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Data-driven model learning in linear dynamic networks

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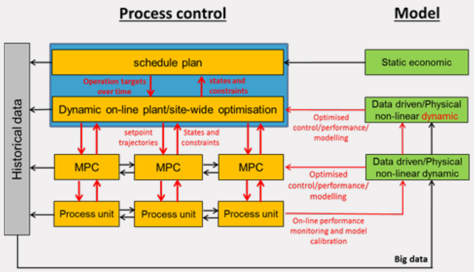
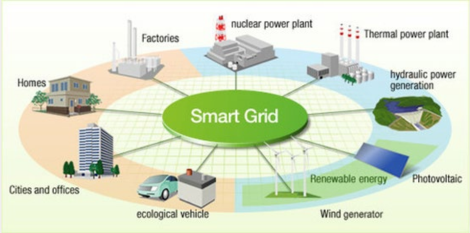
Introduction – dynamic networks

Decentralized process control



Smart power grid

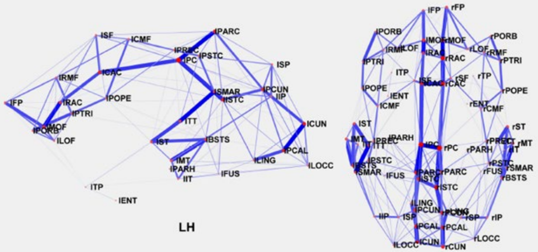


Pierre et al. (2012)

Autonomous driving

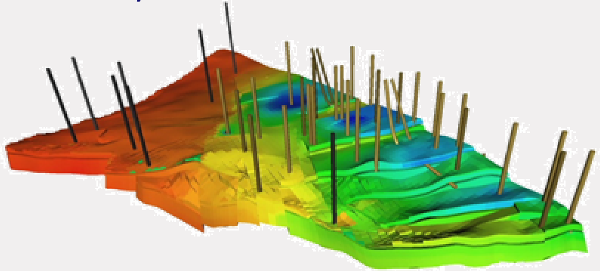
www.envidia.com

Brain network



P. Hagmann et al. (2008)

Hydrocarbon reservoirs



Mansoori (2014)

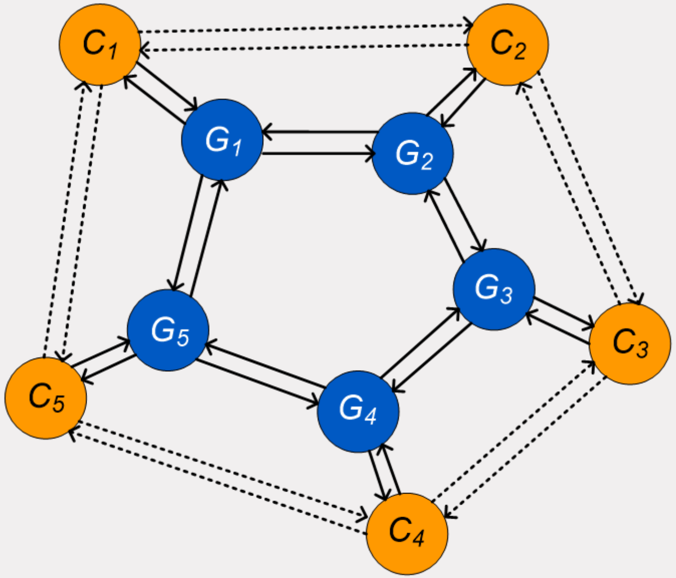
Introduction

Overall characterization from a system's perspective:

- (Large-scale) interconnected systems
- Each subsystem is **dynamic** (dynamic relations between time series)
  a subsystem's output is dependent on past inputs
- Optimal operation of the systems through
  distributed / multi-agent type monitoring, control and optimization problems
- Data is "everywhere", big data era
- Model-based operations require accurate/relevant models
- → **Learning models from data** (including physical insights when available)

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?

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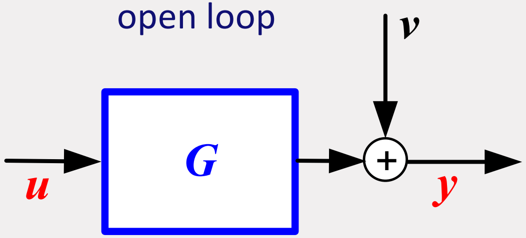
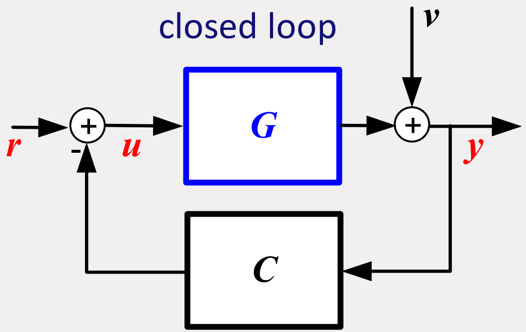
Introduction

The classical (multivariable) identification problems[1] :





Estimate a plant model $\hat{G}$ on the basis of measured time series signals u(t), y(t), and possibly r(t), t=0,……N, focusing on *continuous LTI dynamics*.

G represents a (linear) differential equation (of a particular finite order)

We have to move from a simple and fixed configuration to deal with ***structure*** in the problem.

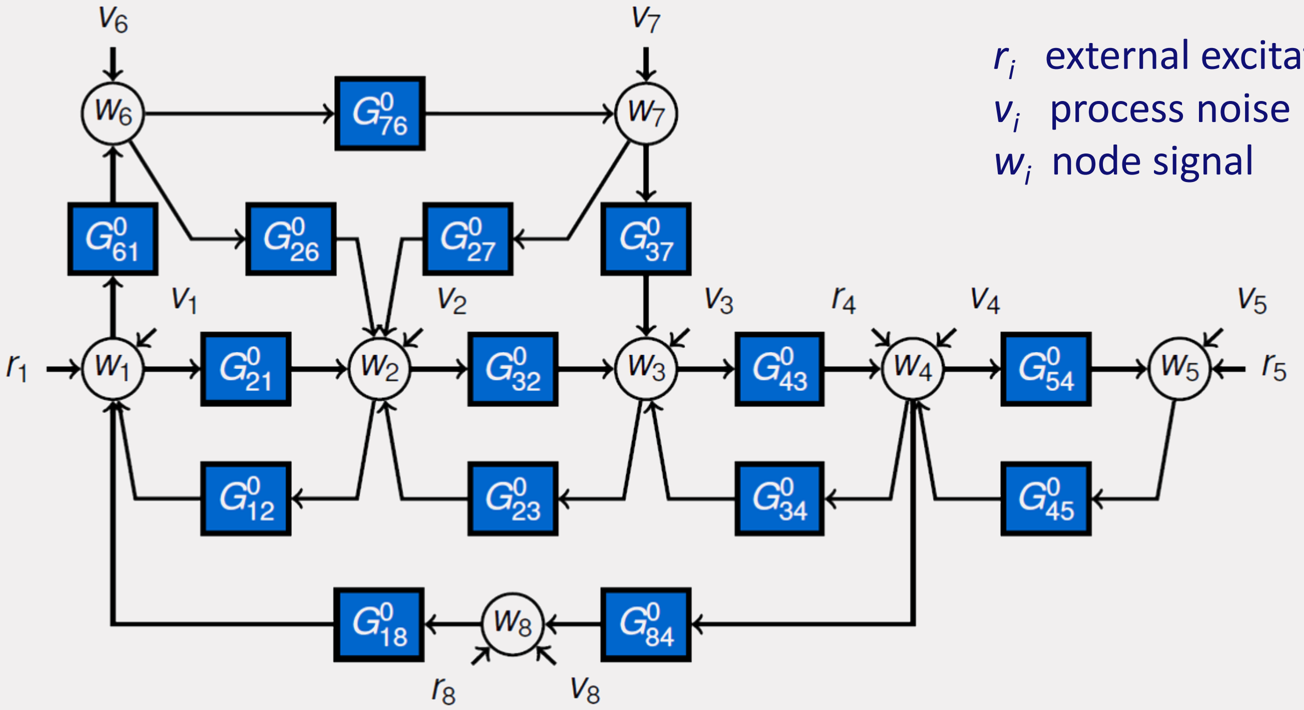
[1] Ljung (1999), Söderström and Stoica (1989), Pintelon and Schoukens (2012)

Contents

- Introduction and motivation
- How to model a dynamic network?
- Relevant learning problems
- One example: generic identifiability

