# MetaCaDI: A Meta-Learning Framework for Scalable Causal Discovery with Unknown Interventions

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## The Challenge: Few-Shot Causal Discovery with Unknown Interventions

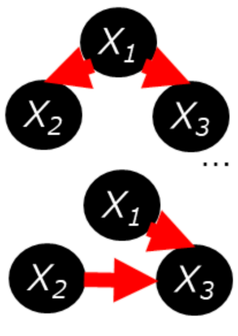
**Input:** Small Dataset $\mathbf{D}$
**Output:** Unknown **Causal Graph** and Unknown **Intervention Targets**

**This task is very difficult!**

**Proposed Solution:** Use Related Data
Assume each $\mathbf{D}$ is from a **Shared Causal Graph** with **Different Intervention Targets**

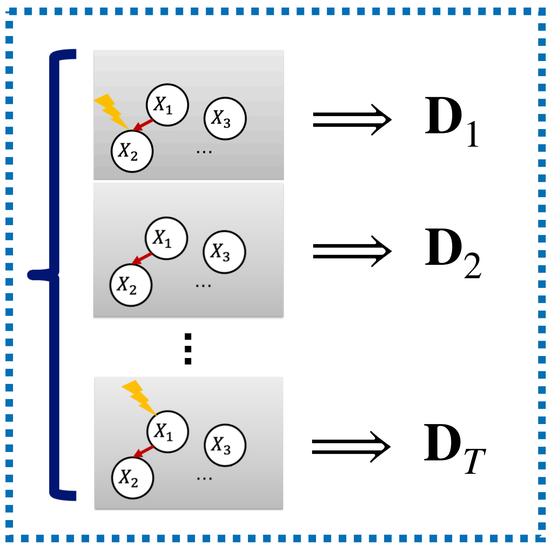
**Posterior Distribution** $P(G, I \mid \mathbf{D})$

**Causal Graph**




**Intervention Targets**

| $X_1$ | $X_2$ | $X_3$ |
|---|---|---|
| 0.7 | 0.1 | 0.2 |

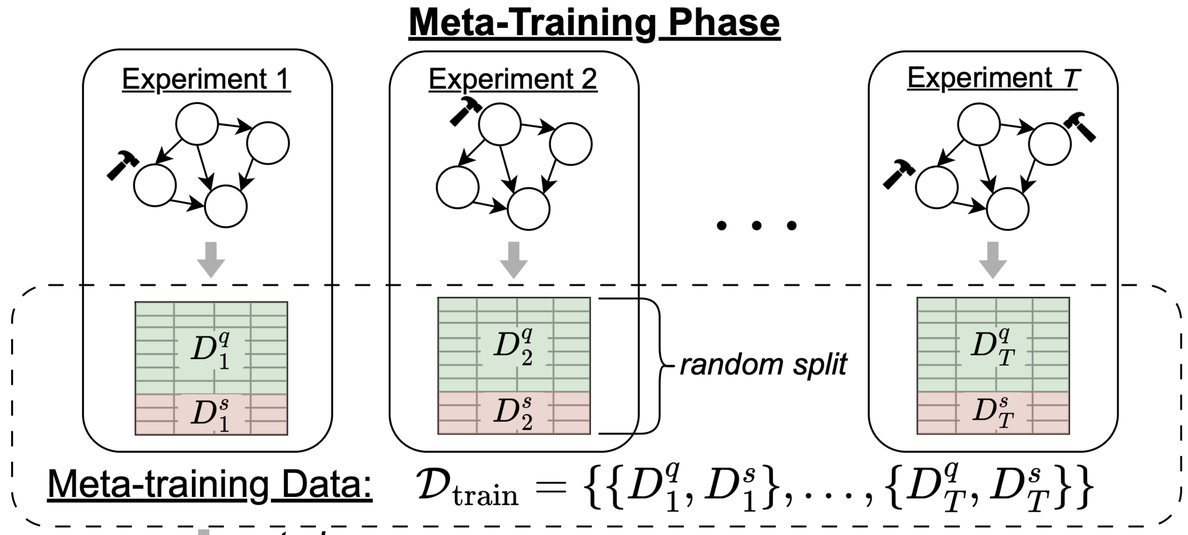



Small Dataset $\mathbf{D}$ → **Train** → **Model** → $P(G, I \mid \mathbf{D})$

## *Meta*-Learning for *Ca*usal *D*iscovery with Unknown *I*nterventions

### Meta-Learning Setup

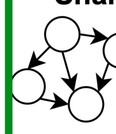
**Meta-Training Phase**




Meta-training Data: $\mathcal{D}_{\text{train}} = \{\{D_1^q, D_1^s\}, \ldots, \{D_T^q, D_T^s\}\}$

*meta-learn*

MetaCaDI Model
**Shared Graph Posterior**



$\sim \mathrm{P}_{\phi,\psi}(\mathbf{A} \mid \mathcal{D}_{\text{train}})$

Rapid adaptation mechansim for $D'_{t'}$

**Meta-test Phase**

Meta-test Data: $\mathcal{D}_{\text{test}} = \{D'_1, D'_2, \ldots, D'_{T'}\}$

$\mathrm{P}_{\Upsilon,\Phi}(\mathbf{m_1} \mid D'_1)$ $\mathrm{P}_{\Upsilon,\Phi}(\mathbf{m_2} \mid D'_2)$ $\mathrm{P}_{\Upsilon,\Phi}(\mathbf{m}_{T'} \mid D'_{T'})$

**Intervention Target Posteriors**

### Model Components

**Likelihood Model**: Masked Auto-encoder

$$X_i = (1 - m_i) \cdot f_i^{\text{obs}}(\mathbf{A}_{:,i} \circ \mathbf{X}) + m_i \cdot f_i^{\text{intv}}(\mathbf{A}_{:,i} \circ \mathbf{X}) + \epsilon_i$$

**Differentiable DAG Sampler**
Adjacency Matrix $\mathbf{A} = \Pi^{\mathrm{T}} U \Pi$
$U \sim \mathrm{P}_\phi(U)$ Upper Triangular Matrix
$\Pi \sim \mathrm{P}_\psi(\Pi)$ Permutation Matrix

**Intervention Predictor**
Sample $m_i \in \{0,1\}$ indicating if the $i^{th}$ variable was intervened on.
$m_i \sim \mathrm{P}(m_i \mid \mathbf{A}, D'_t)$

**Task Adaptation**: Closed-form solution for the last layer of $f_i^{\text{intv}}$

$$f_i^{\text{intv}}(\mathbf{A}_{:,i} \circ \mathbf{X}) = \mathbf{w}_i^\top h(\mathbf{A}_{:,i} \circ \mathbf{X})$$

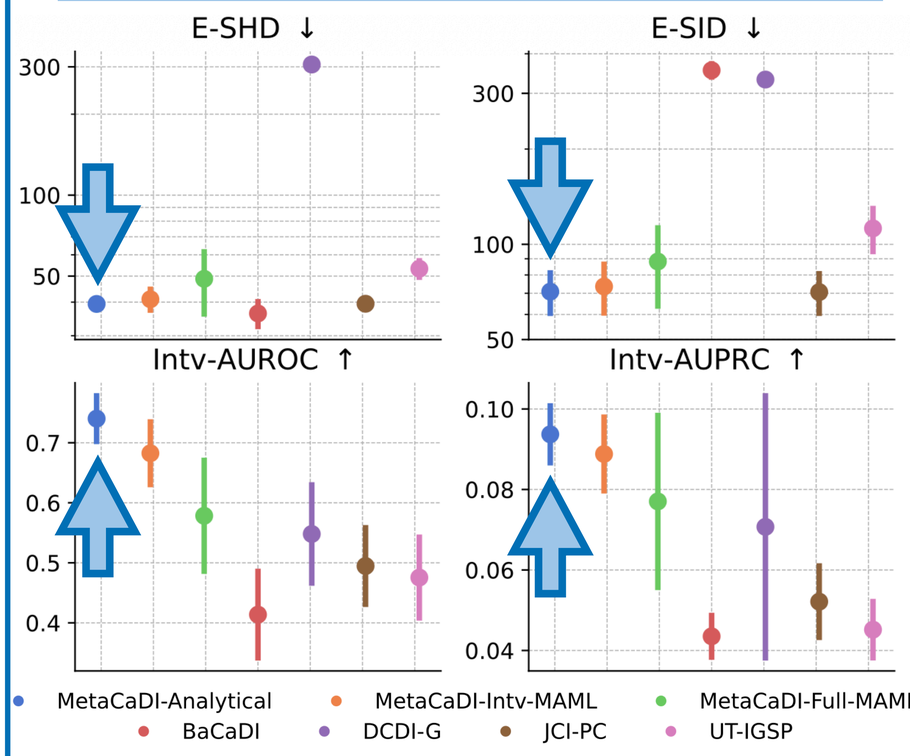
$$\hat{\mathbf{w}}_i = (\mathbf{H}_i^\top \mathbf{H}_i + \lambda \mathbf{I})^{-1} \mathbf{H}_i^\top (D'_t)_{:,i}$$

**Analytical Adaptation** (No Gradients!)
This closed-form solution adapts the model to the new task. All the heavy lifting is done during meta-training.

## Results

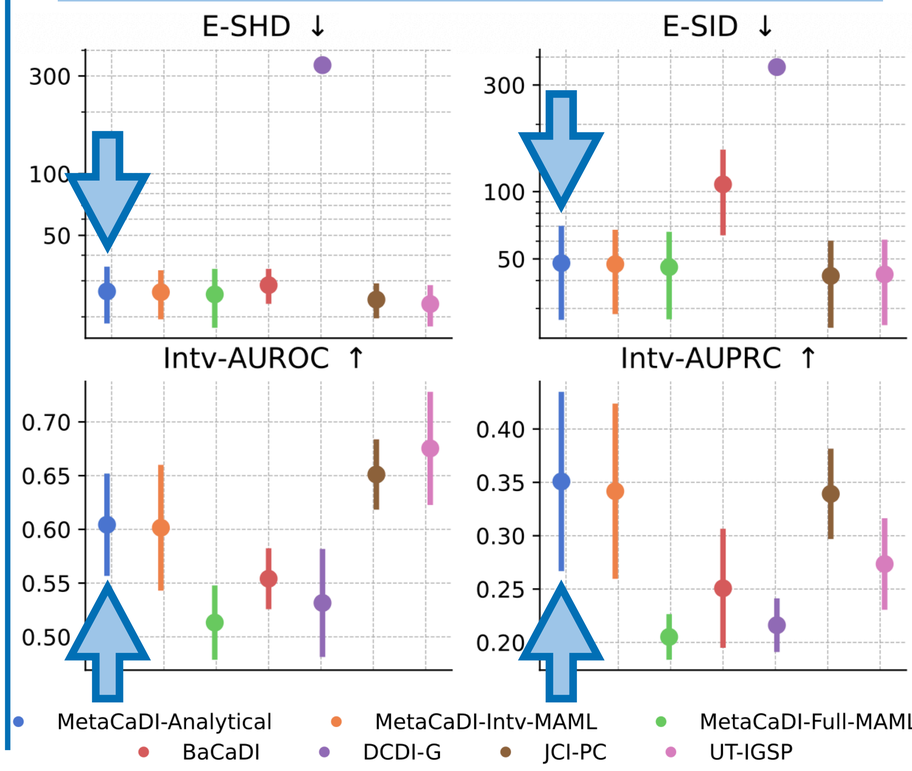
### SERGIO Dataset

Realistic gene expression simulator, scale-free graphs, hard gene knockouts.




### Synthetic Dataset

Non-linear (Gaussian Process), Erdős-Rényi graphs, soft interventions.

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