PML_lab-7_205229118_Mahalakshmi.S

April 27, 2021

0.1 Lab7. Loan Approval Classification using SVM

Objectives In this lab, you will build a classification model to classify the loan applicants into eligible applicants or not eligible applicants using Support Vector Machine.

Step1. [Understand Data]. Using Pandas, import "train_loan.csv" file and print properties such as head, shape, columns, dtype, info and value_counts

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt

tralon_data = pd.read_csv('train_loan.csv')
tralon_data.head()
```

[1]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

[2]:
```
tralon_data.shape
```

[2]:
```
(614, 13)
```

[3]:
```
tralon_data.columns
```

[3]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[4]:
```
tralon_data.dtypes
```

[4]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

[5]:
```
tralon_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

[6]:
```
tralon_data.value_counts
```

```
[6]: <bound method DataFrame.value_counts of       Loan_ID  Gender Married Dependents
Education Self_Employed  \
0    LP001002    Male      No          0      Graduate            No
1    LP001003    Male     Yes          1      Graduate            No
2    LP001005    Male     Yes          0      Graduate           Yes
3    LP001006    Male     Yes          0  Not Graduate            No
4    LP001008    Male      No          0      Graduate            No
..        …       …      …          …             …             …
609  LP002978  Female      No          0      Graduate            No
610  LP002979    Male     Yes         3+      Graduate            No
611  LP002983    Male     Yes          1      Graduate            No
612  LP002984    Male     Yes          2      Graduate            No
613  LP002990  Female      No          0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               …                  …          …                …
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
0               1.0         Urban           Y
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
..              …           …          …
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[614 rows x 13 columns]>
```

0.1.1 Step2. [Data Cleaning]

0.1.2 Replace numbers as string by integer in "Dependents" column

[7]:
```
tralon_data.Dependents.value_counts()
```

[7]:
```
0      345
1      102
2      101
3+      51
Name: Dependents, dtype: int64
```

[8]:
```
#Replace numbers as string by integer in 'Dependents' column
def string(x):
    if x == '0':
        return 'bad'
    elif x == '1':
        return 'average'
    elif x == '2':
        return 'good'
    else:
        return 'excellent'
```

[9]:
```
tralon_data['Dependents'] = tralon_data['Dependents'].apply(string)
```

0.1.3 Fill missing data in categorical columns (Gender, Married, Dependents, Education, Self_Employed, Credit_History) by its mode value

0.1.4 Handle missing values in numberical columns

[10]:
```
tralon_data.isna().sum()
```

[10]:
```
Loan_ID               0
Gender               13
Married               3
Dependents            0
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

[11]:
```
#categorical
tralon_data['Gender'].fillna(tralon_data['Gender'].mode()[0], inplace=True)
tralon_data['Married'].fillna(tralon_data['Married'].mode()[0], inplace=True)
tralon_data['Dependents'].fillna(tralon_data['Dependents'].mode()[0],␣
↪inplace=True)
tralon_data['Loan_Amount_Term'].fillna(tralon_data['Loan_Amount_Term'].
↪mode()[0], inplace=True)
tralon_data['Credit_History'].fillna(tralon_data['Credit_History'].mode()[0],␣
↪inplace=True)
tralon_data['Self_Employed'].fillna(tralon_data['Self_Employed'].mode()[0],␣
↪inplace=True)
#numerical
tralon_data['LoanAmount'].fillna(tralon_data['LoanAmount'].mean(), inplace=True)
```

0.1.5 Drop Loan_ID column

[12]:
```
tralon_data=tralon_data.drop(['Loan_ID'],axis=1)
```

0.1.6 Step3. [OPTIONAL: Exploratory Data Analysis - Who got their loan approved]

Draw count plot for

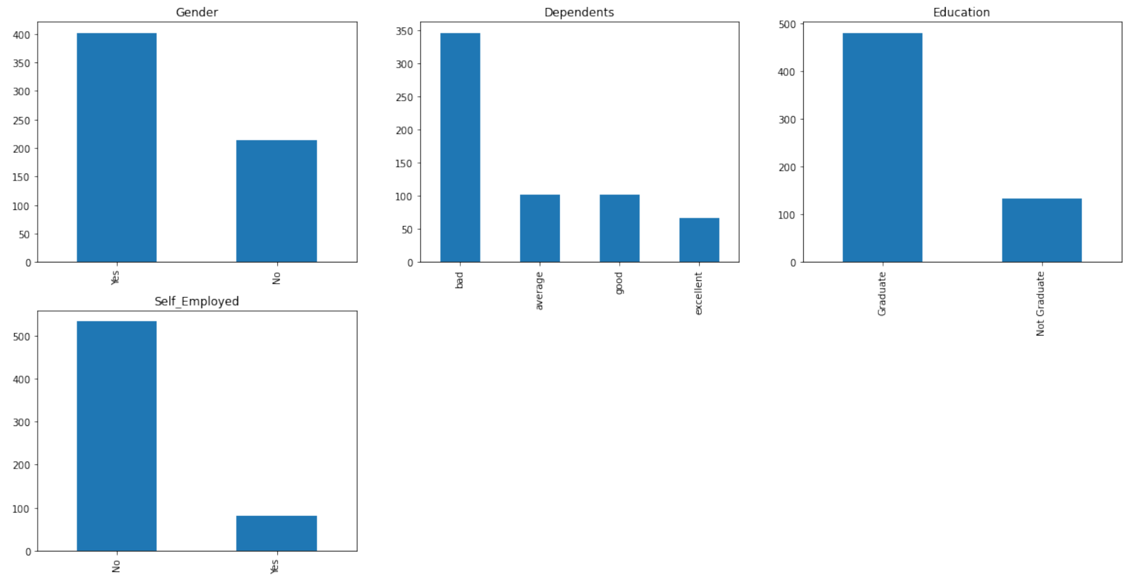
Married?

Dependants?

Graduates?

Self-employed?

[13]:
```
plt.subplot(231)
tralon_data['Married'].value_counts().plot(kind='bar',title='Gender',figsize =␣
↪(20,10))

plt.subplot(232)
tralon_data['Dependents'].value_counts().plot(kind='bar',title='Dependents')

plt.subplot(233)
tralon_data['Education'].value_counts().plot(kind='bar',title='Education')

plt.subplot(234)
tralon_data['Self_Employed'].value_counts().
↪plot(kind='bar',title='Self_Employed')

plt.show()
```



0.1.7 Step4. [Extract X and y] from the dataframe

[14]:
```
X = tralon_data.drop(['Loan_Status'],axis=1)
y = tralon_data.Loan_Status
```

0.1.8 Step5. [One Hot Encoding]

Perform OHE on categorical columns, use this method: X = pd.get_dummies(X)

[15]:
```
import warnings
warnings.filterwarnings('ignore')
```

[16]:
```
X = pd.get_dummies(X)
```

0.1.9 Step6. [Model Building]

Split X and y for training and testing

[17]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
 ↪3,random_state=0)
```

Using StandardScaler, fit_transform on X_train and transform on X_test values

[18]:
```
from sklearn.preprocessing import StandardScaler
st_sc = StandardScaler()
```

[22]:
```
stand_sc = st_sc.fit_transform(X_train)
stand_sc1 = st_sc.transform(X_test)
```

create LinearSVC model, train and test

[23]:
```python
from sklearn.svm import LinearSVC
lin_model = LinearSVC()
lin_model.fit(stand_sc,y_train)
```

[23]:
```
LinearSVC()
```

[25]:
```python
linsvc_y_predict = lin_model.predict(stand_sc1)
linsvc_y_predict
```

