

Identifiability, indistinguishability, and other problems in biological modeling

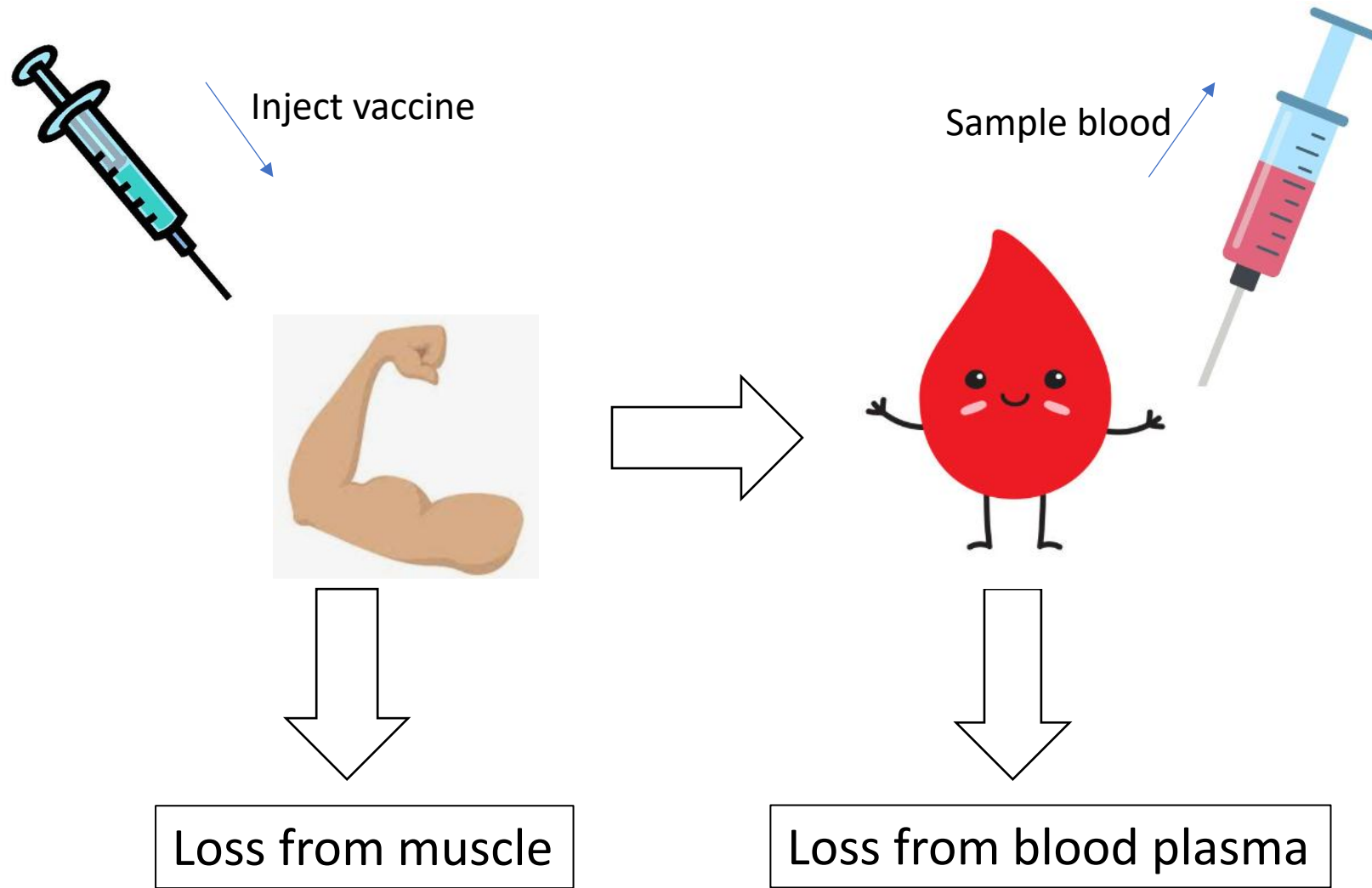
Nikki Meshkat

Santa Clara University

New Directions in Algebraic Statistics

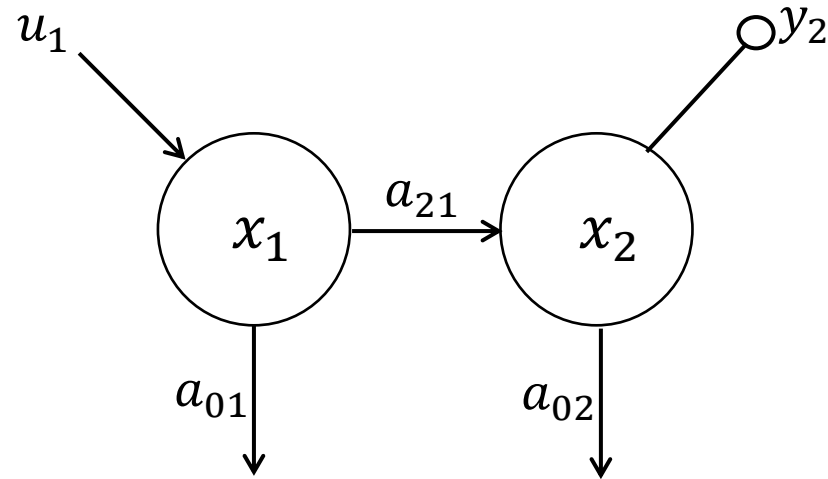
July 22, 2025

Consider a vaccine injection model (IM)*:



*Example 13.6 from DiStefano, *Dynamics Systems Biology Modeling and Simulation*

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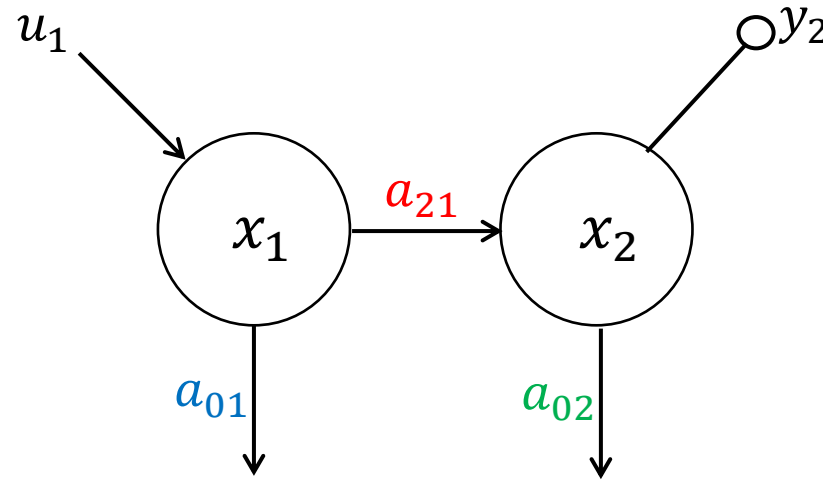


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- More generally, what can we say about classes of identifiable models? Submodels? Joined models? etc

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- If there are others, what does that mean?
- More generally, what can we say about classes of identifiable models? Submodels? Joined models? etc
- What do we do with an unidentifiable model?

How to test identifiability – Diff. alg. approach

- Have ODE model:

$$\dot{x}_1 = -(a_{01} + a_{21})x_1 + u_1$$

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$$y_2 = x_2$$

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- Can we eliminate unknown variables $x_1, \dot{x}_1, x_2, \dot{x}_2$?
- Must determine *input-output equation* (in terms of $u_1, y_2, \dot{u}_1, \dot{y}_2, \dots$)

Determine input-output equations

Have system $\dot{x} = Ax + u$, $y_2 = x_2$

Rewrite system as $(\partial I - A)x = u$, where $\partial = d/dt$

$$\begin{pmatrix} \partial + a_{01} + a_{21} & 0 \\ a_{21} & \partial + a_{02} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} u_1 \\ 0 \end{pmatrix}$$

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Then by Cramer's Rule:

$$x_2 = \frac{\det \begin{pmatrix} \partial + a_{01} + a_{21} & u_1 \\ a_{21} & 0 \end{pmatrix}}{\det \begin{pmatrix} \partial + a_{01} + a_{21} & 0 \\ a_{21} & \partial + a_{02} \end{pmatrix}}$$

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Thus $\ddot{y}_2 + (a_{01} + a_{02} + a_{21})\dot{y}_2 + (a_{01}a_{02} + a_{21}a_{02})y_2 = a_{21}u_1$

Obtain coefficient map

Assume we can uniquely determine coefficients from perfect data

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Extract coefficients from input-output equations to get coefficient map:

$$p \mapsto c(p) \\ (a_{01}, a_{21}, a_{02}) \mapsto (a_{01} + a_{21} + a_{02}, \quad a_{01}a_{02} + a_{21}a_{02}, \quad a_{21})$$

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Model is (generically):

- Globally identifiable if c is generically one-to-one
- Locally identifiable if c is generically finite-to-one
- Unidentifiable if c is generically infinite-to-one

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Parameter a_{ij} is (generically):

- Globally identifiable if its value can be recovered uniquely
- Locally identifiable if its value can be recovered up to a finite set
- Unidentifiable if its value can't be recovered even up to a finite set

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$$a_{01} + a_{02} + a_{21} = a_{01}^* + a_{02}^* + a_{21}^*$$
$$a_{01}a_{02} + a_{21}a_{02} = a_{01}^*a_{02}^* + a_{21}^*a_{02}^*$$
$$a_{21} = a_{21}^*$$

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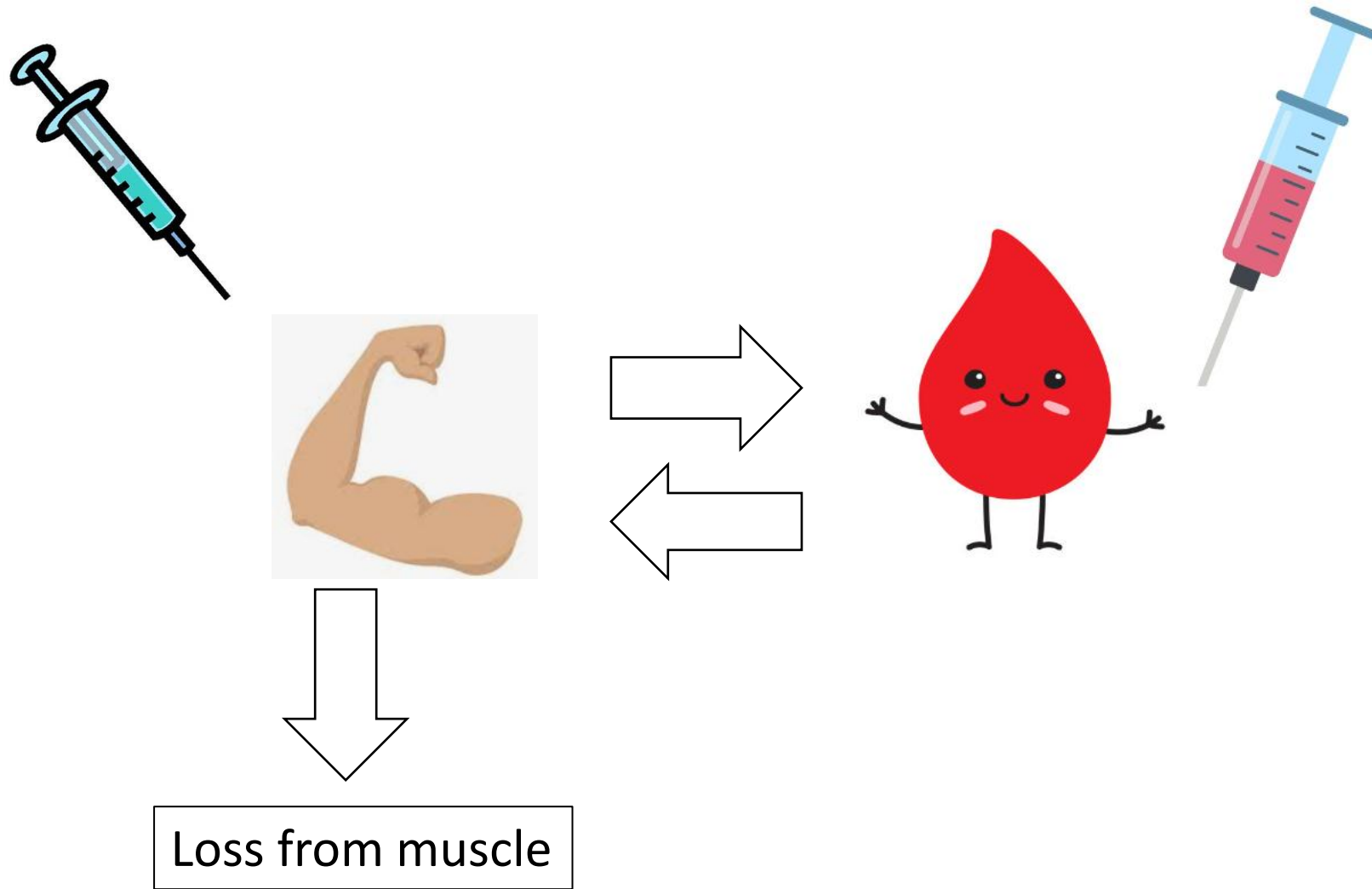
$$a_{01} = a_{01}^*$$

$$a_{02} = a_{02}^*$$

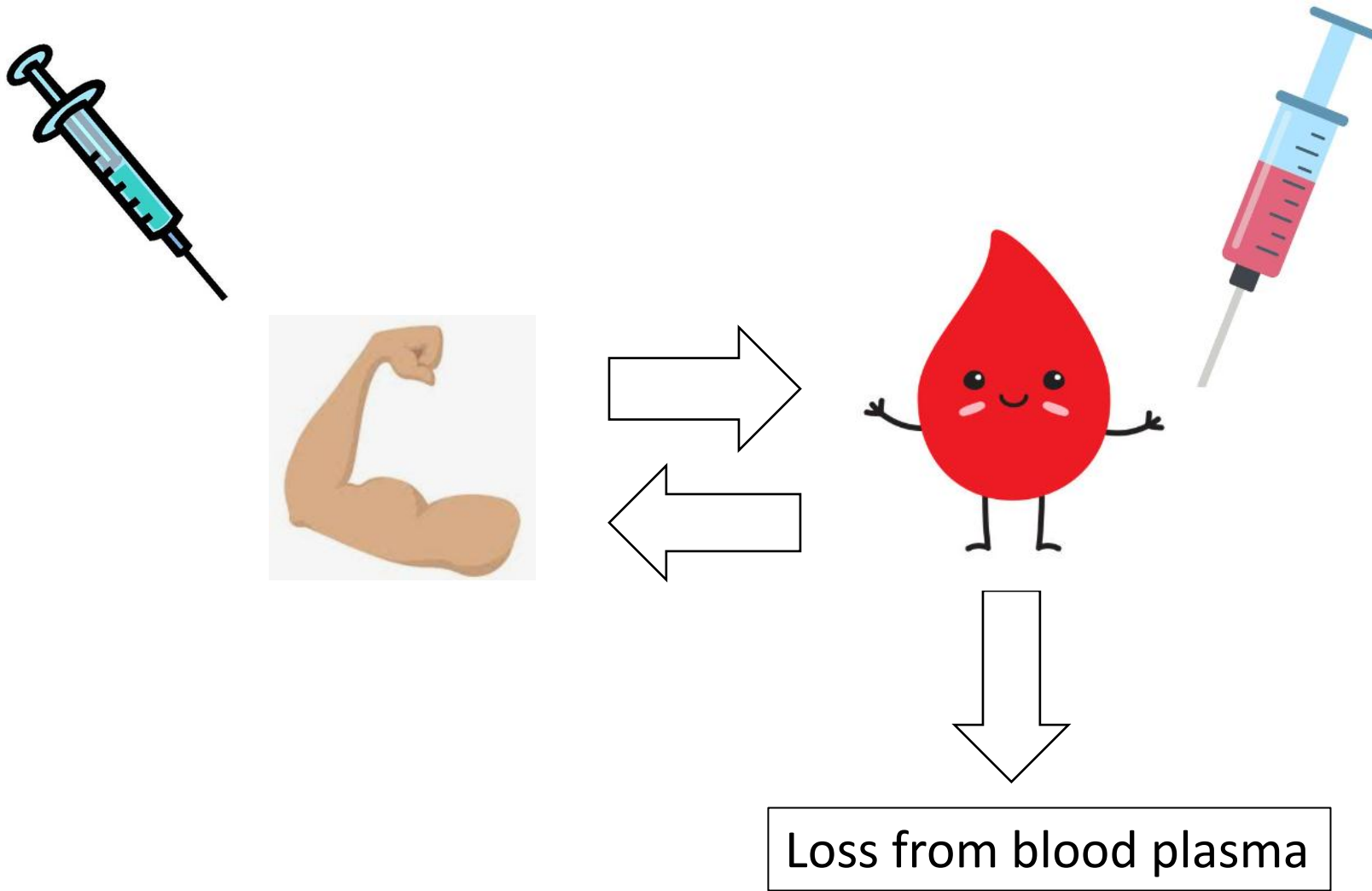
$$a_{21} = a_{21}^*$$

Model is globally identifiable

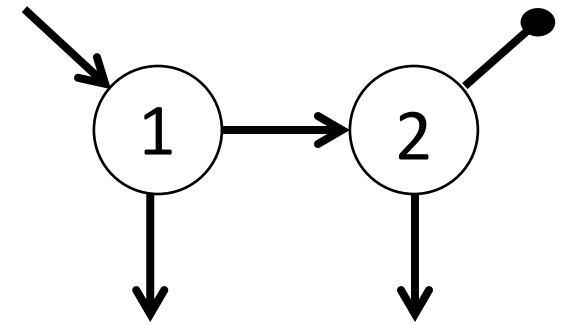
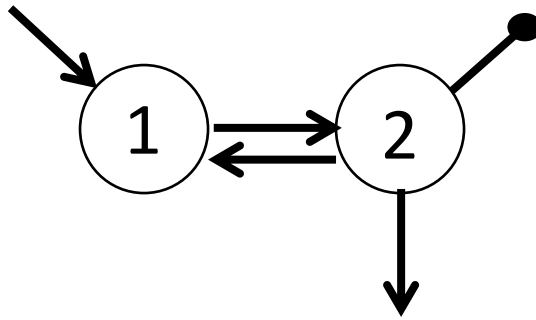
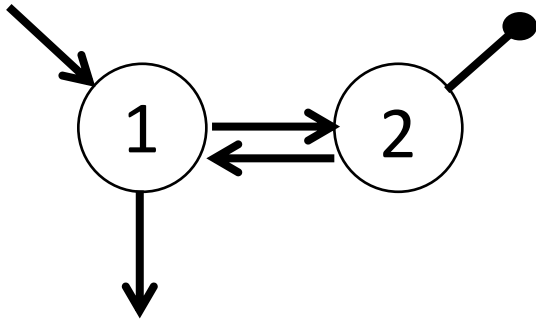
What if I change my model?



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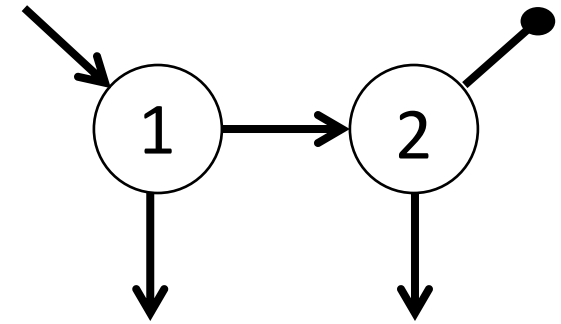
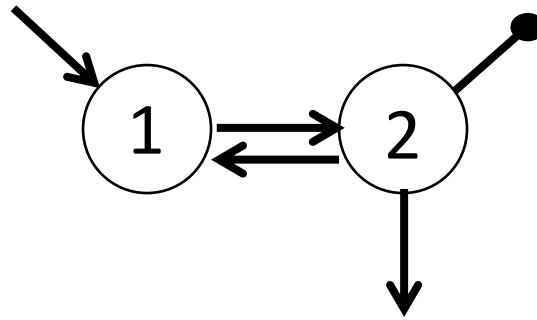
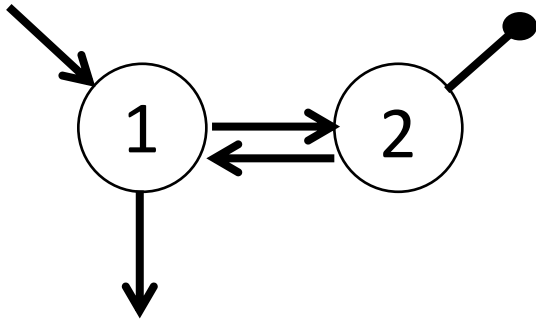


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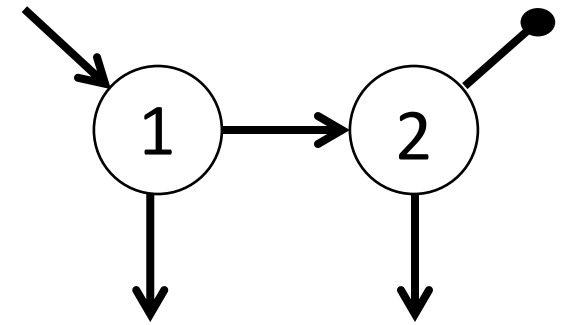
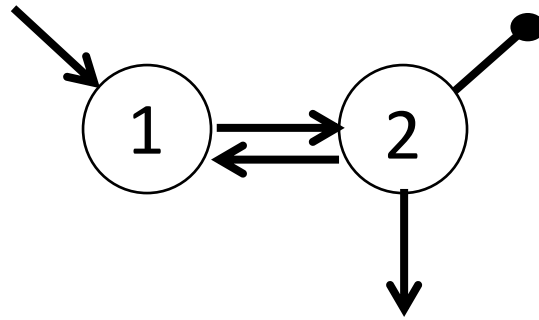
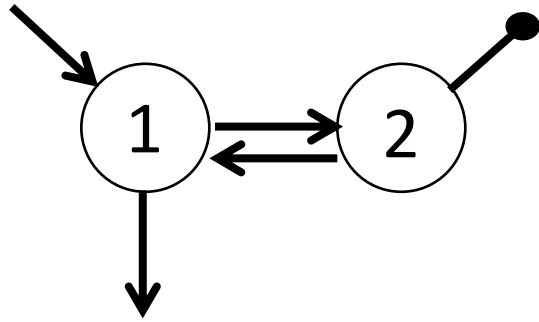
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Are these the same models or different models?
(...what do we mean by “**same**”?)

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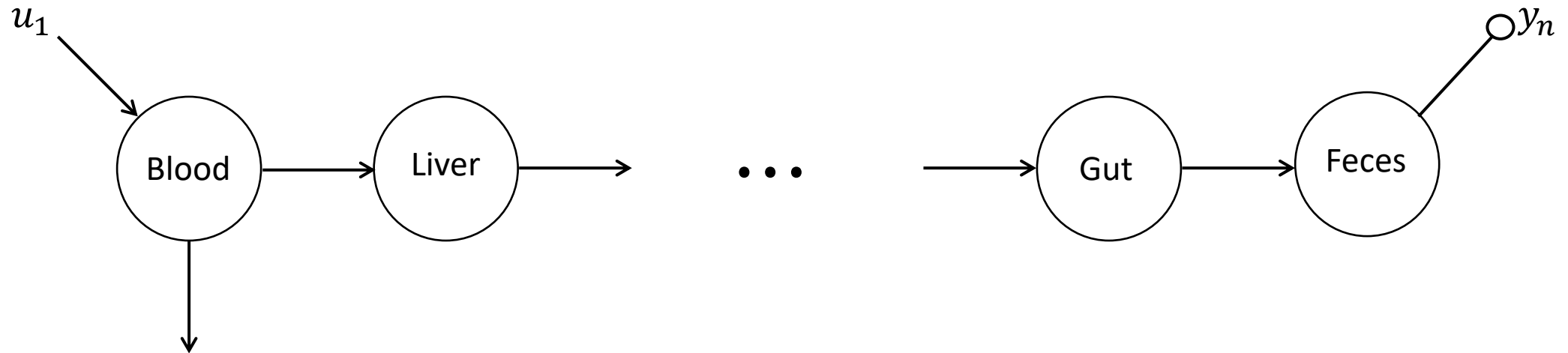
Are these the same models or different models?

