$$\theta^*(t) = \arg\min_{\theta(t)} \int_0^T g(x(t), \theta(t)) dt \approx \arg\min_{\theta(t)} \sum_{t=0}^T g(x_t, \theta(t))$$

error of the model on [0, T]

 $\theta(t)$ is constant on clusters

$$[\Theta^*, \Gamma^*(t)] = \arg\min_{\Theta, \Gamma} \int_0^T \sum_{k=1}^K \gamma_k(t) \cdot g(x(t), \theta_k) \ dt \approx \arg\min_{\Theta, \Gamma} \sum_{t=0}^T \sum_{k=1}^K \gamma_{k,t} \cdot g(x_t, \theta_k)$$

 $\theta_1, \theta_2, \dots, \theta_k$ - model parameters on clusters

 $\gamma_1(t), \gamma_2(t), \dots, \gamma_k(t)$ - cluster indicator functions

$$\theta_1$$
 θ_2 θ_3 $\gamma_1(t)$ $\gamma_2(t)$ $\gamma_3(t)$

continuous real-valued functions $\gamma_k(t) \in [0, 1]$

smooth $\gamma_k(t) \Rightarrow \text{regularisation}$

$$\gamma_k(t) \in \{0,1\}, \quad \gamma_k(t) = \left\{ \begin{array}{ll} 1 & \text{if k-th cluster is active in t} \\ 0 & \text{if k-th cluster is inactive in t} \end{array} \right.$$

$$0 \le \gamma_k(t) \le 1, \quad \forall t : \sum_{k=1}^K \gamma_k(t) = 1$$

s.t.
$$0 \le \gamma_k(t) \le 1, \ \forall t : \sum_{k=1}^K \gamma_k(t) = 1$$

$$\int_{0}^{T} \sum_{k=1}^{K} \gamma_{k}(t) \cdot g(x(t), \theta_{k}) \ dt + \varepsilon^{2} \sum_{k=1}^{K} \int_{0}^{T} (\partial_{t} \gamma_{k}(t))^{2} dt \quad \approx \quad \sum_{t=0}^{T} \sum_{k=1}^{K} \gamma_{k,t} \cdot g(x_{t}, \theta_{k}) + \varepsilon^{2} \sum_{k=1}^{K} \sum_{t=0}^{T-1} (\gamma_{k,t+1} - \gamma_{k,t})^{2} dt$$

$$[\Theta^*, \Gamma^*] = \arg\min_{\Theta, \Gamma} \sum_{t=0}^{T} \sum_{k=1}^{K} \gamma_{k,t} \cdot g(x_t, \theta_k) + \varepsilon^2 \sum_{k=1}^{K} \sum_{t=0}^{T-1} (\gamma_{k,t+1} - \gamma_{k,t})^2$$

s.t.
$$0 \le \gamma_{k,t} \le 1, \ \forall t : \sum_{k=1}^{K} \gamma_{k,t} = 1$$

$$L(\Theta, \Gamma)$$

set feasible initial approximation Γ_0

while
$$||L(\Theta_{it}, \Gamma_{it}) - L(\Theta_{it-1}, \Gamma_{it-1})|| > \varepsilon_L$$

 $solve \ \Theta_{it} = \arg\min_{\Theta} L(\Theta, \Gamma_{it}) \quad (with \ fixed \ \Gamma_{it})$
 $solve \ \Gamma_{it} = \arg\min_{\Gamma} L(\Theta_{it}, \Gamma) \quad (with \ fixed \ \Theta_{it})$
 $it = it + 1$

end while

$$\begin{array}{rcl} \theta_1 & = & [0,0,0] \\ \theta_2 & = & [1,0,0] \\ \theta_3 & = & [0,1,0] \end{array}$$

$$\sum_{t=0}^{T} \|x_t - \theta(t)\|^2 \to \min$$

 $y^t \in \{0,1\}$: binary data

$$P_X^t = \left(P(x_1^t), ..., P(x_n^t), 1\right)^T$$
 probability vector

Log-likelihood at time t:

$$\mathcal{L}(t) = y^t \log \left(\Lambda_X(t)^T P_X^t \right) + (1 - y^t) \log \left(1 - \Lambda_X(t)^T P_X^t \right)$$

Want to solve the estimation problem

$$\max_{\Lambda_X(t):\ t\in[0,T]}\ \int_0^T \mathcal{L}(t)dt$$

such that:

$$0 < \Lambda_X(t)^T P_X^t < 1, \quad \forall t$$

$$Y^{t} = a + bY^{t-1} + cX^{t-1} +$$
noise

$$c \cong 0 \quad c \neq 0 \quad \Lambda \cong 0 \quad \Lambda = P[y^t | x^t] \quad \varepsilon = P[y^t \text{ and NOT } x^t] \quad y^t \quad X \quad x^t \quad Y$$

$$X \text{ not } X Y \{y^t\}, t = 0, \dots, T \{x^t\}, t = 0, \dots, T$$

$$\begin{array}{lcl} P[y^t] & = & P[y^t \text{ and } x^t] + P[y^t \text{ and NOT } x^t] \\ & = & \Lambda P[x^t] + \varepsilon \end{array}$$

X has a causality impact on Y if

for any t, event y^t is happening if (and only if) event x^t happened.

fit a stochastic model for Y and X, e.g. a linear VAR-X:

If model with $c\cong 0$ is more statistically-significant than the one with $c\neq 0$

X has no **Granger-causality** impact on Y

Law of the Total Probability:

If $\Lambda \cong 0$ there is no causality impact from X on Y.

$$P[y^t] = \Lambda_1(t)P[x_1^t] + \Lambda_2(t)P[x_2^t] + \dots + \Lambda_n(t)P[x_n^t]$$
$$+P[y^t \text{ and } \text{not}(x_1^t \text{ or } \dots \text{ or } x_n^t)]$$

where $\Lambda_i(t) = P[y^t|x_i^t]$ is possibly time-dependent due to unresolved scales.

If $\Lambda_i \cong 0$ there is no causality impact from X_i on Y.