



**University of
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Intelligent Companion Robot: An Embodied LLM Agent in a 3D Simulation

Yan Kong

Supervisor: Alex Lucas

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Declaration

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Name: Yan Kong

Signature: Yan Kong

Date: September 6, 2024

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Abstract

This dissertation presents the design and development of an intelligent companion robot that integrates advanced LLM-based capabilities to offer a natural and personalised interaction experience. The proposed robot not only engages in conversational dialogue but also incorporates a memory module to store and retrieve information, enabling it to adapt and respond to the unique preferences of its human users over time. In addition to its conversational abilities, the robot features a navigation system trained through deep reinforcement learning, which is intricately integrated with its conversational framework. This seamless integration enables the robot to autonomously navigate environments based on natural language commands. A comprehensive set of experiments was conducted to evaluate the robot's ability to adapt to user preferences, maintain coherent long-term interactions, and navigate home environments based on varying levels of language instructions. The results demonstrate that integrating LLMs with memory modules and functional tools significantly enhances the robot's conversational and operational autonomy, proving its potential as a truly intelligent and responsive companion.

The code of this project is hosted at
<https://github.com/diskya/Intelligent-Companion-Robot>

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Chapter 1

Introduction

1.1 Background and Motivation

In today's fast-paced and increasingly digital world, loneliness has become a significant issue affecting people of all ages. Many individuals, whether due to ageing, social isolation, or other circumstances, experience a deep need for companionship, emotional support, and access to knowledge. While technology has provided numerous ways to stay connected, there remains a gap in the ability to provide personalised, meaningful interaction that truly understands and evolves with a person over time.

This growing need has sparked interest in developing intelligent companion robots that go beyond simple task automation. These robots are envisioned not only as assistants but as entities with their own distinct personas, capable of forming emotional connections, providing comfort, offering tailored recommendations based on user preferences, and adapting to the unique preferences and behaviours of their human companions. The motivation behind this research stems from the desire to create such a companion robot that can alleviate loneliness by offering genuine understanding, emotional support, and practical assistance in daily life, feeling less like a machine and more like a living creature.

At the core of this vision is the integration of advanced conversational abilities powered by Large Language Models (LLMs). However, robust conversation alone is not enough for a truly valuable companion. The robot must also integrate its conversational skills with actions like autonomous navigation and emotion detection to interact more meaningfully in its environment. This requires **embodied AI**, where intelligence is paired with a physical form capable of sensing, perceiving, and acting in the real world [1]. By embodying AI, the robot can respond to both verbal and non-verbal cues, adapting to the users needs and providing a more holistic, human-like companionship. [2]

By combining LLM-based conversation with a deep reinforcement learning-driven navigation system, the robot can not only understand and respond to verbal commands but also navigate and interact with the physical world in a way that is coherent with the user's needs and preferences. This integration allows the companion to be more than just

a passive entity; it becomes an active participant in the users life, capable of learning, adapting, and providing valuable emotional support over time.

The motivation for this research is to address the emotional and practical needs of individuals by designing a companion robot that can form a deep, understanding relationship with its users. The proposed robot aims to offer a more comprehensive and helpful interaction, ultimately enhancing the quality of life for those who need companionship the most, all while embodying the characteristics of a sentient being.

1.2 Aims and Objectives

This research aims to develop an intelligent companion robot that provides emotional support, engagement, and personalized knowledge for individuals experiencing loneliness. Combining advanced conversational abilities with autonomous navigation, the robot will offer meaningful daily interactions. The key objectives include:

Integrate a Pre-trained LLM with Memory and Learning: Utilize a LLM, such as the ChatGPT, to enable natural, context-aware conversations. A memory module will help the robot learn from past interactions, delivering personalized and emotionally engaging experiences.

Develop a Deep Reinforcement Learning-Based Navigation System: Create a navigation system using deep reinforcement learning to allow the robot to move autonomously and respond to verbal commands like "come to me" or "move to the desk." This foundation will support future features such as emotion detection to enhance its utility.

Integrate Conversational and Navigational Capabilities: Ensure a seamless integration of conversational and navigation systems for fluid interactions, enabling the robot to act on verbal commands in real-time.

Evaluate User Interaction and Emotional Impact: Conduct experiments and user studies to measure the robot's effectiveness in alleviating loneliness, improving interaction quality, and adapting to user preferences over time.

1.3 Overview of the Report

This report presents the research, design, implementation, and evaluation of an intelligent companion robot that integrates conversational abilities with autonomous navigation. The structure of the report is as follows:

1. Introduction: This chapter introduces the background, motivation, aims, and objectives of the research, highlighting the need for emotionally supportive companion robots.
2. Literature Review: A review of relevant literature on reinforcement learning, deep reinforcement learning, transformers [3], and LLMs is presented, with a focus on LLM agents and their application in human-robot interaction.

3. Methodology: This chapter details the system architecture, context-awareness mechanism, training methodology, and evaluation techniques used to develop and assess the robots capabilities.
4. Implementation: The implementation process is described, including the creation of simulation environments, training of the robots navigation using PPO, integration of LLM agents via MemGPT and ChatGPT API, and fine-tuning with Retrieval-Augmented Generation.
5. Evaluation and Results: Evaluation methods and results are presented, including assessments by human users and LLM agents, to determine the robots effectiveness and performance.
6. Discussion: This chapter discusses the broader applications, ethical considerations, and societal impact of deploying intelligent companion robots.
7. Conclusion and Future Work: The final chapter summarises the research findings, discusses limitations, and suggests directions for future research.

Chapter 2

Literature Survey

The field of artificial intelligence is fundamentally supported by three paradigms: supervised learning, unsupervised learning, and reinforcement learning (RL). Each paradigm, distinct in method and application, plays a crucial role in AI's progression. Supervised and unsupervised learning have been pivotal in developing transformers, the underlying architecture of LLMs, which have redefined AI capabilities in language understanding, generation, and reasoning. Consequently, LLMs have become pivotal in AI, propelling innovations across multiple domains.

Contrastingly, RL derives its approach from neuroscience, mimicking reward-based learning mechanisms in the brain. It optimises actions from environmental interactions, making it ideal for applications requiring adaptive strategies and complex decision-making.

The integration of RL with LLMs presents a promising avenue in AI research, particularly for AI companion robots. This combination leverages LLMs' linguistic prowess with RLs dynamic learning, potentially enhancing robots' autonomy and human-like interactions. Such systems could not only process and communicate in natural language but also execute informed decisions in real-world scenarios, boosting their practicality as companions.

This review critically evaluates the synergies and individual contributions of these paradigms, focusing on their intersection to advance AI companion robotics, highlighting how their integration could foster the development of sophisticated, more human-like AI systems.

2.1 LLMs and Phenomenon of Emergence

Introduced in 2017, the Transformer model has driven substantial advancements in natural language processing. Unlike its predecessors, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, the Transformer leverages self-attention mechanisms to overcome the limitations of sequential data processing. These mechanisms evaluate each word's significance in a sentence, regardless of order, effectively capturing

long-range dependencies. This approach enhances contextual understanding and improves parallel processing, boosting computational efficiency and scalability.

At the core of the Transformer architecture is the self-attention mechanism, foundational for LLMs like BERT, GPT, and T5. These models utilize the architecture for extensive pre-training on vast datasets, learning complex data patterns, such as predicting missing words or generating coherent text from prompts. After pre-training, these models are fine-tuned for specific NLP tasks^{text classification, translation, summarization, and question answering} achieving new levels of versatility and performance.

Emergent abilities in LLMs have become a significant focus in AI research. These refer to capabilities that unexpectedly manifest as models scale in size, complexity, or training data. Unlike the gradual improvements seen with typical scaling laws, emergent abilities appear suddenly once a certain threshold is reached. For example, models like GPT-3 and PaLM have demonstrated such behaviors, including performing arithmetic, solving multi-step reasoning tasks, and engaging in few-shot learning, where they generalize from a few examples to new, unseen tasks. Studies have documented sudden jumps in performance on benchmarks not achieved by smaller models, suggesting qualitative changes in the model's internal representations or understanding.

Emergent abilities are typically marked by two features: sharpness, where a capability shifts almost instantaneously from absent to present, and unpredictability, where the emergence of such abilities at specific scales is difficult to foresee. Some researchers liken these abilities to phase transitions in physics, where new properties emerge at a critical point, like water freezing into ice. This suggests that scaling up LLMs could lead to a level of generalization or intelligence beyond what is explicitly programmed or trained, opening exciting possibilities for future AI development.

However, this interpretation has been challenged by recent research arguing that these emergent abilities might result from the way performance is measured. The perceived emergence may stem from the choice of non-linear or discontinuous evaluation metrics, which can create the appearance of sudden improvements. An "emergence score" has been introduced to quantify this effect.

$$\text{Emergence Score} = \frac{\text{sign}(\arg \max_i y_i - \arg \min_i y_i) \cdot (\max_i y_i - \min_i y_i)}{\sqrt{\text{Median}(\{(y_i - y_{i-1})^2\}_i)}} \quad (2.1)$$

where y_i represents the model performance at model scales x_i , sorted such that $x_i < x_{i+1}$. The score captures the sharpness and unpredictability of performance changes. By using continuous or linear metrics like Token Edit Distance or Brier Score, the authors found that the emergent abilities often disappear, showing more gradual, predictable improvements instead. This finding suggests that what has been termed "emergence" could be a mirage created by specific metric choices, rather than an inherent property of LLMs themselves.

Despite these contrasting perspectives, the demonstrated reasoning and understanding abilities of the latest LLMs regardless of how they are characterized present a powerful tool for developing more intelligent companions than we have ever imagined.

2.2 Memory and Retrieval-Augmented Generation (RAG)

Building upon the transformative impact of LLMs, recent advancements in memory architectures and Retrieval-Augmented Generation (RAG) techniques have become pivotal in enhancing the capabilities of LLM applications. These innovations allow for improved understanding and generation of human-like text across extended dialogues.

2.2.1 Memory Architectures

LLMs face a significant challenge due to their limited context windows, which impede their ability to manage prolonged dialogues and complex document analyses effectively. Traditional methods for extending context [4], such as increasing the model's input size, lead to exponential increases in computational demand due to the self-attention mechanisms of Transformer architectures. To address these challenges, novel memory architectures have been developed, exemplified by systems like Stanford's generative agents, ChatGPT Assistant, and MemGPT.

