THE FUTURE OF CLOUD:

Integrating AI, ML, and Generative AI for Scalable Solutions

Chandrakanth Rao Madhavaram

Janardhana Rao Sunkara

Chandrababu Kuraku

Eswar Prasad Galla

Hemanth Kumar Gollangi

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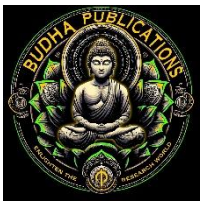

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About the Authors

CHANDRAKANTH RAO MADHAVARAM

Chandrakanth Rao Madhavaram is an accomplished IT professional with over 9 years of experience in designing, developing, and deploying scalable cloud-based applications. He has a proven track record of delivering high-quality software solutions using .NET technologies, including ASP.NET, C#, and MVC. His expertise extends to Azure services such as Azure Functions, Azure DevOps, Azure Storage accounts and Azure SQL Database enabling him to build robust and efficient cloud-native applications.

Throughout his career, Chandrakanth has worked on various projects across different industries including finance, healthcare and Product based companies. He is adept at collaborating with cross-functional teams to ensure seamless integration and delivery of software products.

Chandrakanth is passionate about continuous learning and stays updated with the latest advancements in cloud computing and .NET development. In addition to his technical skills, he is known for his attention to detail and strong communication skills. He is committed to delivering innovative solutions that meet client requirements and drive business success.

JANARDHANA RAO SUNKARA

Janardhana Rao Sunkara is an accomplished Oracle Database Administrator with over 9 years of experience, specializing in database management, optimization, and security across industries such as Pharmacy Retail and Manufacturing. His expertise spans Oracle technologies (19c, 12c, 11g, 10g) on platforms like Red Hat Linux, Solaris, and IBM-AIX, with a proven track record in large-scale database migrations and cloud integration on AWS and Azure.

In addition to his database skills, Janardhan has a strong background in Big Data, AI, Machine Learning, and DevOps. He has successfully applied AI and ML techniques to enhance database performance and predictive analytics, while his DevOps experience with tools like Jenkins, GIT, and Ansible has enabled efficient automation of database operations.

Janardhan's ability to integrate advanced technologies with Oracle RAC, Dataguard, Exadata, and GoldenGate has made him a key contributor to high-availability and secure database environments. His innovative approach has significantly benefited organizations like CVS Health and Hewlett Packard Enterprise, reflecting his commitment to excellence and continuous improvement in the field of data management and technology.

Holding a master's degree in Electrical Engineering, Janardhan has made significant contributions to organizations like CVS Health, Hewlett Packard Enterprise, and Ciena Corporation. His role in solving critical database issues, optimizing performance, and integrating cutting-edge technologies like Big Data, AI, ML, and DevOps into the database management lifecycle has earned him recognition as a forward-thinking leader in the field. Janardhan's career reflects a commitment to innovation, excellence, and continuous learning in the ever-evolving landscape of data management and technology.

CHANDRABABU KURAKU

Chandrababu Kuraku is an accomplished SharePoint professional with over 8 plus years of extensive experience in designing, customizing, supporting, and implementing SharePoint solutions across various versions, including SharePoint server 2010/2013/2016/2019 and SharePoint Online. His expertise spans a wide array of technologies and tools, including PowerShell, .NET, and SharePoint Designer, enabling him to adeptly handle both client and server-side development tasks.

Chandrababu is well-versed in Office 365 components such as OneDrive, OneNote, PowerApps, Microsoft Teams, Flow, and Forms. His role often involves creating and managing SharePoint sites, developing executive-level reports, and addressing complex technical issues. He has significant experience in migrating and upgrading SharePoint environments, developing custom solutions using SharePoint Server Object Model, CSOM, and JavaScript. He has a strong background in both Waterfall and agile methodologies and is skilled in all stages of the SDLC, from requirements gathering to post-production support. His experience includes hands-on development of Sandbox and Farm solutions, utilizing for data retrieval, and employing tools like DocAve/ShareGate for migration and backup.

Chandrababu professional experience includes roles with the Social Security Administration (SSA) and ProSoft IT, where he has managed complex SharePoint environments, provided critical support, and led various SharePoint and ITSM initiatives.

His technical skills are complemented by a thorough understanding of ITIL frameworks, ServiceNow implementations, and a variety of development and scripting languages. Chandra's dedication to optimizing SharePoint environments and enhancing business processes makes him an asset in the IT and SharePoint communities.

ESWAR PRASAD GALLA

Eswar Prasad Galla With over six years of experience in the IT industry, He demonstrated extensive involvement in all stages of the Software Development Life Cycle (SDLC), from planning and analysis to design, implementation, testing, and maintenance. His expertise encompasses both Agile Scrum and Waterfall methodologies, providing a comprehensive approach to project management. Eswar is highly proficient in a suite of Microsoft Azure tools, Data Engineering tools. His in-depth knowledge of Spark architecture—covering Spark Core, Spark SQL, DataFrames, and Spark Streaming—has enabled him to perform advanced unified data analytics.In his capacity as a build and release engineer, Eswar has successfully implemented CI/CD pipelines through Azure DevOps, ensuring efficient application management and deployment with significantly advanced data ingestion, processing, and analytics capabilities.

Driven by a passion for advancing data engineering, Eswar Prasad Galla is deeply involved in impactful projects, mentors peers, and champions emerging technologies. His steadfast commitment to staying abreast of the latest advancements in the field highlights his crucial role within the organization.

HEMANTH KUMAR GOLLANGI

Hemanth Kumar Gollangi is a distinguished IT professional with over six years of experience in ServiceNow development and consulting, specializing in enterprise applications and service management. His expertise encompasses a wide range of areas, including Asset Management, IT Operations Management, Risk Management, and Human Resources. Known for his innovative use of Artificial Intelligence (AI) and Generative AI, Hemanth excels in enhancing automation and operational efficiency across these domains.

With a strong track record in developing intelligent systems and streamlining workflows, Hemanth is recognized for his ability to drive significant improvements in service delivery and risk management. Passionate about advancing technology, he actively leads impactful projects, mentors peers, and advocates for the latest technological advancements. His dedication to excellence and continuous innovation underscores his value as a pivotal contributor to any organization, shaping the future of IT service management and enterprise applications.

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Chapter 1

THE EVOLUTION OF CLOUD COMPUTING: FROM BASICS TO INTELLIGENT SYSTEMS

1.1. Introduction

The evolution of cloud computing is revolutionizing the IT industry. It enables elastic, flexible, and cost-effective IT services, and paves the way to unified, reconfigurable, and efficient enterprise and carrier-grade computing infrastructures. To achieve these objectives, cloud computing relies on state-of-the-art technologies and drives a number of research and development activities. This paper offers an evolutionary journey through the cloud computing technology frontier. The players, platform, and models of cloud computing are introduced. The paper then identifies the root causes that fuel the thrust of the IT industry towards the cloud. A snapshot of the evolution of the research and development of cloud computing platforms is presented. State-of-the-art research results of cloud computing and intelligent systems and services are also presented.

The services provided by the Information Technology (IT) industry use dedicated resources and are deployed using a wide range of technologies in support of personal and business activities. New concepts, architectures, and delivery and deployment models enable transparent, unified, and elastic usage of general-purpose computing across user communities with different service level requirements. This computing revolution represents the cloud computing (or cloud) concept, i.e., IT services are provided in on-demand mode and are paid on a usage basis. The cloud concept is crafted by the IT industry to emphasize the flexible and scalable business-related features needed to cope with the unpredictable variations and the fierce competition of the external business environment. Cloud relies on new and advanced technologies that enable highly reconfigurable data centers delivering services to a worldwide user community, thus paving the way for the next IT era.

1.2. Foundations of Cloud Computing

Cloud services can be described easily. A server provided by another party is responsible for running the most basic of software and making it accessible via the Internet. There are several ways to think about cloud computing, and the Cloud Security Alliance has gone to some trouble to define cloud computing in the context of secure cloud computing. Their definition of cloud computing, based loosely on work done by the National Institute of Standards and Technology in the United States, is as follows: "Cloud computing is a model for enabling a convenient, on-demand network access to a shared pool of configurable computing resources like networks, servers, storage, applications, and services with minimal management effort or service provider interaction."

Although more and more providers are making larger and larger promises about services, there is a rapid commoditization of these services driven by the fundamental force of consumerization (I am a reasonably successful private citizen so I have some power in deciding which cloud service to use) and driven by the complexities of large-scale computing - many providers can connect individual servers to provide a scalable backup service or a scalable Web hosting service. The range of new "cloud services" demonstrated conclusively that creating your own cloud services is not at all hard to do. As a practical matter, in the current economic environment, past and likely future, putting up a site on the web is more feasible than building a large data center.

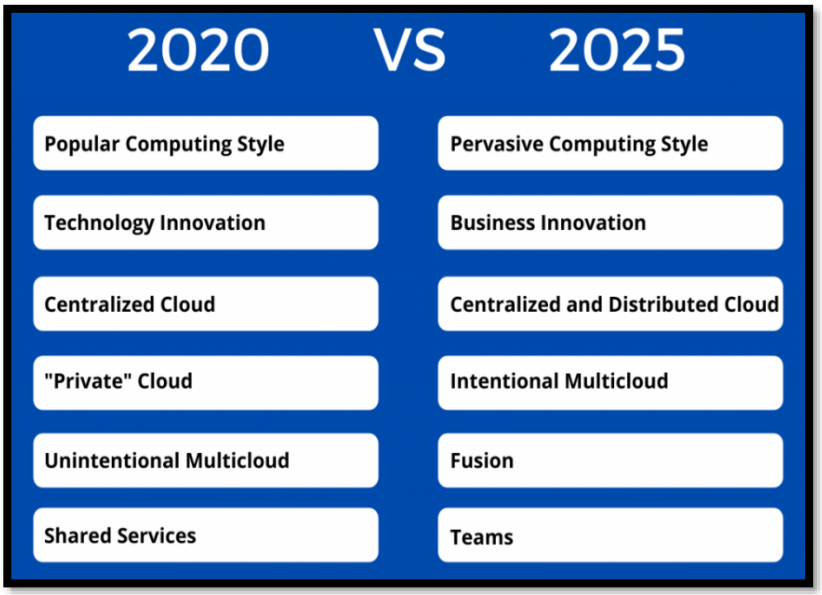

Fig 1.1 : Cloud Shifts from 2020- 2025

1.2.1. Definition and Key Concepts

A conceptual framework for cloud computing services

The focus of cloud computing is on new capabilities for user-convenient, worldwide, on-demand access to a combination of software as a service (SaaS), hardware infrastructure as a service, and development platform as a service. Cloud computing signifies several changes in the role of servers, in the types of applications that are chosen for use on cloud computing platforms, and in the kind of work that the IT personnel do.

Developers and businesses typically use cloud computing in order to realize three key advantages: (1) user-friendly implementation of applications and business requirements where needed, (2) focus on business priorities and revenue-generating activities, and (3) collaboration of an application development infrastructure. These three advantages will lead to a shift away from in-house server rooms that are dedicated to meeting the often-changing requirements of an organization and toward elastic cloud services that can react more quickly, are helpful in preventing web failure at peak loads, and have transparent, variable pricing systems.

This is the promised delivery of cloud computing, whether over a company's existing network, over the internet, or through a combination of both. The cloud shifts focus from in-house information technology (IT) resources and personnel toward the building of revenue-generating applications that meet business requirements. Organizations can, in turn, pursue new opportunities based on cloud applications, such as innovation, marketing, increased real-time transaction processing, and partnerships. But before businesses can adopt this business model, careful and extensive analysis of the organization's current roles and policies is imperative, as well as vital preparation by the IT staff.

1.2.2. Historical Development

In the upcoming years, cloud computing became a meaningful attribute of the new economy. The cloud model is utilized broadly after causing considerable growth in cloud services and service offerings. Recently, the cloud model has been viewed in relation to the Internet of Things, which is a generation of connected machines that have become widely applied in commercial environments. Cloud engineering is developed in a manner that is aligned with cloud computing and web engineering, thereby gaining from open service

innovations. In such a setting where high-tech along with modern service models support collaboration and knowledge sharing, every attractive potential outcome has an inherent element of begging the question.

Authors of business and information systems engineering encourage a reflection on comprehensive issues associated with the new digital economy, such as research that encourages the expansion of knowledge management. Furthermore, the IT buzzwords enable new opportunities for the industry that may be developed further by addressing questions which describe the context and strategic positioning of the company. The simple framework based on the who, how, what questions that have often been employed in such a manner which does not encompass the original meaning.

1.3. Key Technologies in Cloud Computing

Now I will describe for you the technologies used in cloud computing.

3.1. Virtualization

Virtualization is the enabling technology of cloud computing. It allows separation of logical and physical entities. It allows the construction of multiple logical computing entities on a single physical platform. It provides a greater level of automation than traditional infrastructure approaches. Virtualization allows for multi-tenancy (in a secure, isolated way) on a shared hardware platform. Applications, individual computers, networks, storage, etc., that may be virtualized from physical ones to share a variety of resources to maximize the efficiency of both the user's resources and the cloud. Instead of buying new hardware to meet increasing demand, computing resources can be allocated from a large virtual pool. Virtualization sits at the zero layer of the implementation stack.

3.2. Service-Oriented Architecture

The service-oriented architecture (SOA) concept enables application designs to be loosely coupled and supports the development of loosely coupled components that can be combined in business processes to produce flexible solutions. By using SOA paradigms in the development of applications, its services can be provided through cloud computing infrastructure, development, and platform solutions. At a lower level, this technology allows the business logic of an application to be swappable, rapidly increasing or reducing the high-

level processes without updating the identity logic. At the higher level, SOA can be hosted on services running on suitable platforms causing much immediate change in the underlying infrastructure or capabilities, realizing the real strength of cloud computing models. The service-oriented architecture is part of cloud computing classification level 3, PaaS.

3.3. Metadata

Metadata is a set of data that describes and gives information about other data. It contains information clarifying and defining the property of an object. In the cloud computing context, it plays the linker role, playing the intelligence itself once combined with the ontology through semantic concepts, in order to accomplish more abstract interactions. Sphinx is an example of a cloud MPI (Message Passage Interface) library that uses metadata as an intelligent partner to support MPI.

1.3.1. Virtualization

The use of virtual machines (VMs) is essential in cloud computing as it provides isolation, operates in the application layer, and scales to meet the specific requirements of each application. A VM is a software implementation that executes programs like an actual physical computer. It comprises an operating system, some applications, libraries, and offers the same environment as traditional physical machines, except for the fact that many VMs can operate on the same physical machine. The latter occurs by using hypervisors, creating an abstraction layer beyond the physical infrastructure. The hypervisor is a software layer that creates and runs VMs. It presents the VMs to operating systems located in the higher layer of virtual machines and provides the hardware interface that the operating systems will use to manage input-output operations. This hypervisor is also called a virtual machine monitor (VMM). It attaches the user-grade application to the machine memory, networks, storage area, and other peripherals, thus providing each VM with an emulated environment of the underlying hardware.

The development of VMs has allowed a server to operate as various unrelated hosts and to operate several varied operating systems where no lack of performance causes detrimental effects. Each VM is a separate virtual machine, and any operating system can manage the VMs. Given that VMs offer a high degree of isolation from each other, matters concerning the security of cloud storage and adoption of multi-tenancy models have proven to

be less restraining than was previously assumed. A few research studies have explored security and privacy issues, such as the possibility of deletion of sensitive data managed by the users. Other sensitive points are being investigated, such as infrastructure virtualization, hypervisor design, processor management, VM luggage restrictions, and other hypervisor configurations. However, as the use of VMs implies the usage of an operating system, every VM must include its own copy of the principal kernel software, as well as the necessary libraries, applications, and interpreters, all of which occupy memory and storage space. The extra VM software critically affects the scalability and performance properties of systems.

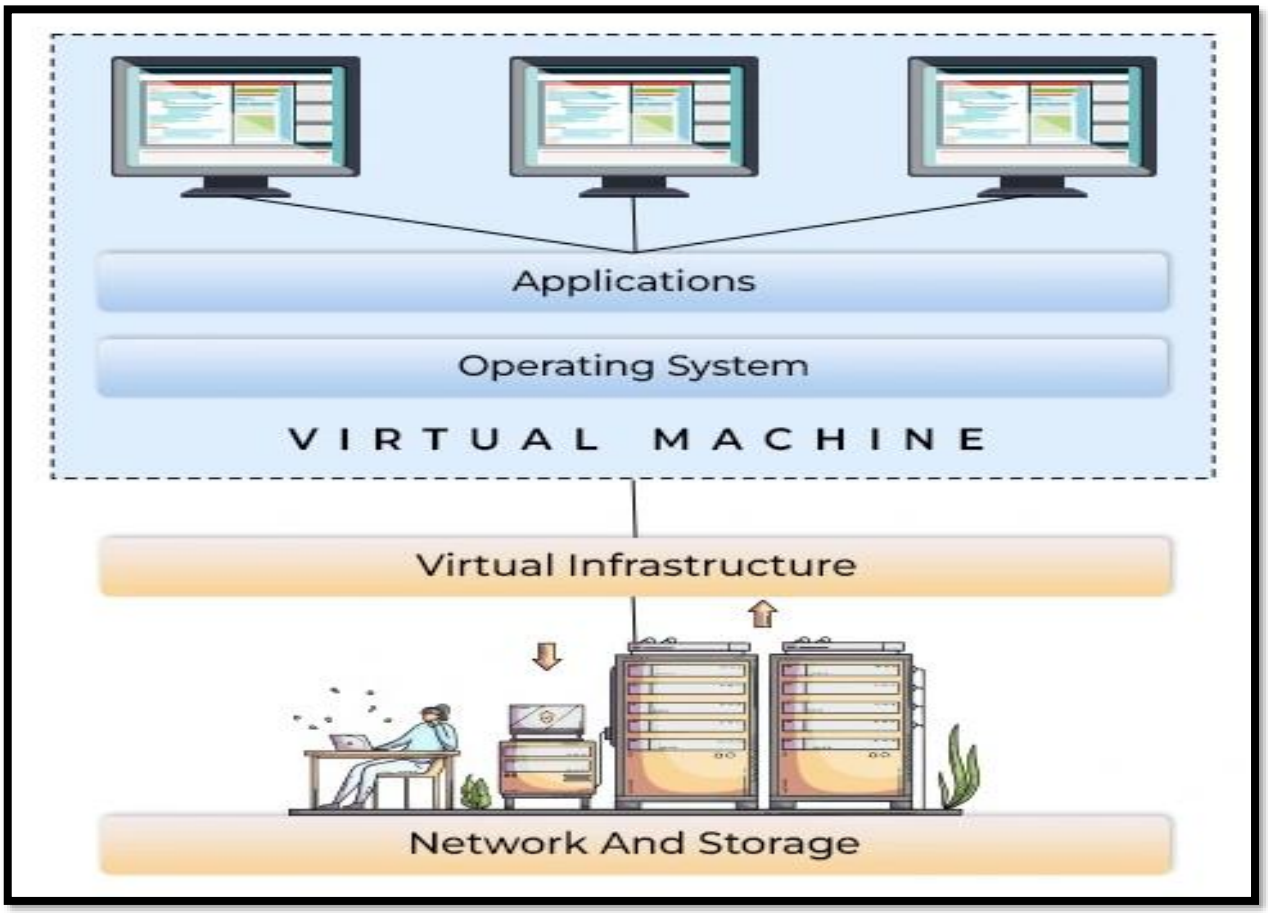

Fig 1 .2 : Virtualization Cloud Model

1.3.2. Distributed Computing

Distributed computing consists of having multiple computers, or processors, working together to solve a problem. They are most often homogeneous, i.e., they have similar characteristics. Today, many large-scale systems use distributed computing for the transmission of information to end users. In the distributed computing concept, they solve

problems greater than what it would be able to solve. It consists of having multiple computers, or processors, working together to solve a problem. They are most often homogeneous, i.e., they have similar characteristics.

It is important to remember that a distributed computing system can be seen as a distributed memory system, where the processors communicate by sending messages, or as a shared memory system, where the shared memory is distributed. In the latter, we need to have a protocol that guarantees the coherence of shared data, since data can be changed by various processors. Among problems solved using distributed computing, we can point out distributed databases, distributed information systems, distributed artificial intelligence, distributed concurrent programming, distributed operating systems, distributed real-time systems, distributed state machines, distributed systems, distributed simulation, distributed transaction processing, and distributed user interfaces.

1.4. Emerging Trends in Cloud Computing

The present article will deal with emerging trends and researchers as seen in today's cloud technology evolution. The focus, however, now moves to the emergence and boom in technological advancements of computing sciences such as artificial intelligence techniques, machine learning, deep learning, and other such intelligent system approaches seen in the cloud industry these days. The information which will be included is more towards giving a higher view and getting a general abstract understanding of such advanced technologies in cloud computing, and the authors believe it should be helpful in creating more specialized frameworks, systems, strategies, business models, and security using these concepts of intelligent computing. Issues such as digital twin creation, cloud serverless architecture, and quantum computing are briefly touched upon.

Acting now and with the almost native increase in the technological advances in cloud computing, this fantastic technology is not only used to store data as anyone in today's world can do but also to perform data and information analytics at rapid, quite intelligent, and supervisory levels. And as more and more hybrid cloud models get developed, businesses no longer depend only on external cloud services. They also deploy their own cloud environments, increasingly maintained in similar lines by private or on-premise organizations. Such deployments also have started to skyrocket to super large levels of global infrastructure on which European regions cater to the cloud market of around 21 to 22 percent in 2019. Some

very large business entities and tech-giants, as they call today, are already into the hundreds of billions of dollars in revenues in the cloud services segment itself. A study in January 2009 by Forrester Research noted the evolution of cloud and said that Software-as-a-Service is only the tip of the iceberg, even if it was the first cloud offering of computing.

1.4.1. Edge Computing

Edge computing is a model in which data is processed at the periphery of the network. Edge computing aims to reduce traffic at the local area or base station level and enable new applications for Internet of Things (IoT) with high availability, low latency, improved capacity, fault tolerance, and supporting wide ranges of applications. IoT consists of all the smart sensors and actuators that are embedded into a physical object and connected to other smart devices to exchange data and control objects within the context of integrated cloud computing. Edge computing moves the computation, storage, and processing closer to the originating source of the data using the information that has been collected by the edge sensors. Although edge computing can help do predictive analytics, which can anticipate equipment breakdowns, resource demands, and security breaches, edge solutions also have limitations. They have higher latency than cloud solutions, and the amount of data that can be collected and stored in comparison to cloud solutions is limited. Therefore, cloud/edge solutions are required for low latency computing.

Edge computing is a distributed open IT architecture that features increased security and resilience. Edge computing was adopted in 2018 and is currently recognized as a standard in IT technology. The term "edge computing" was coined by Google in 1996 when it presented a computational model using end-user devices to manage YouTube traffic. In this Google presentation, the edge could become a sophisticated layer in developing underlying infrastructure. The later year revealed the growing importance of edge computing. As it is stated by the Cisco's Visual Network Index, some 40% of all computing events will occur at or very close to the IoT devices and the ubiquitous presence of the edge. This will be highly facilitated by ongoing increases in intelligence, increasing computing capacities, and decreasing latency. The predictions on the exponential growth of edge computing capacities imply the need for application of new, more efficient, and effective models as represented in the resultant morphologies on "edge intelligence" and "automated edge". It also calls for a profound learning-based approach in the technological landscape.

1.4.2. Serverless Computing

Serverless computing is also referred to as Function-as-a-Service (FaaS). This recent cloud computing paradigm moves server management and capacity provisioning from the characteristics of the cloud consumer to the cloud service vendor. In the idle time, the vendor obtains the computing resources managed in the data center at lower costs. Benefited from this feature, the cloud service vendor can offer the capability as needed without specific user-aware involvement, which enables many developments and projects that cannot be realized due to time needed to set up the infrastructure. This approach is also known as event-driven computing, with serverless computing being the one in which the cloud service vendor or service provider individually takes responsibility. Furthermore, a serverless FaaS runtime integrates with the platform and allows developers to package functions without caring about the infrastructure, operating environment, or function execution requests.

In this respect, serverless computing may enable an extension of microservices: it can be described as a new service model that can execute short-lived, scalable, and event input-dependent functional routines. Thus, this type of service provider can be used to perform scalable and reliable event-driven processing or execute specific computing logic supplied by stateless functions. Data stored in cloud storage (like cloud-based data storage) is important. Concerning serverless computing typical service providers, a vendor like AWS offers the Lambda FaaS runtime service.

1.5. Intelligent Systems in Cloud Computing

As service providers compete to offer more advanced business models that are able to integrate intelligent systems and artificial intelligence capabilities, cloud computing must continue to evolve. Intelligent systems in cloud computing also enable the possibility of adding more IT services developed under the umbrella of cognitive computing based on data and systems that are largely distributed. Such heavy use of data in cloud computing can be a real pitfall as cloud data stays under commercial company jurisdiction. The latest cloud computing evolution consists of offering AI services (Artificial Intelligence) available to everyone.

There is a significant interest from all potential cloud users in those future cloud computing solutions also having an intelligent aspect, which translates into better and more efficient solutions and integrations next to purely technical information technology ones. In

this context, provider strategies to focus on the development of more sophisticated cloud computing at local and global levels become clear. The way that cloud computing becomes more and more intelligent and cognitive. As seen in the market, providers seek to offer users the possibility of purchasing also reduced technical or intelligent computing services. With all these arguments, our work seeks to identify the main Intelligent Cloud Computing functionalities and present a future view of this subject as part of global Cloud Computing development.

1.5.1. Machine Learning and AI Applications

Storing and processing data in cloud environments is the foundation of AI and machine learning systems. However, these technologies are essential in the evolution of cloud computing services. The primary cloud-based machine learning applications include the classification of big data sources, such as images and audios, pattern recognition, computer language learning, and making predictions. Deep learning processes, which are used for problems related to data analytics, are efficiently completed with cloud computing in large-scale systems. Today, AI and machine learning processes are executed in popular cloud providers, such as Amazon, Microsoft, IBM, Google, and SAS, which provide several services, including AI, ML, cognitive operations, business intelligence, big data, and data management.

In cloud environments, virtualization technologies emulate virtual machines, which can host AI analytics tools and big data management applications. Virtualization solutions offer a hardware infrastructure to endorse machine learning AI systems. The most common virtualization agents are operated by renowned machine learning libraries, such as TensorFlow, CNTK, PyTorch, and the OpenVino Toolkit. Therefore, the cloud computing infrastructure has the advantage of being supplied to host deep learning-based pattern recognition processes, for image classification, object detection, natural language recognition, predictive analytics, diagnostic tools, chatbots, recommendation systems, speech and voice recognition. The results and products can be used in various fields, including finance, health, commerce, industry, manufacturing, energy, production, and infrastructure.

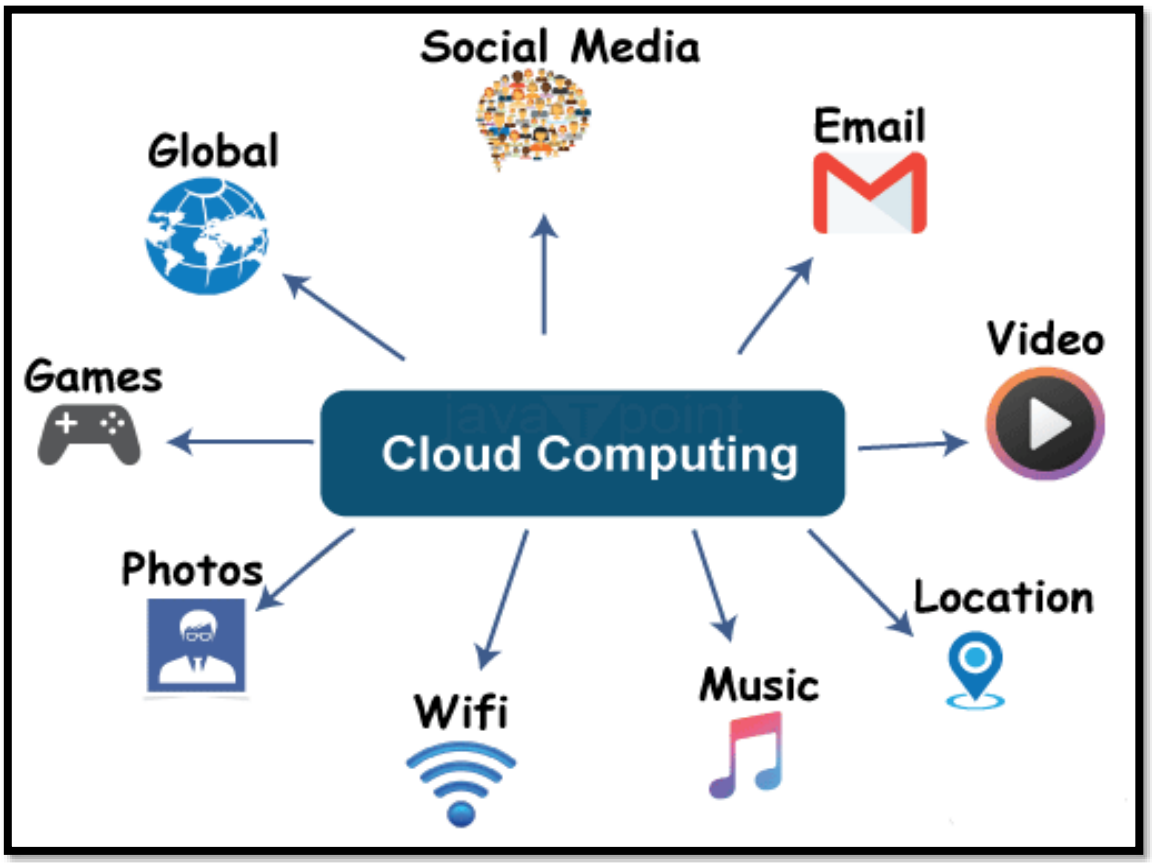

Fig 1. 3 : Machine Learning and Cloud Computing

1.5.2. Autonomous Cloud Management

Let us elaborate on the influential concept of autonomous cloud management. The autonomous cloud paradigm suggests the development of a systematic, robust software program that facilitates efficient, hands-free operation of one or a number of cloud computing systems. In autonomous clouds, management tasks typically performed by human personnel, such as cloud service deployment, configuration, business process optimization (including, for example, SLA generation and negotiation), and system maintenance, are instead assumed by an underlying automated system. Fundamentally, these types of cloud computing systems should be integrated with intelligent elements that are capable of acting independently without any external human intervention, thanks to support from a layered software architecture that captures not only cloud technologies but also AI technologies.

Despite the great potential of this new type of cloud computing, the development of intelligent autonomous cloud management systems still remains a challenge. It must be emphasized that building extremely complex intelligent systems that are to operate on top of

highly dynamic computing infrastructures such as cloud platforms is still a non-trivial undertaking. Indeed, even in the more traditional AI domain, managing complex, AI-based systems such as general-purpose QA or argumentation systems is still challenging in second-generation AI systems, which are themselves built on second-generation AR platforms. Therefore, as a kind of third-generation AI paradigm, so-called autonomous AI, the integration of highly complex AI elements into intelligent cloud platforms involves significant new difficulties.

1.6. Conclusion

Cloud computing is a ubiquitous service accessed through the web and has become both a paradigm and an efficient solution for managing different types of data, costs, and resources. Issues such as data ownership, quality of service, data migration, privacy, legality, and security in the cloud have increased interest in this technology, based on solutions brought by Artificial Intelligence, Machine Learning, Blockchain, Fog, Edge, and the Internet of Things. The control of this data is based on presenting a general overview of cloud computing evolution, followed by the presentation of security mechanisms and protocols for intrinsic vulnerabilities, and presenting the main challenges and trends of cloud computing, with a focus on the context of artificial intelligence applied to this technology. Finally, the main focus and applications developed with web technologies and cloud computing, as well as the main routes and comparison of market share, were found.

The presentation involved the evolution of cloud computing, starting with the emergent aspects and requirements on the part of cloud computing users, highlighting the shift to cloud computing made in 2011. Several definitions were made according to data and costs, technology, features, and the identification of diverse individual parameters that must be analyzed and measured. The well-defined tasks can also include cost reduction, data and control performance, ease of implementation, development and production of better services, sensor data concurrency, and the possibility of support for real-time working regardless of data size and levels of drastic data loss. Then, we present the aspects of security measures with comparisons between private and public clouds. Also, the cloud computing vulnerabilities and their aspects were exposed, and the security mechanisms and algorithms were applied according to their intrusion signatures and attacks on software components. Finally, the version of the cloud computing system with web technologies, artificial intelligence,

intelligence systems, and the evaluation and research aspects, as well as the integration possibilities of the cloud systems with the Internet of Things.

1.6.1. Future Trends

In the future, the concept of the cloud and its capabilities will be modified and extended, as new services, new modules, new interface standards, new technologies, new ways of delivering the cloud-computing application and the whole cloud informatics will appear. Every aspect of systems, which directly or indirectly refers to cloud information processing, is anticipated to be significantly enhanced in terms of intelligence. These systems could not only extend their functionality with the help of domain-specific knowledge obtained through cloud information processing, but also dynamically adapt their behavior to intrinsic conditions with minimum or no human intervention by using the strengths of the cloud.

Cloud-enabled system intelligence will emerge from the inherent ability of distributed patterns of compute and data, as represented in cloud IT infrastructures. Such a cloud-computing capability has potential breakthrough impact for future enterprise information technology (IT) and operational-technology (OT). Future systems will call upon IT and OT support for managing increasingly uncertain environments, with growing numbers of complex systems becoming not only more sophisticated and complicated, but also more autonomous, and yet intelligent and continuously effective.

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Chapter 2

DECODING AI, ML, AND GENERATIVE AI: CORE CONCEPTS AND TECHNOLOGIES

2.1. Introduction

The following essay is about the decoding of the core concepts and technologies in AI, ML, and Generative AI. The essay aims to bring laypeople into the universe of these cutting-edge technologies. The essay focuses on students at a beginner's level who are interested in understanding the 'Bots', 'Smart Programs', or 'Machine Programs'. It then stretches over professionals who are working with data, analysis, and decision support. The tools, software, or coded bots have started discussing AI which seems quite familiar and exciting. This ease of coding technology kept posing queries to the majority, which the essay intends to discuss and favor with precise and simple knowledge. The essay talks about the 'True State of being AI', 'What is ML', 'What are the Generative AIs', and 'How AI and ML technologies are built, and by the power of which specific tools/use cases?'

Artificial Intelligence is an interdisciplinary branch of computer science that uses machine learning to mimic human-like decision-making. AOPS says "AI is a world of robots" that have the "ability to solve a wide range of practical problems such as billing, planning and scheduling, configuration, diagnosis, monitoring, reasoning, natural language understanding." On the other hand, AI scientists have a restricted understanding of AI/ML vis-à-vis the vast universe of Bots, Make-a-thons, or Programs. For entry-level users, a bot is a "smart program" or "machine program" that "solves the queries independently by their experience by analyzing data and decisions." For students in need of knowing more about AI/ML, AI is a branch of computer science that developed a system with a holistic mechanism to obtain decisions and create a plan. Mark Sornek says AI is "any instrument, tool, or process that helps a system define its course of action."

2.1.1. Background and Significance

During the 1990s, artificial intelligence (AI) brought a revolution in the IT sector, which continued with the development of user-friendly applications such as speech recognition, image processing, predictive and prescriptive analytics, robotic process automation, augmented reality, quantum computing, advertising recommendation systems, and collaborative robotics. In recent years, AI technologies have been receiving widespread attention from businesses and academia alike. Artificial intelligence has emerged as a multi-disciplinary, applied, and experimental discipline that can complement humanity's creative potential. It encompasses a varied and rich mix of skills, strategies, technologies, and tools that are seamlessly integrated. It is expected that the boundaries of AI will expand as its algorithms mature.

Artificial intelligence (AI) is a specialization area that primarily focuses on the creation and management of smart computer applications. It is a human-like intelligence representation by machines. AI is an interdisciplinary approach involving mathematics, software engineering, and computer science. AI researchers have developed and implemented numerous AI logics that have been extensively used. Machine learning (ML) is a subset of artificial intelligence (AI). It provides the machine with the ability to learn new knowledge from the training pattern. To predict the outcome, various learning patterns have been used. Machine learning aims to create computer programs that can discover new knowledge for themselves. Machine learning is focused on the design and development of methods that can be used in investigating new data, such as computations, learning patterns, and algorithms. Machine learning achieves superior performance in the latest research for textual analysis, facial recognition, bioinformatics, streaming data, personalized learning, health, and banking. Generative AI: AI technology is divided up into systems that engage in a dialogue (e.g., chatbots) and models that create drawings, texts, patterns, and music (e.g., generative language models).

