

Data

$y_1 \ y_2 \ \dots \ y_n$

$x_1 \ x_2 \ \dots \ x_n$

Model

$$\left\{ \begin{array}{l} \text{for } i \text{ in } 1 \dots n \\ y_i \sim \mathcal{N}(\mu_i, \sigma^2) \\ \mu_i = \beta_0 + \beta_1 x_i \end{array} \right.$$

assumed model
normal
linear
model

unknowns: $\beta_0, \beta_1, \sigma^2$

Inference

classical

Bayesian

data model unknowns

Bayes's theorem

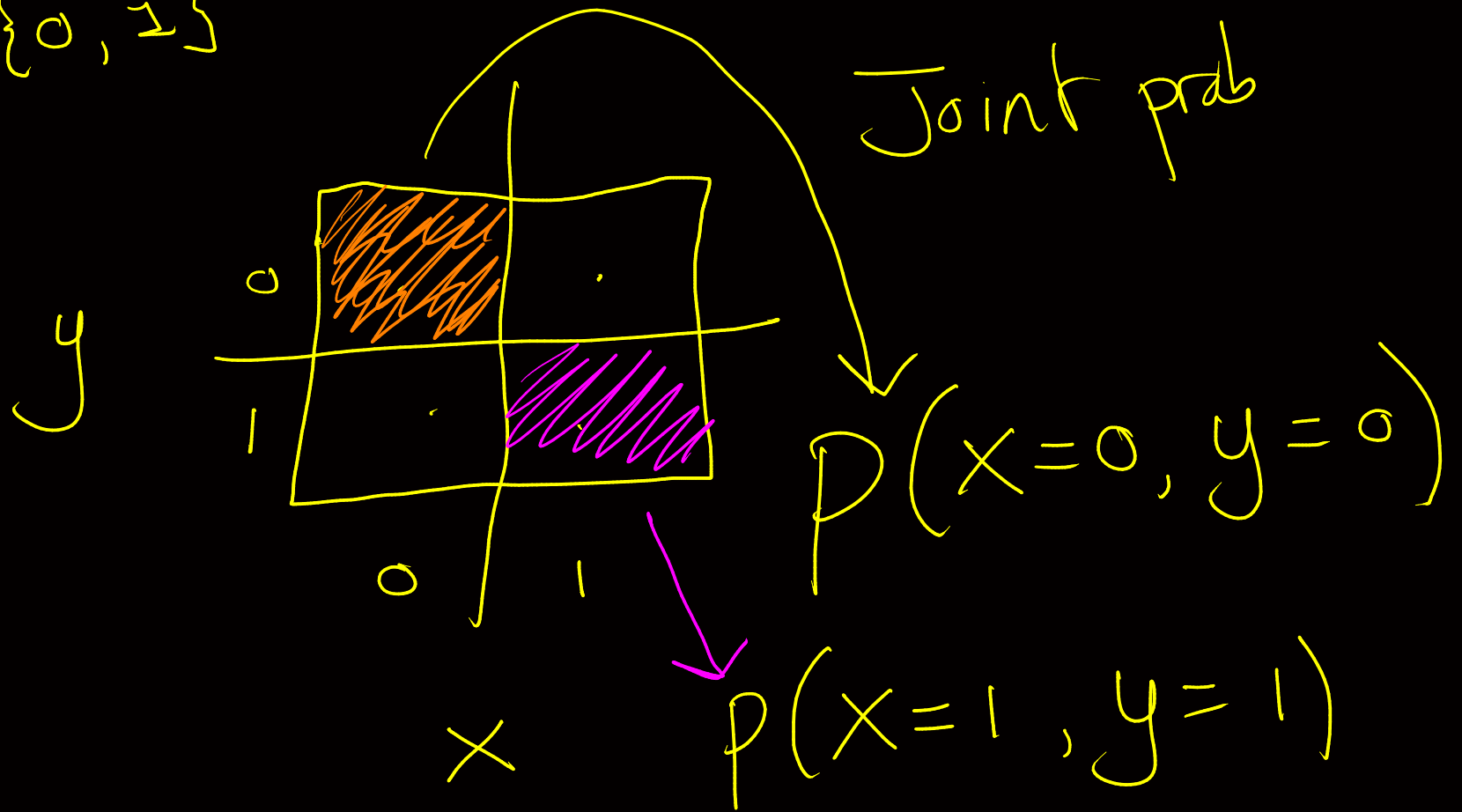
$$\underbrace{P(\text{unknowns} \mid \text{data}, \text{model})}_{\text{posterior}}$$

$$\tilde{\beta}_0 \quad \tilde{\beta}_1 \quad \tilde{\sigma} \quad p(\text{unknowns} = \tilde{\beta}_0, \tilde{\beta}_1, \tilde{\sigma} \mid \text{data}, \text{model})$$

$$= \frac{p(\text{data} \mid \tilde{\beta}_0, \tilde{\beta}_1, \tilde{\sigma}, \text{model}) p(\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\sigma} \mid \text{model})}{\int p(\text{data} \mid \tilde{\beta}_0, \tilde{\beta}_1, \tilde{\sigma}, \text{model}) p(\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\sigma} \mid \text{model})}$$

$$X \in \{0, 1\}$$

$$Y \in \{0, 1\}$$



$$p(x=0, y=1)$$

$$= p(x=0 | y=1) p(y=1)$$

$$= p(y=1 | x=0) p(x=0)$$

$$p(y=1 | x=0) p(x=0) = p(x=0 | y=1) p(y=1)$$

$$p(y=1 | x=0) = \frac{p(x=0 | y=1) p(y=1)}{p(x=0)}$$

y_1, y_2, \dots, y_n $n=250$

$y_i \in \{H, T\}$

Prob of
Heads

$\left\{ \begin{array}{l} \text{for } i \text{ in } 1 \dots n \\ y_i \sim \text{Bernoulli}(\theta) \end{array} \right\}$

T

H

θ

Bernoulli

$$y_1, y_2, \dots, y_n$$

$$\theta$$

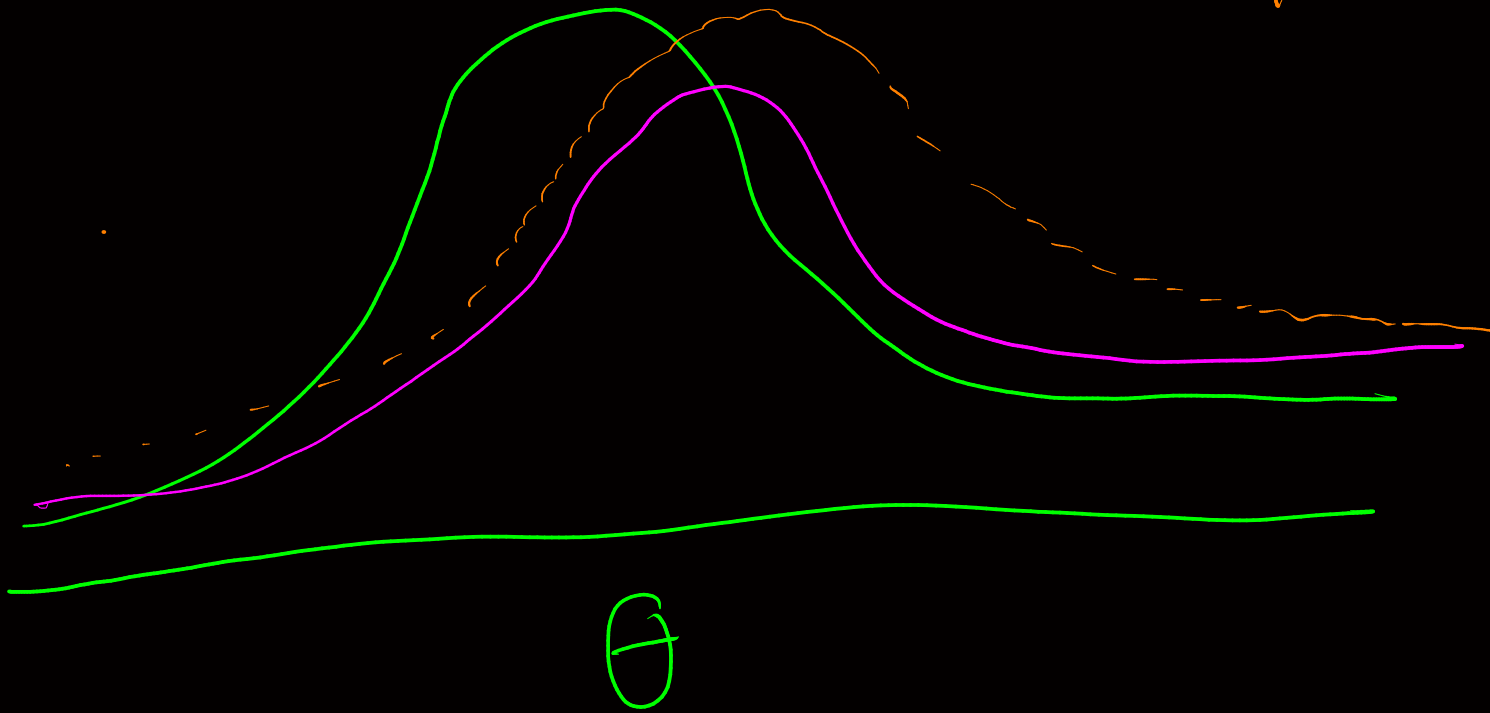
$$\text{Likelihood: } p(y_1, \dots, y_n | \theta)$$

$$= \prod p(y_i | \theta)$$

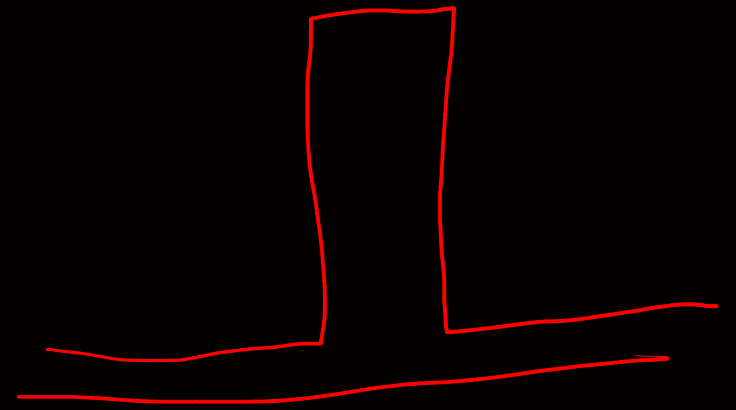
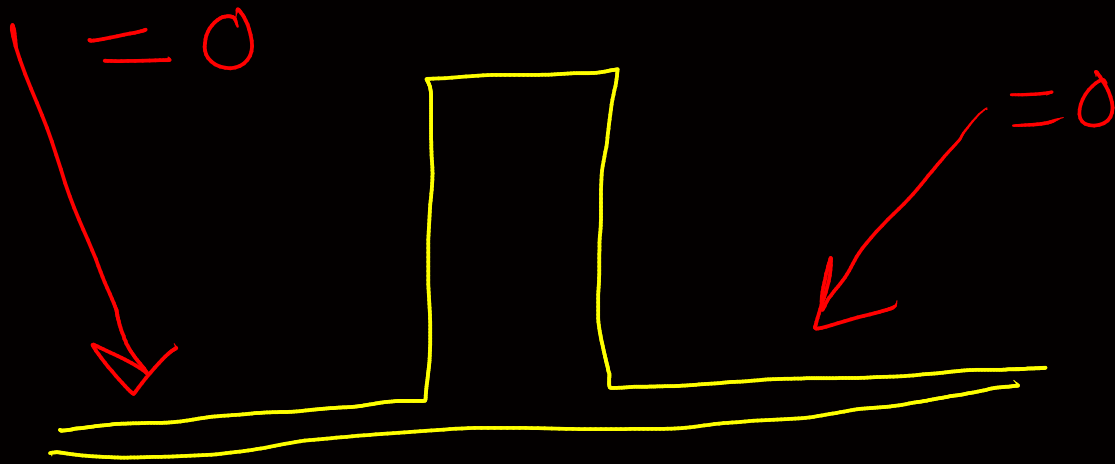
$$\frac{p(D | \theta = 0.4)}{p(D | \theta = 0.6)}$$

