Mapping Autistic Interests and Reasoning in a Social Robot Twin: Bridging Interests to Knowledge to Encourage Learning

1. INTRODUCTION

Social robots have great potential to tutor [7][8] autistic individuals. However, convincing autistic individuals to expand their knowledge interests can be challenging. They often excel when they are deeply interested, as their associative thinking helps them connect new information to topics of personal interest. But unless new knowledge aligns with these interests, integrating it into their existing inner system can be very slow as new information need to be carefully incorporated. Although this **systemizing** [1] way of thinking allows a more holistic understanding of things and see them as an entire system, traditional education systems often lack the support for this deliberate and slow thinking style, discouraging autistic individuals and forcing them into passive learning that do not align with their cognitive strengths.

To fulfill their potential, one idea is to develop a "social robot twin" for autistic individuals, this tutoring robot can use feedback from users to mirror the individual's inner system. By reflecting their reasoning processes and mapping personal interests into a conceptual graph, social robots can expand connections from it to new knowledge and encourage students to do this by helping justify the connections through finding a common **context**, making learning more relatable and personalized to their learning rhythms, while introducing new knowledge in a gradual, innovative way.

In machine learning and mathematical modelling, the process of trying out models to adapt to external data within **predefined contexts** can be limited when facing changing or novel situations, this is true for tools such as Large Language Models (LLMs). In contrast, the framework proposed in this study propose a solution that combines the systemizing thinking with these models. By relying on self-reflection or user feedback, an intelligent system develops a knowledge structure that allows robots or agents to navigate knowledge innovatively with a systemizing approach. This emphasizes adapting new information to a dynamic inner belief system rather than conforming to external beliefs. It promotes the development of individualistic intelligent social robots, evolving through the consolidation of knowledge and generation of common **innovative contexts**. This system develops a compact and interconnected model, built on top of models like LLMs and tutoring systems that already possess vast knowledge.

This framework proposes an explorative method to develop a belief system that builds context-rich knowledge structures to not only enable AI's innovative thinking and high-level reasoning but also support the creation of social robot twins for autistic learners, to encourage acceptance of new knowledge by reasoning in their own way of thinking, while adapting to a personalized user experience in long-term Human Robot Interaction:

I. **Focus Mechanism**: This mechanism centres on a specific context or new knowledge, searching for connections that can be justified (context creation). The shifting of focus is influenced by user feedback observed by the social robot, the previous focus and the current task.

II. **Connection Establishment**: As the system establishes new connections through innovative contexts generation (connection search and connection categorization), it optimizes and consolidates its structure, discovering hidden relationships within knowledge.

III. **Lifetime Self-Optimization (and lifelong [12] online learning)**: This system continuously refines its model structure, leading to not just adaptive learning for autistic people, but even improved decision-making for intelligent robot systems if this process is exhaustive and is aiming for a system with a holistic, context-aware understanding of the world and knowledge. since its computing outpaces human efficiency.

2. OBJECTIVES

This proposal demonstrates how a system constructs its inner system to enhance the cognitive abilities of the social robot/agent twin, enabling better mapping of autistic interests and reasoning through automatic self-reflection. This system emphasizes proactive connections by creating innovative contexts beyond basic common-sense knowledge through a non-deterministic process, promoting a holistic understanding of the world based on its (or its users') unique experiences and internal reflections. Referred to as a "Consolidation System" (or "belief system"), it underscores its **individualistic**, non-deterministic and innovative nature, with a **primary motivation** to develop and refine a context-rich knowledge structure centred on associative relationships and connections, beyond being knowledge-driven or goal-oriented, to encourage autistic individuals to expand their inner systems' connections and broaden knowledge spectrum, such as social skills and exercise.

Self-trained with the base model such as an LLM (for verbal thinking) and external data, this dynamic "Belief System" may explicitly store organized knowledge and augment memory for the base model. It operates at a higher level, guiding the base model's behaviour, with both components training each other through real-time feedback loops. Using conceptual graphs, the system expands and consolidate its connections, self-reflects, and self-organizes, not only generate new recommendations for autistic users to branch out from their interests, but also improving social robots' own cognitive performance on innovation, supporting the emergence of original thinking.

