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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.

Learning Outcomes

After completing this lab, you will be able to

- Apply data cleaning methods
- Perform EDA and understand who got their loans approved
- Do feature engineering with One Hot Encoding
- Create LinearSVC model, train and predict on the data
- Print accuracy, confusion matrix and classification report
- Compare LinearSVC model with SVC and SGDClassifier models

Business Use Case

Heber Housing Finance deals in all home loans. They have presence across all urban, semi urban and rural areas. Customer first apply for home loan after that company validates the customer eligibility for loan. However doing this manually takes a lot of time. Hence, it wants you to automate the loan approval process (real time) based on customer information. So you should identify all features and build a model that enable the company to approve the load application or not.

The dataset contains the details of 614 loan applicants, where each applicant is described with 12 features. Loan_Status is the target feature (ie., dependent variable) and all others are independent variables.

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

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt

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

Out[1]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapp
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [2]:

```
train_data.shape
```

Out[2]:

```
(614, 13)
```

In [3]:

```
train_data.columns
```

Out[3]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
t',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Statu
s'],
      dtype='object')
```

In [4]:

```
train_data.dtypes
```

Out[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
```

In [5]:

```
train_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
```

In [6]:

```
train_data.value_counts
```

Out[6]:

```
<bound method DataFrame.value_counts of       Loan_ID  Gender Married Depend
ents     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]>
```

Step2. [Data Cleaning]

- Replace numbers as string by integer in “Dependents” column
- Fill missing data in categorical columns (Gender, Married, Dependents, Education, Self_Employed, Credit_History) by its mode value
- Handle missing values in numberical columns
- Drop Loan_ID column

In [7]:

```
train_data.Dependents.value_counts()
```

Out[7]:

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

In [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'
```

In [9]:

```
train_data['Dependents'] = train_data['Dependents'].apply(string)
```

In [10]:

```
train_data.isna().sum()
```

Out[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
```

In [11]:

```
#categorical
train_data['Gender'].fillna(train_data['Gender'].mode()[0], inplace=True)
train_data['Married'].fillna(train_data['Married'].mode()[0], inplace=True)
train_data['Dependents'].fillna(train_data['Dependents'].mode()[0], inplace=True)
train_data['Loan_Amount_Term'].fillna(train_data['Loan_Amount_Term'].mode()[0], inplace=Tru
train_data['Credit_History'].fillna(train_data['Credit_History'].mode()[0], inplace=True)
train_data['Self_Employed'].fillna(train_data['Self_Employed'].mode()[0], inplace=True)
#numerical
train_data['LoanAmount'].fillna(train_data['LoanAmount'].mean(), inplace=True)
```

In [12]:

```
train_data=train_data.drop(['Loan_ID'],axis=1)
```

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

Draw count plot for

- Married?
- Dependants?
- Graduates?
- Self-employed?

In [13]:

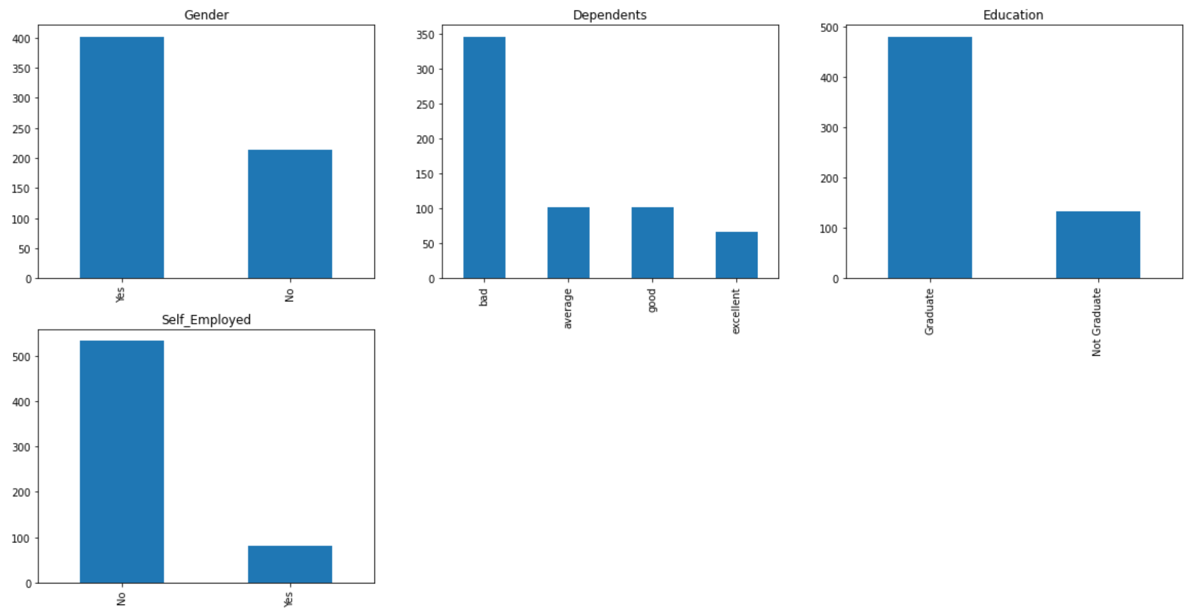
```
plt.subplot(231)
train_data['Married'].value_counts().plot(kind='bar',title='Gender',figsize = (20,10))

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

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

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

plt.show()
```



Step4. [Extract X and y] from the dataframe

In [14]:

```
X = train_data.drop(['Loan_Status'],axis=1)
y = train_data.Loan_Status
```

Step5. [One Hot Encoding]

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

In [15]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [16]:

```
X = pd.get_dummies(X)
```

Step6. [Model Building]

- Split X and y for training and testing
- Using StandardScaler, fit_transform on X_train and transform on X_test values
- create LinearSVC model, train and test
- print accuracy value
- Print confusion matrix between y_test and y_pred
- Print classification_report

In [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)
```

In [18]:

```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
```

In [19]:

```
ss = scale.fit_transform(X_train)
ss1 = scale.transform(X_test)
```

In [20]:

```
from sklearn.svm import LinearSVC
model = LinearSVC()
model.fit(ss,y_train)
```

Out[20]:

```
LinearSVC()
```

In [21]:

```
Lsvc_y_pred = model.predict(ss1)
Lsvc_y_pred
```

Out[21]:

```
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)
```

In [22]:

```
from sklearn.metrics import accuracy_score,confusion_matrix, classification_report
accuracy_score(y_test,Lsvc_y_pred)
```

Out[22]:

```
0.8324324324324325
```

In [23]:

```
confusion_matrix(y_test,Lsvc_y_pred)
```

Out[23]:

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

In [24]:

```
print(classification_report(y_test,Lsvc_y_pred))
```

```
              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
```

Step7. [Performance Comparisons]

1. Compare the performance of LinearSVC against LogisticRegression

In [25]:

```
from sklearn.linear_model import LogisticRegression

lgr= LogisticRegression()
lgr.fit(ss,y_train)
lr_y_pred = lgr.predict(ss1)

from sklearn.svm import LinearSVC

l_svc = LinearSVC()
l_svc.fit(ss,y_train)
lsvc_y_pred = l_svc.predict(ss1)

print("LogisticRegression:",accuracy_score(y_test,lr_y_pred))
print("LinearSVC         :",accuracy_score(y_test,lsvc_y_pred))
```

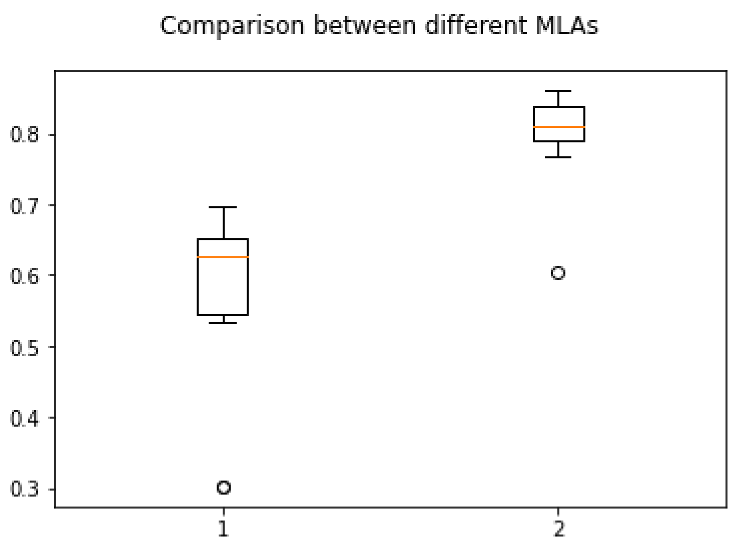
```
LogisticRegression: 0.8324324324324325
LinearSVC         : 0.8324324324324325
```

In [26]:

```
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
    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: 0.564120 (0.138692)
LR: 0.797231 (0.070487)
```



2. Compare the performance of LinearSVC against SGDClassifier

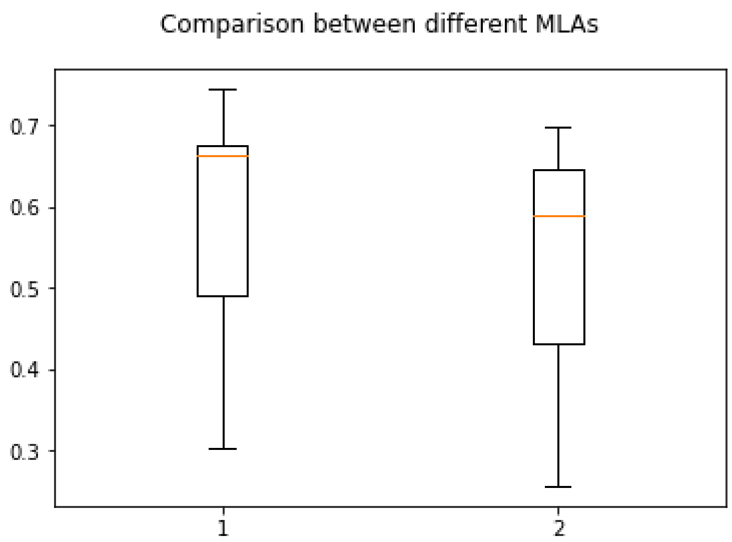
In [27]:

```
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
    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: 0.577796 (0.156098)
SGD: 0.529236 (0.153889)
```



In [28]:

```
from sklearn.linear_model import SGDClassifier

sgd = SGDClassifier()
sgd.fit(ss,y_train)
sgdc_y_pred = sgd.predict(ss1)

from sklearn.svm import LinearSVC

l_svc = LinearSVC()
l_svc.fit(ss,y_train)
lsvc_y_pred = l_svc.predict(ss1)

print("SGDClassifier:", accuracy_score(y_test,sgdc_y_pred))
print("LinearSVC    :",accuracy_score(y_test,lsvc_y_pred))
```

```
SGDClassifier: 0.6324324324324324
LinearSVC    : 0.8324324324324325
```

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

In [29]:

```
from sklearn.svm import SVC

l_svc = LinearSVC()
l_svc.fit(ss,y_train)
lsvc_y_pred = l_svc.predict(ss1)


poly_svc = svm.SVC(kernel='poly', C = 1.0)
poly_svc.fit(ss,y_train)
psvc_y_pred=poly_svc.predict(ss1)


rbf_svc = svm.SVC(kernel='rbf', C = 1.0)
rbf_svc.fit(ss,y_train)
rbfsvc_y_pred=rbf_svc.predict(ss1)


sigmoid_svc = svm.SVC(kernel='sigmoid', C = 1.0)
sigmoid_svc.fit(ss,y_train)
sigsvc_y_pred=sigmoid_svc.predict(ss1)


