Bayesian Statistics: basics and elementary examples

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Course layout

Aim: practical use of general methodology

minimum level of formality

Literature: Bishop, Ch.M. Pattern recognition and machine learning.

Springer, 2006.

Details: scholar.google.com

Marks: individual assignment

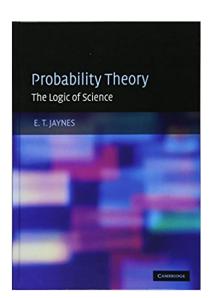
Probability theory

Probability theory as:

- extension of logic
- language
- necessity for making decisions under uncertainty

Alternatives:

- Dempster Shafer
- ► fuzzy logic



Probability of patients illness:

illness	Dr. #1 likelihood	Dr.#2 likelihood	posterior
brain tumor	99.9%	0%	
concussion	0%	99.9%	
meningitis	0.1%	0.1%	

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Counterintuitive results

1. Is probability theory wrong?

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Counterintuitive results

- 1. Is probability theory wrong?
- 2. Is model wrong?

Probability calculus discrete

Random variables:

$$X \in \{x_1, \dots, x_M\}$$
$$Y \in \{y_1, \dots, y_L\}$$

Joint probability

$$P(X = x_i, Y = y_j) = \frac{n_{i,j}}{N}$$

where N ($N \to \infty$) is the number of realizations and $n_{i,j}$ is the number of trials where $X = x_i, Y = y_i$.

Rules:

1. sum rule

$$P(X = x_i) = \sum_{i=1}^{L} P(X = x_i, Y = y_i),$$

2. product rule

$$P(X, Y) = p(Y|X)p(X)$$

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Rules:

1. sum rule

$$p(x) = \int p(x, y) dy$$

product rule

$$p(x,y) = p(y|x)p(x) = p(x|y)p(y)$$

Random variable: X, realization x

Probability density function: $p_X(x)$, $\int p_X(x)dx = 1$

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Engineering (ML) notation: meaning given by context.

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

Noisy observation:

$$d = m + e$$
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Noisy observation:

$$d = m + e$$
,

What is the distribution of m given d?

$$p(m|d) \propto p(m,d) = \int p(d|m,\omega)p(m,\omega)d\omega$$

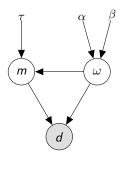
Noise model (likelihood): Gaussian

$$\begin{split} & p(e_i) = \mathcal{N}(0, \omega^{-1}) = \sqrt{\frac{\omega}{2\pi}} \exp\left(-\frac{1}{2}\omega e^2\right) \\ & p(d_i) = \mathcal{N}(m, \omega^{-1}) = \sqrt{\frac{\omega}{2\pi}} \exp\left(-\frac{1}{2}\omega (d-m)^2\right) \end{split}$$

Prior:

$$p(m|\omega) = \mathcal{N}(0, \tau\omega) = \sqrt{\frac{\omega\tau}{2\pi}} \exp\left(-\frac{1}{2}\tau\omega m^2\right)$$

 $p(\omega) = G(\alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)}\omega^{\alpha-1} \exp(-\beta\omega)$



Noisy observation:

$$d = m + e$$

$$p(m|d) \propto p(m,d) = \int p(d|m,\omega)p(m,\omega)d\omega$$

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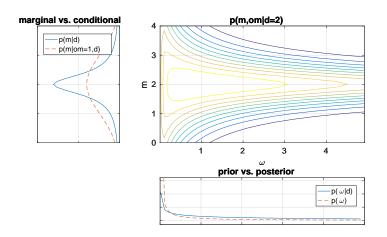
Find:

$$p(m, \omega|d) = ?$$

$$p(m|\omega, d) = ?$$

$$p(m|d) = ?$$

$$p(\omega|d) = ?$$



Likelihood:

Prior:

1. Gaussian

informative

2. Other

non-informative

Likelihood:

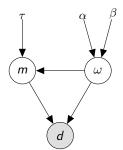
Prior:

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▶ informative

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Likelihood:

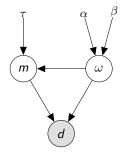
- 1. Gaussian

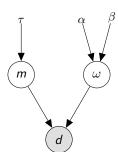
informative

Prior:

2. Other

▶ non-informative



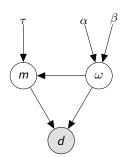


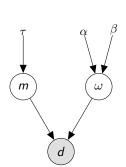
Likelihood:

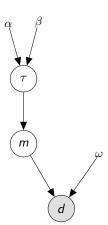
- 1. Gaussian
- 2. Other

Prior:

- informative
- non-informative







Alternative model

- $p(m|\omega) = \int p(d|m,\omega)p(m|\alpha)p(\alpha)d\alpha$
- ► graphical model