**Machine Learning Methods for Causal Inference**

I provide below a list of machine learning approaches for computing the individual treatment effect (ITE) and the average treatment effect (ATE) for observational data. The code (R-package) for most of the methods is available either on GitHub or on CRAN. I also provide a link to the corresponding paper describing the methods. Some of these papers are very technical, so I wont recommend getting wrapped up in the details, but the idea is just to give you a big picture view and some guidance on the methods.

I have played a little with some of these methods, but I am currently working on another method, which I will like to see its performance in this project. I will try to clean up the R code and post on the GitHub account for project.

As you may notice, most of the methods/papers are fairly recent (2015-2017), which suggest that machine learning is picking up steam in causal inference. Perhaps this is the right time to write a perspective paper. So, at the end of this challenge, if you guys are interested, lets write a perspective paper: **Causal Inference: a machine learning perspective**. I have always hold the view that machine learning has not yet caught up with causal inference, but it appears its catching up fast. I have been doing transfer learning (or domain adaptation) and reinforcement learning but didn’t realize these learning techniques can be modified for causal learning.

1. **Causal Forest**. Extension of the Random forest for heterogeneous treatment effect. R-package <https://github.com/susanathey/causalTree>, paper <https://arxiv.org/pdf/1510.04342.pdf>. I expect this method to perform very well.
2. **BART:** a general predictive model that is applicable to many settings, one of which is causal inference problems. It builds an ensemble of trees with a regularization prior placed on each tree in the ensemble, so it influence on the overall fit is small. R-package: ***causaldrf***  <https://cran.r-project.org/web/packages/causaldrf/vignettes/Using_causaldrf.pdf> . Paper

<https://www.researchgate.net/profile/Jennifer_Hill3/publication/236588890_Bayesian_Nonparametric_Modeling_for_Causal_Inference/links/0deec5187f94192f12000000/Bayesian-Nonparametric-Modeling-for-Causal-Inference.pdf>

Code to reproduce results in the paper <http://www.tandfonline.com/doi/abs/10.1198/jcgs.2010.08162>

1. **This is a good paper to read for this project;** it will be great to implement all the methods. <https://arxiv.org/pdf/1701.05306.pdf>. We can do the same simulation experiments.
2. **X-Learner:** meta-learner algorithms (based algorithms: random forest and BART). See R-package here: <https://github.com/soerenkuenzel/hte>. The paper is very technical - provided here only for reference: <https://arxiv.org/pdf/1706.03461.pdf>
3. **The Double Selection Estimator (DSE):** Used the LASSO as a covariate selection method, and with instrumental variables. Implemented in the R-package ***hdm****:* <https://cran.r-project.org/web/packages/hdm/index.html>. Paper (only for reference) <https://arxiv.org/pdf/1311.2645.pdf>
4. **The Approximate Residual Balancing Estimator (ARBE):** Use elastic-net or LASSO and a covariate balancing approach to remove or minimize residual bias. R-package <https://github.com/swager/balanceHD>.Paper (only for reference): <https://arxiv.org/pdf/1604.07125.pdf>
5. **Double Machine Learning Estimator (DMLE):** This estimator is a more general version of Targeted Maximum Likelihood Estimator (TMLE), which I have used, but don’t really appreciate. So I will be interested to see how DMLE performs. However, to implement DMLE will require reading the paper: <https://arxiv.org/pdf/1608.00060.pdf> and the R code for the paper: <https://github.com/VC2015/DMLonGitHub/>

Additional References

1. Machine Learning Methods for Estimating Heterogeneous Causal Effects. <https://pdfs.semanticscholar.org/86ce/004214845a1683d59b64c4363a067d342cac.pdf>
2. Ensemble based methods (Super Learner) <https://stanford.edu/~jgrimmer/het.pdf>
3. Causal Inference and Data Science: Why They Need Each Other. <https://cds.nyu.edu/wp-content/uploads/2014/04/causal-and-data-science-and-BART.pdf>

BART: <https://www.researchgate.net/publication/262085259_Modeling_Heterogeneous_Treatment_Effects_in_Survey_Experiments_with_Bayesian_Additive_Regression_Trees>

1. Causal Random forest: <https://bfi.uchicago.edu/sites/default/files/file_uploads/4B_hettreat-split-relabel-Chicago%20-%20InsertSearch.pdf>