In [1]:

```
"""
ECGR 5105 - Intro to Machine Learning
Homework 4 - Part 1
Phillip Harmon
"""
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:

```
#Load and Build the Dataset
from sklearn.datasets import load_breast_cancer

loaded  = load_breast_cancer()

labels  = np.reshape(loaded.target, (len(loaded.target),1))
inputs  = pd.DataFrame(loaded.data)
names   = np.append(loaded.feature_names, 'label')

dataset = pd.DataFrame(np.concatenate([inputs,labels],axis=1))
dataset.columns = names

dataset
```

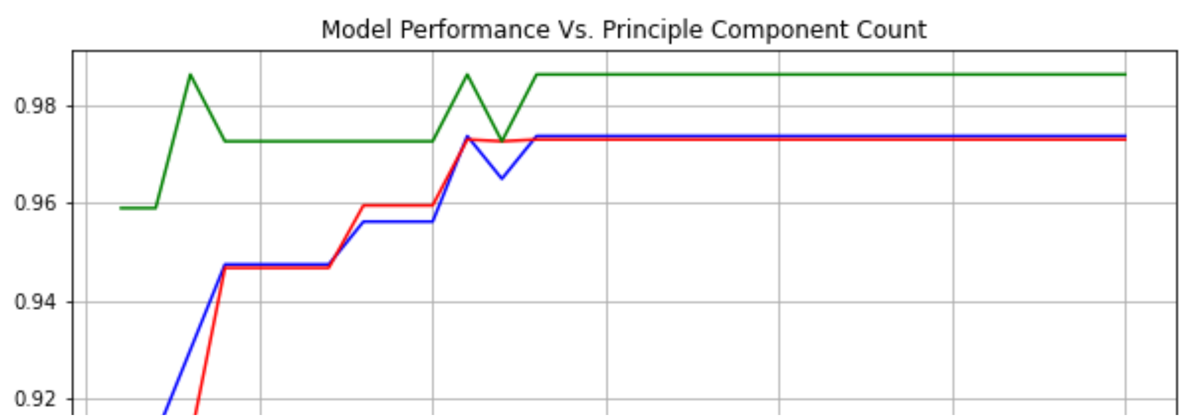
Out[2]:

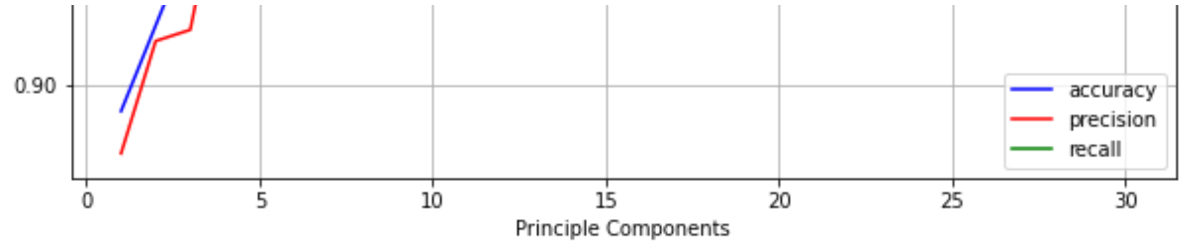
| | mean radius | mean texture | mean perimeter | mean area | mean smoothness | mean compactness | mean concavity | mean concave points | mea symmetr |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 17.99 | 10.38 | 122.80 | 1001.0 | 0.11840 | 0.27760 | 0.30010 | 0.14710 | 0.241 |
| **1** | 20.57 | 17.77 | 132.90 | 1326.0 | 0.08474 | 0.07864 | 0.08690 | 0.07017 | 0.181 |
| **2** | 19.69 | 21.25 | 130.00 | 1203.0 | 0.10960 | 0.15990 | 0.19740 | 0.12790 | 0.206 |
| **3** | 11.42 | 20.38 | 77.58 | 386.1 | 0.14250 | 0.28390 | 0.24140 | 0.10520 | 0.259 |
| **4** | 20.29 | 14.34 | 135.10 | 1297.0 | 0.10030 | 0.13280 | 0.19800 | 0.10430 | 0.180 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | . |
| **564** | 21.56 | 22.39 | 142.00 | 1479.0 | 0.11100 | 0.11590 | 0.24390 | 0.13890 | 0.172 |
| **565** | 20.13 | 28.25 | 131.20 | 1261.0 | 0.09780 | 0.10340 | 0.14400 | 0.09791 | 0.175 |
| **566** | 16.60 | 28.08 | 108.30 | 858.1 | 0.08455 | 0.10230 | 0.09251 | 0.05302 | 0.159 |
| **567** | 20.60 | 29.33 | 140.10 | 1265.0 | 0.11780 | 0.27700 | 0.35140 | 0.15200 | 0.239 |
| **568** | 7.76 | 24.54 | 47.92 | 181.0 | 0.05263 | 0.04362 | 0.00000 | 0.00000 | 0.158 |

569 rows × 31 columns

In [3]:
```
#Sort and clean the Dataset
from sklearn.preprocessing import MinMaxScaler, StandardScaler

x = dataset.iloc[:,0:-1].values
y = dataset.iloc[:,-1].values

scaler = MinMaxScaler()
x = scaler.fit_transform(x)
```

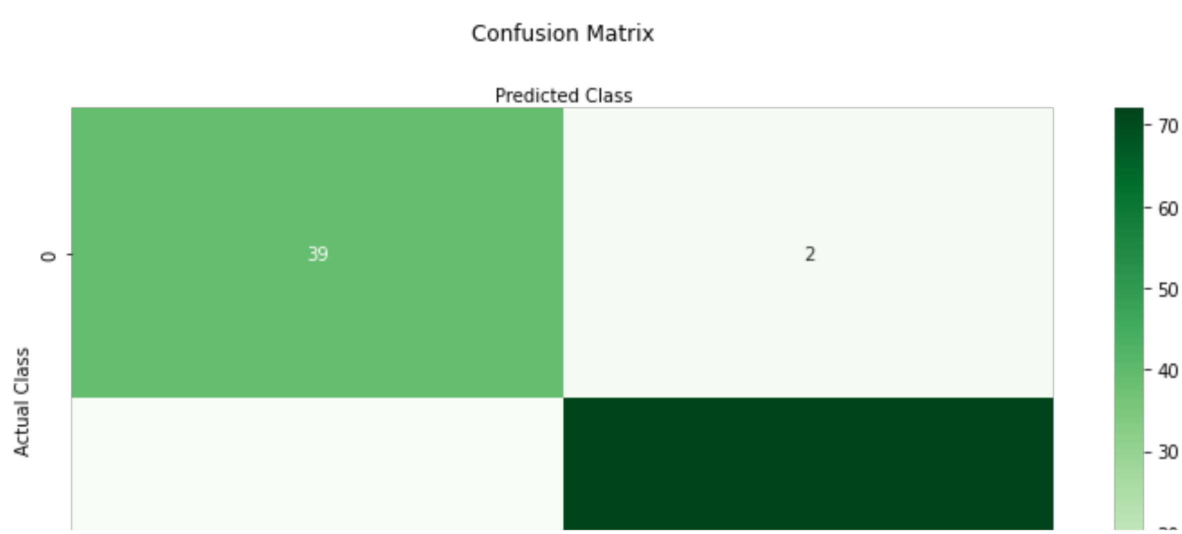
In [4]:
```
#Explore Default SVC with A range of PCA Component Counts
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, cla

frameLog = []
modelLog = []
accuracyLog = []
precisionLog = []
recallLog = []
cols = []
maxPC = len(x[0])+1

for k in range(1,maxPC):

    pca = PCA(n_components = k)
    pcs = pca.fit_transform(x)
    cols.append('PC'+str(k))
    pcFrame = pd.DataFrame(data=pcs,columns=cols)
    frameLog.append(pcFrame)

    xt, xv, yt, yv = train_test_split(pcFrame, y,
                                      train_size = 0.8, test_size = 0.2,
                                      random_state=1337)

    model = SVC(random_state=1337)
    model.fit(xt,yt)
    modelLog.append(model)

    yp = model.predict(xv)
    accuracyLog.append(accuracy_score(yv,yp))
    precisionLog.append(precision_score(yv,yp))
    recallLog.append(recall_score(yv,yp))

plt.rcParams["figure.figsize"] = (10,5)
plt.grid()
plt.xlabel('Principle Components')
plt.title('Model Performance Vs. Principle Component Count')
plt.plot(range(1,maxPC),accuracyLog,color='blue',label='accuracy')
plt.plot(range(1,maxPC),precisionLog,color='red',label='precision')
plt.plot(range(1,maxPC),recallLog,color='green',label='recall')
plt.legend();
```




0.90
accuracy
precision
recall
0
5
10
15
20
25
30
Principle Components

In [5]:
```
#Print Best Results
K = accuracyLog.index(max(accuracyLog))
print("According to the plot above, the highest accuracy occurs at a lowest di
xt, xv, yt, yv = train_test_split(frameLog[K], y,train_size = 0.8, test_size =
yp = modelLog[K].predict(xv)
print("Classification Report for K={}".format(K+1))
print("------------------------------------------------------")
print(classification_report(yv,yp))

