Thursday, November 19: Looking back and looking forward

Matthew J. Salganik

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

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- Principles for designing, testing, deploying, and auditing predictive systems (some social, but some technical, think of google paper on high-interest credit card)

Learning objectives:

- Students will be able to describe theories of predictability and unpredictability in different scientific domains.
 - Students will be able to compare and correctly apply commonly used measures of predictive performance.
- Sudents will be able to evaluate the appropriateness of prediction as a scientific or policy goal.
- ▶ Students will be able to make predictions about the future of prediction.
- Students will be able to create new research that helps understand the limits of predictability.

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