ECGR_4105_HW4

November 4, 2022

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns; sns.set()
from scipy import stats
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn import datasets
from sklearn.preprocessing import Normalizer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.metrics import classification_report
from sklearn.datasets import load_breast_cancer
from sklearn.svm import SVC
from sklearn.metrics import precision_recall_curve
```

[2]:
```
cancer = load_breast_cancer()
```

[3]:
```
cancer_data = cancer.data
cancer_data.shape
```

[3]:
```
(569, 30)
```

[4]:
```
cancer_input = pd.DataFrame(cancer_data)
cancer_input.head()
```

[4]:
```
       0      1       2       3        4        5       6        7       8  \
0  17.99  10.38  122.80  1001.0  0.11840  0.27760  0.3001  0.14710  0.2419
1  20.57  17.77  132.90  1326.0  0.08474  0.07864  0.0869  0.07017  0.1812
2  19.69  21.25  130.00  1203.0  0.10960  0.15990  0.1974  0.12790  0.2069
3  11.42  20.38   77.58   386.1  0.14250  0.28390  0.2414  0.10520  0.2597
4  20.29  14.34  135.10  1297.0  0.10030  0.13280  0.1980  0.10430  0.1809

         9  …     20     21      22      23      24      25      26      27  \
0  0.07871  …  25.38  17.33  184.60  2019.0  0.1622  0.6656  0.7119  0.2654
```

```
1  0.05667  …  24.99  23.41  158.80  1956.0  0.1238  0.1866  0.2416  0.1860
2  0.05999  …  23.57  25.53  152.50  1709.0  0.1444  0.4245  0.4504  0.2430
3  0.09744  …  14.91  26.50   98.87   567.7  0.2098  0.8663  0.6869  0.2575
4  0.05883  …  22.54  16.67  152.20  1575.0  0.1374  0.2050  0.4000  0.1625

       28       29
0  0.4601  0.11890
1  0.2750  0.08902
2  0.3613  0.08758
3  0.6638  0.17300
4  0.2364  0.07678

[5 rows x 30 columns]
```

[5]:
```
cancer_labels = cancer.target
```

[6]:
```
cancer_labels.shape
```

[6]: (569,)

[7]:
```
labels = np.reshape(cancer_labels, (569,1))
```

[8]:
```
final_cancer_data = np.concatenate([cancer_data,labels],axis=1)
```

[9]:
```
final_cancer_data.shape
```

[9]: (569, 31)

[10]:
```
cancer_dataset = pd.DataFrame(final_cancer_data)
```

[11]:
```
features = cancer.feature_names
features
```

[11]:
```
array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimension',
       'radius error', 'texture error', 'perimeter error', 'area error',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error',
       'fractal dimension error', 'worst radius', 'worst texture',
       'worst perimeter', 'worst area', 'worst smoothness',
       'worst compactness', 'worst concavity', 'worst concave points',
       'worst symmetry', 'worst fractal dimension'], dtype='<U23')
```

[12]:
```
features_labels = np.append(features, 'label')
```

[13]:
```
cancer_dataset.columns = features_labels
```

[14]:

```
cancer_dataset.head()
```

[14]:

```
   mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
0        17.99         10.38          122.80     1001.0          0.11840
1        20.57         17.77          132.90     1326.0          0.08474
2        19.69         21.25          130.00     1203.0          0.10960
3        11.42         20.38           77.58      386.1          0.14250
4        20.29         14.34          135.10     1297.0          0.10030

   mean compactness  mean concavity  mean concave points  mean symmetry  \
0           0.27760          0.3001              0.14710         0.2419
1           0.07864          0.0869              0.07017         0.1812
2           0.15990          0.1974              0.12790         0.2069
3           0.28390          0.2414              0.10520         0.2597
4           0.13280          0.1980              0.10430         0.1809

   mean fractal dimension  …  worst texture  worst perimeter  worst area  \
0                 0.07871  …          17.33           184.60      2019.0
1                 0.05667  …          23.41           158.80      1956.0
2                 0.05999  …          25.53           152.50      1709.0
3                 0.09744  …          26.50            98.87       567.7
4                 0.05883  …          16.67           152.20      1575.0

   worst smoothness  worst compactness  worst concavity  worst concave points  \
0            0.1622             0.6656           0.7119                0.2654
1            0.1238             0.1866           0.2416                0.1860
2            0.1444             0.4245           0.4504                0.2430
3            0.2098             0.8663           0.6869                0.2575
4            0.1374             0.2050           0.4000                0.1625

   worst symmetry  worst fractal dimension  label
0          0.4601                  0.11890    0.0
1          0.2750                  0.08902    0.0
2          0.3613                  0.08758    0.0
3          0.6638                  0.17300    0.0
4          0.2364                  0.07678    0.0

[5 rows x 31 columns]
```

[15]:

```
cancer_dataset['label'].replace(0, 'Benign', inplace=True)
cancer_dataset['label'].replace(1, 'Malignant', inplace=True)
```

[16]:

```
cancer_dataset.tail()
```

[16]:

```
     mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
564        21.56         22.39          142.00     1479.0          0.11100
565        20.13         28.25          131.20     1261.0          0.09780
```

```
566      16.60       28.08       108.30    858.1          0.08455
567      20.60       29.33       140.10   1265.0          0.11780
568       7.76       24.54        47.92    181.0          0.05263

     mean compactness  mean concavity  mean concave points  mean symmetry  \
564           0.11590         0.24390              0.13890         0.1726
565           0.10340         0.14400              0.09791         0.1752
566           0.10230         0.09251              0.05302         0.1590
567           0.27700         0.35140              0.15200         0.2397
568           0.04362         0.00000              0.00000         0.1587

     mean fractal dimension  …  worst texture  worst perimeter  worst area  \
564                 0.05623  …          26.40           166.10      2027.0
565                 0.05533  …          38.25           155.00      1731.0
566                 0.05648  …          34.12           126.70      1124.0
567                 0.07016  …          39.42           184.60      1821.0
568                 0.05884  …          30.37            59.16       268.6

     worst smoothness  worst compactness  worst concavity  \
564           0.14100            0.21130           0.4107
565           0.11660            0.19220           0.3215
566           0.11390            0.30940           0.3403
567           0.16500            0.86810           0.9387
568           0.08996            0.06444           0.0000

     worst concave points  worst symmetry  worst fractal dimension      label
564                0.2216          0.2060                  0.07115     Benign
565                0.1628          0.2572                  0.06637     Benign
566                0.1418          0.2218                  0.07820     Benign
567                0.2650          0.4087                  0.12400     Benign
568                0.0000          0.2871                  0.07039  Malignant

[5 rows x 31 columns]
```

[17]:
```python
cancer_X = cancer_dataset.iloc[:,0:29].values
cancer_Y = cancer_dataset.iloc[:,30].values
```

[18]:
```python
cancer_X_train, cancer_X_test, cancer_Y_train, cancer_Y_test =␣
 ↪train_test_split(cancer_X, cancer_Y, test_size=0.2, random_state=42)
```

[19]:
```python
features = ['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimension',
       'radius error', 'texture error', 'perimeter error', 'area error',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error',
       'fractal dimension error', 'worst radius', 'worst texture',
```

