SAS Tutorial

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Before beginning this tutorial, you 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 run successfully.

In SAS,

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

1 Reading in Data and Basic Statistical Functions

1.1 Read in the data.

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

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

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

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

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

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

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

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

DATA step: infile & input statements

1.2 Find the dimensions of the data set.

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

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

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

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

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


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


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

Output:

1.3 Find basic information about the data set.

The CONTENTS procedure prints information about a SAS data set.

```
proc contents data = student;
run;

                          The CONTENTS Procedure

Data Set Name          WORK.STUDENT                  Observations          19
Member Type            DATA                          Variables             5
Engine                 V9                            Indexes               0
Created                06/26/2017 14:00:08           Observation Length    32
Last Modified          06/26/2017 14:00:08           Deleted Observations  0
Protection                                           Compressed            NO
Data Set Type                                        Sorted                NO
Label
Data Representation    WINDOWS_64
Encoding               wlatin1  Western (Windows)

                     Engine/Host Dependent Information

Data Set Page Size          65536
Number of Data Set Pages    1
First Data Page             1
Max Obs per Page            2039
Obs in First Data Page      19
Number of Data Set Repairs  0
ExtendObsCounter            YES
Filename                    C:\Users\ElainePC\AppData\Local\Temp\SAS
```

```
                                Temporary
                                Files\_TD6744_ELAINEHP_\student.sas7bdat
Release Created                 9.0401M4
Host Created                    X64_10PRO
Owner Name                      ElaineHP\ElainePC
File Size                       128KB
File Size (bytes)               131072

                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 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
```

1.5 Calculate mean of numeric variables.

The MEANS procedure prints the mean 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.

TRY THIS AT HOME: Run this procedure without the options on the tables statment.

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

TRY THIS AT HOME: Run this procedure to return all *male* students.

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

TRY THIS AT HOME: Run this procedure and do not reduce the output.

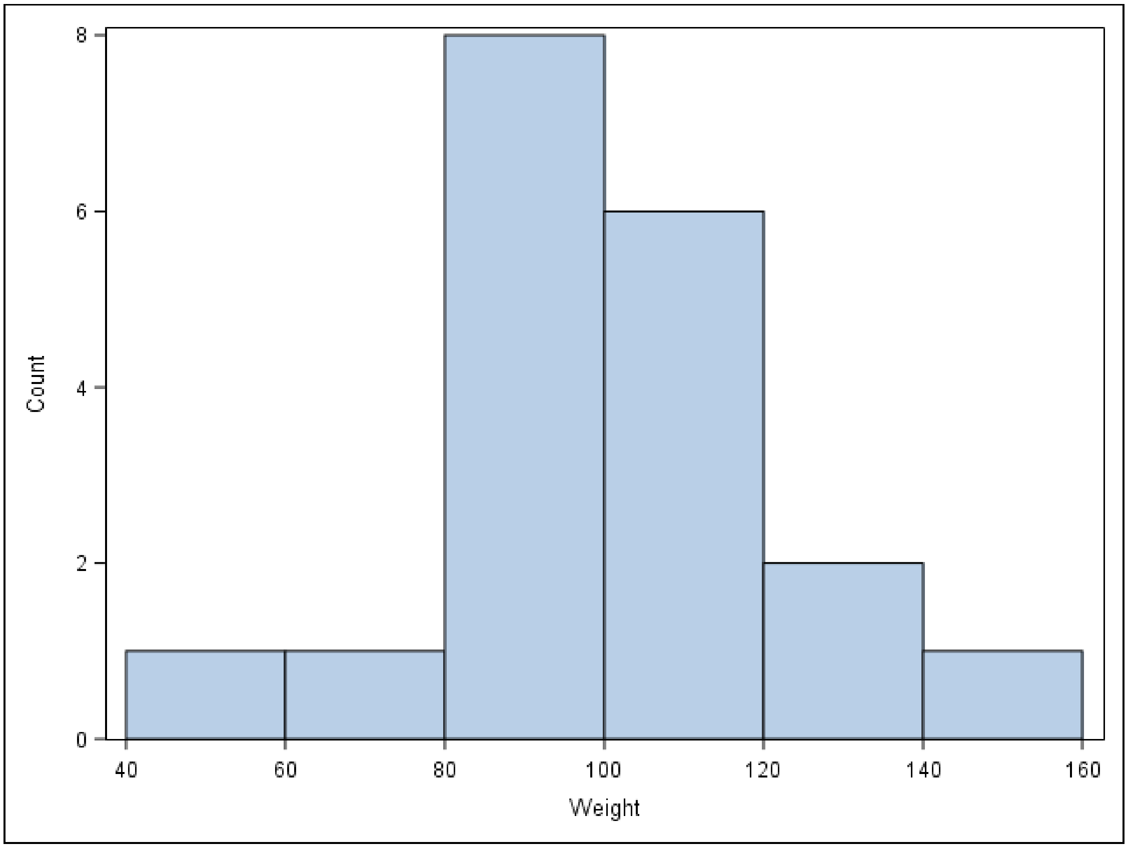
---

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.

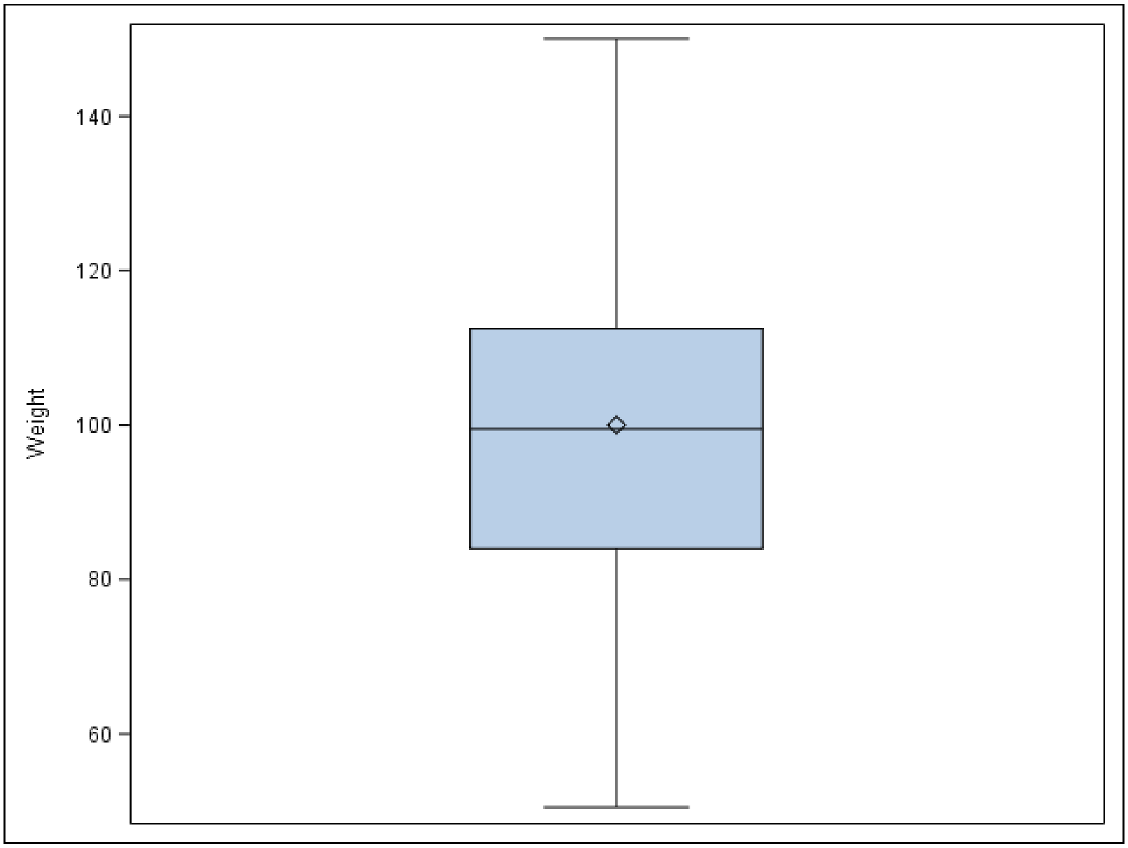
2.1 Visualize a single continuous variable by producing a histogram.

```
/* 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: 

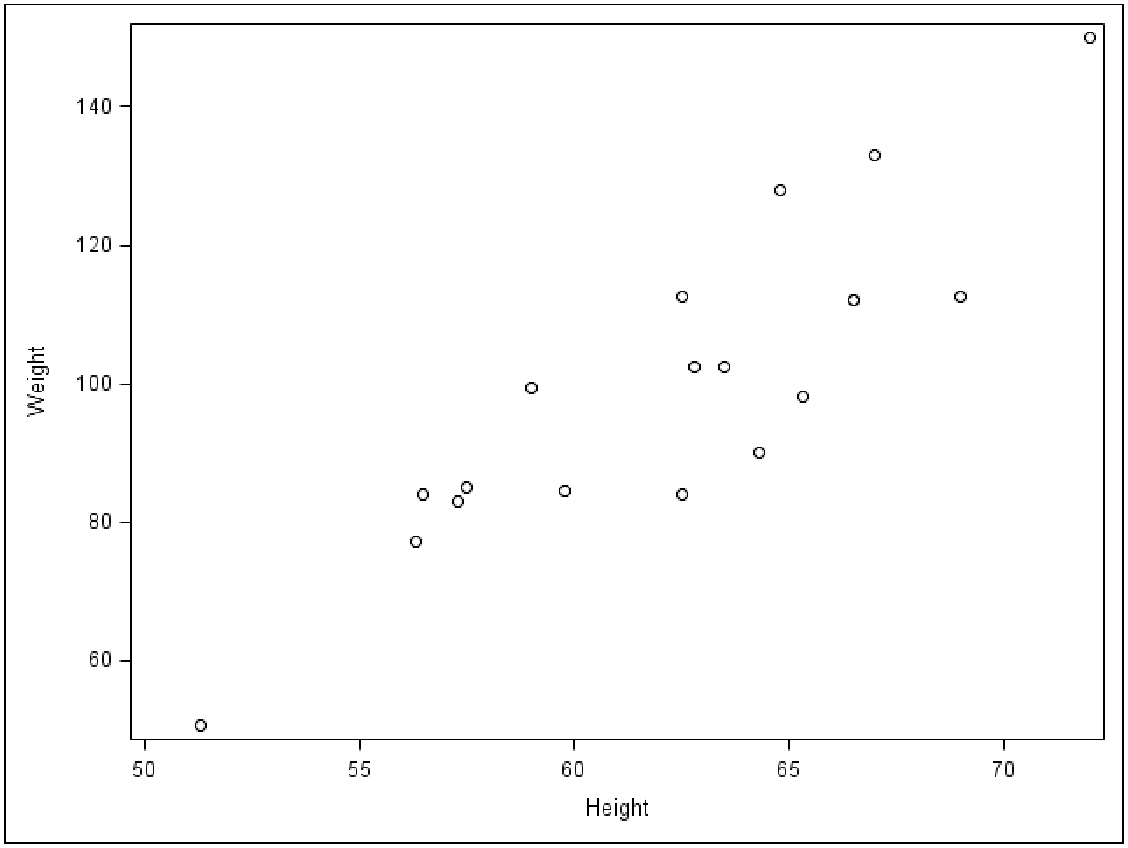
2.2 Visualize a single continuous variable by producing a boxplot.

