Srinidhi-HW4

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3 CSE 276C - Homework 4

4 Problem 1:

Solution:

Principal Component Analysis - Training and test images are read from Train_subset and Test_subset csv files respectively and stored in numpy arrays - PCA is performed on the training images and componets are plotted to calculate the optimal number of components and for the given dataset **90** components are selected for best accuracy - PCA transform is applied on the training images and support vector machine classifier is used for image classification - Accuracy obtained: **71.44%** - First and second Eigen images are plotted below. - For better understanding, PCA with 2 components is calculated and reduced components are plotted below

Linear Discriminant Analysis - LDA is performed on the images that which have been passed through PCA pipeline with 90 components - Output of LDA has 42 components which results in highest accuracy - Accuracy obtained: **80.62%** - LDA is calculated with 2 compnents for plotting eigen vectors - LDA plot is as shown below

Performance improvement - Increased training images could be used for achieving better accuracy - Sophisticated classifiers such as Convolutional Neural Network, Random forest regression, K-Nearest Neighbors could be used to improve classification accuracy

Note: Confusion matrix for PCA is added for better understanding.

[1]:
```
from time import time
import numpy as np
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
import matplotlib.pyplot as plt
from PIL import Image
import csv
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.metrics import plot_confusion_matrix
```

```python
import math
import seaborn as sn
```

[2]:
```python
train_file = 'KaggleDataset/Train_subset.csv'
test_file = 'KaggleDataset/Test_subset.csv'
train_image = []
train_label = []
test_images = []
test_label = []

#Read the images
with open(train_file, 'r') as csvfile:
    datareader = csv.reader(csvfile)
    next(datareader, None)
    for row in datareader:
        im = Image.open(row[8])
        im = im.resize((32, 32))
        train_image.append(np.array(im).flatten())
        train_label.append(row[7])

with open(test_file, 'r') as testFile:
    r = csv.reader(testFile)
    next(r, None)
    for row in r:
        im = Image.open(row[8])
        im = im.resize((32, 32))
        test_images.append(np.array(im).flatten())
        test_label.append(row[7])

train_image = np.array(train_image).astype(float)
train_label = np.array(train_label).astype(int)
test_images = np.array(test_images).astype(float)
test_label = np.array(test_label).astype(int)
```

[3]:
```python
print(train_image.shape)
print(train_label.shape)
print(test_images.shape)
print(test_label.shape)
```

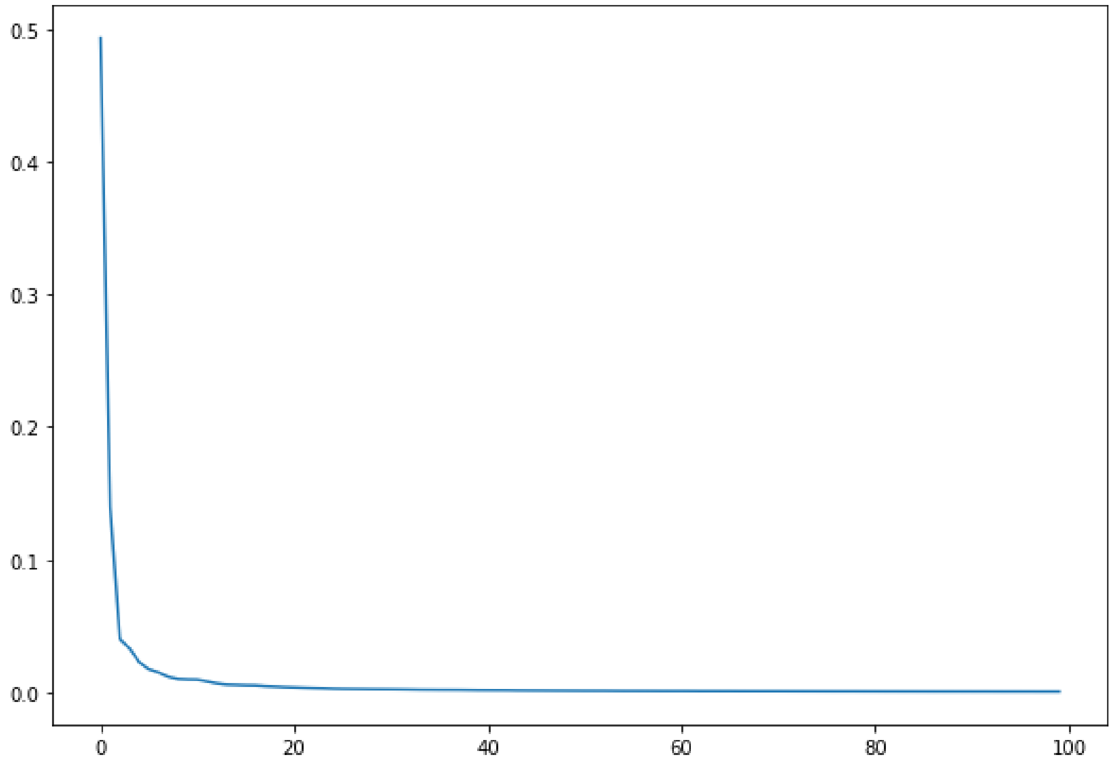
```
(10000, 3072)
(10000,)
(5000, 3072)
(5000,)
```