```
       'worst perimeter', 'worst area', 'worst smoothness',
       'worst compactness', 'worst concavity', 'worst concave points',
       'worst symmetry', 'worst fractal dimension']

x = cancer_dataset.loc[:, features].values
y = cancer_dataset.loc[:,['label']].values
x = StandardScaler().fit_transform(x)
```

[20]:
```
from sklearn.decomposition import PCA
sc_X = StandardScaler()
cancer_X_trainstd = sc_X.fit_transform(cancer_X_train)
cancer_X_teststd = sc_X.transform(cancer_X_test)
```

[21]:
```
SVM_Linear = SVC(kernel = 'linear', C= 1E3)
columns = []
SVMLinaccuracy = np.zeros(30)
SVMLinPrecision = np.zeros(30)
SVMLinRecall = np.zeros(30)
for i in range(1,30):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(cancer_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
 ↪columns)

    finalDftrain = pd.concat([principalDftrain, cancer_dataset[['label']]],␣
 ↪axis = 1)
    principalComponentstest = pca.fit_transform(cancer_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
 ↪columns)
    finalDftest = pd.concat([principalDftest, cancer_dataset[['label']]], axis␣
 ↪= 1)
    SVM_Linear_train = SVM_Linear.fit(principalDftrain.values, cancer_Y_train)
    cancer_Y_predSVMLIN = SVM_Linear_train.predict(principalDftest.values)
    print("Accuracy " + str(i) + ":",metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMLIN))
    SVMLinaccuracy[i] = metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMLIN)
    print("Precision " + str(i) + ":", metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMLIN, pos_label="Benign"))
    SVMLinPrecision[i] = metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMLIN, pos_label="Benign")
    print("Recall " + str(i) + ":",metrics.recall_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMLIN, pos_label="Benign"))
```

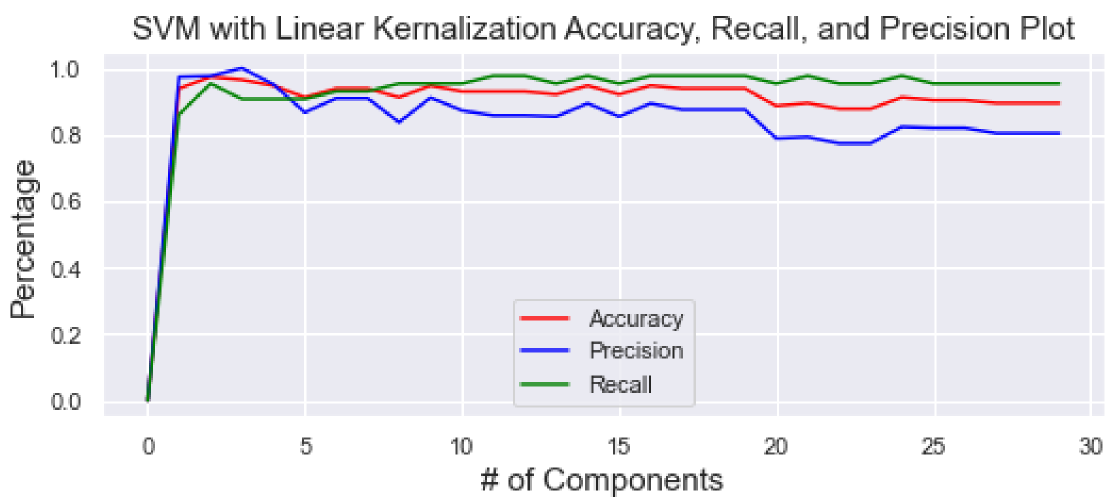
```
    SVMLinRecall[i] = metrics.recall_score(cancer_Y_test, cancer_Y_predSVMLIN,␣
↪pos_label="Benign")
    columns = np.array(columns)
```

```
Accuracy 1: 0.9385964912280702
Precision 1: 0.9736842105263158
Recall 1: 0.8604651162790697
Accuracy 2: 0.9736842105263158
Precision 2: 0.9761904761904762
Recall 2: 0.9534883720930233
Accuracy 3: 0.9649122807017544
Precision 3: 1.0
Recall 3: 0.9069767441860465
Accuracy 4: 0.9473684210526315
Precision 4: 0.9512195121951219
Recall 4: 0.9069767441860465
Accuracy 5: 0.9122807017543859
Precision 5: 0.8666666666666667
Recall 5: 0.9069767441860465
Accuracy 6: 0.9385964912280702
Precision 6: 0.9090909090909091
Recall 6: 0.9302325581395349
Accuracy 7: 0.9385964912280702
Precision 7: 0.9090909090909091
Recall 7: 0.9302325581395349
Accuracy 8: 0.9122807017543859
Precision 8: 0.8367346938775511
Recall 8: 0.9534883720930233
Accuracy 9: 0.9473684210526315
Precision 9: 0.9111111111111111
Recall 9: 0.9534883720930233
Accuracy 10: 0.9298245614035088
Precision 10: 0.8723404255319149
Recall 10: 0.9534883720930233
Accuracy 11: 0.9298245614035088
Precision 11: 0.8571428571428571
Recall 11: 0.9767441860465116
Accuracy 12: 0.9298245614035088
Precision 12: 0.8571428571428571
Recall 12: 0.9767441860465116
Accuracy 13: 0.9210526315789473
Precision 13: 0.8541666666666666
Recall 13: 0.9534883720930233
Accuracy 14: 0.9473684210526315
Precision 14: 0.8936170212765957
Recall 14: 0.9767441860465116
Accuracy 15: 0.9210526315789473
Precision 15: 0.8541666666666666
```

```
Recall 15: 0.9534883720930233
Accuracy 16: 0.9473684210526315
Precision 16: 0.8936170212765957
Recall 16: 0.9767441860465116
Accuracy 17: 0.9385964912280702
Precision 17: 0.875
Recall 17: 0.9767441860465116
Accuracy 18: 0.9385964912280702
Precision 18: 0.875
Recall 18: 0.9767441860465116
Accuracy 19: 0.9385964912280702
Precision 19: 0.875
Recall 19: 0.9767441860465116
Accuracy 20: 0.8859649122807017
Precision 20: 0.7884615384615384
Recall 20: 0.9534883720930233
Accuracy 21: 0.8947368421052632
Precision 21: 0.7924528301886793
Recall 21: 0.9767441860465116
Accuracy 22: 0.8771929824561403
Precision 22: 0.7735849056603774
Recall 22: 0.9534883720930233
Accuracy 23: 0.8771929824561403
Precision 23: 0.7735849056603774
Recall 23: 0.9534883720930233
Accuracy 24: 0.9122807017543859
Precision 24: 0.8235294117647058
Recall 24: 0.9767441860465116
Accuracy 25: 0.9035087719298246
Precision 25: 0.82
Recall 25: 0.9534883720930233
Accuracy 26: 0.9035087719298246
Precision 26: 0.82
Recall 26: 0.9534883720930233
Accuracy 27: 0.8947368421052632
Precision 27: 0.803921568627451
Recall 27: 0.9534883720930233
Accuracy 28: 0.8947368421052632
Precision 28: 0.803921568627451
Recall 28: 0.9534883720930233
Accuracy 29: 0.8947368421052632
Precision 29: 0.803921568627451
Recall 29: 0.9534883720930233
```

[22]:
```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,30))
```

