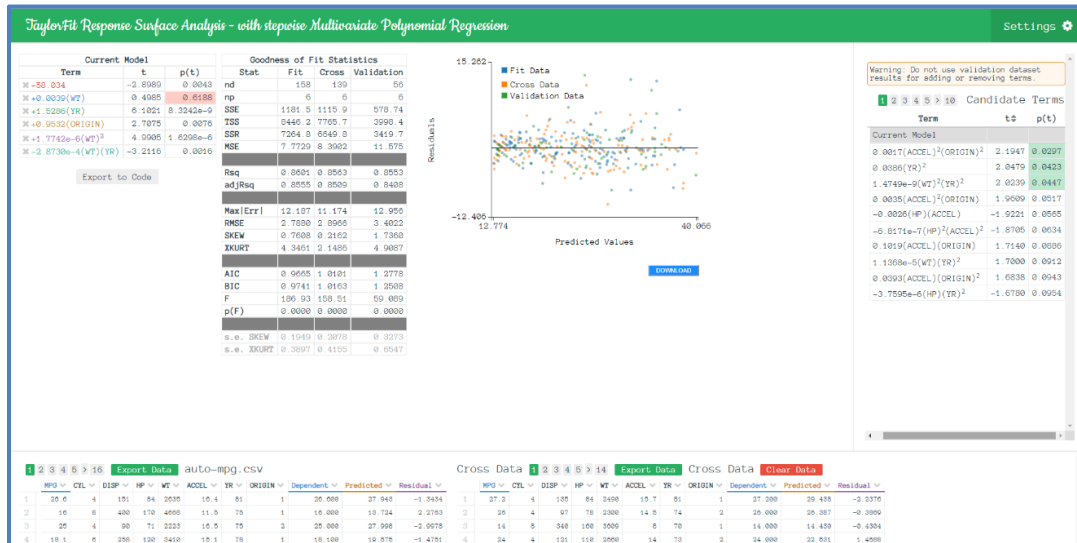
It is also possible to enter the *FIT*, *CROSS* and *VALIDATE* sub-datasets from separate CSV files. But all three datafiles must have the same number of columns and corresponding columns must contain the same variables.

If the *VALIDATION* sub-dataset is entered from the beginning of the session, the user must avoid the temptation of looking at the model performance with those data. ***Validation data should not be used for making decisions about adding or removing terms from the model.*** In fact, to avoid this temptation, it is recommended that the *VALIDATION* dataset not be imported into *TaylorFit* until model development is completed (Step 7). There is a separate button in the *Data Pane* labeled “*Import Validation Data*” for doing this.

Arrangement of the TaylorFit Window

After the data have been imported, you will see that the window is divided into three “panes,” each of which expands when the cursor is moved over it. The ***Data Pane*** is at the bottom. Each sub-dataset is shown as a separate ***Data Table***. Only ten rows of each dataset are shown at a time. Additional pages of ten at a time can be viewed by clicking on the numbers or arrows at the top of each table. If the first row of the datafile contains alphabetic names or acronyms to identify the columns, they will be displayed in the heading of the Table. If the

datafile does not have names, then *TaylorFit* will default to naming the columns as follows: X_0 , X_1 , X_2 ,



Note the other two other panes in the *TaylorFit* window: The upper right pane will be referred to as the **Candidate Term Table**. Above that is a button called **Settings**. The larger pane to the upper left is referred to as the **Results Pane**. The *Results Pane* contains three objects: the **Current Model Table**, the **Goodness-of-Fit Table**, and the **Residuals Plot**. These will be discussed below with Step 4.

Selecting the Dependent Variable

By default, the first column in the *Data Table* is selected as the dependent variable; all other columns are then independent variables. The user can select any other column to be the dependent variable by clicking on the down-arrow in the heading of that column and selecting “Mark as Dependent.” Changing the dependent variable in the any dataset makes the same change in all the other datasets that have been imported.

Columns containing alphanumeric data (other than the headings in the first row, if present) are ignored. Also, the user can click on the down-arrow in the column heading in the Data Table and select “Ignore column.” Ignored columns will not be used in generating candidate terms for the model.

Note that *TaylorFit* automatically generates three columns in each *Data Table* to the right of the data you entered as follows:

- **Dependent** – This column repeats the column selected as the dependent variable.
- **Predicted** – This is the value predicted by the model using the independent variables from the corresponding row.
- **Residual** – Also known as “error” values, this is the measured dependent variable minus the model predicted variable.

Data Transformation

Often a modeler will want to make mathematically transform a variable in the *Data Table* before using it for modeling. *TaylorFit* has the following transformations built-in: logarithmic (base 10), k -order difference, standardized, or scaled. To transform a column, click the down arrow in the heading of the column and select **transform column**. You can then select the desired transform. When this is done, a new column will appear to the right of the data containing the transformed data, and the original column will be marked to be ignored. For example, you cannot perform the regression on both X_3 and $\log(X_3)$.

You can use the graphical tools to examine the transformed column. If you decide not to use that particular transform, you can use the drop-down menu on the transformed column to **Delete Transform Column**. The *Transform Column* and *Delete Transform Column* menu items only appear in the *FIT* dataset but affects all the datasets. You can also transform a transformed column, if desired!

There are a number of reasons for doing using transformations. The meaning and possible motivations for using these transformations are as follows.

Logarithmic transform

If a variable's range covers many orders of magnitude, or its distribution is skewed to the left, it might be better to fit the logarithm of the variable instead of the variable itself. This transformation is also used with data that are always positive and non-zero, but for which the standard deviation is almost as large, or even larger, than the mean. This often occurs, for example, with measurements of pollution concentrations in the environment. Most levels may be low, but some will be much higher than the average. Logarithmic transformation may produce a more symmetric distribution that is easier to model.

k-order Differencing

This may be appropriate for time-series data. With such data, if the dependent variable changes slowly, time-series models may have very high values of R^2 . But only reflects the strong predictive effect of the previous value. For example, to predict today's temperature, you would do very well to just use yesterday's temperature. A more meaningful prediction would be to predict the change in temperature.

If you choose *k-order Difference*, you can select the value of k in the field next to the button. If $k = 1$ the transformation is a 1st-order difference. If $y_{i,k}$ is the value of y_i at time step k , then the 1st-order difference of $X_{i,k}$ is $D_{i,1} = y_{i,k} - y_{i,k-1}$. Higher-order differences are formed by taking the difference of the next-lower order difference. I.e. $D_{2,k} = D_{1,k} - D_{1,k-1}$. In general, $D_{n,k} = D_{n-1,k} - D_{n-1,k-1}$.

Standardize

If different columns have very large or very small numerical values (i.e. are in scientific notation with large positive or negative exponents), this transformation will "normalize" them. This transformation is also used to avoid having model coefficients that are very large or very

small. The original values will have the mean of the column subtracted, and then be divided by the sample standard deviation. This gives the transformed column a mean of zero and standard deviation of 1. Values above the mean will be positive, and those below the mean will be transformed to negative numbers, which will prevent the column from being used with negative exponents.

Scale by RMS

With this transformation, each value in the selected column is divided by the root-mean-square of that column. This has similar motivation to *standardize* but preserves the sign of the variable so it can be used with negative exponents.

Examining the Data

A professor once said, “Always look at your data.” In other words, don’t rely only on computed statistical calculations. By their nature statistics hide some of the information in the data. In fact, the *degrees of freedom* is the number of additional pieces of information that would be needed to fully describe the data. You should study the raw data, plus examine them graphically and using summary statistics, before you start the modeling process.

Start by scanning through the numerical values. Of course, with very large datasets, it may not be possible to look at every individual value. But one should examine the distribution of each independent and dependent variable. This can be done both graphically and numerically.

Statistical descriptors include: mean, standard deviation, skewness, excess kurtosis, and various percentile values such as the maximum (the 100th percentile), the median (the 50th percentile), and the minimum (the 0th percentile). Right now, these calculations must be done outside of *TaylorFit*, such as by using a spreadsheet program. A future version is expected to include these in the *Data Table*.

Graphical examination of the distribution can start with the histogram and/or the cumulative distribution (which is the integral of the histogram). Next, look at how the variables compare with each other. Graphically, this means creating X-Y plots of each variable versus each other variable. (For N variables, there will be $(N^2+N)/2$ combinations to check.) Numerically, it involves creating a cross-correlation table, which can be done in a spreadsheet or similar programs.

Other plots that may be of interest are the quantile-quantile plot (Q-Q Plot) and the autocorrelation plot. Although these may be of interest for examining the data, they are of most use in examining model residuals. Accordingly, these two plots will be discussed in Step 7.

