

# Identification in interconnected systems – modeling, structural aspects and MATLAB toolbox

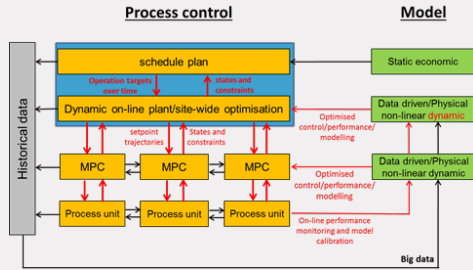
Paul Van den Hof

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14 November 2023

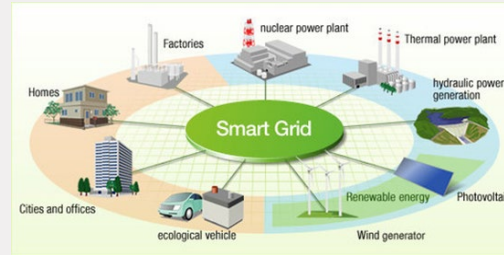
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# Introduction – dynamic networks

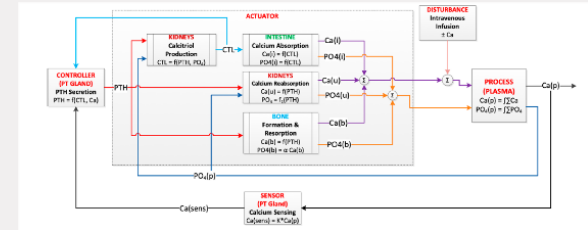
## Decentralized process control



## Smart power grid

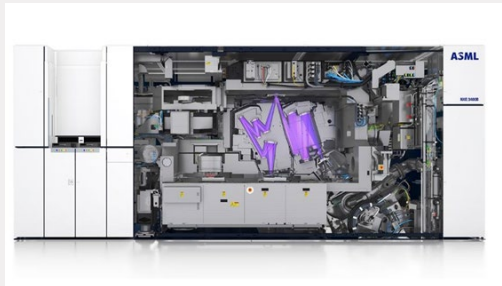


## Physiological models

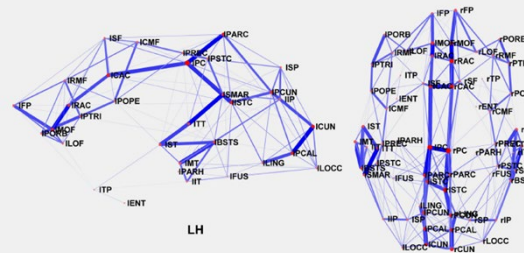


Christie, Achenie and Ogunnaike (2014)

## Complex machines

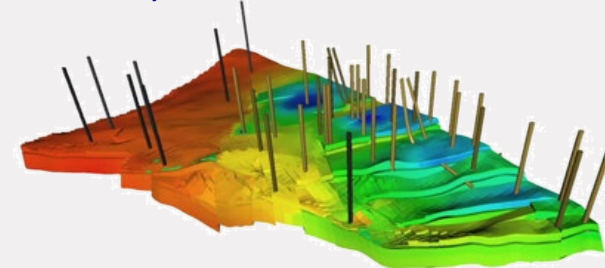


## Brain network



P. Hagmann et al. (2008)

## Hydrocarbon reservoirs



Mansoori (2014)

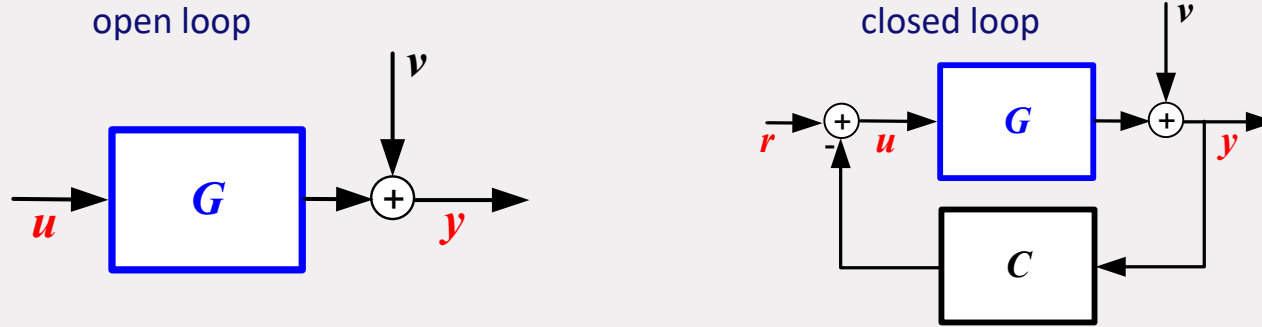
# Introduction

## Overall trend:

- (Large-scale) interconnected dynamic systems
- Distributed / multi-agent type monitoring, control, optimization, diagnostics
- Data is “everywhere”, AI/machine learning tools
- Model-based operations require accurate/relevant models
- → **Learning models/actions from data** (including physical insights when available)

# Introduction

The classical (multivariable) data-driven modeling problems<sup>[1]</sup>:



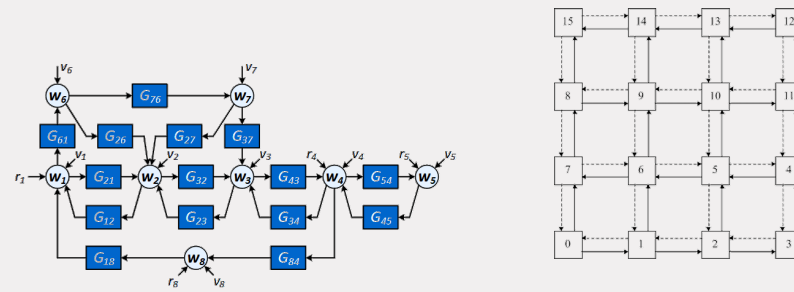
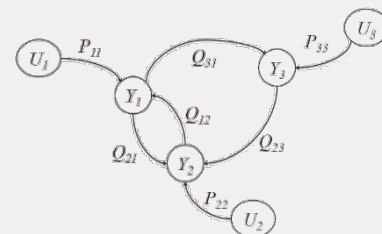
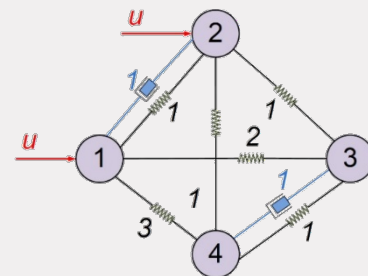
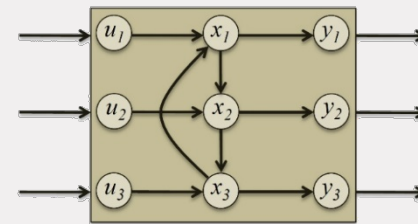
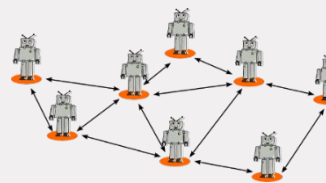
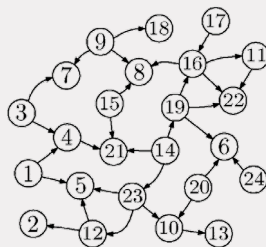
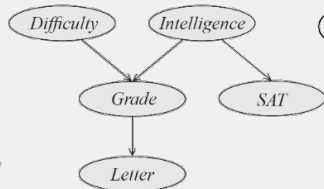
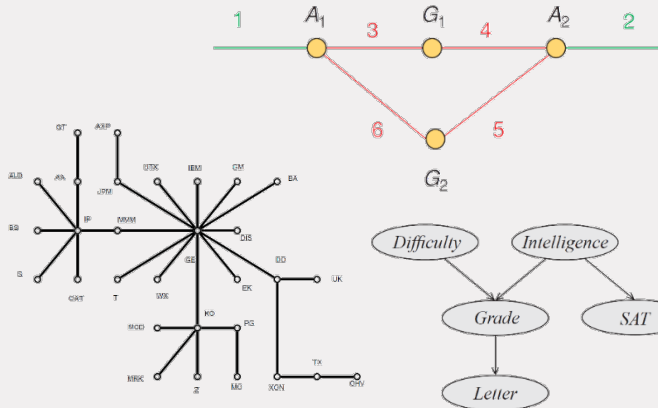
Identify a model of  $G$  on the basis of measured signals  $u, y$  (and possibly  $r$ ), focusing on *continuous LTI dynamics*.

In interconnected systems (networks) the **structure / topology** becomes important to include

<sup>[1]</sup> Ljung (1999), Söderström and Stoica (1989), Pintelon and Schoukens (2012)

# Network models

- dynamic elements with cause-effect
- handling feedback loops (cycles)
- centered around measured signals
- allow disturbances and probing signals



D. Materassi and M.V. Salapaka (2012)

R.N. Mantegna (1999)

[www.momo.cs.okayama-u.ac.jp](http://www.momo.cs.okayama-u.ac.jp)

J.C. Willems (2007)

D. Koller and N. Friedman (2009)

E.A. Carara and F.G. Moraes (2008)

P.E. Paré et al (2013)

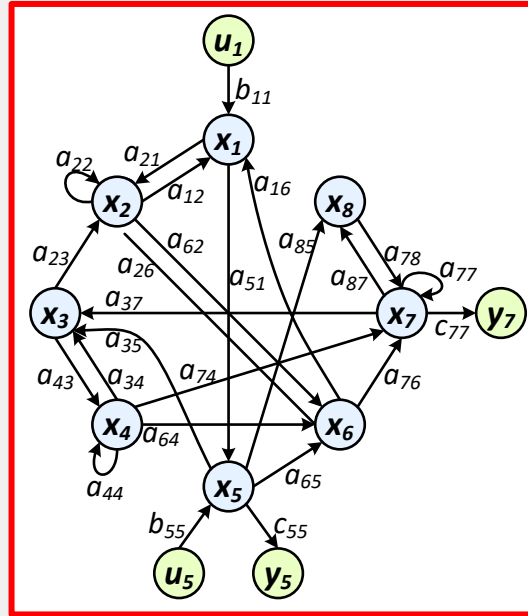
P.M.J. Van den Hof et al (2013)

X.Cheng (2019)

E. Yeung et al (2010)



# Network models



State space representation

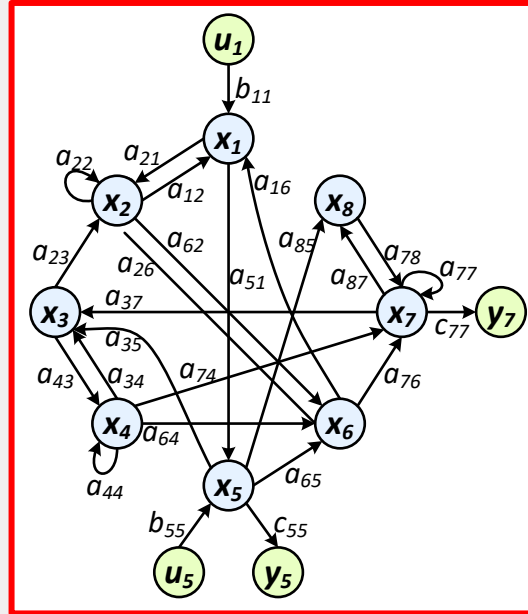
$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k)\end{aligned}$$

- States as **nodes** in a (directed) graph
- State transitions (1 step in time) reflected by  $a_{ij}$
- Transitions are encoded in links
- Ultimate break-down of system structure
- Actuation ( $u$ ) and sensing ( $y$ ) reflected by separate links

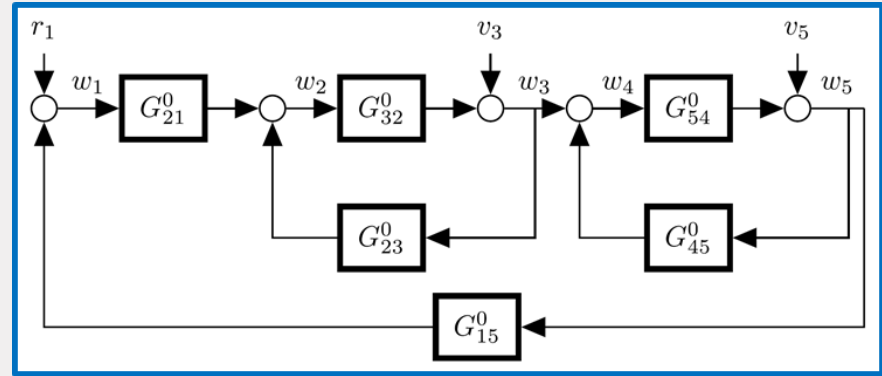
For data-driven modeling problems:

- Lump unmeasured states in dynamic **modules**

# Network models



State space representation [1]

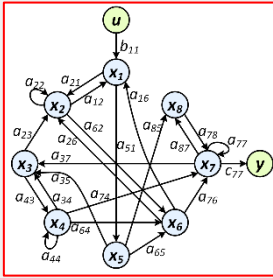


Module representation [2]

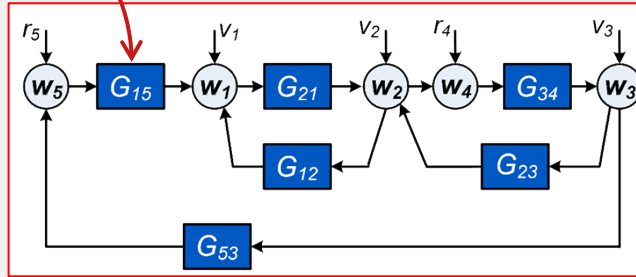
[1] Goncalves, Warnick, Sandberg, Yeung, Yuan, Scherpen,...

[2] VdH, Dankers, Goncalves, Warnick, Gevers, Bazanella, Hendrickx, Materassi, Weerts,...

