L03_dataset

Introduction

This exercise will focus on different datasets such as the MOON, MNIST, IRIS and the Path of Exile dataset of the Harbinger League. Path of Exile is a video gamer developed by GGG and who offer through their API a dataset of their current "League" which has around ~60000 data with several arguments.

Vanilla Datasets

Qa Data load function

We begin with a 100% synthetic dataset called moon. It creates two interleaved half-moon like datasets, and is frequently used as an XOR-like problem set (especially in Deep Learning).

Create a `MOON_GetDataSet()` that generates moon data, based on Scikit-learn's `make_moon()` function.

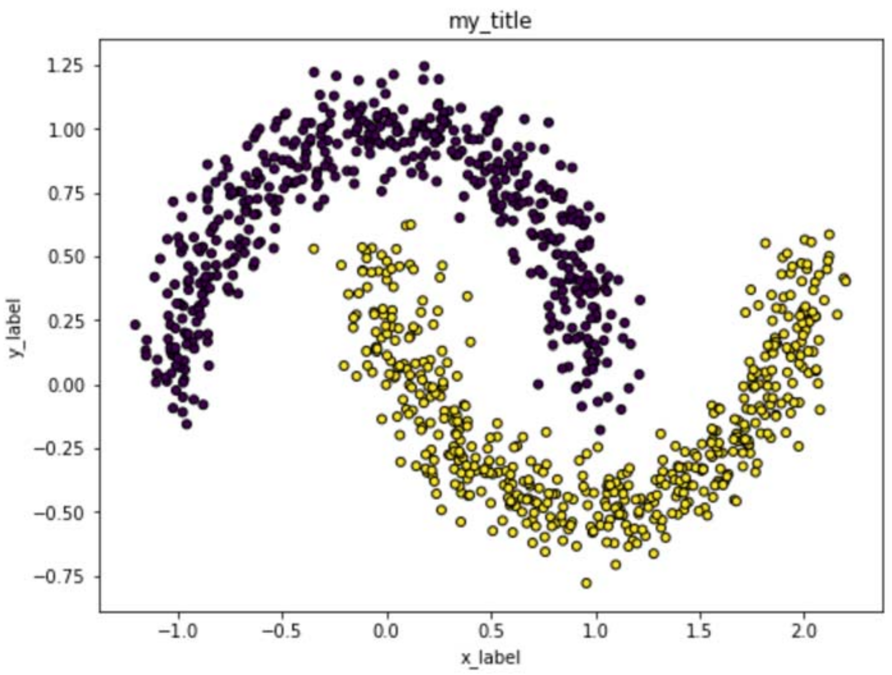
Extend the `MOON_GetDataSet()` function signature to include some of the parameters found in `make_moon()` , like 'n_sample'.

Also create a `MOON_Plot()` function, that plots the data...good thing here is that the feature set is 2D and easy to handle!

Qa implementation

```
In [1]: # Assignment Qa:
        %matplotlib inline
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.datasets import make_moons

        def MOON_GetDataSet(n_samples):
            return make_moons(n_samples, noise = 0.1)

        def MOON_Plot(X, y,title="my_title", xlabel="x_label", ylabel="y_label"):
            plt.figure(figsize=(8,6))
            plt.scatter(X[:, 0], X[:, 1], marker='o', c=y, s=25, edgecolor='k')
            plt.title(title)
            plt.xlabel(xlabel)
            plt.ylabel(ylabel)

        # TEST CODE:
        X, y=MOON_GetDataSet(n_samples=1000)
        print("X.shape=",X.shape,", y.shape=",y.shape)
        MOON_Plot(X,y)
```

```
X.shape= (1000, 2) , y.shape= (1000,)
```



Qa results

The moon dataset have been successfully retrieved at printed. It's important to note that the noise argument in make_moons(noise = 0.1) defines noise-separation between the points and the perfect plot.

Qb Try it with a train-test split function

Now, use a train-test split function from Scikit-learn, that is able to split a `(X, y)` dataset tuple into a train-set and a test-set.

Plot the train and test data using your `MOON_Plot` function.