Step 4 – Initial Settings

As previously mentioned, the *TaylorFit* window displays three “panes,” each of which expands when you move the cursor over each of them:

- Across the bottom is the *Data Pane*, discussed in Step 3.
- Above the *Data Pane* are two panes. Towards the left is the *Results Pane*. This pane includes three items:
 - The *Current Model Table* – This Table shows the term of the model as currently defined. Each row in this Table corresponds to one term of the model. The current model thus consists of the sum of each of these terms. The first column shows the coefficient of the term and the corresponding variables, their exponent and their lag (if a time-series). The second and third columns show the *t*-statistic and the probability of a larger *t*, labelled *p(t)*. The button below this Table “Export to Code” opens a box with the current model in a form that can be used in *Javascript*, *Excel*, *C++*, *Matlab*, *Python* or *R* formats. You can copy and paste from the export popup into your programs.
 - The *Global Statistics Table* – This Table shows summary statistics computed separately for the *FIT*, *CROSS*, and *VALIDATE* datasets in columns 2, 3, and 4 respectively. These statistics are described below.
 - A *Residuals Plot* showing the residual errors versus the predicted value for the *FIT* dataset. Residuals for the *FIT* dataset are shown as blue points; residuals for the *CROSS* dataset are shown as orange points. If a *VALIDATE* file has been imported, the residuals associated with those data are shown as green points. Clicking on the legend inside the plot turns the corresponding set of data points on or off. For example, if you only want to see the residuals for the *FIT* data, click on the legend for *Cross Data* and *Validation Data*.
- On the right side above the data pane is the *Candidate Terms Pane*.
- At the upper right is the *Settings Button*. This shows buttons actually hides a fourth pane that allows the user to select statistics for display or for use as fitting criteria, and to select the fitting parameters described below. These will be described in detail below.

The Settings Button

The *Settings Button* opens a pane in which the user can choose:

- The Goodness-of-Fit statistics to for comparing candidate terms
- The *fitting parameters* (multiplicands, exponents, and lags)
- Buttons for turning *time-series* on and off, for changing the display precision, and a field for changing the value of α

- Options for clearing or saving the project (described in Step 7)

When done inside this pane, just click on the *Settings* button again to close the pane.

Statistics

The user can choose which statistics to display in the *Candidate Terms* Table to evaluate the terms and the overall model. The use of these statistics is described here. Their formal descriptions and computational formulae are provided in a later chapter.

Two statistics are shown by default in the *Candidate Terms Table* and the *Current Model Table*. These term statistics are associated with individual terms, not the overall model. The *term statistics* are:

- t*: This one of the most important statistics during model building. It is a measure of how significantly a term contributes to the fit. For example, if there is a large amount of data (at least 100 “degrees of freedom” – see below) then a value of $t = 1.98$ indicates there is a 5% probability ($\alpha = 0.05$) or less that this term occurs because of chance; $t = 2.63$ corresponds to a 1% probability ($\alpha = 0.01$).
- p(t)*: The two-tailed probability of a larger value of t . Typically, we would add a term to the model if $p(t) \leq \alpha$ (typically 0.05) for that term and remove a term if its $p(t) > \alpha$.

Other statistics are shown in the second Table in the Results Pane. This is the *Global Goodness of Fit Statistics* Table. The values shown in this Table are global statistics; that is, they relate to the entire model, rather than individual terms in the model.

The Data Statistics are computed separately for each sub-dataset – *FIT*, *CROSS* and *VALIDATE*. All the other statistics are computed from these plus the *SSE*:

- nd*: The number of data points; usually the number of rows in the data file.
- np*: The number of coefficients in the model, including the intercept if there is one. Essentially, it is the number of terms in the model.
- df*: Although not shown in the Table, *df* is the number of degrees of freedom of the residuals; $df = n_d - n_p$
- TSS*: *Total Sum of Squares*: $TSS = \sum (y_i - \bar{y})^2$, where y_i are the dependent data points from the FIT dataset, \bar{y} is the mean of those points
- TMS*: *Total mean square* = $TSS/(n_d-1)$ (Used below; not shown in the Table)

The other statistics are termed Global Goodness-of-Fit (GoF) Statistics. The *GoF* statistics are measurements that describe how well the overall (current) model fits the data. Their use is described in Step 5. The *GoF* statistics are:

- SSE*: Sum of squares of the errors (or residuals); $SSE = \sum (y_i - \hat{y}_i)^2$ where \hat{y}_i are the model predicted values corresponding to each y_i .
- MSE*: *Mean square error* = SSE/df ; this is an estimate of the error sample variance

<i>RMSE</i> :	The square root of <i>MSE</i> ; an estimate of the standard deviation of the residuals
<i>Max Err </i> :	The largest of the absolute value of the errors
<i>MSR</i> :	<i>Mean square of the regression</i> = $(TSS - SSE)/n_p$ (Used below; not shown in the Table)
<i>RSQ</i> :	R^2 , the square of the multiple correlation coefficient; $R^2 = 1 - SSE/TSS$
<i>adjRSQ</i> :	<i>Adjusted R^2</i> – similar to R^2 , but takes into account the degrees of freedom <i>adjusted R^2</i> = $1 - MSE/TMS$
<i>F</i> :	The <i>F</i> -statistic = MSR/MSE ; similar to the <i>t</i> -statistic for a term, but applies to the overall fit. A larger value indicates a better fit.
<i>p(F)</i> :	The probability of <i>F</i> being this large or larger by chance. The smaller the value, the better the fit.
<i>AIC</i> :	<i>Akaike Information Criterion</i> = $\log_{10}(MSE) + 2 \cdot n_p/df$
<i>BIC</i> :	<i>Bayesian Information Criterion</i> = $\log_{10}(MSE) + \log_{10}(n_d) \cdot n_p/df$
<i>SKEW</i>	Skewness
<i>s.e. SKEW</i>	Estimated standard error of the skewness
<i>XKURT</i>	Excess kurtosis = kurtosis – 3.0
<i>s.e. XKURT</i>	Estimated standard error of the excess kurtosis

All the *GoF* statistics are displayed in the *Global Statistics Table* in the Results Pane. But they will only show in the *Candidate Terms Table* if you select them. The *GoF* statistics can be seen as buttons in the *Settings Pane*. Selecting one or more of these *GoF* statistics by clicking on its button adds a column to the *Candidate Terms Table* showing what the value of that statistic would be if the corresponding term were added to the current model. The top row of the selected *GoF* column in the *Candidate Terms Table* shows the value of that *GoF* for the *CROSS* sub-dataset, if one has been imported. This is used in cross-validation, as described below. The *Candidate Terms Table* can be sorted by any column by clicking on the corresponding heading.

Note that you might occasionally find the value of R^2 or $adjR^2$ to be outside the range of 0.0 to 1.0, which seems illogical for a squared value. This occurs in two cases:

- (1) It may occur with the *FIT* dataset when there is no intercept term in the model;
- (2) It may occur with the *CROSS* or *VALIDATE* datasets if the current model predictions are worse than just using the average of the dependent values from the *FIT* data as predictor.

This occurs because *TaylorFit*'s computational formula is $R^2 = 1 - SSE/TSS$. If $SSE > TSS$ then $R^2 < 0$. Essentially, this makes the value of R^2 into a comparison between the current model and the "worst case" model: $y = \bar{y}$ where \bar{y} is the mean of the dependent variable from the corresponding dataset. The sum of squares of the "errors" (*SSE*) in this worst case model is the *TSS*. Thus, if the prediction is doing worse than just using the mean as a predictor, then $SSE > TSS$, and R^2 will be negative (and possibly even less than -1). This is an indication of a poor model (which may occur in early stages of modeling).

Some programs (e.g. *R* and *Excel*) avoid this problem by using $TSS = \sum (y_i)^2$ for the special case where there is no intercept. Essentially, this changes R^2 to a comparison with a different “worst case” model: $\hat{y} = 0$. A problem with this approach is that it can cause the value of R^2 to improve when the intercept is removed from the model, even if the *SSE* increases! Some modelers recommend that the intercept should always be included in the model, which eliminates this problem. In *TaylorFit* this decision is up to the user. *TaylorFit* always starts by including the intercept as the first term in the model. However, the modeler can choose to remove it at any time by clicking on the *X* at the left of the term in the *Current Model* Table.

If you find that the *VALIDATE* and/or the *CROSS* sub-datasets have much poorer *GoF* statistics than the *FIT* sub-dataset, it may be that these sub-datasets do not equally represent the distributional properties of each other. For example, this could occur if the *FIT* sub-dataset contains an outlier or an influential point not contained in the other sub-datasets.

