

CS 215

Data Analysis and Interpretation

Bayesian Statistical Analysis

Suyash P. Awate

Bayesian Statistical Analysis

- Thomas Bayes
 - 18th-century mathematician, statistician



Portrait purportedly of Bayes used in a 1936 book,^[1] but it is doubtful whether the portrait is actually of him.^[2] No earlier portrait or claimed portrait survives.

Bayesian Statistical Analysis

- List of things named after Thomas Bayes

Bayes [edit]

- Bayes error rate
- Bayes estimator
- Bayes factor
- Bayes linear statistics
- Bayes prior
- Bayes' theorem (or rule)
- Empirical Bayes method
- Evidence under Bayes theorem
- Hierarchical Bayes model
- Laplace–Bayes estimator
- Naive Bayes classifier
- Random naive Bayes

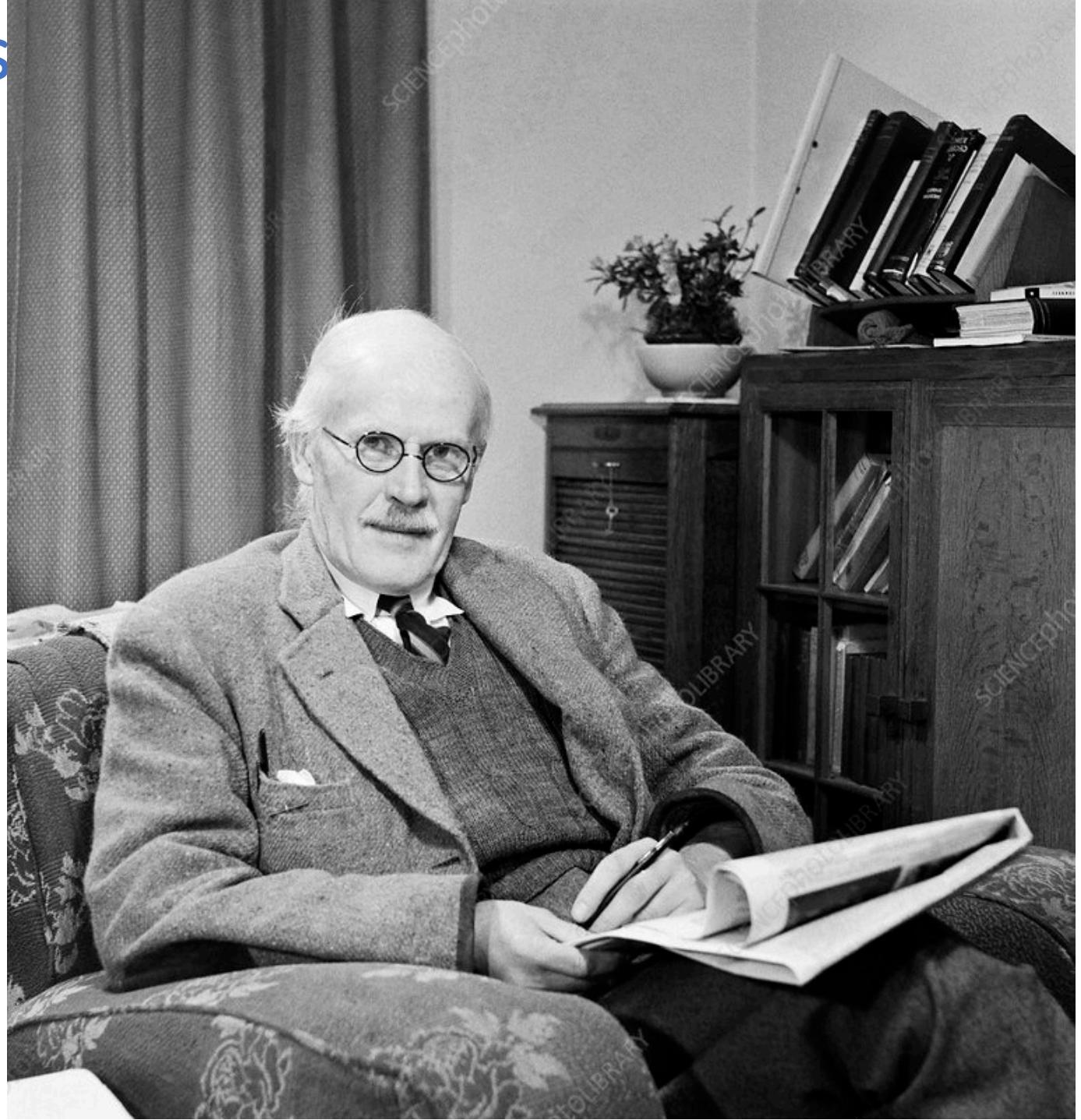
Bayesian [edit]

- Approximate Bayesian computation
- Bayesian average
- Bayesian approaches to brain function
- Bayesian econometrics
- Bayesian efficiency
- Bayesian experimental design
- Bayesian game
- Bayesian inference
- Bayesian inference in phylogeny
- Bayesian information criterion
- Bayesian linear regression
- Bayesian model selection

- Bayesian multivariate linear regression
- Bayesian network
- Bayesian poisoning
- Bayesian probability
- Bayesian programming
- Bayesian search theory
- Bayesian spam filtering
- Bayesian statistics
- Bayesian tool for methylation analysis
- Bayesian vector autoregression
- Dynamic Bayesian network
- International Society for Bayesian Analysis
- Quantum Bayesianism
- Recursive Bayesian estimation
- Robust Bayesian analysis
- Variable-order Bayesian network

Bayesian Statistical Analysis

- Sir Harold Jeffreys
 - 20th-century mathematician, statistician
 - “Bayes’ theorem is to the theory of probability what Pythagoras’s theorem is to geometry”



Bayesian Statistical Analysis

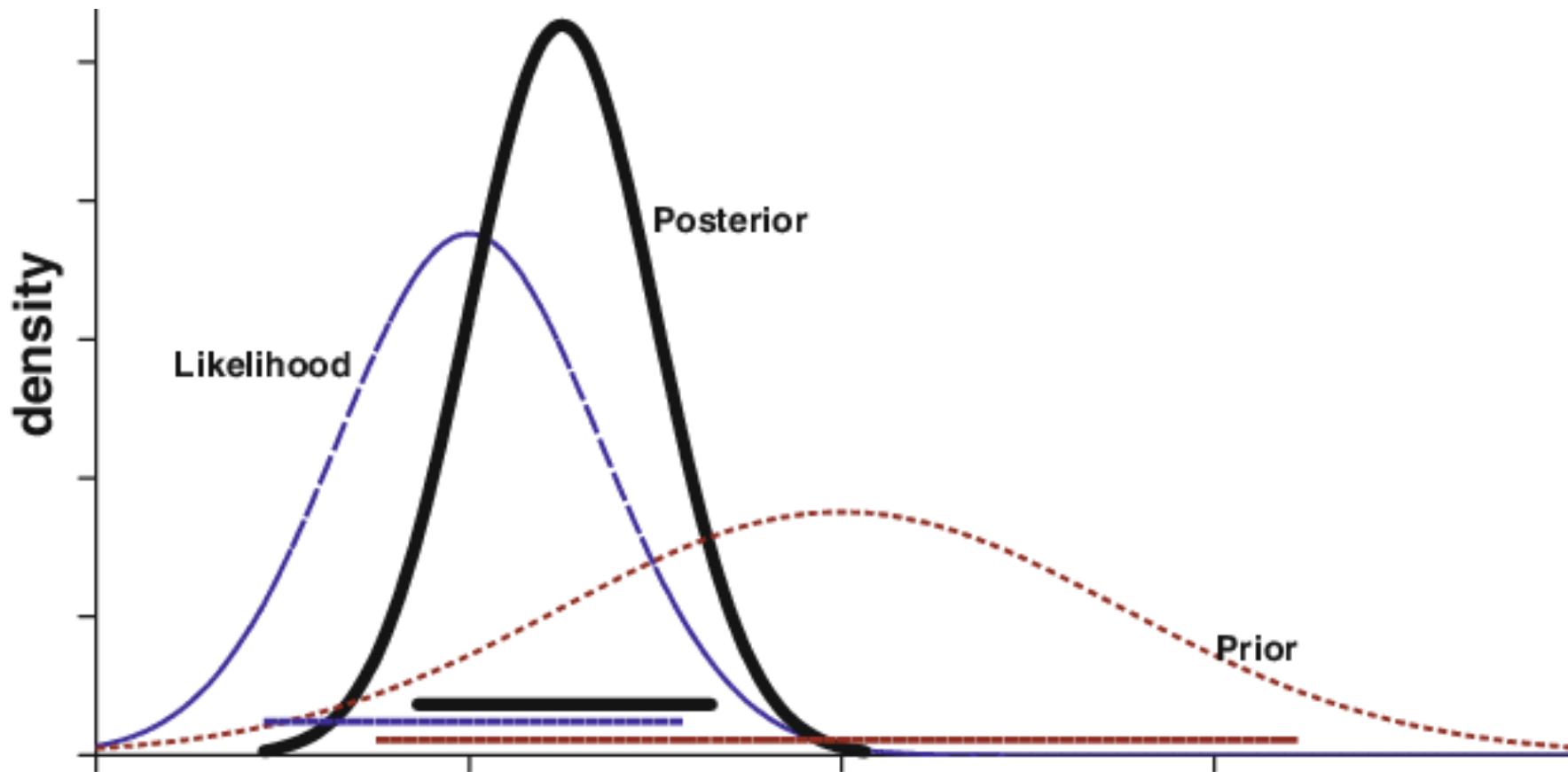
- Bayes theorem
 - X = **discrete** random variable (e.g., modeling some **unknown entity**)
 - Y = **continuous/discrete** random variable (e.g., modeling **observed data**)
 - Consider joint distribution: $P(X, Y)$
 - Likelihood : $P(Y=y | X=x)$
 - Conditional
 - “Evidence” : $P(Y=y) = \sum_x P(X=x, Y=y)$
 - Marginal. Accounts for various ways in which data could have been generated.
 - Prior : $P(X)$
 - Before data is observed. Models beliefs (e.g., evolved over past experiences / learning)
 - Posterior : $P(X=x | Y=y)$
 - After data is observed. Data updates the beliefs.
 - Posterior $P(X=x | Y=y)$
= Likelihood $P(Y=y | X=x) * \text{Prior } P(X=x)$
/ Evidence $P(Y=y)$

Bayesian Statistical Analysis

- Bayes theorem
 - $X = \text{continuous}$ random variable (e.g., modeling some **unknown entity**)
 - $Y = \text{continuous/discrete}$ random variable (e.g., modeling **observed data**)
 - Consider joint distribution: $P(X, Y)$
 - Likelihood : $P(Y=y | X=x)$
 - Conditional
 - “Evidence” : $P(Y=y) = \int_x P(X=x, Y=y) dx$
 - Marginal. Accounts for various ways in which data could have been generated.
 - Prior : $P(X)$
 - Before data is observed. Models beliefs (e.g., evolved over past experiences / learning)
 - Posterior : $P(X=x | Y=y) dx$ (event probability)
 - After data is observed. Data updates the beliefs.
 - Posterior $P(X=x | Y=y) dx$
= Likelihood $P(Y=y | X=x) * \text{Prior } P(X=x) dx$
/ Evidence $P(Y=y)$

Bayesian Statistical Analysis

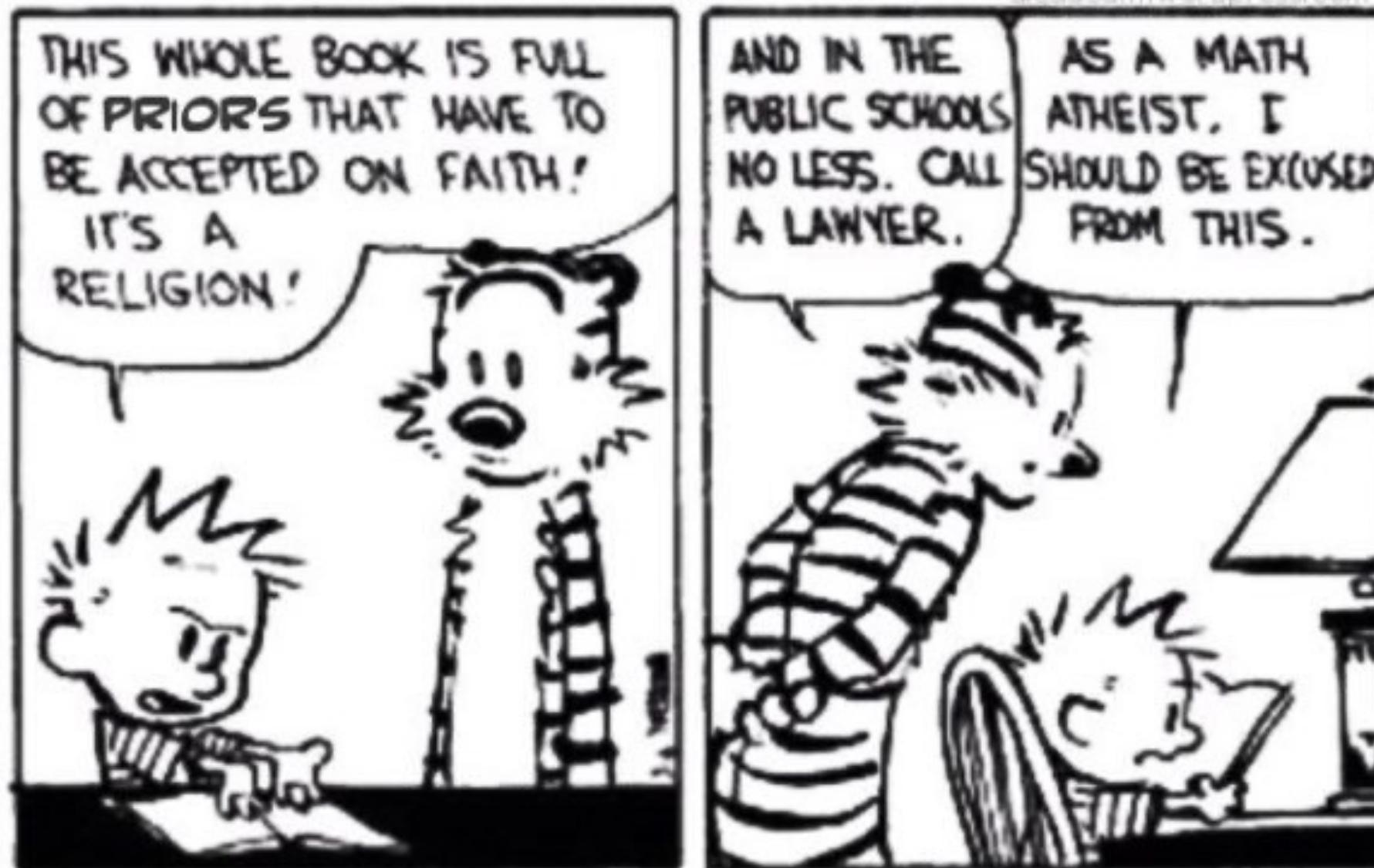
- Instead of making inferences about X based on **likelihood** function, Bayesian analysis makes inferences about X based on the **posterior**
- When can/should/do prior models make a difference ?
 - When the data sample size is **finite**



Bayesian Statistical Analysis

BAYESIAN INFERENCE

aleadeum.wordpress.com



Bayesian Estimation

- Example: Coin Flip

Consider that we don't know if a coin is fair / unfair

We have 2 possibilities in our mind:

- (1) Coin fair, i.e., $P(\text{head}) = p = 0.5$
- (2) Coin biased towards heads with $P(\text{head}) = q = 0.7$

We have a belief (**prior** to observing data) that $P(\text{CoinFair}) = 0.8$

Now we experiment with the coin, collect data, and recompute the probability that the coin is fair

$$P(\text{CoinFair}|\text{Data}) = P(\text{Data}|\text{CoinFair})P(\text{CoinFair})/P(\text{Data})$$

Bayesian Estimation

- Example: Coin Flip

Given: We have data as n observations with r heads and $(n - r)$ tails.

What does the data do to our belief ?

$$P(\text{Data}|\text{CoinFair}) = C_r^n 0.5^r 0.5^{n-r}$$

$$P(\text{Data}|\text{CoinUnfair}) = C_r^n 0.7^r 0.3^{n-r}$$

$$P(\text{Data}) = P(\text{Data}|\text{CoinFair})P(\text{CoinFair}) + P(\text{Data}|\text{CoinUnfair})P(\text{CoinUnfair})$$

$$P(\text{CoinFair}|\text{Data}) = \frac{0.5^r 0.5^{n-r} \times 0.8}{0.5^r 0.5^{n-r} \times 0.8 + 0.7^r 0.3^{n-r} \times 0.2}$$

Bayesian Estimation

- Example: Coin Flip

Case 1:

If $n = 20, r = 11$,

then $P(\text{CoinFair}|\text{Data}) = 0.9074$ that is more than 0.8.

