# Data-driven model learning in linear dynamic networks

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ICMS Symposium, “Getting a grip on complex systems”
4 April 2022, Eindhoven

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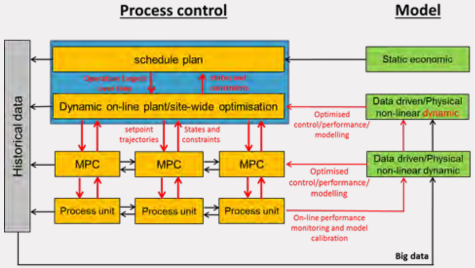
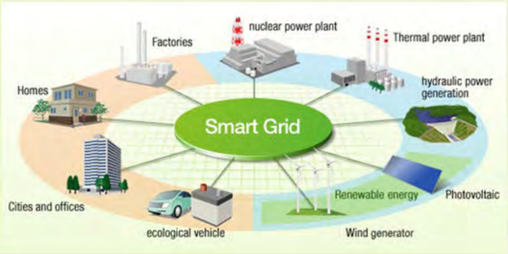
European Research Council

# Introduction – dynamic networks

## Decentralized process control



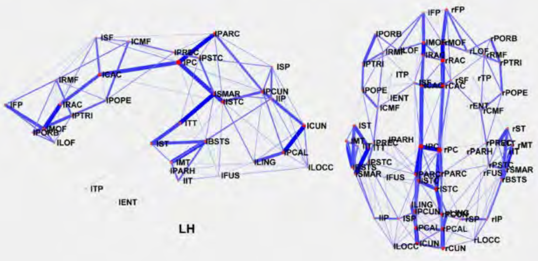

## Smart power grid




Pierre et al. (2012)

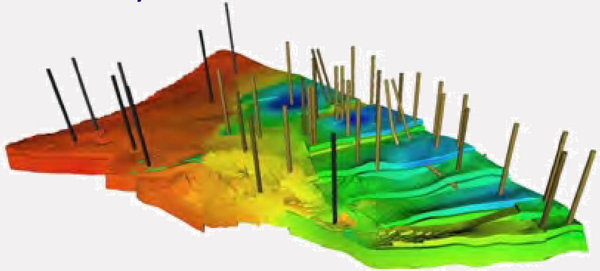
## Complex machines

## 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 and optimization problems
- Data is “everywhere”, big data era, AI/machine learning tools
- Model-based operations require accurate/relevant models
- → **Learning models from data** (including physical insights when available)

# Introduction

## Drivers for data-processing / data-analytics:

Providing the tools for **online**

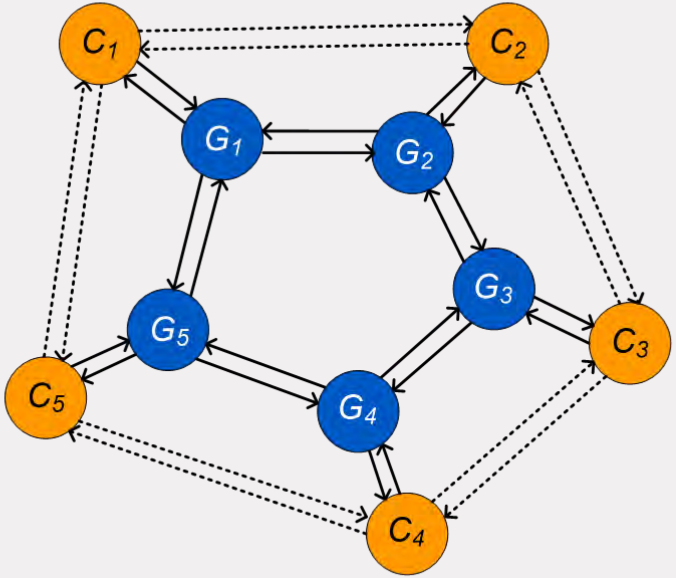
- Model estimation / calibration / adaptation

to accurately perform online model-based **X**:

- Monitoring
- Diagnosis and fault detection
- Control and optimization
- Predictive maintenance
- ………………….

# Introduction

Distributed / multi-agent control:

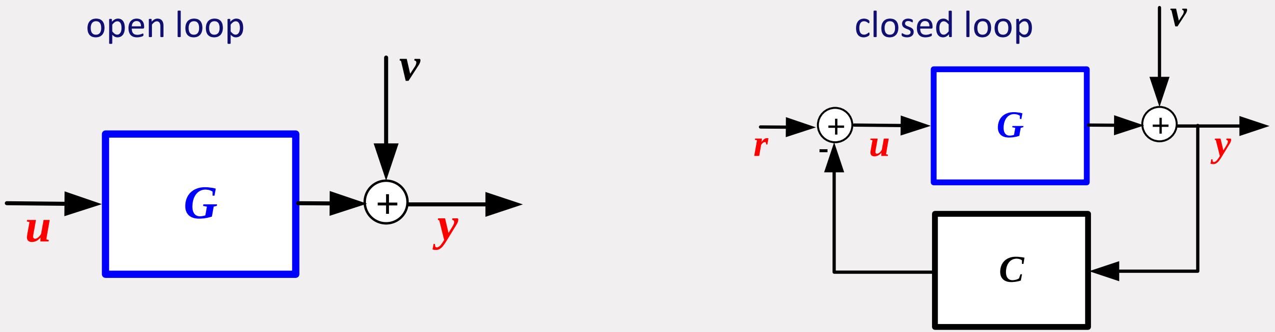



With both physical and communication links between systems $G_i$ and controllers $C_i$

How to address data-driven modelling problems in such a setting?

# Introduction

The classical (multivariable) data-driven modeling problems[1] :




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

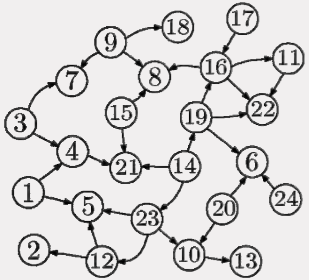
In interconnected systems (networks) the **structure / topology** becomes important to include

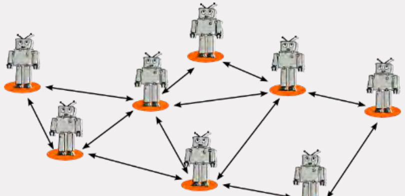
[1] Ljung (1999), Söderström and Stoica (1989), Pintelon and Schoukens (2012)

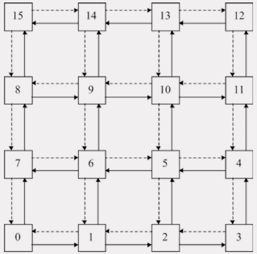
# Contents

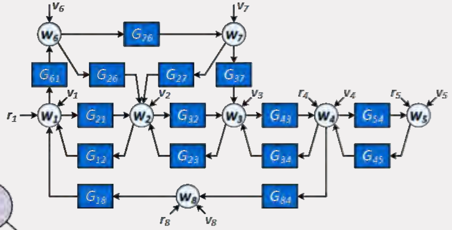
# Dynamic networks for data-driven modeling

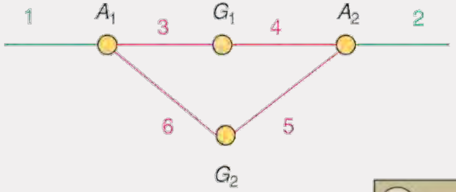
# Network models

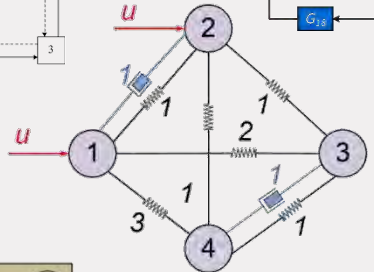


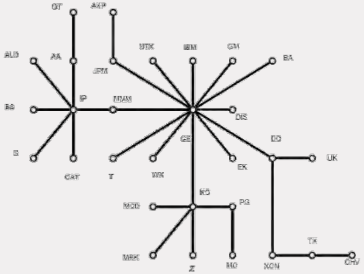


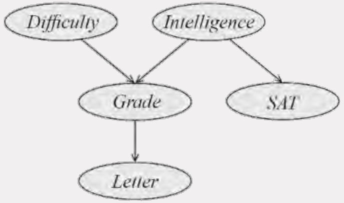


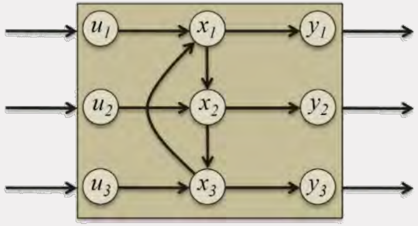


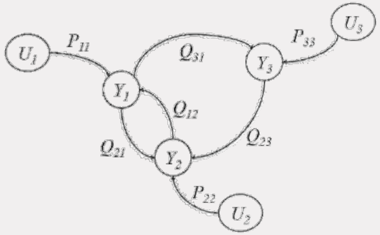




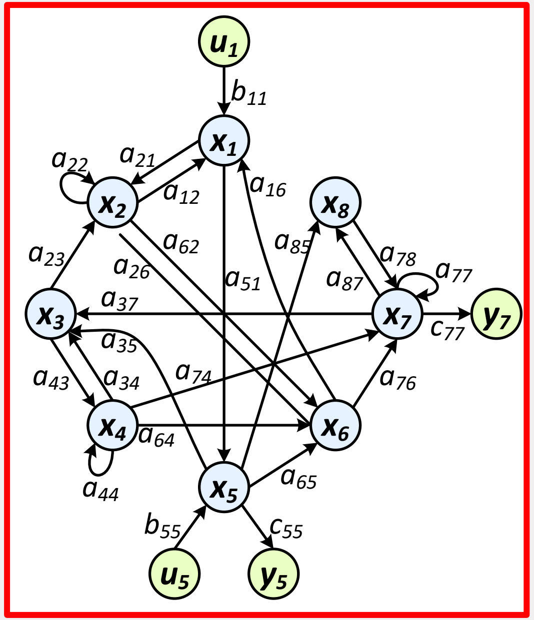



D. Materassi and M.V. Salapaka (2012)
www.momo.cs.okayama-u.ac.jp
J.C. Willems (2007)
E.A. Carara and F.G. Moraes (2008)
P.M.J. Van den Hof et al (2013)
X.Cheng (2019)
R.N. Mantegna (1999)
D. Koller and N. Friedman (2009)
P.E. Paré et al (2013)
E. Yeung et al (2010)

# Network models

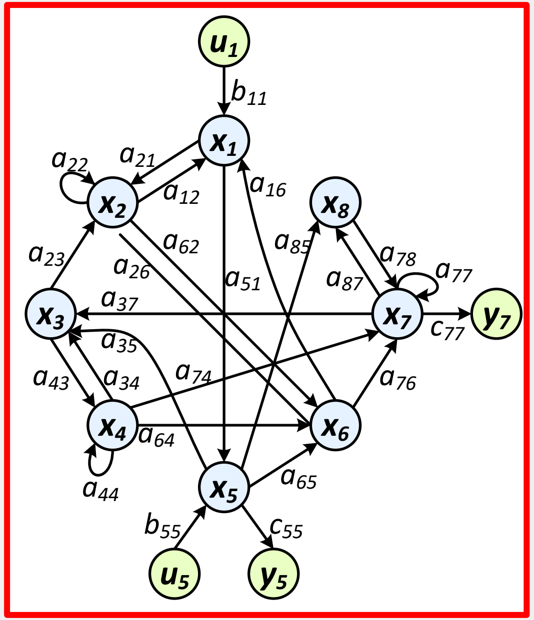



**State space representation**

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

- States as **nodes** in a (directed graph)
- State transitions (1 step in time) reflected by $a_{ij}$
- Transitions are encoded in **links**
- Effect of transitions are summed in the nodes
- Self loops are allowed
- Actuation ($u$) and sensing ($y$) reflected by separate links

# Network models




**State space representation**

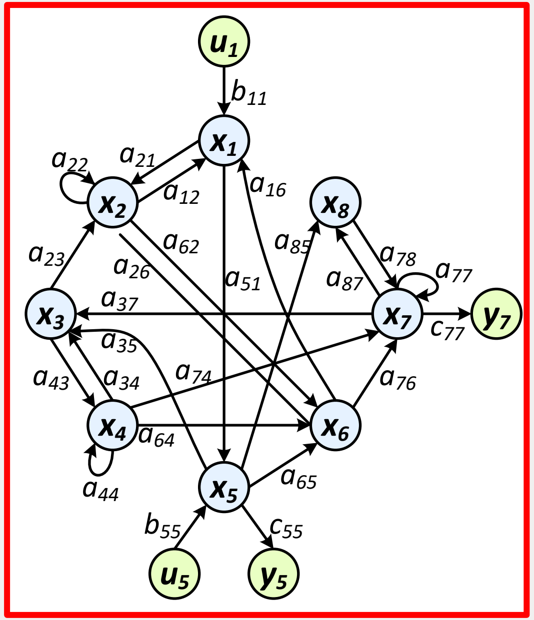
$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned}$$

- Ultimate break-down of structure in the system
- to smallest possible level of detail

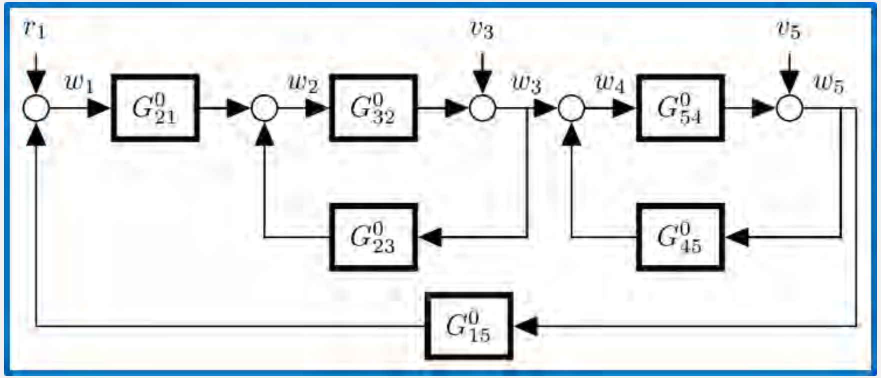
For data-driven modeling problems:

- Stronger role for measurable inputs and outputs
- i/o dynamics can be lumped in dynamic **modules**

# Network models




State space representation [1]

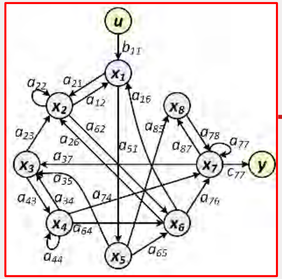



Module representation [2]

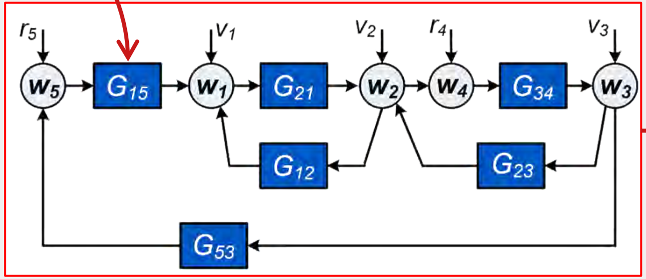
[1] Goncalves, Warnick, Sandberg, Yeung, Yuan, Scherpen,...

