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Inferring Roll-Call Scores from Campaign Contributions Using Supervised Machine Learning

In this paper, the authors develop a novel general method to map revealed preference data generated in one context onto a target latent dimension recovered from data generated in a different context. In particular, this methodology is applied to accurately predict US congress roll-call scores of non-incumbent candidates (or any other candidate for which previous voting records are not available) using data from contributing donors.

More in details the paper includes a detailed literature review of the "two space theory" underlying ideal point estimation models (where observed actions are mapped to a latent space of higher dimension), scaling models (which conversely high-dimensional informations are mapped onto a low-dimensional predictive space) and how a measure of ideology can be learnt with these two approaches. In either case serious limitations are present and the author illustrate them in a very pedagogic way, e.g. "Why issue salience matters when interpreting ideal point estimates" with extensive experiments supporting the claim. The last existing technique analysed "bridging applications", relies on the doubtful dimensionality assumption that makes it inapplicable in the task of predicting roll-call scores at national level using data from individual states.

The rest of the paper present and document the author's novel approach based on supervised learning. A short literature review on the used machine learning concepts is provided (regression-based modeling, supervised task, support vector regression, random forests), but it lacks some deeper insights justifying their use and advantages. However the parallel drawn between text-document matrixes and candidate-contributor matrix is really interesting and allows to reuse part of the theory of supervised methods for text classification in this article research. While the author justification on the limited choice of supervised model (computational cost) is understandable, some supplementary material or a follow-up study using more advanced methods would be expected: SVR with different kernels, gradient boosted forests neural regressor and model ensembling of diverse estimator are all common techniques in supervised machine learning and it would be interesting to see if the increase statistical power is sufficient to completely close the gap with the reference DW-NOMINATE scores. A last point on the technical aspects, is that regularisation as a way to reduce overfitting is mentioned but not explained in enough detail: I recommend to include some theoretical background and to explicit the type of regularisation used in the experiments; in particular an L1 regularisation could help to for the problem of feature reduction that the author encountered.

The rest of the results section is very convincing with thorough quantitative analysis, showing the surprising good performance of the selected supervised models (matching previous predictions based on first midterm) and qualitative analysis that reveal interesting insights. In particulate it is found that many of the most important features contribute to the model by discriminating within party, thus explaining the vastly superior performance of the party-mean baseline. This aspect is further studied using partial dependence plots which classify organisational donors by being more moderate or far out within the party they support.

Finally, additional analysis on predictive performance of non-incumbent reveals very good performances, on par with the previous sections. These quantitative results are strongly supported by a qualitative analysis which reveals that the biggest errors are made with congressman that switched party in the following term.

Overall the paper is very clear, and will hopefully be used as a reference for providing a strong statistical method to analyse complex social phenomena.