New Frontiers in Associative Memories

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Abstract

This workshop will discuss the latest multidisciplinary developments in Associative Memory. A number of leading researchers in this topic from around the world have already agreed to attend and present their latest results. We anticipate sharing their presentations and outlining future research directions in this emerging field with the rest of the ICLR community.

Associative Memory (AM) is a core notion in psychology responsible for our ability to link people's names to their faces and to remember the smell of a strawberry when we see one. Mathematical formalizations of AM date back to the 1960s-1980s [1–3]. For instance, the celebrated Hopfield Networks of Associative Memory [3, 4], described in the early 1980s, have made a significant impact on the communities of machine learning researchers, neuroscientists, and physicists. A recent surge of novel theoretical and practical developments [5–7] have reinvigorated this seemingly established field and placed it in the spotlight of modern ideas in deep learning [8–11] and contemporary artificial network models of the brain [12–14] (see also Quanta Magazine article), culminating in the recent 2024 Nobel Prize in Physics[1] *"for foundational discoveries and inventions that enable machine learning with artificial neural networks"*. The explosion of interest in large language models (LLMs) and their limitations pertaining to hallucinations and limited context window have also found synergies with the ideas of AM [15–18].

However, there still remain significant gaps between the language, methods, and ideas that are used in the theoretical work pertaining to this topic and mainstream machine learning literature. The main goal of our workshop is to bring together key researchers and developers working on AM from the perspectives of machine learning, computational neuroscience, statistical physics, and software engineering, to build upon the first iteration of this workshop at NeurIPS 2023 towards closing the gaps and converging to a common language, methods, and ideas. While the first iteration focused mainly on energy-based AM theory and software, this iteration will primarily target algorithmic and architectural synergies between the rich literature on AM (stemming from neuroscience, statistical physics and machine learning) and LLMs. Recent developments have opened up a new frontier for Associative Memory and Hopfield Networks [19]. The announcement of the Nobel Prize is Physics 2024 has further placed this area of research in the spotlight. We believe that 2025 is the right time to bring this topic to ICLR. We would consider our workshop a success if it sparks enough interest from the communities of AM theorists, LLM practitioners, computational neuroscientists, and software developers, which are largely disjoint, to work together towards understanding the language and methods used by each of the sub-fields. We hope that this convergence will lead to efforts towards the development of novel architectures and algorithms uniquely suitable for Associative Memory networks, and to the integration of these modules into modern large scale AI systems.

Key Milestones and Recent Developments. Traditional Hopfield Networks represent a beautiful mathematical formalization of associative memory capabilities, but are limited by a memory storage capacity that is linearly bounded by the number of feature neurons [3]. This bound presents a problem for machine learning applications in which the dimension of the feature space is typically fixed, while the number of stored patterns is significantly bigger than the number of feature neurons. In 2016 a

[1] https://www.nobelprize.org/prizes/physics/2024/summary/

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generalization of the traditional Hopfield Network, called Dense Associative Memory (or Modern Hopfield Network) was proposed, in which the number of stored memories can be decoupled from the dimensionality of the feature space, and can be made very large [5]. In 2020, it was noticed that this new family of AM networks can be reduced to the attention mechanism in transformers [20] if a particular activation function is chosen as a softmax [7, 12] and the update of the network is applied only once instead of recurrently. This idea has been extended to full transformer block in [10]. Similar conclusions have recently been made with memory networks [21].

These new theoretical developments have been incorporated into several software engineering packages, such as Hopfield Layers and HAMUX. They have also been applied to a wide range of interesting machine learning problems, such as multiple instance learning [8], language [22], image analysis [10, 11], graphs [10, 23], temporal sequences [24–26], clustering [27], and others. Additional models with a broader set of activation functions have also been studied in [28, 29]. These formulations have also been connected to anatomical structures of biological circuits [12, 13, 30, 14].

Driving Questions. Given the heavily interdisciplinary nature of the field of AM, this workshop will connect the disciplines even further, leading to progress in each area, with a specific focus on how AMs can enhance current AI technologies. The following will be our driving questions:

(Q1) What can we learn from the theory of AMs and how it can help us develop modern memory systems with unique capabilities?

(Q2) Are there neuroscience inspirations that can allow us to progress the field of AM from the focus on memorization and memory capacity to a focus on generalization?

(Q3) How can we bring in existing tools and capabilities from machine learning literature to extend the capabilities of current AMs?

(Q4) How can the theoretically grounded capabilities of energy based AMs enhance existing machine learning tasks?

(Q5) How can AM capabilities be useful in mitigating challenges with existing LLM technologies such as high computational costs of attention (long context), lack of reliability and interpretability, and hallucinations?

