svm

November 23, 2020

1. :

- k
-
- “ ” onehot

1. See the distribution of the data and the integrity of the data:

- check percentages over 50 k
- Check to see if each column is null
- Special values, such as ”? No processing is done, and the oneHot encoding is replaced later

[101]:
```python
import numpy as np
import pandas as pd
from IPython.display import display
import visuals as vs
import warnings

warnings.filterwarnings('ignore')

data_census = pd.read_csv("census.csv")

data = data_census
display(data.dtypes)
display(data.head(10))

# total number of the dataset
n_records = data.shape[0]

# Number of the records where individual's income is more than $50000
n_less_50k, n_exceeds_50k = data.income.value_counts()

# precentage of individuals whose income is more than $50000
exceeds_percentage = (n_exceeds_50k) / n_records * 100

print("The total records is {}".format(n_records))
print("Invididuals making more than $50k: {}".format(n_exceeds_50k))
print("Invididuals making less than $50k: {}".format(n_less_50k))
```

```
print("Percentage of individuals making more than %50k: {:.2f}%".
 ↪format(exceeds_percentage))

# check whether there is null data in the training dataset
print("\n",'==== check whether there is null in dataset ====')
display(data.isnull().any(axis = 0))

'''
# check other values like "?" in work class
print("\n", "==== value counts in workclass ====")
display(data.workclass.value_counts())

# check values "?" in occupation
print("\n","==== value counts in occupation ====")
display(data.occupation.value_counts())
'''
```

```
age                    int64
workclass             object
education_level       object
education-num        float64
marital-status        object
occupation            object
relationship          object
race                  object
sex                   object
capital-gain         float64
capital-loss         float64
hours-per-week       float64
native-country        object
income                object
dtype: object


   age          workclass education_level  education-num  \
0   39          State-gov       Bachelors           13.0
1   50   Self-emp-not-inc       Bachelors           13.0
2   38            Private         HS-grad            9.0
3   53            Private            11th            7.0
4   28            Private       Bachelors           13.0
5   37            Private         Masters           14.0
6   49            Private             9th            5.0
7   52   Self-emp-not-inc         HS-grad            9.0
8   31            Private         Masters           14.0
9   42            Private       Bachelors           13.0

           marital-status          occupation    relationship    race  \
0           Never-married        Adm-clerical   Not-in-family   White
```

```
1      Married-civ-spouse     Exec-managerial         Husband   White
2                Divorced   Handlers-cleaners   Not-in-family   White
3      Married-civ-spouse   Handlers-cleaners         Husband   Black
4      Married-civ-spouse      Prof-specialty            Wife   Black
5      Married-civ-spouse     Exec-managerial            Wife   White
6   Married-spouse-absent       Other-service   Not-in-family   Black
7      Married-civ-spouse     Exec-managerial         Husband   White
8           Never-married      Prof-specialty   Not-in-family   White
9      Married-civ-spouse     Exec-managerial         Husband   White

       sex  capital-gain  capital-loss  hours-per-week  native-country income
0     Male        2174.0           0.0            40.0   United-States  <=50K
1     Male           0.0           0.0            13.0   United-States  <=50K
2     Male           0.0           0.0            40.0   United-States  <=50K
3     Male           0.0           0.0            40.0   United-States  <=50K
4   Female           0.0           0.0            40.0            Cuba  <=50K
5   Female           0.0           0.0            40.0   United-States  <=50K
6   Female           0.0           0.0            16.0         Jamaica  <=50K
7     Male           0.0           0.0            45.0   United-States   >50K
8   Female       14084.0           0.0            50.0   United-States   >50K
9     Male        5178.0           0.0            40.0   United-States   >50K

The total records is 45222
Inviduals making more than $50k: 11208
Inviduals making less than $50k: 34014
Percentage of individuals making more than %50k: 24.78%

 ==== check whether there is null in dataset ====

age                False
workclass          False
education_level    False
education-num      False
marital-status     False
occupation         False
relationship       False
race               False
sex                False
capital-gain       False
capital-loss       False
hours-per-week     False
native-country     False
income             False
dtype: bool


 ==== value counts in workclass ====
```

```
 Private             33307
 Self-emp-not-inc     3796
 Local-gov            3100
 State-gov            1946
 Self-emp-inc         1646
 Federal-gov          1406
 Without-pay            21
Name: workclass, dtype: int64



 ==== value counts in occupation ====

 Craft-repair         6020
 Prof-specialty       6008
 Exec-managerial      5984
 Adm-clerical         5540
 Sales                5408
 Other-service        4808
 Machine-op-inspct    2970
 Transport-moving     2316
 Handlers-cleaners    2046
 Farming-fishing      1480
 Tech-support         1420
 Protective-serv       976
 Priv-house-serv       232
 Armed-Forces           14
Name: occupation, dtype: int64
```

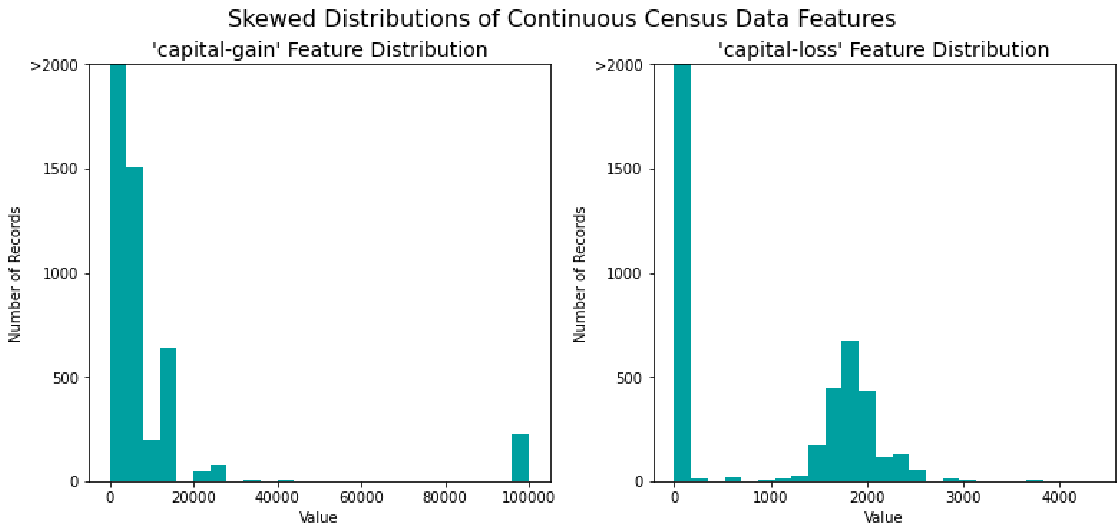
2. :

-
-
- on-hot

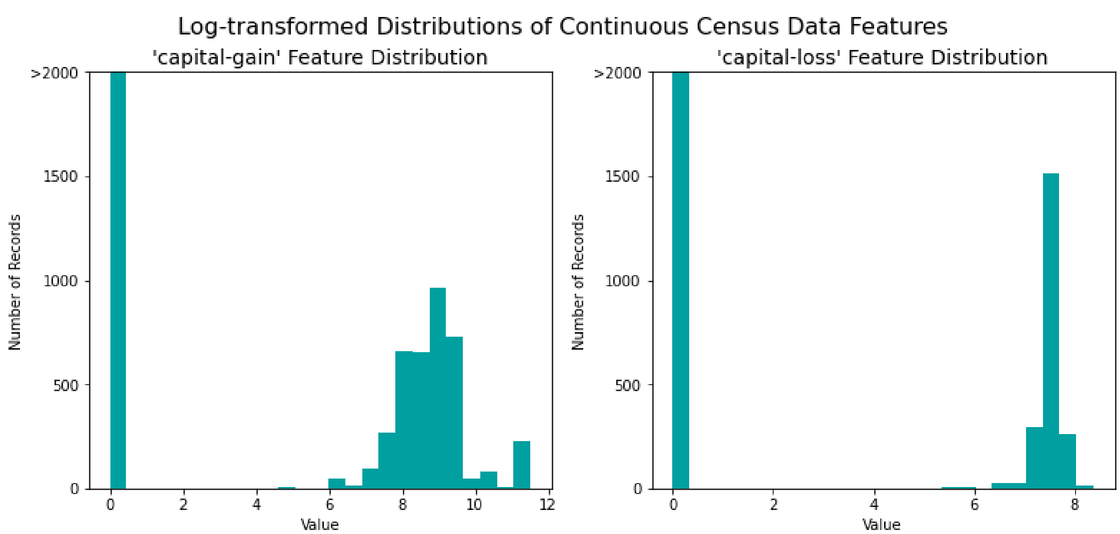
2. Preprocess the data:

- For very different columns, apply a logarithmic transformation
- Regularization of continuous features
- Non-numeric eigenvalues are on-hot coded

[4]:
```
vs.distribution(data)
```



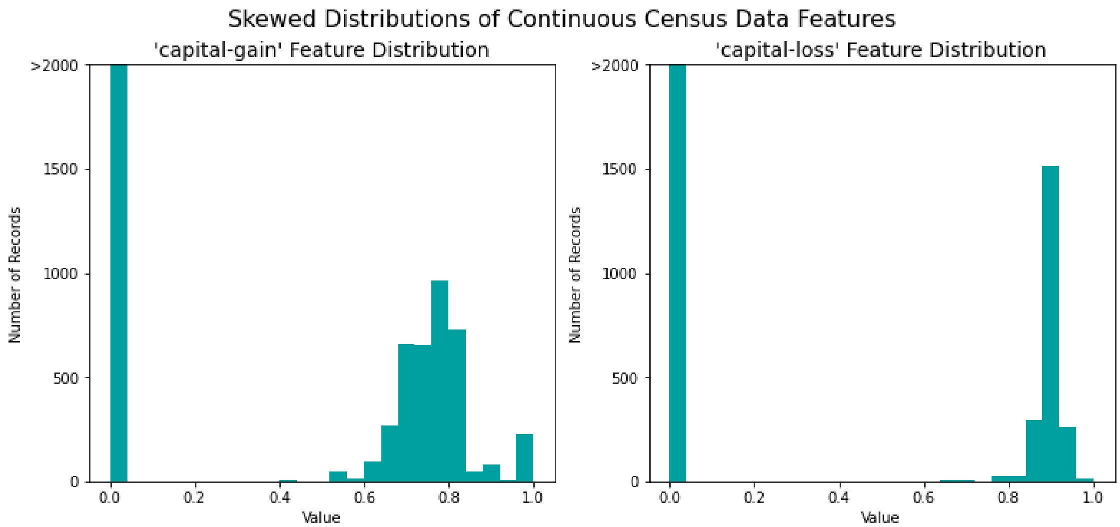

```
[5]: # split the data
income_raw = data['income']
features_raw = data.drop('income', axis = 1)

# Log-transform the skewed features
skewed = ['capital-gain', 'capital-loss']
features_log_transformed = pd.DataFrame(data = features_raw)
features_log_transformed[skewed] = features_raw[skewed].apply(lambda x: np.
 ↪log(x + 1))

# Visualize the new log distributions
vs.distribution(features_log_transformed, transformed = True)
```