[25]:
```
array(['Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y'], dtype=object)
```

print accuracy value

[26]:
```python
from sklearn.metrics import accuracy_score,confusion_matrix,␣
↪classification_report
accuracy_score(y_test,linsvc_y_predict)
```

[26]:
```
0.8324324324324325
```

Print confusion matrix between y_test and y_pred

[27]:
```python
confusion_matrix(y_test,linsvc_y_predict)
```

[27]:
```
array([[ 22,  29],
       [  2, 132]], dtype=int64)
```

Print classification_report

[28]:
```python
print(classification_report(y_test,linsvc_y_predict))
```

```
              precision    recall  f1-score   support

           N       0.92      0.43      0.59        51
           Y       0.82      0.99      0.89       134

    accuracy                           0.83       185
```

```
   macro avg       0.87      0.71      0.74       185
weighted avg       0.85      0.83      0.81       185
```

0.1.10 Step7. [Performance Comparisons]

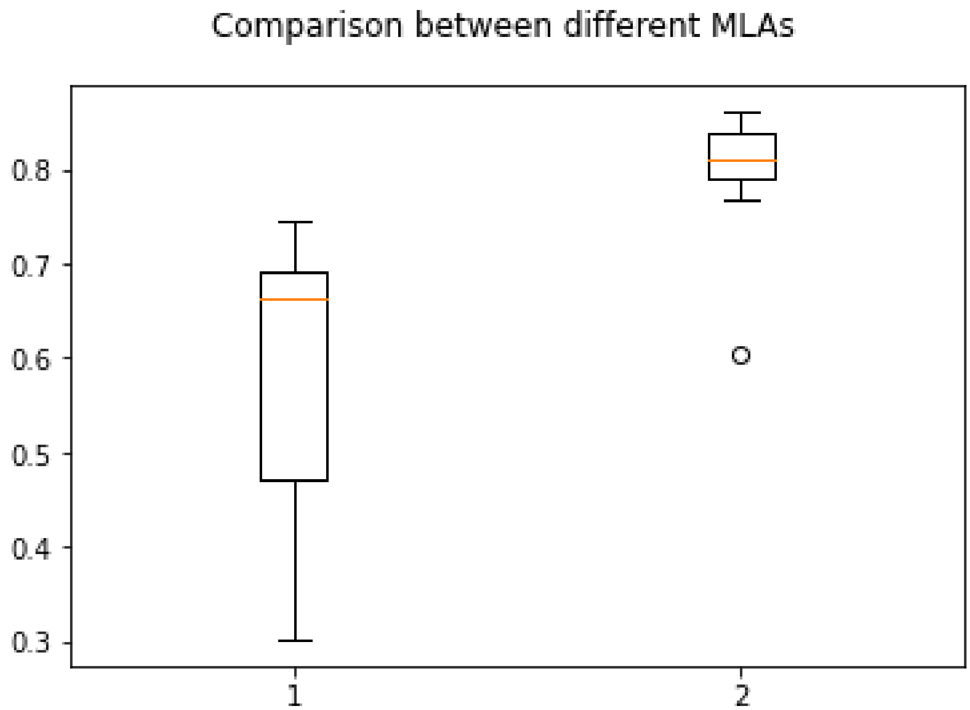
1. Compare the performance of LinearSVC against LogisticRegression

[29]:
```
from sklearn.linear_model import LogisticRegression

logreg= LogisticRegression()
logreg.fit(stand_sc,y_train)
logreg_y_predict = logreg.predict(stand_sc1)

from sklearn.svm import LinearSVC

ln_svc = LinearSVC()
ln_svc.fit(stand_sc,y_train)
lnsvc_y_predict = ln_svc.predict(stand_sc1)

print("LogisticRegression:",accuracy_score(y_test,logreg_y_predict))
print("LinearSVC         :",accuracy_score(y_test,lnsvc_y_predict))
```

```
LogisticRegression: 0.8324324324324325
LinearSVC         : 0.8324324324324325
```

