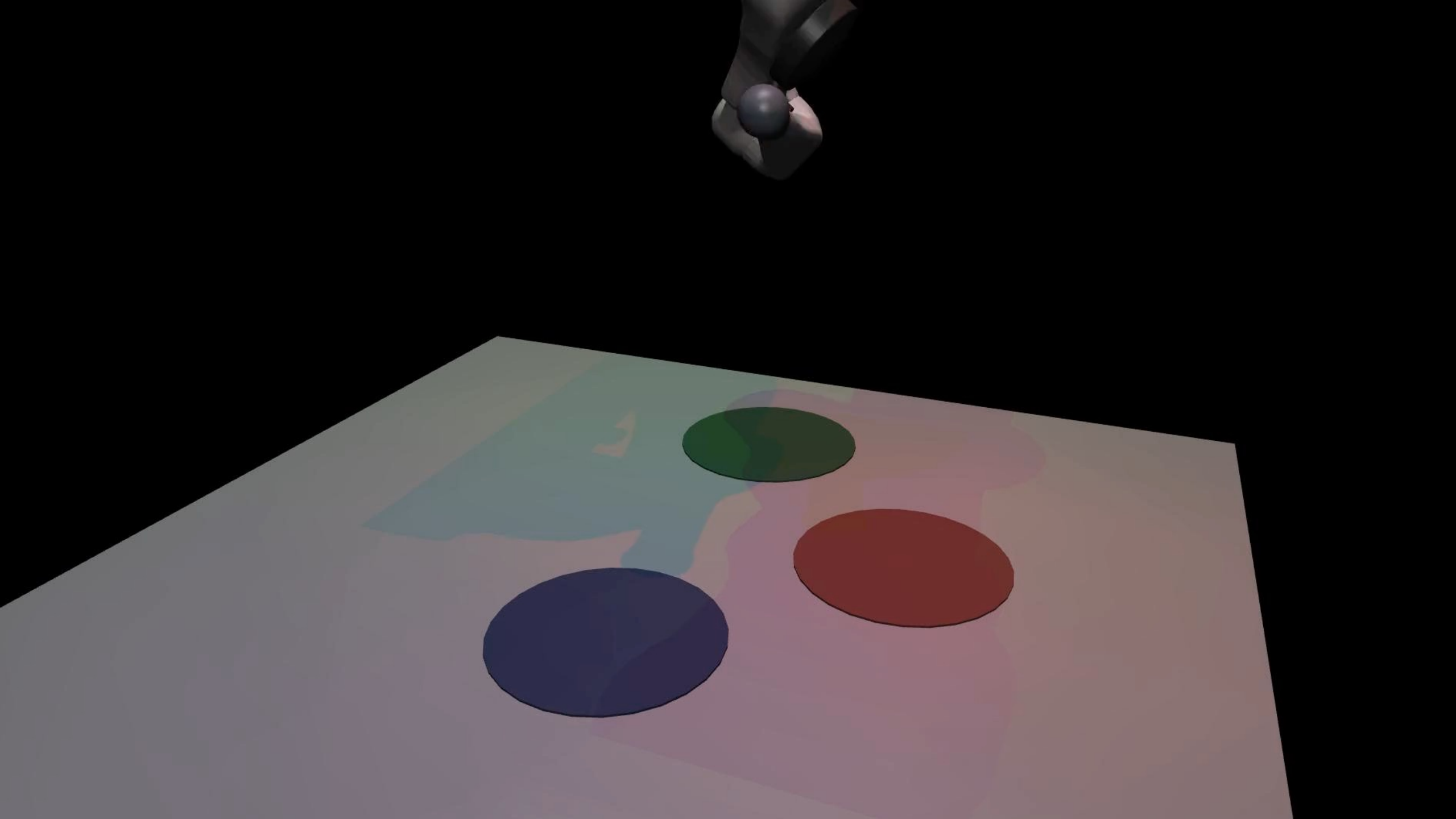
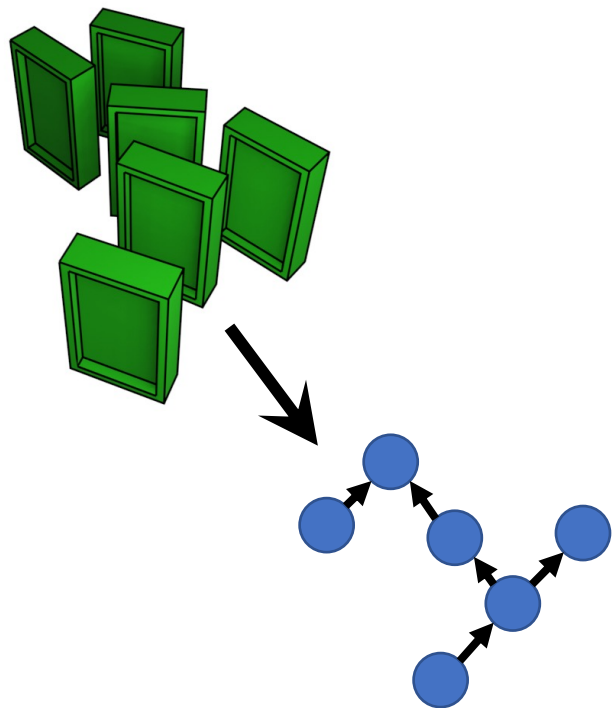


Weakly supervised causal representation learning

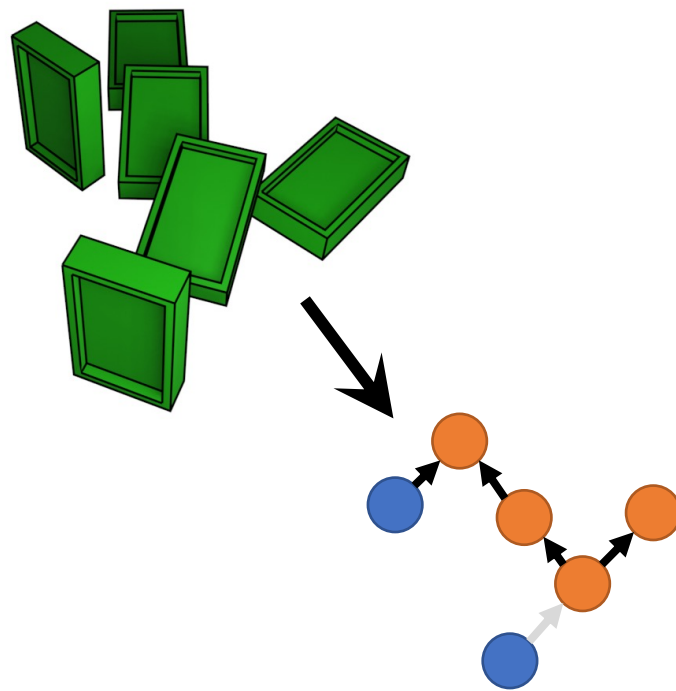
Johann Brehmer

Qualcomm Technologies Netherlands B. V.

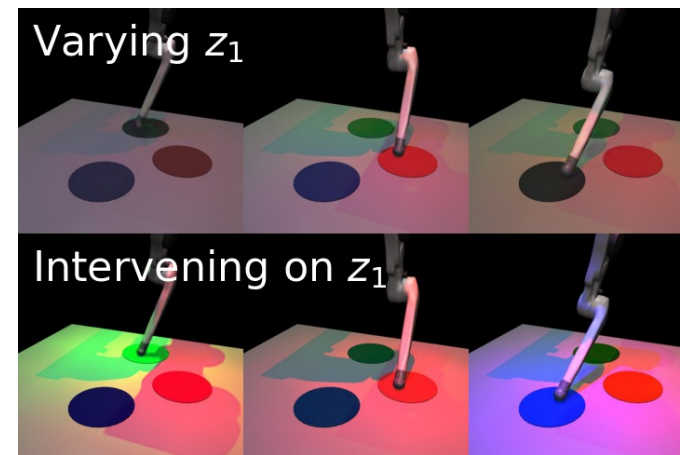




Can we **learn causal variables & causal structure from pixels**, without labels?



We prove: this is possible with **weak supervision**, when observing effects of interventions

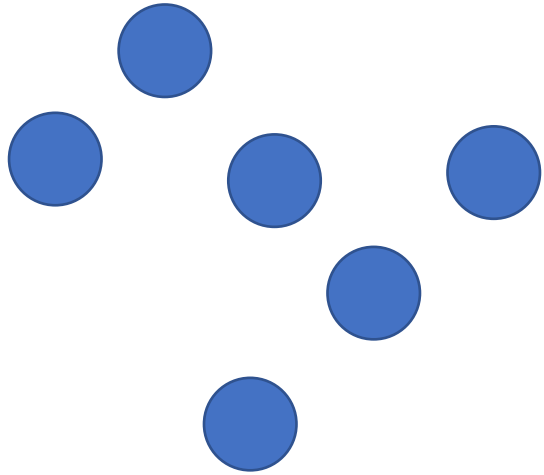


In practice, **implicit latent causal models** can identify the causal structure in image datasets

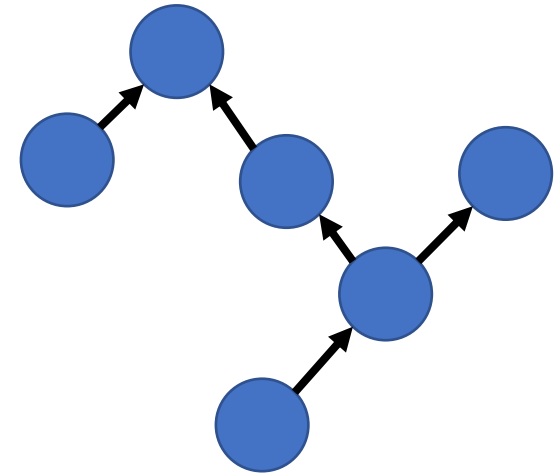
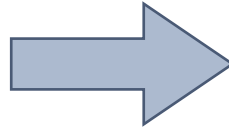
Problem

