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K- Means Based Probabilistic Neural Network (KPNN) For Designing Physical Machine – Classifier

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Abstract: ***Cloud Computing necessitates virtual machines that can deploy users to a machine in a sub-optimal fashion for effective and maximum utilization of resources conserving overall energy within the specified duration. PNN is an effective probabilistic classifier which has been applied for a wide variety of computer application problems. However, for big data applications, we need either pre-processing algorithms for efficient classification with lower computing time or Mathematical tracking operators to speed up a parametric approach. This paper focuses to combine the traditional K means algorithm and a PNN to process the data obtained from Google cluster to classify them into pre-specified groups so as to implement PM classifier design to monitor the Cloud usage pattern. It is found after validation of KPNN with different data sets that KPNN works better than PNN in terms of accuracy even when the number of classes increases and turns out to be a computationally attractive tool.***

Keywords ***: classification, clustering, PNN Probabilistic Neural Network***

I. INTRODUCTION

In the current scenario, cloud computing is getting treated as a vital technology to overcome many of the resource-wasting bottlenecks [1]. In the cloud computing environment, virtualization is the key technology to achieve the maximum utilization of resources. To utilize the cloud environments, virtual machines will be created and allocated to the end-users based on their specifications [2]. As a cloud service provider, they are supposed to manage their resources effectively so that poor utilization or keeping the resources in an idle mode can be minimized. For the effective utilization of resources, one of the primary jobs is to track the resources utilization rate of the physical machines. The resources that are to be taken into an account to track are CPU utilization rate, RAM utilization rate, Network bandwidth utilization rate and Hard Disk capacity of each physical machine [3]. The reason behind in tracking the physical hosts is that virtual machines are going to be created and served from the physical host [4-5]. Based on the tracking results of the utilization rate, the physical hosts can be identified as either under loaded system(UL) or normal loaded system(NL) or overload system(OL)[6-7]. To do this, clustering techniques are to be employed as the preliminary step to group the utilization rates data. Grouping of the unlabeled data based on some similarity factors are called as data clustering [9]. Variety of data clustering applications can be seen in real-world problems such as knowledge discovery, pattern recognition, fault detection, face recognition, e.t.c.[8]. Among the various data clustering techniques, K-means clustering is one of the known and popular unsupervised learning tasks, that is broadly accepted technique because of its simplicity to implement the technique as well as high speed in data clustering [10].

Probabilistic Neural Network(PNN) is one of the best classifiers over the other neural network-based classifiers. The proposed paper comprise of sections, in which section 2 discuss about the working principles of K-means algorithm. Section 3 contains a brief discussion on PNN working flow, then discussed the impact of K-means based PNN under section 4. Finally done the experiments on proposed technique using “Google cluster” data set in section 5.

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II. PROCEDURE FOR PAPER SUBMISSION

A. *K-means algorithm - An overview:*

Similar data points are grouped under a group with the calculation based on distance[11-14].

The classic K-means algorithm is as follows:

1. Initialize the cluster centroid randomly.

$$Y=\{y_1,y_2,....y_k\}$$

2. Repeat the process until the condition is satisfied.

For each i, set the cluster $clus_i$ to be the set of points in Y, and that $clus_i$ to be very much closer than the $clus_j$, for all $i \neq j$.

3. For each i let $clus_i$ be the center of cluster $Clus_i$(mean of the vectors in $clus_i$).

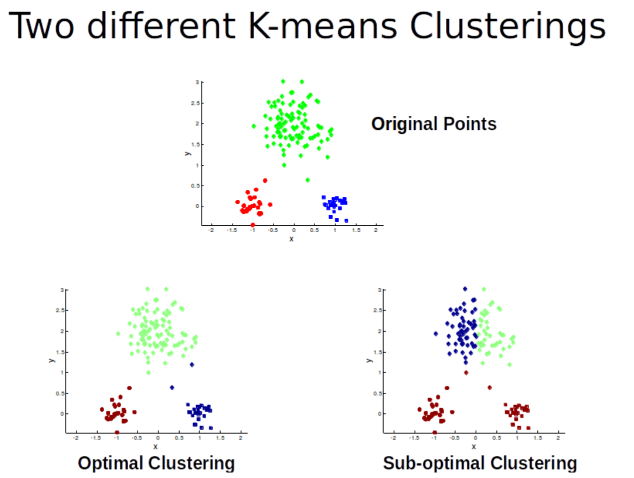
4. Repeat till the convergence met.

.Properties of K-means:

1. It can be used for finding out the local optimum value.
2. It can fetch the convergence often very earlier stage itself.
3. Selecting the initial points are very much worthier and will have a very high impact on the results that are obtained by this algorithm.

B. Diagram of different K-means Clustering's

K-means algorithm is a popular unsupervised learning algorithm to group a set of data points into a predefined cluster. Euclidean distance-based centroid calculation is the most extensively implementing procedure in this K-means clustering technique. Similarity measures among cluster.



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III. PROBABLIISTIC NEURAL NETWORK

A. *Introduction*

Signal classification and pattern recognition problems are common in the areas of engineering, science and research. Input and output of the systems may vary in time based on features and certain functions. Degree of uncertainty may occur in results often due to systematic error and noise. These results are then converted into values between 0 and 1 to ensure a degree of certainty, which in turn generates ambiguity. Methods to solve this sort of problem is being investigated.

By considering the Bayesian decision model PNN (Probabilistic Neural Network) proposed by Specht, with learning properties of artificial neural networks. PNN model is more advantageous because it uses an activation function derived from statistics as well as it has strong fault tolerance and can be implemented in hardware.[15-17]

In the following sections, the concept and architecture of the Probabilistic Neural Network will be discussed. Its application to a real-time problem and the capability of results is also verified.

B. *The Concept*

Probabilistic neural network (PNN) has many similarities with Parzen window pdf estimator. A PNN comprises of several sub-networks, each of which is a Parzen window pdf estimator for the classes. Parzen window is a technique for classification and density estimation[18]. It is a nonparametric procedure that fusions and approximates training set distribution by placing the number of windows as replicas of a function.

C. *Approach and Mathematical Aspects*

Let us assume that there are certain inputs and/or target vectors. The test input will be assigned to one class among the K defined classes and conditional density will also be estimated[19]. To ascertain optimal decision, prior results are combined by the rule of Bayes to obtain A- Posteriori class probabilities.

As per Specht's implementation, Gaussian kernels are used as a window:

p(s, x) = exp(-||x-s||2 / 2 sigma2)

In the above equation, the smoothing parameter (sigma) is the only free parameter.

D. *PNN Architecture*

PNN architecture consists of the following four layers[20]:

Input Layer: The input nodes are a set of measurements which are meant for providing input to the system.

***Pattern/ Exemplar layer*:** Each sample has a corresponding pattern unit. This layer consists of kernel function used to compute the Gaussian distance of each sample from the input.

exp[(xTw*ki*-1) / s2]

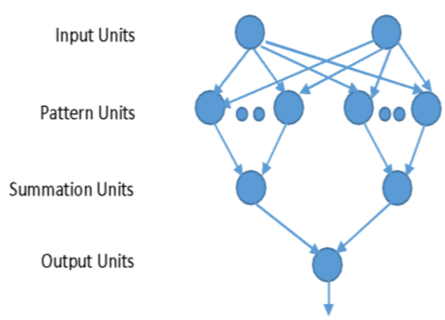
***Summation/ Class layer*:** The output of the previous layer is the input for all the summation nodes. This layer performs an average operation on the outputs

S*i=1N k* exp[(xTw*ki*-1) / s2]

***Output / Decision layer*:** This layer performs the decision of selecting the largest value. It produces binary output for two values.

S*i=1Nk*exp[(xTw*ki*-1) / s2] > S*i=1Nj*exp[(xTw*kj*-1) / s2]

E. *PNN Architecture*



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IV. TEST VERIFICATION METHODS

A. *Need for verification*

It is clear that PNN is a good technique for classification as it is related to the concept of the Parzen window. But, certain verification methodologies with varying inputs need to be conducted to ascertain the robustness of Neural networks approach and to assess its acceptability[21]. The selection of the input pattern is crucial.

The results of the tests will indicate the suitable type of input pattern representation which generates successful output. In this case, the Iris plant database of R.A. Fisher[22] has been used for the test verification procedure.

B. *IRIS Plant Database*

The IRIS dataset[23] classifies a plant as belonging to either of the three different classes of IRIS plant by performing pattern classification. The data set includes three classes of 50 objects each. The total of 150 instances, which are equally separated between the three classes, contains the following four attributes:

1. sepal length followed by 2. sepal width followed by 3. petal length followed by 4. petal width.

The attributes can be described as categorical, nominal or continuous. The three classes are Iris Setosa, Iris Versicolor and Iris Verginica. To train the network test process accepts the training set, to validate the network here validation set is used, to adjust it to design parameters and a test set which is used to test the performance of the selected design of the neural network. The aim is to identify/classify the IRIS plant based on analysis of pattern, petal and sepal size.

C. *Test* pattern corresponding successful classification of Iris Versicolor:

It is clear from the test verification carried out on the PNN paradigm that the network has worked well with regard to an analogue input. This is a strong point of this approach as few other paradigms are not adaptable towards handling analogue inputs and in a few cases even require a large scale modification in NN topology itself. Further, the PNN is able to handle noisy data well and trains well from training patterns. The training phase is a case of adjusting only the smoothing parameter also called the free parameter.

(Table: 1)
Sample attributes information for Iris dataset

Attribute information for Iris Versicolor	Attribute information for Iris Virginica
[6.1, 2.9, 4.7, 1.4]- Training pattern 1	[6.1, 2.7, 5.1, 1.9]- Training pattern 1
[5.9, 3.2, 4.8, 1.8]- Training pattern 2	[6.8, 3.0, 5.5, 2.1]- Training pattern 2
[6.3, 2.5, 4.9, 1.5]- Training pattern 3	[5.7, 2.5, 5.0, 2.0]- Training pattern 3
[6.7, 3.0, 5.0, 1.7]- Training pattern 4	[5.8, 2.8, 5.1, 2.4]- Training pattern 4

V. K MEANS BASED PNN

a) The first step is to collect the log data from **Google cluster,** then cluster the collected data into three groups using K-means clustering algorithm.
b) The second step is to assign the labels on the obtained clustered data as Under Load(UL), Normal Load(NL) and Overload(OL).
c) The third step is to generate the centroids from the clustered data. To generate the centroids the primary step is to obtain the elements count of each cluster. Next step is deciding what will be the value to be given for k, so that k= sqrt(n), Here, n represents the number of elements in a cluster.
d) Based on the value obtained from the above equation, k sub-clusters will be formed on each cluster.
e) Obtained sub-clusters will be acting as training sets for PNN to classify the test input as either Under loaded(UL) or Normal loaded(NL) or Overloaded(OL).
f) The fourth step is that the input to be given to verify the accuracy of the trained PNN.
g) As we have expected it gave us the accuracy rate of 91% in classifying and identifying the class of the data set that has been given.

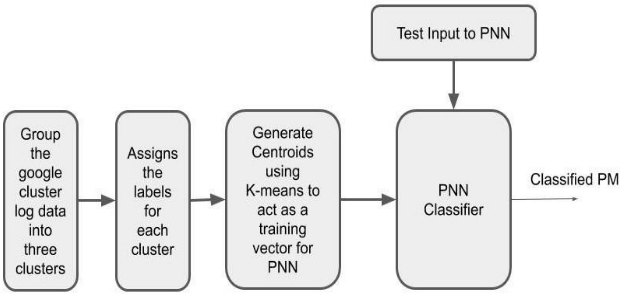

Figure 5.1 Systematic flow of K-means based PNN architecture

VI. EXPERIMENTS AND OBSERVATIONS:

As we all know that PNN is a well-known classifier in disclosing the class of the data that has been given. Though PNN classified the Iris plant data as well as any data with remarkable accuracy rate, the reason behind in adopting the K-means as a preprocessing step is that, K-means will help to identify how many numbers of optimal training sets are needed to classify the physical machines based on running virtual machines' utilization rate that is installed in that physical machine. Faster convergence can be realized with the adoption PNN as a classifier to classify PM either as normally loaded system(NL) or under loaded system(UL) or overloaded system (OL).

Before going to use this KPNN with PM– data, we have tested its efficiency with other data sets for ascertaining its efficiency. with lower sized, moderately sized data sets. The results of those experiments with data size, application-focused classification accuracy are furnished in the following table :

As a primary step, **Google cluster** data has been normalized and clustered into three clusters using K-means clustering algorithm. Clusters are tagged appropriately with proper labels either as under load or normal load or overload. Again K-means are applied to each cluster to find the set of centroids to act as a training sets for each cluster. K-means generated centroids helps the PNN to get trained with those classifications. Test data has given as an input to the PNN to realize whether it could classify the elements properly. As expected PNN works out well for our test data with an accuracy rate of 91%.

(Table: 2)
Results of classification accuracy of KPNN for various data sets

S.No	Application	Data size	# of classes	# of Attributes	Kernel function	Classification error (%)
1	Iris plant database [23]	150	3	4	RBF	2
2	Bioinformatics[24]	450	8	14	Polynomial	7
3	Vehicle[25]	560	4	18	linear	6
4	CPT data for soil classification[26,27]	470	4	4	linear	2
5	QCM sensor SASTRA VOC data[28]	800	3	3	RBF	3
6	VOC database[29]	200	24	16	RBF	2
7	SnO 2 sensor VOC Data[30]	910	2	2	RBF	2
8	Boiler Flue Gas[30]	420	4	5	RBF	2

(Table: 3)
Sample Data set from Google cluster log:
UL stands for Under Load, **NL** stands for Normal Load and **OL** stands for Overload

CPU Utilization rate (%)	RAM Utilization rate (%)	Disk Utilization (%)	Class
0.000185	0.01521	0.0001793	UL
0.06232	0.1224	0.0003576	OL
0.0002003	0.01523	0.0001831	UL
0.0001497	0.01515	0.0001602	UL
0.0001707	0.0152	0.0001717	UL
0.02725	0.09131	0.0002117	NL
0.0614	0.1223	0.0003557	OL
0.06024	0.103	0.0003548	OL
0.02689	0.09119	0.0002117	NL
0.02756	0.09143	0.0002136	NL

VII. CONCLUSION

In this paper, we have discussed various factors of K - means and PNN with special reference to processing VM data. The cluster centres serve as good inputs to PNN and the cluster centres themselves are found to be good training sets. For various data sets with sizes ranging from 150 to 4000, KPNN is found to be a good classifier with higher classification accuracy. However, this needs to be tested for very large data sets where the cluster centres need to be reduced to a reasonable extent to form support vectors to ensure good classification accuracy. Future work includes Machine learning algorithms to forecast the utilization for effective VM migration.

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