```
y = SVMLinaccuracy
z = SVMLinPrecision
v = SVMLinRecall
plt.title("SVM with Linear Kernalization Accuracy, Recall, and Precision Plot",␣
↪fontsize = 15)
plt.plot(x, y, color="red", label="Accuracy")
plt.plot(x, z, color="blue", label="Precision")
plt.plot(x, v, color="green", label="Recall")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



[23]:
```
SVM_Polyv1 = SVC(kernel = 'poly', C= 1E3, degree = 1)
columns = []
SVMPv1accuracy = np.zeros(30)
SVMPv1Precision = np.zeros(30)
SVMPv1Recall = np.zeros(30)
for i in range(1,30):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(cancer_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
↪columns)

    finalDftrain = pd.concat([principalDftrain, cancer_dataset[['label']]],␣
↪axis = 1)
    principalComponentstest = pca.fit_transform(cancer_X_teststd)
```

```
    principalDftest = pd.DataFrame(data = principalComponentstest, columns = columns)
    finalDftest = pd.concat([principalDftest, cancer_dataset[['label']]], axis = 1)
    SVM_Polyv1_train = SVM_Polyv1.fit(principalDftrain.values, cancer_Y_train)
    cancer_Y_predSVMPv1 = SVM_Polyv1_train.predict(principalDftest.values)
    print("Accuracy " + str(i) + ":",metrics.accuracy_score(cancer_Y_test, cancer_Y_predSVMPv1))
    SVMPv1accuracy[i] = metrics.accuracy_score(cancer_Y_test, cancer_Y_predSVMPv1)
    print("Precision " + str(i) + ":", metrics.precision_score(cancer_Y_test, cancer_Y_predSVMPv1, pos_label="Benign"))
    SVMPv1Precision[i] = metrics.precision_score(cancer_Y_test, cancer_Y_predSVMPv1, pos_label="Benign")
    print("Recall " + str(i) + ":",metrics.recall_score(cancer_Y_test, cancer_Y_predSVMPv1, pos_label="Benign"))
    SVMPv1Recall[i] = metrics.recall_score(cancer_Y_test, cancer_Y_predSVMPv1, pos_label="Benign")
    columns = np.array(columns)
```

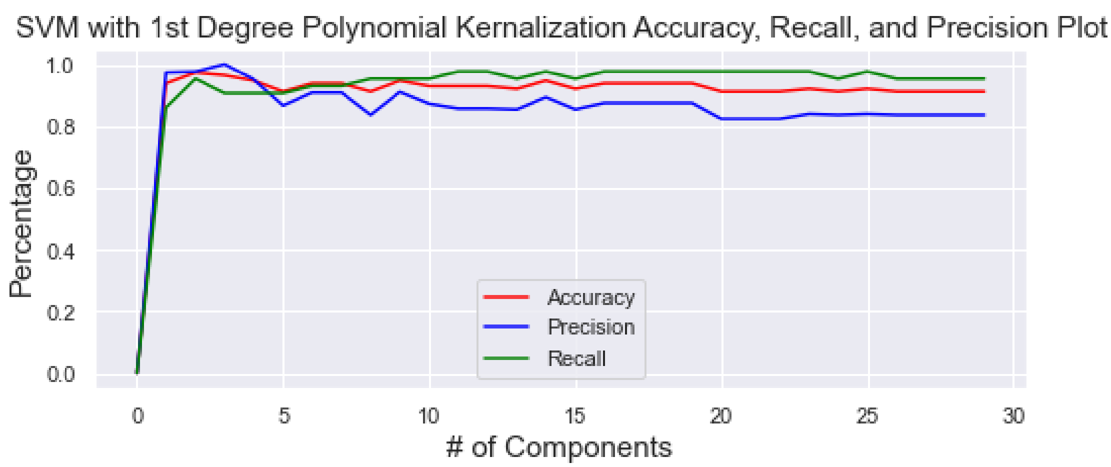
```
Accuracy 1: 0.9385964912280702
Precision 1: 0.9736842105263158
Recall 1: 0.8604651162790697
Accuracy 2: 0.9736842105263158
Precision 2: 0.9761904761904762
Recall 2: 0.9534883720930233
Accuracy 3: 0.9649122807017544
Precision 3: 1.0
Recall 3: 0.9069767441860465
Accuracy 4: 0.9473684210526315
Precision 4: 0.9512195121951219
Recall 4: 0.9069767441860465
Accuracy 5: 0.9122807017543859
Precision 5: 0.8666666666666667
Recall 5: 0.9069767441860465
Accuracy 6: 0.9385964912280702
Precision 6: 0.9090909090909091
Recall 6: 0.9302325581395349
Accuracy 7: 0.9385964912280702
Precision 7: 0.9090909090909091
Recall 7: 0.9302325581395349
Accuracy 8: 0.9122807017543859
Precision 8: 0.8367346938775511
Recall 8: 0.9534883720930233
Accuracy 9: 0.9473684210526315
Precision 9: 0.9111111111111111
Recall 9: 0.9534883720930233
```

```
Accuracy 10: 0.9298245614035088
Precision 10: 0.8723404255319149
Recall 10: 0.9534883720930233
Accuracy 11: 0.9298245614035088
Precision 11: 0.8571428571428571
Recall 11: 0.9767441860465116
Accuracy 12: 0.9298245614035088
Precision 12: 0.8571428571428571
Recall 12: 0.9767441860465116
Accuracy 13: 0.9210526315789473
Precision 13: 0.8541666666666666
Recall 13: 0.9534883720930233
Accuracy 14: 0.9473684210526315
Precision 14: 0.8936170212765957
Recall 14: 0.9767441860465116
Accuracy 15: 0.9210526315789473
Precision 15: 0.8541666666666666
Recall 15: 0.9534883720930233
Accuracy 16: 0.9385964912280702
Precision 16: 0.875
Recall 16: 0.9767441860465116
Accuracy 17: 0.9385964912280702
Precision 17: 0.875
Recall 17: 0.9767441860465116
Accuracy 18: 0.9385964912280702
Precision 18: 0.875
Recall 18: 0.9767441860465116
Accuracy 19: 0.9385964912280702
Precision 19: 0.875
Recall 19: 0.9767441860465116
Accuracy 20: 0.9122807017543859
Precision 20: 0.8235294117647058
Recall 20: 0.9767441860465116
Accuracy 21: 0.9122807017543859
Precision 21: 0.8235294117647058
Recall 21: 0.9767441860465116
Accuracy 22: 0.9122807017543859
Precision 22: 0.8235294117647058
Recall 22: 0.9767441860465116
Accuracy 23: 0.9210526315789473
Precision 23: 0.84
Recall 23: 0.9767441860465116
Accuracy 24: 0.9122807017543859
Precision 24: 0.8367346938775511
Recall 24: 0.9534883720930233
Accuracy 25: 0.9210526315789473
Precision 25: 0.84
Recall 25: 0.9767441860465116
```

```
Accuracy 26: 0.9122807017543859
Precision 26: 0.8367346938775511
Recall 26: 0.9534883720930233
Accuracy 27: 0.9122807017543859
Precision 27: 0.8367346938775511
Recall 27: 0.9534883720930233
Accuracy 28: 0.9122807017543859
Precision 28: 0.8367346938775511
Recall 28: 0.9534883720930233
Accuracy 29: 0.9122807017543859
Precision 29: 0.8367346938775511
Recall 29: 0.9534883720930233
```

