Sparse and Locally Constant Gaussian Graphical Models: Supplementary Material

Jean Honorio,   Luis Ortiz,   Dimitris Samaras
Department of Computer Science
Stony Brook University
Stony Brook, NY 11794
{jhonorio,leortiz,samaras}@cs.sunysb.edu

Nikos Paragios
Laboratoire MAS
Ecole Centrale Paris
Chatenay-Malabry, France
nikos.paragios@ecp.fr

Rita Goldstein
Medical Department
Brookhaven National Laboratory
Upton, NY 11973
rgoldstein@bnl.gov

1 Parameter Settings for Experiment of Convergence to the Ground Truth

In the results of Figure 2 (Kullback-Leibler divergence with respect to the best method, average precision, recall and Frobenius norm between the recovered model and the ground truth), we measured the ability of our method to recover the ground truth structure from data. Meinshausen-Buhlmann approximation, covariance selection, graphical lasso and our algorithm were executed for sparseness parameter $\rho = 0.2$, local constancy parameter $\tau = 0.3$ and $K = 10$ iterations for small datasets of four samples. Sparseness parameter $\rho = 0.03$, local constancy parameter $\tau = 0.02$ and $K = 10$ iterations was used for large datasets of 400 samples. Those parameters were selected because they produced the smallest Kullback-Leibler divergence to the ground truth when using our method. The best parameter values for the Meinshausen-Buhlmann approximation, covariance selection and graphical lasso did not significantly differ from the ones selected by using this method.

2 Preprocessing and Parameter Settings for Experiments on Real-World Datasets

An experiment on cardiac MRI was performed in order to recover global deformation such as rotation and shrinking. A short-axis cardiac MRI sequence collected by [1] was used. The segmentation of the myocarde at the end diastole performed by an expert was used for cropping. Preprocessing of the dataset was performed in DROP[1] for computing the displacements of the pixels from the initial reference frame. The cardiac MRI sequence contains 24 images of 100×100 pixels. After preprocessing, the number of pixels that correspond to the heart was reduced to 122. We applied our algorithm with sparseness parameter $\rho = 0.35$, local constancy parameter $\tau = 0.05$ and $K = 10$ iterations.

An experiment on a walking sequence was performed in order to find long range interactions between different parts. The silhouette consisting of 40 landmarks was manually labeled in a video sequence of 79 frames from the Human Identification at a Distance dataset[2]. We applied our algorithm with sparseness parameter $\rho = 2.5$, local constancy parameter $\tau = 0.25$ and $K = 10$ iterations.

---

[1] http://campar.in.tum.de/Main/Drop
[2] http://www.cc.gatech.edu/cpl/projects/hid/

An experiment on functional brain MRI was performed in order to discover differences in processing monetary rewards between cocaine addicted subjects versus healthy control subjects. The time series consists of 87 frames taken every 3.5 seconds. The dataset collected by [2] contains 28 subjects: 16 drug-addicted and 12 healthy non-drug-using control individuals. Preprocessing of the dataset was performed in SPM2[3], and it included deforming all time series to the same spatial reference template (Talairach space), spatial smoothing, cropping and regular sampling. Each subject has a sequence of 87 images of $53 \times 63 \times 46$ voxels. After preprocessing, the number of voxels was reduced to 869. We applied our algorithm with sparseness parameter $\rho = 0.15$, local constancy parameter $\tau = 0.01$ and $K = 10$ iterations.

3   Statistical Significance of Generalization Experiments

In the results of Table 3 (Cross-validated log-likelihood on the testing set), we measured the generalization performance of our method. We applied the likelihood ratio test, showing that most of our results are statistically significant. The likelihood ratio test was performed as follows: given the log-likelihood L_1 of a model with κ_1 parameters (number of non-zero entries in the precision matrix), and the log-likelihood L_0 of a simpler model with $\kappa_0 < \kappa_1$ parameters, at significance level $1 - \alpha = 0.95$ we reject the simpler model if:

$$2(L_1 - L_0) \geq \chi^2_{(\alpha=0.05, DOF=\kappa_1-\kappa_0)}$$

References

[1] J. Deux, A. Rahmouni, and J. Garot. Cardiac magnetic resonance and 64-slice cardiac CT of lipomatous metaplasia of chronic myocardial infarction. *European Heart Journal*, 2008.

[2] R. Goldstein, D. Tomasi, N. Alia-Klein, L. Zhang, F. Telang, and N. Volkow. The effect of practice on a sustained attention task in cocaine abusers. *NeuroImage*, 2007.

---

[3]http://www.fil.ion.ucl.ac.uk/spm/