Psychological Forest: Integrating Machine Learning and Psychology to Predict Choice Behavior

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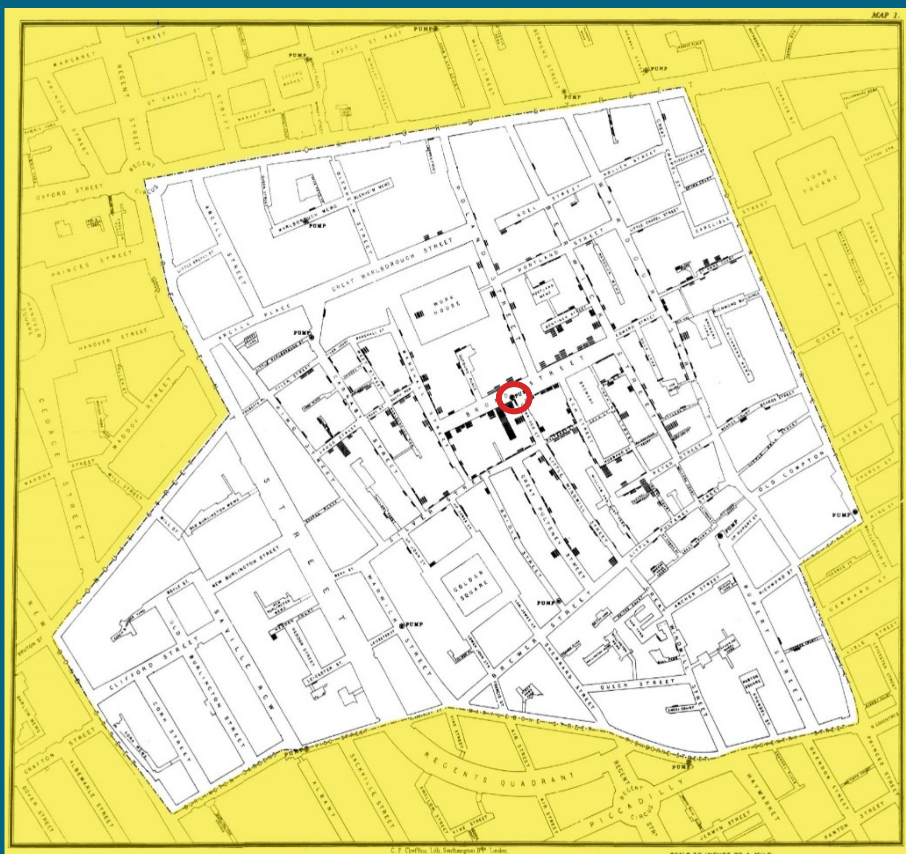
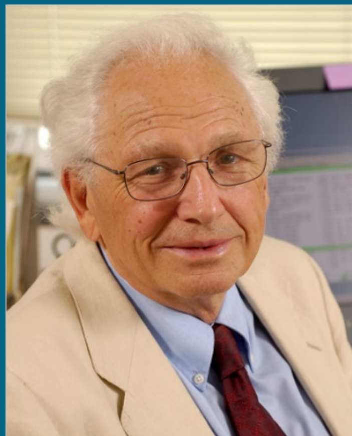
Plonsky, O., Erev, I., Hazan, T., & Tennenholtz, M. (2017). Psychological Forest: Predicting human behavior. *Proceedings of the Thirty-first AAAI Conference on Artificial Intelligence.*

- Specific correct prediction
- Wrong process model
  poison; murky water; broken well
- The value of predictions
  Without identifying the process



John Snow

- Without the theory, how would he know to mark the water pumps location?
- What are the important elements of the theory?

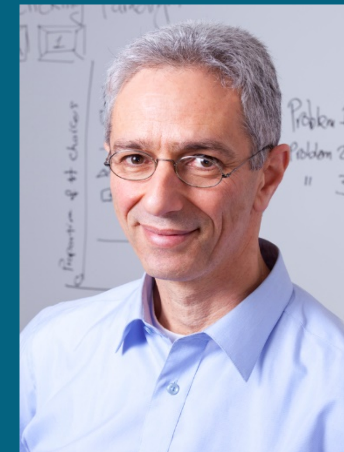


Frederick
Jelinek

“Every time I fire a linguist the performance of the speech recognizer goes up”

Data science:
Social science theories not useful for predictions

Ido
Erev



Choice prediction competitions

Behavioral science:
Data science / machine learning rank very low

- Prediction: Find $\mathbf{f}(\cdot)$ such that $\mathbf{f}(\mathbf{x}) \approx \mathbf{y}$
  - Machine learning people are the experts on this!
- What is $\mathbf{x}$?
  - Behavioral scientists are many times the experts on this!

Proposed method:

Behavioral scientists develop theory-grounded features, data scientists provide best tools for their integration

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Agenda:

1. Demonstration in a basic, challenging setting
2. Why should you care (beyond prediction)?

The Data

The latest choice prediction competition (Erev et al., 2017)

- Repeated choice between described gambles
  - Includes ambiguous and/or multi-outcome gambles
- 150 choice problems
  - One 11-dimensional space
  - Includes replications of the Allais paradox, the St. Petersburg paradox, the Ellsberg paradox, the reflection effect, overweighting of rare events, underweighting of rare events…
- 334,500 unique consequential decisions
  - 25 decisions per participant per problem
  - First 5 decisions w/o feedback, then 20 with full feedback

The Prediction Competition

- The organizers published:
  - Data of 90 choice problems (*train set*)
  - A baseline model that captures the data well
  - A call to submit better models
- Models evaluated based on their prediction accuracy
  - Predict aggregate choice rates
  - Of the other 60 choice problems (*test set*)
- 25 Models submitted
  - Excellent benchmarks

The Baseline model: BEAST

BEAST (= Best Estimate And Sampling Tools) assumes:

- Sensitivity to (best estimate of) the expected value
- Four behavioral tendencies (implemented as "sampling tools")
  - To treat all outcomes as equally likely
  - To maximize the probability of winning
  - To assume the worst (pessimism)
  - To prefer the option minimizing prob. of immediate regret

What is x?

- "Objective" features
  - 11 parameters Defining the choice problem
- "Naïve features"
  - Difference in EVs, Difference in SDs…
- "Psychological features" isolated from BEAST
  - Pessimism:

    $diffMins = Min_B – Min_A$

    = minimal outcome of B – minimal outcome of A
  - Minimization of regret:

    $pB\_better = P[F_B^{-1}(x) > F_A^{-1}(x)] - P[F_A^{-1}(x) > F_B^{-1}(x)]$

    = *P[B providing better outcome than A] – P[A providing better outcome than B]*

What type of f?

- Off the shelf machine learning algorithms
  - Random Forest
  - Support Vector Machines (SVM)
  - Neural Nets
  - *k* Nearest Neighbor (*k*NN)
- Train each algorithm-features combination on train set
- Predict the test set

Results

Table 3: Test set predictions for algorithm-features combinations

Algorithm	Features used ($MSE * 100$) Obj.	Naïve	Psych.	Obj.+ Naïve	Obj.+ Psych.	Obj.+Naïve +Psych.
Random forest	6.13*	1.56*	0.98	1.42*	0.93	**0.87**
SVM						
radial	5.52*	1.63*	1.08	1.72*	1.10	1.01
polynomial	7.87*	5.52*	1.23	3.37*	1.51*	1.40
Neural net (1 hidden)						
3-node	7.39*	1.75*	1.81*	4.80*	2.45*	2.43*
6-node	10.4*	2.16*	1.89*	5.67*	2.43*	2.40*
12-node	10.0*	2.98*	1.98*	5.54*	2.57*	2.28*
Neural net (2 hidden)						
3-3 nodes	8.39*	1.91*	1.62*	4.84*	2.48*	2.61*
6-6 nodes	9.29*	3.46*	1.85*	5.21*	2.44*	2.36*
kNN						
k=1	8.17*	3.13*	1.87*	6.03*	3.06*	2.73*
k=3	7.87*	2.22*	1.64*	4.91*	2.75*	2.56*
k=5	7.15*	1.95*	1.62	4.72*	2.46*	2.37*

f

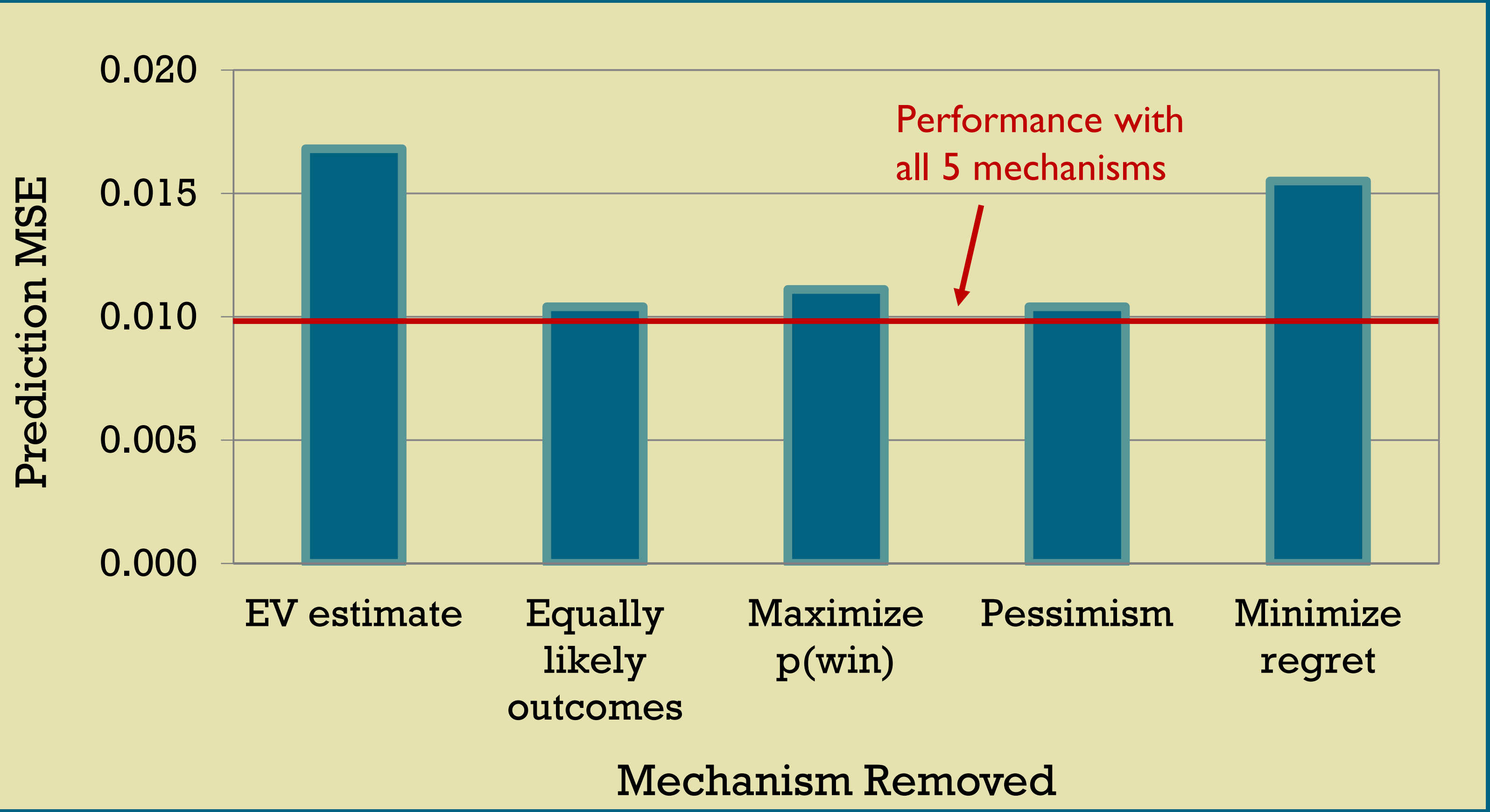
x

Results

- Without psychological features:
  All algorithms do poorly
  - Ranked between 15th and dead-last in the competition
- With psychological features:
  Random forest outperforms the competition's winner
  - When supplied with the other features as well
  - "Psychological Forest"

What Can We Learn?

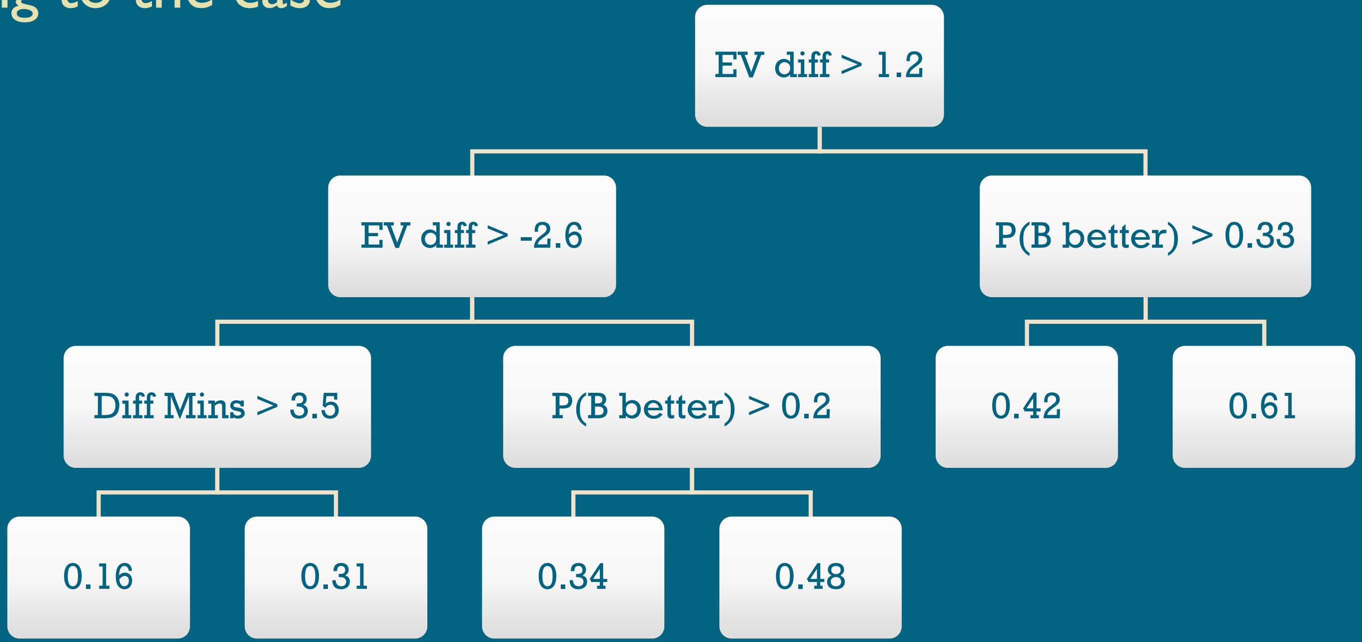
- Disentangling theory from auxiliary assumptions
  - Is it the specific model or its underlying theory?
  - Which mechanism is most important?



Future directions

Why Random Forest?

- Aggregation of many (500+) decision trees
- Each tree uses a random subset of features
- And classifies the new problem to one of many cases
- In each case, it predicts the average behavior in other problems that belong to the case



Why Random Forests?

- We don’t know yet
- But, it aggregates decision trees:
  - Stochastic by nature
  - Dichotomous processing
  - Similarity-based
- One conjecture
  - Decisions follow what worked in similar past situations
    - But similarity can have many forms
  - Each tree represents one possible similarity function
    - Classifying new situations to categories of situations
  - The popular behavior in a category is a proxy for what worked best in similar situations

A new prediction competition

- Clarify best approaches for prediction
  - Psychological models
  - Integration of social and data science
  - Pure machine learning
- Same paradigm: description + feedback
  - Slightly larger space
- Three distinct tasks
  - New people, new problems
  - Familiar people, new problems
  - Familiar people, familiar problems

Summary

What can data scientists learn from behavioral scientists?

- Where to look
- What is likely to be important

What can behavioral scientists learn from data scientists?

- How to test entangled theoretical elements separately
- Not being limited to one functional form

Thank you for listening