Modelling of Network Traffic Usage Using Self-Organizing Maps Techniques

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***Abstract*—Currently, the Internet is one important part of the campus infrastructure that supports the teaching and learning activities. The important part of the internet facility is the provided bandwidth as Bandwidth management to teaching and learning is indispensable. In this study, an analysis and cluster of the university internet traffic is required as bandwidth management decision support. Therefore, Self-Organizing Maps (SOM) as a clustering algorithm bandwidth usage was implemented. The results showed that the SOM method can perform clustering. Furthermore, the clustering result could be a recommendation management bandwidth for network administrator.**

***Keywords*—network traffic; bandwidth management; clustering; self-organizing maps**

I. Introduction

Currently, the bandwidth is one important part of the infrastructure of the University in order to support an operational activities of technology-based learning. However, the bandwidth capacity is sometimes limited at certain hours especially during lecture hours. Therefore, well management of bandwidth capacity is indispensable in order to reduce the waste of bandwidth usage, steady access, helps network administrators to control bandwidth usage as well as.

An analysis to overcome bandwidth management is required as bandwidth mapping is required. Hence, the capacity of bandwidth usage can be monitored. Furthermore, the mapping (cluster) will provide a model that can support the network administrator's decision in providing the bandwidth at any point.

In this study, cluster network traffic by using machine learning methods is explored. Self-Organizing Maps (SOM) as a clustering method was implemented. There are two reasons for using SOM rather than other clustering methods; first it does not require a prior knowledge of the number of clusters formed and easily display the output as a two-dimensional grid of samples. The problem of this research was to determine the effect of learning rate by using SOM algorithm in order to get a good cluster models. The purpose of this study was to test the feasibility of SOM clustering and how it works in the real world problems particularly on network traffic.

The rest of this paper is organized as following; recent related work is discussed and presented in section 2. Section 3, proposed the SOM clustering approach. In section 4 a set of experiments is described using SOM clustering methods. Finally, conclusion and future work are presented.

II. Related Work

In the recent years, network traffic clustering has been introduced as an efficient method for managing and operating bandwidth distribution collections by network administrators in response to clients' queries. Many clustering techniques are implemented. For example, using SOM has proved to be an effective clustering method widely used in various fields such as pattern and speech recognitions [1, 2], energy [3], hydrology [4], medical [5], financial [6], and prediction [7, 8]. In managing internet traffic, reference [9] have used machine learning (i.e., Gaussian Mixture Model (GMM) with Expectation Maximization (EM)) to classify internet traffic in order to overcome the limitations of traditional port-based and payload based classification approaches. The results have shown that the proposed approach can significantly improve the quality of the resultant traffic clusters. Meanwhile, reference [10] have utilized

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hierarchical clustering and self-organizing maps (SOM) to maintain the stability of the resulting subsystems and to reduce the total loss of load in the system. Both methods are tested on a method of slow coherency based islanding, a 68-generator 16-bus test systems. The results showed that both methods were able to complete the task of clustering while SOM is able to save time and effort for a defensive islanding computing. Later, reference [11] have attempted to extract the features of the traffic through the IP flow attributes which are collected from the network structure by using machine learning as a modification of the Ant Colony Optimization metaheuristic. The purpose of this study was to inform the network manager of the anomaly. This study proposed a system ACODS (Ant Colony Optimization for Digital Signature) to manage and identify anomaly detection and identification in large-scale networks based on a seven-dimensional traffic analysis.

III. METHODOLOGY

In this section, a brief information on the general network traffic clustering model will be presented by using Self-Organizing Maps (SOM) model.

A. Clustering

In principle, the cluster is a grouping work of the same object, or more similar to other objects. There are many clustering methods that have been developed. Then, each method has its characters, advantages and disadvantages. Clustering is grouped dependent on structure, membership and solidity clusters. The SOM method is categorized partition structure and exclusive member clusters. Nevertheless, a critical issue in clustering is the dissimilarity measurement data or objects in the group [12-14]. In this study, the Euclidean Distance method for measuring the shortest distance between two data has been used.