[30]:
```
from sklearn import svm,model_selection
models = []
models.append(('SVC', LinearSVC()))
models.append(('LR', LogisticRegression()))

# evaluate each model in turn
results = []
names=[]
scoring = 'accuracy'
for name,model in models:
    kfold = model_selection.KFold(n_splits=10)
    cv_results = model_selection.cross_val_score(model, X_train, y_train,␣
 ↪cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
# boxplot algorithm comparison
fig = plt.figure()
fig.suptitle('Comparison between different MLAs')
ax = fig.add_subplot(111)
plt.boxplot(results)
plt.show()
```

```
SVC: 0.580066 (0.155858)
LR: 0.797231 (0.070487)
```

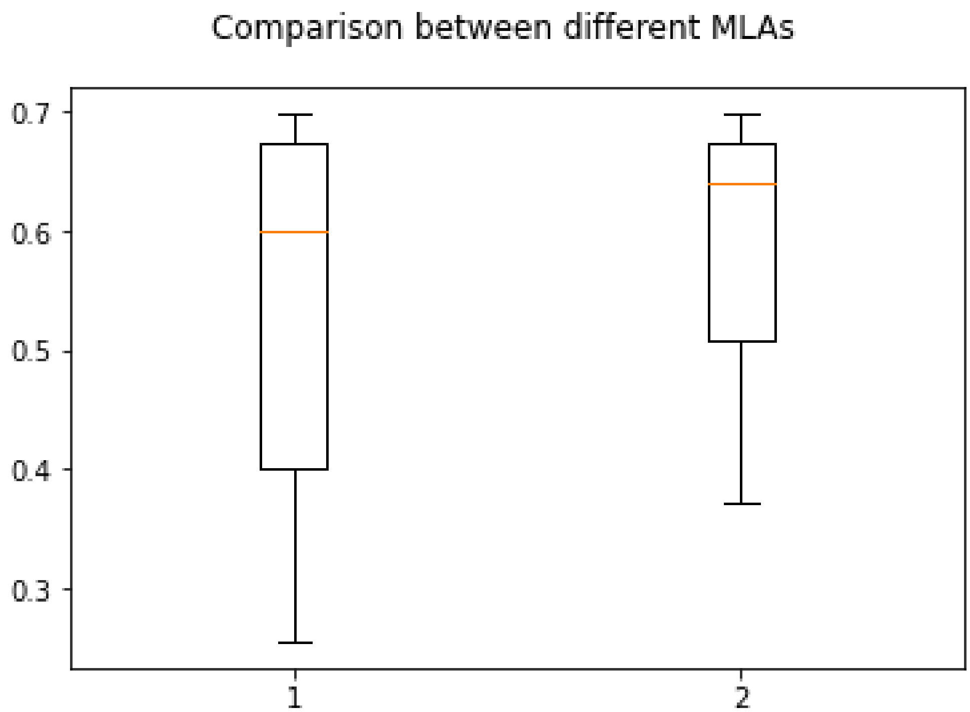


2. Compare the performance of LinearSVC against SGDClassifier

[31]:
```python
from sklearn.linear_model import SGDClassifier

modelss = []
modelss.append(('SVC', LinearSVC()))
modelss.append(('SGD', SGDClassifier()))

# evaluate each model in turn
results = []
names=[]
scoring = 'accuracy'
for name,model in modelss:
    kfold = model_selection.KFold(n_splits=10)
    cv_results = model_selection.cross_val_score(model, X_train, y_train,␣
 ↪cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
# boxplot algorithm comparison
```

```python
fig = plt.figure()
fig.suptitle('Comparison between different MLAs')
ax = fig.add_subplot(111)
plt.boxplot(results)
plt.show()
```

```
SVC: 0.543189 (0.160649)
SGD: 0.585050 (0.117652)
```



