





# **Dynamic network setup**

$$w_j(t) = \sum_{k \in \mathcal{N}_j} G_{ji}(q) w_i(t) + r_j(t) + v_j(t)$$

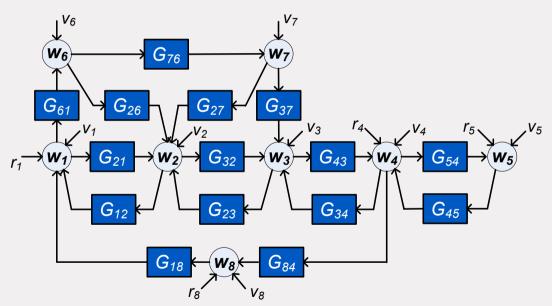
 $w_j$  node signals,  $j=1,\cdots L$ 

 $G_{ii}$  modules (LTI)

 $r_{j}$  external excitation

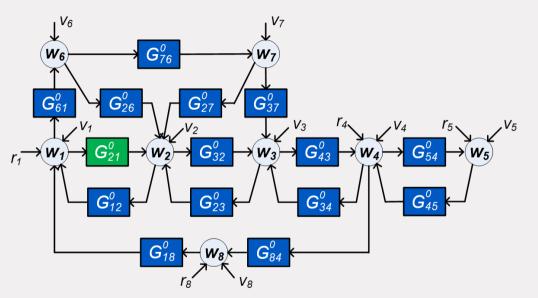
 $v_{\it j}$  disturbance signal

$$w = Gw + Rr + He$$





# Single module identification



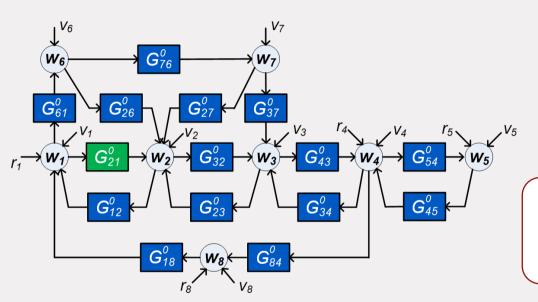
### The problem:

For a network with known topology: Identify  $G_{21}^0$  on the basis of selected measured signals (w, r)

Preference for "local" measurements and limited excitation



# Single module identification



### **Options:**

- Indirect method<sup>[1],[2]</sup> Dependent on excitation from  $m{r}$  only
- Direct method<sup>[1],[3],[4]</sup>
  Excitation from (r, v)Maximum likelihood results

TU/e

<sup>[1]</sup> VdHof et al., Automatica 2013

<sup>[2]</sup> Gevers et al., SYSID 2018; Bazanella et al., CDC 2019

### **Direct method**

Full network equation:

$$w = Gw + Rr + He$$

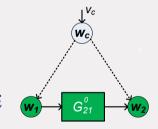
Signal selection

Predictor model after signal selection:

$$w_{\!\mathcal{Y}} = ar{G}w_{\!\mathcal{D}} + ar{R}r_{\!\mathcal{P}} + ar{H}\xi_{\!\mathcal{Y}}$$

This can be handled in a direct-type identification method if

- 1.  $ar{G}_{ji} = G_{ji}$  for the target module
- 2.  $\bar{R}$  is a selection matrix
- 3. There are no confounding variables that affect the estimation of  $ar{G}_{ji}$

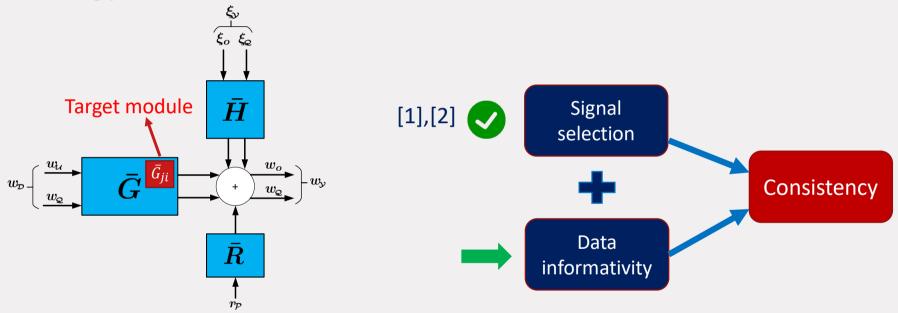


This can lead to a MIMO predictor model.



