On choice anomalies, cognitive limitations, predictions, and the big data revolution

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The first part of this session reviews a paper that tries to advance the development of a descriptive model of decisions under risk, under ambiguity, with and without experience. We consider models that capture 14 classical choice anomalies, and compare them based on their predictive value.

The second part (Ori's talk) describes an effort to clarify the relationship of the results to the big-data/machine-learning revolution.

The third part (Doron's talk) tries to clarify the underlying processes by distinguishing between adjustment and transfer.

From anomalies to forecasts: Toward a descriptive model of decisions under risk, under ambiguity, and from experience

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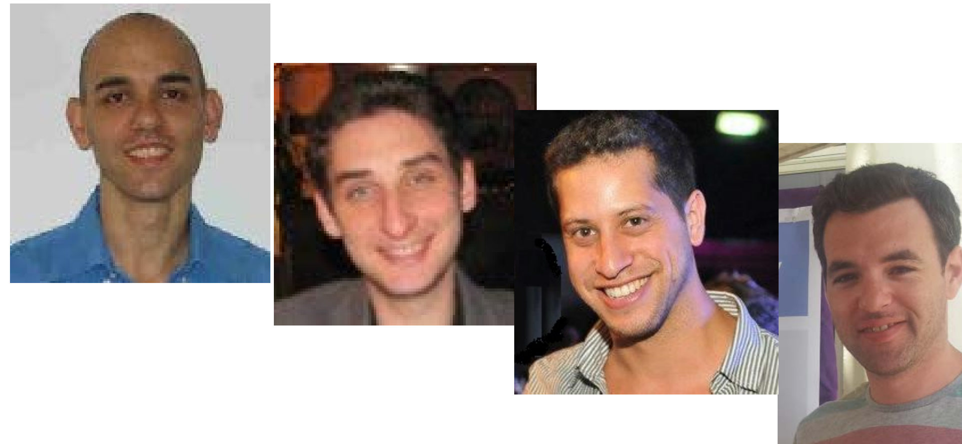

Psychological review, 2017;
http://departments.agri.huji.ac.il/economics/teachers/ert_eyal/CompDEPsychRev2016.12.22.pdf

Behavioral decision research is often criticized on the ground that it highlights interesting choice anomalies, but rarely supports clear forecasts.

This critique rests on the observation that the classical anomalies are explained with several descriptive models, and in many cases these models suggest contradicting behavioral tendencies.

Kahneman & Tversky (1979) tried to address this problem by replicating four of the most important anomalies in one paradigm, and presenting one model, prospect theory, to capture all four.

Certainty/ Allais Paradox

Reflection effect

Loss aversion

Over weighting rare events

Choose between:
A 3000 with certainty
B 4000 with p = 0.8; 0 otherwise

The success of prospect theory has triggered follow-up studies that attempt to reconcile this model with other choice anomalies.

Certainty/ Allais Paradox

Reflection effect

Loss aversion

Over weighting rare events

Under weighting rare events

Ellsberg Paradox

Small stakes eliminate loss aversion

Get something effect

Reversed reflection

St. Petersburg paradox

Splitting effect

Break Even effect

Payoff variability effect

Correlation effect

This research suggests, however, that different additions (that imply different models or parameters) are needed to capture different choice domains.

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For example, the best models of decisions from description assume the weighting of subjective values by subjective values of their probabilities (**and capture overweighting of rare events**), but the best models of repeated decisions with feedback assume reliance on small samples of past experience (**and imply underweighting of rare events**.

The early attempts to address this difficulty assume “contingent decision making.” For example, different processes (and models) for decisions from description (under risk), under ambiguity, and from experience.

But which type of models should we use if our goal is, for example, to design an incentive system that facilitate safe driving? Drivers would be informed of the incentives and would also gain experience using the mechanism.

We try to extend Kahneman & Tversky's (1979) analysis. Unlike most previous attempts, we build on their "replication in one setting and than one model" method, and not on their theory.

- At the first stage, we identified an 11 dimension space that can, in theory, give rise to 14 anomalies described above.
- Study 1 tries to replicate the 14 anomalies in an experimental paradigm defined by this space. The replication required the study of 30 problems.
- Study 2 examines behavior in 60 randomly selected problems from the same space.
- Feasibility: We presented a single model that can capture the results of all 90 problems.
- Competition: On Nov 2014 we published the results and the baseline model on the web, and challenged other researchers to participate in a competition that focuses on predicting the behavior in Study 3. This study was similar to Study 2, but involved a different sample of problems and subjects. The submission deadline was May 17, 2015

The 11 dimensions:

Each problem in our space is a choice between two basic prospects:

Option A: *HA* with probability *pHA*; or *LA* otherwise.
Option B: Up to 10 outcomes, defined by 5 parameters

A 9^{th} parameter, *Corr, captures the correlation between the prospects*

The 10^{th} parameter, *Amb*, captures ambiguity

The 11^{th} parameter *FB* captures the DMs' feedback. This parameter was studied within experiment. The DMs faced each problem for 25 trials, and got feedback after each choice from the 6^{th} trial.

Example of a basic experimental task, trial 1, initial screen

Please select one of the following options:

A:

3 with certainty

B:

4 with $p = 0.8$

0 with $p = 0.2$

A	B

Example of a basic experimental task, trial 1, limited feedback

A:
3 with certainty

B:
4 with p = 0.8
0 with p = 0.2

A

B

You selected B

Example of a basic experimental task, trial 6, initial screen

Please select one of the following options:

A:
3 with certainty

B:
4 with p = 0.8
0 with p = 0.2

A	B

Example of a basic experimental task, trial 6, feedback screen

A:
3 with certainty

B:
4 with $p = 0.8$
0 with $p = 0.2$

A
3

B
4

You selected B, your payoff is 4
Had you selected A your payoff would be 3

Example of an ambiguous task, trial 1, initial screen

Please select one of the following options:

A:
10 with p =0.5
0 with p = 0.5

B:
10 with p = q1
0 with p = q2

A

B

The Allais (common ratio) paradox/certainty effect (Allais, 1953, K&T, 1979)

Problem 1	Block	1, No FB	5, with FB
A	3 with certainty	(58%)	
B	4 with p= .8, 0 otherwise	42%	

Problem 2	Block		
A'	3 with p =.25, 0 otherwise	(39%)	
B'	4 with p= .2, 0 otherwise	61%	

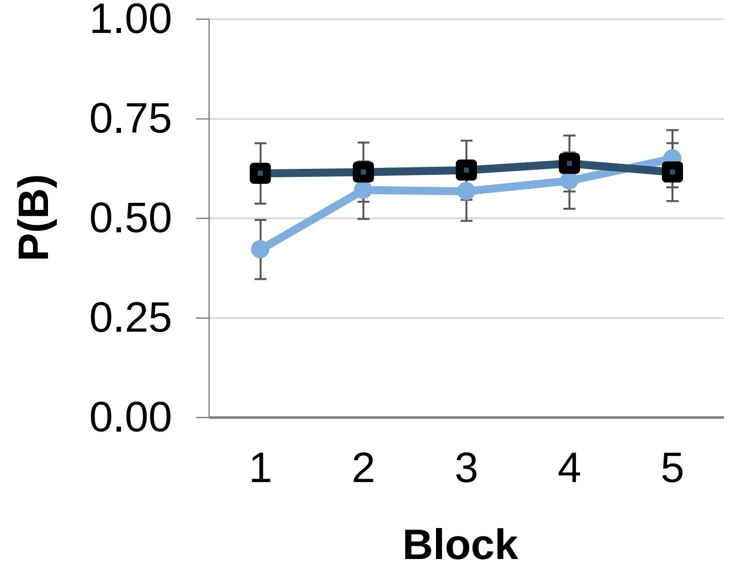
Certainty effect from description.

The Allais (common ratio) paradox/certainty effect (Allais, 1953, K&T, 1979)

Problem 1 Block		1, No FB	5, with FB
A	3 with certainty	(58%)	
B	4 with p= .8, 0 otherwise	42%	65%

Problem 2 Block			
A'	3 with p =.25, 0 otherwise	(39%)	
B'	4 with p= .2, 0 otherwise	61%	62%

Certainty effect from description.
The addition of feedback increases maximization and eliminates the paradox



The reflection effect

	Block	1 (No FB)	5 (with FB)
A	3 with certainty		
B	4 with p= .8, 0 otherwise	42%	

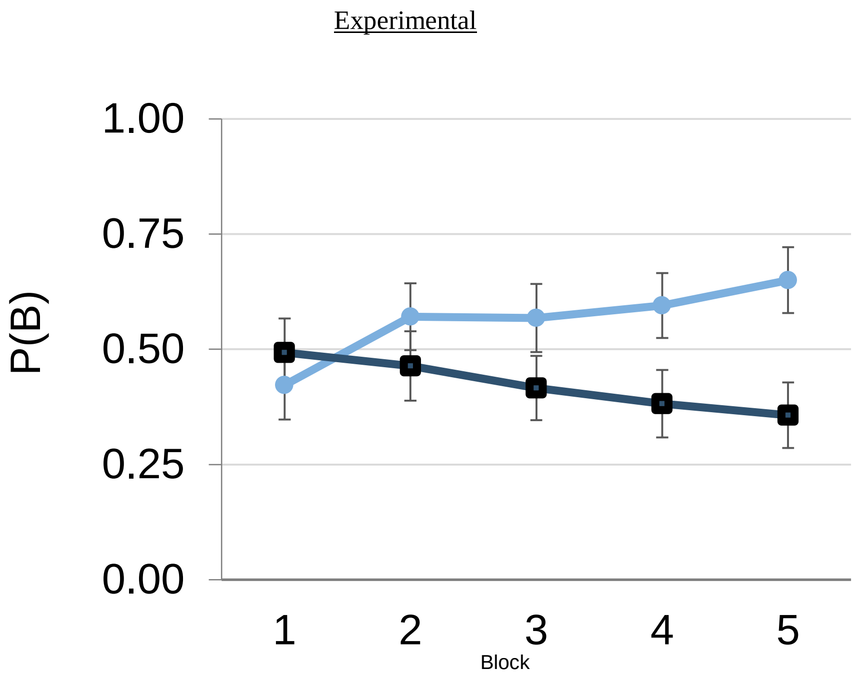
A	-3 with certainty		
B	-4 with p= .8, 0 otherwise	49%	

The reflection effect

	Block	1 (No FB)	5 (with FB)
A	3 with certainty		
B	4 with p= .8, 0 otherwise	42%	65%

A	-3 with certainty		
B	-4 with p= .8, 0 otherwise	49%	36%

Risk aversion in the gain and weak risk seeking in the loss domain, feedback eliminates this pattern and increase maximization



Insurance, lotteries, Over and under-weighting of rare events
(Kahneman & Tversky, 1979; Barron & Erev, 2003; Hertwig et al., 2004)

			Block	1 (No FB)	5 (with FB)
	A	2 with certainty			
Buy lottery	B	101 with p= .01, 1 otherwise		55%	
Buy insurance	A	-1 with certainty		(52%)	
	B	-20 with p= .05, 0 otherwise		48%	

Some overweighting of rare events before feedback

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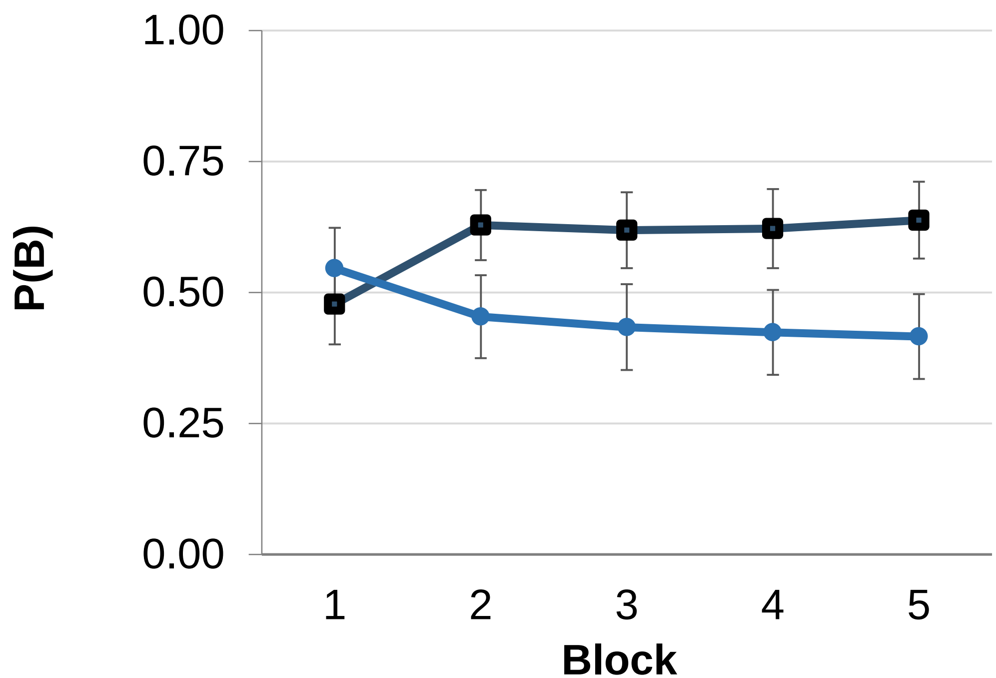
Some overweighting of rare events before feedback, and robust underweighting with feedback



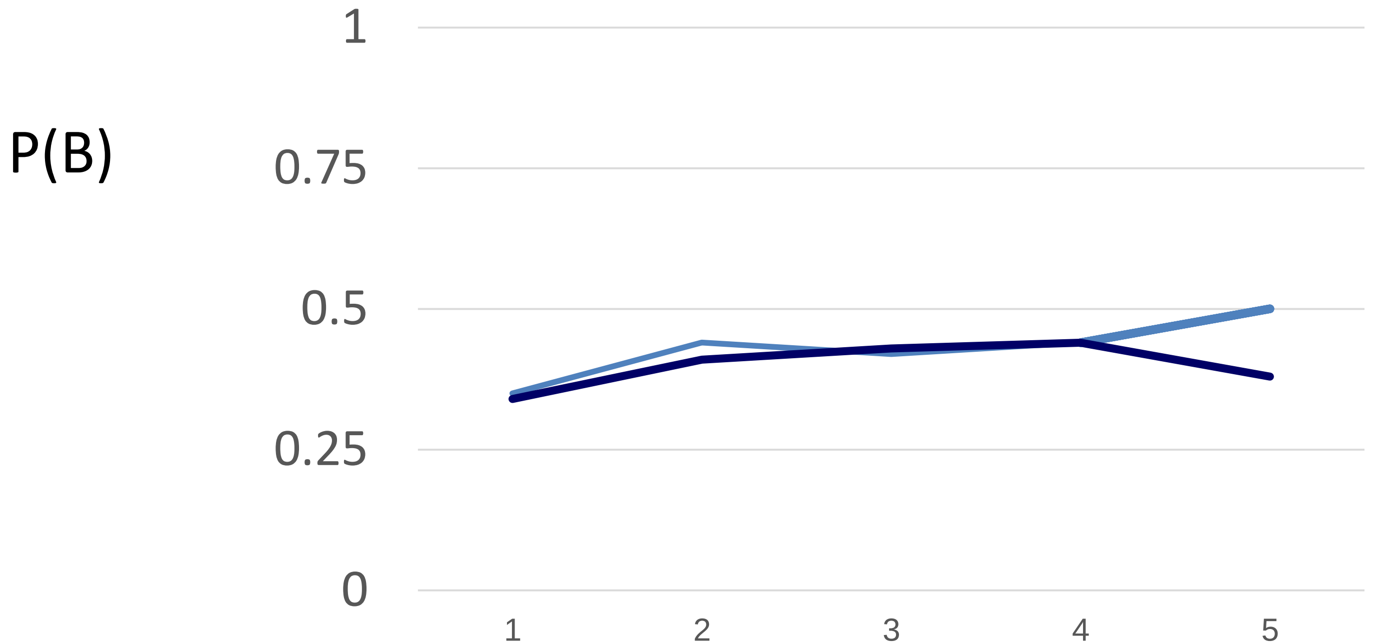
Loss aversion

	Block	1 (No FB)	5 (with FB)
A	0 with certainty		
B	+50 with p = 0.5; -50 otherwise (EV = 0)	34%	
A	13 with certainty		
B	50 with p= .6; -45 otherwise (EV = 12)	35%	

Loss aversion

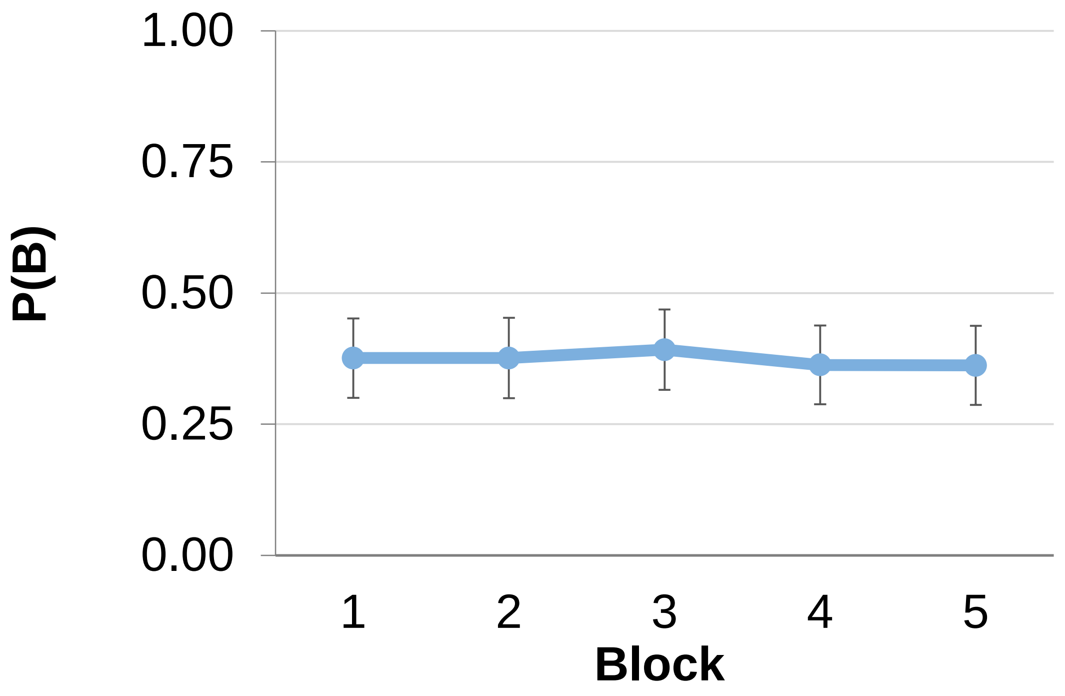
		Block	1 (No FB)	5 (with FB)
A	0 with certainty			
B	+50 with p = 0.5; -50 otherwise (EV = 0)		34%	38%

A	13 with certainty		
B	50 with p= .6; -45 otherwise (EV = 12)	35%	50%



The St. Petersburg “paradox” (after Bernoulli, 1738)

	Block	1 (No FB)	5 (with FB)
A	9 with certainty		
B	2 with p=.5 4 with p=.25 8 with p=.125 16 with p=.0625 32 with p=.03125 64 with p=.0015625 128 with p=.00078125 256 with p=.00078125	38%	36%

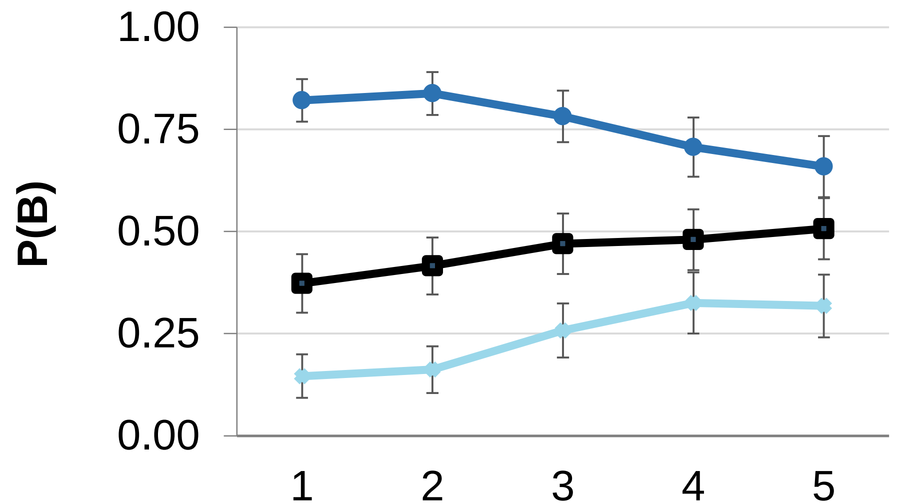


Risk aversion.

The Ellsberg paradox (Ellsberg, 1961)

	Block	1, No FB	5, with FB
A	10 with p= 0.5; 0 otherwise		
B	10 or 0	37%	51%
A	10 with p= 0.9; 0 otherwise		
B	10 or 0	15%	32%
A	10 with p= 0.1; 0 otherwise		
B	10 or 0	82%	66%

Ambiguity aversion plus
a bias toward uniform priors.
Experience eliminates this
effect

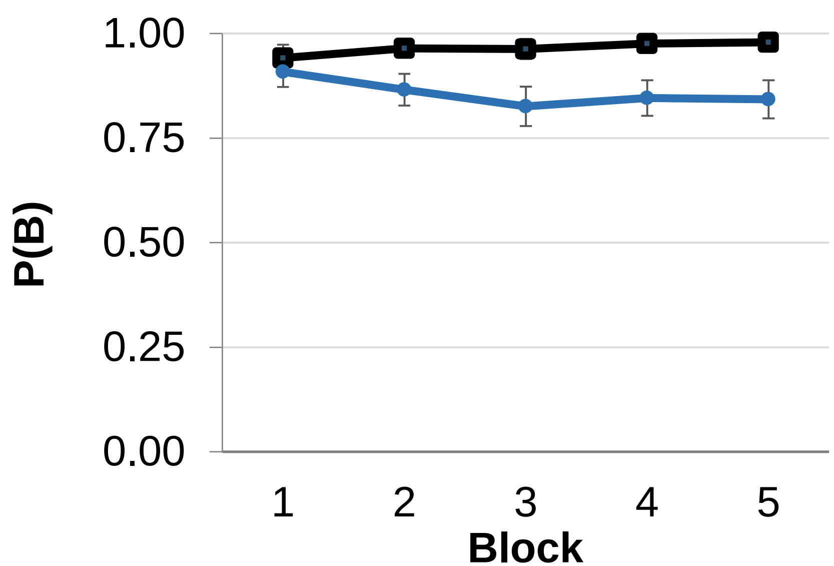


Regret (Loomes & Sugden, 1982) and correlation (Diederich & Busemeyer, 1999) effects.   P(E) = 0.5

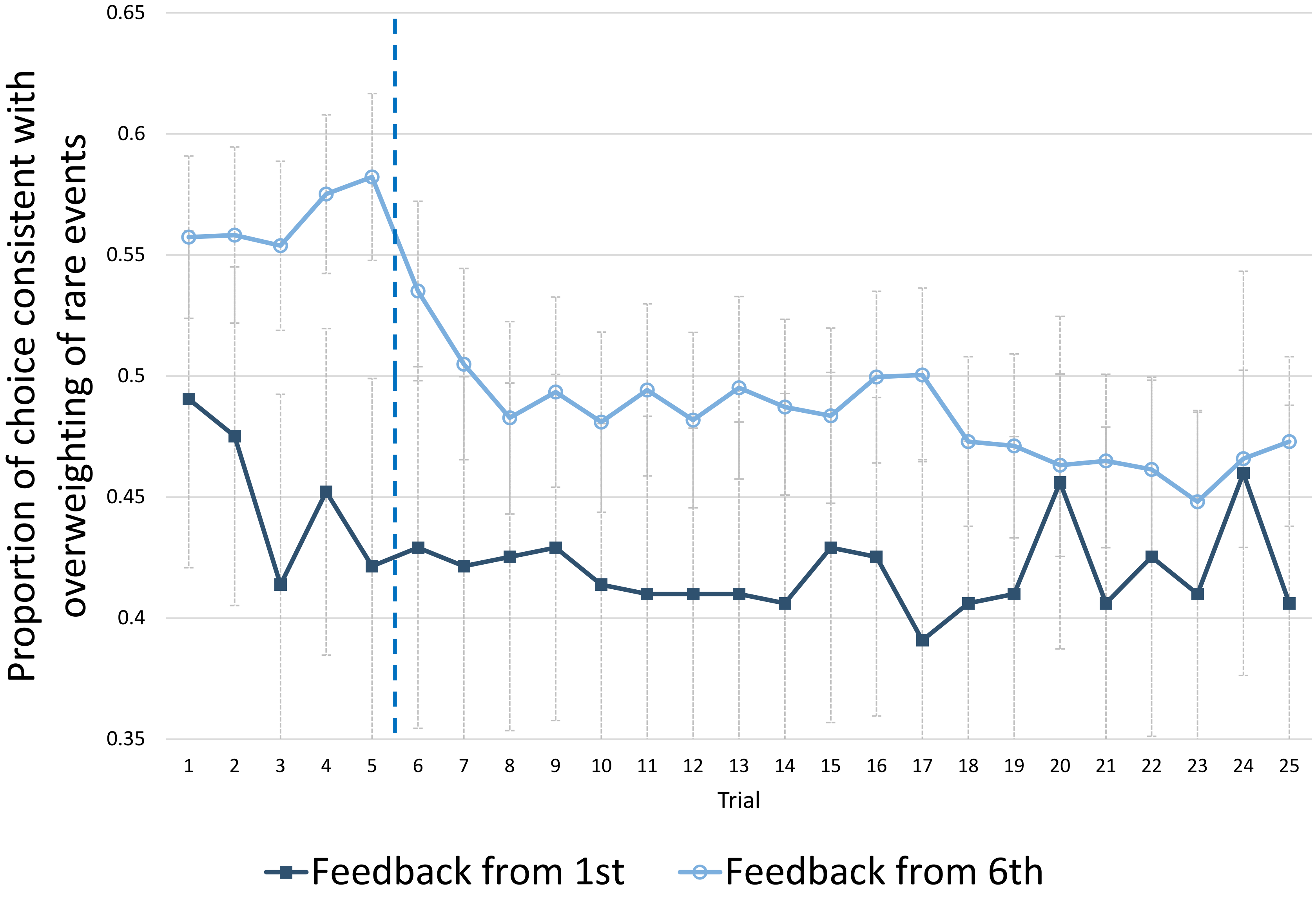
		Block	1 (No FB)	5 (with FB)
A	6 if E, 0 otherwise			
B	8 **if** E, 0 otherwise		97%	99%

A	6 if E, 0 otherwise		
B	**9 if not-E**, 0 otherwise	96%	85%

Weak sensitivity for regret/correlation without feedback, feedback increases the regret correlation/effect.



The impact of repetition and feedback



BEAST (Best Estimate And Sampling Tools) the best model that we could find assumes very different processes than assumed by the leading models. It does not assume subjective weighting of subjective values (like prospect theory), and does not assume cognitive shortcuts (like the priority Heuristic)

Rather it assumes the approximation of the EV, plus four extra stochastic processes that involve sampling from memory using the following tools:

- *Pessimism* (sample the worst outcome)
- *Uniform* (all outcomes are equally likely)
- *Sign* (implies high sensitivity to the payoff sign).
- *Unbiased* (implies minimizing probability of regret)

Feedback increases the probability of the unbiased sampling, but the samples stay small. Reliance on small samples implies a bias toward the option that minimizes the probability of regret, and underweighting of rare events

The competition

On December 2014 we posted the results of Study 1 and 2 (90 choice problems) on the web, and challenged decision scientists to participate is a competition to predict the results of study 3.

We offered BEAST and challenged the participants to offer BEAUTY

Study 3 was run on April, 2015.

The submission deadline was May 17 2015.

R, Matlab, or SAS (examples in the site)

Competition participants

53 registered teams
25 submissions from 5 continents

Three classes of submissions:

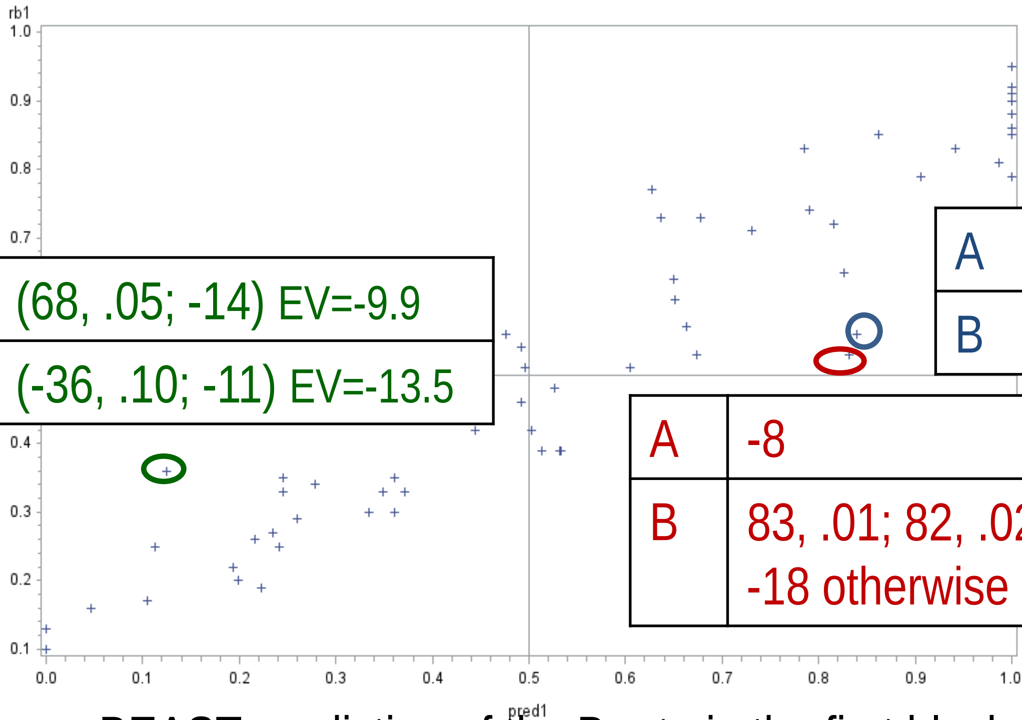
- 4 Subjective functions models (Prospect theory-like)
- 15 BEAST-like (EV plus sampling tools)
- 6 Machine learning models

Main results:
All 12 top models were variants of BEAST. The difference between these models were statistically insignificant. **The winner is Cohen's BEAST.**

The best ML model, submitted by Noti, Levi, Kolumbus, & Daniely, was almost as good as the BEASTs

Competition results: BEAST predictions are relatively good: Correlation above 0.94 between the predicted and observed B-rates in all five blocks.

Observed B rate (in the first, no feedback, block)



A	(68, .05; -14) EV=-9.9
B	(-36, .10; -11) EV=-13.5

A	5
B	-9, 92, 100, 104, or 106

A	-8
B	83, .01; 82, .02; 81, .04; 80, .05; 79, .04; 78, .02; 77, .01 -18 otherwise (0.8) EV =1.6

BEAST prediction of the B rate in the first block

Implication to mechanism design, nudge, and behavioral insights

Decisions from description reflect sensitivity to the EVs and four biases (pessimism, equal weighting, maximizing payoff sign, and minimizing probability of regret).

Feedback decreases the first three biases, but increases sensitivity to the probability of regret.

The best model is a BEAST, but it has one clear prediction:

Experience increases maximization when the EV rule, and reliance on small samples, point to the same direction. This happens when the best option minimizes the probability of regret (also better most of the time).

Relationship to the Machine Learning / Data Science revolution