

# Switching Systems Mode Estimation Using A Model-Based Diagnosis Method

Elom Domlan, José Ragot, Didier Maquin

Centre de Recherche en Automatique de Nancy, CNRS UMR 7039  
Institut National Polytechnique de Lorraine  
2, Avenue de la forêt de Haye,  
54516 Vandœuvre-Lès-Nancy Cedex,  
FRANCE



2007 Diagnostics of Processes and Systems

# Introductory Example

## Regression model with two modes

$$y(k) = \Theta_{\mu_k} \Psi_k^T + \varepsilon(k)$$

$$\Psi_k = ( y(k-1) \quad y(k-2) \quad u(k-1) )$$

$$\Theta_{\mu_k} = \begin{cases} ( a_{11} & a_{12} & b_{11} ) & \text{if } \mu_k = 1 \\ ( a_{21} & a_{22} & b_{21} ) & \text{if } \mu_k = 2 \end{cases}$$

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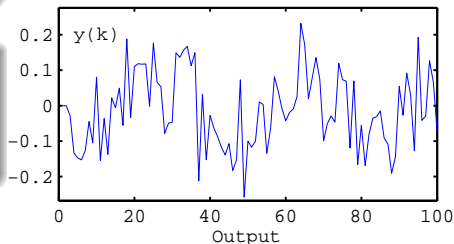
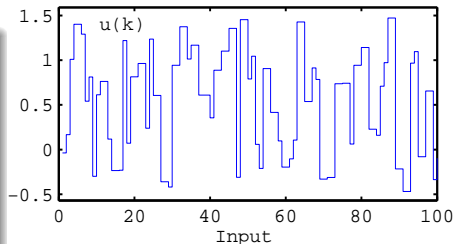
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$$\begin{cases} ( a_{11} & a_{12} & b_{11} ) = (-0.41 & 0.21 & -0.14) \\ ( a_{21} & a_{22} & b_{21} ) = (-0.23 & -0.11 & 0.16) \end{cases}$$



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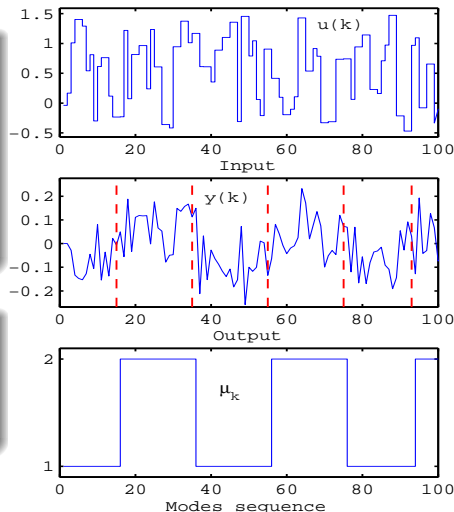
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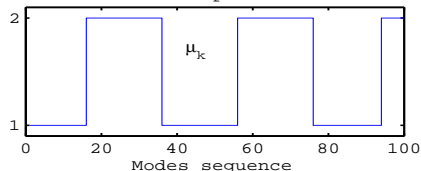
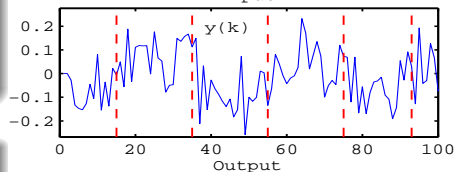
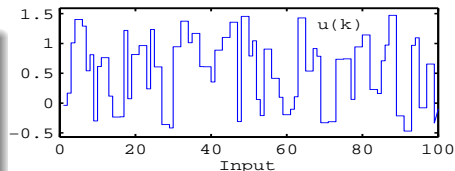
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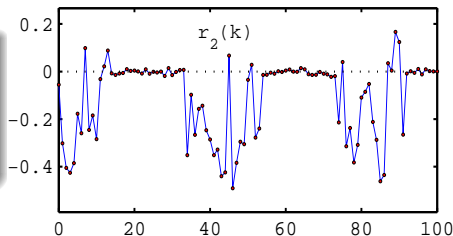
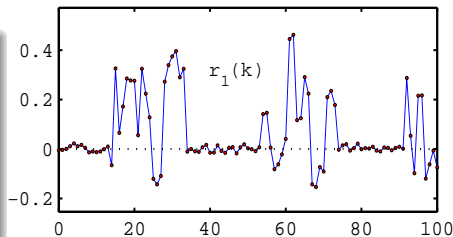
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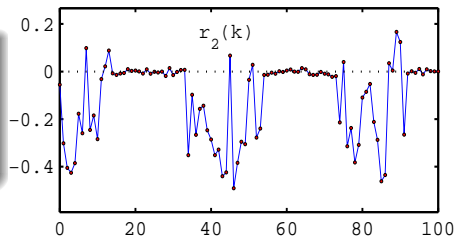
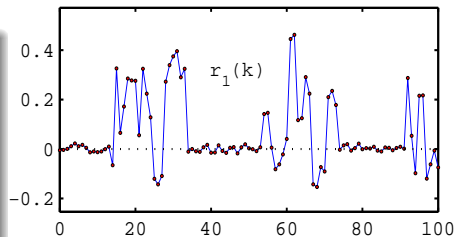
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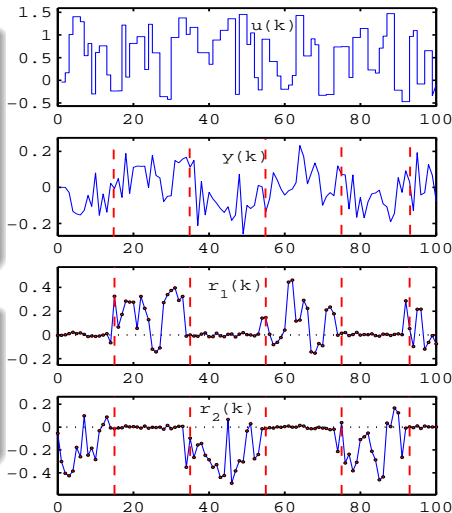
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# Outline

- 1 Problem Statement
- 2 Active Mode Estimation
- 3 Discernability
- 4 Academic Example
- 5 Conclusion

## Assumptions

- Input
- Output
- Number of modes
- Matrices describing the different modes

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## Assumptions

- Input
- Output
- Number of modes
- Matrices describing the different modes

## Goals

- Active mode
- Switching times

## Model

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{A}_{\mu_k} \mathbf{x}(k) + \mathbf{B}u(k) \\ \mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \end{cases}$$

$$u(\cdot) \in \mathbb{R}^p, y(\cdot) \in \mathbb{R}^q, \mathbf{x}(\cdot) \in \mathbb{R}^n$$

$$\mathbf{A}_{\mu_k} \in \{\mathbf{A}_1, \mathbf{A}_2, \dots, \mathbf{A}_s\}, \mathbf{s} \in \mathbb{N}^* \setminus \{1\}$$

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## Definition (Path)

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## Notations

- $|\mu|$  : length of the path  $\mu$   
 $\mu = (\mu_1 \cdot \mu_2 \cdot \dots \cdot \mu_N) \Rightarrow |\mu| = N$ .
- $\Theta_N$  : set of all paths of length  $N$ .
- $\mathcal{O}_{\mu,N}$  : observability matrix

$$\mathcal{O}_{\mu,N} = \begin{pmatrix} C \\ CA_{\mu_1} \\ \vdots \\ CA_{\mu_{N-1}} \cdots A_{\mu_1} \end{pmatrix}$$

# Active Mode Estimation

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$$\Downarrow$$
$$Y_{k-h,k} = O_{\mu,h}x(k-h) + T_{\mu,h}U_{k-h,k-1}$$

$$T_{\mu,h} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ CB & 0 & & \\ \vdots & & & \\ CA_{\mu_{k-1}} \dots A_{\mu_{k-h+1}} B & CA_{\mu_{k-1}} \dots A_{\mu_{k-h+2}} B & \dots & CB \end{pmatrix}$$

$$Y_{k-h,k} = (y(k-h) \dots y(k))^T$$
$$U_{k-h,k-1} = (u(k-h) \dots u(k-1))^T$$



$$Y_{k-h,k} = \mathcal{O}_{\mu,h} \mathbf{x}(k-h) + T_{\mu,h} U_{k-h,k-1}$$



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with  $\Omega_{\mu,h} \mathcal{O}_{\mu,h} = 0$



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$$Y_{k-h,k} = \mathcal{O}_{\mu,h} \mathbf{x}(k-h) + T_{\mu,h} U_{k-h,k-1} + E_{k-h,k}$$

## Influence on the residuals

$$\mu = \mu^* \Rightarrow r_{\mu^*,h}(k) = \Omega_{\mu^*,h} E_{k-h,k} \neq 0$$



$$|\varepsilon(k)| \leq \delta \Rightarrow [r_{\mu,h}(k)]$$



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Definition (discernible paths : free-noise case)

$\mu^1$  and  $\mu^2$  are discernible on a time window  $[k - h, k]$  if :

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## Theorem (Path discernability : free-noise case)

Two paths  $\mu^1$  and  $\mu^2$  are discernible on an observation window  $[k-h, k]$  if :

$$\Omega_{\mu^i, h} \mathcal{O}_{\mu^j, h} \neq 0, \quad i, j \in \{1, 2\}, i \neq j$$

or

$$\Omega_{\mu^i, h} (T_{\mu^j, h} - T_{\mu^i, h}) U_{k-h, k} \neq 0 \quad i, j \in \{1, 2\}, i \neq j$$

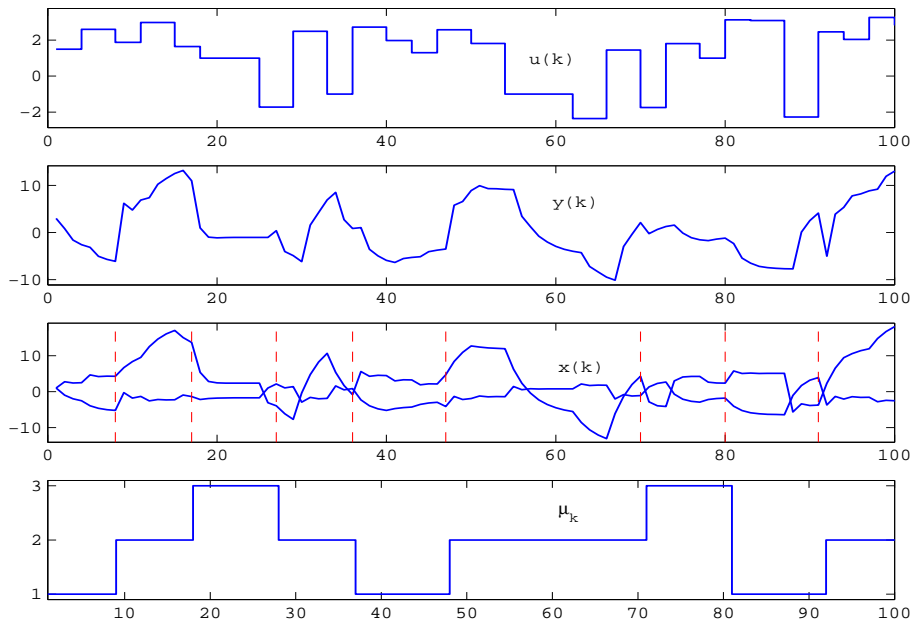
## System matrices

$$A_1 = \begin{pmatrix} -0.211 & 0 \\ 0 & 0.521 \end{pmatrix} A_2 = \begin{pmatrix} 0.691 & 0 \\ 0 & -0.310 \end{pmatrix} A_3 = \begin{pmatrix} 0.153 & 0 \\ 0 & 0.410 \end{pmatrix}$$

$$B = \begin{pmatrix} 2 & -1 \end{pmatrix}^T C = \begin{pmatrix} 1 & 2 \end{pmatrix}$$



# Academic Example



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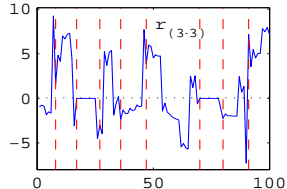
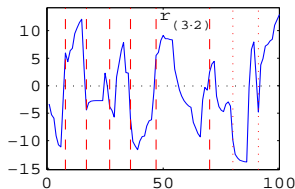
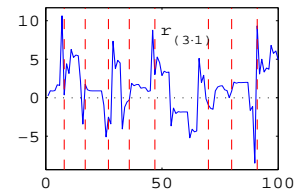
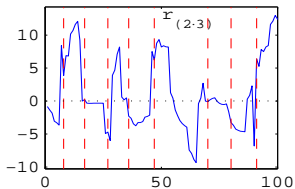
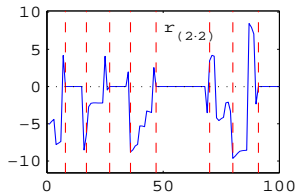
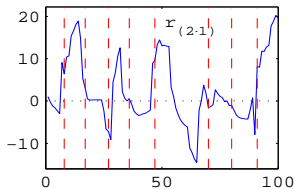
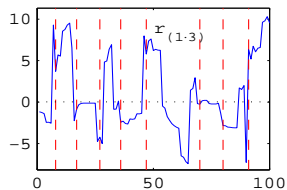
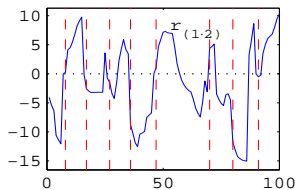
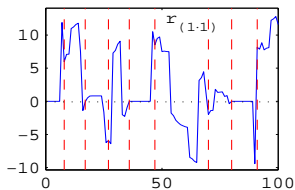
Path of length 2 on  $[k - 2, k]$

Path number	1	2	3	4	5	6	7	8	9
$\mu_1$	1	1	1	2	2	2	3	3	3
$\mu_2$	1	2	3	1	2	3	1	2	3

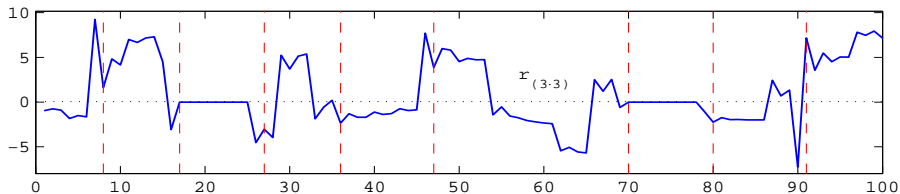
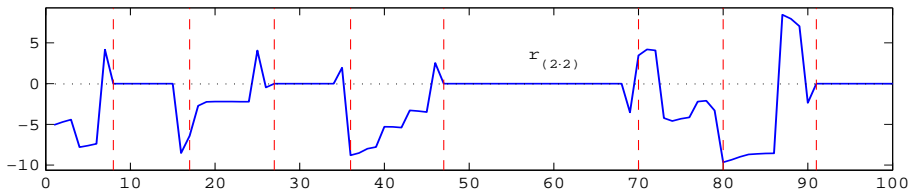
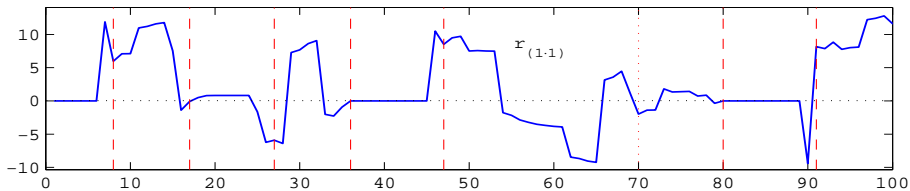
Observability matrices

$$\left\{ \begin{array}{l} \mathcal{O}_{(1 \cdot 1),h} = \begin{pmatrix} C \\ CA_1 \\ CA_1 A_1 \end{pmatrix} \\ \mathcal{O}_{(2 \cdot 1),h} = \begin{pmatrix} C \\ CA_1 \\ CA_2 A_1 \end{pmatrix} \\ \mathcal{O}_{(3 \cdot 1),h} = \begin{pmatrix} C \\ CA_1 \\ CA_3 A_1 \end{pmatrix} \end{array} \right. \quad \left\{ \begin{array}{l} \mathcal{O}_{(1 \cdot 2),h} = \begin{pmatrix} C \\ CA_2 \\ CA_1 A_2 \end{pmatrix} \\ \mathcal{O}_{(2 \cdot 2),h} = \begin{pmatrix} C \\ CA_2 \\ CA_2 A_2 \end{pmatrix} \\ \mathcal{O}_{(3 \cdot 2),h} = \begin{pmatrix} C \\ CA_2 \\ CA_3 A_2 \end{pmatrix} \end{array} \right. \quad \left\{ \begin{array}{l} \mathcal{O}_{(1 \cdot 3),h} = \begin{pmatrix} C \\ CA_3 \\ CA_1 A_3 \end{pmatrix} \\ \mathcal{O}_{(2 \cdot 3),h} = \begin{pmatrix} C \\ CA_3 \\ CA_2 A_3 \end{pmatrix} \\ \mathcal{O}_{(3 \cdot 3),h} = \begin{pmatrix} C \\ CA_1 \\ CA_3 A_3 \end{pmatrix} \end{array} \right.$$

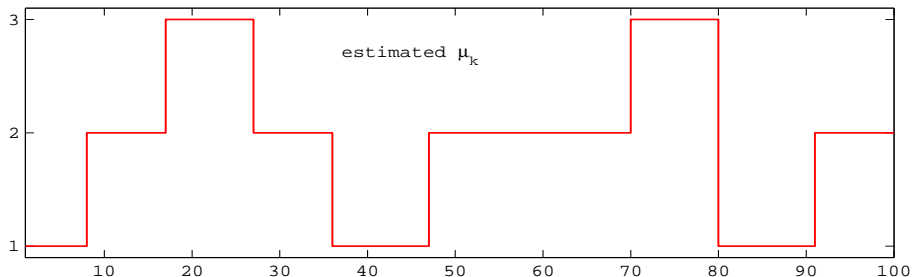
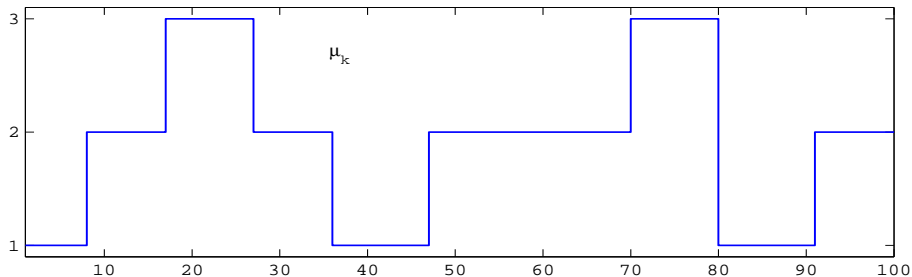
# Academic Example



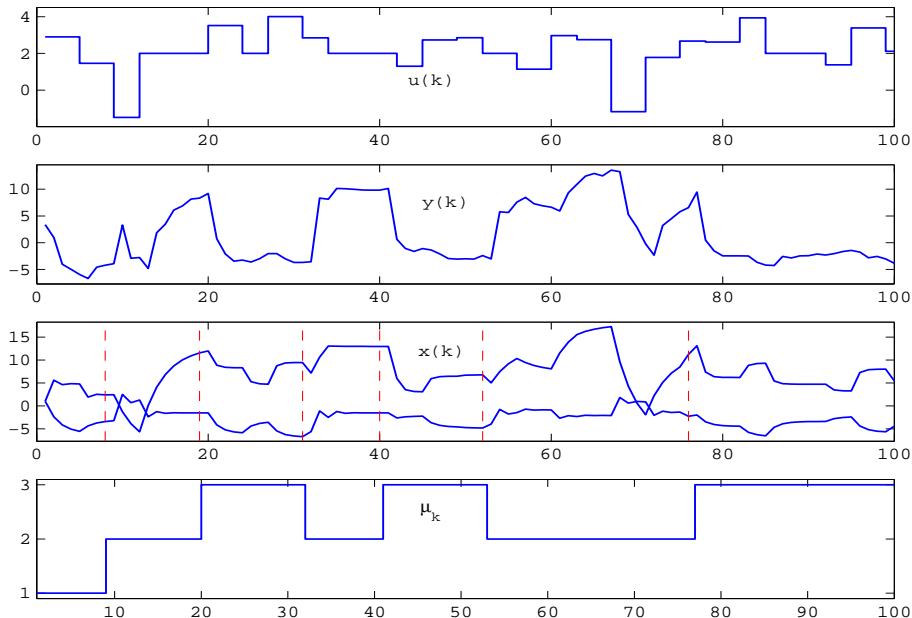
# Academic Example



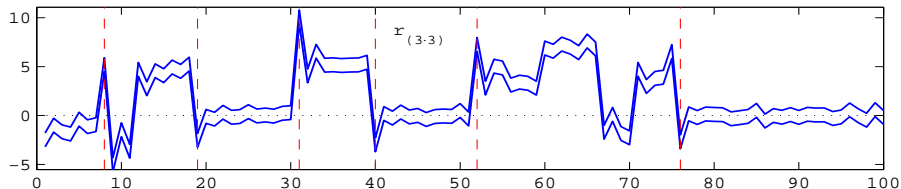
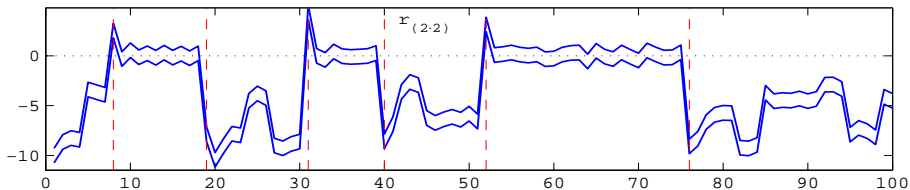
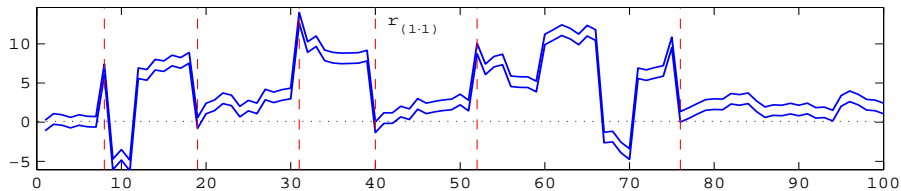
# Academic Example



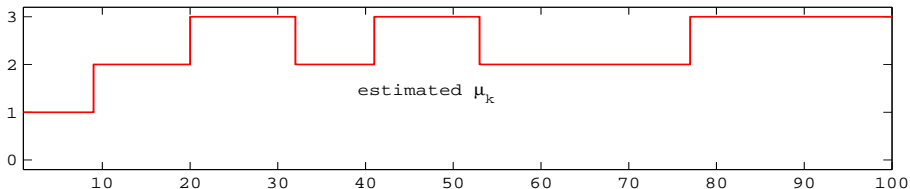
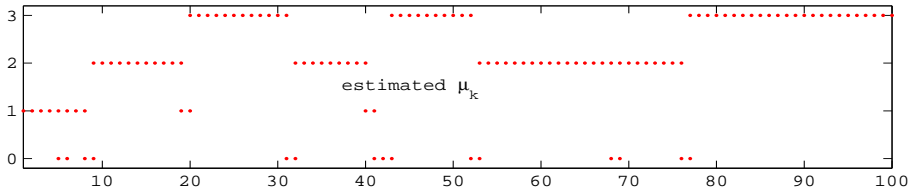
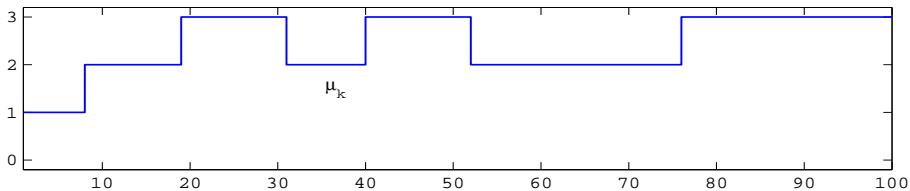
# Academic Example



# Academic Example



# Academic Example





## Conclusion

- Active mode estimation
- Discernability analysis

## Future work

- Discernability conditions in the presence of noise
- Continuous state estimation
- Mode estimation with partial knowledge of the modes

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