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Long-Term Memory Pattern Recognition using LSTM-based Reflex Agents: A Game-Based Learning Approach

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Abstract

This paper presents a novel educational framework that leverages Long Short-Term Memory (LSTM) networks and their variations to simulate the concept of long-term dependency learning through an interactive game-based model. The frame-work introduces a dual-sequence pattern learning environment where a primary sequence is influenced by a secondary memory sequence. A reflex-based AI agent mimics LSTM behavior by combining information from both sequences to predict the next element in the main sequence. This system aims to help learners intuitively understand how LSTMs and related models retain and utilize past information to inform current decisions. Feedback- driven gameplay fosters deeper engagement, while gradually increasing complexity helps solidify the concept of long-term dependencies. The model effectively bridges theoretical under-standing with hands-on learning by simulating the memory- driven decision-making process characteristic of recurrent neural networks.

Keywords

Long Short-Term Memory (LSTM), Reflex Agent, Memory-Augmented Learning, Recurrent Neural Net- works (RNNs), Educational Game, AI in Education, Sequence Prediction

I INTRODUCTION

Understanding the memory-retention properties of neu- ral networks, especially LSTM networks, poses significant challenges for learners. This paper introduces an innovative educational platform where learners engage with a game- based environment that simulates LSTM behavior using reflex agents. The game presents two sequences: a main

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input and a memory input, drawing parallels to LSTM's hidden and cell states.

II. RELATED WORK

Prior educational tools like TensorFlow Playground and Google's Teachable Machine have helped demystify neural networks but lack interactive gameplay that simulates memory- based learning. Game-based learning in AI has been explored in reinforcement learning contexts but not explicitly for mem- ory retention modeling like LSTM [6]–[8].

III. PROPOSED FRAMEWORK

The system is built on three primary modules:

- Dual-sequence display interface
- Reflex agent mimicking LSTM gate behavior
- Adaptive gameplay difficulty based on user performance

IV. SYSTEM ARCHITECTURE

The architecture includes the following layers:

- Input Layer: Accepts the main and memory sequences.
- Rule Engine: Applies reflex logic.
- Prediction Engine: Predicts the next element.
- Feedback Module: Provides real-time performance feed- back.

Fig. 1. System architecture showing sequence inputs, reflex logic, and output feedback.

V. ALGORITHM DESIGN

Algorithm 1 Reflex Agent-based Sequence Prediction

1: Initialize MainSequence M and Memory Sequence S
2: for each time step to do
3: Extract window of past n elements from M and S
4: Apply pattern matching rule R to combine Mt and St
5: Predict next value Pt in M
6: Compare Pt with actual Mt+1 and update score
7: Adjust difficulty level based on accuracy
8: end for

VI. MAPPING TO LSTM ARCHITECTURE

- Memory sequence acts like LSTM's cell state [1].
- Main sequence reflects the hidden state.
- Reflex rules simulate gating mechanisms.

This simplified mapping allows learners to intuitively grasp the structure and functionality of LSTM network.

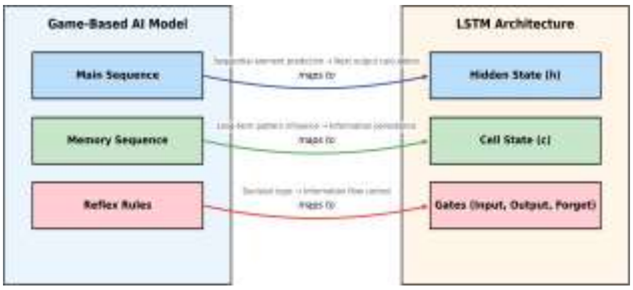

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Fig. 2. Mapping of game sequences and reflex logic to LSTM components.

VII. GAME MECHANICS

The game progresses through levels:

- **Level 1:** Simple direct pattern recognition.
- **Level 2:** Introduction of memory dependency [2].
- **Level 3:** Increasing pattern length, noise, and complex- city.

Fig. 3. Game interface and progression from basic to advanced pattern prediction.

VIII. EVALUATION

A pilot study is proposed where students interact with the system. Evaluation metrics include:

- Pre- and post-test scores
- Prediction accuracy over time
- Feedback engagement levels

IX. CONCLUSION AND FUTURE WORK

This paper presented a novel game-based learning approach to teach LSTM concepts through a dual-sequence reflex sys- tem. The simplified model enables intuitive understanding of long-term memory retention and prediction in RNNs. Future work includes real LSTM integration, support for GRUs, and adaptive difficulty scaling via reinforcement learning.

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