**Can we learn causal representations
from pixels?**

Causal discovery / inference



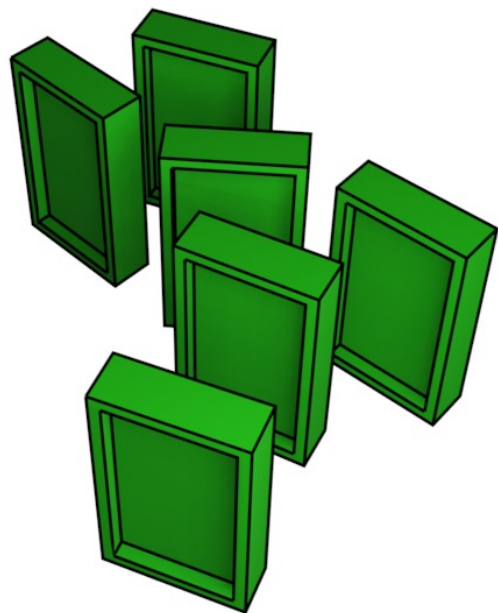
Given: dataset in terms of
high-level causal variables



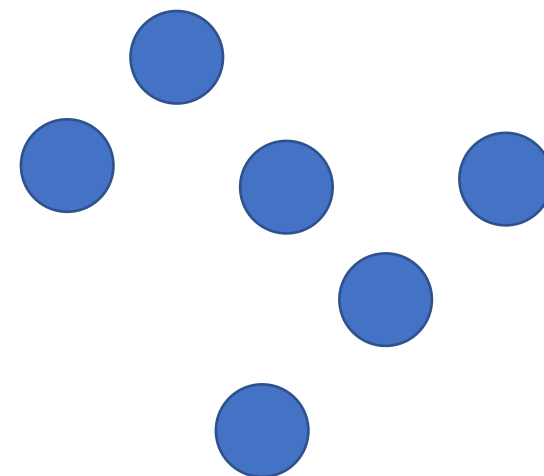
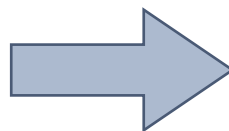
Goal: learn the
causal structure

But: what if we don't observe the causal variables?

Disentangled representation learning



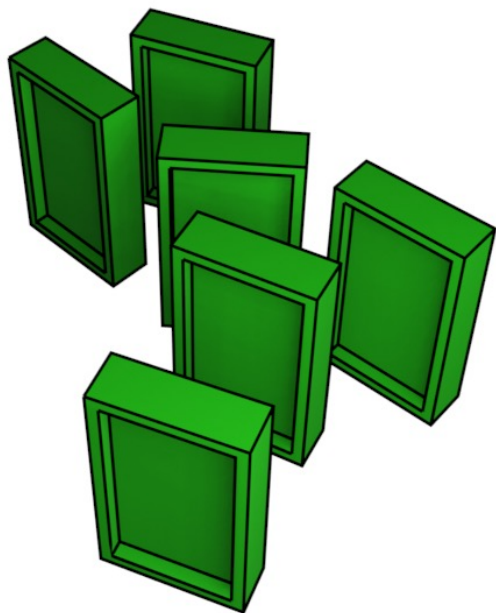
Given: **low-level, unstructured data representation**
(e.g. pixels)



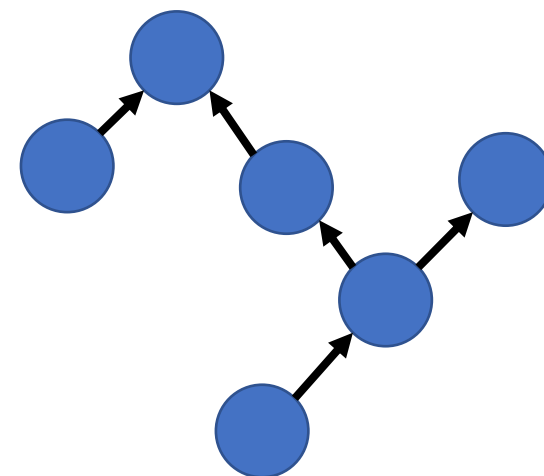
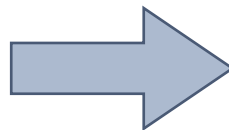
Goal: learn encoder to
high-level variables
(e.g. object positions, states, ...),
usually **assuming independence**

But: useful high-level concepts are rarely independent

Causal representation learning

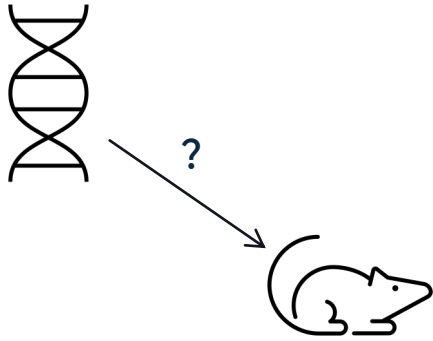


Given: **low-level, unstructured data representation**
(e.g. pixels)

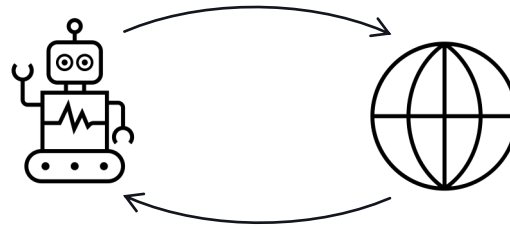


Goal: learn encoder to
high-level variables
(e.g. object positions, states, ...)
and their relations /
causal structure

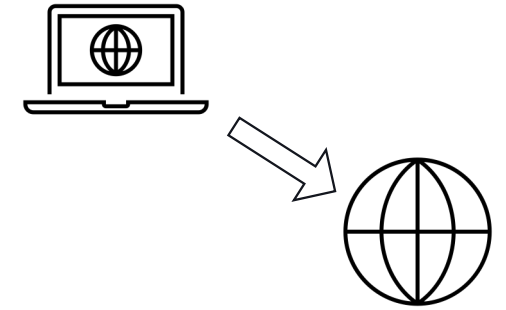
Why learn causal representations?



Causal structure may be of **scientific interest**



Causal representations are **abstractions** that may be **useful for planning**



Causal models may be more **robust to changes**

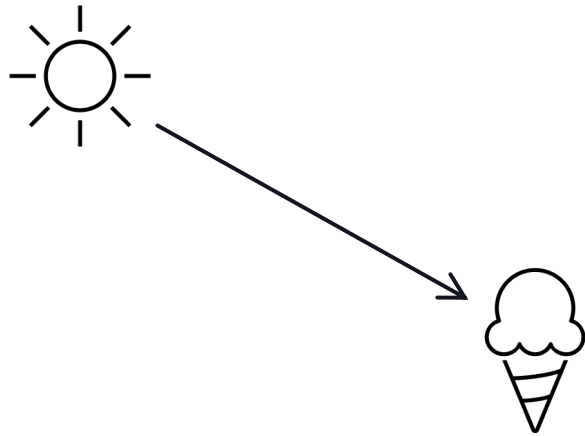
Arguably, these potential benefits have not yet been clearly demonstrated

[Recent review: B. Schölkopf et al, "Towards causal representation learning", IEEE Advances in Machine Learning and Deep Neural Networks 2021]

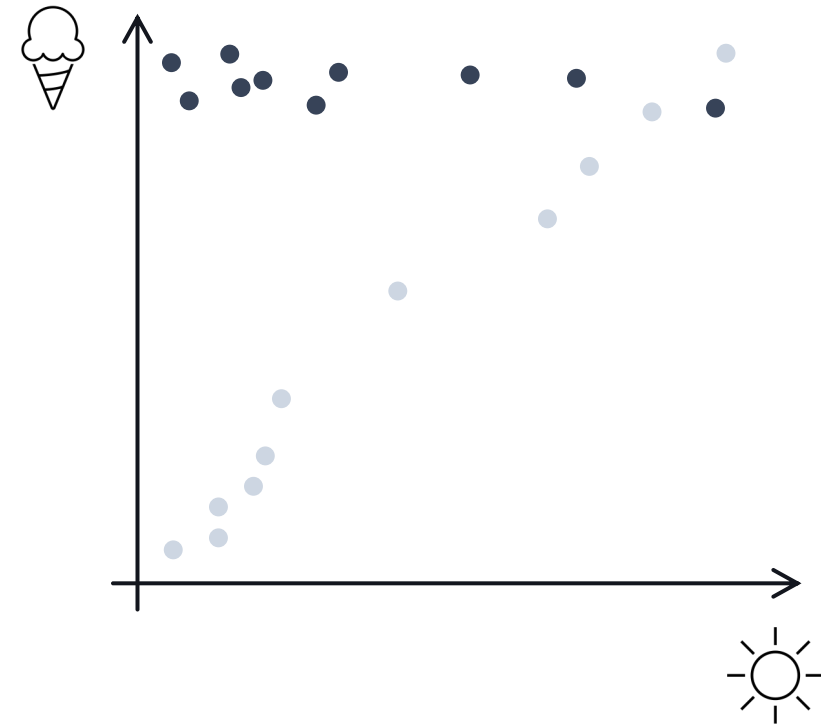
Background

Causality and identifiability

Causality



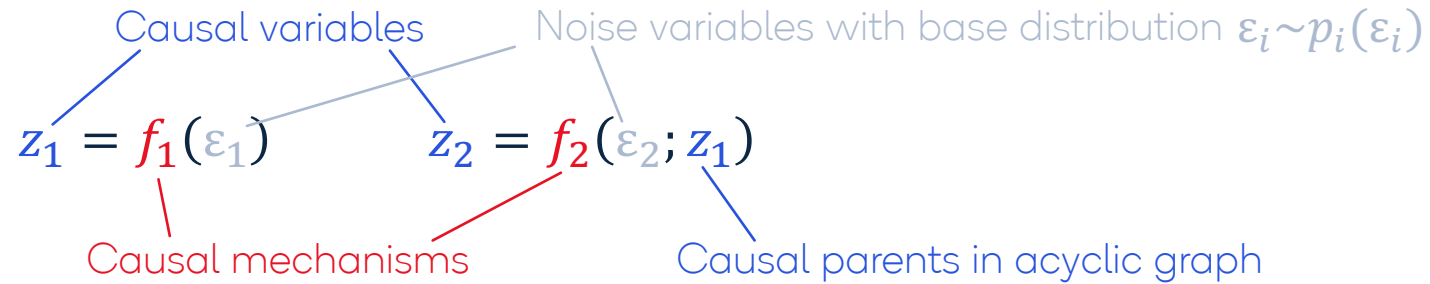
Semantically, causal models label relations between random variables as **cause-effect relations**



