Referee Report on Athey (2018, forthcoming)

Shuyan Huang

Research Question & Methodology

The author aims to answer the following research question: What's the current impact of machine learning on economics, and what's the future trend of this impact. This research question is clearly defined in the introduction part of the paper by saying that machine learning has already greatly influenced economics, and it's "not too difficult to predict some of the effects"(Athly, 2018:p.1)[1] based on the current situation.

The author compellingly answers this question by developing the path as below.

First, the author gives a narrow yet practical definition of machine learning, and based on this definition, reviews common tasks and techniques of supervised learning and unsupervised learning. The author introduces these techniques with an emphasis on their potential to be used in economics researches. For example, the author points out that unsupervised learning can contribute to empirical economics analysis "as an intermediate step"(Athly, 2018:p.3)[1] for its ability to generate covariates independent of outcomes.

Second, the author contrasts the fields of machine learning and economics by comparing the major concerns of the two fields, and the different ways to address these concerns. Machine learning focus on the predictive power of the model on test sets, and thus pays attention to the "trade-off between expressiveness of the model and risk of overfitting"(Athly, 2018:p.4)[1]. The key concern of economists is "causal effect estimation"(Athly, 2018:p.5)[1], which economists pursue often at the cost of predictive power by methods like instrumental variables. The other concern of economics, is "whether the assumptions required to 'identify' a causal effect are satisfied"(Athly, 2018:p.6)[1]. The author further analyses how machine learning can contribute to these two concerns in economics. While model selection procedures in machine learning can help economists to be more systematic and "comprehensive in checking alternative specifications"(Athly, 2018:p.5)[1] when estimating causal effects, it can't help with testing the assumptions.

Third, the author lists several applications of machine learning methods in policy analysis. This specific subfield of economics is selected because the aim of policy analysis coincides with machine learning's emphasis on prediction and many applications have been successful in this subfield. However, the author also points out some problems in the application of machine learning to policy analysis, such as "interpretability"(Athly, 2018:p.8)[1], "fairness and nondiscrimination"(Athly, 2018:p.9)[1], "stability and robustness"(Athly, 2018:p.9)[1], "manipulability"(Athly, 2018:p.9)[1].

Fourth, as a key part of empirical economics research, causal inference has also been combined with machine learning. The author lists a few strategies of causal effect identification that are recently being developed in the intersection of machine learning and causal inference, paying specific attention to "average treatment effects"(Athly, 2018:p.12)[1], "heterogeneous treatment effects and optimal policies"(Athly, 2018:p.13)[1], "contextual bandits"(Athly, 2018:p.16)[1], "robustness and supplementary analysis"(Athly, 2018:p.17)[1], "panel data and difference-in-difference models"(Athly, 2018:p.18)[1], and "factor models and structural models"(Athly, 2018:p.19)[1].

Finally, based on the analysis above, the author gives her predictions "about the impact of machine learning on economics"(Athly, 2018:p.21)[1] in a broad context, covering not only the potential new research questions and methods, but also fundamental impacts on the economics community.

I evaluate the way that the author answers the research question as appropriate and sufficient because this paper not only shows the current impact of machine learning, but also dives into the reasons why machine learning is influencing economics in these specific ways, by showing the main concerns of these two fields and the advantages of using machine learning in addressing the concerns of economics.

Also, on the future impact of machine learning on economics, the author gives predictions that are both comprehensive and solid, building upon the preceding analysis on the nature of these two fields, and her observations of current trend both in and outside academia.

Literature

The author broadly refers to the literature of machine learning, economics, and interdisciplinary studies. However, both machine learning and economics are large fields so it's impossible to be comprehensive. Instead, the author particularly contributes to the current literature of applying machine learning to policy analysis(Athey(2017)[2], Dudik et al.(2014), Jiang and Li(2015)[3], Thomas and Brunskill(2016)[4]), combining machine learning methods and causal inference(Belloni et al.(2014)[5], Wager and Athey(2017)[6]), and predicting the future impact of machine learning in social science fields(Jordan and Mitchell(2015)[7], Grimmer(2015)[8]).

Nevertheless, there are some minor defects in the author's citations.

First, by saying that the contribution of stochastic gradient descent "is computational rather than conceptual"(Athly, 2018:p.7)[1], the author is missing the literature in machine learning and optimization theory, which stresses that optimization is intrinsically learning itself(Zinkevich(2003)[9], Srebro(2010)[10]).

Second, when discussing the problem of interpretability in machine learning models applied to policy analysis, the author points out that "whether there are other ways to mathematically formalize what it means for a model to be interpretable, or to analyze empirically the implications of interpretability"(Athly, 2018:p.9)[1] is a field worth future research. However, the author cites the study of Yeomans et al.(2016), which compares computer recommender systems to human recommenders. This is very weakly related to the topic the author has suggested. Yeomans et al.(2016) shows that people trust human recommenders more because they are easier to understand. But it's neither a mathematical framework of interpretability, nor a empirical study of the implication of it. And the author fails to refer to the literature in interpretability of machine learning models(Lipton and Zachary(2016)[11], Garcia at al.(2009)[12]).

Third, when discussing the problem of stable and robustness in machine learning models applied to policy analysis, the author concludes with "There are many interesting methodological issues involved in finding models that have stable performance and are robust to changing circumstances", without mentioning any related work. In machine learning literature, there are some interesting studies on this topic, for example Nie at al.(2010)[13] shows that norm regulation is a key component in building robust machine learning models.

Fourth, when predicting that "we will see a lot more research into the societal impacts of machine learning"(Athly, 2018:p.26)[1], the author does not mention the latest studies on this topic. Actually, this has been a field of heated discussion and many, especially MIT media lab, have made a lot of contributions to it(Awad et al.(2018)[14], Crandal et al.(l2018)[15]).

Grammatical, Spelling, Style Errors

I find several grammatical and spelling errors in the paper. In page 7, there's a "probabiity"(Athly, 2018:p.7)[1]. In page 11, this sentence is grammatically confusing:"Techniques like instrumental variables seek to use only some of the information that is in the data the clean or exogenous or experiment-like variation in pricesacrificing predictive accuracy in the current environment to learn about a more fundamental relationship that will help make decisions about changing price"(Athly, 2018:p.11)[1]. Maybe this sentence should write like this: "Techniques like instrumental variables seek to use only some of the information that is in the data (the clean or exogenous or experiment-like variation in price), sacrificing predictive accuracy in the current environment to learn about a more fundamental relationship that will help make decisions about changing price". Also in page 11, the author says "First, we can consider the type of identification strategy for identifying causal effects"(Athly, 2018:p.11)[1]. I think the plural form "types" should be used. In page 20, "users typical morning location" and "users willingness"(Athly, 2018:p.20)[1] should be "users' typical morning location" and "users' willingness". On page 22, "This article has al discussed the first three predictions in some detail"(Athly, 2018:p.22)[1] should be "This article has already discussed the first three predictions in some detail".

I also find the author's explanation of the distinction between causal inference and prediction redundant in structure. There's a long explanation with an example on page 10, however, this has been comprehensively discussed in page 5 and 6 with enough details, examples and references. I don't think it's necessary to explain it in detail when reintroducing the topic on page 10.

Extension

The method the author uses in this paper is basically contrasting two research fields, reviewing their current intersections and predicting the future impact of one on the other. This method can be extended into a broad range of interdisciplinary studies. One topic of interest is the impact of network methods on the field of economics. Specifically, network allows simulating aggregate outcomes based on simple individual models, while most literature in economics that empirically study aggregate outcomes start from aggregate models. Many economists have already incorporate network methods in their researches, for example, Banerjee at al.(2013)[16] models people's behavior in the process of the diffusion of microfinance, and combines network simulation and traditional econometric identification methods to find out the factors that influence the diffusion. Using the method of Athey(2018), we can conceptually discuss how network methods fit into the application of economics, and predict how network methods can extend the possibility margin of economics research.

References

1. Athey, S. The impact of machine learning on economics. In *The Economics of Artificial Intelligence: An Agenda* (University of Chicago Press, 2018).
2. Athey, S. Beyond prediction: Using big data for policy problems. *Science* **355**, 483–485 (2017).
3. Jiang, N. & Li, L. Doubly robust off-policy value evaluation for reinforcement learning. *arXiv preprint arXiv:1511.03722* (2015).
4. Thomas, P. & Brunskill, E. Data-efficient off-policy policy evaluation for reinforcement learning. In *International Conference on Machine Learning*, 2139–2148 (2016).
5. Belloni, A., Chernozhukov, V. & Hansen, C. High-dimensional methods and inference on structural and treatment effects. *J. Econ. Perspectives* **28**, 29–50 (2014).
6. Wager, S. & Athey, S. Estimation and inference of heterogeneous treatment effects using random forests. *J. Am. Stat. Assoc.* (2017).
7. Jordan, M. I. & Mitchell, T. M. Machine learning: Trends, perspectives, and prospects. *Science* **349**, 255–260 (2015).
8. Grimmer, J. We are all social scientists now: how big data, machine learning, and causal inference work together. *PS: Polit. Sci. & Polit.* **48**, 80–83 (2015).
9. Zinkevich, M. Online convex programming and generalized infinitesimal gradient ascent. In *Proceedings of the 20th International Conference on Machine Learning (ICML-03)*, 928–936 (2003).

10. Srebro, N. & Tewari, A. Stochastic optimization for machine learning. *ICML Tutor.* (2010).

11. Lipton, Z. C. The mythos of model interpretability. *arXiv preprint arXiv:1606.03490* (2016).

12. García, S., Fernández, A., Luengo, J. & Herrera, F. A study of statistical techniques and performance measures for genetics-based machine learning: accuracy and interpretability. *Soft Comput.* **13**, 959 (2009).

13. Nie, F., Huang, H., Cai, X. & Ding, C. H. Efficient and robust feature selection via joint l2, 1-norms minimization. In *Advances in neural information processing systems*, 1813–1821 (2010).

14. Awad, E. *et al.* The moral machine experiment. *Nature* **563**, 59 (2018).

15. Crandall, J. W. *et al.* Cooperating with machines. *Nat. communications* **9**, 233 (2018).

16. Banerjee, A., Chandrasekhar, A. G., Duflo, E. & Jackson, M. O. The diffusion of microfinance. *Science* **341**, 1236498 (2013).