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Smoke and Mirrors in Causal Downstream Tasks



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Motivation: *Experimental Ecology*

X

Treated Group
Batch: 1, Position: 6, Time: 2m45s



Y



No Action

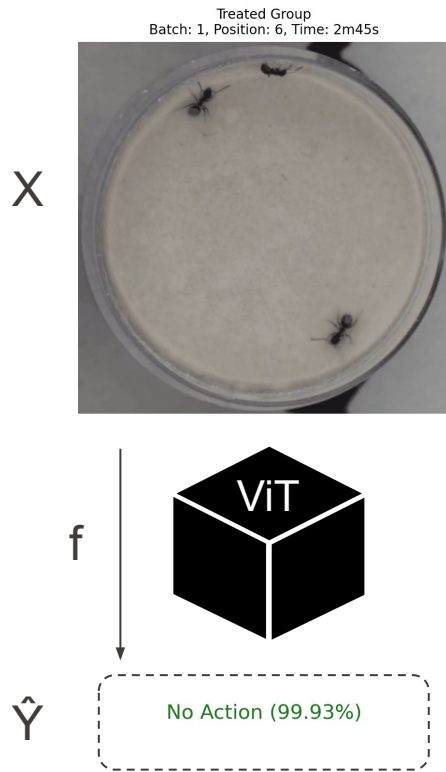
Objective:

$$ATE := \mathbb{E}[Y|do(T = 1)] - \mathbb{E}[Y|do(T = 0)]$$

Treatment
(e.g., virus)

Behaviour
(e.g., grooming)

Motivation: *Experimental Ecology*



Objective:

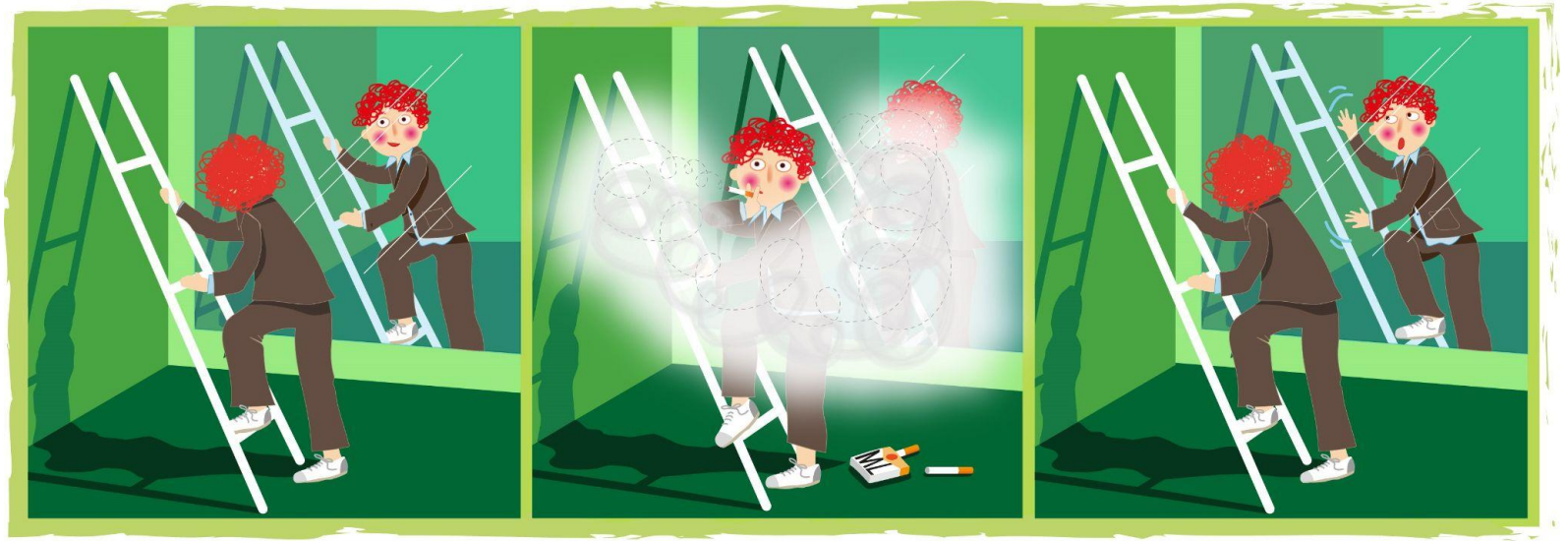
$$ATE \approx \mathbb{E}[f(\mathbf{X})|do(T = 1)] - \mathbb{E}[f(\mathbf{X})|do(T = 0)]$$

Treatment
(e.g., virus)

Predicted Behaviour
(e.g., grooming)

