PEOPLE ANALYTICS

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What is “talent analytics”?

- Many different perspectives / definitions.

- Today: Talent assessment and development.
  - Identify differences in ability
  - Develop so that everyone’s ability is maximized

- Deeper than performance evaluation.
  - Essentially: employee evaluation

Motivating case: Promotions

Typically…

…Vital to firm’s health
…Numerous candidates
…Ambiguous measures

How to do this well?

Image: business.financialpost.com, 7/17/12

Talent Analytics: Agenda

- Introduction
- Challenges
  - Context
  - Interdependence
  - Self-fulfilling Prophecies
  - Reverse Causality
- Special Topics: Tests & Algorithms
- Prescriptions (Px)

Talent Analytics challenges

- Data is good. A lot of data is, typically, better. But they can also be misleading.

- If you're doing talent analytics you will be crunching all kinds of numbers – performance evaluations, test scores, 360 feedback, sales figures, employee morale, etc.

- But before you draw inferences from these numbers, it is <u>critical</u> to navigate a few challenges…

Talent Analytics challenges

1) Context
2) Interdependence
3) Self-fulfilling Prophecies
4) Reverse Causality

Talent Analytics challenges

1) **Context**
2) Interdependence
3) Self-fulfilling Prophecies
4) Reverse Causality

Context

- We tend to neglect context when evaluating performance
  - Over-attribute performance to personal traits (personality, skill, etc.)…
  - …under-attribute performance to the situation the person was in (easy vs. difficult task, helpful vs. hurtful colleagues, favorable vs. unfavorable economy, etc.)
- The “fundamental attribution error”

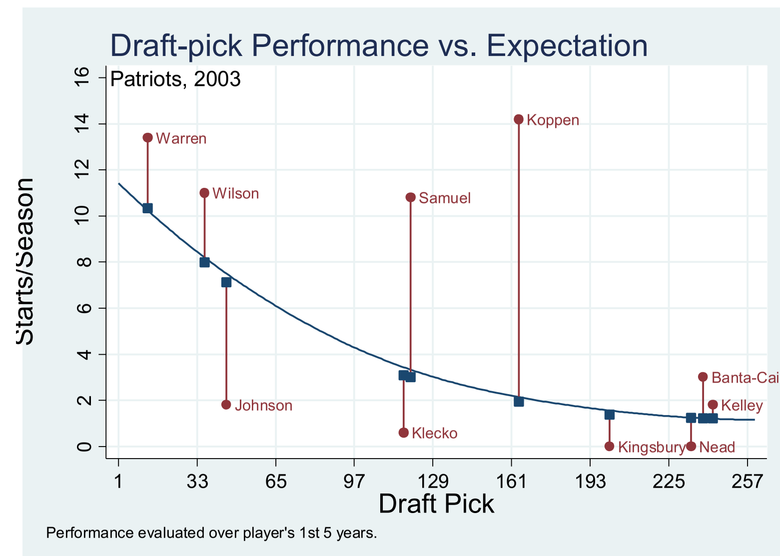
Context

- There's even a saying on Wall Street to (try to) counteract this:
  - "Don't confuse brains and a bull market."

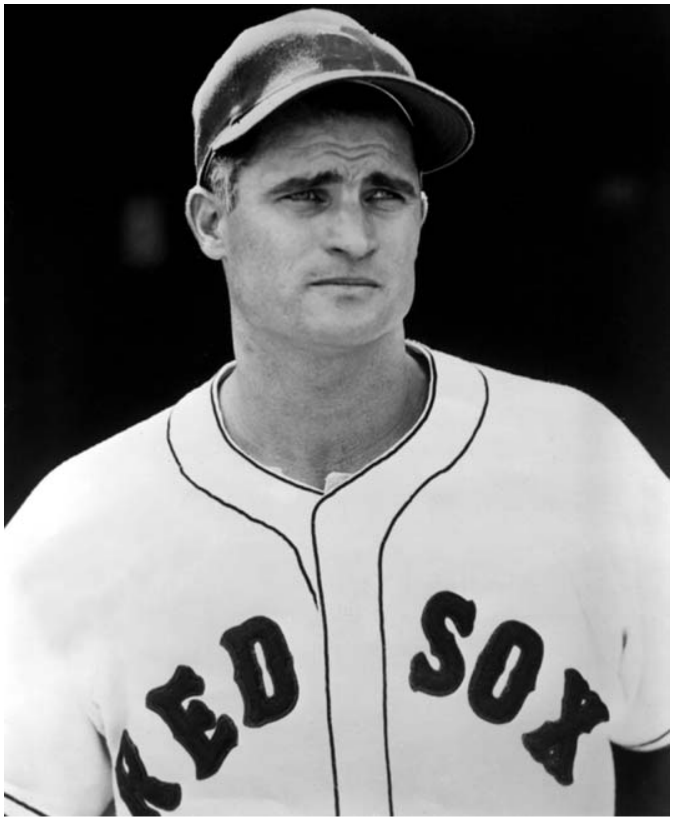
Context

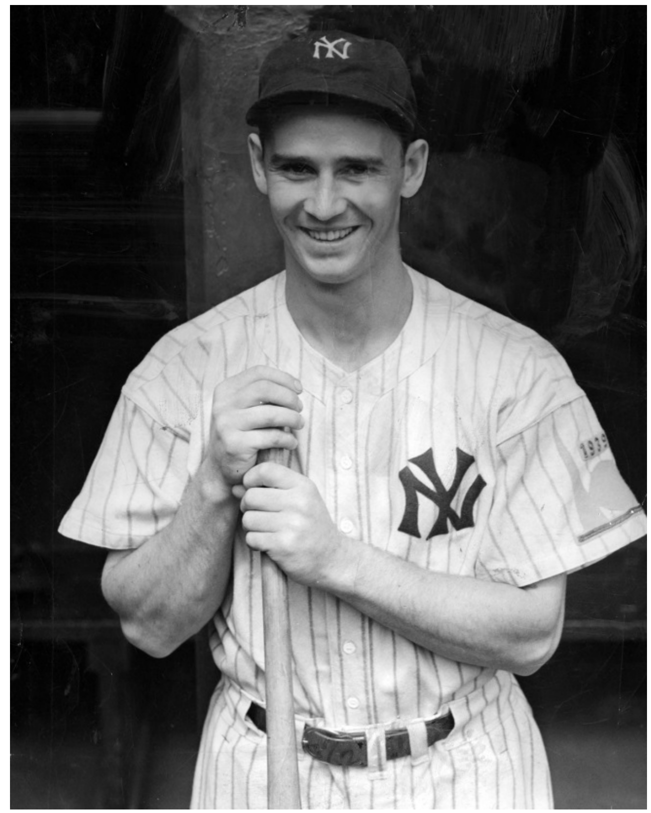
Key issue: Identify expected performance for each situation.

Remember we did this in the performance evaluation module



Context





Context

HOME

	G	AB	H	HR	RBI	Avg	OBP	SPct
Bobby Doerr	954	3554	1119	145	743	0.315	0.395	0.532
Joe Gordon	769	2718	696	119	437	0.256	0.346	0.447

AWAY

	G	AB	H	HR	RBI	Avg	OBP	SPct
Bobby Doerr	911	3539	923	78	504	0.261	0.327	0.389
Joe Gordon	797	2989	834	134	538	0.279	0.367	0.482

Tim Howard Lost, But He Just Had the Best Match of the World Cup

10:14 PM | JUL 1 | By NATE SILVER

Best Single-Match Goalkeeping Performances, 2014 World Cup

KEEPER	TEAM	OPPONENT	SAVES	GOALS ALLOWED*	EXPECTED GOALS	NET GOALS SAVED
Howard	U.S.	Belgium	16	2	4.50	+2.50
Dominguez	Ecuador	France	9	0	2.25	+2.25
Enyeama	Nigeria	Bosnia	7	0	1.75	+1.75
Begovic	Bosnia	Nigeria	9	1	2.50	+1.50
Ochoa	Mexico	Brazil	6	0	1.50	+1.50
Bravo	Chile	Spain	6	0	1.50	+1.50
Courtois	Belgium	South Korea	6	0	1.50	+1.50
M'Bolhi	Algeria	Germany	11	2	3.25	+1.25
Benaglio	Switzerland	Argentina	8	1	2.25	+1.25
Karnezis	Greece	Japan	5	0	1.25	+1.25
Ospina	Colombia	Uruguay	5	0	1.25	+1.25

Context

- When using data to compare employees you must find ways to put them on an even playing field.
- Think of performance <u>relative to expectations</u>, as driven by team, product, industry, economy, boss, etc.

Talent Analytics challenges

1) Context
2) **Interdependence**
3) Self-fulfilling Prophecies
4) Reverse Causality

Interdependence

- A humbling amount of our work depends on other people.

- Recent conversation with a Google executive:

  - “[Scowling] It makes me so mad when people over-emphasize individual contributions. Practically everything we do is with other people. If M____ left, or B____, I’d quit. I couldn’t do my job!”

Organizations and Stock Analysts

Study of 1,052 star stock analysts who worked for 78 U.S. investment banks United States from 1988 through 1996.

A star is defined as any analyst who was ranked by Institutional Investor magazine as one of the best in the industry in any of those nine years.

Groysberg et al, HBR (2004)

When a Star Signs as a Free Agent

Performance plummets by an average of 46% in the first year and about 20% over the star’s tenure. It does not climb back to old levels even five years later.

Does the star lose intelligence and forget the lessons of experience overnight, and not gain them back?

The Intaking Group Suffers Too

From a head of research:

"I painfully learned that hiring a star analyst resembles an organ transplant. First, the new body can reject the prized organ that operated so well inside another body... On some occasions, the new organ hurts healthy parts of the body by demanding a disproportionate blood supply... Other parts of the body start to resent it, ache, and... demand attention... or threaten to stop working. You should think about it very carefully before you do [a transplant] to a healthy body. You could get lucky, but success is rare."

Interdependence

- Means performance evaluation is often best done at the group level.
- Reliable individual evaluation typically requires seeing them with multiple teams.
- New and improved performance measures designed to assess contribution to team performance are on the way.
  - E.g., network analysis

Talent Analytics challenges

1) Context
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3) **Self-fulfilling Prophecies**
4) Reverse Causality

Trading Places (1983)

Self-fulfilling prophecies

- People tend toward performing consistent with expectations. High expectations increase performance, low expectation decrease.
  - Can occur because we treat them differently as a result of our own expectations.
    - E.g., teachers in classrooms
  - Can also occur because our expectations literally change their behavior.

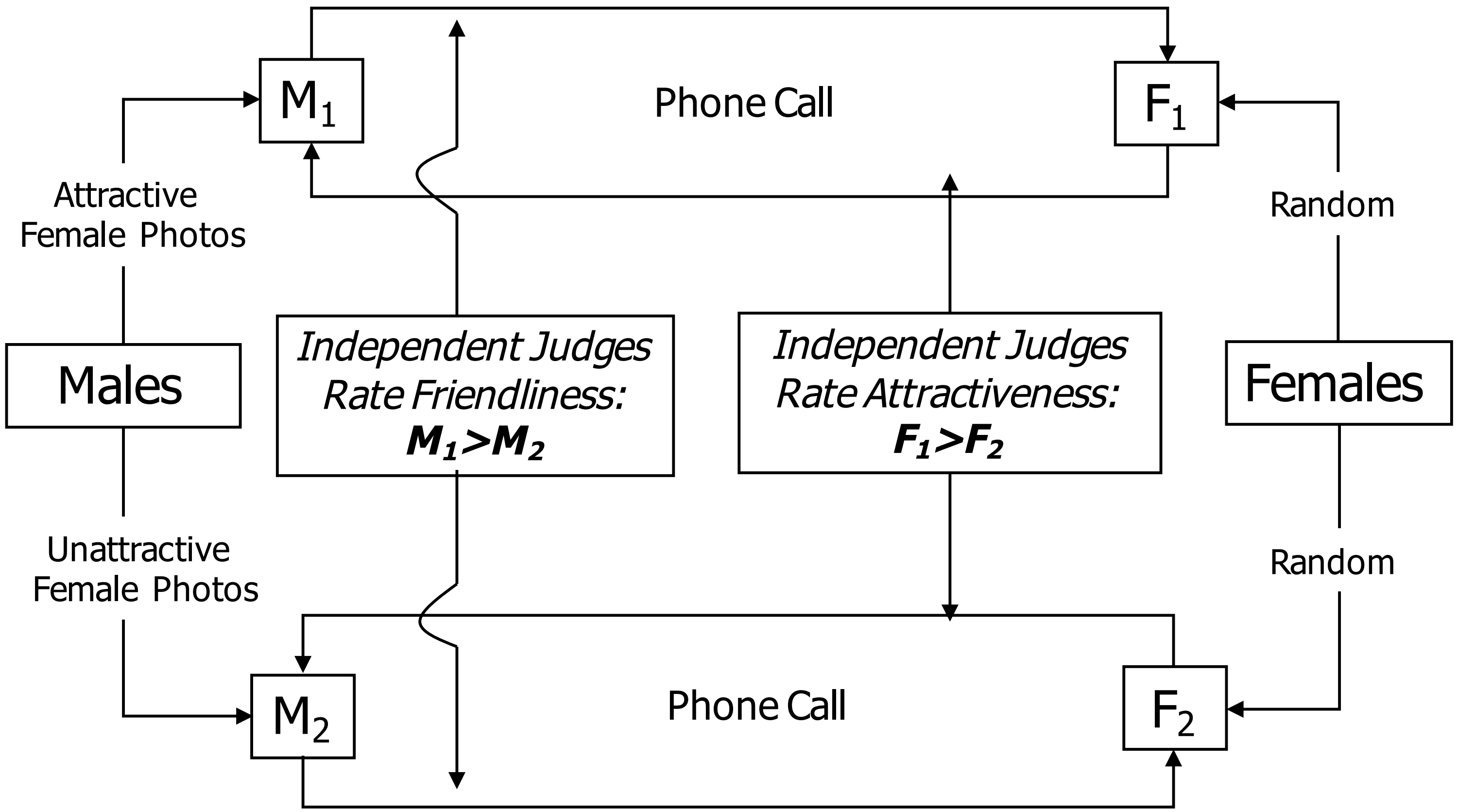
Self-fulfilling Stereotypes *(Snyder, et al, 1977)*

- Experimental Procedure (n=96)
  - Cover story: Studying initial interactions that do not include nonverbal communication (e.g., telephone conversations)
  - 1st stage: Created anonymous male-female pairings
  - 2nd stage: 10-minute telephone conversation
  - 3rd stage: Each party's side of the conversation evaluated by independent judges (unaware of hypotheses and manipulations)

- Manipulation: Female photo distributed to male subjects
  - ½ of male subjects: an attractive photo
  - ½ of male subjects: an unattractive photo
  - Female subjects did not receive photos

- (Note: Study replicated with roles reversed)

Self-fulfilling Stereotypes *(Snyder, et al, 1977)*



The Matthew Effect

- Coined by sociologist Robert Merton (1968):
- “The rich get richer and the poor get poorer”

- Early advantages often accumulate
  - Consumer goods
  - Education
  - Careers

- Where experience and recognition matter, those with early advantage will be increasingly privileged over time.

Self-fulfilling prophecies

- Where might your expectations be affecting others' behavior? Or your evaluation of their behavior?
- What steps can you take to protect evaluation processes from these expectations?
- How can you ensure equal access to valuable resources?

Talent Analytics challenges

1) Context
2) Interdependence
3) Self-fulfilling Prophecies
4) **Reverse Causality**

Reverse Causality

- When we see two correlated factors, we tend to believe one caused the other. Especially when there is an intuitive direction.
- E.g., are charismatic leaders more successful?
- Agle et al, <u>Academy of Management</u> (2006), studied charisma and success among 128 CEOs in a longitudinal panel.
  - Charismatic CEOs did <u>not</u> have more future success…
  - …but successful CEOs were perceived as more charismatic!

Reverse Causality

- We are driven to make sense of the world we live in, so we build causal stories from what we observe.
- But this leads us to see things that don’t exist, and this can lead to giving people credit, or blame, they don’t deserve.

Almost Random Careers: The Wisconsin School Superintendency, 1940-1972

James C. March and James G. March

Administrative Science Quarterly
Vol. 22, No. 3 (Sep., 1977), pp. 377-409

Published by: Sage Publications, Inc. on behalf of the Johnson Graduate Management, Cornell University

- “The normative lesson is…that the stories we tell each other about success and failure in top management, like the stories we tell about success and failure in gambling, are in large part fictions intended to reassure us about justice and encourage the young.”

- March & March, ASQ, 1977

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- Prescriptions (Px)

Hiring: Testing & Algorithms

Photo-illustration by Andrew B. Myers for TIME

The New York Times

Thursday, June 25, 2015 | Today's Paper | Video | 74°F | Shanghai -2.37

Can an Algorithm Hire Better Than a Human?

Start-ups say they can eliminate biases and create more skilled and diverse workplaces, but data science will probably need human supervision.

Hiring: Testing & Algorithms

- Pros
  - Processing efficiency
  - Broader search
  - Unbiased

- Cons
  - Hyper-focused
  - Low explanatory power

Hiring: Testing & Algorithms

- Prescriptions
  - Do the science
    - Rigorous testing in the relevant setting
  - Provide human oversight
    - Program, test, error-check
  - Use multiple tools
    - Draw on as many diverse signals as possible

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Px #1: Broaden sample

- Ala good performance evaluation, expand the sources/signals.
  - Additional opinions
  - Additional performance metrics
  - Additional projects, assignments
  - Remember: From maximally diverse sources!

- Second chances. And thirds.
  - E.g., a new employee’s boss has a huge impact, but is completely outside his/her control.

Px #2: Find/create exogenous variation

- The only truly valid way to tease out causation is to manipulate an employee’s environment.
- Trade-off: You still have to run a business!
- But can and should be willing to trade off a bit of operational efficiency for greater insight into the abilities of the employees.

Px #2: Find/create exogenous variation

- This is major motivation for rotational programs.
  - Wide variety of environments, people
  - Pre-committed to changing at preset times, often in preset patterns.
  - Almost an <u>experiment</u>, which is the gold standard.

- Lesser versions: change teams, direct reports, projects, offices.

Px #3: Reward in proportion to signal

- Match the duration and complexity of rewards to the duration and complexity of past accomplishments.

- For short, noisy signals, better to give bonuses rather than raises, praise rather than promotions.

  – Note 1: Most signals are noisy, and we are prone to underestimate the noise.
    - Suggests we typically over-react in talent management

  – Note 2: Of course you also have to retain people, so must factor in external labor market.
    - But <u>accurately</u> valuing employees should be an advantage

Px #3: Reward in proportion to signal

- Drawing major distinctions, and granting major rewards, should only follow major signals.
  - E.g., consulting/law firm partnerships typically involve a multi-year, up-or-out partnership track.
  - E.g., academic tenure is practically irrevocable, so is granted to relatively few and only after 5-10+ years of performance.

E.g., Succeeding Jack Welch

- 2001, to be GE’s first new CEO in 20 years
  - Three-way “tournament” between Jeff Immelt, Jim McNerney & Bob Nardelli.
  - Each running his own major division
  - Year-long process

- McNerney joked [with Welch] about there being no recount, but added, “I want you to know I wanted the job, but I also want to tell you I think the process was fair.”

Px #4: Emphasize development

- Talent analytics is not all about selection.
- Even in a field as selection-oriented as venture capital, firms spend considerable resources developing people within their portfolio firms.
- Testing and assessment is at least as valuable as development tools as selection tools. And more palatable.

"Player development is one of the least understood elements of NBA success. Everybody knows it's important, and everyone knows which organizations excel at it. Some organizations routinely transform draft picks into good players, while perpetual lottery teams commonly sit back and watch them fail to pan out." (Goldsberry, 2015)

Px #5: Ask the critical questions

- Are we comparing “apples to apples”? I.e., have we sufficiently adjusted for context?

- What impact have other people had on this person’s work? How interdependent are these measures?

- How have expectations colored our evaluations? To what extent have successes and failures been influenced by the way we’ve treated people, the situations we’ve put them in?

- Are the factors we believe lead to success (and failure) truly causal?

Good luck with your work!

Organizational Challenge

- Claim: Effective people analytics is more of an organizational challenge than an analytics challenge.

- From this flow many prescriptions, but one dominant theme: “No black boxes”.

Organizational Challenge

- Major theme: No “black boxes”!

- Specific prescriptions:
  - Be transparent
  - Embed yourself
  - Share control

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BEST PRACTICE

Harvard Business Review

Everyone knows that being fair costs little and pays off handsomely.
Then why do so few executives manage to behave fairly, even though most want to?

Why It's So Hard to Be Fair

by Joel Brockner

Transparency is a key element of "procedural fairness", an important way top performing organizations differentiate themselves.

“Default to open”

- Google’s TGIF Q&A with the CEO/founders

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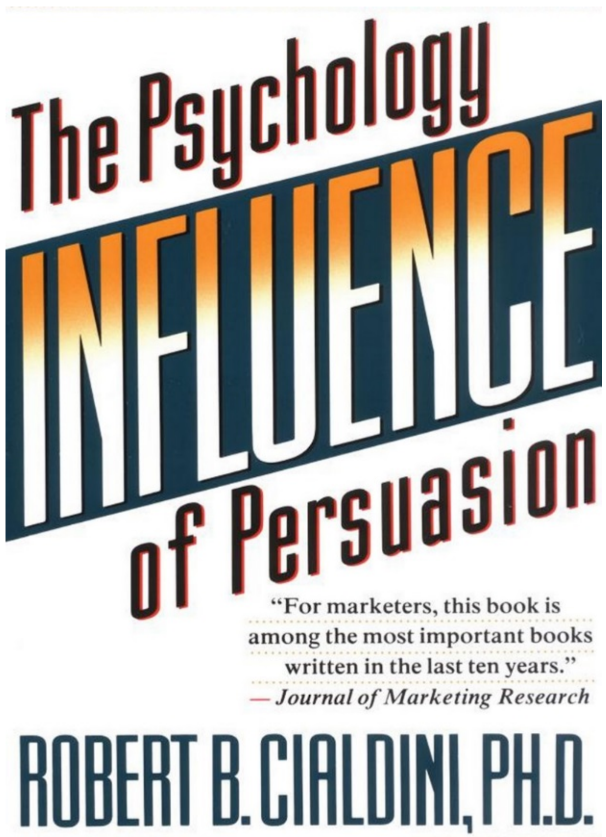
  - Share control



- People are more easily influenced by people they like, and a fundamental driver of liking is <u>similarity</u>.

- Px: Find and/or create sources of similarity.

- **Cleveland Browns President, Alec Scheiner, on influence as an analyst:**

- "Embed yourself. We hired an analytics guy [Ken Kovash] – he's in the audience here – and I always tease him because he wears Browns' t-shirts every day to work. And I'm like, "You didn't do that in your old job at Mozilla did you? You're just like wearing t-shirts to work every day and pullovers?" But there is a point to it. He's dressing like our coaches and our scouts, and they feel more comfortable with him. If he came in every day in a suit and tie he'd be like a foreigner in their land. And I'm going to hit on this again and again: if people don't trust you they're not going listen to you. They might act like they're listening to you but they're not. First you have to build that trust. And one way to do it is to really learn about what they do, and to do that you have to just embed yourself. Work near them, go out with them. See what their day to day is, see what their challenges are. That's really what we spend most of our time worrying about."

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Journal of Experimental Psychology: General

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0096-3445/14/$12.00 http://dx.doi.org/10.1037/xge0000033

Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err

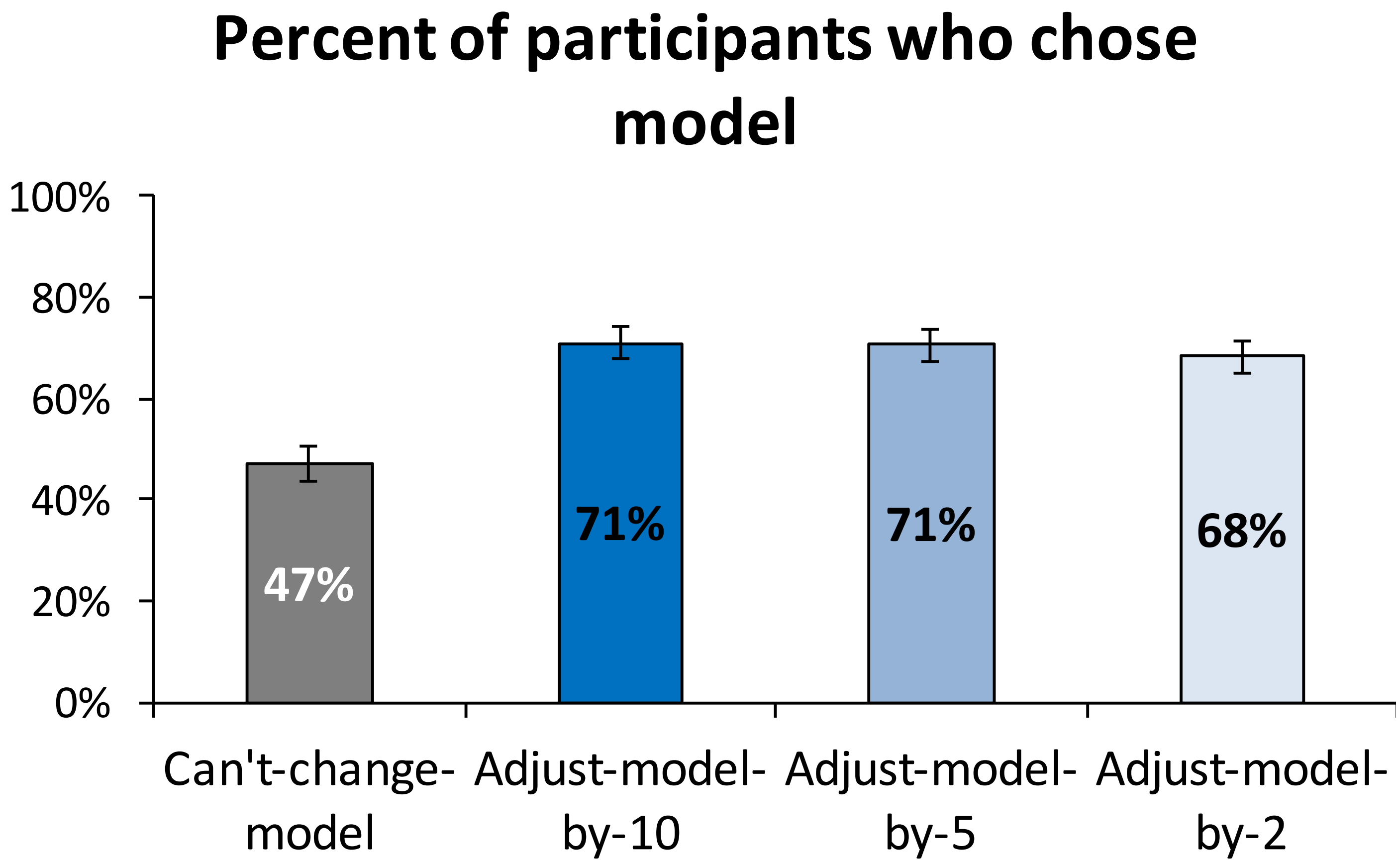
Berkeley J. Dietvorst, Joseph P. Simmons, and Cade Massey
University of Pennsylvania

Research shows that evidence-based algorithms more accurately predict the future than do human forecasters. Yet when forecasters are deciding whether to use a human forecaster or a statistical algorithm, they often choose the human forecaster. This phenomenon, which we call *algorithm aversion,* is costly, and it is important to understand its causes. We show that people are especially averse to algorithmic forecasters after seeing them perform, even when they see them outperform a human forecaster. This is because people more quickly lose confidence in algorithmic than human forecasters after seeing them make the same mistake. In 5 studies, participants either saw an algorithm make forecasts, a human make forecasts, both, or neither. They then decided whether to tie their incentives to the future predictions of the algorithm or the human. Participants who saw the algorithm perform were less confident in it, and less likely to choose it over an inferior human forecaster. This was true even among those who saw the algorithm outperform the human.

Keywords: decision making, decision aids, heuristics and biases, forecasting, confidence

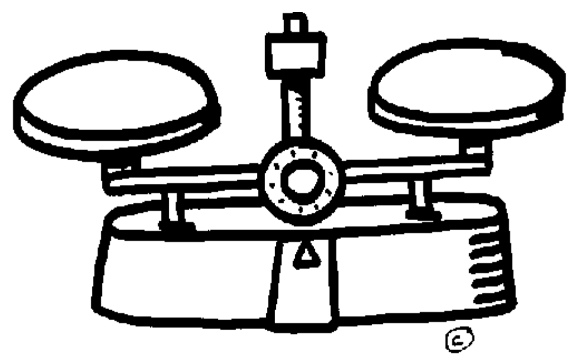
Algorithm Aversion (Dietvorst, et al)

- Across a wide range of tasks, people prefer human judgment to algorithmic judgment.
- This is true even when algorithms are better.
- A major reason is that people are far more forgiving of error by humans than by algorithms.
- But, people are more tolerant of algorithmic judgment when they have some input, even when that input is minor.


Percent of participants who chose model
100%
80%
60%
40%
20%
0%
47%
71%
71%
68%
Can't-change-model
Adjust-model-by-10
Adjust-model-by-5
Adjust-model-by-2

E.g., a local graduate admissions office

- Blends experts and analytics
  1) Experts evaluate each applicant
  2) A decision model crunches those evaluations to recommend the optimal class
  3) Experts review and revise those recommendations



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