I develop *machine learning methods* for *reasoning about real-world events*.

The ability to reason about real-world events is crucial for effective decision-making in various domains. Figure 1 shows an example in education. Similarly, reasoning about user activities on social media platforms, such as their posts, likes, and shares, can provide insights for predicting and responding to social events. In healthcare, reasoning about medical events like diagnosis and treatments can assist human doctors in planning future hospital visits and designing personalized exercise routines. I envision a future where computers empowered by machine learning can reason about real-world events. In pursuit of this vision, my research is dedicated to addressing key problems in the following research areas:

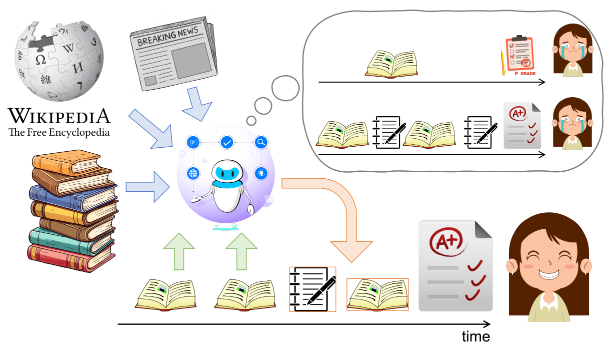

Figure 1: An AI agent in education, which is empowered by machine learning and can assist human teachers. It leverages diverse sources of information (e.g., textbooks and online articles) to acquire knowledge about the subject matter and how to improve students' learning experience. Given the past events of a student (e.g., previous lessons and test results), the agent applies relevant knowledge and reasons about the potential outcomes of possible interventions. It then plans a personalized course of lessons and tests, which it suggests to the human teacher, to enhance the student's performance and enjoyment.

- *Event sequence modeling.* Modeling event sequences can discover how past events influence future events, thus providing valuable insights for predicting the future. For example, by learning from historical financial data, a model may identifiy useful patterns such as "airline stocks often rise after oil price drops".

  In this area, my research has introduced a family of *neural and neuro-symbolic* models that can capture complex patterns in real data and significantly outperform previous models on the task of event prediction. In addition, my research leverages principles from *classical statistics* to discover opportunities for *accelerating* both the training and inference processes of these neural models. Please see §1.

- *Natural language understanding.* Knowledge about real-world events is commonly documented by human experts in text forms, such as textbooks and news articles. Natural language technologies are a promising means to empower computers to acquire such knowledge and use it for real-world reasoning.

  In this area, my research develops deliberative reasoning methods that integrate *modern large language models (LLMs)* with *classical logical inference methods*, which combine the desirable properties of both paradigms and thus can outperform each individual paradigm on complex reasoning tasks. Please see §2.

- *World model learning.* Understanding real-world dynamics is an essential property of intelligent agents for complex real-world applications. I have planned future research in pursuit of world models, including projects that embed LLMs into *classical reinforcement learning (RL) frameworks*, empowering LLMs to learn *world dynamics* through real-world interactions. Please see §3.

Commercial and broader public engagement and impact. I am passionate about broadening the impact of my work through sustained collaborations beyond academia. While my work has primarily centered on academic research, I place a strong emphasis on the practical applicability of my work. Particularly, I take care to design my methods in a way that allows them to be seamlessly integrated into large-scale production settings. My methods for event sequence modeling have been integrated into real-world products such as Alipay, the world's largest mobile digital payment platform, which serves more than one billion users. This emphasis has also fostered extensive collaboration with leading tech companies and has attracted research funding from them. Looking forward, I will seek out opportunities to collaborate with external organizations in transforming fundamental research into real-world applications, aiming to make a broader societal impact.

1 Neural Probabilistic Methods for Event Sequence Modeling

The topic of my PhD thesis is event sequence modeling, with a particular emphasis on modeling the distribution $p(\text{sequence of events})$. Knowing $p(\text{sequence of events})$ is essential for probabilistic inference: $p(\text{future events} \mid \text{past events})$ enables the prediction of future events; similarly, $p(\text{unobserved events} \mid \text{observed events})$ enables the imputation of missing events. For example, by analyzing future hospital visit trajectories drawn from $p(\text{future visits} \mid \text{a patient's past visits})$, one can propose answers to a range of questions such as "When will the patient's next visit occur?" (by averaging the times of the first future visits across all trajectories) and "How likely is the patient to survive the next three months?" (by determining the frequency of death events within the next three months from sampled future trajectories).

