Machine Learning for Healthcare: Representation, Learning and Interaction

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Healthcare is one of the most critical topics for human well-beings. Integrating artificial intelligence (AI) into healthcare has the potential to significantly enhance people' quality of life, improve clinicians' efficiency, and reduce the financial cost. However, several fundamental questions need to be answered for its success: *How can we effectively represent complex healthcare data, especially Electronic Health Records (EHR data)? How could we develop generalizable models within complex clinical environments? How could we bridge the gap between AI techniques and clinical needs?* My scientific goal is to advance the integration of machine learning into clinical practice by designing and improving clinical AI systems that are informative, interactive, and affordable. Clinical AI offers numerous prospective benefits: (1) **Informative Knowledge Representation** can encode complex medical heuristics and clinical expertise. This approach aims to represent patient behavior patterns through clinical lab tests and temporal clinical visit data to enhance the informativeness and effectiveness of Clinical AI systems; (2) **Interactive Agents** can efficiently learn, integrate, and update knowledge from continuously changing environments, ensuring optimal model performance over time; (3) **Convenient and Affordable Platform** ensures more accessible and timely healthcare solutions while reducing overall costs by leveraging techniques that minimize dependence on clinicians, families, and societal resources. My past research mainly spans over three pillars:

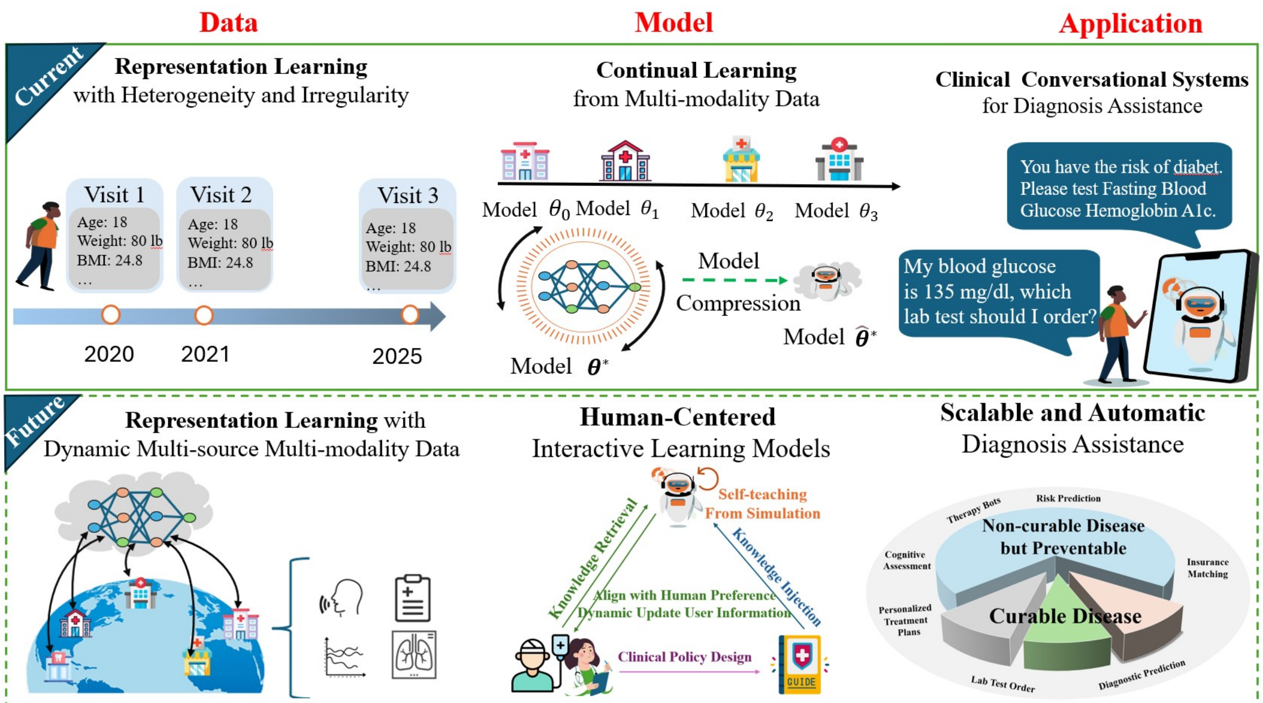


Figure 1: My research focuses on the development of informative representations, interactive learning approaches, and affordable deployment strategies for clinical AI systems.

- **Addressing the heterogeneity and irregularity of <u>EHR data</u>.** The primary goal is to extract patient behavior patterns from clinical lab tests and temporal clinical visits to improve the informativeness and effectiveness of Clinical AI systems. Quantifying various types of EHR data requires extracting informative patterns, modeling their complex relationships, and selecting discriminative features for downstream clinical tasks. My work on heterogeneous data representation is also applicable to other domains in industry and has been recognized and adopted by the Visa Research, resulting in two patents.

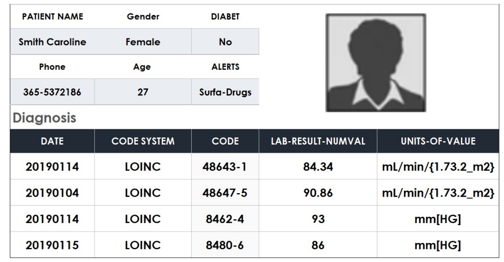
- **Bridging gaps between <u>data</u> and <u>models</u> (generalized clinical AI models)**. The main goal is to continuously learn, integrate, retain, and update the model in the dynamic environment. For example, AI models are notorious for forgetting previous knowledge when adapting to new information. To balance forgetting and adaptation, we aim to identify flat regions in the sharpness-aware landscape to mitigate forgetting. Furthermore, I explored the compression of sequential information into a smaller model, reducing both storage and computational costs.

- **Narrowing the space between <u>data</u>, <u>models</u> and <u>clinical applications</u> (a conversational system for diagnosis assistence).** For example, DiaLLMs learns a unified foundation model to simulate the clinician's diagnostic reasoning process and narrows the diagnosis space by learning a hierarchical structure between lab tests and diagnosis labels. Additionally, DiaLLMs+ simulates the clinical decision-making process for ordering lab tests, helping to eliminate unnecessary orders and leading to more cost-efficient outcomes for patients.

1 Representation Learning for EHR Data: Heterogeneity and Irregularity

EHR data is inherently heterogeneous and irregular. Heterogeneity arises from diverse data types, including demographic information (textual data), lab test (numerical and categorical data) and diagnosis (binary data). Irregularity reflects the asynchronous nature of temporal measurements as exemplified by clinic-based cohort studies where metrics such as heart rate and hemoglobin levels are recorded at non-aligned intervals. My research advances the state-of-the-art in modeling tabular data representation and longitudinal data representation learning.

1.1 Heterogeneous Tabular Data Representation: Real-world tabular data consists of continuous numerical features (in a continuous space) and discrete categorical features (in a discrete space). Learning a unified representation allows for simulating complex distributions and facilitates downstream tasks. Inspired by quantum jumps, we introduced a learnable linear constant function to discretize continuous numerical features into intervals [ICML'24]. A simple yet powerful logic-based neural network is proposed to model intricate column-wise relationships, with scalability to accommodate to high-dimensional features. TabLog acts as a robust backbone, with its impact extending beyond academia, including two submitted patents developed through collaboration with Visa Research.



PATIENT NAME	Gender	DIABET
Smith Caroline	Female	No
Phone	Age	ALERTS
365-5372186	27	Surfa-Drugs

Diagnosis

DATE	CODE SYSTEM	CODE	LAB-RESULT-NUMVAL	UNITS-OF-VALUE
20190114	LOINC	48643-1	84.34	mL/min/{1.73.2_m2}
20190104	LOINC	48647-5	90.86	mL/min/{1.73.2_m2}
20190114	LOINC	8462-4	93	mm[HG]
20190115	LOINC	8480-6	86	mm[HG]

Figure 2: An Example of Electronic Health Record (EHR) Data.

1.2 Irregular Temporal Feature Transformation: When arranged in temporal order, patient visit data from EHRs form a *longitudinal sequence* with irregular, outcome-dependent intervals. We propose a kernel-based method to model the data-generating process across vertical temporal levels and horizontal dimensions [AAAI'24], incorporating multiple variables and patients. In the first stage, longitudinal data is embedded into a latent space. The second stage computes a covariance matrix to capture complex relationships, and the third stage clusters patients based on behavioral similarity. We propose a novel approach called the Inducing Clusters Longitudinal Deep Kernel Gaussian Process (ICDKGP). ICDKGP approximates the data-generating process using a zero-mean Gaussian Process with a deep kernel that models complex, unknown correlations. Additionally, it includes a deterministic non-zero mean function to account for abrupt discontinuities.

2 Continual Learning from Multi-modality Data

A growing number of healthcare institutions and clinical departments now routinely collect and utilize EHR data from large patient populations, creating vast, multi-modality longitudinal datasets. Effectively harnessing these data sources holds significant potential to improve healthcare delivery and quality. This presents several critical challenges in developing a unified model for ever-growing and multi-modality EHR data. For example, can we design a method that effectively learns, integrates and adapts clinical knowledge from multiple specialized hospitals? Additionally, can we compress these sequential, dynamic, multi-modality data into a compact small model? My research focuses on developing a *generalizable* and *efficient* clinical AI model leveraging dynamic, sequential, and multi-modality data.

2.1 Continual Learning from Multi-Modality Data While previous approaches focus on single-domain EHR data, my research introduces a continual learner that adapts to streaming data [ICDM'22,CIKM'23]. Typically, when a model continuously adapts to new data from different sources, it changes its parameters, resulting in the forgetting of previously learned knowledge. To balance anti-forgetting and data adaptation, we aim to find parameters in a 'flat' region of the loss landscape, minimizing sensitivity to distribution shifts [KDD'22]. This is framed as an automated flat region identification task, framed as a minimax game over parameter perturbations.

2.2 Continual Learning with a Small Model and Intelligent Data: Clinical AI models are typically deployed on medical equipment or wearable devices, which require high efficiency due to limited computational resources. Previous methods can adaptively learn a unified model from multiple sources, but the model size increases with the growing data, resulting in high computational costs and storage challenges. To address these challenges, I learn a small model and intelligence data from large AI models through parameter pruning [SDM'24]. We conduct a theoretical analysis of loss landscapes with parameter pruning, and design a directional pruning (SDP) strategy that is informed by the sharpness of the loss function with respect to the model parameters. SDP ensures model with minimal loss of predictive accuracy, accelerating the learning of sparse models at each stage. To accelerate model update, we introduce an intelligent data selection (IDS) strategy that can identify critical instances for estimating loss landscape, yielding substantially improved data efficiency.

3 Clinical LLMs for Diagnosis Assistance

Clinical AI is not a singular technology but a collection of software-driven processes that operate at the intersection of clinicians, patients, and AI techniques. Despite its potential to enhance healthcare, significant challenges remain in incorporating human needs and simulating human preferences to balance clinician workloads, patient costs, and the safety of AI techniques. This raises critical questions for developing affordable clinical AI: Which aspects of AI deployment can effectively replace human labor? To what extent can clinical costs be minimized by replacing such labor? My research focuses on developing a human-centered clinical conversational system that benefits both clinicians and patients. For example, DiaLLMs is a clinical large language model (LLM) designed to predict potential diagnoses and provide explanatory features based on patient symptom trajectories, thereby alleviating the diagnostic burden on clinicians. DiaLLMs+ extends the capabilities of DiaLLMs by analyzing patients' clinical records and offering necessary lab test recommendations. It aims to lower analytical costs by minimizing unnecessary lab tests. Through these strategies, I aim to make clinical AI more economically accessible while maintaining its efficacy and reliability.

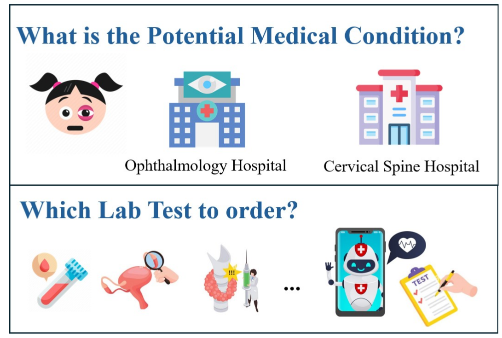


Figure 3: Clinical Foundation models for human interactions and diagnosis assistance.

3.1 DiaLLMs: Towards Human-centered Clinical Foundation Models While I initially built a unified model considering data derived from multi-source, e.g., multiple institutions, in subsequent work I incorporated clinician needs to create a human-centered clinical foundation model aligned with clinician preferences, simulating interactions between humans and AI models. Conventional clinical language models, like Google's Med-PALM, primarily focus on general medical knowledge (e.g., medical licensing exams), which limits their applicability in realistic clinical tasks such as diagnostic prediction. Additionally, real-world diagnosis follows a hierarchical structure, progressing from high-level systems to specific diagnoses. For example, Diabetes diagnosis starts with identifying broad metabolic disorders, narrowing down to glucose regulation issues, and ultimately refining the diagnosis to specific types such as gestational diabetes. To bridge these gaps, I collected and released descriptions for 30,639 clinical codes and 447 diagnosis-organ correspondences, standardizing EHR data into a human-interpretable text [Arxiv'24a]. Additionally, I reformulated the hierarchical diagnosis prediction as a multi-step reasoning framework using proximal policy optimization within a reinforcement learning paradigm.

3.2 DiaLLMs+: Clinical Foundation Models under Cost Pressure I am currently developing clinical language models aimed at reducing clinical analytical costs. In longitudinal follow-ups of patient health status, efficiently acquiring relevant patient covariates is crucial, as screening and lab tests often incur significant expenses. For example, patients may be subjected to a series of unnecessary lab tests when consulted by less experienced physicians, driven by the need to rule out a wide range of potential diagnoses, thus contributing to avoidable costs. To address this issue, DiaLLMs+ [Arxiv'24b] extends DiaLLMs by decomposing the acquisition policy into two sub-policies: a feature selector and an acquisition scheduler. The feature selector focuses on selecting necessary and reliable clinical tests based on existing test results and patient symptoms. The acquisition scheduler further considers the impact of the time intervals between symptoms, optimizing the timing and relevance of the tests. Additionally, we introduce an instruction tuning-based method that prioritizes underrepresented populations by age, gender, and race, for whom timely and accurate predictions of disease progression are particularly valuable.

4 The Future: Informative, Interactive, and Affordable Clinical Artificial Intelligence

My long-term goal is to develop systems that can dynamically interact with and assist clinicians and patients in real-world settings, enhancing their physical, emotional, and social well-being. This involves learning, retrieving, and integrating clinical knowledge, while facilitating communication through verbal, visual, and textual channels to better understand their needs and intentions. The system provides evidence-based, equitable clinical consultant aimed at improving overall well-being. Furthermore, the approach emphasizes the cost-effective deployment of clinical AI models to ensure that healthcare benefits are accessible to all. These goals require new fundamental advances in informative, interactive, and affordable clinical artificial intelligence, while addressing trustworthy, privacy, robustness, personalization, and fairness concerns. I plan to continue my research along this path by approaching from the following directions:

Multi-source Multi-modality Clinical Foundations Models As mentioned earlier, patient data is distributed across various institutions in a sequential manner. Meanwhile, clinical knowledge is encoded in multiple modalities, including medical guidelines, patient symptom trajectories, medical imaging, therapy sessions, and more. My goal is to develop multi-source, multi-modality clinical AI foundation models that can dynamically learn, integrate, retrieve and update clinical knowledge. These models will facilitate communication with downstream tasks through verbal, visual, and textual channels, enhancing the understanding of human needs and intentions. This new paradigm of dynamic multi-source, multi-modality will necessitate a reevaluation of current benchmarks, learning paradigms, and evaluation criteria. Learning over dynamic multi-source multi-modalities will require quantifying information gain while balancing the drawbacks of increased complexity, increased heterogeneity, decreased robustness due to more modalities and decreased generalization ability due to multi-source data. These insights can also be applied to other computer science subfields that involve heterogeneous and interconnected data, such as graph learning, federal learning, reinforcement learning and multi-modality learning. I am passionate about collaborating with leading researchers in Natural Language Processing, Computer Vision, Machine Learning, Bioinformatics and Data Mining to advance our collective understanding of multi-source, multi-modality data in the context of clinical concepts and patient behaviors.

Human-centered Interactive Learning Models Traditional clinical AI focuses on outcome prediction in a data-driven, excelling in well-defined, structured tasks. However, healthcare decisions often involve ambiguity, incomplete data, and conflicting information. My future work aims to integrate human judgment into AI systems, enabling them to adapt to complex and uncertain scenarios, thereby assisting clinicians in making informed decisions when data is unclear. This framework enables **collaboration between clinical AI models, medical guidance databases, and healthcare professionals** by incorporating learning from clinical practice, leveraging prior medical guidelines, and using interactions between physicians and patients to retrieve, evaluate, and refine clinical decisions. Besides, patients may not always express their needs directly, making it challenging to fully understand their symptoms. Additionally, emotions, mental health, and social circumstances significantly impact treatment outcomes. I am motivated to develop **Social-emotional clinical AI** to assist healthcare professionals by providing insights into patients' emotional states, helping overcome communication barriers. By recognizing signs of depression, anxiety, or stress, AI can recommend interventions, alert healthcare providers, or offer real-time emotional support, thereby contributing to holistic patient care.

Diagnosis Assistance: Timely, Scalable and Fair My current research focus on the curable diseases. However, in real-world settings, some diseases are curable upon detection, while others are primarily preventable. This distinction highlights the critical need for early prediction of preventable acute care events. Consequently, I am motivated to expand my research to encompass a broader range of diseases and to design **Risk-aware Clinical AI for Disease Prevention**. I am particularly passionate about developing AI models that predict the risk of preventable diseases and offer counterfactual explanations. This approach can assist in monitoring indicators of well-being, interpreting behavioral cues, and suggesting personalized physical and social activities to improve patients' overall health. In addition to diagnosis prediction and prevention, diagnosis assistance involves complex clinical procedures such as insurance recommendations, lab test ordering, and remote diagnostics. My vision is to develop **Scalable Clinical AI Services** that seamlessly integrate these functions. Finally, a powerful clinical AI technology alone is not the goal; the key is ensuring these technologies benefit a broader population. Equitable access to clinical AI is crucial for addressing healthcare disparities. My future plan is to develop **Fair and Affordable Clinical AI** systems that can **serve diverse populations**, regardless of socioeconomic status, geographic location, or resource availability. Building on my current work with diagnosis-based clinical foundation models, I aim to create systems that meet the clinical needs of various groups, recommend tailored services, and ultimately reduce healthcare costs. I plan to continue my collaborations with medical schools and establish new partnerships to explore real clinical needs and deploy clinical AI systems that complement traditional clinical practices.

I look forward to leading a team that advances this research agenda, strengthened by both existing and new collaborations with experts across various fields, including computer science, statistics, robotics, medicine, and psychology. My goal is to make significant contributions to the scientific understanding of clinical artificial intelligence and help develop the next generation of AI systems that can assist and enhance human capabilities.

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