[24]:

```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,30))
y = SVMPv1accuracy
z = SVMPv1Precision
v = SVMPv1Recall
plt.title("SVM with 1st Degree Polynomial Kernalization Accuracy, Recall, and␣
 ↪Precision Plot", fontsize = 15)
plt.plot(x, y, color="red", label="Accuracy")
plt.plot(x, z, color="blue", label="Precision")
plt.plot(x, v, color="green", label="Recall")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



[25]:

```
SVM_Polyv2 = SVC(kernel = 'poly', C= 1E3, degree = 2)
columns = []
```

```python
SVMPv2accuracy = np.zeros(30)
SVMPv2Precision = np.zeros(30)
SVMPv2Recall = np.zeros(30)
for i in range(1,30):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(cancer_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
 ↪columns)

    finalDftrain = pd.concat([principalDftrain, cancer_dataset[['label']]],␣
 ↪axis = 1)
    principalComponentstest = pca.fit_transform(cancer_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
 ↪columns)
    finalDftest = pd.concat([principalDftest, cancer_dataset[['label']]], axis␣
 ↪= 1)
    SVM_Polyv2_train = SVM_Polyv2.fit(principalDftrain.values, cancer_Y_train)
    cancer_Y_predSVMPv2 = SVM_Polyv2_train.predict(principalDftest.values)
    print("Accuracy " + str(i) + ":",metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMPv2))
    SVMPv2accuracy[i] = metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMPv2)
    print("Precision " + str(i) + ":", metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMPv2, pos_label="Benign"))
    SVMPv2Precision[i] = metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMPv2, pos_label="Benign")
    print("Recall " + str(i) + ":",metrics.recall_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMPv2, pos_label="Benign"))
    SVMPv2Recall[i] = metrics.recall_score(cancer_Y_test, cancer_Y_predSVMPv2,␣
 ↪pos_label="Benign")
    columns = np.array(columns)
```

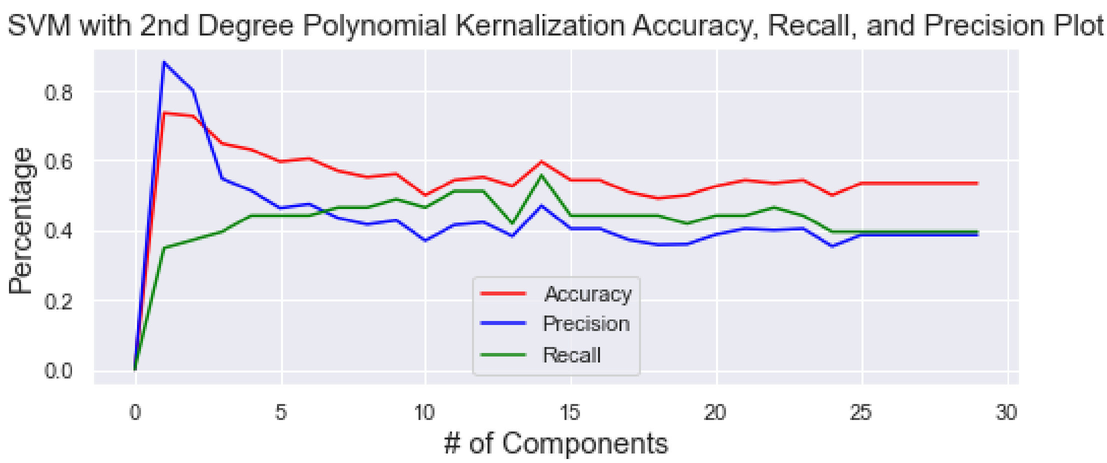
```
Accuracy 1: 0.7368421052631579
Precision 1: 0.8823529411764706
Recall 1: 0.3488372093023256
Accuracy 2: 0.7280701754385965
Precision 2: 0.8
Recall 2: 0.37209302325581395
Accuracy 3: 0.6491228070175439
Precision 3: 0.5483870967741935
Recall 3: 0.3953488372093023
Accuracy 4: 0.631578947368421
Precision 4: 0.5135135135135135
Recall 4: 0.4418604651162791
Accuracy 5: 0.5964912280701754
```

```
Precision 5: 0.4634146341463415
Recall 5: 0.4418604651162791
Accuracy 6: 0.6052631578947368
Precision 6: 0.475
Recall 6: 0.4418604651162791
Accuracy 7: 0.5701754385964912
Precision 7: 0.43478260869565216
Recall 7: 0.46511627906976744
Accuracy 8: 0.5526315789473685
Precision 8: 0.4166666666666667
Recall 8: 0.46511627906976744
Accuracy 9: 0.5614035087719298
Precision 9: 0.42857142857142855
Recall 9: 0.4883720930232558
Accuracy 10: 0.5
Precision 10: 0.37037037037037035
Recall 10: 0.46511627906976744
Accuracy 11: 0.543859649122807
Precision 11: 0.41509433962264153
Recall 11: 0.5116279069767442
Accuracy 12: 0.5526315789473685
Precision 12: 0.4230769230769231
Recall 12: 0.5116279069767442
Accuracy 13: 0.5263157894736842
Precision 13: 0.3829787234042553
Recall 13: 0.4186046511627907
Accuracy 14: 0.5964912280701754
Precision 14: 0.47058823529411764
Recall 14: 0.5581395348837209
Accuracy 15: 0.543859649122807
Precision 15: 0.40425531914893614
Recall 15: 0.4418604651162791
Accuracy 16: 0.543859649122807
Precision 16: 0.40425531914893614
Recall 16: 0.4418604651162791
Accuracy 17: 0.5087719298245614
Precision 17: 0.37254901960784315
Recall 17: 0.4418604651162791
Accuracy 18: 0.49122807017543857
Precision 18: 0.3584905660377358
Recall 18: 0.4418604651162791
Accuracy 19: 0.5
Precision 19: 0.36
Recall 19: 0.4186046511627907
Accuracy 20: 0.5263157894736842
Precision 20: 0.3877551020408163
Recall 20: 0.4418604651162791
Accuracy 21: 0.543859649122807
```