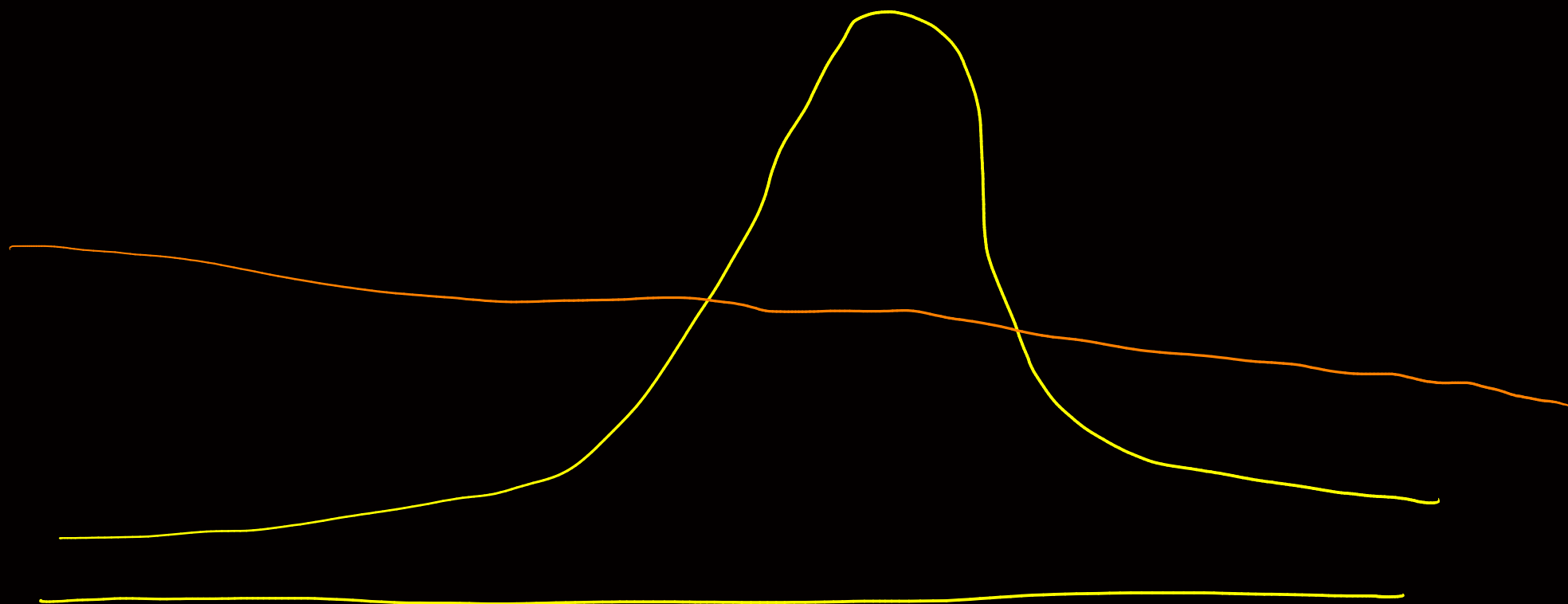
$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{\int_0^1 p(D|\theta)p(\theta) d\theta}$$

marginal likelihood



$$p(\theta|D) \propto p(D|\theta) \times p(\theta)$$

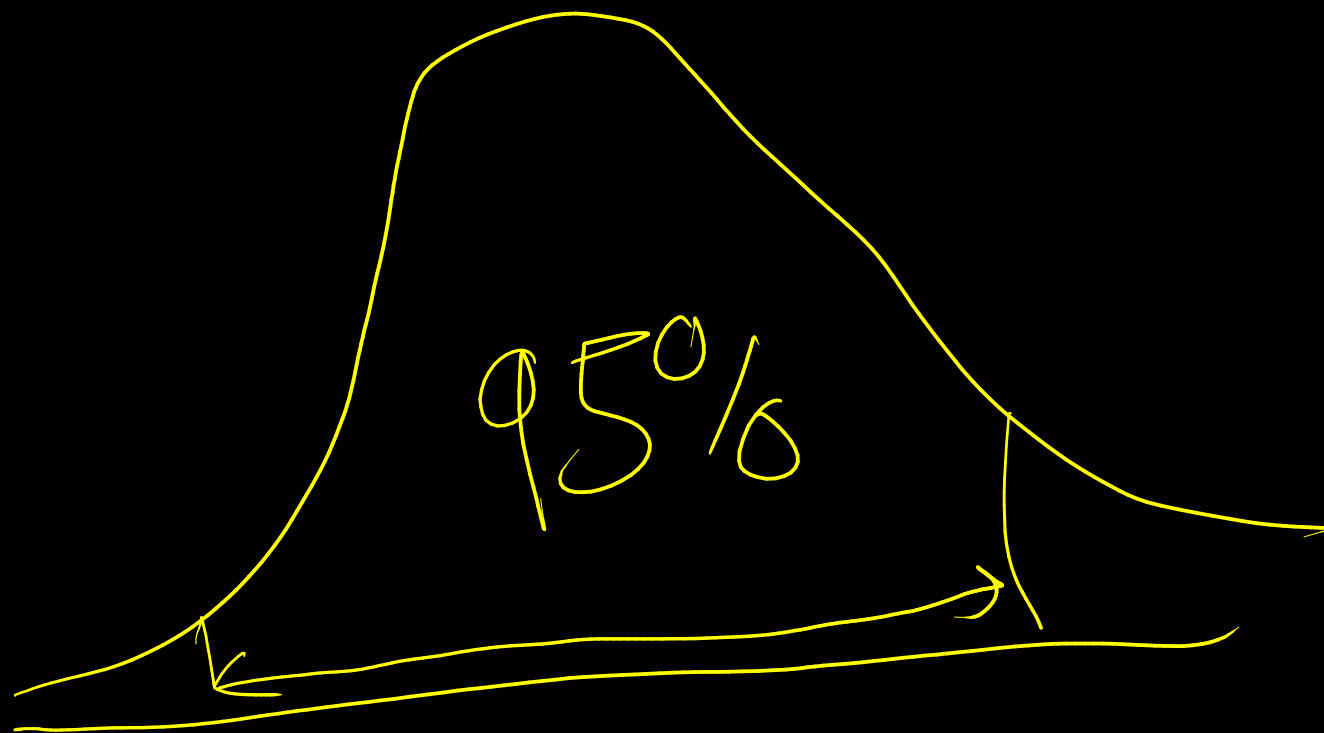




$$\frac{1}{\sigma^2}$$

$$\theta$$

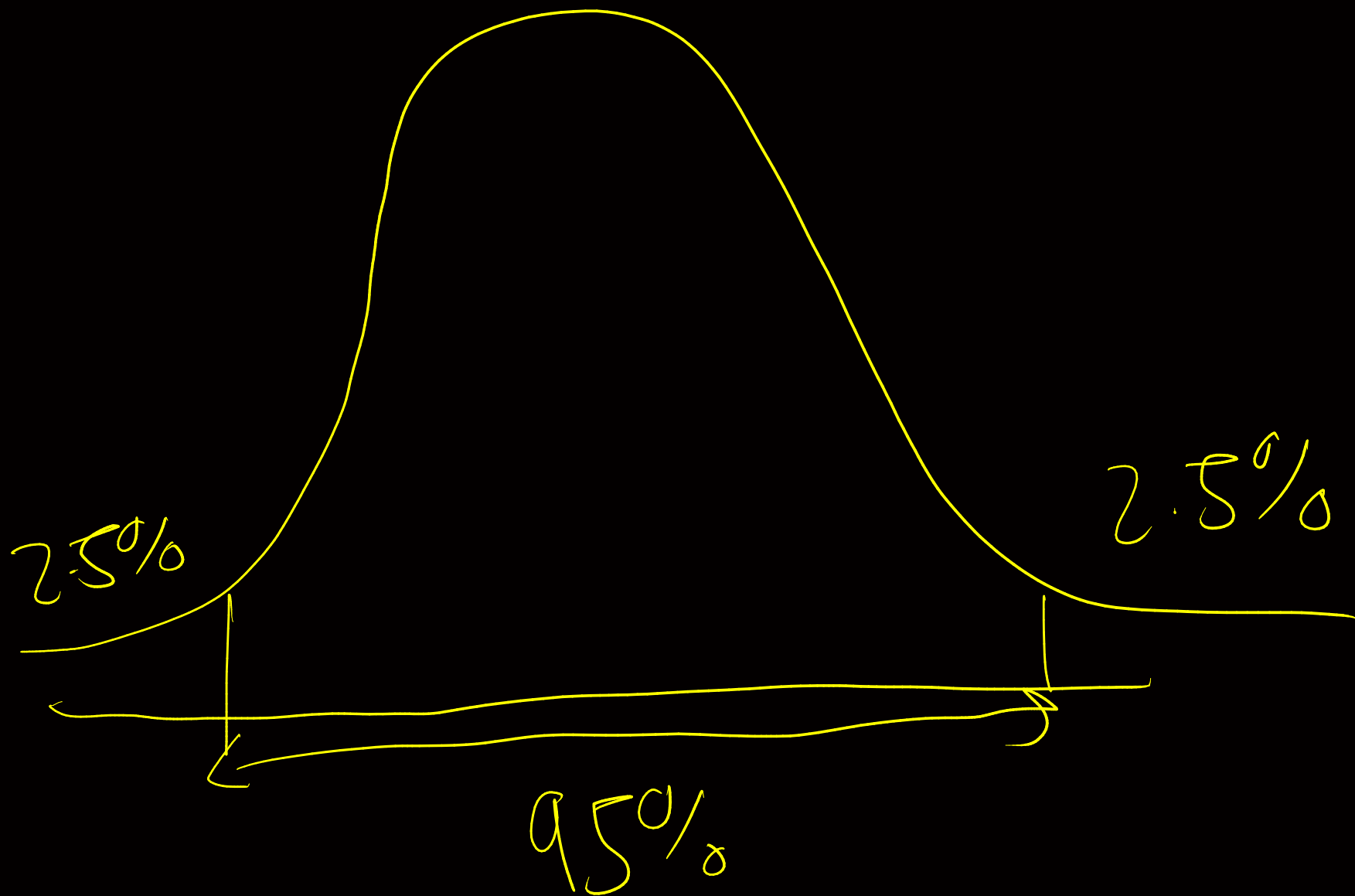
$$\log \left(\frac{\theta}{1-\theta} \right)$$