So the data has strengthened our belief !

Why has this happened ? Because 11 heads out of 20 is more like the fair coin.

Case 2:

If $n = 20, r = 13$,

then $P(\text{CoinFair}|\text{Data}) = 0.6429$ that is less than 0.8.

So the data has weakened our belief !

Why has this happened ? Because 13 heads out of 20 is more like the unfair coin.

Case 3:

If $n = 20, r = 12$,

then $P(\text{CoinFair}|\text{Data}) = 0.8077$ that is close to 0.8.

We have 2 possibilities in our mind:

(1) Coin fair, i.e., $P(\text{head}) = p = 0.5$

(2) Coin biased towards heads with $P(\text{head}) = q = 0.7$

We have a belief (**prior** to observing data) that $P(\text{CoinFair}) = 0.8$

Bayesian Estimation

- Example: Gaussian (**Unknown mean**, Known variance)

Given: Data $\{x_i\}_{i=1}^N$ drawn from a Gaussian PDF with known variance σ^2 , but unknown mean μ

Bayesian strategy: Model mean as a random variable M along with an associated PDF $P(M)$

Bayesian strategy: Prior belief on M is that it is drawn from a Gaussian with mean μ_0 and variance σ_0^2

Associated Generative Model here: first draw μ from prior $P(M)$, then draw data from $P(X|M)$ given $M = \mu$

Goal: Estimate μ , given:

- (i) prior PDF $P(M)$,
- (ii) likelihood function using the model $P(X|M)$, and
- (iii) observed data $\{x_i\}_{i=1}^N$

[What if we ignore the likelihood / data ? ($\mu = \mu_0$)]

[What if we ignore the prior ? (ML estimation seen before)]

Bayesian Estimation

- Example: Gaussian (Unknown mean, Known variance)

Given: Data $\{x_i\}_{i=1}^N$ drawn from a Gaussian PDF with known variance σ^2 , but unknown mean μ

Assume sample mean = \bar{x}

Goal: Estimate μ , given:

- (i) prior PDF $P(M)$,
- (ii) likelihood function using the model $P(X|M)$, and
- (iii) observed data $\{x_i\}_{i=1}^N$

- Prior: $P(M=\mu) = G(\mu; \text{mean} = \mu_0, \text{variance} = \sigma_0^2)$
- Likelihood: $P(\text{data} | M=\mu) = \prod_i G(x_i ; \mu, \sigma^2) = \prod_i G(\mu ; x_i, \sigma^2)$
 - Negative exponent here can be written as:
 $0.5 [N \mu^2 - 2 (\sum_i x_i) \mu] / \sigma^2 + \text{terms independent of } \mu$
 - Negative exponent here can be written as:
 $= 0.5 [\mu^2 - 2 (\sum_i x_i/N) \mu] / (\sigma^2/N) + \text{terms independent of } \mu$
- Thus, likelihood is proportional to $G(\mu ; \text{mean} = (\sum_i x_i/N), \text{variance} = \sigma^2/N)$
 - Gaussian mean = sample mean = $(\sum_i x_i / N)$
 - Gaussian variance = σ^2/N

Bayesian Estimation

- Example: Gaussian (Unknown mean, Known variance)

- Product of two Gaussians: $G(z; \mu_1, \sigma_1^2)G(z; \mu_2, \sigma_2^2) \propto G(z; \mu_3, \sigma_3^2)$

$$\text{Numerator exponent} = \frac{(z-\mu_1)^2}{2\sigma_1^2} + \frac{(z-\mu_2)^2}{2\sigma_2^2}$$

$$= \frac{1}{2\sigma_1^2\sigma_2^2} (z^2(\sigma_2^2 + \sigma_1^2) - (2\mu_1\sigma_2^2 + 2\mu_2\sigma_1^2)z + \mu_1^2\sigma_2^2 + \mu_2^2\sigma_1^2)$$

$$= \frac{1}{2\sigma_1^2\sigma_2^2} (z^2(\sigma_2^2 + \sigma_1^2) - (2\mu_1\sigma_2^2 + 2\mu_2\sigma_1^2)z) + c, \text{ where } c = \text{constant independent of } z$$

$$= \frac{\sigma_2^2 + \sigma_1^2}{2\sigma_1^2\sigma_2^2} \left(z^2 - \frac{2\mu_1\sigma_2^2 + 2\mu_2\sigma_1^2}{\sigma_2^2 + \sigma_1^2} z \right) + c$$

$$= \frac{\sigma_2^2 + \sigma_1^2}{2\sigma_1^2\sigma_2^2} (z^2 - 2\mu_3z + \mu_3^2) + c' = \frac{1}{2\sigma_3^2}(z - \mu_3)^2 + c'$$

$$\boxed{\mu_3 = \frac{\mu_1\sigma_2^2 + \mu_2\sigma_1^2}{\sigma_1^2 + \sigma_2^2}, \sigma_3^2 = \frac{\sigma_1^2\sigma_2^2}{\sigma_1^2 + \sigma_2^2}}$$

where c' = constant independent of z and

Bayesian Estimation

- Example: Gaussian (Unknown mean, Known variance)

Given: Data $\{x_i\}_{i=1}^N$ drawn from a Gaussian PDF with known variance σ^2 , but unknown mean μ

Assume sample mean = \bar{x}

Goal: Estimate μ , given:

- (i) prior PDF $P(M)$,
- (ii) likelihood function using the model $P(X|M)$, and
- (iii) observed data $\{x_i\}_{i=1}^N$

Then MAP estimate for the mean $\hat{\mu}$ is:

$$\hat{\mu} = \frac{\bar{x}\sigma_0^2 + \mu_0\sigma^2/N}{\sigma_0^2 + \sigma^2/N}$$

What if $N = 1$?

What if $N \rightarrow \infty$? (data dominates the prior)

What if $\sigma_0 \rightarrow \infty$? (very weak prior: ignore the prior)

What if $\sigma_0 \rightarrow 0$? (very strong prior: ignore the data)

Bayesian Estimation

- Question (Bayes interval estimate):
 - Suppose signal (scalar) of value “s” is sent from location A to B.
 - Because of the noisy communication channel, signal received at B has a Gaussian PDF with mean “s” and variance 60.
 - Value received at B is 40.
 - Find interval (a,b) s.t. the probability of signal “s” being within (a,b) is 0.9
 - A priori, it’s known that “s” was drawn from Gaussian (mean 50, variance 100)

Bayesian Estimation

- Question (Bayes interval estimate):
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Using formulas derived before for the posterior $P(s|x_1 = 40)$ of parameter s given data x_1 ,

$$\text{Posterior mean} = \frac{50*60+40*100}{60+100} = 43.75$$

$$\text{Posterior variance} = \frac{60*100}{60+100} = 37.5$$

$$\mu_3 = \frac{\mu_1\sigma_2^2 + \mu_2\sigma_1^2}{\sigma_1^2 + \sigma_2^2}, \sigma_3^2 = \frac{\sigma_1^2\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

We know that the posterior PDF is Gaussian

Thus, $Z := \frac{s-43.75}{\sqrt{37.5}}$ has a standard normal PDF

For a standard normal Z , we know that probability mass within $Z \in (-1.645, +1.645)$ is 0.9

Bayesian Estimation

- Question (Bayes interval estimate):
 - Suppose signal (scalar) of value “s” is sent from location A to B.
 - Because of the noisy communication channel, signal received at B has a Gaussian PDF with mean “s” and variance 60.
 - Value received at B is 40.
 - Find interval (a,b) s.t. the probability of signal “s” being within (a,b) is 0.9
 - A priori, it’s known that “s” was drawn from Gaussian (mean 50, variance 100)

Thus, we want to find S s.t. $P(-1.645 < Z < 1.645|\text{data}) = 0.9$

$$\text{i.e., } P\left(-1.645 < \frac{S-43.75}{\sqrt{37.5}} < 1.645|\text{data}\right) = 0.9$$

$$\text{i.e., } P(33.68 < S < 53.83|\text{data}) = 0.9$$

Thus, the desired interval is $(a = 33.68, b = 53.83)$

Bayesian Estimation

- **Loss functions and Risk functions**

If the true value was θ , and our estimator produced an estimate as $\hat{\theta}$,
lets say we incur a “loss” based on the “loss function” $L(\hat{\theta}|\theta)$

We know that, given the data, the true value θ is distributed as per the posterior PDF $P(\Theta|x_1, \dots, x_n)$

We define a “risk function” $R(\hat{\theta}) :=$ expected loss
 $:=$ expectation of loss function $L(\hat{\theta}|\Theta)$ under posterior PDF $P(\Theta|x_1, \dots, x_n)$

Goal: Choose optimal estimate as $\hat{\theta}^*$ that minimizes the risk function $R(\hat{\theta})$

Bayesian Estimation

- Loss functions and Risk functions

Example: Squared-error loss function: $L(\hat{\theta}|\theta) = (\hat{\theta} - \theta)^2$

Risk function $R(\hat{\theta}) = E_{P(\Theta|x_1, \dots, x_n)}[(\hat{\theta} - \Theta)^2]$ = mean squared error

Let risk-function minimizer be $\hat{\theta}^*$

Then,

$$\left(\frac{\partial}{\partial \hat{\theta}} E_{P(\Theta|x_1, \dots, x_n)}[(\hat{\theta} - \Theta)^2] \right) \Big|_{\hat{\theta}=\hat{\theta}^*} = 0$$

Thus, $\hat{\theta}^* = E_{P(\Theta|x_1, \dots, x_n)}[\Theta]$ = Posterior mean

Bayesian Estimation

- Loss functions and Risk functions

Example: Zero-one loss function (case of discrete RV Θ): $L(\hat{\theta}|\theta) = I(\hat{\theta} \neq \theta)$

$$\text{Risk function } R(\hat{\theta}) = E_{P(\Theta|x_1, \dots, x_n)}[I(\hat{\theta} \neq \Theta)]$$

$$= \sum_{\theta \neq \hat{\theta}} P(\theta|x_1, \dots, x_n)$$

$$= 1 - P(\theta = \hat{\theta}|x_1, \dots, x_n)$$

Thus, the risk function is minimized at $\hat{\theta}^* := \arg \max_{\theta} P(\theta|x_1, \dots, x_n)$ = MAP estimate

Bayesian Estimation

- Loss functions and Risk functions

Example: Zero-one loss function (case of continuous RV Θ)

Assume that the loss function is an *inverted* rectangular pulse with height 1 and an infinitesimally small width $\epsilon > 0$ (we do NOT set $\epsilon = 0$), with center of the pulse at the true value θ . i.e.,

$$L(\hat{\theta}|\theta) = 0; \text{ if } \hat{\theta} \in (\theta - \epsilon/2, \theta + \epsilon/2)$$

$$L(\hat{\theta}|\theta) = 1; \text{ otherwise}$$

The risk function

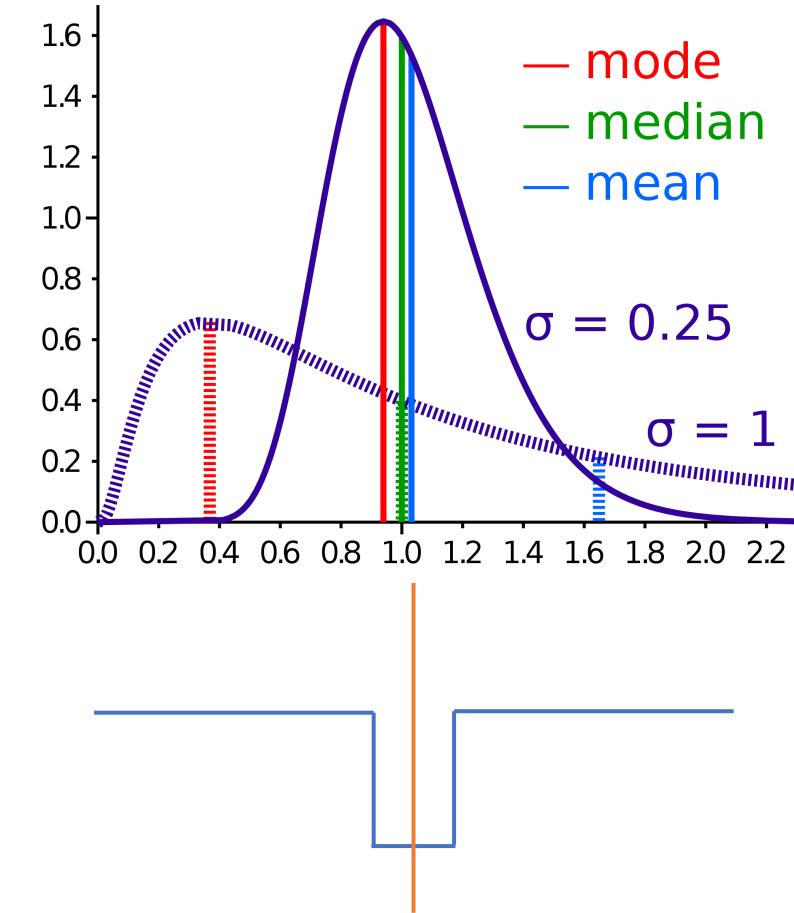
$$1 - \int_{\hat{\theta}-\epsilon/2}^{\hat{\theta}+\epsilon/2} P(\theta|x_1, \dots, x_n) d\theta$$

Now take the limit

$$\lim_{\epsilon \rightarrow 0} \arg \max_{\hat{\theta}} \int_{\hat{\theta}-\epsilon/2}^{\hat{\theta}+\epsilon/2} P(\theta|x_1, \dots, x_n) d\theta$$

The optimum $\hat{\theta}^*$ is when the pulse center is placed at the mode of the PDF, i.e.,

$$\hat{\theta}^* = \arg \max_{\hat{\theta}} P(\theta|x_1, \dots, x_n)$$



Bayesian Estimation

- Loss functions and Risk functions

Example: Absolute-error loss function $L(\hat{\theta}|\theta) = |\hat{\theta} - \theta|$

Let $x = \{x_i\}_{i=1}^N$

Risk function $= E_{P(\Theta|x)}[|\hat{\theta} - \Theta|]$

$$= \int_{-\infty}^{\infty} |\hat{\theta} - \theta| P(\theta|x) d\theta$$

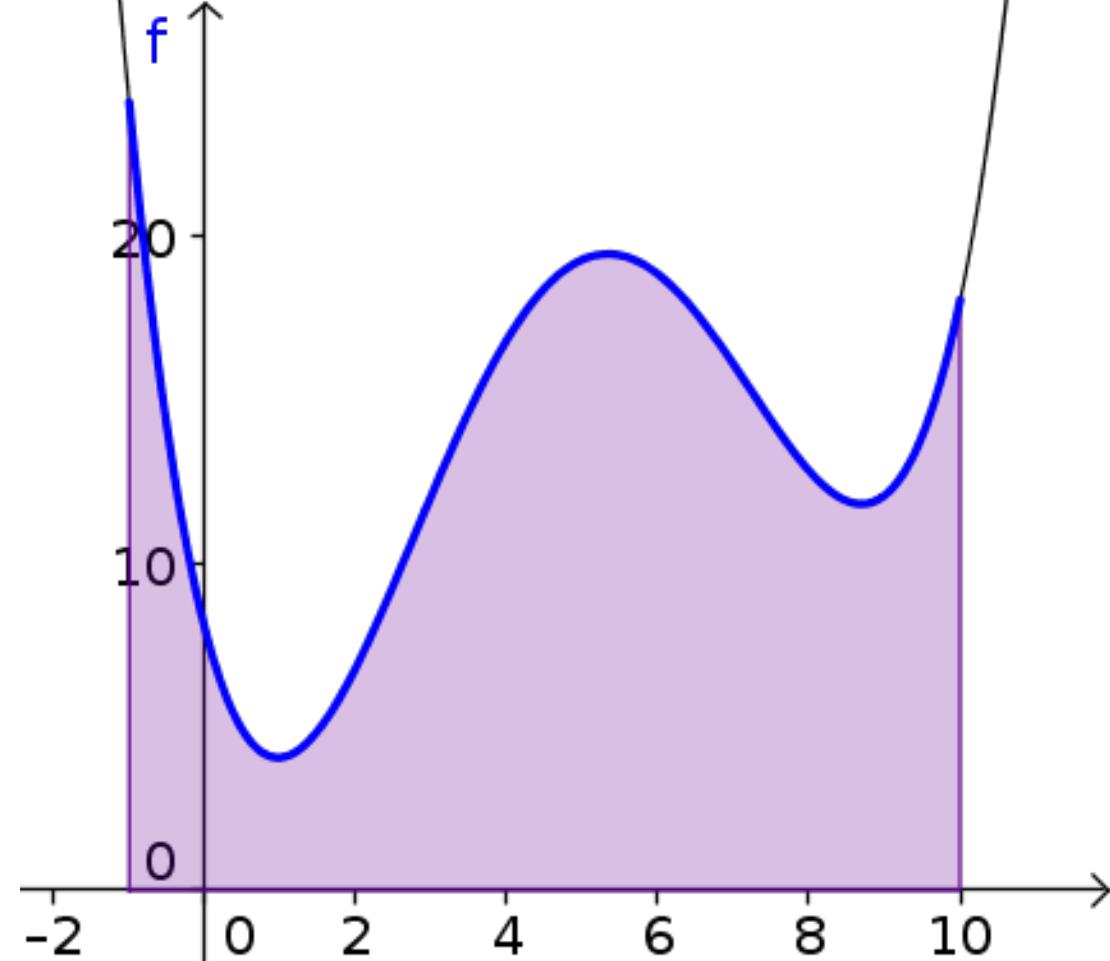
$$= \int_{-\infty}^{\hat{\theta}} (\hat{\theta} - \theta) P(\theta|x) d\theta + \int_{\hat{\theta}}^{\infty} (\theta - \hat{\theta}) P(\theta|x) d\theta$$

The risk function is minimized when its derivative is zero

How to take the derivative of an integral where the limits of the integral are also a function of the variable of interest ?

