Learning How Humans Play Board Games with GPT-4IAR

UNIVERSITY OF HELSINKI
FACULTY OF SCIENCE

Victor Yeom-Song[1], Daisy Lin[3], Ionatan Kuperwajs[3], Heiko Schütt[3], Wei Ji Ma[3], Luigi Acerbi[1,2]

[1]Department of Computer Science, University of Helsinki, Finland [2]Finnish Center for Artificial Intelligence FCAI,

[3]Center for Neural Science and the Department of Psychology, New York University

FCAI Finnish Center for Artificial Intelligence

Main Points

- Board games are a good model to study human planning and decision making
- Learning a good model that predicts gameplay can be a great tool to study the inner mechanisms of planning
- We present a model that shows great promise for this task!

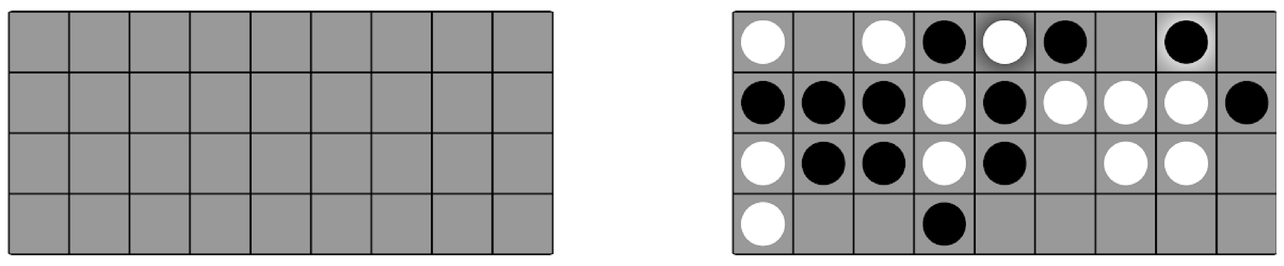
Introduction

Motivation

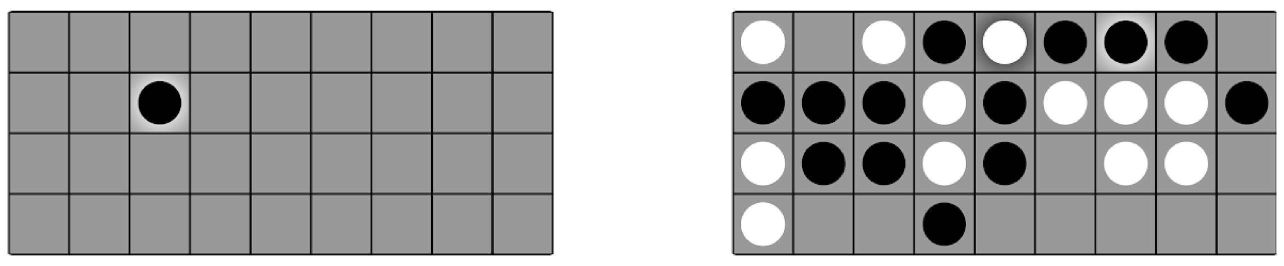
In Cognitive Science, planning and decision making are active areas of research. There is great interest in understanding the inner mechanisms of how expertise affects the way humans plan, and the main focus for this type of study has been placed on games [1].

Game and Task

We study the game known as 4-in-a-row (4IAR), proposed first by van Opheusden et al. [2]. This is a generalization of Tic-Tac-Toe, where players seek to connect 4 pieces of their color in a 4×9 board. Black to move, predict the next action on these boards:



The first board has too much entropy, and on the second the human lapses!



It is *really* hard to learn how a human plays!

This game is simple enough that it is feasible to tractably model (as opposed to e.g. chess), while maintaining enough complexity for it to extract intricacies of how we strategize.

An interpretable model

The first model to study how expertise affects how humans plan was proposed by van Opheusden et al. [3, 2]. This is a hand-crafted cognitive model that seeks to be highly interpretable, which asserts that the planning process follows a decision tree structure whose depth increases with expertise.

Going Further

Deep neural networks are able to capture complex patterns which may have been missed in building the previous model. Thus, a fully connected network was used by Kuperwajs et al. [4] to impose a noise ceiling on the move predictions. This can, in turn, be used to gauge the "goodness" of the model, as well as understand which behaviors the interpretable model struggles to capture, and improve it for the corresponding scenarios. On a dataset with ~10M data points, the network achieves a cross-entropy loss of 1.866 and an accuracy of 41.71 %.

Transformers and Attention

The crux of the Transformer architecture, first proposed by Vaswani et al. [5], is the attention mechanism. As presented in the survey by Lin et al. [6], the architecture has had great success in tasks with sequential data, and recently it has been used to tackle sequential decision making [7, 8, 9]. We propose to use this architecture for 4IAR.

The Data

Currently we use the computational model proposed by van Opheusden et al. [2] to generate synthetic games, and use ~1M data points for training. Inspired by the Trajectory Transformer, presented by Janner et al. [7], we represent a sequence of a board, an action and duration of a move through tokens:

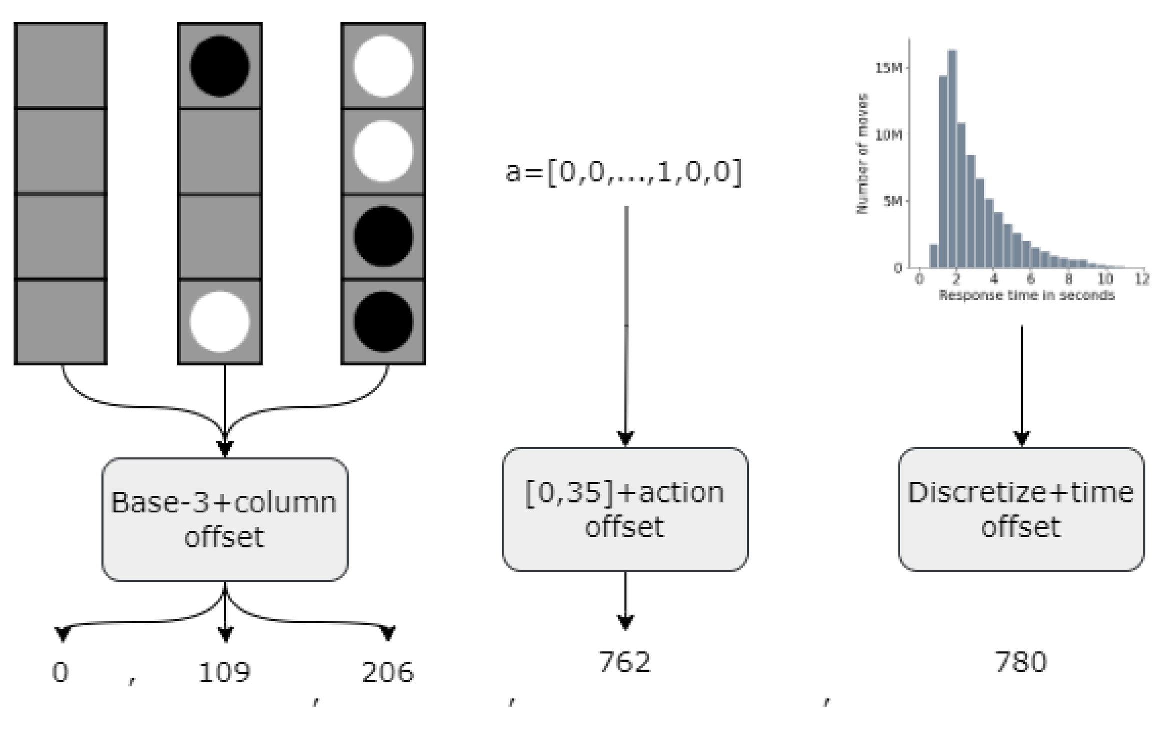


Figure 1. Tokenization scheme of board states, actions and durations.

The Architecture

In a similar fashion as the data, the architecture is influenced by the Trajectory Transformer [7]. A conceptual diagram is shown:

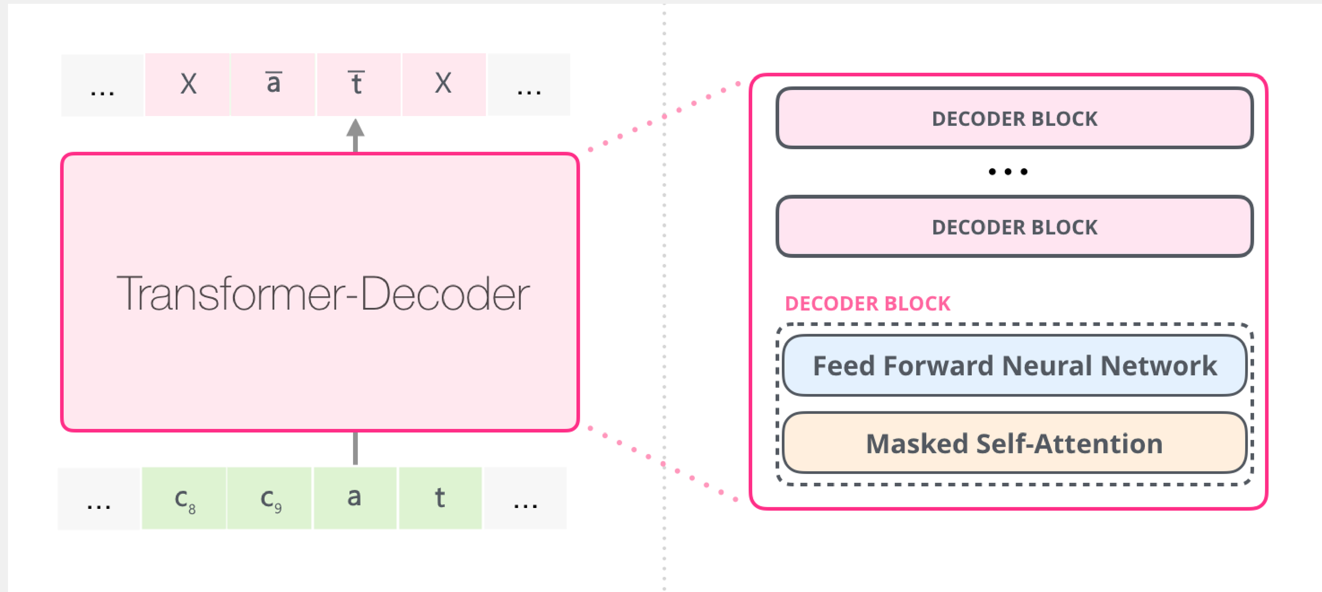


Figure 2. Proposed Neural Network Architecture. Figure adapted from "The Illustrated GPT-2".

We have used a model with approximately 85 million parameters (network weights and biases), which results from using the same hyperparameters as the standard GPT-2 [10] on a smaller vocabulary size. With this setup, we produce the results shown here.

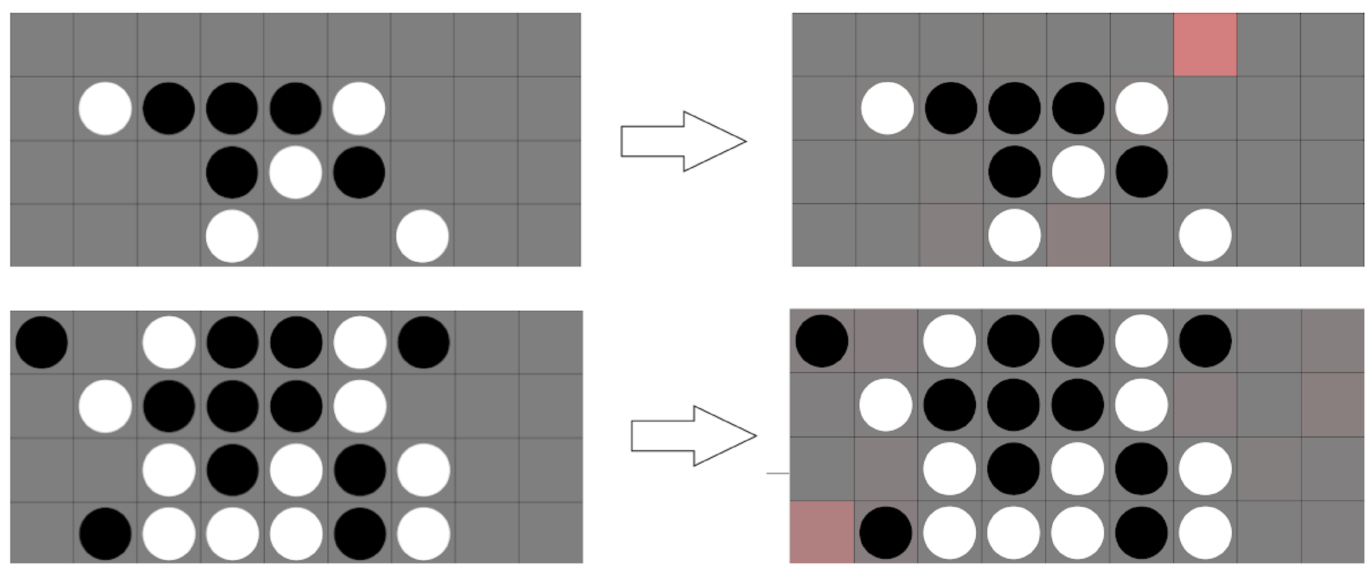
Experiments

Metrics

- Cross-Entropy Loss;
- Prediction accuracy on moves (AccMove) and reaction times (AccRT);
- For reaction times, RMS Error (RMSE).

Some results

With the plan to train this architecture on the ~10M point data set in the future, we present some preliminary results from the network trained on the synthetic set.



Model comparisons

	Cross Entropy Loss	AccMove (%)	AccRT (%)	RMSE (# bins)
Untrained GPT-4IAR	7.19	0.03	0.06	5.66
Trained GPT-4IAR	1.44	45.6	21.3	3.23
Fully Connected	1.866	41.71	—	—

These preliminary results are promising. The network is shown to learn the task well, and shows good signs for being able to predict how long an agent may take to produce a move!

Next Steps

- Train the network on the same data set as Kuperwajs et al. [4].
- Conduct scaling studies, changing the number of parameters used to verify if we are using the optimal hyperparameters.
- Produce comparisons between our architecture and the fully connected network to look for possible temporal dependencies.

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