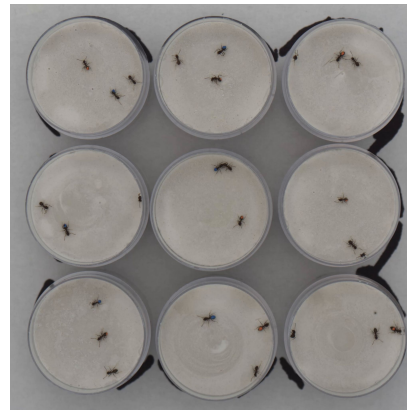
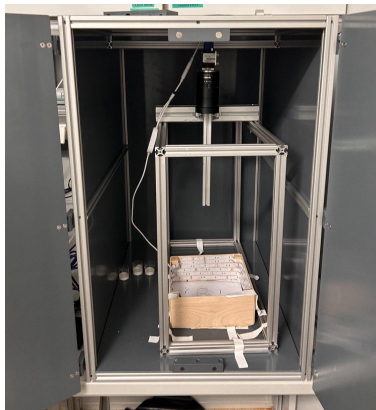
Treatment Effect Bias

$$TEB := \left(\underbrace{\mathbb{E}_{\mathbf{X}|do(T=1)}[f(\mathbf{X})] - \mathbb{E}_{Y|do(T=1)}[Y]}_{\text{Interventional Bias under Treatment}} \right) - \left(\underbrace{\mathbb{E}_{\mathbf{X}|do(T=0)}[f(\mathbf{X})] - \mathbb{E}_{Y|do(T=0)}[Y]}_{\text{Interventional Bias under Control}} \right)$$



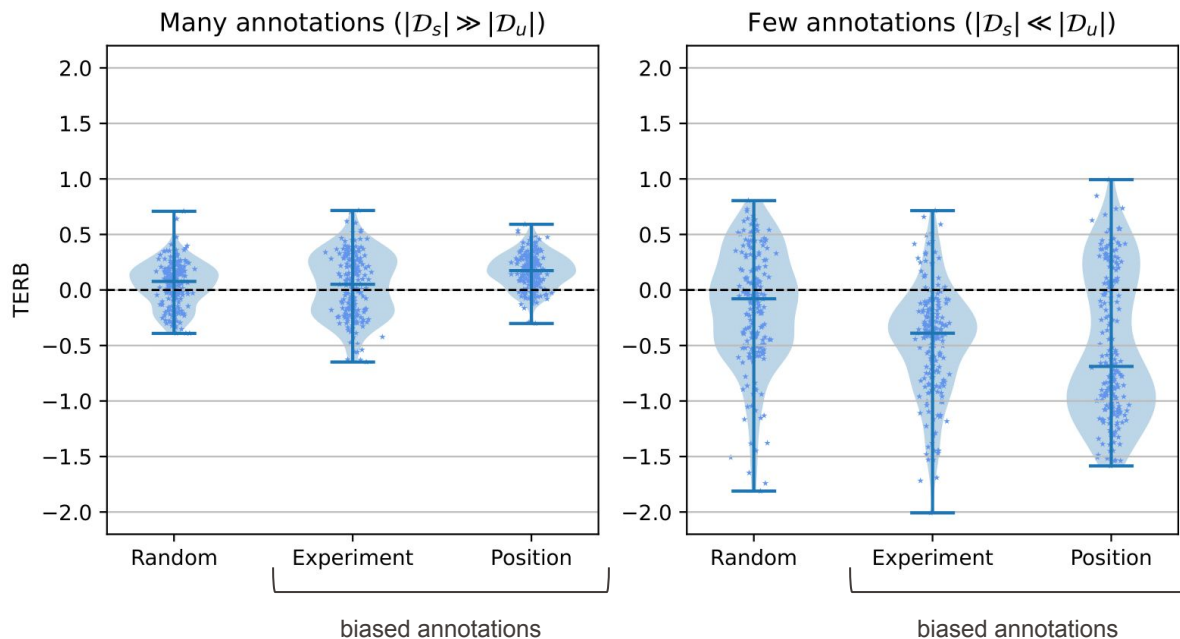
Contributions

- Formulation challenges in (Factual) Estimation for Causal Downstream Tasks
 - Potential mitigations
 - Experimental evidence (synthetic and real-world data)
- [New Benchmark] ISTAnt*



