ml-gwp02

July 2, 2024

[ ]:
```
# load libraries
import matplotlib.pyplot as plt
import numpy as np
import math
import pandas as pd
from scipy.optimize import brute, fmin
from scipy.integrate import quad
import yfinance as yf
import pandas_datareader as pdr  # Access FRED
import yfinance as yf
from sklearn.preprocessing import MinMaxScaler
import tensorflow as tf
```

1 STEP 3 - Computations

Category 5: Linear Discriminant Analysis (LDA)

The method of LCA is illustrated next. The application case is German credit data, where people are classified as good or bad credit risks based on 20 attributes (such as the status of existing checking account, credit duration and history, etc.). More detailed information about the dataset can be found at https://archive.ics.uci.edu/dataset/144/statlog+german+credit+data.

[ ]:
```
# load libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
```

[ ]:
```
!pip install ucimlrepo
from ucimlrepo import fetch_ucirepo

# fetch dataset
```

```python
statlog_german_credit_data = fetch_ucirepo(id=144)

# data (all attributes)
X_all = statlog_german_credit_data.data.features
y = statlog_german_credit_data.data.targets

# metadata
print(statlog_german_credit_data.metadata)

# variable information
print(statlog_german_credit_data.variables)
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-
packages (0.0.7)
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.10/dist-
packages (from ucimlrepo) (2.0.3)
Requirement already satisfied: certifi>=2020.12.5 in
/usr/local/lib/python3.10/dist-packages (from ucimlrepo) (2024.6.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.0->ucimlrepo) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2024.1)
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.0.0->ucimlrepo) (1.25.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.16.0)
```


```
{'uci_id': 144, 'name': 'Statlog (German Credit Data)', 'repository_url':
'https://archive.ics.uci.edu/dataset/144/statlog+german+credit+data',
'data_url': 'https://archive.ics.uci.edu/static/public/144/data.csv',
'abstract': 'This dataset classifies people described by a set of attributes as
good or bad credit risks. Comes in two formats (one all numeric). Also comes
with a cost matrix', 'area': 'Social Science', 'tasks': ['Classification'],
'characteristics': ['Multivariate'], 'num_instances': 1000, 'num_features': 20,
'feature_types': ['Categorical', 'Integer'], 'demographics': ['Other', 'Marital
Status', 'Age', 'Occupation'], 'target_col': ['class'], 'index_col': None,
'has_missing_values': 'no', 'missing_values_symbol': None,
'year_of_dataset_creation': 1994, 'last_updated': 'Thu Aug 10 2023',
'dataset_doi': '10.24432/C5NC77', 'creators': ['Hans Hofmann'], 'intro_paper':
None, 'additional_info': {'summary': 'Two datasets are provided.  the original
dataset, in the form provided by Prof. Hofmann, contains categorical/symbolic
attributes and is in the file "german.data".   \r\n \r\nFor algorithms that need
numerical attributes, Strathclyde University produced the file "german.data-
numeric".  This file has been edited and several indicator variables added to
make it suitable for algorithms which cannot cope with categorical variables.
Several attributes that are ordered categorical (such as attribute 17) have been
```

coded as integer.   This was the form used by StatLog.\r\n\r\nThis dataset
requires use of a cost matrix (see below)\r\n\r\n … 1
2\r\n----------------------------\r\n 1   0
1\r\n-----------------------\r\n 2   5   0\r\n\r\n(1 = Good, 2 =
Bad)\r\n\r\nThe rows represent the actual classification and the columns the
predicted classification.\r\n\r\nIt is worse to class a customer as good when
they are bad (5), than it is to class a customer as bad when they are good
(1).\r\n', 'purpose': None, 'funded_by': None, 'instances_represent': None,
'recommended_data_splits': None, 'sensitive_data': None,
'preprocessing_description': None, 'variable_info': 'Attribute 1: (qualitative)
\r\n Status of existing checking account\r\n   A11 :   … <   0
DM\r\n\t   A12 : 0 <= … < 200 DM\r\n\t   A13 :   … >= 200 DM /
salary assignments for at least 1 year\r\n   A14 : no checking
account\r\n\r\nAttribute 2: (numerical)\r\n\t   Duration in
month\r\n\r\nAttribute 3: (qualitative)\r\n\t   Credit history\r\n\t
A30 : no credits taken/ all credits paid back duly\r\n   A31 : all
credits at this bank paid back duly\r\n\t   A32 : existing credits paid back
duly till now\r\n   A33 : delay in paying off in the past\r\n\t
A34 : critical account/ other credits existing (not at this
bank)\r\n\r\nAttribute 4: (qualitative)\r\n\t   Purpose\r\n\t   A40 : car
(new)\r\n\t   A41 : car (used)\r\n\t   A42 : furniture/equipment\r\n\t
A43 : radio/television\r\n\t   A44 : domestic appliances\r\n\t   A45 :
repairs\r\n\t   A46 : education\r\n\t   A47 : (vacation - does not
exist?)\r\n\t   A48 : retraining\r\n\t   A49 : business\r\n\t   A410 :
others\r\n\r\nAttribute 5: (numerical)\r\n\t   Credit amount\r\n\r\nAttibute
6: (qualitative)\r\n\t   Savings account/bonds\r\n\t   A61 :   …
< 100 DM\r\n\t   A62 :   100 <= … < 500 DM\r\n\t   A63 :   500 <= …
< 1000 DM\r\n\t   A64 :   .. >= 1000 DM\r\n   A65 :
unknown/ no savings account\r\n\r\nAttribute 7: (qualitative)\r\n\t
Present employment since\r\n\t   A71 : unemployed\r\n\t   A72 :   …
< 1 year\r\n\t   A73 : 1 <= … < 4 years \r\n\t   A74 : 4 <= … < 7
years\r\n\t   A75 :   .. >= 7 years\r\n\r\nAttribute 8:
(numerical)\r\n\t   Installment rate in percentage of disposable
income\r\n\r\nAttribute 9: (qualitative)\r\n\t   Personal status and
sex\r\n\t   A91 : male   : divorced/separated\r\n\t   A92 : female :
divorced/separated/married\r\n   A93 : male   : single\r\n\t   A94
: male   : married/widowed\r\n\t   A95 : female : single\r\n\r\nAttribute 10:
(qualitative)\r\n\t   Other debtors / guarantors\r\n\t   A101 : none\r\n\t
A102 : co-applicant\r\n\t   A103 : guarantor\r\n\r\nAttribute 11:
(numerical)\r\n\t   Present residence since\r\n\r\nAttribute 12:
(qualitative)\r\n\t   Property\r\n\t   A121 : real estate\r\n\t   A122
: if not A121 : building society savings agreement/ life insurance\r\n
A123 : if not A121/A122 : car or other, not in attribute 6\r\n\t   A124 :
unknown / no property\r\n\r\nAttribute 13: (numerical)\r\n\t   Age in
years\r\n\r\nAttribute 14: (qualitative)\r\n\t   Other installment plans
\r\n\t   A141 : bank\r\n\t   A142 : stores\r\n\t   A143 :
none\r\n\r\nAttribute 15: (qualitative)\r\n\t   Housing\r\n\t   A151 :
rent\r\n\t   A152 : own\r\n\t   A153 : for free\r\n\r\nAttribute 16:

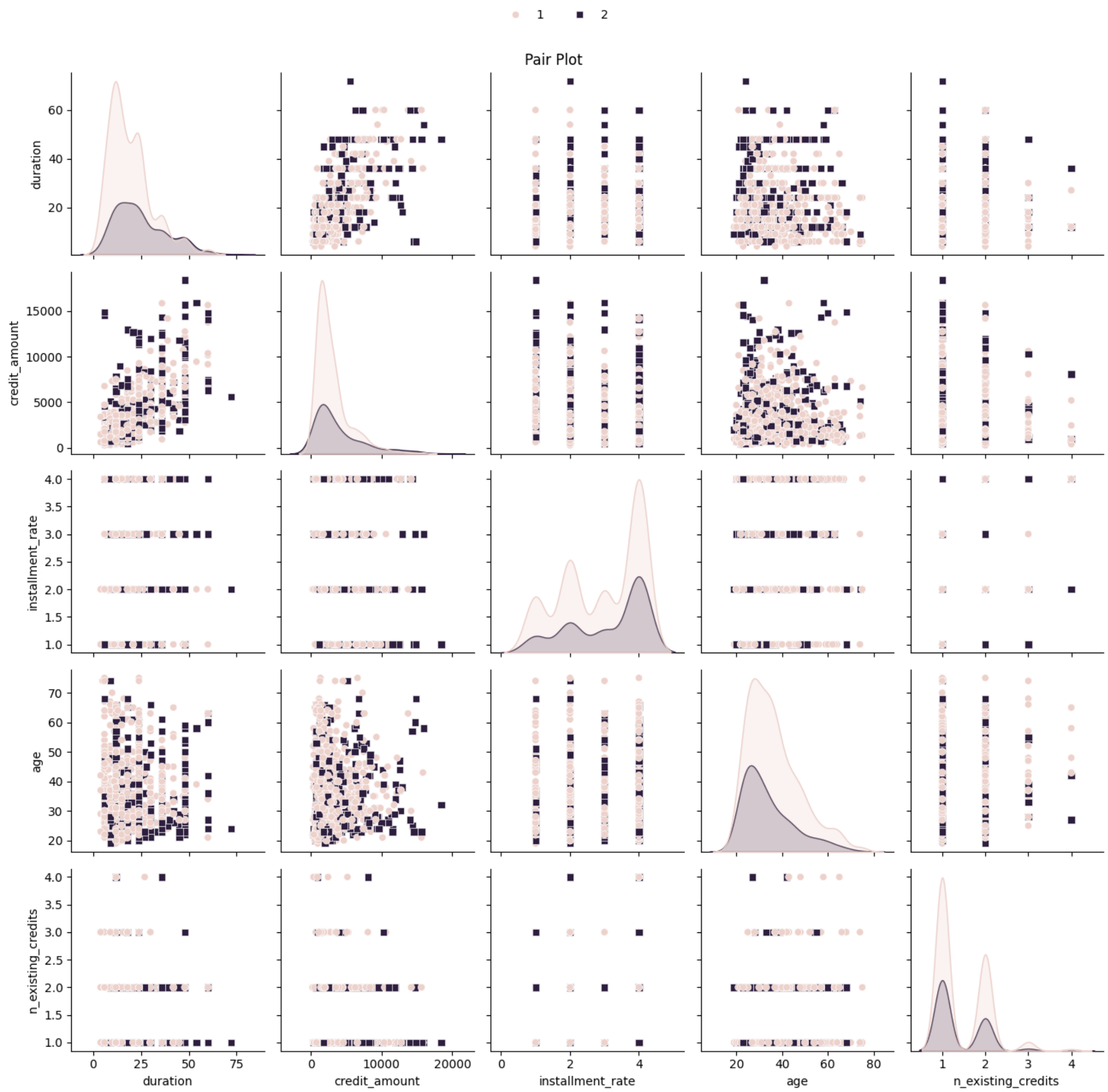
```
(numerical)\r\n              Number of existing credits at this
bank\r\n\r\nAttribute 17: (qualitative)\r\n\t      Job\r\n\t      A171 :
unemployed/ unskilled  - non-resident\r\n\t      A172 : unskilled -
resident\r\n\t      A173 : skilled employee / official\r\n\t      A174 :
management/ self-employed/\r\n\t\t     highly qualified employee/
officer\r\n\r\nAttribute 18: (numerical)\r\n\t      Number of people being
liable to provide maintenance for\r\n\r\nAttribute 19: (qualitative)\r\n\t
Telephone\r\n\t      A191 : none\r\n\t      A192 : yes, registered under the
customers name\r\n\r\nAttribute 20: (qualitative)\r\n\t      foreign
worker\r\n\t      A201 : yes\r\n\t      A202 : no\r\n', 'citation': None}}
           name     role         type     demographic  \
0    Attribute1  Feature  Categorical            None
1    Attribute2  Feature      Integer            None
2    Attribute3  Feature  Categorical            None
3    Attribute4  Feature  Categorical            None
4    Attribute5  Feature      Integer            None
5    Attribute6  Feature  Categorical            None
6    Attribute7  Feature  Categorical           Other
7    Attribute8  Feature      Integer            None
8    Attribute9  Feature  Categorical  Marital Status
9   Attribute10  Feature  Categorical            None
10  Attribute11  Feature      Integer            None
11  Attribute12  Feature  Categorical            None
12  Attribute13  Feature      Integer             Age
13  Attribute14  Feature  Categorical            None
14  Attribute15  Feature  Categorical           Other
15  Attribute16  Feature      Integer            None
16  Attribute17  Feature  Categorical      Occupation
17  Attribute18  Feature      Integer            None
18  Attribute19  Feature       Binary            None
19  Attribute20  Feature       Binary           Other
20        class   Target       Binary            None

                                          description   units missing_values
0                 Status of existing checking account    None             no
1                                            Duration  months             no
2                                      Credit history    None             no
3                                             Purpose    None             no
4                                       Credit amount    None             no
5                               Savings account/bonds    None             no
6                            Present employment since    None             no
7   Installment rate in percentage of disposable i…    None             no
8                             Personal status and sex    None             no
9                          Other debtors / guarantors    None             no
10                            Present residence since    None             no
11                                           Property    None             no
12                                                Age   years             no
13                            Other installment plans    None             no
```

```
14                                              Housing    None              no
15           Number of existing credits at this bank    None              no
16                                                  Job    None              no
17  Number of people being liable to provide maint…    None              no
18                                            Telephone    None              no
19                                       foreign worker    None              no
20                                      1 = Good, 2 = Bad    None              no
```

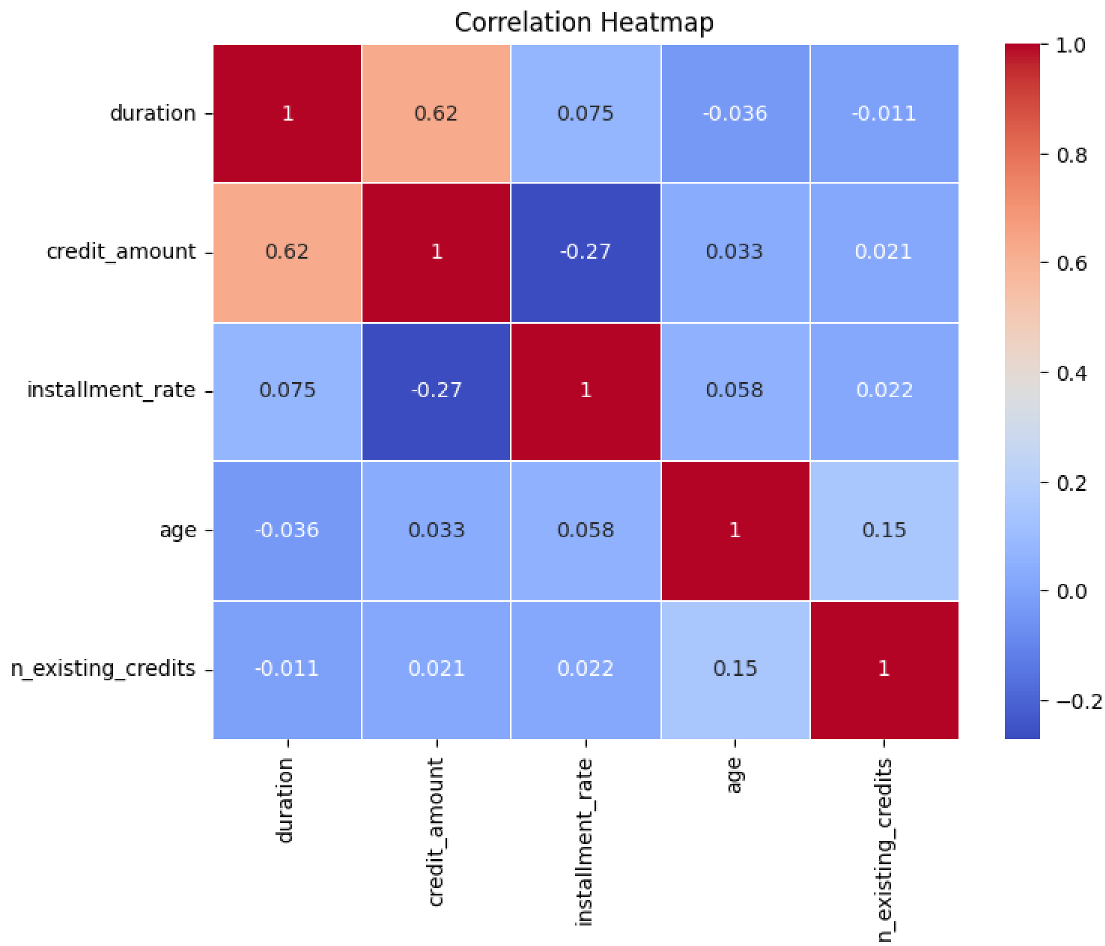
[ ]:
```
#we'll now retrieve only a few numerical attributes, corresponding to numerical␣
↪data where classification can be applied
X = pd.DataFrame(data = {'duration': X_all['Attribute2'], 'credit_amount':␣
↪X_all['Attribute5'], 'installment_rate': X_all['Attribute8'], 'age':␣
↪X_all['Attribute13'], 'n_existing_credits': X_all['Attribute16']})

# create dataset with
df_dataset = pd.DataFrame(X)
df_dataset = df_dataset.join(y)

print(df_dataset)
```

```
     duration  credit_amount  installment_rate  age  n_existing_credits  class
0           6           1169                 4   67                   2      1
1          48           5951                 2   22                   1      2
2          12           2096                 2   49                   1      1
3          42           7882                 2   45                   1      1
4          24           4870                 3   53                   2      2
..        …             …               …   …                 …     …
995        12           1736                 3   31                   1      1
996        30           3857                 4   40                   1      1
997        12            804                 4   38                   1      1
998        45           1845                 4   23                   1      2
999        45           4576                 3   27                   1      1

[1000 rows x 6 columns]
```

[ ]:
```
# Create a pair plot to visualize relationships between different features and␣
↪species.
ax = sns.pairplot(df_dataset, hue='class', markers=["o", "s"])
plt.suptitle("Pair Plot ")
sns.move_legend(
    ax, "lower center",
    bbox_to_anchor=(.5, 1), ncol=5, title=None, frameon=False)
plt.tight_layout()
plt.show()
```



[ ]:
```python
# check correlation heatmap
correlation_matrix = X.corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



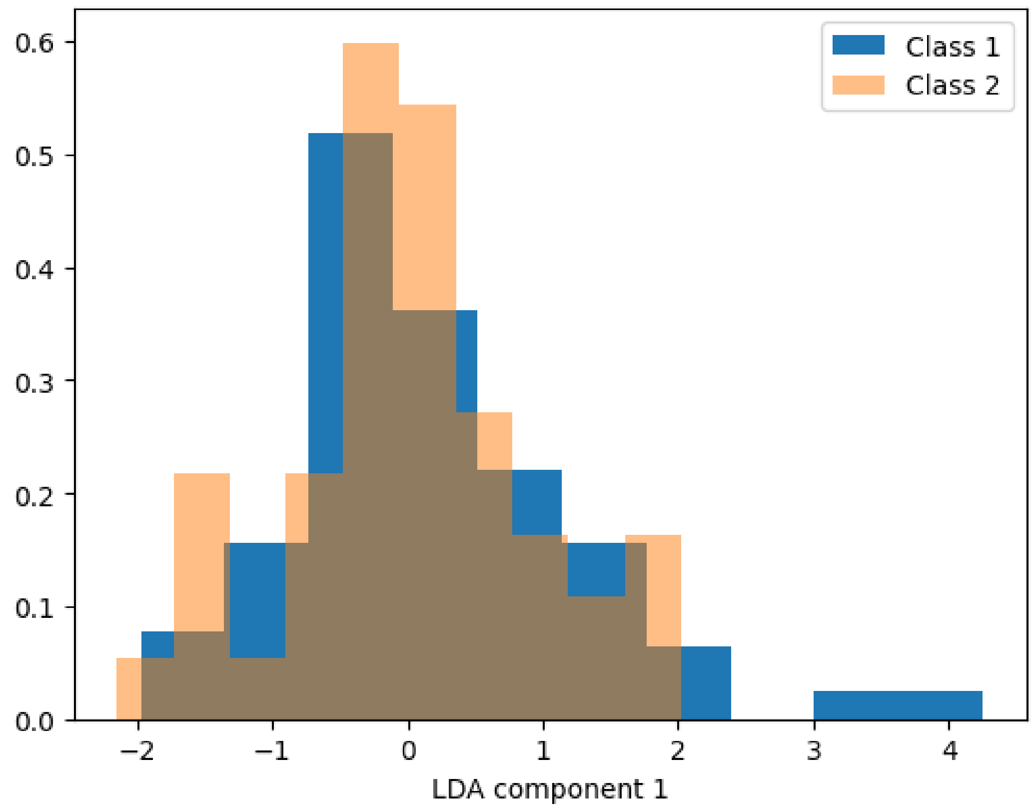
[ ]:
```
#now let's split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[ ]:
```
# apply LDA now
lda = LinearDiscriminantAnalysis()
X_train = lda.fit_transform(X_train, y_train)
X_test = lda.transform(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

[ ]:
```
tmp_Df = pd.DataFrame(X_test, columns=['LDA Component 1'])
tmp_Df['class']=y_train
tmp_Df = tmp_Df.dropna()
```

```
[ ]: df_class1 = tmp_Df.loc[tmp_Df['class'] == 1]
     df_class2 = tmp_Df.loc[tmp_Df['class'] == 2]

     plt.figure()
     plt.hist(df_class1['LDA Component 1'], label='Class 1', density=True)
     plt.hist(df_class2['LDA Component 1'], alpha = 0.5, label = 'Class 2',␣
      ↪density=True)
     plt.legend()
     plt.xlabel('LDA component 1')
     plt.show()
     plt.close()
```



From the previous example, it was observed that using one LDA component (requirement when applying the LinearDiscriminantAnalysis function, since there are two target classes only one LDA component can be used) cannot retrieve differences in the dataset. Let's try now to the the LDA components by resolving an eigenproblem:

```
[ ]: mean_vectors = []
     for cl in [1,2]:
         mean_vectors.append(np.mean(X[y.values==cl].values, axis=0))
         print('Mean Vector class %s: %s\n' %(cl, mean_vectors[cl-1]))
```

```
Mean Vector class 1: [1.92071429e+01 2.98545714e+03 2.92000000e+00
3.62242857e+01
 1.42428571e+00]

Mean Vector class 2: [2.48600000e+01 3.93812667e+03 3.09666667e+00
3.39633333e+01
 1.36666667e+00]
```

[ ]:
```
S_W = np.zeros((5,5))
for cl,mv in zip([1,2], mean_vectors):
    class_sc_mat = np.zeros((5,5))                  # scatter matrix for every␣
 ↪class
    for row in X[y.values == cl].values:
        row, mv = row.reshape(5,1), mv.reshape(5,1) # make column vectors
        class_sc_mat += (row-mv).dot((row-mv).T)
    S_W += class_sc_mat                             # sum class scatter matrices
print('within-class Scatter Matrix:\n', S_W)
```

```
within-class Scatter Matrix:
 [[ 1.38559084e+05  2.01215620e+07  7.97660000e+02 -2.26806143e+03
  -1.01214286e+01]
 [ 2.01215620e+07  7.76928399e+09 -8.91258073e+05  1.50179962e+06
   4.54002952e+04]
 [ 7.97660000e+02 -8.91258073e+05  1.24371667e+03  8.24623333e+02
   1.61266667e+01]
 [-2.26806143e+03  1.50179962e+06  8.24623333e+02  1.28198384e+05
   9.52420476e+02]
 [-1.01214286e+01  4.54002952e+04  1.61266667e+01  9.52420476e+02
   3.32653810e+02]]
```

[ ]:
```
overall_mean = np.mean(X.values, axis=0)

S_B = np.zeros((5,5))
for i,mean_vec in enumerate(mean_vectors):
    n = X[y.values==i+1].values.shape[0]
    mean_vec = mean_vec.reshape(5,1) # make column vector
    overall_mean = overall_mean.reshape(5,1) # make column vector
    S_B += n * (mean_vec - overall_mean).dot((mean_vec - overall_mean).T)

print('between-class Scatter Matrix:\n', S_B)
```

```
between-class Scatter Matrix:
 [[ 6.71050671e+03  1.13091399e+06  2.09721000e+02 -2.68397657e+03
  -6.83995714e+01]
 [ 1.13091399e+06  1.90591637e+08  3.53440393e+04 -4.52327490e+05
  -1.15273012e+04]
 [ 2.09721000e+02  3.53440393e+04  6.55433333e+00 -8.38813333e+01
```

```
 -2.13766667e+00]
[-2.68397657e+03 -4.52327490e+05 -8.38813333e+01  1.07350019e+03
  2.73575238e+01]
[-6.83995714e+01 -1.15273012e+04 -2.13766667e+00  2.73575238e+01
  6.97190476e-01]]
```

[ ]:
```python
eig_vals, eig_vecs = np.linalg.eig(np.linalg.inv(S_W).dot(S_B))

for i in range(len(eig_vals)):
    eigvec_sc = eig_vecs[:,i].reshape(5,1)
    print('\nEigenvector {}: \n{}'.format(i+1, eigvec_sc.real))
    print('Eigenvalue {:}: {:.2e}'.format(i+1, eig_vals[i].real))
```

```
Eigenvector 1:
[[ 1.18826489e-01]
 [ 3.14005978e-04]
 [ 7.99780807e-01]
 [-7.60125459e-02]
 [-5.83483437e-01]]
Eigenvalue 1: 6.63e-02

Eigenvector 2:
[[-1.14324977e-01]
 [ 3.14173074e-04]
 [ 8.00206403e-01]
 [-7.60529953e-02]
 [-5.83793932e-01]]
Eigenvalue 2: 0.00e+00

Eigenvector 3:
[[ 1.14620018e-01]
 [-3.92357189e-04]
 [-4.46101180e-01]
 [ 6.38322522e-02]
 [ 8.85314226e-01]]
Eigenvalue 3: -1.61e-18

Eigenvector 4:
[[-1.14286197e-01]
 [ 3.14098328e-04]
 [ 7.99392008e-01]
 [-7.60224680e-02]
 [-5.84920138e-01]]
Eigenvalue 4: -1.46e-21

Eigenvector 5:
[[-1.12142418e-01]
```

```
 [ 3.91315663e-04]
 [ 4.40141242e-01]
 [-5.84488938e-02]
 [-8.88978818e-01]]
Eigenvalue 5: -1.83e-18
```

```
[ ]: # Make a list of (eigenvalue, eigenvector) tuples
eig_pairs = [(np.abs(eig_vals[i]), eig_vecs[:,i]) for i in range(len(eig_vals))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eig_pairs = sorted(eig_pairs, key=lambda k: k[0], reverse=True)

# Visually confirm that the list is correctly sorted by decreasing eigenvalues

print('Eigenvalues in decreasing order:\n')
for i in eig_pairs:
    print(i[0])
```

```
Eigenvalues in decreasing order:

0.06628051101093899
1.8280693869518575e-18
1.6060487550572407e-18
1.4633063233143985e-21
0.0
```

```
[ ]: print('Variance explained:\n')
eigv_sum = sum(eig_vals)
for i,j in enumerate(eig_pairs):
    print('eigenvalue {0:}: {1:.2%}'.format(i+1, (j[0]/eigv_sum).real))
```

```
Variance explained:

eigenvalue 1: 100.00%
eigenvalue 2: 0.00%
eigenvalue 3: 0.00%
eigenvalue 4: 0.00%
eigenvalue 5: 0.00%
```

The previous value shows that 100 % of the variance is captured by one LDA component (by one eigenvalue). Therefore, no more eigenvalues are needed. This might explain why the previous application (prior to the eigenproblem) converged to using only one LDA component. Despite this results, let's proceed to check the resulting transformations in the space-state of two LDA components

```
[ ]: W = np.hstack((eig_pairs[0][1].reshape(5,1), eig_pairs[1][1].reshape(5,1)))
print('Matrix W:\n', W.real)
```

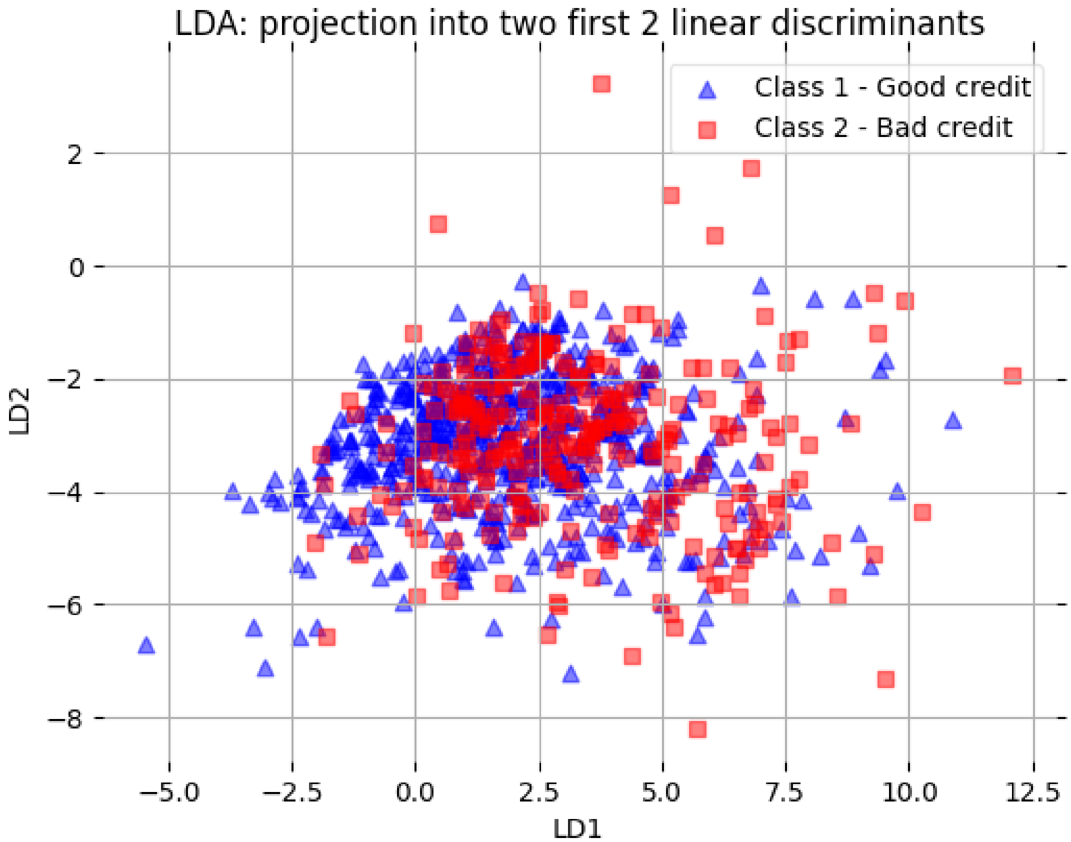
```
Matrix W:
```

```
[[ 1.18826489e-01 -1.12142418e-01]
 [ 3.14005978e-04  3.91315663e-04]
 [ 7.99780807e-01  4.40141242e-01]
 [-7.60125459e-02 -5.84488938e-02]
 [-5.83483437e-01 -8.88978818e-01]]
```

[ ]:
```
X_lda = X.dot(W)
```

[ ]:
```
from matplotlib import pyplot as plt

label_dict = {1: 'Class 1 - Good credit', 2: 'Class 2 - Bad credit'}

def plot_step_lda():

    ax = plt.subplot(111)
    for label,marker,color in zip(
        range(1,3),('^', 's'),('blue', 'red')):

        plt.scatter(x= X_lda.values[:,0][ (np.transpose(y.values == label))[0]],
                y= X_lda.values[:,1][ (np.transpose(y.values == label))[0]],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label]
                )

    plt.xlabel('LD1')
    plt.ylabel('LD2')

    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title('LDA: projection into two first 2 linear discriminants')

    # hide axis ticks
    plt.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")

    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)

    plt.grid()
    plt.tight_layout
    plt.show()
```

```
plot_step_lda()
```



As observed in the previous graph, using two LDA components does not improve the classification, since 0 % of the variance is captured by LD2 (as demonstrated previously). Also, the distribution along LD1 shows no clear pattern for classifying both classes. In conclusion, this dataset might not be a good candidate problem to apply LDA, and other classification algorithms should be tested instead.

Category 6: Support Vector Machines

```
[ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
import seaborn as sns
```

[ ]:
```python
iris = datasets.load_iris()
X = iris.data
y = iris.target

df = pd.DataFrame(data=np.c_[X, y], columns=iris.feature_names + ['target'])

df.head()
```

[ ]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

   target
0     0.0
1     0.0
2     0.0
3     0.0
4     0.0
```

[ ]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42, stratify=y)

#Standardize
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[ ]:
```python
svm_model = SVC(kernel='linear', C=1.0, random_state=42)
svm_model.fit(X_train, y_train)
y_pred = svm_model.predict(X_test)

y_pred
```

[ ]:
```
array([2, 1, 1, 1, 2, 2, 1, 1, 0, 2, 0, 0, 2, 2, 0, 2, 1, 0, 0, 0, 1, 0,
       1, 2, 2, 1, 1, 1, 1, 0, 1, 2, 1, 0, 2, 0, 0, 0, 0, 2, 1, 0, 1, 2,
       1])
```

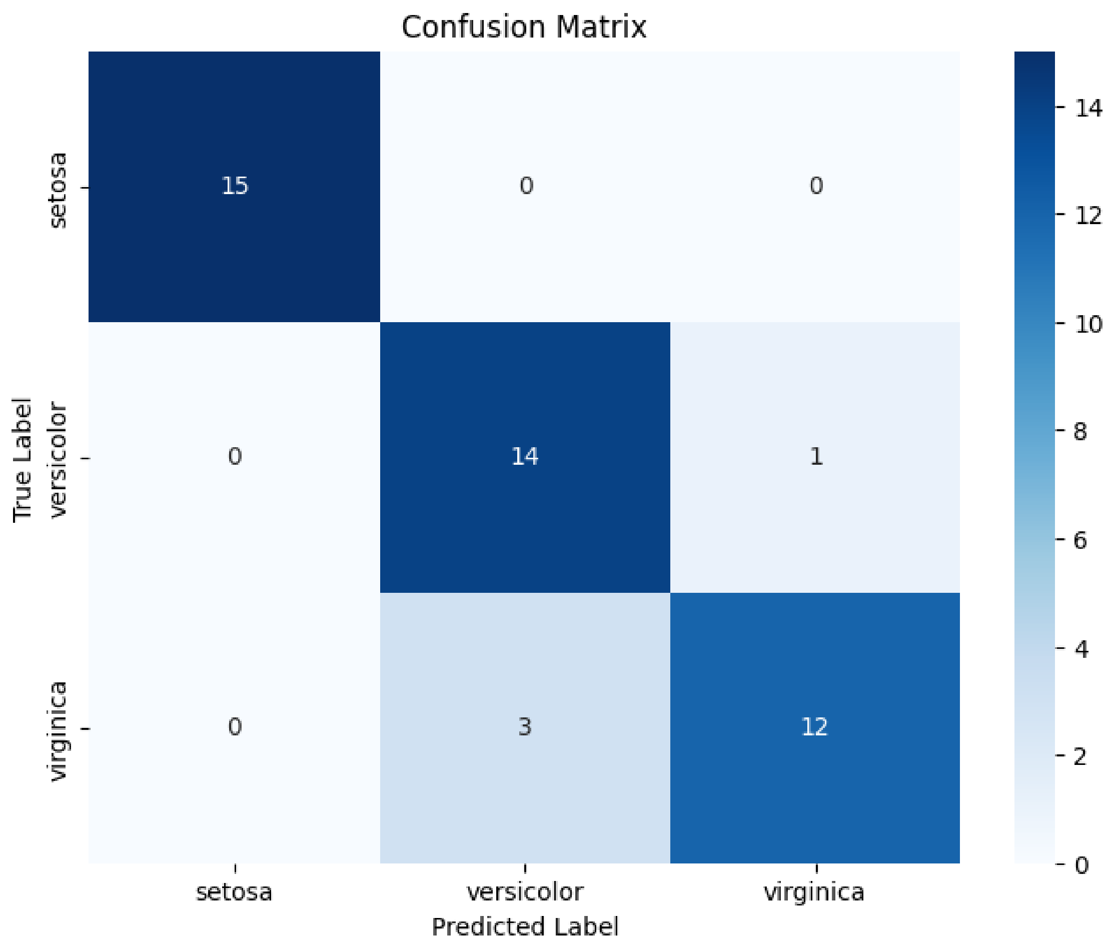
[ ]:
```python
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
```

[ ]:
```python
print(f"Accuracy of the SVM model: {accuracy * 100:.2f}%")
print("\nConfusion Matrix:")
print(conf_matrix)
```

```
print("\nClassification Report:")
print(class_report)
```

```
Accuracy of the SVM model: 91.11%

Confusion Matrix:
[[15  0  0]
 [ 0 14  1]
 [ 0  3 12]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       0.82      0.93      0.87        15
           2       0.92      0.80      0.86        15

    accuracy                           0.91        45
   macro avg       0.92      0.91      0.91        45
weighted avg       0.92      0.91      0.91        45
```

[ ]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=iris.
 ↪target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



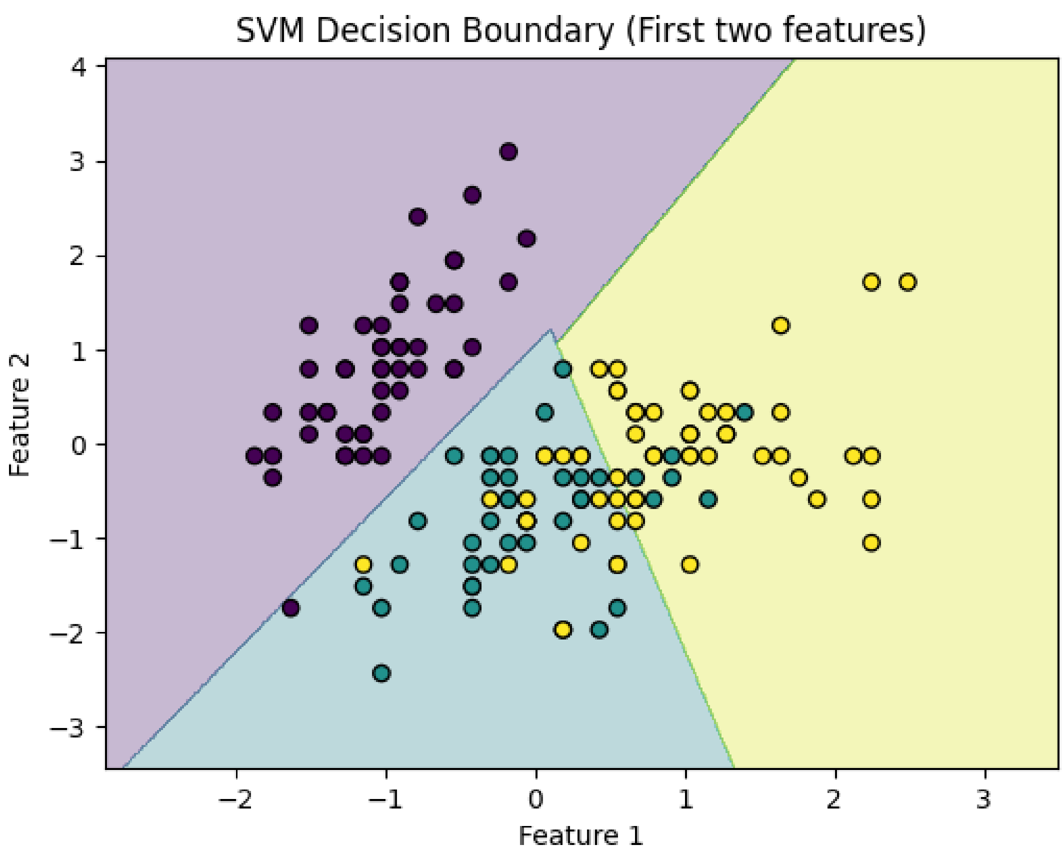
[ ]:
```python
def plot_decision_boundary(X, y, model, title):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))

    Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    #Ploting the decision boundary
    plt.contourf(xx, yy, Z, alpha=0.3)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k', marker='o')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.title(title)
    plt.show()
```

[ ]:
```
X_vis = df.iloc[:, [0, 1]].values
y_vis = df.iloc[:, -1].values

X_vis = scaler.fit_transform(X_vis)
```

[ ]:
```
svm_model_vis = SVC(kernel='linear', C=1.0, random_state=42)
svm_model_vis.fit(X_vis, y_vis)
```

[ ]:
```
SVC(kernel='linear', random_state=42)
```

[ ]:
```
plot_decision_boundary(X_vis, y_vis, svm_model_vis, 'SVM Decision Boundary␣
↪(First two features)')
```



Category 7: Neural Networks

[ ]:
```
### Obtain data from Fred
fred_api_key = "abcdefghijklmnopqrstuvwxyz123456"

def get_fred_data(param_list, start_date, end_date):
    df = pdr.DataReader(param_list, "fred", start_date, end_date)
```

```
    return df.reset_index()

### Independent variables series
series = ["CES0500000003", "MANEMP", "PCUOMFGOMFG", "DGORDER", "FEDFUNDS"]
# get data for series
df = get_fred_data(param_list=series, start_date="2010-01-01",␣
 ↪end_date="2023-12-31")
df.set_index("DATE", drop=True, inplace=True)
print(df.shape)
df.tail(5)
```

```
(168, 5)
```

[ ]:

```
            CES0500000003  MANEMP  PCUOMFGOMFG   DGORDER  FEDFUNDS
DATE
2023-08-01          33.91   12941      251.093  285317.0      5.33
2023-09-01          34.01   12954      252.368  290883.0      5.33
2023-10-01          34.10   12923      249.119  279021.0      5.33
2023-11-01          34.23   12948      246.497  300639.0      5.33
2023-12-01          34.34   12960      243.266  287397.0      5.33
```

[ ]:

```
### Obtain the dependent variable

data = yf.download(tickers="^GSPC", start="2010-01-01", end="2023-12-31",␣
 ↪interval="1mo")
print(data.shape)
data.tail(5)

# Make time zones non-timezone aware so as to allow the join
df.index = df.index.tz_localize(None)
data.index = data.index.tz_localize(None)

# Merge two dataset into one, and remove non-valid data from the dataset
# Fortunately, all data are vaild for this case to test
df2predict = pd.merge(df, data["Adj Close"], left_index=True, right_index=True)
df2predict.isnull().sum()
df2predict = df2predict.dropna()
```

```
[*********************100%%**********************]  1 of 1 completed

(168, 6)
```

[ ]:

```
# scale features based on the data
# This section adjusts all data
scaler = MinMaxScaler()
scale_model = scaler.fit(df2predict[series])
```

```python
df2predict[series] = scale_model.transform(df2predict[series])

# % change for just the target column
df2predict["Adj Close"] = df2predict["Adj Close"].pct_change()

# Drop any missing values
df2predict.dropna(inplace=True)

# Glimpse of data
df2predict.head()
```

[ ]:

```
            CES0500000003    MANEMP  PCUOMFGOMFG   DGORDER  FEDFUNDS  \
DATE
2010-02-01       0.003353  0.022064     0.000000  0.139035  0.015152
2010-03-01       0.004191  0.022064     0.018843  0.151198  0.020833
2010-04-01       0.006706  0.045425     0.033253  0.156929  0.028409
2010-05-01       0.010059  0.068787     0.043229  0.206959  0.028409
2010-06-01       0.010059  0.081765     0.028819  0.176407  0.024621

            Adj Close
DATE
2010-02-01   0.028514
2010-03-01   0.058796
2010-04-01   0.014759
2010-05-01  -0.081976
2010-06-01  -0.053882
```

[ ]:

```python
X = df2predict[series].values
y = df2predict["Adj Close"].values

test_sz = 0.3
train_sz = int((1 - test_sz) * len(X))
X_train = X[:train_sz]
y_train = y[:train_sz]
X_test = X[train_sz:]
y_test = y[train_sz:]
len(X_train), len(X_test)
```

[ ]: (116, 51)

[ ]:

```python
# Build the model based on Tensorflow protocol

tf.random.set_seed(46)  # first we set random seed
# The output layer for this case
model = tf.keras.Sequential([tf.keras.layers.Dense(1)])

# We compile the model specifying loss, and optimizer.
```

```python
model.compile(
    loss=tf.keras.losses.mae,  # Lost function is MAE, mean absolute error␣
 ↪(MAE).
    optimizer=tf.keras.optimizers.SGD(
        learning_rate=0.01, momentum=0.9
    ),
    metrics=["mae"],
)  # performance metric is MAE

model.fit(X_train, y_train, epochs=25, batch_size=10)  # epoch and batch size␣
 ↪specified
```

```
Epoch 1/25
12/12 [==============================] - 0s 3ms/step - loss: 0.3276 - mae:
0.3276
Epoch 2/25
12/12 [==============================] - 0s 2ms/step - loss: 0.1632 - mae:
0.1632
Epoch 3/25
12/12 [==============================] - 0s 2ms/step - loss: 0.1315 - mae:
0.1315
Epoch 4/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0877 - mae:
0.0877
Epoch 5/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0715 - mae:
0.0715
Epoch 6/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0697 - mae:
0.0697
Epoch 7/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0595 - mae:
0.0595
Epoch 8/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0572 - mae:
0.0572
Epoch 9/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0502 - mae:
0.0502
Epoch 10/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0507 - mae:
0.0507
Epoch 11/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0457 - mae:
0.0457
Epoch 12/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0437 - mae:
```

```
0.0437
Epoch 13/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0394 - mae:
0.0394
Epoch 14/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0400 - mae:
0.0400
Epoch 15/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0453 - mae:
0.0453
Epoch 16/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0455 - mae:
0.0455
Epoch 17/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0465 - mae:
0.0465
Epoch 18/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0354 - mae:
0.0354
Epoch 19/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0338 - mae:
0.0338
Epoch 20/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0369 - mae:
0.0369
Epoch 21/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0366 - mae:
0.0366
Epoch 22/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0374 - mae:
0.0374
Epoch 23/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0321 - mae:
0.0321
Epoch 24/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0300 - mae:
0.0300
Epoch 25/25
12/12 [==============================] - 0s 2ms/step - loss: 0.0315 - mae:
0.0315
```

[ ]:
```
<keras.src.callbacks.History at 0x7f48cc59f1c0>
```

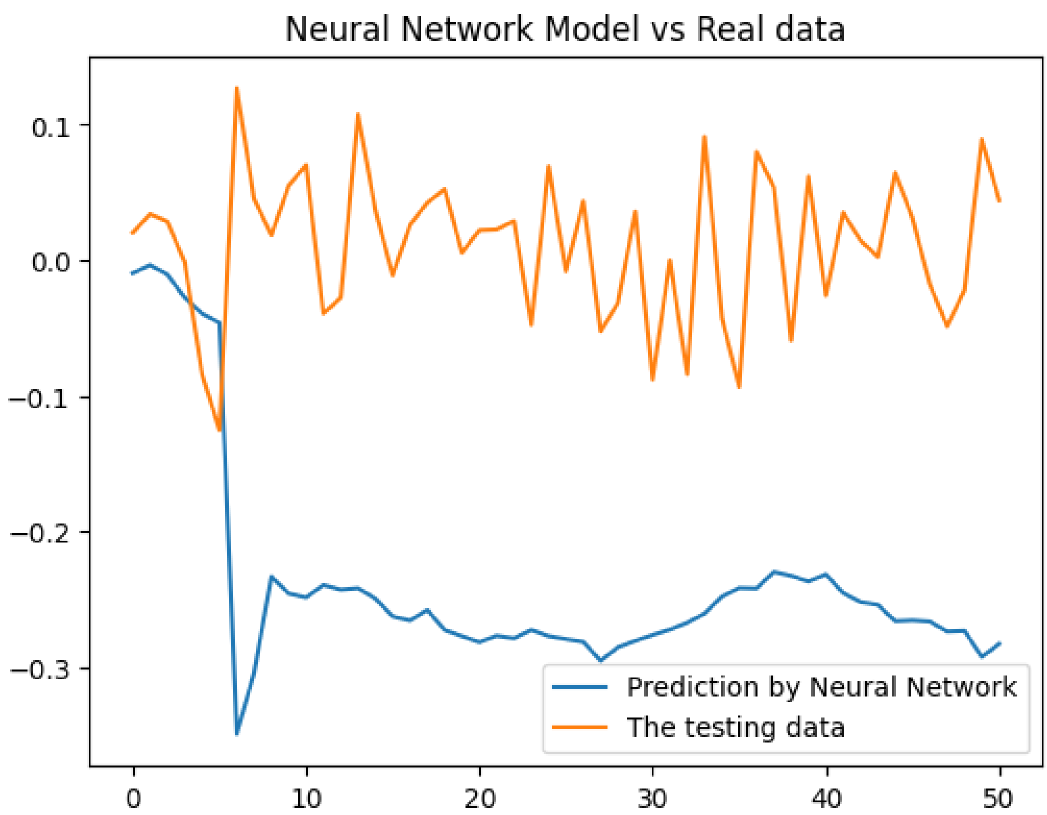
[ ]:
```
# performance
preds = model.predict(X_test)
mae = tf.metrics.mean_absolute_error(y_true=y_test, y_pred=preds.squeeze()).
  ↪numpy()
```

```
mse = tf.metrics.mean_squared_error(y_true=y_test, y_pred=preds.squeeze()).
  ↪numpy()
mae, mse
```

```
2/2 [==============================] - 0s 5ms/step
```

[ ]: (0.25171795, 0.07245903)

[ ]:
```
plt.plot(preds,label="Prediction by Neural Network")
plt.plot(y_test, label="The testing data")
plt.legend()
plt.title('Neural Network Model vs Real data')
plt.show()
```



2 STEP 4

Category 5: Linear Discriminant Analysis (LDA)

[ ]:
```
import numpy as np
import pandas as pd
```

```python
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, accuracy_score
from mlxtend.plotting import plot_decision_regions
```

[ ]:
```python
iris = sns.load_dataset('iris')
X = iris.drop('species', axis=1).values
y = iris['species'].map({'setosa': 0, 'versicolor': 1, 'virginica': 2}).values
```

[ ]:
```python
#Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)

#LDA model
lda = LinearDiscriminantAnalysis()

param_grid = {
    'solver': ['svd', 'lsqr', 'eigen'],
    'shrinkage': [None, 'auto', 0.1, 0.5]
}
```

