Causal Inference from Incomplete Data for Fair Machine Learning Prediction

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Research Area: NextAI-Math-Info
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Outline

To support decisions for individuals (e.g., loan approvals and hiring decisions), machine learning (ML) predictions should be fair with respect to *sensitive features*, such as gender and race. **My aim is to increase the practical applications of this field** by focusing on the real-world data that are difficult to use, which I call *incomplete data*. To achieve this, I will **develop the fundamental causal inference techniques** that employ these data to determine the presence and direction of causal relationships between variables (known as a *causal graph*) and their strength (*causal effects*). From there, I will **work on advancing ML techniques that are both fair and accurate, based on the understanding of causality**.

Research Goals

1. Establishing causal inference techniques for incomplete data
2. Achieving fair ML predictions based on the above causal inference techniques

Originality and Novelty

Novelty Approaches to problem-solving are novel: To ensure the fairness of predictions, I am **revisiting fundamental causal inference techniques** for inferring causal graphs and causal effects and **aiming for their significant improvement.**

Originality I intend to explore **interdisciplinary approaches**, including but not limited to Bayesian posterior inference and statistical modeling of extreme values.

Challenges

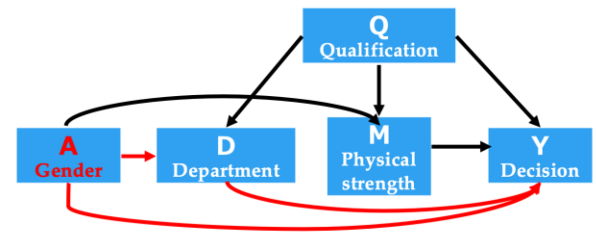
Task setup is far more challenging than existing work: I **focus on realistic scenarios** where we only have access to incomplete data, making it difficult to infer causality.

Input ***Incomplete*** **training data**

Sensitive feature

A Gender	Q Qualification	D Department	M Physical strength	Y Decision
Female	A	Economics	B	Accept
Male	B	Literature	B	Accept
Male	C	Science	C	Reject

Causal graph



Training while imposing constraints on unfair causal effects

Output Fair and accurate ML model

$$\hat{Y} = f_\theta(A, Q, D, M)$$

Future Deployment ＆ Research Plan

Advancement of Statistical Causal Inference (Academic Value) Developing causal inference techniques that do not require strong assumptions will **create a wide range of spin-off effects**, not only in the field of causal inference but also in **various scientific disciplines**, such as medicine, life sciences, neuroscience, and meteorology**, thus contributing to scientific discoveries.**

Support for Decision-Making in the Real World (Social Value) Given that we often encounter incomplete data in real-world decision-making scenarios, **the societal impact of this work is substantial**. Supporting decision-making based on incomplete data while ensuring compliance with laws and regulations will **improve the accuracy, speed, and human cost of decision-making**. It will **lead to an affluent society where we can make effective algorithmic decisions while ensuring that nobody will suffer detrimental treatment.**