[4]:
```python
pca = PCA(whiten=True)
pca.fit(train_image)
```

[4]:
```
PCA(whiten=True)
```

[5]:
```
plt.figure(figsize=(10,7))
plt.plot(pca.explained_variance_ratio_[:100])
```

[5]:
```
[<matplotlib.lines.Line2D at 0x7fc3e05dfd30>]
```



4.1 Considering 90 components for PCA from the above graph

[6]:
```
svc=SVC()
pca = PCA(n_components=90, whiten=True)
pca.fit(train_image)
train_img = pca.transform(train_image)
test_img = pca.transform(test_images)
svc.fit(train_img,train_label)
y_pred=svc.predict(test_img)
print(f"The model with 90 compnents is␣
↪{round(accuracy_score(y_pred,test_label)*100, 2)}% accurate")
```

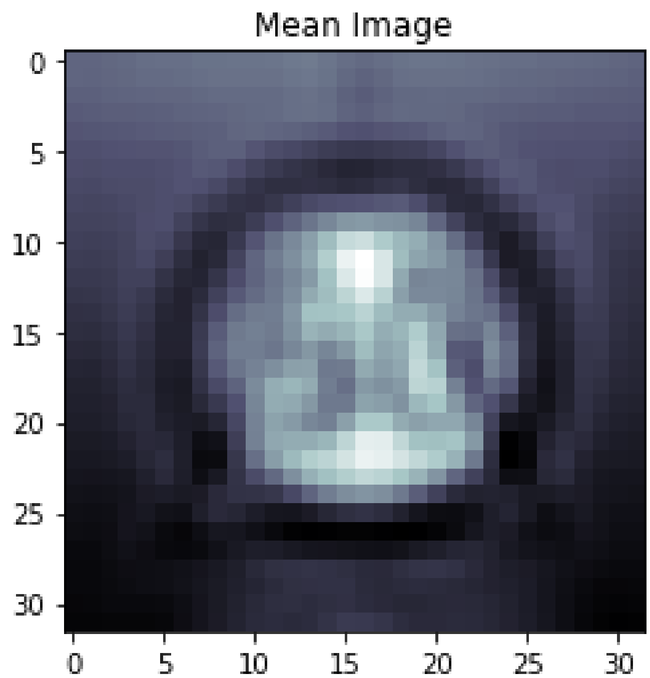
```
The model with 90 compnents is 71.44% accurate
```

[7]:
```
def grayscale_convert(rgb):
    red, green, blue = rgb[:,:,0], rgb[:,:,1], rgb[:,:,2]
    gray = 0.2989 * red + 0.5870 * green + 0.1140 * blue
```

```
    return gray
```

