**Introduction**

Due to the nature of randomized controlled trials, they are hard to create and run properly [1]. This has led to the development of many different causal learning methods in order to determine the causes and effects from previously conducted randomized controlled trials. The Intelligent Randomized Controlled Trials (iRCT) method is a supervised learning method in python that was created to apply existing techniques and methods in new ways. iRCT is a python package that is partly based on the findings of matching estimators by Abadie [2], the use of propensity scoring using logistical regression, and using those propensity scores in order to determine an average treatment effect [3].

**Propensity Scoring**

Propensity scoring is defined as “a conditional probability of being exposed given a set of covariates” [4]. For iRCT the use of propensity scoring is based around the idea that for most datasets there will likely be more than a single covariate outside of the treatment and outcomes, so using a propensity scoring method would allow all covariates to become a single value that could then be used to identify matches.

In iRCT the current propensity scoring method is based around the sklearn package and its linear regression function and pandas for general dataframe manipulation. These different functions are used to determine the weight of the treated rows versus the non-treated rows according to their propensity scores.

**Previous Versions and Developments**

The initial iRCT method was developed was based upon Abadie’s work [2] and was developed with two key assumptions in mind. The first being that the dataset this would be applied to would be relatively small. The second being that there would be only 4 distinct columns, an index column, a covariate column, a treatment column, and an outcome column. Once this original method was tested on simple datasets with these assumptions in place it was clear that a method would need to be developed in order to allow for multiple covariate columns. This initial method can still be found in the iRCT package and is named “firstAttempt\_calculateRelationVal”.

This allowed for the introduction of propensity scoring into the iRCT methodology. Due to propensity scorings ability to combine multiple covariates into a single covariate and the research of using propensity scoring for determining causal effects [5]. This new method would be applied to the main dataset used for all comparisons and tests from here on, COVID3\_4Nodes3. This method was quickly deemed necessary to be adjusted due to the extreme length of calculating just one average treatment effect between a single pair of treatment and outcome. This second method can still be found in the iRCT package and is named “secondAttempt\_calculateRelationVal”.

Finally, in order to deal with the extremely slow process time from the second attempt, it was determined that the problem was how the matching was done due to needing to iterate over every row. There was also the problem of needing to balance the weights of the untreated versus treated rows due to no guarantee of equal amounts. This led to the current function which uses pandas built-in functions in order to query and edit whole columns, as well as accounting for the aforementioned weights. This function can be shown propensity score page of the python-causality-handbook [6].

**Comparison against other causal methods**

There are many pre-existing causal learning methods that already exist such as PC, FCI, rFCI, GES, and FGES. Which are all unsupervised causal learning methods that can allow for a directed acyclic graph (DAG) to be produced showing the causes and effects, however, these functions do not return a magnitude of causality, just a direction. iRCT is different in the regard that it will not produce a DAG for the data, however, given a treatment and an outcome column it will be able to tell you the average number of standard deviations a treated individual will be above or below their untreated counterparts.

For example when running the FCI algorithm on the dataset COVID3\_4Nodes3, FCI produces a DAG that looks like: INSERT DAG OF FCI HERE.

As previously mentioned, there is no magnitude to this direction just that Dyspnea is affected by both COVID and COPD, and ED\_Visit is affected by Dyspnea. However, by using iRCT and having the treatment column be COVID and the outcome column being Dyspnea, the result comes out to be “0.08994794374830722” which means that having COVID would be indicator that on an individual with all the other same covariates (COPD and ED\_Visit) Dyspnea would be on average .09 standard deviations higher.

**Conclusion**

iRCT is not a supplement or replacement for any of the compared causal learning methods, rather it is an additional tool that can be used in order to determine magnitude of average treatment effects which allows for quantifiable measurements of how one variable alone can influence another variable within a randomized controlled trial.

**Sources**

1. [**https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5539637/**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5539637/)
2. [**https://journals.sagepub.com/doi/10.1177/1536867X0400400307**](https://journals.sagepub.com/doi/10.1177/1536867X0400400307)
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5. **Rosenbaum and Rubin (1983).**
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