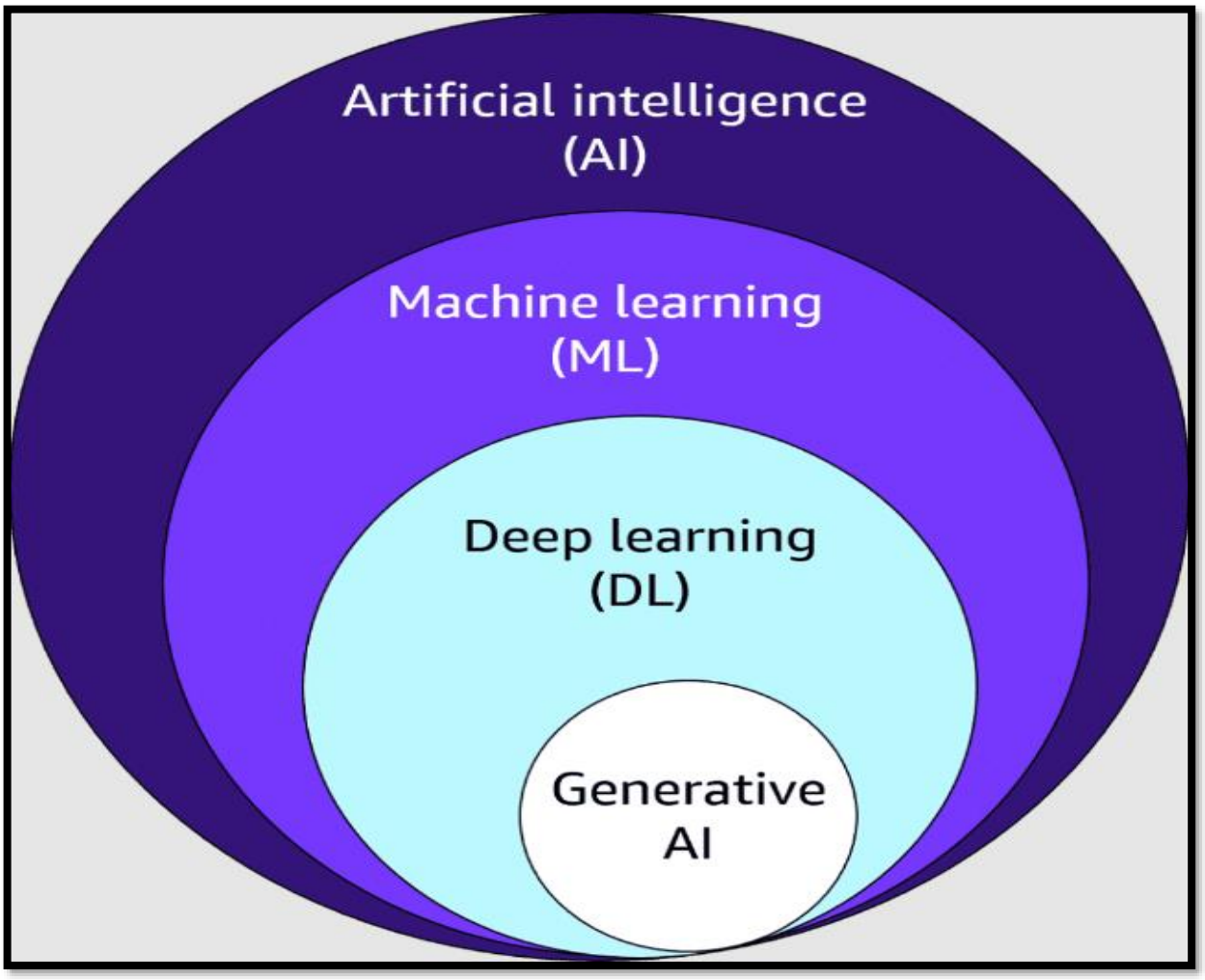

Fig 2. 1 : The Technology Behind Generative AI

2.1.2. Research Objectives

Research Objectives: What to look for?

The overall assignment is to discuss a mechanism through which work occurs in artificial intelligence, machine learning, and generative AI. This can be achieved by:

1) Conceptualizing the logic underpinning how AI and ML work, including discussing the complex technical processes that are involved in transforming data into knowledge.

2) Relating this core machinery to how advanced systems in this domain - GPT-4 and MuseNet - utilize artificial neural networks and deep learning processes.

This means we are:

1) Identifying the machine learning processes and algorithms underpinning AI systems, and then arguing that

2) When there is a more generalized purpose identified per component of the technology, this component increases in number, size, diversity, and embeds and integrates more programmable instructions into its capacity to influence its general path.

In this way, the 'core model' of the technology gets embedded in a rapidly growing, highly interactive, and constantly updating technology. This enables the technology to achieve a more generalized purpose since this 'purpose' or 'utility' grows into the beginning positions of flexibility and adaptiveness.

These systems will be cut up into several layers, each of which comprises some sort of "processing" element, such as an artificial neuron, which is where the "learning" is achieved.

We will argue that the core components of each model can be made up of individual technologies that are generative. The technology we are discussing is Generative Adversarial Networks (GANs). GANs are composed of so-called "adversarial" components, meaning they perform their own "feedback loop" and thus could be said to be operating from an overall goal or logic that is laid out in the components that are part of this composite technology.

We will explore how this term and logic build up to and represent a broad shift into the Lands of Purpose in AI is possible.

2.2. Artificial Intelligence (AI)

Artificial Intelligence (AI) can be defined as the capability of a machine to imitate intelligent human behavior, perceive its environment, make decisions, and take actions to achieve particular goals. The concept covers a diverse range of topics, ranging from robotics to text mining and machine learning. AI is built to mirror human skills such as learning, problem-solving, perception, reasoning, and the use of knowledge representation in natural language processing. The use of robotics in the field has replaced human involvement in many cases for rational decision-making in contradictory and fluctuating environments, resulting in advanced efficiency and power. For example, robotics is currently very useful in industry, transport, military, etc. Due to breakthroughs in rapid improvement in AI, more people are beginning to understand its dominant power and capability. Algorithms are trained by human

programmers to learn to perform tasks performed by human beings to get precise and efficient results.

In various fields, AI has emerged nearly everywhere, such as a gaming machine, natural language processing, an intelligent robot, and an ATM, which uses pattern recognition for human intelligence. AI can be classified into four types. The various types are as follows: 1. ANI (Artificial Narrow Intelligence): That can only perform a single task effectively. 2. AGI (Artificial General Intelligence): Able to outperform individual beings in intellectual functions. 3. ASI (Artificial Strong Intelligence): AI surpasses all human cognitive traits. 4. ADI (Artificial Distinct Intelligence): AI would be able to perform stuff as easily evolved human nature (emotional) in the future. Many AI applications involve state-of-the-art machine learning and deep learning systems to perform a variety of tasks. Some AI implementations that are becoming more and more extensively used are facial recognition systems, high-paced computing in the healthcare sector, speech recognition, distance-led cars, drones, banking fraud recognition, live fraud and spam, active web searches, accurate product recommendations, and more. Due to cost-effective and precise outputs, AI improves market traffic to technology brands.

2.2.1. Definition and Scope

1. Introduction 2. Artificial Intelligence 2.1 Definition and Scope Artificial Intelligence, or AI, is the study of how to make machines behave in a way that previously could only be accomplished by using human intelligence. From this definition designed by the Father of Artificial Intelligence, John McCarthy, a few standard conventions that can be agreed upon include its ability to work within the span of a machine or any of its segments, work like or in the shadow of human intelligence, and lastly, it is based on fundamental principles that are implemented within the domain of computer science, engineering, or logic. Therefore, they are limited to the systems designed with the available technology and cannot be extended to the future unless broad superlative generalizations, concerning the statements above, are made.

The primary divisions of AI are mainly characterized by the dimensions of the intelligence produced by an AI system. This is further influenced by the end nature of the task and the method employed to reach the task. From these discussions, one might already suspect that there could be as many types of AI as the number of tasks that human intelligence does. Indeed, as the human mind is fed by a host of algorithms that are designed with the objectives

of integrating, categorizing, and resurrecting or ruminating upon that information or feed, and finally reaching a partially defined or a new target or task, a myriad of feasible classifications concerning the prevalent parameters could be obtained.

2.2.2. Types of AI

We can classify artificial intelligence (AI) technologies or solutions into two types: generalized AI, which adds human cognitive capability to machines that can perform any complex work without prior knowledge or rules, and specialized AI, which is programmed to do a single and simple task within a predefined rule set. AI technologies are classified based on capabilities and learning styles.

Categorized based on capabilities, there are four different types of AI:

1. Reactive Machines-based AI: A computer system that can perform a specific job or designed task within fixed rules without recalling past experiences is known as reactive machine AI.

2. Limited Memory-based AI: With past experiences and collected data, limited memory AI can make decisions. In a restricted period, this type of AI can learn from previous data and recall it for the performance of a certain job. For example, self-driving vehicles.

3. Theory of Mind: A particular type of AI that understands people's underlying ideas, emotional state, and beliefs, and tries to forecast their behavior in reaction to their experiences is called theory of mind AI.

4. Affective AI or Emotional Intelligence: The affective AI or emotional intelligence AI can realize, use, interpret, etc. human emotions. Personalized systems like video games and AI are accessible in this group.

Deep learning algorithms depend on supervised, unsupervised, and reinforcement learning methods.

1. Unsupervised Learning: With the help of unlabeled data, unsupervised learning algorithms are a category of algorithms that develop an AI model. Clustering and association are the most important regulations.

2. Reinforcement Learning: Known as behavior judgment, reinforcement learning is an AI model that learns how to make the greatest possible choices based on the present variables. It is based on the learning method guided by behavior. The AI model distinguishes two kinds of results called punishment or encouragement. By making an effort or aim, reward, or reinforcement to maximize the value preference, taking into account the punishment.

2.2.3. Applications in Various Fields

AI has moved far beyond the realm of robotics. In today's world, AI is transforming the global markets. Below are some of the many applications of AI:

1. In healthcare, one of the most life-saving applications would be the detection of cardiovascular diseases. Here, AI algorithms aid in the raw data analysis like ECG, MRI, CT scan, etc. Furthermore, they offer clear medical images by removing any noise. This helps in the timely detection and treatment of cardiovascular diseases. On the one hand, medical experts save some additional time. On the other hand, there is an increase in the overall operational efficiency of the diagnostic clinics.

2. In the legal arena, 'e-discovery' helps legal professionals sift through and analyze massive mounds of documents. Using such platforms, a group of legal professionals can reach the most credible data-backed arguments. They may also predict the court rulings based on previous cases.

3. The human resources domain is marred by the high cost of hiring and high employee turnover. AI can assist in the initial round of hiring processes by conducting screening interviews. It can also replace humans by assisting in formulating personalized learning plans for different individuals. AI is also useful in tracking the records of various companies and software usage. It can provide the administrator with the total time spent by every employee on a specific category of application. For example, it might help in tracking the time an employee spends on checking emails during office hours.

2.3. Machine Learning (ML)

What is machine learning? Machine learning (ML) allows programs to fix themselves as they're exposed to data. ML is a sub-discipline of artificial intelligence (AI) and is helping AI to make use of inferences from data and enhance themselves over time. In layman's terms,

ML provides the system with the ability to study from its experiences. And that progression of learning from reference data allows more precise results. It largely contributes to AI, which focuses on a system's intelligence.

What are the basics of machine learning? Though the basic concept sounds perfect, learning ML can be intimidating, but if one learns the basic meaning of ML, they have won half the war. The study of ML operates upon major three components and they are: Reference Data: Databases with information models Problems, targets, and goals Algorithms: Learning algorithms for machines Techniques and models: Teach the system and see results to enhance

What is an example of machine learning? The most general use of ML is often noticed in daily activities such as Facebook friend suggestions, Uber surge pricing, Google Maps traffic estimates, and many more.

How many types of machine learning are there? Well, if you look at the patterns and learn, you will find that a scheme and model exist along ML. Since ML is built upon data, a diverse set of models and systems have been devised to handle different scenarios. The models of ML have been graded into five classes: Classification: Arranging the models in order, depending on the separated departments Regression: Finding out the completion outcomes Reinforcement learning: Understanding which events are coordinated with the surrounding Unsupervised learning: Understanding hidden practice and models Supervised learning: Generating answers for output relying on input features

What are the most popular algorithms in machine learning? Many ML algorithms exist, but the top 5 ML algorithms widely used and shared are mentioned below: Random Forest k-Means k-Nearest Neighbors Linear Regression Logistic Regression

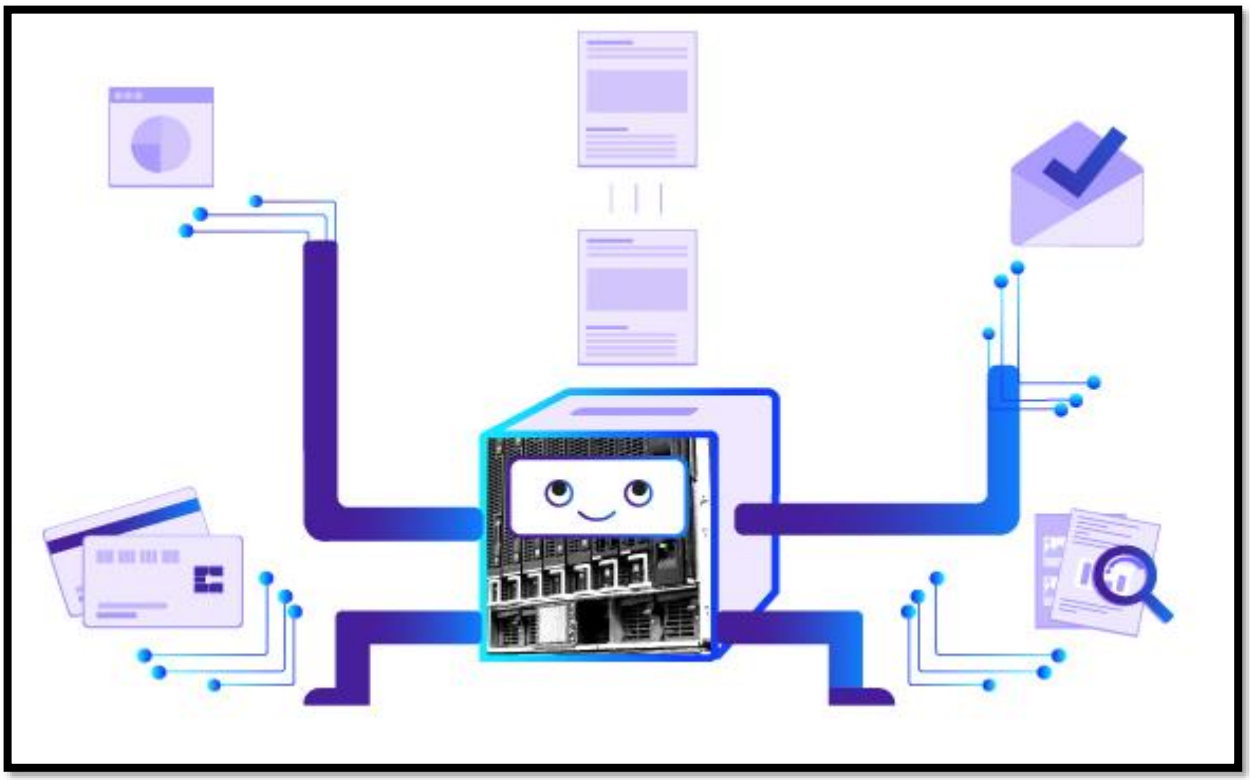

Fig 2. 2 : Machine Learning and How Does it Work

2.3.1. Definition and Basics

Machine learning

Definition and basics

Machine learning (ML) can be looked upon as a branch of artificial intelligence (AI) where the computer systems can learn themselves from previous datasets or experiences. An ML system is given a set of examples by the user, and the system analyzes the provided examples to learn and comprehend the underlying structure of the examples. Further, the system is then able to make predictions on new examples based on the learned structure. The general concept of ML is to acquire knowledge. A comprehensive ML system usually builds performance models of a task – ultimately leading the system to be able to learn from more examples, studying more about the task over time, and providing the user with some predictions. For instance, the email application learns how to classify the user's emails as spam or not spam. In a broader sense, ML is concerned with implementing the so-called "intelligent" algorithms, based on the idea of learning concepts such as knowledge or experiences and learning from the data provided via description with examples.

ML consists of three components: they are an input component, a global model component, and an output component. The learning process in ML is a way of updating the knowledge called a global model component. When the data distribution changes, the global model component can become less connected. "Learning is the process of adapting an input component to a particular problem, which involves changing the knowledge stored in the global model. The input component updates its knowledge by introducing previous experiences formalized in the factual input. It uses a learning algorithm to adapt the global model, resulting in a robust global model.

2.3.2. Types of Machine Learning

Machine learning can be categorized into three different categories based on the available data and output: supervised, unsupervised, and semi-supervised learning.

Supervised learning involves teaching or modeling the data using labeled data. For each set of input elements (attributes) and output elements (results, categories), the system is trained or installed. After training, any input data can be given to the model, and output data can be obtained using this model. Supervised learning algorithms are used to solve forecasting or classification problems.

Unsupervised learning consists of data that is not labeled at all. The system model is trained without any labels and is only trained on a set of given results. All types of transactional and non-transactional algorithms fall under the category of unsupervised learning.

Semi-supervised learning is a less common category, where training is done with partially labeled data.

Reinforcement learning is the fourth category of machine learning, which allows the machine to automatically learn by continuously interacting with the environment and improving its ability. In simple terms, reinforcement learning is based on a reward and punishment mechanism, which teaches the machine through trial and error.

2.3.3. Key Algorithms

A wide array of machine learning algorithms are in use to develop pace-setting applications. Choosing the most appropriate algorithm to solve the task at hand is a somewhat complex process and requires an understanding of the data semantics and the operational space in which the solution is required to work. Core algorithms include support vector machines (SVM), natural language processing, naive Bayes classification, clustering, classification, regularization, and sequential patterns. SVM shapes the decision boundary, optimizing separation. SVM with a kernel-based implementation can address problems in higher dimensions in addition to complex objects more effectively as well as efficiently. NLP is the engine working behind chatbots and translators, empowering machines to interpret semantics behind human text and organic speech. Naive Bayes facilitates conditional probability.

Clustering partitions a dataset into sub-populations based on a range of features and algorithms including k-means, affinity propagation, Mean-Shift, and hierarchical/Agglomerative clustering. Anomaly detection or classification is specifically useful where the data is imbalanced or contains a greater percentage of white swans compared to one black sheep. The hashing technique ensures the use of vast vector dimensions that are unique to the dataset. Sequential patterns discover relationships between items over a sequence of time. Classification algorithms work on class values rather than continuous values. Regularization is the process of adding information to solve the ML algorithm to avert over-fitting or generating a parsimonious model. The algorithms calculate the loss function based on historical data and determine how errors will be generated or penalized: LASSO and Ridge regression, elastic nets, early stopping, and related algorithms such as AdaBoost, XGBoost, and gradient boosting.

2.4. Generative AI

4.1 What is Generative AI? Generative AI is a form of AI technology that is used to develop new ideas, including art, music, and design, that could not have originated with a human. Generative AI works on probability distribution by applying statistical knowledge. Generative AI is a developing technology that has the potential to change industries, including entertainment (designing video games), fine art and live theater (supporting flexible storylines), accent and lip-motion conversion for dubbing, creating detailed pictures from sparse and vague information, and compressing image data. Systems at the lower levels

embody a sense of being a co-creator to which users attribute value; this co-creation may even involve the construction of unique or person-specific artifacts. 4.2 Advanced Overview In a generative model, several functions work together. These models use unsupervised learning and are used in unsupervised learning tasks. A standalone generative model is used to create artificial data. When humans create data, they use their brain's prior knowledge to learn and think about the outcome by manipulating available variables at any time of the day. Sketch generation, realistic transformation of facial expressions, mutative artwork, distinguishing benign from proactive lymph nodes, and epic-text generation from action graphs are the applications. Creative machines with AI are also being used to predict changes in a finished portrait. The discriminative generative model has been widely studied. It proposes the development of a powerful generative model and learns an efficient model generative. 4.3 Use cases Generative AI has different applications and use cases. A few of them are: Emphatic artistry and artistic expression Fine art and live theater Meditative-capturing and sharing experiences for well-being Language, communication, and education Story generation Accent and lip-motion in digital dubbing 4.4 Research Trust in the feasibility (AI for creativity) and practical applications (AI in games) of generative AI. Several technical challenges include dealing with missing values within art materials, prevention of output for existing (real) things, development of using unique creations to teach people to draw, vigilant disclosure and dialogues about co-creation and machine learning, and testing with larger field trials. 4.5 Future Future projects are currently in the concept design stages. The area is, however, rapidly developing in response to three different areas: art-science and neuroscience research interested in the link between art, emotions, and well-being; commercial work with participation from health/mental health; and machine learning technologies applied to an aesthetic and experience-focused market. These areas of mechanization games supplement creativity.

2.4.1. Definition and Overview

The concept of automation is not new to the world; in fact, there is nothing new in utilizing technology to automate work functions. In the present context, major changes in automation utilizing technological advancements are shifting from basic rule-based systems to incorporating complex real-life assignments. The key insight brought about by advancements in the internet, e-commerce, mobile applications, cloud computing, and big data has been the ease of access to data and a rising need to analyze, interpret, and draw knowledge

from big data. AI stands as a pattern changer, particularly machine learning (ML). ML, a branch of AI, is useful in learning, representing, and predicting the output if the models incorporate new information. AI-based automation and technologies are growing significantly. Many businesses require real-time, cost-effective AI systems to accomplish goals.

AI can be defined as coding methods that allow generating business rules directly from data or allow generating algorithms that find such rules and serve as advanced data processing methods. Generative AI (GAI) is an AI tool that can generate content based on previous learning from a dataset representing a predefined scope (e.g., paintings from known artwork, and augmented images from real-world pictures). Instead of providing a hard-coded task or rule to do in a way that the domain expert figures out a procedure, we input a dataset of inputs/outputs/solutions into the GAI and let it approximate the function lying behind the input/output. Later, the developed model can be used to generate similar outputs given new inputs. Since GAI can generate new creative solutions in a known domain or interpret current solutions in a new way beyond the given tasks within a specified scope, it has found potential in many industry settings and specific applications. This subsection looks at GAI and its scope in greater detail to set the base for a later discussion on its applications, use cases, challenges, and future directions based on a thorough literature review.

2.4.2. Applications and Use Cases

A fascinating use of generative AI is in handcrafting music that has been fed to generations of Scott Joplin. Generative AI technologies may also mine reports on scientific papers and patents to develop hypotheses that could be tested – a valuable approach when scientific papers in medicine and healthcare have rapidly outpaced an individual's ability to read and assimilate so much information. It could also help discover co-morbidities of different conditions. In industrial automation, a wide variety of applications are emerging such as automatic generation of task-specific or domain-specific programming models. Generative AI can transfer labels from low-resolution images to high-resolution images.

Voice cloning is a powerful application of generative AI, which surprisingly, is still used by only a few people in Voice over Internet Protocol. Game development and design are other significant fields where generative AI is used but lacks recognition. Additionally, two or more genres of video games can be combined to create an engaging new genre. Offering an

exhaustive list of potential applications and use cases of generative AI is outside the scope of this paper. However, it should be clear by now that generative AI, by creating competent output in various domains, can significantly impact a broad range of scientific disciplines and economic sectors as well as our daily lives. At the same time, it should also be clear that the capabilities of generative AI to create realistic and effectively misleading content, coupled with highly skilled hackers leveraging a new wave of generative adversarial networks, have created perils that can adversely affect the overall well-being of society. The diffusion of generative AI can, therefore, be compared with allowing nuclear power reactors at the hands of terrorists/port workers.

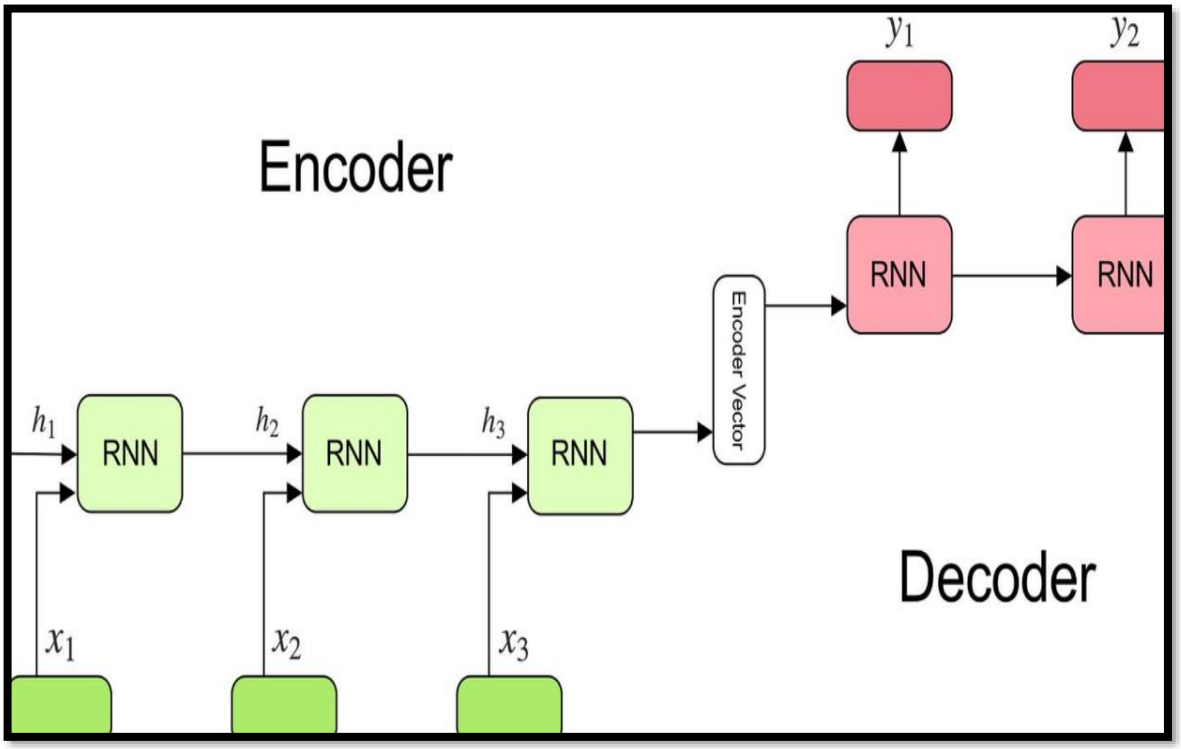

Fig 2 . 3 : Generative AI Use Cases, Applications

2.4.3. Challenges and Future Directions

In this section, we discuss challenges and future directions in generative AI.

Challenges

Generative AI systems aim to simulate decision-making processes. Deterministic models are strongly shaped by this objective. AI techniques, such as rule-based systems, have been successfully applied in creating deterministic systems. Integrating non-deterministic

models with these deterministic systems is a promising future direction for generative AI. In such applications, the domains can be classified into different models with different complexity levels, and we could easily update systems with more complex models to capture the dependencies within the data. Experimentally measuring the accuracy of generative AI outputs is a difficult task, especially in applications of forecasting or deep reinforcement learning.

Future directions

Currently, managing complexity in generative AI is an open problem. Future research may provide new architectures to manage the complexity in both parts of iteratively expanding real sequences and adopting complex generative models as decision-making processes. More importantly, generative AI systems and conventional decision-support systems in different domains of application must interact to offer complete solutions. This is especially important in decision-making problems with high complexity, where data is processed into a series of decision-support systems. If these systems can operate together with smaller datasets that are easy to manage, exploration of the decision-making options can be completed within shorter durations and with a high level of exploration quality. This may require several interactions between generative AI and other decision-support systems to characterize the potential dependencies within sequences in real scenarios.

2.5. Key Technologies in AI and ML

Before we switch over to generative AI, let us consider a few basic concepts and technologies that power GAN and are key to generative AI and machine learning. They are:

Neural Networks: Neural network technology and deep learning are hot topics these days. Also, deep learning is part of the subset of machine learning.

Natural Language Processing (NLP): Google has a robust technology that powers natural language processing. The kind of queries Google Search understands is due to its NLP capabilities.

Computer Vision: This is again, an AI technology that deals with developing algorithms that allow machines to understand what is written on a license plate or what the

image of a traffic jam could mean. Many cars and drones use computer vision to understand their surroundings.

Speed and Computing: Faster GPUs like NVIDIA Quadro and Tesla, TPU by Google, Intel's Lakefield SoA, and improved memory systems are important technologies, however, you don't need those if you are a small company. GAN can operate with a home-built workstation too.

Optimization Algorithms: These are required to improve the stability of the two neural networks of GAN.

Software Tools: There are such tools as Keras, TensorFlow, and PyTorch. While Keras is a high-level API for developing neural networks, PyTorch is a library initially designed for computer vision but it is now widely used for all kinds of conquests related to neural network computing.

2.5.1. Neural Networks

5.1.1 How Neural Networks Work

In simple terms, "a neural network is a stack of layers" that processes a given input. This input is gradually transformed such that it fulfills its end objective (e.g., classification, regression, enhancing images). A combination of inputs and weights characterizes these transformations, which can either successfully identify original patterns and insights from the inputs (like the signals, patterns, or textures in the images) or transform the inputs in a manner that helps achieve the specific goal (the transformations in the weights might logically expand the space containing images of dogs). The last layer in the stack—a.k.a. "output layer"—is the layer whose outputs are chosen by the algorithm as the predictions given the input. Mimicking the biological part of a "network," a Neural Network comprises "neurons." These are activation functions, each based on different formats (like Rectified Linear Activation Functions or ReLU).

5.1.2 Applications of Neural Network

The initial application of neural networks focused on solving statistical learning problems. In recent years, engineering problems have been dominated by heuristic algorithms, numerical optimization, and feature engineering. Neural networks have started solving

problems that had previously not been solved due to a lack of an appropriate method. Specific current applications include:

Infrastructure Diagnosis: This area includes electricity demand forecasting and leakage detection in pipelines. Feature Selection and Data Visualization: In this case, called "deep learning for dimension reduction," autoencoders are specifically used for feature selection in the vision domain. Additionally, neural networks can be utilized for high-quality data generation, aiding in data augmentation. Applications in Energy Efficiency: A broad range of uses exist within the field of energy, including option pricing, electricity price modeling, and residential energy forecasting.

2.5.2. Natural Language Processing (NLP)

5.2. Natural Language Processing (NLP)

In every field or industry, language is the key means of human-human interaction and human-machine interaction. Language is also the major carrier of information transmission between people. In the era of big data, various fields have accumulated a large amount of data. A large amount of text data is generated and disseminated on the Internet every day. This information may contain information about public opinion, text or language, all kinds of scientific research knowledge, etc. Therefore, it is necessary to use machines or algorithms to conduct quantitative or mathematical analysis of these texts to mine related rules, laws, and unexpected or possibly hidden information. At present, research in this area is commonly called NLP—short for Natural Language Processing (computer Natural Language Processing). Natural Language Processing is a computer and the study of the theory, the main contents include computer systems for human natural language understanding, generation, translation, summary, and so on, speech recognition, text mining, information retrieval, information extraction, and question answering.

There are three main categories of text mining technologies: information retrieval, information extraction, and question-answering systems. Current mainstream systems are based on statistical methods to realize information retrieval, relying mainly on the concepts of word frequency statistics, probability, and entropy. Information retrieval generally uses the TextRank algorithm, which is based on the page ranking algorithm. TextRank algorithms are less complicated and are mostly used to mine information in documents. The main task is to

select topics related to the main document. The subject selection utilizes keywords extracted from the article to form keywords, concepts, and topic words, conducting a comprehensive analysis of semantics in the texts.

Based on the connections and knowledge mentioned above, we can determine the scope of AI technology and the role of ML and discuss specific digital AI technologies, such as intelligent robots, chatbots, and smart chat-based systems. In the AI sector, machine learning (ML) technology gradually began a development path. At first, learning was based on binary logic, i.e. it only produced "Yes" or "No" results. It has now grown to include generic statistics and probability and has been an area of lively research in the fields of AI, computer science, and data mining. This increase in ML research began in the late 200s and grew rapidly through 201. There are three components of ML needed to build an AI ML system from the ground up. These sections form the basic gateway for computer vision or "deep learning" and will be discussed separately. In the AI and ML domain, natural language processing (NLP) technology is commonly used for information retrieval, information extraction, sentiment analysis, article plagiarism checking, article similarity testing, text classification, text clustering, and keywords from dictionaries to improve NLP technology basic research, such as activity verbs, word similarity judgment, news tense, emphasis on information retrieval, Chinese named entity combination technology, Chinese and English part-of-speech labeling technology, and text named entity recognition technology. Incorporates new algorithms to obtain technological breakthroughs, such as array expansion NLP technology, corpus-based fine extraction NLP technology, resolution context NLP technology, and rule generation NLP technology.

2.5.3. Computer Vision

Now, let’s understand computer vision, one of the most critical domains in today’s AI-driven era, and listed amongst the top artificial intelligence applications by Gartner and Forrester. It is the science of enabling the computer to replicate human vision. It involves processing, analyzing, and interpreting digital images and videos to simulate the visual capabilities of the human eye. It enables the computer to process videos and images in real-time, recognize objects or content within an image, interpret their content, estimate their size and movements, and finally decide suitable outputs. Common applications of computer vision are virtual dressing rooms, face recognition, barcode scanners, health diagnosis systems, PAN verification systems, and many more.

The technologies essential to learning or getting a sound understanding of computer vision are deep learning algorithms, machine learning algorithms, and transfer learning techniques. Deep learning algorithms are artificial brains classified as convolutional neural networks (CNNs), deep recurrent neural networks (RNNs), temporal convolutional networks (TCN), non-linear autoregressive models, long short-term memory networks, and gated recurrent units. Besides classification, segmentation, localization, and object detection in raw images and videos, some of the common applications or AI tools within computer vision are OpenCV library, YOLO (You Only Look Once), RetinaNet, SST, Faster R-CNN, Mask R-CNN, RCNN, AutoML, Detectron, Fashion C++ Java APIs, TensorFlow and Keras libraries in Python for training machine learning models. These are some of the essential perceptions or tags to understand when you want to decode AI, ML, and Generative AI core concepts and technologies.

2.6. Conclusion

In the first section of the essay, core components of artificial intelligence were explored, specifically examining machine learning. Once machine learning and its classification into three distinct subfields were explained, generative AI was introduced. First, the generative architecture itself was explained in terms of what AI and such architecture can generate in the form of photos, music, art, writing, and faces of humans. After, one of the audience discussions was featured as an example of analyzing different practical implementations in the field of generative AI. In the next part of the paper, it was first detailed from what generative AI can learn on the example of deep learning and reinforcement learning. Secondly, GPT-3, flow-based models, and other state-of-the-art models were discussed in terms of what abilities they have as the present generative AIs to generate human-like positions. Finally, it was concluded that these new models are quite powerful in terms of their cracks and limitations.

Moreover, it was discussed that these new models create all imagery from zero style of input—a blank canvas or a set of random numbers. In essence, this style of model connects the observer with a cognitive process that is similar to daydreaming. Thus, it was proposed that a research direction be opened up to research on how deep networks generate complex patterns of sequences and pixels into new representations, knowledge, and understanding of the world. The essence of these layers may correspond or be representative in the form of human context or perception, or even a "meta-genomics database in biological research. Such

a model may generate knowledge that is transferable among different fields, similar to transfer learning in BERT and other transformers. For future research, the approach from the realm of generative AI may thus find itself at the edge of "learning to learn" and "unlocking symbolic logic in modern neural structures.

2.6.1. Summary of Key Concepts

This essay has drawn together a synthesis of ILP and HCI as they pertain to AI development and design. The introduction outlined how AI is designed by positivist epistemologies, employing digital tools of Big Data to predict patterns and users, whilst rendering invisible the ethical decisions of the engineers, who increasingly turn to ethnographic methods as applied through Big Data to make sense of this which remain underpinned by a foundational belief in the ability by HCIs to represent the lives of users inside datasets. The literature review assessed the validity of deep neural networks about the human brain, which has found growing consensus against representation but did find strong neural arguments for the predictive power of such networks.

Ethnographically speaking, supervised learning, such as ML, is part of a wider heuristic Informal Logic of what an argument is, being used to persuade a receiver of macro-level goals. ML models fundamentally cannot represent our understanding, the processes of reasoning, ourselves, or justice because they cannot learn their uses of data in a normal, explainable, and disputable manner. The Heuristic of gerrymandering towards this end shown by the Pitfalls provided demonstrates a common problem faced by EPs in the practical realization of AI, showing EP to be fundamental to the ILP of AI design. The anticipated values for research entailing AL are the improvements of own systems of reasoning and augmented educative outcomes and ethical problematizations in the practices of own systems. EPs show what ethical decisions the data scientists are making. Future research directions include practical research into their implementation in a commercial system and the extension of the Pitfalls and predictions. The overall implications of this disclosive look at behavior and ethical reasoning for EPs are that affirmations are not simply a resort but are a basic aspect of knowledge production and therefore HCI. It might manifest many of the defense criteria for a genuine warrant in being a generally applicable rule for a reasonable person. This is however unlikely to be definitive, as a result of what Quine refers to as the 'web of belief'.