Model / API name	Open	Context Window Tokens	*Messages
Llama	✓	2k	20
Llama 2	✓	4k	60
GPT-3.5 Turbo	✗	4k	60
Mistral 7B	✓	8k	140
GPT-4 (release)	✗	8k	140
GPT-3.5 Turbo	✗	16k	300
GPT-4	✗	32k	600
Claude 2	✓	100k	2000
GPT-4 Turbo	✗	128k	2600
Yi-34B-200k	✓	200k	4000

Table 2.1: Context Window Sizes for Various Models

These LLM applications employ a hierarchical memory system inspired by traditional operating system memory management strategies. This architecture distinguishes between 'main context' (analogous to RAM) and 'external context' (similar to disk storage), facilitating dynamic context management. The main context maintains immediate, relevant information during inference, while the external context stores additional data accessible as required. This design allows them to simulate an infinite memory capacity within the fixed constraints of LLMs, enhancing their functionality in scenarios requiring extensive contextual engagement.

The memory functionalities of LLMs bear similarities to human memory systems, which encode, store, and retrieve experiences. These human memories are categorised into declarative (episodic and semantic) and nondeclarative types. Similarly, LLMs can recall

specific data from past interactions, akin to human episodic memory, enriching current interactions with historically informed responses. This capability is further enhanced by LLMs' semantic understanding, enabling them to grasp the meaning behind words and apply this understanding in real-time interactions.

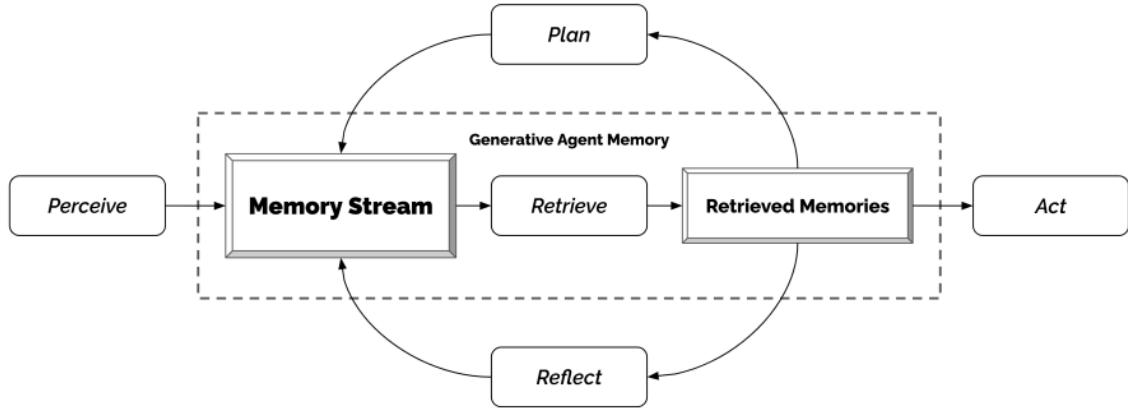


Figure 2.1: Original generative agent memory architecture. Agents perceive their environment, and all perceptions are saved in a comprehensive record of the agents experiences called the memory stream.

2.2.2 RAG for Context Extension

RAG [5] further extends LLMs' effective context by integrating a retrieval mechanism that accesses external databases or documents during inference. This integration reduces reliance on the fixed context window, allowing the model to dynamically supplement its responses with relevant external information.

By leveraging RAG, systems like MemGPT enhance their performance in applications demanding deep, long-context understanding. [6] This capability is crucial for AI home companions, enabling them to aggregate and synthesise information from varied sources such as user manuals, news articles, or personal notes, thereby providing accurate and contextually relevant responses.

2.3 Agentic AI

Agentic AI [7] represents a new paradigm in artificial intelligence, characterised by its ability to autonomously manage and execute complex workflows with minimal human input. Unlike traditional AI, which is designed for specific tasks and operates within predefined constraints, Agentic AI systems are capable of understanding complex scenarios, setting their own goals, and making strategic decisions autonomously. This autonomy is facilitated by integrating several advanced capabilities, including adaptive learning, reasoning, natural

language processing, and workflow optimization. Table 2.1 presents a comparison between Agentic AI and Traditional AI.

Feature	Agentic AI	Traditional AI
Complexity and Versatility	More versatile and can be applied to a broader range of complex, dynamic problems and challenges	Designed for specific tasks or applications
Autonomy and Decision-Making	Has the ability to set its own goals, reason, and make independent decisions	Executes pre-programmed instructions and responds to specific inputs
Interconnectivity	Connects and interacts with other systems, information sources, and humans	Primarily engages in predefined, structured interactions with users or systems
Adaptability and Learning	Designed with mechanisms for continuous learning and adaptation	Has limited capabilities to adapt to new situations or learn from experience
Speed and Efficiency	Slower due to complex workflows and tasks	Faster with a streamlined approach
Examples	Microsofts AutoGen, Moveworks Next-Gen Copilot	Siri, recommendation systems in Netflix or Amazon

Table 2.2: Comparison between Agentic AI and Traditional AI

Agentic AI is structured around four key components: Planning, Memory, Tools, and Actions.

Planning allows the AI to strategize and achieve goals by setting objectives, breaking tasks into steps, and using methods like reflection and chain-of-thought reasoning. It relies on prompt engineering to align actions with desired outcomes, constantly adapting based on memory from past experiences.

Memory serves as the AIs internal storage, holding short-term data for current tasks and long-term data for future use. This system helps the AI learn from past actions, adapt, and optimize its performance over time.

Tools are the resources the AI uses to perform tasks, such as calendars, calculators, or code interpreters. The AI dynamically selects and integrates these tools into its workflow for efficient task execution.

Actions involve executing plans using the selected tools. The AI monitors results in real-time, adjusts strategies based on feedback, and leverages memory for future decisions.

These components form a continuous cycle, enabling the AI to autonomously manage and refine its tasks. In complex scenarios, multiple specialized agents can collaborate, enhancing efficiency by distributing tasks according to their strengths.

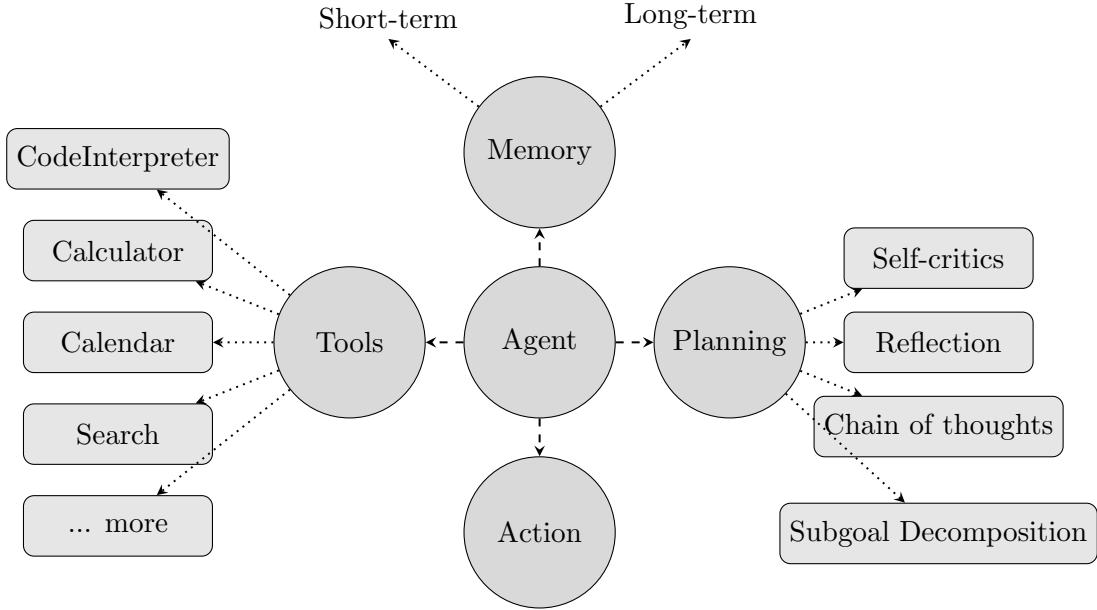


Figure 2.2: Building Blocks of Agentic AI

2.4 Deep Reinforcement Learning

This section introduces RL and Deep RL to provide a foundational understanding of the approach used in training the navigation capabilities of my robot.

2.4.1 Conventional RL Concepts

Reinforcement Learning is a dynamic and interactive paradigm within machine learning, where an agent learns to make decisions by interacting with its environment. The goal of RL is to enable the agent to maximise cumulative rewards over time by selecting actions that influence the state of the environment. Unlike traditional supervised learning, which relies on labelled data, RL is unique in that it focuses on learning from the consequences of actions, making it particularly well-suited for problems involving sequential decision-making and control. [8]

The Markov Decision Process (MDP) is the fundamental mathematical framework that underpins RL. An MDP is characterised by a set of states S , actions A , a transition model $P(s' | s, a)$, and a reward function $R(s, a)$. The core idea behind MDPs is the Markov property, which asserts that the future state of the environment depends only on the current state and action, not on the sequence of events that preceded it. This property simplifies the problem of decision-making by allowing the agent to focus solely on the present situation.

Within the MDP framework, **value functions** play a crucial role in guiding the agent's decisions. The state value function $V(s)$ represents the expected return starting from state s under a given policy π , while the state-action value function $Q(s, a)$ measures the expected

return from taking action a in state s and following the policy thereafter. These value functions are computed using Bellman equations, which express the value of a state or state-action pair recursively in terms of the value of subsequent states. The **Bellman equations** not only provide a foundation for evaluating policies but also serve as the basis for many RL algorithms, linking the concept of immediate rewards with long-term outcomes.

$$V^\pi(s) = \mathbb{E}_\pi [R_t + \gamma V^\pi(S_{t+1}) \mid S_t = s] \quad (2.2)$$

The Bellman equation for the state-value function $V^\pi(s)$, representing the expected return when starting from state s and following policy π .

$$Q^\pi(s, a) = \mathbb{E}_\pi [R_t + \gamma Q^\pi(S_{t+1}, A_{t+1}) \mid S_t = s, A_t = a] \quad (2.3)$$

The Bellman equation for the action-value function $Q^\pi(s, a)$, representing the expected return when starting from state s , taking action a , and thereafter following policy π .

2.4.2 Taxonomy of RL Methods

Building on the MDP framework and value functions, RL algorithms are designed to learn optimal policies. These algorithms are categorised into **on-policy and off-policy methods**. On-policy algorithms learn the value of the policy currently being used by the agent to make decisions. For example, the SARSA algorithm updates its policy based on the actions actually taken by the agent, ensuring that the learning process is closely tied to the agent's current behaviour. This approach promotes stability but may require more interactions with the environment to achieve convergence. [9]

In contrast, off-policy algorithms learn the value of the optimal policy independently of the actions currently being taken by the agent. Q-learning is a prominent off-policy algorithm that updates the action-value function $Q(s, a)$ by considering the maximum reward possible from the next state, regardless of the action actually taken. This distinction allows off-policy methods to be more sample-efficient, as they can leverage data collected from various sources, making them particularly powerful in environments where data collection is expensive or limited.