[6]:

```python
# Import sklearn.preprocessing.StandardScaler
from sklearn.preprocessing import MinMaxScaler

# Initialize a scaler, then apply it to the features
scaler = MinMaxScaler() # default=(0, 1)
numerical = ['age', 'education-num', 'capital-gain', 'capital-loss',␣
↪'hours-per-week']

features_log_minmax_transform = pd.DataFrame(data = features_log_transformed)
features_log_minmax_transform[numerical] = scaler.
↪fit_transform(features_log_transformed[numerical])

# Show an example of a record with scaling applied
display(features_log_minmax_transform.head(n = 5))

vs.distribution(features_log_minmax_transform)
```

```
        age          workclass education_level  education-num  \
0  0.301370          State-gov       Bachelors       0.800000
1  0.452055   Self-emp-not-inc       Bachelors       0.800000
2  0.287671            Private         HS-grad       0.533333
3  0.493151            Private            11th       0.400000
4  0.150685            Private       Bachelors       0.800000

       marital-status          occupation    relationship    race      sex  \
0       Never-married        Adm-clerical   Not-in-family   White     Male
1  Married-civ-spouse     Exec-managerial         Husband   White     Male
2            Divorced   Handlers-cleaners   Not-in-family   White     Male
3  Married-civ-spouse   Handlers-cleaners         Husband   Black     Male
4  Married-civ-spouse      Prof-specialty            Wife   Black   Female

   capital-gain  capital-loss  hours-per-week  native-country
0      0.667492           0.0        0.397959   United-States
1      0.000000           0.0        0.122449   United-States
2      0.000000           0.0        0.397959   United-States
3      0.000000           0.0        0.397959   United-States
4      0.000000           0.0        0.397959            Cuba
```



[7]:
```python
from sklearn.preprocessing import LabelEncoder
# TODO: One-hot encode the 'features_log_minmax_transform' data using pandas.
 ↪get_dummies()
features_final = pd.get_dummies(features_log_minmax_transform)

# TODO: Encode the 'income_raw' data to numerical values
encoder = LabelEncoder()
income = encoder.fit_transform(income_raw)

# Print the number of features after one-hot encoding
encoded = list(features_final.columns)
print("{} total features after on-hot encoding".format(len(encoded)))
features_final.head(1)
```

```
103 total features after on-hot encoding
```

[7]:
```
       age  education-num  capital-gain  capital-loss  hours-per-week  \
0  0.30137            0.8      0.667492           0.0        0.397959

   workclass_ Federal-gov  workclass_ Local-gov  workclass_ Private  \
0                       0                     0                   0

   workclass_ Self-emp-inc  workclass_ Self-emp-not-inc  …  \
0                        0                            0  …

   native-country_ Portugal  native-country_ Puerto-Rico  \
0                         0                            0

   native-country_ Scotland  native-country_ South  native-country_ Taiwan  \
```

```
0                          0                       0                        0

   native-country_ Thailand  native-country_ Trinadad&Tobago  \
0                          0                                 0

   native-country_ United-States  native-country_ Vietnam  \
0                               1                        0

   native-country_ Yugoslavia
0                            0

[1 rows x 103 columns]
```

3.   :

-
- linearSVC, SVC, NuSVC
-
-          results   5

3.Here we try the models:

- write some basic functions
- training (linearSVC, SVC, NuSVC)
- plot pictures
- store the results in the results

[83]:

```python
# Import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt

from pprint import pprint
from time import time
from sklearn import metrics
from sklearn.metrics import auc
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.svm import NuSVC
from sklearn.metrics import fbeta_score,accuracy_score

# print the roc curve
def print_roc_auc(y_test, prediction):

    # print the roc curve
```

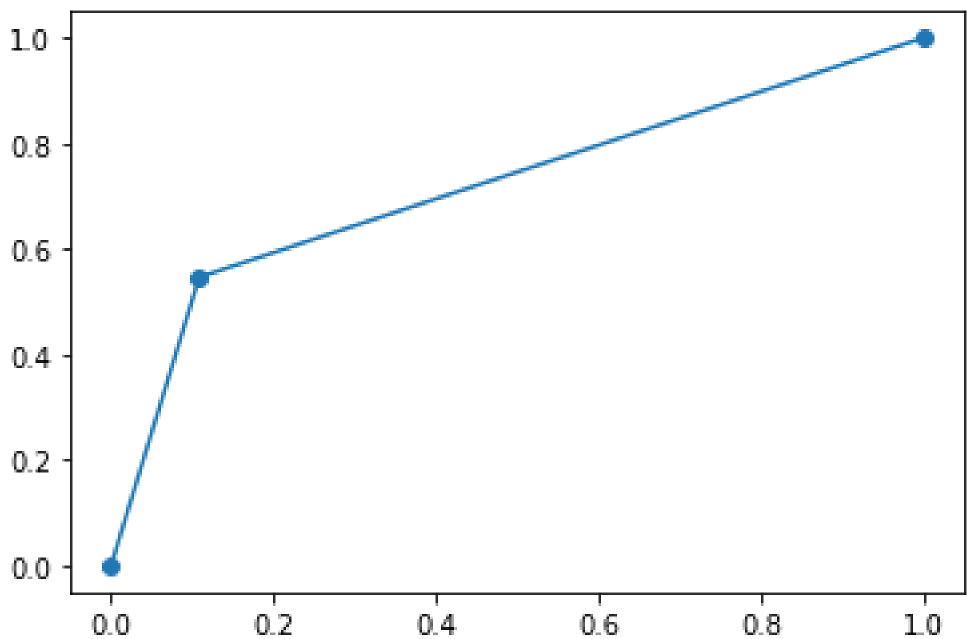
```python
    fpr, tpr, thresholds = metrics.roc_curve(y_test, prediction, pos_label=1)

    # plot the curve
    plt.plot(fpr,tpr,marker = 'o')
    plt.show()

    # print the auc
    C2 = confusion_matrix(y_test, prediction)

    # plot the auc
    sns.heatmap(C2, annot = True)
    AUC = auc(fpr, tpr)

    return AUC

def train_predict(learner, sample_size, X_train, y_train, X_test, y_test):
    '''
    inputs:
       - learner: the learning algorithm to be trained and predicted on
       - sample_size: the size of samples (number) to be drawn from training set
       - X_train: features training set
       - y_train: income training set
       - X_test: features testing set
       - y_test: income testing set
    '''

    results = {}

    # TODO: Fit the learner to the training data using slicing with␣
 ↪'sample_size' using .fit(training_features[:], training_labels[:])
    start = time() # Get start time
    learner = learner.fit(X_train[:sample_size], y_train[:sample_size])
    end = time() # Get end time

    # TODO: Calculate the training time
    results['train_time'] = end - start

    # TODO: Get the predictions on the test set(X_test),
    #       then get predictions on the first 300 training samples(X_train)␣
 ↪using .predict()
    start = time() # Get start time
    predictions_test = learner.predict(X_test)
    predictions_train = learner.predict(X_train[:300])
    end = time() # Get end time

    # TODO: Print the curve
    print_roc_auc(y_test, predictions_test)
```

```
    # TODO: Calculate the total prediction time
    results['pred_time'] = end-start

    # TODO: Compute accuracy on the first 300 training samples which is␣
 ↪y_train[:300]
    results['acc_train'] = accuracy_score(predictions_train, y_train[:300])

    # TODO: Compute accuracy on test set using accuracy_score()
    results['acc_test'] = accuracy_score(predictions_test, y_test)

    # TODO: Compute F-score on the the first 300 training samples using␣
 ↪fbeta_score()
    results['f_train'] = fbeta_score(y_train[:300], predictions_train, beta= 0.
 ↪5)

    # TODO: Compute F-score on the test set which is y_test
    results['f_test'] = fbeta_score(y_test, predictions_test, beta= 0.5)

    # Success
    print("{} trained on {} samples.".format(learner.__class__.__name__,␣
 ↪sample_size))

    # Return the results
    return results

def evaluate(test, pred, accList, f1List):
    f1 = round(f1_score(test, pred, average='weighted') * 100, 2)
    acc = round(accuracy_score(test, pred) * 100, 2)
    accList.append(acc)
    f1List.append(f1)
    return accList, f1List

results = {}

# Split the 'features' and 'income' data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_final,
                                                    income,
                                                    test_size = 0.2,
                                                    random_state = 0)

samples_100 = len(y_train)
samples_10 = int(len(y_train)*0.1)
samples_1 = int(len(y_train)*0.01)

# Show the results of the split
print("Training set has {} samples.".format(X_train.shape[0]))
```