(...what do we mean by “**same**”?)

Not immediately obvious, let's examine other models first...

Path models

Consider a one-way path with input on one end and output on other

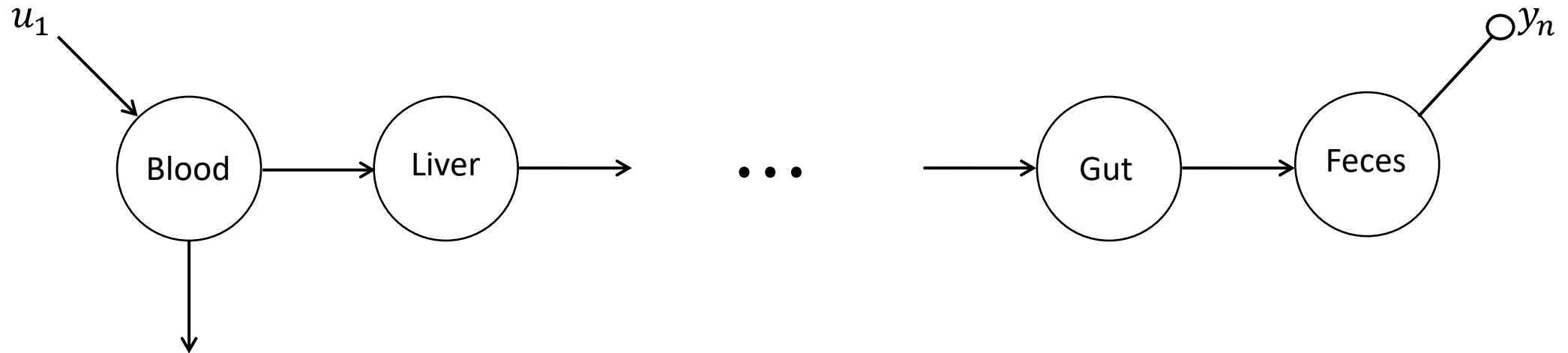


Ex:

- metabolism model*
- time-delay model
- signal delay with attenuation

Path models

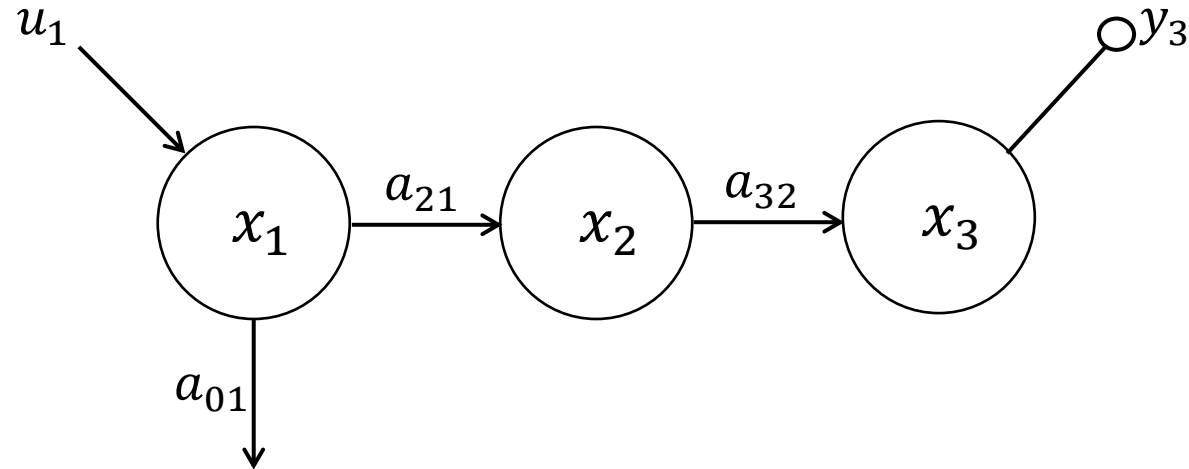
Consider a one-way path with input on one end and output on other



- locally identifiable

Consider the following models:

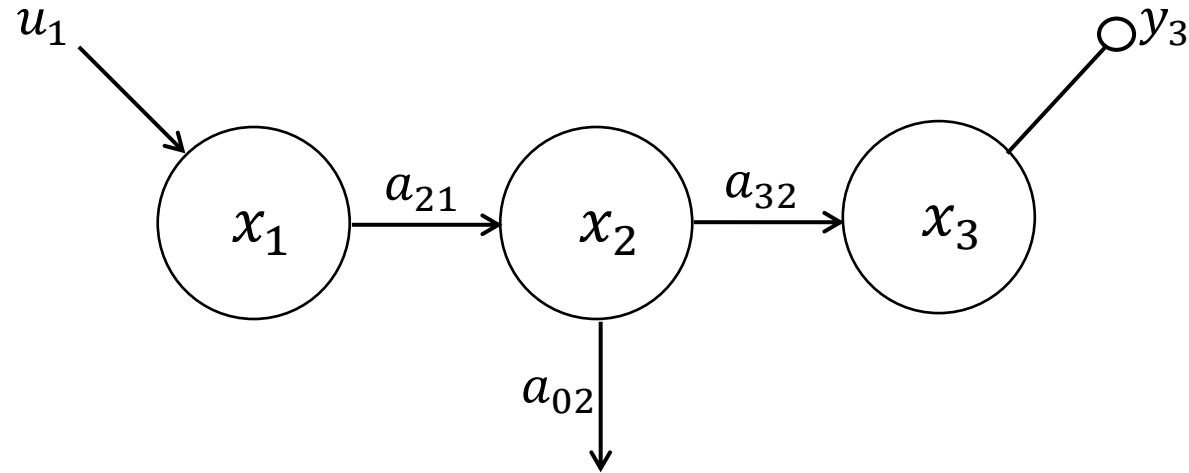
Model 1



I/O eqn $\ddot{y}_3 + (a_{32} + a_{01} + a_{21})\dot{y}_3 + (a_{01}a_{32} + a_{21}a_{32})\dot{y}_3 = a_{21}a_{32}u_1$

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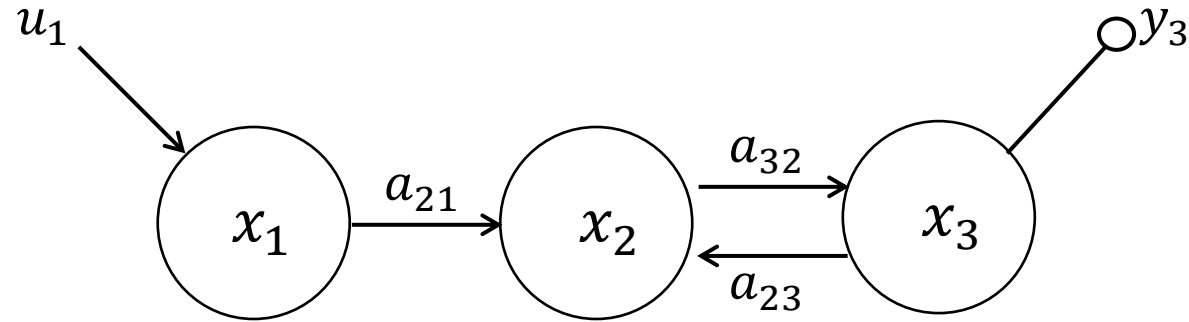
Model 2



I/O eqn $\ddot{y}_3 + (a_{21} + a_{02} + a_{32})\dot{y}_3 + (a_{02}a_{21} + a_{32}a_{21})\dot{y}_3 = a_{32}a_{21}u_1$

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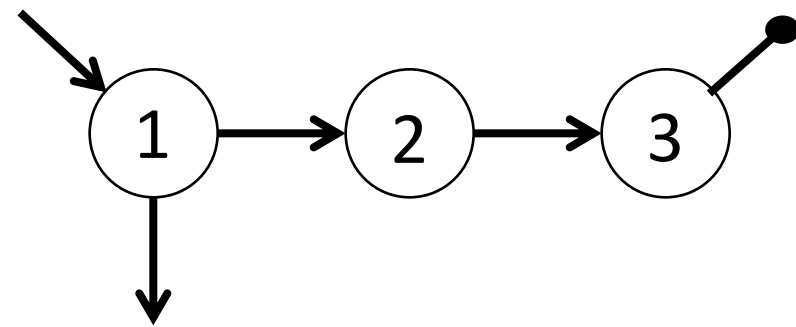
Model 3



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Model 1



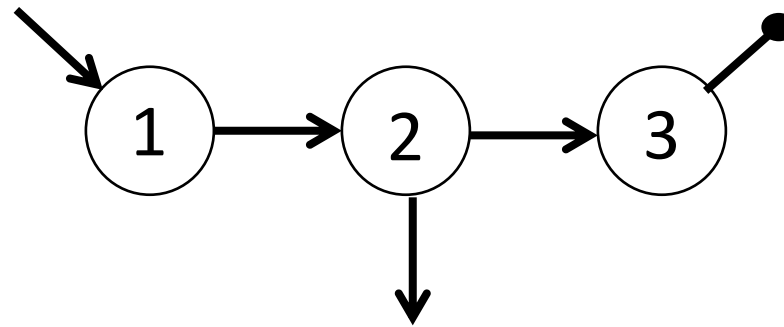
Coefficient maps:

$$a_{32} + a_{01} + a_{21}$$

$$a_{01}a_{32} + a_{21}a_{32}$$

$$a_{21}a_{32}$$

Model 2

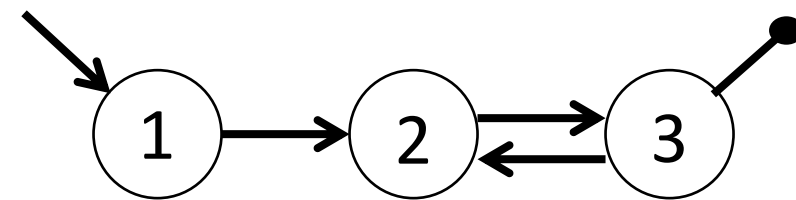


$$a_{21} + a_{02} + a_{32}$$

$$a_{02}a_{21} + a_{32}a_{21}$$

$$a_{32}a_{21}$$

Model 3



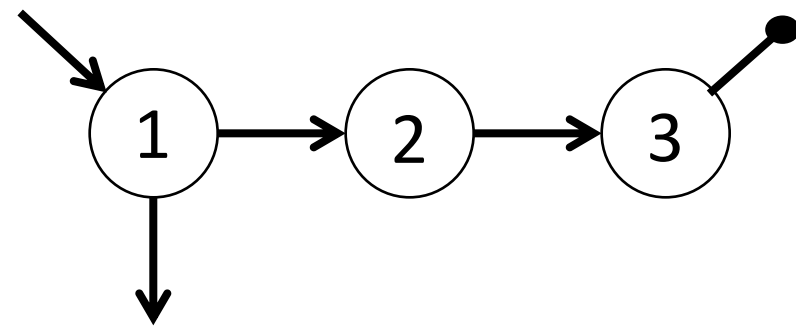
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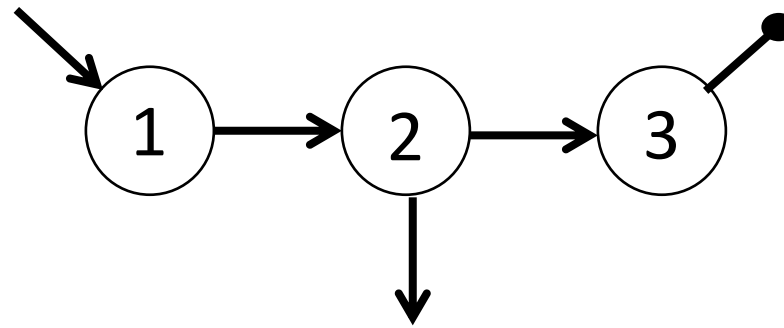
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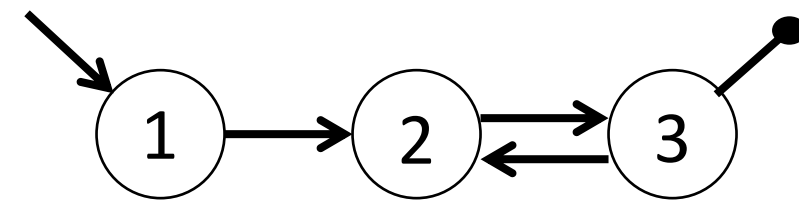
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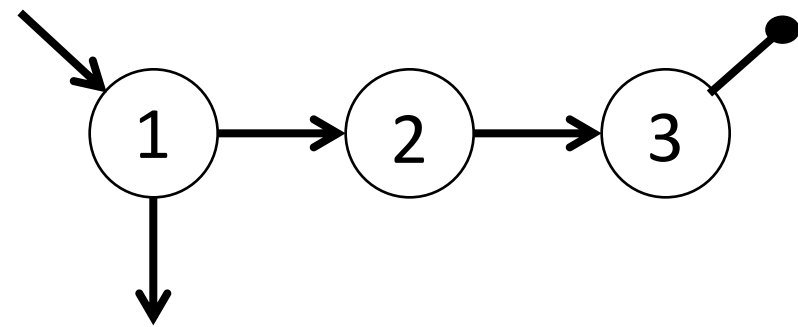
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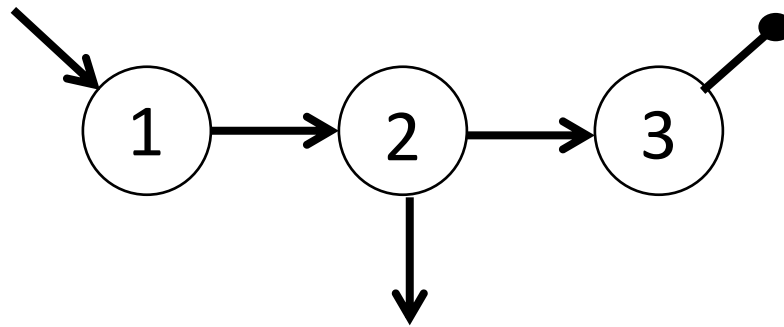
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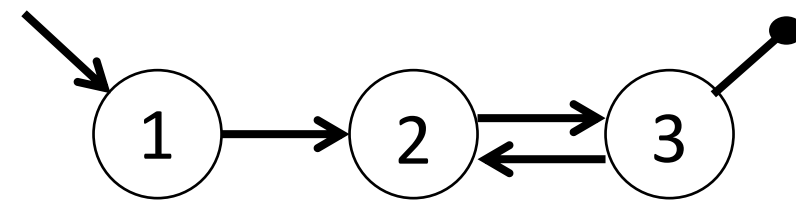
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Model 2



Model 3



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\equiv

a_{21}

\equiv

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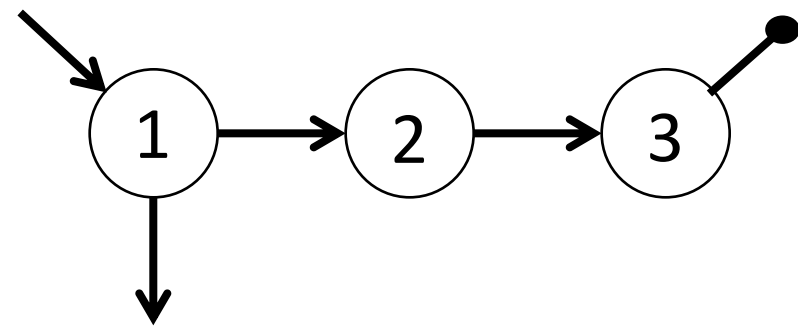
a_{32}

\equiv

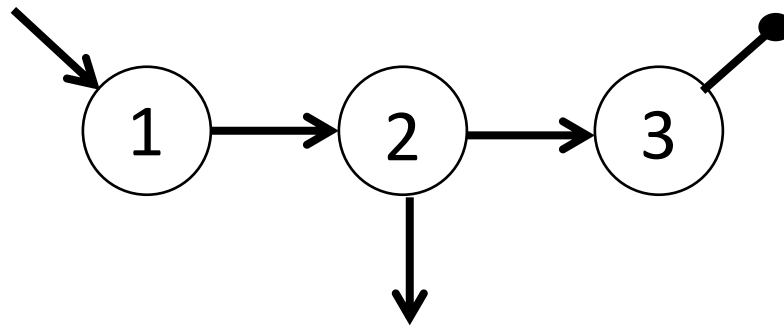
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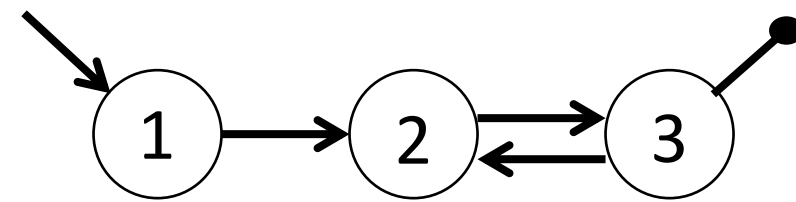
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Model 2



Model 3



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\equiv

a_{32}

Models are
indistinguishable!

Indistinguishability

Two models are indistinguishable if for any choice of parameter values in the first model, there is a choice of parameter values in the second model that will yield the same dynamics, and vice versa

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Necessary conditions:

- Same input/output variables

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- Same structure of I/O eqns, i.e. same u , y , \dot{u} , \dot{y} , ... terms appearing

Indistinguishability

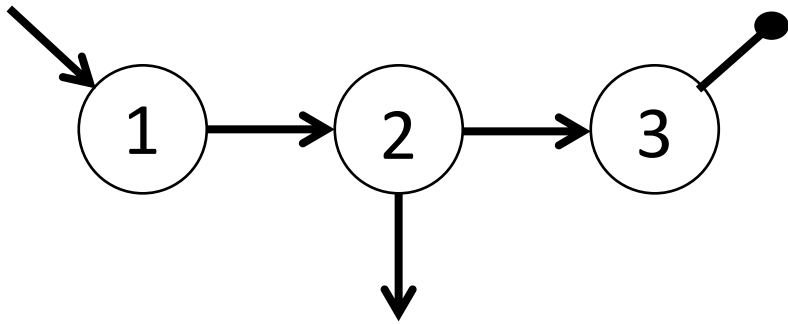
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Necessary conditions:

- Same input/output variables
- Same structure of I/O eqns, i.e. same u , y , \dot{u} , \dot{y} , ... terms appearing
- Coefficients must satisfy the same algebraic dependency relationships

Distinguishable models:

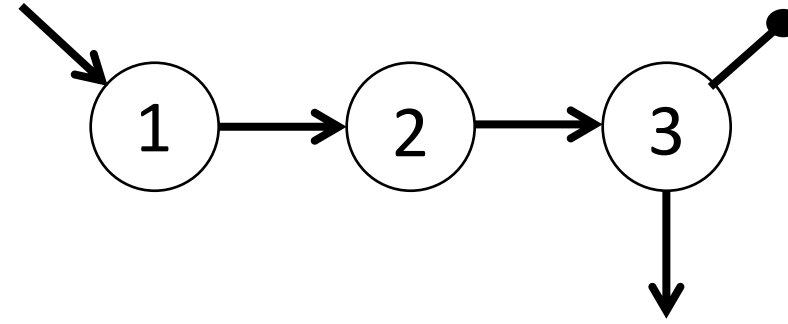
Model 2



I/O eqn:

$$\begin{aligned} \ddot{y}_3 + (a_{21} + a_{02} + a_{32})\ddot{y}_3 \\ + (a_{02}a_{21} + a_{32}a_{21})\dot{y}_3 \\ = a_{32}a_{21}u_1 \end{aligned}$$

Model 4

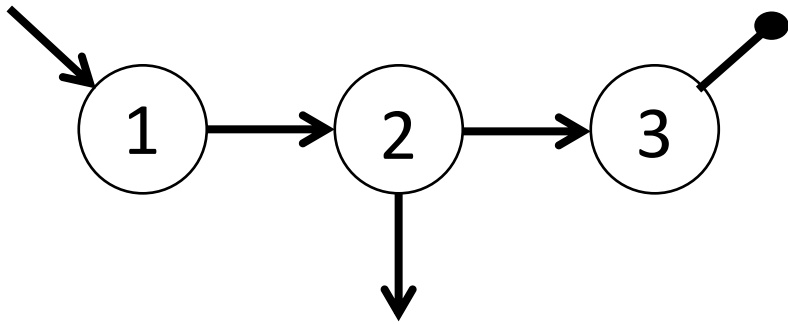


$$\begin{aligned} \ddot{y}_3 + (a_{21} + a_{03} + a_{32})\ddot{y}_3 \\ + (a_{32}a_{21} + a_{32}a_{03})\dot{y}_3 + (a_{21}a_{32}a_{03})y_3 \\ = a_{32}a_{21}u_1 \end{aligned}$$

Not the same I/O eqn structure \Rightarrow Distinguishable!

Distinguishable models:

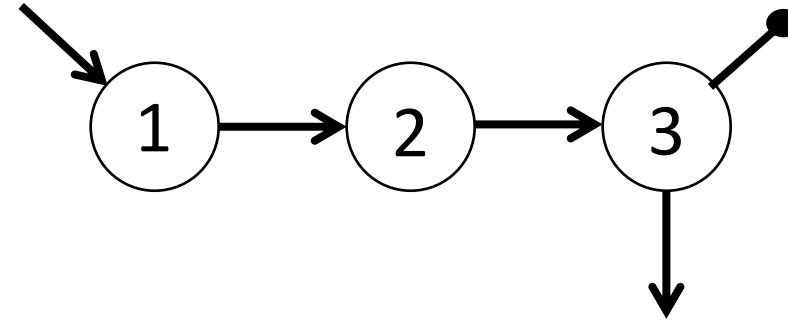
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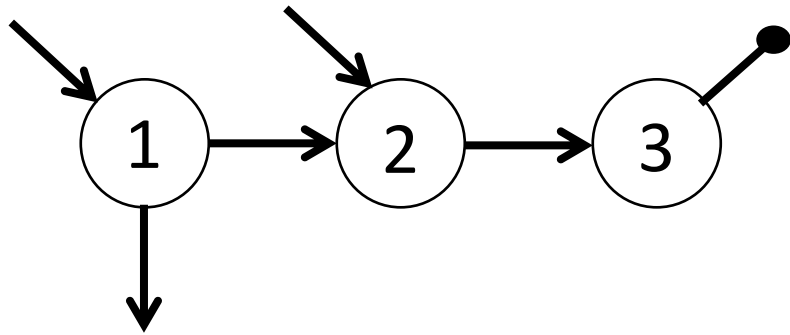


$$\begin{aligned} \ddot{y}_3 + (a_{21} + a_{03} + a_{32})\ddot{y}_3 \\ + (a_{32}a_{21} + a_{32}a_{03})\dot{y}_3 + (a_{21}a_{32}a_{03})y_3 \\ = a_{32}a_{21}u_1 \end{aligned}$$

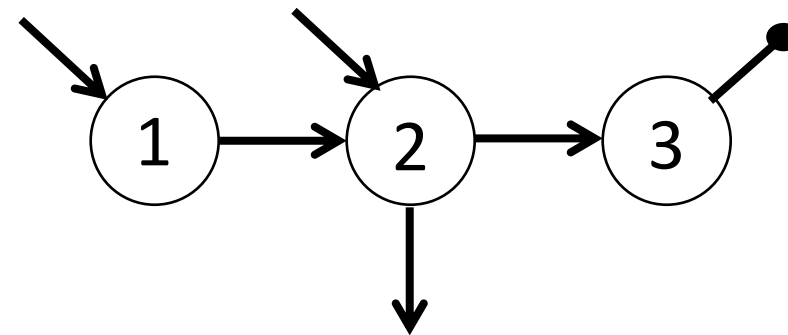
Not the same I/O eqn structure \Rightarrow Distinguishable!

Distinguishable models:

Model 1A



Model 2A



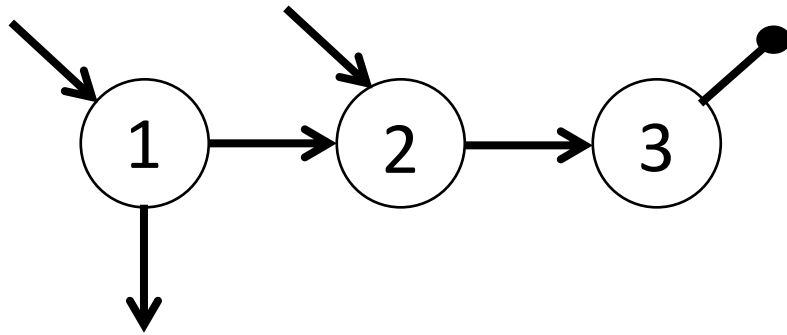
I/O eqn:

$$\ddot{y}_3 + (a_{32} + a_{01} + a_{21})\dot{y}_3 + (a_{01}a_{32} + a_{21}a_{32})\dot{y}_3 = a_{21}a_{32}u_1 + a_{32}\dot{u}_2 + (a_{01}a_{32} + a_{21}a_{32})u_2$$

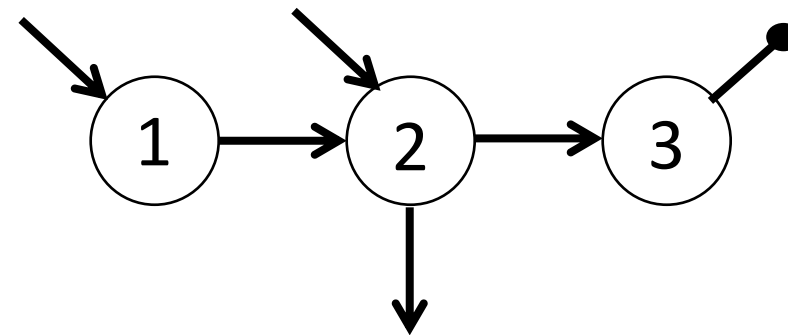
$$\ddot{y}_3 + (a_{21} + a_{02} + a_{32})\dot{y}_3 + (a_{02}a_{21} + a_{21}a_{32})\dot{y}_3 = a_{21}a_{32}u_1 + a_{32}\dot{u}_2 + (a_{21}a_{32})u_2$$

Distinguishable models:

Model 1A



Model 2A



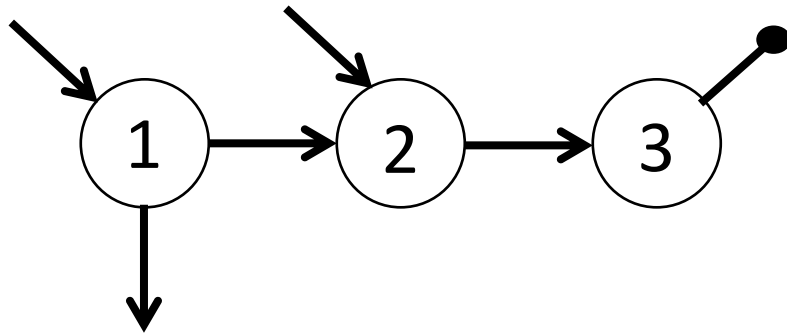
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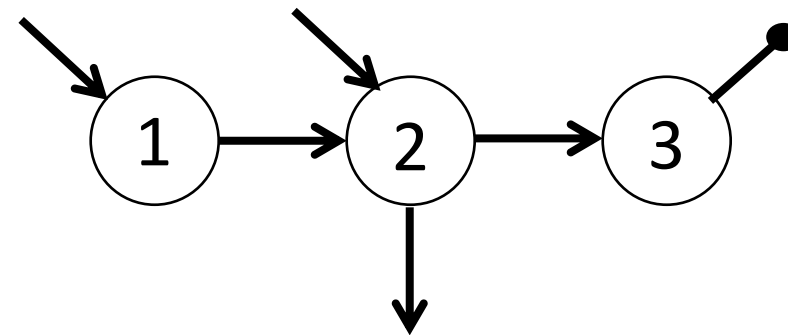
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Distinguishable models:

Model 1A



Model 2A



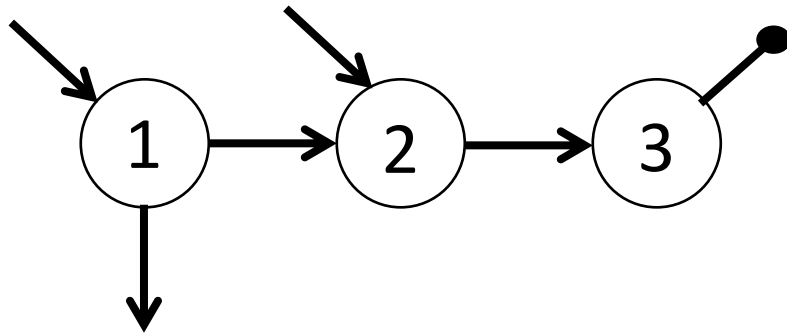
I/O eqn:

$$\ddot{y}_3 + \underbrace{(a_{32} + a_{01} + a_{21})}_{c_1} \dot{y}_3 + \underbrace{(a_{01}a_{32} + a_{21}a_{32})}_{c_2} \dot{y}_3 = \underbrace{a_{21}a_{32}}_{c_3} u_1 + \underbrace{a_{32}\dot{u}_2}_{c_4} + \underbrace{(a_{01}a_{32} + a_{21}a_{32})}_{c_5} u_2$$

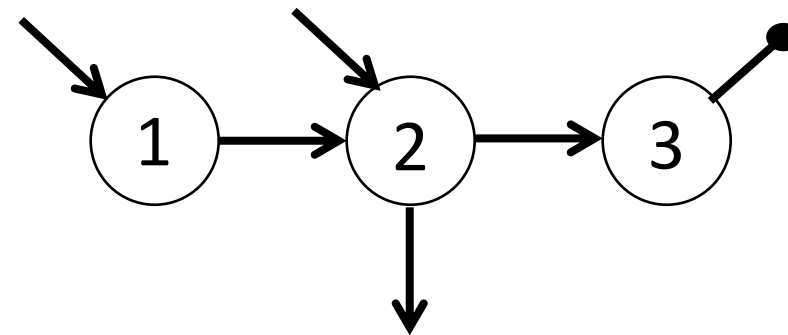
$$\ddot{y}_3 + (a_{21} + a_{02} + a_{32}) \dot{y}_3 + (a_{02}a_{21} + a_{21}a_{32}) \dot{y}_3 = a_{21}a_{32}u_1 + a_{32}\dot{u}_2 + (a_{21}a_{32})u_2$$

Distinguishable models:

Model 1A



Model 2A



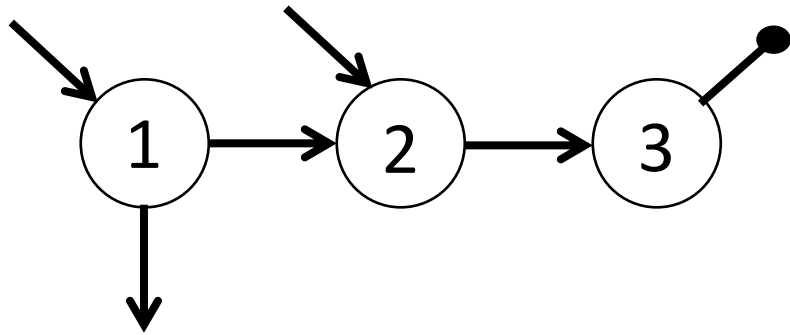
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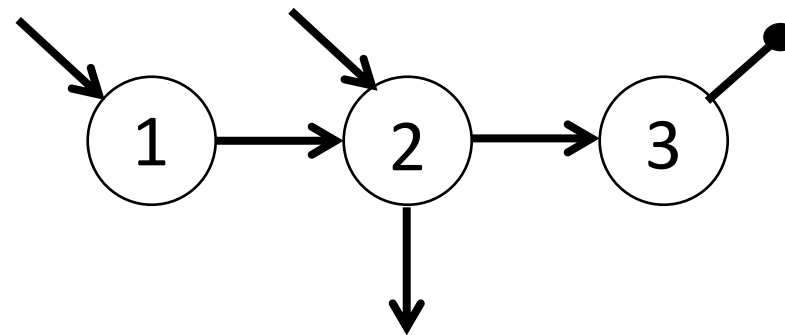
$$\ddot{y}_3 + \overbrace{(a_{21} + a_{02} + a_{32})}^{c_1}\dot{y}_3 + \overbrace{(a_{02}a_{21} + a_{21}a_{32})}^{c_2}\dot{y}_3 = \overbrace{a_{21}a_{32}}^{c_3}u_1 + \underbrace{a_{32}}_{c_4}\dot{u}_2 + \underbrace{(a_{21}a_{32})}_{c_5}u_2$$

Distinguishable models:

Model 1A



Model 2A



Algebraic dependency relationships:

Model 1: $c_2 - c_5 = 0$, $c_1 c_4 - c_4^2 - c_5 = 0$

Model 2: $c_3 - c_5 = 0$, $c_2 c_4^2 - c_1 c_4 c_5 + c_5^2 = 0$

⇒ Distinguishable!

Indistinguishability

Two models are indistinguishable if for any choice of parameter values in the first model, there is a choice of parameter values in the second model that will yield the same dynamics, and vice versa

Necessary conditions:

- Same input/output variables
- Same structure of I/O eqns, i.e. same $u, y, \dot{u}, \dot{y}, \dots$ terms appearing
- Coefficients must satisfy the same algebraic dependency relationships

How to prove indistinguishability?

Indistinguishability

Two models are indistinguishable if for any choice of parameter values in the first model, there is a choice of parameter values in the second model that will yield the same dynamics, and vice versa

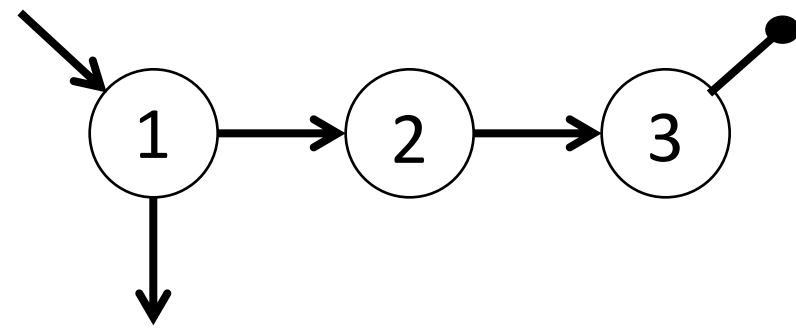
Necessary conditions:

- Same input/output variables
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- Coefficients must satisfy the same algebraic dependency relationships

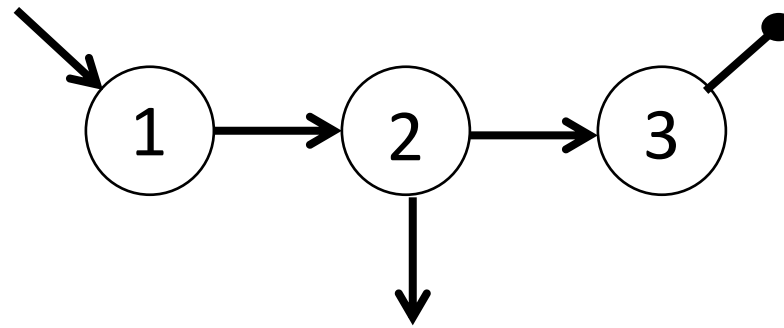
Sufficient: Check that images of coefficient maps are the same

Consider the following models:

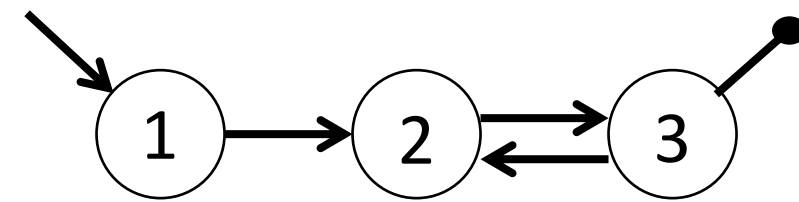
Model 1



Model 2



Model 3



Coefficient maps: all **surjective**

$$a_{32} + a_{01} + a_{21}$$

$$a_{01}a_{32} + a_{21}a_{32}$$

$$a_{21}a_{32}$$

$$a_{21} + a_{02} + a_{32}$$

$$a_{02}a_{21} + a_{32}a_{21}$$

$$a_{32}a_{21}$$

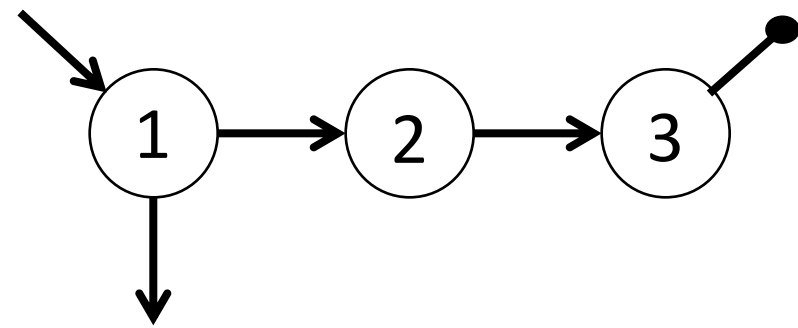
$$a_{21} + a_{23} + a_{32}$$

$$a_{23}a_{21} + a_{32}a_{21}$$

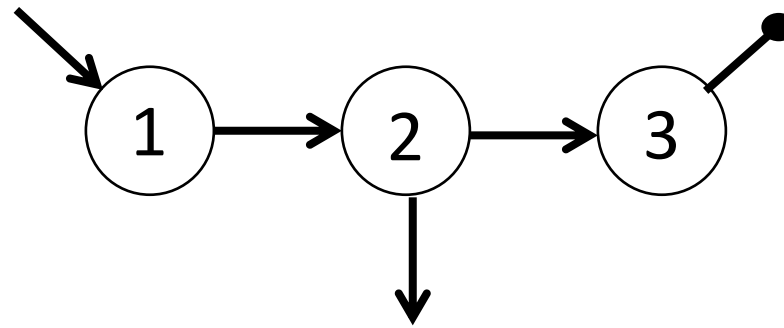
$$a_{32}a_{21}$$

Consider the following models:

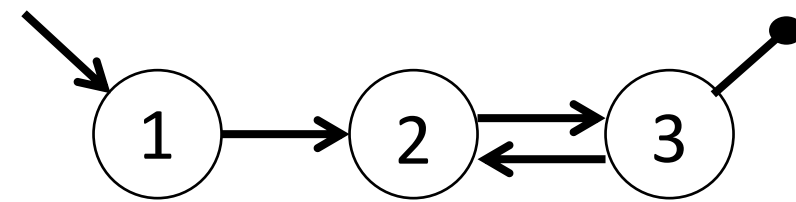
Model 1



Model 2



Model 3



Coefficient maps: all **surjective**

How to tell without computation?

$$a_{32} + a_{01} + a_{21}$$

$$a_{21} + a_{02} + a_{32}$$

$$a_{21} + a_{23} + a_{32}$$

$$a_{01}a_{32} + a_{21}a_{32}$$

$$a_{02}a_{21} + a_{32}a_{21}$$

$$a_{23}a_{21} + a_{32}a_{21}$$

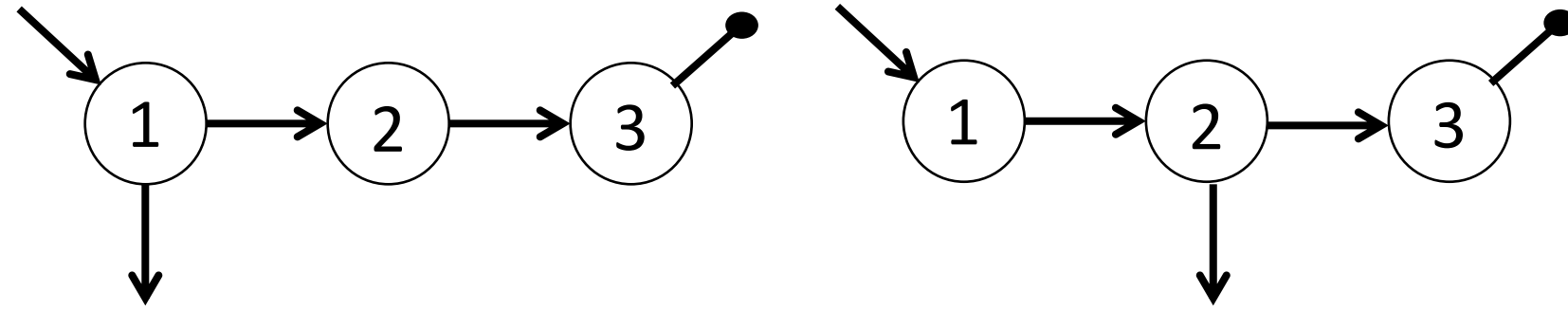
$$a_{21}a_{32}$$

$$a_{32}a_{21}$$

$$a_{32}a_{21}$$

Conditions on graph?

Consider Model 1 and Model 2:

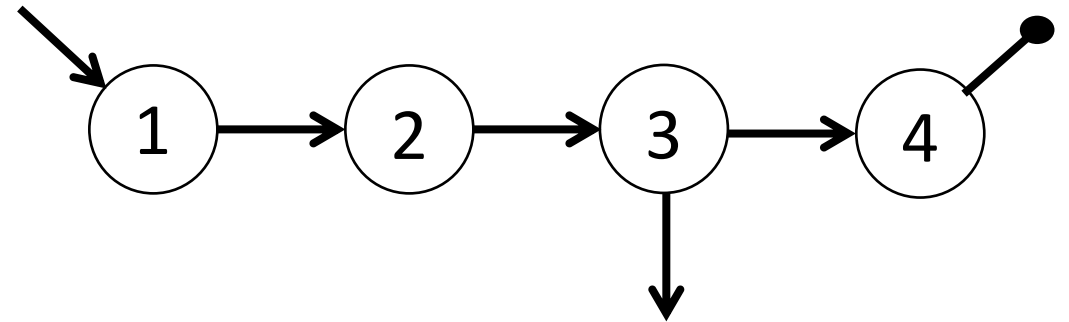
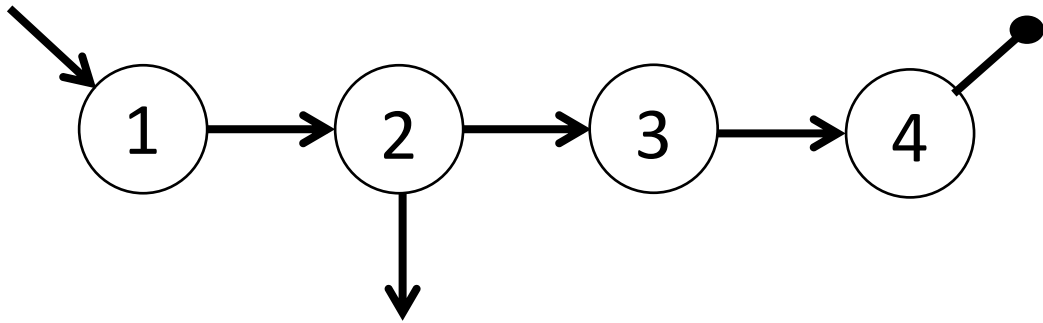


Noticed we “moved the leak down the path”

Can move leak in general

Consider path models with a leak:

- Leak can be in compartment $i = 1, \dots, n - 2$



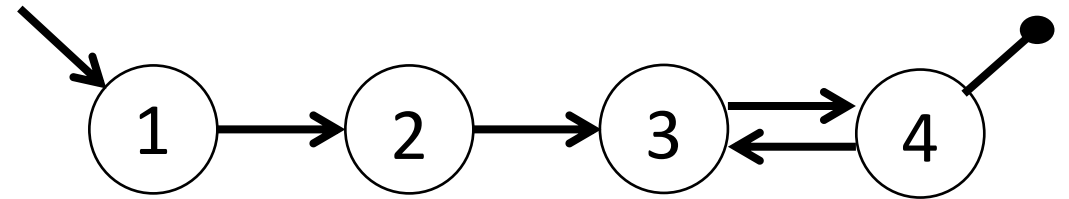
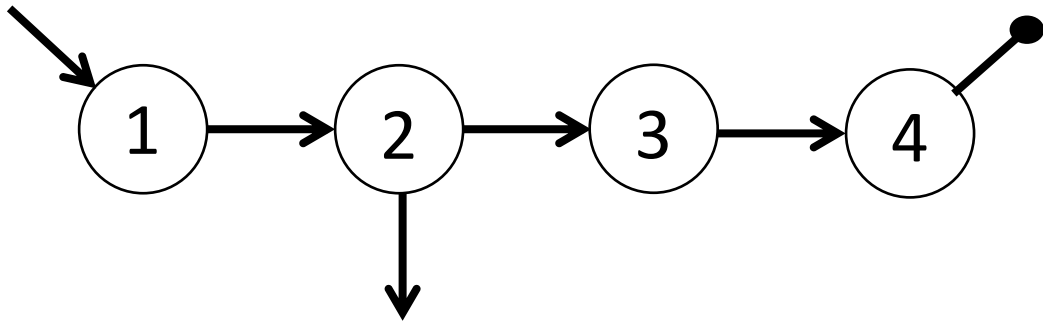
Then we can move the leak down the path

- Leak moves from i to $i + 1$

Can replace leak with backwards edge

Consider path models with a leak:

- Leak can be in compartment $i = 1, \dots, n - 1$



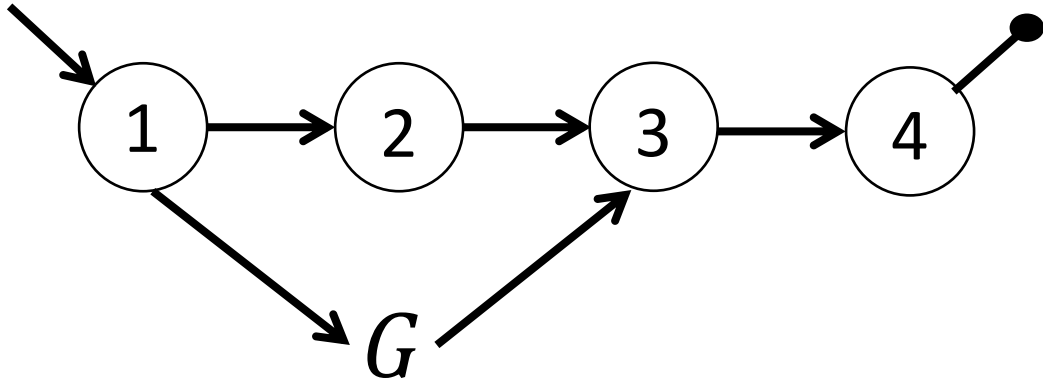
Then we can replace leak with backwards edge

- Edge from compartment n to $n - 1$

Detour indistinguishability

Consider path models with a “detour”:

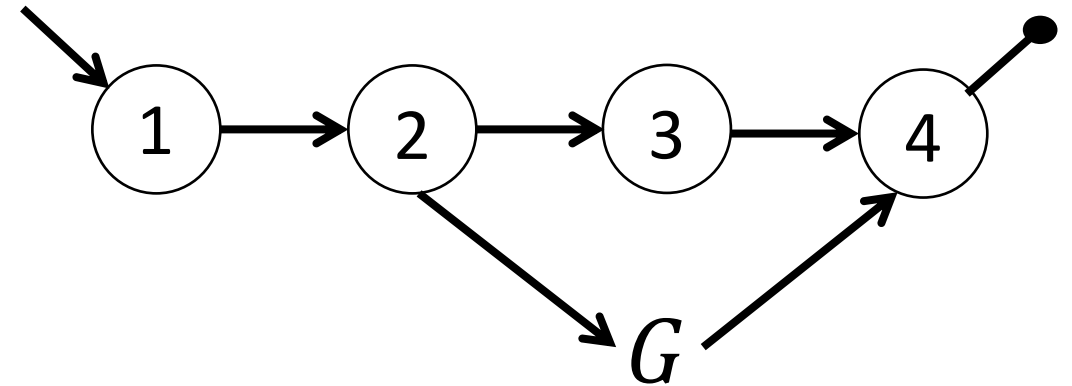
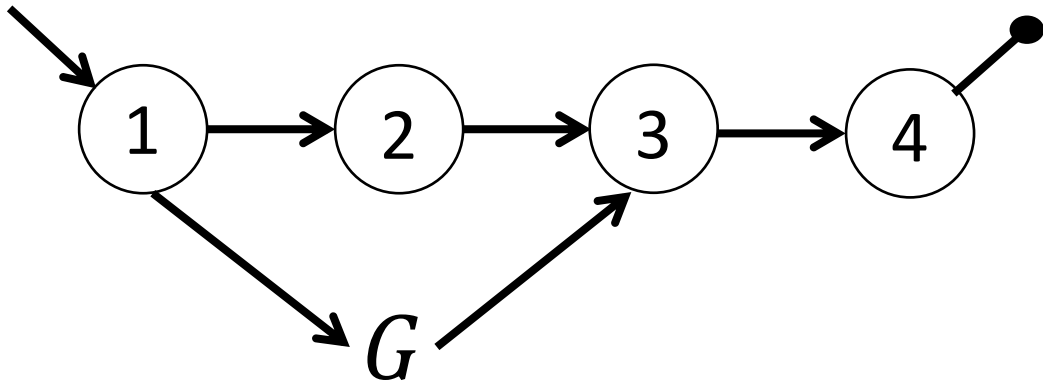
- exit and entry nodes i and j with outgoing and incoming edges connecting to graph G



Detour indistinguishability

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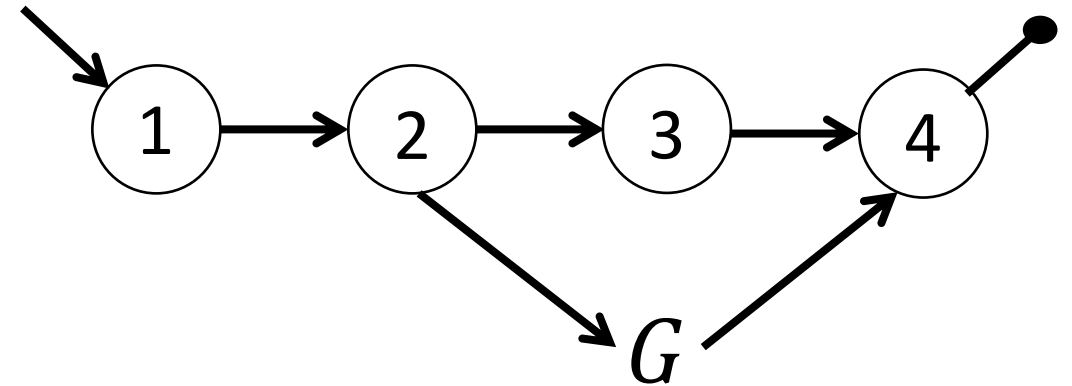
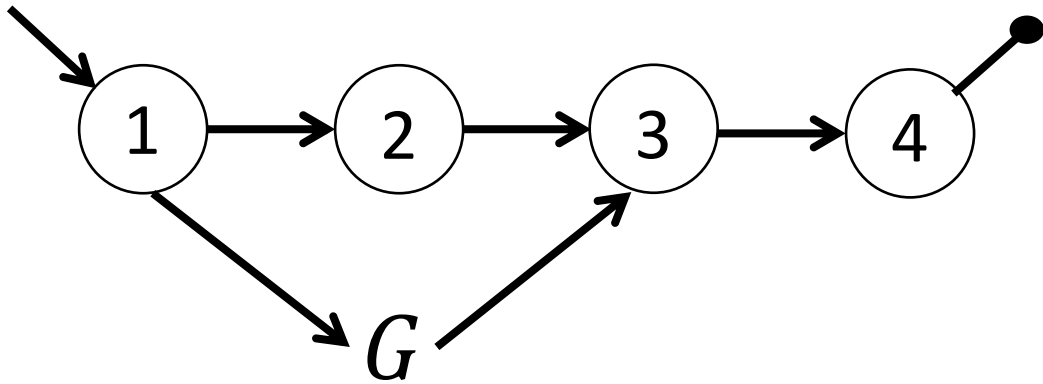
Then we can move the “detour” down the path:

- New exit and entry nodes are $i + k$ and $j + k$

Detour indistinguishability

Consider path models with a “detour”:

- exit and entry nodes i and j with outgoing and incoming edges connecting to graph G



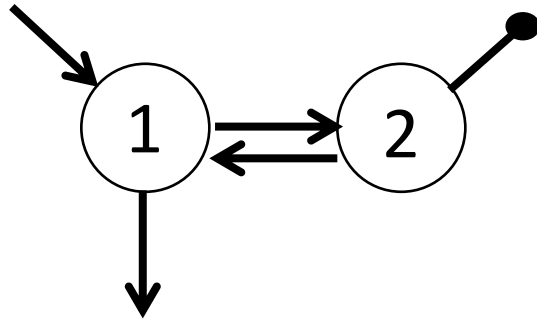
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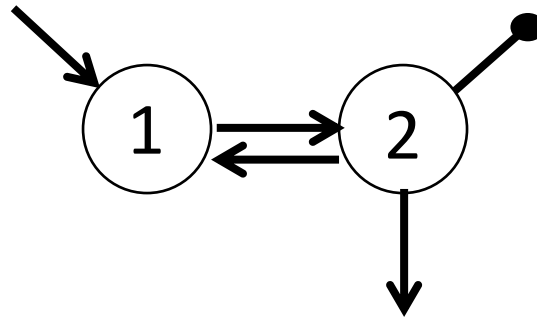
Other families of graphs?

Recall our earlier vaccine models:

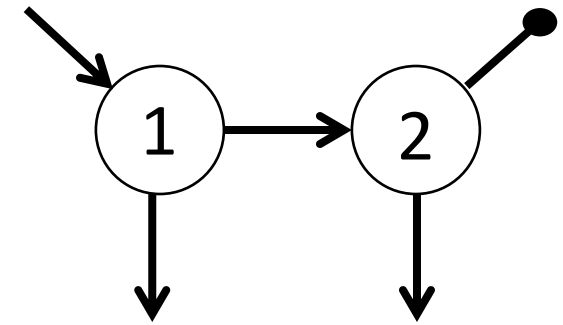
Model A



Model B



Model C



I/O eqn:

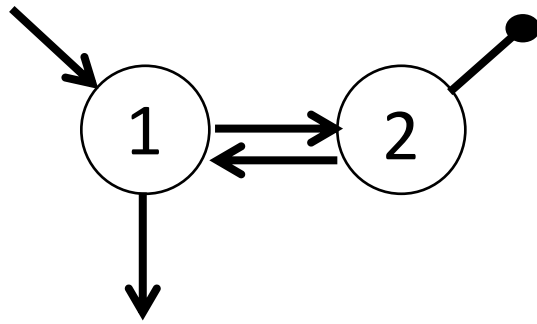
$$\ddot{y}_2 + (a_{01} + a_{12} + a_{21})\dot{y}_2 + a_{01}a_{12}y_2 = a_{21}u_1$$

$$\ddot{y}_2 + (a_{02} + a_{12} + a_{21})\dot{y}_2 + a_{02}a_{21}y_2 = a_{21}u_1$$

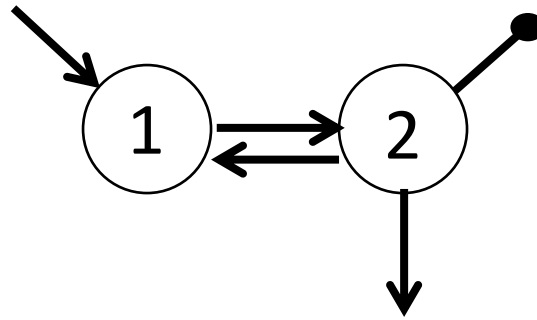
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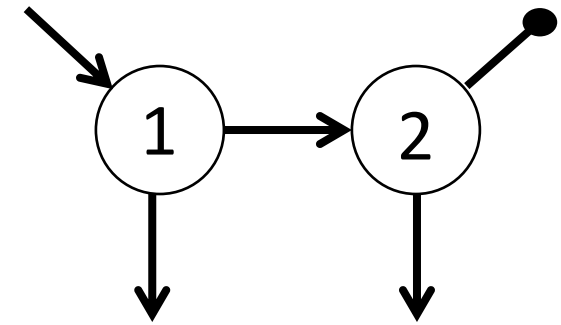
Model A



Model B



Model C



I/O eqn:

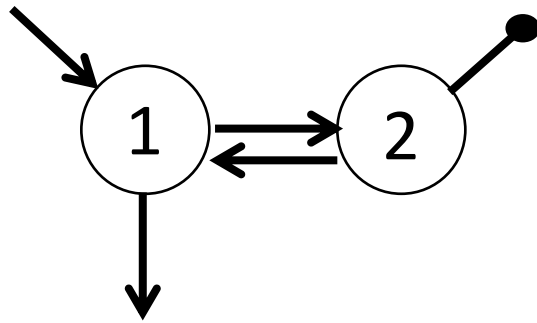
$$\ddot{y}_2 + (a_{01} + a_{12} + a_{21})\dot{y}_2 + a_{01}a_{12}y_2 = a_{21}u_1$$

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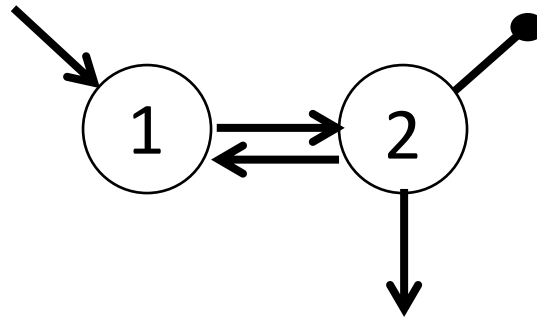
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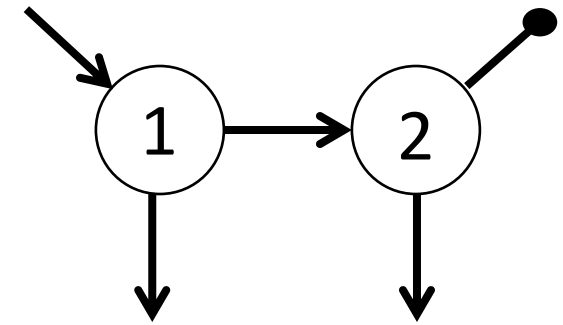
Model A



Model B



Model C



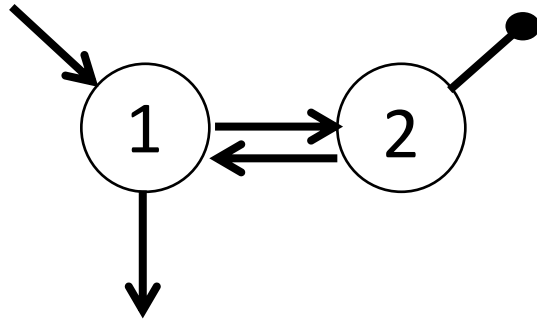
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$$\ddot{y}_2 + (a_{01} + a_{12} + a_{21})\dot{y}_2 + a_{01}a_{12}y_2 = a_{21}u_1$$
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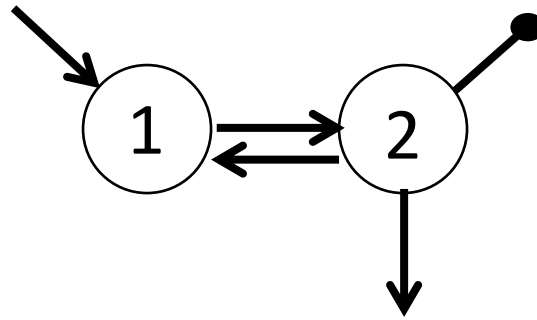
No renaming of parameters results in the same coefficients

Indistinguishable, but not from renaming:

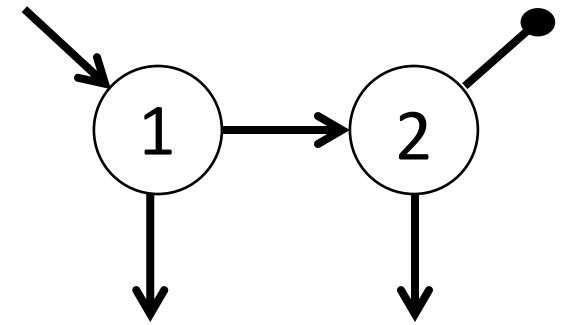
Model A



Model B



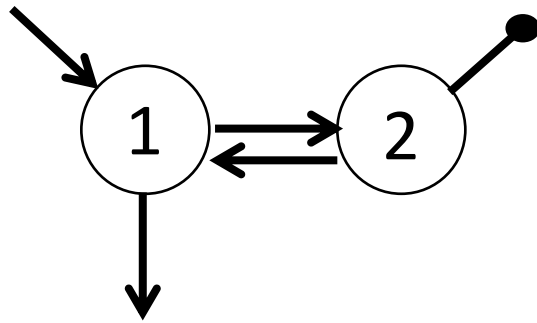
Model C



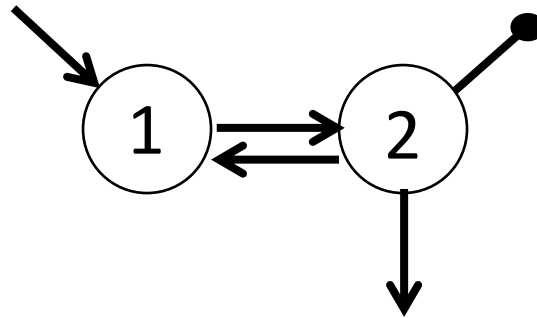
Coeff map: $(a_{01}, a_{12}, a_{21}) \mapsto (a_{01} + a_{12} + a_{21}, a_{01}a_{12}, a_{21})$
 $(a_{02}, a_{12}, a_{21}) \mapsto (a_{02} + a_{12} + a_{21}, a_{02}a_{21}, a_{21})$
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Indistinguishable, but not from renaming:

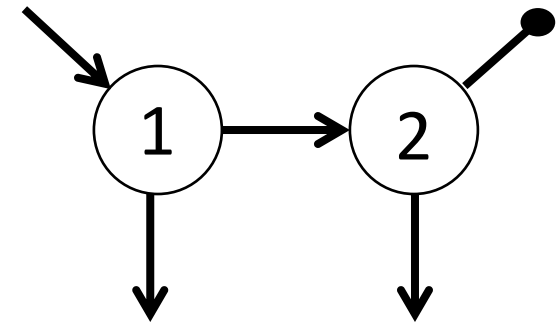
Model A



Model B



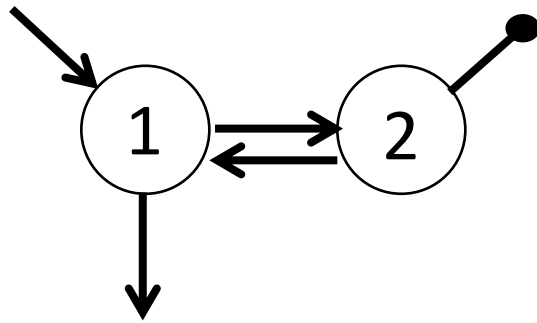
Model C



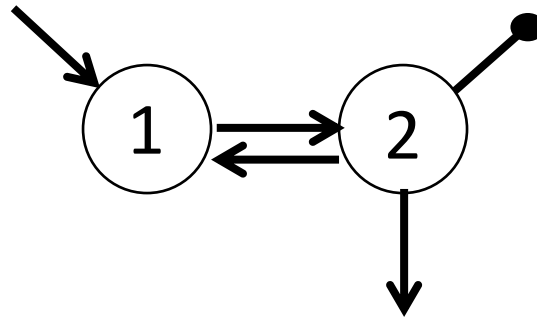
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 $(a_{01}, a_{21}, a_{02}) \mapsto (a_{01} + a_{21} + a_{02}, a_{01}a_{02} + a_{21}a_{02}, a_{21})$
Identifiable and indistinguishable

Indistinguishable, but not from renaming:

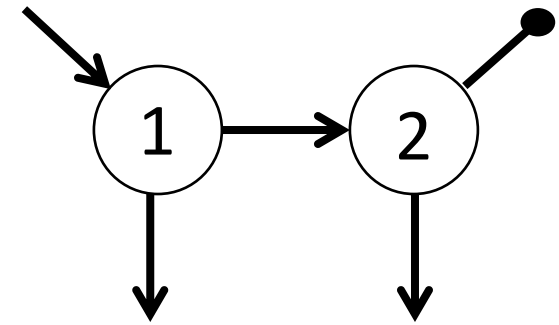
Model A



Model B



Model C



Coeff map: $(a_{01}, a_{12}, a_{21}) \mapsto (a_{01} + a_{12} + a_{21}, a_{01}a_{12}, a_{21})$
 $(a_{02}, a_{12}, a_{21}) \mapsto (a_{02} + a_{12} + a_{21}, a_{02}a_{21}, a_{21})$
 $(a_{01}, a_{21}, a_{02}) \mapsto (a_{01} + a_{21} + a_{02}, a_{01}a_{02} + a_{21}a_{02}, a_{21})$

Special case: #params = #coeffs, identifiable \Leftrightarrow indistinguishable

So what does this all mean?

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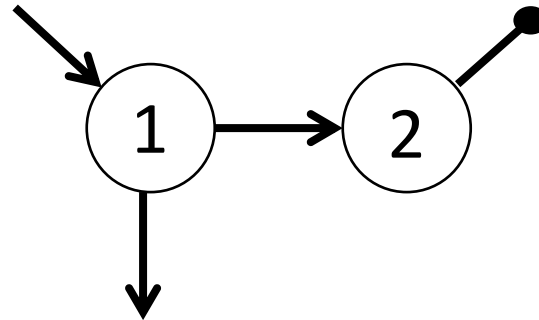
- Does it mean my original model is bad?
 - No!
 - Just says with limited data, there's lots of models that can fit
- If a bunch of models work, is there a best one to choose?
 - Oftentimes, yes
 - Certain models may make more sense in terms of the rate constants to estimate

So what does this all mean?

- Do there exist models with:
 - specified inputs/outputs,
 - specified number of compartments, number of parametersthat are distinguishable from all other models with those specs?

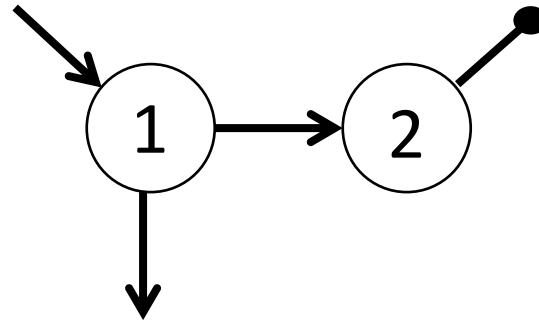
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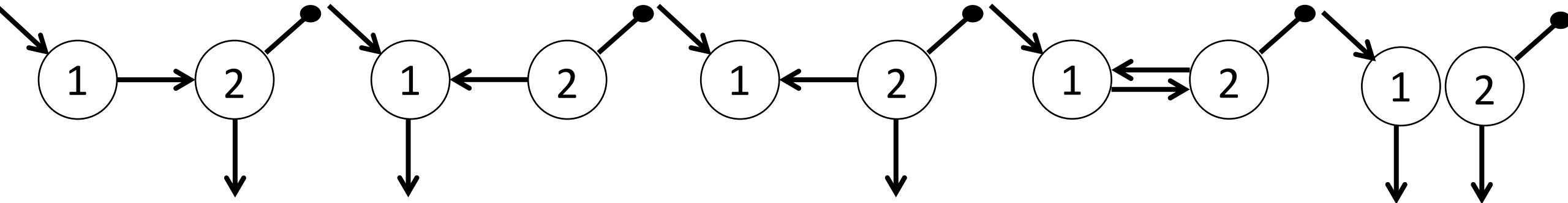


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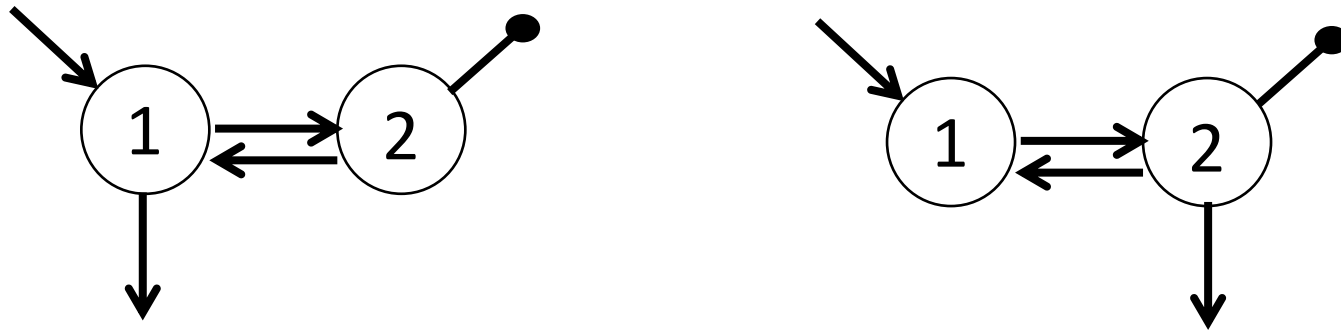


- Distinguishable from



Back to Model A and Model B...

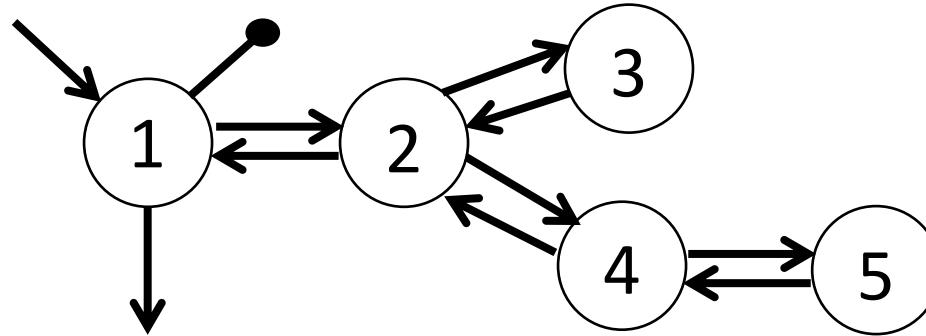
- Recall these models are identifiable



- Belong to the same “family” of models

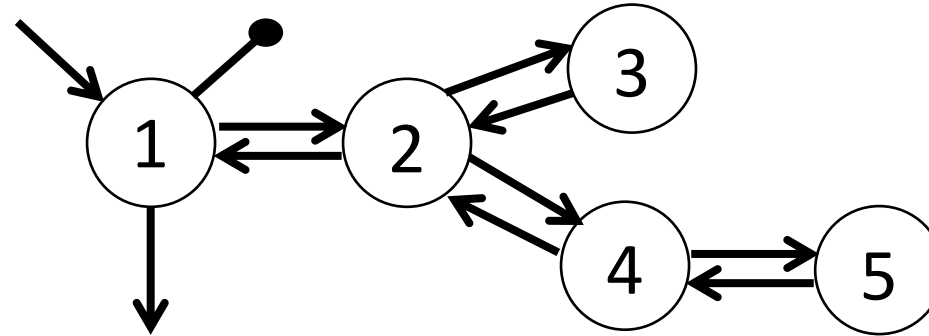
What families of models are **identifiable**?

