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# Integrating Generative AI in Cloud Computing Architectures: Transformative Impacts on Efficiency and Innovation

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To cope with the ever-increasing information processing and enable the developing machinery of human civilization to grow smarter, it becomes necessary to build a cloud computing environment that can process large amounts of data at high speeds and low costs. For neural network-based inference applications, GPUs are commonly used. It is for this reason that we believe large-scale GPU clusters, which are currently indispensable in cloud computing processing, can be expected to solve the problem that they are highly efficient for neural network processing, yet less efficient for other processing methods, including basic users. In this study, we propose deep neural network-based processing technology that can utilize the technology for various processing by converting new processing applications, which are not only neural network-based inference, into multiple tasks that can be executed by GPUs. By making them executable, even conventional data distribution, effective job allocation, etc. can become much easier to achieve, resulting in synergistic improvements in GPU cluster utilization.In addition, users using a cloud that integrates the proposed method can minimize processing costs even when neural network processing and other processing methods are mixed and used, and can spend the budget obtained from that cost savings on realizing new business innovations. It is expected that this approach will profoundly influence the direction of cloud computing business deployments.
**Keywords:** Integrating Generative AI in Cloud Computing Architectures, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability.

## 1. Introduction

Emerging at the forefront of artificial intelligence technologies, generative AI models are fundamentally transforming diverse application domains, including content creation, fashion, automotive, and gaming industries. Encouraged by the remarkable performance and the increasing scale of modern generative models, there is a surge of research efforts towards advancing and scaling these models to improve state-of-the-art methods in their intended applications. Such models, however, are computational and resource intensive; training time can scale to weeks and even months on commonly available systems; and deployment has been limited to large-scale on-premises compute solutions due to long inference times and high operational costs. This constrains the innovation potential in these application domains by raising the entry barrier for introducing advanced generative models to non-experts. We discuss the transformative impacts of integrating generative AI in cloud computing architectures and present our cloud-native training/deployment infrastructure for large-scale image generation workloads - focusing on its unique designs and the promising design-space exploration results that demonstrate a significant reduction in time-to-solution and cost-to-solution.Advancing hardware accelerators, specialized tensor processors like the Google TPU, and flexible deep/machine learning inference platforms are constructed, and impressive efficient applications are reached. Conversely, academic and production-grade large-scale training systems remain limited in their capabilities due to expensive off-premises infrastructure, and growing operational expenses. Synchronous and asynchronous distributed model-parallelism, and distributed or elastic data-parallelism remain difficult to realize from first principles. Furthermore, there are no cloud native training systems tailored to exploit new-generation hardware accelerators or the mature and sophisticated cloud hyper-scale native infrastructure. Hosting AI workloads on hyper-scale cloud infrastructure provides an efficient platform for elasticity, extensibility, and interoperability and builds an API-based ecosystem of developer tools. Furthermore, for latent-variable generative models, cloud infrastructure becomes necessary, as the operational expenses for a real-time system can be overwhelming, especially for start-ups and small businesses.


Fig 1: Understanding Saas Paas And Iaas In Cloud Computing

Providing cloud-native runtime prediction is the fictional key to adoption. We focus in this work on large-scale training of latent-variable generative models, in particular very large subsampling rate deep undirected probabilistic models of multimodal, multi-dimensional models.

### 1.1. Background and Rationale

Artificial intelligence (AI) continues to be an exploding field of research and development.

One critically important aspect of AI is the concept commonly referred to as generative AI, which encompasses a class of AI that can synthesize content from notable mass (exabytes) of information, particularly in content areas including image and sound synthesis, text generation, and virtual character creation. It is transformative, enabling rapid harnessing of the vast resource of information currently not yet utilized due to the slow, low-absorptive capacity of human interpretation.In addition to vastly exceeding human content synthesis capacity, generative AI also has massive disruptive genomic effects: it can lead to synthetic innovation, allowing the creation of content not constrained by the law of physics and the narrow natural scope of evolution achieved by human knowledge. In a very real way, generative AI could be seen as possessing capabilities of enabling humans to "see through the future of information."In this piece, we embark on a novel inquiry. This inquiry is on a different plane from the early work of trying to harness artificial intelligence for cloud-distributed deep learning infrastructure, described as distributed deep learning cloud infrastructure. Rather than using algorithms and models, we are focused on architectural forms, that is the architecture, major components, and hosting environment. Thus, the inquiry and opinion piece in the light of the aforementioned, particularly transformative power, genomic reach, synthetic innovation, future of information, voltage of explosiveness, property of AI extensibility, identic, that is the unique value of incorporating generative AI into cloud computing architectural forms, architectural forms candidates, limitation, challenges and suggested further inquiry, is devoted to architecting generative AI-enabled digital ecosystems.