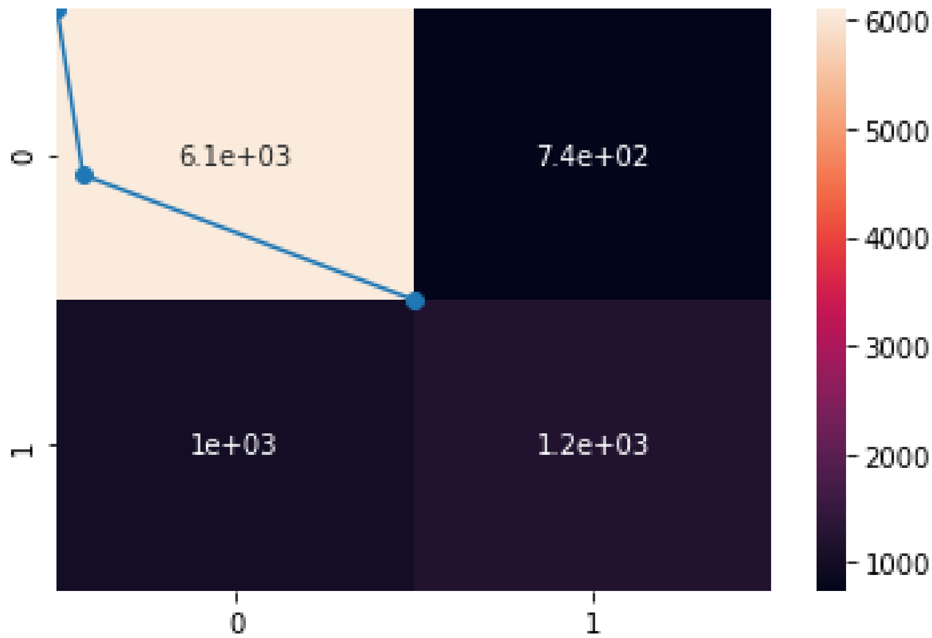
```
print("Testing set has {} samples.".format(X_test.shape[0]))
print(income)
```

```
Training set has 36177 samples.
Testing set has 9045 samples.
[0 0 0 … 0 0 1]
```

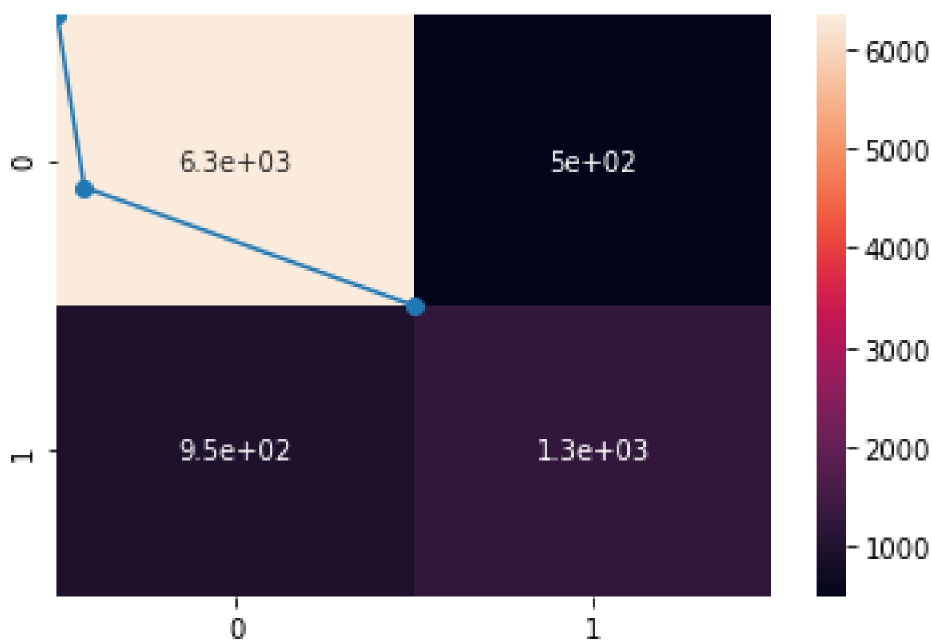
[96]:
```
'''
class sklearn.svm.LinearSVC()
'''

clf = LinearSVC()

for i, samples in enumerate([samples_1, samples_10, samples_100]):
    results[clf.__class__.__name__ + '_' + str(samples)] = train_predict(clf,␣
 ↪samples, X_train, y_train, X_test, y_test)
```



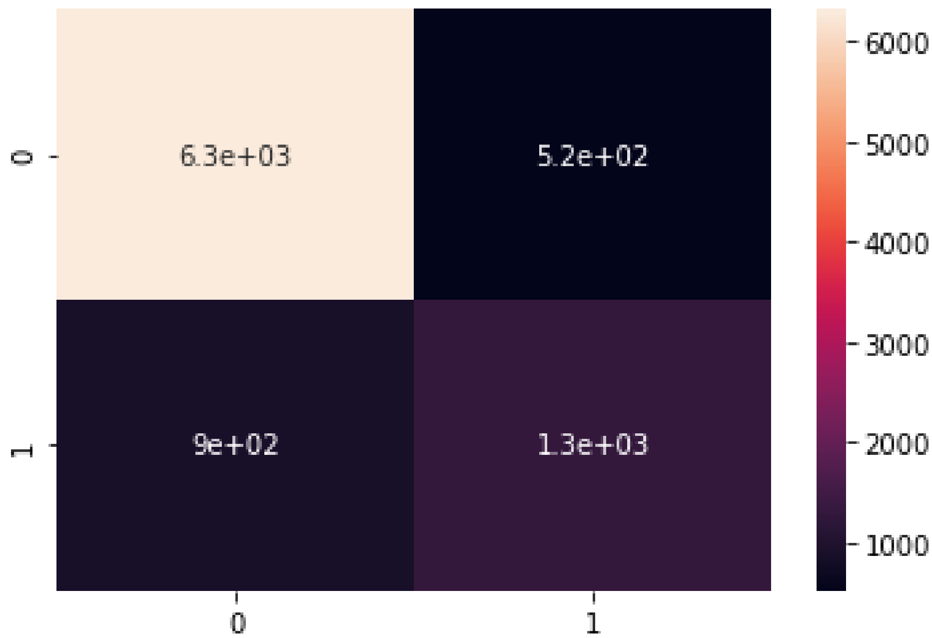

```
LinearSVC trained on 361 samples.
```



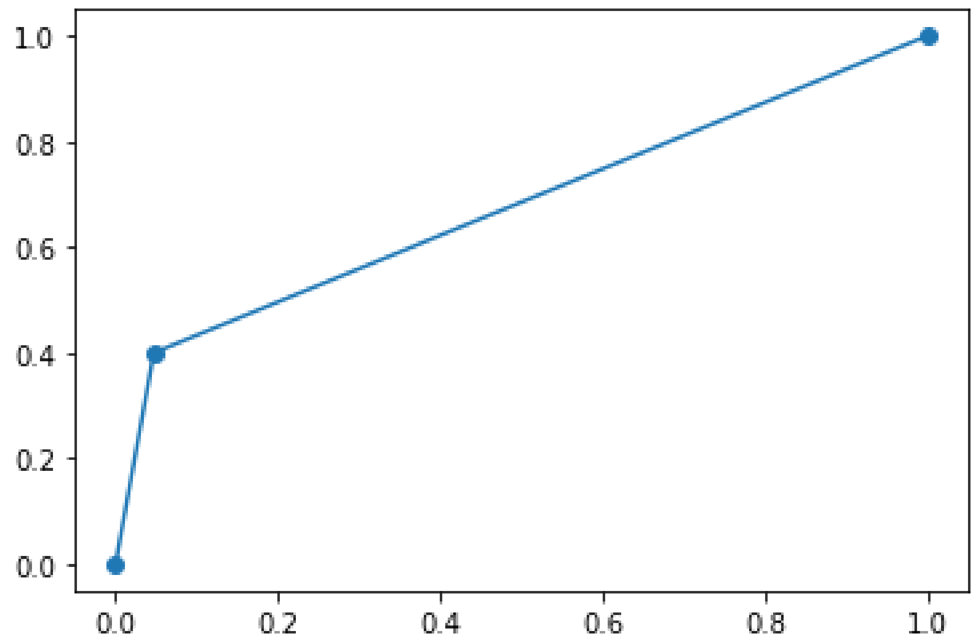
LinearSVC trained on 3617 samples.



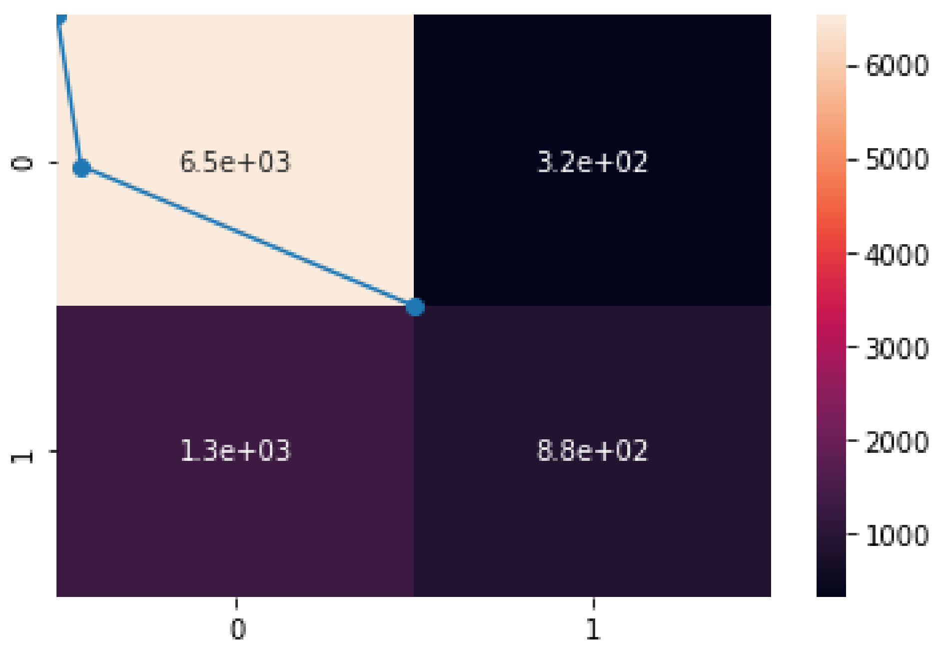
LinearSVC trained on 36177 samples.



