Heatmaps for SVM algorithm

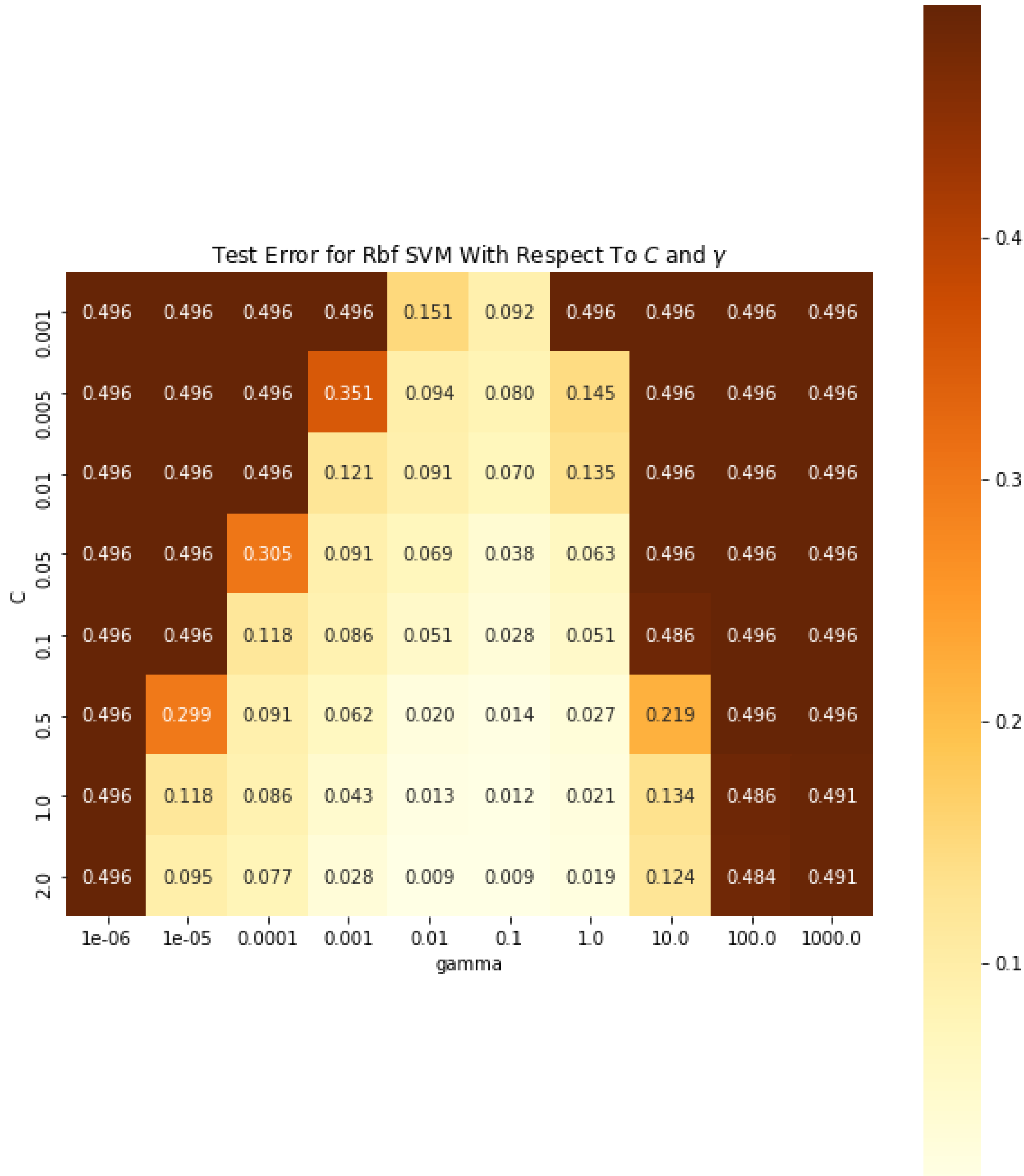
I rerun my code for my rbf-SVM algorithms per Dataset to reset all the variables. Then after each run I print out a heatmap of their performance per hyperparameter setting! Once again, i removed the outputs frome ach algorithm as to not make this notebook 10x longer.

In [ ]:
```
# The following code in this block is for my Dry Bean Dataset:

# We begin by making a massive for-loop to go through 10 trials.
for iterations in range(10):

    # Shuffling the dataset.
    beanData = shuffle(beanData)

    # Setting up X values to be all variables except the area, and Y values to
    # be the area column.
    X = beanData.drop('Area', axis = 1)
    Y = beanData['Area']

    # Printing the number of each iteration as we go up.
    print("Trial Number:", iterations + 1)


    # Setting up a for loop within my iterations loop, which will split my
    # data 4 times, in different ways.
    for split in range(4):
        if split == 0:
            # For the first split, I will do a 80(training)/20(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.2, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 80/20:")

        if split == 1:
            # For the second split, I will do a 70(training)/30(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.3, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 70/30:")

        if split == 2:
            # For the third split, I will do a 60(training)/40(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
```

```
        train_test_split(X, Y, test_size = 0.4, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 60/40:")

    if split == 3:
        # For the fourth split, I will do a 50(training)/50(testing)
        # split, with a Random State of 50.
        X_train, X_test, Y_train, Y_test =
        train_test_split(X, Y, test_size = 0.5, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 50/50:")


    # Setting up a for-loop for my rbf-SVM algorithms.
    for alg in range(1):
        if alg == 0:
            # Creating a SVM classifier with rbf kernel.
            classifierRbf = svm.SVC(kernel = 'rbf')

            # I will use the same C values and gamma values as the
            # CNM06 paper.
            C_Values = [0.001,0.005,0.01,0.05,0.1,0.5,1,2]
            gamma_list = [0.000001, 0.00001,0.0001, 0.001, 0.01,
                          0.1, 1, 10, 100, 1000]

            # Creating parameter grid with C and gamma Values.
            param_grid = {'C': [0.001,0.005,0.01,0.05,0.1,0.5,1,2],
                          'gamma':[0.000001, 0.00001,0.0001, 0.001,
                                   0.01, 0.1, 1, 10, 100, 1000]}

            # Here, I will select hyperparameters via a systematic
            # gridsearch, with a cross validation score of 10 and
            # scoring method set to accuracy:
            GridSearchcvRBF = GridSearchCV(estimator = classifierRbf,
                                           param_grid = param_grid,
                                           scoring='accuracy',
                                           cv = 10, n_jobs = -1)
            GridSearchcvRBF.fit(X_train, Y_train)

            # Creating a classifier that will take in the gridsearch as
            # its regularization parameter to find the best parameters
```

```
                    # for C.
                    classifier_svmRBF =
                    svm.SVC(C = GridSearchcvRBF.best_params_['C'],
                            kernel = 'rbf')

                    # Creating testing and training precitions based on my fitted
                    # X and Y trains.
                    classifier_svmRBF.fit(X_train, Y_train)
                    prediction_svmRBF = classifier_svmRBF.predict(X_test)

                    # Printing the training and testing classification reports.
                    print("Classification report of Test RBF SVM:",
                          classification_report(Y_test, prediction_svmRBF))
```

In [5]:
```
### Heatmap using Dry bean Dataset.
## Heatmap code for RBG kernel.
# We get the parameters used in the order they were used for the RBF Kernel:
results_rbf = pd.DataFrame(GridSearchcvRBF.cv_results_['params'] )

# Next we grab the score resulting from those parameters, and add it
# to the data. Our score is accuracy; I then use 1 - x to display it
# as misclassification error.
results_rbf['score'] = 1 - GridSearchcvRBF.cv_results_['mean_test_score']

# Setting C to be the y-axis and gamma as the x-axis
results_rbf = results_rbf.pivot('C','gamma','score')

# Plot it using the dataframe means.
plt.subplots(figsize = (10,12))
sns.heatmap(results_rbf, annot = True,
            square = True, fmt='.3f', cmap="YlOrBr")
plt.title('Test Error for Rbf SVM With Respect To $C$ and $\gamma$')
plt.show()
```

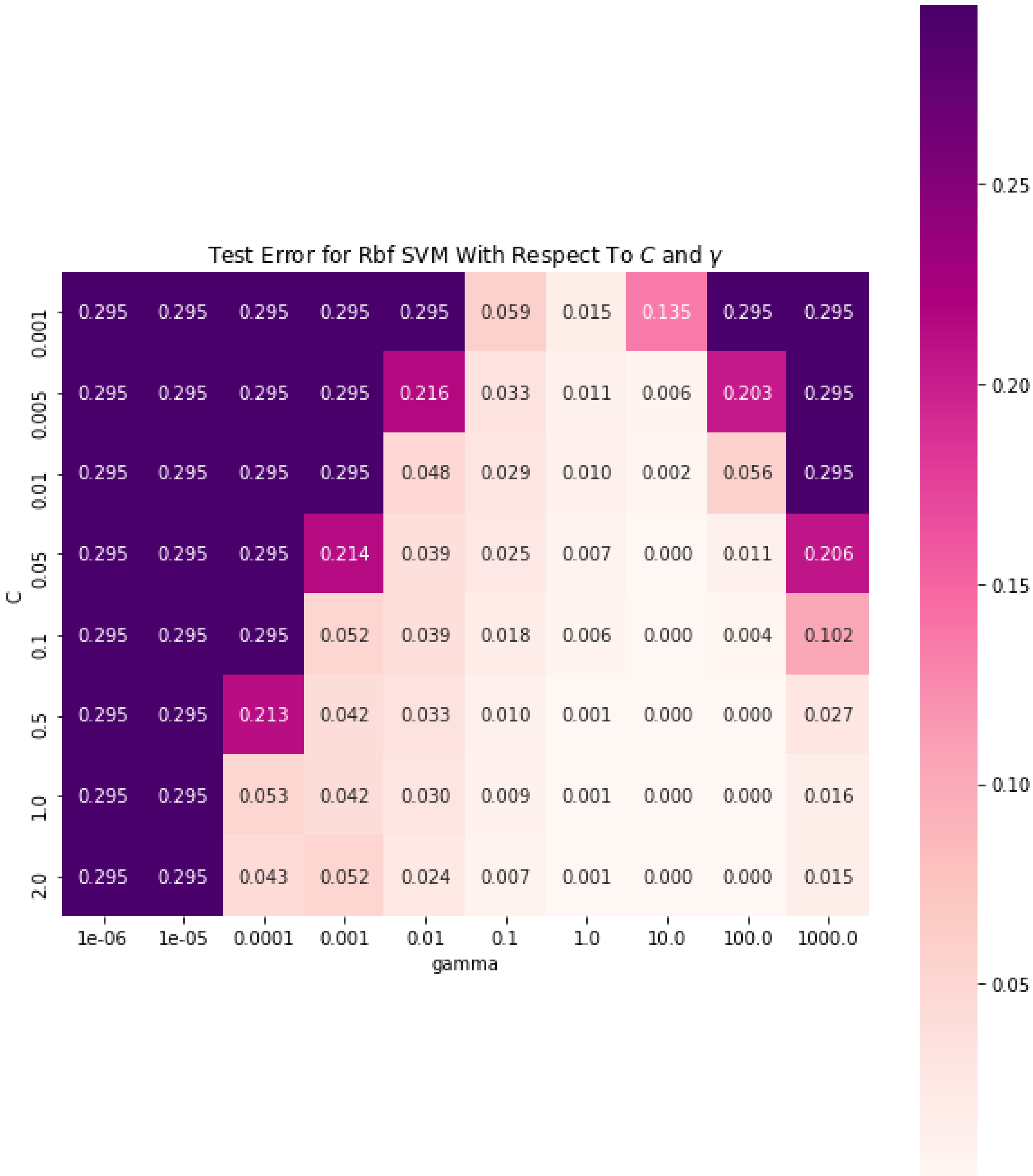

Test Error for Rbf SVM With Respect To C and γ
C
0.001
0.005
0.01
0.05
0.1
0.5
1.0
2.0
gamma
1e-06
1e-05
0.0001
0.001
0.01
0.1
1.0
10.0
100.0
1000.0
0.496 0.496 0.496 0.496 0.151 0.092 0.496 0.496 0.496 0.496
0.496 0.496 0.496 0.351 0.094 0.080 0.145 0.496 0.496 0.496
0.496 0.496 0.496 0.121 0.091 0.070 0.135 0.496 0.496 0.496
0.496 0.496 0.305 0.091 0.069 0.038 0.063 0.496 0.496 0.496
0.496 0.496 0.118 0.086 0.051 0.028 0.051 0.486 0.496 0.496
0.496 0.299 0.091 0.062 0.020 0.014 0.027 0.219 0.496 0.496
0.496 0.118 0.086 0.043 0.013 0.012 0.021 0.134 0.486 0.491
0.496 0.095 0.077 0.028 0.009 0.009 0.019 0.124 0.484 0.491
0.4
0.3
0.2
0.1

In [ ]:
```
# The following code in this block is for my Skin Dataset:

# We begin by making a massive for-loop to go through 10 trials.
for iterations in range(10):

    # Shuffling the dataset.
    skinData = shuffle(skinData)

    # Setting up X values to be all variables except the Y column,
    # and Y values to be the Y column.
    X = skinData.drop('Y', axis = 1)
    Y = skinData['Y']

    # Printing the number of each iteration as we go up.
    print("Trial Number:", iterations + 1)


    # Setting up a for loop within my iterations loop, which will split my
    # data 4 times, in different ways.
    for split in range(4):
        if split == 0:
            # For the first split, I will do a 80(training)/20(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.2, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 80/20:")

        if split == 1:
            # For the second split, I will do a 70(training)/30(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.3, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 70/30:")

        if split == 2:
            # For the third split, I will do a 60(training)/40(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
```

```
        train_test_split(X, Y, test_size = 0.4, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 60/40:")

    if split == 3:
        # For the fourth split, I will do a 50(training)/50(testing)
        # split, with a Random State of 50.
        X_train, X_test, Y_train, Y_test =
        train_test_split(X, Y, test_size = 0.5, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 50/50:")


    # Setting up a for-loop for my rbf-SVM algorithms.
    for alg in range(1):
        if alg == 0:
            # Creating a SVM classifier with rbf kernel.
            classifierRbf = svm.SVC(kernel = 'rbf')

            # I will use the same C values and gamma values as the
            # CNM06 paper.
            C_Values = [0.001,0.005,0.01,0.05,0.1,0.5,1,2]
            gamma_list = [0.000001, 0.00001,0.0001, 0.001, 0.01,
                          0.1, 1, 10, 100, 1000]

            # Creating parameter grid with C and gamma Values.
            param_grid = {'C': [0.001,0.005,0.01,0.05,0.1,0.5,1,2],
                          'gamma':[0.000001, 0.00001,0.0001, 0.001,
                                   0.01, 0.1, 1, 10, 100, 1000]}

            # Here, I will select hyperparameters via a systematic
            # gridsearch, with a cross validation score of 10 and
            # scoring method set to accuracy:
            GridSearchcvRBF = GridSearchCV(estimator = classifierRbf,
                                           param_grid = param_grid,
                                           scoring='accuracy',
                                           cv = 10, n_jobs = -1)
            GridSearchcvRBF.fit(X_train, Y_train)

            # Creating a classifier that will take in the gridsearch as
            # its regularization parameter to find the best parameters
```

```
                    # for C.
                    classifier_svmRBF =
                    svm.SVC(C = GridSearchcvRBF.best_params_['C'],
                            kernel = 'rbf')

                    # Creating testing and training precitions based on my fitted
                    # X and Y trains.
                    classifier_svmRBF.fit(X_train, Y_train)
                    prediction_svmRBF = classifier_svmRBF.predict(X_test)

                    # Printing the training and testing classification reports.
                    print("Classification report of Test RBF SVM:",
                          classification_report(Y_test, prediction_svmRBF))
```

In [5]:
```
### Heatmaps using Skin Dataset.
## Heatmap code for RBG kernel.
# We get the parameters used in the order they were used for the RBF Kernel:
results_rbf = pd.DataFrame(GridSearchcvRBF.cv_results_['params'] )

# Next we grab the score resulting from those parameters, and add it to
# the data. Our score is accuracy; I then use 1 - x to display it as
# misclassification error.
results_rbf['score'] = 1 - GridSearchcvRBF.cv_results_['mean_test_score']

# Setting C to be the y-axis and gamma as the x-axis
results_rbf = results_rbf.pivot('C','gamma','score')

# Plot it using the dataframe means.
plt.subplots(figsize = (10,12))
sns.heatmap(results_rbf, annot = True, square = True, fmt='.3f', cmap="RdPu")
plt.title('Test Error for Rbf SVM With Respect To $C$ and $\gamma$')
plt.show()
```

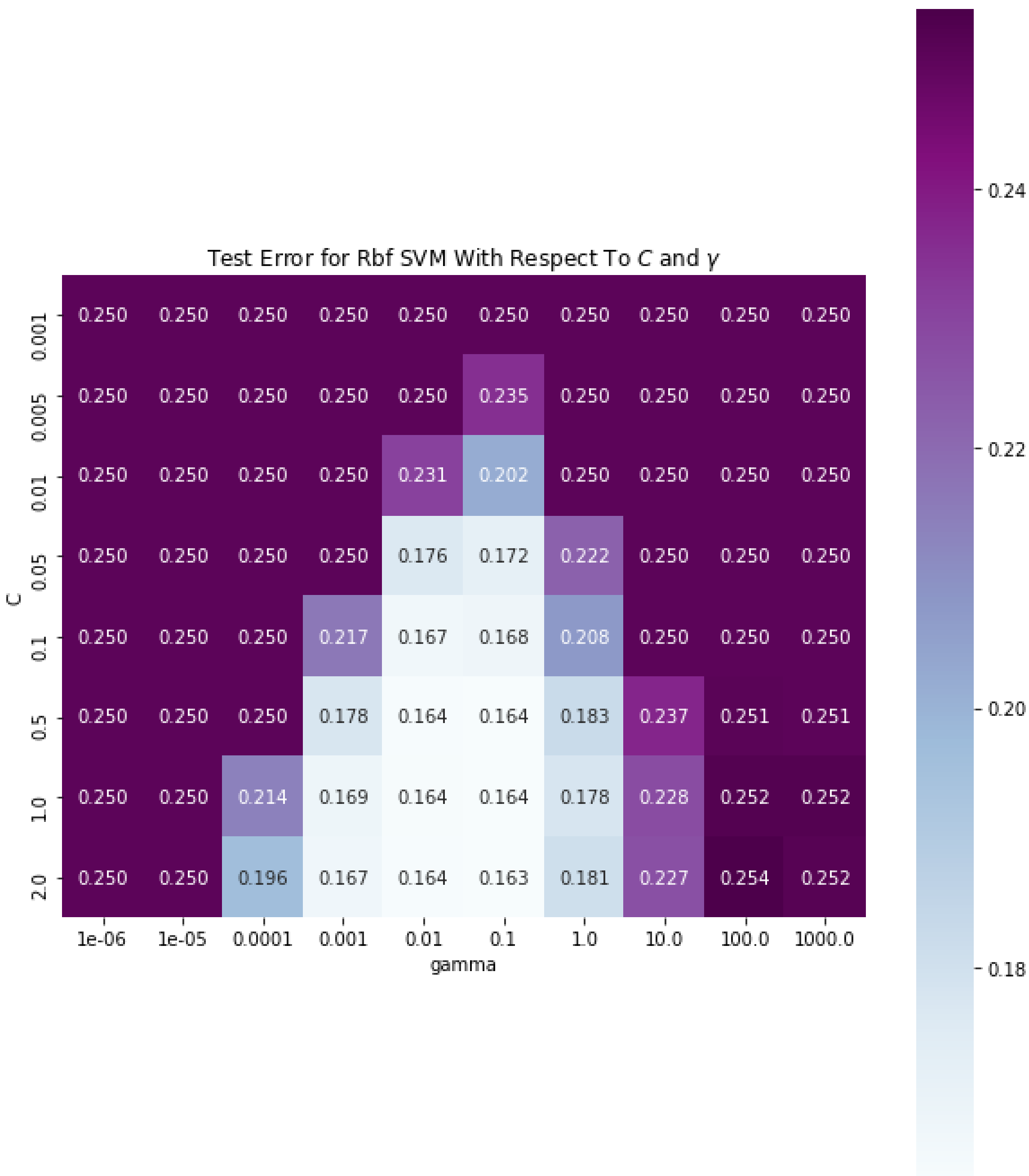

Test Error for Rbf SVM With Respect To C and γ
0.295 0.295 0.295 0.295 0.295 0.059 0.015 0.135 0.295 0.295
0.295 0.295 0.295 0.295 0.216 0.033 0.011 0.006 0.203 0.295
0.295 0.295 0.295 0.295 0.048 0.029 0.010 0.002 0.056 0.295
0.295 0.295 0.295 0.214 0.039 0.025 0.007 0.000 0.011 0.206
0.295 0.295 0.295 0.052 0.039 0.018 0.006 0.000 0.004 0.102
0.295 0.295 0.213 0.042 0.033 0.010 0.001 0.000 0.000 0.027
0.295 0.295 0.053 0.042 0.030 0.009 0.001 0.000 0.000 0.016
0.295 0.295 0.043 0.052 0.024 0.007 0.001 0.000 0.000 0.015
C
0.001
0.005
0.01
0.05
0.1
0.5
1.0
2.0
1e-06 1e-05 0.0001 0.001 0.01 0.1 1.0 10.0 100.0 1000.0
gamma
0.25
0.20
0.15
0.10
0.05

In [ ]:
```
# The following code in this block is for my Adult Dataset:

# We begin by making a massive for-loop to go through 10 trials.
for iterations in range(10):

    # Shuffling the dataset.
    adultData = shuffle(adultData)

    # Assiigning X values to be all columns except salary,
    # and Y values to be salary.
    X = adultData.drop('salary', axis = 1)
    Y = adultData['salary']

    # Printing the number of each iteration as we go up.
    print("Trial Number:", iterations + 1)


    # Setting up a for loop within my iterations loop, which will split my
    # data 4 times, in different ways.
    for split in range(4):
        if split == 0:
            # For the first split, I will do a 80(training)/20(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.2, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 80/20:")

        if split == 1:
            # For the second split, I will do a 70(training)/30(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.3, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 70/30:")

        if split == 2:
            # For the third split, I will do a 60(training)/40(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
```

```
        train_test_split(X, Y, test_size = 0.4, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 60/40:")

    if split == 3:
        # For the fourth split, I will do a 50(training)/50(testing)
        # split, with a Random State of 50.
        X_train, X_test, Y_train, Y_test =
        train_test_split(X, Y, test_size = 0.5, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 50/50:")


    # Setting up a for-loop for my rbf-SVM algorithms.
    for alg in range(1):
        if alg == 0:
            # Creating a SVM classifier with rbf kernel.
            classifierRbf = svm.SVC(kernel = 'rbf')

            # I will use the same C values and gamma values as the
            # CNM06 paper.
            C_Values = [0.001,0.005,0.01,0.05,0.1,0.5,1,2]
            gamma_list = [0.000001, 0.00001,0.0001, 0.001, 0.01,
                          0.1, 1, 10, 100, 1000]

            # Creating parameter grid with C and gamma Values.
            param_grid = {'C': [0.001,0.005,0.01,0.05,0.1,0.5,1,2],
                          'gamma':[0.000001, 0.00001,0.0001, 0.001,
                                   0.01, 0.1, 1, 10, 100, 1000]}

            # Here, I will select hyperparameters via a systematic
            # gridsearch, with a cross validation score of 10 and
            # scoring method set to accuracy:
            GridSearchcvRBF = GridSearchCV(estimator = classifierRbf,
                                           param_grid = param_grid,
                                           scoring='accuracy',
                                           cv = 10, n_jobs = -1)
            GridSearchcvRBF.fit(X_train, Y_train)

            # Creating a classifier that will take in the gridsearch as
            # its regularization parameter to find the best parameters
```

```
# for C.
classifier_svmRBF =
svm.SVC(C = GridSearchcvRBF.best_params_['C'],
        kernel = 'rbf')

# Creating testing and training precitions based on my fitted
# X and Y trains.
classifier_svmRBF.fit(X_train, Y_train)
prediction_svmRBF = classifier_svmRBF.predict(X_test)

# Printing the training and testing classification reports.
print("Classification report of Test RBF SVM:",
      classification_report(Y_test, prediction_svmRBF))
```

In [5]:
```
### Heatmaps using Adult Dataset.
## Heatmap code for RBG kernel.
# We get the parameters used in the order they were used for the RBF Kernel:
results_rbf = pd.DataFrame(GridSearchcvRBF.cv_results_['params'] )

# Next we grab the score resulting from those parameters, and add it to
# the data. Our score is accuracy; I then use 1 - x to display it as
# misclassification error.
results_rbf['score'] = 1 - GridSearchcvRBF.cv_results_['mean_test_score']

# Setting C to be the y-axis and gamma as the x-axis
results_rbf = results_rbf.pivot('C','gamma','score')

# Plot it using the dataframe means.
plt.subplots(figsize = (10,12))
sns.heatmap(results_rbf, annot = True, square = True, fmt='.3f', cmap="BuPu")
plt.title('Test Error for Rbf SVM With Respect To $C$ and $\gamma$')
plt.show()
```

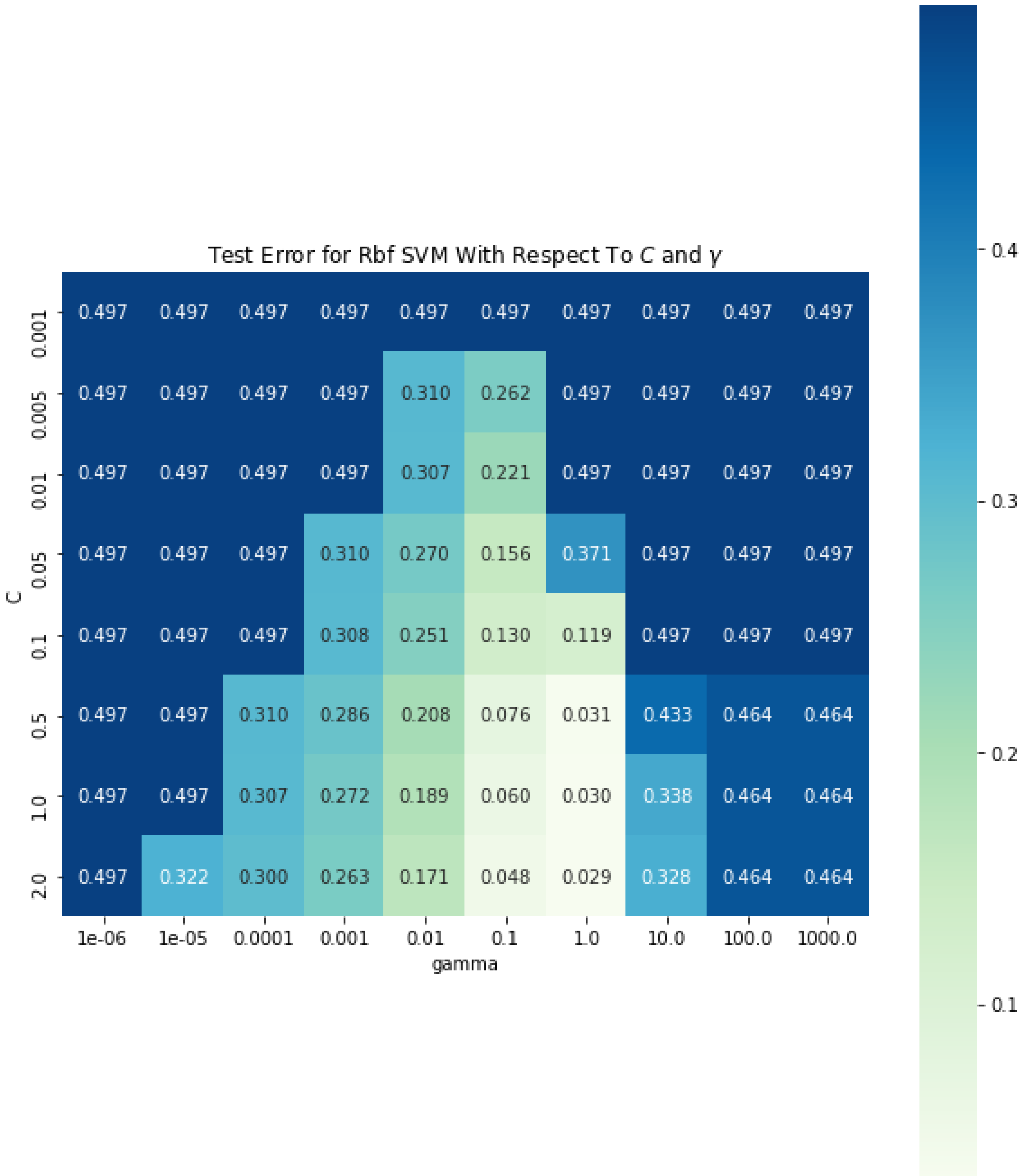

Test Error for Rbf SVM With Respect To C and γ
C
gamma
0.001
0.005
0.01
0.05
0.1
0.5
1.0
2.0
1e-06
1e-05
0.0001
0.001
0.01
0.1
1.0
10.0
100.0
1000.0
0.250 0.250 0.250 0.250 0.250 0.250 0.250 0.250 0.250 0.250
0.250 0.250 0.250 0.250 0.250 0.235 0.250 0.250 0.250 0.250
0.250 0.250 0.250 0.250 0.231 0.202 0.250 0.250 0.250 0.250
0.250 0.250 0.250 0.250 0.176 0.172 0.222 0.250 0.250 0.250
0.250 0.250 0.250 0.217 0.167 0.168 0.208 0.250 0.250 0.250
0.250 0.250 0.250 0.178 0.164 0.164 0.183 0.237 0.251 0.251
0.250 0.250 0.214 0.169 0.164 0.164 0.178 0.228 0.252 0.252
0.250 0.250 0.196 0.167 0.164 0.163 0.181 0.227 0.254 0.252
0.24
0.22
0.20
0.18

