Data Science Using Python, SAS, & R:

A Rosetta Stone for Analytical Languages

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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 is 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;
```

Output:

```
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
```

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              07/03/2017 09:24:00            Observation Length    32
Last Modified        07/03/2017 09:24:00            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

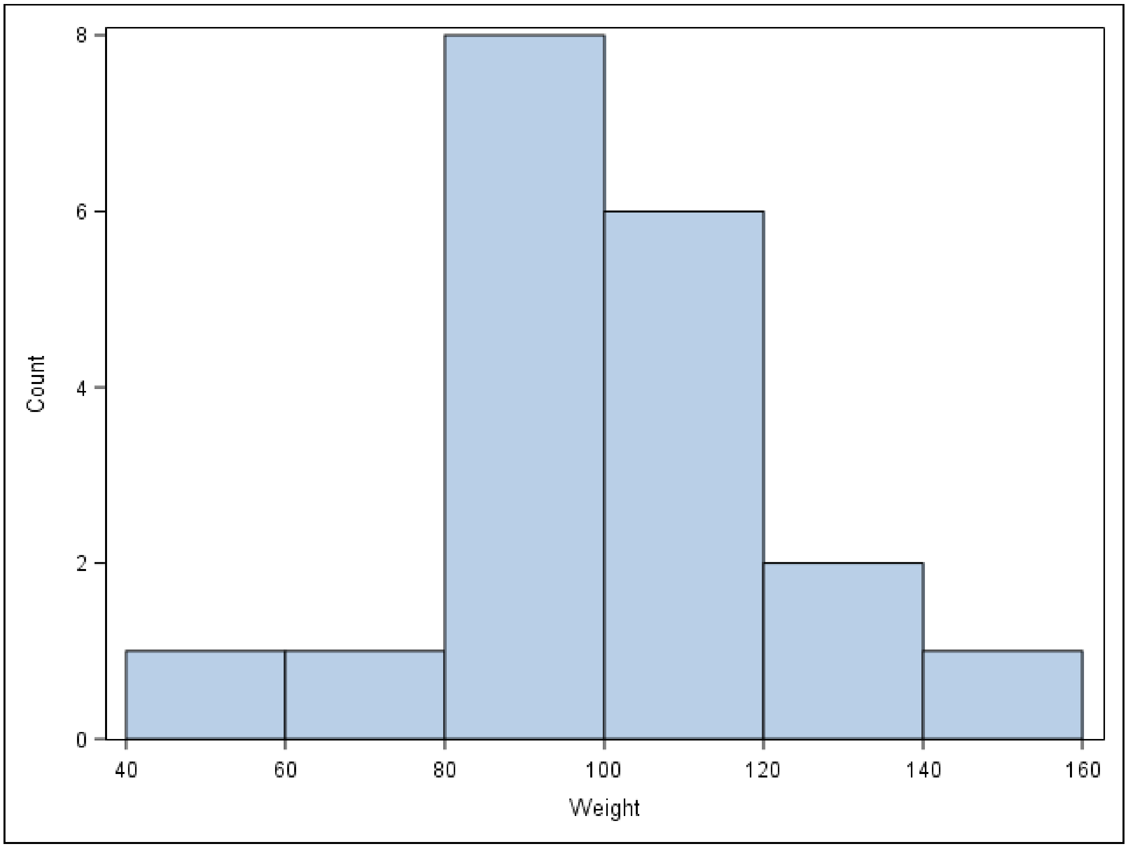
---

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.

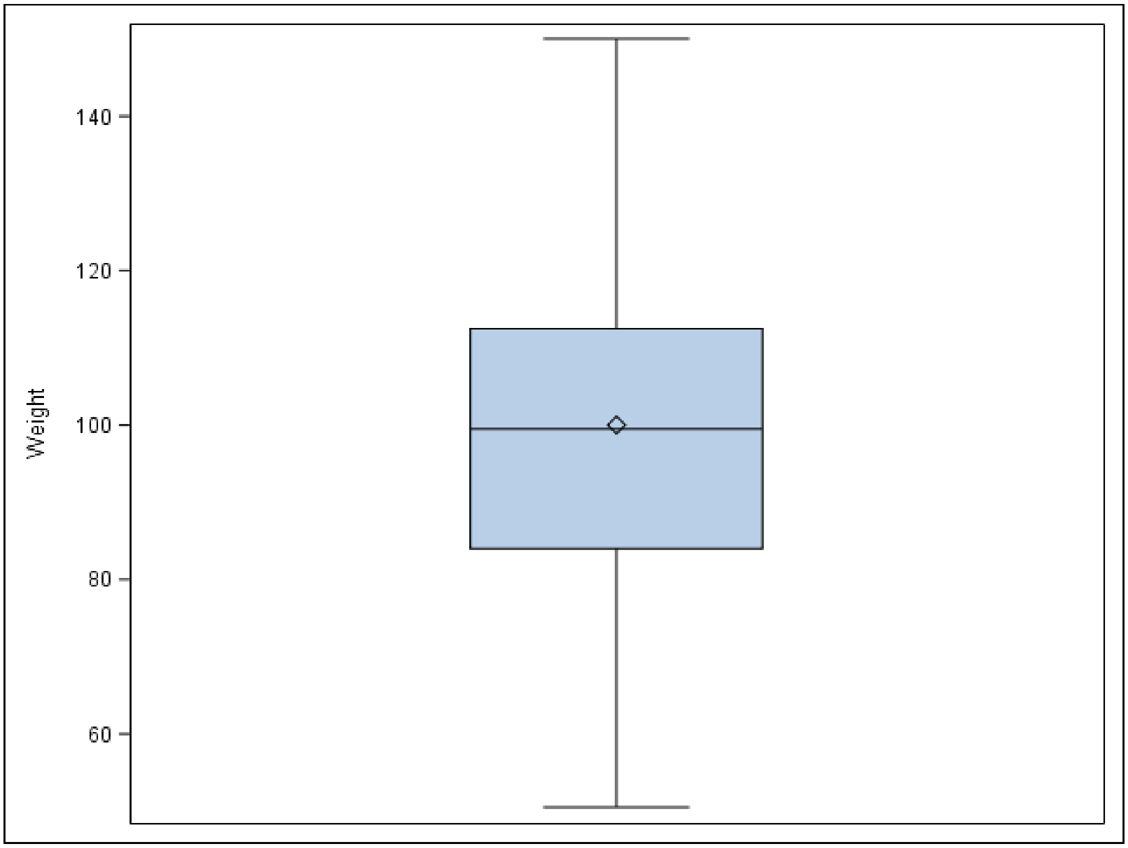
2.1 Visualize a single continuous variable by producing a histogram.