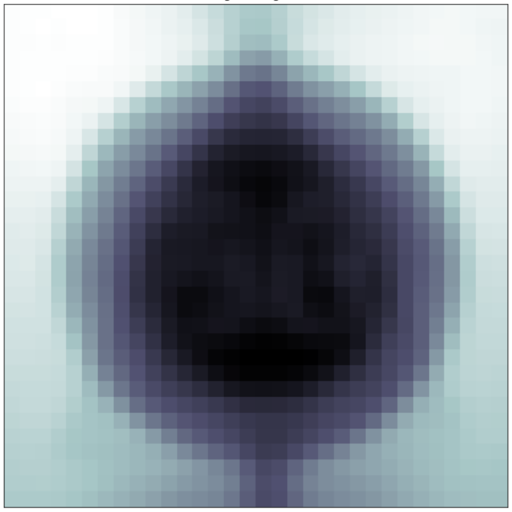
[8]:
```
plt.imshow(grayscale_convert(pca.mean_.reshape(32,32,3)),cmap=plt.cm.bone)
plt.title("Mean Image")
plt.show()


fig = plt.figure(figsize=(20, 20))
for i in range(2):
    ax = fig.add_subplot(1, 2, i + 1, xticks=[], yticks=[])
    ax.imshow(grayscale_convert(pca.components_[i].reshape(32,32,3)),cmap=plt.
 ↪cm.bone)
    ax.set_title("Eigen Image:{}".format(i+1))
```



Eigen Image:1

Eigen Image:2



[9]:
```
# Generate confusion matrix
from sklearn.metrics import confusion_matrix
matrix = confusion_matrix(y_pred, test_label)
```

[10]:
```
import pandas as pd
svc=SVC()
pca = PCA(n_components=2, whiten=True)
pca.fit(train_image)
train_img = pca.transform(train_image)

#Create a dataframe of training images (reduced features)
principalDf = pd.DataFrame(data = train_img
             , columns = ['principal component 1', 'principal component 2'])
#Create a dataframe of training labels
df = pd.DataFrame(train_label, columns = ['Column_A'])
#Concatenate the 2 data frames
finalDf = pd.concat([principalDf, df], axis = 1)
finalDf.head(5)
```

[10]:

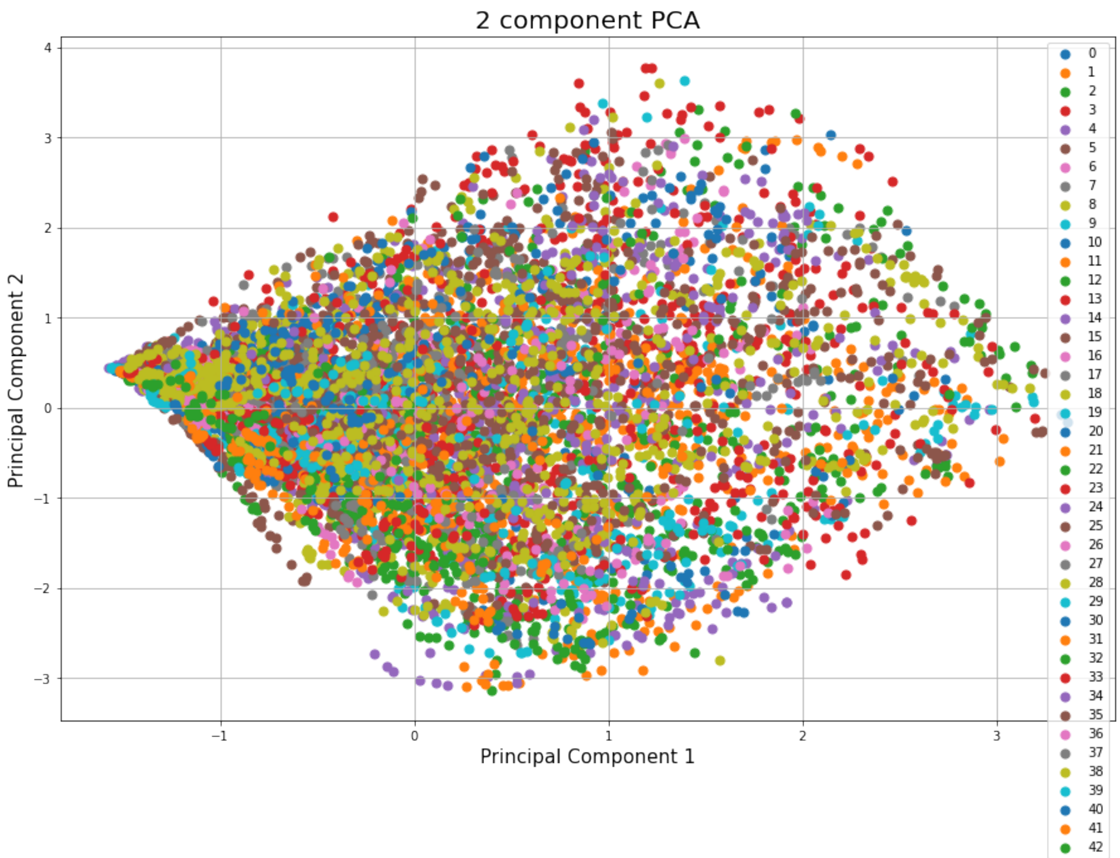
	principal component 1	principal component 2	Column_A
0	0.677933	1.210816	12
1	0.091513	-0.944670	13
2	-0.358298	0.279786	31
3	1.673283	0.930087	12
4	1.770278	-1.029254	9

[11]:
```
fig = plt.figure(figsize = (15,10))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
```

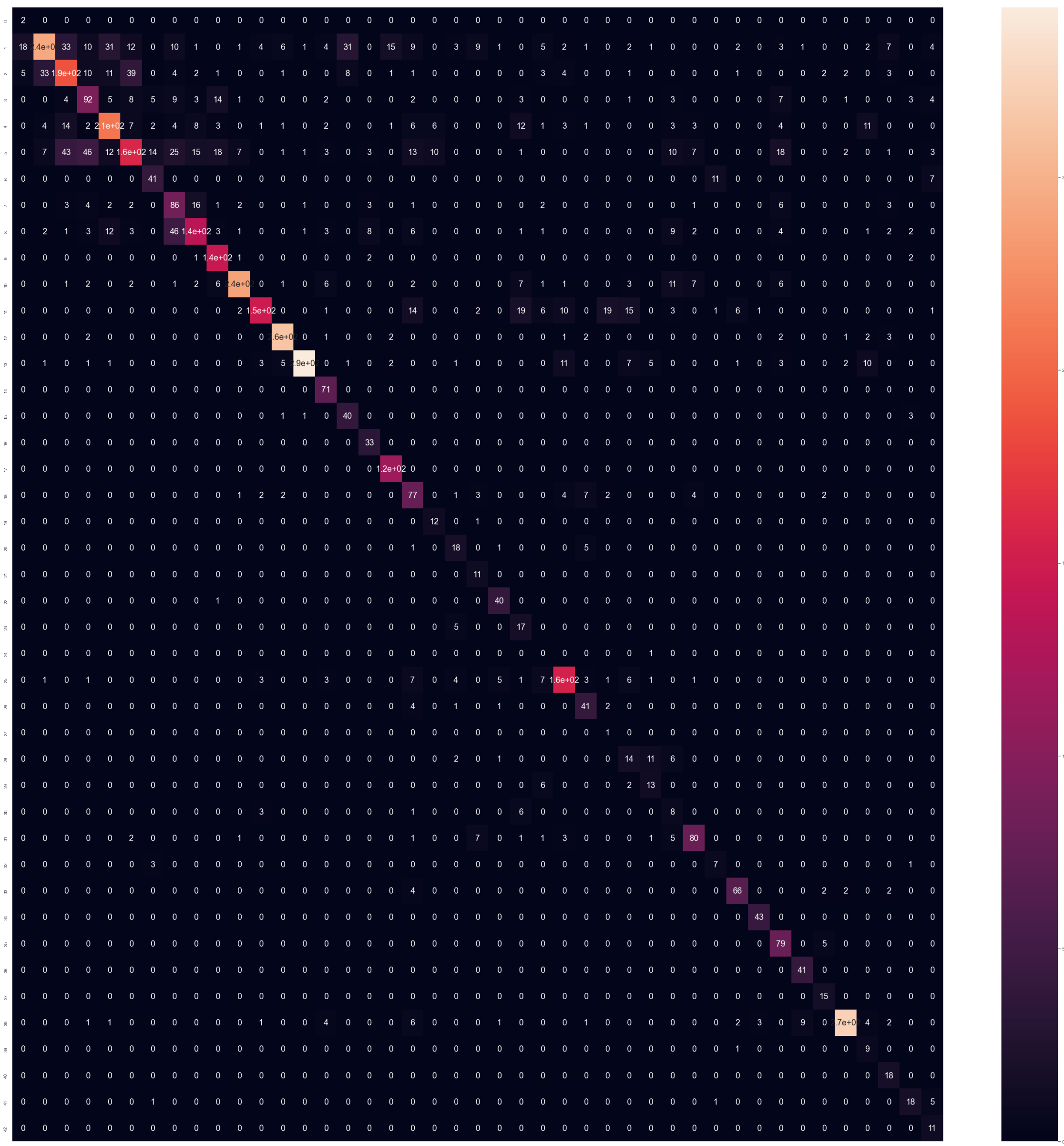
```
#Collect the unique labels for looping
targets = np.unique(train_label)

for target in (targets):
    indicesToKeep = finalDf['Column_A'] == target #Get the index of individual␣
 ↪training labels
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , s = 50)

ax.legend(targets)
ax.grid()
```



