Final Report: Sensitivity Analysis in Causal Inference

Correlation vs. Causation

One of the fundamental challenges in causal inference is distinguishing correlation from causation. While correlation indicates that two variables move together, it does not imply a direct causal relationship. Sensitivity analysis helps determine whether an observed association is due to a true causal effect or if it may be driven by unmeasured confounding variables.

Directed Acyclic Graphs (DAGs)

Directed Acyclic Graphs (DAGs) provide a graphical representation of causal relationships and potential confounders. By visualizing variables and their dependencies, DAGs help identify possible sources of bias and inform the need for sensitivity analysis in cases where confounding variables cannot be directly measured or controlled.

The Potential Outcomes Framework

The potential outcomes framework is a foundational concept in causal inference. It defines two potential outcomes: the outcome under treatment and the outcome under control. The causal effect is estimated by comparing these two potential outcomes. However, in non-experimental settings, we only observe one outcome per individual, making it difficult to infer causality without assumptions about unmeasured confounders.

Omitted Variable Bias (OVB) and Sensitivity Analysis

Omitted Variable Bias (OVB) occurs when a confounding variable that influences both the treatment and outcome is not included in the model. This bias can lead to incorrect estimates of causal effects. Sensitivity analysis quantifies how much an omitted confounder would need to influence the treatment and outcome to significantly alter the causal conclusion.

Robustness Value and Partial R^2

Robustness Value (RV): Measures the strength of an unmeasured confounder required to fully explain away an observed causal effect. A higher RV suggests that the estimated effect is robust to unmeasured confounders, whereas a lower RV indicates greater sensitivity to omitted variables.

Partial R^2: Quantifies how much variation in the treatment and outcome can be attributed to an unmeasured confounder. Higher values suggest that a confounder has a significant influence and could bias the causal estimate.

Importance of Sensitivity Analysis

Sensitivity analysis is essential in observational studies where randomization is not possible. It helps assess the reliability of causal conclusions by determining whether an omitted confounder could invalidate findings. This is particularly important in policy decisions, medical research, and social sciences, where causal inferences inform critical actions.