In [ ]:
```
# The following code in this block is for my Letter Dataset:

# We begin by making a massive for-loop to go through 10 trials.
for iterations in range(10):

    # Shuffling the dataset.
    letterData = shuffle(letterData)

    # Setting up X values to be everything except the letter column,
    # and Y values to be the letter column.
    X = letterData.drop('letter', axis = 1)
    Y = letterData['letter']

    # Printing the number of each iteration as we go up.
    print("Trial Number:", iterations + 1)


    # Setting up a for loop within my iterations loop, which will split my
    # data 4 times, in different ways.
    for split in range(4):
        if split == 0:
            # For the first split, I will do a 80(training)/20(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.2, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 80/20:")

        if split == 1:
            # For the second split, I will do a 70(training)/30(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
            train_test_split(X, Y, test_size = 0.3, random_state = 50)

            # Standardizing features by removing the mean and scaling to a
            # unit variance.
            stsc = StandardScaler()

            # Transforming X train and X test based on the
            # standardization above.
            X_train = stsc.fit_transform(X_train)
            X_test = stsc.fit_transform(X_test)
            print("Data Split 70/30:")

        if split == 2:
            # For the third split, I will do a 60(training)/40(testing)
            # split, with a Random State of 50.
            X_train, X_test, Y_train, Y_test =
```

```
        train_test_split(X, Y, test_size = 0.4, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 60/40:")

    if split == 3:
        # For the fourth split, I will do a 50(training)/50(testing)
        # split, with a Random State of 50.
        X_train, X_test, Y_train, Y_test =
        train_test_split(X, Y, test_size = 0.5, random_state = 50)

        # Standardizing features by removing the mean and scaling to a
        # unit variance.
        stsc = StandardScaler()

        # Transforming X train and X test based on the
        # standardization above.
        X_train = stsc.fit_transform(X_train)
        X_test = stsc.fit_transform(X_test)
        print("Data Split 50/50:")


    # Setting up a for-loop for my rbf-SVM algorithms.
    for alg in range(1):
        if alg == 0:
            # Creating a SVM classifier with rbf kernel.
            classifierRbf = svm.SVC(kernel = 'rbf')

            # I will use the same C values and gamma values as the
            # CNM06 paper.
            C_Values = [0.001,0.005,0.01,0.05,0.1,0.5,1,2]
            gamma_list = [0.000001, 0.00001,0.0001, 0.001, 0.01,
                          0.1, 1, 10, 100, 1000]

            # Creating parameter grid with C and gamma Values.
            param_grid = {'C': [0.001,0.005,0.01,0.05,0.1,0.5,1,2],
                          'gamma':[0.000001, 0.00001,0.0001, 0.001,
                                   0.01, 0.1, 1, 10, 100, 1000]}

            # Here, I will select hyperparameters via a systematic
            # gridsearch, with a cross validation score of 10 and
            # scoring method set to accuracy:
            GridSearchcvRBF = GridSearchCV(estimator = classifierRbf,
                                           param_grid = param_grid,
                                           scoring='accuracy',
                                           cv = 10, n_jobs = -1)
            GridSearchcvRBF.fit(X_train, Y_train)

            # Creating a classifier that will take in the gridsearch as
            # its regularization parameter to find the best parameters
```

```
                # for C.
                classifier_svmRBF =
                svm.SVC(C = GridSearchcvRBF.best_params_['C'],
                        kernel = 'rbf')

                # Creating testing and training precitions based on my fitted
                # X and Y trains.
                classifier_svmRBF.fit(X_train, Y_train)
                prediction_svmRBF = classifier_svmRBF.predict(X_test)

                # Printing the training and testing classification reports.
                print("Classification report of Test RBF SVM:",
                      classification_report(Y_test, prediction_svmRBF))
```

In [7]:
```
### Heatmaps using Letter Dataset.
## Heatmap code for RBG kernel.
# We get the parameters used in the order they were used for the RBF Kernel:
results_rbf = pd.DataFrame(GridSearchcvRBF.cv_results_['params'] )

# Next we grab the score resulting from those parameters, and add it to
# the data. Our score is accuracy; I then use 1 - x to display it as
# misclassification error.
results_rbf['score'] = 1 - GridSearchcvRBF.cv_results_['mean_test_score']

# Setting C to be the y-axis and gamma as the x-axis
results_rbf = results_rbf.pivot('C','gamma','score')

# Plot it using the dataframe means.
plt.subplots(figsize = (10,12))
sns.heatmap(results_rbf, annot = True, square = True, fmt='.3f', cmap="GnBu")
plt.title('Test Error for Rbf SVM With Respect To $C$ and $\gamma$')
plt.show()
```


Test Error for Rbf SVM With Respect To C and γ
C
gamma
0.001
0.005
0.01
0.05
0.1
0.5
1.0
2.0
1e-06
1e-05
0.0001
0.001
0.01
0.1
1.0
10.0
100.0
1000.0
0.497 0.497 0.497 0.497 0.497 0.497 0.497 0.497 0.497 0.497
0.497 0.497 0.497 0.497 0.310 0.262 0.497 0.497 0.497 0.497
0.497 0.497 0.497 0.497 0.307 0.221 0.497 0.497 0.497 0.497
0.497 0.497 0.497 0.310 0.270 0.156 0.371 0.497 0.497 0.497
0.497 0.497 0.497 0.308 0.251 0.130 0.119 0.497 0.497 0.497
0.497 0.497 0.310 0.286 0.208 0.076 0.031 0.433 0.464 0.464
0.497 0.497 0.307 0.272 0.189 0.060 0.030 0.338 0.464 0.464
0.497 0.322 0.300 0.263 0.171 0.048 0.029 0.328 0.464 0.464
0.4
0.3
0.2
0.1