#Analyze using the Confusion Matrix
import seaborn as sns
classes = ['Benign','Malignant']
figure, axis = plt.subplots()
ticks = np.arange(len(classes))
plt.xticks(ticks, classes)
plt.yticks(ticks, classes)
sns.heatmap(pd.DataFrame(confusion_matrix(yv,yp)),
            annot=True, cmap="Greens", fmt='g')
axis.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion Matrix', y=1.1)
plt.ylabel('Actual Class')
plt.xlabel('Predicted Class')
plt.show()
```

```
According to the plot above, the highest accuracy occurs at a lowest dimensio
nality of K=11


Classification Report for K=11
------------------------------------------------------
              precision    recall  f1-score   support

         0.0       0.97      0.95      0.96        41
         1.0       0.97      0.99      0.98        73

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```




In [6]:

```
#Refresh the Dataset
x = dataset.iloc[:,0:-1].values
y = dataset.iloc[:,-1].values

scaler = MinMaxScaler()
x = scaler.fit_transform(x)
```

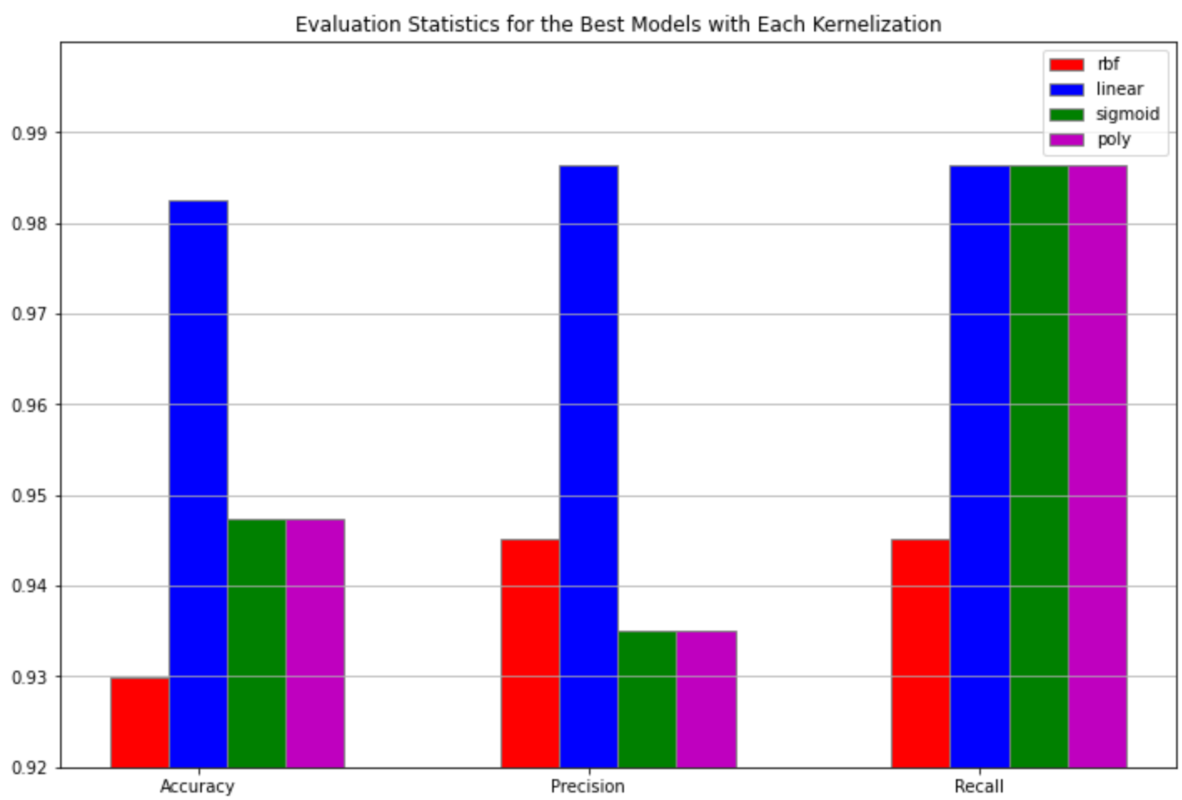
In [7]:
```
#Now to explore different Kernelizations and parameters
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV

kernels = ['rbf','linear','sigmoid','poly']

parameters = {
    'pca__n_components' : range(1,len(x[0])+1),
    'svc__C'            : [1,2,3,4,5,6,7,8,9,10],
    'svc__gamma'        : [0.000001,0.00001,0.0001,0.001,'auto','scale']
}

pca = PCA(random_state=1337)

modelLog = dict()
accuracyLog = dict()
precisionLog = dict()
recallLog = dict()

for colonel in kernels:
    svc = SVC(kernel=colonel, random_state=1337)
    pipeline = make_pipeline(pca,svc)

    grid = GridSearchCV(pipeline,parameters)

    print("\n===============================================================
    print("Searching a variety of Parameters to find the best model with {}-ty
    %time grid.fit(xt,yt)
    print("\nBest model among all parameter options for {}-type kernelization:
    print(grid.best_params_)

    yp = grid.predict(xv)
    print("\nReport for Best Model Found for {}-type kernelization:".format(co
    print("------------------------------------------------------")
    print(classification_report(yv,yp))
    print("Confusion Matrix:")
    print(confusion_matrix(yv,yp))

    modelLog[colonel] = grid
    accuracyLog[colonel] = accuracy_score(yv,yp)
    precisionLog[colonel] = precision_score(yv,yp)
    recallLog[colonel] = recall_score(yv,yp)
```

```
=============================================================================
==============================
Searching a variety of Parameters to find the best model with rbf-type kernel
ization...

Wall time: 1min 36s

Best model among all parameter options for rbf-type kernelization:
{'pca__n_components': 7, 'svc__C': 7, 'svc__gamma': 'scale'}

Report for Best Model Found for rbf-type kernelization:
------------------------------------------------------
```

```
              precision    recall  f1-score   support

         0.0       0.90      0.90      0.90        41
         1.0       0.95      0.95      0.95        73

    accuracy                           0.93       114
   macro avg       0.92      0.92      0.92       114
weighted avg       0.93      0.93      0.93       114

Confusion Matrix:
[[37  4]
 [ 4 69]]

=============================================================================
==============================
Searching a variety of Parameters to find the best model with linear-type ker
nelization...

Wall time: 42.8 s

Best model among all parameter options for linear-type kernelization:
{'pca__n_components': 8, 'svc__C': 3, 'svc__gamma': 1e-06}

Report for Best Model Found for linear-type kernelization:
------------------------------------------------------
              precision    recall  f1-score   support

         0.0       0.98      0.98      0.98        41
         1.0       0.99      0.99      0.99        73

    accuracy                           0.98       114
   macro avg       0.98      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114

Confusion Matrix:
[[40  1]
 [ 1 72]]

=============================================================================
==============================
Searching a variety of Parameters to find the best model with sigmoid-type ke
rnelization...

Wall time: 1min 16s

Best model among all parameter options for sigmoid-type kernelization:
{'pca__n_components': 10, 'svc__C': 7, 'svc__gamma': 'auto'}

Report for Best Model Found for sigmoid-type kernelization:
------------------------------------------------------
              precision    recall  f1-score   support

         0.0       0.97      0.88      0.92        41
         1.0       0.94      0.99      0.96        73

    accuracy                           0.95       114
```

