

# BML lecture #1: Bayesics

<http://github.com/rbardenet/bml-course>

Rémi Bardenet

CNRS & CRIStAL, Univ. Lille, France



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- 2** A warmup: Estimation in regression models
- 3** ML as data-driven decision-making
- 4** Subjective expected utility
- 5** Specifying joint models
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What comes to *your* mind when you hear "Bayesian ML"?

## A quick motivating example before we go formal 1/2

- ▶ Let  $N$  individuals evolve from Susceptible to Infected to Recovered,  $x_n(t) \in \{S, I, R\}$ ,  $1 \leq n \leq N$ ,  $t \in [0, T]$ .
- ▶ Each susceptible individual  $n$  moves to  $R$  according to a Poisson process with intensity

$$\sum_{k: x_k(t)=I} \lambda_{nk}(\theta_{SI}).$$

- ▶ Each infected person recovers after a Gamma( $a, b$ ) time.
- ▶ This allows to express

$$p(x_1(t_{1,1}), \dots, x_1(t_{1,T_1}), \dots, x_n(t_{n,1}), \dots, x_1(t_{n,T_n}) | \theta).$$

where  $\theta = (\theta_{SI}, a, b)$ .

- ▶ Now, consider  $p(\theta | \text{data}) \propto p(\text{data} | \theta) p(\theta)$ .

## A quick motivating example before we go formal 2/2

- ▶ If asked to report an interval on a particular function of  $\theta$ , say  $R_0$ , I would output a small interval  $I$  such that

$$\int_I p(\theta|\text{data}) \, d\theta \geq 0.95.$$

- ▶ If asked whether we should close universities, I would ask for
  - ▶ the cost  $\alpha$  of closing unis when  $R_0 < 1$ ,
  - ▶ the cost  $\beta$  of keeping unis open while  $R_0 > 1$ .
- ▶ Then I would recommend closing if and only if

$$p(R_0 > 1|\text{data}) > \frac{\alpha}{\alpha + \beta}.$$

- ▶ Additionally, I would check that the decision doesn't change if I change my prior  $p(\theta)$  a little.
- ▶ If it did, then I would refine my likelihood and/or wait for more data.

- ▶ *[...] practical methods for making inferences from data, using probability models for quantities we observe and for quantities about which we wish to learn.*
- ▶ *The essential characteristic of Bayesian methods is their explicit use of probability for quantifying uncertainty in inferences based on statistical data analysis.*
- ▶ *Three steps:*
  - 1** *Setting up a full probability model,*
  - 2** *Conditioning on observed data, calculating and interpreting the appropriate “posterior distribution”,*
  - 3** *Evaluating the fit of the model and the implications of the resulting posterior distribution. In response, one can alter or expand the model and repeat the three steps.*

- ▶  $y_{1:n} = (y_1, \dots, y_n) \in \mathcal{Y}^n$  denote observable data/labels.
- ▶  $x_{1:n} \in \mathcal{X}^n$  denote covariates/features/hidden states.
- ▶  $z_{1:n} \in \mathcal{Z}^n$  denote hidden variables.
- ▶  $\theta \in \Theta$  denote parameters.
- ▶  $X$  denotes an  $\mathcal{X}$ -valued random variable. Lowercase  $x$  denotes either a point in  $\mathcal{X}$  or an  $\mathcal{X}$ -valued random variable.



- ▶ Whenever it can easily be made formal, we write densities for our random variables and let the context indicate what is meant. So if  $X \sim \mathcal{N}(0, \sigma^2)$ , we write

$$\mathbb{E}h(X) = \int h(x) \frac{e^{-x^2/2\sigma^2}}{\sigma\sqrt{2\pi}} dx = \int h(x)p(x)dx.$$

Similarly, for  $X \sim \mathcal{P}(\lambda)$ , we write

$$\mathbb{E}h(X) = \sum_{k=0}^{\infty} h(k) e^{-\lambda} \frac{\lambda^k}{k!} = \int h(x)p(x)dx$$

- ▶ All pdfs are denoted by  $p$ , so that, e. g.

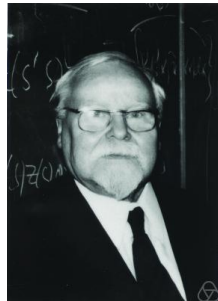
$$\begin{aligned}\mathbb{E}h(Y, \theta) &= \int h(y, \theta)p(y, \theta) dyd\theta \\ &= \int h(y, \theta)p(y, x, \theta) dx dy d\theta \\ &= \int h(y, \theta)p(y, \theta|x)p(x) dx dy d\theta\end{aligned}$$

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- ▶ A state space  $\mathcal{S}$ ,  
Every quantity you need to consider to make your decision.
- ▶ Actions  $\mathcal{A} \subset \mathcal{F}(\mathcal{S}, \mathcal{Z})$ ,  
Making a decision means picking one of the available actions.
- ▶ A reward space  $\mathcal{Z}$ ,  
Encodes how you feel about having picked a particular action.
- ▶ A loss function  $L : \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}_+$ .  
How much you would suffer from picking action  $a$  in state  $s$ .