```
/* 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: 

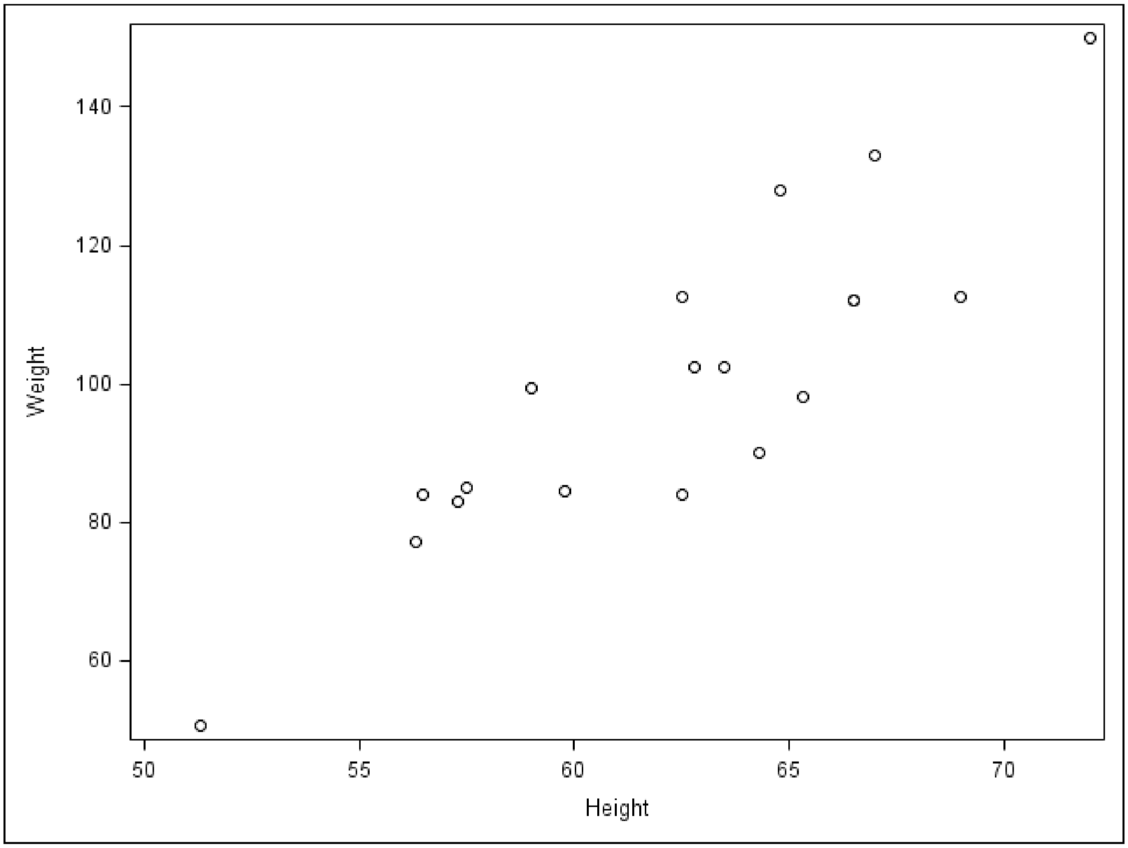
2.2 Visualize a single continuous variable by producing a boxplot.

```
/* 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;
```

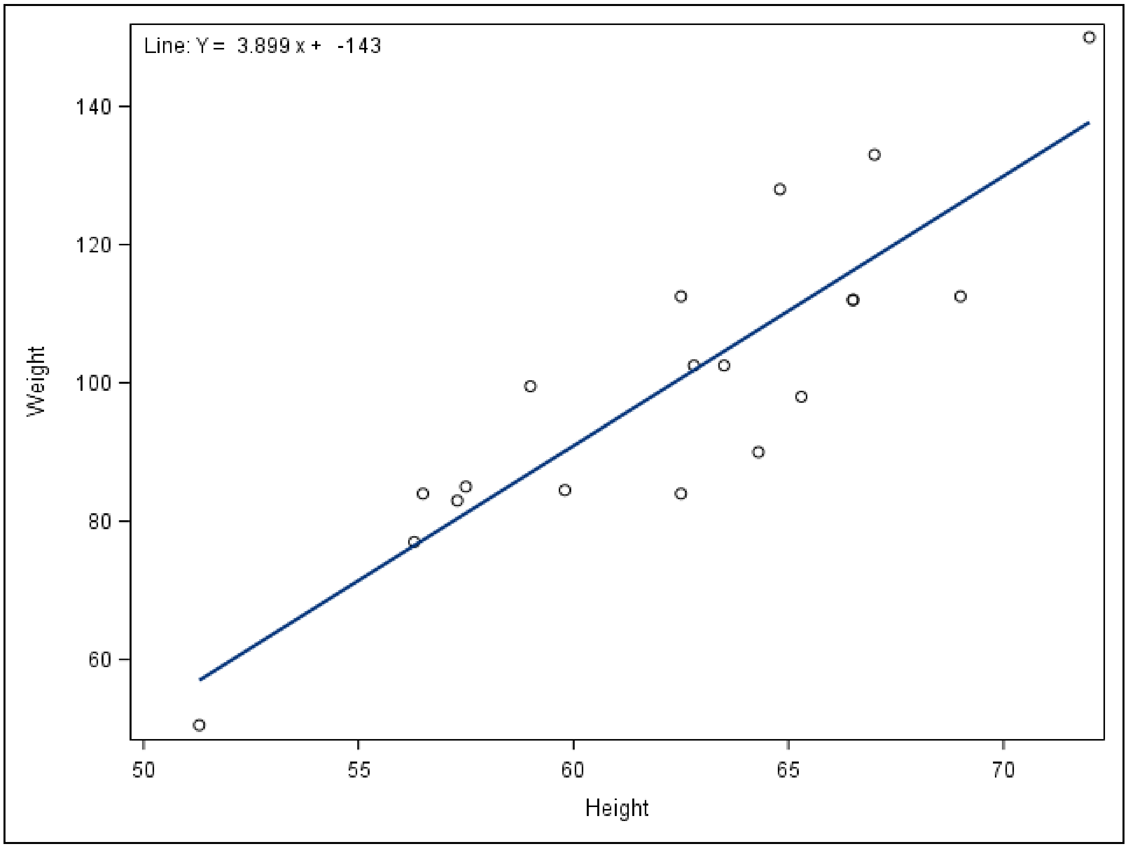
Output: 

