TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Data-driven model learning in interconnected systems

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AI for Time Series Seminar, KU Leuven
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erc
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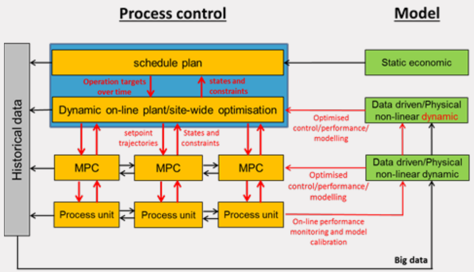
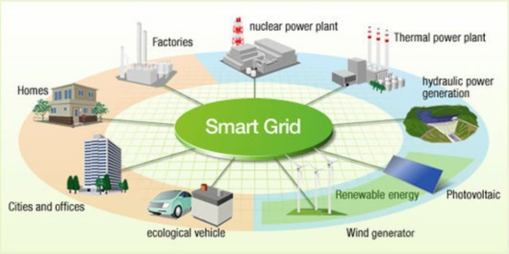
Introduction – dynamic networks

Decentralized process control



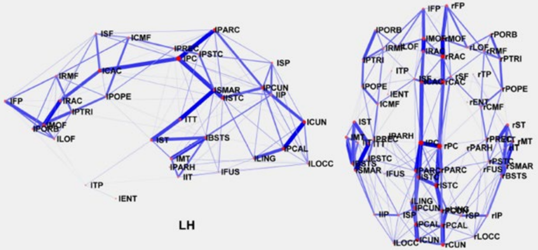
Smart power grid



Pierre et al. (2012)

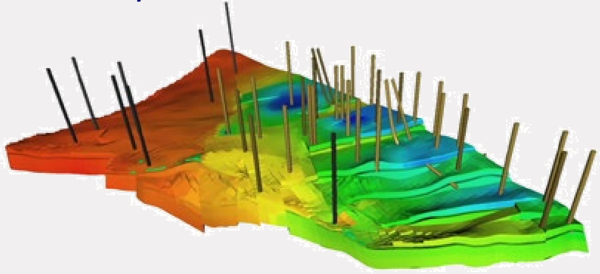
Complex machines

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
- …………………

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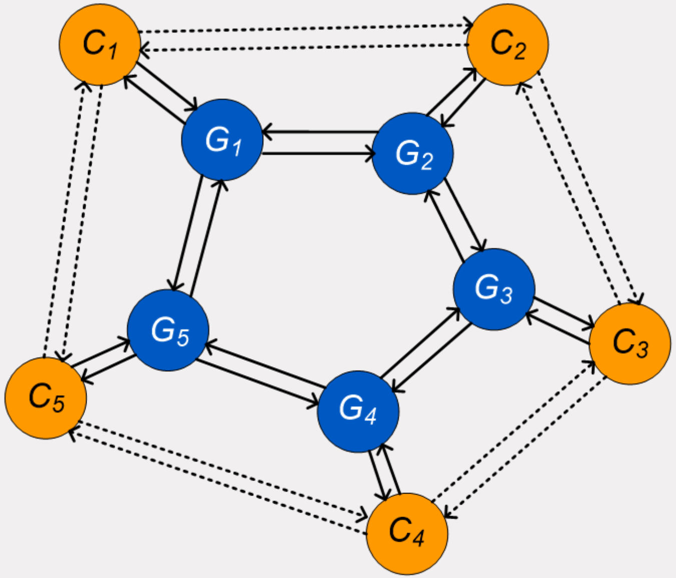
Introduction

Distributed / multi-agent control:

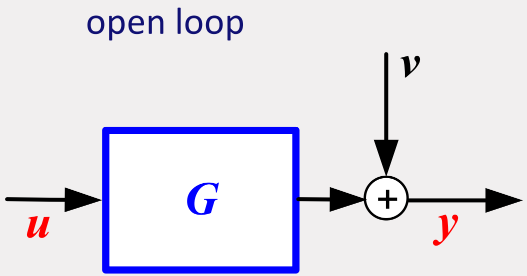


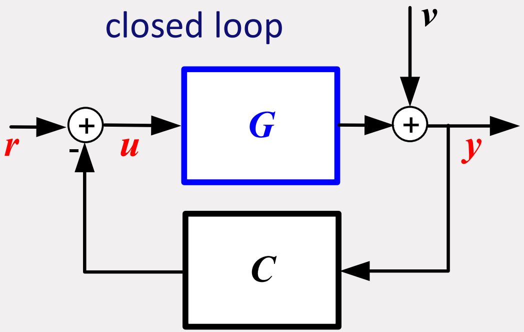
With both physical and communication links between systems G_i and controllers C_i

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

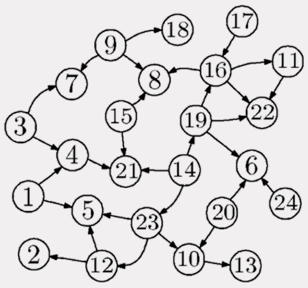
[1] Ljung (1999), Söderström and Stoica (1989), Pintelon and Schoukens (2012)

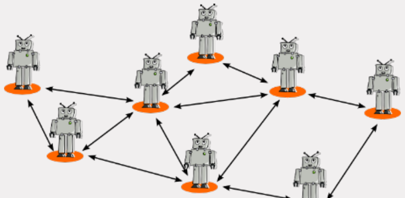
Contents

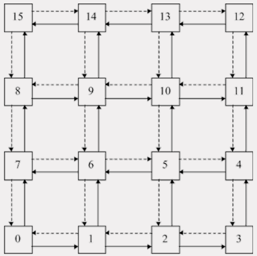
- Introduction and motivation
- How to model a dynamic network?
- Single module identification
- Global network identification
- Diffusively coupled networks
- Extensions - Discussion

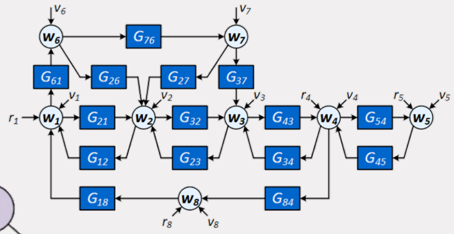
Dynamic networks for data-driven modeling

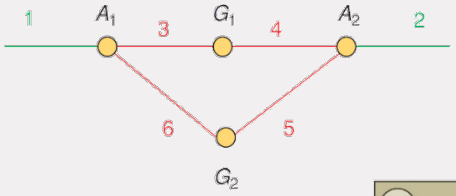
Network models

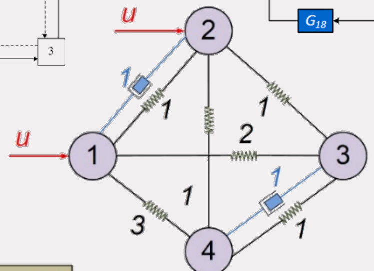


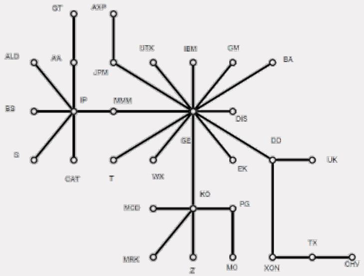


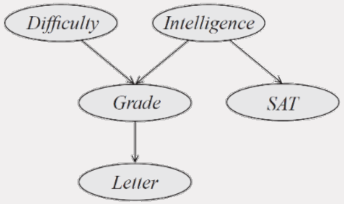


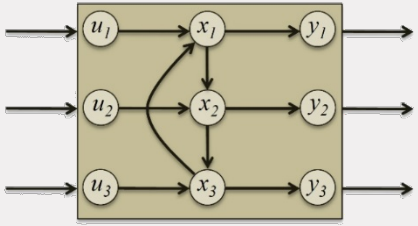


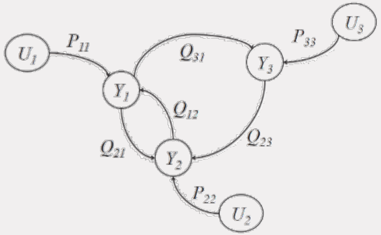












D. Materassi and M.V. Salapaka (2012)

R.N. Mantegna (1999)

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)

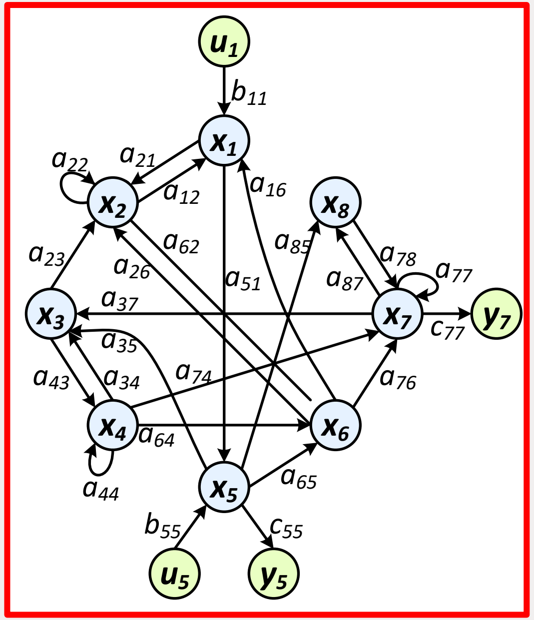
P.E. Paré et al (2013)

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

X.Cheng (2019)

E. Yeung et al (2010)

Network models

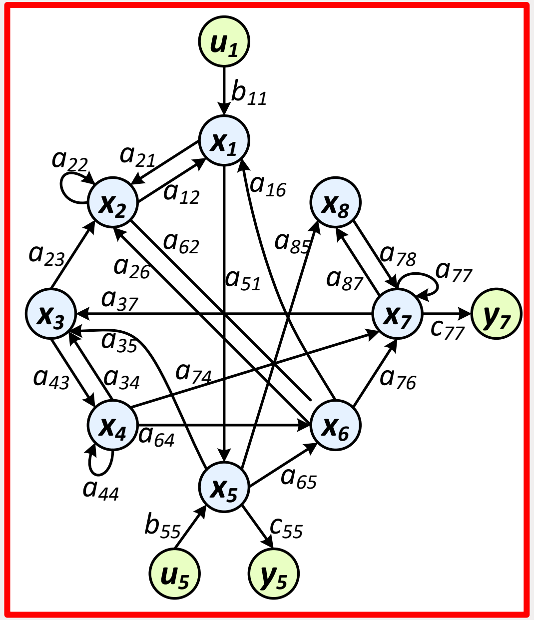


State space representation

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k) + Du(k)$$

- 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

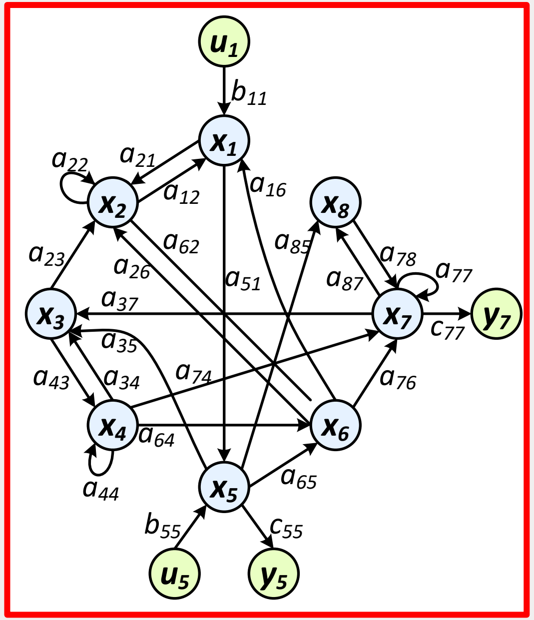
$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned}$$

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

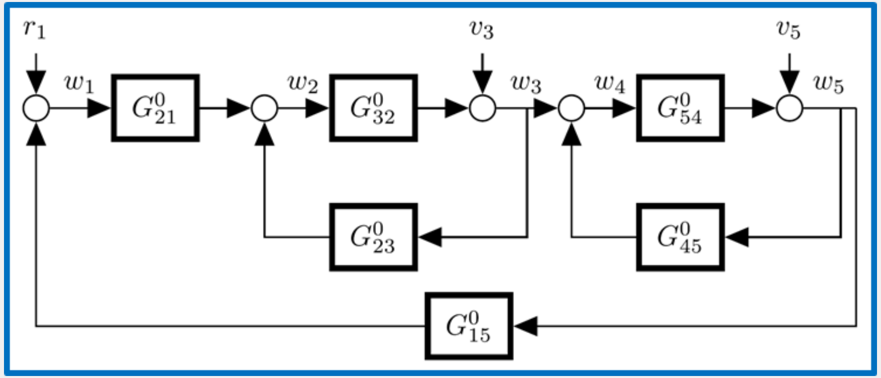
For data-driven modeling problems:

- 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,...