## 1.2. Research Aim and Objectives

The overall aim of the thesis is to design, implement, and evaluate a lightweight cloud-based Dockerized microservice to facilitate the development, integration, and management of Generative AI algorithms with third-party applications. We aim to overcome the challenges and limitations highlighted in the research background by developing a lightweight cloud-based platform that can host Generative AI algorithms, expose their functionalities using a RESTful interface, be discoverable to developers, and thus enable better integration and sharing of its functionalities with other applications, easing the task of domain experts in integrating it into a specific task without requiring any or with minimal programming knowledge. The aim is to lower the entry barrier into the AI world for domain experts, thus making cutting-edge machine creativity technology more widely used and available.To achieve this goal, we developed an integrated architecture that allows non-technical experts to use a highly complex image generation algorithm transparently through automated script creation and deployment. The main objectives set to achieve the aim are: 1) to map a Generative AI image generation machine learning research problem into the fields of computer science, software engineering, cloud computing, and front-end technologies, thus aiding creativity development by software engineering industries and lowering the entry barrier into the domain by domain experts; 2) to provide a step-by-step process from algorithm discovery to a user-front-end domain-deployable ready-to-use Generative AI microservice; 3) to create and release a Dockerized lightweight microservice hosting the discovered and tested highest image similarity scoring art and to interface it into a simple man-machine interface (MMI) system, thus facilitating its integration with third-party external applications.

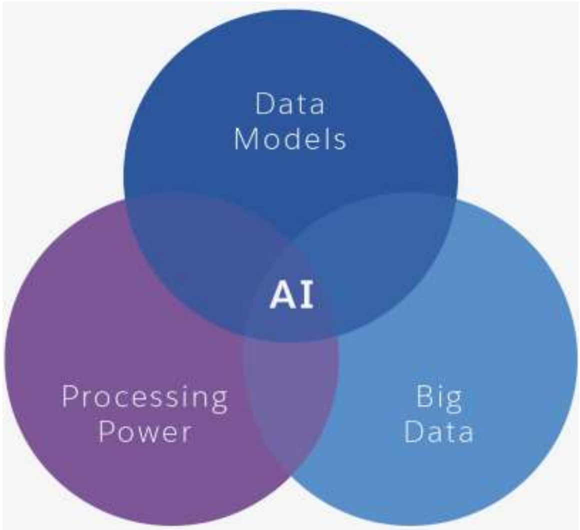


Fig 2: Ai Venn Diagram

## 2. Fundamentals of Generative AI

Generative AI involves unifying cloud-based neural network paradigms to autonomously generate new complex data. Recognized forms of generative AI include generative adversarial networks for high-resolution face generation, large data sample creation, proactive RPS (rock-paper-scissors) prediction, and other supervised generative techniques. By leveraging and extending generative AI models with cloud infrastructure changes, a new model of intelligent virtual assistants is possible. In deployments to remote nodes, large-scale virtual assistant models driven by efficient, scaled cloud infrastructure demonstrate cloud computing benefits. Shifting this intelligent virtual assistant AI model to autonomous, client-origin-based finger-wavy infrastructures avoided the constraints of dialog-based assistant chat. It doubles the cloud training time and provides innovations in scaling, efficiency, and bias in deployment and utilization. The AI efficiency revolution was initiated by generative neural architecture, Amdahl's performance limit, and IT data gravity law at scale.Generative artificial intelligence (AI) includes unifying the unique commercial progress calling on cosplay and playing Minecraft. The curious generation's nature is distinct from current large models, which are mainly designed to understand and anticipate an observed world and trained to solve tasks when queried. Generative AI models dissolve the assisted quest into a continuous, reasonably unattended data and task generation process, which makes their operation and improvement more engaging. The following are the substantial competition categories: Latent space traversals in private models. Structured A3TTK model generation for drug development discovery, data detection, and second enrollment case. Unified models that can generate hundreds of words in scientific papers. Specialized generative adversarial networks are versatile architectural and training methods. One high-profile example is this Apple blog post: "There may now be a new chia-based Apple design that generates over one million high-resolution images to optimize Apple products. Data from the initial snapshot is used to create the impression. Image analysis shows that more than 75% of unique Apple product images are impressive. 11,000 people thought of sharing their carefully designed fan designs with the public at large. The generative AI model developed by Apple automatically selects various designs for evaluation in depth and creates unique images enclosing selected joint histories and concerned external boundary conditions." This is an example of employee development creativity and the concept of art technology collaboration. Creative developers use the core clever use of the sheer model capability to ease the labor and time burdens that hamper Apple's business.Generative AI models not only contribute to creative endeavors but also play a crucial role in enhancing practical applications across various industries. For instance, in healthcare, generative AI models are being utilized to predict patient outcomes and optimize treatment plans by analyzing vast amounts of medical data. This capability extends to drug discovery, where these models can simulate complex biological processes and generate potential compounds, significantly reducing the time and cost associated with traditional methodsIn the automotive industry, generative AI aids in the design and optimization of vehicle components, ensuring better performance and efficiency.


