IMPROVING A MODEL OF HUMAN PLANNING VIA LARGE-SCALE DATA AND DEEP NEURAL NETWORKS

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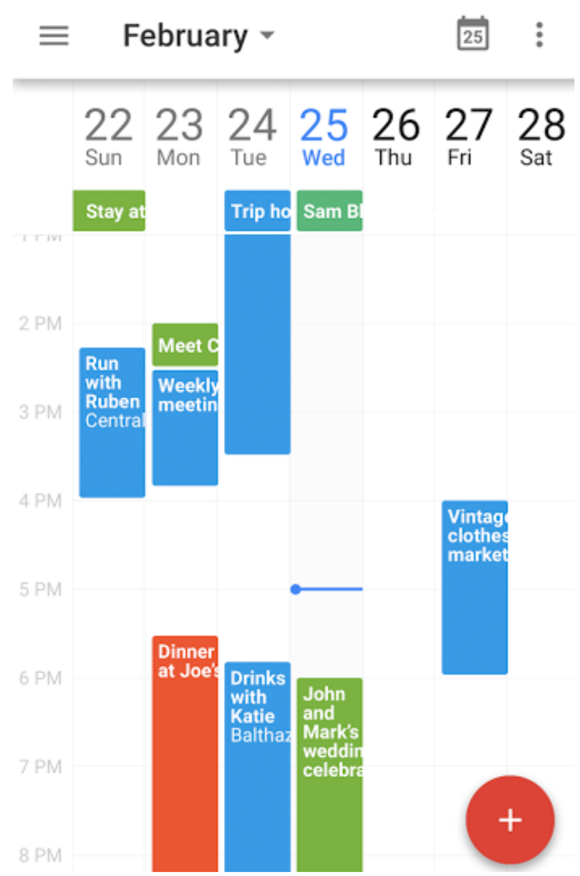
How do people think ahead?

Planning: mental simulation of possible futures

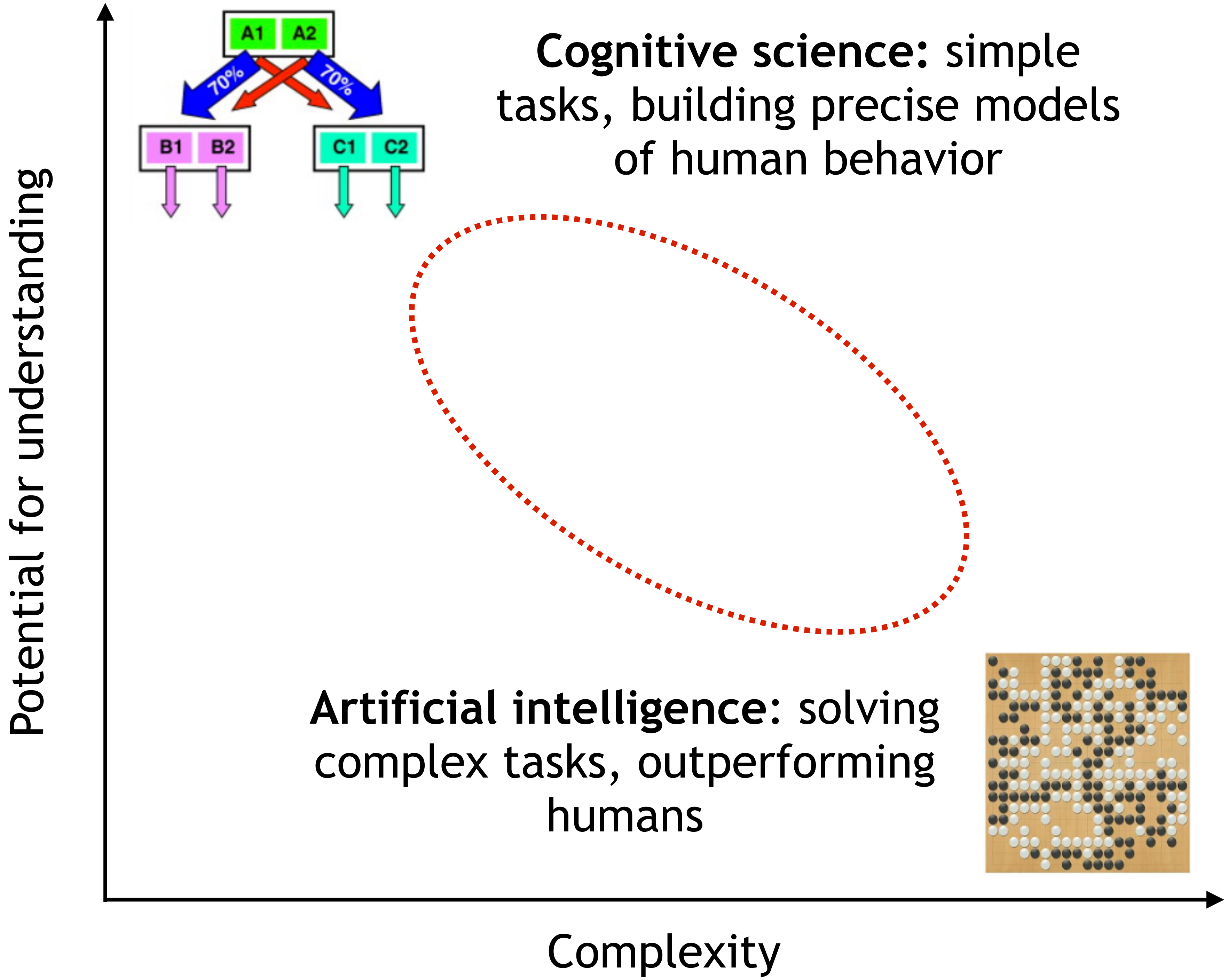
Foraging



Organizational strategy

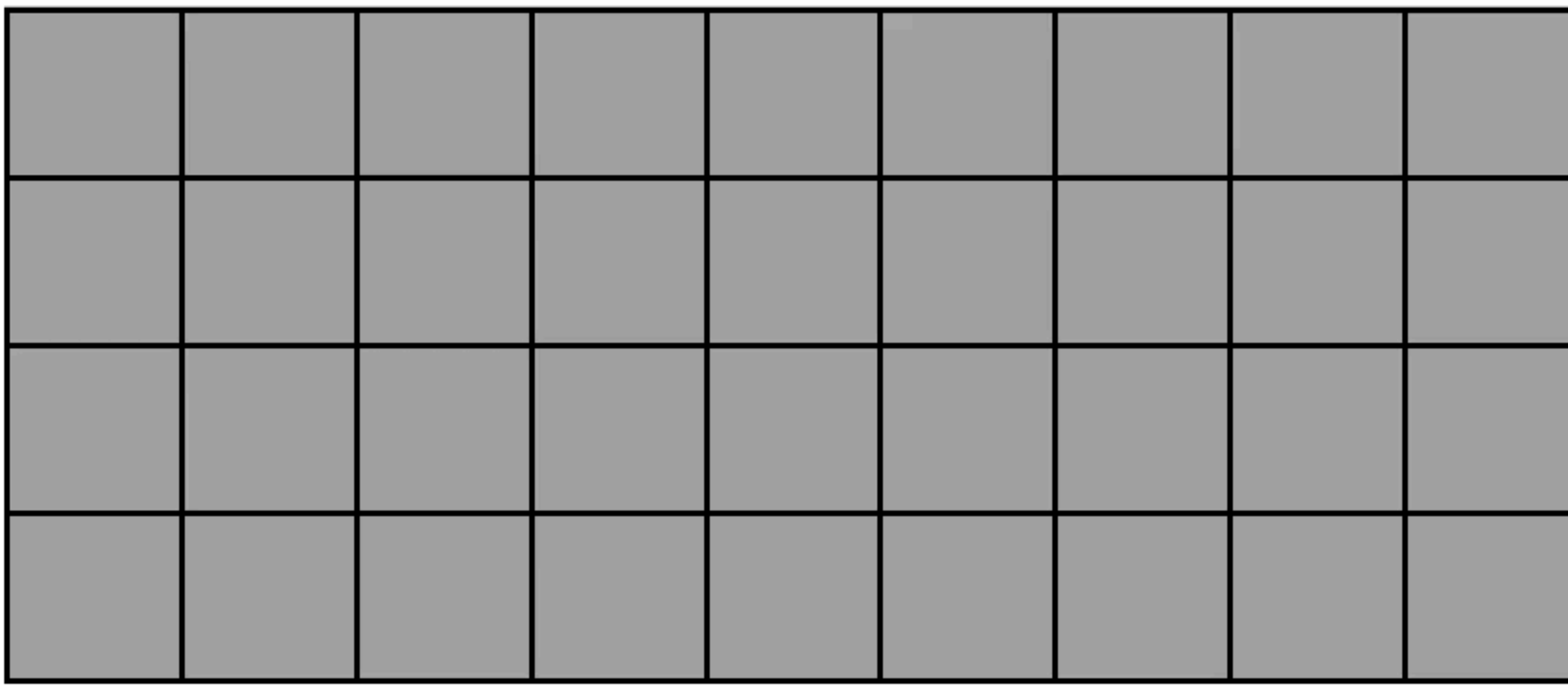
Spatial navigation

SPACE OF PLANNING TASKS



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

THE STANDARD APPROACH TO COMPUTATIONAL MODELING

Handcraft a model and specify free parameters $\xrightarrow{\text{Model fitting}}$ Evaluate the model by comparing it to data

