Research Statement

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The primary goal of my research is to achieve **sustainable AI systems that learn and adapt efficiently over long time horizons**, much like humans. I envision a future where AI systems seamlessly interact with humans and environments, forming lifelong memories and achieving meaningful, long-term engagement. However, current deep learning approaches require vast amount of labeled data to generalize on new environments, while demanding substantial memory resources during inference. This labeling-intensive and memory-hungry paradigm limits the applicability of AI systems to short-term engagement, raising sustainability challenges in terms of labeling efforts, computational costs, and memory consumption.

To address these limitations, my research aims to optimize data usage in deep neural networks, enhancing the efficiency of both training and inference processes. Specifically, my work revolves around three key themes: (1) context and dataset compression, (2) synthetic training data generation, and (3) data characterization. These themes are unified under **a data optimization framework that leverages feedback from the neural network itself**, effectively harnessing the varying information densities of data while minimizing reliance on human intervention. Through this framework, I have introduced novel methods for memory-efficient inference and label-efficient training, paving the way for sustainable AI systems. In the following sections, I will highlight the key contributions of each research theme, outline my ongoing projects, and discuss future directions.

Research Progress

1 Context/Dataset Compression

Humans process real-time information selectively, forming own compressed long-term memories to enable efficient lifelong adaptation to the environment. In contrast, current AI systems exhibit inefficiencies in data processing, requiring vast memory resources—terabytes of storage for training data and tens of gigabytes for hidden context features, as exemplified by Transformer models.

My research addresses these inefficiencies by developing novel methods for compressing data information and constructing long-term memory in neural networks [1, 2, 3]. Specifically, I have proposed techniques that harness inherent capabilities of trained neural networks to compress information. These approaches significantly improve the efficiency of both training and inference, ensuring the sustainability of AI systems through reduced memory requirements.

Compressed memory for Transformers [1]. Transformer-based models, such as ChatGPT, excel at processing long-range dependencies in sequences, enabling coherent response generation given extensive context. However, this capability relies on storing all key-value features for context tokens, which imposes significant memory demands. For instance, in models like LLaMA-70B, storing key-value features for just 1,000 words requires tens of gigabytes of memory. In the interactive scenario, these storage requirements grow rapidly as contexts lengthen, significantly limiting the usability of AI models.

To address this challenge, I developed a novel online key-value compression method coupled with a compressed memory module for Transformer language models. My approach dynamically compresses the key-value vectors into shorter representations, which are then updated in the limited-size memory.

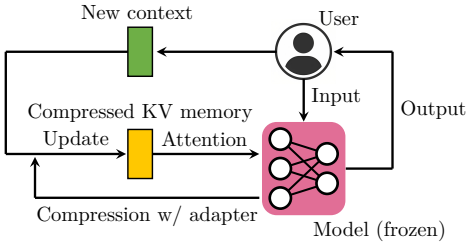
The language model accesses this compressed memory to generate contextually coherent responses. Notably, my approach seamlessly integrates the compression process into the model's inference pipeline by leveraging the model's forward pass for compression. The results are promising: my method reduces the key-value cache size by 5×, while maintaining performance comparable to the original model without compression. This achievement significantly enhances the feasibility of deploying Transformer models in memory-constrained environments.

Condensing training dataset [2]. Current neural networks require vast amounts of training data, raising the key question: *What is the actual dataset size required for effective training?* If similar performance can be achieved with a smaller dataset, it would dramatically reduce the computational costs and storage required for training. To address this question, I conducted research on optimizing small synthetic datasets that match the training performance of the original dataset. Using a novel differentiable data-parameterization technique, I have successfully compressed large-scale datasets such as ImageNet with high efficiency. Notably, my approach achieves 90% of the full dataset's training performance with only 1% of its storage size, significantly outperforming traditional data subset selection methods. Additionally, my approach demonstrated effectiveness in continual learning scenarios by forming condensed example memories, further highlighting its practical utility.

Spherical data dimension reduction [3, 4]. Skeleton structures, such as human keypoints or molecules, are often represented as Cartesian products of spherical surfaces. Capturing the temporal evolution of these structures is crucial in fields like human motion analysis and molecular dynamics. However, conventional representation learning methods struggle with the inherent non-Euclidean geometry of spheres, making this task challenging. To address this issue, I developed an algorithm that optimizes a curve on spherical surfaces by minimizing the sum of geodesic distances to the data points. This approach effectively captures the underlying structure of spherical data and models the temporal evolution by projecting data onto a curve. Building on this research, I aim to further explore dataset compression methods for temporal and structured data, broadening the scope and potential impact of my work.

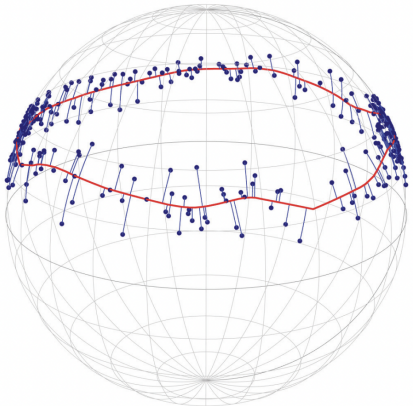
2 Synthetic Training Data Generation

High-quality labeled data is crucial for training high-performing AI models, but it is costly and scarce in certain domains. One promising research direction I have pursued is the use of AI models to synthesize training data. I established principles defining effective training data and developed model-driven data synthesis frameworks that create a self-reinforcing loop, enhancing overall training performance. This approach holds significant potential to drive sustained improvements in AI systems while reducing human labeling efforts.



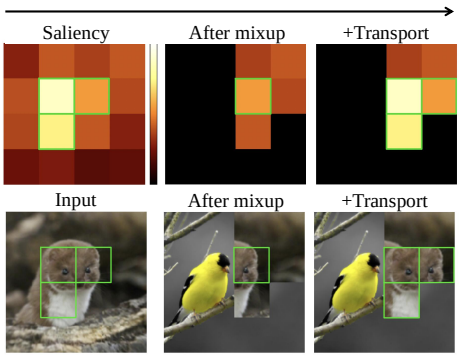
Compressed context memory [1] enables continual inference of Transformers in limited memory space.

Condensed ImageNet samples [2]. My approach optimizes the compressed form of datasets, enabling efficient model training.



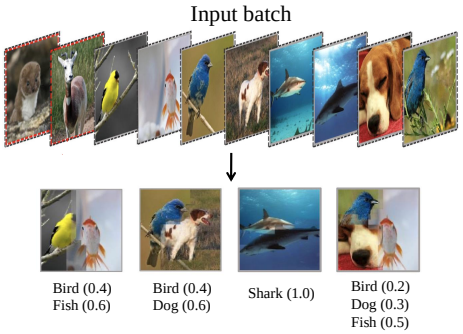
Spherical principal curve [3] encodes the 1D temporal evolution of spherical data.

Saliency-guided data augmentation [5]. Conventional data augmentation methods often rely on predefined functions that randomly alter data without accounting for its individual characteristics, such as object locations in images. This results in the generation of data that are inconsistent with the assigned labels, providing false supervisory signals. To overcome this challenge, I developed a novel approach that leverages the data saliency maps obtained by the model under training. Using this saliency information, I designed an augmentation technique that mixes a data pair while preserving the most informative regions. This feedback-driven method not only improves the model's generalization performance but also guides the model more robust to input noise. The impact of my work extends beyond image processing, with successful applications in various domains including natural language, graph, and point cloud data.



Puzzle Mix [5] generates synthetic training data by mixing salient regions from data pairs. I measure saliency using a model under training, creating a self-reinforcing loop in the training process.

Batch-level data augmentation [6]. In my previous work, I explored the challenge of generating informative data from given data pairs. Building on this, I posed a new question: *What combination of input data is optimal for augmentation?* This question not only opens a fresh research direction but also leads to a novel batch-level approach to data augmentation. Optimizing input combinations, however, presents an NP-hard problem due to the combinatorial complexity involved. Furthermore, if the objective is solely to maximize the saliency of each output, the result could be a lack of variety, producing identical outputs. To address this issue, I formalized the problem to optimize output diversity and developed an efficient combinatorial algorithm capable of synthesizing batch-level data within a few milliseconds. The synthesized data not only enhance neural network training performance but also yield notable improvements in uncertainty calibration for image/speech classifiers.

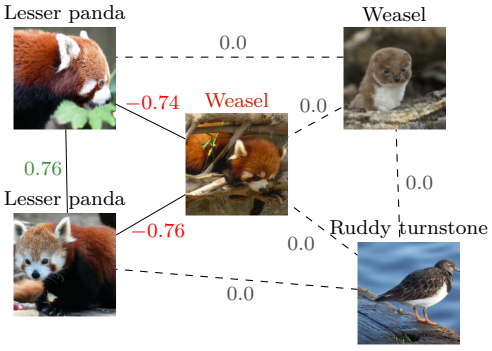


Co-Mixup [6] generates a batch of synthetic data, jointly optimizing the diversity and saliency of outputs.

3 Data Characterization

In my interactions with ML practitioners, I frequently observed that they devote a substantial portion of their efforts to data preprocessing. This stage is often complicated by the large volumes of data accompanied by complex issues such as label errors, outliers, and misalignment. Addressing these challenges is critical to ensuring robust model performance but requires substantial labor and cost.

To streamline this preprocessing stage and facilitate model development, I explored principled approach for data characterization using pretrained models. Moving beyond conventional single-feature metrics like prediction error, I proposed a method that analyzes relationships among data using pretrained models. I introduced *Neural Relation Graph* [7], a fully-connected graph of data points where each edge weight quantifies the degree of complementarity or conflict between data points. This relational structure encodes rich information of data, enabling effective data characterization. Additionally, I designed a visualization tool that transforms these relationships into an intuitive 2D plot, enabling users to interactively explore and preprocess datasets.



Neural relation graph [7] encodes relational structures within data. By characterizing each data point within the graph, my algorithm effectively identifies outliers and mislabeled data.

Ongoing and Future Direction

In summary, my research has focused on optimizing data usage in AI systems to develop sustainable systems capable of (1) efficient memory management during inference and (2) effective learning from limited human-labeled data. I am eager to deepen and broaden my research to achieve tangible impacts in real-world applications and sciences through the following research topics:

- *What is the most effective memory structure for long-context processing?* I am focusing on enabling neural networks to store information with minimal capacity requirements. This problem involves identifying the minimum length descriptors for information within the neural network's memory space (*i.e.*, model weights or hidden features). The objective is to determine the most compact memory structure, allowing neural networks to efficiently store vast volumes of information and support the processing of infinitely long context.
- Another major ambition of mine is to create *multi-modal memory systems*, drawing on my research experience across various domains, including image [2, 5, 6, 7], speech [2, 10], natural language [1, 7], and multi-joint dynamics [3, 9]. A particular focus is video data which presents substantial challenges due to its extensive size and information sparsity, requiring innovative compression techniques. The goal is to develop AI systems capable of long-term video interactions, thereby enhancing the AI's utility in promising areas such as robotic agents.
- I am also interested in empowering AI to uncover novel insights from data in scientific domains. In my recent work on *Targeted Cause Discovery* [8], I explored a data-driven learning approach for discovering causality among human genes, which led to the successful identification of novel causal relationships involving specific cancer-related genes. Moving forward, I am passionate about bridging AI with scientific fields to drive transformative, multi-disciplinary advancements.

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