Discussion:

Does AI help humans make better decisions? A methodological framework for experimental evaluation.

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Model complexity for supervised learning: why simple models almost always work best, and why it matters for applied research.

Paper 1: Does AI help humans make better decisions? A methodological framework for experimental evaluation.

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Y: outcome (e.g., recidivism)

Here 1 is bad (e.g, cash bail or recidivism) and 0 is good (e.g, signature bond or no recidivism).

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First line is due to the the law of total probability; second line just rearrange terms; the third line follows from randomization, exclusion and consistency. In words, we can impute the difference in recidivism under D = 1 by the observed difference in recidivism among the released.

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Question: it seems to me no explicit assumptions were made regarding A, except that Z is independent of A. For instance, A could be confounded with D and Y. The only additional implicit assumption seems to be that Z fully determines whether A affects D, and in its turn, D fully mediates the effect of Z on Y. What exactly is buying us informative bounds? Some intuition would be useful.

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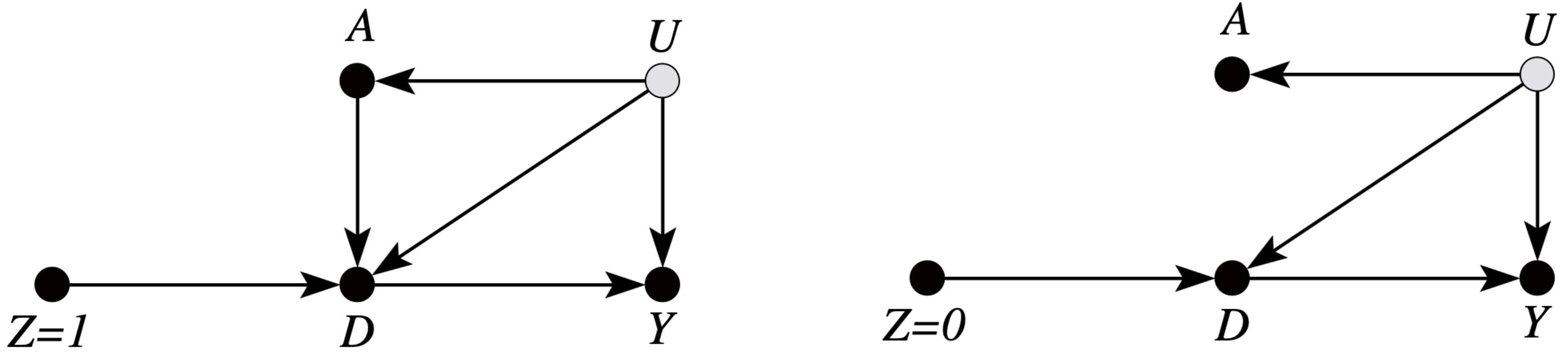

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This doesn't seem to be an AI in the usual meaning that people attribute to the word? Is this description really accurate?

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PSA FACTOR	RESPONSE	POINTS
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Perhaps it makes more sense to frame the empirical example in terms of assessing the quality of **PSA** recommendations instead of **AI** recommendations?

Paper 2: Model complexity for supervised learning: why simple models almost always work best, and why it matters for applied research.

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- **Description/Explanation:** it tries to understand the reasons why ML algorithms has not gained traction in Political Science. Here the ideas of *intrinsic dimension* and *data curation* play a key role.

- **Prescription:** it makes recommendations regarding the use of ML algorithms, such as not using htem in lieu of OLS.