- Bidirectional tree models



What families of models are **identifiable**?

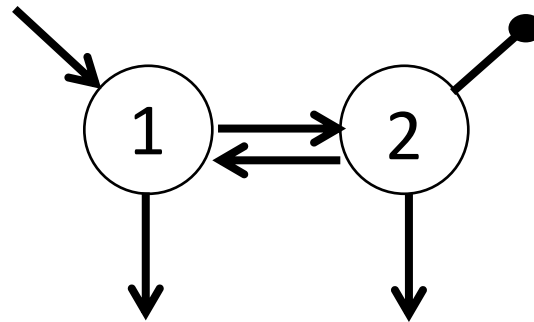
- Bidirectional tree models



- Theorem [Gross et al 2023]: Let M be a bidirectional tree model with single input and output. M is locally identifiable \Leftrightarrow input and output are **at most 1 compartment away** and there is **at most 1 leak**.

What families of models are **identifiable**?

- Bidirectional tree models

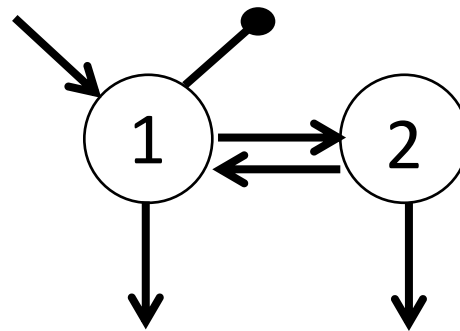


Unidentifiable

- Theorem [Gross et al 2023]: Let M be a bidirectional tree model with single input and output. M is locally identifiable \Leftrightarrow input and output are **at most 1 compartment away** and there is **at most 1 leak**.

What families of models are **identifiable**?

- Bidirectional tree models

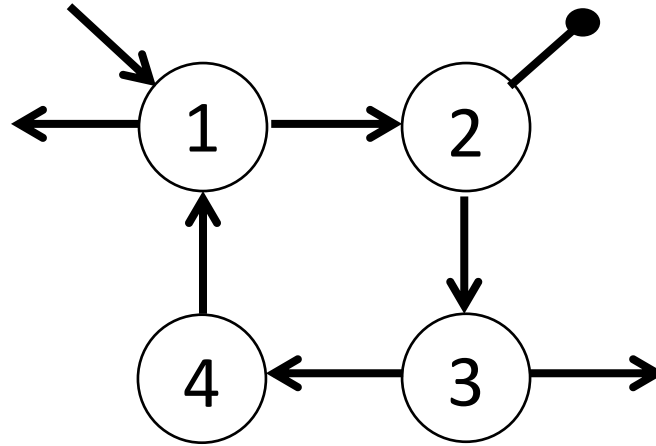


Unidentifiable

- Theorem [Gross et al 2023]: Let M be a bidirectional tree model with single input and output. M is locally identifiable \Leftrightarrow input and output are **at most 1 compartment away** and there is **at most 1 leak**.

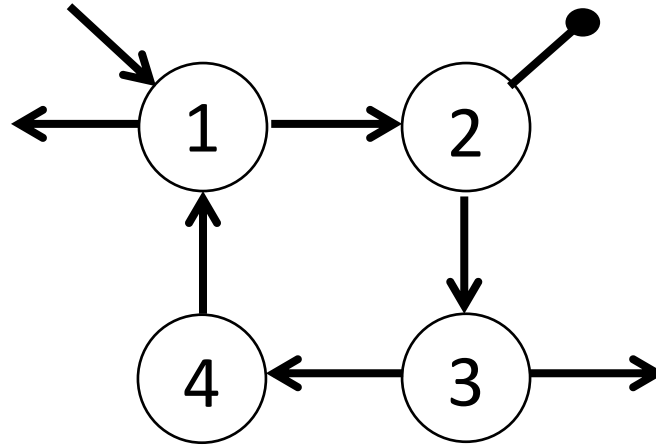
What families of models are **identifiable**?

- Cycle models



What families of models are **identifiable**?

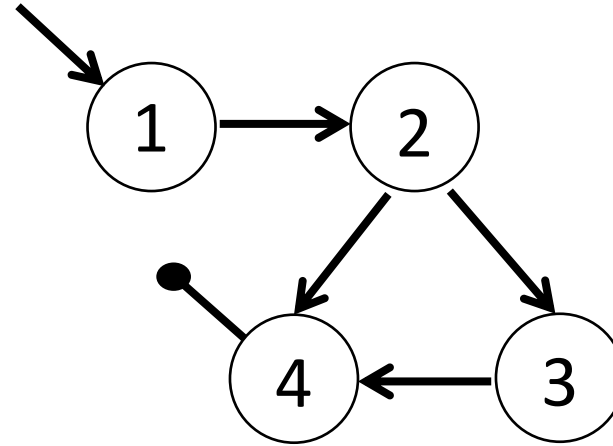
- Cycle models



- Theorem [Saber et al 2024]: A directed-cycle model is locally identifiable \Leftrightarrow it is **leak-interlacing** (between any two leaks there is an input or output)

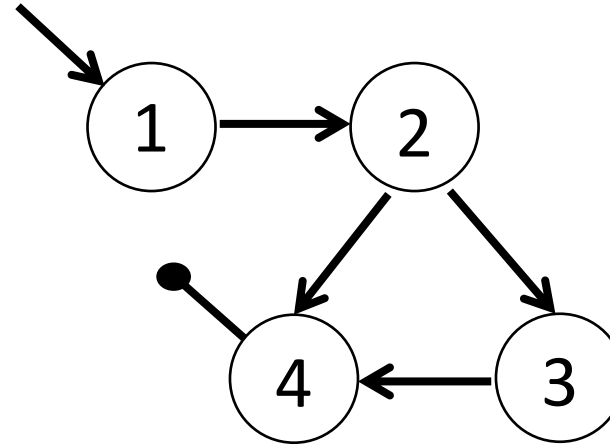
What families of models are **identifiable**?

- Acyclic models



What families of models are **identifiable**?

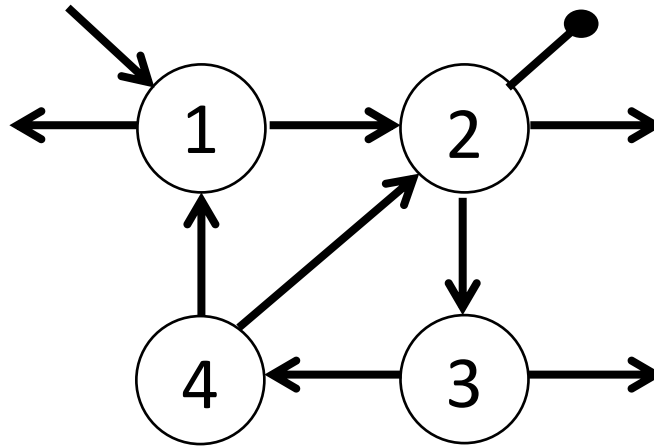
- Acyclic models



- Theorem [Bortner-M, in progress]: Let M be an acyclic model with a single input, single output, no leaks. M is locally identifiable \Leftrightarrow it is **input-output connectable** (every vertex lies on a path from input to output) and has ≤ 1 vertex with > 1 outgoing edges

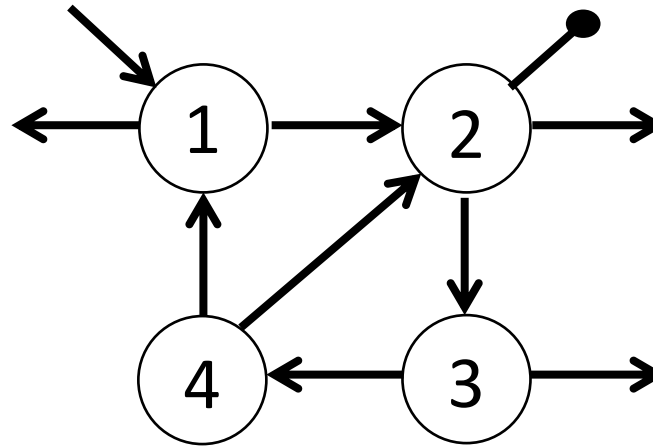
What families of models are **unidentifiable**?

- Strongly connected models w/ too many leaks



What families of models are **unidentifiable**?

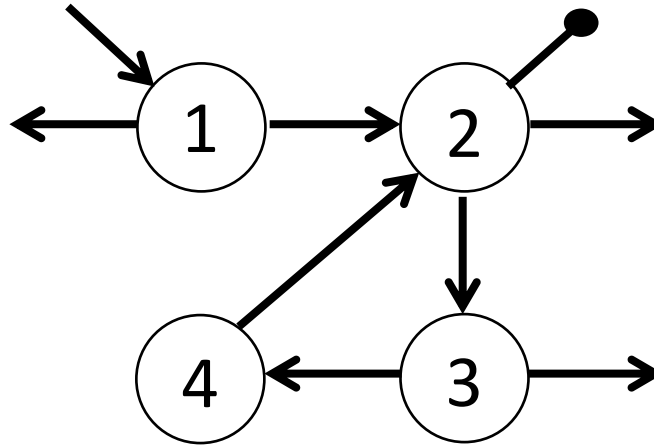
- Strongly connected models w/ too many leaks



- Theorem [Bortner-M 2022]: Let G be strongly connected with one input. If the **number of leaks is greater than the number of I/O compartments**, then M is unidentifiable.

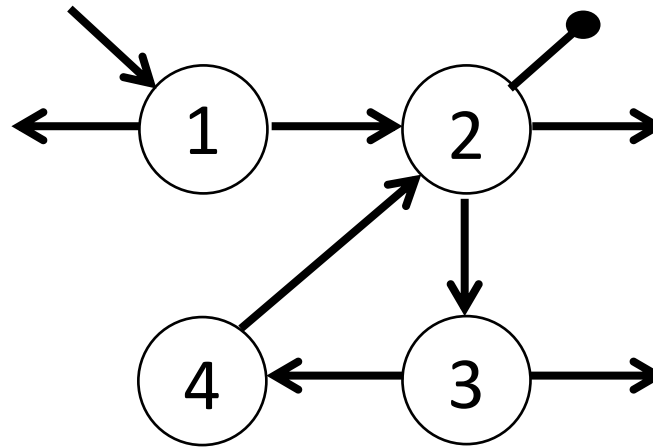
What families of models are **unidentifiable**?

- Strongly input-output connected models w/ too many leaks



What families of models are **unidentifiable**?

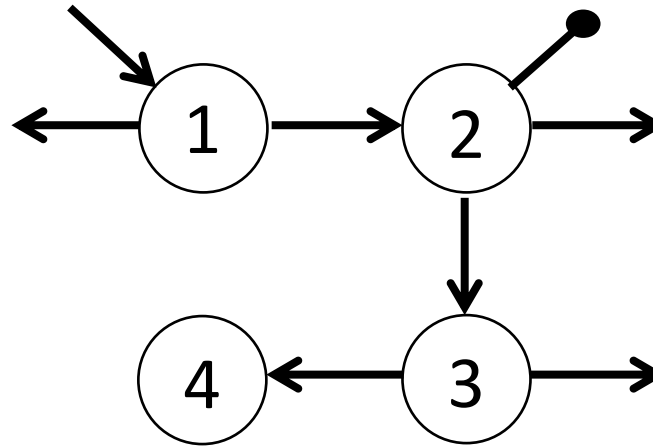
- Strongly input-output connected models w/ too many leaks



- Theorem [Bortner-M 2022]: Let G be strongly input-output connected with one output. If the **number of leaks is greater than the number of I/O compartments**, then M is unidentifiable.

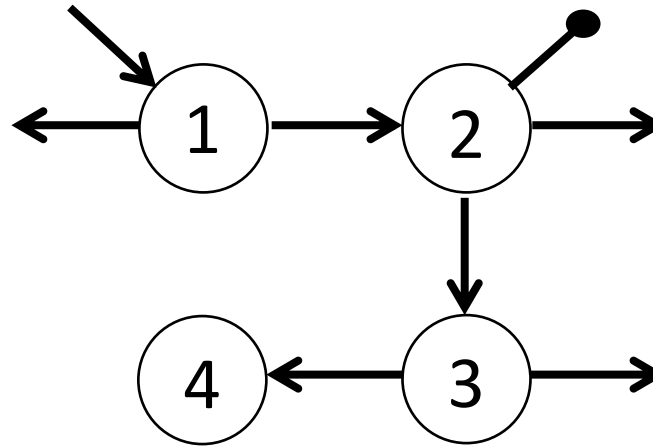
What families of models are **unidentifiable**?

- Not output-connectable



What families of models are **unidentifiable**?

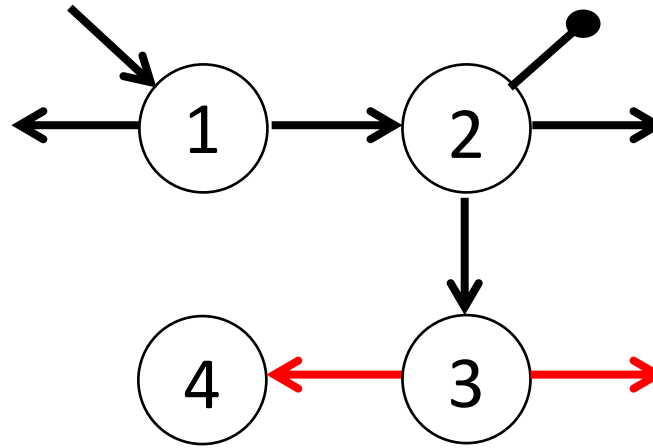
- Not output-connectable



- Theorem [Gross et al 2019]: Let G be a graph that is **not output-connectable**. Then the model is unidentifiable.

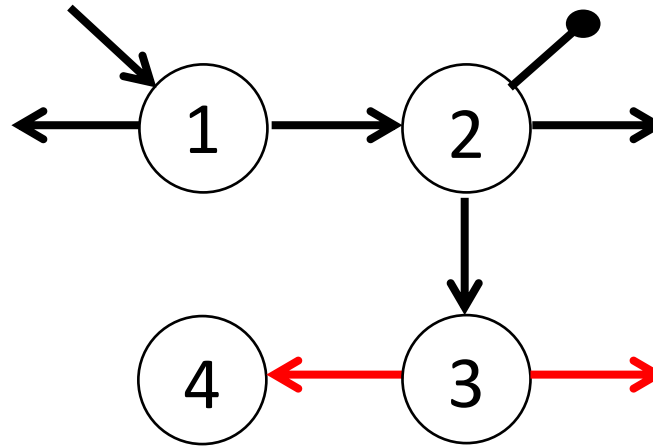
What parameters are unidentifiable?

- Not in output-reachable subgraph



What parameters are unidentifiable?

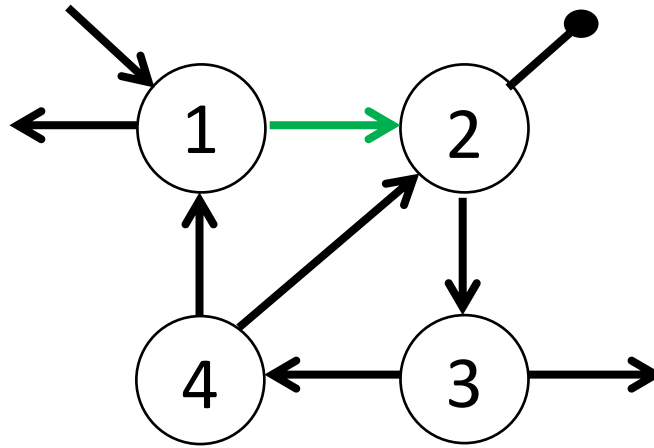
- Not in output-reachable subgraph



- Theorem [Gross et al 2019]: Let j be a compartment **not in the output-reachable subgraph**. Then the parameters a_{0j} , a_{kj} are unidentifiable (if they are nonzero).

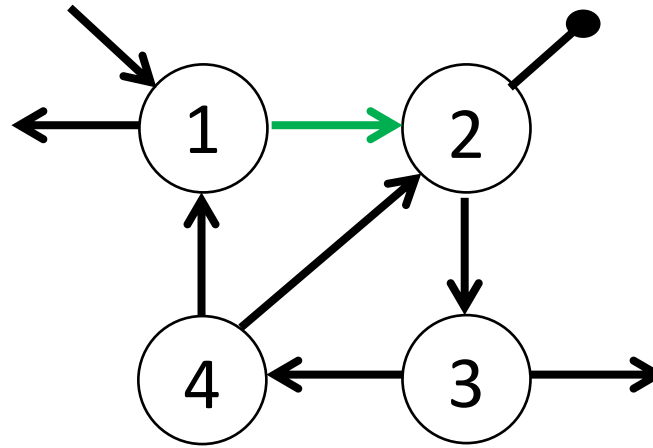
What parameters are **globally identifiable**?

- Edge from input to output in strongly connected graph



What parameters are globally identifiable?

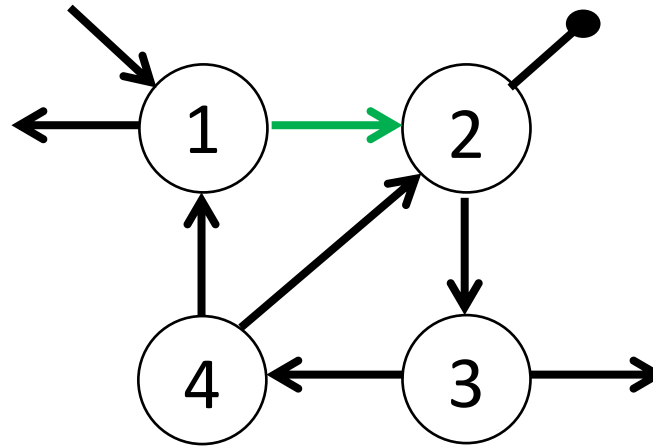
- Edge from input to output in strongly connected graph



- Theorem [Clemens et al 2025]: Let G be a strongly connected graph with input in compartment i and output in compartment j . Then the edge a_{ji} is globally identifiable (if it is nonzero).

What parameters are globally identifiable?

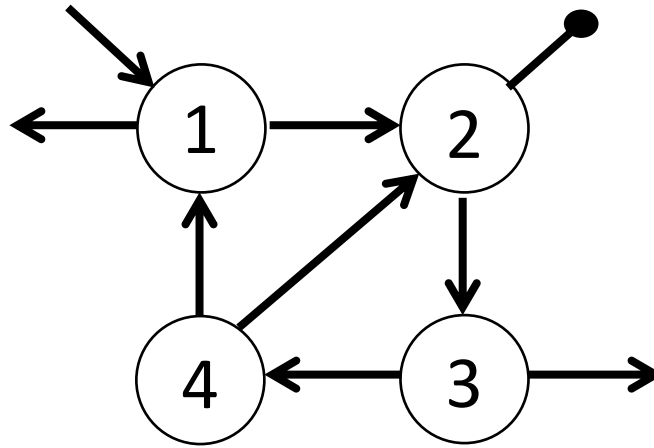
- Edge from input to output in strongly connected graph



- Theorem [Clemens et al 2025]: Let G be a strongly connected graph with input in compartment i and output in compartment j . Then the edge a_{ji} is globally identifiable (if it is nonzero).
- What about the full model itself?

The dream: is a given model identifiable?

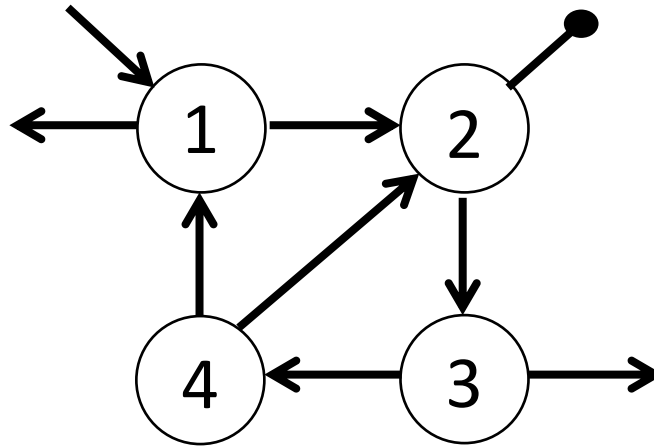
- Model doesn't satisfy previous assumptions



- Is this identifiable or unidentifiable?

The dream: is a given model identifiable?

- Model doesn't satisfy previous assumptions

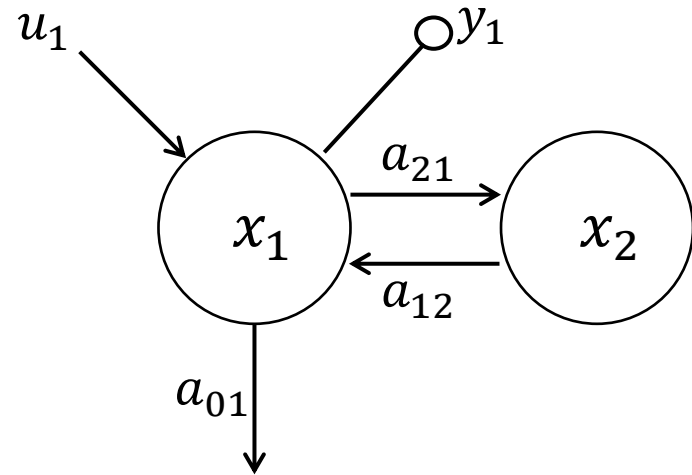


- Is this identifiable or unidentifiable?
- More on this in recent review paper [M-Shiu 2025]

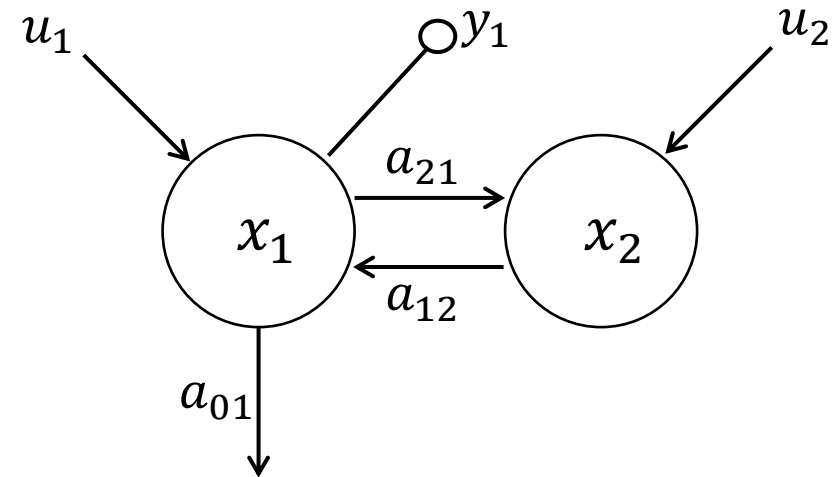
Other interesting questions

Operations that preserve identifiability

- Adding inputs/outputs



Identifiable

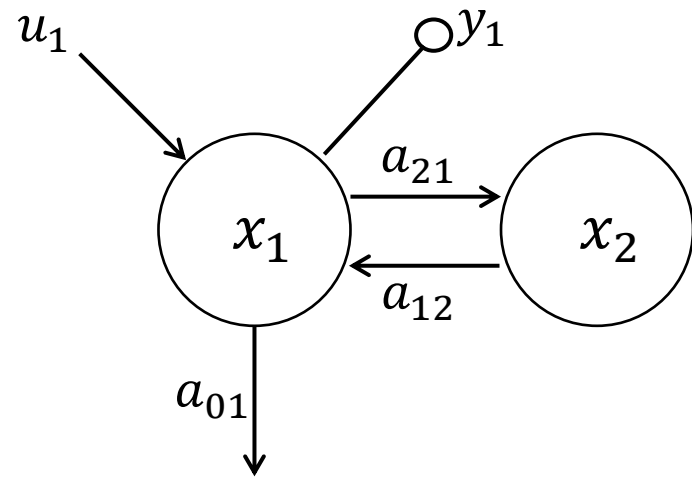


Identifiable

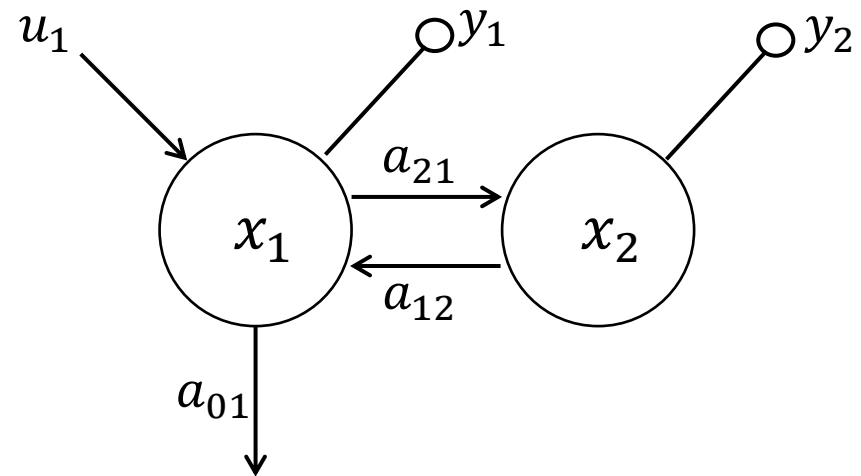
Other interesting questions

Operations that preserve identifiability

- Adding inputs/outputs



Identifiable

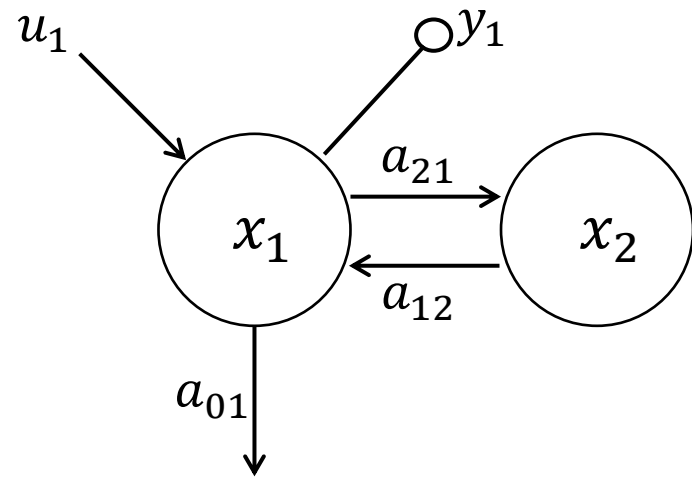


Identifiable

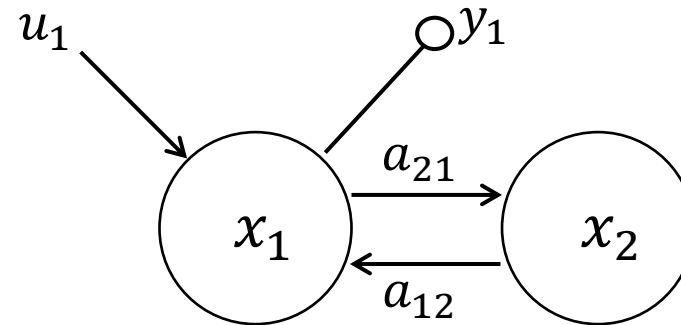
Other interesting questions

Operations that preserve identifiability

- Removing a leak from a strongly connected model w/ single input/output/leak in the same compartment [Gross et al 2019]



Identifiable

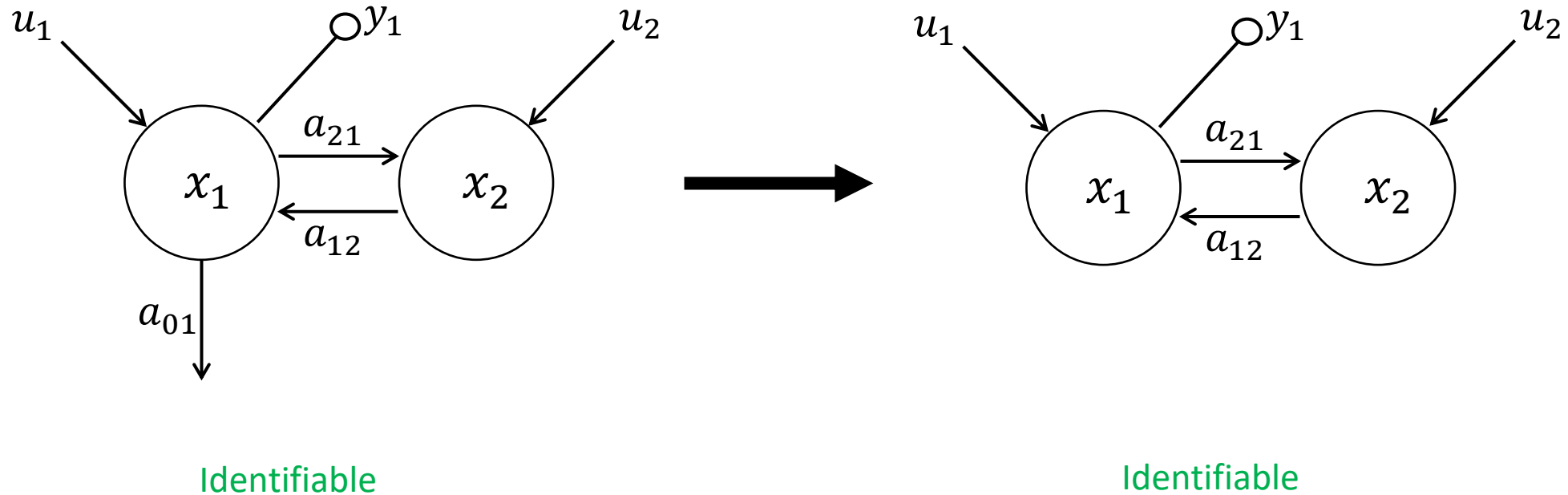


Identifiable

Other interesting questions

Operations that preserve identifiability

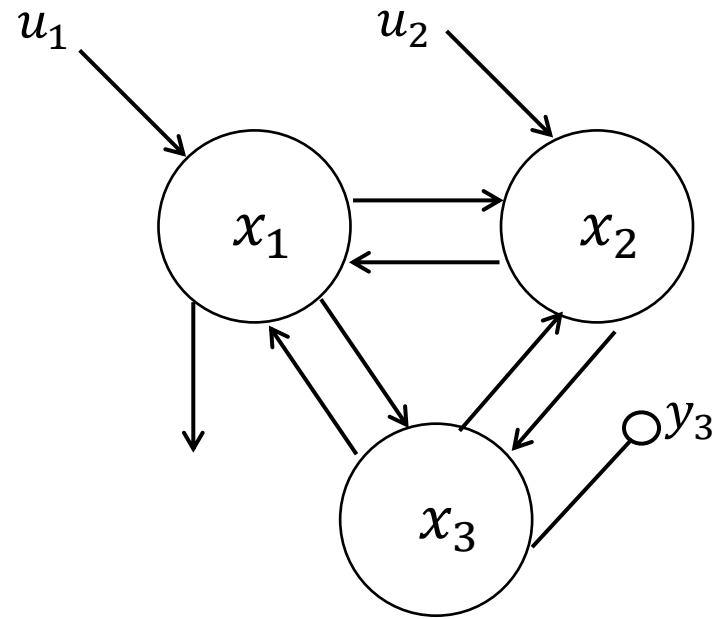
- Conjecture [Gross et al 2019]: For a strongly connected model with at least one input and output and exactly 1 leak, removing the leak preserves identifiability



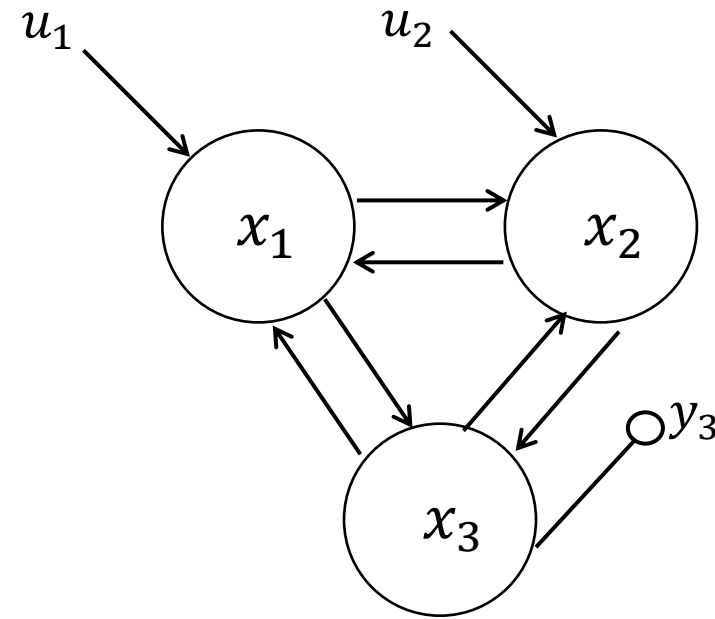
Other interesting questions

Operations that preserve identifiability

- Counterexample [Gogishvili 2024]:



Identifiable

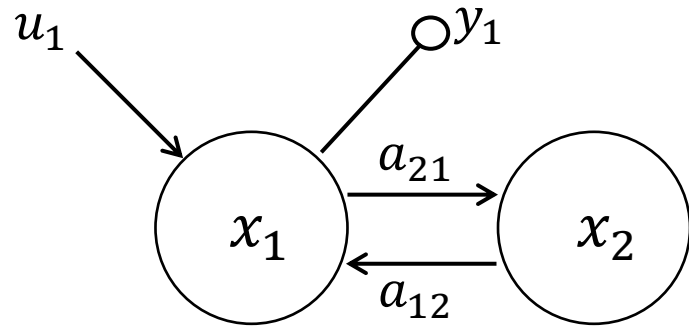


Unidentifiable

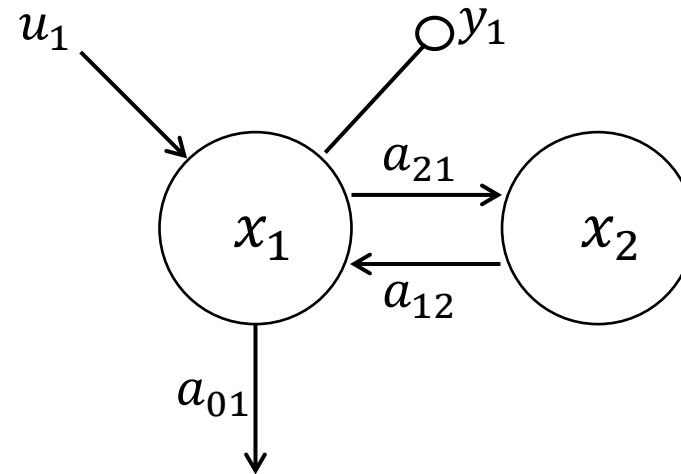
Other interesting questions

Operations that preserve identifiability

- Adding a leak to a strongly connected model w/o leaks [Gross et al 2019]



Identifiable

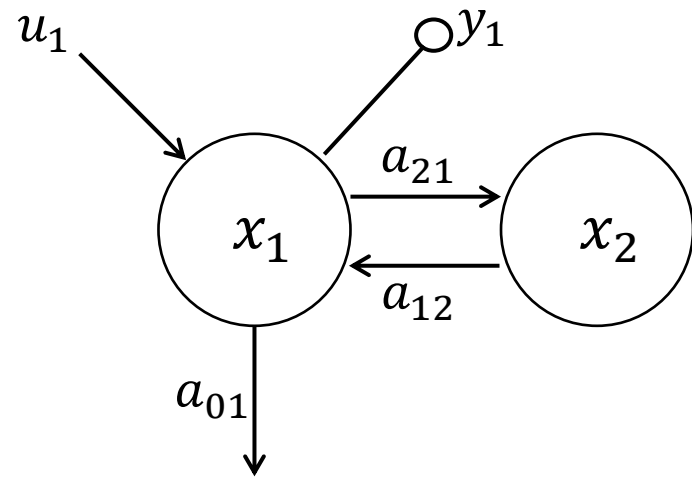


Identifiable

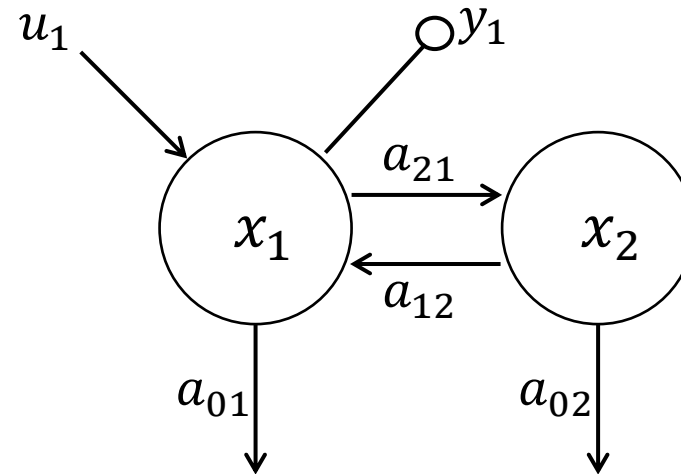
Other interesting questions

Operations that preserve identifiability

- Warning: having no leaks to begin with is necessary!



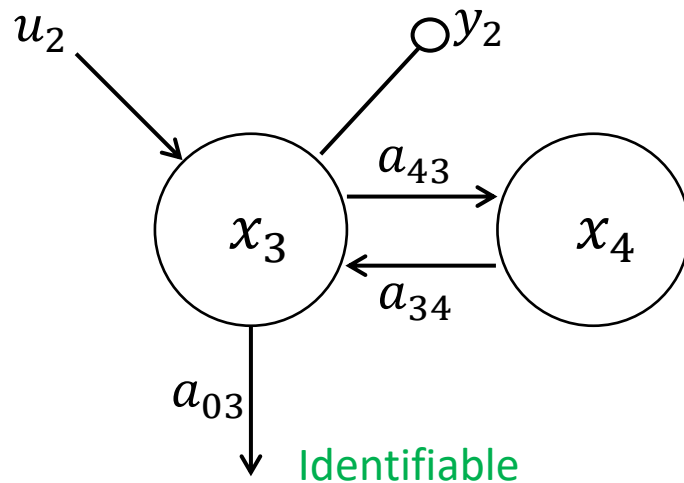
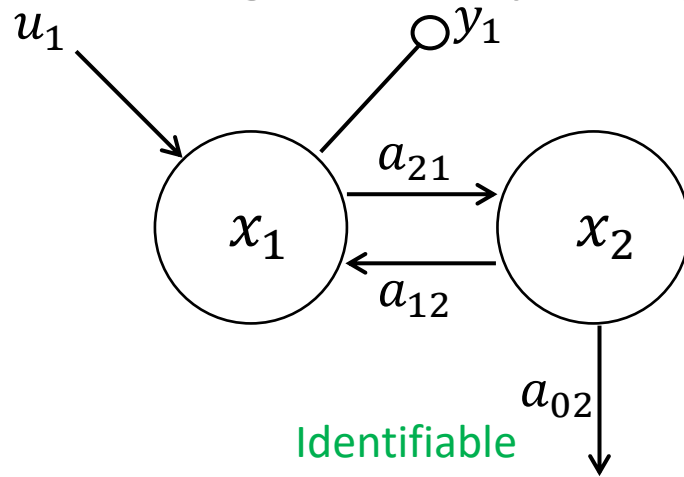
Identifiable



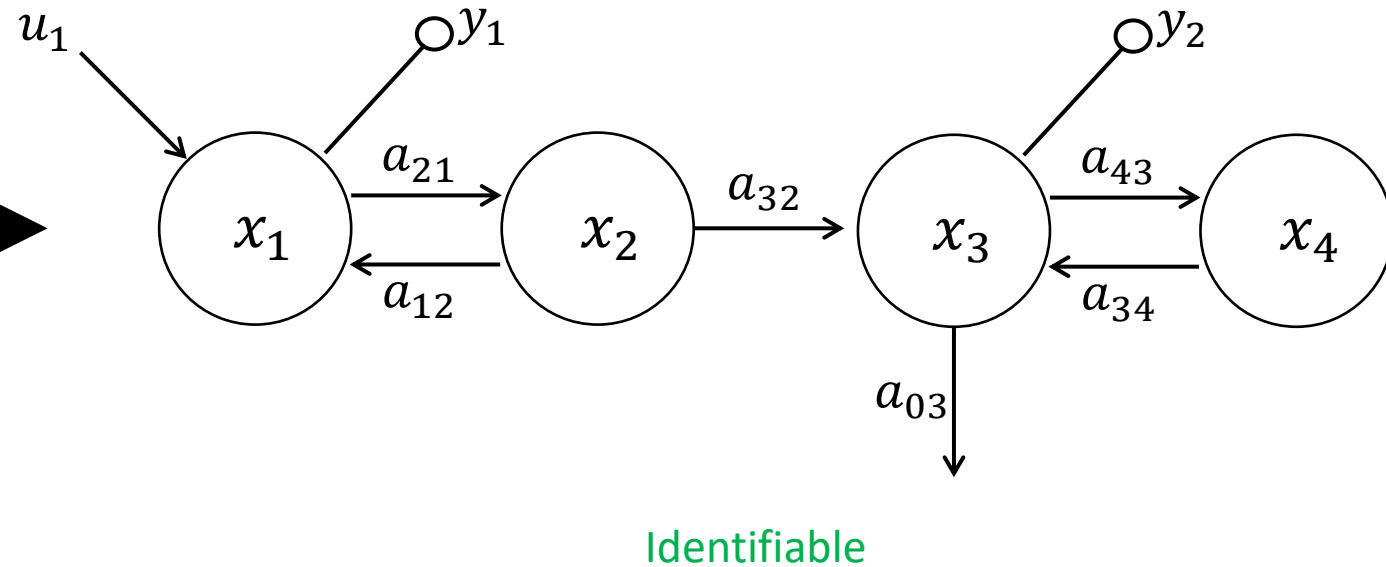
Unidentifiable

Other interesting questions

Joining/decomposing identifiable models

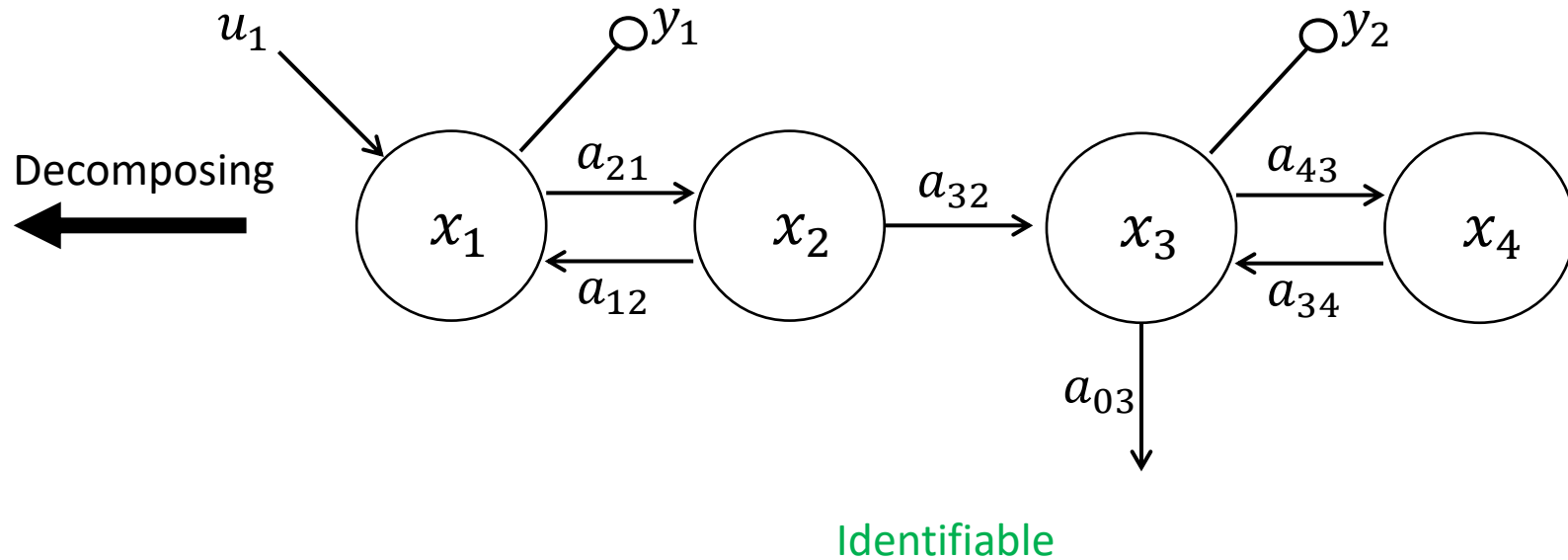
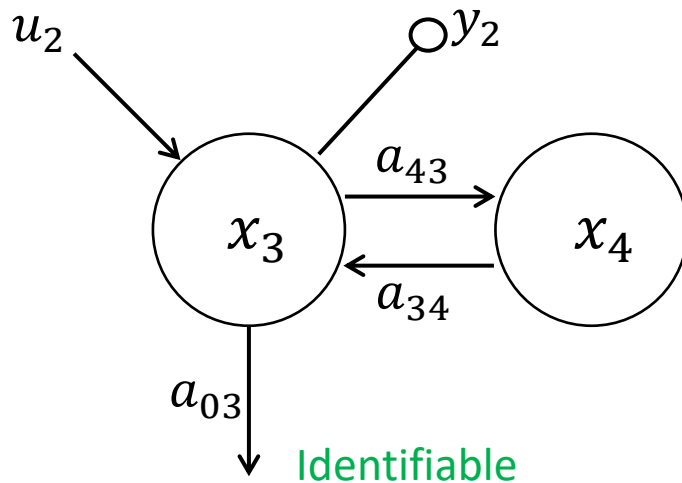
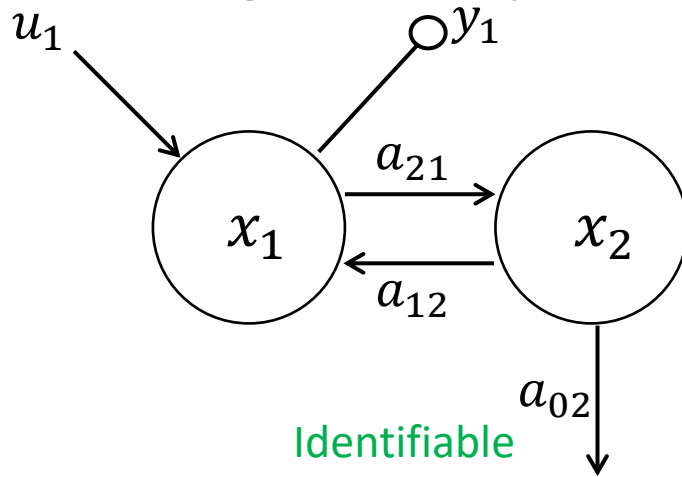


Joining
➔



Other interesting questions

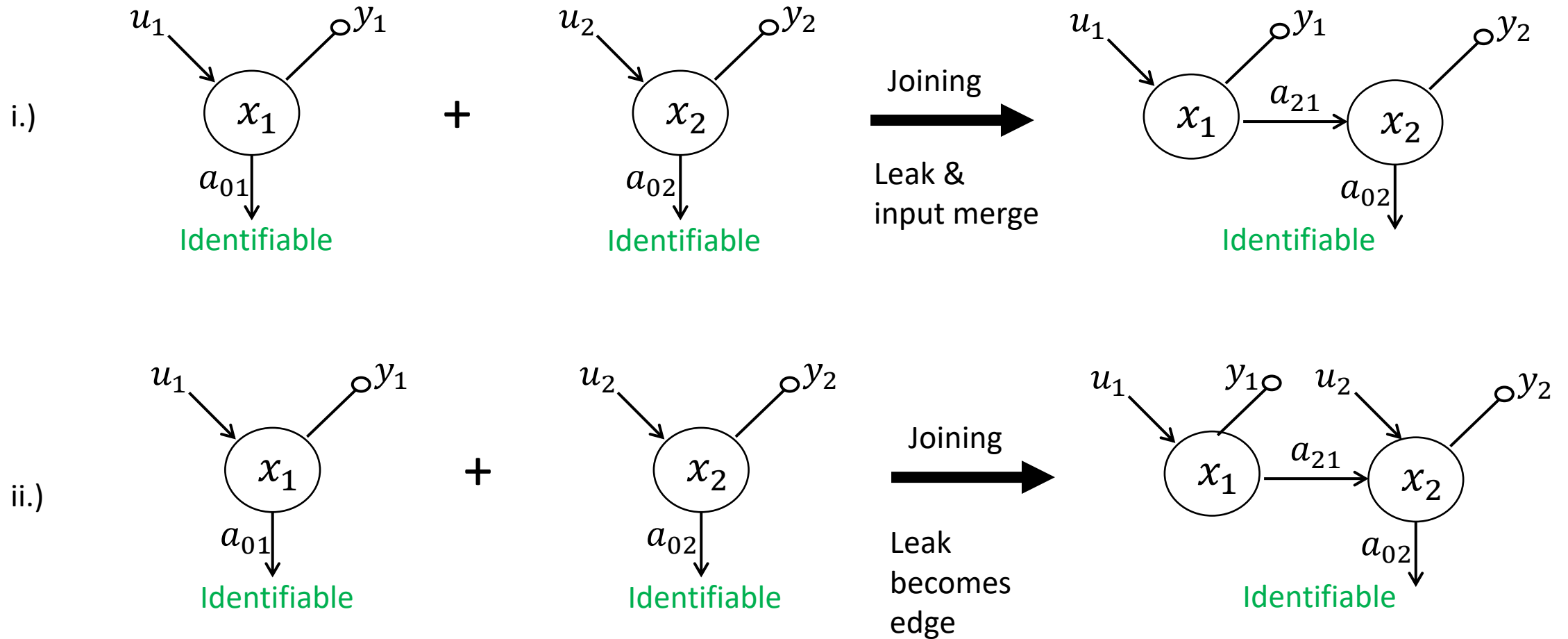
Joining/decomposing identifiable models



Decomposing
←

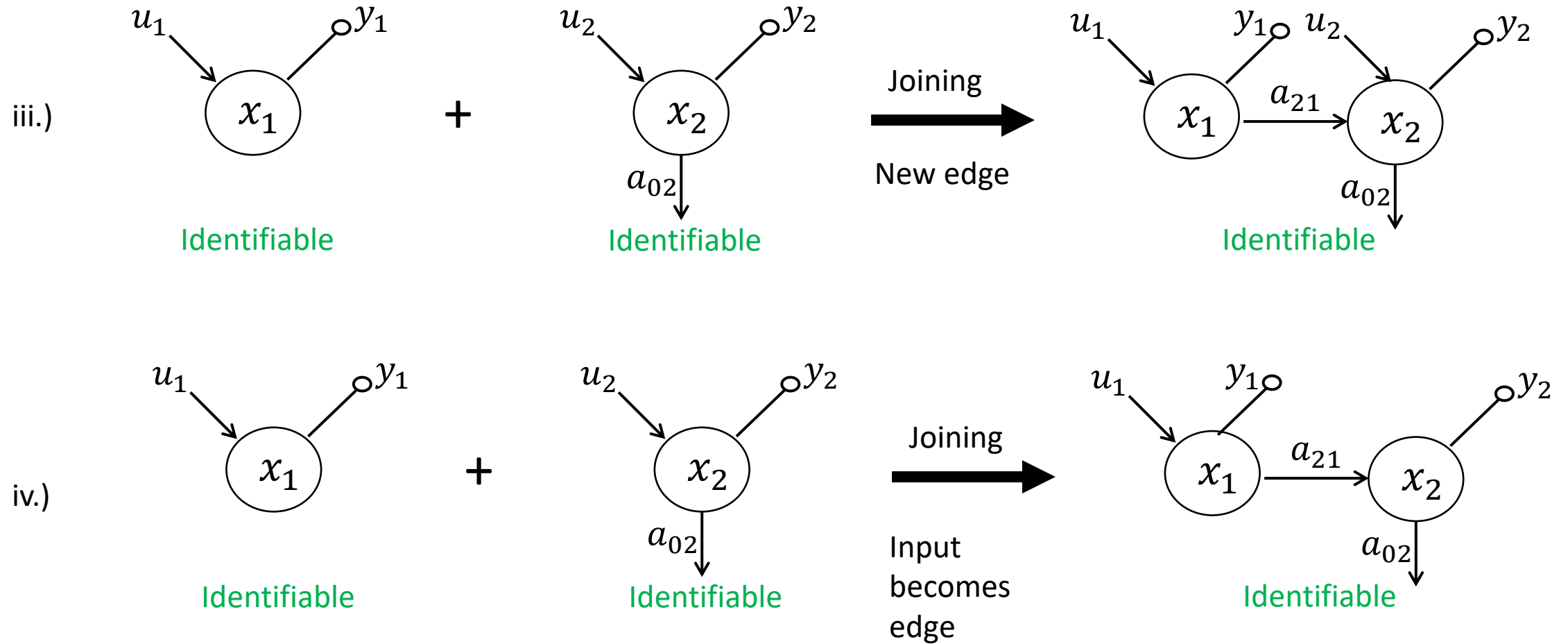
Other interesting questions

Joining strongly connected models [Gross et al 2020]



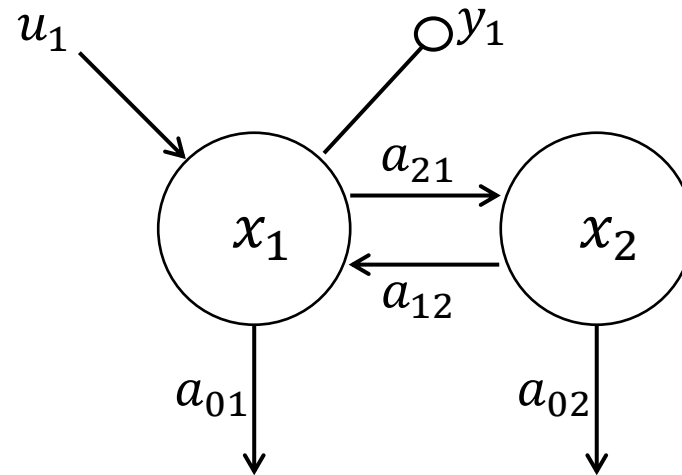
Other interesting questions

Joining strongly connected models [Gross et al 2020]



What to do with an unidentifiable model?

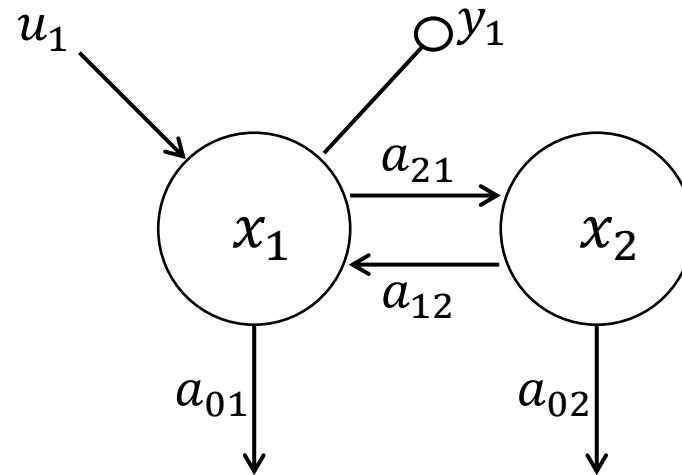
Recall model from earlier slide:



Unidentifiable

What to do with an unidentifiable model?

Recall model from earlier slide:

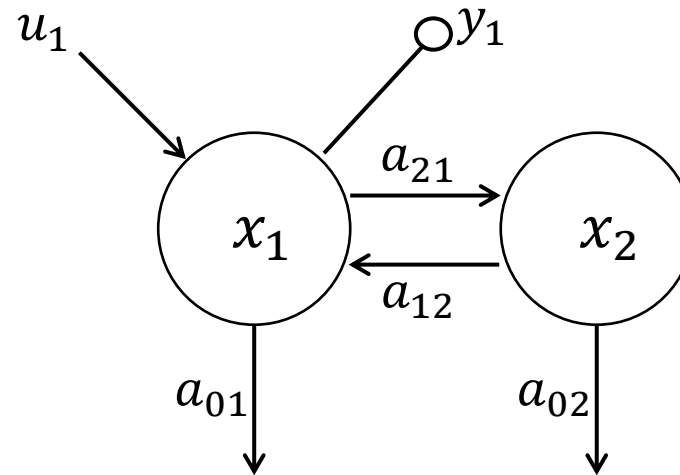


Unidentifiable

$$\ddot{y}_1 + (a_{01} + a_{02} + a_{12} + a_{21})\dot{y}_1 + (a_{01}a_{12} + a_{02}a_{21} + a_{01}a_{02})y_1 = \dot{u}_1 + (a_{02} + a_{12})u_1$$

What to do with an unidentifiable model?

Recall model from earlier slide:



Unidentifiable

$$\ddot{y}_1 + (a_{01} + a_{02} + a_{12} + a_{21})\dot{y}_1 + (a_{01}a_{12} + a_{02}a_{21} + a_{01}a_{02})y_1 = \dot{u}_1 + (a_{02} + a_{12})u_1$$

- How do we fix this?

What to do with an unidentifiable model?

Some options:

- Add more data (increase the number of coefficients)

What to do with an unidentifiable model?

Some options:

- Add more data (increase the number of coefficients)
- Remove edges/leaks (decrease the number of parameters)

What to do with an unidentifiable model?

Some options:

- Add more data (increase the number of coefficients)
- Remove edges/leaks (decrease the number of parameters)
- Set parameters to known values (decrease the # of parameters)

What to do with an unidentifiable model?

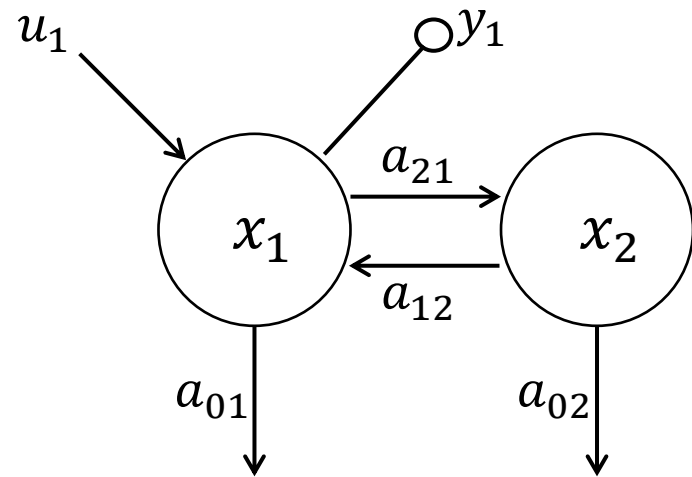
Some options:

- Add more data (increase the number of coefficients)
- Remove edges/leaks (decrease the number of parameters)
- Set parameters to known values (decrease the # of parameters)
- Reparametrize

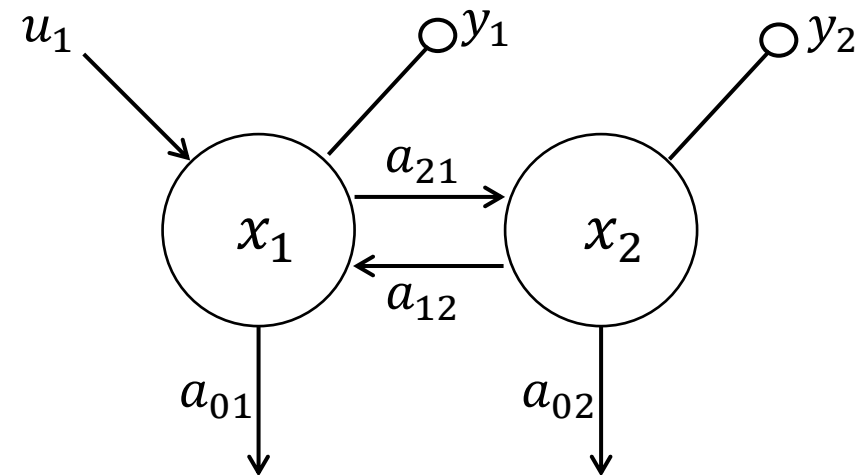
What to do with an unidentifiable model?

Option #1. Adjust model, if experimentally feasible

- Add inputs or outputs



Unidentifiable

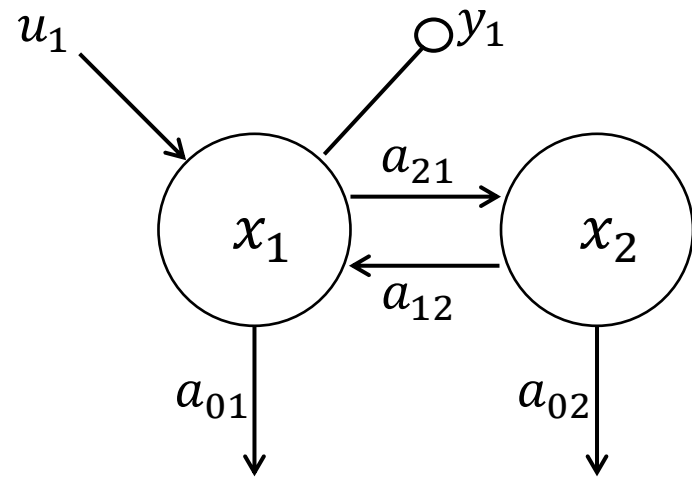


Identifiable

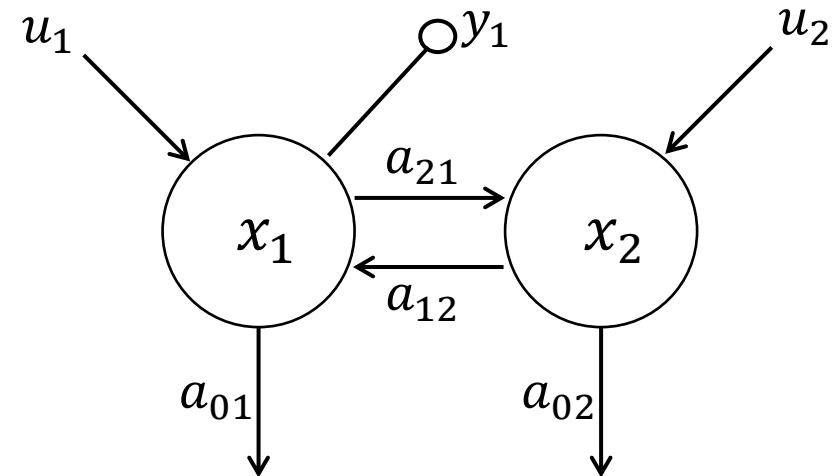
What to do with an unidentifiable model?

Option #1. Adjust model, if experimentally feasible

- Add inputs or outputs



Unidentifiable

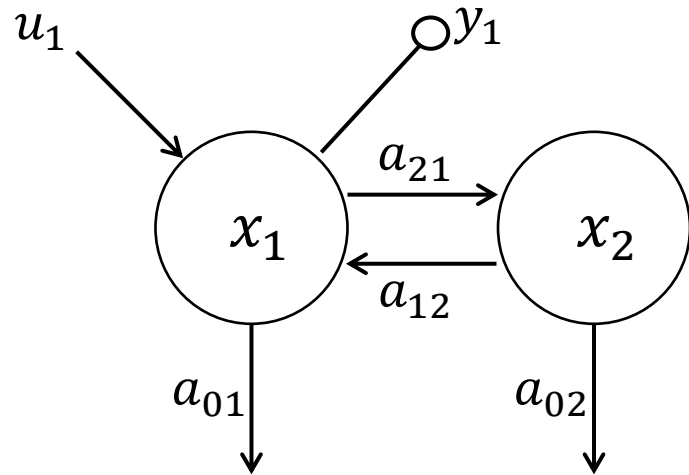


Identifiable

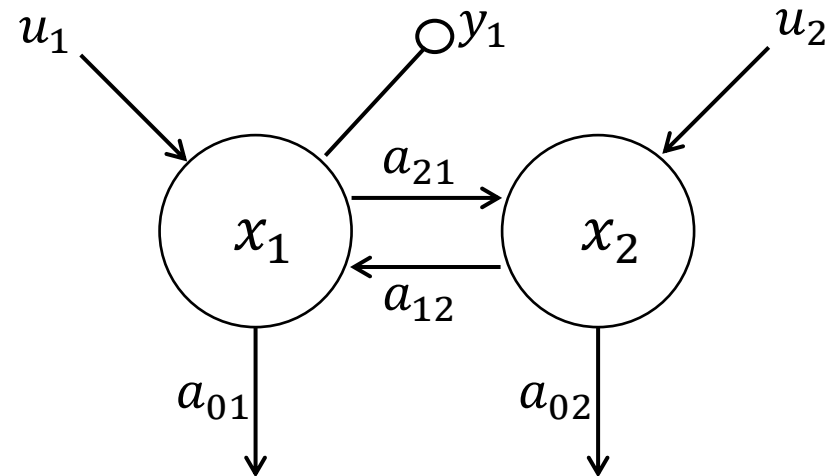
What to do with an unidentifiable model?

Option #1. Adjust model, if experimentally feasible

- Add inputs or outputs
- Open: What is a minimal set of inputs or outputs to obtain identifiability?



Unidentifiable

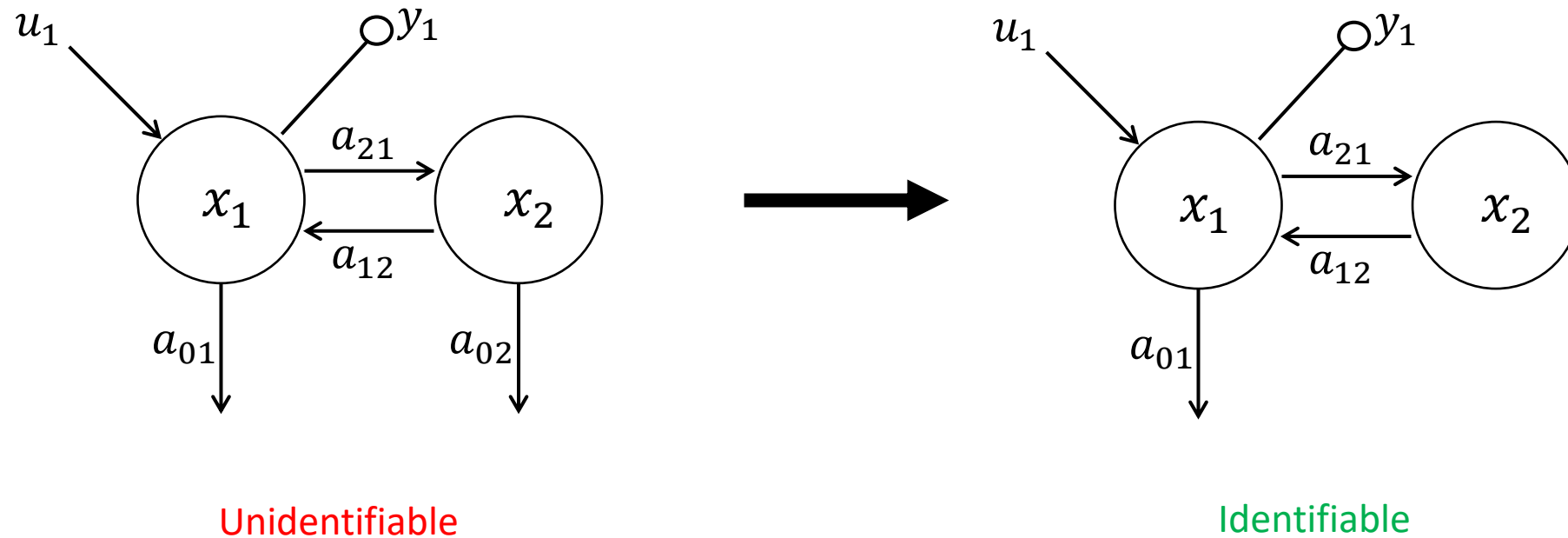


Identifiable

What to do with an unidentifiable model?

Option #2. Adjust model, if experimentally feasible

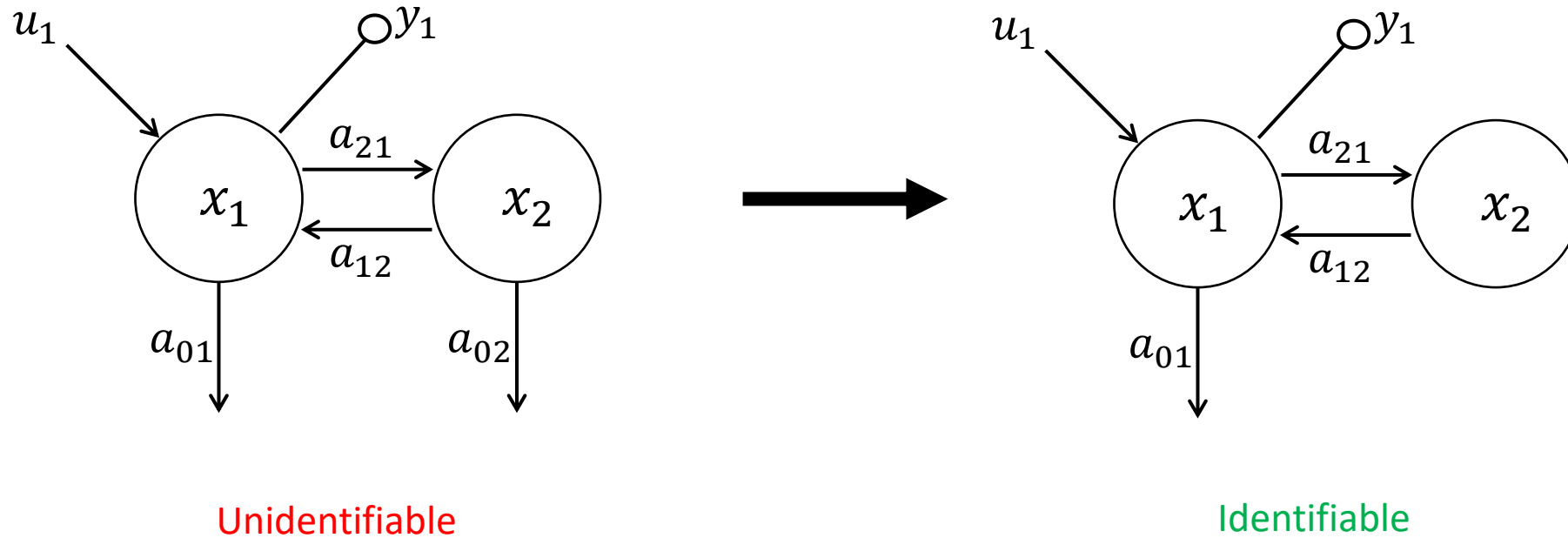
- Remove a leak or edge



What to do with an unidentifiable model?

Option #2. Adjust model, if experimentally feasible

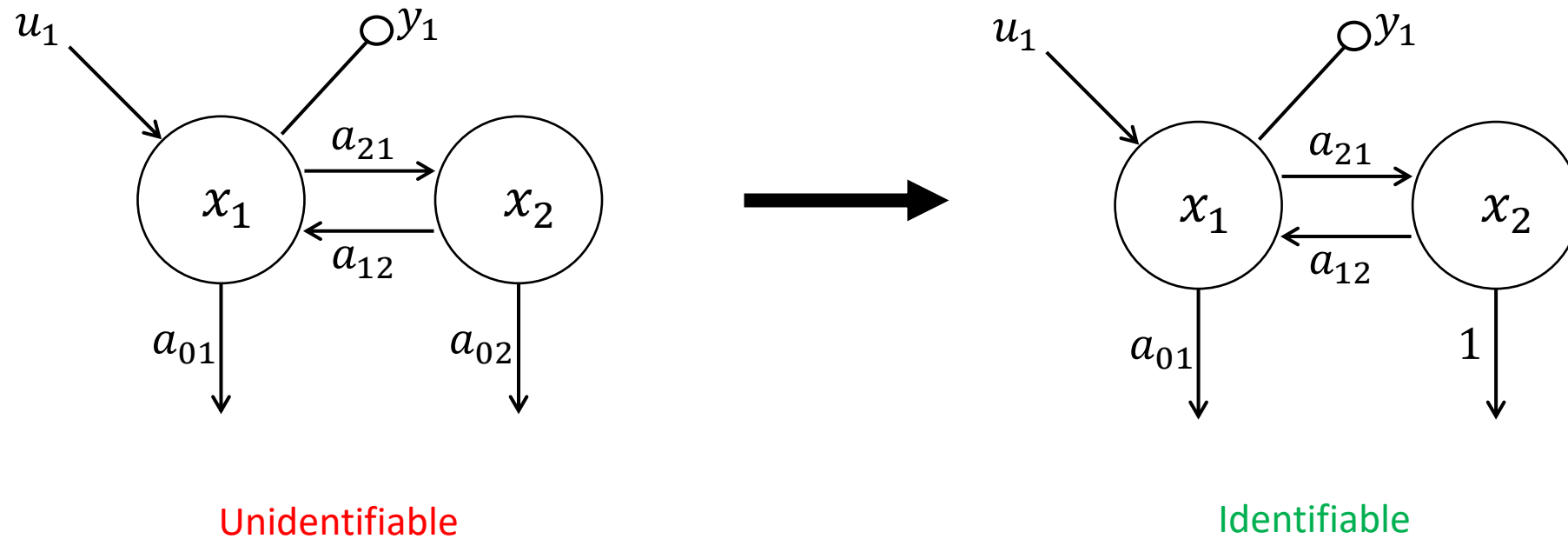
- Remove a leak or edge
- Open: Which edges or leaks should I remove to obtain identifiability?



What to do with an unidentifiable model?

Option #3. Adjust model, if experimentally feasible

- Set parameter to known value



What to do with an unidentifiable model?

Option #4. Find an identifiable reparametrization

- How to do this? Find an appropriate scaling of the state variables [M-Sullivant 2014]:

$$\dot{x}_1 = -(a_{01} + a_{21})x_1 + a_{12}x_2 + u_1$$

$$\dot{x}_2 = a_{21}x_1 - (a_{02} + a_{12})x_2$$

$$y_1 = x_1$$



$$X_1 = x_1$$

$$X_2 = a_{12}x_2$$

$$\dot{X}_1 = -(a_{01} + a_{21})X_1 + X_2 + u_1$$

$$\dot{X}_2 = a_{12}a_{21}X_1 - (a_{02} + a_{12})X_2$$

$$y_1 = X_1$$

Beyond linear

Can we answer these same types of questions for nonlinear models?

Ex: *SIR* Model

$$\begin{aligned}\dot{S} &= \mu N - \frac{\beta SI}{N} - \mu S \\ \dot{I} &= \frac{\beta SI}{N} - (\mu + \gamma)I \\ \dot{R} &= \gamma I - \mu R \\ y &= kI\end{aligned}$$

$$\text{I/O: } (-\beta\mu + \mu^2 + \mu\gamma)y^2 + \frac{(\beta\mu + \beta\gamma)}{kN}y^3 + \mu y\dot{y} + \frac{\beta}{kN}y^2\dot{y} - \dot{y}^2 + y\ddot{y} = 0$$

$$\text{Un-id: } \beta = \beta^* \quad \gamma = \gamma^* \quad \mu = \mu^* \quad kN = k^*N^*$$

$$\text{Reparam: } S' = \frac{S}{N}, \quad I' = \frac{I}{N}, \quad R' = \frac{R}{N}$$

Beyond linear

What to do with an unidentifiable model?

Table 1: **Unidentifiable models in epidemiology.** This table lists classes of compartmental models analyzed recently and, when relevant, how unidentifiable models were adjusted to become identifiable.

Model(s)	Model adjustment(s)
8 disease models [13] plus 3 more [12]	fix initial conditions, fix some parameters, more outputs, simplify model
26 disease models [28]	fix some parameters, more outputs
Covid [29]	fix some parameters
Covid [30]	rescale model
Measles [31]	fix some parameters
Seasonal influenza [32]	rescale model

References

N. Meshkat and S. Sullivant, Identifiable reparametrizations of linear compartmental models, *J. Symb. Comp.* 63 (2014) 46-67

E. Gross, H. Harrington, N. Meshkat, A. Shiu, Linear compartmental models: input-output equations and operations that preserve identifiability, *SIAM J. Appl. Math.* 79 (4) (2019) 1423-1447.

E. Gross, H. Harrington, N. Meshkat, A. Shiu, Joining and decomposing reaction networks, *J. Math. Biol.* 80 (2020) 1683-1731

C. Bortner and N. Meshkat, Identifiable paths and cycles in linear compartmental models, *Bull. Math. Biol.* 84 (5) (2022)

C. Bortner, E. Gross, N. Meshkat, A. Shiu, S. Sullivant, Identifiability of linear compartmental tree models and a general formula for input-output equations, *Adv. in Appl. Math.* 146 (2023)

N. Gogishvili, Database for identifiability properties of linear compartmental models, *arXiv* 2406.16132 (2024)

S. Ahmed, N. Crepeau, P. R. Dessauer Jr, A. Edozie, O. Garcia-Lopez, T. Grimsley, J. Lopez Garcia, V. Neri, A. Shiu, Identifiability of directed-cycle and catenary linear compartmental models, Preprint, *arXiv* 2412.05283 (2024)

N. Meshkat, A. Shiu, Identifiability of Compartmental Models: Recent progress and future directions, *arXiv* 2507.04496 (2025)

Generalization

Theorem (M-Sullivant-Eisenberg) Let $M = (G, In, Out, Leak)$ be a linear compartmental model with at least one input. Then the following equations are input-output equations for M for each $i \in Out$:

$$\det(\partial I - A)y_i = \sum_{j \in In} (-1)^{i+j} \det(\partial I - A)_{ij} u_1$$

Idea behind proofs

- Formula for input-output equation:

$$\ddot{y}_1 - \underbrace{(a_{11} + a_{22})}_{\text{Coefficients of characteristic polynomial of } A} \dot{y}_1 + \underbrace{(a_{11}a_{22} - a_{12}a_{21})}_{\text{... of } A_{11}} y_1 = \dot{u}_1 - \underbrace{a_{22}u_1}_{\text{... of } A_{11}}$$

- Coefficients factor through cycles in graph

$$c_1 = -(a_{11} + a_{22}) \quad c_2 = a_{11}a_{22} - a_{12}a_{21} \quad c_3 = -a_{22}$$

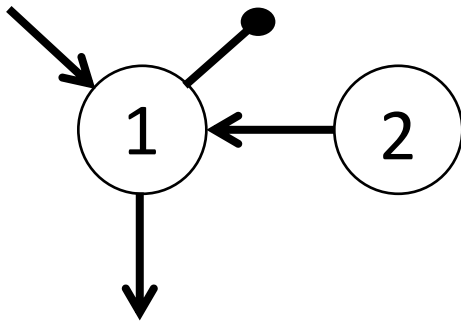
- Number of independent cycles in graph:

$$\underbrace{m - n + 1}_{\text{\# cycles}} + \underbrace{n}_{\text{\# self cycles}} = m + 1$$

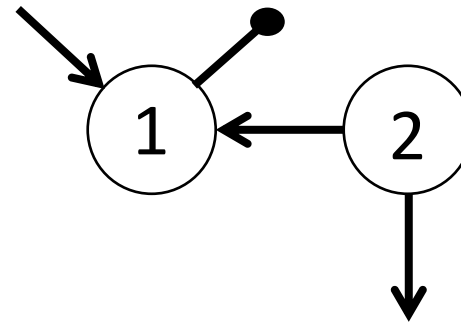
- Ident. reparam. $\Leftrightarrow \dim(\text{im}(c))$ is maximal (= # independent cycles)

Distinguishable models:

Model 1



Model 2



I/O eqn:

$$\ddot{y}_1 + (a_{01} + a_{12})\dot{y}_1 + a_{01}a_{12}y_1 = \dot{u}_1 + a_{12}u_1$$

$$\ddot{y}_1 + (a_{02} + a_{12})\dot{y}_1 = \dot{u}_1 + (a_{02} + a_{12})u_1$$

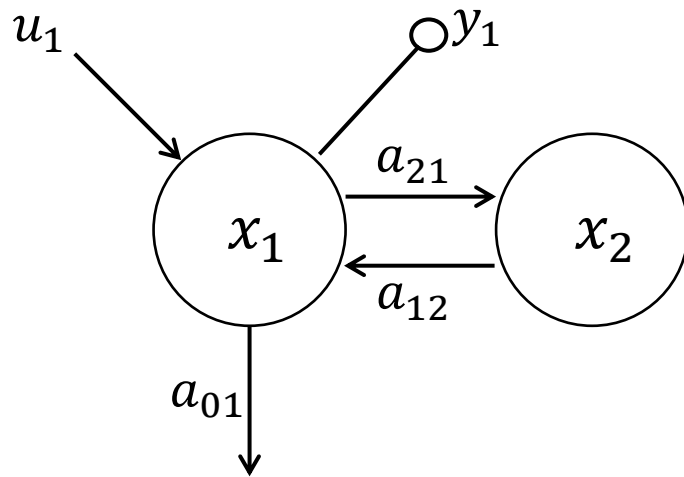
Not the same I/O eqn structure \Rightarrow Distinguishable!

Can identifiability break down?

- Recall *generic* identifiability
- Can analyze singular locus:

$$\ddot{y}_1 + (a_{01} + a_{12} + a_{21})\dot{y}_1 + a_{01}a_{12}y_1 = \dot{u}_1 + a_{12}u_1$$

$$c(a_{01}, a_{12}, a_{21}) = (a_{01} + a_{12} + a_{21}, a_{01}a_{12}, a_{12})$$



Identifiable

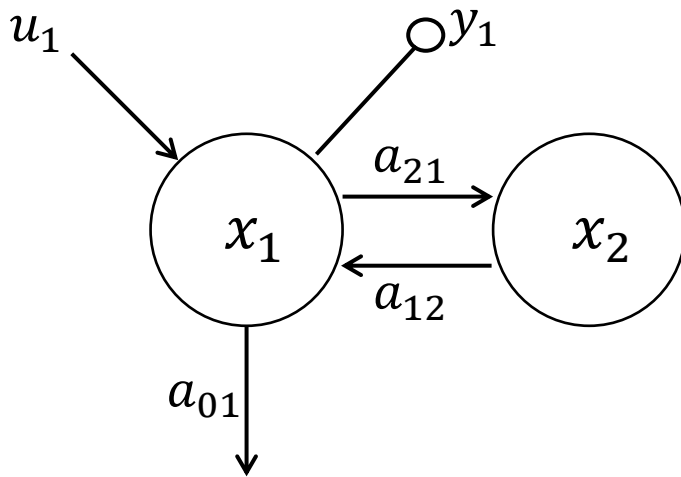
$$Jac(c) = \begin{pmatrix} 1 & 1 & 1 \\ a_{12} & a_{01} & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

Can identifiability break down?

- Recall *generic* identifiability
- Can analyze singular locus:

$$\ddot{y}_1 + (a_{01} + a_{12} + a_{21})\dot{y}_1 + a_{01}a_{12}y_1 = \dot{u}_1 + a_{12}u_1$$

$$c(a_{01}, a_{12}, a_{21}) = (a_{01} + a_{12} + a_{21}, a_{01}a_{12}, a_{12})$$



Identifiable

$$Jac(c) = \begin{pmatrix} 1 & 1 & 1 \\ a_{12} & a_{01} & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

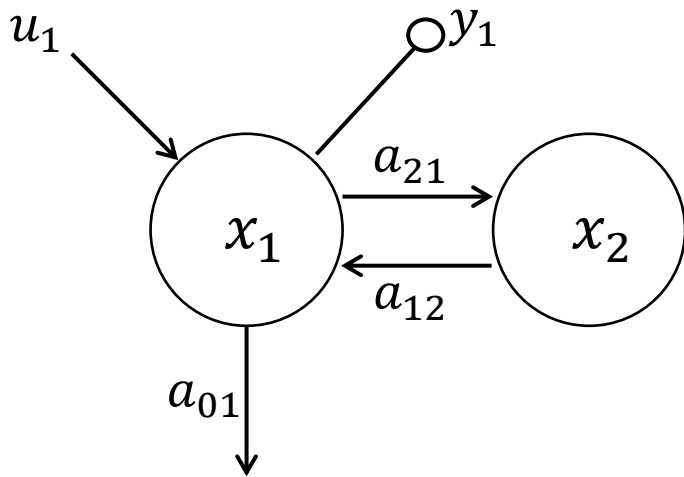
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Can identifiability break down?

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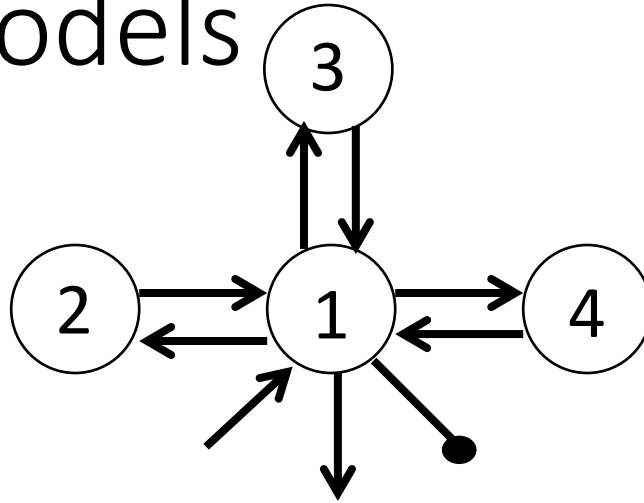
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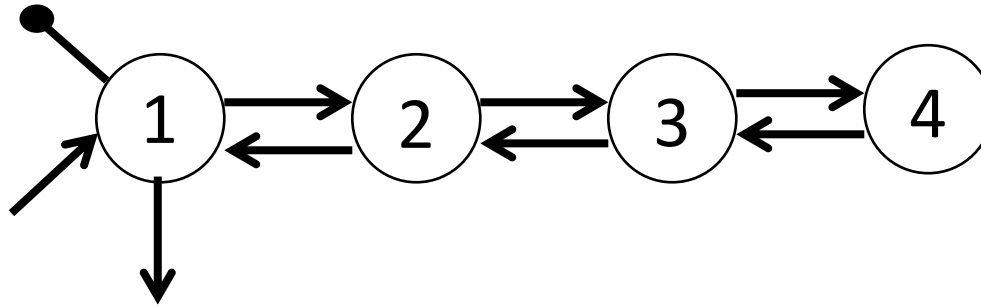
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- Can we find formulas for singular locus equations?

Identifiable models

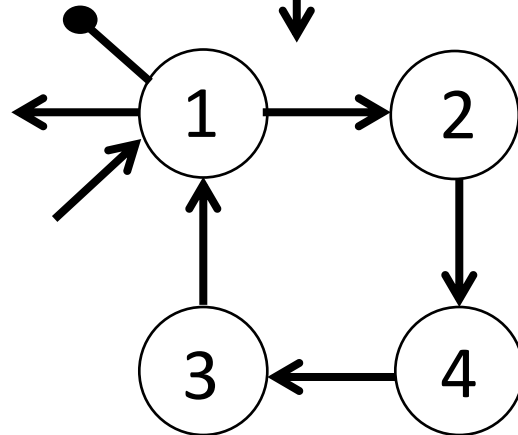
- Mammillary



- Catenary



- Cycle



All identifiable for the case of single input/output/leak in 1st compartment

Singular locus

Model	Equation of singular locus	Identifiability degree
Catenary (path)	Conjecture: $a_{12}^{n-1}(a_{21}a_{23})^{n-2} \dots (a_{n-1,n-2}a_{n-1,n})$	1
Cycle	$a_{32}a_{43} \dots a_{n,n-1}a_{1,n} \prod_{2 \leq i < j \leq n} (a_{i+1,i} - a_{j+1,j})$	$(n-1)!$
Mammillary (star)	$a_{12}a_{13} \dots a_{1,n} \prod_{2 \leq i < j \leq n} (a_{1i} - a_{1j})^2$	$(n-1)!$

- What does this tell us?
 - For cycle and mammillary models, **nonzero** and **distinct** parameter values yield identifiability
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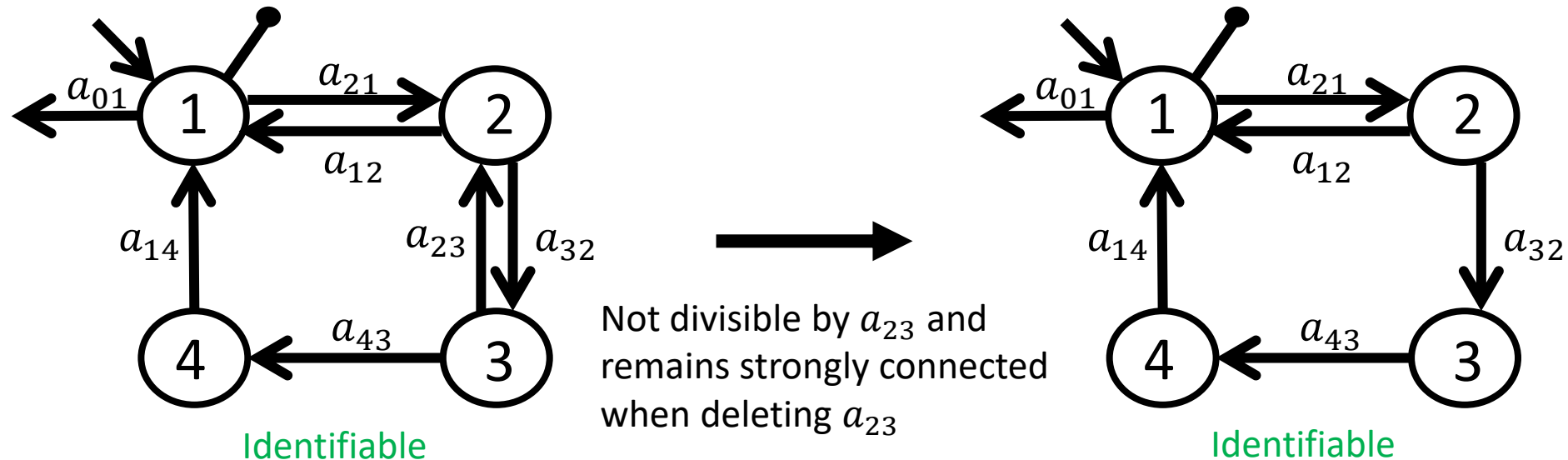
Other families of graphs?

Application: identifiable submodels

- Theorem (Gross-M-Shiu 2021):
 - Strongly connected models: If singular locus equation is not divisible by a parameter, then delete parameter. If it remains strongly connected, then the submodel is identifiable.

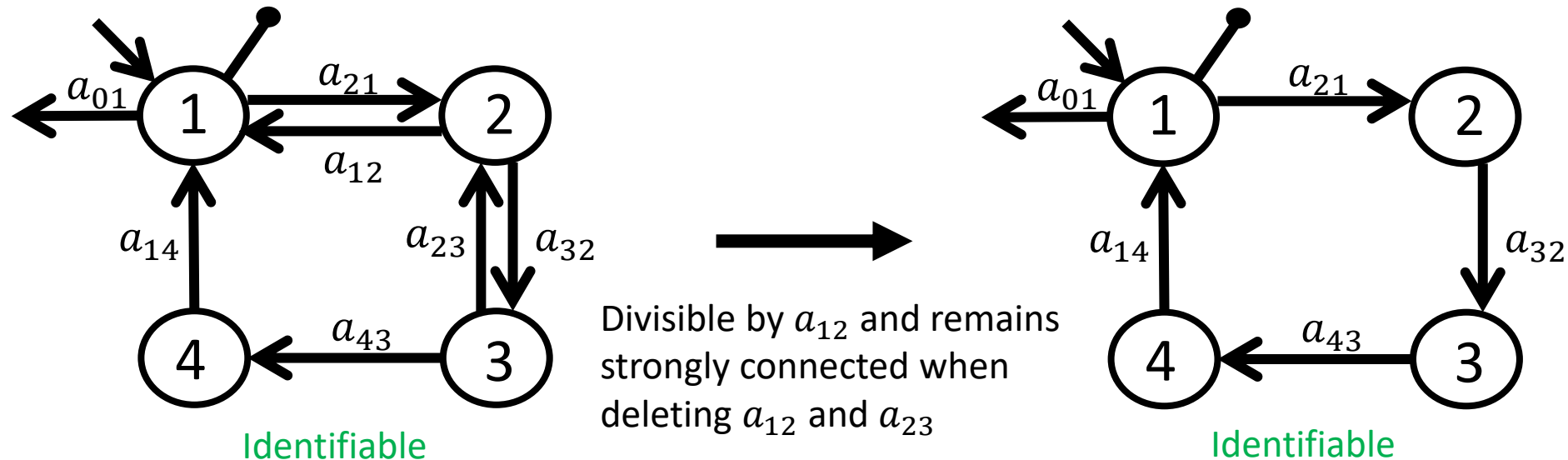
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Application: identifiable submodels

- Converse doesn't hold:
 - Strongly connected models: If singular locus equation is divisible by a parameter, then delete parameter. If it remains strongly connected, then the submodel may be identifiable.
 - Ex: $a_{12}a_{14}a_{21}^2a_{32}(a_{12}a_{14} - a_{14}^2 - a_{12}a_{23} + a_{14}a_{23} + a_{14}a_{32} - a_{12}a_{43} + a_{14}a_{43} - a_{32}a_{43})(a_{12}a_{23} + a_{12}a_{43} + a_{32}a_{43})$



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$$\begin{aligned}-(a_{01} + a_{21}) &= c_3 - c_1 \\ a_{12}a_{21} &= (c_1 - c_3)c_3 - c_2 \\ -(a_{02} + a_{12}) &= -c_3\end{aligned}$$

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New map is 1-1 $\rightarrow c(q_1, q_2, q_3) = (-q_1 - q_3, q_1 q_3 - q_2, -q_3)$