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

# Dynamic network models - zooming

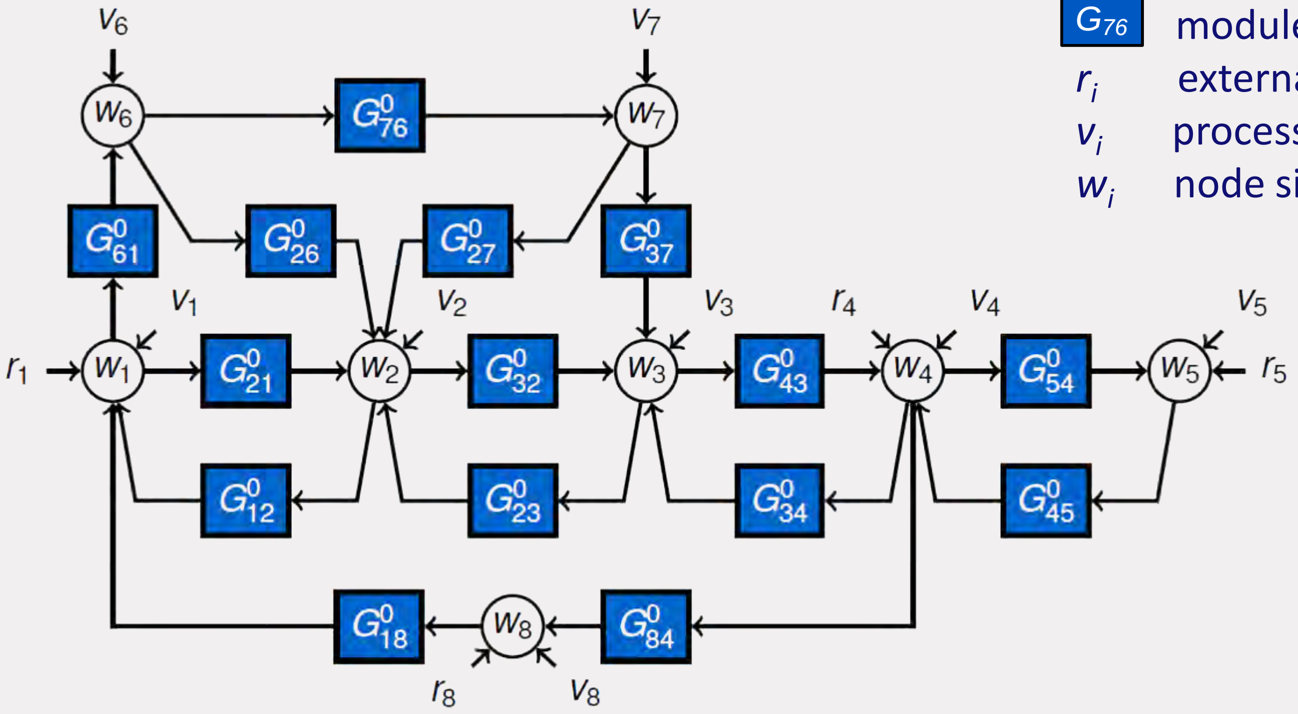



Increasing level of detail



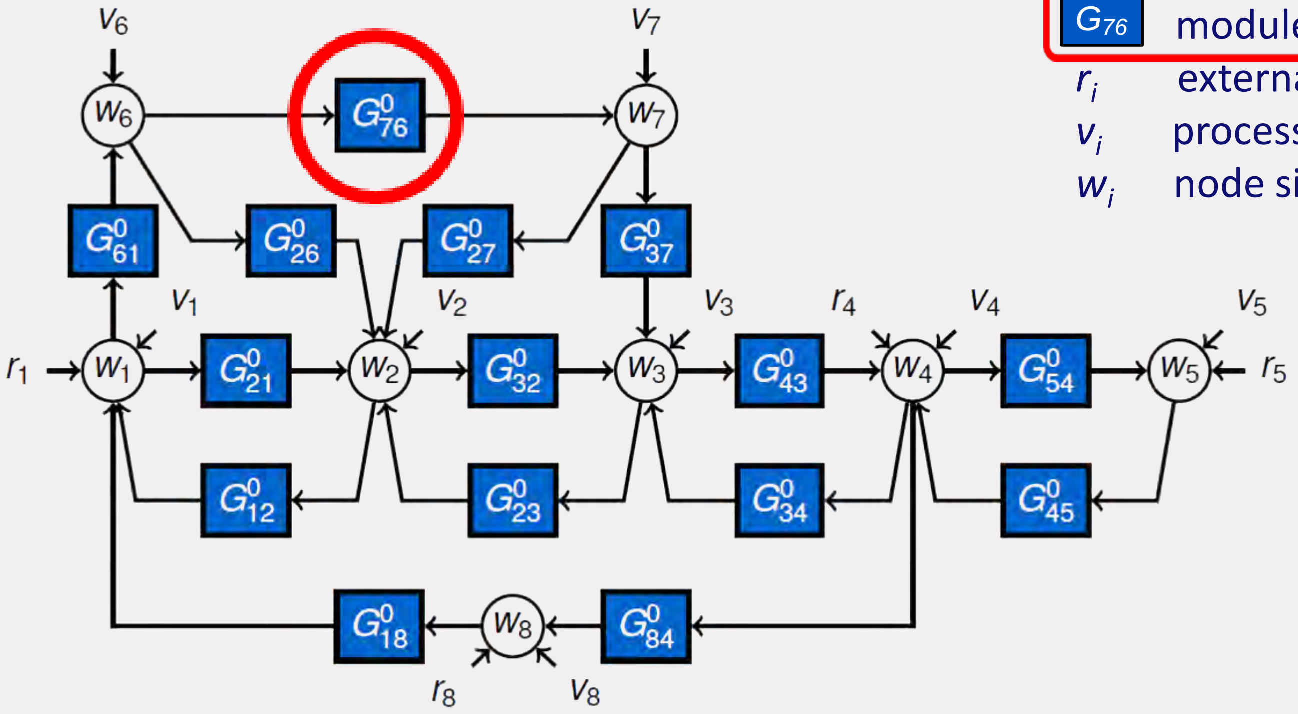

Decreasing structural information

# Dynamic network setup




$G_{76}$ module
$r_i$ external excitation
$v_i$ process noise
$w_i$ node signal

# Dynamic network setup




$G_{76}$ module
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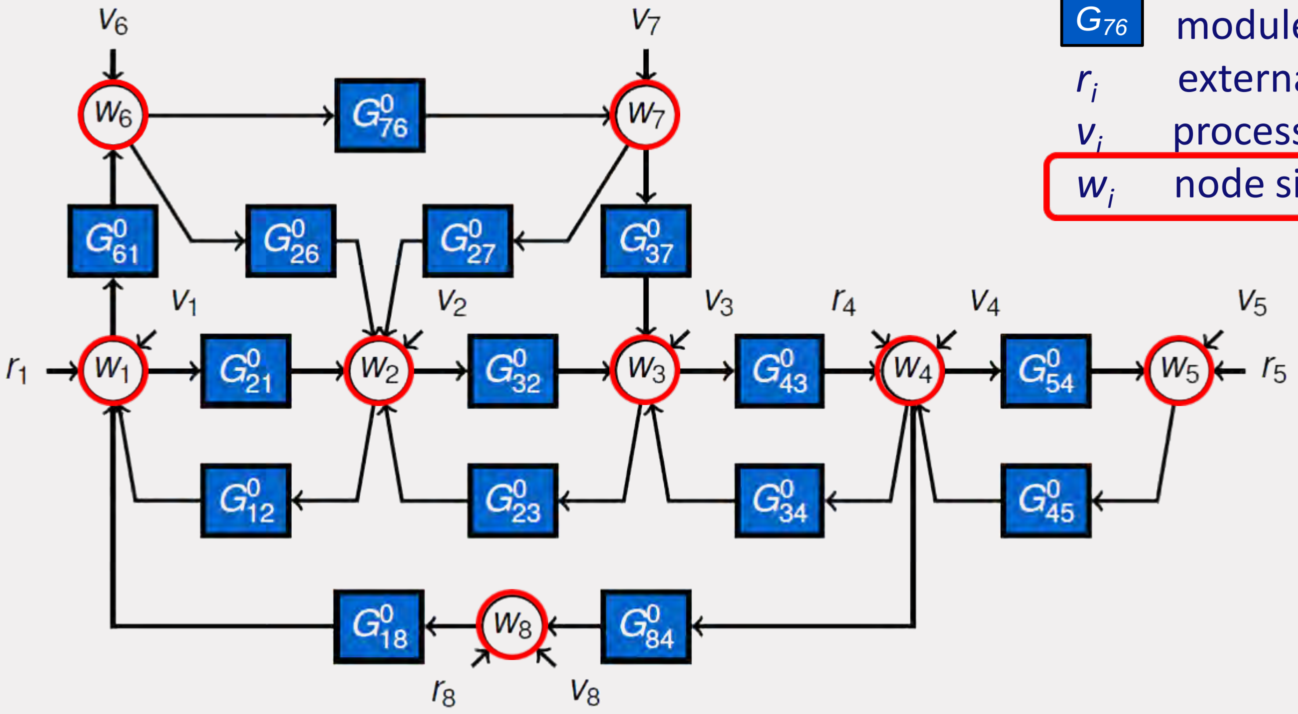
TU/e

# Dynamic network setup

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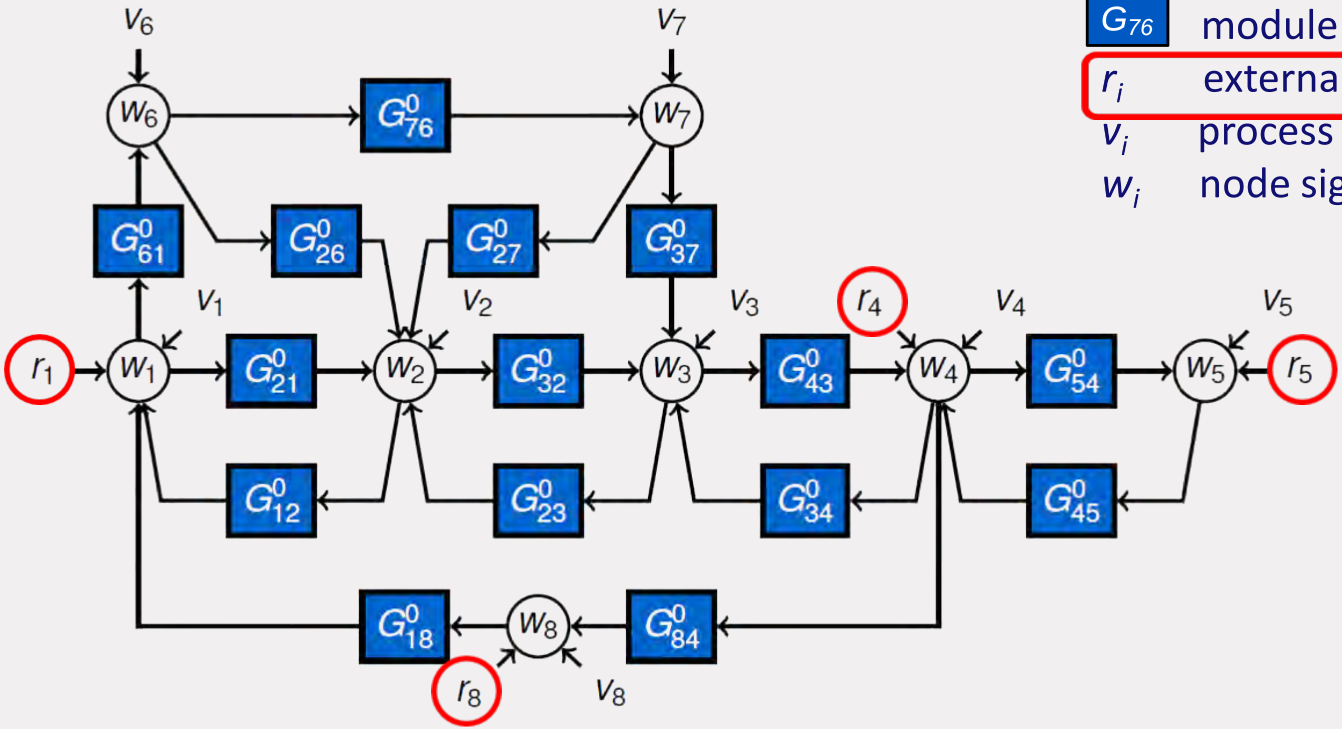
# Dynamic network setup




$G_{76}$ module

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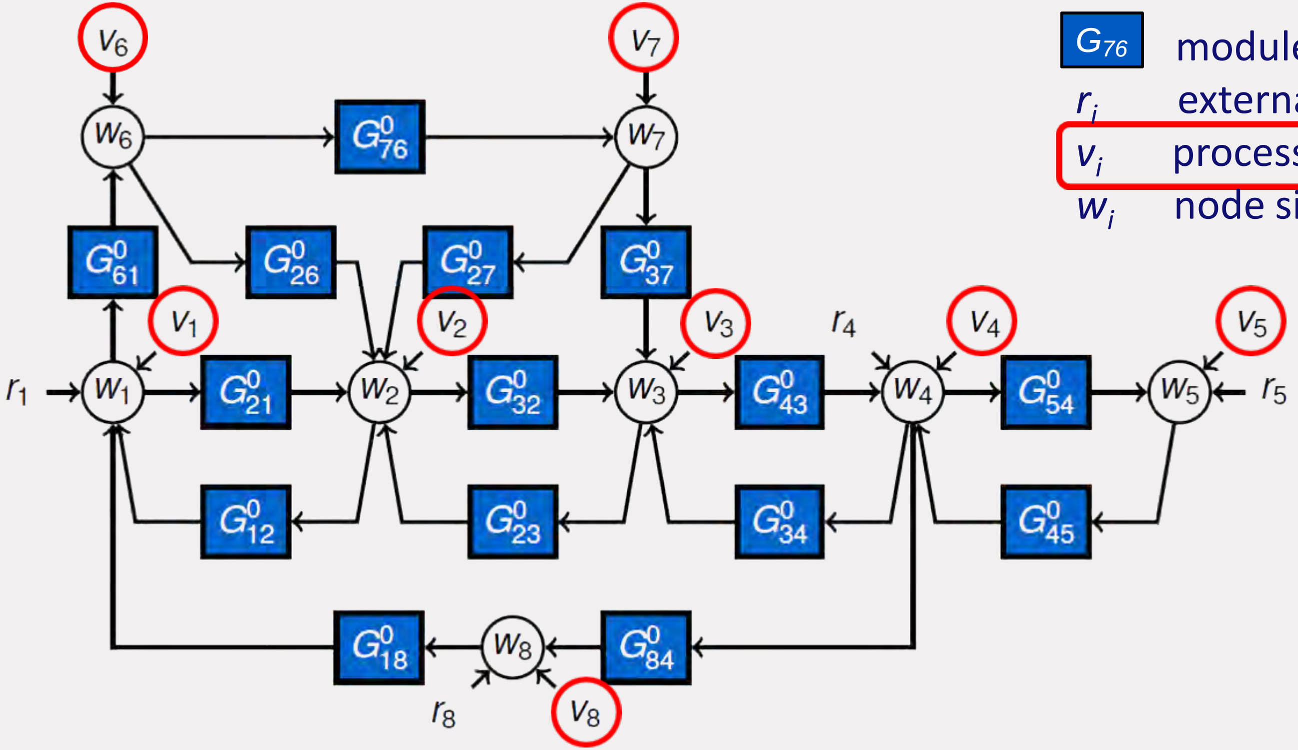
# Dynamic network setup

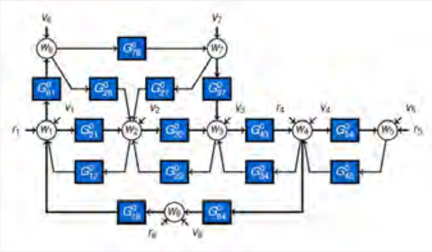



$G_{76}$ module
$r_i$ external excitation
$v_i$ process noise
$w_i$ node signal

# Dynamic network setup

**Basic building block:**

$$w_j(t) = \sum_{k \in \mathcal{N}_j} G^0_{jk}(q) w_k(t) + r_j(t) + v_j(t)$$



$w_j$: node signal
$r_j$ : external excitation signal
$v_j$ : (unmeasured) disturbance, stationary stochastic process
$G^0_{jk}$: module, rational proper transfer function, $\mathcal{N}_j \subset \{\mathbb{Z} \cap [1, L] \backslash \{j\}\}$
$q$: shift operator, $q^{-1} w(t) = w(t-1)$

Node signals: $w_1, \cdots w_L$
Interconnection structure / topology of the network is encoded in $\mathcal{N}_j, \ j = 1, \cdots L$

J. Gonçalves and S. Warnick, IEEE TAC, 2008.
PVdH et al., Automatica, 2013.

# Dynamic network setup

## Collecting all equations:

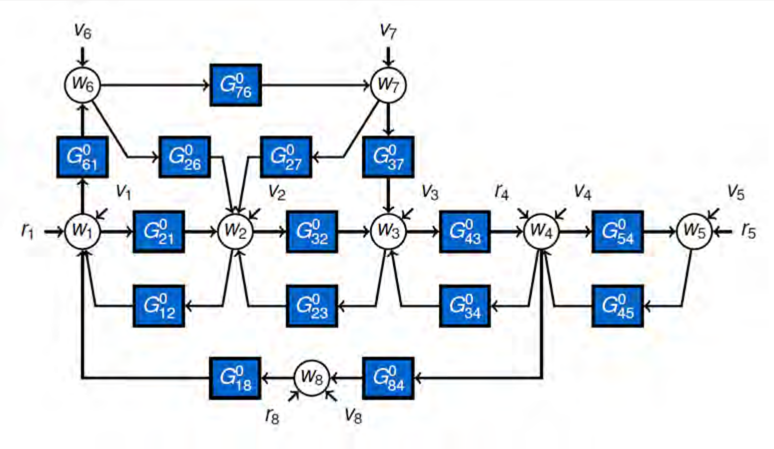
$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & G^0_{12} & \cdots & G^0_{1L} \\ G^0_{21} & 0 & \ddots & G^0_{2L} \\ \vdots & \ddots & \ddots & \vdots \\ G^0_{L1} & G^0_{L2} & \cdots & 0 \end{bmatrix}}_{\text{Network matrix } G^0(q)} \begin{bmatrix} w_1 \\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

$$w(t) = G^0(q)w(t) + R^0(q)r(t) + v(t); \qquad v(t) = H^0(q)e(t); \quad cov(e) = \Lambda$$

- 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.

J. Gonçalves and S. Warnick, IEEE TAC, 2008.
PVdH et al., Automatica, 2013.

# Dynamic network setup

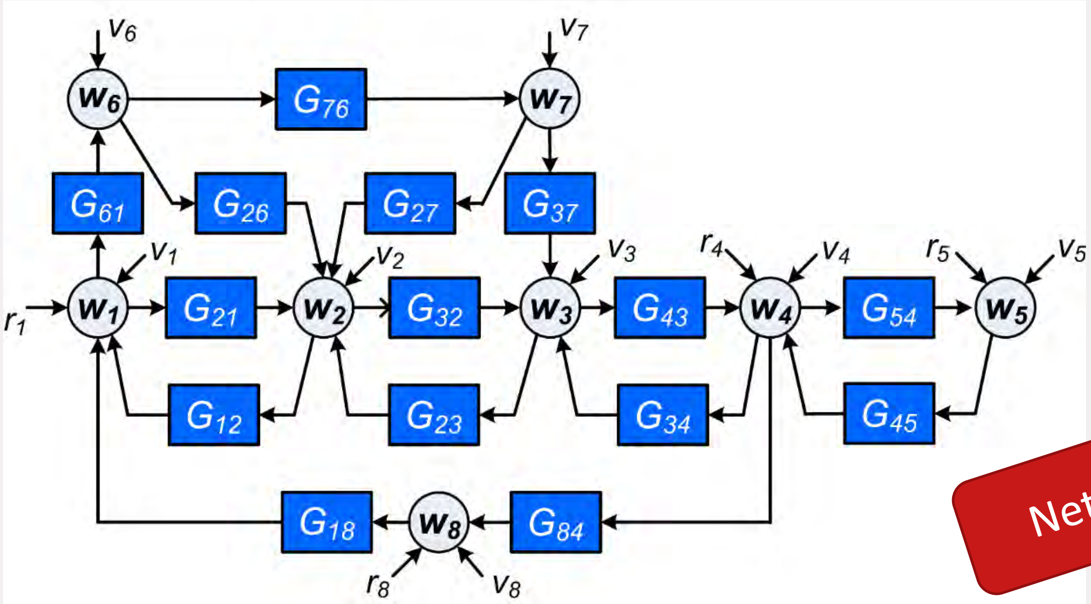


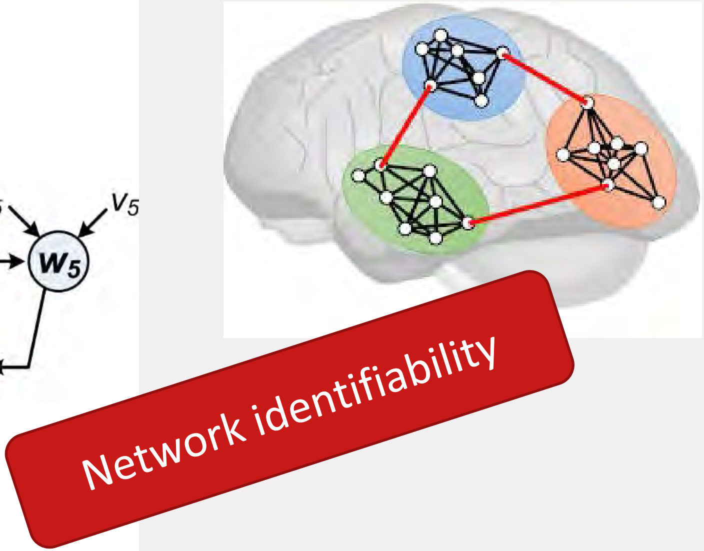

Many challenging data-driven modeling questions can be formulated

Measured time series:

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

# Model learning problems




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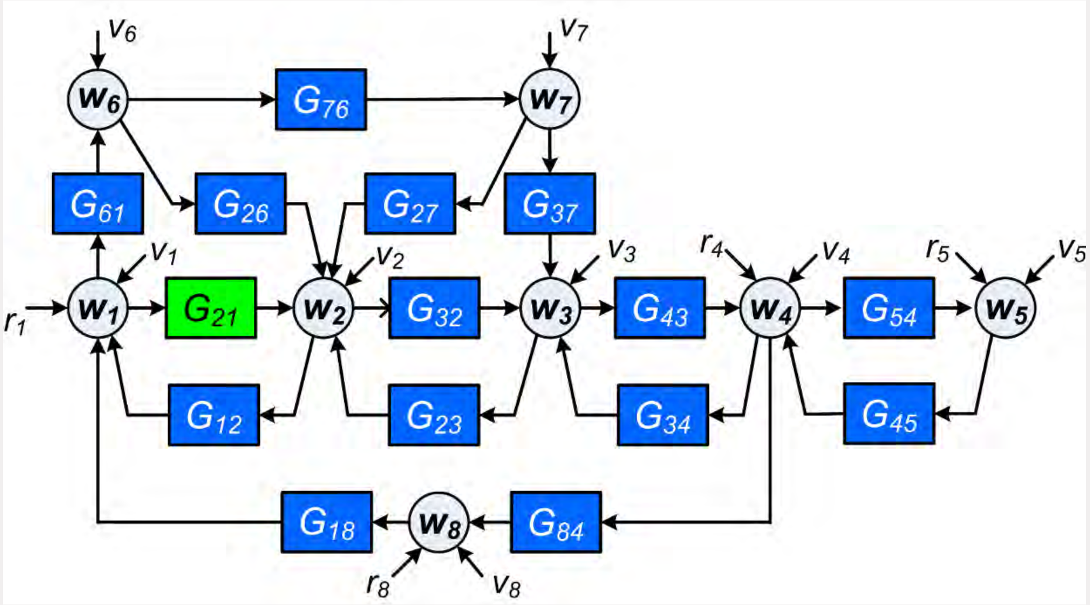
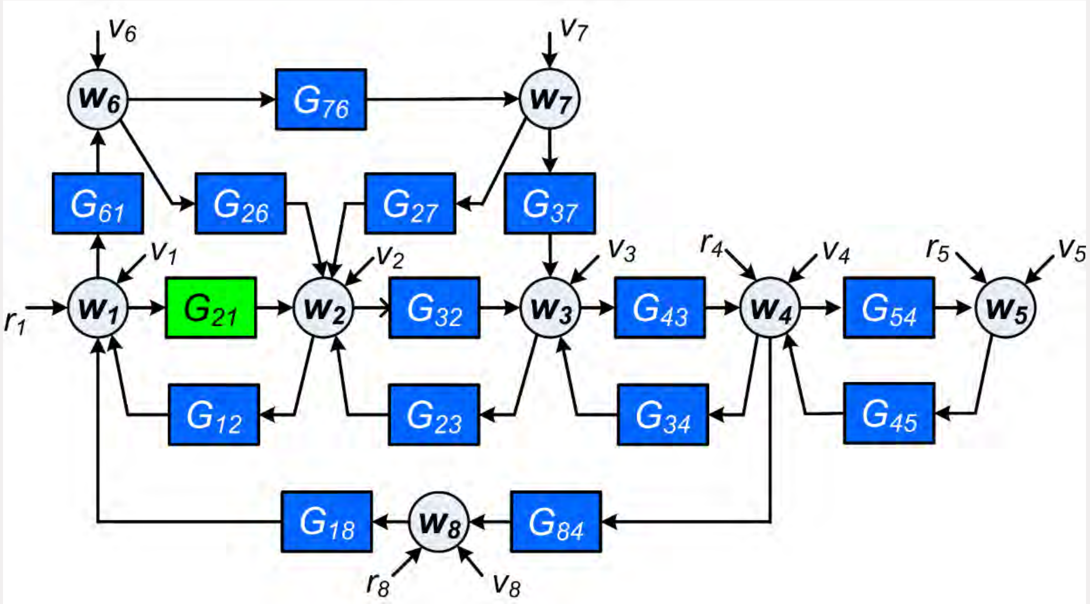
# Model learning problems



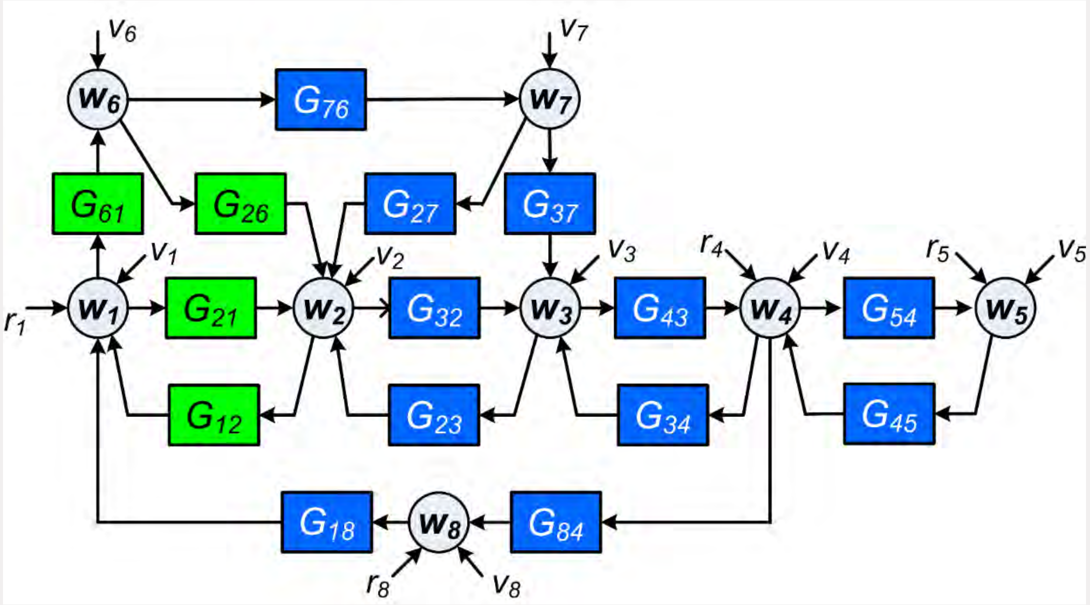

How/when can we learn a local module from data
(with known/unkown network topology) ?    Which signals to measure?

# Model learning problems



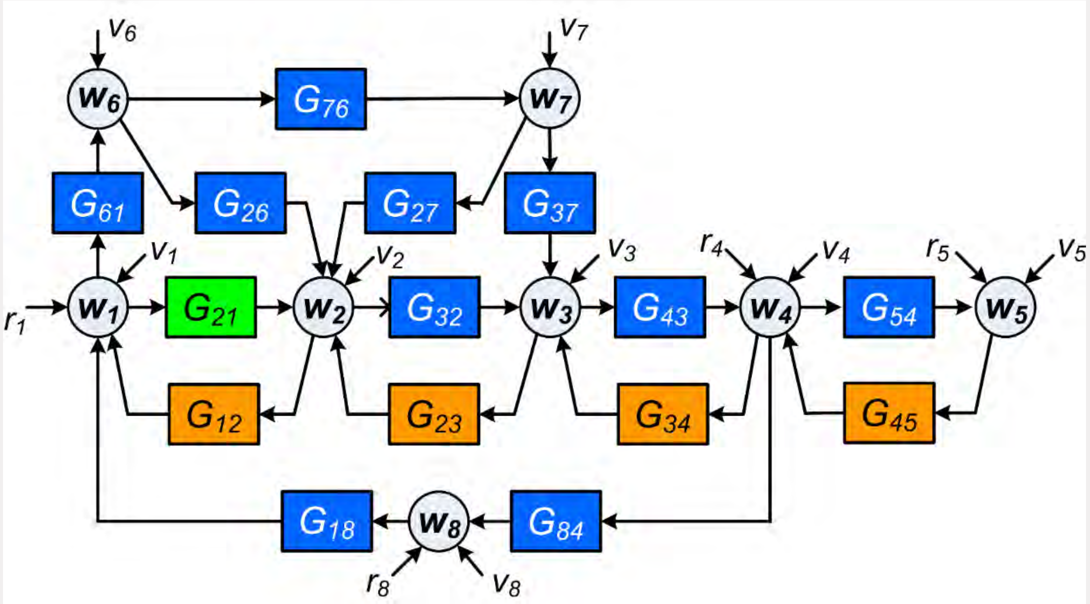

Where to optimally locate sensors and actuators?

# Model learning problems



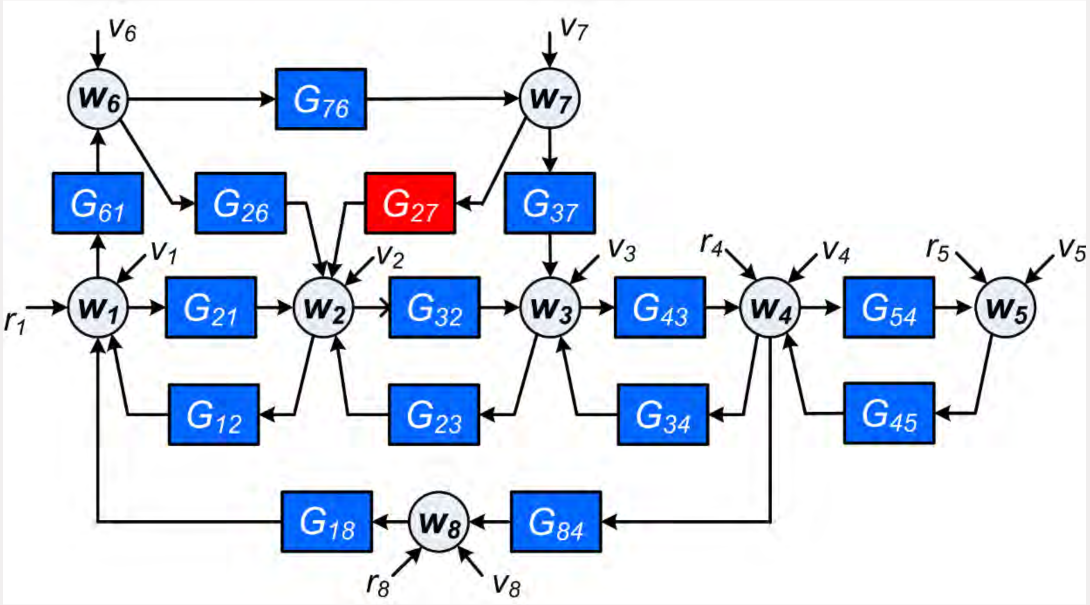

Same questions for a subnetwork

# Model learning problems



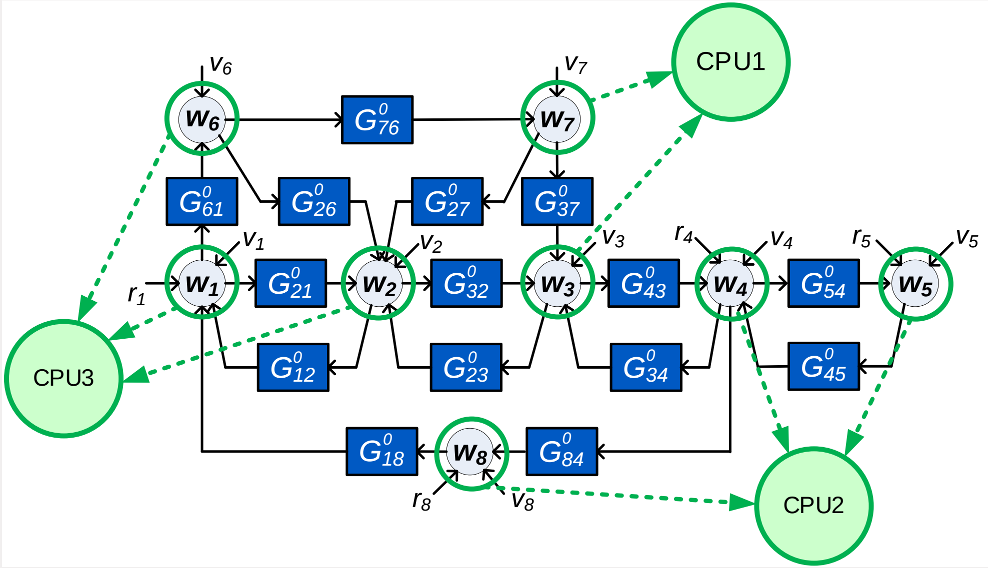

How can we benefit from known modules?

# Model learning problems



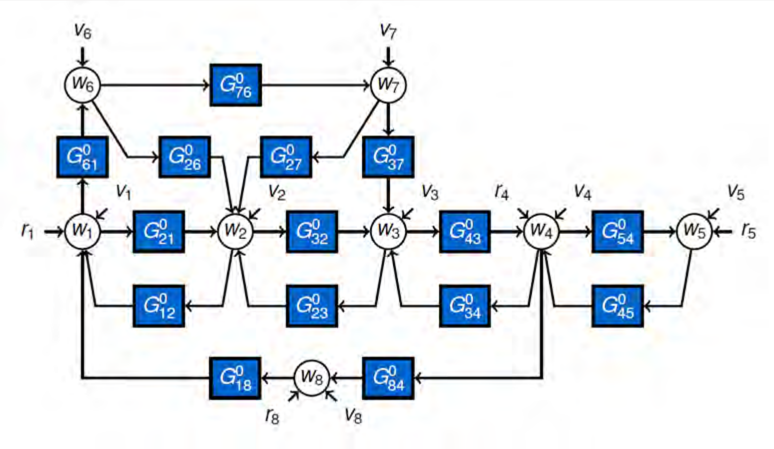

Fault detection and diagnosis; detect/handle nonlinear elements

# Model learning problems




Can we distribute the computations?

# Dynamic network setup



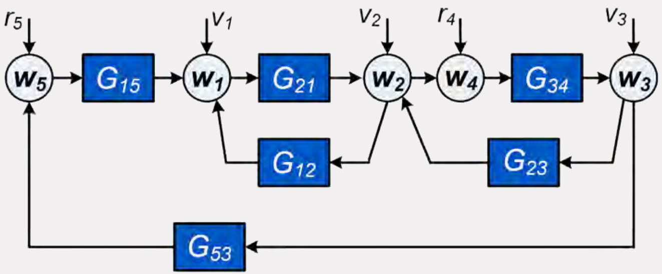

Measured time series:

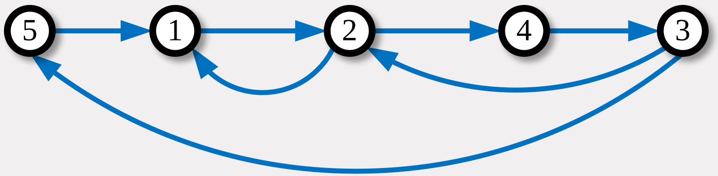
$$\{w_i(t)\}_{i=1,\cdots L};\ \{r_j(t)\}_{j=1,\cdots K}$$

Many challenging data-driven modeling questions can be formulated

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

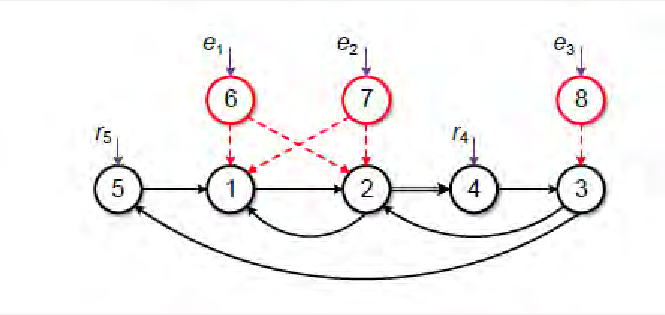
# Dynamic network setup – directed graph



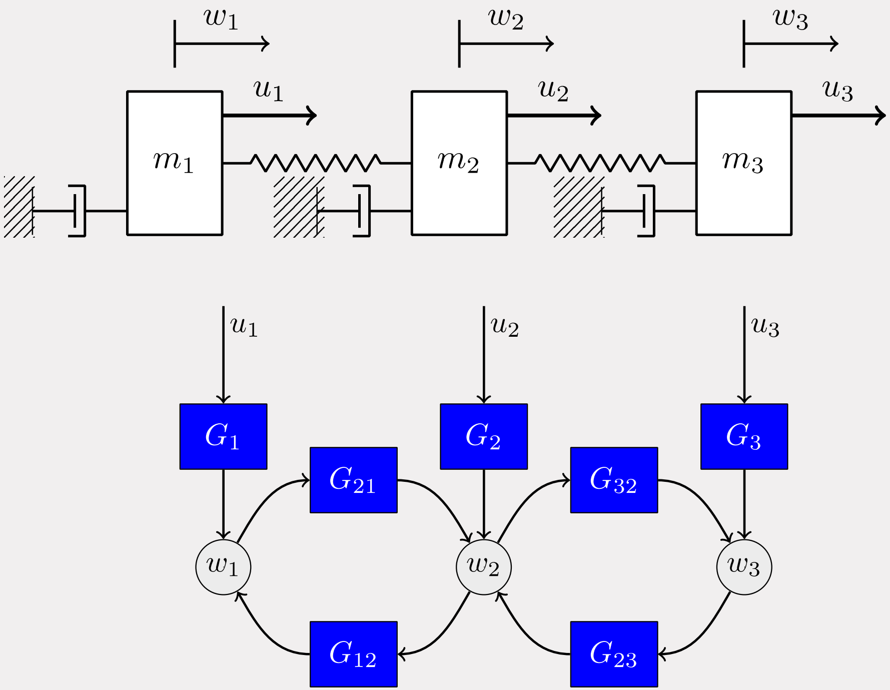




Nodes are vertices; modules/links are edges

Extended graph:
including the external signals
and disturbance correlations



# Application: Networks of (damped) oscillators




- Power systems, vehicle platoons, thermal building dynamics, …
- Spatially distributed
- Bilaterally coupled



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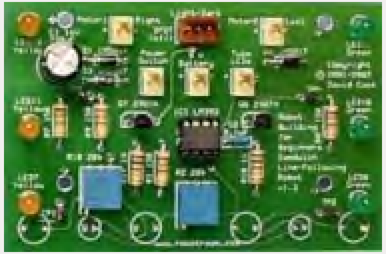
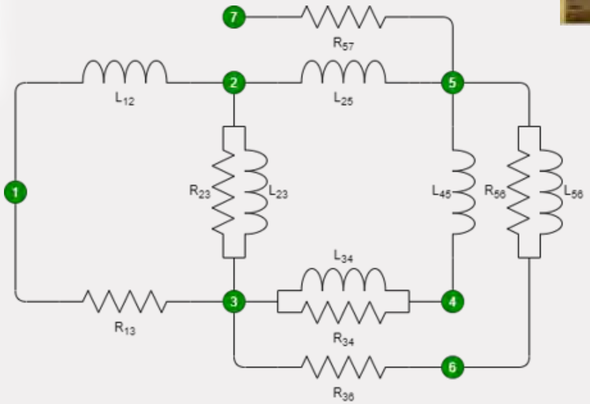
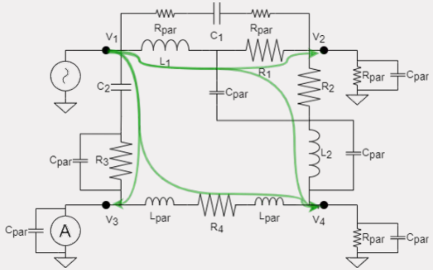
# Application: Printed Circuit Board (PCB) Testing

Source: Altium



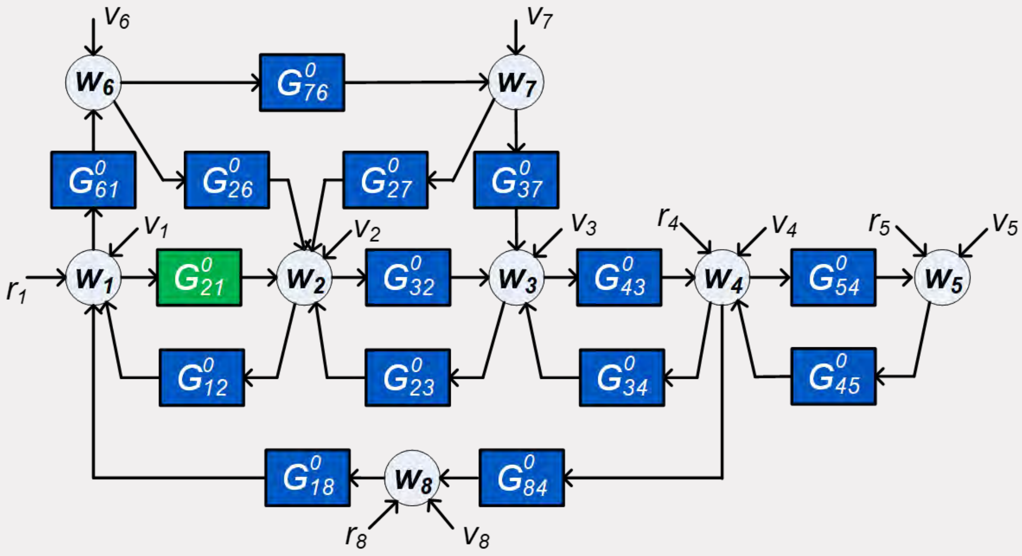

Detection of

- component failures
- parasitic effects

# Contents

# Single module identification

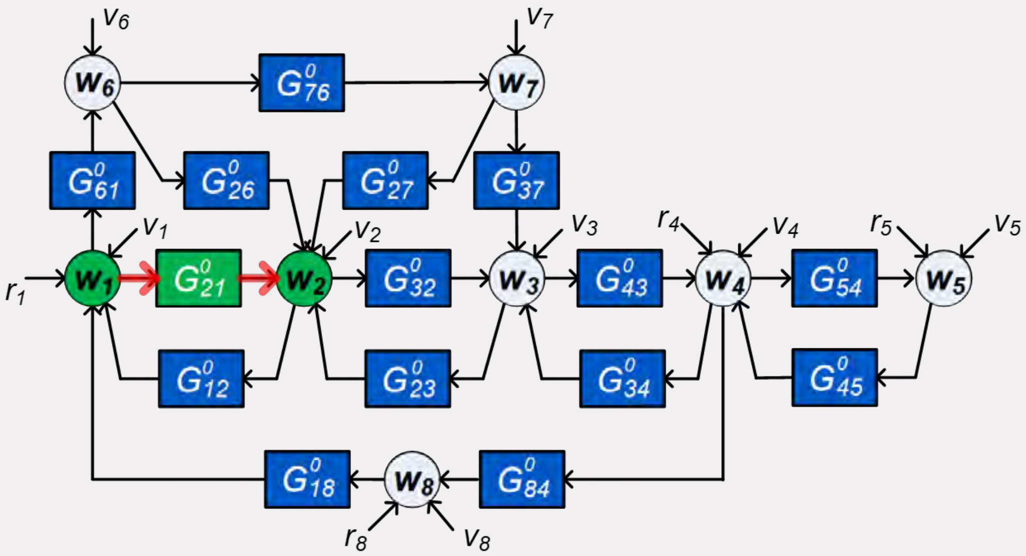
# Single module identification




For a network with known topology:

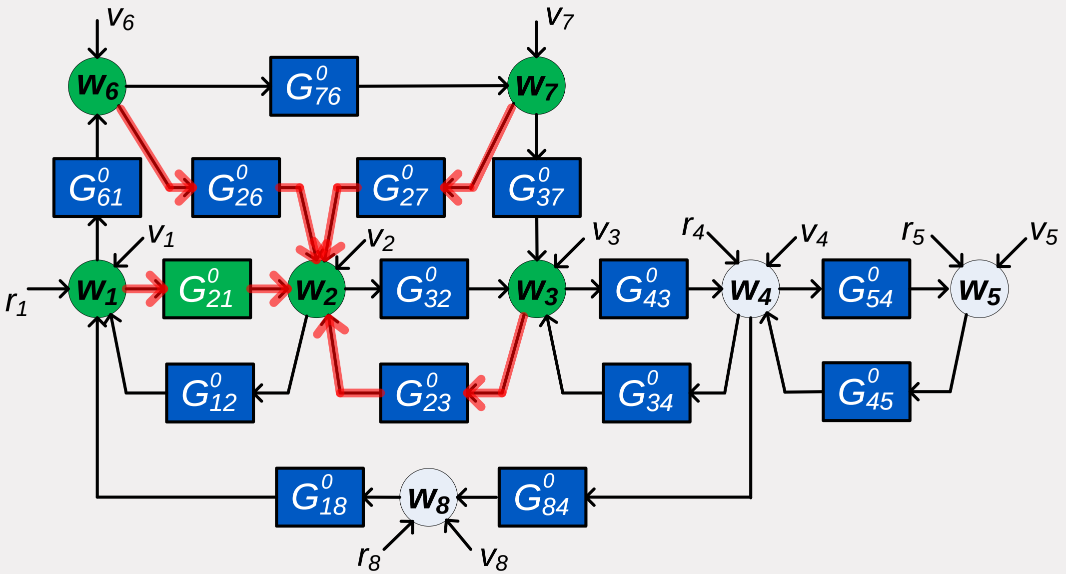
- Identify $G^0_{21}$ on the basis of measured signals
- Which signals to measure? Preference for local measurements
- When is there enough excitation / data informativity?

# Single module identification

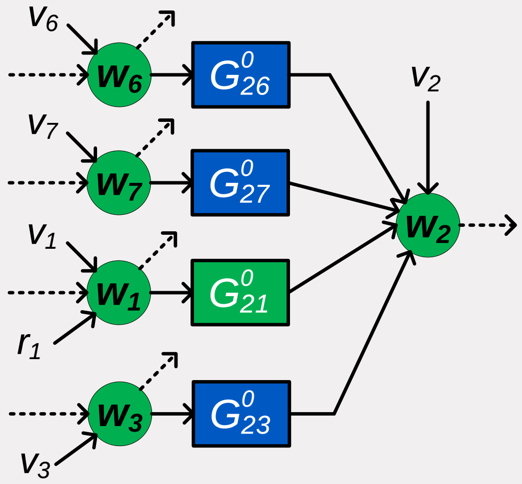



Naïve approach: identify based on $w_1$ and $w_2$ : in general does not work.

# Single module identification



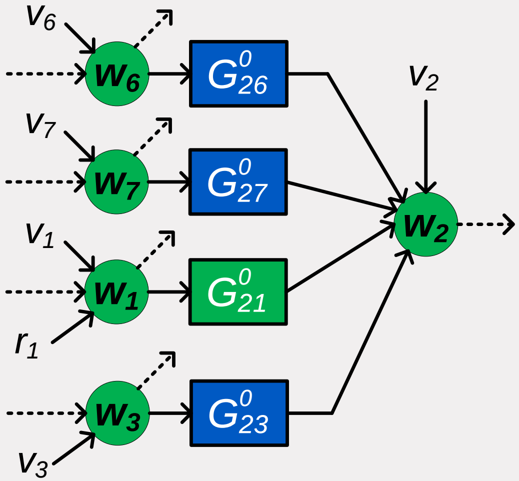

Identifiying $G^0_{21}$ is part of a 4-input, 1-output problem




If noises $v_k$ are correlated it may even be part of a MIMO problem

# Single module identification

Identifiying $G_{21}^{0}$ is part of a 4-input, 1-output problem




**Input signals will be correlated**:

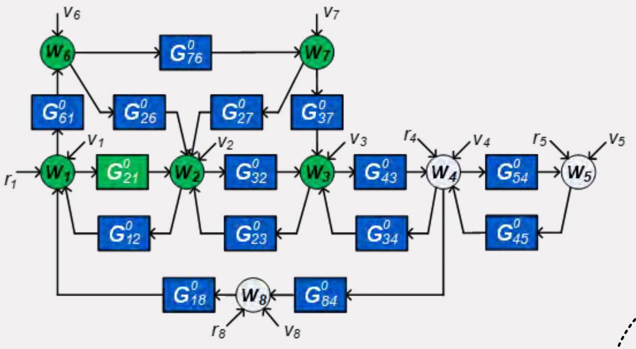
similar as in a closed-loop situation

What is required for
**identifiability / data informativity**?

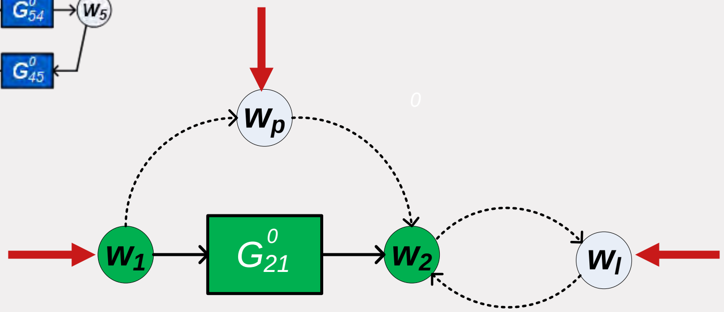
Ability to distinguish between models
independent of id-method

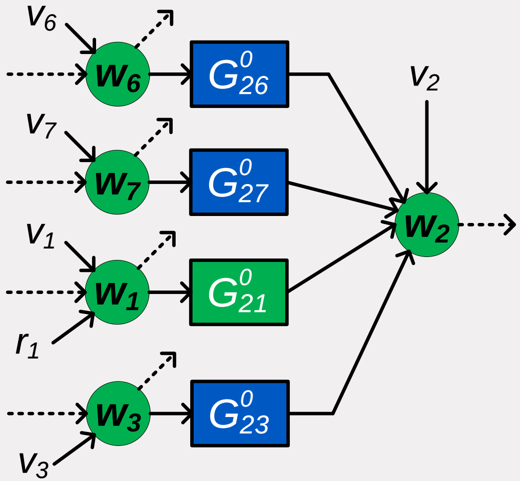
Information content of signals
dependent on id-method

# Single module identification



Identifiying $G^0_{21}$ is part of a 4-input, 1-output problem



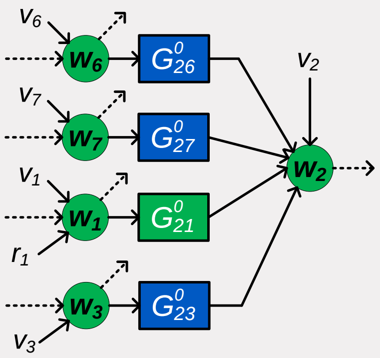


All parallel paths, and loops around the output, plus input $w_1$ should have an independent external signal $r$ or $v$

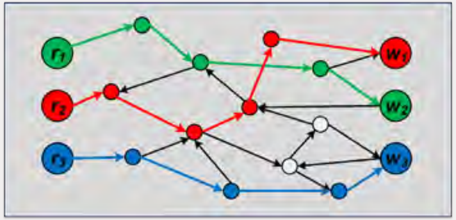
and typically need to be blocked by a measured node

[1] Weerts et al., Automatica 2018, CDC 2018
[2] Bazanella et al. CDC2017; Hendrickx et al., IEEE-TAC, 2019.
[3] Dankers et al., TAC 2016
[4] Shi et al., Automatica 2022

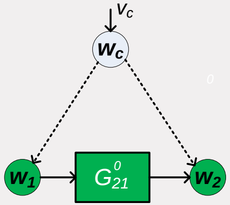
# Single module identification




All inputs require an independent excitation (through vertex disjoint paths) from $r$, $e$



If excitation is relying on disturbances and correlated to $v_2$




Confounding variable [1][2]

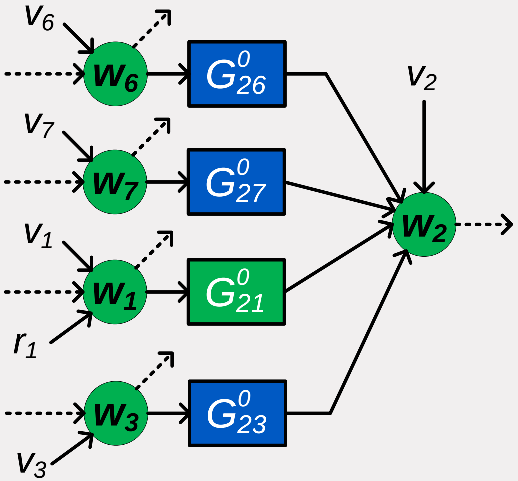
To be handled by:

- Adding more input signals (blocking the cv)
- Including the input as output (MIMO) [3]


[1] J. Pearl, *Stat. Surveys, 3*, 96-146, 2009
[2] A.G. Dankers et al., *Proc. IFAC World Congress*, 2017.
[3] K.R. Ramaswamy et al., TAC November 2021

# Single module identification

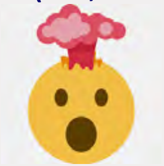
Typical solution:




- MISO (sometimes MIMO) estimation problem
- to be solved by any (closed-loop) identification algorithm, e.g. direct/indirect method

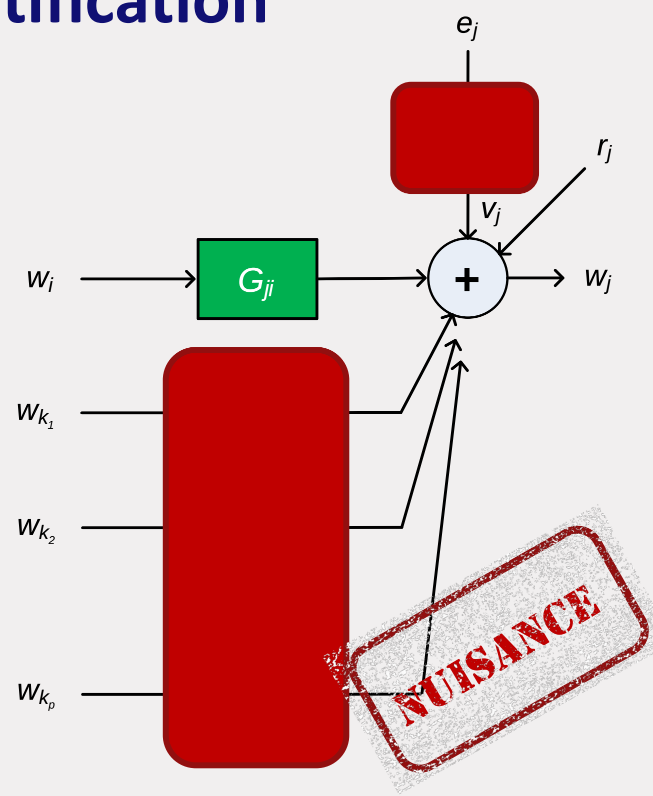
# Machine learning in local module identification

- 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



Increases variance
Computationally challenging

- We need only the target module. No NUISANCE!

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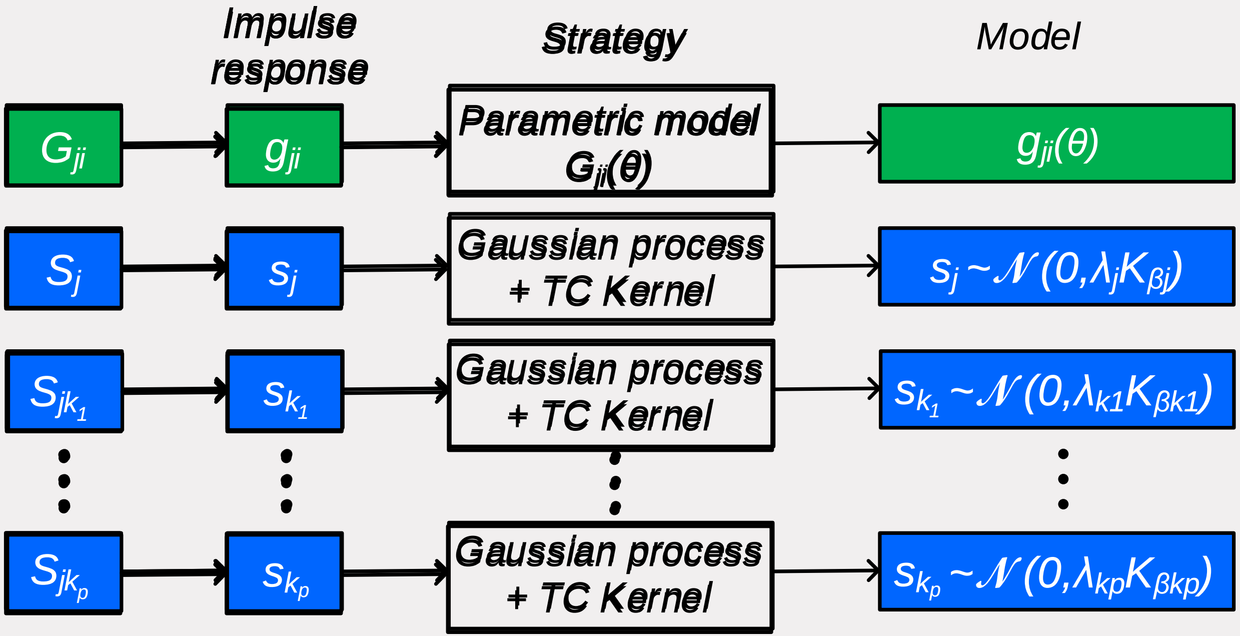
# Machine learning in local module identification




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

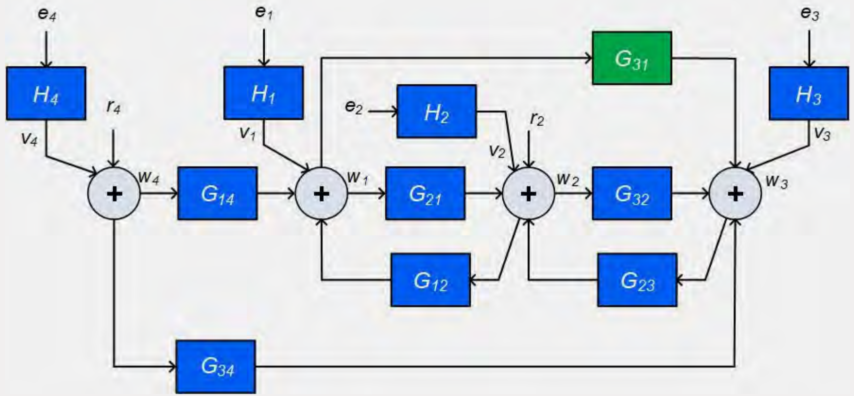
Maximize marginal likelihood of output data: $\hat{\eta} = \underset{\eta}{\operatorname{argmax}}\, p(w_j; \eta)$

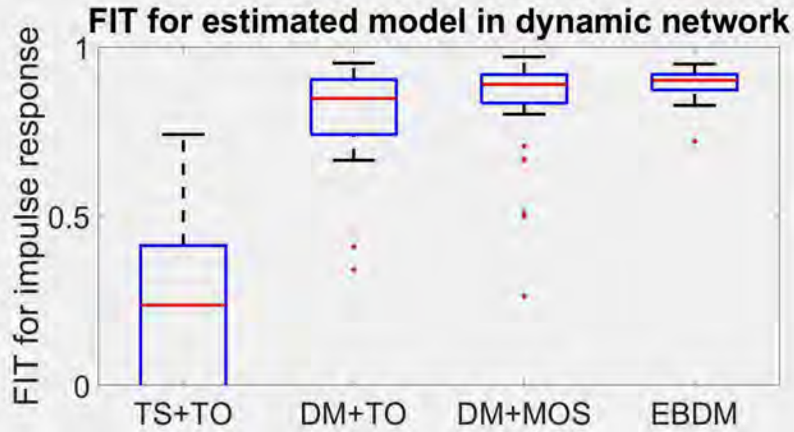
$$\eta := \begin{bmatrix} \theta & \lambda_j & \lambda_{k_1} & \dots & \lambda_{k_p} & \beta_j & \beta_{k_1} & \dots & \beta_{k_p} & \sigma_j^2 \end{bmatrix}^{\top}$$

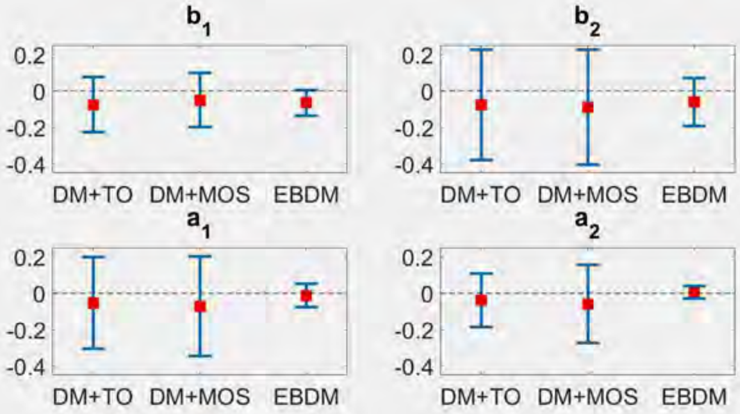

[1] Everitt et al., Automatica 2017.
[2] K.R. Ramaswamy et al., Automatica, 2021.

# Numerical simulation

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



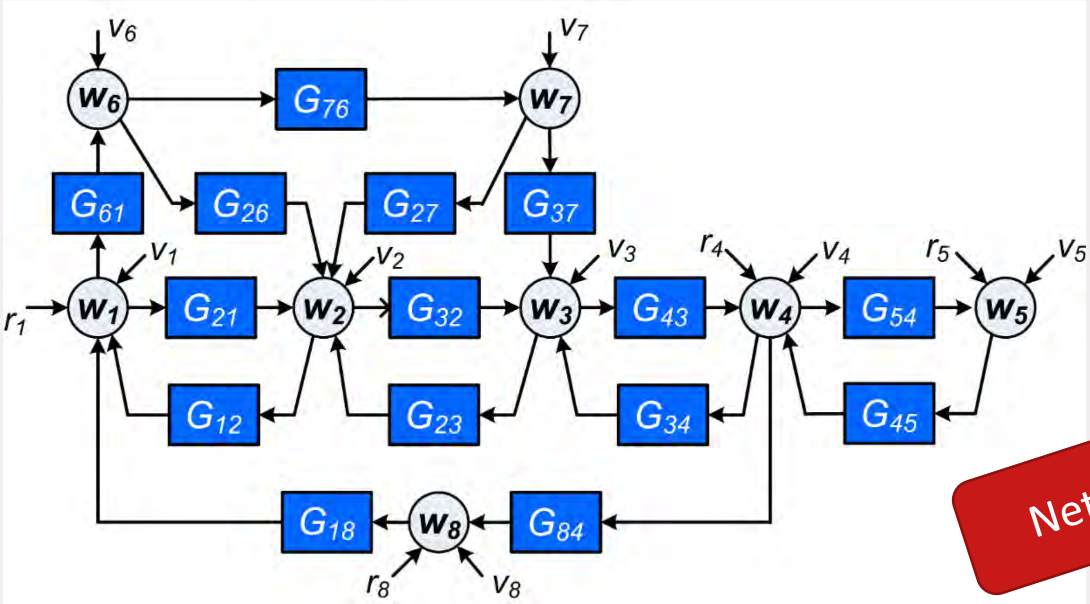
# Summary single module identification

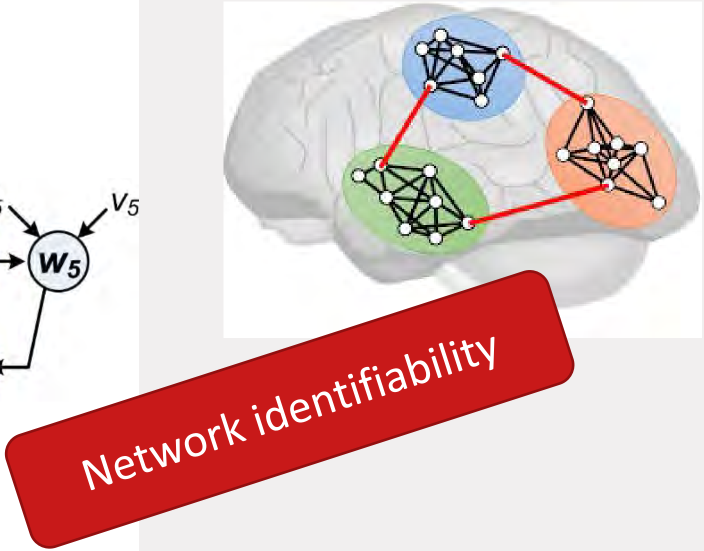
- Path-based conditions for **network identifiability** (where to excite?)
- Graph tools for checking conditions
- Degrees of freedom in selection of measured signals – sensor selection
- Methods for **consistent** and **minimum variance** module estimation, and effective (scalable) algorithms
- A priori known modules can be accounted for

# Contents

- Introduction and motivation
- How to model a dynamic network?
- Single module identification
- Global network identification
- Diffusively coupled networks
- Extensions - Discussion

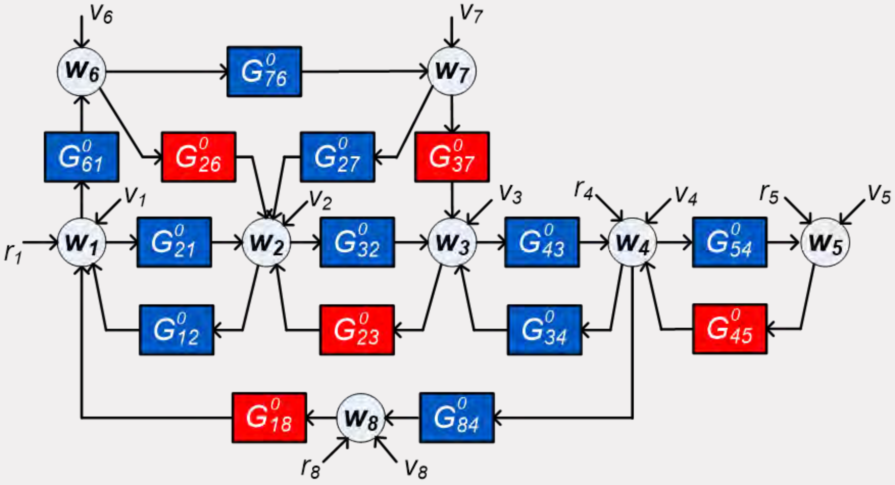
# Full network identification




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

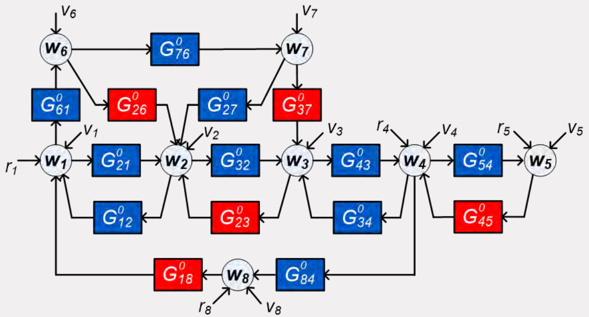
# Network identifiability




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

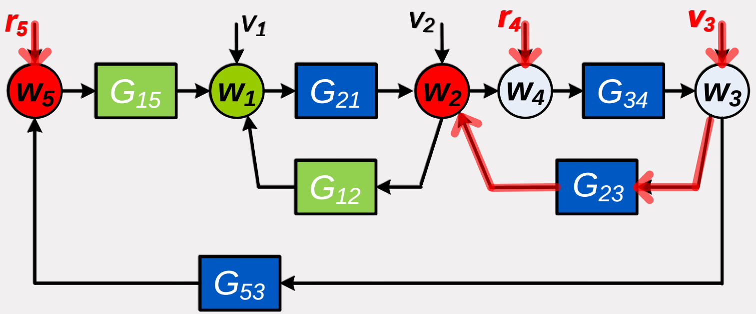
Generic identifiability of $\mathcal{M}$ :

- 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.

# Example 5-node network

Conditions for identifiability ➡ rank conditions on transfer function



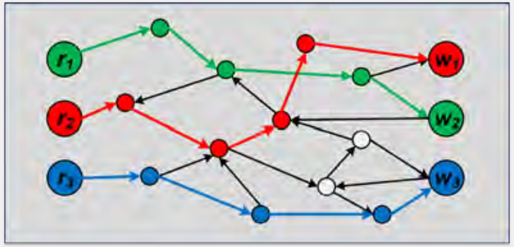

Full row rank of

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

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

Generic rank = number of vertex-disjoint paths

2 vertex-disjoint paths → 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



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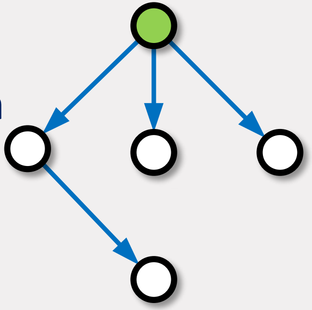
# Synthesis solution for network identifiability

Allocating external signals for generic identifiability:

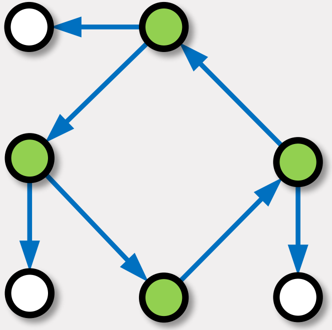
1. Cover the graph of the network model set by a set of **disjoint pseudo-trees**

   Pseudo-trees:

   Tree with root in green



   Cycle with outgoing trees;
   Any node in cycle is root



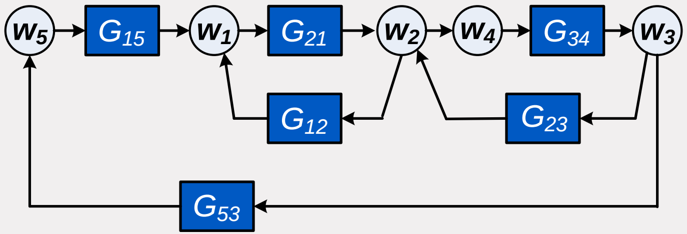
   Edges are **disjoint** and all out-neighbours of a node are in the same pseudo-tree

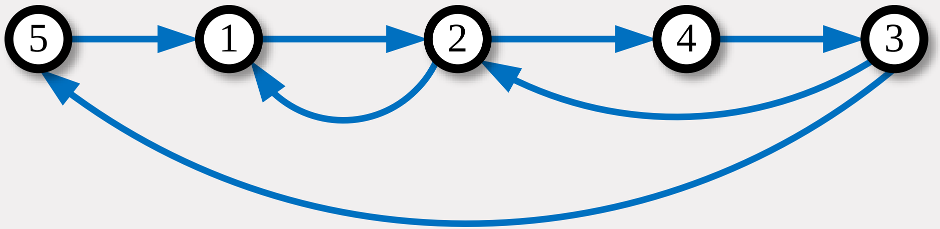
2. Assign an independent external signal ( $r$ or $e$) at a root of each pseudo-tree.

   This guarantees generic identifiability of the model set.

[1] X. Cheng, S. Shi and PVdH, TAC, February 2022.

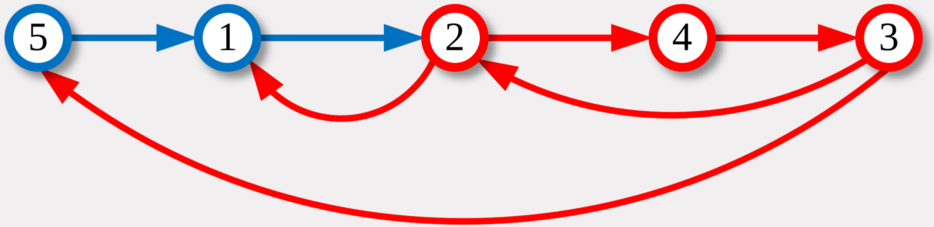
# Where to allocate external excitations for network identifiability?




All indicated modules are parametrized

Two disjoint pseudo-trees

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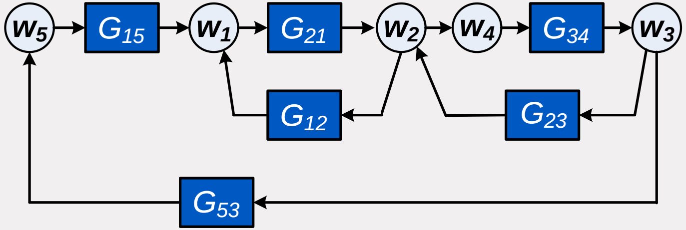
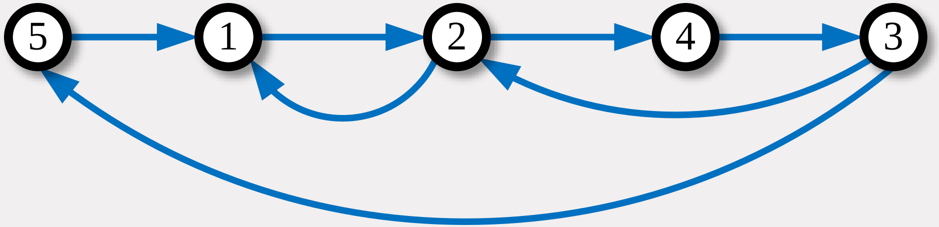
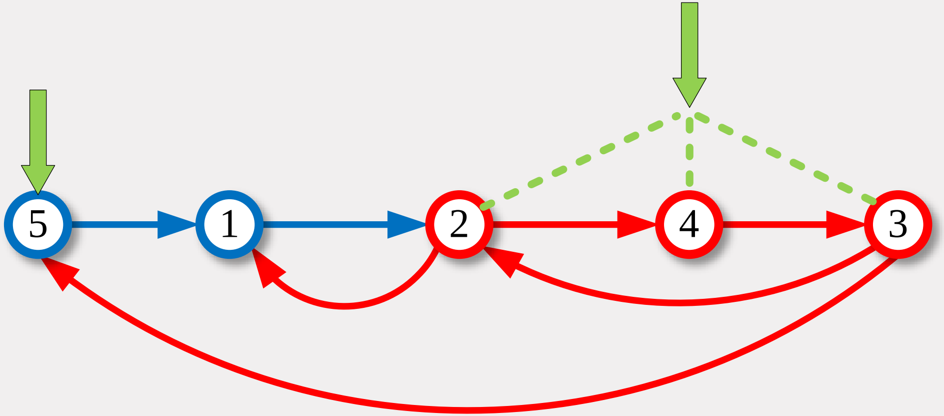
# Where to allocate external excitations for network identifiability?




Two independent excitations guarantee
generic network identifiability




[1] X. Cheng, S. Shi and PVdH, CDC 2019.

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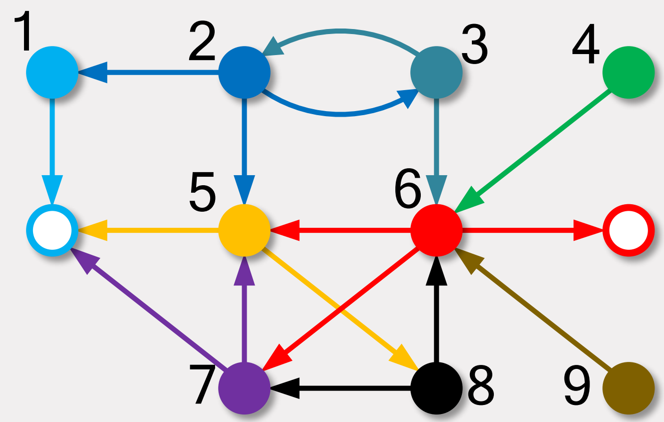
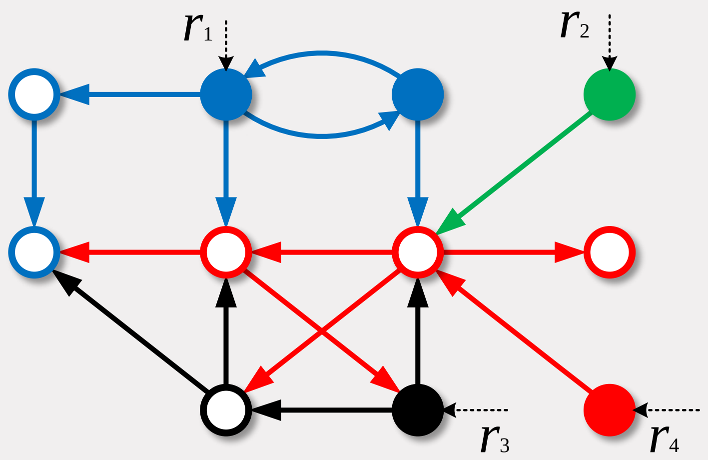
# Where to allocate external excitations for network identifiability?




Pseudo-tree merging algorithm [1]




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

[1] X. Cheng, S. Shi and PVdH, TAC, February 2022.

# 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 [1]

[1] Bazanella, CDC 2019.

# Algorithms for identification of full network

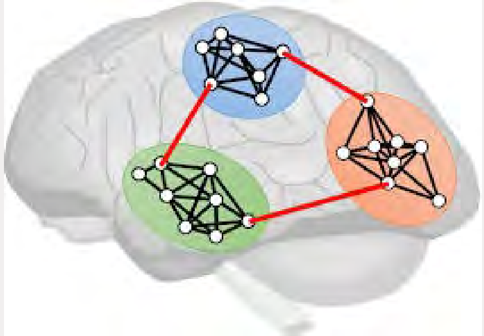
(Prediction error) identification methods will typically lead to large-scale **non-convex** optimization problems

**Convex relaxation** algorithms are being developed[1,2] as well as machine learning tools

[1] Weerts, Galrinho et al., SYSID 2018

[2] Fonken et al., Automatica 2022, to appear.

# Topology identification



- Topology resulting from full dynamic model

- Alternative: non-parametric models (Wiener filters [1])
  or kernel-based approaches [2][3]

- modeling module dynamics by Gaussian processes,

  kernel with 2 parameters for each dynamic module

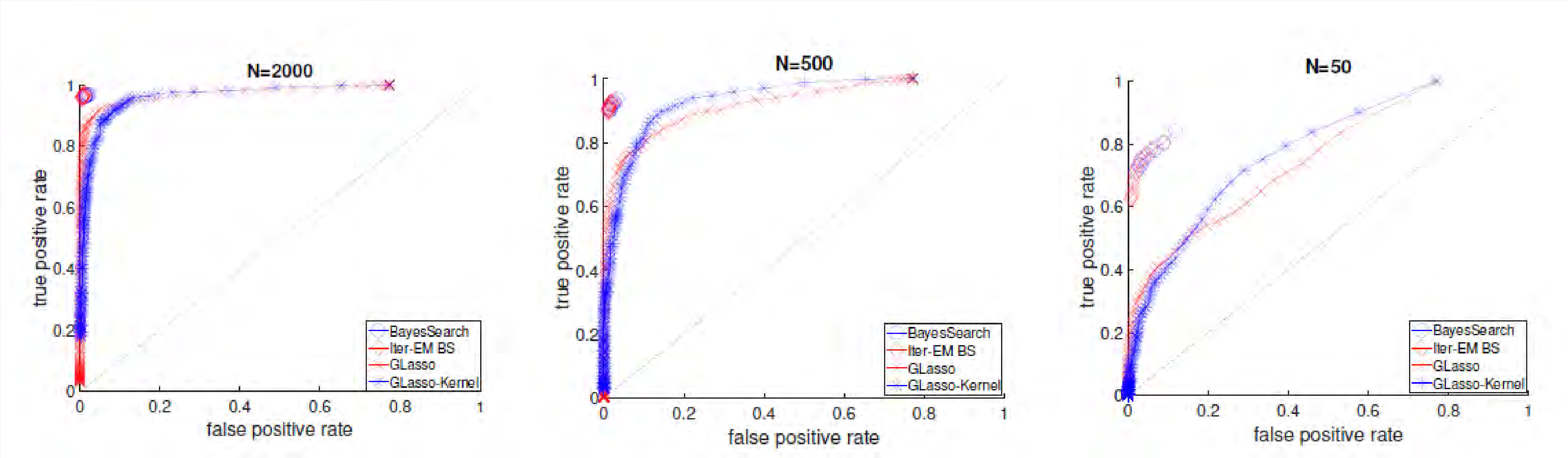
- Optimizing likelihood of the data as function of parameters and topology:

$$p(\{w(t)\}_{t=1}^{N} | \theta, \mathcal{G})$$

- Forward-backward search over topologies + empirical Bayes (EM) for parameters

[1] Materassi & Innocenti, TAC 2010.
[2] Chiuso & Pillonetto, Automatica, 2012.
[3] Shi, Bottegal, PVdH, ECC 2019

# Topology identification

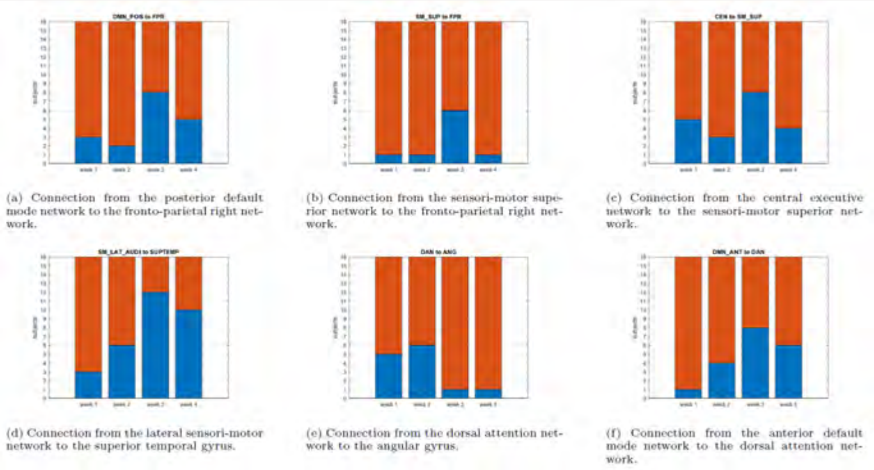



50 MC realizations of network with 6 nodes.

[1] Shi, Bottegal, PVdH, ECC 2019

# Neurodynamic effect of listening to Mozart music

Identifying changes in network connections in the brain, after intensely listening for one week




(a) Connection from the posterior default mode network to the fronto-parietal right network.

(b) Connection from the sensori-motor superior network to the fronto-parietal right network.

(c) Connection from the central executive network to the sensori-motor superior network.

(d) Connection from the lateral sensori-motor network to the superior temporal gyrus.

(e) Connection from the dorsal attention network to the angular gyrus.

(f) Connection from the anterior default mode network to the dorsal attention network.

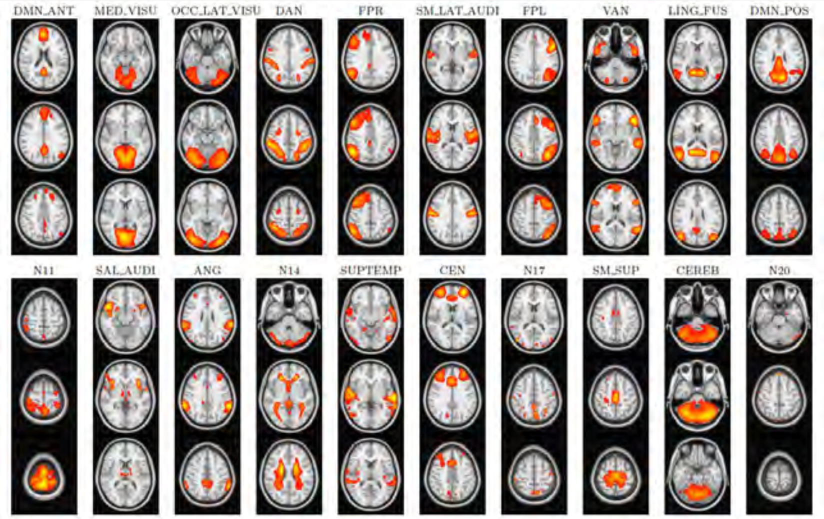



Figure 3: Spatial maps of the 20 active brain networks found through the ICA decomposition. Each image consists of 3 relevant horizontal slices of the brain, where the spatial map is indicated by the red color scale.

# Contents

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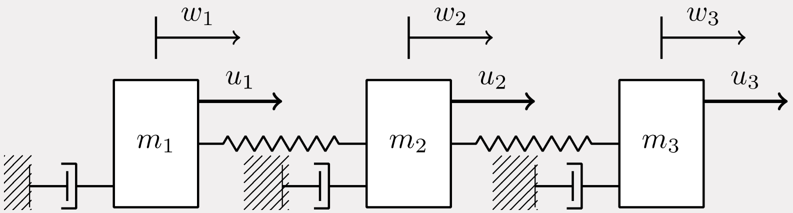
# Diffusively coupled networks

# Back to the basics of physical interconnections

In connecting physical systems, there is often no predetermined direction of information [1]


**Example**: resistor / spring connection in electrical / mechanical system:

Resistor

$$I = \frac{1}{R}(V_1 - V_2)$$

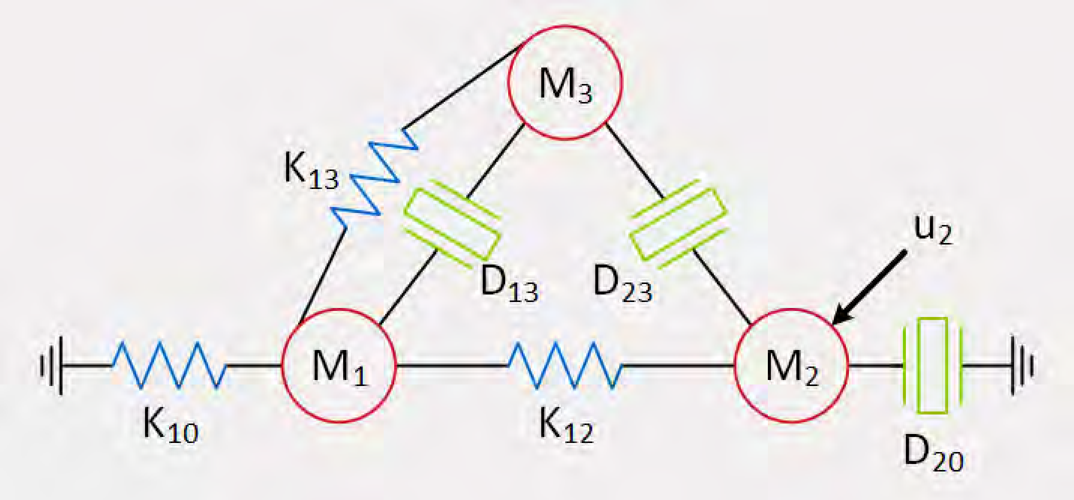
Spring

$$F = K(x_1 - x_2)$$

Difference of node signals drives the interaction: **diffusive coupling**

[1] J.C. Willems (1997,2010)

# Diffusively coupled physical network

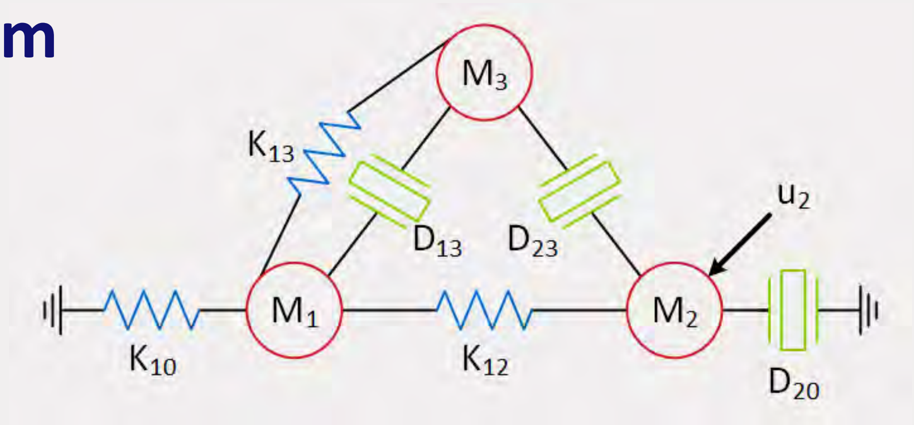



Equation for node *j*:

$$M_j\ddot{w}_j(t)+D_{j0}\dot{w}_j(t)+\sum_{k\neq j} D_{jk}(\dot{w}_j(t)-\dot{w}_k(t))+K_{j0}w_j(t)+\sum_{k\neq j} K_{jk}(w_j(t)-w_k(t))=u_j(t),$$

# Mass-spring-damper system

- Masses $M_j$
- Springs $K_{jk}$
- Dampers $D_{jk}$
- Input $u_j$




$$\begin{bmatrix} M_1 & & \\ & M_2 & \\ & & M_3 \end{bmatrix}\begin{bmatrix} \ddot{w}_1 \\ \ddot{w}_2 \\ \ddot{w}_3 \end{bmatrix} + \begin{bmatrix} 0 & & \\ & D_{20} & \\ & & 0 \end{bmatrix}\begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{10} & & \\ & 0 & \\ & & 0 \end{bmatrix}\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

$$+ \begin{bmatrix} D_{13} & 0 & -D_{13} \\ 0 & D_{23} & -D_{23} \\ -D_{13} & -D_{23} & D_{13}+D_{23} \end{bmatrix}\begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{12}+K_{13} & -K_{12} & -K_{13} \\ -K_{12} & K_{12} & 0 \\ -K_{13} & 0 & K_{13} \end{bmatrix}\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} = \begin{bmatrix} 0 \\ u_2 \\ 0 \end{bmatrix}$$

$$[\ \underbrace{A(p)}_{diagonal} + \underbrace{B(p)}_{Laplacian}\ ]\, w(t) = u(t) \qquad A(p), B(p) \text{ polynomial} \qquad p = \frac{d}{dt}$$

# Mass-spring-damper system

$$[\ \underbrace{A(p)}_{diagonal} + \underbrace{B(p)}_{Laplacian}\ ]\, w(t) = u(t) \qquad A(p), B(p) \text{ polynomial}$$

$$[\ \underbrace{Q(p)}_{diagonal} - \underbrace{P(p)}_{hollow\&symmetric}\ ]\, w(t) = u(t)$$

This fully fits in the earlier module representation:

$$w(t) = Gw(t) + \underbrace{Rr(t) + He(t)}_{Q^{-1}(p)u(t)}$$

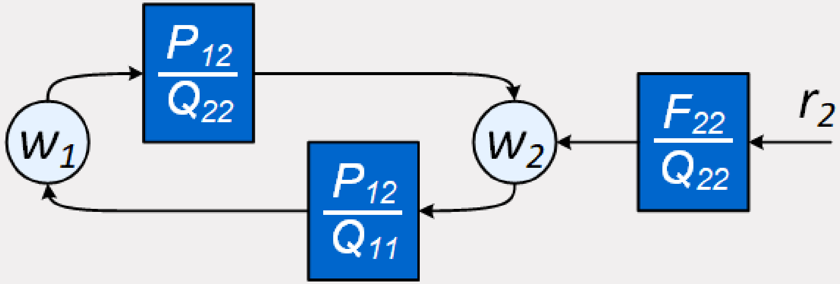
with the additional condition that:

$$G(p) = Q(p)^{-1}P(p) \qquad Q(p), P(p) \text{ polynomial}$$

$P(p)$ symmetric, $Q(p)$ diagonal

# Module representation

Consequences for node interactions:




- Node interactions come in pairs of modules
- Where numerators are the same

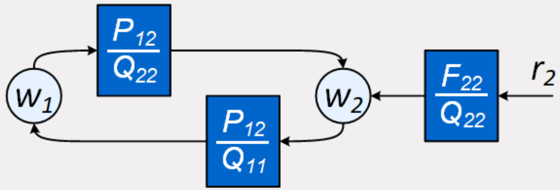
Framework for network identification remains the same

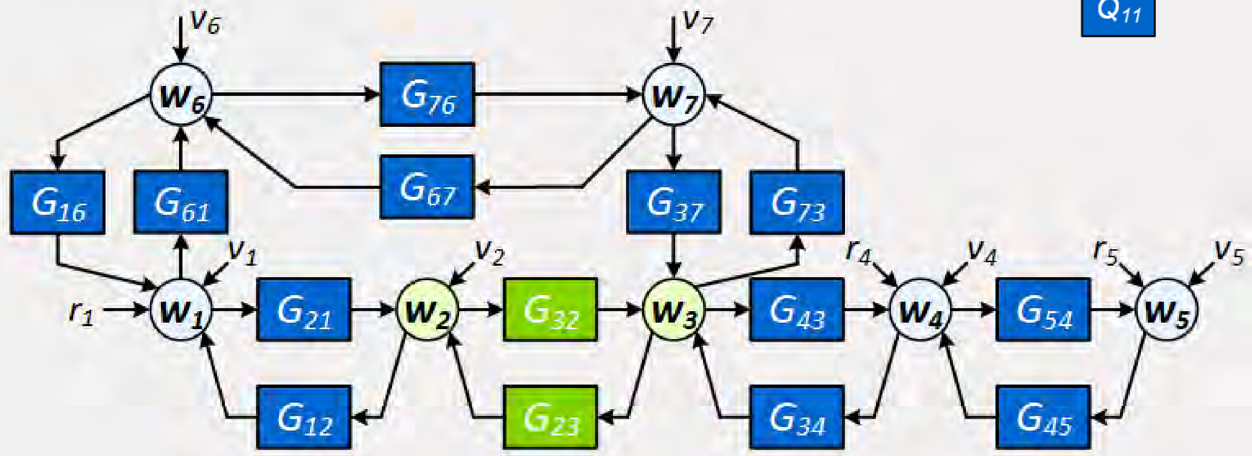
- Symmetry can simply be incorporated in identification

# Local network identification

Identification of **one** (physical) interconnection

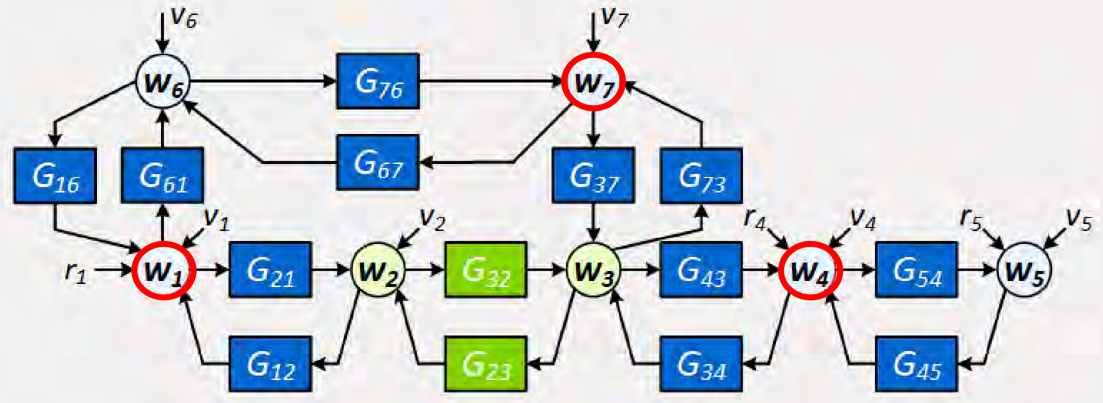
Identification of **two** modules $G_{jk}$ and $G_{kj}$



# Immersion conditions

For simultaneously identifying two modules in one interconnection:




The parallel path and loops-around-the-output condition, now simplifies to:

Measuring/exciting all neighbouring nodes of $w_2$ and $w_3$ leads to a solution

E.E.M. Kivits et al., CDC 2019.

# Summary diffusively coupled networks

- Diffusively coupled networks fit within the module framework (special case)

  - no restriction to second order equations

- Earlier identification framework can be utilized

- Local identification is well-addressed (and stays really local)

- Framework is fit for representing **cyber-physical systems**
  (combining physical bi-directional links, and cyber uni-directional links).

# Extensions - Discussion

# Extensions - Discussion

- **Including sensor noise** [1]
  - Errors-in-variabels problems can be more easily handled in a network setting

- **Distributed estimation (MISO models)** [2]
  - Communication constraints between different agents
  - Recursive (distributed) estimator converges to global optimizer (more slowly)

- **Experiment design** [3],[4]
  - design of least costly experiments

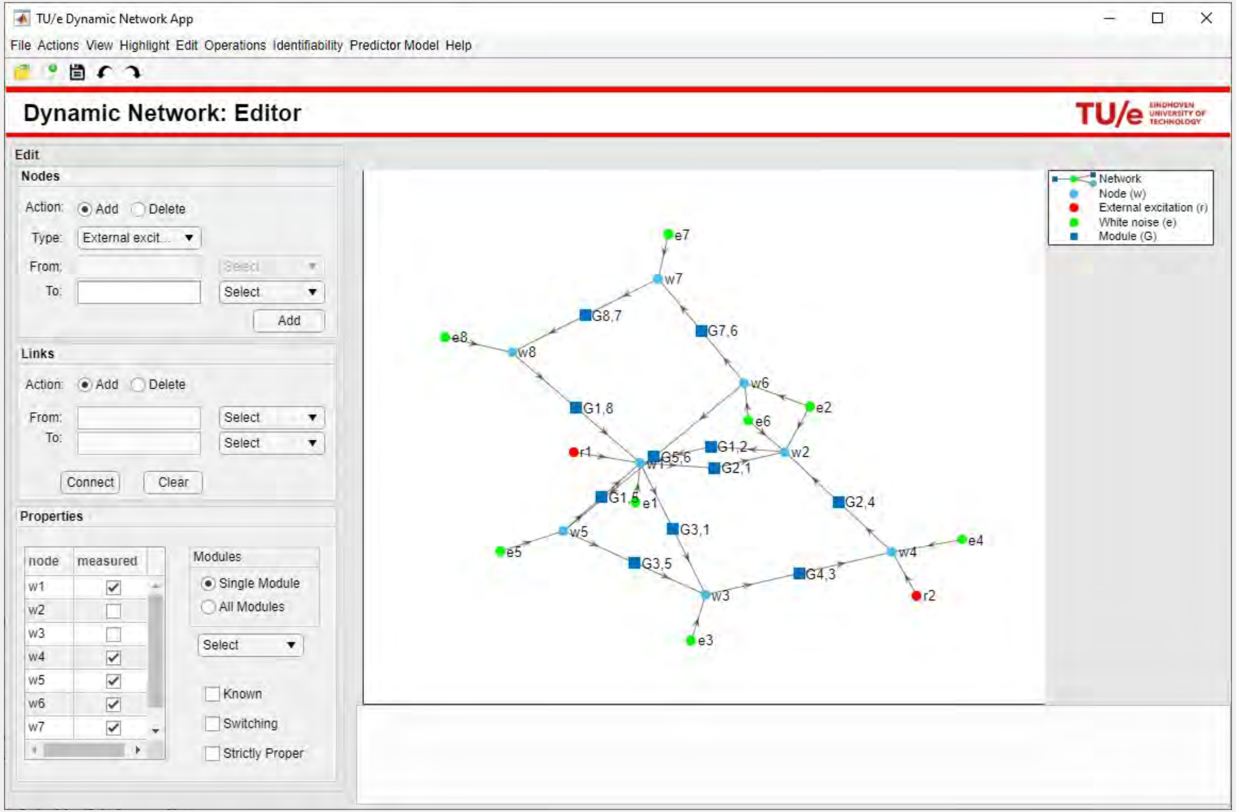
[1] Dankers et al., Automatica, 2015.
[2] Steentjes et al., IFAC-NECSYS, 2018.
[3] Gevers and Bazanella, CDC 2015.
[4] Morelli, Bombois et al., ECC 2019;

# Summary

- **Dynamic network modeling:**

  intriguing research topic with many open questions
- The (centralized) LTI framework is only just the beginning
- Further move towards data-aspects related to distributed control
- and large-scale aspects
- and more real-life applications

# Matlab Toolbox



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

## Research team:

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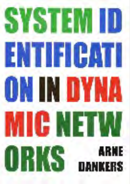
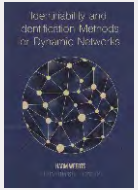



Arne Danckers



Harm Weerts

Shengling Shi

Giulio Bottegal

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# Further reading


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