Fitting Parameters

The real power of *TaylorFit* comes from the user’s ability to choose three sets of fitting parameters that control the generation of candidate terms. This allows formation of polynomial interaction terms, which can create complex response surfaces. The three types of fitting parameters are:

- The maximum *number of multiplicands* in a candidate term, N_m
- The set of possible exponents, $EXP = \{exp\}$
- The set of possible lags, $LAGS = \{lag\}$

The default values for the *fitting parameters* when *TaylorFit* is first started are:

$$N_m = 1; EXP = \{1\}; LAGS = \{0\}$$

If these settings for the *fitting parameters* are used with *TaylorFit*, the result will be a *Multilinear Regression (MLR)* model. *TaylorFit*’s power comes from extending the *fitting parameters* to produce *Multivariate Polynomial Regression (MPR)* models.

Note: The coefficients that multiply each term in the model are also called parameters. To avoid confusion, we will always refer to “fitting parameters” for the sets of multiplicands, exponents and lags discussed here. We will only use the term “coefficient” for the multiplier at the front of each term in the model.

MAXIMUM NUMBER OF MULTIPLICANDS: This an integer that represents the maximum number of multiplicands a single term of the model may have. For example, if *Y* is to be regressed onto independent variables *Q*, *R*, and *S*, terms with one multiplicand ($N_m = 1$) include *Q*, or Q^2 , or S^{-1} , etc. Examples of terms with $N_m=2$ include $Q \cdot R$, or $R \cdot S^2$, etc., but not $Q \cdot R \cdot S$. The intercept is always a potential candidate term, although the user can choose to add it to the model or to remove it, according to needs and preference. A maximum number of multiplicands of 2 or 3 is often sufficient.

EXPONENTS: This section shows the exponent list which the program will use to select possible exponents in the model terms. The exponents may be integer or non-integer, positive

or negative. Zero is included by default (resulting in formation of the intercept as a candidate term) and should not appear in the list. Including negative values, as in the example, enables ratios of independent variables to be tested for model inclusion. This ability to include exponents that are not positive integers is also known as *fractional polynomial regression*. In most cases you will just want to use positive and negative integers.

For example consider the case where Y is the dependent variable, and Q , R and S are the independent variables. If the user selects $N_m = 2$ and $EXP = \{-1, 1, 2\}$, then possible candidate terms may include: Q , Q^{-1} , Q^2R^{-1} , or QR^{-1} . The last of these is the ratio Q/R . In this example the following terms could not be generated in the candidate term Table: QRS , Q^3R , RS^2 . If one wishes to include such terms the set of exponents should be expanded to $\{-2, -1, 1, 2, 3\}$.

LAGS: A lag is an index that tells *TaylorFit* to point to previous time periods. Use of lags is described in the next section.

Note: *Selection of fitting parameters only affects the generation of candidate terms. It does not affect terms already in the current model. For example, suppose the user selects $N_m = 3$ and adds terms to the model with three multiplicands. Subsequently the user may then change to $N_m = 2$. The three-multiplicand terms in the current model stay there, but the candidate term table will only show terms with one or two multiplicands.*

There is also a field under the *Settings* button to change the “*Display Precision*.” This is the number of digits that *TaylorFit* displays for the model coefficients and all statistics. Internally, *TaylorFit* stores these values with about 16 digits of precision. Changing the *Display Precision* does not alter the internal storage or the precision used in the model produced by the *Export to Code* button.

Setting TaylorFit_up for Time-Series Analysis

If the dataset is a time-series, you must start by turning on the *Time Series* switch under the *Settings Button*. Then, you should set the lags.

As was previously mentioned, a *lag* is an index that tells *TaylorFit* to point to previous time periods (in previous rows of the dataset) to find independent variables. Thus, for example, a company’s sales in a particular year might depend on its sales in previous years. By default in *TaylorFit* the set of lags starts out as zero ($LAGS = \{0\}$).

To start with, use $LAG = \{1\}$. To do this, click the + sign in the LAGS field and enter 1. Then click on the zero lag to disable it. There may be cases where the zero should not be disabled. This will occur only if the independent variables *on the same row as the dependent variable* would be expected to be available as predictors for the dependent variable on that row. For example, if you want to predict a company’s sales for a year, you might include the advertising expenses for that year, since they may be budgeted, and therefore known, before the sales figures are known. But more often, independent variable data contemporaneous with the dependent variable is not known ahead of time, and the lag zero should be disabled.

Making additional changes to Lags is discussed further in Step 6.

Selecting Fitting Criteria and Initial Fitting Parameters

Besides selecting the Fitting Parameters, the user has a choice of statistics to use as fitting criteria. The user should select one or more statistics to display in the candidate term table by clicking on the corresponding button at the top of the Settings Pane. Then, by clicking on the corresponding heading in the candidate table, that table will be sorted according to that statistic. This makes that statistic the effective criterion for choosing terms to add into the model.

Current recommendations are: If the *FIT* and *CROSS* datasets are identical, or no separate *CROSS* data file has been added, use a conservative criterion. The F-statistic will be a fairly conservative choice, although the *AIC* or *BIC* are also conservative. When using cross-validation (see below) and you therefore have independent *FIT* and *CROSS* files (cross-validation), it is not as necessary to be so conservative in adding terms. The user could consider using the *MSE* or *adj-R²* criteria.

Start with a multilinear model, then go from there.

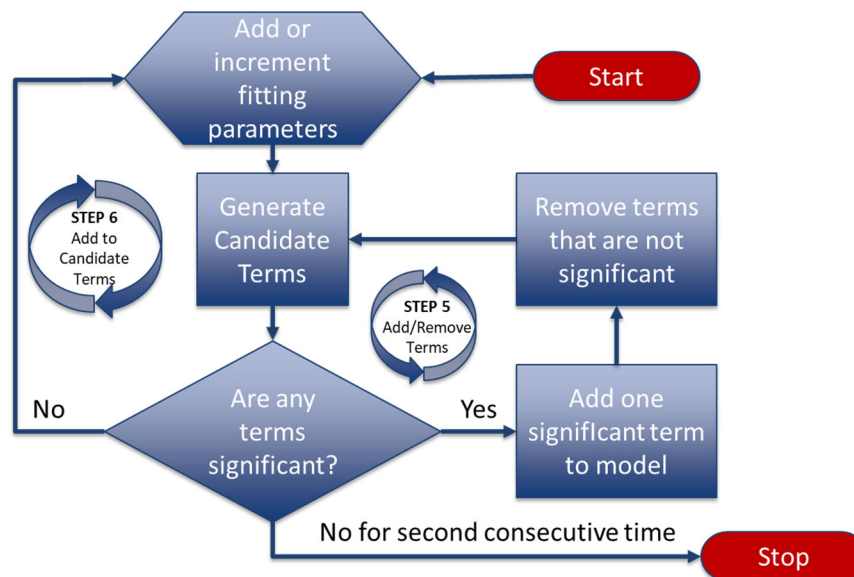
Next, the user should select the Fitting Parameters (N_m , *EXP*, *LAGS*). A strategy for selecting initial fitting parameters is to set $N_m = 1$, *EXP* = {1}. If the data are a time-series, use an initial setting *LAGS* = {1}. These settings correspond to developing linear models: multilinear regression (MLR) in the case of non-time series, and first-order autoregressive (AR(1)) in the case of time-series.

Next, proceed to Step 5. The initial settings described above will result in linear models. If a non-time-series, the result will be a multilinear regression (MLR). If a time-series, the resulting model will be what is known as a first-order autoregressive (AR(1)) model. Subsequently, as described below in Step 6, the *fitting parameters* are increased in increments, say by changing the *Maximum Multiplicands* to 2, fitting again, then sequentially adding exponents (and additional lags if a time-series).

Step 5 – Stepwise Addition and Removal of Terms

Once the data are loaded and initial *fitting parameters* have been selected, the user can begin building the model by adding and removing terms iteratively until the model cannot be improved. Only then should the *fitting parameters* be changed to enable more complex models (as discussed in Step 6), and the iterative procedure repeated. Steps 5 and 6 are repeated until adding multiplicands, exponents, and/or lags does not significantly improve the model. The flowchart in Fig. 1 illustrates the steps involved. Step 5 is an “inner” loop of the procedure; Step 6 is the “outer” loop. These two loops are the core of the *TaylorFit* modeling procedure.

Figure 1. Flowchart for stepwise regression with multivariate polynomials.



Building the Model

Once the fitting parameters (N_m , EXP and $LAGS$) are selected, the desired fitting criterion has been selected and set as a sort criterion in the *Candidate Terms Table*, the user should proceed to add and remove terms to the model. The following description assumes that cross-validation is not being done. Recall that when a modeling project is started for the first time, the constant (i.e. intercept) term is added automatically. The user can choose to remove it at any time.

Addition Step: Begin by examining the terms in the *Candidate Terms Table*. The first term should be the one that produces the best performance according to the selected criterion. The user decides at this point which term should be added to the current model. To be selected, a term should either have a *GoF* that is better than that of the *Current Model*, and/or has a $p(t)$ below an addition threshold value known as α (usually 0.05, or 5%). Notice that the program highlights $p(t)$ values that are less than α in green background to make it easier to select. If there is no separate cross-validation and/or final validation dataset, then a more stringent addition threshold value for α , such as 1%, and/or one of the relatively conservative *GoF* criteria, should be considered.