Leibniz's Integral Rule:

$$\frac{\partial}{\partial a} \int_{l(a)}^{u(a)} f(z, a) dz = \int_{l(a)}^{u(a)} \frac{\partial f}{\partial a} dz + f(z = u(a), a) \frac{\partial u}{\partial a} - f(z = l(a), a) \frac{\partial l}{\partial a}$$



Bayesian Estimation

- Loss functions and Risk functions

In our case, $f(z \equiv \theta, a \equiv \hat{\theta}) \propto (\hat{\theta} - \theta)P(\theta|x)$

Leibniz's Integral Rule:

$$\frac{\partial}{\partial a} \int_{l(a)}^{u(a)} f(z, a) dz = \int_{l(a)}^{u(a)} \frac{\partial f}{\partial a} dz + f(z = u(a), a) \frac{\partial u}{\partial a} - f(z = l(a), a) \frac{\partial l}{\partial a}$$

Example: Absolute-error loss function $L(\hat{\theta}|\theta) = |\hat{\theta} - \theta|$

Let $x = \{x_i\}_{i=1}^N$

$$\text{Risk function} = E_{P(\Theta|x)}[|\hat{\theta} - \Theta|]$$

$$= \int_{-\infty}^{\infty} |\hat{\theta} - \theta| P(\theta|x) d\theta$$

$$= \int_{-\infty}^{\hat{\theta}} (\hat{\theta} - \theta) P(\theta|x) d\theta + \int_{\hat{\theta}}^{\infty} (\theta - \hat{\theta}) P(\theta|x) d\theta$$

The risk function is minimized when its derivative is zero

In our case, for the 1st integral: $f(z = u(a), a) = 0$ and the lower-limit term doesn't arise

In our case, for the 2nd integral: $f(z = l(a), a) = 0$ and the upper-limit term doesn't arise

Bayesian Estimation

- Loss functions and Risk functions

In our case, $f(z \equiv \theta, a \equiv \hat{\theta}) \propto (\hat{\theta} - \theta)P(\theta|x)$

Leibniz's Integral Rule:

$$\frac{\partial}{\partial a} \int_{l(a)}^{u(a)} f(z, a) dz = \int_{l(a)}^{u(a)} \frac{\partial f}{\partial a} dz + f(z = u(a), a) \frac{\partial u}{\partial a} - f(z = l(a), a) \frac{\partial l}{\partial a}$$

Thus, the derivative of our risk function w.r.t. $\hat{\theta}$ is:

$$= \int_{-\infty}^{\hat{\theta}} (+1)P(\theta|x)d\theta + \int_{\hat{\theta}}^{\infty} (-1)P(\theta|x)d\theta$$

$$= \int_{-\infty}^{\hat{\theta}} P(\theta|x)d\theta - \int_{\hat{\theta}}^{\infty} P(\theta|x)d\theta$$

This is zero when $\hat{\theta}$ = median of $P(\theta|x)$

Example: Absolute-error loss function $L(\hat{\theta}|\theta) = |\hat{\theta} - \theta|$

Let $x = \{x_i\}_{i=1}^N$

$$\text{Risk function} = E_{P(\Theta|x)}[|\hat{\theta} - \Theta|]$$

$$= \int_{-\infty}^{\infty} |\hat{\theta} - \theta| P(\theta|x)d\theta$$

$$= \int_{-\infty}^{\hat{\theta}} (\hat{\theta} - \theta) P(\theta|x)d\theta + \int_{\hat{\theta}}^{\infty} (\theta - \hat{\theta}) P(\theta|x)d\theta$$

The risk function is minimized when its derivative is zero

Bayesian Estimation

• Loss functions and Risk functions

Thus, the derivative of our risk function w.r.t. $\hat{\theta}$ is:

$$\int_{-\infty}^{\hat{\theta}} P(\theta|x)d\theta - \int_{\hat{\theta}}^{\infty} P(\theta|x)d\theta$$

This is zero when $\hat{\theta}$ = median of $P(\theta|x)$



The median will be a minimizer if the 2nd derivative is positive. Is that so ?

In this case, for both integrals, $\frac{\partial f}{\partial a} = 0$

In this case, for 1st integral, the lower-limit term doesn't arise

In this case, for 2nd integral, the upper-limit term doesn't arise

Thus, the 2nd derivative of our risk function w.r.t. $\hat{\theta}$, evaluated at $\hat{\theta}$ = median of $P(\theta|x)$, is:

$$= P(\hat{\theta}|x) + P(\hat{\theta}|x) \geq 0$$

Example: Absolute-error loss function $L(\hat{\theta}|\theta) = |\hat{\theta} - \theta|$

Let $x = \{x_i\}_{i=1}^N$

$$\text{Risk function} = E_{P(\Theta|x)}[|\hat{\theta} - \Theta|]$$

$$= \int_{-\infty}^{\infty} |\hat{\theta} - \theta| P(\theta|x)d\theta$$

$$= \int_{-\infty}^{\hat{\theta}} (\hat{\theta} - \theta) P(\theta|x)d\theta + \int_{\hat{\theta}}^{\infty} (\theta - \hat{\theta}) P(\theta|x)d\theta$$

The risk function is minimized when its derivative is zero

Note: for the median $\hat{\theta}$ to be unique, the CDF must be continuous and strictly increasing at $\hat{\theta}$, which means that the PDF must be positive at $\hat{\theta}$.

Bayesian Estimation

- Example: i.i.d. Bernoulli

Rewrite PDF as $P(x|\theta) = \theta^x(1-\theta)^{1-x}$, where $x \in \{0, 1\}$

$$P(\theta|x_1, \dots, x_n) = P(x_1, \dots, x_n|\theta)/P(x_1, \dots, x_n)$$

where Numerator = $\theta^{\sum_i x_i} (1-\theta)^{n-\sum_i x_i}$

Given: X_1, \dots, X_n are i.i.d. Bernoulli with parameter θ and PDF $P(x=1|\theta) = \theta, P(x=0|\theta) = 1 - \theta$

Data: x_1, \dots, x_n

Estimate $\theta \in (0, 1)$

Prior $P(\theta) = 1, \forall \theta \in (0, 1)$

If we want the posterior mean, then we need to care about the denominator as well

Denominator

$$= \int_0^1 \theta^{\sum_i x_i} (1-\theta)^{n-\sum_i x_i} d\theta$$

To handle the integral in the denominator, we use the result / trick:

Let $x = \sum_i x_i$

$$\int_0^1 \theta^m (1-\theta)^r d\theta = m!r!/(m+r+1)!$$

Then, $P(\theta|x_1, \dots, x_n) = \frac{(n+1)!}{x!(n-x)!} \theta^x (1-\theta)^{n-x}$

Bayesian Estimation

- Example: i.i.d. Bernoulli

ML estimator \equiv MAP estimator; because $P(\theta) = 1$

Note: ML estimator $= \max_{\theta} \log (\theta^{\sum_i X_i} (1 - \theta)^{n - \sum_i X_i})$
 $= \max_{\theta} X \log \theta + (n - X) \log(1 - \theta)$, where $X := \sum_i X_i$
 $= X/n$
 $= \sum_i X_i/n$

Check that the 2nd derivative is negative

(Use the facts: $X \geq 0$ and $n - X \geq 0$ and $0 < \theta < 1$)

$$E_{P(\theta|x_1, \dots, x_n)}[\theta] = \int_0^1 \theta \frac{(n+1)!}{x!(n-x)!} \theta^x (1 - \theta)^{n-x} d\theta = \frac{x+1}{n+2}$$

$$\text{Bayes posterior-mean estimator} = \frac{\sum_i X_i + 1}{n + 2}$$

Given: X_1, \dots, X_n are i.i.d. Bernoulli with parameter θ and PDF $P(x = 1|\theta) = \theta, P(x = 0|\theta) = 1 - \theta$

Data: x_1, \dots, x_n

Estimate $\theta \in (0, 1)$

Prior $P(\theta) = 1, \forall \theta \in (0, 1)$

Rewrite PDF as $P(x|\theta) = \theta^x (1 - \theta)^{1-x}$, where $x \in \{0, 1, \dots, n\}$

$$P(\theta|x_1, \dots, x_n) = P(x_1, \dots, x_n|\theta)/P(x_1, \dots, x_n)$$

where Numerator $= \theta^{\sum_i x_i} (1 - \theta)^{n - \sum_i x_i}$

$$\int_0^1 \theta^m (1 - \theta)^r d\theta = m!r!/(m + r + 1)!$$

Let $x = \sum_i x_i$

$$\text{Then, } P(\theta|x_1, \dots, x_n) = \frac{(n+1)!}{x!(n-x)!} \theta^x (1 - \theta)^{n-x}$$

Bayesian Estimation

- Example: i.i.d. Bernoulli

Note: ML estimator = $\max_{\theta} \log (\theta \sum_i X_i (1 - \theta)^{n - \sum_i X_i})$
= $\max_{\theta} X \log \theta + (n - X) \log(1 - \theta)$, where $X := \sum_i X_i$
= X/n
= $\sum_i X_i/n$

$$E_{P(\theta|x_1, \dots, x_n)}[\theta] = \int_0^1 \theta \frac{(n+1)!}{x!(n-x)!} \theta^x (1-\theta)^{n-x} d\theta = \frac{x+1}{n+2}$$

$$\text{Bayes posterior-mean estimator} = \frac{\sum_i X_i + 1}{n + 2}$$

Given: X_1, \dots, X_n are i.i.d. Bernoulli with parameter θ and PDF $P(x = 1|\theta) = \theta, P(x = 0|\theta) = 1 - \theta$

Data: x_1, \dots, x_n

Estimate $\theta \in (0, 1)$

Prior $P(\theta) = 1, \forall \theta \in (0, 1)$

Note: When $n = 0$, Bayes estimate = 0.5, the mid-point of the interval (0, 1). This is what we get when we solely rely on the prior

Note: Asymptotically, i.e., as $n \rightarrow \infty$, the Bayes (mean) estimator tends to the ML estimator

What happens to the Bayes estimate and ML estimate when true $\theta = 0$ or true $\theta = 1$? Assume n is large.

Conjugate Prior

- Motivation

If the posterior PDFs $P(\theta|x)$ are in the same family as the prior PDF $P(\theta)$, then:

- (i) the prior and posterior are called *conjugate* PDFs, and
- (ii) the prior is called the conjugate prior for the likelihood function

Advantage of conjugate priors: When the prior gives closed-form analytical expressions, then the posterior also gives closed-form analytical expressions, and its denominator / normalizing constant has a closed-form expression

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{\int P(x|\theta)P(\theta)d\theta}$$

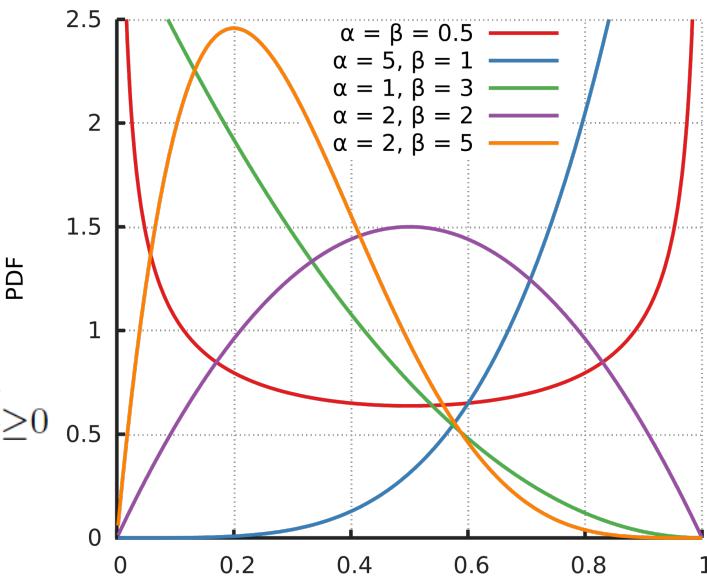
Otherwise, a difficult numerical integration may be required to approximate the normalizing factor

Conjugate Prior

• Example

Example: Binomial Likelihood and Beta prior

- 1) Likelihood of s successes in n tries: $P(s, n|\theta) = {}^n C_s \theta^s (1 - \theta)^{n-s}$, where $n \in \mathbb{N}$, $s \in \mathbb{I}_{\geq 0}$
- 2) Prior: $P(\theta) = \text{beta}(\theta; a \in \mathbb{R}^+, b \in \mathbb{R}^+) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1 - \theta)^{b-1}$, Note: $a > 0, b > 0$
- 3) Posterior $\propto \theta^{s+a-1} (1 - \theta)^{n-s+b-1} \equiv \text{beta}(\theta; a+s, b+n-s)$



- We know that the **mean** of the beta PDF $\text{beta}(\theta; a, b)$ is $a/(a + b)$

Thus, Bayes (mean) estimate = posterior mean = $(a + s)/(a + b + n)$
 $= w(a/(a + b)) + (1 - w)(s/n)$, where weight $w = (a + b)/(a + b + n)$

Note: When the sample size $n = 0$, the posterior mean = $a/(a + b) =$ prior mean

Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mean \rightarrow ML estimate

If prior $P(\theta) = 1$ is uniform over $\theta \in (0, 1)$, i.e., $\text{beta}(\theta, 1, 1)$

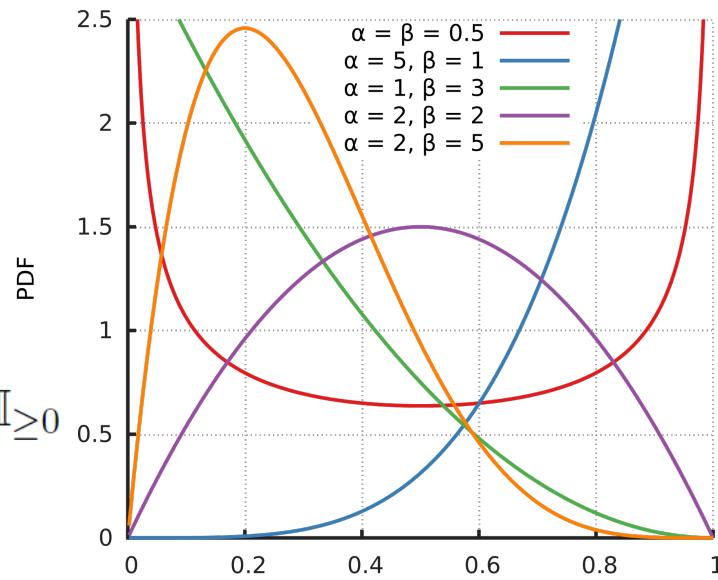
In that case, the likelihood determines the posterior

Conjugate Prior

- Example

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- We know that the **mode** of the beta PDF $\text{beta}(\theta; a, b)$ is $(a-1)/(a+b-2)$ for $a, b > 1$

