Bayesian philosophy, non-informative priors, exchangeability

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THE UNIVERSITY OF UTAH

Outline

- Bayesian vs. frequentist
- Uninformative priors
- Exchangeability, de Finetti's theorem

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Bayesian vs. Frequentist

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  - We want to estimate it from observations

$$\boldsymbol{\theta}_{ML} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \sum_{i=1}^{N} \log p(\mathbf{x}_i | \boldsymbol{\theta})$$

  - How to quantify your uncertainty?
    - confidence level, note that $\boldsymbol{\theta}_{ML}$ is a R.V., but $\boldsymbol{\theta}$ is not.

Bayesian vs. Frequentist

- Let us consider to estimate a parameter $\boldsymbol{\theta}$, e.g., the chance of head (tossing a coin), from observed data $\mathbf{x}_1, \ldots, \mathbf{x}_N$
- Bayesian: $\boldsymbol{\theta}$ is a random variable as well!

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  - We want to estimate it from observations

$$p(\boldsymbol{\theta}|\mathcal{D}) \propto p(\boldsymbol{\theta}) \prod_{i=1}^{N} p(\mathbf{x}_i|\boldsymbol{\theta})$$

  - How to quantify your uncertainty?

Posterior distribution! $p(\boldsymbol{\theta}|\mathcal{D})$

Bayesian vs. Frequentist

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  - ❑ We can make probabilistic statements about $\boldsymbol{\theta}$ (mean, variance, quantiles, etc.).

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  - ❑ We can make probabilistic statements about $\boldsymbol{\theta}$ (mean, variance, quantiles, etc.).
  - ❑ We can make Bayesian prediction that integrates all the possible outcomes

$$p(\mathbf{x}^*|\mathbf{x}_1,\ldots,\mathbf{x}_N) = \int p(\mathbf{x}^*|\boldsymbol{\theta})p(\boldsymbol{\theta}|\mathbf{x}_1,\ldots,\mathbf{x}_N)$$

Bayesian vs. Frequentist

- Is Bayesian analysis subjective?
  - Not necessary: Bayesian provides a convenient way to incorporate subjective believes (important for AI!) But it can also uses uninformative priors (this is objective Bayesian!)
  - Frequentist models make assumptions, too!
  - Whether using frequent or Bayesian models, always **check the assumptions you make**

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Uninformative priors

- In many cases, we have little idea of what form the distribution should take
- Though conjugate priors are computationally nice, objective Bayesians instead prefer priors which *has little influence* on the posterior distribution. Such a prior is called an *uninformative prior*.
- Let the data speak for themselves

Uninformative priors

- What priors do you have immediately in mind?

Uninformative priors

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Uniform distribution!

Uninformative priors

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Uniform distribution!

Now that I do not know which parameter is more likely to be sampled, let us just assume the chances are equal!

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

- Uniform distribution

For finite states: $p(\lambda) = 1/K$

For finite interval: $p(\lambda) = 1/(b-a)$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

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  What about unbounded domains? $\lambda \in \mathbb{R}$

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What about unbounded domains? $\lambda \in \mathbb{R}$

$$p(\lambda) \propto \mathrm{const}$$

$$p(\mathbf{x}|\lambda)$$

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What about unbounded domains? $\lambda \in \mathbb{R}$

$$p(\lambda) \propto \text{const}$$

This is an *improper* prior, because normalization diverges

We can still use it as long as the posterior is *proper*

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

- Problem of uniform distribution: *transformation invariance*

$$p(\lambda) \propto \text{const}$$

$$\lambda = \eta^2$$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

- Problem of uniform distribution: *transformation invariance*

$$p(\lambda) \propto \mathrm{const}$$

$$\lambda = \eta^2$$

$$p_\eta(\eta) = p_\lambda(\lambda) \left| \frac{\mathrm{d}\lambda}{\mathrm{d}\eta} \right| = p_\lambda(\eta^2) 2\eta \propto \eta$$

Uninformative priors

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- Problem of uniform distribution: *transformation invariance*

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$$\lambda = \eta^2$$

$$p_\eta(\eta) = p_\lambda(\lambda)\left|\frac{\mathrm{d}\lambda}{\mathrm{d}\eta}\right| = p_\lambda(\eta^2)2\eta \propto \boxed{\eta}$$

When we do variable transformations, the prior is no longer uninformative!