In most cases the top term will be selected. But sometimes the user may select another term with almost as strong statistics, but which is preferable for some reason. For example, if a linear term is almost as good as a 3-multiplicand term, the linear term might be chosen to give preference to a simpler model.

Once a term is selected, the user just clicks on the chosen term. This term will move from the *Candidate Term Table* to the bottom of the *Current Model Table*. *TaylorFit* then goes into a computation in which the *GoF* statistics Table, the residual plot, and the *Candidate Term Table* are all updated.

After each new term is added to the *Current Model*, the user should go to the removal step.

Removal Step: After each Addition Step, the user should examine the *Current Model Table* to see if any of the terms in the model have decreased in significance below the value of α . Notice that the program highlights $p(t)$ values in the *Current Model Table* that are greater than α in light red background to make it easier to select. Start with the term with the largest value of $p(t)$ and continue until there are no more terms with $p(t) > \alpha$.

Iterate: After the removal step is complete, the user should return to perform another addition step. If at any time no term meets the criterion for either addition or removal, the user then continues on to Step 6 – Changing Fitting Parameters.

If after the *Setting Parameters* have been incremented in Step 6 and no *Candidate Terms* make the cut for addition, the user may then stop the modeling exercise and go to Step 7 for model validation.

Cross-validation

If there are enough data to form two or three sub-datasets, it is recommended to enter them separately as *FIT*, *CROSS*, and *VALIDATE* datasets. Refer back to Step 1 for the discussion on ensuring similarity between the three sub-datasets and the quantity of data needed.

Cross-validation is a powerful way to prevent problems such as *overfitting* (also referred to as “memorizing the noise in the data”) or *spurious correlation* (also called *chance correlation*). See the section below on Modeling Tips and Potential Pitfalls.

The *CROSS* dataset is also known as a *Cross-Validation* dataset. With cross-validation, model generation proceeds almost the same as described in the previous section, with the only difference being in how a term is selected in the addition step.

For cross-validation, two criteria must be satisfied simultaneously. Specifically, $p(t)$ for a candidate term must be less than the *significance level* α , and the selected *GoF* statistic for the *CROSS* dataset with the candidate term included must be better than the same *GoF* statistic for the current model.

Note that the *GoF* statistics in the *Candidate Term Table* for each term indicate what those statistics would be if that term were added to the current model. The *GoF* for the current model without that term is displayed in a row at the top of the *Candidate Terms* Table.

Keep in mind the following: For purposes of sorting the candidate terms to determine which is best for inclusion in the model, *t*-statistics are always computed using the *FIT* sub-dataset. However, global statistics (e.g. *SSE*, *MSE*, R^2 , *Max|err|*, *F*-statistic, *AIC* and *BIC*) in the *Candidate Terms* Table are always computed using the *CROSS* sub-dataset if one has been designated, and the *FIT* file if not.

As an example, take a look at the *Candidate Term* Table below. Note that all the values of $p(t)$ are very small and are highlighted in green. But only the first term in the list has its value highlighted in the column for the *F*-statistic. It's value of *F* is 111.19. This is greater than the value of *F* for the current model applied to the *CROSS* sub-dataset, which has $F = 97.046$. Thus, the term for (WT)(ACCEL) meets the dual criteria for being added to the current model. On the other hand, look at the second term, (WT)(ORIGIN). It's *t*-statistic is significant, but the value of *F* (96.547) is lower than for the current model (97.046). Although still statistically significant, it is less so, and thus this term is judged to not significantly improve the prediction capability with the *CROSS* sub-dataset. It doesn't satisfy the dual criteria, so this term should not be added into the *Current Model*.

Candidate Terms			
Term	F	t	p(t)
Current Model	97.046		
-2.6516e-4(WT)(ACCEL)	111.19	-7.3247	1.4614e-11
-0.0027(WT)(ORIGIN)	96.547	-6.3532	2.4909e-9
0.0472(ACCEL)(YR)	91.110	6.8359	2.0251e-10
0.3968(YR)(ORIGIN)	82.922	5.8908	2.5145e-8
-0.0020(DISP)(ACCEL)	79.212	-6.1606	6.6020e-9
-0.0039(HP)(ACCEL)	77.488	-4.3134	2.9344e-5
-0.1120(CYL)(ACCEL)	76.802	-5.8317	3.3544e-8
-0.0348(HP)(ORIGIN)	73.967	-3.7373	2.6569e-4
-0.0199(DISP)(ORIGIN)	68.770	-5.0863	1.0968e-6
-1.7797e-4(CYL)(WT)	67.788	-4.6137	8.5434e-6

The same cross-correlation procedure can be done with some of the other global statistics. Use of *MSE* or $adj-R^2$ will generally be less conservative (produce models with more terms). Use of *F*, $p(F)$, *AIC* or *BIC* tend to produce simpler models. Using *Max|Err|* produces what is known as *mini-max optimization*.

The *Settings* pane allows the user to add other global statistics to the *Candidate Term* Table such as *SSE*, *SSR*, R^2 , *SKEW*, and, *XKURT*. However, these are just for monitoring purposes. They should not be used for selecting terms to add to the model.

Step 6 – Changing Fitting Parameters

As mentioned above, the real power of *TaylorFit* comes from the user's ability add to the *fitting parameters* that generate multivariate polynomial candidate terms. This enables the creation of models with complex response surfaces to more accurately capture the behavior contained in the data, and with less bias than linear models.

After each time an addition/removal cycle is completed and the model cannot be improved either by adding a term from the *Candidate Term* Table, or by removing a term from the *Current Model* Table, the user should try expanding the domain of candidate terms. This is done by increasing the maximum number of multiplicands, and/or by adding to the list of exponents, and/or (if the data are a time-series) adding to the list of lags. This step is illustrated by the outer loop in Figure 1. The following will discuss strategies for increasing multiplicands and exponents first, then have a separate discussion of lags for time-series models.

Incrementing the Multiplicands and Adding Exponents

As described above, it is suggested that the user should start with a linear model. In the case of non-time series, this is the multilinear regression model. That is, add and remove terms with $N_m = 1$ and $EXP = \{1\}$, until the model cannot be improved (according to the selected criterion) by the addition or removal of any single term.

Then, the maximum number of multiplicands and the list of exponents can be increased. There is no single way to do this. This decision is part of the art of modeling. The Table below shows a possible sequence to consider.

Cycle	N_m	Exponents
1	1	1
2	2	1
3	2	1, 2
4	2	-1, 1, 2
5	2	-1, 1, 2, 3
6	3	-1, 1, 2, 3

As the user gains experience, she/he may make other choices. Note that as the maximum number of multiplicands and the number of exponents grows, the number of possible candidate terms (which is displayed on the *Settings* page as $N_{Candidates}$) may become very large. For example, if there are eight independent variables, the multilinear regression model (as in cycle 1 in the Table above) results in eight possible candidate terms. Increasing N_m to 2 results in 29 possible candidate terms. With $N_m = 2$ and two exponents (as in cycle 3 above), there will be 99 candidate terms. Finally, with up to four multiplicands and four exponents (as in cycle 6 above) there would be 2,605 possible candidate terms.

The speed of the calculations will depend not only how many candidate terms there are, but how many rows there are in the data. Although these factors may slow the computations, it's worth repeating as stated before, "data are expensive; computations are cheap." If a model produces useful results, it may be worth waiting for.

Changing α

The α is the threshold probability level used for tests of significance for the t -statistics. These statistics are deemed statistically significant if their calculated values (in the *Candidate Term Table* and the *Current Model Table* are less than α . The user can change the value of α on the Settings screen. This does not change any calculations within TaylorFit. The only thing that changes is the color highlighting in the *Candidate Term Table* and the *Current Model Table*:

- Values of $p(t) \leq \alpha$ in the *Candidate Term Table* are highlighted in green.
- Values of $p(t) > \alpha$ in the *Current Model Table* are highlighted in red.

The default value of α is 0.05. The user may want to use a lower value, say, 0.01, which will result in simpler models with fewer terms.

Adding to the Lags (Time-Series Only)

If the dataset is a time-series, then the user should select the lags to be considered by *TaylorFit* for forming candidate terms. As with the selections of the other settings, the user should start simple by selecting only $LAGS = \{1\}$. Essentially, the independent variables from the previous row is used to predict any particular row. In subsequent iterations, the user may include additional lags. These may be added one-at-a-time sequentially.