So, posterior mode $= (a+s-1)/(a+b+n-2)$
 $= w((a-1)/(a+b-2)) + (1-w)(s/n)$, where weight $w = (a+b-2)/(a+b+n-2)$

Note: When the sample size $n = 0$, the posterior mode $= (a-1)/(a+b-2) =$ prior mode

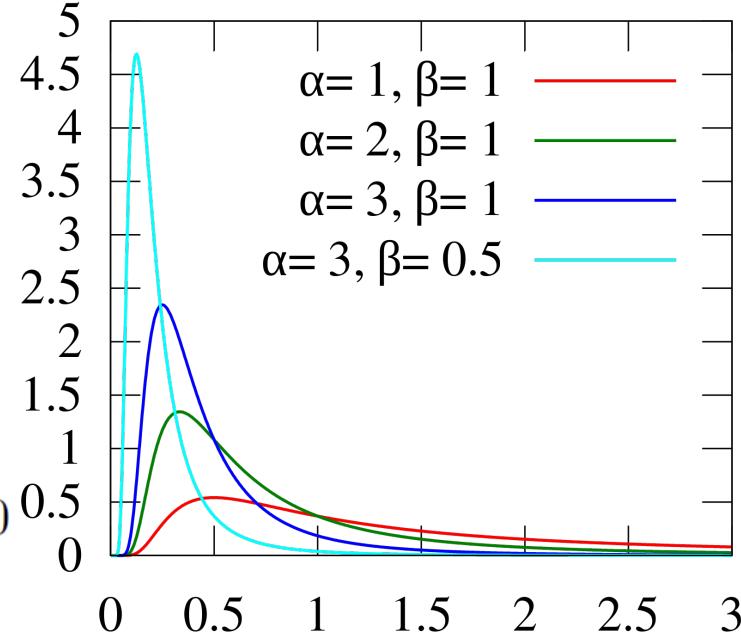
Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mode \rightarrow ML estimate

Conjugate Prior

- Example

Example: Gaussian (known mean μ , unknown variance θ) and Inverse Gamma

- 1) Likelihood: $P(x_1, \dots, x_n | \mu, \theta) \propto \prod_{i=1}^n \theta^{-0.5} \exp(-0.5(x_i - \mu)^2 / \theta)$
- 2) Prior = Inverse Gamma PDF: $P(\theta; a, b) \propto \theta^{-a-1} \exp(-b/\theta)$, where $a > 0, b > 0$
- 3) Posterior = Inverse Gamma PDF: $P(\theta; a + n/2, b + \sum_i (x_i - \mu)^2 / 2)$



- Mean of the inverse Gamma $P(\theta; a, b) = b/(a - 1)$, for $a > 1$

$$\begin{aligned}\text{Thus, Bayes estimate} &= \text{posterior mean} = (b + \sum_i (x_i - \mu)^2 / 2) / (a + n/2 - 1) \\ &= (2b + \sum_i (x_i - \mu)^2) / (2a + n - 2) \\ &= w(b/(a - 1)) + (1 - w) \sum_i (x_i - \mu)^2 / n, \text{ where weight } w = (2a - 2) / (2a + n - 2)\end{aligned}$$

Note: When the sample size $n = 0$, the weight $w = 1$ and the posterior mean = $b/(a - 1) =$ prior mean

Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mean \rightarrow ML estimate

Conjugate Prior

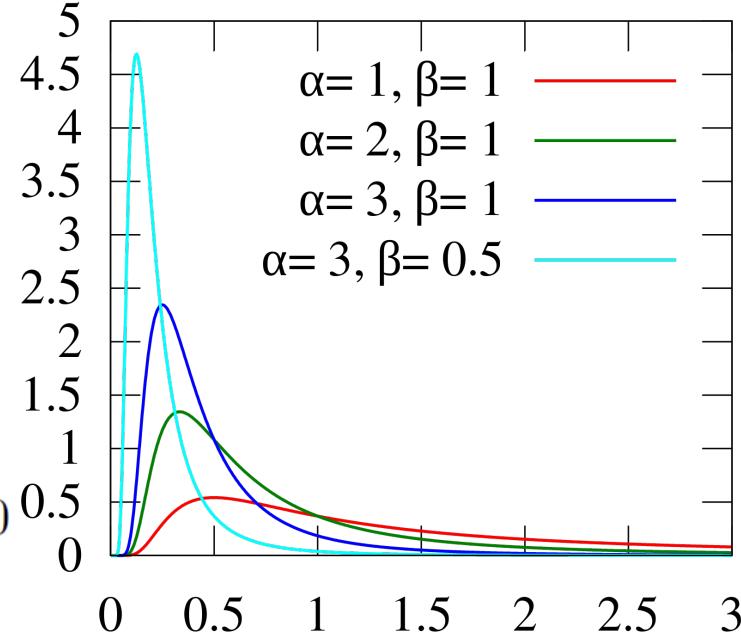
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- Mode of the inverse Gamma $P(\theta; a, b) = b/(a + 1)$

$$\text{So, posterior mode} = (b + \sum_i (x_i - \mu)^2 / 2) / (a + n/2 + 1)$$

$$= (2b + \sum_i (x_i - \mu)^2) / (2a + n + 2)$$

$$= w(b/(a + 1)) + (1 - w) \sum_i (x_i - \mu)^2 / n, \text{ where weight } w = (2a + 2) / (2a + n + 2)$$

Note: When the sample size $n = 0$, the weight $w = 1$ and the posterior mode = $b/(a + 1) =$ prior mode

Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mode \rightarrow ML estimate

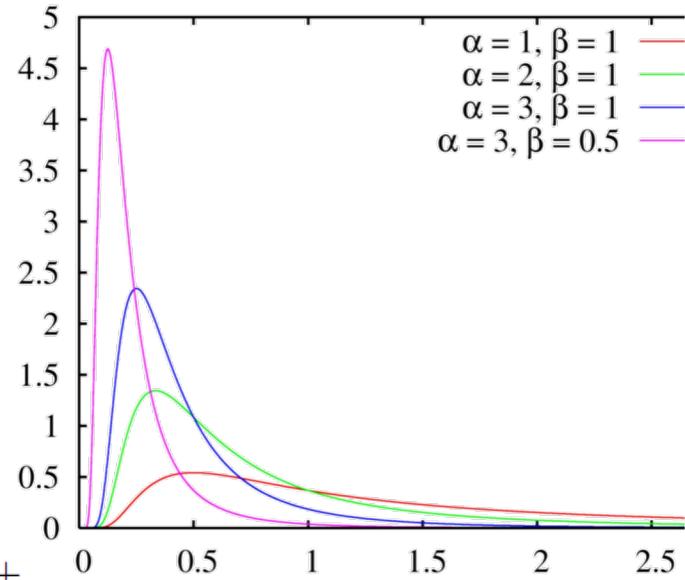
Conjugate Prior

- Example

Example: Poisson PDF and Gamma prior

Use this example to motivate the general result for exponential families later

- 1) Likelihood: $P(k_1, \dots, k_n | \lambda) = \prod_i \lambda^{k_i} \exp(-\lambda)/k_i!$, where $\lambda \in \mathbb{R}^+, k_i \in \mathbb{I}^+$
- 2) Prior: $P(\theta) = \text{Gamma}(\lambda|\alpha, \beta) \propto \lambda^{\alpha-1} \exp(-\beta\lambda)$, where $\alpha \in \mathbb{R}^+, \beta \in \mathbb{R}^+, \lambda \in \mathbb{R}^+$
- 3) Posterior: $\propto \lambda^{\sum_i k_i + \alpha - 1} \exp(-n\lambda - \beta\lambda) \equiv \text{Gamma}(\lambda; \sum_i k_i + \alpha, n + \beta)$



- For a Gamma distribution $\text{Gamma}(\lambda|\alpha, \beta)$, we know that the **mean** is α/β

$$\begin{aligned} \text{Thus, the Bayes estimate} &= \text{posterior mean} = (\sum_i k_i + \alpha)/(n + \beta) \\ &= w(\alpha/\beta) + (1 - w) \sum_i k_i/n, \text{ where weight } w = \beta/(\beta + n) \\ &= w(\alpha/\beta) + (1 - w)\hat{\lambda}_{\text{MLE}} \end{aligned}$$

Note: When the sample size $n = 0$, the weight $w = 1$ and the posterior mean = α/β = prior mean

Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mean \rightarrow ML estimate

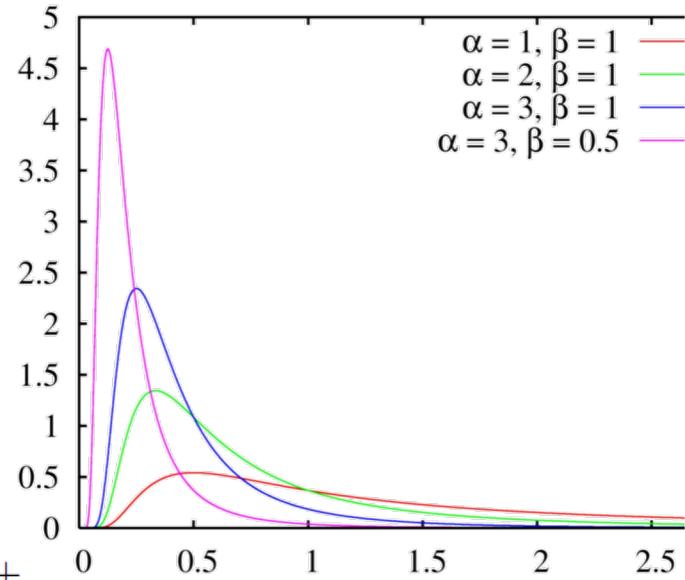
Conjugate Prior

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- For a Gamma distribution $\text{Gamma}(\lambda|\alpha, \beta)$, we know that the **mode** is $(\alpha - 1)/\beta$ when $\alpha \geq 1$. When $\alpha < 1$, the case is tricky.

$$\begin{aligned}\text{Then, posterior mode} &= (\sum_i k_i + \alpha - 1)/(n + \beta) \\ &= w((\alpha - 1)/\beta) + (1 - w) \sum_i k_i/n, \text{ where weight } w = \beta/(\beta + n)\end{aligned}$$

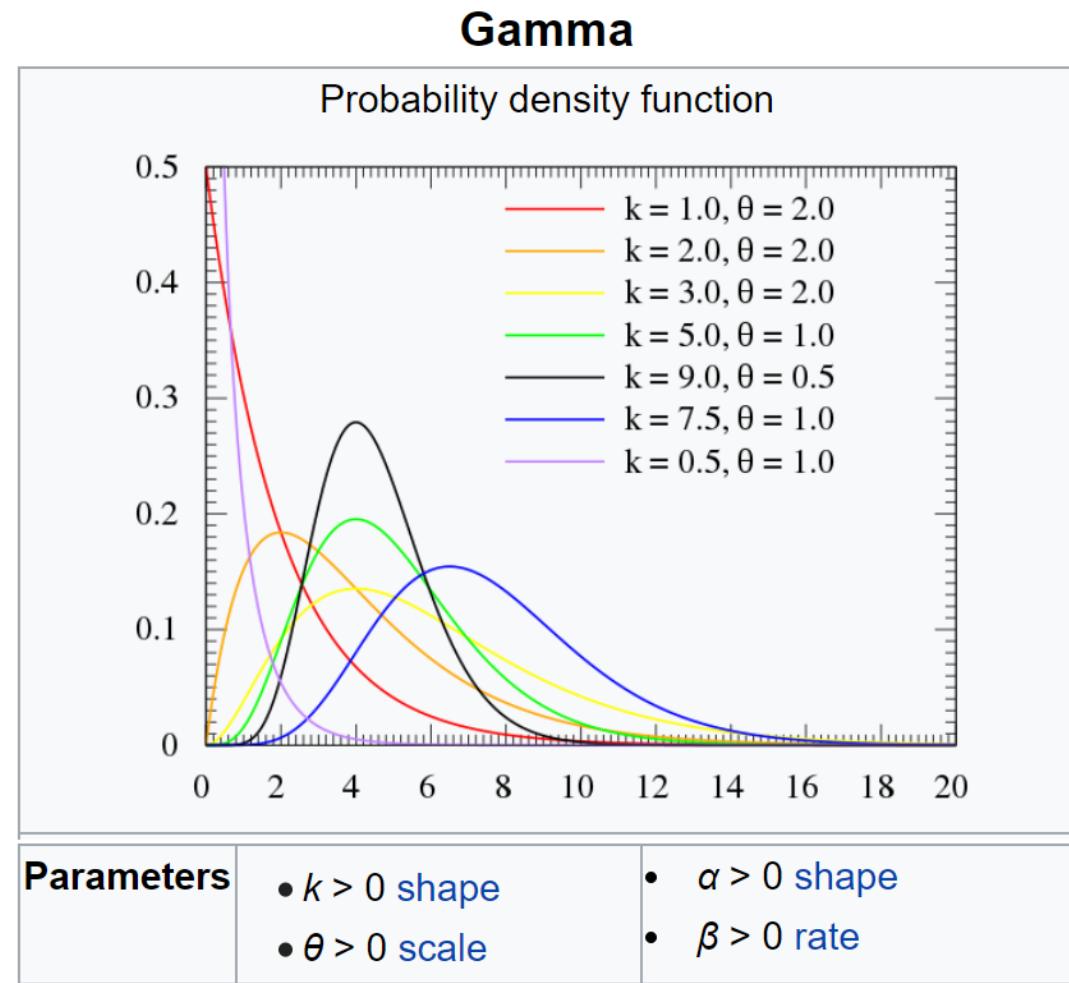
Note: When the sample size $n = 0$, the weight $w = 1$ and the posterior mode = $(\alpha - 1)/\beta$ = prior mode

Note: As the sample size $n \rightarrow \infty$, the weight $w \rightarrow 0$ and the posterior mode \rightarrow ML estimate

Conjugate Prior

- Gamma distribution

PDF	$f(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-\frac{x}{\theta}}$	$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$
CDF	$F(x) = \frac{1}{\Gamma(k)} \gamma\left(k, \frac{x}{\theta}\right)$	$F(x) = \frac{1}{\Gamma(\alpha)} \gamma(\alpha, \beta x)$
Mean	$k\theta$	$\frac{\alpha}{\beta}$
Median	No simple closed form	No simple closed form
Mode	$(k - 1)\theta$ for $k \geq 1$, 0 for $k < 1$	$\frac{\alpha - 1}{\beta}$ for $\alpha \geq 1$, 0 for $\alpha < 1$

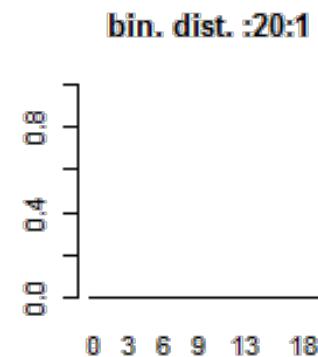
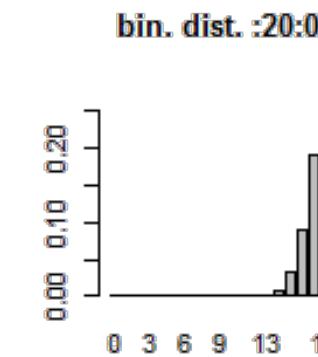
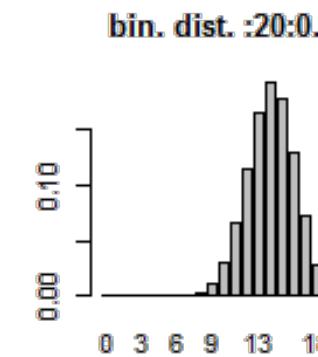
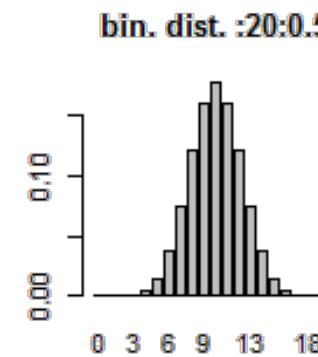
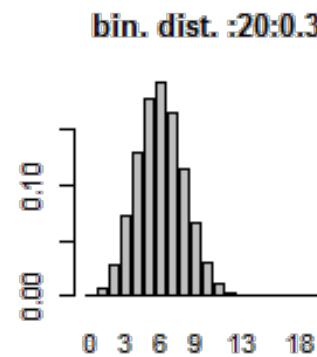
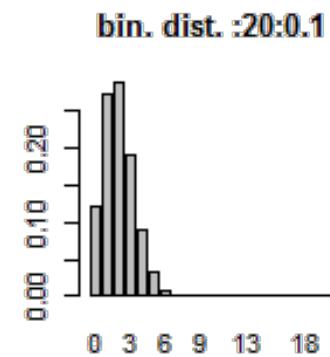


Fisher Information

- Key questions
 - How much “information” can a sample of data provide about the unknown parameter being estimated/inferred from the data ?
 - Comparing two scenarios of parameter estimation, when is parameter estimation “easier” ?
 - When will “less” data suffice in getting “good” estimates ?
 - How good can an estimator ever be (e.g., how low can its squared error ever be) when the true parameter has a specific value ?
 - How does Fisher information relate to this question

Fisher Information

- Some intuition, motivation towards formulating Fisher information
 - Example 1
 - Bernoulli distribution with success probability (p)
 - Variance = $p(1-p)$ is small when p close to 0 or 1
 - Binomial distribution (n tries) with success probability (p)
 - Variance = $np(1-p)$ is small when p close to 0 or 1
 - Bottom: $n=20$; $p = 0.1, 0.3, 0.5, 0.7, 0.9, 1$

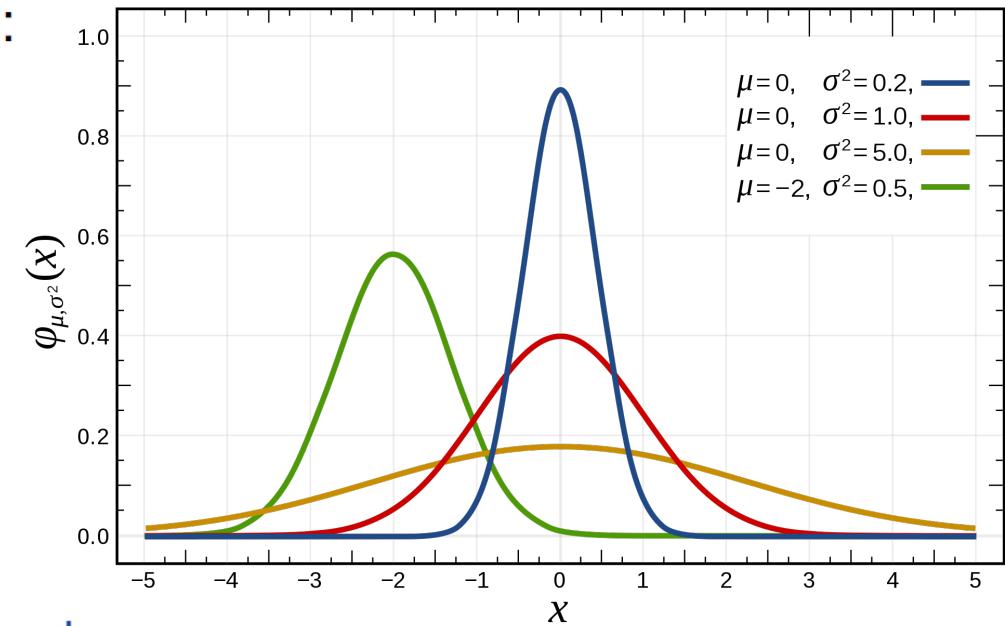


Fisher Information

- Some intuition, motivation towards formulating Fisher information

Example 2: Estimating Gaussian mean $\theta := \mu$ in two cases:

- (i) when variance σ^2 (known) is huge, and
- (ii) when σ^2 (known) is tiny.



Data drawn from $G(x; \mu, \sigma^2)$ in 2nd case has a smaller spread.

Likelihood function in 2nd case more peaked.

For a small sample of size N (say, $N = 5$),
mean estimate (sample mean; always unbiased = always high accuracy)
is much more precise (= much lower variance) in 2nd case

Fisher Information

- Towards formulating Fisher information

First, consider the average (expected) derivative of the log-likelihood function:

$$\begin{aligned} & E_{P(X|\theta_{\text{true}})} \left[\frac{\partial}{\partial \theta} \log P(X|\theta) \Big|_{\theta=\theta_{\text{true}}} \right] \\ &= \int_x P(x|\theta) \frac{\partial P(x|\theta)}{\partial \theta} / P(x|\theta) dx \\ &= \int_x \frac{\partial}{\partial \theta} P(x|\theta) dx \\ &= \frac{\partial}{\partial \theta} \int_x P(x|\theta) dx \\ &= \frac{\partial}{\partial \theta} 1 \\ &= 0 \end{aligned}$$

The expectation / integral isn't over θ ,
but over different instances of observed data $x \sim P(X|\theta_{\text{true}})$

Liebniz integral rule allows switching order of integration and differentiation
when integral limits (i.e., support of PDF/PMF) aren't a function of θ

The expectation is zero for all θ_{true}

Fisher Information

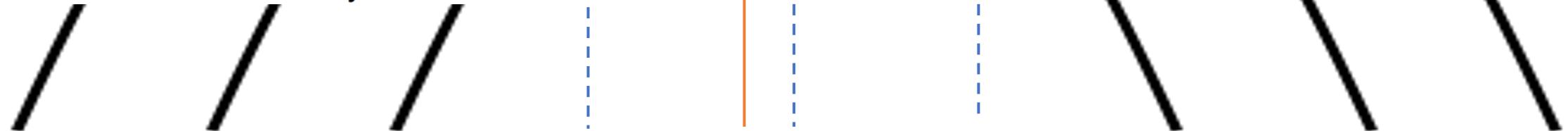
- Towards formulating Fisher information $I(\cdot)$

Now, consider the expected squared slope (slope variance) of the log-likelihood function $\log P(X|\theta)$, evaluated at $\theta = \theta_{\text{true}}$, i.e.,

$$I(\theta_{\text{true}}) := E_{P(X|\theta_{\text{true}})} \left[\left(\frac{\partial}{\partial \theta} \log P(X|\theta) \Big|_{\theta_{\text{true}}} \right)^2 \right]$$

The Fisher information $I(\theta_{\text{true}}) \geq 0$

If $\log P(X|\theta)$ didn't contain θ , then the derivative would be 0, and the data wouldn't contain any information about θ



Fisher Information

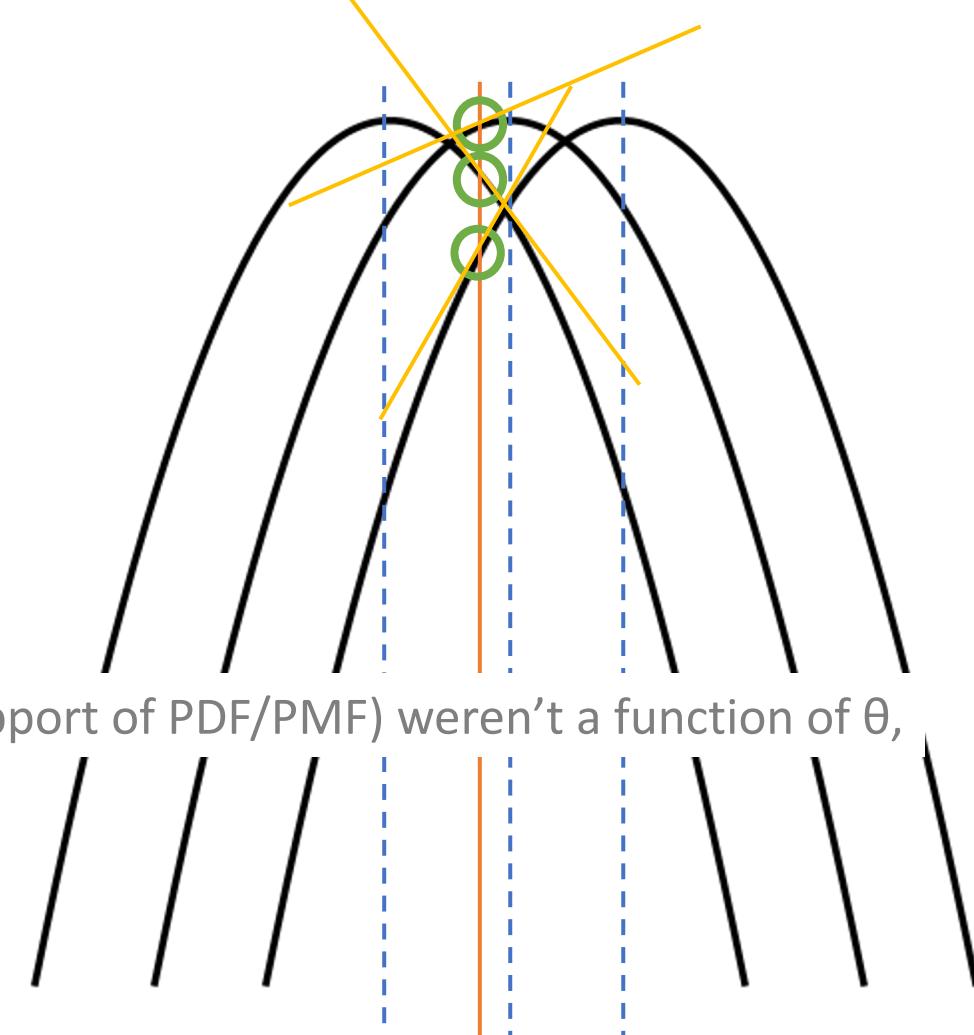
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Fisher Information

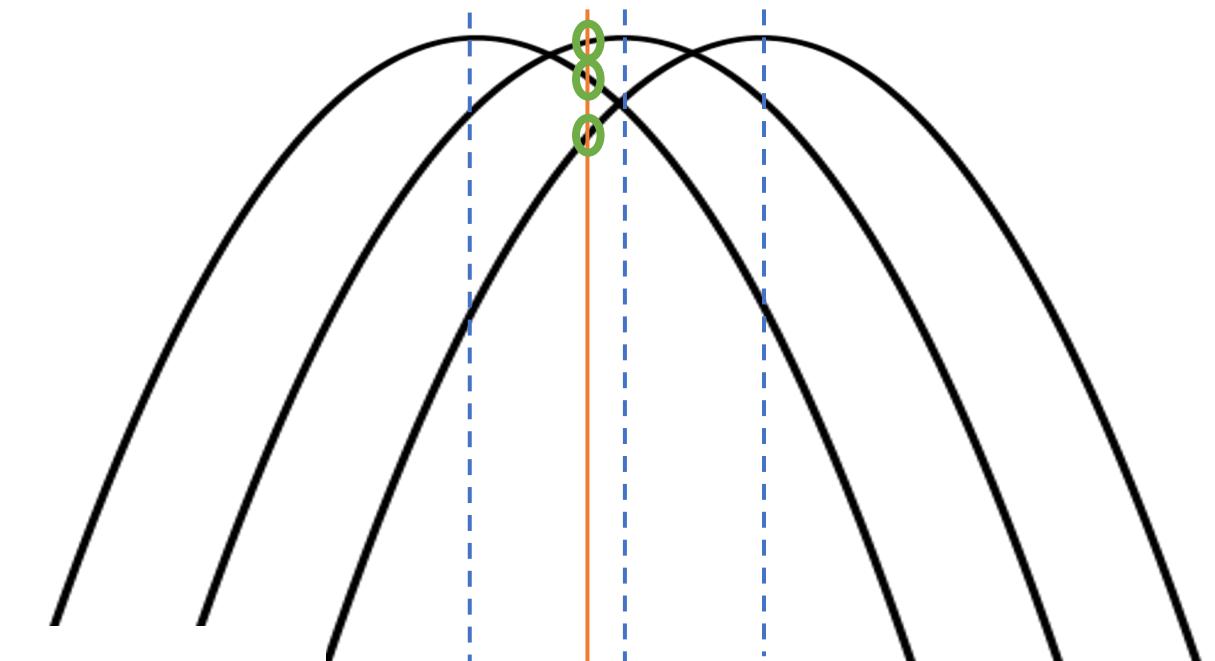
- Alternate (equivalent) formulation for Fisher information
 - Consider

$$\frac{\partial^2}{\partial \theta^2} \log P(X|\theta) = \frac{\frac{\partial^2 P(X|\theta)}{\partial \theta^2}}{P(X|\theta)} - \left(\frac{\frac{\partial P(X|\theta)}{\partial \theta}}{P(X|\theta)} \right)^2 = \frac{\frac{\partial^2 P(X|\theta)}{\partial \theta^2}}{P(X|\theta)} - \left(\frac{\partial \log P(X|\theta)}{\partial \theta} \right)^2$$

Now, (i) evaluate LHS and RHS at $\theta := \theta_{\text{true}}$ and (ii) take expectation w.r.t. $P(X|\theta_{\text{true}})$:

$$\begin{aligned} & E_{P(X|\theta_{\text{true}})} \left[\frac{\partial^2}{\partial \theta^2} \log P(X|\theta) \Big|_{\theta=\theta_{\text{true}}} \right] \\ &= E_{P(X|\theta_{\text{true}})} \left[\frac{\frac{\partial^2 P(X|\theta)}{\partial \theta^2}}{P(X|\theta)} \Big|_{\theta=\theta_{\text{true}}} \right] - I(\theta_{\text{true}}) \\ &= -I(\theta_{\text{true}}), \text{ because} \end{aligned}$$

$$E_{P(X|\theta_{\text{true}})} \left[\frac{\frac{\partial^2 P(X|\theta)}{\partial \theta^2}}{P(X|\theta)} \Big|_{\theta=\theta_{\text{true}}} \right] = \int_x \frac{\partial^2 P(x|\theta)}{\partial \theta^2} dx = \frac{\partial^2}{\partial \theta^2} \int_x P(X|\theta) dx = 0$$

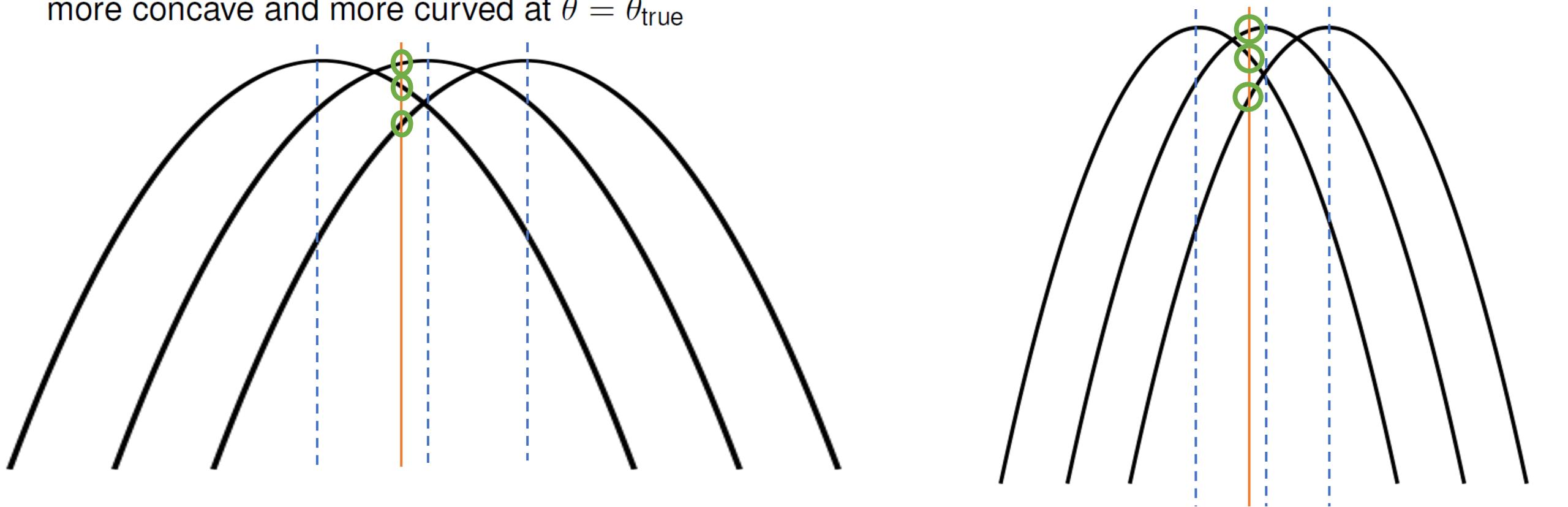


Fisher Information

- Alternate (equivalent) formulation for Fisher information

So, Fisher information is the expectation (over $x \sim P(X|\theta_{\text{true}})$) of the negative 2nd-derivative (curvature) of the log-likelihood function $\log P(x|\theta)$ evaluated at $\theta = \theta_{\text{true}}$

So, larger Fisher information means the log-likelihood function $\log P(x|\theta)$ is expected to be more concave and more curved at $\theta = \theta_{\text{true}}$



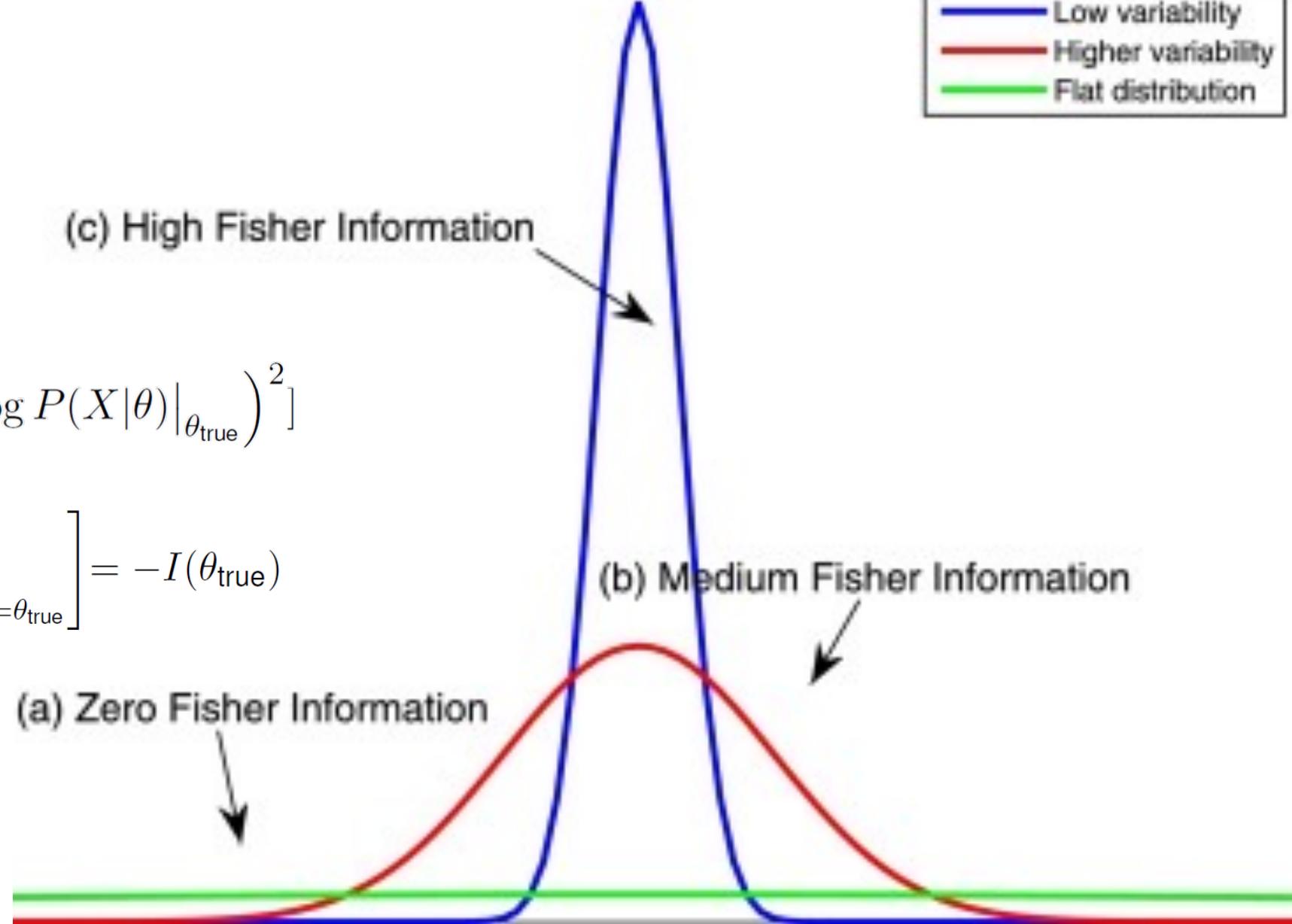
Fisher Information

- Low variability
- Higher variability
- Flat distribution

- Two formulations

$$I(\theta_{\text{true}}) := E_{P(X|\theta_{\text{true}})} \left[\left(\frac{\partial}{\partial \theta} \log P(X|\theta) \Big|_{\theta=\theta_{\text{true}}} \right)^2 \right]$$

$$E_{P(X|\theta_{\text{true}})} \left[\frac{\partial^2}{\partial \theta^2} \log P(X|\theta) \Big|_{\theta=\theta_{\text{true}}} \right] = -I(\theta_{\text{true}})$$



Fisher Information

- Example: Bernoulli random variable

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

$$\frac{\partial}{\partial \theta} \log P(x|\theta) = x/\theta - (1 - x)/(1 - \theta)$$

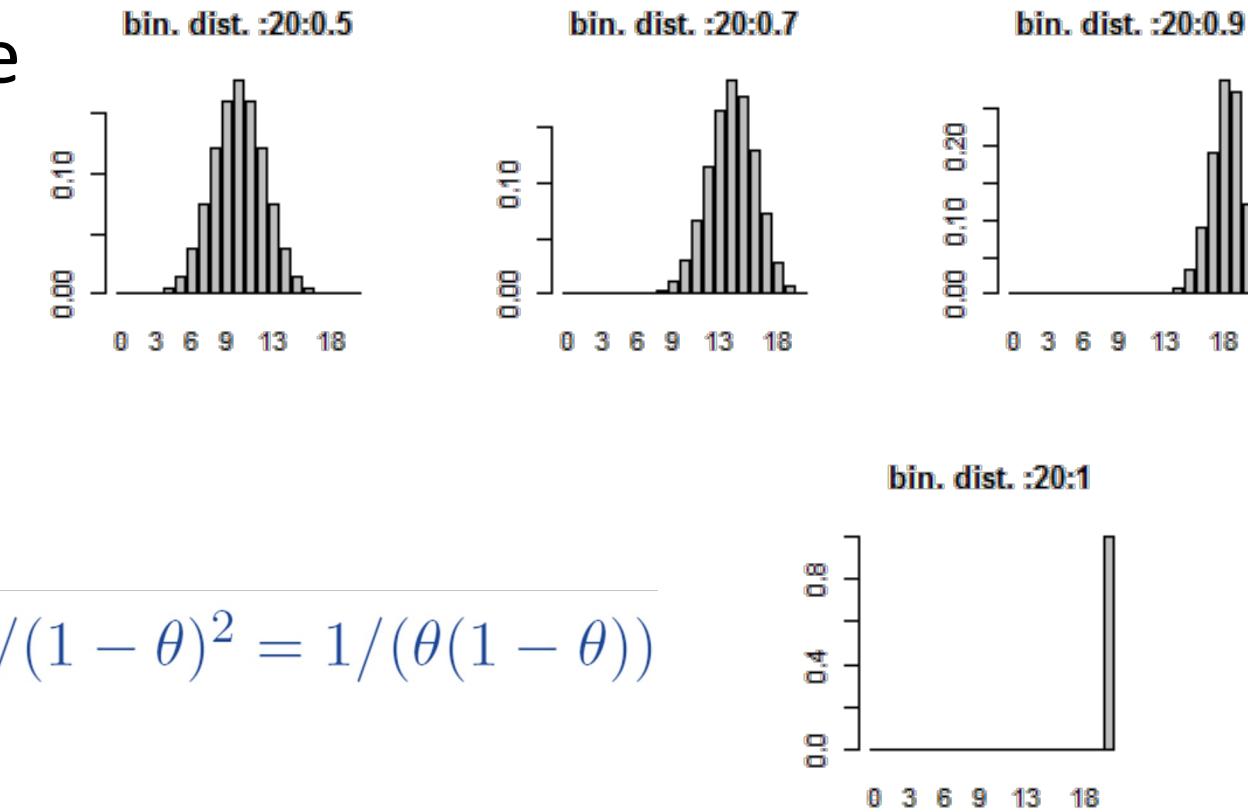
$$\frac{\partial^2}{\partial \theta^2} \log P(x|\theta) = -x/\theta^2 - (1 - x)/(1 - \theta)^2$$

$$I(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \log P(x|\theta)\right] = \theta/\theta^2 + (1 - \theta)/(1 - \theta)^2 = 1/(\theta(1 - \theta))$$

So, $I(\theta)$ is large when θ close to 0 or 1

For a dataset of size N , $I_N(\theta) = N/(\theta(1 - \theta))$

So, $I_N(\theta)$ increases with N (as we should expect)



Fisher Information

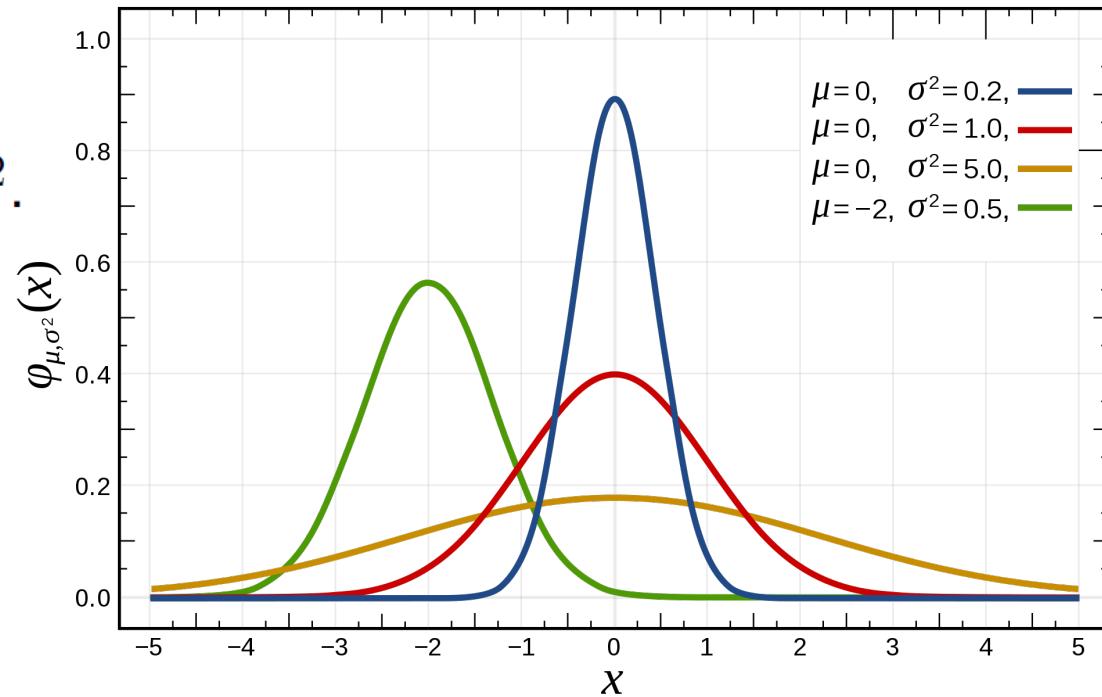
- Example: Gaussian random variable

Unknown mean parameter $\theta = \mu$. Known variance σ^2 .

$$\frac{\partial}{\partial \mu} \log P(x|\mu) = (x - \mu)/\sigma^2$$

$$\frac{\partial^2}{\partial \mu^2} \log P(x|\mu) = -1/\sigma^2$$

$$I(\mu) = 1/\sigma^2$$



Here, $I(\mu)$ is independent of μ , but rather depends on the other parameter σ^2

For a dataset of size N , $I_N(\mu) = N/\sigma^2$

Fisher Information

- Example: Gaussian random variable
 - Known mean. Unknown variance.

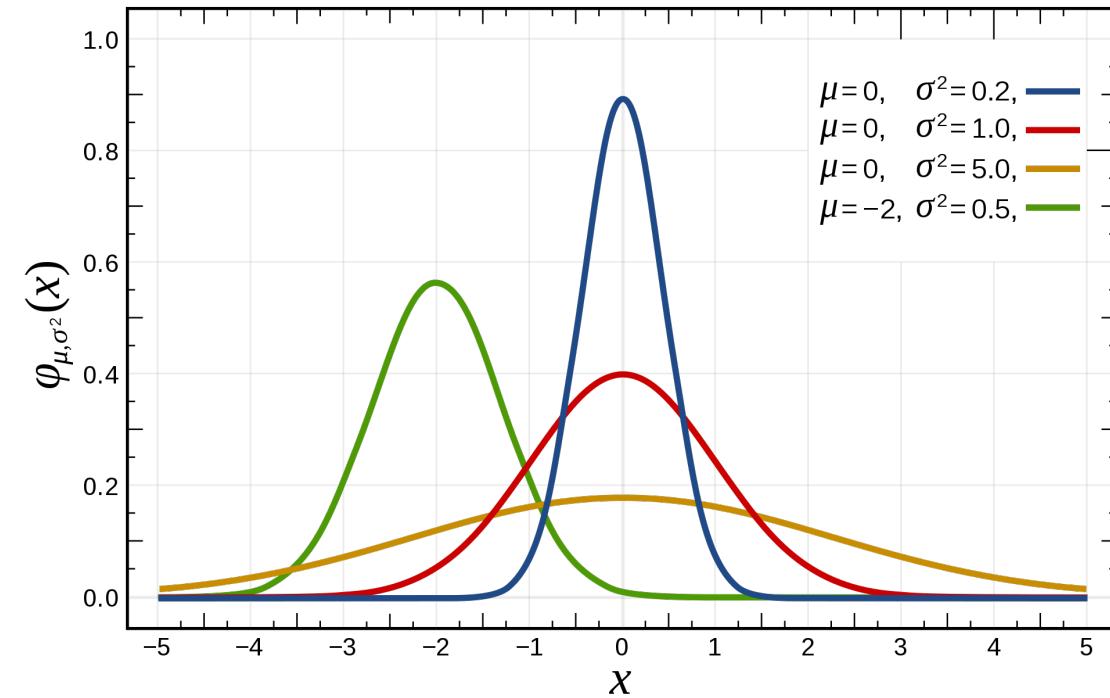
$$f(x|\theta) = \frac{1}{\sqrt{2\pi\theta}} \exp\left\{-\frac{(x-\mu)^2}{2\theta}\right\}$$

$$l(x|\theta) = -\frac{(x-\mu)^2}{2\theta} - \frac{1}{2} \log 2\pi - \frac{1}{2} \log \theta$$

$$l'(x|\theta) = \frac{(x-\mu)^2}{2\theta^2} - \frac{1}{2\theta},$$

$$l''(x|\theta) = -\frac{(x-\mu)^2}{\theta^3} + \frac{1}{2\theta^2}$$

$$I(\theta) = -E[l''(X|\theta)] = -E\left[-\frac{(X-\mu)^2}{\theta^3} + \frac{1}{2\theta^2}\right] = \frac{1}{2\theta^2}$$



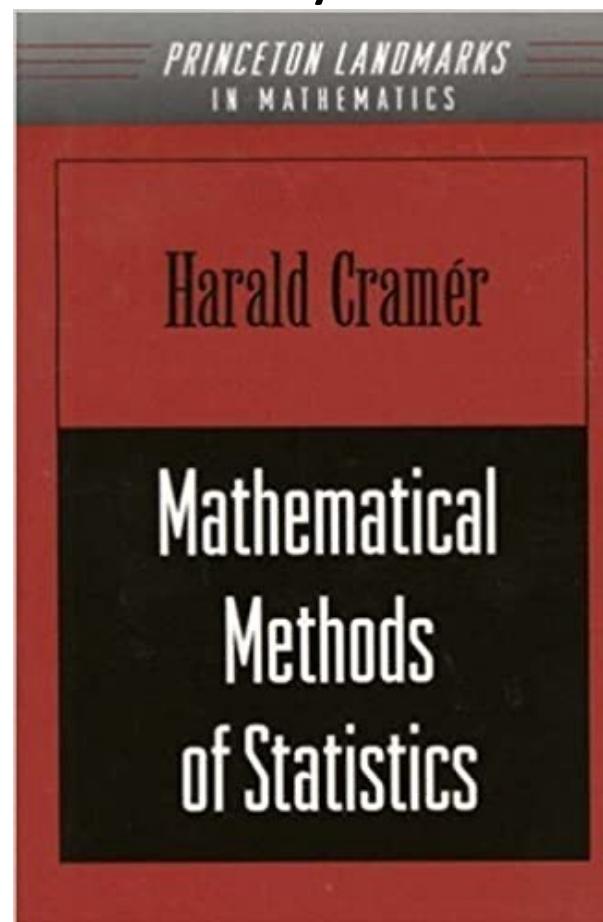
Cramer-Rao Lower Bound

- How good can (some classes of) estimators ever be ?

Cramer-Rao Lower Bound

- Harald Cramér

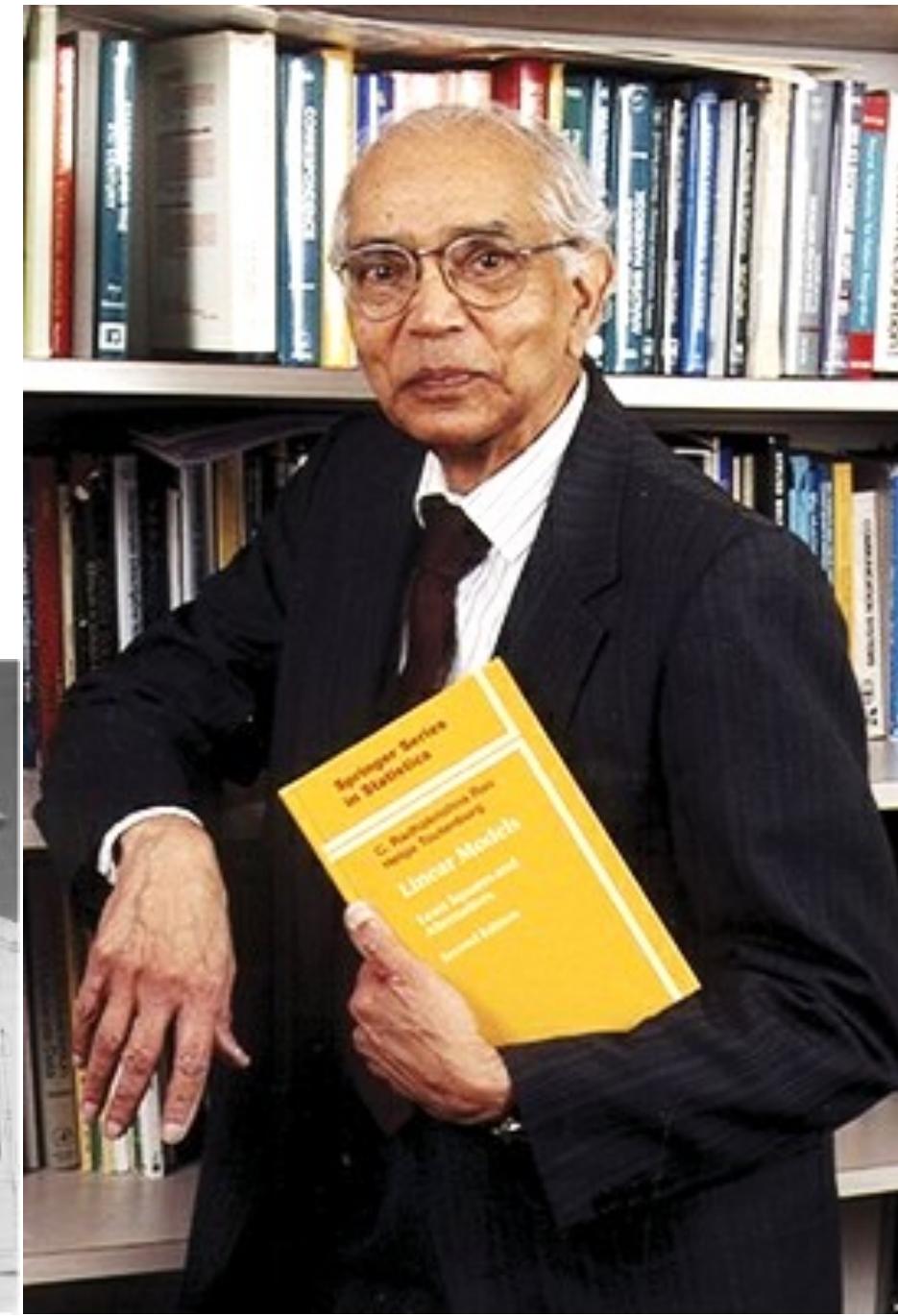
- Swedish mathematician, actuary, statistician, specializing in mathematical statistics
- “One of the giants of statistical theory”
 - Sir John Kingman



Cramer-Rao Lower Bound

- Calyampudi Radhakrishna Rao (Born 1920)

- Doctoral advisor: Fisher
- American Statistical Assoc.: “a living legend”
- bhavana.org.in/c-r-rao-a-life-in-statistics/
- magazine.amstat.org/blog/2020/09/01/crrao/



Cramer-Rao Lower Bound

- Analysis Let RV X model a dataset.

Assumption: Consider an **unbiased** estimator $\hat{\theta}(X)$

$$\text{Then, } E_{P(X|\theta_{\text{true}})}[\hat{\theta}(X) - \theta_{\text{true}}] = 0 = \left(\int_x P(x|\theta)[\hat{\theta}(x) - \theta]dx \right) \Big|_{\theta=\theta_{\text{true}}}$$

This holds for all θ_{true} .

That is, $\int_x P(x|\theta')[\hat{\theta}(x) - \theta']dx$ is a function of θ' that is identically zero. So, its derivative is also identically zero.

$$\text{Thus, } 0 = \frac{\partial}{\partial \theta} \left(\int_x P(x|\theta)[\hat{\theta}(x) - \theta]dx \right) \Big|_{\theta=\theta_{\text{true}}}$$

For convenience, lets call θ_{true} as θ

$$\text{Thus, } \int_x [\hat{\theta}(x) - \theta] \frac{\partial}{\partial \theta} P(x|\theta) dx = \int_x P(x|\theta) dx = 1$$

Assuming integral limits (i.e., support of PDF/PMF) aren't a function of θ

Cramer-Rao Lower Bound

- Analysis

For convenience, lets call θ_{true} as θ

$$\text{Thus, } \int_x [\hat{\theta}(x) - \theta] \frac{\partial}{\partial \theta} P(x|\theta) dx = \int_x P(x|\theta) dx = 1$$

$$\begin{aligned} \text{Thus, } 1 &= \int_x [\hat{\theta}(x) - \theta] P(x|\theta) \frac{\partial}{\partial \theta} \log P(x|\theta) dx \\ &= \int_x \left([\hat{\theta}(x) - \theta] \sqrt{P(x|\theta)} \right) \left(\sqrt{P(x|\theta)} \frac{\partial}{\partial \theta} \log P(x|\theta) \right) dx \\ &= \left[\int_x \left([\hat{\theta}(x) - \theta] \sqrt{P(x|\theta)} \right) \left(\sqrt{P(x|\theta)} \frac{\partial}{\partial \theta} \log P(x|\theta) \right) dx \right]^2 \end{aligned}$$

Using Cauchy-Schwarz inequality, $1 \leq \int_x [\hat{\theta}(x) - \theta]^2 P(x|\theta) dx \cdot \int_x P(x|\theta) \left(\frac{\partial}{\partial \theta} \log P(x|\theta) \right)^2 dx$

Thus, $\text{Var}(\hat{\theta}(X)) \geq I(\theta)^{-1}$

Cramer-Rao Lower Bound

- Application example
 - For any Gaussian random variable, when mean is unknown, when variance is known (σ^2), when sample size = n:
 - We knew that ML estimator (sample mean) is unbiased
 - We knew that variance of ML estimator = σ^2/n
 - We know that Fisher information = n/σ^2
 - So, CRLB implies that any unbiased estimator of the mean will have variance $\geq \sigma^2/n$
 - So, ML estimator is efficient, i.e., minimum-variance unbiased estimator (MVUE)
- When ML estimator is unbiased and minimum-variance (as per CRLB), then why do we need the Bayesian estimator ?
 - For a finite data sample, Bayesian estimation can reduce mean/expected squared error, at the cost of introducing a bias in the estimator

$$\text{Var}(\hat{\theta}(X)) \geq I(\theta)^{-1}$$

Bayesian Statistical Analysis

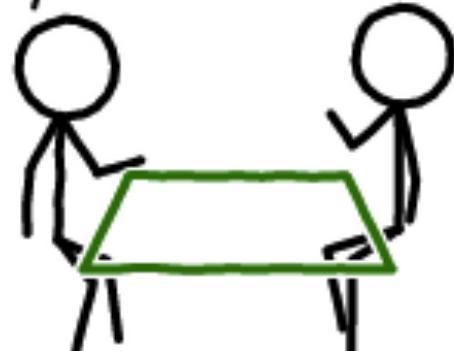
BAYESIAN VERSUS FREQUENTIST

I DON'T KNOW WHY WE
STILL HAVE THIS
"DEBATE" EACH YEAR.

WANT TO TOSS
FOR IT?

I KNOW
ITS A BIT PASSÉ

SURE



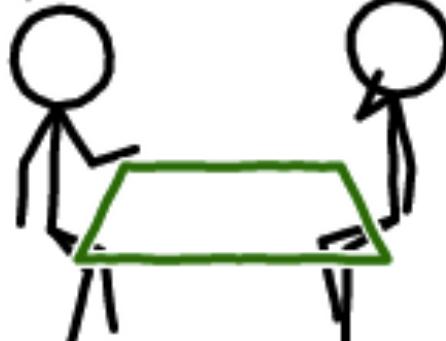
BAYESIAN

FREQUENTIST

MAYBE IT IS
MAYBE IT ISN'T

WAIT A MINUTE -
IS THAT YOUR
BIASED COIN?

HMM TRICKY



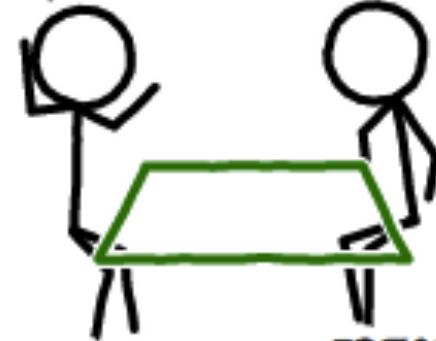
BAYESIAN

FREQUENTIST

WELL OK THEN
TAKING ALL THESE
THINGS INTO
CONSIDERATION . . .
HEADS!

AHA! PRIOR
CONSTRUCTION!
BAYES WINS AGAIN!

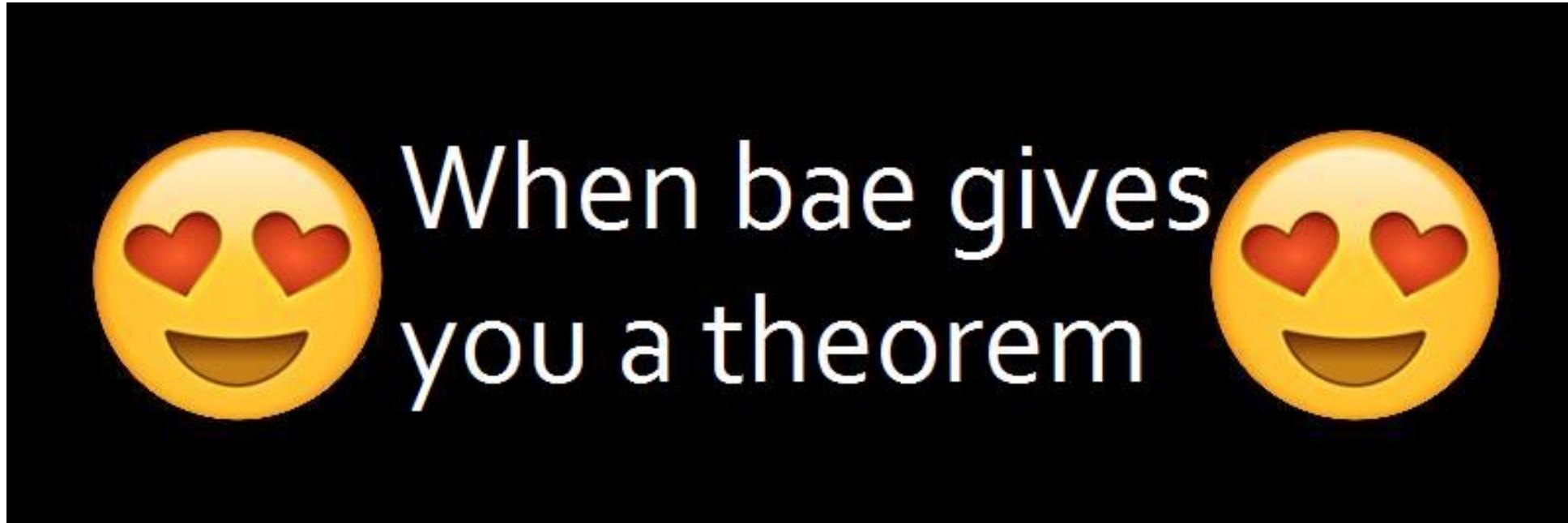
DAMN



BAYESIAN

FREQUENTIST

Bayes Theorem



$$p(B|A) = \frac{p(A|B)p(B)}{p(A)}$$

Bayesian Statistical Analysis

Bayes theorem is bae!

vivekdadhich.hashnode.dev



Vivek Dadhich



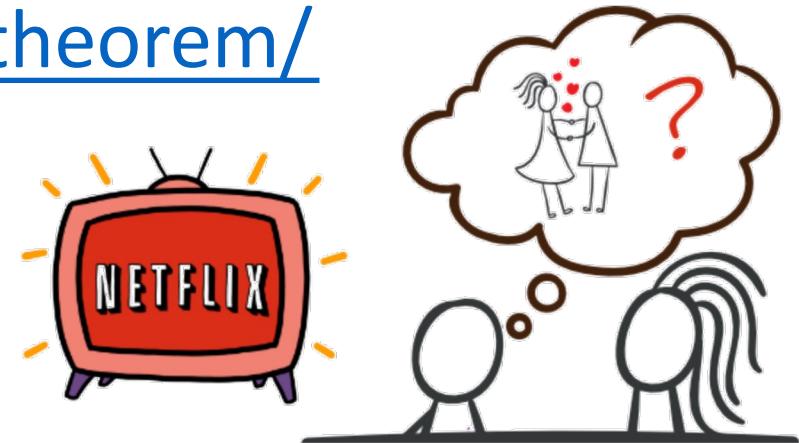
Bayesian Statistical Analysis

- The story around Bae's theorem:

kevinalu.design/content/20200516-bayes-theorem/

Bae's theorem

Bae's theorem can be defined as:



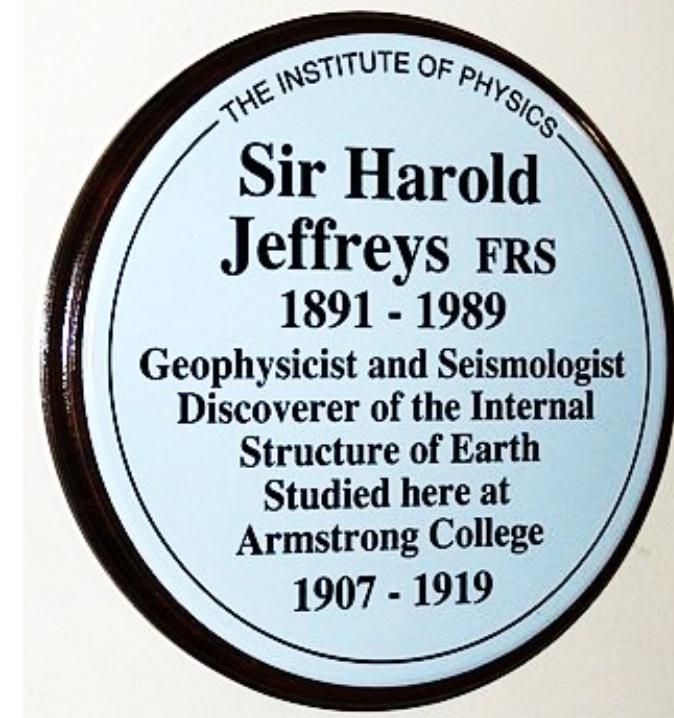
Is Shannon inviting you over for chill, or just Netflix?

$$P(\text{chill} \mid \text{netflix}) = \frac{P(\text{netflix} \mid \text{chill}) P(\text{chill})}{P(\text{netflix})}$$

Bae's theorem: Given evidence of interest, we should update our beliefs on the hypothesis that our person of interest will become bae.