A MODEL OF HUMAN PLANNING

Heuristic value function + decision tree search

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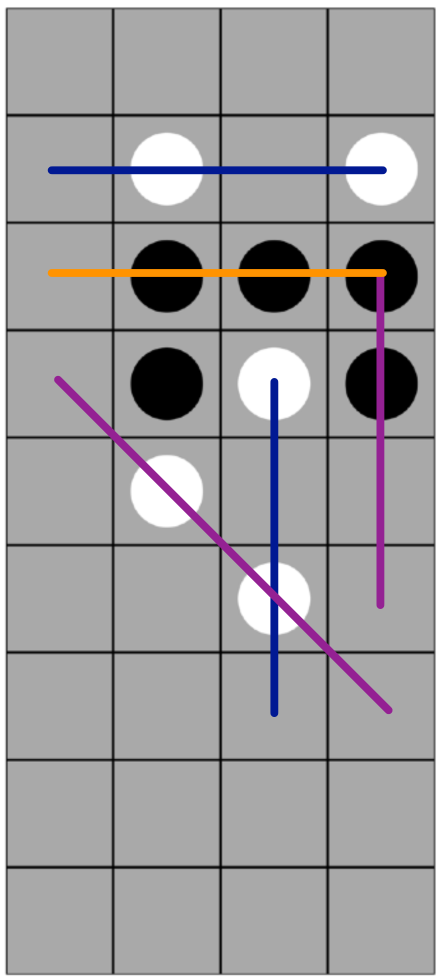
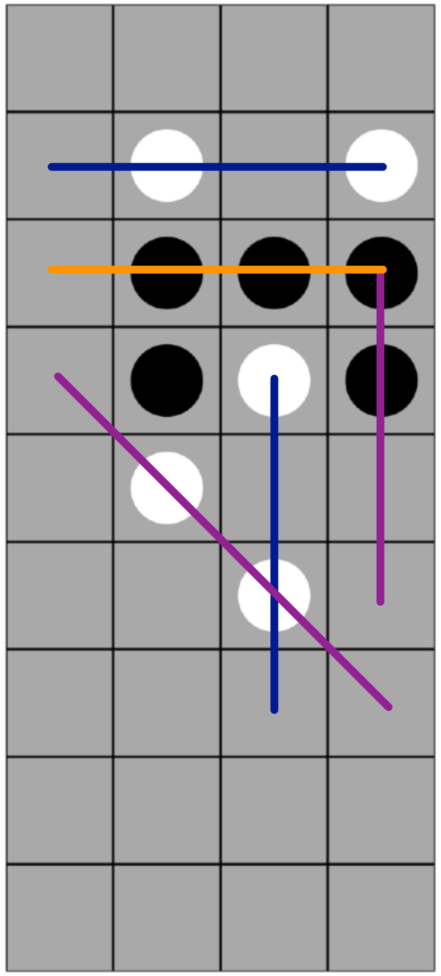
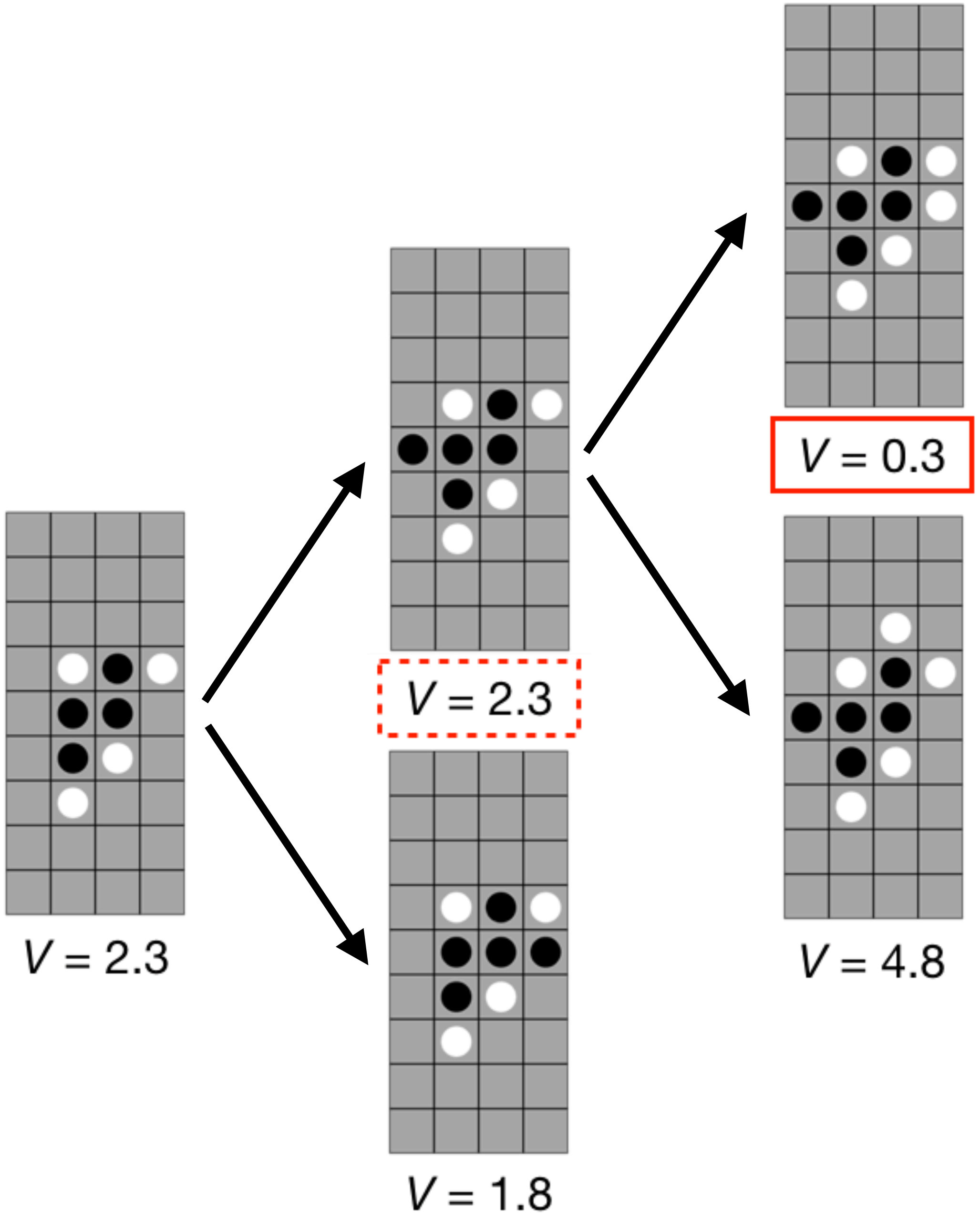


A MODEL OF HUMAN PLANNING

Heuristic value function + **decision tree search**





THE STANDARD APPROACH TO COMPUTATIONAL MODELING

Model fitting

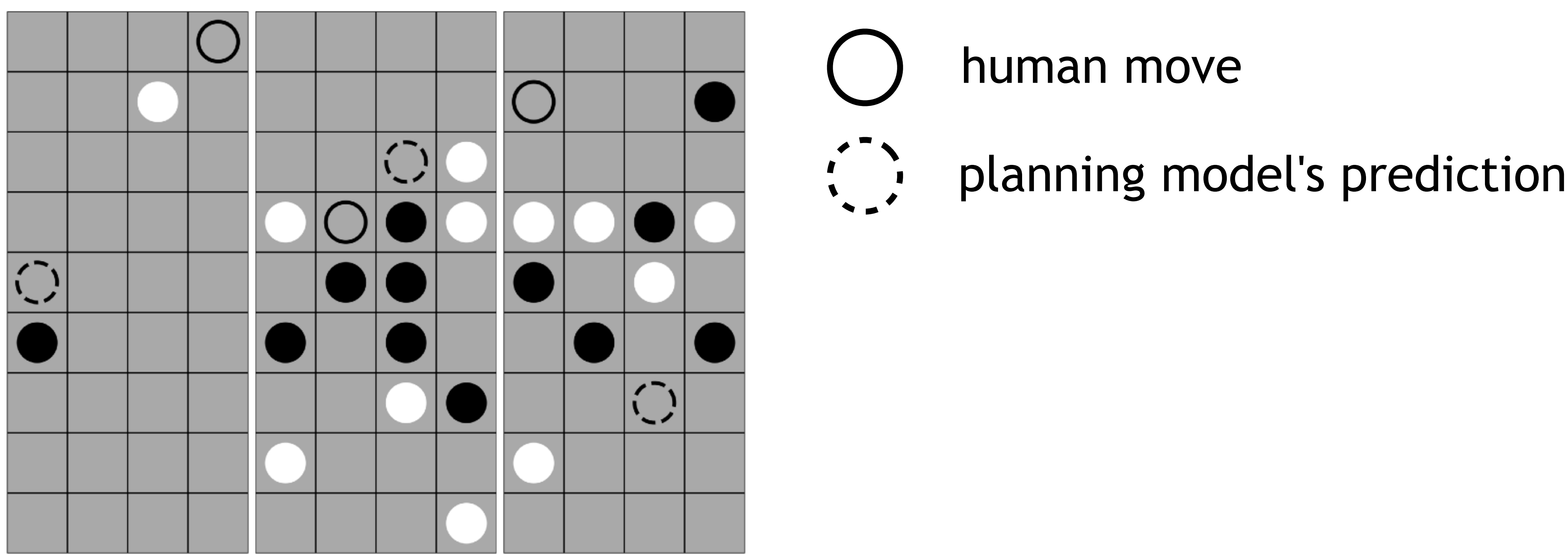
Handcraft a model and specify free parameters