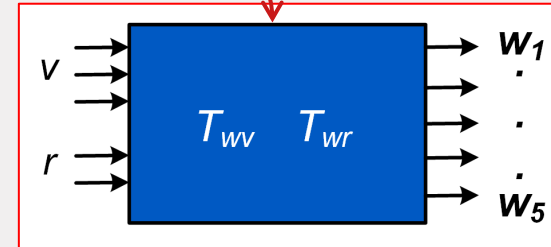
# Dynamic network models - zooming



Increasing level of detail

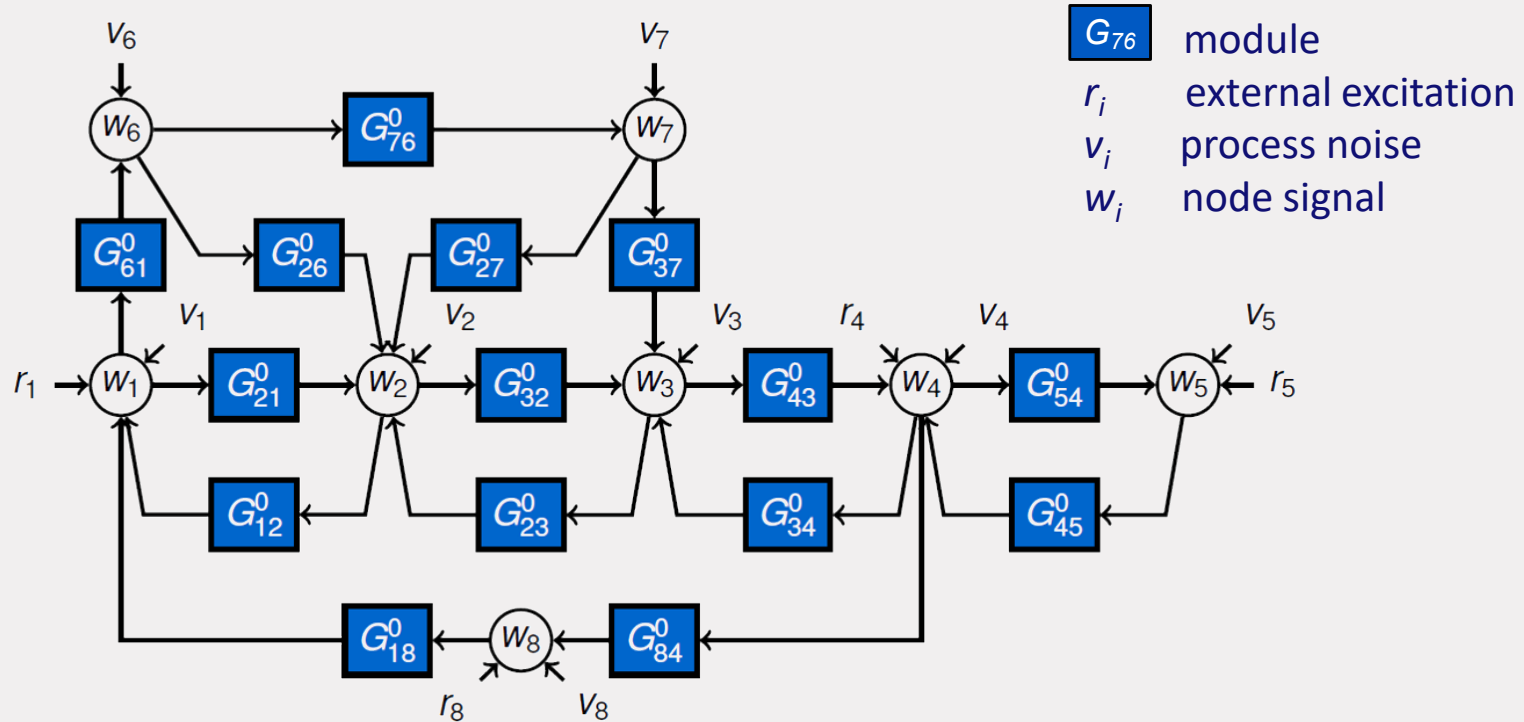


Decreasing structural information

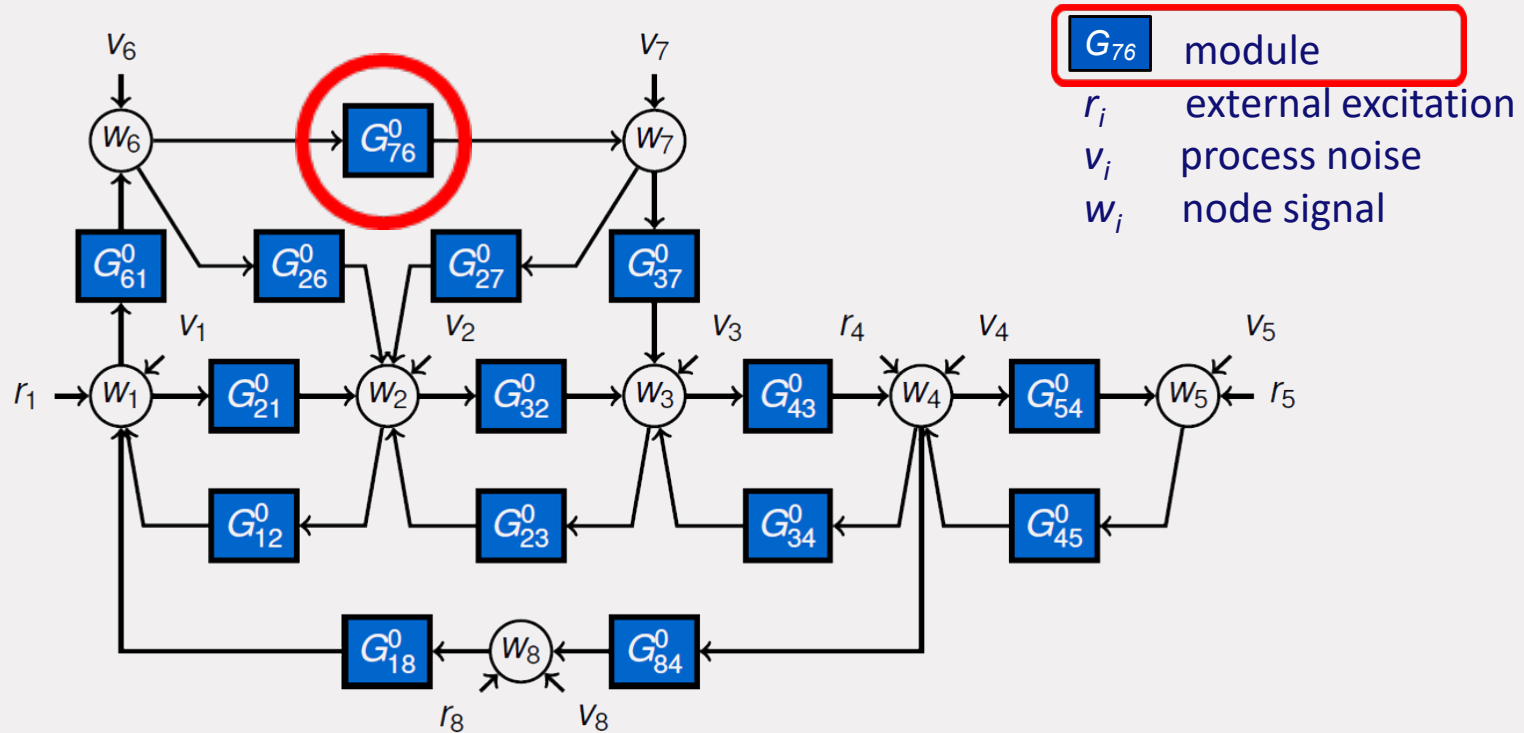




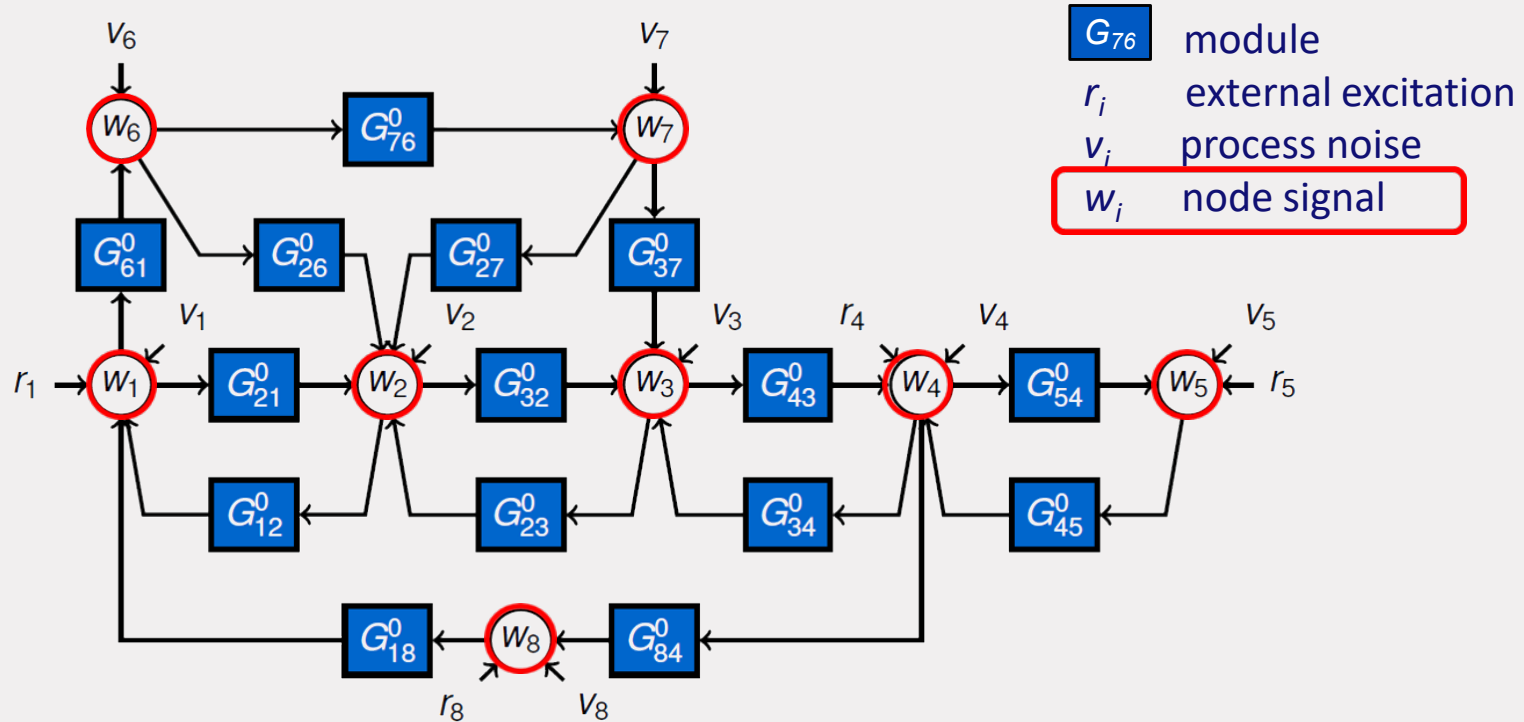
# Dynamic network setup



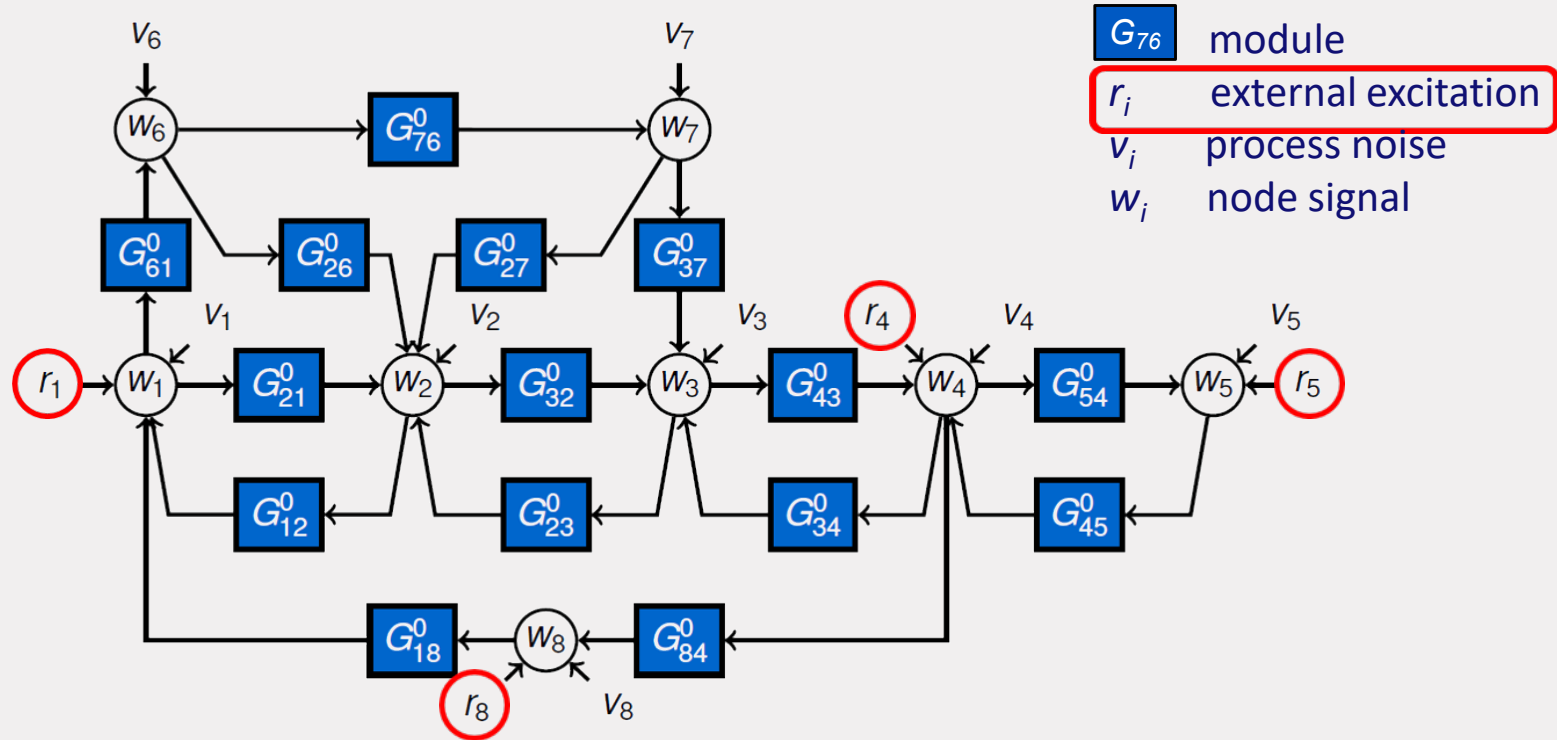
# Dynamic network setup



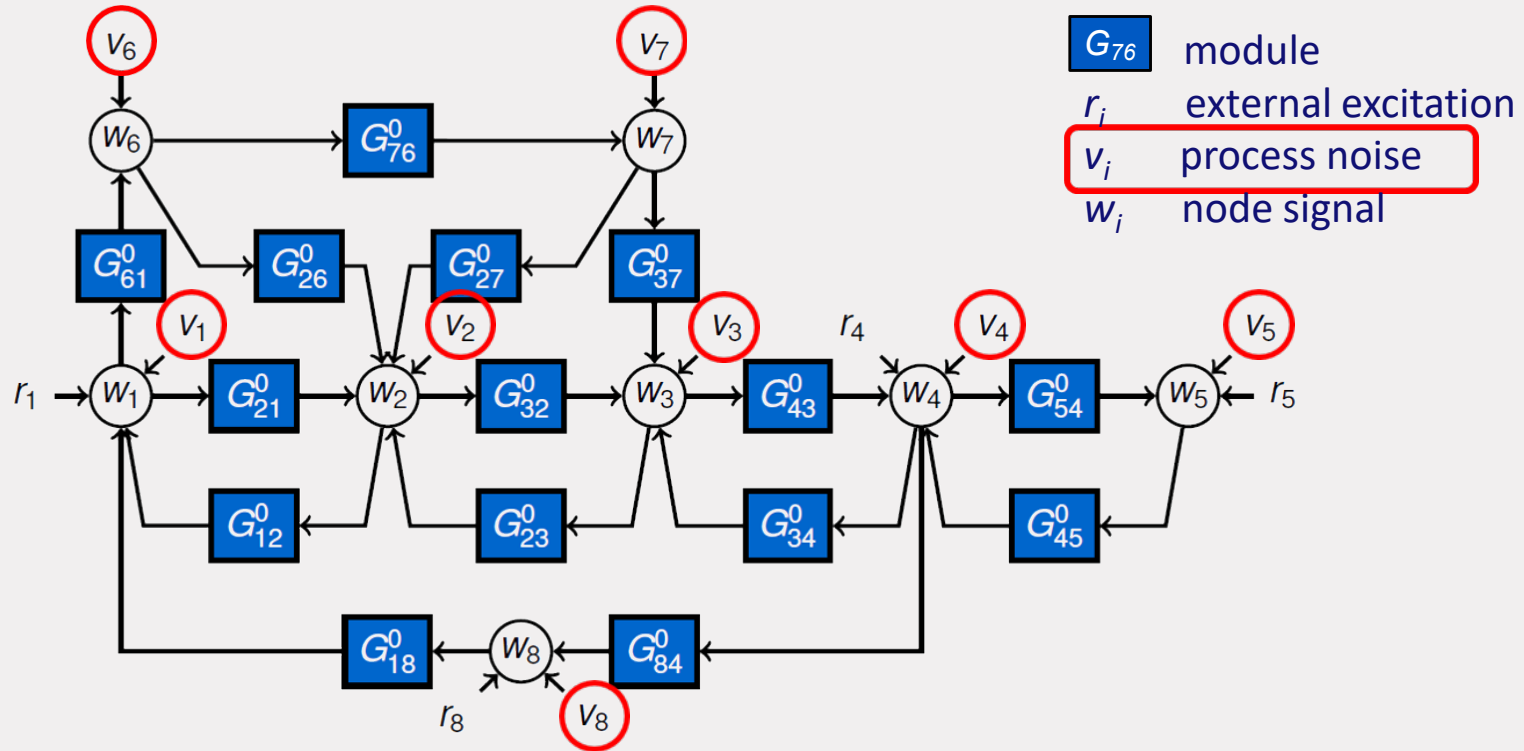
# Dynamic network setup



# Dynamic network setup



# Dynamic network setup



# Dynamic network setup

Collecting all equations:

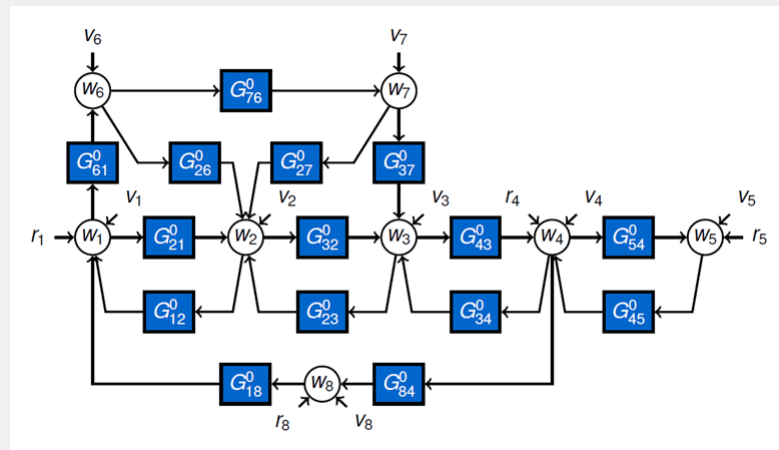
$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & G_{12}^0 & \cdots & G_{1L}^0 \\ G_{21}^0 & 0 & \cdots & G_{2L}^0 \\ \vdots & \ddots & \ddots & \vdots \\ G_{L1}^0 & G_{L2}^0 & \cdots & 0 \end{bmatrix}}_{\text{Network matrix } G^0(q)} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} + R^0 \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_K \end{bmatrix} + H^0 \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_p \end{bmatrix}$$

$$w(t) = G^0(q)w(t) + \underbrace{R^0(q)r(t)}_{u(t)} + v(t); \quad v(t) = H^0(q)e(t); \quad \text{cov}(e) = \Lambda$$

- Typically  $R^0$  is just a (static) selection matrix, indicating which nodes have an excitation signal.