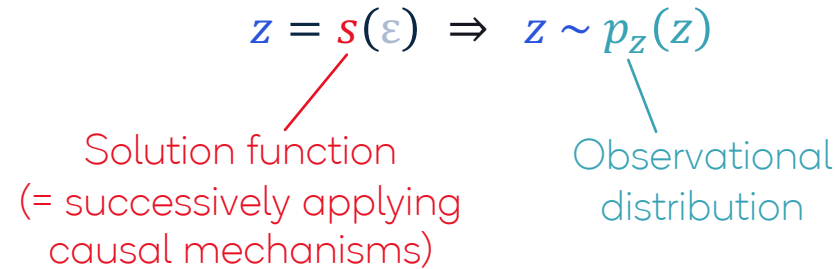
Functionally, causal models describe **probability distributions and how they change** under changing conditions

Structural causal models (SCMs)

- SCM:



- Solution:



- Interventions:



Identifiability

- An representation / SCM \mathcal{M} is **identifiable** if

$$p_{\mathcal{M},x}(x) = p_{\mathcal{M}',x}(x) \Rightarrow \mathcal{M} \sim \mathcal{M}'$$

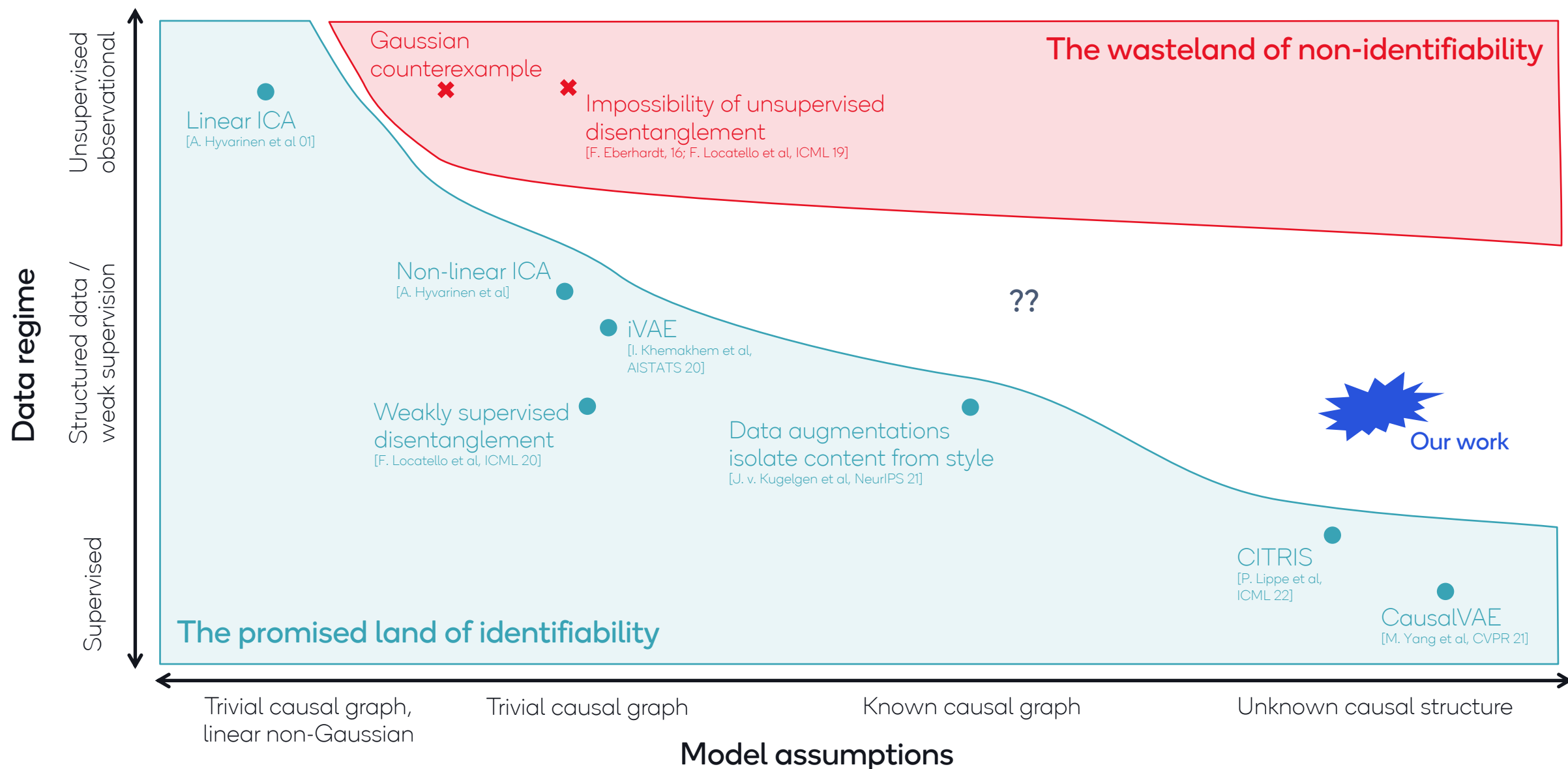
Any two model
(from some family)

Data regime
(e.g. observational
distribution on pixel level)

Equivalence relation
(e.g. same up to
permutations)

- Identifiability means we can **find ground-truth causal structure** through maximum-likelihood training
 - if it is within the specified model family
 - up to the equivalence relation
 - in the limit of infinite data
 - assuming perfect training

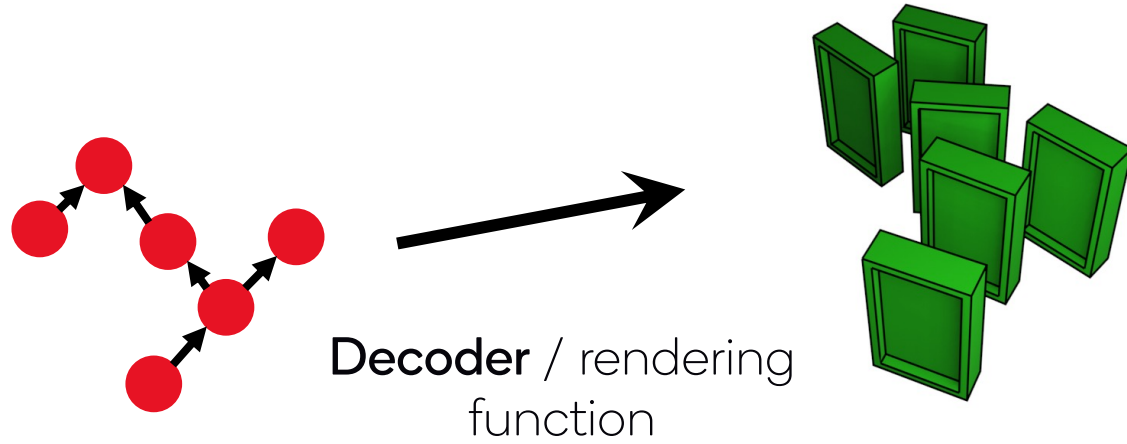
When are causal representations are identifiable?