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;
```

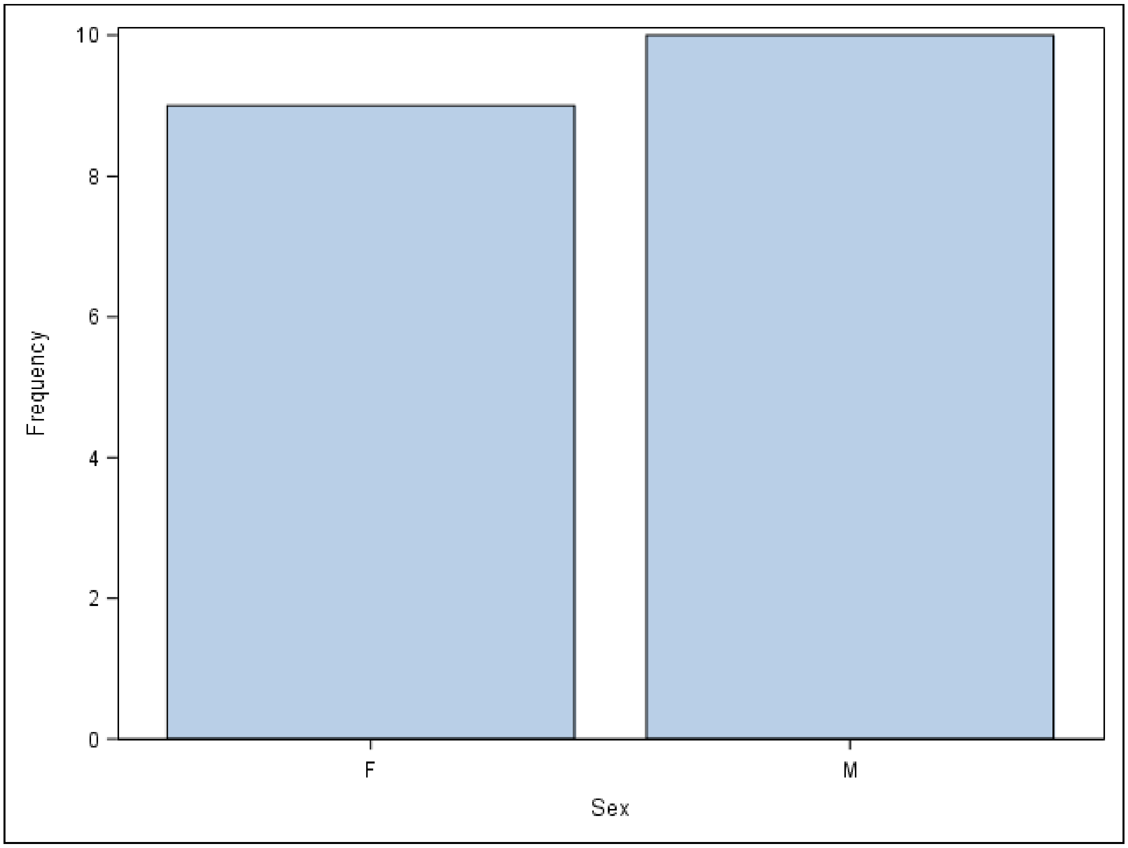
```
/* Use proc sgplot with the reg statement so it prints the line of best fit,
   and use the inset statement to print the equation of the line
   of best fit */
proc sgplot data = student noautolegend;
  reg y = Weight x = Height;
  inset "Line: Y = &Slope x + &Int" / position=topleft;
run;
```

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;
```

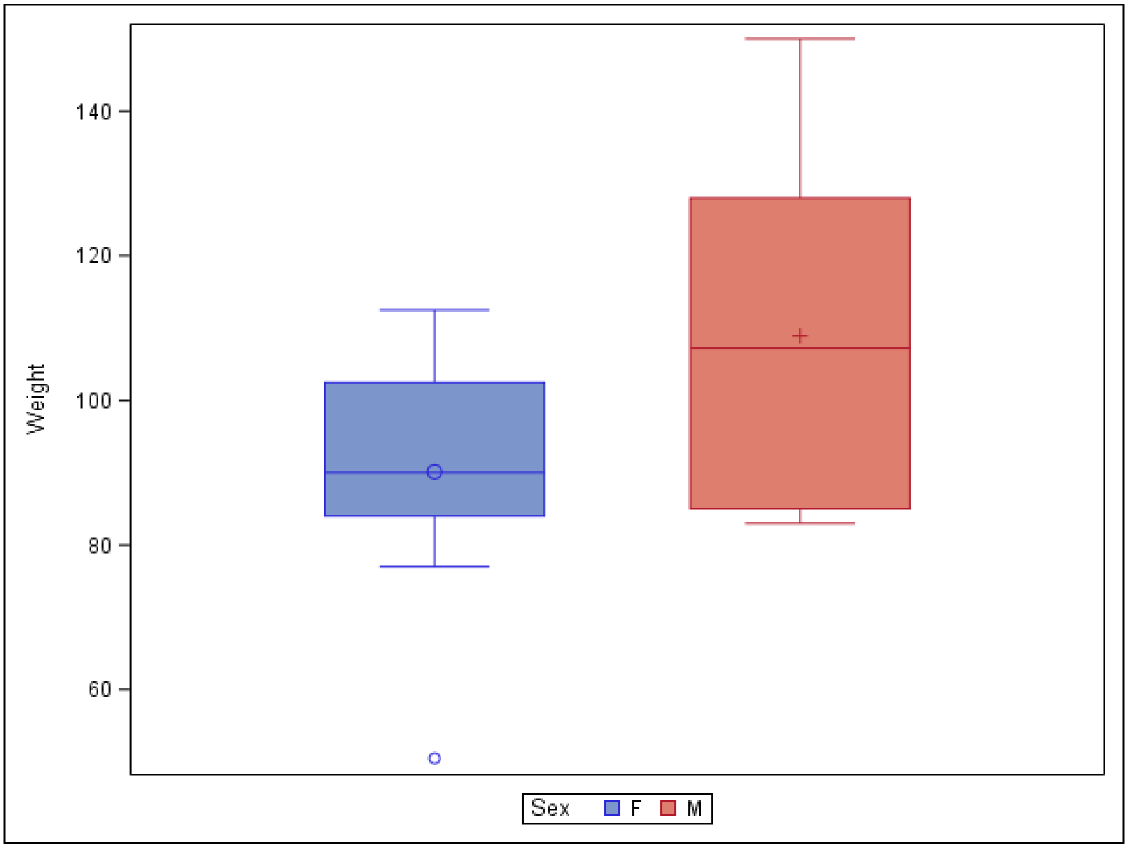
Output: 