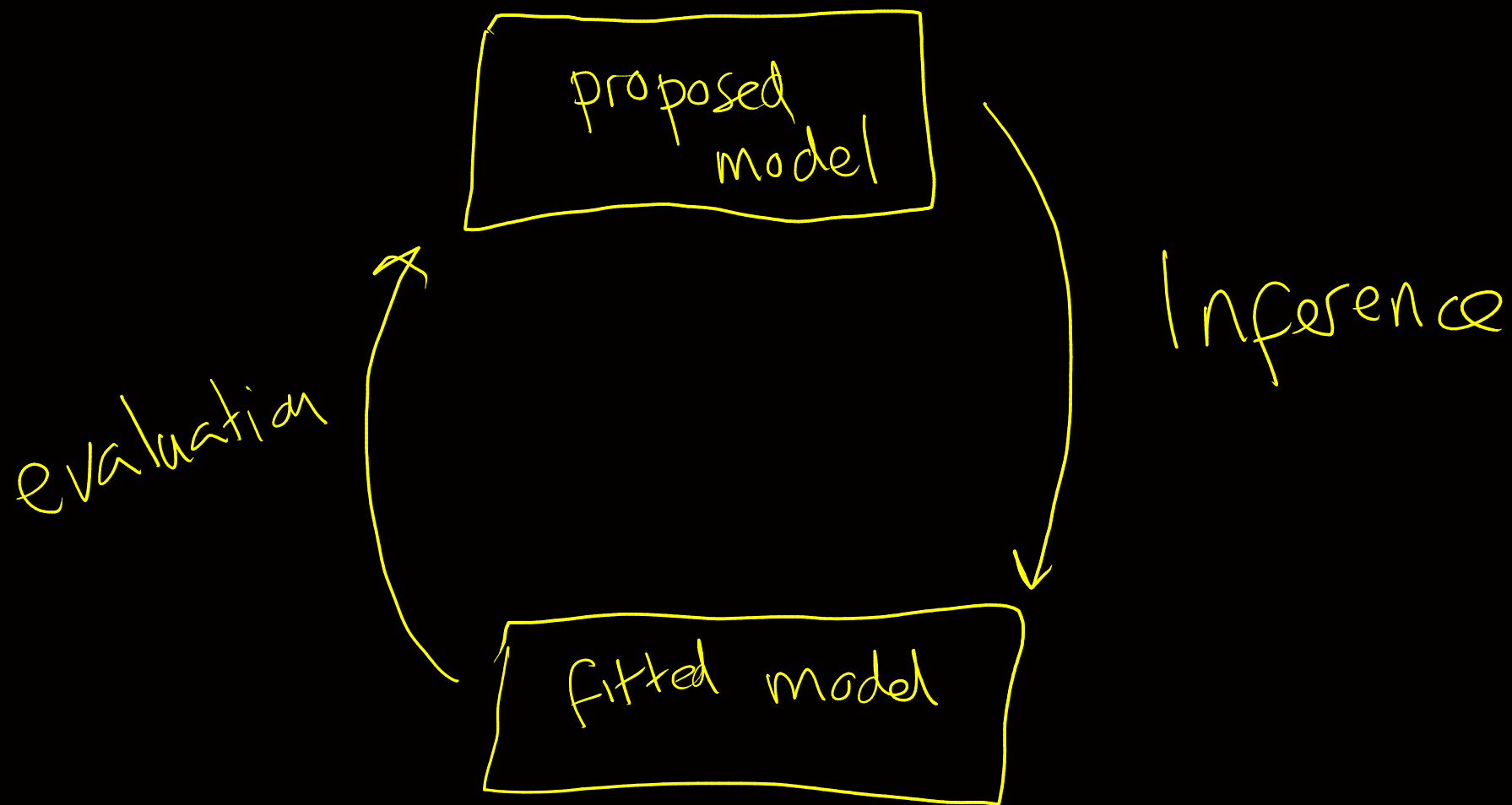


95%

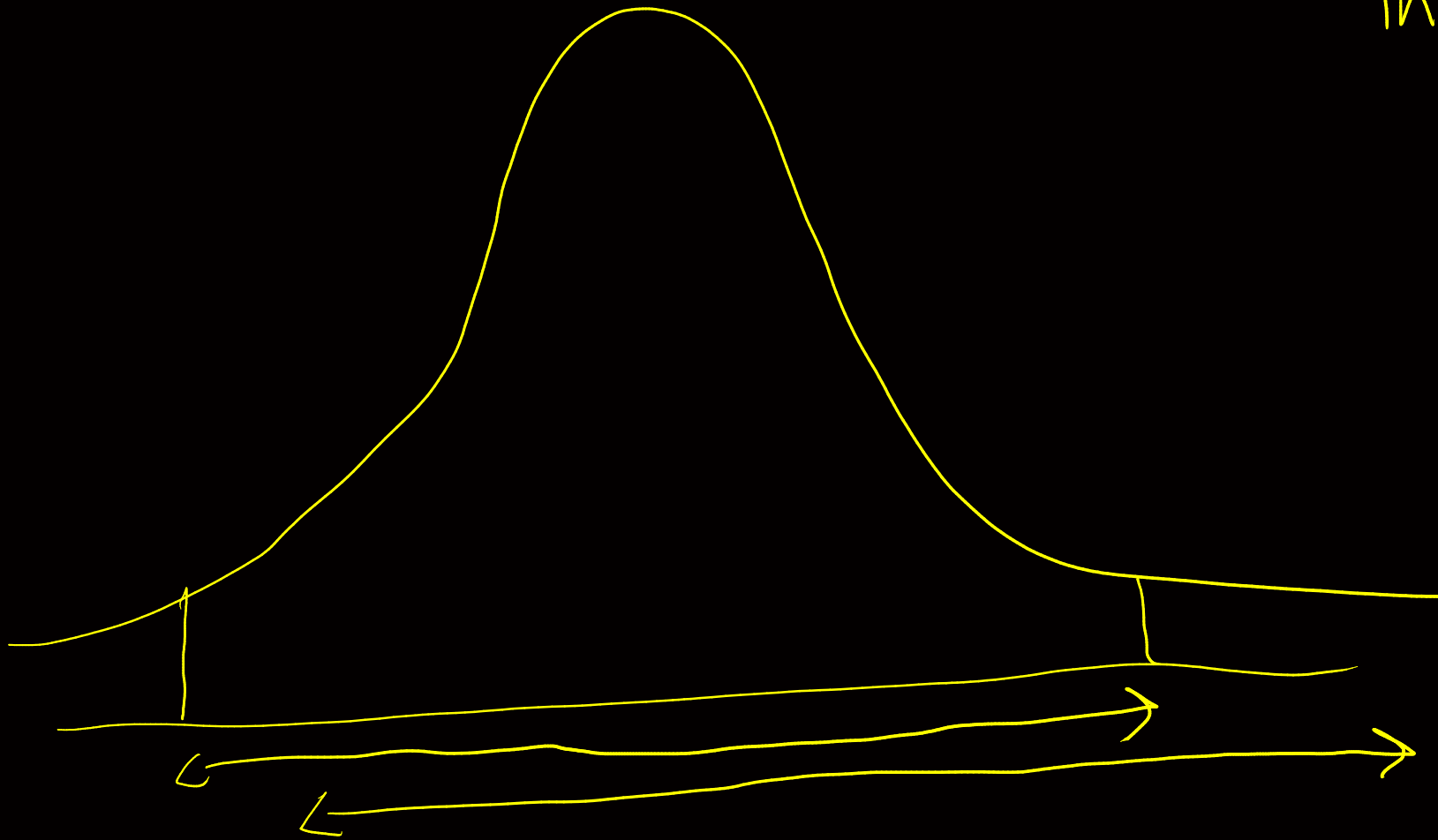
95 HPD

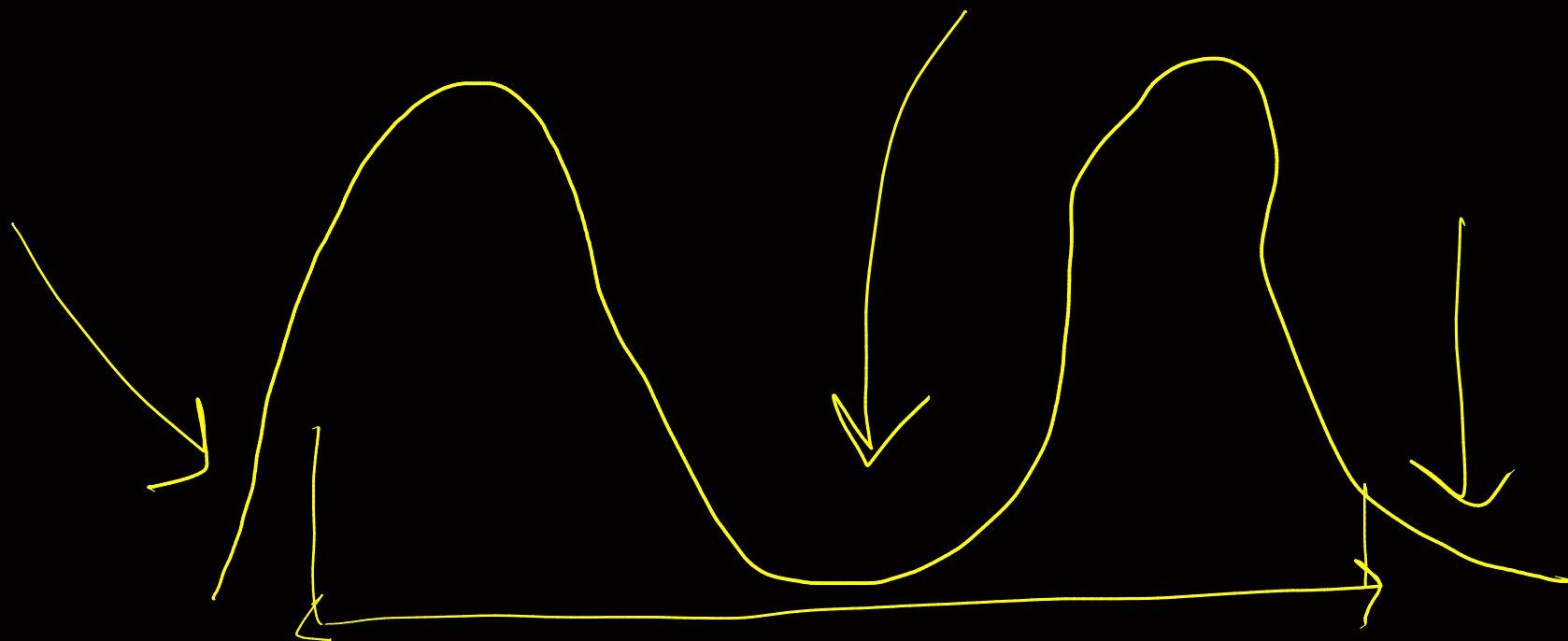


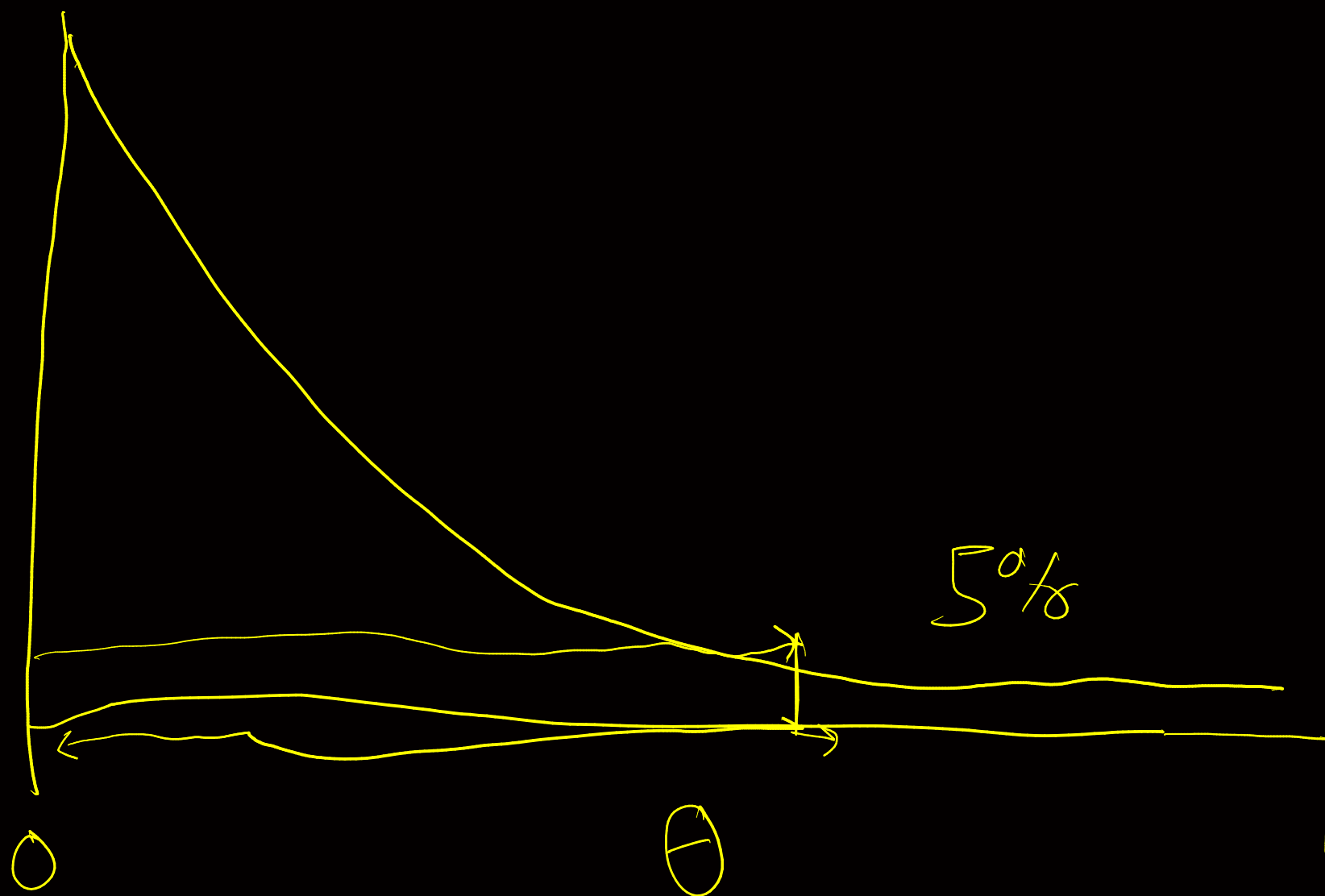




95% posterior interval







$y_1 \quad y_2 \quad \dots \quad y_n$

