

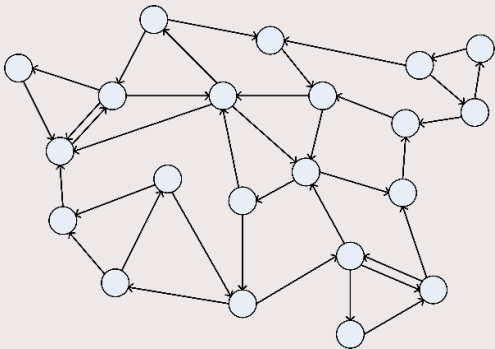
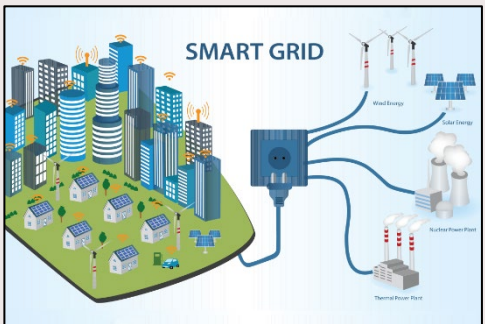
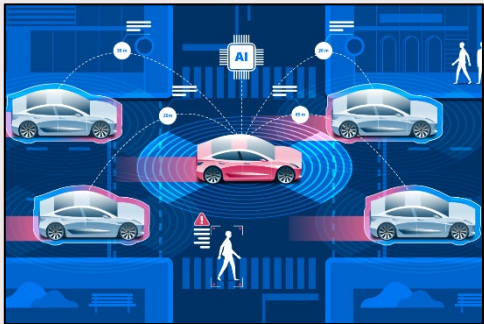
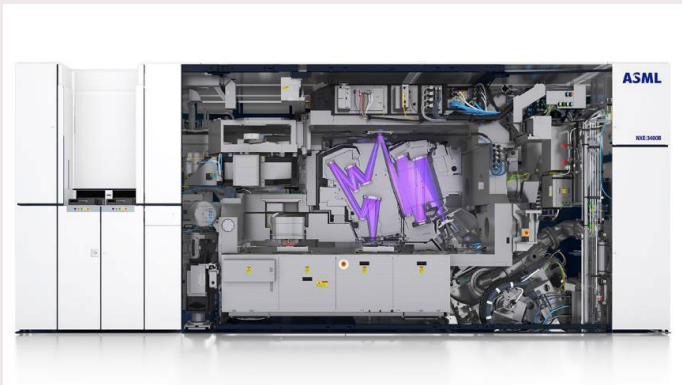


# Local identification in dynamic networks using a multi-step least squares method

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Stefanie Fonken, Karthik Ramaswamy, Paul Van den Hof

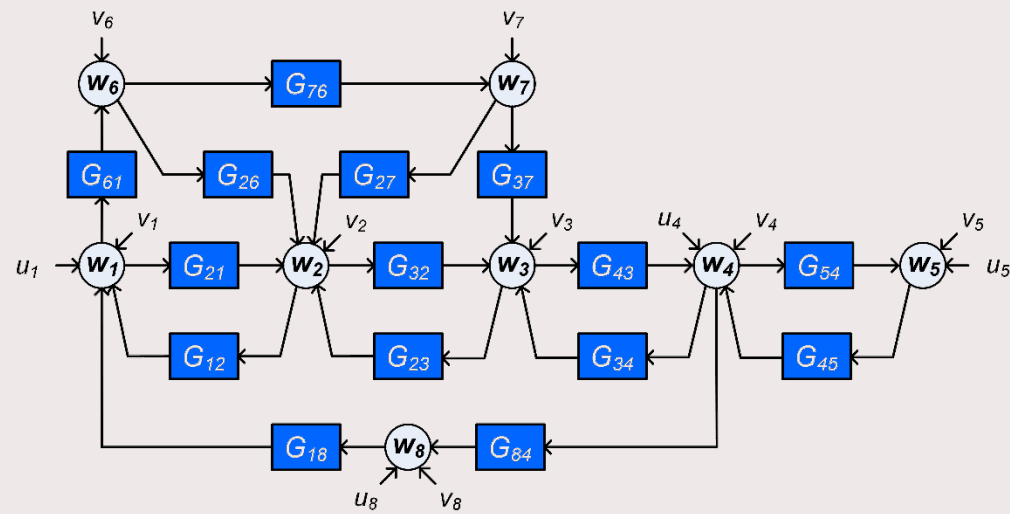
# Motivation – Modern Engineering



# Dynamic networks

## Dynamic network framework [1]

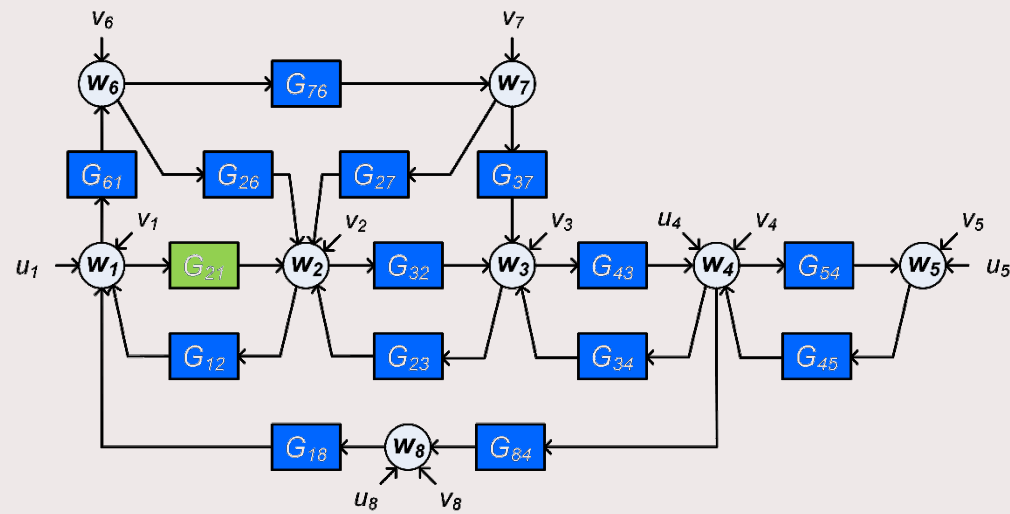
- $w(t)$ : Nodes
- $G_{ji}^0$  : Modules
- External signals
  - $u(t)$  : Excitation
  - $v(t) = H^0(q)e(t)$  : Disturbance



$$w = G^0 w + u + H^0 e$$

# Challenges in Dynamic networks

- Topology [1]
- Identifiability [2]
- Identification [3]
  - Full network
  - **Local identification**



# Content

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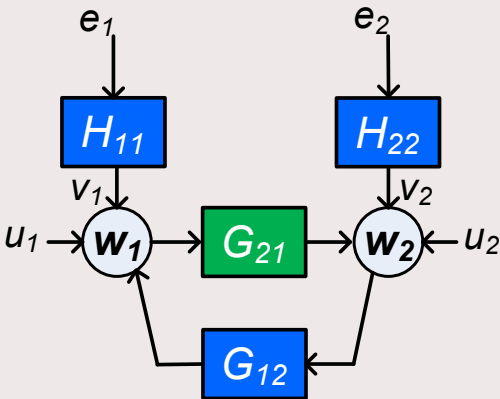


# Local identification

Single module identifiability <sup>[1]</sup>

- Method independent
- Identifiability:      no  $u$ -signal required

Method	Transfer		# $u$ -signals needed
Local Direct <sup>[2]</sup>	$w \rightarrow w$	Consistency & ML	0
Indirect <sup>[3]</sup>	$u \rightarrow w$	Consistency	1



[1] Shi, et al. 2021, 2022, 2023  
[2] Ramaswamy, et al., TAC, 2021.  
[3] Gevers, et al., IFAC, 2018. Hendrickx, et al., TAC, 2019. Bazanella, et al., CDC, 2019.

## Single module identifiability

- Method independent
- Identifiability: one  $u$ -signal required

The diagram illustrates a MIMO\* system with two antennas and two users. Two input signals,  $u_1$  and  $u_2$ , enter nodes  $w_1$  and  $w_2$  respectively. Node  $w_1$  is connected to three blocks:  $H_{11}$  (blue),  $H_{21}$  (blue), and  $G_{21}$  (green). Node  $w_2$  is connected to three blocks:  $H_{12}$  (blue),  $H_{22}$  (blue), and  $G_{12}$  (blue). Two noise signals,  $e_1$  and  $e_2$ , enter blocks  $H_{11}$  and  $H_{22}$  respectively. The outputs of the blocks are signals  $v_1$  and  $v_2$ , which are fed back into nodes  $w_1$  and  $w_2$  respectively. A red box labeled "MIMO\*" is present in the bottom left corner.

\*MIMO: Multivariate noise model to model confounding variables as correlated noise

# Research question

How can we obtain relaxed conservatism compared to current direct methods in **local** identification?

- Requires fewer u-signals
- Keep advantages of the current direct methods

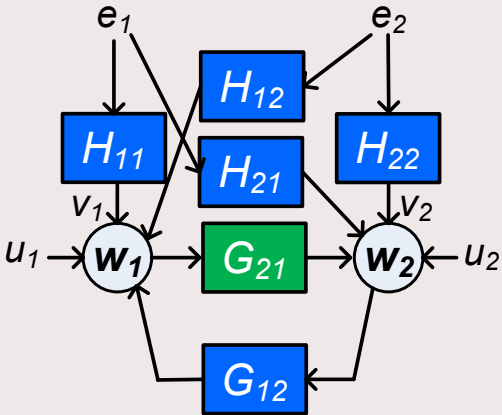


## Local identification – confounding variables

# Single module identifiability

- Method independent
- Identifiability: one  $u$ -signal

Method	Transfer		# u-signals needed
Local Direct	$w \rightarrow w$	Consistency & ML	2
Indirect	$u \rightarrow w$	Consistency	1
Multi-step Least squares <sup>[1]</sup>			1



## Full network identification

# Multi-step method [1,2]

Full network identification  $w = Gw + He + u$

1. High order ARX model to reconstruct the innovation

Estimate  $u \rightarrow w$  with high-order ARX and reconstruct  $\hat{e}$  ← Indirect method

$$w = Gw + (H - I)e + Ie + u$$

$$w = Gw + (H - I)\hat{e} + Ie + u \rightarrow \text{No confounding variables}$$

2. Parametric target module estimate

Use  $\hat{e}$  as additional measured input

$$w_j = \sum_k \underline{G_{jk}w_k} + \sum_\ell \underline{(H_{j\ell} - I_{jj})\hat{e}_\ell} + e_j + u_j \leftarrow \text{Direct method}$$

Estimate MISO models for each row  $j \in \mathcal{L}$  using Weighted Null Space Fitting<sup>[3]</sup> → convex

# Local Identification using a multi-step method


1. Selection of nodes
2. High order ARX model to reconstruct the innovation signal
3. Parametric target module estimate

Data Informativity:


*sufficient number of  $u$ -signals?*

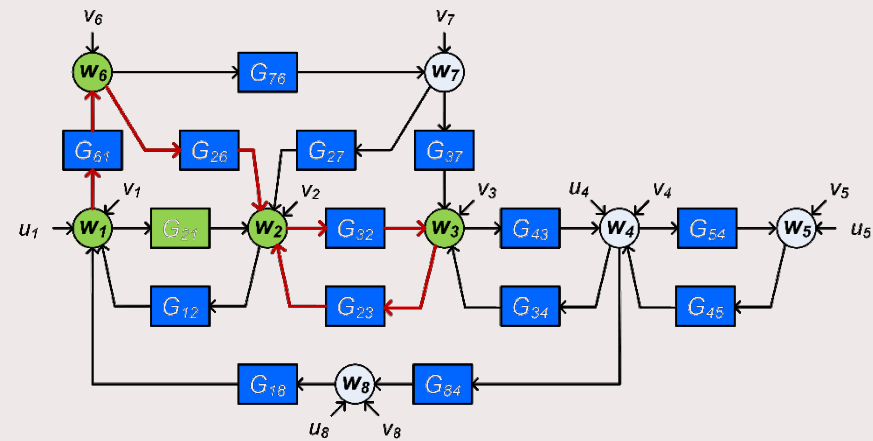
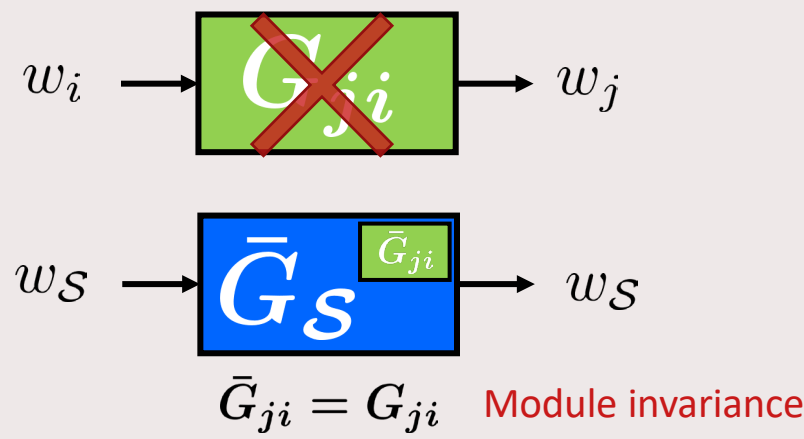
# Local Identification – 1. Selection of nodes

Select nodes  
Immerse [1]



Block parallel paths and loops around the output [1]





# Local identification <sup>[1,2]</sup> – 1. Selection of nodes

Decompose  $w_{\mathcal{S}}$  in<sup>[1]</sup>

$$j \in \mathcal{Y} \quad \left[ \begin{array}{c} w_{\mathcal{Y}} \\ w_{\mathcal{U}} \end{array} \right] = \left[ \begin{array}{c} \bar{G} \\ \bar{G}_{\mathcal{U}} \end{array} \right] \left[ \begin{array}{c} w_{\mathcal{Y}} \\ w_{\mathcal{U}} \end{array} \right] + \left[ \begin{array}{c|c} \bar{H} & 0 \\ \hline 0 & \bar{H}_{\mathcal{U}} \end{array} \right] \left[ \begin{array}{c} \xi_{\mathcal{Y}} \\ \xi_{\mathcal{U}} \end{array} \right] + \left[ \begin{array}{c} u_{\mathcal{Y}} \\ u_{\mathcal{U}} \end{array} \right] \quad [2]$$

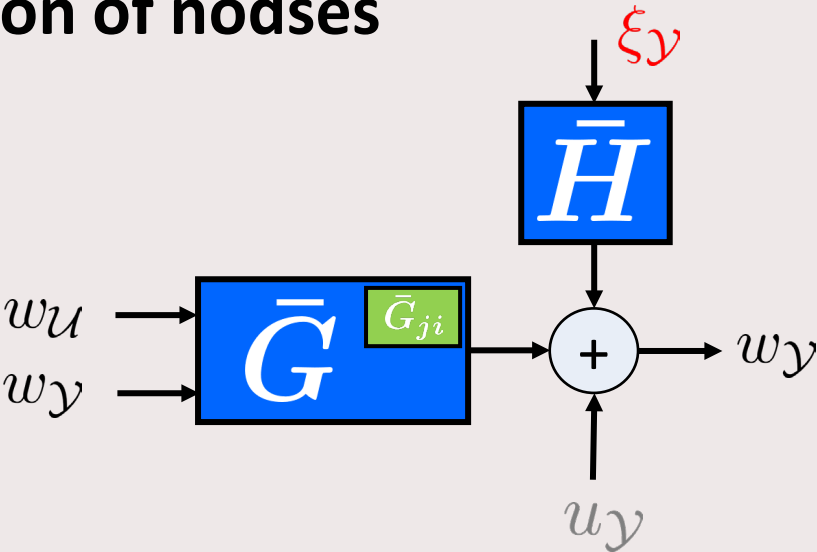
→ No confounding variables  $w_{\mathcal{U}} \rightarrow w_{\mathcal{Y}}$

- Confounding variable → Correlated noise

$$w_{\mathcal{Y}} = \bar{G} \left[ \begin{array}{c} w_{\mathcal{Y}} \\ w_{\mathcal{U}} \end{array} \right] + \bar{H} \xi_{\mathcal{Y}} + u_{\mathcal{Y}}$$

# Local identification – 1. Selection of nodes

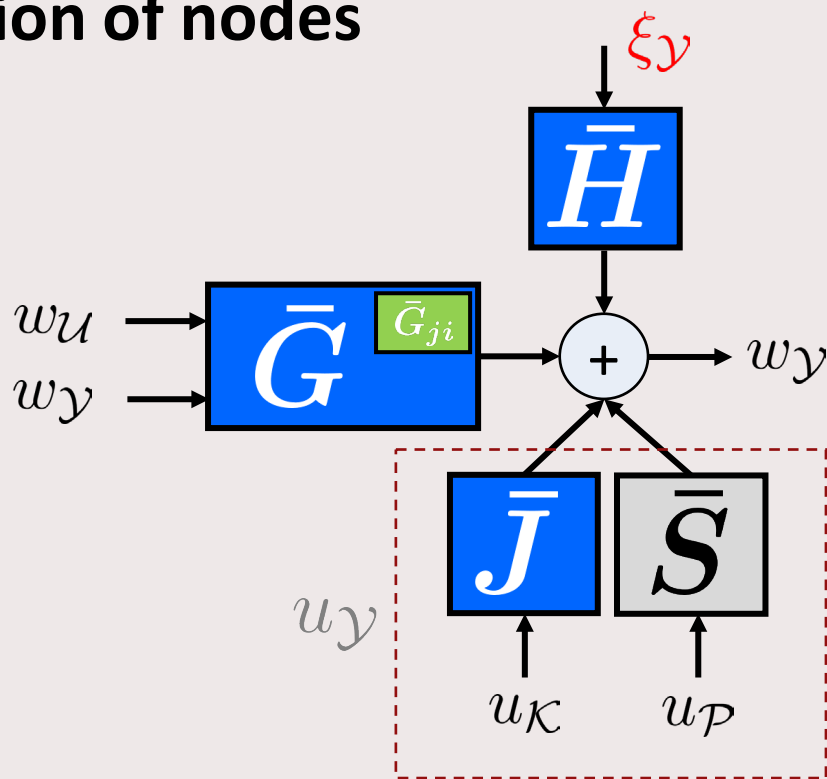
$$w_y = \bar{G} \begin{bmatrix} w_y \\ w_u \end{bmatrix} + \bar{H} \xi_y + \textcircled{u_y}$$



# Local identification – 1. Selection of nodes

Immersed network:  $u_{\mathcal{Y}}^{[1]}$

$$u_{\mathcal{Y}} = \underbrace{\bar{J}(q)}_{\text{Dynamic}} u_{\mathcal{K}} + \underbrace{\bar{S}}_{\text{Known}} u_{\mathcal{P}}$$





# Local identification

$$w_{\mathcal{Y}} = \bar{G}(q) \begin{bmatrix} w_{\mathcal{Y}} \\ w_{\mathcal{U}} \end{bmatrix} + \bar{H}(q)\xi_{\mathcal{Y}} + \bar{J}(q)u_{\mathcal{K}} + \bar{S}u_{\mathcal{P}}$$

## 2. High order ARX model to reconstruct the innovation

Estimate  $u_{\mathcal{K} \cup \mathcal{P}} \rightarrow w$  with high-order ARX and reconstruct  $\hat{\xi}_{\mathcal{Y}}$

## 3. Parametric target module estimate

Use  $\hat{\xi}_{\mathcal{Y}}$  as additional measured input

$$w_j = \sum_{k \in \mathcal{N}_j^-} \bar{G}_{jk} w_k + \sum_{\ell \in \mathcal{Y}} (\bar{H}_{j\ell} - I_{jj}) \hat{\xi}_{\ell} + \xi_j + \sum_{m \in \mathcal{K}_j} \bar{J}_{jm} u_m + u_{\mathcal{P}_j}$$

Estimate the  $j$ -th MISO model  $j \in \mathcal{Y}$

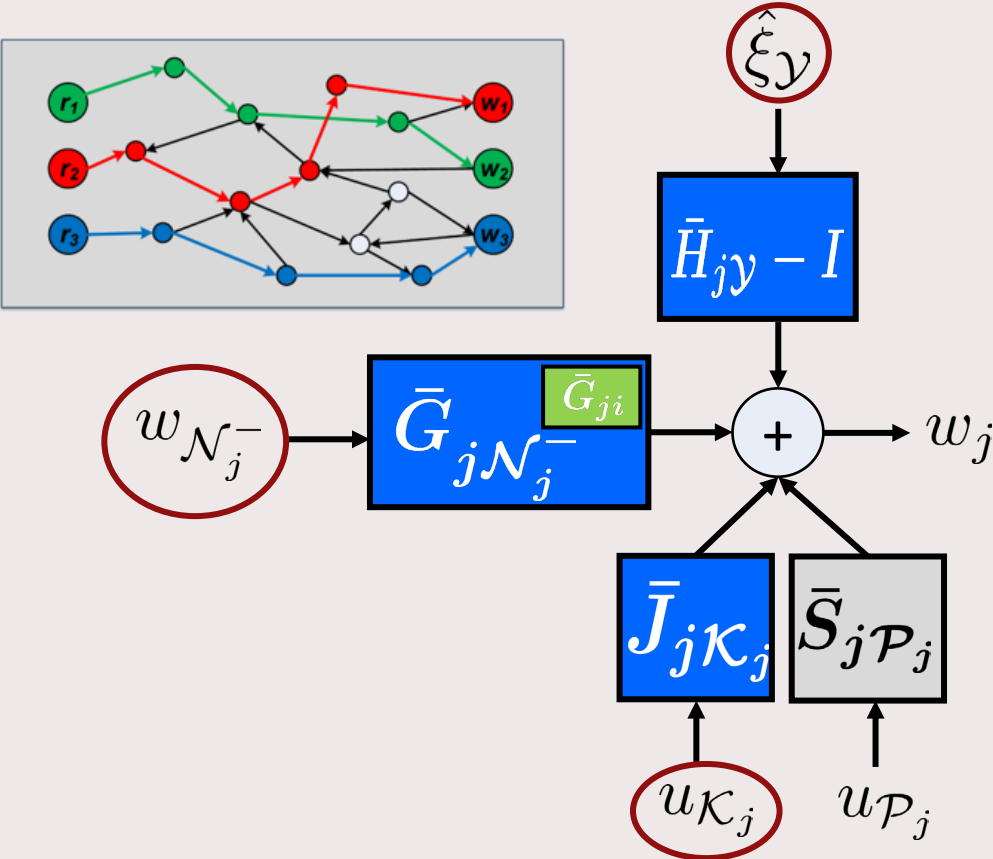
# Local identification

Data informativity [1]

$\Phi_{\kappa}(\omega) \succ 0 \quad \kappa = \begin{bmatrix} w_{\mathcal{N}_j^-} \\ \xi_{\mathcal{Y}} \\ u_{\mathcal{K}_j} \end{bmatrix}$

Data informativity holds generically if there are  $dim(\kappa)$  vertex disjoint paths from

$\begin{bmatrix} \xi_{\mathcal{S}} \\ u_{\mathcal{L}} \end{bmatrix} \rightarrow \begin{bmatrix} w_{\mathcal{N}_j^-} \\ \xi_{\mathcal{Y}} \\ u_{\mathcal{K}_j} \end{bmatrix}$



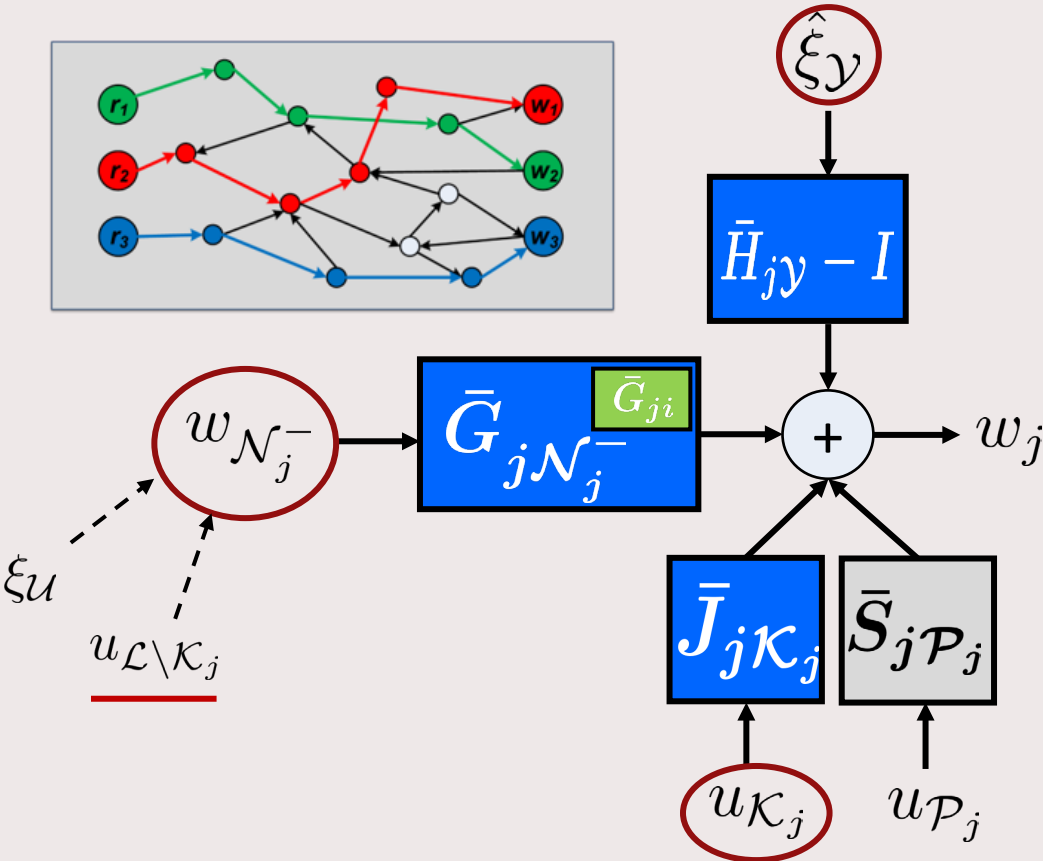
# Local identification

Data informativity [1]

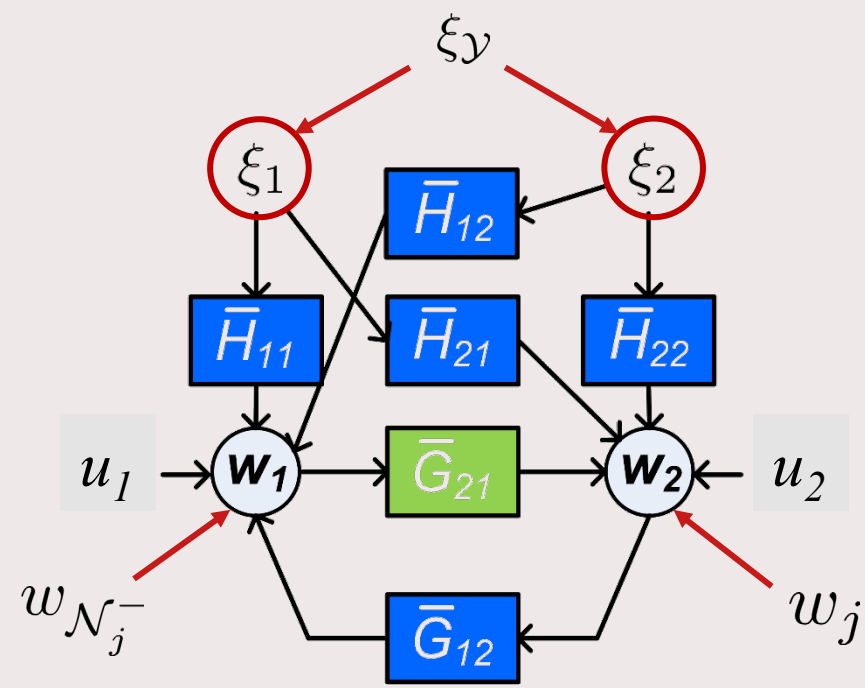
$$\Phi_{\kappa}(\omega) \succ 0 \quad \kappa = \begin{bmatrix} w_{\mathcal{N}_j^-} \\ \xi_{\mathcal{Y}} \\ u_{\mathcal{K}_j} \end{bmatrix}$$

Data informativity holds generically if there are  $dim(w_{\mathcal{N}_j^-})$  vertex disjoint paths from

$$\begin{bmatrix} \xi_{\mathcal{U}} \\ u_{\mathcal{L} \setminus \mathcal{K}_j} \end{bmatrix} \rightarrow w_{\mathcal{N}_j^-}$$



# Local identification



$$\mathcal{Y} = \{1, 2\}, \mathcal{U} = \emptyset$$

$$u_{\mathcal{L} \setminus \mathcal{K}_j} = u_1, u_2 \quad \notin \mathcal{K}_j = \emptyset$$

$$\Phi_{\kappa} \succ 0$$

$$\left[ \begin{array}{c} \xi_{\mathcal{U}} \\ u_{\mathcal{L} \setminus \mathcal{K}_j} \end{array} \right] \rightarrow w_{\mathcal{N}_j^-} \quad \left[ \begin{array}{c} \emptyset \\ u_1, u_2 \end{array} \right] \rightarrow w_1$$

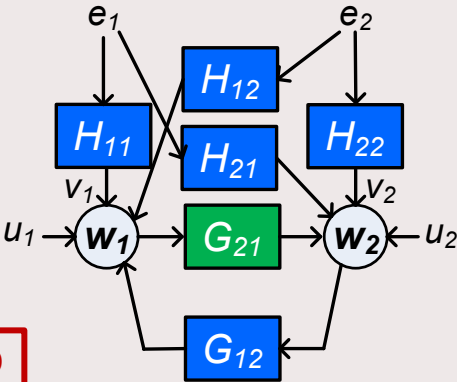
$w_1$  is persistently exciting holds generically if there is 1 vertex disjoint paths from  $u_1$  OR  $u_2 \rightarrow w_1$

# Local identification

## Single module identifiability

- Method independent
- Identifiability: 1  $u$ -signal

Method	Transfer		# $u$ -signals needed
Local Direct	$w \rightarrow w$	Consistency & ML	2
Indirect	$u \rightarrow w$	Consistency	1
Multi-step Least squares	1. Indirect 2. Direct	Consistency & ML?	1



MIMO

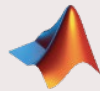
MISO

# Conclusion

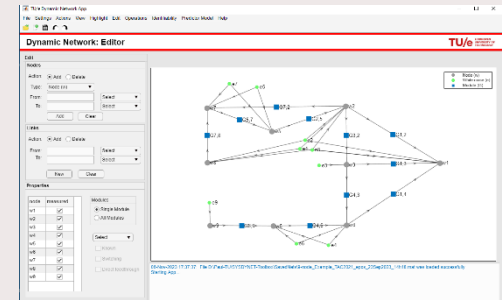
Combining indirect and direct methods:

- Requires fewer u-signals than current direct method
- Keeps advantages of the current direct methods
- Parametric estimation with Weighted Null Space Fitting → Convex

Available in Toolbox



[www.sysdynet.net](http://www.sysdynet.net)



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