Bayesian ML 2021-22: project topics

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1 Nature of the project

Students should form groups of two, each group undertaking one project. We suggest in Section 4 a few scientific papers that can each lead to a project, but you can choose another paper, subject to our approval.

For the paper your group will have chosen, you should: (1) explain the theoretical, computational and/or empirical methods, (2) emphasize the main 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. The whole point is to read the paper with a critical mind.

2 Assignment of papers

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

https://lite.framacalc.org/cdlr2k2rpq-9sey

with the title of the paper, a link to it (if available), and the composition of the group. We ask that you fill in the form **before February 17 23:59**.

3 Format of the deliverable

You can use either Python or R for the programming part. 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, a Jupyter notebook to demo the code, and a readme file with instructions to (compile/install and) run the code.

to both teachers[1] **no later than March 21 23:59**. There will be no deadline extension.

The last step of your project will be a presentation in front of the class on March 24.

[1] if the above link is broken, this means: julyan.arbel@inria.fr, and remi.bardenet@gmail.com

4 Proposed papers

Lecture on Bayesics

[A1] 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.

[A2] Peter Grünwald. The safe Bayesian. In *Proceedings of the International Conference on Algorithmic Learning Theory*, pages 169–183. Springer, 2012.

[A3] Romain Lopez, Pierre Boyeau, Nir Yosef, Michael Jordan, and Jeffrey Regier. Decision-making with auto-encoding variational Bayes. *Advances in Neural Information Processing Systems*, 33:5081–5092, 2020.

Lecture on MCMC

[B1] Matthew D Hoffman, Andrew Gelman, et al. The No-U-Turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, 15(1):1593–1623, 2014.

[B2] Jun Liu. The Collapsed Gibbs Sampler in Bayesian Computations With Applications to a Gene Regulation Problem . *Journal of the American Statistical Association*, 1994.

[B3] Stephan Mandt, Matthew Hoffman, and David Blei. A variational analysis of stochastic gradient algorithms. In *International conference on machine learning*, pages 354–363. PMLR, 2016.

Lecture on variational inference

[C1] Thomas P Minka. Expectation propagation for approximate Bayesian inference. In *Uncertainty in Artificial Intelligence*, 2001.

[C2] Kolyan Ray and Botond Szabó. Variational Bayes for high-dimensional linear regression with sparse priors. *Journal of the American Statistical Association*, pages 1–12, 2021.

[C3] 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.

[C4] Michalis K Titsias. Variational learning of inducing variables in sparse Gaussian processes. In *International Conference on Artificial Intelligence and Statistics*, pages 567–574, 2009.

Lecture on foundations

[D1] Rianne de Heide and Peter D Grünwald. Why optional stopping can be a problem for Bayesians. *Psychonomic Bulletin & Review*, 28(3):795–812, 2021.

Lecture on Bayesian nonparametrics

[E1] Fadhel Ayed, Juho Lee, and Francois Caron. Beyond the chinese restaurant and Pitman-Yor processes: Statistical models with double power-law behavior. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 395–404. PMLR, 09–15 Jun 2019.

[E2] Michael Lavine. Some aspects of Polya tree distributions for statistical modelling. *The Annals of Statistics*, pages 1222–1235, 1992.

[E3] Jeffrey W Miller and Matthew T Harrison. Inconsistency of Pitman-Yor process mixtures for the number of components. *The Journal of Machine Learning Research*, 15(1):3333–3370, 2014.

[E4] Jim Pitman and Marc Yor. The two-parameter Poisson-Dirichlet distribution derived from a stable subordinator. *The Annals of Probability*, 25(2):855–900, 1997.

Lecture on Bayesian deep learning

[F1] Wenbo Guo, Sui Huang, Yunzhe Tao, Xinyu Xing, and Lin Lin. Explaining deep learning models-a Bayesian non-parametric approach. *NeurIPS*, 2018.

[F2] Mohammad Emtiyaz E Khan, Alexander Immer, Ehsan Abedi, and Maciej Korzepa. Approximate Inference Turns Deep Networks into Gaussian Processes. In *Advances in Neural Information Processing Systems*, pages 3088–3098, 2019.

[F3] A. Matthews, M. Rowland, J. Hron, R. Turner, and Z. Ghahramani. Gaussian process behaviour in wide deep neural networks. In *International Conference on Learning Representations*, volume 1804.11271, 2018.

[F4] Mikhail Yurochkin, Mayank Agarwal, Soumya Ghosh, Kristjan Greenewald, Nghia Hoang, and Yasaman Khazaeni. Bayesian nonparametric federated learning of neural networks. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 7252–7261. PMLR, 09–15 Jun 2019.