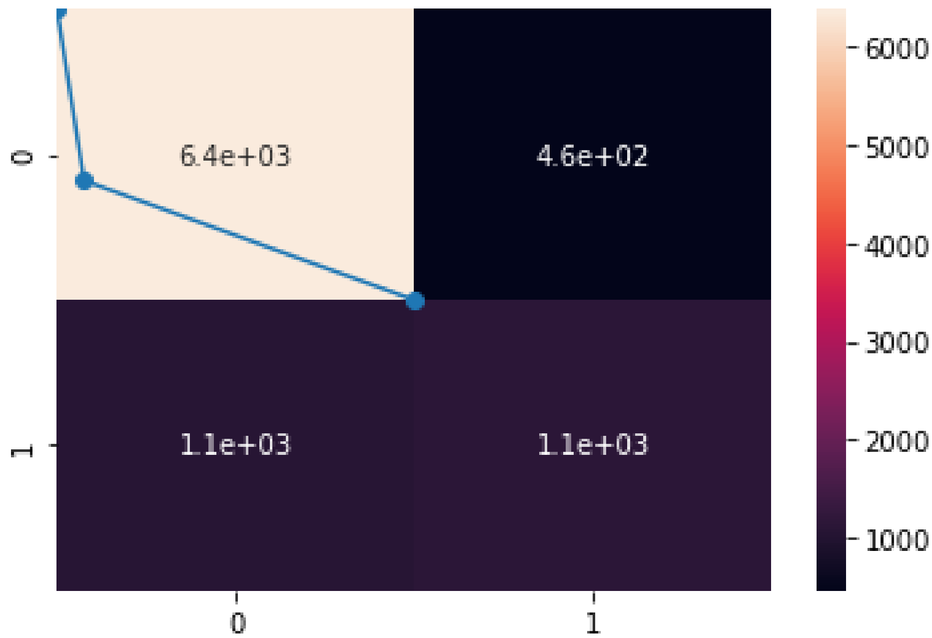
[93]:
```
# svm.SVC()

clf_rbf = SVC(kernel = 'rbf')
clf_linear = SVC(kernel = 'linear')
clf_poly = SVC(kernel = 'poly')

for clf in [clf_rbf, clf_linear, clf_poly]:
    for i, samples in enumerate([samples_1, samples_10, samples_100]):
        results[clf.__class__.__name__ + '_'  + getattr(clf, 'kernel') + '_' +␣
↪str(samples)] = train_predict(clf, samples, X_train, y_train, X_test, y_test)
```



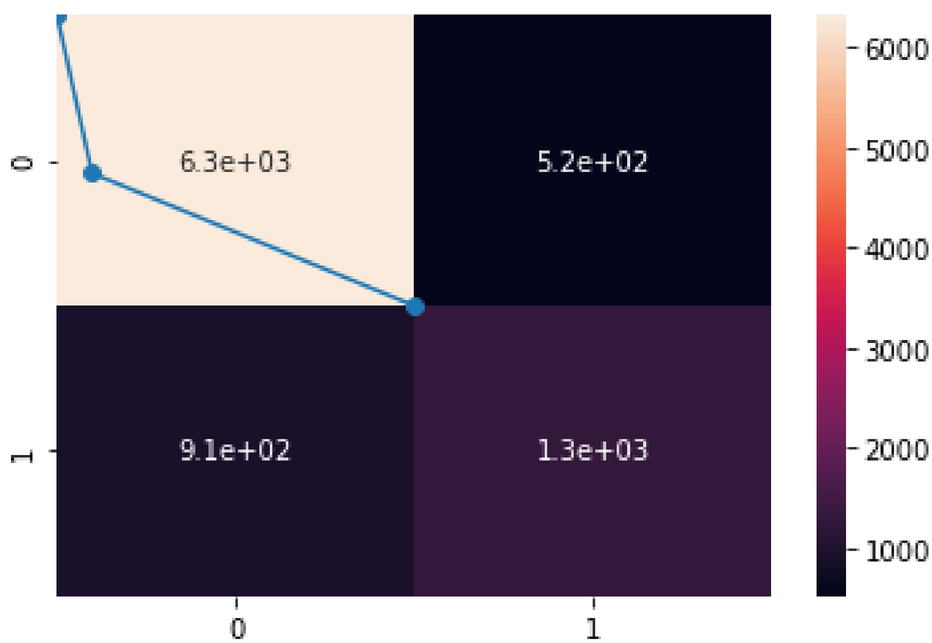
SVC trained on 361 samples.



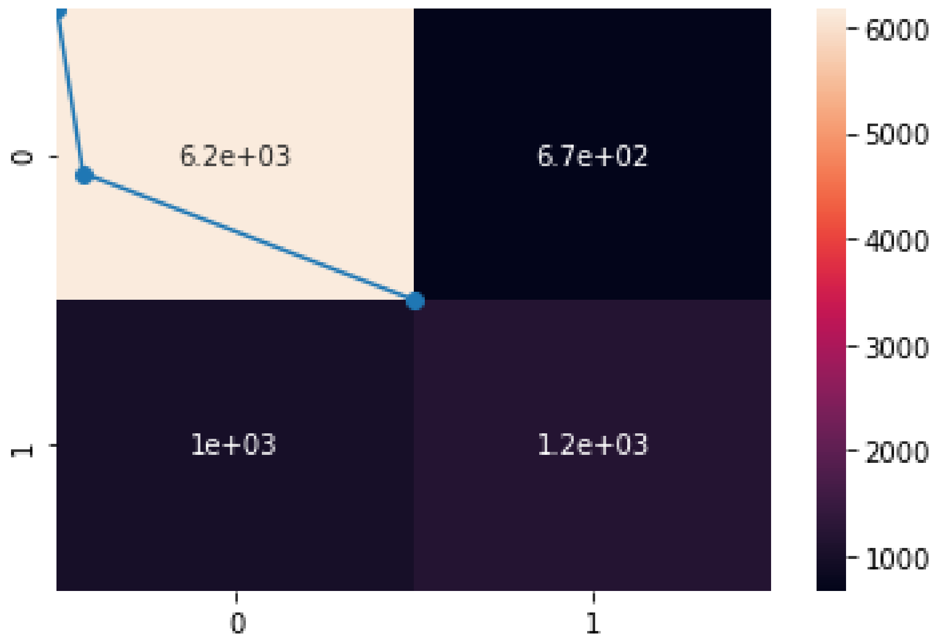
SVC trained on 3617 samples.



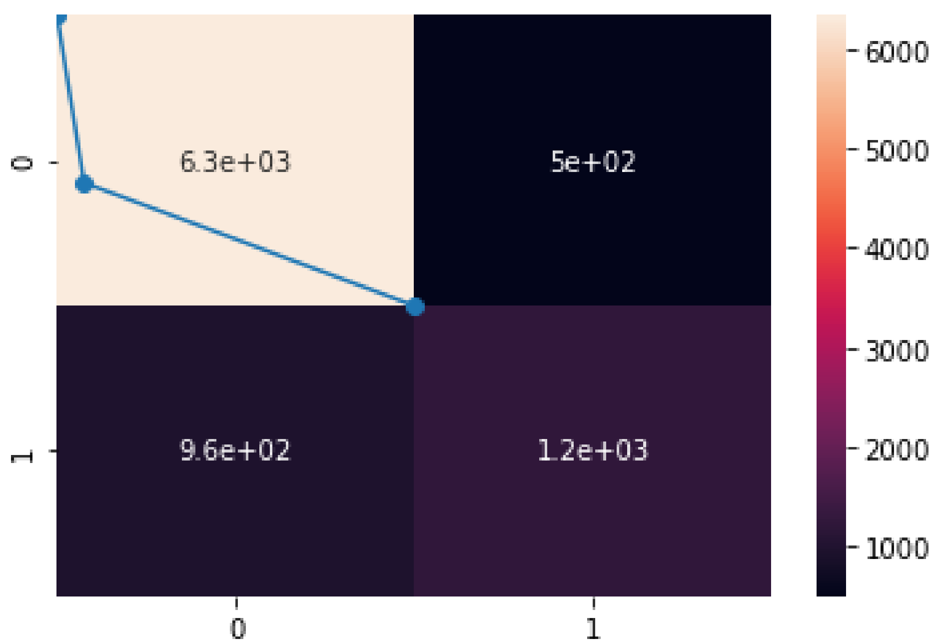
SVC trained on 36177 samples.



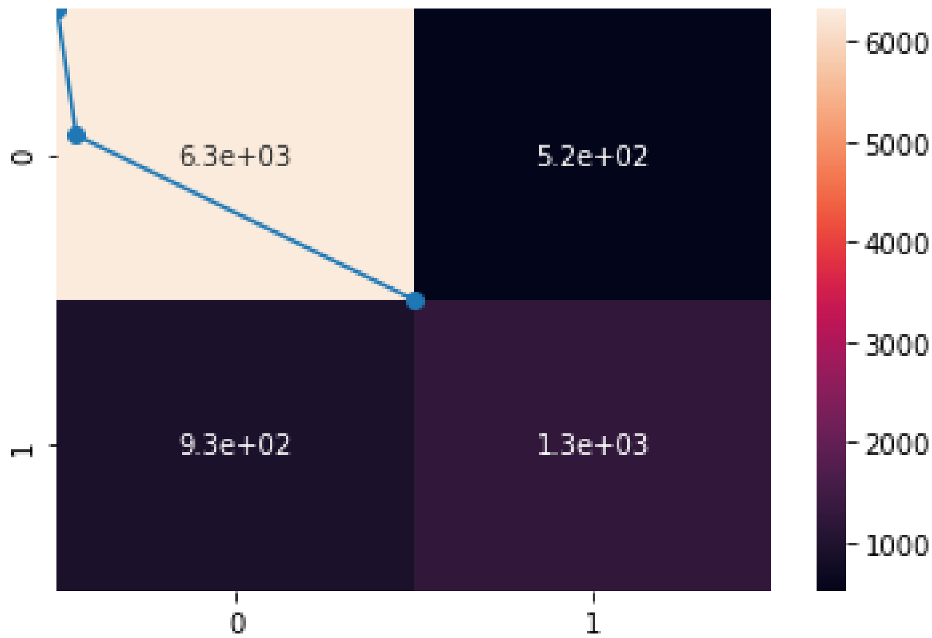
SVC trained on 361 samples.



