Modeling Human-Like Learning in AI: Evaluating Recurrent Neural Networks' Capacity to Replicate Human Leaps of Insight in Sequential Decision-Making

Nina Mizrahi, Computational Neuroscience, Scripps College

W. M. Keck Science Department
Claremont McKenna • Scripps • Pitzer

Introduction

- This thesis investigates the differences between human and artificial intelligence (AI) learning through gameplay in Hexxed.io, a six-sided puzzle game designed to explore problem-solving strategies and learning dynamics .
- Neural networks excel at complex tasks like chess and Go, but lack the spontaneous creativity and adaptability of human problem-solving, relying instead on extensive and costly training processes[1].
- Human learning often involves "leaps of insight"—sudden cognitive shifts to optimal strategies or theories that allow for faster understanding—characterized by a top-down approach that draws on conceptual frameworks and prior knowledge. In contrast, AI relies on bottom-up processes, incrementally refining performance through repeated exposure to data and patterns[2]. (See Figure 1)
- This research examines the extent to which Recurrent Neural Networks (RNNs) can emulate the top-down dynamics of human learning using bottom-up mechanisms such as gradient descent, gating, and backpropagation, while also analyzing the contribution of non-linearity and input features to model learning.

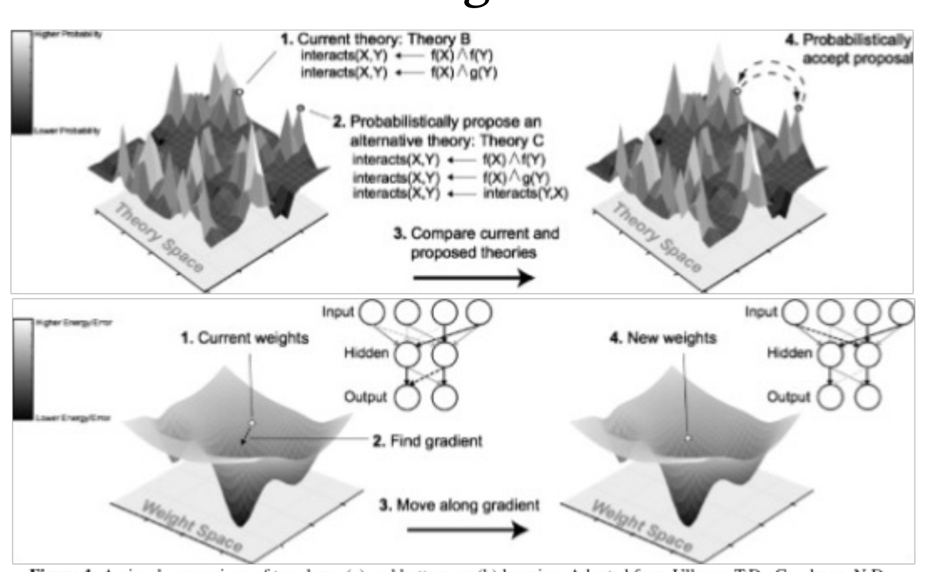
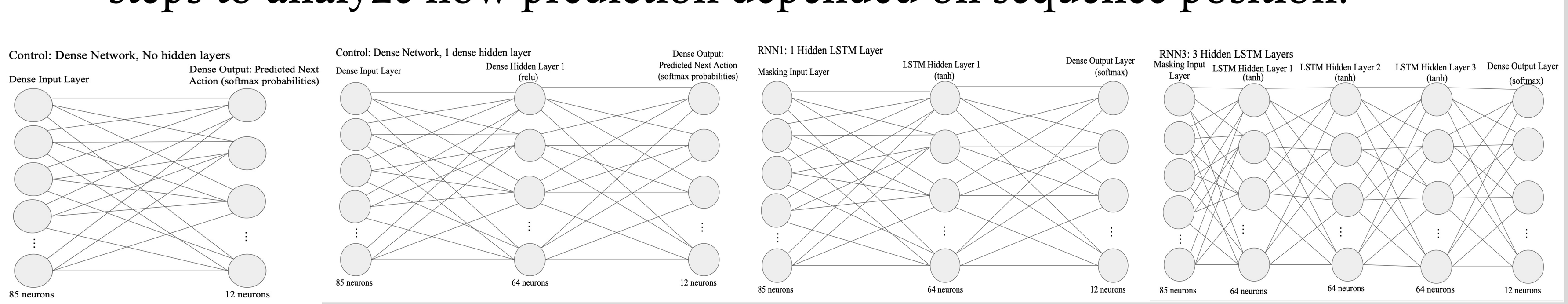


Figure 1: A visual comparison of top-down (a) and bottom up (b) learning. Adapted from Ullman, T.D., Goodman, N.D., & Tenenbaum, J.B. (2012). *Theory learning as stochastic search in the language of thought.* Cognitive Development, 27(4), 455-480.

Methods

- RNNs, specifically dense networks with Long Short-Term Memory (LSTM) layers, were trained on gameplay data from 1,647 human players who demonstrated leaps of insight.
- Human action sequences were processed into vectorized representations of board states and previous actions to train 3 RNNs with varying depths (see figures below). These models were compared to negative control models (NCM), and both a linear and non-linear baseline control network. All models were trained on each independent feature (e.g., board states or previous actions) to isolate their contribution to performance.
- Sequence tracking calculated the average accuracy across all sequence steps to analyze how prediction depended on sequence position.



Results

Figure 3 shows the plotted loss and accuracies for all models:

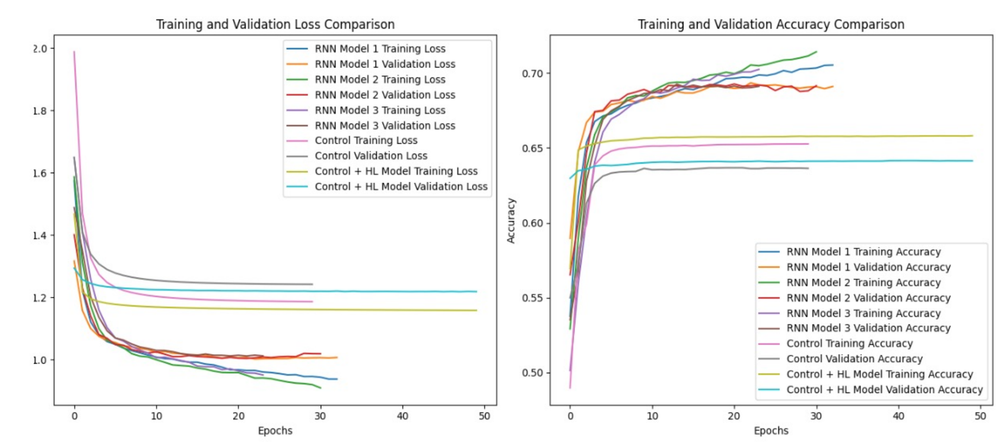


Figure 3: comparison of model performance across models trained on gamestate

- ❖ All models achieved accuracy >0.4746 demonstrate that they are identifying meaningful patterns in the data rather than relying on chance or the frequency of a single action.
- ❖ RNNs significantly outperformed the baseline models in capturing temporal and contextual patterns. The single-layer RNN achieved the highest accuracy of all models (68%).
- ❖ Adding more LSTM layers did not improve performance, suggesting that our specific task complexity was sufficiently captured by simpler architectures.

Figure 4 shows plotted loss and accuracies for models trained on each isolated feature:

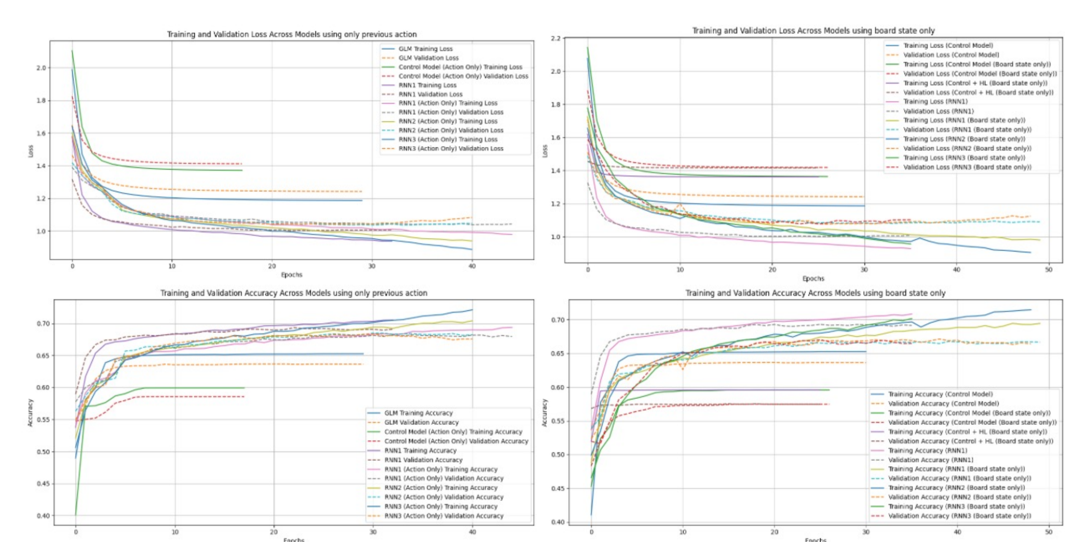


Figure 4: comparison of loss and accuracy across models using previous action (left) and board state (right).

- ❖ Models do best when provided full game state
- ❖ previous action is a more informative feature for predicting the next action compared to the board state alone
- ❖ RNN's performance did not decline as sharply as controls, indicating RNNs can generalize better without being overly reliant on specific features.

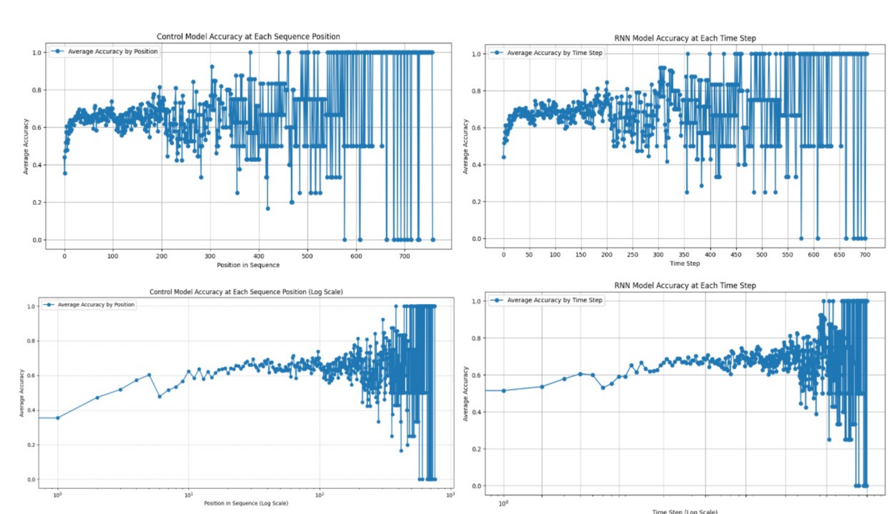


Figure 5: comparison of baseline control and RNN1 accuracy at each sequence position

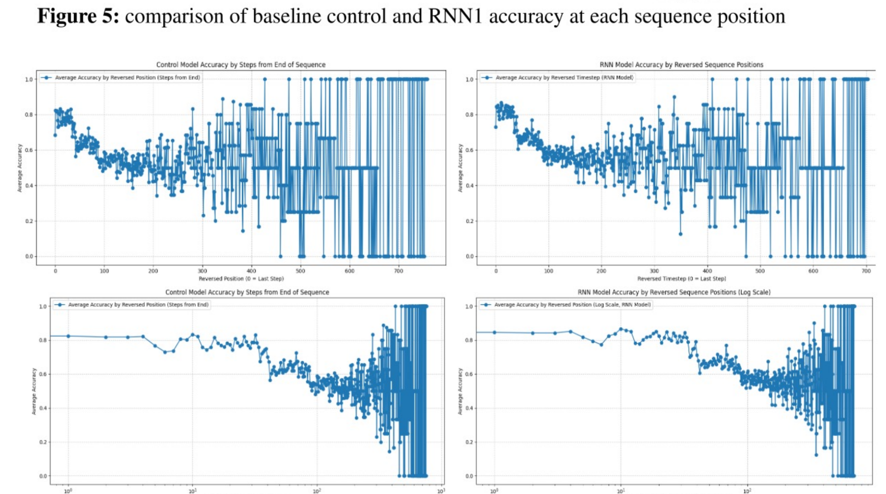


Figure 5.5: Comparison of baseline control and RNN1 accuracy at each reversed sequence position

Sequence tracking
- Similar distribution of accuracy within the first ~200 steps was the same between the two models
- growing accuracy up to the first 200 positions
- peak in accuracy around position 300

Sequence tracking from reversed position
- same patterns present as were observed in sequence tracking
- Plateaus in accuracy begin to appear at position 300 and are closer in count compared to above which started around 350

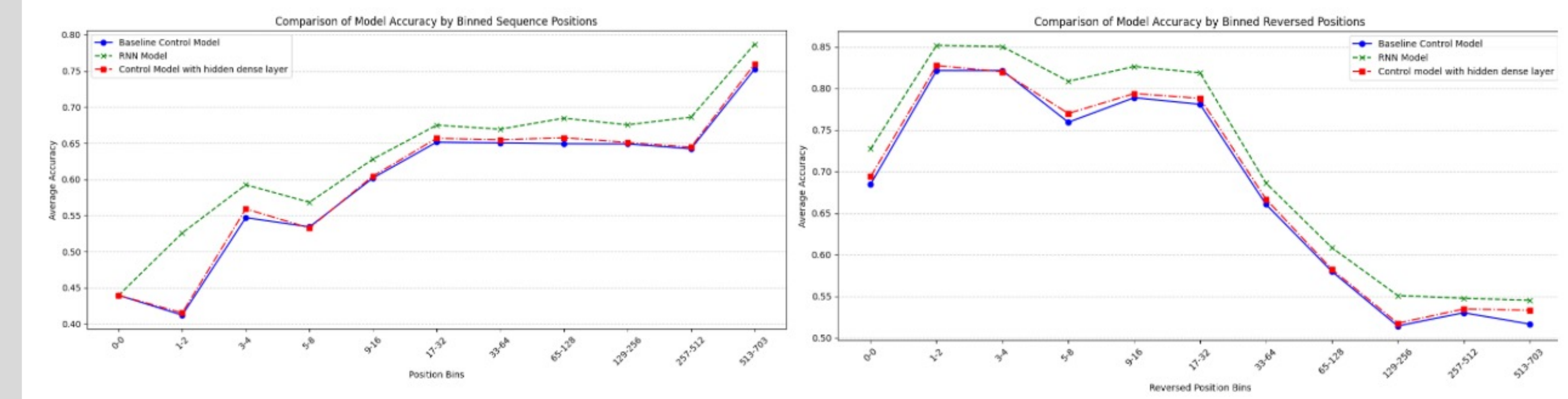


Figure 6: Comparison of model accuracies by binned positions

- ❖ RNN1 model outperforms both of the controls with higher accuracy at every position, both reversed and chronological
- ❖ All models follow roughly the same accuracy trends across bins, in terms of where they increase, decrease, and plateau
- ❖ The control model with an added hidden layer, though having marginally higher accuracy than the baseline control at certain position bins, was nearly identical.

Discussion

- Temporal dependencies, rather than non-linearity, were the primary drivers of the RNNs' increased ability to predict human actions, suggesting that temporal dependencies are critical for accurately modeling human-like decision-making.
- Though they were able to accurately approximate human learning behavior by 6.37%. RNN models relied heavily on patterns more explicitly present in the training data, failing to infer or generalize transferable strategies when handling longer sequences (>200 steps) that were underrepresented in the data. Therefore they failed to replicate the true leaps of insight which characterize top-down learning.
- Future studies should explore hybrid models that integrate reinforcement learning with RNNs, combining bottom-up pattern recognition with top-down goal-driven learning to make AI systems more human-like in how they learn and adapt.

Literature Cited

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2. Ullman TD, Goodman ND, Tenenbaum JB. Theory learning as stochastic search in the language of thought. Cognitive Development. 2012;27(4):455-480. doi:10.1016/j.cogdev.2012.07.005

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