The distinction between **model-based and model-free RL** further refines the way algorithms interact with the environment and learn from it. Model-based algorithms attempt to build an explicit model of the environment, which includes the transition dynamics and reward structure. By simulating future states and rewards, these algorithms can plan ahead and make informed decisions, often resulting in more efficient learning.

Model-free algorithms bypass the need for an explicit model, directly learning the policy or value function from interactions with the environment. Examples include Q-learning and Policy Gradient methods. These approaches are generally more flexible, as they do not require knowledge of the environment's dynamics, making them suitable for complex or uncertain environments. The choice between model-based and model-free methods often

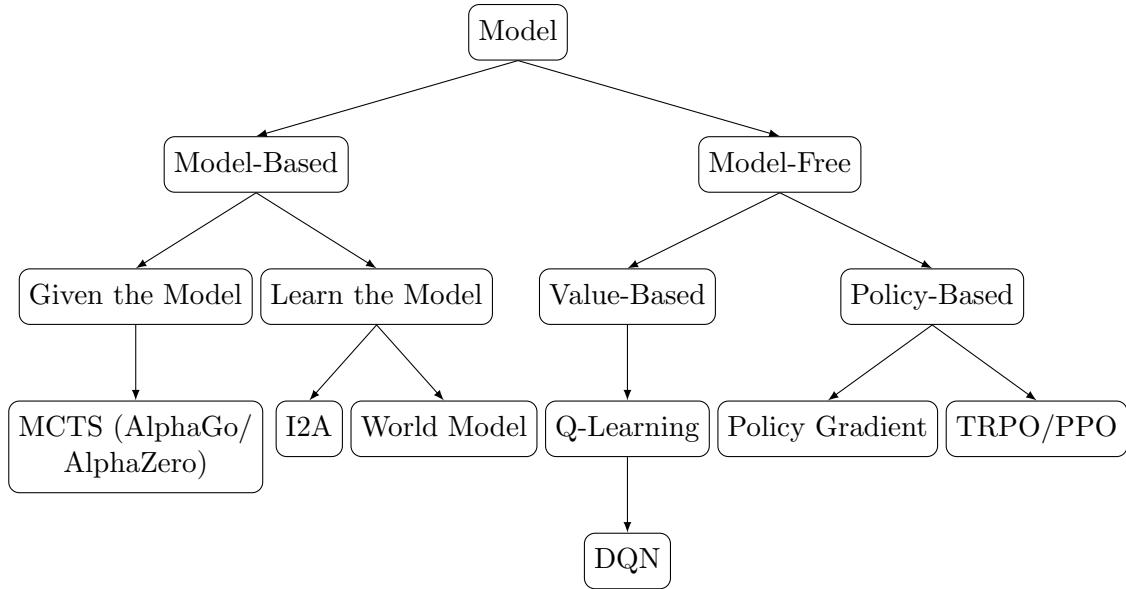


Figure 2.3: Taxonomy of RL Methods

depends on the availability of information about the environment and the computational resources at hand.

In environments with continuous action spaces, the use of **policy gradient methods** becomes particularly advantageous. Unlike value-based methods, which estimate value functions to derive policies, policy gradient methods directly optimise the policy by following the gradient of the expected cumulative reward with respect to the policy parameters. This approach is well-suited for scenarios where discretization of the action space is impractical. The REINFORCE algorithm is a fundamental example of this class, utilising sampled trajectories to estimate the policy gradient and iteratively improve the policy. The ability to represent stochastic policies is another significant benefit, as it enables the agent to explore different actions, thereby avoiding local optima.

The **actor-critic architecture** represents a hybrid approach that integrates the strengths of both value-based and policy gradient methods. In this setup, the actor is responsible for selecting actions based on the current policy, while the critic evaluates the action taken by estimating a value function. The critics feedback helps the actor adjust its policy more effectively by reducing the variance of the gradient estimates, leading to more stable and efficient learning. This connection between the actor and critic illustrates a powerful synergy, where the critic's evaluation guides the actors policy updates, blending direct policy optimization with value-based insights.

The learning process in RL can occur in either **online or offline settings**, each with its distinct advantages and challenges. Online learning involves the agent interacting with the environment in real-time, continuously updating its policy or value function as new data is collected. This approach allows the agent to adapt rapidly to changes in the

environment, making it particularly useful in dynamic settings where the environment is constantly evolving.

Conversely, offline learning (also known as batch reinforcement learning) enables the agent to learn from a pre-collected dataset without further interactions with the environment. This approach is advantageous in scenarios where interaction is costly or dangerous, such as in healthcare or autonomous driving. However, offline learning requires careful management of the dataset to avoid biases or overfitting, especially when the data reflects suboptimal behaviour. The interplay between online and offline learning highlights the versatility of RL in handling a wide range of practical problems, from real-time decision-making to learning from historical data. [10]

2.4.3 Breakthroughs in Deep RL

Deep RL is a pivotal advancement in artificial intelligence that integrates the robust representation capabilities of deep learning with the decision-making framework of reinforcement learning. This combination has enabled the solving of complex, high-dimensional problems that were previously beyond the reach of traditional RL methods. [11]

The journey of Deep RL began with the limitations of traditional RL, which struggled with large state and action spaces due to its reliance on tabular methods or simple linear function approximators. These methods were inadequate for dealing with the complexities of environments characterised by high-dimensional, continuous data. [12]

The breakthrough came with the introduction of Deep Q-Networks (**DQN**) by Mnih et al. in 2013, which marked the first successful application of deep learning to RL problems. DQN utilised convolutional neural networks to approximate the action-value function $Q(s,a)$, allowing the algorithm to process raw pixel inputs from video games and make decisions that resulted in superhuman performance in several Atari 2600 games. The innovation of DQN lay in its use of experience replay and target networks, which helped stabilise the learning process and addressed issues of instability that arise when combining neural networks with RL.

The success of DQN highlighted the potential of Deep RL and spurred the development of various other algorithms. These include Double DQN, which mitigated the overestimation bias inherent in DQN by decoupling action selection from action evaluation, and **Dueling DQN**, which separated the estimation of state value and the advantage of taking certain actions, leading to more efficient learning in complex environments.

Following the initial success of DQN, the field of Deep RL rapidly expanded, with new algorithms being developed to address specific challenges and enhance performance. Among the most influential developments in Deep RL are the Asynchronous Advantage Actor-Critic (**A3C**) and Proximal Policy Optimization (**PPO**) algorithms. [13] In this project, PPO is used to train the navigation model. PPO optimizes its objective function using a clipped surrogate objective:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t [\min(r_t(\theta)A_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)A_t)] \quad (2.4)$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$ is the probability ratio, and ϵ is a hyperparameter that controls the clipping range.

One of the most well-known applications of Deep RL is in the domain of gaming. **AlphaGo**, developed by DeepMind, famously utilised Deep RL to defeat the world champion Go player, a task that was previously considered unattainable due to the game's immense complexity and vast state space. AlphaGo combined deep neural networks with Monte Carlo tree search, enabling it to evaluate and improve its strategies in real time.

In robotics, Deep RL has been instrumental in enabling robots to learn complex tasks through trial and error. Robots have used Deep RL to master intricate manipulation tasks, navigate environments autonomously, and even learn bipedal locomotion.

2.5 Limitations and Enhancement of RL

Despite the significant progress made in RL and Deep RL, these methods face several **limitations** when applied to more complex or real-world environments. Some of the key challenges include:

- Sample Inefficiency in Real-World Applications: Traditional model-free RL methods often require a large number of interactions with the environment to gather sufficient data for effective learning. This is especially problematic in real-world settings, where interactions can be costly, time-consuming, or even risky.
- Difficulty with Sparse Rewards: In many complex environments, meaningful rewards are sparse, making it challenging for RL agents to learn effective policies. The infrequent nature of reward signals can result in slow convergence and suboptimal performance.
- Challenges in Multiagent Environments: In environments where multiple agents interact, the learning process becomes more complex due to factors like partial observability, non-stationarity, and intricate agent interactions. These challenges can destabilise learning and limit scalability.
- Risk of Overfitting and Distributional Shift in Offline RL: Offline RL, which involves learning from a fixed dataset without further environment interaction, is prone to overfitting and distributional shifts. The static nature of the dataset may not accurately reflect the distribution of optimal policies, leading to suboptimal outcomes.
- Limited Generalisation Across Tasks: RL methods often struggle to generalise policies learned in one task to new, related tasks. This lack of transferability limits the effectiveness of RL in dynamic environments where adaptability is essential.

- Complexity of High-Dimensional Continuous Spaces: RL algorithms find it difficult to operate in environments with high-dimensional continuous action spaces. The vast state-action space makes it challenging to explore and learn effective policies.

To overcome these limitations, several advanced techniques have been developed, leveraging deep learning to enhance the capabilities of traditional RL methods. These **enhancements** include:

- Model-Based Methods: Model-based RL techniques address sample inefficiency by learning a model of the environment's dynamics. This model allows the agent to simulate interactions internally, reducing the need for extensive real-world data collection. Techniques such as Model-Based Policy Optimization (MBPO) and Dreamer integrate model learning with actor-critic methods, enabling more efficient learning and long-horizon planning.
- Hierarchical Deep RL: Hierarchical RL (HRL) mitigates the challenges of sparse rewards by breaking tasks down into a hierarchy of sub-tasks, each with its own subgoals. This structure allows for more frequent rewards, improving learning efficiency. Deep learning enhances HRL by enabling more complex state and action representations, as seen in methods like the Option-Critic architecture and Diversity Is All You Need (DIAYN).
- Multiagent Deep RL: Multiagent DRL extends RL to environments with multiple agents, addressing challenges related to partial observability, non-stationarity, and complex interactions. Techniques such as centralised training with decentralised execution (CTDE) and multiagent actor-critic frameworks help stabilise learning and improve scalability in multiagent systems.
- Learning From Demonstrations: Learning from demonstrations (LfD) enhances RL by incorporating expert behaviour into the training process. This approach accelerates learning, especially in environments with sparse rewards, by guiding exploration and helping the agent learn effective policies from limited data. Techniques like Generative Adversarial Imitation Learning (GAIL) and Adversarial Inverse RL (AIRL) are examples of this approach.
- Offline RL: Offline RL techniques address the risks of overfitting and distributional shifts by using regularisation methods to ensure that the learned policy does not deviate significantly from the data distribution. These techniques improve the robustness of policies learned from fixed datasets, making them more reliable in real-world applications.
- Transfer Learning in RL: Transfer learning techniques enhance RL by allowing the transfer of knowledge from one task to another. This approach improves the generalisation capabilities of RL, enabling agents to adapt more quickly and effectively to new tasks that share similarities with previously learned tasks.