```
/* 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;
```

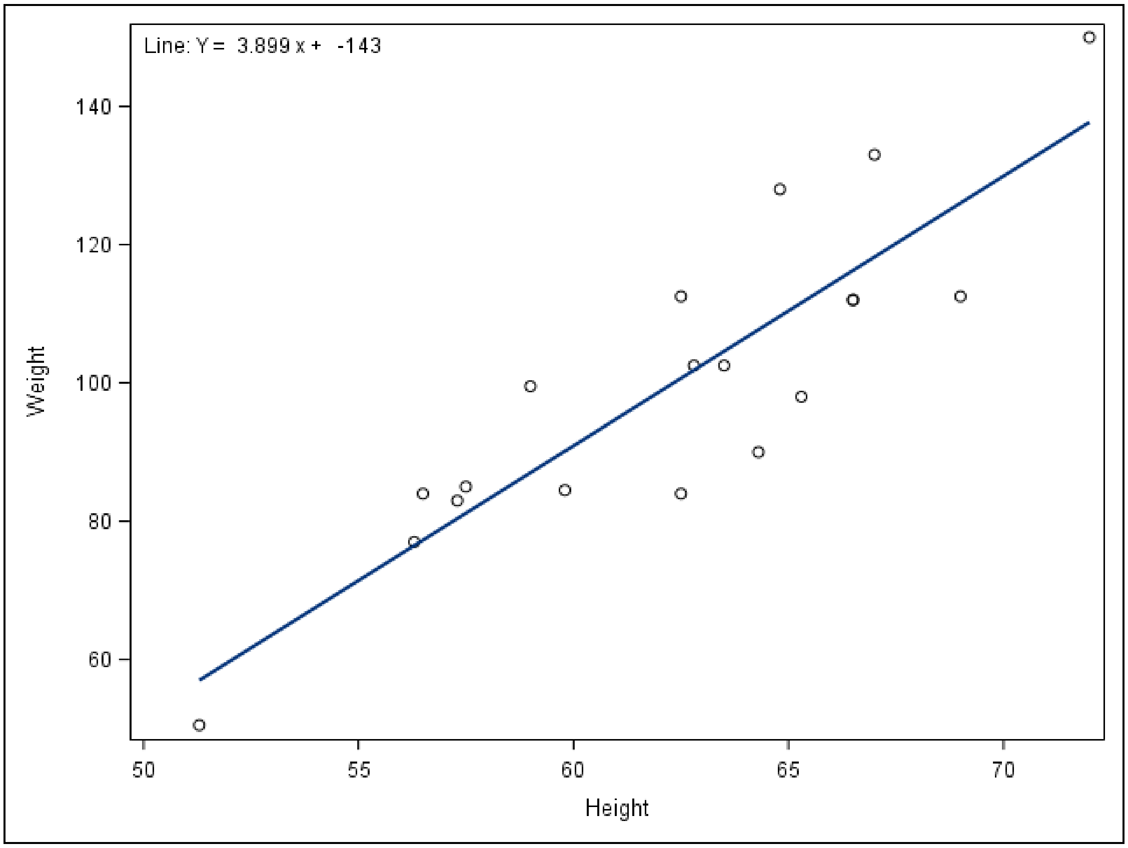
Output: 

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;
```

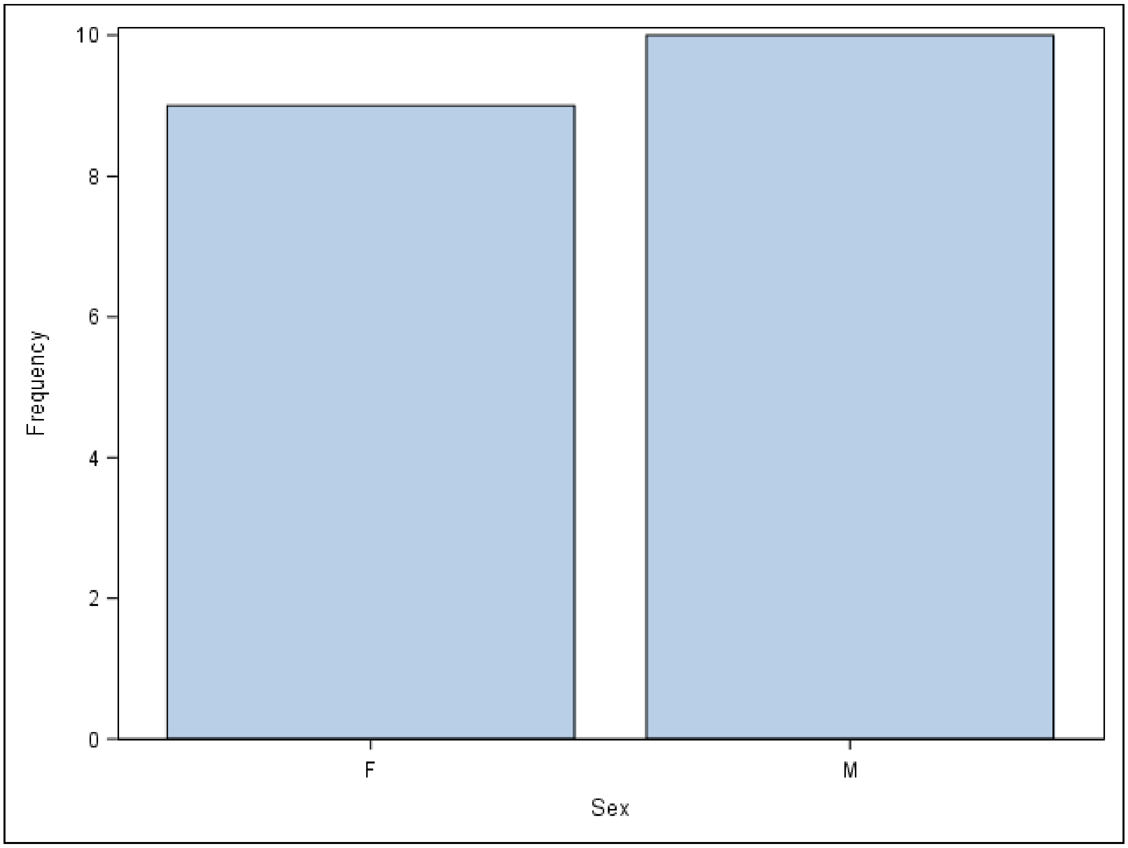
```
/* Use proc sgplot with the reg statement so it prints the line of best fit,
   and use the inset statement to print the equation of the line
   of best fit */
proc sgplot data = student noautolegend;
  reg y = Weight x = Height;
  inset "Line: Y = &Slope x + &Int" / position=topleft;
run;
```

Output: 

REG Procedure | DATA step: set statement | macro variables | call symput() function

