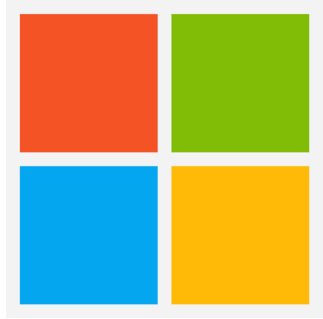


ICLR 25



# Robust Root Cause Diagnosis using In-Distribution Interventions



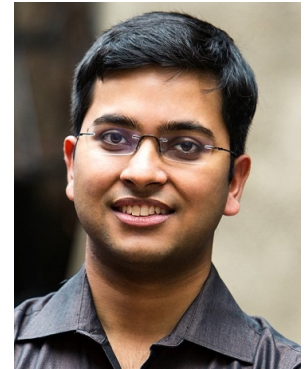
Lokesh  
Nagalapatti



Ashutosh  
Srivatsava



Sunita  
Sarawagi



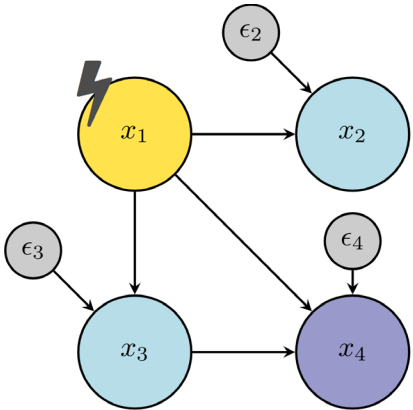
Amit  
Sharma

# Diagnosing Anomalies in Microservices/Industry

- Given that a fault occurred at a particular component of an industry, goal is to diagnose its root cause.
- The goal of RCD is:
  1. Predict the root cause node that triggered the anomaly at target node.
  2. Propose remediation action at the root cause node to fix the anomaly at the target.
- A Causal Inference problem.

# Root Cause diagnosis

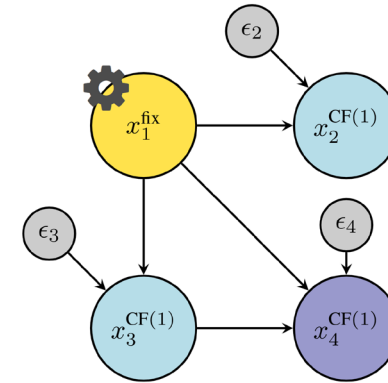
$X_1$  suffered an abnormal intervention



(a) Root Cause sample

Fault occurred at  $x_4$

Suppose we apply a fix at  $X_1$  and set it to its normal value  $x_1^{\text{fix}}$

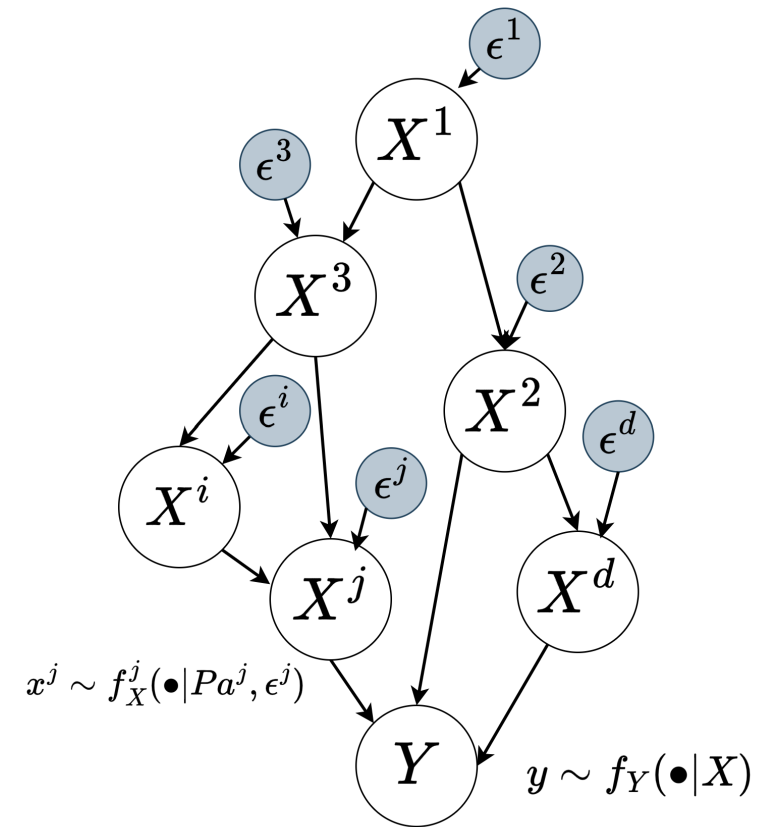


(b) True Counterfactual

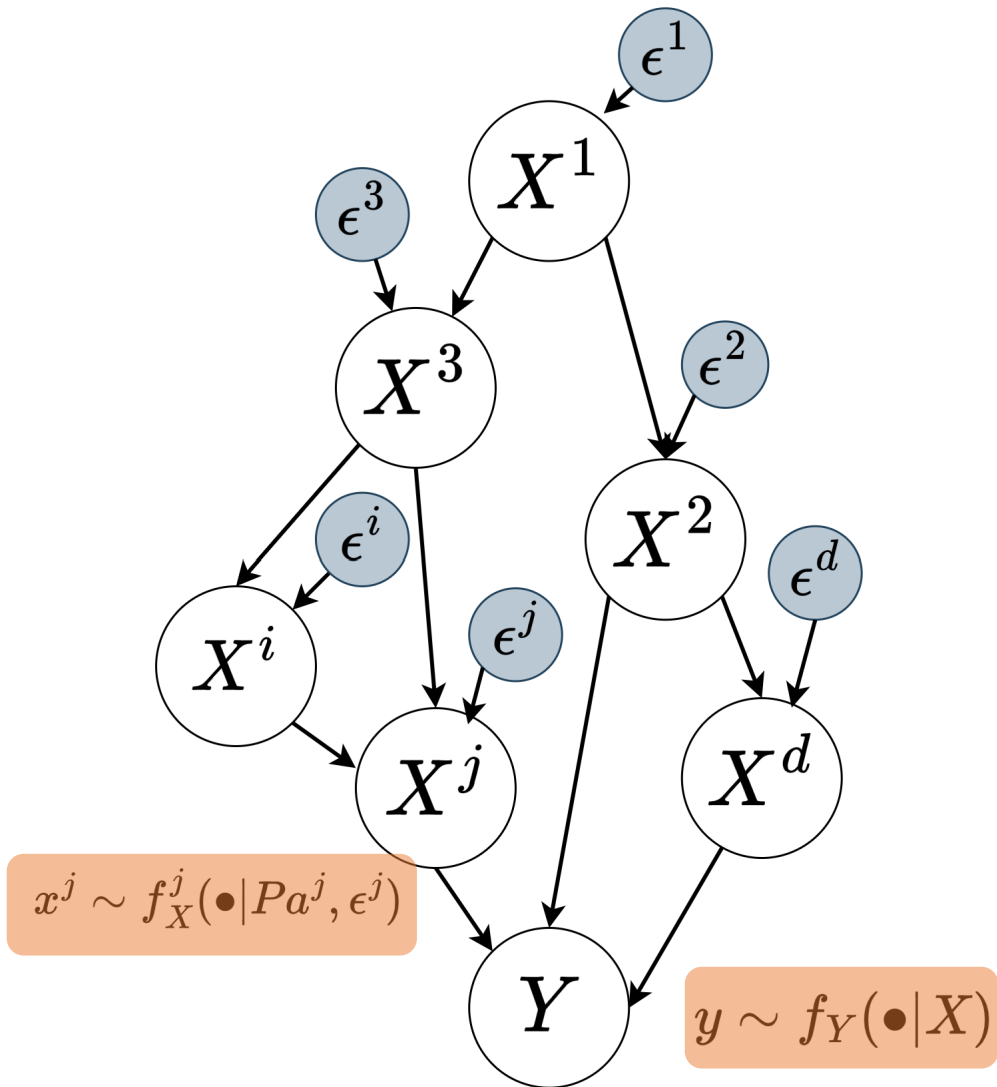
As a consequence of the fix, the corresponding CF  $X_4$  should come back to normal value.

# Training Dataset

- We are given a logged dataset of values of nodes observed through time.
- And the Causal Graph connecting the nodes.



# Advantage of knowing the causal graph



Further if the node functions are additive in  $\epsilon$

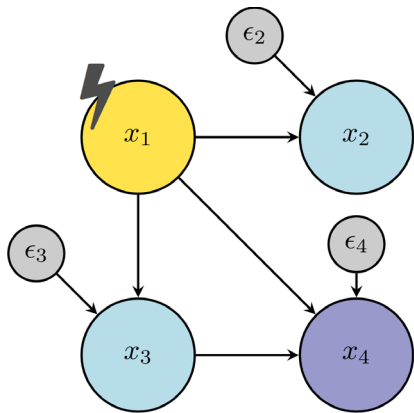
$$x^j = f_X^j(pa^j) + \epsilon^j$$

Then Abduction is possible:

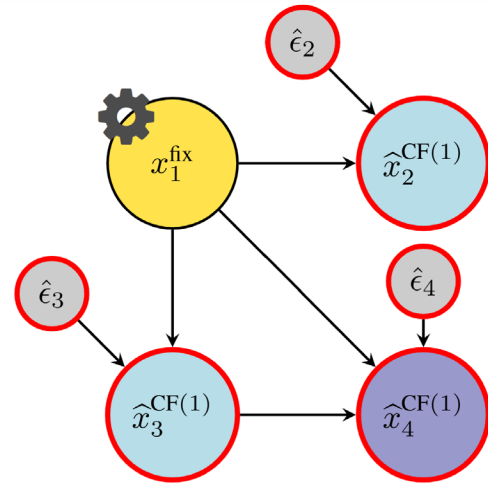
$$\epsilon^j = x^j - f_X^j(pa^j)$$

Each of these functions can be learned using observational datasets upto good accuracies because each one involves fitting a very low dim regression problem

# Prior works Estimate Counterfactuals



(a) Root Cause sample



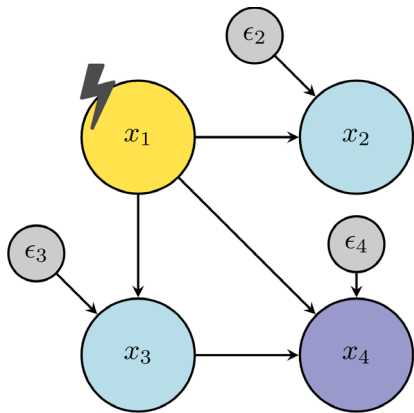
(c) Est. Counterfactual



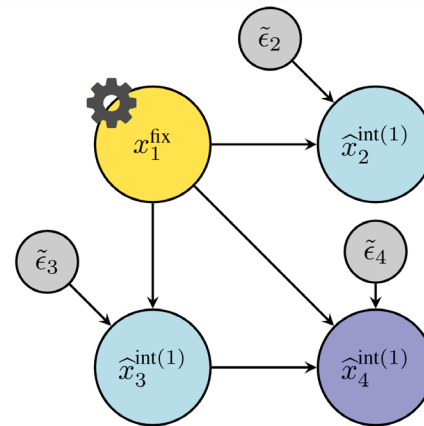
Abduction involves estimation of  $\epsilon_4$  at an abnormal  $x_1$

1. Abduction:  $\hat{\epsilon}_4 = x^j - f_X^j(x_1)$
2. Action: Set  $x_1 = x_1^{\text{fix}}$
3. Prediction:  $\widehat{x_4^{\text{CF}}} = f_4(\widehat{x_1^{\text{fix}}}) + \hat{\epsilon}_4$

# Our Approach: In Distribution Intervention



(a) Root Cause sample



(d) Est. Intervention

1. Action: Set  $x_1 = x_1^{\text{fix}}$
2. Prediction:  $\widehat{x_4^{\text{int}}} = f_4(\widehat{x_1^{\text{fix}}}) + \tilde{\epsilon}_4$   
where  $\tilde{\epsilon}_4$  is a sampled value

Consequence: We always evaluate  $\widehat{f}_4$  at in-distribution values

# Results on Petshop Dataset

		Low		High		Temporal	
Recall@		k=1	k=3	k=1	k=3	k=1	k=3
Correlation	Random Walk ( <a href="#">Yu et al., 2021</a> )	0.00	0.10	0.00	0.20	0.00	0.33
	Ranked Correlation ( <a href="#">Hardt et al., 2023</a> )	0.40	0.60	0.70	0.90	0.50	0.67
	$\epsilon$ -Diagnosis ( <a href="#">Shan et al., 2019</a> )	0.00	0.00	0.00	0.00	0.17	0.17
Causal Anomaly	Circa ( <a href="#">Li et al., 2022</a> )	0.60	0.80	0.60	1.00	0.67	1.00
	Traversal ( <a href="#">Chen et al., 2014</a> )	0.80	0.80	0.90	0.90	1.00	1.00
	Smooth Traversal ( <a href="#">Okati et al., 2024</a> )	0.40	0.60	0.00	0.60	0.50	1.00
Causal Fix	HRCDD ( <a href="#">Ikram et al., 2022</a> )	0.07	0.21	0.00	0.07	0.25	0.75
	TOCA ( <a href="#">Okati et al., 2024</a> )	0.40	0.40	0.20	0.20	0.00	0.00
	CF Attribution ( <a href="#">Budhathoki et al., 2022b</a> )	0.40	0.60	0.40	0.70	0.00	0.50
	IDI (Ours)	0.90	0.90	0.90	0.90	1.00	1.00



*Thank  
you!*