Theory

Causal representations can be identified from weak supervision

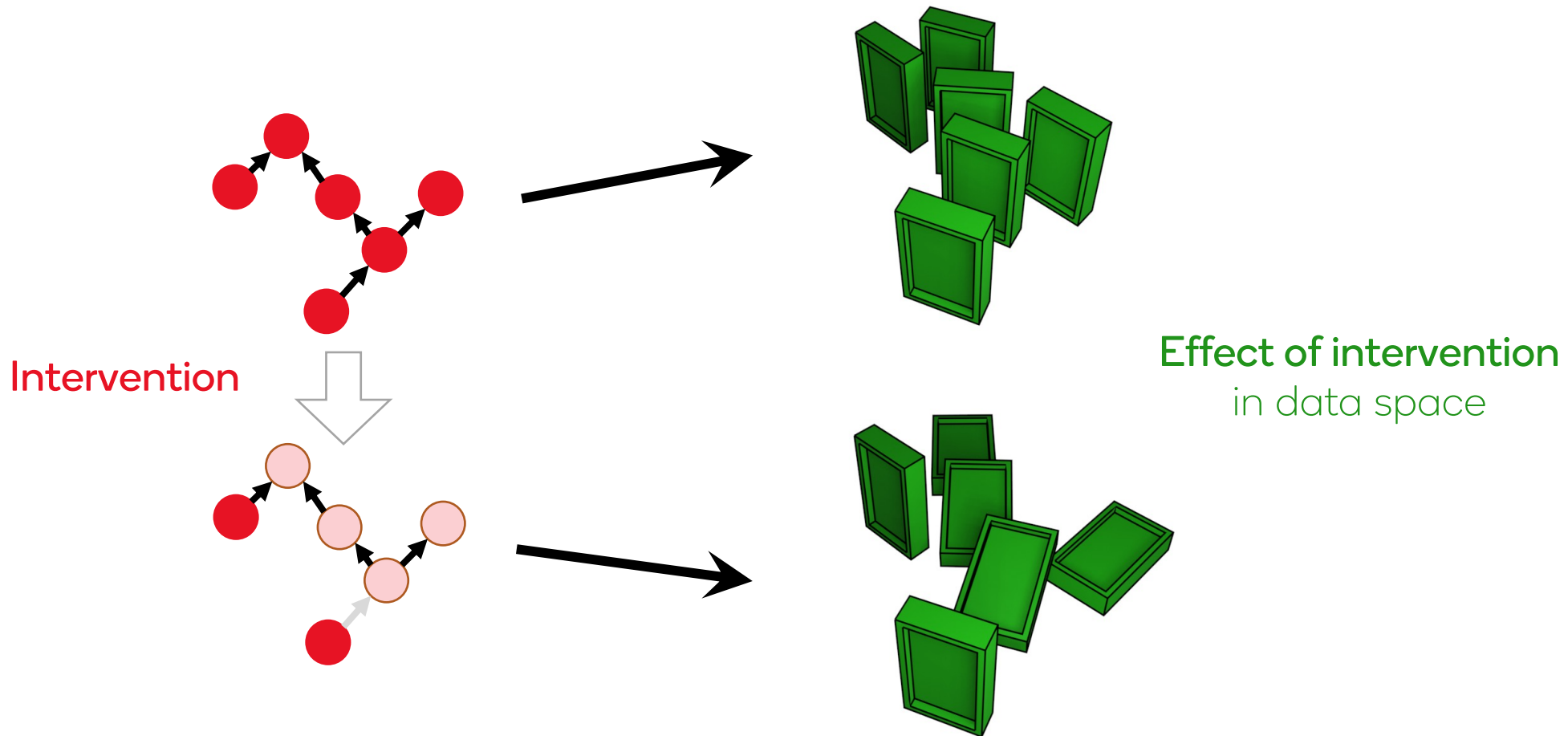
Latent causal model



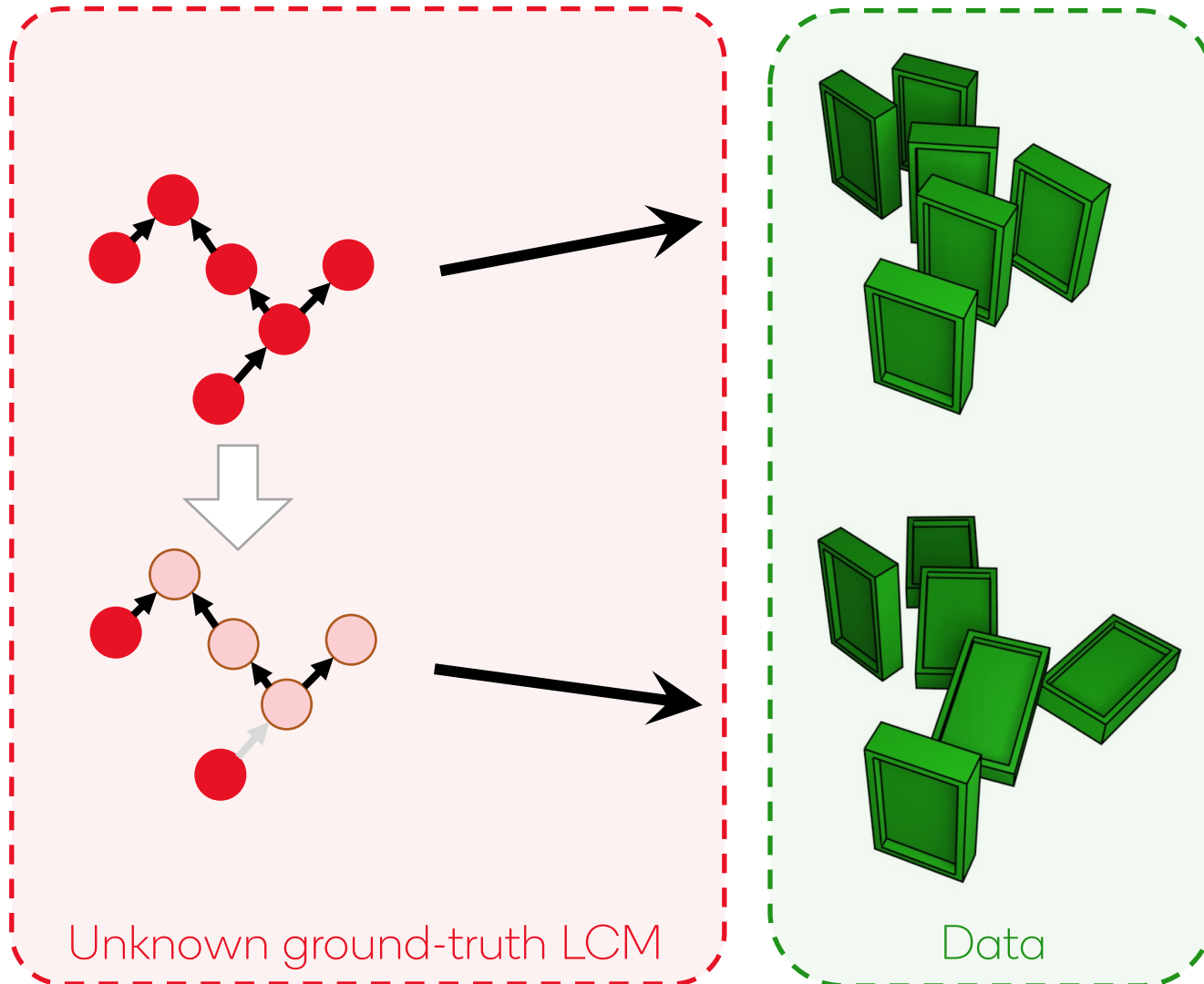
High-level variables with
a structural causal model
between them

Low-level data (pixels)

Interventions

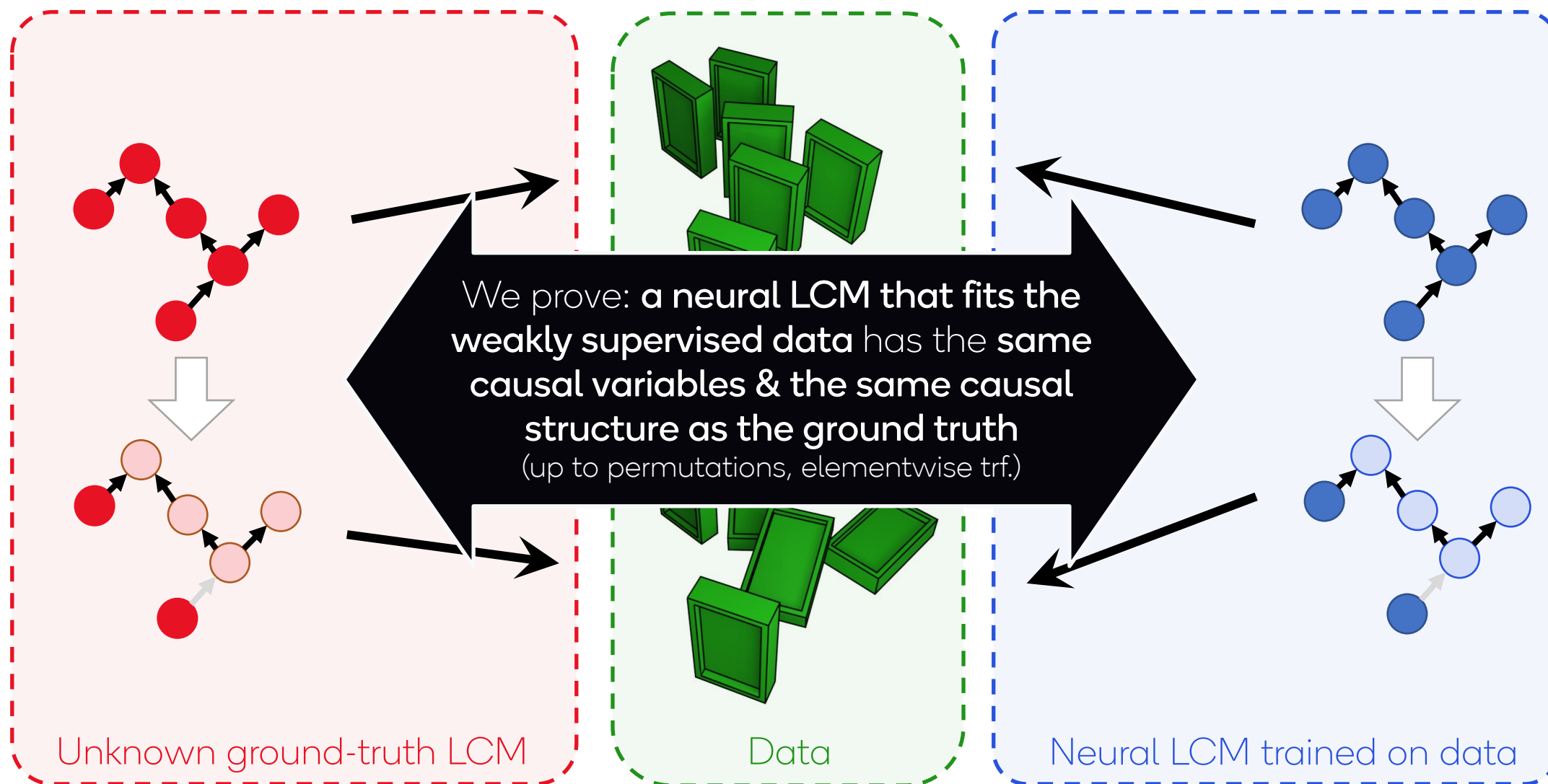


Weakly supervised data setting



- We assume access to **data pairs of the system before and after interventions**
 - Equivalent to counterfactuals
 - Causal abstraction of time-series data
- Otherwise, **no labels**
 - Only pixel-level data is observed
 - Intervention targets are unknown

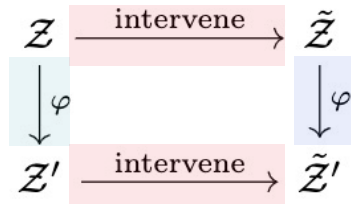
Identifiability theorem



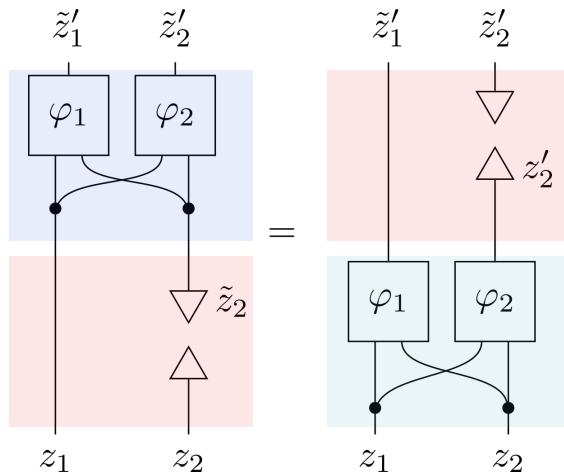
Proof sketch

1. Consider two LCMs with causal variables \mathbf{z} and \mathbf{z}' , both matching the data.
Define $\varphi : \mathbf{z} \rightarrow \mathbf{z}'$.