- The topology of the network is encoded in the structure (non-zero entries) of  $G^0$ .
- $r$  and  $e$  are called **external signals**.



# Dynamic network setup



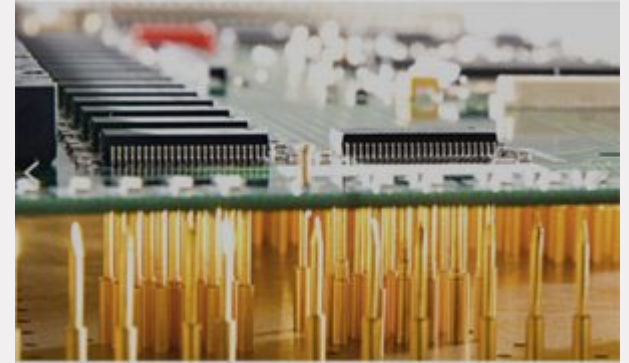
Measured time series:

$$\{w_i(t)\}_{i=1,\dots,L}; \{r_j(t)\}_{j=1,\dots,K}$$

Many challenging data-driven modeling and diagnostics challenges appear

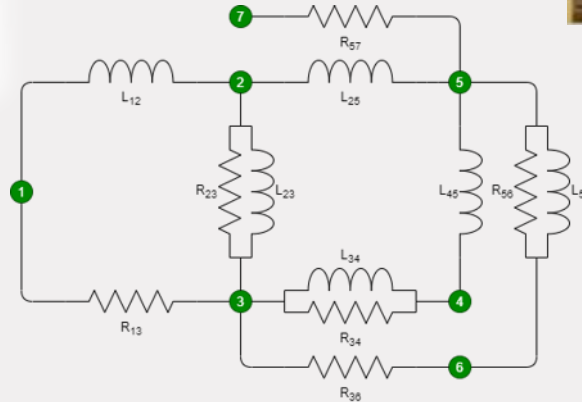
- Identification of a local module (known topology)
- Identification of the full network
- Topology estimation
- Identifiability
- Sensor and excitation allocation
- Diagnostics and fault detection
- Distributed identification
  
- User prior knowledge of modules
- Scalable algorithms

# Application: Printed Circuit Board (PCB) Testing

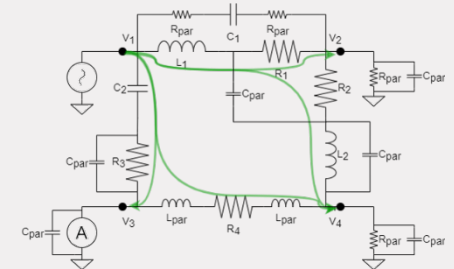


Detection of

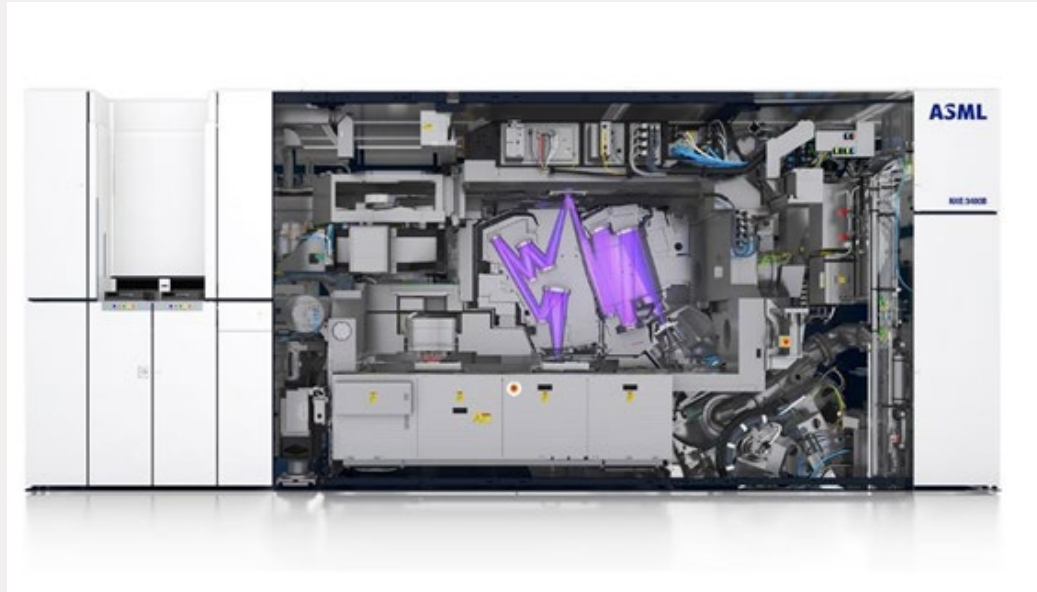
- component failures
- parasitic effects



Source: Altium

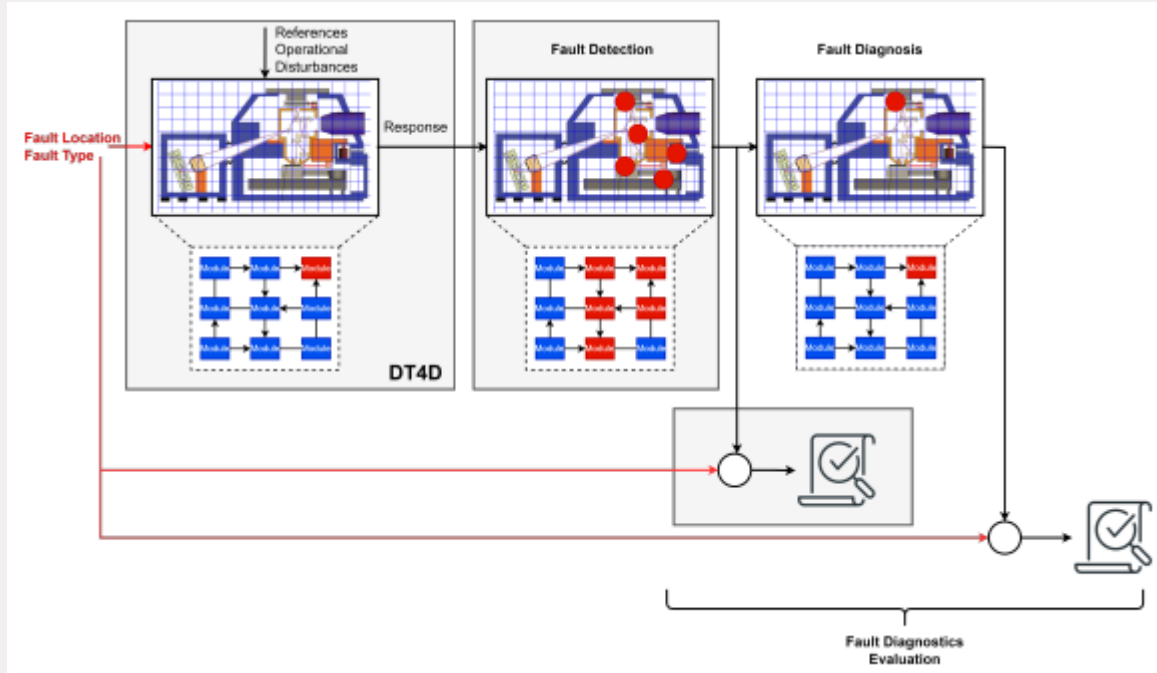


# Application: diagnostics in lithography waferscanners



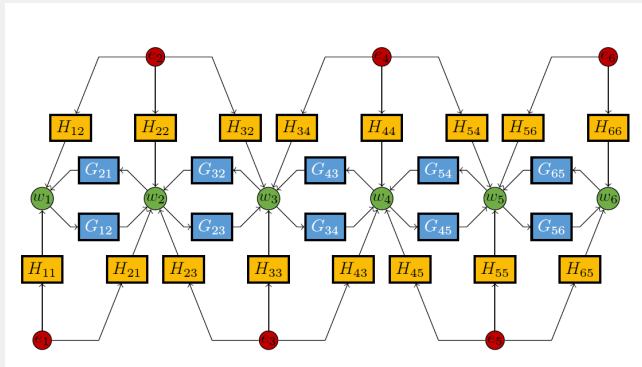
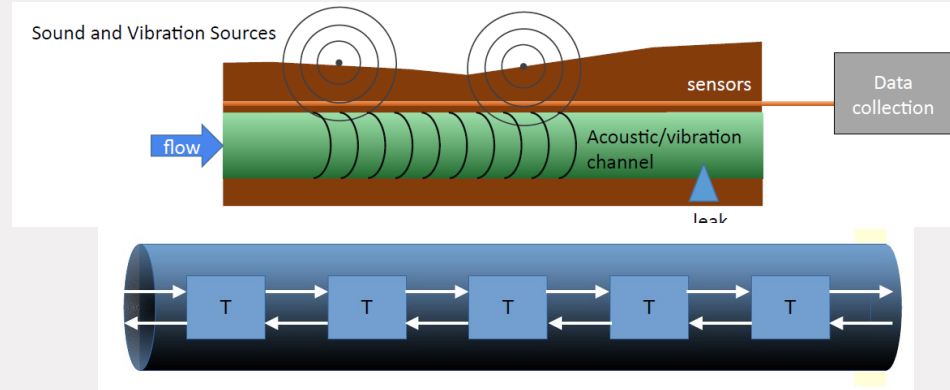
- 200M€ machine
- Highly complex machine dynamics
- Many interconnected subsystems
- Need for very fast recovery from faults
- Tools for automated diagnostics

# Application: diagnostics in lithography waferscanners



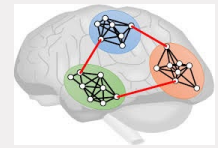
- Digital twin, for detection and diagnosis
- Exploit interconnection structure

# Leak detection in gas pipelines with acoustic sensors



- Use operational data to detect changes in network model dynamics
- Map model changes to physical causes

# Neurodynamic effect of listening to Mozart music



Identifying changes in network connections in the brain, after intensely listening for one week (Sonate K448), based on fMRI data

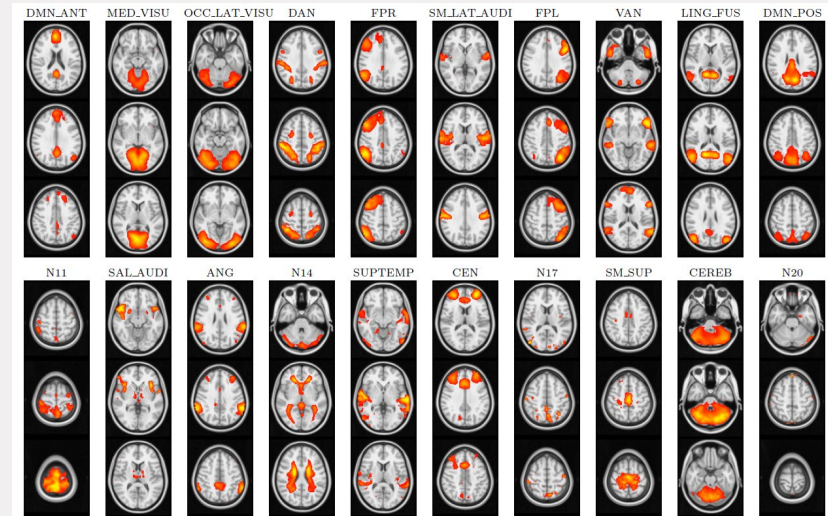
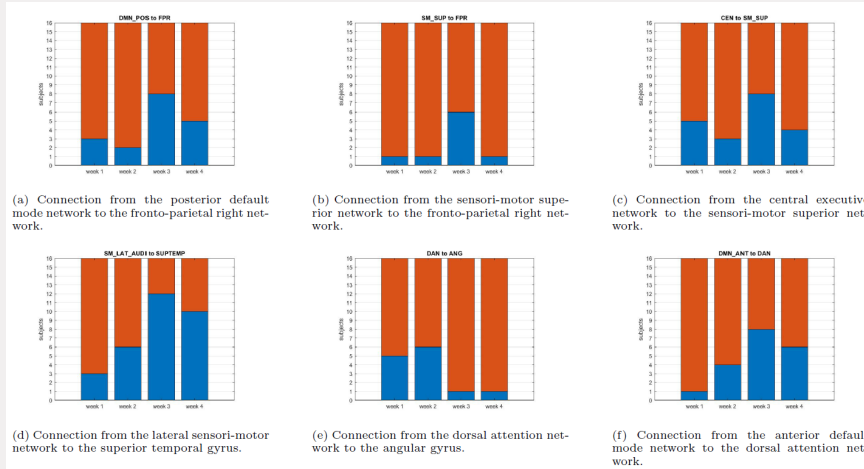


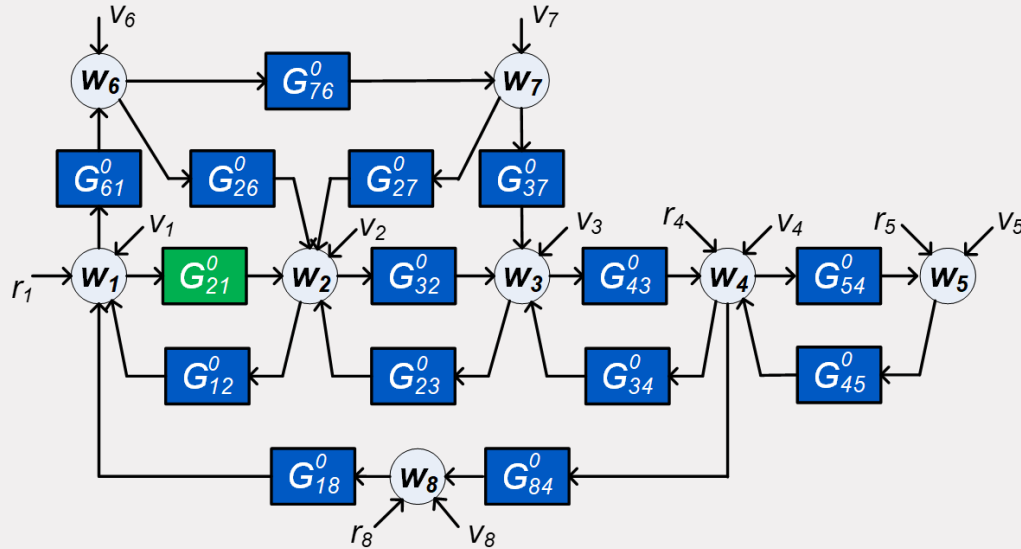
Figure 3: Spatial maps of the 20 active brain networks found through the ICA decomposition. Each image consists of 3 relevant horizontal slices of the brain, where the spatial map is indicated by the red color scale.



# Single module identification

known topology

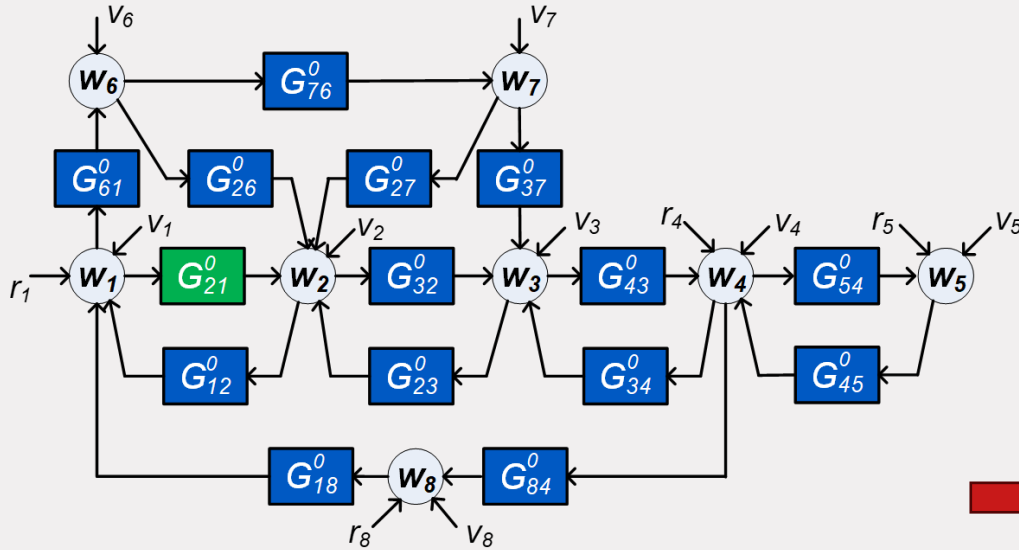
# Single module identification



For a network with  
known topology:

- Identify  $G_{21}^0$  on the basis of measured signals
- Which signals to measure?  
Preference for local measurements
- When is there enough excitation / data informativity?

# Single module identification



Different types of methods:

## Indirect methods:

- Rely on mappings  $r \rightarrow w$  and on sufficient excitation signals  $r$

## Direct methods:

- Rely on mappings  $w \rightarrow w$  and use excitation from both  $r$  and  $v$  signals

# Single module identification

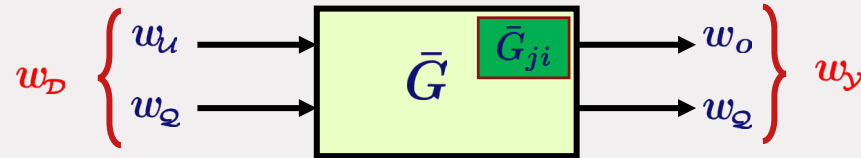
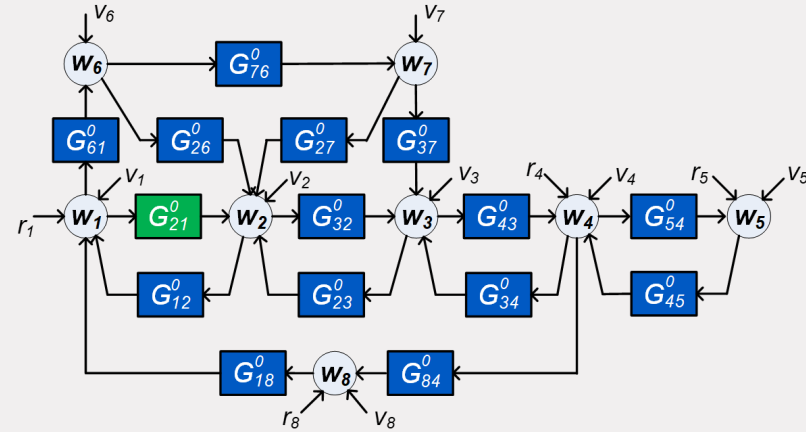
## Local direct method:

(consistency and minimum variance properties)

## Select a subnetwork:

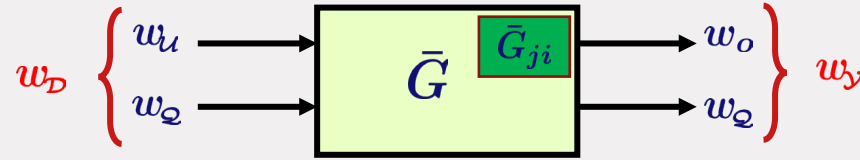
- Predicted outputs:  $w_y$
- Predictor inputs:  $w_D$

such that prediction error minimization leads to an accurate estimate of  $G_{21}^0$



**Note:** same node signals can appear in input and output

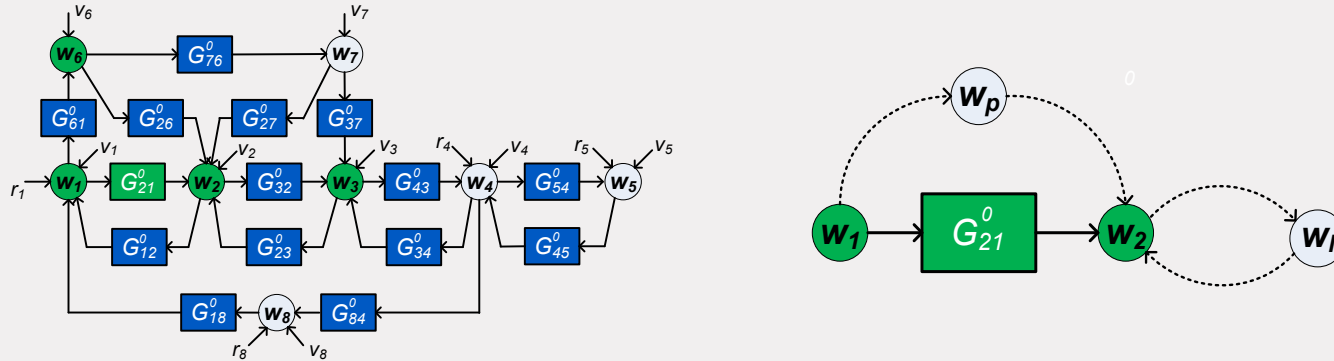
# Single module identification



Conditions for arriving at an accurate (consistent) model:

1. Module invariance:  $\bar{G}_{ji} = G_{ji}^0$  when removing discarded nodes (immersion)
2. Handling of confounding variables
3. Data-informativity
4. *Technical condition on presence of delays*

# Single module identification - module invariance



A sufficient condition for module invariance:

All parallel paths, and loops around the output, should be "blocked" by a measured node that is present in  $w_D$

All other signals can be removed/immersed from the network<sup>[2]</sup>

Alternative graph-based formulation in terms of disconnecting sets in [3]

[1] Dankers et al., TAC 2016  
[3] Shi et al., Automatica 2022

[2] Generalizations available in Linder&Enqvist (2017), Weerts et al, (2020)



# Single module identification - confounding variables

## Confounding variable <sup>[1][2]</sup>:

Unmeasured signal that has (unmeasured paths) to both the input and output of an estimation problem.

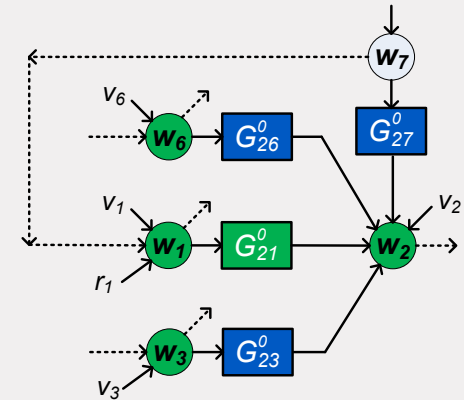
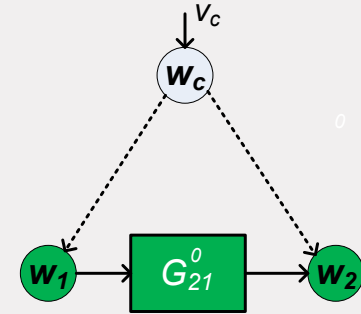
In networks they can appear in two different ways:

### Direct:

- If disturbances on inputs and outputs are correlated.

### Indirect:

- If non-measured in-neighbors of an output affect signals in the inputs.

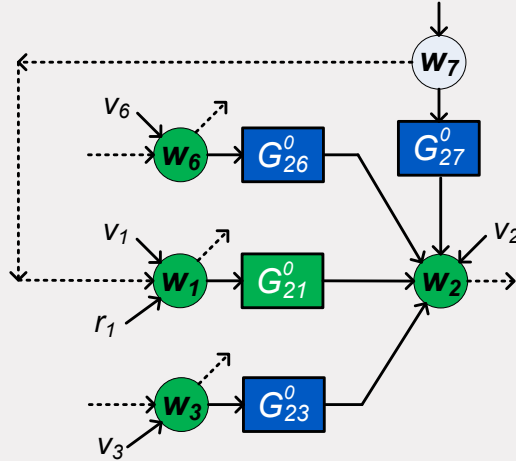


[1] J. Pearl, *Stat. Surveys*, 3, 96-146, 2009

[2] A.G. Dankers et al., *Proc. IFAC World Congress*, 2017.

# Confounding variables

- **Direct** confounding variables



e.g.,  $v_1$  is correlated with  $v_2$

In identification we know how to handle correlated disturbances: we model them!

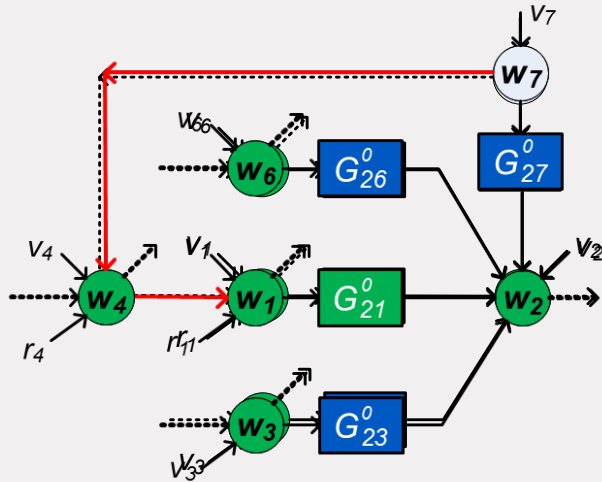
## Solution:

Include  $w_1$  as output and use a multivariate noise model

$$w_D = \{w_1, w_3, w_6\} \quad w_Y = \{w_1, w_2\}$$

# Confounding variables

- **Indirect** confounding variable:



Non-measurable  $w_7$  is a confounding variable

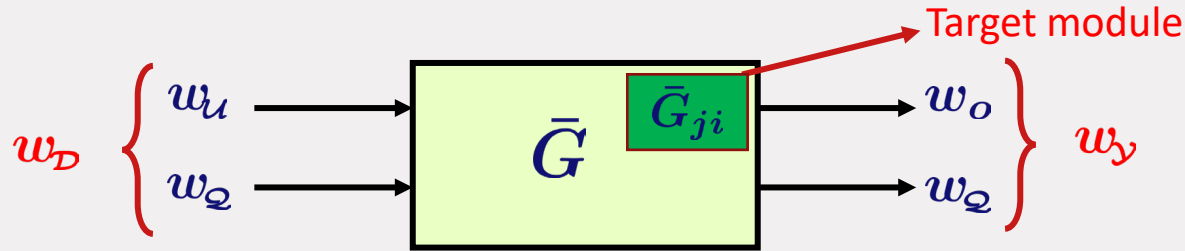
Two possible solutions:

1. Include  $w_4$   $\Rightarrow$  add predictor input  
 $w_D = \{w_1, w_3, w_4, w_6\}$      $w_y = \{w_2\}$
2. Predict  $w_1$  too  $\Rightarrow$  add predictor output  
 $w_D = \{w_1, w_3, w_6\}$      $w_y = \{w_1, w_2\}$

- There are degrees of freedom in choosing the predictor model

# Direct method

General setup:

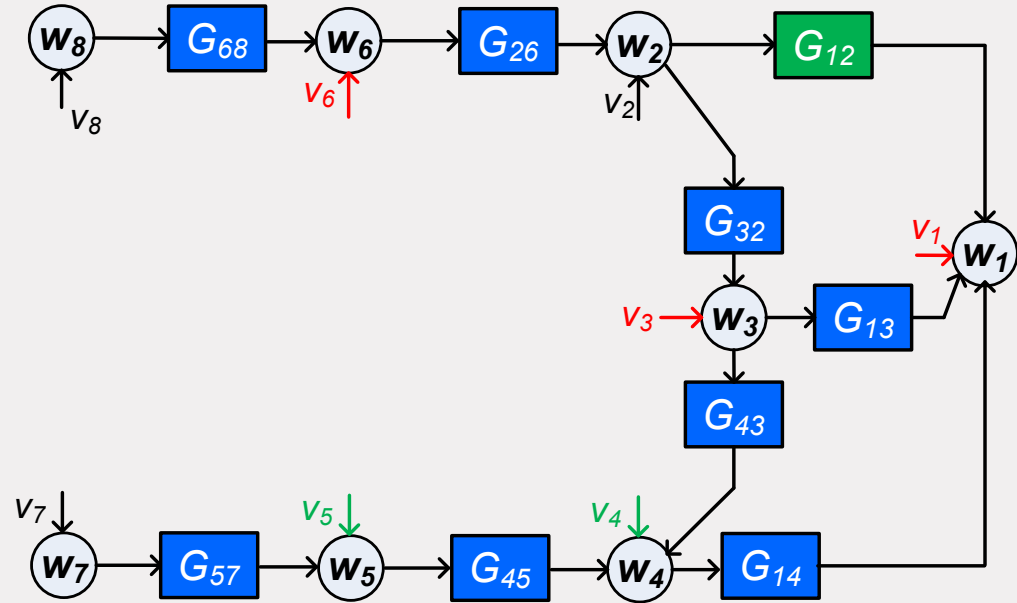


**Different algorithms** for arriving at predictor models:

- Full input case: include all in-neighbors of  $w_y$
- Minimum measurement case: maximize number of outputs
- User selection case : dedicated choice based on measurable nodes

# Different strategies – direct method

- Full input case
- Minimum measurements case
- User selection case



Network with  $v_1$  correlated with  $v_3$  and  $v_6$ .  
 $v_4$  correlated with  $v_5$ .

# Full input case

We include all in-neighbors of the predicted outputs as predictor inputs

Maximum use of information in signals

$$w_D = \{2, 3, 4\} \quad w_y = \{1\}$$

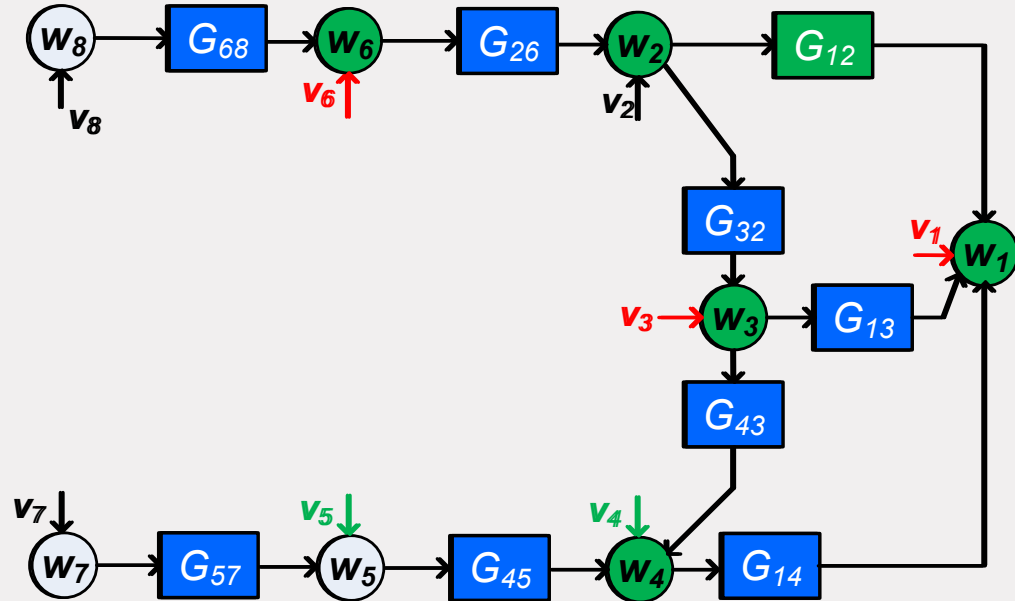
Handling direct confounding variable:

$$w_D = \{2, 3, 4\} \quad w_y = \{1, 3\}$$

Handling indirect confounding variable:

$$w_D = \{2, 3, 4, 6\} \quad w_y = \{1, 3\}$$

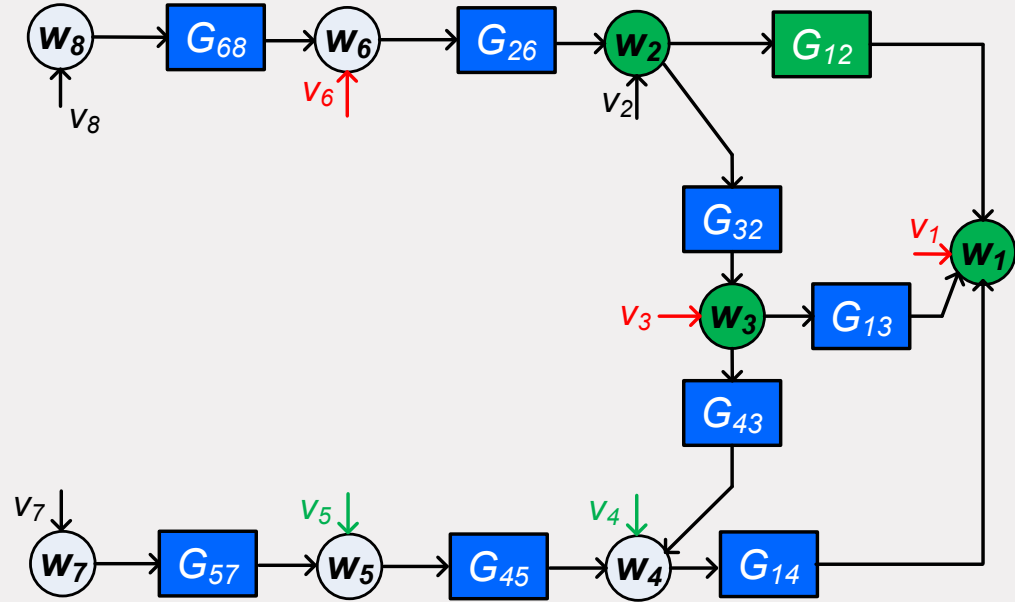
Direct identification  $w_D \rightarrow w_y$



# Minimum measurements case

- Select signals to satisfy the parallel path and loop condition
- Handle all confounding variables by including signals in output

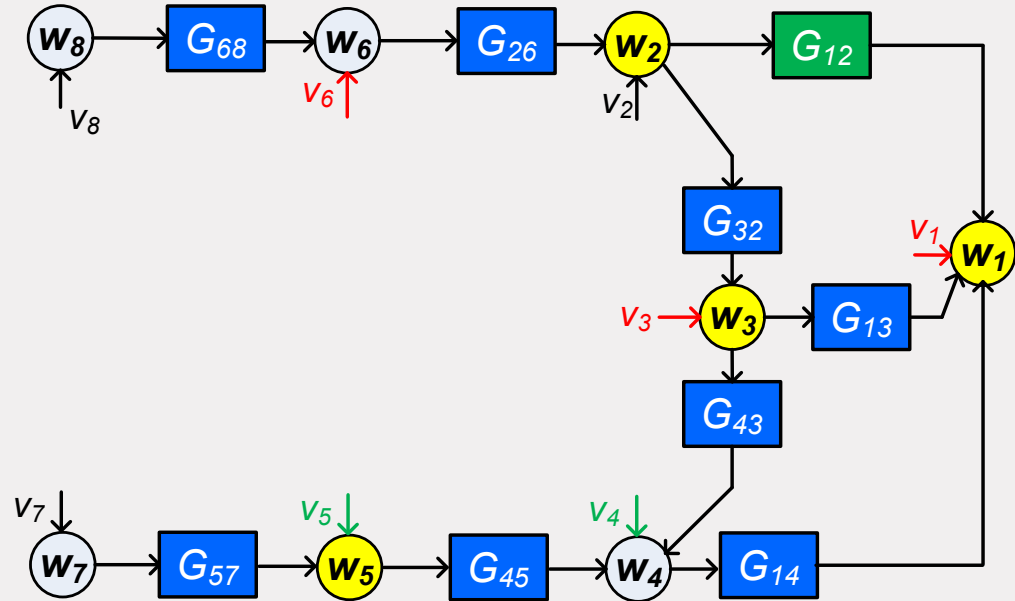
$$w_D = \{2, 3\} \quad w_y = \{1, 2, 3\}$$



Direct identification  $w_D \rightarrow w_y$

# User selection case

- The user does not have access to all node signals
- Four node signals can be measured
- Parallel path and loop condition is satisfied
- Start with:  
 $w_D = \{2, 3\}$   $w_y = \{1\}$





# User selection case

$$w_D = \{2, 3\} \quad w_y = \{1\}$$

Handling direct confounding variable:

$$w_D = \{2, 3\} \quad w_y = \{1, 3\}$$

Indirect confounding variables:

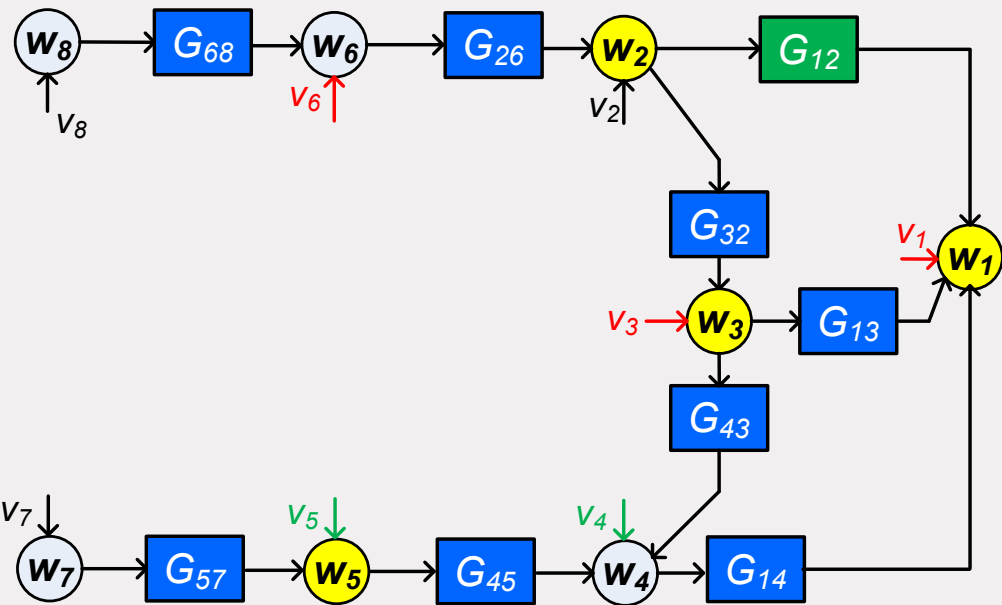
$(v_4, v_5)$ :

$$w_D = \{2, 3, 5\} \quad w_y = \{1, 3, 5\}$$

$v_6$ :

$$w_D = \{2, 3, 5\} \quad w_y = \{1, 2, 3, 5\}$$

Direct identification  $w_D \rightarrow w_y$



# Different strategies for same network and target module

Same network with different identification setups that lead to **consistent estimate of the target module** with **Maximum likelihood properties** based on the strategy used.

Full input case	Minimum measurements case	User selection case
$\begin{bmatrix} w_2 \\ w_3 \\ w_4 \\ w_6 \end{bmatrix} \rightarrow \begin{bmatrix} w_1 \\ w_3 \end{bmatrix}$	$\begin{bmatrix} w_2 \\ w_3 \end{bmatrix} \rightarrow \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$	$\begin{bmatrix} w_2 \\ w_3 \\ w_5 \end{bmatrix} \rightarrow \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_5 \end{bmatrix}$

Data informativity conditions still need to be added.

# Single module identification

Serious **degrees of freedom** in selecting the predictor model to satisfy the first two conditions:

1. Module invariance – PPL test
2. Handling confounding variables

While presuming that data-informativity can always be satisfied by adding sufficient # of r-signals.

# Single module identification – data-informativity

When focusing on estimating only the row with target module  $\bar{G}_{ji}$

$$w_j(t) = \bar{G}_{j*}(q, \theta) w_{\mathcal{D}}(t) + \bar{H}_{j*}(q, \theta) \xi_{\mathcal{V}}(t) + \bar{J}_{j*}(q, \theta) u_{\mathcal{K}}(t) + \bar{S}_{j*} u_{\mathcal{P}}(t)$$

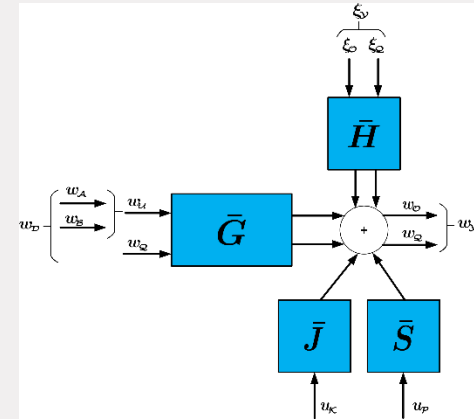
Typical data-informativity condition for estimating  $\bar{G}_{ji}$ :

$\kappa^{[j]}$  persistently exciting

$$\Phi_{\kappa^{[j]}}(\omega) > 0 \text{ for almost all } \omega$$

$$\kappa^{[j]}(t) := \begin{bmatrix} w_{\mathcal{D}_j}(t) \\ \xi_{\mathcal{V}_j}(t) \\ u_{\mathcal{K}_j}(t) \end{bmatrix}$$

inputs corresponding to parametrized terms in the predictor model

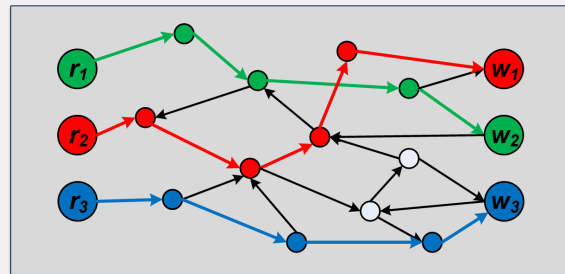


Rank-based condition can generically be satisfied based on a graph-based condition

# Data informativity (path-based condition)

A signal  $y(t) = F(q)x(t)$  with  $x$  persistently exciting, is persistently exciting iff  $F$  has **full row rank**.

This condition can be verified in a generic sense, by considering the **generic rank** of  $F$  [1],[2]



$$b_{\mathcal{R} \rightarrow \mathcal{W}} = 3$$

linking to the maximum number of **vertex disjoint paths** between inputs and outputs

$\kappa^{[j]}$  persistently exciting holds **generically** if there are  $\dim(\kappa^{[j]})$  **vertex disjoint paths** between external signals  $\{u, e\}$  and  $\kappa^{[j]} = \begin{bmatrix} w_{\mathcal{D}_j} \\ \xi_{\mathcal{Y}_j} \\ u_{\mathcal{K}_j} \end{bmatrix}$

Equivalently:

$\dim(w_{\mathcal{D}_j})$  vertex disjoint paths between  $\{u, e\} \setminus \{\xi_{\mathcal{Y}_j}, u_{\mathcal{K}_j}\}$  and  $w_{\mathcal{D}_j}$

[1] Van der Woude, 1991

[2] Hendrickx, Gevers & Bazanella, CDC 2017, TAC 2019.

[3] VdH et al., CDC 2020.

# Data informativity (path-based condition)

Equivalently:

$\dim(w_{\mathcal{D}_j})$  vertex disjoint paths between  $\{u, e\} \setminus \{y_j, u_{\kappa_j}\}$  and  $w_{\mathcal{D}_j}$

All input nodes need excitation, and  
white noise terms that have a link to  $w_y$  are excluded.

The **more inputs**, the more external signals required

The **more outputs**, less noise signals can be used

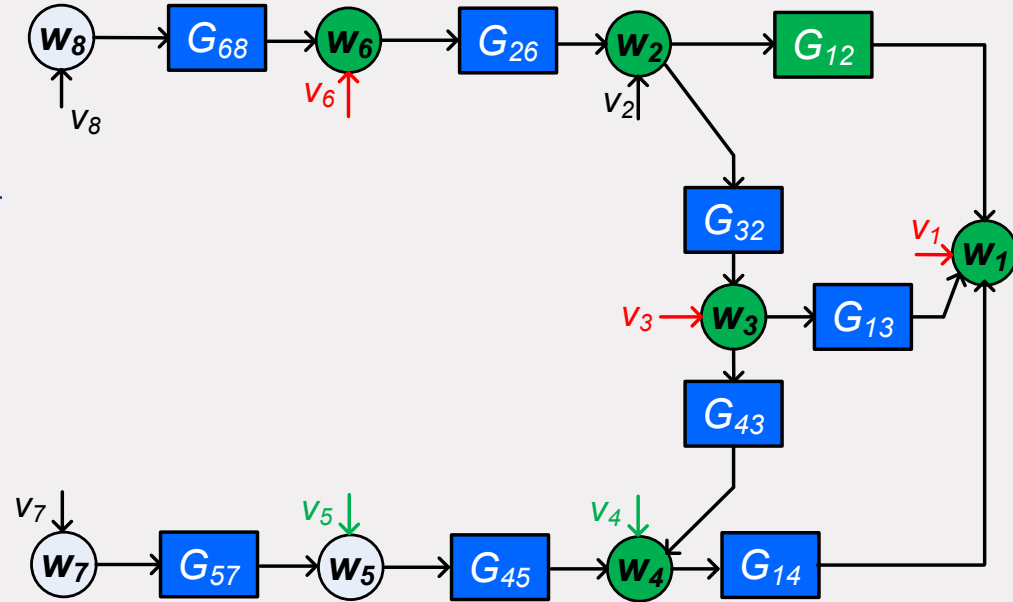
# Full input case

Predictor model:

$$w_D = \{2, 3, 4, 6\} \quad w_y = \{1, 3\}$$

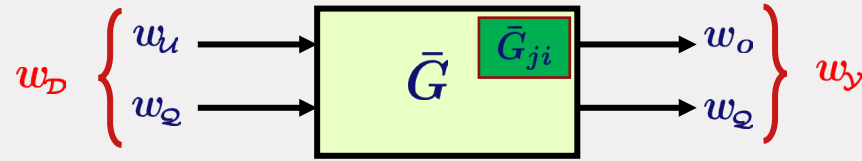
Excluded disturbances:  $v_1, v_3, v_6$

$w_2$  is excited by  $v_2$   
 $w_3$  is **not** excited  
 $w_4$  is excited by  $v_4$   
 $w_6$  is excited by  $v_8$



An additional excitation signal is required on  $w_3$

# Single module identification



## Conditions for arriving at an accurate model:

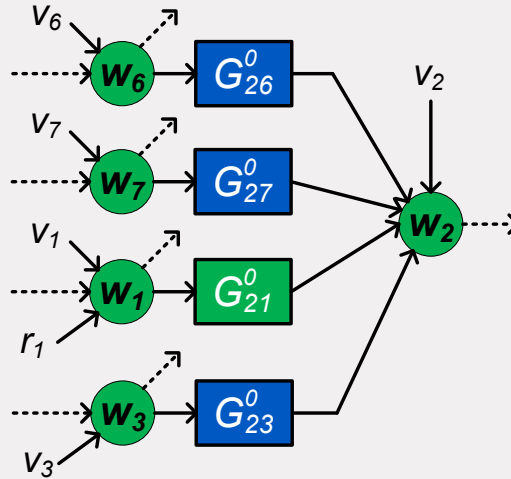
1. Module invariance:  $\bar{G}_{ji} = G_{ji}^0$
2. Handling of confounding variables
3. Data-informativity
4. *Technical conditions on presence of delays*

**Path-based conditions on the network graph**



# Single module identification

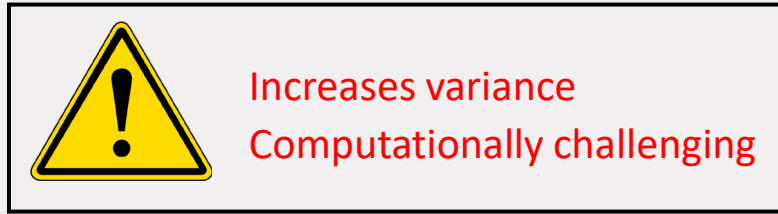
Typical solution:



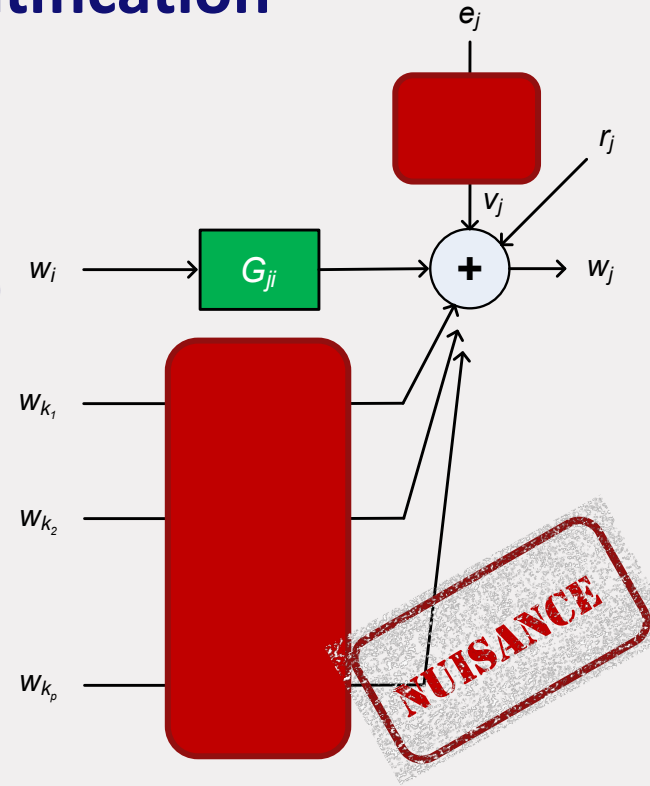
- MISO (sometimes MIMO) estimation problem
- to be solved by your favorite estimation algorithm

# Machine learning in local module identification

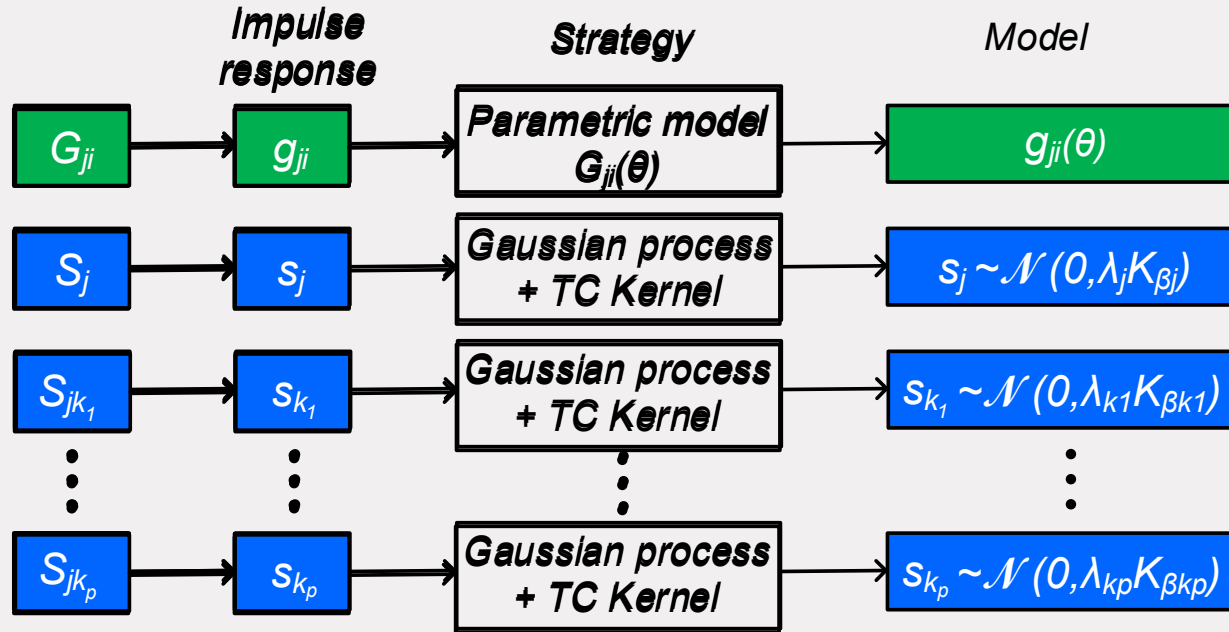
- MISO identification with all modules parameterized
- Brings in two major problems :
  - ▶ Large number of parameters to estimate
  - ▶ Model order selection step for each module (CV, AIC, BIC)
- For 5 modules, combinations = 244,140,625



- We need only the target module. No **NUISANCE**!



# Machine learning in local module identification



- smaller no. of parameters
- simpler model order selection step
- scalable to large dynamic networks
- simpler optimization problems to estimate parameters



Maximize marginal likelihood of output data:  $\hat{\eta} = \underset{\eta}{\operatorname{argmax}} p(w_j; \eta)$

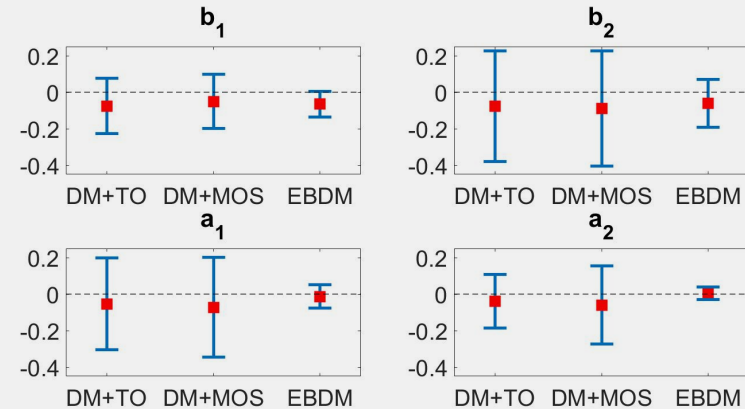
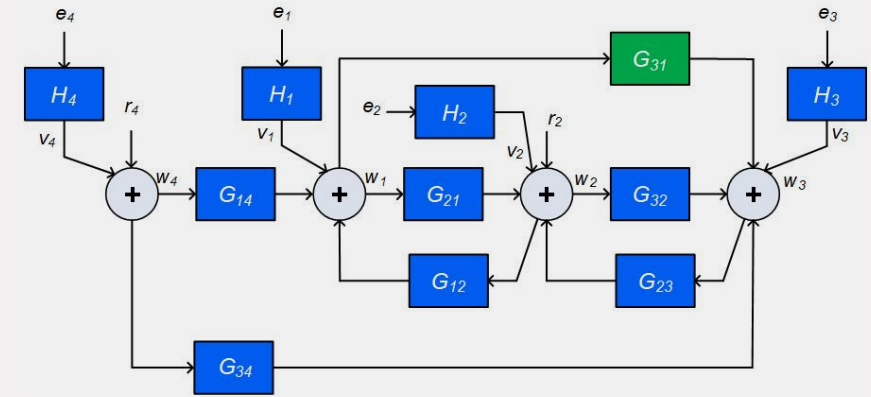
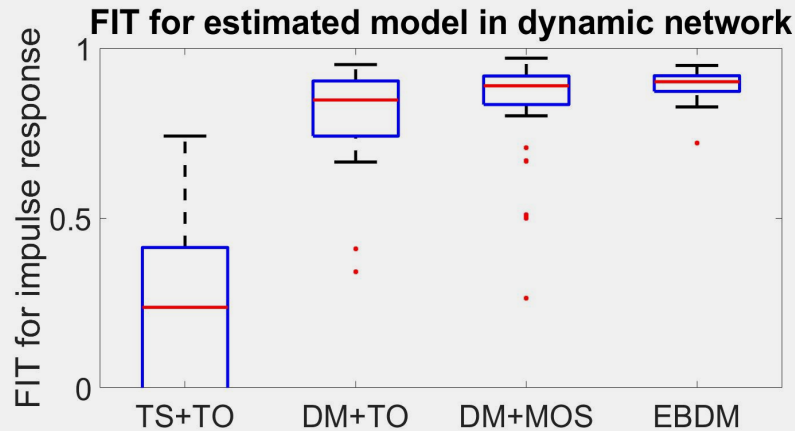
$$\eta := [\theta \quad \lambda_j \quad \lambda_{k_1} \quad \dots \quad \lambda_{k_p} \quad \beta_j \quad \beta_{k_1} \quad \dots \quad \beta_{k_p} \quad \sigma_j^2]^\top$$

[1] Everitt et al., *Automatica* 2017.

[2] K.R. Ramaswamy et al., *Automatica*, 2021.

# Numerical simulation

- ▶ Identify  $G_{31}$  given data
- ▶ 50 independent MC simulation
- ▶ Data = 500



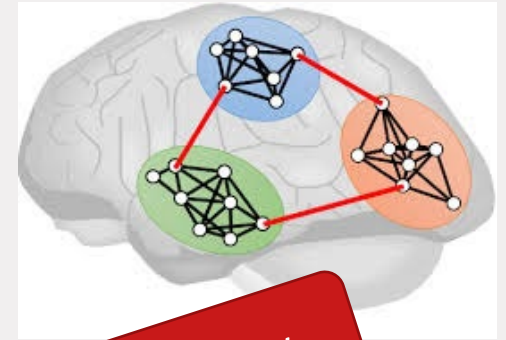
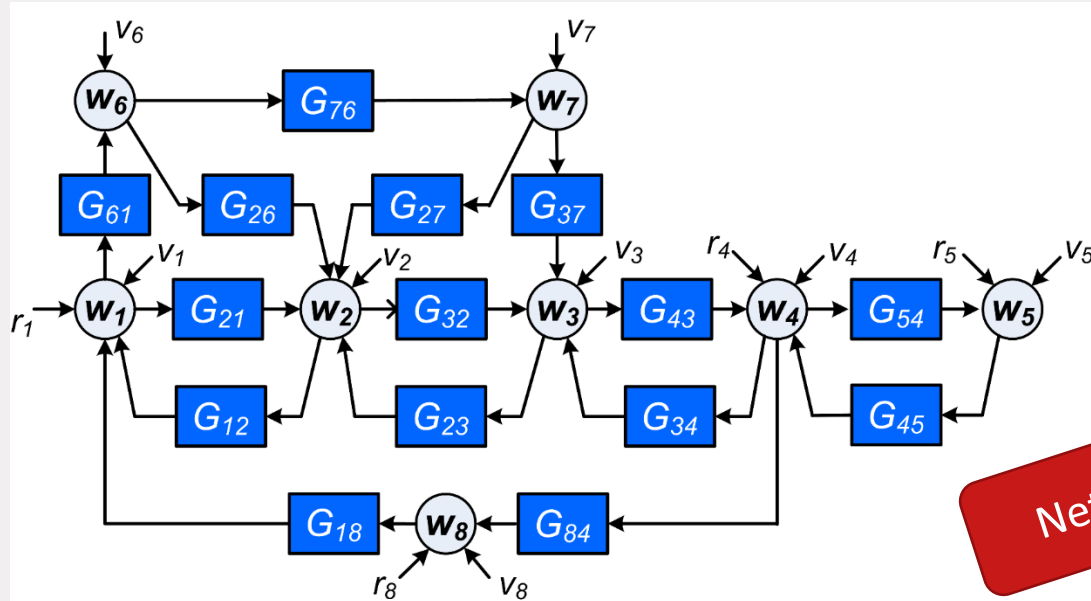
# Summary single module identification

- **Path-based conditions** that the predictor model should satisfy
- Different algorithms for synthesizing predictor model, with freedom in sensor / actuator placement
- Methods for **consistent** and **minimum variance** module estimation, and effective (scalable) algorithms
- Algorithms can be preceded by (nonparametric) local **topology estimation**<sup>[1]</sup>

[1] Rajagopal, Ramaswamy and VdH, *CDC* 2021.

# Generic network identifiability

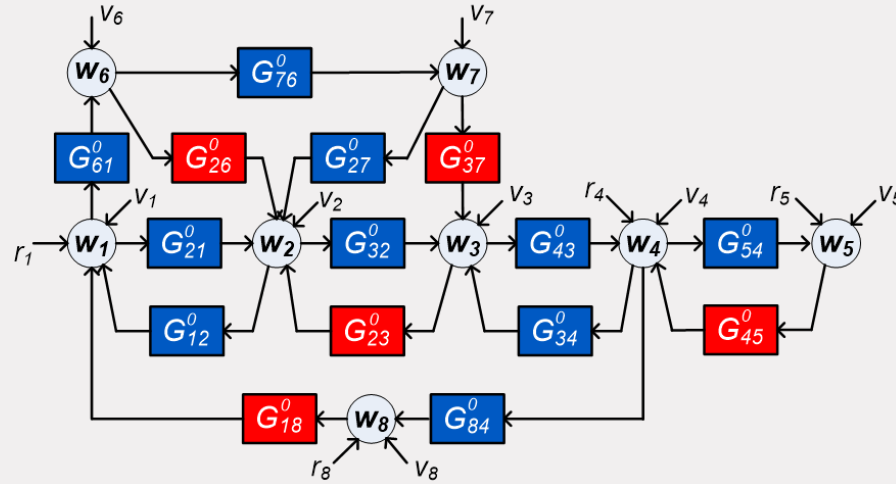
# Full network identification



Network identifiability

Under which conditions can we estimate the topology and/or dynamics of the full network?

# Network identifiability



blue = unknown  
red = known

**Question:** Can different dynamic networks be *distinguished* from each other from measured signals  $w, r$ ?



# Network identifiability

The identifiability problem:

The network **model**:

$$w(t) = G(q)w(t) + R(q)r(t) + \underbrace{H(q)e(t)}_{v(t)}$$

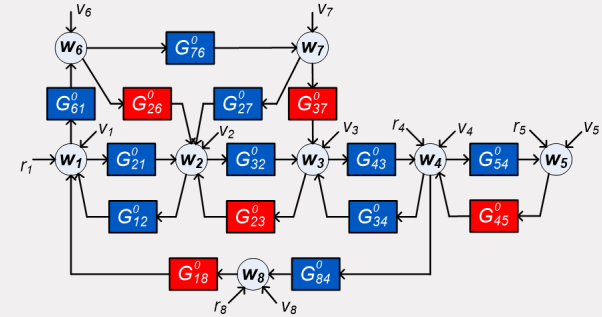
can be transformed with any rational  $P(q)$  :

$$P(q)w(t) = P(q)\{G(q)w(t) + R(q)r(t) + H(q)e(t)\}$$

to an **equivalent model**:

$$w(t) = \tilde{G}(q)w(t) + \tilde{R}(q)r(t) + \tilde{H}(q)e(t)$$

➡ **Nonuniqueness**, unless there are structural constraints on  $G, R, H$ .



[1] Weerts, Linder et al., Automatica, 2019.

[2] Bottegal et al., SYSID 2017

# Network identifiability

Consider a **network model set**:

$$\mathcal{M} = \{(G(\theta), R(\theta), H(\theta))\}_{\theta \in \Theta}$$

representing structural constraints on the considered models:

- modules that are fixed and/or zero (topology)
- locations of excitation signals
- disturbance correlation

**Generic identifiability** of  $\mathcal{M}$ :

- There do not exist distinct equivalent models (generating the same data)
- for almost all models in the set.

[1] Weerts et al., SYSID2015; Weerts et al., Automatica, March 2018;

[2] Bazanella, CDC2017; Hendrickx et al., IEEE-TAC, 2019.

# Network identifiability

## Definition Network identifiability<sup>[1]</sup>

For a network model set  $\mathcal{M}$ , consider a model  $M(\theta_0) \in \mathcal{M}$  and the implication

$$\left. \begin{array}{l} T_{wr}(q, \theta_0) = T_{wr}(q, \theta_1) \\ \Phi_{\bar{v}}(\omega, \theta_0) = \Phi_{\bar{v}}(\omega, \theta_1) \end{array} \right\} \implies \{ M(\theta_0) = M(\theta_1), \\ \text{for all } M(\theta_1) \in \mathcal{M}$$

Then  $\mathcal{M}$  is

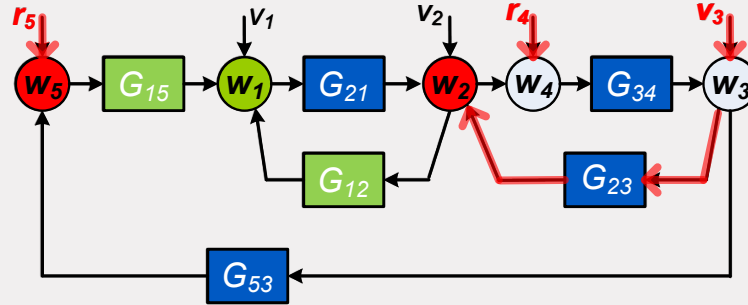
- **globally identifiable** from  $(w, r)$  at  $M(\theta_0)$  if the implication holds for  $M(\theta_0)$ ;
- **globally identifiable** from  $(w, r)$  if it holds for all  $M(\theta_0) \in \mathcal{M}$ ;
- **generically identifiable**<sup>[2]</sup> from  $(w, r)$  if it holds for almost all  $M(\theta_0) \in \mathcal{M}$ ;

[1] Weerts et al., Automatica, March 2018;

[2] Hendrickx et al., IEEE-TAC, 2019.

# Example 5-node network

Conditions for identifiability  $\longrightarrow$  rank conditions on transfer function



Full row rank of

$$\begin{bmatrix} v_3 \\ r_4 \\ r_5 \end{bmatrix} \rightarrow \begin{bmatrix} w_2 \\ w_5 \end{bmatrix}$$

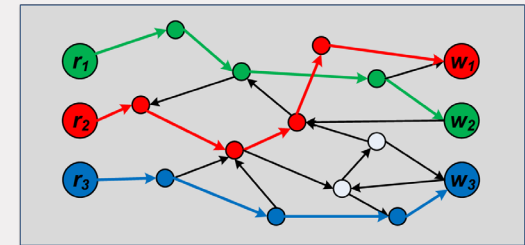
For the **generic case**, the rank can be calculated by a graph-based condition<sup>[1],[2]</sup>:

Generic rank = number of vertex-disjoint paths

2 vertex-disjoint paths  $\rightarrow$  full row rank 2



The rank condition has to be checked for all nodes.



[1] Van der Woude, 1991

[2] Hendrickx, Gevers & Bazanella, CDC 2017, TAC 2019

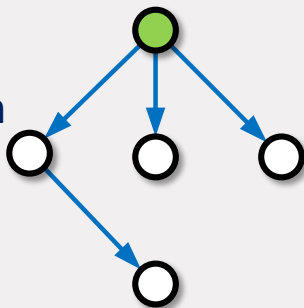
# Synthesis solution for network identifiability

Allocating external signals for **generic identifiability**:

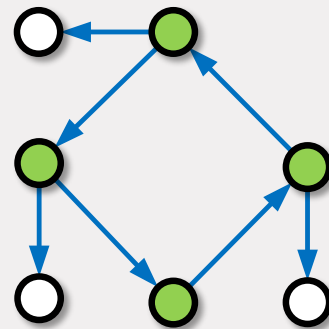
1. Cover the graph of the network model set by a set of **disjoint pseudo-trees**

Pseudo-trees:

Tree with root in green



Cycle with outgoing trees;  
Any node in cycle is root

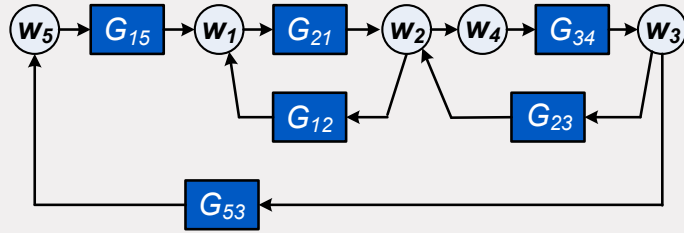


Edges are **disjoint** and all out-neighbours of a node are in the same pseudo-tree

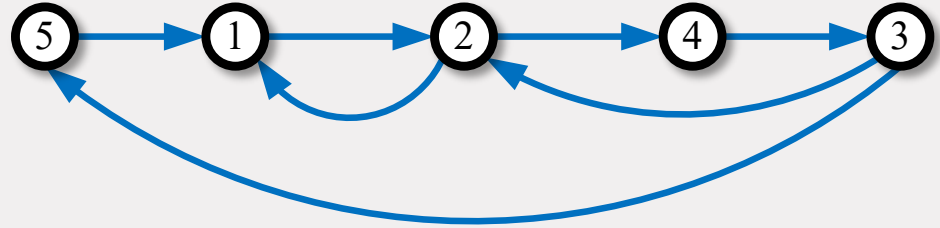
2. Assign an independent external signal (  $r$  or  $e$  ) at a root of each pseudo-tree.

This guarantees **generic identifiability** of the model set.

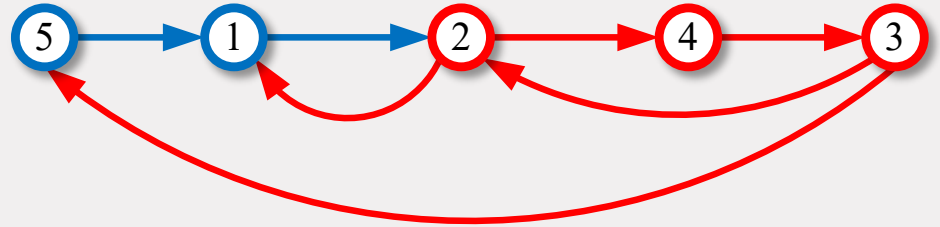
# Where to allocate external excitations for network identifiability?



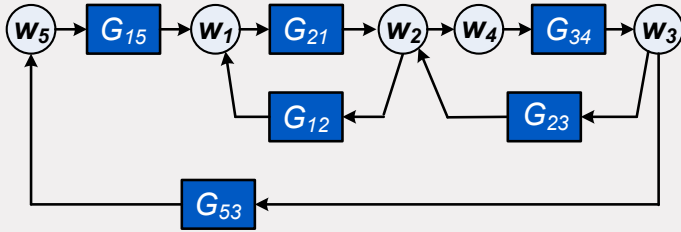
All indicated modules are parametrized



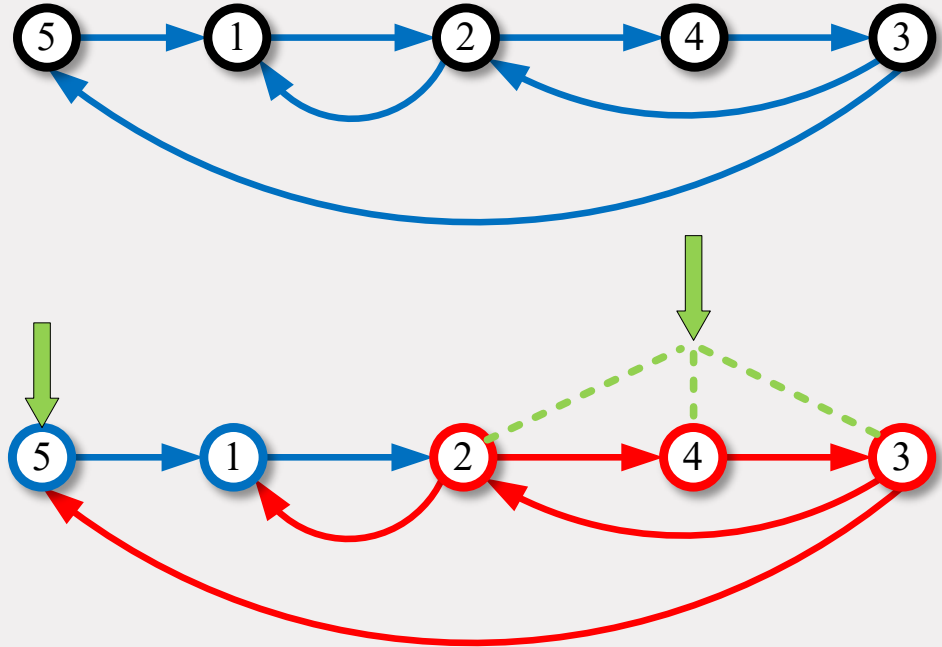
Two disjoint pseudo-trees



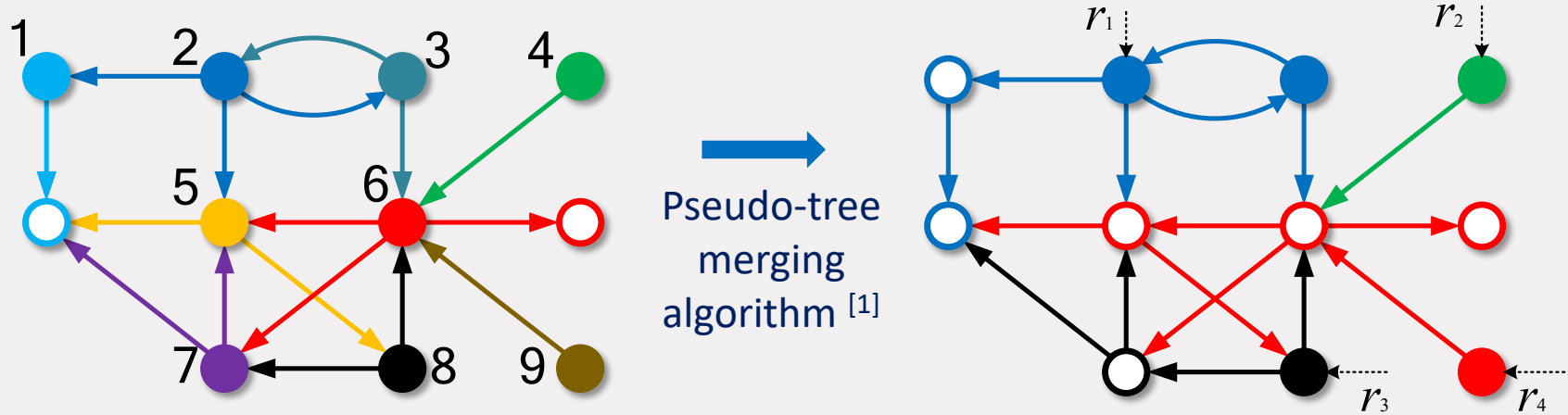
# Where to allocate external excitations for network identifiability?



Two independent excitations  
guarantee  
generic network identifiability



# Where to allocate external excitations for network identifiability?



- Nodes are signals  $w$  and external signals  $(r, e)$  that are input to a parametrized link
- Known (nonparametrized) links do not need to be covered



# Summary identifiability of full network

Identifiability of network model sets is determined by

- Presence and location of external signals, and
  - Correlation of disturbances
  - Topology of parametrized modules
- Graphic-based tool for synthesizing allocation of external signals

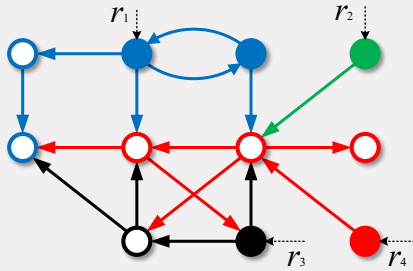
## Extensions:

- Situations where not all node signals are measured <sup>[1]</sup>

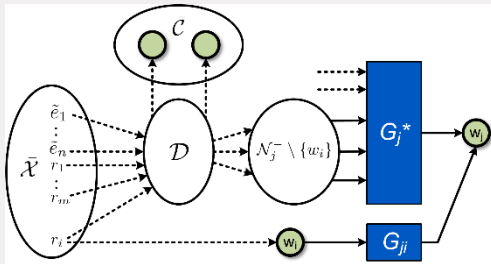
[1] Bazanella, CDC 2019.

# Related topics...

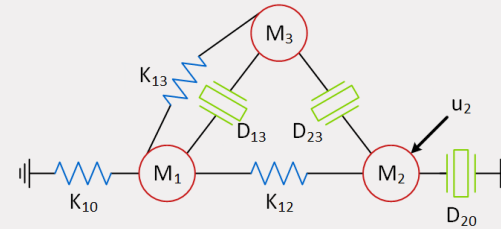
- Excitation allocation for full network identifiability<sup>[1]</sup>



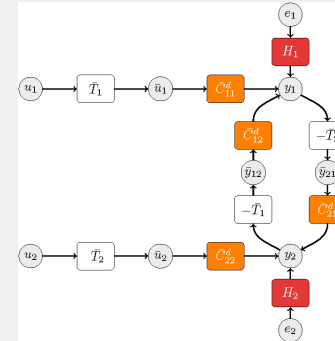
- Subnetwork identifiability<sup>[3]</sup>



- Diffusively coupled networks<sup>[2]</sup>



- Distributed controller identification<sup>[4]</sup>



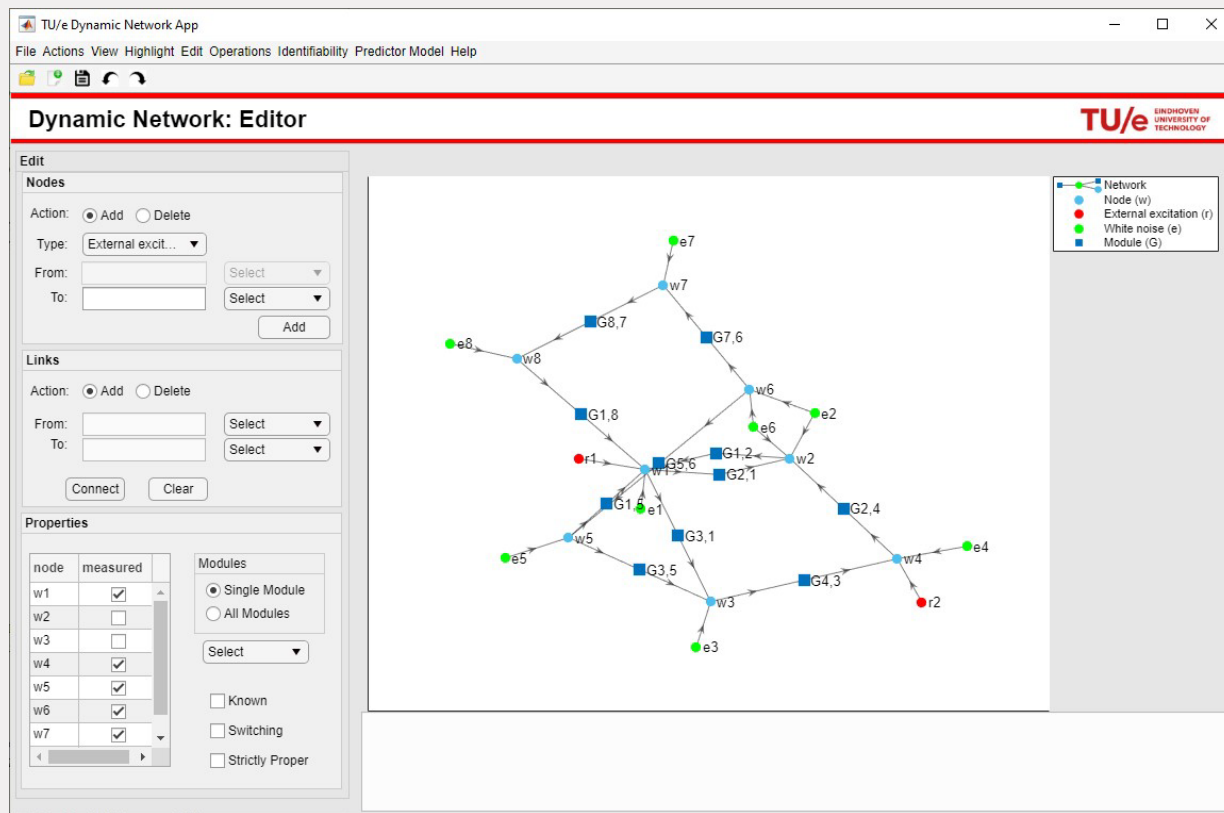
[1] Cheng et al., IEEE-TAC, February 2022.

[3] Shi et al., IEEE-TAC, January 2023.

[2] Kivits et al., IEEE- TAC, June 2023.

[4] Steentjes, PhD thesis, June 2022.

# Algorithms implemented in SYSDYNET App and Toolbox



**Structural** analysis and operations on dynamic networks

- Edit and manipulate
- Assign properties to nodes and modules
- Immersion of nodes, PPL test
- Generic identifiability analysis and synthesis
- Predictor model construction for single module ID

to be complemented with

- estimation algorithms for single module and full network ID;
- topology estimation

Beta-version to be downloaded from [www.sysdynet.net](http://www.sysdynet.net)

# ERC SYSDYNET Team: data-driven modeling in dynamic networks

## Research team:



Arne Dankers

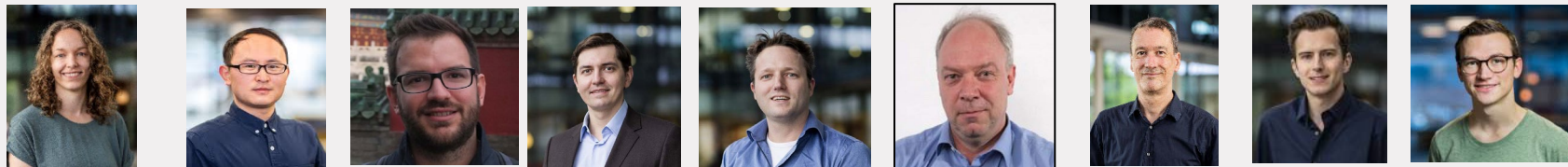
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Minneapolis, Vienna, Louvain-la-Neuve, Linköping, KTH Stockholm, Padova, Brussels, Salt Lake City, Lyon.

# Further reading

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- S. Shi, X. Cheng and P.M.J. Van den Hof (2023). Single module identifiability in linear dynamic networks with partial excitation and measurement. *IEEE Trans. Automatic Control*, Vol. 68(1), pp. 285-300, January 2023.
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**The end**