Data Science Using Python, SAS, & R

A Rosetta Stone for Analytical Languages

Elaine Kearney

Table of Contents

SAS Tutorial

Welcome to the SAS tutorial version of *Data Science Using Python, SAS, & R: A Rosetta Stone for Analytical Languages*. This tutorial includes examples of common data science tasks, organized in the same way across 3 data science languages. Before beginning this tutorial, please check to make sure you have SAS 14.2 installed (this is not required, but this was the release used to generate the following examples). SAS Enterprise Miner Workstation 14.2 was used to produce some of the following results.

You also may need to insure that your SAS environment is connected with an R environment so that the R code that SAS calls at the end of this tutorial from the IML Procedure runs successfully.

Note: In SAS,

```
*  This is a single line comment ;
/* This is a paragraph
   comment */
```

Now let's get started!

---

1 Reading in Data and Basic Statistical Functions

1.1 Read in the data.

The IMPORT Procedure is useful for reading in SAS data sets of a variety of different types.

a) Read the data in as a .csv file.

```
proc import out = student
  datafile = 'C:/Users/class.csv'
  dbms = csv replace;
  getnames = yes;
run;
```

b) Read the data in as a .xls file.

```
proc import out = student_xls
  datafile = 'C:/Users/class.xls'
  dbms = xls replace;
  getnames = yes;
run;
```

c) Read the data in as a .json file.

There is more code involved in reading a .json file into SAS so that all the format is correct, however we will not at this time dive into the explanation for all this code, but please see the links below.

```
data student_json;
  INFILE 'C:/Users/class.json' LRECL  = 3456677  TRUNCOVER SCANOVER
    dsd
    dlm=",}";
  INPUT
    @'"Name":' Name : $12.
    @'"Sex":' Sex : $2.
    @'"Age":' Age :
    @'"Height":' Height :
    @'"Weight":' Weight :
    @@;
run;
```

DATA step: infile & input statements

1.2 Find the dimensions of the data set.

The shape of a SAS data set is available by running the IMPORT Procedure and looking at the notes in the log file.

```
proc import out = student
  datafile = 'C:/Users/class.csv'
  dbms = csv replace;
```

```
  getnames = yes;
run;
```

```
NOTE: The infile 'C:/Users/class.csv' is:
      Filename=C:¥Users¥class.csv,
      RECFM=V,LRECL=32767,File Size (bytes)=411,
      Last Modified=2017年06月06日 11時46分38秒,
      Create Time=2017年06月06日 08時46分20秒

NOTE: 19 records were read from the infile 'C:/Users/class.csv'.
      The minimum record length was 17.
      The maximum record length was 21.
NOTE: The data set WORK.STUDENT has 19 observations and 5 variables.
NOTE: DATA statement used (Total process time):
      real time           0.11 seconds
      cpu time            0.10 seconds


NOTE: This SAS session is using a registry in WORK.  All changes will be lost at the end of this session.
19 rows created in WORK.STUDENT from C:/Users/class.csv.


NOTE: WORK.STUDENT data set was successfully created.
NOTE: The data set WORK.STUDENT has 19 observations and 5 variables.
NOTE: PROCEDURE IMPORT used (Total process time):
      real time           0.51 seconds
      cpu time            0.32 seconds
```

Output:

1.3 Find basic information about the data set.

The CONTENTS procedure prints information about a SAS data set.

```
proc contents data = student;
run;
```

```
                          The CONTENTS Procedure

Data Set Name          WORK.STUDENT                 Observations          19
Member Type            DATA                         Variables             5
Engine                 V9                           Indexes               0
Created                07/04/2017 15:02:21          Observation Length    32
Last Modified          07/04/2017 15:02:21          Deleted Observations  0
Protection                                          Compressed            NO
Data Set Type                                       Sorted                NO
Label
Data Representation    WINDOWS_64
Encoding               wlatin1  Western (Windows)


                Alphabetic List of Variables and Attributes

            #    Variable    Type    Len    Format     Informat

            3    Age         Num       8    BEST12.    BEST32.
            4    Height      Num       8    BEST12.    BEST32.
            1    Name        Char      7    $7.        $7.
            2    Sex         Char      1    $1.        $1.
            5    Weight      Num       8    BEST12.    BEST32.
```

1.4 Look at the first 5 (last 5) observations.

The PRINT procedure prints a SAS data set, according to the specifications and options provided.

```
/* obs= option tells SAS how many observations to print, starting
   with the first observation */
proc print data = student (obs=5);
run;

   Obs     Name        Sex              Age         Height          Weight

     1     Alfred       M                14             69           112.5
     2     Alice        F                13           56.5              84
     3     Barbara      F                13           65.3              98
     4     Carol        F                14           62.8           102.5
     5     Henry        M                14           63.5           102.5
```

--

```
/* print the last 5 observations */
proc print data = student(firstobs=15);
run;

   Obs     Name        Sex              Age         Height          Weight

    15     Philip       M                16             72             150
    16     Robert       M                12           64.8             128
    17     Ronald       M                15             67             133
    18     Thomas       M                11           57.5              85
    19     William      M                15           66.5             112
```

1.5 Calculate means of numeric variables.

The MEANS procedure prints the means of all numeric variables of a SAS data set, as well as other descriptive statistics.

```
proc means data = student mean;
run;

                            The MEANS Procedure

                         Variable             Mean
                         ------------------------
                         Age            13.3157895
                         Height         62.3368421
                         Weight        100.0263158
                         ------------------------
```

1.6 Compute summary statistics of the data set.

Summary statistics of a SAS data set are available by running the MEANS procedure and specifying statistics to return.

```
/* SAS uses a different method than Python and R to compute
   quartiles, but the method in each language can be changed */
/* maxdec= option tells SAS to print at most 2 numbers behind
   the decimal point */
proc means data = student min q1 median mean q3 max n maxdec=2;
run;

                            The MEANS Procedure

                                     Lower
 Variable         Minimum         Quartile          Median            Mean
 ------------------------------------------------------------------------
 Age                11.00            12.00           13.00           13.32
 Height             51.30            57.50           62.80           62.34
 Weight             50.50            84.00           99.50          100.03
 ------------------------------------------------------------------------


                                  Upper
              Variable         Quartile         Maximum     N
              ----------------------------------------------
              Age                 15.00           16.00    19
              Height              66.50           72.00    19
              Weight             112.50          150.00    19
              ----------------------------------------------
```

1.7 Descriptive statistics functions applied to columns of the data set.

```
/* The var statement tells SAS which variable to use for the
   procedure */
proc means data = student stddev sum n max min median maxdec=2;
  var Weight;
run;

                            The MEANS Procedure

                        Analysis Variable : Weight

      Std Dev            Sum    N         Maximum         Minimum         Median
 ------------------------------------------------------------------------
        22.77        1900.50   19          150.00           50.50          99.50
 ------------------------------------------------------------------------
```

1.8 Produce a one-way table to describe the frequency of a variable.

The FREQ procedure prints the frequency of categorical or discrete variables of a SAS data set.

a) Produce a one-way table of a discrete variable.

```
proc freq data = student;
  tables Age / nopercent norow nocol;
run;

                            The FREQ Procedure

                                                 Cumulative
                      Age     Frequency      Frequency
                      -----------------------------
                       11            2              2
                       12            5              7
                       13            3             10
                       14            4             14
                       15            4             18
                       16            1             19
```

b) Produce a one-way table of a categorical variable.

```
proc freq data = student;
  tables Sex / nopercent norow nocol;
run;

                            The FREQ Procedure

                                                 Cumulative
                      Sex     Frequency      Frequency
                      -----------------------------
                      F              9              9
                      M             10             19
```

The tables statement allows you to specify multiple variables at once, separated only by a space, so both of these tables could have been created with one FREQ procedure call. The options on the tables statement (nopercent norow nocol) prevent SAS from printing percents in the table, which are printed by default.

1.9 Produce a two-way table to visualize the frequency of two categorical (or discrete) variables.

```
/* The "*" between two variables on the tables statement
   indicates to produce a two-way table of the two variables */
proc freq data = student;
  tables Age*Sex / nopercent norow nocol;
run;
```

```
                            The FREQ Procedure

                            Table of Age by Sex

                    Age        Sex

                    Frequency|F       |M       |  Total
                    ---------+--------+--------+
                          11 |      1 |      1 |      2
                    ---------+--------+--------+
                          12 |      2 |      3 |      5
                    ---------+--------+--------+
                          13 |      2 |      1 |      3
                    ---------+--------+--------+
                          14 |      2 |      2 |      4
                    ---------+--------+--------+
                          15 |      2 |      2 |      4
                    ---------+--------+--------+
                          16 |      0 |      1 |      1
                    ---------+--------+--------+
                    Total           9       10       19
```

FREQ Procedure

1.10 Select a subset of the data that meets a certain criterion.

The SAS DATA step is used for all things data manipulation and in Section 2 we will explore it further.

```
data females;
  set student;
  where Sex = "F";
run;
proc print data = females(obs=5);
run;

   Obs     Name       Sex              Age          Height          Weight

     1     Alice       F                13           56.5              84
     2     Barbara     F                13           65.3              98
     3     Carol       F                14           62.8           102.5
     4     Jane        F                12           59.8            84.5
     5     Janet       F                15           62.5           112.5
```

DATA step: set & where statements

1.11 Determine the correlation between two continuous variables.

```
/* The nosimple option reduces the output of this procedure */
proc corr data = student pearson nosimple;
```

```
var Height Weight;
run;
                            The CORR Procedure

                      2  Variables:    Height   Weight

                  Pearson Correlation Coefficients, N = 19
                         Prob > |r| under H0: Rho=0

                                  Height        Weight

                    Height       1.00000       0.87779
                                                <.0001

                    Weight       0.87779       1.00000
                                  <.0001
```

CORR Procedure

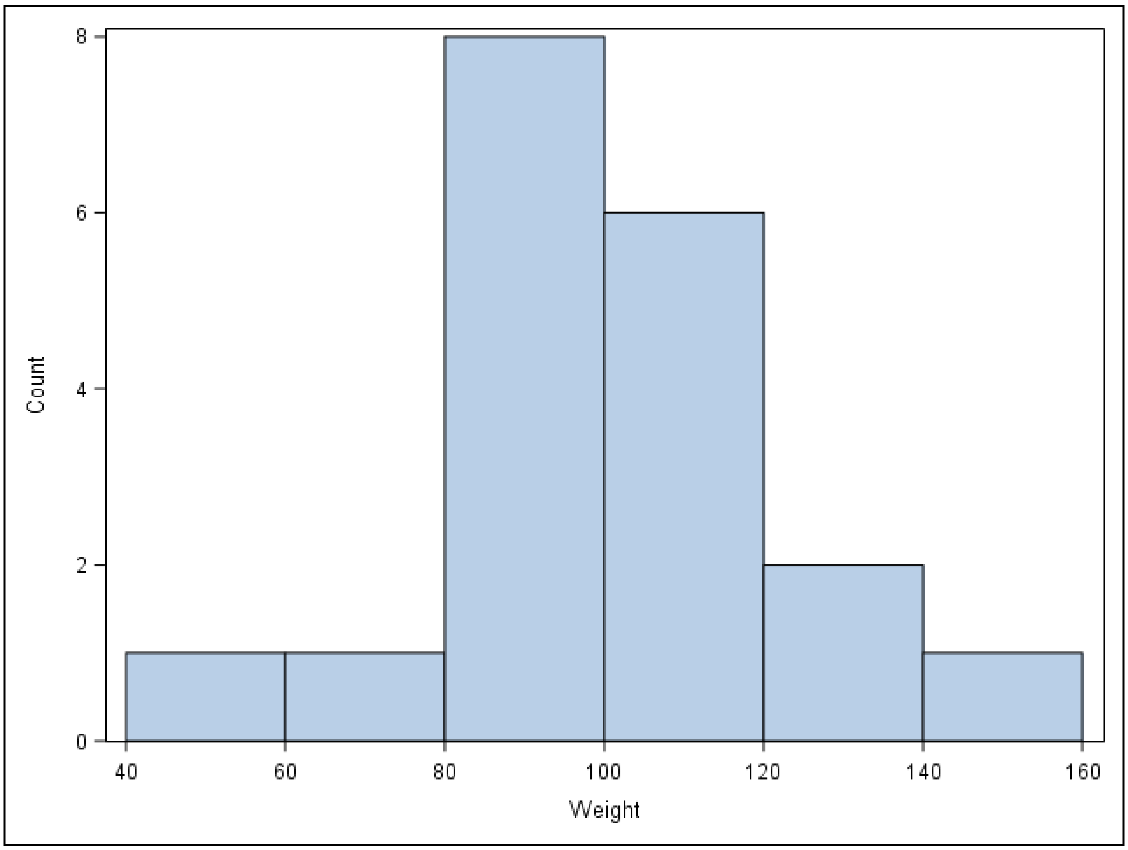
---

2 Basic Graphing and Plotting Functions

The SGPLOT procedure is a very useful SAS procedure for producing plots from data. For more information on other statements within the SGPLOT procedure, please see the Appendix Section 2.

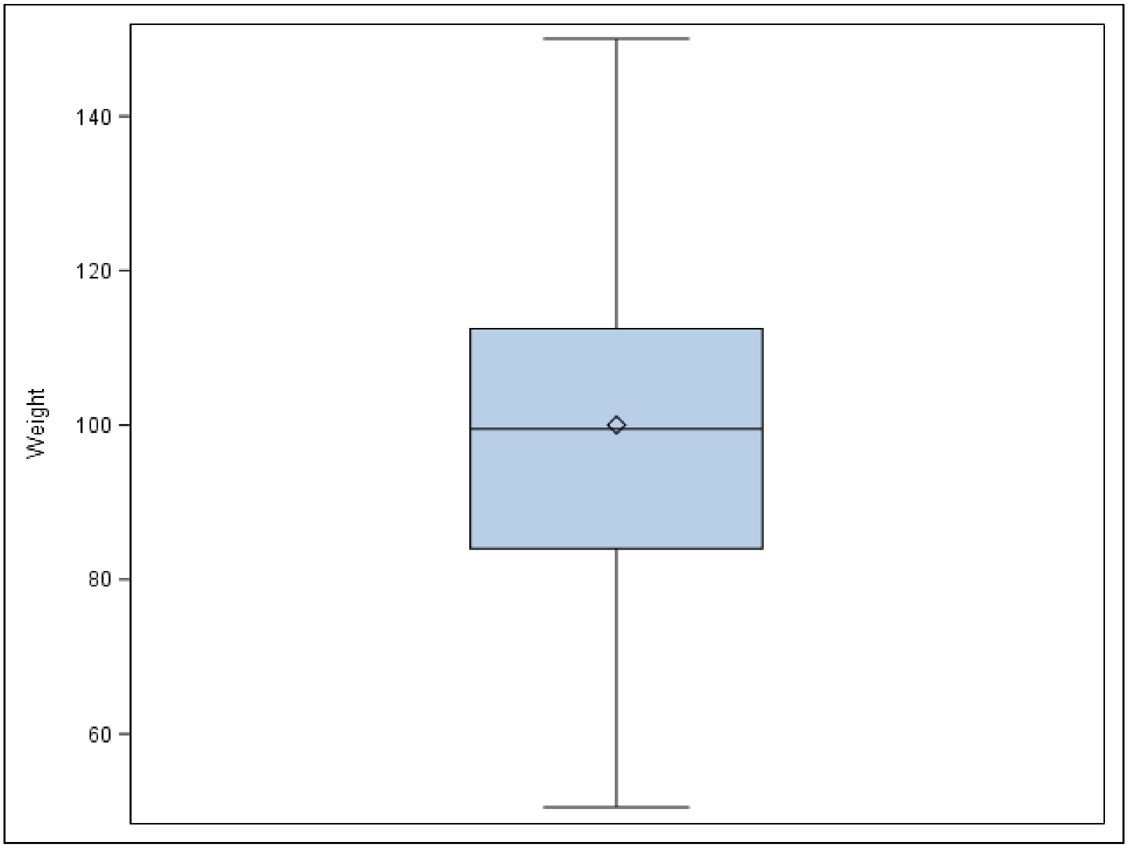
2.1 Visualize a single continuous variable by producing a histogram.

```
/* Notice the specifcation of the bins, as well as the xaxis values */
/* SAS denotes "count" as what R & Python denote as "frequency" */
proc sgplot data = student;
  histogram weight / binwidth=20 binstart=40 scale=count;
  xaxis values=(40 to 160 by 20);
run;
```

Output:


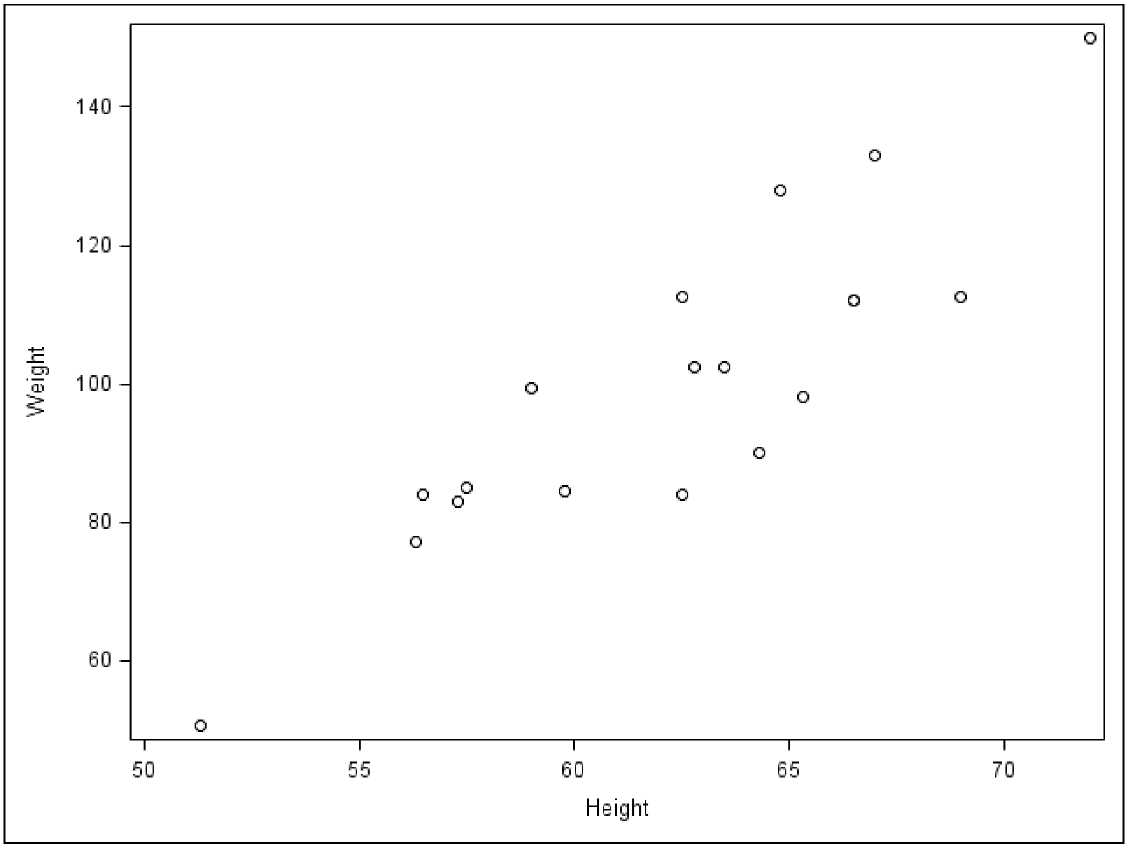
2.2 Visualize a single continuous variable by producing a boxplot.

```
/* SAS automatically prints the mean on the boxplot */
proc sgplot data = student;
  vbox Weight;
run;
```

Output: 

2.3 Visualize two continuous variables by producing a scatterplot.

```
/* Notice here you specify the y variable followed by the x variable */
proc sgscatter data = student;
  plot Weight * Height;
run;
```

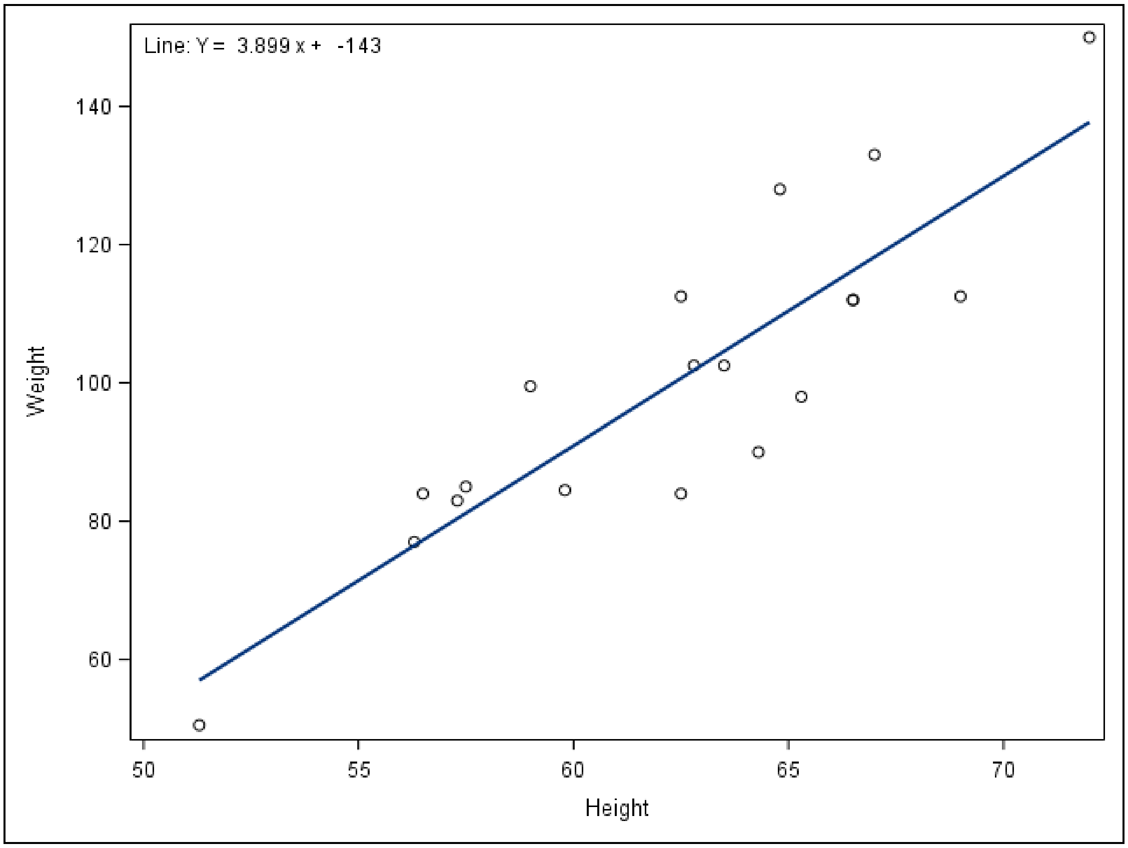
Output: 

SGSCATTER Procedure

2.4 Visualize a relationship between two continuous variables by producing a scatterplot and a plotted line of best fit.

```
/* Use proc reg to get the parameter estimates for the line of best fit,
   but don't print the graph (ods graphics off) */
ods graphics off;
proc reg data = student;
  /* Syntax indicates Weight as a function of Height */
  model Weight = Height;
  ods output ParameterEstimates=PE;
run;
ods graphics on;

/* data _null_ indicates to not create a data set, but
   run the code within the data step to create macro
   variables to store the parameter estimates */
data _null_;
  set PE;
  if _n_=1 then call symput('Int', put(estimate, BEST6.));
  else call symput('Slope', put(estimate, BEST6.));
run;
```

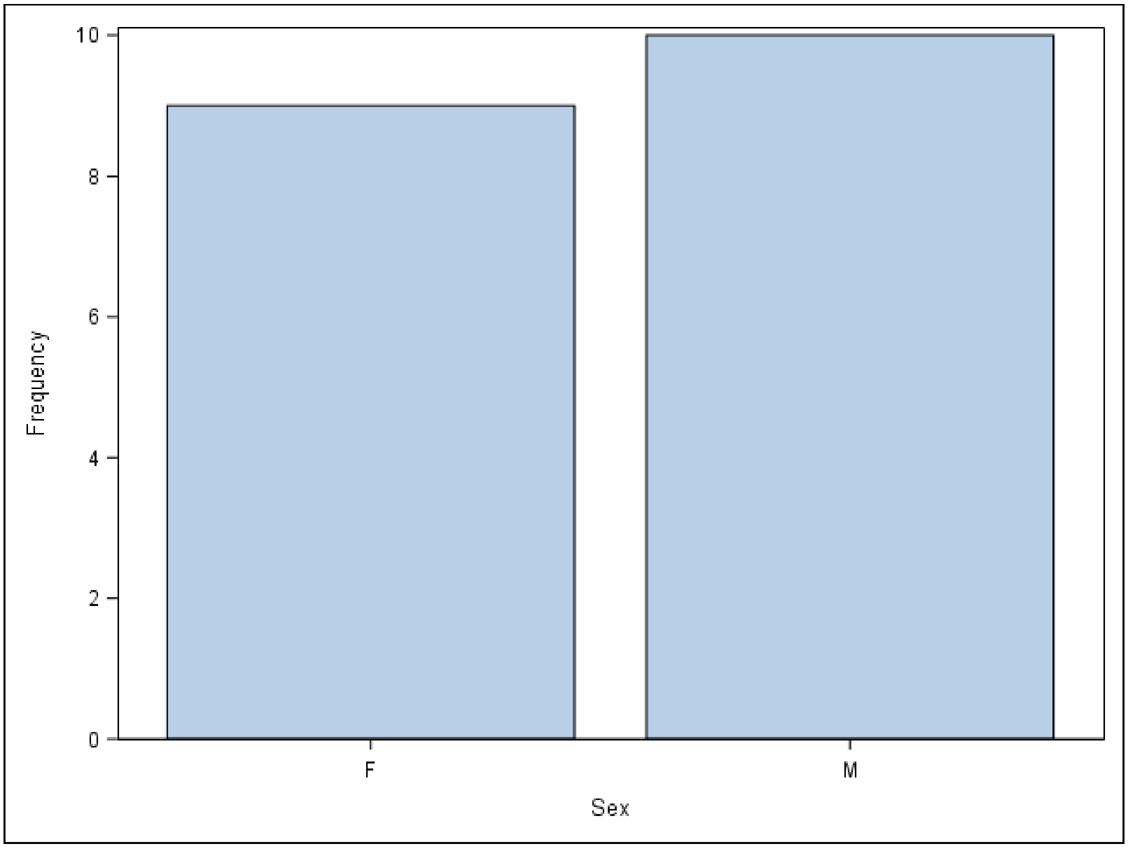
```
/* Use proc sgplot with the reg statement so it prints the line of best fit,
   and use the inset statement to print the equation of the line
   of best fit */
proc sgplot data = student noautolegend;
  reg y = Weight x = Height;
  inset "Line: Y = &Slope x + &Int" / position=topleft;
run;
```

Output: 

REG Procedure | set statement | macro variables | call symput()

2.5 Visualize a categorical variable by producing a bar chart.

```
/* Notice here you must first sort by Sex and then plot the vertical
  bar chart */
proc sort data = student;
  by Sex;
run;
proc sgplot data = student;
  vbar Sex;
run;
```

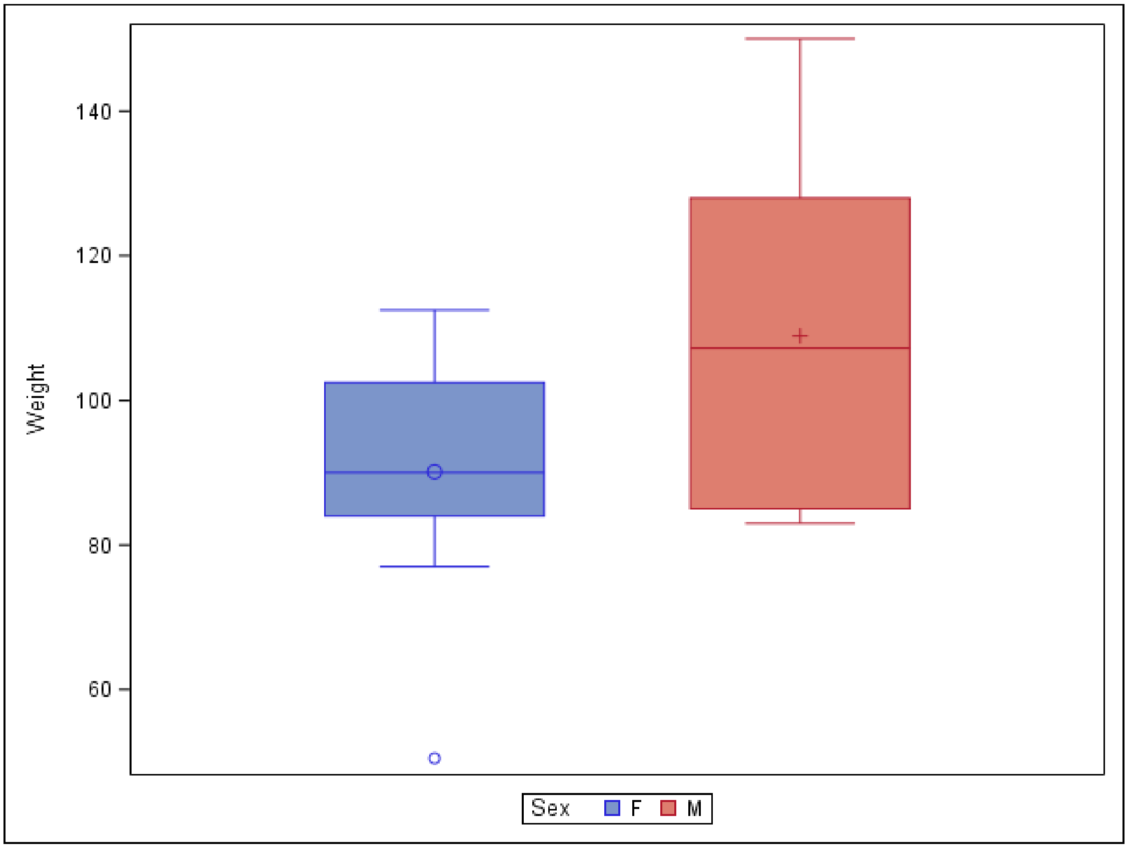
Output: 

SORT Procedure

2.6 Visualize a continuous variable, grouped by a categorical variable, using side-by-side boxplots.

More advanced side-by-side boxplot with color.

```
proc sgplot data = student;
  vbox Weight / group=Sex;
run;
```

Output: 

3 Basic Data Wrangling and Manipulation

Many of the following examples make use of the SAS DATA step for manipulating and altering data sets, and a main part of the DATA step is the set statement.

3.1 Create a new variable in a data set as a function of existing variables in the data set.

```
data student;
  set student;
  BMI = Weight / (Height**2) * 703;
run;
proc print data = student(obs=5);
run;

Obs    Name      Sex              Age         Height          Weight     BMI

  1    Alfred     M                14             69           112.5    16.6115
  2    Alice      F                13           56.5              84    18.4986
  3    Barbara    F                13           65.3              98    16.1568
  4    Carol      F                14           62.8           102.5    18.2709
  5    Henry      M                14           63.5           102.5    17.8703
```

3.2 Create a new variable in a data set using if/else logic of existing variables in the data set.

```
data student;
  set student;
  if (BMI < 19.0) then BMI_class = "Underweight";
  else BMI_class = "Healthy";
run;
proc print data = student(obs=5);
run;

Obs Name     Sex             Age        Height        Weight    BMI     BMI_class

  1 Alfred    M               14            69         112.5 16.6115 Underweight
  2 Alice     F               13          56.5            84 18.4986 Underweight
  3 Barbara   F               13          65.3            98 16.1568 Underweight
  4 Carol     F               14          62.8         102.5 18.2709 Underweight
  5 Henry     M               14          63.5         102.5 17.8703 Underweight
```

if-then/else statement

3.3 Create a new variable in a data set using mathemtical functions applied to existing variables in the data set.

Using the log(), exp(), sqrt(), & abs() functions.

```
data student;
  set student;
  LogWeight = log(Weight);
  ExpAge = exp(Age);
  SqrtHeight = sqrt(Height);
  if (BMI < 19.0) then BMI_Neg = -BMI;
  else BMI_Neg = BMI;
  BMI_Pos = abs(BMI_Neg);
  /* Create a Boolean variable, which is handled differently
     in SAS than in Python and R */
  BMI_Check = (BMI_Pos = BMI);
run;
proc print data = student(obs=5);
run;


Obs Name    Sex         Age       Height       Weight   BMI     BMI_class

  1 Alfred   M           14           69        112.5 16.6115 Underweight
  2 Alice    F           13         56.5           84 18.4986 Underweight
  3 Barbara  F           13         65.3           98 16.1568 Underweight
  4 Carol    F           14         62.8        102.5 18.2709 Underweight
  5 Henry    M           14         63.5        102.5 17.8703 Underweight

      Log                     Sqrt                            BMI_
Obs  Weight       ExpAge      Height     BMI_Neg     BMI_Pos    Check

  1 4.72295    1202604.28    8.30662    -16.6115    16.6115      1
  2 4.43082     442413.39    7.51665    -18.4986    18.4986      1
  3 4.58497     442413.39    8.08084    -16.1568    16.1568      1
  4 4.62986    1202604.28    7.92465    -18.2709    18.2709      1
  5 4.62986    1202604.28    7.96869    -17.8703    17.8703      1
```

if-then/else statement

3.4 Drop variables from a data set.

```
data student;
  set student (drop = LogWeight ExpAge SqrtHeight BMI_Neg BMI_Pos BMI_Check);
run;
proc print data = student(obs=5);
run;

Obs Name    Sex         Age       Height       Weight   BMI     BMI_class

  1 Alfred   M           14           69        112.5 16.6115 Underweight
  2 Alice    F           13         56.5           84 18.4986 Underweight
  3 Barbara  F           13         65.3           98 16.1568 Underweight
  4 Carol    F           14         62.8        102.5 18.2709 Underweight
  5 Henry    M           14         63.5        102.5 17.8703 Underweight
```

drop= data set option

3.5 Sort a data set by a variable.

a) Sort data set by a continuous variable.

```
proc sort data = student;
  by Age;
run;
proc print data = student(obs=5);
run;

Obs Name     Sex            Age        Height       Weight    BMI    BMI_class

  1 Joyce     F              11          51.3         50.5 13.4900 Underweight
  2 Thomas    M              11          57.5           85 18.0733 Underweight
  3 James     M              12          57.3           83 17.7715 Underweight
  4 Jane      F              12          59.8         84.5 16.6115 Underweight
  5 John      M              12            59         99.5 20.0944 Healthy
```

b) Sort data set by a categorical variable.

```
proc sort data = student;
  by Sex;
run;
/* Notice that the data is now sorted first by Sex and
   then within Sex by Age */
proc print data = student(obs=5);
run;

Obs Name     Sex            Age        Height       Weight    BMI     BMI_class

  1 Joyce     F              11          51.3         50.5 13.4900 Underweight
  2 Jane      F              12          59.8         84.5 16.6115 Underweight
  3 Louise    F              12          56.3           77 17.0777 Underweight
  4 Alice     F              13          56.5           84 18.4986 Underweight
  5 Barbara   F              13          65.3           98 16.1568 Underweight
```

SORT Procedure

3.6 Compute descriptive statistics of continuous variables, grouped by a categorical variable.

```
proc means data = student mean;
  by Sex;
  var Age Height Weight BMI;
run;

---------------------------------- Sex=F ----------------------------------

                            The MEANS Procedure
```

```
                         Variable           Mean
                         ------------------------
                         Age          13.2222222
                         Height       60.5888889
                         Weight       90.1111111
                         BMI          17.0510391
                         ------------------------


---------------------------------- Sex=M ----------------------------------

                         Variable           Mean
                         ------------------------
                         Age          13.4000000
                         Height       63.9100000
                         Weight      108.9500000
                         BMI          18.5942434
                         ------------------------
```

MEANS Procedure

3.7 Add a new row to the bottom of a data set.

```
/* Look at the tail of the data currently */
proc print data = student(firstobs=15);
run;

Obs Name    Sex          Age       Height       Weight   BMI    BMI_class

 15 Alfred   M            14           69        112.5 16.6115 Underweight
 16 Henry    M            14         63.5        102.5 17.8703 Underweight
 17 Ronald   M            15           67          133 20.8285 Healthy
 18 William  M            15         66.5          112 17.8045 Underweight
 19 Philip   M            16           72          150 20.3414 Healthy

data student;
  set student end = eof;
  output;
  if eof then do;
    Name = 'Jane';
    Sex = 'F';
    Age = 14;
    Height = 56.3;
    Weight = 77.0;
    BMI = 17.077695;
    BMI_Class = 'Underweight';
    output;
  end;
run;
proc print data = student(firstobs=16);
run;
```

```
Obs Name     Sex            Age        Height        Weight    BMI    BMI_class

 16 Henry     M              14          63.5         102.5 17.8703 Underweight
 17 Ronald    M              15            67           133 20.8285 Healthy
 18 William   M              15          66.5           112 17.8045 Underweight
 19 Philip    M              16            72           150 20.3414 Healthy
 20 Jane      F              14          56.3            77 17.0777 Underweight
```

if-then/else & output statements | do loop, end= & firstobs= data set options

3.8 Create a user-defined function and apply it to a variable in the data set to create a new variable in the data set.

```
proc fcmp outlib=sasuser.userfuncs.myfunc;
  function toKG(lb);
    kg = 0.45359237 * lb;
  return(kg);
endsub;

options cmplib=sasuser.userfuncs;

data studentKG;
  set student;
  Weight_KG = toKG(Weight);
run;

proc print data = studentKG(obs=5);
run;


   Obs     Name       Sex             Age          Height          Weight

     1     Joyce       F               11            51.3            50.5
     2     Jane        F               12            59.8            84.5
     3     Louise      F               12            56.3              77
     4     Alice       F               13            56.5              84
     5     Barbara     F               13            65.3              98

                                     Weight_
   Obs       BMI       BMI_class        KG

     1     13.4900    Underweight    22.9064
     2     16.6115    Underweight    38.3286
     3     17.0777    Underweight    34.9266
     4     18.4986    Underweight    38.1018
     5     16.1568    Underweight    44.4521
```

FCMP Procedure

4 More Advanced Data Wrangling

4.1 Drop observations with missing information.

```
/* Notice the use of the fish data set because it has some missing
   observations */
proc import out = fish
  datafile='C:/Users/fish.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* First sort by Weight, requesting those with NA for Weight first,
   which SAS does automatically */
proc sort data = fish;
  by Weight;
run;
proc print data = fish(obs=5);
run;

      Obs    Species          Weight          Length1          Length2

        1     Bream                .             29.5               32
        2     Roach                0               19             20.5
        3     Perch              5.9              7.5              8.4
        4     Smelt              6.7              9.3              9.8
        5     Smelt                7             10.1             10.6

      Obs         Length3          Height           Width

        1            37.3         13.9129          5.0728
        2            22.8          6.4752          3.3516
        3             8.8           2.112           1.408
        4            10.8          1.7388          1.0476
        5            11.6          1.7284          1.1484

data new_fish;
  set fish;
  /* Notice the not-equal operator (^=) and how SAS denotes
     missing values (.) */
  if (Weight ^= .);
run;
proc print data = new_fish(obs=5);
run;

      Obs    Species          Weight          Length1          Length2

        1     Roach                0               19             20.5
        2     Perch              5.9              7.5              8.4
        3     Smelt              6.7              9.3              9.8
```

```
        4      Smelt                 7            10.1            10.6
        5      Smelt               7.5              10            10.5

      Obs          Length3          Height           Width

        1             22.8          6.4752          3.3516
        2              8.8           2.112           1.408
        3             10.8          1.7388          1.0476
        4             11.6          1.7284          1.1484
        5             11.6           1.972            1.16
```

SORT Procedure | if-then/else statement

4.2 Merge two data sets together on a common variable.

a) First, select specific columns of a data set to create two smaller data sets.

```
/* Notice the use of the student data set again, however we want to reload it
   without the changes we've made previously  */
proc import out = student
  datafile = 'C:/Users/class.csv'
  dbms = csv replace;
  getnames = yes;
run;
data student1;
  set student(keep= Name Sex Age);
run;
proc print data = student1(obs=5);
run;

                   Obs     Name       Sex             Age

                     1     Alfred      M               14
                     2     Alice       F               13
                     3     Barbara     F               13
                     4     Carol       F               14
                     5     Henry       M               14

data student2;
  set student(keep= Name Height Weight);
run;
proc print data = student2(obs=5);
run;

              Obs     Name             Height          Weight

                1     Alfred               69           112.5
                2     Alice              56.5              84
                3     Barbara            65.3              98
                4     Carol              62.8           102.5
                5     Henry              63.5           102.5
```

keep= data set option

b) Second, we want to merge the two smaller data sets on the common variable.

```
data new;
  merge student1 student2;
  by Name;
run;
proc print data = new(obs=5);
run;

   Obs     Name       Sex              Age          Height          Weight

     1     Alfred      M                14              69           112.5
     2     Alice       F                13            56.5              84
     3     Barbara     F                13            65.3              98
     4     Carol       F                14            62.8           102.5
     5     Henry       M                14            63.5           102.5
```

DATA step: merge statement

c) Finally, we want to check to see if the merged data set is the same as the original data set.

```
proc compare base = student compare = new brief;
run;

                           The COMPARE Procedure
                 Comparison of WORK.STUDENT with WORK.NEW
                              (Method=EXACT)

NOTE: No unequal values were found. All values compared are exactly equal.
```

COMPARE Procedure

4.3 Merge two data sets together by index number only.

a) First, select specific columns of a data set to create two smaller data sets.

```
data newstudent1;
  set student(keep= Name Sex Age);
run;
proc print data = newstudent1(obs=5);
run;

                   Obs     Name       Sex              Age

                     1     Alfred      M                14
                     2     Alice       F                13
                     3     Barbara     F                13
```

```
                     4     Carol        F                14
                     5     Henry        M                14

data newstudent2;
  set student(keep= Height Weight);
run;
proc print data = newstudent2(obs=5);
run;

                    Obs          Height          Weight

                      1              69           112.5
                      2            56.5              84
                      3            65.3              98
                      4            62.8           102.5
                      5            63.5           102.5
```

keep= data set option

b) Second, we want to join the two smaller data sets.

```
data new2;
  merge newstudent1 newstudent2;
run;
proc print data = new2(obs=5);
run;

   Obs     Name        Sex              Age          Height          Weight

     1     Alfred       M                14              69           112.5
     2     Alice        F                13            56.5              84
     3     Barbara      F                13            65.3              98
     4     Carol        F                14            62.8           102.5
     5     Henry        M                14            63.5           102.5
```

merge statement

c) Finally, we want to check to see if the joined data set is the same as the original data set.

```
proc compare base = student compare = new2 brief;
run;

                                   The COMPARE Procedure
                         Comparison of WORK.STUDENT with WORK.NEW2
                                      (Method=EXACT)

NOTE: No unequal values were found. All values compared are exactly equal.
```

COMPARE Procedure

4.4 Create a pivot table to summarize information about a data set.

```
/* Notice we are using a new data set that needs to be read into the
   environment */
proc import out = price
  datafile = 'C:/Users/price.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* The following code is used to remove the "," and "$" characters from the
   ACTUAL column so that values can be summed */
data price;
  set price;
  num_actual = input(actual, dollar10.);
run;

proc sql;
  create table categorysales as
    select country, state, prodtype,
    product, sum(num_actual) as REVENUE
    from price
  group by country, state, prodtype, product;
quit;
proc print data = categorysales(obs=5);
run;

     Obs    COUNTRY    STATE         PRODTYPE     PRODUCT     REVENUE

       1    Canada     British Co    FURNITURE     BED       197706.6
       2    Canada     British Co    FURNITURE     SOFA      216282.6
       3    Canada     British Co    OFFICE        CHAI      200905.2
       4    Canada     British Co    OFFICE        DESK      186262.2
       5    Canada     Ontario       FURNITURE     BED       194493.6
```

input() function | SQL Procedure

4.5 Return all unique values from a text variable.

```
proc iml;
  use price;
    read all var {STATE};
  close price;

  unique_states = unique(STATE);
  print(unique_states);
quit;

                              unique_states
       COL1       COL2       COL3       COL4       COL5       COL6
```

```
  ROW1 Baja Calif British Co California Campeche   Colorado   Florida

                              unique_states
       COL7       COL8       COL9       COL10      COL11      COL12

  ROW1 Illinois   Michoacan  New York   North Caro Nuevo Leon Ontario

                              unique_states
                  COL13      COL14      COL15      COL16

             ROW1 Quebec     Saskatchew Texas      Washington
```

IML Procedure | unique() function

5 Preparation & Basic Regression

5.1 Pre-process a data set using principal component analysis.

```
/* Notice we are using a new data set that needs to be read into the
   environment */
proc import out = iris
  datafile = 'C:/Users/iris.csv'
  dbms = csv replace;
  getnames = yes;
run;

data features;
  set iris(drop=Target);
run;

proc princomp data = features noprint outstat = feat_princomp;
  var SepalLength SepalWidth PetalLength PetalWidth;
run;

data eigenvectors;
    set feat_princomp;
    where _TYPE_ = "SCORE";
run;
proc print data = eigenvectors;
run;

                                 Sepal        Sepal       Petal        Petal
  Obs     _TYPE_     _NAME_     Length        Width      Length        Width

   1      SCORE      Prin1      0.52237     -0.26335     0.58125      0.56561
   2      SCORE      Prin2      0.37232      0.92556     0.02109      0.06542
   3      SCORE      Prin3     -0.72102      0.24203     0.14089      0.63380
   4      SCORE      Prin4     -0.26200      0.12413     0.80115     -0.52355
```

drop= data set option | PRINCOMP Procedure

5.2 Split data into training and testing data and export as a .csv file.

```
/* outall option tells SAS to add a flag showing which observations were
   chosen */
/* seed = 29 specifies the seed for random values so the results are
   reproducible */
proc surveyselect data = iris outall out = all method = srs samprate = 0.7
                              seed = 29;
run;

data train (drop = selected) test (drop = selected);
    set all;
    if (selected = 1) then output train;
  else output test;
```

```
run;

proc export data = train
   outfile = 'C:\Users\iris_train.csv'
   dbms = csv;
run;
proc export data = test
   outfile = 'C:\Users\iris_test.csv'
   dbms = csv;
run;
```

SURVEYSELECT Procedure | drop= data set option | EXPORT Procedure

5.3 Fit a logistic regression model.

```
/* Notice we are using a new data set that needs to be read into the
   environment */
proc import out = tips
  datafile = 'C:/Users/tips.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* The following code is used to determine if the individual left more than
   a 15% tip */
data tips;
  set tips;
  if (tip > 0.15*total_bill) then greater15 = 1;
  else greater15 = 0;
run;

/* The descending option tells SAS to model the probability that
  greater15 = 1 */
proc genmod data=tips descending;
  model greater15 = total_bill / dist = bin link = logit lrci;
run;

                           The GENMOD Procedure

                             Model Information

                      Data Set              WORK.TIPS
                      Distribution           Binomial
                      Link Function             Logit
                      Dependent Variable    greater15

                  Number of Observations Read         244
                  Number of Observations Used         244
                  Number of Events                    135
                  Number of Trials                    244
```

```
                             Response Profile

                     Ordered                          Total
                       Value     greater15     Frequency

                           1     1                   135
                           2     0                   109

PROC GENMOD is modeling the probability that greater15='1'.

                  Criteria For Assessing Goodness Of Fit

     Criterion                     DF            Value        Value/DF

     Log Likelihood                          -156.8714
     Full Log Likelihood                     -156.8714
     AIC (smaller is better)                  317.7428
     AICC (smaller is better)                 317.7926
     BIC (smaller is better)                  324.7371


Algorithm converged.

            Analysis Of Maximum Likelihood Parameter Estimates

                                                Likelihood Ratio
                                    Standard      95% Confidence          Wald
 Parameter     DF    Estimate        Error           Limits           Chi-Square

 Intercept      1      1.6477      0.3547      0.9722      2.3667          21.58
 total_bill     1     -0.0725      0.0168     -0.1069     -0.0408          18.65
 Scale          0      1.0000      0.0000      1.0000      1.0000

                            Analysis Of Maximum
                           Likelihood Parameter
                                 Estimates

                          Parameter    Pr > ChiSq

                          Intercept        <.0001
                          total_bill       <.0001
                          Scale

NOTE: The scale parameter was held fixed.
```

if-then/else statement | GENMOD Procedure

5.4 Fit a linear regression model.

```
/* Fit a linear regression model of tip by total_bill */
proc reg data = tips outest=RegOut;
    tip_hat: model tip = total_bill;
quit;

                              The REG Procedure
                               Model: tip_hat
                          Dependent Variable: tip

                  Number of Observations Read         244
                  Number of Observations Used         244

                            Analysis of Variance

                                        Sum of           Mean
 Source                   DF          Squares         Square    F Value    Pr > F

 Model                     1        212.42373      212.42373     203.36    <.0001
 Error                   242        252.78874        1.04458
 Corrected Total         243        465.21248

           Root MSE              1.02205    R-Square     0.4566
           Dependent Mean        2.99828    Adj R-Sq     0.4544
           Coeff Var            34.08782

                             Parameter Estimates

                             Parameter       Standard
   Variable       DF          Estimate          Error     t Value     Pr > |t|

   Intercept       1           0.92027        0.15973        5.76       <.0001
   total_bill      1           0.10502        0.00736       14.26       <.0001
```

REG Procedure

---

6 Supervised Machine Learning

6.1 Fit a logistic regression model on training data and assess against testing data.

a) Fit a logistic regression model on training data.

```
/* Notice we are using new data sets that need to be read into the
   environment */
proc import out = train
  datafile = 'C:/Users/tips_train.csv'
  dbms = csv replace;
  getnames = yes;
run;
proc import out = test
  datafile = 'C:/Users/tips_test.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* The following code is used to determine if the individual left more than
   a 15% tip */
data train;
  set train;
  if (tip > 0.15*total_bill) then greater15 = 1;
  else greater15 = 0;
run;
data test;
  set test;
  if (tip > 0.15*total_bill) then greater15 = 1;
  else greater15 = 0;
run;

/* The descending option tells SAS to model the probability that
  greater15 = 1 */
proc genmod data=train descending;
  model greater15 = total_bill / dist = bin link = logit lrci;
  store out = logmod;
run;
                           The GENMOD Procedure

                            Model Information

                     Data Set                WORK.TRAIN
                     Distribution              Binomial
                     Link Function                Logit
                     Dependent Variable       greater15
```

Number of Observations Read	195
Number of Observations Used	195
Number of Events	109
Number of Trials	195

Response Profile

Ordered Value	greater15	Total Frequency
1	1	109
2	0	86

PROC GENMOD is modeling the probability that greater15='1'.

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Log Likelihood		-125.2918	
Full Log Likelihood		-125.2918	
AIC (smaller is better)		254.5836	
AICC (smaller is better)		254.6461	
BIC (smaller is better)		261.1296	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter	DF	Estimate	Standard Error	Likelihood Ratio 95% Confidence Limits		Wald Chi-Square
Intercept	1	1.6461	0.3946	0.8973	2.4501	17.40
total_bill	1	-0.0706	0.0185	-0.1088	-0.0359	14.59
Scale	0	1.0000	0.0000	1.0000	1.0000	

Analysis Of Maximum Likelihood Parameter Estimates

Parameter	Pr > ChiSq
Intercept	<.0001
total_bill	0.0001
Scale	

```
NOTE: The scale parameter was held fixed.
```

b) Assess the model against the testing data.

```
/* Prediction on testing data */
proc plm source = logmod noprint;
    score data = test out = preds pred = pred / ilink;
run;

/* Determine how many were correctly classified */
data preds;
    set preds;
    if (pred < 0.5) then label = 0;
    else label = 1;
    if (label = greater15) then Result = "Correct";
    else Result = "Wrong";
run;

proc freq data = preds;
tables Result / nopercent norow nocol;
run;

                            The FREQ Procedure

                                               Cumulative
                    Result      Frequency       Frequency
                    ---------------------------------
                    Correct           34              34
                    Wrong             15              49
```

GLM Procedure | PLM Procedure |FREQ Procedure

6.2 Fit a linear regression model on training data and assess against testing data.

a) Fit a linear regression model on training data.

```
/* Notice we are using new data sets that need to be read into the
  environment */
proc import out = train
  datafile = 'C:/Users/boston_train.csv'
  dbms = csv replace;
  getnames = yes;
run;
proc import out = test
  datafile = 'C:/Users/boston_test.csv'
  dbms = csv replace;
  getnames = yes;
run;
```

```
proc reg data = train outest=RegOut;
  predY: model Target = _0-_12;
quit;

                             The REG Procedure
                               Model: predY
                        Dependent Variable: Target

                  Number of Observations Read          354
                  Number of Observations Used          354

                           Analysis of Variance

                                       Sum of           Mean
 Source                    DF         Squares         Square    F Value    Pr > F

 Model                     13           22145     1703.47137      68.48    <.0001
 Error                    340      8458.20364       24.87707
 Corrected Total          353           30603

           Root MSE              4.98769    R-Square     0.7236
           Dependent Mean       22.48249    Adj R-Sq     0.7131
           Coeff Var            22.18479

                           Parameter Estimates

                        Parameter       Standard
   Variable     DF       Estimate          Error    t Value    Pr > |t|

   Intercept     1       36.10820        6.50497       5.55      <.0001
   _0            1       -0.08563        0.04277      -2.00      0.0461
   _1            1        0.04603        0.01715       2.68      0.0076
   _2            1        0.03641        0.07601       0.48      0.6322
   _3            1        3.24796        1.07414       3.02      0.0027
   _4            1      -14.87294        4.63609      -3.21      0.0015
   _5            1        3.57687        0.53699       6.66      <.0001
   _6            1       -0.00870        0.01685      -0.52      0.6059
   _7            1       -1.36890        0.25296      -5.41      <.0001
   _8            1        0.31312        0.08237       3.80      0.0002
   _9            1       -0.01288        0.00460      -2.80      0.0054
   _10           1       -0.97690        0.17100      -5.71      <.0001
   _11           1        0.01133        0.00336       3.37      0.0008
   _12           1       -0.52672        0.06256      -8.42      <.0001
```

b) Assess the model against the testing data.

```
/* Predicton on testing data */
proc score data = test score=RegOut type=parms predict out = Pred;
    var _0-_12;
run;
```

```
/* Compute the squared differences between predicted and target */
data Pred;
    set Pred;
    sq_error = (predY - Target)**2;
run;

/* Compute the mean of the squared differences (mean squared error) as an
   assessment of the model */
proc means data = Pred mean;
  var sq_error;
run;
                            The MEANS Procedure

                       Analysis Variable : sq_error

                                    Mean
                            ------------
                              17.7713080
                            ------------
```

REG Procedure | SCORE Procedure | MEANS Procedure

6.3 Fit a decision tree model on training data and assess against testing data.

a) Fit a decision tree classification model.

i) Fit a decision tree classification model on training data and determine variable importance

```
/* Notice we are using new data sets that need to be read into the
   environment */
proc import out = train
    datafile = 'C:/Users/breastcancer_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/breastcancer_test.csv'
    dbms = csv replace;
    getnames = yes;
run;

/* HPSPLIT procedure is used to fit a decision tree model */
proc hpsplit data = train seed = 29;
    target Target;
    input _0-_29;
    /* Export information about variable importance */
    output importance=import;
```

```
    /* Export the model code so this can be used to score testing data */
    code file='hpbreastcancer.sas';
run;

/* Output of this model gives assessment against training data
     and variable importance */
                           The HPSPLIT Procedure

                          Performance Information

                    Execution Mode       Single-Machine
                    Number of Threads    4

                         Data Access Information

                Data          Engine    Role     Path

                WORK.TRAIN    V9        Input    On Client

                             Model Information

          Split Criterion Used                              Entropy
          Pruning Method                            Cost-Complexity
          Subtree Evaluation Criterion              Cost-Complexity
          Number of Branches                                      2
          Maximum Tree Depth Requested                           10
          Maximum Tree Depth Achieved                             6
          Tree Depth                                              3
          Number of Leaves Before Pruning                        15
          Number of Leaves After Pruning                          6
          Model Event Level                                       1

            Number of Observations Read                    398
            Number of Observations Used                    398



                           The HPSPLIT Procedure

                        Model-Based Confusion Matrix

                                 Predicted           Error
                Actual             1           0      Rate

                1                242           1    0.0041
                0                 10         145    0.0645

                Model-Based Fit Statistics for Selected Tree
```

```
     N           Mis-
Leaves       ASE   class Sensitivity Specificity  Entropy     Gini      RSS

     6    0.0229 0.0276      0.9959      0.9355   0.1297   0.0457  18.2063

              Model-Based Fit Statistics for Selected Tree

                                  AUC

                               0.9852

                           Variable Importance

                                Training
              Variable    Relative    Importance      Count

              _23            1.0000       11.2865          1
              _27            0.4072        4.5962          1
              _1             0.3487        3.9356          2
              _6             0.2355        2.6581          1
```

ii. Assess the model against the testing data.

```
/* Score the test data using the model code */
data scored;
    set test;
    %include 'hpbreastcancer.sas';
run;

/* Use prediction probabilities to generate predictions, and compare these
     to the true responses */
/* If the prediction probability is less than 0.5, classify this as a 0
   and otherwise classify as a 1.  This isn't the best method -- a better
   method would be randomly assigning a 0 or 1 when a probability of 0.5
   occurrs, but this insures that results are consistent */
data scored;
    set scored;
    if (P_Target1 < 0.5) then prediction = 0;
    else prediction = 1;
    if (Target = prediction) then Result = "Correct";
  else Result = "Wrong";
run;

/* Determine how many were correctly classified */
proc freq data = scored;
  tables Result / nopercent norow nocol;
run;
```

```
                         The FREQ Procedure

                                             Cumulative
                  Result      Frequency       Frequency
                  ---------------------------------
                  Correct          157             157
                  Wrong             14             171
```

HPSPLIT Procedure | %include & if-then/else statements | FREQ Procedure

b) Fit a decision tree regression model.

i) Fit a decision tree regression model on training data and determine variable importance.

```
proc import out = train
    datafile = 'C:/Users/boston_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/boston_test.csv'
    dbms = csv replace;
    getnames = yes;
run;

/* HPSPLIT procedure is used to fit a decision tree model */
proc hpsplit data = train seed = 29;
    target Target / level = int;
    input _0-_12;
    /* Export information about variable importance */
    output importance=import;
    /* Export the model code so this can be used to score testing data */
    code file='hpboston.sas';
run;

/* Output of this model gives assessment against training data
   and variable importance */
```

```
                           The HPSPLIT Procedure

                          Performance Information

                    Execution Mode        Single-Machine
                    Number of Threads     4

                         Data Access Information

                Data           Engine     Role      Path

                WORK.TRAIN     V9         Input     On Client
```

```
                    Model Information

Split Criterion Used                         Variance
Pruning Method                        Cost-Complexity
Subtree Evaluation Criterion          Cost-Complexity
Number of Branches                                  2
Maximum Tree Depth Requested                       10
Maximum Tree Depth Achieved                        10
Tree Depth                                         10
Number of Leaves Before Pruning                   188
Number of Leaves After Pruning                    101

  Number of Observations Read                  354
  Number of Observations Used                  354



                  The HPSPLIT Procedure

       Model-Based Fit Statistics for Selected Tree

                N
           Leaves          ASE          RSS

              101       0.9750        345.2

                   Variable Importance

                            Training
     Variable    Relative    Importance      Count

     _5            1.0000         132.8         13
     _12           0.6026       79.9998         16
     _7            0.3968       52.6772          9
     _4            0.2663       35.3541         12
     _0            0.2324       30.8579          7
     _9            0.1574       20.8933          8
     _6            0.1202       15.9544         12
     _10           0.1063       14.1112          4
     _11           0.0855       11.3541          8
     _2            0.0713        9.4695          5
     _8            0.0696        9.2408          3
     _1            0.0583        7.7437          3
```

ii. Assess the model against the testing data.

```
/* Score the test data using the model code */
data scored;
    set test;
```

```
    %include 'hpboston.sas';
run;

/* Compute the squared differences between predicted and target */
data scored;
    set scored;
    sq_error = (P_Target - Target)**2;
run;

/* Compute the mean of the squared differences (mean squared error) as an
     assessment of the model */
proc means data = scored mean;
  var sq_error;
run;

                            The MEANS Procedure

                       Analysis Variable : sq_error

                                       Mean
                               ------------
                                 24.6222895
                               ------------
```

HPSPLIT Procedure | %include statement | MEANS Procedure

6.4 Fit a random forest model on training data and assess against testing data.

a) Fit a random forest classification model.

i) Fit a random forest classification model on training data and determine variable importance.

```
proc import out = train
    datafile = 'C:/Users/breastcancer_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/breastcancer_test.csv'
    dbms = csv replace;
    getnames = yes;
run;

/* Output includes information about variable importance */
proc hpforest data = train;
    input _0 - _29 / level = interval;
    target Target / level = nominal;
```

```
    save file = 'hpbreastcancer2.bin';
run;

                          The HPFOREST Procedure

                          Performance Information

                    Execution Mode       Single-Machine
                    Number of Threads    4

                         Data Access Information

                Data          Engine    Role     Path

                WORK.TRAIN    V9        Input    On Client

                            Model Information

         Parameter                          Value

         Variables to Try                       5    (Default)
         Maximum Trees                        100    (Default)
         Inbag Fraction                       0.6    (Default)
         Prune Fraction                         0    (Default)
         Prune Threshold                      0.1    (Default)
         Leaf Fraction                    0.00001    (Default)
         Leaf Size Setting                      1    (Default)
         Leaf Size Used                         1
         Category Bins                         30    (Default)
         Interval Bins                        100
         Minimum Category Size                  5    (Default)
         Node Size                         100000    (Default)
         Maximum Depth                         20    (Default)
         Alpha                                  1    (Default)
         Exhaustive                          5000    (Default)
         Rows of Sequence to Skip               5    (Default)
         Split Criterion                        .    Gini
         Preselection Method                    .    BinnedSearch
         Missing Value Handling                 .    Valid value

                          Number of Observations

                Type                                        N

                Number of Observations Read               398
                Number of Observations Used               398

                         Baseline Fit Statistics
```

Statistic	Value
Average Square Error	0.238
Misclassification Rate	0.389
Log Loss	0.669

Fit Statistics

Number of Trees	Number of Leaves	Average Square Error (Train)	Average Square Error (OOB)	Misclassification Rate (Train)
1	16	0.03015	0.0750	0.03015
2	35	0.01947	0.0739	0.04523
3	53	0.01284	0.0724	0.00754
4	66	0.01225	0.0658	0.01005
5	80	0.01156	0.0700	0.00754
6	92	0.01124	0.0712	0.00754
7	106	0.00938	0.0633	0.00251
8	122	0.00879	0.0623	0.00000
9	139	0.00887	0.0611	0.00000
10	157	0.00867	0.0611	0.00000
11	171	0.00889	0.0589	0.00251
12	188	0.00874	0.0557	0.00000
13	203	0.00847	0.0551	0.00000
14	223	0.00841	0.0552	0.00000
15	241	0.00804	0.0537	0.00251
16	253	0.00795	0.0496	0.00251
17	268	0.00827	0.0489	0.00503
18	283	0.00813	0.0485	0.00251
19	300	0.00793	0.0471	0.00251
20	315	0.00783	0.0471	0.00251
21	329	0.00763	0.0465	0.00251
22	345	0.00747	0.0453	0.00000
23	361	0.00740	0.0448	0.00000
24	375	0.00744	0.0442	0.00000
25	392	0.00749	0.0449	0.00251
26	406	0.00764	0.0448	0.00251
27	420	0.00750	0.0440	0.00251
28	437	0.00764	0.0438	0.00000
29	451	0.00776	0.0431	0.00000
30	466	0.00774	0.0426	0.00000
31	484	0.00778	0.0432	0.00251
32	502	0.00759	0.0426	0.00000
33	518	0.00749	0.0420	0.00251
34	535	0.00747	0.0418	0.00000
35	550	0.00742	0.0415	0.00000
36	562	0.00746	0.0411	0.00000

37	578	0.00741	0.0411	0.00000
38	594	0.00731	0.0404	0.00000
39	609	0.00717	0.0407	0.00000
40	623	0.00720	0.0404	0.00000
41	642	0.00712	0.0405	0.00000
42	661	0.00702	0.0399	0.00000
43	679	0.00687	0.0397	0.00000
44	692	0.00677	0.0396	0.00000
45	710	0.00665	0.0392	0.00000
46	731	0.00652	0.0391	0.00000
47	741	0.00654	0.0387	0.00000
48	754	0.00661	0.0392	0.00000
49	769	0.00656	0.0393	0.00000
50	780	0.00657	0.0395	0.00000
51	795	0.00658	0.0395	0.00000
52	812	0.00657	0.0399	0.00000
53	829	0.00653	0.0399	0.00000
54	843	0.00662	0.0402	0.00000
55	856	0.00662	0.0403	0.00000
56	869	0.00663	0.0401	0.00000
57	883	0.00655	0.0396	0.00000
58	898	0.00653	0.0397	0.00000
59	914	0.00653	0.0394	0.00000
60	929	0.00661	0.0397	0.00000
61	946	0.00658	0.0396	0.00000
62	959	0.00655	0.0393	0.00000
63	975	0.00657	0.0394	0.00000
64	988	0.00660	0.0393	0.00000
65	1008	0.00662	0.0396	0.00000
66	1020	0.00671	0.0397	0.00000
67	1036	0.00675	0.0401	0.00000
68	1054	0.00672	0.0397	0.00000
69	1072	0.00678	0.0401	0.00000
70	1088	0.00686	0.0405	0.00000
71	1103	0.00692	0.0407	0.00000
72	1122	0.00692	0.0410	0.00000
73	1137	0.00695	0.0411	0.00000
74	1156	0.00682	0.0406	0.00000
75	1171	0.00678	0.0406	0.00000
76	1188	0.00668	0.0403	0.00000
77	1202	0.00665	0.0402	0.00000
78	1215	0.00661	0.0402	0.00000
79	1229	0.00661	0.0400	0.00000
80	1247	0.00658	0.0399	0.00000
81	1263	0.00657	0.0395	0.00000
82	1276	0.00659	0.0394	0.00000
83	1292	0.00659	0.0393	0.00000
84	1305	0.00652	0.0388	0.00000
85	1322	0.00649	0.0387	0.00000
86	1342	0.00644	0.0386	0.00000

87	1359	0.00647	0.0387	0.00000
88	1373	0.00655	0.0388	0.00000
89	1389	0.00655	0.0389	0.00000
90	1404	0.00652	0.0385	0.00000
91	1418	0.00658	0.0386	0.00000
92	1432	0.00652	0.0383	0.00000
93	1447	0.00649	0.0381	0.00000
94	1460	0.00654	0.0382	0.00000
95	1481	0.00657	0.0386	0.00000
96	1495	0.00650	0.0383	0.00000
97	1509	0.00646	0.0381	0.00000
98	1522	0.00651	0.0382	0.00000
99	1537	0.00649	0.0382	0.00000
100	1554	0.00647	0.0382	0.00000

Fit Statistics

Misclassification Rate (OOB)	Log Loss (Train)	Log Loss (OOB)
0.0750	0.6942	1.727
0.0895	0.1558	1.545
0.0952	0.0429	1.358
0.0893	0.0453	1.059
0.0877	0.0447	1.139
0.0871	0.0457	1.054
0.0803	0.0417	0.860
0.0821	0.0414	0.800
0.0842	0.0424	0.742
0.0787	0.0429	0.743
0.0734	0.0445	0.739
0.0732	0.0447	0.626
0.0732	0.0443	0.574
0.0781	0.0447	0.574
0.0756	0.0436	0.571
0.0729	0.0433	0.457
0.0678	0.0439	0.404
0.0603	0.0436	0.404
0.0628	0.0430	0.349
0.0628	0.0429	0.349
0.0628	0.0425	0.348
0.0628	0.0420	0.294
0.0653	0.0418	0.294
0.0628	0.0416	0.292
0.0628	0.0420	0.294
0.0628	0.0423	0.243
0.0603	0.0418	0.241
0.0603	0.0429	0.241
0.0578	0.0433	0.239

0.0578	0.0436	0.239
0.0628	0.0437	0.241
0.0578	0.0435	0.240
0.0553	0.0430	0.238
0.0553	0.0431	0.237
0.0553	0.0432	0.237
0.0528	0.0430	0.236
0.0528	0.0431	0.236
0.0528	0.0428	0.185
0.0553	0.0427	0.186
0.0528	0.0426	0.185
0.0553	0.0424	0.186
0.0553	0.0422	0.184
0.0553	0.0418	0.184
0.0553	0.0415	0.184
0.0578	0.0410	0.183
0.0578	0.0410	0.183
0.0528	0.0411	0.182
0.0578	0.0412	0.182
0.0553	0.0412	0.183
0.0553	0.0415	0.183
0.0528	0.0414	0.183
0.0578	0.0417	0.184
0.0578	0.0415	0.184
0.0578	0.0420	0.186
0.0578	0.0420	0.186
0.0528	0.0421	0.186
0.0528	0.0418	0.185
0.0528	0.0418	0.185
0.0528	0.0417	0.184
0.0553	0.0418	0.184
0.0528	0.0417	0.184
0.0553	0.0415	0.184
0.0578	0.0416	0.184
0.0578	0.0416	0.184
0.0578	0.0418	0.184
0.0578	0.0421	0.185
0.0603	0.0422	0.186
0.0578	0.0421	0.185
0.0553	0.0425	0.186
0.0578	0.0428	0.187
0.0578	0.0430	0.188
0.0578	0.0432	0.189
0.0603	0.0431	0.189
0.0603	0.0427	0.188
0.0578	0.0425	0.188
0.0553	0.0423	0.187
0.0578	0.0423	0.187
0.0578	0.0422	0.187
0.0578	0.0421	0.187

0.0553	0.0421	0.186
0.0578	0.0420	0.185
0.0553	0.0420	0.185
0.0553	0.0419	0.184
0.0553	0.0417	0.183
0.0528	0.0416	0.183
0.0553	0.0414	0.183
0.0528	0.0415	0.183
0.0528	0.0416	0.184
0.0503	0.0417	0.184
0.0477	0.0416	0.183
0.0503	0.0417	0.183
0.0503	0.0415	0.183
0.0528	0.0414	0.134
0.0503	0.0417	0.134
0.0528	0.0419	0.135
0.0503	0.0416	0.135
0.0477	0.0415	0.134
0.0477	0.0416	0.134
0.0477	0.0415	0.134
0.0452	0.0416	0.135

Loss Reduction Variable Importance

Variable	Number of Rules	Gini	OOB Gini	Margin	OOB Margin
_7	69	0.057751	0.05100	0.115502	0.10851
_27	116	0.057536	0.04812	0.115072	0.10648
_22	66	0.053462	0.04054	0.106925	0.09267
_23	92	0.049798	0.03969	0.099596	0.08961
_20	84	0.045727	0.03686	0.091453	0.08190
_2	43	0.030053	0.02561	0.060105	0.05721
_0	44	0.026259	0.01873	0.052518	0.04483
_13	47	0.018831	0.01425	0.037662	0.03329
_6	55	0.021984	0.01321	0.043968	0.03523
_3	16	0.010751	0.01275	0.021502	0.02310
_26	84	0.017139	0.00693	0.034279	0.02387
_21	73	0.009979	0.00400	0.019958	0.01367
_10	31	0.007944	0.00273	0.015889	0.01089
_12	31	0.007102	0.00217	0.014204	0.00929
_17	31	0.002941	0.00049	0.005882	0.00286
_5	12	0.001882	-0.00010	0.003764	0.00152
_16	17	0.001134	-0.00055	0.002268	0.00089
_11	23	0.001679	-0.00057	0.003358	0.00096
_8	22	0.001543	-0.00077	0.003086	0.00052
_18	22	0.001787	-0.00105	0.003573	0.00081
_9	23	0.001656	-0.00105	0.003312	0.00063
_4	22	0.002237	-0.00114	0.004475	0.00147
_1	58	0.008366	-0.00147	0.016732	0.00648

```
   _24                 80    0.010527    -0.00149    0.021054     0.00906
   _25                 55    0.005040    -0.00151    0.010081     0.00449
   _28                 70    0.008423    -0.00168    0.016846     0.00617
   _15                 16    0.001345    -0.00203    0.002690    -0.00059
   _14                 29    0.001679    -0.00282    0.003357    -0.00110
   _19                 49    0.003804    -0.00413    0.007609    -0.00028
   _29                 74    0.005801    -0.00418    0.011603     0.00225
```

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
ods select none;
proc hp4score data = test seed = 29;
    score file = 'hpbreastcancer2.bin' out = scored;
run;
ods select all;

/* Determine how many were correctly classified */
data scored;
    set scored;
    if (I_Target = Target) then Result = "Correct";
    else Result = "Wrong";
run;

proc freq data = scored;
  tables Result / nopercent norow nocol;
run;
                            The FREQ Procedure

                                                Cumulative
                    Result     Frequency      Frequency
                    ----------------------------------
                    Correct         166            166
                    Wrong             5            171
```

HPFOREST Procedure | HP4SCORE Procedure | FREQ Procedure

b) Fit a random forest regression model.

i) Fit a random forest regression model on training data and determine variable importance.

```
proc import out = train
    datafile = 'C:/Users/boston_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/boston_test.csv'
    dbms = csv replace;
    getnames = yes;
run;
```

```
proc hpforest data = train;
    input _0-_12 / level = interval;
    target Target / level = interval;
    save file = 'hpboston2.bin';
run;
                          The HPFOREST Procedure

                          Performance Information

                    Execution Mode       Single-Machine
                    Number of Threads    4

                         Data Access Information

                Data          Engine    Role     Path

                WORK.TRAIN    V9        Input    On Client

                             Model Information

         Parameter                              Value

         Variables to Try                           4    (Default)
         Maximum Trees                            100    (Default)
         Inbag Fraction                           0.6    (Default)
         Prune Fraction                             0    (Default)
         Prune Threshold                          0.1    (Default)
         Leaf Fraction                        0.00001    (Default)
         Leaf Size Setting                          1    (Default)
         Leaf Size Used                             1
         Category Bins                             30    (Default)
         Interval Bins                            100
         Minimum Category Size                      5    (Default)
         Node Size                             100000    (Default)
         Maximum Depth                             20    (Default)
         Alpha                                      1    (Default)
         Exhaustive                              5000    (Default)
         Rows of Sequence to Skip                   5    (Default)
         Split Criterion                            .    Variance
         Preselection Method                        .    BinnedSearch
         Missing Value Handling                     .    Valid value

                          Number of Observations

                Type                                         N

                Number of Observations Read                354
```

Number of Observations Used 354

Baseline Fit Statistics

Statistic	Value
Average Square Error	86.450

Fit Statistics

Number of Trees	Number of Leaves	Average Square Error (Train)	Average Square Error (OOB)
1	187	19.2696	47.7098
2	375	11.0807	42.1586
3	576	6.4927	30.3271
4	771	4.7796	24.0581
5	959	4.5159	23.4567
6	1155	4.9110	22.6319
7	1347	4.1583	23.0376
8	1547	3.7435	21.2464
9	1748	3.4531	21.2850
10	1946	3.1073	20.2032
11	2136	3.2121	19.2041
12	2332	3.1237	18.8289
13	2525	3.3520	18.5622
14	2725	3.3115	17.9458
15	2923	3.1540	17.8672
16	3119	3.0182	17.6951
17	3315	2.7891	15.9191
18	3504	2.7262	16.0389
19	3698	2.6796	15.9793
20	3900	2.8163	15.6942
21	4070	2.7165	15.1308
22	4272	2.6627	14.6898
23	4466	2.5744	14.2357
24	4656	2.5878	14.4372
25	4849	2.6107	14.5108
26	5040	2.5906	14.6795
27	5225	2.5775	14.6166
28	5424	2.5216	14.3960
29	5622	2.4921	14.4397
30	5818	2.5032	14.5353
31	6015	2.5228	14.6958
32	6210	2.4405	14.2739
33	6408	2.3779	14.1679
34	6593	2.3615	14.1160

35	6794	2.3589	14.2134
36	6992	2.3770	14.2171
37	7193	2.3638	14.1494
38	7382	2.3157	13.7835
39	7571	2.2690	13.6246
40	7763	2.3111	13.6521
41	7952	2.3123	13.5831
42	8147	2.2668	13.4014
43	8342	2.2944	13.4622
44	8534	2.2773	13.4879
45	8728	2.2414	13.2354
46	8922	2.1857	12.7618
47	9113	2.1506	12.4622
48	9314	2.1330	12.3839
49	9515	2.1665	12.5092
50	9686	2.1353	12.3193
51	9878	2.1413	12.3478
52	10071	2.1221	12.1762
53	10278	2.1642	12.3399
54	10470	2.1210	12.2085
55	10669	2.1326	12.1800
56	10853	2.1096	12.0564
57	11043	2.1039	11.9939
58	11233	2.0865	11.9888
59	11431	2.0720	11.9272
60	11629	2.0357	11.7004
61	11827	2.0487	11.6981
62	12021	2.0268	11.6102
63	12206	2.0241	11.4748
64	12391	2.0136	11.4391
65	12578	2.0078	11.4480
66	12773	2.0233	11.5387
67	12967	2.0191	11.5206
68	13169	2.0308	11.5832
69	13352	2.0610	11.6571
70	13549	2.0565	11.5252
71	13750	2.0540	11.5122
72	13948	2.0511	11.6108
73	14138	2.0443	11.4405
74	14326	2.0287	11.4350
75	14519	2.0236	11.4495
76	14710	1.9999	11.3821
77	14908	2.0339	11.4657
78	15109	2.0242	11.3819
79	15310	2.0145	11.3343
80	15502	1.9998	11.2962
81	15695	1.9964	11.3274
82	15893	1.9886	11.3253
83	16089	1.9816	11.3216
84	16291	1.9744	11.2669

```
                    85          16489      2.0029     11.3804
                    86          16681      1.9990     11.3564
                    87          16878      1.9991     11.4100
                    88          17083      2.0381     11.5193
                    89          17280      2.0384     11.4551
                    90          17475      2.0309     11.4513
                    91          17669      2.0407     11.4609
                    92          17863      2.0317     11.4285
                    93          18051      2.0250     11.4155
                    94          18243      2.0299     11.4424
                    95          18432      2.0422     11.4762
                    96          18617      2.0505     11.5087
                    97          18814      2.0622     11.5379
                    98          19016      2.0520     11.4880
                    99          19218      2.0431     11.4302
                   100          19414      2.0474     11.4846

                   Loss Reduction Variable Importance

                Number                    OOB       Absolute   OOB Absolute
  Variable    of Rules        MSE         MSE          Error          Error

  _5              1543   25.93319    22.96802       1.684712       1.314268
  _12             4449   25.87533    21.34090       1.756483       1.040169
  _2               885    7.53671     4.21854       0.488903       0.216959
  _10              998    4.80360     2.90700       0.324724       0.143773
  _4              1086    4.70452     1.81534       0.435269       0.181240
  _9              1313    2.72208     1.02070       0.281023       0.086734
  _0               407    2.08458     0.86465       0.164101       0.067590
  _7              2355    6.98533     0.45692       0.632151       0.157534
  _1               144    0.15616    -0.05707       0.023033      -0.006782
  _3               192    0.56394    -0.13892       0.041797      -0.008208
  _8               807    0.71031    -0.14351       0.106171      -0.014238
  _6              1576    1.47345    -0.53679       0.247212      -0.017716
  _11             3559    3.04629    -1.16077       0.477189      -0.031938
```

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
ods select none;
proc hp4score data = test seed = 29;
    score file = 'hpboston2.bin' out = scored;
run;
ods select all;

/* Compute the squared differences between predicted and target */
data scored;
    set scored;
    sq_error = (P_Target - Target)**2;
run;
```

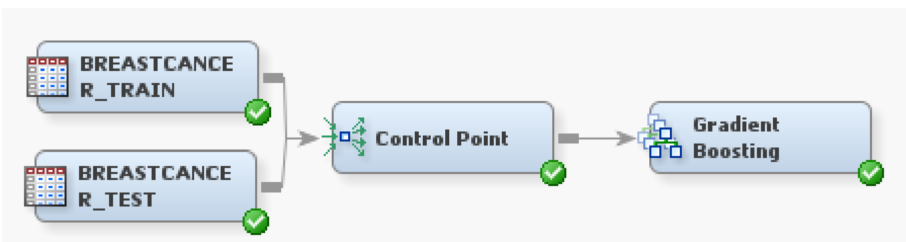
```
/* Compute the mean of the squared differences (mean squared error) as an
   assessment of the model */
proc means data = scored mean;
  var sq_error;
run;
                              The MEANS Procedure

                         Analysis Variable : sq_error

                                       Mean
                                ------------
                                   8.5493412
                                ------------
```

HPFOREST Procedure | HP4SCORE Procedure | MEANS Procedure

6.5 Fit a gradient boosting model on training data and assess against testing data.

a) Fit a gradient boosting classification model.

Currently, there is not a gradient boosting procedure available in Base SAS Therefore, the best method to create a gradient boosting model as of now is using SAS Enterprise Miner. Create the following diagram in SAS Enterprise Miner:

Diagram: 

For the Gradient Boosting node, set Seed = 29, set Shrinkage = 0.01, and set Train Proportion = 100.

This diagram results in the following variable importance and misclassification against training & testing data:

Output:

Variable Name	Importance
_23	1
_27	0.988671
_7	0.382448
_13	0.294633
_22	0.178301
_1	0.113222
_24	0.068714
_20	0.044286
_19	0.03198

Statistics Label	Train	Test
Sum of Frequencies	398	171
Sum of Case Weights Times Freq	796	342
Misclassification Rate	0.035176	0.040936
Maximum Absolute Error	0.717472	0.743284
Sum of Squared Errors	99.49027	40.19162
Average Squared Error	0.124988	0.117519
Root Average Squared Error	0.353536	0.342811
Divisor for ASE	796	342
Total Degrees of Freedom	398	.

Output:

```
Classification Table

Data Role=TRAIN Target Variable=Target Target Label=' '

                              Target        Outcome      Frequency       Total
Target       Outcome        Percentage     Percentage      Count       Percentage

  0             0             100.000        90.968         141         35.4271
  0             1               5.447         9.032          14          3.5176
  1             1              94.553       100.000         243         61.0553
```

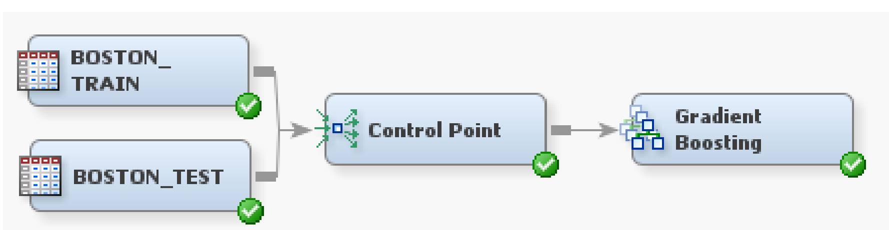
Output:

Gradient Boosting node

b) Fit a gradient boosting regression model.

Again, there is not a gradient boosting procedure available in Base SAS, currently. Create the following diagram in SAS Enterprise Miner:

Diagram:



For the Gradient Boosting node, set Seed = 29, set Shrinkage = 0.01, and set Train Proportion = 100.

This diagram results in the following variable importance and root mean squared error against training & testing data:

Variable Name	Importance
_12	1
_5	0.953865
_0	0.074612

Output:

Output:

Statistics Label	Train	Test
Sum of Frequencies	354	152
Sum of Case Weights Times Freq	354	152
Maximum Absolute Error	27.01107	21.83158
Sum of Squared Errors	17560.66	7109.598
Average Squared Error	49.60639	46.77367
Root Average Squared Error	7.04318	6.839128
Divisor for ASE	354	152
Total Degrees of Freedom	354	.

Gradient Boosting node

6.6 Fit an extreme gradient boosting model on taining data and assess against testing data.

a) Fit an extreme gradient boosting classification model.

Fit an extreme gradient boosting classification model on training data and assess the model against the testing data.

For more information on the R code used below, please see the R Tutorial.

```
proc iml;
  submit / R;
    train = read.csv('C:/Users/breastcancer_train.csv')
    test = read.csv('C:/Users/breastcancer_test.csv')

    library(xgboost)
      set.seed(29)

    xgbMod <- xgboost(data.matrix(subset(train, select = -c(Target))),
                      data.matrix(train$Target), max_depth = 3, nrounds = 2,
                      objective = "binary:logistic", n_estimators = 2500,
                      shrinkage = .01)
    # Prediction on testing data
    predictions <- predict(xgbMod, data.matrix(subset(test, select =
                                                       -c(Target))))
    pred.response <- ifelse(predictions < 0.5, 0, 1)

    # Determine how many were correctly classified
    Results <- ifelse(test$Target == pred.response, "Correct", "Wrong")
    table(Results)
  endsubmit;
quit;

[1] train-error:0.037688
[2] train-error:0.020101
Results
```

```
Correct   Wrong
    165       6
```

Fit an extreme gradient boosting regression model on training data and assess the model against the testing data.

```
proc iml;
  submit / R;
    train = read.csv('C:/Users/boston_train.csv')
    test = read.csv('C:/Users/boston_test.csv')

    library(xgboost)
      set.seed(29)

    xgbMod <- xgboost(data.matrix(subset(train, select = -c(Target))),
                      data.matrix(train$Target / 50), max_depth = 3,
                      nrounds = 2, n_estimators = 2500, shrinkage = .01)

    # Predict the target in the testing data, remembering to
    # multiply by 50
    prediction = data.frame(matrix(ncol = 0, nrow = nrow(test)))
    prediction$target_hat <- predict(xgbMod,
                                     data.matrix(subset(test,
                                                 select = - c(Target))))*50

    # Compute the squared difference between predicted tip and actual tip
    prediction$sq_diff <- (prediction$target_hat - test$Target)**2

    # Compute the mean of the squared differences (mean squared error)
    # as an assessment of the model
    mean_sq_error <- mean(prediction$sq_diff)
    print(mean_sq_error)
  endsubmit;
quit;

[1] train-rmse:0.146609
[2] train-rmse:0.114851
[1] 36.13079
```

IML Procedure

6.7 Fit a support vector model on training data and assess against testing data.

a) Fit a support vector classification model.

i) Fit a support vector classification model on training data.

Note: In implementation scaling should be used.

```
proc import out = train
    datafile = 'C:/Users/breastcancer_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/breastcancer_test.csv'
    dbms = csv replace;
    getnames = yes;
run;

/* Fit a support vector classification model */
proc hpsvm data = train noscale;
  input _0-_29 / level = interval;
    target Target / level = nominal;
    code file='hpbreastcancer3.sas';
run;
                            The HPSVM Procedure

                          Performance Information

                    Execution Mode       Single-Machine
                    Number of Threads    4

                         Data Access Information

                Data          Engine    Role     Path

                WORK.TRAIN    V9        Input    On Client

                            Model Information

                 Task Type                  C_CLAS
                 Optimization Technique     Interior Point
                 Scale                      NO
                 Kernel Function            Linear
                 Penalty Method             C
                 Penalty Parameter          1
                 Maximum Iterations         25
                 Tolerance                  1e-06

                Number of Observations Read             398
                Number of Observations Used             398

                             Training Results

             Inner Product of Weights              4.68178411
             Bias                                  -23.154522
```

Total Slack (Constraint Violations)	32.0538338
Norm of Longest Vector	4974.69727
Number of Support Vectors	40
Number of Support Vectors on Margin	30
Maximum F	51.3038307
Minimum F	-12.975435
Number of Effects	30
Columns in Data Matrix	30

Iteration History

Iteration	Complementarity	Feasibility
1	1098868.5951	77182929.263
2	1093.5799104	38409.486516
3	399.18453843	11593.175439
4	151.7107168	3299.973204
5	27.079643495	507.367502
6	3.9248813407	34.38606498
7	0.8746382131	3.030830576
8	0.8372881014	3.0263712E-8
9	0.1618601056	5.0387567E-9
10	0.1116181725	2.4391745E-9
11	0.0559596	8.900468E-10
12	0.0340160454	3.048639E-10
13	0.0234420432	1.00729E-10
14	0.015014891	1.898637E-11
15	0.0085767524	9.910531E-11
16	0.003826273	6.162429E-11
17	0.0015691956	5.733211E-11
18	0.0002432757	7.195363E-11
19	1.1925775E-6	1.40731E-10
20	1.9061115E-9	8.307455E-10

Classification Matrix

	Training Prediction		
Observed	1	0	Total
1	238	5	243
0	8	147	155
Total	246	152	398

Fit Statistics

Statistic	Training
Accuracy	0.9673
Error	0.0327

```
                          Sensitivity      0.9794
                          Specificity      0.9484
```

HPSVM Procedure

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
data scored;
    set test;
    %include 'hpbreastcancer3.sas';
run;

/* Determine how many were correctly classified */
data scored;
    set scored;
    if (I_Target = Target) then Result = "Correct";
    else Result = "Wrong";
run;

proc freq data = scored;
  tables Result / nopercent norow nocol;
run;

                            The FREQ Procedure

                                                Cumulative
                    Result     Frequency     Frequency
                    ----------------------------------
                    Correct         163           163
                    Wrong             8           171
```

%include & if-then/else statements | FREQ Procedure

b) Fit a support vector regression model.

Not available in this current release.

6.8 Fit a neural network model on training data and assess against testing data.

a) Fit a neural network classification model.

i) Fit a neural network classification model on training data.

```
/* Notice we are using new data sets */
proc import out = train
  datafile = 'C:/Users/digits_train.csv'
  dbms = csv replace;
  getnames = yes;
run;
```

```
proc import out = test
  datafile = 'C:/Users/digits_test.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* In order to use the NEURAL Procedure we first need to create a data
   mining database (DMDB) that reflects the original data */
proc dmdb batch data = train
    out = dmtrain
    dmdbcat = digits;
  var _0 - _63;
  class Target;
  target Target;
run;
proc dmdb batch data = test
    out = dmtest
    dmdbcat = digits;
  var _0 - _63;
  class Target;
  target Target;
run;

/* Now we can fit the neural network model */
/* Neural network produces a lot of output which is why here
   "nloptions noprint" is specified */
proc neural data = train dmdbcat = digits random = 29;
  nloptions noprint;
  input _0 - _63 / level = interval;
  target Target / level = nominal;
  archi MLP hidden=100;
  train maxiter = 200;
  score out = out outfit = fit;
  score data = test out = gridout;
run;
```

DMDB Procedure | NEURAL Procedure

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
data scored;
    set gridout;
    rename I_Target = Prediction;
run;

/* This produces a confusion matrix */
proc freq data = scored;
    tables Target*Prediction / nopercent norow nocol;
run;
```

The FREQ Procedure

Table of Target by Prediction

Target Prediction(Into: Target)

Frequency	0	1	2	3	4	Total
0	58	0	0	0	0	58
1	1	56	0	0	0	58
2	0	0	58	0	0	58
3	0	0	0	58	0	59
4	0	0	0	0	51	54
5	0	0	0	0	0	59
6	0	0	0	0	0	41
7	0	0	0	0	0	51
8	0	4	0	0	0	45
9	0	0	0	0	0	57
Total	59	60	58	58	51	540

(Continued)

Table of Target by Prediction

Target Prediction(Into: Target)

Frequency	5	6	7	8	9	Total
0	0	0	0	0	0	58
1	0	1	0	0	0	58
2	0	0	0	0	0	58
3	1	0	0	0	0	59
4	1	1	0	1	0	54
5	58	0	0	0	1	59

```
          6 |       0 |      41 |       0 |       0 |       0 |      41
   ---------+--------+--------+--------+--------+--------+
          7 |       1 |       0 |      50 |       0 |       0 |      51
   ---------+--------+--------+--------+--------+--------+
          8 |       0 |       0 |       0 |      39 |       2 |      45
   ---------+--------+--------+--------+--------+--------+
          9 |       2 |       0 |       0 |       2 |      53 |      57
   ---------+--------+--------+--------+--------+--------+
   Total           63       43       50       42       56      540
```

FREQ Procedure

b) Fit a neural network regression model.

i) Fit a neural network regression model on training data.

```
proc import out = train
  datafile = 'C:/Users/boston_train.csv'
  dbms = csv replace;
  getnames = yes;
run;
proc import out = test
  datafile = 'C:/Users/boston_test.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* In order to use the NEURAL Procedure we first need to create a data
   mining database (DMDB) that reflects the original data */
proc dmdb batch data = train
    out = dmtrain
    dmdbcat = boston;
  var _0 - _12 Target;
  target Target;
run;
proc dmdb batch data = test
    out = dmtest
    dmdbcat = boston;
  var _0 - _12 Target;
  target Target;
run;

/* Now we can fit the neural network model */
/* Neural network produces a lot of output which is why here
   "nloptions noprint" is specified */
proc neural data = train dmdbcat = boston random = 29;
  nloptions noprint;
  archi MLP hidden=100;
  input _0 - _12 / level = interval;
  target Target / level = interval;
  train maxiter = 250;
```

```
  score data = test outfit = netfit out = gridout;
run;
```

DMDB Procedure | NEURAL Procedure

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
data scored(keep = sq_error P_Target Target);
    set gridout;
    sq_error = (P_Target - Target)**2;
run;

/* Determine mean squared error */
proc means data = scored mean;
var sq_error;
run;

                            The MEANS Procedure

                       Analysis Variable : sq_error

                                       Mean
                               ------------
                                 16.1149499
                               ------------
```

MEANS Procedure

---

7 Unsupervised Machine Learning

7.1 KMeans Clustering

```
proc import out = iris
    datafile = 'C:/Users/iris.csv'
    dbms = csv replace;
    getnames = yes;
run;

data iris;
    length Species $ 20;
    set iris;
    if (Target = 0) then Species = "Setosa";
    if (Target = 1) then Species = "Versicolor";
    if (Target = 2) then Species = "Virginica";
run;

proc fastclus data=iris maxclusters=3 out=kmeans random = 29 noprint;
    var PetalLength PetalWidth SepalLength SepalWidth;
run;

proc freq data = kmeans;
    tables Species*Cluster / nopercent nocol norow;
run;
```

```
                            The FREQ Procedure

                        Table of Species by CLUSTER

              Species     CLUSTER(Cluster)

              Frequency  |       1|       2|       3|  Total
              -----------+--------+--------+--------+
              Setosa     |      0 |     50 |      0 |     50
              -----------+--------+--------+--------+
              Versicolor |      0 |      0 |     50 |     50
              -----------+--------+--------+--------+
              Virginica  |     33 |      0 |     17 |     50
              -----------+--------+--------+--------+
              Total            33       50       67     150
```

FASTCLUS Procedure | FREQ Procedure

7.2 Spectral Clustering

For more information on the R code used below, please see the R Tutorial.

```
proc iml;
  submit / R;
```

```
    iris = read.csv('C:/Users/iris.csv')
      iris$Species = ifelse(iris$Target == 0, "Setosa",
                            ifelse(iris$Target == 1, "Versicolor",
                                   "Virginica"))
      features <- as.matrix(subset(iris, select = c(PetalLength,
                                                    PetalWidth, SepalLength,
                                                    SepalWidth)))
    library(kernlab)
    set.seed(29)
    spectral <- specc(features, centers = 3, iterations = 10,
                      nystrom.red = TRUE)
    labels <- as.data.frame(spectral)
    table(iris$Species, labels$spectral)
  endsubmit;
quit;


              1  2  3
  Setosa     50  0  0
  Versicolor  0 47  3
  Virginica   0  3 47
```

IML Procedure

7.3 Ward Hierarchical Clustering

```
proc import out = iris
  datafile = 'C:/Users/iris.csv'
  dbms = csv replace;
  getnames = yes;
run;

data iris;
  length Species $ 20;
  set iris;
    if (Target = 0) then Species = "Setosa";
    if (Target = 1) then Species = "Versicolor";
    if (Target = 2) then Species = "Virginica";
run;

proc cluster data = iris method = ward print=15 ccc pseudo noprint;
   var petal: sepal:;
   copy species;
run;

proc tree noprint ncl=3 out=out;
   copy petal: sepal: species;
run;

proc freq data = out;
```

```
  tables Species*Cluster / nopercent norow nocol;
run;
```

Output:

Table of Species by CLUSTER				
	CLUSTER			
Species	1	2	3	Total
Setosa	50	0	0	50
Versicolor	0	49	1	50
Virginica	0	15	35	50
Total	50	64	36	150

CLUSTER Procedure | TREE Procedure | FREQ Procedure

7.4 DBSCAN

For more information on the R code used below, please see the R Tutorial.

```
proc iml;
  submit / R;
    iris = read.csv('C:/Users/iris.csv')
      iris$Species = ifelse(iris$Target == 0, "Setosa",
                            ifelse(iris$Target == 1, "Versicolor",
                                   "Virginica"))
      features <- as.matrix(subset(iris, select = c(PetalLength,
                                                    PetalWidth, SepalLength,
                                                    SepalWidth)))
    library(dbscan)
      set.seed(29)
    dbscan <- dbscan(features, eps = 0.5)
    labels <- dbscan$cluster
    table(iris$Species, labels)
  endsubmit;
quit;

            labels
              0  1  2
  Setosa      1 49  0
  Versicolor  6  0 44
  Virginica  10  0 40
```

IML Procedure

7.5 Self-organizing map

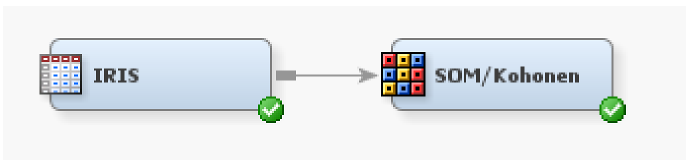
Currently, there is not a self-organizing map procedure available in Base SAS. Therefore, the best method to create a self-organizing map as of now is using SAS Enterprise Miner.

First, you need to read in the Iris data set, setting the Species/Target variable to be dropped before investigation.

Setup:

Name	Role	Level	Report	Order	Drop
PetalLength	**Input**	**Interval**	**No**		**No**
PetalWidth	**Input**	**Interval**	**No**		**No**
SepalLength	**Input**	**Interval**	**No**		**No**
SepalWidth	**Input**	**Interval**	**No**		**No**
Target	**Target**	**Interval**	**No**		**Yes**

Then create the following diagram in SAS Enterprise Miner:

Diagram: 

For the SOM/Kohonen node set the following options:

1. Choose the Kohonen SOM method.
2. Set row and column to both be 4.
3. Under the "Kohonen" options section, set "Use Defaults" to "No", and open the Kohonen Options window by clicking the ... box.
4. Set the following options in the popup window:

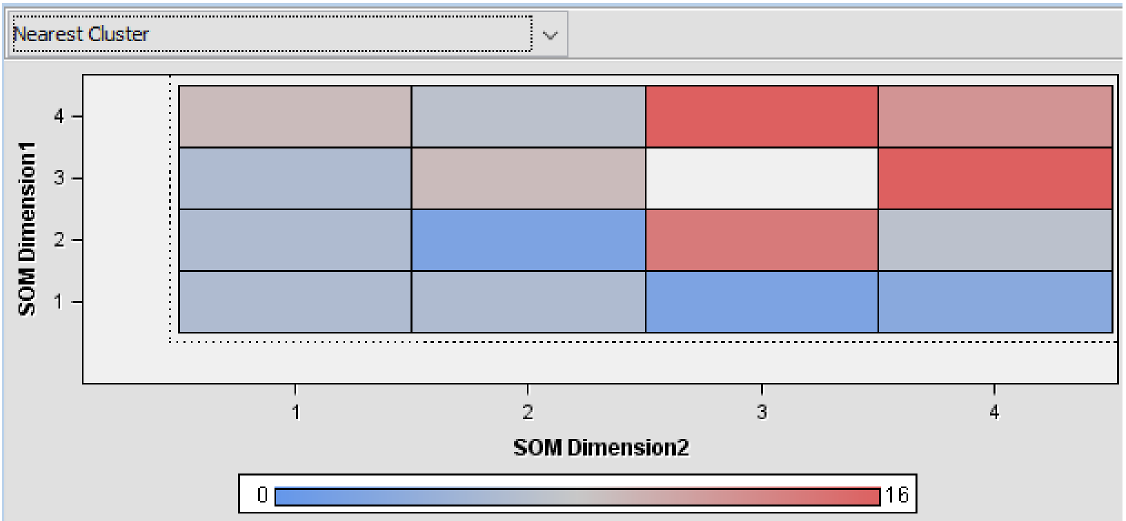
Kohonen Options

Options:

Property	Value
Learning Rate	0.05
Initial Rate	0.05
Final Rate	0.01
Number of Steps	1000
Convergence Criterion	1.0E-4
Max Iterations	100
Max Steps	1200

This model produces the following output which is similar to the output of R and Python:

Output:



Nearest Cluster
SOM Dimension1
4
3
2
1
1
2
3
4
SOM Dimension2
0
16

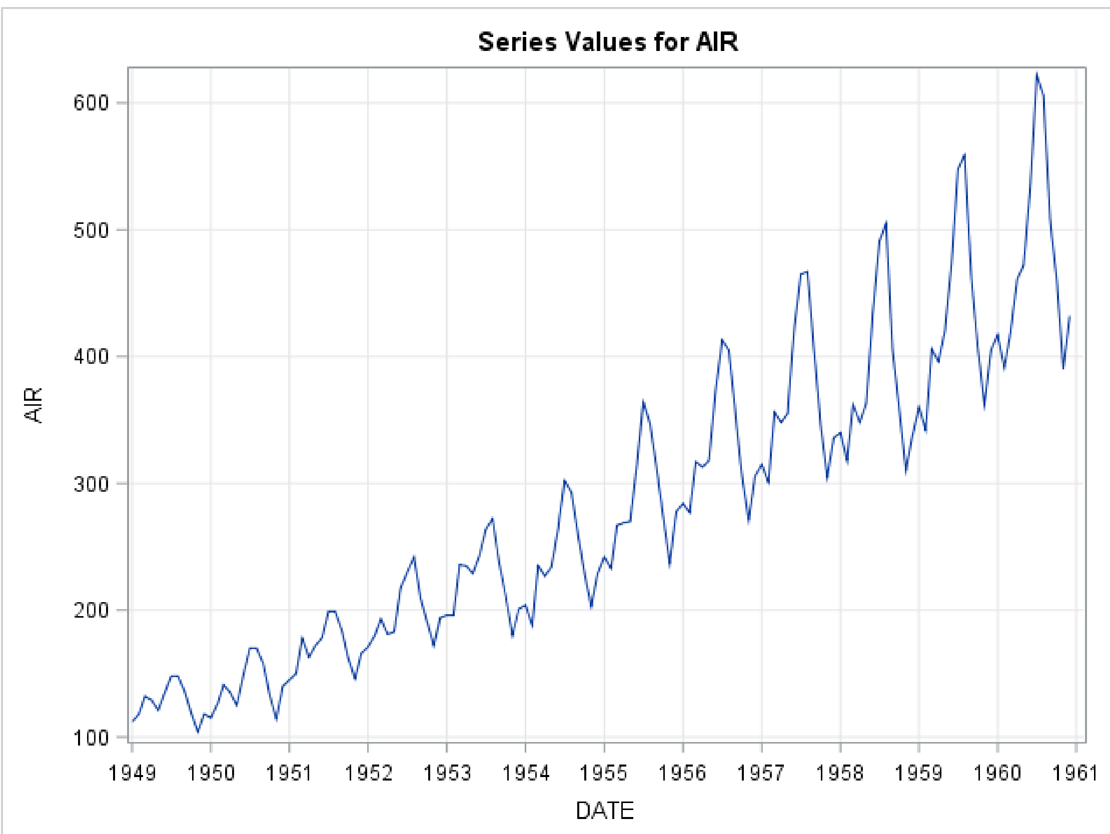
8 Forecasting

8.1 Fit an ARIMA model to a timeseries.

a) Plot the timeseries.

```
/* Read in new data set */
proc import out = air
  datafile = 'C:/Users/air.csv'
  dbms = csv replace;
  getnames = yes;
run;

proc timeseries data = air plot = series;
    id date interval = month;
    var air;
run;
```

Output:

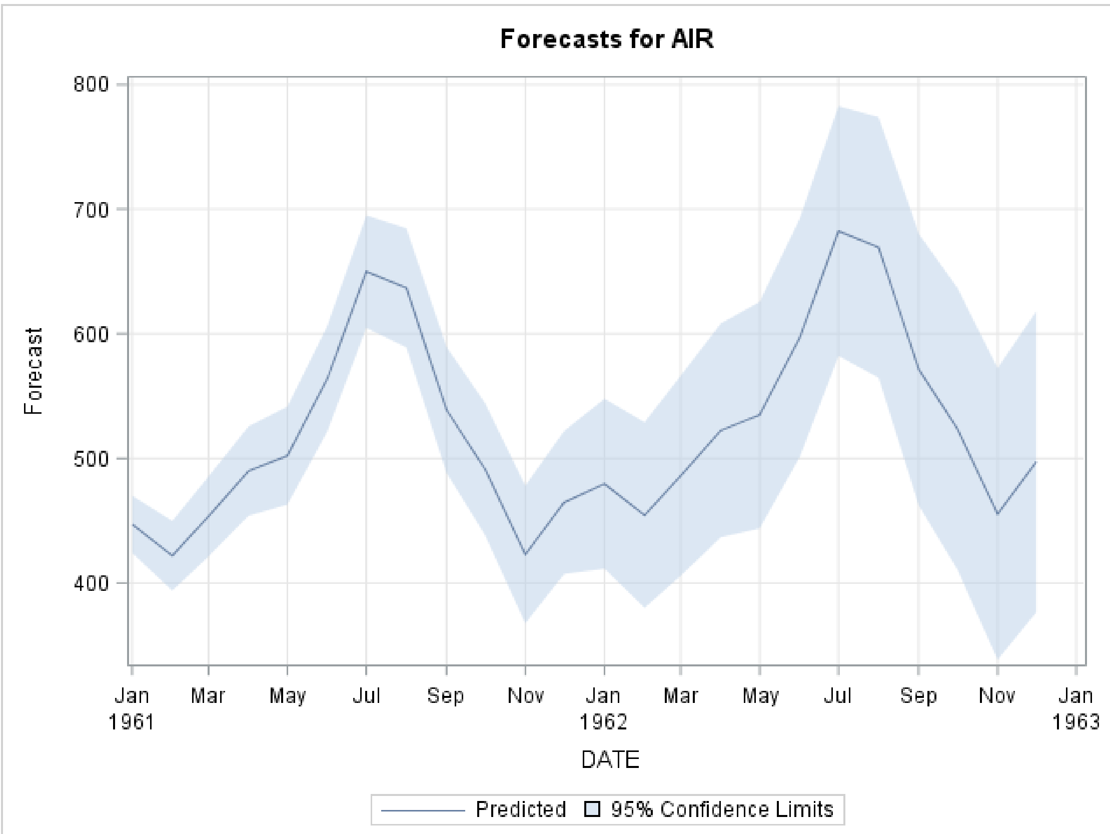


TIMESERIES Procedure

b) Fit an ARIMA model and predict 2 years (24 months).

The output of this code has been limited for space reasons.

```
proc arima data = air;
    identify var = air(1,12) noprint;
    estimate q=(1)(12) noint method=ml noprint;
    forecast id=date interval=month out=forecast;
run;

/* SAS automatically predicts 2 years out and plots the predictions */
```

Output: 

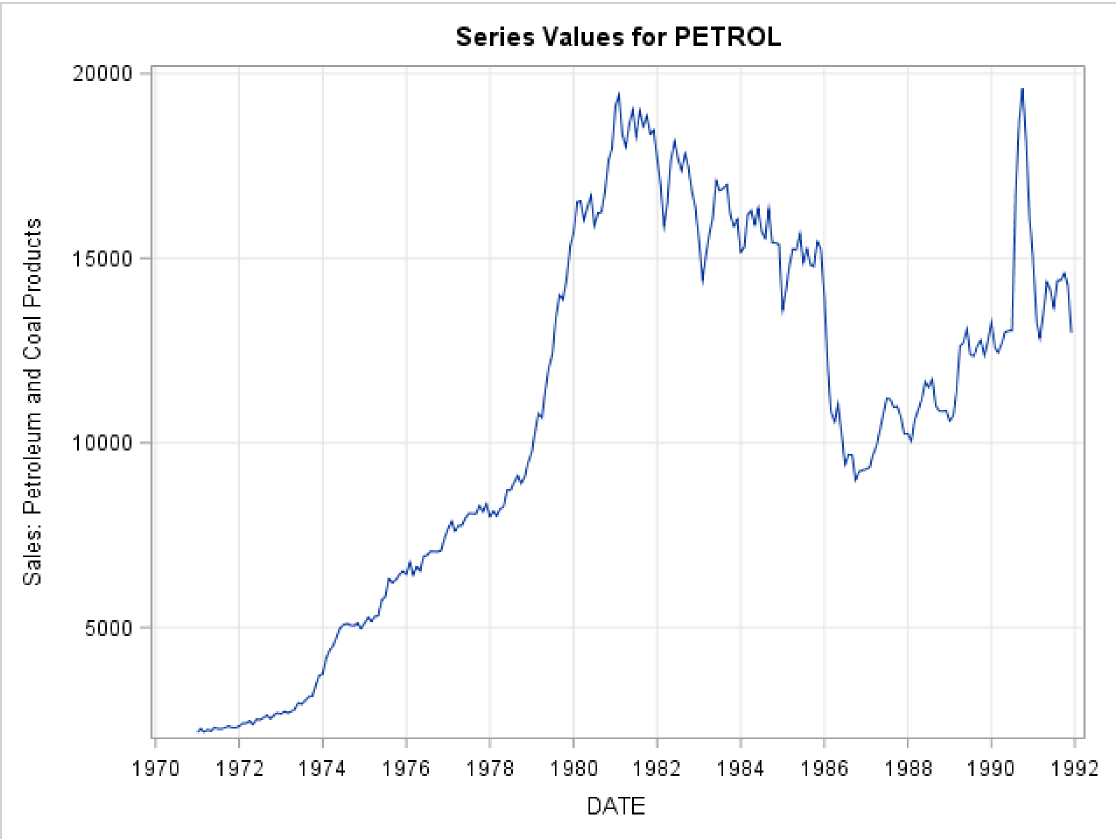
ARIMA Procedure

8.2 Fit a Simple Exponential Smoothing model to a timeseries.

a) Plot the timeseries.

```
proc import out = usecon
  datafile = 'C:/Users/usecon.csv'
  dbms = csv replace;
  getnames = yes;
run;
proc timeseries data = usecon plot = series;
    id date interval = month;
    var petrol;
run;
```

```
                          The TIMESERIES Procedure

                               Input Data Set

                  Name                          WORK.USECON
                  Label
                  Time ID Variable                     DATE
                  Time Interval                       MONTH
                  Length of Seasonal Cycle               12
```



Output:

TIMESERIES Procedure

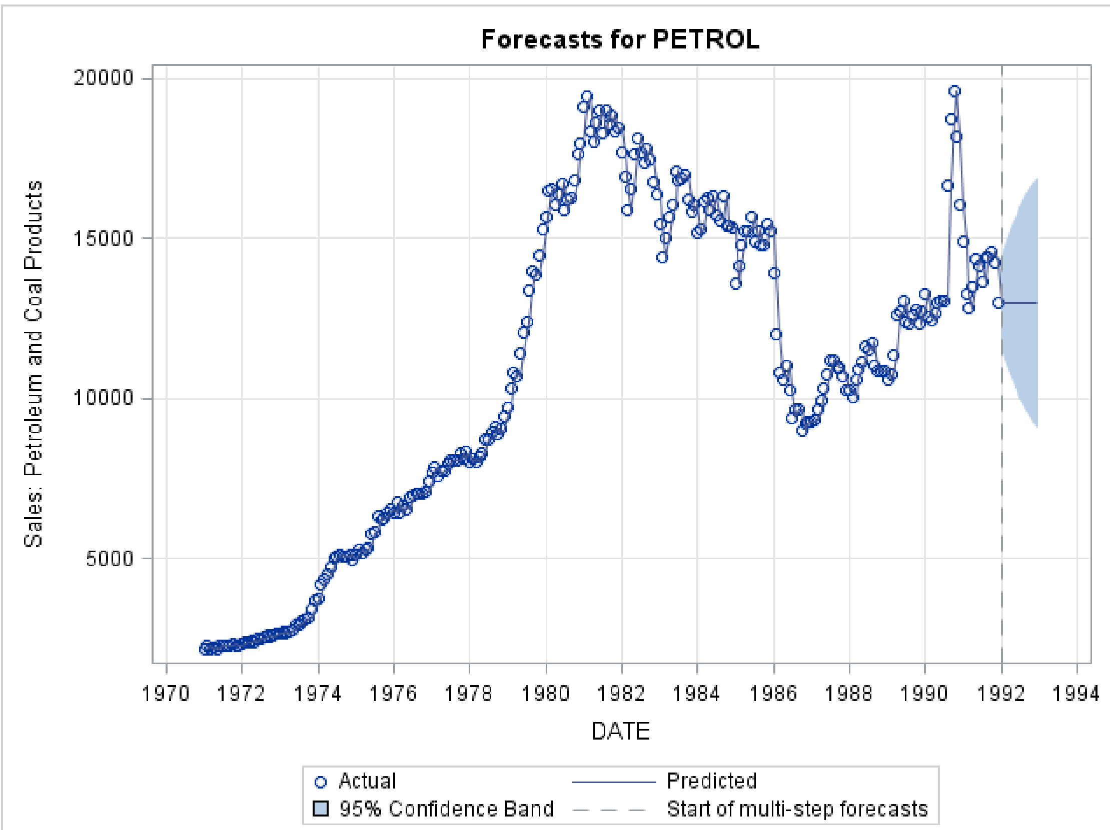
b) Fit a Simple Exponential Smoothing model, predict 2 years (24 months) out and plot predictions.

```
proc esm data = usecon out = forecast lead = 24 plot = forecasts;
    id date interval = month;
    forecast petrol / model = simple;
run;
```

```
                             The ESM Procedure

                               Input Data Set

                  Name                          WORK.USECON
```

```
Label
Time ID Variable                    DATE
Time Interval                      MONTH
Length of Seasonal Cycle              12
Forecast Horizon                      24

         Variable Information

Name                              PETROL
Label
First                            JAN1971
Last                             DEC1991
Number of Observations Read          252
```

Output:



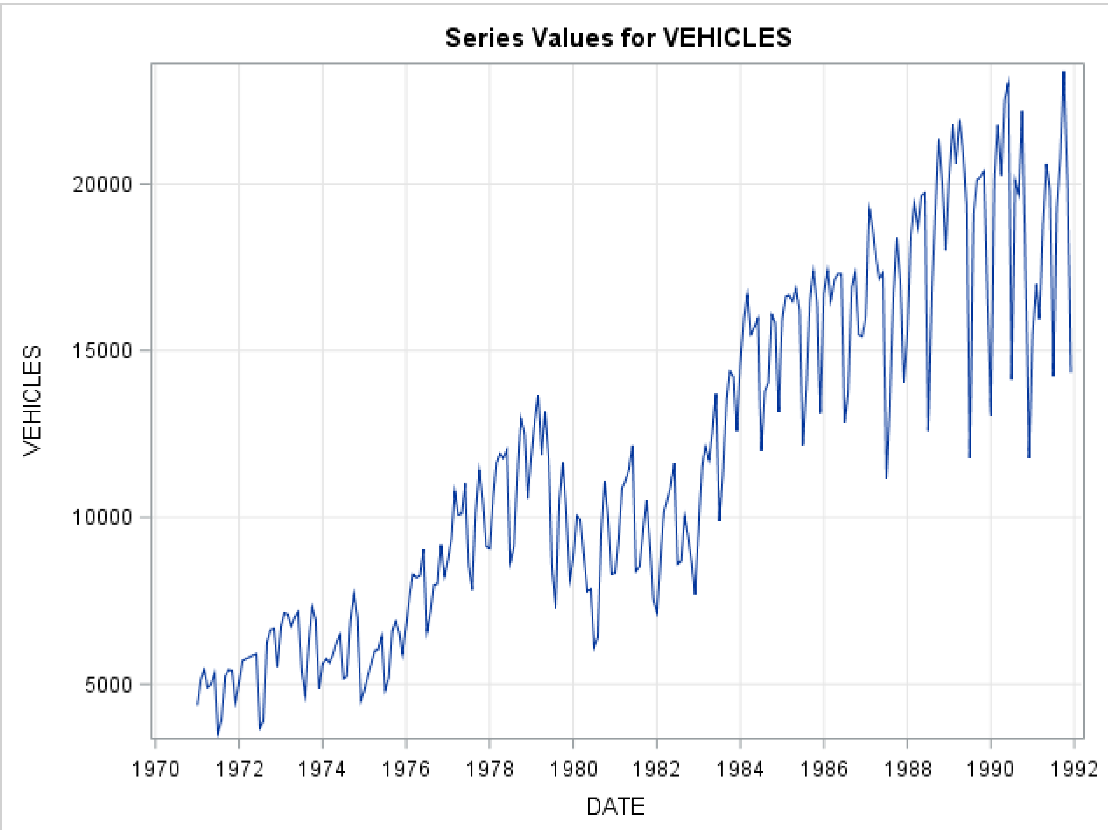
ESM Procedure

8.3 Fit a Holt-Winters model to a timeseries.

a) Plot the timeseries.

```
proc timeseries data = usecon plot = series;
    id date interval = month;
    var vehicles;
run;
```

```
                  The TIMESERIES Procedure

                       Input Data Set

         Name                            WORK.USECON
         Label
         Time ID Variable                       DATE
         Time Interval                         MONTH
         Length of Seasonal Cycle                 12
```

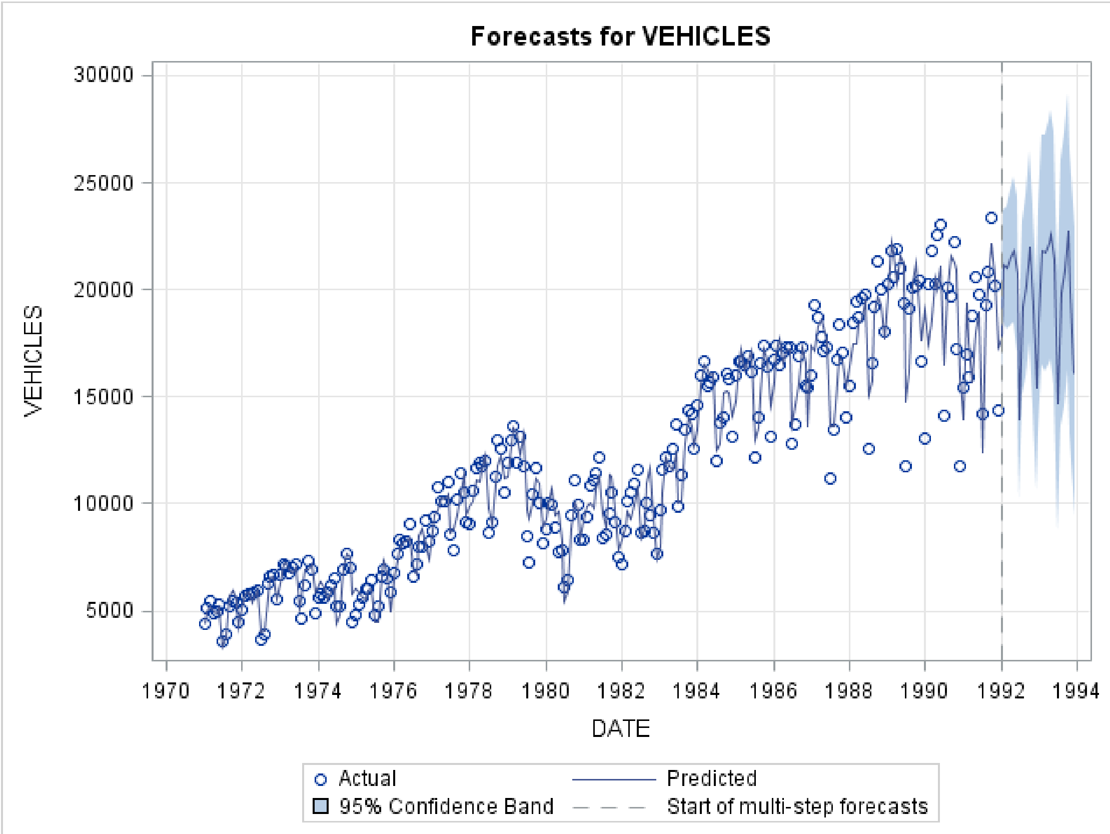


Output:

TIMESERIES Procedure

b) Fit a Holt-Winters additive model, predict 2 years (24 months) out and plot predictions.

```
proc esm data = usecon out = forecast lead = 24 plot = forecasts;
    id date interval = month;
    forecast vehicles / model = addwinters;
run;
```

Output: 

ESM Procedure

---

9 Model Evaluation & Selection

9.1 Evaluate the accuracy of regression models.

a) Evaluation on training data.

```
proc import out = train
  datafile = 'C:/Users/boston_train.csv'
  dbms = csv replace;
  getnames = yes;
run;
proc import out = test
  datafile = 'C:/Users/boston_test.csv'
  dbms = csv replace;
  getnames = yes;
run;

/* Random Forest Regression Model */
ods select none;
proc hpforest data = train ;
    input _0-_12 / level = interval;
    target Target / level = interval;
    save file = 'rfMod.bin';
run;
ods select all;

/* Evaluation on training data  */
ods select none;
proc hp4score data = train;
    score file = 'rfMod.bin' out = scored_train;
run;
ods select all;

/* Determine coefficient of determination score */
proc iml;
  use scored_train;
    read all var _ALL_ into data;
  close scored_train;
  tip = data[,1];
  pred_rf = data[,2];
  r2_rf = 1 - ( (sum((tip - pred_rf)##2)) / (sum((tip - mean(tip))##2)) );
  print(r2_rf);
quit;

                                   r2_rf

                                 0.9756497
```

b) Evaluation on testing data.

```
/* Random Forest Regression Model (rfMod) */

/* Evaluation on testing data  */
ods select none;
proc hp4score data = test;
    score file = 'rfMod.bin' out = scored_test;
run;
ods select all;

/* Determine coefficient of determination score */
proc iml;
  use scored_test;
    read all var _ALL_ into data;
  close scored_test;
  tip = data[,1];
  pred_rf = data[,2];
  r2_rf = 1 - ( (sum((tip - pred_rf)##2)) / (sum((tip - mean(tip))##2)) );
  print(r2_rf);
quit;

                                   r2_rf

                                 0.8905308
```

The formula used here for the coefficient score is based off the Python skearn formula for r2_score.

HPFOREST Procedure | HP4SCORE Procedure | IML Procedure

9.2 Evaluate the accuracy of classification models.

a) Evaluation on training data.

```
proc import out = train
    datafile = 'C:/Users/digits_train.csv'
    dbms = csv replace;
    getnames = yes;
run;
proc import out = test
    datafile = 'C:/Users/digits_test.csv'
    dbms = csv replace;
    getnames = yes;
run;

/* Random Forest Classification Model */
ods select none;
proc hpforest data = train;
    input _0-_63 / level = interval;
    target Target / level = nominal;
```

```
    save file = 'rfMod.bin';
run;

/* Evaluation on training data */
proc hp4score data = train;
    score file = 'rfMod.bin' out = scored;
run;
ods select all;

data scored(keep = Target I_Target correct);
    set scored;
    correct = (I_Target = Target);
run;

/* Determine accuracy score */
proc iml;
    use scored;
      read all var _ALL_ into data;
    close scored;

    accuracy_forest = (1/nrow(data)) * sum(data[,2]);

    print(accuracy_forest);
quit;

                              accuracy_forest

                                            1
```

b) Evaluation on testing data.

```
/* Random Forest Classification Model (rfMod) */

/* Evaluation on testing data */
ods select none;
proc hp4score data = test;
    score file = 'rfMod.bin' out = scored;
run;
ods select all;

data scored(keep = Target I_Target correct);
    set scored;
    correct = (I_Target = Target);
run;

/* Determine accuracy score */
proc iml;
    use scored;
      read all var _ALL_ into data;
    close scored;
```

```
    accuracy_forest = (1/nrow(data)) * sum(data[,2]);

    print(accuracy_forest);
quit;
                              accuracy_forest

                                    0.9722222
```

The formula used here for the accuracy score is based off the Python skearn formula for accuracy_score.

HPFOREST Procedure | HP4SCORE Procedure | IML Procedure

9.3 Evaluation with cross validation.

a) KFold

The HPFOREST output for the 5 models has been removed from the output in this tutorial for the sake of space.

```
proc import out = breastcancer
    datafile = 'C:/Users/breastcancer.csv'
    dbms = csv replace;
    getnames = yes;
run;

data folds;
    set breastcancer;
    *randomly assign observation to one of K groups;
    call streaminit(29);
    rand=ceil(5*rand('UNIFORM'));
    output;
run;

%macro hp_KFolds();

data train1 test1 train2 test2 train3 test3
     train4 test4 train5 test5;
    set folds;
    %do i = 1 %to 5;
        %do j = 1 %to 5;
            if (rand = &j) then do;
                if (&i ^= &j) then output train&i;
                else output test&i;
            end;
        %end;
    %end;
    drop rand;
```

```
run;

%do i = 1 %to 5;

ods select none;
proc hpforest data = train&i;
    input _0-_29 / level = interval;
    target Target / level = nominal;
    save file = 'hpbreastcancer&i.bin';
run;

proc hp4score data = test&i;
    score file = 'hpbreastcancer&i.bin' out = scored_&i;
run;
ods select all;

data scored_&i;
    set scored_&i;
    correct = (I_Target = Target);
run;

proc freq data = scored_&i noprint;
  tables correct / out=FreqCount&i;
run;

%end;

%mend;

%hp_KFolds()

data FreqCount;
    set FreqCount1 FreqCount2 FreqCount3 FreqCount4 FreqCount5;
    if (correct = 1);
run;

proc means data = FreqCount mean std;
  var PERCENT;
run;
                            The MEANS Procedure

          Analysis Variable : PERCENT Percent of Total Frequency

                               Mean         Std Dev
                       ----------------------------
                         96.0918078       1.8699234
                       ----------------------------
```

HPFOREST Procedure | HP4SCORE Procedure | FREQ Procedure | MEANS Procedure | macro programming

b) ShuffleSplit

The HPFOREST output for the 5 models has been removed from the output in this tutorial for the sake of space.

```
proc import out = breastcancer
    datafile = 'C:/Users/breastcancer.csv'
    dbms = csv replace;
    getnames = yes;
run;

proc surveyselect data = breastcancer out = cv seed = 29 samprate = 0.7
                                        outall reps = 5;
run;

data train1 train2 train3 train4 train5 test1 test2 test3 test4 test5;
     set cv;
     if (replicate = 1) then do;
        if (selected = 1) then output train1;
        else output test1;
   end;
   if (replicate = 2) then do;
        if (selected = 1) then output train2;
        else output test2;
   end;
   if (replicate = 3) then do;
        if (selected = 1) then output train3;
        else output test3;
     end;
   if (replicate = 4) then do;
        if (selected = 1) then output train4;
        else output test4;
   end;
   if (replicate = 5) then do;
        if (selected = 1) then output train5;
        else output test5;
     end;
run;

%macro hp_replicate();

%do i = 1 %to 5;

ods select none;
proc hpforest data = train&i;
    input _0-_29 / level = interval;
```

```
    target Target / level = nominal;
    save file = 'hpbreastcancer&i.bin';
run;

proc hp4score data = test&i;
    score file = 'hpbreastcancer&i.bin' out = scored_&i;
run;
ods select all;

data scored_&i;
    set scored_&i;
    correct = (I_Target = Target);
run;

proc freq data = scored_&i noprint;
  tables correct / out=FreqCount&i;
run;

%end;

%mend;

%hp_replicate()

data FreqCount;
    set FreqCount1 FreqCount2 FreqCount3 FreqCount4 FreqCount5;
    if (correct = 1);
run;

proc means data = FreqCount mean std;
  var PERCENT;
run;
                        The SURVEYSELECT Procedure

                Selection Method    Simple Random Sampling

                   Input Data Set           BREASTCANCER
                   Random Number Seed                 29
                   Sampling Rate                     0.7
                   Sample Size                       399
                   Selection Probability         0.70123
                   Sampling Weight                     0
                   Number of Replicates                5
                   Total Sample Size                1995
                   Output Data Set                    CV
```

```
                         The MEANS Procedure

          Analysis Variable : PERCENT Percent of Total Frequency

                                Mean         Std Dev
                       ----------------------------
                          95.7647059       0.6443795
                       ----------------------------
```

SURVEYSELECT Procedure | HPFOREST Procedure | HP4SCORE Procedure | FREQ Procedure | MEANS Procedure | macro programming

---

Appendix

1 Built-in SAS Data Types

- CHAR The SAS implementation of a string as a fixed-length character string of length *n*.

- DOUBLE A decimal point number implemented as a 64-bit double precision, floating-point number.

2 SAS Procedures

ARIMA

CLUSTER

COMPARE

CONTENTS

CORR

DMDB

FCMP

ESM

EXPORT

FASTCLUS

FREQ

GENMOD

HP4SCORE

HPFOREST

HPSPLIT

HPSVM

IML

IMPORT

MEANS

NEURAL

PRINCOMP

PRINT

PLM

REG

SCORE

SGPLOT

- histogram
- inset
- reg
- scatter
- vbox

SGSCATTER

SORT

SQL

SURVEYSELECT

TIMESERIES

TREE

3 SAS DATA step

Statements:

%include

if-then/else

infile

input

merge

output

set

where

Alphabetical Index

Data Frame

A two-dimensional tabular structure with labeled axes (rows and columns), where data observations are represented by rows and data variables are represented by columns.

Dictionary

An associative array which is indexed by keys which map to values. Therefore, a dictionary is an unordered set of key:value pairs where each key is unique. In SAS, a dictionary can be implemented using a hash table. Please see the following example.

```
/* Results will be displayed in the log */
data class_dict;
declare hash mydict();
mydict.defineKey("Name");
mydict.defineData("Age");
mydict.defineDone();
do while (not eof);
  set sashelp.class end = eof;
  rc = mydict.add();
  output;
end;
Name = 'James';
rc = mydict.find();
put rc= Name= Age=;
```

Output:
```
rc=0 Name=James Age=12
rc=160038 Name=James Age=12
```

Series

A series is a one-dimension data frame, which is also called an array in SAS. Please see the following example.

```
array my_array{4} a1-a4 (1 3 5 9);
```

For more information on SAS packages and functions, along with helpful examples, please see SAS.