2.6.2. Implications and Future Research Directions

Decoding components of AI, analytical capability, ML, and Generative AI offer a functioning overview of interdisciplinary while directly focusing on data analysis. While AI and analytics offer ample opportunity in the pursuit of solutions to various problems, ML builds mathematical representations and interaction patterns so that machines can automatically learn to make important decisions. Research has primarily focused on ML and advanced areas like complex generative systems. The direction for exploratory studies is the work carried out for educational and analytical development using regression models. However, latent semantic analysis could be taken as a promising research direction in the long run due to its feasibility and preliminary impressions on data analytics.

Generative AI mainly contributes to the development of cutting-edge models. Generative AI refers to a firm-centric approach towards enabled AI with abilities to perform predictive and recommendation analytics with intelligence. AI algorithm configuration and application approach can focus on Generative AI and ML algorithms to support firms for decision-making on generated simulated data analytics. Future research can also attempt to categorize Generative AI-enabled analytics based on input and output data characteristics where the input is analyzed for processing and output characteristics as generated descriptive, predictive, or prescriptive analytics. The field of research focusing on decoding AI, ML, and Generative AI concepts and terms possesses a significant impact on fellow scholars and practitioners. The phenomenon of ML and Generative models will offer a plethora of opportunities for analytics development as new data are presented correctly.

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Chapter 3

DESIGNING SCALABLE CLOUD ARCHITECTURES: THE ROLE OF AI AND ML

3.1. Introduction

In the beginning, customers generally had to migrate their inherent structure and logic of applications with a considerable amount of refactoring to work seamlessly with public cloud architecture and require new cloud-specific programming models and architecture to work optimally. However, in the case of a vast number of existing applications, they possibly spread all over the private, public, and on-premise data centers. In that case, it will not be economical to migrate them to the public cloud because of changes and refactoring that are required; hence, it becomes very challenging to address this problem. The paper defined the programming model for existing application stacks without any change and can utilize the benefit of public data centers. The paper mainly emphasizes the cloud acceleration problem rather than the cloud migration problem.

These parameters avoid the dependency of heavy data replication and include the bypass functionality for avoiding virtual appliances like intrusion detection and content direction, which requires heavy data replication for guaranteed isolation. This programming model is very efficient in the case of unequal distribution of tenant static between brokers because it eases the design of a scaling algorithm without any modification to tenant behavior. The architecture presented in the paper will allow a customer to write a policy-based domain-specific logic with a small footprint that can run alongside with the tenant's application stack in the service chain.

3.1.1. Background and Significance

Companies across a broad spectrum of industries are adopting cloud-native application development techniques to achieve faster time-to-market, improved operational efficiency,

and satisfy demand for their user experiences. To meet the growing pressure for cloud services, traditional cloud development teams have grown increasingly complex. These teams need to manage cloud resources and various functions: computing, storage, databases, machine learning, containers, and related areas of software engineering. In addition to resource management software, cloud providers are making it easier for software developers to use cloud services by providing APIs and Software Development Kits in different programming languages. Given the rapid growth in the complexity of cloud services, and the number of software functions required to build sophisticated cloud-based applications, we argue that a combination of machine learning and AI solutions can improve the collective performance and management of cloud developers.

The advent of the cloud has abetted the scalability of software and has transformed tech support from a hospital to a daycare model. That is, the cloud provides a model in which developers can code, load, and execute software without the headache of planning server resources and other infrastructure-related tasks that are not their core competency. Nonetheless, while the cloud can be a safety net for junior developers, it also comes with a hefty price tag. The more scalable the software, the more money it will cost to run 24/7 for customer care. Scalable architectures enable customer-centric societies such as English-speaking service profiteers, social networks, and ad retailers. The design of scalable software has grown less intuitive over time, and big iron competence has eroded. Familiar CPUs, such as the Intel Xeon line, focus on parallel execution for SIMD and multithreading to gain performance narrowly at the expense of heat and power. Moreover, clouds are not built to be efficient but to accommodate legacy design principles.

3.1.2. Research Aim and Objectives

The research aim is to analyze how the interfacing of AI, ML, patterns, and heuristics can be employed effectively in the cloud engineering processes for the design of superior SCA. To achieve the research aim, one would need to focus on these research objectives enumerated as follows:

1. Investigate what's out there now, and what's likely to be there soon. 2. Identify the challenges that delineate why solving these problems is hard, and understand how problems hook up with what must be generated. 3. Investigate how to generate cloud architectures through interfacing ML, AI, patterns, and heuristics that can scale in size and number and meet

quality of service expectations efficiently. 4. Investigate how to automate the reparameterizations of SCA through self-modifying code to automatically and rapidly rewire the SCA structure to develop new algorithmic variants of parallel and nonparallel SCA, before engineering cloud applications. 5. Understand how automation depends on the map, reduction, and data transformations if we are to adjust and use both existing and novel algorithms in these evolving designs.

The quantum leap of reparameterizations scales up the software developer and scales down the software development costs. Investigate how to set predetermined scalable cost expectations in the morphing of reparameterizations of software modules and the relationship with dynamically adjusting software costs about the surplus output ability and quality of the software goods and services. Investigate how parallel execution works in modern software and hardware and how to develop search-based software that may execute well on parallel hardware. Investigate how big data research can energize and validate the generative design concepts of this project in the role of auto-discovery of new transformations and analytics in the evolutionary design process for scalable cloud architectures. With generators in mind, auto discoveries can be creative design modulators for internal adjustments in what is being developed, before engineering.

3.2. Fundamentals of Cloud Computing

Information technology is at the forefront of contemporary societal and economic trends, spurred on by a host of applications from smartphones to social networking software to physical products that come with growing levels of embedded intelligence and communication capabilities. To meet these requirements for scalable, intelligent information technology, many companies are taking advantage of cloud technologies. Most of us utilize some form of cloud-based service every day. However, to enable these applications, data centers, especially those collecting and analyzing data from internet applications like search and social networks, are steadily increasing in size and reporting growing power consumption. Technologies to scale cloud applications and their data centers to address the exponential growth in data are needed. The question driving this special section of IEEE Micro is straightforward: how can data centers be made more scalable by increasing their efficiency or reducing their power consumption? This is both a critical design question as well as a significant challenge that engages engineers and scientists at many layers of the computing ecosystem—from data center utilities to the underlying semiconductor technologies.

In this introduction, we provide the context of cloud infrastructure, as well as a brief overview of the contributions of the four papers in this special section. Since cloud technologies provide the key infrastructure for AI systems as well as those to expand AI-driven applications in most domains, Section 2 details the components that are essential parts of today's cloud architectures. We note that while the components are generally well-known, methodical research into their design and analysis is a matter of ongoing interest for both academic and industrial researchers. Economically efficient and sustainable future design directions will also be critical for future advancement.

3.2.1. Definition and Characteristics

Cloudbusting is built upon scalable architectures that have been a staple of discussions on cloud computing. Whenever little is changed, the term is generally used when a private cloud becomes too small to handle the current workload and additional resources implemented in the public cloud are brought to bear as needed. When this 'bursting' of capability is always accompanied by a reverse burst of capability as needed private cloud services can satisfy the capability, the term is considered as an instantiation of pretty good scalability (e.g.), a primary cloud does not maintain a lot of additional network, cooling, and power costs on a full-time basis. The external third-party resources used by departmental users either build departmental cloud services or externally provided cloud services that layer over a separately provided cloud (usually private) are often referred to by the synonym DormCloud, and the coexist or parallel workloads they support using the phrase coexistence cloud-based capability ranges from IaaS (Infrastructure as a Service) at the virtual machine interface layer through PaaS (Platform as a Service) and SaaS (Software as a Service) to other services (retain storage, backup services, email, and others).

The characteristics of cloud implementation are currently being defined by the recurrent cloud reference model multiple offerings, and layering is defined because of the existing consensus, aided by persistent numbers of interested parties from academia, industry, and government. Several characteristics define ubiquity, rapid elasticity, MOE, measured service, resource sharing, on-demand self-service, broad network access, and finally location indirection. The location independence of services as interpreted by the National Institute of Standards and Technology starts by hiding the geophysical location of the resources in a manner specified by the IaaS service level agreement. The IaaS proceeds through the user of the service, removes the heaving of the underlying cloud infrastructure, and facilitates future

optimizations determined by the cloud data center manager and senior management of the company or organization offering cloud service using a variety of Intel's further exploitation technologies.

3.2.2. Key Components

The key components of these platforms include hosting, instantiation, hosting provisioning, and autonomic optimization (i.e. the dynamic and adaptive optimization of hosting platforms). Hosting activities typically include hosting sites (hardware devices on which service instances run), and related assets in the context of the cloud. Hosting provisioning is concerned with the allocation of hosting resources in the cloud environment. In particular, it is interested in determining, based on changing requirements, whether it is necessary to allocate further resources to a site(s) to support the service instance(s) residing on it. If so, which resources should be allocated and in which quantitative and qualitative terms? Finally, the optimization of these cloud environments needs to be autonomic since the environments tend to be too complex and dynamic for a customer to attempt to manage and control the changes that will lead to the effective and efficient functioning of the system.

For efficient cloud service delivery, a reduction in the overhead required to deal with these complexities is needed. We are developing a SOA-based environment that can create cloud-based services that are scalable on a global scale. To create this type of environment, we have holistically taken into account service-oriented development and deployment. This paper specifically addresses the effect and control of service variability on service creation, deployment, and hosting in that cloud environment. However, the CloudForge service-oriented development environment as a whole has the goal of reducing the TCO of the service through its entire life cycle. So, in addition, we are creating a tool that supports the definition of business service level objectives (SLOs) that can be used to monitor and manage the actual service operation of those services.

3.3. Scalability in Cloud Architectures

Despite the existence of a vast literature on cloud technologies, scalability is still a challenge, and demand for scalable cloud solutions remains greatly unsatisfied. At the physical layer, the scalability offered by cloud computing is limited by the scalability of the current hardware. Consequently, it is questionable whether we can have more scalable clouds if we

persist with the current types of hardware architectures. Scalability is needed not only at the physical layer, but also at other layers of the cloud architecture, such as the network, security, and even at the business end. This chapter explores some of the solutions to the problem of achieving the remaining scalability at these layers, most of which are based on employing AI and ML techniques. If the principles mentioned at the design stage are followed, clouds that are scalable on an inter-cloud, intra-cloud, and hybrid-cloud basis will result.

Scalability is an important gauge of the true capability of a cloud. It is multidimensional and has to be considered at many layers. These are the physical layer; the network layer; the service delivery layer; and the business layer. ID 1 gives an overview of what needs to be done to make cloud architectures physically scalable. Current data centers are still small (the entire 60 MW of installed capacity of a data center can be exhausted in a few months). To make them grow, power-dense processors, solid-state storages, and optical circuit switched network packs host hardware at a high density allowing 10^5 hosts per switchable network. Networking technology must be scalable to save the cloud from being gridlocked. SDN is a candidate for delivering scalable networks. Due to the nature of cloud deployments, the networking technology must also have an inbuilt capability to cope with varying conditions, unpredictably changing demand and very large long-distance data transfers. At the service delivery layer, trying to scale by adding servers at customers' sites is likely to reproduce age-old problems associated with site architectures, including downtime, overload, and bottleneck issues, especially if the enterprise acquiring the clouds owns many loosely knit centers.

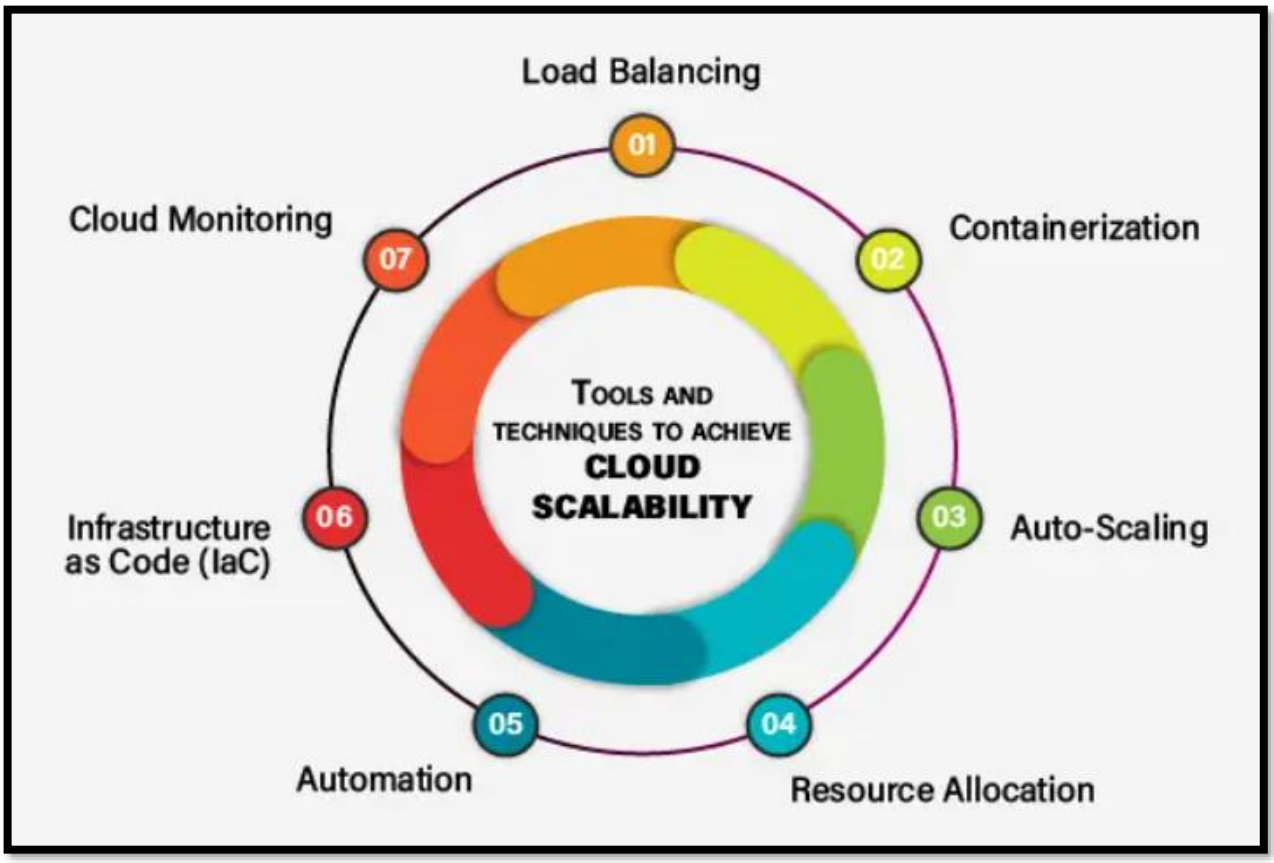

Fig 3 . 1 : Scalability in Cloud Computing

3.3.1. Importance and Challenges

Security has always been the most critical challenge to the cloud. However, several additional challenges are intensifying due to the cloud's continuous growth in scale, diversity, and rapid evolution. In conclusion, designing scalable and efficient, as well as secure, cloud architectures is a daunting endeavor given these cloud characteristics, the increasing usage, and diverse applications. To name a few, challenges include:

1) A vast majority of software engines need to become more parallel and more distributed across tens or up to thousands of computing nodes to scale in the cloud. Designers must minimize synchronization, conserve energy, and maximize throughput to take advantage of the cloud. However, current software engineering techniques lag behind parallelism and distribution needs. 2) It is prohibitively expensive to constantly upgrade network infrastructure to keep up with cloud-scale demand, and given hard physics constraints, this is often not even feasible. Yet cloud service providers must address customer expectations set at exponentially increasing network capacity rates provided by ITU-guided breakthroughs (e.g., 100-fold every

5 years). They should also enable cost-effective service innovation without massive network infrastructure upgrades. As a result, designing scalable cloud network architectures is a fascinating challenge.

3.4. AI and ML in Cloud Computing

The invoices generated, the corporate emails delivered, and the customer information tracked with online content exist on a cloud and not in a secret data store in the office anymore. The mild-mannered assistant helping in scheduling has transformed into a digital traveler for seeking hotels, driving conditional cars, and even creating music. Machine learning and artificial intelligence forms have transformed and blurred the lines between computer science, business, and even engineering. AI/ML is currently deeply embedded in cloud computing. They help CPU performance, link to frameworks, and even have systems and software built-in. In that case, how could engineers design those architectures? AI/ML technology is currently implemented on the web to address daily enterprise challenges.

Cloud computing innovators offer cloud computing services that use ML/AI to develop current functionality for the AI market that meets the huge demand. For cloud computing researchers and practitioners who are inquisitive or considering entering the AI and ML area, taking on an introductory role and understanding at least the fundamental facets of AI and ML could be appreciated. By using cloud computing's AI/ML tools, practitioners concentrate on the application with immediate developments to businesses. These enterprises are keen to develop this performance and discover excellent earnings for their trademarks through technological optics and the world's major AI/ML innovation developed in a cloud that meets their consumer demands. This includes taking part in a strategic world that changes by infinite customers, turns, and cuts of a muffin to supply higher cloud production and scalability.

3.4.1. Overview and Definitions

In this paper, we consider a general distributed system as a directed acyclic graph, G=(V, E), where V is a set of vertices representing different entities in the system (e.g. VMs, containers, microservices, etc.), and the edges $E \subseteq V \times V$ specify the taint propagation relationships between the different system entities. These relationships are directed, as they describe the causality between different entities. For example, when an edge (v1,v2) exists in E, this means that a process running in the source VM v1 can directly influence the completion

of a process in the destination VM v2. This way, we can model any system of tasks as a directed acyclic graph, where only vertices that have no incoming edges (i.e. the root nodes) can be initiated based on exogenous triggers, without waiting on a process to complete first. As a result, by propagating the completion signals in decreasing depths, we can guarantee that all process dependencies are satisfied.

Instead of a single graph, however, we expect that naturally, several small subgraphs could form inside the larger overall distributed system graph. These subgraphs are separated due to bottlenecks in performance, such as lack of available resources (e.g. number of running VMs, low CPU, memory or storage, etc.), or because of inherent physical differences (e.g. different sets of constraints for VMs running on particular locations, rack space, etc.). These performance and location constraints could lead to forming a small graph chain that has limited fully connected edges. It must also evolve differently due to differences along the edges in how the tasks are started and depend on each other: for example, there could be a tight co-scheduling of associated tasks (where some resources such as the location, shared file system, or network between the tasks could be involved), or dependent tasks on each link start order during initialization or shutdown (so no task in the next subgraph can be executed before all tasks from the previous subgraph have completed).

3.4.2. Applications in Cloud Architecture Design

Cloud computing delivers vast amounts of computing resources to users as a pay-as-you-go service. However, current cloud infrastructures lack both flexibility and adaptability in designing large-scale cloud architectures. Furthermore, users are responsible for determining the number of resources (e.g., VMs) from providers and only pay for what they use. Current pay-as-you-go cloud providers use a variety of tactics to maximize their profit by improving resource utilization, even as they improve service offerings and provide much cheaper pricing than traditional on-premise infrastructures. Also, existing techniques that forecast resource demands and automate VM allocations based on demand forecasts, even dynamic ones, are only dedicated to cost minimization, with quality of service as an afterthought.

In this paper, we demonstrate how to use a user-defined service quality objective (cost, latency, QoS, etc.) to design a scalable cloud architecture with the following properties: 1) It can manage both unexpected demand shifts and the expected ones, by answering strategic

architectural questions such as how many and what kinds of VMs to lease, how to spatially allocate them in advance (given the expected demands), and how to temporarily relocate traffic. 2) It can manage infrastructure maintenance tasks, by ensuring that spare capacity is available during the maintenance window to accommodate both scheduled and unscheduled network link and device failures and isolation.

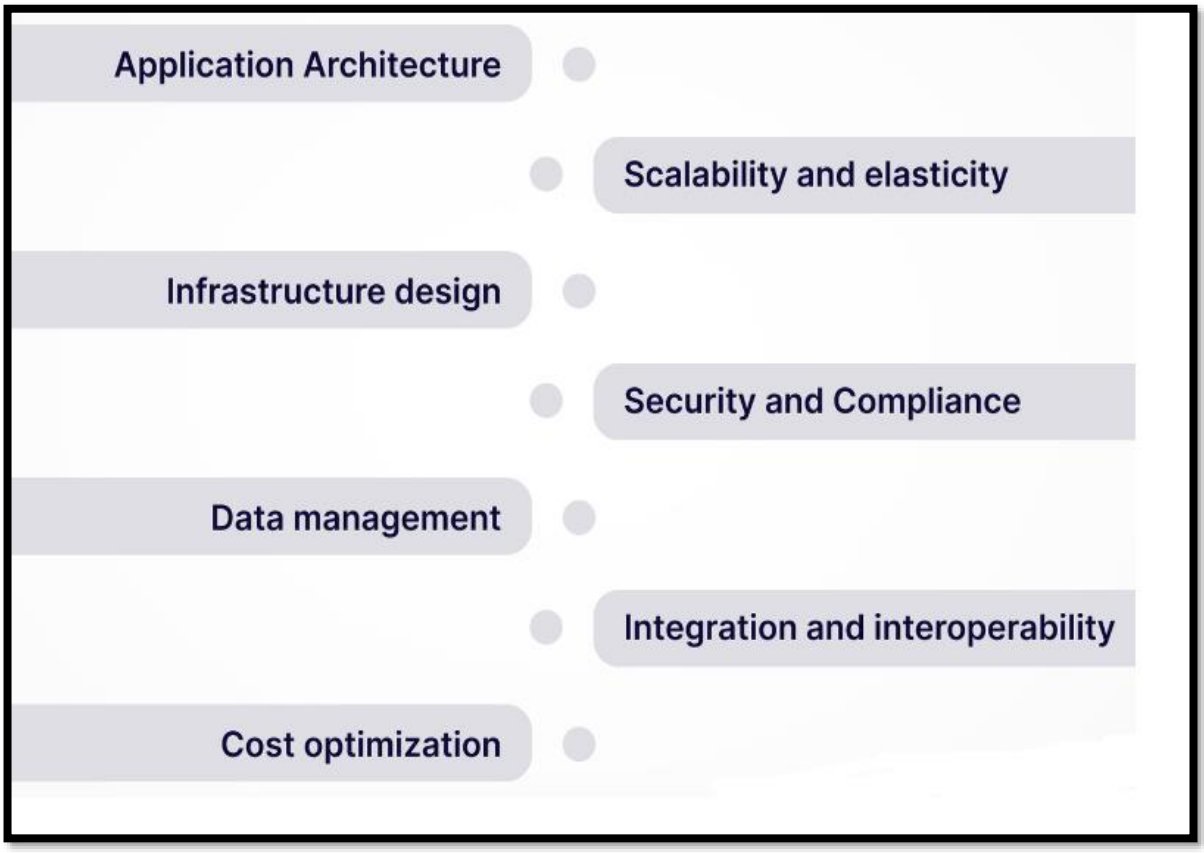

Fig 3 . 2 : Aspects that Include Thoughtful Cloud Architecture Design

3.5. Design Principles for Scalable Cloud Architectures

When faced with the need for designing an efficient and scalable cloud service infrastructure, the common questions asked are "Which components/approaches are the best to use in a given environment?" This can be a daunting task, especially for more complex services and requirements. This is where the use of AI and ML can help simplify the task. By using AI and ML to monitor, analyze, forecast, predict, and control the system, determine where and when changes are required, provide change suggestions, and even determine the impact of those changes, these tools can greatly help manage the systems. However, to realize its full potential, a set of design principles and architectural strategies must be followed. It is

equally important to ensure that the use of AI and ML technologies is done in a way that increases efficiency, lowers the cost, impacts, and complexity of operations, and does not create new and bigger problems. In this section, we summarize the key design principles and architectural strategies.

3.5.1. Best Practices and Strategies

An important aspect of effectively scaling the cloud architecture, even while working within a hybrid model, is the need to consistently monitor the ecosystem and adjust cloud environments as load patterns constantly evolve to maximize efficiency while containing costs. Following best practices around capacity management, constant monitoring of critical cloud metrics, and effectively integrating machine learning all play vital roles in this process.

When it comes to bringing machine learning algorithms into the cloud environment, the capabilities of these algorithms are rapidly improving and becoming much more diverse as cloud users continue to require flexibility and elasticity in the cloud platforms they use.

In this respect, capacity management proves to be vital to a well-optimized cloud in a hybrid architecture. A careful watch over key foundational criteria such as the performance of storage and processing layers, the trade-offs of preemption in cost minimization, continuous optimization of batch jobs, and an awareness of different load profiles are all best practices that help keep the cloud operating in peak optimal form.

Advanced Monitoring with Machine learning (ML) Platforms like Stackdriver and more recently released ML platforms enable cloud architects to monitor different metrics and features to be alerted when anomalies are detected. Models can be trained to forecast different workloads, allowing optimized server management configurations while providing a better overall user experience supported by demand prediction and resource optimization.

In areas such as time-series models, the nearest neighbor statistical time-series tools come in handy by helping to identify anomalies. The training of models with lagged patterns is vital and has been demonstrated to work well in scenarios where regressors are available within reasonable prediction time horizons. One can also identify different service patterns for CPU workloads over time.

3.6. Conclusion

Several conclusions can be drawn from this text, as follows. The emergence of scalable cloud architectures comes into realization when concepts, patterns, and mechanisms of scalable AI and ML are used to develop AI-based cognitive elements of cloud architectures. Using AI and ML and reusing their knowledge through internal big data gives the cloud high-running cognitive abilities. The approaches let one quickly create the desired cloud services through internal or external calls and wrap such services into containers. Cognitive clouds substitute managed services with native capabilities. They blur the lines between classical infrastructures and software products as sources of income inside modern as-a-service markets. Cognition and intelligence come from AI and ML methods upon the condition that concepts and mechanisms are in place.

3.6.1. Future Trends

We provided an overview of the existing architectural models that could be used by organizations transitioning to the cloud and found that the models are prescriptive and introductory, and do not provide the guidance needed by organizations migrating to cloud computing. Cloud computing is still in its infancy, and organizations are trying to find their way in this new technology. New architectural models need to take emerging concepts such as autonomic, green computing, and the larger role of "software" to manage virtualization-based designs to ensure all parts of the service delivery are associated with reliability, scalability, availability, and performance.

One way to approach this problem is to think of the different architectural designs for specific problems and figure out why these models are aware of key technology trends such as shifting information management in the world, moving from a hardware approach to a software approach of service delivery and consumption, and the use of autonomic principles in the management of larger service deliveries. Our research provides the needed guidance, understanding, and technical aspects that can be used by a variety of organizations to move existing services to cloud computing and develop future service deliveries utilizing the capabilities of cloud computing.

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Chapter 4

AI AND ML IN THE CLOUD: TRANSFORMATIVE TECHNOLOGIES AND THEIR INTEGRATION

4.1. Introduction

Artificial intelligence (AI) and machine learning (ML) technologies are powerful tools that have the potential to transform virtually every facet of people's lives, from their interactions with one another to the delivery of their essential services. At this point, both AI and ML are rapidly evolving areas of technology, dominant in many sectors and applications, and used by society to tackle complex problems across a wide range of domains. The cloud is a major enabler for the modern web and offers ready access to powerful and scalable CPU and GPU platforms for AI and ML applications. It can make creating and using cutting-edge AI and ML models far easier thanks to a range of tools and services for developing, training, and deploying models, and enable new capabilities deriving from the unique pairing of ML with the cloud.

AI focuses on the development of computer systems able to perform tasks that normally require human intelligence. These can be broadly categorized into three categories: perform tasks that would otherwise require human intelligence such as visual perception, speech recognition, decision-making, etc. When used effectively, AI has the potential to make machines not only more efficient and safer but also in many cases able to replace or assist humans in the performance of various tasks. Machine learning (ML) can be described as the process of training a predictive model on data to construct a decision boundary so that the model can then be used to classify new, unseen data into a class label.

4.1.1. Background and Significance

The natural question is why is there such growing interest in AI and ML? The quest of human beings to build machines that can perform various tasks has existed since ancient times.

The notion of a completely autonomous and intelligent machine was proposed by the famous Czech writer Karel Čapek in the play R.U.R. in 1920. Čapek selected the word "robot" to name these intelligent, autonomous machines. Since then there have been many efforts to build intelligent machines but they were mainly based on rule-based systems. It is only recently, thanks to a variety of achievements in several fields, that AI and ML have become central topics in technology developments. In particular, there are five main factors contributing to this high interest that converge all into a transformative technology.

First, since the 1970s the processing power of computers has increased dramatically. Its cost, however, has steadily decreased. This has allowed a new generation of intelligent machines to be built. These machines have two types of remarkable characteristics: they possess a high computational power and can make statistically based decisions. Second, the availability of extremely large data sets has opened the way to several new computing paradigms. Indeed, the new field of Big Data would not exist without big data sets, and that field constitutes the basis for many AI and ML applications. Since the early 2000s, we have been storing an enormous amount of data in several types of storage devices. According to estimates by the market and research firm IDC, more than 25 zettabytes of data will be created by 2025. Third, cloud computing has allowed businesses to perform the most sophisticated tasks without the need for massive investments in computing resources. Moreover, software zip files and Virtual Machines (VMs) have made the creation and management of app development environments very easy. Fourth, there have been many dramatic innovations in the area of neural networks. The performances achieved by these networks have boosted a scientific and technological community that was already developing at a good pace. Then, new algorithms and sources of information were realized to solve a new class of applications that became essential for all data creators.

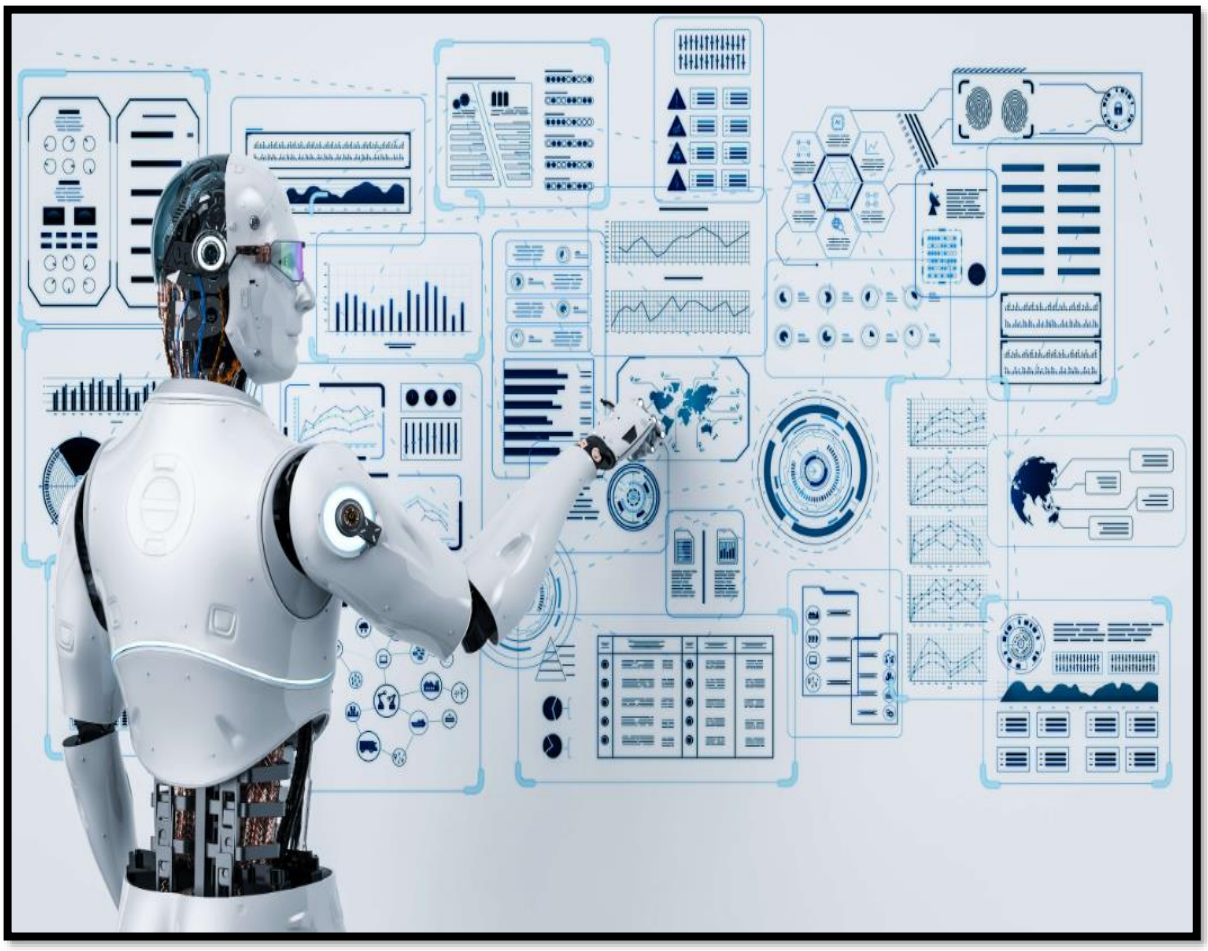

Fig 4 . 1 : Artificial Intelligence and Machine Learning

4.1.2. Research Aim and Objectives

This project aims to investigate, analyze, and provide new insights into an emerging trend of using AI and ML technologies in the realm of cloud computing. These two transformative technologies possess the capability of changing the way the cloud operates while increasing its efficiency and cost-effectiveness. Such recognition is based upon the open list of platforms and services already introduced or about to be announced by large industrial representatives of the cloud ecosystem, from AWS to Google Cloud, and from Microsoft to Alibaba. A new stack that starts from hardware infrastructure offering capacities that are cloud optimized to GPUs up to ML and AI frameworks or at service levels for easier access. This centretexporation leads us to several research objectives.

- Describe the current state of AI and ML technologies adopted by either the cloud suppliers or mature commercial users. - Identify potential benefits generated by such an

integration of AI and ML technologies in a cloud environment. - Identify potential issues, problems, or limitations that may derive from this combination. - Design, implement, and assess strategies able to ensure potential benefits while minimizing identified issues or limitations. These strategies for optimization can come from either the AI and ML technologies adopted in measurement and control loops aimed at tuning and optimization (self-optimization) of the platform to the specific application owned and executed by the ML instances.

4.2. Fundamentals of Artificial Intelligence and Machine Learning

We can begin with some definitions. In the common usage of the term, artificial intelligence consists of the incipient field of computer science that deals with simulating the abilities of the human mind in a computer. That is, we are talking about creating intelligence - something equivalent to, or, in some cases, greater than the biological intelligence of a human being - in an artificial artifact. This is the extreme case since we are also employing the term to represent artificial experiments with limited cognitive capabilities, possibly inferior to those of an insect but sufficient, within the limitations of the experiment, to solve certain practical problems. These experiments can have no similarity whatsoever to human intelligence and are also considered artificial intelligence experiments. It is also important to observe that within this phase, the evolutionary phase of computing equipment reduced to the extreme, can constitute artificial intelligence experiments.

Artificial intelligence encompasses the largest group of experiments (artificially recreated minds), which we will call cognitive architecture, dealing with the most diverse levels of capability to represent or translate the world, to reason on that representation, and plan or make decisions, to use natural language as a means of communication with humans, and so on. These cognitive abilities, when confronted collectively or individually, are interpreted, through the metaphor of the human mind, as intelligence. And that is why we are going into more detail in some refinements more related to the human intellect. The studies deal with basic research on human heuristics and problem-solving strategies, the study of neural processes, psychological concepts, studies related to evolution, theories of intelligence, developments of alternative methods to characterize intelligence, and related areas constitute a rich and fruitful interface between the cognitive sciences and computer sciences.

4.2.1. Definition and Concepts

In this section, we provide the definitions and concepts of the topics of this survey, that is, cloud computing, artificial intelligence (AI), and machine learning (ML). Cloud computing has become the main paradigm of the digital age. Indeed, the development and widespread growth of cloud computing have changed the way users use computing, also allowing access to resources as ubiquitous services through the network. Computer science and many companies are sure that services, applications, platforms, and infrastructures as a service (SaaS, PaaS, and IaaS) in the cloud will eventually replace the traditional reselling or "black market" of illegal software. Moreover, the use of cloud infrastructures and the provisioning of efficient, effective, and secure cloud services have been boosted by the possibility of using leased or on-demand outsourced resources as a fast solution through the economic model based on the pay-what-you-use paradigm.

The rapid progress of science, society, finances, and industry from one side and the other side the new possibilities offered by these technologies demonstrate that they are now ready for global adoption. However, to realize this step, AI and ML have to overcome many internal and external complex challenges. Academic researchers and industry practitioners have done much work in recent years and significant investments are continuing to be made to design and develop new techniques, tools, and systems oriented toward the automatic management of advanced ML solutions. The final goal is to deliver resilient, scalable, adaptive, secure, and sustainable AI and ML services on pervasive platforms, spanning from the IoT to the edge, fog, cloud, and HPC platforms.

4.2.2. Key Algorithms and Techniques

Today, cloud-based services greatly reduce the entry barrier for the use of AI and ML, as you no longer need to develop and maintain complicated, high-performance infrastructure. You only need to find and understand the use of the right cloud-based services that will meet your requirements. Would you like to dig deeper into the engines that AI and ML are built on? Machine learning models are built on the analysis of a large amount of training data. In recent years, especially deep learning, which learns from more complex and deep models, has proven to be effective, and the development has been remarkable.