Dynamic network setup

Directed graph with subsystems on the links, and signals in the nodes



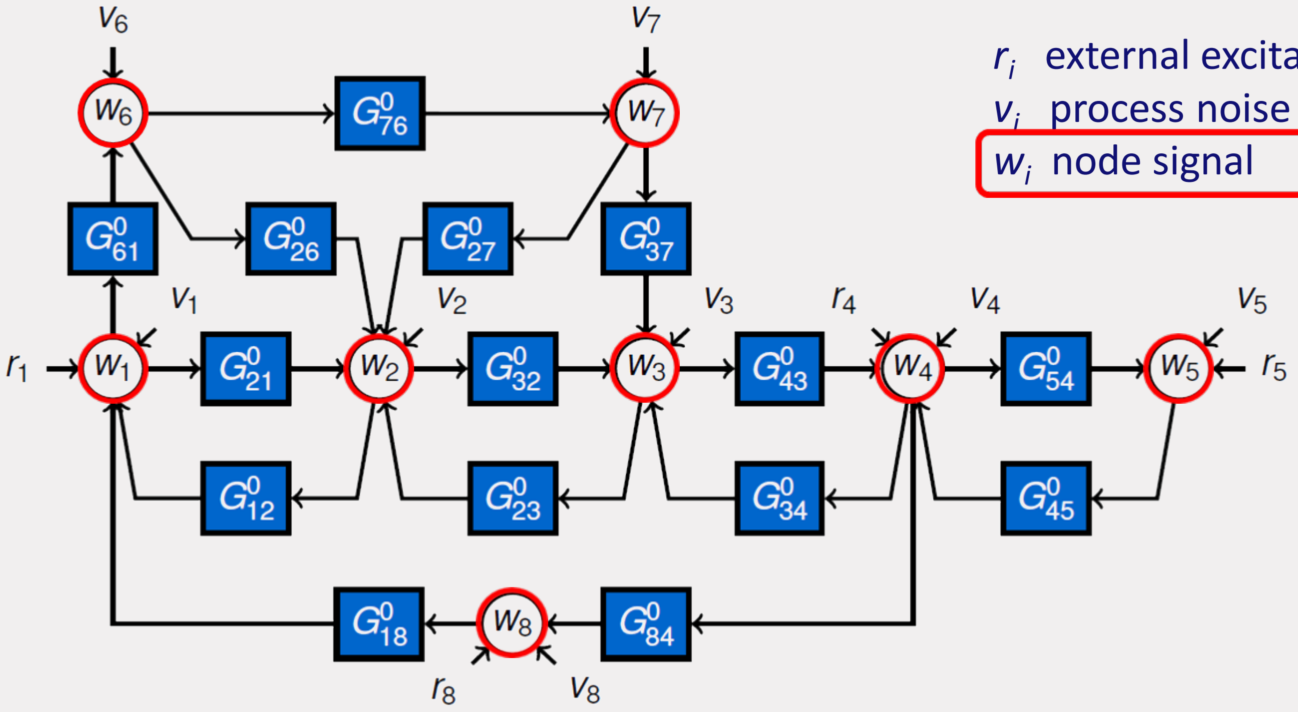
r_i external excitation

v_i process noise

w_i node signal

Dynamic network setup

Directed graph with subsystems on the links, and signals in the nodes



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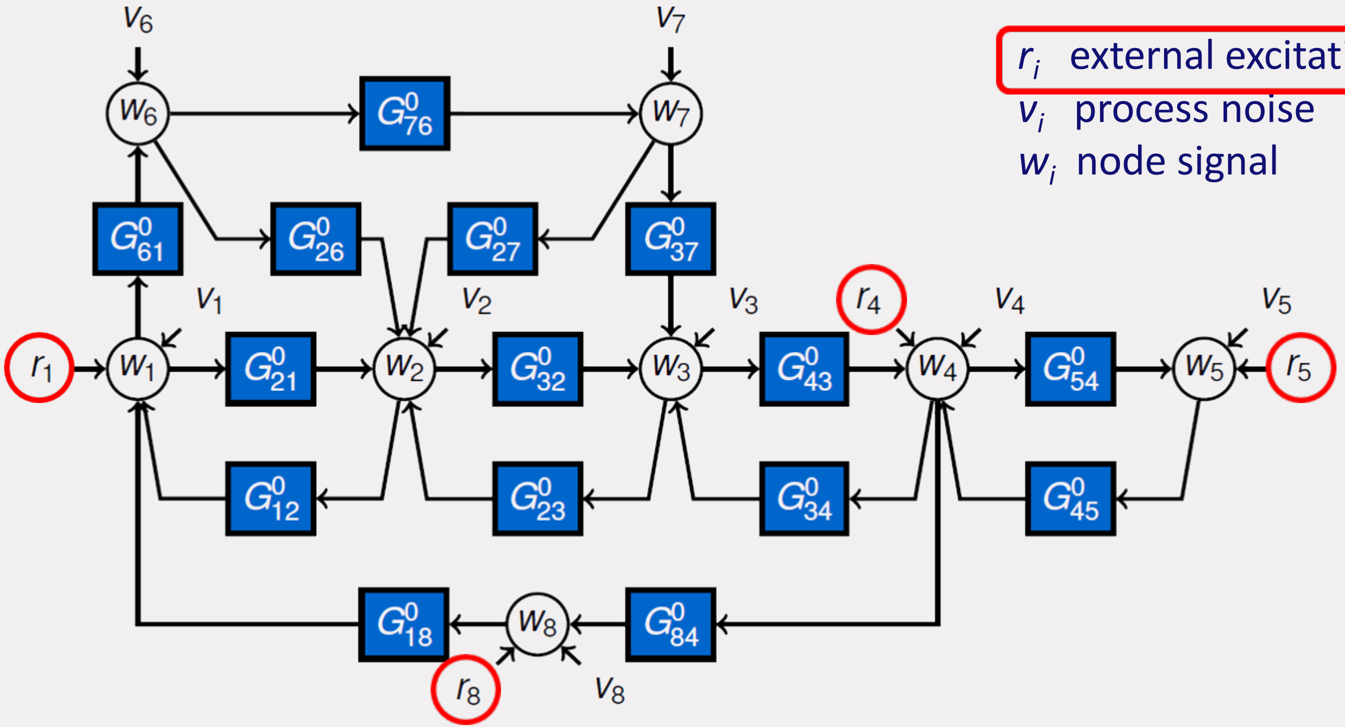

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Dynamic network setup

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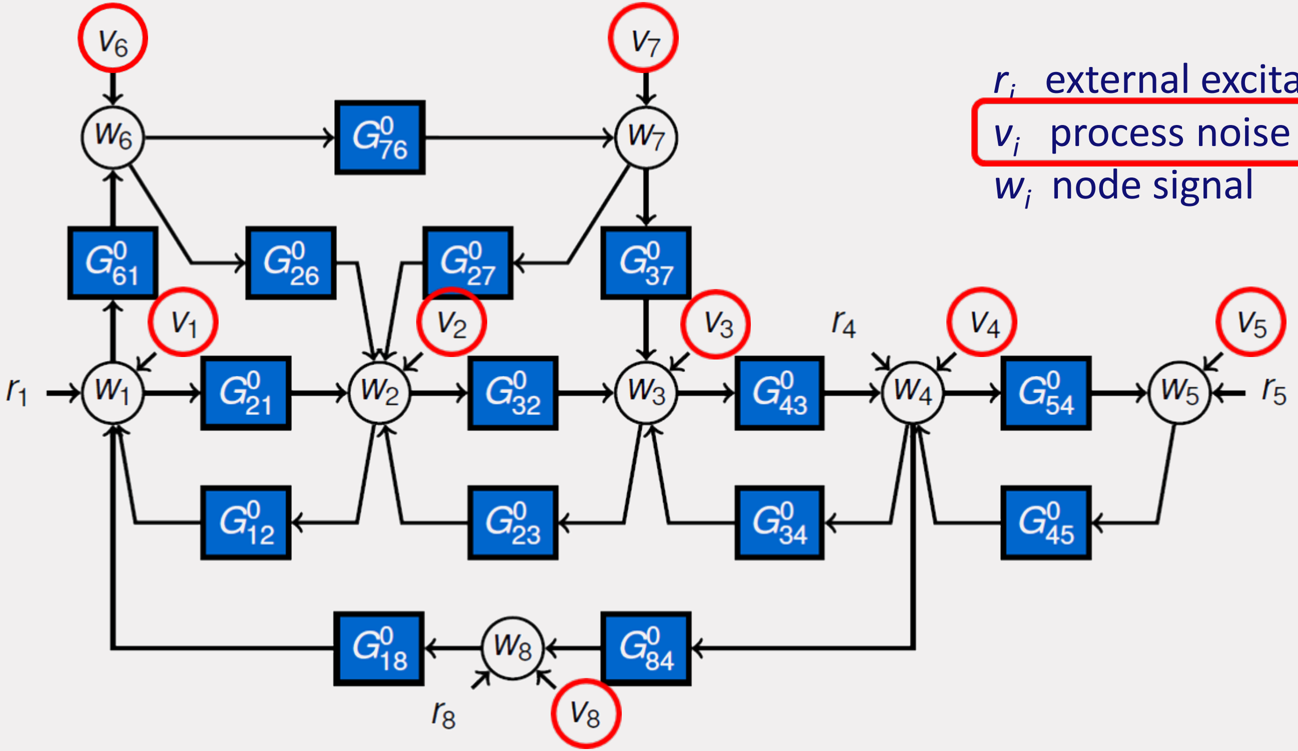

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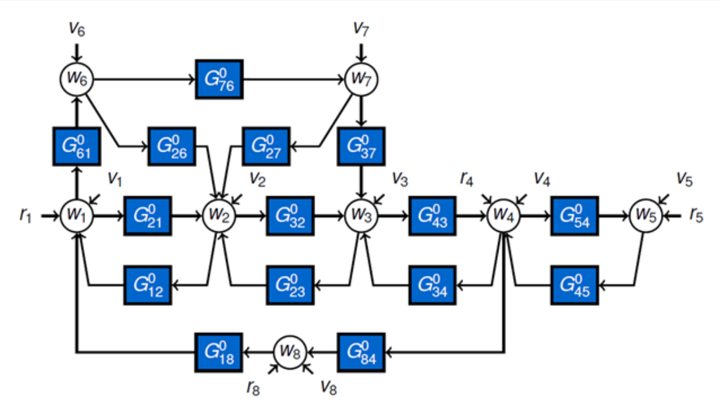
Dynamic network setup



Assumptions:

- Total of L nodes
- Network is well-posed and stable
- Modules are dynamic, may be unstable
- Disturbances are stationary stochastic and can be correlated

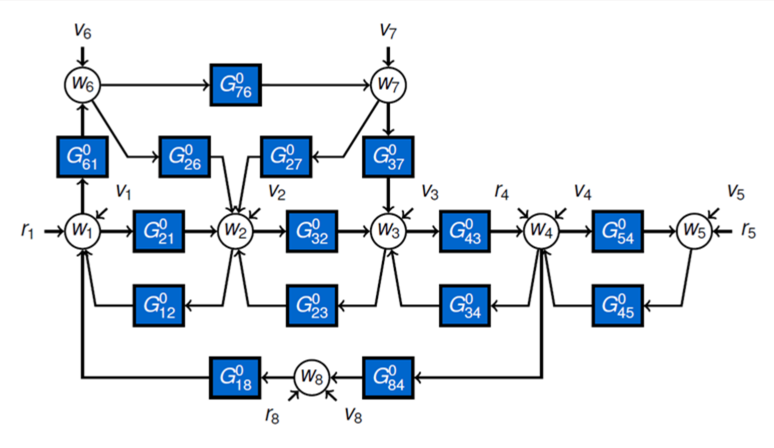
$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & G^0_{12} & \cdots & G^0_{1L} \\ G^0_{21} & 0 & \ddots & G^0_{2L} \\ \vdots & \ddots & \ddots & \vdots \\ G^0_{L1} & G^0_{L2} & \cdots & 0 \end{bmatrix}}_{G^0(q)} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} + R^0 \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_K \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_L \end{bmatrix}$$

$$q^{-1}w(t) = w(t-1)$$

$$w(t) = G^0(q)w(t) + R^0(q)r(t) + v(t)$$

PVdH et al., Automatica, 2013.