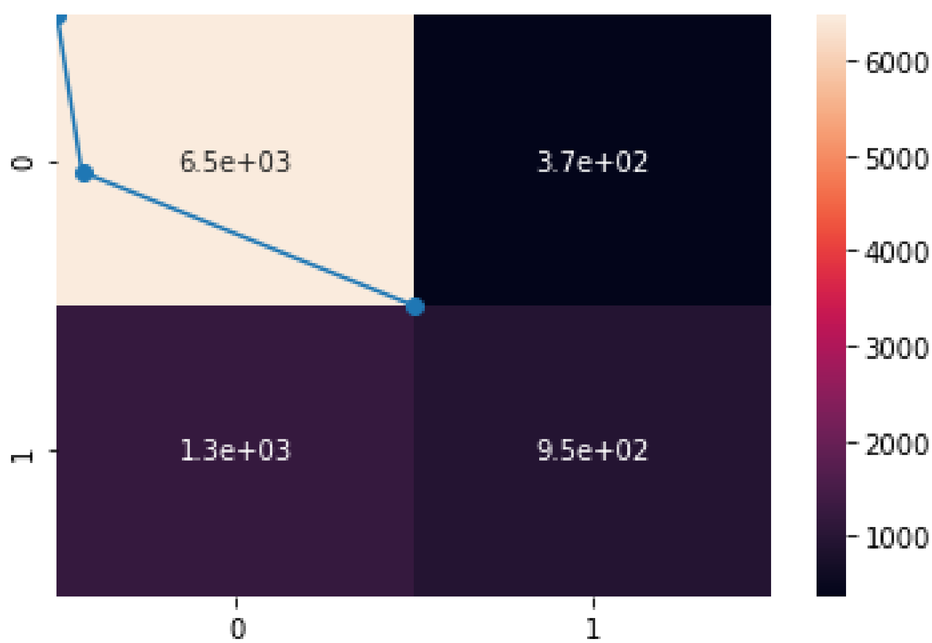
SVC trained on 3617 samples.



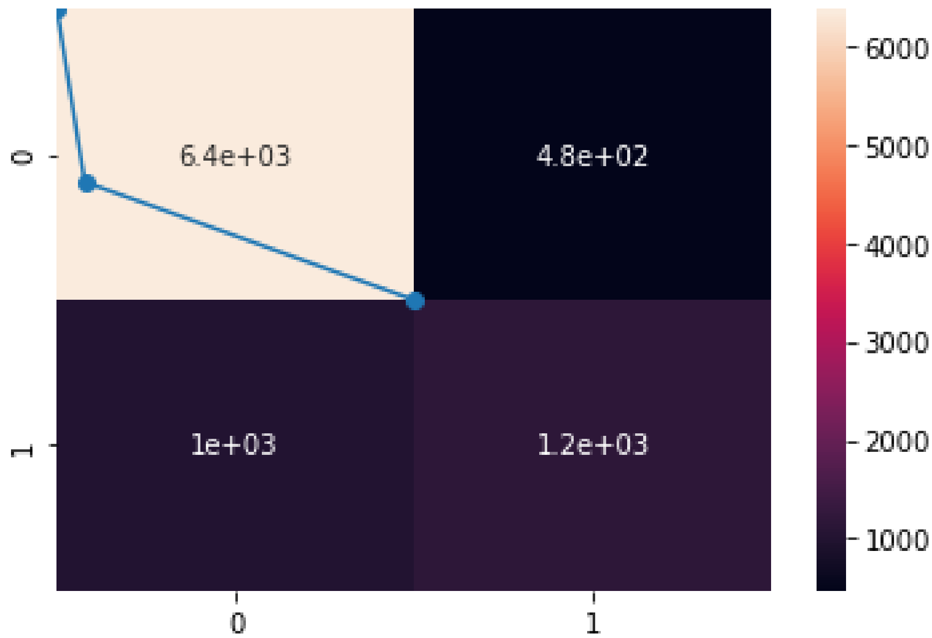
SVC trained on 36177 samples.



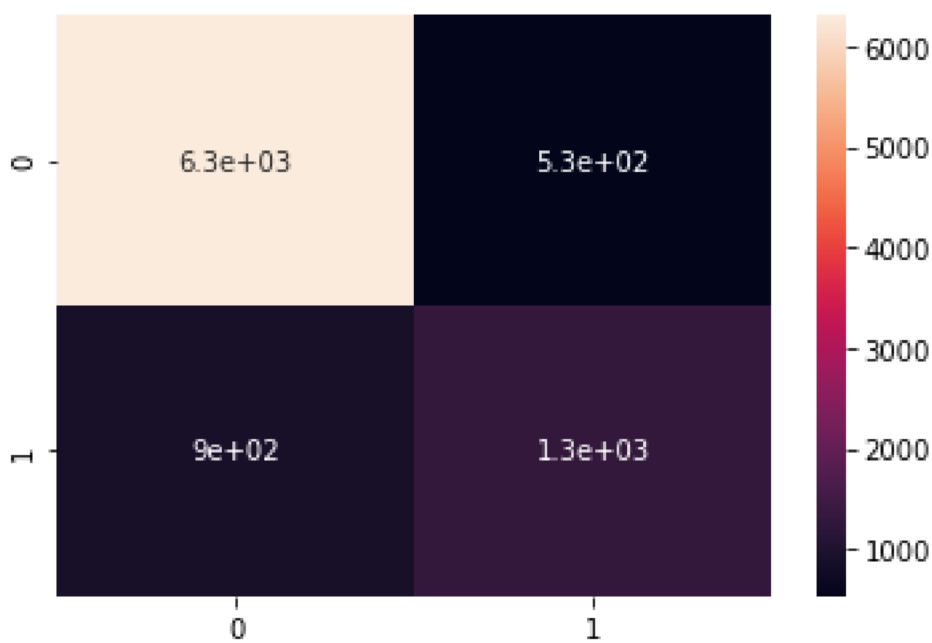
SVC trained on 361 samples.



SVC trained on 3617 samples.

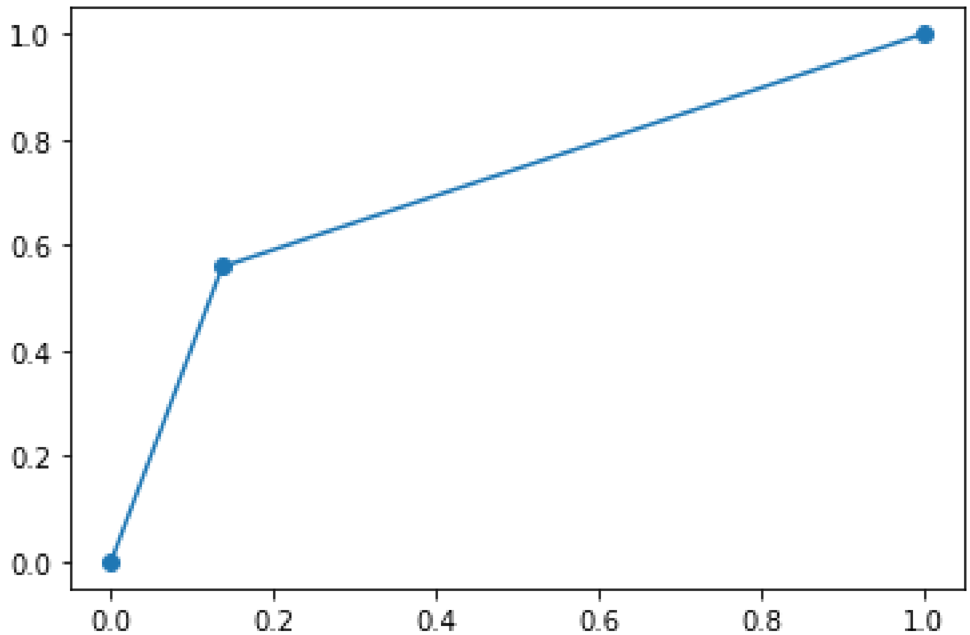



```
SVC trained on 36177 samples.
```