B. The Self Organizing Maps Principle

Self-Organizing Maps (SOM) was proposed by Prof. Teuvo Kohonen in 1982 as one type of neural network (NN), unsupervised learning classified [8, 13]. The SOM comprises an input and output layers *n x m* where *n* units are a length of training vector and *m* units are number of categories then input units are fully connected with weights to output units (Fig. 1).

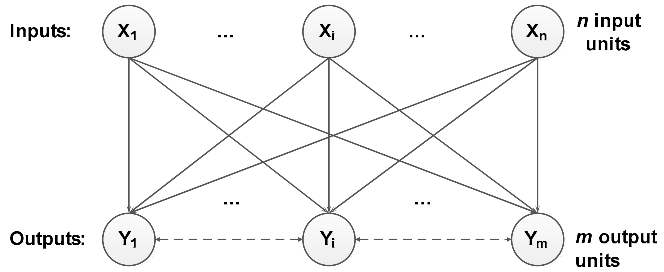

Fig. 1. The SOM Architecture

The SOM consists of nodes distributed in a two-dimensional map. The constructed topological map can visualize the clustered input variables and present the inter-relational features of input variables [15-18]. In principles, SOM learns to classify input vectors according to how they are grouped in the input space. In this paper, the SOM is explored to perform the network traffic clustering.

In principle, the operating methods of SOM consists of the following steps: 1. Select random input, 2. Compute winner neuron, 3. Update neurons, 4. Repeat for all data input, and 5. Classify the input data. Meanwhile, details of the SOM algorithm in the clustering of dataset could be written as follows.

1. Set the number of variables (m), the amount of data (n), the number of clusters (K)
2. Initialization:
   a. Weight of initial input (w_{ij}), use (1)

$$w_{ij} = \frac{MinP_i + MaxP_i}{2} \tag{1}$$

Where, w_{ij} is weight between input variable j to neuron in i, $MinP_i$ is minimum value of input variable i, $MaxP_i$ is maximum value of input variable i.
b. Weight of bias b_i, use (2).

$$b_i = e^{\left[1-ln\left(\frac{1}{K}\right)\right]} \tag{2}$$

Where, b_i is weight of bias i, K is number of target neurons
c. Set parameter learning rate (α)
d. Set maximum epoch (*MaxEpoch*)
- Epoch = Epoch + 1
- Select random data, such as *z* data.
- Find the distance between all data of each weight *z* with input (D_i), use (3).

$$D_i = \sqrt{\sum_{j=1}^{m} (w_{ij} - p_{zj})^2} \tag{3}$$

Summation distance (A_i):

$$A_i = -D_i + b_i$$

Find for greatest value of A_i:

1. $Max_A = max_{(ai)}$, with i = 1,2,…,K
2. IDX = 1, so, $ai = Max_A$
   - Set output neuron i y_i;
     $y_{(i)} = 1; if\ i = IDX$
     $y_{(i)} = 0; if\ i\ \neq IDX$
   - IDX Update weight that to IDX neuron
     $w_{ij(new)} = w_{ij(old)} + \alpha(x_i - w_{ij(old)})$
     $W_{(IDX,j)} = w_{(IDX,j)} + p(_{(z,j)} - w_{(IDX,j)})$
   - Update weight of bias
     $c(i) = (1-\alpha)e^{(1-\ln b(i))} + \alpha ab(i)$
     $= e^{(1-ln\ c(i))}$

The learning process will continue until maximum epoch is reached.

C. Data Collection and Data Transformation

In this paper, the datasets recorded from ICT unit of Universitas Mulawarman for 5 months (from January to May 2016) were tested. In order to obtain good clustering results and to ensure none of the variables used overwhelm the training result, a normalization data process is required [17, 18]. In this paper, the datasets before going through the network are normalized between 0.05 and 1. If X, X_{max}, X_{min} are the original as the maximum and minimum values of the raw data, then the normalization of X called X_n, can be obtained by the following transformation function (4).

$$X_n = 0.05 + 0.95 \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

The network traffic dataset after normalization can be seen in Table I.

TABLE I. NETWORK TRAFFIC DATASET JANUARY-MAY 2016

No	Rectorat	Forestry	Science	Eco.	No	Rectorat	Forestry	Science	Eco.
1	0.341	0.391	0.343	0.332	77	0.390	0.365	0.402	0.000
2	0.080	0.195	0.061	0.174	78	0.392	0.271	0.358	0.200
3	0.069	0.468	0.042	0.212	79	0.385	0.320	0.483	0.225
4	0.097	0.586	0.048	0.007	80	0.080	0.311	0.237	0.004
5	0.564	0.687	0.352	0.362	81	0.107	0.205	0.069	0.043
6	0.429	1.000	0.680	0.476	82	0.415	0.325	0.508	0.348
7	0.411	0.705	0.467	0.259	83	0.436	0.348	0.485	0.275
8	0.423	0.569	0.465	0.212	84	0.433	0.312	0.384	0.291
9	0.379	0.623	0.364	0.447	85	0.331	0.409	0.358	0.203
10	0.078	0.496	0.044	0.167	86	0.099	0.280	0.115	0.001
11	0.057	0.345	0.028	0.007	87	0.040	0.000	0.000	0.001
12	0.659	0.583	0.444	0.410	88	0.065	0.000	0.000	0.001
13	0.642	0.724	0.414	0.384	89	0.401	0.384	0.441	0.319
14	0.471	0.663	0.480	0.556	90	0.412	0.396	0.473	0.324
15	0.421	0.597	0.295	0.452	91	0.483	0.393	0.413	0.282
16	0.354	0.450	0.394	0.771	92	0.441	0.501	0.000	0.227
17	0.043	0.372	0.119	0.210	93	0.411	0.308	0.090	0.375
18	0.059	0.269	0.054	0.313	94	0.081	0.131	0.065	0.007
19	0.507	0.569	0.506	0.460	95	0.045	0.188	0.039	0.116
20	0.499	0.510	0.445	0.612	96	0.387	0.182	0.166	0.199
21	0.379	0.912	0.000	0.394	97	0.433	0.178	0.477	0.265
22	0.327	0.000	0.000	0.425	98	0.395	0.171	0.381	0.182
23	0.365	0.571	0.420	0.388	99	0.445	0.212	0.350	0.199
24	0.143	0.423	0.106	0.044	100	0.407	0.314	0.425	0.215
25	0.033	0.259	0.043	0.030	101	0.116	0.192	0.072	0.014
26	0.401	0.459	0.459	0.525	102	0.093	0.000	0.000	0.007
27	0.406	0.311	0.535	0.589	103	0.784	0.225	0.389	0.334
28	0.441	0.317	0.580	0.738	104	1.000	0.144	0.326	0.344
29	0.454	0.413	0.490	0.669	105	0.395	0.132	0.269	0.183
30	0.408	0.622	0.369	0.456	106	0.362	0.128	0.145	0.258
31	0.098	0.607	0.207	0.328	107	0.607	0.155	0.286	0.184
32	0.050	0.409	0.054	0.050	108	0.432	0.119	0.000	0.003
33	0.426	0.772	0.470	1.000	109	0.412	0.129	0.000	0.025
34	0.378	0.000	0.000	0.346	110	0.463	0.156	0.245	0.204
35	0.505	0.665	0.361	0.653	111	0.408	0.373	0.326	0.231
36	0.393	0.812	0.508	0.263	112	0.365	0.284	0.085	0.000
37	0.402	0.795	0.506	0.429	113	0.614	0.332	0.331	0.194
38	0.081	0.418	0.115	0.031	114	0.248	0.200	0.439	0.187
39	0.034	0.367	0.021	0.376	115	0.071	0.200	0.098	0.038
40	0.065	0.605	0.054	0.140	116	0.092	0.160	0.069	0.012
41	0.431	0.800	0.614	0.683	117	0.075	0.266	0.404	0.227
42	0.537	0.874	0.566	0.564	118	0.072	0.446	0.376	0.367
43	0.446	0.791	0.532	0.588	119	0.112	0.281	0.428	0.208
44	0.321	0.599	0.460	0.455	120	0.000	0.390	0.471	0.252
45	0.052	0.191	0.063	0.055	121	0.000	0.313	0.489	0.405
46	0.037	0.211	0.067	0.237	122	0.000	0.250	0.000	0.005
47	0.418	0.814	0.601	0.682	123	0.000	0.183	0.023	0.003
48	0.407	0.909	0.536	0.477	124	0.000	0.354	0.402	0.218
49	0.392	0.827	0.572	0.615	125	0.000	0.000	0.000	0.100
50	0.417	0.787	0.689	0.498	126	0.000	0.344	0.328	0.170
51	0.362	0.770	0.530	0.761	127	0.000	0.000	0.000	0.076
52	0.109	0.506	0.129	0.004	128	0.000	0.224	0.011	0.008
53	0.058	0.477	0.039	0.020	129	0.000	0.266	0.063	0.123
54	0.425	0.800	0.667	0.690	130	0.000	0.177	0.000	0.017
55	0.555	0.765	0.549	0.499	131	0.000	0.364	0.409	0.366
56	0.546	0.876	0.591	0.333	132	0.000	0.327	0.280	0.208
57	0.583	0.765	0.925	0.911	133	0.074	0.327	0.399	0.254
58	0.450	0.919	0.677	0.522	134	0.302	0.296	0.000	0.026
59	0.112	0.226	0.000	0.000	135	0.374	0.349	0.418	0.236
60	0.078	0.512	0.038	0.000	136	0.111	0.248	0.286	0.010
61	0.378	0.795	0.577	0.385	137	0.060	0.205	0.104	0.009
62	0.362	0.777	0.524	0.531	138	0.459	0.309	0.504	0.364
63	0.377	0.943	1.000	0.304	139	0.449	0.290	0.534	0.203

TABLE I. NETWORK TRAFFIC DATASET JANUARY-MAY 2016 (*CONTINUE*)

No	Rectorat	Forestry	Science	Eco.	No	Rectorat	Forestry	Science	Eco.
64	0.424	0.835	0.653	0.474	140	0.387	0.336	0.486	0.302
65	0.346	0.751	0.745	0.576	141	0.305	0.287	0.408	0.411
66	0.103	0.632	0.159	0.013	142	0.304	0.300	0.332	0.420
67	0.052	0.362	0.107	0.020	143	0.081	0.232	0.030	0.051
68	0.407	0.488	0.587	0.407	144	0.081	0.129	0.042	0.210
69	0.331	0.355	0.330	0.310	145	0.317	0.326	0.389	0.391
70	0.086	0.204	0.065	0.000	146	0.310	0.326	0.424	0.378
71	0.318	0.000	0.000	0.001	147	0.325	0.332	0.462	0.449
72	0.380	0.250	0.306	0.001	148	0.268	0.298	0.418	0.340
73	0.083	0.208	0.112	0.000	149	0.317	0.285	0.219	0.242
74	0.062	0.213	0.034	0.000	150	0.060	0.257	0.056	0.055
75	0.386	0.364	0.457	0.001	151	0.082	0.228	0.014	0.029
76	0.373	0.289	0.264	0.000	152	0.362	0.259	0.000	0.232

The network traffic dataset plot after normalization can be seen in Fig. 2.

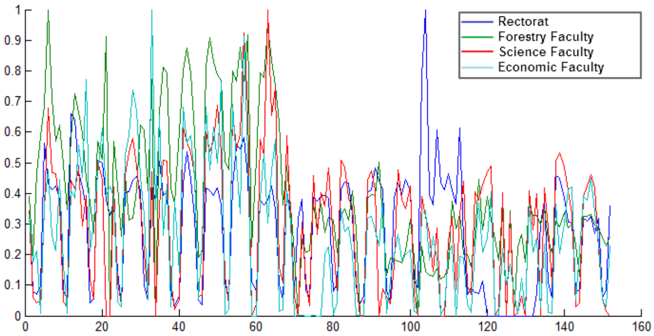

Fig. 2. Plot of Daily Network Traffic January – May 2016

D. Performance Metrics

In this experiment, Euclidean distance was applied in order to measure the performance of the proposed model. The Euclidean measure corresponds to the shortest geometric distance between two points [18]. The formulation as shown as in (5).

$$d = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \tag{5}$$

IV. EXPERIMENTAL RESULTS

This section presents the results obtained for the SOM methods in clustering network traffic datasets. In the SOM methods, initialization weighted intra-layer has been randomly developed. In this experiment, the training data were divided into three categories: min, max and average or high, medium, and lower. The weighting matrix of size *m* is the number of clusters and *l* is the number of attribute data pattern training. In this experiment, three clusters were formed by using 2 x 3 dimension. Then, distance between two points was calculated by Euclidean Distance. Meanwhile, learning rate (η) 0.1 to 0.9 was tested. The results are shown in the following Fig. 3. In this experiment, the SOM method parameters were used as follow; cluster size was 2 x 3 m, learning rate were 0.1 to 0.9, and iteration 152. Then, several experiments in order to get the good cluster have been conducted. Table II shows the Euclidean distance results in various parameters.

TABLE II. EUCLIDEAN DISTANCE RESULTS

Cluster	LR	Distance								
2	0.1	0.290	0.018							
3		0.290	0.018	0.498						
4		1.488	0.022	0.075	0.483					
5		0.290	0.632	0.018	0.815	0.620				
6		0.675	0.483	0.664	0.495	0.075	0.022			
7		0.684	0.043	0.002	0.822	0.484	1.088	0.096		
8		0.484	0.043	0.002	0.593	0.950	1.039	0.096	0.273	
9		0.396	1.057	0.483	1.116	0.075	0.022	0.433	0.990	0.791
Cluster	LR	Distance								
2	0.2	0.555	0.027							
3		0.095	0.767	0.020						
4		0.081	0.661	0.034	0.460					
5		0.616	0.081	0.034	0.460	0.776				
6		0.034	0.362	0.533	0.081	0.791	0.593			
7		0.179	0.396	0.408	0.832	0.528	0.114	0.370		
8		1.010	0.624	0.641	0.745	0.776	0.490	0.018	0.290	
9		1.052	0.000	0.622	0.455	0.038	0.572	0.092	0.335	1.147
Cluster	LR	Distance								
2	0.3	1.057	0.022							
3		0.025	0.088	0.970	0.846					
4		0.085	0.795	0.433	0.032					
5		0.487	0.085	0.433	0.032	1.132				
6		0.417	0.085	0.433	0.505	1.313	0.032			
7		0.034	0.373	0.088	1.144	0.001	0.708	0.470		
8		0.679	0.204	0.085	0.032	0.889	0.784	0.519	0.372	
9		1.232	1.269	0.558	0.085	0.032	0.895	0.433	0.315	1.139
Cluster	LR	Distance								
2	0.4	0.081	0.028							
3		0.582	0.028	0.081						
4		0.028	0.081	0.999	0.436					
5		0.523	0.375	0.031	0.718	0.081				
6		0.375	0.031	0.667	0.493	0.516	0.081			
7		0.719	0.714	0.031	0.375	0.526	0.081	0.941		
8		0.563	0.662	0.028	0.336	0.081	0.997	0.512	0.762	
9		0.081	0.258	0.623	0.193	0.375	0.543	0.031	0.587	0.576
Cluster	LR	Distance								
2	0.5	0.075	0.030							
3		0.074	0.031	0.231						
4		0.031	0.231	0.074	1.034					
5		0.075	0.966	0.589	0.923	0.030				
6		0.215	0.074	0.486	0.031	0.231	0.939			
7		0.109	1.525	0.696	0.521	0.031	0.033	0.497		
8		1.054	0.033	0.031	0.696	0.644	1.062	0.521	0.109	
9		0.031	0.430	0.876	0.696	0.212	0.655	0.075	0.003	0.832
Cluster	LR	Distance								
2	0.6	0.068	0.031							
3		0.031	0.068	0.387						
4		0.031	0.860	0.068	0.703					
5		0.444	0.068	0.031	0.316	0.953				
6		0.068	0.378	0.387	0.031	0.247	0.738			
7		0.668	0.068	0.404	1.522	0.031	0.551	0.979		
8		0.767	0.633	1.053	0.068	0.428	0.031	0.530	0.256	
9		0.387	0.538	0.031	0.749	0.882	0.543	0.068	0.667	0.651
Cluster	LR	Distance								
2	0.7	0.063	0.031							
3		0.031	0.631	0.063						
4		0.183	0.302	0.031	0.063					
5		0.995	0.031	0.434	0.063	0.619				
6		0.031	0.549	0.808	0.063	0.900	1.153			
7		1.141	0.962	0.031	0.730	0.183	0.063	0.699		
8		1.267	0.183	0.063	1.390	0.031	0.514	1.067	1.231	
9		0.680	0.756	0.063	0.031	0.524	1.328	0.183	0.872	0.755
Cluster	LR	Distance								
2	0.8	0.032	0.058							
3		0.032	0.058	1.195						
4		0.032	0.643	0.058	0.810					
5		1.056	0.058	0.440	0.032	0.007				
6		0.058	1.508	1.590	0.032	1.022	0.974			
7		1.028	0.032	0.058	0.993	1.391	0.440	0.007		
8		1.728	0.007	0.994	0.032	0.058	0.170	0.440	0.689	
9		0.007	0.032	1.307	0.058	0.801	0.440	0.581	1.313	0.619
Cluster	LR	Distance								
2	0.9	0.033	0.055							
3		0.055	0.033	0.464						
4		0.464	0.881	0.055	0.033					
5		0.055	0.464	0.335	0.033	0.888				
6		0.461	0.055	0.696	0.727	0.033	0.508			
7		0.464	0.723	0.055	0.033	0.283	0.718	0.680		
8		0.431	0.033	0.570	1.097	0.464	0.441	1.093	0.055	
9		0.461	0.696	0.033	0.426	0.555	0.366	0.055	0.788	1.707

The SOM clustering results by using 4, 5, 6, and 8 clusters with learning rate 0.9 can be display in Fig. 3.

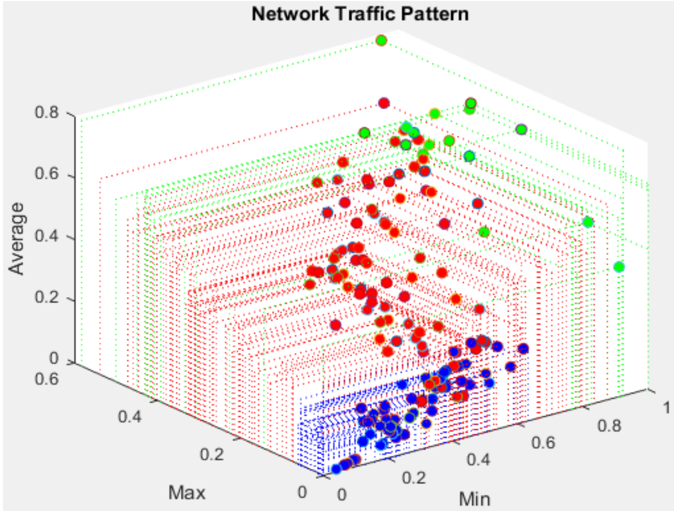

Fig. 3. SOM Clustering Results 4, 5, 6 and 8 Clusters with Learning Rate 0.9

V. CONCLUSIONS

In this study, network traffic data of Universitas Mulawarman ICT Unit was used. The SOM method was applied to identify the relationship between clients with similar characteristics. The output clusters were evaluated using Euclidean distance as a performance of the proposed method. The results showed that SOM method with Euclidean distance as a performance metrics was able to produce a good cluster, especially in network traffic clustering.

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