Technical Scope. The research topics of interest at this workshop include (but are not limited to):

- Novel architectures and training algorithms for energy-based associative memory, Hopfield Networks, Dense Associative Memories, and related models.
- Hybrid memory augmented architectures with unique capabilities and benefits, such as memory augmented LLMs, Transformers, and RNNs.
- The connection between associative memory and neuroscience, including both insights from neuroscience for better AI, and AI-inspired neurobiological work.
- Theoretical properties of associative memories with insights from statistical physics, contraction analysis, control theory, and related areas.
- The connection between traditional machine learning tasks (such as clustering, dimensionality reduction, kernel machines) with associative memories.
- Applications of associative memories and energy-based models to various data domains, such as language, images, sound, graphs, temporal sequences, computational chemistry and biology, as well as multi-modal data.

Schedule. The workshop will include invited talks, contributed talks, a poster session, and a panel discussion. See Table 1 for a preliminary schedule. Each invited talk will take 30 minutes including questions; each contributed talk will take 15 minutes. Although many of the invited speakers have extensively published on Associative Memory in major AI conferences and journals, we have requested that their presentations focus on novel ideas and unifying perspectives, rather than reiteration of the already published work.

Invited Speakers. AMs stand in between three disciplines: machine learning, neuroscience and statistical physics. We have thus tried to compose a list of invited speakers that properly represents

Table 1: Preliminary schedule. **C**: Participation confirmed. **W**: Invitation sent, waiting for response.

Time	Event	Participants
09:00-09:10	Opening Remarks	Dmitry Krotov
09:10-09:40 09:40-10:10	Invited: AM overview & role in ML Invited: AM in Computer Science	Parikshit Ram (IBM Research) [**C**] Elvis Dohmatob (MILA) [**C**]
10:10-10:40	Coffee Break & Poster Session	☕☕☕
10:40-11:40	4 Contributed Talks	–
11:40-13:30	Lunch Break & Poster Session	🍱🍔🍕
13:30-14:00	Invited: AM and Transformers	Leon Bottou (META AI) [**C**]
14:00-14:45	3 Contributed Talks	–
14:45-15:15	Coffee Break & Poster Session	☕☕☕
15:15-15:45	Invited: AM in Statistical Physics	Elena Agliari (Sapienza Univ. di Roma) [**C**]
15:45-17:30	Panel Discussion: Associative Memory and LLM	Mikhail Burtsev (London Inst for Math Sci) [**C**], Rogerio Feris (IBM Research) [**C**], Xueyan Niu (Huawei 2012 Labs) [**W**], Edoardo Ponti (University of Edinburgh) [**C**], Mariya Toneva (MPI Software Sciences) [**C**], Ying WEI (Zhejiang University) [**W**], Moderated by Hilde Kuehne.
17:30-17:40	Conclusions & Outlook	Sara Solla
17:40-19:00	Poster Session	

each of these fields. Dr Leon Bottou (META AI) is widely cited in ML and AI for his various seminal works on optimization and generalization, and has recently published on AMs [21, 31]. We are extremely excited to state that he has already confirmed his participation, and will speak about his ongoing work at the interface of AM and novel transformer architectures. Dr Parikshit Ram (IBM Research) has recently designed novel ways of solving traditional ML tasks using AMs [27, 32, 33]. He will provide an overview of AM from a ML perspective, and discuss his new recent results connecting AMs to clustering, kernel methods, and density estimation. Dr Elvis Dohmatob (MILA, META AI) will speak about AM in Computer Science. Dr Dohmatob has extensively contributed to this area of research, see e.g., [34, 35]. Prof Elena Agliari (Sapienza Università di Roma) has done a lot of exciting work on Hopfield Networks and their computational properties [36, 37]. She will speak about the insights into AM that stem from statistical physics. We will use RocketChat (or similar conference supported tool) to allow remote participants to engage with questions.

Panel: Associative Memory and LLM. Large Language Models (LLMs) are the most popular area of research in AI. Despite impressive results on various language tasks, LLMs remain factually inaccurate (hallucinate), and have a limited context window due to quadratic (as a function of the number of tokens) cost of the attention operation. Memory augmentation of LLMs is a promising direction of research that tackles these problems. In the past few years, hundreds of papers have been written proposing various memory augmentations of LLMs, see for example [15–18]. We have invited some of the key researchers in the field driving these ideas. The panel consists of researchers from both industry and academia, as well as, early career assistant professors to principal research scientists. All of them share interest in understanding and mitigating the various limitations of current LLM technologies (e.g., hallucinations, lack of reasoning and compositionality, etc), and actively pursuing associative memory based solutions. We intend to discuss promises and pitfalls of memory augmentation of LLMs, Retrieval-Augmented Generation (RAG)-based techniques, and related methods. We hope to unify various ideas and architectural innovations scattered across the literature and outline general trends in associative memory augmentations. All the invited panelists will be given 5 minutes for opening remarks, the remaining time (over one hour, see Table 1) will be dedicated to an interactive discussion among the panelists and with the audience. We will utilize RocketChat (or similar tool) for both in-person and remote participation.

Attendance. Given the recent developments, exciting results, and revived interest in Associative Memory, Hopfield Networks, their connection to the attention mechanism, diffusion models, and LLMs, we expect to have around 300 participants. If accepted, we will publicize this workshop by reaching out to speaker/organizer professional networks, as well as, various ML and statistical physics mailing lists (such as ML-News, WikiCfP), social media (such as X/Twitter, LinkedIn, r/MachineLearning, Facebook), and various affinity group mailing lists.

Diversity Statement. Diversity among organizers, invited speakers, panelists, and program committee members was one of the key objectives in organizing our workshop. While the AI community traditionally suffers from under-representation of certain groups of researchers and more work certainly needs to be done on this front, we are happy to report that we have achieved a good combination of men and women in all the participating groups (invited speakers, panelists, organizers). There are Black, East Asian, South Asian, White, and Latino researchers among the invited speakers, panelists, and organizers. Geographically, the participants are located in various parts of the USA, Canada, UK, Europe, and Asia. The invited speakers, panelists, and organizers represent both academic institutions, and industrial R&D labs. Our confirmed invited speakers and panelists span a wide range of career stages, from esteemed renowned researchers (e.g., L.Bottou), to early career researchers (e.g., E.Dohmatob). Sara Solla has a long history of involvement in the mentoring of women and other underrepresented minorities. She will oversee the diversity efforts for this workshop and will collaborate on this with other organizers.

Contributed Papers, Talks and Posters. We plan to have seven slots for oral contributed talks of 15 minutes each, thus giving almost as much time to the contributed talks as the invited talks (not including the already interactive panel discussion). The remaining accepted contributed talks will be presented as posters at the 80-minute poster session. We will use OpenReview to manage the contributed submissions. Each contributed submission will receive three reviews, and we expect each reviewer to evaluate no more than three submissions. We will assess submitted contributions using the rules for conflict of interest used for the main track ICLR conference, e.g., reviewers cannot be from the same organization as authors, recent coauthors cannot review each other's submissions. We expect to have approximately 40 contributed submissions. We have already secured a sufficient pool of qualified reviewers: members of the program committee, the organizers, and some of the invited speakers. If necessary, we will identify additional reviewers well qualified to evaluate contributions on the topic of the workshop. The tentative deadline for submission of contributed papers will be February 3, 2025, and the final decisions will be announced no later than March 5, 2025. The workshop will be non-archival.

Previous Related Workshop. A previous version of this workshop was held at NeurIPS 2023 (`https://amhn.vizhub.ai`). There were over 40 accepted papers, 7 contributed talks, and close to 200 attendees and we hope to build upon this success with new speakers and participants in 2025. H.Kuehne and D.Lee of the current organizers co-organized the previous workshop. J.Kempe, D.Krotov, and S.Solla are organizing this workshop for the first time this year. While the focus of the last workshop was on energy-based AMs and software tools required to build those models, this version of the workshop will be dedicated to general AMs (irrespective of energy-based constraints) and will focus on architectural and algorithmic innovations and potential synergies of AM-inspired insights and LLMs.

Workshop materials and outcomes. All the relevant material and outcomes (recorded invited and contributed talks, panel discussion, and accepted papers) will be made available on the workshop website for offline viewing for participants unable to attend in-person or follow along live.

Points of Difference. We believe that our workshop will be unique in terms of its interdisciplinary nature, bringing together participants from ML/AI, statistical physics, neuroscience, and LLM practitioner communities. We will be building upon the recent revived interest in the connection between physics and AI, and will provide a platform to leverage this connection to improve rapidly growing LLM technologies. Additionally, the recent announcement of the Nobel Prize in Physics 2024 has further bolstered AI community's interest in Associative Memory. The confluence of exciting theoretical and practical developments with the increasing interest of the community in the topic makes ICLR 2025 an ideal venue for hosting this workshop.

Organizers

Julia Kempe [NYU, kempe@nyu.edu]: Julia is a Silver Professor of Computer Science, Mathematics and Data Science at the Center for Data Science and the Courant Institute of Mathematical Sciences at New York University, and a Visiting Senior Researcher at Meta FAIR. From 2018-2023 she was the Director of NYU's Center for Data Science and a member of the NYU President's Senior Leadership. From 2011-18 she worked as a quantitative researcher in finance. Before that she was a Research Director at the CNRS in Computer Science in Paris, and Associate Professor of Computer Science at Tel Aviv University. Her interests range from earlier work in quantum computing and quantum complexity, to machine learning theory and applications. Her awards include the CNRS Bronze Medal, Knighthood in the French Order of Merit, and Membership in the Academia Europea. Julia has organised a multitude of workshops, conferences and seminars; most recently at NYU and the Flatiron Institute. This is the only workshop at ICLR she is involved with organizing this year.

Dmitry Krotov [MIT-IBM Watson AI Lab and IBM Research, krotov@ibm.com]: Dmitry is a physicist working on neural networks and machine learning. He is a member of the research staff at the MIT-IBM Watson AI Lab and IBM Research in Cambridge, MA. Prior to this, he was a member of the Institute for Advanced Study in Princeton. His research focuses on the computational properties of Associative Memory and implementing ideas coming from neuroscience and physics in modern AI systems. He received a PhD in Physics from Princeton University in 2014. This is the only workshop at ICLR he is involved with organizing this year.

Hilde Kuehne [Tuebingen AI Center, h.kuehne@uni-tuebingen.de]: is a professor for Multimodal Learning at the Tuebingen AI Center. Her research focuses on multimodal learning and video understanding. She has published high-impact works in the field and was awarded with the ICCV 2021 Test-of-time Award and the PAMI Mark Everingham Prize. She is an Associate Editor of TPAMI, serves as area chair for various conferences, including CVPR, ICCV, and NeurIPS, and served as program chair for WACV 2024. She is committed to more diversity in STEM and is a board member of the Women in Computer Vision Initiative. This is the only workshop at ICLR she is involved with organizing this year.

Daniel D. Lee [Cornell University, ddl46@cornell.edu]: Daniel is the Tisch University Professor in Electrical and Computer Engineering at Cornell Tech and his research group works on latent variable machine learning models, computational neuroscience, and robotic systems. He is also a visiting scholar at the Flatiron Institute Center for Computational Mathematics (CCM) and the Korea Institute for Advanced Study (KIAS). In the past, he has organized a number of events at conferences including NeurIPS, ICML, ICRA and IROS. This is the only workshop at ICLR he is involved with organizing this year.

Sara A. Solla [Northwestern University, solla@northwestern.edu]: Sara is Professor of Neuroscience and Professor of Physics and Astronomy at Northwestern University. Her work in theoretical and computational neuroscience uses conceptual, mathematical, and computational frameworks from statistical physics, statistical inference, and nonlinear dynamics, acquired during her training as a theoretical physicist and her research experience in machine learning at AT&T Bell Labs. She currently investigates information processing in the brain at the systems level. Sara has organized NeurIPS Workshops, and has been NeurIPS Chair of the Program Committee and NeurIPS Conference Chair. She is now a member of the NeurIPS Board. This is the only workshop at ICLR she is involved with organizing this year.

Program Committee A list of Program Committee members, with an indication of which members have already agreed to participate:[2]

Sugandha Sharma (MIT) [C], Hamza Tahir Chaudhry (Harvard)[C], Jacob Zavatone-Veth (Harvard)[C], Tom Burns (Brown U)[C], Bao Pham (RPI)[C], Mikail Khona (MIT), Hidenori Tanaka (Harvard), Bishwajit Saha (RPI) [C], Satyananda Kashyap (IBM Research) [C], Tankut Can (Emory U) [C], Andrey Gromov (META AI), Paolo Glorioso (Stanford U) [C], Tom George (UCL), Andy Keller (University of Amsterdam) [C], David Lipshutz (Flatiron Institute), Arian Khorasani (MILA)

[2]C: Confirmed. 31 researchers confirmed till date.

[C], Jascha Achterberg (Cambridge U) [C], Binxu Wang (Harvard), Francisco Acosta (UCSB), Leo Kozachkov (MIT)[C], Parikshit Ram (IBM Research) [C], Rogerio Feris (IBM Research) [C], Mikhail Burtsev (London Inst for Math Sci) [C], Eleanor Spens (UCL) [C], Dmitry Krotov (IBM Research) [C], Julia Kempe (NYU) [C], Hilde Kuehne (U of Bonn) [C], Sara Solla (Northwestern U) [C], Daniel Lee (Cornell) [C], Benjamin Hoover (GA Tech) [C], Luca Ambrogioni (Donders Institute), Matteo Negri (Università di Roma Sapienza) [C], Gabriel Raya (Tilburg University) [C], Hongzhi Wang (IBM Research)[C], Carlo Lucibello (Bocconi University) [C], Paul Francois (U of Montreal) [C], Mohammed J. Zaki (RPI)[C], Olawale Onabola (MILA) [C], Danil Tyulmankov (U South CA) [C].

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