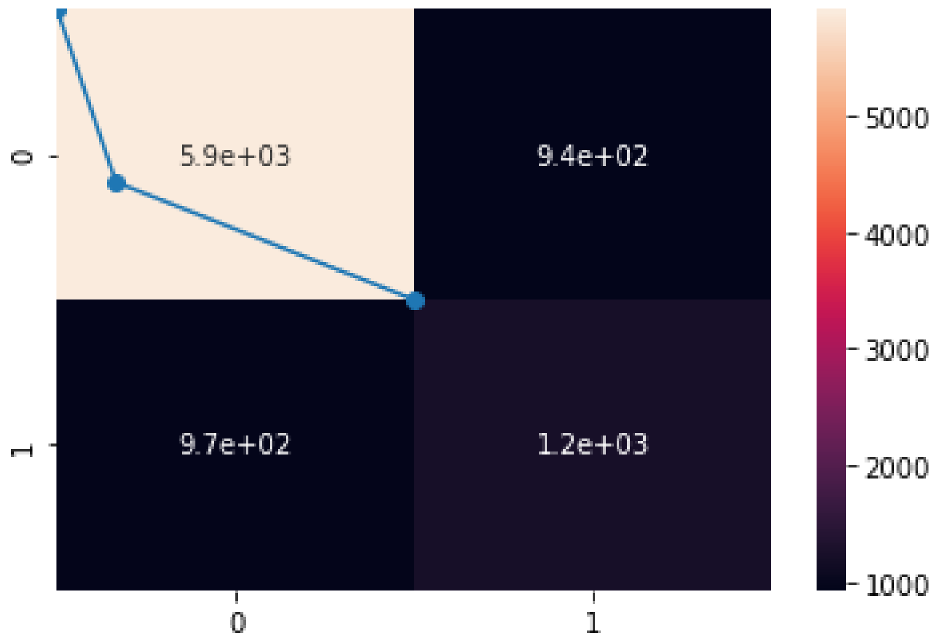


[98]:
```
# svm.NuSVC()

clf_rbf = NuSVC(nu = 1/10, kernel = 'rbf')
```

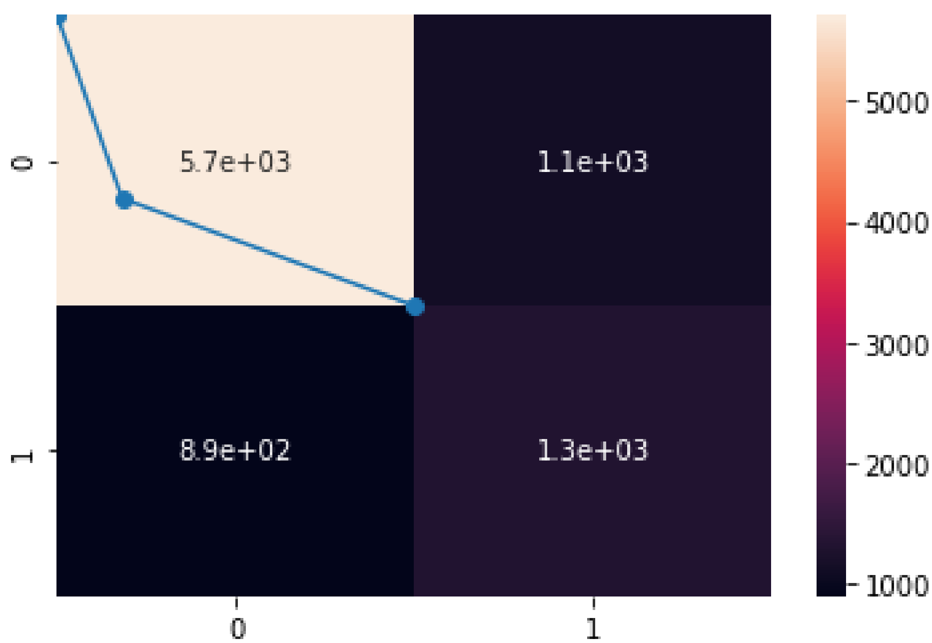
```
clf_linear = NuSVC(nu = 1/10, kernel = 'linear')
clf_poly = NuSVC(nu = 1/10, kernel = 'poly')

for clf in [clf_rbf, clf_linear, clf_poly]:
    for i, samples in enumerate([samples_1, samples_10, samples_100]):
        results[clf.__class__.__name__ + '_'  + getattr(clf, 'kernel') + '_' +␣
 ↪str(samples)] = train_predict(clf, samples, X_train, y_train, X_test, y_test)
```



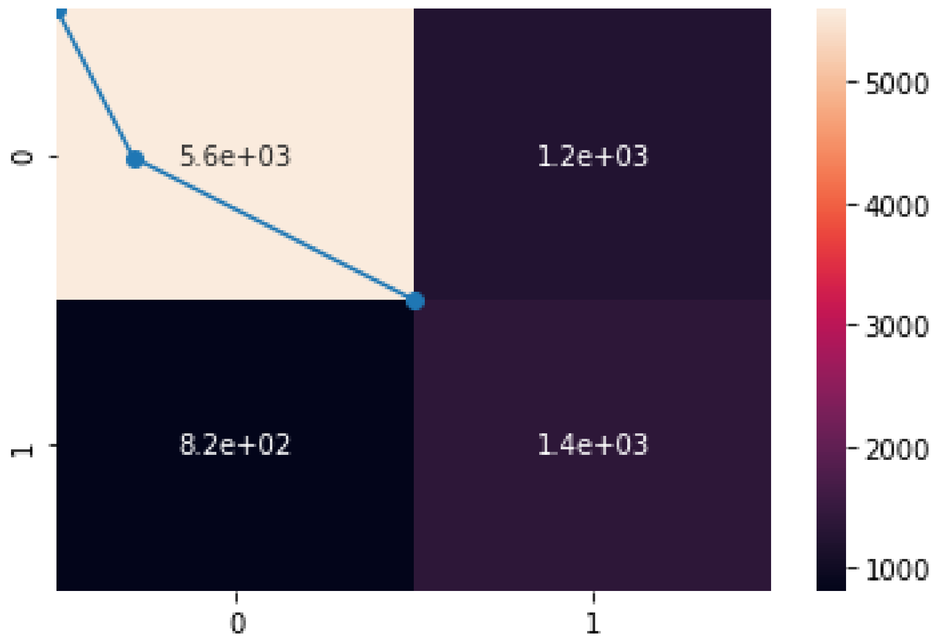

```
NuSVC trained on 361 samples.
```



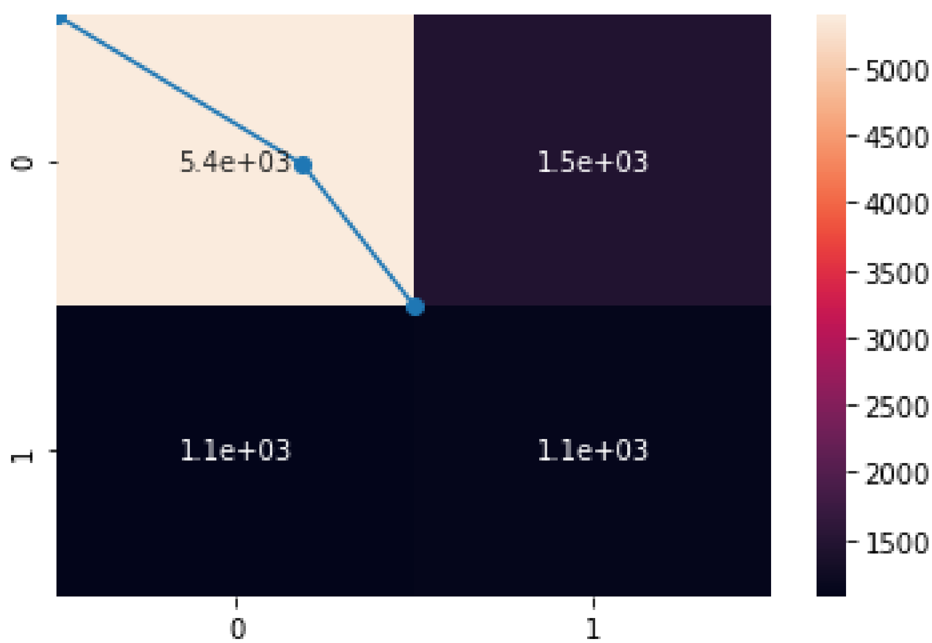
NuSVC trained on 3617 samples.



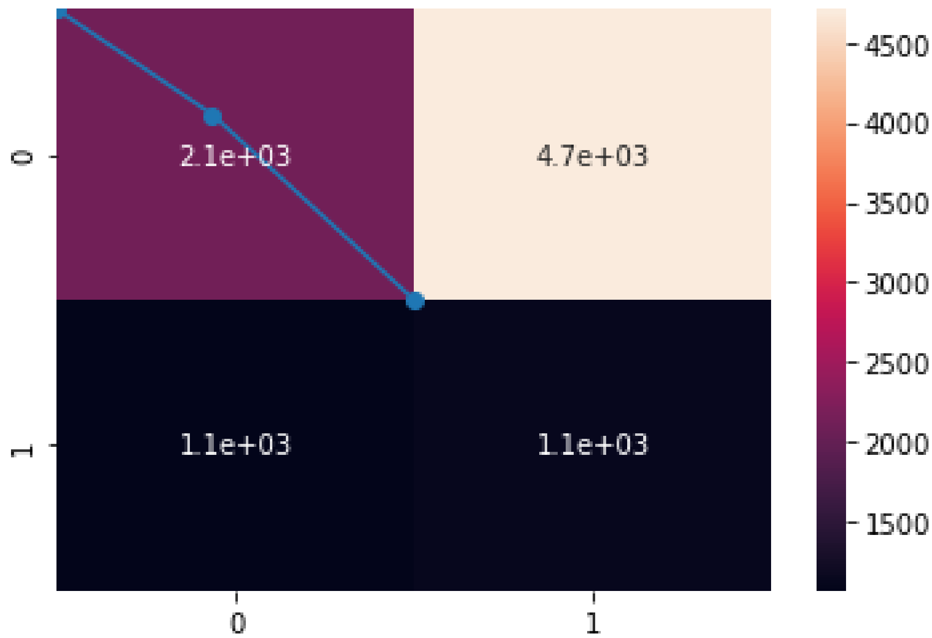
NuSVC trained on 36177 samples.



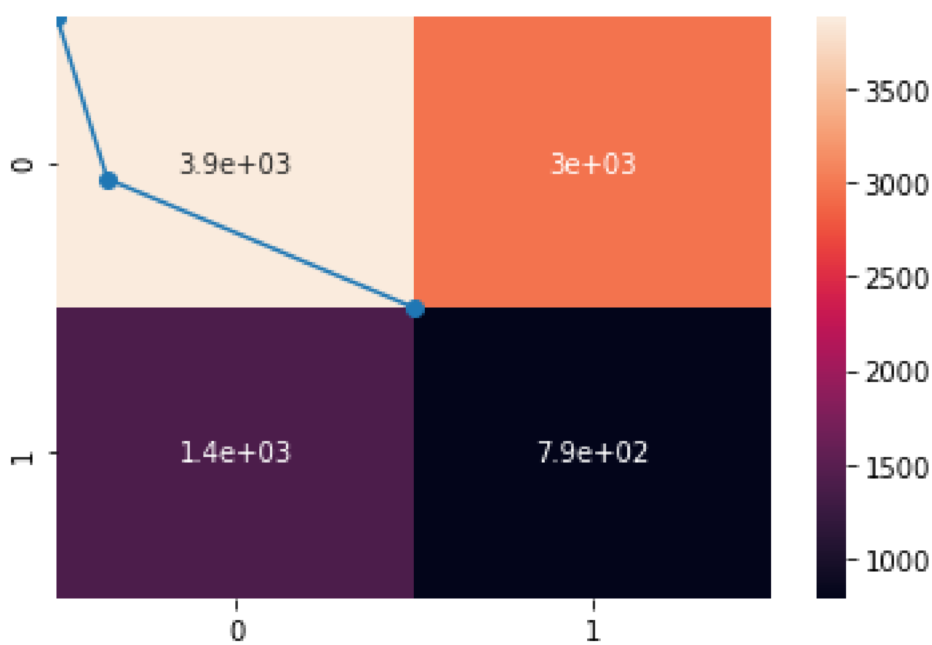
NuSVC trained on 361 samples.