print("LinearSVC   :",accuracy_score(y_test,lsvc_y_pred))
print("poly SVC    :",accuracy_score(y_test,psvc_y_pred))
print("rbf SVC     :",accuracy_score(y_test,rbfsvc_y_pred))
print("Sigmoid SVC :",accuracy_score(y_test,sigsvc_y_pred))
```

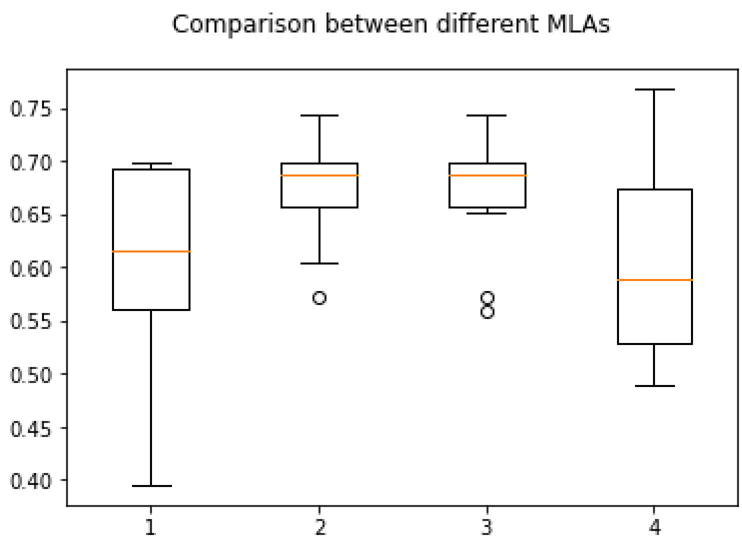
```
LinearSVC   : 0.8324324324324325
poly SVC    : 0.8162162162162162
rbf SVC     : 0.8324324324324325
Sigmoid SVC : 0.8054054054054054
```

In [30]:

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

# evaluate each model in turn
results = []
names=[]
scoring = 'accuracy'
for name,model in modelsss:
    kfold = model_selection.KFold(n_splits=10)
    cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold, 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: 0.605980 (0.091265)
SVC POLY: 0.671096 (0.047891)
SVC rbf: 0.666445 (0.055735)
SVC POLY: 0.603710 (0.092483)
```



4. Interpret the results

In [31]:

```
import numpy as np
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import auc

MLA  = [model,lgr,sgd,poly_svc,rbf_svc,sigmoid_svc]
MLA_columns = []
MLA_compare = pd.DataFrame(columns = MLA_columns)

row_index = 0
for alg in MLA:

    predicted = alg.fit(ss, y_train).predict(ss1)
    predicted=np.where(predicted=='Y',1,0)
    y_testb=np.where(y_test=='Y',1,0)
    fp, tp, th = roc_curve(y_testb, predicted)
    MLA_name = alg.__class__.__name__
    MLA_compare.loc[row_index,'MLA used'] = MLA_name
    MLA_compare.loc[row_index, 'Train Accuracy'] = round(alg.score(ss,y_train), 4)
    MLA_compare.loc[row_index, 'Test Accuracy'] = round(alg.score(ss1,y_test), 4)
    MLA_compare.loc[row_index, 'Precission'] = precision_score(y_testb, predicted)
    MLA_compare.loc[row_index, 'Recall'] = recall_score(y_testb, predicted)
    MLA_compare.loc[row_index, 'AUC'] = auc(fp, tp)
    row_index+=1

MLA_compare
```

Out[31]:

	MLA used	Train Accuracy	Test Accuracy	Precission	Recall	AUC
0	SVC	0.7506	0.8054	0.810127	0.955224	0.683494
1	LogisticRegression	0.8042	0.8324	0.819876	0.985075	0.708224
2	SGDClassifier	0.7203	0.7514	0.818841	0.843284	0.676544
3	SVC	0.8368	0.8162	0.820513	0.955224	0.703102
4	SVC	0.8135	0.8324	0.819876	0.985075	0.708224
5	SVC	0.7506	0.8054	0.810127	0.955224	0.683494

In [32]:

```
import seaborn as sns
# Creating plot to show the train accuracy
plt.subplots(figsize=(8,4))
sns.barplot(x="MLA used", y="Train Accuracy",data=MLA_compare,palette='hot',edgecolor=sns.c
plt.xticks(rotation=90)
plt.title('MLA Train Accuracy Comparison')
plt.show()
```