

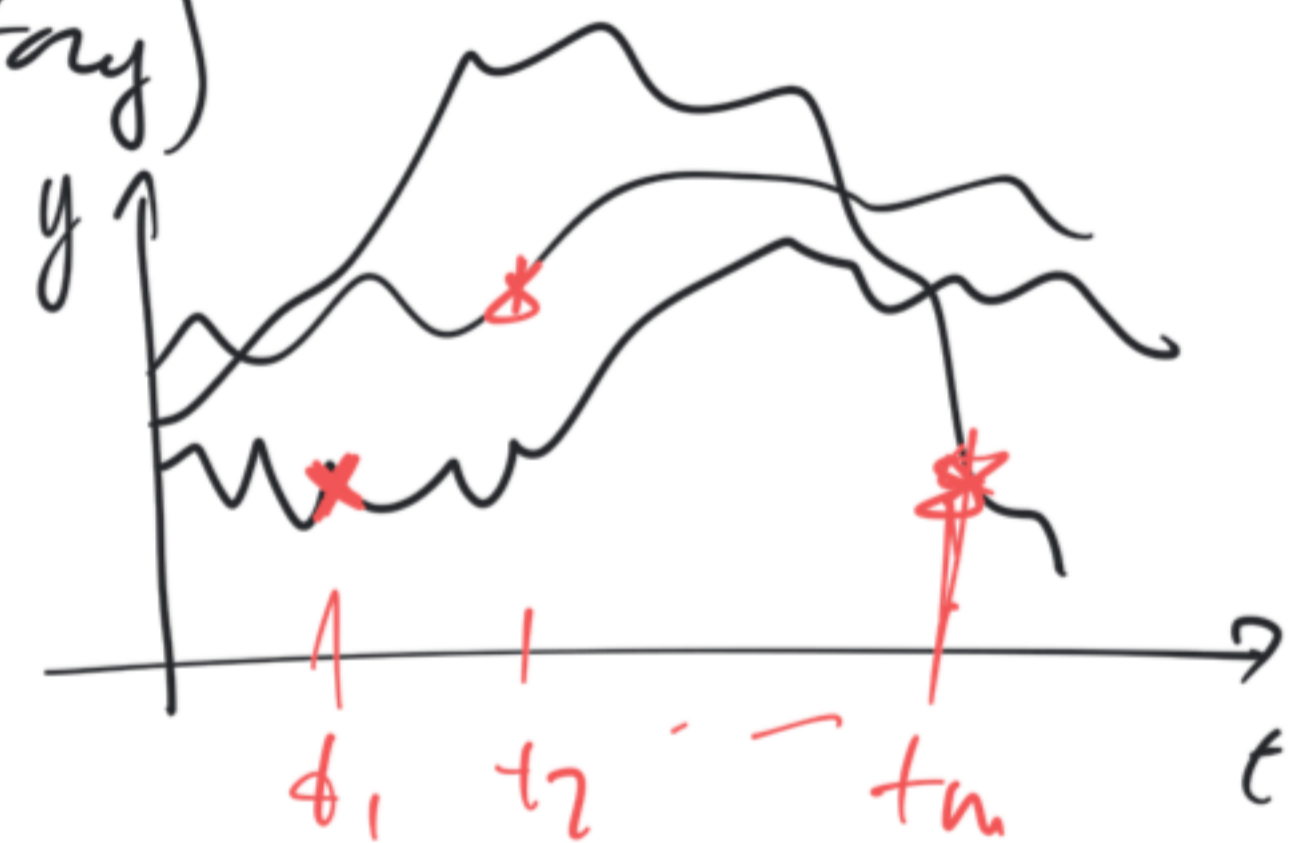
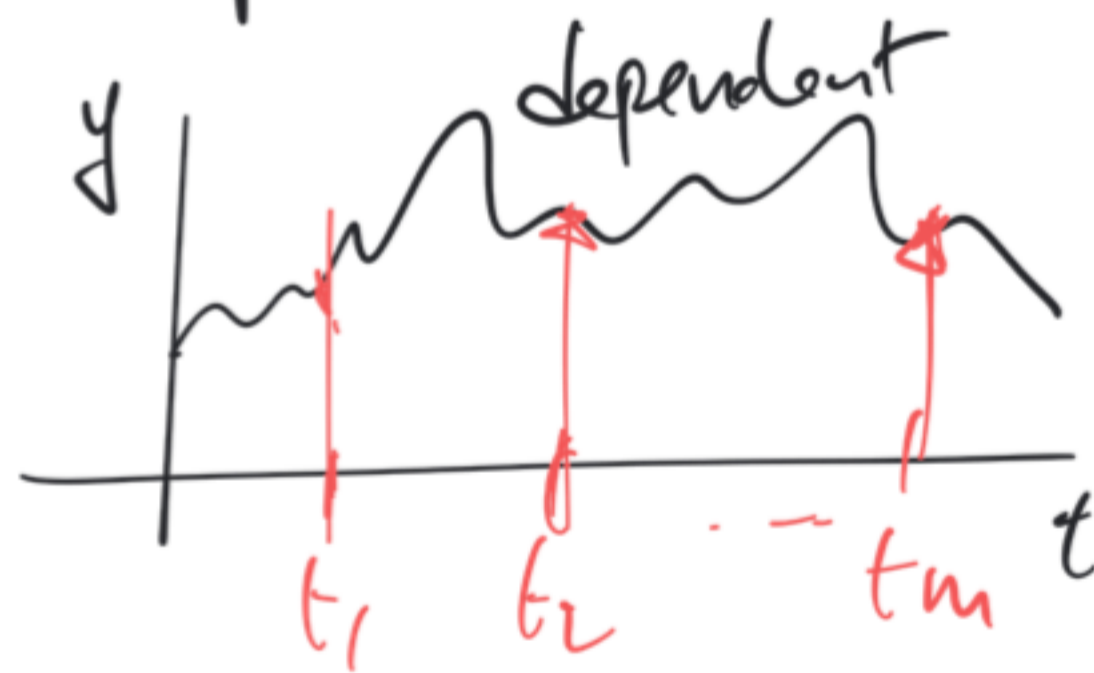
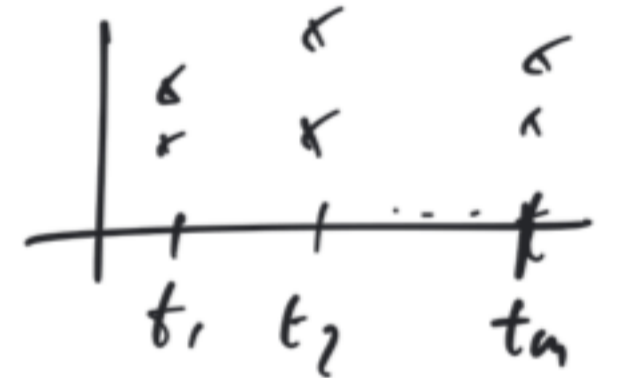
PARAMETER ESTIMATION

- PARAMETRIC MODEL FAMILY, M_{θ} , $\theta = \theta_1, \dots, \theta_k$ PARAMETERS $\theta_j \in \mathbb{R}_{\geq 0}$
 $\forall M_{\theta}$, LET $x(t|\theta)$ BE THE STATE OF M_{θ} AT TIME t .

(M_{θ} can be ODE, or CTMC, a STOCHASTIC HYBRID MODEL, ...)

- OBSERVATIONS $y_j(t_i)$, $j=1, \dots, N$ indep, $i=1, \dots, m$ times

FOR FIXED j , $y_j(t_1), \dots, y_j(t_m)$ can be either independent or dependent (from the same trajectory)



- MODEL OF EXPERIMENTAL NOISE (measurement errors)
 \hookrightarrow GAUSSIAN NOISE $\mathcal{N}(0, \sigma)$ $\Rightarrow y_j(t_i) \sim x(t_i, \theta_{true}) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \sigma)$

GOAL: FIND $\theta^* \in \Theta$ s.t. $x(t, \theta^*)$ is "as close as possible" to $y_j(t_i)$
 parameter space

OBSERVATIONS

- AVERAGE CONCENTRATION OF PROTEIN P AT A FIXED t_i ACROSS A CELL POPULATION
 $\Rightarrow y_0(t_i)$ ARE TIME INDEPENDENT, and they are averages.

\rightarrow stoch. or determ. models

- SINGLE CELL DATA OF P , AT A FIXED TIME

$\Rightarrow y_0(t_i)$ ARE TIME INDEP., but of a single stochastic run

- SINGLE CELL OBSERVED AT DIFFERENT TIME POINTS t_1, \dots, t_n
 $\Rightarrow y_n(t_i)$ ARE TIME DEPENDENT

stochastic models

2 WAYS: MAXIMUM LIKELIHOOD OR BAYESIAN INFERENCE.

LIKELIHOOD: $f(Y|\theta) : \Theta \rightarrow \mathbb{R}$
function of θ

$$f(Y|\theta) = P(Y|M_\theta) = \prod_{i=1}^n P(y_0(t_i), \dots, y_n(t_i) | M_\theta)$$

MAXIMUM LIKELIHOOD

$$\theta^* = \underset{\theta}{\text{arg max}} f(Y|\theta)$$

LIKELIHOOD FOR ODE (RRE)

1) AVERAGE DATA (indep. w/ time)

$$P(y_i(t_1), \dots, y_i(t_m) | \theta) = \prod_1 P(y_i(t_i) | \theta)$$

Problem: compute $P(y_i(t_i) | \theta)$

$$x(t_i) = x(t_i, \theta)$$

$$P(y_i(t_i), x(t_i) | \theta) = P(y_i(t_i) | x(t_i), \theta) \cdot \underbrace{P(x(t_i) | \theta)}_{\delta_{x(t_i, \theta)}}$$

$\propto P(y_i(t_i) | x(t_i, \theta))$ this is the obs. wise

SOLUTION OF ODE WITH PARAM. θ AT TIME t_i .

$$= \underbrace{\mathcal{N}(x(t_i, \theta) | \sigma^2)}_{1\text{-dim}} \left[\text{or } \underbrace{\mathcal{N}(\theta | \Sigma)}_{n\text{-dim}}, \Sigma = \sigma^2 I_n \right]$$

$$\propto \exp\left(-\frac{(y_i(t_i) - x(t_i, \theta))^2}{2\sigma^2}\right)$$

let's take the log!

$$L(\theta) = \log f(\Delta | \theta)$$

$$= \sum_{j=1}^N \sum_{i=1}^m - (y_{ij}(t_i) - x(t_i, \theta))^2 / \sigma^2$$

(Fitting σ^2)

I need to optimize (minimize)

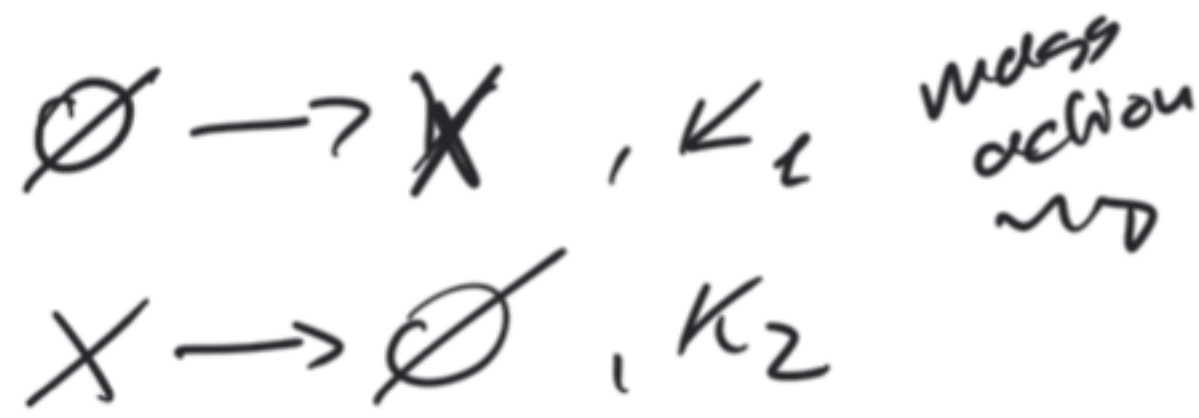
$$f(\theta) = \sum_{i,j} (y_{ij}(t_i) - x(t_i, \theta))^2$$

sum of squares.

θ^* argmax $f(\theta)$

$$\left(\theta^* = \frac{f(\theta^*)}{N \cdot m} \right)$$

IDENTIFIABILITY



$$\dot{X} = k_1 - k_2 X$$

$$k_1 - k_2 X = 0$$

(equilibrium)

$$X(t) \xrightarrow{t \rightarrow \infty} \frac{k_1}{k_2}$$

$$k_1 = \alpha_1 \cdot \gamma \quad k_2 = \alpha_2 \cdot \gamma$$

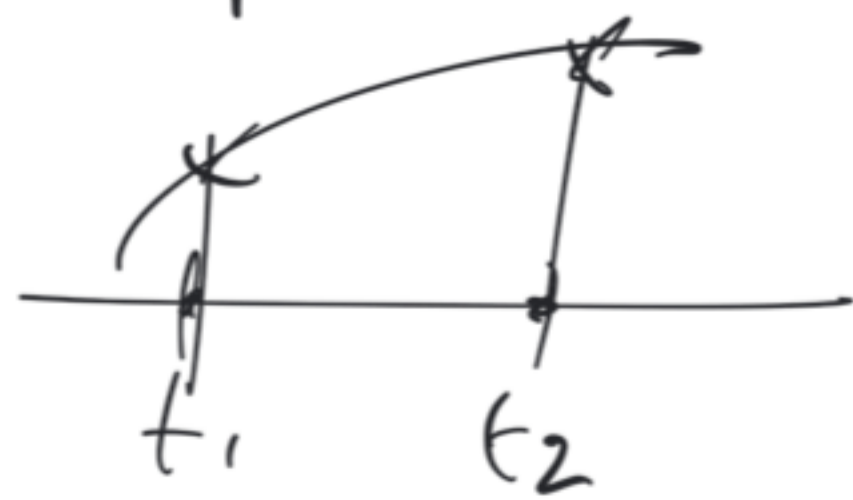
$$\frac{k_1}{k_2} = \frac{\alpha_1}{\alpha_2} \text{ indep. from } \gamma.$$

See onono

$y_j(t)$, for t large so that the system is at steady state.

$$y_i(t) \approx y_j(\infty) \approx \left(\frac{k_1}{k_2} \right) = \theta \quad \left(y_j \approx \mathcal{N}(\theta, \sigma^2) \right)$$

I can find θ but not k_1 and k_2 .



$$e^{-k_2 t}$$

With observations at time t_1 NOT at steady state, and $t_2 > t_1$, I can identify my system.

$$\emptyset \rightarrow X$$

$$\emptyset \rightarrow Y$$

$$X \rightarrow \emptyset$$

$$Y \rightarrow \emptyset$$

but we observe $Z = X + Y$

We cannot distinguish between ratios of X and of Y .