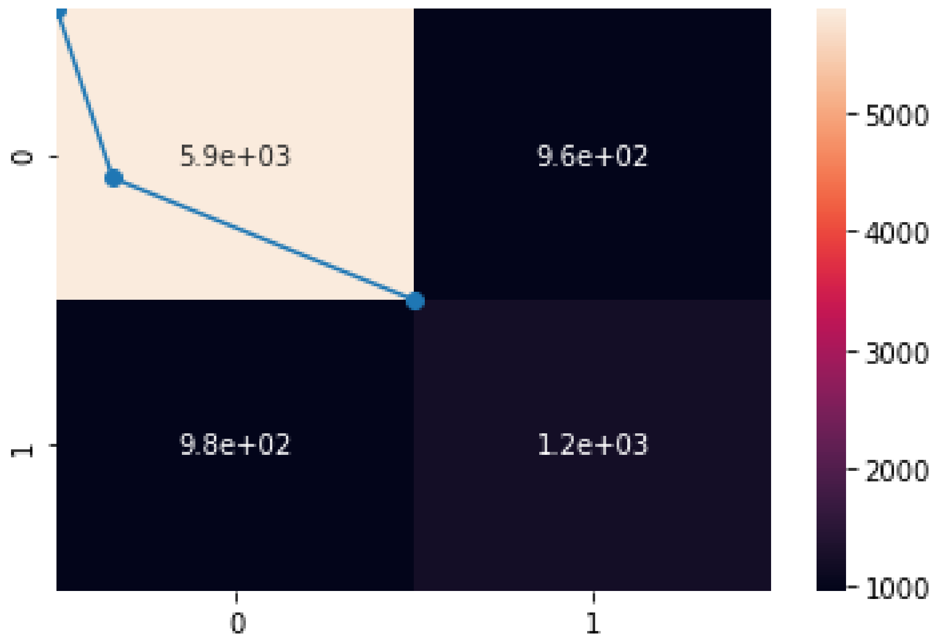
NuSVC trained on 3617 samples.



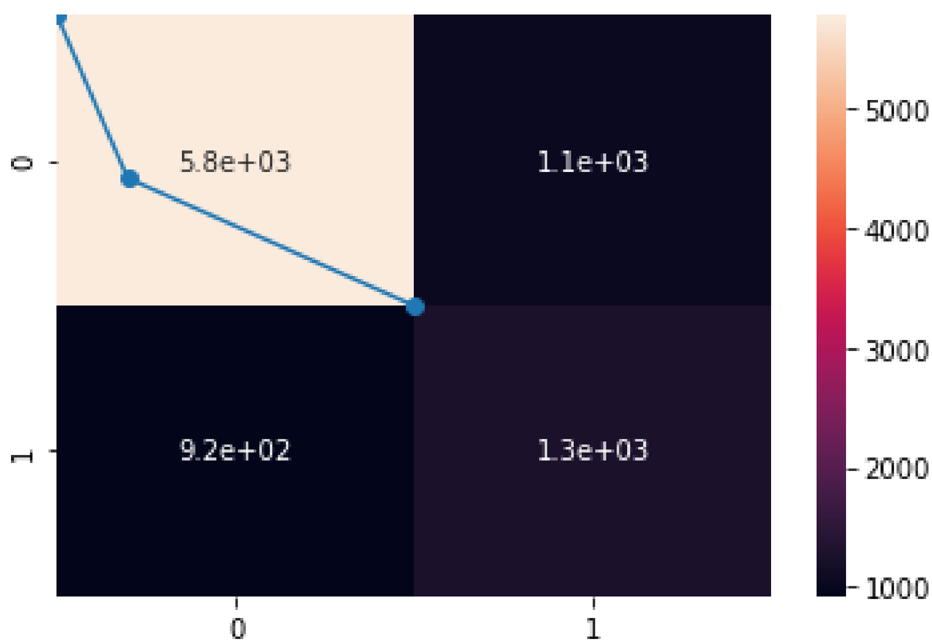
NuSVC trained on 36177 samples.



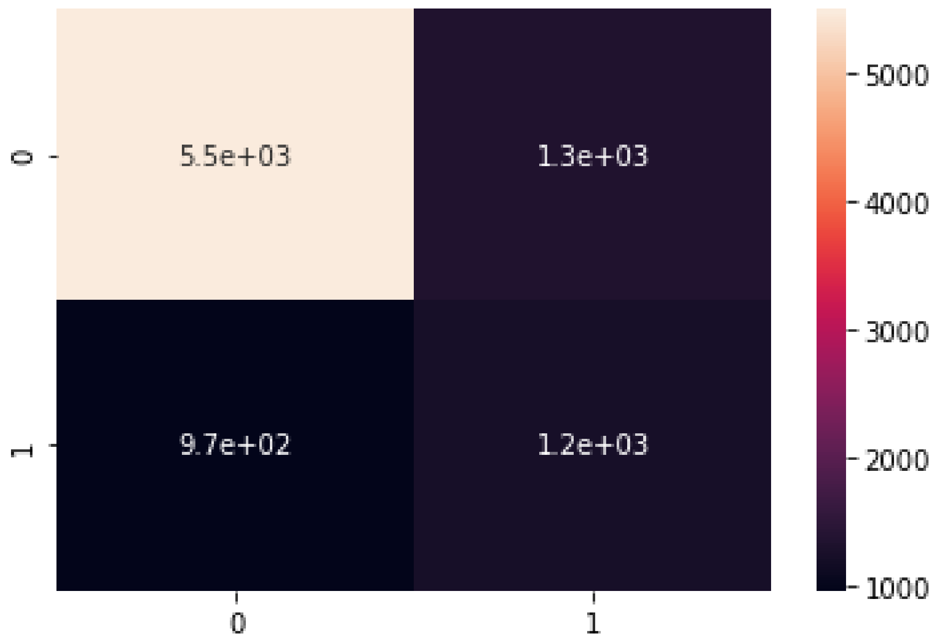
NuSVC trained on 361 samples.



NuSVC trained on 3617 samples.



NuSVC trained on 36177 samples.



0.0.1 4. :

- C gamma csv
- SVC
- TODO:

0.0.2 4.find the best parameter:

- find the best C and gamma parameter
- i have run the code and store the result in the params.csv
- TODO: if the params.csv need to display, we can disscuss it later

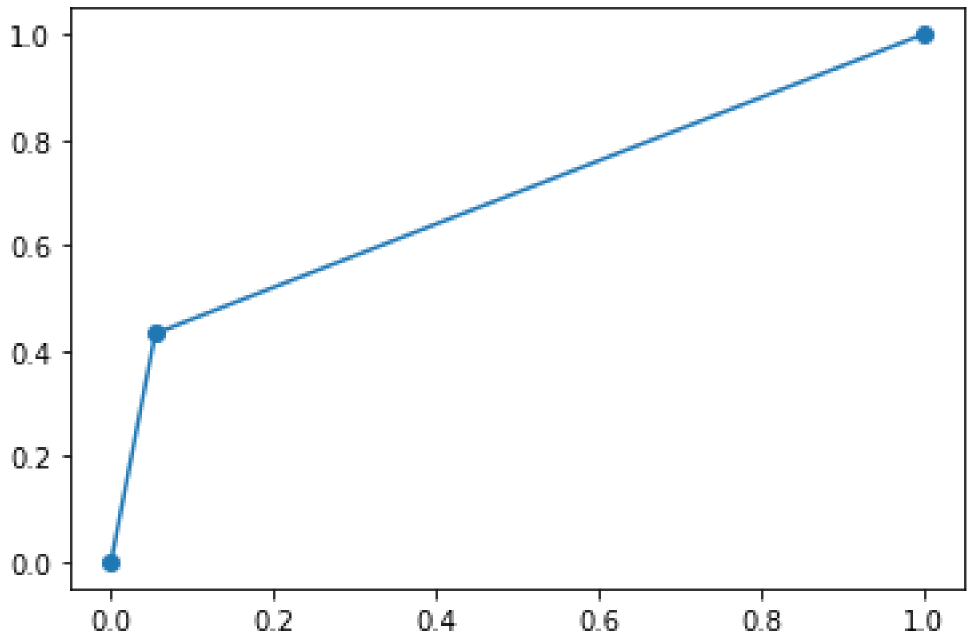
[ ]:
```
from sklearn.svm import SVC
from sklearn.decomposition import PCA
from time import time
from sklearn.model_selection import cross_val_score


'''
====================== find the best c and the gamma ␣
 ↪============================
====================== this will cost 30 minutes to run␣
 ↪==========================
====================== i saved the result in the params.csv␣
 ↪======================
```

```
X = []
Y = []
Z = []
M = []

print("start")
start = time()
pca = PCA(n_components = 13)
X_new = pca.fit_transform(X_train)
end = time()
print(end - start)

start = time()
for C in range(1, 10, 1):
    for gamma in range(1, 11, 1):
        accuracy = cross_val_score(SVC(C = C/10, gamma = gamma/10), X_new,␣
↪y_train, cv = 5, scoring = 'accuracy', n_jobs=-1).mean()
        X.append(C/10)
        Y.append(gamma/10)
        Z.append(accuracy)
        print(X[-1], Y[-1], Z[-1])
        end = time()
        print(end - start)
print(X)
print(Y)
print(Z)

for i in range(len(X)):
    M.append([X[i], Y[i], Z[i]])

df = pd.DataFrame(M, columns = ["C", "gamma", "accuracy"])
df.to_csv("params.csv", index = False)
'''
```

