MODEL-BASED AND MODEL-FREE DECISION-MAKING IN A COMPLEX PLANNING TASK

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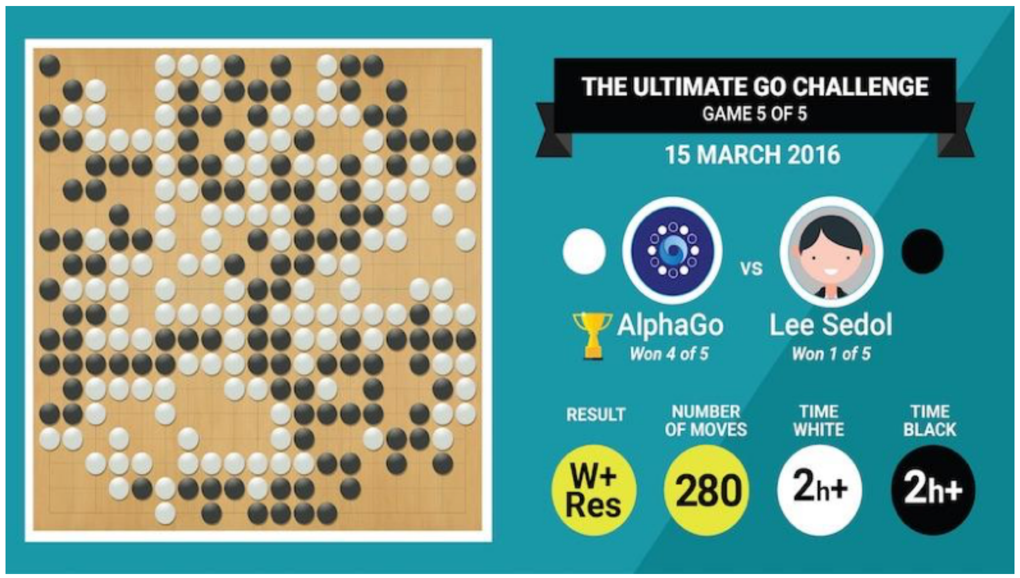
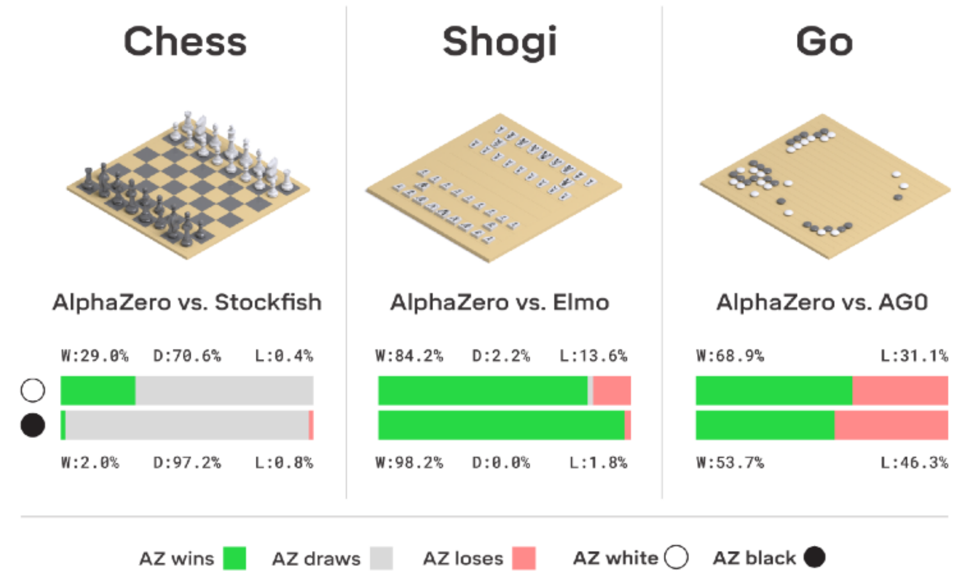
COMPLEX PLANNING IN GAMES



Silver et al., *Nature*, 2016



Silver et al., *Science*, 2017

Sequence of decisions

1st move: 361 options
2nd move: 360 options
3rd move: 359 options
⋮

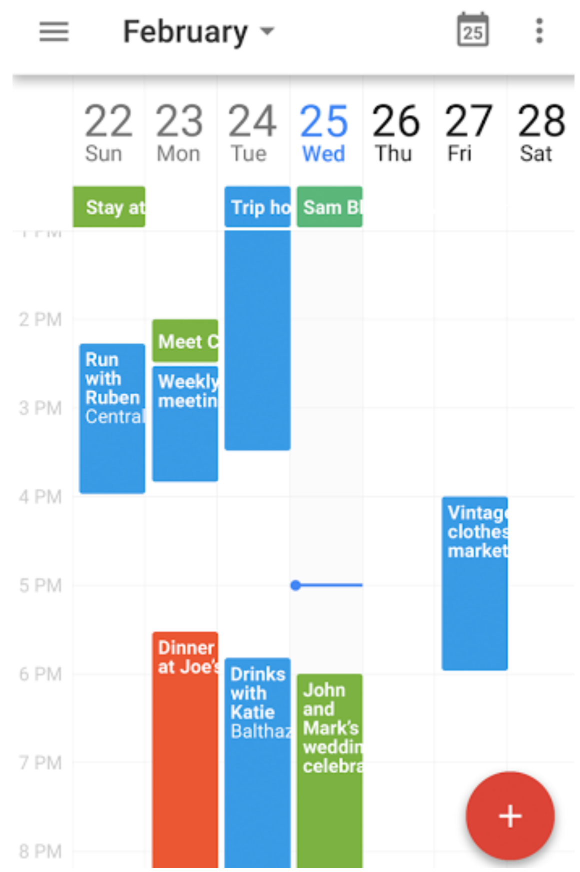
Complex planning problem

↓

Mental simulation of possible futures

Are complex planning problems limited to games?

Foraging



Organizational strategy

Spatial navigation

COMPLEX PLANNING

Complex planning problems:

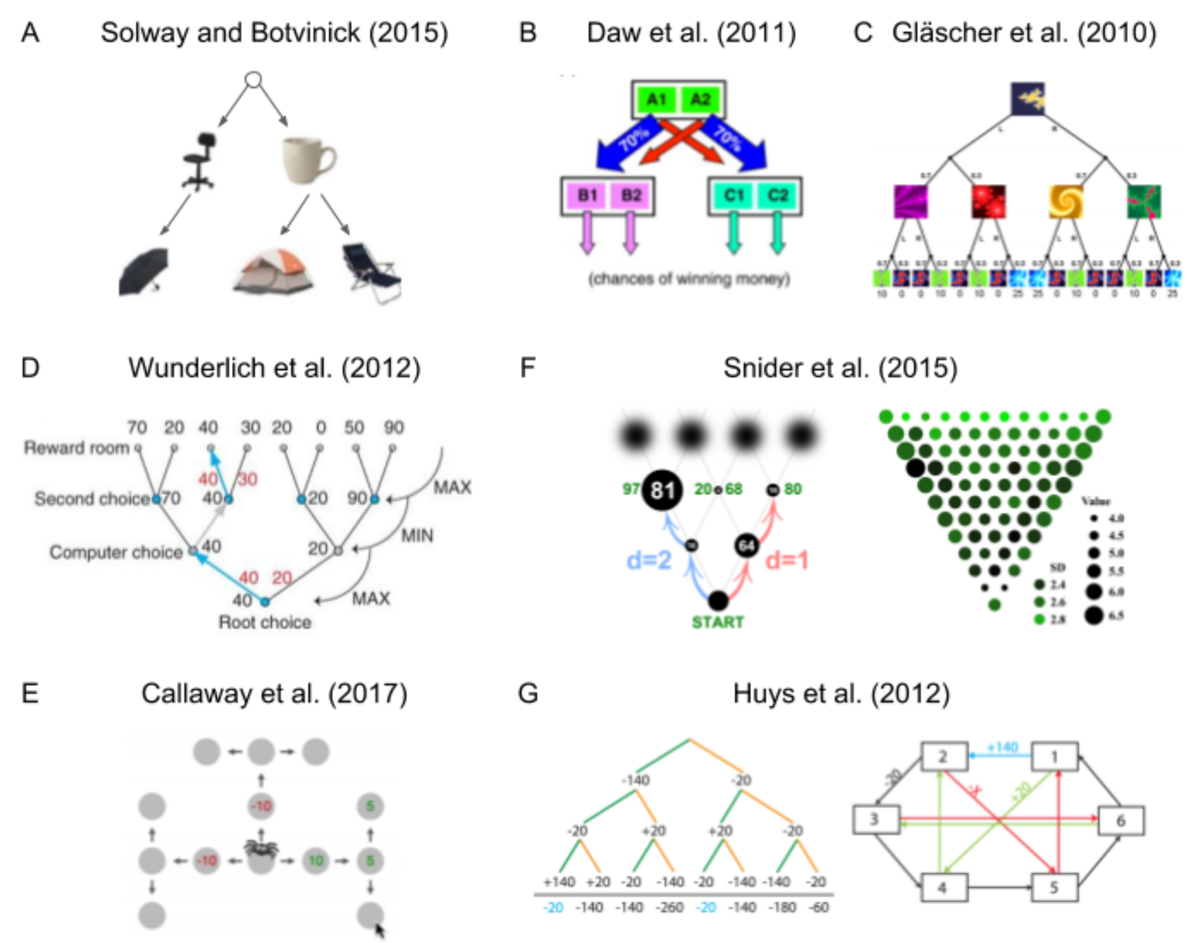
- Incredibly challenging for agents
- Common in natural behavior

How do humans solve such problems?

Are these solutions similar to AI algorithms?

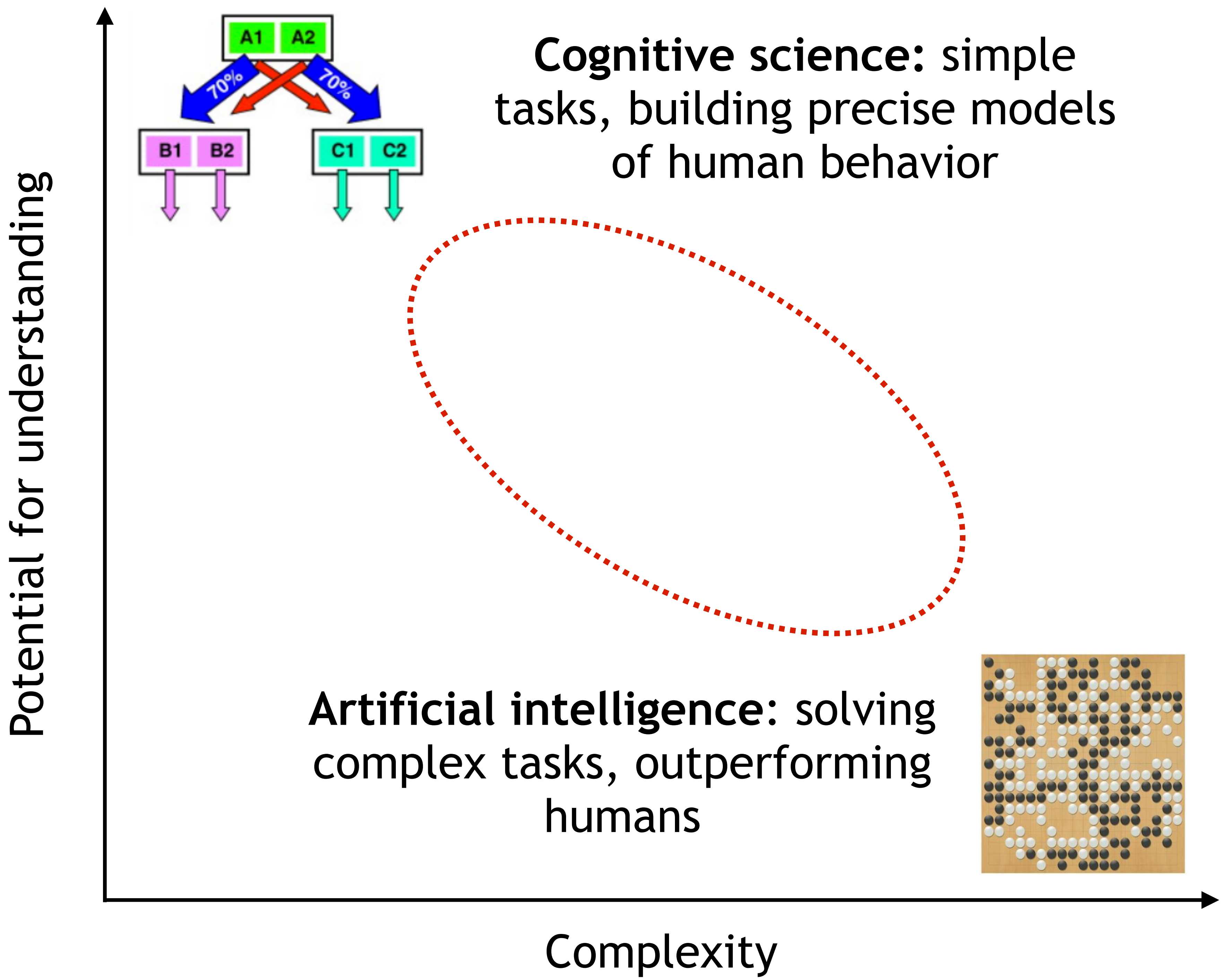
What tasks do we use to study these questions?

