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

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Abstract —Bigorganizations which contain a various types of department where the information has to be passed to different departments for number of users.Whatever changes happening in the department regarding the products that should be sent through email to all the various department like an updated news.We can achieve this by passing the information to all the departments by using a Multi-Layer graph without any noise and traffic. Where the information can be updated immediately to all the department through email. So the people in various departments can knew what is happening in the other department so that they can make changes according to that.

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

I. INTRODUCTION

Multilayer arises when more than one source available, where each source has to pass the information to the other. For instance in email communication there will be direct communication link to process the email which is called as relational information. Example of relational information is within the time period whether the user sent or received the email from the other users. But there is a possibility where we can define the behavioral relationship based on person's interests and movements [1]. These behavioral relationships are anecdotal from information that will not connect directly to the user. In this paper we are going show how to deal with the big organization by using the Multi-Layer network.

By using a hierarchical latent – variable model we show how to perform the antidotal in Multi-Layer network. The technique Bayesian Model Averaging designed to help account for the uncertainty inherent in the model selection process, something which traditional statistical analysis often neglects.[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

A typical graph layer is comprised of a set ofX 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.

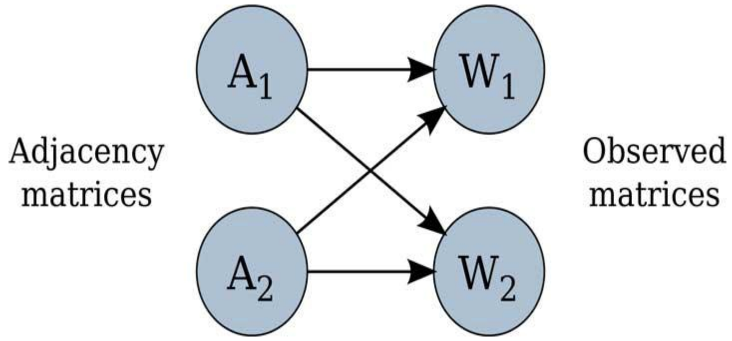

Fig. 1 Adjacency and Observed Matrices

A Multi-Layer graph G=(V , E) where V={V1………Vp} common to all layers, and the edges E={e1…….el) common to all L layers. Assume in a real world 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. Using the standard parametric method we require posterior distribution of A1….Al for computing.But there is difficulty to measure A1…Al from the single W1 where it needs a lot of parameters.

III. HIERARCHICAL MODEL

The hierarchical model simplifies [6] the implication procedure by conditionally decoupling w1…..wi. 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.

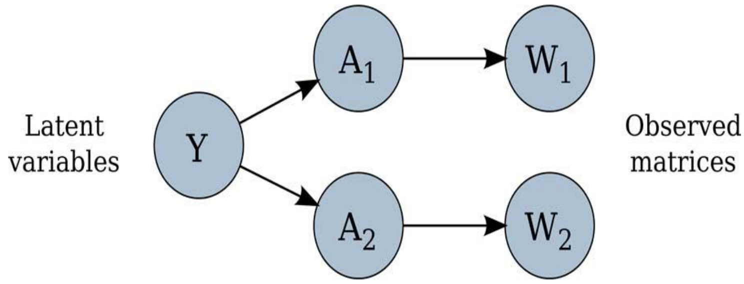

Fig. 2 Latent Variable

Here we introduced the latent variable y which conditionally decouples the posterior distribution of the two layers , 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.

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

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

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

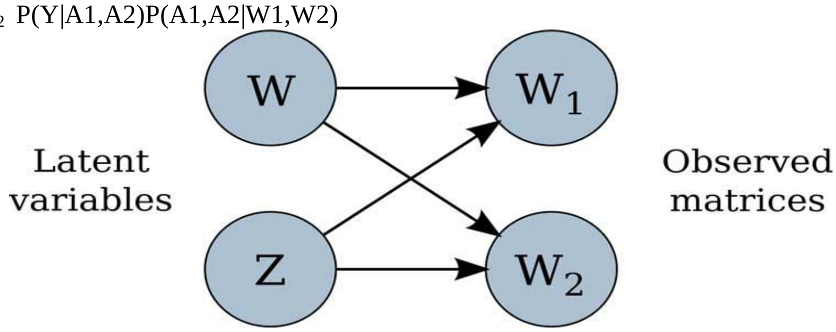

Fig. 3 Model with similarity matrix and selection variable

IV. POSTERIOR MIXTURE MODELLING

In Fig. 3 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.

$P_2 (W1|W) = P_2 (W1)$ (3)

$P_1 (W2|W) = P_1 (W2)$ (4)

The latent variable W given the observed variable W1, W2.

$P (W|W_1.W_2)$ (5)

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

$=ƐP (W|W_1, W_2, Z=1) + (1-Ɛ) P (W|W_1, W_2, Z=2)$ (8)

Let us consider the first term

$P(W|W_1,W_2,Z=1)=P(W_1W_1,W_2,Z=1) = \frac{P(W1\,W1,w2,Z=1)}{\Sigma w P\,(W1\ W1,W2,Z=1)}$ (9)

$=\frac{P(W)P1(W1|W)P1(W2)}{\Sigma wP\,(W)P1(W1|W)P1(W2)}$ (10)

Equation (10) becomes

$P(W|W1,W2,Z=1)= \frac{P(W)P1(W1|W)}{P1(W1)}$ (11)

Performing the same equation on other side and combining

$P (W|W1, W2)$ (12)

$=Ɛ\,\frac{P(W)P1(W1|)}{P1(W1)} + (1-Ɛ)\,\frac{P(W)P2(W2|W)}{P2(W2)}$ (13)

$=P(W)[ϒ1P1(W1|W) + ϒ2P2(W2|W)]$ (14)

Here ϒ1=Ɛ/P1 (W1) and ϒ2=Ɛ/P2 (W2),

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

$\arg\max_w [ϒ1P1(W1|W)+ϒ2P@(2|W]$ (15)

Assume that both P (W1|W) and P (W2|W) are isotropic gaussians,

P (W1|W) =N (W1, $\sigma^2 I_p$) (16)

P (W2|W) =N (W2, $\sigma 2I_p$) (17)

Then W=$^\beta$W1 + (1-$^\beta$) W2 (18)

Where 0≤ $^\beta$ ≤ 1.

V. CONCLUSION

The planned methodology of detailed multi-layer network modeling, hierarchical,posterior,where we can achieve the connectivity information in the big organization. We can pass all the information through email where it can update immediately if there is any changes occur in all the department. From the above description we can make that observed matrices also to be visible to the user for the communication. These Techniques can be achieved by adding some extra features parito and posterior implementation.

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