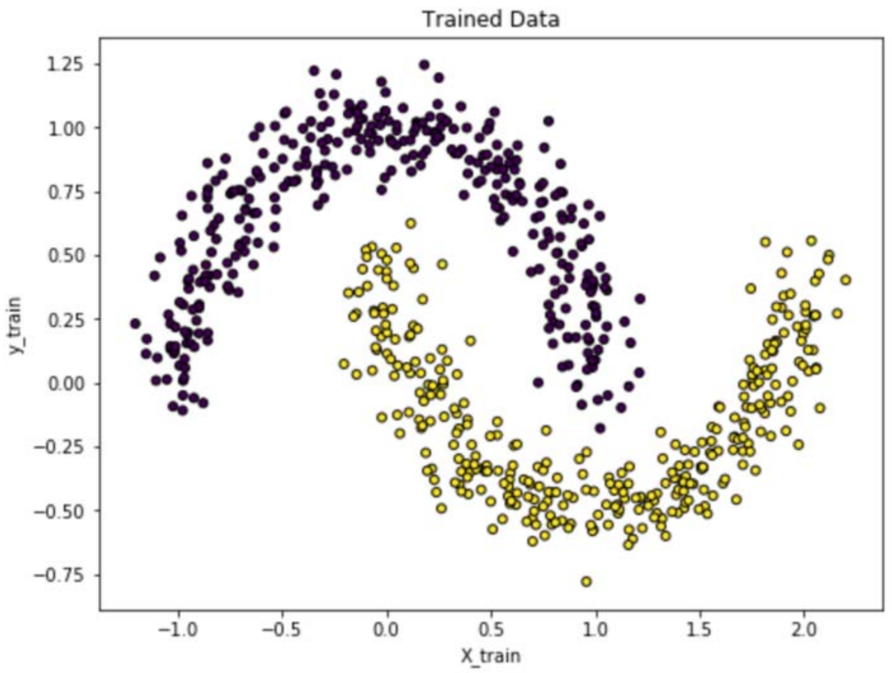
Extend the plot function to add a plot title and x- and y-labels to the plot, say as default parameters

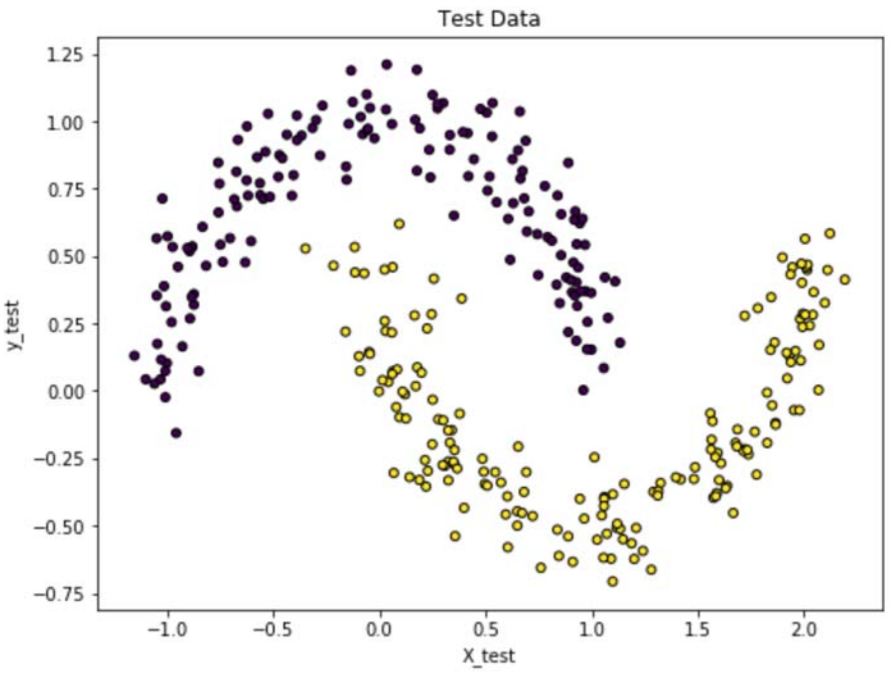
```
def MOON_Plot(X, y, title="my title", xlable="", ylabel=""):
    # implementation here...
```

or similar. Use the titles "train" and "test" when plotting the train and test data.

Qb implementation

```
In [3]: # Assignment Qb:
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_st
        ate=42)
        MOON_Plot(X_train,y_train,'Trained Data', 'X_train', 'y_train')
        MOON_Plot(X_test,y_test,'Test Data', 'X_test', 'y_test')
```





Qb results

The two plots show the difference of the trained and tested data. The main conclusion here is of course the test data set size has been set to 33% of the data, thus there are fewer points.

MNIST

Qc Data load function

Now for the MNIST data set, creating an easy to use data-loader, `MNIST_GetDataSet()` .

There are several ways of getting the MNIST dataset. You could base the data loader on the `fetch_mldata('MNIST original')` function or try to use the `keras.datasets.mnist.load_data()` function.

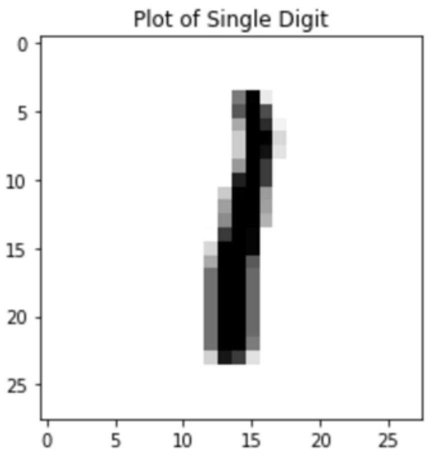
The later function pre-splits into a train-test set, and to be compatible with the former, you must concatenate the train-test and return a plain `X, y` set.