Uninformative priors

$p(\mathbf{x}|\lambda)$

- Let us take *translation invariance* into account

If the likelihood takes the form

$$p(x|\lambda) = f(x - \lambda)$$

Uninformative priors

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- Let us take *translation invariance* into account

If the likelihood takes the form

$$p(x|\lambda) = f(x - \lambda)$$

λ is *location* parameter, and the density exhibits *shift invariance*

$$\widehat{x} = x + c \qquad \hat{\lambda} = \lambda + c$$

$$p(\hat{x}|\hat{\lambda}) = f(\hat{x} - \hat{\lambda})$$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

- We want to construct a prior that reflects this shift invariance (why: more consist with the likelihood, less influence on the posterior!)

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

- We want to construct a prior that reflects this shift invariance (why: more consist with the likelihood, less influence on the posterior!)
- How? We choose a prior that assigns equal probability mass to an arbitrary interval [A, B] as to the shifted interval [A+c, B+c]

$$p(\mathbf{x}|\lambda)$$

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- How? We choose a prior that assigns equal probability mass to an arbitrary interval [A, B] as to the shifted interval [A+c, B+c]

$$\int_A^B p(\lambda)\mathrm{d}\lambda = \int_{A+c}^{B+c} p(\lambda)\mathrm{d}\lambda$$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

$$\boxed{\lambda = \bar{\lambda} + c}$$

$$\int_A^B p(\lambda)\mathrm{d}\lambda = \int_{A+c}^{B+c} p(\lambda)\mathrm{d}\lambda \quad = \int_A^B p(\lambda + c)\mathrm{d}\lambda$$

$$p(\lambda) = p(\lambda + c)$$

$$p(\lambda) \propto \text{const}$$

Uninformative priors

$p(\mathbf{x}|\lambda)$

Example: for a Gaussian likelihood

$$p(x|\mu) = \mathcal{N}(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(- \frac{1}{2\sigma^2} (\underline{x - \mu})^2 \right)$$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

Example: for a Gaussian likelihood

$$p(x|\mu) = \mathcal{N}(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma}} \exp\Big(-\frac{1}{2\sigma^2}\underline{(x-\mu)}^2\Big)$$

shift invariance density

Conjugate prior

$$p(\mu|\alpha, v^2) = N(\mu|\alpha, v^2) = \frac{1}{\sqrt{2\pi v}} \exp\Big(-\frac{1}{2v^2}(\mu-\alpha)^2\Big)$$

$$p(\mathbf{x}|\lambda)$$

Uninformative priors

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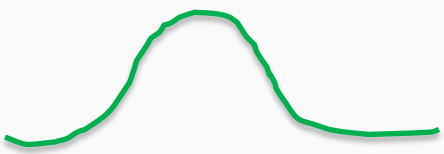

$$v^2 \longrightarrow \infty \quad \Rightarrow \quad p(\mu) \propto \text{const}$$

$$p(\mathbf{x}|\lambda)$$

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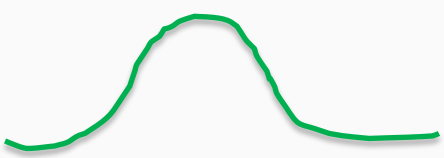

$$v^2 \longrightarrow \infty \quad \Longrightarrow \quad p(\mu) \propto \text{const}$$