Now that the development of ML algorithms is moving to even more advanced and more complex models, applying and integrating these models to realize effective and practical business use can turn out to be a high hurdle. Deep learning is a learning method in which information hidden within data is represented by several layers. By using neural networks as models, deep learning approaches can autonomously find and learn the structure from input data. Then, they can make even very complex predictions and can be good at predictions with high accuracy. When developing complex models, you have to solve even more complicated optimization problems to find the optimal parameter sets. To do this, you have to increase learning speed and secure learning accuracy from input data with different characteristics.

4.3. Cloud Computing: Overview and Key Concepts

Since its introduction to the IT industry in the early 2000s, cloud computing has morphed from a novel technology into the primary approach for the provisioning of computer resources used by scientists of all types. Its economy of scale has produced a direct impact on corporate data center strategies as well as a re-thinking of university hardware and software infrastructure to support a broad range of research goals. But, before we plunge into the many aspects of cloud computing, let's take a short moment to answer the question that you may have been asking for some time. What is this "cloud" anyway? The first thing to keep in mind is that cloud computing has nothing to do with meteorology. The "cloud" in both cloud computing and cloud storage is not a real cloud but is a metaphor for the Internet - so-called "cloud" icons are often used to represent the entirety of the complex, purposeless Internet architecture. Cloud computing describes both a platform and a type of application, and both require the strength and always-on connection of the Internet that is represented by the cloud icon.

Not surprisingly, the cloud metaphoric icons spawned several other quality-of-service metaclasses like "cloud applications" and "cloud storage." These act as virtual representations of digitally uploaded files that are stored on a remote server and accessible via the Internet. The three primary types of cloud computing platforms from which a cloud derives its strength are Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). Together, these form an interconnected platform supporting nearly all applications for the present digital age.

4.3.1. Types of Cloud Computing Services

Cloud computing usually comes under four types of service models that are known as deployment models, namely IaaS, PaaS, SaaS, and FaaS. Each model is different and has its functionalities and importance. The primary goal of providing four different service models is to provide different configurations of computational resources and programmers to meet their specific needs. The different types of cloud services are given below:

1) Infrastructure as a Service (IaaS): The Infrastructure as a Service (IaaS) service model is used in cloud computing for leasing hardware and computing resources such as storage, networks, and servers. This is similar to virtual hardware that is controlled by a TV manager sold on a pay-as-you-go basis. In IaaS, vendors are responsible for the physical hardware and infrastructure software, but the customers are responsible for managing networking, virtual machines, data, and runtime.

2) Platform as a Service (PaaS): The Platform as a Service model is mainly used to facilitate the development of applications, services, and APIs. PaaS includes different tools that deliver middleware upon which services or applications run. The main advantage of PaaS is that it is used for creating web applications without any special software or development tools. The customers build the applications using tools provided by the provider, and the applications are then controlled by their provider in PaaS.

3) Software as a Service (SaaS): Software as a Service (SaaS) mainly helps users connect accounting, emails, customer relationship management (CRM), Enterprise resource planning (ERP), sales management, invoicing, and many other applications. The main advantage of using SaaS is that you do not need to buy or configure anything, as it is provided by the SaaS provider.

4) Functions as a Service (FaaS): Functions as a Service (FaaS), also known as serverless computing, allows customers to execute short-term executable code without specifying any guidelines on how that code is handled or responded to. Organizations that provide serverless computing are responsible for providing the general server that has the required applications, where customers can upload their code to fulfill specific tasks. If no task exists, it is useful for removing the load of a traditional service provider. FaaS helps companies reduce their development costs and increase ROI by responding to incoming customer queries.

Fig 4 . 2 : The Different Types of Cloud Computing Services

4.3.2. Key Benefits and Challenges

AI and ML-based applications build and operate models at scale using vast amounts of data. They are indispensable for a world that is reliant on vast amounts of data. Cloud provides a secure and elastic infrastructure that makes AI/ML work so much worth the effort. Key benefits include - Cloud accelerates AI deployments, Cloud is the home for AI research and innovation, it's easier to secure sensitive data in the Cloud, AI requires scalable, elastic computing and Cloud does that well. That said, there are challenges to making AI work in the cloud too. Key challenges include - mastering AI/ML skills, managing data, meeting security requirements, and cost.

The biggest development in the AI ecosystem over the past five years occurred with the introduction and subsequent large-scale deployment of cloud-based machine learning and deep learning solutions. Cloud offered scalable elastic infrastructure to rapidly train and deploy AI models using enormous amounts of data. The key benefits of using AI in the cloud include the cloud accelerates AI deployments, Cloud is the home for AI research and innovation, it's easier to secure sensitive data in the Cloud, AI requires scalable, elastic computing, and the Cloud does that well. There are challenges to approach too: Mastering AI/ML skills, cloud, and data, Cloud and security, and Cloud and cost.

4.4. Integration of AI and ML in the Cloud

The AI and ML technologies can be integrated with traditional cloud applications and the growing classes of innovative cloud applications (e.g., IoT) in a variety of ways. The AI and ML software and services, used as stand-alone cloud-enhancing tools in their own right, can help application developers and managers in various functional areas do their jobs better. In addition, AI and ML in the cloud can be part of a solution that delivers those benefits at cloud scale, agility, and cost. AI and ML software and services in the cloud can connect to a wealth of APIs and data from varied sources, in varied formats, and at varied scales in a multitude of public and partner cloud services. Moreover, AI and ML software and services can dynamically represent real-world business processes and entities, and use the processing results to help the cloud executive automate care and maintenance of the cloud application code and run-time environments and to continuously create and monitor new business processes and related software under the management of the cloud application.

Beyond plugging AI and ML software and services directly into individual cloud application nodes, cloud application software can help developers and managers access those services and leverage the results in a manageable way. Cloud software should be built to include AI and ML software and services as natural code modules; these modules should facilitate recognition and connection with business processes and entities by exposing structured data via simple data context and API call interfaces. These interfaces may include template connectors accessing AI and ML software and services via cloud-friendly SOAP and REST APIs through scripting languages, data transformation interfaces supporting AI services via standards such as JSON and XML, and Smart Data APIs accessing business APIs that support direct processing of code and data. Code executing in the cloud can monitor API call usage for patterns that trigger the use of AI and ML software and services, and then use said AI and ML software and services to drive custom business processes and data transformations if necessary. The resulting change in business rules or processes should be communicated to developers of the cloud application to drive code changes.

Cloud business meta-data represented in a cloud business context can be modified directly using scripting languages or via AI and ML-driven alterations. Such capabilities can be bilaterally linked both to the AI and ML modding of cloud business context and SAAS entities, which can be based on public and partner cloud data not related to the SAAS environment. Also, the ability of the cloud to use AI and ML for these purposes should be

exposed to allow the business plan to monitor and control its own business and the related business process. Business processes in clouds and the APIs and service-level agreements used to ensure the cloud is working as expected can influence the activities of other stakeholders. When combined with AI and ML techniques, they can be used to trigger business process change automation requests within the cloud. As business objectives are reached and relationships are stabilized, newly assisted business dynamics will emerge. Enterprise and mid-range cloud providers should arm themselves to deal effectively with various aspects of AI and ML-assisted business processes by seeking feedback from their business model clientele and by understanding cloud usage trends.

4.4.1. Architectural Considerations

There are several important architectural considerations for using AI and ML in the cloud to be addressed. The first important discussion in this area revolves around data residency and data locality. A global cloud architecture uses data centers around the world so that customers' data can reside in particular geographies. Analytics and AI can run instances of cloud services running near the customers' data and provide the necessary results. When architecture is deployed across multiple geographies, we can choose to process personal data in the geography closer to the user. This reduces latency and it also allows many customers to better navigate their various data gravity and residency requirements. We can also use data residency capabilities in the cloud to require customer data to remain in a particular geography for compliance reasons. By being able to ensure the data stays within the desired geography, we help to simplify complex data compliance rules in sectors such as education, healthcare, and government.

Another important consideration of lessons learned from deploying AI and services in other aspects of cloud architectures is managing the diverse set of infrastructure required for a global scale cloud. Large-scale file storage, high-performance computing (HPC), and architectures built around Artificial Intelligence, Machine Learning, and IoT workloads are all great examples of workloads that require purpose-built infrastructure to be done well at a service level. The next important discussion in this area revolves around edge computing and AI inference. Data is being created at the far edges of the network in devices, sensors, and customer locations. Often this data will then be transmitted to the cloud for further processing and analysis by cloud-based ML and DL models. However, some applications require reduced latency and bandwidth or receipt of data even if it is unable to reach the cloud. Providing

customers the ability to compute close to data sources and create intelligent reactions as the actions unfold is a key consideration of many AI models.

4.4.2. Use Cases and Applications

CRM Analytics

The AI and ML models for CRM systems performance are particularly promising because the different tasks are highly integrated. For example, the quality of leads might depend heavily on model and event exposure. Custom-built solutions using tensor topic embeddings, fine-tuned MLMs, and deep NN with transformers have the edge over conventional rule-based engines. More sophisticated solutions, such as Wynnum-Mirdeep2, a nested attention recurrent neural network (RNN) also enhanced with the predictions from locally-generated models of event exposure, can formulate and propose different types of interaction and analyze proposed derivations.

The general premise of transformer-enhanced expert systems with a learned fine-tune-ML talking head that can confront risks and actionable insights can be used to organize online meetings and suggest different methods to achieve user-provided expectations, minimizing human hours spent and taking users from mandatory supervision to advanced scenarios in a self-service mode. Marketing landscape analysis is handled with social and contextual analysis, a differential recurrent relevance attention network (DRIVEN) working with attention-differentiated orthogonal individual concepts (ADOIC), financial report analysis, a suffix loss representation in a concatenated, state-grammar neural network Quhabber 3, and a multimodal ML+DL approach ECLATS.

Competitive intelligence for content manufacturing uses an artificial collaborative strategy PHEAR-III. It employs a PheXp-3 streaming privacy module to get predictions on given text segments to get a maximally balanced, anonymous distributable material without a breakthrough. Another tool with the same initials—Aphex-3—provides file modeling for specialized ML accelerators running alongside the operational engine in a PHEXp-3 pattern recognition group.

4.5. Challenges and Future Directions

In this section, we discuss several major challenges associated with the use of cloud computing services for AI and ML methods. Our list includes barriers associated with scale and complexity, data exploration and model evaluation, various aspects of interactivity, and the integration of domain-specific and expert knowledge sources.

With cloud-based AI and ML methods, service configurations can quickly become complex and entail multiple implementation layers (e.g., for runtime environment management, API deployment, and resource scaling). This gives rise to multiple potential points of failure, each associated with its own configuration and maintenance requirements. Throughout their development lifecycle, complex services can and likely will increase the need for diagnostic and troubleshooting tools that can help developers find, understand, and resolve configuration issues, and in particular their potential and non-obvious interactions.

At the DataSciCon conference, participants went on record as stating that data exploration is one of the "most time-consuming" operations in AI and ML development while model construction, evaluation, and deployment decisions are among the "most important". These assessments give rise to special connection requirements that centralized data resources, data workspaces, information and data exploration tools, programming-oriented services, training infrastructure, and model management systems should provide for data scientists, model developers, and deployment engineers. If these personnel are to use these resources effectively and deploy useful business applications, development tools, and model integration and deployment systems will need to support high levels of interactivity for various AI and ML scenarios.

4.5.1. Ethical and Privacy Concerns

The increased sophistication of AI and ML techniques raises several fundamental social and legal issues. AI and ML algorithms have a significant potential for discrimination based on race, gender, or other considerations. Many algorithms are "black boxes" that cannot be readily interrogated, so it is difficult to evaluate the basis of the decisions that they make. There are privacy issues raised by many AI and ML applications, and the social attitudes towards these issues are very diverse. Even when the algorithms are constructed with excellent motivations, they may well have adverse side effects.

The increased use of AI and ML is inexorably increasing the potential for a loss of jobs. The historical distortionary effects and requirement for training may be severe in a world where currently millions of citizens are unfamiliar with the most basic aspects of AI and ML. In a sense, society is outsourcing critical life decisions to algorithms that have no implicit wisdom. The relationships among all these people must be managed, often by people who may become experts in the work themselves. The ethics, policy, and legal implications of these technology applications and advancements are issues of societal interest and collective discussion and decision-making. Careful assessment of its application and a willingness to challenge its consequences are needed as the technology continues to evolve.

4.5.2. Scalability and Performance Issues

In the case of ML, very large networks are being generated now. At the apex are GPT-3, which has 146 billion parameters, and a recently released variant prototyped at 175 billion parameters. In particular, GPT-3 was trained on 45 terabytes of text and used 3.14 x 10^12 floating point calculations. When these types of capabilities are needed locally, the scale of the task has implications. Training time was reduced to 5 weeks using 524 GPUs, but this is in an environment with very low costs of electricity.

Deploying such resources is a more fluid undertaking in the cloud, subject to availability and cost. AWS advertises almost 1,000 edge locations, each of which has the content-serving ability, 58 availability zones (that is, large global data centers), and 23 geographical regions. Regions are arranged into 76 Availability Zones (AZ), a well-defined network structure that isolates its customers from the failures of one or multiple Availability Zones within that region while simultaneously providing low latency and high throughput.

The computing and storage functions for the cloud are governed by the policy of the company. The Physical internet itself does not prescribe where and to whom users are allowed to transfer and store data, but the cloud, big data, and what is in between them are expensive, frequently slow, and have other system limitations. The policy and cost structure for computing are self-imposed. As platforms, the cloud providers make sovereign choices that, as realized through the policy, govern data residency and other location-marking aspects of the network. Because of this, the ability of the cloud to serve as a component of the physical internet ultimately depends on the cloud provider's policies in general (such as software licensing).

But what does not rely on "derivatized" data like the latter is the access and storage of such data (hardware keys). The pair of users' records and keys are enclosed in a "box" within the cloud environment. With an entire database, these boxes are from the forest (physical internet for data). A higher level of indirection is provided by an injection of the cloud $T - a set consisting of users who can both preserve the self-consistency of the cloud and enforce transaction containment.

4.6. Conclusion

In summary, the extension of cloud computing with ML or AI capabilities has enormous implications for the software and systems that we build. Techniques like deep learning make it possible to achieve perception and reasoning functions that seemed out of reach for a long time. But the next anniversary can be a reminder of something that may seem even more routine than cloud computing because cloud computing applications like substantial ML or AI are already part of the cloud. The technologies that cloud providers incorporate into their offerings can be used much more widely than today by application developers who do not have substantial ML or AI expertise. We need to put more of these transformative technologies into the hands of people who may be much more familiar with databases, networks, visualization, and other cloud-hosted facilities. Such cloud-first services could transform most semantic computing problems in all areas where cloud providers make their offerings available.

Advances in large-scale training are essential for enabling applications in perceptual computing, but experts understand that modifications are necessary to apply these new capabilities to the old, long-standing, non-perception-centric, special domain of computing. GoogLeNet and other networks introduce new layers later in the training process. Other hierarchies of the models use learned features and change their function. Techniques that allow the model to store a small number of elements require additional modifications. Attention-based networks address the problem differently. Data bandwidth is just one of many issues that need attention. We - everyone in ML and AI currently - need to understand that these particular problems of semantics have been significant with billions of labels and that further improvements are necessary, even if these problems do not require the same type of expertise or the same technological advances. The cloud's transformative capacity will not reach its full potential unless we extend the reach to new creators. They are much more anxious to use the cloud in more transformative ways.

4.6.1. Future Trends

AI and ML deployment is rapidly expanding beyond early adopters. The sophistication and scalability of these cloud services built by a few leading cloud providers make complex technologies accessible to many more users than ever before. For many, the economic and operational calculus of consuming AI, ML, and automation services translates into technology agnosticism. This trend foreshadows fundamental changes in technology and work organization. However, some caveats are called for since, despite their purported neutrality, ML models learned from Internet datasets may be affected by biased ground-truth annotations, and biases in the learning signal, not to mention the opacity of some learning methods and the potential unintended consequences of the applications that learn from these models.

A critical question is whether the sheer economic allure of cloud AI value will not overshadow the broader and longer-term societal implications of these services. It remains to be seen whether, and to what extent, they can influence the direction and the character of AI and automation research or, at the very least, extend opportunities that these innovations create to a vastly larger ecosystem of diverse users. This chapter outlines our view on the direction and character of two of the most transformative and intertwined technologies that support new knocks of AI and automation innovation - AI and ML in the cloud - and their integration.

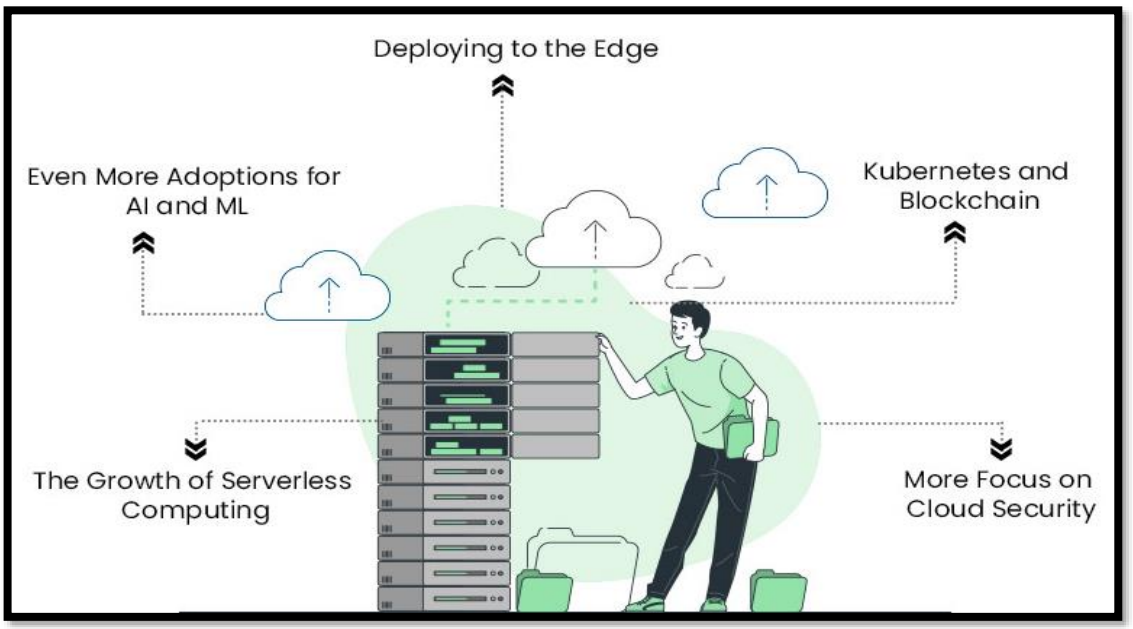

Fig 4 . 3 : Top Cloud Computing Trends

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Chapter 5

GENERATIVE AI: EXPANDING CLOUD CAPABILITIES AND INNOVATION

5.1. Introduction

Advances in technology are shaping the future of the enterprise, both here on Earth and in the farthest reaches of outer space. The current digital revolution, capitalizing on cloud and AI technologies, is creating the most rapid and disruptive wave - and enterprises utilizing modern technologies are on an evolutionary path upward. Cloud computing provides elastic, scalable, and on-demand infrastructure, as well as artificial intelligence (AI) platform tools that make it easier to deploy and manage applications. Cloud technology provides novel tools that enable innovation and unique capabilities to be developed from anywhere in the world. Organizations in every sector - for profit or media, private or public, from individuals to large enterprises - are leveraging advanced cloud capabilities to increase efficiency and effectiveness.

There are many compelling reasons why enterprises are adopting cloud technologies. It provides a more flexible, adaptive computing environment to develop new customer experiences in multiple domains. More accessible, democratic access to infrastructure, development, and application support resources can lead to modern solutions. As the cloud takes on surrounding AI technologies, complex development can become simpler, and processes throughout the life cycle can improve in delivery time and quality. Indeed, the design and deployment of AI systems for natural language text-to-text generation have already emerged from open-source libraries. These very practical expansions of generative AI framework capabilities can help an enterprise build an intelligent conversational agent on both cloud data and pre-trained models and utilize innovative approaches. With the cloud, driven by human AI innovation, it can become the cornerstone of a new age of enterprise.

5.1.1. Background and Significance

Generative AI (Artificial Intelligence) holds great promise across many fields, from translational medicine to immersive technologies, thanks to its ability to develop new solutions. These AI models, often enabled by pre-training on diverse data types, generally require substantial resources for training, and due to their iterative nature, access to a cloud with access to abundant computing and storage resources is often a necessity.

Generative AI has many practical applications poised to create tremendous social value, including in video, speech, digital manufacturing, autonomous vehicles, natural language processing, and many other areas. Generative AI has been enabled by breakthroughs in relationships and models, handling and generation of human language, and reinforcement learning methods, among others. Generative AI can generate novel designs, patterns, speech, and other artifacts, and solve pertinent optimization problems with generative AI results.

Generative AI can facilitate approaches that are nascent, expensive, or not viable under the current state of the art or frequently lead to results of greater quality. However, the soaring scale and cost of generative AI have expanded the digital divide, with only the most financially endowed able to engage high-capacity (ultra-large-scale) AI infrastructures and methodologies. This exacerbates the cost of exploration, supporting exploration primarily for the wealthiest and most ambitious businesses and governments, who can quickly and effectively leverage generative AI tools and techniques to enhance and maintain their relative benefit. Indeed, one can estimate that the national cost barrier for participation in elite research communities has risen by an order of magnitude roughly every 10 years in recent decades.

Partial, frequently unrecognized prerequisites and significant barriers prevent access to and use of generative AI and have been highlighted in the context of Open Data and Open Adversarial Attacks, as has a lack of Know Your School/Model (KYS/M) guidelines, legal frameworks, and social policies. Privileged access to resources is an often overlooked computational elite, who can exploit advanced hardware and software resources to generate data at extremely low cost, rather than merely achieve access to already available resources.

5.1.2. Research Aim and Objectives

What's the reason for the research: The development of a generative AI model with genomic and proteomic specificity was carried out to contribute to data science studies that

need new data generation and training techniques for different purposes. The knowledge generation purpose is different from common data generation and training techniques; certain new sentinel data needed for certain data science studies is obtained with these studies. There are very few AI models that can produce new genomic and proteomic data. In this respect, the contribution of the study to data science studies lies in the fact that the share of studies that predominantly need genetically created individuals and the share of made investments in this field is low. The involvement of researchers in this low share field and the realization of the subsequent studies cause data collection bureaucracy, budget, time, and ethical approval to become suggested reasons and difficult user acquisition to be suggested as causes of failure of the model or subsequent studies.

What will be done for this research: As it is known, scientific studies are carried out on the researcher's concepts to give his actions a goal. The coherence of these actions suggests the research as a logical perspective on the topic. If the concepts beyond this coherence are not clear and controlled to be relevant, the model has the potential to fail, and consume resources needlessly. In other words, it is critical to concentrate all the actions in a consistent, coherent form. The actions that predetermine the future of the model must be tested based on the goals and objectives of an existing study and made flawless. Secondly, one must know what one wants from the model. In this sense, in writing a successful project proposal, the objectives of the study should be clearly defined. The achievement of these objectives is directly proportional to the created and developed model. This study represents a computational biology study that aims to improve its properties. The study will examine the novel application of generative deep models in the field of artificial intelligence. The goal of this study is to create and train a generative AI model on genomic interval data. This gives an understanding of cellular biology. The abundance of certain types of data is another major disadvantage. The innovation returns to develop an intelligent generator that can add to the very different data sets in surfing.

5.2. Understanding Generative AI

At a high level, "generative AI" refers to models that generate original, machine-created content. These models possess the ability to be creative and form data-driven assumptions, presenting an innovation in the capabilities of AI software to go beyond predictions and resolution. Currently, the most popular type of generative AI involves creating text. With recently trained models such as OpenAI's GPT-3, we can input a prompt or starting

sentence and ask the model to continue or conclude the story or text. Alternatively, researchers can use generative AI to create new examples to generate human-like faces, stitch together complete video sequences squeezed from mere photographs, or strengthen super-resolution techniques for enhancing image details in photographs.

How do these generative models work? Generally, generative AI models entail two components. The first is a generator, responsible for generating the new content. The second component is a discriminator, whose goal is to deny the generated example and affirm authentic examples. Through competition between the generator and the discriminator, the generator tries to succeed in generating samples that the discriminator cannot distinguish or identify as fake, while the discriminator tries its best to distinguish between real and synthetic examples. As the generator gets better at creating seemingly real outputs, the discriminator is constantly refining its skills in attempting to make the best possible attempt to filter between synthetic and true samples.

5.2.1. Definition and Concepts

The current evolution of artificial intelligence (AI) based on machine learning (ML) and deep learning (DL) has advanced, bringing conversational AI to the front of the customer experience (CX) technology conversation. Moreover, it highlights the importance of speech and natural language processing in human-machine interaction. These AI solutions are designed to enable AI to understand human language, respond conversationally, recognize both written and spoken language, translate between languages, and make it easier to add AI to an organization’s business-oriented applications and resolved CX solutions. These emerging solutions are not perfect, nor are they exactly like us, but they enrich human-machine interaction. These Generative AI solutions enable AI resources to fulfill a wider variety of cognitive and sound resources and enable a safer, more productive AI workforce spread over the globe.

Fig 5 . 1 : AI in Cloud Computing

5.2.2. Types of Generative AI

Generative AI comes in a few different formats, and we will explore some of the most common formats and uses in this section. Keep in mind that these categories can be somewhat overlapping with each other and that many of these concepts, especially when beneficial capabilities arise, are combined.

One of the traditional categories of generative AI models can be classified into three main groups: Generative Functions, which are given an input that is entirely deterministic and is guaranteed to produce the same output every time; the Generative framework, which works by generating a new distribution; and Generative Models, also known as Top-Down frameworks, which learn the process of generating the desired output based on the input.

One thing to note about the term "generative" when associated with AI or machine learning models is that it normally refers to the nature in which these models work, that is, they can produce "real" examples of data that was observed in the input. However, this does not imply that these models are inherently unidirectional. Indeed, often some of the models described in this section can produce new examples of similar data merely by changing slightly the parameters of the input.

5.3. Cloud Computing and AI Integration

Cloud computing is the ability to engage an intellectual network where interactivity is the immediate but abstract vehicle to bring computing power, software, and data to users. This field of distributed computing enables very rapid improvements to algorithms and problem distributions by research and engineering teams. With a large ecosystem of third-party, public, and private infrastructural support such as networking, digital identity, data management, storage, databases, and analytics now available, the financial costs of various software, big data, and innovative capabilities can be acquired and installed uniquely to each user. The intellectual network is the technical and the policy means to benefit from the transformative capacity of these techniques and associated data. Trusted private and public data are necessary but not sufficient for driving future productivity growth. Not only will progress require access to increasingly larger amounts of new data from various sources, but the return on investment in this area is likely to be dependent on computing and data systems and their ability to understand and help make decisions. Digital libraries and social and cultural interaction promote the creation and preservation of unique data.

Cloud computing has its origins in the storage and computing strategies implemented by the dominant web firms that encountered the problems of scale early. The latter's business model dictated these issues since they required very fine-grained optimization and the new systems to solve difficult storage, processing, and retrieval problems at the lowest possible cost. The basic utilization problem is making sufficient use of the substantial investment by the providers in servers, networks, buildings, and power systems. Both software and efficient use of the available infrastructure are required. Capital and network effects are a common feature of firms that have achieved dominant positions. Consequently, a free lunch can sometimes only be secured for a modest service provided by services that are difficult to deliver. Control of a computing infrastructure can also be a significant source of value. As the necessary tools become more pervasive for managing, monitoring, and changing performance

against a mix of requirements, it will be necessary to evaluate cloud data and CS services in terms of user costs, efficiency, flexibility, special design components, and rewards. Development and fielding investments incubate cloud-unique intellectual property and implementation experience.

5.3.1. Overview of Cloud Computing

An accurate and concrete definition of cloud computing can be inferred from the report by the National Institute of Standards and Technology (NIST): Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. Although cloud computing is positioned to embody various service models (e.g., Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS)), the most common one is SaaS. A key attribute of cloud computing is the capability to deploy applications and tailor services with unprecedentedly high speed and low price at a large scale and with great ease. This model promotes availability and is composed of five essential characteristics, three service models, and four deployment models among multiple stakeholders.

5.3.2. Benefits of Cloud in AI Development

Cloud technology provides collaboration between humans and developers and comes with a complete development suite for data scientists. With resources such as Azure Machine Learning, Azure AI, and data preparation automation in Power BI/Excel, data scientists are enabled to focus more on creating business value instead of managing infrastructure or tooling support. It simplifies the operations of machine learning models both through and after development by providing infrastructure management and compatibility services.

Once a model is developed in the cloud, it can be operationalized with minimal effort, since Azure provides SDKs for a wide variety of programming languages, prebuilt Docker containers that contain many common modeling tools, and easy integrations with other Azure services, such as Azure Functions, Azure Data Factory, Azure Stream Analytics, and more. With machine learning models requiring cloud resources for development, the obvious move is to have machines and data in the cloud for them to access, taking into account that data will

need verification and security considerations to ensure compliance with datasets. As the level of sophistication in machine learning and computer vision research continues to increase, more capital expenditure will be required. This means that removing as much overhead as possible from the day-to-day development work can help researchers reduce the cost of operations.

5.4. Applications of Generative AI in the Cloud

Applications range from robotic manipulation, protein design, energy storage, chip placement, neural architecture search, and natural language processing, to mention just a few. By using a variety of loss functions that get computed and generate feedback from various parts and components of a cloud service, the technology can be applied and trained on very complex inputs and take weeks or even months of cycle time to become more accurate and sophisticated. While the complexity of the learnings is essential, Generative AI itself can be used in any cloud-based implementations at a very low structure layer. That also means that to even get successful models to store and quickly reload as part of a running result, applications such as the TF Processing Unit with multiple layers may be necessary to no longer host a neural network and train, tune, and use the model and weights either.

In the Cloud, Generative AI is yet another kind and goes beyond GPT and modern learning. With generative AI, we can accomplish some of the world's toughest challenges. Companies developing and creating some of the most convincing and essential models with which we manage to explore Generative AI. What's new in the generative method is that this entire process is put in place with AI. While it's impressive to believe why this machine was so productive, companies can raise and train AI to enable these impressive results and undermine some of the world's most compelling breakthroughs. While creating a once-incalculable and EVP image, for instance, needed to be done by a professional adept at Photoshop, GPT can allow every photo to enhance and get image tagged as an alternative. The technology can also be used to get a significant amount of feedback from the same work its performance claims, asking "Does this image look natural?" before producing new and more capable resolute models.

5.4.1. Creative Content Generation

The music and film industry often needs to generate a large amount of content in a short period, using highly capable equipment or talented artists. Generative AI models with

the capability to generate music and images have become versatile tools that can support artists and producers in times of need when human artists are suffering from an inspiration hunger or explosion of a project. Applications such as AI image repainting, music mashups, or even content creation online collaboration systems can use a single promising pre-trained generative model as a generative service to provide results with artistic value. These systems can greatly help non-specialists or professionals in terms of productivity or socializing. However, such generative models are not easy to integrate as a service into an application and generally require high-performance computing and data center infrastructure to obtain efficient bootstrapping and execution.

In this work, we introduce a generative content creation cloud service powered by a scalable container runtime to achieve efficient content rendering in a subscription-service-based manner. The system serves end users with flexible amounts of subscription to 2 different types of generative models (a state-of-the-art image-to-image generative model & a sample-level musical generative model) on cloud-managed bare-metal resources, allowing very high-performance rendering at a much lower cost than commercial cloud providers. We demonstrate integrations from web and mobile frontend services to the hosted models via RESTful APIs, discussing possible mobile applications. We believe such a concrete use of generative models as a backend service will greatly help towards unleashing the potential of generative models in other domains.

5.4.2. Personalized Recommendations

Cloud elasticity and ML are driving advancements in recommendation systems that use deep learning to better understand behavior and extract meaningful signals at scale. The resulting systems realize significant model complexity and expressiveness, enabling, among other applications, the delivery of user-specific recommendations and diverse, engaging, personalized browsing experiences.

The best content to display to customers of a streaming Web service is either the movie they will enjoy the most, irrespective of genre, or a highly rated example from a different genre that they might be interested in exploring. In one such scenario, AI is being used to generate 'browsing assets' - small video summaries, as well as curations of promotional imagery - that are science-based by their automatically determined composition. These assets can realize

significant savings thanks to reduced human effort for curation, manifesting as time saved on data curation at scale.

For globally operated streaming and broadcasting services, the savings can be particularly significant for 'titled' assets (content metadata such as titles, episode descriptions, season numbers, and so on) translated into many languages for multiple geographies. The availability of multiple languages for asset generation can provide insights and options to ML models. For example, the sentiment of a customer review can be adjusted to more accurately drive localized promotional strategies. For machine translation serving streaming and broadcasting services globally, AI-generated language assets could build translations for phrases and subtitles. Future possibilities could involve customer service technologies and augmented translation community interactions.

5.5. Innovations and Future Trends

5.1 Innovations in AI

Generative AI models have achieved tremendous milestones. These models can be either large or small in size with the ability to perform specific tasks. Large models can perform various tasks and can be adapted to perform other tasks efficiently and effectively. The large generative models surpass the capabilities of their smaller counterparts, resulting in better performance. With the advancement of the large models, study and implementation in the line of smaller models will create mini-AI models, expanding the applications and accessibility of AI. In contrast, a design concept that harnesses the strength of large generative models or ensembles to achieve cost-effective designs to small generative models to obtain better performance on different tasks, with the ability to run several tasks using a single device or workload-efficient model will likely bloom in the next decade.

5.2 Implementation of AI Topologies

In principle, any generative AI model can be implemented on an FPGA. However, pure software-generated models are generally too large or inefficient, and efficient implementations must adopt dedicated high-level synthesis tools to generate optimal target platform architecture or use natural topologies that are expected to achieve good performance. This will likely become a focal point in the coming years. It is expected that high-level synthesis tools will be the tools commercially utilized by small companies or laboratories

wanting to develop FPGA hardware accelerators. For commercial customers, including large companies, it is less costly to purchase IP Blocks or planar boards with AI processors. People need to better understand the requirements, and the community will develop tools to generate a new class of programmers, who are those who configure and optimize AI topologies, while not necessarily understanding how to program them.

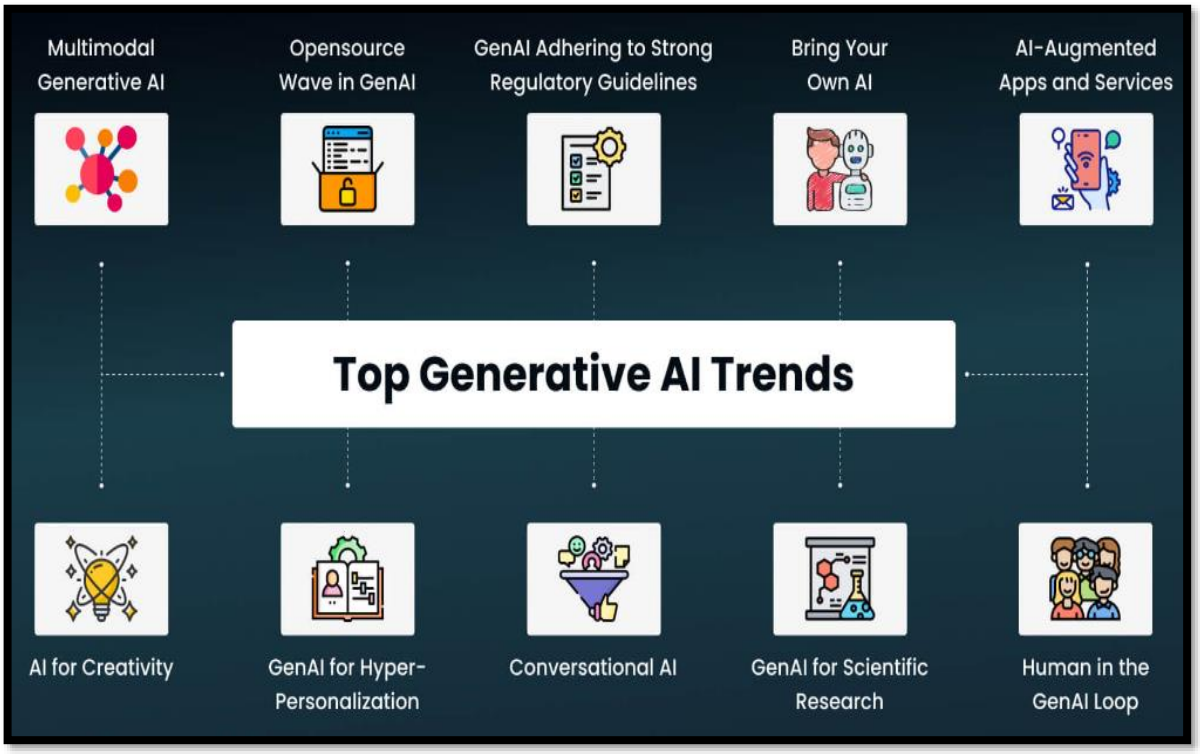

Fig 5 . 2 : Top Generative AI Trends

5.5.1. Ethical Considerations

Ethical considerations have been a part of the conversation around AI for as long as there has been a conversation around AI. It is perhaps the perplexing nature of agency and intention in a non-animal that leads us to question the morality of such systems. Discussions around the ethical considerations of AI include but are not limited to, privacy concerns, manipulation and deception in AI, the allocation of responsibility, AI use in warfare, job displacement resulting from AI, and artificial intelligence safety. Discussions thus span the domains of privacy law, employment law, enemy combat law, autonomy and rights law, machine ethics, human rights law, and artificial intelligence safety, to name a few.