For example, if the user has data that have been collected on a daily basis, so each row represents a successive day of data, then starting with $LAGS = \{1\}$ indicates that each day's dependent variable is modeled based only on the previous day's dependent variable measurements. This is called a *first-order autoregressive (AR(1)) model*. Lag zero should only be included if it makes physical sense for the current value of the dependent variable to depend on current values of the independent variables. Next, the user may add the dependence from two days ago, adding lag 2 so that $LAGS = \{1,2\}$. This would produce an AR(2) model. Subsequently, lags should be increase to $LAGS = \{1,2,3\}$. Et cetera.

The user may choose to skip lags to incorporate "seasonality" effects. For example, if the data represent daily measurements, and $LAGS = \{1, 2, 7\}$, then *TaylorFit* will test independent variables from yesterday, the day before yesterday, and one week ago for their ability to predict today's dependent variable.

Note that for all lags other than zero, TaylorFit will test for lagged values of the dependent variable, as well as lagged independent variables.

For example, consider the well-known Lydia Pinkham time-series dataset with two columns - Sales (S) and advertising budget (A), and 54 rows for successive years from 1907 to 1960. These data can be loaded automatically from the *TaylorFit* start page by clicking the button labeled "Lydia Pinkham – Load Example Data." We would like to use these data to develop a model to predict sales using previous years' sales and advertising. We might expect this year's sales to depend upon this year's advertising, so lag zero would be appropriate. Lags 1 and 2 seem to be relevant. That is, sales in one year shows some dependence upon both sales and advertising in the two previous years. However, there is no expectation of a seasonal effect in this case (unless a dependence on the 11-year sunspot cycle is expected!).

In time-series modeling we have the same problem as described above in determining the order to change the *Fitting Parameters*. Again, is up to the user, and is part of the art of modeling. A suggestion is to increase the number of lags repeatedly until no new terms are significant before increasing N_m or adding to *EXP*, and again after each time those other fitting parameters are changed.

Step 7 – Ending the Model Development/Validation

When to Stop

Ideally, the modeler should only stop when the model cannot be improved (with respect to the chosen criterion) by addition or removal of any single term, after the fitting parameters have just been augmented. Before moving on to final validation, the current model should be examined statistically and graphically as described in the next two sections. If the models are found inadequate in some way, the modeling effort can be continued. Or, it may be concluded that the proposed independent variables do not in fact have predictive power for these data!

Throughout the model-building process, it is a good idea to keep an eye on the plot of residuals versus predicted values that is displayed in the *Results Pane*. Besides model accuracy, a goal of modeling is for the residuals to be random. If trends are visible in this plot, then the model-building process is not complete. Another problem that can be revealed by this plot is the presence of outliers or influential points. Note that the residuals for the *FIT*, *CROSS*, and *VALIDATE* sub-datasets are shown on the same plot but in different colors. Clicking on the corresponding legend can turn individual sub-dataset results on and off.

A modeler may wish to keep models relatively simple. This can be done by using a more conservative cross-validation criteria, and/or a lower significance level (e.g. use $\alpha = 0.01$).

The models developed by *TaylorFit* may be described as “sub-optimal.” *TaylorFit* does not explore all the possible MPR models. But it will find ones that are “pretty good.” If the modeler wants to explore a wider family of models to seek improvement, here is a strategy to try: Add a number of terms that are not statistically significant, but are either close to significant, or just because the modeler judges those terms to have potential predictive power. Then return to the add-and-remove cycle until again the model cannot be improved with a single change. It is likely that you will have found a path to a different model, possibly with better performance.

The following two sections suggest ways to examine the model fit using statistical and graphical approaches. These approaches can be used at all stages of the model development process, including during model identification, when deciding whether to stop model development, when performing final validation, and for checking the final re-fitted model.

Examine the Statistical Goodness-of-Fit

The global *Goodness-of-Fit* statistics shown in the *Results Pane* provide a variety of useful measures. Most can be used for comparing competing models, although the *F*-statistic, R^2 , and adjusted- R^2 provide “absolute” measures.

The *MSE* is one of the fundamental values at the root of the calculation of adjusted R^2 , the *F*-statistic, the *AIC*, and the *BIC*. The *MSE* is an unbiased estimate of the variance of the residuals. The square root of the *MSE* is the *RMSE*, making it an estimate of the residual standard deviation. The *RMSE* will have the same scale and units as the dependent variable, which makes it easy to compare with the data. It also provides a rough way to estimate the confidence interval of the predictions as $\pm 2 \cdot RMSE$. To be precise, the factor 2 should be replaced

by the critical value of t . Also, it should be noted that the confidence interval for individual residual values can be computed precisely. This is described in the chapter on *Formal Definitions* below.

The maximum absolute value of the error ($\text{Max}|Err|$) is sometimes of interest. One such situation is when *TaylorFit* is being used to fit an *MPR* model to results of a numerical model. The value of R^2 may be expected to be very close to 1.0 if enough terms are included, and the maximum absolute error may be a desired objective. Using it as the cross-validation criterion may be appropriate in this situation.

The R^2 is the best-known and most commonly used *GoF* criterion for regression, although it (like *SSE*) is likely to result in over-fitting if used as a criterion for adding terms to the model. The $\text{adj-}R^2$ is an improvement, since it includes a penalty for model complexity. This makes it a better criterion, and one which is the same as using *MSE* or *RMSE*.

The *F*-statistic also penalizes model complexity. It has the advantage that it can be used in a statistical test of the hypothesis that the modeled variance is greater than the residual variance. That is, that the model as a whole is a significantly better predictor of the dependent variable than just using the mean of the dependent variable. This test is done by computing the probability that a larger value of *F* could occur by chance. This probability is denoted $p(F)$. As long as $p(F) < \alpha$, the model may be accepted. Generally, the higher the value of *F*, the lower will be $p(F)$, and the more certain one may be of the statistical significance of the model. Besides serving for this test, *F* can be used as a criterion for cross-validation. The higher the value of *F*, the better the model. This is a more conservative criterion than using, say, *MSE*, and will result in a simpler model (with fewer terms). Note that the value computed for $p(F)$ depends on the residuals being normally distributed and independent of each other (as tested below). However, even if they do not satisfy this condition $p(F)$ can be used as a relative probability for comparing fits.

AIC and *BIC* are criteria based on information-theoretic considerations. They may be used to compare models with different number of terms. If different models have the same number of terms, then these statistics correspond to comparison based on *MSE*. As with the *F*-statistic, they are fairly conservative criteria that may result in simpler models.

Skewness and Excess Kurtosis are statistical parameters that can help determine how well the distribution of the residuals correspond to the normal, or Gaussian, distribution. Skewness measures asymmetry of the distribution; a large excess kurtosis indicates a greater probability of extreme values (“fat tails”). Ideally both values should be close to zero. The *Goodness of Fit Statistics* Table also includes the standard error of the skewness and kurtosis – s.e. SKEW and s.e. XKURT, respectively. As an approximation, both statistics should be within 2 times their standard error of zero or, to put it more simply, the absolute value of each statistic should be less than twice their standard error. For example, if s.e. SKEW = 0.1205, then SKEW = -0.2534 is significant skew, but SKEW = -0.1727 is not.

Summary statistics should be examined for predictions, residuals and terms. These include: mean, standard deviation, skewness, excess kurtosis, and various percentile values such as the maximum (the 100th percentile), the median (the 50th percentile), and the minimum (the 0th

percentile). Right now, these calculations must be done outside of *TaylorFit*, such as by using a spreadsheet program. A future version is expected to include these in the *Data Table*.

Examine the Graphical Goodness-of-Fit

One of the most popular ways to graphically display goodness of fit in the literature is by a plot of predicted values on the Y-axis versus observed dependent data on the X-axis. This is appropriate – **never!** Instead, the plot should be observed versus predicted. The reason is that observed values equal predictions plus residuals. The latter are – or should be – random. Adding random variables to the x-axis will skew the plot and make it appear to have outliers at the upper and lower extremes. (See Draper and Smith reference for details.)

An even better graphical approach is to plot the residuals on the y-axis and predicted values on the x-axis. This is what is done in the plot that shows continuously in the *Results Pane* of *TaylorFit*. The goal of modeling is for this plot to appear as a random scatter of points, with no apparent trends.

Furthermore, the residuals should be plotted versus all the dependent variables as well as the sequence in which they appear in the data. This can be done using the XY Plot function in the column headers in the *Data Pane*. Click on the heading of the *Residual* column and select XY

Never plot predicted versus observed!

Plot. What appears is a plot of the residuals on the y-axis, and “index” on the x-axis.

“Index” means that the values are plotted in sequence in the order they appear in the

corresponding sub-dataset. Click on the down-arrow next to “Index” within the plot to select any of the other columns for the x-axis to examine the residuals versus each of the independent variables. None of these plots should show obvious correlations. Do not use the dependent variable as the x-axis value for the reason described above.

