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Toward A Collaborative AI Framework for Assistive Dementia Care

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Abstract

We envision an integrated framework for supporting the development and deployment of human-aware, general artificial intelligence (AI) that needs to collaborate in uncertain, changing environments. We examine the technology and system requirements of building assistive care agents for dementia or cognitive impaired patients through the continuum of care. We summarize the new AI capabilities and show examples of how an evolving, adaptive development approach would be able to support the basic functionalities and applications in a sound, practical, and scalable manner. We highlight the challenges and the opportunities involved in realizing the proposed framework, and call for future research and development efforts from the AI community to work in this challenging and important domain.

Human Aware AI in the Continuum of Care

AI research has made significant progress in the past two decades, transitioning from laboratory experiments into value creation activities. Recent trends in **robust and beneficial** AI emphasize not only on making AI more capable, but also on maximizing the societal benefits of AI (Russell, Dietterich et al. 2015); success in the field should be based on goodness of fit measures with respect to both the population needs and the individual requirements.

The future of healthcare delivery must transform from discrete processes to integrated services, from curative and rehabilitative to promotive and preventive, and from clinician focused to patient-centric in a seamless continuum of care. Human aware AI that works with, alongside, and for humans will facilitate gathering relevant information, gaining useful insights, and taking timely actions to improve quality and outcome of the health services.

Dementia is a spectrum of neurodegenerative disorders manifested in progressive memory and cognitive decline, leading to inability to perform essential activities of daily living. Treatment is available only to manage the symptoms and slow down the progression of dementia. The prevalence of dementia is rapidly increasing worldwide, causing heavy social and economic burden. An estimated 47 million people are affected with dementia in 2016, with an estimated societal cost of US$818 billion (Alzeimer's Disease International 2016). Integrated care research for dementia is limited and focuses on applying existing information technologies in the care settings (Bharucha et al. 2009). Current solutions for assistive living for dementia are usually component based and standalone (Gillespie et al. 2012). The technologies are limited, proprietary, expensive, and difficult to be integrated and adapted to different environments, evolving needs, and personal preferences (Hattink et al. 2016).

Disruptive AI that improves, leverages, and extends human cognition can help prevent, diagnose, and predict the conditions, minimize the risks, mitigate the symptoms, support the daily activities, and optimize the caregiving and treatment functions for dementia patients at home, in the community, and at the clinics and hospitals.

We examine the AI challenges aim at supporting caregivers in promoting and prolonging independent and active living of dementia patients. The relevant tasks through the care continuum change over time, and vary according to the cognitive status of the patients, sometimes compounded with other illnesses and disabilities. There are no one-size-fits-all solutions; the required care supporting capabilities and services are extremely complex and highly personal.

A Dream Team of General AI Assistants

We focus on direct assistance to the human live-in, visiting, designated, or professional caregivers. These include the family members who are unable to provide round-the-clock care, or clinical managers or nurses who only provide support in some critical tasks at different stages of the care continuum. Caregiving is a very demanding job that involves both social and economical opportunity costs. There is also a severe shortage of health care workers and an increasing number of ageing caregivers worldwide (Brodaty and Donkin 2009).

We envision a *future* setting where a capable AI or agent system plays multiple, collaborative roles at home, in the community, and for the health care institutions. It serves as a *personal assistant* to the patient. It serves as a *surrogate, deputy, or apprentice* to the family caregiver. It serves as a *care coordinator* and *service and communication manager* in the community. It also serves as a *case manager* and *nurse assistant* for the health care professionals in short-term and long-term care facilities, clinics and hospitals.

The AI can be deployed either as a single agent or as a set of agents working together, connected to an internet-of-things setting, at home, in the community, at the clinics and hospitals, and in the public places. This new model will potentially bring about improvement in workflow efficiency, quality of care, and patient safety as compared to the current batch-mode operation, piecemeal interpretation, and component-based service approach to care delivery.

The agents must adhere to the main caregiving objectives for dementia patients: Ensuring safety in different settings; guiding and assisting with instrumental activities of daily living; maintaining wellness through physical and mental health assessment, up-keeping, improvement, and social interactions. All information is communicated, stored, and analyzed in an efficient, and secured manner.

The major caregiving tasks in different settings include:
Personal and Home care: AI agents as personal assistants to patients and home caregivers help to collect and analyze personal health information; this would in turn support physical and behavioral monitoring, risk assessment, emergency notification, companionship, cognitive training, reminding and assisting in instrumental activities of daily living, family and social communication, and health record keeping and updating.
Prevention and community care: AI agents as coordination advisors to community caregivers help to keep track of individual profiles and preferences, plan and schedule customized social interactions, and manage preventive and wellness improvement events, community health screening sessions, home visits, and home nursing care programs.
Clinical and hospital care: AI agents as case managers for doctors and nurses help to co-ordinate the health and medical records, the visit schedules, and the attending clinical teams; they also help to manage information fusion and analysis for diagnosis, staging, and treatment planning, and assist in home transition discharge risk assessment, treatment and care plan updating and maintenance, and establish personalized home and community monitoring plans.

The relevant tasks and the required capabilities are contextualized, change over time, and grow in demand and complexity. The co-ordination and collaboration of the AIs serving different roles must rely on a basic set of common functions that may take on different forms in different settings. The objective is to help all the caregivers of the individual dementia patients, by providing personalized and effective services and support through the care continuum.

Collaborative Artificial General Intelligence

We examine the technical and social capabilities required to provide seamless support for dementia patients through the continuum of care. We summarize the design desiderata for the AIs in the "dream team" of care support.

General Intelligence and Ability to Grow

The AI should evolve, adapt, and change according to different requirements and environments, and by automatically adjusting, periodically extending, or even completely changing the underlying AI architecture.

Recent neuroscience findings show that the general human brain architecture gradually evolves and grows, acquiring and learning capabilities that lead to superb specialization, automatic reconfiguration, and co-ordination with different body parts to perform low level sensory, perception, and high level abstraction and problem solving tasks, and interact with the complex environments (Glasser et al. 2016).

An AI does not need to possess all the human capabilities, but needs to work effectively through exploiting the relevant capabilities to complete the tasks. The AI needs to improve and "grow" with an expanding job scope, as the dementia patient's physical and cognitive capabilities deteriorate, diminish, or get more unpredictable.

Understanding the World and Service Objectives

The AI should understand its operating environment, and its service objectives. The world consists of physical environments that may or may not change, other agents and devices, and humans. There must be a representation of the world, the tasks and the objectives. There must be an evaluation function on how well the goal or objective has been met. There may be multiple objectives, some may be conflicting and tradeoffs must be made. There must also be an understanding of the laws of physics, effects of time, and other factors that affect the world and the task objectives.

Spectrum of Learning and Adapting to Context

The AI should learn the knowledge, skills, and capabilities to cope with changing demands and the varying and expanding scope of care support through the continuum. Signals from the environmental internet-of-things, personal health records and monitors require pattern recognition and analysis from big data with large volume, velocity, and veracity. Deciphering personal directives and preferences, decision support based on direct instructions and occasional episodes and events require "small" data analysis with incremental learning from small samples. As the scope of dementia care tasks changes over time, learning should utilize both stored knowledge (memory based reasoning) and new explorations and exploitations (reinforcement learning).

Action Planning and Reactive Execution

To function in the real-word, there must be representations of allowable actions, potential effects, and any unintended consequences. The AI should be able to recognize the effects and recover or adapt in case of undesired outcomes. The AI should also be able to make decisions, and receive, integrate, organize, and transmit relevant information on-demand and in real-time. The AI should know when to call for help, and to interact with the other agents and humans to complete the tasks to meet different objectives.

Communication and Coordination

The AI should communicate and collaborate and coordinate with other dream team agents. Each AI should also be able to communicate with humans (patients, caregivers at home) and other agents (community agents, institutional agents). The activities should be coordinated, e.g., sending alerts and reminders, sending health records, checking on social or clinical intervention plans. The mode of communication would involve natural language, video, speech, signal processing, and image and text analysis.

Emotion Cognition and Operational Empathy

Research in emotional and social intelligence addresses some of the important aspects of making human-AI interactions effective and efficient. Human-factors engineering work should bring better interfaces to facilitate interactions between AI and the caregivers. Studies in behavioral psychology, for example, on cognitive biases and judgmental heuristics (Kahneman 2011), could also be helpful. These findings and observations are not for the AI to emulate or possess, but to understand and potentially correct judgmental biases of the humans in common and shared tasks.

Self-Awareness and Self-Discipline

The AI should understand the limited capabilities of itself and the other agents or humans it is working with. Mechanisms of self-checking, self-restraining, and self-reconfiguration must be incorporated together with human-intercepted regulatory actions.

A Human-Aware AI Research Framework

While dementia is a progressive condition currently with no cure, substantial benefits can be gained from minimizing the risks of developing dementia and maximizing the effects of preventive measures and mitigating treatments.

Research: We propose a new framework, the HEARTWare Initiative[1] that supports development of the fundamental technologies of the next generation assistive care agents. The technology foci start with five core AI topics:

[1] **HEARTWare**:Human-awarE ARTificial intelligence for (health) cARE

1) Representation and Reasoning: Existing representation formalisms target modular, domain specific tasks. Some aim at capturing categorical concepts and the systematic thought processes, others try to emulate or support the derivation of final outcomes, with less emphasis on the underlying interpretations. For example, deep learning neural networks are good at feature extraction and abstraction for pattern recognition in decision making; Bayesian networks focus on how different factors causally influence the final outcome in diagnosis and estimation. New representations with multi-level, multifaceted abstractions and extensions are needed to support exact and approximate inferences for large-scale, real-life information retrieval and problem solving (Cuong et al. 2014).

2) Perception and Learning: Robust and efficient multi-modal information fusion and organization techniques are needed to integrate the different input information (Dezfouli et al. 2014). Machine learning techniques target at different tasks; their performance and practicality are closely related to the availability and characteristics of the prior knowledge and data at hand, and the inherent biases and variances. Automated selection and adaptation of the machine learning techniques to use with varying representations and available information are also needed.

3) Planning and Decision Making: Planning and decision making is performed at two levels – sensing, perception, and acting (including guiding, navigating and interacting) in the physical (or simulated) environments, and problem solving and decision making at the cognitive and behavioral level. Modern decision support architectures emphasize learning and acting at the same time. The main challenges include working with complex state and action spaces, exploration and exploitation tradeoff, the lack of memory, and the inability to use prior knowledge to speed up the planning process (Bai et al. 2015; Wang and Odoni 2014). New advancements in transfer learning and hierarchical learning are also needed to improve the performance and practicality of reinforcement learning (Nguyen et al. 2015; Li et al. 2016).

4) Communication and Social Intelligence: The ability to effectively communicate in natural language is also key to support and complement human actions, especially for dementia patients who are progressively losing communication capabilities. While an assistive care agent does not need to be equipped with full social skills such as attention, emotion understanding, and human machine communication and interaction at a human-compatible level, it should be situated and functional in a world model with the relevant constraints and expectations.

These technologies in turn constitute four common areas of capabilities for a general AI in the care team:

a) Multi-modal information processing: How to collect, *represent and reason with* heterogeneous data to support analytics and decision making under resource constraints and strict security, privacy and confidentiality?

b) Personal decision support: How to design data analytics and decision support functions for different individuals in different care settings?

c) Integrative AI companion: How to integrate information from the environment sensors, wearables, telehealth communication, and human-aware AI to provide care support for different individuals and care settings?

d) Effective process management: How to optimize the information collection, integration, and analysis tasks to provide cost-effective scheduling and resource management for the caregivers across the continuum of care?

Development: We envision a PEAPOD[2] architecture that includes an adaptive, evolving infrastructure of a *"Care Support as a Service"* (CareSaaS) model. To deliver the assistive care team functionalities for individual patients, we encapsulate the AI services as a set of toolboxes (the "peas") that can be customized and updated to implement the information gathering, analysis, and decision support capabilities; these toolboxes are then delivered in different service packages and applications in the different care settings (the "pods") to serve the different roles of personal assistants, care coordinators, and case managers. The packages should incorporate strict standards of privacy and confidentiality for storage and dissemination of personal and health related information.

Evaluation: The PEAPOD platform and packages should also systematically and effectively address a set of critical technical and design challenges, and meet a set of new evaluation criteria for cost-effective, adaptive implementation of AI-based, healthcare information systems.

The main *technical and design challenges* (the DUES to "pay") involve the varying workflow processes and domain constraints that generate the heterogeneous, multimodal data (Domain challenges), the different stakeholder and user capabilities and preferences (User challenges), the limited resources and costs involved in development and operation (Economic challenges), and the changing task requirements, functions, and implementations of the applications (System challenges).

The main *evaluation considerations* (the CHIC index) should include how efficiently changes and extensions can be made to the system (Change management), how user-friendly the system is (Human-centric design), how the system effectively integrates a myriad of devices, apps, tools, and processes (Integrative innovation), and how readily the system can be customized and scaled to work in different settings (Context-sensitive application).

[2] **PEAPOD –** A people-oriented, adaptive, operational platform to facilitate preventive, participatory, predictive, and personal (P4) decision making in the Continuum of Care

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