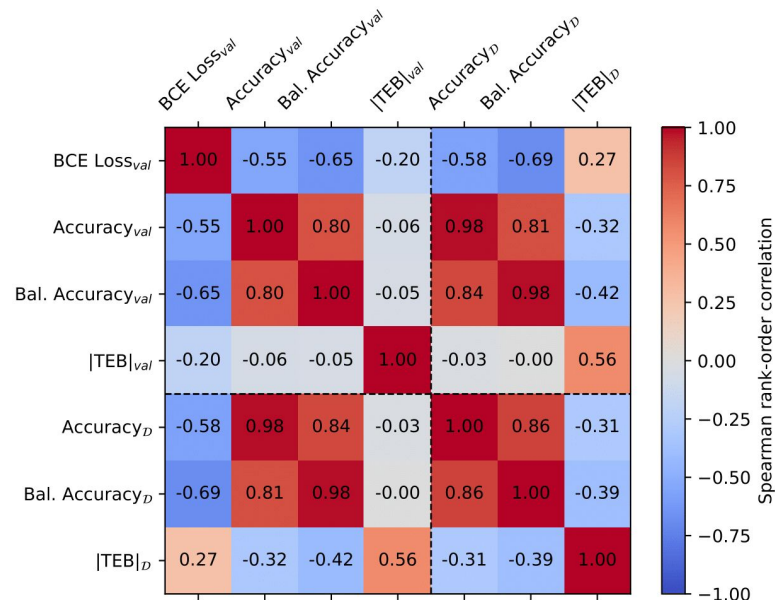
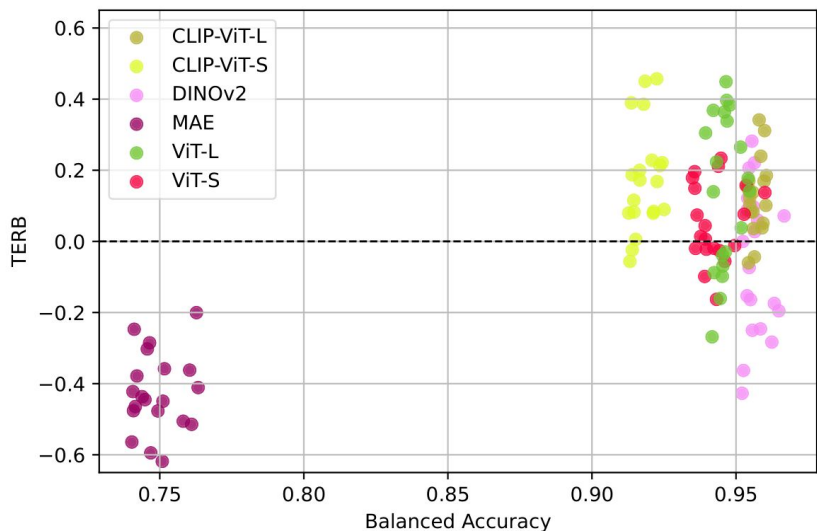
Issue 1: Annotation Bias

Unbiased supervision (i.e., annotation) is crucial to close backdoor paths and avoid confounding effects



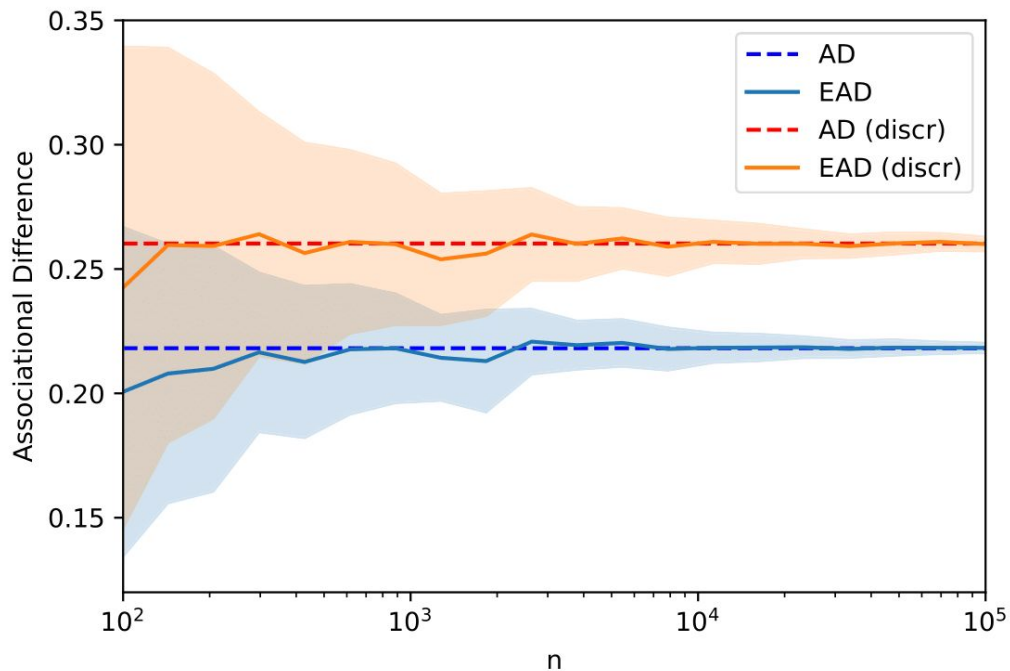
Issue 2: Encoder Bias

Prediction is not Causal Estimation. New methodologies to mitigate the treatment effect bias during adaptation should be investigated.



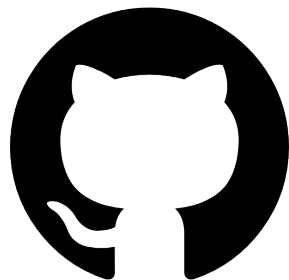
Issue 3: *Discretization Bias*

Don't arbitrarily discretize predictions for downstream treatment effect estimation.



Reproducibility

Code:



<https://github.com/CausalLearningAI/ISTAnt>
<https://github.com/CausalLearningAI/CausalMNIST>

Data:



<https://doi.org/10.6084/m9.figshare.26484934.v2>

**Thank you for your
attention**