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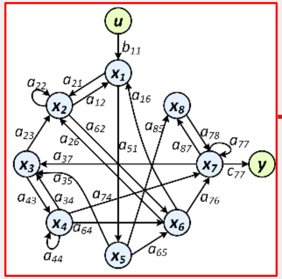
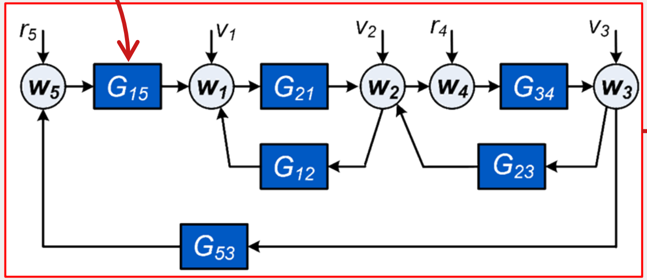
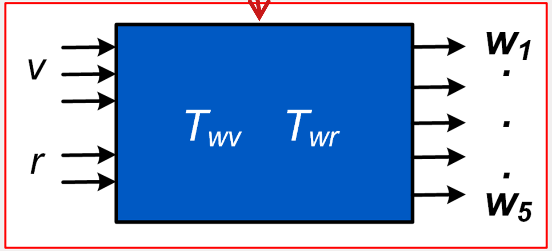
Dynamic network models - zooming



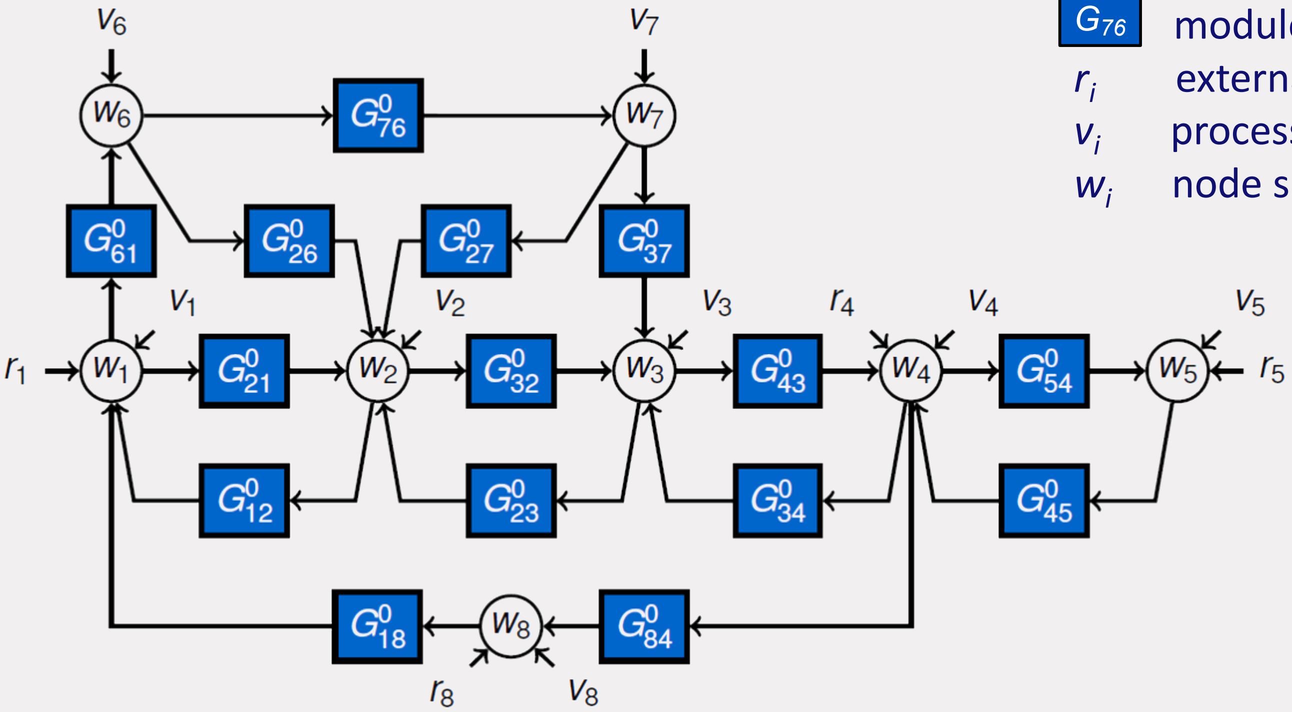
Increasing level of detail





Decreasing structural information

Dynamic network setup



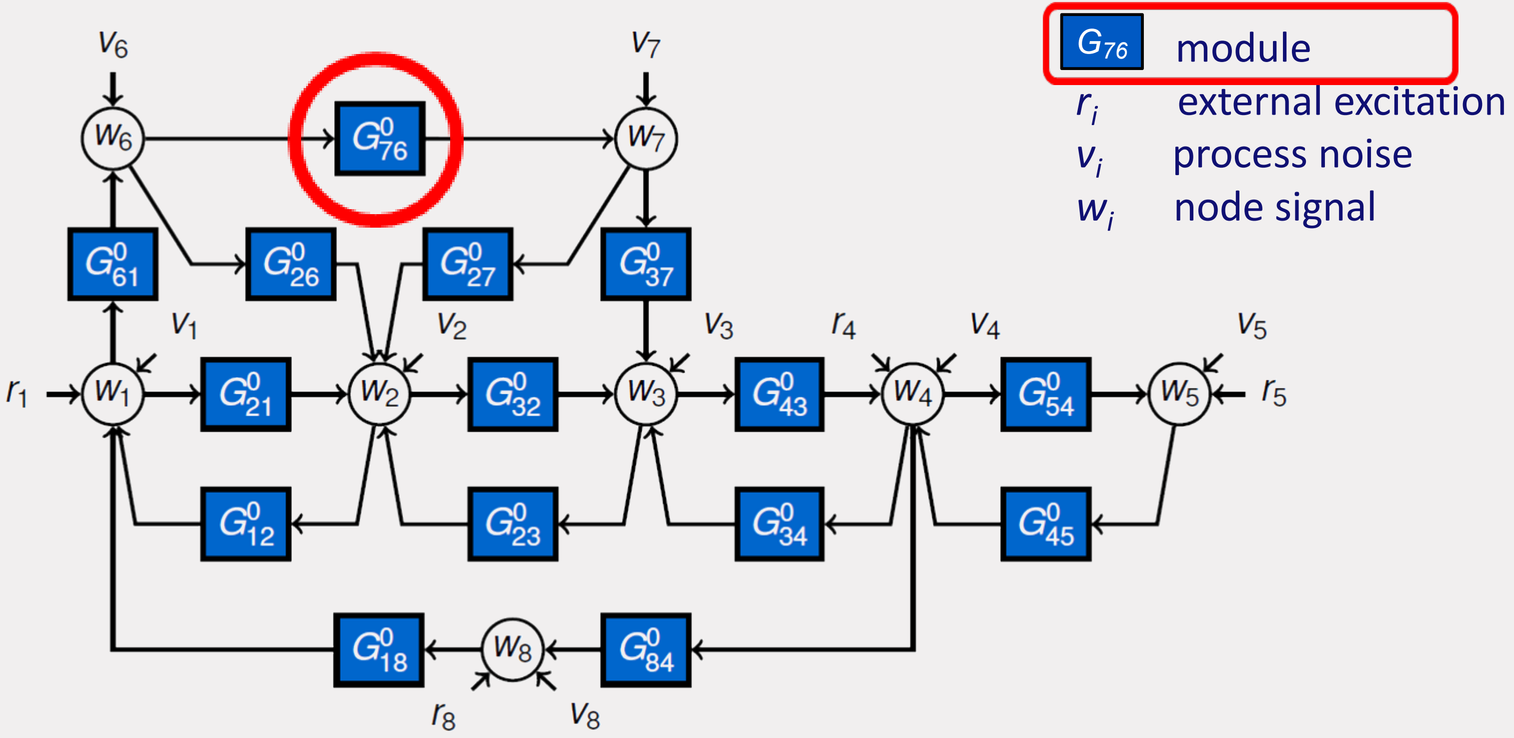
G_{76} module

r_i external excitation

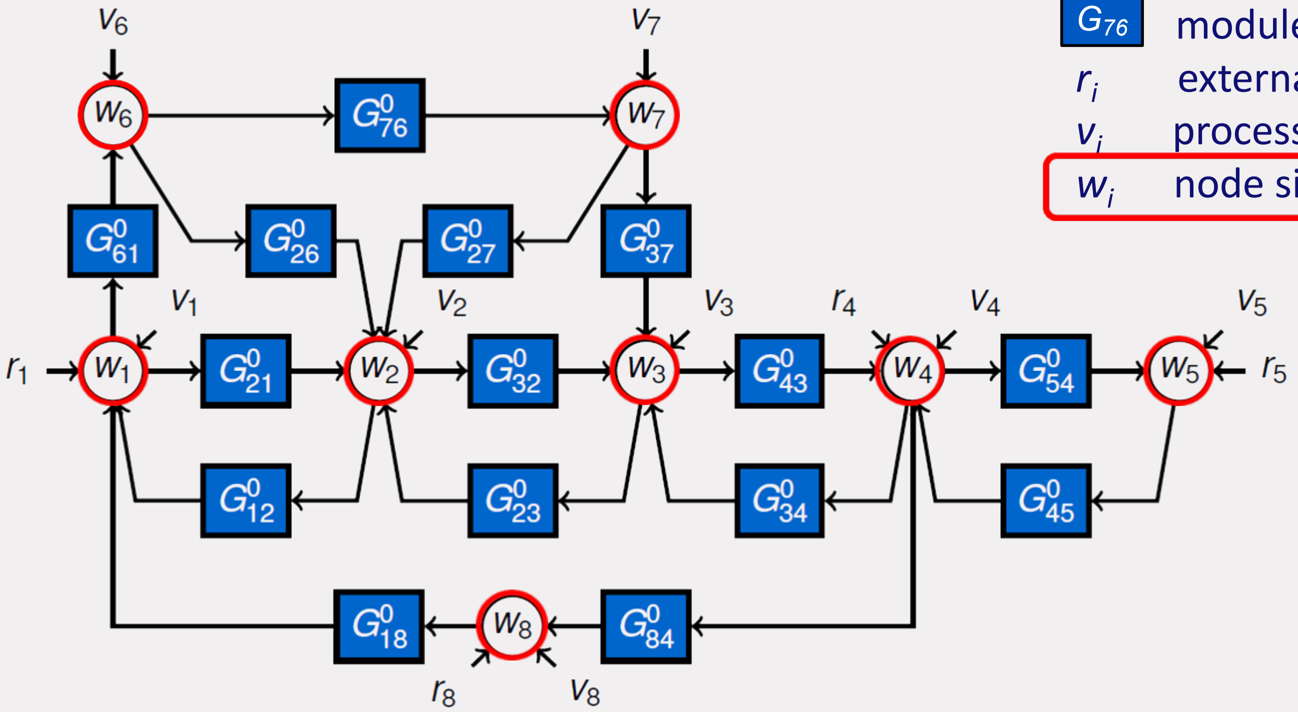
v_i process noise

w_i node signal

Dynamic network setup



Dynamic network setup



G_{76} module

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w_i node signal

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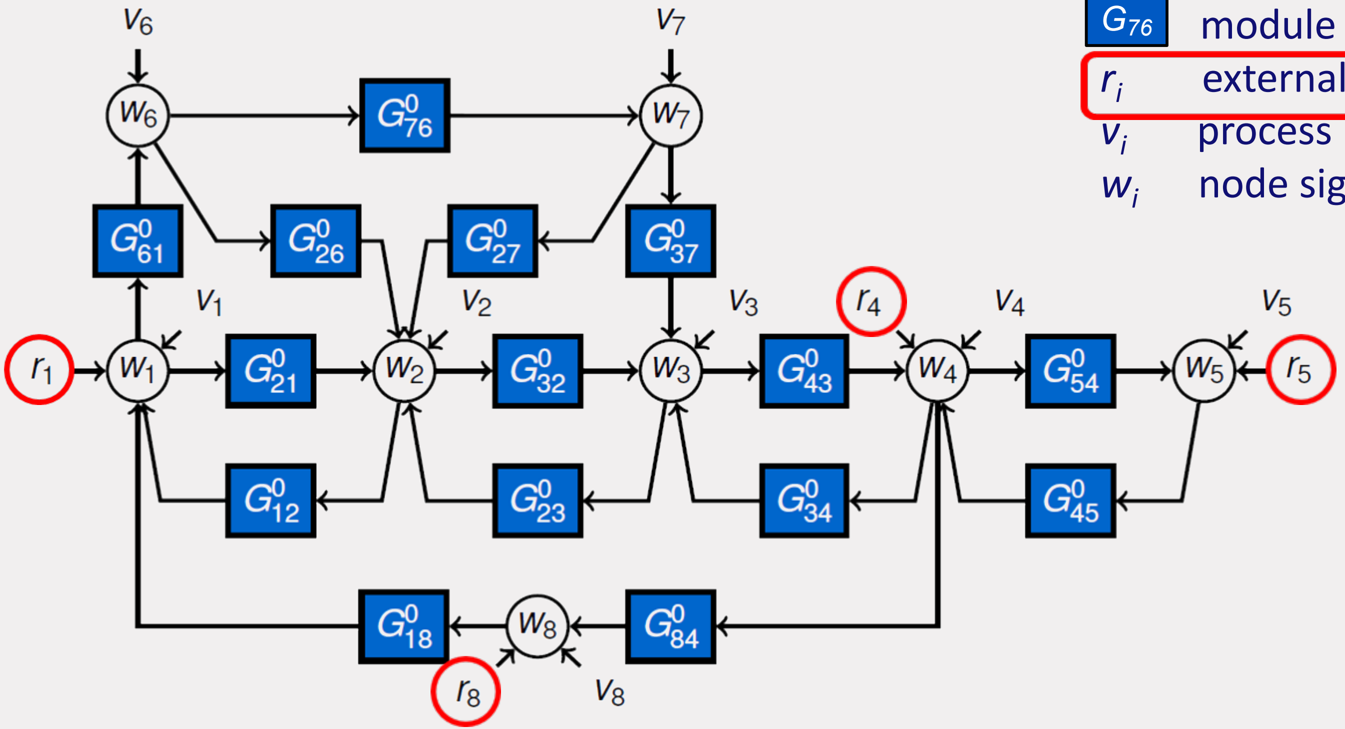
Dynamic network setup



