Exercice Lab: DBSCAN Clustering

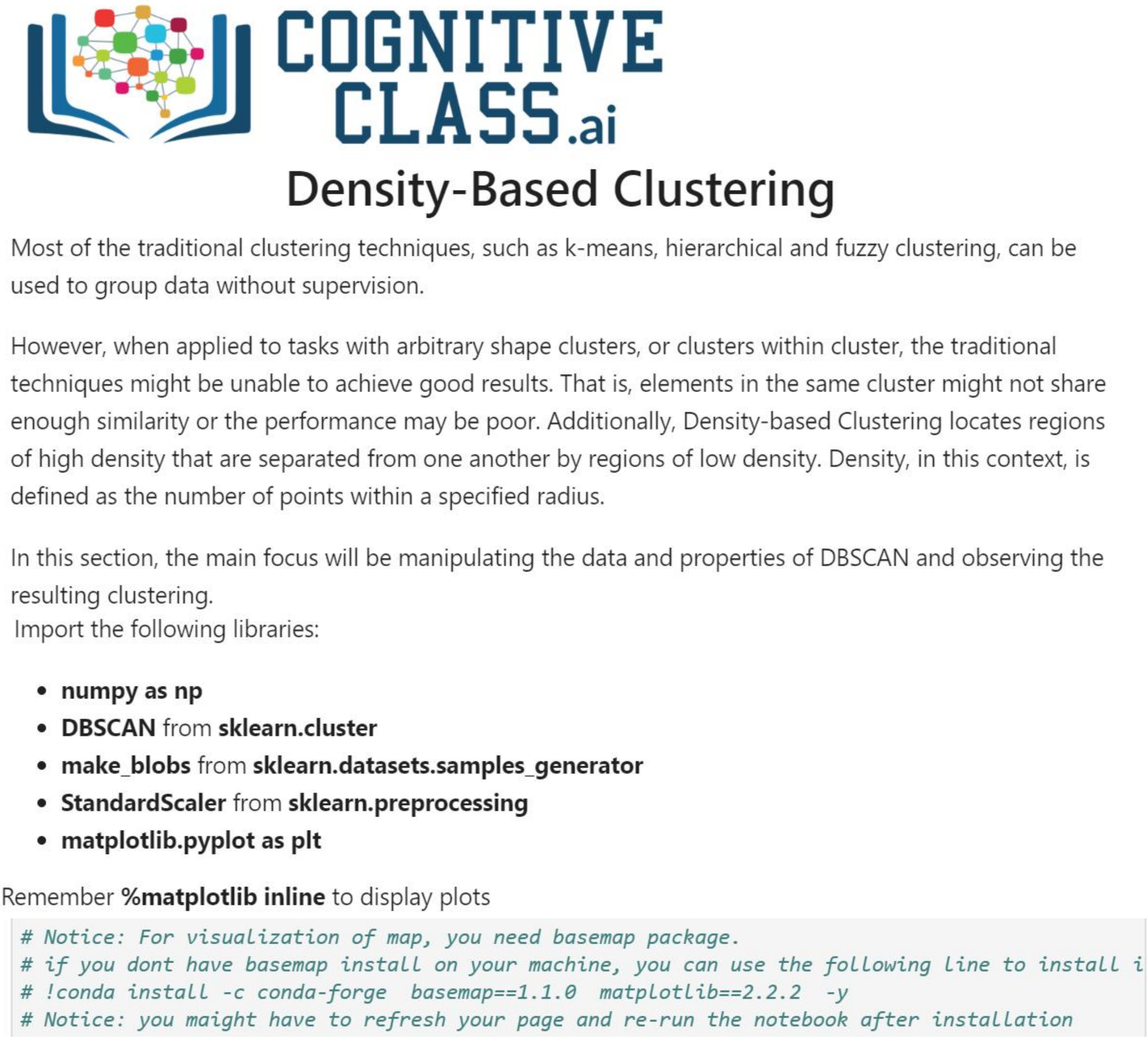
https://www.coursera.org/learn/machine-learning-with-python/ungradedLti/ZYKWP/lab-dbscan-clustering

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.

Please notice that the practice labs (except the last week assignment) are optional and are provided for you to practice and understand the topic. Therefore, you do not need to submit those, as they are not graded, and won't be updated as complete. Just run the codes to see the results, and feel free to change it.

Ce cours utilise l'outil d'un tiers, Lab: DBSCAN Clustering, pour améliorer votre expérience d'apprentissage. L'outil référence des informations de base comme votre nom, votre adresse e-mail et votre ID Coursera.



COGNITIVE CLASS.ai

Density-Based Clustering

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 i
     # !conda install -c conda-forge  basemap==1.1.0  matplotlib==2.2.2  -y
     # Notice: you maight have to refresh your page and re-run the notebook after installation
```

Code
# Notice: For visualization of map, you need basemap package.
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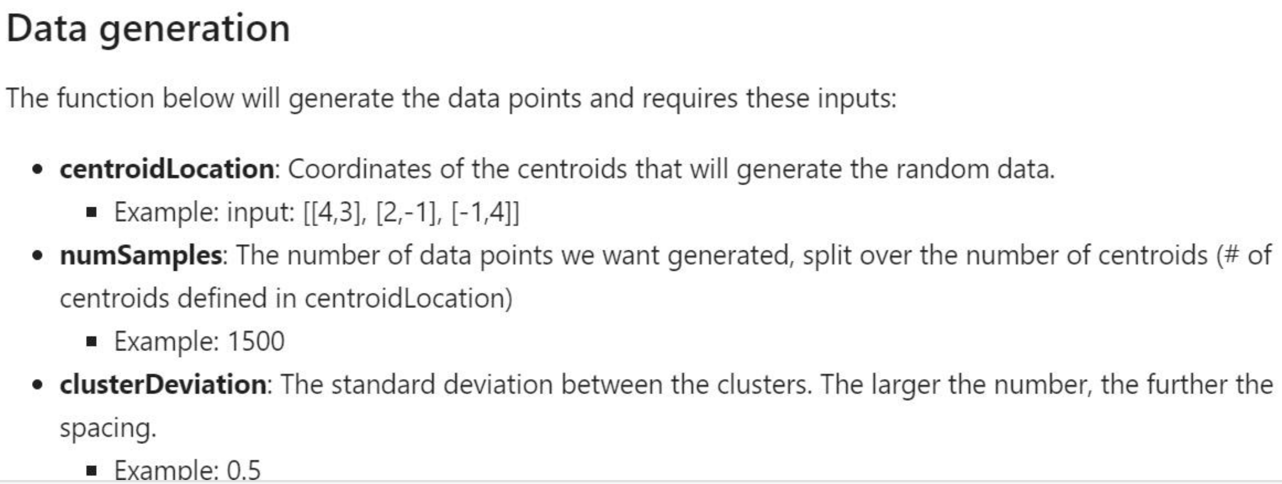
# !conda install -c conda-forge basemap==1.1.0 matplotlib==2.2.2 -y
# Notice: you maight have to refresh your page and re-run the notebook after installation

```
[2]: 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
```

Code

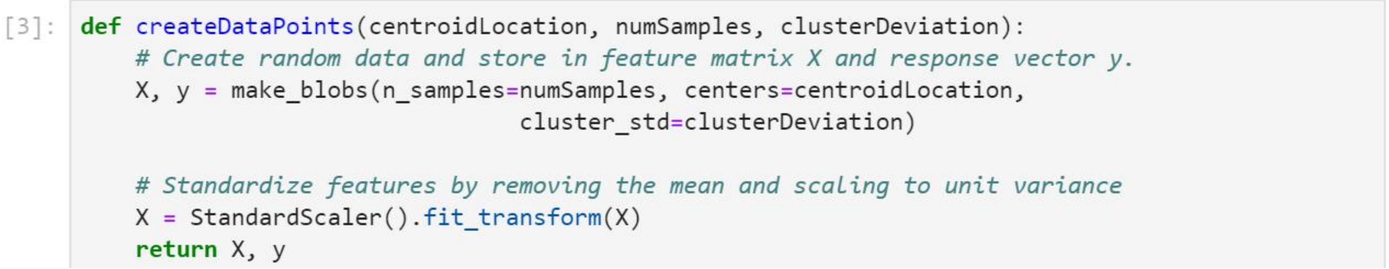
import numpy as np
from sklearn.cluster import DBSCAN
from sklearn.datasets.samples_generator import make_blobs
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
%matplotlib inline



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 between the clusters. The larger the number, the further the spacing.
    - Example: 0.5



```
[3]: 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
```

Code

def createDataPoints(centroidLocation, numSamples, clusterDeviation):
    # Create random data and store in feature matrix X and response vector y.
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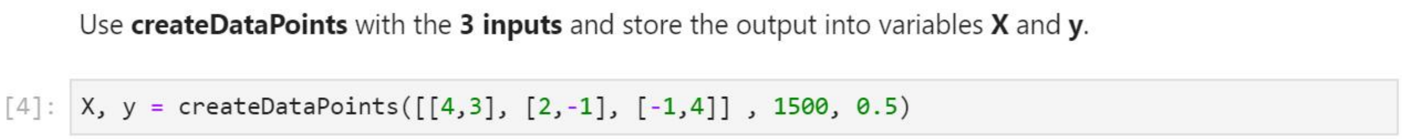
```
    return X, y
```

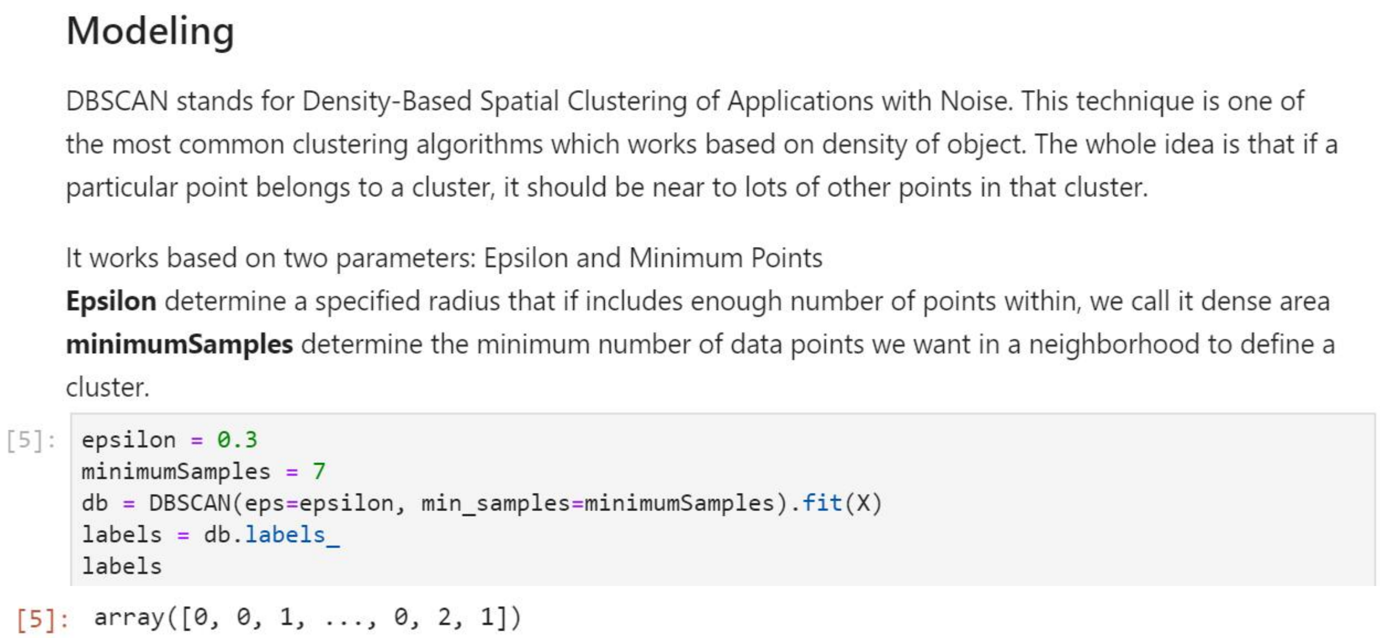


Use **createDataPoints** with the **3 inputs** and store the output into variables **X** and **y**.

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

Code

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



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.

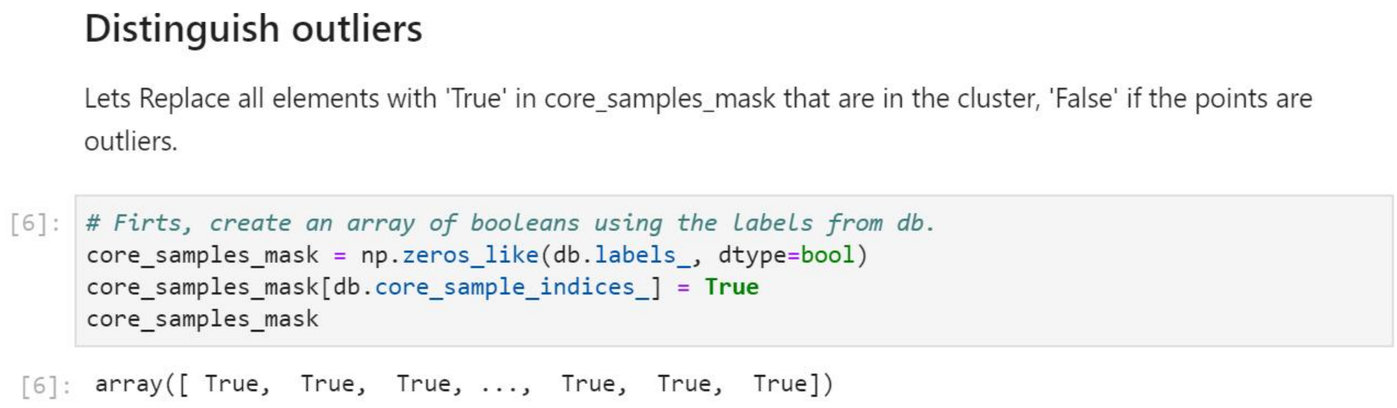
It works based on two parameters: Epsilon and Minimum Points
Epsilon determine a specified radius that if includes enough number of points within, we call it dense area
minimumSamples determine the minimum number of data points we want in a neighborhood to define a cluster.

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

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

Code

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



Distinguish outliers

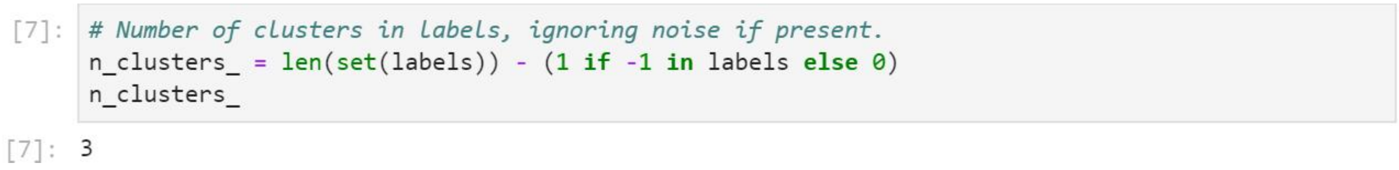
Lets Replace all elements with 'True' in core_samples_mask that are in the cluster, 'False' if the points are outliers.

```
# 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
```

```
array([ True,  True,  True, ...,  True,  True,  True])
```

Code

```
# 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
```

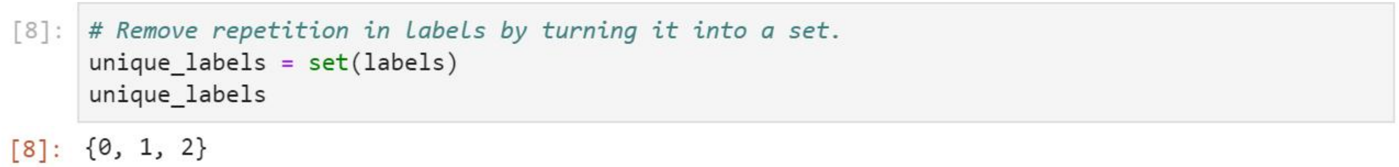


```
[7]: # Number of clusters in labels, ignoring noise if present.
     n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
     n_clusters_

[7]: 3
```

Code

Number of clusters in labels, ignoring noise if present.
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_clusters_

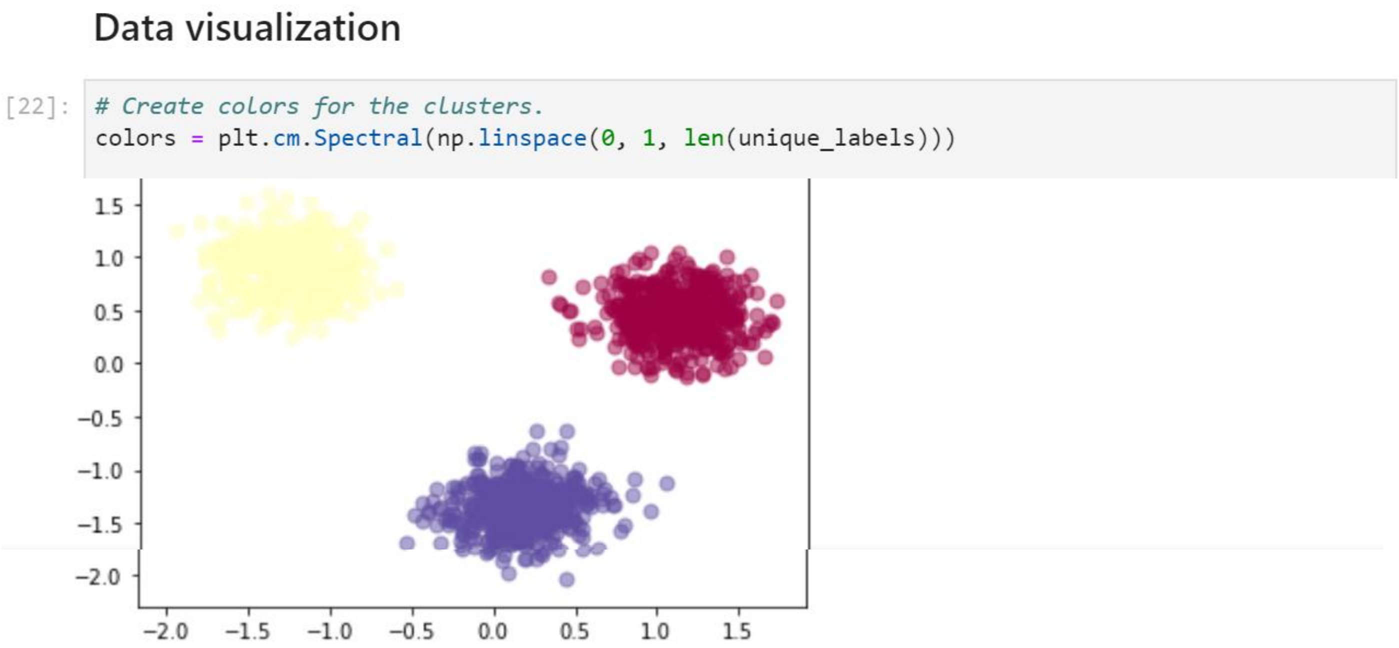


```
[8]: # Remove repetition in labels by turning it into a set.
     unique_labels = set(labels)
     unique_labels

[8]: {0, 1, 2}
```

Code

Remove repetition in labels by turning it into a set.
unique_labels = set(labels)
unique_labels



Data visualization

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

Code

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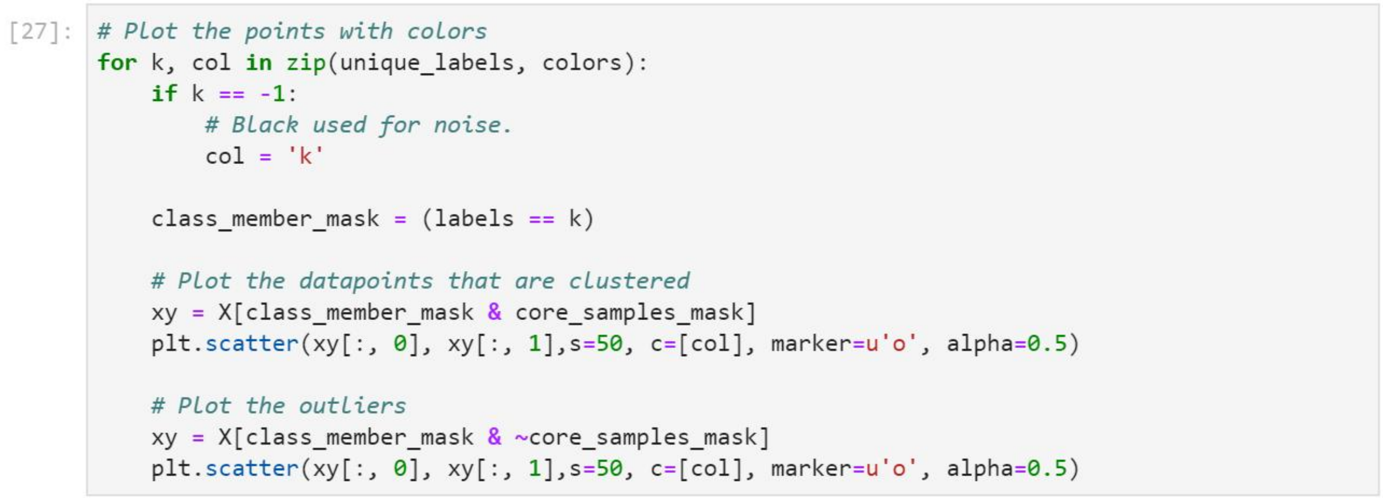
colors = plt.cm.Spectral(np.linspace(0, 1, len(unique_labels)))



```
[27]: # 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)
```

Code

```
# Plot the points with colors
for k, col in zip(unique_labels, colors):
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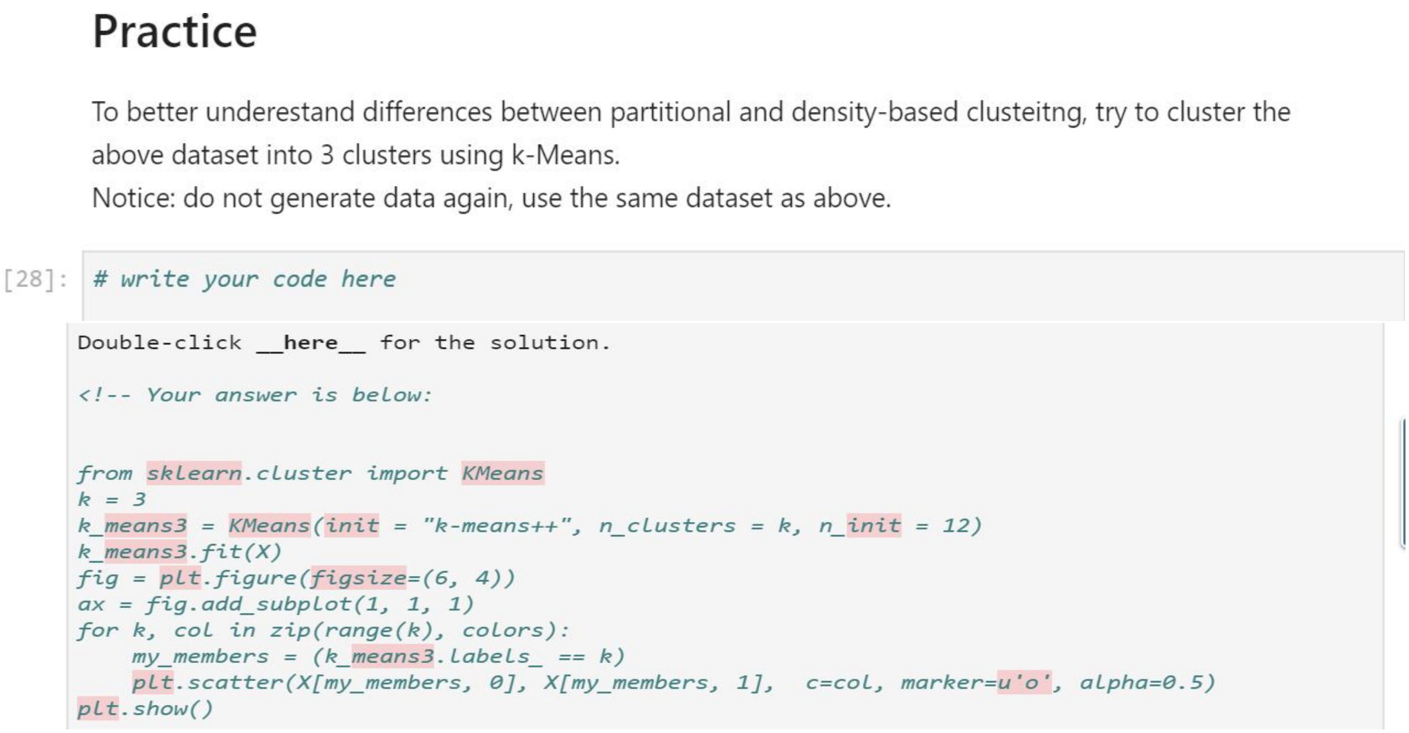


Practice

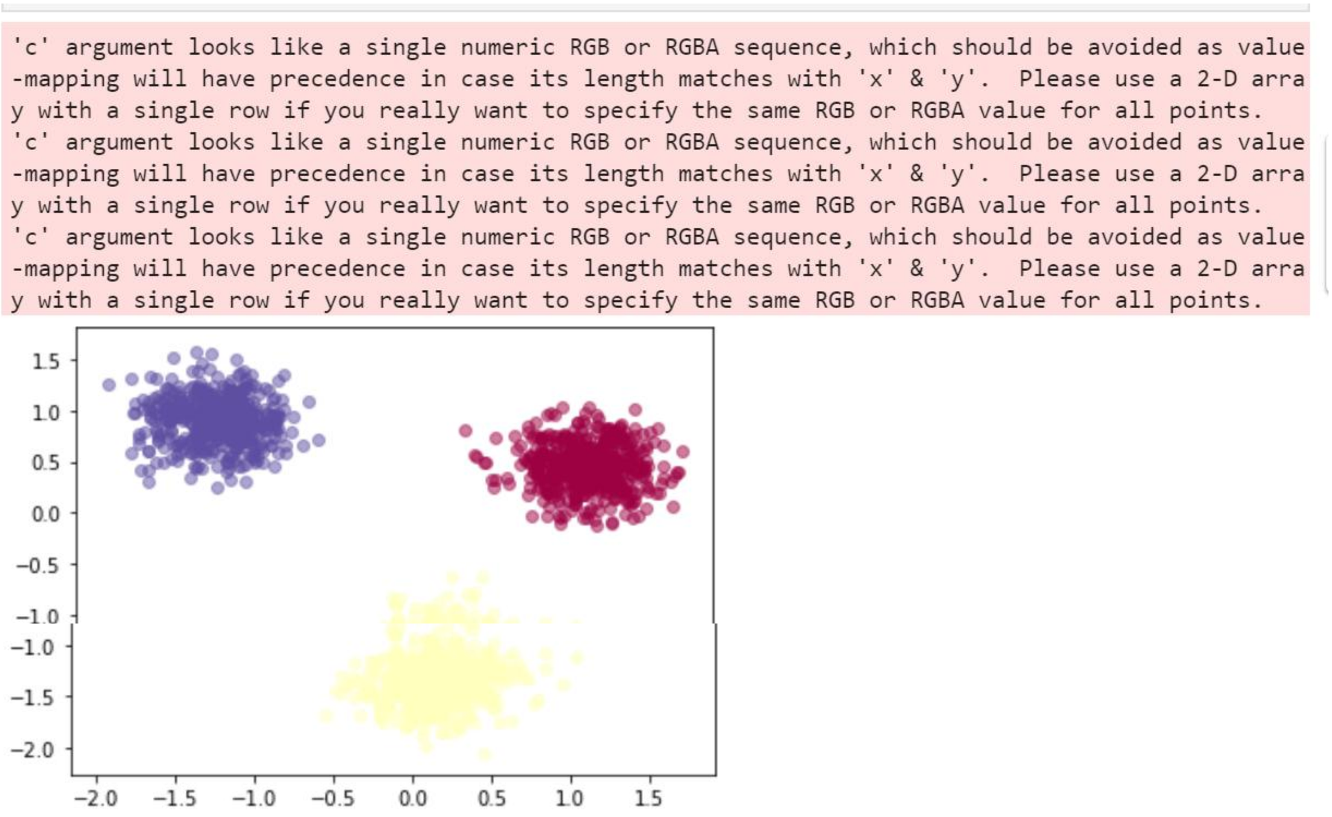
To better underestand differences between partitional and density-based clusteitng, try to cluster the above dataset into 3 clusters using k-Means.
Notice: do not generate data again, use the same dataset as above.

```
[28]: # write your code here
```

```
Double-click __here__ for the solution.

<!-- Your answer is below:


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 arra
y with a single row if you really want to specify the same RGB or RGBA value for all points.
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```

Code
Double-click __here__ for the solution.

<!-- Your answer is below:

```
from sklearn.cluster import KMeans
k = 3
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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 specially very good for tasks like class identification on 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:

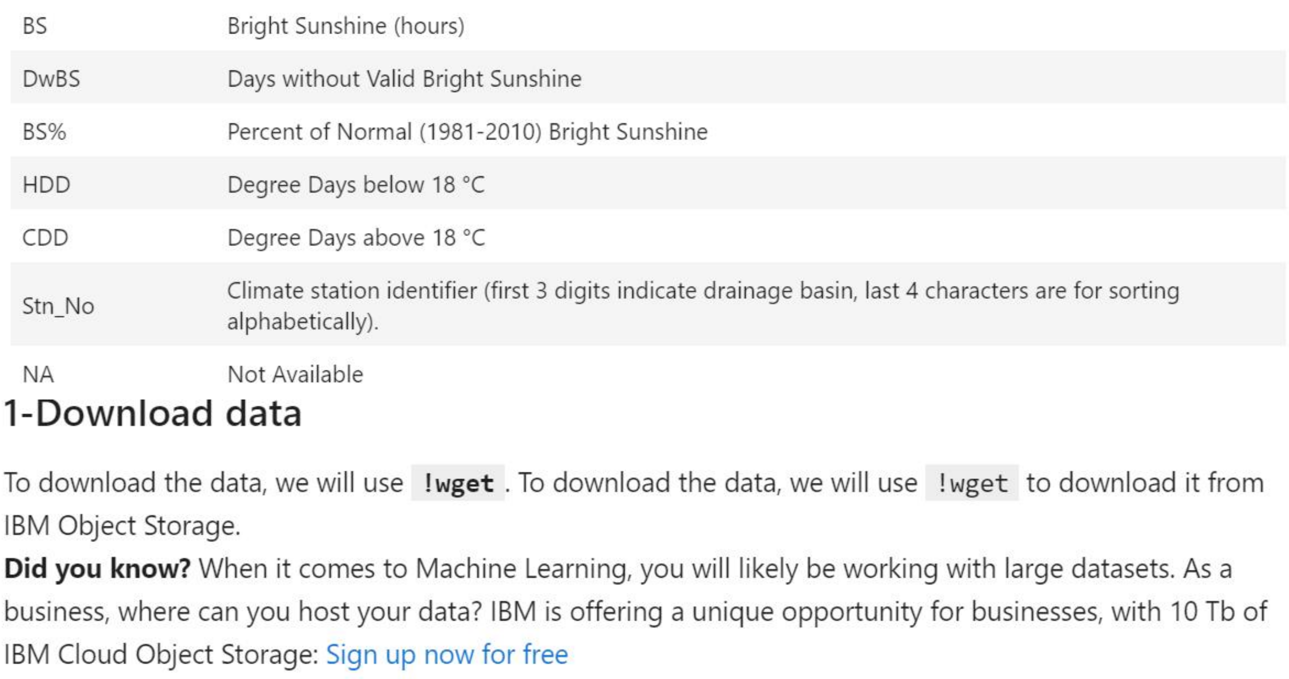
1. Loading data

- Overview data
- Data cleaning
- Data selection
- Clusteing

About the dataset

Environment Canada Monthly Values for July - 2015

Name in the table	Meaning
Stn_Name	**Station Name**
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

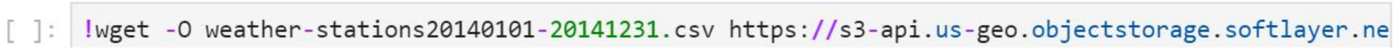


BS	Bright Sunshine (hours)
DwBS	Days without Valid Bright Sunshine
BS%	Percent of Normal (1981-2010) Bright Sunshine
HDD	Degree Days below 18 °C
CDD	Degree Days above 18 °C
Stn_No	Climate station identifier (first 3 digits indicate drainage basin, last 4 characters are for sorting alphabetically).
NA	Not Available

1-Download data

To download the data, we will use `!wget`. 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

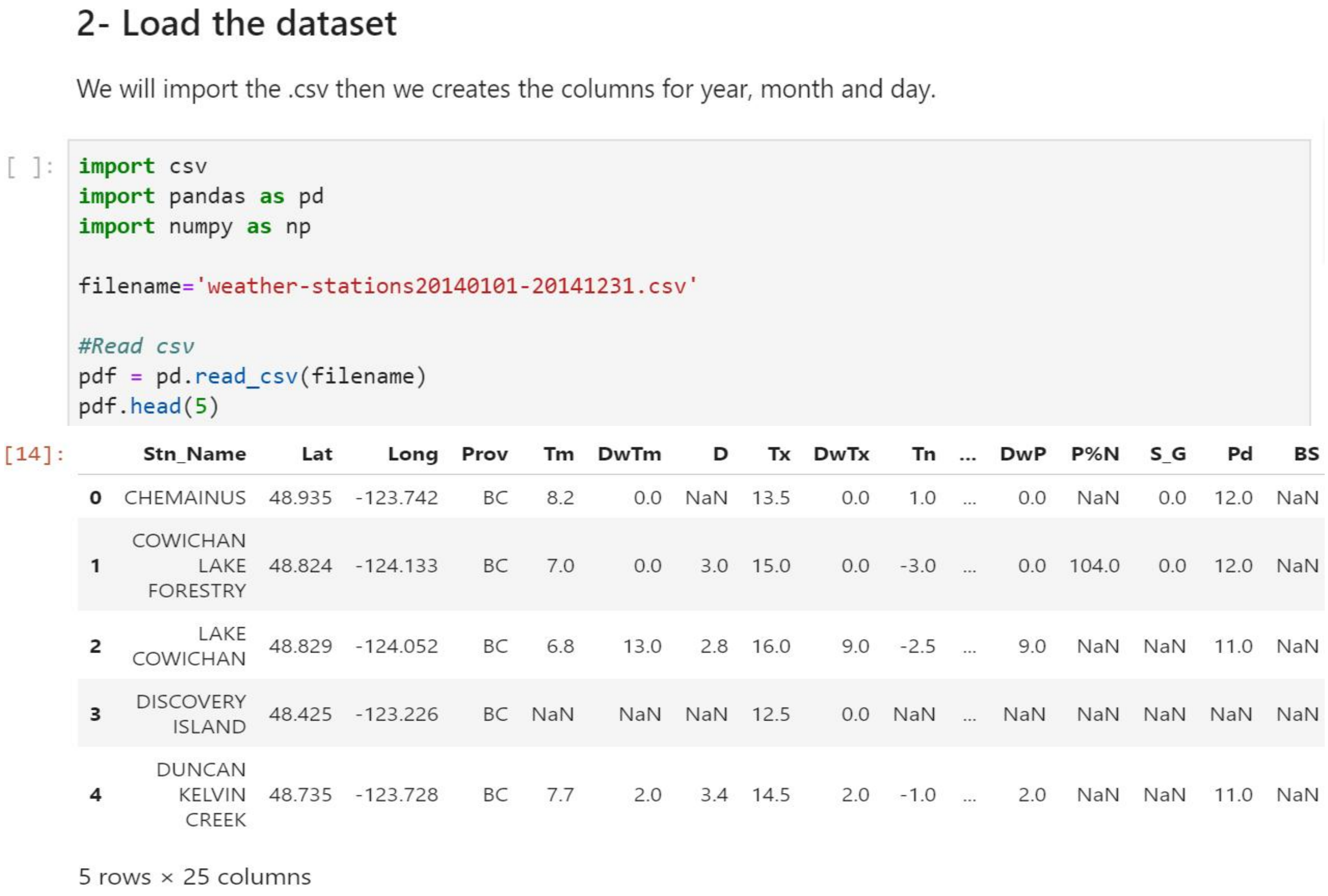


[ ]:

```
!wget -O weather-stations20140101-20141231.csv https://s3-api.us-geo.objectstorage.softlayer.ne
```

Code

!wget -O weather-stations20140101-20141231.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/ML0101ENv3/labs/weather-stations20140101-20141231.csv



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)
```

[14]:

	Stn_Name	Lat	Long	Prov	Tm	DwTm	D	Tx	DwTx	Tn	...	DwP	P%N	S_G	Pd	BS
0	CHEMAINUS	48.935	-123.742	BC	8.2	0.0	NaN	13.5	0.0	1.0	...	0.0	NaN	0.0	12.0	NaN
1	COWICHAN LAKE FORESTRY	48.824	-124.133	BC	7.0	0.0	3.0	15.0	0.0	-3.0	...	0.0	104.0	0.0	12.0	NaN
2	LAKE COWICHAN	48.829	-124.052	BC	6.8	13.0	2.8	16.0	9.0	-2.5	...	9.0	NaN	NaN	11.0	NaN
3	DISCOVERY ISLAND	48.425	-123.226	BC	NaN	NaN	NaN	12.5	0.0	NaN	...	NaN	NaN	NaN	NaN	NaN
4	DUNCAN KELVIN CREEK	48.735	-123.728	BC	7.7	2.0	3.4	14.5	2.0	-1.0	...	2.0	NaN	NaN	11.0	NaN

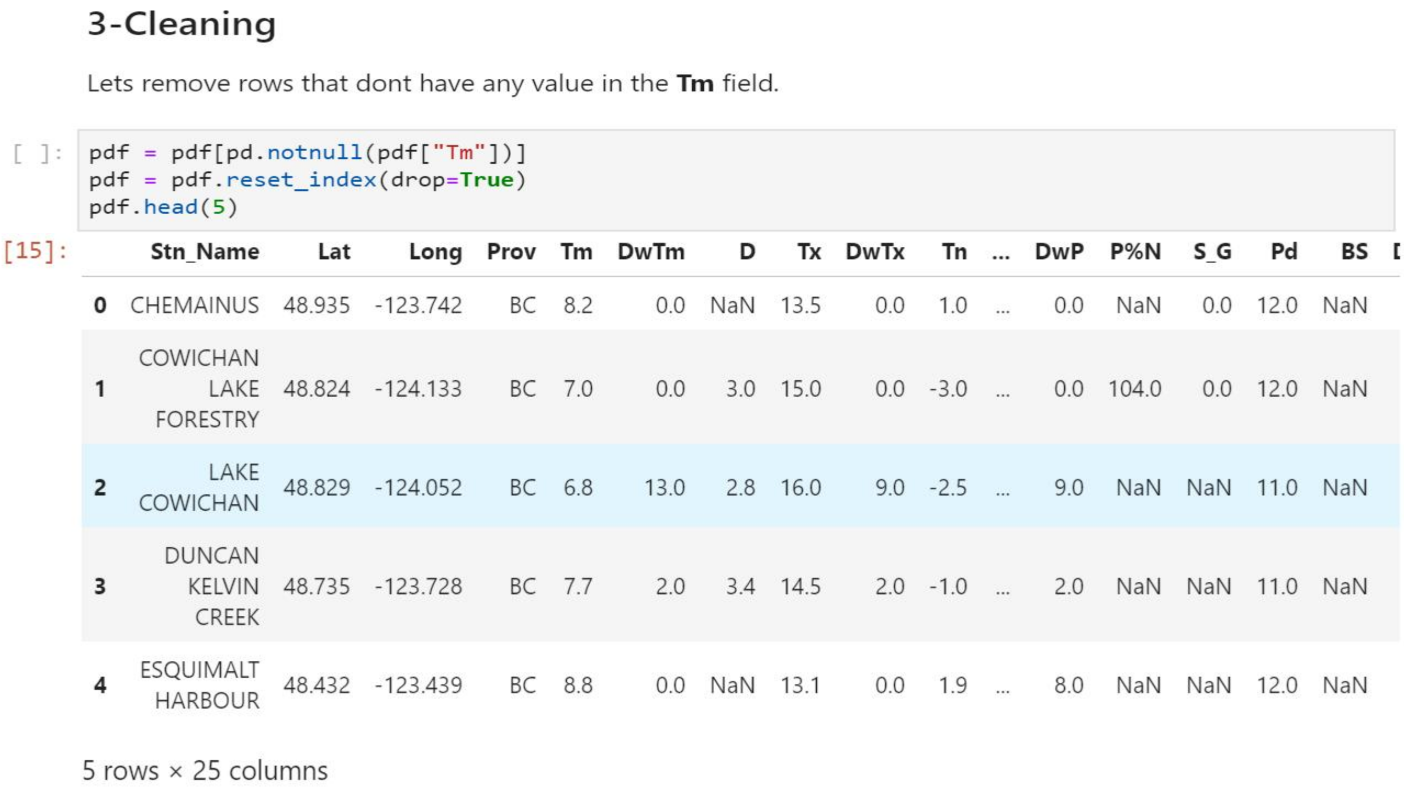
5 rows × 25 columns

Code

```
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)
```



3-Cleaning

Lets remove rows that dont have any value in the **Tm** field.

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

[15]:

	Stn_Name	Lat	Long	Prov	Tm	DwTm	D	Tx	DwTx	Tn	...	DwP	P%N	S_G	Pd	BS
0	CHEMAINUS	48.935	-123.742	BC	8.2	0.0	NaN	13.5	0.0	1.0	...	0.0	NaN	0.0	12.0	NaN
1	COWICHAN LAKE FORESTRY	48.824	-124.133	BC	7.0	0.0	3.0	15.0	0.0	-3.0	...	0.0	104.0	0.0	12.0	NaN
2	LAKE COWICHAN	48.829	-124.052	BC	6.8	13.0	2.8	16.0	9.0	-2.5	...	9.0	NaN	NaN	11.0	NaN
3	DUNCAN KELVIN CREEK	48.735	-123.728	BC	7.7	2.0	3.4	14.5	2.0	-1.0	...	2.0	NaN	NaN	11.0	NaN
4	ESQUIMALT HARBOUR	48.432	-123.439	BC	8.8	0.0	NaN	13.1	0.0	1.9	...	8.0	NaN	NaN	12.0	NaN

5 rows × 25 columns

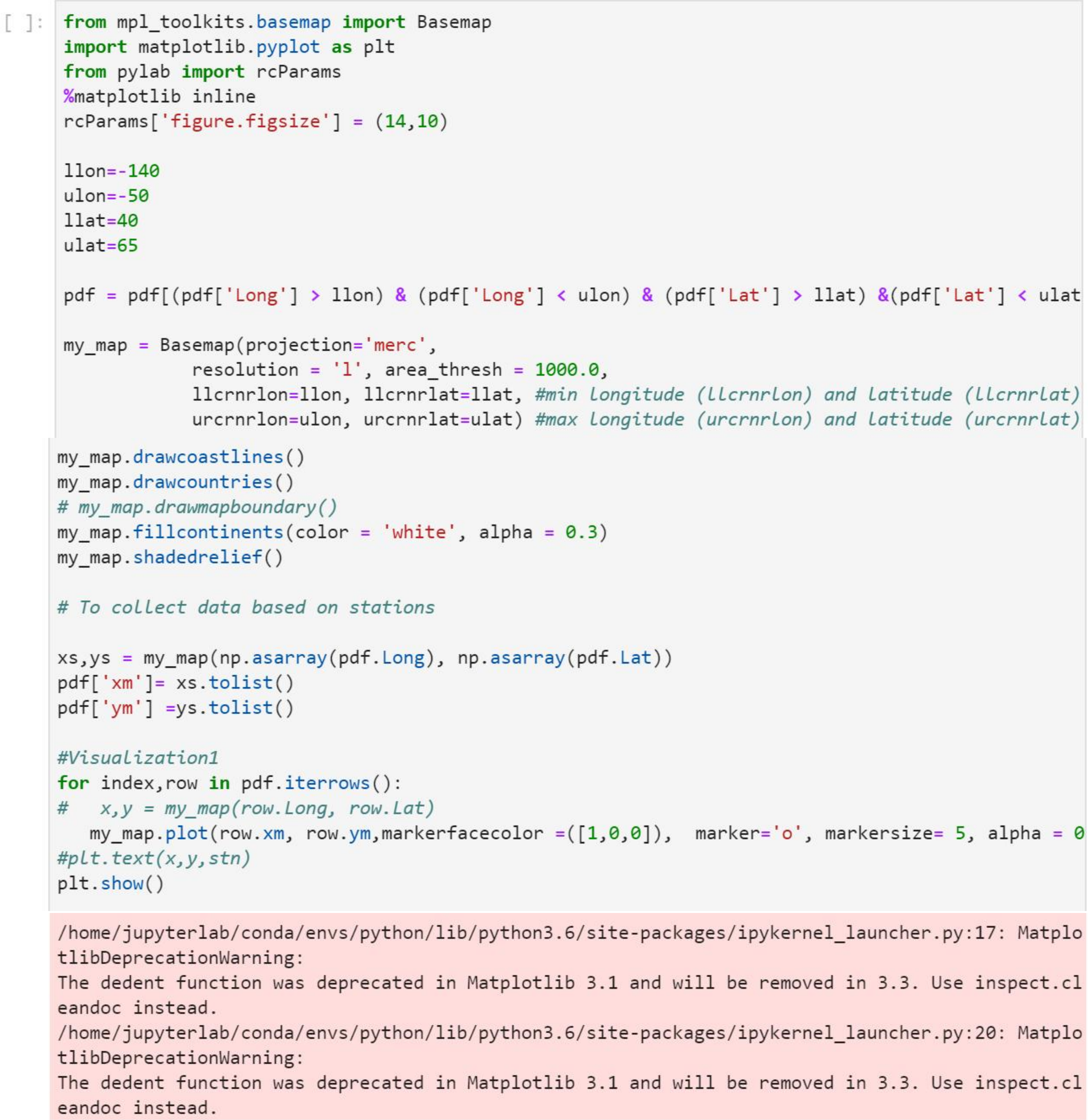
Code

```
pdf = pdf[pd.notnull(pdf["Tm"])]
pdf = pdf.reset_index(drop=True)
pdf.head(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
#plt.text(x,y,stn)
plt.show()
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:17: Matplo
tlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
eandoc instead.
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:20: Matplo
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The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
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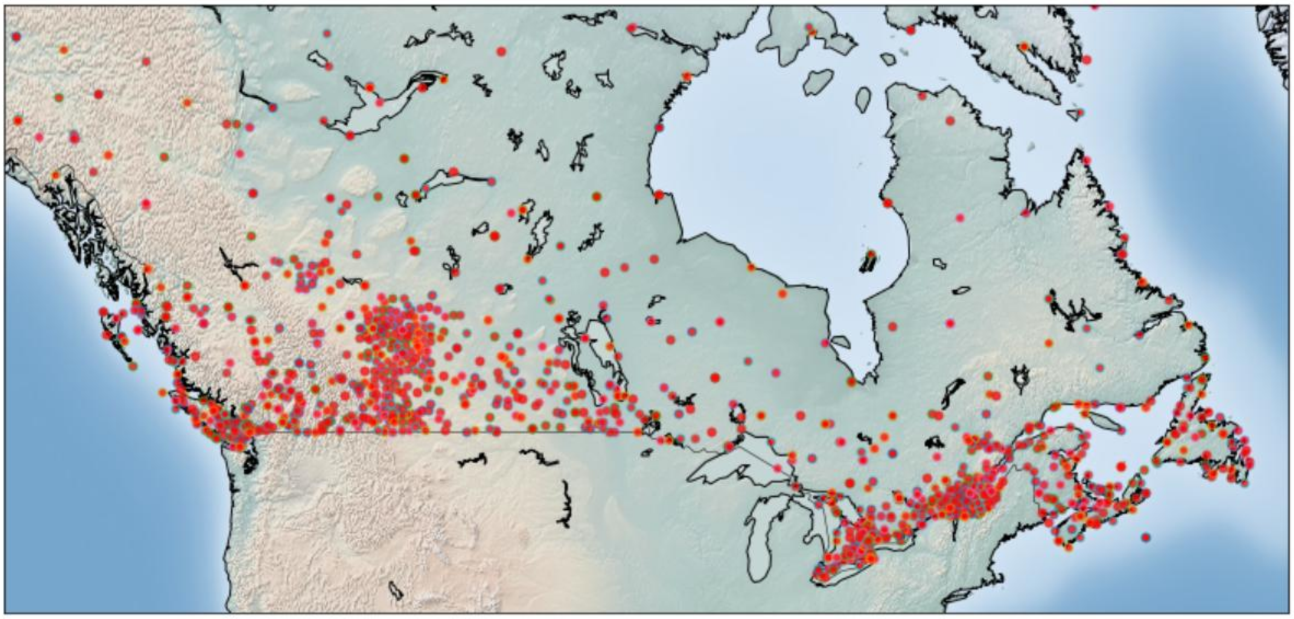
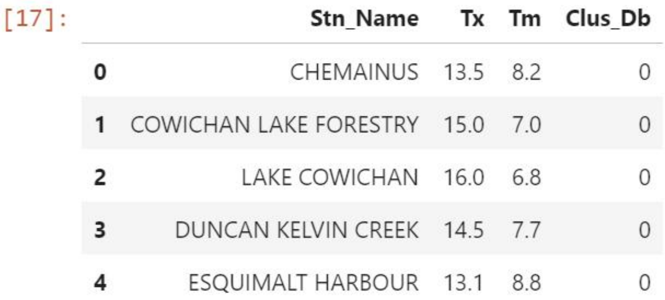
```





[17]:

	Stn_Name	Tx	Tm	Clus_Db
0	CHEMAINUS	13.5	8.2	0
1	COWICHAN LAKE FORESTRY	15.0	7.0	0
2	LAKE COWICHAN	16.0	6.8	0
3	DUNCAN KELVIN CREEK	14.5	7.7	0
4	ESQUIMALT HARBOUR	13.1	8.8	0

Code

```
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)]

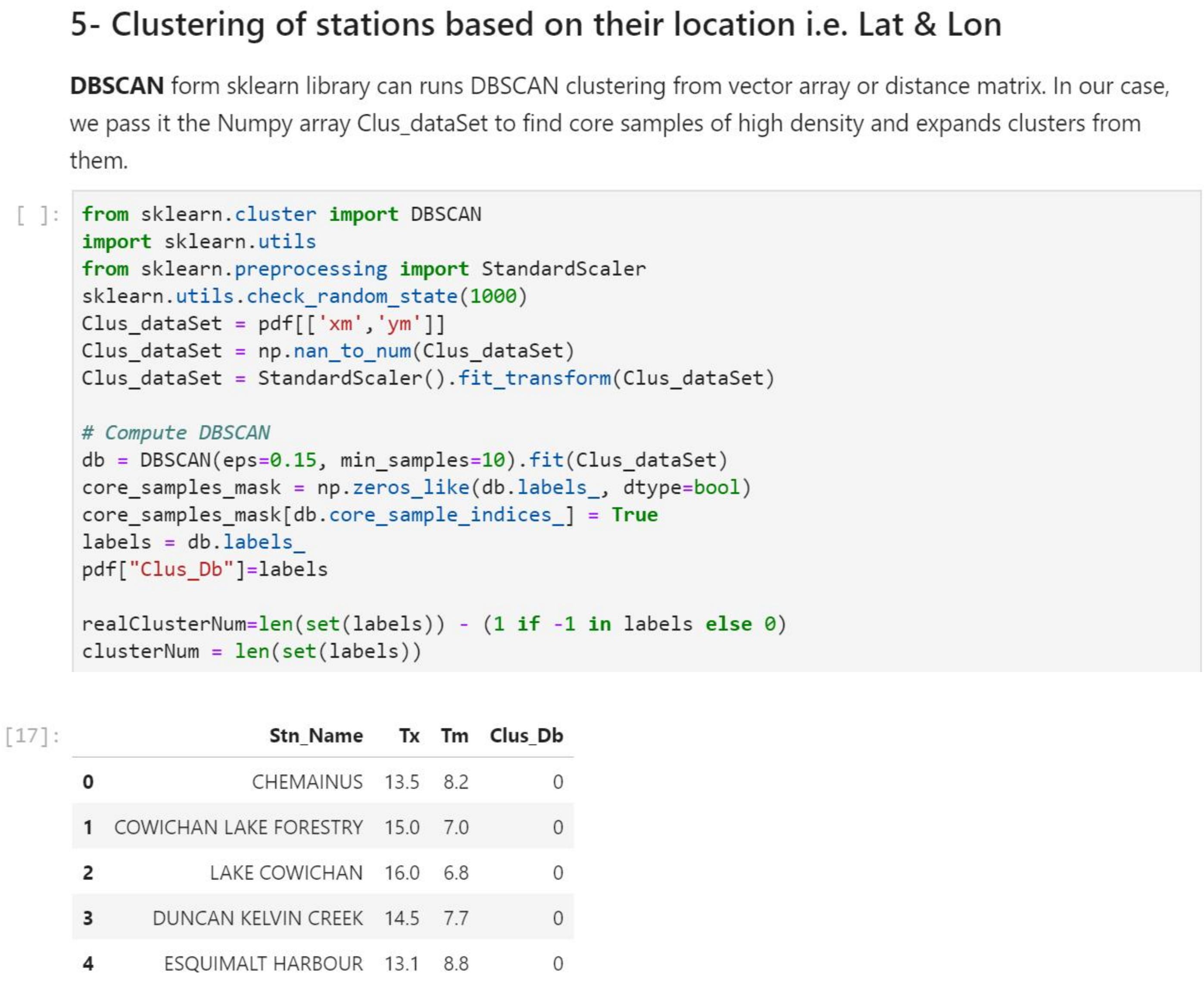
my_map = Basemap(projection='merc',
        resolution = 'l', area_thresh = 1000.0,
        llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and latitude (llcrnrlat)
        urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and latitude (urcrnrlat)

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()
```



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))
```

[17]:

	Stn_Name	Tx	Tm	Clus_Db
0	CHEMAINUS	13.5	8.2	0
1	COWICHAN LAKE FORESTRY	15.0	7.0	0
2	LAKE COWICHAN	16.0	6.8	0
3	DUNCAN KELVIN CREEK	14.5	7.7	0
4	ESQUIMALT HARBOUR	13.1	8.8	0

Code

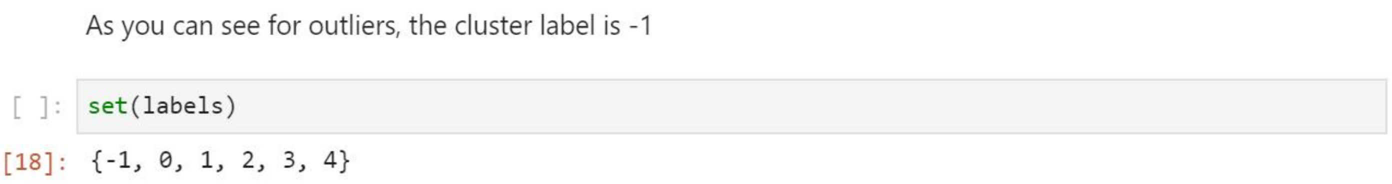
```
from sklearn.cluster import DBSCAN
import sklearn.utils
```

```
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)

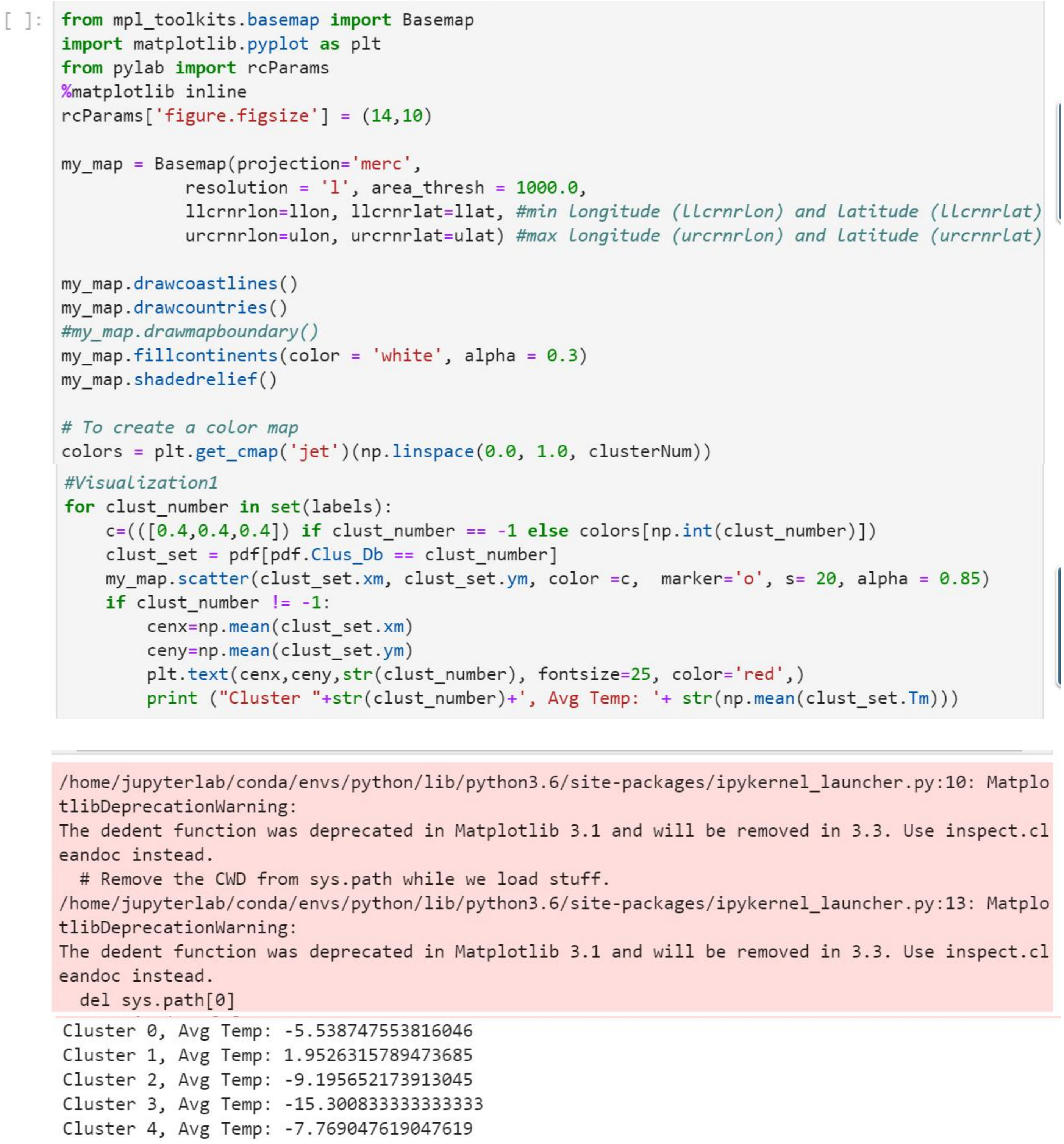
[18]: {-1, 0, 1, 2, 3, 4}
```

Code

```
set(labels)
```

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)

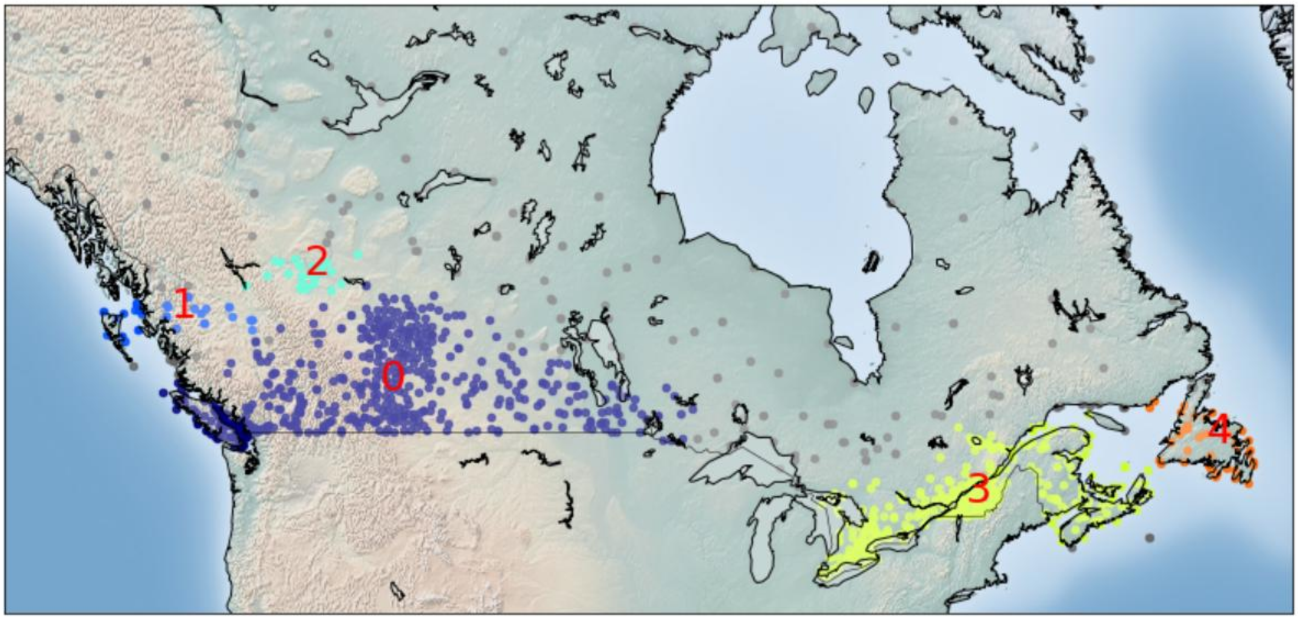
     my_map = Basemap(projection='merc',
                 resolution = 'l', area_thresh = 1000.0,
                 llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and latitude (llcrnrlat)
                 urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and latitude (urcrnrlat)

     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)))
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:10: Matplo
tlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
eandoc instead.
  # Remove the CWD from sys.path while we load stuff.
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:13: Matplo
tlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
eandoc instead.
  del sys.path[0]
```

```
Cluster 0, Avg Temp: -5.538747553816046
Cluster 1, Avg Temp: 1.9526315789473685
Cluster 2, Avg Temp: -9.195652173913045
Cluster 3, Avg Temp: -15.300833333333333
Cluster 4, Avg Temp: -7.769047619047619
```



Code

```
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)

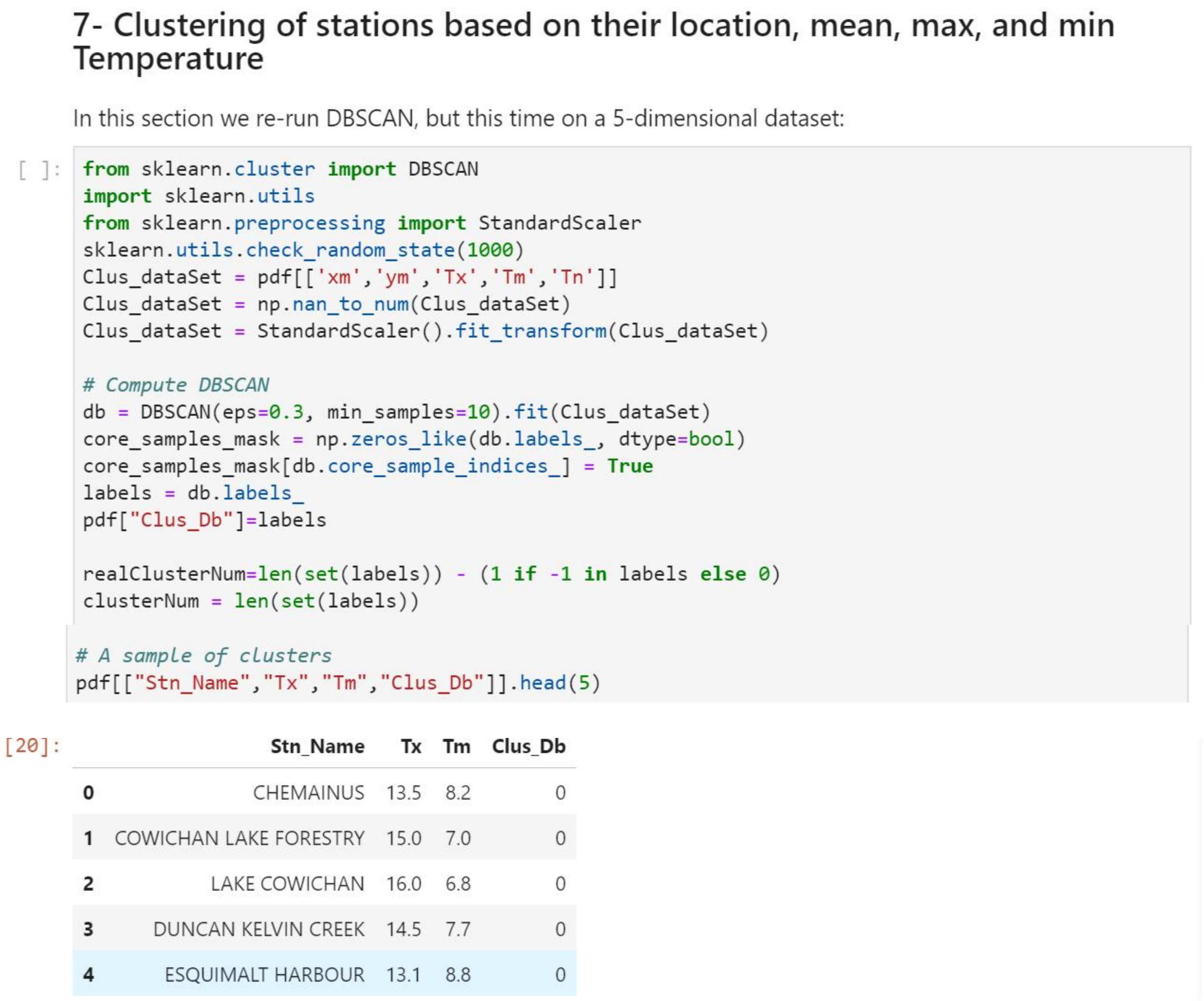
my_map.drawcoastlines()
my_map.drawcountries()
#my_map.drawmapboundary()
my_map.fillcontinents(color = 'white', alpha = 0.3)
my_map.shadedrelief()

# 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)))
```



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)
     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)
```

[20]:

	Stn_Name	Tx	Tm	Clus_Db
0	CHEMAINUS	13.5	8.2	0
1	COWICHAN LAKE FORESTRY	15.0	7.0	0
2	LAKE COWICHAN	16.0	6.8	0
3	DUNCAN KELVIN CREEK	14.5	7.7	0
4	ESQUIMALT HARBOUR	13.1	8.8	0

