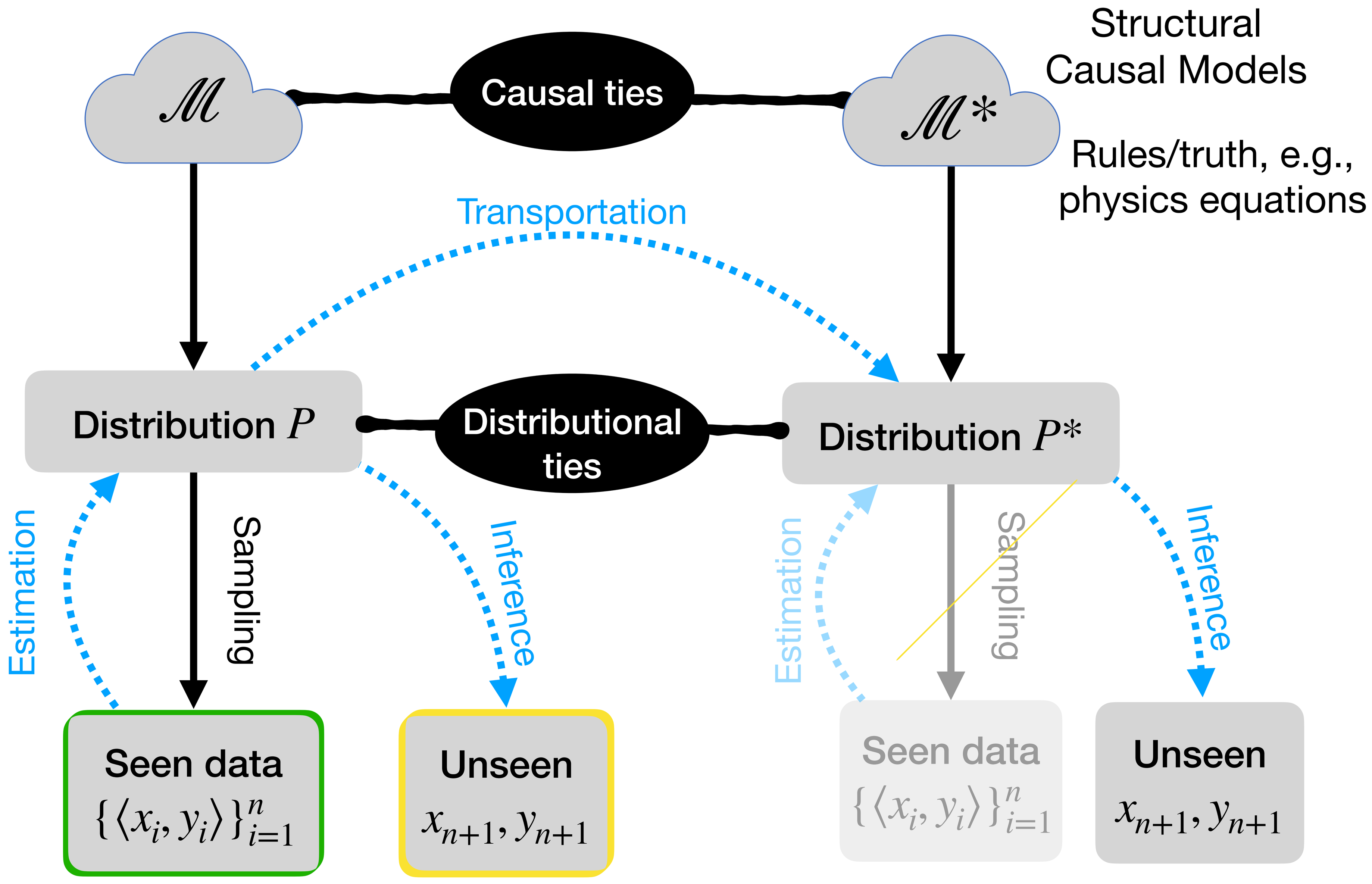
Causal Transportability: A framework for understanding generalization

Kasra Jalaldoust and Elias Bareinboim

The Generalization Scheme



Challenges of generalization:

1. Generalizable features $\mathbf{Z} \subset \mathbf{X}$.

2. Explicit vs. implicit causal ties

3. Robust risk evaluation (partial-TR).

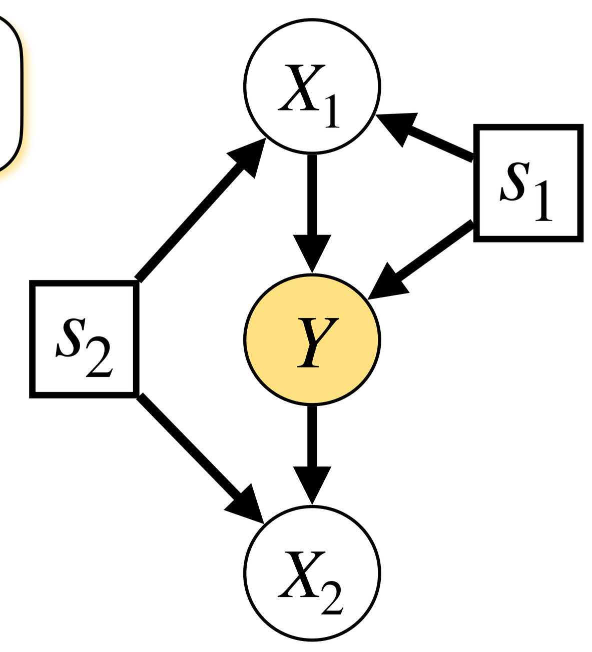
4. Substitute causal ties with target datapoints?

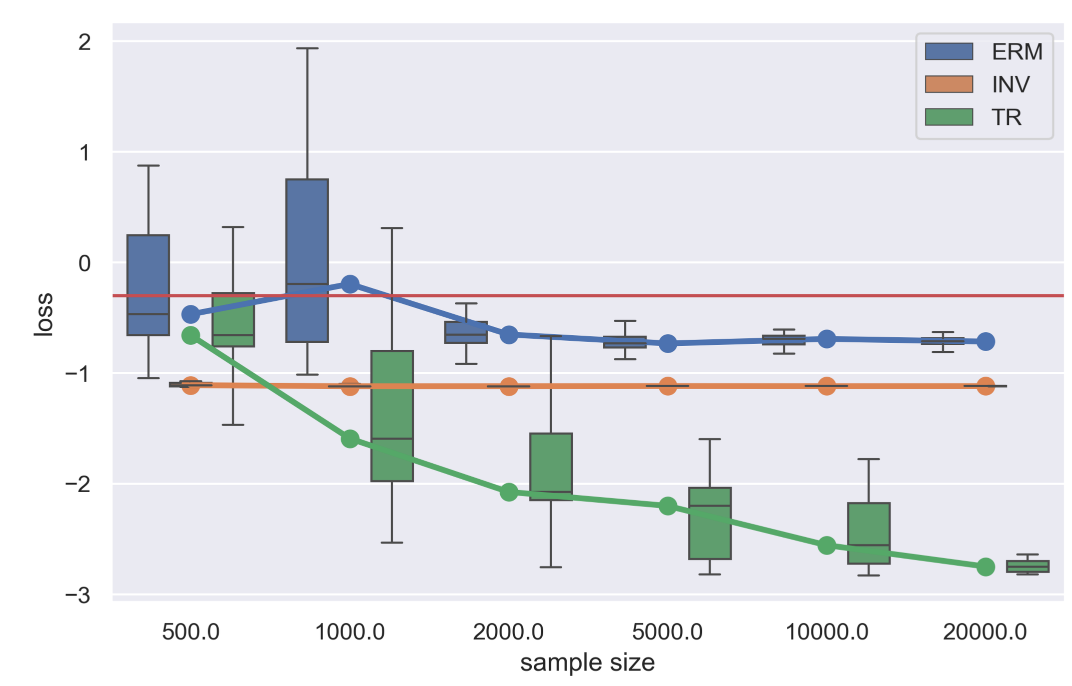
5. Characterizing fast and slow adaptation.

1. Beyond covariate shift assumption: Transporting features!

Can I compute $P^*(y \mid \mathbf{z})$ from source data only?

$$P^*(y \mid x_1, x_2) \propto P^1(x_2 \mid y, x_1) \cdot P^2(y \mid x_1)$$





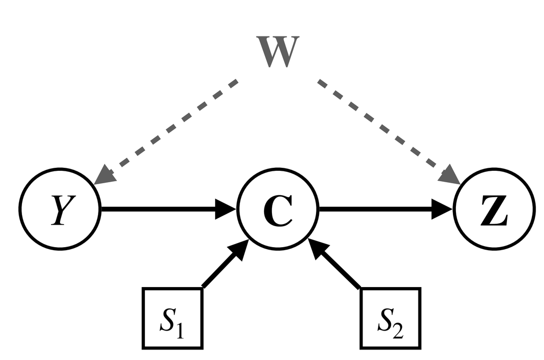
2. What if don't know the graph, but I have access to a *rich enough* set of source domains? Implicit causal ties.

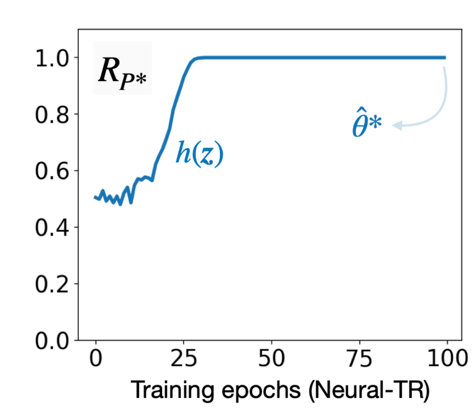
Causal Mechanistic Stability: Every mechanism that has remained stable among the source domains will remain stable in the target domain $\Longrightarrow$ if $\mathbb{E}_{P^*}[Y \mid \phi(\mathbf{X})]$ is computable, then $P^i(y \mid \phi(\mathbf{X})) = P^j(y \mid \phi(\mathbf{X}))$ for every pair of source domains i, j.

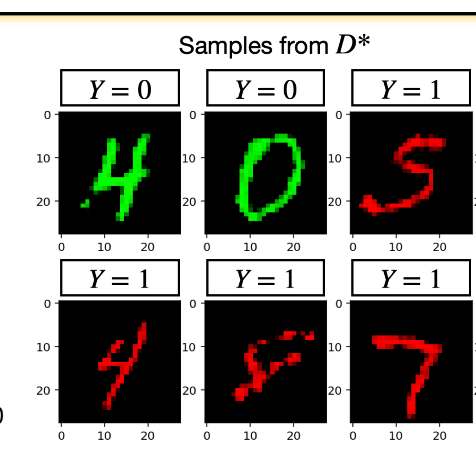
3. Robust Risk Evaluation and Search: In case of not TR, what is the worst-case risk of a classifier?

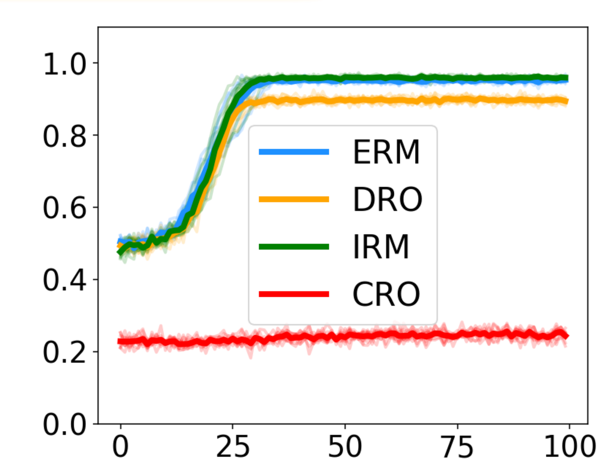
$$h^* \in \arg\min_{h \in \mathcal{H}} \max_{\text{valid } \mathcal{M}} \mathbb{E}_{P^{\mathcal{M}}}[\,|h(\mathbf{X}) - Y|\,]$$

(CRO) (Neural-TR)









4&5. Adaptability: Under insufficient causal ties, we can use transportability for data-efficient fine-tuning!

In different real-world scenarios we see fast and slow adaptation.

In settings where DG is *hard*, we see that with proper configuration DA is possible with extremely small data. Does causal modeling explain this?

Preliminary results suggest that excess risk of adaptation can be characterized in terms of the causal ties.