### **Direct method**

Resulting predictor model:



There can be common signals in input and output:  $w_{\mathcal{Q}}$ 



<sup>[1]</sup> Dankers et al., IEEE Trans. Autom Control, 2016

<sup>[2]</sup> Ramaswamy et al., IEEE Trans. Autom Control, 2021

# Data informativity (classical definition)

Predictor model:  $\hat{w}_{\mathcal{V}}(t,\theta) = W(q,\theta)z(t)$ 

with 
$$z(t) := egin{bmatrix} w_{\mathcal{Y}}(t, heta) &= W\left(q, heta)z(t) \\ w_{\mathcal{D}}(t) \\ v_{\mathcal{P}}(t) \end{bmatrix}$$
 for a model set  $\mathcal{M}$  parametrized by  $\theta \in \Theta$ 

Then a data sequence  $\{z(t)\}_{t=0,...}$  is informative with respect to  $\mathcal{M}$ if for any two models in  $\mathcal{M}$ :

$$\left[ ar{\mathbb{E}}[(W_1(q){-}W_2(q))z(t)]^2 = 0 \implies W_1(e^{i\omega}) \equiv W_2(e^{i\omega}) 
ight]$$

A sufficient condition for this is that z is persistently exciting:

$$\Phi_z(\omega)>0$$
 for almost all  $\omega$ 



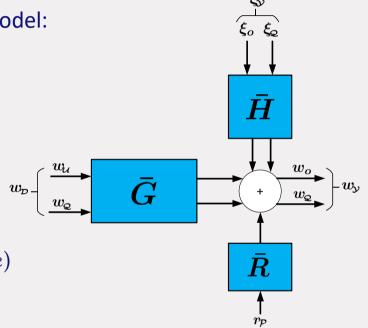
# **Spectrum condition - network case**

In the situation of our specific predictor model:

$$\Phi_{\kappa}(\omega)>0$$
 for almost all  $\omega$ 

$$\kappa(t) := egin{bmatrix} w_{\mathcal{D}}(t) \ \xi_{\mathcal{Y}}(t) \end{bmatrix}$$

- Note that  $\kappa$  is a filtered version of (r,e)
- with (r, e) persistently exciting



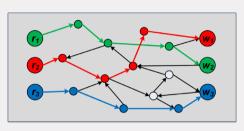


# Data informativity (path-based condition)

By exploiting the fact that

$$oldsymbol{\kappa}(t) = F(q) egin{bmatrix} r(t) \ e(t) \end{bmatrix}$$

- p.e. of  $\kappa$  is determined by the row rank of F
- which can be evaluated generically [1],[2] by the number of vertex disjoint paths between inputs and outputs



$$b_{\!\scriptscriptstyle \mathcal{R} 
ightarrow \mathcal{W}} = 3$$

we arrive at the **final result**:

Persistence of excitation of  $\kappa$  holds generically if there are

 $|\mathcal{D}|$  vertex disjoint paths between external signals  $(r_{\mathcal{P}}, x_{\mathcal{U}})$  and  $w_{\mathcal{D}}$ 

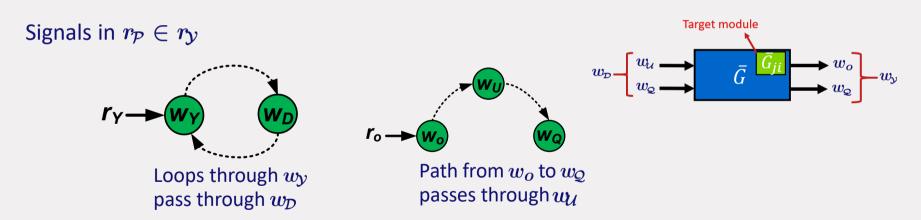


<sup>[1]</sup> Van der Woude, 1991

<sup>[2]</sup> Hendrickx, Gevers & Bazanella, CDC 2017, TAC 2019.

# **External signals on original network**

Generic data informativity check becomes:  $|\mathcal{D}|$  vertex disjoint paths between external signals  $(r_{\mathcal{P}}, x_{\mathcal{U}})$  and  $w_{\mathcal{D}}$ 



Signals in  $x_{\mathcal{U}}$ : All external signals (r,e) that have a direct or unmeasured path to  $w_{\mathcal{U}}$ 



# **Example**

Target: identify  $G_{21}$ 

Predictor model:  $\underbrace{\{w_1\}}_{w_{\mathcal{D}}} o \underbrace{\{w_1,w_2\}}_{w_{\mathcal{V}}}$ 

2 x 2 noise model accounts for confounding variable

$$w_{\mathcal{Q}} = \{w_1\} \quad w_{\mathcal{U}} = \emptyset \quad x_{\mathcal{U}} = \emptyset$$

# $H_{11}$ $H_{21}$ $H_{22}$ $V_{1}$ $G_{21}$ $W_{2}$ $G_{12}$

### Result 1:

Neither  $r_1$  nor  $r_2$  can contribute to  $r_p \longrightarrow$  data informativity condition is not satisfied

**Result 2**: Change predictor model to:  $\underbrace{\{w_1, \textcolor{red}{w_2}\}}_{w_{\mathcal{D}}} o \underbrace{\{w_1, w_2\}}_{w_{\mathcal{Y}}}$ 

Both  $r_1$  and  $r_2$  contribute to  $r_{\mathcal{P}} \longrightarrow$  data informativity condition is satisfied



### **Conclusion**

- Data-informativity condition specified for direct identification of single modules in dynamic networks, with given topology
- For satisfying data-informativity generically, path-based conditions can be formulated on the network graph
- Together with the path-based conditions for appropriate predictor model selection, a full set of path-based conditions is formulated for consistent estimation of a single module
- To be used also for external signal allocation (experimental setup)