2. Interventions commute with φ :



3. We assume perfect interventions. Then then \tilde{z}'_i is independent of \mathbf{z}_j . For 2 variables:



4. We assume \mathbb{R} -valued variables. Statistical independence then implies functional independence. Thus, $\varphi_i(\mathbf{z}_i, \mathbf{z}_j)$ must be constant in \mathbf{z}_j .
5. Since this holds for any i , φ must be a permutation plus elementwise transformations.
6. Finally, we can show that the causal graphs and intervention targets in the two models are consistent with this transformation.
7. Thus the two models are isomorphic.

Assumptions

Assumption

Weakly supervised data is available

Causal variables are \mathbb{R} -valued

Causal mechanisms are diffeomorphic

No hidden confounders

Decoder is deterministic

Interventions are perfect

(Post-intervention values of intervention targets are independent of pre-intervention state)

Interventions are complete

(The dataset contains interventions on any single causal variable)

Possible relaxation

Maybe (work in progress)

Maybe (work in progress)

Difficult

Difficult

Plausible (as in iVAE)

Difficult (counterexamples)

Relaxation to n-target interventions plausible
(incomplete interventions → partial identifiability)

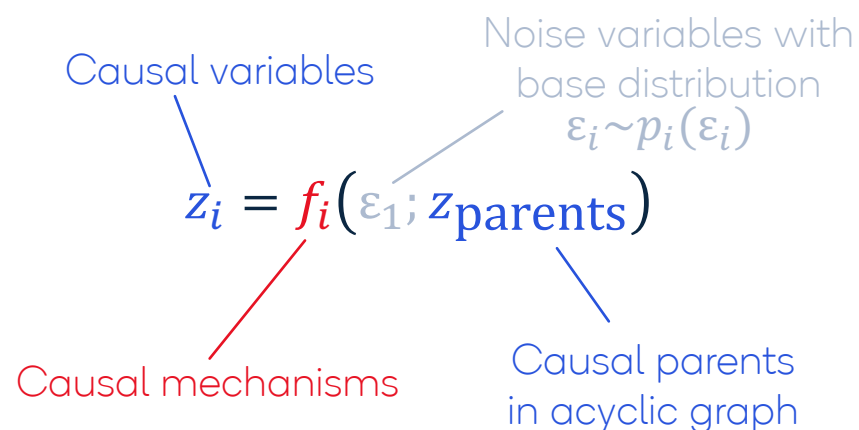
Practice

Implicit is better than explicit

Explicit and implicit representations of causal structure

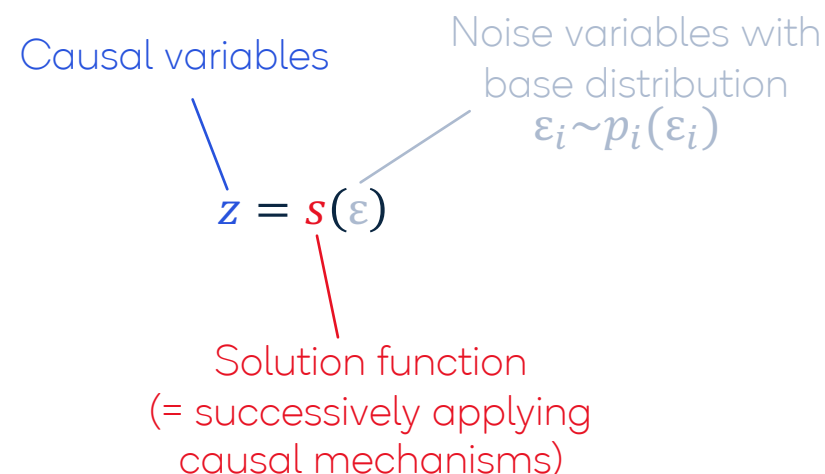
Explicit representation

through graph & causal mechanisms:



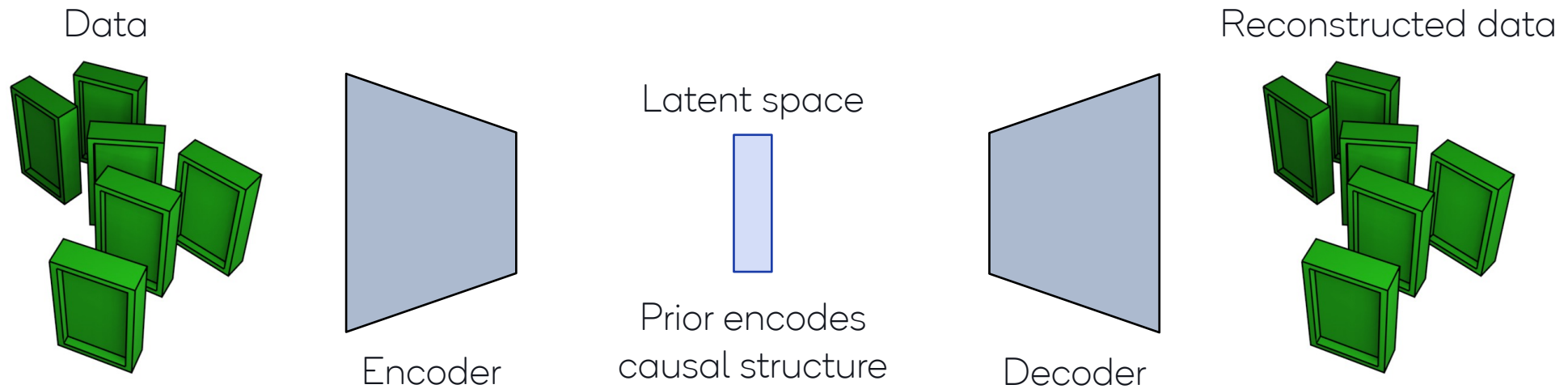
Implicit representation

through solution function:

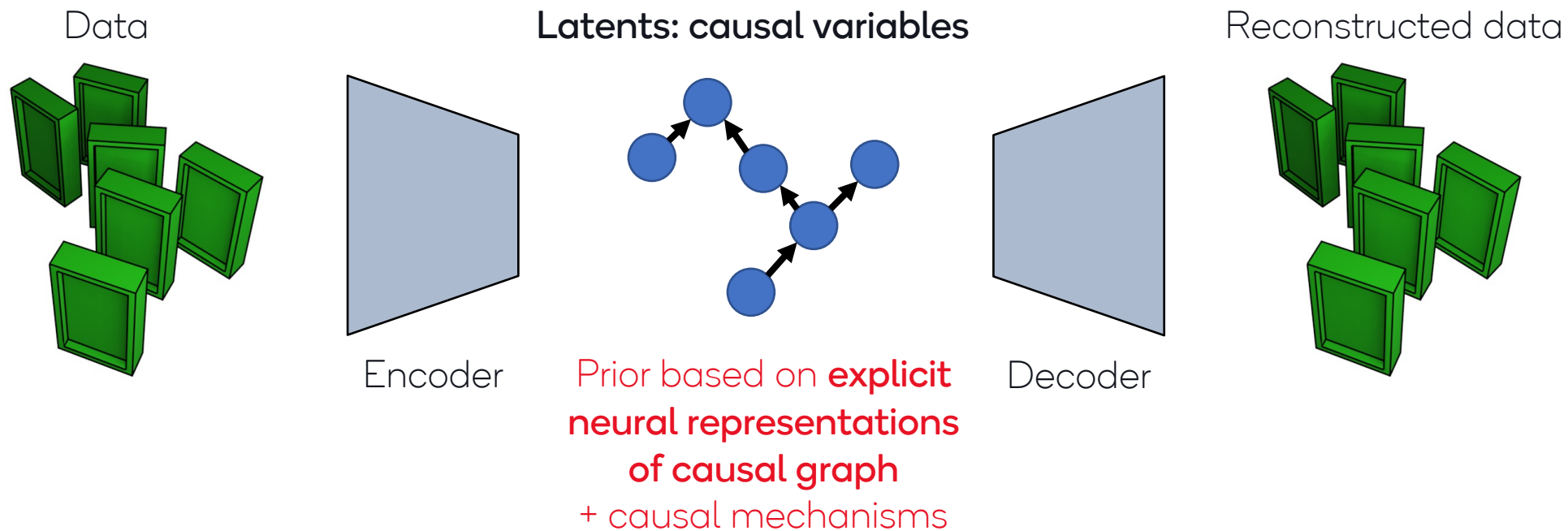


Under our assumptions, explicit and implicit representation **contain the same information**

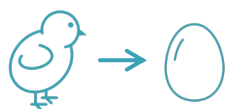
Operationalizing latent causal models



Explicit latent causal models



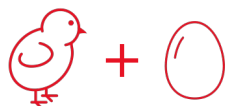
Explicit latent causal models in practice