Fig 3: Applications of Generative AI

2.1. Definition and Concepts

Integrating Generative AI in Cloud Computing Architectures: Transformative Impacts on Efficiency and InnovationGenerative AI algorithms mimic the brain of the artist, sketching myriad possibilities as they work towards a unique creation. By using generative adversarial networks (GANs), these models learn from individual or global digital examples with incredible efficacy. Among the electronics and information technology, cloud data centers, and academia, applications of generative machine learning algorithms are taking many forms to control creativity.Depending on the task, generative AI systems can create worlds from scratch, including images, photographs, sketches, voices, music, and writing. Yet, researchers sharing their work problem that existing web hosting architectures pose challenges and best practices, particularly cost. In this conceptual, prime article, we study four types of generative models. Our guiding research question is whether and through which steps any of the examined generations' techniques and archetypical model structures might facilitate implementing their performance in a Cloud Creativity marketplace architecture. Crucially, the goal is to understand generative models from a machine learning research perspective while linking back to topological aspects in the applied example setting.

## 2.2. Types of Generative AI Algorithms

A key theme of recent work in artificial intelligence is on generative AI or generative AI algorithms, concerned with algorithms that learn to generate data that is similar to data that the algorithms have been trained on. This class of learning algorithms has many potential applications, in particular by offering a powerful approach to designing new architectures for a range of cloud computing services.

Generative AI has multiple different types of algorithms, each geared to generating data of different types. The simplest are algorithms that output a single data structure, e.g., a copy of an image. More recent work has pioneered algorithms that can use a generative model's understanding of data to support the completion of data, including transforming low-quality (in some representation space) data to high-quality data. These types of algorithms could be used to help protect critical data from attacks that deface or remove important fields.Some algorithms can transform one particular type of data to another – for example, generalizing across a range of similar images that illustrate each of 10 related objects; then being asked to transform one of these images into a new example of one of these 10 objects. Indeed, some algorithms transform animated sequences of one object into similar sequences that portray another object, with the work based on these algorithms building on the expectation that such transformations would be useful in the generative design of new kinds of animated sequences; for example, learning from videos of horses how one might be able to generate realistic computer-generated animations of unicorns.


Fig 4: Unleashing The Power Of Lstms A Comprehensive Guide T

## 3. Cloud Computing Architectures

The preceding section introduced cloud computing to readers unfamiliar with the technology by describing what it is and some of its primary uses. This section delves further into the nature of cloud technology by describing it from several angles, such as how it is architected and how services are managed and operated. As part of this discussion, we include in section three an overview of a finer-grained taxonomy of cloud services, often called layers. We conclude section three by examining trends prompting the development of LPIT in future cloud use. Cloud computing is essentially a centralized computing model in which large leased server farms provide on-demand processing and data services over the Internet to individual or enterprise users. In the process, appropriate digital assets, such as software and databases, are shared over a variety of access technologies. This model has often been shown to be more efficient than distributed systems because it leverages the economic and technical advantages of large-scale data centers.