Also create a `MNIST_PlotDigit()` , that is able to plot a single digit from the dataset, and try to plot some of the digits in the dataset (set TEST CODE below).

Qc implementation

In [6]:
```
## Assignment Qc:

# Note we are using fetch_openml which is the newer version of fetch_mldata
from sklearn.datasets import fetch_openml
#from keras.datasets import mnist

# Function to plot a single digit
def MNIST_PlotDigit(data):
    image = data.reshape(28, 28)
    plt.imshow(255-image, cmap='gray')
    plt.title('Plot of Single Digit')


# Function to return mnist dataset as X-y tuple
def MNIST_GetDataSet():
    X, y = fetch_openml('mnist_784', version=1, return_X_y=True)
    return (X, y)

# TEST CODE:
X, y = MNIST_GetDataSet()
print("X.shape=",X.shape, ", y.shape=",y.shape)

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=50000, shuffle
=True)

print("X_train.shape=",X_train.shape,", X_test.shape=",X_test.shape)
MNIST_PlotDigit(X_train[12])
```

```
X.shape= (70000, 784) , y.shape= (70000,)
X_train.shape= (50000, 784) , X_test.shape= (20000, 784)
```



Qc results

With the use of the mnist dataset given from sklearn.datasets.fetch_openml, we were able to implement a function that is able to print a single digit of the mnist dataset.

Iris

Qd Data load function

Creating the iris data loader, `IRIS_GetDataSet()` , this time we use the iris loader located in `sklearn.datasets.load_iris()` .

Qd implementation

In [8]:
```
# Assignment Qd
from sklearn.datasets import load_iris

def IRIS_GetDataSet():
    return load_iris()
```

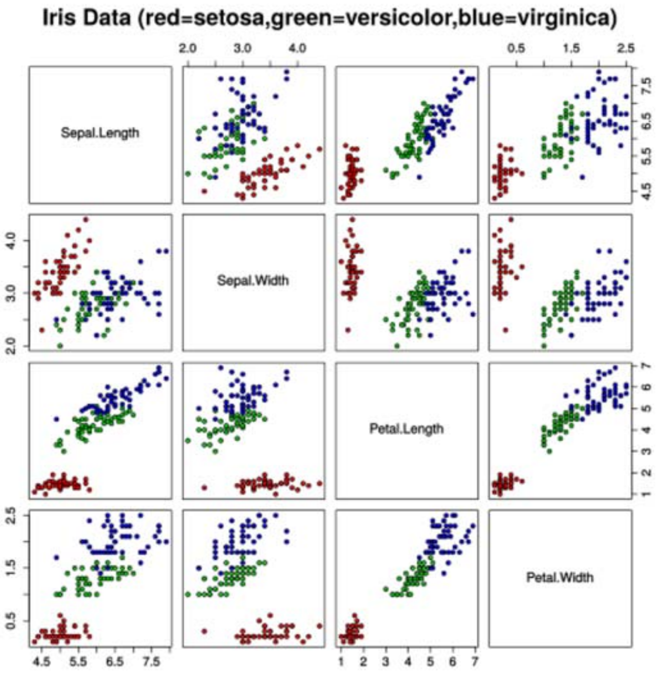
Qd results

With the use of sklearn.datasets.load_iris() we were able to successfully create a function to retrieve the data. In the next assignment, we show how to use the iris dataset.

Qe Examine the data via scatter plots

Now, as a data-scientist, it is always good to get some grasp on how your data looks like. For the iris data we now want to plot some of the features-against-some-of-the other-features to see how they separate in the given 2D-feature space.

