

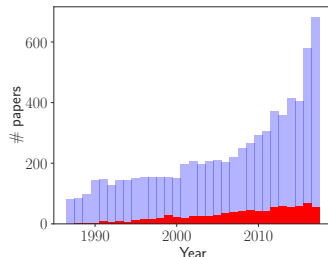
Bayesian machine learning

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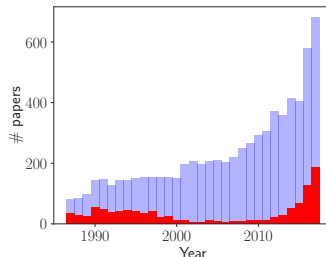
CNRS & CRIStAL, Univ. Lille, France



Trends in abstracts



(a) "Bayesian" @NeurIPS



(b) "Neural" @NeurIPS

- The Bayesian deep learning workshop is increasingly popular (accepted papers: 39 in 2016, 68 in 2017 and 136 in 2018).

We can extract topics

model models data process latent Bayesian Dirichlet hierarchical nonparametric inference
features learn problem different knowledge learning image object example examples
method neural Bayesian using linear state based kernel approach model
belief propagation nodes local tree posterior node nbsp given algorithm
learning data Bayesian model training classification performance selection prediction sets
inference Monte Carlo Markov sampling variational time algorithm MCMC approximate
function optimization algorithm optimal learning problem gradient methods bounds state
learning networks variables structure network Bayesian EM paper distribution algorithm
Bayesian gaussian prior regression non estimation likelihood sparse parameters matrix
model information Bayesian human visual task probability sensory prior concept

Figure: Topics extracted from NeurIPS and JMLR abstracts using variational inference for latent Dirichlet allocation.

Goals of the course

By the end of the course, the students should

- ▶ have a high-level view of the main approaches to making decisions under uncertainty.
- ▶ be able to detect when being Bayesian helps and why.
- ▶ be able to design and run a Bayesian ML pipeline for standard supervised or unsupervised learning.
- ▶ have a global view of the current limitations of Bayesian approaches and the research landscape.
- ▶ be able to understand the abstract of most Bayesian ML papers.

High-level outline

1. Principles of decision theory [3, 2]
2. Formalizing a problem in a Bayesian way [3, 4]
3. Bayesian computation: MCMC and variational methods [5, 1]
4. Bayesian nonparametrics
5. Bayesian deep learning

Course webpage

Check out github.com/rbardenet/bml-course

There will be four practical sessions

- ▶ Bring your laptops.
- ▶ We'll start with Python. Make sure you install
 - ▶ Anaconda with Python 3.5+
 - ▶ pymc3 with dependencies (including theano)
 - ▶ run a few examples from pymc3's docs to check.

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If you're looking for a PhD on Monte Carlo methods

We are hiring, check out

`rbardenet.github.io/pdf/phd-proposal.pdf`

and write me an email quickly with vita and transcripts.



References I

- [1] D. M. Blei, A. Kucukelbir, and J. D. McAuliffe. “Variational inference: A review for statisticians”. In: *Journal of the American Statistical Association* 112.518 (2017), pp. 859–877.
- [2] D. Kreps. *Notes on the Theory of Choice*. Westview press, 1988.
- [3] G. Parmigiani and L. Inoue. *Decision theory: principles and approaches*. Vol. 812. John Wiley & Sons, 2009.
- [4] C. P. Robert. *The Bayesian choice: from decision-theoretic foundations to computational implementation*. Springer Science & Business Media, 2007.
- [5] C. P. Robert and G. Casella. *Monte Carlo statistical methods*. Springer, 2004.