Limit of the conjugate prior

Uninformative priors

- Let us take *translation invariance* into account

If the likelihood takes the form

$$p(x|\sigma) = \frac{1}{\sigma} f\left(\frac{x}{\sigma}\right) \qquad \sigma > 0$$

f normalizes regularly

Uninformative priors

- Let us take *translation invariance* into account

If the likelihood takes the form

$$p(x|\sigma) = \frac{1}{\sigma} f\left(\frac{x}{\sigma}\right)$$

$\sigma > 0$ f normalizes regularly

σ is *scale* parameter, and the density exhibits *scale invariance*

$$\widehat{x} = cx \qquad \widehat{\sigma} = c\sigma$$

$$p(\widehat{x}|\widehat{\sigma}) = \frac{1}{\widehat{\sigma}} f\left(\frac{\widehat{x}}{\widehat{\sigma}}\right)$$

Verify it by yourself

Uninformative priors

- We want to construct a prior that reflects this scale invariance (why: more consist with the likelihood, less influence on the posterior!)

Uninformative priors

- We want to construct a prior that reflects this scale invariance (why: more consist with the likelihood, less influence on the posterior!)

- How, consider an arbitrary interval [A, B], the prior should assign equal mass over an arbitrary scaled interval [A/c, B/c]

$$\int_A^B p(\sigma)\,\mathrm{d}\sigma = \int_{A/c}^{B/c} p(\sigma)\,\mathrm{d}\sigma$$

Uninformative priors

$$\boxed{\bar{\sigma} = c\sigma}$$

$$\int_A^B p(\sigma)\,\mathrm{d}\sigma = \int_{A/c}^{B/c} p(\sigma)\,\mathrm{d}\sigma = \int_A^B p\left(\frac{1}{c}\sigma\right)\frac{1}{c}\,\mathrm{d}\sigma$$

$$p(\sigma) = p\left(\frac{1}{c}\sigma\right)\frac{1}{c}$$

$$p(\sigma) \propto 1/\sigma$$

Uninformative priors

Example: for a Gaussian likelihood

$$p(x|\sigma) = \mathcal{N}(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma}\exp\left(-\frac{1}{2}\left[\frac{x-\mu}{\sigma}\right]^2\right)$$

Uninformative prior

$$p(\sigma) \propto 1/\sigma \xrightarrow{\lambda = 1/\sigma^2} p(\lambda) \propto 1/\lambda$$

Conjugate prior

$$p(\lambda|a,b) = \mathrm{Gam}(\lambda|a,b) \propto \lambda^{a-1}\exp(-b\lambda)$$

$$a = 0, b = 0 \longrightarrow p(\lambda) \propto 1/\lambda$$

Uninformative Priors

- Jeffreys priors

$$\pi_J(\boldsymbol{\theta}) \propto |I(\boldsymbol{\theta})|^{\frac{1}{2}}$$

Fisher information $$I(\theta) = -\mathbb{E}_\theta\left[\frac{d^2 \log p(X|\theta)}{d\theta^2}\right]$$

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Expectation w.r.t $p(X|\theta)$

Uninformative Priors

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$$\pi_J(\boldsymbol{\theta}) \propto \left|I(\boldsymbol{\theta})\right|^{\frac{1}{2}}$$

Fisher information $$I(\theta) = -\mathbb{E}_{\theta}\left[\frac{d^2 \log p(X|\theta)}{d\theta^2}\right]$$ Note, for vector case, it becomes the Hessian

Expectation w.r.t $p(X|\theta)$

Jeffreys priors - example

Binomial likelihood

$$X \sim \mathrm{Bin}(n, \theta), 0 \leq \theta \leq 1$$

$$p(x|\theta) = \binom{n}{x} \theta^x (1-\theta)^{n-x}$$

Jeffreys priors - example

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Let’s construct a Jeffreys prior over θ

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Let's construct a Jeffreys prior over θ

$$\log p(x|\theta) = x \log \theta + (n-x) \log(1-\theta)$$

$$\frac{d}{d\theta} \log p(x|\theta) = \frac{x}{\theta} - \frac{n-x}{1-\theta}$$

$$\frac{d^2}{d\theta^2} \log p(x|\theta) = -\frac{x}{\theta^2} - \frac{n-x}{(1-\theta)^2}$$