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;
```

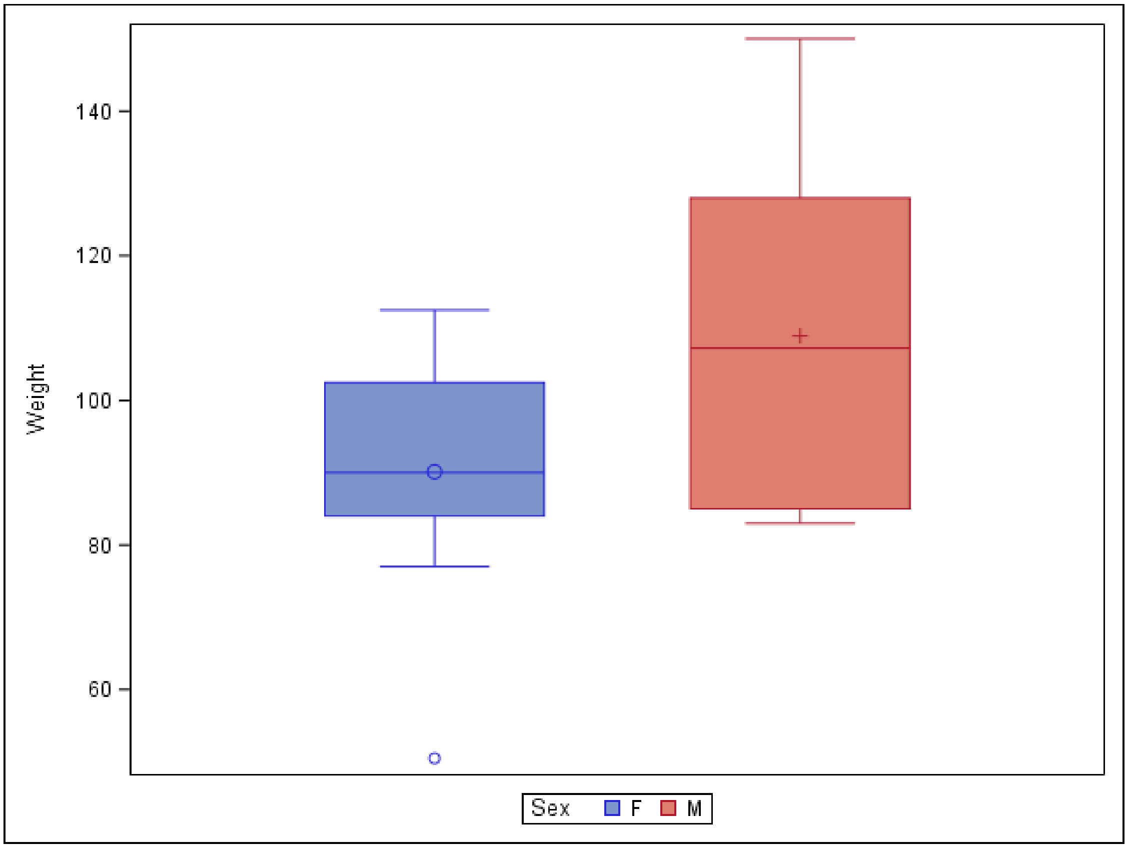
Output: 

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() function, the exp() function, the sqrt() function, and the abs() function.

```
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

log(), exp(), sqrt(), & abs() functions

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
```

SORT Procedure

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
```

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.
```

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
```

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);
    set all;
    where (selected = 1);
run;
```

```
data test (drop = selected);
    set all;
    where (selected = 0);
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 Value	greater15	Total 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

Parameter	DF	Estimate	Standard Error	Likelihood Ratio 95% Confidence Limits		Wald 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 Regression & Machine Learning: Modeling & Prediction

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;
run;

                            The FREQ Procedure

                                                Cumulative    Cumulative
       Result      Frequency      Percent     Frequency      Percent
       -----------------------------------------------------------------
       Correct            34        69.39            34        69.39
       Wrong              15        30.61            49       100.00
```

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

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;
    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	6
Number of Leaves Before Pruning	15
Number of Leaves After Pruning	9
Model Event Level	1

Number of Observations Read	398
Number of Observations Used	398

The HPSPLIT Procedure

Model-Based Confusion Matrix

Actual	Predicted 1	0	Error Rate
1	242	1	0.0041
0	4	151	0.0258

Model-Based Fit Statistics for Selected Tree

N Leaves	ASE	Mis-class	Sensitivity	Specificity	Entropy	Gini	RSS
9	0.0121	0.0126	0.9959	0.9742	0.0841	0.0242	9.6349

Model-Based Fit Statistics for Selected Tree

AUC
0.9881

Variable Importance

```
                             Training
               Variable     Relative     Importance      Count

               _23            1.0000       11.3559           2
               _27            0.4047        4.5962           1
               _1             0.3466        3.9356           2
               _6             0.2341        2.6581           1
               _8             0.1664        1.8898           1
               _0             0.1631        1.8516           1
```

HPSPLIT Procedure

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;

                             The FREQ Procedure

                                                Cumulative    Cumulative
       Result      Frequency      Percent     Frequency       Percent
       -------------------------------------------------------------
       Correct          157        91.81           157         91.81
       Wrong             14         8.19           171        100.00
```

%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.

```
/* Notice we are re-using data sets but it is good to re-read the
   original versions back 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;

/* HPSPLIT procedure is used to fit a decision tree model */
proc hpsplit data = train;
    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                         61

            Number of Observations Read                    354
            Number of Observations Used                    354



                            The HPSPLIT Procedure

                    Model-Based Fit Statistics for Selected Tree

                               N
                          Leaves           ASE           RSS

                              61        2.0825         737.2

                             Variable Importance

                                         Training
                   Variable    Relative    Importance      Count

                   _5            1.0000         132.6          8
                   _12           0.5997       79.5242          8
                   _7            0.3952       52.4071          6
                   _4            0.2640       35.0099          9
                   _0            0.2273       30.1348          3
                   _9            0.1569       20.8019          7
                   _6            0.1108       14.6883          6
                   _10           0.1064       14.1112          4
                   _11           0.0797       10.5698          5
                   _8            0.0679        8.9986          2
                   _2            0.0476        6.3100          2

/* 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 ass
```

```
essment
  of the model */
proc means data = scored mean;
  var sq_error;
run;
                            The MEANS Procedure

                       Analysis Variable : sq_error

                                        Mean
                                ------------
                                  27.2078085
                                ------------
```

