

## Background

- Availability and access to **large healthcare datasets**, collected over a long period, holding valuable information
- Commonly explored through **traditional Machine Learning algorithms** (Regressions, Neural Networks, Curve fitting algorithms)
- Perform great in finding patterns out of datasets
  - lacks extensive **interpretability** to be used in the healthcare sector
- Without exploring underlying **causal relationships**, the algorithms fail to explain their reasoning
- **Causal Inference**, a relatively newer branch of Artificial Intelligence, deals with the issue of interpretability
  - works towards an **explanation of causality** in data through **graphical models** (Pearl et al. 2016)

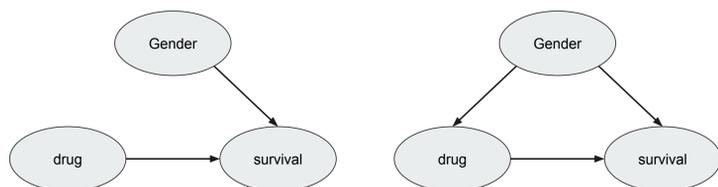


Figure 1: Causal Structure for experimental studies through RCTs versus observational studies (presence of confounding variable as backdoor)

## Highlights of Research Idea

- Our research goal is to use Causal Inference to build an **applied framework** that lets researchers **leverage observational datasets** in understanding **causal relationships** between different variables (events, treatments, outcomes, demographic features)
- To achieve that, our objectives are:
  - **Emulation:** to **emulate** a Randomized Controlled Trial (RCT) from observational dataset with consideration on randomization and **minimal biases**
  - **Theories:** to generate theories that explain causal relationships through standard statistical analyses (e.g. Odds Ratio, Survival Analysis) using Causal Inference framework
  - **Application:** to apply it to find the **efficacy of antipsychotic drugs** prescribed in the **treatment of Delirium in the ICU**.

## Approach

- **Data Mining:** extraction of relevant data from large dataset, exploratory data analysis
- **Statistical Analyses:** emulating target trial, relevant statistical analyses on emulated trial endpoint efficacy measurement along with survival analysis
- **Causal Structure Model Generation:** structure learning algorithms, background knowledge and existing literature
- **Causal Inference:** Fundamentally work through theories of Causal Inference by studying existing publications and books, estimation of effects using causal structure, generation of theories relating Survival Analysis and Causal Inference

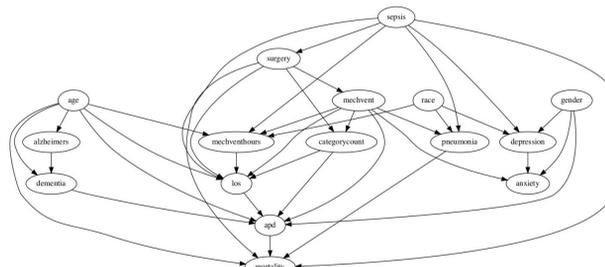


Figure 2: A work-in-progress showcasing causal structure for delirium patients in ICU

## Forward Thinking

- The research area of emulating RCTs using an observational dataset is **highly expected**, however relatively **newer**, and still contains many **assumptions**
- Researchers have shown the **possibility of using observational datasets** in emulating RCTs for antiretroviral therapy (Lodi et al. 2019), and for ARDS (Bikak et al. 2018)
  - Still not perfected, contains biases, lacks trust and validity
  - We plan to build our approach on top of these existing research works and find novel ways to address the shortcomings
- The forward-thinking in our proposition would be:
  - to propose a standard **mathematical and statistical framework** to build (emulate) RCTs from Observational dataset with minimal bias
  - to propose Causal Inference approach to existing statistical methodologies, like **Survival Analysis**
  - to showcase new way to explore large datasets and interpret their **underlying causal structure**

## Significance

- **Delirium** occurs in about 80% cases in the Intensive Care Unit (ICU) and is commonly treated with **antipsychotic drugs (APD)** (Girard et. al. 2008)
- **Controversy** over usage of APDs in treating Delirium, since RCTs **do not agree** in clear evidence of similar efficacy or safety
- Observational data has potential to resolve this issue through Causal Inference
  - **MIMIC III** database, an extensive EHR dataset with 53,423 distinct hospital admissions (Adibuzzaman et. al. 2016)
- Elimination of **controversies**, **Cost-effective** virtual RCTs, Datasets from around the **globe**
- Causal Inference in observational datasets is not limited to only health sector, it also helps in explaining problems in the field of **Social Science**, **Economics** etc.

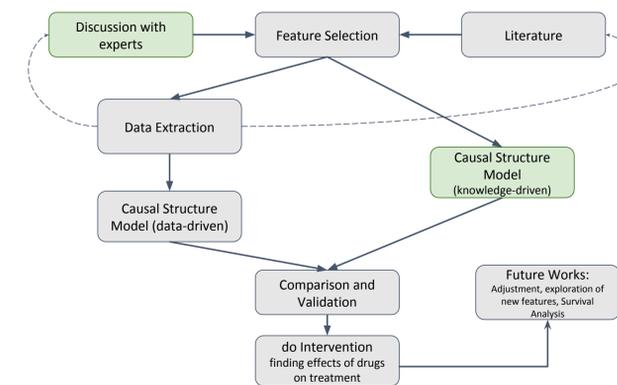


Figure 3: Workflow diagram

## References

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5. Lodi, S., Phillips, A., Lundgren, J., Logan, R., Sharma, S., Cole, S. R., ... & Horban, A. (2019). Effect estimates in randomized trials and observational studies: comparing apples with apples. *American journal of epidemiology*, 188(8), 1569-1577.