Models for ML: Project topics

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1 Nature of the project

Groups can consist either of 1 or 2 people. 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 theoretical, computational and/or empirical methods,
2. emphasize the main points of the paper,
3. apply it to real data of your choice when applicable,
4. 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 1 April**, please fill the spreadsheet at

https://lite.framacalc.org/9ft2-paper-assignment-m1-lille

with the title of your paper and the group members.

3 Format of the deliverable

You can use either Python or R for the programming part. Please send, by **10 April**,

- one report as a pdf (≤ 8 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 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 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] C. M. Bishop. Bayesian PCA. In *Advances in neural information processing systems*, pages 382–388, 1999.

[A2] A. Corduneanu and C. M. Bishop. Variational Bayesian model selection for mixture distributions. In *Artificial intelligence and Statistics*, volume 2001, pages 27–34, 2001.

[A3] P. Domingos. Bayesian averaging of classifiers and the overfitting problem. In *International conference on machine learning*, volume 2000, pages 223–230, 2000.

[A4] D. McAllester. Some PAC-Bayesian theorems. In *Conference on learning theory*, 1998.

[A5] T. P. Minka. Expectation propagation for approximate bayesian inference. In *Uncertainty in Artificial Intelligence*, 2013.

For groups of two (or one very motivated person)

[B1] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent Dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022, 2003.

[B2] L. Cucala, J.-M. Marin, C. P. Robert, and D. M. Titterington. A Bayesian reassessment of nearest-neighbor classification. *Journal of the American Statistical Association*, 104(485):263–273, 2009.

[B3] P. Domingos and M. Pazzani. On the optimality of the simple Bayesian classifier under zero-one loss. *Machine learning*, 29(2-3):103–130, 1997.

[B4] 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.

[B5] T. Leonard and J. Hsu. Bayesian inference for a covariance matrix. *The Annals of Statistics*, 20(4):1669–1696, 1992.