Effective neural probabilistic models. We[1] developed the neural Hawkes process (NHP) [15], one of the first neural event sequence models. It employs a novel *continuous-time* LSTM to capture the complex patterns in which past events may influence the future. On a range of real-world datasets including MIMIC Clinical Database [28], NHP has achieved significant improvements over previous state-of-the-art in predicting future events given the past (e.g., given a patient's electronic health records, predicting when the patient will visit the hospital again and which department the patient will visit). We then developed the neural Datalog through time (NDTT) [12], a neural-symbolic extension of NHP. NDTT uses a temporal deductive database to precisely and efficiently track domain-specific knowledge about events and their participants, configuring a structurally sparse neural architecture that can scale up to domains that have millions of types of events. Further, we developed Transformer versions of both NHP and NDTT [11], which enhance performance and efficiency. These models have become standard baselines for comparing new methods [2, 23] and are often integrated as a core part in models for downstream tasks such as anomaly detection [22, 24].

Efficient training and inference. Training a neural event sequence model and performing inference with it present non-trivial challenges. While maximum likelihood estimation (MLE) is a standard training method for probabilistic models in general, estimating the likelihood can be computationally expensive for event sequence models. To address this issue, we developed a novel training method [13] based on the principle of noise-contrastive estimation (NCE). Our NCE method provably maximizes the likelihood without computing it. As a result, our method significantly reduces the computational cost compared to MLE in practice. This method has enabled us to develop HYPRO [10], the first energy-based event sequence model: its likelihood is intractable to compute but can be bypassed by our NCE method. HYPRO significantly outperforms autoregressive models in long-horizon event prediction, the task of predicting multiple future events over a time period given the past. For inference, we introduced the first general sequential Monte Carlo method [14] that efficiently approximates $p(\text{unobserved events} \mid \text{observed events})$.

Event-based decision making. An important application of event sequence models is their integration into RL agents to learn intervention policies. Our research has demonstrated that event sequence models are useful in both classical model-based RL frameworks [4, 8] and more recent goal-conditioned frameworks [6]. For example, in a simulated kidney transplantation environment, our RL agent equipped with an event sequence model can learn to plan personalized follow-up schedules for kidney transplant recipients, improving their survival by 8% [8]. Timing is crucial in such scenarios: a timely visit is necessary for monitoring a patient and handling adverse reactions, but an overly dense schedule may be a waste of resources. Empowered by an event sequence model, our RL agent learns a sensible policy, scheduling more frequent visits for recipients with higher levels of creatinine (an indicator for risk of graft rejection).

2 Reasoning with Large Language Models

Since starting my current Research Assistant Professor position, I have been working on harnessing and enhancing the reasoning capabilities of LLMs. Modern LLMs such as GPTs have demonstrated strong

[1] Throughout this statement, "we" refers to "my collaborators and I" that coauthored the paper being discussed in the context.

```
Hypothesis: Ava is blessed.
F-1: Ava is a queen.
F-2: Ava is just.
F-3: Just queens are good.
F-4: Good people are blessed.
```

Listing 1: A multi-step logical reasoning problem, where "F" means "fact".

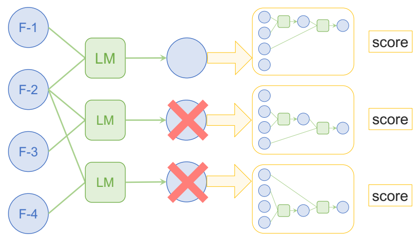

Figure 2: LEAP works on the problem in Listing 1. At each step, an LLM proposes multiple deductions. Then we look ahead into possible future steps of each proposal, and rank these proposals based on the lookahead information.

performance on various tasks that require knowledge memorization and generalization, such as answering science questions [18, 25]. The training data of LLMs includes a large amount of text discussing knowledge about real-world events and their participants. I am interested in developing machine learning methods that enable LLMs to reflect on such knowledge and reason about real-world events.

Challenges arise as LLMs are not good solvers for problems that require deliberative reasoning. Recent research has shown that LLMs struggle to solve multi-step logic puzzles and multi-digit multiplication [16]. My research investigates a new approach that uses *LLMs as proposers*. In particular, I integrate LLMs with other machinery: LLMs propose solutions or logical pathways towards solutions; the other machinery analyzes and utilizes LLM-generated proposals to construct a final solution.

LLMs as proposers of reasoning paths. A key problem in this area is multi-step logical reasoning, the problem of deducing new facts from known information and determining the truth value of a hypothesis. Listing 1 shows a simple example. We developed LEAP [7], the first LLM-based logical reasoning system that performs explicit *lookahead* planning during inference. For a hypothesis, it performs multiple steps of deduction to reach a conclusion about its truth value: at each step, an LLM proposes multiple ways to continue the deduction; LEAP rolls out future steps of each LLM-proposed way, and only pursues those most conducive to discovering the truth value of the hypothesis. Through explicit lookahead planning, LEAP is able to make well-informed decisions at each step. It achieves high accuracy on multiple benchmark datasets, outperforming methods that use LLMs as independent solvers, including chain-of-thought prompting [21]. We are currently extending LEAP to address more complex reasoning problems.

We generalized the "lookahead" idea to designing a novel Transformer architecture [1]. Our Lookahead Transformer estimates the next-token distribution by drawing multiple continuations of the past from an ordinary Transformer and attending to these continuations to consider the potential sentences resulting from different next-token choices. On multiple tasks including morphological inflection and Boolean satisfiability, our new model is able to outperform the ordinary Transformer of comparable size.

LLMs as proposers of cause events. Following the philosophy of "LLMs as proposers", we developed LAMP [5], the first framework that integrates an LLM into the prediction process of an event sequence model. Event sequence models struggle to make accurate predictions on large-scale datasets of real-world socio-political events such as GDELT [30] and ICEWS [29]. Understanding the relationships between these events requires a substantial amount of world knowledge, which can not be inferred solely from previous events. LAMP leverages an LLM to fill in the missing piece: it draws candidate predictions from an event sequence model; instructed by a few expert-annotated demonstrations, the LLM learns to propose cause events for each candidate; a search module identifies any previous events that match the LLM-proposed causes; a ranking model assesses the candidate predictions by analyzing retrieved events and ranks them based on the strength of the supporting evidence. LAMP significantly outperforms state-of-the-art event sequence models on both GDELT and ICEWS, achieving accuracy improvements of several times.

3 Future: From Language Models Towards World Models

A goal of my research is to enable intelligent agents—like what's shown in Figure 1—that assist human users in real-world tasks, anticipating consequences of decisions and suggesting high-reward actions. LLMs emerge as a promising means to reach this goal: they are able to learn useful patterns from training data and can generate contextually sensible output, showing a potential to work as building blocks of *world models*. However, they have key limitations: what they have learned are patterns of text, but not dynamics of the world; their bounded context windows can not handle very long inputs; they often hallucinate. Over the next five years, I plan to continue basic research in the areas of §1 and §2, as well as study new problems related to addressing these limitations. Some problems require expertise out of my primary focus, and I will actively seek collaboration with experts in related areas.

3.1 Situated Adaptation of LLMs ***to learn real-world dynamics***

To enable LLMs to learn real-world dynamics, I plan to *situate* LLMs within decision-making pipelines in real-world domains such as robotics, allowing them to interact with environments and *adapt* their behavior in response to feedback. This idea draws insights from the success of the "LLMs as proposers" principle in §2. It also opens up research opportunities to draw insights from classical model-based RL methods [27]: an LLM can function as an environment model and facilitate policy learning by offering a reasonable prior over the environment dynamics; the policy generates actions that directly interact with the environment and collects feedback to improve the LLM. I have established collaboration with robotics experts at TTIC. Our recent research [3] demonstrates that an LLM can learn dynamics of a compact environment and enhance a robot's ability to perform multi-step planning. Precisely, an LLM is instructed—with human-crafted examples—to maintain an estimate of the state of the environment, which is often unobservable, and track its transition as new actions are taken. Then our planner conditions each action on the estimate of the current state. This method outperforms strong baseline methods including Code-as-Policies [19], achieving significantly higher success rates on a range of multi-step planning tasks such as object manipulation. Looking ahead, I am interested in devising methods that enable LLMs to learn more complex world dynamics.

3.2 Inductive Learning ***to handle unbounded experiences with bounded context windows***

The bounded context windows of LLMs restrict their ability to handle long inputs. Consequently, when performing a long-term task (such as being a life-long assistant or companion), LLMs may fail to retain the full context, thus making poorly-informed decisions. Humans also have limited memory capacities. But humans often perform *inductive learning*, summarizing long and detailed *experiences* into short and abstract *guidelines*. Here an experience refers to any form of interaction with an environment, ranging from simple cases of "placing a cup" to complex tasks of "winning a competitive game". A guideline is a general rule that applies to many experiences, such as "player 1 usually uses strategy X in this game." Guidelines take less memory but can still inform decision-making in future similar situations. I plan to develop machine learning methods that enable LLMs to perform human-like inductive learning. An LLM maintains a repository of guidelines, and updates the repository as it has new experiences. As more experiences accumulate, the repository will expand, albeit at a slower pace than the accumulation of experiences. The repository is structured, allowing for effective and efficient retrieval. Retrieved guidelines will take significantly fewer tokens within the context window compared to using the relevant previous experiences.

3.3 Representation Analysis and Engineering ***to mitigate hallucination***

Recent research has found that the internal representations of deep neural networks can form semantically meaningful structures [20, 26] and can be used to control the output of the networks [17]. My research [9] discovers the formation of linearly separable clusters in the internal representations of LLMs, where each layer exhibits a pattern of clusters useful for certain downstream tasks. Leveraging this discovery, we developed a transfer learning method that only adapts certain suitable layers to a given task, significantly reducing computation cost [9]. Moving forward, I am intrigued by the potential of engineering the internal representations of LLMs to mitigate hallucination. Conceptually, we may identify patterns of representations (e.g., clusters and subspaces of each layer) responsible for this undesirable behavior and then modify the patterns.

Acknowledgments and Future Funding Plans

My research has been generously supported by a Bloomberg Data Science PhD Fellowship and a series of research gifts from Adobe. I plan to submit my first NSF CISE Small proposal in my first year as an Assistant Professor, and its topic will be event reasoning with large language models. In addition, I am keen on partnering with colleagues and competing for large NSF and DARPA funding programs.

References

Part I – My Relevant Preprints

[1] Li Du, **Hongyuan Mei**, and Jason Eisner. "Autoregressive Modeling with Lookahead Attention". In: *arXiv preprint arXiv:2305.12272* (2023).

[2] Siqiao Xue, Xiaoming Shi, Zhixuan Chu, Yan Wang, Fan Zhou, Hongyan Hao, Caigao Jiang, Chen Pan, Yi Xu, James Y Zhang, Qingsong Wen, Jun Zhou, and **Hongyuan Mei**. "Easytpp: Towards open benchmarking the temporal point processes". In: *arXiv preprint arXiv:2307.08097* (2023).

[3] Takuma Yoneda, Jiading Fang, Peng Li, Huanyu Zhang, Tianchong Jiang, Shengjie Lin, Ben Picker, David Yunis, **Hongyuan Mei**, and Matthew R. Walter. "Statler: State-Maintaining Language Models for Embodied Reasoning". In: *arXiv preprint arXiv:2306.17840* (2023).

Part II – My Relevant Refereed Publications

[4] Chao Qu, Xiaoyu Tan, Siqiao Xue, Xiaoming Shi, James Zhang, and **Hongyuan Mei**. "Bellman Meets Hawkes: Model-Based Reinforcement Learning via Temporal Point Processes". In: *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*. 2023.

[5] Xiaoming Shi, Siqiao Xue, Kangrui Wang, Fan Zhou, James Y. Zhang, Jun Zhou, Chenhao Tan, and **Hongyuan Mei**. "Language Models Can Improve Event Prediction by Few-Shot Abductive Reasoning". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2023.

[6] Zhiyue Zhang, **Hongyuan Mei**, and Yanxun Xu. "Continuous-Time Decision Transformer for Healthcare Applications". In: *Proceedings of the International Conference on Artificial Intelligence and Statistics (AISTATS)*. 2023.

[7] Hongyu Zhao, Kangrui Wang, Mo Yu, and **Hongyuan Mei**. "Explicit Planning Helps Language Models in Logical Reasoning". In: *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2023.

[8] William Hua, **Hongyuan Mei**, Sarah Zohar, Magali Giral, and Yanxun Xu. "Personalized Dynamic Treatment Regimes in Continuous Time: A Bayesian Joint Model for Optimizing Clinical Decisions with Timing". In: *Bayesian Analysis* (2022).

[9] Shuo Xie, Jiahao Qiu, Ankita Pasad, Li Du, Qing Qu, and **Hongyuan Mei**. "Hidden State Variability of Pretrained Language Models Can Guide Computation Reduction for Transfer Learning". In: *Findings of the Conference on Empirical Methods in Natural Language Processing (Findings of EMNLP)*. 2022.

[10] Siqiao Xue, Xiaoming Shi, Y James Zhang, and **Hongyuan Mei**. "HYPRO: A Hybridly Normalized Probabilistic Model for Long-Horizon Prediction of Event Sequences". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2022.

[11] Chenghao Yang, **Hongyuan Mei**, and Jason Eisner. "Transformer Embeddings of Irregularly Spaced Events and Their Participants". In: *Proceedings of the International Conference on Learning Representations (ICLR)*. 2022.

[12] **Hongyuan Mei**, Guanghui Qin, Minjie Xu, and Jason Eisner. "Neural Datalog Through Time: Informed Temporal Modeling via Logical Specification". In: *Proceedings of the International Conference on Machine Learning (ICML)*. 2020.

[13] **Hongyuan Mei**, Tom Wan, and Jason Eisner. "Noise-Contrastive Estimation for Multivariate Point Processes". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2020.

[14] **Hongyuan Mei**, Guanghui Qin, and Jason Eisner. "Imputing Missing Events in Continuous-Time Event Streams". In: *Proceedings of the International Conference on Machine Learning (ICML)*. 2019.

[15] **Hongyuan Mei** and Jason Eisner. "The Neural Hawkes Process: A Neurally Self-Modulating Multivariate Point Process". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2017.

Part III – Other References

[16] Nouha Dziri, Ximing Lu, Melanie Sclar, Xiang Lorraine Li, Liwei Jian, Bill Yuchen Lin, Peter West, Chandra Bhagavatula, Ronan Le Bras, Jena D Hwang, et al. "Faith and Fate: Limits of Transformers on Compositionality". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2023.

[17] Kenneth Li, Aspen K Hopkins, David Bau, Fernanda Viégas, Hanspeter Pfister, and Martin Wattenberg. "Emergent world representations: Exploring a sequence model trained on a synthetic task". In: *Proceedings of the International Conference on Learning Representations (ICLR)*. 2023.

[18] OpenAI. "GPT-4 Technical Report". In: *arXiv preprint arXiv:2303.08774* (2023).

[19] Jacky Liang, Wenlong Huang, F. Xia, Peng Xu, Karol Hausman, Brian Ichter, Peter R. Florence, and Andy Zeng. "Code as Policies: Language Model Programs for Embodied Control". In: *arXiv preprint arXiv:2209.07753* (2022).

[20] Thomas McGrath, Andrei Kapishnikov, Nenad Tomašev, Adam Pearce, Martin Wattenberg, Demis Hassabis, Been Kim, Ulrich Paquet, and Vladimir Kramnik. "Acquisition of chess knowledge in alphazero". In: *Proceedings of the National Academy of Sciences (PNAS)* (2022).

[21] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. "Chain-of-thought prompting elicits reasoning in large language models". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2022.

[22] Siqi Liu and Milos Hauskrecht. "Event Outlier Detection in Continuous Time". In: *Proceedings of the International Conference on Machine Learning (ICML)*. 2021.

[23] Song Wei, Shixiang Zhu, Minghe Zhang, and Yao Xie. "Goodness-of-fit test for mismatched self-exciting processes". In: *Proceedings of the International Conference on Artificial Intelligence and Statistics (AISTATS)*. 2021.

[24] Alex Boyd, Robert Bamler, Stephan Mandt, and Padhraic Smyth. "User-Dependent Neural Sequence Models for Continuous-Time Event Data". In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2020.

[25] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. "Language Models are Few-Shot Learners". In: *arXiv preprint arXiv:2005.14165* (2020).

[26] Vardan Papyan, XY Han, and David L Donoho. "Prevalence of neural collapse during the terminal phase of deep learning training". In: *Proceedings of the National Academy of Sciences (PNAS)* (2020).

[27] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

[28] Alistair E. W. Johnson, Tom J. Pollard, Lu Shen, H. Lehman Li-wei, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G. Mark. “MIMIC-III, a Freely Accessible Critical Care Database”. In: *Scientific data* (2016).

[29] Elizabeth Boschee, Jennifer Lautenschlager, Sean O’Brien, Steve Shellman, James Starz, and Michael Ward. *ICEWS Coded Event Data*. 2015.

[30] Leetaru and Schrodt. “Gdelt: Global data on events, location, and tone, 1979–2012”. In: *ISA annual convention* (2013).