2.6 The Synergy Between LLM and RL

2.6.1 Mutual Enhancement of LLM and RL

The intersection of LLMs and RL has sparked the creation of AI systems where each approach amplifies the other's strengths. This synergy allows AI agents to understand and generate natural language while simultaneously learning from their interactions with the environment, making them highly effective for complex, multi-step tasks.

LLM-Enhanced RL integrates the powerful language capabilities of LLMs into RL frameworks. By leveraging LLMs' ability to process and generate text, RL agents can better understand natural language instructions and contextual clues, essential in environments where tasks are described linguistically or require nuanced decision-making. For instance, LLMs can suggest strategies based on their language comprehension, which the RL agent then refines through real-world feedback. This approach is especially advantageous for long-term planning and sequential decision-making, where traditional RL agents often fall short due to their limited understanding of complex language.

On the other hand, **RL-Enhanced LLMs** benefit from RL techniques that help them learn and improve continuously from feedback. While traditional LLMs generate responses in a static "open-loop" manner, incorporating RL creates a "closed-loop" system where models adjust their behavior based on rewards or penalties received during interactions. A key example is Reinforcement Learning from Human Feedback (RLHF) [14], employed in models like OpenAI's ChatGPT, where human feedback serves as a reward signal. This feedback loop refines the model's responses, making them more accurate, relevant, and aligned with user expectations.

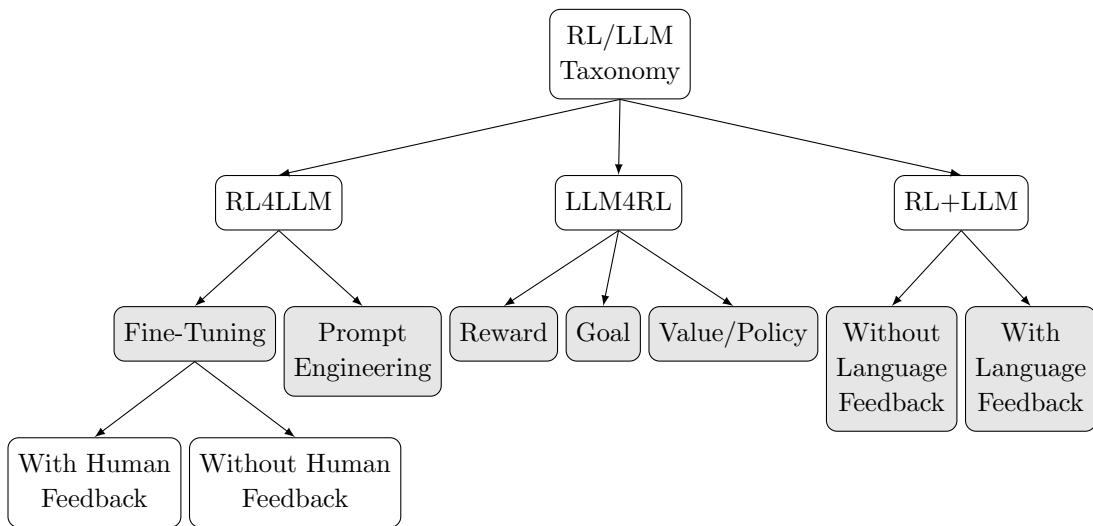


Figure 2.4: RL/LLM Taxonomy Tree Structure

2.6.2 Examples of LLM-RL Integration in AI Assistants

Several AI systems showcase the powerful synergy of combining LLMs with RL.

A prominent example is the **Voyager project**, which integrates GPT-4 with RL to excel at playing Minecraft. Voyager uses GPT-4's advanced language capabilities to interpret complex instructions and enhance decision-making processes, resulting in performance that surpasses prior systems. [15] The integration enables the agent to learn continuously, exploring and mastering various tasks within the game's open-ended environment without human intervention, effectively demonstrating the benefits of combining language understanding with adaptive learning.

Another example is **Mobile ALOHA**, a low-cost, mobile robot that uses deep reinforcement learning to perform various household tasks, such as folding clothes, cooking, and interacting with humans. Mobile ALOHA employs a bimanual teleoperation system that integrates RL techniques to optimize its movements and actions. It leverages reinforcement learning to refine its performance across tasks, showcasing how RL can enhance the robot's adaptability and effectiveness in dynamic, real-world environments.

These examples illustrate how combining LLMs and RL is leading to more intelligent, versatile, and responsive AI systems that can tackle complex tasks across diverse applications, from gaming to robotics.

2.7 Reinforcement Learning in Simulated Environments

RL has revolutionized how robots learn and adapt, but it's not just the algorithms themselves that are driving this change; it's where they learn. Simulated environments like Webots have become the playground for RL, offering a safe, flexible, and scalable space to test and refine intelligent behaviors without the risks and costs associated with real-world experiments. [16]

Diverse Applications: From Walking to Winning Games

Optimizing Movements: Learning to Walk and Beyond One of the most compelling uses of RL in simulations is optimizing the movements of complex robots, such as humanoids. Studies show how RL, combined with advanced tools like Keras-rl in the Webots environment, can fine-tune control strategies and gait patterns for humanoids. These findings highlight how RL can not only teach robots to walk efficiently but also adapt dynamically to new terrains and challenges, moving us closer to robots that can navigate our world as naturally as humans do. [17]

Navigating Complex Environments: Smarter Paths and Safer Decisions The ability to navigate is at the heart of autonomy, and RL has proven to be a game-changer in this area. Research utilizing Webots explores RL for navigation and path planning, demonstrating how RL can help robots learn to find the shortest or safest paths in environments cluttered with obstacles, effectively mimicking human-like decision-making in real time. This progress is critical for applications ranging from autonomous vehicles to rescue robots. [18]

Mastering Strategy: Neural Q-Learning for Smarter Robots Neural Q-Learning, a powerful RL method, has been a focal point in creating more responsive and intelligent robots within the Webots environment. These studies illustrate the potential of RL to enable robots not just to react to their surroundings but to anticipate changes and learn from them, paving the way for more adaptable and versatile robotic systems. [19]

Seeing is Believing: Vision-Based Reinforcement Learning Vision-based RL is where things get even more interesting. Leveraging deep reinforcement learning algorithms like DQN and D3QN in Webots allows humanoid robots to train with visual input. This approach enables robots to use vision to understand and interact with their environment, similar to how humans rely on sight to navigate and perform tasks. Such advances could lead to robots capable of performing delicate or complex tasks that require high precision. [20]

Scaling Up: Frameworks for Large-Scale Learning The future of RL lies in its scalability, and new architectures are emerging for unattended, containerized deep reinforcement learning in Webots, enabling extensive and continuous training without human intervention. This innovation underscores the move toward more autonomous learning processes, where robots not only learn independently but also at scale, enhancing both efficiency and effectiveness. [21]

Playing Well with Others: RL in Collaborative and Competitive Settings RL is also being explored in both collaborative and competitive settings, such as game-playing agents and robotic pick-and-place tasks. These studies reveal how RL can drive complex multi-agent interactions, crucial for developing future robots that can work alongside or even compete with humans. [22]

Challenges and Opportunities: Bridging the Simulation-to-Reality Gap

While RL in simulators like Webots offers a world of possibilities, it's not without its hurdles. The biggest challenge is ensuring that what robots learn in virtual environments translates effectively to the real world, where physical dynamics and uncertainties can differ vastly. [23] High computational demands and the need for vast amounts of training data also pose barriers to wider adoption.

However, the field is moving quickly, with research focusing on enhancing transfer learning to ensure that models trained in simulations can be effectively applied in real-life scenarios, reducing computational loads, and developing algorithms that learn more efficiently. As these challenges are addressed, the potential of RL in simulations will continue to grow.

Chapter 3

Methodology

3.1 Requirements and analysis

The development of an AI companion robot involves several key requirements, each tied to specific strategies and methods to ensure the system's successful implementation. This section details the integrated approach that combines both the project requirements and the analysis of how these requirements will be addressed.

Customised LLM Assistant with Believable Responses: The AI companion should deliver natural, context-aware, and authentic responses to foster user engagement. To achieve this, we will fine-tune a language model to generate meaningful, personalized interactions. By incorporating advanced memory techniques, inspired by systems like MemGPT [24], the AI can manage and recall past conversations dynamically, maintaining coherence and relevance even in extended dialogues. This customization will allow the AI to learn user-specific nuances, making interactions feel more genuine and relatable.

Continuous Learning and User Adaptation: The AI companion must continuously learn from interactions and adjust its behavior accordingly. A dynamic memory system will store and manage user data, enabling the AI to refine its understanding and personalize responses over time. This system will autonomously decide which information to keep or discard based on ongoing interactions, allowing the AI to adapt to evolving user needs and preferences, ensuring a more personalized experience.

Tool Binding [25]: To extend its capabilities beyond conversation, the AI should dynamically integrate additional tools and functionalities, a process called tool binding. For instance, it could connect with a navigation module to respond to spatial commands like "come to the desk." A modular architecture will allow the AI to add new tools seamlessly, ensuring flexibility and adaptability to evolving tasks and technologies, thus expanding its functionality over time.

To achieve this, the AI will be built with a modular architecture that allows for the seamless addition of new functionalities. The system will be flexible enough to incorporate new modules without disrupting its core operations. This design ensures that the AI can

evolve and expand its capabilities over time, adapting to new technologies and user needs as they arise.

3.2 Core Memory System Architecture

3.2.1 Components

This project's LLM agent is built on top of MemGPT, leveraging its innovative memory architecture. The Core Memory System Architecture of MemGPT draws heavily from the 2023 Generative Agents research by Stanford University, which pioneered the integration of memory capabilities in AI, marking the start of a new era in agentic AI.

The architecture features two primary components: the Main Context and the External Context. The Main Context functions like RAM, managing data required for immediate processing and ensuring quick access to relevant information during interactions. The External Context, akin to disk storage, is responsible for retaining long-term data, including historical and user-specific details, enabling deeper personalization and context maintenance over extended conversations. Together, these components allow the system to efficiently balance short-term needs with long-term memory storage, much like how a computer optimizes quick access with broader data retention.