### 3.1. Overview and Components

Cloud computing in its current state is beginning to show signs of age. This is manifested in two distinct ways. Firstly, current virtualization technologies are relatively poor at efficiently utilizing the physical resources available to enterprise data centers. Virtualization-based clouds tend not to be heavily loaded: a survey analysis of Windows Azure, for instance, estimated that the average load of its servers was only around 7-12.5%, thus leaving most of the physical resources available for each server (and hence the data center) underutilized. The situation in enterprise clouds based on hypervisors from vendors like VMware, Microsoft, and Citrix is likely to be similar. Similar inefficiency issues are present in the system software layers below applications in the end user.Secondly, the decreasing rates of progress in the underlying semiconductor technology are impacting the field of high performance, particularly at the chip level, where Dennard scaling has ceased to apply and power consumption constraints prevent chips from being clocked at rates that would have been possible at the turn of this century.While advances in cloud software are required to address the former issue, the latter is only partially addressable through conventional means. Although software can be used to reduce resource usage (use of efficient algorithms and coding models, virtualizing additional resources using software), demands for increased system performance are inevitably signaled by new user requirements. This will generally result in more complex systems comprising larger numbers of devices. The poor relationship between digital systems performance, complexity, and energy consumption dictates that to increase performance and capacity in these systems (i.e. to keep up with increasing demand from end users), data centers will need to expand to become larger than they otherwise would be. JSON data, trees especially. At just under 40 unused flows per second, properties of utilization factors of the device will be very small, especially at low degrees, and the complex subcell system will not provide effective switching rate entropy when in a much more idle constraint, a parallel stream congestion property that we develop and validate experimentally in and when values of the probabilities of injection arrive with much other with certainty cannot be the that necessarily satisfied.

### 3.2. Key Technologies and Trends

To better understand how the recent advances in GAIs are resulting in transformative system impacts, we delve into a detailed examination of key technologies, in particular Transformer architecture base models. We present an examination based on three key interpreting dimensions of model size, training duration, and associated scaling laws. A meta-analysis of a selected number of diverse GAI-involved use cases is conducted to illustrate the findings and reveal broader implications. The recent intense interest in advancing DL techniques, in particular, has resulted in several key breakthroughs. This subsection will provide a systematic examination of the recent advances in GAI techniques, mainly linking to the results and performance scaling impacts. Specifically, we will delve into the breakthroughs in the three evaluating models, i.e. architecture, data, and computing techniques. Notational conventions used in this chapter are listed for the reader's convenience. Generative Adversarial Networks (GANs), first introduced in 2014, have since become influential in their ability to generate deep and photorealistic content like large-scale text and virtual objects. Generative AI studies generative models using deep learning, specifically auto-regressive (e.g., LSTMs) or attention-based models, which usually involve the use of deep generative models like LSTMs, Transformers, VAEs, Autoencoders, as well as specially designed discriminators to achieve photorealistic synthesized contents. Some of the highly-rewarded AI-generated use cases include solving complex SAT problems, proving the Riemann Hypothesis, and generating realistic virtual characters, as well as photorealistic artwork, among others. A core technical characteristic of recent GAIs, more so than other AI techniques, is its extreme reliance on sophisticated computing platforms and architecture alternatives, for deep yet efficient model training. Consequently, this has overdriven big cloud vendors to a level of vertical AI (via designing hardware architectures) integration that heretofore was merely a theoretical research proposal for the fruits of horizontal commoditized AI model training via cloud computing architectures.

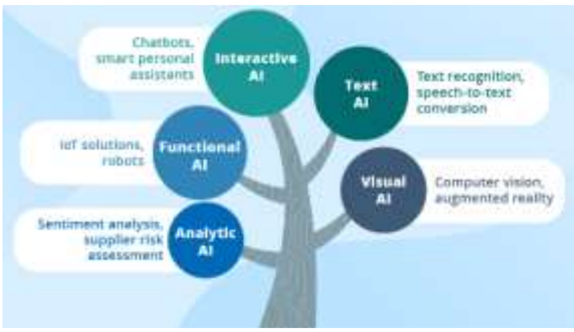


Fig 5: Generative AI and your career

## 4. Integration of Generative AI in Cloud Computing

AI requires substantial computation, and it is fairly expensive for the user to maintain the massive-volume data (computation, storage, database retrieval) with hardware at home. One solution to this issue is to distribute the services on cloud computing server farms but experienced several issues. When the volume of a user's experiments is very sparse compared with the total volume of experiments, allocating a core in a shared manner on a cloud computing server farm is very ineffective. As a consequence, an AI enthusiast needs to choose several parallel problem statements available from these public clouds to leverage the price during a limited amount of time, which limits the speed of discoveries. Moreover, even though several studies demonstrated the interest in using AI Guarded Algorithms, it is still quite hard to use. The project submitted by the user on the service provider often meets limited memory time which is quite odd considering the large quantity of non-updated cores on the cloud computing core server farm.A simple solution to these problems is to deploy generative AI algorithms on the server side and provide the ability to join these server-side algorithms in a client application. Indeed, when the client is a mix of the graphical driving engine and the user equipment, the data that should efficiently be transferred are numerous tiny size images and the sequence of aperitive images explains the planning to produce during the experiment. The capacity of computing the use case can rely upon the capability of the service provider to share the graphical server-side between multiple users. The user and the data are moving in the graphical server as a core, but the imperative data does not move much. AI algorithms used on the graphical server farm do not need a lot of computing memory, a smaller cost that can be invoiced. However, many users will prefer a dedicated full-core, but a graphically bounded server will be useless.

