

Introduction to MATLAB® Tutorial

MATLAB® is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB®, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java™.

Installing and Activating MATLAB®

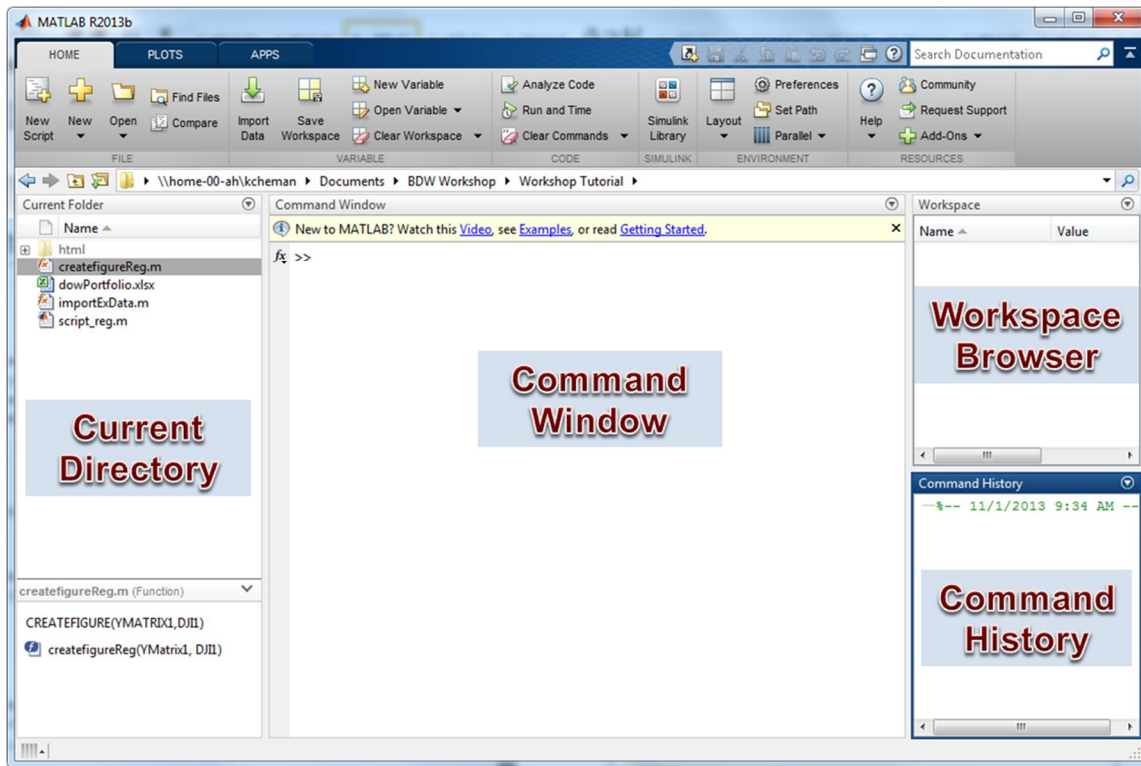
Follow the instructions that you received by email or during the Workshop to install and activate MATLAB®. You will now be able to launch MATLAB® through November 15, 2013. You have access to the following products:

- MATLAB® R2013b
- Statistics Toolbox
- Neural Network Toolbox
- Curve Fitting Toolbox
- Optimization Toolbox

User Interface

When you start MATLAB®, the desktop appears in its default layout. The desktop includes these panels:

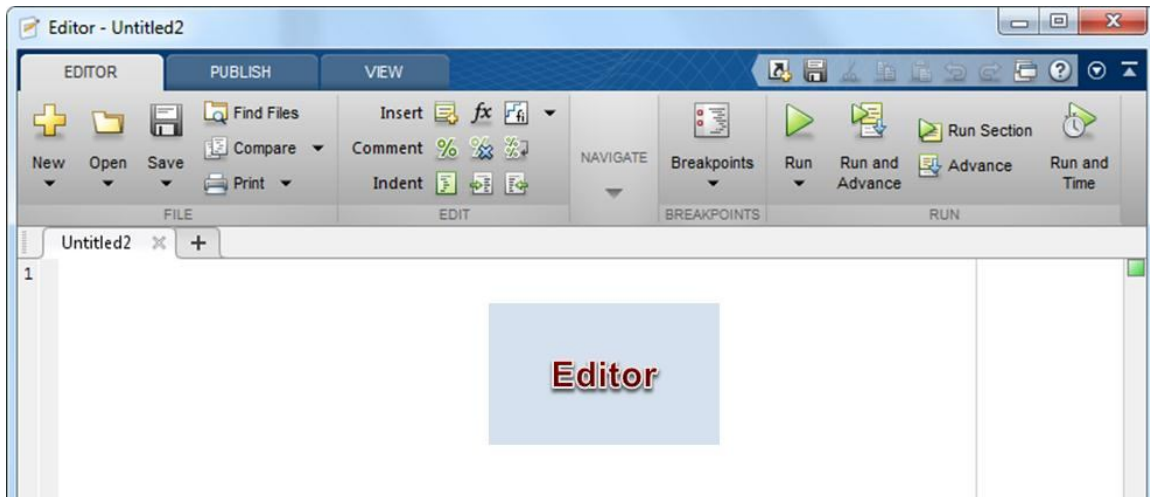
- Current Directory – Access your files.
- Command Window – Enter commands at the command line, indicated by the prompt: `>>`.
- Workspace Browser – Explore data that you create or import from files.
- Command History – View or rerun commands that you entered at the command line.



Other features of the desktop include:

- Toolstrip containing the Home, Plots and Apps tabs; each tab groups functionality associated with common tasks. Additional tabs, such as Editor, Publish and Variable, appear in the Toolstrip as needed to support your workflow.
- Quick access toolbar displays frequently used options such as cut, copy, paste and help. You can customize the options available in the quick access toolbar to suit your typical workflow.
- Search Documentation box allows you to search the documentation.

The MATLAB® Editor allows you to create a new file (e.g., script or function) in MATLAB®. You can open a new, untitled file by (1) typing `edit` at the command line or (2) using the New button from the Toolstrip.

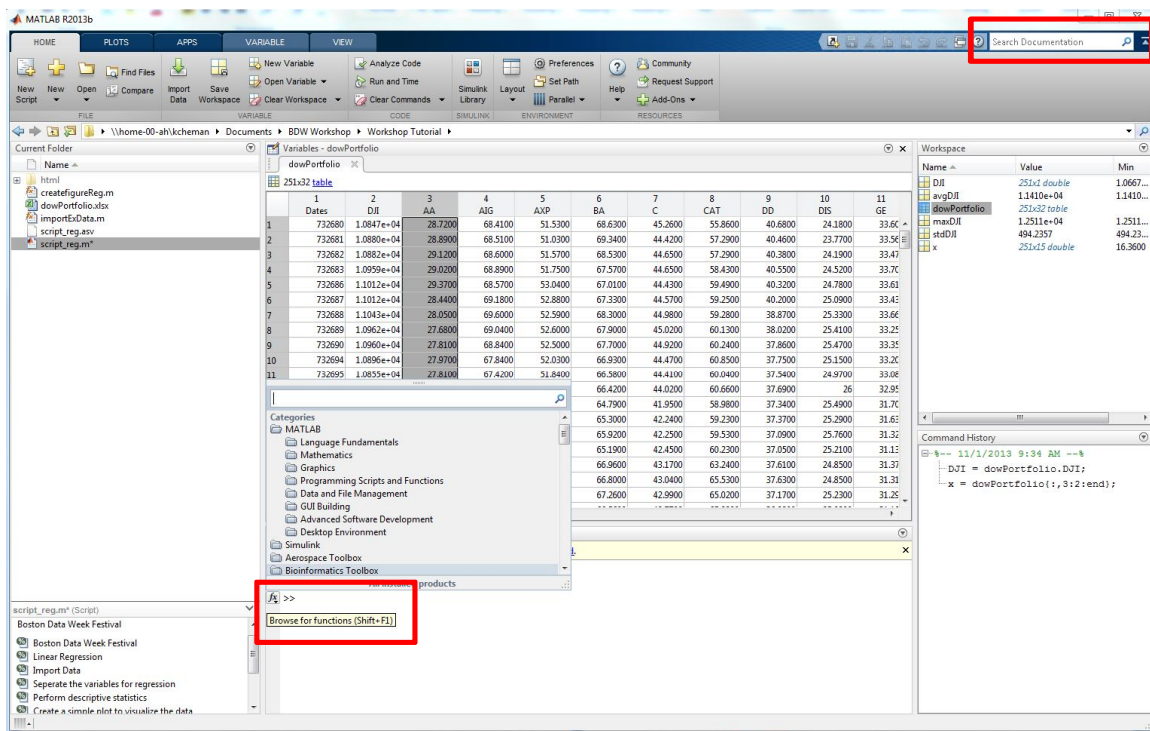


Documentation: http://www.mathworks.com/help/matlab/learn_matlab/desktop.html

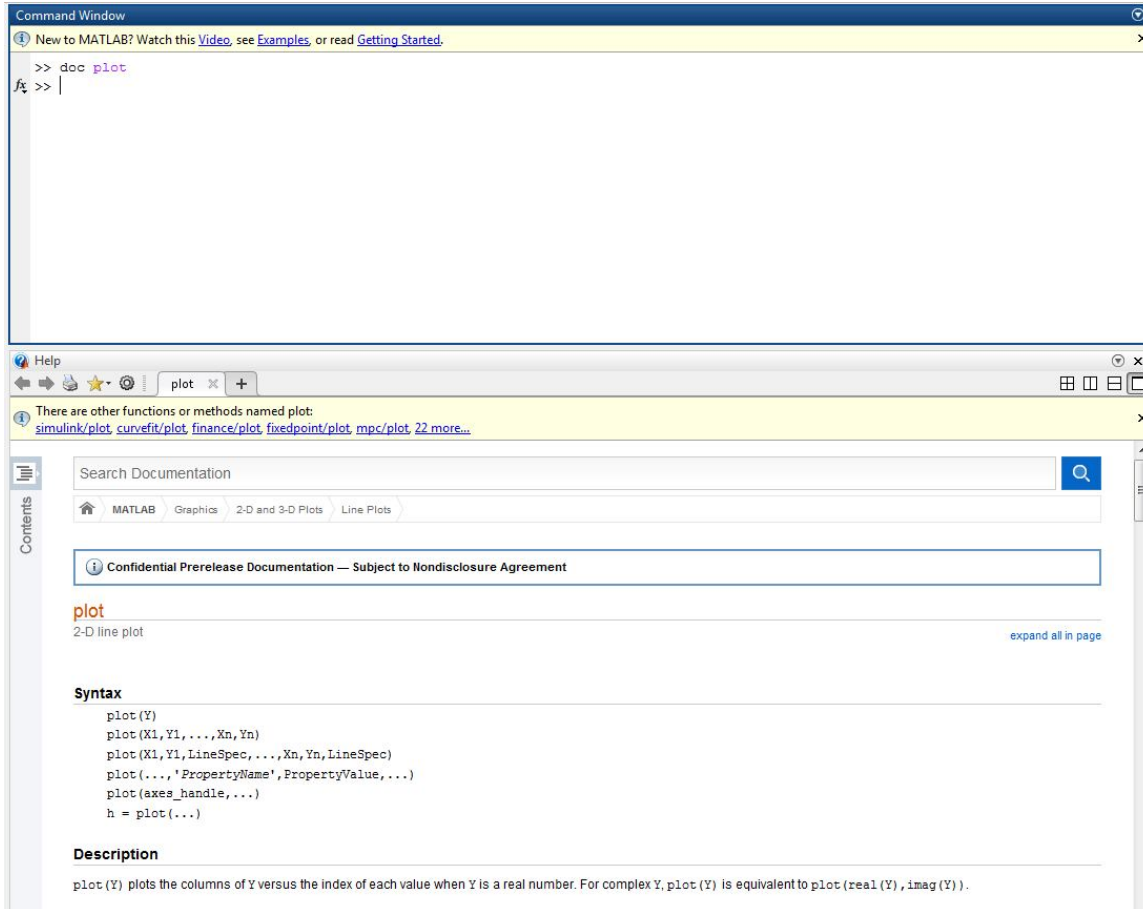
Getting Help

There are several ways to get MATLAB® help:

- Click the Function Browser in the Command Window. (See graphic below.)
- Search Documentation in the top right of the user interface.



- Search the Documentation from the command line using `doc`.



Command Window

New to MATLAB? Watch this [Video](#), see [Examples](#), or read [Getting Started](#).

```
>> doc plot
fx >> |
```

Help

There are other functions or methods named plot:
[simulink/plot](#), [curvefit/plot](#), [finance/plot](#), [fixedpoint/plot](#), [mpc/plot](#), [22 more...](#)

Search Documentation

MATLAB Graphics 2-D and 3-D Plots Line Plots

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plot
 2-D line plot expand all in page

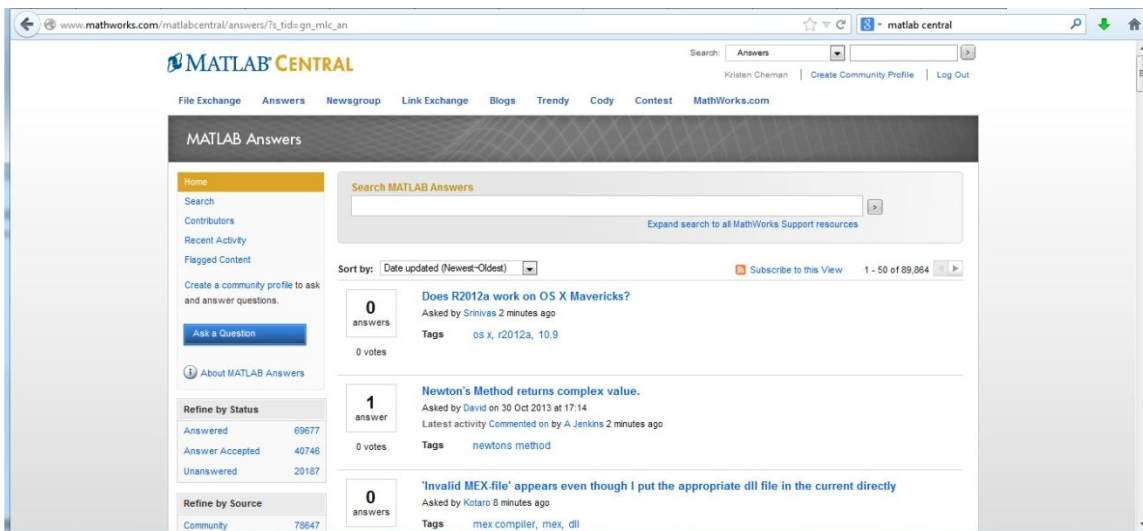
Syntax

```
plot(Y)
plot(X1,Y1,...,Xn,Yn)
plot(X1,Y1,LineSpec,...,Xn,Yn,LineSpec)
plot(...,'PropertyName',PropertyValue,...)
plot(axes_handle,...)
h = plot(...)
```

Description

plot(Y) plots the columns of Y versus the index of each value when Y is a real number. For complex Y, plot(Y) is equivalent to plot(real(Y),imag(Y)).

- Visit www.mathworks.com -> Support and search Documentation.
- Post a question to MATLAB® Central.



www.mathworks.com/matlabcentral/answers/?s_tid=gn_mlc_an

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 Latest activity Commented on by A Jenkins 2 minutes ago
 Tags newtons method

0 answers
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 Asked by Kotaro 8 minutes ago
 Tags mex compiler, mex, dll

MATLAB Warm-up

Manipulating Data

You can define variables at the command line. Try:

```
a = 3;
```

```
b = 4
```

Notice the difference when you remove the semicolon at the end of a line.

MATLAB® has several built in functions to easily create data: `rand`, `zeros`, `ones`, `magic`, and `diag` are examples.

Create a 4-by-3 matrix of random numbers:

```
x = rand(4,3)
```

You notice that `()` are used for indexing, order of operations, and passing arguments to a function. `[]` are used for concatenation and defining multiple outputs.

For example, you can define the following vectors:

```
vec1 = [1:5]
```

```
vec2 = [0:5:25]
```

```
vec3 = [25:-3:2]
```

Create a vector of every other value from 3 to 10:

```
vec = [3:2:10]
```

There are three types of indexing that you can use to extract data from an array:

1. Extract a single element.

Try extracting the third element in vector `vec1`:

```
third = vec1(3)
```

Try extracting the elements at locations (1,2) and (2,3) from matrix `x`:

```
loc1 = x(1,2)
```

```
loc2 = x(2,3)
```

2. Extract multiple elements.

Try extracting the first and fourth elements in vector `v` and call it `v1`. Then extract the third through last elements vector `v` and call it `v2`:

```
v1 = vec1([1 4])  
v2 = vec1(3:end)
```

Try extracting the third row from matrix `X` and call it `m1`. Then extract the first two rows, but only the first and second column in those rows; call it `m2`.

```
m1 = X(3,:)   
m2 = X(1:2,1:2)
```

3. Logical indexing. This allows you to use a single, logical array for the matrix subscript.

Try the following:

```
newX = X(X>.5)
```

MATLAB® allows you to easily perform matrix and element-wise operations and scalar expansion. For example, if we define two matrices:

```
A = [1 2; 3 4]  
B = [5 6; 7 8]
```

Then:

```
C = A*B  
D = A.*B  
E = A.^3 + B^2
```

Other useful operations are: `^` (power), `\` (left divide), and `'` (transpose).

Try:

```
A+1
```

Try:

```
A+[1 2]
```

Data Analysis

You may have interest in descriptive statistics about your dataset. Both MATLAB® and the Statistics Toolbox offer functions to assist you.

Try the following:

1. Generate a 10-by-10 array of random numbers between 1 and 10.

```
randarray = rand(10,10)*10
```

2. Find the maximum value of each column.

```
maxval = max(randarray)
```

3. Calculate the mean of each column.

```
meanval = mean(randarray)
```

4. Calculate the standard deviation of each column.

```
sigma = std(randarray)
```

Documentation: <http://www.mathworks.com/help/matlab/descriptive-statistics.html>

Scripts and Functions

Program files can be *scripts* that simply execute a series of MATLAB® statements, or they can be *functions* that also accept input arguments and produce output. Both scripts and functions contain MATLAB® code, and both are stored in text files with a `.m` extension.

Try the following:

1. Create a new script that computes the area of a triangle. In the script type:

```
b = 5;  
h = 3;  
a = 0.5*(b.* h)
```

2. Save the file as `triarea.m`.
3. Call the script from the command line by typing: `triarea`.

To calculate the area of a triangle with different dimensions, you would need to update the values of `b` and `h` in the script and rerun it.

Instead you could convert the script into a function.

The function calling syntax looks like:

```
[out1, out2, ..., outN] = functionname(in1, in2, ..., inN)
```

1. Revise the file to look like a function:

```
function a = triarea(b,h)  
a = 0.5*(b.* h);
```

2. Save the file and then call the function with different base and height values from the command line without modifying the script. Try:

```
a1 = triarea(1,5)
```

```
a2 = triarea(2,10)
a3 = triarea(3,6)
```

Logic

Once data is loaded, you may want to perform operations on it:

Conditional Control Statements: `if`, `elseif`, and `else`

The `if`, `elseif`, and `else` commands evaluate an expression and execute a group of statements when the expression is true. The syntax is:

```
if expression
    statements
    :
elseif expression
    statements
    :
else
    statements
    :
end
```

Try creating a conditional statement to check if a number is even or odd:

```
x = 10;
if mod(x,2) == 0
    disp('x is even ')
else
    disp('x is odd ')
end
```

Documentation: <http://www.mathworks.com/help/matlab/ref/if.html>

For Loops

For loops allow you to execute statements a specified number of times. The syntax is:

```
for index = values
    statements
    :
end
```

Try creating a for loop to perform 10! (factorial):

```
f = 1;
for ii = 1:10
    f = f*ii;
end
```


Type `f` on the command line to see the result. Then, use MATLAB's built in `factorial` to check your work.

```
factorial(10)
```

Documentation: <http://www.mathworks.com/help/matlab/ref/for.html>

Problem #1: Linear Regression Models

Introduction

Regression analysis is a statistical technique for estimating the relationships among variables. Independent variables (often denoted by X) are also called explanatory or predictor variables and the dependent variable (often called y) is the response variable.

