

# Expectations and Sampling Methods

Aubrey Yan

# What we've focused on so far...

Monte Carlo Method

Importance Sampling

Rejection Sampling

Bayesian Inference (prior, posterior...)

Maximum Likelihood Estimation

# Monte Carlo Method

coin-flipping, card-drawing, needle-tossing...

RV:  $X$ , pmf/pdf:  $f_X(x)$

$$\mathbb{E}(g(X)) = \sum_{x \in \mathcal{X}} g(x) f_X(x)$$

$$\mathbb{E}(g(X)) = \int_{x \in \mathcal{X}} g(x) f_X(x) dx$$

$$\tilde{g}_n(x) = \frac{1}{n} \sum_{i=1}^n g(x_i)$$

MC estimate

$$\lim_{n \rightarrow \infty} P(|\tilde{g}_n(X) - \mathbb{E}(g(X))| \geq \epsilon) = 0.$$

$$\mathbb{E}(\tilde{g}_n(X)) = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n g(X_i)\right) = \frac{1}{n} \sum_{i=1}^n \mathbb{E}(g(X_i)) = \mathbb{E}(g(X)).$$

unbiased

# Importance Sampling

RV:  $X$ , density:  $h(x)$

$$\int_{x \in A} g(x) dx = \int_{x \in A} g(x) \frac{h(x)}{h(x)} dx = \int_{x \in A} \frac{g(x)}{h(x)} h(x) dx = \mathbb{E}_h \left( \frac{g(X)}{h(X)} \right)$$

MC Estimator:

$$\widetilde{g}_n^h(X) = \frac{1}{n} \sum_{i=1}^n \frac{g(X_i)}{h(X_i)} \quad \text{where} \quad X_i \sim h(x).$$

# Rejection Sampling

RV:  $X$ , pdf:  $f(x)$ , “proposal function”:  $g(x)$

$$u * M * g(x) \leq f(x) \Rightarrow u \leq \frac{f(x)}{M * g(x)}$$

Optimal:

$$M = \sup \left\{ \frac{f(x)}{g(x)} \right\}$$

# Bayesian Inference

**Frequentist Statistics** tests whether an event (hypothesis) occurs or not.

P-values, Confidence Intervals

**Bayesian Statistics** is a mathematical procedure that applies probabilities to statistical problems.

Conditional Probability:  $P(A|B) = \frac{P(A \cap B)}{P(B)}$

Bayes Theorem:  $P(\theta|D) = \frac{P(D|\theta) * P(\theta)}{P(D)}$

$P(\theta)$ : prior                       $P(D|\theta)$ : likelihood

$P(D)$ : evidence                       $P(\theta|D)$ : posterior

# Maximum Likelihood Estimation

Assuming a statistical model parameterized by a fixed and unknown  $\theta$ , the **likelihood function**,  $L(\theta)$ , is the probability of the observed data  $\mathbf{x}$  considered as a function of  $\theta$ .

$$l(\theta) = \ln L(\theta)$$

MLE satisfies  $dl(\theta)/d\theta=0$

# Safety and Efficacy of the BNT162b2 mRNA Covid-19 Vaccine

<https://static.us.edusercontent.com/files/607fZpdG97uurk89EkNQaRWX>

Vaccine Efficacy against Covid-19 at least 7 days after 2nd dose

Group	Cases	No. subjects
BNT162b2	8	17,411
Placebo	162	17,511
Total	170	34,922



# Safety and Efficacy of the BNT162b2 mRNA Covid-19 Vaccine

Beta Binomial Model with Transformation:

$\Theta \sim \text{Beta}(0.7000102, 1)$  prior

$$\theta = \frac{\pi_v}{\pi_v + \pi_p}$$

Claims:

1. Vaccine efficacy  $\Psi = (1-2\theta)/(1-\theta) = 95\%$
2. Posterior probability  $P(\Psi > 30\%) > 0.9999$

# Safety and Efficacy of the BNT162b2 mRNA Covid-19 Vaccine

$$X \sim \text{Binom}(n_v = 17411, p = \pi_v)$$

$$Y \sim \text{Binom}(n_p = 17511, p = \pi_p).$$

$W = X | (X+Y=n) :$

$$W \sim \text{Binom}(n = n_v + n_p, \theta = \frac{n_v \pi_v}{n_v \pi_v + n_p \pi_p})$$

$$W \sim \text{Binom}(n = 170, \theta = \frac{\pi_v}{\pi_v + \pi_p})$$

# Vaccine Efficacy = 95%

Observation:  $w = 8$

$$L(\theta) = P(W = 8) \propto \theta^8 (1 - \theta)^{170 - 8}, \quad 0 < \theta < 1$$

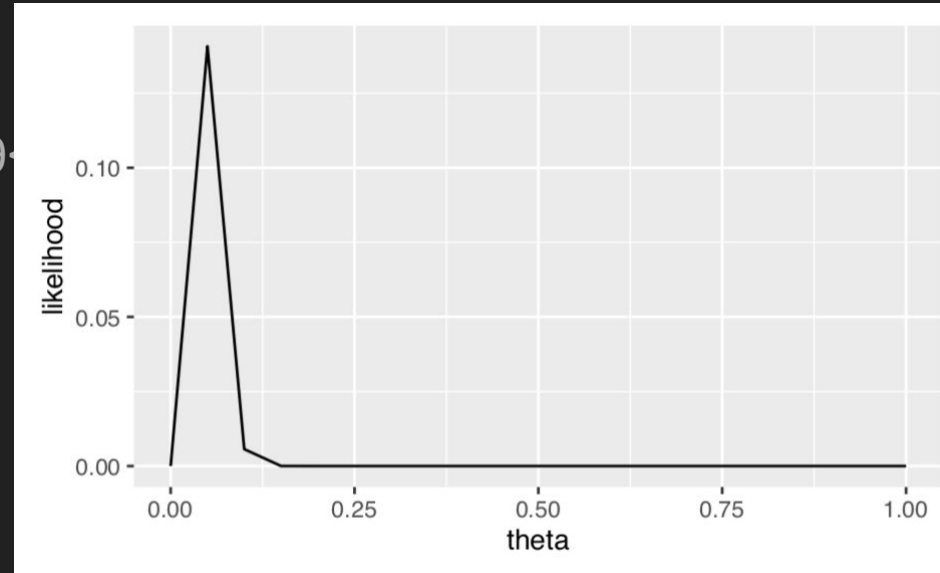
$$l(\theta) = 8 \ln \theta + 162 \ln(1 - \theta)$$

$$\text{MLE satisfies } l'(\theta) = 8/\theta - 162/(1 - \theta) = 0$$

$$\hat{\theta} = 4/85 = 0.04706$$

$$l''(\theta) < 0$$

(Newton-Raphson method provides the same result)



# Vaccine Efficacy = 95%

$$H_0 : \theta = 0.0476$$

$$H_1 : \theta \neq 0.0476$$

$$L(\theta) \propto \theta^8 (1 - \theta)^{(170-8)}$$

$$\lambda = \frac{L(\theta_0)}{L(\hat{\theta})} = \frac{0.0476^8 (1 - 0.0476)^{162}}{\frac{4}{85}^8 \left(1 - \frac{4}{85}\right)^{162}} = 0.999449$$

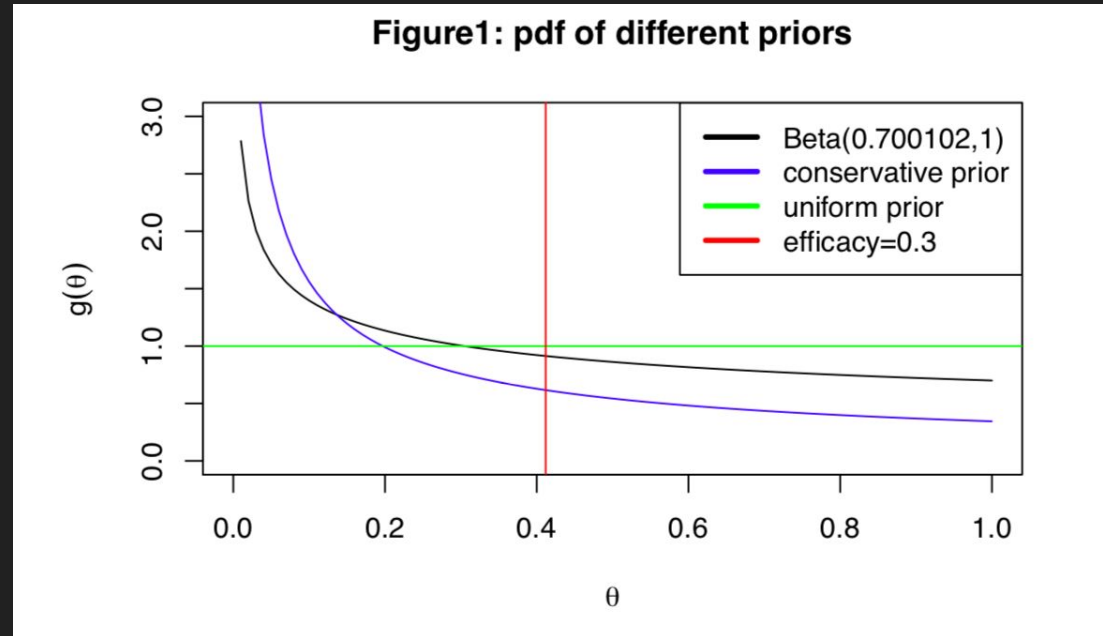
$$m = -2 \ln \lambda = 0.001102$$

$$p\text{-value} = P(\text{chisq}(df = 1) \geq m) = 1 - \text{pchisq}(q = m, df = 1) = 0.9735143$$

Posterior probability  $P(\Psi > 30\%) > 0.9999$

Corresponding to  $\theta$ :  $P(\theta \leq 0.4118) > 0.9999$

P-value =  $5.988e-28 \ll 0.0001$



# Bayesian Inference

$$E(\Psi) = 0.1$$

$$E(\theta) = (1-0.1)/(2-0.1)$$

$$= a/(a+\beta)$$

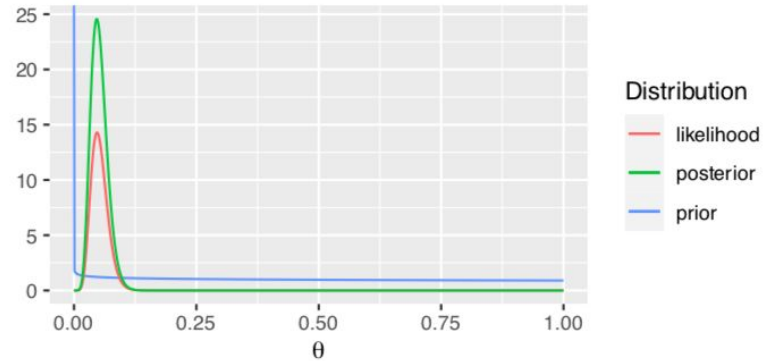
$$\beta = 1:$$

new prior Beta(0.9, 1),

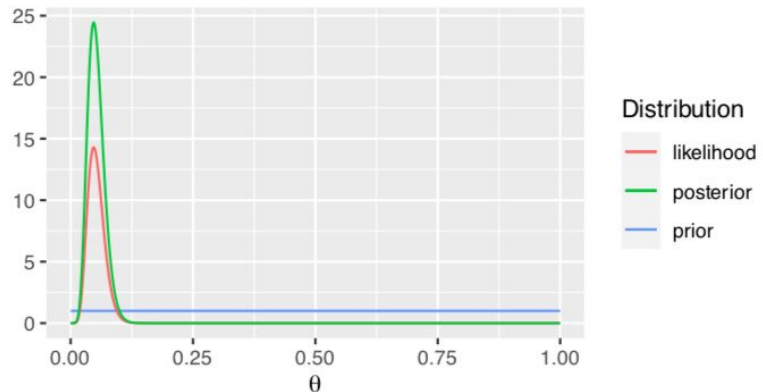
uniform prior Beta(1, 1)

Posterior: Beta(0.9+8, 1+170-8),  
Beta(1+8, 1+170-8)

Posterior, conservative prior and likelihood (multiplied by 100)



Posterior, inform prior and likelihood (multiplied by 100)



# Bayesian Inference

Table 1: Median and 95% HPD interval for  $\theta$

Distribution	Median	Lower	Upper	Width
Conservative Prior	0.4629374	0	0.9446	0.9446
Conservative Posterior	0.0501	0.0213	0.0854	0.064
Uniform Prior	0.5	0.05	1	0.95
Uniform Posterior	0.0506	0.0217	0.086	0.0643
Posterior Paper	0.0489	0.0206	0.0839	0.0633

Med = 94.73%

95% posterior interval = [90.67%, 97.82%]

THANK YOU