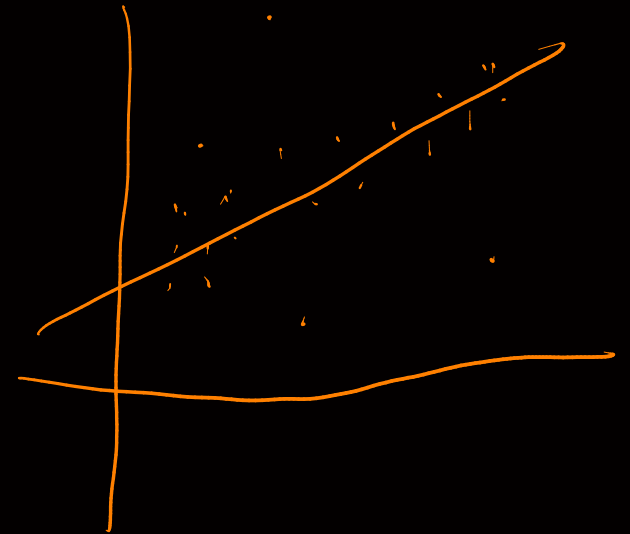
$x_1 \quad x_2 \quad \dots \quad x_n$

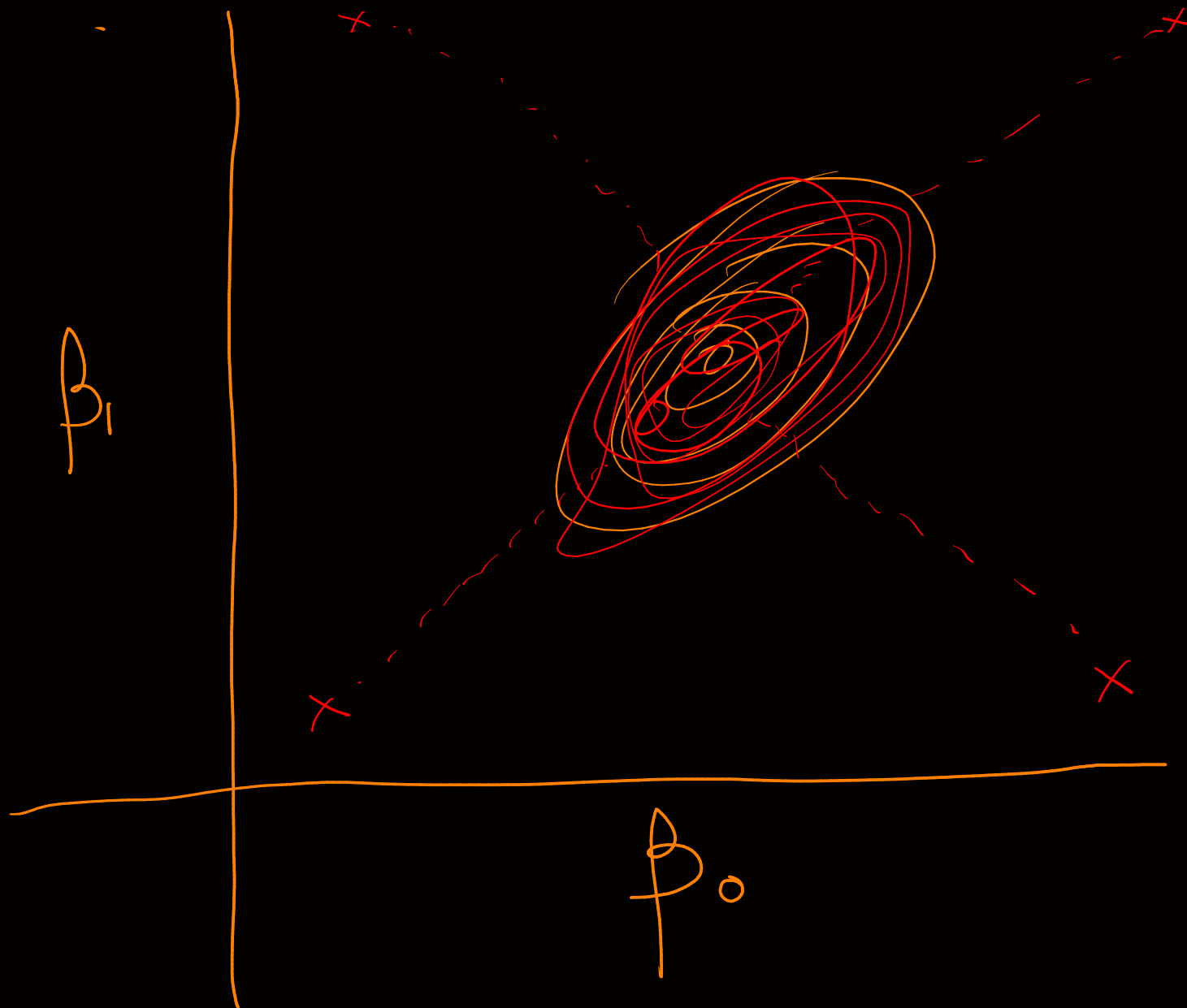
for i in $1 \dots n$

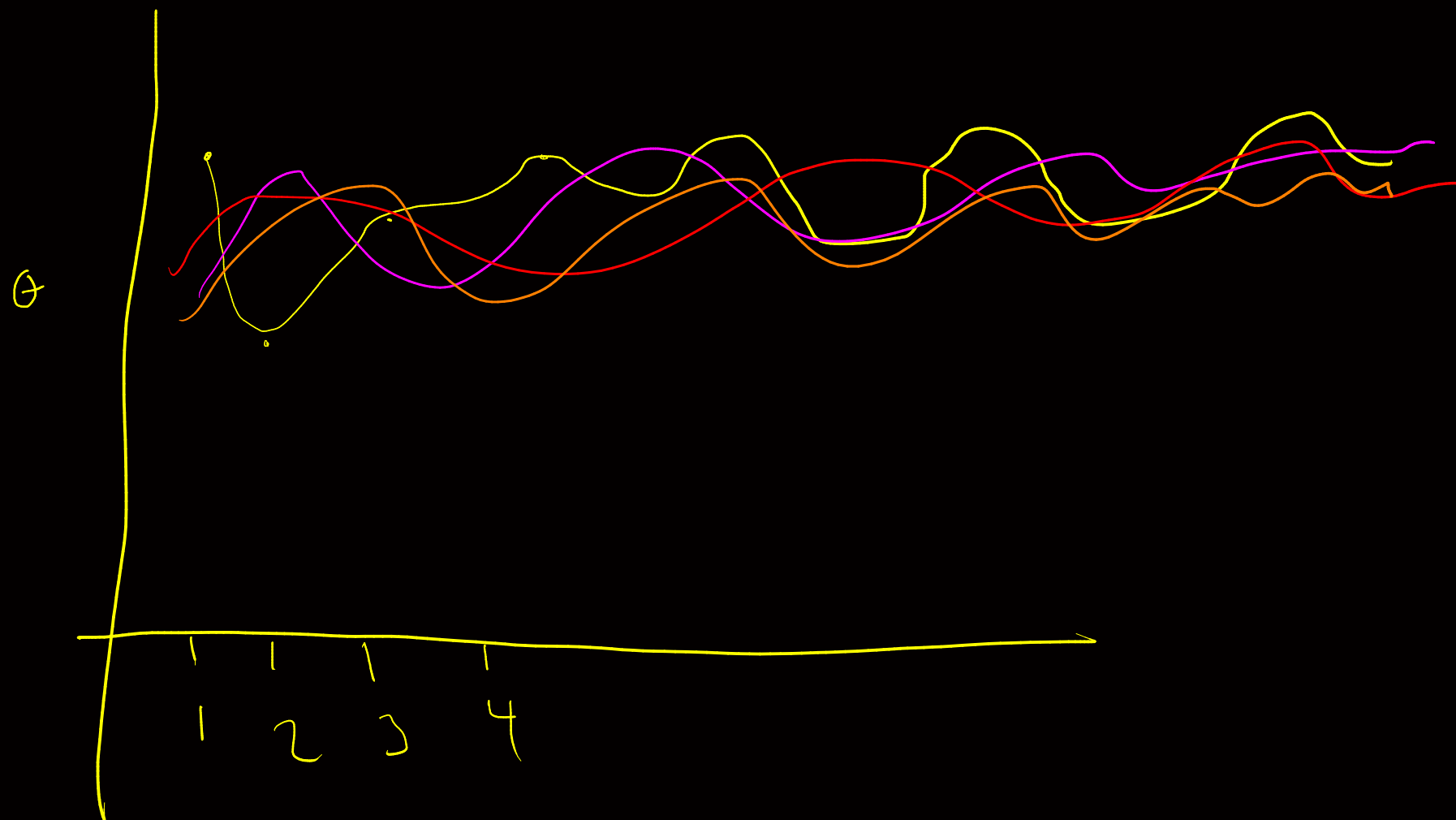
$y_i \sim N(\mu_i, \underline{\sigma}^2)$

$$\mu_i = \underline{\beta}_0 + \underline{\beta}_1 x_i$$

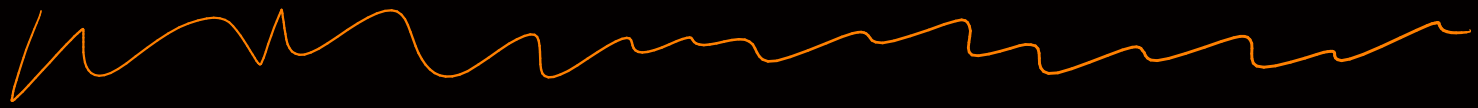
$y_i \sim \text{Student}(\mu_i, \sigma)$



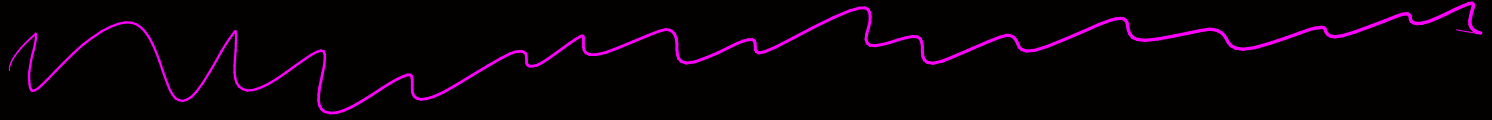




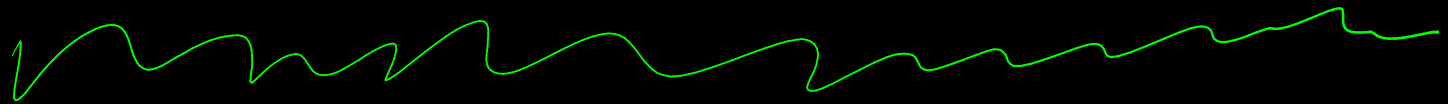
\hat{R} 2, 10



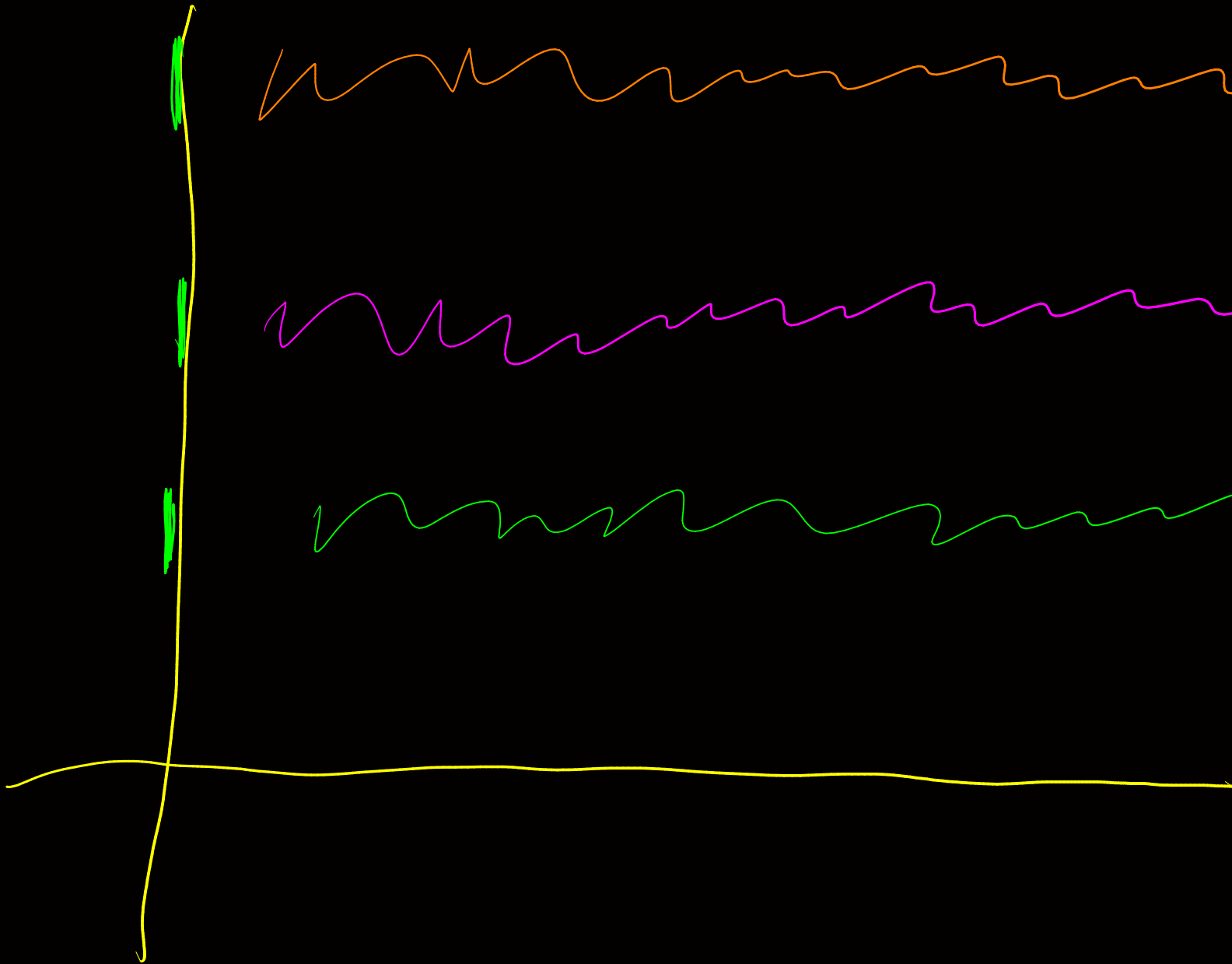
1

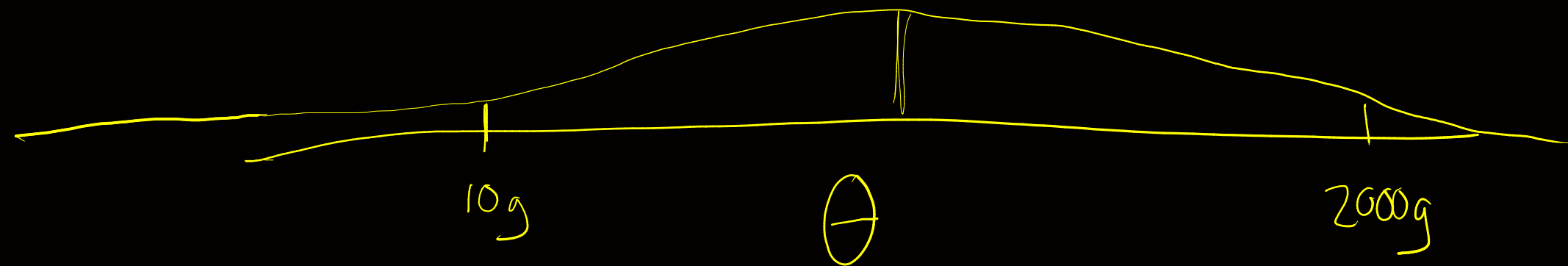
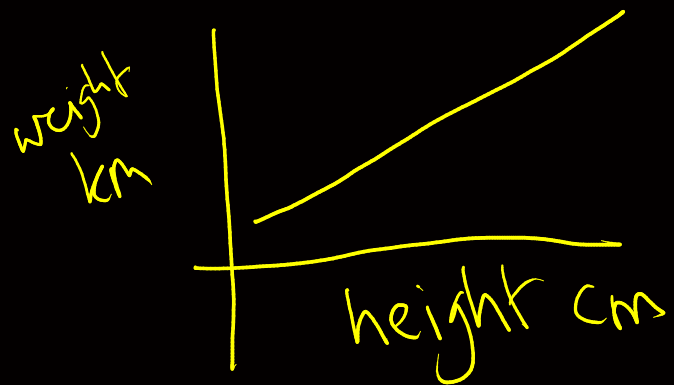


2



3





- * change settings
- * change priors
- * variants of linear models

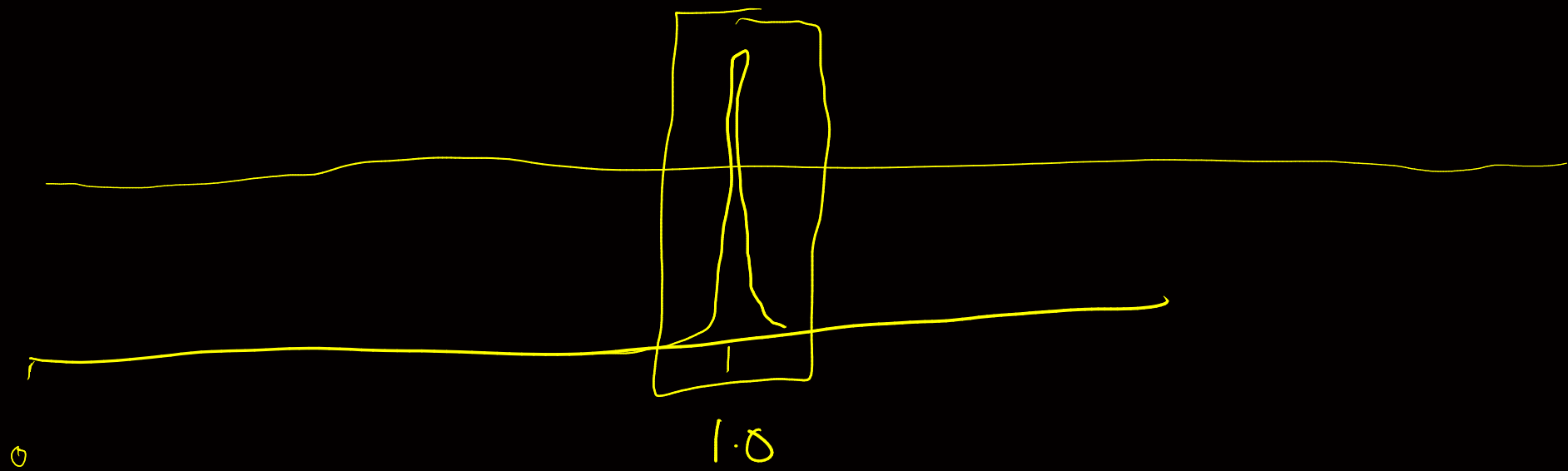
- * model comparison

- * generalized linear

logistic

Poisson / negative binomial / zero-inflated

- * multilevel model

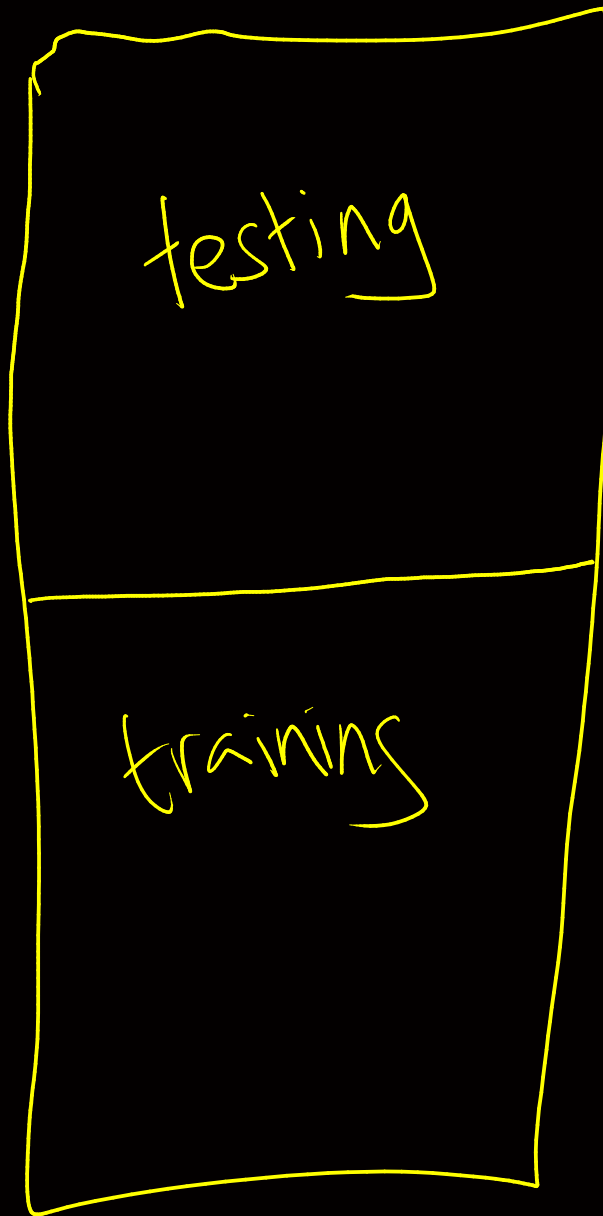


for i in $1 \dots n$

$$y_i \sim t(\nu, \mu_i, \sigma)$$

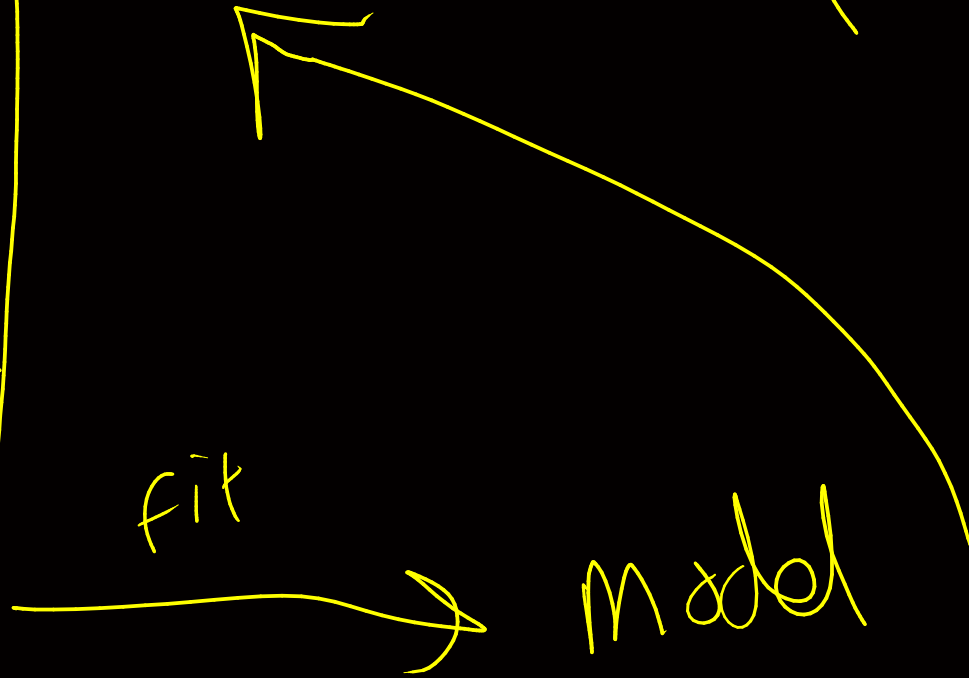
$$\mu_i = \beta_0 + \sum_{k=1}^K \beta_k x_{ki}$$

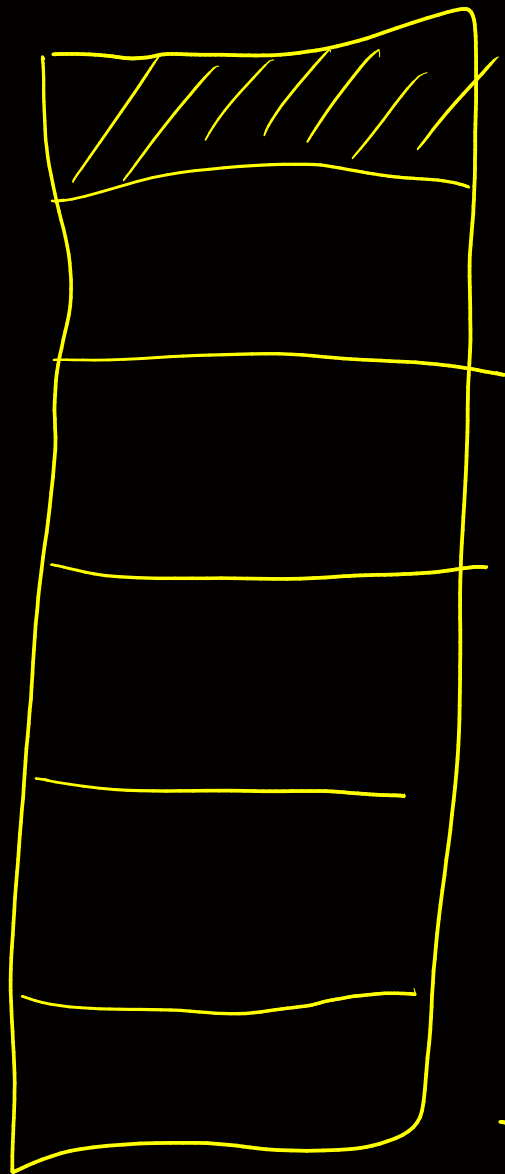
K fold CV



fit

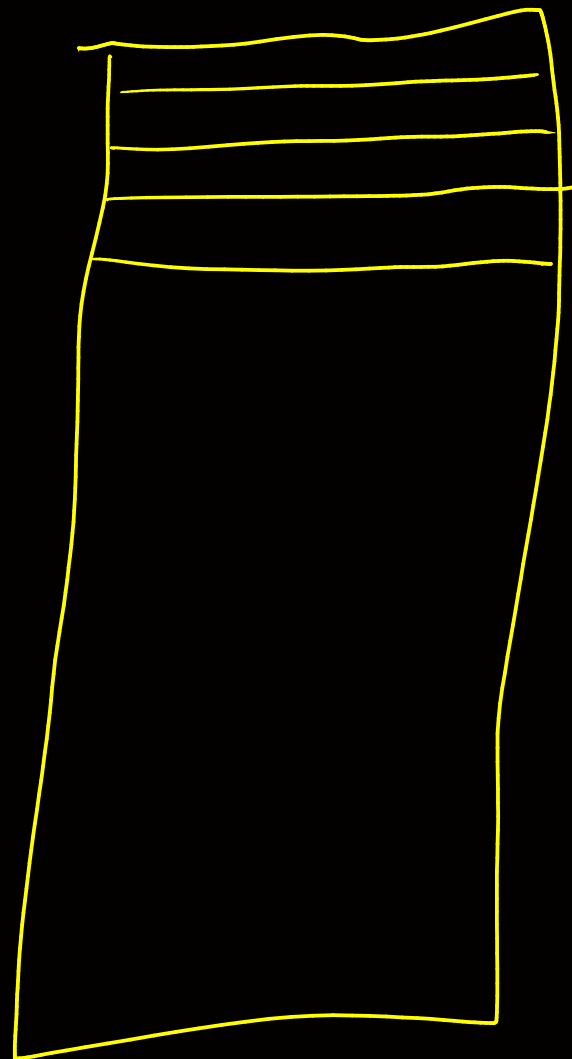
model





$n-1, n$

100 CV



AIC

Akaike Information
Criterion

fit data

complexity

bias
variance

$$-2LL + \underline{\underline{2k}}$$

$$\approx -2 \log \underline{\underline{elpd}}$$

$$n \gg k$$

AICc

WAIC

Watanabe

widely

Akaike IC

applicable

looiC
-2 elpld

m_0, m_1

D

$$p(m_0 | D) = \frac{P(D|m_0) p(m_0)}{P(D|m_0) p(m_0) + P(D|m_1) p(m_1)}$$

$$\frac{p(m_0 | D)}{p(m_1 | D)} = \underbrace{\frac{p(D|m_0)}{p(D|m_1)}}_{\text{BF}} \times \frac{p(m_0)}{p(m_1)}$$

$$p(D|M_0)$$

prior predictive density

$$= \int p(D|\theta, M_0) p(\theta|M_0)$$

marginal likelihood

0.05

0.01

0.001

Not
significant

4

7

10

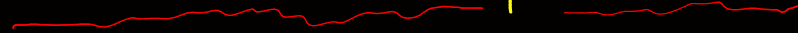
0

4

Δ IC

0.05

P



$$\Delta IC = (-2 \log e|pd_1) - (-2 \log e|pd_2)$$

$$= -2 \log \left(\frac{P(\tilde{D} | M_1)}{P(D | M_2)} \right)$$

$$e^{80}$$

1C
-2 LLR

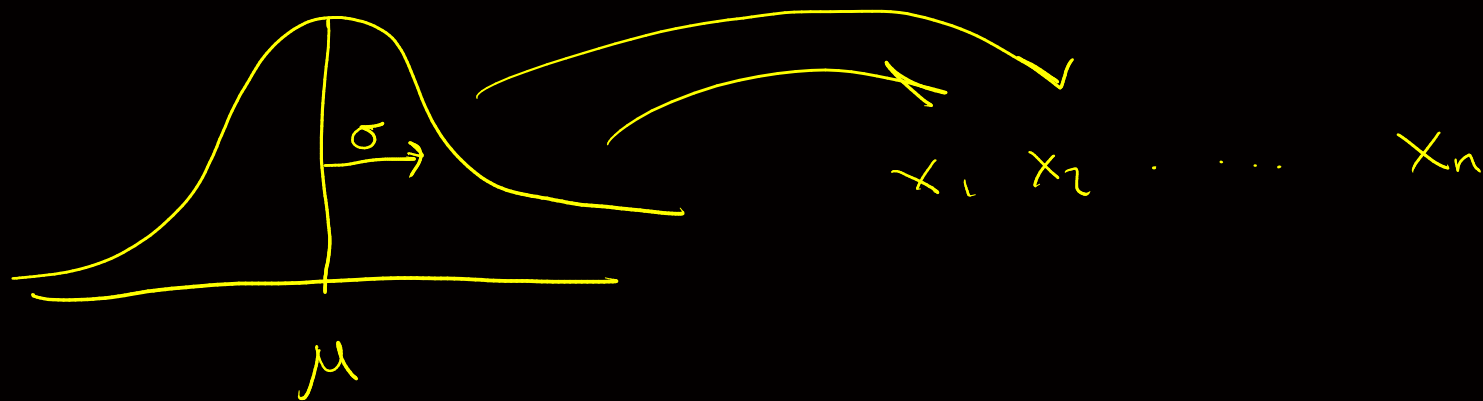
$$\log \left[\frac{P(D|M_9)}{P(D|M_8)} \right] \stackrel{\log BF}{\approx} 16$$

$$\frac{P(D|M_9)}{P(D|M_8)} \approx e^{16}$$

$$\Delta IC = (-2 LLR_1) - (-2 LLR_2)$$

$$-2 (LLR_1 - LLR_2)$$

$$-2 \log \left(\frac{L_1}{L_2} \right)$$



$$\bar{x} = \frac{1}{n} \sum x_i$$

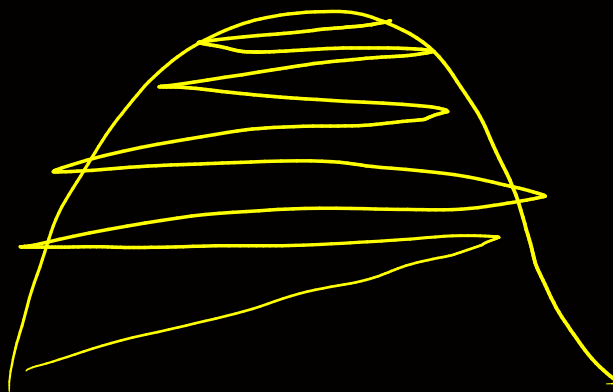
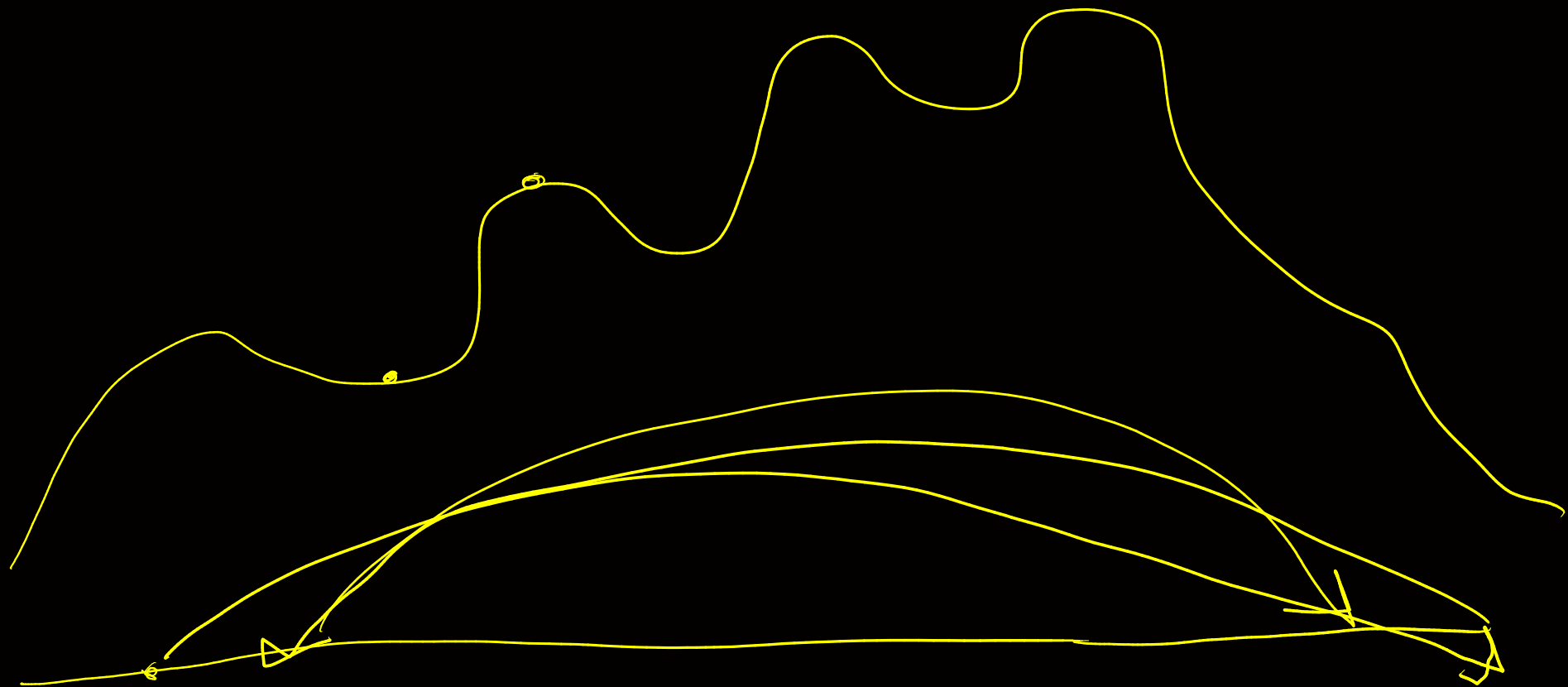
$$s_p = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n}}$$

mle for μ

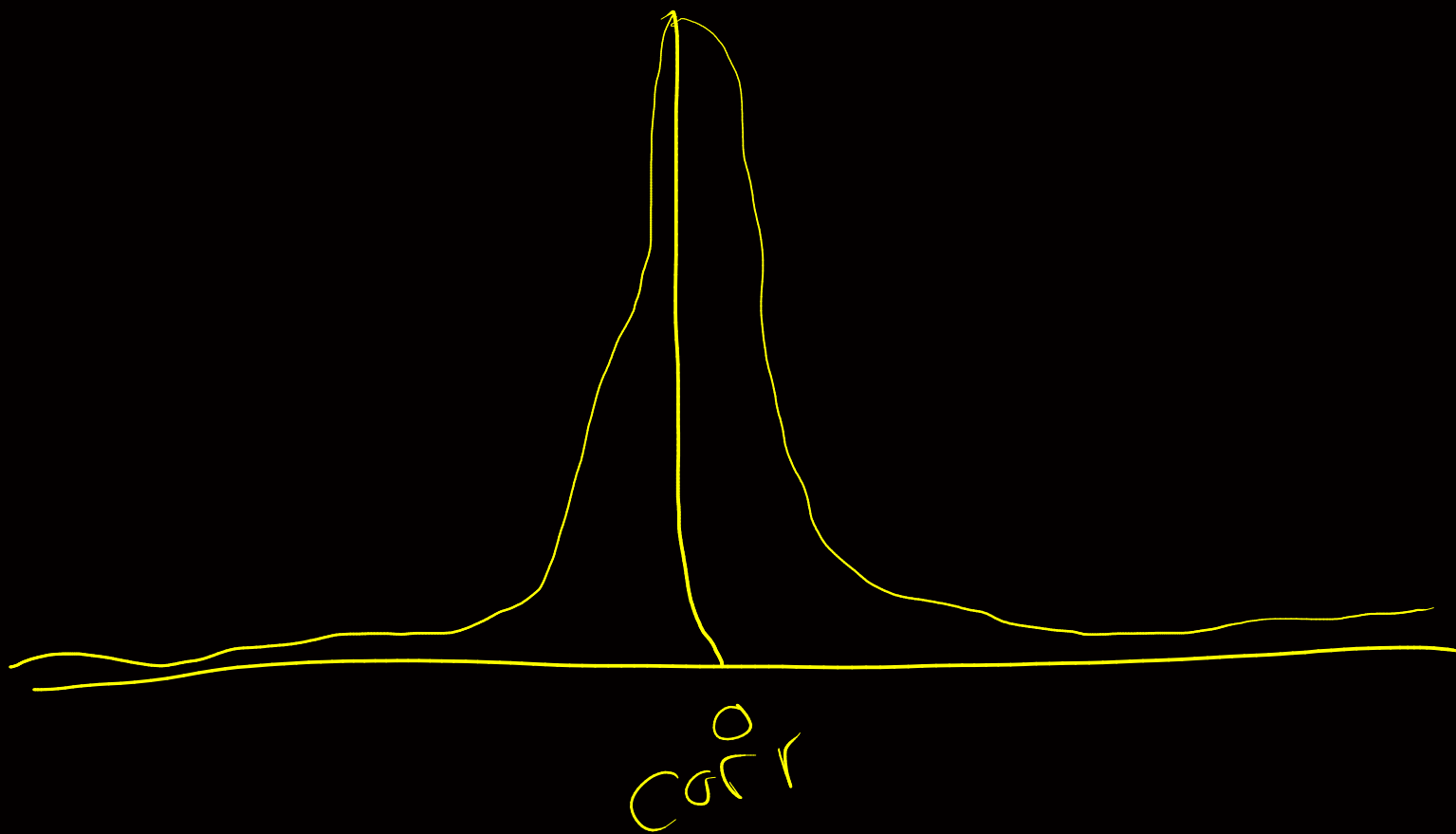
mle for σ

$$s = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}}$$

rmle for σ









$$\beta_0 + \beta_1 x_1 + \beta_2 x_2$$

A vertical line with a small hook at the top points from the β_1 term in the equation above.

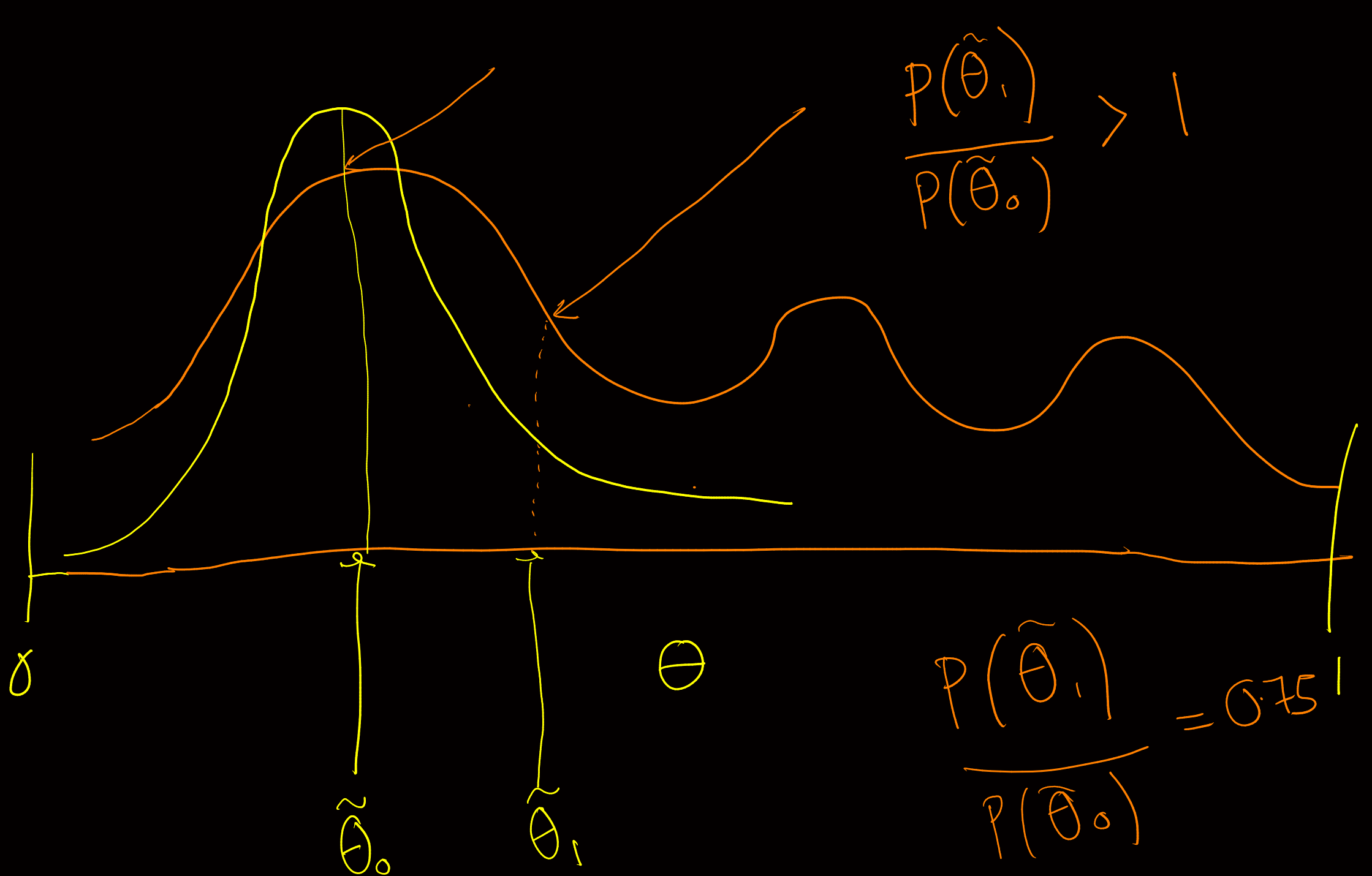
brms

↓ Stan

↓ C++

compiling

↓ sampler



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

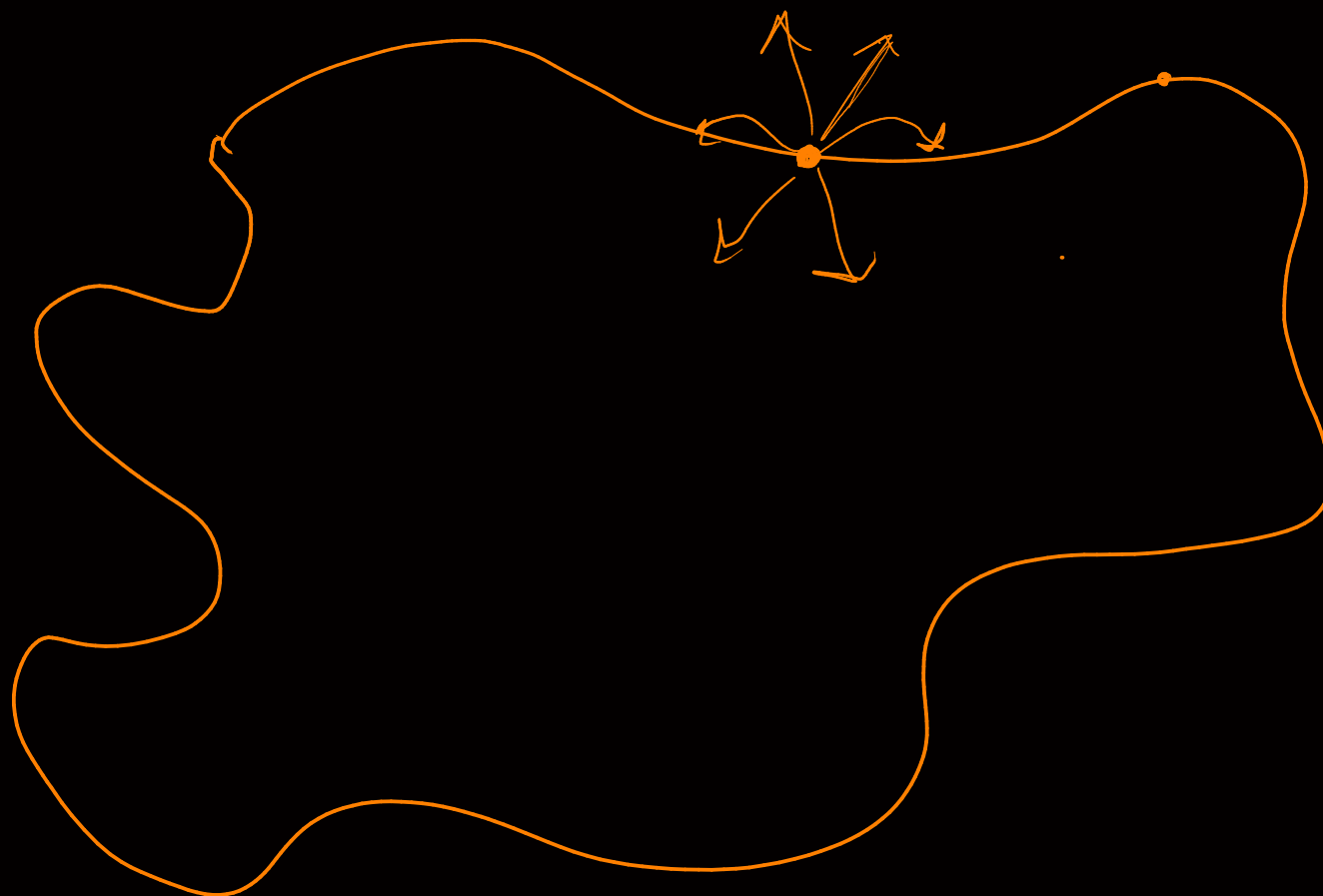
$\tilde{\theta}_0$

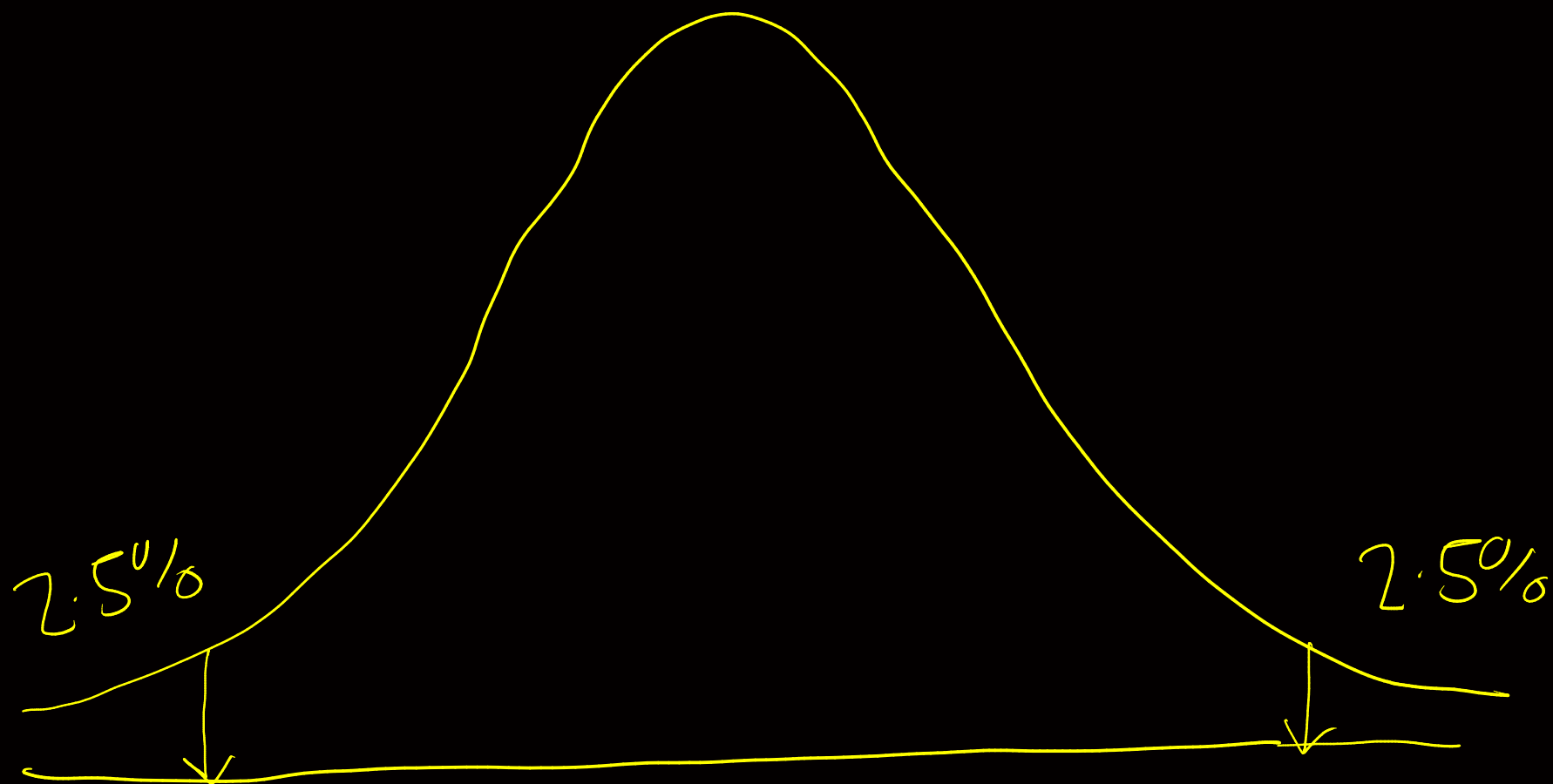
$\tilde{\theta}_1$

$$\frac{p(\tilde{\theta}_1|D)}{p(\tilde{\theta}_0|D)}$$

$$= \frac{p(D|\tilde{\theta}_0)p(\tilde{\theta}_0)}{\int p(D|\theta)p(\theta)d\theta} \frac{p(D|\tilde{\theta}_1)p(\tilde{\theta}_1)}{\int p(D|\theta)p(\theta)d\theta}$$

typical
set





$$p(x=0) = \int p(x=0|y) p(y) dy$$