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!pip install minisom
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Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/sim
Collecting minisom
  Downloading MiniSom-2.3.0.tar.gz (8.8 kB)
Building wheels for collected packages: minisom
  Building wheel for minisom (setup.py) ... done
  Created wheel for minisom: filename=MiniSom-2.3.0-py3-none-any.whl size=9018 sha256=efb7f8d6
  Stored in directory: /root/.cache/pip/wheels/d4/ca/4a/488772b0399fec45ff53132ed14c948dec4b30
Successfully built minisom
Installing collected packages: minisom
Successfully installed minisom-2.3.0
```

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
# Minisom library and module is used for performing Self Organizing Maps
from minisom import MiniSom
# Loading Data
data = pd.read_csv('Credit_Card_Applications.csv')
# X
data
# Shape of the data:
data.shape
# Info of the data:
data.info()
# Defining X variables for the input of SOM
X = data.iloc[:, 1:14].values
y = data.iloc[:, -1].values
# X variables:
pd.DataFrame(X)
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
X = sc.fit_transform(X)
pd.DataFrame(X)
# Set the hyper parameters
som_grid_rows = 10
som_grid_columns = 10
iterations = 20000
sigma = 1
learning_rate = 0.5
# define SOM:
som = MiniSom(x = som_grid_rows, y = som_grid_columns, input_len=13, sigma=sigma, learning_rate=lear
# Initializing the weights
som.random_weights_init(X)
# Training
som.train_random(X, iterations)
# Weights are:
#wts = som.weights
# Shape of the weight are:
#wts.shape
# Returns the distance map from the weights:
som.distance_map()
from pylab import plot, axis, show, pcolor, colorbar, bone
bone()
```

```

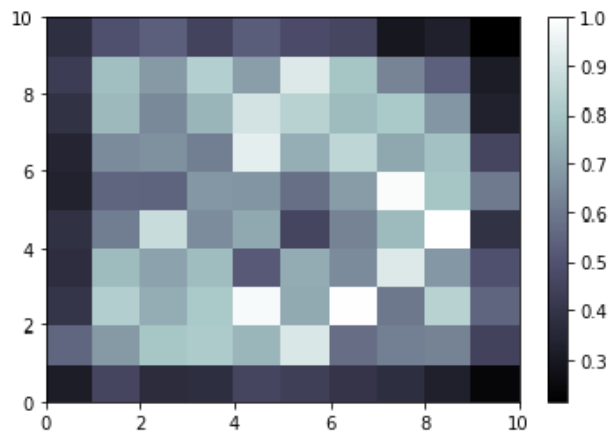
colorbar()
show()
bone()
pcolor(som.distance_map().T)
colorbar() #gives legend
markers = ['o', 's'] # if the observation is fraud then red circular color or else g
colors = ['r', 'g']
for i, x in enumerate(X):
    w = som.winner(x)
    plot(w[0] + 0.5,
         w[1] + 0.5,
         markers[y[i]],
         markeredgecolor = colors[y[i]],
         markerfacecolor = 'None',
         markersize = 10,
         markeredgewidth = 2)
show()

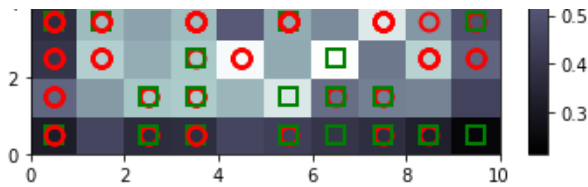
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
#   Column      Non-Null Count  Dtype
---  -
0   CustomerID  690 non-null    int64
1   A1           690 non-null    int64
2   A2           690 non-null    float64
3   A3           690 non-null    float64
4   A4           690 non-null    int64
5   A5           690 non-null    int64
6   A6           690 non-null    int64
7   A7           690 non-null    float64
8   A8           690 non-null    int64
9   A9           690 non-null    int64
10  A10          690 non-null    int64
11  A11          690 non-null    int64
12  A12          690 non-null    int64
13  A13          690 non-null    int64
14  A14          690 non-null    int64
15  Class       690 non-null    int64
dtypes: float64(3), int64(13)
memory usage: 86.4 KB

```





```
mappings = som.win_map(X)
mappings
mappings.keys()
len(mappings.keys())
mappings[(9,8)]
frauds = np.concatenate((mappings[(4,7)], mappings[(5,8)]), axis = 0)
frauds
# the list of customers who are frauds:
frauds1 = sc.inverse_transform(frauds)
pd.DataFrame(frauds1)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
00.0	19.50	0.165	2.0	11.0	4.0	0.040	0.0	0.0	0.0	0.0	1.0	2.0	380.0
10.0	29.75	0.665	2.0	9.0	4.0	0.250	0.0	0.0	0.0	0.0	1.0	2.0	300.0
20.0	21.75	11.750	2.0	8.0	4.0	0.250	0.0	0.0	0.0	0.0	1.0	2.0	180.0
30.0	50.25	0.835	2.0	6.0	4.0	0.500	0.0	0.0	0.0	0.0	1.0	2.0	240.0
40.0	26.17	2.000	2.0	5.0	3.0	0.000	0.0	0.0	0.0	0.0	1.0	2.0	276.0
50.0	22.92	1.250	2.0	11.0	4.0	0.250	0.0	0.0	0.0	0.0	1.0	2.0	120.0
60.0	24.83	4.500	2.0	9.0	4.0	1.000	0.0	0.0	0.0	0.0	1.0	2.0	360.0
70.0	18.08	0.375	3.0	13.0	1.0	10.000	0.0	0.0	0.0	0.0	1.0	1.0	300.0
80.0	45.33	1.000	2.0	11.0	4.0	0.125	0.0	0.0	0.0	0.0	1.0	2.0	263.0
90.0	23.50	1.500	2.0	9.0	4.0	0.875	0.0	0.0	0.0	0.0	1.0	2.0	160.0
100.0	27.67	2.040	2.0	9.0	4.0	0.250	0.0	0.0	0.0	0.0	1.0	2.0	180.0
110.0	32.25	1.500	2.0	8.0	4.0	0.250	0.0	0.0	0.0	0.0	1.0	2.0	372.0
120.0	24.50	0.500	2.0	11.0	8.0	1.500	1.0	0.0	0.0	0.0	0.0	2.0	280.0
130.0	28.08	15.000	1.0	10.0	9.0	0.000	1.0	0.0	0.0	0.0	0.0	2.0	0.0
140.0	40.83	10.000	2.0	11.0	8.0	1.750	1.0	0.0	0.0	0.0	0.0	2.0	29.0
150.0	18.83	4.415	1.0	8.0	8.0	3.000	1.0	0.0	0.0	0.0	0.0	2.0	240.0
160.0	25.17	2.875	2.0	14.0	8.0	0.875	1.0	0.0	0.0	0.0	0.0	2.0	360.0
170.0	20.50	11.835	2.0	8.0	8.0	6.000	1.0	0.0	0.0	0.0	0.0	2.0	340.0
180.0	24.58	0.670	2.0	6.0	8.0	1.750	1.0	0.0	0.0	0.0	0.0	2.0	400.0