[40]:

```python
from sklearn.linear_model import SGDClassifier

sgdc = SGDClassifier()
sgdc.fit(stand_sc,y_train)
sgdc1_y_predict = sgdc.predict(stand_sc1)

from sklearn.svm import LinearSVC

ln_svc = LinearSVC()
ln_svc.fit(stand_sc,y_train)
lnsvc_y_predict = ln_svc.predict(stand_sc1)

print("SGDClassifier:", accuracy_score(y_test,sgdc1_y_predict))
print("LinearSVC    :",accuracy_score(y_test,lnsvc_y_predict))
```

```
SGDClassifier: 0.7675675675675676
LinearSVC    : 0.8324324324324325
```

3. Compare LinearSVC against SVC with various kernels such as 'linear', 'poly', 'rbf' and 'sigmoid'

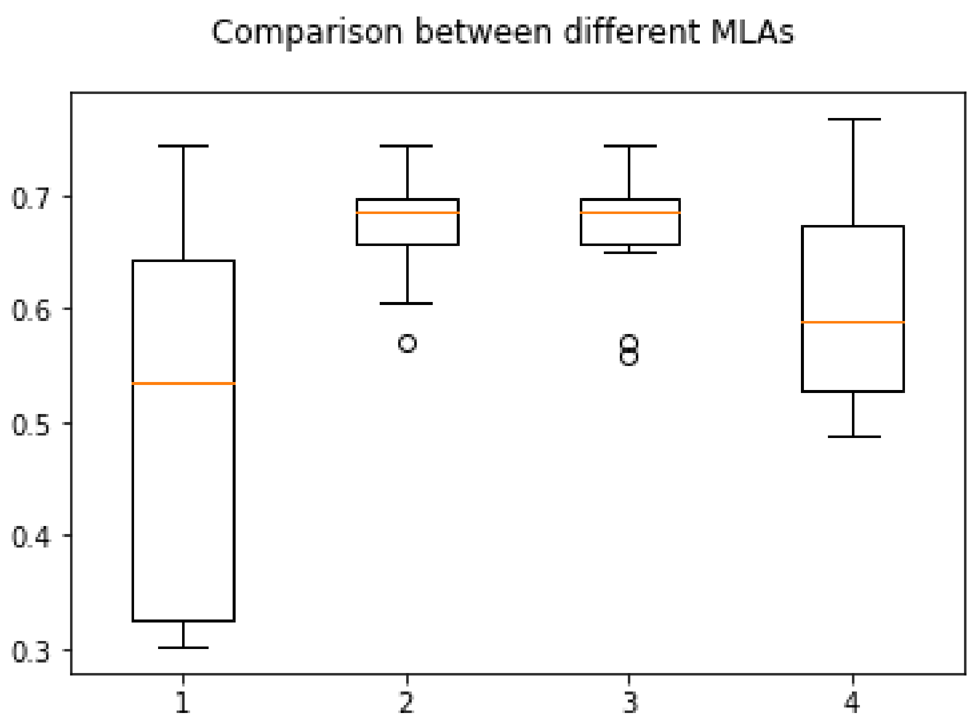
[41]:
```
from sklearn.svm import SVC

ln_svc = LinearSVC()
ln_svc.fit(stand_sc,y_train)
lnsvc_y_predict = ln_svc.predict(stand_sc1)


poly_svc = svm.SVC(kernel='poly', C = 1.0)
poly_svc.fit(stand_sc,y_train)
polsvc_y_predict=poly_svc.predict(stand_sc1)


rbf_svc = svm.SVC(kernel='rbf', C = 1.0)
rbf_svc.fit(stand_sc,y_train)
rbfsvc_y_predict=rbf_svc.predict(stand_sc1)


sig_svc = svm.SVC(kernel='sigmoid', C = 1.0)
sig_svc.fit(stand_sc,y_train)
sigsvc_y_predict=sig_svc.predict(stand_sc1)


print("LinearSVC   :",accuracy_score(y_test,lnsvc_y_predict))
print("poly SVC    :",accuracy_score(y_test,polsvc_y_predict))
print("rbf SVC     :",accuracy_score(y_test,rbfsvc_y_predict))
print("Sigmoid SVC :",accuracy_score(y_test,sigsvc_y_predict))
```

```
LinearSVC   : 0.8324324324324325
poly SVC    : 0.8162162162162162
rbf SVC     : 0.8324324324324325
Sigmoid SVC : 0.8054054054054054
```

