Natural, effective collaboration between intelligent agents and humans on complex tasks is the next frontier in artificial intelligence (AI) and machine learning (ML) research [1]. Intelligent agents are often envisioned as an enabling technology for personalizing education, improving public health outcomes, advancing human learning, increasing scientific productivity etc. To address these challenges, intelligent agents must be designed to operate effectively within human systems. Generative AI (GenAI) methods have enabled human-machine interaction using natural modalities such as language, diagrams, images etc. GenAI agent frameworks build upon this breakthrough to support development of agents for automating knowledge-based or informational tasks. For effective human-AI collaboration, agents must be imparted with capabilities that enable them to reason about the structure and dynamics of the world, diversity of tasks, and individual needs of humans.

I have over 15 years of experience in developing intelligent agents that collaborate with humans in various roles. In my work, I apply a systems lens and build agent architectures with diverse AI & ML components. Additionally, I adopt insights about human decision making, behavior, and learning from social sciences to build agents that are both human-like and human-aware. My work is interdisciplinary and has been published at venues for AI [2, 3, 4, 5, 6], HCI/HRI [7, 8, 9], AI & society [10, 11, 12, 13], and human cognition & cognitive systems [14, 15, 16, 17, 18]. It has been supported by government agencies (DARPA, ARPA-E, AFOSR, and NSF/NIH) as well as corporations (Xerox, Kaiser Permanente). Further, it supports a growing patent portfolio.

1 Research Context, Vision, and Experience

A Systems Lens Effective human-agent collaboration in the real world requires a systems lens [19] - not only must an agent understand the world, make productive decisions given its observations, and act to puruse its goals, it must also exchange information with human partners through natural modalities. Agent architectures that enable collaboration must bring together several intelligent capabilities - vision, learning, reasoning, task execution, dialog etc. - in a single integrated framework. I take a four-pronged approach towards developing collaborative agents. First, I build agents that are *human-like*; I draw upon the insights in cognitive science about the nature of the human mind to build agent systems that have multiple intelligent capabilities including vision, goal-oriented reasoning, AI planning, natural language processing, control etc. Second, I develop methods for *human-aware* behavior; I adapt descriptive models of human decisions, behavior, and learning in social sciences into prescriptive models that can be used within an agent's decision making processes. Along the third prong, I embed agents in interfaces and embodiments to study the principles of natural collaborative human-AI interaction. Along the fourth, I evaluate agent efficacy using experimental methods from social sciences and human-centered metrics (e.g, flexibility, acceptability), beyond benchmark datasets and computation-centric metrics (e.g, accuracy).

Advances in Agent Architectures A persistent dogma of AI & ML technology is the design-and-deploy cycle that assumes that the structure and dynamics of the deployment environment are known at design time and are stationery post deployment. Classical AI systems are programmed by an AI designer based on their understanding of the deployment environment. Along similar lines, ML systems are trained on datasets presumed to reflect the generative processes in the deployment environment. If the assumptions, that deployment environment is known and is stationery, are violated, AI & ML technology has to be taken offline and reprogrammed or retrained. In a stark contrast, humans adapt and learn with volition whenever the need arises.

I build intelligent agents that adapt to an evolving world and changing task requirements; autonomously and with human teaching. I served as principal investigator for Open-World Learning (OWL DARPA SAIL-ON) and Interactive Task Learning (ITL DARPA GAILA). The agent architectures I build commit to the vision that complex intelligent behavior results from an interplay of diverse reasoning and learning methods. I received the AAAI 2018 Blue Sky award [20] for a framework of autonomous learning that integrates lower-level ML processes with higher-level learning strategies under the volitional control of an agent.

OWL studies how agents can autonomously adapt in evolving, non-stationery environments. We introduce the idea of a *novelty* [2] - a meaningful change in the operational characteristics of the environment (e.g., change in gravity or a new tool is made available) that occurs after an agent has been deployed. Model-free learning architectures, such as deep reinforcement learning, experience catastrophic failures when novelties are introduced. Our agent architecture [2, 3] builds upon an explicit representation of a *world model* (e.g., a planning domain) encoding the structure and dynamics of the environment. The world model is reasoned and adapted

with model-based reasoning (e.g., AI planning) and related machine learning methods. Our approach can elegantly handle novelties without the need for full retraining or reprogramming. Inspired by human cognition, we pioneered a meta-cognitive reasoning process that maintains explicit expectations about the agent behavior in canonical, non-novel settings given its world model. Violations of those expectations indicates the presence of a novelty that the architecture characterizes in terms of changes to its world model. It then, accommodates through a novel model diagnosis and repair process. Our architecture is resilient, quick (learns $20x$ faster than deep reinforcement learning), and interpretable, encouraging human trust in learning agents.