Tasks for studying human planning



However, these tasks are low in complexity and not fully combinatorial

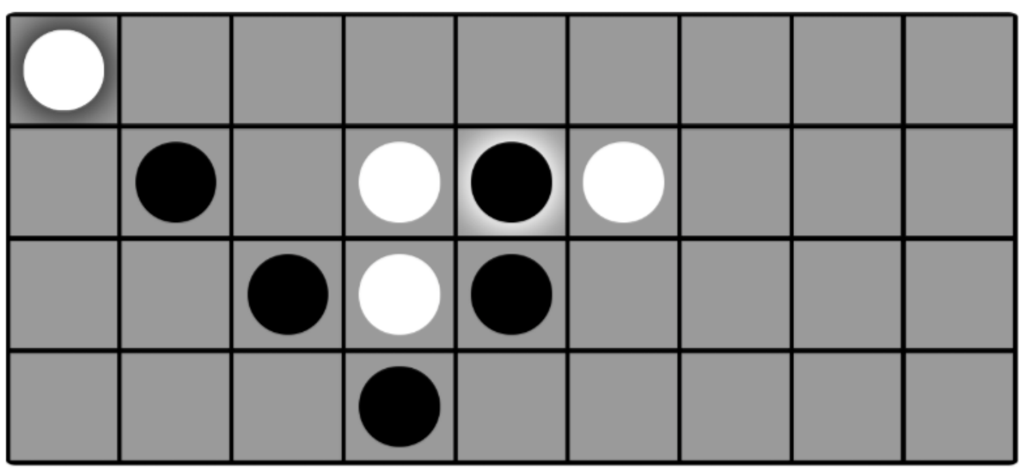
SPACE OF PLANNING TASKS



Needed: a combinatorial planning task of intermediate complexity with high potential for modeling human behavior

FOUR-IN-A-ROW

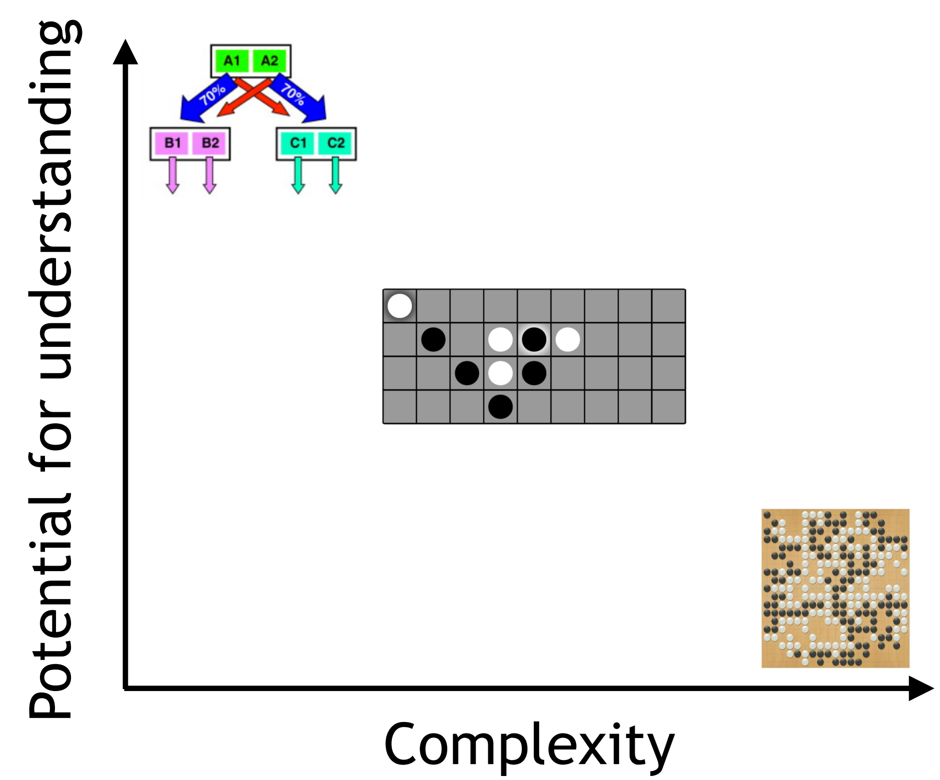
- 4-by-9 board
- 2 players, black plays first
- Alternate placing pieces on the board, trying to complete four in a row in any orientation



$1.2*10^{16}$ possible states

State space comparison

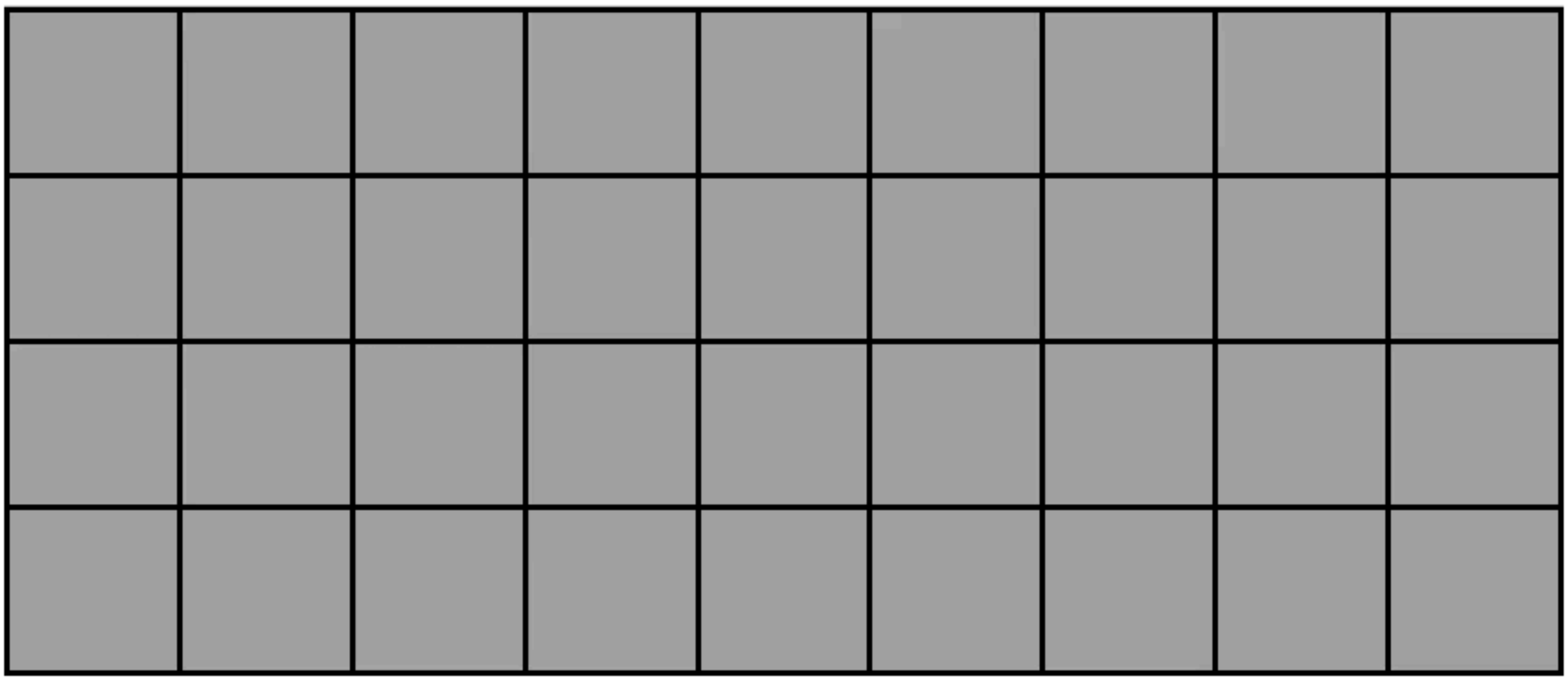
Task	State space complexity	Human cognition studies	AI studies
Solway and Botvinick task	3	[Solway and Botvinick, 2015]	
Daw et al. "two-step" task	3	[Daw et al., 2011]	
Gläscher et al. task	5	[Gläscher et al., 2010]	
Wunderlich et al. task	7	[Wunderlich et al., 2012a]	
Callaway et al. task	$\lesssim 20$	[Callaway et al., 2017]	
Snider et al. task	66	[Snider et al., 2015]	
Huys et al. task	2 to 128	[Huys et al., 2012] [Huys et al., 2015]	
Four-in-a-row	$1.2 \cdot 10^{16}$	[van Opheusden et al., 2017]	[Beck, 2008]
Chess	$\sim 10^{47}$	[de Groot, 1946] [Chase and Simon, 1973] [Holding, 1985]	[Shannon, 1950] [Campbell et al., 2002] [Silver et al., 2017]
Go	$2.1 \cdot 10^{170}$		[Silver et al., 2016]



