Bayesian ML: project topics

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1 Nature of the project

A group is made of either one or two students. Each group is to pick one of the papers listed below, and each paper can be chosen only once. The assignment in on a first-come first-served basis. Groups of two must choose a paper from the "long/difficult" list. For groups of one, there will be bonus points for picking a paper identified as "long/difficult", but it will be possible to get the maximum grade with a paper identified as "short/easy". You can also choose to work on a paper of your choice, subject to our explicit approval; in that case, we trust you not to pick a paper that you are or have been working on in another class.

The whole point is to read your paper with a critical mind. For the paper your group will have chosen, you should: (1) explain the contents of the paper, (2) emphasize the strong and weak points of the paper, and (3) apply it to real data of your choice when applicable. Bonus points will be considered if you are creative and add something insightful that is not in the original paper: this can be a theoretical point, an illustrative experiment, etc. Be explicit in your introduction what is your creative contribution.

2 Assignment of papers

As a first step, we ask each group to fill the spreadsheet at

https://lite.framacalc.org/zr1v1h3ld6-9z79

with the title of the paper, a link to it (if available), and the composition of the group. Please fill the form **before Thursday 16 February**.

3 Format of the deliverable

Please have each group send

- one report as a pdf ($\leq$ 5 pages) in the NeurIPS template,

- the link to a GitHub or GitLab repository containing your code and a detailed readme file with instructions to (compile/install and) run the code.

to both remi.bardenet@gmail.com and julyan.arbel@inria.fr**no later than March 16th**. We will then meet on March 23rd for presentations (10+5 minutes per group).

4 Proposed papers

Short and "easy" papers

[Easy1] B. Calderhead. A general construction for parallelizing Metropolis-Hastings algorithms. *Proceedings of the National Academy of Sciences*, 111(49):17408–17413, 2014.

[Easy2] Carlos M Carvalho, Nicholas G Polson, and James G Scott. Handling sparsity via the horseshoe. In *Artificial Intelligence and Statistics*, pages 73–80. PMLR, 2009.

[Easy3] Yutian Chen, Max Welling, and Alex Smola. Super-samples from kernel herding. In *Proceedings of UAI*, 2010.

[Easy4] Lionel Cucala, Jean-Michel Marin, Christian P Robert, and D Michael Titterington. A Bayesian reassessment of nearest-neighbor classification. *Journal of the American Statistical Association*, 104(485):263–273, 2009.

[Easy5] Ghassen Jerfel, Serena Wang, Clara Wong-Fannjiang, Katherine A Heller, Yian Ma, and Michael I Jordan. Variational refinement for importance sampling using the forward Kullback-Leibler divergence. In *Uncertainty in Artificial Intelligence*, pages 1819–1829. PMLR, 2021.

[Easy6] Romain Lopez, Pierre Boyeau, Nir Yosef, Michael I Jordan, and Jeffrey Regier. Decision-making with auto-encoding variational Bayes. In *Advances in Neural Information Processing Systems*, 2020.

[Easy7] Nicholas G Polson and Steven L Scott. Data augmentation for support vector machines. *Bayesian Analysis*, 6(1):1–23, 2011.

[Easy8] M. Rabinovich, E. Angelino, and M. Jordan. Variational consensus Monte Carlo. In *Advances in Neural Information Processing Systems*, pages 1207–1215, 2015.

[Easy9] Y. W. Teh, D. Newman, and M. Welling. A collapsed variational Bayesian inference algorithm for latent Dirichlet allocation. In *Advances in neural information processing systems*, pages 1353–1360, 2007.

Long or difficult papers

[Hard1] Francis Bach. On the equivalence between kernel quadrature rules and random feature expansions. *The Journal of Machine Learning Research*, 18(1):714–751, 2017.

[Hard2] A. Belhadji, R. Bardenet, and P. Chainais. Kernel interpolation with continuous volume sampling. In *International Conference on Machine Learning (ICML)*, 2020.

[Hard3] P. Germain, F. Bach, A. Lacoste, and S. Lacoste-Julien. Pac-Bayesian theory meets Bayesian inference. In *Advances in Neural Information Processing Systems*, pages 1884–1892, 2016.

[Hard4] P. Grünwald and T. Van Ommen. Inconsistency of Bayesian inference for misspecified linear models, and a proposal for repairing it. *Bayesian Analysis*, 12(4):1069–1103, 2017.

[Hard5] Matthew D Hoffman and Andrew Gelman. The no-U-turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, 15(1):1593–1623, 2014.

[Hard6] Pierre E Jacob, John O'Leary, and Yves F Atchadé. Unbiased Markov chain Monte Carlo methods with couplings. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 82(3):543–600, 2020.

[Hard7] A. Korba, A. Salim, M. Arbel, G. Luise, and A. Gretton. A non-asymptotic analysis for Stein variational gradient descent. *Advances in Neural Information Processing Systems*, 33:4672–4682, 2020.

[Hard8] P. Rigollet and A. Tsybakov. Exponential screening and optimal rates of sparse estimation. *The Annals of Statistics*, 39(2):731–771, 2011.