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.

```
/* Notice we are re-using data sets but it is good to re-read the
   original version back 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;

/* 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

Average Square	Average Square	Misclassification

Number of Trees	Number of Leaves	Error (Train)	Error (OOB)	Rate (Train)
1	16	0.03015	0.0750	0.03015
2	35	0.01947	0.0739	0.04523
3	53	0.01284	0.0724	0.00754
4	66	0.01225	0.0658	0.01005
5	80	0.01156	0.0700	0.00754
6	92	0.01124	0.0712	0.00754
7	106	0.00938	0.0633	0.00251
8	122	0.00879	0.0623	0.00000
9	139	0.00887	0.0611	0.00000
10	157	0.00867	0.0611	0.00000
11	171	0.00889	0.0589	0.00251
12	188	0.00874	0.0557	0.00000
13	203	0.00847	0.0551	0.00000
14	223	0.00841	0.0552	0.00000
15	241	0.00804	0.0537	0.00251
16	253	0.00795	0.0496	0.00251
17	268	0.00827	0.0489	0.00503
18	283	0.00813	0.0485	0.00251
19	300	0.00793	0.0471	0.00251
20	315	0.00783	0.0471	0.00251
21	329	0.00763	0.0465	0.00251
22	345	0.00747	0.0453	0.00000
23	361	0.00740	0.0448	0.00000
24	375	0.00744	0.0442	0.00000
25	392	0.00749	0.0449	0.00251
26	406	0.00764	0.0448	0.00251
27	420	0.00750	0.0440	0.00251
28	437	0.00764	0.0438	0.00000
29	451	0.00776	0.0431	0.00000
30	466	0.00774	0.0426	0.00000
31	484	0.00778	0.0432	0.00251
32	502	0.00759	0.0426	0.00000
33	518	0.00749	0.0420	0.00251
34	535	0.00747	0.0418	0.00000
35	550	0.00742	0.0415	0.00000
36	562	0.00746	0.0411	0.00000
37	578	0.00741	0.0411	0.00000
38	594	0.00731	0.0404	0.00000
39	609	0.00717	0.0407	0.00000
40	623	0.00720	0.0404	0.00000
41	642	0.00712	0.0405	0.00000
42	661	0.00702	0.0399	0.00000
43	679	0.00687	0.0397	0.00000
44	692	0.00677	0.0396	0.00000
45	710	0.00665	0.0392	0.00000
46	731	0.00652	0.0391	0.00000
47	741	0.00654	0.0387	0.00000

48	754	0.00661	0.0392	0.00000
49	769	0.00656	0.0393	0.00000
50	780	0.00657	0.0395	0.00000
51	795	0.00658	0.0395	0.00000
52	812	0.00657	0.0399	0.00000
53	829	0.00653	0.0399	0.00000
54	843	0.00662	0.0402	0.00000
55	856	0.00662	0.0403	0.00000
56	869	0.00663	0.0401	0.00000
57	883	0.00655	0.0396	0.00000
58	898	0.00653	0.0397	0.00000
59	914	0.00653	0.0394	0.00000
60	929	0.00661	0.0397	0.00000
61	946	0.00658	0.0396	0.00000
62	959	0.00655	0.0393	0.00000
63	975	0.00657	0.0394	0.00000
64	988	0.00660	0.0393	0.00000
65	1008	0.00662	0.0396	0.00000
66	1020	0.00671	0.0397	0.00000
67	1036	0.00675	0.0401	0.00000
68	1054	0.00672	0.0397	0.00000
69	1072	0.00678	0.0401	0.00000
70	1088	0.00686	0.0405	0.00000
71	1103	0.00692	0.0407	0.00000
72	1122	0.00692	0.0410	0.00000
73	1137	0.00695	0.0411	0.00000
74	1156	0.00682	0.0406	0.00000
75	1171	0.00678	0.0406	0.00000
76	1188	0.00668	0.0403	0.00000
77	1202	0.00665	0.0402	0.00000
78	1215	0.00661	0.0402	0.00000
79	1229	0.00661	0.0400	0.00000
80	1247	0.00658	0.0399	0.00000
81	1263	0.00657	0.0395	0.00000
82	1276	0.00659	0.0394	0.00000
83	1292	0.00659	0.0393	0.00000
84	1305	0.00652	0.0388	0.00000
85	1322	0.00649	0.0387	0.00000
86	1342	0.00644	0.0386	0.00000
87	1359	0.00647	0.0387	0.00000
88	1373	0.00655	0.0388	0.00000
89	1389	0.00655	0.0389	0.00000
90	1404	0.00652	0.0385	0.00000
91	1418	0.00658	0.0386	0.00000
92	1432	0.00652	0.0383	0.00000
93	1447	0.00649	0.0381	0.00000
94	1460	0.00654	0.0382	0.00000
95	1481	0.00657	0.0386	0.00000
96	1495	0.00650	0.0383	0.00000
97	1509	0.00646	0.0381	0.00000

98	1522	0.00651	0.0382	0.00000
99	1537	0.00649	0.0382	0.00000
100	1554	0.00647	0.0382	0.00000

Fit Statistics

Misclassification Rate (OOB)	Log Loss (Train)	Log Loss (OOB)
0.0750	0.6942	1.727
0.0895	0.1558	1.545
0.0952	0.0429	1.358
0.0893	0.0453	1.059
0.0877	0.0447	1.139
0.0871	0.0457	1.054
0.0803	0.0417	0.860
0.0821	0.0414	0.800
0.0842	0.0424	0.742
0.0787	0.0429	0.743
0.0734	0.0445	0.739
0.0732	0.0447	0.626
0.0732	0.0443	0.574
0.0781	0.0447	0.574
0.0756	0.0436	0.571
0.0729	0.0433	0.457
0.0678	0.0439	0.404
0.0603	0.0436	0.404
0.0628	0.0430	0.349
0.0628	0.0429	0.349
0.0628	0.0425	0.348
0.0628	0.0420	0.294
0.0653	0.0418	0.294
0.0628	0.0416	0.292
0.0628	0.0420	0.294
0.0628	0.0423	0.243
0.0603	0.0418	0.241
0.0603	0.0429	0.241
0.0578	0.0433	0.239
0.0578	0.0436	0.239
0.0628	0.0437	0.241
0.0578	0.0435	0.240
0.0553	0.0430	0.238
0.0553	0.0431	0.237
0.0553	0.0432	0.237
0.0528	0.0430	0.236
0.0528	0.0431	0.236
0.0528	0.0428	0.185
0.0553	0.0427	0.186
0.0528	0.0426	0.185

0.0553	0.0424	0.186
0.0553	0.0422	0.184
0.0553	0.0418	0.184
0.0553	0.0415	0.184
0.0578	0.0410	0.183
0.0578	0.0410	0.183
0.0528	0.0411	0.182
0.0578	0.0412	0.182
0.0553	0.0412	0.183
0.0553	0.0415	0.183
0.0528	0.0414	0.183
0.0578	0.0417	0.184
0.0578	0.0415	0.184
0.0578	0.0420	0.186
0.0578	0.0420	0.186
0.0528	0.0421	0.186
0.0528	0.0418	0.185
0.0528	0.0418	0.185
0.0528	0.0417	0.184
0.0553	0.0418	0.184
0.0528	0.0417	0.184
0.0553	0.0415	0.184
0.0578	0.0416	0.184
0.0578	0.0416	0.184
0.0578	0.0418	0.184
0.0578	0.0421	0.185
0.0603	0.0422	0.186
0.0578	0.0421	0.185
0.0553	0.0425	0.186
0.0578	0.0428	0.187
0.0578	0.0430	0.188
0.0578	0.0432	0.189
0.0603	0.0431	0.189
0.0603	0.0427	0.188
0.0578	0.0425	0.188
0.0553	0.0423	0.187
0.0578	0.0423	0.187
0.0578	0.0422	0.187
0.0578	0.0421	0.187
0.0553	0.0421	0.186
0.0578	0.0420	0.185
0.0553	0.0420	0.185
0.0553	0.0419	0.184
0.0553	0.0417	0.183
0.0528	0.0416	0.183
0.0553	0.0414	0.183
0.0528	0.0415	0.183
0.0528	0.0416	0.184
0.0503	0.0417	0.184
0.0477	0.0416	0.183

0.0503	0.0417	0.183
0.0503	0.0415	0.183
0.0528	0.0414	0.134
0.0503	0.0417	0.134
0.0528	0.0419	0.135
0.0503	0.0416	0.135
0.0477	0.0415	0.134
0.0477	0.0416	0.134
0.0477	0.0415	0.134
0.0452	0.0416	0.135

Loss Reduction Variable Importance

Variable	Number of Rules	Gini	OOB Gini	Margin	OOB Margin
_7	69	0.057751	0.05100	0.115502	0.10851
_27	116	0.057536	0.04812	0.115072	0.10648
_22	66	0.053462	0.04054	0.106925	0.09267
_23	92	0.049798	0.03969	0.099596	0.08961
_20	84	0.045727	0.03686	0.091453	0.08190
_2	43	0.030053	0.02561	0.060105	0.05721
_0	44	0.026259	0.01873	0.052518	0.04483
_13	47	0.018831	0.01425	0.037662	0.03329
_6	55	0.021984	0.01321	0.043968	0.03523
_3	16	0.010751	0.01275	0.021502	0.02310
_26	84	0.017139	0.00693	0.034279	0.02387
_21	73	0.009979	0.00400	0.019958	0.01367
_10	31	0.007944	0.00273	0.015889	0.01089
_12	31	0.007102	0.00217	0.014204	0.00929
_17	31	0.002941	0.00049	0.005882	0.00286
_5	12	0.001882	-0.00010	0.003764	0.00152
_16	17	0.001134	-0.00055	0.002268	0.00089
_11	23	0.001679	-0.00057	0.003358	0.00096
_8	22	0.001543	-0.00077	0.003086	0.00052
_18	22	0.001787	-0.00105	0.003573	0.00081
_9	23	0.001656	-0.00105	0.003312	0.00063
_4	22	0.002237	-0.00114	0.004475	0.00147
_1	58	0.008366	-0.00147	0.016732	0.00648
_24	80	0.010527	-0.00149	0.021054	0.00906
_25	55	0.005040	-0.00151	0.010081	0.00449
_28	70	0.008423	-0.00168	0.016846	0.00617
_15	16	0.001345	-0.00203	0.002690	-0.00059
_14	29	0.001679	-0.00282	0.003357	-0.00110
_19	49	0.003804	-0.00413	0.007609	-0.00028
_29	74	0.005801	-0.00418	0.011603	0.00225

ii) Assess the model against the testing data.

```
/* Prediction on testing data */
ods select none;
```

```
proc hp4score data = test seed = 29;
    score file = 'hpbreastcancer2.bin' out = scored;
run;
ods select all;

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

proc freq data = scored;
  tables Result;
run;
NA
                            The FREQ Procedure

                                               Cumulative    Cumulative
       Result     Frequency     Percent     Frequency      Percent
       ------------------------------------------------------------
       Correct         166        97.08           166         97.08
       Wrong             5         2.92           171        100.00
```

b) Fit a random forest regression model.

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

```
/* Notice we are re-using data sets but it is good to re-read the original
  versions back 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 hpforest data = train;
    input _0-_12 / level = interval;
    target Target / level = interval;
    save file = 'hpboston2.bin';
run;
                          The HPFOREST Procedure

                          Performance Information
```

```
          Execution Mode       Single-Machine
          Number of Threads    4

               Data Access Information

      Data          Engine    Role     Path

      WORK.TRAIN    V9        Input    On Client

                  Model Information

Parameter                          Value

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

                Number of Observations

      Type                                     N

      Number of Observations Read            354
      Number of Observations Used            354