[12]:
```
#Create a dataframe for confusion matrix
df_cm = pd.DataFrame(matrix, range(43), range(43))
plt.figure(figsize=(50,50))
sn.set(font_scale=1) # for label size
sn.heatmap(matrix, annot=True, annot_kws={"size": 20}) # font size
plt.show()
```



4.2 Linear Discriminant Analysis

[13]:
```
svc=SVC() #Support vector machine classifier instance
pca = PCA(n_components=90, whiten=True) #PCA with 90 components
pca.fit(train_image) #Fit the training image

#Transform training and test images with 90 components
train_img = pca.transform(train_image)
test_img = pca.transform(test_images)
```

[14]:
```
#Perform Linear Discriminant Analysis on the training images with reduces␣
↪feature set (90 components)
lda = LDA()
train_img_lda = lda.fit_transform(train_img, train_label)
test_img_lda = lda.transform(test_img)
```

[15]:
```
#Perform classification using SVM
svc_lda = SVC()
svc_lda.fit(train_img_lda, train_label)
y_pred = svc_lda.predict(test_img_lda)
print(f"The model with 90 compnents is␣
↪{round(accuracy_score(y_pred,test_label)*100, 2)}% accurate")
```

```
The model with 90 compnents is 80.62% accurate
```

[16]:
```
#Use 2 components LDA
lda = LDA(n_components=2)
#Perform and fit LDA for training images
train_img_fit = lda.fit(train_img, train_label)
train_image_lda = lda.transform(train_img)
#Create dataframes to plot the values
principalDf = pd.DataFrame(data = train_image_lda
             , columns = ['lda component 1', 'lda component 2'])
df = pd.DataFrame(train_label, columns = ['Classification Labels'])
finalDf = pd.concat([principalDf, df], axis = 1)
finalDf.head(5)
```