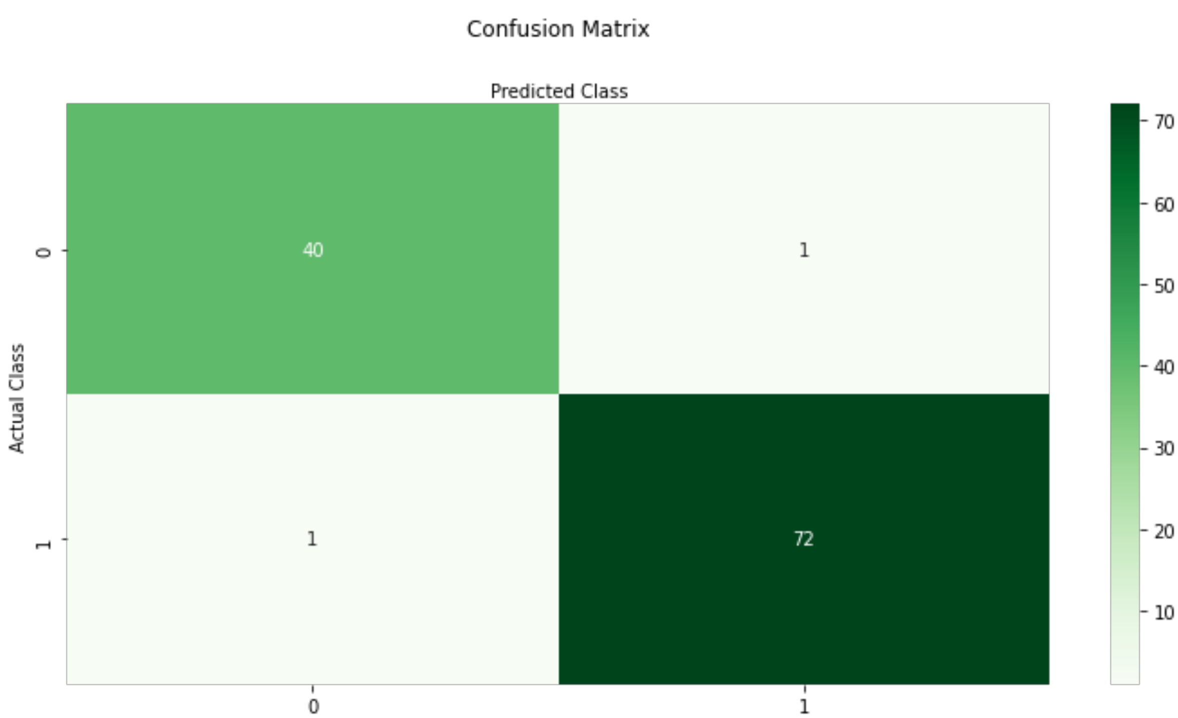
```
   macro avg       0.95      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

Confusion Matrix:
[[36  5]
 [ 1 72]]

============================================================================
==============================
Searching a variety of Parameters to find the best model with poly-type kerne
lization...

Wall time: 1min 8s

Best model among all parameter options for poly-type kernelization:
{'pca__n_components': 8, 'svc__C': 10, 'svc__gamma': 'scale'}

Report for Best Model Found for poly-type kernelization:
------------------------------------------------------
              precision    recall  f1-score   support

         0.0       0.97      0.88      0.92        41
         1.0       0.94      0.99      0.96        73

    accuracy                           0.95       114
   macro avg       0.95      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

Confusion Matrix:
[[36  5]
 [ 1 72]]
```

