

Comments slides for Thursday, Oct 1:
Recommender systems; engineering limits

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

Observations/comments/questions/provocations:

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- ▶ Algorithm vs mechanism

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- ▶ Very careful paper by Herlocker et al (2004) on rec sys doesn't talk about bias and fairness.
- ▶ predictive accuracy metrics (discussed briefly subsets and normalized mean absolute error), classification accuracy metrics (not as interesting to me), and rank accuracy metrics (interesting to me, but what about ties); I like the idea of comparing them empirically but there are other ways to compare too

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 - ▶ Phase II: Preclinical Research. (paper focusing only on accuracy)
 - ▶ Phase III: Clinical Research. (deployed setting where accuracy is not the only objective and there are engineering constraints)
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- ▶ Netflix Prize vs real Netflix: Lab experiments vs field experiments. How can we measure this difference empirically.
- ▶ How do the kind of measurement problems you worked on in class today combine?
If there is an error term made up of the sum of two random variables A and B , then $Var(A + B) = Var(A) + Var(B) + 2Cov(A, B)$.

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