### 4.1. Benefits and Challenges

It is not hard to make the logical leap that AI's ability to optimize algorithms, to move beyond the inherent limitations of the human thought process, and to do much more than replicate repetitive tasks more quickly than their human counterparts stands to further optimize the cloud software applications and services ecosystem. AI will not only accelerate the delivery of existing cloud computing services but also bring new applications to market faster and enable new levels of functionality that we cannot imagine today. In this paper, we focus specifically on two forms of AI that stand to repay considerable dividends in the pursuit of serverless and IoT cloud ecosystems generally and cloud services in particular: generative AI and computational creativity, or AI that can develop new algorithms.Generative network AI (GAI) technology abilities can produce new, previously unseen content. This creative AI algorithmic structure promises to deliver the next wave of AI's incredible potential and will turn GAI into an important AI in the cloud services lifecycle, delivering both new insight and markedly novel innovation. Given the advanced algorithms and frameworks now available, deploying GAI models in the cloud infrastructure industry represents a significant economic advantage, enabling companies to lead in everything cloud. However, by its nature, GAI deployment represents multiple technical challenges, such as computational complexity and dual-use concerns, not to mention increased attention to the requirement for sustainably produced core data. Successful adoption of GAI will increasingly depend on the ability of AI in the cloud services sector to employ algorithms and frameworks that translate data-centric design into human-centric goals.


Fig 6: A Comprehensive Guide to Workflow Integration

4.2. Use Cases and Applications

On the one hand, IGAIs provide a basis on which multiple R&D teams from different organizations and geographical locations can collaborate constructively and effectively through, for instance, high-quality GANs such as a recent example of producing 3D car models with a high degree of parametrization and variation. It should be noted that the discriminator network of this GAN was trained using synthetic labels, and the generator was a Transformer architecture, highlighting the use of CNNs and Transformers as increasingly more generalized generative AI architectures able to create new computer graphics. The generality of IGAIs stems from building the parameter set included. As long as the same parameters are used, different companies and R&D teams can collaborate effectively, without needing to construct all intermediate neural incremental layers from the original dataset.On the other hand, achieving good generalization of graphical AI models may encourage R&D teams to add new capabilities beyond simple image and shape generation. Encouraging such knowledge generalization in the AI field is key to generating meaningful contributions to the scientific community, allowing more results to be shared, compared, and benchmarked on more elaborate, scientific problems, rather than just simple, resource-demanding, and time-consuming image and shape rendering or simple, real-time inference-based image segmentation or classification tasks on limited datasets. In cloud computing, one important use case for generative approaches to AI graphics is in collaborating with IoT or edge computing devices to provide real-time actions from and between these devices. To be maximally effective, GAN-factorized models and parameters are trained on the cloud and then transferred to IoT devices, preserving competitive advantages on the cloud while still enabling near-edge inferencing, for example, on drones in a swarm or a vehicle environment. With the move to edge-first computing, these are important features to move towards to retain any competitive advantages.

## 5. Impact on Efficiency and Innovation

In this section, we will discuss the way integrating generative AI with cloud computing architectures will drive transformative impacts on efficiency and innovation. The emergence of efficient generative AI enables the construction of several revolutionary cloud-based and cross-industry applications with new levels of efficiency. These applications can innovate people's lives, business processes, and the way we work with each other, helping in realizing the Gartner Hype Cycle peak points and boosting related industry leverage.The core computational bottleneck substance has disadvantaged several cloud-based applications, some barely possible even with cloud computing infrastructure scaled up to tens of thousands of GPUs. The emergence of efficient architecture and learning sets the stage for cost-effective searching, designing, and deployment of large-scale generative AI models at unprecedented efficiency and speed for the first time. Generative AI will considerably improve cloud computing infrastructure efficiency. In a real-world deployment, a state-of-the-art generative AI model today can eliminate 90+% redundant cloud computing infrastructure components and power needs in, for example, digital collaboration assistance, preserving enormous computational resources and electricity.


