A JOINT ANALYSIS OF DROPOUT AND LEARNING FUNCTIONS IN HUMAN DECISION-MAKING WITH MASSIVE ONLINE DATA

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Task performance ⇄ Task engagement

What is the theoretical and empirical basis for this relationship?

KEY IDEAS ON SKILL ACQUISITION AND MOTIVATION

Skill acquisition

- Simple rules for learning as a function of practice
  Newell et al., 1981
  Heathcote et al., 2000
- Practice, grit, and perseverance influence learning
  Stafford et al., 2014
  Duckworth et al., 2014
- Self-regulated learning as a theoretical and applied field
  Gureckis et al., 2012
  Lieder et al., 2017

Intrinsic motivation

- Moderate challenges encourage people to continue
  Schimdhuber et al., 2010
  Ten et al., 2021
- Peak and end experiences change task perception
  Miron-Schatz, 2009
  Cockburn et al., 2015
- Gameplay is influenced by rewards and the peak-end effect
  Farzan et al., 2008
  Gutwin et al., 2016

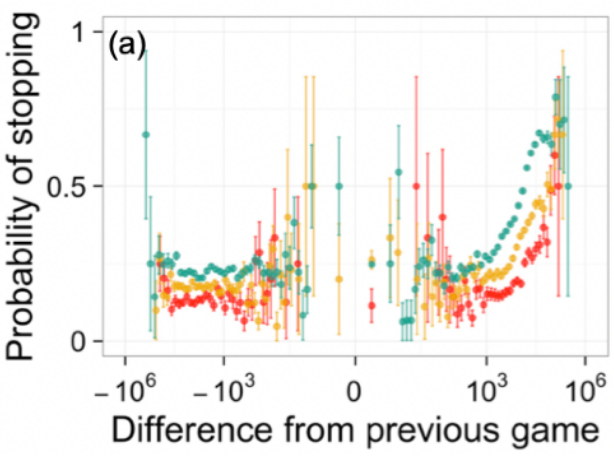
The literature on skill acquisition and motivation show that understanding the relationship between learning and dropout is complicated

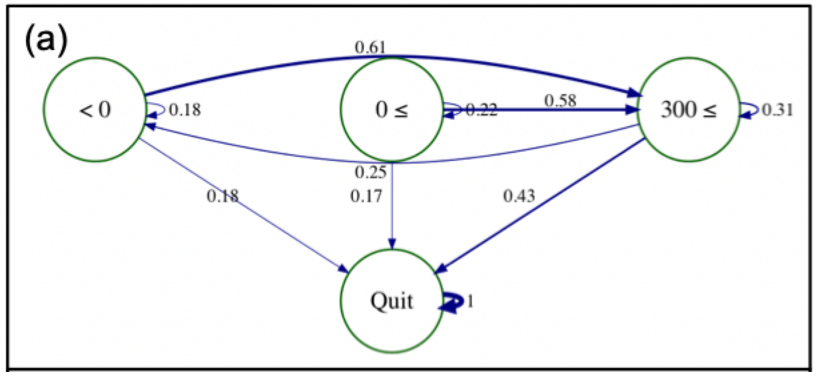
JOINT ACCOUNTS OF LEARNING AND DROPOUT

To fully account for such data, a **joint account of learning and dropout is required**

Relating quitting times and performance

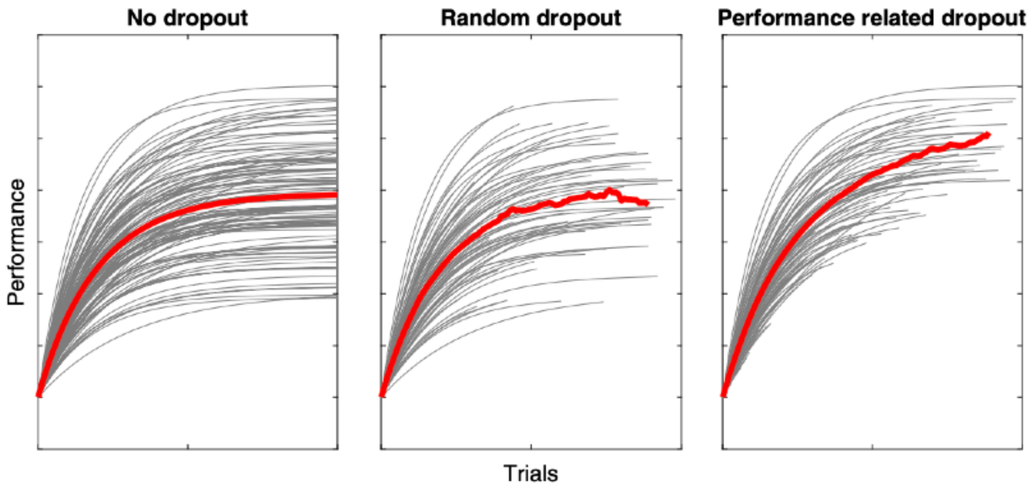
Agarwal et al., 2017
Okada et al., 2018





Group learning functions that account for differences in dropout

Steyvers et al., 2019

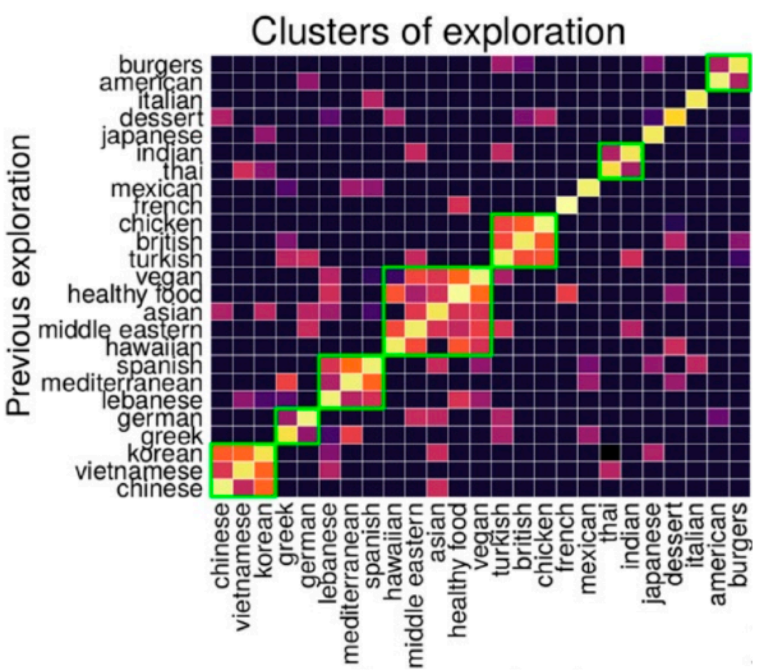


If we want to study learning and dropout in tandem, what kind of data set should we use?

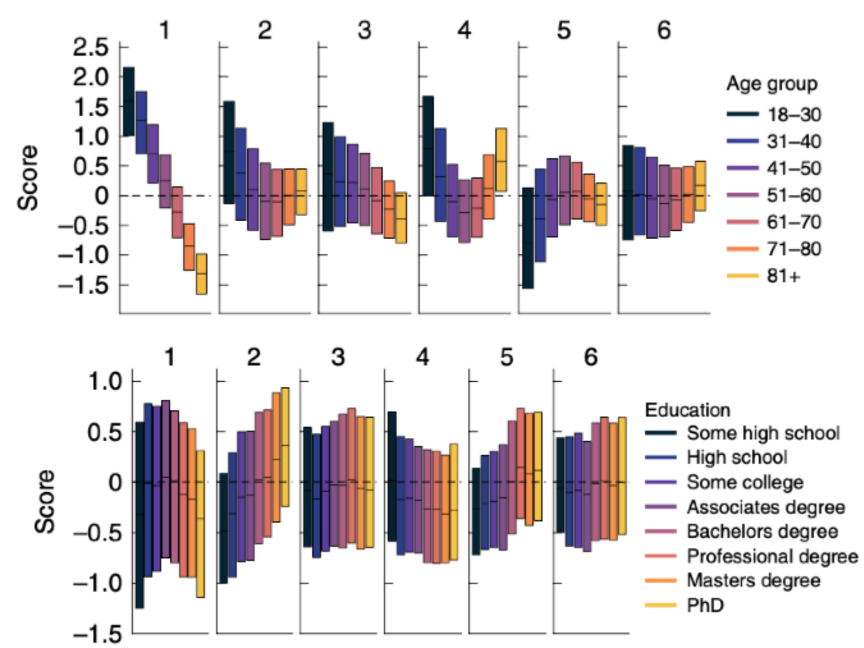
MASSIVE DATA IN COGNITIVE SCIENCE

Large-scale data sets collected via online experiments are becoming **more common in cognitive science**

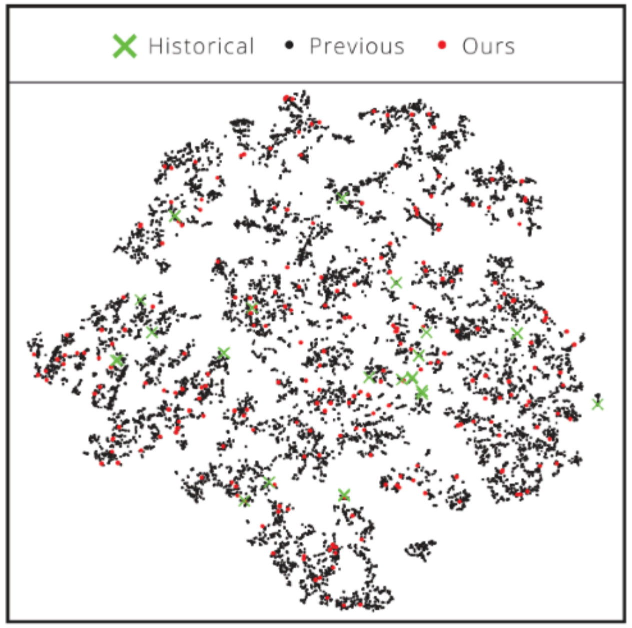
- Obtain rich data in participants' real-world environments
- Study a wide range of cognitive mechanisms or leverage machine learning methods
- Investigate if results or models derived from constrained lab settings generalize



Schulz et al., 2019



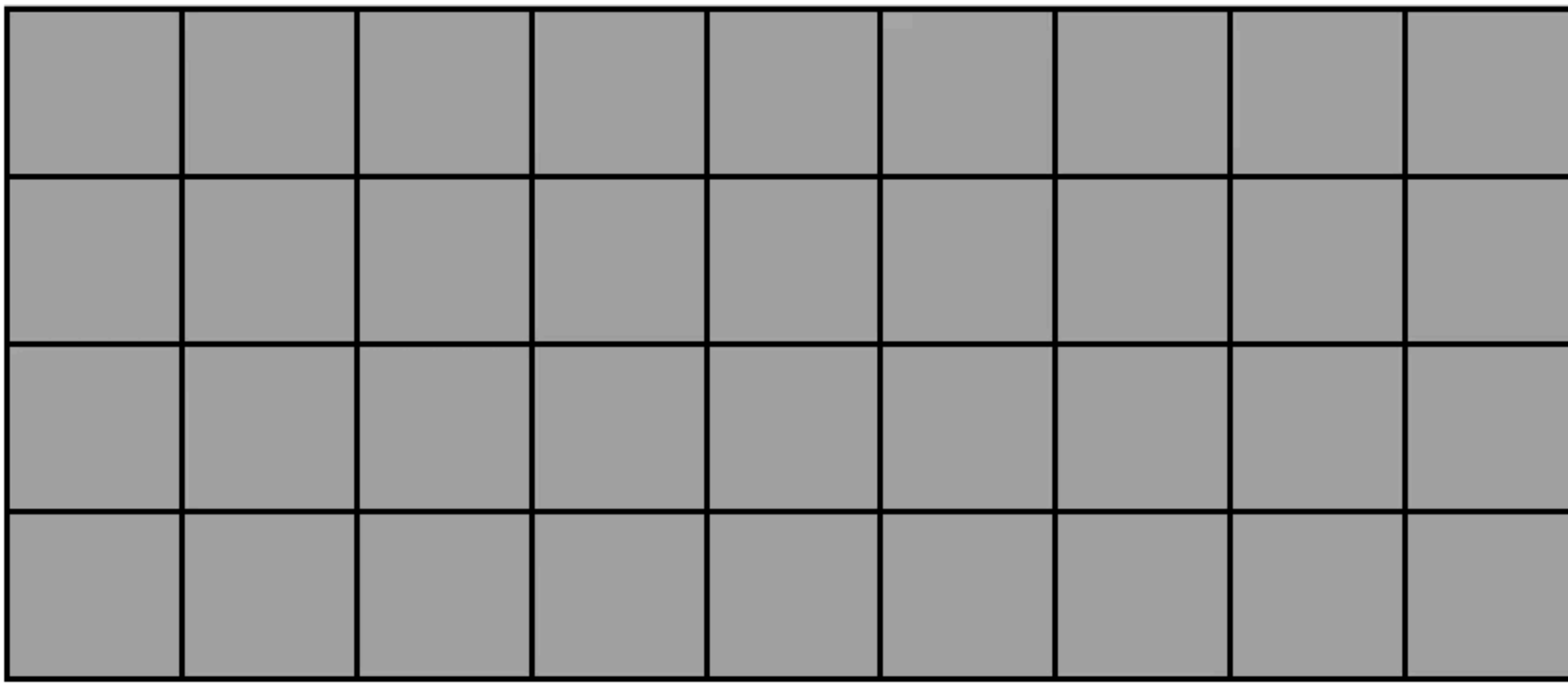
Steyvers et al., 2020



Peterson et al., 2021

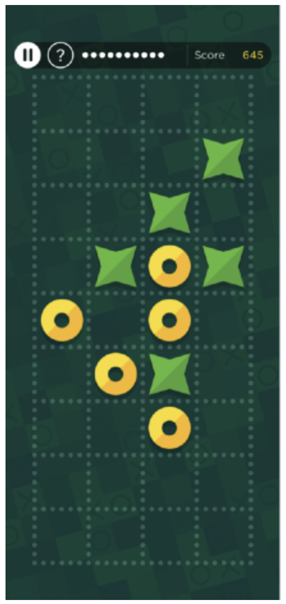
4-IN-A-ROW

In the lab, we developed a **combinatorial planning task** of intermediate complexity with high potential for modeling human behavior



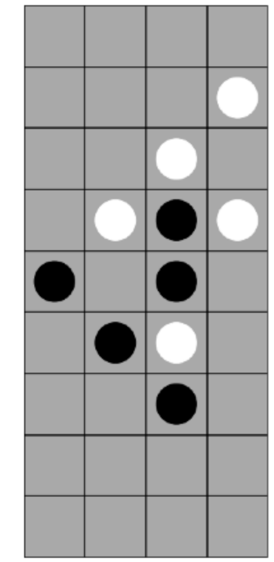
van Opheusden, Galbiati, **Kuperwajs**, Bnaya, Li, Ma, *PsyArxiv*, 2021

SCALING UP 4-IN-A-ROW



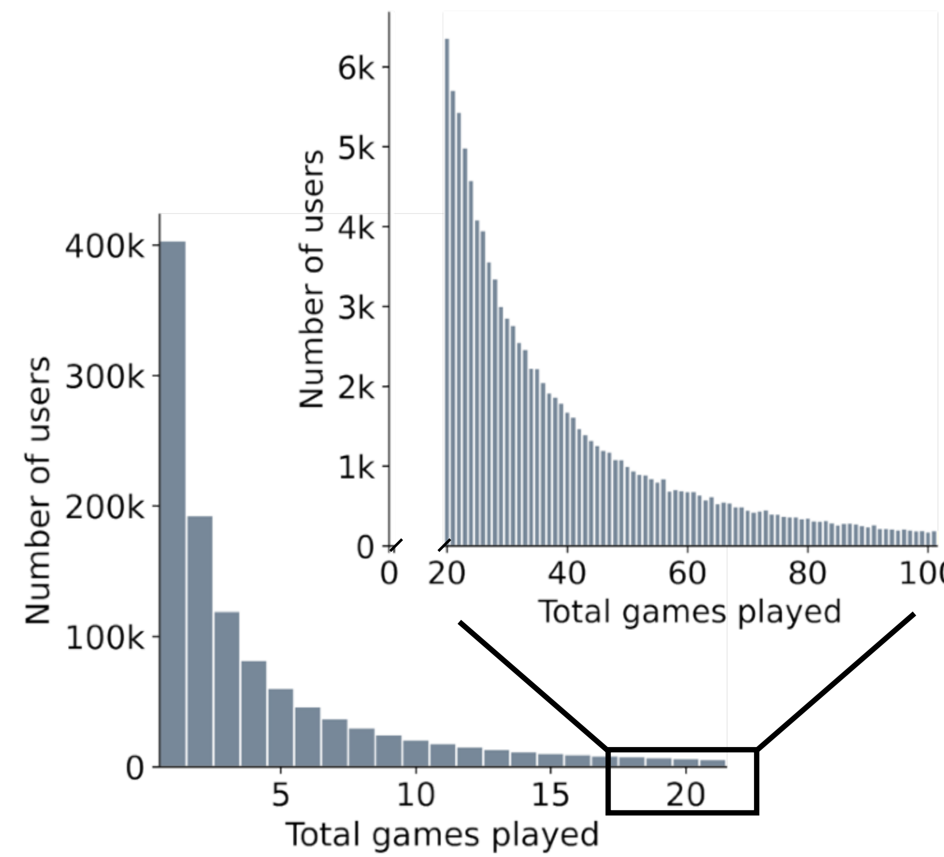
Game development
Anonymized data

Task specification
AI opponents



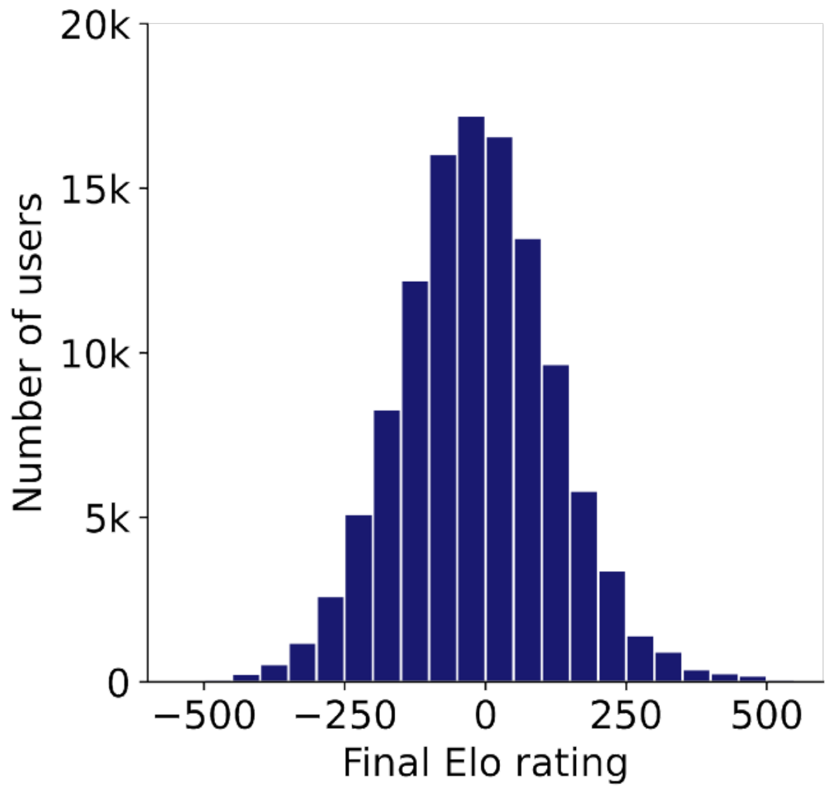
Features of the data set:

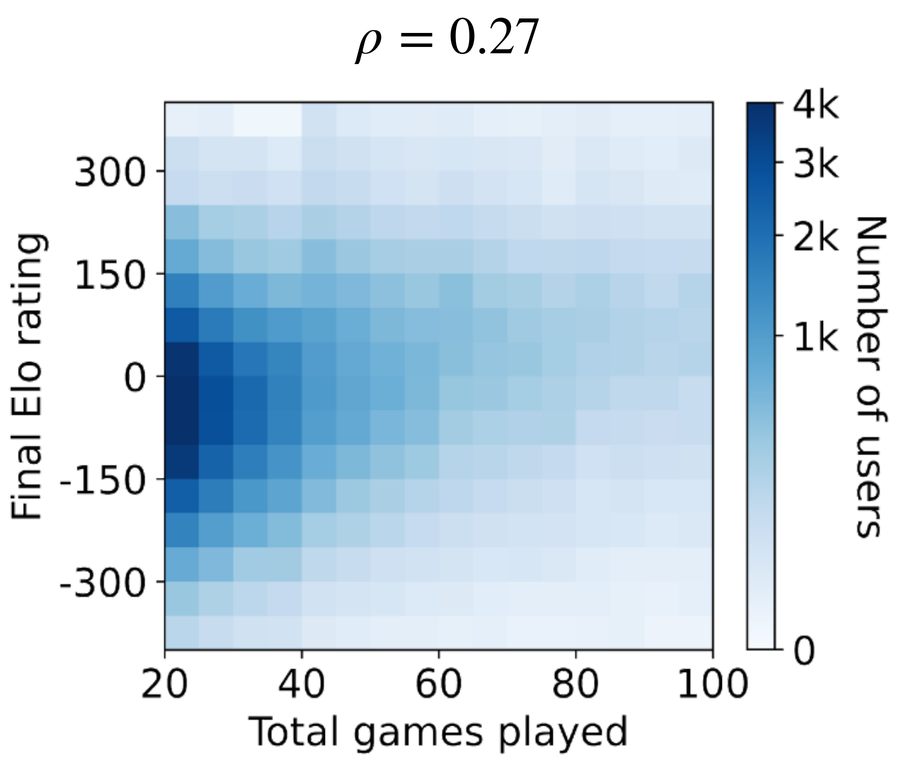
- Human vs. AI games
- User always plays first
- ~10.8 million games
- ~1.2 million unique users
- ~1.5 million new games/month



PLAYING STRENGTH AND EXPERIENCE

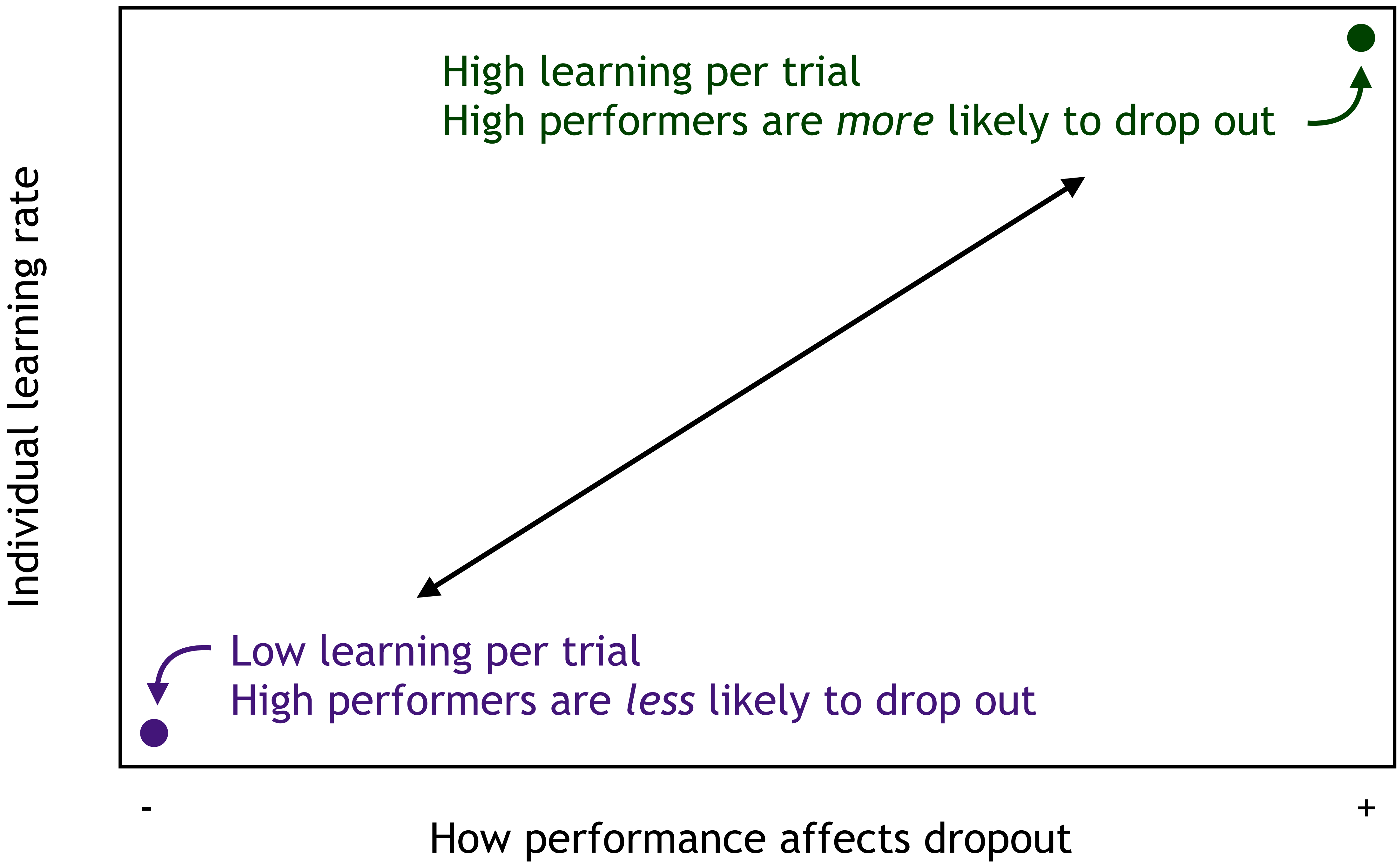
Characterizing the endpoint of task performance and engagement





Final playing strength and total number of games played are correlated,
but how do users get to this point?

THE SPACE OF LEARNING AND DROPOUT



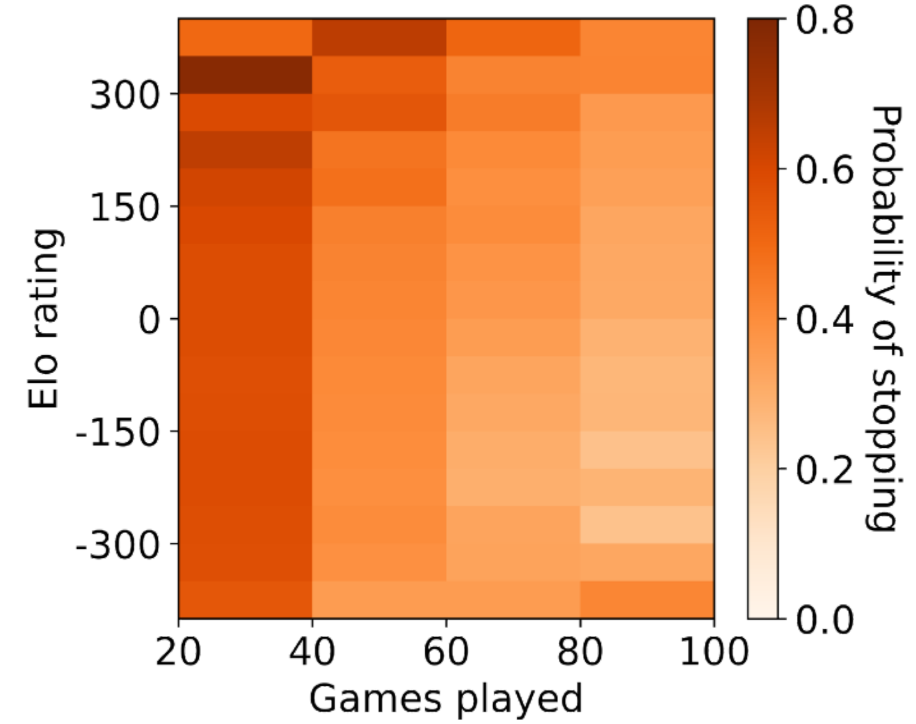
What factors underlie learning and dropout in complex tasks, and how do these interact?

DROPOUT BEHAVIOR

Hypothesis: dropout behavior is driven by **current playing strength** and **number of games played**

Logistic regression analysis

- Stopping probability decreases as users play more games
- Stopping probability increases with higher Elo ratings



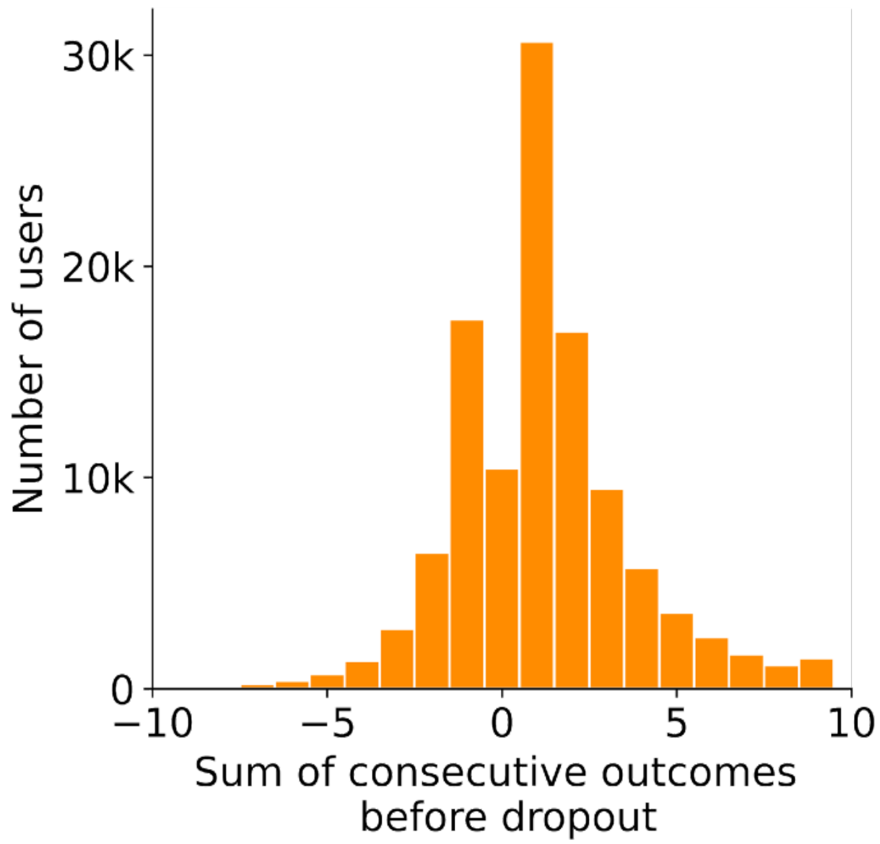
Users stop participating due to lack of a challenge or information gain, but no evidence for the inverse trend where the task is too difficult

DROPOUT BEHAVIOR

What about the peak-end effect?

Analyze behavior directly before drop out

- Negative values: consecutive losses
- Positive values: consecutive wins
- Zero: consecutive draws

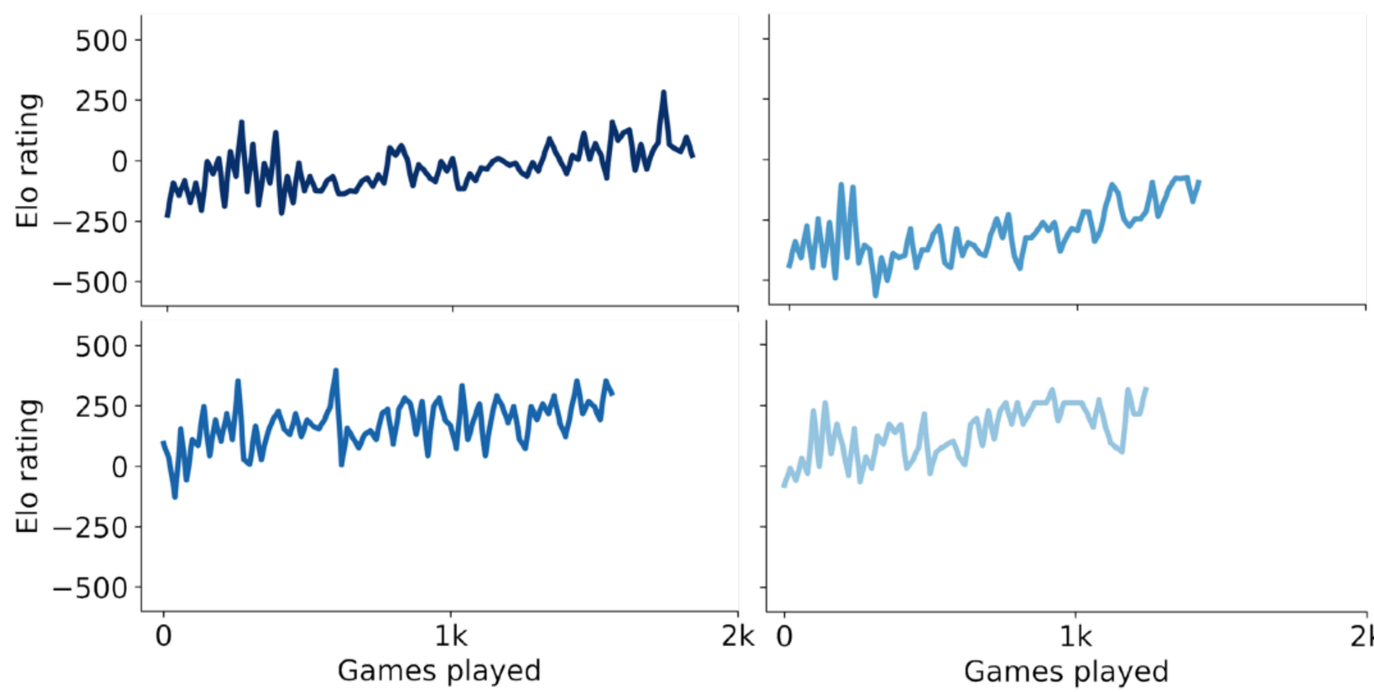


No evidence for dropout behavior being driven by long streaks of wins or losses

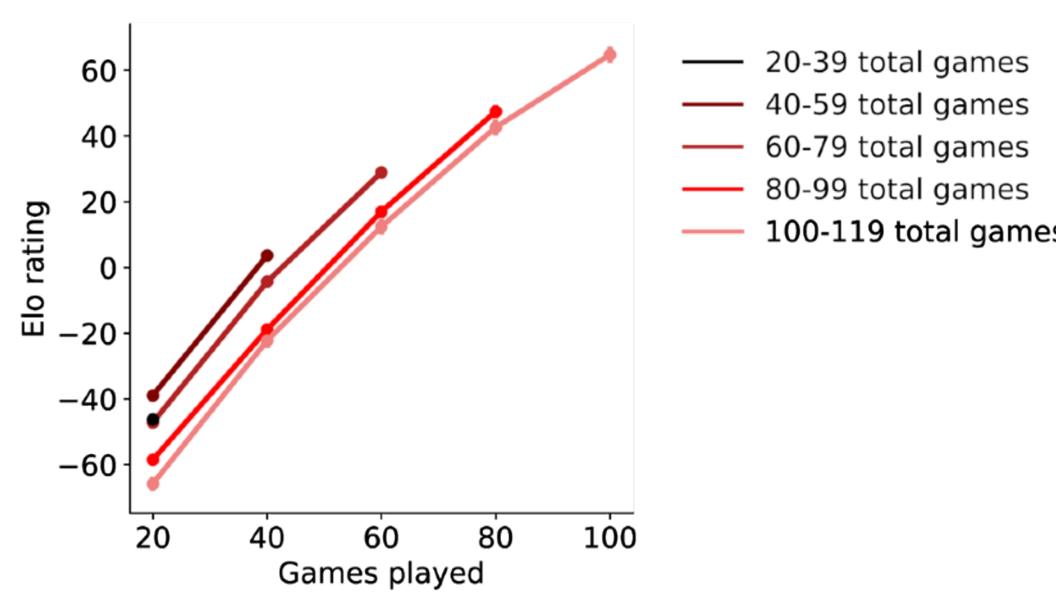
LEARNING TRAJECTORIES

Users exhibit a **reliable increase in playing strength**, both at the individual and population level

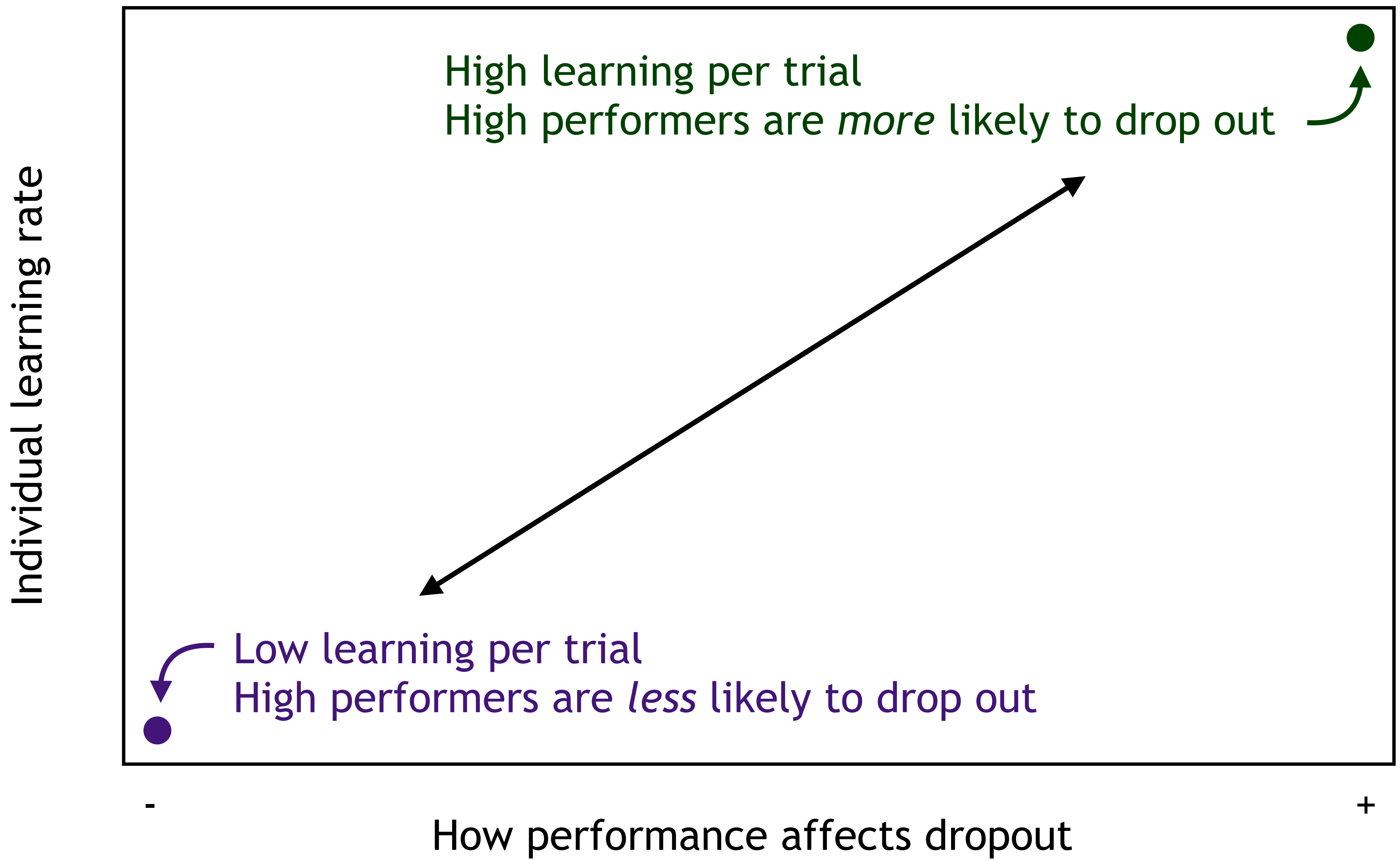
Individual trajectories for experienced users



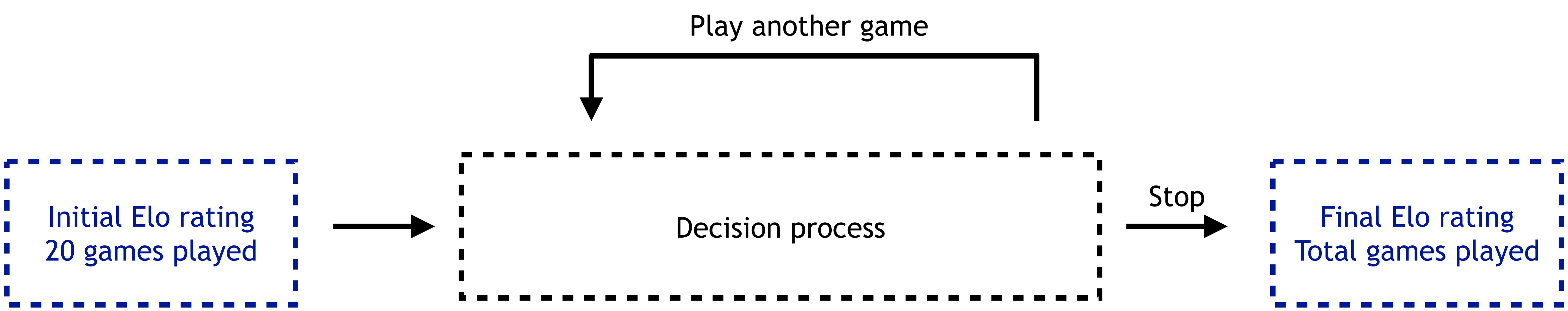
Average trajectories for different experience levels



THE SPACE OF LEARNING AND DROPOUT



JOINT MODELING OF LEARNING AND DROPOUT



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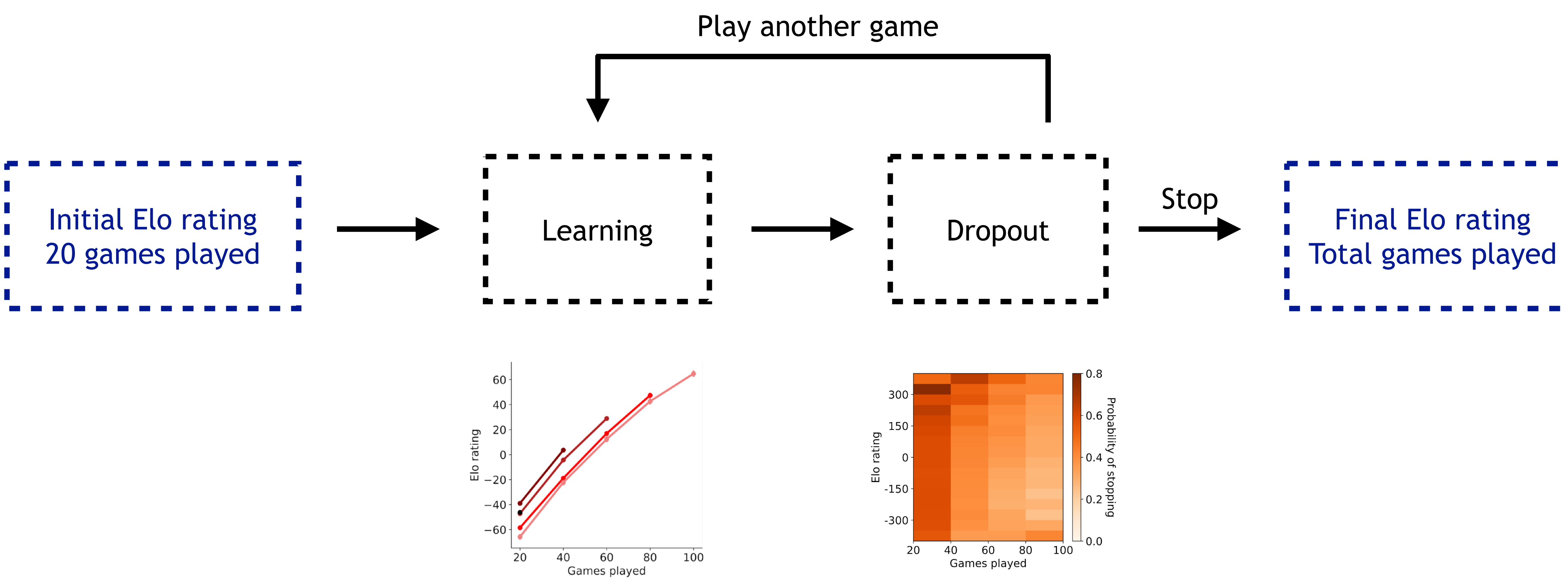
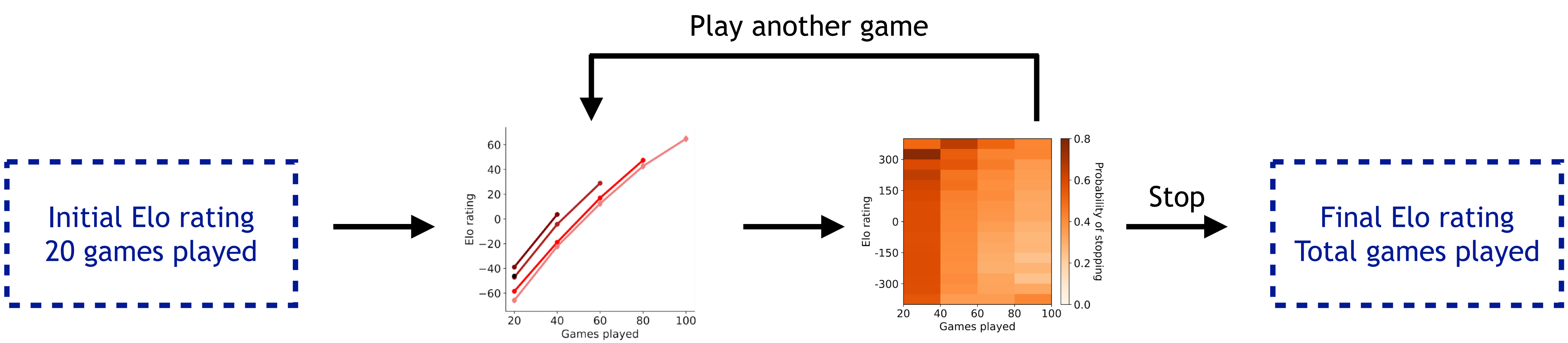
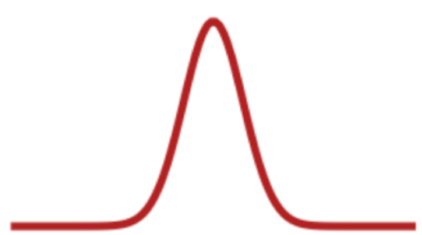


JOINT MODELING OF LEARNING AND DROPOUT



Model component #1: individual learning rates



Change Elo

$\alpha + \sigma_{\text{noise}}$

- Each user has an underlying learning rate, and playing a game leads to a noisy increase in Elo rating
- Run a linear regression per user
- α is drawn from a Normal with its mean and variance at the weighted mean and variance of the user slopes
- σ_{noise} is drawn from a Normal per iteration with its mean at 0 and its variance at the variance of the residuals

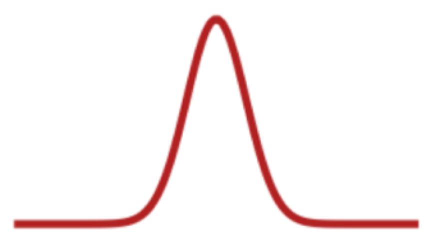
Update rule

$r \leftarrow r + \alpha + \sigma_{\text{noise}}\eta$

JOINT MODELING OF LEARNING AND DROPOUT

Play another game

Initial Elo rating
20 games played



Change Elo

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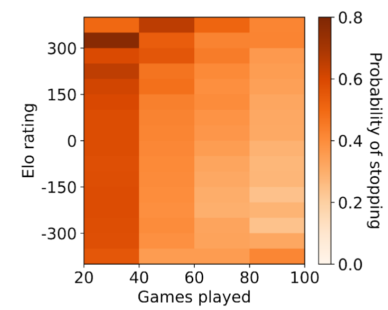


Stop

Final Elo rating
Total games played

Decide if to stop

P_{stop}

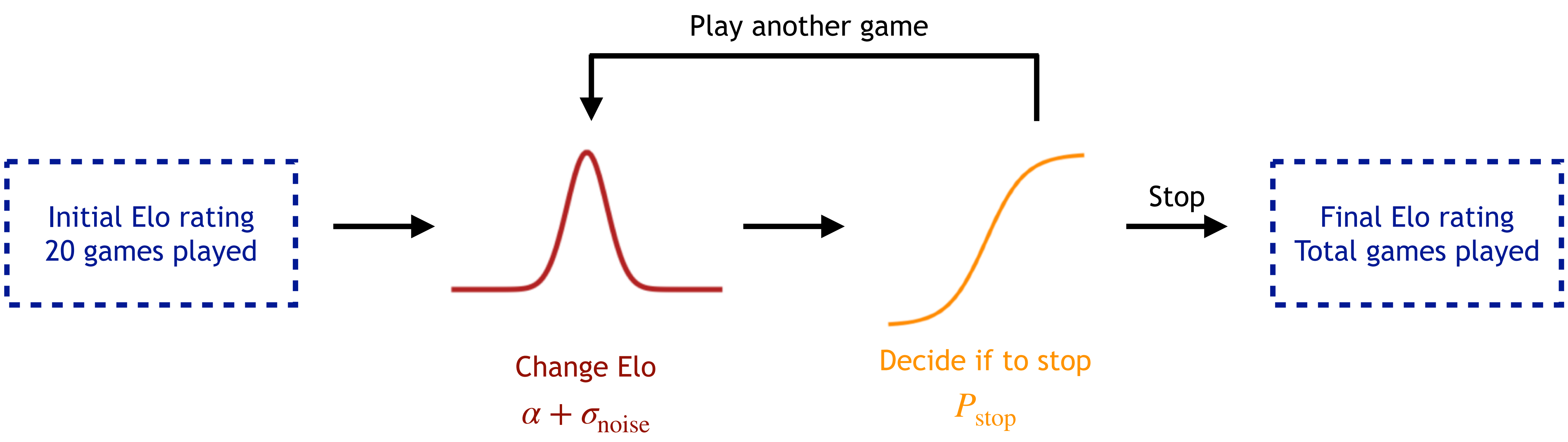
Model component #2: stopping rule

- Each user decides to stop or continue playing based on their current Elo rating and number of games played
- Utilize the coefficients from the logistic regression on users' dropout behavior

Logistic regression

$$P_{\text{stop}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 n + \beta_2 r)}}$$

JOINT MODELING OF LEARNING AND DROPOUT

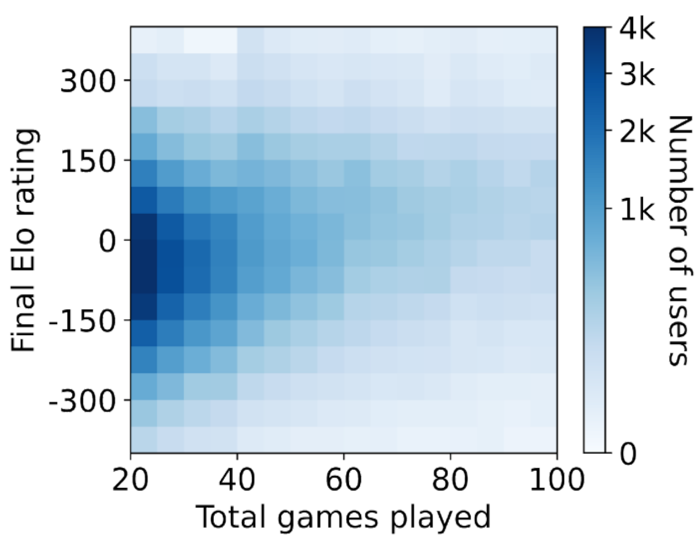


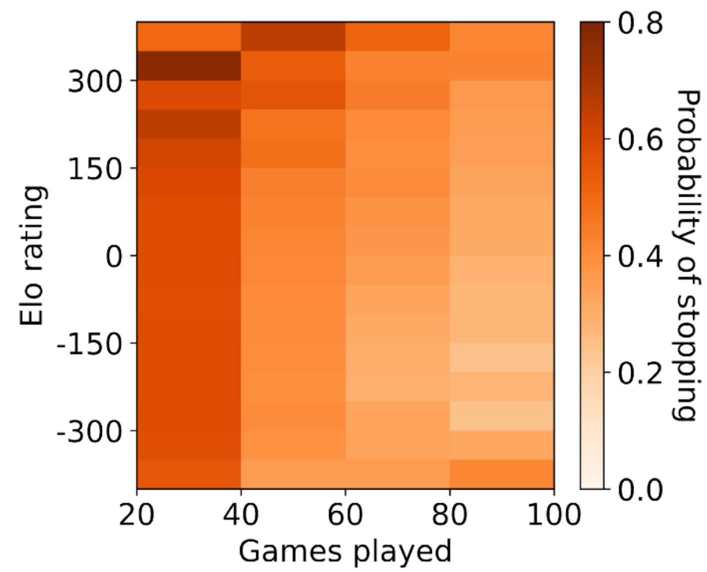
Now, we can run the model forward to see if it replicates the empirical results

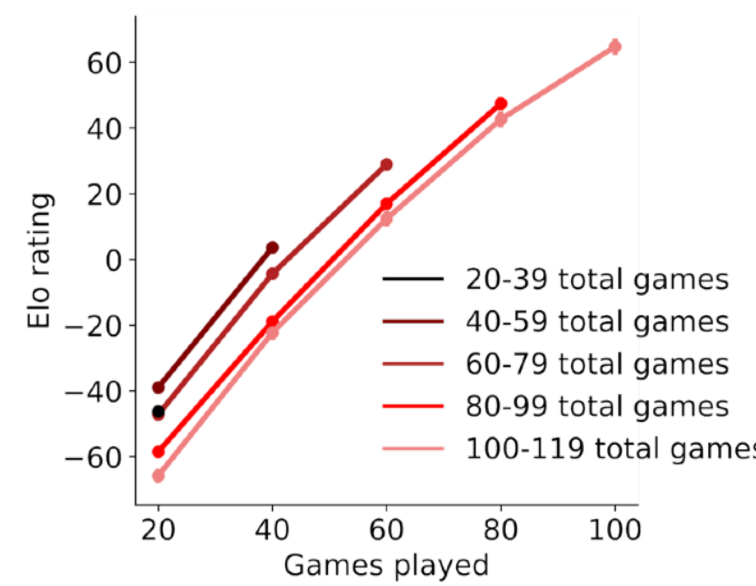
RESULTS FROM THE JOINT MODEL

Task performance | Dropout behavior | Learning trajectories

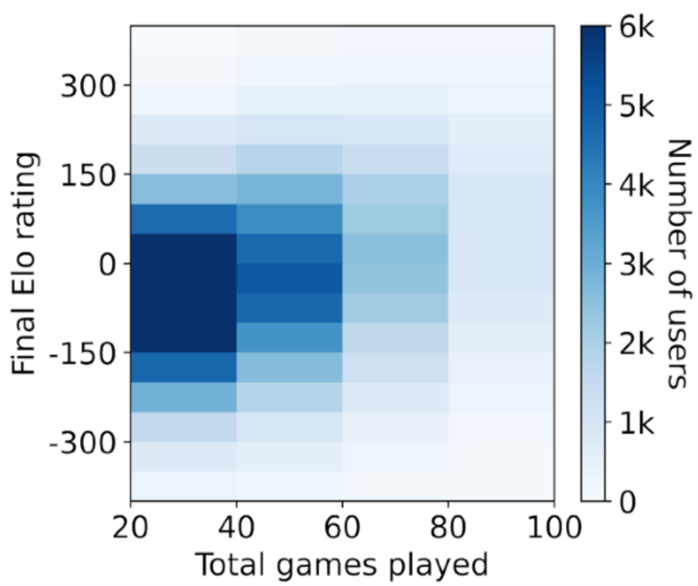
Data

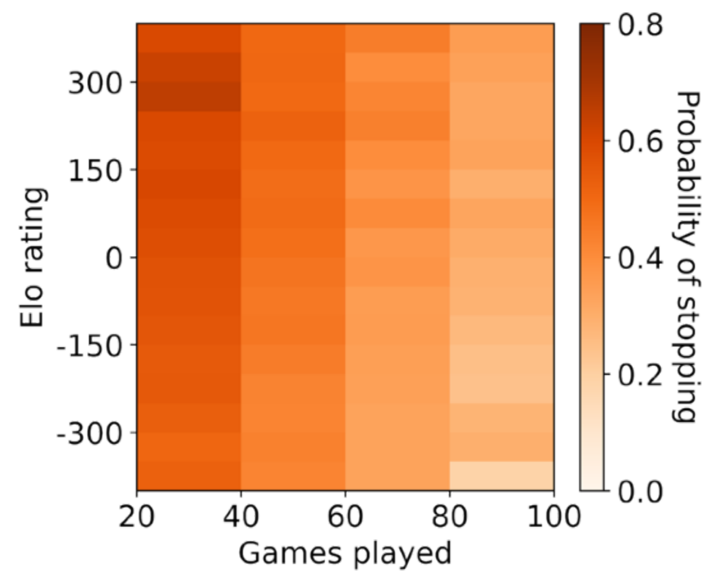


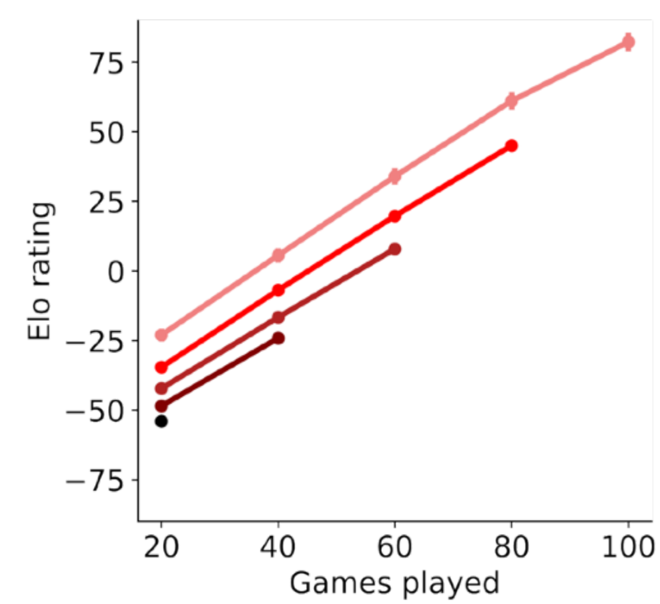




Model



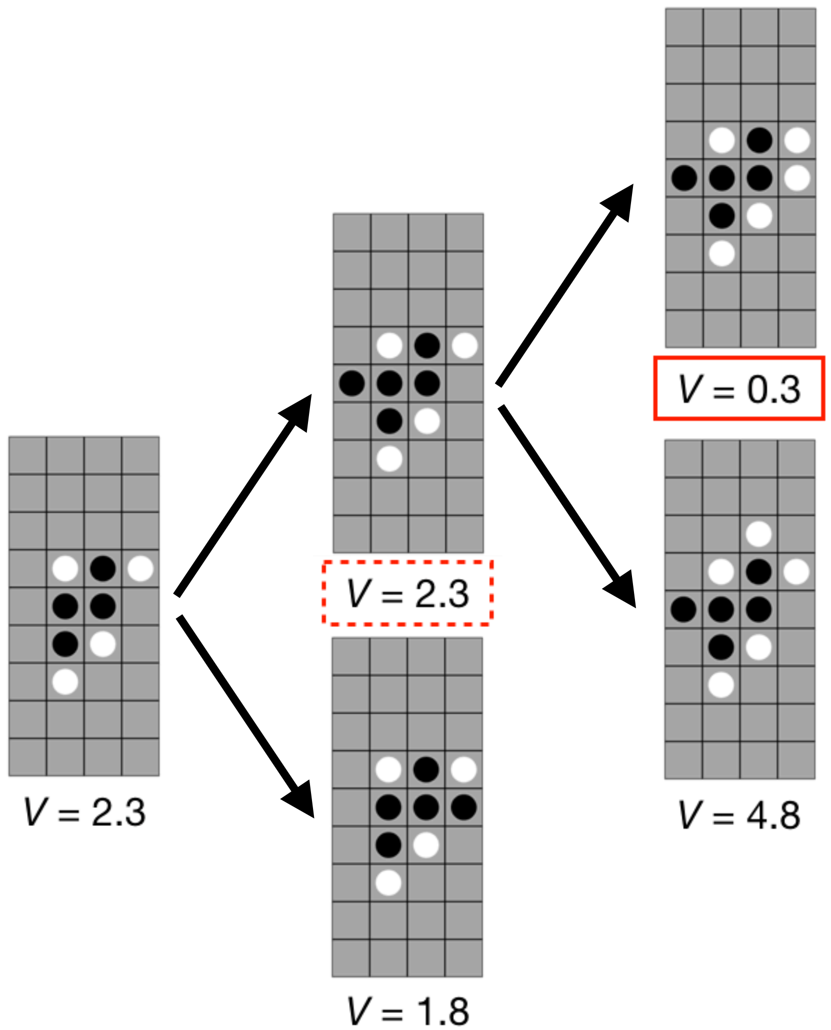




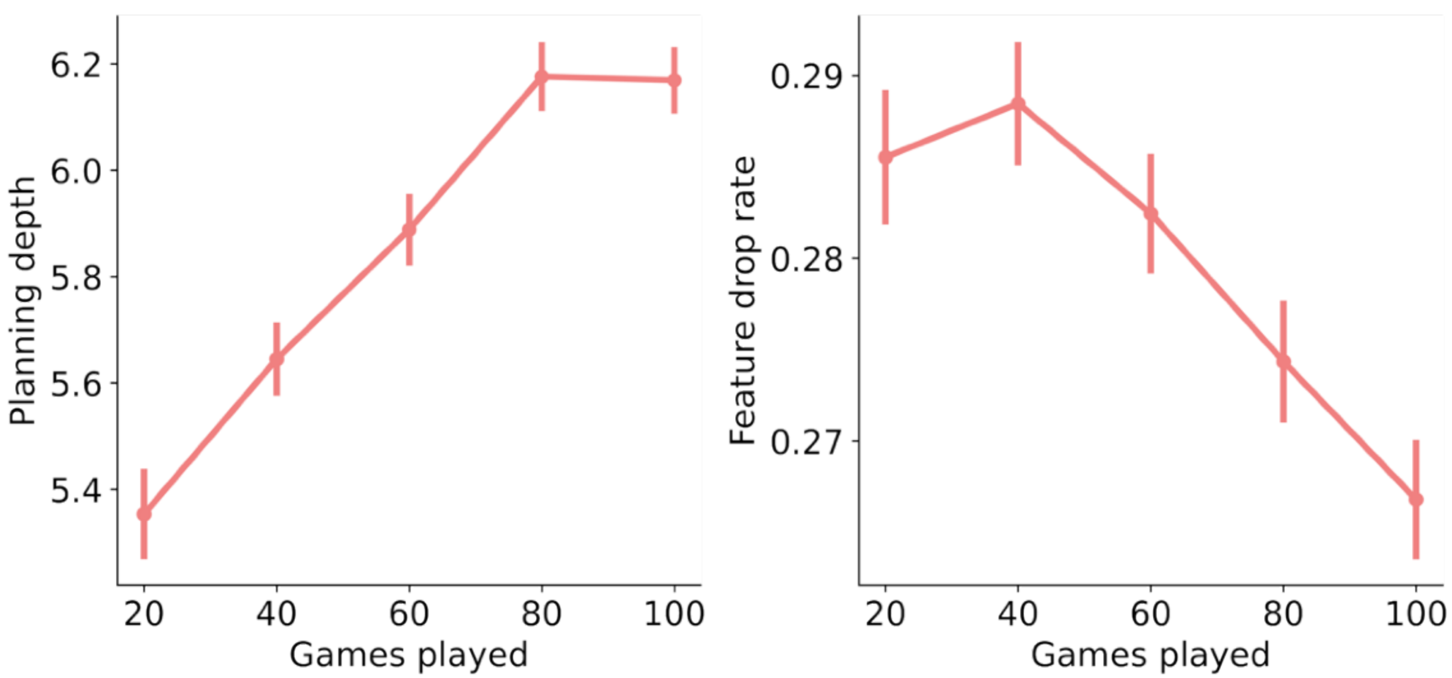
Ongoing work: can we understand learning and dropout at a process level?

RECONCILING LEARNING AND DROPOUT WITH PLANNING

Modeling human planning with decision tree search



Derived metrics that explain improvements in task performance



SUMMARY

Leveraged a large-scale data set of participants playing a two-player game to interrogate their dropout and learning functions

- Established that final playing strength and experience are correlated
- Current playing strength and experience drive dropout
- Playing strength increases with experience and can be traced to metrics derived from a planning model
- A joint model of dropout and learning accounts for the patterns found in the data

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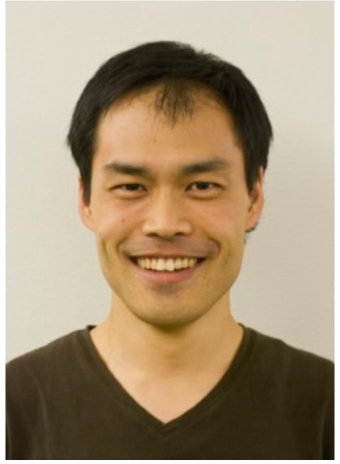


Wei Ji Ma

Extra slides

A MODEL OF HUMAN PLANNING

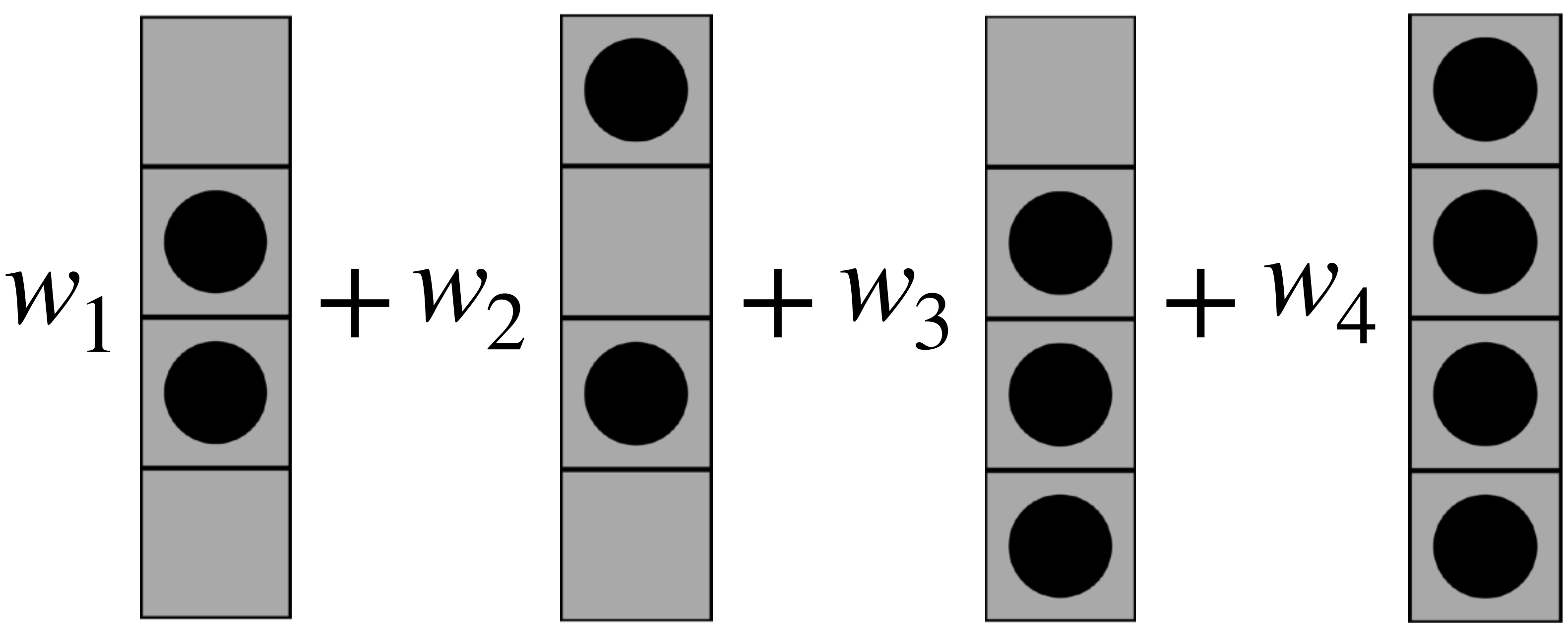
Heuristic value function + decision tree search

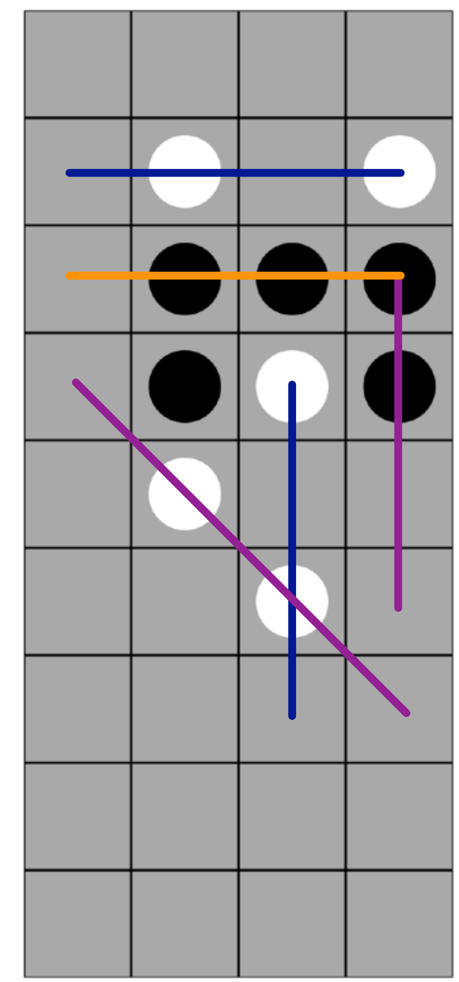
A MODEL OF HUMAN PLANNING

Heuristic value function + decision tree search

Positional features | Learned weights | Scaling constant | Opponent

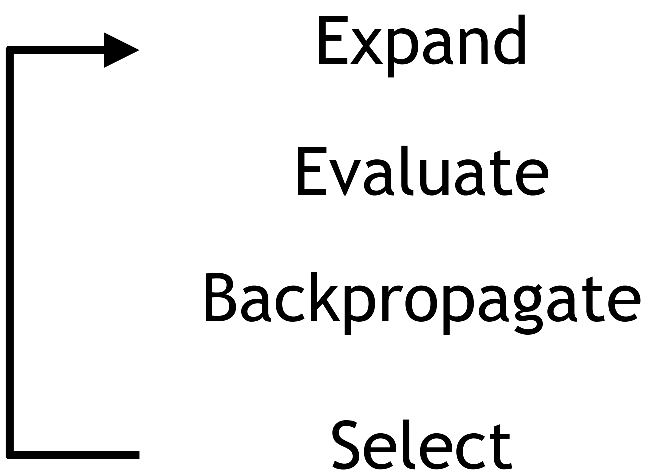
$$V(s) = c_{\text{self}} \sum_{i=0}^{4} w_i f_i(s, \text{self}) - c_{\text{opp}} \sum_{i=0}^{4} w_i f_i(s, \text{opp})$$