GAMEPLAY

A game between two novice players

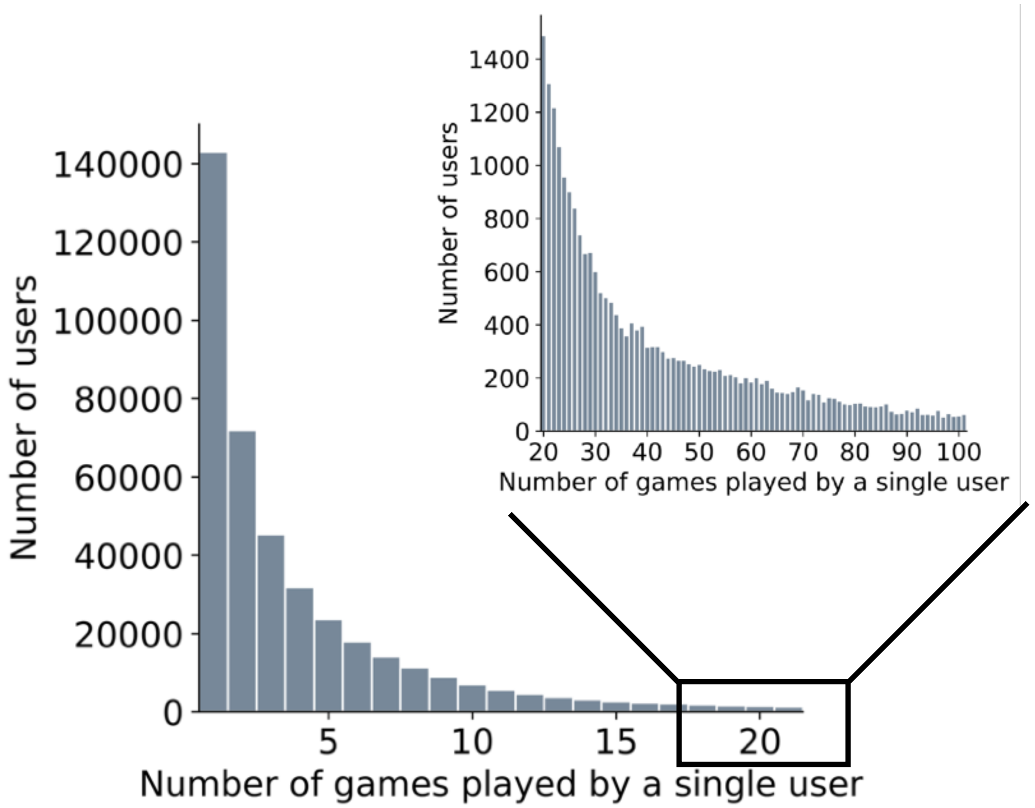
Opheusden, Galbiati, Bnaya, Li, Ma, *CogSci*, 2017



LARGE-SCALE DATA

Game development
Anonymized data

Task specification
AI opponents



- Human vs. AI games
- User always plays first
- ~3.2 million games
- ~430,000 unique users
- ~1.5 million new games/month

OUTLINE

Given this task of intermediate complexity, we want to:

- Build an AI-inspired prospective model of human play
- Fit the model to data, and explore signatures of retrospective decision-making in the large data set
- Develop models for integrating prospection and retrospection (ongoing work)

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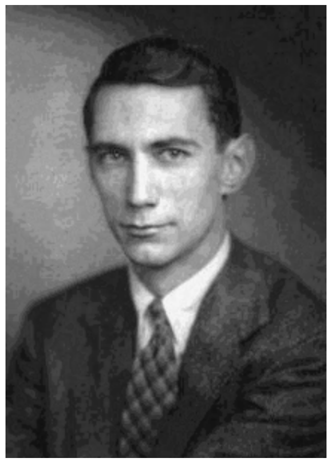
THE AI OF GAMES



Claude Shannon

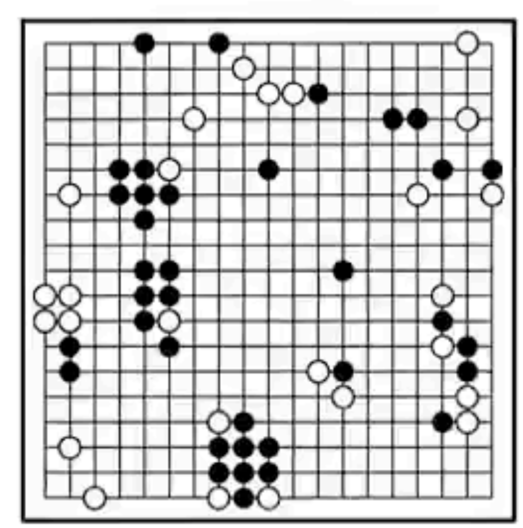
Philosophical Magazine, Ser.7, Vol. 41, No. 314 - March 1950.

XXII. Programming a Computer for Playing Chess[1]

By CLAUDE E. SHANNON

Visualizing selective search

Silver et al., *Nature*, 2016



Two key ingredients:

(1) **Evaluation function**: quantified value of how good a position is

(2) **Selective search strategy**: look-ahead when a move seems promising according to the evaluation function

EVALUATION FUNCTION

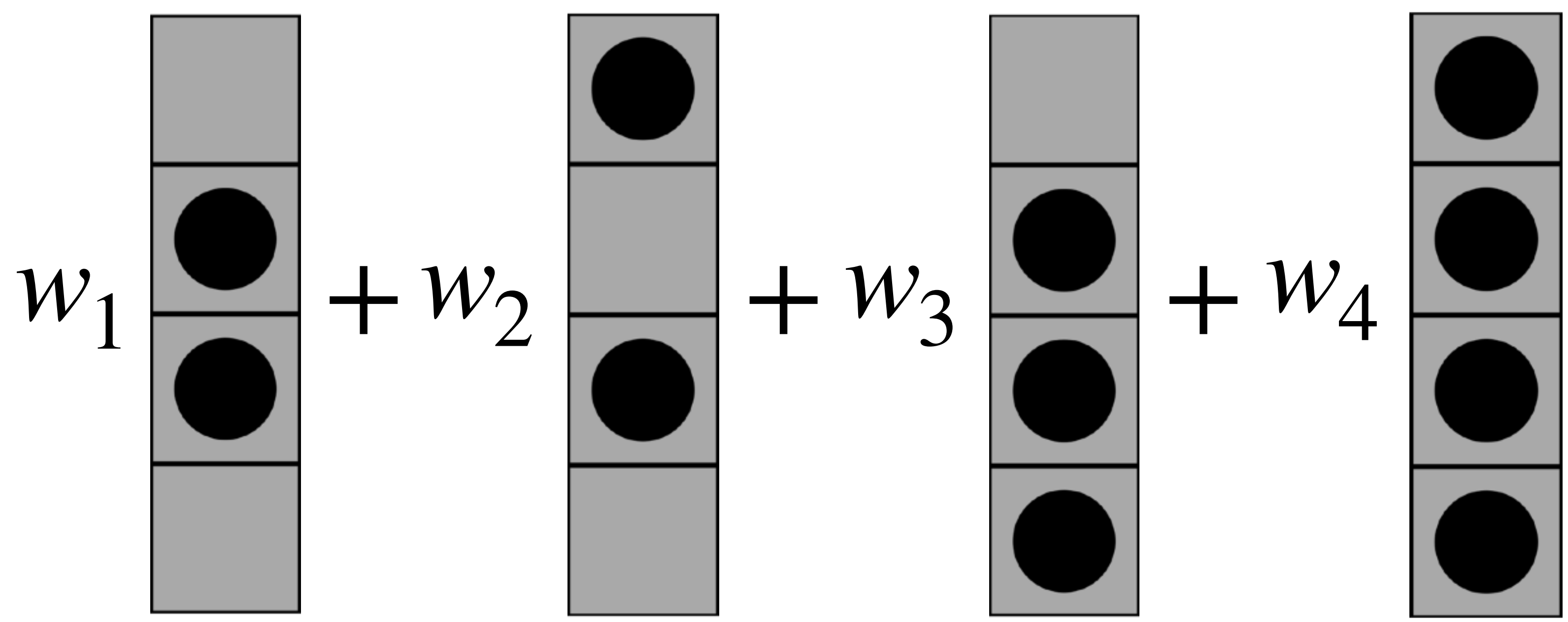
Key ingredient #1

Positional features

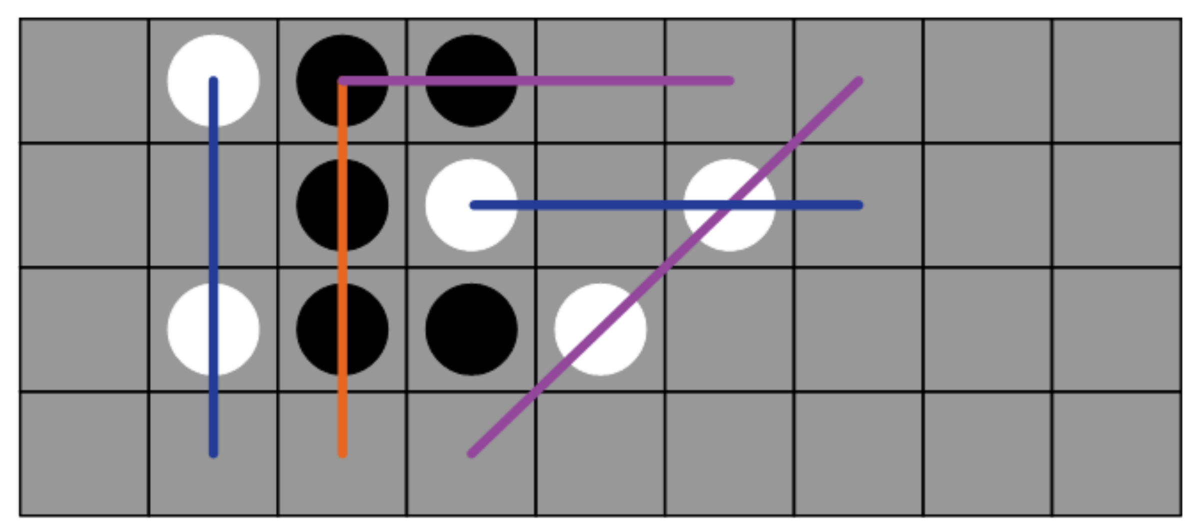
Learned weights

Scaling constant

Opponent

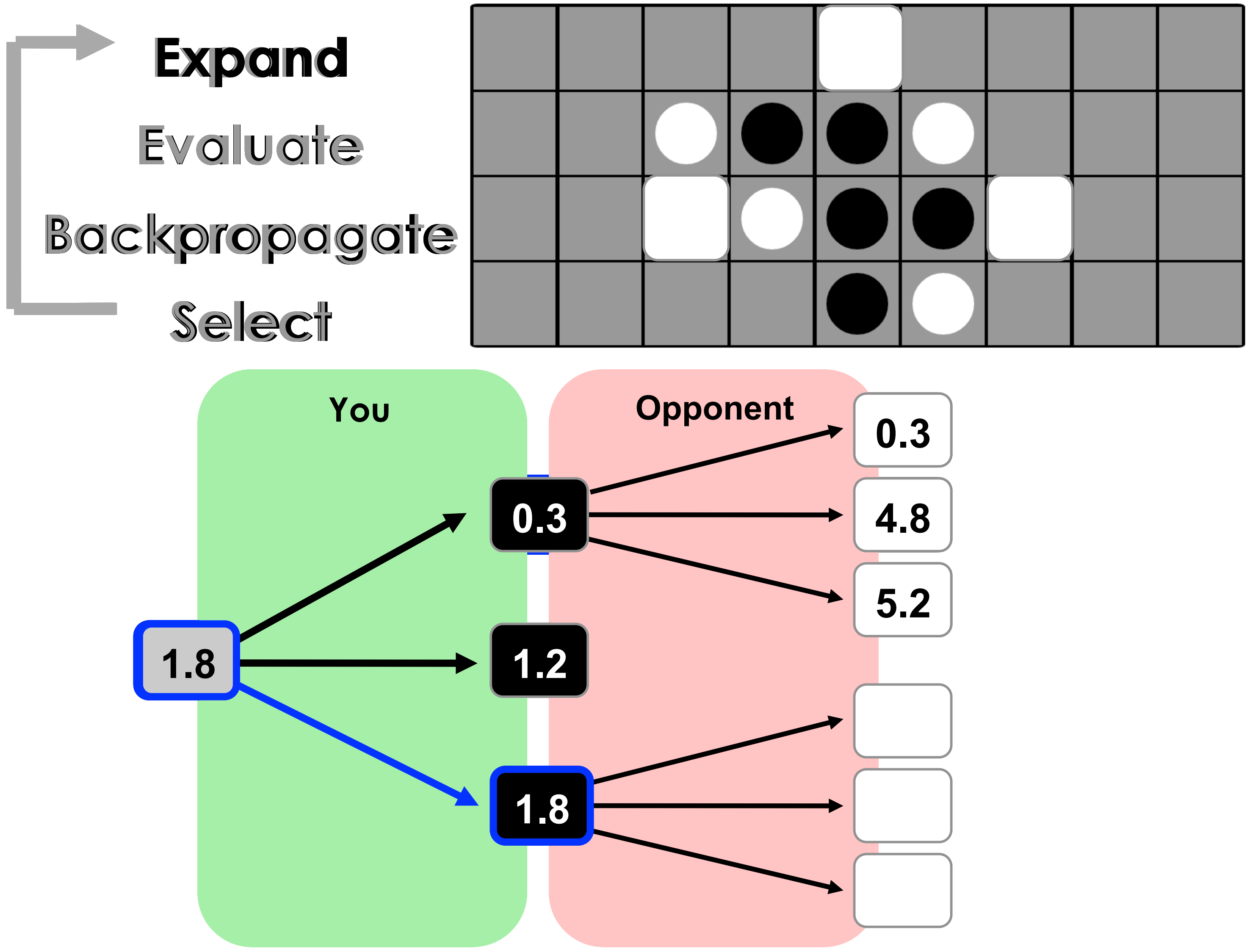


$$V(s) = c_{self} \sum_{i=0}^{4} w_i f_i(s, self) - c_{opp} \sum_{i=0}^{4} w_i f_i(s, opp)$$



DECISION TREE SEARCH

Key ingredient #2



OTHER COMPONENTS OF THE MODEL

Pruning

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

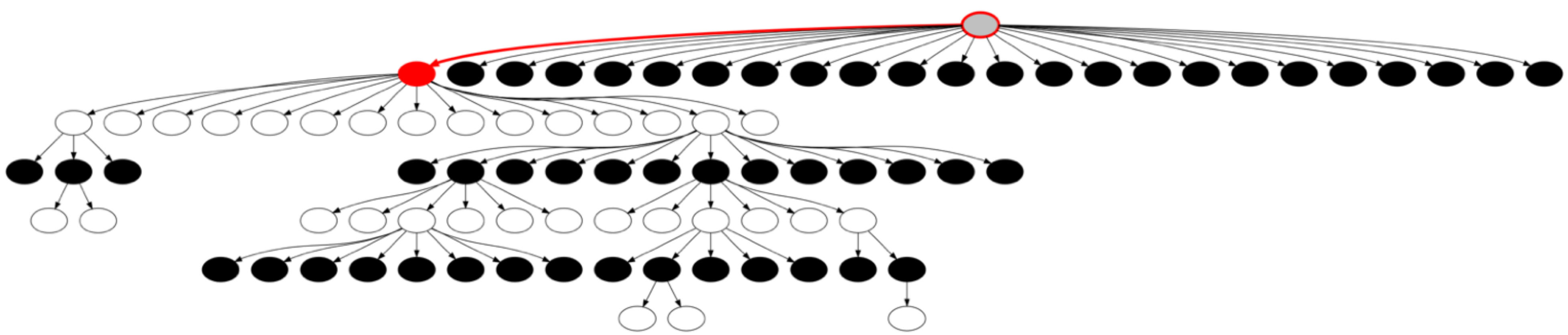
"Human-like" modes of failure

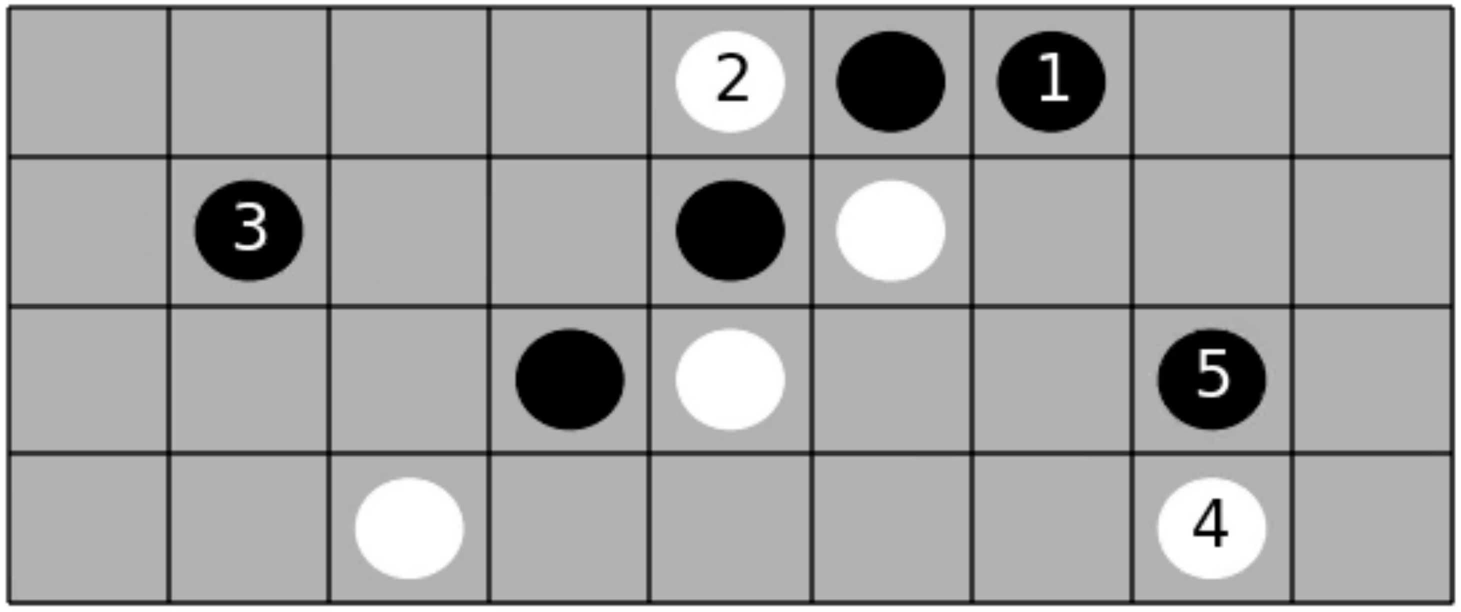
- Gaussian noise added to $V(s)$
- Feature dropping (δ): overlook features when calculating $V(s)$
- Lapse rate (λ): make a random move

Stopping criterion to terminate search

- Randomly with a small probability (γ)
- When the preferred move hasn't changed for a number of iterations OR the difference between the best and second best moves is above a threshold (N)

A SINGLE MODEL SIMULATION





Principal variation 1

Principal variation 2

Principal variation 3

Principal variation 4

Decision

OUTLINE

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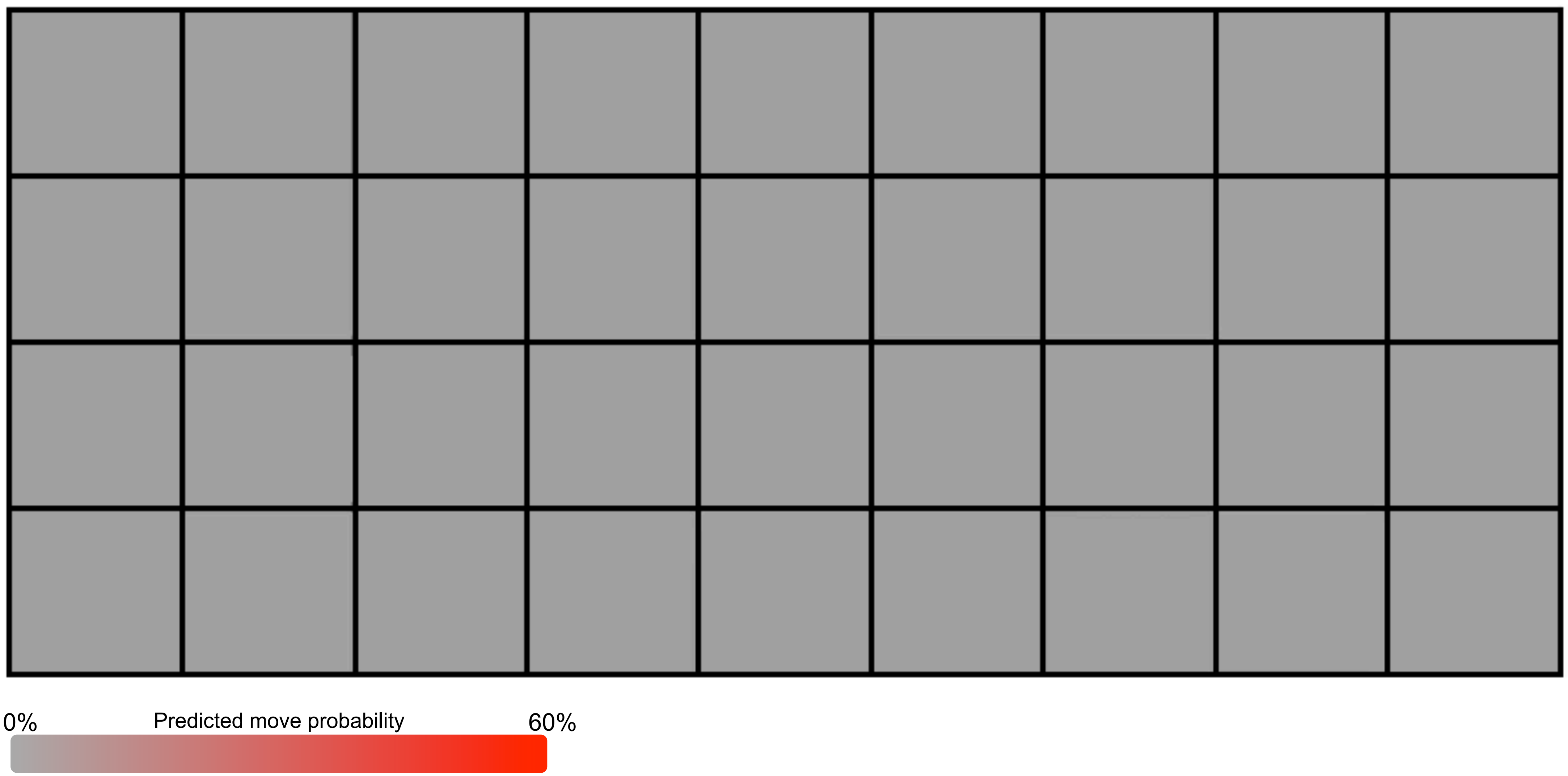
FITTING THE MODEL TO HUMAN PLAY

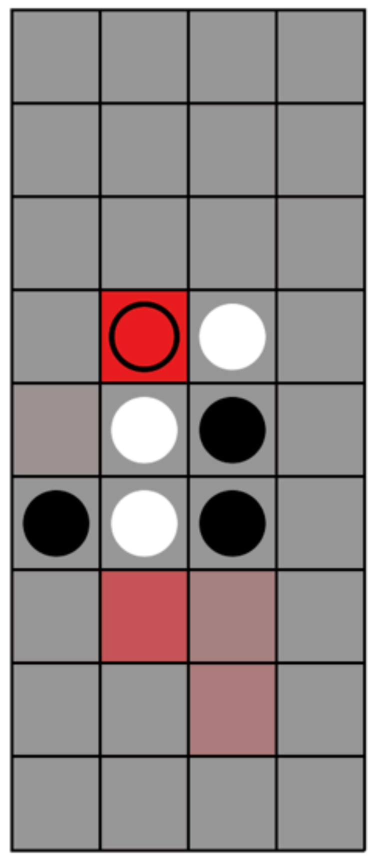


Model is simulated many times in each position, returning the probability that the subject moves on a given square

MODEL PERFORMANCE

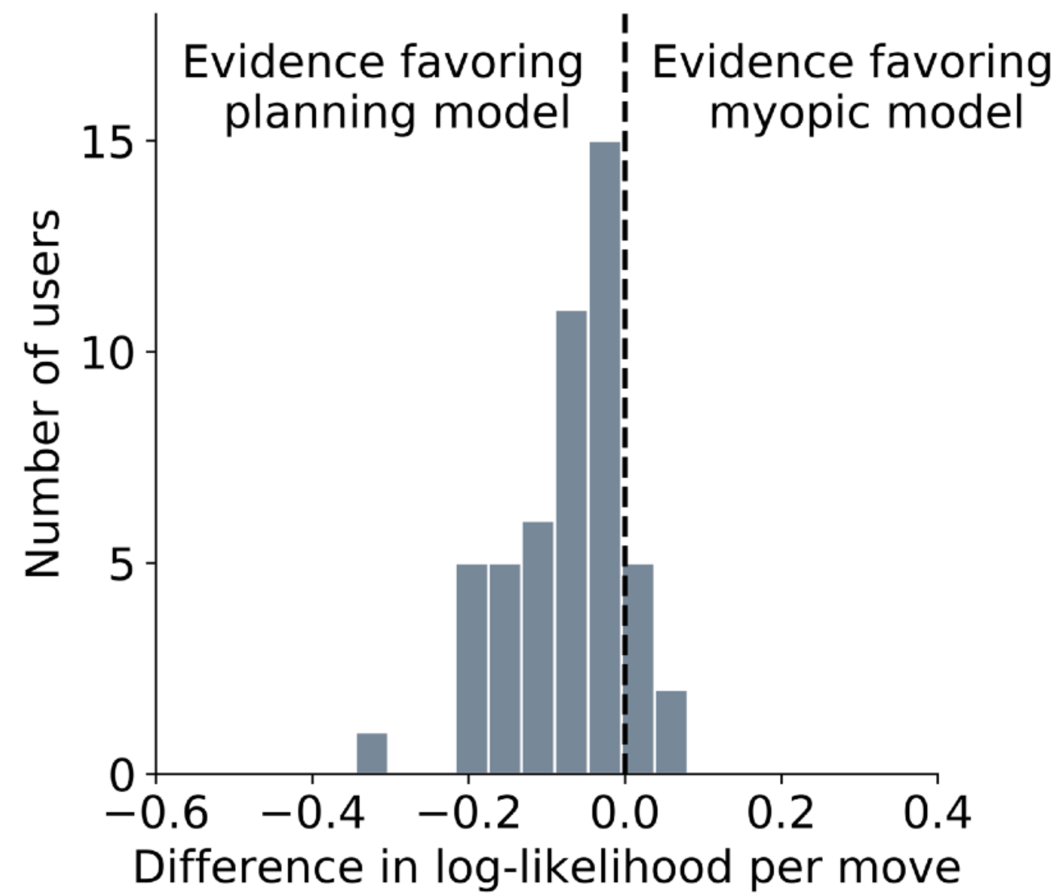
50 pseudo-randomly selected users

Move predictions



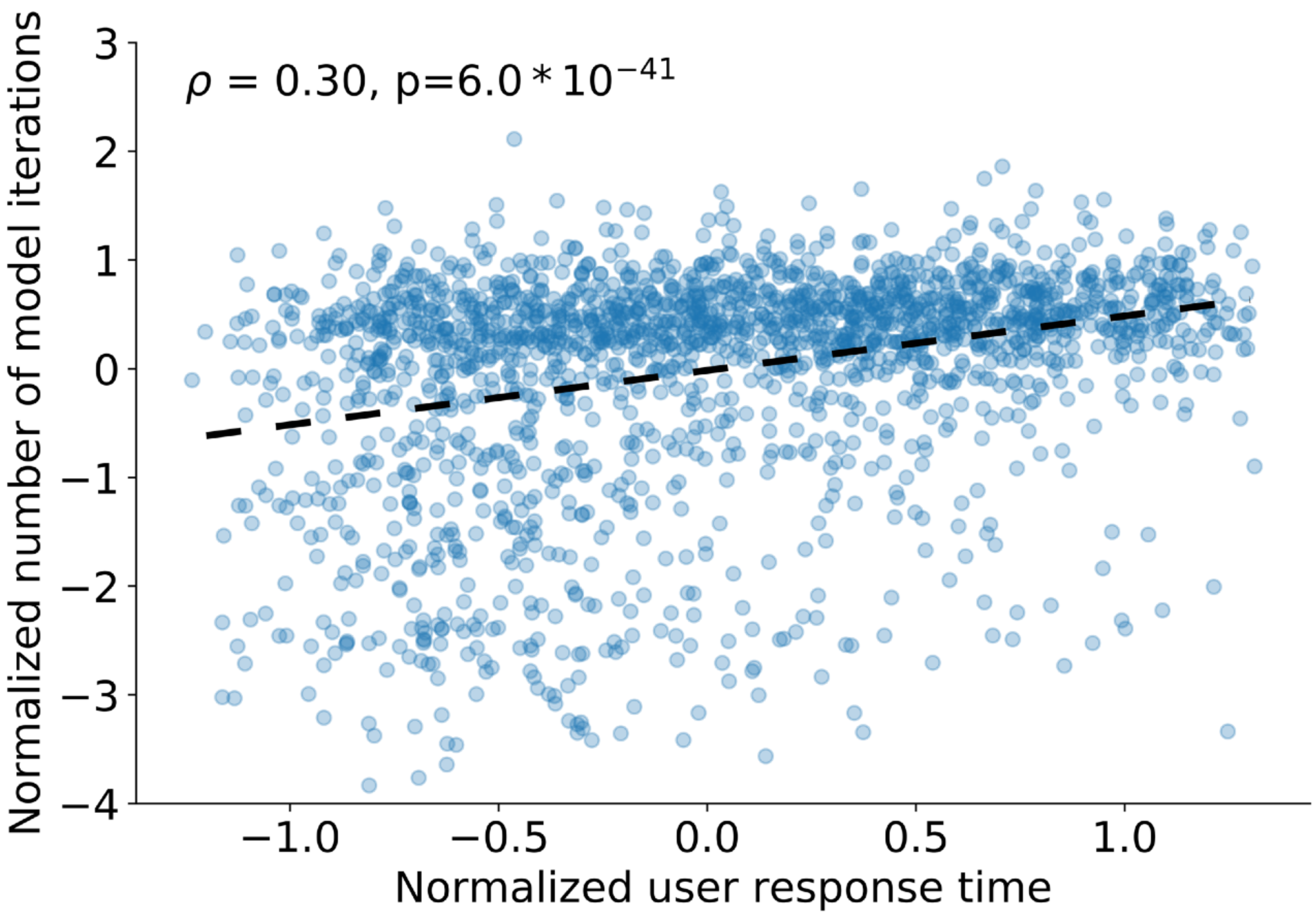
~25% correct
High compared to chance (4%)

Model comparison

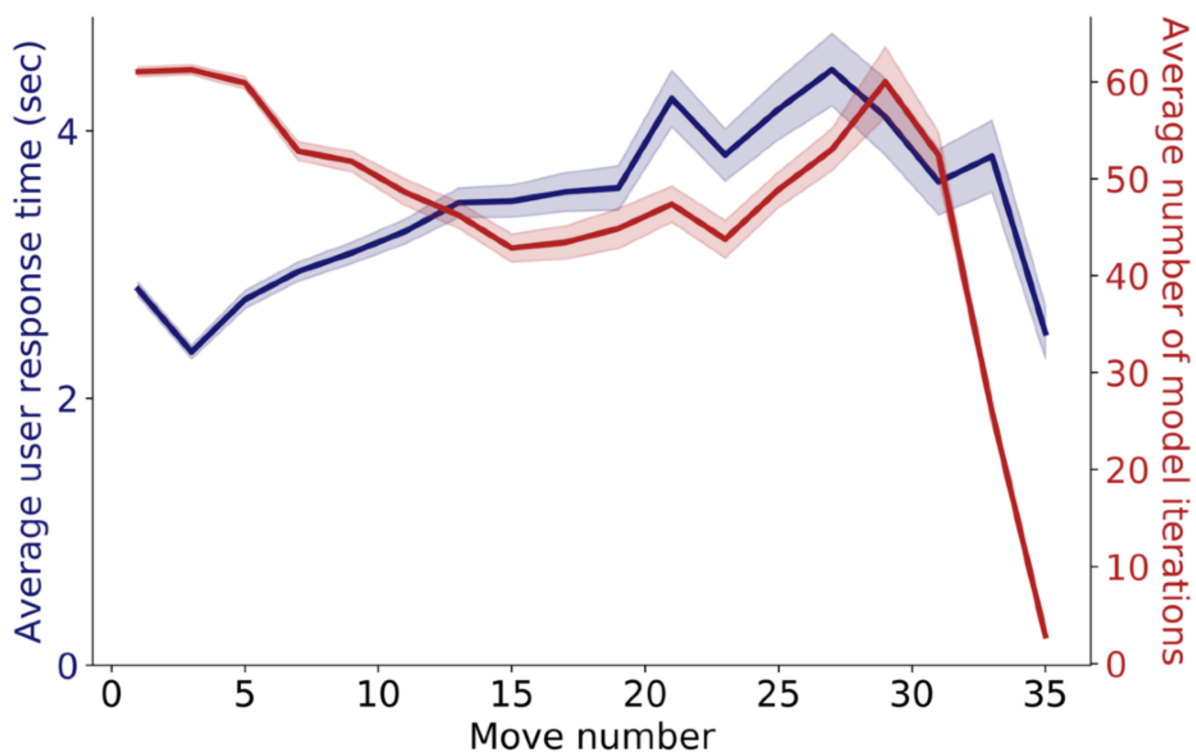


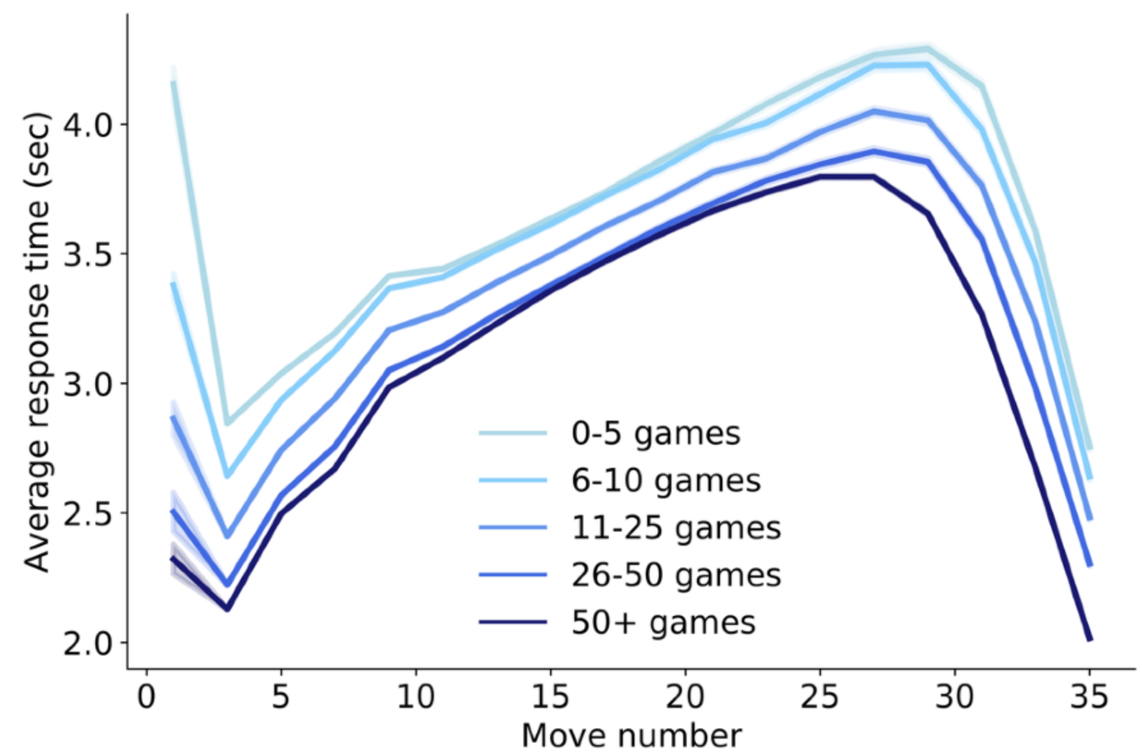
RESPONSE TIME PREDICTIONS

Prediction: when the model builds a **larger tree**, people's **response times increase**



RESPONSE TIME PREDICTIONS



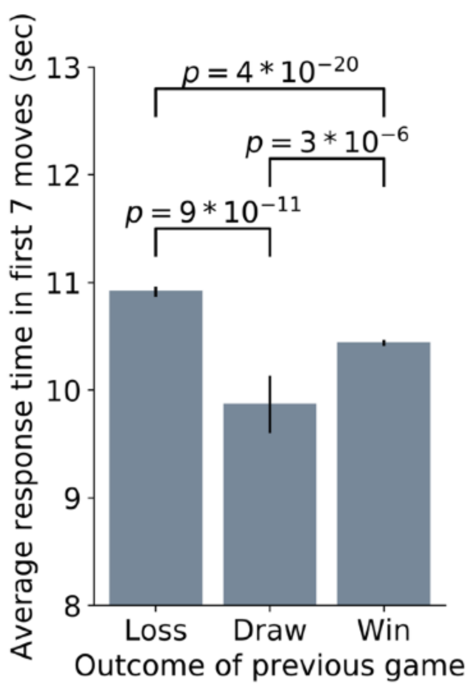


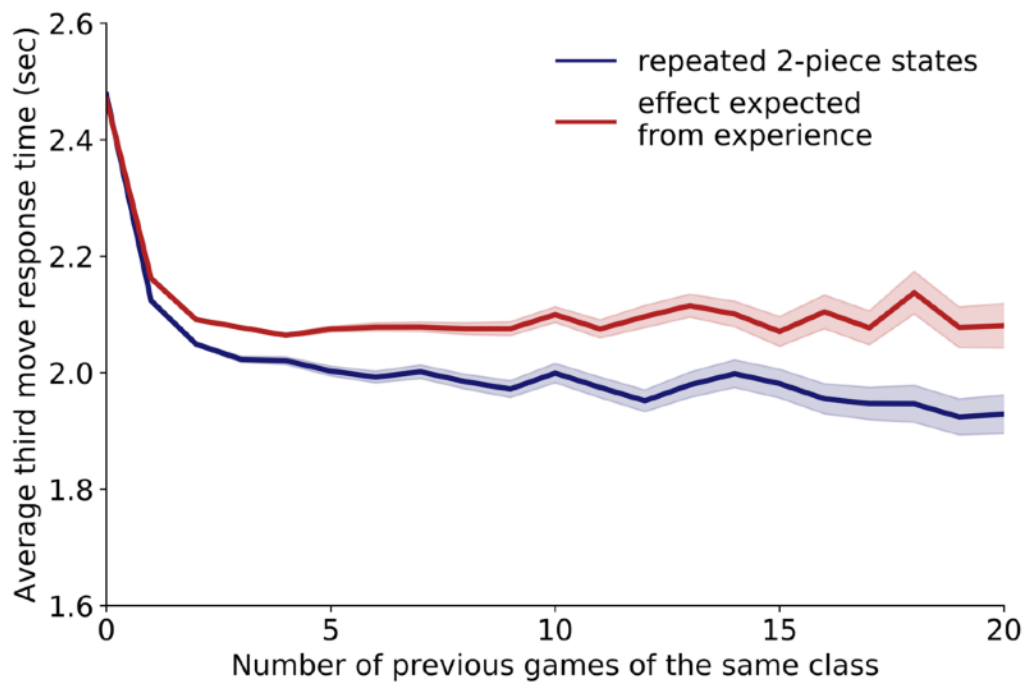
Model fails to predict human response times trends at the individual move level irrespective of experience level

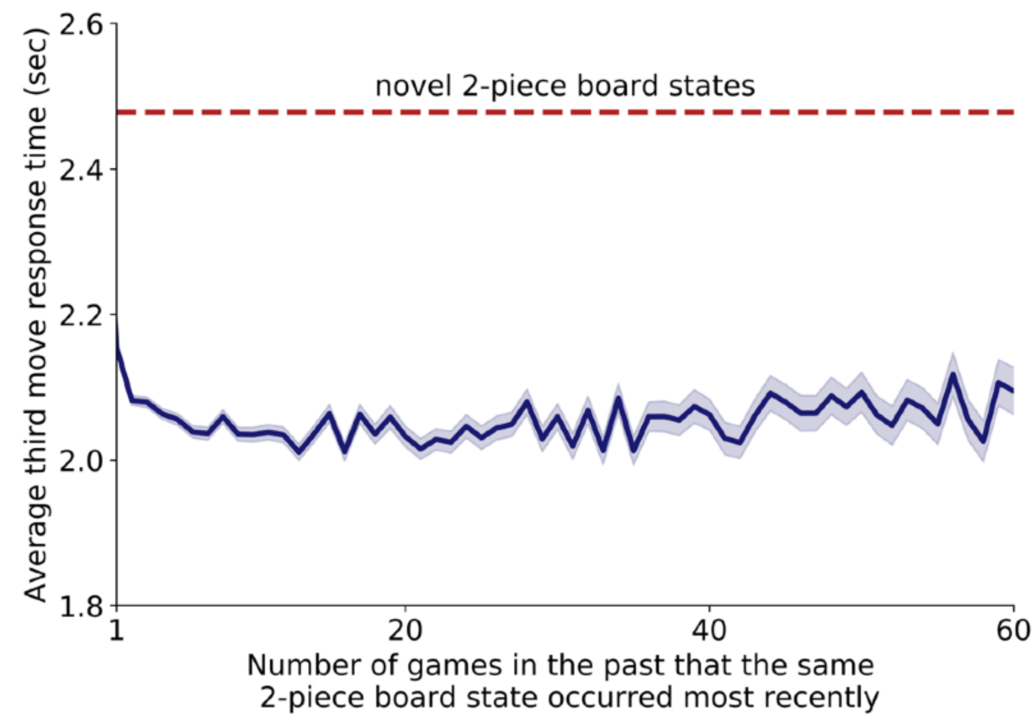
Possible explanation: **model-free RL or retrospective decision-making**

MODEL-FREE RESPONSE TIMES

RL prediction #1: response times increase after a loss





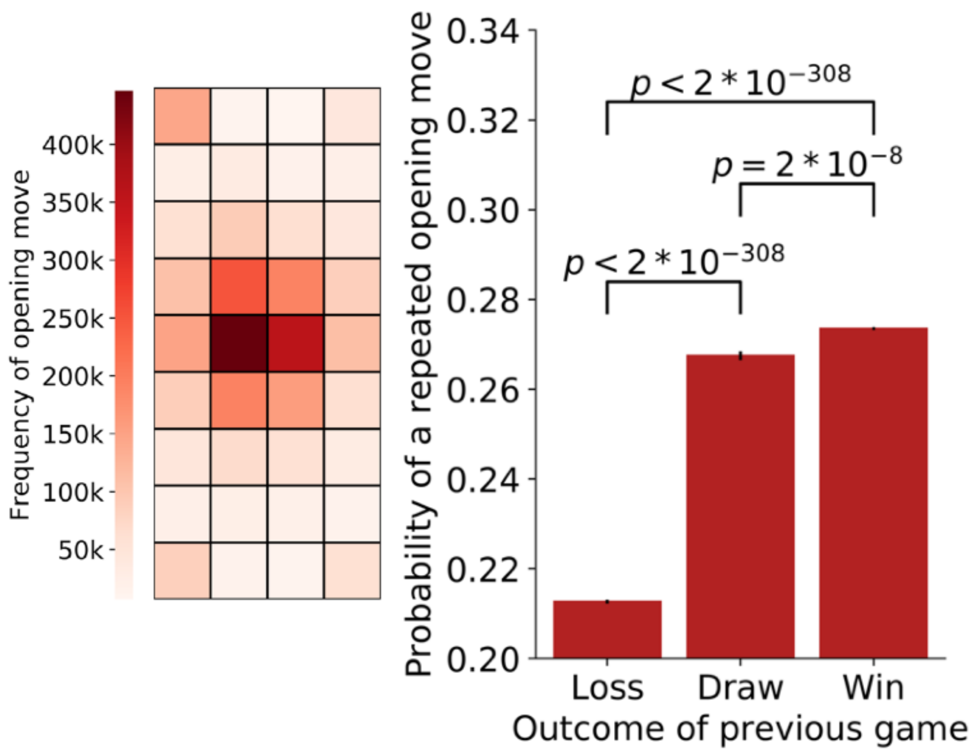


Control for experience

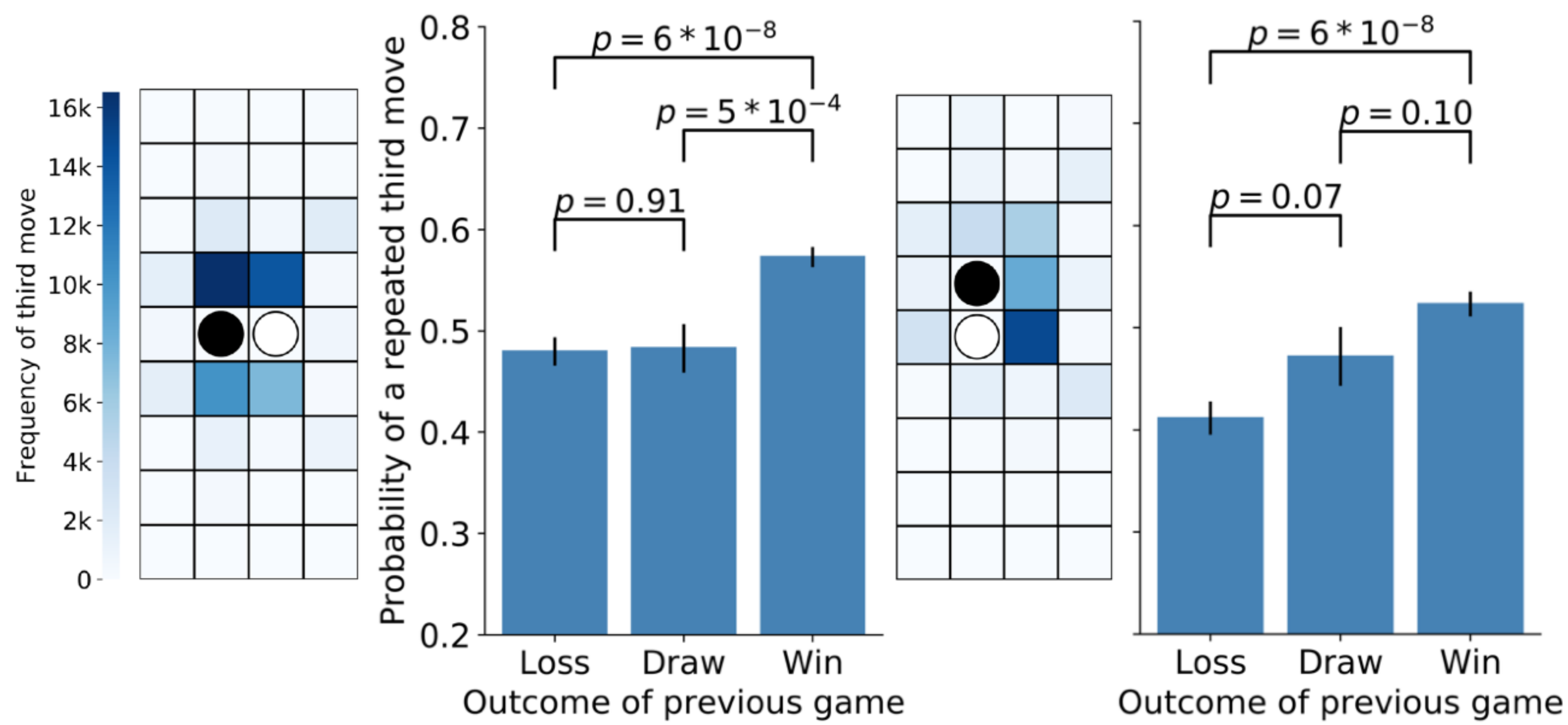
Control for memory

MODEL-FREE ACTION SELECTION

RL prediction #2: win-stay-lose-shift in early game positions



Opening move



3rd move

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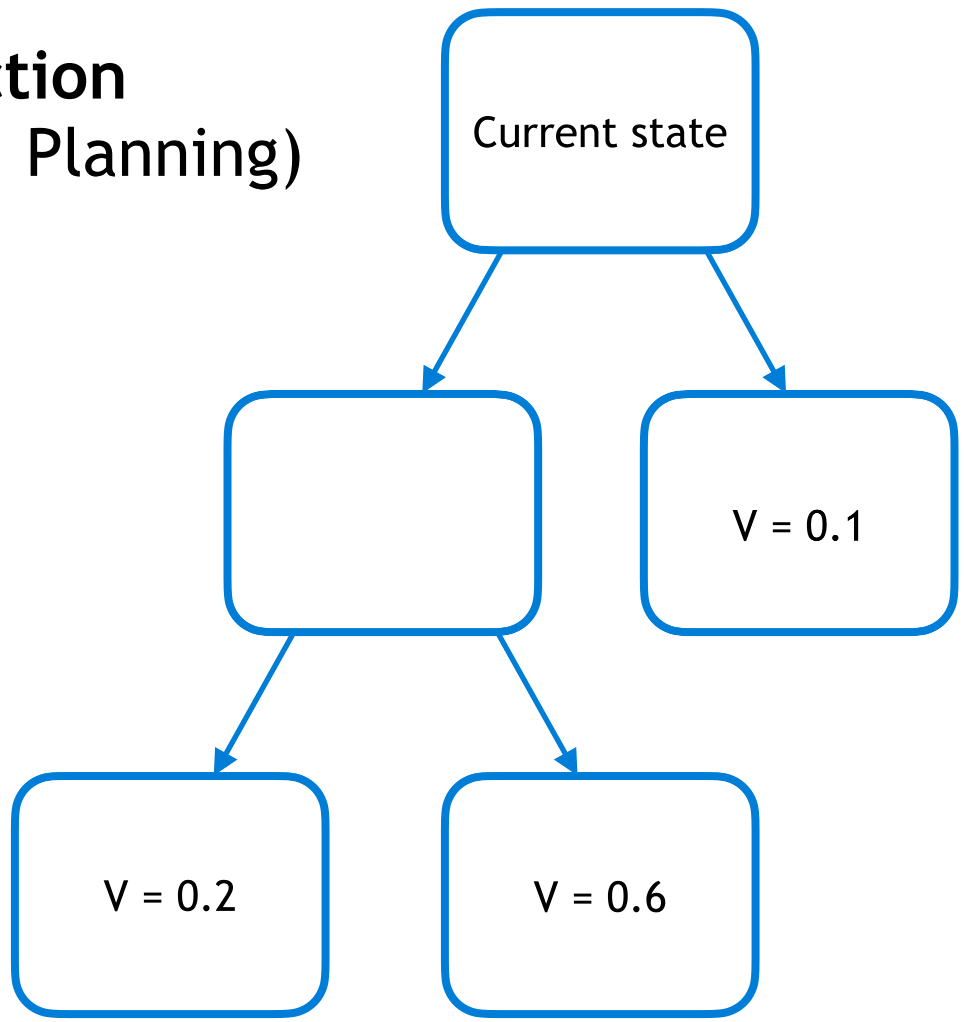
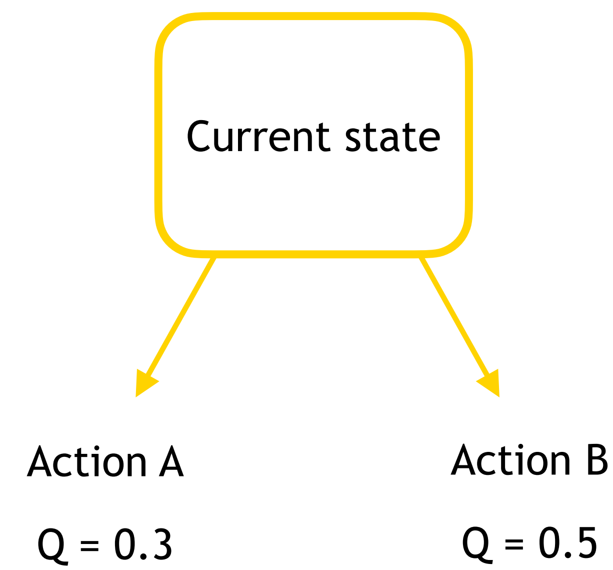
DUAL SYSTEMS FOR SEQUENTIAL DECISION-MAKING

Prospection
(Model-Based, Planning)



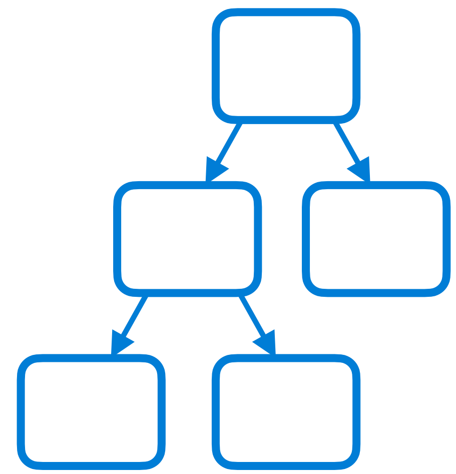
Retrospection
(Model-Free, Habitual)



What algorithms do humans use to **integrate prospective and retrospective decision-making** in a more complex task?

MIXTURE MODEL: THEORY SKETCH

Goal: compute a measure of uncertainty for both systems over p_{win}, and run the one with lower uncertainty



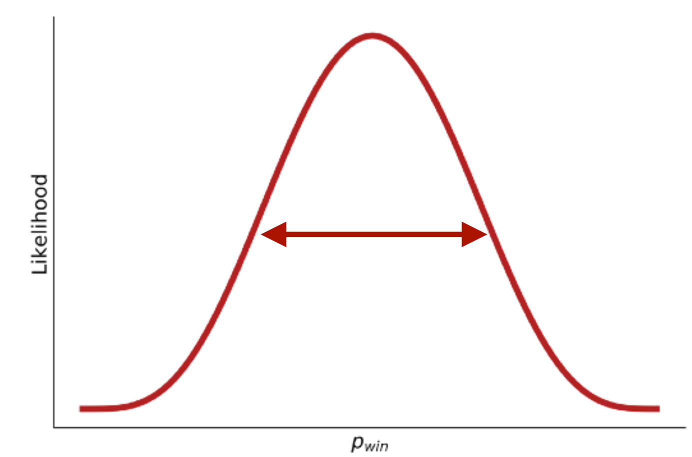
Planning model

Q-learning

How do we calculate uncertainty?

Generative model $P(n_{wins} | n_{past}, p_{win}) \sim Binomial$

Inference $P(p_{win} | n_{win}, n_{past}) \sim Beta$



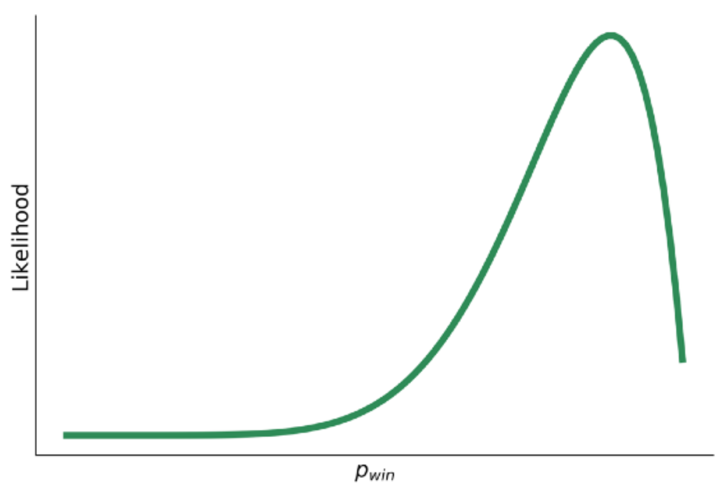
Typically, uncertainty is the **variance** of the best action's posterior distribution
However, we care about **comparing with alternative actions**

MIXTURE MODEL: THEORY SKETCH

Toy example for **expected regret** using Q-learning and two possible actions

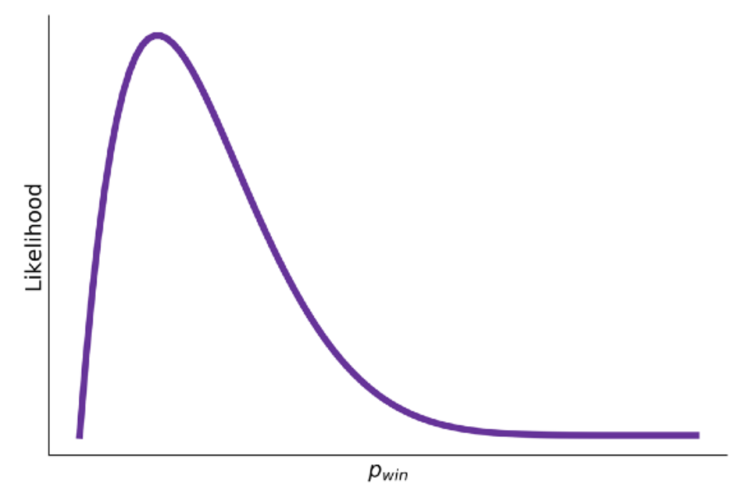
Posterior for the **chosen action**

$$n_{wins} = 7$$
$$n_{past} = 8$$



Posterior for the **alternative action**

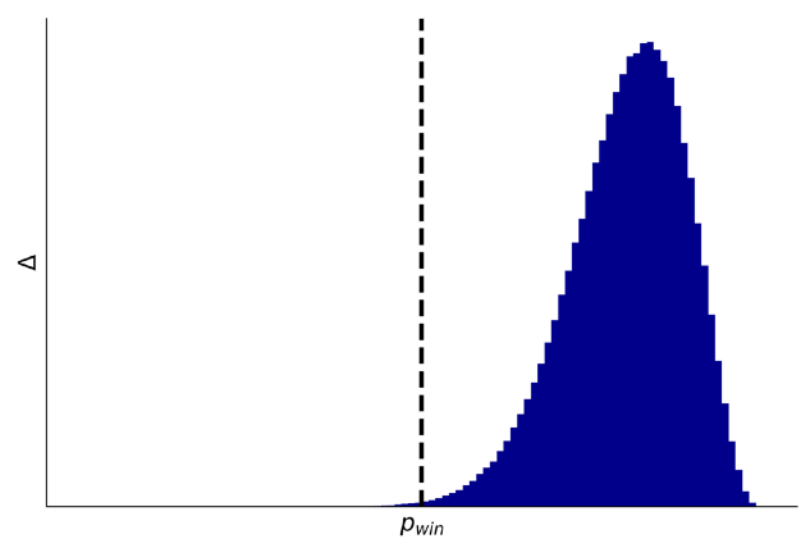
$$n_{wins} = 1$$
$$n_{past} = 8$$



Difference distribution obtained via sampling

$$\Delta = p_{chosen} - p_{alternative}$$

$$Expected\ regret = \int_{-\infty}^{0} \Delta f(\Delta) d\Delta$$



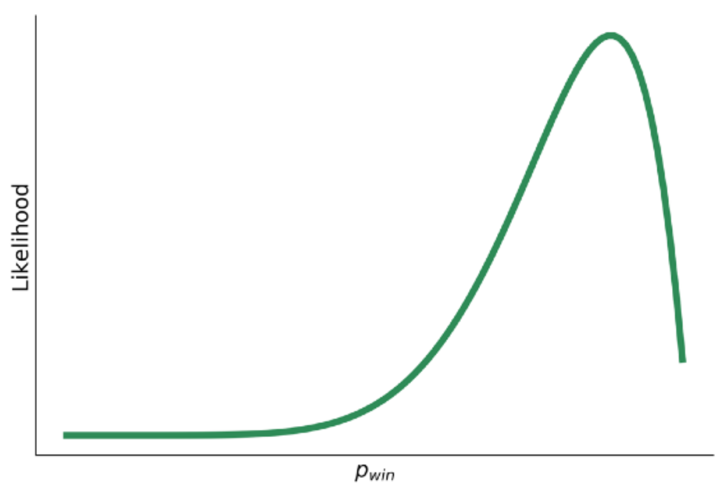
Low expected regret

MIXTURE MODEL: THEORY SKETCH

Toy example for **expected regret** using Q-learning and two possible actions

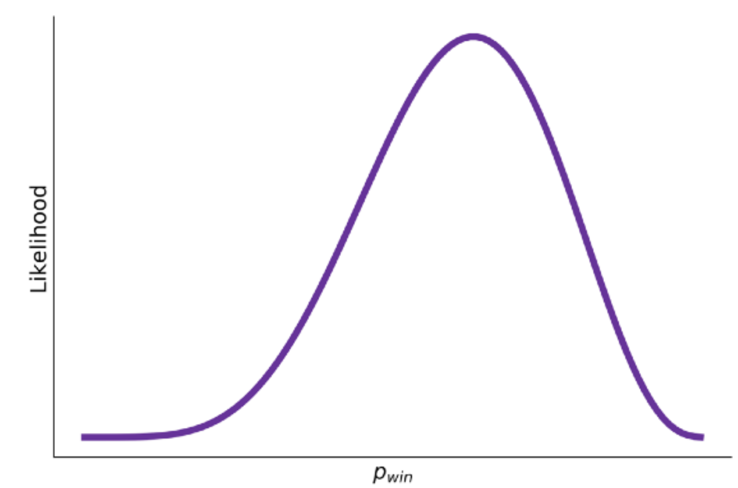
Posterior for the **chosen action**

$n_{wins} = 7$
$n_{past} = 8$



Posterior for the **alternative action**

$n_{wins} = 5$
$n_{past} = 8$



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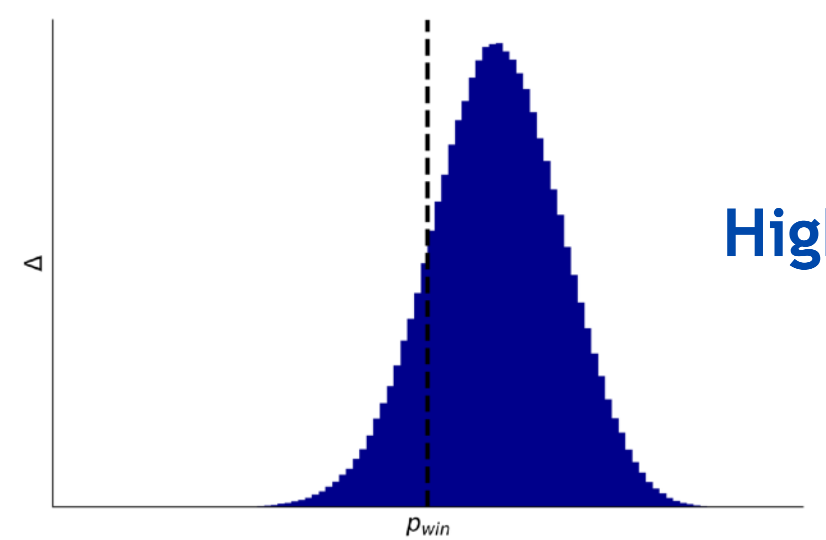
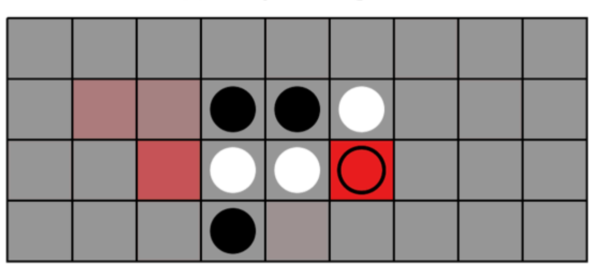


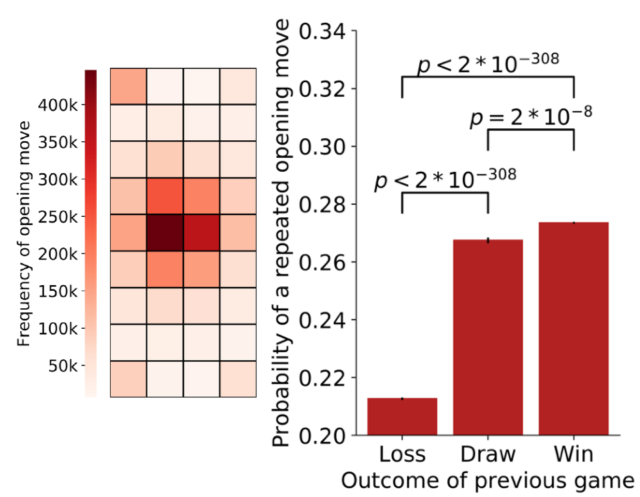
Higher expected regret

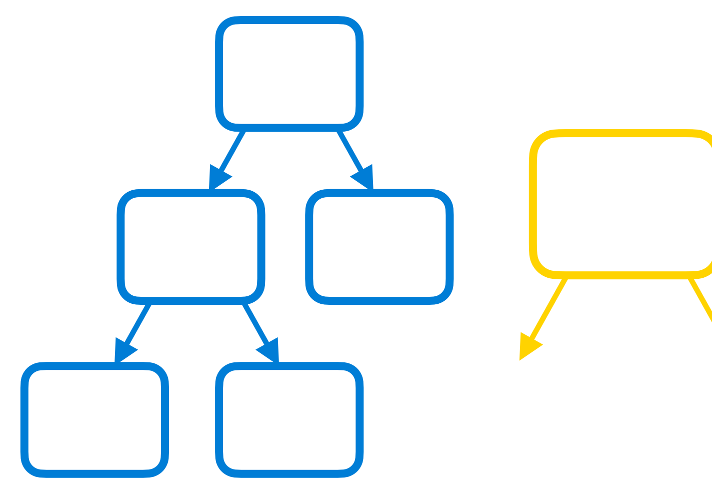
SUMMARY

Computational modeling of human decision-making in complex planning tasks is tractable

- Built a computational model inspired by concepts in classical artificial intelligence
- Fit the planning model to human play, providing evidence for decision tree search
- Found signatures of model-free decision-making early in gameplay using a large data set
- Started investigating the integration of model-based and model-free algorithms





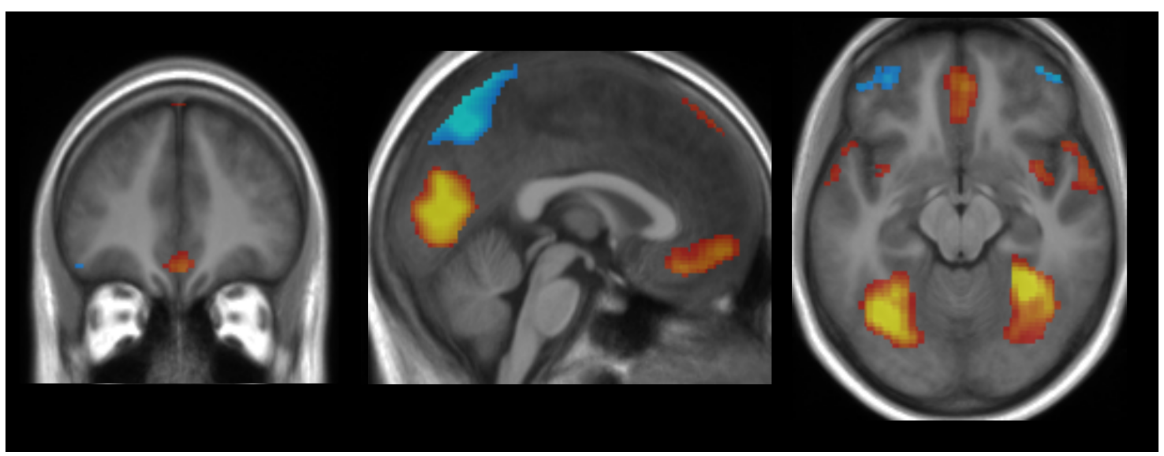


NEURAL BASIS OF COMPLEX PLANNING

Humans

Nathaniel Daw

Marcelo Mattar



n=35

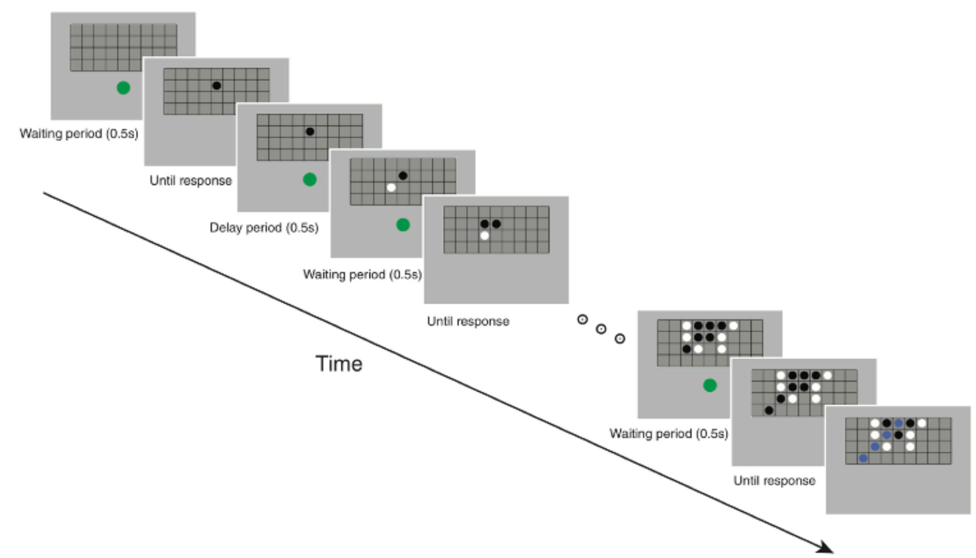
Are there fMRI signatures of board states and values in human players?

Non-human primates

Daeyeol Lee

Neural correlates of strategic reasoning during competitive games

Hyojung Seo,[1*] Xinying Cai,[1†] Christopher H. Donahue,[1‡] Daeyeol Lee[1,2,3*]



Can non-human primates learn complex planning tasks? If so, what neural substrates support planning versus other forms of decision-making?

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