Predicting human decisions with behavioral theories and machine learning

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Abstract

Behavioral decision theories aim to explain human behavior. Can they help predict it? An open tournament for prediction of human choices in fundamental economic decision tasks is presented. The results suggest that integration of certain behavioral theories as features in machine learning systems provides the best predictions. Surprisingly, the most useful theories for prediction build on basic properties of human and animal learning and are very different from mainstream decision theories that focus on deviations from rational choice. Moreover, we find that theoretical features should be based not only on qualitative behavioral \textit{insights} (e.g. “loss aversion”), but also on quantitative behavioral \textit{foresights} generated by functional descriptive models (e.g. Prospect Theory). Our analysis prescribes a recipe for derivation of explainable, useful predictions of human decisions.

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Many societal and engineering problems can benefit enormously from accurate predictions of human decisions. For example, good predictions of human decisions to moral dilemmas can inform the development of autonomous vehicles and the design of life-saving kidney exchange programs (1–3). Machine learning methods have had impressive success in predicting human decisions when trained on large amount of data (4–7). However, when the data available for training is relatively small, like in many decision-making domains of interest to social scientists, purely data-driven methods have had mixed success. For example, such methods led to good performance in prediction of human decisions in economic games (8, 9), but performed much worse than purely behavioral models in prediction of human decisions between lotteries (10, 11).

To improve predictive performance, one can leverage the available data with knowledge from behavioral decision theories, commonly by supplying a machine learning system with theoretically-driven features (11–13). The most natural candidates for such features are behavioral insights: qualitative human tendencies documented by the behavioral literature, such as loss aversion (14, 15). Machine learning methods provided with various insights as features are then meant to learn from the data how to integrate them for best predictions. A less common type of theoretically-driven features are behavioral foresights. These are quantitative descriptive models, such as Prospect Theory (15, 16), that serve to provide a functional integration of several behavioral tendencies. In other words, a foresight provides a model-based theory-driven prediction for behavior in a task, whereas an insight merely reflects one aspect that might impact behavior in the task.
The distinction between insights and foresights is akin to an old distinction between experts making a global prediction and merely identifying elements likely to be important in making a prediction (17, 18). For example, Einhorn gave expert pathologists biopsy slides taken from patients diagnosed with Hodgkin’s disease and asked them to come up with histological characteristics they considered important for prediction of survival time, as well as provide global outcome predictions. The results showed that the predictions of a statistical tool combining only the expert-derived characteristics are far more accurate than the predictions provided by the experts themselves, and the predictions are not always improved when the global predictions are added as additional features (17). Similarly, foresights, which are essentially a researcher’s integration of several behavioral insights, might not be as useful for prediction as the insights they are composed of. Advances in machine learning over the past five decades make it even more reasonable to assume that a computational system is likely to provide a more useful integration of the behavioral insights, rendering the use of foresights useless.

Nevertheless, here we demonstrate, using the results of an open competition for the prediction of human choices in a fundamental economic decisions task, that successful (i.e. reasonably predictive) behavioral models (foresights) make very useful features and that both behavioral insights and behavioral foresights are vital for achieving state-of-the-art predictions of human decisions. Our analysis prescribes a recipe for the design of effective tools for predicting human decisions when data are limited: Start with a quantitative descriptive model of behavior in the task (a foresight), decompose it to its behavioral-decision-theory elements (insights), and then supply a machine learning algorithm with both the foresights and the insights as features, assuming that their best integration will be recovered from the available data. Our results further
indicate that the most useful sets of features rely on models that differ from the popular

descriptive decision theories in important ways.

**Choice Prediction Competition**

Five of the authors of this paper (OP, RA, EE, MT, & IE; hereinafter the organizers)

organized CPC18: a choice prediction competition for human choice between lotteries over time

(https://cpc-18.com). Choice between lotteries underlies both the foundations of rational
economic theory (19, 20) and the analyses of robust deviations from rational choice (15, 21). The
data used in the competition is the largest of its kind ever collected. It contains 270 binary choice
problems selected from a single space, including demonstrations of 14 classical choice anomalies
documented in behavioral decision research (e.g. the St. Petersburg’s (22), Allais’ (23) and
Ellsberg’s (24) paradoxes). Importantly, it also includes choice behavior over time after the
decision-maker receives feedback regarding previous choices, as well as choice problems in
which the probabilities of one option are unknown at the time of choice (decisions under
ambiguity). Of the 270 problems, 150 were used in a previous choice prediction competition
(CPC15) (10). These problems were complemented with 60 additional problems (Experiment 1)
to form a public dataset available for training of competing models. CPC18 included two
independent tracks. In this paper, we focus mainly on the first track, in which participants were
required to develop a model predicting the distribution of play in 60 additional problems
(Experiment 2). These 60 problems and the results of Experiment 2 were published only after the
deadline for submission to the competition has passed².

² In the second track, participants were required to predict the decisions made by specific individual
decision-makers in problems that were part of the training data (of course, choices of those individuals in those
problems was not available for training). That is, the first track requires modelling of the average population choice
given a choice problem, whereas the second track requires modelling of individual decision-makers. Therefore, the
The organizers also published two baseline models for the first track. Such models facilitate the evaluation of developed models at an early stage, as they provide a benchmark for the level of performance achievable in the prediction task. The first baseline was a purely behavioral model (i.e. it did not use machine learning), an adaptation of the model BEAST (acronym for best estimate and sampling tools) which has proven to be a very good predictor for behavior in CPC15 (10). Notably, BEAST does not share the assumptions made by popular decision theories like Expected Utility Theory (19) and Prospect Theory (15, 21). Rather, it assumes choice over time is mainly driven by two behavioral mechanisms: sensitivity to the expected values and to the probability of experienced regret (and less sensitivity to four additional mechanisms, see supplementary text). The second baseline model was Psychological Forest (11), a hybrid of machine learning and behavioral theories. It includes both behavioral insights, the theoretical foundations of BEAST, and a behavioral foresight, the predictions of BEAST itself, as features. In choosing to include both types of features, the developers of Psychological Forest made, to the best of our knowledge, a rather unique design choice. More specifically, the developers of the model first decomposed BEAST to six theoretical decision mechanisms it assumes, then hand-crafted 13 features based on these six mechanisms, and finally used these 13 features, as well as the quantitative predictions of BEAST itself, in a Random Forest algorithm (25) (see supplementary text). Notably, the organizers could not find a good predictive baseline model that did not use any behavioral foresights (e.g. using only training data in the second track is effectively much larger than the training data in the first track, and we might expect that in the first track data-driven methods would benefit more from augmentation of behavioral features. The SI provides further details on the second track. Two of the authors of this paper (ECC & JFC) made the winning submission to this second track.
insights). They posited that if not using foresights can help predictions, the results of the competition would reflect it.

Forty-six teams registered to the first track of the competition. Team members included 69 researchers representing 34 institutions from 16 countries. Many of the teams invested significant efforts in developing their models. For example, in a post-competition survey ($N = 29$; see supplementary text), the reported mean number of hours spent on development of models was 66 ($SD = 92$). Twenty models were submitted in time. All submitted models but one made at least some use of behavioral decision theories, suggesting it is not easy to predict behavior in this task without them. Seven submissions were hybrid models integrating machine learning with behavioral theories. All hybrid submissions used both behavioral insights and behavioral foresights as features, suggesting using both types of features is useful for prediction.

The winning submission, made by five of the authors of this paper (DB, JCP, DR, TLG, & SJR), is based on the machine learning-behavioral decision theories hybrid baseline Psychological Forest. Specifically, it uses an Extreme Gradient Boosting algorithm (26) with the same features used in Psychological Forest (i.e. including both the behavioral insights and the behavioral foresight, the predictions of BEAST). Further details on the winning submission are in the supplementary text. To interpret the level of predictive performance of the winner and other predictors, we use a monotonous transformation of the prediction mean squared error (MSE) called an equivalent number of observations (ENO) (27). ENO of a model is an estimate for the number of agents for whom data should be collected until their mean behavior provides a better prediction for the behavior of the next agent than the predictions of the model. The ENO of the winner is 23.7, meaning we would need to observe the choices of 24 decision-makers.
before the observed choice will become a better prediction for behavior of a new agent than the predictions of the winner.

The only submission that did not integrate any knowledge from behavioral decision theories was ranked only 16th, predicting significantly worse than the winner (95% bootstrap CI for the differences in squared errors over the problems in the test set: [0.044,0.483]), and achieving ENO of 15.2. The best submission that did not use any machine learning (i.e. a purely behavioral model heavily based on BEAST) was ranked 2nd and did not predict significantly worse than the winning submission (95% bootstrap CI for the differences in squared errors over the problems in the test set: [−0.135,0.175]), obtaining ENO of 22.7. According to a bootstrap analysis, 14 submissions did not predict significantly worse than the winner. Table S1 provides details on these submissions.

The results of the competition imply that for prediction of human decisions in this fundamental economic decisions task, consideration of behavioral decision theories is vital. Furthermore, they show that the best predictions are obtained by a machine learning model that uses both behavioral insights and a behavioral foresight as features.

**Post-competition Analyses**

**Both insights and foresights?**

Every hybrid machine learning-behavioral decision theory submission included both behavioral insights and at least one behavioral foresight as features. We checked whether both types of features were really necessary by training models that do not include each type and checking their predictive performance in the competition’s data. Specifically, we trained on CPC18’s training data both a random forest (using R package randomforest (28)) and an extreme gradient boosting algorithm (using R package xgboost (29)) each using a subset of the features
used by the baseline psychological forest and the competition’s winner. We then let the trained models predict CPC18’s held-out competition data. In the “only insights” condition, the only feature removed was the predictions of BEAST (the foresight). In the “only foresight” condition, the models were trained using 15 features: 14 dimensions defining the choice problem and the predictions of BEAST. In training, hyper-parameters used were the same as in the baseline and winner.

Figure 1 displays the results of this analysis. It shows that both the winner and the hybrid baseline models trained without either type of behavioral features provide predictions that are worse – sometime much worse – than when the models include both types of features. These results imply that using both behavioral insights, and especially successful behavioral foresights is key for obtaining good predictive performance.
Figure 1. CPC18 Prediction error with and without insight and foresight features. Higher ENO (equivalent number of observations) and lower MSE (mean squared error) scores are better. Each algorithm was trained on the CPC18 training data (human decisions in 210 choice problems) using in addition a set of non-theoretical features defining the choice problem. Predictions are made for CPC18 test data (human decisions in 60 choice problems). Psychological Forest is the hybrid baseline model for the competition. The winner used the same feature set but replaced the algorithm used. Insights are features crafted from qualitative human tendencies found in behavioral decision research. Foresights are quantitative predictions of a descriptive model integrating multiple insights.

Which foresight is most useful for predictions?

Interestingly, all 7 hybrid submissions used as a foresight the predictions of BEAST or the predictions of a close variant of BEAST. As mentioned, BEAST is very different than classical decision models. Most classical decision models were developed to explain inconsistencies between observed behavior and the rational benchmark, under the assumption that agents facing decisions under risk understand and believe the descriptions of the payoff distributions. In contrast, BEAST, which builds on research investigating the effects of feedback, was developed to predict behavior also when this assumption is violated. For example, feedback
strongly affects behavior even in decisions under risk, where it does not add information for agents who understand and believe the instructions (30–34). Does the prevalent use of BEAST rather than more classical decision models as foresights imply that BEAST is more effective for prediction of choice behavior? If so, it may suggest that the underlying assumptions BEAST makes are more useful for predicting behavior than those made by classical decisions models.

We checked how the predictions of BEAST, either on its own, or when used as a foresight-feature in a machine learning system, compare with the predictions of more classical decision models. The comparison regards only a subset of the competition’s data which was the main focus of classical decision research: decisions under risk without feedback (i.e. we only used choices made in problems without ambiguity in the first block of five trials in each problem). In this no-feedback subset of the data, which includes 230 different choice problems, BEAST should be at a significant disadvantage since its main assumptions concern the effects of feedback.

To perform this comparison, each model we considered, except BEAST, was fitted to the aggregate choice rates of the 182 of these problems that were part of CPC18’s training data, using a grid search. Then, the trained models all predicted the aggregate choice in the 48 problems that were part of CPC18’s competition data. BEAST was compared to two versions Cumulative Prospect Theory (21), the Priority Heuristic (35), and to the Decisions by Sampling (36) model. The SI provides the implementations used. After deriving the predictions of each model, we also used those predictions as a foresight feature in an off-the-shelf random forest algorithm (using package randomForest (28) in R), without any training of hyperparameters. As additional features, (beyond the foresight feature), we used the 12 between-problem parameters
that define each choice problem. The reported MSEs are the average of 20 runs of the random forest.

The results of this exercise (Table 1) first show that, in every case, using the predictions of a theoretical model as a foresight feature leads to improved predictions than using the predictions themselves. Further they show that BEAST, with parameters fitted to the entire training data (including problems with ambiguity and choice following feedback) predicts the decisions-under-risk subset of the data far better than any of the classical decision models tested (fit only on the decisions-under-risk subset of the training data). For this subset of the data, the ENO of BEAST used as a sole behavioral feature is 16.75. The second-best predictor, a stochastic version of Cumulative Prospect Theory, only achieves ENO of 7.57, so its predictive accuracy is less than half that of BEAST. This exercise suggests that using the predictions of a theoretical model as a foresight feature is always a good idea, but to get good predictive performance, the theoretical model itself needs to have good a-priori predictions\(^3\). Therefore, we suggest that when predicting human decision with limited data, one should start with a good descriptive model, and the better the predictions of the descriptive model, the better the final predictions are likely to be. More importantly, these results suggest that the assumption that agents understand and believe the instructions, which underlies classical behavioral decision research, should be reconsidered.

**Table 1:** Prediction error for decision under risk subset of competition data

\(^3\) More accurately, when the machine learning algorithm is tree-based, the theoretical model need not necessarily have a low prediction error, but a high resolution score (65) essentially meaning the model discriminates well between different inputs which provide different outputs. For example, using as feature the predictions of BEAST, \(\hat{y}_i\), is just as useful as using its complement, \(1-\hat{y}_i\), though the prediction error of the latter is clearly much higher than that of the former (yet they have the exact same resolution score, as linear transformations do not change the resolution).
### Table

| Model                      | On its own | As a Foresight |
|----------------------------|------------|----------------|
|                            | MSE        | ENO            | MSE        | ENO            |
| BEAST                      | 0.0100     | 15.24          | 0.0092     | 16.75          |
| Stochastic CPT             | 0.0198     | 7.24           | 0.0190     | 7.57           |
| Deterministic CPT          | 0.1406     | 0.97           | 0.0232     | 6.13           |
| Decision by Sampling       | 0.0434     | 3.20           | 0.0311     | 4.51           |
| Priority Heuristic         | 0.2378     | 0.57           | 0.0375     | 3.72           |

*Note. All models except BEAST were trained on the outcomes of 182 decisions under risk problems from CPC18 training set. BEAST was trained to fit the same problems but also following feedback, as well as 28 decisions under ambiguity problems. Trained models predicted 48 decisions-under-risk problems in the CPC18 held-out set. Predictions are either taken at face value or used as a feature (foresight) in a Random Forest algorithm. ENO = equivalent number of observations. MSE = Mean Squared Error. BEAST = Best Estimate and Sampling Tools. CPT = Cumulative Prospect Theory.*

### Robustness Checks and Additional Datasets

We checked for the robustness of our proposed method in two additional datasets of human decisions in extensive form games (37). To avoid having too many researchers’ degrees of freedom (i.e. being able to select the method and/or analyses contingent on the outputs of the analyses; , 38), we repeated the same exact procedure used in the development of Psychological Forest: We started with a descriptive model that was proposed as a baseline in a choice prediction competition (i.e. developed before the collection of the test data), decomposed it to its theoretical insights and then used both the predictions of the model and the insights as features within a Random Forest algorithm (see SI). The results show that in both cases, the predictions of the constructed hybrid model outperform the predictions of the descriptive model in the test set of the competition and those of the same model using only one type of behavioral features (see details in SI). Moreover, in one of the datasets, the constructed hybrid model also outperformed all other models submitted to the competition, thus providing a new state-of-the-art for these data.
Interpreting the Predictions of the Hybrid Model

A central aspect determining the usability of a predictive model by some stakeholders is interpretability. Decision-makers want not only a prediction for what is going to happen, but also a reason for why it is going to happen (39). Data-driven methods usually have very good predictive performance, but their outputs are rarely easily explainable. Descriptive models normally do not have such weakness, though their predictive power is often worse than that of data-driven methods. A nice characteristic of the method we introduce here is that in many cases, the predictions made by the hybrid model are highly correlated with the predictions made by the descriptive model used as foresight. For example, the correlation between the predictions of the winning submission in CPC18 and the foresight it uses, BEAST, is 0.963. This characteristic is of course more likely when the descriptive model performs reasonably well on its own. When it does, the main mechanisms underlying the foresight can be used to explain why the hybrid model predicts what it predicts. On its own, analyzing the mechanics of an Extreme Gradient Boosting algorithm supplied with 38 features (the number of features used by the winning submission) is impractical. However, since we know the prediction correlation with BEAST is so high, we can reason that in almost every case, the predicted decisions are driven mainly by the expected values and the probability of experienced regret from an option (i.e. the main mechanics of BEAST).

Discussion

A main goal in behavioral science is to explain behavior. Congruently, most behavioral scientists tend to focus on uncovering causal mechanisms and discovering interesting phenomena (40). In theory, outputs of this type of research can be useful for prediction as well. Based on our analysis, we think that to facilitate the move from elegant explanations to useful predictions, two
points should be considered. First, most explanation-focused research concentrates on identifying and isolating specific mechanisms affecting behavior. For prediction, these can serve as useful behavioral insight features. Yet, our finding that behavioral foresights, which aim to integrate multiple mechanisms, is vital for deriving good predictions, suggests that behavioral scientists should focus more on the interactions and relative importance of the various mechanisms and develop quantitative models integrating these mechanisms.

Second, the focus on interesting phenomena in behavioral science inevitably leads to the study of uncommon situations. These can shed light on many important theoretical questions, but for prediction, it is better to build on insights that are robust across a wide array of situations. We speculate that this second point is the reason for the predictive superiority of BEAST over classical decision models even on a subset of the data it should have a disadvantage in (Table 1). Research leading to classical decision models focused on the set of situations in which agents understand and believe the information they are given, but if this set is not widespread then the resulting models will be less useful for predictions. In contrast, BEAST builds on research of basic learning processes. Many of these processes are shared by both people and animals (41, 42), which may hint to their commonality in nature. We thus think behavioral scientists would be wise to reconsider the sets of situations they investigate.

We believe that the noisy and complex nature of human behavior raises many challenges to machine learning methods whose study can be of interest to the machine learning community. Specifically, in our setting, state-of-the-art predictions of human decisions requires a combination of theoretical elements from behavioral decision research and data-driven machine learning systems. This calls for more use of data science practices within behavioral sciences as well as more use of behavioral theories when data scientists aim to predict human behavior (43).
That is probably easier said than done. For example, Psychological Forest was developed by behavioral scientists using one of the easiest-to-train off-the-shelf machine learning algorithms, Random Forest. Yet, to further improve performance, the expertise and experience of data scientists using a more sophisticated algorithm were required. Similarly, many data scientists reading behavioral theory papers might not be able to easily translate them to a set of features that can be used within their systems. A nuanced understanding of the mechanics may be required in order to do so. Hence, it seems that the best prospect for development of good predictive models of human behavior may lie in more collaborations between behavioral scientists and data scientists.

Methods

Experimental task.

The task used in CPC18 is of binary choice under risk, under ambiguity, and from experience. The experimental paradigm is identical to that used in CPC15 (10). Decision-makers are faced with descriptions of two monetary prospects (Option A and Option B) and are asked to choose between them repeatedly for 25 trials. In the first five trials, decision-makers do not receive feedback on their choice. After each trial thereafter (trials 6-25), decision-makers get full feedback concerning the outcomes generated by each option in that trial (both the obtained payoff and the forgone payoff are revealed). Each option in each problem represents a payoff distribution with between one and 10 possible outcomes. In addition, Option B may be ambiguous in which case its description does not include the probabilities of its possible outcomes, and the payoffs provided by the two options may be correlated. Figures S1-S3 show examples of the experimental screen in three problems.
More specifically, each choice problem participants faced belongs to a 14-dimensional space of problems, an extension of the space studied in CPC15 (10), in which it has been shown that 14 classical behavioral decision making phenomena emerge (these are: Allais’ paradox (23), the reflection effect (15), overweighting of rare events (15), loss aversion (15), St. Petersburg’s paradox (22), Ellsberg’s paradox (24), low magnitudes eliminate loss aversion (44), break-even effect (45), get-something effect (46), splitting effect (47), underweighting of rare events (48), reversed reflection effect (48), payoff variability effect (49), correlation effect (50)). The extension of the current space is that now both options (rather than just one) can have up to 10 outcomes.

Two of the 14 dimensions in the space (Block and Feedback), are studied within problem. The 25 choice trials are divided to 5 blocks of 5 trials each, such that Feedback is absent in the 1st block and complete in the other four blocks. The other 12 dimensions uniquely define a choice problem: 5 dimensions represent each of the two options’ payoff distributions, and two additional dimensions define whether Option B is ambiguous (in which case its description does not include the probabilities of its possible outcomes) and whether the payoffs provided by the two options are correlated. The SI provides a detailed description of the space of problems investigated.

**Experimental data.**

The data used in CPC18 includes 694,500 decisions made by 926 different decision-makers made across 270 binary choice problems drawn from the space we consider. Problems are divided into 9 cohorts. Each decision-maker faced one cohort of 30 problems in random order and made 25 choices in each problem. The first five cohorts were also used in CPC15 (10), and details on these data are provided elsewhere. The problems in the four additional cohorts
were randomly selected from the space of problems investigated in CPC18 according to a pre-defined problem selection algorithm (see SI). Two cohorts of problems were then run in each of two new experiments that used similar design and participant pool to those used for CPC15.

In each experiment, 240 decision-makers (Experiment 1: 139 females, $M_{\text{Age}} = 24.5$, Range$_{\text{Age}} = [18,37]$; Experiment 2: 141 females, $M_{\text{Age}} = 24.7$, Range$_{\text{Age}} = [18,50]$) participated in the experiment, half at the Technion and half at the Hebrew University of Jerusalem. Most participants were undergraduate students. Informed consent was elicited from all participants at the beginning of the experimental session. The experiment lasted approximately 45 minutes. Participants were paid for one randomly selected choice they made, in addition to a show-up fee. The final payoff ranged between 10 and 136 shekels, with a mean of 40 (about 11 USD) for Experiment 1 and between 10 and 183 shekels, with a mean of 41.9 for Experiment 2.

Experiments were approved by the Social and Behavioral Sciences Institutional Review Board in the Technion and by the Ethics Committee for Human Studies at the Faculty of Agriculture, Food, and Environment at the Hebrew University of Jerusalem.

**Choice prediction competition.**

In May-June 2017, the organizers ran Experiment 1. They then used the combined data from Experiment 1 and from CPC15 to develop their baseline models (see SI) and made the data publicly available (51). In January 2018, they published the call to participate in the competition in major mailing lists and on social media. The competition included two independent challenges, and in this paper, we focus on the first (see SI for second track details). In that challenge, the goal was to provide, for each of 60 choice problems from Experiment 2 (run in June-July 2018), a prediction for the progression over time of the mean aggregate choice rate of one of the options (without loss of generality, Option B). Specifically, the 25 trials of each
problem were pooled to five blocks of five trials each, and the goal was to predict the mean aggregate choice rates in each of the five time-blocks. Since the exact nature of the problems was unknown to modelers at the time of model development, a competing model was required to get as input the values of the parameters defining each problem and provide as output a sequence of five predictions (each in the range \([0,1]\)) for the mean choice rates in that problem.

Interested participants were required to register for the competition in advance. Each person could register as the (co-)author of no more than two submissions per track, and be the first author of no more than one submission per track. In addition, each person could make one additional early-bird submission, sent to the organizers by the end of January 2018. Submissions had to be made on or before the Submission Deadline (July 24th, 2018). For the first track, this meant sending the organizers a complete, functional, documented code of the submission. The code could be written in Python, Matlab, R, or SAS. The code was required to read the parameters of a choice problem and provide as output a prediction for the choice rates in five time-blocks.

One day after the Submission Deadline, the organizers published the competition set problems. That is, submissions to the first track were blind to the problems on which they were tested. Participants were then required to run their code on the competition set problems and submit the predictions. Finally, the organizers published the data to be predicted so participants could evaluate their prediction error. The organizers verified the code for each of the top 10 submissions produces the reported predictions and published the results.

Submitted models were evaluated and ranked based on the prediction accuracy as measured by the Mean Squared Error (MSE) between the observed and the predicted choice rates (300 predictions corresponding to 60 problems X 5 blocks). In addition, the organizers
computed, using a bootstrap analysis, a confidence interval for the difference in prediction MSEs between each submission and the winner, for different subsamples of problems. Specifically, we simulated 2501 sets of 60 test problems each by sampling with replacement from the original test set, computed the MSE of each submission in each simulated set, and then computed the difference in MSE between the winner and each submission. This allows the creation of a 95% CI for the difference in predictive performance between the winner and the other submissions using Package boot (52) in R.

**Data availability.**

The complete raw experimental data are available in Zenodo with the identifier doi:10.5281/zenodo.2571510.(53)

**Code availability.**

Code for the software used to generate the experimental data, for the competition’s baseline models, and for the winning submission is available from the authors upon a reasonable request. Code for baseline models is also available from the competition’s website (https://cpc-18.com). Code for submissions that did not win the competition is available from the authors upon reasonable request, contingent on permission from the developers of those submissions.
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Author Contributions

OP, RA, EE, MT, and IE organized the competition and discussed its results and implications at all stages. OP, EE, and IE designed the experiments and collected the experimental data. IE developed the first baseline model. OP, RA and IE programmed the baseline models. OP and EE built and maintained the competition’s website and managed submissions. DB, JCP, DR, TLG, and SJR submitted the winning model for the first track. ECC and JFC submitted the winning model for the second track. OP performed the post-competition analyses and wrote the manuscript. All authors commented on the manuscript and contributed to its writing.
Supplementary Information

Choice Prediction Competition

Space of problems.

The space of problems used in CPC18 includes 14 dimensions. Dimensions Block and Feedback are studied within problem: The 25 choice trials are divided to 5 blocks of 5 trials each, such that Feedback is absent in the 1st block and complete in the other four blocks. The dimension Amb sets whether Option B is ambiguous. Dimension Corr sets the correlation between the options’ payoffs. The 10 dimensions defining the payoff distributions of the options are: \( L_A, H_A, pH_A, LotNum_A, LotShape_A, L_B, H_B, pH_B, LotNum_B, LotShape_B \). In particular, Option A provides a lottery, which has expected value of \( H_A \), with probability \( pH_A \) and provides \( L_A \) otherwise (with probability \( 1 - pH_A \)). Similarly, Option B provides a lottery, which has expected value of \( H_B \), with probability \( pH_B \), and provides \( L_B \) otherwise (with probability \( 1 - pH_B \)). The distribution of the lottery of Option A (Option B) around its expected value \( H_A \) (\( H_B \)) is determined by the parameters \( LotNum_A \) (\( LotNum_B \)) that defines the number of possible outcomes in the lottery, and \( LotShape_A \) (\( LotShape_B \)) that defines whether the distribution is symmetric around its mean, right-skewed, left-skewed, or undefined (if \( LotNum = 1 \)).

When a lottery is defined (i.e. \( LotNum_A \) and/or \( LotNum_B > 1 \)), its shape can be either “Symm”, “R-skew,” or “L-skew”. When the shape equals “Symm” the lottery’s possible outcomes are generated by adding the following terms to its EV (\( H_A \) or \( H_B \)): \(-k/2, -k/2+1, \ldots, k/2-1, \) and \( k/2 \), where \( k = LotNum-1 \) (hence the lottery includes exactly \( LotNum \) possible outcomes). The lottery’s distribution around its mean is binomial, with parameters \( k \) and \( ½ \). In other words, the lottery’s distribution is a form of discretization of a normal distribution with mean \( H_A \) or \( H_B \).
Formally, if in a particular trial the lottery is drawn (which happens with probability $p_{HA}$ or $p_{HB}$), the outcome generated is:

\[
\begin{align*}
\text{H} - \frac{k}{2}, & \quad \text{with probability } \binom{k}{0} \left(\frac{1}{2}\right)^k \\
\text{H} - \frac{k}{2} + 1, & \quad \text{with probability } \binom{k}{1} \left(\frac{1}{2}\right)^k \\
& \vdots \\
\text{H} - \frac{k}{2} + k, & \quad \text{with probability } \binom{k}{k} \left(\frac{1}{2}\right)^k
\end{align*}
\]

When the lottery’s shape equals “R-skew,” its possible outcomes are generated by adding the following terms to its EV: $C^+ + 2^1, C^+ + 2^2, \ldots, C^+ + 2^n$, where $n = LotNum$ and $C^+ = -n - 1$.

When the lottery’s shape equals “L-skew,” the possible outcomes are generated by adding the following terms to its EV: $C^- - 2^1, C^- - 2^2, \ldots, C^- - 2^n$, where $C^- = n + 1$ (and $n = LotNum$).

Note that $C^+$ and $C^-$ are constants that keep the lottery’s distribution at either $H_A$ or $H_B$. In both cases (R-skew and L-skew), the lottery’s distribution around its mean is a truncated geometric distribution with the parameter $\frac{1}{2}$ (with the last term’s probability adjusted up such that the distribution is well-defined). That is, the distribution is skewed: very large outcomes in R-skew and very small outcomes in L-skew are obtained with small probabilities.

**Problem selection algorithm.**

The 120 problems in Experiments 1 and 2 were generated according to the following algorithm:

1. Draw randomly $EV_A' \sim \text{Uni}(-10, 30)$ (a discrete uniform distribution)

2. Draw number of outcomes for Option A, $N_A$:

   2.1. With probability .4 ($N_A = 1$), set: $L_A = H_A = EV_A'$; $pH_A = 1$; $LotNum_A = 1$; and $LotShape_A = \text{“-”}$
2.2. With probability .6 \((N_A > 1)\), draw \(pH_A\) uniformly from the set \{.01, .05, .1, .2, .25, .4, .5, 6, .75, .8, .9, .95, .99, 1\}

2.2.1. If \(pH_A = 1\) then set \(L_A = H_A = EV_A'\)

2.2.2. If \(pH_A < 1\) then draw an outcome \(temp ~ \text{Triangular}[-50, EV_A', 120]\)

\[2.2.2.1. \text{If } \text{Round}(temp) > EV_A' \text{ then set } H_A = \text{Round}(temp); \]
\[L_A = \text{Round}((EV_A' - H_A \cdot pH_A)/(1 - pH_A))\]

\[2.2.2.2. \text{If } \text{Round}(temp) < EV_A' \text{ then set } L_A = \text{Round}(temp); \]
\[H_A = \text{Round}([EV_A' - L_A(1 - pH_A)]/pH_A)\]

\[2.2.2.3. \text{If round(temp) = } EV_A' \text{ then set } L_A = H_A = EV_A'\]

2.2.3. Set lottery for Option A:

2.2.3.1. With probability 0.6 the lottery is degenerate. Set \(LotNum_A = 1\) and \\
\(LotShape_A = "-"\)

2.2.3.2. With probability 0.2 the lottery is skewed. Draw \(temp\) uniformly from the set \{-7, -6, -3, -2, 2, 3, \ldots, 7, 8\}

\[2.2.3.2.1. \text{If } temp > 0 \text{ then set } LotNum_A = temp \text{ and } LotShape_A = "R-skew" \]

\[2.2.3.2.2. \text{If } temp < 0 \text{ then set } LotNum_A = -temp \text{ and } LotShape_A = "L-skew" \]

2.2.3.3. With probability 0.2 the lottery is symmetric. Set \(LotShape_A = "\text{Symm}"\) and draw \(LotNum_A\) uniformly from the set \{3, 5, 7, 9\}

3. Draw difference in expected values between options, \(DEV: DEV = \frac{1}{5} \sum_{i=1}^{5} U_i\), where \(U_i \sim \text{Uni}[-20, 20]\)

4. Set \(EV_B' = EV_A + DEV\), where \(EV_A\) is the real expected value of Option A.

\[4.1. \text{If } EV_B' < -50 \text{ stop and start the process over}\]

5. Draw \(pH_B\) uniformly from the set \{.01, .05, .1, .2, .25, .4, .5, .6, .75, .8, .9, .95, .99, 1\}
5.1. If $pH_B = 1$ then set $L_B = H_B = \text{Round}(EV_B')$

5.2. If $pH_B < 1$ then draw an outcome $temp \sim \text{Triangular}[-50, EV_B', 120]$

5.2.1. If $\text{Round}(temp) > EV_B'$ then set $H_B = \text{Round}(temp)$;

\[ L_B = \text{Round}[(EV_B' - H_B \cdot pH_B)/(1 - pH_B)] \]

5.2.2. If $\text{Round}(temp) < EV_B'$ then set $L_B = \text{Round}(temp)$;

\[ H_B = \text{Round}[(EV_B' - L_B(1 - pH_B))/pH_B] \]

6. Set lottery for Option B:

6.1. With probability 0.5 the lottery is degenerate. Set $\text{LotNum}_B = 1$ and $\text{LotShape}_B = "-"$

6.2. With probability 0.25 the lottery is skewed. Draw $temp$ uniformly from the set
\{-7, -6, \ldots , -3, -2, 2, 3, \ldots , 7, 8\}

6.2.1. If $temp > 0$ then set $\text{LotNum}_B = temp$ and $\text{LotShape}_B = "R-skew"

6.2.2. If $temp < 0$ then set $\text{LotNum}_B = -temp$ and $\text{LotShape}_B = "L-skew"

6.3. With probability 0.25 the lottery is symmetric. Set $\text{LotShape}_B = "\text{Symm}"$ and draw

$\text{LotNum}_B$ uniformly from the set \{3, 5, 7, 9\}

7. Draw $\text{Corr}$: 0 with probability .8; 1 with probability .1; -1 with probability .1

8. Draw $\text{Amb}$: 0 with probability .8; 1 otherwise.

In addition, in the following cases the generated problem is not used for technical reasons: (a) there was a positive probability for an outcome larger than 256 or an outcome smaller than -50; (b) options were indistinguishable from participants’ perspectives (i.e., had the same distributions and $\text{Amb} = 0$); (c) $\text{Amb} = 1$, but Option B had only one possible outcome; and (d) at least one option had no variance, but the options were correlated.

Moreover, problems in Experiment 2 were selected using a stratified sampling procedure from a large pool of problems selected according to the above algorithm. This procedure was
aimed to obtain for Experiment 2 roughly the same number of problems of the types “each option up to 2 outcomes”, “exactly one problem with more than 2 outcomes”, and “both options with more than 2 outcomes” as their numbers in Experiment 1.

**Baseline models.**

The organizers presented two baseline models, both heavily influenced by the model BEAST (Best Estimate and Sampling Tools) (10). BEAST relies on six behavioral mechanisms. Specifically, it assumes that each option’s prospect is evaluated as the sum of three terms: the best estimate for the prospect’s expected value (EV), estimation noise which is reduced when the problem is “trivial”, and the average of a small mentally drawn sample. Elements in the small mental sample are drawn using one of four sampling tools (that imply 4 behavioral mechanisms): unbiased (a draw from the objective distributions, implying sensitivity to the probability of immediate regret, and preference for the option which is better most of the time (54)), equal weighting (a draw from a distribution in which all the prospects’ outcomes are considered equally likely (55)), sign (a draw from a distribution in which all the prospects’ payoffs with the same sign have the same valence, implying sensitivity to payoff sign), and contingent pessimism (a bias towards the worst possible outcome, implying pessimism).

The first baseline model presented, BEAST.sd (BEAST subjective dominance), is a purely behavioral (i.e. uses no element of statistical learning) extension of BEAST which changes the definition of a “trivial” problem for the purpose of reduced noise. BEAST used an objective definition (the existence of stochastic dominance), whereas BEAST.sd uses a subjective definition. Specifically, a problem is likely to be perceived as trivial if both the EV rule and the equal weighting rule favor the same prospect, and the choice of that prospect does not lead to immediate regret. BEAST.sd further assumes that in complex problems (a problem in
which one option has at least 2 possible outcomes and the other has at least 3 possible outcomes),
the estimation noise is increased. Finally, BEAST.sd assumes faster learning from feedback in
ambiguous problems.

The second baseline, psychological forest (11), is a hybrid model using a random forest
algorithm with 31 features. Fourteen of the features are the dimensions that define the choice
problem (see section Space of problems): $L_A, H_A, pH_A, LotNum_A, LotShape_A, L_B, H_B, pH_B,$
$LotNum_B, LotShape_B, Amb, Corr, Block,$ and Feedback ($= 0$ in the first block; $= 1$ otherwise).
Sixteen additional features are behavioral insights. Four of these were defined by the developers
of psychological forest as “naïve”, as they capture basic domain knowledge that will be likely
integrated into an algorithm even without any knowledge of behavioral theories. These include
the difference between the prospects’ expected values, the difference between their standard
deviations, the difference between their minimal outcomes, and the difference between their
maximal outcomes. Twelve additional features were considered “psychological”. They were
hand-crafted in direct relation to the underlying logic of BEAST, and each was inspired by at
least one of the six behavioral mechanisms in BEAST. For example, to capture sensitivity to the
probability of regret, psychological forest includes the difference between the probability that
Option A provides a better payoff than Option B and the probability that Option B provides a
better payoff than option A. Positive (negative) values of this feature imply that Option A (B) is
more likely to lead to less immediate regret than Option B (A). The equations defining the
features all appear in the original psychological forest paper.

Random forest is an ensemble algorithm that during training constructs a series of many
individual decision trees and provides as a prediction the mean prediction of all individual trees.
During training, each tree is constructed using only a random subsample of the training data, and
at each split, a random subset of features is considered. These properties are meant to decrease
correlation between the different trees. Psychological Forest was originally created using
package randomForest (28) in R, using the default set of hyperparameters for regression. In
particular, at each split, one third of the features was considered for splitting the data.

Open source code for both baselines, in several programming languages, is available
through the competition’s website (https://cpc-18.com).

**Competition’s winner.**

The winning model was an extreme gradient boosting regressor (26) using the XGBoost
Python package and trained using the same input features as the psychological forest baseline
model described above. Like the random forest regressor used for psychological forest, gradient
boosted regressors are ensembles of individual “weak learners”, typically tree-based regressors.
In contrast to random forest, which averages the results of many decision trees, gradient boosting
is a stepwise optimization procedure that minimizes error by adding one tree at a time to predict
the residuals of an initial tree or the current ensemble of previous trees. The hyperparameters of
the winning XGBoost model were the implementation defaults except for the following, which
were found using the skopt Python package for black-box Bayesian hyperparameter
optimization: Booster = “gbtree”; Gamma (minimum loss reduction required to make a further
partition on a leaf node of the tree) = 0.01224; Boosting Learning Rate = 0.01088; Maximum
Tree Depth = 3; Number of Estimators (Trees) = 978; Alpha (L1 regularization term on weights)
= 0.04306; Lambda (L2 regularization term on weights) = 2.90538; Subsample ratio of columns
when constructing each tree = 0.99120; Subsample ratio of the training instance = 0.50796.
Second track of the choice prediction competition.

CPC18 included two parallel and independent tracks. The paper focuses on the first track and here we briefly describe the second track. A more focused account of the second track will appear in a future paper.

Second track task.

The second track in CPC18 focused on prediction of the choices made by individual decision makers. The goal was to predict, for each of 30 “target” individual decision makers, the progression over time (in five time blocks of five trials each) of the mean choice rate of Option B in each of five “target” choice problems. Specifically, the organizers randomly selected 30 of the 240 decision makers who participated in Experiment 1 to be the target decision makers. For each of them, the organizers then randomly selected five of the 30 problems they faced and removed the data from the training data available to participants in the competition. The training data in this track thus included full sequences, of 25 choices each, made by each of the 30 target individuals in 25 different (non-target) choice problems (taken from the same space of problems), as well as data regarding behavior of other (non-target) decision makers in the five target problems. Thus, models submitted to this track has to provide 750 predictions in the range [0, 1] (30 target decision makers X 5 target problems per decision maker X 5 blocks of choices per problem).

Protocol for participation in the second track was slightly different, and simpler, than for the first track. Specifically, participants were not required to submit their codes to the organizers, only their numeric predictions. The reason for this change is that participants in the second track knew in advance the (anonymous) identity of the target decision makers they are tested on and
their corresponding target problems (the nature of the test problems in the first track was unknown at time of submission).

**Second track baseline models.**

The organizers presented two baseline models for the second track. The first, naïve baseline, predicts that each individual target decision maker in each block of its individual target problems would behave the same as the average decision maker behaves in the same block of that problem. The average decision maker’s behavior is estimated as the mean aggregate behavior of all decision makers for which training data exists (there are at least 90 decision makers for each such problem).

Surprisingly, the organizers did not find it easy to defeat this naïve baseline by a large margin. Using many statistical learning techniques, and employing knowledge extracted from the psychological literature (e.g. based on BEAST), the best baseline that they could find was the use of a Factorization Machine (FM) (56), a predictor based on Support Vector Machines and factorization models, which is employed in collaborative filtering settings (i.e. settings in which the goal is to generate predictions regarding the tastes of particular users, for whom some data exists, using information on the tastes of many other users, as in the Netflix Challenge). Each observation supplied to the baseline implementation of the FM is composed of a long binary feature vector with only two non-zero elements that correspond to the active decision maker and the active block within an active problem. The response is the observed choice rate of the active decision maker in the active block of the active problem (first transformed to imply the maximization rate of the problem, and then after making the prediction transformed back to implying the choice rate of Option B). This means the FM model did not directly use the knowledge that behavior across different blocks of the same problem is likely correlated.
Second track submissions and results.

Twelve submissions were made before the deadline. None of the submissions provided better predictions than the naïve baseline (including the FM baseline model). In fact, the winning submission (made by two of the authors of the paper, ECC and JFC) was very similar in concept to this naïve baseline. The primary difference was that the choice-problem and block-wise average was calculated with a 10-fold cross-validation procedure. The training data supplied to contestants were split into ten sets of training, validation, and test data such that each test and validation dataset included data only from those choice problems that were known to be in the held-out dataset. The prediction for a given test observation in fold $i$ on choice problem $j$ in block $k$ was the average choice made in the training data in fold $i$ for problem $j$ in block $k$. MSE was calculated for each of the ten validation datasets, and the fold with the lowest MSE was identified. The training data from that best performing fold was used to make predictions on the held-out data following the same choice-problem and block-wise average procedure.

Four submissions did not provide statistically inferior predictions to those of the winner. Table S2 provides details on these submissions. Importantly, all the best submissions heavily relied on the predictions of the naïve baseline.

Registrants Post-competition Survey

After results of CPC18 were published, the organizers sent co-authors of registered teams E-mail invitations to complete a short anonymous survey with questions regarding their effort and thoughts on the competition. A total of 72 invitations were sent (out of 82 registered persons; to register, a team had to supply an Email address of only the lead author and the organizers could not recover the addresses of 10 co-authors), and 36 researchers answered the survey. Nine
people indicated they were only registered to the first track of CPC18, 7 indicated they were only registered to the second track, and 20 indicated they were registered to both tracks.

Responders came from diverse backgrounds, ranging from computer science and artificial intelligence to cognitive or mathematical psychology. The most common main field of research was behavioral economics with 25% of the answers. Responders indicated they had a moderate amount to a lot of coding experience (M = 3.42, SD = 1.21) and a moderate amount of experience modeling human behavior (M = 2.94; SD = 1.45).

Twenty-four of the 29 responders who were registered to the first track indicated they also tried working on a submission to that track (only 3 stated they did not try to work on a submission, and 2 did not answer the question), and 16 of them submitted a model by the deadline. Those who tried working on a submission to the first track stated they spent on average 66.5 hours (SD = 92.2) working on CPC18, and that they tried developing an average of 12.6 different models to the data (SD = 33.3). Sixteen of the 24 also stated they were able to develop a model that outperforms the baseline models.

Nineteen of the 27 responders who were registered to the second track indicated they also tried working on a submission to that track (6 stated they did not try to work on a submission, and 2 did not answer the question), and 10 of them submitted a model by the deadline. Those who tried working on a submission to the second track stated they spent on average 84.7 hours (SD = 118.9) working on CPC18, and that they tried developing an average of 29.1 different models to the data (SD = 59.6). Only 5 of the 19 stated they were able to develop a model that outperforms the baseline models in this track. Note the reported averages for hours spent on CPC18 and numbers of models developed for the two tracks include in some cases the same
response (for persons working on submissions to both tracks), and thus they should not be interpreted as the mean effort invested in each track, but as a general effort invested in CPC18.

**Foresight Comparisons Implementation Details**

**Cumulative prospect theory.**

We compared BEAST to two versions of cumulative prospect theory (CPT) (21): deterministic and stochastic. The only difference between the two versions was that in the stochastic version, CPT’s weighted values of the options’ prospects \(WV(A), WV(B)\), were transformed to a probabilistic prediction for choice of Option B over Option A using a standard logit transformation:

\[
P(B > A) = \frac{e^{\mu WV(B)}}{e^{\mu WV(A)} + e^{\mu WV(B)}},
\]

where \(\mu\) captures the sensitivity to the difference between the weighted values.

For both versions, we used the following specification for CPT. The weighted value for a prospect with possible outcomes \(x_1 \leq \ldots \leq x_k \leq 0 \leq x_{k+1} \leq \ldots \leq x_n\) is:

\[
WV(X) = \sum_{i=1}^{k} \pi_i u(x_i) + \sum_{j=k+1}^{n} \pi_j u(x_j)
\]

where \(u(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -\lambda (-x)^\alpha, & \text{if } x < 0 \end{cases}\)

is a subjective utility function with \(\alpha\) a diminishing sensitivity parameter (note we use the same parameter for gains and losses, following the suggestion in (57)), and \(\lambda\) a loss aversion parameter, and:
\[ \pi_i = w(p_i) \]
\[ \pi_n = w(p_n) \]
\[ \pi_i = w(p_1 + \ldots + p_i) - w(p_1 + \ldots + p_{i-1}) \]
\[ \pi_j = w(p_j + \ldots + p_n) - w(p_{j+1} + \ldots + p_n) \]
\[ w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1 - p)^\gamma} \]

The latter is a two-parameter subjective weighting function (58) with \( \gamma \) a probability sensitivity parameter and \( \delta \) the function’s elevation parameter.

For the deterministic version, best fit for the training data was obtained for \( \alpha = 0.88, \gamma = 0.89, \delta = 0.9, \lambda = 1.2 \). For the stochastic version, best fit was obtained for \( \alpha = 0.91, \gamma = 0.84, \delta = 0.83, \lambda = 1.14, \) and \( \mu = 0.25 \).

**Priority heuristic.**

The priority heuristic (PH) (35) is said to be triggered only for choice between lotteries with similar EVs. Following others (59), we screened each problem according to the ratio between the options’ EVs: If it is greater than 2, then PH is not triggered. We assumed instead that in such cases the option with the higher EV is selected. If the ratio is smaller than 2, PH is used as follows (note PH requires no fitting of parameters, so it was not technically fit to the training data):

1. Consider the minimal possible outcomes of the two options. If the difference between them exceeds an outcome aspiration level, stop and choose the option with the higher minimal outcome. Otherwise, continue to step 2. The outcome aspiration level is 1/10 of the highest absolute possible outcome in the problem, rounded to the nearest prominent number (1, 2, 5, 10, 20, 50, 100, 200, 500 etc.).
2. Consider the probabilities associated with each of the minimal outcomes of the two options. If the difference between them exceeds 0.1, stop and choose the option with the lower probability for a minimal outcome. Otherwise, continue to step 3.

3. Consider the maximal possible outcome of the two options. If the difference between them exceeds the outcome aspiration level, stop and choose the option with the higher maximal outcome. Otherwise, continue to step 4.

4. Consider the probabilities associated with each of the maximal outcomes of the two options. If the difference between them exceeds 0.1, stop and choose the option with the higher probability for a maximal outcome. Otherwise, predict indifference between the lotteries.

**Decision by sampling.**

The decision by sampling model for risky choice (36, 60) states that choice is set by a series of ordinal comparisons between target attribute values and a comparison attribute value. An accumulator tallies the number of favorable comparisons to one of the options and when the tally hits a threshold, the option that won more comparisons is chosen. Target attribute values are chosen randomly at each time step. Comparison attribute values are also chosen randomly, though they can be chosen either from the alternative option or from long term memory.

We used the implementation from [http://www.stewart.warwick.ac.uk/software/DbS/source_code.html](http://www.stewart.warwick.ac.uk/software/DbS/source_code.html). As “context” that is used for long term memory retrievals, we used the supplied csv files from the same source, providing “real world distributions of amounts and probabilities”. Before implementing the code, amounts (from the “real world distribution”) were converted from British Pounds to Israeli Shekels at an exchange rate of 4.5 shekel per pound.
Three free parameters were fitted to the decisions under risk subsample from the training data: outcome threshold and probability threshold, which are the minimal amount and probability by which a target attribute value should exceed the comparison attribute value to be considered favorable, and a choice threshold, which is the number of comparisons an option needs to win in order to be chosen. Best fit was obtained for the values 1, 0.1, and 1, for outcome threshold, probability threshold, and choice threshold respectively.

Analysis of Additional Datasets

Method

Data.

The data comes from two related choice prediction competitions for human decisions in simple extensive form games (37). It includes 240 two-person games in which each of the players simultaneously chooses between one of two actions. Player 1 chooses either in or out, and Player 2 chooses either right or left. If Player 1 chooses out, the choice of Player 2 does not impact the payoff of either player, but if Player 1 chooses in, the two payoffs are dictated by the choice of Player 2. The games, uniquely defined by 6 game-parameters, include versions of the ultimatum game (61), the dictator game (62), the trust game (63) and the gift exchange game (64), in addition to many other different types of games. The two competitions were held to predict the decisions of the first players and those of the second players. Games were explicitly described to both players, and there was no feedback nor communication between the players. The experiments used the strategy-method according to which players mark their choices without knowledge regarding the choices the other players make. Therefore, in each pair, choices made by the two players were independent. Additional information regarding the setting is given in the
original paper and in the competitions’ website:

https://sites.google.com/site/extformpredcomp/home.

In each competition, data regarding choices made in 120 problems (training data) was made public. The goal was to predict the choice behavior in the other 120 problems (test data). To facilitate development of models, the organizers of the two competitions presented their best baseline models trained on the train data. Baselines for both competitions were similar and assumed players consider one of seven strategies: (a) choosing rationally (according to the rational model), (b) choosing rationally, but in case of indifference choosing such that the other player’s payoff is maximized, (c) maximize the worst personal payoff, (d) choose rationally, but assuming the other player chooses randomly (level-1), (e) maximize the joint payoff, (f) minimize the difference between the two players’ payoffs, (g) maximize the payoff of the player with the lowest payoff. The difference between the two baseline models was in the implied behavior in each strategy, and in the parameters used. Moreover, not all seven strategies apply to both players (e.g. for the second player, choosing rationally and maximizing the worst payoff are exactly the same). Each competition received 14 submissions. The baseline model for prediction of the first players was ranked 8th in the competition with MSE = 0.00853. The winner of that competition obtained MSE = 0.00735. The baseline model for prediction of the second players was ranked 11th in the competition with MSE = 0.00415. The winner of that competition obtained MSE = 0.00346.

Development of hybrid models.

To develop the models based on the insight-foresight method we propose, we started with the baseline models and decomposed them to the theoretical mechanisms they imply are the main drivers of choice. Specifically, the behavioral insights we derived are the predictions made by the
seven strategies assumed by the baseline models. In addition, we also used as foresight the predictions made by the baseline models themselves (fitted on the training data). Finally, we also added the six game-parameters as “objective” features. We then applied an off-the-shelf Random Forest algorithm (using randomForest package (28) in R), without any training of hyperparamters, and with the objective features, the insights-features, and the foresight-feature to the data. We repeated the process 15 times and the predictions were averaged. Error were computed based on an average of 20 such runs.

**Technical details of results**

In prediction of the decisions made by the first players, the hybrid model using both insights and foresights based on the competition’s baseline obtained MSE = 0.00693. This thus provides a new state-of-the-art level of prediction for these data, outperforming the winner of the competition. Running a similar model without the foresight feature gives MSE = 0.00768. A model without the insight features gives MSE = 0.00985.

In prediction of the decisions made by the second players, the hybrid model using both insights and foresights based on the competition’s baseline obtained MSE = 0.00400. Such a submission to the competition would have been ranked 5th (jointly). Analyses of the four submissions that obtained better predictions suggests that all of them used behavioral ideas that were not implemented in the current model (or the baseline). Therefore, the hybrid improves upon the baseline but cannot outperform models that use additional theoretical elements it is not supplied with (particularly for such small data). Running a similar model without the foresight feature gives MSE = 0.00462. A model without the insight features gives MSE = 0.00735.
Figure S1. Example of a translated experimental screen in a choice problem with $Amb = 0$ and $Corr = -1$. 

Please select option 'A' or option 'B'.

A:
6 with probability 0.5
0 with probability 0.5

B:
9 with probability 0.5
0 with probability 0.5

The correlation between the obtained payoffs in both alternatives is negative.
Figure S2. Example of a translated experimental screen in an ambiguous choice problem with $Amb = 1$ and $Corr = 0$. 

Please select option 'A' or option 'B'

A: 
10 with probability $p_1$  
0 with probability $p_2$

B: 
10 with probability 0.5  
0 with probability 0.5

$p_1$ and $p_2$ are probabilities that remain constant in every trial of this game, and add up to one.

There is no correlation between the obtained payoffs in the two options.
Figure S3. Example of a translated experimental screen (in a choice problem with $Amb = 0$, $Corr = 0$, $LotNumA = 4$) when full feedback is given (blocks 2–5). The participant here chose Option B.
Table S1.
Submissions not statistically worse than the winner in the first track.

| Rank | ID  | Type    | Prediction | MSE   | ENO  | Short description                                                                 |
|------|-----|---------|------------|-------|------|-----------------------------------------------------------------------------------|
| 1    | BP47| Hybrid  |            | 0.569 | 23.7 | Winner: See text                                                                   |
| 2    | MS63| Behavioral |         | 0.589 | 22.7 | BEAST.sd modified to have different weights to the best estimate of the expected value and the outcome of the mental simulations. Weights depend on the availability of feedback and the possibility of a loss. Additional noise when predictions are extreme |
| 3    | MS03| Behavioral |         | 0.605 | 22.0 | Same as MS63 with additional biases favoring dominant options whose dominance structure is clear and options avoiding losses (or with low probability for losses) under several conditions concerning differences in number of outcomes, minimal outcomes, maximal outcomes, EVs, and modes of the two options. |
| 4    | HK73| Behavioral |         | 0.613 | 21.7 | BEAST.sd modified to have different weights to the best estimate of the expected value and the outcome of the mental simulations, as a personal trait, and a possible alternation in choice in non-feedback trials. |
| 5    | KH04| Behavioral |         | 0.614 | 21.6 | BEAST.sd modified to have different weights to the best estimate of the expected value and the outcome of the mental simulations, as a personal trait. |
| 6    | KH75| Hybrid   |            | 0.621 | 21.4 | Ensemble of 12 models: 5 similar to BEAST, 6 similar to Psychological Forest (differing in foresight prediction) and one logistic regression model |
submitted to CPC15

|   |     |      |  |  |
|---|-----|------|---|---|
| 7 | CJ25| Hybrid | 0.640 | 20.6 | Ensemble of BEAST.sd and a random forest algorithm using several insights from Psychological Forest, several new insights (e.g. difference in expected regret) and several foresights, including BEAST.sd and cumulative prospect theory. |
| 8 | LC33| Behavioral | 0.648 | 20.3 | BEAST.sd modified to have different weights to the best estimate of the expected value and the outcome of the mental simulations. Weights depend on the availability of feedback. |
|   | Psych. Forest | Hybrid | 0.663 | 19.8 | Baseline: See text |
| 9 | SS88| Hybrid | 0.668 | 19.6 | Psychological Forest modified to use foresight BEAST.sd instead of BEAST, and two other features: one marking how distant the mean aggregate (predicted) behavior is from 50%, the other marking the (predicted) over-time trend in decision makers’ choice. |
| 10 | SA49| Hybrid | 0.672 | 19.5 | Psychological Forest modified to use BEAST.sd instead of BEAST as foresight, and a feature marking how distant the mean aggregate (predicted) behavior is from 50%. |
| 11 | HB89| Behavioral | 0.692 | 18.8 | BEAST.sd modified to replace the EV part of the model with a utility model accounting for dispersion and skewness. |
|   | BEAST.sd | Behavioral | 0.702 | 18.5 | Baseline: See text |
| 12 | RY01| Behavioral | 0.706 | 18.4 | BEAST.sd modified to increase noise when predictions are extreme. |
| 13 | BH45| Behavioral | 0.741 | 17.4 | BEAST.sd modified to replace the EV part of the model with a utility model accounting for dispersion and |
|   | Model | Type       | MSE  | RMSE |
|---|-------|------------|------|------|
| 14 | SB18  | Hybrid     | 0.749 | 17.2 |
|    |       |            |      |      |
|    |       | Psychological Forest modified to include many additional foresights, each of which is the difference between the options’ utilities assuming either some version of cumulative prospect theory or some version of regret theory. |
| 15 | ML35  | Behavioral | 0.823 | 15.4 |
|    |       |            |      |      |
|    |       | BEAST.sd modified to include increased error in problems with and aversion to options with many outcomes and high payoff range. |

**Note.** Only models providing predictions not statistically worse than the winner are presented. To test for differences in predictive performance, we used a bootstrap procedure with 2501 samples from the competition set problems and computed a percentile-type 95% CI for the difference between MSEs of the winner and each model. ENO = Equivalent number of observations.
Table S2.
Submissions not statistically worse than the winner in the second track

| Rank | ID  | MSE (x100) | Short description |
|------|-----|------------|-------------------|
| -    | Naïve | 9.399     | Baseline: See text |
| 1    | CC31 | 9.405     | Winner: See text |
| 2    | CL34 | 9.415     | For target agents whose behavior in the non-target games is more similar to a variant of BEAST (Submission LC33 from the first track), use as prediction the variant of BEAST. For other agents, predict like the naïve baseline. |
| -    | FM  | 9.630     | Baseline: See text |
| 3    | EH51 | 9.706     | Logistic regression with the following predictors: prediction of the naïve baseline, dummy for higher-EV option, target individual maximization rate in non-target problems, output of a logistic transformation of the difference between options’ EVs, and several interactions between these predictors and a dummy for a non-ambiguous problem. |
| 4    | CJ26 | 9.803     | Ensemble of the naïve baseline and a random forest algorithm as in Submission CJ25 from the first track. |
| 5    | EC02 | 9.973     | A type of tree-based regression (Cubist) using each dimension that described a problem, various averages based on those dimensions and subject information, as well as features calculated by BEAST.sd. |

Note. Only models providing predictions not statistically worse than the winner are presented. To test for differences is predictive performance, we used a bootstrap procedure with 2501 samples from the group of target decision makers and computed a percentile-type 95% CI for the difference between MSEs of the winner and each model.