               Baseline Fit Statistics

         Statistic                     Value

         Average Square Error         86.450

                     Fit Statistics
```

Number of Trees	Number of Leaves	Average Square Error (Train)	Average Square Error (OOB)
1	187	19.2696	47.7098
2	375	11.3683	43.2860
3	576	6.6232	31.3383
4	773	4.8837	24.8313
5	958	4.0583	21.5074
6	1155	3.7023	18.2075
7	1355	3.2854	20.0734
8	1551	2.8333	16.4209
9	1745	2.9038	17.4034
10	1942	2.9196	17.6812
11	2122	2.7632	16.6404
12	2313	2.6170	16.7454
13	2509	2.6299	16.6065
14	2706	2.5418	16.4241
15	2901	2.4397	15.5039
16	3091	2.2983	15.2623
17	3292	2.3907	15.3176
18	3478	2.2574	14.6200
19	3677	2.1693	14.2939
20	3873	2.2105	14.2776
21	4066	2.1068	14.0666
22	4261	2.1419	13.9742
23	4457	2.1239	14.1427
24	4641	2.0986	13.8644
25	4838	2.1718	13.9556
26	5042	2.2465	14.1226
27	5236	2.1678	13.7884
28	5415	2.2207	13.8642
29	5610	2.1705	13.6529
30	5800	2.1763	13.4050
31	5994	2.3066	13.7989
32	6176	2.3564	13.6090
33	6360	2.2905	13.4957
34	6553	2.2505	13.0359
35	6745	2.1593	12.4862
36	6941	2.1614	12.6334
37	7125	2.1541	12.5703
38	7319	2.1364	12.7408
39	7522	2.1109	12.6118
40	7712	2.1543	12.6576
41	7898	2.1385	12.6186
42	8080	2.1784	12.6728
43	8270	2.2877	12.9858
44	8463	2.2850	12.8440

45	8658	2.2836	12.8810
46	8857	2.2888	13.1012
47	9045	2.2843	13.0514
48	9233	2.3148	13.0745
49	9431	2.2789	13.0634
50	9623	2.2752	12.9776
51	9831	2.2498	12.9791
52	10026	2.2526	12.9777
53	10221	2.2672	12.9902
54	10408	2.2593	13.0558
55	10596	2.2957	13.2262
56	10788	2.2959	13.1870
57	10977	2.3256	13.2589
58	11173	2.3208	13.2695
59	11364	2.2901	13.1079
60	11552	2.2612	13.1308
61	11742	2.2491	13.0531
62	11938	2.2204	12.9735
63	12136	2.2213	13.0562
64	12333	2.2066	13.0283
65	12525	2.2162	13.0132
66	12718	2.2031	12.9627
67	12911	2.1974	13.0353
68	13108	2.2049	13.1707
69	13289	2.2056	13.0791
70	13484	2.1924	12.9408
71	13674	2.1686	12.8484
72	13866	2.2003	13.0394
73	14057	2.1860	13.0218
74	14242	2.1825	12.9853
75	14439	2.1844	12.9505
76	14621	2.1770	12.9093
77	14815	2.1590	12.9136
78	15000	2.1914	12.9766
79	15186	2.2442	13.1019
80	15376	2.2233	13.1474
81	15566	2.2257	13.1030
82	15762	2.2025	13.0779
83	15953	2.2114	13.0018
84	16145	2.2128	13.0747
85	16321	2.2574	13.2711
86	16510	2.2372	13.2143
87	16706	2.2161	13.1554
88	16890	2.1980	13.1078
89	17085	2.1905	12.9783
90	17284	2.1902	12.9538
91	17477	2.1743	12.9489
92	17668	2.1681	12.9888
93	17858	2.1504	12.9055
94	18052	2.1521	12.9346

```
                 95         18240     2.1390    12.8186
                 96         18429     2.1394    12.8283
                 97         18619     2.1219    12.6850
                 98         18821     2.1138    12.5864
                 99         19016     2.1106    12.5023
                100         19210     2.1227    12.5373

                Loss Reduction Variable Importance

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

  _5            1607    25.96700   21.44497       1.674146       1.271060
  _12           4298    26.08398   21.20143       1.747167       1.062741
  _2             862     7.51862    4.32709       0.481668       0.225365
  _10           1008     4.43794    2.90609       0.311778       0.121390
  _4            1080     4.85033    2.54304       0.447890       0.205106
  _9            1323     2.91508    1.36073       0.295646       0.085797
  _0             410     2.31937    0.03880       0.191909       0.033169
  _1             162     0.10618   -0.03221       0.019840      -0.004146
  _8             781     0.72275   -0.26446       0.099445      -0.021106
  _3             183     0.54563   -0.30985       0.039416      -0.008242
  _7            2419     6.78473   -0.42270       0.617601       0.110761
  _11           3469     3.02608   -0.76432       0.470083      -0.028214
  _6            1508     1.95177   -0.90383       0.285909       0.000426
```

ii) Assess the model against the testing data.

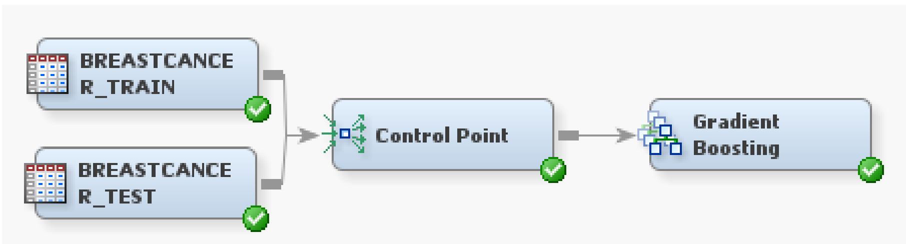
```
/* Prediction on testing data */
ods select none;
proc hp4score data = test seed = 29;
    score file = 'hpboston2.bin' out = scored;
run;
ods select all;

/* 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;

                        The MEANS Procedure

                   Analysis Variable : sq_error

                              Mean
```

```
------------
   9.1427096
------------
```

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 currently is using SAS Enterprise Miner. Create the following diagram in SAS Enterprise Miner:

Output: 

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
_21	0
_10	0
_14	0
_16	0
_18	0
_2	0
_15	0
_29	0
_3	0
_0	0
_17	0
_25	0
_11	0
_12	0
_28	0
_6	0
_26	0
_4	0
_5	0
_8	0
_9	0

Output:

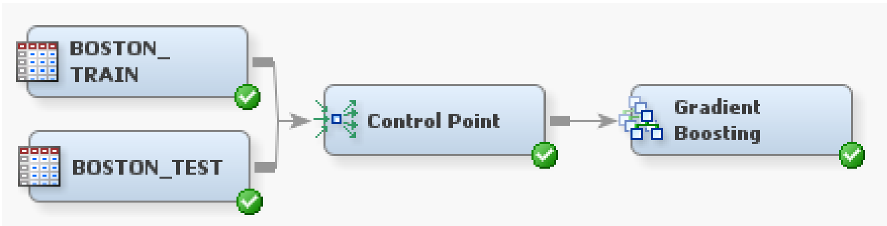
Statistics Label	Train	Test
Sum of Frequencies	398	171
Sum of Case Weights Times Freq	796	342
Misclassification Rate	0.035176	0.040936
Maximum Absolute Error	0.717472	0.743284
Sum of Squared Errors	99.49027	40.19162
Average Squared Error	0.124988	0.117519
Root Average Squared Error	0.353536	0.342811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

Output:

```
Classification Table

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

                            Target      Outcome     Frequency      Total
Target      Outcome       Percentage   Percentage     Count      Percentage

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

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:

Output: 

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:

Output:

Variable Name	Importance
_12	1
_5	0.953865
_0	0.074612
_4	0
_1	0
_11	0
_3	0
_2	0
_10	0
_8	0
_7	0
_6	0
_9	0

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	.

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.

```
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(Targ
et))))
    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 a
n 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
```

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.

```
/* Notice we are re-using data sets but it is good to re-read the original
   versions back 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;

/* 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
```

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;
run;
                            The FREQ Procedure
```

```
                                            Cumulative    Cumulative
       Result      Frequency      Percent     Frequency      Percent
       -----------------------------------------------------------
       Correct          167        97.66           167         97.66
       Wrong              4         2.34           171        100.00
```

HPSVM Procedure, %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 that need to be read into the
   environment */
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;
```

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
```

b) Fit a neural network regression model.

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

```
/* Notice we are re-using data sets but it is good to re-read the original
   versions back 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;
```

```
/* 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;
```

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

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;
run;
```

```
                          The FASTCLUS Procedure
              Replace=FULL  Radius=0  Maxclusters=3 Maxiter=1

                               Initial Seeds

Cluster      PetalLength       PetalWidth      SepalLength       SepalWidth
---------------------------------------------------------------------------
   1         6.700000000      2.200000000      7.700000000      3.800000000
   2         1.500000000      0.400000000      5.700000000      4.400000000
   3         4.500000000      1.700000000      4.900000000      2.500000000

                 Criterion Based on Final Seeds =   0.3712

                              Cluster Summary

                                     Maximum Distance
                          RMS Std           from Seed     Radius    Nearest
 Cluster      Frequency   Deviation    to Observation   Exceeded    Cluster
 ------------------------------------------------------------------------
    1              33      0.3883            1.2923                       3
    2              50      0.2788            1.2394                       3
    3              67      0.4180            1.8532                       1
```

Cluster Summary

Cluster	Distance Between Cluster Centroids
1	1.8341
2	3.4222
3	1.8341

Statistics for Variables

Variable	Total STD	Within STD	R-Square	RSQ/(1-RSQ)
PetalLength	1.76442	0.42974	0.941475	16.086593
PetalWidth	0.76316	0.23898	0.903258	9.336801
SepalLength	0.82807	0.44824	0.710915	2.459187
SepalWidth	0.43359	0.32558	0.443729	0.797684
OVER-ALL	1.06880	0.37038	0.881525	7.440564

Pseudo F Statistic = 546.88

Approximate Expected Over-All R-Squared = 0.62721

Cubic Clustering Criterion = 24.526

WARNING: The two values above are invalid for correlated variables.

