

OCT 18

$$\Gamma(n) = (n-1)!$$

Review: Maximum likelihood

example: Gamma distribution

$$f(x) = \frac{\lambda^r x^{r-1} e^{-\lambda x}}{\Gamma(r)} \quad x \geq 0$$

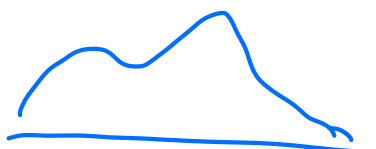
sum of exponential random var.

Note: If $X_1, \dots, X_r \sim \text{exp}(\lambda)$
 $\sum_{i=1}^r X_i \sim \text{Gamma}(r, \lambda)$

X_1, X_2, \dots, X_n IID from this distribution

How do I estimate r and λ

NEW
TODAY: p -values


$$\Gamma(r) = \int_0^{\infty} \lambda^r x^{r-1} e^{-\lambda x} dx$$

Background

Given data X_1, \dots, X_n

- Pose model for data (e.g. appropriate distribution)
- Identify unknown parameters
- Use data to estimate parameters

Example: Want to estimate probability of engine failure in first 100k miles

Data: 250 engines, 31 failures

Model: ? Binomial(n, p) $n=250$ $X = \# \text{ failures}$
 $X \sim \text{Binomial}(250, p)$

Estimate: ? p unknown, estimate by $31/250$

Bonus: How certain are we?

Simulation / Theory

$$X_i = \begin{cases} 1 & \text{if failure} \\ 0 & \text{o/w} \end{cases}$$

$$X_1, \dots, X_{250}$$

$$S_n = \sum_{i=1}^{250} X_i$$

Bernoulli(p)

Bin($1, p$)

$$E X_i = 1 \cdot p + 0(1-p) = p$$

(Expected value)

sample mean

Can always estimate expectation $E X_i$ by

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$$

In this case $\bar{x} = \frac{\# \text{ failures}}{250}$

Simulate 1000 times this model

$$S \sim \text{Binomial}(250, p)$$

$$\frac{S_1}{250}$$



$$S_1, \dots, S_{1000}$$

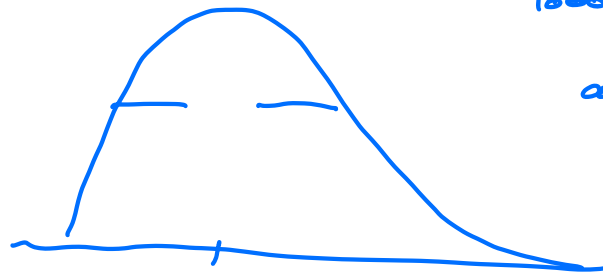
$$\bar{S} =$$

$$\frac{S_{1000}}{250}$$



↳ DON'T KNOW, BUT...

WE USE ESTIMATE $\hat{p} = 3/250$



$$31/250$$

p ← used in simulation

1000 simulated values of \hat{p}
approx to distn of \hat{p}

Computing sample standard deviation

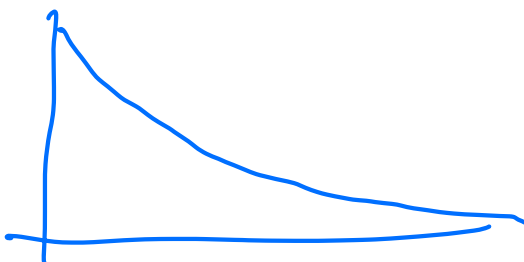
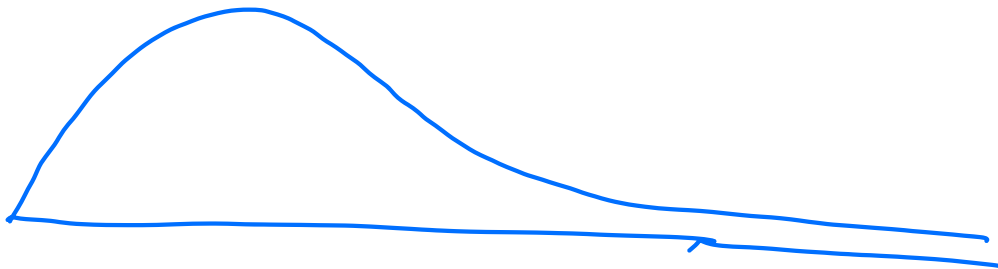
$$x_1, \dots, x_n$$

$$\sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} = \hat{\sigma}$$

Estimate of

$\sigma = \text{STANDARD DEVIATION OF } X_i$

$$\sqrt{\text{Var}(X_i)} = \sqrt{E(X_i - EX_i)^2}$$



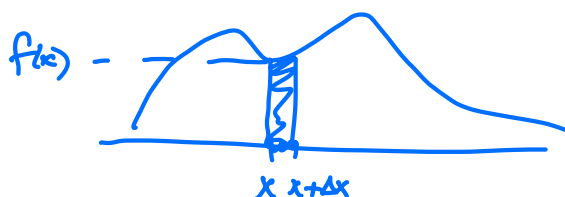
Likelihood function

observed values x_1, \dots, x_n

1st write $P(\text{DATA} | r, \lambda) = P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n | r, \lambda)$
 $= f(x_1) \dots f(x_n)$

$n = 4$ $x_1 = 2.1, x_2 = 3.5, x_3 = 3.1, x_4 = 1.8$

If X has density $f(x)$ $f(x)dx \approx P(x \leq x+dx)$



$$f(x_1) \dots f(x_n) = \frac{1}{\prod_{i=1}^n \Gamma(r)} \frac{\lambda^r}{\pi_i^{r-1}} e^{-\lambda x_i} P(\text{DATA} | r, \lambda)$$

Regarding as a function of parameters (ie x_1, \dots, x_n fixed)
 r, λ



$$L(r, \lambda) = \frac{1}{\Gamma(r)^n} (\prod x_i)^{r-1} e^{-\lambda \sum x_i}$$

$$\log \prod_{i=1}^n f(x_i) = \sum_{i=1}^n \log f(x_i)$$

Comment: maximizing $\log L$ same as maximizing L

