Identifying When Effect Restoration Will Improve Estimates of Causal Effect

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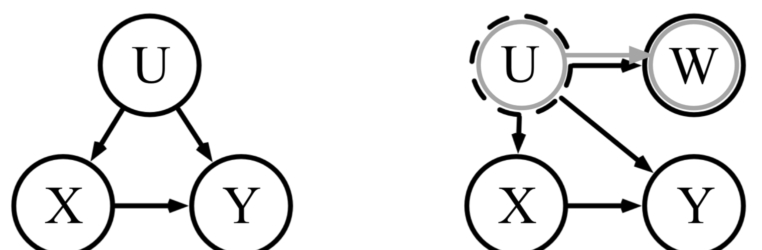
Motivation

Growing use of ML has led to an interest in combining models learned on different data sets and using those models to make inferences that would not have been possible with a single model.



Graphical models with confounding.

Being particularly valuable in causal inference, researchers in causal graphical models have studied how to learn a single model from multiple data sets with overlapping sets of variables [8].

What happens when there are confounding variables introducing bias in estimates of treatment effect?

Objectives

We study how to accurately condition on confounding variables even when those variables are not accurately measured in a dataset.

We use effect restoration, a technique originally proposed by Kuroki & Pearl [3] to adjust for measurement error in confounding variables.

RQ1. How does the actual causal structure affect the accuracy of effect restoration?

RQ2. Practically, what conditions are necessary for effect restoration to substantially improve estimates of causal effect?

RQ3. For a given set of observations, X,Y, and W, what are the sufficient conditions to identify the underlying graphical structure?

Background

We use graphical models and Pearl's do-calculus. We denote the direct effect of X on Y as P(Y | do(X)). This represents the effect of manipulating the values of X, which is different from passive observation P(Y | X) (i.e. conditioning).

$$P(Y \mid do(X=x)) = \sum_{U} \frac{P(X,Y,U)}{P(X \mid U)}$$

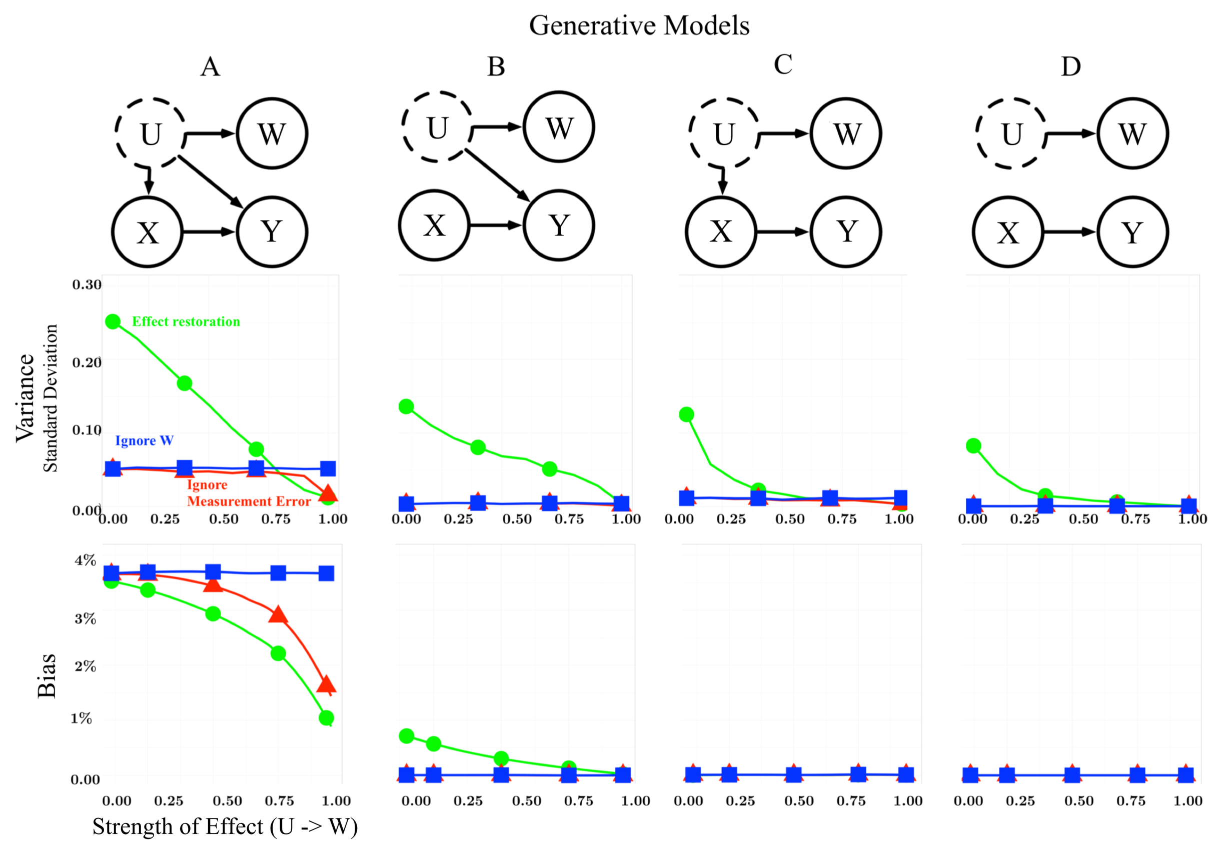
Given this interventional distribution, for a binary X, the treatment effect (TE) of X on Y can be calculated as:

$$TE = \log\left(\frac{P(Y_1 \mid do(X_1))}{P(Y_0 \mid do(X_1))}\right) - \log\left(\frac{P(Y_1 \mid do(X_0))}{P(Y_0 \mid do(X_0))}\right)$$

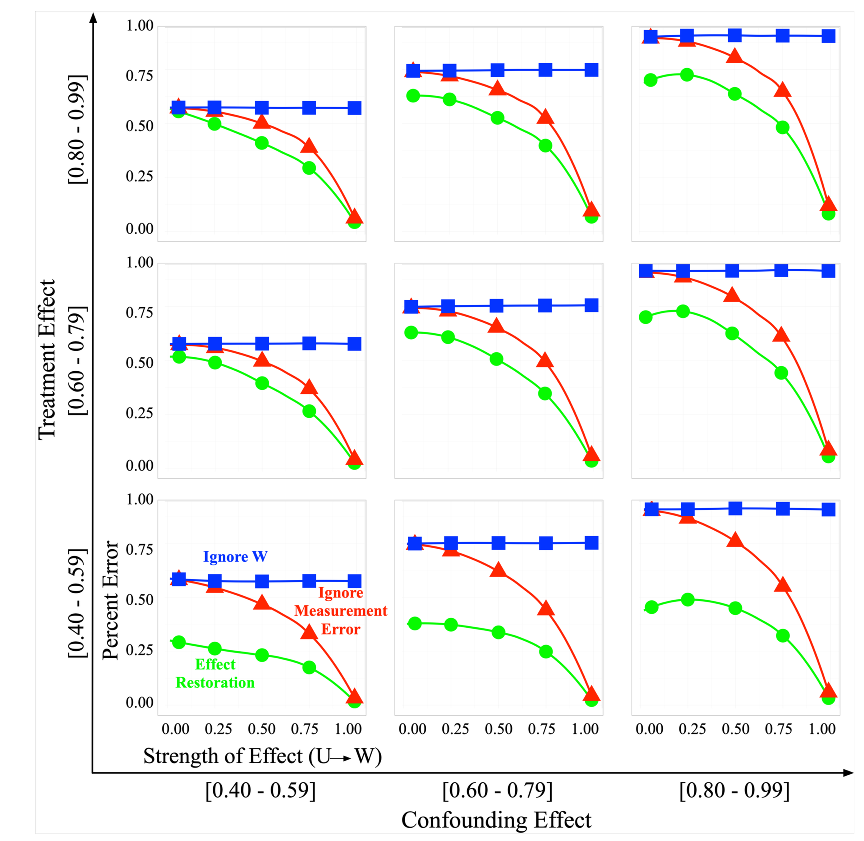
Kuroki & Pearl used the do-calculus and knowledge of the error distribution to correct the causal estimate made using observed values [3]. They propose that TE of X on Y can be restored bias-free given an observed surrogate variable for the confounder U (i.e., W) and a known error distribution (i.e., P (W | U)).

Effects of Underlying Structure on Bias and Variance

How does the actual causal structure affect the accuracy of effect restoration?



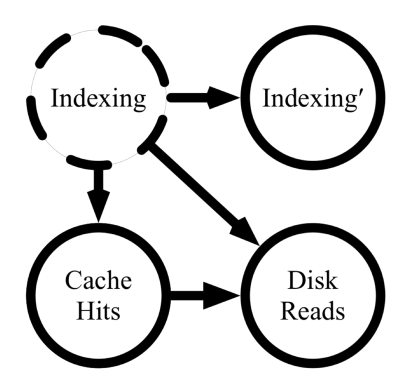
Case A

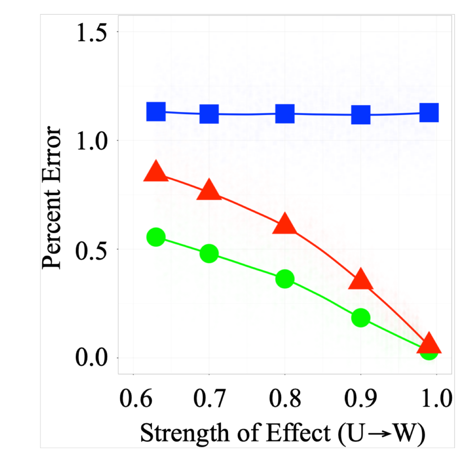


Applying effect restoration regardless of the underlying structure can result in an incorrect estimate.

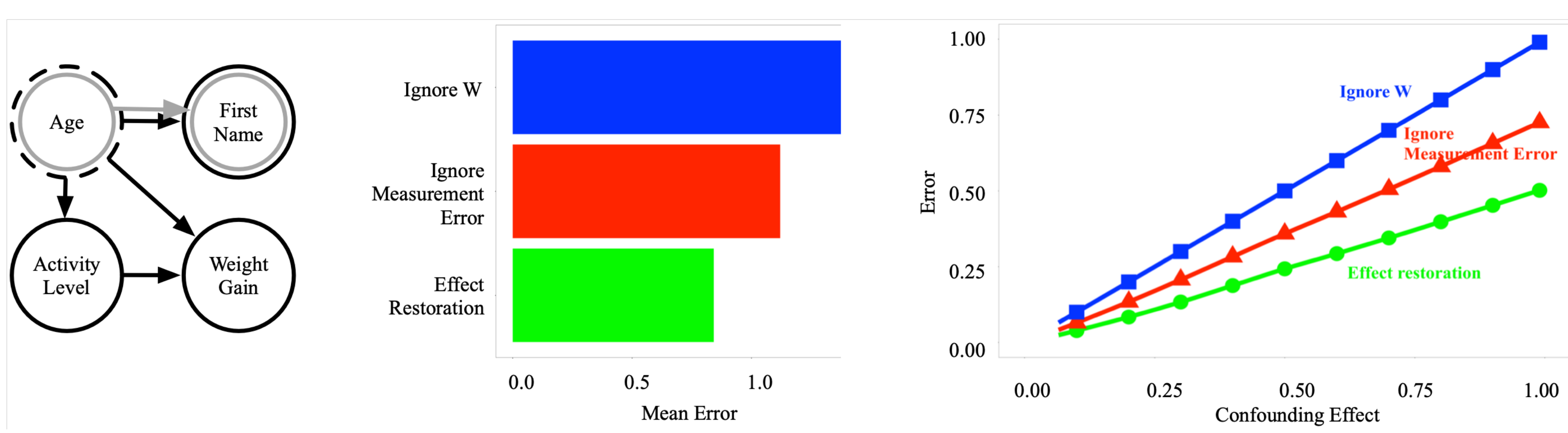
Effect restoration is most effective when the treatment effect is small and the confounding effect is high.

Empirical Evaluation of Effect Restoration

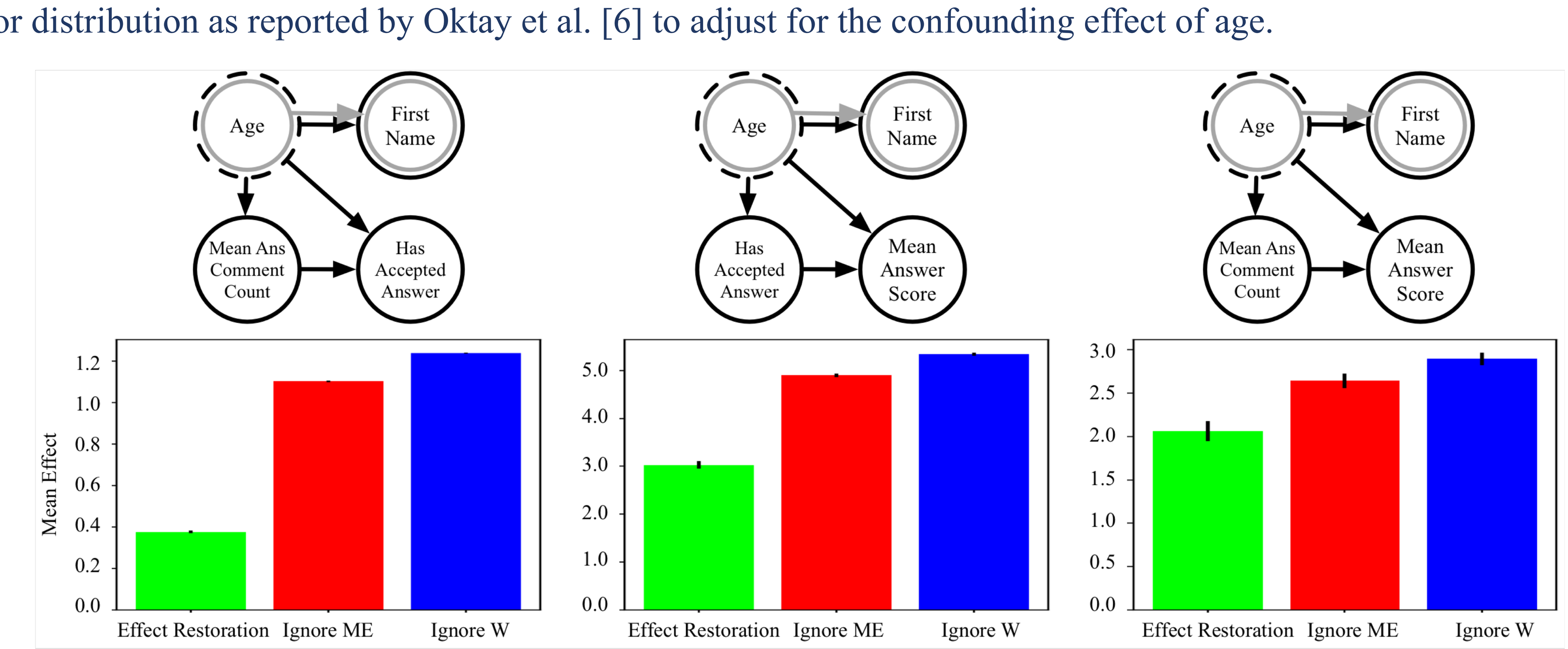




Effect Restoration in Real Data. We use the experimental data compiled by Garant and Jensen [2] about the effects of interventions on large-scale software systems. Specifically, we use their experimental data set about PostgreSQL, a large open-source relational database management system.



Effect Restoration with Predictive Models – Synthetic Data. We generate synthetic data as seen in the graphical model. We then use the inferred age values with the corresponding error distribution as reported by Oktay et al. [6] to adjust for the confounding effect of age.



Effect Restoration with Predictive Models – Real Data. Despite Stack Overflow users self-reporting their age, the data is often missing and incorrect. One way to adjust for this is to apply predictive models to infer users' ages and perform effect restoration using those estimated values and error distribution.

Detecting the Underlying Structure

Can we detect when to apply effect restoration?

Instead of assuming that the confounding bias exists, we propose to verify if it exists by using d-separation and typical temporal ordering constraints on the variables.

Note that U may or may not be a confounding variable for X and Y. Our goal is to identify sufficient conditions to determine if U is a confounding variable and only apply effect restoration when it is.

	U is temporally prior to X and Y				U is temporally posterior to X and Y				Cycle
	A	B	C	D	E	F	G	H	I
$X \perp Y$	✖	✖	✖	✖	✖	✖	✖	✖	N/A
$X \perp Y \mid W$	✖	✖	✖	✖	✖	✖	✖	✖	N/A
$X \perp W$	✖	✔	✖	✔	✖	✖	✖	✖	N/A
$X \perp W \mid Y$	✖	✖	✖	✔	✖	✔	✖	✖	N/A
$Y \perp W$	✖	✖	✖	✔	✖	✖	✖	✖	N/A
$Y \perp W \mid X$	✖	✖	✔	✔	✖	✖	✔	✖	N/A

Conditional (In)dependence Relationships for All Simple Graphical Structures.

Related Work

- Many methods for estimating causal effects assume that all confounders are observed. This assumption, also known as causal sufficiency [7], implies that all variables that are causes of ≥ 2 observed variables in a data set are also observed.
- Apart from randomized experiments, several methods have been proposed to account for unobserved confounders in non-experimental contexts including instrumental variable designs [1] and sensitivity analysis techniques [4].
- Our approach resembles transfer learning approaches in ML [5], yet departs from this paradigm because we first obtain knowledge from a predictive learning task and then use such knowledge for a subsequent causal estimation task.

Future Steps

- Generalize effect restoration for mixed-type data sets.
- Study the use of high-capacity predictive models and their limitations.
- Explore implications of effect restoration for estimating joint causal structures.

References

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