Statistique bayésienne: Project topics

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The project must be done by groups of three students. Groups of two students must be authorized by us. The project should not exceed 15 pages, with reasonable font size and margins. We suggest the following topics but you can choose another one, subject to our approval. For the following topics, you should: (1) explain the theoretical, computational and/or empirical method, (2) emphasize the main points of the paper, and (3) either apply it to real data (that you will find) or make Monte Carlo simulations. You can use any language among Python, R or C for the programming. Please send

- your report as a pdf,
- a zipped folder containing your code and a detailed readme file with instructions to (compile and) run the code.

to Anna.Simoni@ensae.fr and remi.bardenet@gmail.com **no later than January 27, 2017.**

As a first step, we ask you to send us an email **by November 30, 2016** with your ordered choices of three papers (among the ones proposed below) for your project. Then, we are going to assign you one paper based on your three choices. In this assignment we will try to satisfy your first preference as much as possible and also a balance among the different parts of the course. The same paper cannot be taken by more than one group.

Proposed topics

1. Yao, W. and Lindsay, B.G. (2009), Bayesian Mixture Labeling by Highest Posterior Density. *Journal of the American Statistical Association*, Vol. 104, n. 486.

2. Tanner, M.A. and The Wong, W.H. (1987), Calculation of Posterior Distributions by Data Augmentation. *Journal of the American Statistical Association*, Vol. 82, n. 398, pp. 528-540.

3. Durante, D., Paganin, S., Scarpa, B. and Dunson, D.B. (2015) Bayesian modeling of networks in complex business intelligence problems. *Journal of the Royal Statistical Society Series C Applied Statistic*, forthcoming. https://arxiv.org/abs/1510.00646

4. Lee, J., Thall, P.F., Ji, Y. and Müller Peter (2015), Bayesian Dose-Finding in Two Treatment Cycles Based on the Joint Utility of Efficacy and Toxicity. *Journal of the American Statistical Association*, Vol. 110, n. 510, pp. 711-722.

5. Hans, C. (2011), Elastic Net Regression Modeling With the Orthant Normal Prior. *Journal of the American Statistical Association*, Vol. 106, n. 496, pp. 1383-1393.

6. Chib, S. (1995), Marginal Likelihood from the Gibbs Output. *Journal of the American Statistical Association*, Vol. 90, n. 432, pp. 1313-1321.

7. Goldsmith-Pinkham, P. and G.W. Imbens (2013), Social Networks and the Identification of Peer Effects. *Journal of Business & Economic Statistics*, Vol. 31, n. 3, pp. 253-264.

8. Chamberlain, G. and G.W. Imbens (2003), Nonparametric Applications of Bayesian Inference. *Journal of Business & Economic Statistics*, Vol. 21, n.1, pp. 12-18.

9. McCulloch, R. and P. Rossi (1994), An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics*, Vol. 64, pp. 207-240.

10. Efron B. (2015), Frequentist accuracy of Bayesian estimates. *Journal of the Royal Statistical Society*, Vol. 77, pp. 617-646.

11. Wu, Y. and S. Ghosal (2008), Posterior Consistency for some Semi-parametric Problems. *Sankhya: The Indian Journal of Statistics*, Vol. 70, pp. 0-46.

12. Banerjee, S. and A. Ghosal (2015), Bayesian estimation of a sparse precision matrix. *Journal of Multivariate Analysis*, Vol. 136, pp. 147-162.

13. Das, P. and S. Ghosal (2016), Bayesian Quantile Regression Using Random B-spline Series Prior. Working Paper: http://www4.stat.ncsu.edu/ sghosal/papers/quantile regression.pdf

14. Chu, W. and Ghahramani, Z. (2005), Preference Learning with Gaussian Processes, In *Proceedings of ICML*.

15. Titsias, M. (2009), Variational Learning of Inducing Variables in Sparse Gaussian Processes, In *Proceedings of AISTATS*.

16. Teh, Y. W. and Jordan, M. I. and Beal, M. J. and Blei, D. M. (2006), Hierarchical Dirichlet processes, *Journal of the American Statistical Association*.

17. Huszar, F. and Duvenaud, D. (2012), Optimally-Weighted Herding is Bayesian Quadrature, In *Proceedings of UAI*.

18. Snoek, J. and Larochelle, H. and Adams, R. (2012), Practical Bayesian Optimization of Machine Learning Algorithms, In *Proceedings of NIPS*, 2012.