G_{76} module

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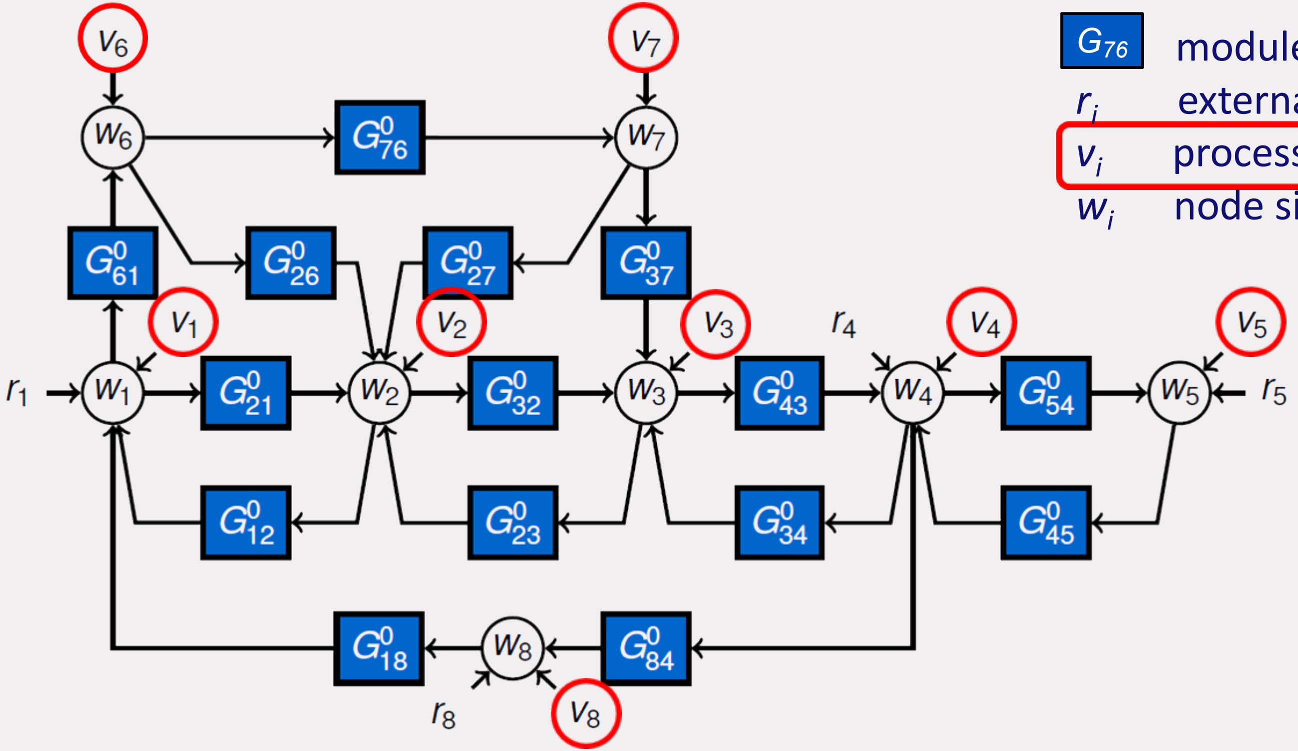
Dynamic network setup

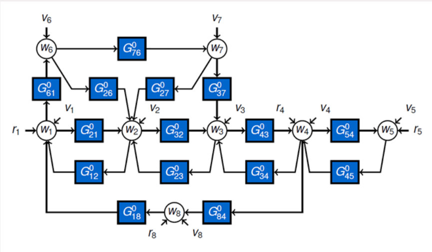


G_{76} module
r_i external excitation
v_i process noise
w_i node signal

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:

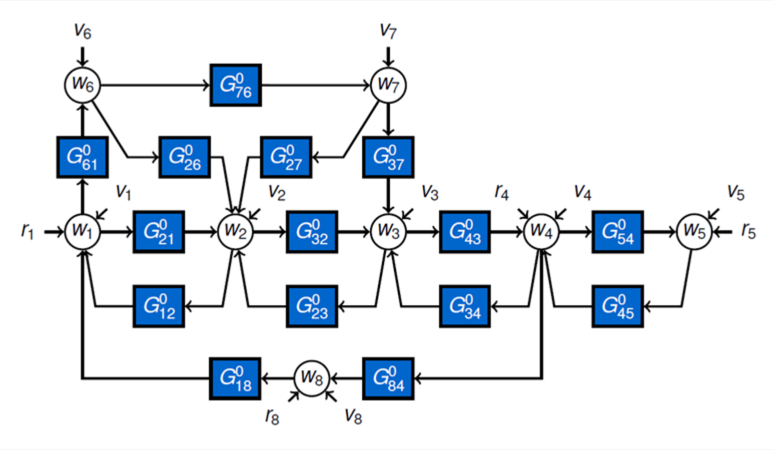
$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & G^0_{12} & \cdots & G^0_{1L} \\ G^0_{21} & 0 & \ddots & G^0_{2L} \\ \vdots & \ddots & \ddots & \vdots \\ G^0_{L1} & G^0_{L2} & \cdots & 0 \end{bmatrix}}_{\text{Network matrix } G^0(q)} \begin{bmatrix} w_1 \\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

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

- 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

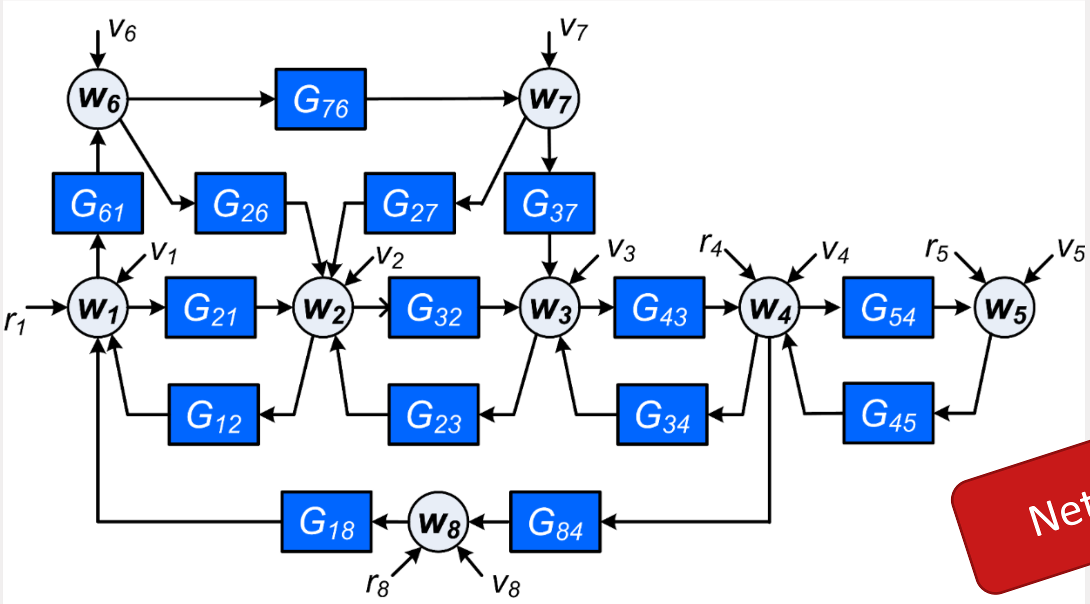


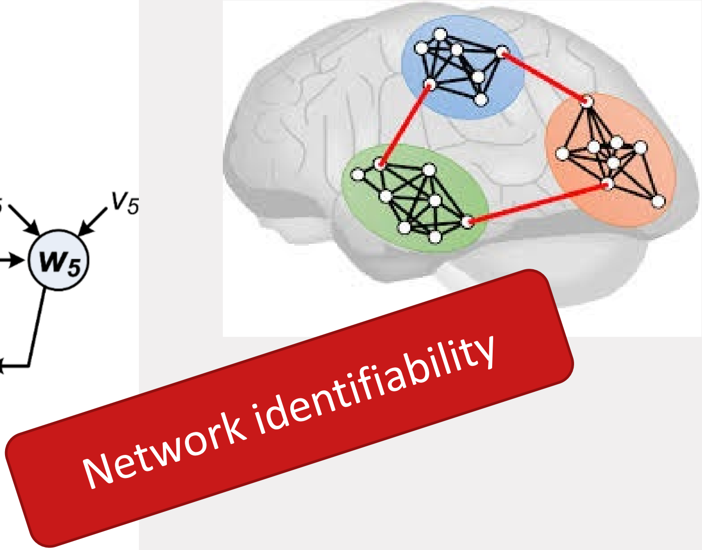
Many challenging data-driven modeling questions can be formulated

Measured time series:

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

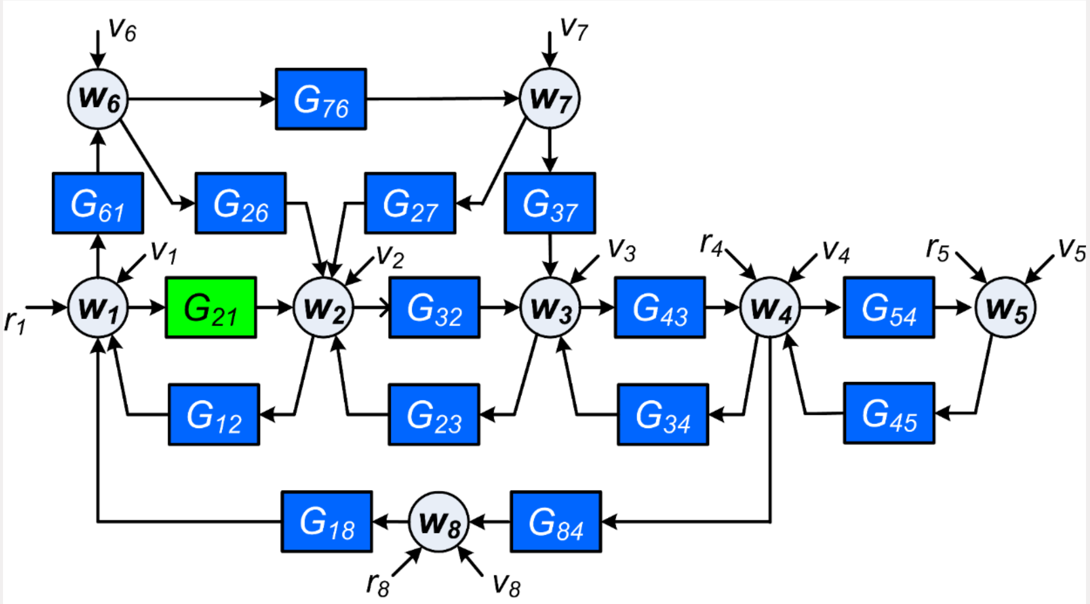
Model learning problems





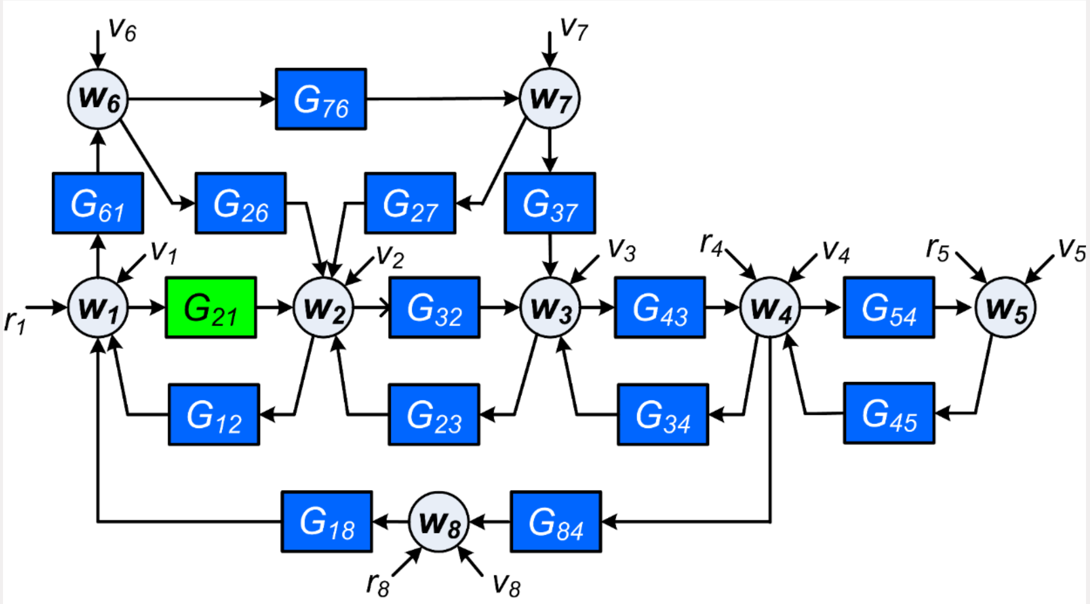
Under which conditions can we estimate the topology and/or dynamics of the full network?

Model learning problems



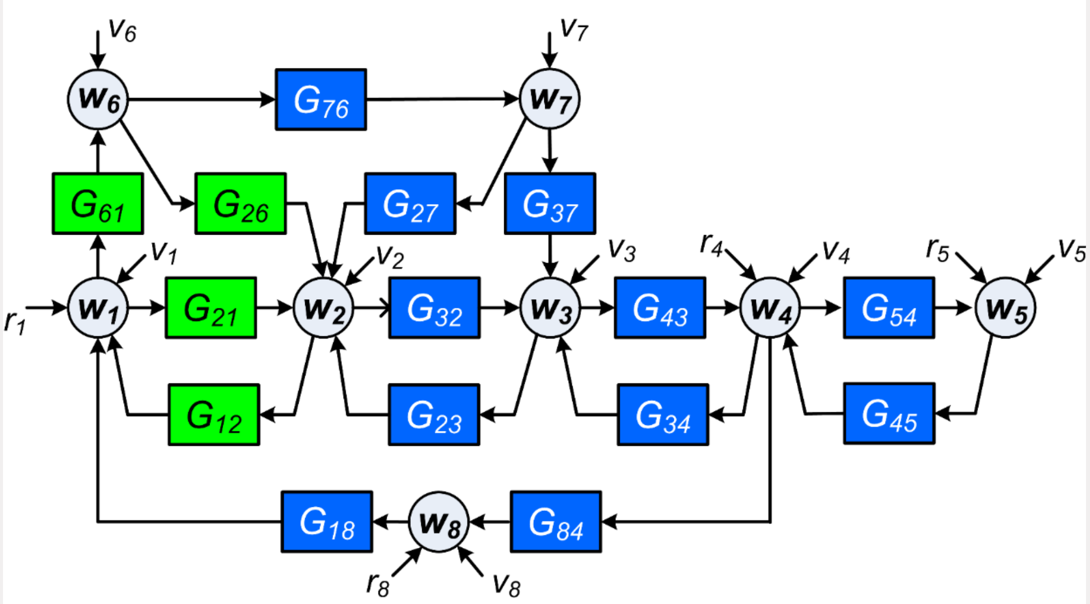
How/when can we learn a local module from data (with known/unkown network topology) ? Which signals to measure?