In [8]:
```
#Plot the results
w = 0.15
fig = plt.subplots(figsize = (12,8))

rbf = [accuracyLog['rbf'],precisionLog['rbf'],recallLog['rbf']]
linear = [accuracyLog['linear'],precisionLog['linear'],recallLog['linear']]
sigmoid = [accuracyLog['sigmoid'],precisionLog['sigmoid'],recallLog['sigmoid']
poly = [accuracyLog['poly'],precisionLog['poly'],recallLog['poly']]

br1 = np.arange(len(rbf))
br2 = [wx + w for wx in br1]
br3 = [wx + w for wx in br2]
br4 = [wx + w for wx in br3]

plt.bar(br1, rbf, color='r', width=w, edgecolor='grey', label='rbf')
plt.bar(br2, linear, color='b', width=w, edgecolor='grey', label='linear')
plt.bar(br3, sigmoid, color='g', width=w, edgecolor='grey', label='sigmoid')
plt.bar(br4, poly, color='m', width=w, edgecolor='grey', label='poly')

plt.xticks([wx + w for wx in range(len(rbf))], ['Accuracy', 'Precision', 'Reca
yscale = 100
ylims = [int(yscale*min(accuracyLog.values())),yscale]
ytick = range(ylims[0],ylims[1])
plt.yticks([i/yscale for i in ytick])
plt.legend()
plt.title("Evaluation Statistics for the Best Models with Each Kernelization")
plt.ylim((ylims[0]/yscale,ylims[1]/yscale))
plt.grid(axis='y')
plt.show()
```



In [10]:
```python
#Best model Analysis
model = modelLog['linear']

print("Classification Report")
print("-------------------------------------------------------")
print(classification_report(yv,model.predict(xv)))

#Analyze using the Confusion Matrix
classes = ['Benign','Malignant']
figure, axis = plt.subplots()
ticks = np.arange(len(classes))
plt.xticks(ticks, classes)
plt.yticks(ticks, classes)
sns.heatmap(pd.DataFrame(confusion_matrix(yv,model.predict(xv))),
            annot=True, cmap="Greens", fmt='g')
axis.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion Matrix', y=1.1)
plt.ylabel('Actual Class')
plt.xlabel('Predicted Class');
```

```
Classification Report
-------------------------------------------------------
              precision    recall  f1-score   support

         0.0       0.98      0.98      0.98        41
         1.0       0.99      0.99      0.99        73

    accuracy                           0.98       114
   macro avg       0.98      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114
```



In [ ]:

In [1]:
```
"""
ECGR 5105 - Intro to Machine Learning
Homework 4 - Part 2
Phillip Harmon
"""
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
#Read in the CSV into a dataframe
csvData = pd.read_csv("./Housing.csv")

csvCols = len(csvData.columns)
csvRows = len(csvData)

dataLabels = ['price','area','bedrooms','bathrooms','stories','parking']
data = csvData[dataLabels]

boolLabels = ['mainroad','guestroom','basement','hotwaterheating','airconditio
boolData = csvData[boolLabels]

def yn_bool_convert(val):
    return val.map({ "yes" : 1 , "no" : 0 })

boolData = boolData.apply(yn_bool_convert)

dataset = pd.concat([data,boolData],axis=1,join='outer')

dataset
```

Out[2]:

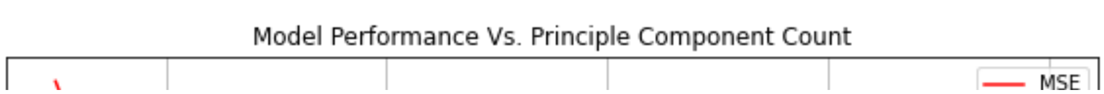
| | price | area | bedrooms | bathrooms | stories | parking | mainroad | guestroom | basement |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 13300000 | 7420 | 4 | 2 | 3 | 2 | 1 | 0 | 0 |
| **1** | 12250000 | 8960 | 4 | 4 | 4 | 3 | 1 | 0 | 0 |
| **2** | 12250000 | 9960 | 3 | 2 | 2 | 2 | 1 | 0 | 1 |
| **3** | 12215000 | 7500 | 4 | 2 | 2 | 3 | 1 | 0 | 1 |
| **4** | 11410000 | 7420 | 4 | 1 | 2 | 2 | 1 | 1 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **540** | 1820000 | 3000 | 2 | 1 | 1 | 2 | 1 | 0 | 1 |
| **541** | 1767150 | 2400 | 3 | 1 | 1 | 0 | 0 | 0 | 0 |
| **542** | 1750000 | 3620 | 2 | 1 | 1 | 0 | 1 | 0 | 0 |
| **543** | 1750000 | 2910 | 3 | 1 | 1 | 0 | 0 | 0 | 0 |
| **544** | 1750000 | 3850 | 3 | 1 | 2 | 0 | 1 | 0 | 0 |

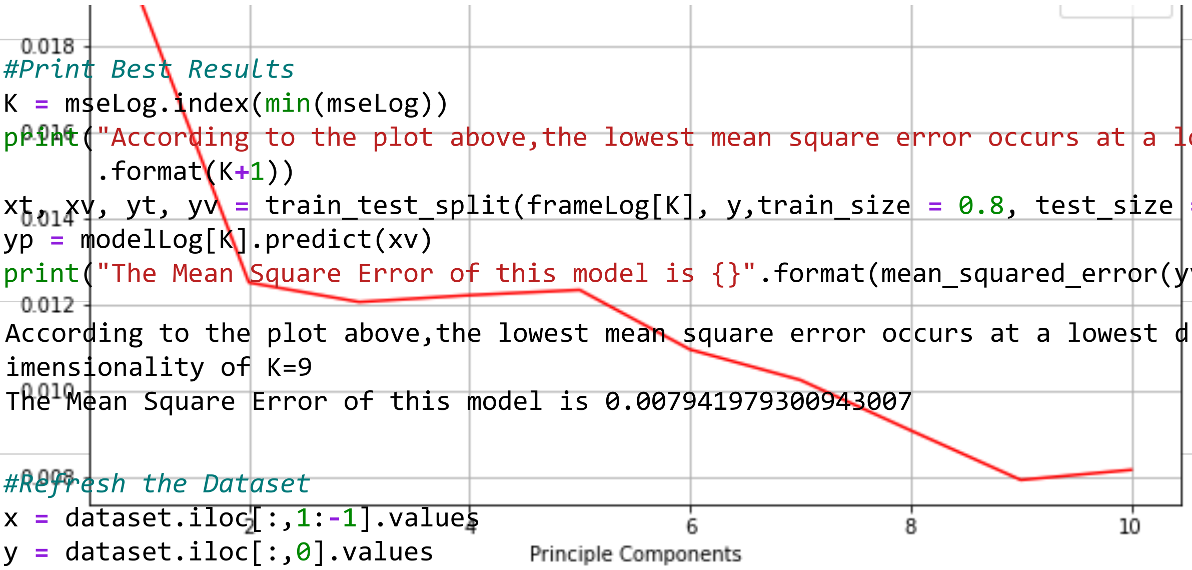
545 rows × 12 columns

In [13]:
```
#Sort and clean the Dataset
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split

x = dataset.iloc[:,1:-1].values
y = dataset.iloc[:,0].values

scaler = MinMaxScaler()
x = scaler.fit_transform(x)
y = scaler.fit_transform(y.reshape(len(y),1))
```