Several specialized plots are included to assist in verifying that the residuals are independent and normally distributed. These include the histogram, the CD plot, the Q-Q Plot, and the autocorrelation plot. The *histogram* is displayed as a bar graph. The number of bars (or “buckets”) in the bar graph can be increased or decreased by clicking on the buttons in the graph. This should approximate a symmetrical “bell-shaped” or Gaussian shape. The *cumulative distribution* (CD) plot is the integral of the histogram but shows all the data. If the data are Gaussian the CD plot will have a sigmoidal shape (i.e. be “S”-shaped). The final check on Gaussian distribution is the *quantile-quantile* or “QQ” plot. This is a direct comparison to the Gaussian distribution. If the residuals are perfectly normally distributed, they will fall exactly on the straight line shown. Some deviation is expected though, especially at the extreme values.

The last graphical examination technique built into *TaylorFit* is the *autocorrelation* plot. This plot is essential to checking residuals in time-series models but may also be useful with non-time-series. This is essentially a bar-graph of correlation coefficient of a residual with its lagged value. The correlation coefficient is on the y-axis and the lag on the x-axis. Thus, the bar at lag 2 represents the correlation of residuals at any time step with the residual from two time steps before. The orange and green lines are the upper and lower (respectively) confidence intervals for the correlation coefficient. When the model is complete, all bars should fall between the upper and lower confidence limits. Autocorrelation is not expected with non-time-series data,

especially if the data were randomized before being exported into *TaylorFit*. But it might occur if the data were collected with the dependent and/or one or more of the independent variables exhibiting a strong trend.

Final Validation

In order for a model to be scientifically valid for prediction purposes, it must be validated using data independent of those data used to create the model. *TaylorFit* is structured so that the *FIT* and *CROSS* sub-datasets are used for *identification* (determining which terms should be in a model) and *fitting* (determining model coefficients). (Note that with *TaylorFit*, only the *FIT* sub-dataset is used to compute model coefficients. Both *FIT* and *CROSS* sub-datasets can be used for model identification.) When model identification and fitting are complete, the final step is validation – determining how well the model works with independent data.

Final validation is done as follows: First of all, import the validation data. If this was not done at the start of the modeling project, it can be done when the model is completed. In fact, it is

Independent final validation is the gold standard for modeling

better to wait until the modeling is completed, to avoid the temptation of looking at the performance of the model with the validation data during the model identification process. If the validation data were not imported at the beginning, it can be done now by clicking on the

button in the *Data Pane* called “*Import Validation Data*.” Notice that a new column appears in the *Goodness of Fit Statistics Table* with the heading “*Validation*.” These are the statistics used to judge the validity of the current model. Only $p(F)$ is meaningful on an absolute scale. As long as it is less than α , then the model is statistically significant.

Often data are scarce and there are not enough to partition the dataset into two, let alone three, parts. In such cases it may be necessary to do without a separate *VALIDATE* dataset, or to use a single dataset for both *FIT* and *CROSS* purposes. However, in this case the resulting model should be used with extreme caution for making predictions, and the modeler should emphasize these limitations to any constituents who may use the model or its results. Without validation, the model may be used to express *correlation* among the variables. That is, the model can show how the independent variables affect the dependent variable. But predicting the outcome of the dependent variable using new measurements of the independent variables is risky and not scientifically valid. In statistics-speak, another way to describe this is to say that without final validation the model is representative of the *sample*, and should be used with caution to make inferences about the *population*.

There is a situation in which cross-validation and final validation is not required. This is when *TaylorFit* is being used to generate an MPR model of data that were themselves generated by a model. Here, all relevant independent variables are known, and there are, in a fundamental sense, no errors. Why would one want to replace one model with another? There are several reasons. One would be to replace a computationally complex model with a much simpler one. For example, one could replace an implicit iterative computation with an explicit one, or a numerical simulation with a time-series model. Another reason might be to simplify model analysis, such as sensitivity analysis.

Final Model Re-Fitting and Exporting Information

Once the decision is made that the current model is valid, change the *FIT* dataset to include all the available data, including those data formerly used for the *CROSS* and *VALIDATE* datasets. The only way to do this currently is to perform the following steps:

- a. Under the *Settings* button click on *Export Project*. This will save the *current model*, the *GoF* Table and the *Data* in a file with name ***model.tf*** in the download folder on your computer. You should note the terms in the *current model* either by writing them down, or by saving the output of the *Export to Code* button.
- b. Under the *Settings* button click on *Clear Project*. This will bring you back to the *TaylorFit* start page.
- c. Click on the *Import Data* button. But this time, use the *ALL* dataset (see section on *Data Files* in chapter *How TaylorFit Works*) as the *FIT* dataset.
- d. Perform addition steps but add only those terms that appeared in the final model until you wind up with the identical model.
Caution: Do not add any new terms during this procedure. The final model should have exactly the same terms as in the exported project.
- e. At this point, the *Current Model* Table will have the model with coefficients updated using all the data, and the *FIT* column of the *Goodness-of-Fit Statistics* Table will have the updated statistics.

For clarity, we call the result the *Final Re-Fitted Model*. You can use the final re-fitted model for your ultimate purposes including making predictions and for model analysis, evaluation and distribution.

The *Export Data* button in the *Data Pane* saves the *Data Tables* in a CSV file. Although the user already has the data in a CSV file to start with, the exported files will also have the final re-fitted model *predictions and the residuals* in additional columns, as well as any additional columns that have been generated such as *transformed columns, sensitivities, and importance ratios*. This will facilitate any additional graphical or numerical data analysis the user may wish to perform on these derived results, such as using external programs for producing publication-quality graphics.

The *Export Project* button under the *Settings* button saves a file with filename “*model.tf*” that contains the data, the fitting parameters, and the current model. This can be used at any stage of the modeling process so the user can return later to where she/he was and continue the project from the point of interruption. However, depending upon the browser being used, even if the *TaylorFit* browser tab is closed, the project may still be there if the *TaylorFit* link is reopened.

The user can also copy and paste the *Current Model* Table or the *Goodness of Fit Statistics* Table from *TaylorFit* into other programs such as spreadsheets or word processors.

Finally, the *Export to Code* button below the *Current Model Table* generates code with the proper syntax that can be copied and pasted into *JavaScript, Excel, C++, MatLab, Python* or *R* software for computing the model predictions.

Step 8 – Model Analysis and Evaluation

Now it is time to look at what the model is telling you and what behaviors it reveals using a combination of graphical and analytical methods.

Graphical analysis

The final re-fitted model should be examined using the same graphical methods described for Step 7 above. In addition, you might want to produce plots of the model without the data. You can do this using software outside of *TaylorFit* such as *MatLab* or *Excel*. The *Export to Code* button under the *Current Model* Table facilitates this.

Since the essence of *Multivariate Polynomial Regression* is the “multivariate” part, it may be a problem to plot the response of the model to more than one or two independent variables. The model can be plotted versus a single independent variable in an ordinary X-Y plot.

The problem then becomes what value(s) to use for the other independent variables. A starting point may be to hold those other values at their mean or median values. Or, a parametric plot can show several model curves corresponding to several values of the second independent variable over its range. Only variables that appear together in the same term will interact with each other and would benefit from such a parametric plot. Constructing plot such as these involving one or two of the most sensitive independent variables may be adequate, although a thorough analysis would require a systematic examination of all the variables.

Sensitivity analysis

One important way to analyze the behavior of a model is to examine its sensitivity to particular independent variables. The sensitivity of the model with respect to the variable (x_i) may be defined as the slope of the model prediction curve (see mathematical definitions in chapter *Formal Definitions*).

For *MLR* models, the sensitivity is a constant equal to the coefficient of the term containing the independent variable. But for *MPR* models the sensitivity may not be constant. In general, it will depend on the value of the independent variable and may also depend upon the values of other independent variables that interact with it. Thus, it would be appropriate to represent the sensitivity as a distribution.

TaylorFit can compute the sensitivity of the model to any independent variable by computing a value for each row in the dataset. This is done by clicking on the down arrow in the heading of one of the independent variables and selecting “Show Sensitivity.” *TaylorFit* computes the sensitivities for each row and displays them in a new column to the right of the residuals. This column can then be examined using the same graphical tools as for the other columns. Of particular interest would be the *histogram* and *cumulative distribution* plots. If the *Export Data* button is clicked the new sensitivity column will be saved in a CSV file along with the other data.

Importance ratios

A problem with sensitivity as defined above is that values computed for different variables cannot be compared with each other. Sensitivity has units equal to the ratio of the units for the dependent variable and the selected independent variable. Thus, sensitivity itself depends upon the units used. A way to make the different sensitivities comparable is to cancel out the units using a measure of the spread of the variables. *TaylorFit* uses the standard deviation to do this. The resulting measure of sensitivity is called the *Importance Ratio (IR)*. The *IR* is proportional to the sensitivity by the ratio of the standard errors of the respective variables:

To start with, use the *CD Plot* to examine the range of values for the sensitivity or the *I.R.* Note that it might be possible for them to change sign over their range. I.e., the sensitivity may be positive for some sets of independent variable values, and positive for others. This is an example of a type of behavior that linear models cannot describe.

