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Simulation of Optimization Technique to Explore Multi-Layer Network

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Abstract: In an organization if employee wants to transfer information regarding the work to another employee, it is not possible manually if that organization is big which has so many departments, So at this case we have to use technique to transfer information as soon as possible. If some changes had happened in any department we have to intimate to other department at that time we can send the information through email to all other departments. We can achieve this by using multi-layer , optimization technique of WSN without any noise and traffic. So that the information can be updated immediately to all the departments through email generated by the particular person. So that the people in different department can come to knew what is happening in other departments, according to that they can make change in their departments.

Keywords: Posterior Method, Multi-Layer Graph, Simulator, Observed Matrices, Latent Variable, Hierarchical Model

I. INTRODUCTION

More than one source are available multilayer will arise, so that each source has to pass the information to other. When you take email there will be a direct communication link which is use to process the email is called relational information. Relational information is the user is sent or received the information from the other users within the particular time period. Based on person interest and movement we can define the behavioral relationship [1]. It will not connect directly to the user because the behavioral relationship is anecdotal form information. In this paper we are analyzing how to deal with the changes communication through email in the organization by using a multi-layer graph.

We show how to perform the antidotal in Multi-Layer network by using a hierarchical latent – variable model. In order to account for the uncertainty inherent in the model selection process, something which traditional statistical analysis often neglects, the technique Bayesian Model Averaging is used.[3] By averaging over many different competing models, BMA incorporates model uncertainty into conclusions about parameters and prediction. By using the techniques from BMA model the layers of the network are conditionally decoupled using the latent selection variable, this make it possible to write the posterior probability of latent variables given in the Multi-Layer network.

II. MULTI-LAYER GRAPH

Multi-layer graphs, where each layer contains a unique set of edges over the same underlying vertices (users). Edges in different layers typically have related but distinct semantics, depending on the application multiple layers might be used to reduce noise through averaging. A typical graph layer is comprised of a set of X and Y (and optionally, Z) coordinates axes, one or more data plots, and associated label objects (axis titles, text labels and drawing objects). The graph layer is the basic graph unit, and it can be moved or sized independently of other graph layers.[2]You have two dependent variables that you want to plot against a single dependent variable.

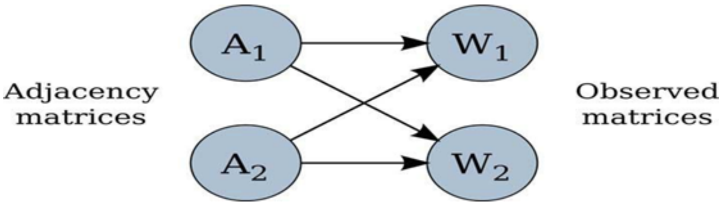

Fig. 1 Adjacency and Observed Matrices

A Multi-Layer graph G=(V , E) where V={V1………Vp} open to all layers, and the edges E={e1…….el) open to all L layers. Assume that in a real world if the observed data noisy reflection of a Multi-Layer graph. For acceptability we have to work on the adjacency representation [4] where all Ai € R_{p*p} the adjacency layer of the matrix i, Wi€ R_{p*p} corresponding observed adjacency matrix. Fig 1 depicts the model graphically. In some cases the Wi will be a binary where simply gives the presence or absence of the connection. Here the job is to estimate A1….Al given the observation W1…..Wi. We require posterior distribution of A1….Al for computing by using the standard parametric method. But there is difficulty to measure A1…Al from the single W1 where it needs a lot of parameters.

III. POSTERIOR MIXTURE MODELLING

To decouples the posterior distribution of the two layers we introduced the latent variable y, by shifting the adjacency matrix A1, A2 to Y. Using latent variable Y as a compact discussion we can find how these

adjacency combine to form a Multi-Layer network.

$$P(W1,W2|A1,A2,Y) = P(W1|A1,y)P(W2|A2,Y) \quad (1)$$

$$P(W1,W2|A1,A2) = \int_x P(W1,W2|A1,A2,Y)P(Y|A1,A2)dY \quad (2)$$

$$P(Y|W1,W2) = \Sigma_{A1,A2}\ P(Y|A1,A2)P(A1,A2|W1,W2)$$

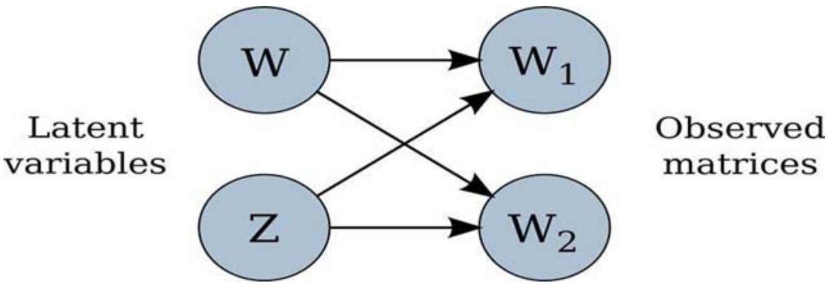

Fig. 2 Model with similarity matrix and selection variable

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

$$L^{norm} := I - D^{-1/2} A D^{-1/2}$$

where D is the diagonal matrix

$$Dii = \Sigma AIJ$$

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]