Jeffreys priors - example

$$\frac{d^2}{d\theta^2}\log p(x|\theta) = -\frac{x}{\theta^2} - \frac{n-x}{(1-\theta)^2}$$

$$\mathbb{E}[x] = n\theta$$

$$\begin{aligned} I(\theta) &= -\mathbb{E}_\theta\left[\frac{d^2 \log p(x|\theta)}{d\theta^2}\right] \\ &= \frac{n\theta}{\theta^2} + \frac{n-n\theta}{(1-\theta)^2} \\ &= \frac{n}{\theta} + \frac{n}{1-\theta} \\ &= \frac{n}{\theta(1-\theta)} \end{aligned}$$

$$\pi_J(\theta) = I(\theta)^{\frac{1}{2}} \propto \theta^{-\frac{1}{2}}(1-\theta)^{-\frac{1}{2}}$$

$$\text{Beta}(\tfrac{1}{2}, \tfrac{1}{2})$$

Jeffreys priors - example

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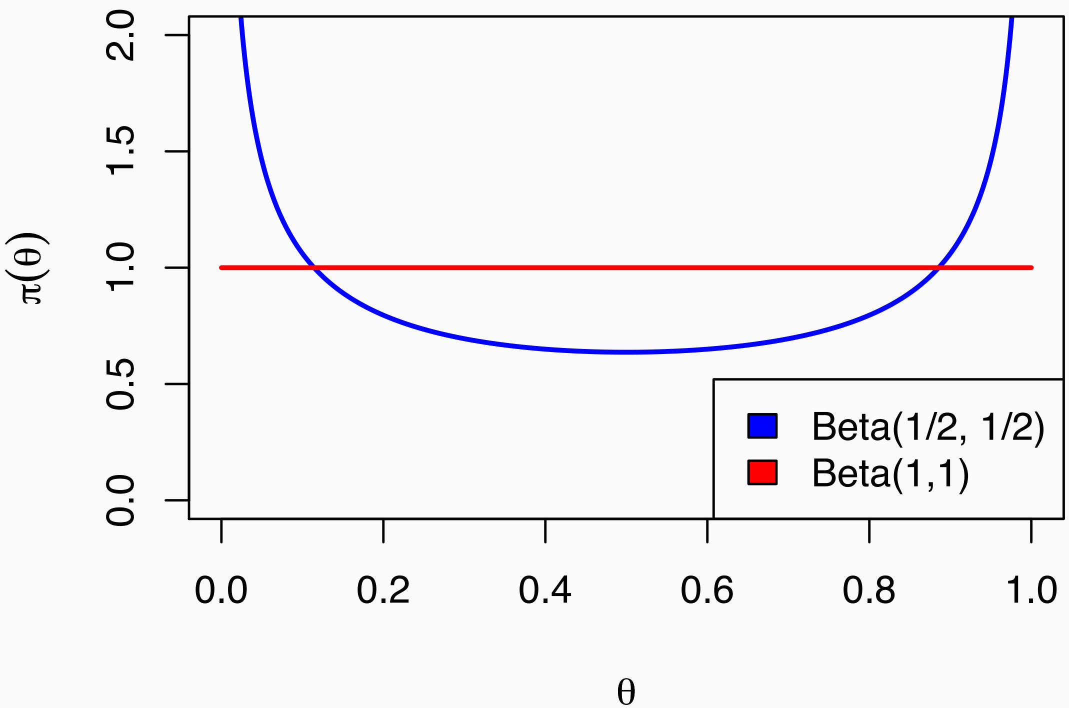

Data takes least effect

$$\theta = \frac{1}{2}$$

Data takes greatest effect

$$\theta = 0 \text{ or } 1$$

Prior is consistent with the data effect!

Jeffreys priors – translation invariance

$\theta \sim \pi_J(\theta)$

- Let us consider a general translation $\phi = h(\theta)$

$p(\phi) = p(\theta) \cdot \left|\frac{d\theta}{d\phi}\right|$

What is the Jeffreys prior over ϕ ?

$\frac{d^2 \log p(X|\phi)}{d\phi^2}$

$$\pi_J(\phi) \propto |\mathbf{I}(\phi)|^{\frac{1}{2}}$$

Use Chain rule

$$\begin{aligned}
\mathbf{I}(\phi) &= -\mathbb{E}\left[\frac{\mathrm{d}^2 \log p(X|\phi)}{\mathrm{d}\phi^2}\right] \\
&= -\mathbb{E}\left[\frac{\mathrm{d}^2 \log p(X|\theta)}{\mathrm{d}\theta^2}\left(\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right)^2 + \frac{\mathrm{d}\log p(X|\theta)}{\mathrm{d}\theta}\frac{\mathrm{d}^2\theta}{\mathrm{d}\phi^2}\right]
\end{aligned}$$

$$\frac{d^2 \log p(x|\phi)}{d\phi^2}$$

$$= \frac{d\left(\underbrace{\frac{d \log p(x|\phi)}{d\phi}}\right)}{d\phi} \qquad f(\phi) = \frac{d f(\phi)}{d\phi}$$

$$= \frac{d f(\phi)}{d\theta} \cdot \frac{d\theta}{d\phi}$$

$$\frac{d\,\overbrace{\frac{d \log p(x|\phi)}{d\phi}}^{f(\phi)}}{d\theta}$$

$$\frac{d}{d\theta} f(\phi) = \left[\frac{d \log p(x|\phi)}{d\theta}\right] \cdot \frac{d\theta}{d\phi}$$

$$= \frac{d\left[\frac{d \log p(x|\phi)}{d\theta}\right]}{d\theta} \cdot \frac{d\theta}{d\phi}$$

$$+ \frac{d \log p(x|\phi)}{d\theta} \left| \frac{d\left(\frac{d\theta}{d\phi}\right)}{d\theta} \right|$$

$$\frac{d(xy)}{d\theta} = \frac{dx}{d\theta} \cdot y + x \cdot \frac{dy}{d\theta}$$

$$\frac{d^2 \log p(x|\phi)}{d\phi^2} = \left[\frac{d^2 \log p(x|\theta)}{d\theta^2} \left(\frac{d\theta}{d\phi}\right)^2 + \right.$$

$$\frac{d\frac{d\theta}{d\phi}}{d\phi} \cdot \frac{d\phi}{d\theta}$$

$$\frac{d \log p(x|\theta)}{d\theta} \cdot \frac{d^2\theta}{d\phi^2} \cdot \cancel{\frac{d\phi}{d\theta}} \; \cancel{\frac{d\theta}{d\phi}}$$

Jeffreys priors – translation invariance

We know $\mathbb{E}\left[\frac{\mathrm{d}\log p\left(X|\theta\right)}{\mathrm{d}\theta}\right] = 0$ Why?

$$\frac{dp(x|\theta)}{d\theta}\, dx$$

$$\forall\theta, \int p\left(X|\theta\right) dX = 1 \Rightarrow$$

$$\begin{aligned}
0 &= \frac{\mathrm{d}}{\mathrm{d}\theta}\int p\left(X|\theta\right) dX \\
&= \int \frac{\mathrm{d}p\left(X|\theta\right)}{\mathrm{d}\theta}\frac{p\left(X|\theta\right)}{p\left(X|\theta\right)}\mathrm{d}X \\
&= \int \left[\frac{\mathrm{d}p\left(X|\theta\right)}{\mathrm{d}\theta}\frac{1}{p\left(X|\theta\right)}\right] p\left(X|\theta\right)\mathrm{d}X \\
&= \int \left[\frac{\mathrm{d}\log p\left(X|\theta\right)}{\mathrm{d}\theta}\right] p\left(X|\theta\right)\mathrm{d}X \\
&= \mathbb{E}\left[\frac{\mathrm{d}\log p\left(X|\theta\right)}{\mathrm{d}\theta}\right]
\end{aligned}$$

$$\frac{d\log p(x|\theta)}{d\theta} = \frac{1}{p(x|\theta)}\frac{dp(x|\theta)}{d\theta}$$

Jeffreys priors – translation invariance

$$\mathbf{I}(\phi) = -\mathbb{E}\left[\underbrace{\frac{\mathrm{d}^2 \log p(X|\theta)}{\mathrm{d}\theta^2}}_{\mathbf{I}(\theta)}\left(\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right)^2 + \underbrace{\frac{\mathrm{d}\log p(X|\theta)}{\mathrm{d}\theta}\frac{\mathrm{d}^2\theta}{\mathrm{d}\phi^2}}_{=0}\right]$$

$$\mathbf{I}(\phi) = \mathbf{I}(\theta)\left(\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right)^2$$

$p(\theta) \propto \pi_J(\theta)$

$$\frac{p(\theta) \cdot \left|\frac{d\theta}{d\phi}\right|}{p(\phi)}$$

$$\pi_J(\phi) \propto \sqrt{\mathbf{I}(\phi)} = \underbrace{\sqrt{\mathbf{I}(\theta)}}_{\pi_J(\theta)}\left|\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right|$$

Jeffreys priors – translation invariance

$$\sqrt{\mathbf{I}\left(\phi\right)} = \sqrt{\mathbf{I}\left(\theta\right)}\left|\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right|$$

Now, we can see

When we directly construct Jeffreys prior

$$\pi_J(\phi) \propto \sqrt{\mathbf{I}(\phi)}$$

The same!

When we derive the prior via variable transformation

$$\pi_J(\phi) \propto \sqrt{\mathbf{I}\big(h^{-1}(\phi)\big)}\left|\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right| = \sqrt{\mathbf{I}\left(\theta\right)}\left|\frac{\mathrm{d}\theta}{\mathrm{d}\phi}\right|$$

Jeffreys priors – translation invariance

- Now we can show, for a Gaussian likelihood

$$p(x|\mu,\sigma) = \mathcal{N}(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma}}\exp\Big(-\frac{1}{2\sigma^2}(x-\mu)^2\Big)$$

$$\pi_J(\mu) \propto 1$$

$$\pi_J(\sigma) \propto \frac{1}{\sigma}$$

Leave it as your exercise

Jeffreys prior

- Usually not conjugate
  - If you choose Jeffreys prior over μ, σ for a Gaussian likelihood

  The posterior of μ will be a student *t* distribution

- Works well for single parameter, but not for models with multidimensional parameters (e.g., poor convergence properties, not very reasonable estimates)

Reference priors

- formalize what exactly we mean by an "uninformative prior": *a function that maximizes some measure of distance or divergence between the posterior and prior, as data observations are made.*
- A commonly used divergence is KL divergence

$$\mathrm{KL}\big(p(\theta|t)\|p(\theta)\big) = \int p(\theta|t)\log\frac{p(\theta|t)}{p(\theta)}d\theta$$

t

Reference priors

- We choose the prior that maximizes the expected KL divergence between the posterior and the prior

$$I(\Theta, T) = \int p(t) \int p(\theta|t) \log \frac{p(\theta|t)}{p(\theta)} d\theta dt$$

$$= \int \int p(\theta, t) \log \frac{p(\theta, t)}{p(\theta)p(t)} d\theta dt$$

$p(\theta)$

θ

$$p^*(\theta) = \arg\max_{p(\theta)} I(\Theta, T)$$

Mutual information

Outline

- Bayesian vs. frequentist
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Bayesian *vs.* Frequentist

- Given a distribution $p(x|\theta)$ governed by θ
- Frequentist: I believe θ is objective constant, I need to estimate it from IID samples $x_1, \ldots, x_N$
- Bayesian: I believe θ is some *latent random variable* – it was first sampled from a prior distribution $p(\theta)$, then given θ , we sample the observations $x_1, \ldots, x_N$

Bayesian *vs.* Frequentist

- Bayesian: I believe θ is some *latent random variable* – it was first sampled from a prior distribution $p(\theta)$, then given θ , we sample the observations $x_1, \ldots, x_N$

- Although it sounds a philosophical choice, can we justify Bayesian modeling with some mathematical evidence?

Exchangeability

- Most statistical analysis are based on IID observations $x_1, \ldots, x_N$

$$p(X_1 = x_1, \ldots, X_N = x_N) = \prod_{n=1}^{N} p(X_n = x_n)$$

- While the assumption is convenient, it may not be reasonable in many problems: weather conditions, stock prices, precipitation, disease rate, …

- Exchangeability is a much *weaker* assumption

Exchangeability

1 2 3

3 1 2

$\pi(1)$ $\pi(2)$ $\pi(3)$

$p(x_1, \ldots x_n)$

- Finite exchangeability: Given N random variables, and arbitrary permutation $\pi(1), \ldots, \pi(N)$

$$X_1, \ldots, X_N \stackrel{d}{=} X_{\pi(1)}, \ldots, X_{\pi(N)}$$

$$\Updownarrow$$

$\forall x_1, \ldots, x_N$ in the domain

$$p(X_1 = x_1, \ldots, X_N = x_N) = p(X_1 = x_{\pi(1)}, \ldots, X_N = x_{\pi(N)})$$

1, 2, 3 ***e.g.***

$$\begin{cases} p(X_1 = 1, X_2 = 2, X_3 = 3) = p(X_1 = 2, X_2 = 3, X_3 = 1) \\ = p(X_1 = 3, X_2 = 1, X_3 = 2) = \ldots \end{cases}$$

Exchangeability – infinite sequence

- An infinite sequence of random variables $\{X_i\}_{i=1}^{\infty}$ is exchangeable if $\forall n = 1, 2, \ldots$

$$X_1, ..., X_n \overset{d}{=} X_{\pi(1)}, ..., X_{\pi(n)}, \quad \forall \pi \in S(n),$$

where $S(n)$ are all possible permutations over the first n variables

Exchangeability

- Essentially assume the *symmetry* of the density

$$p(X_1 = x_1, \ldots, X_N = x_N) = p(X_1 = x_{\pi(1)}, \ldots, X_N = x_{\pi(N)})$$

$p(x_1)p(x_2)\cdots p(x_n)$

$$\text{IID} \;\underset{\not\Leftarrow}{\Rightarrow}\; \text{exchangeability}$$

$$p(X_1 = \text{rainy}, X_2 = \text{dry}) = p(X_1 = \text{dry}, X_2 = \text{rainy})$$

$$\| $$

$$p(X_1 = \text{rainy}) \cdot p(X_2 = \text{dry})$$

Exchangeability - one specific example

- Polya's Urn
  - Given an urn with B_0 black and W_0 white balls, draw balls with the following procedure
    - (1) Draw a ball at random from the urn and note its color
    - (2) If the ball is black then $X_i = 1$; otherwise $X_i = 0$
    - (3) $i = i + 1$
    - (4) Place *a* balls of the same color in the urn
    - (5) Goto (1)

$a = 0$

Exchangeability - one specific example

- Polya's Urn
  - Given an urn with B_0 black and W_0 white balls, draw balls with the following procedure
    - (1) Draw a ball at random from the urn and note its color
    - (2) If the ball is black then $X_i = 1$; otherwise $X_i = 0$
    - (3) i = i + 1
    - (4) Place *a* balls of the same color in the urn
    - (5) Goto (1)

$$\begin{array}{c|c} B & B_0 \\ \hline W & W_0 \end{array} \qquad \begin{array}{c} B_0 + 2(a-1) \\ W_0 + (a-1) \end{array}$$

$X_1 \quad X_2 \quad X_3 \quad X_4$

$$p(1,1,0,1) = \frac{B_0}{B_0+W_0} \times \frac{B_0+a-1}{B_0+W_0+a-1} \times \frac{W_0}{B_0+W_0+2a-2} \times \frac{B_0+2a-2}{B_0+W_0+3a-3}$$

$$p(1,0,1,1) = \frac{B_0}{B_0+W_0} \times \frac{W_0}{B_0+W_0+a-1} \times \frac{B_0+a-1}{B_0+W_0+2a-2} \times \frac{B_0+2a-2}{B_0+W_0+3a-3}$$

