Final Project Proposal

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1 Optimization problem

One of the most important tasks is estimating the partial correlation between blocks, that is estimation of $D=\Sigma^{-1}$. Denote $\eta_k=\log(\frac{\hat{p}_{k,k}}{1-\hat{p}_{k,k}})$, where $\hat{p}_{k,k}=\frac{\sum_{z[i]=z[j]=k}Y_{i,j}}{n_k}$ and n_k is the number of all the possible edges in block k. We assume n iid observed networks $Y^{(i)}$ with unobserved iid $p^{(i)}$ (or iid $\eta^{(i)}$). The statistics $\hat{\eta}^{(i)}$ are thus also iid. By using the lasso method, we can get

$$\hat{\theta}^{a,\lambda} = \underset{\theta:\theta_a=0}{\operatorname{arg\,min}} \left(n^{-1} \| \hat{\boldsymbol{\eta}}_a - \hat{\boldsymbol{\eta}}\theta \|_2^2 + \lambda \| \theta \|_1 \right). \tag{1}$$

Then based on $\{\hat{\theta}^{a,\lambda}: a\in\{1,\cdots,K\}\}$, we have the estimation of edge set E, denoted by \hat{E}^{λ} . In order to get a good estimator of E, it is important have a good estimator, $\hat{\theta}^{\lambda}_a$. In the final project, my optimization problem is solving the minimization equation (1).

2 Method

The 'lars' [1] and 'glmnet' are two well-known R packages for solving the lasso problem. One of the interesting thing is to implement the algorithms myself, then compare it with the two packages.

Right now, I still do not have a good data for the block dependent model. For the final project, I will first simulate the data from the model. Then apply my implementation and the two packages to the simulate data and compare the results.

3 Research plan

Before Nov.17, I will finish reading the material of the algorithms. Then I will complete the algorithm first in R before Nov.28. Before Dec. 5, I will finish writing my code in Julia.

References

[1] Hastie, T., Tibshirani, R., & Friedman, J. (2009). Unsupervised learning (pp. 485-585). Springer New York