Cluster Means

Cluster	PetalLength	PetalWidth	SepalLength	SepalWidth
1	5.827272727	2.127272727	6.900000000	3.096969697
2	1.464000000	0.244000000	5.006000000	3.418000000
3	4.452238806	1.453731343	5.947761194	2.761194030

Cluster Standard Deviations

Cluster	PetalLength	PetalWidth	SepalLength	SepalWidth
1	0.4577613511	0.2401467354	0.5012484414	0.2909948974
2	0.1735111594	0.1072095031	0.3524896872	0.3810243980
3	0.5360795421	0.3011736428	0.4831582365	0.2953966126

The FREQ Procedure

Table of Species by CLUSTER

```
            Species     CLUSTER(Cluster)

            Frequency  |
            Percent    |
            Row Pct    |
            Col Pct    |       1|       2|       3|  Total
            -----------+--------+--------+--------+
            Setosa     |      0 |     50 |      0 |     50
                       |   0.00 |  33.33 |   0.00 |  33.33
                       |   0.00 | 100.00 |   0.00 |
                       |   0.00 | 100.00 |   0.00 |
            -----------+--------+--------+--------+
            Versicolor |      0 |      0 |     50 |     50
                       |   0.00 |   0.00 |  33.33 |  33.33
                       |   0.00 |   0.00 | 100.00 |
                       |   0.00 |   0.00 |  74.63 |
            -----------+--------+--------+--------+
            Virginica  |     33 |      0 |     17 |     50
                       |  22.00 |   0.00 |  11.33 |  33.33
                       |  66.00 |   0.00 |  34.00 |
                       | 100.00 |   0.00 |  25.37 |
            -----------+--------+--------+--------+
            Total            33       50       67      150
                          22.00    33.33    44.67   100.00
```

7.2 Spectral Clustering

```
proc iml;
  submit / R;
    iris = read.csv('C:/Users/iris.csv')
      iris$Species = ifelse(iris$Target == 0, "Setosa",
                            ifelse(iris$Target == 1, "Versicolor", "Virginica
"))
      features <- as.matrix(subset(iris, select = c(PetalLength,
                                                    PetalWidth, SepalLength,
SepalWidth)))
    library(kernlab)
    set.seed(29)
    spectral <- specc(features, centers = 3, iterations = 10, nystrom.red = T
RUE)
    labels <- as.data.frame(spectral)
    table(iris$Species, labels$spectral)
  endsubmit;
quit;


              1  2  3
  Setosa     50  0  0
```

```
  Versicolor  0 47  3
  Virginica   0  3 47
```

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;
run;
```

7.4 DBSCAN

```
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
```

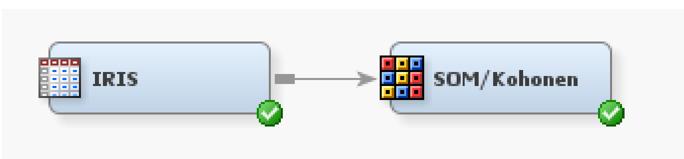
7.5 Self-organizing map

Currently, there is not a self-organizing map procedure available in Base SAS. Therefore, the best method to create a self-organizing map currently 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.

Output:

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:

Output: 

For the SOM/Kohonen node set the following options:

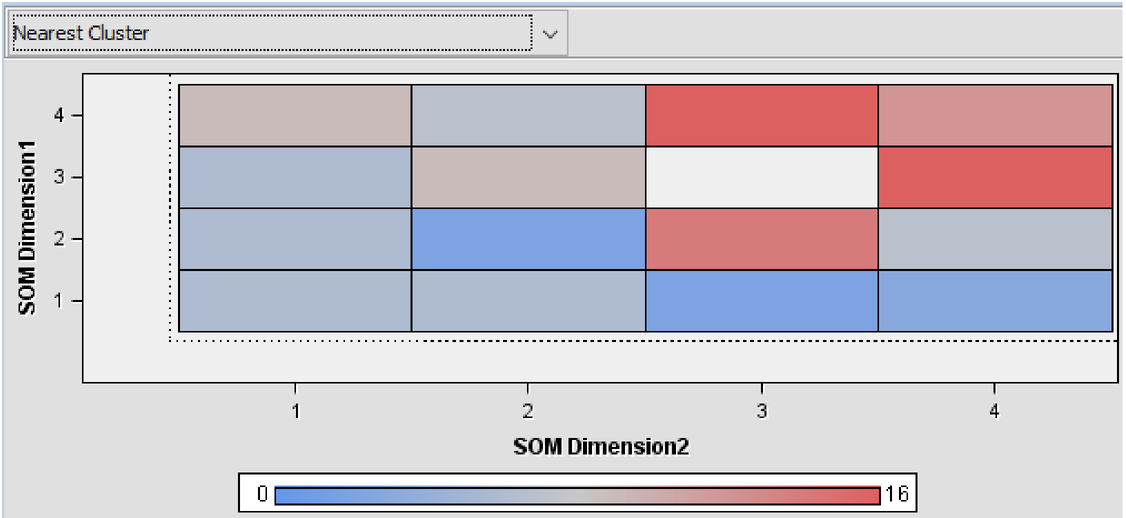
1. Choose the Kohonen SOM method.
2. Set row and column to both be 4.
3. Under the "Kohonen" options section, set "Use Defaults" to "No", and open the Kohonen Options window by clicking the ... box.
4. Set the following options in the popup window:

Kohonen Options

Output:

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: 

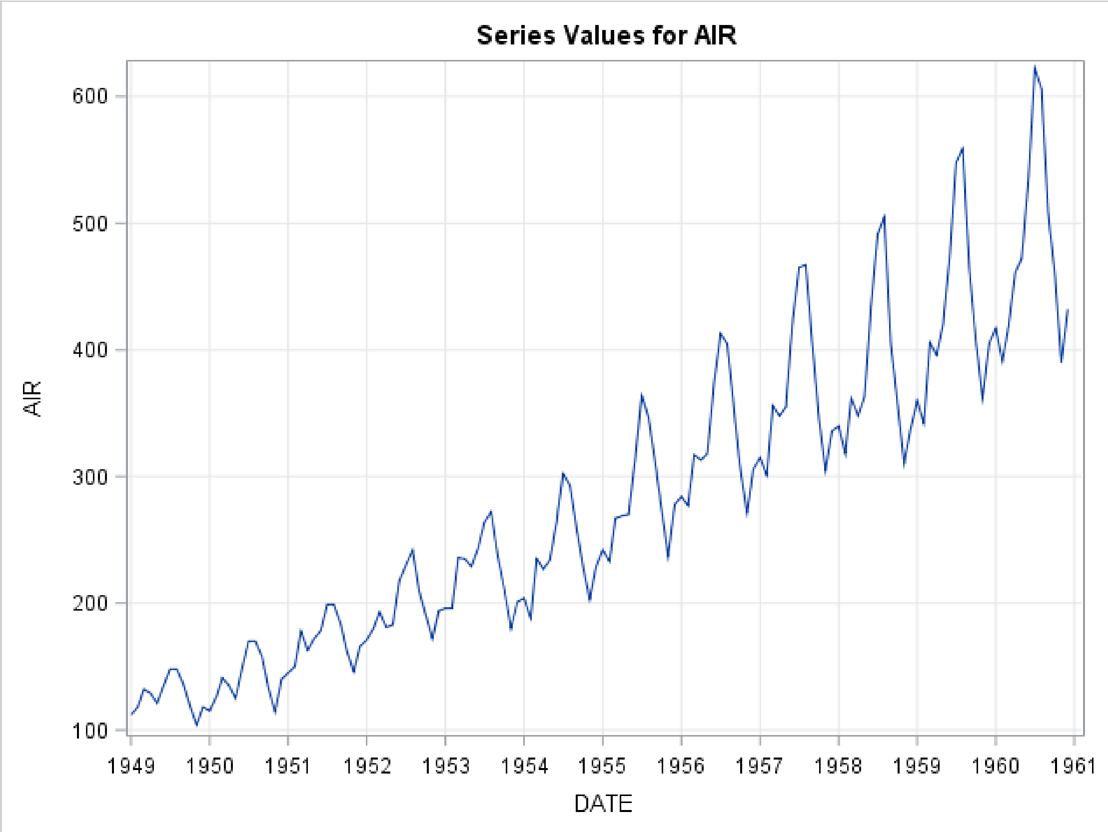
---

8 Forecasting

8.1 Fit an ARIMA model to a timeseries.

a) Plot the timeseries.