The sequence $\{X_i, i>=1\}$ is exchangeable but not IID

De Finetti's theorem

(de Finetti 1931) A binary sequence $\{X_i\}_{i=1}^{\infty}$ is *exchangeable* iff there exists a distribution function F on [0, 1] such that for all n,

CDF

$$p(x_1, \ldots, x_n) = \int_0^1 \theta^{t_n}(1-\theta)^{n-t_n}\, dF(\theta),$$

$dF(\theta)$

where $p(x_1, \ldots, x_n) = P(X_1 = x_1, \ldots, X_n = x_n)$ and $t_n = \sum_{i=1}^{n} x_i$.

$p(\theta)\mathrm{d}\theta$

1. There is a latent random variable θ
2. It has a prior distribution

$\theta \sim p(\theta)$

$F(\theta)$

De Finetti's theorem

It further holds that *F is the distribution function of the limiting frequency:*

$$\theta \quad Y = \bar{X}_\infty = \lim_{n\to\infty} \sum_i X_i/n, \quad P(Y \leq y) = F(y)$$

and *the Bernoulli distribution is obtained by conditioning with* $Y = \theta$*:*

$$P(X_1 = x_1, \ldots, X_n = x_n \mid Y = \theta) = \theta^{t_n}(1-\theta)^{n-t_n}.$$

$P(\theta)$

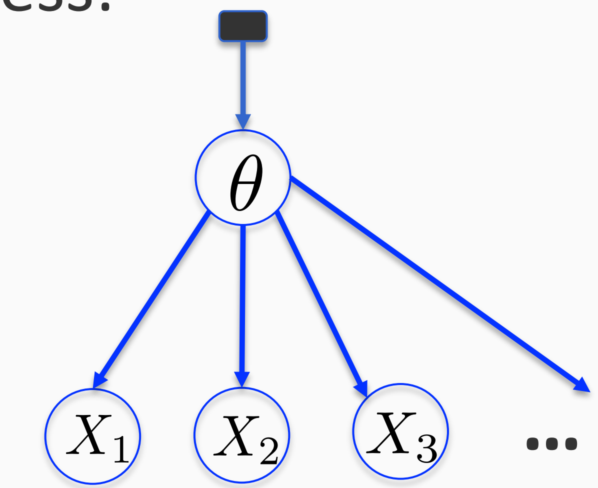
De Finetti's theorem – the underlying sampling process

- If our binary observations $\{X_i\}_{i=1}^{\infty}$ are exchangeable, it implies a hierarchical sampling process:

$$\theta \sim p(\theta)$$

Conditional independent

$$X_1, X_2, \ldots | \theta \sim \prod_{i=1}^{\infty} p(X_i|\theta)$$



This justifies Bayesian modeling --- prior distribution objectively exists!

Exchangeability

- Very widely used assumption in Bayesian modeling
- More flexible than IID, but is also restrictive
- Some classical/popular models

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "**Latent dirichlet allocation**." *Journal of machine Learning research* 3.Jan (2003): 993-1022.

Airoldi, Edoardo M., et al. "**Mixed membership stochastic blockmodels**." *Journal of machine learning research* 9.Sep (2008): 1981-2014

Lloyd, J., Orbanz, P., Ghahramani, Z., & Roy, D. M. (2012). **Random function priors for exchangeable arrays with applications to graphs and relational data**. In *Advances in Neural Information Processing Systems* (pp. 998-1006).

What you need to know

- Bayesian vs. Frequentist
- What is uninformative prior
- What are shift invariance, scale invariance in likelihood? How to derive the corresponding uninformative prior?
- What is Jeffery's prior? Arbitrary translation invariance
- Exchangeability
- De-Finette theorem (how does it justify Bayesian)s