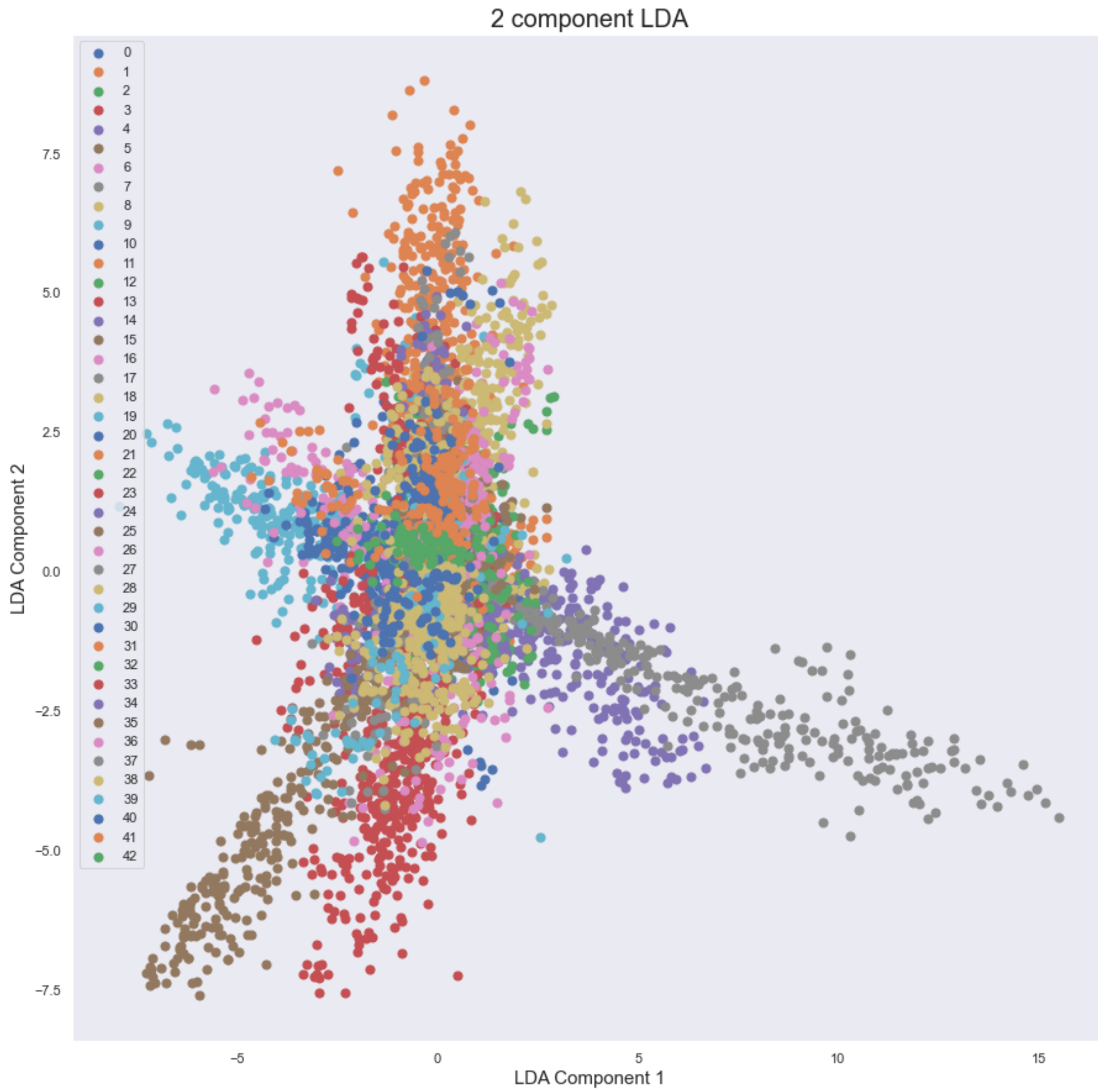
[16]:

	lda component 1	lda component 2	Classification Labels
0	0.097407	0.175069	12
1	-2.994762	-7.065612	13
2	0.133392	1.426983	31
3	-0.848033	1.449090	12
4	-5.316744	1.744225	9

[17]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('LDA Component 1', fontsize = 15)
ax.set_ylabel('LDA Component 2', fontsize = 15)
ax.set_title('2 component LDA', fontsize = 20)
targets = np.unique(train_label)

for target in (targets):
    indicesToKeep = finalDf['Classification Labels'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'lda component 1']
               , finalDf.loc[indicesToKeep, 'lda component 2']
               , s = 50)

ax.legend(targets)
ax.grid()
```



5 Problem 2: Lotka Volterra Model

5.0.1 Solution:

- Algorithm uses Runge Kutta 4 solver to calculate solve the differential equation
- h = 0.001
- Initial conditions are described in x=[x1, x2]=[0.3, 0.2]
- Graph is plotted for calculated x1 and x2 values intermediately

5.0.2 Interpretation:

- As it can be observed in the graph;

- In the absence of predator population, prey population increases until predator population starts to increase
- When the predator population increases, prey population starts to decrease
- Predators without food (prey) start to decrease in numbers until a point where prey start to increase due to reduced predatorial numbers
- Cycle repeats

5.0.3 Equation interpretation:

- Prey reproduce exponentially and this is represented by the term bx1
- The rate of predation upon the prey is assumed to be proportional to the rate at which the predators and the prey meet, this is represented above by p * x1 * y
- r * x1 * x2 represents predator population growth
- d * x2 represents loss of predators

[18]:
```
import numpy as np
from matplotlib import pyplot as plt
```

[19]:
```
# Using my rk4 solver from previous homework
def runge_kutta(r, t, h):
        k1 = h*lotka_volterra(r, t)
        k2 = h*lotka_volterra(r+0.5*k1, t+0.5*h)
        k3 = h*lotka_volterra(r+0.5*k2, t+0.5*h)
        k4 = h*lotka_volterra(r+k3, t+h)
        return (k1 + 2*k2 + 2*k3 + k4)/6

#Lotka-Volterra model funciton
def lotka_volterra(cond, t):
        b = p = r = d = 1.0
        x = cond[0] #Initial condition for prey
        y = cond[1] #Initial condition for predator
        fxd = x*(b - p*y) #Prey population update function
        fyd = (r*x - d)*y #Predator population update function
        return np.array([fxd, fyd], float)
```

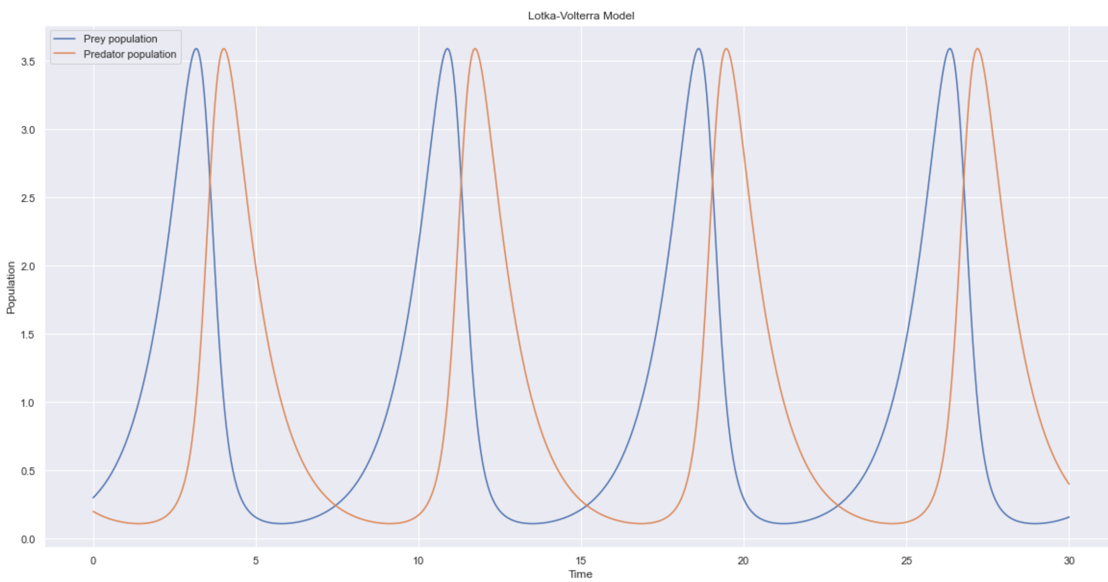
[20]:
```
h=0.001
tpoints = np.arange(0, 30, h)
xpoints, ypoints  = [], []
x = np.array([0.3, 0.2], float)