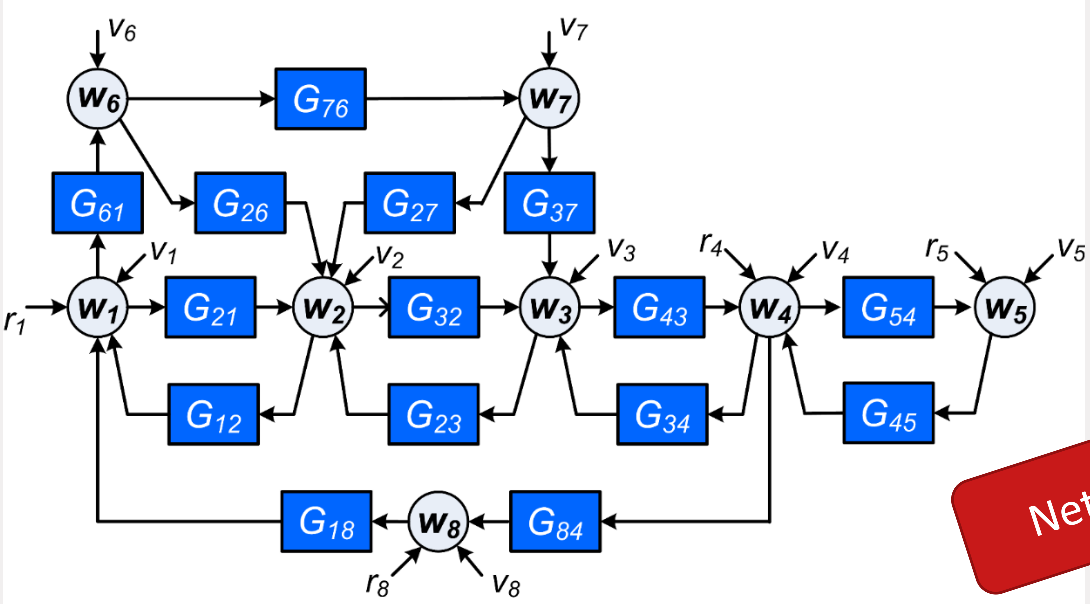
Model learning problems

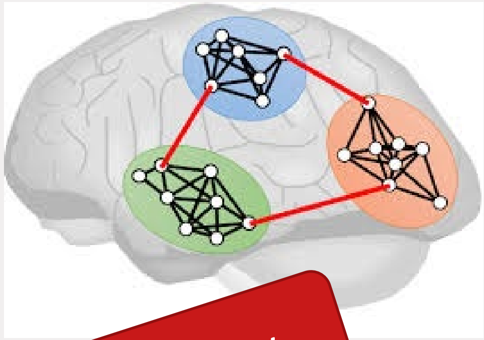


Many new data-driven modeling / learning questions can be formulated:

- Identification of a local module (known topology)
- Identification of the full network
- Topology estimation
- Sensor and excitation selection
- Fault detection
- Experiment design
- User prior knowledge of modules
- Scalable algorithms

Model learning problems

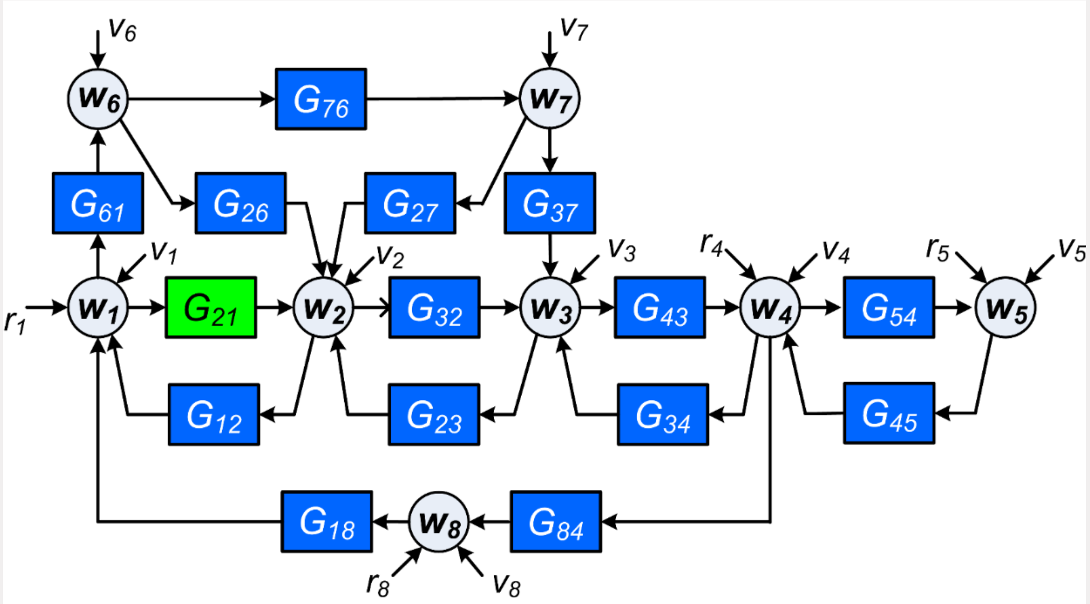




Network identifiability

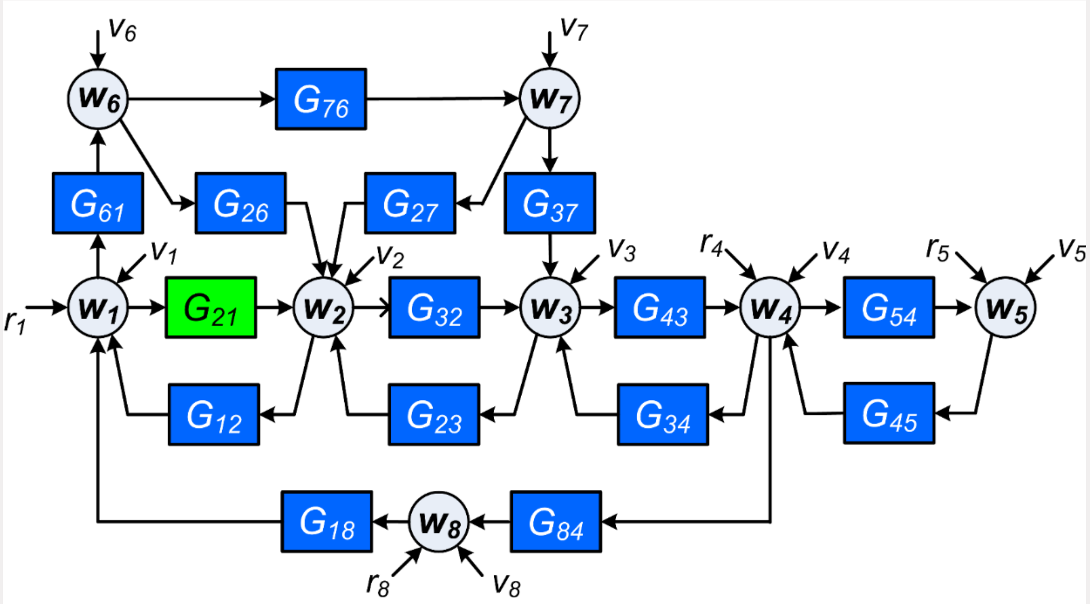
Under which conditions can we estimate the topology and/or dynamics of the full network?

Model learning problems



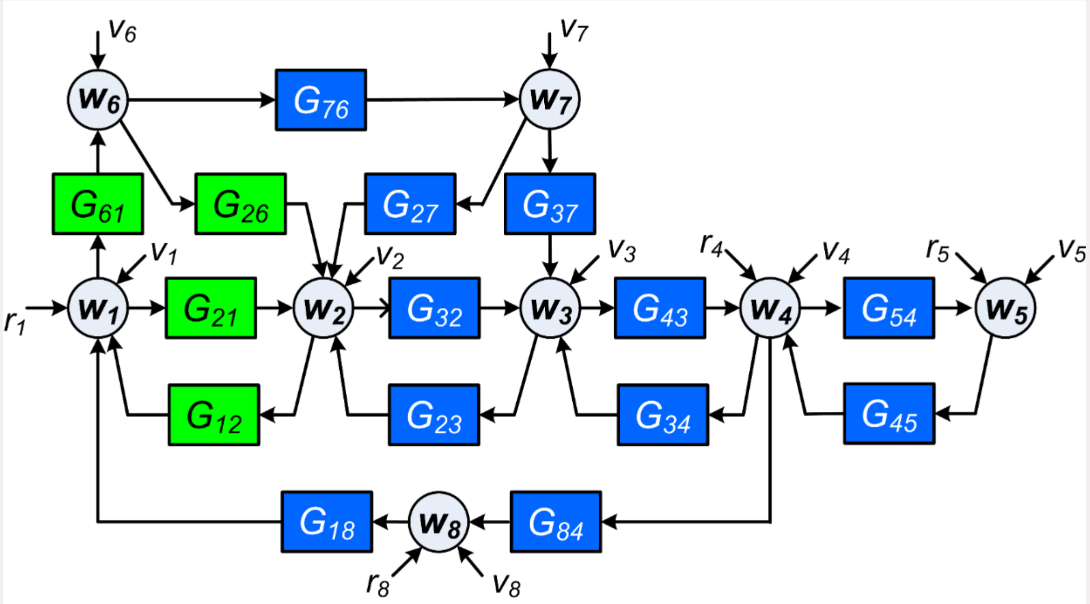
How/when can we learn a local module from data
(with known/unkown network topology) ? Which signals to measure?

Model learning problems



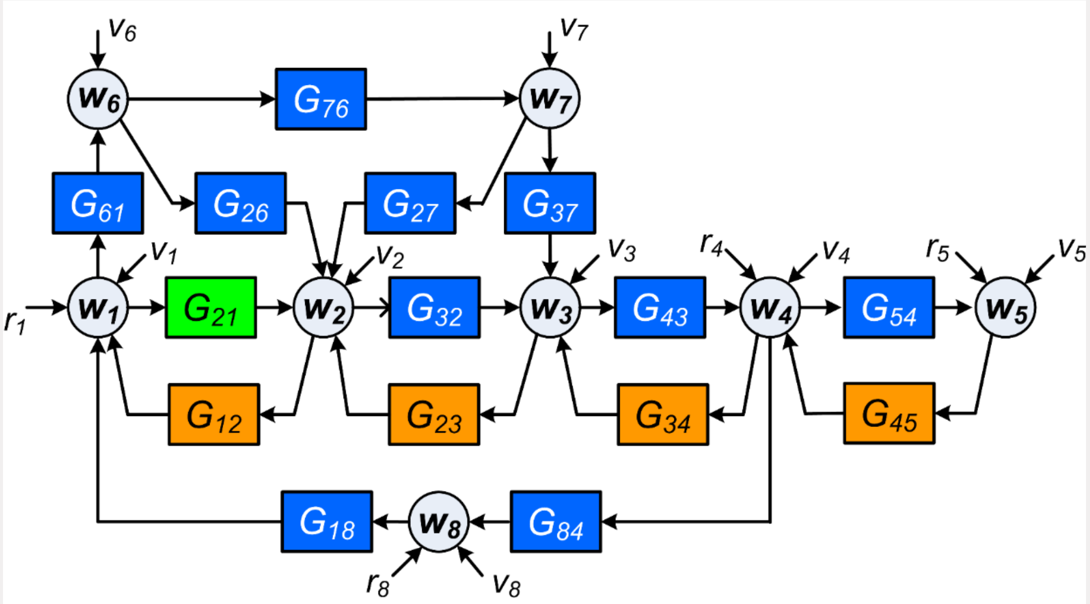
Where to optimally locate sensors and actuators?

Model learning problems



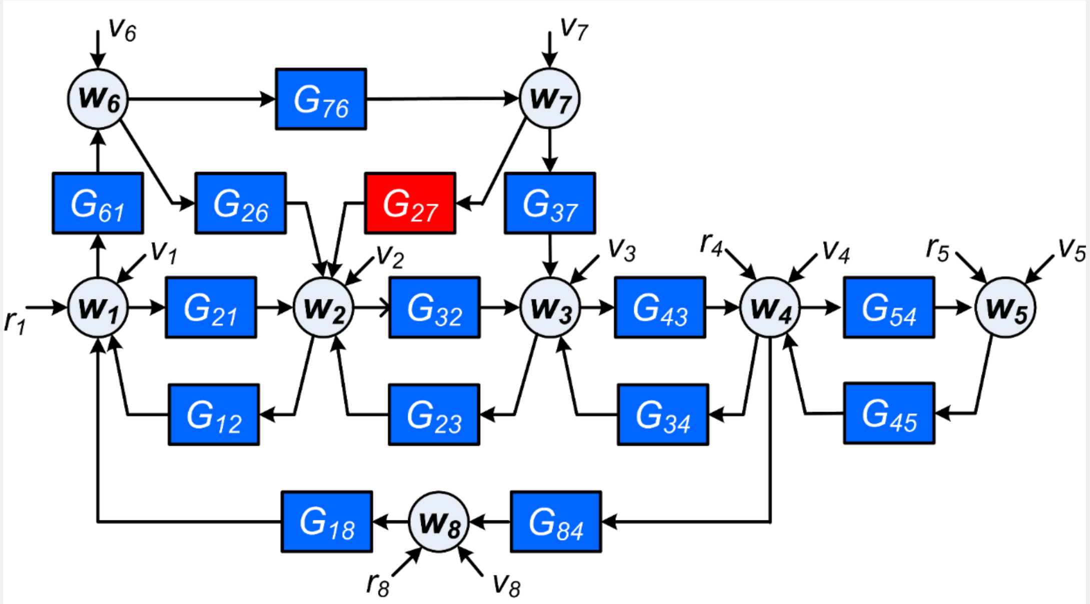
Same questions for a subnetwork

Model learning problems



How can we benefit from known (orange) modules?

Model learning problems



Fault detection and diagnosis; detect/handle nonlinear elements

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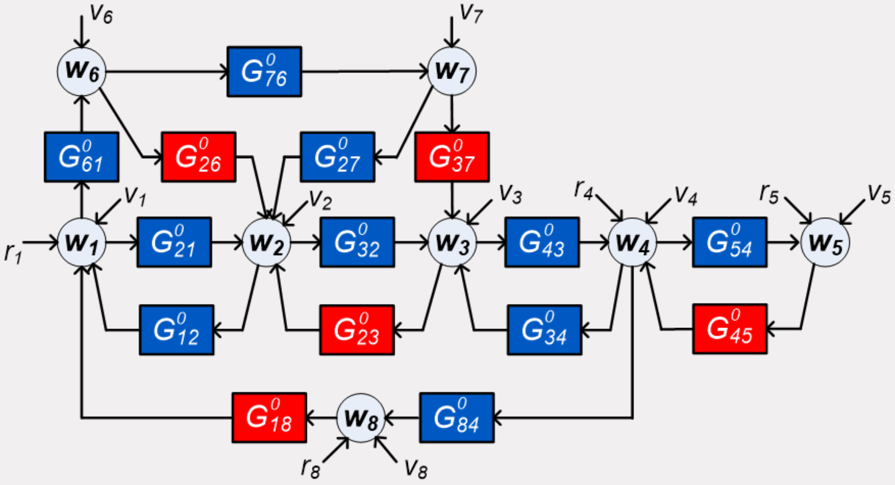
Network identifiability



blue = unknown
red = known

Question: Can different dynamic networks be *distinguished* from each other from measured signals w_i, r_i ?

A parametrized network model set $\mathcal{M}$ is **identifiable** if there is a unique mapping $T \rightarrow \mathcal{M}$ where T are the transfer function objects that can be uniquely identified from the data.

Network identifiability

Identifiability of network model sets is determined by

- Presence and location of external signals, and
- Possible correlation between disturbance signals
- Prior knowledge on modules (fixed / parametrized)

Network identifiability

Theorem – generic identifiability

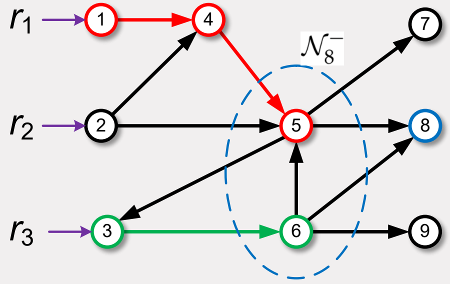
For each node signal w_j, let $\mathcal{P}_j$ be the set of in-neighbours of w_j that map to w_j through a parametrized module.

Then, under fairly general conditions,

$\mathcal{M}$ is generically network identifiable if and only if for all j :

- There are $|\mathcal{P}_j|$ vertex disjoint paths from external excitation signals $(r, e)^1$ to the node signals in $\mathcal{P}_j$

[1] that appear nonparametrized in w_j



[1] Van der Woude, 1991

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

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

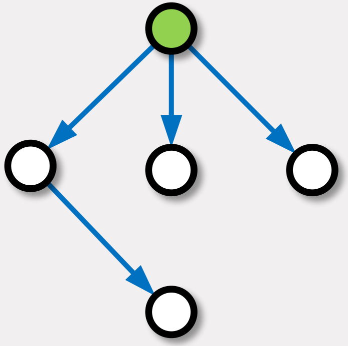
Graph-based synthesis solution for full network

Decompose network in disjoint pseudo-trees:

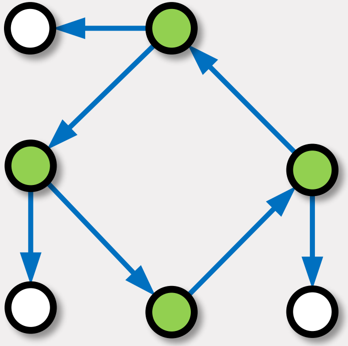
- Connected directed graphs, where nodes have maximum indegree 1
- Edges are disjoint and all out-neighbours of a node are in the same pseudo-tree

Two typical pseudo-trees:

Tree with root in green



Cycle with outgoing trees;
Any node in cycle is root



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

Graph-based synthesis solution for full network

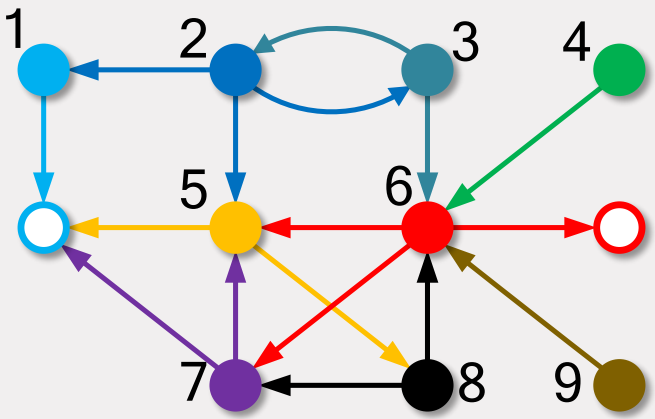
Result[1]

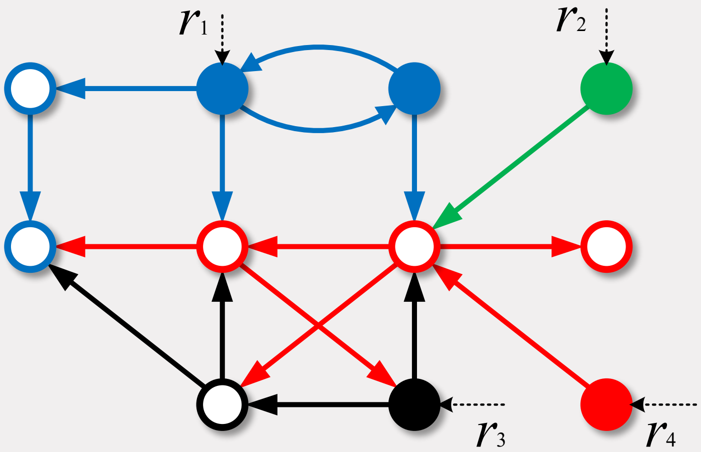
A network is generically identifiable if

- It is decomposed in disjoint pseudo-trees, and
- Each pseudo-tree has an independent excitation at a **root**

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

Where to allocate external excitations for network identifiability?





- Nodes are signals w and external signals (r, e) when they are input to parametrized links
- Result extends to the presence of known (nonparametrized links): they can be excluded from the covering

Extensions - Discussion

Extensions - Discussion

- **Learning algorithms to deal with reduced rank noise** [1]
  - number of disturbance terms is larger than number of white sources
  - Optimal identification criterion becomes a constrained quadratic problem with ML properties for Gaussian noise
  - Reworked Cramer Rao lower bound
  - Some parameters can be estimated variance free

- **Including sensor noise** [2]
  - Errors-in-variabels problems can be more easily handled in a network setting

[1] Weerts et al., Automatica, December 2018.
[2] Dankers et al., Automatica, 2015.

Extensions - Discussion

- **Machine learning tools for estimating large scale models** [1,2]

  - Choosing correctly parametrized model sets for all modules is impractical
  - Use of Gaussian process priors for kernel-based estimation of models

- **From centralized to distributed estimation (MISO models)** [3]

  - Communication constraints between different agents
  - Recursive (distributed) estimator converges to global optimizer (more slowly)

[1] Everitt et al., Automatica, 2018.
[2] Ramaswamy et al., CDC 2018.
[3] Steentjes et al., IFAC-NECSYS, 2018.

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Discussion

- **Dynamic network identification:**
  intriguing research topic with many open questions
- The (centralized) LTI framework is only just the beginning
- Structural basis for learning algorithms
- Extensions to non-directional graphs (physical networks)
- Including switching / time-varying links

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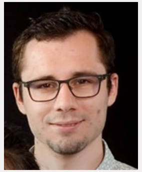

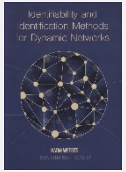

Harm Weerts

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Further reading

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Papers available at www.pvandenhof.nl

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