Assignment #9

MACS 30000, Dr. Evans

Due Friday, Dec. 14 at 5:30pm

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Referee Report: "Inferring Roll Call Scores from Campaign Contributions Using Supervised Machine Learning," by Bonica (2018)

In this paper, the author tries to find a new methodological approach to answer the following question: How to forecast legislative voting behavior for candidates who have yet to compile a voting record? (Bonica, 2018: p2)

Methodology

The author compellingly develops the paper and answers this question as follows.

First, the authors stated the problem by introducing "the spatial theory underlying ideal point estimation models", which is "two-space" theory, the "action space" and "basic space". (Bonica, 2018: p2) In the latent ideological space, there is "a projection matrix that maps ideal points onto issue dimensions". (Bonica, 2018: p2) Therefore, the projection matrix is "exogenous to the preferences and choices it influences". (Bonica, 2018: p2). As for the ideal points, those which are voted more will be of greater importance. The author proposed two weighting assumptions and made a figure to compare them.

Second, after discussing the limitations of traditional bridging applications, the author proposed "a general methodology for mapping revealed preference data generated in one context onto a target latent dimension recovered from data generated in a different context". (Bonica, 2018: p5)

Third, the author introduced the "methodology for inferring DW- NOMINATE scores for candidates based on alternative sources of data". (Bonica, 2018: p5) In this part, the author shortly introduced the machine learning and its implementation. Further, they introduced "DW - NOMINATE" as the target variable that "measured along a continuous dimension, which suggests a regression-based modeling approach". (Bonica, 2018: p6)

Fourth, after addressing all the definitions and assumptions, the author tested the training dataset with different machine learning skills and compared the results, which showed that the supervised models performed better than unsupervised models in general. (Bonica, 2018: p9) Then, the author applied the models to testing data. The results further validate the efficiency of supervised models.

In the argument, there are some limitations. One is that, as ideology itself is a difficult subject to quantify and to research on. Therefore, the way the author suggested, which is the DW- NOMINATE scores, is unnecessarily perfect even if it is widely accepted by the professors. The other is that, for the result of different models, although supervised models have a better prediction, the RMSE is larger, which weaken the credulity of the results.

Literature review

Although the author covered a comprehensive literature, cited a broad perspective of papers, including political economics, machine learning, mass media and discussed a broad perspective of issues related to the research, the topic is too expansive to fully covered while some citation is unnecessary.

First, the author provides insight and the new angel into the field by introducing the machine learning into the prediction of nonincumbent's vote based on their fund-raising behavior before entering the office. However, by entering a new realm, some classical papers should not be missed out, for example, the literature which discussed the interpretability of different models (Lipton and Zachary, 2016; Garcia at all, 2009).

Second, in the Support Vector Regression and random forest part, the former one was given detailed explanation while the later one cited only one paper in this area, the literature on the framework and estimate of the random forest should be cited here (Liwa, 2012; Strobl, 2007; Pal, 2005).

Third, in the model fitting part, the author used the package in R and only briefly explained the models and chosen smoothing parameter of K = 10. However, the choice of smoothing parameter should be

more careful since the result is sensitive with large RMSE. Works of literature on cross-validation (Kohavi, 1995; Rodriguez, 2010) and choosing smoothing parameter (Thompson, 1991) should be included here.

Fourth, one citation is not needed in the references. The author mentioned his former papers (Bonica, 2014; Bonica, 2016a; Bonica, 2016b). However, the paper of "Ideology and Interests in the Political Marketplace" (Bonica, 2013) has never talked about in the article but it is cited in the reference.

Grammatical, Spelling, Style Errors

Some phrasing is misleading and might need more modification.

In the third paragraph on page nine, the sentence "Finding that even sophisticated statistical methods are unable to leverage the informational value of campaign contributors to generate accurate predictions about how candidates would behave if elected would serve to further undermine an important policy rationale for campaign finance disclosure laws." (Bonica, 2018: p9) is somehow complicated in structure and might lead to misunderstanding among readers. A simplified version is as follows. "Even sophisticated statistical methods are unable to leverage the informational value of campaign contributors to generate accurate predictions about how candidates would behave if elected. This would serve to further undermine an important policy rationale for campaign finance disclosure laws."

In addition, some content is not needed in the argument. In the third paragraph on page six, the introduction of text analysis in machine learning is completely irrelevant. (Bonica, 2018: p6) This paper is focusing on the different models of prediction in machine learning. Text analysis is another realm in machine learning. There is no need to mention the text analysis as it has nothing to do with the content of this research.

What's more, some definitions are not given sufficient explanation. In the second paragraph on page seven, the random forest is introduced as a separate title. However, only one paragraph is composed, which provides little insight for readers. The suggestion is that the author should write a more detailed introduction and usage of this model.

Extensions

As for the suggestion on the extension of this paper, I suggest a better analysis of the definition of ideology and research methods since this is the basis of following computational analysis. (Seliger, 1976; Rosenberg, 1998; Bawn, 1999) Without the solid foundation of theories, the applied models or regressions can't be valid even though advanced techniques are employed and smaller RMSEs are obtained. The current estimator, namely the DW- NOMINATE score is not as unbiased as the author depicts. Literatures on biased estimate of DW- NOMINATE should be considered when choosing it as the indicator of political stance. (Lewis, 2004) Based on literature, "the standard errors are in the range of 1%–4% of the range of DW-NOMINATE coordinates". (Carroll, 2009: p1) Other ways of measuring the political ideology are already researched on. Aldrich (2007) "developed multidimensional extension of the original cpg measure based on (Aldrich, Berger and Rohde 2002)". Griffin (2005) questioned the representation of voters and find that voter preferences predict the aggregate roll-call behavior of Senators while nonvoter preferences do not. To better research this field, the work described above is necessary.

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