

Pre-read for Tuesday Sept 22:
Armed conflict, part 1

Matthew J. Salganik

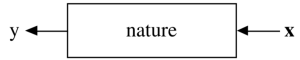
COS 597E/SOC 555 Limits to prediction
Fall 2020, Princeton University

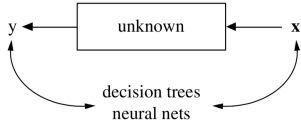
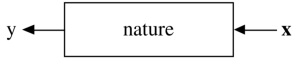
Two themes:

- ▶ prediction vs causation

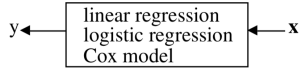
Two themes:

- ▶ prediction vs causation
- ▶ algorithmic modeling vs data modeling





Algorithmic modeling



Data modeling

Breiman (2001)

Predicting armed conflict: Time to adjust our expectations?

Lars-Erik Cederman^{1*} and Nils B. Weidmann^{2*}

Reading notes:

- ▶ Response to crazy claims about the magic of big data and machine learning

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- ▶ Lumpers vs splitters, they are splitters
- ▶ Critical of the idea that big data and machine learning will revolutionize conflict prediction. Why?

War Is in the Error Term

Erik Gartzke

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- ▶ Notice that he then talks about how to test the predictions from that model, not the model itself

Testing War in the Error Term

Damon Coletta and Erik Gartzke

Reading notes:

- ▶ Beware that not all proofs are right

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- ▶ Beware that not all proofs are right
- ▶ (Speculation) Many models that purport to show inherent unpredictability may prove hard to test empirically because they involve hard to measure parameters

The perils of policy by p-value: Predicting civil conflicts

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Journal of Peace Research

47(4) 363–375

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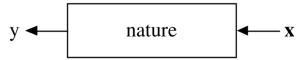
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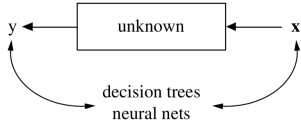
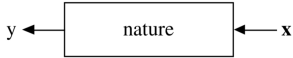
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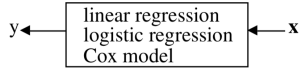
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Algorithmic modeling



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- ▶ Ward and colleagues argue that we should bring in predictive performance as a way to evaluate these models.
- ▶ If you are from a data modeling tradition, try to see how your approach misses that can be provided by the algorithmic modeling tradition. If you are from an algorithmic modeling tradition, try to see what your approach misses that can be provided by the data modeling tradition.

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