





THE MAXIMUM KEELHOLD WAY

Given some data...

$$y = \{y_1, \dots, y_n\}$$

Defining a derivative model:

$$P(y|\theta) \equiv \mathcal{L}_y(\theta)$$

Maximize the likelihood over the parameter space:

$$\hat{\theta} = \operatorname{argmax}_{\theta \in \Omega} [L_y(\theta)]$$

Any further inference uses this ML estimator:

$$\rho = f(\hat{\theta})$$

THE MAXIMUM LIKELIHOOD WAY

Given some data...

$$y = \{y_1, \dots, y_n\}$$

Define an observational model:

$$P(y | \theta) = L_y(\theta)$$

Maximize the likelihood over the parameter space:

$$\hat{\theta} = \operatorname{argmax}_{\theta \in \Omega} [L_y(\theta)]$$

Any further inference uses this ML estimator:

$$\rho = f(\hat{\theta})$$

LOG LIKELIHOOD SURFACE

Likelihood $P(y \mid \theta)$

$y \sim \text{Normal}(\alpha + \beta x, \sigma)$