- ▶  $\mathcal{S} = \mathcal{X}^n \times \mathcal{Y}^n \times \mathcal{X} \times \mathcal{Y}$ , i.e.  $s = (x_{1:n}, y_{1:n}, x, y)$ .
- ▶  $\mathcal{Z} = \{0, 1\}$ .
- ▶  $\mathcal{A} = \{a_g : s \mapsto 1_{y \neq g(x; x_{1:n}, y_{1:n})}, \quad g \in \mathcal{G}\}$ .
- ▶  $L(a_g, s) = 1_{y \neq g(x; x_{1:n}, y_{1:n})}$ .

**PAC bounds; see e.g. (Shalev-Shwartz and Ben-David, 2014)**

Let  $(x_{1:n}, y_{1:n}) \sim \mathbb{P}^{\otimes n}$ , and independently  $(x, y) \sim \mathbb{P}$ , we want an algorithm  $g(\cdot; x_{1:n}, y_{1:n}) \in \mathcal{G}$  such that if  $n \geq n(\delta, \varepsilon)$ ,

$$\mathbb{P}^{\otimes n} \left[ \mathbb{E}_{(x,y) \sim \mathbb{P}} L(a_g, s) \leq \varepsilon \right] \geq 1 - \delta.$$

▶  $\mathcal{S} =$

▶  $\mathcal{Z} =$

▶  $\mathcal{A} =$

▶

▶  $\mathcal{S} =$

▶  $\mathcal{Z} =$

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▶

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## The subjective expected utility principle

- 1 Choose  $\mathcal{S}, \mathcal{Z}, \mathcal{A}$  and a loss function  $L(a, s)$ ,
- 2 Choose a distribution  $p$  over  $\mathcal{S}$ ,
- 3 Take the the corresponding Bayes action

$$a^* \in \arg \min_{a \in \mathcal{A}} \mathbb{E}_{s \sim p} L(a, s). \quad (1)$$

## Corollary: minimize the posterior expected loss

Now partition  $s = (s_{\text{obs}}, s_{\text{u}})$ , then

$$a^* \in \arg \min_{a \in \mathcal{A}} \mathbb{E}_{s_{\text{obs}}} \mathbb{E}_{s_{\text{u}} | s_{\text{obs}}} L(a, s).$$

In ML,  $\mathcal{A} = \{a_g\}$ , with  $g = g(s_{\text{obs}})$ , so that (1) is equivalent to

$$a^* = \delta(s_{\text{obs}}) = \arg \min_{a \in \mathcal{A}} \mathbb{E}_{s_{\text{u}} | s_{\text{obs}}} L(a, s).$$



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## A recap on probabilistic graphical models

- ▶ PGMs (aka “Bayesian” networks) represent the dependencies in a joint distribution  $p(y)$  by a directed graph  $G = (E, V)$ .
- ▶ Two important properties:

$$p(y) = \prod_{v \in V} p(y_v | y_{\text{pa}(v)}) \quad \text{and} \quad y_v \perp y_{\text{nd}(v)} | y_{\text{pa}(v)}.$$

- ▶ Also good to know how to determine whether  $A \perp B | C$ ; see (Murphy, 2012, Section 10.5).







# Classification as a decision problem





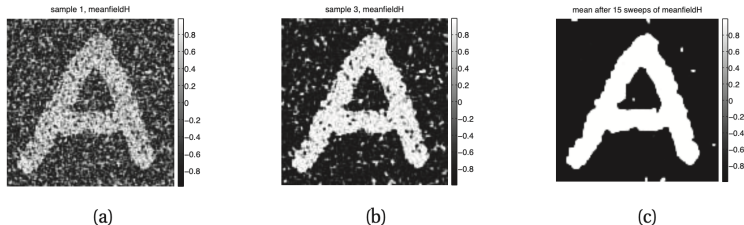








# Image denoising as a decision problem



**Figure:** Taken from (Murphy, 2012, Chapter 21)

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### An issue (or is it?)

Depending on how they interpret and how they implement SEU, you will meet many types of Bayesians (46656, according to Good).

### A few divisive questions

- ▶ Using data or the likelihood to choose your prior; see Lecture #5.
- ▶ Using MAP estimators for their computational tractability, like in inverse problems

$$\hat{x}_\lambda \in \arg \min \|y - Ax\| + \lambda \Omega(x).$$

- ▶ When and how should you revise your model (likelihood or prior)?
- ▶ MCMC vs variational Bayes (more in Lectures #2 and #3)

- [1] A. Gelman et al. *Bayesian data analysis*. 3rd. CRC press, 2013.
- [2] K. Murphy. *Machine learning: a probabilistic perspective*. MIT Press, 2012.
- [3] S. Shalev-Shwartz and S. Ben-David. *Understanding machine learning: From theory to algorithms*. Cambridge university press, 2014.