In [14]:
```
#Explore Default SVC with A range of PCA Component Counts
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error

frameLog = []
modelLog = []
ypLog = []
cols = []
mseLog = []
maxPC = len(x[0])+1

for k in range(1,maxPC):

    pca = PCA(n_components = k)
    pcs = pca.fit_transform(x)
    cols.append('PC'+str(k))
    pcFrame = pd.DataFrame(data=pcs,columns=cols)
    frameLog.append(pcFrame)

    xt, xv, yt, yv = train_test_split(pcFrame, y,
                                      train_size = 0.8, test_size = 0.2,
                                      random_state=1337)

    model = SVR()
    model.fit(xt,yt.reshape(len(yt)));
    modelLog.append(model)

    yp = model.predict(xv)
    ypLog.append(yp)
    mse = mean_squared_error(yv,yp)
    mseLog.append(mse)
    print("Mean Square Error for k={} : {}".format(k,mse))

plt.rcParams["figure.figsize"] = (10,5)
plt.grid()
plt.xlabel('Principle Components')
plt.title('Model Performance Vs. Principle Component Count')
plt.plot(range(1,maxPC),mseLog,color='red',label='MSE')
plt.legend()
plt.show()
```

```
Mean Square Error for k=1 : 0.019142182400062203
Mean Square Error for k=2 : 0.012508623252327536
Mean Square Error for k=3 : 0.012057577267394445
Mean Square Error for k=4 : 0.012215030504956328
Mean Square Error for k=5 : 0.012336924027756229
Mean Square Error for k=6 : 0.010958769375877015
Mean Square Error for k=7 : 0.010254626182776064
Mean Square Error for k=8 : 0.009088906999969016
Mean Square Error for k=9 : 0.007941979300943007
Mean Square Error for k=10 : 0.008175404555258076
```






In [15]:
```
#Print Best Results
K = mseLog.index(min(mseLog))
print("According to the plot above,the lowest mean square error occurs at a lo
      .format(K+1))
xt, xv, yt, yv = train_test_split(frameLog[K], y,train_size = 0.8, test_size =
yp = modelLog[K].predict(xv)
print("The Mean Square Error of this model is {}".format(mean_squared_error(yv
```

```
According to the plot above,the lowest mean square error occurs at a lowest d
imensionality of K=9
The Mean Square Error of this model is 0.007941979300943007
```

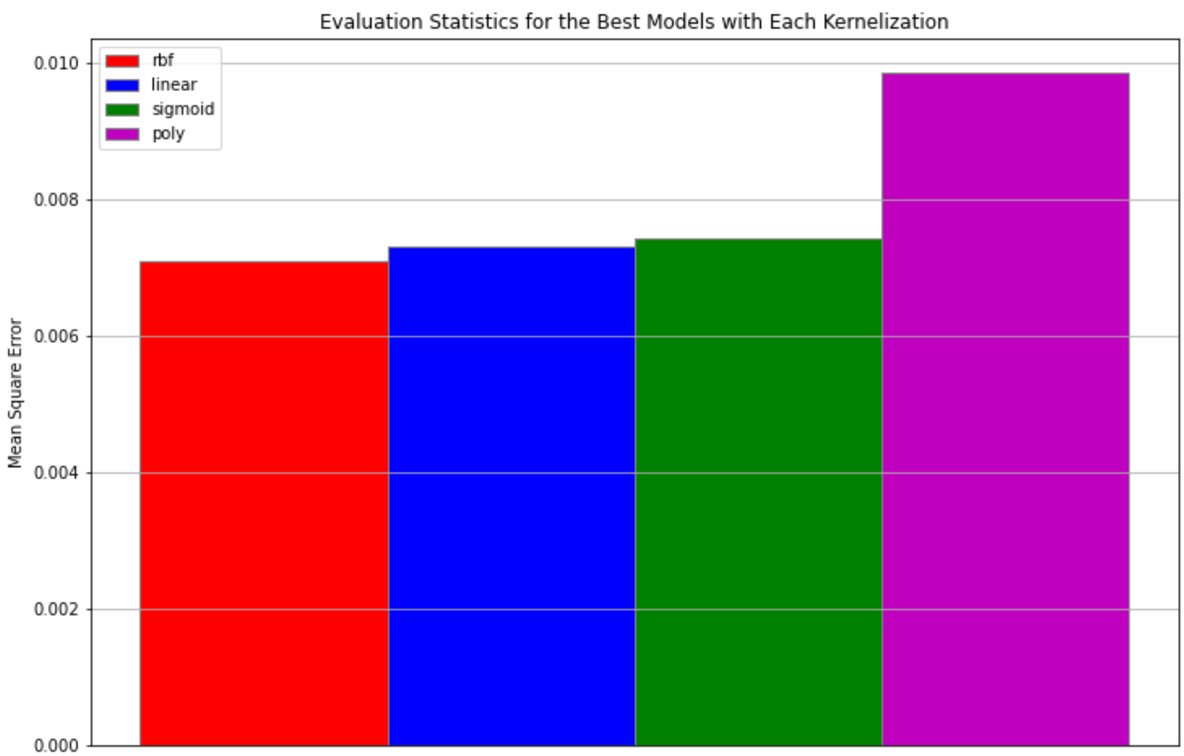
In [25]:
```
#Refresh the Dataset
x = dataset.iloc[:,1:-1].values
y = dataset.iloc[:,0].values

scaler = MinMaxScaler()
x = scaler.fit_transform(x)
y = scaler.fit_transform(y.reshape(len(y),1))

xt, xv, yt, yv = train_test_split(x, y,train_size = 0.8, test_size = 0.2,rando
```

In [26]:
```
#Now to explore different Kernelizations and parameters
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV, learning_curve
from sklearn.metrics import r2_score

kernels = ['rbf','linear','sigmoid','poly']

parameters = {
    'pca__n_components' : range(1,len(x[0])+1),
    'svr__C'            : [1,2,3,4,5,6,7,8,9,10],
    'svr__gamma'        : [0.000001,0.00001,0.0001,0.001,'auto','scale']
}

pca = PCA(random_state=1337)

modelLog = dict()
mseLog = dict()

for colonel in kernels:
    svr = SVR(kernel=colonel)
    pipeline = make_pipeline(pca,svr)

    grid = GridSearchCV(pipeline,parameters)

    print("\n===============================================================
    print("Searching a variety of Parameters to find the best model with {}-ty
    %time grid.fit(xt,yt.reshape(len(yt)))
    print("\nBest model among all parameter options for {}-type kernelization:
    print(grid.best_params_)

    yp = grid.predict(xv)
    mse = mean_squared_error(yv,yp)
    mseLog[colonel] = mse
    print("MSE Value for {}-type kernelization is {}".format(colonel,mse))

    modelLog[colonel] = grid
```

```
==============================================================================
==============================
Searching a variety of Parameters to find the best model with rbf-type kernel
ization...

Wall time: 22.4 s

Best model among all parameter options for rbf-type kernelization:
{'pca__n_components': 10, 'svr__C': 1, 'svr__gamma': 'auto'}
MSE Value for rbf-type kernelization is 0.0071054664994934175

==============================================================================
==============================
Searching a variety of Parameters to find the best model with linear-type ker
nelization...

Wall time: 31.7 s
```

```
Best model among all parameter options for linear-type kernelization:
{'pca__n_components': 10, 'svr__C': 1, 'svr__gamma': 1e-06}
MSE Value for linear-type kernelization is 0.007316419318936263

================================================================================
==============================
Searching a variety of Parameters to find the best model with sigmoid-type ke
rnelization...

Wall time: 24.6 s

Best model among all parameter options for sigmoid-type kernelization:
{'pca__n_components': 10, 'svr__C': 3, 'svr__gamma': 'auto'}
MSE Value for sigmoid-type kernelization is 0.007431607456766796

================================================================================
==============================
Searching a variety of Parameters to find the best model with poly-type kerne
lization...

Wall time: 25.3 s

Best model among all parameter options for poly-type kernelization:
{'pca__n_components': 8, 'svr__C': 10, 'svr__gamma': 'auto'}
MSE Value for poly-type kernelization is 0.009865793251773653
```

In [35]:
```
#Plot the results
w = 0.1
fig = plt.subplots(figsize = (12,8))

plt.bar(0, mseLog['rbf'], color='r', width=w, edgecolor='grey', label='rbf')
plt.bar(0.1, mseLog['linear'], color='b', width=w, edgecolor='grey', label='li
plt.bar(0.2, mseLog['sigmoid'], color='g', width=w, edgecolor='grey', label='s
plt.bar(0.3, mseLog['poly'], color='m', width=w, edgecolor='grey', label='poly

plt.tick_params(
    axis='x',          # changes apply to the x-axis
    which='both',      # both major and minor ticks are affected
    bottom=False,      # ticks along the bottom edge are off
    top=False,         # ticks along the top edge are off
    labelbottom=False) # labels along the bottom edge are off
plt.ylabel("Mean Square Error")
plt.legend()
plt.title("Evaluation Statistics for the Best Models with Each Kernelization")
plt.grid(axis='y')
```




In [ ]: