



# Design of in-line controllers for continuously operating networks with structural uncertainty (CAREER #1553504)

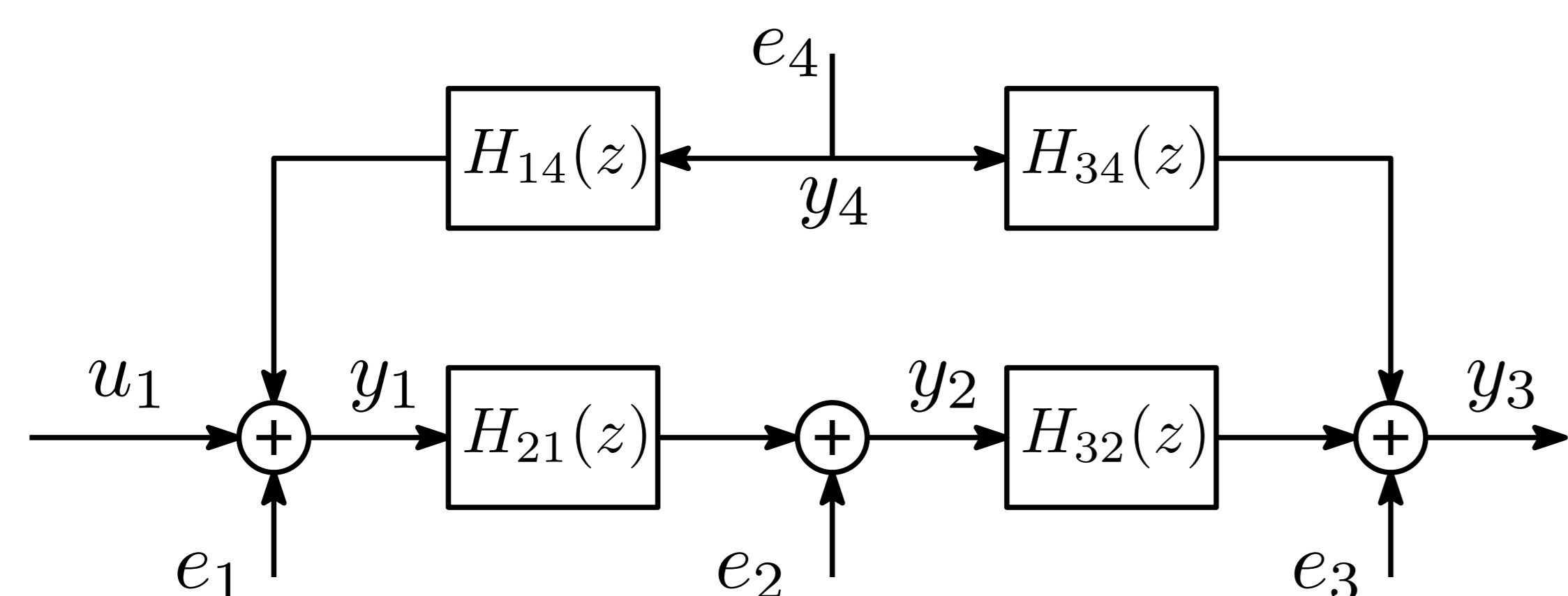
P.I.: Donatello Materassi, Electrical Engineering and Computer Science Department, University of Minnesota

## Linear Dynamic Influence Networks: an I/O model for noninvasively sensed systems

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix} + \begin{pmatrix} H_{11}(z) & \dots & H_{1n}(z) \\ \vdots & \dots & \vdots \\ H_{n1}(z) & \dots & H_{nn}(z) \end{pmatrix} \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

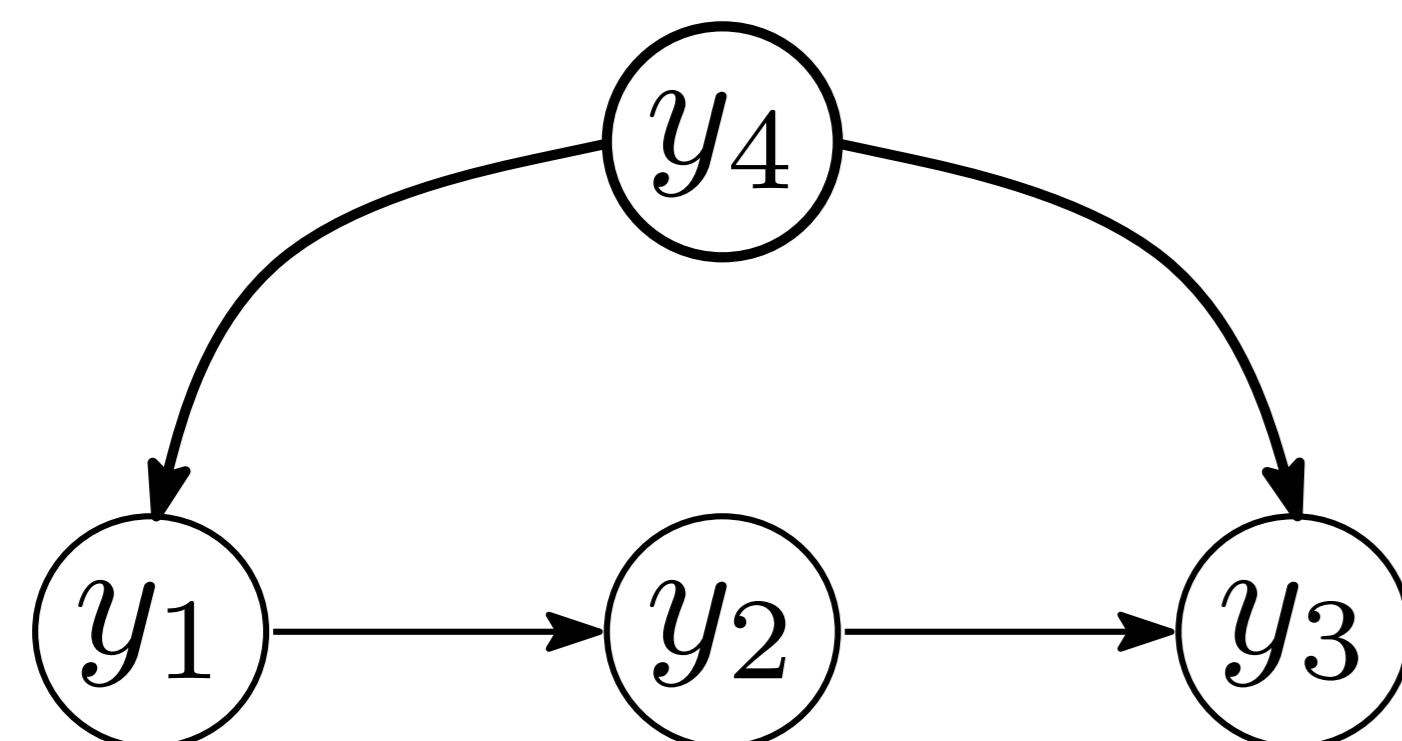
- The inputs  $y_i$  are observable
- The inputs  $u_i$  are unknown
- $u_i$  and  $u_j$  are independent, for  $i \neq j$

### A graphical model interpretation



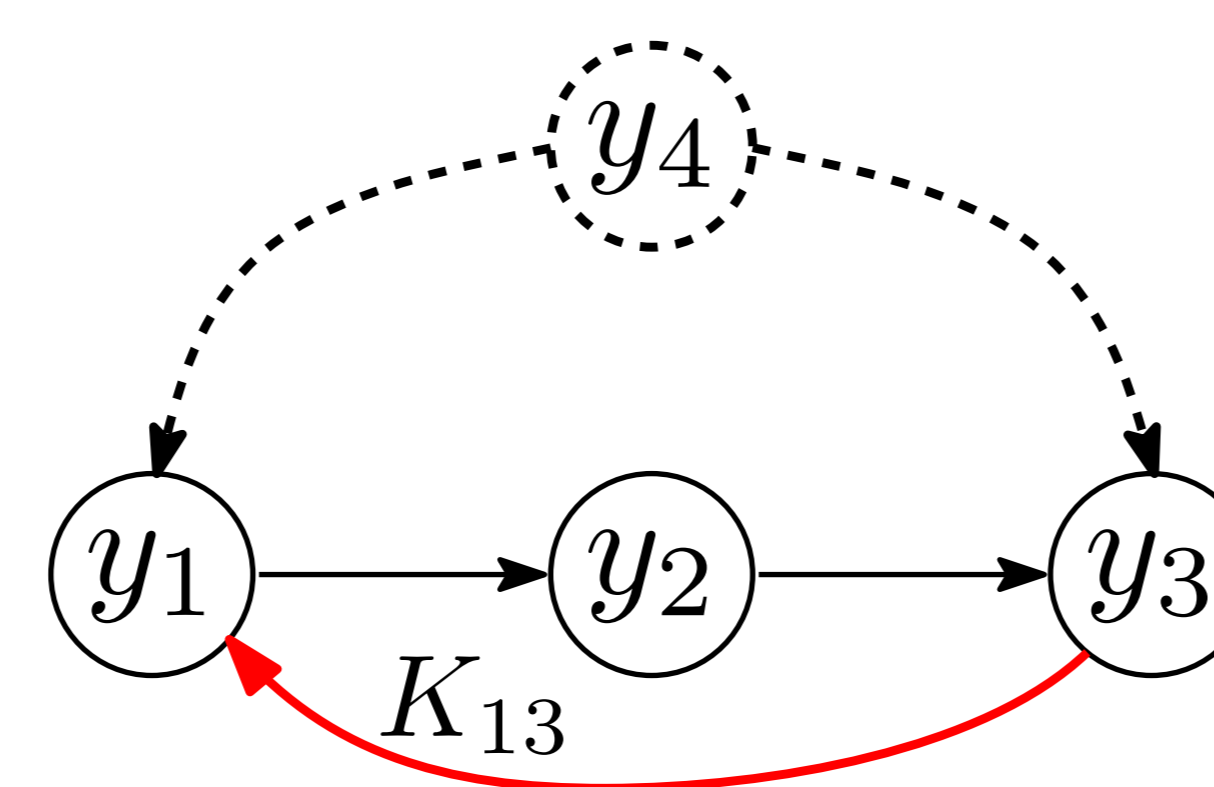
Given a block diagram

- the outputs are nodes
- if  $H_{ji}(z) \neq 0$  draw, a link from  $y_i$  to  $y_j$ .



This representation extends graphical models of random variables to describe stochastic processes

## Design Control Challenge I



- ▶ Transfer functions are unknown
- ▶ Graph is partially known (with unknown structure)
- ▶  $y_4$  is not measurable (and not known if it is present)
- ▶ Known Power Spectral Densities  $\Phi_{y_i y_j}$ ,  $i, j = 1, 2, 3$

Find the closed loop behavior

In the absence of  $y_4$  the solution is easy

$$H_{32}(z)H_{21}(z) = \frac{\Phi_{y_3 y_2} \Phi_{y_2 y_1}}{\Phi_{y_2} \Phi_{y_1}}$$

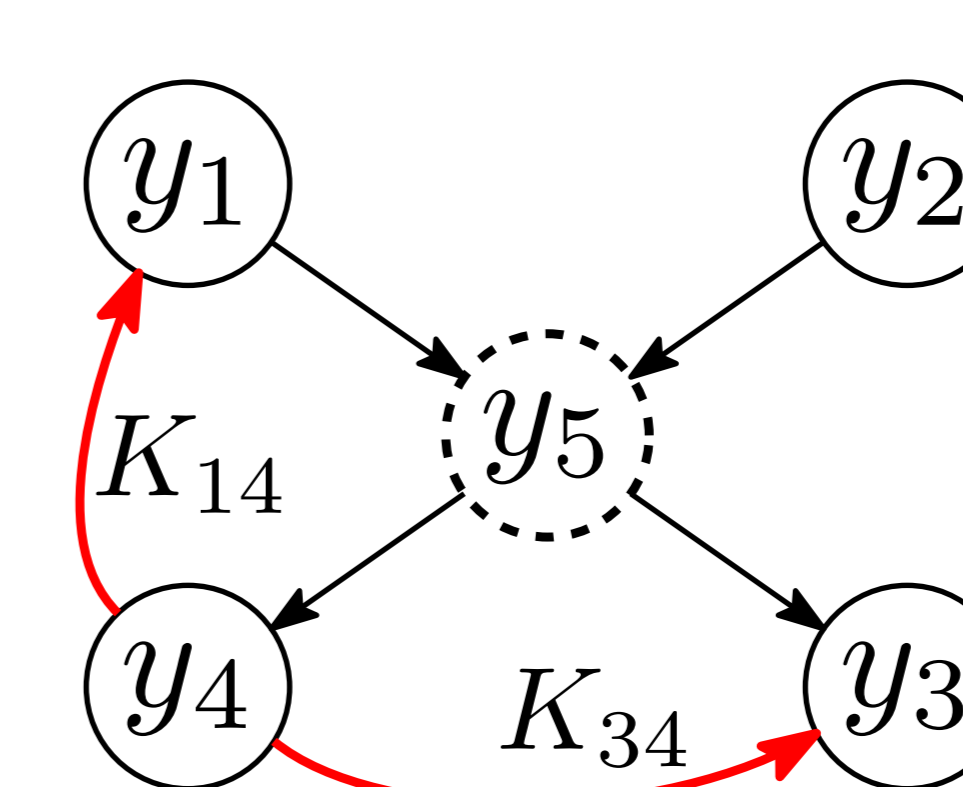
$$G_{y_1 \rightarrow y_3} = \frac{H_{32}H_{21}}{1 - H_{32}H_{21}} = \frac{\frac{\Phi_{y_3 y_2} \Phi_{y_2 y_1}}{\Phi_{y_2} \Phi_{y_1}}}{1 - K_{13} \frac{\Phi_{y_3 y_2} \Phi_{y_2 y_1}}{\Phi_{y_2} \Phi_{y_1}}} = \frac{\frac{\Phi_{y_3 y_1}}{\Phi_{y_1}}}{1 - K_{13} \frac{\Phi_{y_3 y_1}}{\Phi_{y_1}}}$$

In the presence (or absence) of  $y_4$  (see [?])

$$G_{y_1 \rightarrow y_3} = \frac{\frac{\Phi_{y_2 y_1}}{\Phi_{y_1}} (\Phi_{y_3 y_1} \Phi_{y_3 y_2}) \begin{pmatrix} \Phi_{y_1} & \Phi_{y_1 y_2} \\ \Phi_{y_2 y_1} & \Phi_{y_2} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}}{1 - K_{13} \frac{\Phi_{y_2 y_1}}{\Phi_{y_1}} (\Phi_{y_3 y_1} \Phi_{y_3 y_2}) \begin{pmatrix} \Phi_{y_1} & \Phi_{y_1 y_2} \\ \Phi_{y_2 y_1} & \Phi_{y_2} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}}$$

This formula is robust with respect to uncertainties in the structure: a novel notion of robustness!

## Design Control Challenge II



- ▶ Transfer functions are unknown
- ▶ Graph is a tree (with unknown structure)
- ▶  $y_5$  is not measurable and it is not known if it is present
- ▶ Known Power Spectral Densities  $\Phi_{y_i y_j}$ ,  $i, j = 1, 2, 3, 4$

Find the closed loop behavior

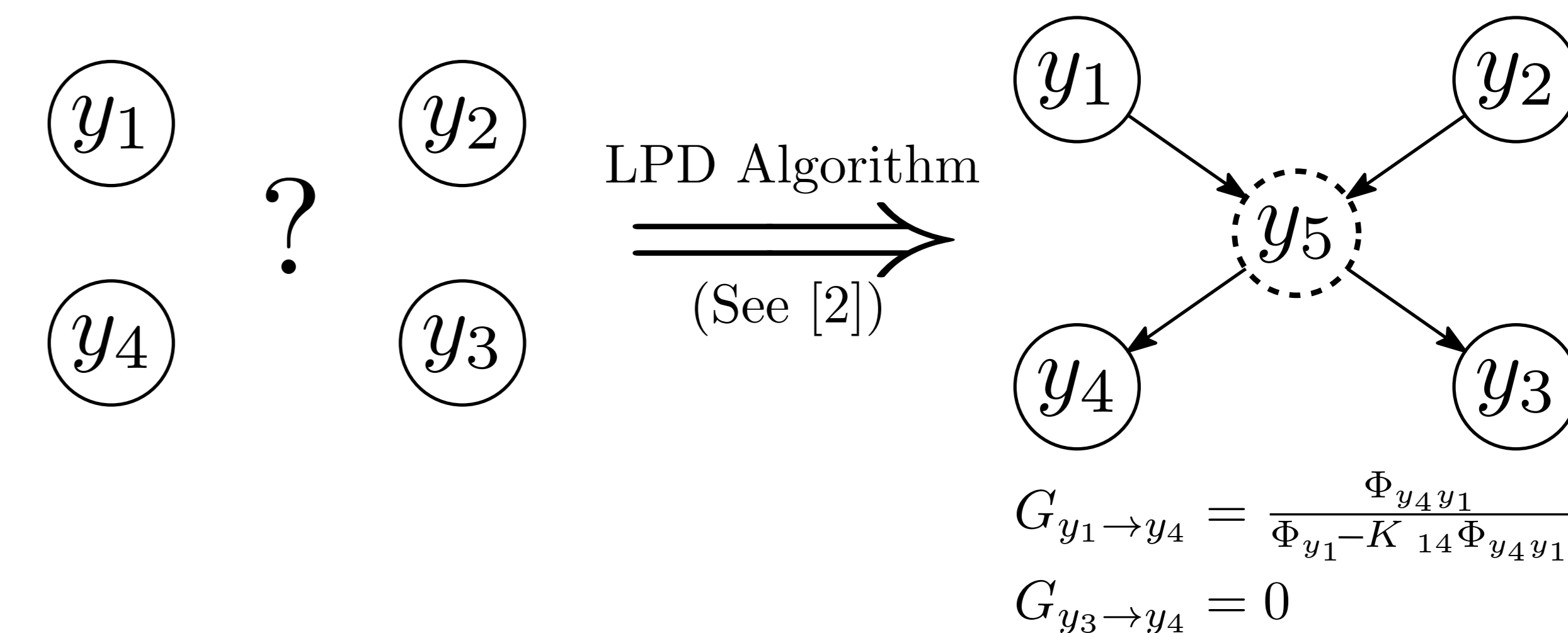
A distance that is additive along paths of a rooted tree, such as

$$d(y_i, y_j) = - \int_0^{2\pi} \log \left( \frac{|\Phi_{e_i e_j}|^2}{|\Phi_{e_i}| |\Phi_{e_j}|} \right) d\omega,$$

enables the detection of hidden nodes (see [?])

$$y_5 \text{ is present} \Leftrightarrow d(y_1, y_4) - d(y_4, y_3) \neq d(y_1, y_3)$$

enables the inference of skeleton and link orientations (see [?])



## References

- [1] F. Sepeher, D. Materassi, *Inferring the structure of polytree networks of dynamic systems with hidden nodes*, IEEE Transactions on Automatic Control, 2019
- [2] F. Sepeher, D. Materassi, *An Algorithm to Learn Polytree Networks with Hidden Nodes*, NeurIPS, 2019
- [3] J. Constanzo, D. Materassi, B. Sinopoli, *Using Viterbi and Kalman to detect topological changes in dynamic networks*, American Control Conference, 2017