ITL investigates teachable agents that dynamically learn *task models* through natural human-AI interaction. At the University of Michigan, I led the development of Rosie, a world model-based agent that learns interactively. It was built upon a cognitive agent architecture [21] and implemented a new paradigm for task model acquisition [18, 6], from situated task-oriented dialog [17, 15]. It was the first in the literature to demonstrate interactive learning of grounded, comprehensive task-relevant knowledge (elements of a planning domain) in a single, integrated agent system. At PARC/SRI, I built upon these ideas and developed a research agenda on embodied agents built with modern ML methods that learn from humans. We studied how humans naturally teach [7] and found that teaching is an intentional process in which teachers introduce new concepts, define them and provide examples, evaluate the competency of the learner, and expand what was taught previously. To exploit such iterative, incremental teaching, we developed an embodied agent architecture [14] that learns new task models using graph inference and generalization [22]. Most recently, we exploit large-language models to understand task-related natural language in embodied agents [23].

Applications of Agent Technology I have built intelligent agents for various applications where the agents adopt an assistive role to a human, supporting their sense making, decision making, problem solving, and learning. This work brings together methods from human factors research such as need finding studies, cognitive task analysis, quantitative/qualitative human studies with engineering of intelligent systems. I adapt descriptive models of human decisions, behavior, & learning from social sciences - cognitive science, pyschology, behavioral economics - to develop *prescriptive human models* that enable agents to reason about their human partners.

In my recent work [24], we investigate how generative AI systems (GenAI) can support humans in sense-making - understanding their medical scans and reports. We found that in addition to being incorrect frequently, the responses produced were characteristically different from how a physician responds. While a physician discussed the specifics of the case being discussed focusing on information that help the patient make productive decisions, GenAI produced general diagnostic knowledge about the disease. For better alignment, we are applying collaborative theory of discourse [19] to adapt GenAI's constitution on the fly. Particularly, we develop response-generation guidance for GenAI based on our analysis of the physicians answers.

Under NSF/NIH Smart and Connected Health, I developed interactive, coaching agents embodied in a mobile interface that help people develop healthy exercise and nutirion behaviors [25, 9]. The agents used a parameterized, prescriptive, adaptive model of humans' aerobic capability in conjunction with AI scheduling methods. Going beyond benchmark datasets typical in AI & ML research, we pioneered a novel staged approach for evaluating collaborative agents [9, 13]. The evaluation approach 1) characterized alignment with human experts, 2) assess efficacy of the user interface [13], 3) benchmark the space of agent adaptation with simulated profiles, and 4) demonstrated a 20% increase in exercise volume over 6 weeks for 21 participants. The agents were built [8, 12, 11] upon insights from behavioral psychology (adaptive goal setting [26], self-efficacy [27]) and cognitive science (the Common Model of Cognition [21]). My work [25, 9] was the first and is one of the very few demonstrations of AI operating with humans in ecological settings for long-time horizons.

Under ARPA-E TransNet, I built an agent that influences people to adopt sustainable modes of transport [5, 10] to bring down a city's energy consumption. This work brings together interdisciplinary methods from human factors research, behavioral economics, AI & ML, and transportation systems to address a complex societal issue. We identified factors underlie people's transit-related choices through semi-structured interviews and surveys [8]. Then, we developed a deep learning prescriptive model of traveler mode adoption drawing upon the rational choice theory [28]. This model biases plan selection in an AI planning framework [29] to generate energy-efficient plans for each individual traveler that are acceptable to them given their personal travel context. Through choice experiments [5] and transit simulations, we demonstrated 5% energy and 15% time savings in Los Angeles.

2 Future Directions

Leveraging my expertise in diverse reasoning and ML methods, I aim to extended GenAI agent frameworks such that they are flexible, reliable, and trusted. Specifically, I want to advance AI systems science along three critical thrusts. *Advanced autonomy* incorporates models of the world, task, and humans within GenAI agentic architectures. *Cooperative multi-dimensional inference* leverages both statistical inference and structured reasoning together to solve complex problems. And *unified architectures* comprised of deep learning and model-based reasoning & learning components, that are capable of complex collaborative behavior in the real world.

Advanced Autonomy Current generation of GenAI agentic frameworks (AutoGen[30], LangGraph[31]) enable a flexible orchestration of various capabilities in service of a complex, multi-step task. However, they implement level 0 autonomy or *autonomy of behavior* where a user can delegate a task to an agentic system. However, the steps and order of execution are specified by an AI designer or the user. I want to enable advanced autonomy in agentic systems. With *autonomy of reasoning*, the agentic system can itself determine which steps to execute and when. To support contextual, flexible, and intentional reasoning, we need to develop and integrate predictive models within agentic frameworks. *World models* encode the structure and dynamics of the world, enabling agentic systems to condition their behavior on expectations of future states (level 1 autonomy). *Task models* encode parameters, soft & hard constraints, and goals, enabling an agentic system to reason about task execution reliably (level 2 autonomy). *Human models* encode the beliefs, desires, and intentions of human partners as well as drive expectations about their behavior, decision making, and learning; enabling agentic systems to individualize execution to a user's needs (level 3 autonomy). Levels 4+ are *autonomy of learning* where the agentic system can acquire these predictive models autonomously through experience (OWL) or teaching (ITL).

Cooperative Multi-dimensional Inference Foundation models' [32] strengths are complementary to classical AI methods (e.g., knowledge graphs, search, planning etc.). They are robust to noise, uncertainty, and the variation inherent in the real world. However, unlike classical AI, they implement implicit inference that is not easily understood, structured, or controlled, limiting their use in critical cases. While LLMs can handle natural variation in human expression, they are unable to reason methodically about action and causation like a planning system. Planning systems, on the other hand, cannot deal with noise and partial-observability, motivating the use of foundation vision models. Emergence of methods such as retrieval augmented generation (RAG) demonstrates that inference within foundation models is not sufficient for complex tasks and must be augmented. I want to study the space of configurations of foundation models and reasoning approaches such that they can benefit from the strength of others. A variety of configurations are possible, each differing in how the inference load is distributed between the two kinds of systems. From reasoning systems augmenting foundation models' context with additional information, reasoning systems adapting foundation models' consitution based on task and conversation status status, reasoning systems validating foundation model responses (LLM-modulo [33]), to foundation models as user/world interfaces to reasoning systems, and foundation models as source of knowledge when reasoning systems are incomplete. Through a principled study, I will uncover the tradeoffs in using different configurations in terms of data needs, inference time, accuracy, assurability etc. Understanding of these tradeoffs will be useful in developing design guidance for agentic systems for real-world problems.

Unified Architectures Human intelligence comprises multiple intelligent capabilities: perception, planning, action & control, long/short-term memory, learning etc. in an integrated architecture [34]. The earlier generation of cognitive architectures [21] sought to build a similar infrastructure for machines using symbolic reasoning methods. While these architectures had contextual, flexible behavior, real world with noise, uncertainty, and partial observability presented an operational challenge. The discovery of modern subsymbolic inference (transformers [35] and their applications as foundation models [32]) has opened up the possibility of unified cognitive architectures that balance subsymbolic and symbolic inference to operate flexibly and robustly in the real world. Going beyond the original goals of cognitive architectures research that focuses on the cognitive and rational bands [36], I want to develop architectures that are inherently collaborative, addressing the social band as well.

To situate unified architecture research, I want to study learning from social interactions - one of the most fundamental forms of learning in the human society. Parents, teachers, experts enable effective and efficient learning in children, students, and novices. In these interactions, the facilitator trainer and the primary learner

form a joint system, with the former helping the latter in achieving critical conditions of learning. I would like to study the human-agent collaborative learning dyad from a variety of perspectives. Continuing my ongoing research, I will develop intelligent agents that learn novel domain concepts and task knowledge through natural interaction, online and during performance. In addition, I want to design agents that support humans in learning and upskilling, helping them become resilient our rapidly changing economy and the world. This vision includes helping humans learn new tasks such as assembling a new artifact [37] using augmented reality embodiment or teaching humans new science and mathematics concepts using conversational and visual interfaces. One of the challenges facing the state of art in agents is that they act/generate language with limited understanding of the human interacting with them. Human needs vary significantly based on their prior knowledge and the task they are performing. For instance, a novice learning how to program needs significant help in not only understanding programming constructs but also in evaluating if a AI-generated solution is correct or not. On the other hand, an expert programmer can evaluate generated solutions and consequently, is looking to quickly access the space of plausible solutions to pick an appropriate one. To enable agents to be reactive to human needs, I want to explore how models of human learning [38], capabilities [39], task-oriented dialog [40] etc. can be leveraged to modulate agent decision making and response in an unified architecture.

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