ML0101EN-Clus-DBSCN-weather-py-v1

September 19, 2021

1 Density-Based Clustering

Estimated time needed: **25** minutes

1.1 Objectives

After completing this lab you will be able to:

- Use DBSCAN to do Density based clustering
- Use Matplotlib to plot clusters

Most of the traditional clustering techniques, such as k-means, hierarchical and fuzzy clustering, can be used to group data without supervision.

However, when applied to tasks with arbitrary shape clusters, or clusters within cluster, the traditional techniques might be unable to achieve good results. That is, elements in the same cluster might not share enough similarity or the performance may be poor. Additionally, Density-based clustering locates regions of high density that are separated from one another by regions of low density. Density, in this context, is defined as the number of points within a specified radius.

In this section, the main focus will be manipulating the data and properties of DBSCAN and observing the resulting clustering.

Import the following libraries:

numpy as np

DBSCAN from sklearn.cluster

make_blobs from sklearn.datasets.samples_generator

StandardScaler from sklearn.preprocessing

matplotlib.pyplot as plt

Remember %matplotlib inline to display plots

[1]:
```
# Notice: For visualization of map, you need basemap package.
# if you dont have basemap install on your machine, you can use the following␣
↪line to install it
!conda install -c conda-forge  basemap matplotlib==3.1 -y
# Notice: you maight have to refresh your page and re-run the notebook after␣
↪installation
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: failed with initial frozen solve. Retrying with flexible
solve.
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /home/jupyterlab/conda/envs/python

  added / updated specs:
    - basemap
    - matplotlib==3.1


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    basemap-1.2.1              |   py36hd759880_1        15.2 MB  conda-forge
    dbus-1.13.6                |       h48d8840_2         572 KB  conda-forge
    gst-plugins-base-1.14.0    |       hbbd80ab_1         4.8 MB
    gstreamer-1.14.0           |       h28cd5cc_2         3.2 MB
    matplotlib-3.1.0           |   py36h5429711_0         5.0 MB
    pyqt-5.9.2                 |   py36hcca6a23_4         5.7 MB  conda-forge
    qt-5.9.7                   |       h5867ecd_1        68.5 MB
    sip-4.19.8                 |py36hf484d3e_1000         290 KB  conda-forge
    ------------------------------------------------------------
                                           Total:       103.3 MB

The following NEW packages will be INSTALLED:

  dbus               conda-forge/linux-64::dbus-1.13.6-h48d8840_2
  gst-plugins-base   pkgs/main/linux-64::gst-plugins-base-1.14.0-hbbd80ab_1
  gstreamer          pkgs/main/linux-64::gstreamer-1.14.0-h28cd5cc_2
  matplotlib         pkgs/main/linux-64::matplotlib-3.1.0-py36h5429711_0
  pyqt               conda-forge/linux-64::pyqt-5.9.2-py36hcca6a23_4
  qt                 pkgs/main/linux-64::qt-5.9.7-h5867ecd_1
  sip                conda-forge/linux-64::sip-4.19.8-py36hf484d3e_1000

The following packages will be UPDATED:

  basemap                                  1.2.0-py36hd759880_4 -->
1.2.1-py36hd759880_1



Downloading and Extracting Packages
```

```
pyqt-5.9.2           | 5.7 MB    | ##################################### | 100%
gstreamer-1.14.0     | 3.2 MB    | ##################################### | 100%
matplotlib-3.1.0     | 5.0 MB    | ##################################### | 100%
sip-4.19.8           | 290 KB    | ##################################### | 100%
basemap-1.2.1        | 15.2 MB   | ##################################### | 100%
gst-plugins-base-1.1 | 4.8 MB    | ##################################### | 100%
qt-5.9.7             | 68.5 MB   | ##################################### | 100%
dbus-1.13.6          | 572 KB    | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

[3]:
```
import numpy as np
from sklearn.cluster import DBSCAN
from sklearn.datasets.samples_generator import make_blobs
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
%matplotlib inline
```

1.1.1 Data generation

The function below will generate the data points and requires these inputs:

centroidLocation: Coordinates of the centroids that will generate the random data.

Example: input: [[4,3], [2,-1], [-1,4]]

numSamples: The number of data points we want generated, split over the number of centroids (# of centroids defined in centroidLocation)

Example: 1500

clusterDeviation: The standard deviation of the clusters. The larger the number, the further the spacing of the data points within the clusters.

Example: 0.5

[4]:
```
def createDataPoints(centroidLocation, numSamples, clusterDeviation):
    # Create random data and store in feature matrix X and response vector y.
    X, y = make_blobs(n_samples=numSamples, centers=centroidLocation,
                                cluster_std=clusterDeviation)

    # Standardize features by removing the mean and scaling to unit variance
    X = StandardScaler().fit_transform(X)
    return X, y
```

Use createDataPoints with the 3 inputs and store the output into variables X and y.

[5]:
```
X, y = createDataPoints([[4,3], [2,-1], [-1,4]] , 1500, 0.5)
```

1.1.2 Modeling

DBSCAN stands for Density-Based Spatial Clustering of Applications with Noise. This technique is one of the most common clustering algorithms which works based on density of object. The whole idea is that if a particular point belongs to a cluster, it should be near to lots of other points in that cluster.

It works based on two parameters: Epsilon and Minimum Points
Epsilon determine a specified radius that if includes enough number of points within, we call it dense area
minimumSamples determine the minimum number of data points we want in a neighborhood to define a cluster.

[6]:
```
epsilon = 0.3
minimumSamples = 7
db = DBSCAN(eps=epsilon, min_samples=minimumSamples).fit(X)
labels = db.labels_
labels
```

[6]:
```
array([0, 1, 1, …, 0, 0, 0])
```

1.1.3 Distinguish outliers

Let's Replace all elements with 'True' in core_samples_mask that are in the cluster, 'False' if the points are outliers.

[7]:
```
# Firts, create an array of booleans using the labels from db.
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
core_samples_mask
```

[7]:
```
array([ True,  True,  True, …,  True,  True,  True])
```

[8]:
```
# Number of clusters in labels, ignoring noise if present.
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_clusters_
```

[8]:
```
3
```

[9]:
```
# Remove repetition in labels by turning it into a set.
unique_labels = set(labels)
unique_labels
```

[9]:
```
{-1, 0, 1, 2}
```

1.1.4 Data visualization

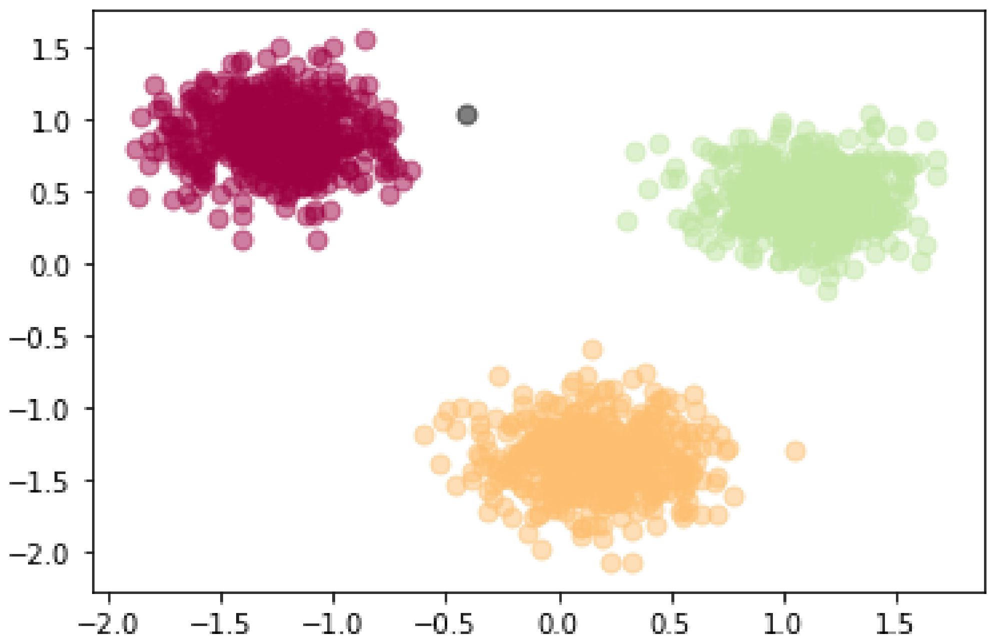
[10]:
```
# Create colors for the clusters.
colors = plt.cm.Spectral(np.linspace(0, 1, len(unique_labels)))
```

[11]:
```
# Plot the points with colors
for k, col in zip(unique_labels, colors):
    if k == -1:
        # Black used for noise.
        col = 'k'

    class_member_mask = (labels == k)

    # Plot the datapoints that are clustered
    xy = X[class_member_mask & core_samples_mask]
    plt.scatter(xy[:, 0], xy[:, 1],s=50, c=[col], marker=u'o', alpha=0.5)

    # Plot the outliers
    xy = X[class_member_mask & ~core_samples_mask]
    plt.scatter(xy[:, 0], xy[:, 1],s=50, c=[col], marker=u'o', alpha=0.5)
```



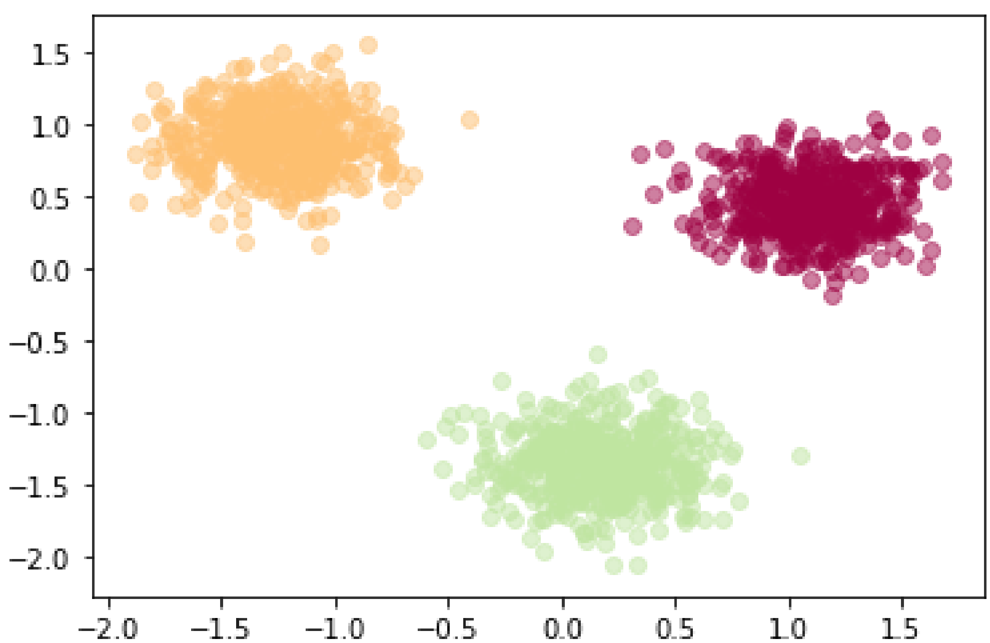
1.2 Practice

To better understand differences between partitional and density-based clustering, try to cluster the above dataset into 3 clusters using k-Means.
Notice: do not generate data again, use the same dataset as above.

[13]:

```python
from sklearn.cluster import KMeans
k = 3
k_means3 = KMeans(init = "k-means++", n_clusters = k, n_init = 12)
k_means3.fit(X)
fig = plt.figure(figsize=(6, 4))
ax = fig.add_subplot(1, 1, 1)
for k, col in zip(range(k), colors):
    my_members = (k_means3.labels_ == k)
    plt.scatter(X[my_members, 0], X[my_members, 1],  c=col, marker=u'o',␣
 ↪alpha=0.5)
plt.show()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
'x' & 'y'.  Please use a 2-D array with a single row if you really want to
specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
'x' & 'y'.  Please use a 2-D array with a single row if you really want to
specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
'x' & 'y'.  Please use a 2-D array with a single row if you really want to
specify the same RGB or RGBA value for all points.
```



Click here for the solution

```
from sklearn.cluster import KMeans
k = 3
k_means3 = KMeans(init = "k-means++", n_clusters = k, n_init = 12)
k_means3.fit(X)
fig = plt.figure(figsize=(6, 4))
ax = fig.add_subplot(1, 1, 1)
for k, col in zip(range(k), colors):
    my_members = (k_means3.labels_ == k)
    plt.scatter(X[my_members, 0], X[my_members, 1],  c=col, marker=u'o', alpha=0.5)
plt.show()
```

Weather Station Clustering using DBSCAN & scikit-learn

DBSCAN is especially very good for tasks like class identification in a spatial context. The wonderful attribute of DBSCAN algorithm is that it can find out any arbitrary shape cluster without getting affected by noise. For example, this following example cluster the location of weather stations in Canada. <Click 1> DBSCAN can be used here, for instance, to find the group of stations which show the same weather condition. As you can see, it not only finds different arbitrary shaped clusters, can find the denser part of data-centered samples by ignoring less-dense areas or noises.

Let's start playing with the data. We will be working according to the following workflow:

1. Loading data

- Overview data
- Data cleaning
- Data selection
- Clusteing

1.2.1 About the dataset

Environment Canada
Monthly Values for July - 2015

Name in the table

Meaning

Stn_Name

Station Name</font

Lat

Latitude (North+, degrees)

Long

Longitude (West - , degrees)

Prov

Province

Tm

Mean Temperature (°C)

DwTm

Days without Valid Mean Temperature

D

Mean Temperature difference from Normal (1981-2010) (°C)

Tx

Highest Monthly Maximum Temperature (°C)

DwTx

Days without Valid Maximum Temperature

Tn

Lowest Monthly Minimum Temperature (°C)

DwTn

Days without Valid Minimum Temperature

S

Snowfall (cm)

DwS

Days without Valid Snowfall

S%N

Percent of Normal (1981-2010) Snowfall

P

Total Precipitation (mm)

DwP

Days without Valid Precipitation

P%N

Percent of Normal (1981-2010) Precipitation

S_G

Snow on the ground at the end of the month (cm)

Pd

Number of days with Precipitation 1.0 mm or more

BS

Bright Sunshine (hours)

DwBS

Days without Valid Bright Sunshine

BS%

Percent of Normal (1981-2010) Bright Sunshine

HDD

Degree Days below 18 °C

CDD

Degree Days above 18 °C

Stn_No

Climate station identifier (first 3 digits indicate drainage basin, last 4 characters are for sorting alphabetically).

NA

Not Available

1.2.2 1-Download data

To download the data, we will use `!wget` to download it from IBM Object Storage.
Did you know? When it comes to Machine Learning, you will likely be working with large datasets. As a business, where can you host your data? IBM is offering a unique opportunity for businesses, with 10 Tb of IBM Cloud Object Storage: Sign up now for free

[ ]:
```
!wget -O weather-stations20140101-20141231.csv https://cf-courses-data.s3.us.
↪cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-ML0101EN-SkillsNetwork/labs/Module%204/data/
↪weather-stations20140101-20141231.csv
```

1.2.3 2- Load the dataset

We will import the .csv then we creates the columns for year, month and day.

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

filename='weather-stations20140101-20141231.csv'

#Read csv
pdf = pd.read_csv(filename)
pdf.head(5)
```

1.2.4 3-Cleaning

Let's remove rows that don't have any value in the **Tm** field.

```
[ ]: pdf = pdf[pd.notnull(pdf["Tm"])]
     pdf = pdf.reset_index(drop=True)
     pdf.head(5)
```

1.2.5 4-Visualization

Visualization of stations on map using basemap package. The matplotlib basemap toolkit is a library for plotting 2D data on maps in Python. Basemap does not do any plotting on it's own, but provides the facilities to transform coordinates to a map projections.

Please notice that the size of each data points represents the average of maximum temperature for each station in a year.

```
[ ]: from mpl_toolkits.basemap import Basemap
     import matplotlib.pyplot as plt
     from pylab import rcParams
     %matplotlib inline
     rcParams['figure.figsize'] = (14,10)

     llon=-140
     ulon=-50
     llat=40
     ulat=65

     pdf = pdf[(pdf['Long'] > llon) & (pdf['Long'] < ulon) & (pdf['Lat'] > llat)␣
      ↪&(pdf['Lat'] < ulat)]

     my_map = Basemap(projection='merc',
                 resolution = 'l', area_thresh = 1000.0,
                 llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and␣
      ↪latitude (llcrnrlat)
                 urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and␣
      ↪latitude (urcrnrlat)

     my_map.drawcoastlines()
     my_map.drawcountries()
     # my_map.drawmapboundary()
     my_map.fillcontinents(color = 'white', alpha = 0.3)
     my_map.shadedrelief()

     # To collect data based on stations

     xs,ys = my_map(np.asarray(pdf.Long), np.asarray(pdf.Lat))
     pdf['xm']= xs.tolist()
     pdf['ym'] =ys.tolist()

     #Visualization1
```

```
for index,row in pdf.iterrows():
#   x,y = my_map(row.Long, row.Lat)
   my_map.plot(row.xm, row.ym,markerfacecolor =([1,0,0]),  marker='o',␣
 ↪markersize= 5, alpha = 0.75)
#plt.text(x,y,stn)
plt.show()
```

1.2.6 5- Clustering of stations based on their location i.e. Lat & Lon

DBSCAN form sklearn library can runs DBSCAN clustering from vector array or distance matrix. In our case, we pass it the Numpy array Clus_dataSet to find core samples of high density and expands clusters from them.

[ ]:
```
from sklearn.cluster import DBSCAN
import sklearn.utils
from sklearn.preprocessing import StandardScaler
sklearn.utils.check_random_state(1000)
Clus_dataSet = pdf[['xm','ym']]
Clus_dataSet = np.nan_to_num(Clus_dataSet)
Clus_dataSet = StandardScaler().fit_transform(Clus_dataSet)

# Compute DBSCAN
db = DBSCAN(eps=0.15, min_samples=10).fit(Clus_dataSet)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
pdf["Clus_Db"]=labels

realClusterNum=len(set(labels)) - (1 if -1 in labels else 0)
clusterNum = len(set(labels))


# A sample of clusters
pdf[["Stn_Name","Tx","Tm","Clus_Db"]].head(5)
```

As you can see for outliers, the cluster label is -1

[ ]:
```
set(labels)
```

1.2.7 6- Visualization of clusters based on location

Now, we can visualize the clusters using basemap:

[ ]:
```
from mpl_toolkits.basemap import Basemap
import matplotlib.pyplot as plt
from pylab import rcParams
%matplotlib inline
rcParams['figure.figsize'] = (14,10)
```

```
my_map = Basemap(projection='merc',
            resolution = 'l', area_thresh = 1000.0,
            llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and␣
 ↪latitude (llcrnrlat)
            urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and␣
 ↪latitude (urcrnrlat)

my_map.drawcoastlines()
my_map.drawcountries()
#my_map.drawmapboundary()
my_map.fillcontinents(color = 'white', alpha = 0.3)
my_map.shadedrelief()

# To create a color map
colors = plt.get_cmap('jet')(np.linspace(0.0, 1.0, clusterNum))



#Visualization1
for clust_number in set(labels):
    c=(([0.4,0.4,0.4]) if clust_number == -1 else colors[np.int(clust_number)])
    clust_set = pdf[pdf.Clus_Db == clust_number]
    my_map.scatter(clust_set.xm, clust_set.ym, color =c,  marker='o', s= 20,␣
 ↪alpha = 0.85)
    if clust_number != -1:
        cenx=np.mean(clust_set.xm)
        ceny=np.mean(clust_set.ym)
        plt.text(cenx,ceny,str(clust_number), fontsize=25, color='red',)
        print ("Cluster "+str(clust_number)+', Avg Temp: '+ str(np.
 ↪mean(clust_set.Tm)))
```

1.2.8 7- Clustering of stations based on their location, mean, max, and min Temperature

In this section we re-run DBSCAN, but this time on a 5-dimensional dataset:

[ ]:
```
from sklearn.cluster import DBSCAN
import sklearn.utils
from sklearn.preprocessing import StandardScaler
sklearn.utils.check_random_state(1000)
Clus_dataSet = pdf[['xm','ym','Tx','Tm','Tn']]
Clus_dataSet = np.nan_to_num(Clus_dataSet)
Clus_dataSet = StandardScaler().fit_transform(Clus_dataSet)

# Compute DBSCAN
db = DBSCAN(eps=0.3, min_samples=10).fit(Clus_dataSet)
```

```python
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
pdf["Clus_Db"]=labels

realClusterNum=len(set(labels)) - (1 if -1 in labels else 0)
clusterNum = len(set(labels))


# A sample of clusters
pdf[["Stn_Name","Tx","Tm","Clus_Db"]].head(5)
```

1.2.9 8- Visualization of clusters based on location and Temperture

[ ]:
```python
from mpl_toolkits.basemap import Basemap
import matplotlib.pyplot as plt
from pylab import rcParams
%matplotlib inline
rcParams['figure.figsize'] = (14,10)

my_map = Basemap(projection='merc',
            resolution = 'l', area_thresh = 1000.0,
            llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and␣
 ↪latitude (llcrnrlat)
            urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and␣
 ↪latitude (urcrnrlat)

my_map.drawcoastlines()
my_map.drawcountries()
#my_map.drawmapboundary()
my_map.fillcontinents(color = 'white', alpha = 0.3)
my_map.shadedrelief()

# To create a color map
colors = plt.get_cmap('jet')(np.linspace(0.0, 1.0, clusterNum))



#Visualization1
for clust_number in set(labels):
    c=(([0.4,0.4,0.4]) if clust_number == -1 else colors[np.int(clust_number)])
    clust_set = pdf[pdf.Clus_Db == clust_number]
    my_map.scatter(clust_set.xm, clust_set.ym, color =c,  marker='o', s= 20,␣
 ↪alpha = 0.85)
    if clust_number != -1:
        cenx=np.mean(clust_set.xm)
```

```
        ceny=np.mean(clust_set.ym)
        plt.text(cenx,ceny,str(clust_number), fontsize=25, color='red',)
        print ("Cluster "+str(clust_number)+', Avg Temp: '+ str(np.
↪mean(clust_set.Tm)))
```

Want to learn more?

IBM SPSS Modeler is a comprehensive analytics platform that has many machine learning algorithms. It has been designed to bring predictive intelligence to decisions made by individuals, by groups, by systems – by your enterprise as a whole. A free trial is available through this course, available here: SPSS Modeler

Also, you can use Watson Studio to run these notebooks faster with bigger datasets. Watson Studio is IBM's leading cloud solution for data scientists, built by data scientists. With Jupyter notebooks, RStudio, Apache Spark and popular libraries pre-packaged in the cloud, Watson Studio enables data scientists to collaborate on their projects without having to install anything. Join the fast-growing community of Watson Studio users today with a free account at Watson Studio

1.2.10 Thank you for completing this lab!

1.3 Author

Saeed Aghabozorgi

1.3.1 Other Contributors

Joseph Santarcangelo

1.4 Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-11-03	2.1	Lakshmi	Updated url of csv
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab

##