Problem Definition

The Dow Jones Index (DJI) is used as a benchmark of market performance. The Dow Jones Index (response variable) is a weighted average of 30 big named stocks or components (predictor variables). The problem is to perform multiple linear regression on a subset of predictors (15 out of 30) to see how well you can predict the response.

Dataset: `dowPortfolio.csv`

This dataset includes (1) trading days between January 3 and December 29, 2006 in the first column, (2) the DJI for each date in column 2, and (3) each component of the DJI in columns 3 through 32. (The Dow Jones Index is a weighted average of columns 3 through 32.)

Importing Data

With the User Interface

1. Right- or double-click on the filename in the Current Folder window to launch the Import wizard. The wizard will display the file in a spreadsheet-like format.
2. Select the range to import, data type, and import rules. You can use the defaults, but change the data type to Table.

3. Choose Generate Function. Save the function as `importExData.m`.

4. Press Import Selection to save the table as a variable called `dowPortfolio`.

From the Command Line

You can also import from the command line, using the `readtable` command:

```
readtable('dowPortfolio.csv');
```

Supported File Formats

You can import a long list of file formats using MATLAB®, including text, spreadsheet, and XML.

Documentation: http://www.mathworks.com/help/matlab/import_export/supported-file-formats.html

Useful Data Types

Tables

In this example, you imported your data as a `table` data type. Tables serve as an excellent container for tabular data of dissimilar types and allow you to import data of different sizes and data types. In this case, all fields are numeric and the date is converted to a `datetime` type.

Documentation: <http://www.mathworks.com/help/matlab/tables.html>

Categorical Arrays

Also useful are categorical arrays, which allow you to store arrays of qualitative data with values from a finite set of discrete, nonnumeric data.

Documentation: <http://www.mathworks.com/help/matlab/categorical-arrays.html>

Create New Variables from `table`

To create new variables from the table:

1. Double-click on the `dowPortfolio` variable in the Workspace to open and view the table.
2. Right-click on column 2 containing the DJI data.
3. In the drop down menu, select New Workspace Variable from Selection -> Separate Workspace Variable(s).

A new variable `DJI` appears in the Workspace and MATLAB® echoes the commands in the Command History:

```
DJI = dowPortfolio.DJI;
```

This variable `DJI` represents your response variable.

4. From the command line, create a new variable `x` from the variable `dowPortfolio`, which combines only 15 components of the DJI—say every other column starting with column 3.

```
x = dowPortfolio{:,3:2:end};
```

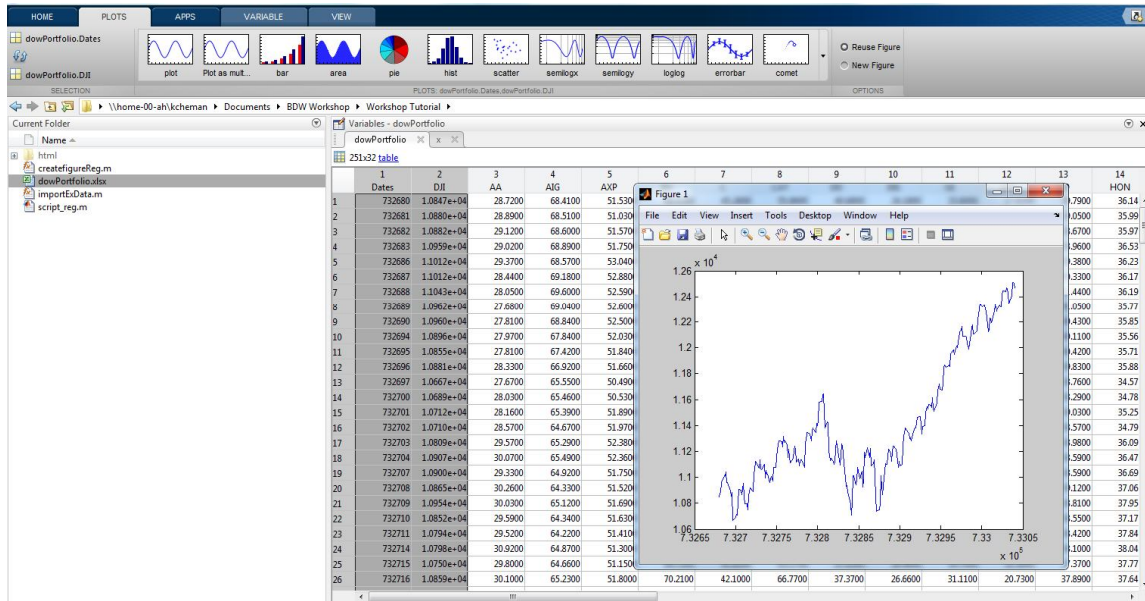
This variable `x` contains your predictors and you will use it later to try to model `DJI` using just these 15 components. (Note: These 15 components were selected arbitrarily; you could create a model with all of the components or other subsets of the components too.)

Documentation: <http://www.mathworks.com/help/matlab/matrices-and-arrays.html>

Data Analysis and Visualization

The Plots tab allows you to create various plots from single line graphs to bar and pie charts to histograms to scatter plots. Some plot options may be greyed out, if they don't make sense based on your data selection.

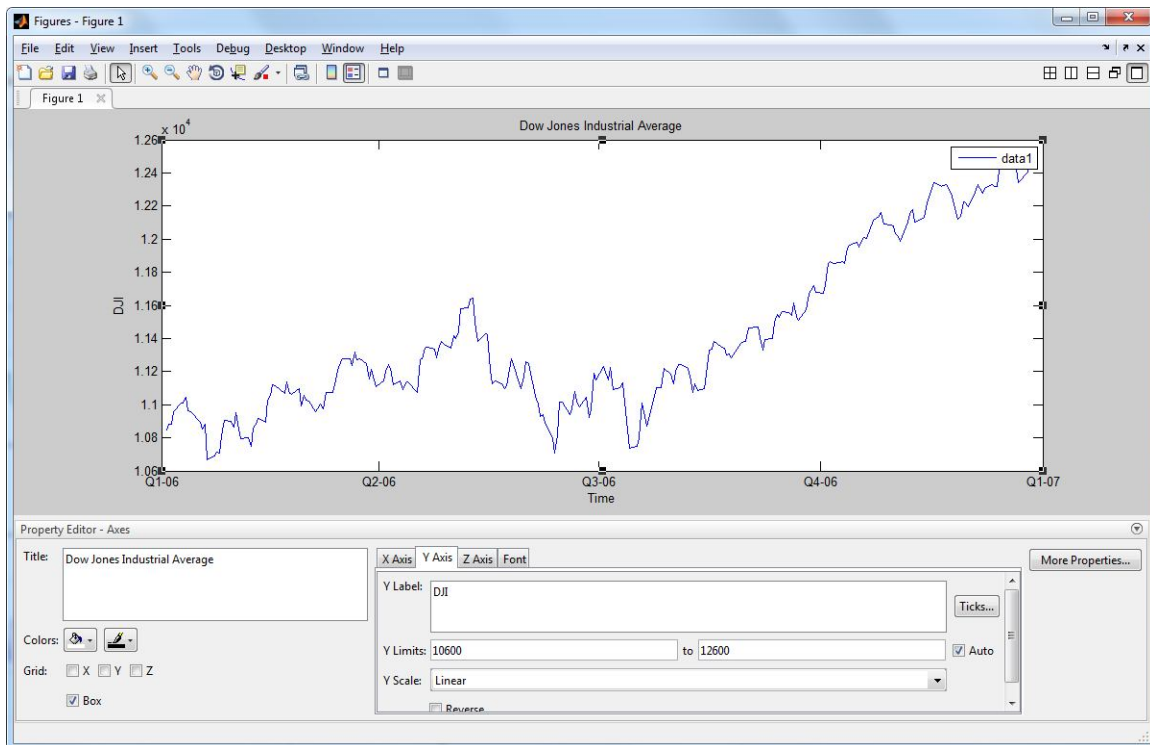
1. Open the table and select the `Dates` and `DJI` columns. Choose the plot icon to see the DJI over time.



You'll notice that MATLAB® echoes the command in the Command Window, so that you can recreate the steps easily.

```
plot(dowPortfolio.Dates,dowPortfolio.DJI)
```

2. Correct the dates in the plot by typing `datetick` in the Command Window.
3. Add chart labels from the Figure window.



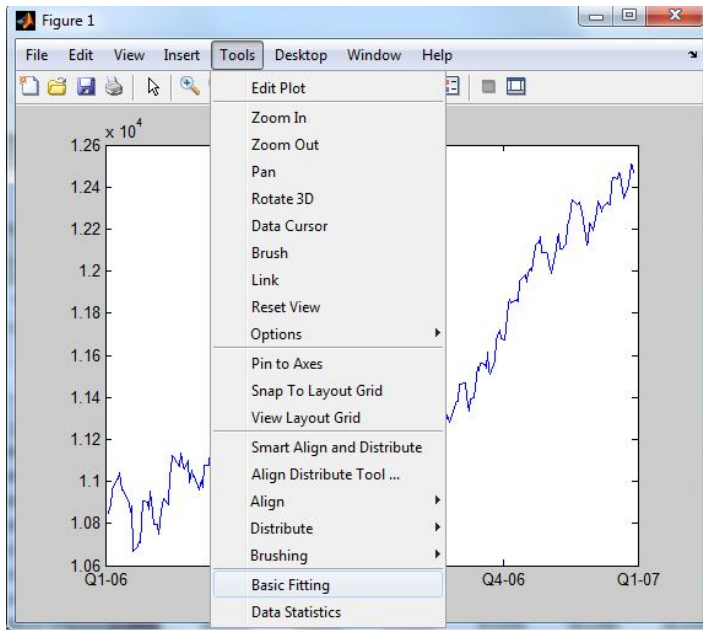
4. Auto-generate the code to produce this figure by selecting File -> Generate Code in the Figure window. Save the code as `createfigureReg.m`.

Basic Fitting

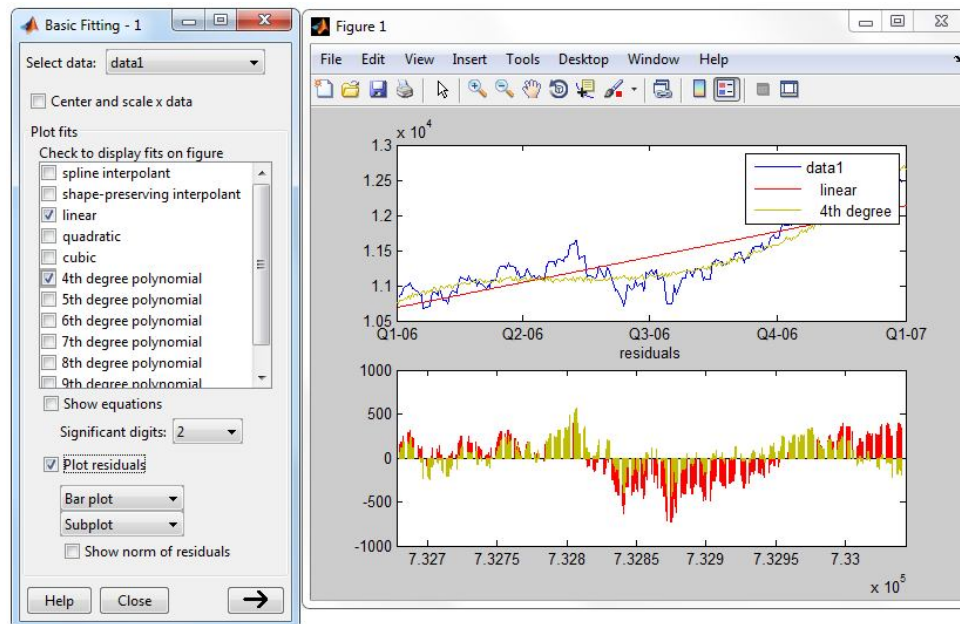
The Basic Fitting Tool allows you to:

- Select a model and plotting options
- Examine and export model coefficients and norms of residuals
- Examine and export interpolated and extrapolated values

1. From the Figure window, you can access the Basic Fitting Tool by selecting Tools -> Basic Fitting:



2. Check several plot fits to compare them against DJI.
3. Plot residuals.
4. Use the arrow button to view the model equations.



Documentation: http://www.mathworks.com/help/matlab/data_analysis/interactive-fitting.html?searchHighlight=basic+fitting#f1-15488

Linear Regression

You can also use built-in functions and write your own code to apply regression techniques, such as linear regression. Next, perform linear regression between the 15 predictors in `x` against the response `DJI`.

1. Pull up the documentation for `fitlm`. Look at your options for function syntax.
2. Create a linear regression model of the responses (`DJI`), fit to the data matrix (`x`) by using the `fitlm` function:

```
lm = fitlm(x, DJI)
```

You get the following output:

- Linear regression model (In this case, it is a linear formula with 16 terms, including 15 predictors.)
 - Estimated coefficients for each variable in the regression model (`Estimate`)
 - Standard error for each intercept in the regression model (`SE`)
 - t-statistic (`tStat`) – The t-statistic for your variable gets compared with values in the *Student's t distribution* to determine the p-value (which is the number that you really need to be looking at).
 - p-values (`pValue`) - The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A predictor that has a low p-value (< 0.05) is likely to be a meaningful addition to your model because changes in the predictor's value are related to changes in the response variable.
3. Look at the R-squared value to get insight into how well the model fits the data. Recall that an R-squared value of 1 indicates that the regression line perfectly fits the data.


```
>> lm = fitlm(x, DJI)

lm =

Linear regression model:
y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12 + x13 + x14 + x15

Estimated Coefficients:

```

	Estimate	SE	tStat	pValue
(Intercept)	1674.4	209.14	8.0063	5.4417e-14
x1	20.002	2.736	7.3107	4.1424e-12
x2	20.467	3.2729	6.2535	1.8768e-09
x3	6.5581	4.7669	1.3758	0.17021
x4	35.557	3.2222	11.035	4.3654e-23
x5	-12.739	7.4771	-1.7037	0.089752
x6	17.62	2.1444	8.217	1.4048e-14
x7	26.132	3.156	8.28	9.3319e-15
x8	1.5341	2.4949	0.61489	0.53922
x9	35.566	3.1673	11.229	1.0519e-23
x10	9.998	2.8989	3.4489	0.0006669
x11	15.592	1.8224	8.5558	1.5303e-15
x12	11.152	3.7587	2.9669	0.0033184
x13	8.0455	2.8473	2.8256	0.0051244
x14	14.038	2.6178	5.3627	1.9592e-07
x15	17.909	2.477	7.2299	6.7464e-12

```

Number of observations: 251, Error degrees of freedom: 235
Root Mean Squared Error: 36.7
R-squared: 0.995, Adjusted R-Squared 0.994
F-statistic vs. constant model: 3.01e+03, p-value = 4.04e-259

```

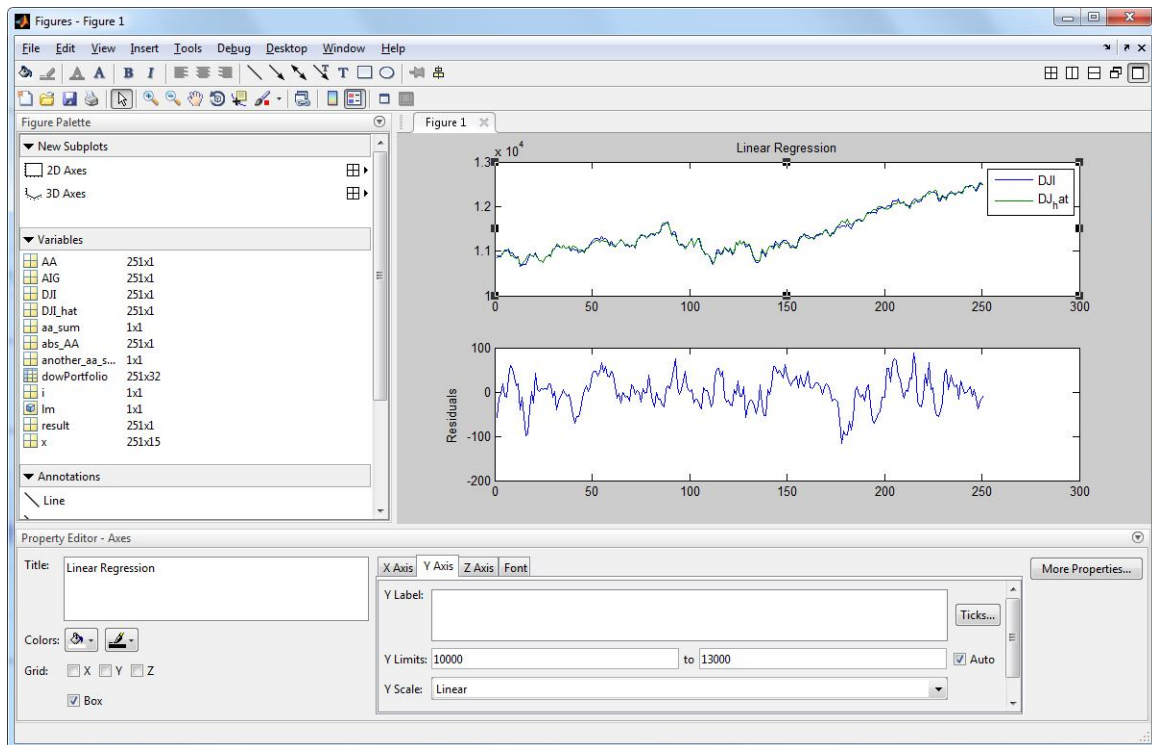
4. Test the performance of your model by generating a predicted DJI using the `predict` function:

```
DJI_hat = predict(lm,x)
```

Visualize Results

You can create graphics to visualize the model results, as well as the residuals, which indicate how well the model fits the dataset.

1. Select `DJI` and `DJI_hat` in the Workspace. In the Plots tab, select Plot as multiple series. A figure is displayed that shows a plot of `DJI` (the response variable) with `DJI_hat` (the prediction for `DJI`). You can see that the prediction for `DJI` very closely resembles the original `DJI`.
2. Use the Figure Palette to add a subplot to the Figure that shows the residuals (i.e., `DJI - DJI_hat`). You'll notice that the residuals are small compared to the size of the `DJI` variable, indicating that our prediction was a good one.



Stepwise Regression

Stepwise regression is a way of calibrating or adjusting your model to make it simpler by using fewer predictors by performing multiple linear regressions. Now, you will use stepwise regression to reduce the 15 predictors in x to a smaller subset of predictors. The reason for doing this is to determine a fewer number of stocks that you can buy, which perform as well as the DJI itself.

1. The `stepwiselm` function is used to implement stepwise regression in MATLAB®. Open the documentation to see your argument options.
2. Implement stepwise regression. Restrict the upper bound to be a linear model, so that you don't have interactions or higher order terms.

```
lm_red = stepwiselm(x,DJI,'constant','Upper','linear')
```

3. Look at the output. How many predictors does the new model have? (Answer: 12)

```

1. Adding x7, FStat = 2398.5537, pValue = 8.0782481e-130
2. Adding x4, FStat = 502.0912, pValue = 1.543296e-61
3. Adding x9, FStat = 185.6019, pValue = 6.726219e-32
4. Adding x13, FStat = 73.5263, pValue = 1.12224e-15
5. Adding x1, FStat = 25.5263, pValue = 8.53497e-07
6. Adding x2, FStat = 47.1903, pValue = 5.32413e-11
7. Adding x15, FStat = 42.9937, pValue = 3.26982e-10
8. Adding x11, FStat = 32.0349, pValue = 4.26864e-08
9. Adding x6, FStat = 53.9176, pValue = 3.20583e-12
10. Adding x14, FStat = 18.3626, pValue = 2.64482e-05
11. Adding x10, FStat = 21.7863, pValue = 5.08089e-06
12. Adding x12, FStat = 8.0564, pValue = 0.0049259

```

```
lm_red =
```

Linear regression model:

```
y ~ 1 + x1 + x2 + x4 + x6 + x7 + x9 + x10 + x11 + x12 + x13 + x14 + x15
```

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	1538	188.14	8.1744	1.7696e-14
x1	22.073	2.4122	9.1505	2.6389e-17
x2	21.769	2.9582	7.3591	2.9925e-12
x4	34.001	2.9665	11.462	1.6577e-24
x6	16.933	2.0814	8.1351	2.2813e-14
x7	25.782	2.8471	9.0557	5.0415e-17
x9	35.519	2.5892	13.718	6.0048e-32
x10	10.341	2.8544	3.6228	0.00035625
x11	16.384	1.5967	10.261	1.084e-20
x12	9.476	3.3385	2.8384	0.0049259
x13	8.5033	2.7781	3.0609	0.0024603
x14	13.949	2.3551	5.9231	1.0988e-08
x15	17.605	2.3542	7.478	1.4438e-12

Number of observations: 251, Error degrees of freedom: 238

Root Mean Squared Error: 36.7

R-squared: 0.995, Adjusted R-Squared 0.994

F-statistic vs. constant model: 3.77e+03, p-value = 8.23e-264

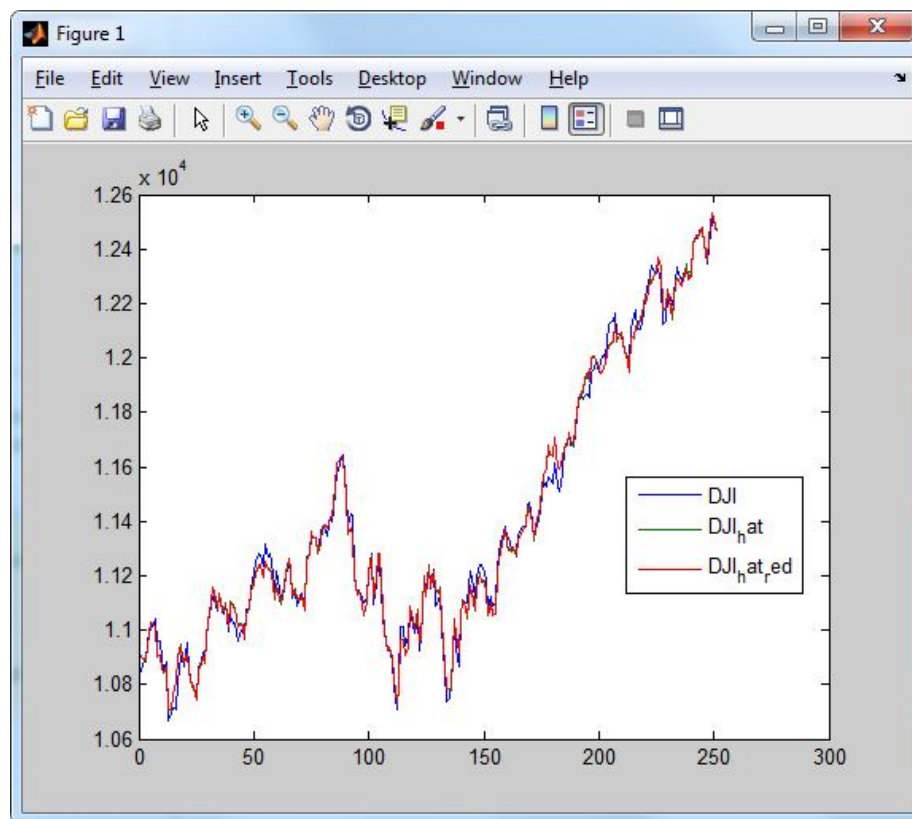
- Look at the R-squared value of the `lm_red` model (with reduced predictors). How does it compare to the previous R-squared value?
- Predict the DJI with the new stepwise model using the `predict` function:

```
DJI_hat_red = predict(lm_red,x);
```

- Plot the original response variable DJI with the two predictions `DJI_hat` (from the `fitlm` model) and `DJI_hat_red` (from the `stepwiselm` model) either by (1) using the interface to select the three variables in the Workspace and using the Plots tab or (2) at the command line:

```
figure
```

```
plot(DJI, 'DisplayName', 'DJI', 'YDataSource', 'DJI');hold  
all;plot(DJI_hat, 'DisplayName', 'DJI_hat', 'YDataSource', 'DJI_hat');plot  
(DJI_hat_red, 'DisplayName', 'DJI_hat_red', 'YDataSource', 'DJI_hat_red');  
hold off;figure(gcf);  
  
legend('show', 'Location', 'Best')
```



7. Notice that both models resulted in predictions that were close to the original DJI.

Scripts

The script for this example problem is called `script_reg.m`, which utilizes the auto-generated functions `importExData.m` and `createfigureReg.m`.

```

1 %% Boston Data Week: Festival
2 % MATLAB Tutorial
3
4 %% Linear Regression
5 % In this example, we are recreating the Dow Jones Index by regressing over
6 % some of its components.
7
8 %% Import Data
9 % We used the MATLAB generated code to read in data from an Excel file.
10 dowPortfolio = importExcel('dowPortfolio.xlsx');
11
12 %% Separate the variables for regression
13 % We are using only 15 DJ components here
14 DJI = dowPortfolio.DJI;
15 N = dowPortfolio(:,32:end);
16
17 %% Perform descriptive statistics
18 maxDJI = max(DJI);
19 avgDJI = mean(DJI);
20 stdDJI = std(DJI);
21
22 %% Create a simple plot to visualize the data
23 plot(dowPortfolio.Date,DJI);
24 datetick
25
26 %% Create Linear Regression Model
27 % We used the documentation to learn about modeling technique and which
28 % functions may be used to perform regression.
29 lm = fitlm(N,DJI);
30 DJI_hat = predict(lm,N);
31
32 %% Visualize Results
33 % We created a custom graphic to visualize the model results and the
34 % residuals. We also updated the auto-generated code to link the two axes.
35 createFigureReg(DJI, DJI_hat,DJI-DJI_hat)
36
37 %% Stepwise regression
38 % We performed stepwise regression to create a more parsimonious model.
39 lm_red = stepwiselm(N,DJI,'constant','upper','linear')
40 DJI_hat_red = predict(lm_red,N);
41
42 figure
43 plot(DJI,'DisplayNone','DJI','YDataSource','DJI');hold all;plot(DJI_hat,'DisplayNone','DJI_hat_red','YDataSource','DJI_hat_red');hold off;figure(gcf);
44 legend('show','Location','best')

```

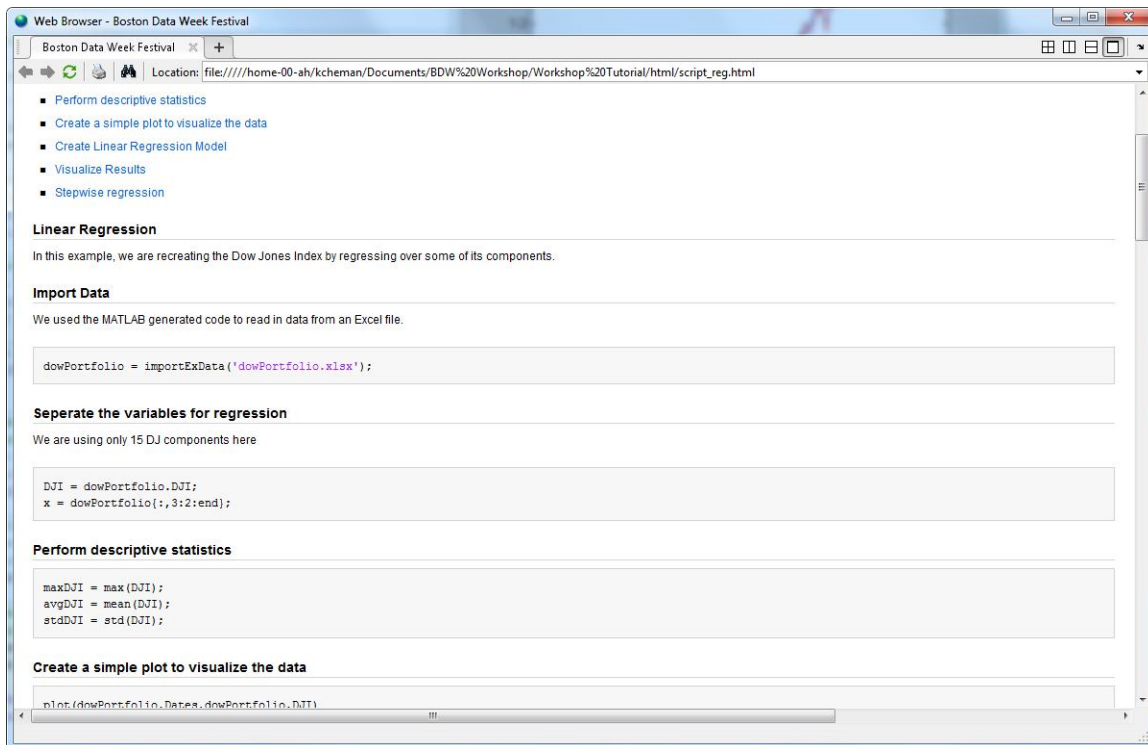
MATLAB® allows you to run sections of code at a time, working in chunks. A code section contains contiguous lines of code that you want to evaluate as a group in a MATLAB® script, beginning with two comment characters (%%).

Documentation: <http://www.mathworks.com/help/matlab/scripts.html>

Publishing Reports

By now, you should have a main linear regression script and two supporting functions.

The Publish tab allows you to execute code, including creating plots and evaluating results. You can then share your results (as HTML) with anyone, even if they don't have MATLAB®.



Documentation: http://www.mathworks.com/help/matlab/matlab_prog/publishing-matlab-code.html?searchHighlight=publish

Saving Your Work

The `save` function allows you to save all variables from the current Workspace into a MATLAB® formatted binary file (MAT-file).

Documentation: <http://www.mathworks.com/help/matlab/ref/save.html>

Problem #2: Neural Networks

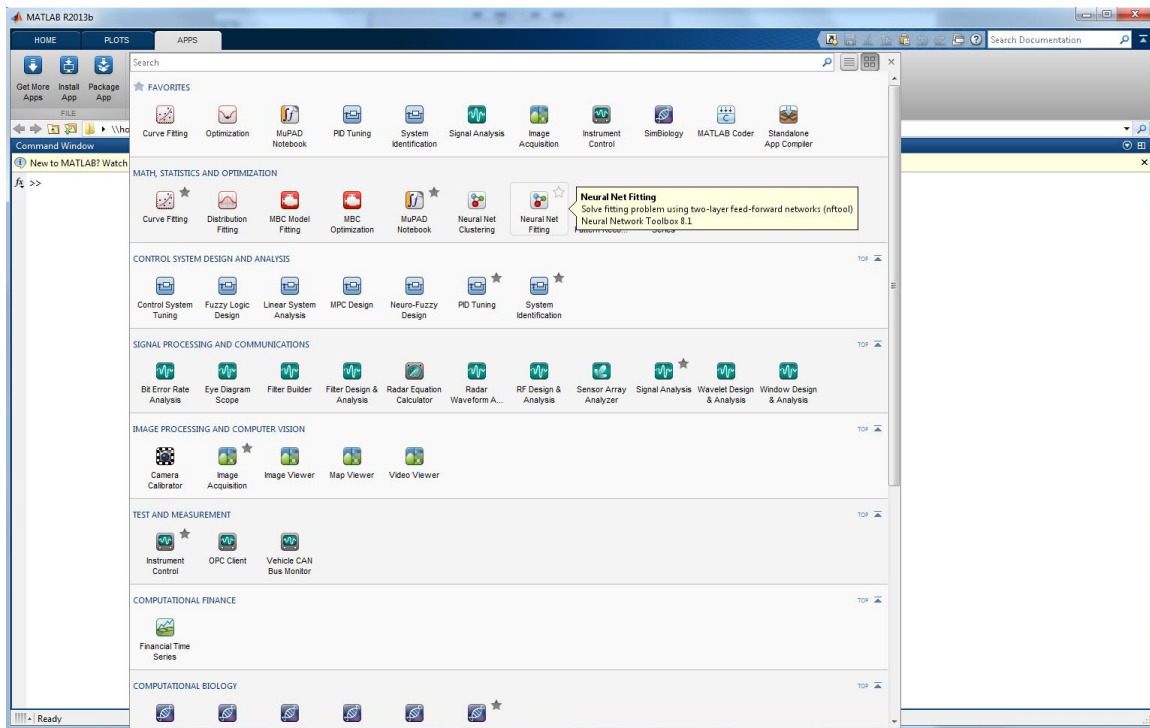
This time, start with all 30 components as predictors. Utilize a neural network to model the response `DJI` using the predictors `x30`. You can do this in MATLAB® in two ways:

1. Use an App (`nftool`), as described in [Using the Neural Network Fitting Tool](#).
2. Use command-line functions, as described in [Using Command-Line Functions](#).

It is generally best to start with the App, and then to use the App to automatically generate command-line scripts.

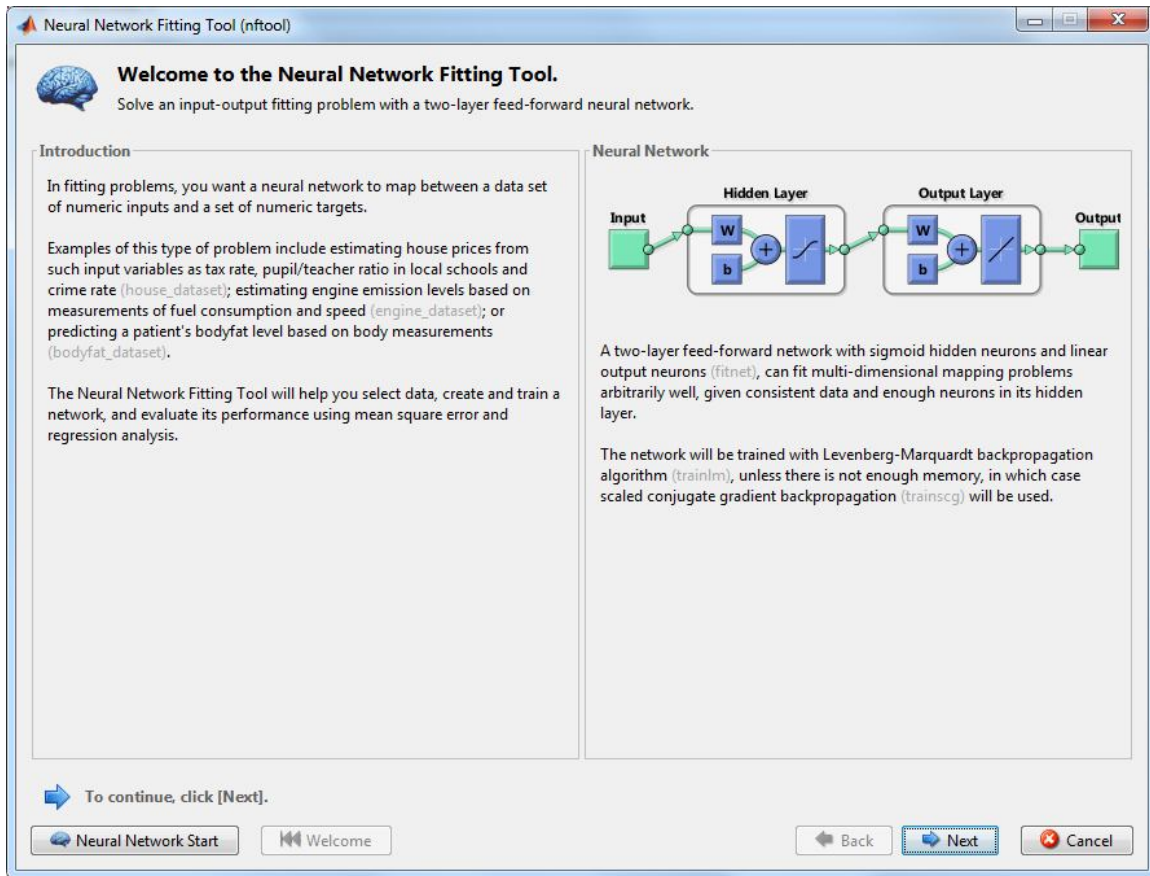
1. From the command line, create a new variable `x30` with all 30 predictors.


```
x30 = dowPortfolio(:,3:32);
```
2. Locate the Neural Network Fitting Tool in the Apps tab.

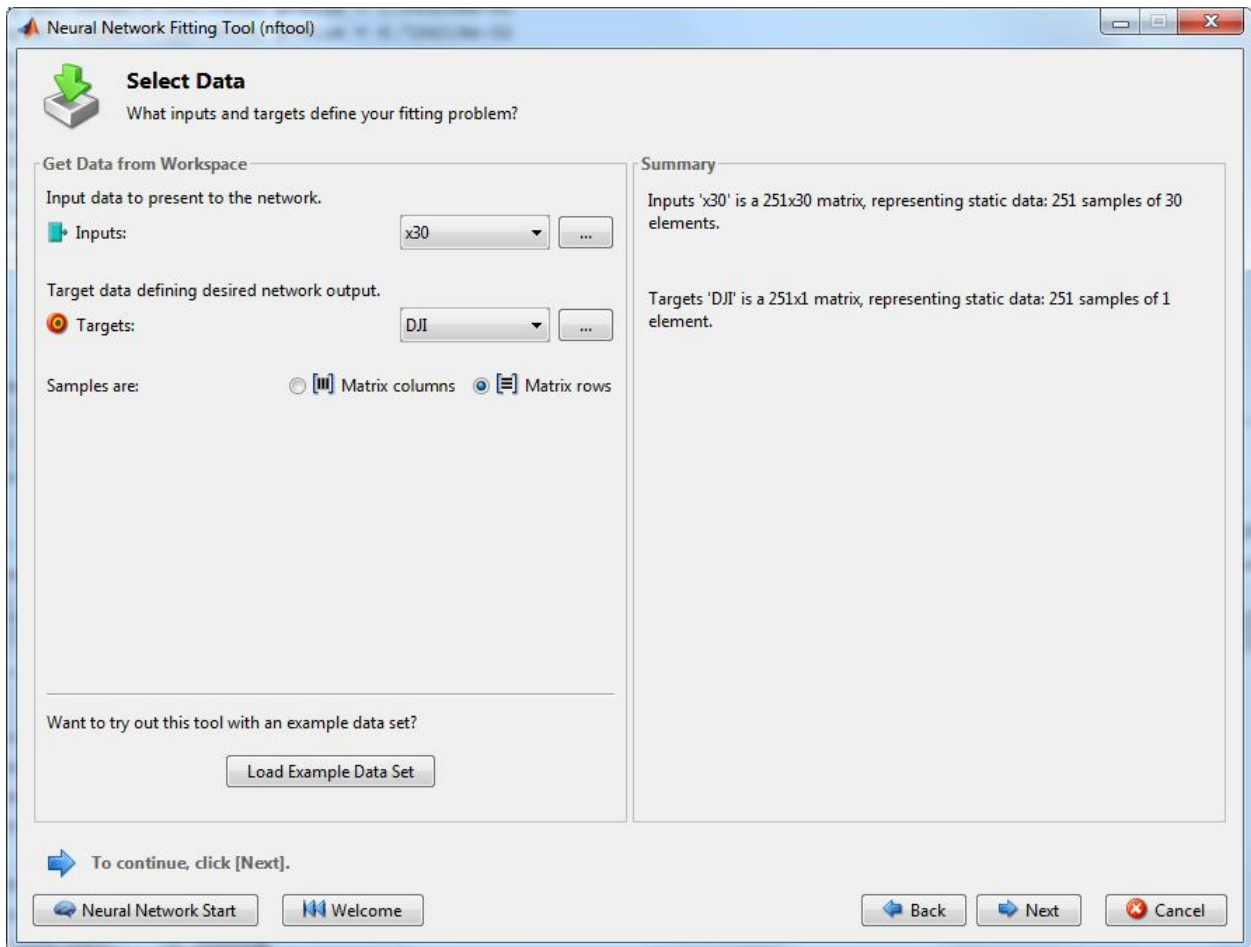



The App provides a step-by-step walk through for curve fitting (or other neural network applications), including from data selection through training, validation, and testing.







3. Launch the Neural Network Fitting Tool. The first panel describes the kind of problems that a fitting network is suitable for.



4. Select Data. Set the variable `x30` (predictors) as inputs and `DJI` (response) as the target. Recall that your samples are represented as rows in `x30`, so use the radio button to select Matrix rows.



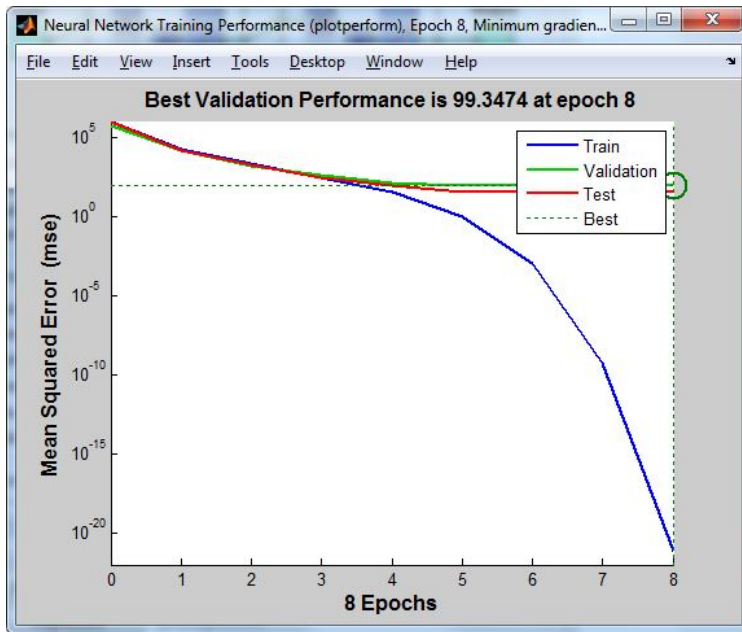
5. Divide the dataset into Training, Validation, and Testing data. Use the defaults for this example.
6. Define the architecture of the neural network. On this panel, you can choose the details of the network used to solve the problem. With more neurons, you can solve more difficult problems; with fewer neurons, the more compact your network will be. Use the defaults for this example. If you don't get a good solution, you can later return here to make changes.
7. Train the network to fit the inputs and targets. Training runs until generalization stops improving (i.e., mean square error increases). You will see the  Training network icon as the application is running and MSE and R statistics when it finishes.

Results			
	 Samples	 MSE	 R
 Training:	175	7.19562e-22	9.99999e-1
 Validation:	38	99.34742e-0	9.99836e-1
 Testing:	38	39.68767e-0	9.99911e-1

- Look at the output to see details of the training algorithms and status, including network accuracy, as well as useful plots.

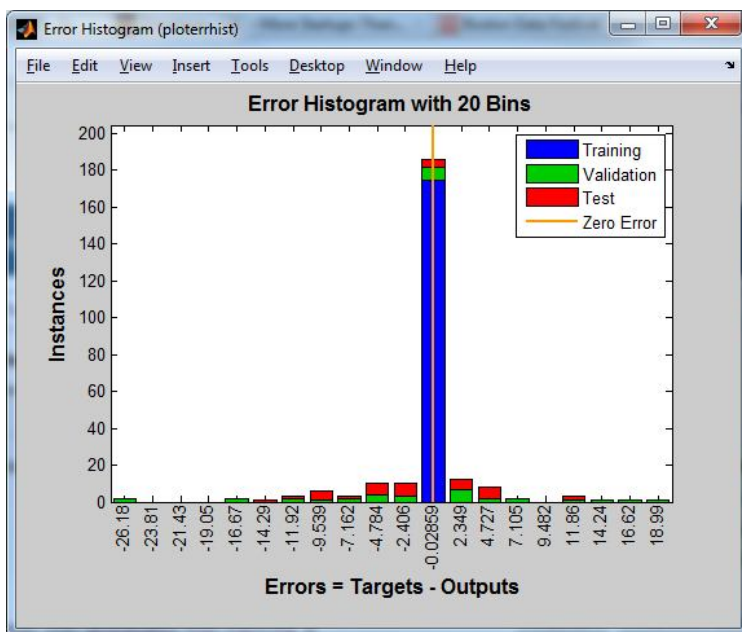


- Generate a Performance plot to see how the mean squared error decreases as training (the blue plot) continues. Training stops when validation (the green plot) stops decreasing. The red line shows how well the network did on the test data, showing how well your network will generalize to new data.



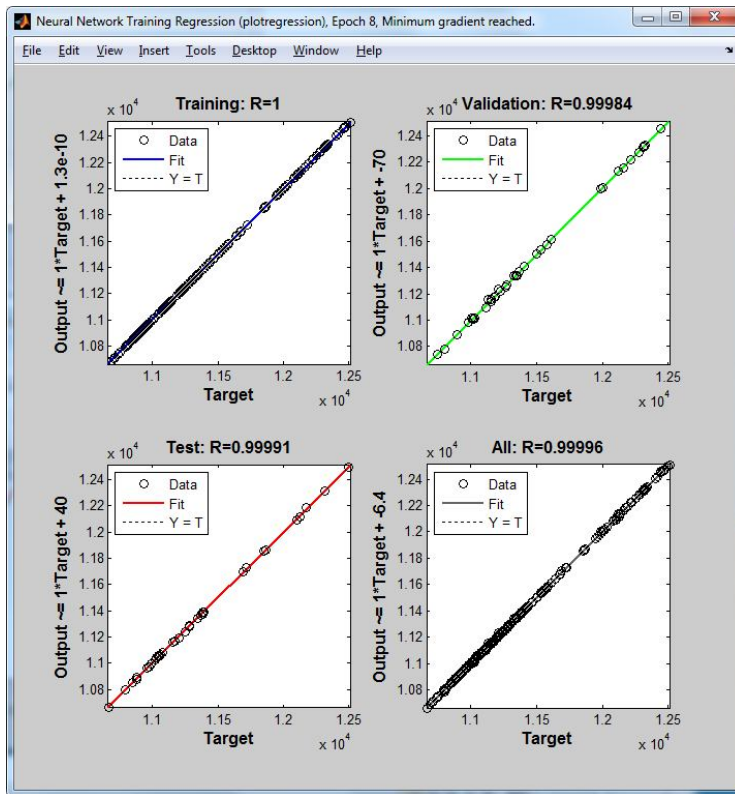
Note that an epoch is a single pass through the entire training set. At the beginning of each epoch, MATLAB® readjusts the network weights, based on where it left off in the previous epoch.


- The Error Histogram shows you the distribution of errors. Most of the errors are grouped around 0—as indicated by the vertical yellow line. If they're not, you may need more neurons for better results.



- View the Regression plot to see network outputs versus targets with respect to targets for training, validation, and test sets.

The regression line (in color) shows how well the network outputs are centered around the targets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. (The perfect fit is represented by the dotted line.) The overall distance between the regression line and dotted line is summarized by the R-value, which should be near 1 for a good fit. The following regression plots display the network outputs. For this problem, the fit is good for all data sets, since with R values are nearly 1 in each case.

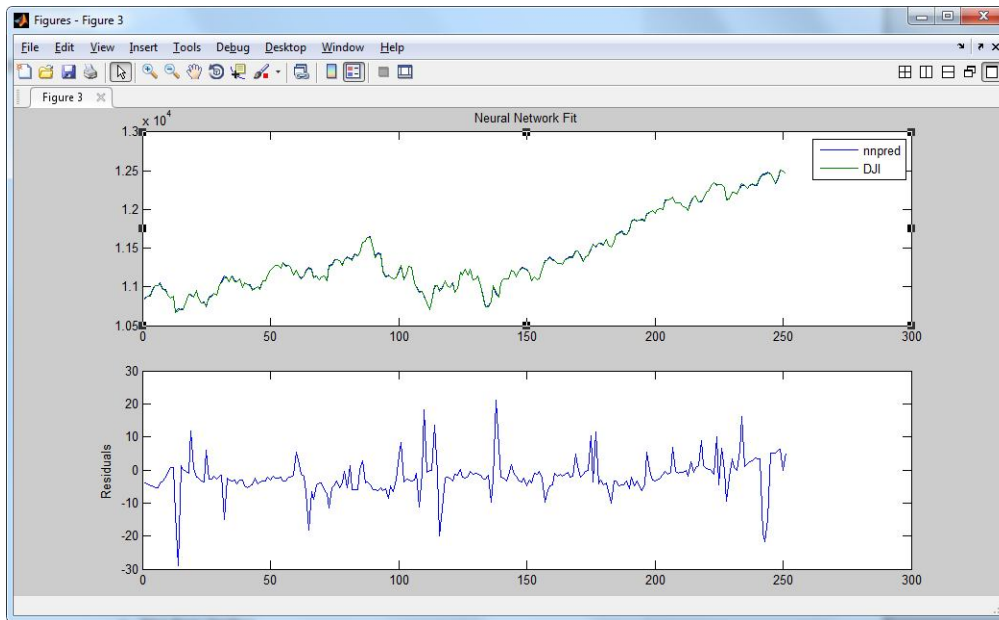


12. Evaluate network. You can use this panel to get tips on improving the network, such as adjusting the network size or using a larger dataset. You can also test the training network on additional data. Skip this step for this example.
13. Deploy solution. Click  to save your variables to the Workspace. (You can also use the this panel to generate a script that captures all of the neural network fitting steps.)
14. You should now see an object called `net` in the Workspace; this is your neural network. Predict the DJI using the network and your input data:


```
nnpred = net(x30')
```

Note that you must use the transpose of `x30`, since you defined the network to use Matrix rows as input samples.

15. Plot the prediction `nnpred'` (Note: again use `'`) with the original `DJI`, as well as the residuals:



Additional information: <http://www.mathworks.com/help/nnet/gs/fit-data-with-a-neural-network.html>

Video: <http://www.mathworks.com/videos/getting-started-with-neural-network-toolbox-68794.html>

Extra Credit Problem (Try on your own): Regression using Machine Learning

Linear (and non-linear) regression techniques can be used to fit models when you know the structure of the model apriori. For example, with a linear model, you can assume the linear dependence of the predictors. Linear regression is a parametric regression technique. The Statistics Toolbox also offers nonparametric regression techniques, such as Regression Trees.

1. Use the data in Activity 1 (i.e., `DJI` and `x`) and perform the same regression fit using the `RegressionTree` class.
2. Use the class's `predict` method to predict the responses.

Additional Machine Learning Resources

Machine Learning

Discovery Page: <http://www.mathworks.com/discovery/machine-learning.html>

Relevant Products

- Statistics Toolbox (<http://www.mathworks.com/products/statistics/>)
- Neural Network Toolbox (<http://www.mathworks.com/products/neural-network/>)
- Curve Fitting Toolbox (<http://www.mathworks.com/help/curvefit/>)

Supervised Learning

MATLAB® and its toolboxes include two categories of supervised learning algorithms:

- Classification: for categorical response values, where the data can be separated into specific “classes”
 - Support vector machines (SVM) for binary classification
 - Neural networks
 - Naïve Bayes classifiers
 - Decision trees for regression and classification
 - Linear and Quadratic Discriminant Analysis Classification
 - Nearest neighbors (kNN) for classification
- Regression: for continuous-response values
 - Multiple Linear regression with multiple predictor variables
 - Stepwise regression for variable selection
 - Multivariate regression
 - Regularization
 - Mixed effects models
 - Model assessment for plotting and diagnostic statistics
 - Nonlinear regression
 - Nonlinear mixed-effects models
 - Nonlinear Model Assessment
 - Generalized linear regression
 - Decision trees for regression and classification

There is a useful Getting Started guide in the documentation:

<http://www.mathworks.com/help/stats/supervised-learning-machine-learning-workflow-and-algorithms.html#bswluhd>

The guide walks you through the steps in Supervised Learning: Prepare Data, Choose an Algorithm, Fit a Model, etc.

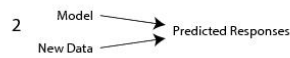
Supervised Learning (Machine Learning) Workflow and Algorithms

R2013b

On this page...

[Steps in Supervised Learning \(Machine Learning\)](#)[Characteristics of Algorithms](#)**Steps in Supervised Learning (Machine Learning)**

Supervised learning (machine learning) takes a known set of input data and known responses to the data, and seeks to build a predictor model that generates reasonable predictions for the response to new data.



Suppose you want to predict if someone will have a heart attack within a year. You have a set of data on previous people, including age, weight, height, blood pressure, etc. You know if the previous people had heart attacks within a year of their data measurements. So the problem is combining all the existing data into a model that can predict whether a new person will have a heart attack within a year.

Supervised learning splits into two broad categories:

- Classification for responses that can have just a few known values, such as `'true'` or `'false'`. Classification algorithms apply to nominal, not ordinal response values.
- Regression for responses that are a real number, such as miles per gallon for a particular car.

You can have trouble deciding whether you have a classification problem or a regression problem. In that case, create a regression model first, because they are often more computationally efficient.

While there are many Statistics Toolbox™ algorithms for supervised learning, most use the same basic workflow for obtaining a predictor model. (Detailed instruction on the steps for ensemble learning is in [Framework for Ensemble Learning](#).) The steps for supervised learning are:

1. [Prepare Data](#)
2. [Choose an Algorithm](#)
3. [Fit a Model](#)
4. [Choose a Validation Method](#)
5. [Examine Fit and Update Until Satisfied](#)
6. [Use Fitted Model for Predictions](#)

Prepare Data

All supervised learning methods start with an input data matrix, usually called `X` here. Each row of `X` represents one observation. Each column of `X` represents one variable, or predictor. Represent missing entries with `NaN` values in `X`. Statistics Toolbox supervised learning algorithms can handle `NaN` values, either by ignoring them or by ignoring any row with a `NaN` value.

You can use various data types for response data `Y`. Each element in `Y` represents the response to the corresponding row of `X`. Observations with missing `Y` data are ignored.

- For regression, `Y` must be a numeric vector with the same number of elements as the number of rows of `X`.
- For classification, `Y` can be any of these data types. This table also contains the method of including missing entries.

Data Type	Missing Entry
Numeric vector	<code>NaN</code>
Categorical vector	<code><undefined></code>

The guide also lists the characteristics of various algorithms to help you choose which one to try first.

Characteristics of Algorithms

This table shows typical characteristics of the various supervised learning algorithms. The characteristics in any particular case can vary from the listed ones. Use the table as a guide for your initial choice of algorithms, but be aware that the table can be inaccurate for some problems.

Characteristics of Supervised Learning Algorithms

Algorithm	Predictive Accuracy	Fitting Speed	Prediction Speed	Memory Usage	Easy to Interpret	Handles Categorical Predictors
Trees	Low	Fast	Fast	Low	Yes	Yes
SVM	High	Medium	*	*	*	No
Naive Bayes	Low	**	**	**	Yes	Yes
Nearest Neighbor	***	Fast***	Medium	High	No	Yes***
Discriminant Analysis	****	Fast	Fast	Low	Yes	No
Ensembles	See Suggestions for Choosing an Appropriate Ensemble Algorithm and General Characteristics of Ensemble Algorithms					

* — SVM prediction speed and memory usage are good if there are few support vectors, but can be poor if there are many support vectors. When you use a kernel function, it can be difficult to interpret how SVM classifies data, though the default linear scheme is easy to interpret.

** — Naive Bayes speed and memory usage are good for simple distributions, but can be poor for kernel distributions and large data sets.

*** — Nearest Neighbor usually has good predictions in low dimensions, but can have poor predictions in high dimensions. For linear search, Nearest Neighbor does not perform any fitting. For kd-trees, Nearest Neighbor does perform fitting. Nearest Neighbor can have either continuous or categorical predictors, but not both.

**** — Discriminant Analysis is accurate when the modeling assumptions are satisfied (multivariate normal by class). Otherwise, the predictive accuracy varies.

Additional information: <http://www.mathworks.com/discovery/supervised-learning.html>

Unsupervised Learning

MATLAB® and its toolboxes include the most common unsupervised learning method - cluster analysis for exploratory data analysis to find hidden patterns or grouping in data:

- Hierarchical clustering to produce nested sets of clusters
- k-Means clustering by minimizing mean distance
- Gaussian mixture models
- Self-organizing maps to identify prototype vectors for clusters of examples, example distributions, and similarity relationships between clusters
- Hidden Markov models for data generation

Additional information:

<http://www.mathworks.com/discovery/unsupervised-learning.html>

<http://www.mathworks.com/discovery/cluster-analysis.html>

Machine Learning Webinar

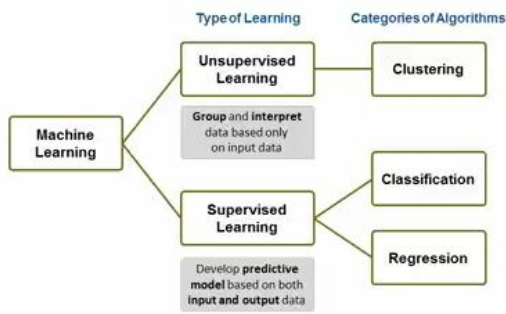
To learn more about how to get started using machine learning tools to detect patterns and build predictive models from datasets, visit the following Webinar link: <http://www.mathworks.com/videos/machine-learning-with-matlab-81984.html>.

Videos and Webinars

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Machine Learning with MATLAB

Overview – Machine Learning



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In this webinar you will learn how to get started using machine learning tools to detect patterns and build predictive models from your datasets. In this session, you will learn about several machine learning techniques available in MATLAB and how to quickly explore your data, evaluate machine learning algorithms, compare the results, and apply the best machine learning for your problem.

Highlights include unsupervised and supervised machine learning techniques including:

- K-means and other clustering tools
- Neural Networks
- Decision trees and ensemble learning
- Naive Bayes Classification
- Linear, logistic and nonlinear regression

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Introducing Fixed-Point Designer for MATLAB

Working with Large Data Sets

Big data sets may not fit into available memory, may take too long to process, or may stream too quickly to store. Standard algorithms are usually not designed to process big data sets in reasonable amounts of time or memory. MATLAB® provides a number of tools to tackle these challenges.

Working with Big Data in MATLAB

1. **64-bit Computing.** The 64-bit version of MATLAB drastically increases the amount of data you can hold in memory – typically up to 2000 times more than any 32-bit program. While 32-bit programs limit you to addressing only 2 GB of memory, 64-bit MATLAB lets you address up to the physical memory limits of the OS. For Windows 8, that's 500 GB for desktop versions and 4 TB for Windows Server.
2. **Memory Mapped Variables.** The `memmapfile` function in MATLAB lets you map a file, or a portion of a file, to a MATLAB variable in memory. This allows you to efficiently access big data sets on disk that are too large to hold in memory or that take too long to load.
3. **Disk Variables.** The `matfile` function lets you access MATLAB variables directly from MAT-files on disk, using MATLAB indexing commands, without loading the full variables into memory. This allows you to do block processing on big data sets that are otherwise too large to fit in memory.
4. **Intrinsic Multicore Math.** Many of the built-in mathematical functions in MATLAB, such as `fft`, `inv`, and `eig`, are **multithreaded**. By running in parallel, these functions take full advantage of the multiple cores of your computer, providing high-performance computation of big data sets.
5. **GPU Computing.** If you're working with GPUs, GPU-optimized mathematical functions in Parallel Computing Toolbox provide even higher performance for big data sets.
6. **Parallel Computing.** Parallel Computing Toolbox provides a parallel `for`-loop that runs your MATLAB code and algorithms in parallel on multicore computers. If you use MATLAB Distributed Computing Server, you can execute in parallel on clusters of machines that can scale up to thousands of computers.
7. **Cloud Computing.** You can run MATLAB computations in parallel using MATLAB Distributed Computing Server on Amazon's Elastic Computing Cloud (EC2) for on-demand parallel processing on hundreds or thousands of computers. Cloud computing lets you process big data without having to buy or maintain your own cluster or data center.
8. **Distributed Arrays.** Using Parallel Computing Toolbox and MATLAB Distributed Computing Server, you can work with matrices and multidimensional arrays that are distributed across the memory of a cluster of computers. Using this approach, you can store and perform computations on big data sets that are too large to fit in a single computer's memory.
9. **Streaming Algorithms.** Using **System objects**, you can perform stream processing on incoming streams of data that are too large or too fast to hold in memory. In addition, you can generate embedded C/C++ code from your MATLAB algorithms using MATLAB Coder, and run the resulting code on high-performance real-time systems.
10. **Image Block Processing.** The `blockproc` function in Image Processing Toolbox lets you work with really big images by processing them efficiently a block at a time. Computations run in parallel on multiple cores and GPUs when used with Parallel Computing Toolbox.
11. **Machine Learning.** Machine learning is helpful for extracting insights and developing predictive models with big data sets. A wide variety of machine learning algorithms including boosted and bagged decision trees, K-means and hierarchical clustering, K-nearest neighbor search, Gaussian mixtures, the expectation maximization algorithm, hidden Markov models, and neural networks are available in Statistics Toolbox and Neural Network Toolbox.

Additional information: <http://www.mathworks.com/discovery/big-data-matlab.html>