In [ ]:
```
import numpy as np
import pandas as pd
import sklearn
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()

#Extra imports to simplify code
from sklearn.model_selection import LearningCurveDisplay, learning_curve
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, precision_score, recall_scor
e, accuracy_score
from sklearn.metrics import mean_squared_error as MSE
from sklearn.model_selection import train_test_split
from collections import Counter
from sklearn.model_selection import cross_validate, StratifiedKFold
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

# Imported models
from sklearn.tree import DecisionTreeClassifier as dtc
from sklearn.linear_model import Perceptron
from sklearn.naive_bayes import GaussianNB as gnb
from sklearn.linear_model import LinearRegression as linr
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier as mlp
from sklearn.ensemble import GradientBoostingClassifier as gbc

# Extra models
from sklearn.linear_model import RidgeClassifier as lnrc
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import Ridge
```

Preprocessing

- Removing none types from columns
- Converting all textual data into numeric data

In [ ]:
```
# Remove none types from columns where relavant

df = pd.read_csv('okcupid_profiles.csv', encoding='utf-8')

df.replace([np.nan], None, inplace = True)
df.replace(['used up', 'rather not say'], None, inplace = True)
df = df.dropna(subset=['body_type','drinks', 'drugs', 'education', 'ethnici
ty',
                       'height', 'income', 'job', 'last_online', 'location
',
                       'smokes', 'speaks'])

df.replace([None], 'none', inplace = True)

df['sign_data'] = df['sign'].apply(lambda x: x.split()[0])
df['sign_intensity'] = df['sign'].apply(lambda x: " ".join(x.split()[1:]))
df['religion_data'] = df['religion'].apply(lambda x: x.split()[0])
df['religion_intensity'] = df['religion'].apply(lambda x: " ".join(x.split
()[1:]))
#print(sorted(df['religion_data'].unique()))


# Removing nulls from sign_intensity

### This line of code will replace empty entries in religion intensity and
### sign_intensity with -1
#df.replace([''], -1, inplace = True)


df['religion_intensity'].replace([''], None, inplace = True)
df['sign_data'].replace(['none'], None, inplace = True)
df['sign_intensity'].replace([''], None, inplace = True)
df['sign_intensity'].replace(['and it matters a lot'], 'and it&rsquo;s fun
to think about', inplace = True)
#df['sign_intensity'].replace(['and it matters a lot'], None, inplace = Tru
e)
df = df.dropna(subset=['sign_data', 'sign_intensity', 'religion_intensity
'])
print(df['sign_intensity'].unique())
```

```
['but it doesn&rsquo;t matter' 'and it&rsquo;s fun to think about']
```

In [ ]:
```
# Change labels into numbers

# Status -    Sorted based on how committed the person currently are
df['status_data'] = df['status']
df['status_data'].replace(['single'], 0, inplace = True)
df['status_data'].replace(['available'], 1, inplace = True)
df['status_data'].replace(['unknown'], 2, inplace = True)
df['status_data'].replace(['seeing someone'], 3, inplace = True)
df['status_data'].replace(['married'], 4, inplace = True)

# Sex
df['sex_data'] = df['sex']
df['sex_data'].replace(['m'], 0, inplace = True)
df['sex_data'].replace(['f'], 1, inplace = True)

# Height independent of sex
df['height_data'] = np.where(df['sex_data']==1, df['height'] - 63.8, df['he
ight'] - 69.4)


# Orientation - Split into [straight, bisexual, gay]
df['orientation_data'] = df['orientation']
df['orientation_data'].replace(['straight'], 0, inplace = True)
df['orientation_data'].replace(['bisexual'], 1, inplace = True)
df['orientation_data'].replace(['gay'], 2, inplace = True)

# Body type -   Sorted based on body fat %
df['body_type_data'] = df['body_type']
df['body_type_data'].replace(['jacked'], 0, inplace = True)
df['body_type_data'].replace(['athletic'], 1, inplace = True)
df['body_type_data'].replace(['fit'], 2, inplace = True)
df['body_type_data'].replace(['thin'], 3, inplace = True)
df['body_type_data'].replace(['skinny'], 4, inplace = True)
df['body_type_data'].replace(['average'], 5, inplace = True)
df['body_type_data'].replace(['a little extra'], 6, inplace = True)
df['body_type_data'].replace(['curvy'], 7, inplace = True)
df['body_type_data'].replace(['full figured'], 8, inplace = True)
df['body_type_data'].replace(['overweight'], 9, inplace = True)

# Diet
diet_labels = sorted(df['diet'].unique())
df['diet_data'] = df['diet']
for x in range(len(diet_labels)):
  df['diet_data'].replace([diet_labels[x]], x, inplace = True)

# Drinks -      Sorted basd on frequency
drinks_labels = ['not at all', 'rarely', 'socially', 'often', 'very often',
'desperately']
df['drinks_data'] = df['drinks']
for x in range(len(drinks_labels)):
  df['drinks_data'].replace([drinks_labels[x]], x, inplace = True)

# Drugs -       Sorted basd on frequency
drugs_labels = ['never', 'sometimes', 'often']
df['drugs_data'] = df['drugs']
```

```
for x in range(len(drugs_labels)):
  df['drugs_data'].replace([drugs_labels[x]], x, inplace = True)

# Education -   Grouped into general level of education
education_primary = ['dropped out of high school', 'dropped out of space ca
mp',
                     'working on high school', ]
education_secondary = ['high school', 'graduated from high school',
                       'working on space camp', 'graduated from space camp
',
                       'space camp',]
education_collegecurrent = ['working on college/university', 'working on tw
o-year college',
                     'dropped out of college/university', 'dropped out of t
wo-year college',
                     ]
education_college = ['graduated from college/university', 'graduated from t
wo-year college',
                     'college/university', 'two-year college', ]
education_gradschoolcurrent = ['working on masters program', 'working on la
w school',
                              'dropped out of masters program', 'dropped ou
t of law school',
                              ]
education_gradschool = ['graduated from masters program', 'graduated from l
aw school',
                        'masters program', 'law school', ]
education_phdcurrent = ['working on ph.d program', 'dropped out of ph.d pro
gram',
                        'working on med school', 'dropped out of med school
']
education_phd = ['graduated from ph.d program', 'graduated from med school
',
                 'ph.d program', 'med school']

education_labels = [education_primary, education_secondary, education_colle
gecurrent,
                    education_college, education_gradschoolcurrent, educati
on_gradschool,
                    education_gradschool, education_phdcurrent, education_p
hd]
df['education_data'] = df['education']
for x in range(len(education_labels)):
  df['education_data'].replace(education_labels[x], x, inplace = True)

# Ethnicity -   Extremely problematic, not worth using, column will be remo
ved
#               from training and testing dataset

# Job -         Groups aren't distinguisable so labels have been sorted
#               alphabetically
job_labels = sorted(df['job'].unique())
df['job_data'] = df['job']
for x in range(len(job_labels)):
  df['job_data'].replace([job_labels[x]], x, inplace = True)
```

```
# Last Online - Dates are converted into minutes
max_date = np.array([int(_) for _ in df['last_online'].max().split('-')])
def convert(str_date):
  time = [int(_) for _ in str_date.split('-')]
  my_quant_diffs = max_date - np.array([int(_) for _ in time])
  return np.dot(np.array([525949, 43829, 1440, 60, 1]), my_quant_diffs)
df['last_online_data'] = df['last_online'].apply(convert)

# Offspring  - Grouped into [none, one, many] # of kids
df['offspring_data'] = df['offspring']
classifiers = (["doesn't have kids, but might want them", "doesn't want kid
s",
 "doesn't have kids, but wants them", "doesn't have kids", 'wants kids',
 "doesn't have kids, and doesn't want any", 'might want kids'],
 ['has a kid', "has a kid, but doesn't want more", 'has a kid, and wants mo
re',
  'has a kid, and might want more'],
 ['has kids', "has kids, but doesn't want more", 'has kids, and might want
more',
 'has kids, and wants more']
 )
for i in range(3):
  df['offspring_data'].replace(classifiers[i], i, inplace=True)
df['offspring_data'].replace(['none'], -1, inplace = True)

# Religious Data -  Sorted roughly based on similarity of belief (ranging f
rom
#                   theists to atheists)

religion_labels = ['catholicism', 'christianity', 'hinduism', 'islam', 'jud
aism','buddhism','other', 'none', 'agnosticism','atheism',]
for x in range(len(religion_labels)):
  df['religion_data'].replace([religion_labels[x]], x, inplace = True)
for i, intensity in enumerate(['and laughing about it', 'and somewhat serio
us about it',  'but not too serious about it', 'and very serious about it
']):
  df['religion_intensity'].replace([intensity], i, inplace=True)
df['religion_intensity'].replace([''], -1, inplace = True)


# Sign Data -     Sorted according to appearance in the year
sign_labels = ['capricorn', 'aquarius', 'pisces', 'aries', 'taurus', 'gemin
i',
               'cancer', 'leo', 'virgo', 'libra', 'scorpio', 'sagittarius']
for x in range(len(sign_labels)):
  df['sign_data'].replace([sign_labels[x]], x, inplace = True)
for i, intensity in enumerate(['but it doesn&rsquo;t matter', 'and it&rsqu
o;s fun to think about', 'and it matters a lot']):
  df['sign_intensity'].replace([intensity], i, inplace=True)


# Smokes Data -   Sorted based on frequency
df['smokes_data'] = df['smokes']
for i, how_much in enumerate(['no', 'trying to quit', 'when drinking', 'som
etimes', 'yes']):
  df['smokes_data'].replace([how_much], i, inplace=True)
```

```
# Language information -  Split into monolingual and polylingual
df['speaks_data'] = np.where(df['speaks'].str.split().str.len() <= 1, 0, 1)

# Essay informtion -      Converted to just length of essays
for i in range(10):
  df['essay{}_data'.format(i)] = df['essay{}'.format(i)].str.split().str.le
n()
essay_labels = ['essay0_data','essay1_data','essay2_data','essay3_data',
                'essay4_data','essay5_data','essay6_data','essay7_data',
                'essay8_data','essay9_data']
essay_lens = pd.DataFrame()
for x in essay_labels:
  essay_lens[x] = df[x]
df['essay_len'] = essay_lens.sum(axis=1, numeric_only= True)
```

In [ ]:

```
def verify_numeric():
  #Call this function to verify that the converted numeric data is actually
  #numeric
  print(df['status_data'].unique())
  print(df['sex_data'].unique())
  print(df['orientation_data'].unique())
  print(df['body_type_data'].unique())
  print(df['diet_data'].unique())
  print(df['drinks_data'].unique())
  print(df['drugs_data'].unique())
  print(df['education_data'].unique())
  print(df['job_data'].unique())
  print(df['offspring_data'].unique())
  print(df['religion_data'].unique())
  print(df['religion_intensity'].unique())
  print(df['sign_data'].unique())
  print(df['sign_intensity'].unique())
```

Columns

In [ ]:
```
# Clone the numeric columns into a seperate data frame, columns selected ar
e in the columns array
numeric = None
numeric = pd.DataFrame()
columns = ['sign_intensity', 'age', 'height', 'income',
           'sign_data', 'religion_data', 'religion_intensity', 'status_data
',
           'sex_data', 'height_data', 'orientation_data', 'body_type_data',
           'diet_data', 'drinks_data', 'drugs_data', 'education_data', 'job
_data',
           'last_online_data', 'offspring_data', 'smokes_data', 'speaks_dat
a',
           'essay0_data', 'essay1_data', 'essay2_data', 'essay3_data', 'ess
ay4_data',
           'essay5_data', 'essay6_data', 'essay7_data', 'essay8_data', 'ess
ay9_data', 'essay_len']
for x in columns:
  numeric[x] = df[x]
print("The dataset has " + str(len(columns)) + " columns")
numeric.corr()
```

```
The dataset has 32 columns
```

Out[ ]:

	sign_intensity	age	height	income	sign_data	religion_data	relig
sign_intensity	1.000000	0.021602	-0.110963	-0.006411	0.007643	-0.080336	
age	0.021602	1.000000	-0.037120	0.000567	-0.005894	-0.056212	
height	-0.110963	-0.037120	1.000000	0.073559	0.011844	0.125301	
income	-0.006411	0.000567	0.073559	1.000000	0.010196	0.024006	
sign_data	0.007643	-0.005894	0.011844	0.010196	1.000000	0.004750	
religion_data	-0.080336	-0.056212	0.125301	0.024006	0.004750	1.000000	
religion_intensity	0.000466	0.051624	-0.063581	-0.014319	-0.005993	-0.205683	
status_data	0.001815	-0.058474	-0.007334	0.009979	-0.003050	0.092302	
sex_data	0.145914	0.059859	-0.656208	-0.095417	-0.008136	-0.107106	
height_data	-0.011825	0.006265	0.716013	0.009053	0.008144	0.066698	
orientation_data	0.077667	-0.032686	0.021632	-0.021797	-0.001841	0.059427	
body_type_data	0.050065	-0.000470	-0.191954	-0.062823	-0.004206	-0.019359	
diet_data	0.025280	-0.018713	0.009933	0.014144	0.004090	0.113079	
drinks_data	-0.011177	-0.119073	0.035032	0.042534	0.002447	0.029076	
drugs_data	0.044252	-0.156981	0.093973	0.073086	0.005173	0.200056	
education_data	-0.074440	0.231623	-0.048147	-0.033175	-0.001360	0.020370	
job_data	-0.022060	-0.166056	-0.026612	-0.035386	-0.015297	-0.031306	
last_online_data	0.025968	-0.020112	-0.020365	0.014760	-0.008884	-0.062916	
offspring_data	0.013163	0.375803	-0.039183	0.012703	0.000893	-0.045462	
smokes_data	0.076484	-0.173290	0.062399	0.042483	0.014422	0.044415	
speaks_data	0.012155	-0.081794	0.001311	0.023040	0.009366	0.068272	
essay0_data	0.036122	0.096799	-0.002888	0.003825	0.001375	0.052091	
essay1_data	0.027798	0.039007	0.014873	-0.008937	0.010083	0.115020	
essay2_data	0.022363	-0.000338	0.022394	-0.012182	0.002101	0.094299	
essay3_data	0.004596	-0.040876	0.034261	-0.016500	0.009199	0.092727	
essay4_data	0.034648	-0.062347	0.012181	-0.011396	0.020706	0.188936	
essay5_data	-0.008407	-0.011660	0.011108	-0.022577	0.017878	0.085077	
essay6_data	0.014758	0.006736	0.021251	-0.007265	0.011959	0.114126	
essay7_data	0.017612	-0.014784	-0.012598	-0.011433	0.010057	0.059744	
essay8_data	0.018945	-0.015840	0.016580	0.006390	0.015444	0.081079	
essay9_data	0.028810	0.016405	-0.002404	0.009862	0.005279	0.100486	
essay_len	0.041236	0.024429	0.013648	-0.007162	0.015349	0.162612	

32 rows × 32 columns

Generating train and test sets with three ratios:

- 50/50
- 70/30
- 80/20

In [ ]:
```
# Seed for different samplings is 1234
sampling_seed = 1234

data = numeric[columns[1:]]
label = numeric[columns[0]]
data1_train, data1_test, label1_train, label1_test = train_test_split(data,
label ,random_state=sampling_seed, test_size=0.5)
data2_train, data2_test, label2_train, label2_test = train_test_split(data,
label ,random_state=sampling_seed, test_size=0.3)
data3_train, data3_test, label3_train, label3_test = train_test_split(data,
label ,random_state=sampling_seed, test_size=0.2)
```

In [ ]:
```
print("The labels have a split of " + str(Counter(label)[0]/len(numeric['si
gn_intensity'])))
print("The dataset has " + str(len(numeric['sign_intensity'])) + " rows")
```

```
The labels have a split of 0.47594098993519923
The dataset has 14506 rows
```

Functions

In [ ]:
```
# Code block for functions
def plot_learning_curve_many(models, names, train_data, train_label):
  # Create plot with n subplots where n is the number of models plugged int
o the function
  fig, ax = plt.subplots(nrows=1, ncols=len(models), figsize=(6*len(model
s), 6), sharey=True)
  options = {
    "X": train_data,
    "y": train_label,
    "cv" : StratifiedKFold(n_splits=10, random_state=seed,shuffle=True),
    "n_jobs": -1,
    "line_kw": {"marker": "o"},
    "std_display_style": "fill_between",
    "score_type": "both",
    "score_name": "Accuracy",
  }
  #Iterate through models and plot the learning curves
  for ax_idx, model in enumerate(models):
    LearningCurveDisplay.from_estimator(model, **options, ax=ax[ax_idx])
    handles, label = ax[ax_idx].get_legend_handles_labels()
    ax[ax_idx].legend(handles[:2], ["Training Score", "Test Score"])
    ax[ax_idx].set_title(f"Learning Curve for " + names[ax_idx])

def plot_learning_curve(model, name, train_data, train_label, curr_split):
  # Create plot with n subplots where n is the number of models plugged int
o the function
  fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(6, 6), sharey=True)
  options = {
    "X": train_data,
    "y": train_label,
    "cv" : StratifiedKFold(n_splits=10, random_state=seed,shuffle=True),
    "n_jobs": -1,
    "line_kw": {"marker": "o"},
    "std_display_style": "fill_between",
    "score_type": "both",
    "score_name": "Accuracy",
  }
  #Iterate through models and plot the learning curves
  LearningCurveDisplay.from_estimator(model, **options, ax=ax)
  handles, label = ax.get_legend_handles_labels()
  ax.legend(handles[:2], ["Training Score", "Test Score"])
  ax.set_title(f"Learning Curve for " + name + " on split " + str(curr_spli
t))

def plot(data, label, xlabel, ylabel):
  %matplotlib inline
  figure, axis = plt.subplots(1,1)
  plt.xlabel(xlabel)
  plt.ylabel(ylabel)
  axis.scatter(data[ 0], data[ 1], c = label, s=30, cmap = 'rainbow');

def graph_cm(y_test, y_test_pred, classes, name, curr_split):
  cm = confusion_matrix(y_test, y_test_pred)
  figure, axis = plt.subplots()
  im = axis.imshow(cm, interpolation='nearest', cmap=plt.cm.Reds)
```

```
  axis.figure.colorbar(im, ax=axis)
  axis.set(xticks=np.arange(cm.shape[1]),yticks=np.arange(cm.shape[0]),
           xticklabels=classes,yticklabels=classes,xlabel='Predicted label
',
           ylabel='True label')
  axis.set_title(f"Confusion Matrix for best "+ name+ " on split "+ str(cur
r_split))
  thresh = (cm.max()- cm.min())/2 + cm.min()
  for i in range(cm.shape[0]):
      for j in range(cm.shape[1]):
          axis.text(j, i, format(cm[i, j], 'd'),
                  ha="center", va="center",
                  color="white" if cm[i, j] > thresh else "black")
  plt.show()

def homebrew_cross_validate(model, name, splits, curr_split, seed):
  plot_learning_curve(model, name, splits[curr_split][0],
                      splits[curr_split][1], curr_split)
  scores = cross_validate(model, splits[curr_split][0], splits[curr_spli
t][1],
                      cv = StratifiedKFold(n_splits=10, random_state=seed,s
huffle=True),
                      #Specify returned scores here
                        scoring = ['accuracy','precision_weighted',
                                   'recall_weighted','f1_weighted'])
  print("\n" + name + " Metrics for 10-fold on split " + str(curr_split))
  print("Fold\tAccuracy\tPrecision\tRecall\t\tF1")
  for x in range(len(scores['test_accuracy'])):
    print(str(x) + "\t\t" + str(round(scores['test_accuracy'][x], 3))+ "  \
t\t" +
          str(round(scores['test_precision_weighted'][x], 3))+ "  \t\t" +
          str(round(scores['test_recall_weighted'][x], 3))+ "  \t" +
          str(round(scores['test_f1_weighted'][x], 3)))
  return cross_validate(model, splits[curr_split][0], splits[curr_spli
t][1],
                      cv = StratifiedKFold(n_splits=10, random_state=seed,s
huffle=True),
                        scoring = ['accuracy','precision_weighted',
                                   'recall_weighted','f1_weighted'],
                        return_estimator = True)

def homebrew_cross_validate_TWO(model, name, splits, curr_split, seed):
  plot_learning_curve(model, name, splits[curr_split][0],
                      splits[curr_split][1], curr_split)
  scores = cross_validate(model, splits[curr_split][0], splits[curr_spli
t][1],
                      cv = StratifiedKFold(n_splits=10, random_state=seed,s
huffle=True),
                      # Specify returned scores here
                        scoring = ['accuracy','precision_weighted',
                                   'recall_weighted','f1_weighted',
                                   'neg_root_mean_squared_error'])
  #print(list(scores.keys()))
  print("\n" + name + " Metrics for 10-fold on split " + str(curr_split))
  print("Fold\tAccuracy\tPrecision\tRecall\t\tF1\t\t\tRMSE")
  for x in range(len(scores['test_accuracy'])):
```

```
    print(str(x) + "\t\t" + str(round(scores['test_accuracy'][x], 3))+ "  \
t\t"+
          str(round(scores['test_precision_weighted'][x], 3))+ "  \t\t" +
          str(round(scores['test_recall_weighted'][x], 3)) + "  \t\t" +
          str(round(scores['test_f1_weighted'][x], 3)) + "  \t\t" +
          str(round(scores['test_neg_root_mean_squared_error'][x], 3)))
  return cross_validate(model, splits[curr_split][0], splits[curr_spli
t][1],
                      cv = StratifiedKFold(n_splits=10, random_state=seed,s
huffle=True),
                        scoring = ['accuracy','precision_weighted',
                                   'recall_weighted','f1_weighted',
                                   'neg_root_mean_squared_error'],
                        return_estimator = True)
def redefine_columns():
  print(df.columns.tolist())
  sampling_seed  = 1234
  numeric = pd.DataFrame()
  columns = ['sign_intensity',
             'age',
             'sex_data',
             'orientation_data',
             'education_data',
             'smokes_data',
             'height',
             'religion_data',
             'essay_len'
             ]
  for x in columns:
    numeric[x] = df[x]
  data = numeric[columns[1:]]
  label = numeric[columns[0]]
  data1_train, data1_test, label1_train, label1_test = train_test_split(dat
a, label ,random_state=sampling_seed, test_size=0.5)
  data2_train, data2_test, label2_train, label2_test = train_test_split(dat
a, label ,random_state=sampling_seed, test_size=0.3)
  data3_train, data3_test, label3_train, label3_test = train_test_split(dat
a, label ,random_state=sampling_seed, test_size=0.2)

  splits = [[data1_train, label1_train], [data2_train, label2_train], [data
3_train, label3_train]]
  tests = [[data1_test, label1_test], [data2_test, label2_test], [data3_tes
t, label3_test]]
  labels = ['No', 'Yes']
```

Making predictions using models

Models used for predictions:

- Decision Tree
- Perceptron
- Naive Bayes
- Logistic Regression
- Linear Regression
- SVM with Linear Kernel
- SVM with RBF kernel
- Gradient Boosting
- Multi Layer Perceptron

Extra models:

- Gaussian Naive Bayes
- Linear Ridge Regression
- ???
- Linear Regression with Regularization

In [ ]:
```
seed = 1234
splits = [[data1_train, label1_train], [data2_train, label2_train], [data3_train, label3_train]]
tests = [[data1_test, label1_test], [data2_test, label2_test], [data3_test, label3_test]]

labels = ['No', 'Yes']
```

Pipeline

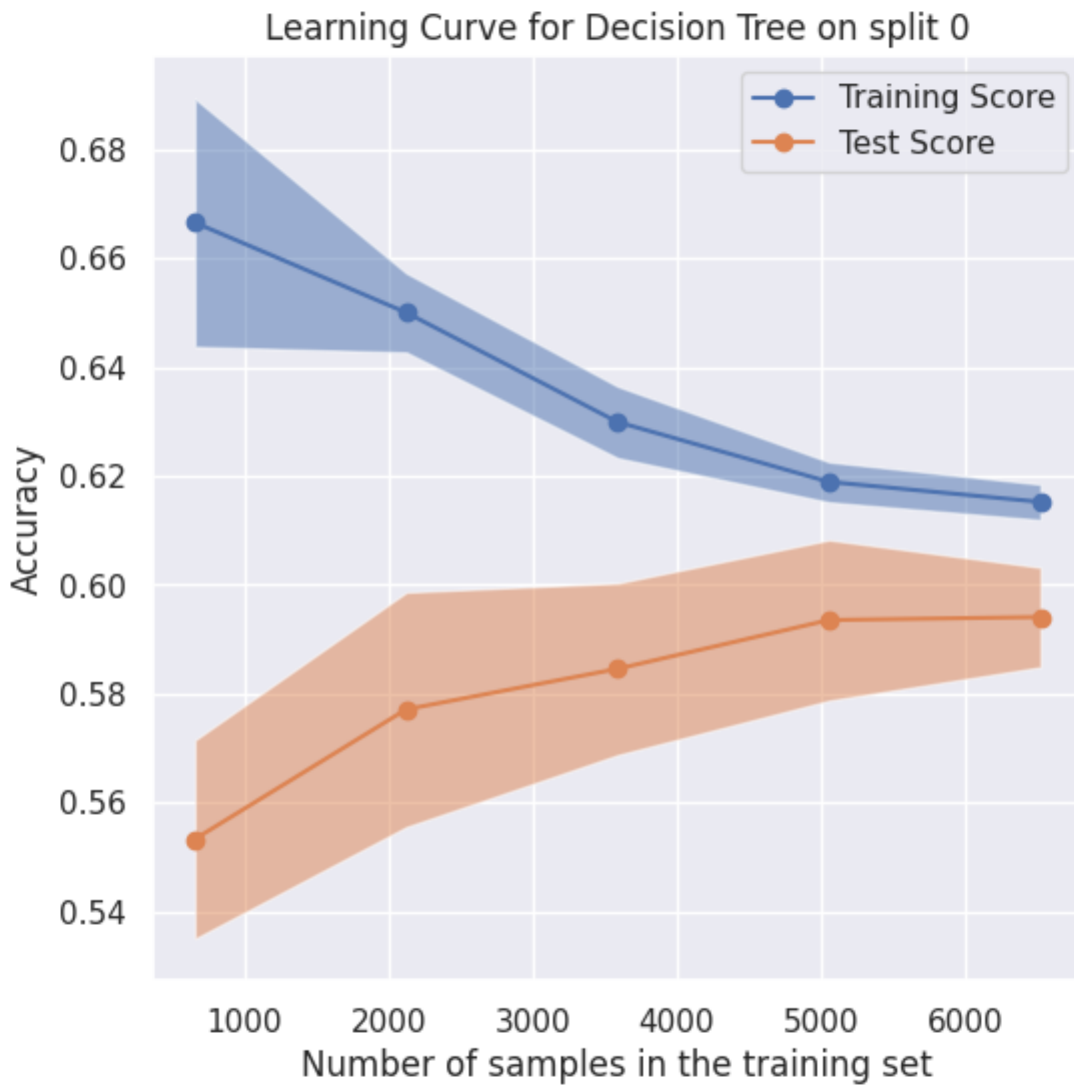
In [ ]:
```
def pipe(model, name, splits = splits, seed = seed):
  models = []
  for curr_split in range(3):
    models.append(homebrew_cross_validate(model, name, splits, curr_split,
seed))
  return models

def best_model_metrics (models, name, best_models, tests = tests, labels =
['No', 'Yes']):
  for x in range(len(best_models)):
    best_model = models[x]['estimator'][best_models[x]]
    y_pred = best_model.predict(tests[x][0])
    graph_cm(tests[x][1], y_pred, labels, name, x)
    print("Classification report for best " + name + " on unseen data on sp
lit " + str(x))
    print(classification_report(tests[x][1], y_pred))
    print("\n\n\n")

def pipe_for_regression(model, name, splits = splits, seed = seed):
  models = []
  for curr_split in range(3):
    models.append(homebrew_cross_validate_TWO(model, name, splits, curr_spl
it, seed))
  return models
```

1 - Decision Tree

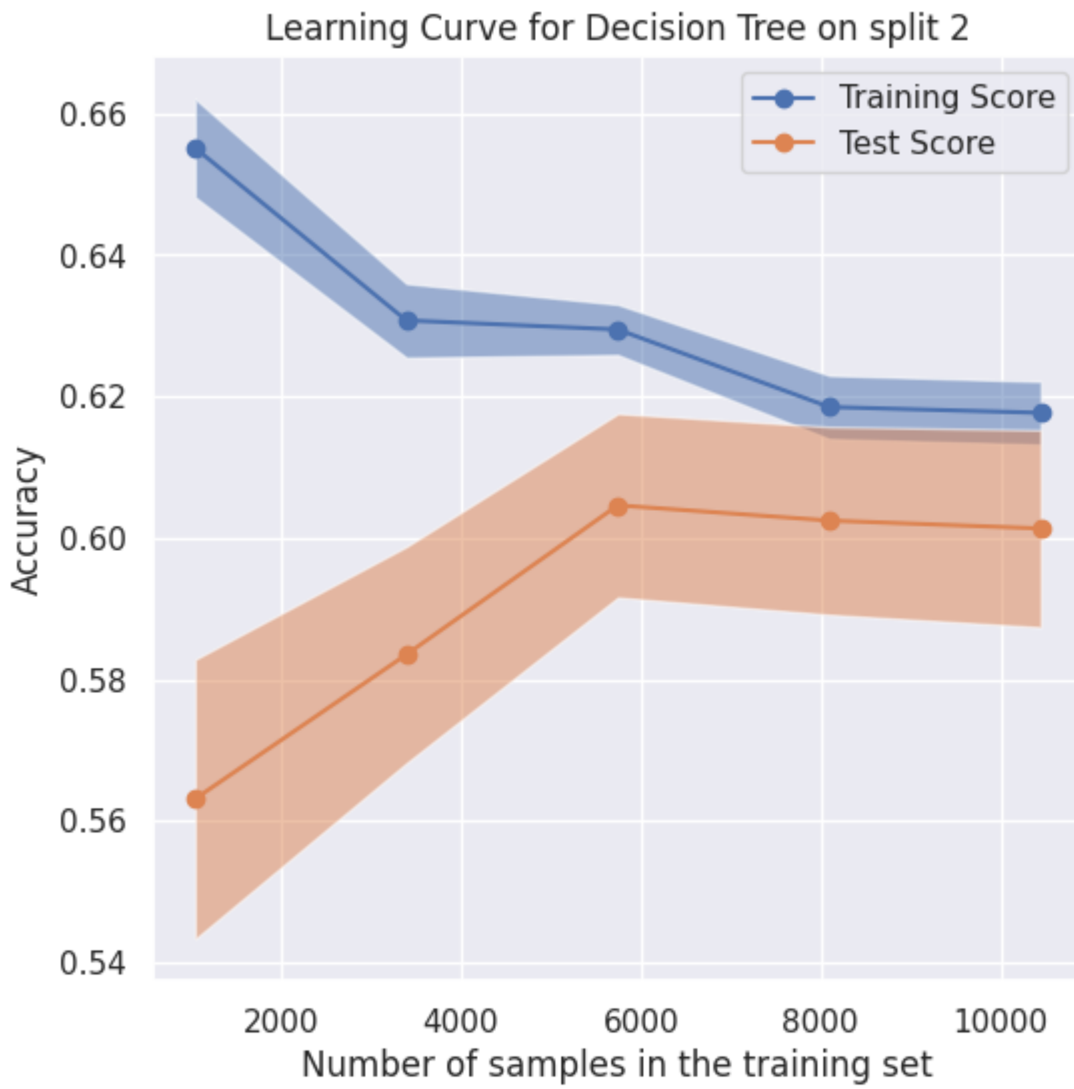
- Decision tree performs better with a lower max_depth, suggesting that there might be a lot of noise in the data
- Choice of criterion doesn't seem to matter in this instance because the model is not very performant.

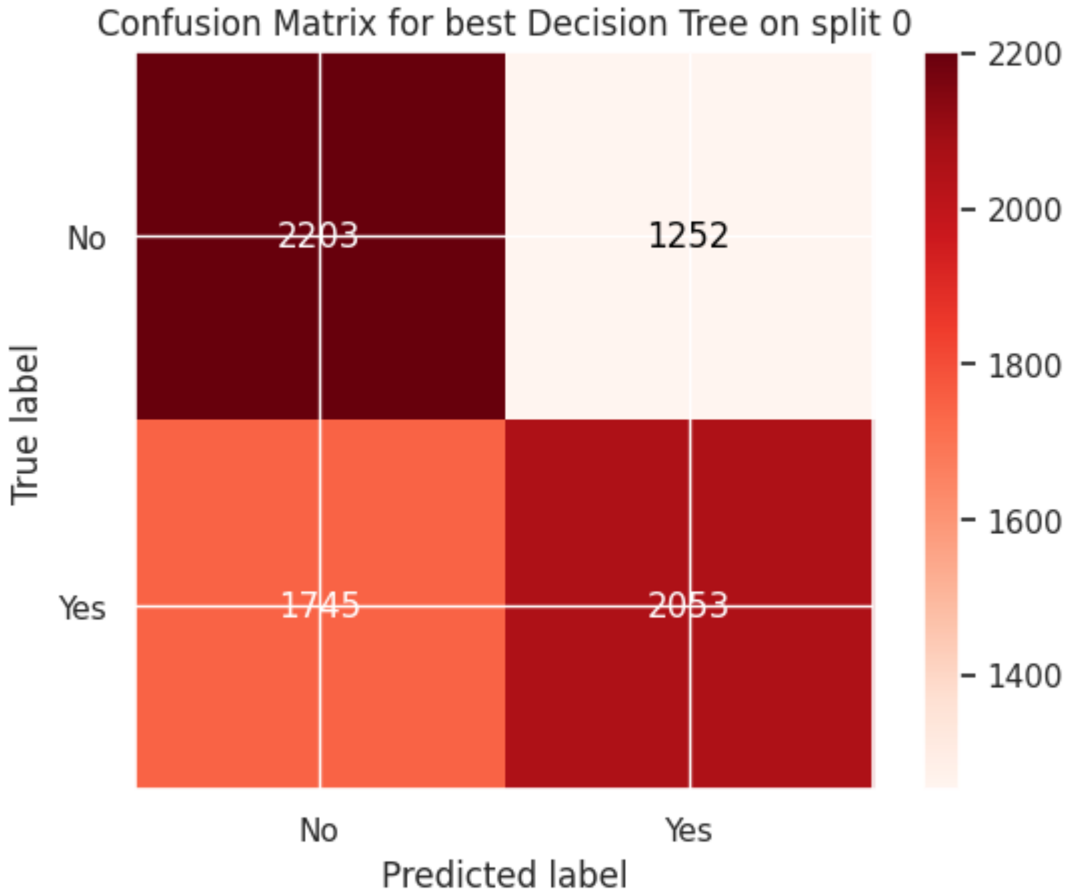
In [ ]:
```
models = pipe(dtc(criterion = 'entropy', max_depth = 5, random_state=seed),
              "Decision Tree")
best_models = [0, 5, 8]
best_model_metrics(models, "Decision Tree", best_models)
```

```
Decision Tree Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.603           0.611           0.603   0.602
1               0.579           0.577           0.579   0.576
2               0.601           0.602           0.601   0.601
3               0.603           0.602           0.603   0.602
4               0.593           0.599           0.593   0.592
5               0.601           0.605           0.601   0.601
6               0.603           0.606           0.603   0.603
7               0.581           0.584           0.581   0.58
8               0.593           0.594           0.593   0.593
9               0.585           0.585           0.585   0.585

Decision Tree Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.603           0.603           0.603   0.602
1               0.584           0.586           0.584   0.584
2               0.578           0.58            0.578   0.578
3               0.614           0.615           0.614   0.614
4               0.572           0.574           0.572   0.573
5               0.634           0.634           0.634   0.634
6               0.604           0.603           0.604   0.603
7               0.58            0.584           0.58    0.58
8               0.578           0.579           0.578   0.579
9               0.61            0.609           0.61    0.609

Decision Tree Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.577           0.581           0.577   0.577
1               0.593           0.592           0.593   0.591
2               0.586           0.586           0.586   0.586
3               0.603           0.602           0.603   0.602
4               0.6             0.6             0.6     0.6
5               0.615           0.617           0.615   0.615
6               0.601           0.6             0.601   0.6
7               0.598           0.599           0.598   0.598
8               0.628           0.627           0.628   0.627
9               0.614           0.614           0.614   0.614
```

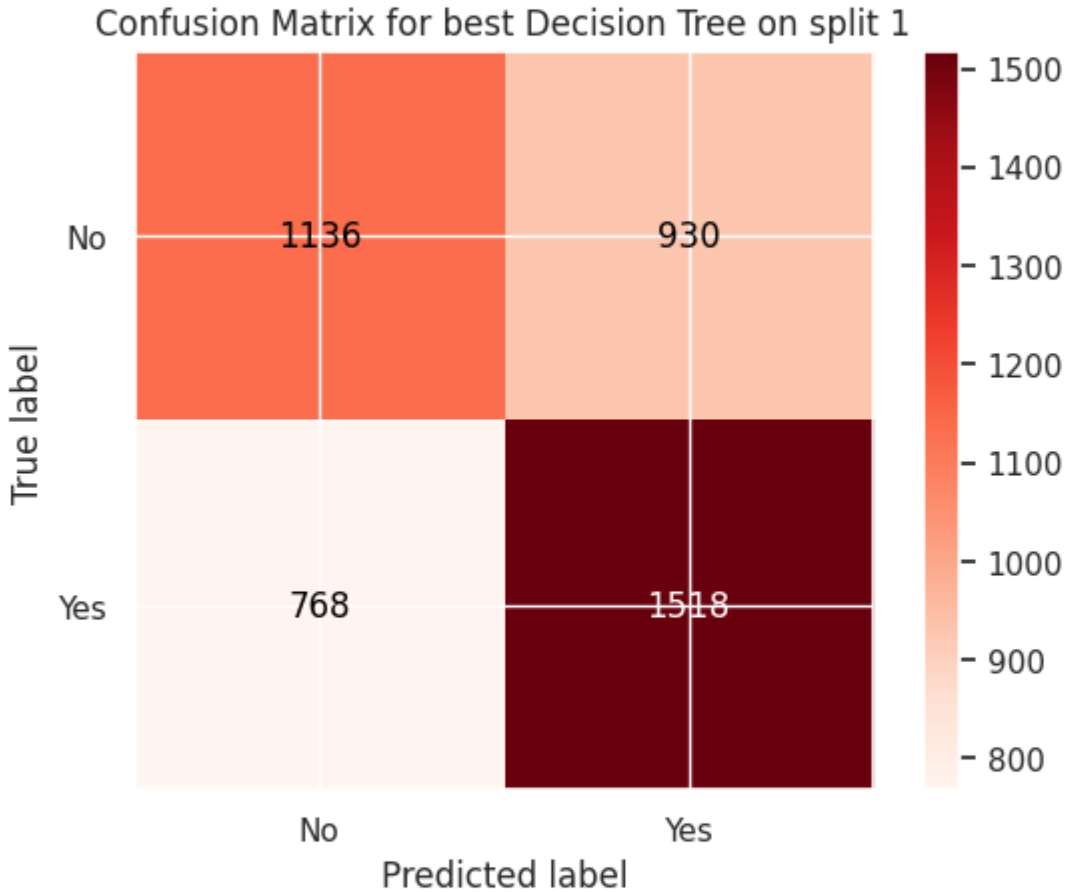

Learning Curve for Decision Tree on split 0
Training Score
Test Score
0.68
0.66
0.64
0.62
0.60
0.58
0.56
0.54
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Decision Tree on split 1
Training Score
Test Score
Accuracy
0.700
0.675
0.650
0.625
0.600
0.575
0.550
0.525
2000
4000
6000
8000
Number of samples in the training set

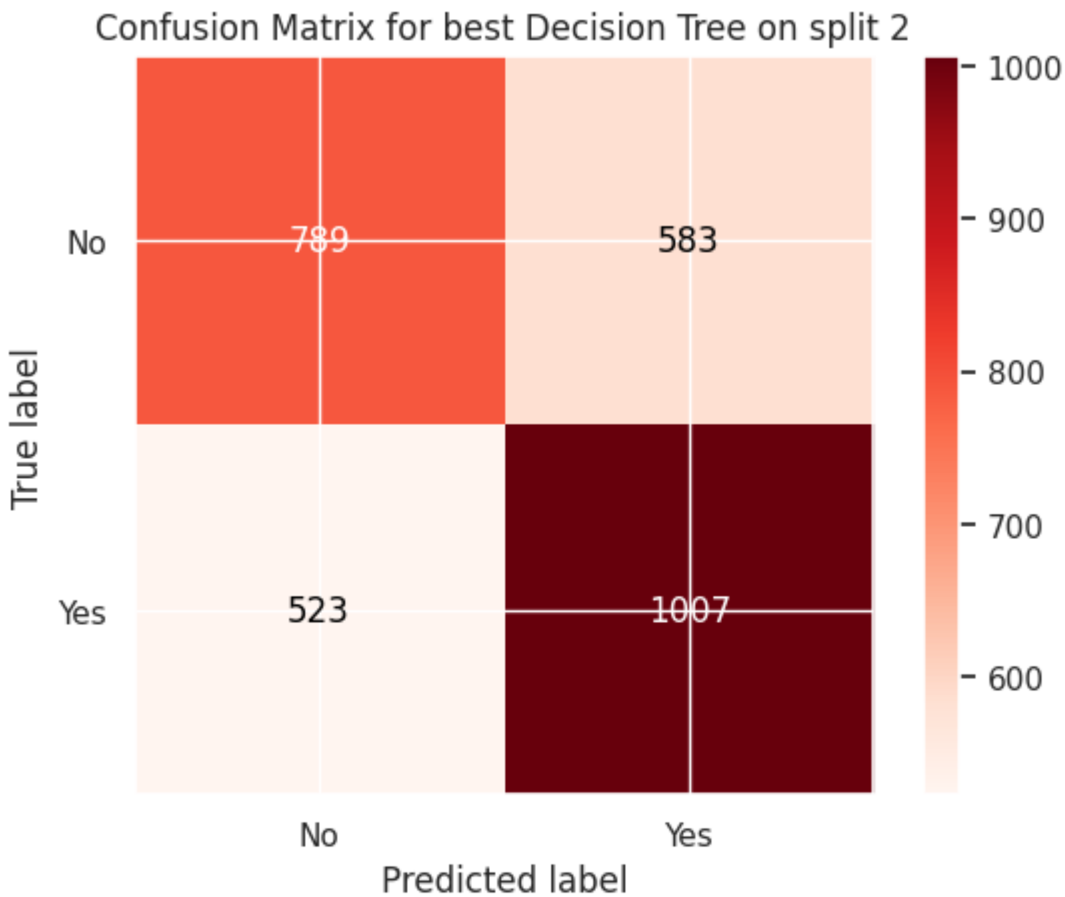

Learning Curve for Decision Tree on split 2
Training Score
Test Score
0.66
0.64
0.62
0.60
0.58
0.56
0.54
Accuracy
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Decision Tree on unseen data on split 0
              precision    recall  f1-score   support

           0       0.56      0.64      0.60      3455
           1       0.62      0.54      0.58      3798

    accuracy                           0.59      7253
   macro avg       0.59      0.59      0.59      7253
weighted avg       0.59      0.59      0.59      7253
```




```
Classification report for best Decision Tree on unseen data on split 1
              precision    recall  f1-score   support

           0       0.60      0.55      0.57      2066
           1       0.62      0.66      0.64      2286

    accuracy                           0.61      4352
   macro avg       0.61      0.61      0.61      4352
weighted avg       0.61      0.61      0.61      4352
```




```
Classification report for best Decision Tree on unseen data on split 2
              precision    recall  f1-score   support

           0       0.60      0.58      0.59      1372
           1       0.63      0.66      0.65      1530

    accuracy                           0.62      2902
   macro avg       0.62      0.62      0.62      2902
weighted avg       0.62      0.62      0.62      2902
```

2 - Perceptron

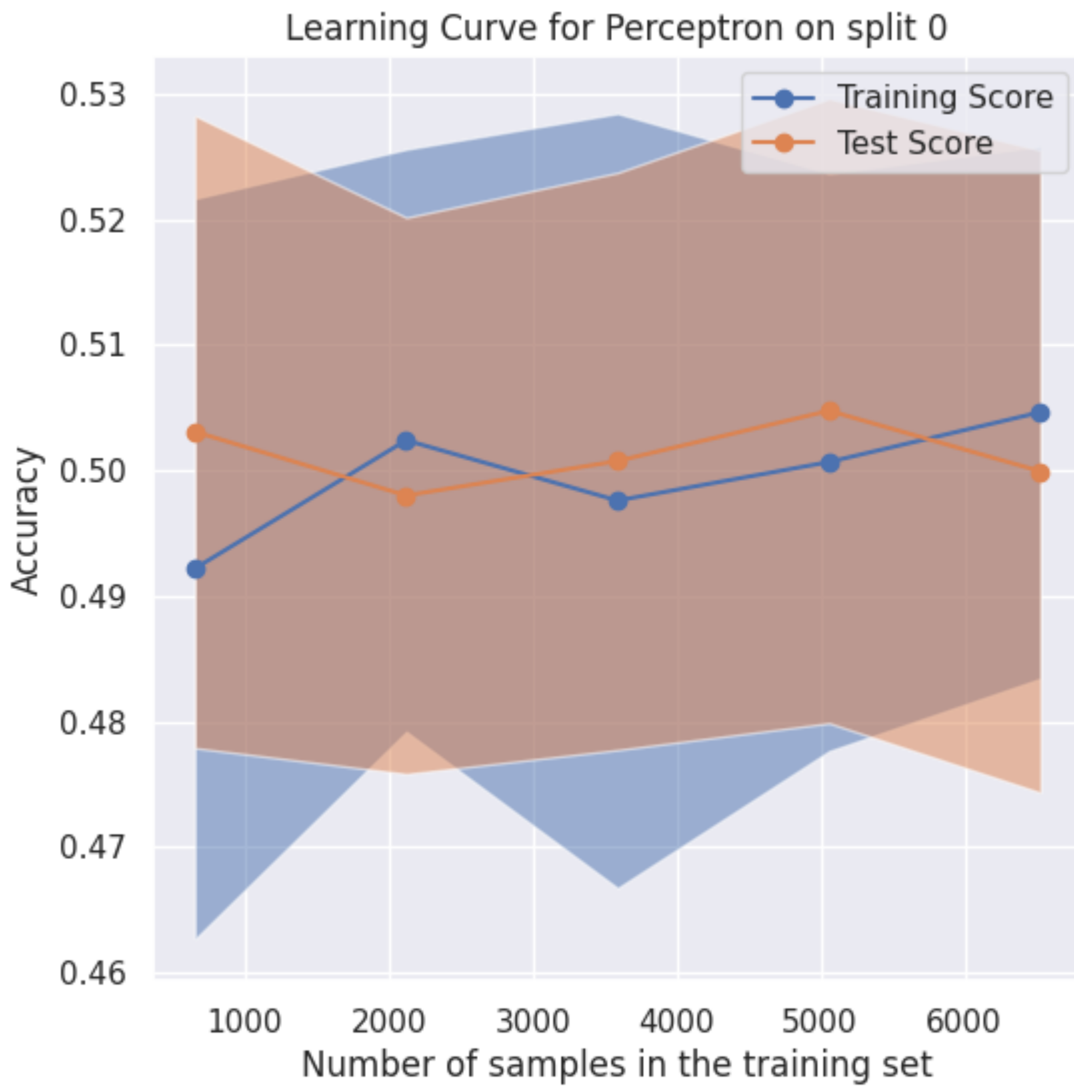
- Doesn't fit with the full dataset

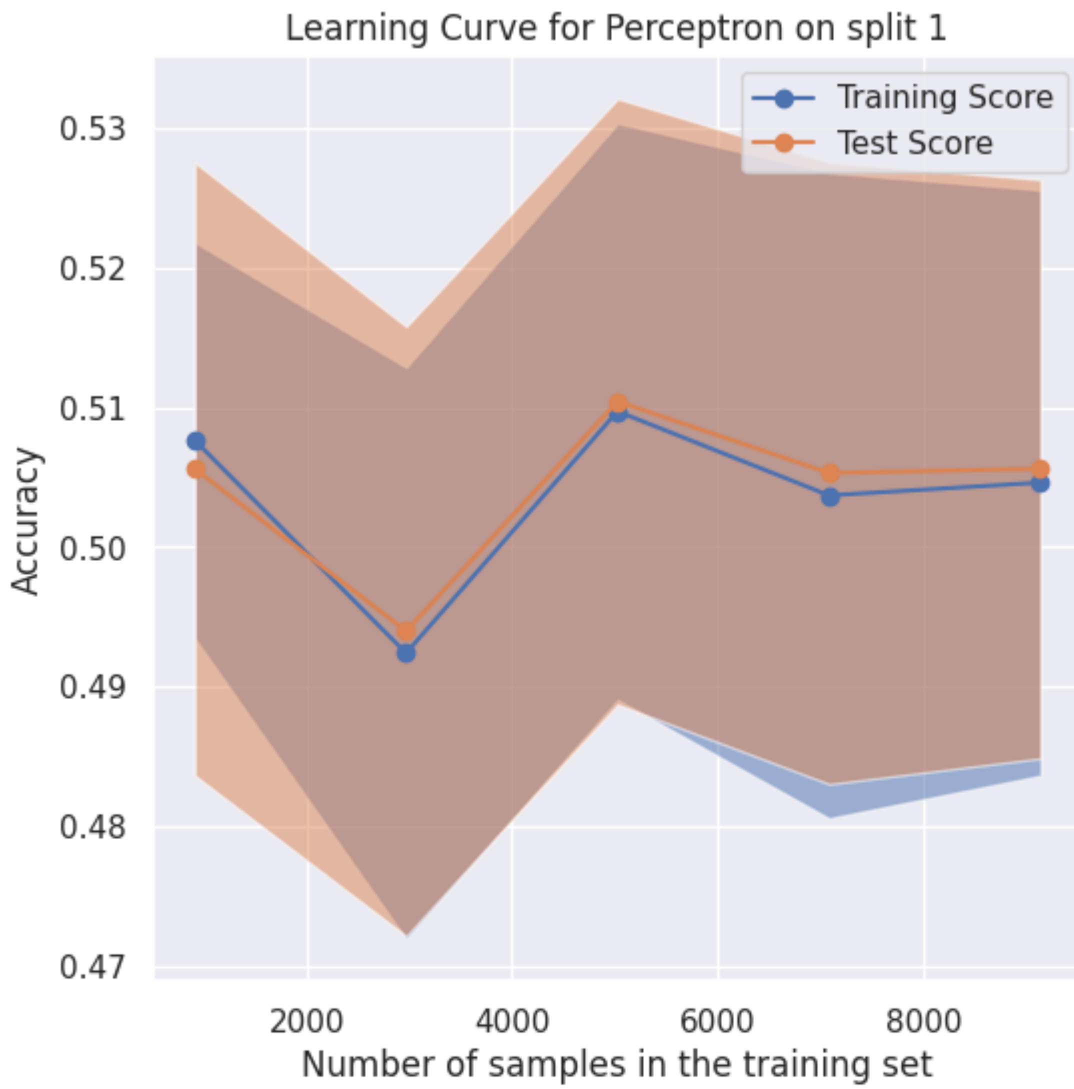
In [ ]:
```
models = pipe(Perceptron(random_state=seed, tol = 0.0001, fit_intercept=False),
              "Perceptron")
best_models = [7, 5, 4]
best_model_metrics(models, "Perceptron", best_models)
```

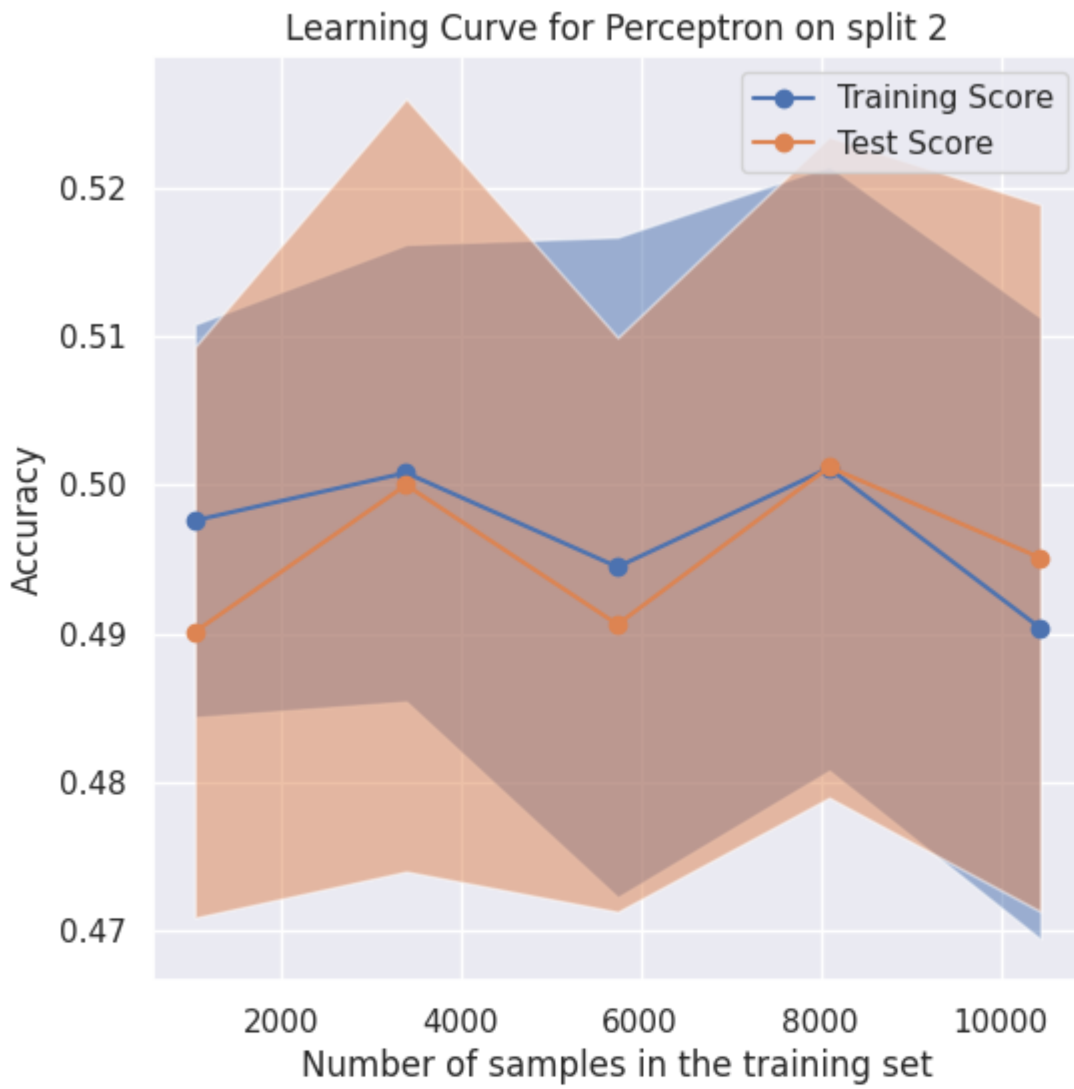
```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

Perceptron Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.525           0.275           0.525   0.361
1               0.474           0.225           0.474   0.306
2               0.485           0.496           0.485   0.46
3               0.524           0.275           0.524   0.36
4               0.526           0.751           0.526   0.364
5               0.524           0.513           0.524   0.363
6               0.476           0.226           0.476   0.307
7               0.535           0.531           0.535   0.509
8               0.523           0.274           0.523   0.36
9               0.459           0.452           0.459   0.378

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

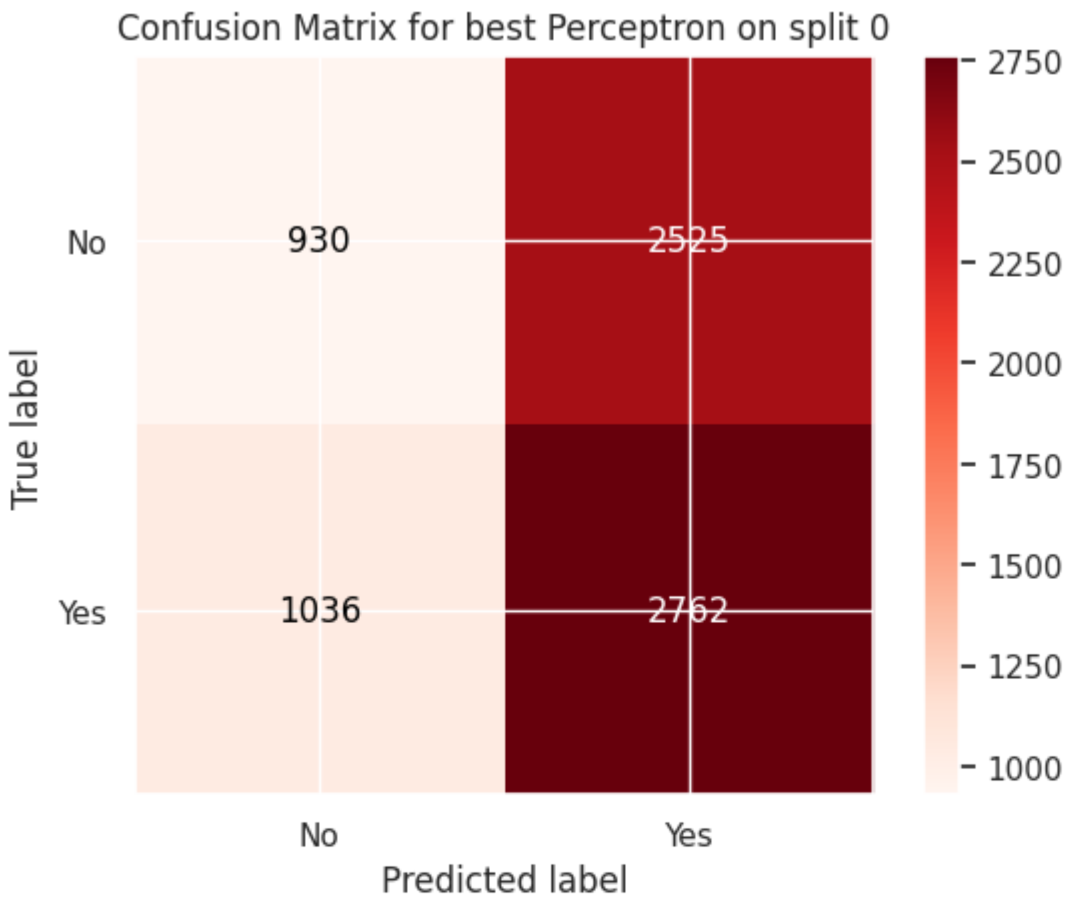
```
Perceptron Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.486           0.498           0.486   0.455
1               0.485           0.562           0.485   0.345
2               0.476           0.227           0.476   0.307
3               0.525           0.517           0.525   0.487
4               0.525           0.751           0.525   0.363
5               0.538           0.537           0.538   0.489
6               0.477           0.227           0.477   0.308
7               0.52            0.273           0.52    0.358
8               0.525           0.543           0.525   0.376
9               0.473           0.48            0.473   0.426

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

Perceptron Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.471           0.478           0.471   0.438
1               0.49            0.512           0.49    0.429
2               0.477           0.228           0.477   0.308
3               0.477           0.228           0.477   0.308
4               0.527           0.521           0.527   0.472
5               0.523           0.274           0.523   0.36
6               0.532           0.528           0.532   0.491
7               0.5             0.515           0.5     0.473
8               0.524           0.592           0.524   0.363
9               0.492           0.505           0.492   0.466
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to contr
ol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

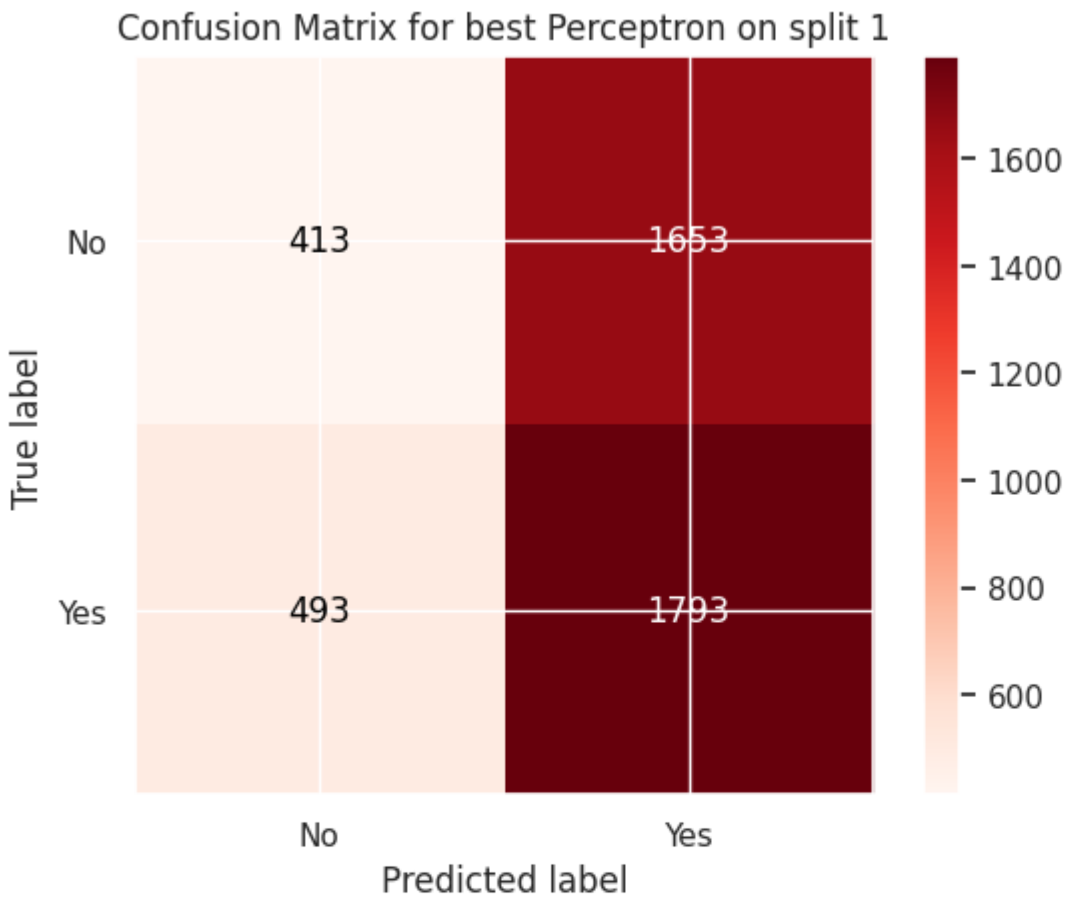



Learning Curve for Perceptron on split 1
Training Score
Test Score
Accuracy
0.53
0.52
0.51
0.50
0.49
0.48
0.47
2000
4000
6000
8000
Number of samples in the training set

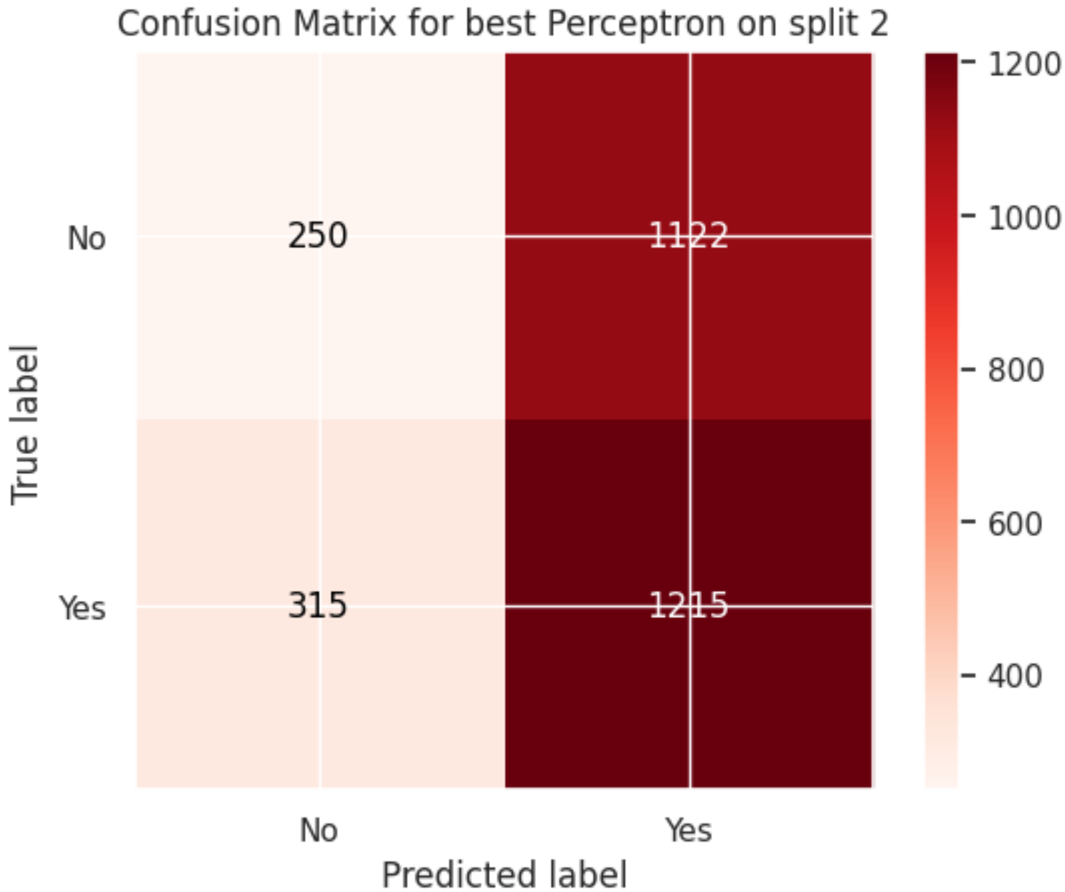

Learning Curve for Perceptron on split 2
Training Score
Test Score
Accuracy
0.52
0.51
0.50
0.49
0.48
0.47
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Perceptron on unseen data on split 0
              precision    recall  f1-score   support

           0       0.47      0.27      0.34      3455
           1       0.52      0.73      0.61      3798

    accuracy                           0.51      7253
   macro avg       0.50      0.50      0.48      7253
weighted avg       0.50      0.51      0.48      7253
```




```
Classification report for best Perceptron on unseen data on split 1
              precision    recall  f1-score   support

           0       0.46      0.20      0.28      2066
           1       0.52      0.78      0.63      2286

    accuracy                           0.51      4352
   macro avg       0.49      0.49      0.45      4352
weighted avg       0.49      0.51      0.46      4352
```

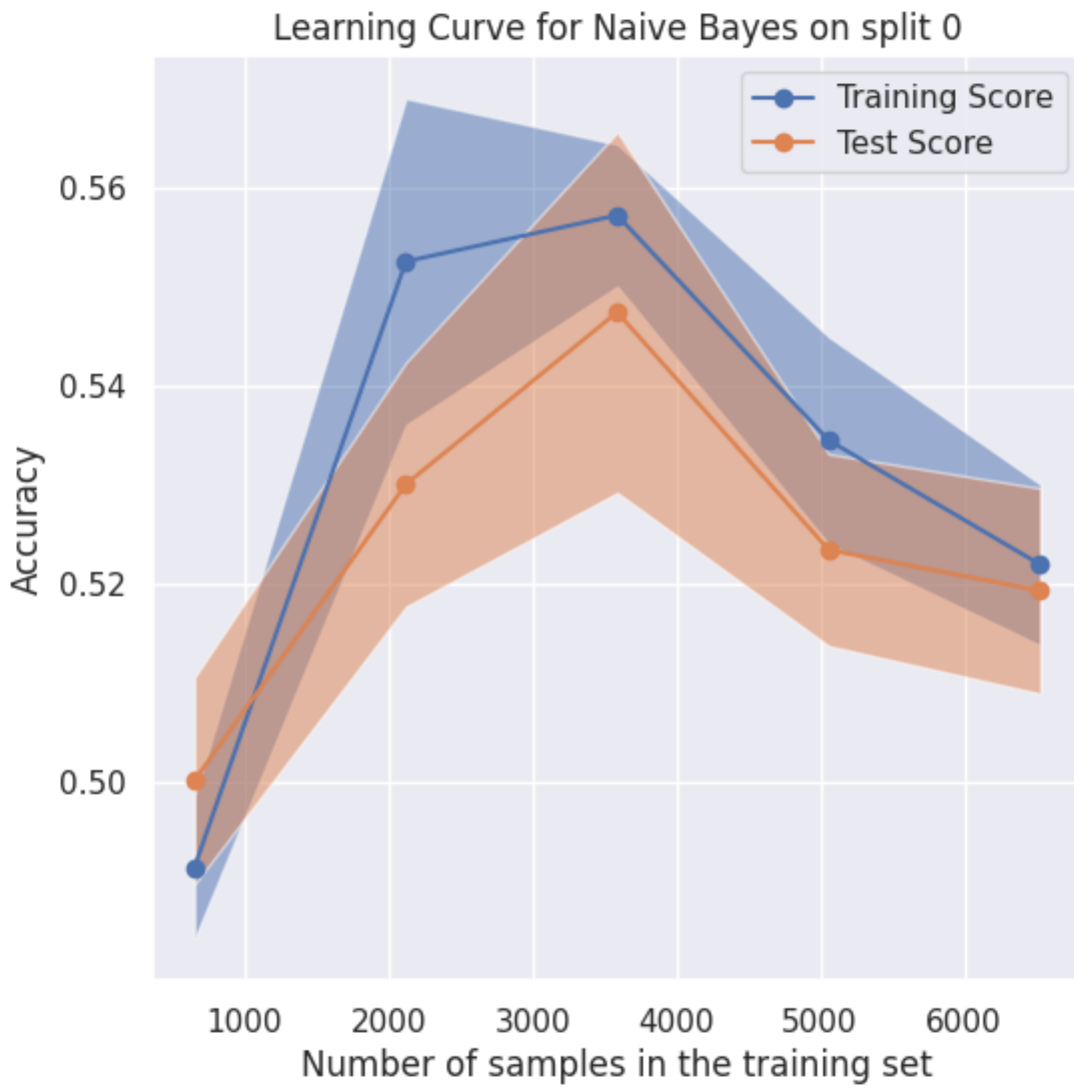


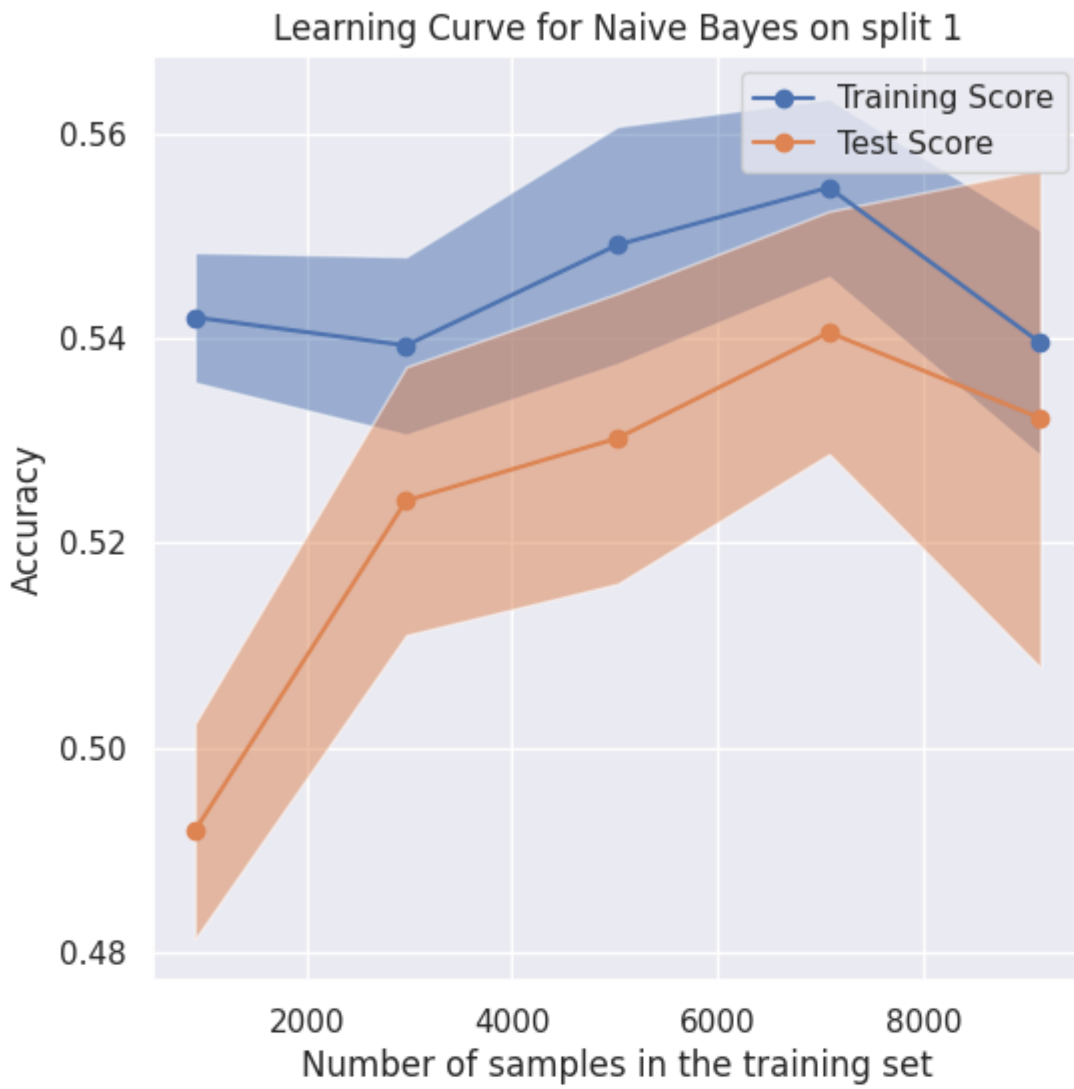

```
Classification report for best Perceptron on unseen data on split 2
              precision    recall  f1-score   support

           0       0.44      0.18      0.26      1372
           1       0.52      0.79      0.63      1530

    accuracy                           0.50      2902
   macro avg       0.48      0.49      0.44      2902
weighted avg       0.48      0.50      0.45      2902
```

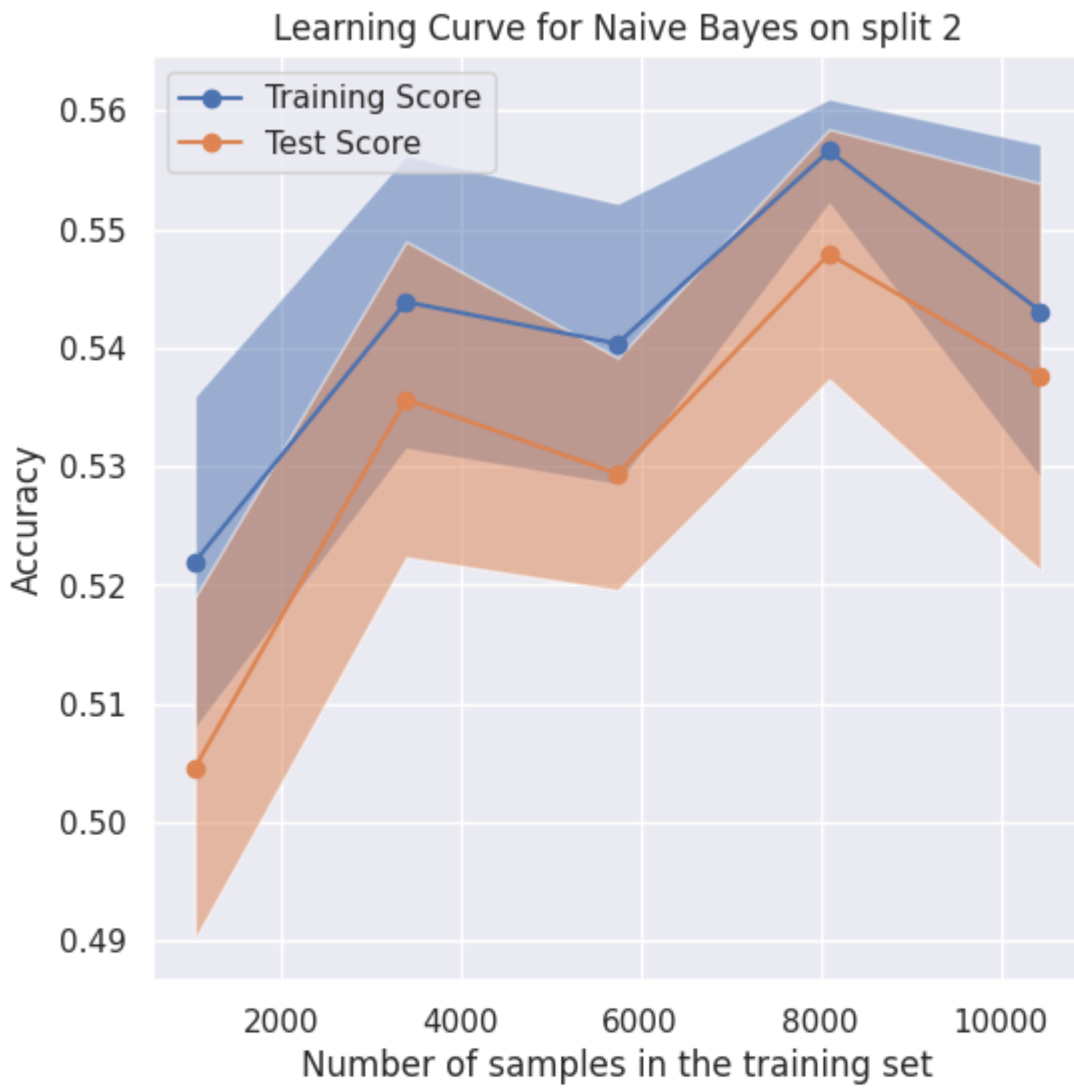
3 - Naive Bayes

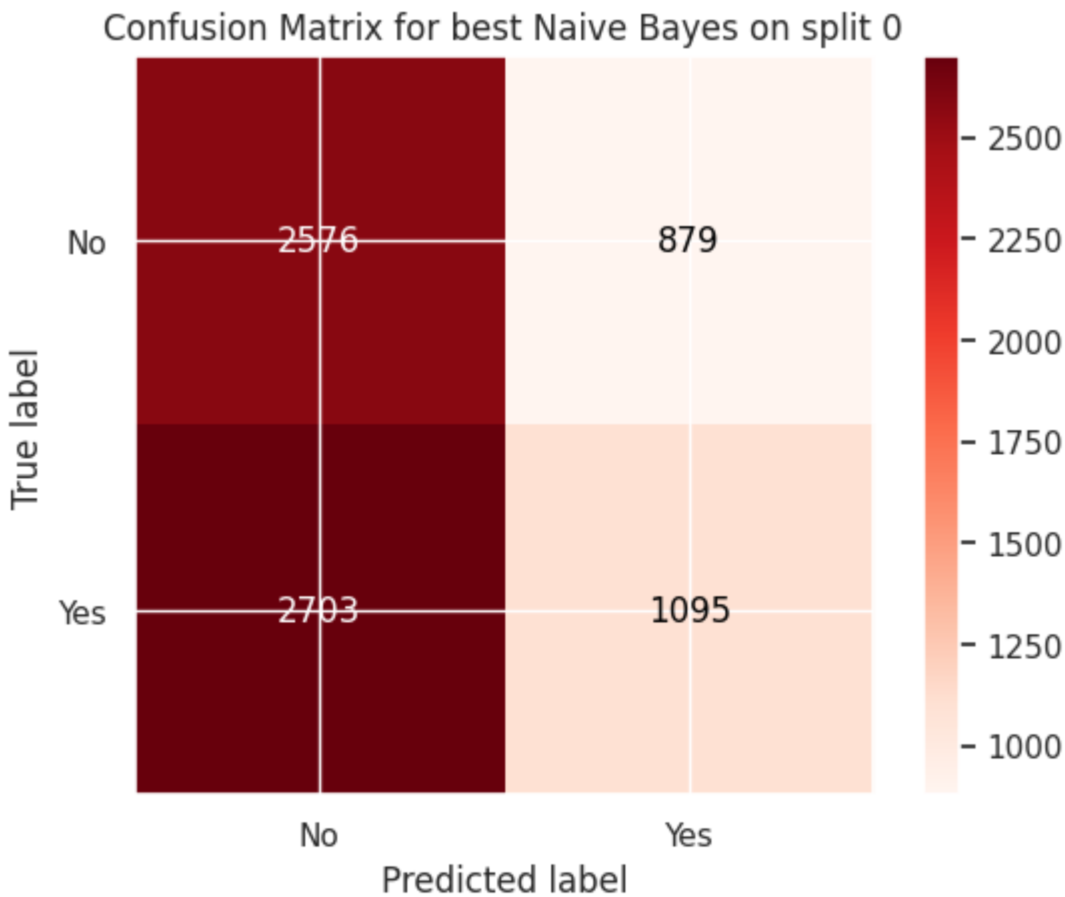
In [ ]:
```
models = pipe(gnb(),
              "Naive Bayes")
best_models = [2,8,2]
best_model_metrics(models, "Naive Bayes", best_models)
```

```
Naive Bayes Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.523           0.542           0.523   0.503
1               0.522           0.543           0.522   0.499
2               0.534           0.563           0.534   0.506
3               0.514           0.533           0.514   0.49
4               0.532           0.565           0.532   0.499
5               0.517           0.531           0.517   0.501
6               0.499           0.515           0.499   0.471
7               0.516           0.537           0.516   0.488
8               0.503           0.511           0.503   0.496
9               0.526           0.545           0.526   0.506

Naive Bayes Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.542           0.541           0.542   0.541
1               0.489           0.497           0.489   0.479
2               0.511           0.523           0.511   0.497
3               0.578           0.58            0.578   0.578
4               0.553           0.556           0.553   0.552
5               0.54            0.544           0.54    0.539
6               0.514           0.525           0.514   0.502
7               0.537           0.535           0.537   0.535
8               0.546           0.548           0.546   0.546
9               0.512           0.526           0.512   0.495

Naive Bayes Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.542           0.542           0.542   0.542
1               0.555           0.555           0.555   0.555
2               0.564           0.565           0.564   0.564
3               0.534           0.54            0.534   0.531
4               0.547           0.56            0.547   0.539
5               0.538           0.539           0.538   0.538
6               0.523           0.528           0.523   0.522
7               0.522           0.535           0.522   0.508
8               0.547           0.546           0.547   0.545
9               0.506           0.524           0.506   0.477
```

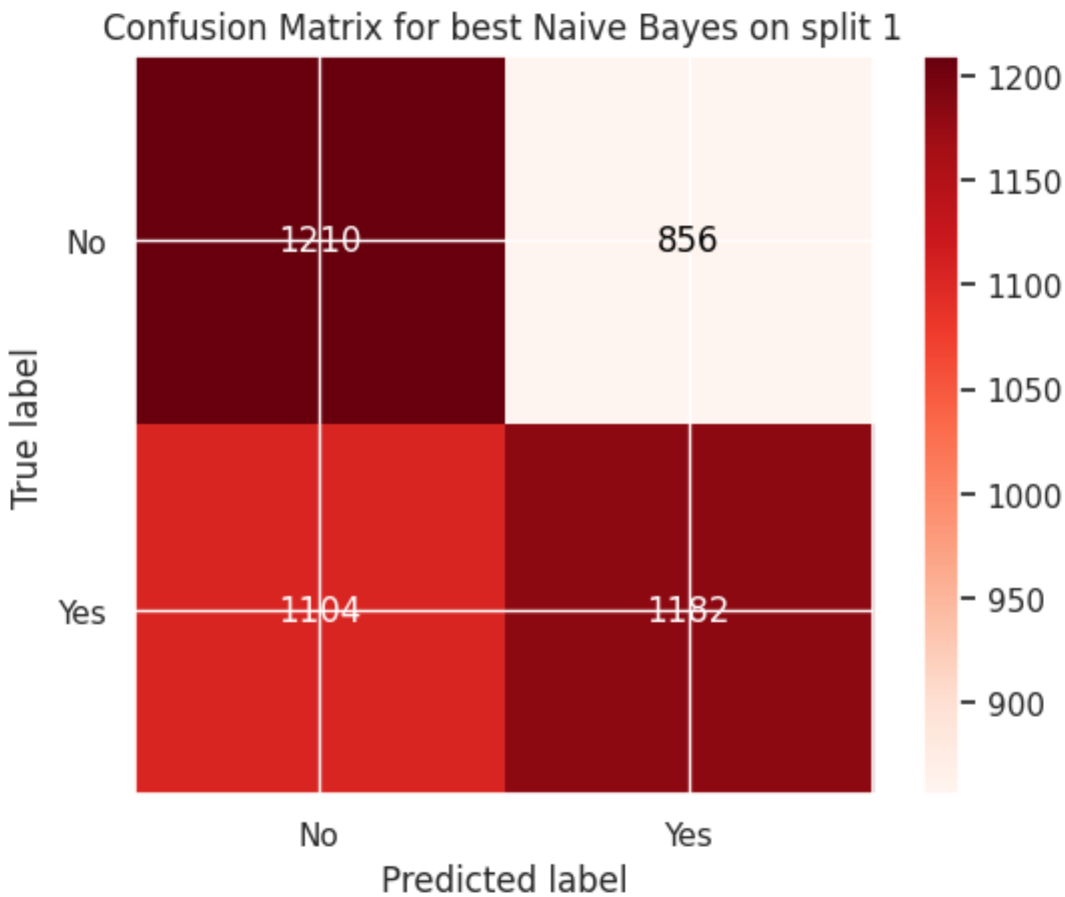

Learning Curve for Naive Bayes on split 0
Training Score
Test Score
0.56
0.54
0.52
0.50
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Naive Bayes on split 1
Training Score
Test Score
Accuracy
0.56
0.54
0.52
0.50
0.48
2000
4000
6000
8000
Number of samples in the training set

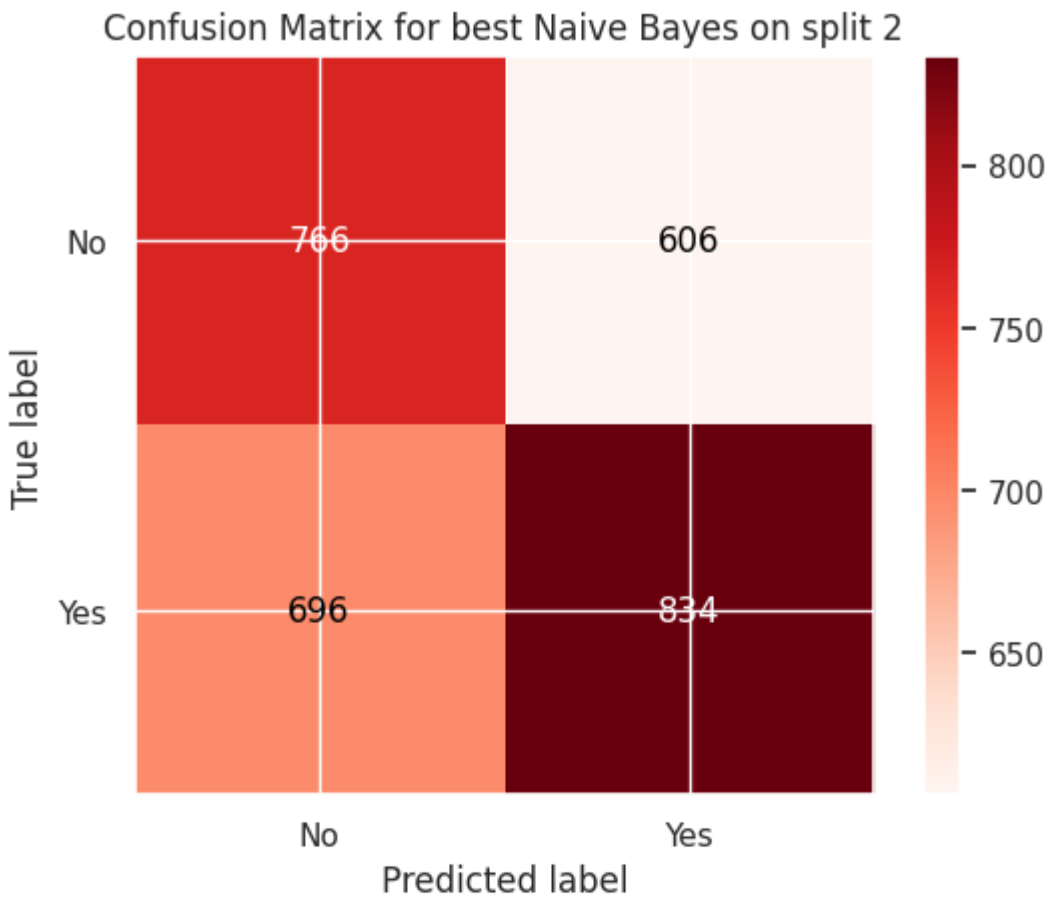

Learning Curve for Naive Bayes on split 2
Training Score
Test Score
0.56
0.55
0.54
0.53
0.52
0.51
0.50
0.49
Accuracy
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Naive Bayes on unseen data on split 0
              precision    recall  f1-score   support

           0       0.49      0.75      0.59      3455
           1       0.55      0.29      0.38      3798

    accuracy                           0.51      7253
   macro avg       0.52      0.52      0.48      7253
weighted avg       0.52      0.51      0.48      7253
```




```
Classification report for best Naive Bayes on unseen data on split 1
              precision    recall  f1-score   support

           0       0.52      0.59      0.55      2066
           1       0.58      0.52      0.55      2286

    accuracy                           0.55      4352
   macro avg       0.55      0.55      0.55      4352
weighted avg       0.55      0.55      0.55      4352
```




```
Classification report for best Naive Bayes on unseen data on split 2
              precision    recall  f1-score   support

           0       0.52      0.56      0.54      1372
           1       0.58      0.55      0.56      1530

    accuracy                           0.55      2902
   macro avg       0.55      0.55      0.55      2902
weighted avg       0.55      0.55      0.55      2902
```

4 - Linear regression

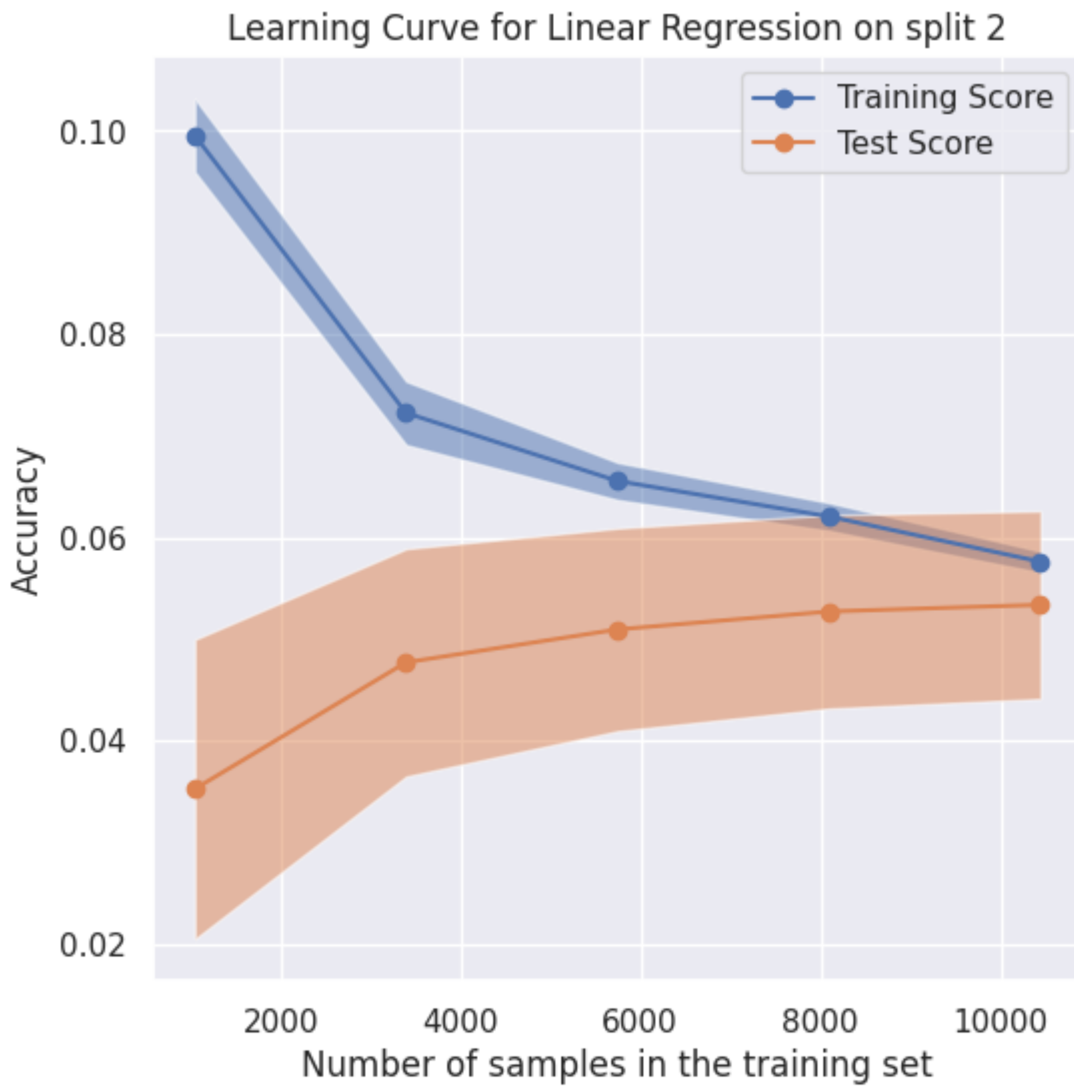
- Impossible to compare with other models
- Use RMSE for evaluating models (smaller is better)

In [ ]:
```
import warnings
warnings.filterwarnings("ignore")
# Linear Regression generates errors because
models = pipe_for_regression(linr(),
              "Linear Regression")
best_models = [5, 4, 6]
```

```
Linear Regression Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
        RMSE
0               nan             nan             nan             nan
        -0.483
1               nan             nan             nan             nan
        -0.487
2               nan             nan             nan             nan
        -0.487
3               nan             nan             nan             nan
        -0.485
4               nan             nan             nan             nan
        -0.49
5               nan             nan             nan             nan
        -0.482
6               nan             nan             nan             nan
        -0.489
7               nan             nan             nan             nan
        -0.493
8               nan             nan             nan             nan
        -0.489
9               nan             nan             nan             nan
        -0.486

Linear Regression Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
        RMSE
0               nan             nan             nan             nan
        -0.485
1               nan             nan             nan             nan
        -0.49
2               nan             nan             nan             nan
        -0.486
3               nan             nan             nan             nan
        -0.488
4               nan             nan             nan             nan
        -0.484
5               nan             nan             nan             nan
        -0.486
6               nan             nan             nan             nan
        -0.489
7               nan             nan             nan             nan
        -0.488
8               nan             nan             nan             nan
        -0.489
9               nan             nan             nan             nan
        -0.485

Linear Regression Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
        RMSE
0               nan             nan             nan             nan
        -0.485
1               nan             nan             nan             nan
        -0.491
2               nan             nan             nan             nan
```

```
           -0.487
3                    nan                 nan                 nan                 nan
           -0.485
4                    nan                 nan                 nan                 nan
           -0.488
5                    nan                 nan                 nan                 nan
           -0.485
6                    nan                 nan                 nan                 nan
           -0.481
7                    nan                 nan                 nan                 nan
           -0.487
8                    nan                 nan                 nan                 nan
           -0.485
9                    nan                 nan                 nan                 nan
           -0.486
```


Learning Curve for Linear Regression on split 1
Training Score
Test Score
Accuracy
0.10
0.08
0.06
0.04
0.02
0.00
2000
4000
6000
8000
Number of samples in the training set

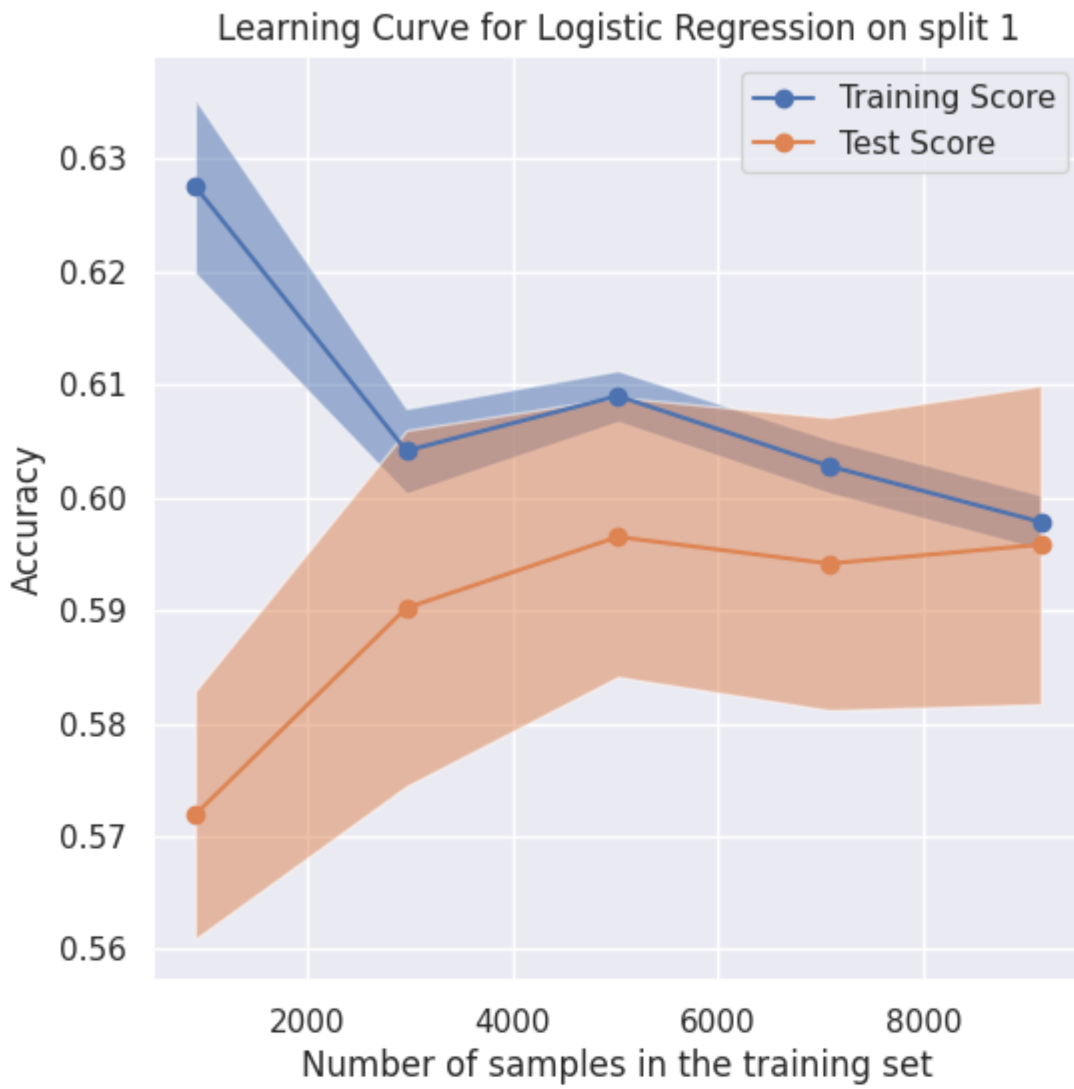


5 - Logistic Regression

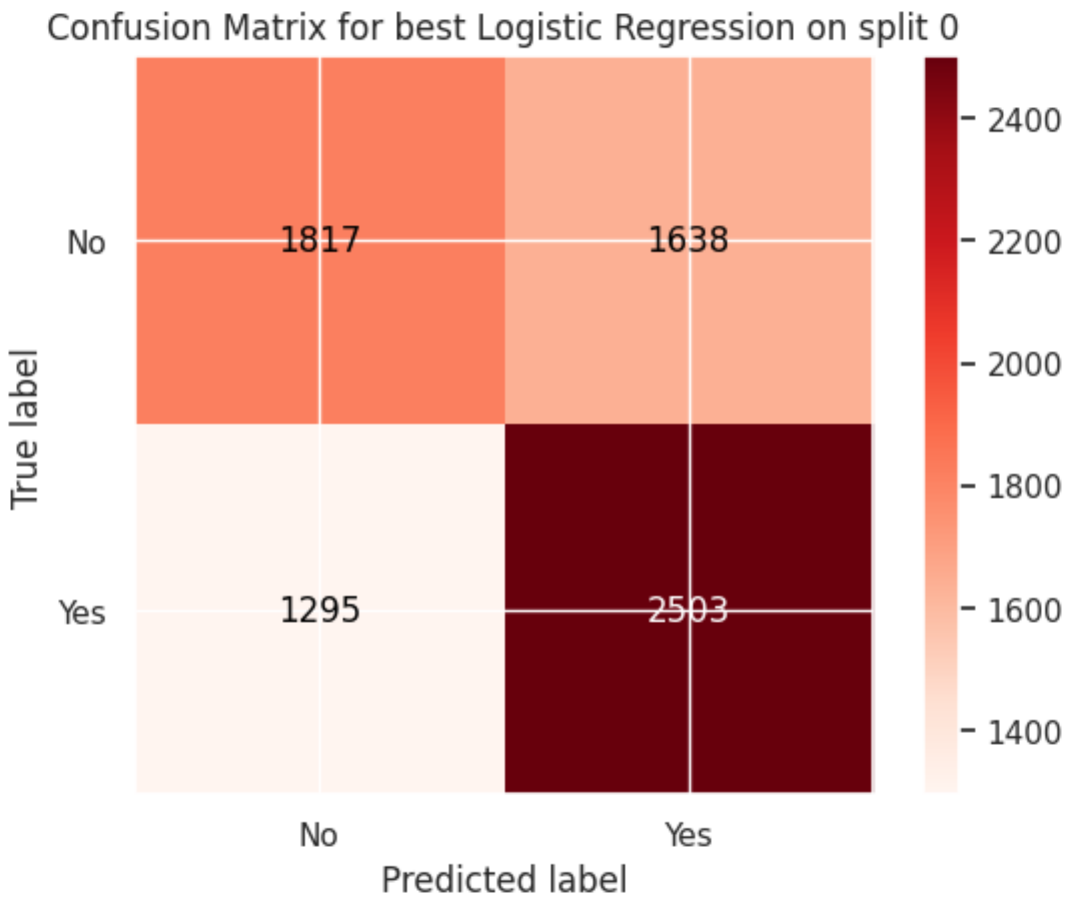
In [ ]:
```
models = pipe(LogisticRegression(solver= 'newton-cholesky', max_iter=100, r
andom_state=seed),
              "Logistic Regression")
best_models = [0, 4, 8]
best_model_metrics(models, "Logistic Regression", best_models)
```

```
Logistic Regression Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.618           0.618           0.618   0.617
1               0.598           0.597           0.598   0.597
2               0.591           0.59            0.591   0.588
3               0.604           0.603           0.604   0.603
4               0.59            0.589           0.59    0.589
5               0.593           0.592           0.593   0.591
6               0.592           0.591           0.592   0.59
7               0.554           0.554           0.554   0.554
8               0.579           0.578           0.579   0.578
9               0.617           0.616           0.617   0.615

Logistic Regression Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.594           0.594           0.594   0.594
1               0.589           0.587           0.589   0.586
2               0.584           0.583           0.584   0.583
3               0.593           0.592           0.593   0.592
4               0.621           0.62            0.621   0.618
5               0.612           0.611           0.612   0.609
6               0.581           0.58            0.581   0.578
7               0.597           0.598           0.597   0.597
8               0.575           0.574           0.575   0.574
9               0.614           0.613           0.614   0.611

Logistic Regression Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.586           0.585           0.586   0.585
1               0.581           0.579           0.581   0.579
2               0.589           0.588           0.589   0.588
3               0.61            0.609           0.61    0.609
4               0.597           0.596           0.597   0.595
5               0.597           0.596           0.597   0.595
6               0.608           0.607           0.608   0.606
7               0.579           0.578           0.579   0.578
8               0.613           0.612           0.613   0.612
9               0.609           0.609           0.609   0.609
```

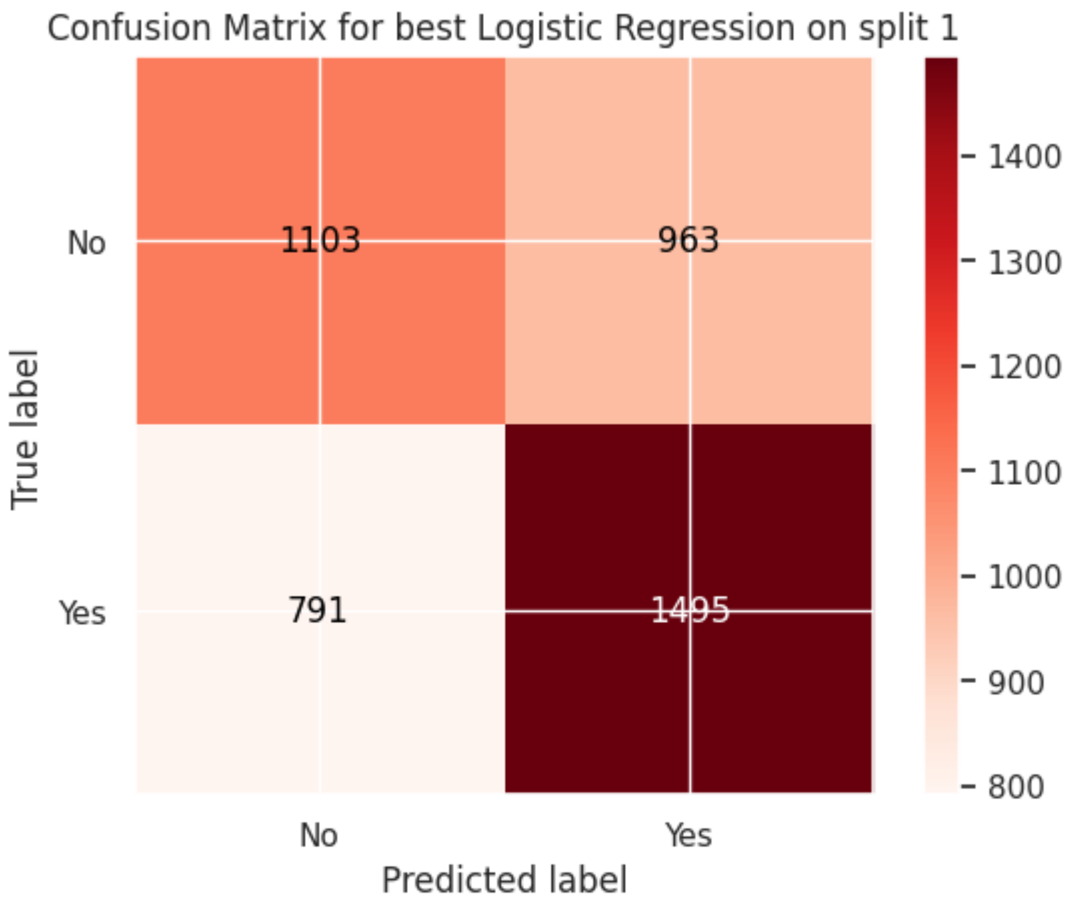

Learning Curve for Logistic Regression on split 0
Training Score
Test Score
0.63
0.62
0.61
0.60
0.59
0.58
0.57
0.56
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Logistic Regression on split 1
Training Score
Test Score
Accuracy
0.63
0.62
0.61
0.60
0.59
0.58
0.57
0.56
2000
4000
6000
8000
Number of samples in the training set

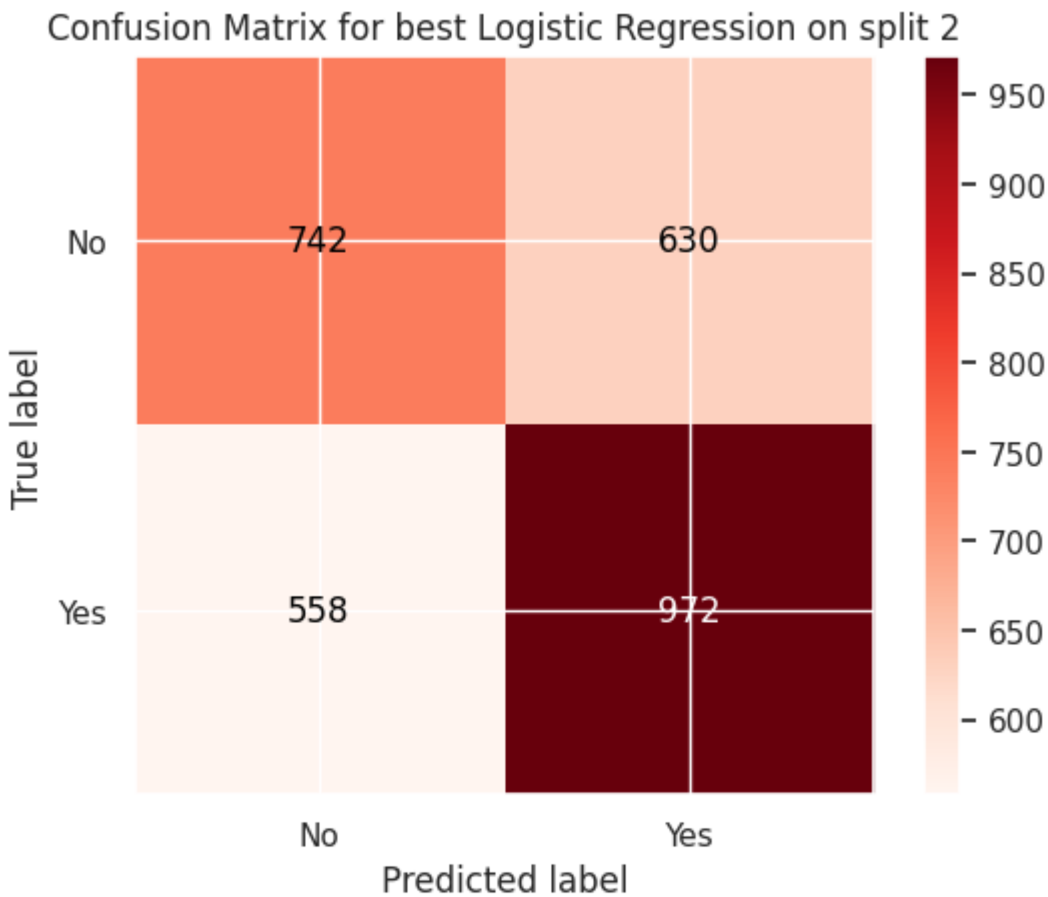

Learning Curve for Logistic Regression on split 2
Training Score
Test Score
0.63
0.62
0.61
0.60
0.59
0.58
Accuracy
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Logistic Regression on unseen data on split
0
              precision    recall  f1-score   support

           0       0.58      0.53      0.55      3455
           1       0.60      0.66      0.63      3798

    accuracy                           0.60      7253
   macro avg       0.59      0.59      0.59      7253
weighted avg       0.59      0.60      0.59      7253
```




```
Classification report for best Logistic Regression on unseen data on split
1
              precision    recall  f1-score   support

           0       0.58      0.53      0.56      2066
           1       0.61      0.65      0.63      2286

    accuracy                           0.60      4352
   macro avg       0.60      0.59      0.59      4352
weighted avg       0.60      0.60      0.60      4352
```

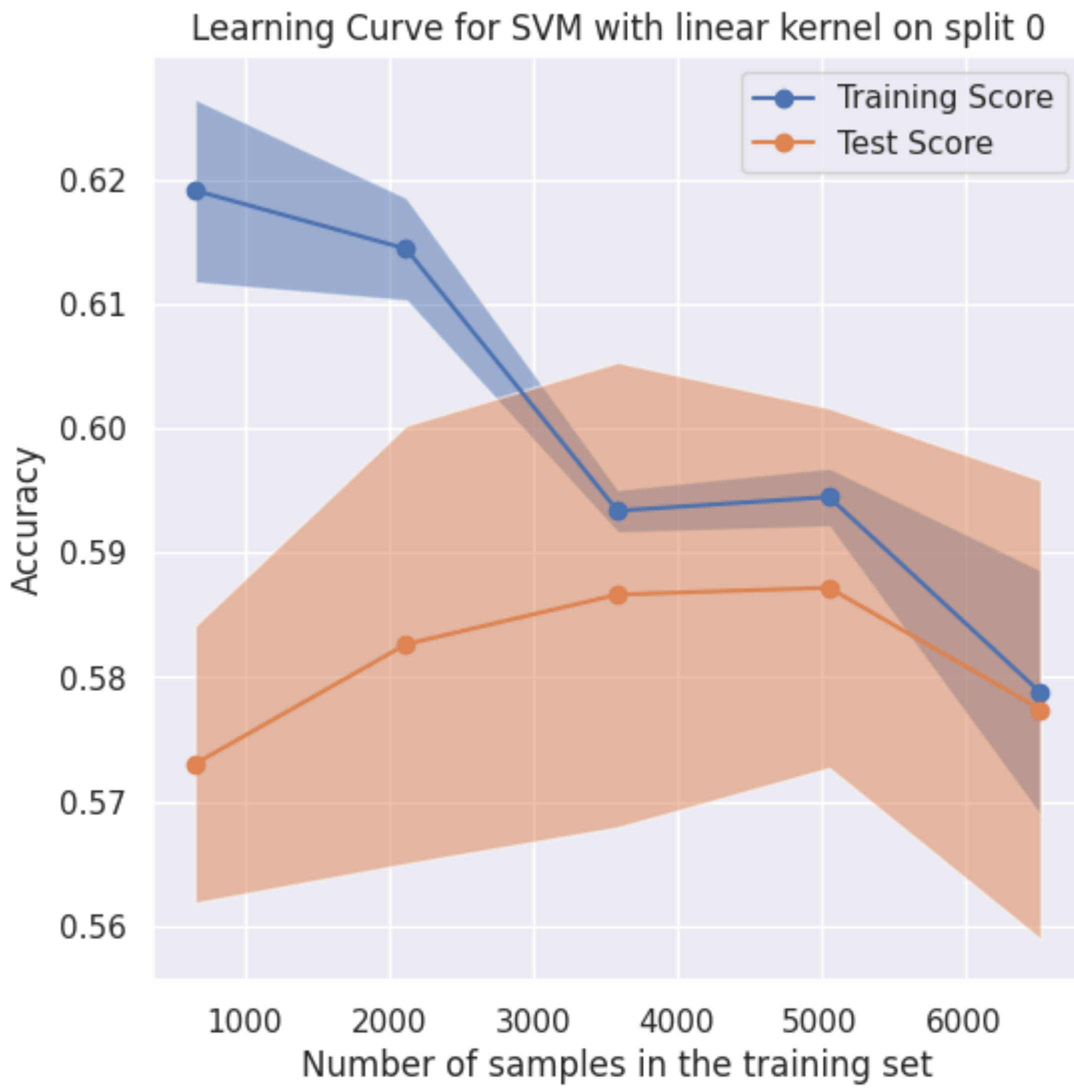


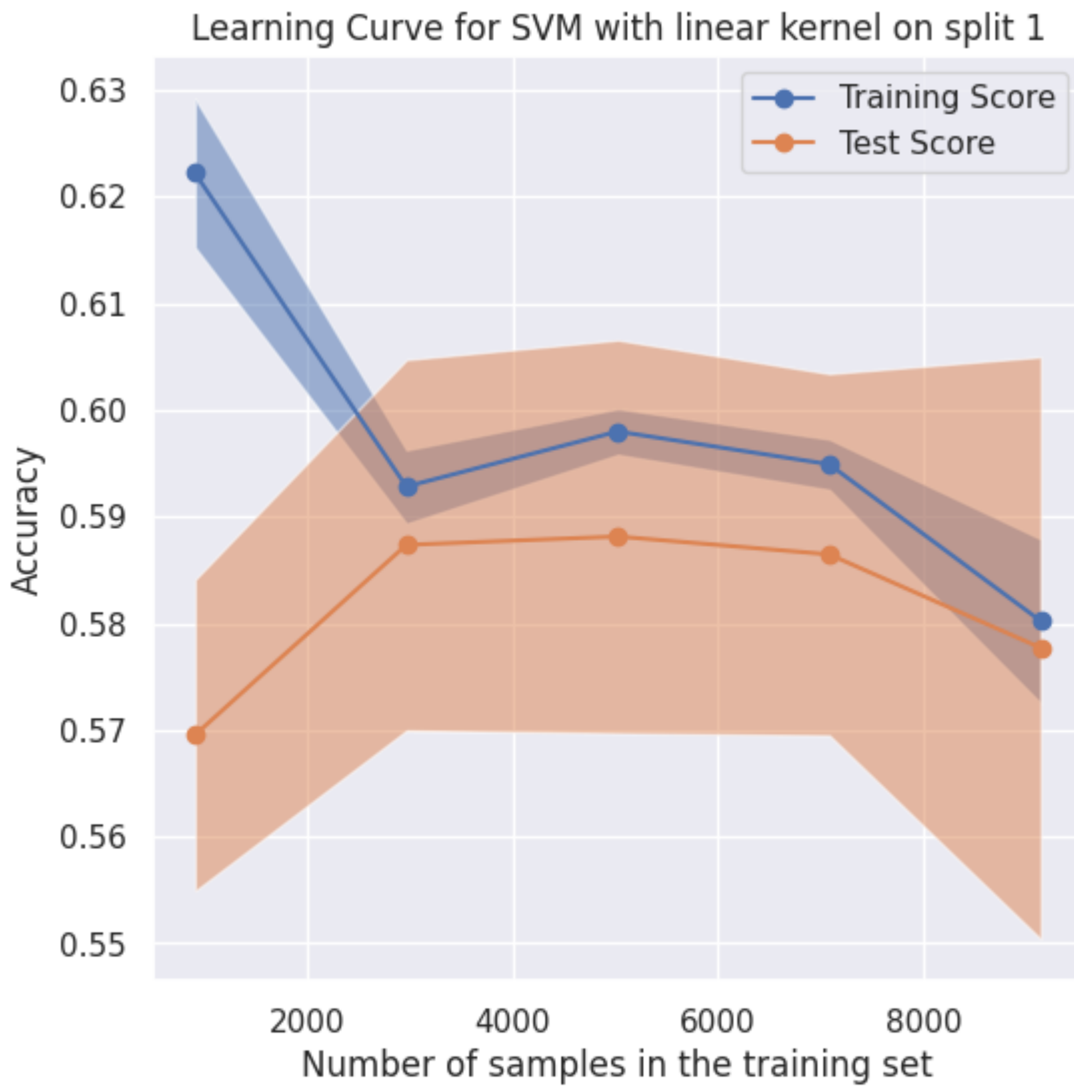

```
Classification report for best Logistic Regression on unseen data on split
2
              precision    recall  f1-score   support

           0       0.57      0.54      0.56      1372
           1       0.61      0.64      0.62      1530

    accuracy                           0.59      2902
   macro avg       0.59      0.59      0.59      2902
weighted avg       0.59      0.59      0.59      2902
```

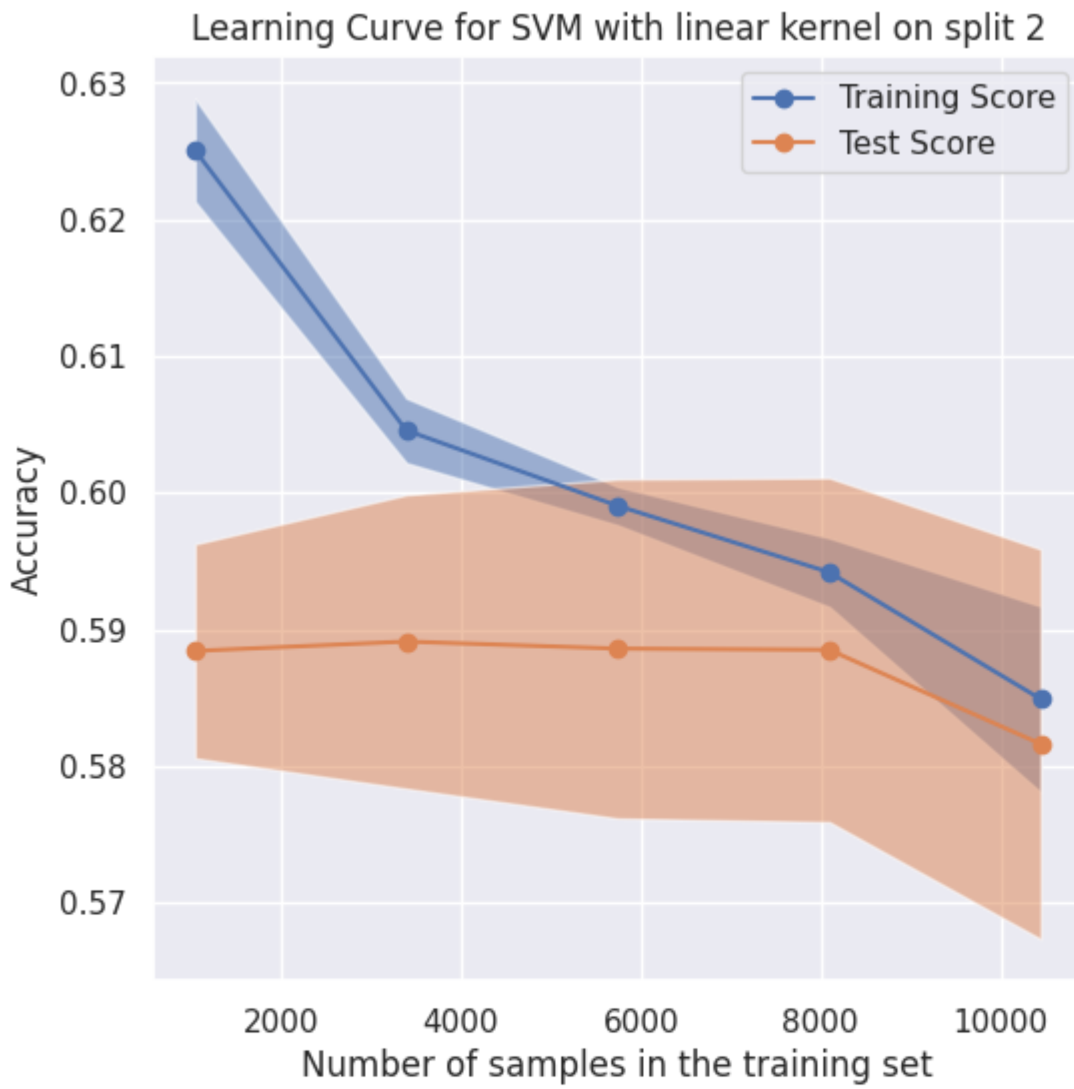
6 - SVM with linear Kernel

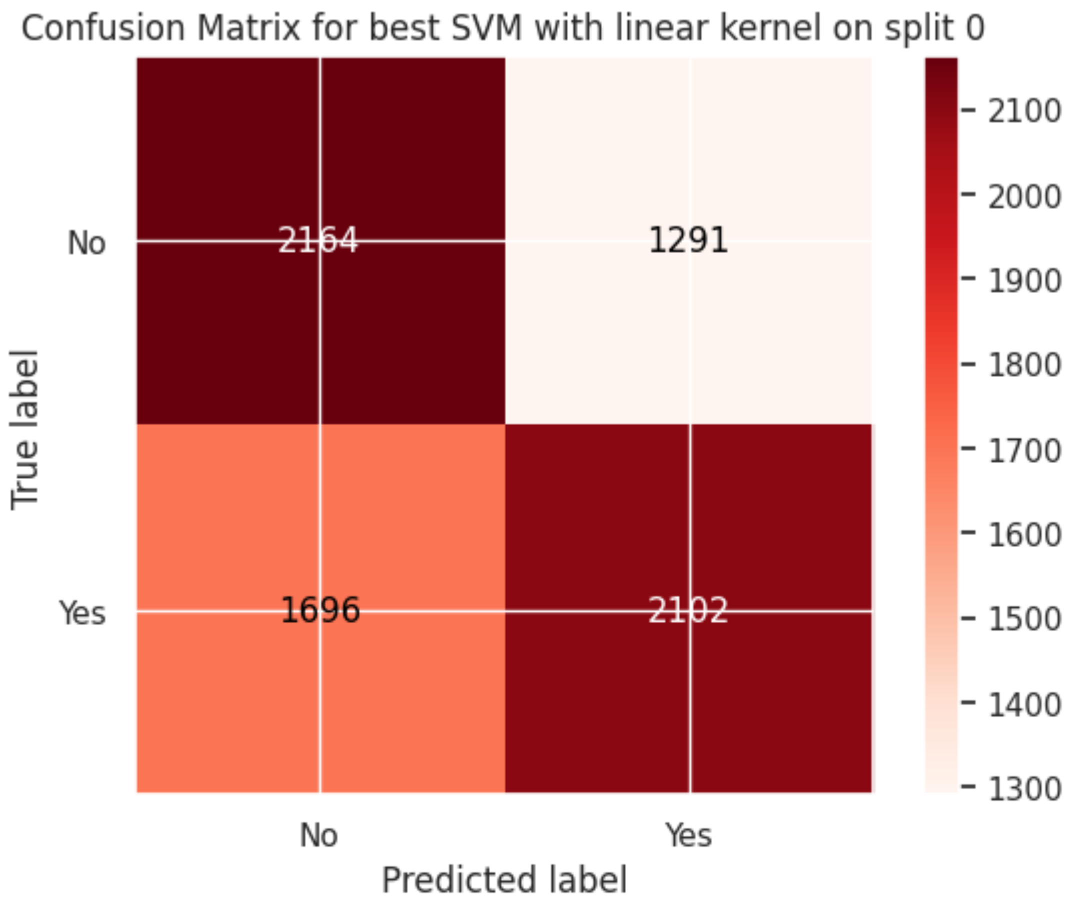
In [ ]:
```
models = pipe(make_pipeline(StandardScaler(),SVC(kernel = 'linear',random_s
tate=seed, class_weight='balanced',cache_size=1000, gamma='scale')),"SVM wi
th linear kernel")
best_models = [0, 4, 5]
best_model_metrics(models, "SVM with linear kernel", best_models)
```

```
SVM with linear kernel Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.612           0.616           0.612   0.611
1               0.551           0.562           0.551   0.545
2               0.59            0.591           0.59    0.59
3               0.596           0.598           0.596   0.596
4               0.577           0.581           0.577   0.576
5               0.577           0.583           0.577   0.575
6               0.585           0.588           0.585   0.585
7               0.572           0.577           0.572   0.571
8               0.564           0.572           0.564   0.561
9               0.549           0.558           0.549   0.545

SVM with linear kernel Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.593           0.595           0.593   0.592
1               0.536           0.544           0.536   0.532
2               0.56            0.563           0.56    0.56
3               0.584           0.587           0.584   0.584
4               0.623           0.623           0.623   0.623
5               0.61            0.612           0.61    0.61
6               0.575           0.578           0.575   0.575
7               0.547           0.561           0.547   0.537
8               0.552           0.555           0.552   0.551
9               0.6             0.603           0.6     0.6

SVM with linear kernel Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.586           0.589           0.586   0.586
1               0.561           0.563           0.561   0.561
2               0.576           0.581           0.576   0.575
3               0.587           0.588           0.587   0.587
4               0.567           0.57            0.567   0.567
5               0.605           0.607           0.605   0.605
6               0.561           0.57            0.561   0.557
7               0.584           0.587           0.584   0.584
8               0.591           0.594           0.591   0.591
9               0.598           0.602           0.598   0.598
```

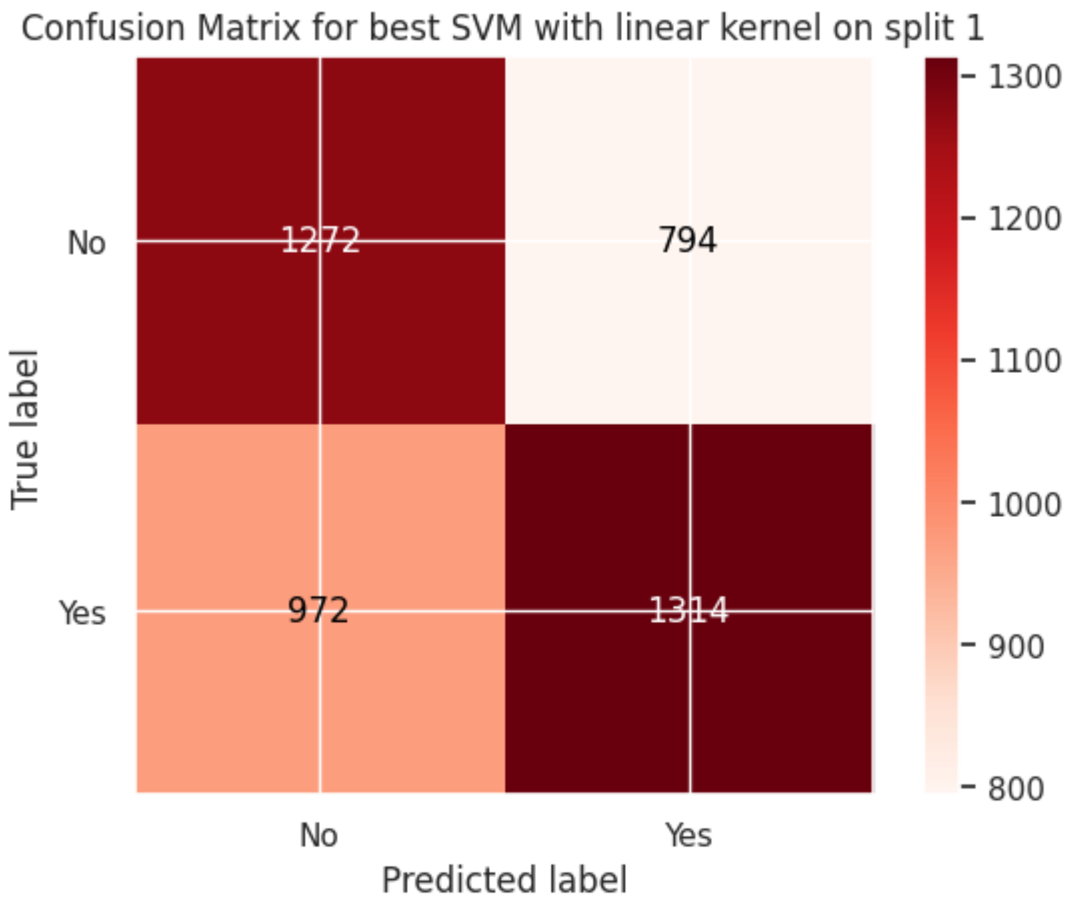

Learning Curve for SVM with linear kernel on split 0
Training Score
Test Score
Accuracy
0.62
0.61
0.60
0.59
0.58
0.57
0.56
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for SVM with linear kernel on split 1
Training Score
Test Score
Accuracy
0.63
0.62
0.61
0.60
0.59
0.58
0.57
0.56
0.55
2000
4000
6000
8000
Number of samples in the training set

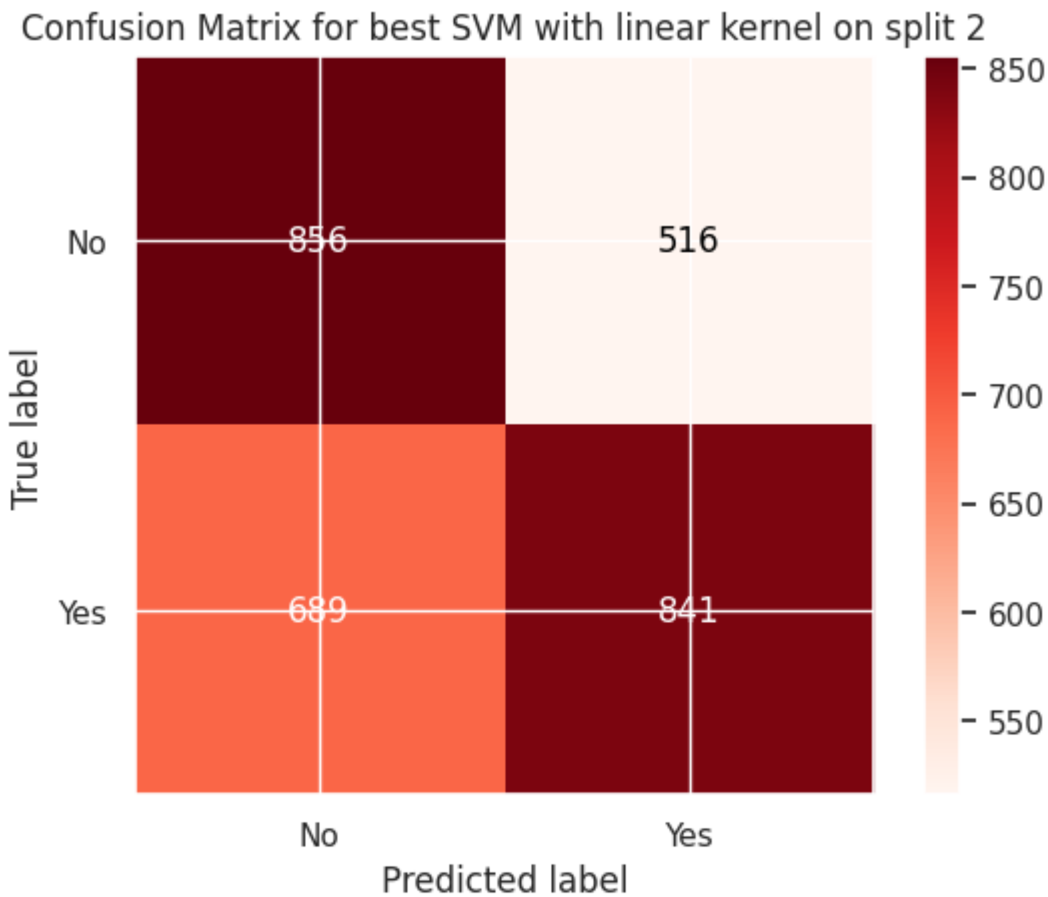

Learning Curve for SVM with linear kernel on split 2
Training Score
Test Score
0.63
0.62
0.61
0.60
0.59
0.58
0.57
Accuracy
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best SVM with linear kernel on unseen data on spl
it 0
              precision    recall  f1-score   support

           0       0.56      0.63      0.59      3455
           1       0.62      0.55      0.58      3798

    accuracy                           0.59      7253
   macro avg       0.59      0.59      0.59      7253
weighted avg       0.59      0.59      0.59      7253
```




```
Classification report for best SVM with linear kernel on unseen data on spl
it 1
              precision    recall  f1-score   support

           0       0.57      0.62      0.59      2066
           1       0.62      0.57      0.60      2286

    accuracy                           0.59      4352
   macro avg       0.60      0.60      0.59      4352
weighted avg       0.60      0.59      0.59      4352
```

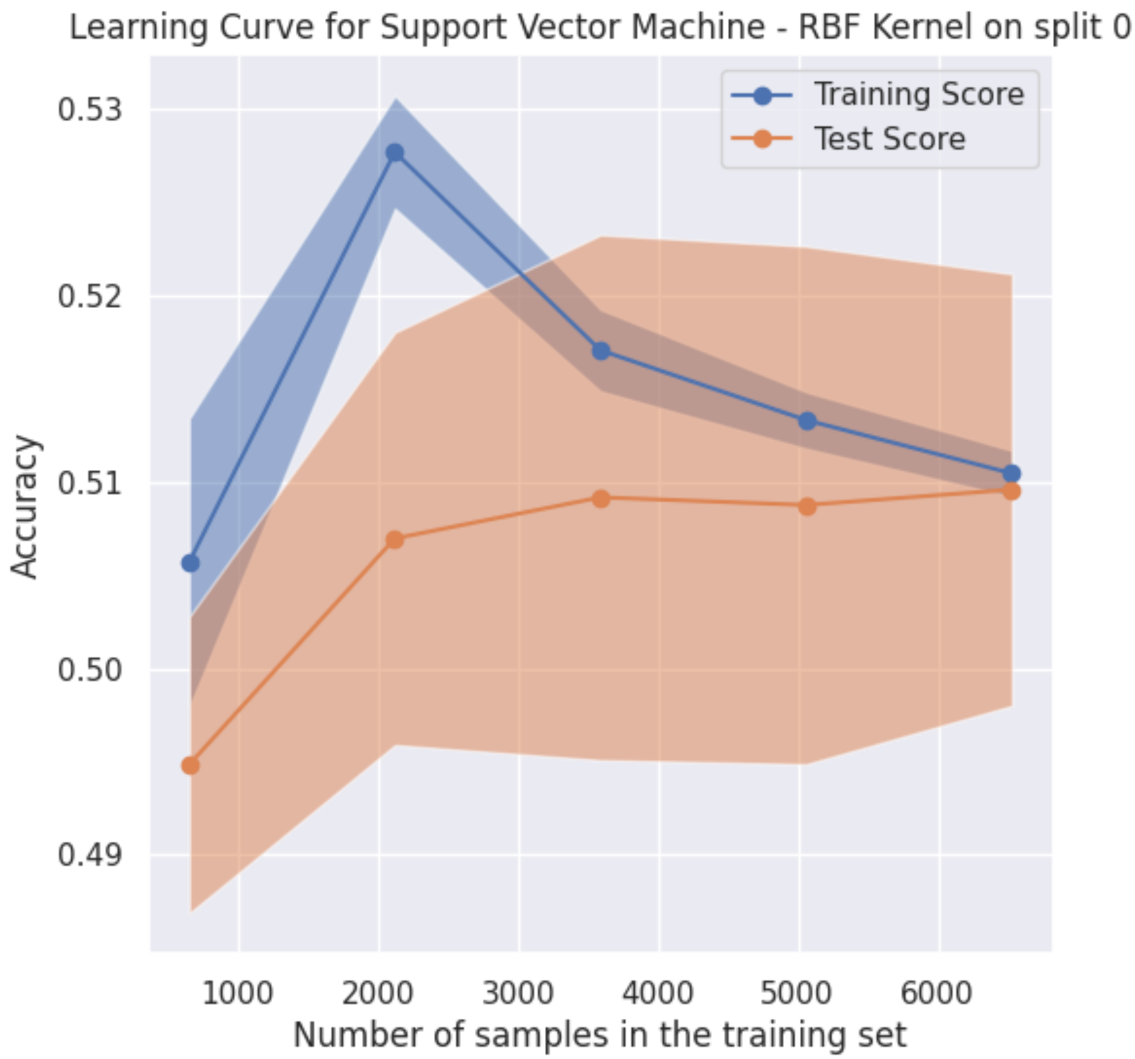


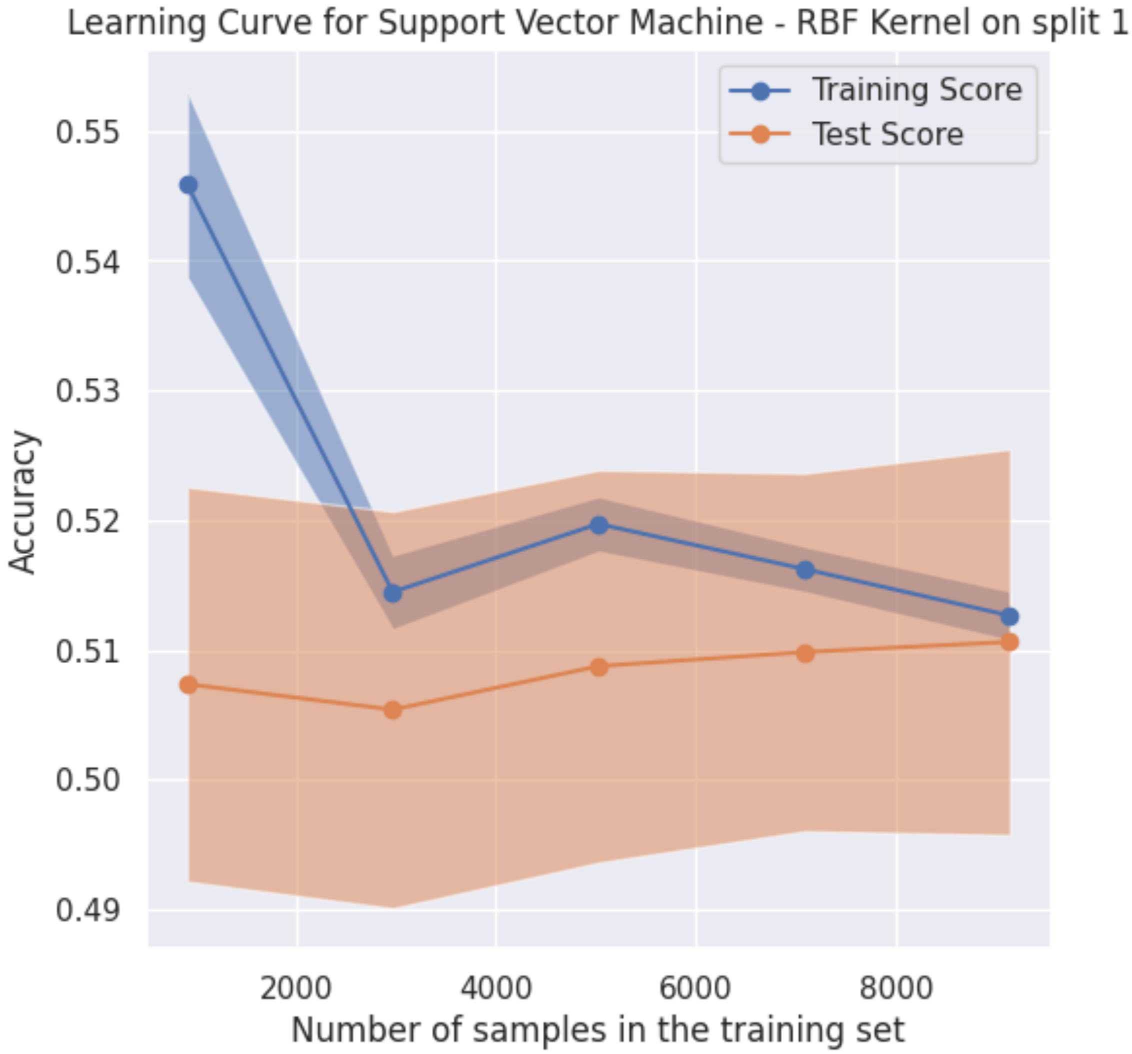

```
Classification report for best SVM with linear kernel on unseen data on spl
it 2
              precision    recall  f1-score   support

           0       0.55      0.62      0.59      1372
           1       0.62      0.55      0.58      1530

    accuracy                           0.58      2902
   macro avg       0.59      0.59      0.58      2902
weighted avg       0.59      0.58      0.58      2902
```

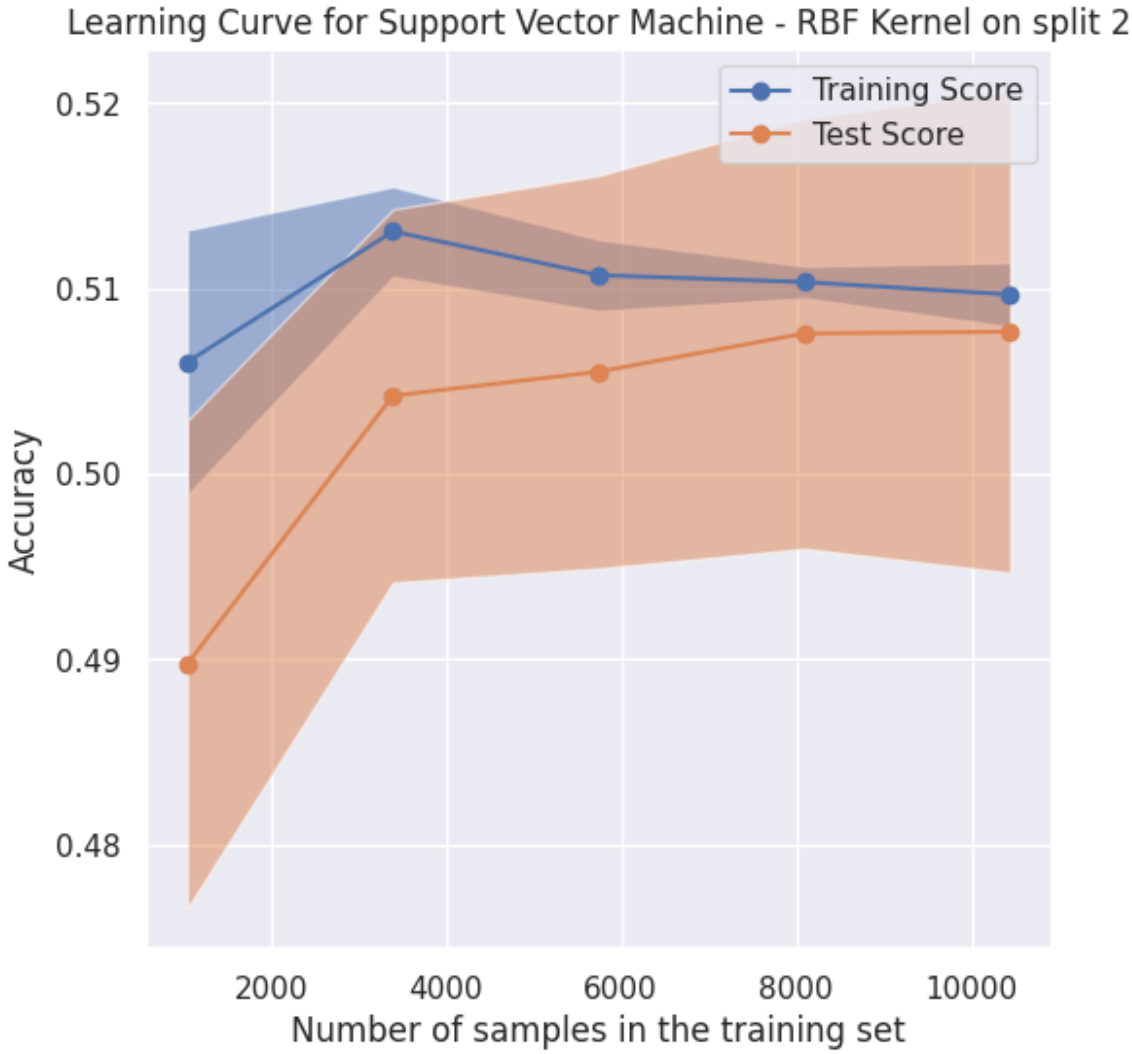
7 - SVM with RBF Kernel

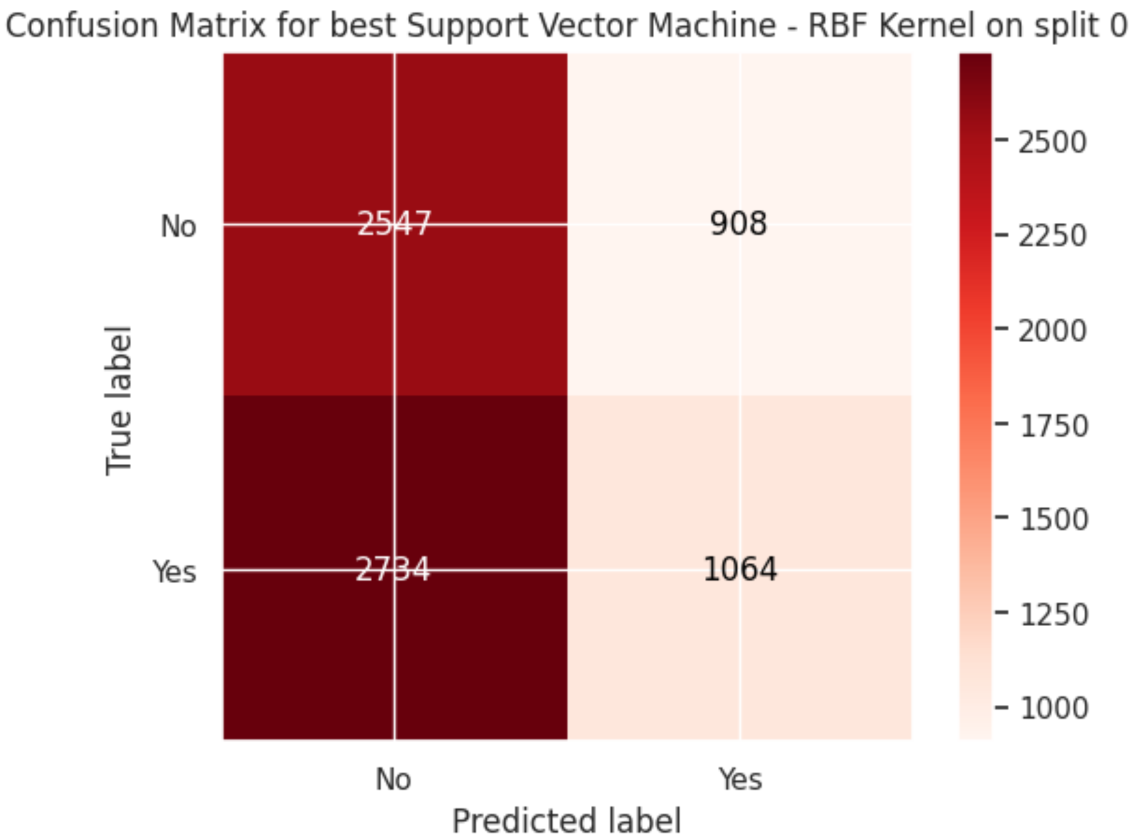
In [ ]:
```
models = pipe(SVC(kernel = 'rbf',random_state=seed, class_weight='balanced
',
                  cache_size=1000, gamma='scale'),
              "Support Vector Machine - RBF Kernel")
best_models = [2, 1, 4]
best_model_metrics(models, "Support Vector Machine - RBF Kernel", best_mode
ls)
```

```
Support Vector Machine - RBF Kernel Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.507           0.529           0.507   0.472
1               0.507           0.523           0.507   0.484
2               0.528           0.553           0.528   0.5
3               0.534           0.554           0.534   0.514
4               0.498           0.511           0.498   0.475
5               0.509           0.525           0.509   0.486
6               0.494           0.507           0.494   0.468
7               0.508           0.527           0.508   0.478
8               0.509           0.527           0.509   0.483
9               0.502           0.521           0.502   0.471

Support Vector Machine - RBF Kernel Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.492           0.504           0.492   0.467
1               0.524           0.544           0.524   0.501
2               0.521           0.538           0.521   0.5
3               0.512           0.526           0.512   0.493
4               0.481           0.49            0.481   0.455
5               0.512           0.531           0.512   0.487
6               0.526           0.546           0.526   0.504
7               0.498           0.51            0.498   0.476
8               0.519           0.54            0.519   0.492
9               0.523           0.546           0.523   0.495

Support Vector Machine - RBF Kernel Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.505           0.519           0.505   0.482
1               0.503           0.52            0.503   0.475
2               0.511           0.527           0.511   0.486
3               0.504           0.519           0.504   0.479
4               0.519           0.536           0.519   0.498
5               0.538           0.568           0.538   0.509
6               0.507           0.521           0.507   0.486
7               0.498           0.513           0.498   0.471
8               0.485           0.495           0.485   0.465
9               0.507           0.523           0.507   0.482
```

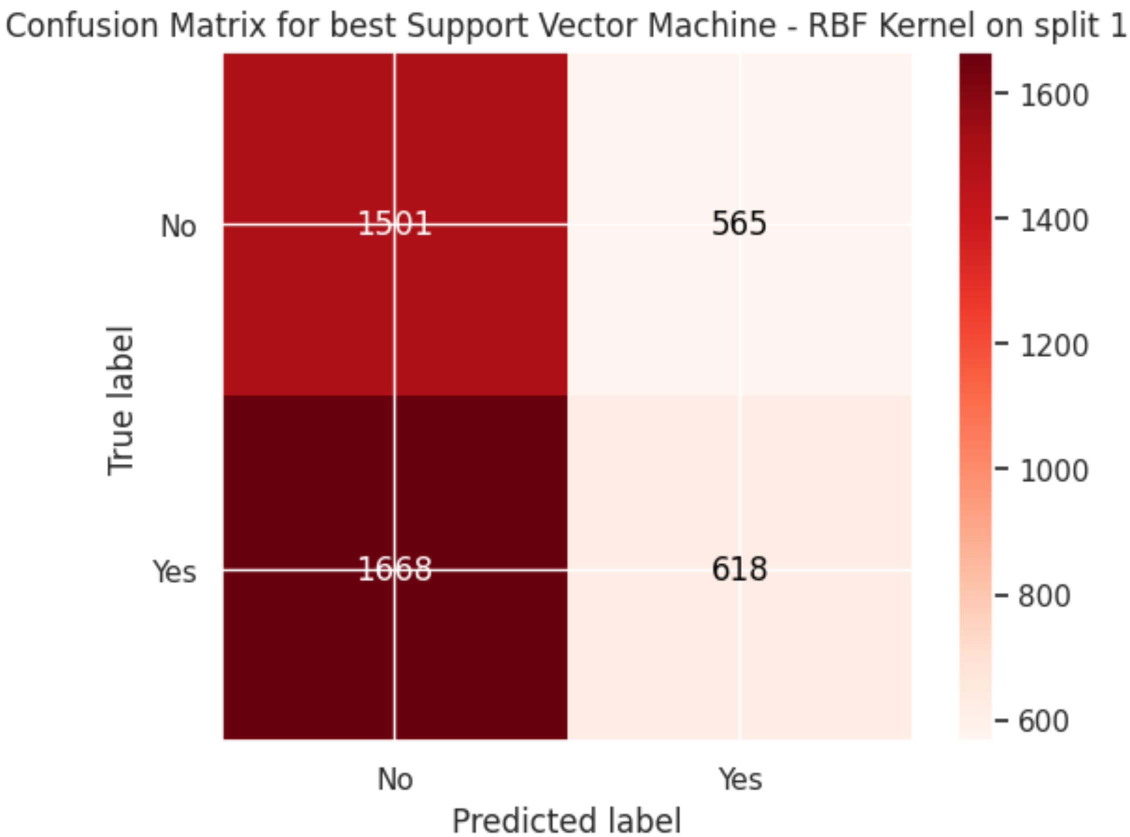

Learning Curve for Support Vector Machine - RBF Kernel on split 0
Training Score
Test Score
Accuracy
0.53
0.52
0.51
0.50
0.49
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Support Vector Machine - RBF Kernel on split 1
Training Score
Test Score
0.55
0.54
0.53
0.52
0.51
0.50
0.49
Accuracy
2000
4000
6000
8000
Number of samples in the training set

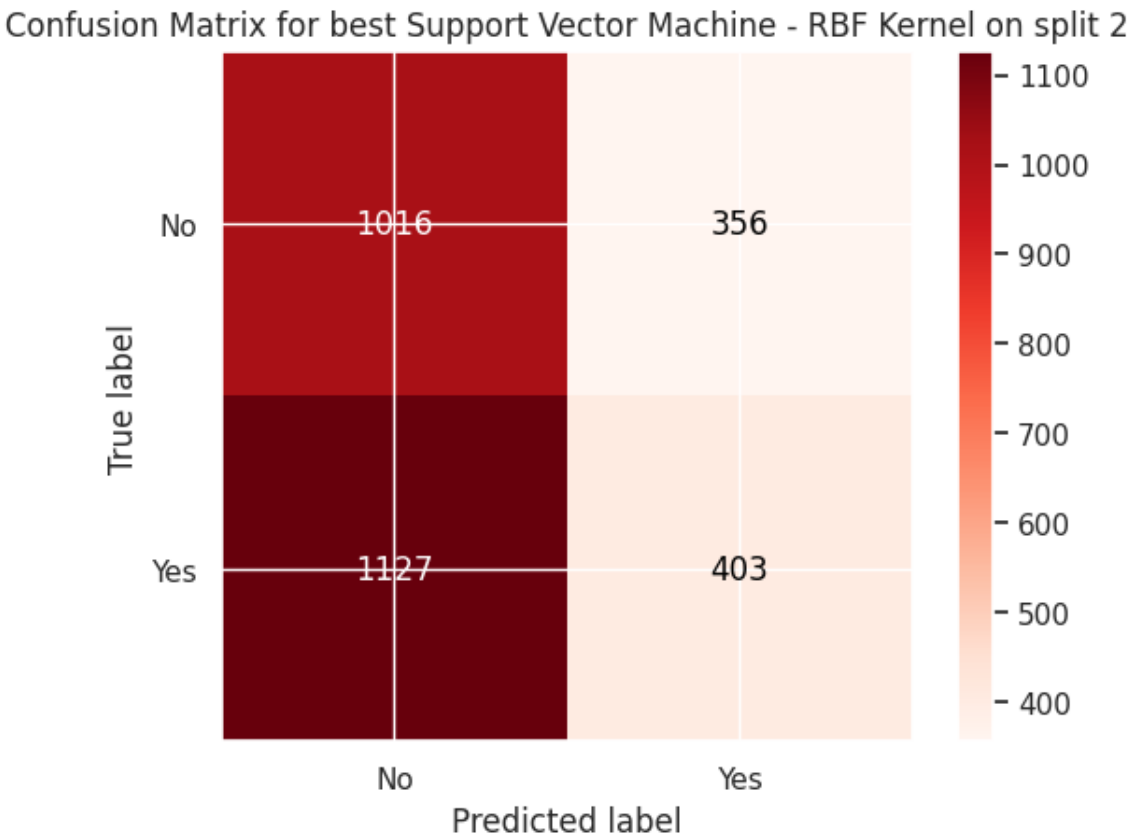

Learning Curve for Support Vector Machine - RBF Kernel on split 2
Training Score
Test Score
Accuracy
0.52
0.51
0.50
0.49
0.48
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Support Vector Machine - RBF Kernel on unsee
n data on split 0
              precision    recall  f1-score   support

           0       0.48      0.74      0.58      3455
           1       0.54      0.28      0.37      3798

    accuracy                           0.50      7253
   macro avg       0.51      0.51      0.48      7253
weighted avg       0.51      0.50      0.47      7253
```




```
Classification report for best Support Vector Machine - RBF Kernel on unsee
n data on split 1
              precision    recall  f1-score   support

           0       0.47      0.73      0.57      2066
           1       0.52      0.27      0.36      2286

    accuracy                           0.49      4352
   macro avg       0.50      0.50      0.46      4352
weighted avg       0.50      0.49      0.46      4352
```




```
Classification report for best Support Vector Machine - RBF Kernel on unsee
n data on split 2
              precision    recall  f1-score   support

           0       0.47      0.74      0.58      1372
           1       0.53      0.26      0.35      1530

    accuracy                           0.49      2902
   macro avg       0.50      0.50      0.47      2902
weighted avg       0.50      0.49      0.46      2902
```

8 - Multi Layer Perceptron

- Reducing number of features allows the model to actually fit to training data
- Performs significantly better than a single perceptron

In [ ]:
```
models = pipe(mlp(hidden_layer_sizes = (100,),shuffle = False, learning_rat
e = 'adaptive',random_state=seed),
              "Multi Layer Perceptron")
best_models = [9,8,6]
best_model_metrics(models, "Multi Layer Perceptron", best_models)
```

Multi Layer Perceptron Metrics for 10-fold on split 0

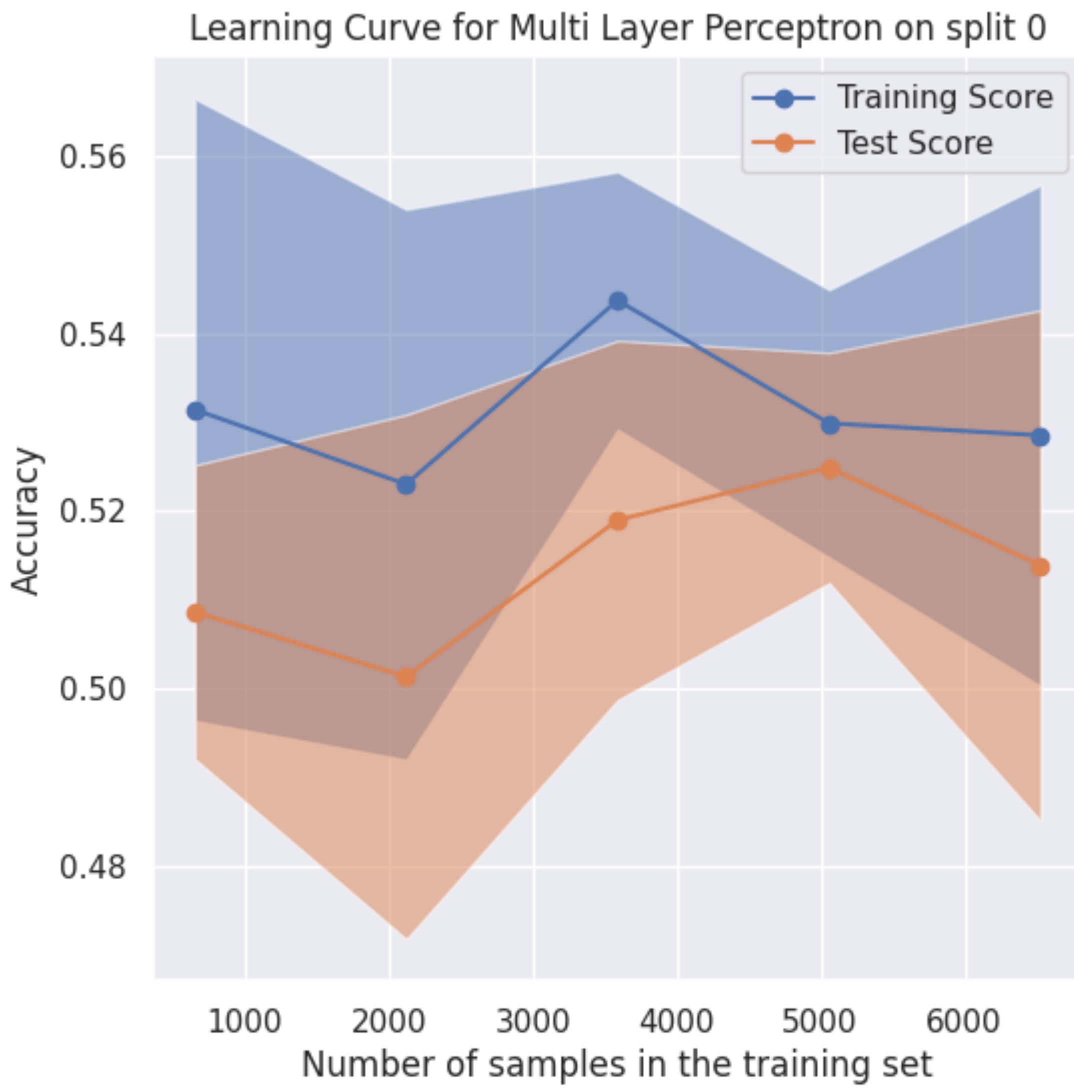
Fold	Accuracy	Precision	Recall	F1
0	0.511	0.536	0.511	0.474
1	0.544	0.545	0.544	0.544
2	0.545	0.553	0.545	0.485
3	0.509	0.508	0.509	0.509
4	0.503	0.522	0.503	0.473
5	0.497	0.514	0.497	0.46
6	0.488	0.548	0.488	0.367
7	0.486	0.486	0.486	0.486
8	0.508	0.518	0.508	0.497
9	0.545	0.564	0.545	0.53

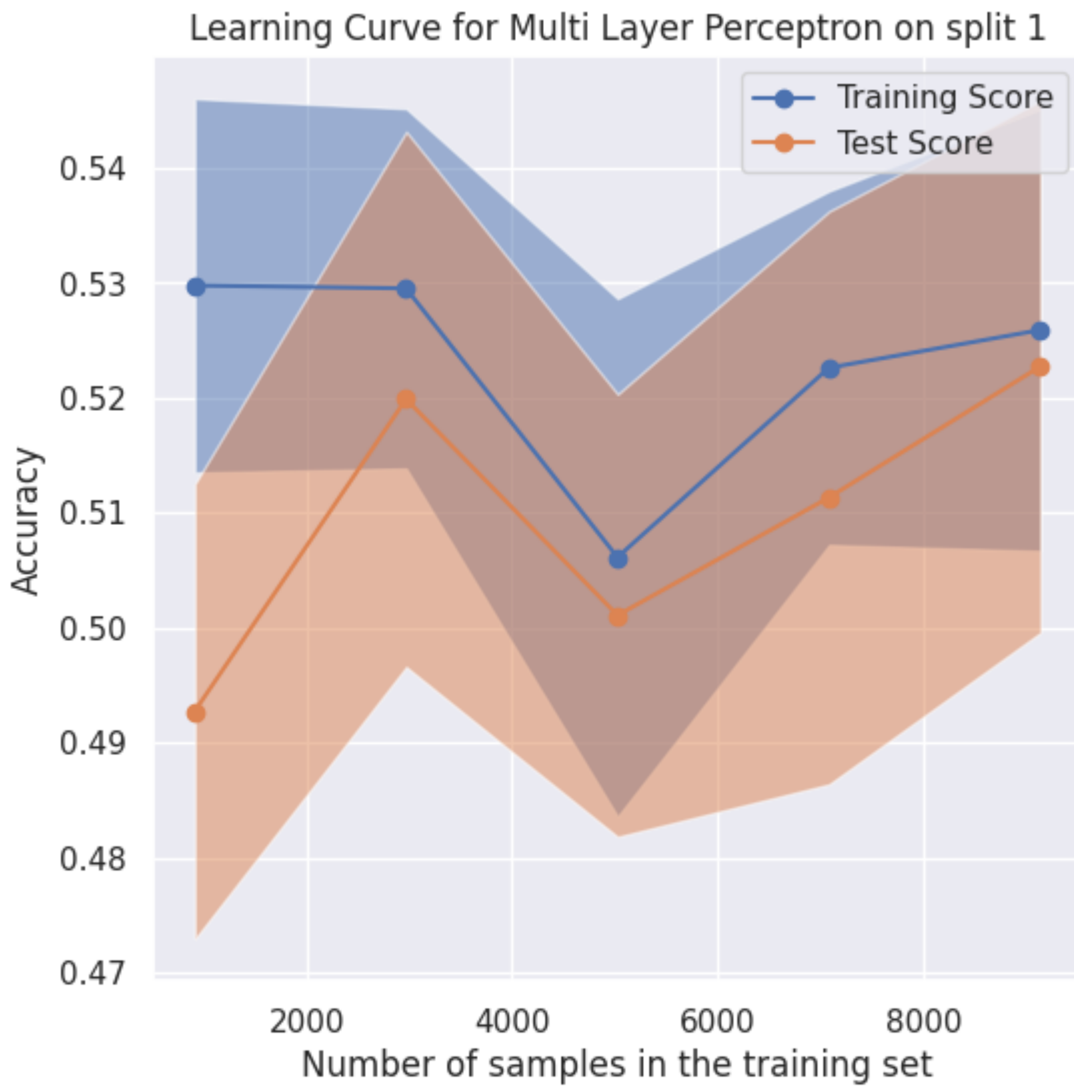
Multi Layer Perceptron Metrics for 10-fold on split 1

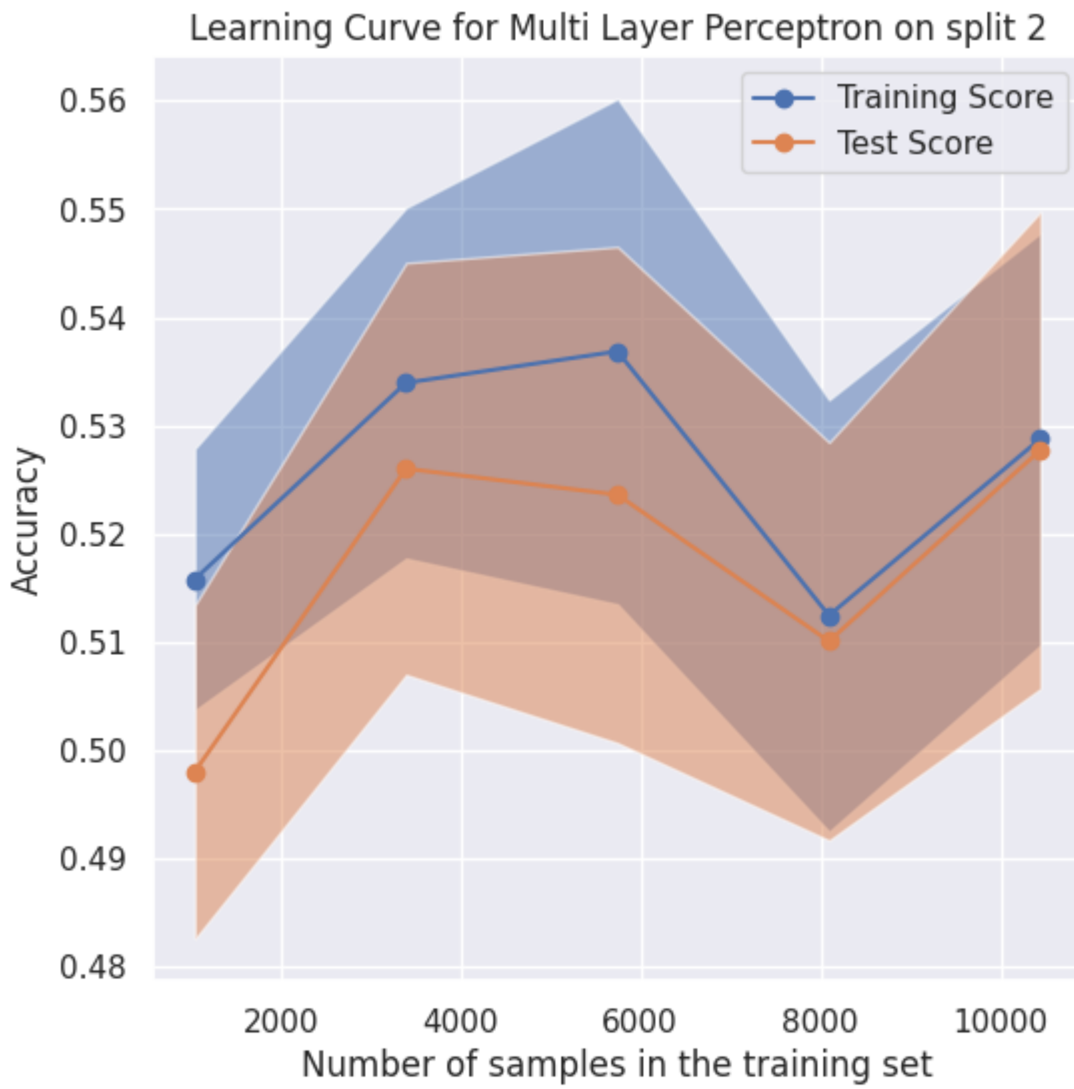
Fold	Accuracy	Precision	Recall	F1
0	0.526	0.521	0.526	0.414
1	0.502	0.536	0.502	0.438
2	0.489	0.499	0.489	0.471
3	0.522	0.513	0.522	0.484
4	0.487	0.527	0.487	0.378
5	0.541	0.552	0.541	0.464
6	0.554	0.579	0.554	0.482
7	0.534	0.533	0.534	0.532
8	0.549	0.547	0.549	0.531
9	0.534	0.59	0.534	0.402

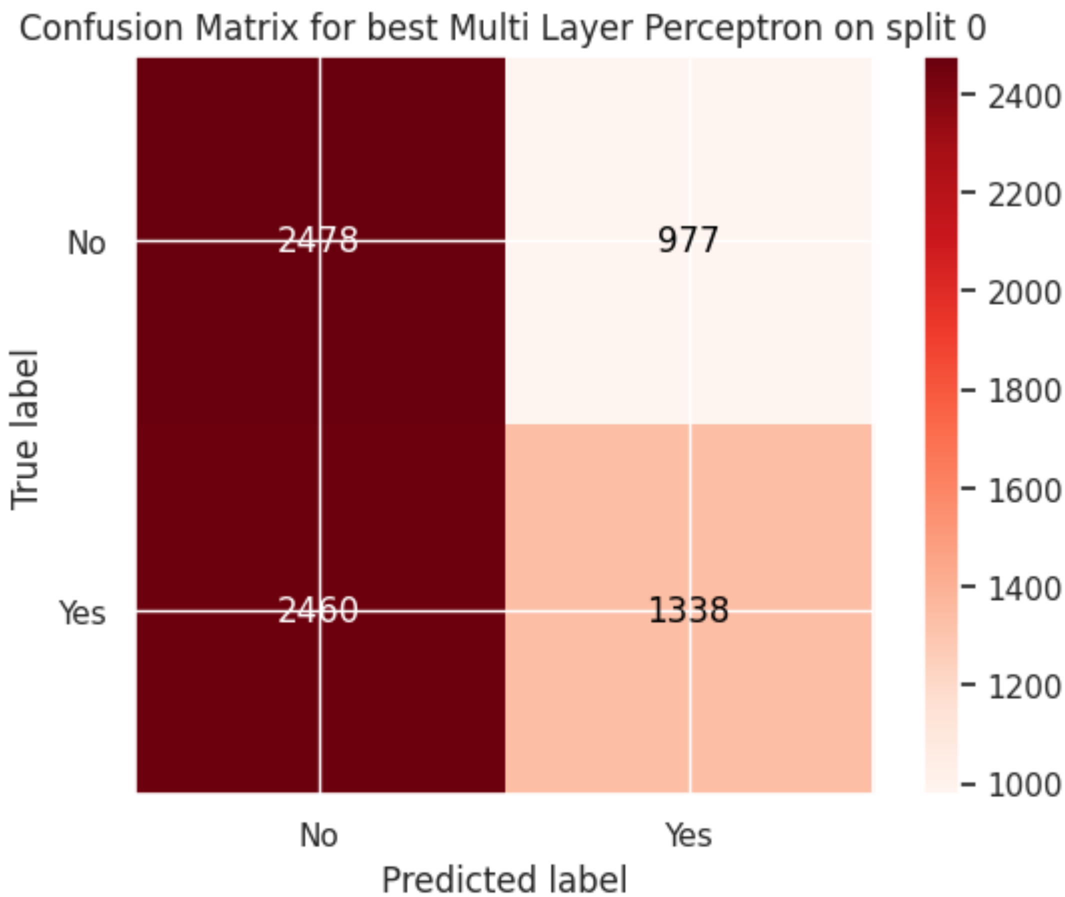
Multi Layer Perceptron Metrics for 10-fold on split 2

Fold	Accuracy	Precision	Recall	F1
0	0.558	0.557	0.558	0.556
1	0.55	0.547	0.55	0.546
2	0.543	0.558	0.543	0.531
3	0.533	0.53	0.533	0.495
4	0.516	0.514	0.516	0.514
5	0.488	0.497	0.488	0.47
6	0.581	0.58	0.581	0.577
7	0.514	0.55	0.514	0.461
8	0.503	0.59	0.503	0.396
9	0.524	0.517	0.524	0.401

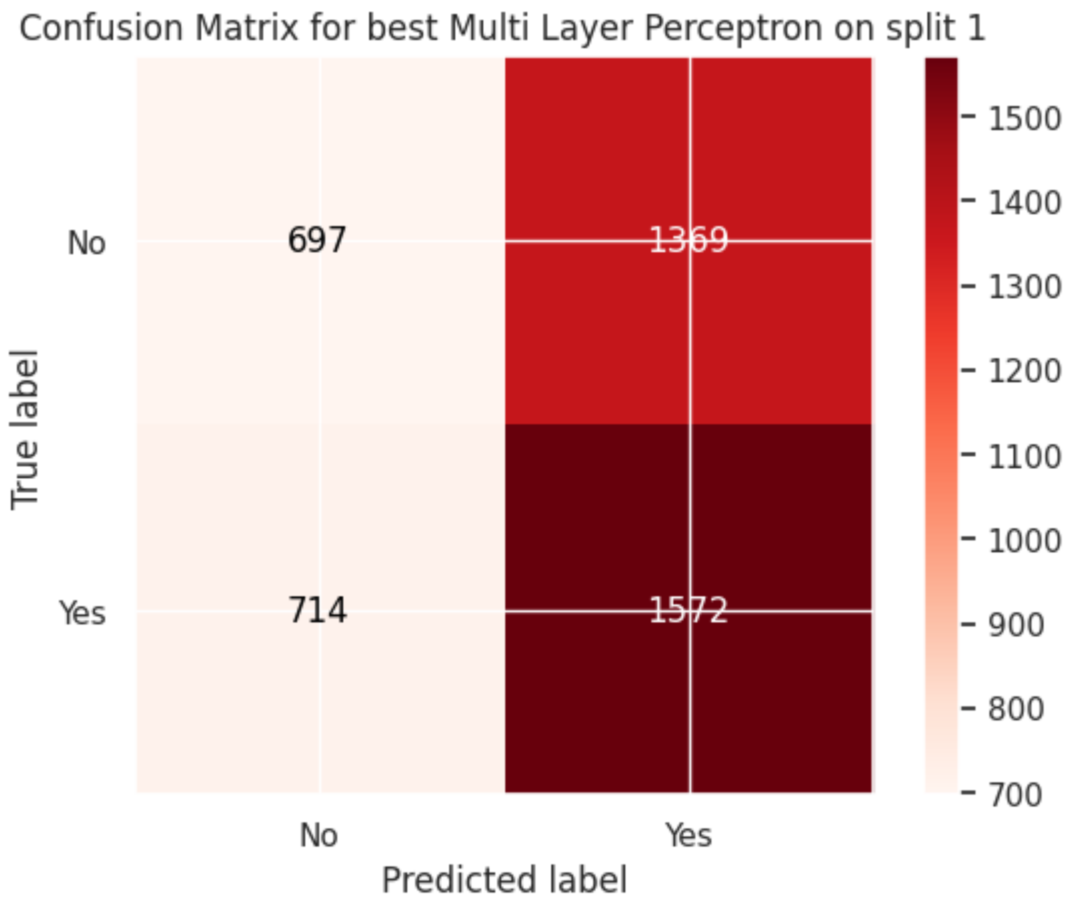

Learning Curve for Multi Layer Perceptron on split 0
Training Score
Test Score
0.56
0.54
0.52
0.50
0.48
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Multi Layer Perceptron on split 1
Training Score
Test Score
Accuracy
0.54
0.53
0.52
0.51
0.50
0.49
0.48
0.47
2000
4000
6000
8000
Number of samples in the training set

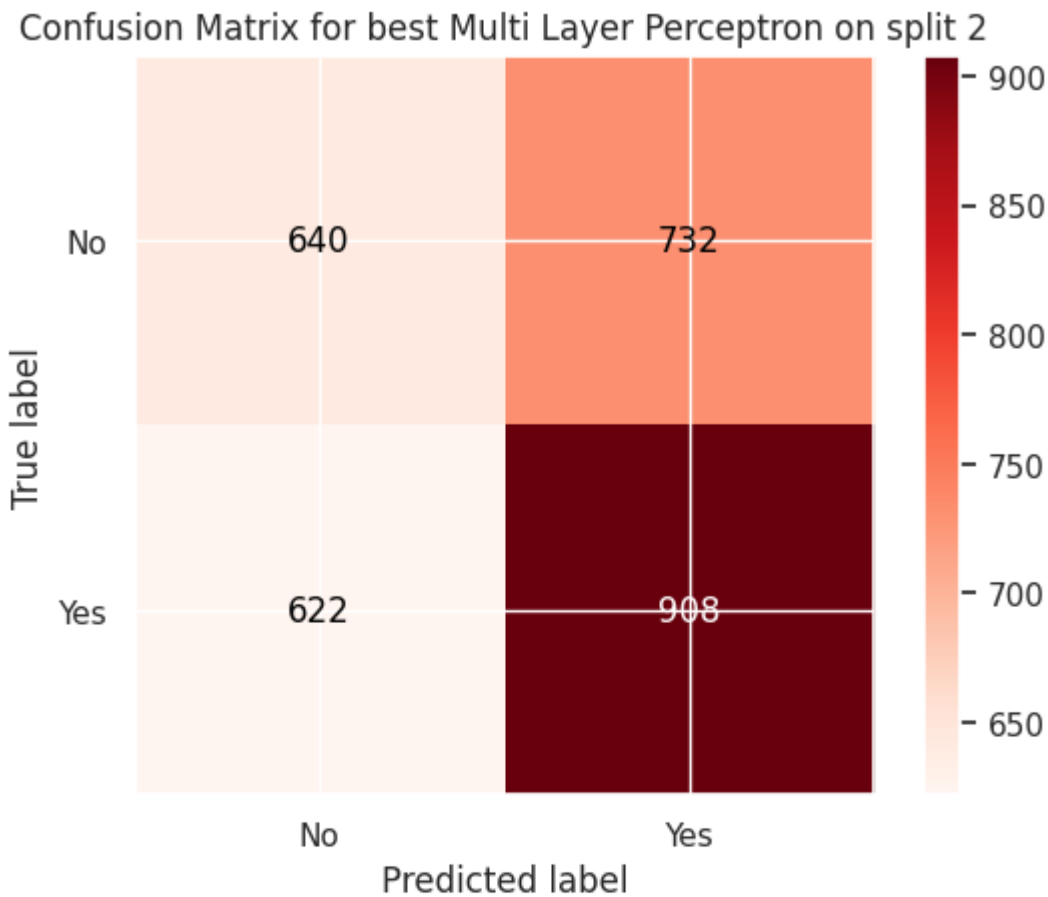

Learning Curve for Multi Layer Perceptron on split 2
Training Score
Test Score
Accuracy
0.56
0.55
0.54
0.53
0.52
0.51
0.50
0.49
0.48
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Multi Layer Perceptron on unseen data on spl
it 0
              precision    recall  f1-score   support

           0       0.50      0.72      0.59      3455
           1       0.58      0.35      0.44      3798

    accuracy                           0.53      7253
   macro avg       0.54      0.53      0.51      7253
weighted avg       0.54      0.53      0.51      7253
```




```
Classification report for best Multi Layer Perceptron on unseen data on spl
it 1
              precision    recall  f1-score   support

           0       0.49      0.34      0.40      2066
           1       0.53      0.69      0.60      2286

    accuracy                           0.52      4352
   macro avg       0.51      0.51      0.50      4352
weighted avg       0.52      0.52      0.51      4352
```



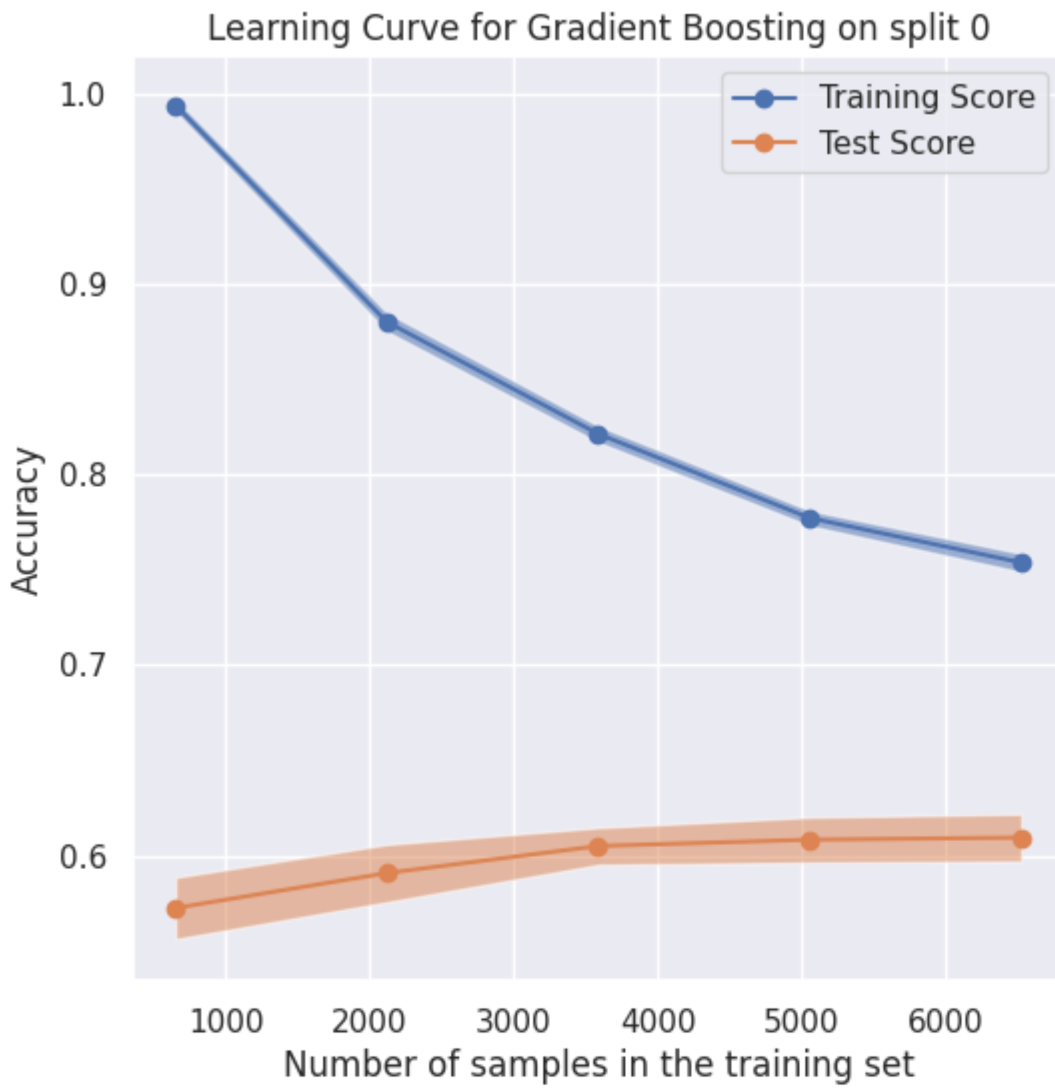

```
Classification report for best Multi Layer Perceptron on unseen data on spl
it 2
              precision    recall  f1-score   support

           0       0.51      0.47      0.49      1372
           1       0.55      0.59      0.57      1530

    accuracy                           0.53      2902
   macro avg       0.53      0.53      0.53      2902
weighted avg       0.53      0.53      0.53      2902
```

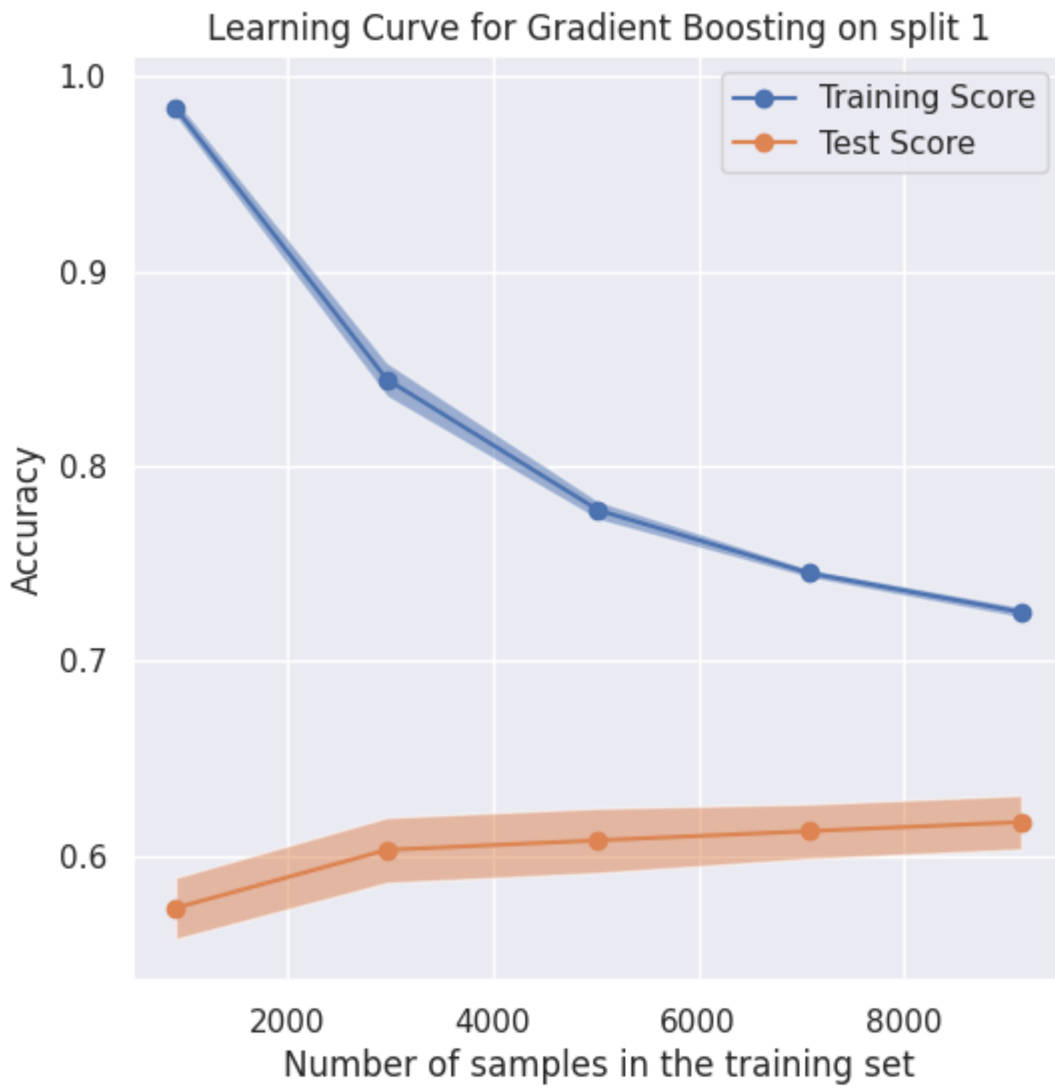
9 - Gradient Boosting

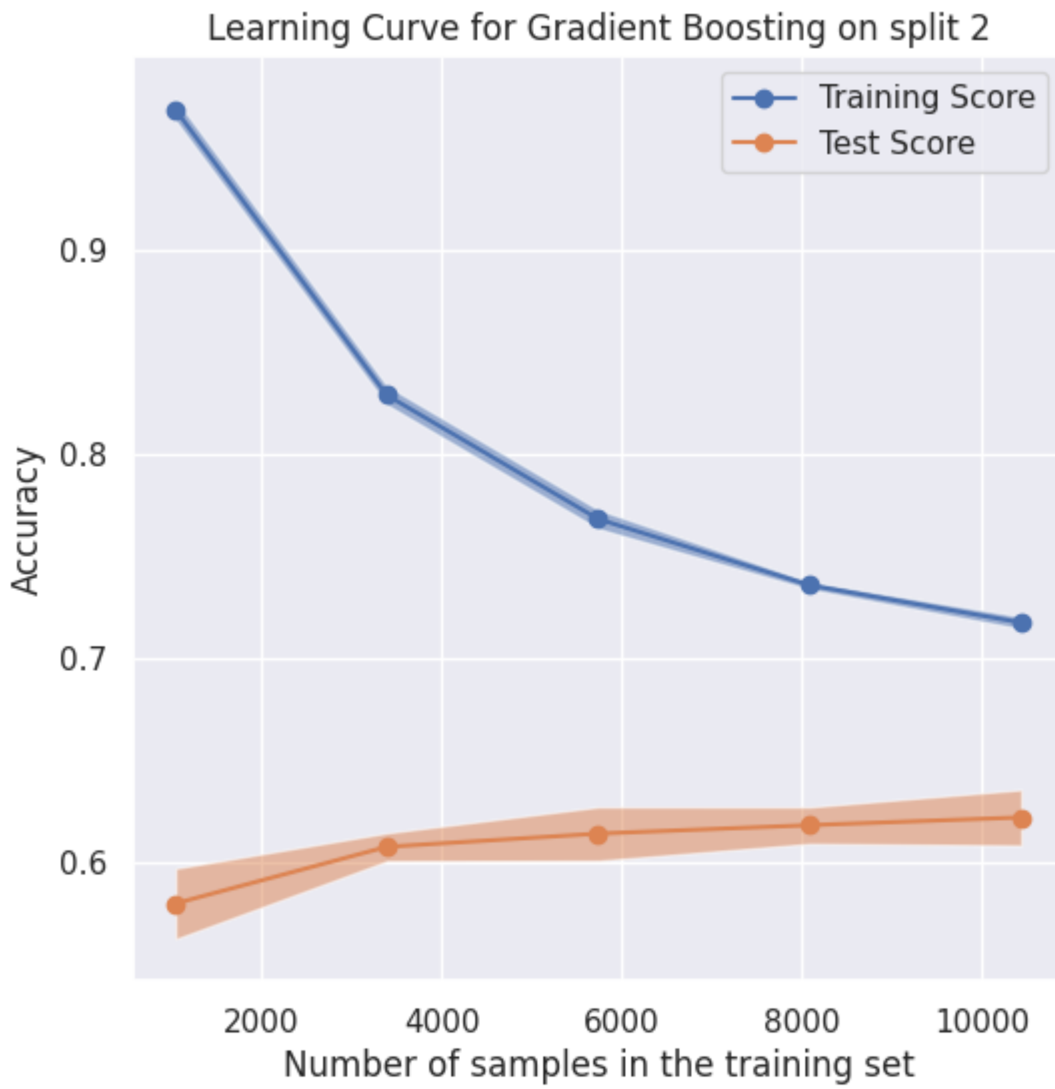
- loss = log loss - works well on probabilistic labels
- learning rate = 0.1
- n_estimators = 100
- subsample = 1.0
- criterion = ‘friedman_mse’
- min_samples_split: 2

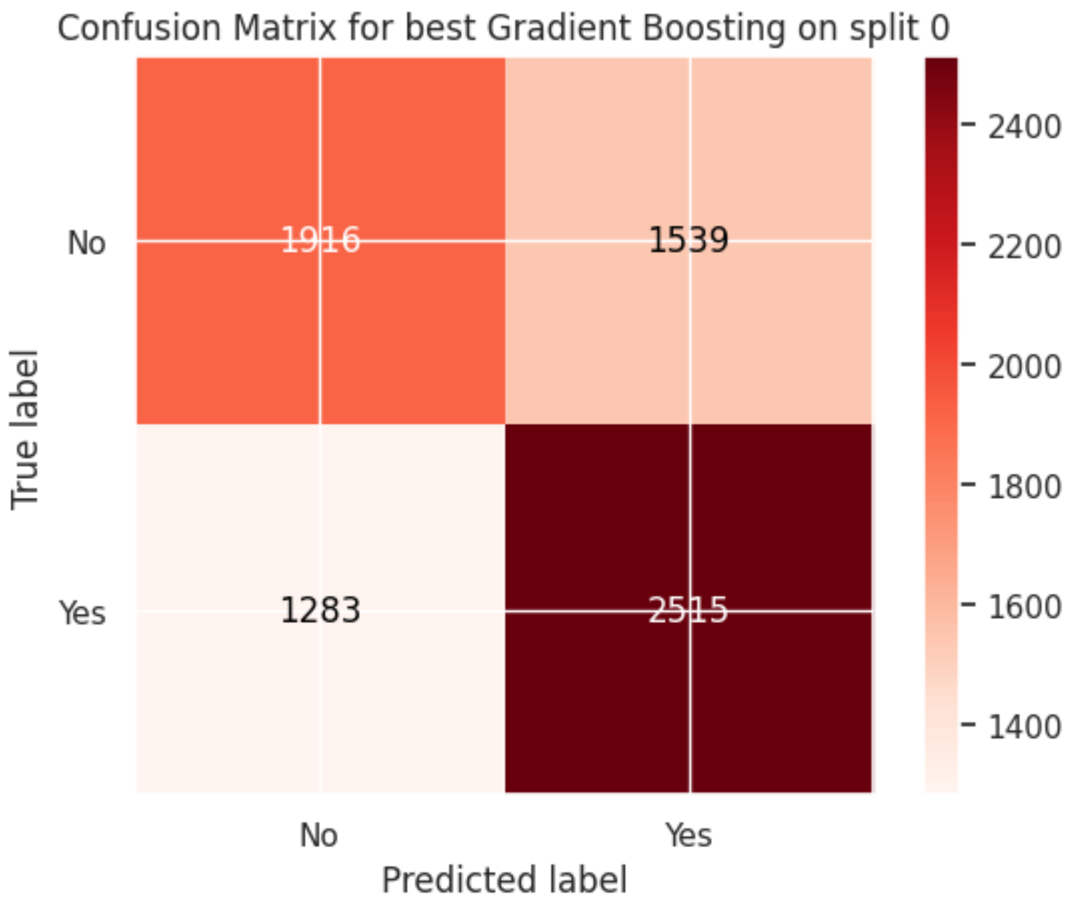
In [ ]:
```
models = pipe(gbc(loss = 'log_loss',learning_rate = 0.1,n_estimators = 100,
                  subsample = 1.0,criterion = 'friedman_mse',max_depth = 4,
                  random_state=seed),
              "Gradient Boosting")
best_models = [4,9,2]
best_model_metrics(models, "Gradient Boosting", best_models)
```

```
Gradient Boosting Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.61            0.609           0.61    0.609
1               0.599           0.598           0.599   0.598
2               0.628           0.627           0.628   0.627
3               0.619           0.619           0.619   0.617
4               0.632           0.631           0.632   0.63
5               0.581           0.58            0.581   0.58
6               0.601           0.601           0.601   0.601
7               0.603           0.602           0.603   0.602
8               0.594           0.594           0.594   0.593
9               0.594           0.594           0.594   0.593

Gradient Boosting Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.631           0.63            0.631   0.63
1               0.6             0.6             0.6     0.598
2               0.604           0.603           0.604   0.603
3               0.602           0.602           0.602   0.601
4               0.622           0.621           0.622   0.619
5               0.633           0.632           0.633   0.632
6               0.613           0.613           0.613   0.608
7               0.6             0.599           0.6     0.599
8               0.617           0.616           0.617   0.616
9               0.647           0.647           0.647   0.646

Gradient Boosting Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.633           0.633           0.633   0.631
1               0.623           0.622           0.623   0.621
2               0.641           0.641           0.641   0.639
3               0.608           0.607           0.608   0.607
4               0.612           0.611           0.612   0.611
5               0.634           0.633           0.634   0.632
6               0.652           0.651           0.652   0.65
7               0.599           0.598           0.599   0.597
8               0.616           0.615           0.616   0.613
9               0.615           0.614           0.615   0.613
```

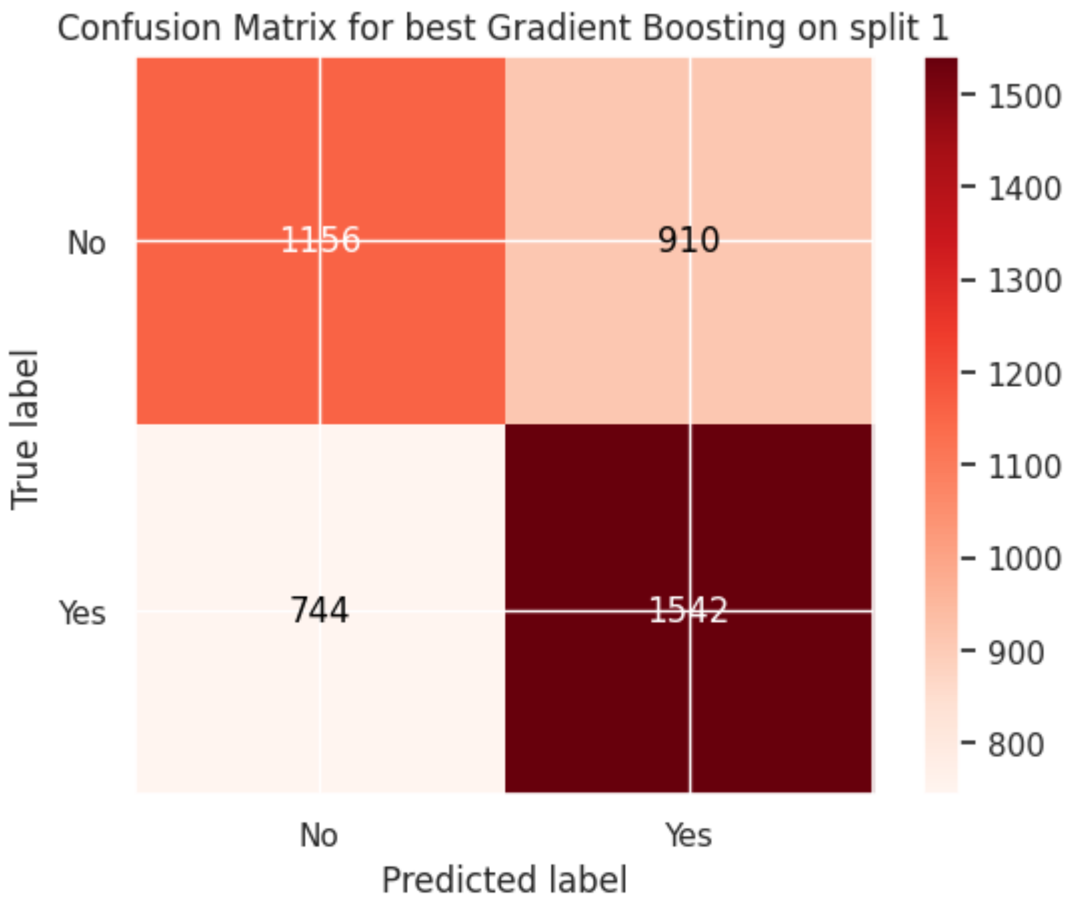

Learning Curve for Gradient Boosting on split 0
Training Score
Test Score
Accuracy
1.0
0.9
0.8
0.7
0.6
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Gradient Boosting on split 1
1.0
0.9
0.8
0.7
0.6
Accuracy
Training Score
Test Score
2000
4000
6000
8000
Number of samples in the training set

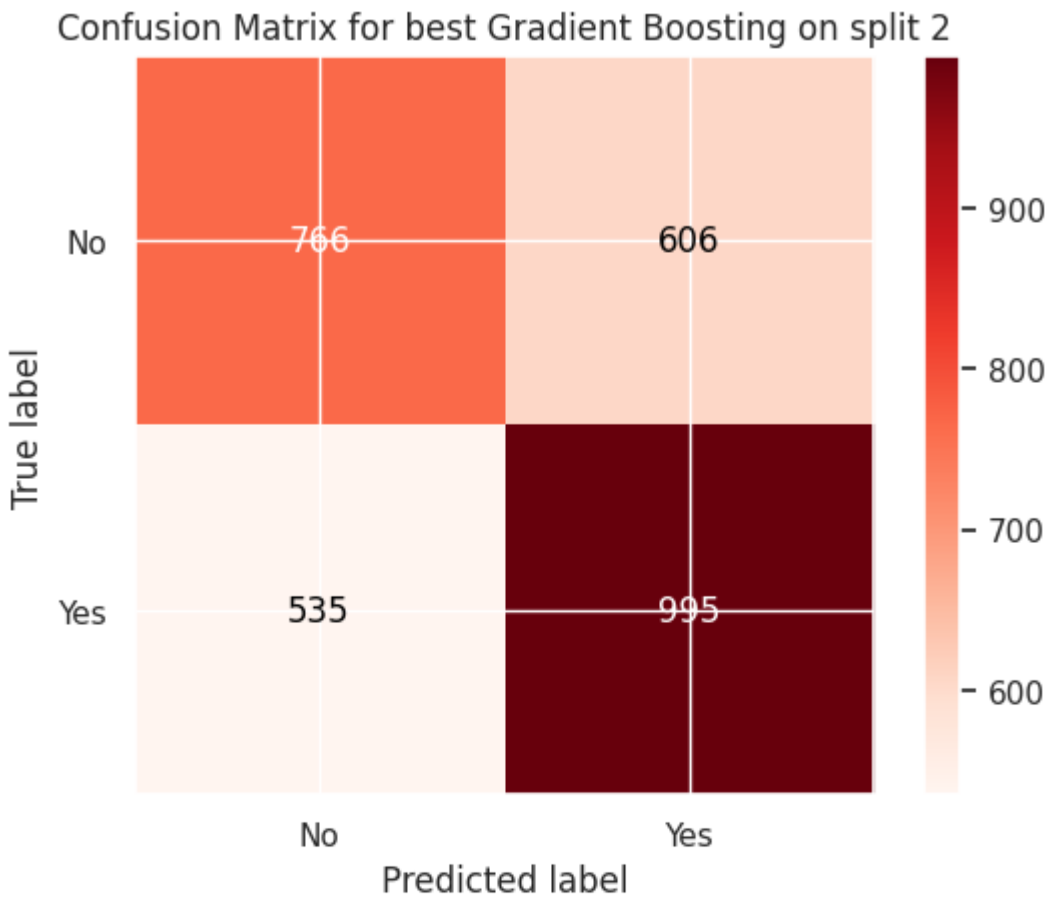

Learning Curve for Gradient Boosting on split 2
Training Score
Test Score
Accuracy
0.9
0.8
0.7
0.6
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Gradient Boosting on unseen data on split 0
              precision    recall  f1-score   support

           0       0.60      0.55      0.58      3455
           1       0.62      0.66      0.64      3798

    accuracy                           0.61      7253
   macro avg       0.61      0.61      0.61      7253
weighted avg       0.61      0.61      0.61      7253
```




```
Classification report for best Gradient Boosting on unseen data on split 1
              precision    recall  f1-score   support

           0       0.61      0.56      0.58      2066
           1       0.63      0.67      0.65      2286

    accuracy                           0.62      4352
   macro avg       0.62      0.62      0.62      4352
weighted avg       0.62      0.62      0.62      4352
```

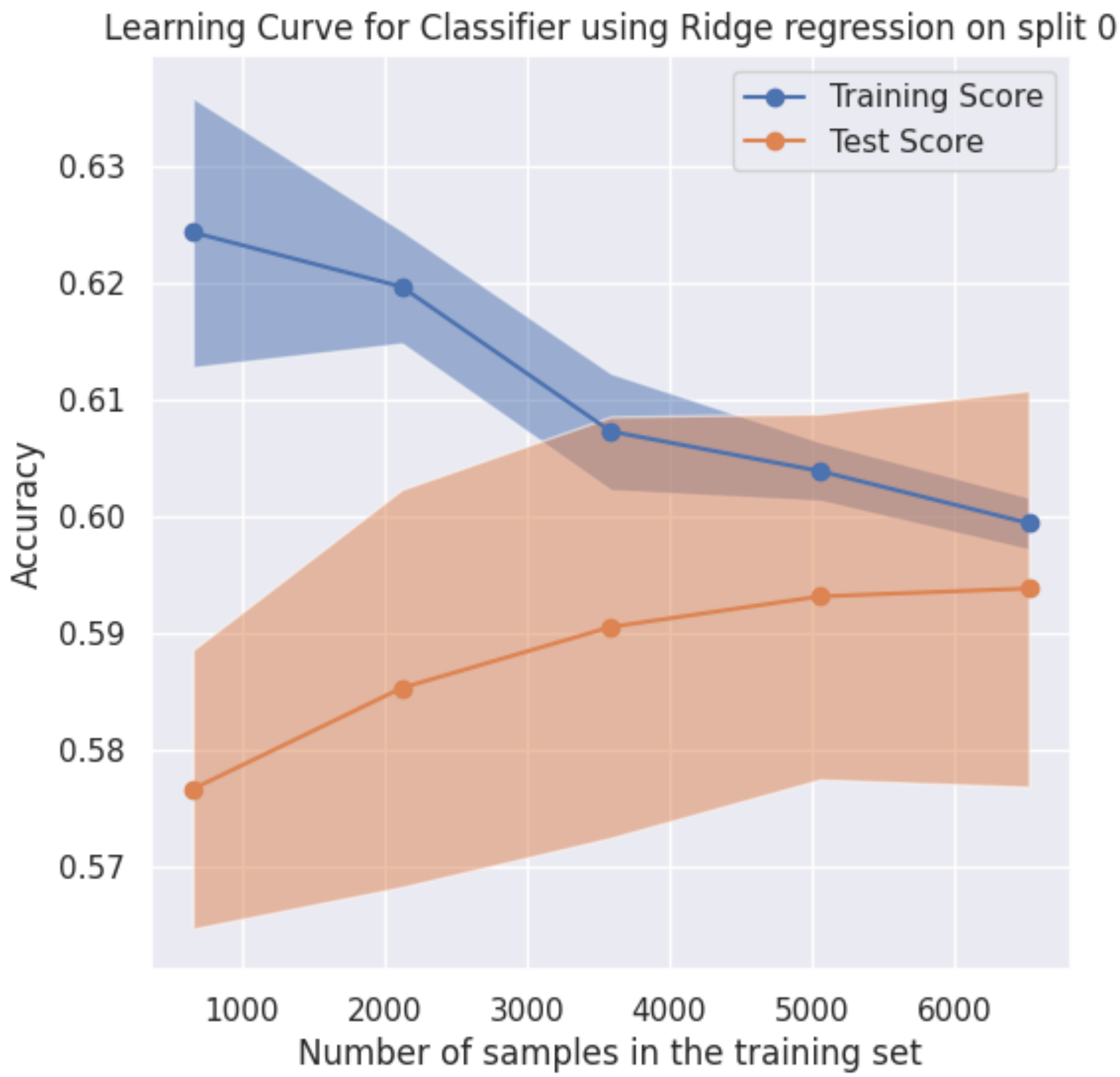


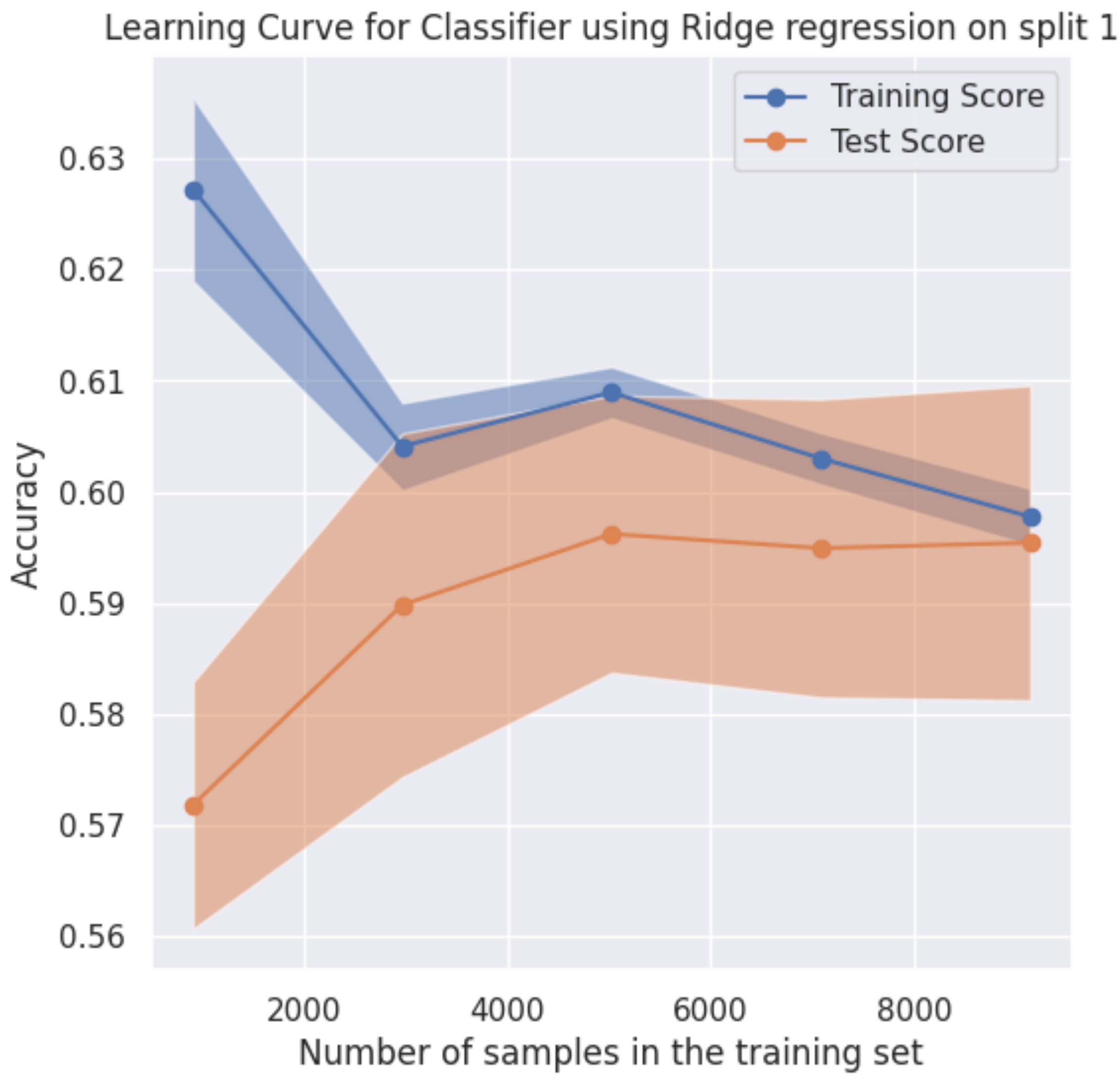

```
Classification report for best Gradient Boosting on unseen data on split 2
              precision    recall  f1-score   support

           0       0.59      0.56      0.57      1372
           1       0.62      0.65      0.64      1530

    accuracy                           0.61      2902
   macro avg       0.61      0.60      0.60      2902
weighted avg       0.61      0.61      0.61      2902
```

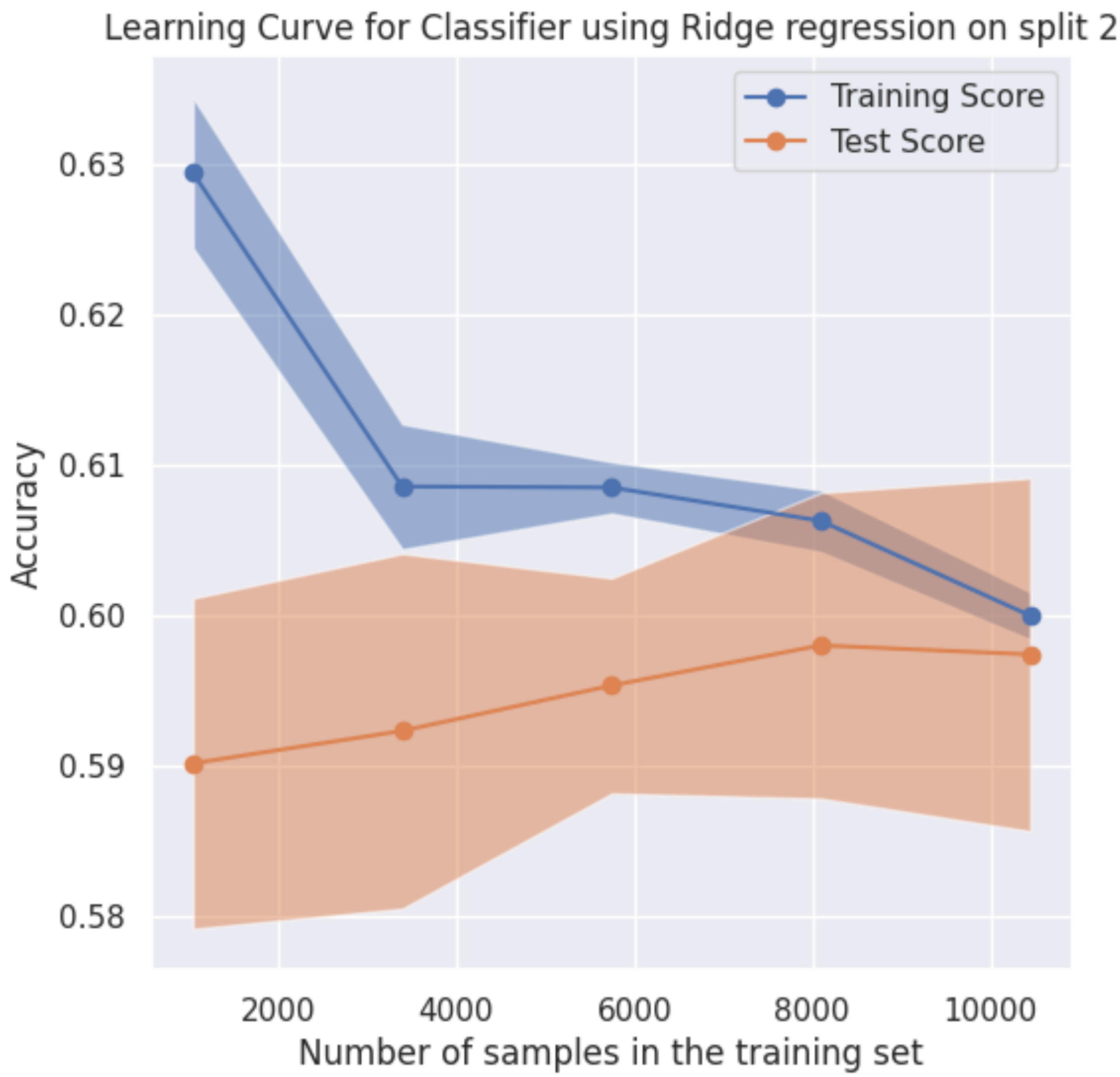
Extra credit 1 - Classifier using Ridge regression

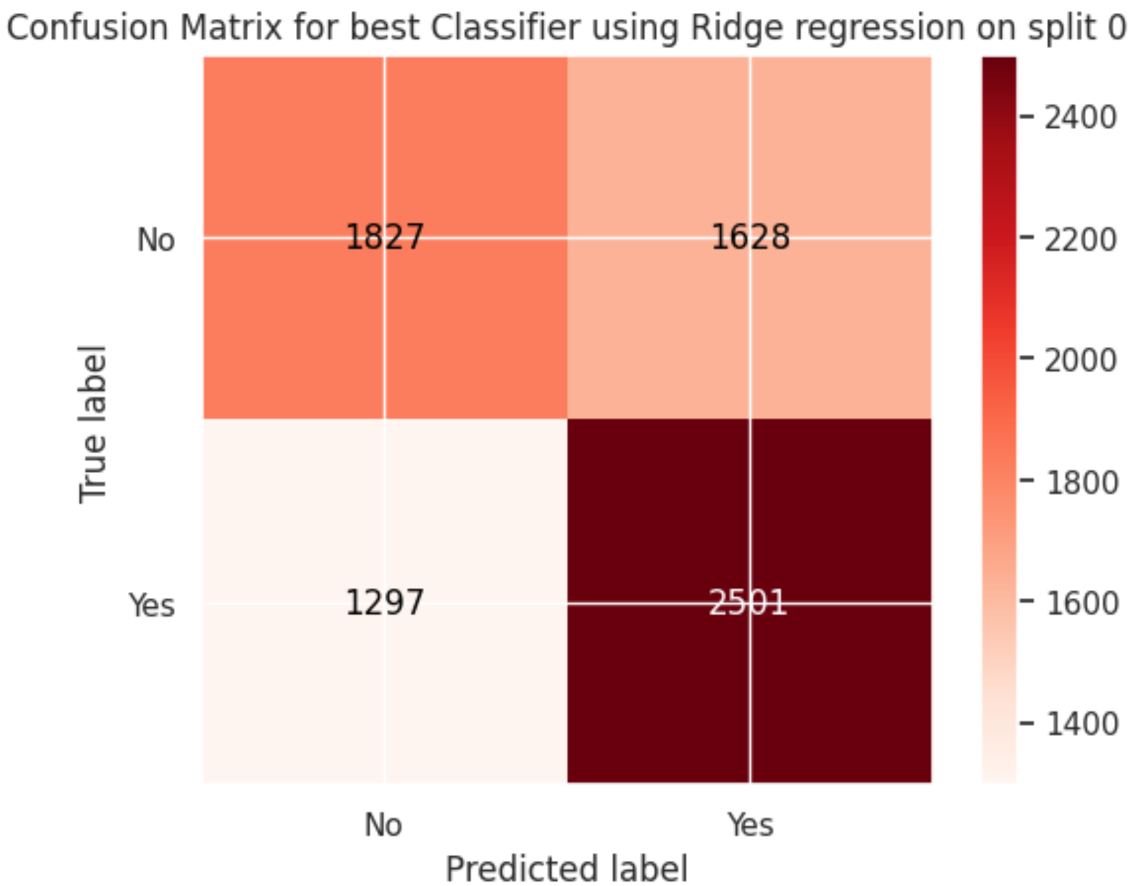
In [ ]:
```
models = pipe(lnrc(random_state = seed), "Classifier using Ridge regression")
best_models = [0,4,9]
best_model_metrics(models, "Classifier using Ridge regression", best_models)
```

```
Classifier using Ridge regression Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.618           0.618           0.618   0.617
1               0.599           0.598           0.599   0.598
2               0.594           0.593           0.594   0.591
3               0.603           0.602           0.603   0.601
4               0.59            0.589           0.59    0.589
5               0.594           0.593           0.594   0.592
6               0.59            0.589           0.59    0.589
7               0.556           0.555           0.556   0.555
8               0.578           0.577           0.578   0.577
9               0.615           0.614           0.615   0.614

Classifier using Ridge regression Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.594           0.593           0.594   0.593
1               0.588           0.586           0.588   0.585
2               0.586           0.585           0.586   0.585
3               0.591           0.59            0.591   0.59
4               0.619           0.618           0.619   0.616
5               0.612           0.611           0.612   0.609
6               0.579           0.578           0.579   0.576
7               0.599           0.6             0.599   0.599
8               0.575           0.574           0.575   0.574
9               0.615           0.614           0.615   0.613

Classifier using Ridge regression Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.585           0.584           0.585   0.584
1               0.584           0.583           0.584   0.582
2               0.592           0.591           0.592   0.59
3               0.609           0.608           0.609   0.608
4               0.596           0.595           0.596   0.595
5               0.594           0.593           0.594   0.593
6               0.608           0.607           0.608   0.606
7               0.581           0.58            0.581   0.58
8               0.612           0.611           0.612   0.611
9               0.614           0.613           0.614   0.613
```

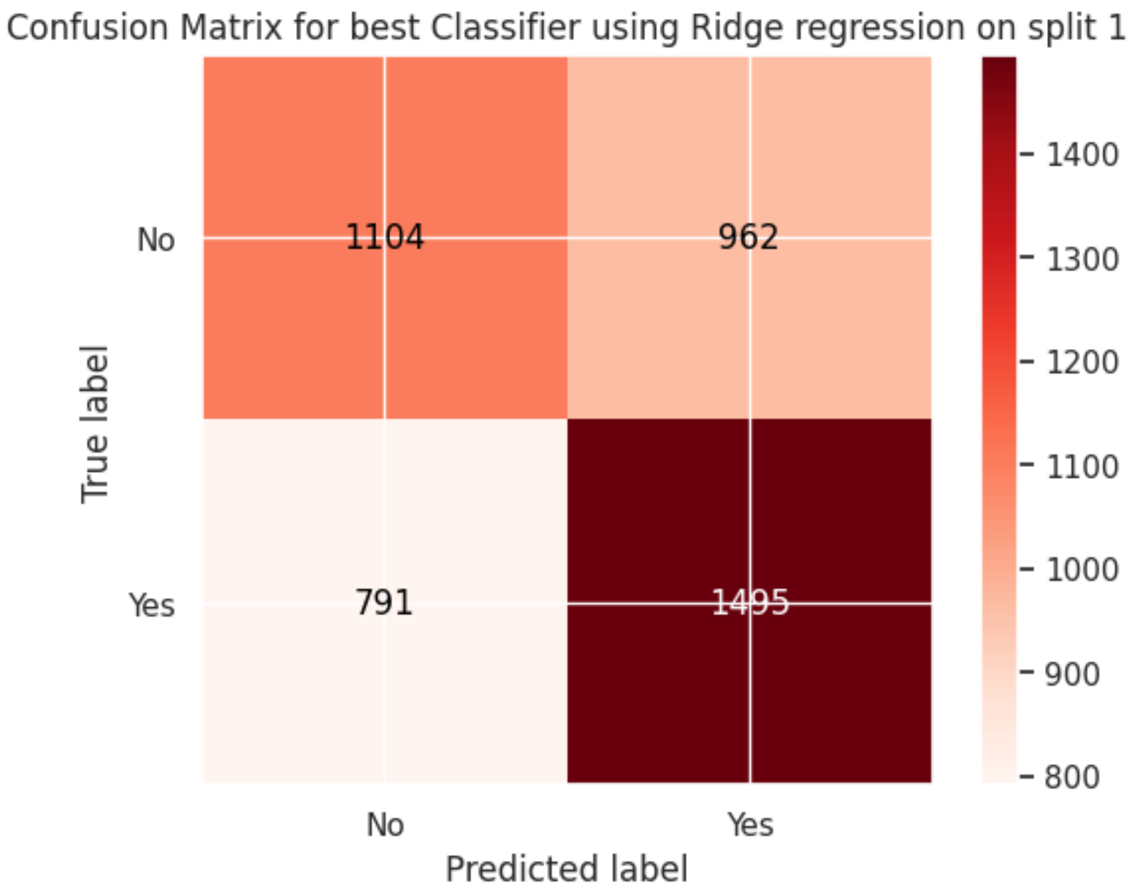

Learning Curve for Classifier using Ridge regression on split 0
Training Score
Test Score
0.63
0.62
0.61
0.60
0.59
0.58
0.57
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Classifier using Ridge regression on split 1
Training Score
Test Score
Accuracy
0.63
0.62
0.61
0.60
0.59
0.58
0.57
0.56
2000
4000
6000
8000
Number of samples in the training set

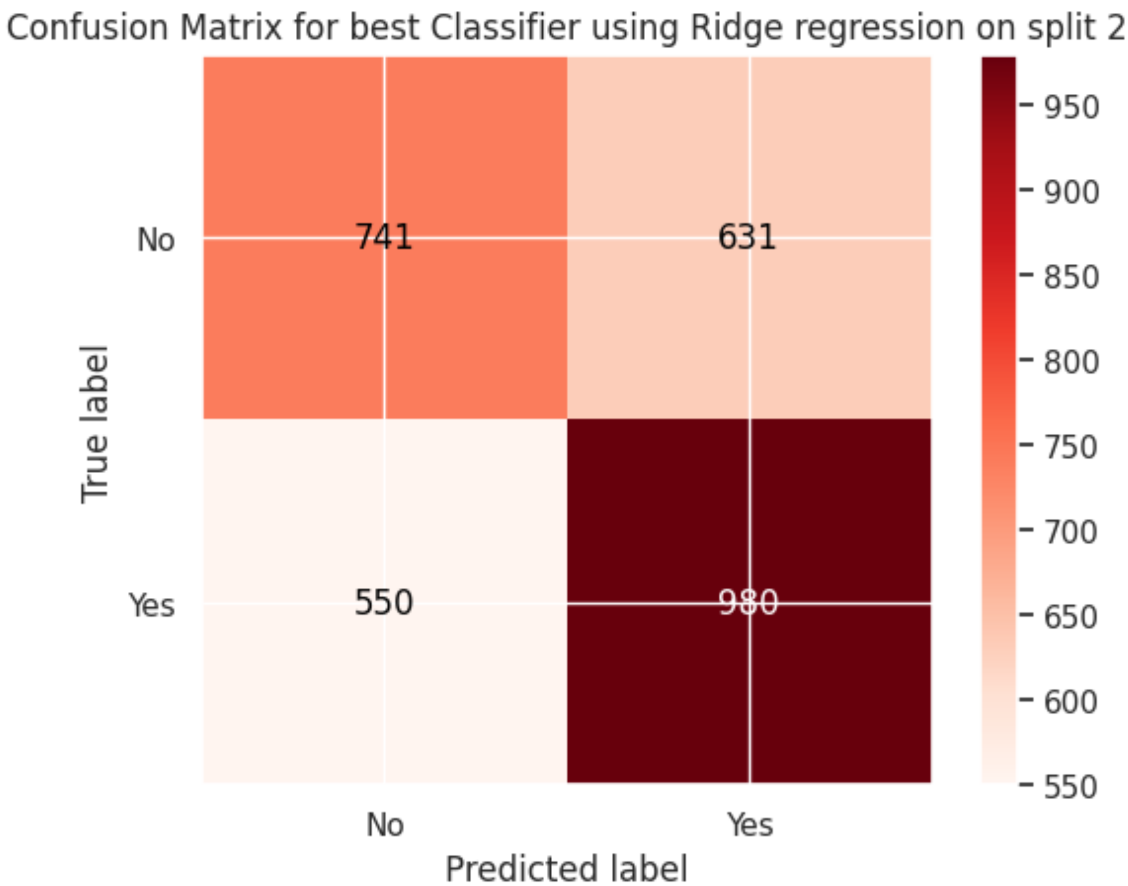

Learning Curve for Classifier using Ridge regression on split 2
Training Score
Test Score
Accuracy
0.63
0.62
0.61
0.60
0.59
0.58
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Classifier using Ridge regression on unseen
data on split 0
              precision    recall  f1-score   support

           0       0.58      0.53      0.56      3455
           1       0.61      0.66      0.63      3798

    accuracy                           0.60      7253
   macro avg       0.60      0.59      0.59      7253
weighted avg       0.60      0.60      0.59      7253
```




```
Classification report for best Classifier using Ridge regression on unseen
data on split 1
              precision    recall  f1-score   support

           0       0.58      0.53      0.56      2066
           1       0.61      0.65      0.63      2286

    accuracy                           0.60      4352
   macro avg       0.60      0.59      0.59      4352
weighted avg       0.60      0.60      0.60      4352
```

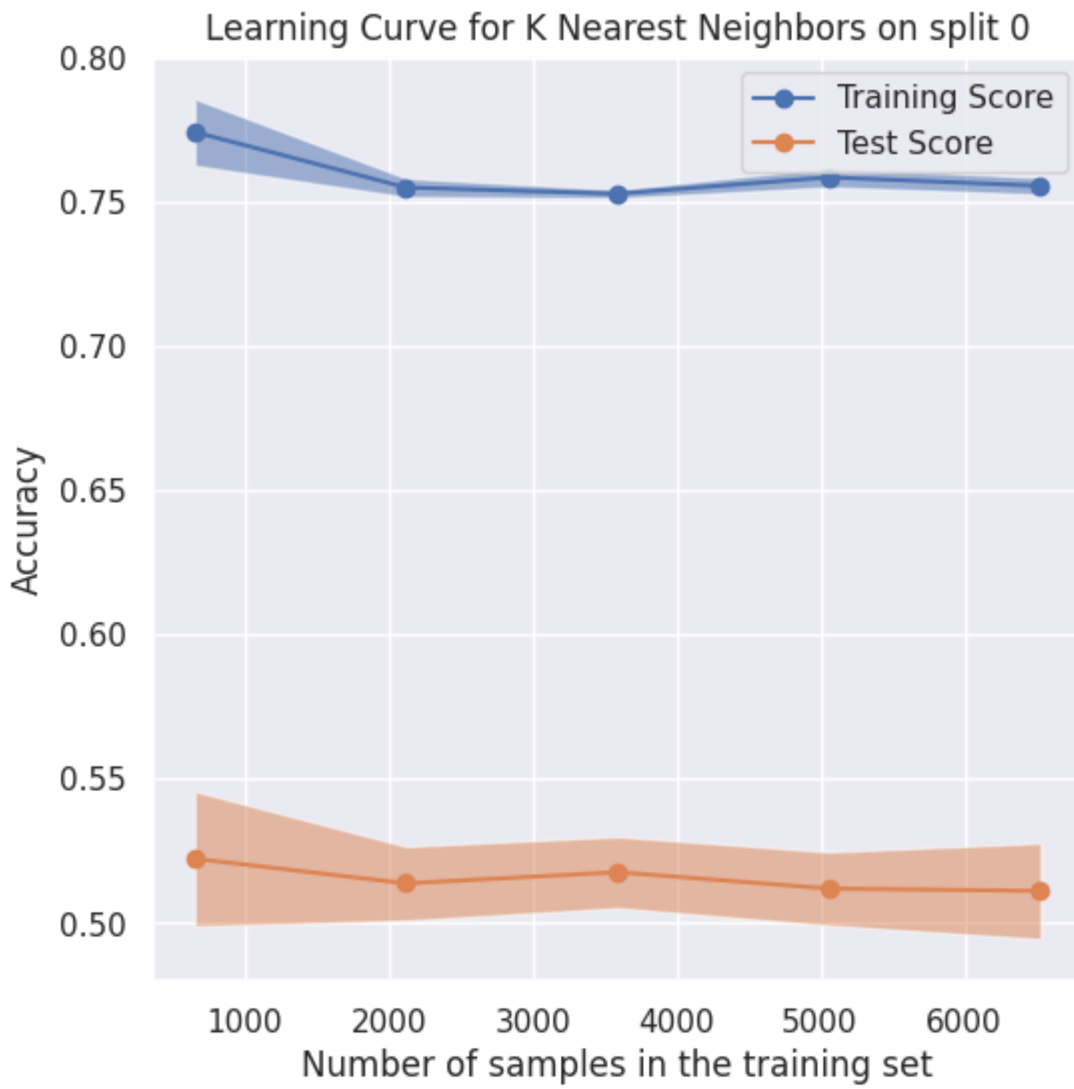


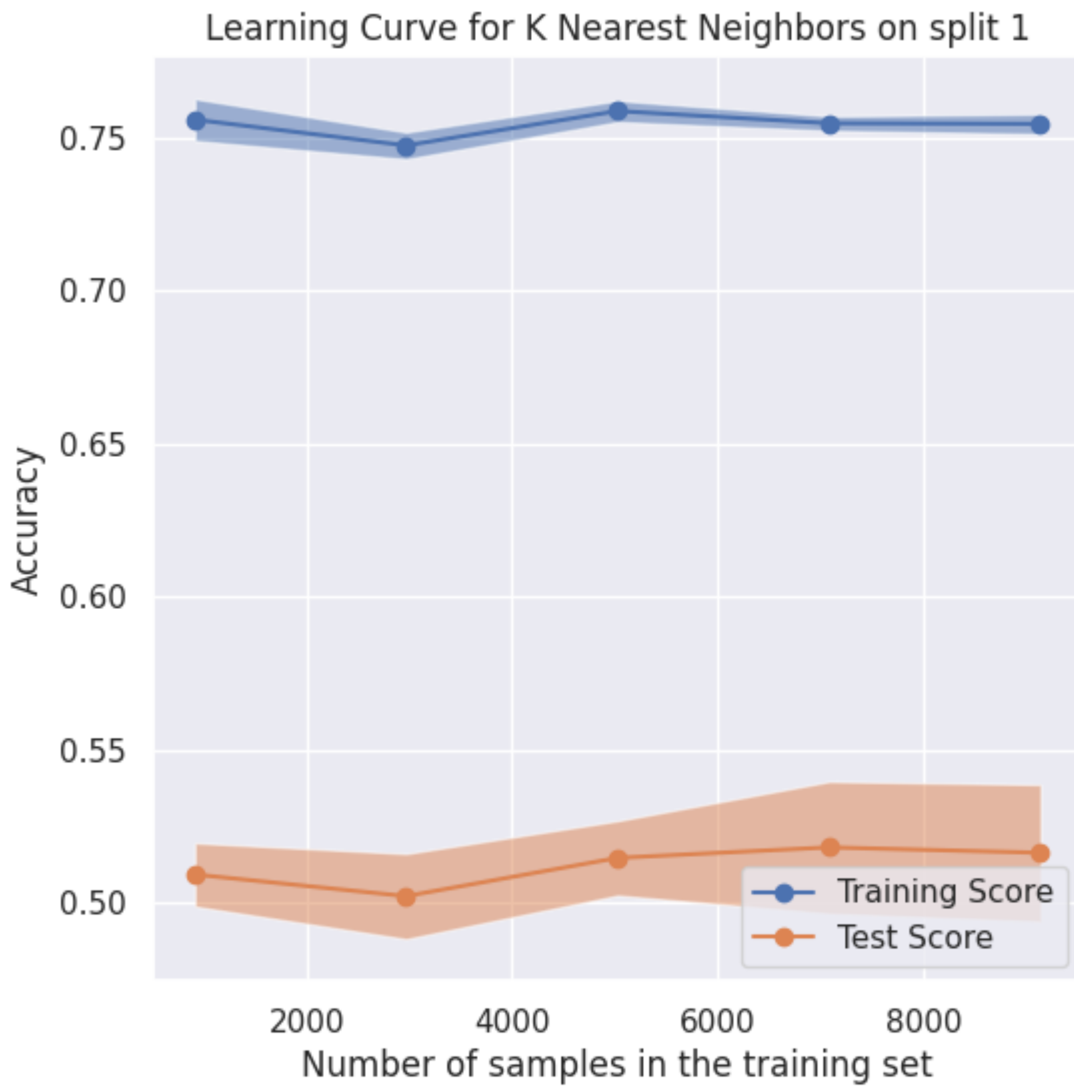

```
Classification report for best Classifier using Ridge regression on unseen
data on split 2
              precision    recall  f1-score   support

           0       0.57      0.54      0.56      1372
           1       0.61      0.64      0.62      1530

    accuracy                           0.59      2902
   macro avg       0.59      0.59      0.59      2902
weighted avg       0.59      0.59      0.59      2902
```

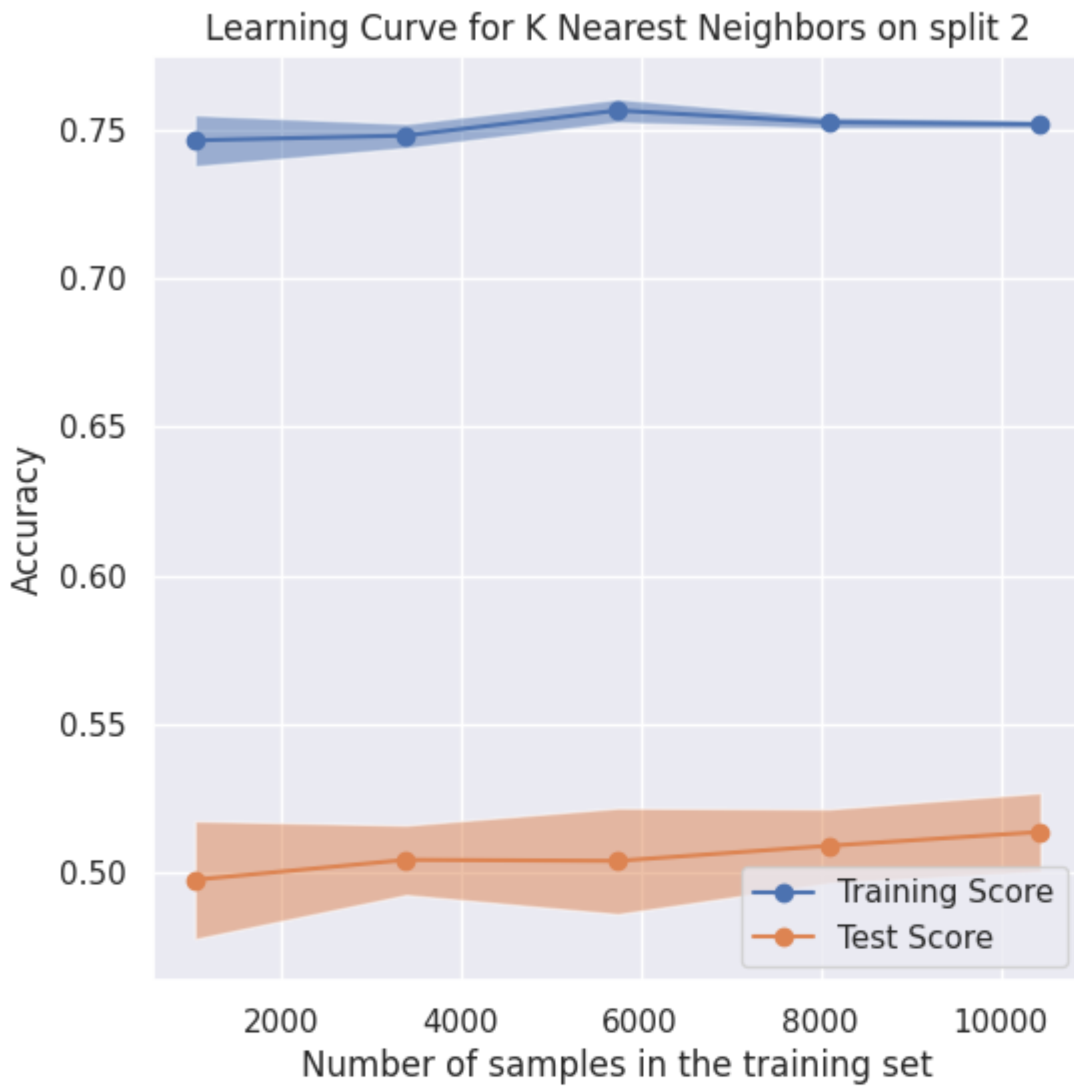
Extra credit 2 - K Nearest Neighbors Classifier

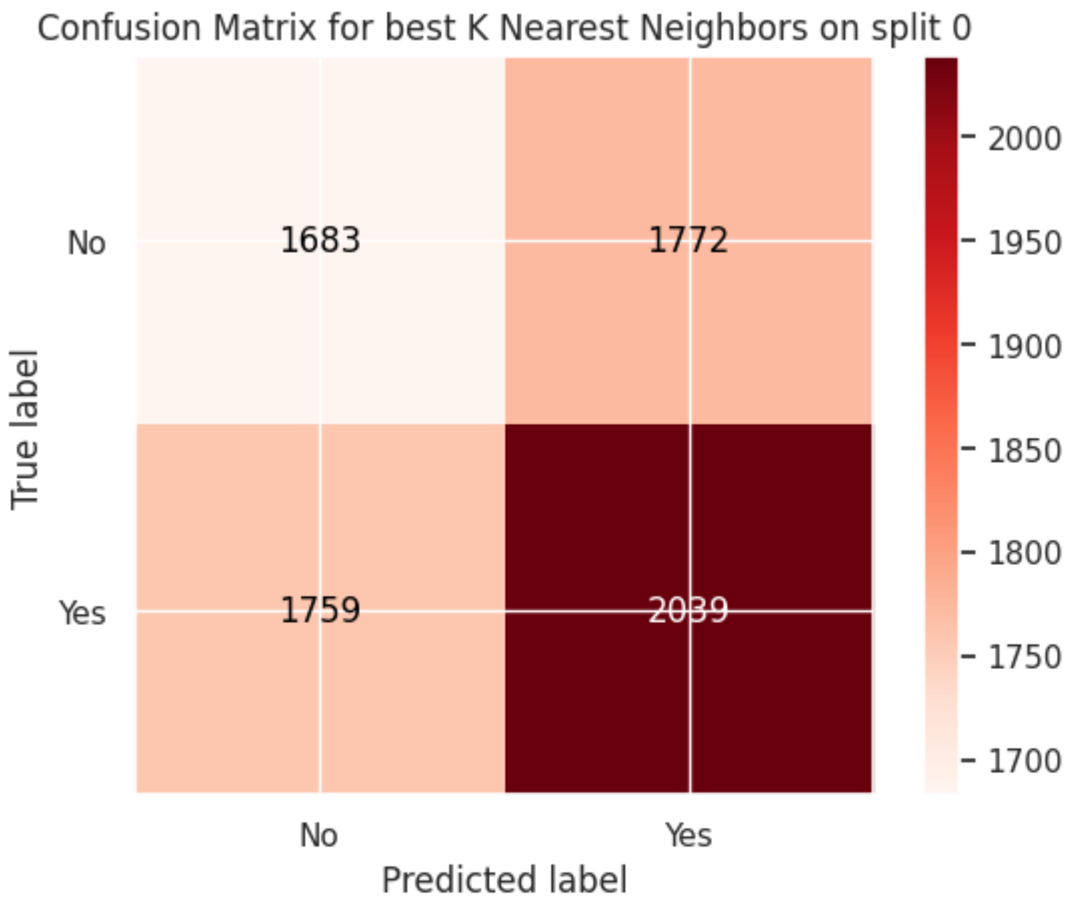
In [ ]:
```
models = pipe(KNeighborsClassifier(n_neighbors=3), "K Nearest Neighbors")
best_models = [2,8,3]
best_model_metrics(models, "K Nearest Neighbors", best_models)
```

```
K Nearest Neighbors Metrics for 10-fold on split 0
Fold    Accuracy        Precision       Recall          F1
0               0.503           0.503           0.503   0.503
1               0.493           0.494           0.493   0.493
2               0.53            0.529           0.53    0.53
3               0.539           0.54            0.539   0.539
4               0.492           0.49            0.492   0.491
5               0.513           0.511           0.513   0.512
6               0.486           0.485           0.486   0.485
7               0.514           0.512           0.514   0.512
8               0.521           0.52            0.521   0.52
9               0.523           0.522           0.523   0.522

K Nearest Neighbors Metrics for 10-fold on split 1
Fold    Accuracy        Precision       Recall          F1
0               0.533           0.532           0.533   0.532
1               0.531           0.53            0.531   0.53
2               0.49            0.489           0.49    0.489
3               0.537           0.538           0.537   0.538
4               0.49            0.489           0.49    0.489
5               0.522           0.521           0.522   0.521
6               0.48            0.478           0.48    0.479
7               0.538           0.537           0.538   0.538
8               0.542           0.541           0.542   0.54
9               0.502           0.502           0.502   0.502

K Nearest Neighbors Metrics for 10-fold on split 2
Fold    Accuracy        Precision       Recall          F1
0               0.517           0.516           0.517   0.516
1               0.5             0.5             0.5     0.5
2               0.527           0.527           0.527   0.527
3               0.535           0.535           0.535   0.535
4               0.493           0.492           0.493   0.492
5               0.5             0.499           0.5     0.499
6               0.522           0.521           0.522   0.521
7               0.501           0.5             0.501   0.5
8               0.521           0.52            0.521   0.521
9               0.522           0.521           0.522   0.521
```

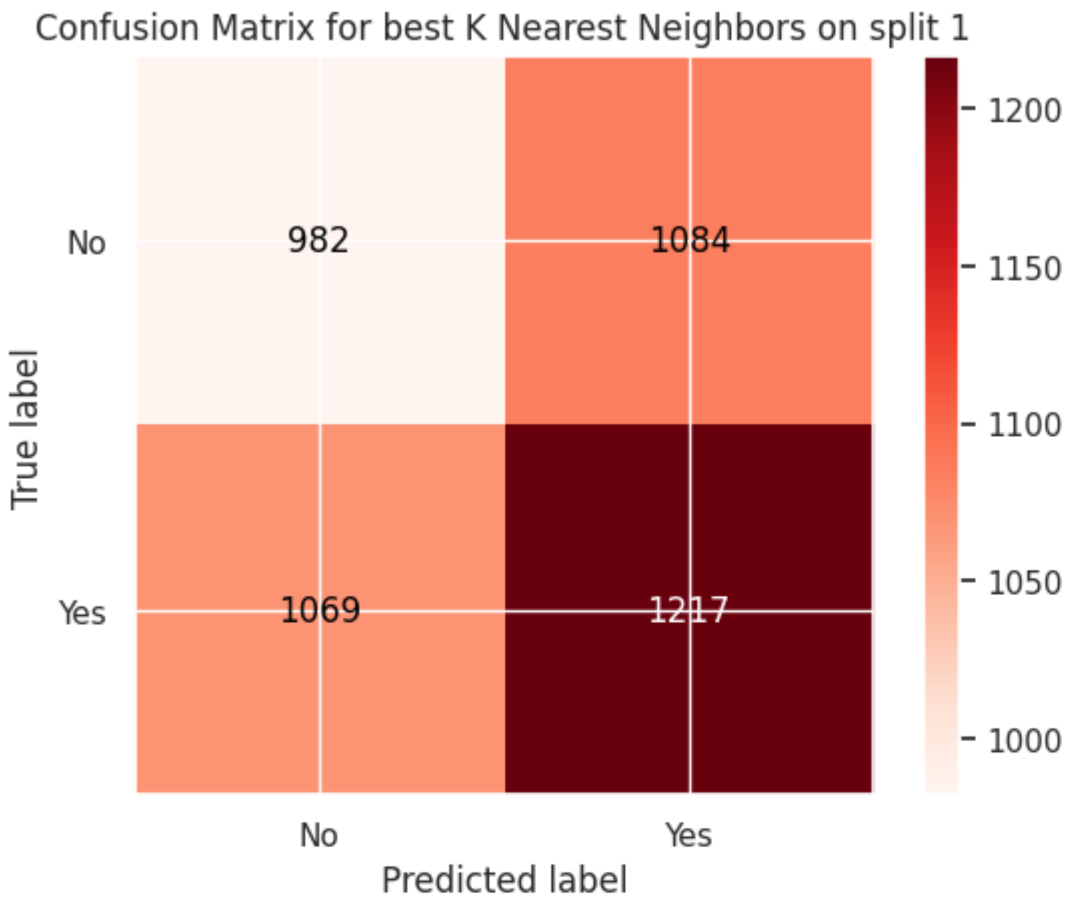

Learning Curve for K Nearest Neighbors on split 0
Training Score
Test Score
Accuracy
0.80
0.75
0.70
0.65
0.60
0.55
0.50
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for K Nearest Neighbors on split 1
Accuracy
0.75
0.70
0.65
0.60
0.55
0.50
2000
4000
6000
8000
Number of samples in the training set
Training Score
Test Score

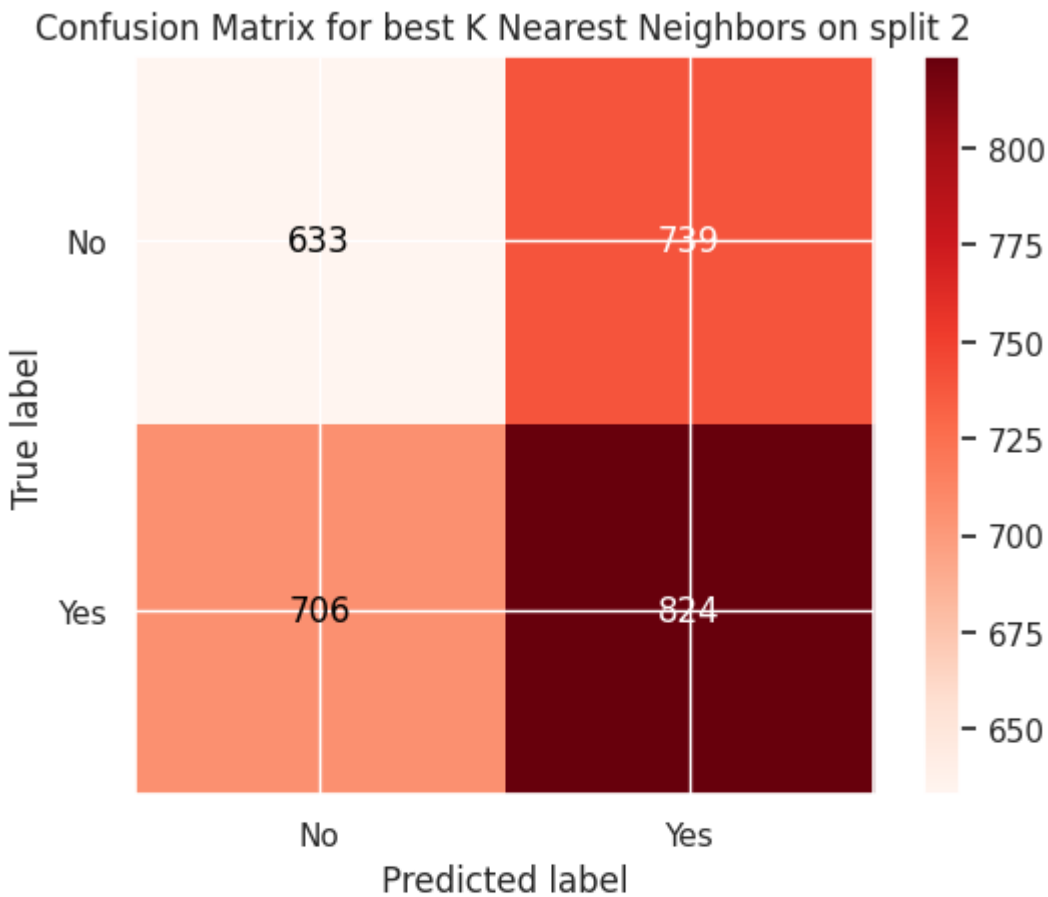

Learning Curve for K Nearest Neighbors on split 2
Accuracy
0.75
0.70
0.65
0.60
0.55
0.50
2000
4000
6000
8000
10000
Number of samples in the training set
Training Score
Test Score




```
Classification report for best K Nearest Neighbors on unseen data on split
0
              precision    recall  f1-score   support

           0       0.49      0.49      0.49      3455
           1       0.54      0.54      0.54      3798

    accuracy                           0.51      7253
   macro avg       0.51      0.51      0.51      7253
weighted avg       0.51      0.51      0.51      7253
```




```
Classification report for best K Nearest Neighbors on unseen data on split
1
              precision    recall  f1-score   support

           0       0.48      0.48      0.48      2066
           1       0.53      0.53      0.53      2286

    accuracy                           0.51      4352
   macro avg       0.50      0.50      0.50      4352
weighted avg       0.51      0.51      0.51      4352
```




```
Classification report for best K Nearest Neighbors on unseen data on split
2
              precision    recall  f1-score   support

           0       0.47      0.46      0.47      1372
           1       0.53      0.54      0.53      1530

    accuracy                           0.50      2902
   macro avg       0.50      0.50      0.50      2902
weighted avg       0.50      0.50      0.50      2902
```

Extra credit 3 - Passive Aggressive Classifier

In [ ]:
```
from sklearn.linear_model import PassiveAggressiveClassifier

models = pipe(PassiveAggressiveClassifier(max_iter=1000, random_state = see
d), "Passive Aggressive Classifier")
best_models = [7,9,6]
best_model_metrics(models, "Passive Aggressive Classifier", best_models)
```

Passive Aggressive Classifier Metrics for 10-fold on split 0

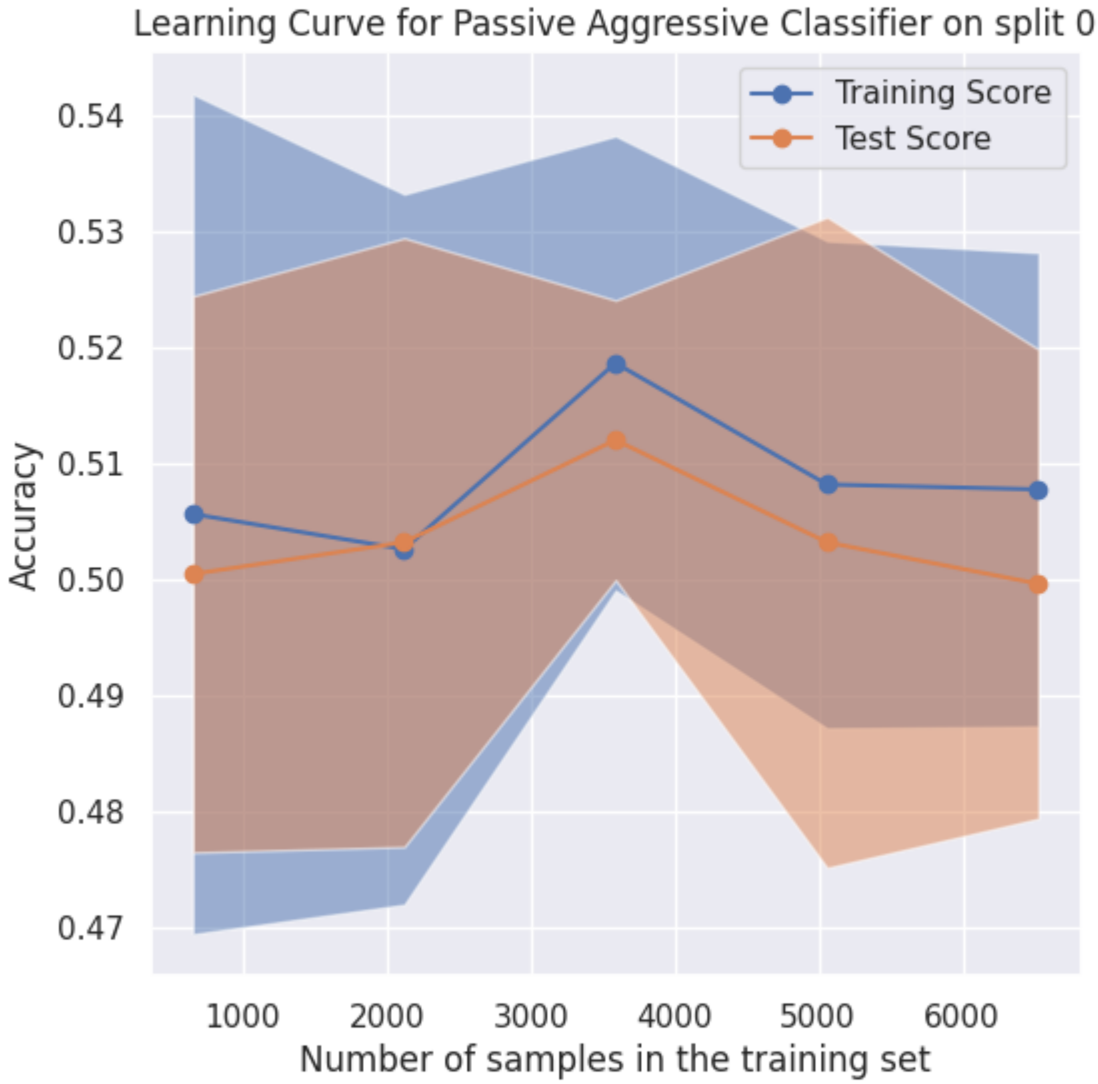
Fold	Accuracy	Precision	Recall	F1
0	0.507	0.501	0.507	0.496
1	0.504	0.489	0.504	0.466
2	0.51	0.532	0.51	0.477
3	0.476	0.485	0.476	0.441
4	0.523	0.506	0.523	0.395
5	0.52	0.41	0.52	0.363
6	0.521	0.505	0.521	0.42
7	0.532	0.604	0.532	0.39
8	0.51	0.499	0.51	0.478
9	0.476	0.493	0.476	0.357

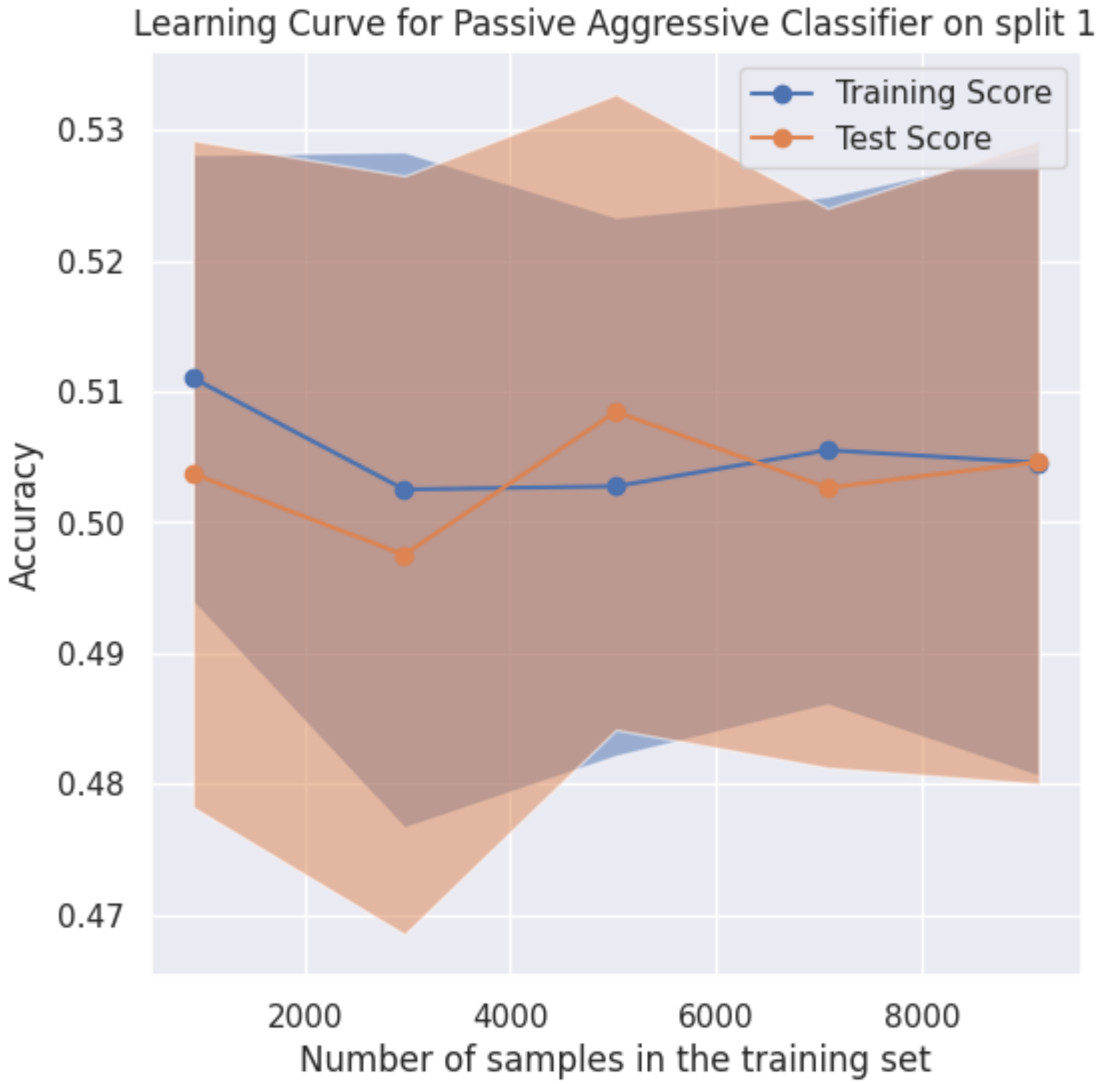
Passive Aggressive Classifier Metrics for 10-fold on split 1

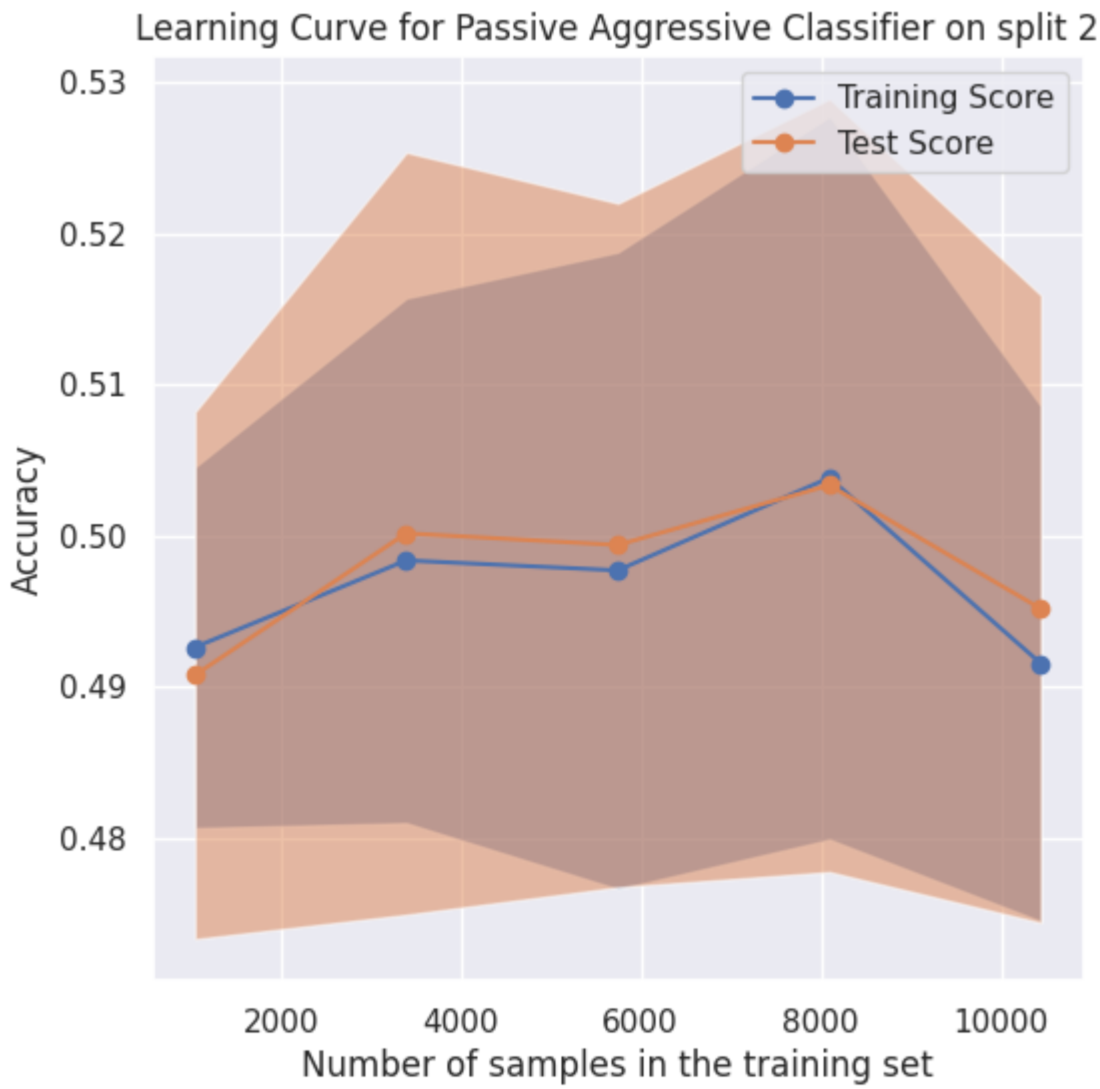
Fold	Accuracy	Precision	Recall	F1
0	0.529	0.524	0.529	0.511
1	0.474	0.473	0.474	0.334
2	0.481	0.497	0.481	0.409
3	0.523	0.433	0.523	0.361
4	0.473	0.226	0.473	0.306
5	0.46	0.464	0.46	0.455
6	0.488	0.502	0.488	0.447
7	0.484	0.5	0.484	0.419
8	0.483	0.494	0.483	0.444
9	0.551	0.574	0.551	0.476

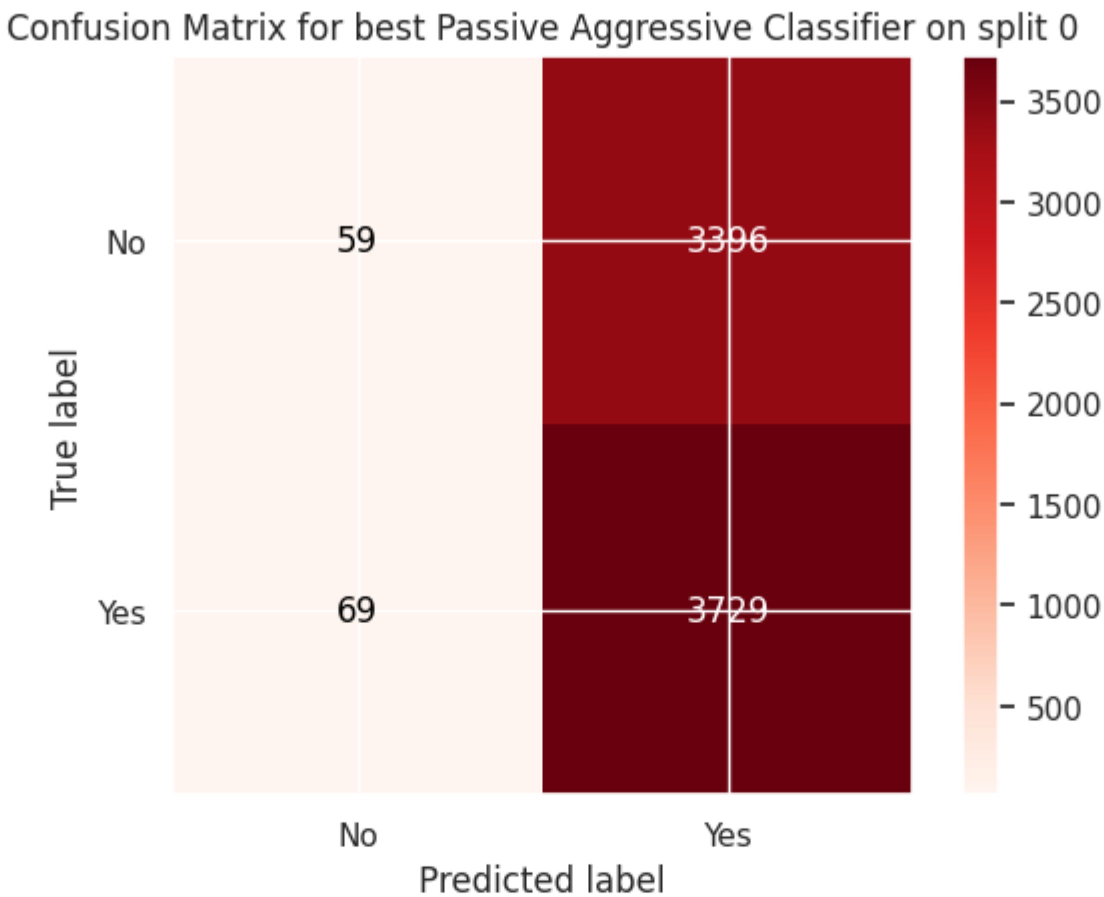
Passive Aggressive Classifier Metrics for 10-fold on split 2

Fold	Accuracy	Precision	Recall	F1
0	0.494	0.501	0.494	0.485
1	0.514	0.533	0.514	0.488
2	0.463	0.463	0.463	0.407
3	0.493	0.508	0.493	0.453
4	0.474	0.482	0.474	0.414
5	0.53	0.528	0.53	0.458
6	0.531	0.679	0.531	0.38
7	0.475	0.482	0.475	0.373
8	0.486	0.491	0.486	0.482
9	0.459	0.443	0.459	0.369

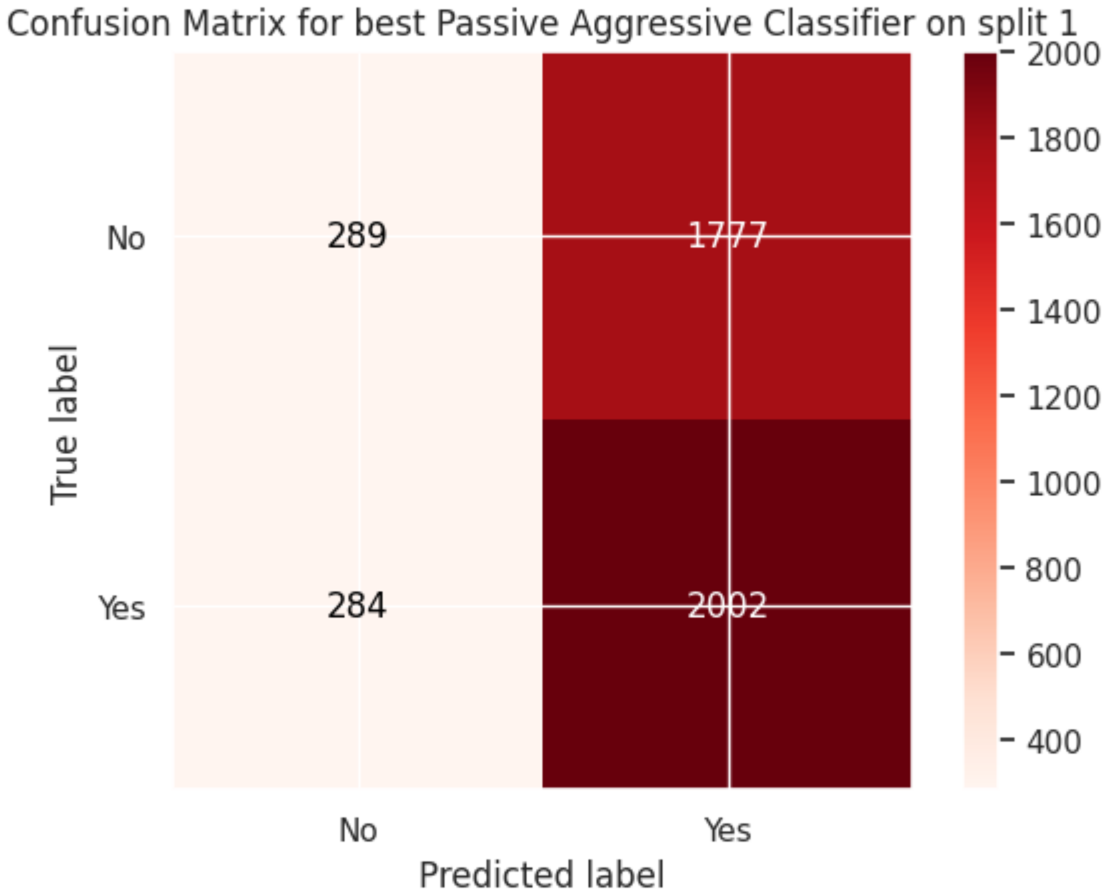

Learning Curve for Passive Aggressive Classifier on split 0
Training Score
Test Score
0.54
0.53
0.52
0.51
0.50
0.49
0.48
0.47
Accuracy
1000
2000
3000
4000
5000
6000
Number of samples in the training set


Learning Curve for Passive Aggressive Classifier on split 1
Training Score
Test Score
0.53
0.52
0.51
0.50
0.49
0.48
0.47
Accuracy
2000
4000
6000
8000
Number of samples in the training set

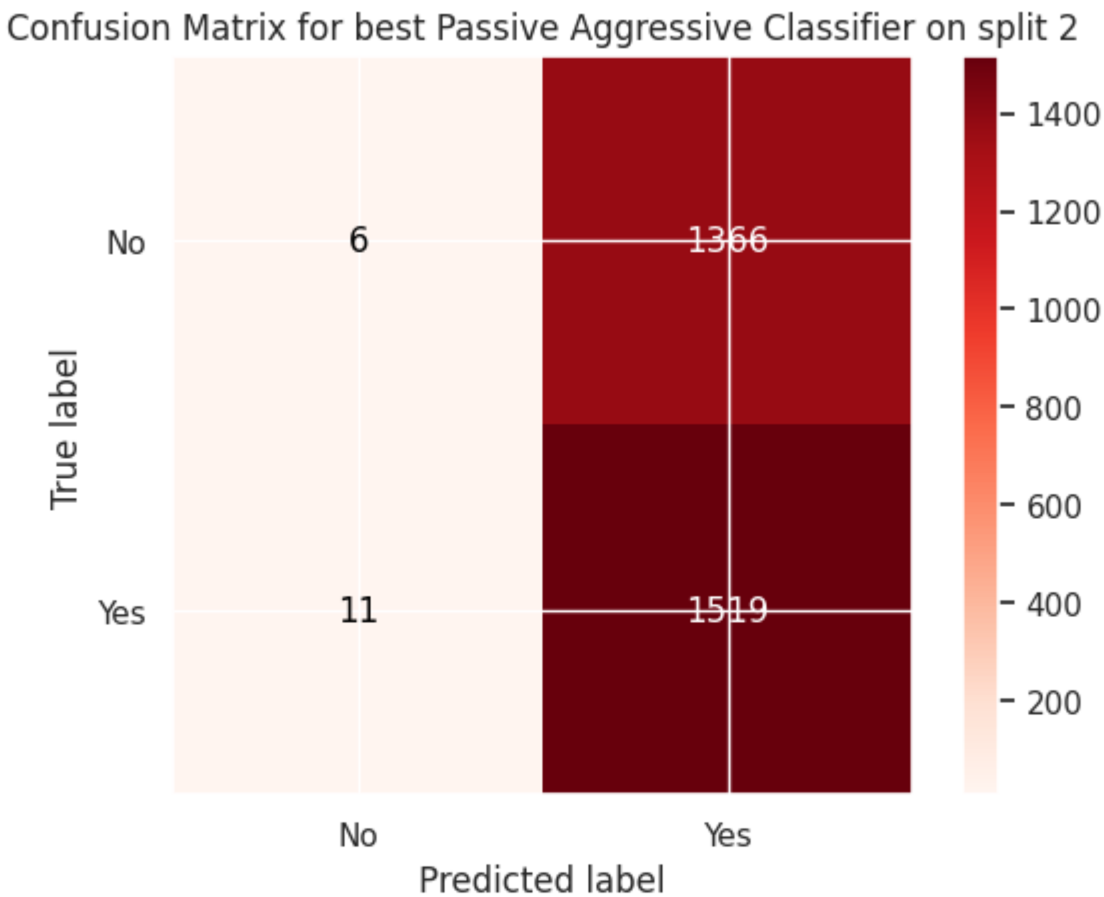

Learning Curve for Passive Aggressive Classifier on split 2
Training Score
Test Score
Accuracy
0.53
0.52
0.51
0.50
0.49
0.48
2000
4000
6000
8000
10000
Number of samples in the training set




```
Classification report for best Passive Aggressive Classifier on unseen data
on split 0
              precision    recall  f1-score   support

           0       0.46      0.02      0.03      3455
           1       0.52      0.98      0.68      3798

    accuracy                           0.52      7253
   macro avg       0.49      0.50      0.36      7253
weighted avg       0.49      0.52      0.37      7253
```




```
Classification report for best Passive Aggressive Classifier on unseen data
on split 1
              precision    recall  f1-score   support

           0       0.50      0.14      0.22      2066
           1       0.53      0.88      0.66      2286

    accuracy                           0.53      4352
   macro avg       0.52      0.51      0.44      4352
weighted avg       0.52      0.53      0.45      4352
```




```
Classification report for best Passive Aggressive Classifier on unseen data
on split 2
              precision    recall  f1-score   support

           0       0.35      0.00      0.01      1372
           1       0.53      0.99      0.69      1530

    accuracy                           0.53      2902
   macro avg       0.44      0.50      0.35      2902
weighted avg       0.44      0.53      0.37      2902
```