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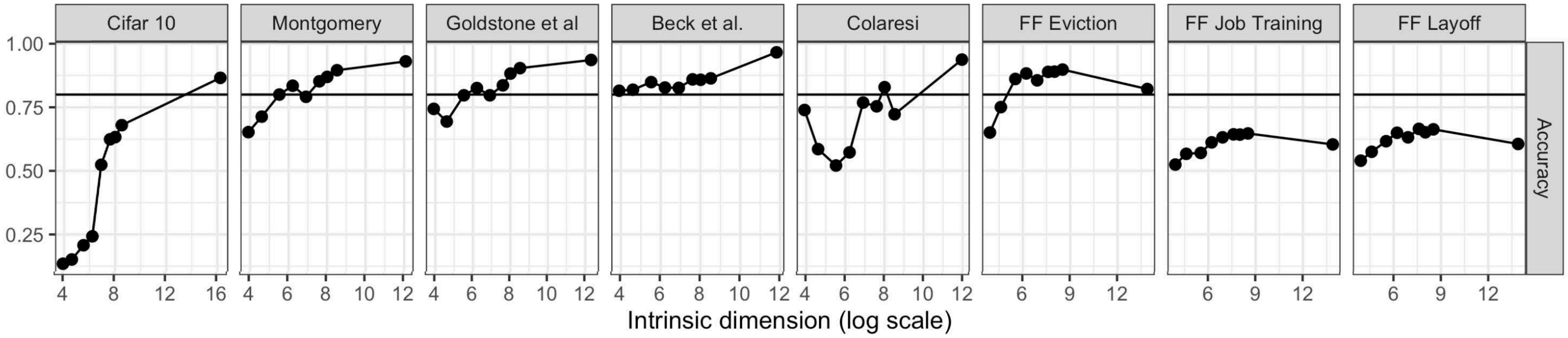
One contribution of this paper is to provide evidence that the intrinsic dimension of Political Science datasets is low, at least when compared to image data (CIFAR-10).

Intrinsic dimension and the appropriateness of ML.



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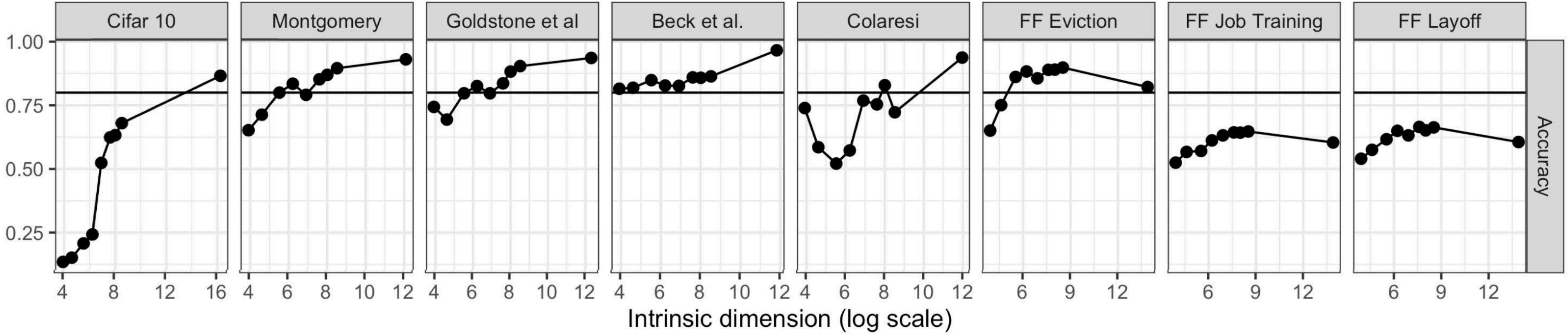

While it is true that the intrinsic dimension of CIFAR-10 is larger than the focus datasets, it does not seem obvious to me that the intrinsic dimension of Political Science datasets is low. In particular, if I understand the scales correctly, the dimensions seem to be in the order of 3,000 to 5,000, and in some cases 162,000 (Montgomery, Goldstone and Beck).

Is this really low?

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The absolute value of the intrinsic dimension did not seem low. At leas to me, it is not obvious that a linear model would have performed better than a properly regularized DNN or Random Forest in the focus datasets. Why not compare linear models against ML methods directly, instead of indirectly via instrisic dimension?

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Moreover, it seems to me that mispecification concerns can still happen even if the intrinsic dimension is low. For example, I could have a model with low intrinsic dimension (say, E[Y|X] = X^2) and yet, if I don't know the correct specification, using linear models would still give me biased estimates (say, if I'm estimating a causal effect), while using a data adaptive algorithms would protect me against misspecification.

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