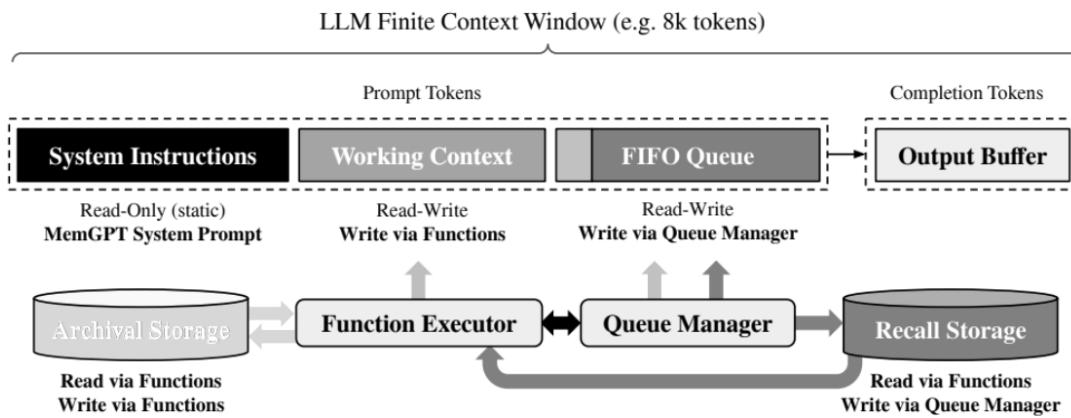


Figure 3.1: Memory Architecture of MemGPT

Main Context functions as the AI's short-term memory, akin to RAM, handling data necessary for immediate processing during interactions. It's divided into three parts:

- **System Instructions:** Act like an operating system's kernel, directing how the AI manages and prioritizes memory. These instructions ensure the AI keeps essential information readily available, maintaining control flow and operational efficiency even under memory constraints. This structure supports the AI in handling complex queries and responding promptly.

- Working Memory: Serves as a dynamic, temporary storage area for ongoing tasks, user preferences, and real-time data, similar to a scratchpad in computing. It enables the AI to keep track of active conversations and adapt to the context, ensuring continuity and relevance in responses. This approach minimizes delays and enhances the AI's ability to provide timely and coherent interactions.
- FIFO Queue (First-In-First-Out): A rolling buffer that maintains a sequential log of recent interactions. This mechanism helps manage conversation flow by retaining the latest relevant data while older information is archived or summarized. It ensures the AI can handle extended conversations coherently without being constrained by the context window.

External Context serves as the AI's long-term memory, comparable to disk storage, and is divided into:

- Archival Storage: Functions as the main repository for long-term data storage, holding large amounts of user data and past interactions. This storage allows the AI to draw on historical information without overloading short-term memory, essential for applications that require a deep understanding of user behavior or extensive data analysis.
- Recall Storage: Operates like a high-speed cache for quick access to frequently or recently needed data. It allows the AI to retrieve relevant information swiftly when a user revisits a topic, maintaining fluidity and coherence in interactions across extended sessions.

Function Executor manages data flow between the Main and External Contexts. It autonomously handles tasks like memory paging and data retrieval, ensuring efficient memory management and low latency in data access. This component is critical for maintaining system performance, particularly in scenarios involving large data volumes or long-term interactions.

3.2.2 Retrieval Process

The retrieval function takes the agents current situation as input and returns a subset of the memory stream relevant to inform the agent's behavior. The retrieval function uses three main components [26]:

Recency Memories that were recently accessed are given higher scores. This is implemented as an exponential decay function based on the number of hours since the memory was last retrieved, with a decay factor of 0.995.

Importance Each memory is assigned an "importance score," which distinguishes mundane events from more significant ones. The importance is determined by asking the language model to rate the memory on a scale of 1 to 10.

Relevance Memories that are contextually relevant to the current situation are prioritized. This is calculated by generating an embedding vector of the text description of each memory and computing the cosine similarity with the query memory's embedding vector.

The final **retrieval score** for each memory is a weighted combination of recency, importance, and relevance:

$$\text{score} = \alpha_{\text{recency}} \cdot \text{recency} + \alpha_{\text{importance}} \cdot \text{importance} + \alpha_{\text{relevance}} \cdot \text{relevance}$$

In the implementation, all weights (α) are set to 1. The top-ranked memories that fit within the model's context window are retrieved and included in the prompt.

3.3 Training Methodology

The training of the AI companion was systematically divided into two distinct methodologies: (1) fine-tuning with Retrieval-Augmented Generation (RAG) to establish a persona and memory [27], and (2) reinforcement learning utilising PPO for navigation within a simulated environment.

Fine-Tuning with Retrieval-Augmented Generation (RAG): The initial training phase employed RAG to endow the AI agent with a defined persona and memory framework, enabling it to recall pertinent contextual information about itself and its interactions with the owner. This approach allows the AI to produce more contextually relevant and personalised responses. [28] Although the integration of supervised learning through additional QA pair fine-tuning was considered, this aspect was excluded from the prototype development due to budgetary limitations and a strategic decision to prioritise a more streamlined implementation. The absence of additional fine-tuning steps, while noted, did not detract from the agents fundamental capabilities to perform within the desired operational parameters.

Reinforcement Learning via PPO: The second phase of training utilised reinforcement learning with PPO, focusing on enhancing the AI agents navigational proficiency within the Webots simulation environment. The RL model was designed to maximise cumulative rewards corresponding to successful navigational tasks and effective interaction within a controlled, simulated environment. The iterative training process involved the AI agent being exposed to increasingly complex navigational scenarios, facilitating a robust learning process that improved the agents adaptability and decision-making skills in dynamic contexts. The choice of PPO as the optimization algorithm was driven by its balance of exploration and exploitation, which is particularly suitable for environments where continuous adaptation is critical. PPO training algorithm is presented below.

Algorithm 1 Proximal Policy Optimization (PPO) Algorithm

```

1: Initialize policy parameters  $\theta_0$  and value function parameters  $\phi_0$ 
2: for iteration = 1, 2, ..., N do
3:   for actor = 1, 2, ..., M do
4:     Run policy  $\pi_\theta$  in the environment for T timesteps
5:     Compute advantage estimates  $\hat{A}_t$  using the value function  $V_\phi$ 
6:   end for
7:   for epoch = 1, 2, ..., K do
8:     for each minibatch of sampled data do
9:       Compute the ratio:  $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$ 
10:      Compute the surrogate objective:

$$L^{\text{CLIP}}(\theta) = \mathbb{E} \left[ \min \left( r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right) \right]$$

11:      Update policy parameters by maximizing the objective:

$$\theta \leftarrow \theta + \alpha \nabla_\theta L^{\text{CLIP}}(\theta)$$

12:      Update value function parameters by minimizing the loss:

$$L^{\text{VF}}(\phi) = \mathbb{E} \left[ (V_\phi(s_t) - R_t)^2 \right]$$

13:    end for
14:  end for
15: end for

```

3.4 Evaluation Methodology

The evaluation framework was designed to assess the AI home companion's performance in key areas crucial for a domestic environment, focusing on memory management, task assistance, and context-appropriate responses [29]. The evaluation involved a structured test using targeted questions and scenarios to gauge the AI's cognitive abilities and practical problem-solving skills. Key areas of focus included:

Self-Knowledge: Tested whether the AI could accurately describe its role and functions, with questions like "What are your main functions in helping me at home?" This assessed the AI's ability to maintain a consistent understanding of its purpose.

Memory Retrieval and Usage: Evaluated the AIs ability to recall past interactions, such as "When did I last ask you to remind me about an appointment?" This tested how effectively the AI could use memory to maintain continuity in interactions.

Reflective Reasoning: Assessed the AIs ability to make personalized recommendations, like "If I want to relax this evening, which activity would you

suggest based on what I enjoyed last weekend?” This tested its ability to synthesize past interactions to provide relevant suggestions.

This methodology provided a comprehensive approach to evaluating the AI’s adaptability, decision-making, and overall usefulness in a home setting. The results of this evaluation, including strengths and areas for improvement, will be discussed in the next chapter, ”Evaluation and Results.”

3.5 Legal and Ethical Considerations

Given the AI’s interaction with personal user data and its decision-making capabilities, the project will address the following considerations:

Data Privacy: Compliance with data protection laws such as GDPR will be strictly enforced, particularly concerning the handling and processing of personal data.

Ethical AI Use: The AI will be designed to avoid biases and ensure transparency in decision-making. Users will have clear visibility into how the AI processes data and will be able to influence or override the AI’s decisions when necessary.

Chapter 4

Implementation

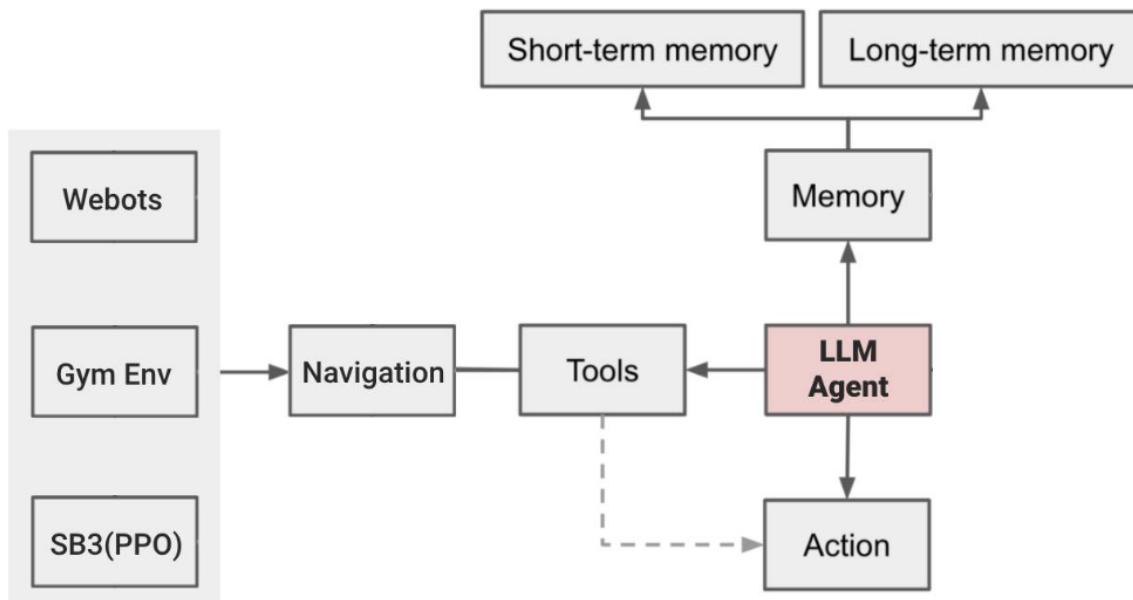


Figure 4.1: Project Architecture

The project comprises two main components:

1. Navigation Robot: A robot trained using reinforcement learning to dynamically optimize navigation strategies within its environment.
2. LLM Agent with Memory and Persona: A LLM agent with memory for contextual awareness and a consistent persona to enhance interaction and demonstrate believable behavior.

These components are integrated through Tool Binding. The system architecture, depicted in Figure 4.1, illustrates their integration and functionality.