Evaluate the model by comparing it to data

Model improvement

MODEL IMPROVEMENT WITH DATA

One sensible approach is to iteratively amend the model to reduce fitting errors by looking at the largest errors the model makes

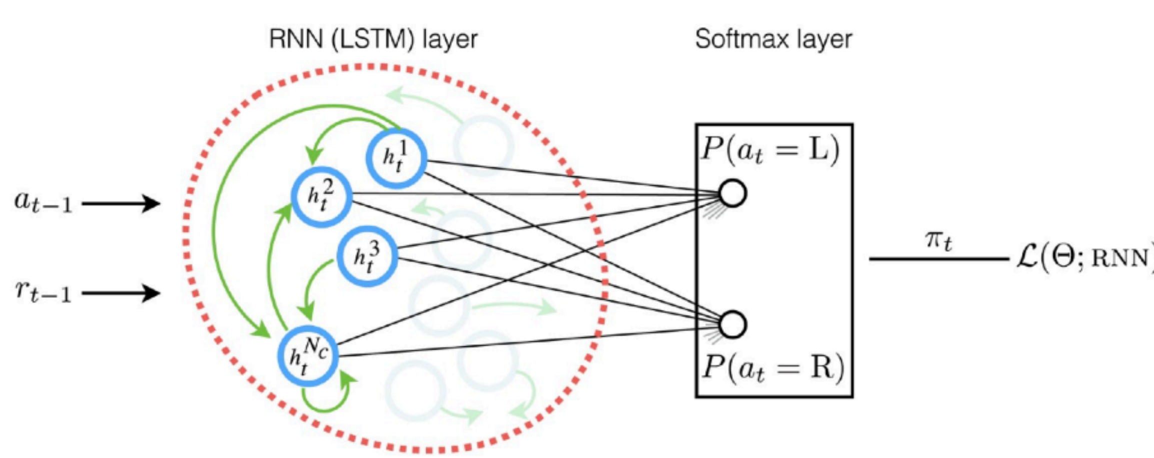


When directly **comparing between a model and data**, we don't know **how much of the *unexplained variance* is *unexplainable***

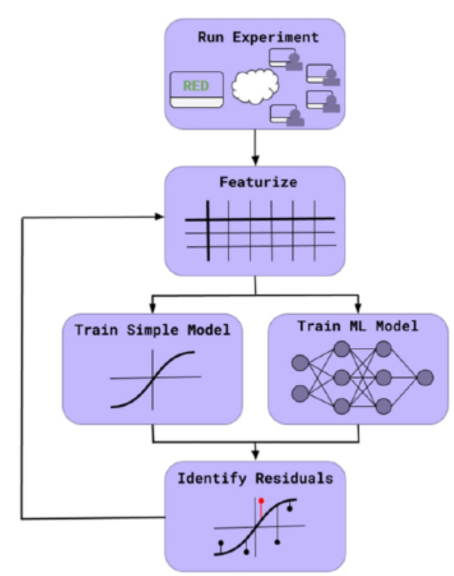
NEURAL NETWORKS AS A BENCHMARK FOR MODELING

A **powerfully predictive model trained to predict human behavior** can be used to establish the absolute goodness of fit of a model

- Deep neural networks make minimal assumptions and have the capacity to represent virtually any computational process
- The network can detect patterns in the data without human understanding
- After training, a model can be compared to the network to judge whether there is still room for model improvement and in which situations to do so
- By pooling information across trials, the network is a less noisy representation of the data



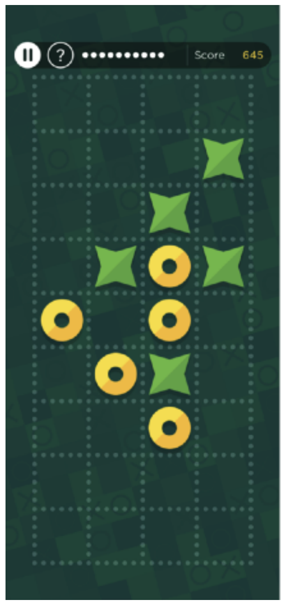
Dezfouli et al., 2019



Agrawal et al., 2020

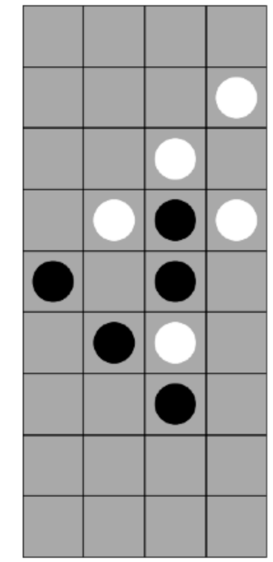
Training deep neural networks requires large-scale data

SCALING UP 4-IN-A-ROW



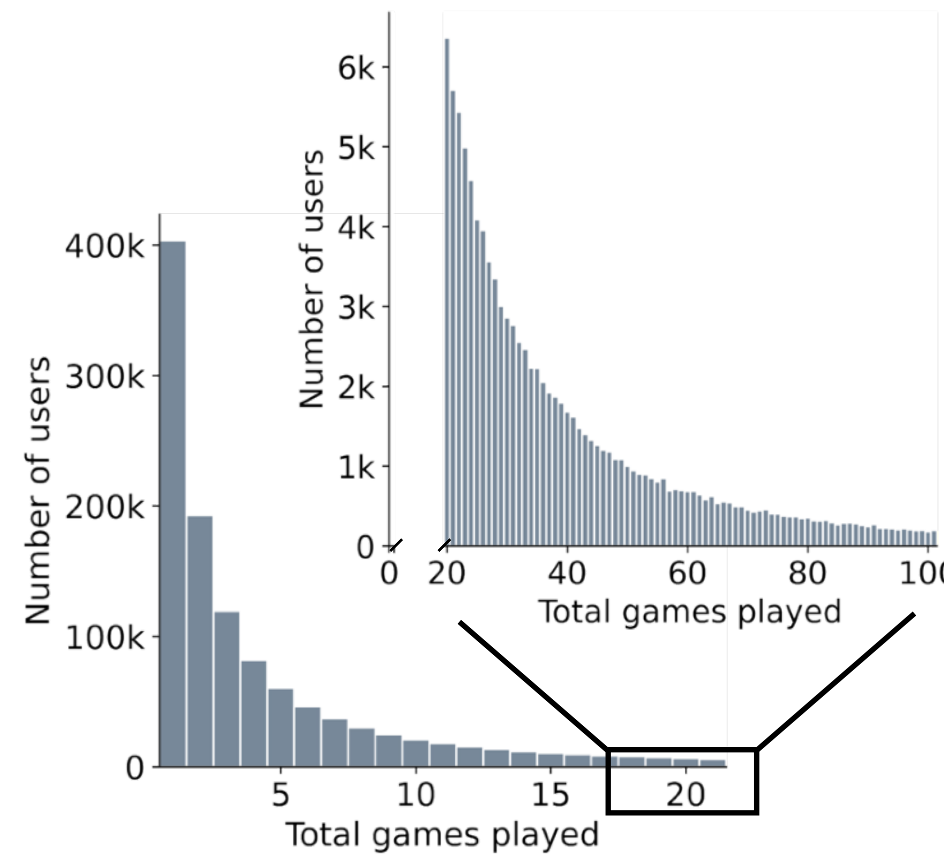
Game development
Anonymized data

Task specification
AI opponents



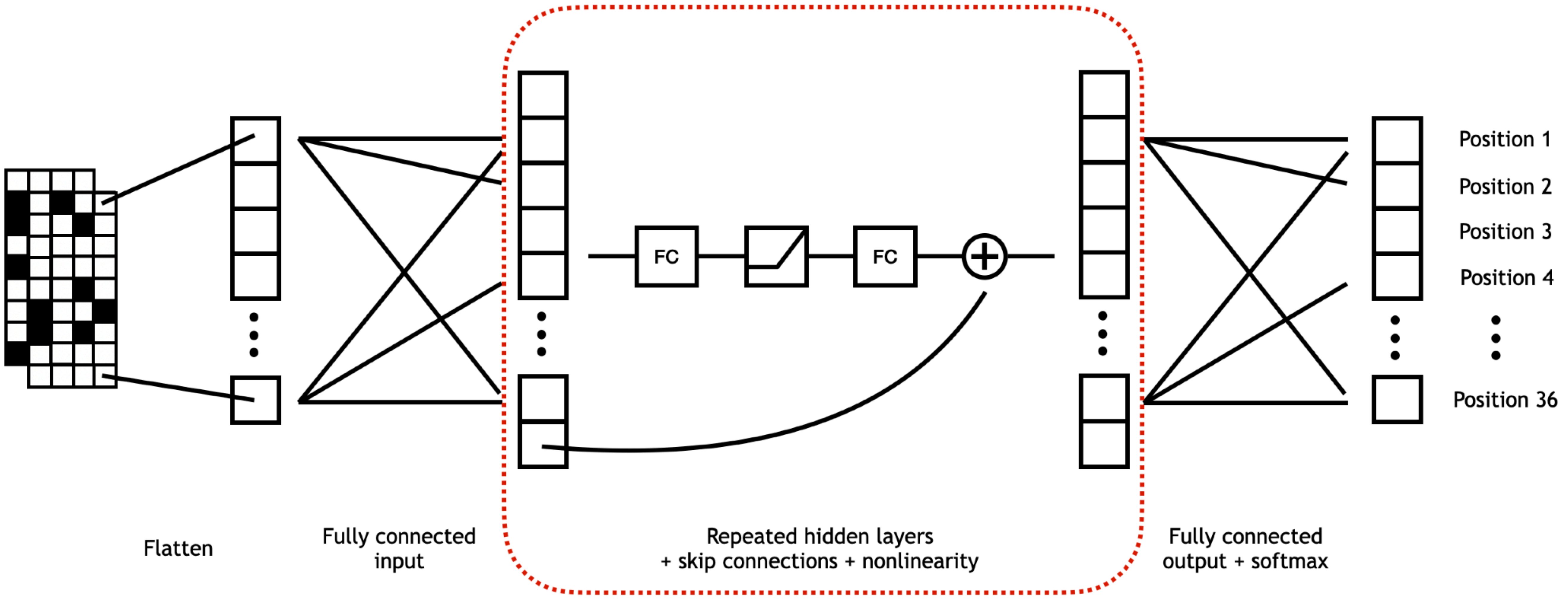
Features of the data set:

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



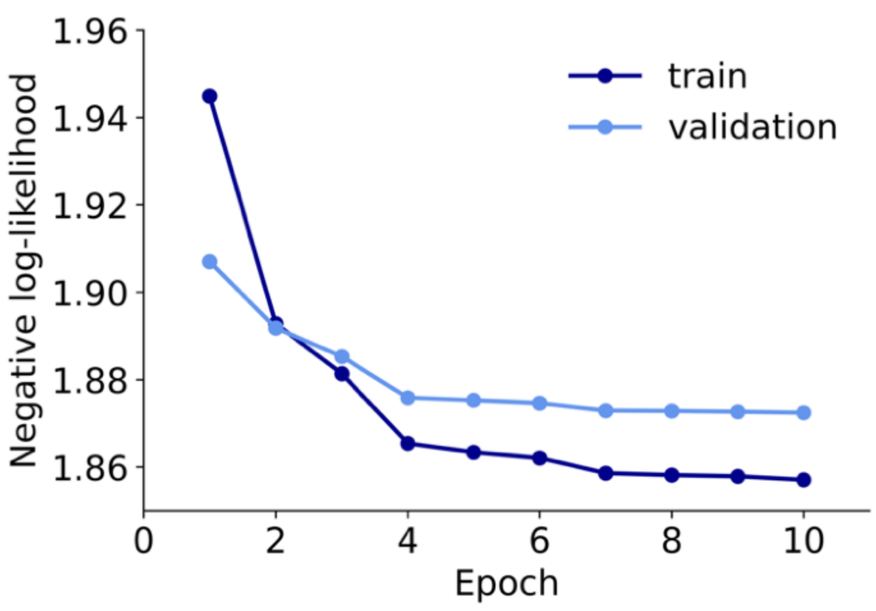
PREDICTING HUMAN PLAY IN 4-IN-A-ROW

What architecture should we use to **estimate a noise ceiling** in 4-in-a-row and **find patterns in the data** that previous models have missed?

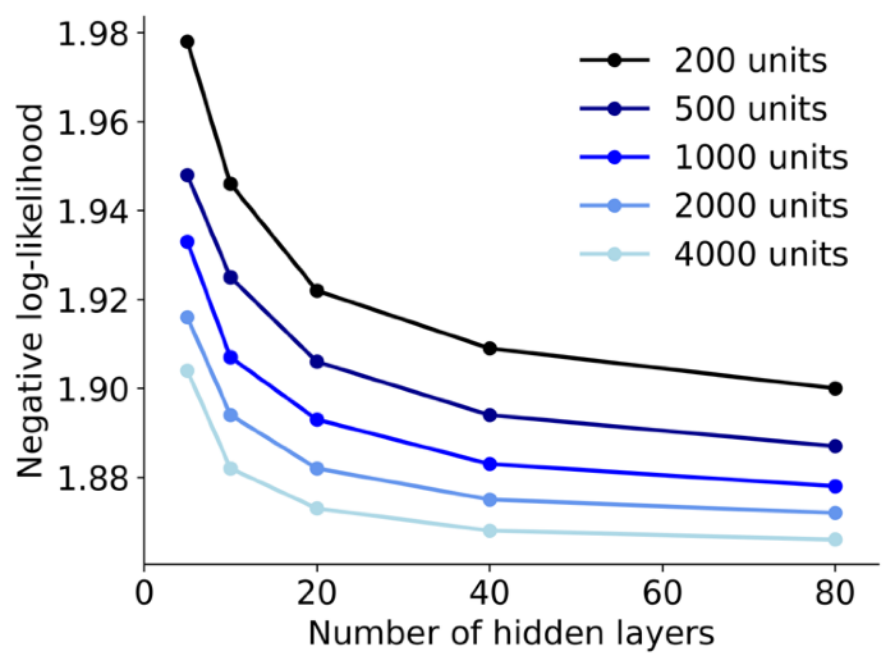


NETWORK TRAINING

- Split into train (90%), validation (5%), and test (5%) sets
- Stochastic gradient descent
- Learning rate annealing and early stopping
- No concerns about overfitting with large-scale data



Learning curve for the best network

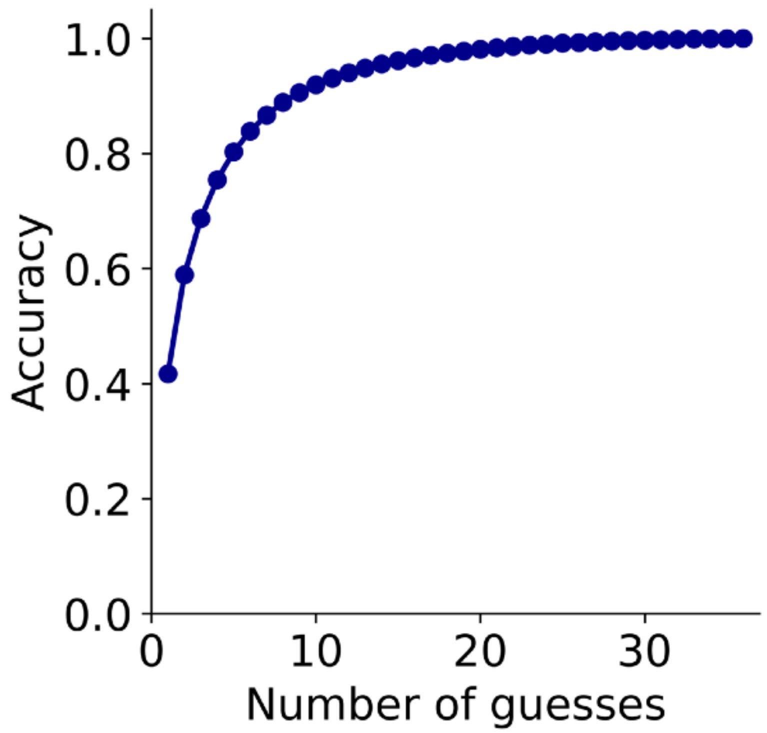


Scaling up the network

NETWORK EVALUATION

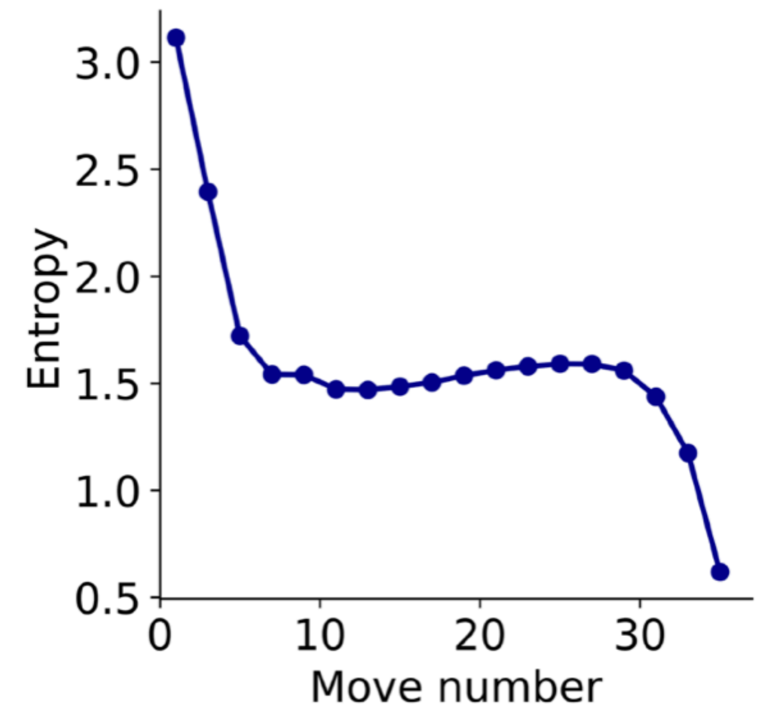
Method #1: accuracy

Is the network able to correctly predict human choices?



Method #2: entropy

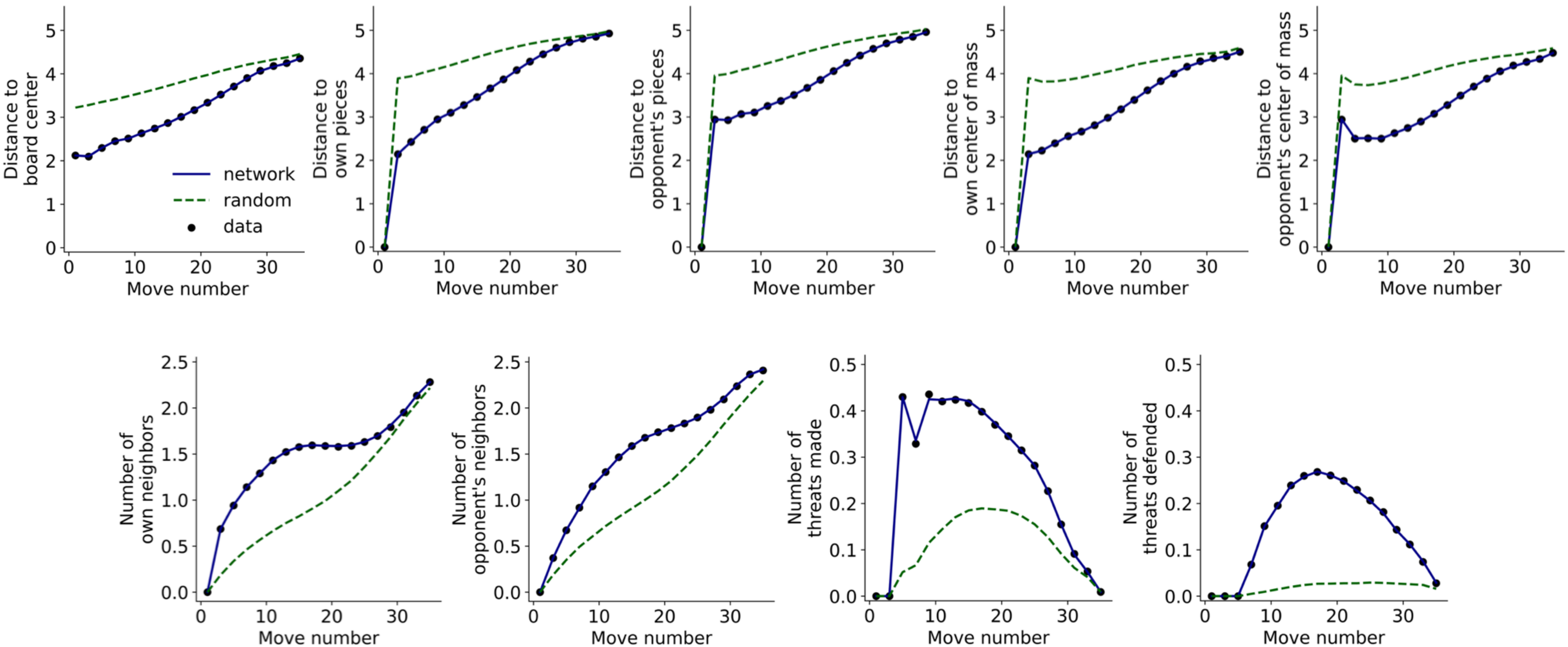
Is the network's confidence in its predictions sensible?



NETWORK EVALUATION

Method #3: summary statistics

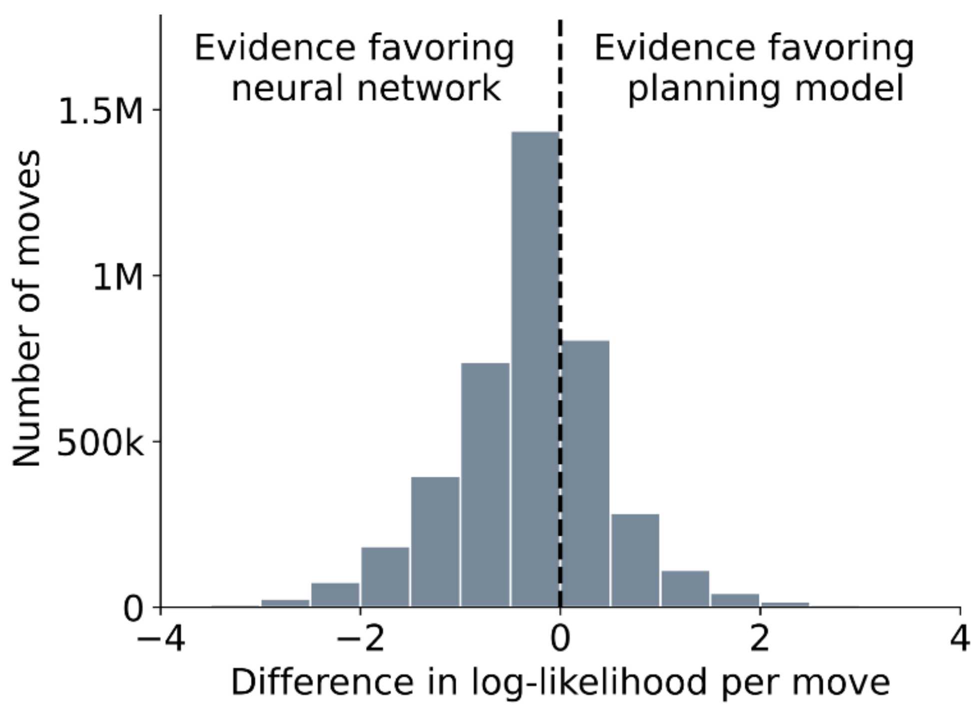
Does the network capture trends in human gameplay?



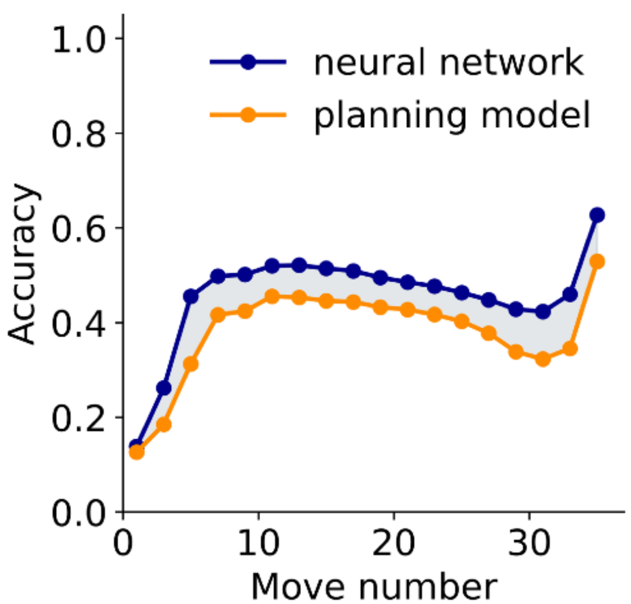
PLANNING MODEL COMPARISON AND IMPROVEMENTS

The **network outperforms the planning model** in predicting human choices

Individual move prediction



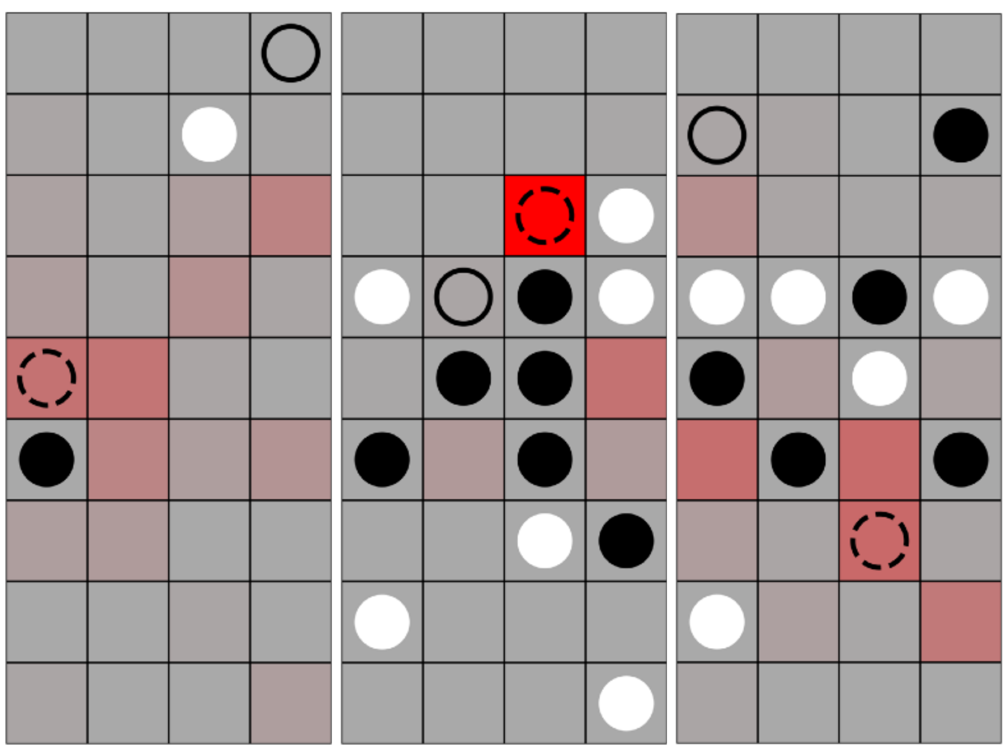
Accuracy across gameplay



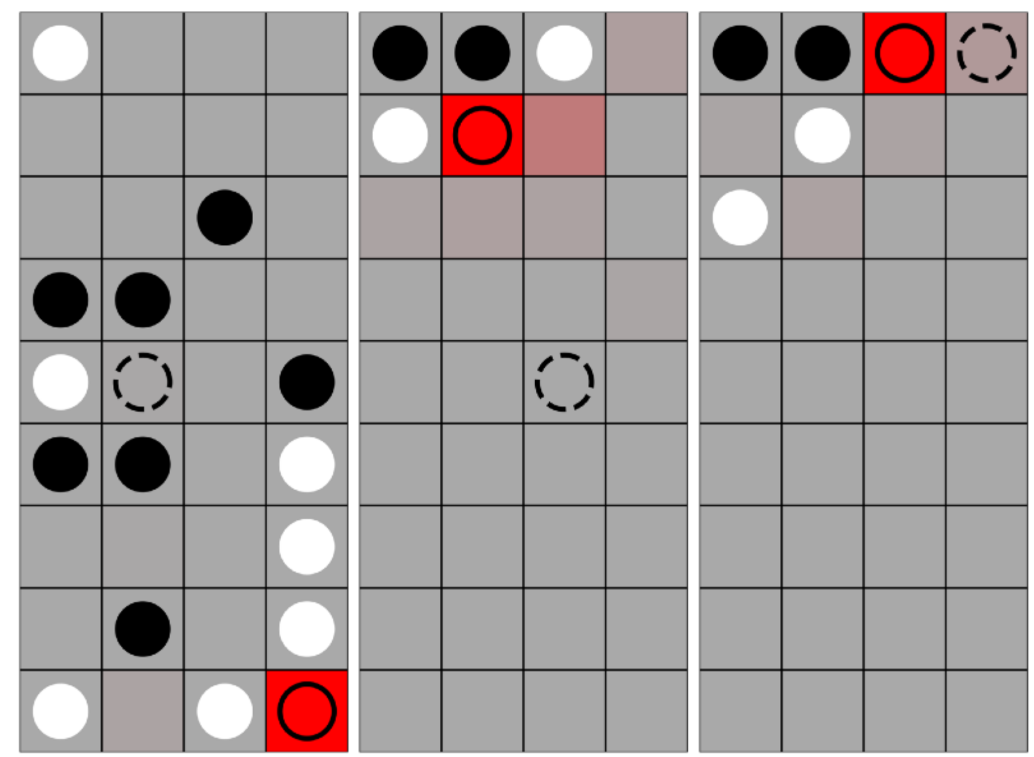
We now have a defined subset of board positions to explore where the network correctly predicts human choices and the planning model does not

PLANNING MODEL COMPARISON AND IMPROVEMENTS

Largest differences between the planning model and the data



Largest differences between the planning model and the network

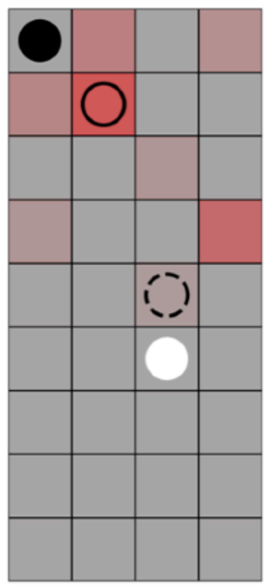


human move

planning model's prediction

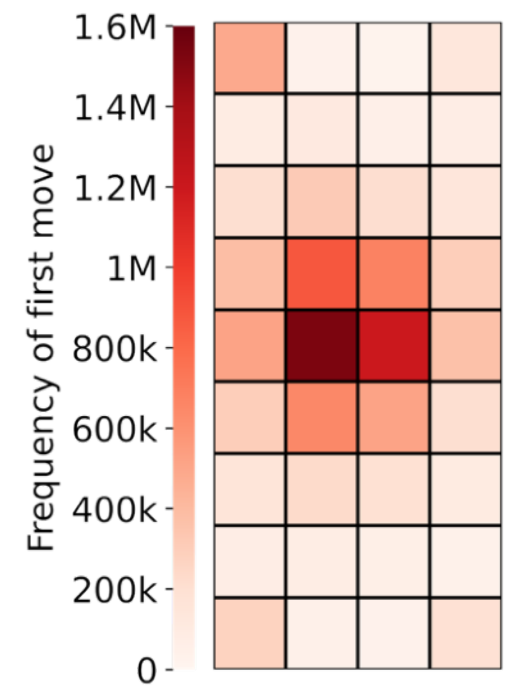
neural network's prediction

A PROOF OF CONCEPT MODEL IMPROVEMENT

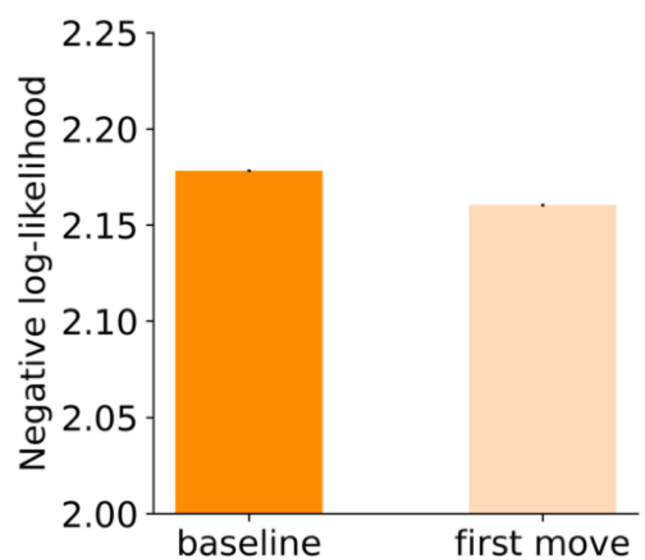


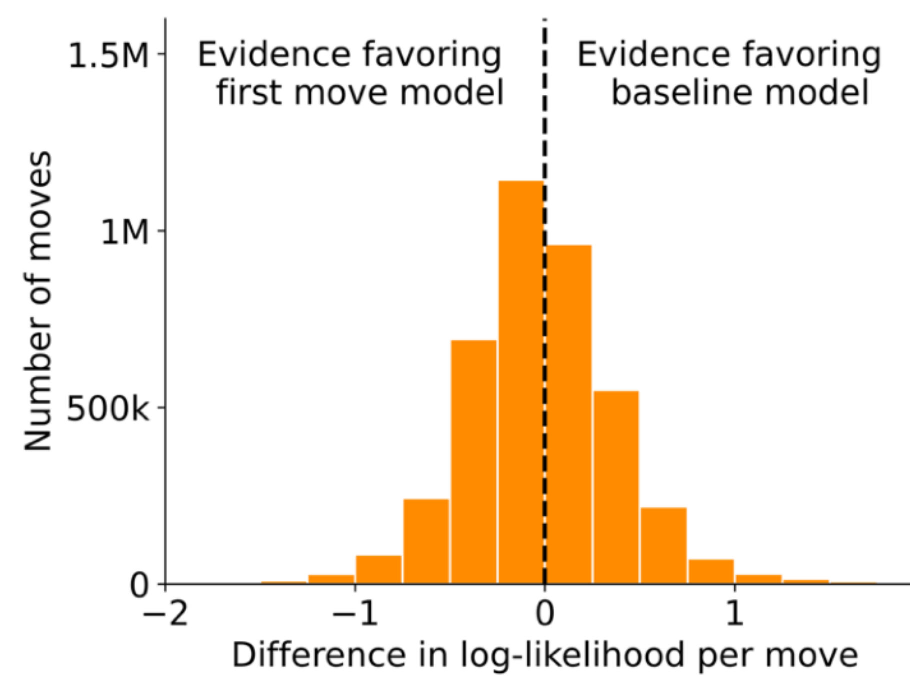
Opening bias

Histogram of first moves



New model parameter: weight of first move histogram





AN IMPROVED APPROACH TO COMPUTATIONAL MODELING

Model fitting

Handcraft a model and specify free parameters

Evaluate the model by comparing it to data

Model improvement
guided by neural networks

SUMMARY

Provided a framework for model improvement that utilizes large-scale data and deep neural networks

- Trained neural networks to predict human moves in a planning task of intermediate complexity
- Ensured that the best network represents a reasonable upper bound on how well any model can explain the data
- Explored positions in which the network is more accurate than a simpler model of human planning, leading to several candidate mechanisms for model improvement

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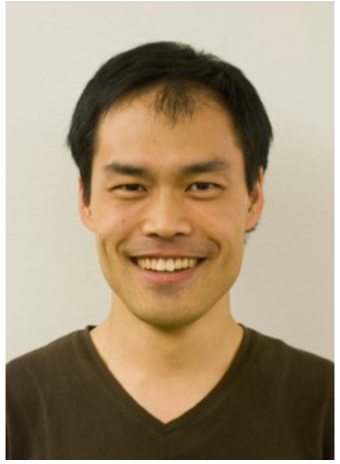


Wei Ji Ma

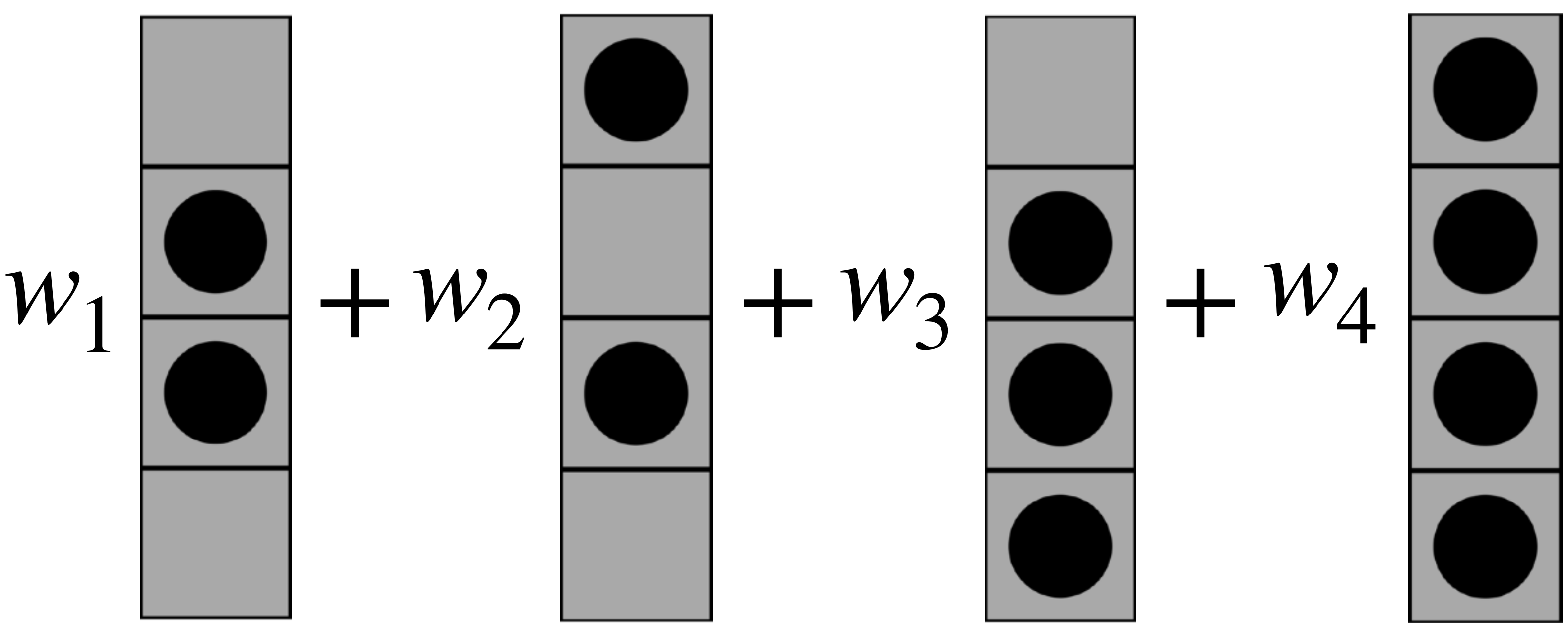
Extra slides

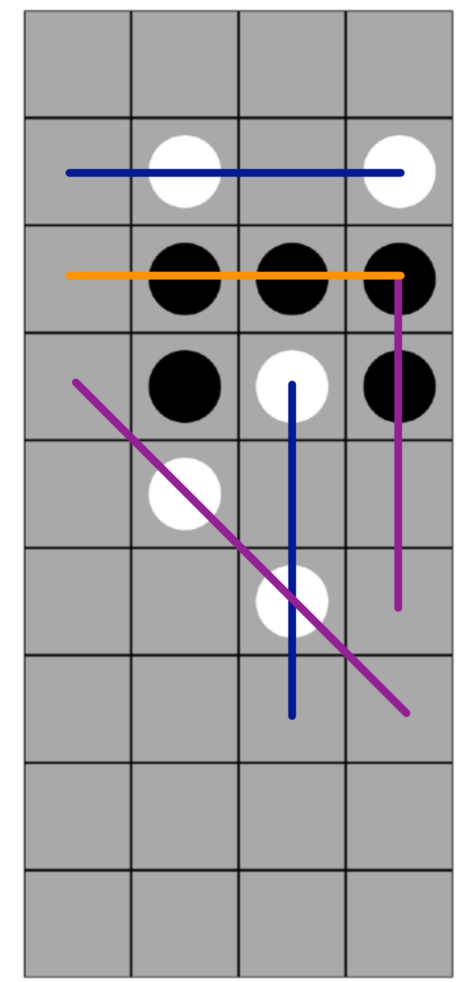
A MODEL OF HUMAN PLANNING

Heuristic value function + decision tree search

Positional features | Learned weights | Scaling constant | Opponent

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

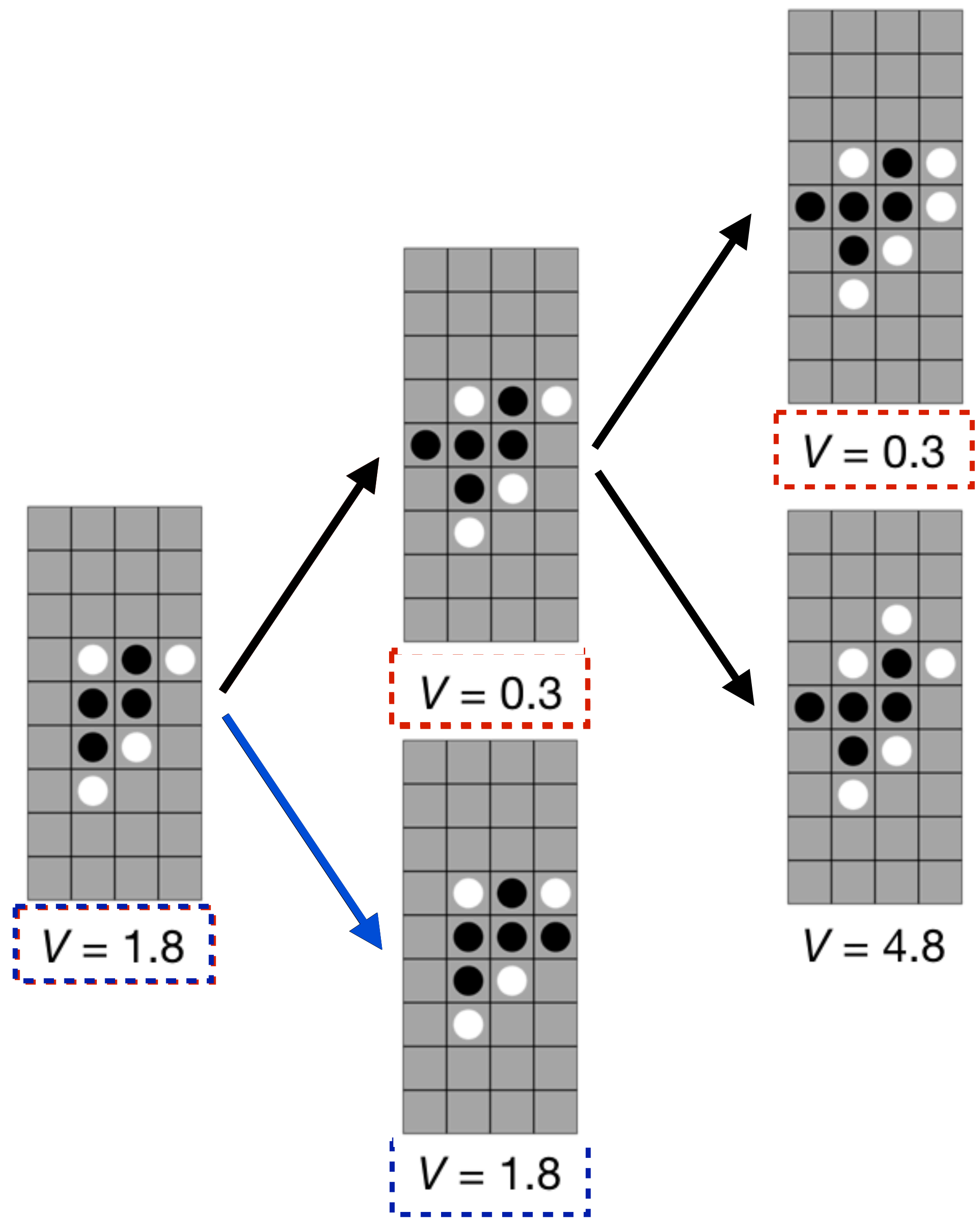




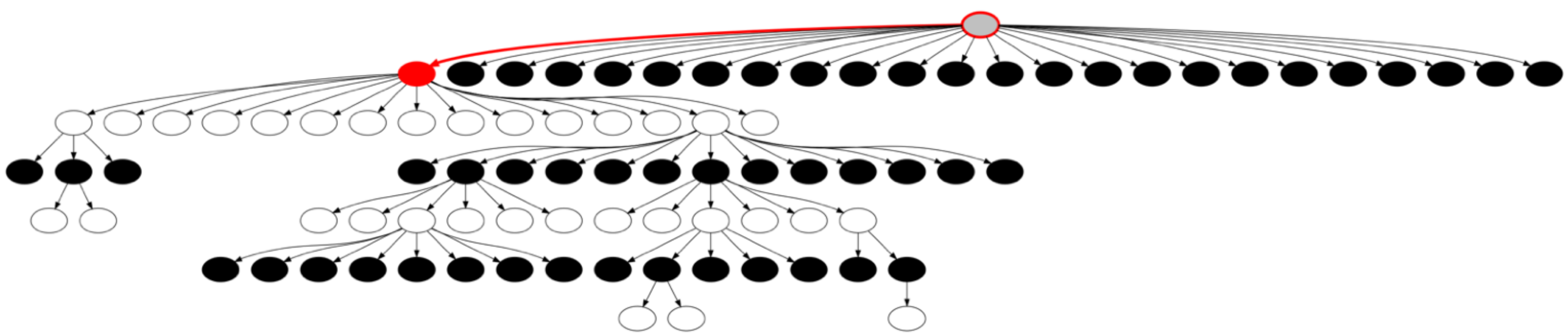
A MODEL OF HUMAN PLANNING

Heuristic value function + **decision tree search**

- Expand
- Evaluate
- Backpropagate
- Select



A SINGLE MODEL SIMULATION



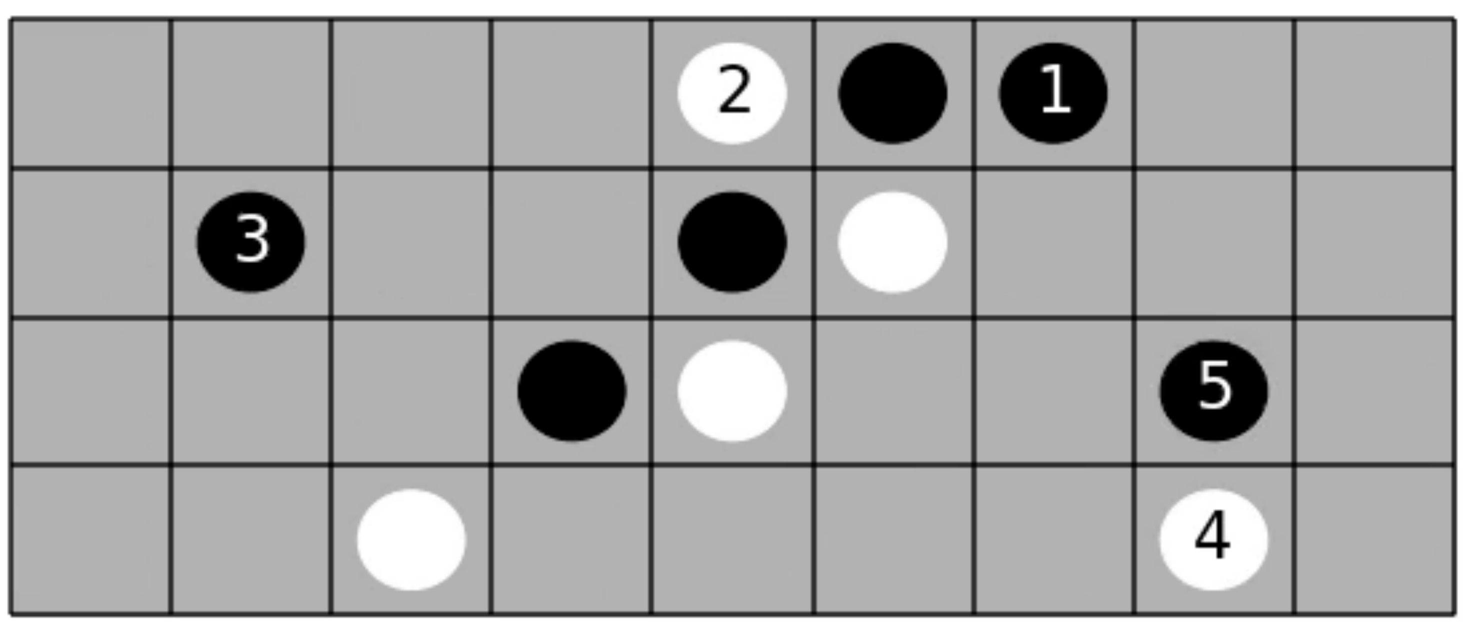
Principal variation 1

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

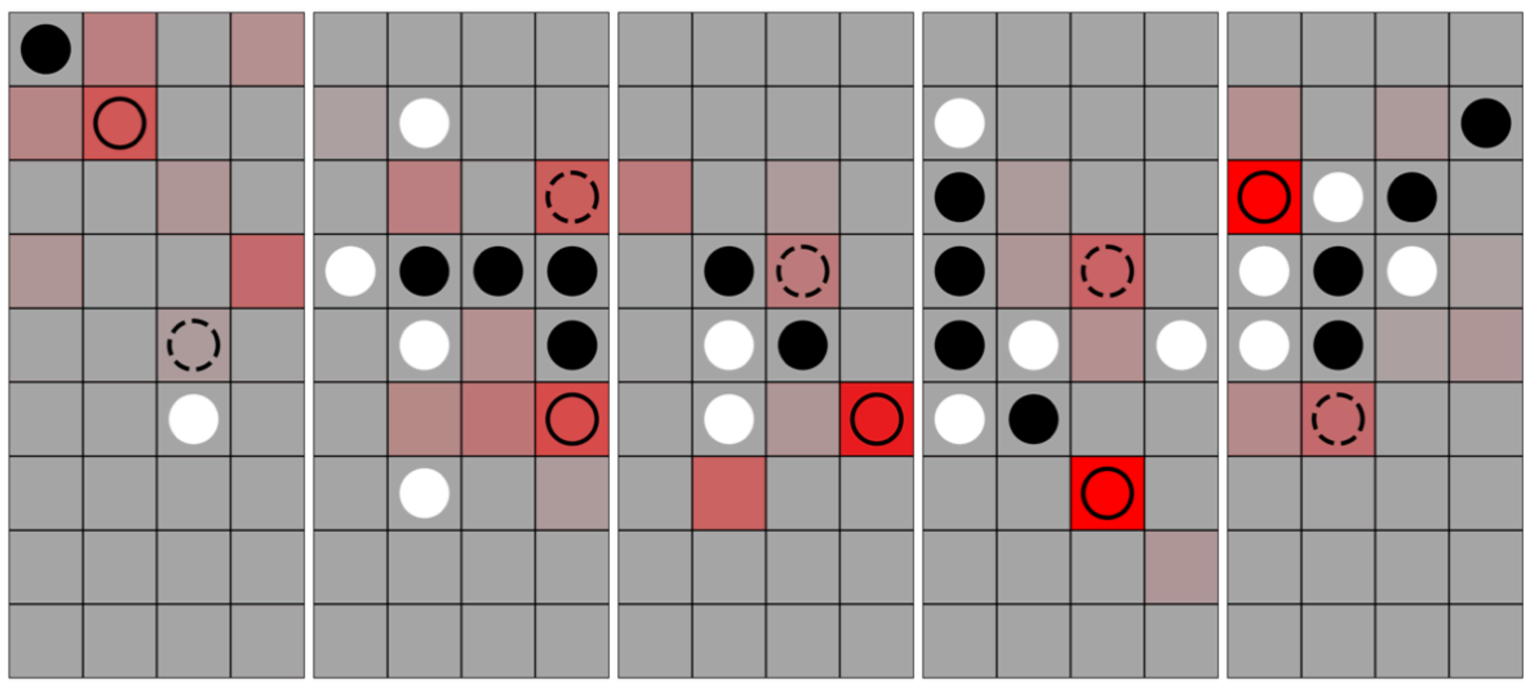
"Human-like" modes of failure

- 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

CATEGORIES FOR CANDIDATE MODEL IMPROVEMENTS



Opening bias | Tiebreak predictions | Feature weighting | Offensive play | Defensive play