The Bayesian viewpoint An introduction

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On reasoning

• Generally credited to Aristotle's Organon.

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- Generally credited to Aristotle's *Organon*.
- ullet If A is true, then B is true.

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Final thought

• Generally credited to Aristotle's *Organon*.

ullet If A is true, then B is true.

ullet Its inverse: If B is false, then A is false.

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- Generally credited to Aristotle's Organon.
- ullet If A is true, then B is true.
- ullet Its inverse: If B is false, then A is false.
- Do we always have the right kind of information to allow this kind of reasoning?

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• Not quite. Sometimes, we need weaker syllogisms.

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- Not quite. Sometimes, we need weaker syllogisms.
- ullet If A is true, then B is true.
- What if we only know that *B* is true?

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- Not quite. Sometimes, we need weaker syllogisms.
- ullet If A is true, then B is true.
- What if we only know that B is true?
- We would like to say: Then, A becomes more plausible.

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- Not quite. Sometimes, we need weaker syllogisms.
- ullet If A is true, then B is true.
- What if we only know that B is true?
- We would like to say: Then, A becomes more plausible.
- ullet Similar reasoning: If A is false, then B becomes less plausible.

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Final thoughts

• Reasoning from consequence.

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- Reasoning from consequence.
- Reasoning from randomness.

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- Reasoning from consequence.
- Reasoning from randomness.
- Reasoning from analogy.

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- Reasoning from consequence.
- Reasoning from randomness.
- Reasoning from analogy.
- In the calculus of plausibility, our prior assessments are all important!

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• Observed data D.

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- Observed data D.
- Want to know something about a variable θ .

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- Observed data D.
- Want to know something about a variable θ .
- Our interest is then in the quantity:

$$p(\theta|D) = \frac{p(D|\theta)\,p(\theta)}{p(D)} = \frac{p(D|\theta)\,p(\theta)}{\int\limits_{\theta} p(D|\theta)\,p(\theta)}$$

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- Observed data D.
- Want to know something about a variable θ .
- Our interest is then in the quantity:

$$p(\theta|D) = \frac{p(D|\theta) p(\theta)}{p(D)} = \frac{p(D|\theta) p(\theta)}{\int\limits_{\theta} p(D|\theta) p(\theta)}$$

• $p(\theta|D)$ is the posterior distribution of the variable θ in light of the observed data, $p(\theta)$ is the prior, and $p(D|\theta)$ is the generative model/likelihood of the dataset.

Exact binomial probability inference

Coin flipping

• Outcome of a single flip given by a function of parameter θ :

$$p(\gamma|\theta) = \theta^{\gamma} (1-\theta)^{(1-\gamma)}$$

Exact binomial probability inference

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• Outcome of a single flip given by a function of parameter θ :

$$p(\gamma|\theta) = \theta^{\gamma} (1-\theta)^{(1-\gamma)}$$

So, if you have z heads out of N flips:

$$p(\{\gamma_i\}|\theta) = \theta^z (1-\theta)^{(N-z)}$$

where z is $\sum_{i} \gamma_{i}$

Specifying the prior

Coin flipping

Beta distribution:

$$\begin{split} p(\theta|a,b) &= \mathsf{beta}(\theta|a,b) \\ &= \theta^{(a-1)} (1-\theta)^{(b-1)} / B(a,b) \end{split}$$

Specifying the prior

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Final though

Beta distribution:

$$\begin{split} p(\theta|a,b) &= \mathsf{beta}(\theta|a,b) \\ &= \theta^{(a-1)} (1-\theta)^{(b-1)} / B(a,b) \end{split}$$

• In terms of the mode ω and concentration κ ,

$$a = \omega(\kappa - 2) + 1$$
 and $b = (1 - \omega)(\kappa - 2) + 1$

where $\kappa > 2$

Final thought

Posterior is also a beta:

$$\begin{split} p(\theta|z,N) &= \frac{p(z,N|\theta)\,p(\theta)}{p(z,N)} \\ &= \theta^z\,(1-\theta)^{N-z}\;\,\frac{\theta^{(a-1)}(1-\theta)^{(b-1)}}{B(a,b)}\bigg/p(z,N) \\ &= \mathrm{beta}(\theta|z+a,N-z+b) \end{split}$$

Final thought

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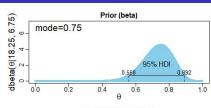
• The posterior is a compromise of prior and likelihood.

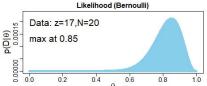
Example 1

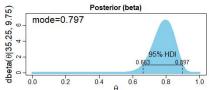
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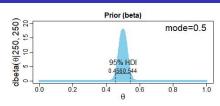


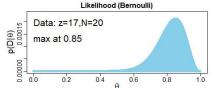
Example 2

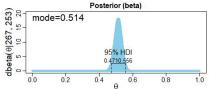
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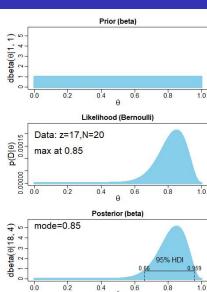


Example 3

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Example3.jpg

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• What are your priorities?

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inal thought

• What are your priorities?

• Subjective vs. objective priors.

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• What are your priorities?

• Subjective vs. objective priors.

• Are analytical solutions always viable?

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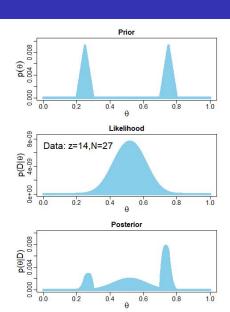
- What are your priorities?
- Subjective vs. objective priors.
- Are analytical solutions always viable?
- (Nope!) MCMC methods to the rescue.

Non-beta prior

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Conjugate prior distributions

Conjugate priors

• Let
$$f_{\mu}(x)=e^{n[\alpha\, \bar x-\psi(\alpha)]}f_0(x)$$
, and

Conjugate prior distributions

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• Let
$$f_{\mu}(x) = e^{n[\alpha \, \bar{x} - \psi(\alpha)]} f_0(x)$$
, and

•
$$g_{n_0,x_0}(\mu) = c e^{n_0[\alpha x_0 - \psi(\alpha)]} / V(\mu).$$

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• Let $f_{\mu}(x)=e^{n[\alpha\, ar x-\psi(\alpha)]}f_0(x)$, and

•
$$g_{n_0,x_0}(\mu) = c e^{n_0[\alpha x_0 - \psi(\alpha)]} / V(\mu).$$

• Then,

$$g(\mu|x)=g_{n_+,\bar{x}_+}(\mu)\text{, where}$$

$$n_+=n_0+n \text{ and } \bar{x}_+=\frac{n_0}{n_+}\,x_0+\frac{n}{n_+}\,\bar{x}$$

Robbins' Formula

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• Consider following claims data for a European automobile insurance company circa 1950s:

Claims	0	1	2	3	4	5	6	7
Counts y_x	7840	1317	239	42	14	4	4	1

Robbins' Formula

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• Consider following claims data for a European automobile insurance company circa 1950s:

Claims	0	1	2	3	4	5	6	7
Counts y_x	7840	1317	239	42	14	4	4	1

• **Key idea** Large data sets of parallel situations carry within them their own Bayesian information.

Last but not least

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• Bayesian Learning (BIC, etc.)

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- Bayesian Learning (BIC, etc.)
- Frequentist vs. Bayesian comparisons