[42]:
```
models1 = []
models1.append(('SVC', LinearSVC()))
models1.append(('SVC POLY', svm.SVC(kernel='poly', C = 1.0)))
models1.append(('SVC rbf', svm.SVC(kernel='rbf', C = 1.0)))
models1.append(('SVC POLY', svm.SVC(kernel='sigmoid', C = 1.0)))

# evaluate each model in turn
results = []
names=[]
scoring = 'accuracy'
for name,model in models1:
```

```
    kfold = model_selection.KFold(n_splits=10)
    cv_results = model_selection.cross_val_score(model, X_train, y_train,␣
↪cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
# boxplot algorithm comparison
fig = plt.figure()
fig.suptitle('Comparison between different MLAs')
ax = fig.add_subplot(111)
plt.boxplot(results)
plt.show()
```

```
SVC: 0.506091 (0.172120)
SVC POLY: 0.671096 (0.047891)
SVC rbf: 0.666445 (0.055735)
SVC POLY: 0.603710 (0.092483)
```



4. Interpret the results

[44]:
```
import numpy as np
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_score
```

```python
from sklearn.metrics import recall_score
from sklearn.metrics import auc

ML  = [model,logreg,sgdc,poly_svc,rbf_svc,sig_svc]
ML_columns = []
ML_compare = pd.DataFrame(columns = ML_columns)

row_index = 0
for alg in ML:

    predicted = alg.fit(stand_sc, y_train).predict(stand_sc1)
    predicted=np.where(predicted=='Y',1,0)
    y_testb=np.where(y_test=='Y',1,0)
    fp, tp, th = roc_curve(y_testb, predicted)
    ML_name = alg.__class__.__name__
    ML_compare.loc[row_index,'ML used'] = ML_name
    ML_compare.loc[row_index, 'Train Accuracy'] = round(alg.
 ↪score(stand_sc,y_train), 4)
    ML_compare.loc[row_index, 'Test Accuracy'] = round(alg.
 ↪score(stand_sc1,y_test), 4)
    ML_compare.loc[row_index, 'Precission'] = precision_score(y_testb,␣
 ↪predicted)
    ML_compare.loc[row_index, 'Recall'] = recall_score(y_testb, predicted)
    ML_compare.loc[row_index, 'AUC'] = auc(fp, tp)
    row_index+=1

ML_compare
```

[44]:

```
              ML used  Train Accuracy  Test Accuracy  Precission    Recall  \
0                 SVC          0.7506         0.8054    0.810127  0.955224
1  LogisticRegression          0.8042         0.8324    0.819876  0.985075
2       SGDClassifier          0.7669         0.7892    0.818792  0.910448
3                 SVC          0.8368         0.8162    0.820513  0.955224
4                 SVC          0.8135         0.8324    0.819876  0.985075
5                 SVC          0.7506         0.8054    0.810127  0.955224

        AUC
0  0.683494
1  0.708224
2  0.690518
3  0.703102
4  0.708224
5  0.683494
```

[45]:

```python
import seaborn as sns
# Creating plot to show the train accuracy
plt.subplots(figsize=(8,4))
```

```
sns.barplot(x="ML used", y="Train␣
↪Accuracy",data=ML_compare,palette='hot',edgecolor=sns.
↪color_palette('dark',7))
plt.xticks(rotation=90)
plt.title('ML Train Accuracy Comparison')
plt.show()
```