Model learning problems



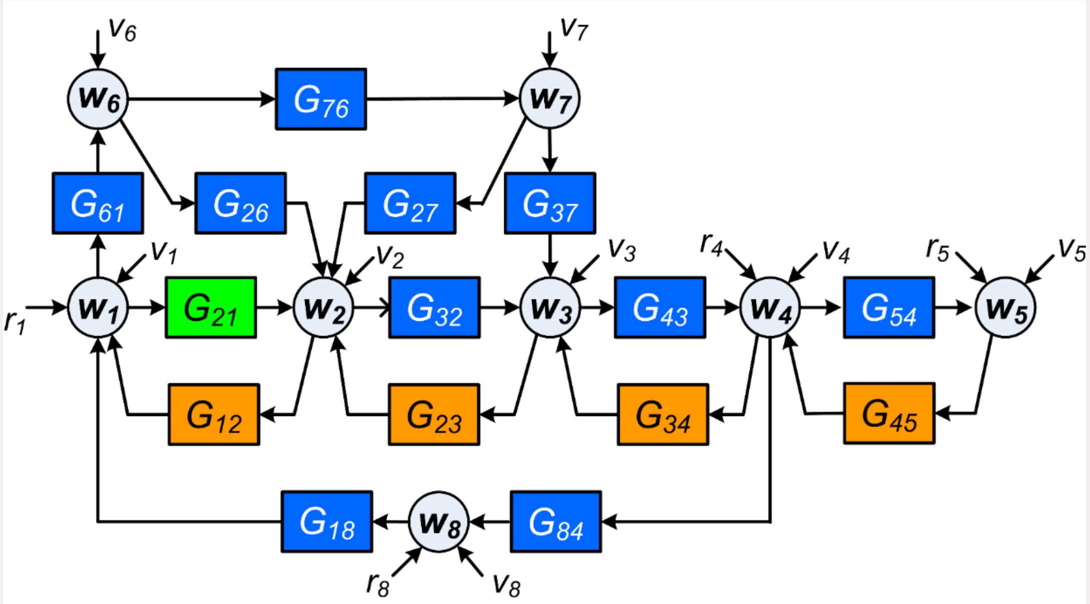
Where to optimally locate sensors and actuators?

Model learning problems



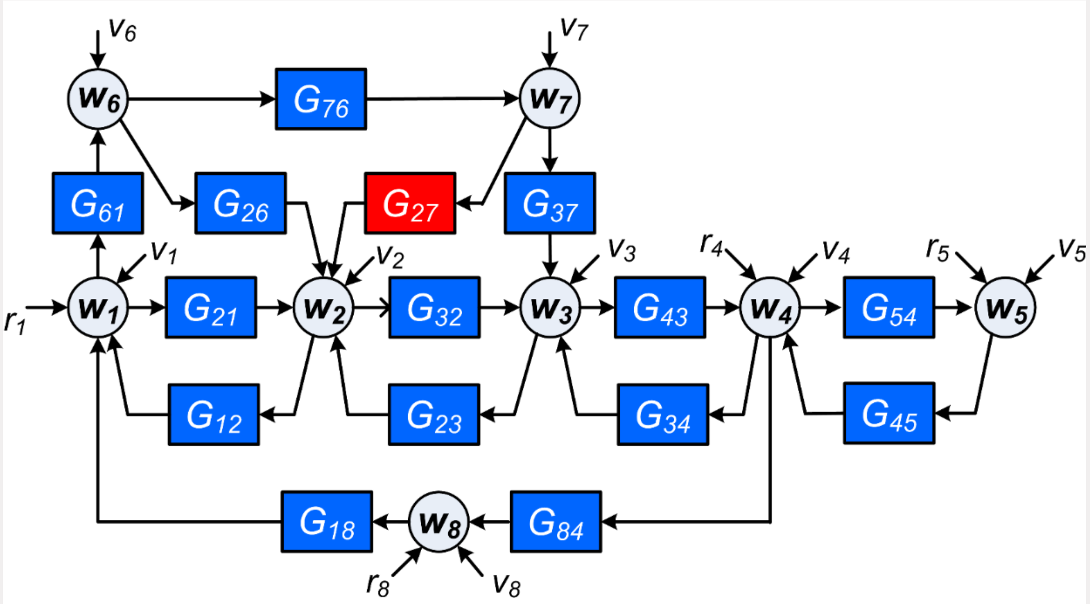
Same questions for a subnetwork

Model learning problems



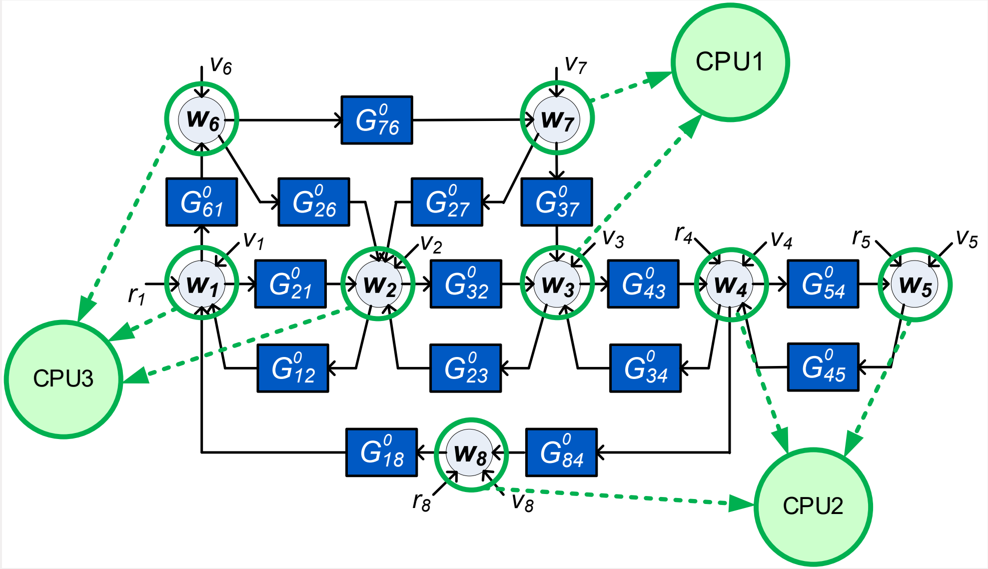
How can we benefit from known modules?

Model learning problems



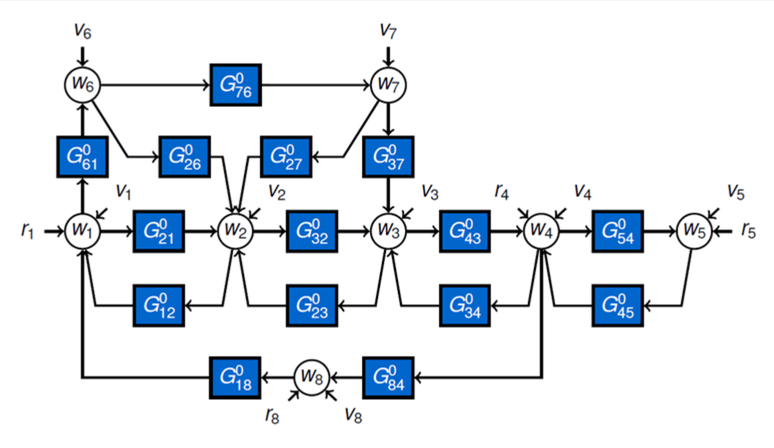
Fault detection and diagnosis; detect/handle nonlinear elements

Model learning problems



Can we distribute the computations?

Dynamic network setup



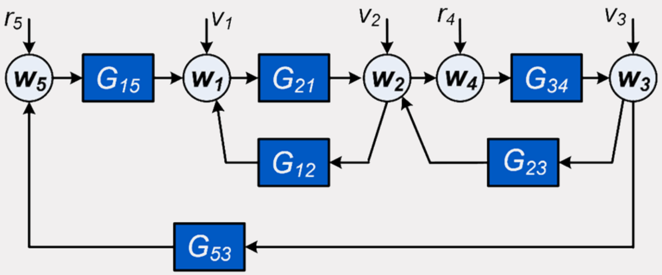
Measured time series:

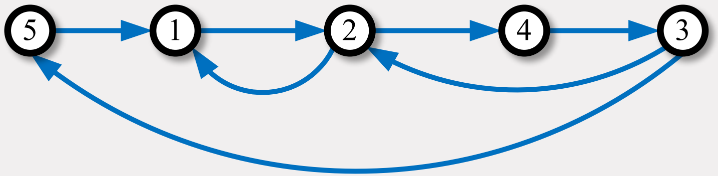
$$\{w_i(t)\}_{i=1,\cdots L}; \ \{r_j(t)\}_{j=1,\cdots K}$$

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**

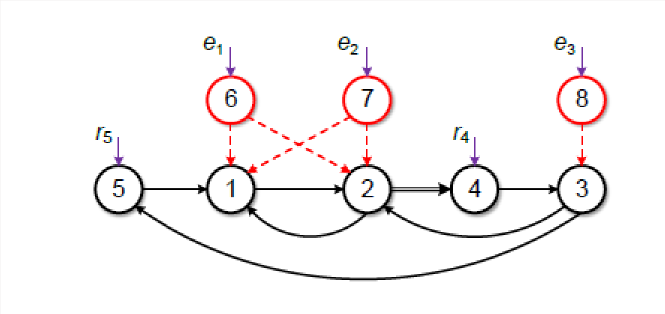
Dynamic network setup – directed graph





Nodes are vertices; modules/links are edges

Extended graph:
including the external signals
and disturbance correlations



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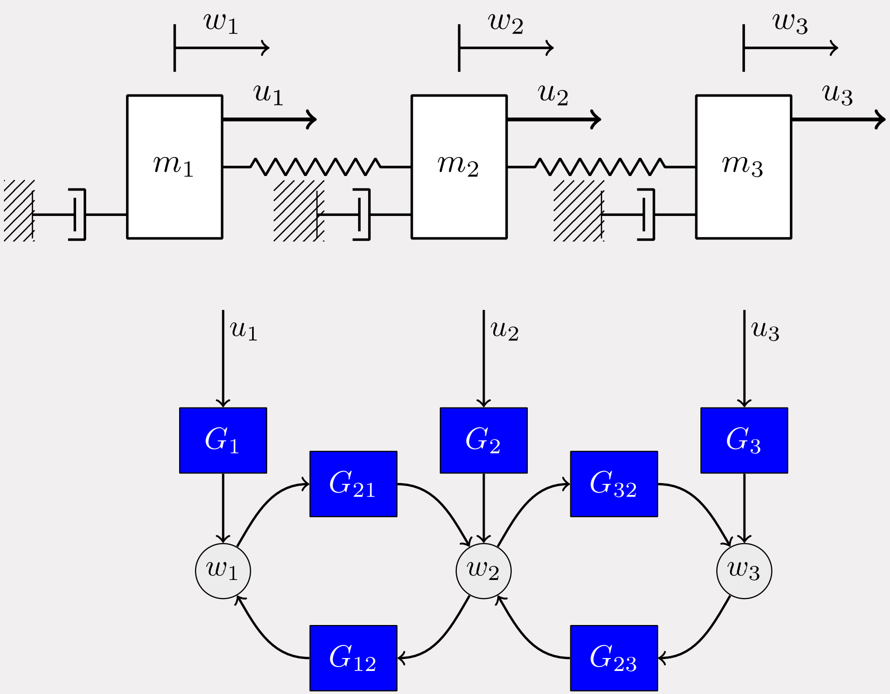
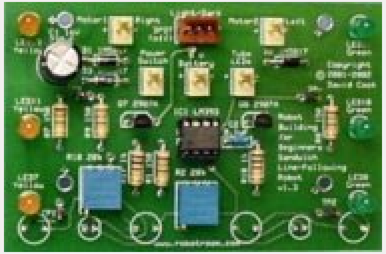
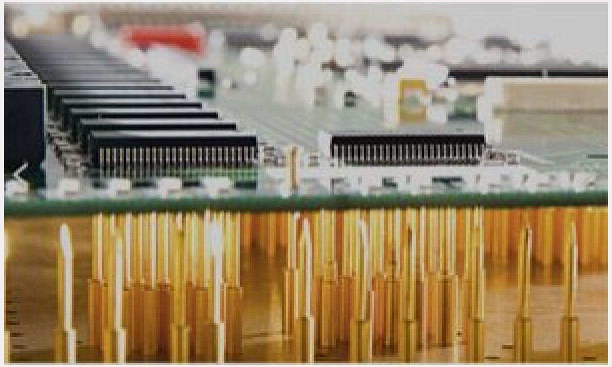
Application: Networks of (damped) oscillators



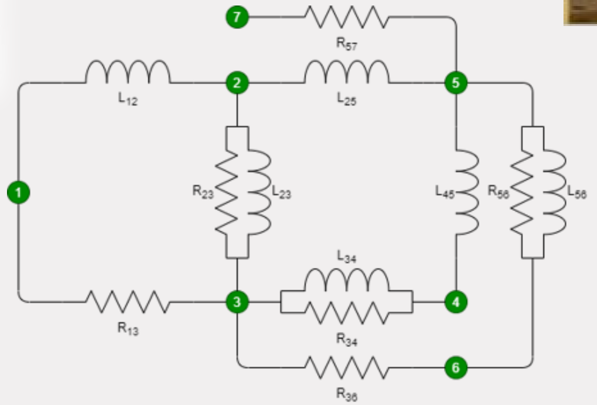
- Power systems, vehicle platoons, thermal building dynamics, …
- Spatially distributed
- Bilaterally coupled

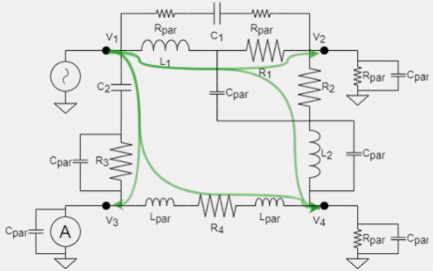
Application: Printed Circuit Board (PCB) Testing





Source: Altium





Detection of

- component failures
- parasitic effects

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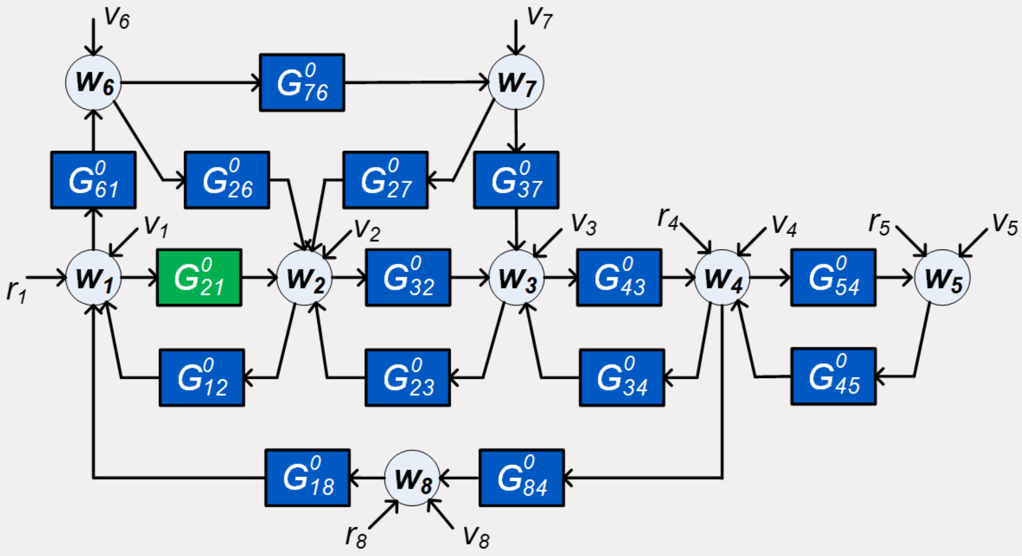
Single module identification

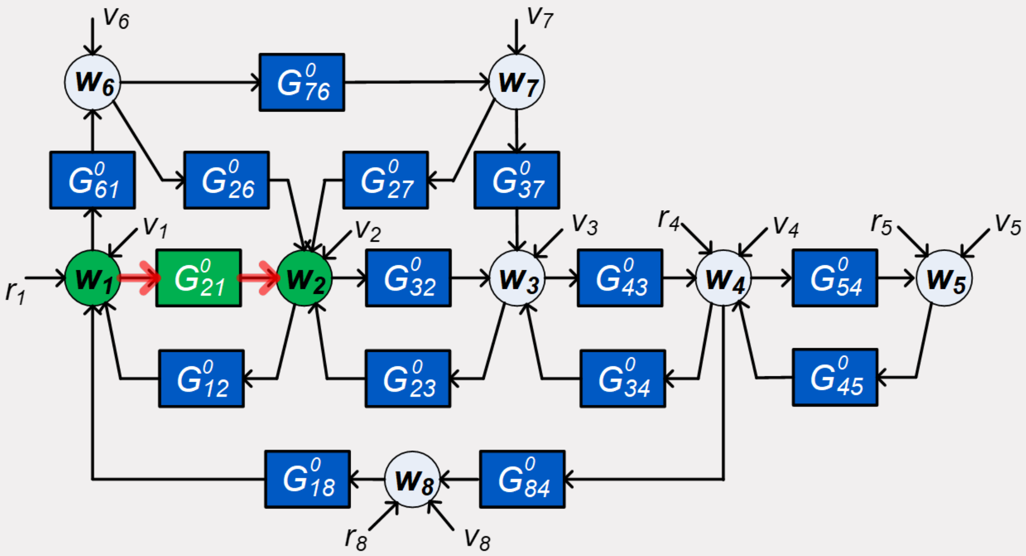
Single module identification



For a network with known topology:

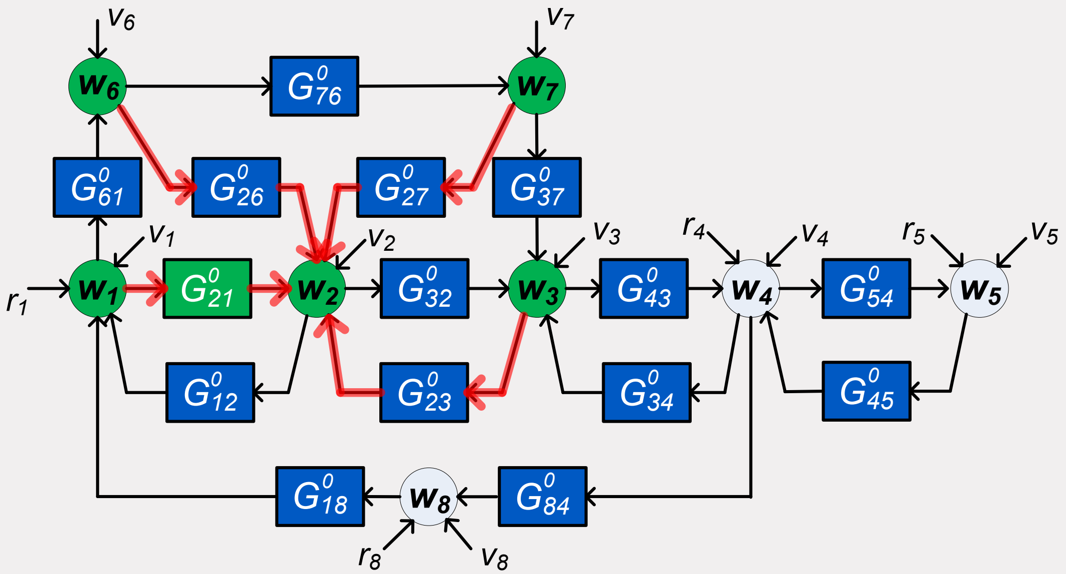
- Identify G_{21}^0 on the basis of measured signals
- Which signals to measure? Preference for local measurements
- When is there enough excitation / data informativity?

Single module identification

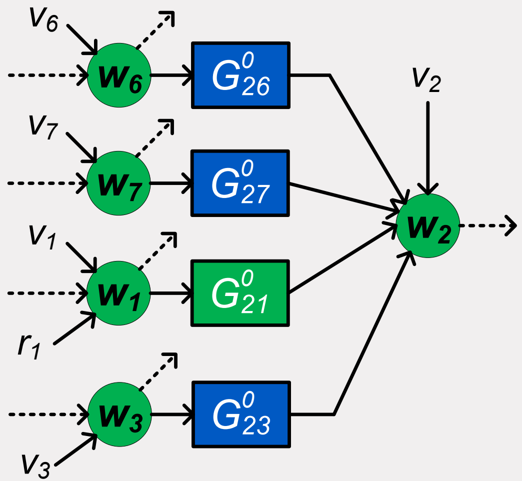


Naïve approach: identify based on w_1 and w_2 : in general does not work.

Single module identification



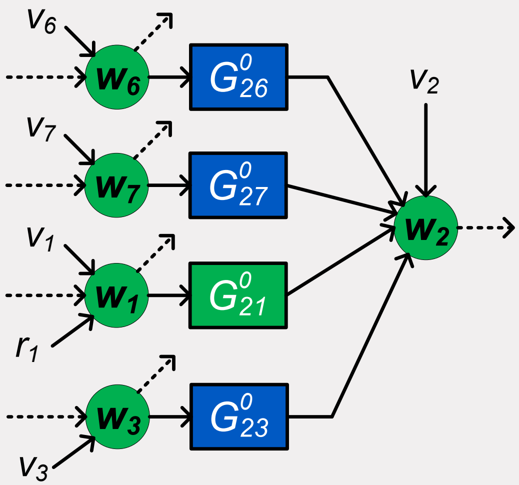
Identifiying G_{21}^{0} is part of a 4-input, 1-output problem



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

Single module identification

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



Input signals will be correlated:

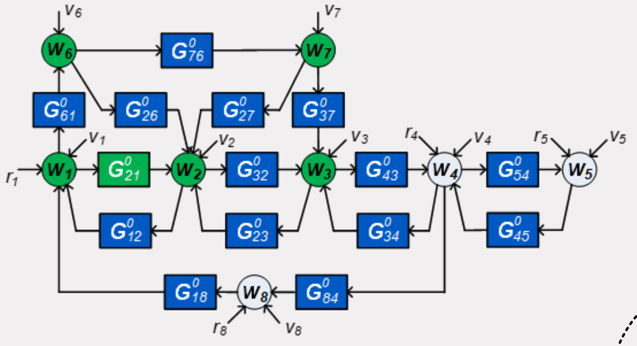
similar as in a closed-loop situation

What is required for
identifiability / data informativity?

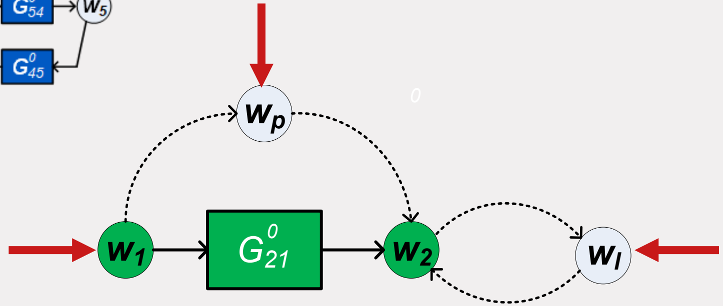
Ability to distinguish between models
independent of id-method

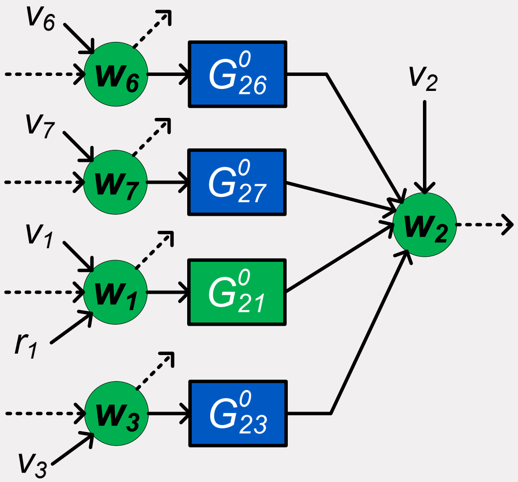
Information content of signals
dependent on id-method

Single module identification



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



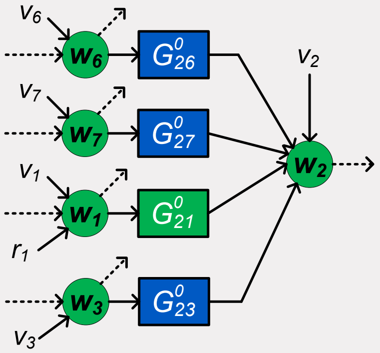


All parallel paths, and loops around the output, plus input w_1 should have an independent external signal r or v

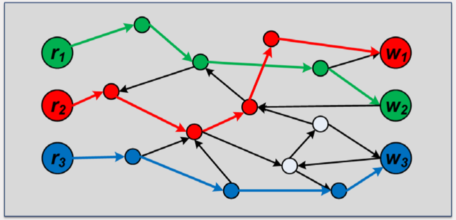
and typically need to be blocked by a measured node

[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

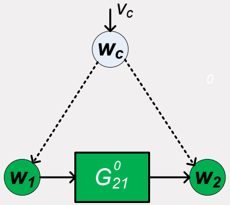
Single module identification



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]

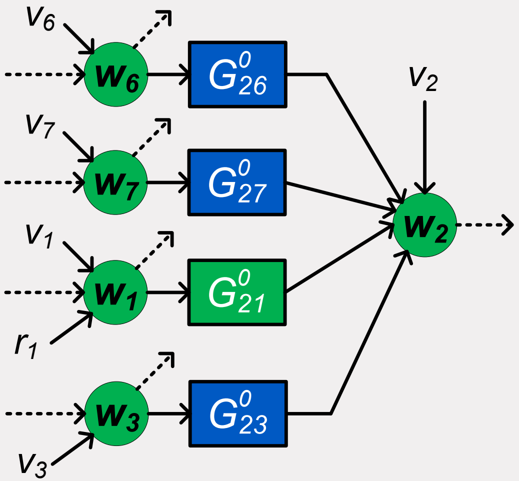
To be handled by:

- 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., *IEEE-TAC*, Nov 2021

Single module identification

Typical solution:



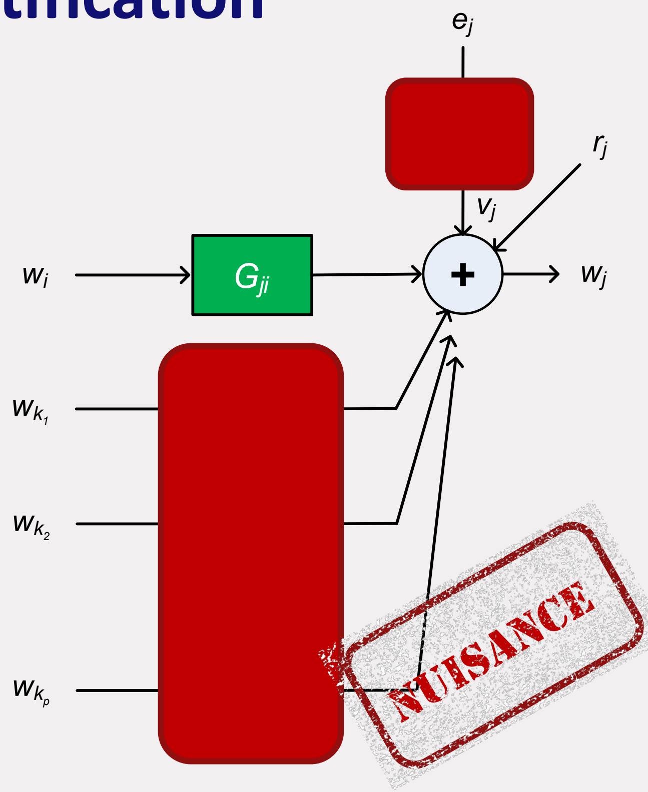
- MISO (sometimes MIMO) estimation problem
- to be solved by any (closed-loop) identification algorithm, e.g. direct/indirect method

Machine learning in local module identification

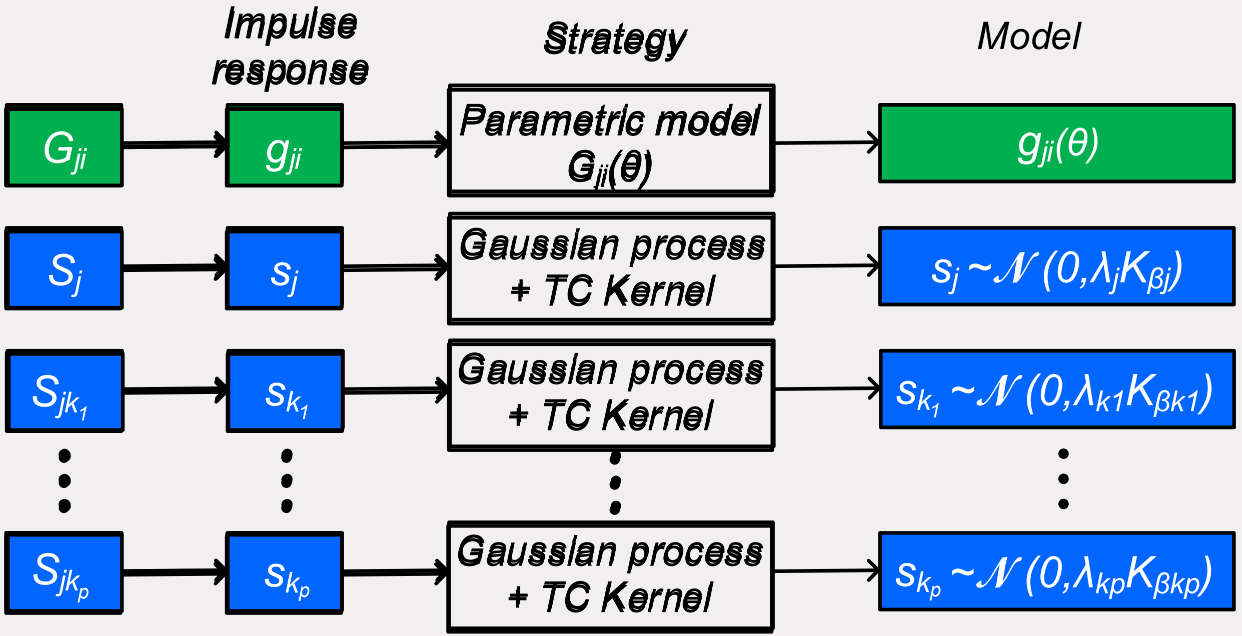
- MISO identification with all modules parameterized
- Brings in two major problems :
  - Large number of parameters to estimate
  - Model order selection step for each module (CV, AIC, BIC)
- For 5 modules, combinations = 244,140,625

Increases variance
Computationally challenging

- We need only the target module. No NUISANCE!



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

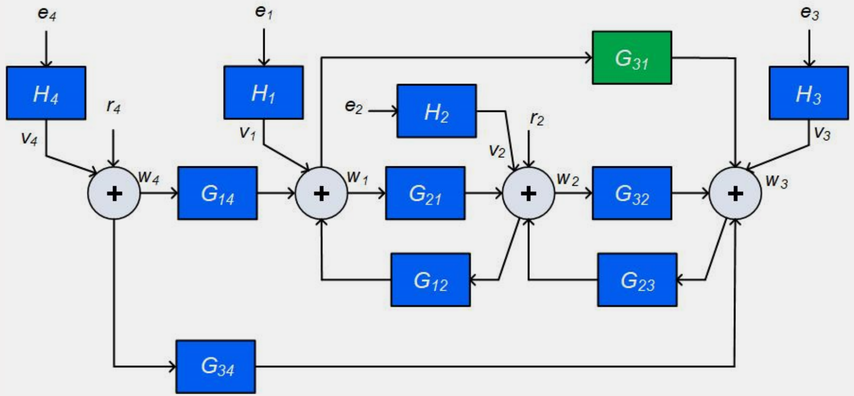
Maximize marginal likelihood of output data: $\hat{\eta} = \underset{\eta}{\operatorname{argmax}}\, p(w_j; \eta)$

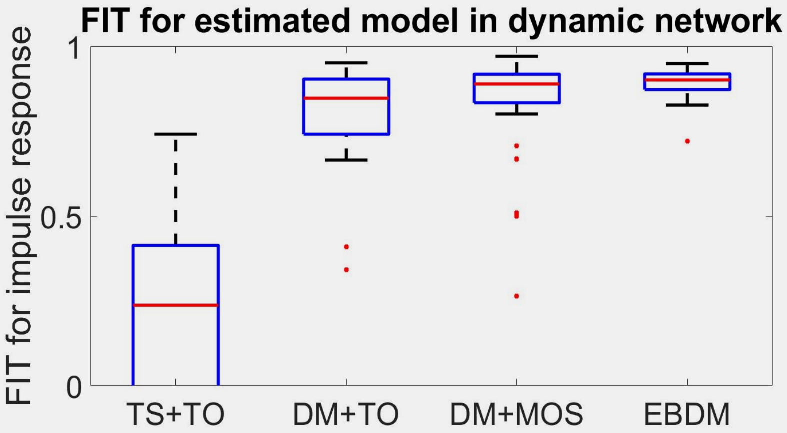
$$\eta := \begin{bmatrix} \theta & \lambda_j & \lambda_{k_1} & \cdots & \lambda_{k_p} & \beta_j & \beta_{k_1} & \cdots & \beta_{k_p} & \sigma_j^2 \end{bmatrix}^{\mathrm{T}}$$

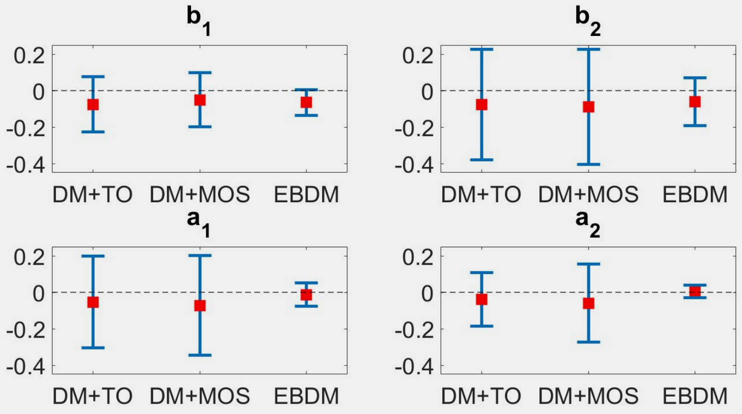
[1] Everitt et al., *Automatica* 2017.
[2] K.R. Ramaswamy et al., *Automatica*, 2021.

Numerical simulation

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







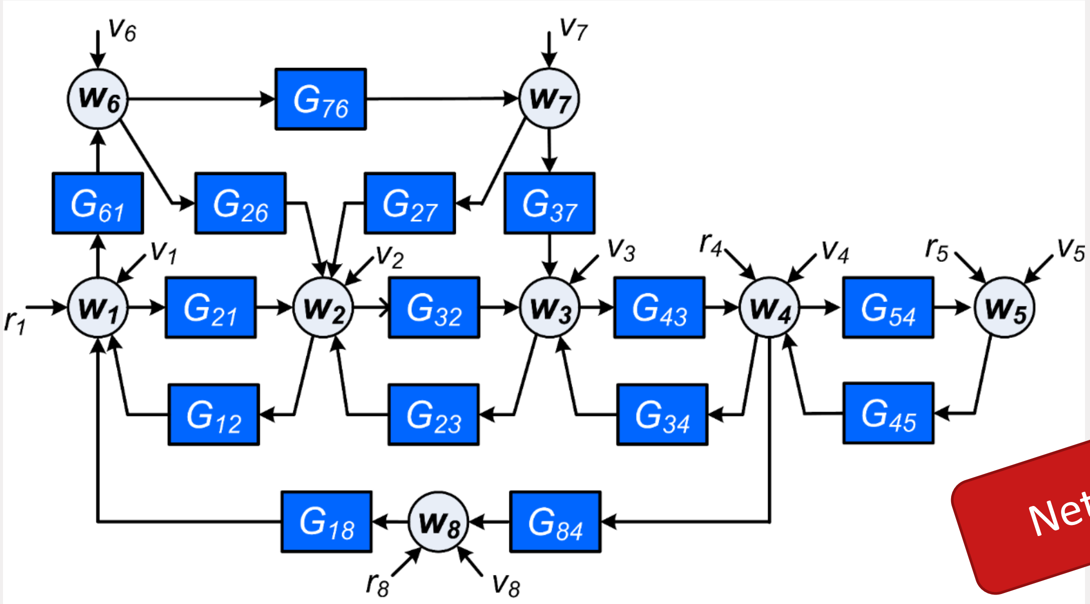
Summary single module identification

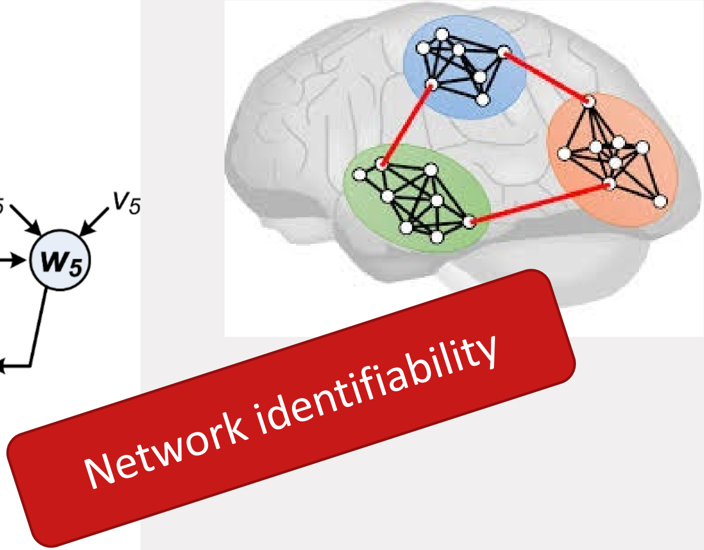
- Path-based conditions for **network identifiability** (where to excite?)
- Graph tools for checking conditions
- Degrees of freedom in selection of measured signals – sensor selection
- Methods for **consistent** and **minimum variance** module estimation, and effective (scalable) algorithms
- A priori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

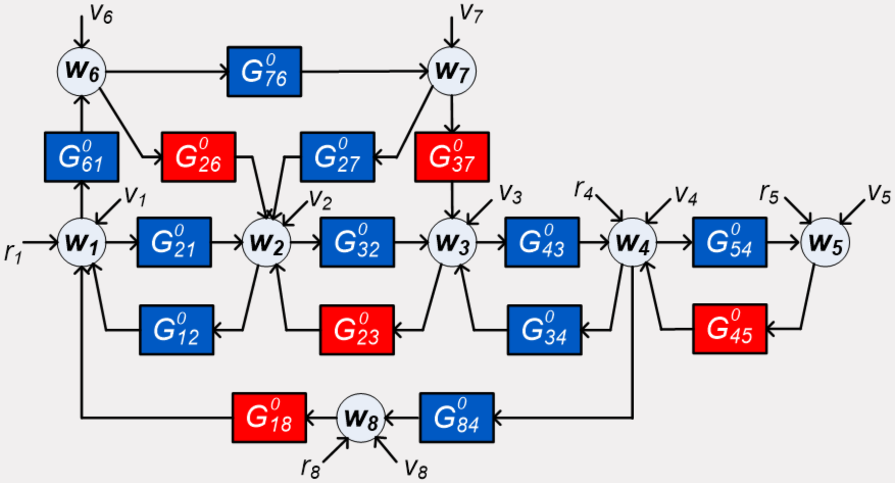
Full network identification





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

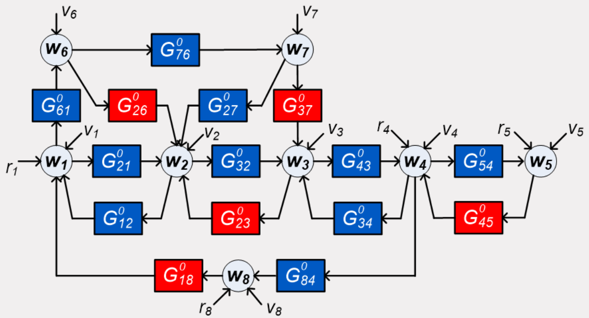
Network identifiability



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 $P(q)$:

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

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

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 2018*

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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.

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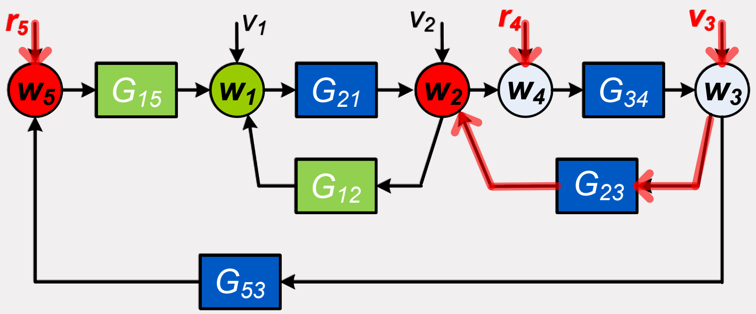
Example 5-node network

Conditions for identifiability → rank conditions on transfer function



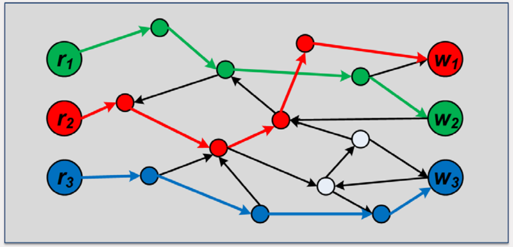
Full row rank of

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

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

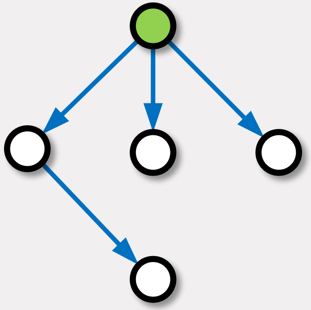
Synthesis solution for network identifiability

Allocating external signals for generic identifiability:

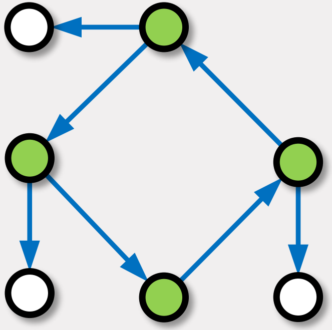
1. Cover the graph of the network model set by a set of **disjoint pseudo-trees**

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.

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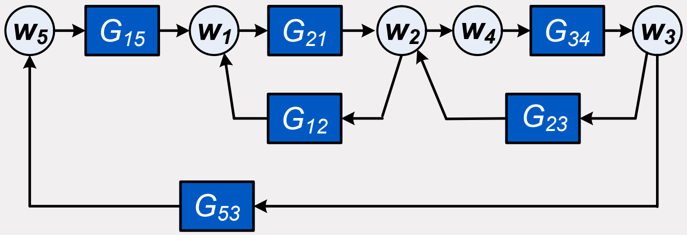
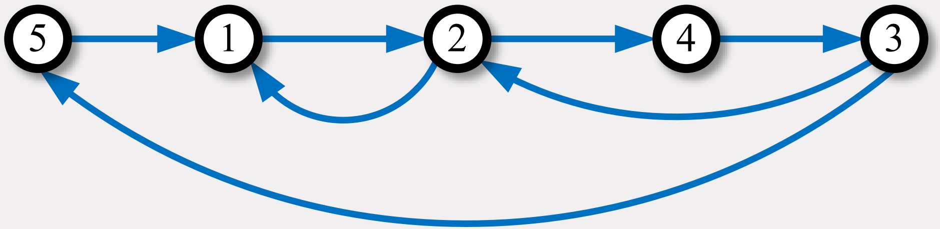
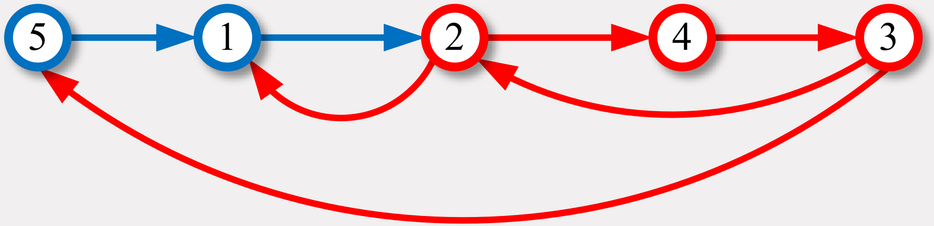
Where to allocate external excitations for network identifiability?



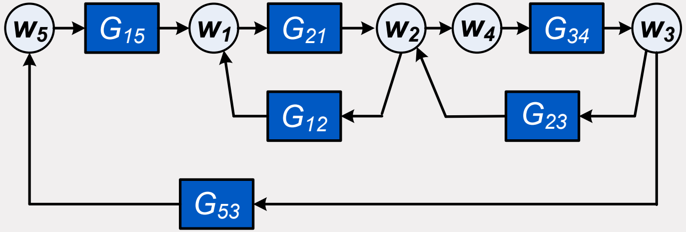


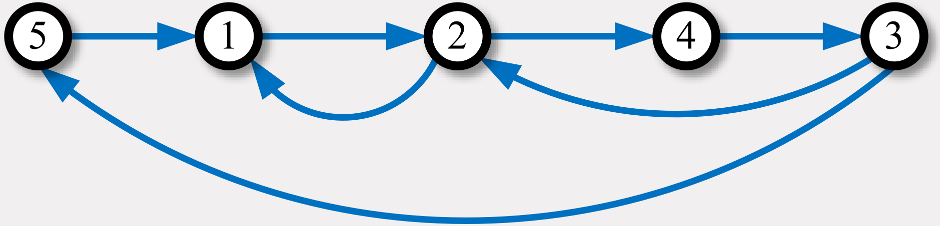
All indicated modules are parametrized

Two disjoint pseudo-trees

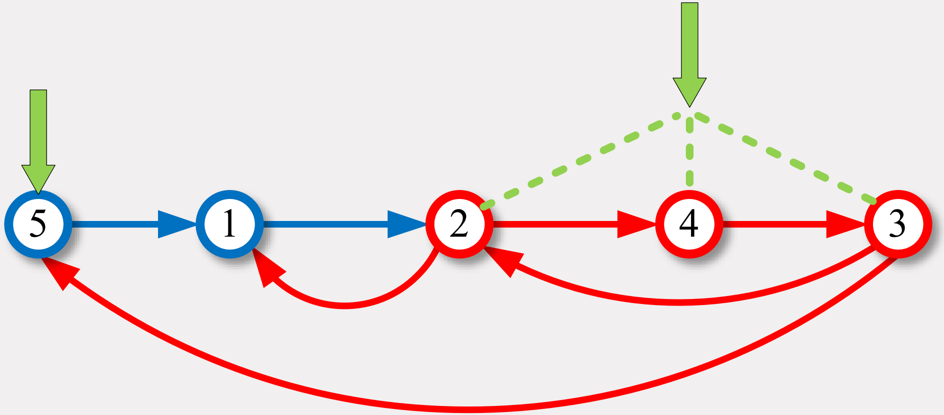


Where to allocate external excitations for network identifiability?

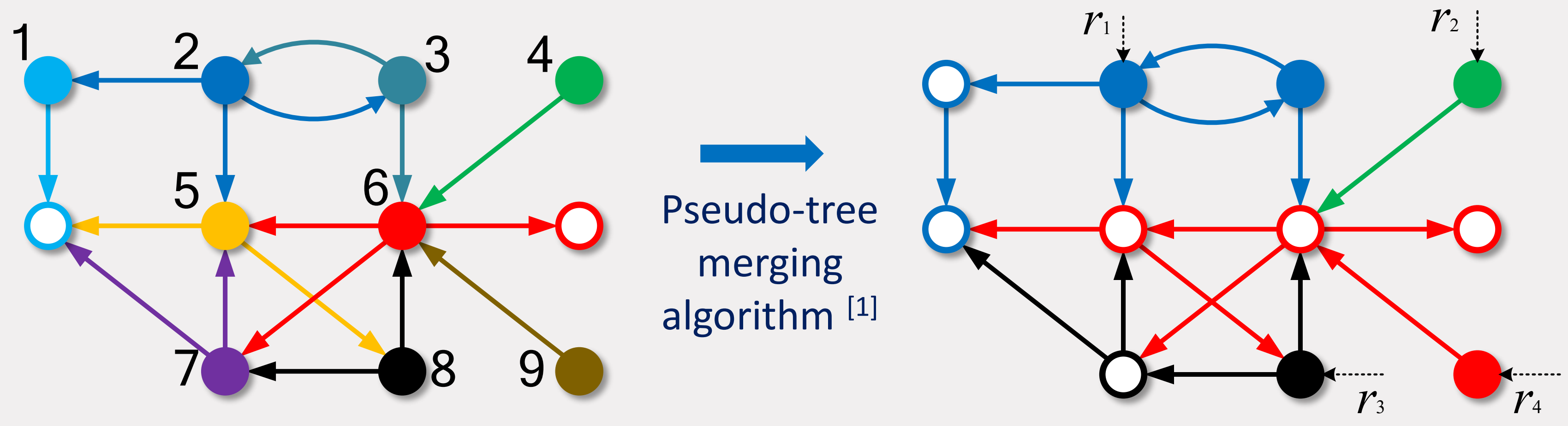




Two independent excitations
guarantee
generic network identifiability



Where to allocate external excitations for network identifiability?



- Nodes are signals w and external signals (r, e) that are input to 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.

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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, July 2022*.

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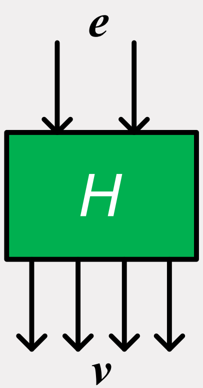
Algorithms for identification of full network

Particular feature for larger networks:

Modeling disturbances as a **reduced rank process**:
(cf dynamic factor analysis[1])



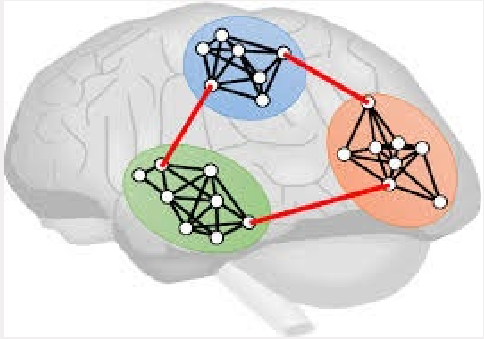
$\mathbf{dim}(e) < \mathbf{dim}(v)$

Consequences for **estimation**[3,4]:

- Optimization becomes a constrained quadratic problem with ML properties for Gaussian noise
- Reworked Cramer Rao lower bound
- Some parameters can be estimated variance free → regularization effect

[1] Deistler et al., EJC, 2010.
[2] Zorzi and Chiuso, Automatica 2017.
[3] Weerts et al., Automatica, dec 2018.
[4] Fonken et al., Automatica, July 2022.

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

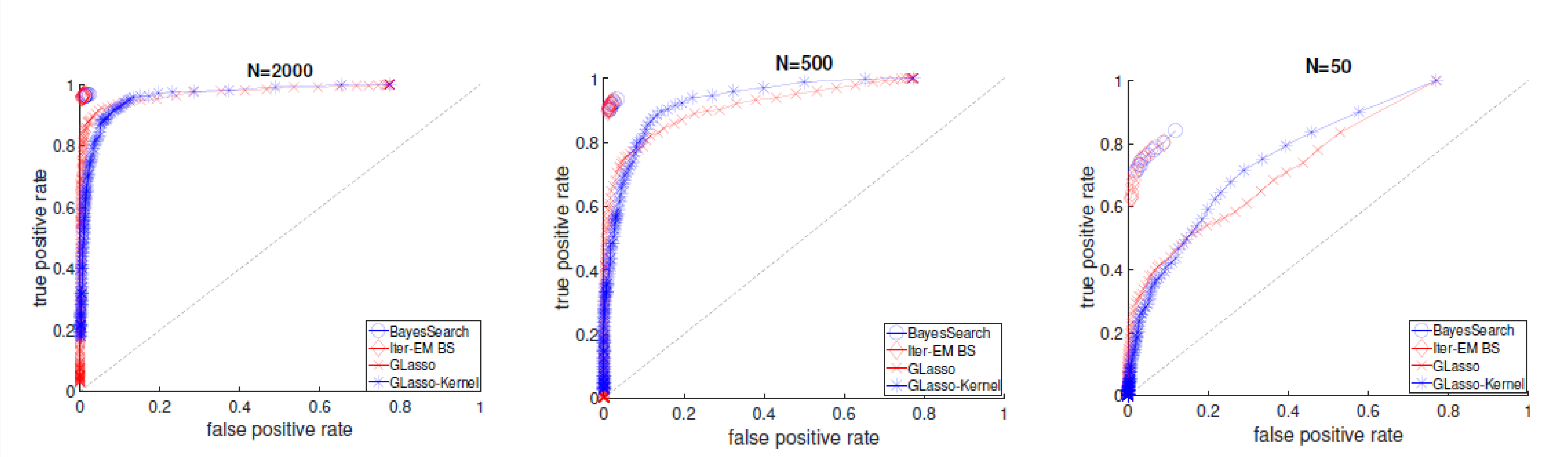
- Optimizing likelihood of the data as function of parameters and topology:

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

- 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

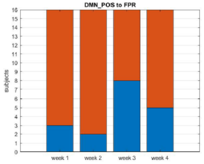


50 MC realizations of network with 6 nodes.

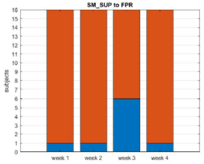
[1] Shi, Bottegal, PVdH, ECC 2019

Neurodynamic effect of listening to Mozart music

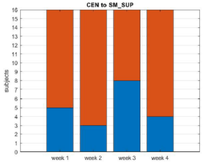
Identifying changes in network connections in the brain, after intensely listening for one week (Sonate K448)



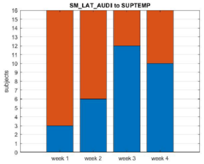
(a) Connection from the posterior default mode network to the fronto-parietal right network.



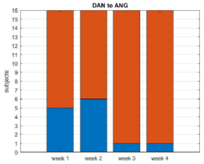
(b) Connection from the sensori-motor superior network to the fronto-parietal right network.



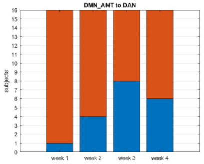
(c) Connection from the central executive network to the sensori-motor superior network.



(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.

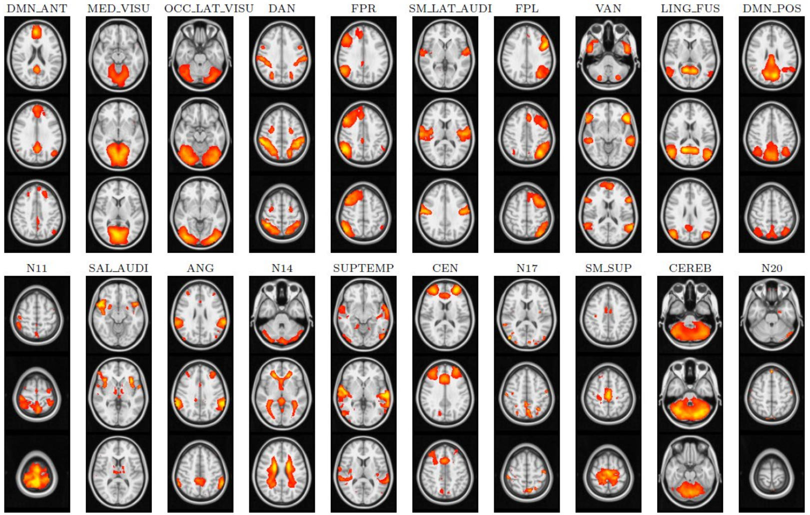


Figure 3: Spatial maps of the 20 active brain networks found through the ICA decomposition. Each image consists of 3 relevant horizontal slices of the brain, where the spatial map is indicated by the red color scale.

[1] R. van Esch, S. Shi, A. Bernas, S. Zinger, A. Aldenkamp, PVdH, *Computers in Biology and Medicine*, *Vol. 127*, December 2020

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Contents

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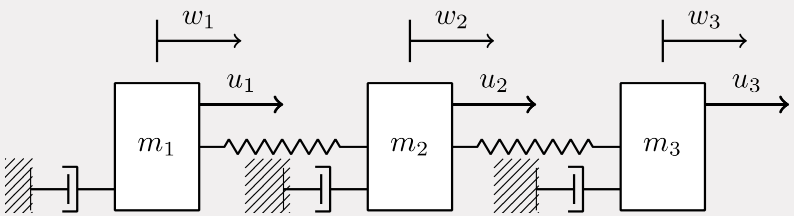
Diffusively coupled networks

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

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

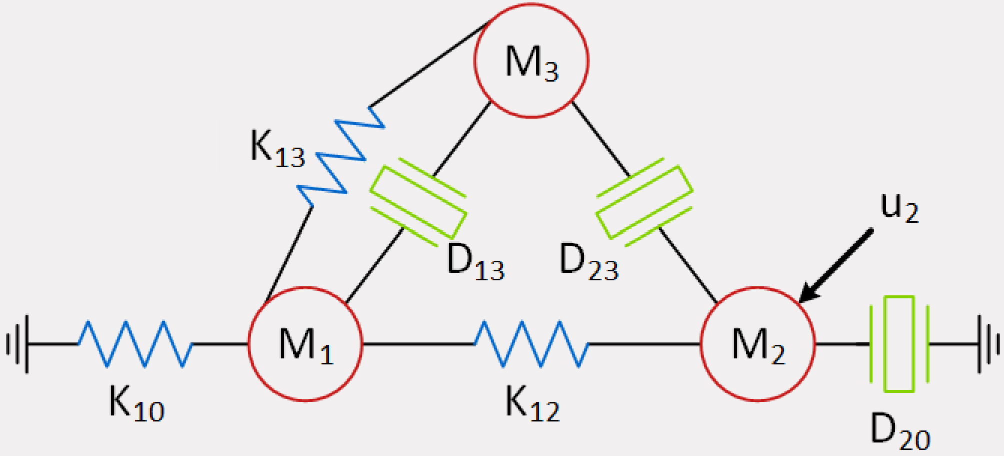
Spring

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

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

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

Diffusively coupled physical network

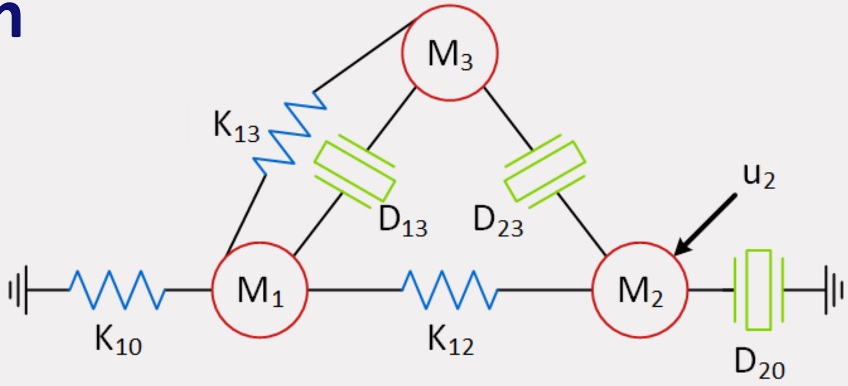


Equation for node *j*:

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

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:

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

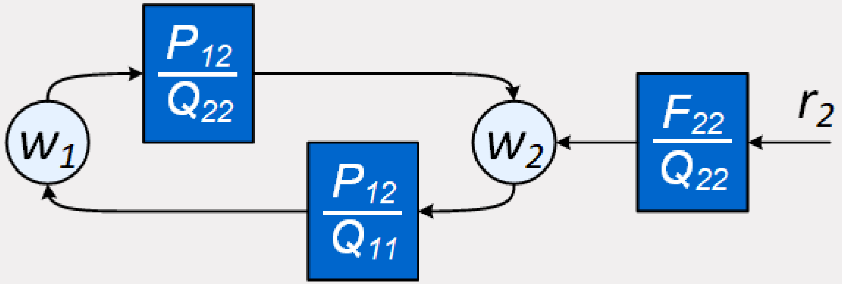
with the additional condition that:

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

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

Module representation

Consequences for node interactions:



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

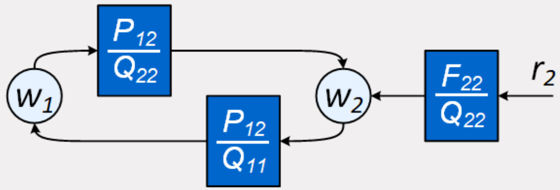
Framework for network identification remains the same

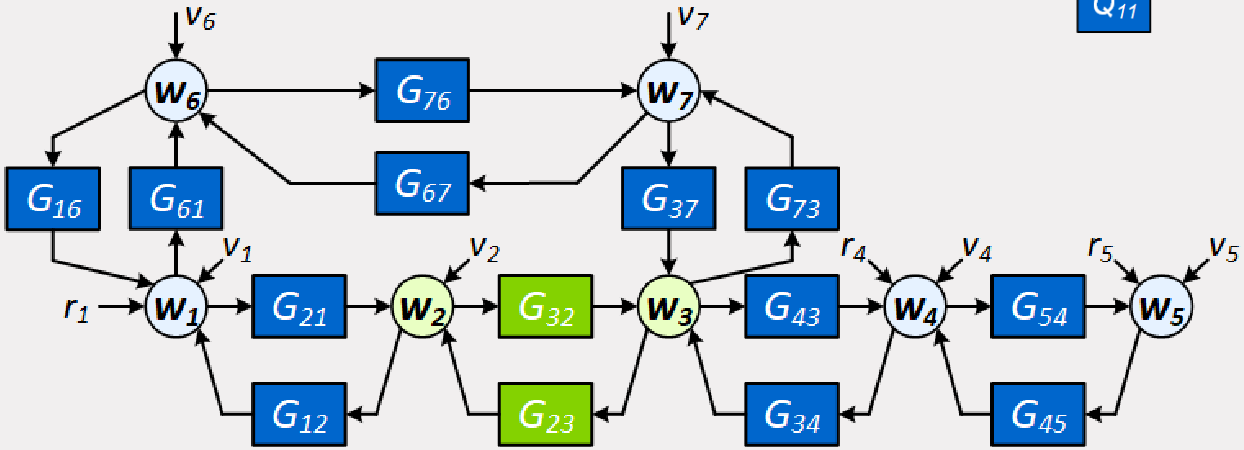
- Symmetry can simply be incorporated in identification

Local network identification

Identification of **one** (physical) interconnection

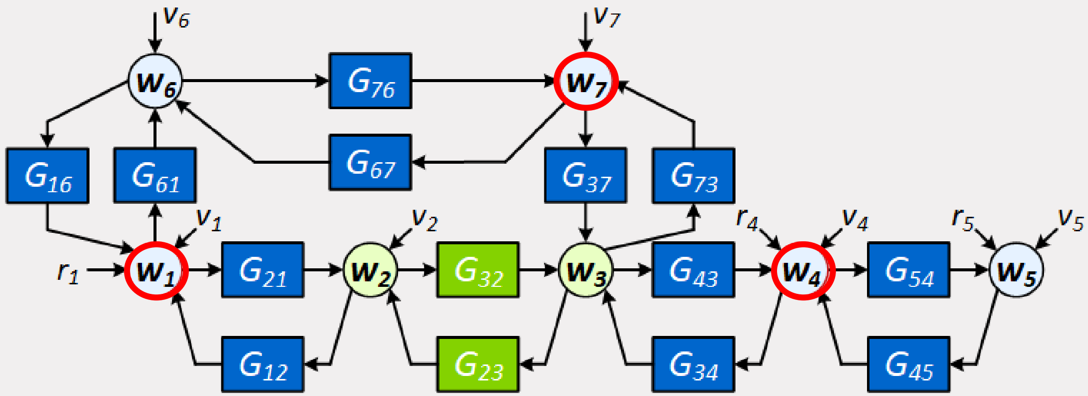
Identification of **two** modules G_{jk} and G_{kj}





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).

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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.

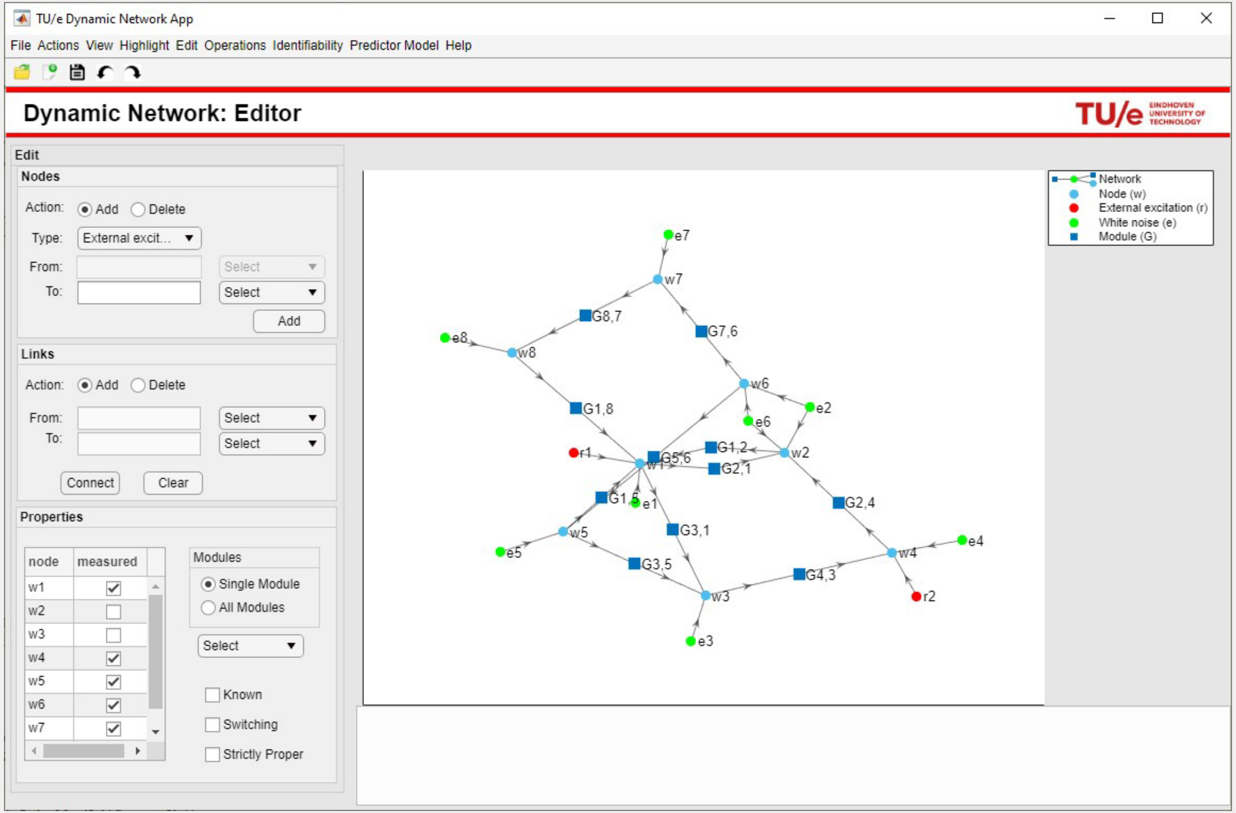
[4] Morelli, Bombois et al., ECC 2019;

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 (diagnostics, fault detection)

Matlab Toolbox



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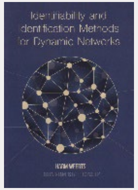
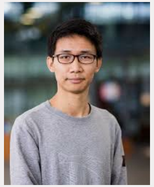
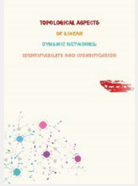
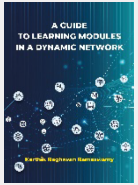


Harm Weerts

Shengling Shi

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Further reading

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Papers available at www.pvandenhof.nl

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