Easy to learn graph given representations



Easy to learn representations given graph

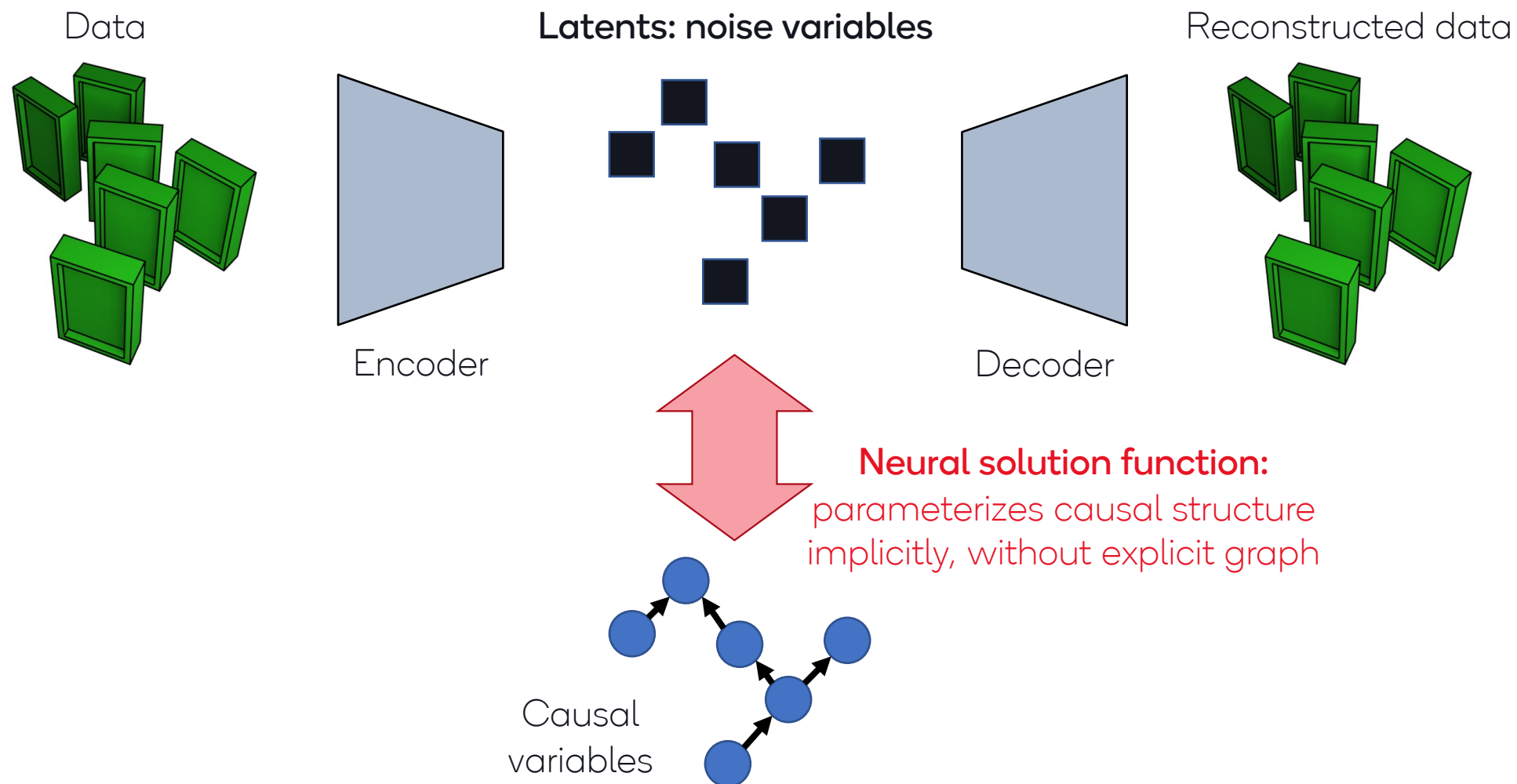


Difficult to learn graph and representation simultaneously

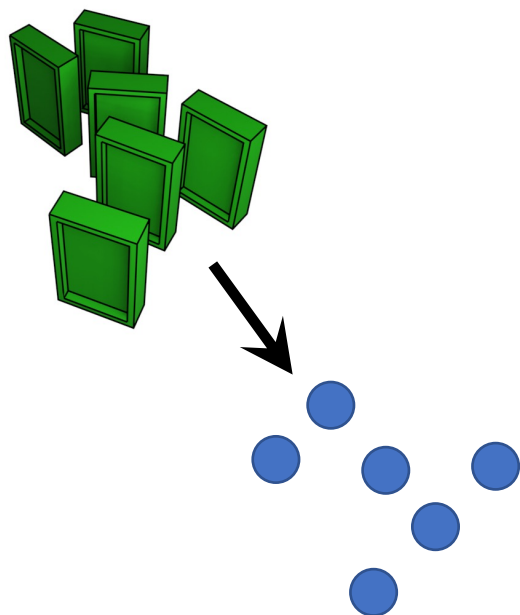
(Evidence for **local minima** in the loss landscape corresponding to wrongly oriented graph edges)

⇒ don't learn a graph if you don't have to

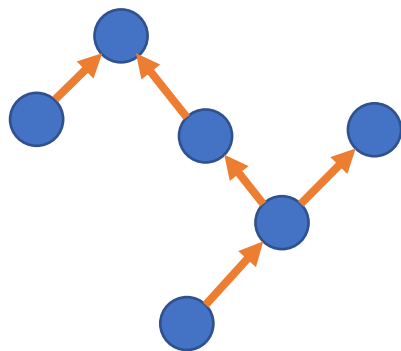
Implicit latent causal models



What can you do with ILCMs?

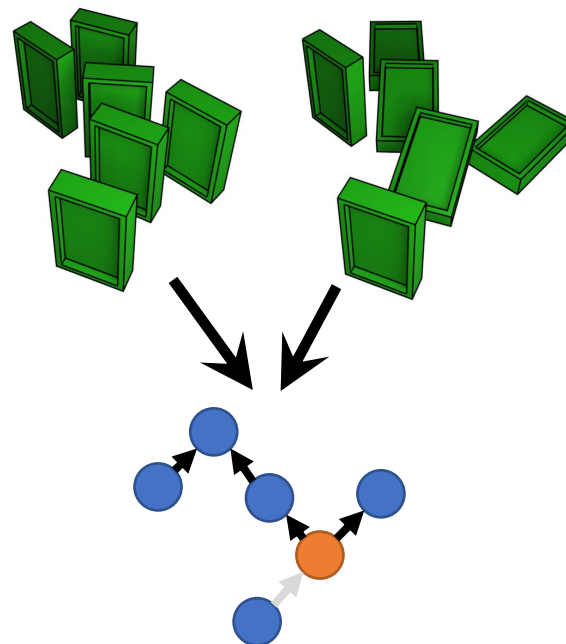


Map pixels to causal variables

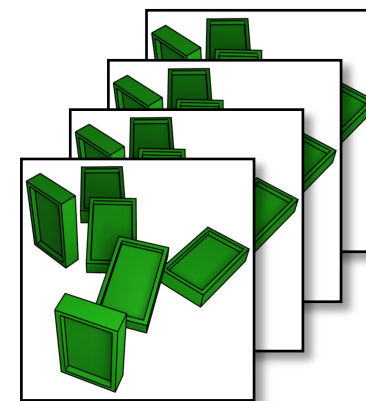


Find the causal graph

- ILCM-E: with off-the-shelf causal discovery algorithm ENCO
- ILCM-H: with our new heuristic



Infer interventions from data pairs



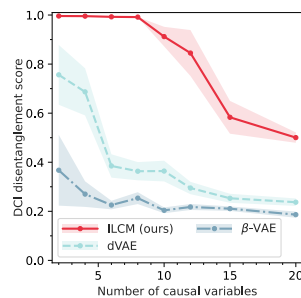
Generate observational, interventional, and counterfactual data

Experiments

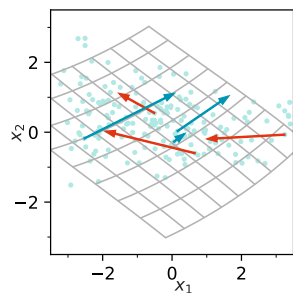
Things work, mostly

Experiments

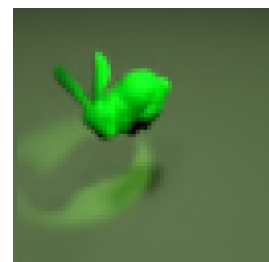
Complexity of causal system



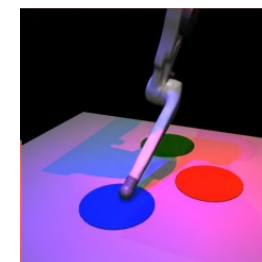
Scaling experiment



2D toy example



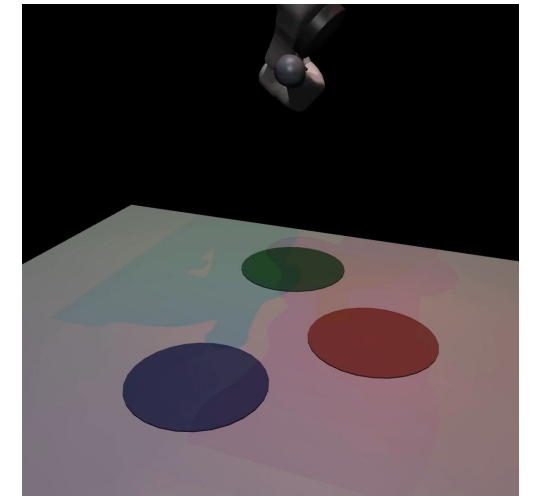
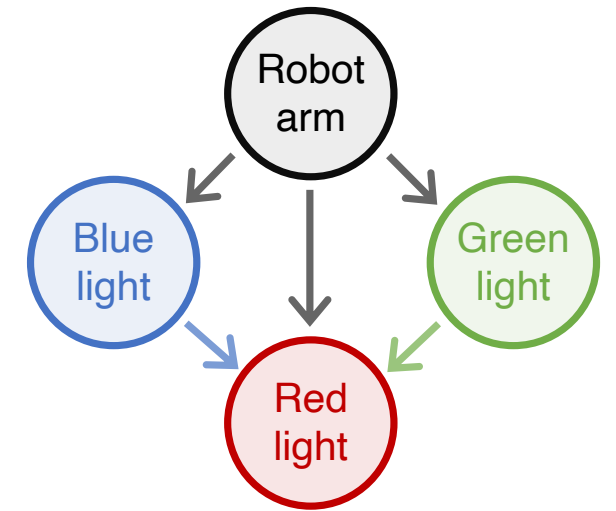
Causal3DIdent



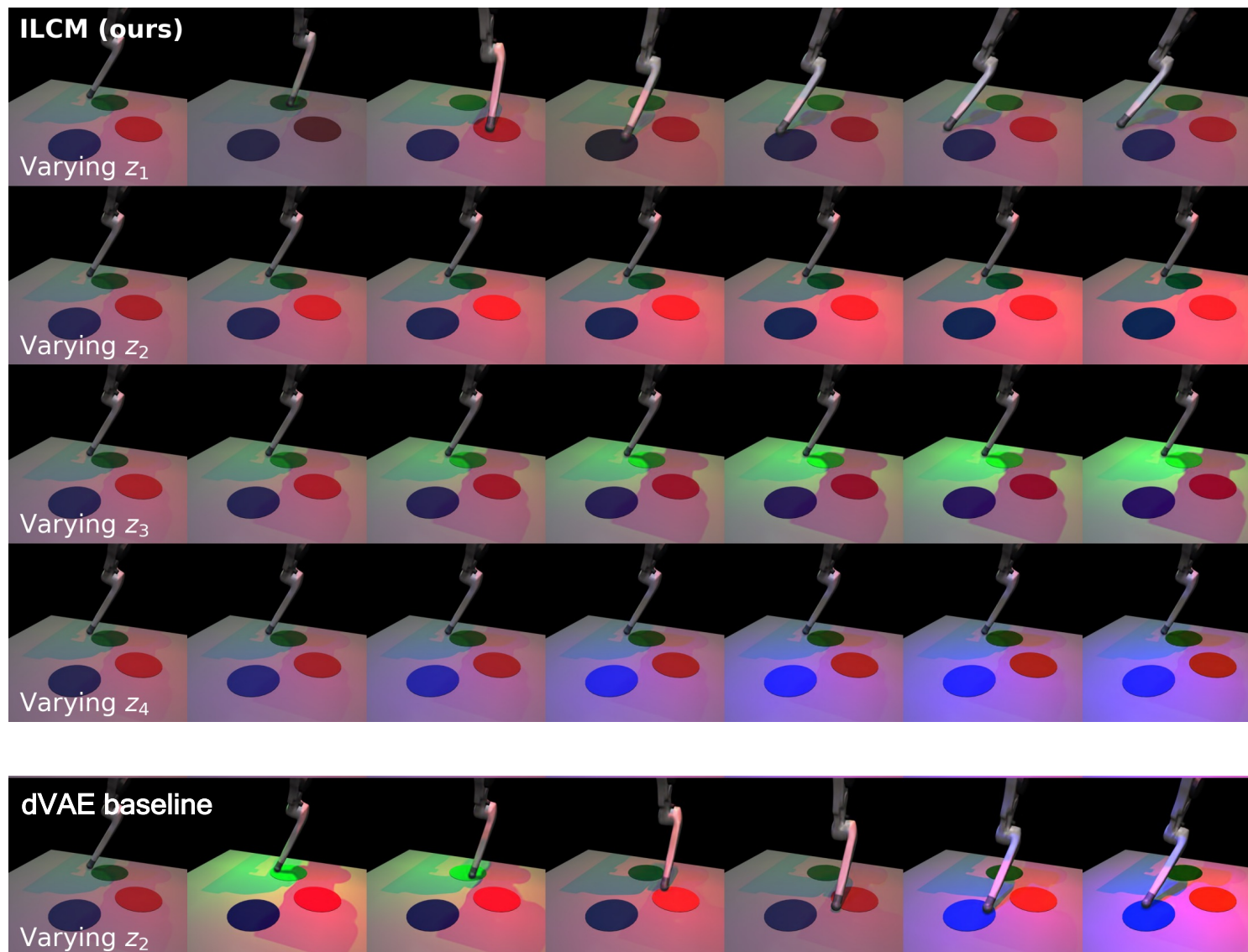
CausalCircuit

CausalCircuit

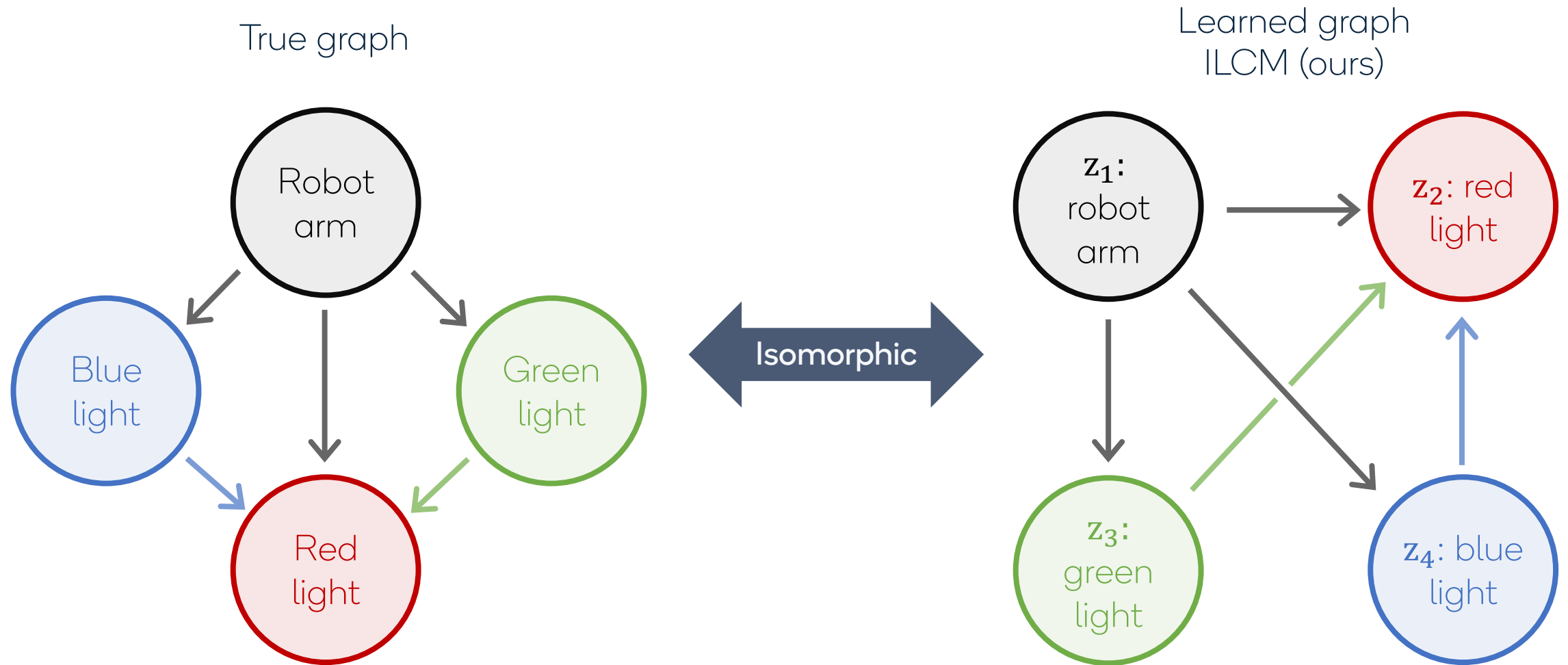
- **New dataset** with more intuitive causal structure
- **Robot arm interacts with touch-sensitive lights, which are connected with a circuit**
 - Robot arm movement based on inverse kinematic model
 - Physics + rendering with MuJoCo
 - 4 continuous causal variables: robot arm restricted to 1D arc + 3 light states
 - 512x512 images from fixed camera position
- ILCMs are trained on pre- and post-intervention data



LCMs **disentangle** the causal variables

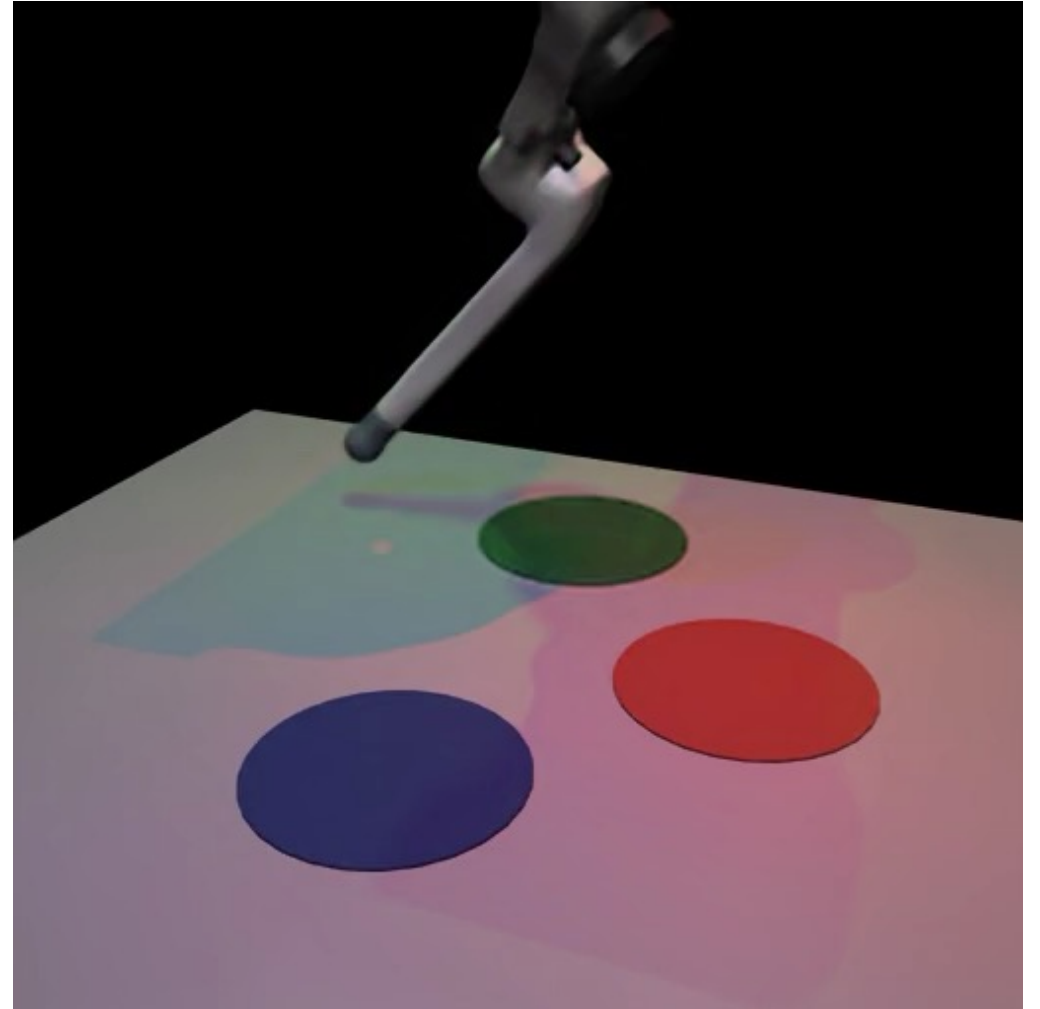


LCMs learn the **correct** graph



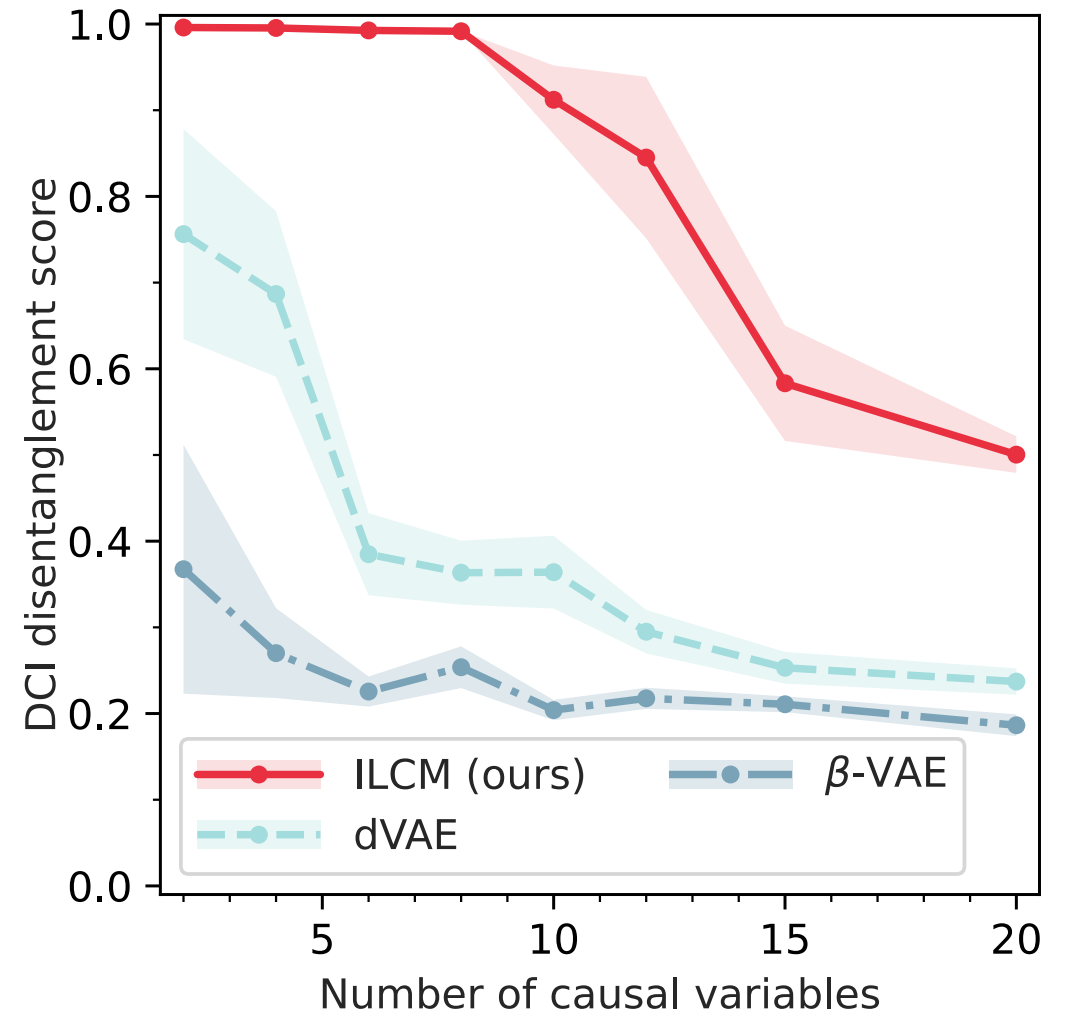
ILCMs let us **reason causally**

ILCM samples, **intervening** on a single latent
(including causal effects)



Do ILCMs **scale**?

- **Toy experiment:**
 - n causal variables
 - linear causal effects
 - $SO(n)$ decoder
- ILCM results **robust up to ~10 variables** without additional tuning



Outlook

**Towards useful
causal representation learning**

A long way to go

Where we are

Identifiability theorems

Pre- & post-intervention data

God-given interventions

Fixed causal variables

Strict DAG-based causality

Toy experiments (up to $O(10)$ variables)

Where we need to get

Demonstrate usefulness on downstream tasks

Realistic data regimes:
observational & interventional data,
video data, ...

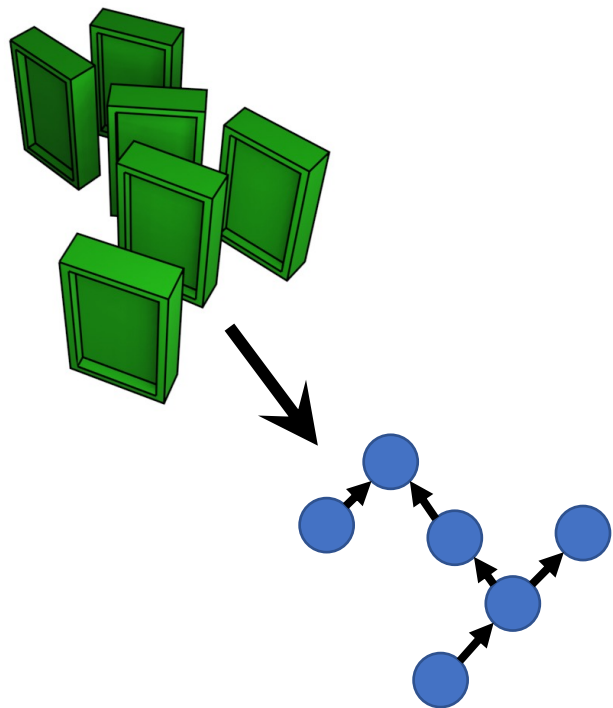
Learning intervention policies

Variable scene composition

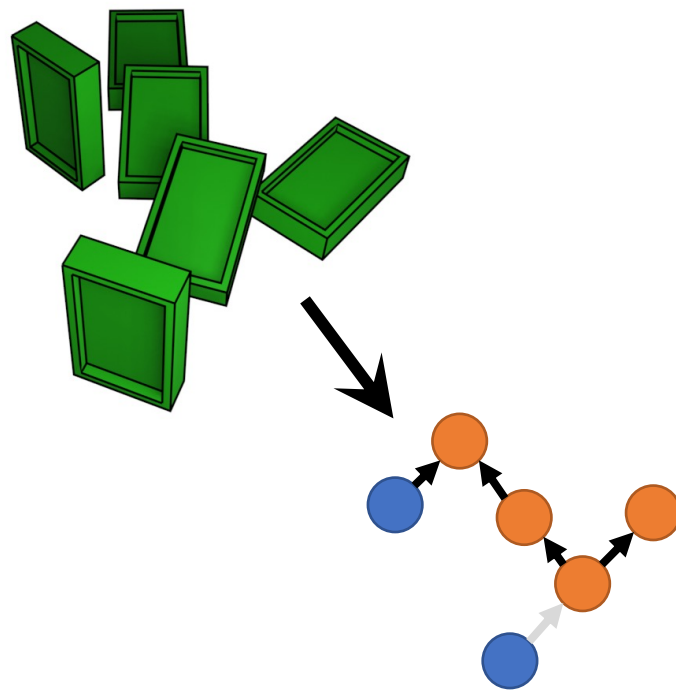
Weaker relational structures

Realistic experiments

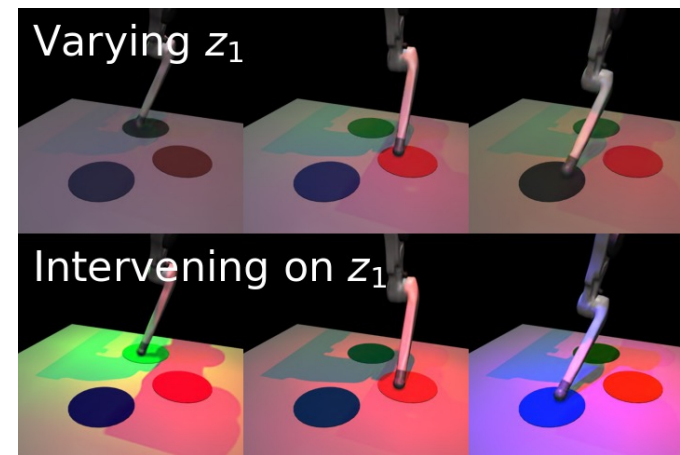




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Weakly supervised causal representation learning

JB, Pim de Haan, Phillip Lippe, Taco Cohen

NeurIPS 2022

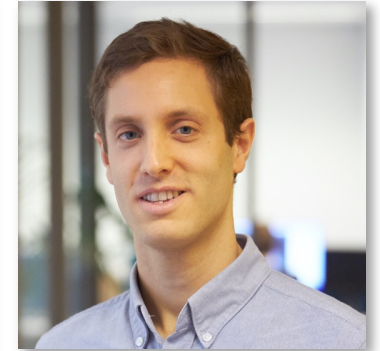
[arXiv:2203.16437](#)



Pim de Haan



Phillip Lippe



Taco Cohen

Towards causal representation learning

Bernhard Schölkopf, Francesco Locatello, Stefan Bauer,
Nan Rosemary Ke, Nal Kalchbrenner, Anirudh Goyal, Yoshua Bengio
IEEE Advances in Machine Learning and Deep Neural Networks 2021

[arXiv:2102.11107](#)

Weakly-supervised disentanglement without compromises

Francesco Locatello, Ben Poole, Gunnar Rätsch, Bernhard Schölkopf,
Olivier Bachem, Michael Tschannen

ICML 2020

[arXiv:2002.02886](#)

Self-supervised learning with data augmentations provably isolates content from style

Julius von Kügelgen, Yash Sharma, Luigi Gresele, Wieland Brendel,
Bernhard Schölkopf, Michel Besserve, Francesco Locatello

NeurIPS 2021

[arXiv:2106.04619](#)

CITRIS: Causal identifiability from temporal intervened sequences

Phillip Lippe, Sara Magliacane, Sindy Löwe, Yuki M. Asano, Taco
Cohen, Efstratios Gavves

ICML 2022

[arXiv:2202.03169](#)

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