# Bayesian ML: Project topics

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## 1 Nature of the project

Groups can consist of either of 1 or 2 persons. Each group must pick a paper in Section 4, on a first-come-first-served basis. For the paper your group has chosen, you should:

1. explain the main theoretical, computational and/or empirical points of the paper,
2. apply it to real data of your choice when applicable,
3. be creative and add something insightful that is not in the original paper: this can be a theoretical point, an illustrative experiment, etc. **State clearly in your introduction what your creative addition is**.

The whole point is to show that you can read a scientific paper with a critical mind.

## 2 Assignment of papers

As a first step, **before 16 December**, please fill the spreadsheet at

https://lite.framacalc.org/9kke-paper-assignment-m2-lille

with the title of your paper and the group members.

## 3 Format of the deliverable

You should use Python for the programming part. Please send, by **11 January**,

- one report as a pdf ($\leq$ 6 pages, with at most 3 pages dedicated to item 1 in Section 1) 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 remi.bardenet@gmail.com. There will be no deadline extension.

# 4 Proposed papers

All PDFs are here: https://nextcloud.univ-lille.fr/index.php/s/c8pKGidzJQzqwyi.

Students working alone can pick any paper, though I'd advise picking one prefixed with an A in the list below, since they're shorter. Groups of two must pick from the B list, consisting of slightly longer or more difficult papers. Although I've only included papers that I think you can read with your current state of knowledge, there are papers that are significantly harder and longer than others. I will take this into account when grading. Be clear in your report about what you have not understood and how you have tried to tackle it.

## For one person

[A1] R. Bardenet, A. Doucet, and C. Holmes. Towards scaling up MCMC: an adaptive subsampling approach. In *Proceedings of the International Conference on Machine Learning (ICML)*, 2014.

[A2] C. M. Bishop. Bayesian PCA. In *Advances in neural information processing systems*, pages 382–388, 1999.

[A3] A. Corduneanu and C. M. Bishop. Variational Bayesian model selection for mixture distributions. In *Artificial intelligence and Statistics*, volume 2001, pages 27–34, 2001.

[A4] D. P. Kingma and M. Welling. Auto-encoding variational Bayes. In *International Conference on Learning Representations*.

[A5] C. E. Rasmussen and Z. Ghahramani. Bayesian Monte Carlo. In *Advances in neural information processing systems*, pages 505–512, 2003.

[A6] M. Welling and Y. W. Teh. Bayesian learning via stochastic gradient Langevin dynamics. In *Proceedings of the International Conference on Machine Learning (ICML)*, 2011.

## For groups of two (or one very motivated person)

[B1] P. Germain, F. Bach, A. Lacoste, and S. Lacoste-Julien. Pac-Bayesian theory meets Bayesian inference. *Advances in Neural Information Processing Systems*, 29:1884–1892, 2016.

[B2] P. Grünwald, T. Van Ommen, et al. Inconsistency of Bayesian inference for misspecified linear models, and a proposal for repairing it. *Bayesian Analysis*, 12(4):1069–1103, 2017.

[B3] A. Kucukelbir, D. Tran, R. Ranganath, A. Gelman, and D. M. Blei. Automatic differentiation variational inference. *The Journal of Machine Learning Research*, 18(1):430–474, 2017.

[B4] T. Leonard and J. Hsu. Bayesian inference for a covariance matrix. *The Annals of Statistics*, 20(4):1669–1696, 1992.