SAP ID:

SHRI VILEPARLE KELAVANI MANDAL'S
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC ACCREDITED with "A" GRADE (CGPA : 3.18)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

COURSE CODE: DJ19DSC501 **DATE: 04/11/2023**

COURSE NAME: Machine Learning - II **CLASS: AY 2023-24**

Jhanvi Parekh

60009210033

D11

LAB EXPERIMENT NO. 7

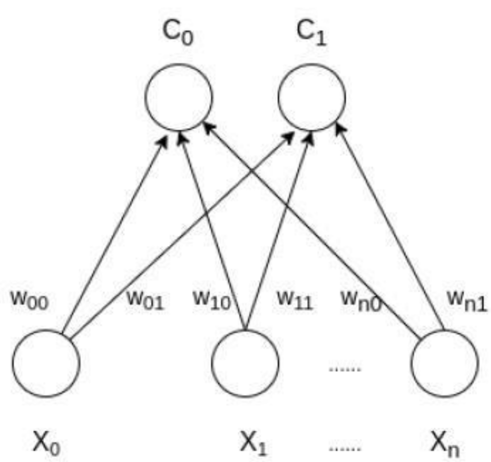
AIM :

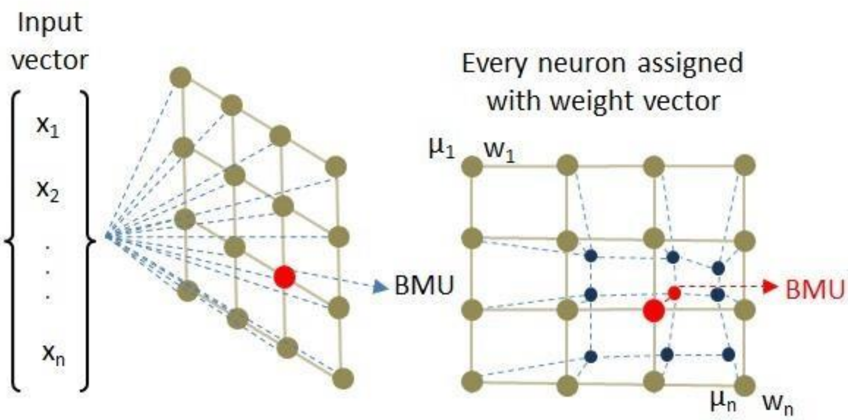
Anomaly detection using Self-Organizing Network.

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.**

LINK:
https://colab.research.google.com/drive/1OsECUaHkG8DOQqtQgUXl7tp19thXugpC?usp=sharing

3. **List Applications of Self-Organizing Networks.**
Applications of Self-Organizing Networks:
1. SON automates network planning, configuration, optimization, and maintenance, particularly in large and complex networks.
2. It optimizes coverage, capacity, and load balancing to enhance network performance and
the user experience.
3. SON manages interference, improves handovers, and enhances energy efficiency, leading
to higher service quality and reduced operational costs.
4. It automates parameter and configuration management, assists in radio access network (RAN) planning, and is crucial for heterogeneous network (HetNet) coordination.
5. SON contributes to load forecasting, spectrum efficiency, quality of service (QoS) management, and mobility optimization, ultimately leading to improved customer experience and reduced churn.

4. **What do you think is the loss function that needs to be computed for SOMs?**
The loss function for Self-Organizing Maps (SOMs) is called the Quantization Error (QE) or Mean Quantization Error. It measures how well the SOM represents input data. To calculate it, you find the Best Matching Unit (BMU) for each input data point, compute the distance between the input point and the BMU, and then sum these distances for all data points. Dividing by the total data points gives you the Mean Quantization Error. The goal is to minimize this error during training, which results in a more accurate and organized representation of the input data on the SOM.

5. **State disadvantages of Kohonen Maps**
Disadvantages of Kohonen Maps (Self-Organizing Maps or SOMs):
1. Sensitive to Initialization: Results can vary based on initial weights.
2. Manual Hyperparameter Tuning: Requires careful tuning of learning rate, neighbourhood.
function, and map size.
3. Computationally Intensive Training: Can be resource-intensive, especially for high dimensional data.
4. Fixed Topology: Limited to a predefined 2D lattice, which may not suit all data distributions.

5. Boundary Effects: Neurons at map edges may not adapt as effectively, causing distortion.
6. Limited Dimension Reduction: May not capture complex non-linear relationships as effectively as other methods.
7. No Probabilistic Interpretation: Lacks natural probabilistic modeling capabilities.
8. Data Type Limitation: More suitable for continuous data, may require preprocessing for
categorical data.
9. Overfitting and Generalization: Risk of overfitting if the SOM is too complex or trained
for too long.
10. Limited Handling of Missing Data: Traditional SOMs do not handle missing data Gracefully.

For reference:

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

```
%pip install minisom
```

```
Collecting minisom
  Downloading MiniSom-2.3.1.tar.gz (10 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: minisom
  Building wheel for minisom (setup.py) ... done
  Created wheel for minisom: filename=MiniSom-2.3.1-py3-none-any.whl size=10588 sha256=441bfb0b8c62a5e524bfbabd0e7f0b7aea768fa04e66c400f
  Stored in directory: /root/.cache/pip/wheels/c7/92/d2/33bbda5f86fd8830510b16aa98c8dd420129b5cb24248fd6db
Successfully built minisom
Installing collected packages: minisom
Successfully installed minisom-2.3.1
```

```
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 dataset
data = pd.read_csv('/content/Credit_Card_Applications.csv')
# X
data
```

	CustomerID	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Class
0	15776156	1	22.08	11.460	2	4	4	1.585	0	0	0	1	2	100	1213	0
1	15739548	0	22.67	7.000	2	8	4	0.165	0	0	0	0	2	160	1	0
2	15662854	0	29.58	1.750	1	4	4	1.250	0	0	0	1	2	280	1	0
3	15687688	0	21.67	11.500	1	5	3	0.000	1	1	11	1	2	0	1	1
4	15715750	1	20.17	8.170	2	6	4	1.960	1	1	14	0	2	60	159	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	15808223	1	31.57	10.500	2	14	4	6.500	1	0	0	0	2	0	1	1
686	15769980	1	20.67	0.415	2	8	4	0.125	0	0	0	0	2	0	45	0
687	15675450	0	18.83	9.540	2	6	4	0.085	1	0	0	0	2	100	1	1
688	15776494	0	27.42	14.500	2	14	8	3.085	1	1	1	0	2	120	12	1
689	15592412	1	41.00	0.040	2	10	4	0.040	0	1	1	0	1	560	1	1

690 rows × 16 columns

```
# Shape of the data:
data.shape
```

```
(690, 16)
```

```
# Info of the data:
data.info()
```

```
<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
```

```
# Defining X variables for the input of SOM
X = data.iloc[:, 1:14].values
y = data.iloc[:, -1].values
# X variables:
pd.DataFrame(X)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	1.0	22.08	11.460	2.0	4.0	4.0	1.585	0.0	0.0	0.0	1.0	2.0	100.0
1	0.0	22.67	7.000	2.0	8.0	4.0	0.165	0.0	0.0	0.0	0.0	2.0	160.0
2	0.0	29.58	1.750	1.0	4.0	4.0	1.250	0.0	0.0	0.0	1.0	2.0	280.0
3	0.0	21.67	11.500	1.0	5.0	3.0	0.000	1.0	1.0	11.0	1.0	2.0	0.0
4	1.0	20.17	8.170	2.0	6.0	4.0	1.960	1.0	1.0	14.0	0.0	2.0	60.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	1.0	31.57	10.500	2.0	14.0	4.0	6.500	1.0	0.0	0.0	0.0	2.0	0.0
686	1.0	20.67	0.415	2.0	8.0	4.0	0.125	0.0	0.0	0.0	0.0	2.0	0.0
687	0.0	18.83	9.540	2.0	6.0	4.0	0.085	1.0	0.0	0.0	0.0	2.0	100.0
688	0.0	27.42	14.500	2.0	14.0	8.0	3.085	1.0	1.0	1.0	0.0	2.0	120.0
689	1.0	41.00	0.040	2.0	10.0	4.0	0.040	0.0	1.0	1.0	0.0	1.0	560.0

690 rows × 13 columns

```
#Scaling the X variables:
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
X = sc.fit_transform(X)
pd.DataFrame(X)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	1.0	0.125263	0.409286	0.5	0.230769	0.375	0.055614	0.0	0.0	0.000000	1.0	0.5	0.05
1	0.0	0.134135	0.250000	0.5	0.538462	0.375	0.005789	0.0	0.0	0.000000	0.0	0.5	0.08
2	0.0	0.238045	0.062500	0.0	0.230769	0.375	0.043860	0.0	0.0	0.000000	1.0	0.5	0.14
3	0.0	0.119098	0.410714	0.0	0.307692	0.250	0.000000	1.0	1.0	0.164179	1.0	0.5	0.00
4	1.0	0.096541	0.291786	0.5	0.384615	0.375	0.068772	1.0	1.0	0.208955	0.0	0.5	0.03
...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	1.0	0.267970	0.375000	0.5	1.000000	0.375	0.228070	1.0	0.0	0.000000	0.0	0.5	0.00
686	1.0	0.104060	0.014821	0.5	0.538462	0.375	0.004386	0.0	0.0	0.000000	0.0	0.5	0.00
687	0.0	0.076391	0.340714	0.5	0.384615	0.375	0.002982	1.0	0.0	0.000000	0.0	0.5	0.05
688	0.0	0.205564	0.517857	0.5	1.000000	0.875	0.108246	1.0	1.0	0.014925	0.0	0.5	0.06
689	1.0	0.409774	0.001429	0.5	0.692308	0.375	0.001404	0.0	1.0	0.014925	0.0	0.0	0.28

690 rows × 13 columns

```
# 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)
```

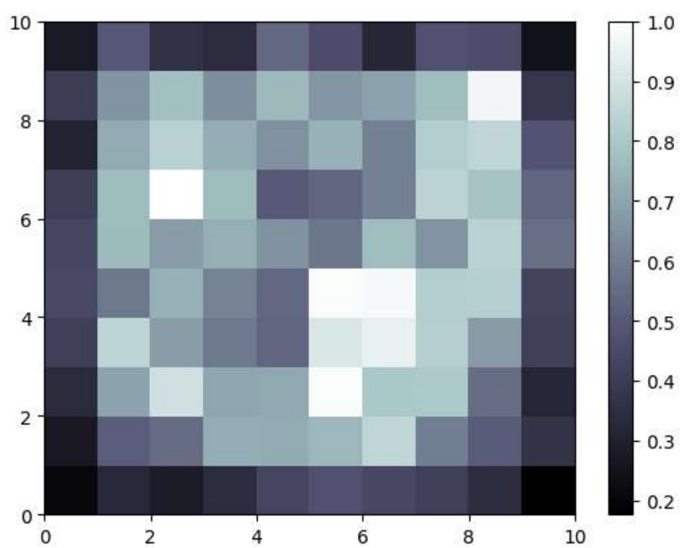
```
# Initializing the weights
som.random_weights_init(X)
```

```
# Training
som.train_random(X, iterations)
```

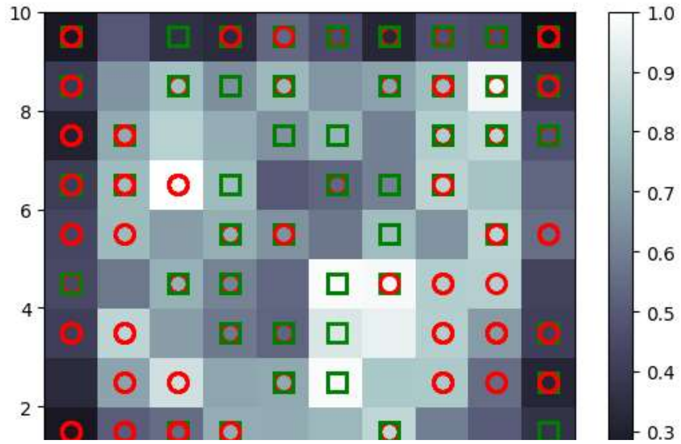
```
# Returns the distance map from the weights:
som.distance_map()
```

```
array([[0.20653198, 0.26974767, 0.33722338, 0.41097152, 0.44517498,
        0.43446436, 0.40562134, 0.30619654, 0.39891016, 0.27533383],
       [0.32591069, 0.51110141, 0.69700109, 0.84549169, 0.5824305 ,
        0.75890413, 0.76310135, 0.71777665, 0.6568074 , 0.49324191],
       [0.28249851, 0.54822149, 0.88536082, 0.68228018, 0.73487754,
        0.68103367, 1.        , 0.83103608, 0.77700266, 0.36176047],
       [0.3387195 , 0.72359102, 0.70218009, 0.58234375, 0.6105265 ,
        0.72923703, 0.76232065, 0.7240216 , 0.640658  , 0.33963576],
       [0.43271479, 0.72226374, 0.71165394, 0.53212154, 0.53778288,
        0.65066009, 0.49582524, 0.64935929, 0.75286207, 0.54040899],
       [0.47416141, 0.75150096, 0.98499814, 0.90754891, 0.98533674,
        0.57964916, 0.53584256, 0.73957779, 0.66135432, 0.46095337],
       [0.44125157, 0.84583117, 0.79989655, 0.9438778 , 0.97971007,
        0.76701044, 0.60679182, 0.60504826, 0.69284463, 0.32292523],
       [0.40889345, 0.59309582, 0.80167565, 0.82152746, 0.81853434,
        0.65380412, 0.83804994, 0.81806739, 0.7676321 , 0.47422435],
       [0.34128138, 0.50737051, 0.55250879, 0.67728976, 0.82173083,
        0.83450653, 0.78199552, 0.84842825, 0.96547039, 0.46243441],
       [0.17701636, 0.36688074, 0.32073465, 0.41306501, 0.42103464,
        0.55909069, 0.53352239, 0.48230329, 0.37854521, 0.24649115]])
```

```
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()
```




```
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)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	1.0	18.83	3.540	1.0	1.0	1.0	0.000	0.0	0.0	0.0	1.0	2.0	180.0
1	1.0	24.50	13.335	1.0	6.0	4.0	0.040	0.0	0.0	0.0	1.0	2.0	120.0
2	1.0	37.50	1.125	1.0	2.0	4.0	1.500	0.0	0.0	0.0	1.0	2.0	431.0
3	1.0	34.00	5.085	1.0	3.0	5.0	1.085	0.0	0.0	0.0	1.0	2.0	480.0
4	1.0	22.50	11.500	1.0	7.0	4.0	1.500	0.0	0.0	0.0	1.0	2.0	0.0
5	1.0	31.57	0.040	1.0	2.0	4.0	4.250	0.0	0.0	0.0	1.0	2.0	460.0
6	1.0	19.17	4.000	1.0	3.0	4.0	1.000	0.0	0.0	0.0	1.0	2.0	360.0
7	1.0	22.00	7.835	1.0	3.0	5.0	0.165	0.0	0.0	0.0	1.0	2.0	184.0
8	1.0	31.57	4.000	1.0	3.0	4.0	0.085	0.0	0.0	0.0	1.0	2.0	411.0
9	1.0	21.50	11.500	2.0	3.0	4.0	0.500	1.0	0.0	0.0	1.0	2.0	100.0
10	1.0	38.67	0.210	2.0	4.0	4.0	0.085	1.0	0.0	0.0	1.0	2.0	280.0
11	1.0	34.83	4.000	2.0	2.0	5.0	12.500	1.0	0.0	0.0	1.0	2.0	184.0
12	1.0	21.83	0.250	2.0	2.0	8.0	0.665	1.0	0.0	0.0	1.0	2.0	0.0
13	1.0	44.33	0.500	2.0	3.0	8.0	5.000	1.0	0.0	0.0	1.0	2.0	320.0
14	1.0	56.00	12.500	2.0	4.0	8.0	8.000	1.0	0.0	0.0	1.0	2.0	24.0
15	1.0	26.17	0.250	2.0	3.0	5.0	0.000	1.0	0.0	0.0	1.0	2.0	0.0