Final Exam

For the Ozone data from the R package mlbench try the following machine learning prediction algorithm. Read the paper Feature Selection with the Boruta Package and implement the algorithm. Build prediction model for the Ozone variable. Which features are most important?

- **1. Boruta RandomForest Algorithm**

NAME: SAJITH GOWTHAMAN NET ID: ek5282

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
df = pd.read_csv("Ozone.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	Unnamed: 0	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V
0	1	1	1	4	3.0	5480.0	8	20.0	NaN	NaN	5000.0	-1
1	2	1	2	5	3.0	5660.0	6	NaN	38.0	NaN	NaN	-1
2	3	1	3	6	3.0	5710.0	4	28.0	40.0	NaN	2693.0	-2
3	4	1	4	7	5.0	5700.0	3	37.0	45.0	NaN	590.0	-2
4	5	1	5	1	5.0	5760.0	3	51.0	54.0	45.32	1450.0	2

In [4]:

```
df.isna().sum()
```

Out[4]:

```
Unnamed: 0      0
V1              0
V2              0
V3              0
V4              5
V5             12
V6              0
V7             15
V8              2
V9            139
V10            15
V11             1
V12            14
V13             0
dtype: int64
```

We find a lot of NaN values associated with the data. For a prediction model, it is advised to take the mean of the values of it's respective columns. As this particular data deals with the temperature, we shouldn't expect sudden ups and downs of the values. Mean value would be suitable.

In [5]:

```
df.mean()
```

Out[5]:

```
Unnamed: 0       183.500000
V1                 6.513661
V2                15.756831
V3                 4.002732
V4                11.526316
V5              5752.966102
V6                 4.868852
V7                58.475783
V8                61.914835
V9                56.846344
V10             2590.943020
V11               17.797260
V12               60.927330
V13              123.300546
dtype: float64
```

In [6]:

```
df.fillna(df.mean(), inplace = True)
```

Let's check the predicting target's data, whether we can do a classification or regression model.

In [7]:

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 366 entries, 0 to 365
Data columns (total 14 columns):
Unnamed: 0    366 non-null int64
V1            366 non-null int64
V2            366 non-null int64
V3            366 non-null int64
V4            366 non-null float64
V5            366 non-null float64
V6            366 non-null int64
V7            366 non-null float64
V8            366 non-null float64
V9            366 non-null float64
V10           366 non-null float64
V11           366 non-null float64
V12           366 non-null float64
V13           366 non-null int64
dtypes: float64(8), int64(6)
memory usage: 40.2 KB
```

Out[7]:

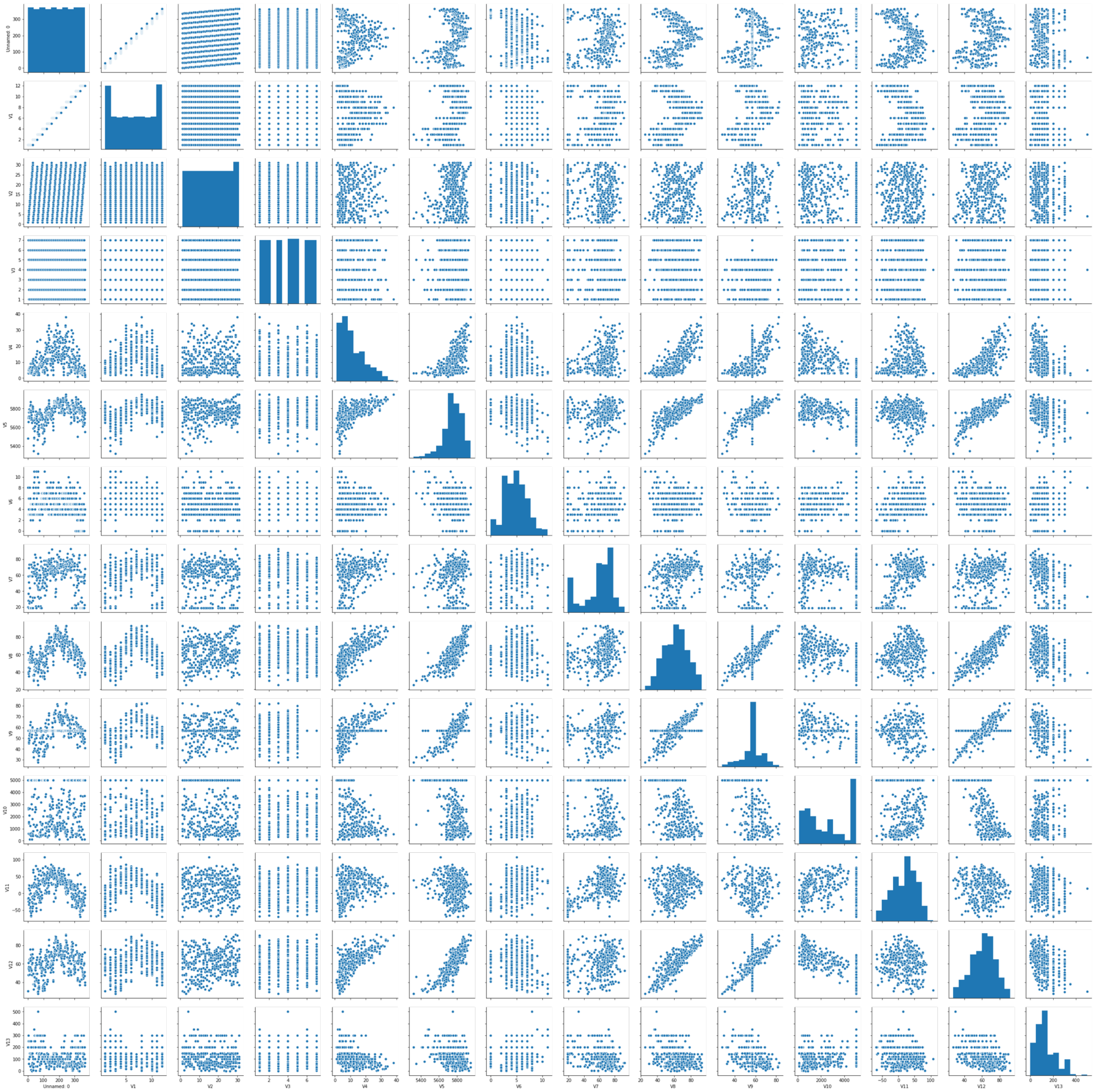
	Unnamed: 0	V1	V2	V3	V4	
count	366.000000	366.000000	366.000000	366.000000	366.000000	36
mean	183.500000	6.513661	15.756831	4.002732	11.526316	575
std	105.799338	3.455958	8.823592	1.997942	7.861472	10
min	1.000000	1.000000	1.000000	1.000000	1.000000	532
25%	92.250000	4.000000	8.000000	2.000000	5.000000	570
50%	183.500000	7.000000	16.000000	4.000000	10.000000	576
75%	274.750000	9.750000	23.000000	6.000000	16.000000	583
max	366.000000	12.000000	31.000000	7.000000	38.000000	595

In [8]:

```
sns.pairplot(df)
```

Out[8]:

<seaborn.axisgrid.PairGrid at 0x12b684d10>



In [9]:

```
df.V4 = round(df.V4)
df.V4 = pd.to_numeric(df['V4'])
```

In [10]:

```
df.V4.unique()
```

Out[10]:

```
array([ 3.,  5.,  6.,  4.,  7.,  9., 11., 10., 12.,
2.,  8., 13., 15.,
       23., 17., 16., 24., 14., 22., 19., 18., 21.,
29., 20., 27., 33.,
       25., 31., 26., 30., 28., 34., 32., 38.,  1.])
```

In [11]:

```
##Let's Load X and Y

X=df.loc[:, df.columns != 'V4'].values
Y=df.iloc[:,4].values.ravel()
```

Boruta Model (with Random Forest):

In [12]:

```
from sklearn.ensemble import RandomForestClassifier
from boruta import BorutaPy
rf = RandomForestClassifier(n_jobs=-1, class_weight=None, max_de
pth=2)

# define Boruta feature selection method
feat_selector = BorutaPy(rf, n_estimators='auto', verbose=2, max
_iter = 30)

# find all relevant features
feat_selector.fit(X, Y)

# check ranking of features
feat_selector.ranking_
```

```
Iteration:      1 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      2 / 30
```

```
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      3 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      4 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      5 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      6 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      7 / 30
Confirmed:      0
Tentative:      13
Rejected:       0
Iteration:      8 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      9 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      10 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      11 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      12 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      13 / 30
Confirmed:      7
```

```
Tentative:      4
Rejected:       2
Iteration:      14 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      15 / 30
Confirmed:      7
Tentative:      4
Rejected:       2
Iteration:      16 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      17 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      18 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      19 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      20 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      21 / 30
Confirmed:      9
Tentative:      2
Rejected:       2
Iteration:      22 / 30
Confirmed:      9
Tentative:      1
Rejected:       3
Iteration:      23 / 30
Confirmed:      9
Tentative:      1
Rejected:       3
Iteration:      24 / 30
Confirmed:      9
```

```
Tentative:      1
Rejected:       3
Iteration:      25 / 30
Confirmed:      9
Tentative:      1
Rejected:       3
Iteration:      26 / 30
Confirmed:      10
Tentative:      0
Rejected:       3


BorutaPy finished running.

Iteration:      27 / 30
Confirmed:      10
Tentative:      0
Rejected:       3
```

Out[12]:

```
array([1, 1, 2, 4, 1, 3, 1, 1, 1, 1, 1, 1, 1])
```

In [13]:

```
feat_selector.support_
```

Out[13]:

```
array([ True,  True, False, False,  True, False,  Tr
ue,  True,  True,
        True,  True,  True,  True])
```

In [14]:

```
print('==============BORUTA==============')
print (feat_selector.n_features_)
```

```
==============BORUTA==============
10
```

I was first getting the top 4 important features. After some tuning I was able to get the all the important features. (Same when I ran with R-Studio)

In [15]:

```
features = [f for f in df.columns if f not in ['V4']]
len(features)
```

Out[15]:

```
13
```

In [16]:

```
important_features = list()
indexes = np.where(feat_selector.support_ == True)
for x in np.nditer(indexes):
    important_features.append(features[x])
print('The Most Important Features Are:{}'.format(important_feat
ures))

unimportant_features = list()
indexes = np.where(feat_selector.support_ == False)
for x in np.nditer(indexes):
    unimportant_features.append(features[x])
print('The Unimportant Features Are:{}'.format(unimportant_featu
res))
```

```
The Most Important Features Are:['Unnamed: 0', 'V1',
'V5', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13']
The Unimportant Features Are:['V2', 'V3', 'V6']
```

Dataset before filtering to the transformed version:

In [17]:

```
imp_df = pd.DataFrame(df[important_features])
imp_df
```

Out[17]:

	Unnamed: 0	V1	V5	V7	V8	V9	
0	1	1	5480.000000	20.000000	61.914835	56.846344	5000
1	2	1	5660.000000	58.475783	38.000000	56.846344	2590
2	3	1	5710.000000	28.000000	40.000000	56.846344	2693
3	4	1	5700.000000	37.000000	45.000000	56.846344	590
4	5	1	5760.000000	51.000000	54.000000	45.320000	1450
...	...	...	...	...	...	...	
361	362	12	5730.000000	53.000000	51.000000	49.280000	111
362	363	12	5690.000000	23.000000	51.000000	49.280000	5000
363	364	12	5650.000000	61.000000	50.000000	46.580000	3704
364	365	12	5550.000000	85.000000	39.000000	41.000000	5000
365	366	12	5752.966102	68.000000	37.000000	56.846344	5000

366 rows × 10 columns

The most important features were found to be 'Unnamed: 0', 'V1', 'V5', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12' and 'V13'

In [18]:

```
#call transform() on X to filter it down to selected features
X_filtered = feat_selector.transform(X)
X_filtered.shape
```

Out[18]:

```
(366, 10)
```

In [19]:

```
X_filtered_df = pd.DataFrame(X_filtered)
```

Dataset after transofrming to the selected features

Perfect, it looks exactly like the expected results! (compared to the one before transforming)

In [20]:

```
X_filtered_df
```

Out[20]:

	0	1	2	3	4	5	
0	1.0	1.0	5480.000000	20.000000	61.914835	56.846344	5000.00
1	2.0	1.0	5660.000000	58.475783	38.000000	56.846344	2590.94
2	3.0	1.0	5710.000000	28.000000	40.000000	56.846344	2693.00
3	4.0	1.0	5700.000000	37.000000	45.000000	56.846344	590.00
4	5.0	1.0	5760.000000	51.000000	54.000000	45.320000	1450.00
...	...	...	...	...	...	...	
361	362.0	12.0	5730.000000	53.000000	51.000000	49.280000	111.00
362	363.0	12.0	5690.000000	23.000000	51.000000	49.280000	5000.00
363	364.0	12.0	5650.000000	61.000000	50.000000	46.580000	3704.00
364	365.0	12.0	5550.000000	85.000000	39.000000	41.000000	5000.00
365	366.0	12.0	5752.966102	68.000000	37.000000	56.846344	5000.00

366 rows × 10 columns

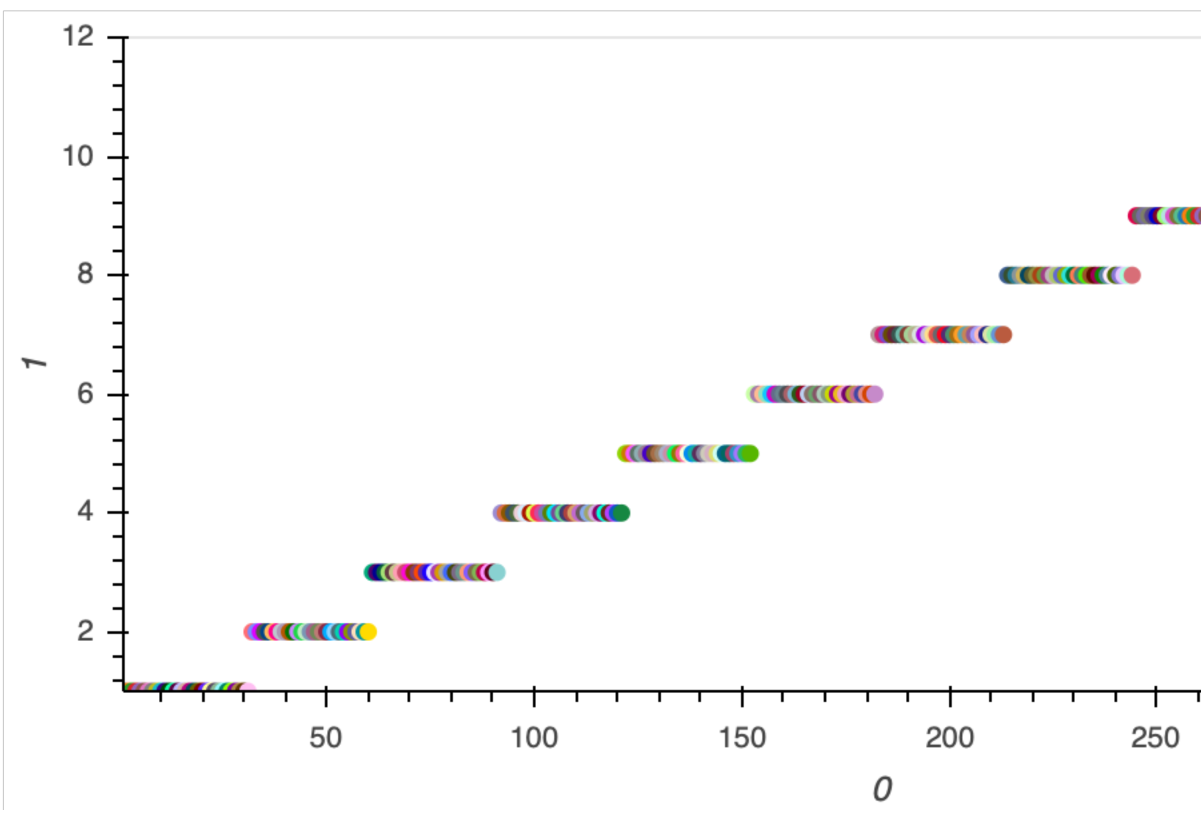
Let's check how the boruta model has changed the distribution of the 10 variables with HvPlot

In [21]:

```
import hvplot.pandas
import holoviews as hv

(X_filtered_df.hvplot(kind='scatter', x='0', y='1', by='0') + X_
filtered_df.hvplot(kind='scatter', x='0', y='1', by='1') + X_fil
tered_df.hvplot(kind='scatter', x='0', y='1', by='1'))
```

Out[21]:



In [24]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn import ensemble

X = imp_df
Y= df.V4
```

In [25]:

```
df_rf_clf = ensemble.RandomForestClassifier(n_estimators=23)
df_rf_clf.fit(X,Y)
```

Out[25]:

```
RandomForestClassifier(bootstrap=True, class_weight=
None, criterion='gini',
                       max_depth=None, max_features=
'auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, mi
n_impurity_split=None,
                       min_samples_leaf=1, min_sampl
es_split=2,
                       min_weight_fraction_leaf=0.0,
n_estimators=23,
                       n_jobs=None, oob_score=False,
random_state=None,
                       verbose=0, warm_start=False)
```

In [26]:

```
predictions = df_rf_clf.predict(X)
```

Predictions For "Ozone" Variable:

In [28]:

```
predictions
```

Out[28]:

```
array([ 3.,  3.,  3.,  5.,  5.,  6.,  4.,  4.,  6.,
7.,  4.,  6.,  5.,
         4.,  4.,  7.,  5.,  9.,  4.,  3.,  4.,  4.,
5.,  6.,  9.,  5.,
         6.,  6.,  6., 11., 10.,  7., 12.,  9.,  2.,
3.,  3.,  2.,  3.,
         3.,  4.,  6.,  8.,  6.,  4.,  3.,  7., 11.,
13.,  4.,  6.,  5.,
         4.,  4.,  6., 10., 15., 23., 17.,  7.,  2.,
3.,  3.,  5.,  4.,
         6.,  7.,  7.,  6.,  3.,  2.,  8., 12., 12.,
16.,  9., 24., 13.,
         8., 10.,  8.,  9., 10., 13., 14.,  9., 11.,
7.,  9., 12., 12.,
         8.,  9.,  5.,  4.,  4.,  9., 13.,  5., 10.,
10.,  7.,  5.,  4.,
         7.,  3.,  3.,  7., 11., 15., 22., 17.,  7.,
10., 19., 18., 12.,
         6.,  9., 19., 21., 29., 16.,  5., 11.,  2.,
2., 12., 16., 22.,
        20., 27., 33., 25., 31., 18., 16., 24., 16.,
12.,  9., 12., 16.,
        12.,  8.,  9., 29., 20.,  5.,  5., 11., 12.,
19., 17., 19., 16.,
        14., 10.,  9.,  7.,  5.,  2., 12., 22., 17.,
26., 27., 14., 11.,
        23., 26., 21., 15., 20., 15., 18., 26., 19.,
13., 30., 26., 15.,
        16., 16., 19., 23., 28., 34., 33., 12., 24.,
17., 10., 14., 13.,
        17., 15., 22., 19., 20., 25., 28., 29., 12.,
23., 26., 14., 13.,
        26., 22., 11., 15., 14., 13.,  9., 12., 15.,
12., 15., 25., 18.,
        14., 22., 24., 19., 16.,  7.,  2.,  4.,  6.,
12.,  9., 15., 17.,
        13., 20., 22., 24., 26., 32., 33., 27., 38.,
23., 19., 19., 15.,
        28., 10., 14., 26., 17.,  3.,  2.,  3., 14.,
29., 18.,  3.,  7.,
         9., 19.,  8., 12., 23., 13., 12.,  7.,  3.,
5., 11., 12.,  5.,
         4.,  5.,  4., 10., 17., 26., 30., 18., 12.,
7., 15., 12.,  7.,
```

```
        28., 22., 18., 14., 24., 10., 14.,  9., 12.,
7.,  7.,  6., 13.,
         5.,  3.,  7.,  8., 10., 12.,  7.,  5.,  6.,
4.,  5., 11., 20.,
         4., 14., 16.,  5.,  3.,  5.,  1.,  5.,  4.,
11.,  6.,  8., 14.,
        18., 12.,  9.,  7., 14.,  4.,  3.,  3.,  3.,
3.,  3.,  3.,  3.,
         6.,  6.,  5.,  3.,  4.,  7.,  5.,  5.,  4.,
3.,  2.,  5.,  3.,
         4.,  4.,  6.,  6.,  3.,  4.,  3.,  8.,  5.,
3.,  2.,  3.,  5.,
         1.,  2.])
```

In [ ]:

```

```