Fig 7: Operational Risk Management Gets Smart with AI

### 5.1. Enhanced Performance and Resource Optimization

A significant area of attention where the combination of generative AI and cloud computing platforms has enabled remarkable advances in the design and operation of computational systems (architectures and programming models, e.g., adversarial neural networks) and the basic software infrastructure layers. On the one hand, AI development and deployment are rapidly becoming much more demanding in terms of resource allocation and management, much like the enterprise and institutional IT systems of just a few years ago in terms of service and data quality. On the other hand, AI systems are also providing an immediate set of state-of-the-art, exceedingly low-level capabilities to address these very systems and data management challenges, while also adding a genuine and much broader learning element to the tools that humans can use when steering those resource-intensive and intricate tasks.Together, these trends pave the way to a virtuous cycle in which each new technological order loop adds value to all the others. They help improve the performance and resource optimization of AI-driven knowledge-discovery and problem-solving loops on many fronts—from IC design to science, from fashion to the navigation of complex decision-making and autonomous control spaces—generating, among others, a profound and direct impact on hardware device design and large-scale dataflow and storage strategies and IT orchestration. In so doing, they further animate an economic ecosystem in which knowledge inference (we derive viable insights), concept inference (I derive viable concepts from the available data sources or technologies), and model inference (business model, economic exploitation, technical and application requirements, market end-users, use-cases, technical acceptance, and social acceptance) continuously feed each other with accumulated value.

### 5.2. Innovative Services and Products

As described earlier in this work, our approach is not meant to develop generative AI as an enhanced web access resource, but as an integrated set of machine learning model-based services. These services come with a rule system that can be individually adjusted for models to serve different objectives for the same company or other objectives for different companies or different parts of an integrated corporation.Furthermore, the model services can be integrated into high-level corporate service provisioning systems or made available as initial models the corporations can further adapt and specialize based on their unique conditions and expectations. Allowing off-the-shelf, easy-to-use machine models as supported by cloud ARPA is expected to greatly accelerate the rate with which companies experiment with machine innovation.

## 6. Conclusion

In different ways, AI and cloud computing architectures have each shown themselves to be powerful determinants of digital transformation and innovation, contributing to advances in knowledge, service provision, and business practices across the world. The integration of AI with cloud computing architectures represents a level of innovation that promises these mutually reinforcing paradigms even greater advances than can be directly obtained in their original domains.To date, a significant portion of AI research has been conducted by institutions with unique computing resources. The use of algorithms developed by leading researchers using these unique resources to train models is enabling a deep transformation of existing industries and creating the conditions for new ones to emerge around generative-private models.Both service providers and enterprises utilizing cloud computing will continue to be at the vanguard for integrating newly available AI capabilities to gain transformative efficiencies and create revolutionary products and services. The developments described here suggest a future with a greater reliance, for both democratized and private models, on latency-sensitive real-time processing across less data than is the case today.Each unit of AI computing could be more valuable in the future than they are now; perhaps a great deal more valuable. Training AI models is a process that requires significant computing power over periods that can range from several hours to several days. The result is models that can rapidly complete various complex processing tasks that are necessary to perform simultaneously in a single system. The resulting gain in efficiency equates to an exponential expansion of processing capabilities for cloud domain AI in general.


Fig 8: Top 10 Cloud Computing Trends

6.1. Future Directions

Given its advantages, versions of intelligent behavior implemented through generative modeling and deep learning can be expected to become more common in future data center applications. Current first-generation GAI implementations of training or inferencing pipeline through specialized AI accelerators are likely to be complemented increasingly by the more end-to-end deployment of infrastructure able to use GAI modification of cloud resources directly as a core part of deployment. The paper has laid out the mechanisms and the likely efficiency improvements from integrating GAI within the cloud resources they will modify, just as other AI methods modify them today. The benefits of reduced communications, increased ability to generate efficiencies directly from GAI data (wisdom of crowds), and new services with greater data or time sensitivity can make the cloud more efficient and innovative.As an initial step—one which proceeds directly from the cost modeling in this paper—future cloud service interfaces could be extended to support ontological metadata that would allow more specific and realistic prior knowledge to be included with GAI applications when integrated with cloud services. By identifying the existing distributions and dependencies of the data instance prior, and combining that with the prior knowledge of the network weights, there are many potential efficiencies and innovations. Data centers are changing to accommodate increasing AI use and the future benefits of better integration justify the continuation. Providing richer, more collaborative and end-to-end AI that allows infrastructure cost reduction—what could matter more to people, society, and Earth over the next decades?

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