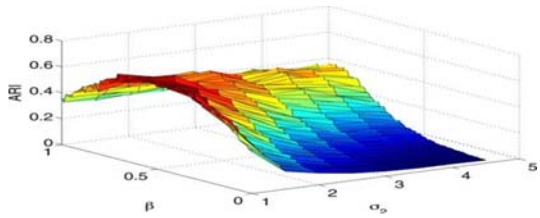

Fig 3: Cluster Simulation

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.

In Fig. 2 We collapsed the A1 A2 data with W1 W2 mainly for concluding w1 and wi can be considered as representation of real world connectivity.

By using the previous model [5] we decomposed Y= (W, Z), where W € R^{p*p} is a similarity matrix which describing the underlying connections between the vertices and model selection variable where Z €{1,2} , Consider P (Z=1) = α , and P (Z = 2) = 1-α. Here W informs all the layers of the network so that a common connectivity structure is observed. So the model produces the observed matrices which correspond to multiple view of the latent variable W.

When Z=2 W and W1 are conditionally independent, Z=1 W and W2 are conditionally independent.

$P_2(W_1|W)=P_2\ (W_1)$ (3)

$P_1(W_2|W)=P_1\ (W_1)$ (4)

The latent variable W given the observed variables W_1,W_2. (5)

$P(W|W_1,W_2)$

$=P(W, Z=1|W_1, W2) + P\ (W, Z=2|W_1. W_2)$ (6)

$=P(W|W_1, W_2, Z=1)\ P\ (Z=1|W_1, W2) + P\ (W|W_1, W_2, Z=2)\ P\ (Z=2|W_1, W2)$ (7)

$= \text{⍰}P(W|W_1, W_2, Z=1) + (1-\text{⍰})\ P\ (W|W_1, W_2, Z=2)$ (8)

Let us consider the first term (9)

$P(W|W_1,W_2,Z=1)=P(W_1W_1,W_2,Z=1)=\frac{P(W1\ W1,W2\ z=1)}{\Sigma WP(W1\ W1,W2\ Z=1)}$

$=\frac{P(W)P1(w1|W)p1(W2)}{\Sigma WP(W)P1(W1|W)P1(W2)}$ (10)

Equation (10) becomes (11)

$P(w|W1,W2,Z=1)=\frac{P(W)P1(W1|W)}{P1(W1)}$

Performing the same equation on other side and combining (12)

$P=(\ W|W1,\ W2)$

$=\text{⍰}\frac{P(W)P1(W1)}{P1(W1)} + (1-\text{⍰})\frac{P(W)P2(W2|W)}{P2(w2)}$ (13)

Here $\Upsilon 1=\text{⍰}/P1\ (W1)$ and $\Upsilon 2=\text{⍰}/P2\ (W2)$,

We can suggest the Maximum likelihood estimate is W if we assume on W is a uniform.

$\arg\max_w\ [\Upsilon 1P1(W1|W)+\Upsilon 2P(2|W)]$

IV. Hierarchical Model

A **hierarchical** database consists of a collection of records that are connected to each other through links. A record is similar to a record in the network **model**. Each record is a collection of fields (attributes), each of which contains only one data value. A link is an association between precisely two records. In this the implication procedure by conditionally decoupling w1…..wi is simplify by the hierarchical model[6] For instance take l=2 where it can view the user that one layer of the network represent the observed extrinsic relationship of the user and the other layer represents the correlated intrinsic behavior.

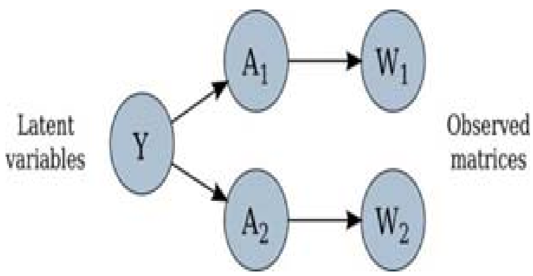

Fig. 4 Latent Variable

V. Conclusion

By using this technique we can transmit the information from one department to various department without noise or traffic. We can achieve connectivity information in the big organization. So that person working in various department can come to knew what is happening in the other department. So that they can make changes according to that. We can update information to all the department through email.It can be achieved by using pareto and posterior implementation for better result.

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