**Emotional Mario: Exploring Emotional Neural Networks in AI**

**Introduction**

* **Introduction to Emotional Mario**
  + Overview of the project
* **Problem Statement and Objectives**
  + Defining the research problem
  + Objectives of the study
* **Framework and Emulator**
  + Description of the framework used
  + Choice of emulator (e.g., Kautenja)
* **Research Methods**
  + Overview of research methodology
  + Techniques employed (e.g., machine learning, reinforcement learning)

**Artificial Intelligence and Emotions**

* **Theories of Emotion**
  + Overview of psychological theories (e.g., basic emotions, appraisal theory)
  + Relevance to artificial intelligence
* **Machine Learning and Reinforcement Learning**
  + Basics of machine learning in AI
  + Application of reinforcement learning to game playing
* **Neural Networks**
  + Introduction to neural networks
  + Role in AI and emotional modeling
* **Requirements for Emotional Neural Networks**
  + Characteristics and challenges

**Double Deep Q-learning Network to Play Super Mario Bros**

* **Environment and Wrappers**
  + Description of the gaming environment
  + Use of wrappers for data preprocessing
* **Reward System**
  + Design and implementation of reward mechanisms
* **Neural Network Architecture**
  + Detailed architecture of the DQN
* **Parameter Tuning and Optimization**
  + Methods for adjusting network parameters
  + Impact on gameplay

**Emotion in DQN**

* **Implementing Emotional Dataset into Framework**
  + Introduction to emotional datasets (e.g., Toadstool Dataset)
  + Integration into the AI framework
* **Blood Volume Pulse (BVP) Integration**
  + Use of BVP values for emotional modeling
  + Techniques for incorporating BVP into AI algorithms
* **Experiments and Results**
  + Details of experimental setup
  + Presentation and analysis of results
  + Comparison with traditional DQN models

**Conclusion**

* **Summary of Findings**
  + Recap of key findings and contributions
* **Limitations and Future Directions**
  + Challenges encountered during research
  + Suggestions for future research avenues

**Abstract**

This bachelor thesis investigates the use of Convolutional Neural Networks (CNNs) in training an AI agent to play a Super Mario game, with an emphasis on enhancing performance through physiological data integration. Initially, a CNN was trained to play Super Mario using reinforcement learning techniques. The study then utilized the Toadstool dataset, originally developed by Henrik Svoren in the paper "Emotional Mario - Using Super Mario Bros. to Train Emotional Intelligent Machines." This dataset includes Blood Volume Pulse (BVP) values and gameplay inputs from ten participants. Gameplay inputs from these sessions were converted into images for further analysis.

A separate CNN was trained to predict BVP values from the gameplay image data. These predicted BVP values were subsequently used to train another CNN to play Super Mario, aiming to enhance the agent's performance by incorporating predicted physiological responses.

The objective of this research is to examine the potential benefits of integrating physiological data into AI training processes, providing insights into how human sensory data can improve AI performance in interactive gaming environments.

**Introduction**

* **Introduction to Emotional Mario** 
  + Overview of the project

Artificial Intelligence (AI) agents that can simulate human emotions represent a significant milestone in the development of intelligent systems. The Emotional Mario project is an experimental approach to enhance the capabilities of traditional learning agents by integrating emotional intelligence. This project specifically aims to improve the performance of AI agents in playing the classic video game Super Mario Bros by incorporating emotional responses into their learning processes.

The Toadstool dataset, introduced by Henrik Svoren in his paper "Emotional Mario - Using Super Mario Bros. to Train Emotional Intelligent Machines," provides a rich source of gameplay and physiological data. This dataset includes Blood Volume Pulse (BVP) values collected from participants during gameplay, which serve as indicators of their physiological and emotional states.

In this study, the Toadstool dataset is used to train a Deep Q-Network (DQN) agent to predict BVP values from game frame images. These images are derived from the gameplay inputs recorded in the dataset. The trained DQN agent's ability to predict BVP values allows it to infer the emotional state of a player based on visual input alone.

The next step involves incorporating this emotionally-aware agent into another DQN agent designed to play Super Mario Bros. This integration is achieved by calculating an intrinsic emotional reward based on the predicted BVP values. The emotional reward is then balanced against the conventional reward system used in reinforcement learning, aiming to enhance the agent's decision-making process and overall gameplay performance.

This approach not only seeks to improve the performance of AI agents in gaming but also contributes to the broader field of affective computing by demonstrating how physiological data can be used to inform and enhance AI behavior. The potential applications of such emotionally intelligent agents extend beyond gaming, offering insights into how machines can better understand and respond to human emotions in various interactive scenarios.

**Research programm**

**Problem Statement and Objectives**

**Defining the Research Problem:**

The work of McDuff and Kapoor on "Visceral Machines," alongside Henrik Svoren et al.'s research with the Toadstool dataset, significantly inspires this study. The goal of creating AI agents that exhibit recognizable emotions and demonstrate independent thinking has been a longstanding aspiration in artificial intelligence. Recent advancements, such as ChatGPT, highlight both substantial progress and ongoing challenges in this field. This project aims to bridge the gap between traditional reinforcement learning techniques and the integration of human emotional responses in AI decision-making processes.

By leveraging physiological data, specifically Blood Volume Pulse (BVP) values, this research explores whether incorporating emotional intelligence can enhance the gameplay performance of AI agents. Emotional intelligence, in this context, is defined as the ability of an agent to learn more effectively by utilizing emotional inputs, thus improving decision-making compared to standard reinforcement learning agents.

The primary objective of this project is to develop an agent that exhibits emotional responses and outperforms traditional reinforcement learning agents in playing Super Mario Bros. A significant challenge is effectively interpreting BVP values so the agent can utilize them in its learning process.

**Objectives of the Study:**

1. **To develop a DQN agent that predicts BVP values from gameplay images.**
2. **To integrate predicted BVP values into the training of a second DQN agent.**
3. **To evaluate the performance of the emotionally aware DQN agent compared to a conventional DQN agent.**
4. **To contribute to the understanding of affective computing and AI through this integration.**

This study aims to demonstrate the potential benefits of using physiological data to enhance AI performance, ultimately advancing the field of emotionally intelligent machines.

**3. Framework and Emulator**

**3.1 Description of the Framework**

For this project, we utilized both PyTorch and TensorFlow to build and train our convolutional neural networks (CNNs). PyTorch was chosen for its widespread use and robust support for reinforcement learning applications, making it an ideal choice for developing our Deep Q-Network (DQN) agents. PyTorch provides extensive tools for constructing neural networks, calculating gradients, and adjusting network parameters based on the inputs received, which are essential for the reinforcement learning process.

TensorFlow was employed primarily for handling larger datasets and efficiently storing and recalling data. TensorFlow's capability to manage extensive data collections and its powerful data processing pipelines made it a suitable choice for our needs. Matplotlib was used for logging and visualizing metrics, enabling us to monitor the performance and progress of our models throughout the training process.

**3.2 Choice of Emulator**

The Kauten GitHub repository for Super Mario Bros was selected as our emulator due to its extensive features and functionalities. This repository includes pre-built methods and variables that facilitate interaction with the game environment without requiring us to manually extract data from the emulator's RAM. Additionally, the repository supports lower polygon counts and simplified graphics, which can enhance the training efficiency of our models.

Initially, we considered using the newer framework stable-retro from the Farama Foundation. However, this would have necessitated manually identifying and extracting all relevant data (such as lives, position, speed, and score) from the emulator's RAM, followed by implementing the required methods. Consequently, we opted for Kauten's implementation, which provided a more straightforward and efficient approach, albeit with some minor modifications to ensure backward compatibility.

**3.3 Integration with the Dataset**

The Toadstool dataset, developed by Henrik Svoren et al., contains session gameplay input values and BVP values for each participant. To utilize this dataset, we recorded and preprocessed each gameplay frame as an 84x84 grayscale image. These images were then used in conjunction with the BVP values to train a neural network capable of simulating those values. Preprocessing the BVP values was necessary to ensure that only relevant and accurate data were used.

Custom wrappers were implemented in the environment to preprocess the data for the agent. These included resize, grayscale, and skip frame wrappers, which optimized the input data for the CNNs. Integration between the emulator and the CNNs was facilitated by gym-retro, which creates environments for games that can be used to train agents, streamlining the process of connecting the gameplay data with our models.

These frameworks and methodologies were chosen to effectively integrate emotional responses into the AI agents, with the goal of improving their performance in playing Super Mario Bros. This approach seeks to explore and expand the capabilities of emotionally intelligent machines within the realm of reinforcement learning.

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