[ ]:
```python
#grid search with cross-validation
grid_search = GridSearchCV(lda, param_grid, cv=5)
grid_search.fit(X_train, y_train)

#best model and its parameters
best_lda = grid_search.best_estimator_
best_params = grid_search.best_params_
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py:378: FitFailedWarning:
15 fits failed out of a total of 60.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py", line 686, in _fit_and_score
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/discriminant_analysis.py", line 615, in fit
```

```
NotImplementedError: shrinkage not supported with 'svd' solver.

  # scoring?
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:952:
UserWarning: One or more of the test scores are non-finite: [0.98095238
0.98095238 0.98095238        nan 0.95238095 0.95238095
        nan 0.98095238 0.98095238        nan 0.96190476 0.96190476]
  _insert_error_scores(out, self.error_score)
```

[ ]:
```python
print("Best Hyperparameters:", grid_search.best_params_)
```

```
Best Hyperparameters: {'shrinkage': None, 'solver': 'svd'}
```

[ ]:
```python
#Training
best_lda.fit(X_train, y_train)

#Evaluation
y_pred = best_lda.predict(X_test)
```

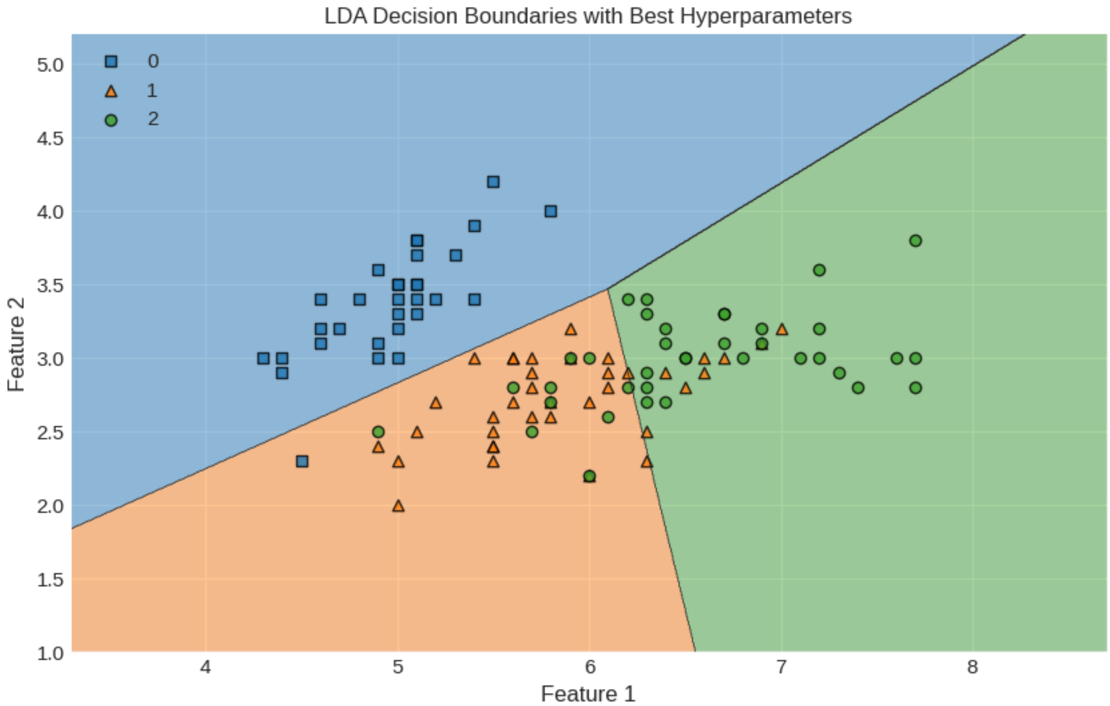
[ ]:
```python
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        13
           2       1.00      1.00      1.00        13

    accuracy                           1.00        45
   macro avg       1.00      1.00      1.00        45
weighted avg       1.00      1.00      1.00        45

Accuracy Score: 1.0
```

[ ]:
```python
def plot_decision_boundaries(X, y, model, title):
    plt.figure(figsize=(10, 6))

    plot_decision_regions(X, y, clf=model, legend=2)

    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.title(title)
    plt.show()
```

[ ]:
```python
X_train_2d = X_train[:, :2]
best_lda_2d = LinearDiscriminantAnalysis(**grid_search.best_params_)
best_lda_2d.fit(X_train_2d, y_train)
```

```
plot_decision_boundaries(X_train_2d, y_train, best_lda_2d, "LDA Decision␣
↪Boundaries with Best Hyperparameters")
```



Category 6: Support Vector Machines (SVM)

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score
import matplotlib.pyplot as plt
from mlxtend.plotting import plot_decision_regions
```

[ ]:
```
iris = sns.load_dataset('iris')
X = iris.drop('species', axis=1).values
y = iris['species'].map({'setosa': 0, 'versicolor': 1, 'virginica': 2}).values

y_binary = np.where(y == 1, 1, 0)  # 1 for 'versicolor', 0 for 'setosa' and␣
↪'virginica'

X_train, X_test, y_train, y_test = train_test_split(X, y_binary, test_size=0.3,␣
↪random_state=42)
```

[ ]:
```
#tune hyperparameters manually
best_score = 0
best_params = {}

for C in [0.1, 1, 10]:
    for gamma in [0.1, 1]:
        for kernel in ['rbf', 'linear']:
            svm = SVC(C=C, gamma=gamma, kernel=kernel)
            svm.fit(X_train, y_train)
            y_pred = svm.predict(X_test)
            score = accuracy_score(y_test, y_pred)
            if score > best_score:
                best_score = score
                best_params = {'C': C, 'gamma': gamma, 'kernel': kernel}

print("Best Hyperparameters:", best_params)
print("Best Accuracy:", best_score)
```

```
Best Hyperparameters: {'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}
Best Accuracy: 1.0
```

[ ]:
```
#training
best_svm = SVC(**best_params)
best_svm.fit(X_train, y_train)
```

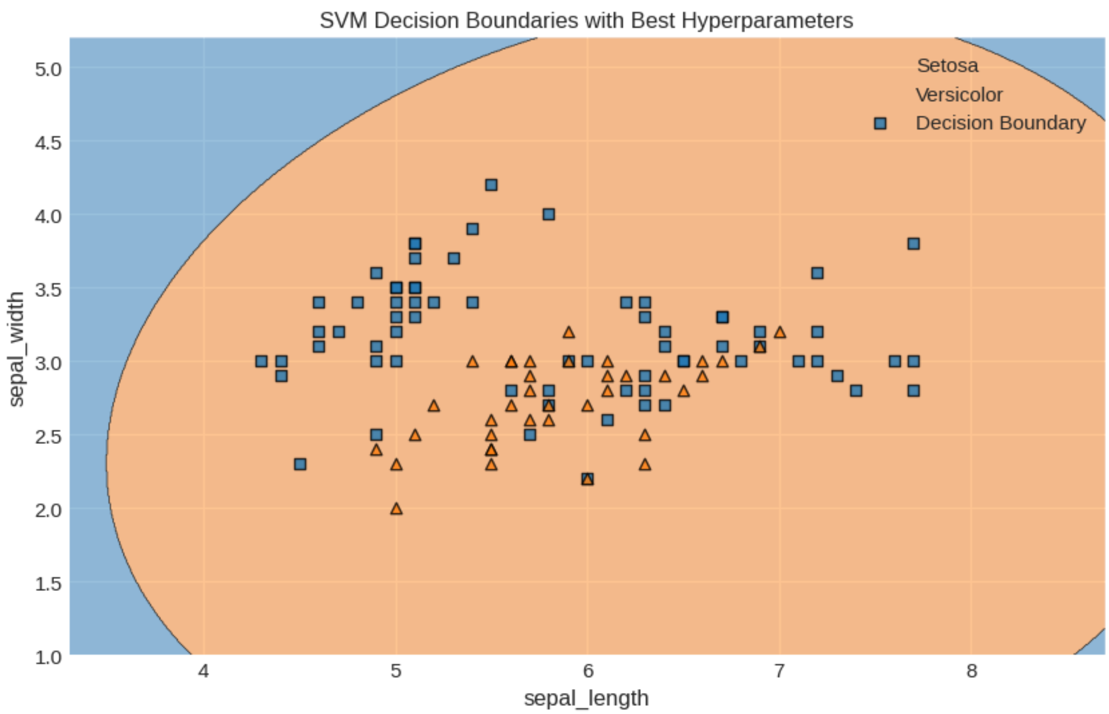
[ ]:
```
SVC(C=1, gamma=0.1)
```

[ ]:
```
# Evaluation
y_pred = best_svm.predict(X_test)
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        32
           1       1.00      1.00      1.00        13

    accuracy                           1.00        45
   macro avg       1.00      1.00      1.00        45
weighted avg       1.00      1.00      1.00        45