Jeffreys Prior

- Sir Harold Jeffreys
 - Mathematician, statistician, geophysicist, astronomer
 - At University of Cambridge he taught mathematics, then geophysics, and finally became the Plumian Professor of Astronomy
 - Jeffreys H (1946).
“An invariant form for the prior probability in estimation problems”.
Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences. 186(1007):453–461.
- What happens to the functional form of the prior PDF on “parameter” if that “parameter” gets transformed ?
 - In general, the prior PDF’s functional form will change
 - e.g., uniform PDF on original parameter may become a non-uniform PDF on transformed parameter



Jeffreys Prior

- Scale-parameter example motivating Jeffreys prior for Gaussian
 - Consider Gaussian($0, \sigma^2$)
 - Consider flat prior on standard deviation σ as Uniform($0, \infty$)
 - Then, what is the prior on transformed-parameter variance $v := \sigma^2$?
 - Using transformation of random variables,
 $P(v) \propto 1/\sqrt{v}$, for $v>0$:
this prior prefers small variance (inconsistent with uniform)
 - Consider Gaussian($0, v$)
 - Consider flat prior on variance as Uniform($0, \infty$)
 - Then, what is the prior on transformed-parameter standard deviation $\sigma := \sqrt{v}$?
 - Using transformation of random variables,
 $P(\sigma) \propto \sigma$, for $\sigma>0$:
this prior prefers large standard deviation (inconsistent with uniform)
- How to bring “consistency” ? What do we mean by “consistency” ?

Jeffreys Prior

- Effect of re-parametrization on functional form of prior PDF

Consider likelihood $P_\theta(X|\theta)$

Define prior $Q(\theta)$

Let transformed / reparametrized random variable be $\beta := f(\theta)$, where $f(\cdot)$ is strictly monotonic

For example, reparametrizing the univariate zero-mean Gaussian PDF by the variance $\beta := \sigma^2$, instead of the standard deviation $\theta := \sigma$.

Thus, instead of modeling likelihood as $P_\sigma(x|\sigma) := \exp(-0.5x^2/\sigma^2)/(\sigma\sqrt{2\pi})$ with prior as $Q(\sigma)$,

we model likelihood as $P_\beta(x|\beta) := \exp(-0.5x^2/\beta)/(\sqrt{\beta}2\pi)$ with prior as $R(\beta)$.

Note that $P_\beta(x|\beta) = P_{\sigma=\sqrt{\beta}}(x|\sigma = \sqrt{\beta})$, or

in general, $P_\beta(x|\beta) = P_{\theta=f^{-1}(\beta)}(x|\theta = f^{-1}(\beta))$ (because the transformation isn't on X).

Jeffreys Prior

- Effect of re-parametrization on functional form of prior PDF

Consider likelihood $P_\theta(X|\theta)$

Let Fisher information $I(\theta) := E_{P_\theta(X|\theta)} \left[\left(\frac{\partial}{\partial \theta} \log P_\theta(X|\theta) \right)^2 \right]$

Define prior $Q(\theta)$ as $\propto \sqrt{I(\theta)}$

Let transformed / reparametrized random variable be $\beta := f(\theta)$, where $f(\cdot)$ is strictly monotonic

Then, what is the prior PDF $R(\beta)$ on the transformed random variable $\beta := f(\theta)$?

The transformation on the random variable gives $R(\beta) \propto Q(f^{-1}(\beta)) \left| \frac{\partial f^{-1}(\beta)}{\partial \beta} \right|$

$$\propto \sqrt{E_{P_{f^{-1}(\beta)}(X|f^{-1}(\beta))} \left[\left(\frac{\partial \log P_{f^{-1}(\beta)}(X|f^{-1}(\beta))}{\partial f^{-1}(\beta)} \frac{\partial f^{-1}(\beta)}{\partial \beta} \right)^2 \right]}$$

$$= \sqrt{E_{P_{f^{-1}(\beta)}(X|f^{-1}(\beta))} \left[\left(\frac{\partial \log P_{f^{-1}(\beta)}(X|f^{-1}(\beta))}{\partial \beta} \right)^2 \right]} = \sqrt{E_{P_\beta(X|\beta)} \left[\left(\frac{\partial \log P_\beta(X|\beta)}{\partial \beta} \right)^2 \right]} = \sqrt{I(\beta)}$$

(chain rule)

because $P_\theta(X=x|\theta) = P_\beta(X=x|\beta)$ when $\beta=f(\theta)$; see previous slide

Jeffreys Prior

- Effect of re-parametrization on functional form of **posterior PDF**
 - Person 1
 - Designs a likelihood function $L^1_\theta(X|\theta)$; it induces a distribution on θ
 - Designs prior distribution on θ as $Q^1_\theta(\theta)$
 - Defines a posterior distribution on θ as $P^1_\theta(\theta|X) \propto L^1_\theta(X|\theta) Q^1_\theta(\theta)$
 - Person 2
 - Designs a likelihood function $L^2_\beta(X|\beta)$; same generative model as A but reparametrized
 - Designs a prior distribution $Q^2_\beta(\beta)$
 - Defines a posterior distribution $P^2_\beta(\beta|X) \propto L^2_\beta(X|\beta) Q^2_\beta(\beta)$
 - Person 1 uses monotone transformation $\beta := F(\theta)$ leading to posterior $P^1_\beta(\beta|X)$
 - Then mass conservation, and transformation of random variables $\theta := \text{Finv}(\beta)$, implies $P^1_\beta(\beta|X) |d\beta| = P^1_\theta(\theta|X) |d\theta|$, or $P^1_\beta(\beta|X) = P^1_\theta(\theta|X) |\frac{d\theta}{d\beta}|$
 - But, for “consistency”, we want $P^2_\beta(\beta|X) = P^1_\beta(\beta|X)$
i.e., $L^2_\beta(X|\beta) Q^2_\beta(\beta) \propto L^1_{\theta=\text{Finv}(\beta)}(X|\theta=\text{Finv}(\beta)) Q^1_{\theta=\text{Finv}(\beta)}(\theta=\text{Finv}(\beta)) |\frac{d\theta}{d\beta}|$
 - This works if $Q^2_\beta(\beta)$ and $Q^1_\theta(\theta)$ are Jeffreys priors on, respectively, β and θ

Jeffreys Prior

- Designing a prior to be invariant to transformations on parameters is what they/Jeffreys called as making the prior “non-informative”
 - In the sense that different parametrizations of the prior/posterior infuses the same information
- Scale-parameter example motivating Jeffreys prior for $\text{Gaussian}(0, v = \sigma^2)$
 - Jeffreys prior for scale-related parameter standard deviation σ is:
 $P(\sigma) \propto 1/\sigma$
 - Jeffreys prior for scale-related parameter variance $v = \sigma^2$ is:
 $P(v) \propto 1/v$
 - These two priors are “consistent”

Bayesian Cramer-Rao Lower Bound

- A research paper
 - Applications of the van Trees Inequality: A Bayesian Cramer-Rao Bound. Bernoulli 1995, <https://www.jstor.org/stable/3318681>
 - Unlike CRLB, Bayesian-CRLB gives us a lower bound for, both, biased and unbiased estimators
- Statement

Let X model a dataset.

Consider likelihood $P(X|\theta)$ with “parameter” / RV θ

Consider a prior PDF $Q(\theta|\alpha)$ on “parameter” / RV θ with hyper-parameter α

$$E_{Q(\theta|\alpha)}[E_{P(X|\theta)}[\hat{\theta}(X) - \theta]^2] \geq (E_{Q(\theta|\alpha)}[I_P(\theta)] + J_Q(\alpha))^{-1}$$

where

$I_P(\theta)$ is the Fisher information of the likelihood associated with PDF / model $P(X|\theta)$, and $J(Q; \alpha)$ is the “prior information” of the prior PDF / model $Q(\theta|\alpha)$

Bayesian Cramer-Rao Lower Bound

- Analysis

Assumption: Consider the prior θ defined on (compact) interval (a, b) such that:

$$Q(\theta|\alpha) \rightarrow 0 \text{ as } \theta \rightarrow a \text{ and as } \theta \rightarrow b$$

For CRLB, we had:

$$\int_x [\hat{\theta}(x) - \theta] \frac{\partial}{\partial \theta} P(x|\theta) dx = \int_x P(x|\theta) dx = 1$$

Then, similar to our strategy in proving CRLB, lets consider

$$\int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) dx d\theta$$

$$= \int_x \left[\int_{\theta} \hat{\theta}(x) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) \right] d\theta dx - \int_x \int_{\theta} \theta \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) d\theta dx$$



1st term includes the inner integral:

$$\int_{\theta} \hat{\theta}(x) \frac{\partial}{\partial \theta} [P(x|\theta)Q(\theta|\alpha)] d\theta = \hat{\theta}(x) \int_{\theta} \frac{\partial}{\partial \theta} [P(x|\theta)Q(\theta|\alpha)] d\theta = \hat{\theta}(x) [P(x|\theta)Q(\theta|\alpha)]_a^b$$

$= 0$, because the prior $Q(\theta|\alpha)$ goes to zero at the boundary points a and b

So, the 1st term reduces to zero

Assuming derivative exists and is integrable

Bayesian Cramer-Rao Lower Bound

- Analysis

Then, similar to our strategy in proving CRLB, let's consider

$$\int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) dx d\theta$$

$$= \int_x \int_{\theta} \hat{\theta}(x) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) d\theta dx - \int_x \left[\int_{\theta} \theta \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) d\theta \right] dx$$

2nd term (without the negative sign) includes an inner integral:

$$\begin{aligned} \int_{\theta} \theta \frac{\partial}{\partial \theta} [P(x|\theta)Q(\theta|\alpha)] d\theta &= [\theta P(x|\theta)Q(\theta|\alpha)]_a^b - \int_{\theta} P(x|\theta)Q(\theta|\alpha) d\theta \\ &= 0 - \int_{\theta} P(x|\theta)Q(\theta|\alpha) d\theta \end{aligned}$$

So, 2nd term (with the negative sign) equals:

$$\int_x \int_{\theta} P(x|\theta)Q(\theta|\alpha) d\theta dx = \int_{\theta} Q(\theta|\alpha) \left(\int_x P(x|\theta) dx \right) d\theta = 1$$

So, our original term equals 1:

$$1 = \int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) dx d\theta$$

Bayesian Cramer-Rao Lower Bound

- Analysis

So, our original term equals 1:

$$1 = \int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) dx d\theta$$

$$\begin{aligned} &= \int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) P(x|\theta)Q(\theta|\alpha) \frac{1}{P(x|\theta)Q(\theta|\alpha)} \frac{\partial}{\partial \theta} (P(x|\theta)Q(\theta|\alpha)) dx d\theta \\ &= \left[\int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta) \sqrt{P(x|\theta)Q(\theta|\alpha)} \sqrt{P(x|\theta)Q(\theta|\alpha)} \frac{\partial}{\partial \theta} \log (P(x|\theta)Q(\theta|\alpha)) dx d\theta \right]^2 \end{aligned}$$

Now, we apply the Cauchy-Schwarz inequality:

$$1 \leq \left[\int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta)^2 P(x|\theta)Q(\theta|\alpha) dx d\theta \right] \cdot \int_{\theta=a}^b \int_x P(x|\theta)Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log P(x|\theta)Q(\theta|\alpha) \right]^2 dx d\theta$$

where

1st integral = expected squared error (NOT variance; because bias of estimator $\hat{\theta}(x)$ may be non-zero)

2nd integral:

Bayesian Cramer-Rao Lower Bound

- Analysis

$$1 \leq \int_{\theta=a}^b \int_x (\hat{\theta}(x) - \theta)^2 P(x|\theta) Q(\theta|\alpha) dx d\theta \cdot \int_{\theta=a}^b \int_x P(x|\theta) Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log P(x|\theta) Q(\theta|\alpha) \right]^2 dx d\theta$$

1st integral = expected squared error

2nd integral:

$$= \int_{\theta=a}^b \int_x P(x|\theta) Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log P(x|\theta) \right]^2 dx d\theta + \int_{\theta=a}^b \int_x P(x|\theta) Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log Q(\theta|\alpha) \right]^2 dx d\theta$$

$$+ 2 \underbrace{\int_{\theta=a}^b \int_x P(x|\theta) Q(\theta|\alpha) \frac{\partial}{\partial \theta} \log P(x|\theta) \frac{\partial}{\partial \theta} \log Q(\theta|\alpha) dx d\theta}_{}$$

where

$$\text{1st term} = \int_{\theta=a}^b Q(\theta|\alpha) \left(\int_x P(x|\theta) \left[\frac{\partial}{\partial \theta} \log P(x|\theta) \right]^2 dx \right) d\theta = E_{Q(\theta|\alpha)} [I_P(\theta)]$$

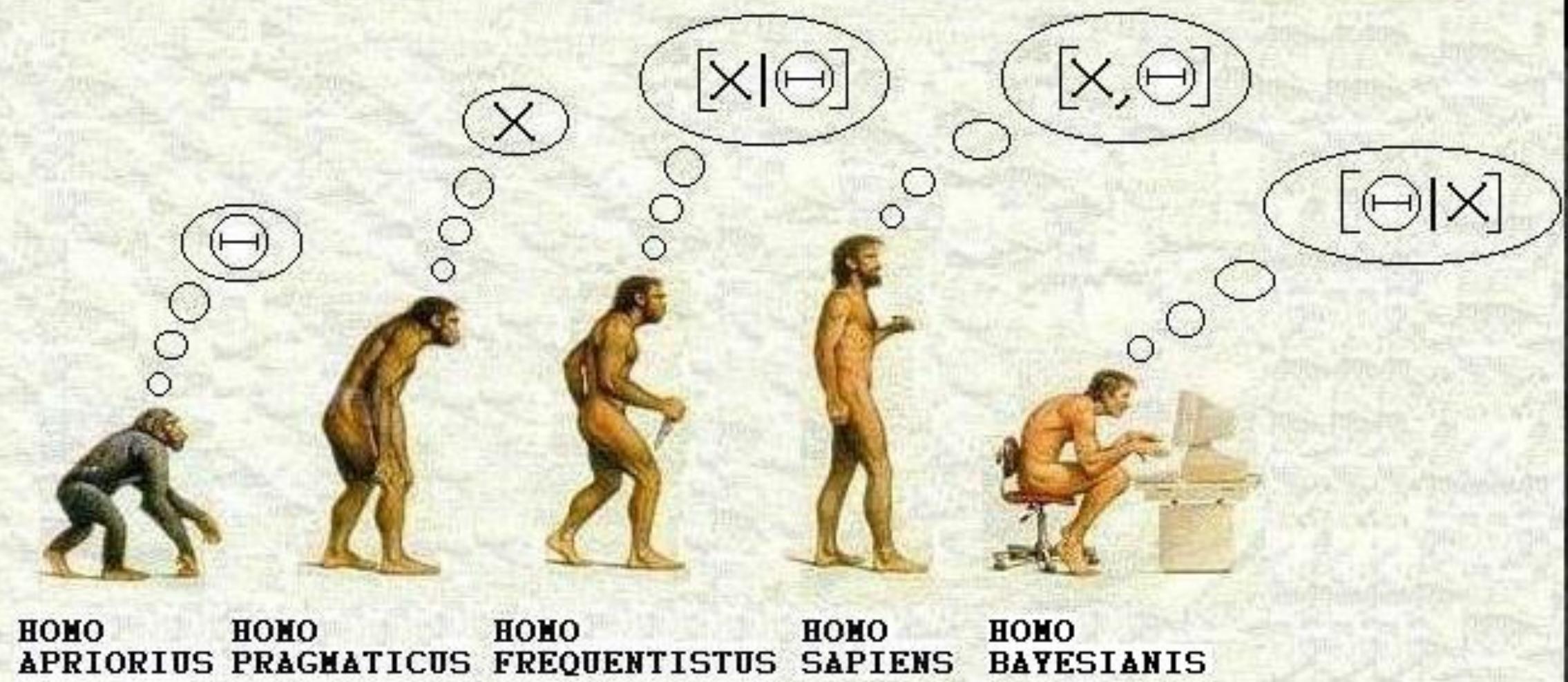
$$\begin{aligned} \text{2nd term} &= \int_{\theta=a}^b \left(\int_x P(x|\theta) dx \right) Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log Q(\theta|\alpha) \right]^2 d\theta = \int_{\theta=a}^b Q(\theta|\alpha) \left[\frac{\partial}{\partial \theta} \log Q(\theta|\alpha) \right]^2 d\theta \\ &= J(Q; \alpha) \end{aligned}$$

$$\text{3rd term} = 2 \int_{\theta=a}^b \frac{\partial}{\partial \theta} Q(\theta|\alpha) \cdot \int_x \frac{\partial}{\partial \theta} P(x|\theta) dx \cdot d\theta = 0, \text{ because the inner integral is zero}$$



Bayesians

(YET ANOTHER) HISTORY OF LIFE AS WE KNOW IT...



Thank You