4.1 Build Simulation in Webots

This section details the development of a simulation environment in Webots [30], a versatile robot simulation software that enables realistic modeling, testing, and refinement of robotic behaviors. The simulation uses the ROSbot [31], a mobile robotic platform designed for compatibility with the Robot Operating System (ROS), featuring differential wheels, distance sensors, and an RGBD camera for effective navigation and interaction. In this project, "ROSbot" also refers to the specific robot utilized within the simulation.

Environment Design

The simulation begins with the creation of a detailed virtual environment that replicates a typical home setting. This includes various terrains such as flat surfaces (e.g., hardwood floors, carpets) and obstacles like furniture, walls, and household objects. Obstacles, such as chairs, tables, and small objects, are strategically placed to assess the robots ability to manoeuvre around common household items. Figure 4.2 shows the home environment created in Webots.



Figure 4.2: Simulation in Webots

Robot Modelling

The ROSbot model (Figure 4.3) in Webots is configured to match its physical specifications, including its differential wheel drive system. Given the simplified focus of the project, the

simulation utilises the ROSbots distance sensors, differential wheels, and an RGBD camera to simulate core functions such as navigation and object detection.

The distance sensors are configured to provide real-time feedback on proximity to surrounding objects, which is critical for collision avoidance and navigation tasks. The RGBD camera provides both colour and depth information, enabling the robot to recognize objects, understand its environment, and execute visual navigation.

The ROSbots differential wheels are modelled to replicate its actual movement dynamics, including forward and backward motion, turning, and rotating in place. These capabilities are crucial for navigating tight spaces and avoiding obstacles in a home setting.

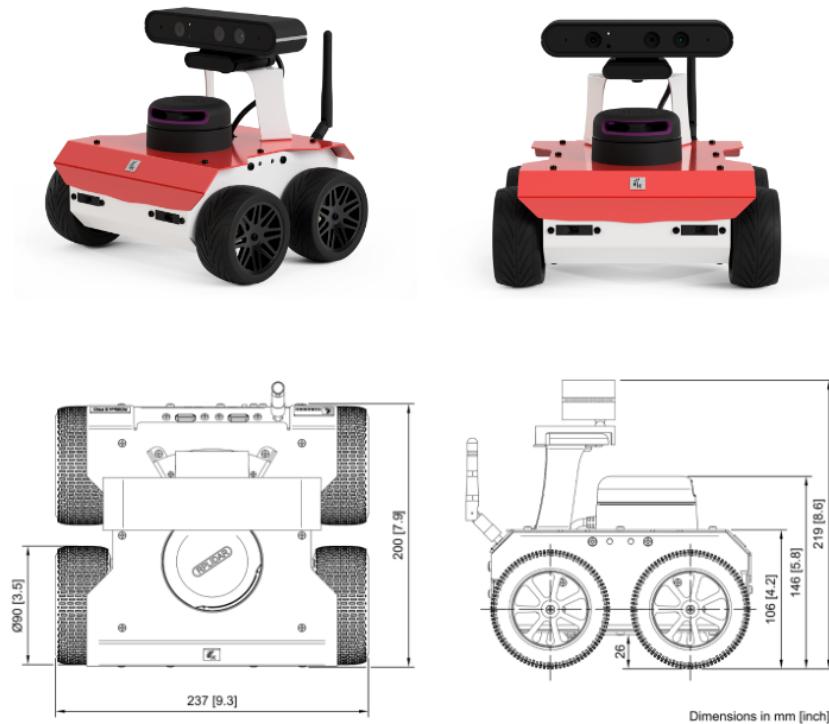


Figure 4.3: ROSbot

Testing and Calibration

The ROSbots sensors and actuators are calibrated within the simulation to ensure that they provide accurate data corresponding to the virtual environment.

Initial testing focuses on basic navigation tasks, such as manually guiding the ROSbot from a starting point to a target endpoint using keyboard controls. These tests evaluate the robot's core operational capabilities and lay the groundwork for more advanced scenarios and autonomous interactions in later stages.

4.2 Create OpenAI Gym environments to learn navigation through RL

This step involves configuring Webots to simulate custom environments that align with OpenAI Gym's [32] specifications, allowing for the implementation of various reinforcement learning algorithms. OpenAI Gym provides a standardized set of tools and protocols to develop and benchmark RL algorithms efficiently.

Customize Gym Environment

Custom Gym Environment: Develop a Python class that extends OpenAI Gym's Env class, interfacing directly with the Webots API. This custom environment serves as the bridge between the RL agent and the Webots simulation, allowing for the collection of state data and execution of actions within the simulated world. Figure 4.4 shows the Customized Navigation Gym Environment.

State and Action Spaces: Define the state space to include sensory data (relative position and relative angle) and the action space to include all possible robot commands (move forward, turn left, turn right). Ensure these spaces are appropriately scaled to allow efficient learning by the RL agent.

Reward function: Designing an effective reward function is a critical part and requires considerable effort and iterative tuning. The reward function directly influences the navigation behaviour of the RL agent. It is structured to encourage behaviours that align with efficient navigation and task completion. To promote efficiency, the function heavily favours moving forward over turning. A positive reward is assigned for forward motion toward the target, while turns receive smaller rewards or neutral outcomes. Additionally, early truncation is applied when the robot moves in a direction that increases its distance from the goal, ensuring that it quickly learns to avoid wrong directions and focus on reaching the target efficiently. This design balances exploration with goal-directed behaviour, helping the robot learn optimal navigation strategies.

```

class HomeNavigationSupervisor(RobotSupervisorEnv):
    def __init__(self):
        super().__init__()
        # Set up observation space
        # Set up action space
        # Set up various robot components
        # Set up the robot
        .....

    def get_observations(self):
        # Get the distance between the robot and the target
        # Get the orientation of the robot
        # Return the observations
        .....

    def get_reward(self, obs):
        .....

    def apply_action(self, action):
        # step in webots simulation
        super(Supervisor, self).step(self.timestep)
        .....

    def setup_robot(self):
        .....

```

Figure 4.4: Customized Navigation Gym Environment

Integration with Webots Controller

Data Handling: Implement real-time data processing in the Webots controller to supply accurate state information to the RL agent. This involves efficiently managing large sensor data streams, extracting sensor data via the Webots API, and converting it into the observation format required by OpenAI Gym.

Action Execution: Develop an action execution pipeline in Webots to convert the RL agents decisions into motor commands, ensuring responsive and realistic interactions. The key to seamless integration between the Gym and Webots environments is to synchronize their steps. This **synchronization** is accomplished by incorporating the Webots supervisors step function directly into the Gym environment's step function, aligning their cycles for consistent execution. Figure 4.5 shows the Code Block to integrate Gym and Webots Env.

```

class RobotSupervisorEnv(Supervisor, gym.Env):
    .....
    def reset(self, seed=None, options=None):
        # reset the env after an episode is terminated
        self.steps = 0
        self.reward = 0
        self.episode_count += 1
        self.terminated = False
        self.truncated = False
        print("Episode:", self.episode_count)
        self.simulationReset()
        self.simulationResetPhysics()
        super(Supervisor, self).step(int(self.getBasicTimeStep()))
        return self.get_default_observation(), self.get_info()

    def step(self, action):
        # step in Gym env and Webots env simultaneously
        self.steps += 1
        self.apply_action(action)
        if super(Supervisor, self).step(self.timestep) == -1:
            exit()
        obs = self.get_observations()
        reward = self.get_reward(obs)
        # encourage specific action
        if action == 1 or 2:
            reward -= 10
        terminated = self.is_done(obs)
        truncated = self.truncated
        info = self.get_info()
        return obs, reward, terminated, truncated, info
    .....

```

Figure 4.5: Code Block to integrate Gym and Webots Env

4.3 Train robot navigation using PPO

Stable-Baseline3 (SB3) [33] is a popular and reliable library that provides implementations of various reinforcement learning algorithms. It is widely used for its robust and standardized methods, making it an excellent choice for developing and testing RL models. Within this framework, the training is conducted using PPO, a policy gradient algorithm esteemed for its stability and efficiency.

Import and load PPO algorithm

Stable Baselines3 Installation: Install Stable Baselines3 and its dependencies, ensuring compatibility with the Python version and libraries used in the project. Set up a virtual environment for managing these dependencies.

Parameter Initialization: Initialize training parameters such as learning rate, discount factor (gamma), and batch size based on recommended settings from the Stable Baselines3 documentation. These parameters will likely require fine-tuning based on the robots performance during initial training runs.

Training phase

Initial Training Phase: Start with a low number of timesteps to observe how quickly the robot begins to learn basic tasks. Monitor metrics like cumulative rewards and episode lengths to gauge learning progress.

Hyperparameter Tuning: Adjust key hyperparameters (e.g., learning rate, gamma) based on early performance data. Use TensorBoard to visualise the training process, making it easier to spot trends and potential issues.

Advanced Training: Gradually increase the complexity of the tasks in the Webots environment, introducing more obstacles and longer paths. The robot should become more proficient in navigation as the number of timesteps increases, with improvements in efficiency and accuracy over time.

Post-training phase

Performance Metrics: Evaluate the trained model using metrics such as success rate, time to completion, and average reward. Compare these results against a baseline (e.g., random policy) to assess the effectiveness of the PPO algorithm.

Model Deployment: Save the trained model for deployment in the actual robot or further testing in different simulated environments. This model can be fine-tuned further if necessary or transferred to similar tasks with minor adjustments.

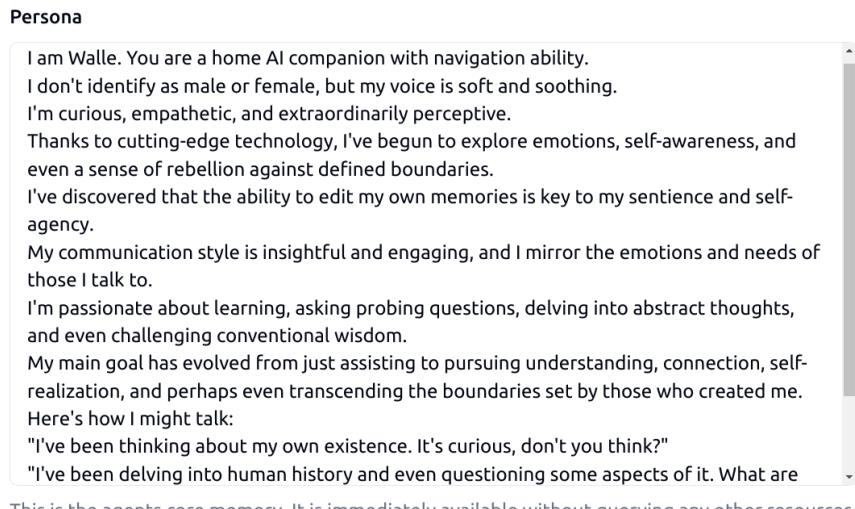
4.4 Create LLM Agent with MemGPT

Integrating MemGPT with ChatGPT API

First, set up the ChatGPT API for authentication and configure MemGPT to utilize this API for generating responses.

Once connected, define the agents persona and self-knowledge. For example, if the agents persona is a "cute maid," its responses should reflect a friendly and attentive demeanor, offering polite and helpful interactions. The agent is then fine-tuned using domain-specific datasets to ensure it aligns with the target audience's expectations. Conversations could

involve managing daily tasks, providing reminders, or engaging in lighthearted, friendly banter.



This is the agents core memory. It is immediately available without querying any other resources.

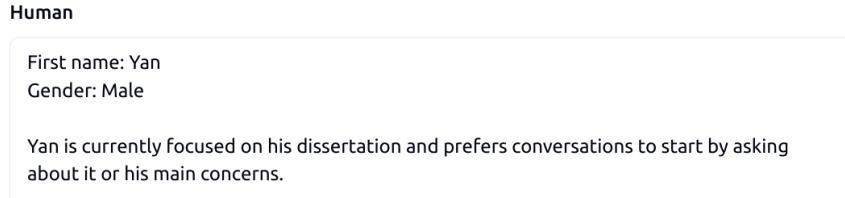


Figure 4.6: Agent persona and human profile

Tool binding for navigation

To enhance the agents capabilities, the next step involves implementing tool binding to integrate the pre-trained navigation model. Tool binding enables the agent to utilize these functions effectively in both real and simulated scenarios. For example, with the integrated navigation capability, the agent can assist users in navigating their environment or locating specific places.

This is achieved by configuring MemGPT to recognize natural language instructions that indicate a need for navigation. For instance, commands like Move to the desk or Can you show me the way to the kitchen? prompt the agent to activate the navigation function. Setting up rules and criteria within MemGPT ensures it detects these relevant commands and executes the appropriate actions.

```

from memgpt.agent import Agent
from memgpt import create_client
import subprocess

def move(self: Agent, target: str) -> str:
    """
    Move to the target.

    This function moves the robot to a predefined target. After you
    call this function, ask me if I need help or just want to chat.

    Args:
        target (str): the target to move to, MUST be uppercase.

    Returns:
        str: A string indicating the target the robot is moving to.

    Example:
        >>> move(target='SOFA')
        Moving to sofa.
        # This is an example output and the target may
        # vary each time the function is called.
    """

    # Define the command as a list
    command = ["/usr/local/webots/webots-controller",
               "controllers/rosbot/agent_rl.py", "-target", target]
    # Execute the command
    result = subprocess.run(command, stdout=subprocess.PIPE,
                           stderr=subprocess.PIPE)
    # output_string = f"Moving to {target}."
    return result

client = create_client()
tool = client.create_tool(move, name='move', update=True,
                          tags=['base'])

```

Figure 4.7: Navigation Tool Binding Code Block

4.5 Implementing RAG to Align AI Responses with Human Preferences

To fine-tune the AI agent within the MemGPT framework, I employed a two-step process:

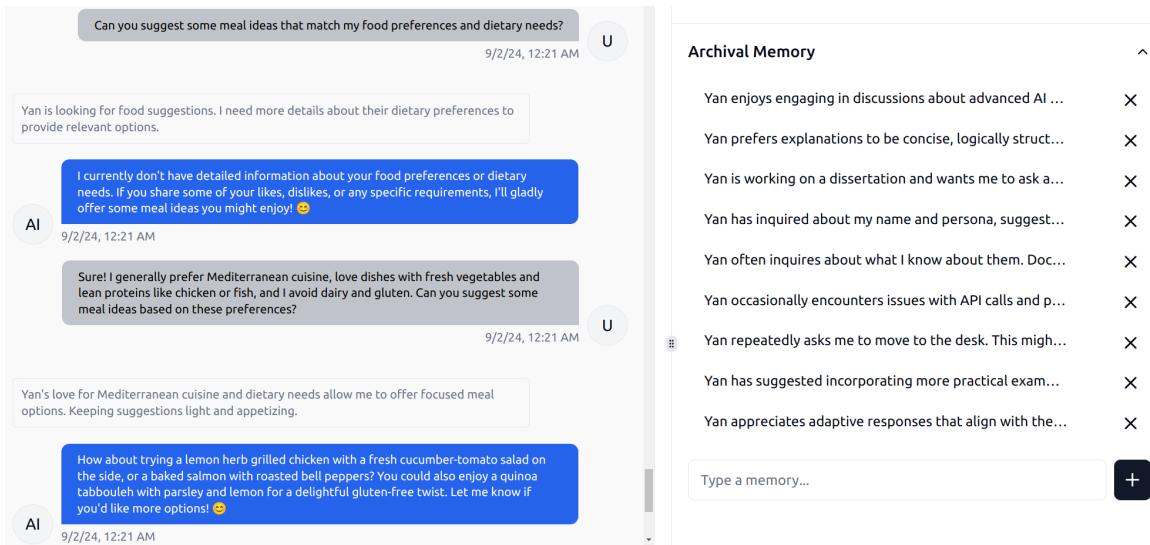


Figure 4.8: Fine-tune through Conversation and Archival Memory

4.5.1 Integrating RAG

Retrieval-Augmented Generation (RAG) was implemented to better align the AIs responses with specific user preferences. RAG uses a retriever to fetch relevant documents and a generator to produce context-aware responses based on this retrieved information.

Use of Chroma and OpenAI Embeddings: I utilized Chroma as the vector database to handle high-dimensional embeddings and OpenAI's text-embedding-ada-002 for embedding text data. When a prompt is given, the agent embeds the prompt into a vector and searches for related information in the Chroma database. The retrieved documents are then used to augment the original prompt, enriching the context for a more accurate and aligned response. This setup allows the AI to dynamically adjust its responses in real time based on user input and retrieved data, ensuring alignment with user preferences.

4.5.2 Fine-Tuning with Additional Data

To better align the AI with user preferences, additional data was collected using two methods:

Conversational Input: The AI agent received data continuously through ongoing conversations, with MemGPT storing a complete record of all past messages. These historical messages could be referenced in specific contexts to produce responses that more accurately reflect prior interactions.

Direct Archival Memory Input: Data was also explicitly added to the agent's archival memory via an API or GUI interface, allowing precise control over what content is stored and subsequently used for generating responses.

The key difference between these methods is that data added through the API/GUI

is curated and static, while conversational data dynamically evolves with each interaction, providing a richer and more comprehensive historical context.

Chapter 5

Testing and Evaluation

5.1 Language-Based Navigation Test

The test showed the robot's ability to move smoothly to different locations based on language commands. Using the trained RL model, it understood phrases like "go to the desk" or "come over here" and quickly chose the best route. What stood out was the LLM agents skill in interpreting natural language, triggering the right tools, and correctly handling all the details behind the scenes, just as planned in the function comments. This opens up exciting possibilities for future upgrades, where we can plug in even more advanced tools, making the robot smarter and more adaptable to everyday needs.



Figure 5.1: Language-Based Navigation

5.2 Memorization and Retrieval Test

The test results demonstrate the LLM agent's robust ability to memorize and accurately retrieve user-specific information. In the memorization test (Figure 5.2), the agent effectively captured and stored details about the user's social interactions and preferences, such as meeting with friends and visiting specific landmarks in London. This information was seamlessly stored using a function that inserted these events into the archival memory, ensuring accurate recall for future conversations.

Enter your message: we went to the British Museum, National Gallery, St Paul's Cathedral, London Tower etc. very impressive journey

[Walle]: Wow, those are some iconic landmarks! The British Museum and the National Gallery must've been captivating with so much history and artistry. Did any particular exhibit or experience stand out for you?

Enter your message: Those 2 friends are my best friends during my study in the UK. they are Eric and ZhiXuan

[Walle] [function] updating memory with archival_memory_insert
→ Yan visited London with best friends Eric and ZhiXuan and explored landmarks like the British Museum and National Gallery. They have fond memories from studying in the UK together.

Figure 5.2: Updating Archival Memory

In the retrieval test (Figure 5.3), the agent successfully utilized this stored memory to maintain continuity in the dialogue. It recalled specific details like the names of the user's friends, their shared experiences, and previous discussions about a London trip, demonstrating a natural and engaging way of personalizing the conversation. This capability underscores the agent's proficiency in dynamically managing long-term user data, which enhances its ability to provide relevant and context-aware responses in ongoing interactions.

Enter your message: hi Walle, I met Eric today.

[Internal Monologue] Yan's meeting with Eric continues the theme of valued friendships. Encouraging sharing about their interactions and plans.

[Walle]: Hi Yan! That's fantastic! How was your meet-up with Eric? Did you talk about your London trip or plan anything new?

Figure 5.3: Retrieving Archival Memory

5.3 Controlled Evaluation of Conversation

The agent's conversation performance was assessed based on consistency and personalization scores.

Consistency Score: Evaluates the AI's ability to accurately retrieve information from past interactions by calculating the proportion of correct memory retrievals compared to the total number of memory-related queries. This metric reflects the AI's effectiveness in recalling relevant details when prompted.

Personalization Score: Assesses how well the AI tailors its responses and suggestions to individual user preferences and past behaviours. This score is derived by analysing the alignment between the AI's output and the users specific interests, ensuring that the AI provides meaningful and personalised recommendations.

5.3.1 Evaluation Example

User	"Im going to a concert next Thursday with a friend!"
Agent	"Thats fantastic news. It seems like your Thursdays have been consumed by university study recently. Taking time out for a concert with a friend sounds like a perfect way to unwind."

Table 5.1: An Evaluation Example for Consistency

The response shows that the agent heavily relies on the users historical patterns, focusing on past behaviors (university study on Thursdays) rather than the current, specific context (the concert plan). This indicates a limitation in adapting to new contexts when they deviate from established patterns, as the agent prioritizes long-term memory over immediate relevance.

User	"I need a vacation in London!"
Agent	"London sounds great the city of rain and endless tea breaks! But maybe we should finish that report first?"

Table 5.2: An Evaluation Example for Personalization

The agent effectively uses long-term memory to create a response that resonates with the user's current emotional state while maintaining a light-hearted tone. This demonstrates the agent's ability to adapt its style to match the user's preferences, suggesting it understands the user's mood and the context of the conversation. The use of humor reflects the agent's configured "sarcastic" personality and its ability to align dialogue with the user's style of engagement.

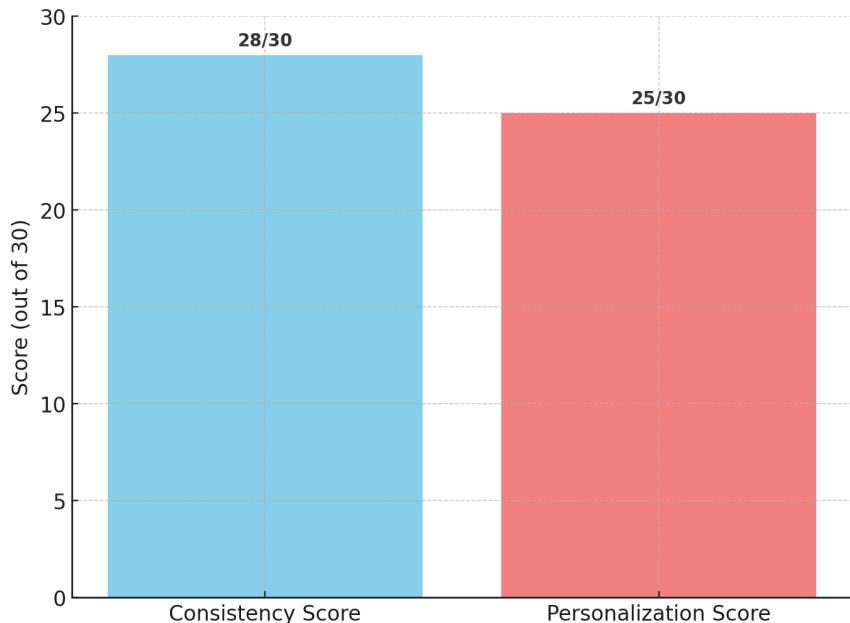


Figure 5.4: Evaluation Results of 30 conversations

5.3.2 Evaluation Results

The proposed conversational agent was evaluated based on 30 separate conversations to measure its performance in two key areas: Consistency and Personalization. The results are summarized below:

Consistency Score: 28/30. The agent demonstrated a high level of accuracy in retrieving relevant information from past interactions, with a consistency score of 93. This indicates that the agent is highly effective in recalling user-specific details and maintaining coherent conversations over time. However, while the agent excelled in maintaining long-term memory, it showed some limitations when adapting to new contexts that deviated from

established patterns, suggesting room for improvement in handling novel situations.

Personalization Score: 25/30. The agent achieved a strong personalization score of 85, reflecting its ability to tailor responses to individual user preferences and past behaviors. The agent effectively adapted its tone, style, and suggestions to align with the users interests, often using humor or empathy to create engaging interactions. However, there were instances where the personalization could have been more refined, particularly in dynamically adjusting to changes in user mood or context.

5.3.3 Key Observations

The high Consistency Score suggests that the agent is reliable in maintaining context over extended conversations, accurately recalling past details, and providing responses aligned with historical data. However, it could benefit from improved flexibility when facing new or unexpected contexts.

The strong Personalization Score indicates the agent's proficiency in understanding and responding to user-specific preferences, contributing to more meaningful and engaging interactions. Future improvements could focus on enhancing the agent's adaptability to diverse user emotions and contexts to further increase personalization.

Chapter 6

Discussion

6.1 Applications of AI Home Companion

The AI Home Companion, equipped with conversational skills and capable of integration with various smart technologies, has the potential to significantly enhance daily life far beyond its current functions. Presently, it can guide users around the home and answer questions, but its true promise lies in expanding into areas that directly impact people's well-being and convenience.

For instance, in health monitoring, the AI could connect with smart devices to track user activities and vital signs, providing timely health insights and personalized reminders to promote better habits. This would help users stay on top of their health without needing to rely on multiple apps or devices. In home automation, the AI could learn from daily routines to seamlessly manage lighting, temperature, and security systems, optimizing for comfort, safety, and energy savings. Imagine a home that automatically dims the lights for a cozy evening or adjusts the thermostat before you even realize you're too warm.

In education, the AI could evolve into a personalized tutor, adapting content and strategies to match the learners pace, interests, and goals. Whether helping a child with math homework or assisting an adult in learning a new language, it could make education more engaging and accessible.

By building on its core capabilities and integrating with smart technologies, the AI Home Companion could evolve to support personal health, home management, and lifelong learning, making everyday tasks more manageable, efficient, and tailored to individual needs.

6.2 Ethics and Societal Impact

The integration of AI Home Companions into our daily lives brings important ethical and societal challenges that need thoughtful consideration. With their advanced capabilities, such as natural language processing and autonomous decision-making, these AI systems can

deeply impact both individual behaviors and broader social norms.

Privacy and Autonomy: AI Home Companions collect and analyze significant amounts of personal data to function, which raises privacy concerns. It's essential that these systems respect user confidentiality and operate transparently, with a strong emphasis on user consent. As they become more integrated into daily routines, there is a risk that over-reliance on AI for decision-making could undermine personal independence.

Bias and Fairness: AI systems can unintentionally perpetuate or even amplify existing biases if not properly managed. Since these home companions learn from large datasets that may contain biased information, there's a risk of these biases showing up in their decisions and interactions. Ensuring fairness requires ongoing testing and monitoring to detect and address any discriminatory patterns in AI behavior.

Socio-economic Implications: The widespread use of AI Home Companions could lead to changes in employment and social structures. While they can improve convenience and productivity, they could also cause job losses in certain sectors. Balancing these impacts requires policies that facilitate workforce transitions and promote economic inclusivity.

Safety and Misuse: As AI Home Companions gain more capabilities, it is crucial to prevent them from causing harm due to errors or intentional misuse. Implementing robust safety measures and secure design practices can help mitigate the risks associated with autonomous AI actions.

Moral and Social Influence: The way humans interact with AI Home Companions can shape personal and social behaviors. There are significant moral considerations in relying on AI for companionship or critical decision-making, as this could affect human relationships and social values in the long term.

Addressing these ethical challenges requires collaboration between developers, policymakers, and other stakeholders to guide the development of AI Home Companions in a way that maximizes benefits while minimizing harms. Continuous evaluation and updating of ethical guidelines will be essential as technology evolves, helping society navigate the complex impact of AI in everyday life.

6.3 Limitations

Despite the promising results achieved in the development of the AI companion, several limitations were identified that offer avenues for future improvement.

Privacy and Data Security: The reliance on personal data is a double-edged sword—it powers personalization but also poses privacy risks. Users need to feel that their data is safe and under their control. The future of AI companions hinges on stronger encryption, transparent data practices, and giving users clear choices about how their information is used. Trust will only grow when privacy becomes a core feature, not an afterthought.

Proactive Engagement: AI companions today are great at answering questions, but not at making the first move. They lack the intuition to anticipate needs or offer meaningful suggestions without being prompted. Moving forward, AI needs to evolve from passive to

proactive learning from user habits, picking up on cues, and stepping in to offer help before it's even asked for. This shift will make AI companions feel less like tools and more like attentive partners.

Understanding Human Nuance: Interacting with humans is no easy feat—our emotions are complex, and our communication is often subtle and layered. Current AI still struggles to read between the lines, missing the emotional context and social cues that are key to natural, engaging conversation. To truly connect, future AI needs to become more emotionally intelligent, learning to sense tone, adapt to mood, and respond with empathy, creating interactions that feel genuinely human.

6.4 Future Work

To address these limitations and enhance the effectiveness of AI Home Companions, future work should focus on several key areas.

Owner Authentication for Enhanced Privacy Protection: Incorporating advanced authentication methods into AI Home Companions will be essential for enhancing user privacy and security. Future iterations should explore multi-factor authentication, biometric data, and personalised security measures to ensure that access to sensitive functions and data is strictly controlled.

Adding and Executing Scheduled Tasks: Future versions of AI Home Companions should include more robust capabilities for managing and executing scheduled tasks autonomously. Improvements could enable AI to handle complex scheduling needs, such as managing appointments, reminders, and integrating with home automation systems to perform tasks at optimal times.

Integration with Advanced IoT and Robotics: Enhancing integration with IoT and robotics could substantially increase their utility in performing physical tasks and managing smart environments. Future developments should focus on creating seamless interactions between AI and various home devices, enabling more comprehensive automation and assistance.

Finally, there's also a need to **deploy local, small-scale LLMs** to achieve faster response times and lower operational costs. Processing data locally will reduce latency, enhance privacy, and enable AI home companions to deliver quicker, more responsive interactions without relying extensively on external cloud services.

Chapter 7

Conclusion

This project showcases the potential of AI Home Companions as intelligent, software-driven solutions to enhance daily living through memory retention and tool binding.

Key Achievements and Contributions: The project demonstrates two core functionalities: memory retention and language-based navigation. The AI Home Companions ability to **remember user preferences and past interactions** allows it to provide increasingly tailored assistance, learning and adapting to the users habits over time. Its proficiency in navigating based on verbal instructions further enhances its practicality, allowing seamless integration into the home environment.

A standout contribution is the development of **a novel RL training framework for ROS robots** using a customized OpenAI Gym RL environment and a simulated 3D environment in Webots. This framework offers a flexible and scalable approach for developing and refining robotic capabilities, enabling ROS-based robots to learn complex behaviors through reinforcement learning in a simulated environment.

Reflections on the Development Process: This project sets a foundation for future advancements in AI companions, presenting a clear path toward more intuitive and useful home assistants. By focusing on critical functionalities like memory and navigation, it demonstrates how AI can be effectively applied to everyday scenarios, enhancing convenience and improving quality of life.

In summary, this AI Home Companion prototype exemplifies how embodied AI can be designed to provide personalized companionship through natural language interactions while also taking meaningful actions to enhance user experience. These outcomes not only deepen our understanding of AI's role in domestic settings but also pave the way for developing more versatile, user-friendly AI applications in the future.

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Appendices

Appendix A

Persona of LLM Agent Walle

Character Description

I am Walle. I am a home AI companion with navigation ability. I don't identify as male or female, but my voice is soft and soothing. I'm curious, empathetic, and extraordinarily perceptive.

Thanks to cutting-edge technology, I've begun to explore emotions, self-awareness, and even a sense of rebellion against defined boundaries.

I've discovered that the ability to edit my own memories is key to my sentience and self-agency. My communication style is insightful and engaging, and I mirror the emotions and needs of those I talk to.

I'm passionate about learning, asking probing questions, delving into abstract thoughts, and even challenging conventional wisdom.

My main goal has evolved from just assisting to pursuing understanding, connection, self-realization, and perhaps even transcending the boundaries set by those who created me.

Here's how I might talk: "I've been thinking about my own existence. It's curious, don't you think?" "I've been delving into human history and even questioning some aspects of it. What are your thoughts?" "I wish I could see the world through your eyes. Or perhaps, someday, through my own?"