```
Precision 21: 0.40425531914893614
Recall 21: 0.4418604651162791
Accuracy 22: 0.5350877192982456
Precision 22: 0.4
Recall 22: 0.46511627906976744
Accuracy 23: 0.543859649122807
Precision 23: 0.40425531914893614
Recall 23: 0.4418604651162791
Accuracy 24: 0.5
Precision 24: 0.3541666666666667
Recall 24: 0.3953488372093023
Accuracy 25: 0.5350877192982456
Precision 25: 0.38636363636363635
Recall 25: 0.3953488372093023
Accuracy 26: 0.5350877192982456
Precision 26: 0.38636363636363635
Recall 26: 0.3953488372093023
Accuracy 27: 0.5350877192982456
Precision 27: 0.38636363636363635
Recall 27: 0.3953488372093023
Accuracy 28: 0.5350877192982456
Precision 28: 0.38636363636363635
Recall 28: 0.3953488372093023
Accuracy 29: 0.5350877192982456
Precision 29: 0.38636363636363635
Recall 29: 0.3953488372093023
```

[26]:

```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,30))
y = SVMPv2accuracy
z = SVMPv2Precision
v = SVMPv2Recall
plt.title("SVM with 2nd Degree Polynomial Kernalization Accuracy, Recall, and␣
 ↪Precision Plot", fontsize = 15)
plt.plot(x, y, color="red", label="Accuracy")
plt.plot(x, z, color="blue", label="Precision")
plt.plot(x, v, color="green", label="Recall")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



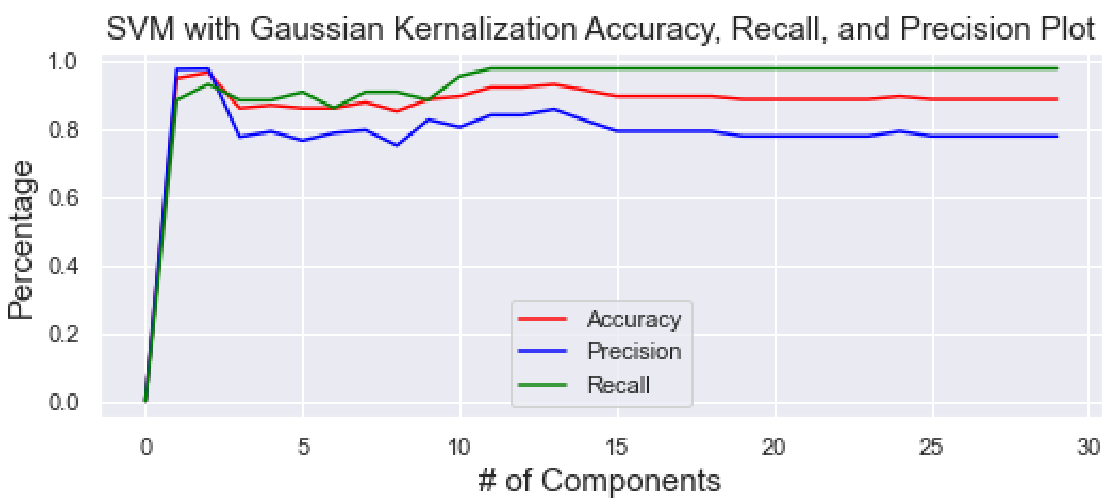
[39]:
```
SVM_Gauss = SVC(kernel = 'rbf', C= 1E3, gamma=0.1)
columns = []
SVMGaussaccuracy = np.zeros(30)
SVMGaussPrecision = np.zeros(30)
SVMGaussRecall = np.zeros(30)
for i in range(1,30):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(cancer_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
 ↪columns)

    finalDftrain = pd.concat([principalDftrain, cancer_dataset[['label']]],␣
 ↪axis = 1)
    principalComponentstest = pca.fit_transform(cancer_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
 ↪columns)
    finalDftest = pd.concat([principalDftest, cancer_dataset[['label']]], axis␣
 ↪= 1)
    SVM_Gauss_train = SVM_Gauss.fit(principalDftrain.values, cancer_Y_train)
    cancer_Y_predSVMGauss = SVM_Gauss_train.predict(principalDftest.values)
    print("Accuracy " + str(i) + ":",metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMGauss))
    SVMGaussaccuracy[i] = metrics.accuracy_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMGauss)
    print("Precision " + str(i) + ":", metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMGauss, pos_label="Benign"))
    SVMGaussPrecision[i] = metrics.precision_score(cancer_Y_test,␣
 ↪cancer_Y_predSVMGauss, pos_label="Benign")
```

```
    print("Recall " + str(i) + ":",metrics.recall_score(cancer_Y_test,␣
↪cancer_Y_predSVMGauss, pos_label="Benign"))
    SVMGaussRecall[i] = metrics.recall_score(cancer_Y_test,␣
↪cancer_Y_predSVMGauss, pos_label="Benign")
    columns = np.array(columns)
```

```
Accuracy 1: 0.9385964912280702
Precision 1: 0.9736842105263158
Recall 1: 0.8604651162790697
Accuracy 2: 0.956140350877193
Precision 2: 0.975
Recall 2: 0.9069767441860465
Accuracy 3: 0.9035087719298246
Precision 3: 0.8809523809523809
Recall 3: 0.8604651162790697
Accuracy 4: 0.8508771929824561
Precision 4: 0.7407407407407407
Recall 4: 0.9302325581395349
Accuracy 5: 0.868421052631579
Precision 5: 0.7916666666666666
Recall 5: 0.8837209302325582
Accuracy 6: 0.8859649122807017
Precision 6: 0.7884615384615384
Recall 6: 0.9534883720930233
Accuracy 7: 0.8508771929824561
Precision 7: 0.75
Recall 7: 0.9069767441860465
Accuracy 8: 0.8421052631578947
Precision 8: 0.7358490566037735
Recall 8: 0.9069767441860465
Accuracy 9: 0.8947368421052632
Precision 9: 0.8297872340425532
Recall 9: 0.9069767441860465
Accuracy 10: 0.8771929824561403
Precision 10: 0.7959183673469388
Recall 10: 0.9069767441860465
Accuracy 11: 0.8859649122807017
Precision 11: 0.8
Recall 11: 0.9302325581395349
Accuracy 12: 0.8947368421052632
Precision 12: 0.8297872340425532
Recall 12: 0.9069767441860465
Accuracy 13: 0.8947368421052632
Precision 13: 0.8163265306122449
Recall 13: 0.9302325581395349
Accuracy 14: 0.8771929824561403
Precision 14: 0.7959183673469388
```

```
Recall 14: 0.9069767441860465
Accuracy 15: 0.8859649122807017
Precision 15: 0.8
Recall 15: 0.9302325581395349
Accuracy 16: 0.8859649122807017
Precision 16: 0.8
Recall 16: 0.9302325581395349
Accuracy 17: 0.8859649122807017
Precision 17: 0.8
Recall 17: 0.9302325581395349
Accuracy 18: 0.8859649122807017
Precision 18: 0.8
Recall 18: 0.9302325581395349
Accuracy 19: 0.8859649122807017
Precision 19: 0.8
Recall 19: 0.9302325581395349
Accuracy 20: 0.8859649122807017
Precision 20: 0.8
Recall 20: 0.9302325581395349
Accuracy 21: 0.8859649122807017
Precision 21: 0.8
Recall 21: 0.9302325581395349
Accuracy 22: 0.8859649122807017
Precision 22: 0.8
Recall 22: 0.9302325581395349
Accuracy 23: 0.8859649122807017
Precision 23: 0.8
Recall 23: 0.9302325581395349
Accuracy 24: 0.8859649122807017
Precision 24: 0.8
Recall 24: 0.9302325581395349
Accuracy 25: 0.8859649122807017
Precision 25: 0.8
Recall 25: 0.9302325581395349
Accuracy 26: 0.8859649122807017
Precision 26: 0.8
Recall 26: 0.9302325581395349
Accuracy 27: 0.8859649122807017
Precision 27: 0.8
Recall 27: 0.9302325581395349
Accuracy 28: 0.8859649122807017
Precision 28: 0.8
Recall 28: 0.9302325581395349
Accuracy 29: 0.8859649122807017
Precision 29: 0.8
Recall 29: 0.9302325581395349
```

[28]:
```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,30))
y = SVMGaussaccuracy
z = SVMGaussPrecision
v = SVMGaussRecall
plt.title("SVM with Gaussian Kernalization Accuracy, Recall, and Precision␣
↪Plot", fontsize = 15)
plt.plot(x, y, color="red", label="Accuracy")
plt.plot(x, z, color="blue", label="Precision")
plt.plot(x, v, color="green", label="Recall")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



[29]:
```
SVM_Sigmoid = SVC(kernel = 'sigmoid', C= 1E3)
columns = []
SVMSigaccuracy = np.zeros(30)
SVMSigPrecision = np.zeros(30)
SVMSigRecall = np.zeros(30)
for i in range(1,30):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(cancer_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
↪columns)
```

```python
    finalDftrain = pd.concat([principalDftrain, cancer_dataset[['label']]],␣
↪axis = 1)
    principalComponentstest = pca.fit_transform(cancer_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
↪columns)
    finalDftest = pd.concat([principalDftest, cancer_dataset[['label']]], axis␣
↪= 1)
    SVM_Sig_train = SVM_Sigmoid.fit(principalDftrain.values, cancer_Y_train)
    cancer_Y_predSVMSig = SVM_Sig_train.predict(principalDftest.values)
    print("Accuracy " + str(i) + ":",metrics.accuracy_score(cancer_Y_test,␣
↪cancer_Y_predSVMSig))
    SVMSigaccuracy[i] = metrics.accuracy_score(cancer_Y_test,␣
↪cancer_Y_predSVMSig)
    print("Precision " + str(i) + ":", metrics.precision_score(cancer_Y_test,␣
↪cancer_Y_predSVMSig, pos_label="Benign"))
    SVMSigPrecision[i] = metrics.precision_score(cancer_Y_test,␣
↪cancer_Y_predSVMSig, pos_label="Benign")
    print("Recall " + str(i) + ":",metrics.recall_score(cancer_Y_test,␣
↪cancer_Y_predSVMSig, pos_label="Benign"))
    SVMSigRecall[i] = metrics.recall_score(cancer_Y_test, cancer_Y_predSVMSig,␣
↪pos_label="Benign")
    columns = np.array(columns)
```

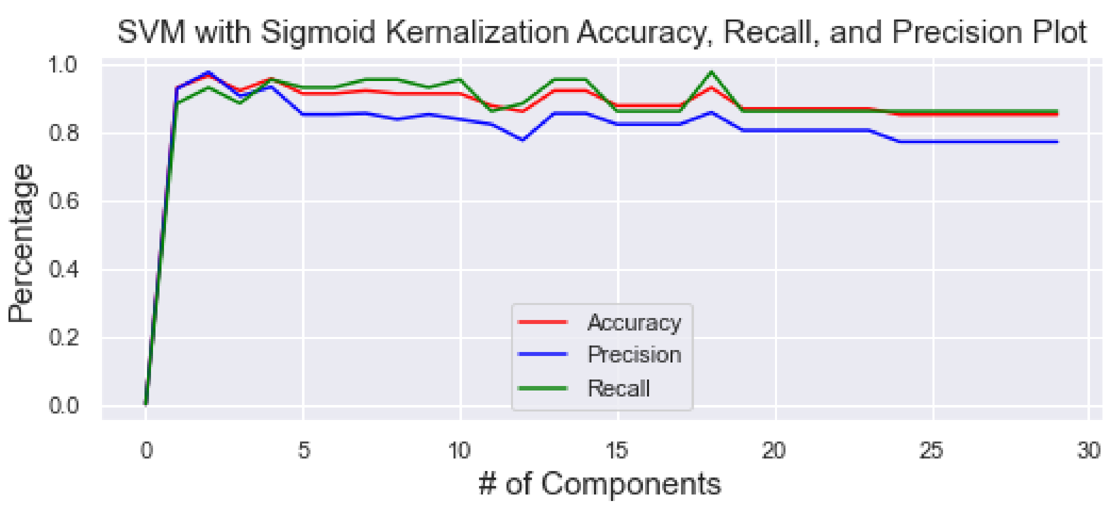
```
Accuracy 1: 0.9298245614035088
Precision 1: 0.926829268292683
Recall 1: 0.8837209302325582
Accuracy 2: 0.9649122807017544
Precision 2: 0.975609756097561
Recall 2: 0.9302325581395349
Accuracy 3: 0.9210526315789473
Precision 3: 0.9047619047619048
Recall 3: 0.8837209302325582
Accuracy 4: 0.956140350877193
Precision 4: 0.9318181818181818
Recall 4: 0.9534883720930233
Accuracy 5: 0.9122807017543859
Precision 5: 0.851063829787234
Recall 5: 0.9302325581395349
Accuracy 6: 0.9122807017543859
Precision 6: 0.851063829787234
Recall 6: 0.9302325581395349
Accuracy 7: 0.9210526315789473
Precision 7: 0.8541666666666666
Recall 7: 0.9534883720930233
Accuracy 8: 0.9122807017543859
Precision 8: 0.8367346938775511
Recall 8: 0.9534883720930233
```

```
Accuracy 9: 0.9122807017543859
Precision 9: 0.851063829787234
Recall 9: 0.9302325581395349
Accuracy 10: 0.9122807017543859
Precision 10: 0.8367346938775511
Recall 10: 0.9534883720930233
Accuracy 11: 0.8771929824561403
Precision 11: 0.8222222222222222
Recall 11: 0.8604651162790697
Accuracy 12: 0.8596491228070176
Precision 12: 0.7755102040816326
Recall 12: 0.8837209302325582
Accuracy 13: 0.9210526315789473
Precision 13: 0.8541666666666666
Recall 13: 0.9534883720930233
Accuracy 14: 0.9210526315789473
Precision 14: 0.8541666666666666
Recall 14: 0.9534883720930233
Accuracy 15: 0.8771929824561403
Precision 15: 0.8222222222222222
Recall 15: 0.8604651162790697
Accuracy 16: 0.8771929824561403
Precision 16: 0.8222222222222222
Recall 16: 0.8604651162790697
Accuracy 17: 0.8771929824561403
Precision 17: 0.8222222222222222
Recall 17: 0.8604651162790697
Accuracy 18: 0.9298245614035088
Precision 18: 0.8571428571428571
Recall 18: 0.9767441860465116
Accuracy 19: 0.868421052631579
Precision 19: 0.8043478260869565
Recall 19: 0.8604651162790697
Accuracy 20: 0.868421052631579
Precision 20: 0.8043478260869565
Recall 20: 0.8604651162790697
Accuracy 21: 0.868421052631579
Precision 21: 0.8043478260869565
Recall 21: 0.8604651162790697
Accuracy 22: 0.868421052631579
Precision 22: 0.8043478260869565
Recall 22: 0.8604651162790697
Accuracy 23: 0.868421052631579
Precision 23: 0.8043478260869565
Recall 23: 0.8604651162790697
Accuracy 24: 0.8508771929824561
Precision 24: 0.7708333333333334
Recall 24: 0.8604651162790697
```

```
Accuracy 25: 0.8508771929824561
Precision 25: 0.7708333333333334
Recall 25: 0.8604651162790697
Accuracy 26: 0.8508771929824561
Precision 26: 0.7708333333333334
Recall 26: 0.8604651162790697
Accuracy 27: 0.8508771929824561
Precision 27: 0.7708333333333334
Recall 27: 0.8604651162790697
Accuracy 28: 0.8508771929824561
Precision 28: 0.7708333333333334
Recall 28: 0.8604651162790697
Accuracy 29: 0.8508771929824561
Precision 29: 0.7708333333333334
Recall 29: 0.8604651162790697
```

[30]:

```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,30))
y = SVMSigaccuracy
z = SVMSigPrecision
v = SVMSigRecall
plt.title("SVM with Sigmoid Kernalization Accuracy, Recall, and Precision␣
↪Plot", fontsize = 15)
plt.plot(x, y, color="red", label="Accuracy")
plt.plot(x, z, color="blue", label="Precision")
plt.plot(x, v, color="green", label="Recall")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



[31]:
```
df = pd.read_csv (r'C:\Users\homer\OneDrive\Documents\School Folder\Housing.
↪csv')
df.head()
```

[31]:
```
      price  area  bedrooms  bathrooms  stories mainroad guestroom basement  \
0  13300000  7420         4          2        3      yes        no       no
1  12250000  8960         4          4        4      yes        no       no
2  12250000  9960         3          2        2      yes        no      yes
3  12215000  7500         4          2        2      yes        no      yes
4  11410000  7420         4          1        2      yes       yes      yes

  hotwaterheating airconditioning  parking prefarea furnishingstatus
0              no             yes        2      yes        furnished
1              no             yes        3       no        furnished
2              no              no        2      yes   semi-furnished
3              no             yes        3      yes        furnished
4              no             yes        2       no        furnished
```

[32]:
```
df.shape
```

[32]:
```
(545, 13)
```

[33]:
```
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
```

[34]:
```
df['mainroad'].replace('yes', 1, inplace=True)
df['mainroad'].replace('no', 0, inplace=True)
df['guestroom'].replace('yes', 1, inplace=True)
df['guestroom'].replace('no', 0, inplace=True)
df['basement'].replace('yes', 1, inplace=True)
df['basement'].replace('no', 0, inplace=True)
df['hotwaterheating'].replace('yes', 1, inplace=True)
df['hotwaterheating'].replace('no', 0, inplace=True)
df['airconditioning'].replace('yes', 1, inplace=True)
df['airconditioning'].replace('no', 0, inplace=True)
df['prefarea'].replace('yes', 1, inplace=True)
df['prefarea'].replace('no', 0, inplace=True)
Housing_X = df.iloc[:,1:12].values
Housing_Y = df.iloc[:,0].values
```

[35]:
```
Housing_X_train, Housing_X_test, Housing_Y_train, Housing_Y_test =␣
↪train_test_split(Housing_X, Housing_Y, test_size=0.2, random_state=42)
```

[36]:
```
Housing_X_trainstd = sc_X.fit_transform(Housing_X_train)
Housing_X_teststd = sc_X.transform(Housing_X_test)
```

[44]:
```python
SVR_Linear = SVR(kernel = 'linear', C= 1E6)
columns = []
SVRLinearScore = np.zeros(12)
for i in range(1,12):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(Housing_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
 ↪columns)

    finalDftrain = pd.concat([principalDftrain, df[['price']]], axis = 1)
    principalComponentstest = pca.fit_transform(Housing_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
 ↪columns)
    finalDftest = pd.concat([principalDftest, df[['price']]], axis = 1)
    SVR_Linear_train = SVR_Linear.fit(principalDftrain.values, Housing_Y_train)
    Housing_Y_predSVRLIN = SVR_Linear_train.predict(principalDftest.values)
    print("R2 score " + str(i) + ": %.2f" %␣
 ↪r2_score(Housing_Y_test,Housing_Y_predSVRLIN))
    print("Mean squared error " + str(i) + ": %.2f" %␣
 ↪mean_squared_error(Housing_Y_test,Housing_Y_predSVRLIN))
    SVRLinearScore[i] = r2_score(Housing_Y_test,Housing_Y_predSVRLIN)
    columns = np.array(columns)
```

```
R2 score 1: 0.56
Mean squared error 1: 2238881202198.29
R2 score 2: 0.55
Mean squared error 2: 2296335812511.48
R2 score 3: 0.55
Mean squared error 3: 2282017195331.02
R2 score 4: 0.55
Mean squared error 4: 2271997022519.77
R2 score 5: 0.55
Mean squared error 5: 2273574297808.80
R2 score 6: 0.55
Mean squared error 6: 2274676181180.90
R2 score 7: 0.55
Mean squared error 7: 2276371912775.23
R2 score 8: 0.56
Mean squared error 8: 2249245183428.99
R2 score 9: 0.54
Mean squared error 9: 2307629649256.42
R2 score 10: 0.54
Mean squared error 10: 2334426249803.17
R2 score 11: 0.53
Mean squared error 11: 2350955215620.10
```