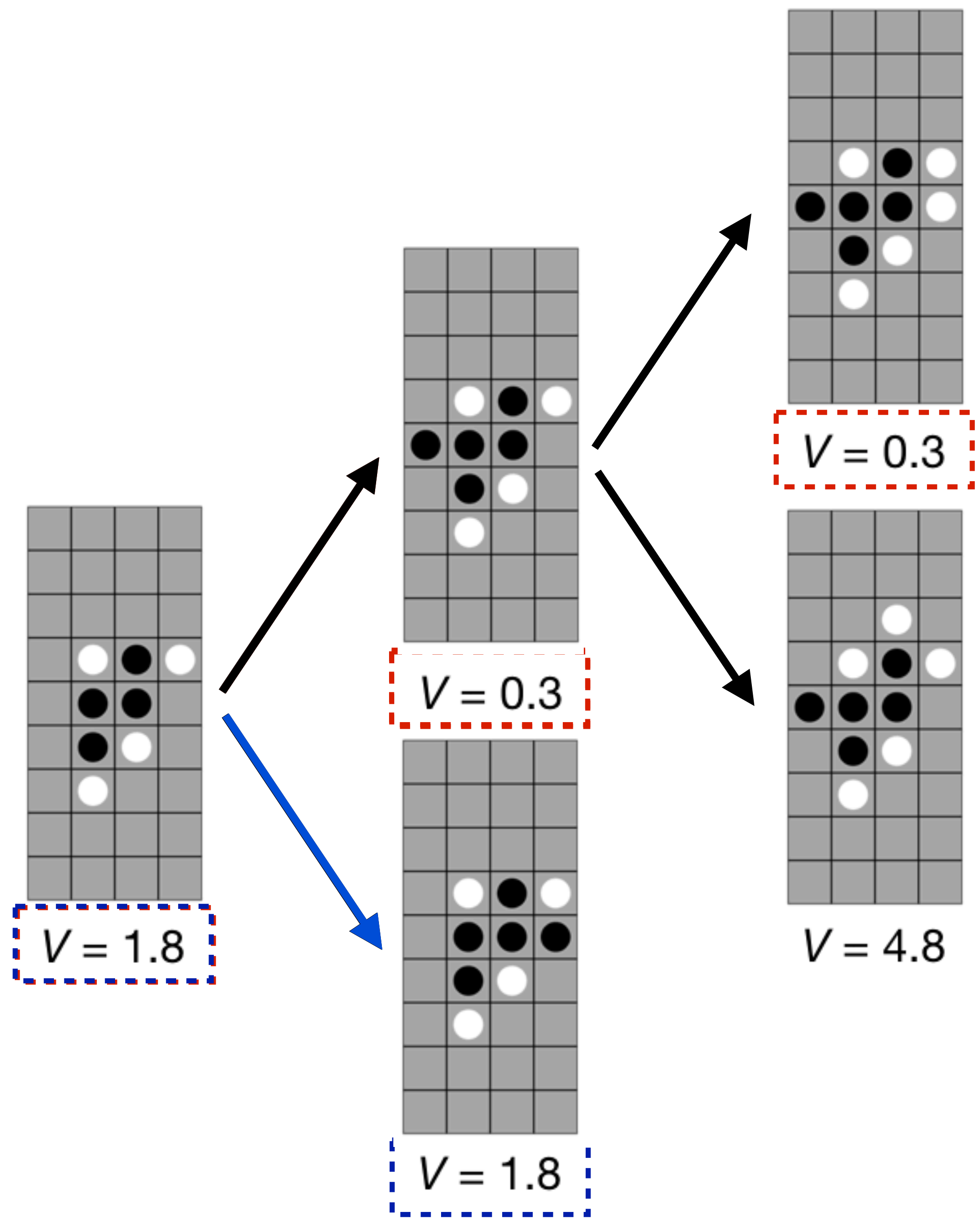




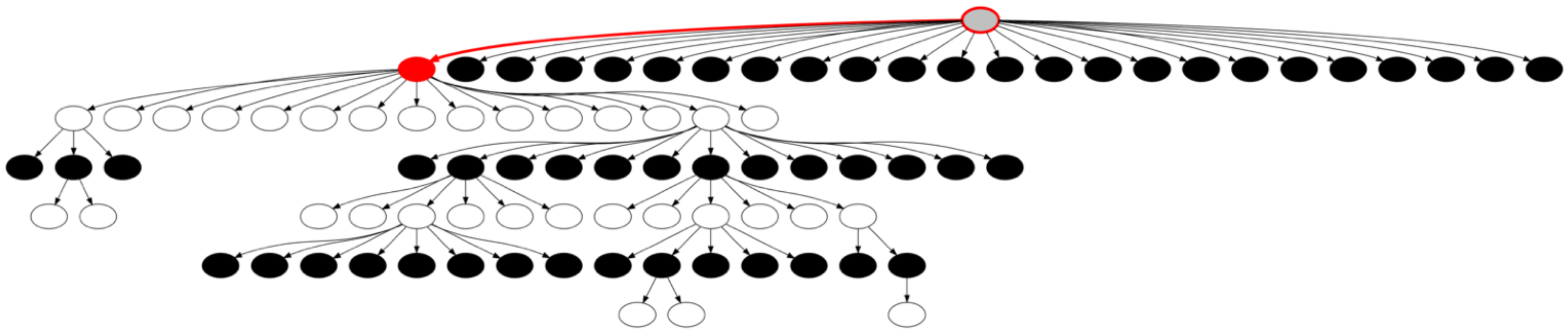
A MODEL OF HUMAN PLANNING

Heuristic value function + **decision tree search**





A SINGLE MODEL SIMULATION



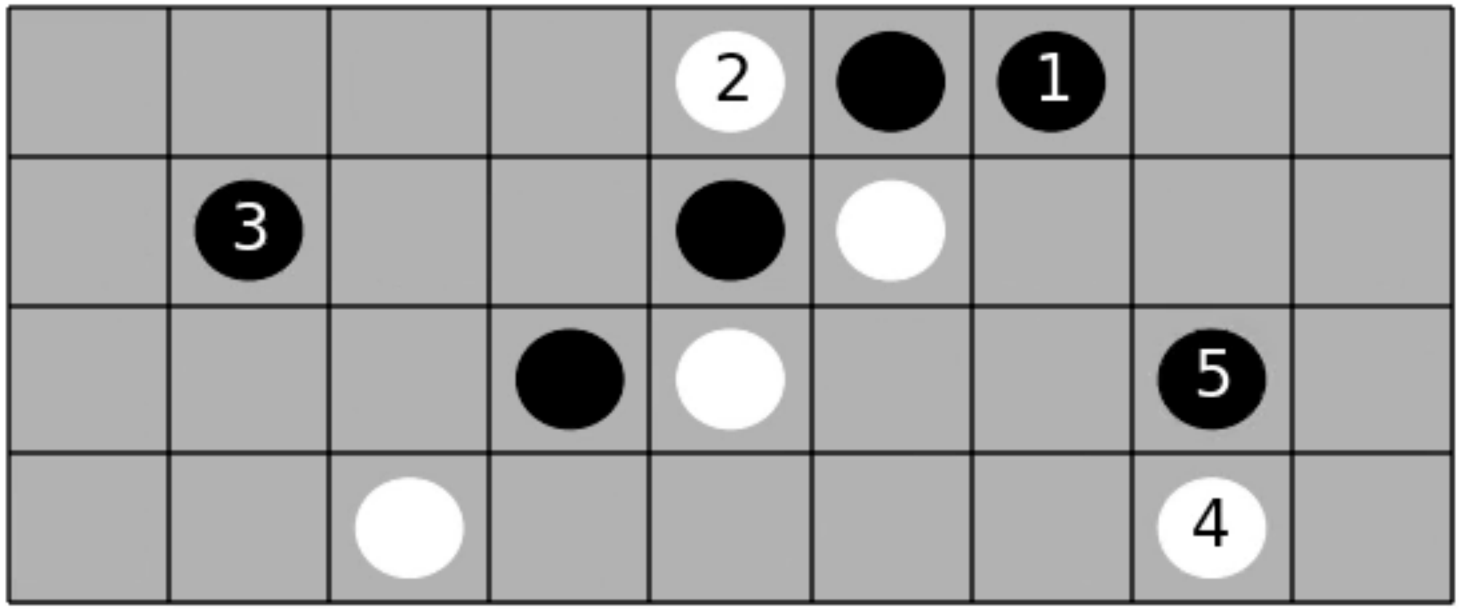
Principal variation 1

Principal variation 2

Principal variation 3

Principal variation 4

Decision



A MODEL OF HUMAN PLANNING

Additional model components

Pruning

- Nodes with a value below that of the best move minus a threshold are removed from the tree

"Human-like" modes of failure

- Gaussian noise
- Feature dropping: overlook features
- Lapse rate: make a random move

Stopping criterion to terminate search

- Randomly with a small probability
- When the preferred move hasn't changed for a number of iterations