Assignment #9
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Referee Report

Article: Athey, Susan, "The Impact of Machine Learning on Economics," in Joshua Gans Ajay K. Agrawal and Avi Goldfarb, eds., The Economics of Artificial Intelligence: An Agenda, National Bureau of Economic Research https://www.nber.org/chapters/c14009.pdf 2018, forthcoming.

The paper "*The Impact of Machine Learning on Economics*" provides an overview of the contributions and applications of machine learning to economics and makes some predictions on the future use of machine learning in economics.

The research questions are that what's the impact machine learning already have on economics and what's the future contributions machine learning can make to economics (Athey, 2018, p.1-2). We can see that the author adequately defined the research question in the title of part 2 to part 5 of this paper. Also, the research question was defined in the abstract part by saying that "This paper provides an assessment of the early contributions of machine learning to economics, as well as predictions about its future contributions." (Athey, 2018, p.1).

The author compellingly answers the research question. Firstly, the author gives a narrow definition of machine learning: "machine learning is a field that develops algorithms designed to be applied to datasets, with the main areas of focus being prediction (regression), classification, and clustering or grouping tasks." (Athey, 2018, p.3). She also illustrates some early use cases of machine learning in economics. For example, unsupervised machine learning provides a way of "dimensionality reduction" (Athey, 2018, p.3), which can congregate the observations with similar characteristics. In empirical economics, it is useful because researchers can create variables to represent the similarities finding by unsupervised machine learning. Machine learning also provides some approaches such as the approach of cross-validation, to select model and "balance expressiveness against over-fitting" (Athey, 2018, p.6), which are meaningful in economic analysis. Secondly, the author introduces that machine learning methods can be used in prediction of policy problems in economics, such as "deciding whether to do a hip replacement operation for an elderly patient" and "examining stop-and-frisk laws" (Athey, 2018, p.7), because these methods provide ways of measuring outcomes "at a very granular level" and have great predictive power(Athey, 2018, p.7). However, the author also mentioned that there are some questions related to these methods, such as "interpretability of models", "fairness and nondiscrimination", "stability and robustness", and "manipulability" (Athey, 2018, p.8-9). Thirdly, the author makes a prediction that "there will be an active and important literature combining ML and causal inference to create new methods, methods that harness the strengths of ML algorithms to solve causal inference problems" (Athey, 2018, p.10). The author is confident about this prediction because machine learning algorithms are already used in causal inference in economics. For example, machine learning can help to estimate average treatment effects and heterogeneity in treatment effects, estimate optimal policies, do robustness and supplementary analysis, and "exploit assumptions about how outcomes vary across units and over time in panel data" (Athey, 2018, p.13-18). Finally, the author makes some "broader predictions of the impact of machine learning on economics" (Athey, 2018, p.21). A number of potential changes will happen when using machine learning in conducting empirical work of economics. For example, "adoption of new methods by empiricists at large scale" and "increase in interdisciplinary research" (Athey, 2018, p.21).

The methods of answering the research question is appropriate and sufficient. In order to answer what's the current impact of machine learning on economics, the author gives sufficient examples in an organized structure. She firstly introduces some early uses of machine learning in economics and then specifically introduces the applications of machine learning in the policy problems and casual inference. In each part, the examples are solid to support that machine learning is really useful in economics. In order to answer what's the future trend of machine learning in economics, she lists her predictions and illustrates each one in details.

It is amazing that the author put the paper not just in the broad literature of machine learning and empirical economics, but also in the literature of public policy and statistics. She uses citations as examples to support her opinions and as supplemental explanations of some details. For example, she uses Varian (2014) as supplemental explanations of most popular machine learning methods. However, since the research includes many examples, it may be redundant to have several citations in the same example. For example, in order to give example of evaluating counterfactual effect in auctions, the author provides four citations including "Laffont et al. (1995), Athey et al. (2011), Athey et al. (2013) and Athey and Haile (2007)" (Athey, 2018, p.6). And in order to provide the applications of machine learning in policy problems, the author gives nine citations including "Strehl et al. (2010); Dudik et al. (2011); Li et al. (2012); Dudik et al. (2014); Li et al. (2014); Swaminathan and Joachims (2015); Jiang and Li (2016); Thomas and Brunskill (2016); Kallus (2017)" (Athey, 2018, p.16). In fact, to be abstract, one or two citations in one example is enough. Also, in some examples, the author just narrates the example without any citation. For example, the author mentions the cross-validation method used in model selection several times in the paper, but she doesn't give any detailed information about this method. Kohavi (1995) provides detailed description of cross-validation method and illustrates that the ten-fold cross-validation method is the best method of model selection for real word datasets.

There are some grammatical, spelling, and style errors in the body of the text in this forthcoming paper. In page 3, the sentence "… with the main areas of focus being prediction (regression), classification, and clustering or grouping tasks." (Athey, 2018, p.3) is easier to understand when changing "being" to "on". In page 5, "becaues the affect both the optimal price set…"(Athey, 2018, p.5) should change "because" to "because". In page 7, "where the probabiity of selecting an arm…" (Athey, 2018, p.7) should change "probabiity" to "probability". In page 18, "since we dont observe the counterfactual outcomes…" (Athey, 2018, p.18) should change "dont" to "don't". In page 20, "users willingness" and "users typical morning location" (Athey, 2018, p.20) should be "users' willingness" and "users' typical morning location". In page 22, "This article has al discussed the first three predictions…" (Athey, 2018, p.22) should be "This article has already discussed the first three predictions…". In page 26, "firms want to know the return on investment on advertising campaigns,2," (Athey, 2018, p.26) has a redundant comma at the end.

The method used in this paper is analyzing current uses of machine learning in economics and then make predictions for the future use. Also, the author illustrates her opinions with sufficient examples. I think this method can be used in interdisciplinary study and learning the relationship between different fields. For example, in mathematical finance, we can learn the impact of mathematical applications on finance and predict what the math tool can be used in financial market in the future. Currently, the contributions of math in finance is that math helps researcher to know about the complex relationship between different financial models using various data, and have a better understand of financial market. In the future, the math also can be better used in insurance and risk management by creating much more efficient and fitting models. Also, this paper's research question is too much broader. I suggest the author focuses on one part of this paper, narrows the research question, and makes some extension to learn this question deeply. For example, she can just concentrate on the applications of machine learning in prediction methods using in policy settings. Besides what has been discussed, she can evaluate the predictive power of different machine learning methods in predicting the policy problems and analyze the advantage of these methods compared to non-machine-learning methods.

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