```
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;
```

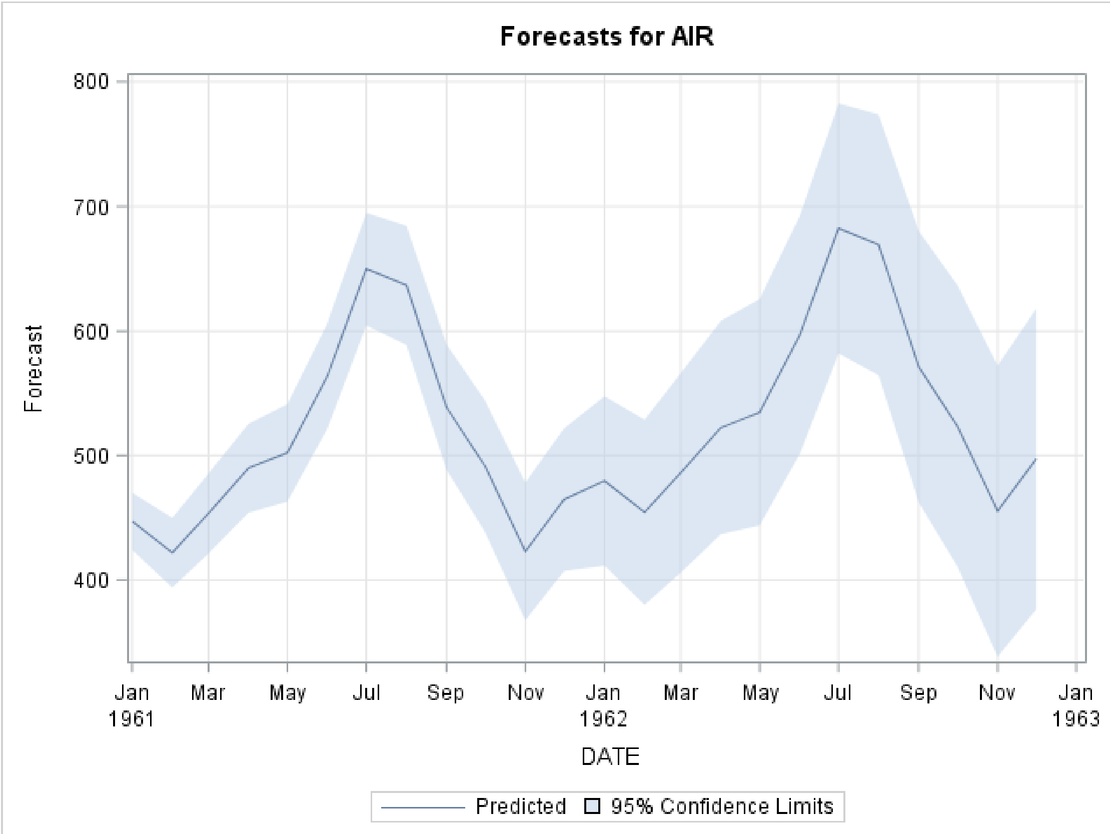
Output: 

b) Fit an ARIMA model, predict 2 years (24 months) out, and plot predictions.

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

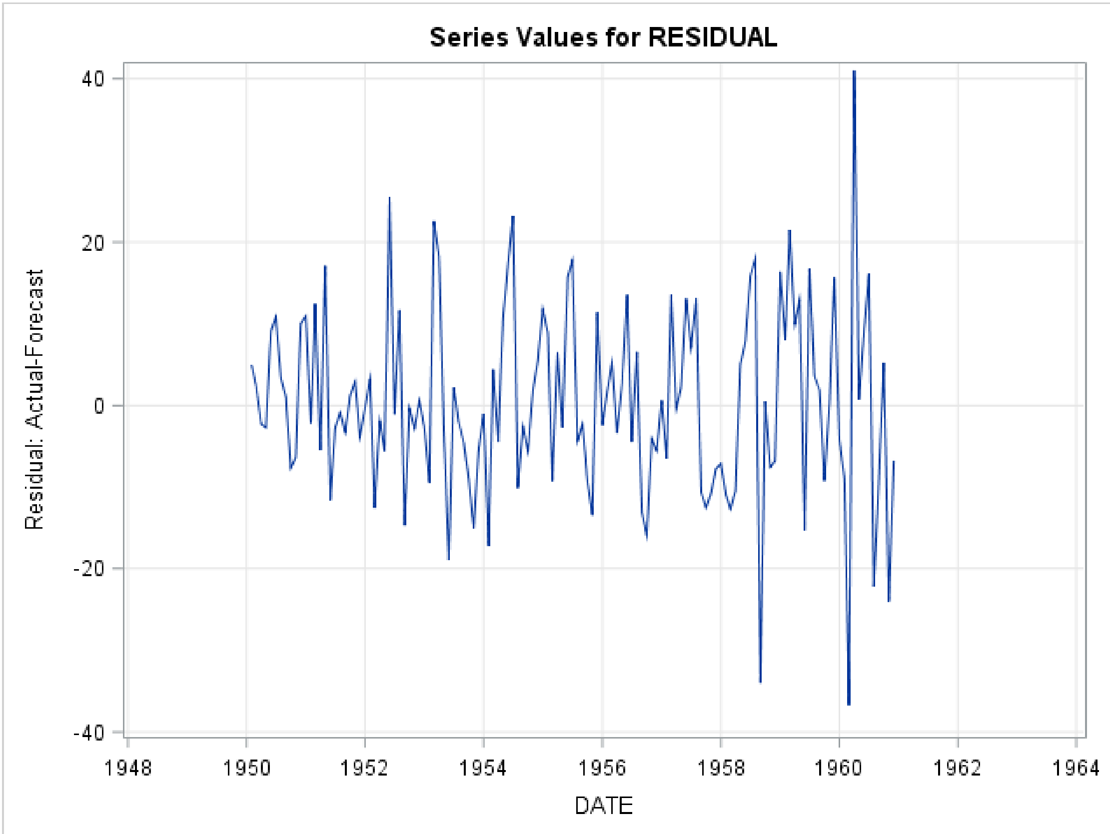
```
proc arima data = air;
    identify var = air(1,12) noprint;
    estimate q=(1)(12) noint method=ml noprint;
    forecast id=date interval=month out=forecast;
run;

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

Output:



c) Plot residuals of predictions and known values.

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

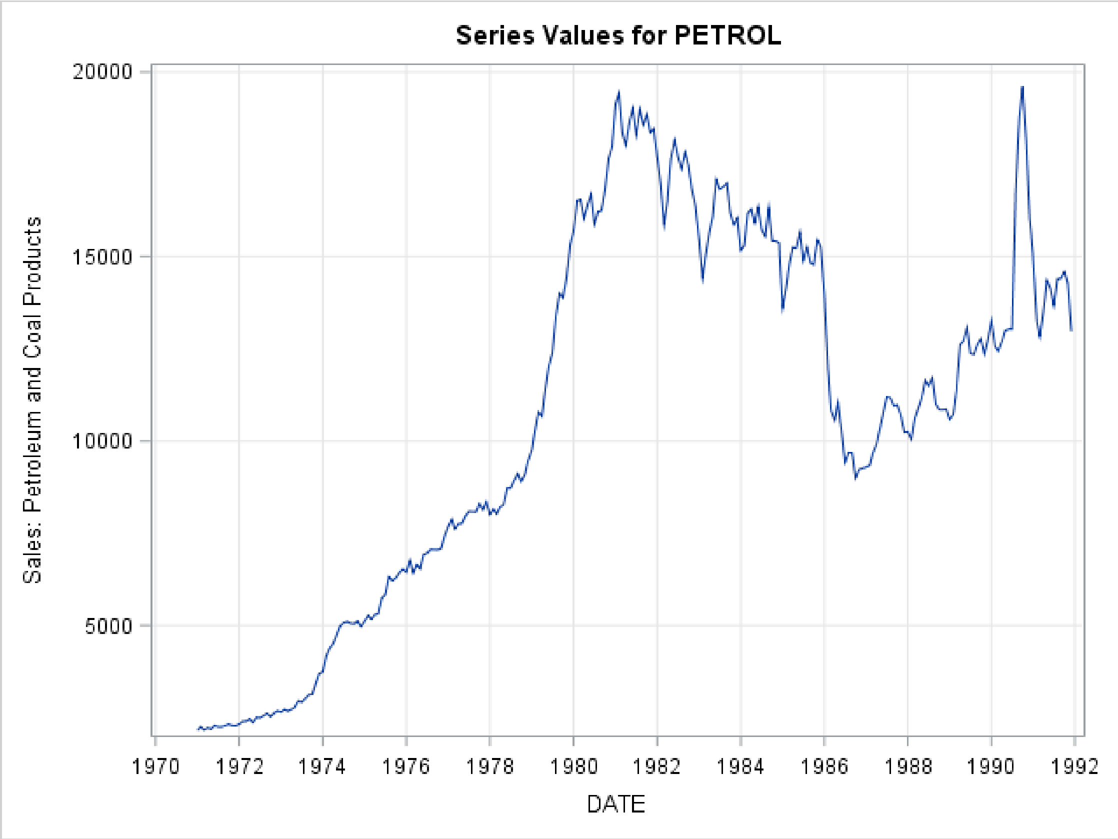
Output: 

