An empirical study of the effects of unconfoundedness on the performance of Propensity Score Matching

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1 Background

- **Propensity Score Matching** is a **causal machine learning algorithm** that is specifically used for the unbiased estimation of **ATT** (1), the **average treatment effect for the treated** [1].

$$E[Y(1) - Y(0)|Z = 1] \tag{1}$$

- PSM operates ideally only under specific conditions, the main assumption being a concept known as **unconfoundedness**.
- **Unconfoundedness** of a dataset means that all variables that affect treatment and outcome have been measured. These variables are known as **confounding variables**, **covariates** or **features** [2].
- Propensity Score Matching entails **forming matched sets of treated and untreated subjects** who share a similar value of the **propensity score** [1].
- The **propensity score** is the probability of getting treatment based on observed confounding variables [1].

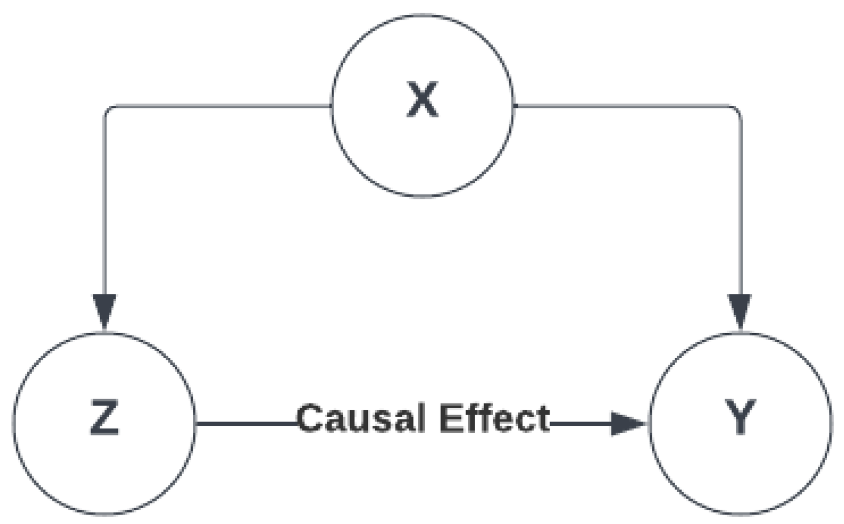

*Figure 1: Diagram of Causal Effect, X represents the **features**, Y the **outcome** and Z is the **binary treatment**.*

2 Research Question

What are the effects of unconfoundedness on the performance of Propensity Score Matching ?

3 Methodology

- **Breaking the unconfoundedness assumption**, in manners of varying gravity, should impact the performance of Propensity Score Matching.
- Run the algorithm on data that **upholds the unconfoundedness condition**.
- Compare these results with measurements obtained from running the algorithm on data with a **progressively increasing number of hidden covariates with varying levels of effect contribution**.
- **Compare its performance to other methods** that try to achieve similar goals will also provide potentially useful insight.

4 Hypotheses

- A hidden variable that only affects **the outcome should not** impact the performance of PSM.
- A hidden variable that only affects **the treatment assignment should** impact the performance of PSM.
- A hidden variable that only affects **the propensity score should not** impact the performance of PSM.
- The **more hidden variables** there are, the **worse the algorithm** performs; this relationship should be **linear**.

5 Limitations

- Because of time constraints, the data used for the experiments is synthetic and generated, thus distancing the results from a strictly realistic scenario.
- The other crucial assumption of PSM, which states that every subject has a nonzero probability to receive either treatment is not discussed in this paper [1].

6 Conclusion

- There are no conclusions to be made yet at this moment in time.

References

[1] Peter C Austin. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate behavioral research*, 46(3):399–424, 2011.

[2] Ruocheng Guo, Lu Cheng, Jundong Li, P Richard Hahn, and Huan Liu. A survey of learning causality with data: Problems and methods. *ACM Computing Surveys (CSUR)*, 53(4):1–37, 2020.

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