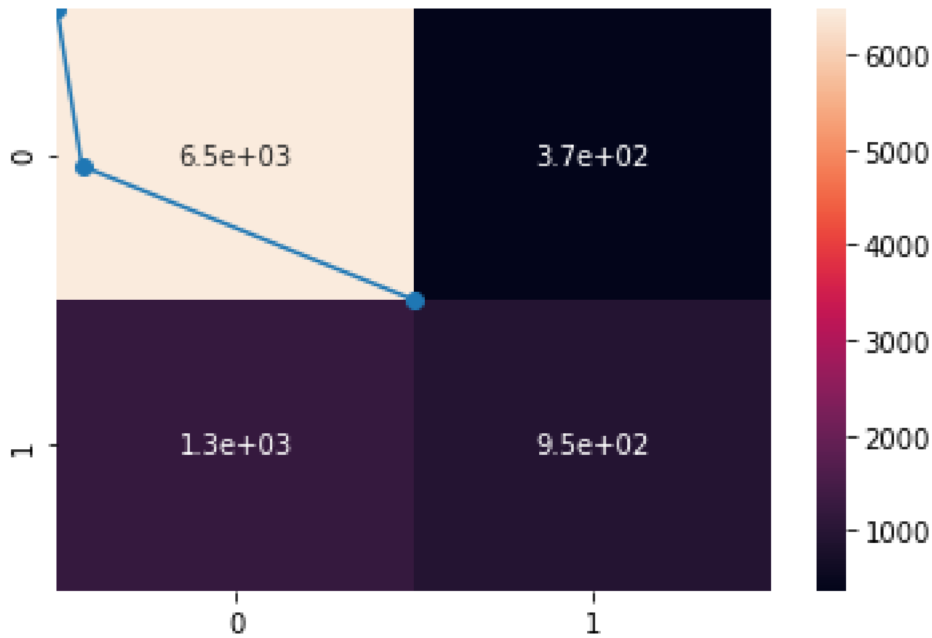
[95]:
```
from sklearn.svm import SVC

params = pd.read_csv('params.csv')

list_x = params["C"]
list_y = params['gamma']

# find the best accuracy
z = list(params['accuracy'])
z = z.index(max(z))

# gamma is 0.9 and C is 0.9
c = list_x[z]
```

```
gamma = list_y[z % 10]

print("the best C is {}, and the best magga is {}".format(c, gamma))

clf_rbf = SVC(kernel = 'rbf', C = c, gamma = gamma)

for i, samples in enumerate([samples_1, samples_10]):
    results[clf.__class__.__name__ + '_'  + getattr(clf, 'kernel') + '_' +␣
 ↪str(samples)] = train_predict(clf, samples, X_train, y_train, X_test, y_test)
```

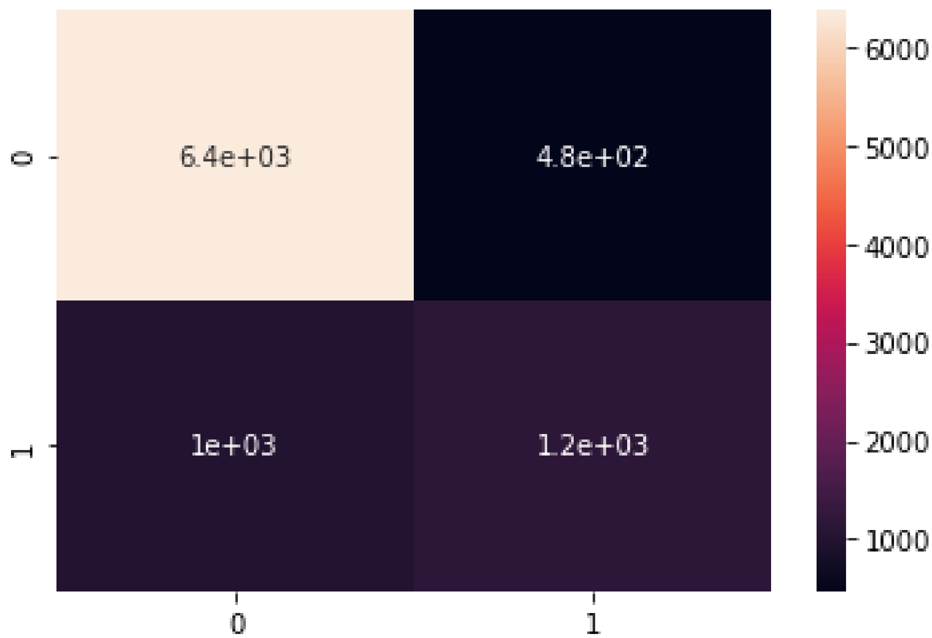
```
the best C is 0.9, and the best magga is 0.9
```




```
SVC trained on 361 samples.
```




```
SVC trained on 3617 samples.
```



5.

- TODO:

5. **display results**

- TODO: we can discuss how to display this results

[102]:
```
pprint(results)
```

```
{'LinearSVC_361': {'acc_test': 0.8075179657269209,
                   'acc_train': 0.8833333333333333,
                   'f_test': 0.6031634798278106,
                   'f_train': 0.7876712328767123,
                   'pred_time': 0.011526346206665039,
                   'train_time': 0.0069997310638427734},
 'LinearSVC_3617': {'acc_test': 0.839690436705362,
                    'acc_train': 0.85,
                    'f_test': 0.6801689591682009,
                    'f_train': 0.7089552238805971,
                    'pred_time': 0.009005069732666016,
                    'train_time': 0.05299782752990723},
 'LinearSVC_36177': {'acc_test': 0.8426755113322277,
                     'acc_train': 0.8466666666666667,
                     'f_test': 0.6855643044619422,
                     'f_train': 0.7007575757575757,
                     'pred_time': 0.011999368667602539,
                     'train_time': 1.43434739112854},
 'NuSVC_linear_361': {'acc_test': 0.7195135433941404,
                      'acc_train': 0.8,
                      'f_test': 0.44847709649052686,
                      'f_train': 0.5874999999999999,
                      'pred_time': 0.11403512954711914,
                      'train_time': 0.009963750839233398},
 'NuSVC_linear_3617': {'acc_test': 0.3610834715312327,
                       'acc_train': 0.33,
                       'f_test': 0.221592020340309,
                       'f_train': 0.21666666666666665,
                       'pred_time': 0.4709646701812744,
                       'train_time': 0.2630431652069092},
 'NuSVC_linear_36177': {'acc_test': 0.5160862354892206,
                        'acc_train': 0.5233333333333333,
                        'f_test': 0.23021165555233403,
                        'f_train': 0.23601398601398604,
                        'pred_time': 3.3668947219848633,
                        'train_time': 29.315741062164307},
 'NuSVC_poly_361': {'acc_test': 0.7851851851851852,
                    'acc_train': 0.9766666666666667,
                    'f_test': 0.559099608129044,
                    'f_train': 0.9705882352941175,
                    'pred_time': 0.15903854370117188,
                    'train_time': 0.011962652206420898},
```

```
'NuSVC_poly_3617': {'acc_test': 0.7796572692095081,
                    'acc_train': 0.9666666666666667,
                    'f_test': 0.5518668621195136,
                    'f_train': 0.9239130434782609,
                    'pred_time': 1.0856084823608398,
                    'train_time': 1.4788916110992432},
'NuSVC_poly_36177': {'acc_test': 0.7436152570480928,
                     'acc_train': 0.84,
                     'f_test': 0.4923849772745395,
                     'f_train': 0.6686046511627908,
                     'pred_time': 9.524660587310791,
                     'train_time': 843.1587979793549},
'NuSVC_rbf_361': {'acc_test': 0.7890547263681592,
                  'acc_train': 0.9733333333333334,
                  'f_test': 0.5665409730525155,
                  'f_train': 0.9672619047619047,
                  'pred_time': 0.2060706615447998,
                  'train_time': 0.017019033432006836},
'NuSVC_rbf_3617': {'acc_test': 0.7764510779436152,
                   'acc_train': 0.95,
                   'f_test': 0.5480825465786615,
                   'f_train': 0.8928571428571427,
                   'pred_time': 1.361992359161377,
                   'train_time': 1.3750581741333008},
'NuSVC_rbf_36177': {'acc_test': 0.7721393034825871,
                    'acc_train': 0.8433333333333334,
                    'f_test': 0.5451407953564985,
                    'f_train': 0.6710526315789473,
                    'pred_time': 11.435608148574829,
                    'train_time': 714.0787835121155},
'SVC_linear_361': {'acc_test': 0.814262023217247,
                   'acc_train': 0.8666666666666667,
                   'f_test': 0.6182324430236156,
                   'f_train': 0.7499999999999999,
                   'pred_time': 0.14303135871887207,
                   'train_time': 0.010973215103149414},
'SVC_linear_3617': {'acc_test': 0.838253178551686,
                    'acc_train': 0.8533333333333334,
                    'f_test': 0.6769868091137033,
                    'f_train': 0.72265625,
                    'pred_time': 1.1729998588562012,
                    'train_time': 0.6620337963104248},
'SVC_linear_36177': {'acc_test': 0.8391376451077943,
                     'acc_train': 0.8533333333333334,
                     'f_test': 0.6780113090792702,
                     'f_train': 0.7196969696969697,
                     'pred_time': 12.941011428833008,
                     'train_time': 96.58239960670471},
```

```
 'SVC_poly_361': {'acc_test': 0.820563847429519,
                  'acc_train': 0.8866666666666667,
                  'f_test': 0.6352377147423093,
                  'f_train': 0.8088235294117647,
                  'pred_time': 0.19303464889526367,
                  'train_time': 0.011025905609130859},
 'SVC_poly_3617': {'acc_test': 0.8349364289662797,
                   'acc_train': 0.87,
                   'f_test': 0.6703532332693827,
                   'f_train': 0.7570422535211266,
                   'pred_time': 1.3188202381134033,
                   'train_time': 0.6846029758453369},
 'SVC_poly_36177': {'acc_test': 0.8422332780541736,
                    'acc_train': 0.8566666666666667,
                    'f_test': 0.6842655514898066,
                    'f_train': 0.7246376811594203,
                    'pred_time': 13.116812705993652,
                    'train_time': 98.34142708778381},
 'SVC_rbf_361': {'acc_test': 0.8180210060807076,
                 'acc_train': 0.8533333333333334,
                 'f_test': 0.6277580071174378,
                 'f_train': 0.732758620689655,
                 'pred_time': 0.22103524208068848,
                 'train_time': 0.014015913009643555},
 'SVC_rbf_3617': {'acc_test': 0.8316196793808734,
                  'acc_train': 0.86,
                  'f_test': 0.662986635676932,
                  'f_train': 0.7352941176470589,
                  'pred_time': 1.602618932723999,
                  'train_time': 0.7985053062438965},
 'SVC_rbf_36177': {'acc_test': 0.8423438363736871,
                   'acc_train': 0.8533333333333334,
                   'f_test': 0.685054319164645,
                   'f_train': 0.7169117647058826,
                   'pred_time': 15.279017448425293,
                   'train_time': 105.80365800857544}}
```

[ ]: