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High-Speed Storage in AI Systems: Unlocking Real-Time Analytics in Cloud-Integrated Frameworks

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Real-time analytics has long held the promise of understanding customers, systems, and computing on the fly, unlocking new insights and data-driven decision-making. However, advancements in data processing, specifically faster, cheaper, and smarter storage for big data, have yet to be realized to make real-time analytical systems a reality. This paper shows how recent advancements in storage technologies have begun to change the game with three critical developments. The first is the development of byte-addressable persistent memory that serves as high-speed storage. The second technology is direct attached storage that minimizes the CPU stack load when accessing data on the device, keeping more of the computer in the data store. Lastly, stateless computational storage targets distributed AI systems, pushing AI computations closer to the data source. These high-speed storage innovations have already begun to be integrated into cloud frameworks, enabling storage stacks to manage these devices for users and creating a roadmap for integrating stateless computing storage as that sector matures. The paper outlines these AI-centric storage designs, explains the coming transformations to cloud computing that these storage innovations are enabling, details their status, and describes the kinds of applications that will improve with these storage designs. These changes are released from two perspectives, one for AI and data processing in the cloud, sustaining data analytics, and another for stream processing in time-series systems. Of particular importance in these designs are the storage controllers, which will be an integral part of AI-optimized data storage critical for real-time and edge settings, showing the latest storage that aims to push computation toward data and keep more of the bits intact as data are transformed at the edge with minimally powerful AI accelerators.

Keywords: Real-time Analytics, Data-driven Decision Making, Big Data Storage, Persistent Memory, High-speed Storage, Byte-addressable Memory, Direct Attached Storage, Computational Storage, Distributed AI Systems, Cloud Frameworks, Storage Stacks, Stateless Computing Storage, AI-centric Storage, Cloud Computing Transformations, Time-series Systems, Stream Processing, AI-optimized Storage, Storage Controllers, Edge Computing, AI Accelerators.

1. Introduction

Within the realm of artificially intelligent systems, concepts like real-time analytics, decision-making, and deep learning rely on rapid data access, processing, and decision-making. As the

modern world undergoes this fourth-wave behavior change of advanced technology adoption, technology interruptions, shadow IT, and the overall churning of global infrastructure, it is necessary to leverage faster, better, and more efficient ways to gain valuable insights from the data. Many AI and machine learning use cases benefit from high-speed storage to meet real-time performance expectations.

It is predicted that 25 million cloud-integrated 'intelligent' systems will exist by the year 2025, helping to extend the AI renaissance and enable all digital workflows within the domain of ambient computing. More than 63% of large- and medium-sized organizations are expected to have low-code integration and automation platforms consisting of data integration, transformation, orchestration, workflow definition, and API management tools. Major service providers who integrate these AI-driven data orchestration and information infrastructure will find that this 'low-code' cloud is cheaper and easier to operate with the new form of convergence. All of these cloud-based platforms will employ AI for operational optimization and business model modernization, thus requiring high-speed storage that is ultra-scalable. In addition, AI-based cloud infrastructure and cloud-integrated AI/ML will demand the seamless transport of enormous datasets, not simply large files or log files, which organizations may wish to write or read to and from cloud infrastructure.

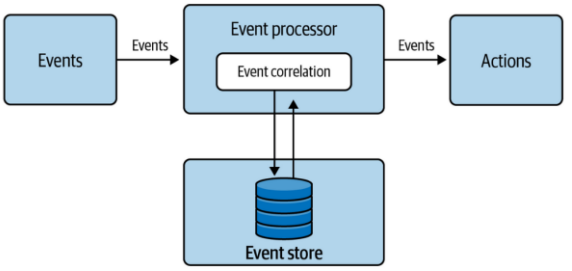

Fig 1 : Building Real-Time Analytics Systems

1.1. Background and Significance

Storage technologies have evolved from mechanical to solid state and data storage over the Internet. The evolution of automated mechanical storage to programmable flash drives and ultimate cloud storage has resulted in increased data access speed and minimization of round-trip time in data read/write operations. The generation of data for AI applications in real life is enormous and requires faster, on-the-go data analysis support. Though solid-state storage minimizes the data read/write time, this type of storage directly retrieves data from the inbuilt storage of the host system, taking ample time for data transfer. In contrast, cloud storage provides quick data read/write functionality over the Internet. Imagine the power of combining AI edge-computing systems with Internet storage. Users can scan and upload data packets from an edge-computing system to the cloud in minutes and start data analysis in real-time.

The implementation of the image-based AI model has reinforced the need for real-time data analysis with standard specifications, particularly in the medical field. This niche area requires the recording of audio in time and frequency, but the audios are of bulky size and can be reframed as audio frames. Each audio frame in STFT can be segmented into time-domain features. Different high-speed arrays like clustered storage systems, solid-state storage, optical

storage systems, and cloud storage can be used in image videos. Integrating such high-speed storage within the cloud mainstream is paramount. The storage within the cloud should be highly efficient, compatible, and versatile, involving a workable span that is independent of the device's capacity. These provisions significantly affect decision-making for industries. Data collected with sensors on the shop floor are directly analyzed and suitable remedies are put in place. High-quality real-time AI computing systems can make quick decisions to handle incidents. Data read-back time from existing storage technologies is high and cannot be used to guide the AI analysis framework. Integrating mainstream storage with edge analytics can play a vital role in providing a quick analysis to make decisions.

$$DT = \frac{D_{\text{total}}}{T_{\text{total}}}$$

Equation 1 : Data Throughput (DT)

D_{total}: Total amount of data processed

T_{total}: Total time for data processing

1.2. Research Objectives

Articulation of the problems of interest and the motivation for the effort to understand and integrate different storage technologies within high-speed AI systems.

What approaches exist for storing data in AI systems and what are the performance differentiators between them? In what AI frameworks and applications are different types of data storage relevant? What are the obstacles to effectively deploying these storage solutions in AI systems? What can be done about them? What tools can be leveraged to further investigate the performance of different storage solutions in AI systems?

The purpose of this work is to understand what state-of-the-art data management and storage systems exist and what gaps arise when integrating them into high-speed AI systems. We first identify persistent memory, burst buffers, cloud storage, and high-performance storage as four potential therapies for developing terascale storage systems that can complement high-performance computing environments. We then lay out specific storage standards that are directly relevant to current artificial intelligence, deep learning, and cloud data movement workloads. We select three AI programming frameworks as a basis for our ongoing analysis based on these recommended technological viewpoints. Researchers often use deep learning to perform real-time predictive analytics and data-driven analyses. The study aims to construct a storage system specially designed to meet the requirements of deep learning, such as high performance and I/O capabilities needed for real-time read access from megabytes to petabyte storage arrays. In this area, there is already a significant body of work, particularly on collaborative work with the Exascale Computing framework.

2. High-Speed Storage Technologies

Solid-state drives (SSDs) have made great strides in the past decade of development, overtaking traditional hard drives as the preferred medium for enterprise or consumer storage to aid in computation. This is primarily due to the cessation of spinning plates for data retrieval,

the time of which is inherently random and uncertain. Instead, read and write operations occur within the realm of billions of parallel flash memory locations per die of NAND technology. Exploration into the multi-level cell (MLC) solid-state could not come at a better time in the late 2000s. MLC SSDs take advantage of a proclivity for parallelism, wherein data is broken down into equal "chunks" and distributed across every die available within an SSD at any singular time.

This dual-port design allows for multiple concurrent connections between multi-lane devices to any given SSD, providing exponential potential in drive throughput. Considering the operation of four NVMe SSDs, two with traditional connectivity and two with NVMe-oF protocol, the latter will have over six times the potential input/output ability. Here is where high-speed storage, also known as persistent memory, will ultimately enable a thorough transformation of maximum allowable shared storage capacity as we now know it. Persistent memory can increase data transfer speeds between SSDs and the CPU cores' cached memory. NAND SSDs have input/output speeds exceeding 10 GB/s read and write, and an average latency of 25 µs with no warm-up. Application and processing computer technology have certainly entered into a realm wherein data throughput capacity and speed are no longer an afterthought. Predictive modeling techniques, more specifically, artificial intelligence, have arguably begun to contribute more substantially to disposable income than chosen paradigms of analysis. Moreover, it has led to this emergent priority.

2.1. Solid-State Drives (SSDs)

Solid-State Drives (SSDs)

The primary solution for high-speed storage is solid-state drives (SSDs). SSDs are non-volatile devices that access data quickly, as there is no latency from mechanical parts moving. SSDs offer greater durability than traditional spinning mechanical drives, making them preferred by IT professionals, data centers, and remote installations. SSDs also consume less power when compared with traditional mechanical drives. Due to these compelling features and their compelling performance, many modern systems use SSDs as primary storage.

In traditional AI frameworks, storage is the main bottleneck that affects the overall pipeline performance. SSDs are known to increase system performance, making them a very suitable storage medium for AI systems, as real-time analytics is prominent in most big data and AI systems today. SSDs come in different form factors and interface types, and their ability to handle IOPS for real-time applications is the main focus of infrastructure for AI-type applications. SSDs are the last of the quiet revolutions, providing far superior performance to their predecessors. SSDs come in different form factors and communication speeds, which differ in the marketplace. For example, an NVMe SSD offers better hardware performance than a regular SATA SSD because of the communication speed and form factor.

The architecture of a system's storage is designed based on the SSD type and port, including implementing PCIe-based storage, which provides more bandwidth between the controller and data processor. Devices can be fully dedicated to orchestrators, etc., related to the architecture of SSD type and SSD port discussion. However, there are still some potential limitations and challenges of using native SSDs as primary storage for an AI system: the cost, storage capacity scalability, wear leveling, and the possibility of storage device hardware failure. Data

processing is a critical aspect of real-time cloud storage integrated frameworks. There exist reliable SSDs in deployed storage-integrated cloud frameworks. Currently, cloud server providers display the offered services on solid-state drives (SSDs) for server solutions and storage-integrated frameworks. SSDs are known to perform better during real-time data processing.

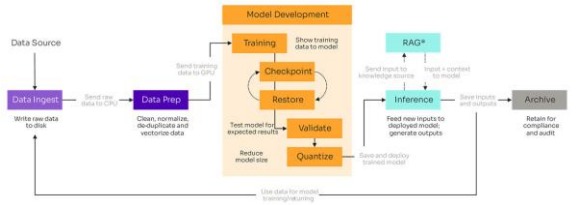

Fig 2: Soladigm SSDs in AI Storage Advancement

2.2. NVMe Over Fabrics (NVMe-oF)

NVMe Over Fabrics (NVMe-oF) is transformative in the technologies underpinning storage systems and networking. NVMe-oF is an extension of the NVMe standard designed to actively engage the capabilities of NVMe across network fabrics, such as Ethernet and InfiniBand, to facilitate scalability and the sharing of SSD resources for multiple systems. There is an increasing impetus to make this technology available in cloud deployments as they move to AI systems. The appeal of NVMe-oF is anticipated to increase momentum towards making NVMe, which is today local storage in cloud computing, networked through NVMe-oF.

NVMe-oF enables a storage subsystem to be directly connected with an application in both bare metal and VM-based cloud scenarios. NVMe-oF is designed to leverage the capabilities of SSDs connected over a fast interconnect that is low latency and high bandwidth. NVMe-oF technology simplifies the development and operational tasks of the system software stack running on all components in full-fledged data centers and cloud environments. The anatomy behind the NVMe-oF storage subsystem architecture and how it integrates with InfiniBand and Ethernet network standards are explained. The deployment of the NVMe-oF subsystem with the corresponding software stack is also indicated with real-time cloud deployment scenarios. Implementing NVMe-oF comes with challenges; these include components that do not have compatibility with NVMe and high operational costs due to the requirement for a completely new infrastructure with a hypervisor that is NVMe-oF aware.

The description includes the different system software stack components. At the bottom of this hierarchy, it explicitly describes the target, which is the network interface and the device interface in an NIC. Overall, this offers opportunities for enhancing real-time analytics in cloud-integrated AI frameworks. It also explains how these components work.

2.3. Persistent Memory Technologies

Persistent memory technologies are developing as a leap forward in storage solutions by combining the speed of memory with the persistence of storage. In addition to high-speed access times, persistent memory retains data regardless of whether the computer is restarted or shut down and can approach Flash/SSD data transfer rates. In these ways, persistent memory and storage-class memory bridge the divide between traditional storage devices and volatile

memory systems. Persistent memory delivers high-speed access to data and can access even more data at faster rates when memory is full by employing the storage function of data retention across power cycles. Already in the server and data center industry, several systems are being implemented to take advantage of this technological advancement transition in the industry.

Data processing tasks, such as those required for running AI workloads, are increasingly crossing the boundaries of these technologies. In these scenarios, persistent memory has the potential to provide substantial performance improvements to real-time analytic capabilities. However, while storage organizations and other vendors in the industry have begun to sell and offer product lines for persistent memory, existing systems have only recently been transitioning to utilize this technology. More recent generations of hardware are further integrating these functions directly into the processor, ushering in a new generation of capabilities for data infrastructure. Organizations most able to adapt and maximize these capabilities through expert partner-driven solutions and strategies will find themselves with unique and powerful solutions unavailable elsewhere.

3. Integration of High-Speed Storage in AI Systems

Integrated or tightly coupled high-speed storage technologies have become the cornerstone of present-day AI systems to process zettabytes of data. On a theoretical level, ultra-fast storage solutions reduce latencies in data access and reduce time overhead to perform computing or processing operations, and as a result, AI applications can process signals, data, or photo translations much quicker. Practically, the core of groundbreaking innovation in AI is due to the radical reductions in training and inference times and the performance of neural networks in running analytics. High-speed storage solutions with their low data access latencies and read data throughput have become distinguishable from traditional storage devices. AI workloads require thousands and millions of weights and biases that are consumed during the training or inference time, and agents retrieve data as they need. The state-of-the-art storage technologies allow these agents to cull images, texts, sounds, sequences, and vectors or more in close to real-time to achieve low latencies and high throughput during the total time to model metrics needed for effective AI decision-making.

On the other hand, it is a non-trivial endeavor to integrate a few high-speed storage devices connecting to servers into multi-node supercomputing AI systems and a company set of AI server racks and seamlessly present a high-performance programmable data plane to the agents and their cloud or datacenter infrastructure. Though pure-speed storage software is the preferred method, it needs to cater to multiple silicon memory, storage, interconnect, and server architecture vendors, plug and play into cleanly networked data center architecture; many basic problems must be addressed when integrating ultra-fast storage systems into AI infrastructure. There are a few challenges such as storage stack optimization, designing integrated storage toolkits, managing the data flow and I/O, queuing, integration into the filesystem and executables or bootstrapping at the server or rack or data center layer, latency in reading bitstreams, protocols, and integration with PCIe that must be addressed. To solve such situations, many different techniques have been used such as DMA access for storage read, hardware offloads, queue up, messaging, direct NIC to storage connection, and push to

the client, read data directly from the storage layer, integrating storage as a core compute rather than just a transparent medium, run client on storage/aggregator nodes and execute storage class functions to process data, remove complexity using in-storage intelligence, embedded core features for storage options, and kernel bypass to not use the host register to push and read data on storage. Rapid growth and advances in the field of storage solutions make the demand for integrating multi-terabyte PCIe Gen4 and Gen5 NVMe SSD range become an immediate solution for the efficient integration into AI solution architectures. These storage systems are typically disaggregated from computing and can be used as a complete accelerator or just as a memory extension required for AI inputs or processing. In the next section, a survey was conducted introducing the concepts of the foundations of ultra-fast storage technologies to introduce multi-terabyte high-speed storage.

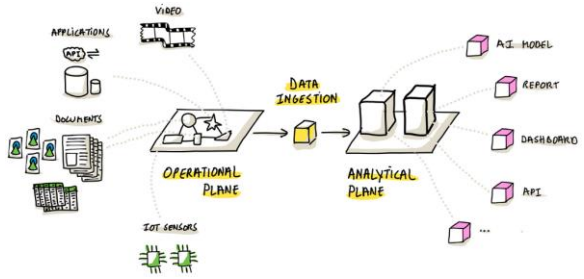

Fig 3 : Data Ingestion

3.1. Challenges and Solutions

Challenges and Solutions. In general, integrating a high-speed storage solution into the AI system is a very complex process due to several reasons.

Technical compatibility: Usually, organizations adopt systems and solutions from a wide range of suppliers and manufacturers, and these infrastructures tend to be diverse. In the same stack, including processors, interconnections, cloud management consoles, and storage, multiple technologies must be employed because of several technological limitations. Thus, it becomes necessary to follow protocols for guaranteeing technical compatibility, which adds storage systems. Systems of an AI application usually adopt the major high-performance storage systems, which can generate a specific protocol problem of connection. Implementation costs: The adoption of storage hardware designed to use the best of the above-mentioned storage reference systems may imply high costs or safety issues during data storage, such as excluding possible solutions of disaggregation. Transfer data/storage complexity: More data should be managed and stored for the best outcome, comprising diverse technologies, data lakes, data mining, and intelligent reporting systems. The high-cost implications of the latest data center employee training: Upgrading an AI workflow consists of multiple activities, from coaching to hardware updating. For employees, it is particularly hard to adapt to new workflows due to AI, owing to its high complexity and memory connections. Data management tends to be optimally conducted at the beginning of a digital transformation, maintaining an efficient data storage schedule. Maybe a re-engineering process would be appropriate.

Potential solutions. To find a solution to this problem, one approach is to enhance interoperability and the ability to handle AI systems across all existing technologies. This can

be achieved by clearly demonstrating the capacities of protocols by offering certain systems standard interfaces. Effective system implementation requires adequately prepared and skilled staff. AI research requires staff, from the data scientist at the R&D center to data analysts, large data engineers, system and network administrators, and general workers who are well-versed in the concepts of AI, possess knowledge of the functioning of the used tools, and are familiar with the handling of tools and strategies before and after dealing with information. Researchers or other staff members possessing the requisite expertise are currently required to oversee their business in the integration of high-capacity storage networking technology in the areas of physical compatibility, safety, and technology.

$$RTAL = \frac{D_{\text{analytics}}}{S_{\text{speed}}}$$

Equation 2 : Real-Time Analytics Latency (RTAL)

$D_{\text{analytics}}$: Amount of data required for real-time analysis

S_{speed}: Speed of the high-speed storage or network connection

4. Real-Time Analytics in Cloud-Integrated Frameworks

With AI's muscle and the cloud's flexibility in commercial arbitration, companies are exploring AI-ready cloud technologies to support their infrastructural needs. Between unleashing data power and realization, AI-driven real-time analytics are the most considered upfront. In this 21st century, the capacity of organizations, irrespective of size, to make fast, informed decisions has taken the driver's seat for achieving a competitive advantage. Real-time data processing is a joy. First of all, many additional hours of manpower are freed up. Secondly, real-time analytics provide the opportunity to address customer requests proactively, and at times even predict their behavior based on what is currently happening. Lastly, real-time analytics enable organizations to work efficiently, as focusing on the most important and relevant data is given priority.

Cloud systems and high-speed storage boast a natural synergy. With year-on-year storage capacity being used, providing unparalleled space and the ability to upload large amounts of data at once, there's no doubt that disk storage and cloud are a match made in data management. This capability could revolutionize the space in real-time analytics, but it's a complex problem. Building a cloud-based storage system will allow organizations to benefit strategically, operationally, and financially from real-time analytics. However, leveraging real-time analytics is not as straightforward as it might sound. This is due to the existence of various challenges in the path to incorporating real-time analytics, such as an increasingly complex attack surface, relating to systems' adaptability or scalability, integration, and data security. Even though their situations are wide-ranging, they all need an infrastructure that will support these systems and drive them to a fully operational stage.

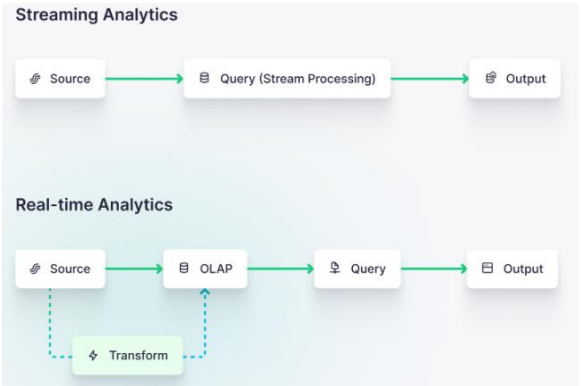

Fig 4 : Real-Time Analytics

4.1. Importance and Use Cases

In its most basic form, real-time analytics diminishes decision-making latency by providing instant, actionable insights. This can prove to be a true competitive differentiator in modern, data-flooded business scenarios, especially with contemporary consumers expecting personalized experiences and products instantly. Real-time retail analytics have already been successfully used in big supermarkets and retail chains. Retailers sometimes apply loyalty tracking, where a store recognizes a customer, obtains their personal information, such as purchase history and location, and uses this data to send them relevant offers. Healthcare, too, can profit from this application to timely update patient information as it becomes critical. Another use case is in finance to warn and prevent fraud in different systems. Any bank that issues credit cards must be able to alert the authorities in case their system encounters fraud in real time. This is mainly to protect their customers and themselves from fraud. Predictions about future activities become more accurate as older data is taken into consideration. In rapid and unpredictable market and consumer dynamics, to turn data and information into value, businesses need help from real-time insights. Especially if operations and decisions are interrelated and should influence each other on the spot. For example, an e-commerce website that attempts to recommend products to a visitor engaging with the platform in real-time. Once the user leaves, that recommendation should change to something else because their needs vary each time they visit the platform. Businesses need to understand customer behavior, and the more real-time information they have, the more of a competitive advantage they gain. After all, in some industries, there's a thin line between making profits and not losing a dollar. Implications go as deep as replacing a doctor to alerting a life insurance company. There are some challenges based on verticals for the adoption of real-time analytics. Some verticals are restricted by law or regulation to execute operations near real-time or somewhat near real-time. Moreover, some verticals are not subject to rapid market dynamics that make real-time analytics extremely lucrative, such as the production of building materials. Game development does use insights to improve the gaming experience; however, the insights aren't real-time, as it would make the game too predictable. There is a vague line that connects real-time analytics with the concept of edge computing. Edge analytics and edge computing allow decisions to be made in half the time as real-time analytics. The technologies show some trends and drivers that favor real-time solutions. For example, in-memory computing and new storage types are both driving trends towards providing better input/output performance.

5. Conclusion

In summary, the study makes evident that high-speed storage is a transformative technology in AI and real-time analytics. Despite its impact in all application areas of AI, the development of high-speed storage technologies is not motivated by the integration of today's accurate, ultra-responsive AI models into today's cloud infrastructure for making the cloud provider's big data services smarter. We discussed three key high-speed storage technologies: PM, 3D XPoint, and RRAM. PM and 3D XPoint can be non-volatile, byte-addressable memory better than DRAM for reasons of their rack-scale access latency, better hardware security, and storage class memory price. RRAM, while not reaching the same memory capacity or price points as PM, benefits from the cost of power deeply, removing the need for continuous DRAM refresh. Non-volatility is presented as a key feature making high-speed storage effective in serverless cloud costs among edge robotics and smart industry use cases, where fine-grain recovery of serverless computation state with the least network backing is vital. We have also listed the remaining topics of high-speed storage, creating a compelling future research agenda. High-speed storage is where the current and future capabilities of AI systems have to be integrated. Current and future signal, video, and image AI workloads are suited to the cloud as they traditionally have and are likely to continue to demand the highest computing capabilities available. If the cloud can deliver more responsive AI outputs, it will sustain and grow this differentiation even in mission-critical embedded or edge applications. Cloud-integrated high-speed storage technologies are the enabler of this business reality. We acknowledge that high-speed storage, while transformational, is still a point of active research and development. To this end, while our analysis is based on the current state of these technologies, we also indicate future development areas in which high-speed storage increases and AI training directly on PM or RRAM requires technological innovation. Our beliefs and supporting data are sourced from recent research, the integration of which has allowed us to paint a compelling vision of the near future, in which those who adopt an infrastructure-integrated innovation mindset will lead to competing inefficient data management.

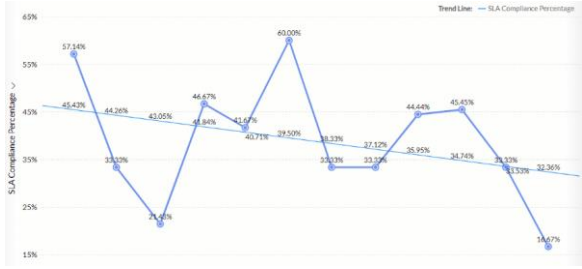

Fig 5 : Analytics Plus

5.1. Summary of Key Findings

5. Key Findings In this essay, we presented a brief introduction to the role of high-speed storage in AI systems. Moreover, we enumerated the key storage technologies that lead to performance improvement and operational efficiency of the storage layer, namely SSDs, NVMe drives, NVMe over Fabrics, NVDIMMs, and Optane persistent memory, as well as Rethink Key/Value Stores. We followed our discussion with a mid-length review of current storage challenges in cloud-integrated AI systems and potential solutions to implement to

move towards an intelligent storage layer. We systematically illustrated where these challenges arise, while steering clear of demonstrations of their resolution. We encompassed those in our previous publications. The exact paragraphs may be found in Section 1.

5.2. Summary of Key Findings 1. Hardware storage technologies have evolved from HDDs to SSDs with NVMe over Fabrics and multi-tier storage systems. Another multi-tier level was included with persistent memory such as Intel Optane in some systems to eliminate the I/O overhead of community data-sharing approaches. 2. Real-time analytics in AI applications provide managers and decision-makers with an information structure that ensures a high level of decision optimization and performance. 3. The proposed solution is based on four steps: intelligent data pre-processing, fast I/O access, autonomic self-adaptation/topology update, and dynamic metadata management. All of them work in unison to bring the storage system and consequently the entire AI system to a complete autonomic self-adaptation, which is required for all decisive mission applications. 4. Cloud computing's layered architecture provides any business with a flexible computational system without the expenses associated with necessary on-site computing facilities.

$$CSAT = \frac{D_{\text{cloud}}}{R_{\text{cloud}}}$$

Equation 3 : Cloud Storage Access Time (CSAT)
D_{cloud}: Data size transferred to/from the cloud

R_{cloud}: Cloud storage access rate (data transfer speed)

5.2. Future Research Directions

Despite recent advancements, the integration of state-of-the-art high-speed storage solutions and emerging AI/ML technologies is still a long way from their horizon. Continuous efforts are required in research towards the next generation of storage architectures to meet the increasing demands of AI/ML frameworks. An efficient collaboration involving storage and system architecture professionals can further advance consolidated storage and computation technologies, enhancing system performance. Furthermore, integrating storage and networking innovations can still provide interesting directions for research to re-explore and can drive the field toward vast improvements in the performance and scalability of AI/ML frameworks. Currently, non-volatile memory and RDMA devices provide high-performance data access and transfer, respectively. The integration of these devices can accelerate data center workloads by allowing data center storage to serve as a high-bandwidth source or target. However, there are unresolved research challenges, including the secure implementation of technologies in viable cloud environments, the enhancement of protections for data locality and selective sharing in multi-tenant cloud environments, and advances in failure recovery policies and mechanisms, which can further drive academic and industrial research developments. Such technologies may emerge shortly, thus requiring future work to enhance system scalability and to adopt the integration of such technologies efficiently. As a field with rapidly advancing technologies, it is recommended that cooperative collaboration among academia, industry, and technology development partners take place regularly to bring advancements to high-speed storage for their AI/ML-enabled data center systems.

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