Accuracy Score: 1.0
```

[ ]:
```
plt.figure(figsize=(10, 6))

plot_decision_regions(X_train, y_train, clf=best_svm, legend=2,
```

```
                        filler_feature_values={2: X[:, 2].mean(), 3: X[:, 3].
 ↪mean()},
                        filler_feature_ranges={2: X[:, 2].std() * 2, 3: X[:, 3].
 ↪std() * 2})

plt.xlabel(iris.columns[0])
plt.ylabel(iris.columns[1])
plt.title('SVM Decision Boundaries with Best Hyperparameters')
plt.legend(['Setosa', 'Versicolor', 'Decision Boundary'])
plt.show()
```



Category 7: Neural Networks

```
[ ]: import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D,␣
 ↪MaxPooling2D
from tensorflow.keras.utils import to_categorical
from scikeras.wrappers import KerasClassifier
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
```

[ ]:
```
#dataset
(X_train, y_train), (X_test, y_test) = mnist.load_data()

#preprocess
X_train = X_train.reshape(X_train.shape[0], 28, 28, 1).astype('float32') / 255
X_test = X_test.reshape(X_test.shape[0], 28, 28, 1).astype('float32') / 255
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

[ ]:
```
#Defining the function to create the neural network model
def create_model(learning_rate=0.01, dropout_rate=0.0):
    model = Sequential([
        Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28,␣
 ↪1)),
        MaxPooling2D(pool_size=(2, 2)),
        Dropout(dropout_rate),
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(dropout_rate),
        Dense(10, activation='softmax')
    ])

    optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)
    model.compile(loss='categorical_crossentropy', optimizer=optimizer,␣
 ↪metrics=['accuracy'])
    return model
```

[ ]:
```
model = KerasClassifier(model=create_model, verbose=0)
```

[ ]:
```
param_grid = {
    'model__learning_rate': [0.001, 0.01],
    'model__dropout_rate': [0.0, 0.2],
    'batch_size': [32, 64],
    'epochs': [5, 10]
}
```

[ ]:
```
skip_grid_search = True

if not skip_grid_search:
    # Perform Grid Search with Cross-Validation
    grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=3,␣
 ↪verbose=2, n_jobs=-1)
    grid_result = grid.fit(X_train, y_train)

    # Print the best hyperparameters
    print("Best Hyperparameters:", grid_result.best_params_)
```

```python
    # Use the best hyperparameters
    best_params = grid_result.best_params_
else:
    # Default parameters for quick demonstration
    best_params = {
        'model__learning_rate': 0.01,
        'model__dropout_rate': 0.2,
        'batch_size': 32,
        'epochs': 5
    }
```

[ ]:
```python
best_model = create_model(learning_rate=best_params['model__learning_rate'],␣
 ↪dropout_rate=best_params['model__dropout_rate'])
history = best_model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
 ↪epochs=best_params['epochs'], batch_size=best_params['batch_size'],␣
 ↪verbose=2)
```

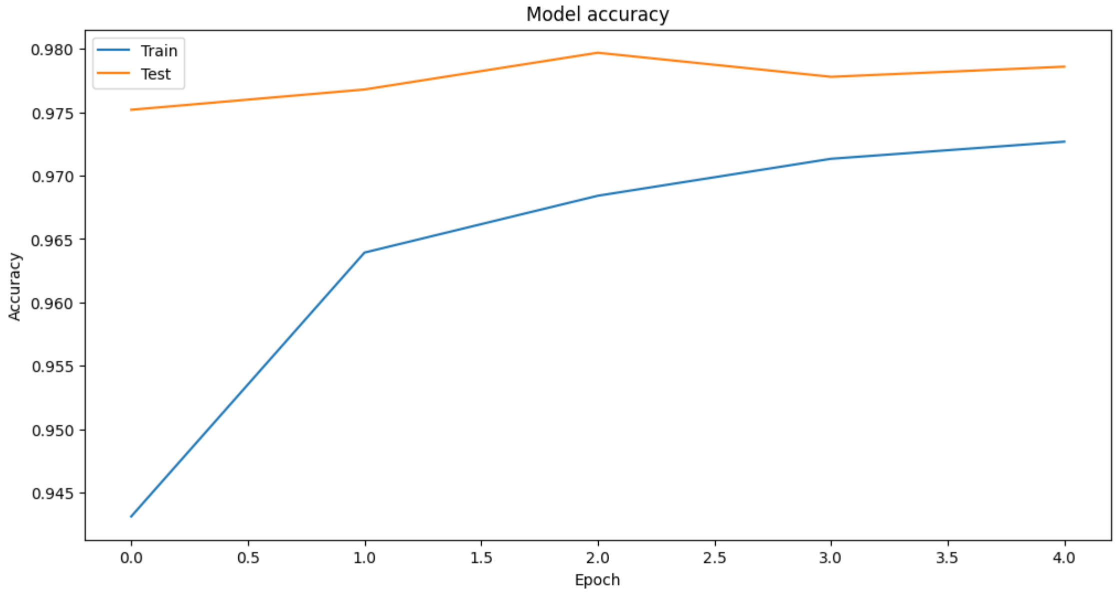
```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Epoch 1/5
1875/1875 - 49s - 26ms/step - accuracy: 0.9431 - loss: 0.1907 - val_accuracy:
0.9752 - val_loss: 0.0788
Epoch 2/5
1875/1875 - 96s - 51ms/step - accuracy: 0.9639 - loss: 0.1244 - val_accuracy:
0.9768 - val_loss: 0.0809
Epoch 3/5
1875/1875 - 64s - 34ms/step - accuracy: 0.9684 - loss: 0.1130 - val_accuracy:
0.9797 - val_loss: 0.0728
Epoch 4/5
1875/1875 - 41s - 22ms/step - accuracy: 0.9713 - loss: 0.1026 - val_accuracy:
0.9778 - val_loss: 0.0875
Epoch 5/5
1875/1875 - 37s - 20ms/step - accuracy: 0.9727 - loss: 0.1029 - val_accuracy:
0.9786 - val_loss: 0.0846
```

[ ]:
```python
scores = best_model.evaluate(X_test, y_test, verbose=0)
print(f"Test Accuracy: {scores[1]*100:.2f}%")
```

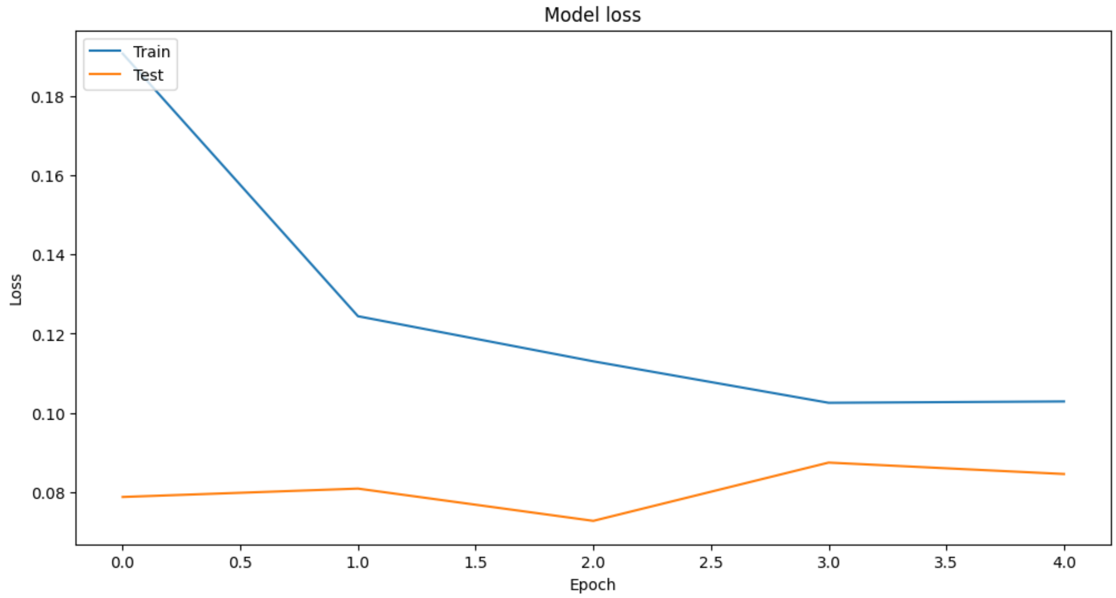
```
Test Accuracy: 97.86%
```

[ ]:
```python
plt.figure(figsize=(12, 6))
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
```

```
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



[ ]:
```
plt.figure(figsize=(12, 6))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```


Model loss
Train
Test
0.18
0.16
0.14
0.12
0.10
0.08
Loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch