SAP ID:

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)**

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**COURSE NAME: Machine Learning – II Laboratory** **CLASS: T.Y.B.Tech (D1)**

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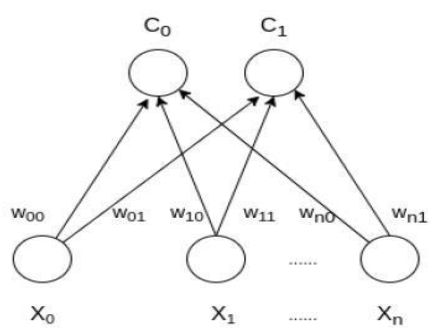
# Experiment 7

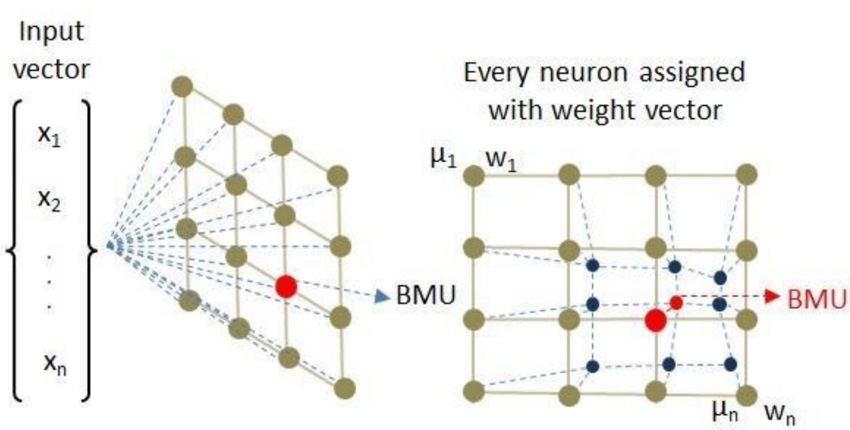
**AIM :** Anomaly detection using Self-Organizing Network.

**THEORY:**

**Self-Organizing Maps:**

Self Organizing Map (or Kohonen Map or SOM) is a type of Artificial Neural Network that follows an unsupervised learning approach and trains its network through a competitive learning algorithm. SOM is used for clustering and mapping (or dimensionality reduction) techniques to map multidimensional data onto lower-dimensional which allows people to reduce complex problems for easy interpretation. SOM has two layers, one is the Input layer and the other one is the Output layer. The architecture of the Self Organizing Map with two clusters and n input features of any sample is given below:



The underlying idea of the SOMs training process is to examine every node and find the one node whose weight is most like the input vector. The winning neuron is known as Best Matching Unit(BMU). The weights of the neighbouring neuron are adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights get altered. The training is carried out in a few steps and over many iterations. The output of the SOMs is a two-dimensional map and color-coding is used to identify any specific group of data points.

**Hyperparameters:**

SOMs are a two-dimensional array of neurons. So, to define SOMs it is required to know how many rows and columns and neurons are needed in order of the x and y dimensions. The parameters of SOM are:

[1] x: som_grid_rows, is the number of rows
[2] y: som_grid_columns, is the number of columns
[3] Sigma is the neighborhood radius - All the nodes that fall in the radius of the BMU get updated according to their respective distance from the BMU.
[4] learning_rate – weight adjustment at each step

**Tasks to be performed:**

1. Use **Credit Card Applications DATASET:**

   **Source:** https://www.kaggle.com/datasets/ujjwal9/credit-card-applications

   The data has 690 records and 16 features along with a class label and customerID. Since SOMs are an unsupervised technique, don't use the class column and also drop the customerID column.

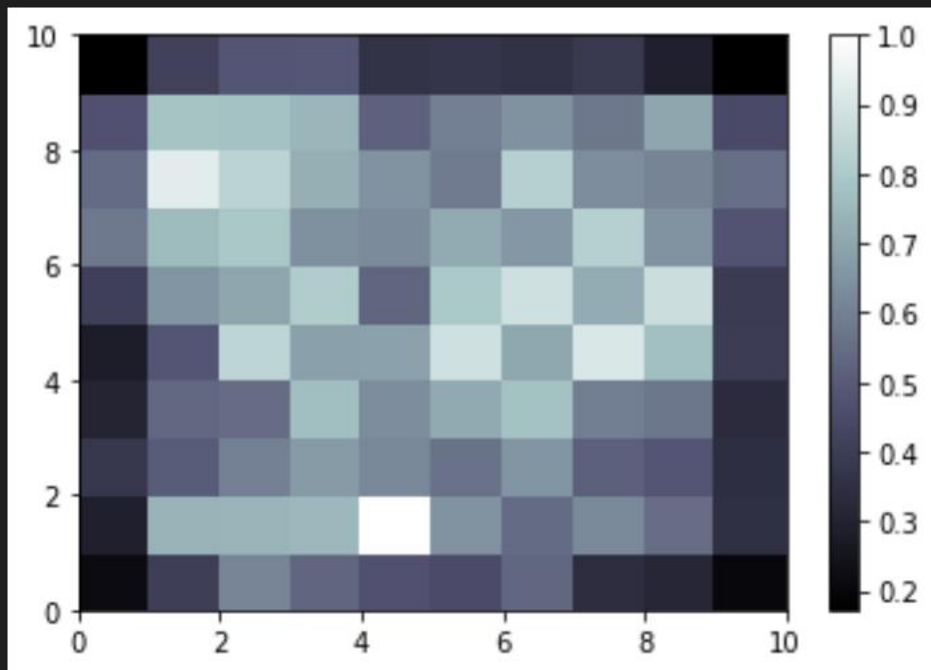
2. **Detect fraud customers in the dataset using SOM and perform hyperparameter tuning. Show map and use markers to distinguish frauds.**
3. **List Applications of Self-Organizing Networks.**
4. **What do you think is the loss function that needs to be computed for SOMs?**
5. **State disadvantages of Kohonen Maps**

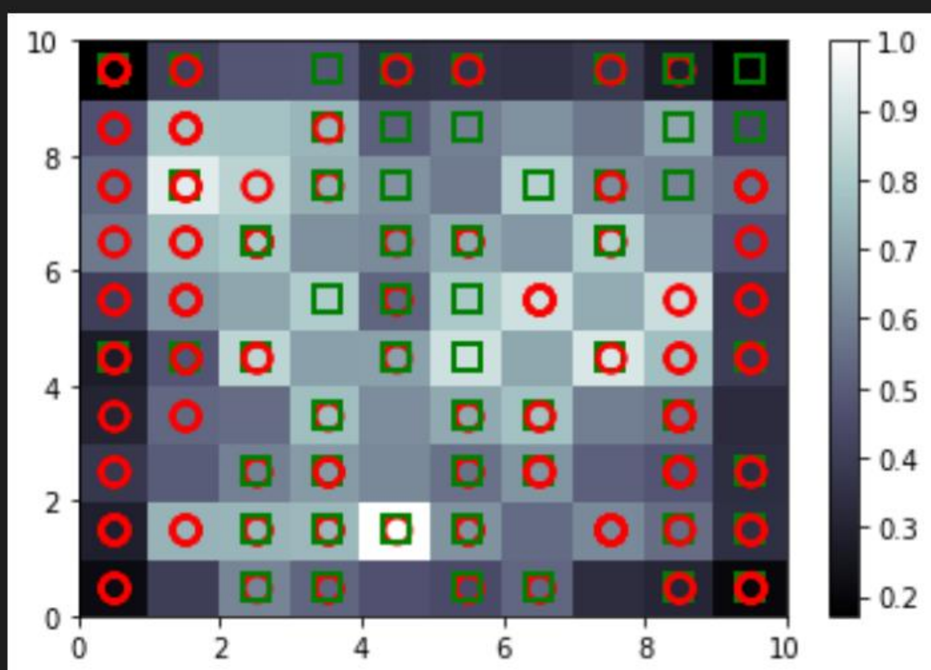
For reference:

https://www.superdatascience.com/blogs/the-ultimate-guide-to-self-organizing-maps-soms

```
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
from sklearn.preprocessing import MinMaxScaler

# Loading Data
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/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)

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=learning_rate)
# Initializing the weights
som.random_weights_init(X)
# Training
som.train_random(X, iterations)
# Returns the distance map from the weights:
som.distance_map()
from pylab import plot, axis, show, pcolor, colorbar, bone
bone()
pcolor(som.distance_map().T)       # Distance map as background
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 green square
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
```


10
8
6
4
2
0
0 2 4 6 8 10
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2


10
8
6
4
2
0
0 2 4 6 8 10
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2

```
mappings = som.win_map(X)
mappings
mappings.keys()
len(mappings.keys())
mappings[(9,8)]
frauds = np.concatenate((mappings[(0,9)], mappings[(8,9)]), axis = 0)
frauds

# the list of customers who are frauds:
frauds1 = sc.inverse_transform(frauds)
pd.DataFrame(frauds1)
```

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| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.0 | 28.17 | 0.585 | 2.0 | 6.0 | 4.0 | 0.040 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 260.0 |
| 1 | 0.0 | 37.33 | 2.500 | 2.0 | 3.0 | 8.0 | 0.210 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 260.0 |
| 2 | 0.0 | 40.83 | 3.500 | 2.0 | 3.0 | 5.0 | 0.500 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 1160.0 |
| 3 | 0.0 | 18.58 | 10.000 | 2.0 | 2.0 | 4.0 | 0.415 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 80.0 |
| 4 | 0.0 | 38.92 | 1.665 | 2.0 | 6.0 | 4.0 | 0.250 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 0.0 |
| 5 | 0.0 | 39.08 | 4.000 | 2.0 | 8.0 | 4.0 | 3.000 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 480.0 |
| 6 | 0.0 | 38.33 | 4.415 | 2.0 | 8.0 | 4.0 | 0.125 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 160.0 |
| 7 | 0.0 | 19.17 | 5.415 | 2.0 | 3.0 | 8.0 | 0.290 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 80.0 |
| 8 | 0.0 | 25.58 | 0.000 | 2.0 | 8.0 | 4.0 | 0.000 | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 184.0 |
| 9 | 0.0 | 32.00 | 6.000 | 2.0 | 2.0 | 4.0 | 1.250 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 272.0 |
| 10 | 0.0 | 16.33 | 0.210 | 2.0 | 6.0 | 4.0 | 0.125 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 200.0 |
| 11 | 0.0 | 71.58 | 0.000 | 2.0 | 8.0 | 4.0 | 0.000 | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 184.0 |
| 12 | 0.0 | 21.92 | 11.665 | 2.0 | 4.0 | 8.0 | 0.085 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 320.0 |
| 13 | 0.0 | 22.67 | 0.790 | 2.0 | 3.0 | 4.0 | 0.085 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 144.0 |
| 14 | 0.0 | 41.58 | 1.040 | 2.0 | 6.0 | 4.0 | 0.665 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 240.0 |
| 15 | 0.0 | 52.50 | 7.000 | 2.0 | 6.0 | 8.0 | 3.000 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 0.0 |
| 16 | 0.0 | 20.75 | 9.540 | 2.0 | 3.0 | 4.0 | 0.040 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 200.0 |
| 17 | 0.0 | 22.75 | 6.165 | 2.0 | 6.0 | 4.0 | 0.165 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 220.0 |
| 18 | 0.0 | 48.17 | 1.335 | 2.0 | 3.0 | 7.0 | 0.335 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 0.0 |
| 19 | 0.0 | 22.42 | 5.665 | 2.0 | 11.0 | 4.0 | 2.585 | 1.0 | 1.0 | 7.0 | 0.0 | 2.0 | 129.0 |
| 20 | 0.0 | 30.67 | 12.000 | 2.0 | 8.0 | 4.0 | 2.000 | 1.0 | 1.0 | 1.0 | 0.0 | 2.0 | 220.0 |
| 21 | 0.0 | 32.17 | 1.460 | 2.0 | 9.0 | 4.0 | 1.085 | 1.0 | 1.0 | 16.0 | 0.0 | 2.0 | 120.0 |
| 22 | 0.0 | 20.42 | 0.835 | 2.0 | 11.0 | 4.0 | 1.585 | 1.0 | 1.0 | 1.0 | 0.0 | 2.0 | 0.0 |
| 23 | 0.0 | 18.75 | 7.500 | 2.0 | 11.0 | 4.0 | 2.710 | 1.0 | 1.0 | 5.0 | 0.0 | 2.0 | 184.0 |
| 24 | 0.0 | 20.67 | 3.000 | 2.0 | 11.0 | 4.0 | 0.165 | 1.0 | 1.0 | 3.0 | 0.0 | 2.0 | 100.0 |
| 25 | 0.0 | 24.50 | 12.750 | 2.0 | 8.0 | 5.0 | 4.750 | 1.0 | 1.0 | 2.0 | 0.0 | 2.0 | 73.0 |
| 26 | 0.0 | 36.00 | 1.000 | 2.0 | 8.0 | 4.0 | 2.000 | 1.0 | 1.0 | 11.0 | 0.0 | 2.0 | 0.0 |
| 27 | 0.0 | 28.17 | 0.375 | 2.0 | 11.0 | 4.0 | 0.585 | 1.0 | 1.0 | 4.0 | 0.0 | 2.0 | 80.0 |
| 28 | 0.0 | 22.50 | 8.500 | 2.0 | 11.0 | 4.0 | 1.750 | 1.0 | 1.0 | 10.0 | 0.0 | 2.0 | 80.0 |
| 29 | 0.0 | 20.67 | 1.835 | 2.0 | 11.0 | 4.0 | 2.085 | 1.0 | 1.0 | 5.0 | 0.0 | 2.0 | 220.0 |
| 30 | 0.0 | 25.42 | 1.125 | 2.0 | 11.0 | 4.0 | 1.290 | 1.0 | 1.0 | 2.0 | 0.0 | 2.0 | 200.0 |
| 31 | 0.0 | 18.42 | 9.250 | 2.0 | 11.0 | 4.0 | 1.210 | 1.0 | 1.0 | 4.0 | 0.0 | 2.0 | 60.0 |
| 32 | 0.0 | 23.25 | 5.875 | 2.0 | 11.0 | 4.0 | 3.170 | 1.0 | 1.0 | 10.0 | 0.0 | 2.0 | 120.0 |