A scatter plot for all iris features against all other may look like

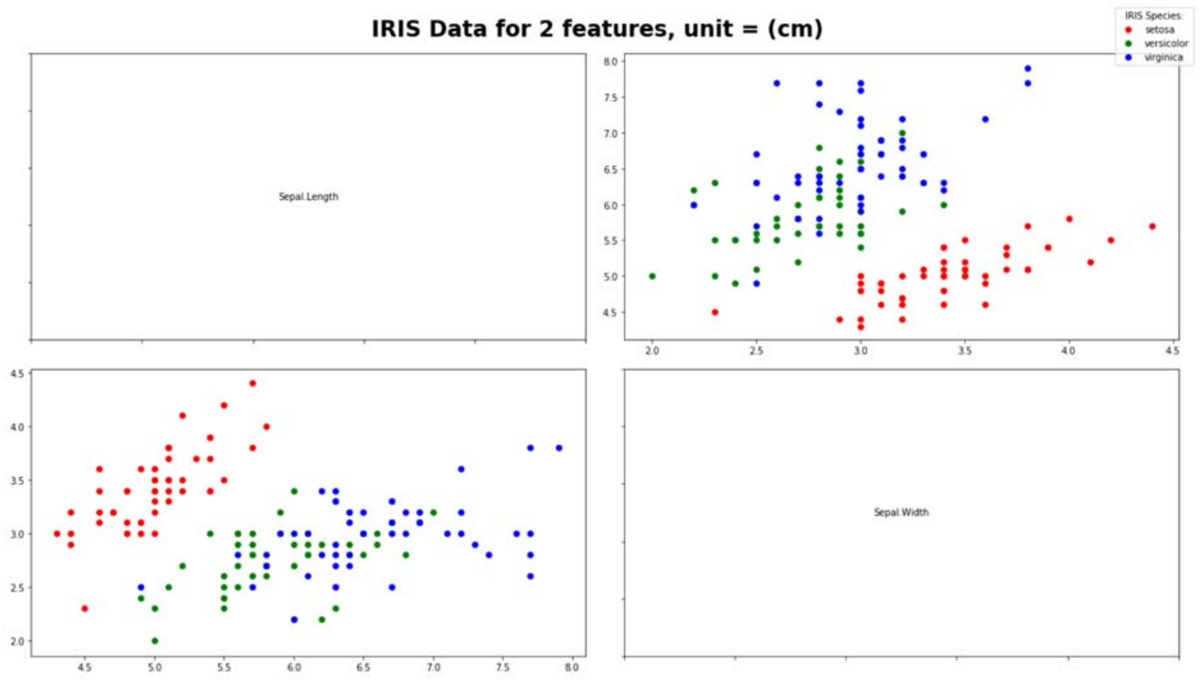


Create a plot function that takes just two feature dimensions and plots them in a 2D plot, and plot all features against all others (resembling the "Iris Data" scatter plot just above).

Qe implementation

In [10]:
```
# Assignment Qe:
def IRIS_Plot2D(iris_data, features=2, feat1=None, feat2=None, ax=None):
    # Check for Subplots
    if ax is None:
        ax = plt.gca()

    # Retrieve IRIS data with amount of features
    X = iris_data.data[:, :features]
    y = iris_data.target

    # Set and return IRIS data with setosa, versicolor and virginica
    # feat1 & feat2: 0 = Sepal.Length, 1 = Sepal.Width, 2 = Petal.Length, 3 = Petal
.Width
    setosa = ax.scatter(X[:50,feat1], X[:50,feat2], c='red', label='setosa', marker
='o')
    versicolor = ax.scatter(X[50:100,feat1], X[50:100,feat2], c="green", label = 'v
ersicolor', marker='o')
    virginica = ax.scatter(X[100:,feat1], X[100:,feat2], c="blue", label ='virginic
a', marker='o')

    return setosa, versicolor, virginica

# Function that plots text in the center of the graph
def PlotTextCenter(str, ax=None):
    # Check for subplots
    if ax is None:
        ax = plt.gca()

    # Disable x- and y-axis number ticks
    ax.set_yticklabels([])
    ax.set_xticklabels([])

    return ax.text(0.5, 0.5, str, horizontalalignment='center',verticalalignment='c
enter')


# Get IRIS Data from Qd
iris = IRIS_GetDataSet()

# Prepare subplots
fig, axes = plt.subplots(nrows=2, ncols=2)
fig.set_size_inches(18, 10.5)
fig.tight_layout(rect=[0, 0.03, 1, 0.95])

# Plot IRIS Data with 2 features
features = 2

PlotTextCenter("Sepal.Length",axes[0,0])
PlotTextCenter("Sepal.Width",axes[1,1])

IRIS_Plot2D(iris,features,1,0,axes[0,1])
IRIS_Plot2D(iris,features,0,1,axes[1,0])

iris_labels = ["setosa", "versicolor", "virginica"]
fig.legend(labels=iris_labels, title="IRIS Species:")
fig.suptitle('IRIS Data for 2 features, unit = (cm)', fontsize=24, fontweight='bold
')
```

```
Out[10]: Text(0.5, 0.98, 'IRIS Data for 2 features, unit = (cm)')
```



Qe results

The plot shows the IRIS dataset in use with the two features being Sepal.Length vs Sepal.Width. Looking closely, we can conclude that these two features plottet against each other resemble the original figure introduced in Qe. Furthemore, expanding these functions to work with 4 features to include Petal.Length and Petal.Width would not be too hard as it has been constructed with care.

Qf Add your function to the `libitmal` python module

Add all your moon, MNIST and iris get and plot functions to the `libitmal` module. Call the file `dataloaders.py` , and test it in a ***new*** jupyter notebook (you need to reset the notebooks to be able to see if you are calling *cached* version of the functions or the new ones, with similar names, in the lib module).

You will use these data loaders later, when we want to train on small datasets.

Qf implementation

```
In [14]: # Assignment Qf
         # We placed the path in: libitmal/dataloaders.py

         # Create a new jupyter notebook for instance: L03_dataset_Qf_tester.ipynb, to test
         if dataloaders.py works.
         # Remember to restart kernel

         # Succesfully tested.
```

Qf results

While the code is commmented, the file for dataloaders.py has been attached as appendix. In order to use it, the user must restart kernel and then import the library. We tested it in a separate document with success.

Your Datasets

Qg Download a data set and do some data exploration of it

You are now a Data Scientist, go an examine your data, perhaps creating some feature scatter plots, just like the ones we just made for iris...

Are there `null` s or not-a-number data in your set? Do you have to filter these out before training?

Try to train-test split the set, perhaps just on a small set of its feature depending on the size of your data (small/medium/large /big), and try out one or two Scikit-learn ML algorithms on it just to see if it is possible.

(We return to the data set and training later...)

Qg implementation

In [16]:
```
# Assignment Qg
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# Dataset: https://www.kaggle.com/gagazet/path-of-exile-league-statistic#poe_stats.
csv
# Tutorial: https://data36.com/pandas-tutorial-1-basics-reading-data-files-datafram
es-data-selection/
# Inspiration for PoE dataset: https://www.kaggle.com/microtang/poe-path-of-exile-s
tatistics-an-exploration
# Subject: Path of Exile (PoE) video game developed by Grinding Gear Games

# Read dataset from csv file
df = pd.read_csv('poe_stats.csv', delimiter = ',')
df.head(5)
```

Out[16]:

	rank	dead	online	name	level	class	
0	1	False	False	Tzn_NecroIsFineNow	100	Necromancer	3dcddd59f5088893f734f39686350990dae168cc
1	1	False	False	RaizNeverFirstQT	100	Necromancer	8f3216db5ac9106c287a834731aafc83c387138
2	1	False	False	GucciStreamerAdvantage	100	Necromancer	c6ec2dae3855c551e0597c06ef2da06fbb551248
3	1	False	False	ChiroxPrime	100	Slayer	c861372da792be0b22c45bf437ccd58437c52e94
4	2	False	False	Cool_NecroIsFineNow	100	Deadeye	24ae924ceed7989ef3d3d6772612832bb467a609

In [18]:
```
# Check out how many players on each ladder
df_ladder = df.groupby('ladder')
df_ladder.size()
```

Out[18]:
```
ladder
Harbinger              14918
Hardcore Harbinger     14905
SSF Harbinger          14981
SSF Harbinger HC       14972
dtype: int64
```

We can observe that SSF Harbinger is the most populated Ladder with 14981 players, followed by SSF Harbinger HC which has 14972 players.

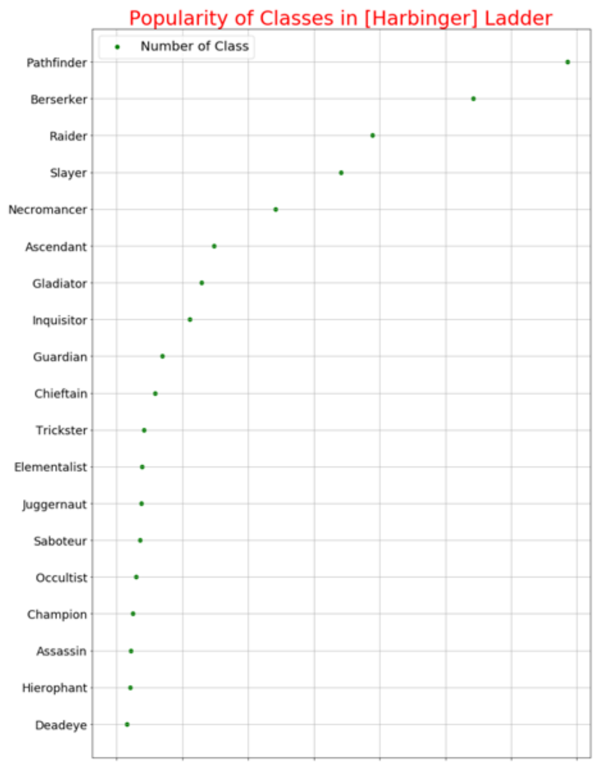
In [19]:
```
# Function to get Ordered Classes in a League
def GetOrderedClassInLadder(ladder):
    # Get Ladder Class grouped by class
    mLadder = df_ladder.get_group(ladder).groupby('class')

    # Arrange Ordered data by Class and Number of classes
    mOrderedData = pd.DataFrame(0, index=np.arange(len(mLadder.size())), columns=['
class','number'])
    mOrderedData['class'] = mLadder.size().index

    # Loop through all data and sort class with number of classes
    for i in range(len(mOrderedData)):
        mOrderedData.iat[i,1] =  int(mLadder.size()[i])
    mOrderedData = mOrderedData.sort_values(by = 'number', ascending=False)
    return mOrderedData

GetOrderedClassInLadder('SSF Harbinger HC').head()
```

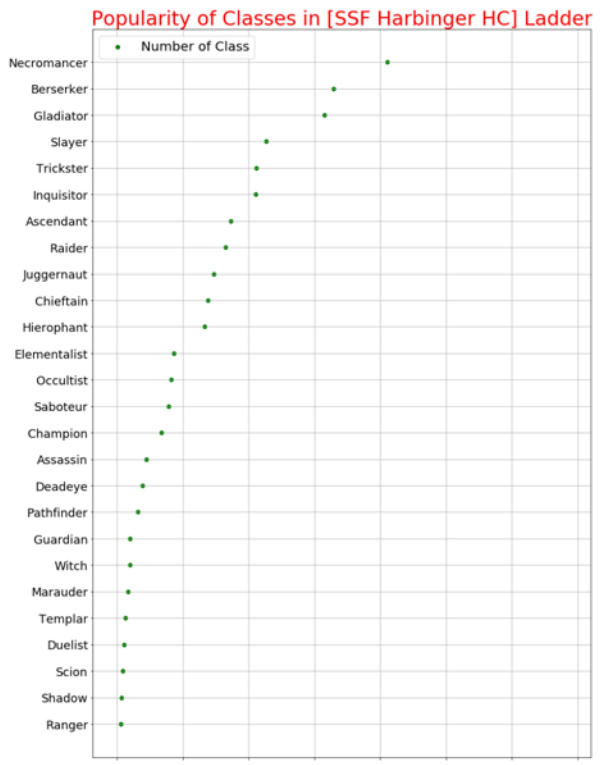
Out[19]:

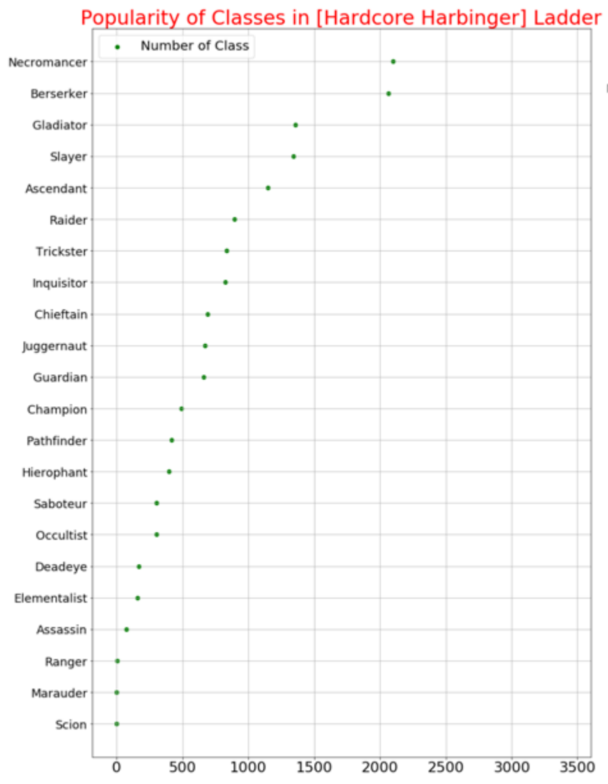
	class	number
14	Necromancer	2055
2	Berserker	1644
8	Gladiator	1576
22	Slayer	1135
24	Trickster	1058

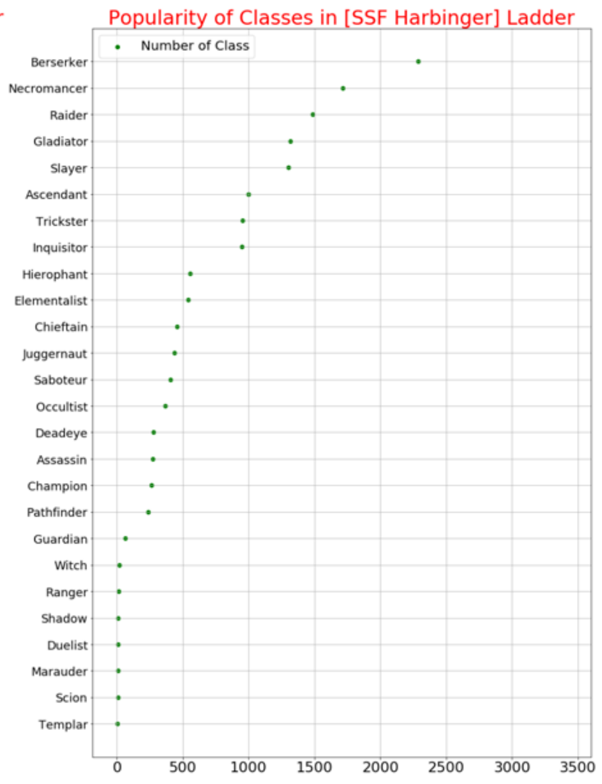
Necromancer is the most popular class in SSF Harbinger HC Ladder with 2055 players. We will compare the amount of classes in each Ladder later.

In [10]:
```
# Function to plot the popularity of classes in each ladder.
def POE_PlotClassVsLadder():
    f, axes = plt.subplots(2, 2, figsize=(30,45), sharex=True)
    mLadderList = df['ladder'].unique()
    mCounter = 0
    for i in range(2):
        for j in range(2):
            plt.sca(axes[i, j])
            currentLadder = mLadderList[mCounter]
            ladderData = GetOrderedClassInLadder(currentLadder)
            ladderData = ladderData.reset_index()
            x = ladderData['number']
            y = ladderData['class']
            labels = ladderData['class']
            plt.scatter(x, y, c='g', label = 'Number of Class')
            plt.xticks(size = 22)
            plt.yticks(y, labels, fontsize=18)
            plt.title('Popularity of Classes in ['+ currentLadder +'] Ladder', font
size = 30, color = 'red')
            plt.legend(loc=2, fontsize =20)
            plt.grid()
            plt.gca().invert_yaxis()
            mCounter += 1
    plt.show()
    return

POE_PlotClassVsLadder()
```







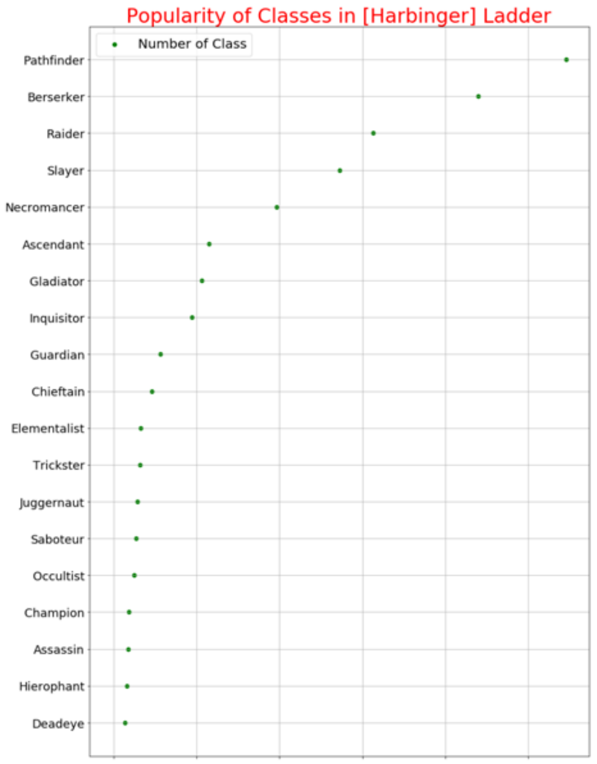


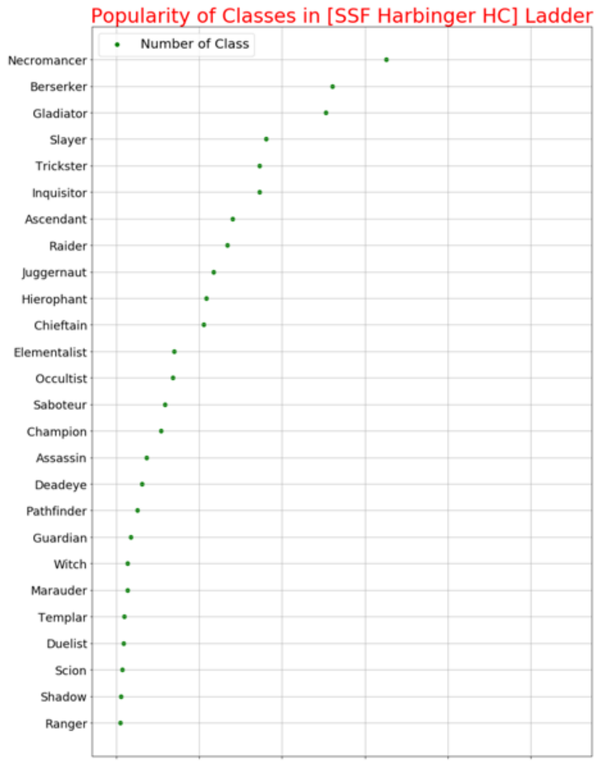
The popularity of the Necromancer and Berserker class is very high in each Ladder while the Pathfinder is only popular in the Harbinger Ladder.

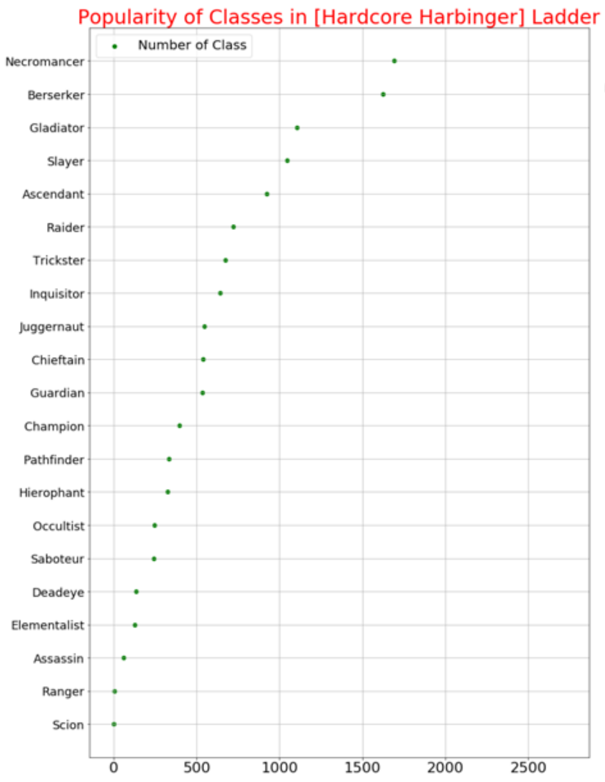
Next action is to do a train-split of the data with sklearn.model_selection.train_test_split()

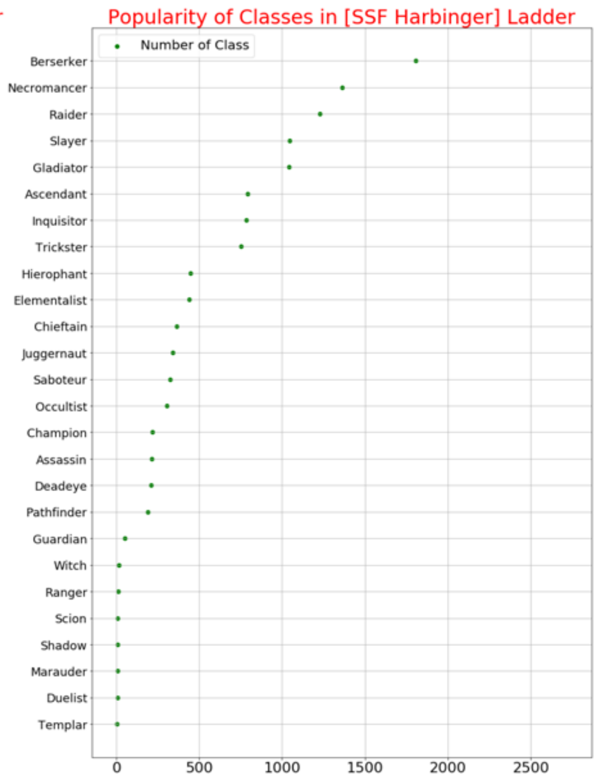
```
In [20]: def Train_GetOrderedClassInLadder(ladder):
             # Get Ladder Class grouped by class
             mLadder = df_train_ladder.get_group(ladder).groupby('class')

             # Arrange Ordered data by Class and Number of classes
             mOrderedData = pd.DataFrame(0, index=np.arange(len(mLadder.size())), columns=['
         class','number'])
             mOrderedData['class'] = mLadder.size().index

             # Loop through all data and sort class with number of classes
             for i in range(len(mOrderedData)):
                 mOrderedData.iat[i,1] =  int(mLadder.size()[i])
             mOrderedData = mOrderedData.sort_values(by = 'number', ascending=False)
             return mOrderedData

         # Switch-Case function to ensure same order of Ladder plots as shown previously
         def switch_ladder(arg):
             switch_case = {
                 0: "Harbinger",
                 1: "SSF Harbinger HC",
                 2: "Hardcore Harbinger",
                 3: "SSF Harbinger",
             }
             return switch_case.get(arg)


         def Train_POE_PlotClassVsLadder():
             f, axes = plt.subplots(2, 2, figsize=(30,45), sharex=True)
             mLadderList = df_train['ladder'].unique()
             mCounter = 0
             for i in range(2):
                 for j in range(2):
                     plt.sca(axes[i, j])
                     currentLadder = switch_ladder(mCounter);
                     ladderData = Train_GetOrderedClassInLadder(currentLadder)
                     ladderData = ladderData.reset_index()
                     x = ladderData['number']
                     y = ladderData['class']
                     labels = ladderData['class']
                     plt.scatter(x, y, c='g', label = 'Number of Class')
                     plt.xticks(size = 22)
                     plt.yticks(y, labels, fontsize=18)
                     plt.title('Popularity of Classes in ['+ currentLadder +'] Ladder', font
         size = 30, color = 'red')
                     plt.legend(loc=2, fontsize =20)
                     plt.grid()
                     plt.gca().invert_yaxis()
                     mCounter += 1
             plt.show()
             return

         df_filter = df[['class','ladder']]
         df_train, df_test = train_test_split(df_filter, train_size = 0.8, shuffle=True)
         df_train_ladder = df_train.groupby('ladder')
         Train_POE_PlotClassVsLadder()
```

```
C:\Users\Admin\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:217
9: FutureWarning: From version 0.21, test_size will always complement train_size
unless both are specified.
  FutureWarning)
```









The four plots show the trained data where the train_size is 80%.

Qg results

The Path of Exile dataset offer ~60000 data of players in the game. We have successfully experimented with the dataset and made plots of Class vs Amount-of-Classes. Furthermore, we used sklearns train_and_split function, where the difference between the positions of the classes changed a bit.

Conclusion

We have successfully retrieved and used datasets for MOON, MNIST and IRIS. Furthermore, we were able to experiment with the Path of Exil dataset which has lead to some basic conclusion of the difference of classes played in the Harbinger Leagues.