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                      Total
                      Value    greater15     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

                                                Likelihood Ratio
                                     Standard    95% Confidence          Wald
 Parameter     DF    Estimate           Error          Limits          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 Leaves	ASE	Mis-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	Number	Average Square Error	Average Square Error	Misclassification Rate

of Trees	of Leaves	(Train)	(OOB)	(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

                 Number                    OOB                      OOB
  Variable     of Rules        Gini        Gini       Margin       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

	Average Square	Average Square

Number of Trees	Number of Leaves	Error (Train)	Error (OOB)
1	187	19.2587	47.6827
2	373	9.9882	41.6020
3	570	6.0568	30.1982
4	756	4.8625	25.4452
5	959	4.5092	25.2461
6	1159	4.1455	27.3987
7	1348	3.9417	28.7395
8	1542	3.6292	26.7044
9	1716	3.2266	25.1359
10	1914	3.4361	22.8508
11	2104	3.5912	22.6209
12	2295	3.6326	21.0885
13	2492	3.7763	20.1024
14	2681	3.4702	18.9298
15	2880	3.2200	18.5691
16	3074	3.1257	18.2704
17	3272	3.0358	17.3437
18	3468	2.8898	16.3768
19	3645	2.7491	16.2209
20	3830	2.6761	15.9297
21	4029	2.5286	15.4681
22	4218	2.4168	15.3111
23	4401	2.3976	15.0104
24	4602	2.3527	14.3947
25	4795	2.2781	13.8745
26	4987	2.2707	13.9010
27	5180	2.2138	13.8274
28	5378	2.1430	13.3164
29	5559	2.2293	13.6510
30	5745	2.2658	13.6913
31	5938	2.2443	13.7661
32	6135	2.3326	14.0631
33	6322	2.3135	13.7518
34	6517	2.2433	13.6646
35	6706	2.2266	13.5036
36	6912	2.2287	13.3922
37	7104	2.1840	13.1858
38	7292	2.1710	13.2080
39	7483	2.1520	13.3737
40	7674	2.2325	13.5223
41	7857	2.2420	13.4492
42	8048	2.3060	13.6438
43	8221	2.2796	13.6726
44	8415	2.2741	13.7024
45	8602	2.2716	13.8300
46	8789	2.3405	14.0838
47	8985	2.2962	13.9585

48	9181	2.2975	14.0563
49	9378	2.2725	13.9144
50	9563	2.3317	14.1207
51	9753	2.3811	14.2680
52	9946	2.3742	14.1453
53	10138	2.3330	14.1255
54	10332	2.2968	13.9347
55	10519	2.2817	14.0177
56	10712	2.2778	13.9130
57	10915	2.2402	13.8886
58	11107	2.2357	13.8180
59	11310	2.2392	13.7352
60	11495	2.2408	13.6216
61	11683	2.2611	13.5266
62	11880	2.2678	13.4674
63	12078	2.2194	13.3283
64	12276	2.1959	13.2215
65	12472	2.2390	13.3741
66	12670	2.2378	13.4624
67	12865	2.2224	13.5014
68	13064	2.2286	13.5705
69	13263	2.2914	13.7943
70	13450	2.3153	13.7210
71	13643	2.2780	13.3410
72	13834	2.2397	13.3023
73	14035	2.2114	13.1643
74	14216	2.1919	13.1724
75	14411	2.1905	13.1487
76	14594	2.1726	13.1694
77	14771	2.1702	13.2216
78	14968	2.1533	13.1445
79	15154	2.1332	13.0833
80	15357	2.1503	13.1250
81	15552	2.1518	13.1957
82	15736	2.1775	13.3838
83	15922	2.1587	13.3901
84	16114	2.1402	13.2081
85	16313	2.1419	13.1710
86	16505	2.1306	13.0946
87	16690	2.1198	13.0328
88	16871	2.1060	12.9980
89	17053	2.1335	13.0962
90	17248	2.1082	12.9330
91	17448	2.1011	12.9468
92	17649	2.0970	12.9264
93	17850	2.0786	12.8399
94	18045	2.0551	12.7811
95	18230	2.0481	12.7833
96	18427	2.0706	12.8666
97	18623	2.0645	12.8777

```
                        98          18815      2.0634     12.8194
                        99          18997      2.0557     12.7202
                       100          19181      2.0933     12.8935

                     Loss Reduction Variable Importance

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

  _5             1609   25.59270   23.95895      1.656441       1.359884
  _12            4308   25.70613   21.12492      1.727942       1.088299
  _2              880    7.13360    5.52171      0.482006       0.265087
  _4             1059    5.61685    2.39774      0.477618       0.206321
  _10            1045    4.12651    2.32382      0.306296       0.111480
  _9             1370    2.95766    0.63242      0.310963       0.058820
  _0              385    2.34261    0.38340      0.176103       0.038569
  _1              143    0.08843   -0.05644      0.016085      -0.010059
  _3              213    0.53321   -0.22198      0.042652      -0.006791
  _7             2320    6.81458   -0.33752      0.608766       0.122749
  _8              776    0.80652   -0.48061      0.106623      -0.037824
  _11            3432    2.53114   -0.56043      0.444825      -0.018812
  _6             1541    1.50208   -0.81090      0.247215      -0.018173
```

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
                            ------------
```

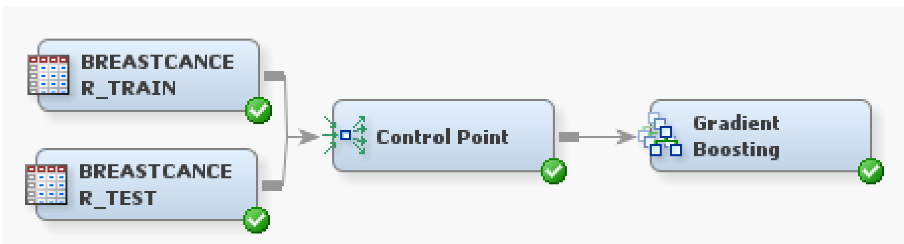
```
                     9.2766848
                 ------------
```

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

Output:

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	.

Classification Table

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

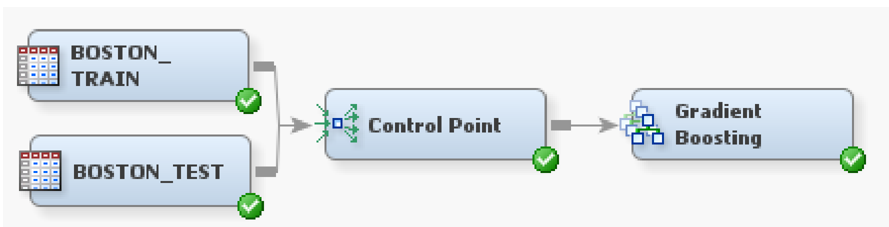
Target	Outcome	Target Percentage	Outcome Percentage	Frequency Count	Total Percentage
0	0	100.000	90.968	141	35.4271
0	1	5.447	9.032	14	3.5176
1	1	94.553	100.000	243	61.0553

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:

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	.

Output:

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.

```
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;
  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                      YES
                 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               35.2508001
             Bias                                    -6.375275
             Total Slack (Constraint Violations)    34.3511008
             Norm of Longest Vector                 3.79226578
             Number of Support Vectors                      71
             Number of Support Vectors on Margin            63
             Maximum F                              11.4630802
             Minimum F                              -4.7061491
             Number of Effects                              30
             Columns in Data Matrix                         30

                             Iteration History

               Iteration    Complementarity     Feasibility

                       1       1002265.3132    88067.240896
                       2       1411.2168312    80.210592636
```

```
                   3       210.36307705    8.0210592E-7
                   4       5.5675772656    1.2652961E-8
                   5       0.8865572275    1.544403E-10
                   6       0.2947605635    3.866263E-11
                   7       0.1606295757    1.766043E-11
                   8       0.0981078445    8.719581E-12
                   9       0.0603316585    4.770961E-12
                  10       0.0258720492      1.4998E-12
                  11       0.0171466879    5.151435E-13
                  12       0.0090859249    1.514344E-13
                  13       0.0023785349    3.508305E-14
                  14       0.0001072635    3.552714E-15
                  15        4.813479E-7    5.617035E-15

                     Classification Matrix

                             Training Prediction
               Observed             1           0       Total

               1                  243           0         243
               0                    7         148         155
               Total              250         148         398

                         Fit Statistics

                     Statistic      Training

                     Accuracy         0.9824
                     Error            0.0176
                     Sensitivity      1.0000
                     Specificity      0.9548
```

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         167            167
                    Wrong             4            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

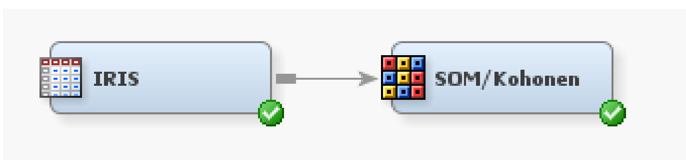
7.5 Self-organizing map

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:

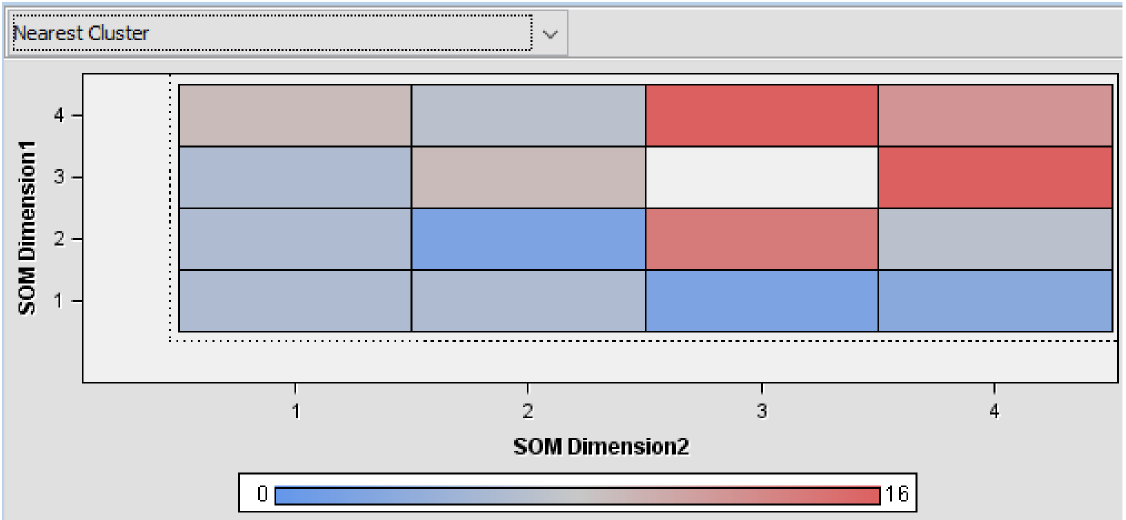
1. Choose the Kohonen SOM method.
2. Set row and column to both be 4.
3. Under the "Kohonen" options section, set "Use Defaults" to "No", and open the Kohonen Options window by clicking the ... box.
4. Set the following options in the popup window:

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: 

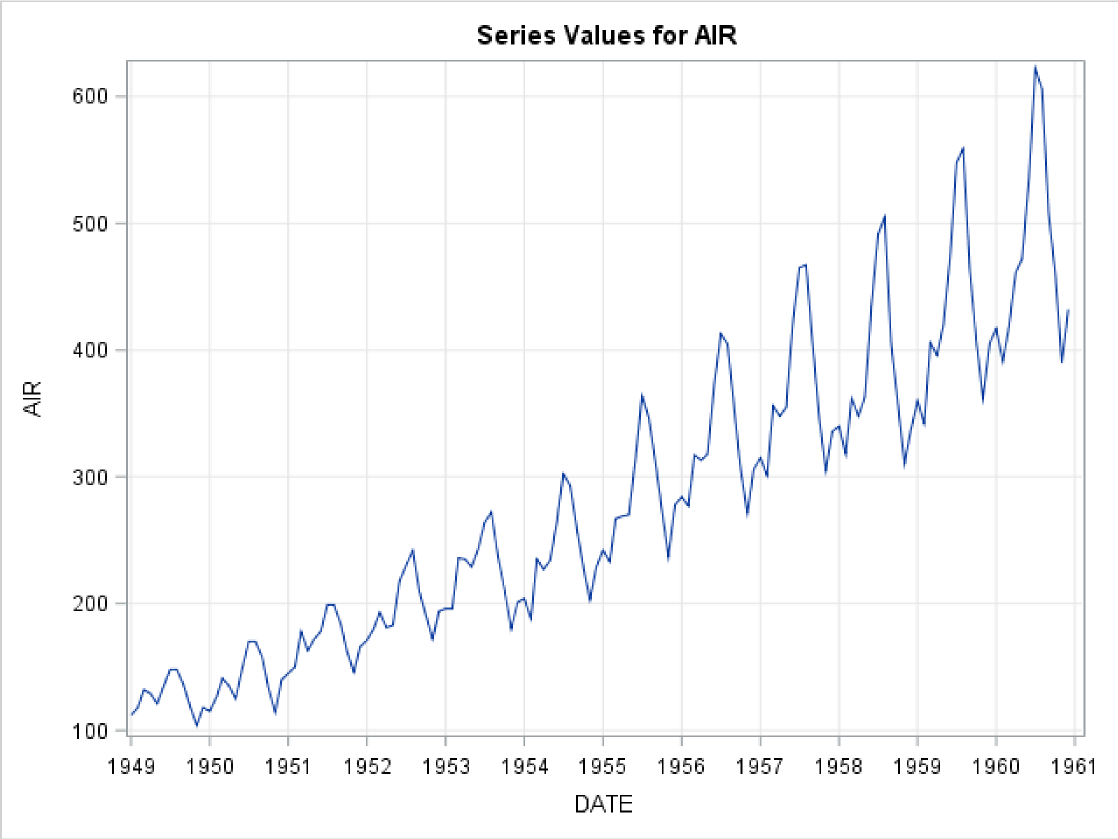
---

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;
```

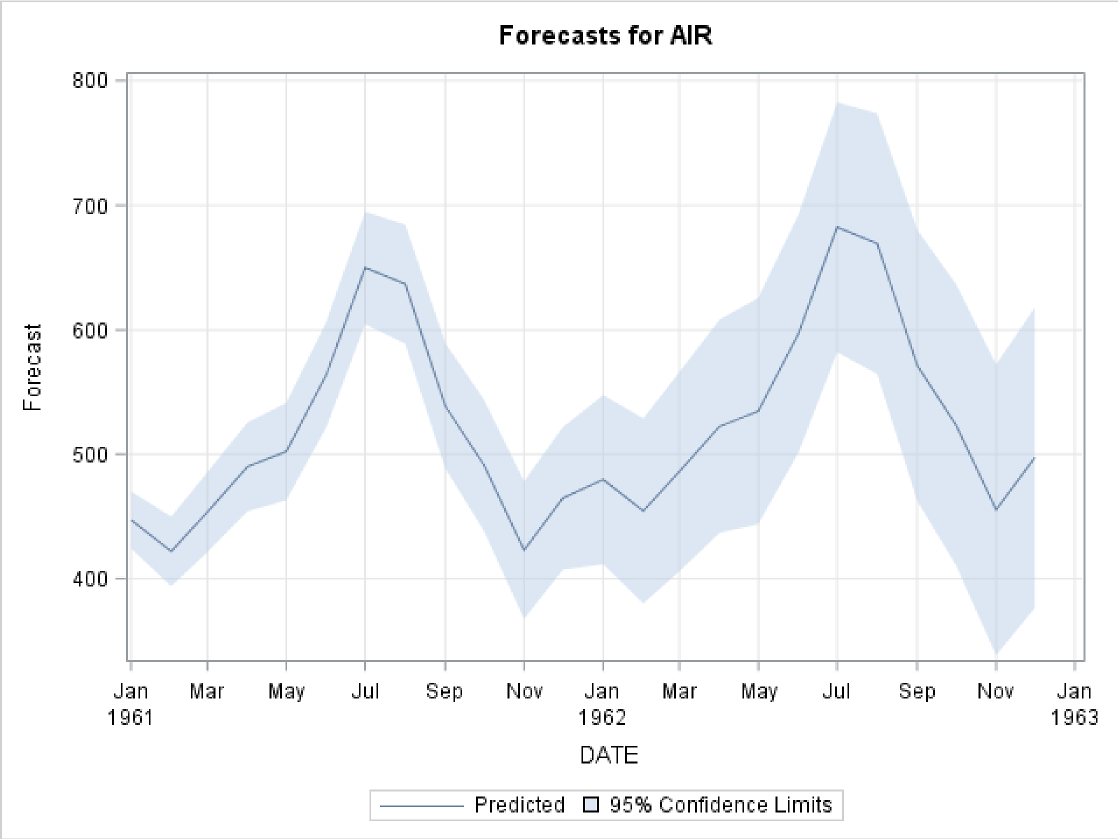
Output: 

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 */
```

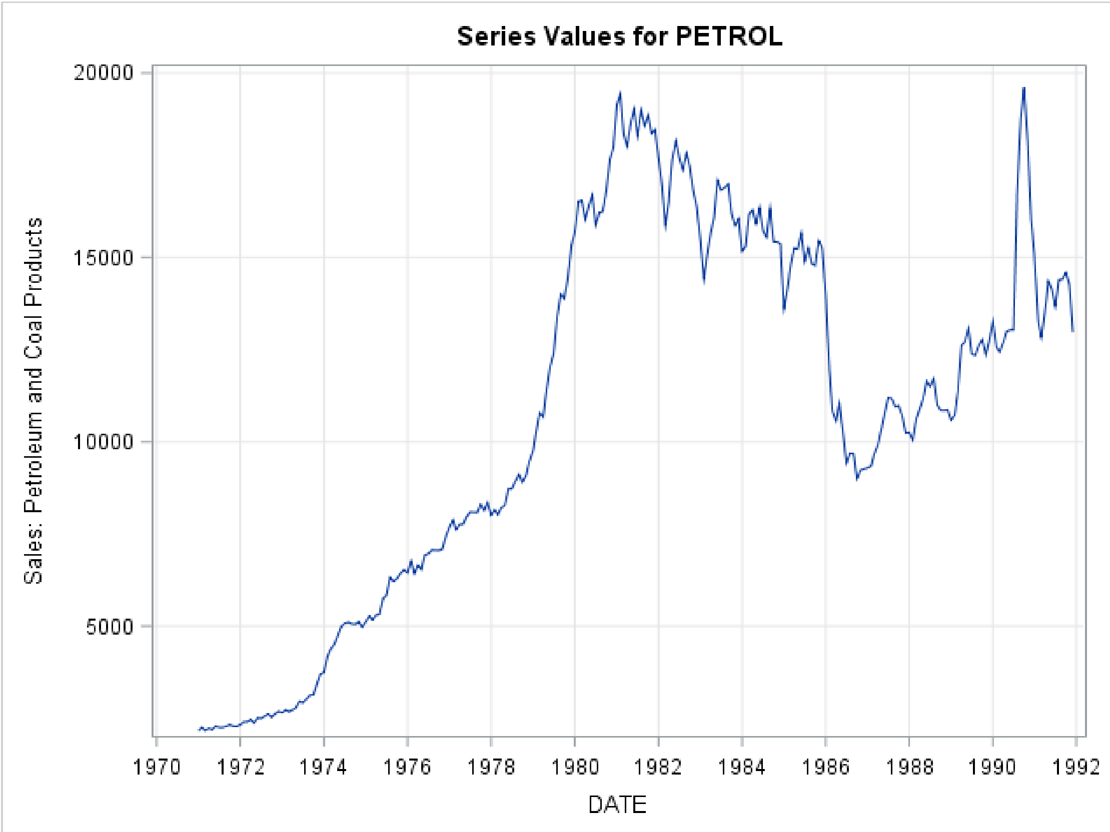
Output: 

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
```

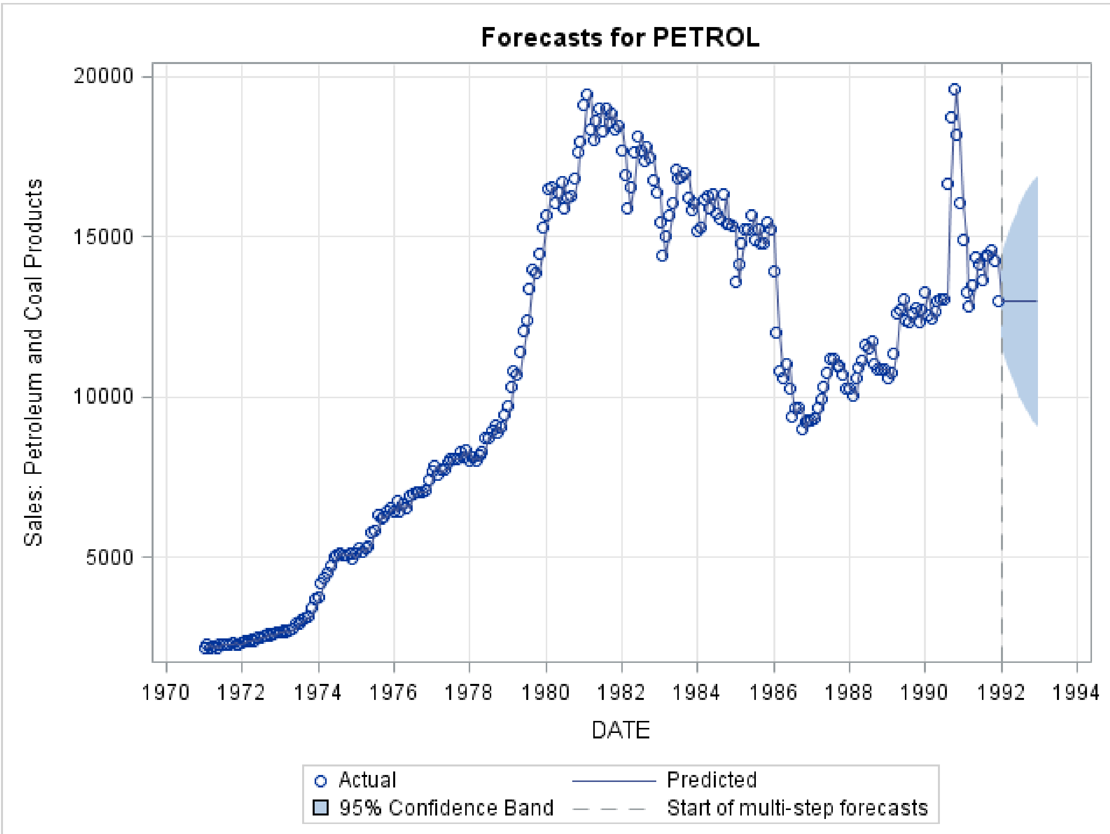
Output: 