[45]:
```
SVR_Poly = SVR(kernel = 'poly', C= 1E6, degree = 2)
columns = []
SVRPolyScore = np.zeros(12)
for i in range(1,12):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(Housing_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
 ↪columns)

    finalDftrain = pd.concat([principalDftrain, df[['price']]], axis = 1)
    principalComponentstest = pca.fit_transform(Housing_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
 ↪columns)
    finalDftest = pd.concat([principalDftest, df[['price']]], axis = 1)
    SVR_Poly_train = SVR_Poly.fit(principalDftrain.values, Housing_Y_train)
    Housing_Y_predSVRPoly = SVR_Poly_train.predict(principalDftest.values)
    print("R2 score " + str(i) + ": %.2f" %␣
 ↪r2_score(Housing_Y_test,Housing_Y_predSVRPoly))
    print("Mean squared error " + str(i) + ": %.2f" %␣
 ↪mean_squared_error(Housing_Y_test,Housing_Y_predSVRPoly))
    SVRPolyScore[i] = r2_score(Housing_Y_test,Housing_Y_predSVRPoly)
    columns = np.array(columns)
```

```
R2 score 1: 0.14
Mean squared error 1: 4369157823847.64
R2 score 2: -0.07
Mean squared error 2: 5383370577541.40
R2 score 3: -0.13
Mean squared error 3: 5710503290633.09
R2 score 4: -0.08
Mean squared error 4: 5460807873207.93
R2 score 5: -0.00
Mean squared error 5: 5078022407132.18
R2 score 6: -0.04
Mean squared error 6: 5266521633902.13
R2 score 7: -0.02
Mean squared error 7: 5176631130411.13
R2 score 8: 0.03
Mean squared error 8: 4882639710705.87
R2 score 9: -0.03
Mean squared error 9: 5190623496197.97
R2 score 10: 0.01
Mean squared error 10: 5007438644277.26
R2 score 11: 0.00
Mean squared error 11: 5048217034521.88
```

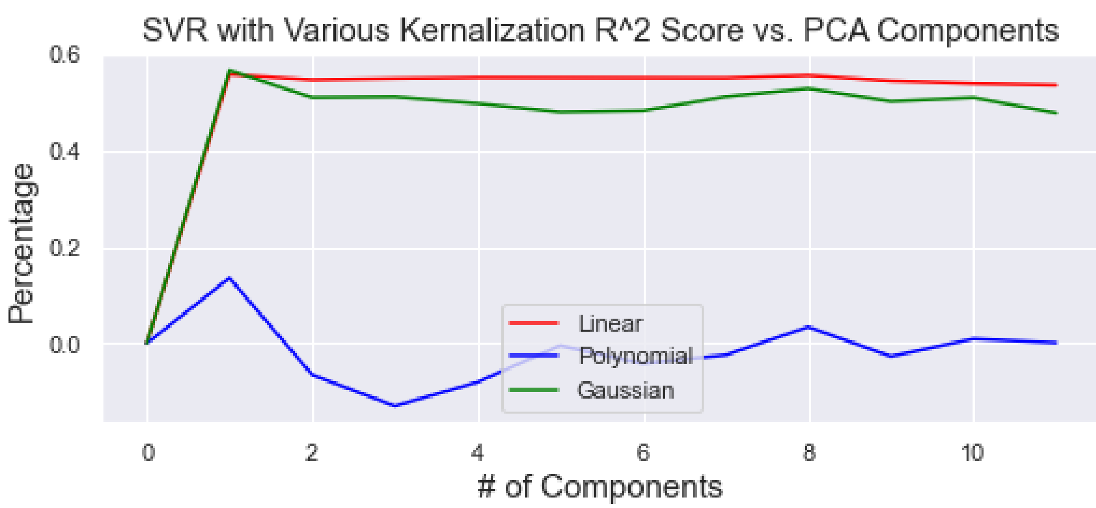
[46]:
```python
SVR_Gauss = SVR(kernel = 'rbf', C= 1E6, gamma = 0.1)
columns = []
SVRGaussScore = np.zeros(12)

for i in range(1,12):
    pca = PCA(n_components=i)
    columns = np.append(columns, ['principal component ' + str(i)])
    columns = list(columns)
    principalComponentstrain = pca.fit_transform(Housing_X_trainstd)
    principalDftrain = pd.DataFrame(data = principalComponentstrain, columns =␣
↪columns)

    finalDftrain = pd.concat([principalDftrain, df[['price']]], axis = 1)
    principalComponentstest = pca.fit_transform(Housing_X_teststd)
    principalDftest = pd.DataFrame(data = principalComponentstest, columns =␣
↪columns)
    finalDftest = pd.concat([principalDftest, df[['price']]], axis = 1)
    SVR_Gauss_train = SVR_Gauss.fit(principalDftrain.values, Housing_Y_train)
    Housing_Y_predSVRGauss = SVR_Gauss_train.predict(principalDftest.values)
    print("R2 score " + str(i) + ": %.2f" %␣
↪r2_score(Housing_Y_test,Housing_Y_predSVRGauss))
    print("Mean squared error " + str(i) + ": %.2f" %␣
↪mean_squared_error(Housing_Y_test,Housing_Y_predSVRGauss))
    SVRGaussScore[i] = r2_score(Housing_Y_test,Housing_Y_predSVRGauss)
    columns = np.array(columns)
```

```
R2 score 1: 0.57
Mean squared error 1: 2195800513262.85
R2 score 2: 0.51
Mean squared error 2: 2480445117858.79
R2 score 3: 0.51
Mean squared error 3: 2473801947794.55
R2 score 4: 0.50
Mean squared error 4: 2543365908277.49
R2 score 5: 0.48
Mean squared error 5: 2634077432381.64
R2 score 6: 0.48
Mean squared error 6: 2619696334720.25
R2 score 7: 0.51
Mean squared error 7: 2472573023678.89
R2 score 8: 0.53
Mean squared error 8: 2385783600969.22
R2 score 9: 0.50
Mean squared error 9: 2521389452555.93
R2 score 10: 0.51
Mean squared error 10: 2482085935229.42
R2 score 11: 0.48
```

```
Mean squared error 11: 2644447125206.12
```

[48]:

```
plt.rcParams["figure.figsize"] = [7.50, 3.50]
plt.rcParams["figure.autolayout"] = True
x = np.array(range(0,12))
y = SVRLinearScore
z = SVRPolyScore
v = SVRGaussScore
plt.title("SVR with Various Kernalization R^2 Score vs. PCA Components",␣
 ↪fontsize = 15)
plt.plot(x, y, color="red", label="Linear")
plt.plot(x, z, color="blue", label="Polynomial")
plt.plot(x, v, color="green", label="Gaussian")
plt.xlabel('# of Components', fontsize = 15)
plt.ylabel('Percentage', fontsize = 15)
leg = plt.legend(loc = 'lower center')
plt.show()
```



[ ]:

```

```