At the present time, *TaylorFit* can only compute sensitivity and importance ratios for non-time-series models.

Comparing different models

As was noted above, *TaylorFit* may produce different models if different strategies are used. For example, a model using *MSE* for cross-validation may be different than one produced using the *F*-statistic. Or, the sequence selected to increment the *Fitting Parameters* may also influence which particular terms wind up in the model. Modeling is art as well as science, and there is no single guaranteed route to a perfect model.

But this raises the issue of how to compare two different models. The approach described here will work not only for comparing two *MPR* models, but to compare *MPR* with *MLR*, or *MPR* with *ANN*, etc. This can be carried out using the data from *TaylorFit*, but the calculation itself will have to be done in external software such as *Excel*.

Disparate models can be compared by using the ratio of their *MSE* values. Note that $MSE = SSE/df$. The *df* is unambiguous with *MLR* or *MPR* models. In the case of *ANN* models there is disagreement in the literature about what the *df* should be. Some references indicate that *df* is much less than the number of weights in the *ANN* (which can be quite high); others indicate it should be higher. A conservative approach would be to just assume that *df* is equal to the number of weights in the *ANN*.

In any case, once the *MSE* is computed, the ratio of the model with the larger *MSE* (call it “model 1”) and the model with the smaller *MSE* (model 2) will be an *F*-statistic for the comparison:

$$F = \frac{MSE_{model\ 1}}{MSE_{model\ 2}}$$

Then, the probability that that value of F or larger can occur by chance can be computed from the F -statistic, and the degrees of freedom for the two models:

$$p(F) = f(F, df_1, df_2)$$

In *Excel*, for example, the critical value F_{crit} can be computed using the built-in function “=FDIST(F,df1, df2).” If $p(F) \leq \alpha$ one may accept that model 2 has a significantly smaller (better) MSE .

Example Datasets

The startup page for www.TaylorFit-RSA.com includes buttons for:

- **Additional information:** This button takes you to the website for *Simetrica, LLC*. This has a primer on TaylorFit modeling and some other information.
- **Download Example Non-time-series Data - Auto MPG:** This download automatically loads an example *non-time-series* dataset into TaylorFit.
- **Download Example Time-series - Lydia Pinkham:** This download automatically loads an example *time-series* dataset into TaylorFit.

Both example datasets are described below. Many other example datasets can be found on the web. A good source of data is at the following website maintained by the University of California, Irvine (UCI):

<https://archive.ics.uci.edu/ml/datasets.html?format=&task=&att=&area=&numAtt=&numIns=&type=&sort=taskUp&view=table>

Reference:

Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.

Auto MPG Dataset

This dataset was taken from a library maintained at Carnegie Mellon University and was downloaded from the UCI website:

<https://archive.ics.uci.edu/ml/datasets/Auto+MPG>

There are data for 398 vehicles from model years 1970 to 1982. The variables, corresponding to the columns of the CSV file, are:

1. MPG: City-cycle fuel consumption in miles per gallon
2. CYL: The number of cylinders in the engine.
3. DISP: The piston displacement volume in cubic inches
4. HP: Engine power in horsepower units
5. WT: Vehicle weight in pounds
6. ACCEL: Acceleration
7. YR: Model year in integer value as last two digits of the year (i.e. 79 means 1979)
8. ORIGIN: This is an integer-valued index indicated whether the origin of the vehicle is from the United States (index = 1), Europe (index = 2), or Japan (index = 3).

The first column should be designated the dependent variable. An additional column was in the original download file containing the name of the car. This was removed because it is unique for each car (row in the data file) and cannot be used as a fitting variable.

As the fitting proceeds, you will note some interesting results that show how the modeler needs to use judgement in the process. Once the modeling process has progressed to a fairly good model, examination of the residuals plot shows that there are a number of cars that are high-MPG outliers. The variables in the data file are not able to explain the high MPG values for

these cars. This indicates that there is likely to be some additional variable, not in the dataset, that would explain the outliers. The modeler should examine the outliers to see if such an explanatory variable could be found. For example, it might be found that these cars have some special technology to improve mileage, such as a hybrid power train or engine cylinder deactivation.

Lydia Pinkham Dataset

The Lydia Pinkham is a company that markets a tonic to women. As a result of a lawsuit, the company's annual sales results (S) and advertising budget (A) for the years 1907 to 1960 were made public. This dataset has been used often as a test case for time-series models. The values in the dataset are in thousands of U.S. dollars.

Modeling Tips and Potential Pitfalls

The first step should always be to statistically and graphically examine the data. Plot each variable (whether independent variable or dependent variable) versus each of the others. Plot a histogram of each variable. Compare fit, test and validation data for lack of similarity, unique situations, different ranges or other statistical properties. This step is ignored at great risk to the modeler!

The final step should always be the statistical and graphical examination of residuals. The residuals should be plotted versus the predictions and versus each independent variable in turn. The purpose of the modeling is to remove any apparent trends in these plots.

The stepwise algorithm does not always converge on a global optimum. This is usually not a problem; sub-optimal may be good enough. With empirical modeling there will always be other approaches to modeling a specific dataset that may give somewhat different behavior. However, with *MPR* models you can try adding and removing terms manually to find better models closer to the optimum.

Sometimes it helps to start by fitting to one independent variable (i.v.), and then add terms that include other i.v.'s. For example, in fitting wastewater treatment plant data for influent flow vs. time of day and lagged flow, first fit best model using time of day only, then allow terms with lagged flow.

Consider adding all linear terms to a model to start with, regardless of their significance. Then increase the exponent list and N_m to include nonlinear terms. Then use backward elimination to pare the model.

You can also fit a fundamental (aka “mechanistic”) model to the data, taking into account as much as possible, and then model the residuals left over after the mechanistic model predictions were subtracted from the data. For example, one investigator obtained the tidal components of waves near an ocean outlet of a bay using the well-known sinusoidal behavior of the tides. Then, he used *TaylorFit* to discover correlations between those residuals and components such as wind and off-shore wave parameters that are not accounted for by the mechanistic models.

Nonlinearities may sometimes be hard to find unless noise level in the data is very low. From experience, when R^2 is 0.75 or lower, the nonlinearity is often masked, and only linear terms are significant. Unless the nonlinearity is strong, it may not show up unless R^2 is 0.8 or 0.9, or if there are a very large number of data points.

Potential Modeling Pitfalls

Here is a summary of several well-known problems that occur in any kind of modeling. The modeler needs to be aware of them and watchful for them.

Overfitting: This is a problem also known as “memorizing the noise in the data.” You will recognize this when you observe that the model does well predicting the *FIT* dataset but does poorly in fitting the final validation data not used in developing the model. The simplest way to avoid this is to use conservative fitting criteria such as *F-statistic*, *AIC*, or *BIC*, which penalize model complexity. However, this may not be sufficient. A better approach is to use cross-validation. The values of R^2 or *SSE* should never be used as a fitting criterion. Adding a term to a model will usually improve these statistics, even if the term is not a significant contributor to the fit. The adjusted- R^2 or *MSE* may be used in place of these.

If not using cross-validation, the number of candidate terms should not be allowed to exceed one-tenth to one-sixth of the number of data, and absolutely should not exceed the number of data.

Multicollinearity: If two or more of the independent variables are correlated with each other, a model that includes both will have misleading *t*-statistics. However, the step-wise regression strategy helps avoid this problem. Once a variable or term is in the model, another variable or term that is highly correlated with it usually will not have significant additional predictive power, and is not likely to be selected into the model.

Chance Correlation: If you fit a random variable to 20 or more random variables, accepting 95% confidence level, you may find correlations. An experiment like this modeled with two multipliers and three exponents got better than 50% R^2 purely by chance. But when cross-validation was used with the same data no spurious correlations were found. Cross-validation helps prevent both overfitting and chance correlation.

Polynomial Wiggle: This is a problem in which the model works well with the *FIT* data, but produces results that are far “out of line” when the model is used to make predictions at points between data points used for fitting. This may be caused by too few degrees of freedom. The remedy is to use a conservative fitting criterion and/or a larger value of α . Cross-validation also mitigates this.

Influential Points: This is a problem in which a small portion of the data are distant (in *n*-space) from the other data. The resulting model does a good job predicting the difference between the two portions of the data, but a poor job within each group. It can also result in a misleadingly high value of R^2 . This can be avoided by partitioning the data and modeling the parts separately.

For example, if you have marketing data on men and women, but 95% of the data are for men, then it would be better to separate them and form two different models - one for the men and one for the women.

The final step in modeling should always include graphical examination of the residuals

When partitioning multivariate data, do a multiple sort (stratified sampling). It might be necessary to bin the variables (sort into groups, number the groups, and sort on the number) so that one variable doesn't dominate the sort.

A related problem is that sometimes you might be interested in modeling one part of the data more than other parts. For example, in modeling the effect of rainfall on river flow, you might only be interested in wet periods, which might comprise a small portion of the total dataset. A future version of the software may include weighting factors, but for now the only approach is to cut out some of the data to reduce its weight, or replicate other areas to increase their weight. Or, the data could be partitioned to model dry periods separately from the wet ones.

Potential Time-Series Issues

If a time-series varies slowly, it is easy to get high R^2 values, even with naïvely simple models. For example, in modeling daily temperature in a river, simply using yesterday's value as a predictor would produce high R^2 . In such cases it would be more meaningful to difference the data and develop a model to predict the difference. That is, instead of predicting tomorrow's value, predict the difference between today and tomorrow.

For time-series with long lags, you can cut the number of variables by using a *variable integrated lag* approach. That is, use as lagged variables linear combinations of lagged variables, such as averages of lagged variables, where you use longer averaging periods the further back in time you go. For example, create independent variables from lag 1, average(lags 2 to 3), average(lags 4 to 7), average(lags 8 to 15), etc. Yet another approach is to use an exponentially decaying weighted moving average.

If the data show sharp changes, discontinuities, or high-frequency transitions, it may be necessary to use a high degree polynomial (say, six or eight, or even higher). And, it would be necessary to test candidate terms with lower degrees at the same time.

Formal Definitions

This chapter provides formal mathematical definitions for the models and statistics used in *TaylorFit* suitable for use in publications.

Non-time-series Multivariate Polynomial Regression Model

The following is a formal definition of the non-time-series Multivariate Polynomial Regression (MPR) model:

Data: $(y_i, x_{1,i}, x_{2,i}, \dots, x_{n_v,i})^T; i = 1, \dots, n_d$

Model: $\hat{y}_i = (\sum_{k=1}^{n_p} a_k Z_{k,i}); Z_{k,i} = \prod_{j=1}^{n_v} x_{j,i}^{b_{j,k}}$

$$e_i = y_i - \hat{y}_i$$

$$\sigma^2 \simeq s^2 \equiv MSE = \frac{\sum_{i=1}^{n_d} e_i^2}{n_d - n_p}$$

Definitions:

y_i	(Measured) dependent variable in row i
\bar{y}	Mean of dependent variables
\hat{y}_i	Predicted value using independent variables from row i
$x_{j,i}$	Independent variable j in row i
n_v	Number of independent variables (i.v.'s)
n_d	Number of data points (rows in dataset)
n_p	Number of coefficients (terms) in the model (including constant term)
$Z_{k,i}$	Model term k using independent variables from row i
$b_{j,k}$	Exponent of independent variable j in term k
e_i	Residual (error) for row i
σ^2	Variance of residuals
s^2	Estimated variance of residuals

Computing Confidence Intervals

As mentioned above, a rough confidence interval for the residuals (and therefore for the predictions) can be estimated as $\pm 2 \cdot RMSE$. More precisely, the value of 2 should be replaced by the critical value of the t -statistic for α and df :

$$\hat{y}_i \pm t_{crit} \cdot \sqrt{MSE}$$

However, this does not take into account the independent variables. Using the values of the independent variables allows more precise estimation of the confidence intervals. At present this must be done external to *TaylorFit*, such as in *MatLab* or *Excel*. First, it is necessary to construct the $n_d \times n_p$ matrix Z in which each row corresponds to a row in the dataset, and each

column is a corresponding term computed from the independent variables in those rows. If there is a constant term in the model, the corresponding column should be filled with 1's. Z_i is then the vector corresponding to row i of matrix Z . Then, the confidence interval (*C.I.*) for the prediction for row i is:

$$C.I. = \hat{y}_i \pm t_{crit} \cdot \sqrt{MSE \cdot (Z_i^T (Z^T Z)^{-1} Z_i)}$$

It is interesting to note that if the dependent values are plotted along with the predictions and their confidence intervals, most of the data would be outside the *C.I.* This seems paradoxical. One might expect 95% of the data to be within the 95% confidence interval. The explanation is that the *C.I.* is the range for the *model prediction*, not for the *data*. Since the data are the predictions plus the residual, they range more widely. The interval for the data is called (ironically) the *prediction interval (P.I.)*, and can be computed as follows:

$$P.I. = \hat{y}_i \pm t_{crit} \cdot \sqrt{MSE \cdot (1 + Z_i^T (Z^T Z)^{-1} Z_i)}$$

Goodness-of-Fit Statistics

The following are formal definitions of the values found in the *Goodness of Fit Statistics* Table. (Note that some of the following are intermediate values not displayed in *TaylorFit*, including *df*, *TMS*, *SSR*, and *MSR*.)

Data statistics

n_d : The number of data used for fitting. For non-time-series models this is the same as the number of rows in the corresponding sub-dataset. For time-series models it is the number of rows minus the maximum value of *LAGS*. (Same as n_d in the formal model definition.)

n_p : The number of coefficients (= number of terms) in the current model, including the constant term, if included in the model. (Same as n_p in the formal model definition.)

df : The residual (or error) degrees of freedom;

$$df = n_d - n_p$$

TSS: Total Sum of Squares:

$$TSS = \sum_{i=1}^{n_d} (y_i - \bar{y})^2$$

TMS: Total Mean Square, the estimated variance of the dependent variable

$$TMS = \frac{TSS}{n_d - 1}$$

Global Goodness-of-Fit

SSE: Sum of squares of the model errors (aka sum of squares of the residuals)

$$SSE = \sum_{i=1}^{n_d} e_i^2$$

MSE: Mean square error; the sample variance of the residuals

$$MSE = \frac{SSE}{df}$$

RMSE: Root mean square error; the estimated standard error of the residuals

$$RMSE = \sqrt{MSE}$$

Max|Err|: The maximum of the absolute values of the errors; used for minimax optimization

$$Max|Err| = Max|e_i|$$

SSR: Sum of squares of the regression:

$$SSR = TSS - SSE$$

MSR: Mean square of the regression (intermediate value not displayed in *TaylorFit*)

$$MSR = \frac{SSR}{n_p}$$

RSQ: R^2 , the square of the multiple correlation coefficient

$$R^2 = 1 - \frac{SSE}{TSS}$$

Adj-RSQ: Adjusted R^2 – similar to R^2 , but with a penalty for model complexity (the number of terms)

$$R_{adj}^2 = 1 - \frac{MSE}{TMS}$$

F: The F -statistic; similar to the t -statistic for a term, but indicates the fit of the overall model, rather than of a particular term

$$F = \frac{MSR}{MSE}$$

$p(F)$: The probability of F being this large or larger by chance. The numerator degrees of freedom is n_p , the denominator degrees of freedom is df .

AIC: Akaike Information Criterion

$$AIC = \log(MSE) + 2 \cdot \frac{n_p}{n_d}$$

BIC: Bayesian Information Criterion

$$BIC = \log(MSE) + \log(n_d) \cdot \frac{n_p}{n_d}$$

SKEW: Skewness, a measure of asymmetry of the residuals distribution

s.e. *SKEW* Standard error of the skewness

XKURT: Excess Kurtosis = Kurtosis - 3.0; This is a shape factor that describes a deviation of the residuals distribution relative to the “normal” distribution; a large excess kurtosis indicates a greater probability of extreme values

s.e. *XKURT* Standard error of the kurtosis

Model statistics

t: The computed t statistic

$$t = \frac{a_1}{s.e._{a1}}$$

s.e._{ai} Standard error of model coefficient a_i

p(t): The two-tailed probability of a larger value of t . Typically, we would add a term to the model if $p(t) \leq \alpha$ for that term and remove a term if its $p(t) > \alpha$. The degrees of freedom for computing this is *df*.

α The significance level. Default value set to $\alpha = 0.05$.

Transformations

Logarithmic

$$\hat{y} = \log_{10}(y)$$

Standardize

$$\hat{y} = \frac{y - \bar{y}}{s.e._y}$$

Scale by *RMS*

$$\hat{y} = \frac{y}{RMS_y}$$

k-order Difference

$$D_{1,k} = y_k - y_{k-1}$$

$$D_{2,k} = D_{1,k} - D_{1,k-1}$$

$$D_{n,k} = D_{n-1,k} - D_{n-1,k-1}$$

Sensitivity and Importance Ratio

Sensitivity:

$$\psi_{x_i} = \frac{\partial y}{\partial x_i}$$

Importance ratio:

$$IR_{x_i} = \frac{\partial y / s.e.y}{\partial x_i / s.e.x_i} = \psi_{x_i} \cdot \frac{s.e.x_i}{s.e.y}$$

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