#Looping through each time step
#Input to a timestep is the output from the previous set
#At t=0, input is [0.3, 0.2]
#Accumulate x1 and x2 values at each timestep based on the previous step
for t in tpoints:
    xpoints.append(x[0])
    ypoints.append(x[1])
    x += runge_kutta(x, t, h)
```

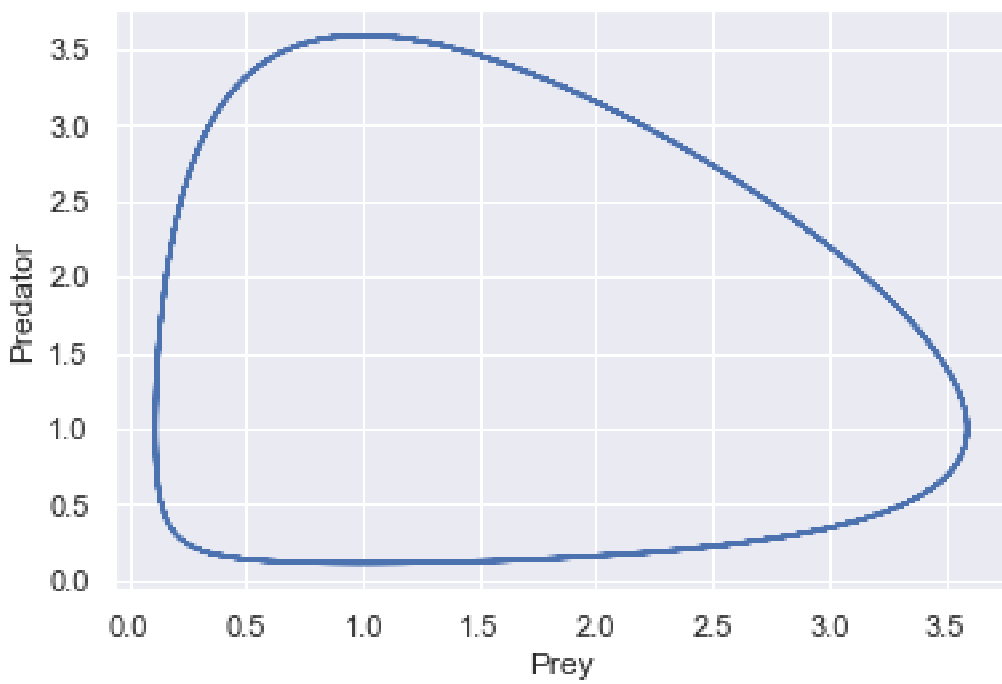
```
plt.figure(figsize=(20,10))
plt.plot(tpoints, xpoints, label='Prey population')
plt.plot(tpoints, ypoints, label='Predator population')
plt.xlabel("Time")
plt.ylabel("Population")
plt.title("Lotka-Volterra Model")
plt.legend()

plt.show()

plt.xlabel("Prey")
plt.ylabel("Predator")
plt.plot(xpoints, ypoints)
```



[20]: `[<matplotlib.lines.Line2D at 0x7fc3f1f15c50>]`


3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Predator
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Prey