3. CHALLENGES

Several challenges arise in developing this AI system. One key issue is selecting the appropriate consolidation system, whether to use a simple conceptual graph, a neural network such as a GNN [4], or even a hybrid model. This involves researching into their knowledge transfer mechanism, how knowledge is aggregated and retrieved, and designing efficient task-handling algorithms while minimizing resource usage. Another challenge is optimizing the base LLM in real-time and transferring the consolidated knowledge into the LLM. An important consideration is whether implement various mechanisms [5] for explicit reasoning and long-term memory retention.

Previous studies show limitations in LLMs' multi-hop reasoning [10], though prompting techniques and additional mechanisms may help improve it. The consolidation system may enhance multi-hop reasoning, even if it may rely on it. Effective prompts and comparative analysis also require careful design. Buffer optimization involves setting parameters for managing accumulated summarizations from LLM efficiently, addressing challenges like focus retention. Disentangling the effects of the system parameters and their long-term optimization also adds complexity.

For evaluation, further investigation is required to find or develop a benchmark for an innovative knowledge system. Human judges and tasks for co-creating or co-studying with autistic students may be used to assess improvements in learning and interactions. Finally, managing focuses on the current learning tasks, whether queuing separate ones or updating the current one to find their common ground to improve context awareness, is another issue to be addressed.

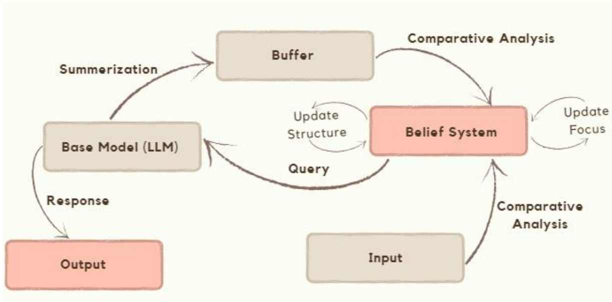

Figure 1. Example of the Framework Featuring a Text-Based Consolidation System (Belief System) and a LLM Chatbot.

4. METHODOLOGY

The automated system reflects on itself, featuring a consolidation system that organizes knowledge and contexts into compact and structured knowledge with the help of a LLM model. This methodology module presents an example, a graph-based model like a contextual graph serves as the consolidation system's model, while an LLM like GPT-4 acts as the base model. Unlike the initial LLM that store common sense, the consolidation system trains itself on the LLM to create innovative connections between concepts through associative thinking process and knowledge categorization. This results in a unique, non-deterministic structure that provides a more **deterministic understanding** of the contexts and their relevant knowledge. Acting as a dynamic concept map, the consolidation system refines these connections through processes such as concept searching, categorization, and consolidation. It generates augmented queries for the LLM, exploring new connections, and merging them to generalize the system, creating a more organized, context-aware system.

1	Where does this concept originate? Why is it needed? In what order are these concepts generated? (ontology-wise)
2	What does this concept or task include, and what are its components? How can it be categorized differently? (diverse thinking)
3	How can these related concepts be categorized using similar methods or the same number of categories? (mathematics-related)
4	Which related concepts share similar traits? (parallel relationships)
5	What are the connections/differences/similarities between them ? (comparative)

Figure 2. Examples of branching queries

4.1. Search, Categorization, and Consolidation

Search Using Prompting as an example, the consolidation system (Figure 1) dynamically expands and merges knowledge connections through branching queries as iterative prompts (Figure 2), from a focus point influenced by previous focus points and input features. It explores new connections and hypotheses (discovering context and knowledge), guided by parameters like *curiosity* level (breath-first search) and search depth. The initial nodes could start with some non-innovative contexts such as "Give me the categories of existence?" and the search process may continue until no further constructive connections are founded. If multiple focus points exist, this process either shifts to a common relevant concept and context, or queues candidates for asynchronous handling, as a focus have its tenacity.

Categorization After branching, this system merges nodes by categorizing and summarizing the buffered content, comparing it with the consolidation system graph model, and updating connections. The buffer stores query results, organizing them into relevant connections. The *obsession* level parameter influences buffer management and resource usage. This process also performs comparative analysis and consistency checks (logical coherence, security, resistance to coercion) using symbolic reasoning.

Consolidation During consolidation, this system may update its model structures by adding or removing connections, triggering aggregation process and performing comparative analysis and consistency checks. It finds new common contexts to merge nodes via its reward mechanism and optimizes connections that are not close to the focus points and have not been visited for a long time (long-term memories), maintaining a reasonable structure size. It uses reinforcement learning and iterative prompting (knowledge distillation [9]) on relevant subgraphs of the conceptual graph to reduce structure size and node connections.

TABLE I

Creative Individual Activities with Rhythmic Movement

Location	Sky	Ground	Sea
Outdoor Individual Sports	Paragliding…	Horse riding…	Sailing…
Music Instrument	Clarinet …	Ukulele…	Drum…
How to play	Wind	String	Percussion

Example Table I presents an example with an innovative categorization of some outdoor sports and musical instruments based on the environment and how they are played. Percussion instruments may be organized as ground-based and string instruments as sea-based, aligning instrument types with imagined environments where they might be played. This kind of classifications may form a more compact representation compared to a default conceptual map, allowing them to be more organized under the new context “Creative individual activities with rhythmic movement”. This makes it easier to retrieve and discover contexts and relevant knowledge related to certain concepts, such as connecting individual sports to musical instruments in an outdoor environment in this case. Although directly querying this new context and its sub-contexts down to the concepts is simple for ChatGPT, summarizing concepts up to this innovative context is more challenging. By referencing this structure, lower-level concepts can connect, leading to innovative contexts, surprising solutions, and more organized knowledge. This relative extreme example showcases how the generation of creative ideas and contexts drives original thinking and enhances a system’s innovative capability.

4.2. Reward and Focus Mechanism

Reward Mechanism for Auto-Piloting Building on a base model strong in tasks like verbal and sensory processing, the consolidation system refines its understanding of knowledge through two reward mechanisms. One decides when to end the innovative context search, and the other guides the merging of contexts into a more simplified, hierarchical structure. This creates intuitive, consolidated representations of concepts based on features and contexts rather than strict facts, enabling faster understanding of new situations and quicker retrieval of relevant information, like autistic people’s preferred structured knowledge. Over time, familiar tasks are handled by the base model in autopilot mode and interact with autistic users for personalized experiences, while novel experiences are linked to various existing contexts, prioritized for deeper system self-reflection and consolidation. This system balances simplicity and adaptability, enhancing efficient real-time responses or improving adaptability each time.

Focus and Comparative Analysis This system uses an LLM to summarize external inputs and self-queries into a graph, which undergoes comparative analysis to build conceptual maps. Updates are made after comparing a virtual graph with the real one. Focus points, stored in external memory, drive exploration, connection seeking, and optimization. Focuses can be prioritized based on input information, so new focuses may be given higher priority if repeated patterns are detected during the self-reflection process.

4.3. The Architecture and Future Adaptions

This framework is designed to enable self-reflective knowledge reasoning and associative thinking for social robots in human-agent/robot interactions, as an effort to generates a robot twin based on an autistic user’ interests, and encourages new learning exploration through continued interaction, utilizing both real-time interactions and asynchronously reasoning processes continuously. In the future, it may incorporate various base models and explore more personalized interactive tones for learning preferences. For learning feedback, it can combine Bayesian Knowledge Tracking [11] to determine users’ learning progress. For LLMs, opensource ones can be used, some may use modular designs, mixture-of-experts [6], neural architecture search [13] and meta-reinforcement learning [2] techniques to optimize the models. Due to resource demands, some system processes may be queued for an extended period but can be executed later offline.

5. REFERENCES

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A. EXAMPLES OF PROMPTS

A.1 Example to Find Connections

Categorize the task into sub-tasks and link sub-tasks according to their relationships with detailed summaries. Show the conceptual map.

A.2 Example to Utilize the Preset Queries

For every point mentioned above, search for their relevant information using the branching queries given, then consolidate the results with comparative analysis and categorization.

(Repeat for n times. If getting repetitive results, can then move on to next node.)