In [1]:
```
"""
ECGR 5105 - Intro to Machine Learning
Homework 4 - Part 2
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"""
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]:

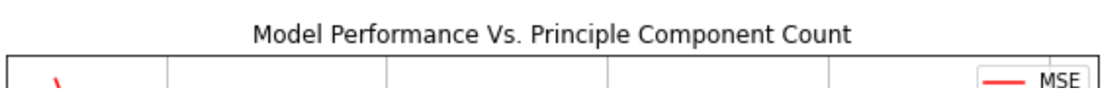
	price	area	bedrooms	bathrooms	stories	parking	mainroad	guestroom	basement
0	13300000	7420	4	2	3	2	1	0	0
1	12250000	8960	4	4	4	3	1	0	0
2	12250000	9960	3	2	2	2	1	0	1
3	12215000	7500	4	2	2	3	1	0	1
4	11410000	7420	4	1	2	2	1	1	1
...	...	...	...	...	...	...	...	...	...
540	1820000	3000	2	1	1	2	1	0	1
541	1767150	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

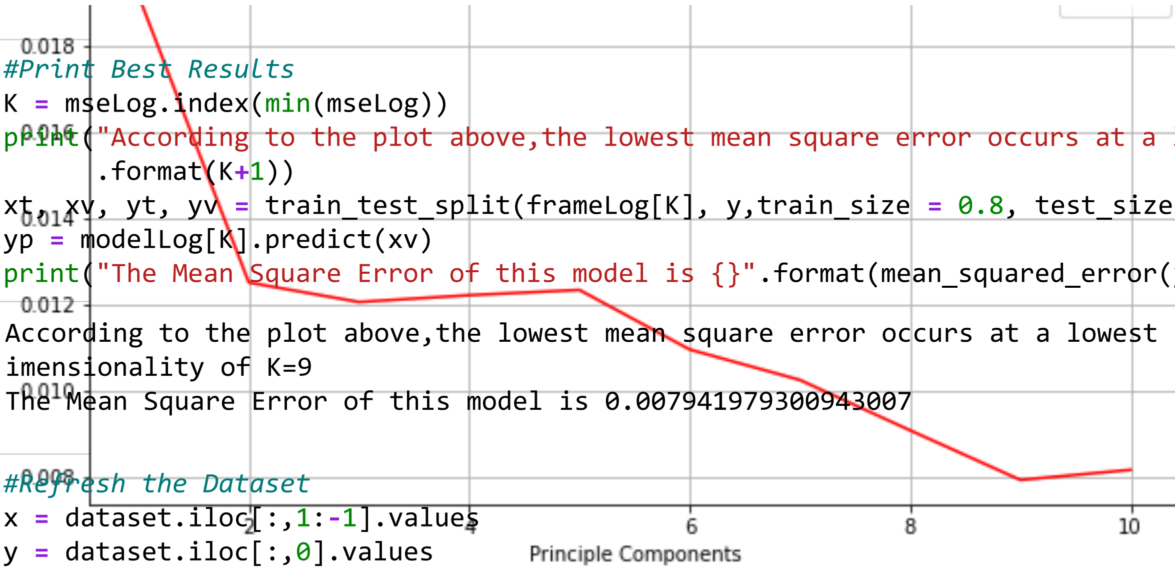
545 rows × 12 columns

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]:
```python
#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
```

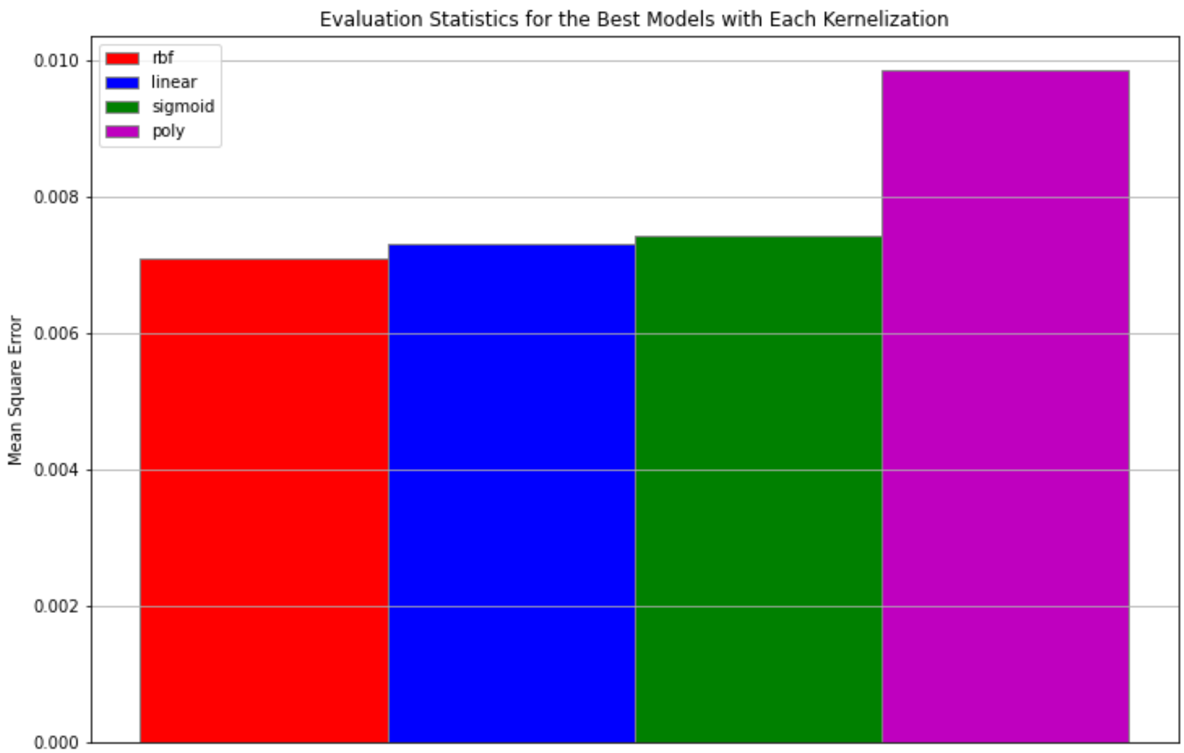
In [25]:
```
#Refresh the Dataset
x = dataset.iloc[:,1:-1].values
y = dataset.iloc[:,0].values

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 [ ]: