Volume 5, Issue 3, March 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Non – linear Multi Objective Optimization Technique to Explore Multi-Layer Network – Phase II

Sangamithra A
Research Scholar - Computer Science
Dept. of SITE, VIT University
Tamil Nadu, India

Dr. M. P. Vani
Associate Professor at Computer Science
Dept. of SITE, VIT University
Tamil Nadu, India

Abstract —The motive is to transfer the data to various departments by using the multi - layer network. Where each one can get the information when any changes occur in any of the department. If we get the information then we can modify the datas which are we currently working in our department. Because in an organization the department are all interlinked. So if changes occur in any one of the department in an organization it will affect the other department also. Which incase cause a big problem at the time of delivering the products. To avoid this problem we are using the multi-layer network where the information get passed to all the departments if there is any changes in any one of the department.

Keywords —Network Simulator, Posterior Mixture Modeling, Network Mapping, Pareto Chart, Cluster

I. INTRODUCTION

In communication and computer network research, network simulation is a technique where a program models the behavior of a network either by calculating the interaction between the different network entities (hosts/packets, etc.) using mathematical formulas, or actually capturing and playing back observations from a production network. The behavior of the network and the various applications and services it supports can then be observed in a test lab; various attributes of the environment can also be modified in a controlled manner to assess how the network would behave under different conditions.

.

II. NETWORK SIMULATOR

A networksimulator is software that predicts the behavior of a computer network. In simulators, the computer network is typically modeled with devices, links, applications etc. and the performance is analyzed. [6] Typically, users can then customize the simulator to fulfill their specific analysis needs. Simulators typically come with support for the most popular protocols and networks in use today, such as WLAN, Wi-Max, TCP, WSN, cognitive radio

Most of the commercial simulators are GUI driven, while some network simulators are CLI driven. The network model configuration describes the state of the network (nodes, routers, switches, and links) and the events (data transmissions, packet error etc.). An important output of simulations are the trace files. Trace files log every packet, every event that occurred in the simulation and are used for analysis. Network simulators can also provide other tools to facilitate visual analysis of trends and potential trouble spots.

Most network simulators use discrete event simulation, in which a list of pending "events" is stored, and those events are processed in order, with some events triggering future events such as the event of the arrival of a packet at one node triggering the event of the arrival of that packet at a downstream node.

Simulation of networks is a very complex task. For example, if congestion is high, then estimation of the average occupancy is challenging because of high variance. To estimate the likelihood of a buffer overflow in a network, the time required for an accurate answer can be extremely large. Specialized techniques such as "control variates" and "importance sampling" have been developed to speed simulation.

III. USES OF SIMULATOR

Network simulators serve a variety of needs. Compared to the cost and time involved in setting up an entire test bed containing multiple networked computers, routers and data links, network simulators are relatively fast and inexpensive. They allow engineers and researchers to test scenarios that might be particularly difficult or expensive to emulate using real hardware - for instance, simulating a scenario with several nodes or experimenting with a new protocol in the network. Network simulators are particularly useful in allowing researchers to test new networking protocols or changes to existing protocols in a controlled and reproducible environment.[7] A typical network simulator encompasses a wide range of networking technologies and can help the users to build complex networks from basic building blocks such as a variety of nodes and links. With the help of simulators, one can design hierarchical networks using various types of nodes like computers, hubs, bridges, routers, switches, links, mobile units etc.

In this Phase 2 We use simulation technique to show the clustering of nodes in the weighted graph can improved using MAC technique. In this the simulation uses the Bayesian posterior representation as P(W1|W) and P(W_2|W) are

isotropic multi variantsGaussians distribution with the mean of W. consider we have to random weighted graph which has 500 nodes and each nodes shared with 10 known clusters. The 10 clusters which are in equal size. The nodes generated in same clusters has the normal distribution N (5, 0.5) where the nodes which are placed in different clusters has the normal distribution N (4.7,0.5). The opposition between the edge weight is to simulate the fundamental community structure with variability. The links are tarnished with I,I,d Gaussian noise on each edge weight with zero mean and different frequencies. The first layer of the network is get corrupted with additive noise distributed as N (0, σ1) and the second layer of the network layer is corrupted with additive noise N (0, σ2) This type of setup agrees the form of W that is derived in (18) in Phase 1. By using a spectral clustering algorithm W is calculated and clustered [7].

IV. POSTERIOR MIXTURE MODELLING

In multivariate statistics and the clustering of data, spectral clustering techniques make use of the spectrum (eigenvalues) of the similarity matrix of the data to performdimensionality reduction before clustering in fewer dimensions. The similarity matrix is provided as an input and consists of a quantitative assessment of the relative similarity of each pair of points in the dataset

Given an enumerated set of data points, the similarity matrix may be defined as a symmetric matrix A, where Aij<=0 represents a measure of the similarity between data points with indexes i and j .

One spectral clustering technique is the normalized cuts algorithm or *Shi–Malik algorithm* introduced by Jianbo Shi and Jitendra Malik commonly used for image segmentation. It partitions points into two sets (B_1 , B_2) based on the eigenvector v corresponding to the second-smallest eigenvalue of the symmetric normalized Laplaciandefined as

$L^{norm} := I\text{-}D^{-1/2}\ AD^{-1/2}$

where D is the diagonal matrix

$D_{ii} = \Sigma A_{IJ}$

A mathematically equivalent algorithm takes the eigenvector corresponding to the largest eigenvalue of the random walk normalized Laplacian matrix $P = D^{-1} A$.

Another possibility is to use the Laplacianmatrix defined as

L := D-A

Partitioning may be done in various ways, such as by computing the median m of the components of the second smallest eigenvector v, and placing all points whose component in v is greater than m in B_1, and the rest in B_2. The algorithm can be used for hierarchical clustering by repeatedly partitioning the subsets in this fashion.

Alternatively to computing just one eigenvector, *k* eigenvectors for some *k*, are computed, and then another algorithm (e.g. k-means clustering) is used to cluster points by their respective *k* components in these eigenvectors.

The efficiency of spectral clustering may be improved if the solution to the corresponding eigenvalue problem is performed in a matrix-free fashion, i.e., without explicitly manipulating or even computing the similarity matrix, as, e.g., in the Lanczos algorithm.

For large-sized graphs, the second eigenvalue of the (normalized) graph Laplacian matrix is often ill-conditioned, leading to slow convergence of iterative eigenvalue solvers.Preconditioning is a key technology accelerating the convergence, e.g., in the matrix-free LOBPCG method. Spectral clustering has been successfully applied on large graphs by first identifying their community structure, and then clustering communities.[3]

Spectral clustering is closely related to nonlinear dimensionality reduction, and dimension reduction techniques such as locally-linear embedding can be used to reduce errors from noise or outliers.[4]

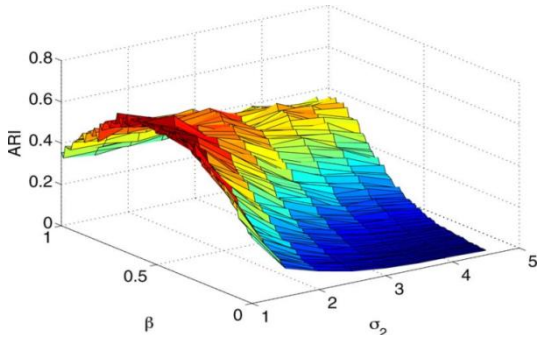


Fig 1: Cluster Simulation

Variances and ARI Sources

σ_1	σ_2	Max ARI	β
1	1	0.6843	0.4747
1	1.5	0.6561	0.5859
1	2	0.5564	0.6364
1	2.5	0.5649	0.6970
1	3	0.4918	0.7879
1	3.5	0.5209	0.7475
1	4	0.4809	0.7374
1	4.5	0.4653	0.7879

From the above table we can estimate the mixture of networks improving the clustering.

V. NETWORK MAPPING AND PARETO CHART

Network mapping is the study of the physical connectivity of networks. Internet mapping is the study of the physical connectivity of theInternet. [4] Network mapping discovers the devices on the network and their connectivity. It is not to be confused with network discovery or network enumerating which discovers devices on the network and their characteristics such as (operating system, open ports, listening network services, etc.). The field of automated network mapping has taken on greater importance as networks become more dynamic and complex in nature.

A Pareto chart [3] is used to graphically summarize and display the relative importance of the differences between groups of data.

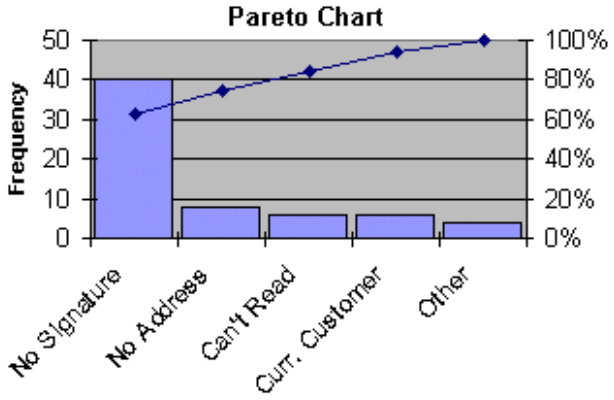


Fig 2 :Sample Pareto Chart Depiction

A Pareto chart can be constructed by segmenting the range of the data into groups (also called segments, bins or categories). For example, if your business was investigating the delay associated with processing credit card applications, you could group the data into the following categories:

No signature
Residential address not valid
Non-legible handwriting
Already a customer
Other

The left-side vertical axis of the pareto chart is labeled Frequency (the number of counts for each category), the right-side vertical axis of the pareto chart is the cumulative percentage, and the horizontal axis of the pareto chart is labeled with the group names of your response variables.