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
```

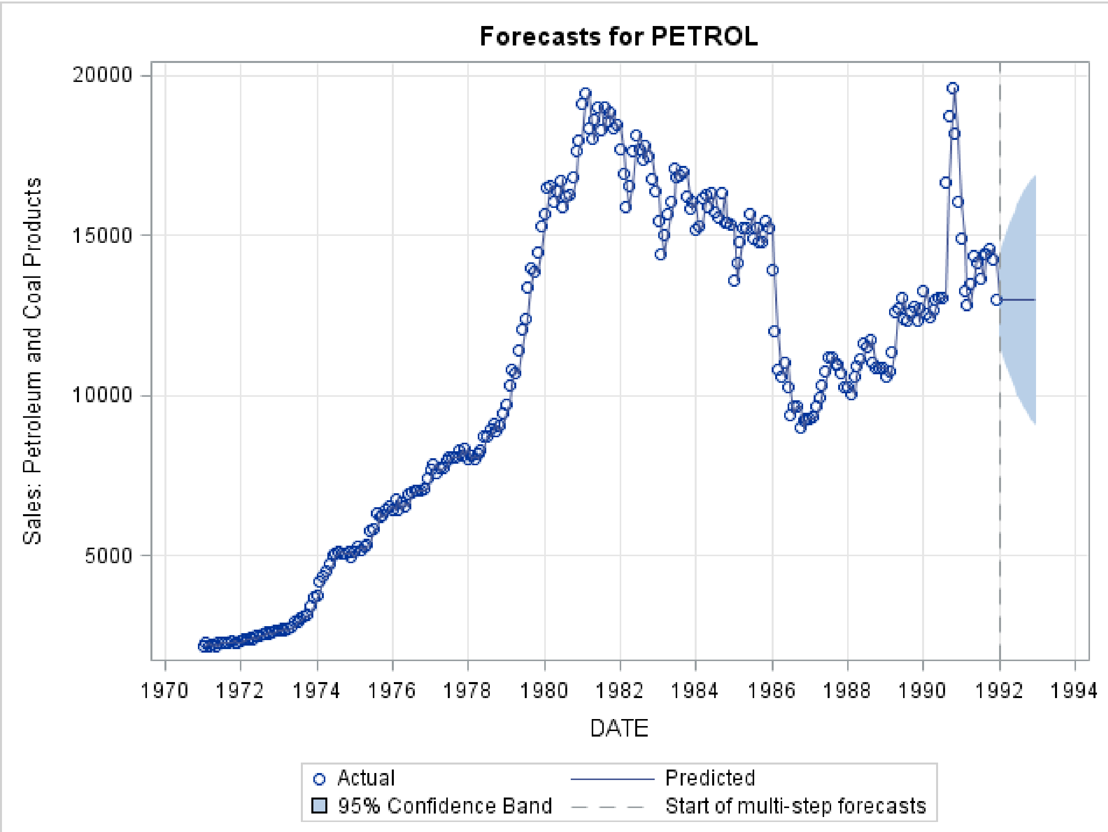
Output: 

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
```

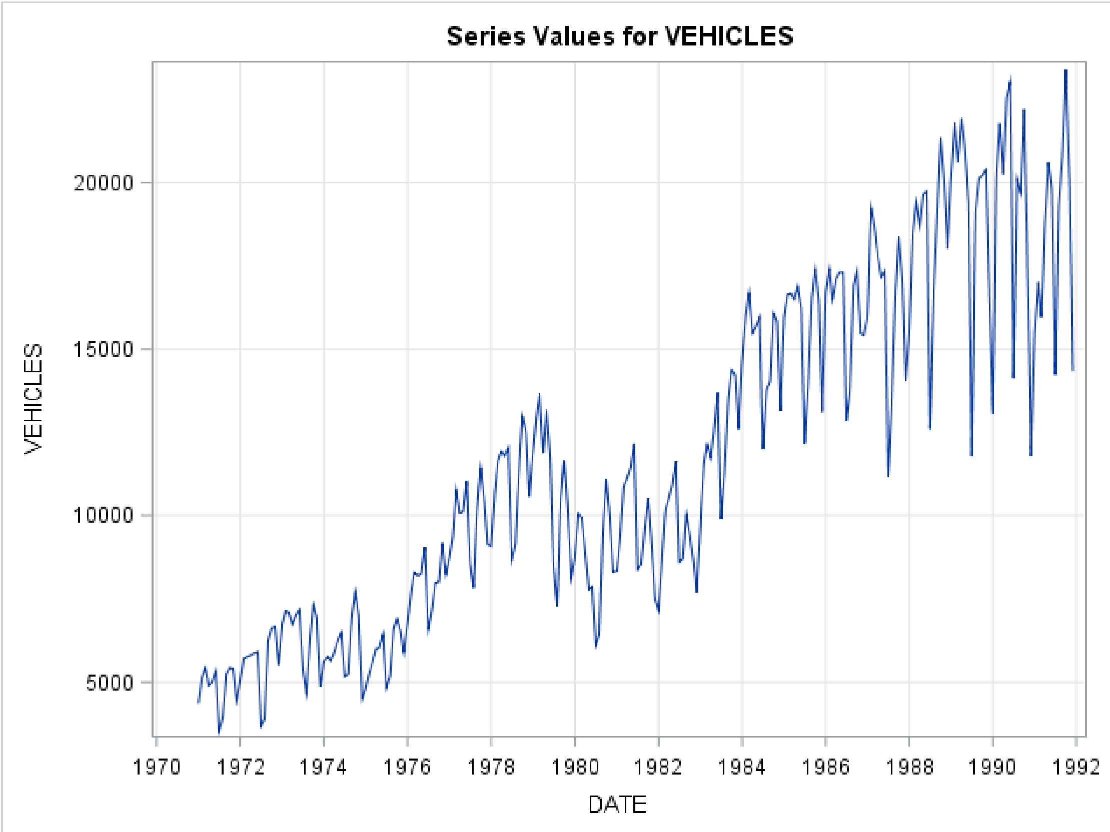
Output: 

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;
```

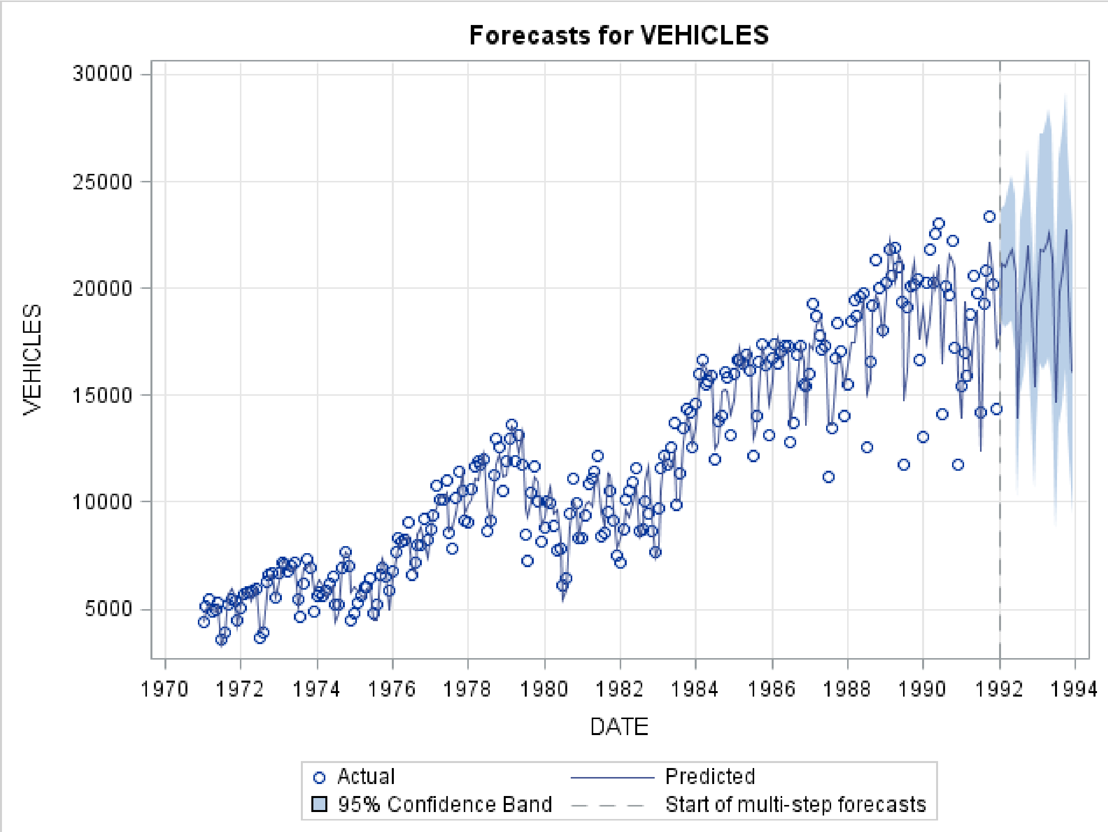
```
                         The TIMESERIES Procedure

                              Input Data Set

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

Output: 

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:



9 Model Evaluation & Selection

9.1 Evaluate the accuracy of regression models.

a) Evaluation on training data.

```
/* Notice we are re-using data sets but it is good to re-read the original
  version back 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;

/* 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

                                 0.9743865
```

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

0.8864763
```

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

REG Procedure, SCORE Procedure, IML Procedure, HPFOREST Procedure, HP4SCORE Procedure

9.2 Evaluate the accuracy of classification models.

a) Evaluation on training data.

```
/* Notice we are re-using data sets but it is good to re-read the original
   versions back into the environment */
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;
ods select all;

/* Evaluation on training data */
ods select none;
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

                                    0.9685185
```

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

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

---

10 Text Analytics

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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

COMPARE Procedure

CONTENTS Procedure

CORR Procedure

FCMP Procedure

EXPORT Procedure

FREQ Procedure

GENMOD Procedure

HP4SCORE Procedure

HPFOREST Procedure

HPSPLIT Procedure

HPSVM Procedure

IML Procedure

IMPORT Procedure

MEANS Procedure

PRINCOMP Procedure

PRINT Procedure

REG Procedure

SCORE Procedure

SGPLOT Procedure

- histogram
- inset
- reg
- scatter
- vbox

SGSCATTER Procedure

SORT Procedure

SQL Procedure

SURVEYSELECT Procedure

3 SAS DATA step

Statements:

%include

if-then/else

infile

input

merge

output

set

where

Alphabetical Index

Data Frame

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

Dictionary

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

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

```
  rc = mydict.add();
  output;
end;
Name = 'James';
rc = mydict.find();
put rc= Name= Age=;
```

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

Series

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

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

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