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

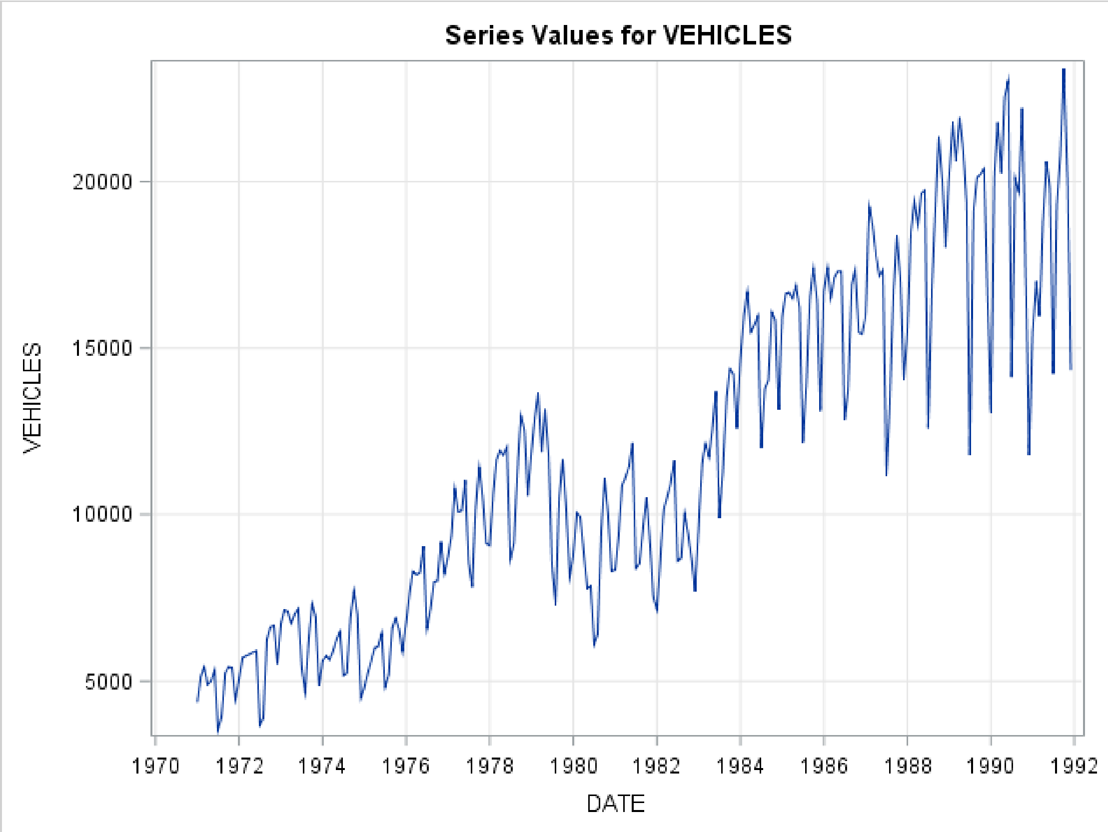
8.3 Fit a Holt-Winters model to a timeseries.

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:

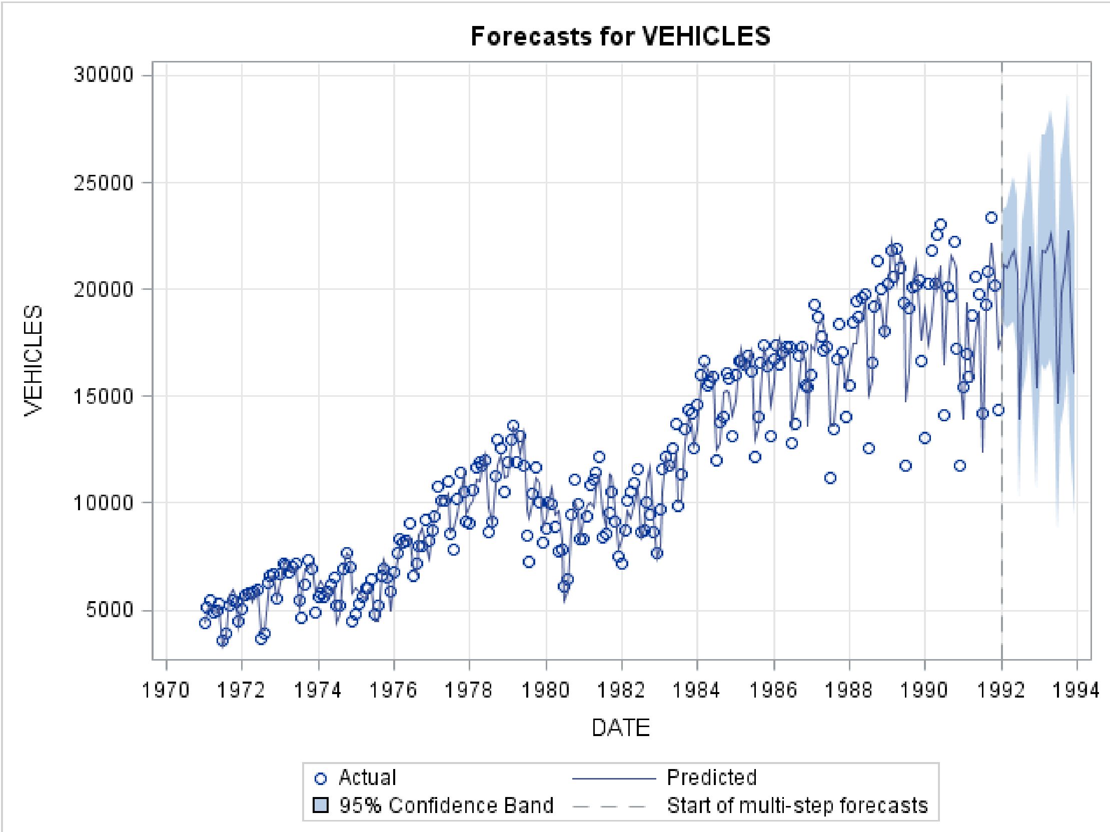


TIMESERIES Procedure

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

                                 0.9762663
```

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

0.8861649
```

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

                                    0.9703704
```

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

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

---

10 Text Analytics

---

11 Deep Learning

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

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CLUSTER

COMPARE

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3 SAS DATA step

Statements:

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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.