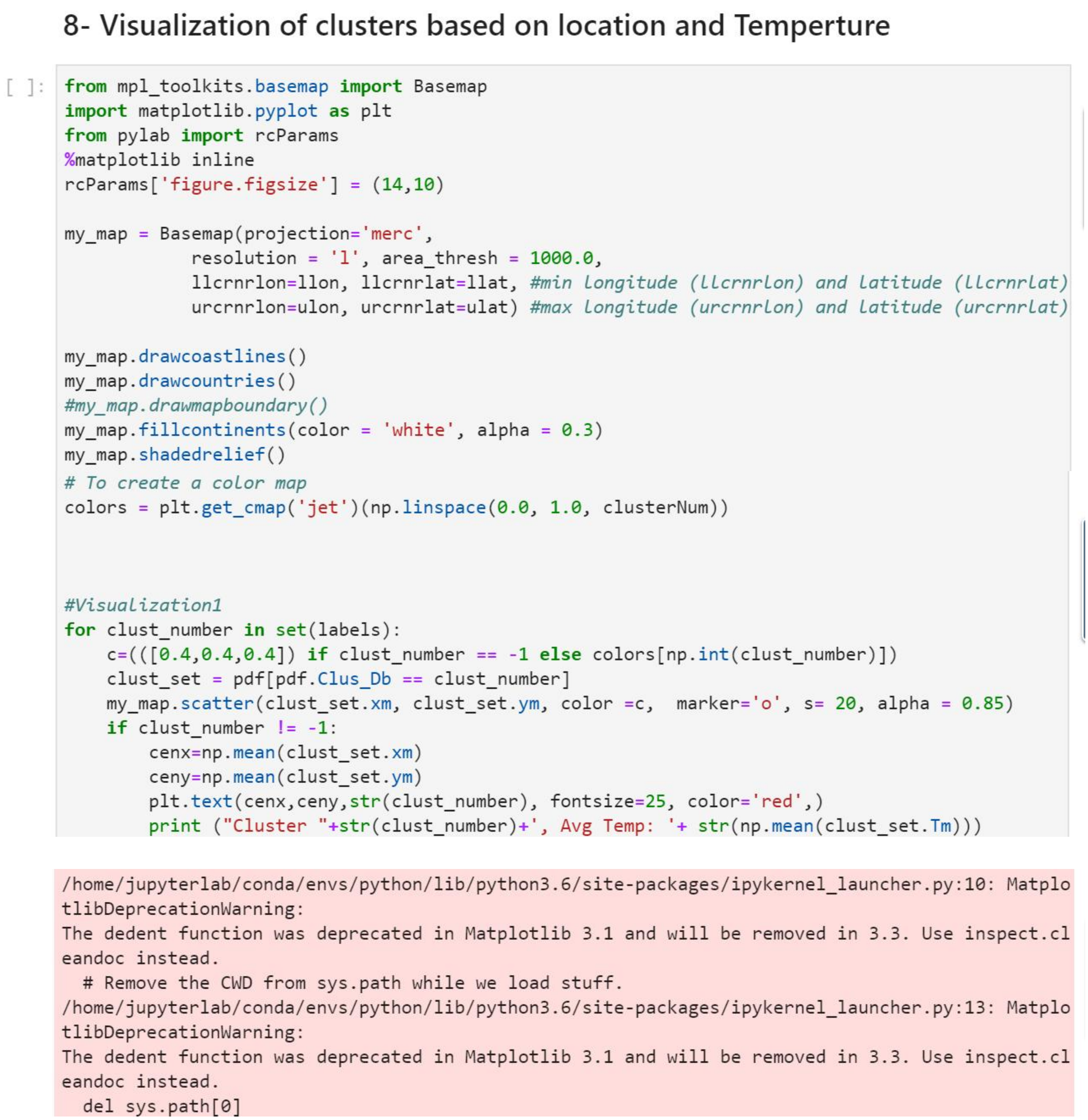
Code

```
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)
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)



8- Visualization of clusters based on location and Temperture

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

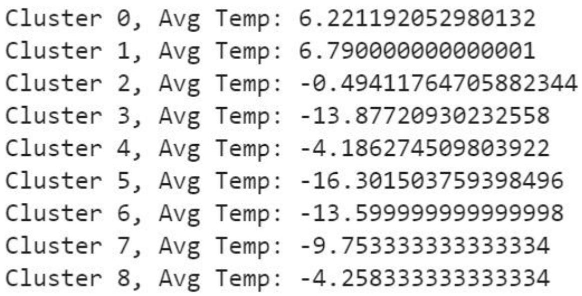
     my_map = Basemap(projection='merc',
                 resolution = 'l', area_thresh = 1000.0,
                 llcrnrlon=llon, llcrnrlat=llat, #min longitude (llcrnrlon) and latitude (llcrnrlat)
                 urcrnrlon=ulon, urcrnrlat=ulat) #max longitude (urcrnrlon) and latitude (urcrnrlat)

     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))

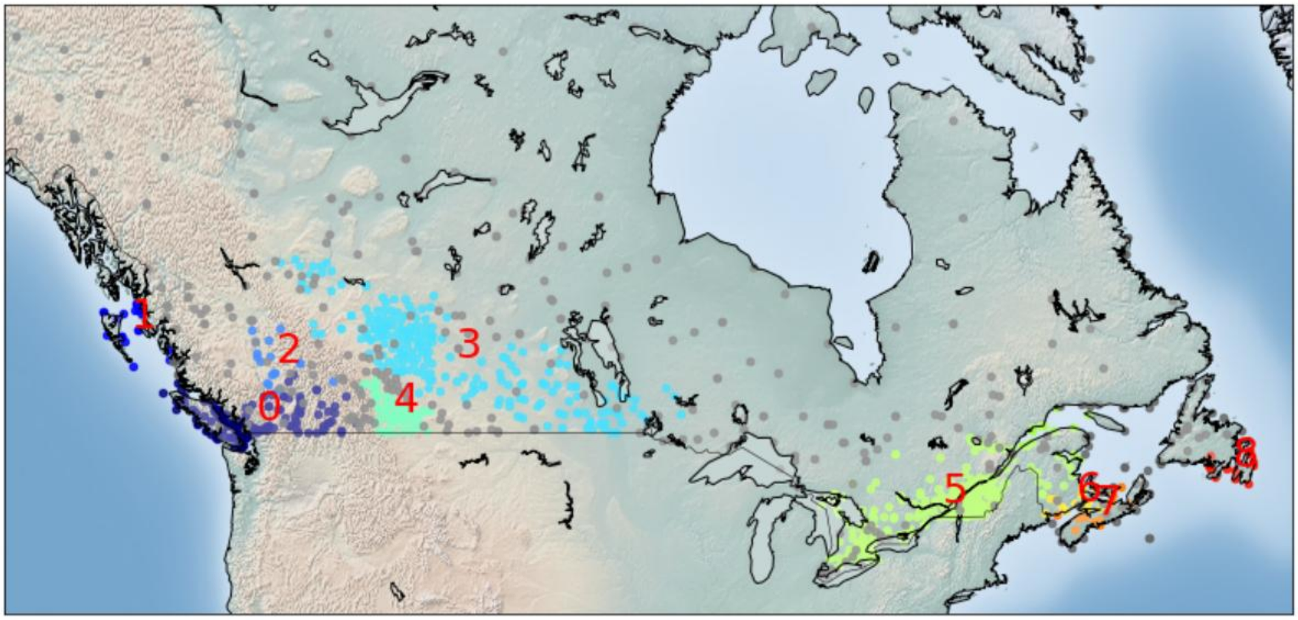


     #Visualization1
     for clust_number in set(labels):
         c=(([0.4,0.4,0.4]) if clust_number == -1 else colors[np.int(clust_number)])
         clust_set = pdf[pdf.Clus_Db == clust_number]
         my_map.scatter(clust_set.xm, clust_set.ym, color =c,  marker='o', s= 20, alpha = 0.85)
         if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

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:10: Matplo
tlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
eandoc instead.
  # Remove the CWD from sys.path while we load stuff.
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:13: Matplo
tlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be removed in 3.3. Use inspect.cl
eandoc instead.
  del sys.path[0]
```



```
Cluster 0, Avg Temp: 6.221192052980132
Cluster 1, Avg Temp: 6.790000000000001
Cluster 2, Avg Temp: -0.49411764705882344
Cluster 3, Avg Temp: -13.87720930232558
Cluster 4, Avg Temp: -4.186274509803922
Cluster 5, Avg Temp: -16.301503759398496
Cluster 6, Avg Temp: -13.599999999999998
Cluster 7, Avg Temp: -9.753333333333334
Cluster 8, Avg Temp: -4.258333333333334
```



Code

```
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)

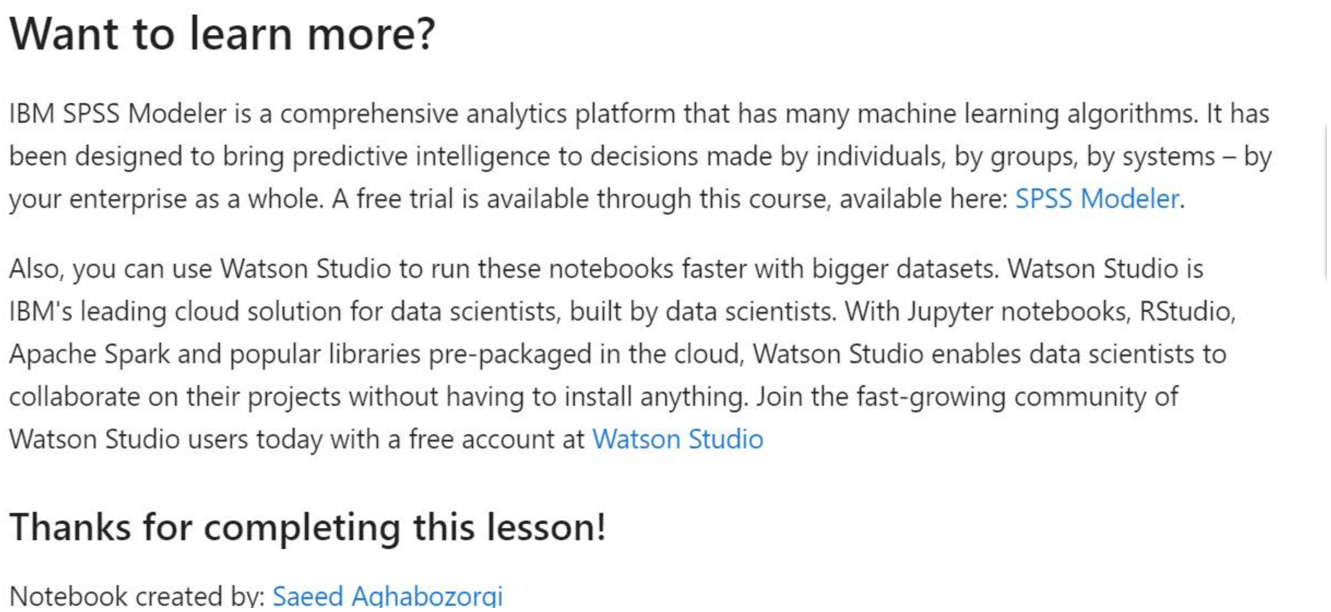
my_map.drawcoastlines()
my_map.drawcountries()
#my_map.drawmapboundary()
my_map.fillcontinents(color = 'white', alpha = 0.3)
my_map.shadedrelief()

# 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

Thanks for completing this lesson!

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