From Predictions to Insights: An Empirical Study of Risky Choice Behavior

MIDS
Capstone Project

Ana B. Barcenas
Yolanda Diao

Project summary

Why risky choices matter?
Insurance contracts, stock investing, personal finance, etc.

Cutting-edge research
Risky decision-making predictions taking into account behavioral phenomena (aka CPC*)

Aggregated decision-making
Predict the rate at which different risky prospects will be chosen in a population.

Individual decision-making
Predict a decision-maker's choices in future risky choices based on their previous behavior and psychological theories.

Application
The Standard Bank of South Africa showed interest on using our insights to predict their customers' decision-making.

* Choice Prediction Competition 2015 and 2018

Key Concepts

- **Risky choices:** When we choose between two uncertain prospects. Within an uncertain prospect, there are different possible outcomes with associated probabilities.
- **Behavioral anomalies:** People do not always choose on higher expected values (EVs).
- **Risky choice paradoxes:**
  - Breakeven effect (Thaler & Johnson, 1990)
  - St. Petersburg paradox (Bernoulli, 1954)

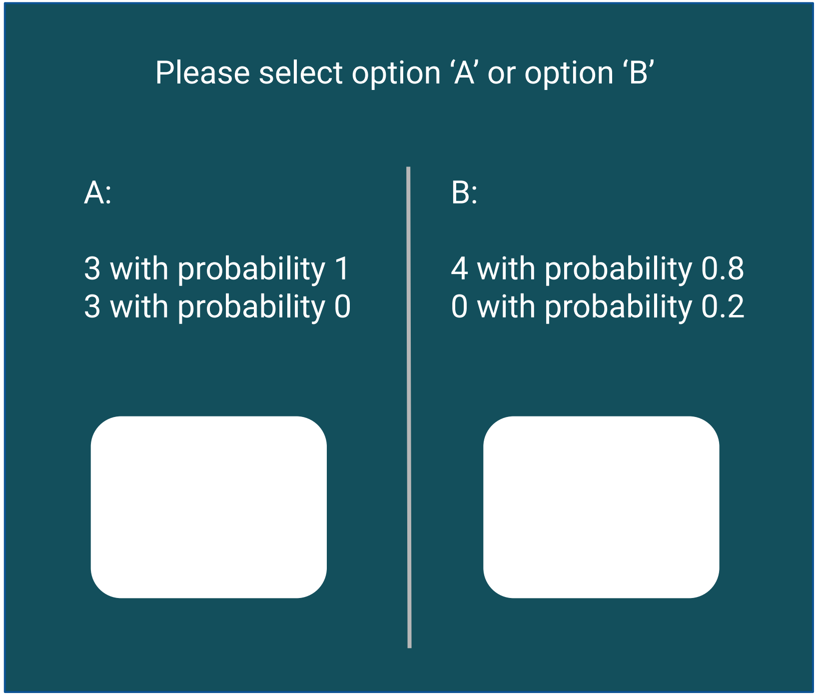
Choice Prediction Competition (CPC18)

Design

Experiment on people's choices over 2 gambles, 25 times in several choice problems.

Features

- Demographic variables: age, gender, location.
- Gamble features: objective, naive, psychological.
- Preference rate for Gamble B.



Choice Prediction Competition (CPC18)

Track I Aggregate-level risky choice prediction

- Neglect individual differences, focus on average choice rates
- Application: general tactics; choice prediction of an individual with no demographic info & choice history

Track II Individual-level prediction of behavior over time

- Admit individual differences, focus on individual choice rates
- Application: choice prediction of an individual based on demographic info & choice history

Aggregated-level predictions

Track I - Replication & Improvement

Algorithm	**Features**		
	Obj. + Naive + Psych.* (Ori, et al.)	Obj. + Naive + Psych. (our implementation)	
	MSE * 100	MSE * 100	R - Squared
Random Forest	0.87	0.815	0.89
XGBoost	-	0.84	0.89
Neural network	-	1.42	-

* Features description on Appendix B

Individual-level predictions

Track II - Replication

Baseline models	Description	Features	MSE
Naïve model	Each decision maker, in each block of its target problem, would behave **the same as the average** decision maker behaves in the same block of that problem.	Game ID Subject ID	0.1038
Factorization machines	A predictor based on Support Vector Machines and matrix factorization techniques. It is designed to capture interactions between features in high dimensional sparse datasets. Each observation supplied is a long binary vector with two non-zero elements that correspond to the active decision maker and the active block within an active problem.	Game ID Subject ID	0.0976

Individual-level predictions

Track II - Constraints

1. Customized methodology focused on predicting progression of behavior over time.
2. Poor interpretability and flexibility.
3. Requires large volume of training data. It relies on features based on many (25) repetitive decisions on several problems (210) by the same individual.

Individual-level predictions

Novel approach - Results

- Leverage psychological features to boost performance.
- Relies on demographic data and problem specifications (ambiguity, payoffs, etc.).
- Focus solely on individual predictions instead of progression of behavior over time.

Algorithm	Important features	MSE
Fixed effects	(1) Sign heuristic and (2) tendency to minimize immediate regret.	0.1224
Random forest	(1) Difference on EVs.	0.1044
XGBoost	(1) Driven by stochastic dominance, and (2) difference on EVs.	0.0988

Application

How is this useful in financial settings?

Use case	Why risk matters?
Personal finance	**Credit card** Determine credit limit based on how accurate your perceptions of wealth are.
	Savings account Determine withdrawal limit to fulfill savings goals.
Insurance	**Car insurance contracts**
Investments	**Risk tolerance** Ability to bare with large swings in the value of your investments.

Application

The Standard Bank of South Africa

Goal: Predict individual customer behavior based on demographic data and psychological features.

Next steps: Collect data on behavioral tendencies and financial-decisions.

1. IRB approval for the study design
2. Choose both abstract and financial problems for the study
3. Collect data from Mechanical Turk
4. First round of predictions with this data

Thank you!

Appendix A

Choice dataset from CPC 15/18

The data includes decisions made by 446 incentivized human participants in 150 different choice problems.

Block 1	Block 2	Block 3	Block 4	Block 5
1	6	11	16	21
2	7	12	17	22
3	8	13	18	23
4	9	14	19	24
5	10	15	20	25

Appendix B.1

Features description

Set name	Features
Objective	Includes the 11 parameters that define each decision problem with an additional block feature that captures the development of choice over time.
Naïve	Includes 4 domain-relevant features that capture very basic properties of the choice problem and represent basic decision rules according to which humans can make a decision.
Psychological	Includes 13 features that aim to capture directly research made by social scientist on decision making and the psychology of choice such as: ● Sensitivity to the difference between the gambles' expected values. ● Tendency to minimize immediate regret. ● Tendency to weight all outcomes as equally likely.

Appendix B.2

Examples of the most important psychological features

Tendency to minimize immediate regret

A:	B:
15 with probability 0.3 10 with probability 0.7	50 with probability 0.1 5 with probability 0.9

Choice: **Gamble A** (90% of the time, the payoff of gamble A will be higher)

Sign
Implies high sensitivity to the payoff sign.

A:	B:
3 with probability 0.5 1 with probability 0.5	200 with probability 0.1 -20 with probability 0.9

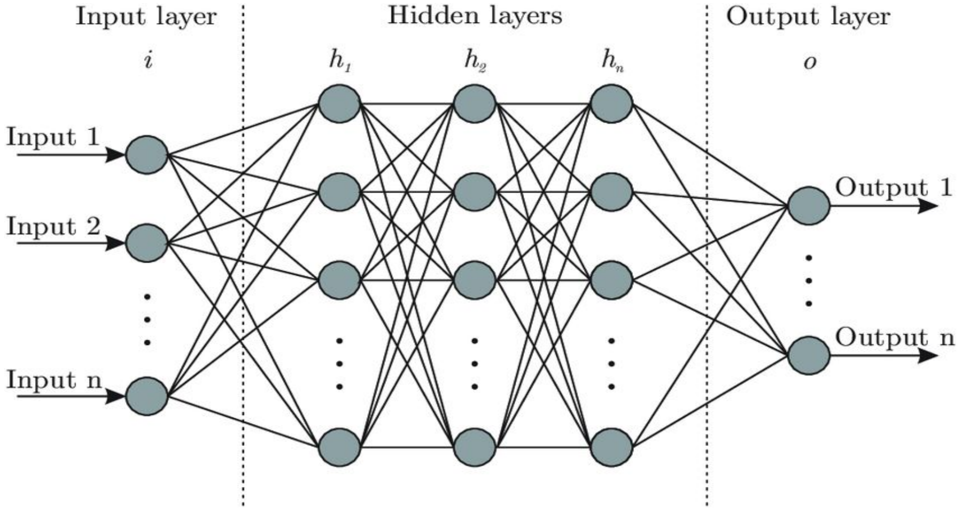
Choice: **Gamble A** (Even though its EV is **equal**)

Dominance
When choice problems are trivial, decision makers often recognize it and choose without performing unnecessary computations. Specifically, if one gamble stochastically dominates the other, the choice problem is trivial.

Appendix C

Neural network model

(David D. Bourgin et al., 2019)



Input Layer (13)

Hidden Layers (200, 275, 100)

Output Layer (1)

Cognitive Model Prior
85K*5 synthetic data
Fine-Tuning
210 problems * 5 blocks real data

Initial Hyperparameters

Activation Funcs: ReLU

Layer-wise Dropout Rate: 0.15

Learning Rate: 0.001

Optimizer: RMSProp

Batch Size: 100

Epochs: 200

Criterion: MSE

Photo Credit: ResearchGate. Net

Appendix D

Fixed effects regression results

OLS Regression Results

Dep. Variable:	B	**R-squared:**	0.313
Model:	OLS	**Adj. R-squared:**	0.313
Method:	Least Squares	**F-statistic:**	1093.
Date:	Thu, 02 Apr 2020	**Prob (F-statistic):**	0.00
Time:	20:13:45	**Log-Likelihood:**	-30634.
No. Observations:	81570	**AIC:**	6.134e+04
Df Residuals:	81535	**BIC:**	6.166e+04
Df Model:	34		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.006e+08	2.11e+07	-4.776	0.000	-1.42e+08	-5.93e+07
C(Gender)[T.1.0]	0.0008	0.003	0.297	0.767	-0.004	0.006
C(LotShapeB)[T.0.3333333333333333]	-0.0161	0.007	-2.451	0.014	-0.029	-0.003
C(LotShapeB)[T.0.6666666666666667]	-0.0176	0.006	-3.137	0.002	-0.029	-0.007
C(LotShapeB)[T.1.0]	-0.0081	0.004	-2.175	0.030	-0.015	-0.001
C(Amb)[T.1.0]	0.0857	0.005	17.452	0.000	0.076	0.095
C(Corr)[T.0.5]	-0.0032	0.007	-0.459	0.646	-0.017	0.010
C(Corr)[T.1.0]	-0.0073	0.010	-0.715	0.474	-0.027	0.013
C(Feedback)[T.1.0]	24.0860	5.041	4.778	0.000	14.206	33.966
C(Dom)[T.0.5]	0.1189	0.008	14.901	0.000	0.103	0.134
C(Dom)[T.1.0]	0.2894	0.012	23.807	0.000	0.266	0.313
C(block)[T.0.25]	-24.0688	5.041	-4.775	0.000	-33.949	-14.189
C(block)[T.0.5]	-24.0690	5.041	-4.775	0.000	-33.949	-14.189
C(block)[T.0.75]	-24.0789	5.041	-4.777	0.000	-33.959	-14.199
C(block)[T.1.0]	-24.0837	5.041	-4.778	0.000	-33.964	-14.204
Age	0.0147	0.008	1.763	0.078	-0.002	0.031
Ha	0.0660	0.010	6.446	0.000	0.046	0.086
pHa	-0.0011	0.006	-0.186	0.852	-0.012	0.010
La	0.1049	0.025	4.174	0.000	0.056	0.154
LotNumA	-0.0321	0.007	-4.489	0.000	-0.046	-0.018
pHb	-0.0291	0.006	-5.269	0.000	-0.040	-0.018
Lb	-0.1573	0.027	-5.785	0.000	-0.211	-0.104
RatioMin	0.0689	0.005	15.163	0.000	0.060	0.078
SignMax	-0.0143	0.009	-1.671	0.095	-0.031	0.002
pBbet_Unbiased1	-0.1901	0.029	-6.465	0.000	-0.248	-0.132
pBbet_UnbiasedFB	0.4495	0.029	15.735	0.000	0.394	0.505
pBbet_Uniform	0.1613	0.009	17.194	0.000	0.143	0.180
pBbet_Sign1	1.4761	0.065	22.804	0.000	1.349	1.603
pBbet_SignFB	-1.4163	0.066	-21.538	0.000	-1.545	-1.287
diffBEV0	3.265e+08	6.84e+07	4.776	0.000	1.93e+08	4.61e+08
diffBEVfb	-4.087e+08	8.56e+07	-4.776	0.000	-5.76e+08	-2.41e+08
diffMins	0.2664	0.040	6.686	0.000	0.188	0.345
diffSignEV	0.0508	0.020	2.502	0.012	0.011	0.091
diffEV	1.91e+08	4e+07	4.776	0.000	1.13e+08	2.69e+08
diffMaxs	0.1389	0.020	7.067	0.000	0.100	0.177
diffSDs	-0.2128	0.025	-8.428	0.000	-0.262	-0.163

Omnibus:	8135.512	**Durbin-Watson:**	1.845
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2448.133
Skew:	0.086	**Prob(JB):**	0.00
Kurtosis:	2.169	**Cond. No.**	1.36e+15