You then determine the number of data points that reside within each group and construct the pareto chart, but unlike the bar chart, the pareto chart is ordered in descending frequency magnitude. The groups are defined by the user.

VI. PARETO SUMMARIZATION

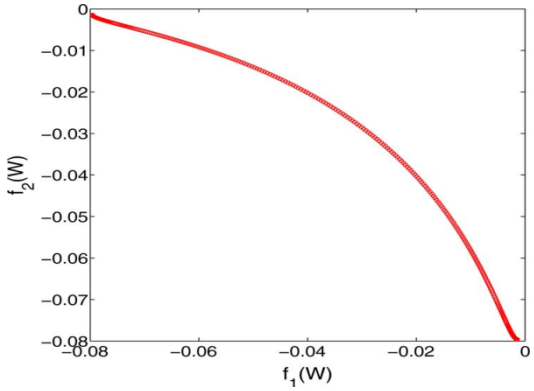
When it is difficult to set a prior parameters in that case we can generate the family of MAP. This MAP estimates and apply multi objective ranking techniques. So that it is easy to find the (15) Multi objective optimization. However,thereareothersolutionstomultipleobjectiveoptimizationsthatdonotuselinearscalarization,suchasParetofrontanalysis[9]–[11].

Consider the multi objective optimization problem

$W = \arg\min_w [f1 (W), f2 (W)]$ (19)

$W = \arg\min_w [\Upsilon f1 (W) + (1-\Upsilon) f2 (W)]$ (20)

The substitute of Scalarization approach is a ranking approach that seeks to find a family of solution W that would be highly ranked by any scalarization. It might be linear or non-linear. This leads to the idea of the pareto optimization. The solution to the multi objective is that without lowering some other objective function it is not possible to improve single optimization. [2]. If $f_i (W1) <= f_i (W2)$ for every objective function f, and there exists some j such that $f_j (W1) < f_j (W2)$ if that the solution W1 dominates the solution W2



The linear scalarization technique is used to identify the pareto optimal points.Pareto front when the solution space is a convex set and the single objective functions are convex function on the solution space [5]. The scalarity technique will not find the entire pareto front if these convexity conditions are not met. Figure 5 shows the example of Pareto front of a multi objective optimization, where f1 and f2 are the two dimensional paths of normal distribution, as shown below:

Fi(W)= (2π)-λ/2|Σi|-i/2e-1/2(w-wi)TΣ-1(W-W1) (21)

$$W1= \begin{bmatrix}10\\8\end{bmatrix} W1= \begin{bmatrix}8\\10\end{bmatrix} \quad \Sigma_1 = \Sigma_2 = 2I_2. \tag{22}$$

This relatively simple distribution has non convex pareto front. We can find optima at the extreme of the curve and does not explain the interior by minimizing the linear combination of f1 and f2.

VII. CONCLUSION

By using these and the techniques used in phase 1 we can communicate with the various layer. While communicating with multiple layer we can send the information without any noise interfering in that particular sources and the destination. This technique is mainly used to show how we can transfer the data in multiple and also by using the maximization value.

REFERRENCES

[1] M Ehrgott "Multiobjective Optimization, "AIMag vol.29, no.4, pp. 47-57, Winter 2008[online].Available: http://search.proquest.com.proxy.lib.um.ich.edu/docview/208128027

[2] X.-S.Yang Multiobjective Optimization New York, NY, USA: Wiley, 2010, pp. 231-246 [online] Available:http://dx.doi.org/10 1002/9780470640425.ch18

[3] http://www.isixsigma.com/tools-templates/pareto/pareto-chart-bar-chart-histogram-and-pareto-principle-8020-rule/

[4] http://en.wikipedia.org/wiki/Network_mapping

[5] http://en.wikipedia.org/wiki/Spectral_clustering

[6] http://en.wikipedia.org/wiki/Network_simulation

[7] A . O.Hero G. Fleury, A.J.Mears, and A . Swaroop , "Multicriteria gene for analysis of differential expression with dna micro arrays," EURASIP J. Appl Signal Process,vol . 2004,pp. 43-52, 2004.