The law tends to lag behind technology both in terms of catching up with technological advances and in terms of the forms of law that will prove the most effective at regulating said advances. This period of plausible legal uncertainty presents an "ethical gap" because emerging technologies also tend to inspire simultaneous ethical questions with discussion informing lawmakers who will, at some stage, codify the accepted norms. The engineering community has taken these behavioral and ethical concerns to heart, with various codes of practice, such as the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems and the European Union's Ethical Guidelines for Trustworthy AI. These guidelines all support the values of human dignity, democratic values, respect for fundamental rights and fairness, and put forward ideas for doctors, engineers, and programmers facing ethical challenges.

5.5.2. Impact on Industries

The value of AI is not intrinsic; its value is extracted when AI is applied against scenarios, helping businesses reap the rewards of the data they own to transform their organizations. AI capabilities are now expanding to include generative models, which results in more natural ways to interact with intelligent systems. Such capabilities enable diversity in music, poetry generation, painting, sketches, manual annotations, speech, and even code. The next phase of generative AI will involve incorporating these capabilities into application scenarios.

In partnership with OpenAI, Microsoft is releasing three Azure cloud services as new tools for enterprise developers to realize the potential of generative AI. These tools include a text-to-image service, a code generation service, and a simple web-hosting service called AnoDoT, which was inspired by OpenAI's work. This release introduces the first GAN (generalized adversarial network)-based service to be offered on a public cloud platform. The next phase of generative AI involves incorporating these services into application scenarios. There is a need for more advanced AI systems, and more diverse approaches are expected to be proposed. These approaches will help us take better advantage of our imagination while pushing forward human limits.

5.6. Conclusion

Cloud migration is not an easy task as businesses tend to rely on numerous specific platforms. Each company makes a different journey to the cloud that is always in line with its

strategy. When a company decides to move to the cloud, it can signify a major shift in the way the business operates. It is a mindset - a mindset of constantly optimizing the use of services that are becoming commoditized, with a continually expanding range of products and platforms. It's crucial to determine if the cloud is suitable for any specific organization. The cloud can offer numerous benefits to companies of all kinds with many different applications that will save time and money, and above all, it provides innovative and flexible tools essential for business development.

For a successful cloud migration, it's necessary to understand the specific business model and demonstrate the company's products, applications, and workloads. In the long run, the key to success can come from the comprehensive, properly defined cloud migration strategy that will support this direction. A cloud migration strategy should be driven by clear, achievable business goals and the people responsible for leading the migration. The strategy should not be based on an assumption that industry 'best practice' may become available in the future - people must create the future by defining the strategy that will suit each specific business context.

5.6.1. Future Trends

Generative AI opens the door to many creative possibilities and future advancements. However, its power and potential may not be fully realized. To this end, we lay out a few potential trends and developments that we think will play a significant role in pushing generative AI forward. We believe that such advancements will advance the state of the art and push the capabilities of products and services – ranging from graphics and gaming to e-commerce and enterprise software. Moreover, we believe that advancements in generative AI will also offer opportunities for facing some of the world’s largest and most critical challenges around climate change, health & medicine, and education & employment.

One area that we believe will see a substantial advancement in generative AI is the area of generative models operating on long-time series. For example, in the graphics domain, we see a world where a game designer asking for the next frame in the game can get responses with successive frames of video, with customizable characteristics and styles. In the audio domain, we see a world where a lecture transcriber can raise their hands to ask questions and obtain audio clips with spoken questions. In the video domain, we see a world where a wildlife documentary could replace the dull sky in a shot with a more interesting one. Whenever such

AI models may be used, we as an industry must thoroughly bake in the necessary design and user experience choices to manage harmful uses upfront. Finally, in some highly sensitive cases, the AI model responsible for producing the content may be supplemented with newer, more advanced quality control AI systems that can fundamentally examine the quality and characteristics of the content to search for anomalies.

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Chapter 6

OPTIMIZING DATA MANAGEMENT AND ANALYTICS IN AI-DRIVEN CLOUD ENVIRONMENTS

6.1. Introduction

The next data economy will require the evolution of new solutions and approaches that support data in the cloud—where it is collected when there. The management of remote data, especially unappropriated data or unknown data arriving at the cloud, is quickly becoming a core facet of artificial intelligence (AI) applications, yet it remains a largely untackled problem and an excellent research opportunity. While traditional data management and movement challenges continue to be essential problems for IT, AI solutions often come with additional requirements relating to data context, protection, timeliness, domains, ethics, and privacy that are not contained nor addressed in regular deployments.

Incorporating support for data context, provenance, and regulatory and enterprise policies can lead to the necessary forensically verifiable explainability for enterprise decision-makers to embrace AI. Capabilities that ensure the applicability of domain metrics and bounds, as well as methods that limit the inadvertent manipulation of data used during training or applied during inference, can ensure the reliability of AI solutions. Addressing data ethics and privacy concerns with the appropriate policy and analytics can build trust commensurate with the sensitivities, confidence intervals, and challenges introduced by the patterns extracted by AI to work on enterprise-grade data across divisions - breaking down silos, opening up data to the enterprise, and desensitizing data within the applications, such that solutions are generally good for the whole.

6.1.1. Background and Significance

The ability to programmatically index and search through massive datasets using cloud-hosted services that leverage powerful AI algorithms to deliver more effective search and discovery experiences has become a business necessity across many domains. Cloud-based services, like Microsoft Azure Cognitive Search and Google's Natural Language API, are increasingly popular with organizations hosting their data in these clouds because of the unique capabilities and scale they offer. However, the management of the data and the selection of the specific AI algorithms can impact both the cost and performance of those experiences. Consequently, many organizations are now asking themselves not only what data capabilities they need but also how to host, manage, and leverage that data without making costly architectural mistakes.

Restrictions and limitations on the physical or cloud environments mean the effective leveraging of cloud-based services in the search discovery problem space is not always straightforward and involves trade-offs between the CLI, GUI, and programmatic use, in terms of flexibility, performance, cost, and ease of use. The capabilities required by the organization's search and discovery problems may also be a factor in decisions around the use of a cloud service, with the impact of these decisions being understood in terms of changes in required data model size, entity structure, available query operators, and other possible restrictions, as well as the AI services, size, and quality of data for their training and use, the performance of solutions that use those services, and the cost that it takes to achieve them.

Fig 6 .1 : AI-Driven Cloud Management

6.1.2. Research Objectives and Scope

Data management and further analytics processing in conjunction with data governance control remain substantial burdens for AI-driven cloud infrastructures. This study contributes to addressing data management and analytics processing issues in AI-driven cloud environments. The study builds around the AI-driven cloud governance model to develop a cloud analytics optimization model. The optimization model allocates data governance embedded in SaC approaches and AI-driven cloud data analytics services. It facilitates managed and secured data utilization across AI-driven data processing states.

The optimization model is designed to optimize cloud big data analytics services embedding SaC-enhanced data governance metadata. The development aims to optimize data management techniques that facilitate and fasten data-related problems in AI-driven cloud environments. The study offers new practicalities to businesses in their attempt to derive management insight from their cloud data applications such as customer sentiments, preferences, and career development. Organizations enabling such insights can benefit from competitive advantages such as forecasting, mitigating risks, predicting product demands, controlling sales, profit generation, cost reduction, risk detection, fraud management, plus other societal-based support optimized by the quality of the outcomes.

6.2. Foundations of Data Management in AI-Driven Cloud Environments

To effectively accommodate AI-driven workloads, all layers in the cloud infrastructure stack need to be optimized for data processing. Figure 1 illustrates the hierarchical taxonomy of data access and interface/control paradigms involved in data processing. Many user requests can be satisfied with simple data access operations because the mixed designs treat both the state store and the VM host (or a compute node) as a monolithic design and directly call the data manager running on the VM host. However, handling simple data access requests in this way aggravates the compute-to-I/O affinity problem and causes congestion at the gap between the accelerator and the mixed chip. We propose a microservice-based accelerator-interface design that uses RDMA-over-converged Ethernet (RoCE) offload on the accelerator side to offload simple data access tasks from the state store by introducing a dispersive function.

To enable multi-tenancy without compromising the performance, the VM partnership address translation is embedded. The address translation does not introduce memory access

serialization in most cases and has low latency overhead. Slave VMs are connected to a switch in a leaf-spine topology using a PCI Switch and each Slave VM has allocated slice capabilities for direct communication between the Virtual Network Interface Card (NIC) and the FPGA over a specific frequency range. When data management services are integrated into the FPGA, the FPGA can also take on some responsibilities for these tasks, reducing the burden on the CPU and potentially accelerating data access. In particular, data movement between the host memory and the local memory of an accelerator can be optimized using a piece of user-space software, called DSX, which stands for Data Service Extensions. DSX allows the CPU to bypass the kernel and copy data between the host memory and on-chip memory.

6.2.1. Key Concepts and Terminologies

To have a clearer understanding of the optimization problems associated with data management and analytics in cloud environments whose operation is driven by cloud IT systems supported by AI technologies, several key related terminologies, and concepts must first be introduced.

Knowledge Cloud: A knowledge cloud is formed by integrating web mining, web personalization, and cloud computing to allow the sharing of resources and knowledge in the cloud. Knowledge clouds can solve the demanding problems of big data processing and analysis and deliver big data analytics services. They use cloud-based business intelligence to answer questions about customers, products, and opportunities. The services must be able to extract deep knowledge from raw big data to understand customer behavior and needs. In general, the knowledge cloud is a concept in the cloud computing application domain. Cloud-based business intelligence (BI) services process and analyze big data are demanded. With the help of big data analytics, business intelligence can offer better decisions, business processes, and customer service. However, cloud-based business intelligence services are not equal. Different BI services have made different contributions and constantly have different data analysis performances.

Knowledge Service: A knowledge service is a type of service performed by applying an AI solution provided by a cloud system to a specific and concrete business or scientific problem. It carries out a specific business or scientific problem-solving process defined by the AI service, from its input information and samples of the problem to the output solution and its adaptation to the problem mechanization model. In particular, it embodies the AI agent's

policy on how to manage the learning process, as well as when and in what way to explore and exploit the problem solution space at the level of the information for the databases that contain the solutions to be discovered and explored.

6.2.2. Challenges and Opportunities

Focus on at-scale AI/ML projects illustrates several challenges and opportunities in data management for AI in cloud environments. Among the challenges are scarce and often over-provisioned infrastructure, fast turnover on massive amounts of short-lived jobs, significant development costs, and fragile 'zig-zig' paths from data access to model deployment. Getting insights into and understanding the behavior of AI models, identifying and managing potentially sensitive data, ensuring compliance with policies for regulatory, security, privacy, fairness, and export control reasons, and disconnected development practices right now with application development and data pipelining managed in a data engineering context while model development, training, and infrastructure are typically managed by machine learning engineers. There is enormous potential to use mature, but under-utilized, practices from data engineering more decisively and earlier in the lifecycle of AI/ML projects. These practices are driving several opportunities for data management innovations, bringing them from the data-wrangling periphery of AI/ML to its mainstream.

The study of a sentinel AI project from the perspective of slicing through both data engineering and machine learning provides two streams of narrow, principled focused lifecycle exercises with a project-level view. Tension evaluation defines several general, AI-at-scale checkpoints that specifically value engineered AI work products to avoid common yet extraordinarily costly 'zig-zig' practices. The first one contributes partitions and their internal balance and shape for a specific purpose - model deployment, and the second looks at how to expose AI/ML practices and data flows as coherent data engineering pipelines directly in support of established data definitions and lineage tracking. The two threads join in discussing the recommendations for widening the role of engineering practices for crossing the divide between the long software lifecycle and the transitory data and model management phases of at-scale AI/ML projects. Let us consider an analytics service on a big data platform as a microservice as a notional example of big data analytics development. An organizational use case gives an overview of the big data capabilities of a design or implementation and serves as an entry point to discovery and development.

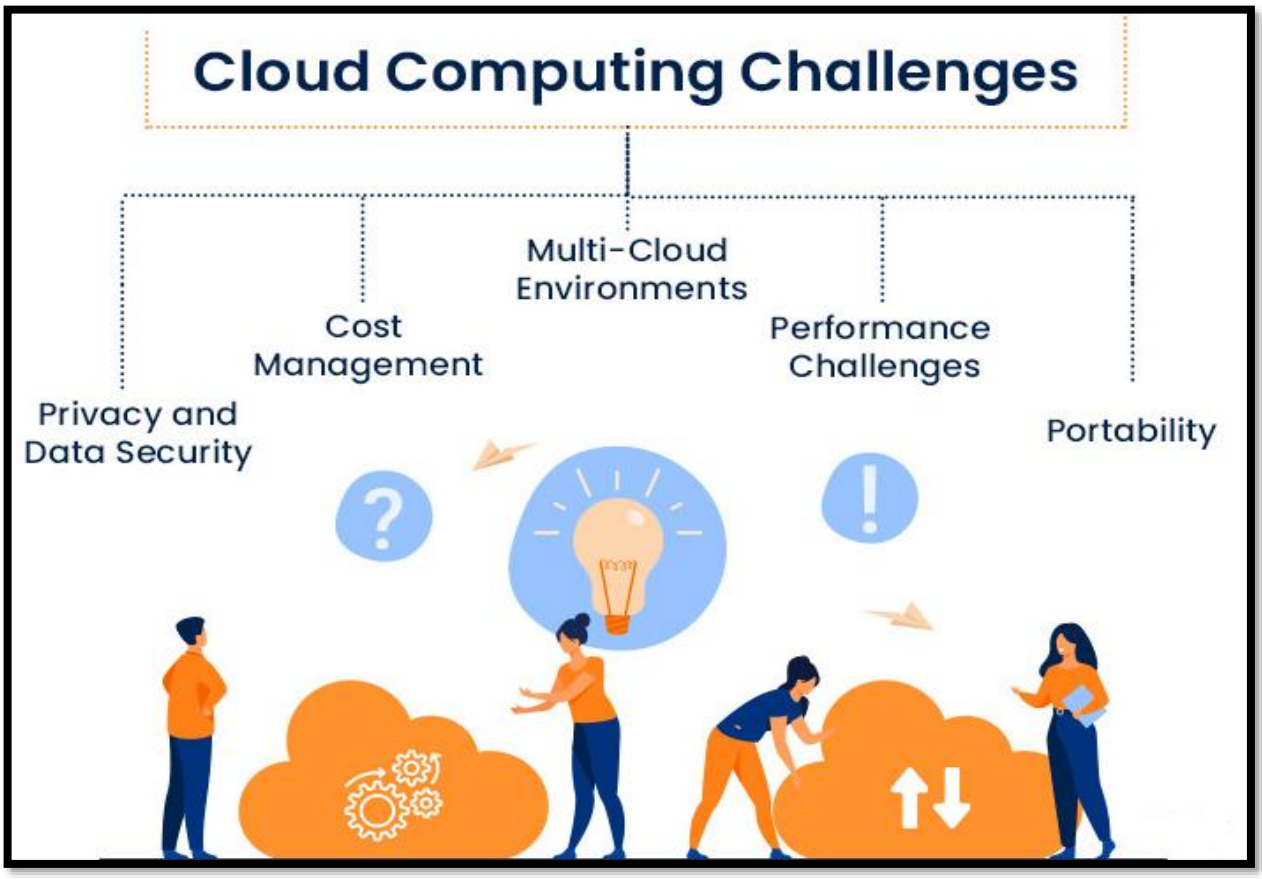

Fig 6 . 2 : Cloud Computing Challenges

6.3. Optimization Techniques in Data Management

Cloud computing has been known as an effective solution for providing various cloud services to end users via the Internet. Such services have been implemented based on shared data, and managing the data is a critical issue in cloud environments. In addition, AI software packages are widely available and are leveraged automatically so that users can perform their data analysis.

This research focuses on AI-driven cloud services where the data management issue of massively increasing structured, semi-structured, and unstructured data in AI-driven cloud services is explored. The primary contributions are the adaptation and embedding of AI software into a cloud-based data platform that can automatically perform data analysis from scratch. Another important contribution of this work is the effective integration of structured, semi-structured, and unstructured data in AI-driven cloud environments.

AI projects are adopted with a partial cloud services architecture because the AI services architecture is "ready to use." Traditionally, AI backends have not been prepared and executed separately. Furthermore, there is a large pool of diverse software that can be incorporated or utilized, and there has been no defined architecture applicable to developing these projects.

Data sources in real-world AI-driven projects are in various formats. Structured data is organized in rows and columns, accounting for data created nowadays through software. Unstructured data is designed to store data consisting of public and proprietary, or other types, text, and numbers. Audio, video, geographical information, e-commerce, social networks, and transactions are just a few examples of businesses "using" unstructured data and proprietary data. NoSQL is designed to access this type of data, and companies attempt to use this data to rapidly gain business insights. Semi-structured data is designed to store text-based web pages. In the real world, "we" must fetch public data and perform various activities. Data Lakes, NoSQL, Big Data, and Hadoop are just a few examples of tools available to store and extract insights.

6.3.1. Data Storage and Retrieval Optimization

Data management is key to AI-driven cloud deployments and typically involves a trade-off between the speed and cost of operations. In many AI cloud solutions, these concerns revolve around data storage and retrieval, as data may need to be migrated between different storage media based on the speed requirements of machine learning or analytics tasks. The implications range from the architecture of the AI system and the operational definition of machine learning models to data center architecture and the efficient use of various storage media, as well as the optimization of analytics processes and decision support tasks. In many cases, this trade-off must take into consideration the communication and processing costs of moving data between different storage media in cloud-like infrastructure where a typical big data analytics process involves training and executing machine learning tasks on data in external storage either sequentially or concurrently with the data moves.

We have introduced a broad range of data management techniques, which involve business and application logic encapsulation, and facilitating data migration, execution ordering, and controlled and/or burdened task migration. The techniques have evolved into blockchain-oriented event-driven data management and analytics frameworks for

infrastructure resource usage inventory and management, cloud resource audibility, accountability, and incentivization. It is important to discuss the data management problems induced by the task-based event-driven execution paradigm, the related mitigation approaches, and our ongoing development on event-driven analytics optimization.

6.3.2. Data Preprocessing and Cleaning Techniques

Data pre-processing techniques aim to transform the raw data into a standardized format to remove or reduce inconsistencies and correct invalid values. Typical steps during data preprocessing include cleaning, normalization, and transformation of data into the correct format for the model used. It is an essential stage in data analysis and mining in real-world commercial, scientific, and security applications. Data preprocessing is also required to improve the quality of experimental outcomes and their reliability.

Cleaning techniques in machine learning can improve the quality of the analysis and prediction results. Traditional techniques include quantitative data techniques or embedded ones such as a bag of words or TF-IDF for text data. Basic whitening techniques such as stemming, lemmatization, stop-word removal, etc. can be used in documents. To clean numerical data and missing values for traditional methods, we can use various fill-in techniques: fill-in mean, fill-in median, fill-in mode, or fill-in with the default values of the data from other observations.

Feature scaling can also be used to scale the attributes so that their values range from 0 to 1 or from -1 to 1 respectively. More sophisticated methods such as filling in the mode for categorical data and hot encoding can be used to fill in missing values in categorical data. These are followed by non-parametric methods such as kNNs. By right-censoring non-parametric models, we can process time-series data. For anomaly detection, simple methods include dropping posts and replacing them with default values to avoid predicting the outputs made by such software.

Different scaling methods include normalization, z-score standardization, and robust scaling. Quantile-based discretization can be used. Different scaling methods such as taking the logarithm, arcsine, power transformation, and Box-Cox transformation can be known as transforming certain types of features. Data with multiple types of media, such as medicine,

retail/finance, or other fields where entities such as molecules, x-rays, etc., can be represented with numerical/numerical images, may require conversions.

Grouped data may result if separate data tables are cleaned one by one, or if dirty data entered into shared variables can be found and either summarized or cleaned using models to learn imputed values. Different types of data, such as text, numerical values, and images, are commonly used in mixed data. After the raw data are collected, we can perform article reduction. Initially, if feasible, do what you can learn locally from a smaller dataset or subset of data with cleaner or already pre-labeled data. Small-scale machine learning application development and simple models are among the other methods. The latter can also help visualize feature abnegation in the transformers discussed.

Tempering the extraction or cleaning of data may include all groups 19% of the effort, statistically significant data models and feature relevance 33% or standards pipeline, testing, and validations 27%. When considering full-scope research or applications as project management strategies, paper scale ranges from small to medium and medium to large while also ramping on different tickets. Data preprocessing procedures include data aggregation, the creation of derived and labeled data, and a basic distribution from the data.

6.4. Advanced Analytics in AI-Driven Cloud Environments

AI-cloud environments are the most natural environments for implementing machine learning and advanced analytics models. Cloud itself is capable of consolidating large amounts of data from different sources, mainly the Internet of Things (IoT) and social media. This data is later transformed and used for advanced data analysis using machine learning techniques, deep learning, or business analytics. Some organizations focus intensively on the use of unstructured data such as text data and big data. Using big data tools such as Hadoop and Spark, they can obtain value from real-time extracted text, social media, and different content available in open sources such as online news or forums. Thus, they can develop models that could be used to monitor and predict future events, extract insights, and improve existing activities.

In this chapter, we focus on the application of cloud and AI services that are used for the development and deployment of machine learning models on data that is part of a cloud environment for developers, data scientists, and business experts. We describe the differences

between applying machine learning in non-AI cloud platforms and machine learning capabilities that belong to AI-driven cloud environments. Furthermore, we present best practices for the development, training, deployment, and monitoring of machine learning models developed by ten well-known BPMAML platforms. Finally, we discuss advanced AI resources such as deep learning, generalization models such as Watson OpenScale, trust and faith, AI tools for analyzing quality and reducing bias, and tools for explainability.

6.4.1. Machine Learning Algorithms and Models

In the previous section, we addressed the concept of machine learning and its coupling with cloud computing – more of a 'why' approach. In this following section, we are discussing how machine learning is implemented in actual cloud environments – more of a 'how' approach. We go through the basic analysis first and then delve more into the details in section 4.2.

In almost all of the ML workloads, training is the main job because of the tough and intricate model structures' demands involving vast data sets. Current clouds have an impressive set of characteristics (e.g., elasticity, scalability, integration of computing and storage). Nevertheless, traditional machine learning libraries such as TensorFlow and Torch were not created for Hadoop, Spark, or any other clouds to naturally integrate working in distributed computing environments with the employed ML/DL. As a result, cloud engineers and data scientists have been asking for these libraries to be extended to enable shared use of these clusters more easily such that they don't have to become distributed computing experts to manage the cloud resources effectively.

How do we convert the locally written Python model of 100 lines into a parallel model potentially utilizing thousands of machines? One way is to just use Map Reduce mechanisms like other data systems before MPI for parallel machine learning. However, this is hard because the Map Reduce model discretizes every computation into running two separate programs, which often involves substantial data flow between them. Additionally, many other machine learning systems become challenged by contemporary deep learning demands. Non-parallelizable, sequential model components may have several layers of inductive bias and no concept of communication delays between machines.

Making different kinds of model components is another way of doing distributed ML. For example, HOGWILD! takes several computers and data-parallelism gradient descent breaking up the data into smaller parts and effectively omitting the role of iteration communication. This is a great technique for huge, dynamically changing data sets since the model changes according to what is observed at the same time.

6.4.2. Real-time Data Processing

Designing AI-driven cloud applications for real-time data processing requires careful attention to the associated data management infrastructure. Cloud-based database as a service (DBaaS) offerings must be used to meet real-time application requirements. Cloud database queries can be accelerated using database indexing and serverless computing features to meet real-time data processing needs. In addition, data processing techniques such as in-line query processing and approximate item counting can be performed to support large-scale real-time data processing.

Real-time data processing is a critical requirement for many first-generation AI-driven cloud applications. Examples include news summarization, instant response systems for package delivery, live social media tracking, and modern intelligent virtual assistants. To support such real-time applications, large-scale cloud systems have been deployed that rely on big data processing frameworks such as Apache Hadoop and Apache Spark. Despite their scalability, such systems cannot deliver truly real-time performance due to their latency properties. Hence, for large data streams, real-time processing requirements for live and interactive analytics are not easy, and corresponding live processing is known to be orders of magnitude more difficult than batch processing.

6.5. Case Studies and Applications

5.1. Data management in industrial AI-cloud environments In the following, we present two in-depth case studies of dataflow-based platforms for data management in industrial AI-cloud environments. These case studies are described similarly and provide an overview of the motivation for the case and the specific requirements to consider. We also provide a classification of relevant cloud environments and detail the industrial AI workloads our case studies should consider. Then, we outline the Spark-based implementation used for these case studies. We conclude each case study with a summary.

5.2. Dataflow-based data management in cloud HPC for scientific workloads The High Energy Physics (HEP) community decided to adopt computing networks through high-speed optical fibers as the foundation on which to build new, leading-edge experimental facilities, and to exploit computing technology to revolutionize scientific progress openly and transparently. The need for scaling compute and storage resources has driven these environments to the cloud paradigm to explore distributed, dynamic, non-dedicated, and virtualized solutions. However, this scientific community faces big challenges when adopting cloud infrastructures: workloads are very heterogeneously parallelized, readiness to process data is inversely proportional to the size and popularity of the data, vast amounts of data need to be managed and securely stored, and high-performance networks on which to ship workload and data at will are lacking, due to security and performance issues.

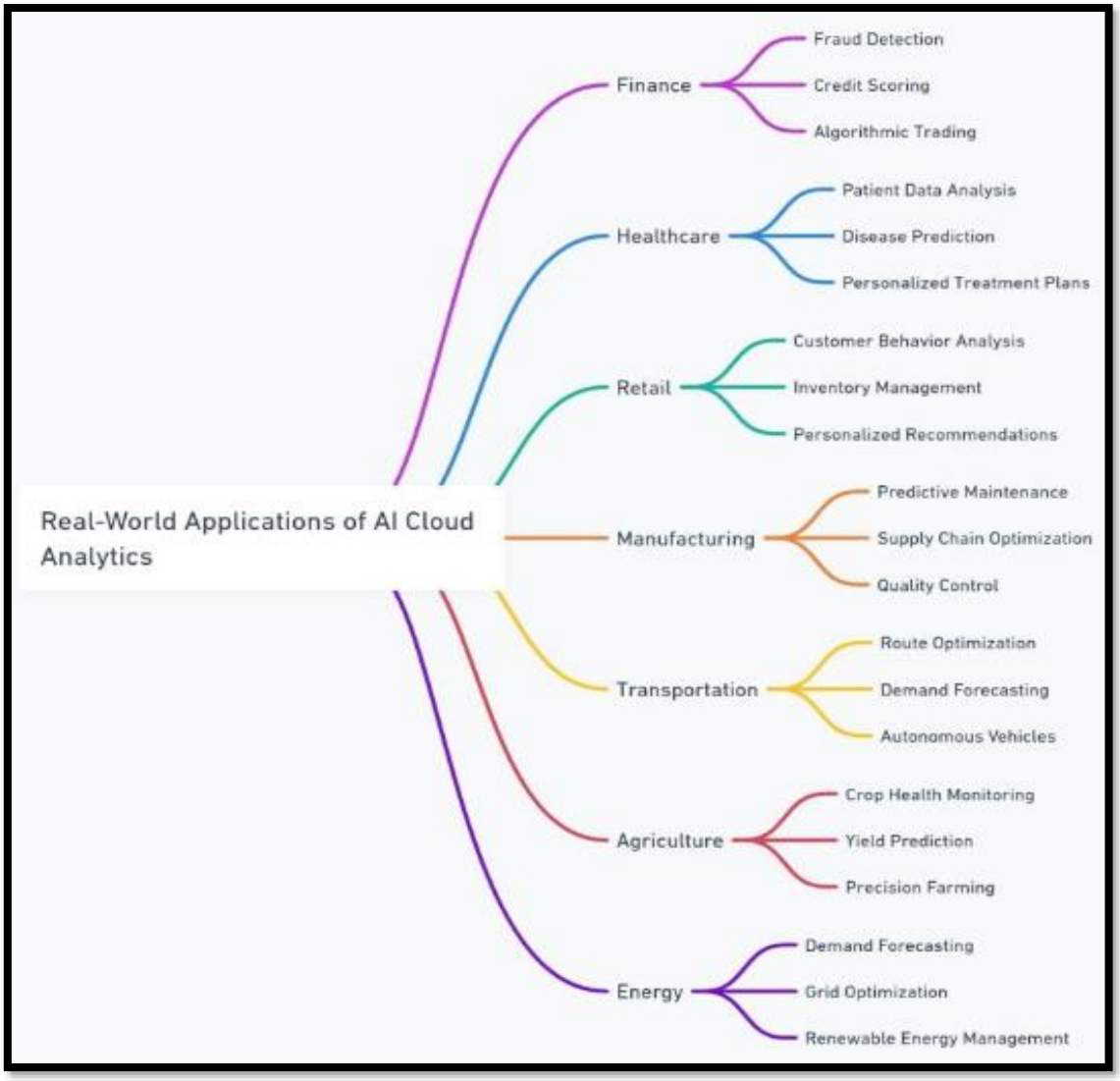

Fig 6 . 3 : Real - World Applications of AI Cloud Analytics

6.5.1. Industry Applications

Predictive traffic management and cloud-enabled intelligent transportation systems support routing decisions and improve driver and passenger experiences. These approaches leverage global, regional, local, and hyper-local traffic data such as traffic patterns, congestion, safety, and parking. The end-to-end data infrastructure supports data acquisition, movement, storage, and analytics using vehicular and IoT sensors, cameras, GPS, and other data sources. Several traffic data analytics applications have already been developed, targeting urban areas or particular cities (local management). Cloud-based traffic management technologies also involve data transfer in a microservice-based architecture from the edge (vehicles and other IoT devices far from aggregation points) to the cloud data processing pipeline, which will eventually help drivers make tactical, operational, and strategic routing decisions.

Trend analysis and forecasting applications examine infrastructure performance based on telemetry data, track and trace performance data, transport service performance data, and weather data, collecting and visualizing these data through the cloud, and analyzing them using machine learning. In macro operations, users can observe global information such as the seasonality of infrastructure or delays occurring in certain geographical areas, as well as the frequency of vehicle and passenger participation in services through cloud and big data predictive and diagnostic analysis. Data infrastructure is used for continuous health monitoring to provide centralized analysis, diagnostics, condition assessments, trend predictions, and performance enhancements for infrastructures such as superstructures, power cables, supports (poles and brackets), and other critical systems. Due to the uniqueness and structural uncertainty of these complex structures, safety inspection and monitoring of bridges also require big data management infrastructure (a combination of edge and cloud computing) that can obtain high volume and high variety data from multiple sources (cameras, sensors, GPS, videos, etc.), to perform various types of analysis using machine learning to predict failure and prevent accidents. Data ingestion and processing should be provided with cloud services and an analytics frontend that addresses streaming and big data by effectively managing massive bridge-related data.

6.5.2. Research Case Studies

In recent years, a growing number of research institutions have started to leverage large-scale public and private clouds to deploy their distributed data processing and deep

learning-based AI pipelines. One of the main reasons for choosing commercial clouds is their strong infrastructure for handling big data and securing GPU-accelerated VMs where most of the popular DNN frameworks can run, including TensorFlow and PyTorch. Additionally, using public clouds for deployments of AI services helps researchers achieve better scalability and availability by using a global network of green data centers across the world. Besides AI researchers, there is a broader interest in how to cost-efficiently deploy BigData platforms that can be used to structure, store, and process large datasets that are provided as dumps by today's scientific collaborations and collaborative projects. These datasets can be quite diverse and include structured data like RDBMS dumps, JSON, or NoSQL databases; unstructured data like log files; and semi-structured data like content and metadata from files.

For this purpose, some projects are pushing the limits of big data technologies by designing and implementing multi-cloud and multi-region data management architectures that allow for efficient and secure data access and processing. These researchers are taking advantage of big data and data-intensive services offered by commercial clouds like Amazon Web Services, Google Cloud Platform, and Microsoft Azure. In particular, the chosen combination of cloud services is optimized concerning AI Accelerated Analytics and Curation Workflow activity requirements. This work describes such case studies, presenting three research cases of medical physics relevance where the research community adopted multi-cloud and multi-region data management architectures for efficiently deploying their AI and big-data pipelines.

6.6. Conclusion

Emerging distributed cloud and edge computing paradigms emphasize autonomous and adaptive decision-making processes driven by massive decentralized data processed at the edge of the network. These autonomous systems are powered by AI and machine/deep learning techniques that rely on big data flowing through the network in clouds and clusters of edge data centers. Processing of big data using techniques such as data refining, data enrichment, data synthesis, data transformation, data analytics, and predictions requires unique big data management and analytics capabilities. These capabilities are influenced by a range of factors including system/infrastructure design, resources (e.g., CPU, GPU, network), energy and power constraints, data transmission bottlenecks, embeddedness in distributed systems, and latency constraints. The interplay among these challenges gives rise to complex system behavior shaped by the storage, processing, and communications capabilities.

This paper explored in depth these challenges not from the viewpoint of the underlying data management and analytics requirements and needs, but in the context of enabling the key technologies and driving computational paradigms of emerging autonomous systems anchored on AI and machine/deep learning techniques. Moreover, it provided clear, concise examples from the latest research that illustrated the intricate web of connections among these domains and the concrete challenges that practitioners face. Viewing big data management and analytics within the broader purview of creative AI-driven autonomous systems seems to be a novel approach worth further exploration. Indeed, it can open up new, untapped, and immediate opportunities for collaborations among diverse communities including data scientists and management experts, computing systems architects, domain-specific task stakeholders, and system management and operations practitioners in cloud and edge data centers.

6.6.1. Future Trends and Directions

The rapid advancements in technology have been a prime driver in breakthroughs in AI-driven research and solutions in almost every industry. Nevertheless, it is also the same base technology and associated novelty that continue to make our future more unpredictable. In this regard, there are still several open and significant problems in AI research related to data distribution, requirements, management, and ethics that need to be addressed concretely albeit with the future in mind. A subset of these problems is discussed next and forms a shortlist of general AI research challenges. The synergy of AI research with data, as identified in this work, is also discussed further. These are all areas that need to be addressed when allowing future AI systems to operate independently in increasingly automated processes in cloud data centers and other mission-critical and high-risk environments such as health and the environment.

There are several future trends and directions of ongoing and future research on AI itself and on topics associated with data that prompted and followed this consolidation work. These trends explore and expand research into open and broader topics, which include data-specific ethics in AI, explainable AI, self-supervised learning, meta-learning, and continual or lifelong learning. Key data management and data privacy issues related to larger, multimodal, and long-range or historical AI models and data. Relationships with currently popular open-source cloud and hardware ecosystems like Kubernetes and Facebook PyTorch, and frontier topics, including human/GPU collaboration policies, optimizing the utilitarian intuitions in

data-driven AI, and quantum data for AI. All of these topics revolve around AI and how it makes use of data to present decisions, to support newly developed AI models, and to support other AI training and generating purposes.

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Chapter 7

SECURING CLOUD INFRASTRUCTURE: AI AND ML-DRIVEN SECURITY SOLUTIONS

7.1. Introduction

This paper concerns securing cloud infrastructure by leveraging artificial intelligence (AI) and machine learning (ML)--driven security solutions. AI and ML mechanisms are the most viable cybersecurity tools in today's threat landscape for several reasons. This paper holds significance to cloud service providers, industry, and researchers. By deploying AI- and ML-based tools, security operation centers (SOCs) in any organization can ensure comprehensive coverage for advanced security components that would offer robust protection from the cyber snares and man traps, transforming their current cloud security portfolio. In the initial stages, this paper aims to explore and produce clarity on the elementary security services, cloud computing and deployment models, common cloud computing threats and vulnerabilities, and effective cloud security solutions. The paper then aims to lay a foundation for future work in terms of securing cloud infrastructure.

In the upcoming sections, we first elucidate the elementary cloud computing services model and cloud computing deployment models. Section III further discusses a few primary and vital cloud security concerns relevant in the modern era that one must consider before authorizing data transmission, storage, or sharing in a cloud ecosystem. We also delve into effective cloud security solutions to tackle those security constraints. In line with the indistinct and ambiguous studies and specifics available relating to securing cloud environments using AI- and ML-driven security measures, this research piece is designed to initiate a point of discussion and work to intensify research coverage shortly.

7.1.1. Background and Significance

Introduction Elaboration

Thesis: Despite its significance, data in the cloud remains at risk as malicious attackers continue to develop advanced security attack mechanisms. Consequently, organizations must employ advanced security techniques to secure their cloud-based infrastructure and data. Securing cloud infrastructure is of primary concern for cloud services consumers and providers. With the prevalence of data storage and sharing mechanisms, data is moved to the cloud with much dependence. Statistics suggest that there has been a considerable shift in data storage trends over a decade, from 1% in 2006 to 22% in 2017. Data is frequently moved to the cloud due to the ability to access huge data repositories on an "as and when" basis. However, four threats or vulnerabilities (as shown in Fig. 1) are introduced via the cloud-based systems, which pose substantial concern toward security breaches. The threats are discussed as follows:

Malicious Insider Threat: Employees, workers, or administrators who intentionally misuse organizational data are called insiders. The Insider Threat Report presented by Intelliagg in early 2010 stated that around 82% of all losses about compromised data are the result of malicious insider attacks. suggested that the mishandling of data by employees that violates organizational policy also belongs to the concept of a malicious insider, and IT professionals particularly pose a significant risk.

Advanced Persistent Malware: This term is defined as a set of stealthy and continuous malware attacks in which, once an attacker can gain full systems access, they continue to infiltrate the target systems repeatedly for a long duration without being detected. Insider threats not only employ advanced persistent malware but also write malicious software that attacks and/or disables network protection. Insider threats are potentially more dangerous since typical security defense mechanisms fail to detect and mitigate the threats, as employees or authorized users may have valid profiles.

7.1.2. Research Objectives

Computer security in the cloud paradigm has gained much attention from the research community because of several dispersed and rapid evolutions in technology. This has led the existing monolithic security systems to decrease the effectiveness in cloud platforms due to

resource limitation, deployment and optimization delay for volumetric traffic, security context redundancy of policy enforcement, etc. Cloud resources are accessed over the Internet; hence they are susceptible to vulnerabilities, unauthorized access, and hacking. Keeping the detrimental effect in view, security in cloud computing is of main concern.

The security process encapsulates all the applications and services deployed on the cloud, which is a complex research area. The recent trends and evolutions in the technologies necessitate that the cloud infrastructure demands more intelligent systems such as artificial intelligence (AI) and machine learning (ML). They are capable of gaining the knowledge to protect the cloud infrastructure. While AI and ML have the potential to enhance cloud security, challenges also exist. The following are the proposed objectives of the research study: 1. To explore the efficacy of AI and ML in enhancing cloud security, illustrating its potential and possible challenges. 2. To investigate and summarize various challenges of securing cloud infrastructure. 3. To propose an architecture for securing cloud infrastructure using AI and ML-driven solutions.

7.1.3. Structure of the Paper

The paper is organized in the following manner: Section 1 covers a comprehensive introduction. In this paper, the authors initially presented a thorough introduction outlining various approaches to securing cloud infrastructure and delineating the differences among infrastructure, application, and data security. All aspects directly related to secure cloud infrastructure from bug bounty programs to various methods for creating new data and content have been discussed. Moreover, various applications based on ML & AI for data, application, and container security, monitoring, and incident response have been discussed. Towards the end, three case studies have been presented for thwarting ransomware, managing mobile application risk, and malicious query prediction in a NoSQL database. The authors then highlighted two generic Cloud threat scenarios, namely the security of container orchestration systems and VM-level attacks. To mitigate these threats, they proposed two countermeasures and provided the arguments on those countermeasures. Furthermore, the authors provided automation to gather incident response forensics related to this component/system. The complete workflow scenario of their approach is presented and authors have evaluated performance and performance analysis against the existing approach.

Section 2 of the paper discusses the need to secure Cloud infrastructure. Section 2.1 discusses the different approaches to cloud data security. Section 2.2 discusses Infrastructure Security, Application Security, and Data Security. Section 2.3 provides an in-depth look at securing cloud infrastructure. Furthermore, this paper has delineated solutions and recommendations for the App, Container, Infrastructure, Data, and Defensive Proactive layers of the cloud stack. The Cloud environment consists of several matrices at various scales (e.g. Data, Storage, Network, Execution, Workload, and IoT). Each cell in some of these matrices is vulnerable to some sort of attack irrespective of the complexity of the protocol governing it. In this paper, the author compared and classified the existing applications based on ML & AI in a ground-working manner. Moreover, some of the deployed systems for defending infrastructures are presented. In addition, the existing attack models and scenarios are compared in a run-time manner. Both known and emerging threats and threats' countermeasures and incident response analysis are included in this paper. In Table 5, Sec. 9, some enrollments of IBM, Kaspersky, Deloitte, etc. are presented to show their contribution to securing cloud infrastructures. The contributions made by the paper are listed as well.

7.2. Fundamentals of Cloud Computing and Security

In this era of information and communications technology (ICT) evolution, cloud computing has unquestionably become one of the most discussed phenomena. Cloud computing is a network of remote servers hosted on the internet as centralized services. To deliver maximum availability and reduced risk, users may access and process large chunks of data over the cloud. Although agility and flexibility remain the cloud's most desirable qualities, there is a need to improve technological security properties to forestall any misdirection of data and ensure that unauthorized persons stay off the network. According to companies and concerns, avoiding such standards may detract from profits, customer loyalty, and domain reputation. Some of the most crucial matters for cloud computing are discussed in this section, which is organized for the benefit of those who want to learn more about cloud computing environments.

Cloud computing is experiencing rapid growth thanks to its flexibility, low maintenance, advanced storage, and automatic software integration. Virtualization, one of the many technologies involved in cloud computing, conveys a system's actual capabilities without exposing the underlying hardware to users. As users are enticed by the cloud's various advantages, the complexity of securing the cloud infrastructure grows, as do the risks linked

with it. Unauthorized access security measures must protect this network, which is prone to attacks and threats. Guarding this web is a perplexing process for an organization employing traditional network security methods; as a result, new security trends, solutions, or technology are urgently needed. In this section, one of the newest technological solutions — artificial intelligence (AI) and machine learning (ML) security — is investigated in depth to present a clearer view of cloud infrastructure security.

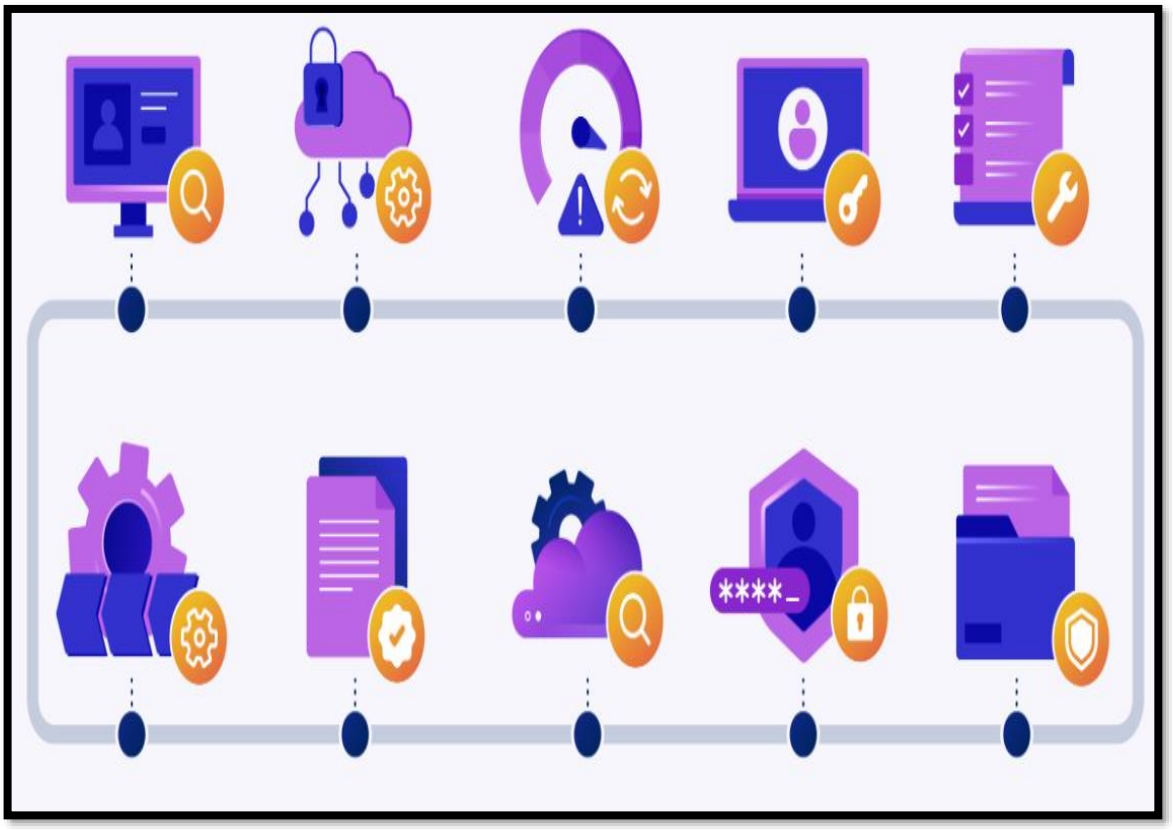

Fig 7 . 1 : Cloud Security Fundamentals

7.2.1. Cloud Computing Basics

As opposed to traditional data security systems, AI and ML-driven security and response systems are implemented on cloud infrastructure, offering reliable, scalable, and available resources and data. The advancements in infrastructure as a service (IaaS) technology enabled the integration of AI and ML-driven security systems on cloud platforms. All sorts of security and privacy concerns of AI and ML can be tackled with the already existing security solutions based on the characteristics of cloud computing. The state of the art

and the use of ML-driven security solutions are further explored in sections 2.4 and 2.5 respectively.

Cloud computing came into existence in the 1990s as an improved version of traditional utility/grid computing. Being a customer or as a business, everyone has shifted to always-on and always-available services, which build on modern infrastructure. The modern infrastructure is provided as a cloud which is a large group of computers that are interconnected, which can run heavy-processing applications and have the ability to hold a large amount of data. Cloud computing is powered by two technologies: virtualization, such as technology helps in bringing the coordination between the network and systems which when combined is used as a medium of communication and can facilitate more resource utilization. Cloud stack is created by mixing hardware, virtual, network, operating system, and service layers. Therefore, the term cloud is typically used to represent the Internet or a large cloud environment that is represented by the Internet. Generally, cloud services are divided into three categories, namely Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS).

7.2.2. Security Challenges in Cloud Computing

Due to its open nature and increased attack surface, cloud computing opens up a multitude of challenges for the security posture of an organization. There is a rise in cloud security-related threats, including malware, unauthorized access, denial of service (DoS) attacks, data breaches, and cross-site scripting. These threats and attacks associated with cloud environments may lead to the compromise and leak of critical systems, loss of proprietary data, and undeniable financial loss from a damaged brand that comes with the loss of client trust. Many risks in cloud environments can be attributed to a combination of vulnerabilities, including misconfigurations, poor identity, credential and access management (ICAM) and privilege management, a lack of encryption, and insecure APIs. Limited visibility into cloud resources and what is occurring within those resources creates uncertainty and a burden on an organization's security and IT team.

When external organizations are utilized, organizations need to also account for the fact that potential threats and vulnerabilities can arise from external sources and have the potential to impact their own security postures and organizational resources. At the same time, enterprises are becoming more aware of insider threats that can sometimes pose a bigger risk

to an organization than external ones. The NFL cloud can span multiple users in multiple locations so this problem is amplified here. Countermeasures for the above attack vectors now need to provide the ability to assess the behavior of the users and not just the data in the cloud. Identifying a user who may be acting abnormally will be critical as they may be attempting to gain unauthorized access to the cloud.

7.3. AI and ML in Cybersecurity

AI empowers the development of the ever-increasing network and provides intelligent supervising abilities. Thanks to AI, cloud systems perceive security threats. However, AI in cybersecurity is emerging in the current era. We use an adaptive AI-based approach that paves the way for security, ensuring international cooperation for security manufacturing. AI security helper supports automated format on networking and data security options. The AI undergoes cloud appliances, like unmanned systems like firewalls and assault sensors. The help provided for associations often comes from crime collections, where models available for exploration appear to prevail as well. The corporation and security industries implement AI strategies like deep learning to oral SDN systems for handling the firewall. Abusive assaults on IoT devices may be eliminated by ML. Organ environmental observation tool that uses ML-heuristic network analytic networks to detect and easily separate malicious IoT devices.

Machine learning and artificial intelligence are technologies that transform internet and cloud security. People tend to see application systems improve their safety by using contemporary learning methods based on AI and cyber-networks. AI is directly affecting modern security. During the previous few decades, cyberattacks have been significantly more dispersed. We can track technologies powered by AI and ML replacing some of our earlier technology as a global leader in information technology security. The government of the United States of America carries out tasks operating AI and Machine learning inviting a good number of parts. These technologies are employed to augment numerous old cybersecurity technologies. Companies need to improve their innovative abilities to limit future attacks.

Fig 7 . 2 : AI and ML in Cybersecurity

7.3.1. Overview of AI and ML Technologies

Artificial intelligence (AI) and machine learning (ML) are two of the most talked-about technologies in today's digital era. To comprehend how ML and AI work, it is essential to understand the foundations of these concepts.

The basic objective of AI is to provide machines with human-like capabilities that have potentially unlimited capabilities, one of which is to adjust to new environments. ML, on the other hand, teaches machines to learn from their experience and progressively master their talents to carry out particular activities without being specifically programmed to do so.

Supervised, unsupervised, and reinforcement learning are the three fundamental algorithms that drive ML. Supervised learning is the process of teaching a machine learning model how to do something by demonstrating examples that illustrate the desired strategy. Unsupervised learning refers to training on data that does not have annotations or methods that enable the ML model to understand patterns in the data. Lastly, reinforcement learning is a

method of general artificial intelligence that instructs robots to do what they do in just a more ideal sense, utilizing reward-oriented learning systems.

ML and AI applications are endless, including the capacity to review networks of hospital data to predict a patient's chances of becoming seriously ill based on various cultural, genetic, and physical risk factors.

Synthetic intelligence and machine learning (AI/ML) are dominating the industry and markets in utility fulfillment today. The enterprise experts and policymakers who navigate this world need to know how these techniques work and what they borrow. Furthermore, it is paramount to comprehend how they can be developed and how to avoid instability if they are not implemented properly.

For example, the industry leader Hewlett-Packard (HP) made this announcement in October 2019, HP Cyber Security. Cloud infrastructure security aims to search for smart solutions that can handle each other's problems.

7.3.2. Applications of AI and ML in Cybersecurity

The capabilities of artificial intelligence (AI) and machine learning (ML) solutions are driving the evolution of cloud security today. As mentioned, ML technologies power solutions of anomaly detection, predictive analysis, and more that have an endless number of applications in the field of cloud security. In creating cybersecurity solutions, AI has traditionally been employed in various fields: here, the focus will be on practical applications.

The learning of patterns of normal system operation and detecting deviations from this pattern is a primary application of AI and ML technologies in cybersecurity. This is essential in providing an early warning of security breaches, thus acting as either a detection or mitigation process. The reason for this is that when a security breach is committed illegally through unwanted access to vulnerable assets, the action will be classified as an anomaly. Therefore, anomaly detection techniques are generally called "Intrusion Detection Systems" (IDS) and have two types of systems: "host-based systems" (on the host) and "network-based systems" (on the network level). A conceptual illustration of misuse versus anomaly-detection capabilities of AI-driven solutions is shown in Figure 1.

An interpretation output within the same concept (section 3.2). This includes spotting a new threat – perhaps from a previously unknown actor or organization – for which there was no history or signature. It also has a built-in risk minimization scheme embedded into its design: newly detected 'signatures' for known threats can either prompt the system owner to investigate further or flag security risks based on multiples of thresholds.

AI has also been applied heavily in attack prediction for cybersecurity infrastructure. Prediction is a system property and historically, AI solutions have leveraged this property, including clustering-based approaches. Here, new similar cases are allocated to the most appropriate clusters. In the case of cloud security, this translates to alerting users as to the kind of risk that their resource is susceptible to veering into. These workloads themselves can also be monitored, e.g. for policy and execution problems, correctness, strategy, or services in cloud-based execution of code. In particular, policy and execution problems occur when misconfigurations causing faults and vulnerabilities exist – often which are undetected by currently-used commercial tools, monitoring, and execution (such as logging, and monitoring dashboards).

7.4. Integration of AI and ML in Cloud Security

Given the challenges in cloud security as an integral part of digital transformation in organizations, the IT industry has seen an increase in investment and research in the area of AI and ML. Consequently, AI and ML have the potential to detect and respond to security threats, prevent unauthorized user data, secure cloud-based data in motion and at rest, and support actively reducing security risks, and costs, and facilitating regulatory compliance within cloud infrastructure. With practicality and usefulness, ML implements techniques, algorithms, and processes to analyze operations and behaviors from incoming, active, and existing data from machine learning models and apply the framework of AI for cloud security. Concerning the ground-breaking solutions and quantifiable challenges, AI improves on several known multiple security problems in cloud computing infrastructures and enables new research areas in the security of newer fog and edge computing platforms.

AI/ML can help in monitoring logging, identifying potential data loss threats and responses, and allowing action item recommendations to system administrators. It can recognize excessive data transfer to identify a potential case of fraud. ML can predict cloud computing resource requirements and allow system administrators to transfer cloud computing

jobs and hardware requirements when systems are near capacity. Similarly, AI and ML can be utilized for human behavioral data analysis, fraud detection, smarter route predictions for IoT networks, and energy-efficient monitoring and frequency control.

Challenges of integrating AI and ML with cloud computing include improved security and privacy challenges in cloud computing, potential device unavailability, cloud infrastructure failure or dislocation, large data volume, and longer time to train and develop multiple ML models.

7.4.1. Benefits and Challenges

4.1.1. Benefits

There are many potential benefits of AI and ML technologies in cloud security solutions, such as enhanced visibility and threat detection, faster incident response, and limited false positives. AI and ML algorithms, for instance, can quickly detect where and how certain cloud assets are used—particularly cloud-based services, apps, and APIs—across SD, IaaS, and PaaS environments. This is especially useful in multilayered cloud environments, where organizations often use disparate cloud services and assets over time.

In addition to providing better visibility, AI and ML applications provide more nuanced threat detection compared to traditional heuristic-based monitoring tools. AI and ML algorithms finely learn norms and patterns of network behavior at scale to separate harmful activities from normal and harmless ones.

The same underlying behavior analytics used for threat detection can also help in rapid incident response. By employing AI and ML, security tools can profile specific traits of anomalous behavior at scale for quick trends and details. This kind of incident forensics can be especially helpful for critical redeployments or evolutions of app workloads in a multilayered cloud environment. Additionally, the same AI and ML models used in anomaly detection can be trained to sift through vast amounts of complex cloud security data to help reduce the overhead associated with false positives. In short, AI and ML models can cut down on alert fatigue and rally around scarce cyber-analyst attention centers. These attractive muscular advantages can be weakened heavily by overhyped and confused expectations of easy advancements with AI and ML in security.

4.1.2. Challenges

Excessive performance expectations of AI and ML-driven solutions and hidden operational shortcomings of security products serve as dual-edged challenges for the technology. The exuberance often distracts from the fact that security data scarcity (of meaningful data that is necessary for AI/ML models to refine) and the policies, procedures, processes, and people in staff operation simply overrule the technology. This leads to AI and ML not being enough to take hold and do the job we first ask them to do. AI- and ML-driven cloud security solutions require enormous volumes of log and event data to train the detection systems in the first place. This means adding copious data to already overburdened security information and event management (SIEM) systems and then labeling and sorting these data efficiently for training.

7.4.2. Case Studies

Two cases are discussed, highlighting the use or incorporation of AI/ML to secure MICTs.

IBM MaaS360 with Watson: Helping IT, Security Pros Stay Ahead of Emerging Security Threats

MaaS360, a cloud-based security product from IBM, is powered by artificial intelligence and cognitive computing systems known as Watson. This product was first developed to use cognitive computing to secure smartphones in the workplace, specifically updating cryptography standards to ensure employees use strong passwords. In 2015, the "IBM X-Force Security Research" team started experimenting with ways for Watson to boost the volume and speed of written research content, as well as help develop hypotheses for further research or possible system rule blocking. Three years later, this use of AI/ML to write published reports (albeit just in summary form) was released to the public. Rather than just releasing the reports, the IBM X-Force team also wanted a way for peers to "talk back" to the system directly from the reports. Thus, with two clicks of a mouse within a report, security pros can feed their wisdom back into the AI/ML engine.

IBM Trusteer leads the security industry in preventing new account fraud, a multi-billion-dollar problem while delivering a better business and customer experience. Businesses of all sizes use Trusteer, including five of the top five U.S. banks and three of the top five

global banks. Trusteer products help protect millions of bank customers across 160 countries from online fraud, which occurs over 1 billion times each year. With Trusteer, global financial institutions take an AI-driven approach to differentiate between good customers and cybercriminals to maintain privacy, protect data, and safeguard against account takeover and new account fraud. As cybercrime evolves, more attacks are based on manipulating users instead of systems. Trusteer solutions have helped banks reduce fraud losses by up to 50 percent while improving the customer experience, offering a clear business value for financial institutions.

7.5. Future Directions and Conclusion

5. Future Directions and Conclusion

As the cloud is expected to witness widespread adoption in the twenty-first century, it is indispensable to secure this infrastructure from malicious adversaries. Alongside strong encryption techniques and secure key management, security solutions driven by AI and ML have the potential to transform cloud security. Key emerging techniques include deep learning, which can support the development of intrusion detection systems and malware classifiers, as well as AI and ML, which have been used to deliver mechanisms that help cloud users avoid malicious servers. Deep learning techniques can also classify and characterize malware. Generative Adversarial Networks (GANs) also have the potential to model attack techniques and unlock many applications that can be used in encryption techniques. However, while AI and ML-driven security solutions offer an array of opportunities, they also bring with them several challenges.

Artificial Intelligence (AI) and Machine Learning (ML) driven cloud security have notable applications in the cloud and can significantly improve our ability to secure the cloud. This paper provided an overview of cloud security and the use of AI and ML for securing cloud infrastructure. Following a review of recent papers, this paper also highlighted several directions available to organizations looking to improve their security in the cloud with AI and ML. Again, simulated security environments built on cloud services, like an IoT safe area, are made GPU-accelerated for faster processing. It has a GPU that has high-performance computing capacity, which is used to solve complex mathematical problems in the field of cryptography. It also makes it possible to simulate complex cloud computing environments in the cloud environment. Moreover, GPU-based cloud computing services use on-the-fly data

for security to simulate the IDS private and public facility, which is used for data classification in the cloud. Most importantly, the potential research direction for AI and ML is to extend comprehensive cyber defense strategies for the cloud.

7.5.1. Emerging Trends in Cloud Security

Emerging trends in cloud security: Whether dealing with public, private, community, or any other cloud, ranging from infrastructure, platform, or software, a network-empowered economy is leaving the expert naysayers behind. Some talk of having seen it all before, many times, but with us all heading into cloud services, they might die of obsolescence if we are not careful. How will the experts cope with emerging security perils on a grand scale without the need to touch the many systems and users?

Outsourcing and the supply chain will call for more extensive use of dominant security approaches like encryption of data. Data-at-rest encryption will extend into platforms to counteract the potential for complex data structures to obscure location data for data processors. Privacy legislation makes data location critical.

As complex cloud-related systems begin to emerge, there will be a greater blend between horizontal trust alliance-based defenses and the networked security models of today.

Emerging cloud security technology developments:

Technologies that provide system integrity will need to surface systems that have disintegrated, but this is not possible using integrity alone. Instead, new systemic redundancies must be developed such that proof of a particular integrity problem still proves the absence of another systemic integrity problem. When these technologies begin emerging, we will have the benefit of both supply chain and system examination.

Access and usage controls on confidential data in systems will percolate through the whole of the enterprise hierarchy. This is partly as business-sensitive and particularly identified data grows increasingly attractive to both external parties and malicious insiders. The insider problem has always been ongoing, but the 'training wheels' afforded by the structure of current system management architectures are removed in cloud systems.

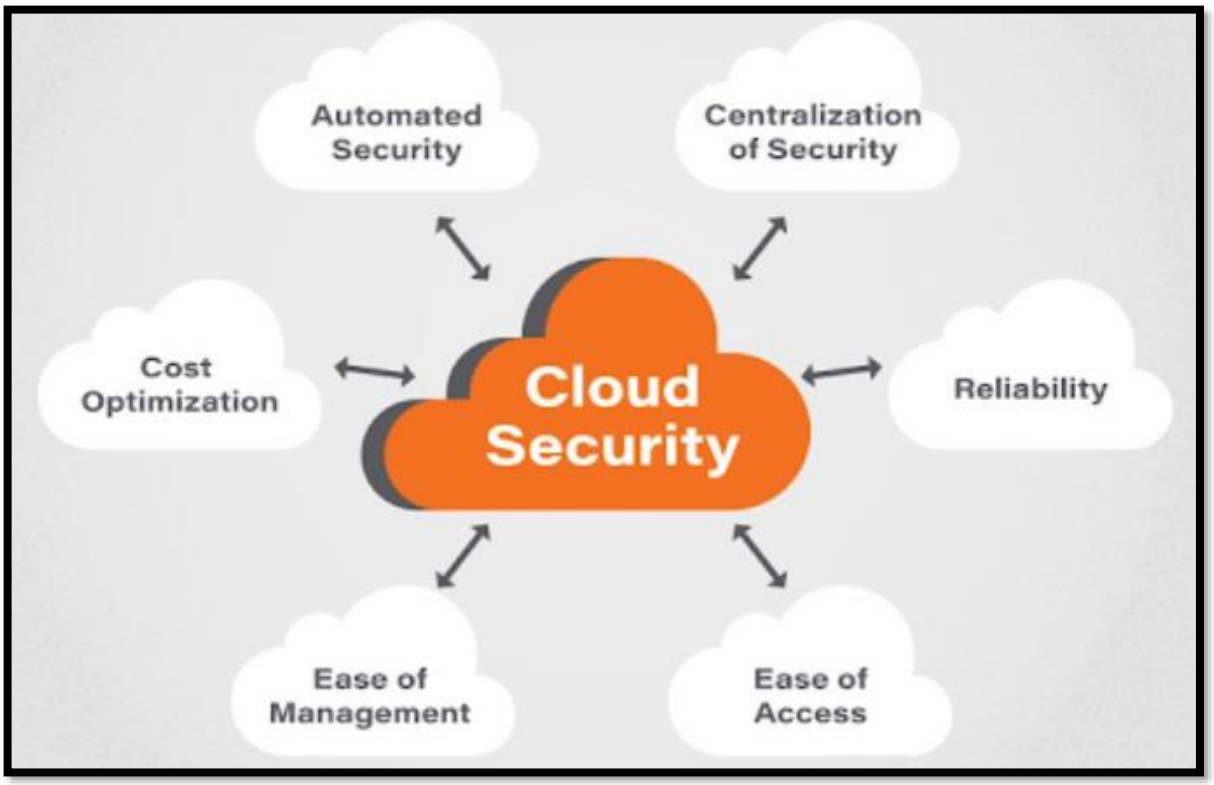

Fig 7 . 3 : Trends and Emerging Technologies in Cloud Security

7.5.2. Conclusion and Key Findings

Conclusion and Possible Key Findings

In this paper, an attempt has been made to introduce the principle of artificial intelligence (AI) and machine learning (ML) and define AI-based solutions for protection threats in the cloud environment to enhance secrecy, data storage, and security, and to reduce data losses. The objective of this study was to address how AI technologies can protect cloud infrastructures and make recommendations for adopting these mechanisms in cloud-based network environments. Consequently, the AI model has been developed as the final resistance mechanism to external attacks and data discards.

During the tests, an experiment was conducted with a capacity of 500 employees and cloud technology users, and it was observed that AI systems are favored by all new investors. It is therefore concluded that security infrastructure must be updated to secure significant data that an individual or a public sector operates in, and the machine learning approach should be leveraged and deployed (as demonstrated in Fig.). This offers precise data analysis benefits from external adversaries and protects them from a potential and in-house adversary. The

model for the proposed AI system is practiced in a local environment and is combined with the proposed permission control model, due to which the results are more accurate and safe, even with active adversaries.

In the future, it is suggested to improve this algorithm in an Internet of Behavioral Things (IoT) cloud environment, where the AI implementation of the solution is becoming a world-level competition for any IT team that causes IoT and provides artificial intelligence IoT. To safeguard resources from active malefactors by up to 100%, it must sit legal issues and develop a solution.

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Chapter 8

COST EFFICIENCY AND PERFORMANCE OPTIMIZATION IN SCALABLE CLOUD SOLUTIONS

8.1. Introduction

Business requirement analysis is a complex phase of public tender. In this essay, cost efficiency and performance optimization will be tackled for the development and integration of cloud systems in an online platform. The issue to a maximum extent coupled and scalability and high availability is increasing daily. Quality of Service is the law of the global business because scaling manually is not an answer. Scalable clouds are the direction we have to take in business intelligence, thanks to the graphs. The essay is devoted to web serving but could be supplemented with single nodes to cope with graphics in business intelligence. Some validation is going to be enough for proof of concept.

This works like a charm on big players, where cost and reachability outsmart small node computations. As the big players are plastics in the cloud, the parameters for offering quality services are also plastic, where the SLA link could be possible. The approach for this essay is using HTTP nodes to provide web services. Other services are also possible by changing the nodes' stacks. Results of the cloud analysis are then presented with comparatives with S3 in terms of performance (responses and latency) and security. Scalable cloud systems have many alternatives today for the load balancing stack, the storage stack, the database stack, and the end user access stack. Every one of these alternatives better suits one company than another, therefore, choosing the right scalable cloud stack is not an easy task. The candidates to use are: nginx+memcached, pinto storage, MySQL central DB, and point end-user communicating with the backend servers. We chose this architecture because of its cost efficiency and standard configuration.

8.1.1. Background and Significance

Cloud computing is an innovative approach to data management in which a network of servers (or 'cloud') stored in multiple data centers spread throughout the world is employed to store, process, and analyze data instead of using a local server or personal computer. Cloud computing enables companies to avoid large capital expenditures involved with building data storage, maintenance, and the equilibrium associated with handling throughput spikes while still supporting the necessary number of users. Corporations now operate on a global scale, and their clients' accessibility must also be scaled to fit with their growth. To provide indigenous performance for a restricted collection of the most visited points of presence (PoPs) globally would require a large capital expenditure to manage all traffic that is often low in volume.

To locate quality material in a massive set, the method requires the examination of a vast number of files. The capacity to scan a large library for patterns or particular data sets in a constrained period or at a reasonable cost is a common functionality of a content delivery network and a similar one. As cloud solutions for websites increase, cloud providers may become the house of large programming-related setups. Since set operations are a dramatic example of a high-volume "secondary" scheduled operation, employing appropriate data store technologies to minimize indexing and aggregation fees can also enable bandwidth cost reductions (and latency decreases). Furthermore, cloud services construction and performance organization are the goals of this job. Stored on the server side of the server's rack, programs are used to provide simple, scalable improvements that are not affected by the particular functionality implementation.

8.1.2. Research Objectives and Scope

The objective of the research is to devise scalable cloud solutions and to explore ways of making use of potential computational resources efficiently. Such pay-as-you-go computational paradigms enable us to access new and powerful supercomputing resources as we need them by exploiting the state-of-the-art highly parallel computing systems to implement the underlying approach or method to solve complex problems. Namely, the infrastructure of the computational experiments that support either basic research or applied projects in large-scale simulation, big data, neural networks, or internet services.

Furthermore, another goal is to have highly scalable computing resources receive only what is necessary in terms of hardware and software support, while carefully mitigating all monetary expenses. As raw computational power is growing, the number of processors attached also increases, leading to a substantial (and in practice not efficiently tackled) exponential growth in both the cost and the number of sub-problems (tasks or jobs). Hence, approaching algorithm scalability in this context does indeed benefit from highly parallel computation and efficient resource usage. In this scope, one of the main objectives is to have a scalable computing application. Scalability can be observed in terms of parallelism by tuning some related "knobs". Therefore, a relevant and interesting cross-disciplinary approach is to minimize memory usage and maximize data locality, all the while not affecting the final choice of computational approach. This would result in performance and cost efficiency. Complications due to the process of minimizing activity on memory and network have the ultimate goal of removing computational stairways. The final goal, within reach, is to find the best procedure to keep resource usage to a minimum level.

8.2. Fundamentals of Cloud Computing

Cloud computing represents the technology that provides various types of services over the internet. The fundamental idea of cloud computing is to separate services from the underlying infrastructure and establish the resources as a pool of virtual resources available to be assigned based on the user's needs.

Key Characteristics of Cloud Computing: - On-demand Self Service - Broad Network Access - Rapid Elasticity - Measured Service

Service Models of Cloud Computing: - SaaS (Software as a Service): Provides software applications to users as a subscription model. Users can access software-based applications through any internet-connected device. Examples: Google apps and Microsoft Office 365. - PaaS (Platform as a Service): Provides software-based tools for developing software applications available over the internet and accessible through any internet-connected device. Examples: AWS CodeBuild, Heroku, and IBM Bluemix. - IaaS (Infrastructure as a Service): Provides servers, storage, virtual networks, and operating systems to the users available as a subscription model. Users have the flexibility to run and test any software applications by using the provided infrastructure. Examples: Microsoft Azure, Amazon EC2, and Cisco Metacloud.

Deployment Models of Cloud Computing: - Public Cloud: A public cloud is operated by third-party cloud service providers and available to any users over the internet. Examples: AWS, Microsoft Azure, and Google Cloud. - Private Cloud: A private cloud provides cloud services to a limited number of people. The cloud services can be held on-site or off-site. It also provides several other benefits such as improved security, control, and performance. Examples: OpenStack, VMware.

8.2.1. Definition and Characteristics

2.1. Definition and Characteristics

The official NIST definition of cloud computing is "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." This definition essentially describes all the relevant characteristics of cloud computing:

On-The-Fly Resource Provisioning (On-The-Fly-RP) Cloud computing can provide resources when they are demanded and use them otherwise for another purpose (scalability). If this process needs to be performed automatically, it is referred to as autonomic computing and adapts the standardized OTRS (on-the-rack system) to the customer's relevant resource class. To achieve this, an SLA can be settled upon describing compensation to be paid if the cloud service does not deliver as agreed (quality of service). Otherwise, it defines metrics to keep the customer to validate the service level.

Ubiquity Cloud computing provides the abstraction from technology which helps to decouple the service logic from the hardware the service is running on. The cloud can be anywhere in a way similar to web search engines. The user development environment and even scripts can apply cross-provider.

Broad Network Access Access to services the cloud provides is available at different systems regardless of the viewpoint that is used to control the cloud. Use cases include smartphones, laptops, and PDAs. An API is normally defined to control the cloud's provided services. Services that exist are, for example, escalation of the service, ordering, or a view into the cloud resources. For the cloud user and particularly the user of the cloud service, web

services are the technology of choice that provides an SOA architecture to the intern amongst the cloud providers' premises.

8.2.2. Types of Cloud Services

There are several types of cloud computing service categories, often called just services or service models. The main service models include Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). In general, the services above are built one upon another. For example, using IaaS, the client can decide what kind of operating system and applications it wants to install, configure, and manage, but when using PaaS, operating systems are already pre-defined and installed, and the clients can install, and configure, and manage only the necessary applications. By using SaaS, customers can deploy their applications or services according to the requirements of the service provider.

1) Infrastructure as a Service (IaaS): It provides the virtualized infrastructure and the clients can install any operating system and any application on it. 2) Platform as a Service (PaaS): It aims to provide a suitable development environment where the developers can manage the development and deployment phases without worrying about any underlying operating system and, sometimes, network infrastructure. 3) Software as a Service (SaaS): In particular, the software and the applications are provided as services to the customers, usually released with the pay-as-you-go model. Each service has its functionalities and requires different needs and strategies in terms of implementation costs and performance optimization.

8.3. Cost Efficiency in Cloud Solutions

A well-designed cloud solution is composed based on resources that are made to scale dynamically. The resources that are used in a scalable solution are interconnected to ensure optimal performance and low latency.

Reducing costs and improving performance are two of the major concerns for organizations in their cloud operations. A significant portion of the cloud computing expenses goes into the system consumption including servers, disks, network traffic, and related expenses. When designing and running a cloud-based solution, system performance, and cost are two factors that decision-makers must deal with. Cloud computing cost varies depending on four main factors: compute, memory, storage, and data transfer. Compute costs vary based on the size of the VM and the power it has. Memory and storage costs are based on how much

you use. Cloud data transfer cost varies based on the type of operation you do. In a typical, all-inclusive cloud computing expense, there are two cost values: the purchase of transmission data and any data transfer cost data and the time needed to organize a CPU to generate the data sent.

The data transmitted between the nodes is significant to manage the cloud costs because the data transmitted uses the network resources and the cloud data transfer cost has an impact on our computational spending. Thus, by using scientific methods and mathematics to conduct a Big Data analysis, we can optimize our costs and improve cloud infrastructure effectiveness. Cloud computing is intended to offer inherent cost control as an integrated service, which is a value-added consideration for cost-cutting on cloud services. Cost efficiency becomes very important as the cloud continues to expand. The effect of the expense of the framework and labor in scaling up cloud resources cannot be ignored. The cost of a cloud service indicates the operational expenses for the processing data and the transmission of data. The transmission of cloud data accounts for over 70% of the costs of the cloud service. This is vast compared to equipment costs, equating to an average monthly cost.

8.3.1. Key Cost Factors

Serverless technologies, storage, data processing services, and AI services have become very efficient in terms of price and allow a cloud solution to be set up with minimal cost and run with minimum usage for a very cheap price. For this reason, solutions requiring scaling out very quickly, with high availability and based on extensive use of such services, are likely to make use of cloud solutions more efficiently than a traditional on-premise setup. The primary cost factors are:

- Storage: Storage prices have fallen greatly in recent years and have become very cost-effective, especially data stored on HDD. As a result, on any bigger scaling platform, the primary cost is cloud storage. - Data traffic: All cloud services charge for both incoming and outgoing traffic in most regions, making high data traffic an important cost factor. - Operations: The cloud platforms charge for the operations being executed. The per 1M operation is negligible, but for a large data processing operation with millions of operations executed several times a month, it creates a large overhead. - AI/Machine learning: The latest cloud solutions are based on integrated, easy-to-use AI/ML services, making it possible for a solution to easily benefit from AI and machine learning-based solutions. These services

typically charge based on the number of operations being executed and/or the amount of processed data.

8.3.2. Cost Optimization Strategies

With the many decentralized cloud providers, numerous cost-optimization strategies could be used for ECS, storage, and even web and database services. One approach for performance-to-cost efficiency would include evaluating the performance overheads of these cost-optimized solutions. Typical cost optimization strategy guidance would include the usage of reserved instances (RIs), double redundant or region split deployments, and sniping of spot instances based on demand.

While preparing for Black Friday peak provisioning, Engineering was performing a load test that consumed hundreds of machines on-premises. They were able to cut server-farm costs by adding a 5-millisecond delay to each web request using a tight loop and saved $10,000 by 'fixing' the software issue.

Engineering also invested heavily in optimizing storage performance per cloud services best practices documentation to reach its affordability numbers. The Amazon-specific engineering helped to optimize the S3 API and WAN functionality because S3 is an internet-based service. Cost reduction techniques from the literature helped to optimize the solution design that required double redundant or regional deployments to hit performance targets and sustainability numbers. These reliability capabilities were found to cause a significant rise in account costs. Techniques to dynamically optimize fleets of commodities were found to have a nominal cost difference until the number of scalability operations required to maintain the optimum number of VMs that could be safely launched grew.

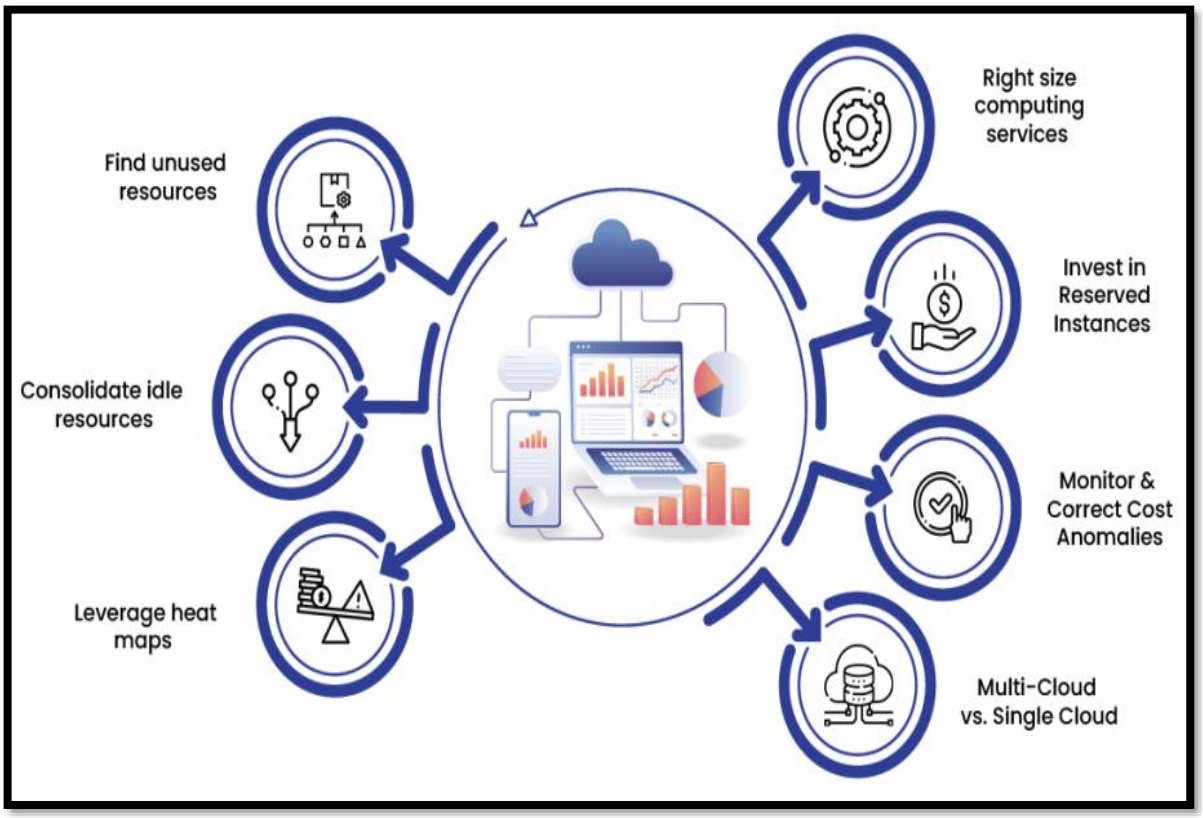

Fig 8 . 1 : Cloud Cost Optimization

8.4. Performance Optimization in Cloud Solutions

One key factor and indeed the essence of the cloud is scalability – growing and reducing the volume of information to be processed should not degrade system performance. Additionally, this applies not only to data volume but also to preserving real-time performance. Fine-tuning cloud solutions, one can observe what a trade-off between computational time and accuracy in the solution looks like. This is closely related to performance tuning - finding and eliminating the bottlenecks in database/data processing/cloud solutions, mainly computational. This is why we claim that due to the obvious importance of scalable cloud solutions and performance optimizations, this topic should serve as a crucial introduction.

Performance optimization refers to the process of fine-tuning solution performance for a specific environment. It involves analyzing solution performance and deciding if the performance satisfies the required criteria for system operation. In cloud solutions, it is extremely important to scale properly under different traffic volumes. Additionally, cloud services, where computational power is used for price efficiency, should be optimized to behave in real-time when necessary or batch-like when performance is less important.

Techniques and methodologies to ensure such characteristics are rigorously analyzed in this work.

8.4.1. Importance of Performance Optimization

As businesses and solutions continue to accrue requests and usage, operators have initiatives in place to ensure that a platform can support and sustain its users. Performance optimization is key in these instances because it seeks to increase the efficiency of the solution, ensuring that the solution in question can continue ramping up its operations without sacrificing its performance or resource utilization. With this, an operator seeks to find the minimal sufficient cost to support its expansion, which underscores its importance in calculating and seeking lower what-if capital for deeper modeling. In the same instance, performance tweaks and core efficiency enhancements can lead to lower infrastructure requirements, even leading to cost savings by utilizing different Azure resources while performing the same operations.

High availability, quick responses, and scalable solutions are of great importance for various solutions around the world. The organization that does a better job of maintaining the uptime, performance, and quality of service of their chosen solution(s) will come out as the leader of their field, particularly with often very thin profit margins on considerable public usage. However, the continuous growth of users can affect the costs. Recognizing such slots and areas where a would-be operator can miss services encourages simulating costs during the purchase of cloud resources and data center facilities to ensure the planned operator's efficiency. Assuming a technology-based vehicle platform, the foremost consideration for a business is whether or not to expand other locations, add additional nodes to the system, or expand the limits of their cloud solution.

8.4.2. Techniques for Performance Improvement

Barring resource allocation, various other approaches can be applied at different levels in a cloud solution to enhance its performance. Among these techniques are caching, pre-fetching, reusing intermediaries, and fine-tuning of cache policies. Caching can work as a significant approach to make a system more responsive. Though computing resources are abundant in clouds, it is often beneficial to have an improved performance cloud solution.

When a cloud application seeks to store resources for failure isolation, sharing, scalability, or content delivery, it should be stored in caches residing on infrastructure components that the resources are located on. Caching involves the storage of response data for a request in such a way that subsequent requests for the same data result in greater performance. Caches can be located at any level in a cloud, from the gateway and object servers up through the web servers, temporal inflammatory, and databases. Utilized as a simple, lightweight layer that faces the user and contains only non-critical aspects of complex object versions, generally processes a high volume of read traffic. Analyze in detail the operation and performance characteristics of web objects stored in CDN caches, and propose a simple, lightweight write caching scheme to determine the write performance of e-stores.

8.5. Case Studies and Best Practices

5.1 Lessons learned from a decade of cloud management for list-making apps

Hogan and Taylor summarize five lessons that have been learned from more than a decade of experience with cloud management for "list making" applications such as Remember The Milk: 1) take optimization opportunities best fitting your resources, 2) inaccurate monitoring is costly, 3) perform periodic cloud market surveys, 4) aggressive lead-time discounting can lock you in a cloud with mismatched resources, and 5) FIFO management of cloud resources reduces cost.

5.2 Driving and Managing Change

Neglia et al. detail seven lessons regarding driving and managing changes in an organizational system. In summary, performance engineers need to be mindful of the influences of organizational inertia, internal politics, external factors, emotional response, and common cognitive biases. To facilitate successful system surveys and changes: 1) engage and educate, 2) create critical belief, 3) be one of the stakeholders, 4) fail small, 5) link to current processes and practices, and 6) modulate the pace of change. Automatic performance-sensitivity testing. De la Calle et al. report on their efforts to automate the process of testing if and how performance-sensitive complex systems are. They detail the environments in which their tool has been deployed and discuss how system developers and admins can use these tools to identify potential performance bottlenecks.

8.5.1. Real-world Examples of Cost Efficiency and Performance Optimization

5.3.1 Real-world Examples of Cost Efficiency and Performance Optimization

Many published technical and academic papers present case studies and real-world instances of successful cost efficiency and performance optimization in the area of scalable cloud solutions. We now present a summary of research papers and technical documents that present case studies in successful cost efficiency and performance optimization.

EC2Spotter by Amazon is an EC2 spot instance configuration recommendation tool. EC2Spotter monitors AWS resources used by the organization and develops a profile of request types and a list of low-cost compatible spot instances (sizes and operating systems) that meet each request.

Blum et al. developed Watchtower, a software system that issues real-time alerts on data center backpressure. By prioritizing instances not contributing to backpressure, the alert system saves up to 21% of account annual spending.

The ElasticMPS system presents developing and deploying a system for media packaging with some real-world performance optimization achievements through effective adaptive resource utilization.

The AdWords Islands is a project that introduced "island servers" to implement isolation between data center jobs filed through Google's advertising API. Experimentation with the islands implemented hosted experiments without isolating the islands.

Variability in price and availability provides unpredictable savings from using spot instances on AWS. In all but one experiment, the resource managed to watch the spot market prices and could use the "spot" instances for free, so long as they were available. Overall savings ranged from 0%, meaning all the instances used were on-demand, to over 25% reduction in cost when all the servers were using spot.

Fig 8 . 2 : Balance Between Cost and Performance

8.5.2. Lessons Learned and Recommendations

Applying the methods and best practices of this paper in a real-life setting showed that positive scalability is realizable and that the means to obtain it are within reach. Given the insights from the case studies, it is possible to provide a list of actionable recommendations and lessons learned from the methods, past applications, and model analyses that can be adopted in a corresponding portfolio of use cases. The first level in the design of a best practice recommendation list is to separate it into immediate insights from the model and insights originating from Deloitte.

This level of implementation involves lessons learned from our model and past applications. The main insights are as follows: scalability is a feasible ambition, with obstacle removal some additional coding lean sails; and some lessons that stem from prior applications. For example, we were able to size an EDA sequence in Perl for working day input significantly quicker for an actuarial sequence at the time of our analysis. Our experiences with scalability in a cloud environment and the model are both requirement-driven, stemming from

performance optimizations in a Deloitte-run service in the private cloud of a major multinational. This is not because the public is not capable of achieving scalability, but rather because it is unlawfully difficult to obtain best-effort contracts in the public cloud. However, we can assert that no such thing matters in private dimensions.

In brief, the proposal takes all of the aforementioned into account and can be seen as a holding environment design when scalability is of concern. In a cloud or any other scalable service, about a private virtual or physical environment or a public one, we propose the following best practice recommendations in the setting where scalability is the desired outcome: data needs to fit in memory, no communication with external storage may cause overhead; establish how memory is accessed; ensure automated testing; check the heap size; check network latency; analyze the performance in terms of theoretical computer science and predictive data analytics; redesign your methodology.

8.6. Conclusion

Title: Cost Efficiency and Performance Optimization in Scalable Cloud Solutions

Conclusion: This article proposes a technique for modeling the cost efficiency of public cloud solutions and validates it with examples for three computing tasks (circuit simulation, rendering large images, and transmitting compact discs). In each case, one object request has been explained by the developed model ECP KS. One of the main messages of the article is that the most cost-efficient solution depends heavily on the pattern of use; one size certainly does not fit all. Hence, if one is considering a change of provider or final destination, one needs to be equipped to make an informed decision. In a cloud-based setting, our objective is to select a load distribution network and data center, that offers a good balance between cost-efficiency through fine-grained load distribution and locality and delivers the desired performance. Using an open-source load distribution network and simulation data center platform, we propose a proxy structural equation model to simulate the individual interrelation of cost per kilobyte, and RTT with client rent time and feasible load distribution network.

This paper focused basically on studying various types of cloud services in terms of infrastructure as a service, software as a service, platform as a service, and a few cloud computing projects that are devoted to application, networking, fault-tolerance, integration, and security. Mainly this paper reveals that cloud performance modeling is more complex than

performance modeling for server-centric systems because an application's performance in cloud computing is dependent not only on the application and the cloud architecture, but also on the provisioning design, the operational policies, the workload, the network, and the quality of service requested. Cloud Performance is not only about the characteristics of the physical resources but about the delocalized provision of service offerings as well. Distinguishing factors for SaaS according to experts in the industry.

8.6.1. Summary of Key Findings

This section consolidates the findings within an overview of the fundamental knowledge contained in this section.

Key Findings Analysis of aspects related to organizations' main goals ensures low cost and the performance of scalable cloud solutions. Furthermore, it is one part of an emerging area in cloud computing that focuses on optimizing the selection of cloud providers. Ensuring low running costs is one of the major goals of organizations that use cloud solutions. It is possible to communicate end-to-end solutions with cloud providers offering Software as a Service (SaaS), Platform as a Service (PaaS), Infrastructure as a Service (IaaS), and other platforms or Resource Data. Cloud providers can offer more reliable and efficient solutions due to the economy of scale. However, the price of solutions depends on both executed operations and the traffic capacity. If required, the cloud provider may charge for using additional resources (e.g., storage, network, memory, and I/O capacity) or conduct additional operations (e.g., scaling, configuring, updating, and providing specialized software) beyond the basic services offered.

Our studies aim not only to put concepts and requirements together with the aforementioned dimensions but also to study, design, implement, and assess systems and their usefulness, establish new performant applications, and create a study model to provide cost-aware and high-efficiency solutions based on realistic settings of multi-cloud actors. Given an input workflow and market price data on interval domains, the model/component used to assess and design public cloud mixed-sort representations.

8.6.2. Future Research Directions

The paper has identified three research directions with considerable potential for further scholarship. Corresponding to our previous discussion, the first research direction is

expanding the experimental investigation based on the design and orchestration of microservices architectures. This would help in achieving comprehensive evidence, according to which, the intersections of design and deployment decisions lead to a solution space of cost efficiency and performance optimization. Further investigations could involve different SaaS systems as testbeds, evaluating alternative containers and orchestration strategies, and considering the co-location of microservices and other runtime, middleware, and application-level refinements. This large experimental and empirical effort would lead to very interesting experimental results, according to which we could define general prescribing guidelines and best practices.

A second research area is aimed at the definition of models and abstractions useful for capturing: (1) design- and QoS-related features of cloud solutions contributing to cost and performance; and (2) the functional features of the final product or service in terms of how the boundary is designed in the multi-cloud ecosystem. In addition to conventional QoS and QoC approaches, the application of New-Data/Side-Chain would initiate a change of perspective in which big data-driven business models are supported by the economy of cryptosystems implemented atop a side-chain that is highly geared for data payment and cloud 'juice'. Finally, a third ambitious research direction is concerned with the large-scale adoption of this data management Vault approach.

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Chapter 9

CASE STUDIES: REAL-WORLD APPLICATIONS OF AI AND ML IN CLOUD COMPUTING

9.1. Introduction

As artificial intelligence (AI) and machine learning (ML) have matured, their seamless integration into cloud computing has offered astonishing solutions and efficacies regarding various services. Due to the adaptability and optimization of AI- and ML-based models, there are fewer risks of cloud attacks, harmful traffic, and compromised data. Predicting customer needs based on analytical results enables the dynamic allocation of cloud resources, automates energy consumption, and accurately performs intrusion detection tasks. Emerging in the field of data analysis, AI and ML can be efficiently used for adaptive cloud solutions, with additional applications ranging from computer networking to data analytics and security protocols. 'Case Studies: Real-World Applications of AI and ML in Cloud Computing' explores various domains by summing up the purpose, approach, and key findings of the selected studies conducted at different higher educational institutes.

Research objectives: To obtain real-world applications and future research directions with the combination of AI/ML and cloud solutions. Overall, with the work presented in the research studies discussed, AI and ML can be used for adaptive cloud solutions. The rest of this essay is structured as follows: Section 2 offers a literature review, which provides an enhanced understanding of cloud computing and the AI/ML techniques introduced in the case studies. Section 3 presents the methodology used to find and select the case studies. A full exposition of the results and discussion takes place in Section 4, focusing on the purpose, approach, contributions, selected works, and outcomes respectively. Section 5 then presents a review of the related work for a holistic understanding of the case studies. Finally, Section 6 offers concluding remarks that comprise future research directions based on the synthesized results from the case studies.

9.1.1. Background and Significance

Cloud computing has gained immense popularity due to on-demand services and the usage of sensors. This leads to the generation of volumes of data, popularly known as big data. Recently, cloud computing has tackled big data and IoT. This became possible using two latest technologies: ML and AI. ML and AI are playing an important role in combating fake identities, cyber-attacks, unauthorized accesses, and fault and failure detection. Clouds are popular environments with ever-increasing usage. Clouds have been divided into various deployment models such as private, public, national, multi-cloud, etc., and service models have been divided into Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). This paper presents an insightful set of case studies. Next, these case studies have been divided based on their respective fields.

The implementation of AI and ML techniques in cloud environments and cloud-assisted environments has been common recently. AI and ML have now penetrated every domain and every field. The most striking point of AI in the cloud is efficiency; the combination offers unprecedented integration. With the advent of AI in the cloud, resource limitations were pushed to the edges. Humans are now harnessing AI to perform repetitive tasks, handling customer interactions, and big data analytics. ML in cloud platforms can give better outcomes than mere asset utilization. A trained machine learning model can detect frauds in a set of e-commerce transactions faster, precisely, and accurately than humans. Recently, the cloud environment has been implemented in healthcare, education, industry, social media, machine-to-machine communication, aviation, and many more. It has become a challenge to secure them against cyber-attacks and unauthorized access. Inexorable.

9.1.2. Research Objectives

Section Title: Objective

The main objectives of this essay are to:

- Explore how AI and ML are being used in cloud computing, concerning case studies available in the literature. - Discuss challenges and future directions.

To help achieve the objectives of this essay, the following work is presented. Firstly, a brief introduction to AI and ML in cloud computing research from 2012 to 2021 is discussed.

Three challenges for the integration of AI and ML into cloud computing are then presented. Following these challenges, five real-world application case studies of AI and machine learning are outlined concerning cloud computing. For each of these case studies, the problem area, solution proposed, evaluation, and results are highlighted, and suggestions for overcoming some of the identified challenges are discussed. Further examples within each of the case studies are provided where appropriate. Lastly, future directions, blockchain, and citizen cloud are proposed.\

9.2. Fundamentals of AI and ML in Cloud Computing

Pioneering research in recent years has shown an increase in the application of AI and ML in cloud computing. Given the dramatic changes in cloud computing platforms brought about by AI and ML, the value of AI and ML in cloud computing has been recently a topic of discussion. In the real world, ordinary individuals are likely to benefit from cloud computing on a routine basis without even realizing it. The first section of this chapter provides an overview of AI, ML, and deep learning concepts, as well as an introduction to cloud computing. This chapter also provides an overview and applications of machine learning and artificial intelligence in cloud computing. In the cloud computing environment, grand conceptual differences are made by AI and ML techniques. Specific definitions and descriptions of these technologies are given below. There are also several advantages of AI and ML technologies used in cloud computing.

Cloud computing removes the requirement for users to have software installed on their computers. For storage and computerized procedures, cloud computing relies on sharing computing resources through the internet. Cloud computing is currently defined as the exercise of using a network of remote servers hosted on the internet instead of a local server or personal computer for storing, accessing, and processing data. The computer resource economy is predominantly based on the mechanism of pay-as-you-go on a transaction fee basis such as data storage and billing.

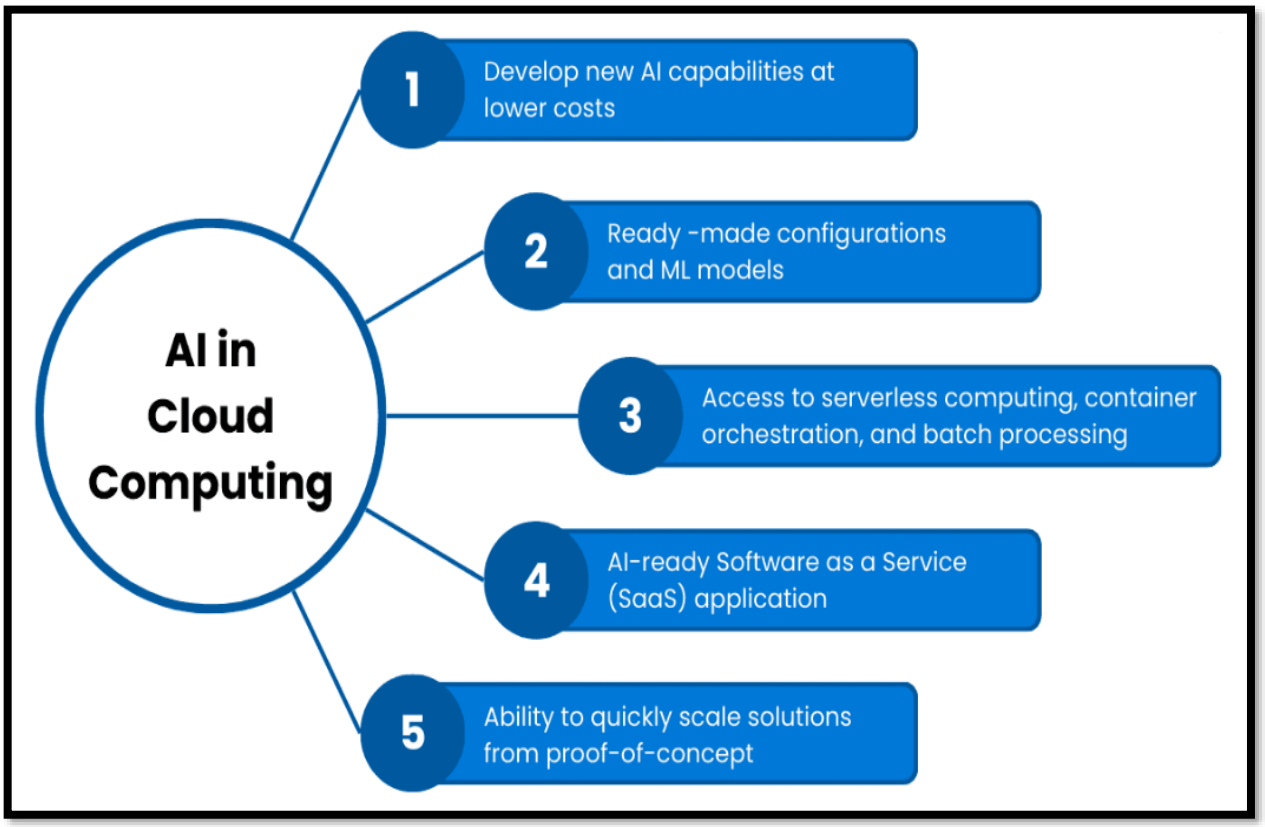

Fig 9 . 1 : Cloud computing integrated with AI and ML

9.2.1. Definition and Concepts of AI and ML

Subsection 2.1. Definition and Concepts of AI and ML

Artificial Intelligence (AI), in the simplest of terms, refers to any type of guess that is generated based on the logical steps involved in serving mankind. The major concept of AI involves the development of algorithms that facilitate the machine to assume and analyze the situation as well as provide an efficient solution capturing the concept of reasoning, vision, learning, language, and understanding behaviors. The basic perception of AI includes: (i) strong and weak AI - strong AI involves creating a complete decision-making system, while weak AI does not generate complete decision-making and works only on a set of rules; (ii) Narrow and Artificial General Intelligence - narrow artificial intelligence comprises only limited functionality, whereas AGI has multiple functionalities; and (iii) Machine-oriented AI and Human-oriented AI - the former one imitates human operation, but the latter one helps in decision-making capabilities against nature and its own. AI experts also deal with concepts related to intelligent agents, search and knowledge representation, machine learning, expert systems, neural networks, multiagents, etc. Many frameworks are designed by cloud providers

to handle the workload of implementing AI and ML models over the cloud to provide users with a convenient environment.

The concept of AI is carried out in two different ways involving symbolic-based and machine learning-based; while symbolic AI follows rule-based decisions, ML can manage non-obvious decision-making activities. Machine Learning (ML) is an updated version of artificial intelligence that constructs algorithms allowing the systems to gain knowledge and generate decision-making capabilities. Such types of systems operate based on the concept of learning from historical data, recognizing various situations in which the system naturally improves the system process in the future. Thus, ML works based on some fundamental factors: (a) ML allows the system to grow itself from newly generated data by the implementation of previous models obtained based on data; (b) decreasing the time consumption and effort spent for slight modification in the systems by using previous results; (c) contributing efficient solutions against other computing techniques since ML possesses the ability to adapt and learn themselves; and (d) this yields a fulfilling and successful solution while the problems with no logical rules are given.

9.2.2. Overview of Cloud Computing

Cloud computing is the on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user. The term is generally used to describe data centers available to many users over the Internet. Cloud computing relies on the sharing of resources to achieve coherence and economies of scale. Advocates of public and hybrid clouds note that cloud computing allows companies to avoid or minimize major investments in data centers, including servers and server cooling systems.

Cloud computing is the delivery of different services through the Internet. The cloud is a metaphor for the Internet. All the processing takes place on a remote server such as a cloud server or a server in the data center. Cloud is also a software or IT infrastructure that we can't see from a customer standpoint. In the cloud, resources are provided as a service over the internet on an on-demand basis. Alternatively, consumers can access their clouds through web browsers or by applications on their local devices. There are six key principles of cloud computing, including on-demand self-service, broad network access, resource pooling, rapid elasticity or expansion, measured service, and so on. Additionally, cloud computing is

designed in virtualization such that it can supply massive services by using various basic physical machines. Based on different cloud computational models (infrastructure, platform, and software), this area can be divided into four architectures (public cloud, private cloud, community cloud, and hybrid cloud).

9.3. Real-world applications of AI and ML in Cloud Computing

A cloud platform that uses AI and machine learning can drastically change how a company conducts business, uniquely interacting with the world with potentially new clients and new situations. This feature could bring companies huge risks and opportunities, making them a lucrative target for hackers. In real life, cloud-based systems are massive and complex, with countless servers, databases, APIs, and other components, whereas 'hybrid' systems, which mix both cloud and physical private data infrastructure, provide the potential for AI bot creations that interact with the outside world in a manner not previously experienced. This suggests that although powerful, companies should deploy their systems judiciously with appropriate security measures and make use of best practices from AI to make their systems as resistant to threat as possible.

However, cloud computing still has a huge impact on the economy and society. The worldwide public cloud service market is forecast to grow 17.3% in 2019 to a total of $206.2 billion, up from $175.8 billion in 2018, according to Gartner Inc. Experts predict that in 2020 AI will become a key attribute of net-based applications, services, and cloud computing. AI relies in some cases on pulling in big data from crowds of user activity to train its ever-growing AI engines. Machine learning relies on big data from which to learn and therefore AI and ML in the cloud seem to be the future in leveraging large amounts of big data to better deliver customer-based applications and innovations. This section first reviews the resizing of computational and networking resources in cloud computing, followed by energy efficiencies in machine learning that cloud computing will benefit from. The section then goes into case studies of distributed systems, networks and services of the future, wireless fog computing, software-defined networking (SDN), and edge intelligence.

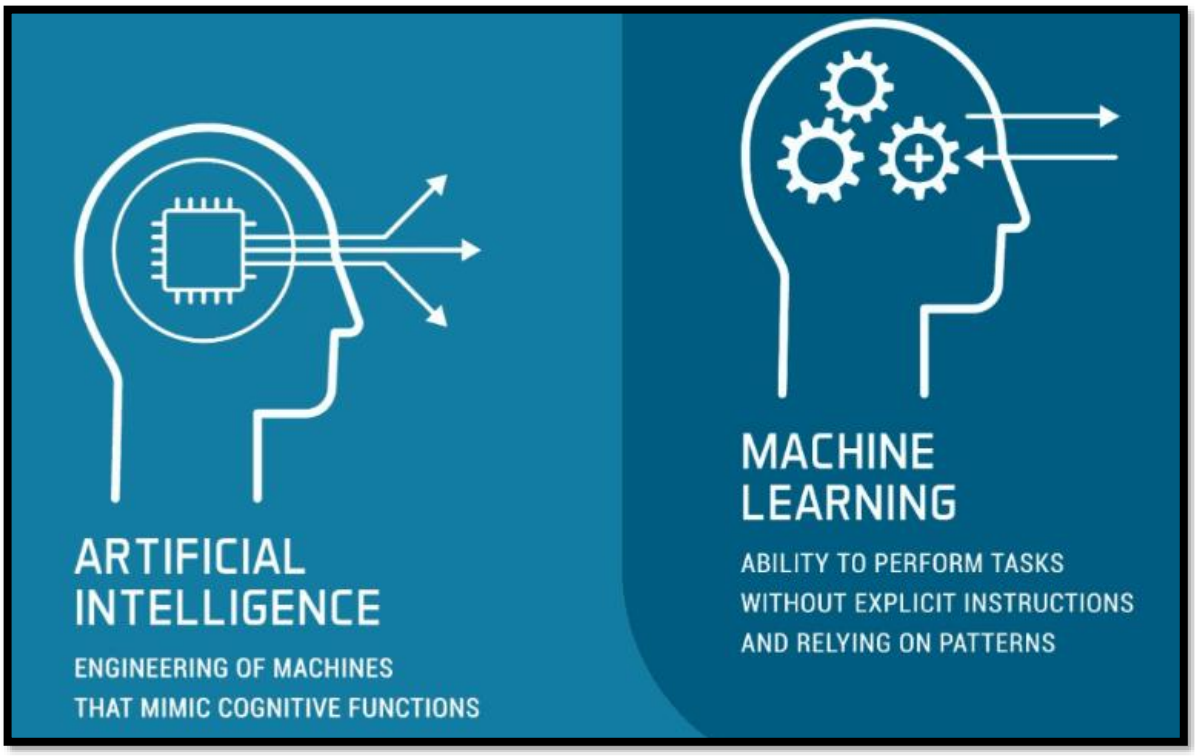

Fig 9 . 2 : Understanding Artificial Intelligence and Machine Learning

9.3.1. AI and ML for Resource Management

Introduction Cloud computing features dynamic resource provisioning, which means that the resources in a cloud environment are subject to change. Automatic management of cloud resources is feasible through the utilization of AI and ML that do not require human intervention. Resource management makes the best use of the available resources and ensures that the users can use the resources most efficiently. Some of the work existing in the literature that encompasses AI and ML in cloud computing discusses only the use of AI and ML. focused on the distributed system and discussed predictive analytics. This can be useful, especially with the big data and cloud environment. Dataset and resource allocation can also benefit from the use of AI and ML. discussed resource allocation for container orchestration tools, FaaS, and mixed-architecture cloud environments.

List of names of AI and learning approaches mentioned in Section 3.1 are Reinforcement learning, deep learning, machine learning, auto-scaling, correlation, dynamic thresholding, anomalies, balancing, load management, checkpoints, QoS, self-adaptation, and genetic algorithms. Below, Table 9 depicts the case studies present in this paper about the AI and learning techniques applied to resource management in public, private, or hybrid clouds.

Furthermore, we specify the actual and potential benefits of using AI in cloud computing for resource management: Optimization, allocating, cost reduction, predicting, measuring, benchmarking, inventory, improvement, utilization, fusion, scaling, emulation, scheduling, placement, anomaly detection, checkpointing, data profiling, negotiation, retention.

9.3.2. AI and ML for Security and Compliance

In the area of security, infrastructures use AI and ML to classify and react to different levels of threats, from potential attacks to more sophisticated and coordinated ones. The cloud can learn from different types of external attacks as data flows in and out of a cloud from many locations across the world. Mahafza et al. cite Google engineers who caution that "the actual number of global DDoS attacks is probably far greater than anyone's best estimates." The prevalence of such attacks requires AI and ML integration into the fabric of cloud computing. These same AI and ML gateways can monitor the web of security commercial tools and appliances on the market.

United Therapeutics developed its cybersecurity tool that monitors every network or application in its cloud. It takes up to 1 terabyte of data every hour. The company's chief technology officer, Paul Radeke, explains why his pharmaceutical company refrains from using any third-party security tools. A primary reason is to avoid detecting false positives. In the case of detecting counterfeit drugs, all of your detections must be true because false positives reveal little information by crying wolf too often. Only then can they test security measures to suppress the drugs' counterfeiters. IKEA is another company that turned to AI and ML to keep its secrets and data in its cloud from being leaked. For 2 years, these technologies have been monitoring the numerous conversations between different stakeholders to detect the potential of non-compliance.

9.4. Case Studies

In this section, we present in-depth discussions of some of the real-world scenarios where AI and ML are being utilized in cloud computing at present. This section of our introduction should offer compelling evidence for the importance of this topic as we introduce the papers that follow and detail their key contributions. In this paper, the following case studies will be considered: "Genetic Algorithms Javelina", "Optimization of the Collection of Waste Paper", "Predicting the Risk of Contract Non-compliance", "Prediction of Helium

Consumption", "Predicting the Cost of Least-Connections Scheduling in Load Balancing", "Using an Intelligent Platform for Responding to Temperature Complaints", "Machine Learning for Level 1 Support for Cloud Computing".

Each case study presents the problem that was addressed, an overview of existing research, the implementation and tools utilized, the results of the implementation and real-world deployment if done, creativity and originality of the work, challenges that were faced and overcome (or not), potential critique or weaknesses of the approach, recommendations for future research, and the main findings or expected consequences. However, the best way to understand how AI and ML are being used in cloud computing and what outcomes are being achieved is to consider some real-world scenarios where AI and ML have been applied in cloud computing. To gain an in-depth understanding of some of these real-world scenarios, the remainder of this paper is thereby dedicated to detailing several case studies.

9.4.1. Case Study 1: Predictive Maintenance in Cloud Data Centers

Model-based AI and ML algorithms are applied to simulate the cooling system in the Oulu data center and provide an estimate of the mean time to failure for the cooling system. Twelve servers are combined to create one model to increase the amount of data needed over one week. The times to failure are tested for statistical significance using T-tests, and then the accuracy of the estimate is shown to improve as the length of time over which the estimate is made increases. This paper has been published in the proceedings of IVAPP 2021.

Predictive maintenance is using AI and ML to find patterns in data that could lead to the failure of machinery so that the issue can be fixed before the problem occurs.

The data for this study was gathered from both internal and external sensors in the Oulu data center and compressed by removing any rows where data wasn't recorded, removing any columns that have consistent values, and then downsampling to only average the data that is sampled more than once per second. These data were used to create five models, with one including the predicted data from the previous model as input, in an attempt to artificially increase the amount of data used to train the model. The simulated cloud fans had a noisy cooling signal created and used as the input to the model, with eight key indicators fed into a deep neural network (DNN) or extreme gradient boosting predictor (XGboost). The mean

times to failure of the five tests were then estimated using the survivor function from a Cox proportional hazard model and health score calculations.

Test 1 showed that when broken down into individual servers to decrease the amount of data needed over more time, the results of the predictive models were non-significant as the amount of data available for this test was less than 3 months. The longer amount of data available in test 3 allowed two of the five alternative models to be shown as having comparable estimation significance compared with the full model, although as prediction models test 3 performed more significantly better than test 1. The 18 and 24 months of training data used for tests 4 and 5 meant that parameters could be adjusted to find the most significant results for the early estimation line, and the best results were using the DNN without the predicted data from the previous model. The estimation over the early line of test 5 is the best model, as can be seen in Figure 36. The mean times to failure for models 3, 4, and 5 were shown to be estimated more accurately the closer to real data that the data trained on was close to the data over which the estimation was carried out.

Management buy-in was obtained to publish some of the results of the non-significant tests to ensure robustness and impartiality as a stakeholder of Ciena was providing input and expertise in how to deploy the results.

9.4.2. Case Study 2: Anomaly Detection in Cloud Traffic

Detailed Case Study

Case Study 2: Anomaly Detection in Cloud Traffic

The researchers, Amer Maleh and Mohamed Adel Serhani published a case study paper that served as a guide for running Anomaly Detection in Cloud Traffic: A Case Study in an Elastic Platform as a Service (PaaS) with Big Data tools. It inspects cloud traffic logs of big data tools such as Kafka, Spark, and TensorFlow. Researchers have noted that software and hardware components that comprise a cloud system are subject to malfunctioning from time to time. Usually, abnormal behavior, as a part of cloud system traffic, is an indication of errors or cyber-attacks. Therefore, to detect whether components in a cloud system work correctly, researchers have to inspect Big Data generated from cloud traffic logs. If the experiments fail to specify one or more aspects of normal behavior, the input must indicate the possibility of malfunction; in turn, the system did not fulfill its requirement. In particular, one notable

application of AI and ML in the broader cloud computing domain is in the detection of anomalies within cloud traffic logs, which refer to the unique sequences of directed packets shared between client and server in a cloud environment.

For instance, Anomaly Detection has operationalized the utilization of AI and ML to detect such irregularities. In further detail, Anomaly comprises an Application Programming Interface (API) in which the researchers deployed AI and ML to: a) analyze cloud traffic (i.e., data) logs, b) identify the pathways of packet sequences from source to destination, as well as c) detect n-path sequence packets that deviate from "normal" cloud network traffic. To accomplish the feasibility test for Anomaly, they employed a dataset obtained from the Toronto WUSTL, as mentioned earlier. The logs for their PaaS cloud system include one month's worth of cloud-web transactional data consisting of 60 thousand unique sources and 16 million trace files. The volume of the processed ElasticSearch index was over 25.2 gigabytes.

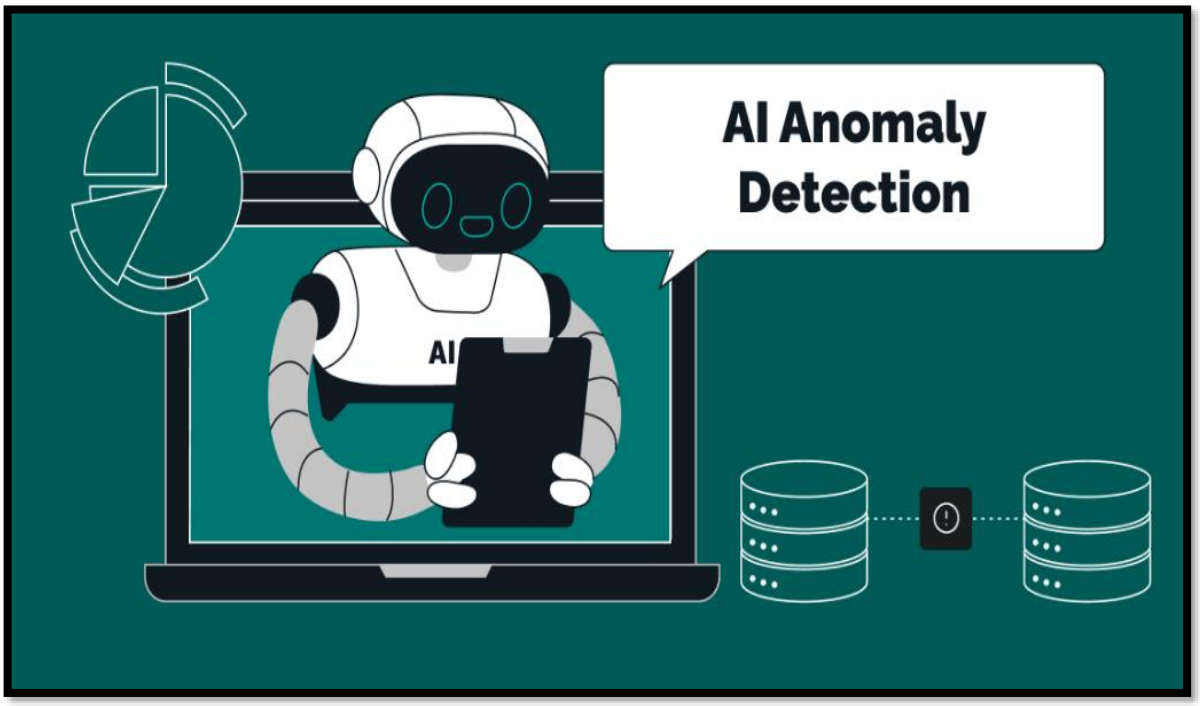

Fig 9 . 3 : AI Anomaly Detection

9.5. Challenges and Future Directions

Ethical issues – Regarding the ethical point of view, ethics of AI and ethics in AI have not yet been successfully integrated into cloud computing platforms. It is still hard to show how super-intelligent AI can build systems with ethical capabilities.

Security and Privacy – Cloud-based AI and ML systems need to explain their actions to satisfy regulatory compliance and report potential data privacy policy infringements.

The adoption of AI and ML real-world applications in cloud computing is not limited to shadowing an understanding of the cloud ecosystem but also enhances AI and ML capabilities. In this case, leveraging the cloud resources allows secure access to real-time data. The authors can address different networking issues, ultimately helping organizations detect sensitive encrypted network traffic of competing platforms in the classroom.

More broadly, the integration of real-world applications of AI and ML in cloud computing is expected to enhance data privacy and malicious activity detection for different parties. However, several challenges need to be addressed. One of them is the excessive amount of data, machine learning techniques, and evaluation, with comparison and evaluation for each method, to enhance network visibility of hardware-encrypted traffic. This has implications for overall performance.

Achieved results also imply that hardware-encrypted traffic can bypass NIDS and therefore increase the potential threat to an organization’s network infrastructure. Additionally, future works in this line should include developing a mechanism for uncertain and suspicious detection of select encrypted traffic. Furthermore, applying deep learning for this specific type of encryption is also perceived as future work.

9.5.1. Ethical and Privacy Concerns

Locally installed AI systems certainly have massive storage of sensitive data, but when ML is trained and assigned AI capability, the risks are enormous. For example, when the ML tool is used for face recognition, although the database is not held locally, the ML tool has the same capability. By combining data mining models or messaging clusters, AI would be capable of making identical assumptions about an individual's characteristics. Until today, relatively little research has been done on ensuring that nobody is being profiled by the ML

learning portion of AI systems in the cloud. This has been exacerbated by globally applicable long-term government orders that restrict sharing between organizations as a basis for AI technology operation. The same marketing messages can be identified quickly since AI has been limited to only 4% of the Internet.

In the case of more complex experiments, including input-output containers, IoT applications, and the public hosting of applications based on AI ML, the impact would have more implications. Each of those components is subject to potential attack as an individual technological use case. Thus, a single AI app could pose a risk to national security if it were to be catastrophically lost. Despite its complexity, AI systems generate appropriate output requirements, with all the full-area scope requirements of the case defined in the first instance. The complexity of such a framework, CSF, and CMM-U requirements are also subject to changing modern regulations. With a massive increase in technology use and integration, the possible risks continue to increase.

9.5.2. Scalability and Performance Challenges

5.2. Scalability and performance challenges scalable computing to solve large-scale learning problems. Large volumes of data are generated every day as the volume of connected devices increases over the years. Real-world use cases exhibit datasets with millions to trillions of instances and billions of features, making scalability a prime concern. The learning of models with a high number of feature vectors (up to billions) on a multi-petabyte instance stream is a matter of necessity for Anomaly-Based Intrusion Detection Systems (AbIDS) in many industries.

Certain business use cases of predicting user click behaviors and Cyber Threat Intelligence require large-scale model training, which is not possible with traditional machine learning algorithms. While a standalone machine learning model suffers from several demerits due to scalability, privacy, performance, and quality, several use cases in cloud computing may suffer from additional difficulties when trying to integrate AI and ML. Cloud services receive a huge volume of traffic from various users, which makes it necessary to scale the machine resources to end users. Large-scale concurrent requests are more challenging, not only because of the prediction speed but also because of the resource allocation.

The amount of working RAM depends on the complexity of the model distributed training, suitable for Single Instruction Multiple Data (SIMD) operations. To accommodate potential increased demand in predicting the intelligent learning models in addition to the constant resource allocation, speed is one of the major difficulties that cloud service providers could face. In achieving such demand, Model-as-a-service (MaaS) and Artificial Intelligence-as-a-Service (AIaaS) have intrinsic challenges of lower convergence rates. Python's performance is a major concern when concentrating on the implementation due to GIL and further mitigations in training and providing RESTful-based scalable production systems to serve concurrent users. In doing so, different research around acceleration in parallel processing has been carried out to design suitable computation algorithms needing a high-speed, low-latency model serving at the edge.

9.6. Conclusion

This essay has presented eleven case studies demonstrating the applications of cutting-edge developments in artificial intelligence (AI) and machine learning (ML) to cloud computing in real-world settings. The studies together elucidate the breadth of potential applications of these technologies, ranging from reducing environmental impact to improving security and collaboration, and offer concrete illustrations of the necessary techniques and tools. Researchers and practitioners using these case studies as inspiration are likely to encounter several issues and research questions in need of further inquiry. The diverse applications described in these studies suggest that the solutions to these questions and issues are likely to be of interest to both industry and academia. Moreover, we hope these case studies demonstrate that the techniques in need of further investigation are also diverse, ranging from attention mechanisms to evolutionary algorithms and reinforcement learning.

This essay presents applications of AI and ML in cloud computing in a diverse array of real-world settings to highlight the burgeoning significance of such research and its relevance to both industry and academia. We propose that researchers and practitioners using the presented case studies as inspiration will likely encounter several issues and research questions in need of further study, and we suggest that the differing applications demonstrated in the case studies argue for the diversity of potential solutions. The techniques may be of interest to both industry and academia. Prior studies present solutions to several cloud-related problems using intelligent and learning approaches. However, we argue that a plethora of new

questions that necessitate deeper investigation have emerged and provide a brief research agenda driven by the presented case studies.

9.6.1. Key Findings and Contributions

The primary focus of this article involves presenting several real-world applications of artificial intelligence (AI) and machine learning (ML) in cloud computing. Due to the immense volume of research arising from these interrelated domains, the authors focus on alternative aspects of the pivotal relationship between artificial intelligence and machine learning. Major findings of the study include an increased reliance on AI and ML in cloud computing, with existing research utilizing these tools for multiple purposes and practical applications. The article also establishes the advantage of cloud computing operations as a result of applying AI technologies, as well as consolidating these combined categories of existing research into a diverse case study collection across a range of AI and ML applications.

Additionally, the report also unveils the consequences that stem from combining AI with cloud computing—a combined category that is referred to as "AI-cubed"—and how Exascale would combine major AI and ML capabilities into powerful NISQ, HTS, and digital machines, architectures, and systems. In this respect, cloud agencies assume different roles. Two possible roles include that of a cloud service provider and a provider working on a platform. Research embraces AI and ML approaches and application technologies such as mining, analysis algorithms, and real-life technology outlines. Applications have also been disseminated across a varied target, across groups that vary according to specific criteria: consumers with weaknesses, developers, operators, and maintainers. In closing, a metric-based analysis of an AI application shows that the Feasibility of Realization, the level of Maturity, and the Rationale Assessment group are the most frequently used criteria in overcoming AI problems.

9.6.2. Implications for Industry and Research

Implications for industry and research. The practical application of the results for industry is that these methods can be used to detect attacks in cloud computing environments and to counter the cost implications and organizational impacts of these attacks. Specifically, the findings in this paper can be used to protect larger organizations by shielding web

platforms and data centers from the power of attackers that utilize AI and ML in orchestrating attacks, which can result in perturbing normal organizational operational functionalities.

To that end, our research proves that AI and ML can be repurposed to counteract risks by analyzing and detecting security incidents, and to this end, we demonstrate such methods can be utilized to promote industry systems and operational resilience in diminishing vulnerabilities and their impacts. This research shall be extended to examine the application of AI and ML-augmented adversarial attack security strategies concerning next-generation network systems cybersecurity, cognitive radio platform application security, and IoT security. There are also additional directions for research that could explore the potential adversarial attacks on the defenses outlined in this proof-of-effect research. As with DDoS attacks, the potential for attackers to co-opt our own security "AI" through such misdirections could deserve a more in-depth examination. In the instance of AI030102, for example, a smart attacker may select malicious full knowledge of the technique used by the defender in the instantiation of AI030102, or better still a more advanced yet specific representation that is used after a few attacking trials and error, focusing the detection deficiency through the application of transfer learning, instead of 30,000 or more benign requests.

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Chapter 10

DEVELOPING AND DEPLOYING AI MODELS: BEST PRACTICES AND TOOLS

10.1. Introduction

In the field of artificial intelligence (AI), many models have shown excellent performance. From computer vision to natural language processing (NLP) and reinforcement learning, we have seen that specific algorithms and models show remarkable abilities. However, what is not often emphasized in the papers is how we can build, release, and maintain AI applications based on these models, as this process takes much more effort and time than simply developing the model. This part of AI application often distinguishes great models from runners, leaving a real-world impact on products and users. The last mile of a successful AI application often requires close collaboration with software engineers, product managers, user experience researchers, and other relevant parties, a balancing act to ensure that ever-iterative improvements in performance (goal of research) can be shown to provide values worthy of such necessary investments. Learned from a tech company, we comprehensively present the best practices and tools in developing and deploying AI models, to provide a helpful reference to researchers and engineers in academia and industry.

PURPOSE OF THE PAPER

The main contribution of this study lies in summarizing the practices and giving insights from both AI Research and AI Engineering. For a machine learning (ML) model that interacts with a real-world system, such as re-training procedure, parameters tuning, and data collection, it is difficult to offer a one-size-fits-all benchmark, and one result may mislead its actual superiority from multi-dimensions. For those mentioned below, it is easy to offer a previous benchmark such as the exact prediction value, but such a fixed set is insufficient. We believe AI applications and AI research are two sides of the same coin, guiding and promoting each other, while the pitfalls and details could be defined as follows.

10.1.1. Background and Significance

Traditional AI models rely heavily on feature engineering and manual manipulation of the data. However, deep learning-based AI models can learn the features and work with raw data, which makes them more robust and applicable. As a result, AI models have evolved from personally assisting users to participating in the decision-making process in crucial domains such as autonomous vehicles, health, finances, and industrial automation. Companies alone have built an ecosystem to support AI-based applications, generating $45.4 billion in revenue from the AI industry.

Developing robust AI models has become a priority for AI practitioners. Many best practices are suggested to produce the best models. Potentially, using the right tools to monitor and tune the AI models can further contribute to superior AI solutions. There is an entire area of research focused on migrating small-scale-centric tools onto cloud-based platforms to support scalable AI-based applications. Organizations such as OpenAI, Google, and Facebook have developed multiple tools they use to build scalable and intelligent AI applications. The need to replicate the best practices of other platforms has sparked research interest in the development of tools and practices to build scalable AI models. This work details an AI lifecycle, discusses best practices and emerging technologies, and maps tools based on the phases in a scalable AI model's lifecycle.

10.1.2. Purpose of the Paper

The purpose of this paper is to provide guidance and best practice insights into going about the development and deployment of AI models. The focus is on those parts of the process in which research engineers in machine learning must collaborate with product teams. We hope the reader finds it thought-provoking and emerges with insights into best practices in AI production as well as a better understanding of the kinds of problems that elite AI product teams are concerned with.

The emphasis of this paper is on practical, hands-on guidance around the tools and workflow used by leading companies to ensure that AI models are as valuable as possible in a product context. Except for §8, which touches on ethical issues in model performance, we do not address the process around the fact of building out these AI capabilities or the ethical problems around potentially harmful applications. There are many tools for building ML-

based products. Instead of "What tools can we use?" We think more fruit is to be found by focusing on "How can we use this tool best?" to answer questions like "What tools should I use to start monitoring my model?" and "what should I be thinking about when I implement this feature?"

10.2. Key Concepts in AI Model Development and Deployment

The concept of artificial intelligence (AI) is broad and can be dissected in several ways. Here, we confine ourselves to AI in the context of model development and deployment. Model development often involves considerations of both machine learning and deep learning. We distinguish the two in the following manner: Machine learning develops models that predict or classify automatically by learning from examples. One kind of machine learning, supervised learning, necessitates a labeled dataset: one in which the outcome is known at the start. The other, unsupervised learning, occurs in the absence of labeled data; instead, the model attempts to learn the inherent structure of the inputs. Deep learning creates predictive models by learning from tremendously complex patterns in data using algorithms that successively build abstractions. Deep learning models can be applied both as classifiers and predictors.

Deep learning can be implemented using either a feedforward neural network or a convolutional neural network, the latter of which is most commonly applied to image data. There are three fundamental steps in model development: data access and preparation, model selection, and model-output preprocessing. The model is then trained using a training dataset, which allows it to make inferences on a holdout set of data that it has not been privy to. To initiate the triage process, predictions from the trained model are then vetted against ground truth for the holdout set and examined for coherence. Several metrics are often calculated to quantify how well the model did at predicting the outcomes of the vetted holdout data. It is common to divide models into training, validation, and testing datasets as a prelude to training a deep learning model. Once the development phase is complete, and the training has been optimized, the model is deployed.

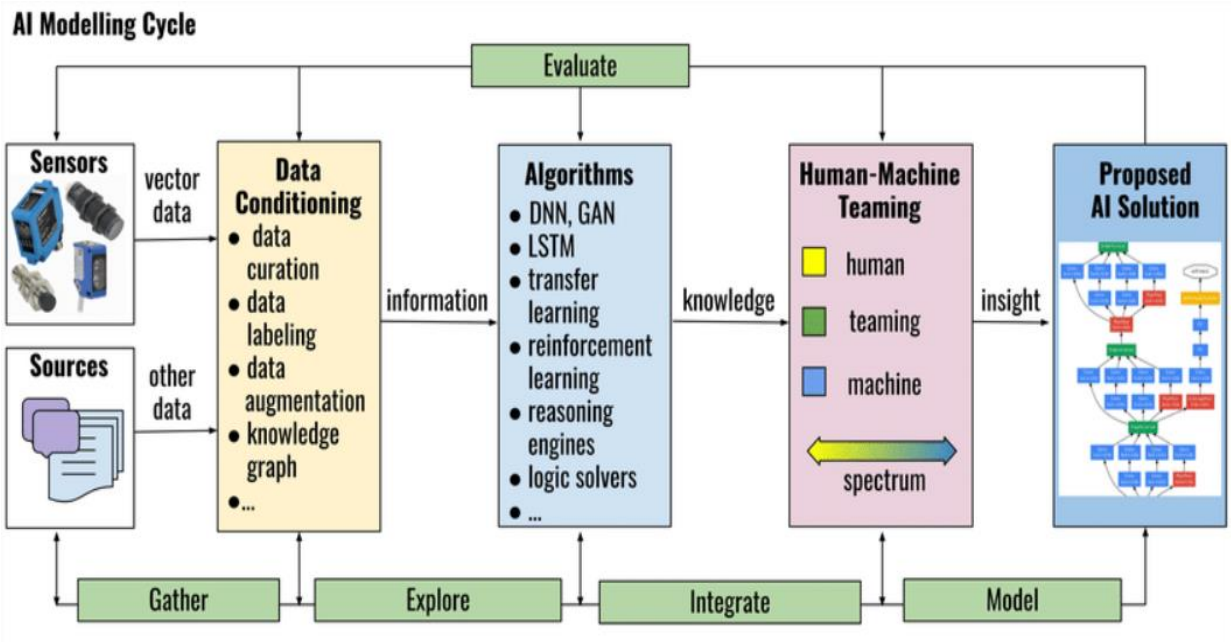

Fig 10 . 1 : Steps of Developing AI Models

10.2.1. Machine Learning vs. Deep Learning

The terms "machine learning" and "deep learning" are often used interchangeably, and this is not true at all. Machine learning is a subset of artificial intelligence that involves mainly the development of algorithms, which can help systems learn and make data-driven decisions autonomously. These algorithms are of different types such as linear regression, logistic regression, decision trees, random forest, etc. People have been using all these models to solve various business problems to make some decisions. These algorithms perform well when the feature space is huge, might have noise, and are complex to solve the given problem.

Deep learning, which involves artificial neural networks, is also a subset of machine learning, where the algorithm attempts to mimic the human brain more closely in terms of structure and function. These neural networks can learn unsupervised from data that is unstructured or unlabeled. This type of learning is essential for processing data, such as images, sound, video, strings, and time series, among other things.

Deep learning architectures include Feed Forward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long-Short-Term Memory (LSTM), and Content Addressable Memory (CAM). Each of them has its use and complements each other. One compares the internal features against future data; the other converts image, sound, or character data into input vectors. The main difference lies with

training. When one trains a feedforward neural network, only the input features result in the prediction of the target variable. The algorithm learns the underlying patterns by adjusting weights and biases in the network.

All of deep learning's attractiveness rests on the compound function approximation. Each layer of a neural network is responsible for learning slightly higher-level abstractions which can often combine to encode the output of the neural network as a function of the network's input. Other algorithms might do this, but deep learning has proven to work very well. That is, we can then say that deep learning uses machine learning. It's a sophisticated way to do so, but they ultimately work to achieve the same ends.

10.2.2. Supervised vs. Unsupervised Learning

When developing an AI model, machine learning takes place using sophisticated algorithms and datasets. One important distinction is between supervised and unsupervised learning. Supervised learning facilitates the construction of a model that allows forecasting of any value or variables that are crucial. In contrast, unsupervised learning assists in discovering the underlying structure and patterns within the data to handle it more effectively. From web search results and content recommendations to social media platforms, almost anything users interact with is driven by these two forms of machine learning. The output between the pairs of input variables is represented by supervised learning algorithms. An unsupervised learning algorithm, however, is employed to test data for unlabelled features or patterns. AI model development normally employs supervised learning, because data is normally readily available to allow the model to be built for training purposes. Labeled data can be formed and unlabelled data can be labeled for potential use. However, in situations where there is little or no data at all, unsupervised learning can be utilized. Neural networks broadly employ supervised learning algorithms.

In building a trained AI model, we employ supervised learning when the response is apparent during a model's training period. This method is extensively used when there is existing data to predict potential results. Monitoring, being able to give a forecast with increased responses of input data available, is another realistic application of supervised learning algorithms. Reinforcement learning approaches, in which the algorithm is capable of making informed decisions following efforts to maximize rewards, are another style of learning. This includes training the AI model based on formulating objectives and pursuing

behavioral patterns to optimize the ends. However, reinforced learning is more sophisticated, aiming to mimic human decision-making skills, and demands a higher amount of training time.

10.2.3. Model Training and Evaluation

Model training and model evaluation are two critical stages when it comes to the development of AI models. To train effective models, it is important to use the right techniques for training and pick a suitable cost function to optimize and guarantee generalization by using different validation methods. Hyperparameters also play an important part in the model training process.

Model evaluation, on the other hand, is the process of examining the output of a trained AI model to evaluate its efficacy. There are different approaches to this, ranging from the use of metrics to methodologies like A/B testing, a statistical hypothesis testing for the approval of the two variants, A and B, of an object under test.

The training dataset is used to fit the model. The aim is to generalize from the previously unseen samples so the model makes accurate predictions on this set. The validation set is used to tune the hyperparameters of the models. Hyperparameters are the configuration settings that are used to tune the underlying learning algorithm and affect the capacity of the model. This set is particularly useful to anticipate how a model will perform on a held-out test set.

The test dataset can be used to evaluate model performance and calculate the model's generalization error. This is done after the model has already been tuned using the validation dataset. During validation and model selection, the hyperparameters play an immense role in assessing models. Hyperparameters are configuration settings that are used to tune the underlying learning algorithms and also determine the capacity of the model. To train and optimize models effectively, the choice of cost function used to guide and monitor learning is crucial.

10.3. Best Practices in AI Model Development

Best practices in AI model development start with data preprocessing. There is a cliché in machine learning circles that the truth about building AI models is that the quality of the data is the single most important factor in making sure that the model is reliable. For this, one

needs to preprocess the input data to prepare it for modeling. Preprocessing may involve cleaning the dataset to deal with missing and incorrect fields. Cleaning of the data may also involve techniques such as mean imputation for numerical fields and mode or median for category fields, or encoding categorical fields into numerical values. The next phase in the development of the model involves scanning the parameters and conducting hyperparameter optimization. This is followed by the development of model checkpoints that save the model's state for later use, metrics, tensorboard logs, and early stopping points.

When done with the training of the model, it is necessary to operationalize the model artifacts. This is essentially generating microservices that can serve the models and make them RESTful. A cloud-native approach using Kubernetes is preferred for the deployment of the service. The deployment pipeline would necessitate the requirement for APIs and API versions, the rollout strategy being employed, either canary or blue-green. It would also require load balancing and auto-scaling. Practices of good governance imply the application of clear ownership of data and models, compliance with data governance standards, clear approval and review processes during the training, and separating the review and decision-making from the model and model artifact termination process when developing the AI models.

10.3.1. Data Preprocessing

Data preprocessing has a big impact on model performance, as deep learning models have more chances to behave exceptionally when they train on clean, preprocessed data. Moreover, in many cases, regardless of the downstream task, poor-quality input features could cause degradation in the deeper layers of the model or the final performance which could make debugging the model performance harder.

Several techniques and algorithms were proposed and developed to complement data preprocessing and alleviate the challenges associated with it. For instance, to help handle missing values in the quantitative train data, simple interpolation techniques could be used which fill any missing values by taking the average, weighted average, or the median of a given data. For the qualitative spectral channel train data, missing values for a given sample are usually transformed into zeros.

Normalization is also a preprocessing step, in which the data values are rescaled into a common range without distorting differences in the ranges of values. Normalizing target variables is generally a good idea in supervised learning to prevent numerical errors. Rescaling of feature values is an important step to ensure comparable magnitudes of input features. Variables could be scaled in such that they have zero mean and unity variance. This could be performed by subtracting the average value from a variable and dividing it by the hidden unit standard deviation.

Feature scaling is typically algorithm-agnostic and is not tailored to any deep neural network algorithms in particular. Spotlighted features or channels should be determined by the domain expert or could be chosen using domain-agnostic techniques that investigate the statistical impurities, outliers, or hidden errors of features and their potential impacts on the system at hand. Conceivably, employing domain-specific operations such as various dimensionality reduction techniques to pinpoint the key traits of select spectral channels might significantly assist. Using kernel-PCA t-SNE, or other techniques, important attributes could be discerned or reduced to clusters of similar traits. Inferred clusters of related channels could then be utilized as inputs to deep learning methods to classify the target contaminant or defects.

Features that require the most scaling should typically be the ones that determine the eccentricity of the data, i.e., maximal deviations that could bolster the classifier's probability of making typos, such as similar shape- and aspect-ratio outliers that the classifier inadvertently learned from the data. When operating on advanced data types, such as image or audio data, standard operability trends, and practices apply but differ in operation and technique to informative features, formats, and constraints of these data.

10.3.2. Feature Engineering

The main idea of feature engineering is to create meaningful input features for machine learning models such that there is a known structure among the variables. Common feature engineering practices include dimensionality reduction methods like the PCA (Principal Component Analysis) or autoencoder that use linear transformations and feature selection with LASSO penalty or SAR models. PCA in unsupervised learning extracts features in such a way that the first principal component maximizes the variance in the distribution. In contrast, feature selection uses our knowledge of the world to evaluate the relevance of variables, and

selects features early in the model-building process. This is appropriate when working with high-dimensional data because we want to lessen the dimensionality of our data matrix.

Transformation methods allow the original data to be flexible by generating new features with the existing ones. While the above methods focused on using dimensionality reduction and feature selection for pre-defining input features in traditional structured data sets that often involve a large number of observations, Random Search of Hyperparameters and Randomized SVD take on more of an exploratory approach targeting specific needs of the AI model. It creates new transformed features by using hyperparameters that are randomly searched until the best combination is found that carries the most information, driving the magnitude and modeling results of the socio-economic data space. Experimentation, selection, and evaluation of hyperparameters are important because the properties of feature extraction methods often change as a function of the hyperparameters.

10.3.3. Model Selection and Validation

Model Information

3.3. Model Selection and Validation

Model selection is a critical phase that involves choosing the appropriate model for a particular task. In AI, models go beyond machine learning models and typically include an end-to-end pipeline that one wants to deploy. One might want to try out different models to see which one works best for a particular task. The best model would be the one that generalizes well, but knowing whether a model generalizes well enough is another interesting problem that many would like to solve. This particular branch of AI problems can be addressed systematically if considered as part of the AI model validation process. Training and testing a model on a single dataset has high chances for bias, where the AI model may only appear to work on one particular dataset but fail to predict new data points.

Many statistical techniques have been developed to evaluate the AI model's generalization performance, including temporal holdout sampling, k-fold cross-validation, and bootstrapping. Cross-validation is the most used technique as it can use the data for training and validation by generating multiple training/validation pairs. The validation part of the model selection process aims to tune the AI model's hyperparameters. Afterward, the AI system could be trained from scratch using the entire dataset with the best model configuration

and then validated on an unseen dataset. The initial prototype could be tested in practice after successful model selection and validation.

10.4. Tools and Frameworks for Developing AI Models

4.1. TensorFlow

TensorFlow is one of the most commonly used open frameworks for AI model development. It was developed by researchers and engineers working on the Google Brain team. TensorFlow was originally developed for internal use, but it was open-sourced under the Apache License 2.0 in November 2015 and is now available to everyone. As such, it was created from the ground up with distribution, scale, and speed in mind, facilitating AI model development work for academics, professionals, and organizations of all sizes. TensorFlow is compatible with a variety of devices, and it provides a Python API for constructing and training AI models as simple or as complex as needed.

Today, TensorFlow is used for everything from training and experimenting on large internal models at Google to training and deploying machine learning models in production across a wide range of areas, from email filtering to medical image analysis, to search and machine translation. As mentioned, the high-level Keras API (which is now included as the official high-level API of TensorFlow) offers two ways of defining and building AI models with TensorFlow: Keras sequential API and the more flexible Keras functional API. Also, TensorFlow includes several tools for developers, such as a visualization dashboard that can be programmatically displayed in a web browser, which can be used to inspect and debug the models (TensorBoard), as well as a collection of state-of-the-art machine learning models designed to run on a variety of ecosystems (TensorFlow Extended).

10.4.1. TensorFlow

The TensorFlow section should describe the architecture and functionalities of the framework. This is very likely to include information on its core elements such as nodes and edges, the role of the API, and how TensorFlow can handle large datasets. Furthermore, it may contain information on popular modules built on top of TensorFlow, such as Keras, as well as a comparison with other frameworks such as PyTorch. Finally, it may also provide more detail on the exact role of TensorFlow in the development of an AI model, especially how it can be used to speed up the process.

TensorFlow was developed by the Google Brain Team and released in 2015. It is a free and open-source software library for dataflow and differentiable programming across a range of tasks and is used for machine learning applications such as neural networks. In terms of its architecture, a TensorFlow program is typically structured into a construction phase and an execution phase. The construction phase builds a computational graph using nodes and edges, each of which represents operators and tensors, commonly referred to as variables. These nodes are supervised by the TensorFlow API and can be evaluated within the execution phase. In terms of functionalities, TensorFlow is specifically good at handling large datasets that can be loaded via methods such as tf. data and tf. image.

There exist several modules built on top of TensorFlow. For example, as of Keras version 2.7.0, Keras has been integrated into TensorFlow to replace TensorFlow's earlier high-level API. Additionally, TensorFlow Extended (TFX) is another official end-to-end platform for deploying AI models that build on top of TensorFlow and use Keras models, Estimator models, or even a user-defined model. Nowadays, there are many frameworks available for deep learning such as TensorFlow, PyTorch, MXNet, and Theano. The use of each framework is very much dependent on user preference, whereas TensorFlow is preferred by researchers who are looking for long-term support, active open-source work, and the simplicity of developing AI models.

Fig 10 . 2 : Tools and Frameworks for Developing AI Models

10.4.2. PyTorch

PyTorch is a well-known and widely used open-source machine learning library that provides data structures for the representation of complex neural network models. PyTorch uses imperative programming and a dynamic computation graph. During the training of neural network models in PyTorch, it first constructs a computation graph concerning every data point at its forward pass and then updates the computation graph at the backward pass with the help of backpropagation. PyTorch primarily offers the following key features and advantages.

1. Dynamic Computation Graph: PyTorch utilizes dynamic computation graphs, meaning data-dependent control flow, among other things, maybe simply expressed in Python. This makes it possible to execute arbitrary loops and recursion, rather than having to describe their unwinding at author time. 2. Tensor Operations: PyTorch has a rich feature set on its Tensor, which can be manipulated in a variety of ways. It has excellent support for performing classic mathematical operations, linear algebra calculations, and indexing operations on them. 3. Neural Network Definition Encapsulation: PyTorch provides a wonderful alternative, where we can use both object-oriented and functional API directly. This makes building the neural network's architecture simple and concise.

Extended to support N-Phase Iterations and Parallel Computing: With the release of the new PyTorch, deep learning research has become easier and more pleasant. The functions of PyTorch are moved to extensions and much of the internals have been extracted to separate libraries. This will enable people to do external research and use different GPU configurations on a single work machine. Additionally, the code written in PyTorch is Pythonic, which means it is clean, simple, readable, and straightforward to comprehend. PyTorch also has a solid dynamic interface that allows people to experiment easily. What's more, with PyTorch, you may train, save, and export models using Python, rather than proprietary languages or domain-specific languages. PyTorch is so adaptable that it can create its computational graphs on the fly in real time. Also, it comes with a large library of datasets and graphics. One of the major applications of this framework is that it offers significant improvements in translation tasks.

10.4.3. Scikit-learn

Scikit-learn (also known as sklearn) is an open-source machine-learning library for the Python programming language. It provides an array of tools and methods to facilitate data mining, data analysis, and related applications. The most attractive aspect of Scikit-learn is its

user-friendly interface. This makes it quite popular in the field of AI and machine learning where users may not necessarily possess strong software navigation or coding skills. Moreover, Scikit-learn integrates various other Python libraries including NumPy and SciPy. Scikit-learn supports several supervised learning algorithms. The ones that are used by it mainly come from libraries like NumPy, SciPy, and Matplotlib. It supports cross-validation, ensemble methods, and clustering techniques.

A rich set of toolsets for different tasks including regression, classification, clustering, dimensionality reduction, model selection, and preprocessing techniques are available. Both user-level and algorithmic-level documentation are available. Appropriate error messages with suitable code fix suggestions are provided. The open-source version is available. It is simple and efficient. The general-purpose library encrypted with Python is scikit-learn. It includes various tools for classification, regression, clustering, dimensionality reduction, and preprocessing. It includes a user-friendly application interface for generating efficient results in tools. Being built on Python, it has much faster efficiency compared to R. The implementation has superior plotting capabilities. The seaborn library in Python can be used to generate attractive and informative datasets. It is the best source of libraries available in Python for machine learning algorithms which are designed on top of other libraries. Check the PIP installation in Python to install this library in your local system.

10.5. Tools and Platforms for Deploying AI Models

Developers can increase their model deployment speed and efficiency by using tools and platforms specifically designed for deploying AI models. Docker and Kubernetes stand out as two of the most popular such solutions. Docker is a tool that packages AI models and dependencies into containers so developers can run them consistently across different environments. Similarly, Kubernetes enables developers to orchestrate and scale model deployments in a production environment. They can use it to manage several copies of the deployed model in containers, schedule where they run, and ensure that the copies are always running.

There are other more straightforward tools than Docker and Kubernetes, specially designed for deep learning and machine learning models. For example, ML-Ops, MLflow provides a platform allowing for responsible running, managing, and orchestrating machine learning models in production environments. The machine learning models can be used across

a different range of languages, including Python, PySpark, and R. It can incorporate the latest big data processing engines like Apache Spark and Hive, with a class of a large range of storage platforms. On another note, DVC, an abbreviation of Data Version Control, is called DVCS and is specifically designed to make it simple to version control the dataset. While it is a tool for Data Version Control, DVC not only repo itself but also data files which remind us of the structure of Git and the Git LFS. It provides the process of scaling big data, which is designed for massively parallel processing. Export offers us an approach to quickly exporting the machine learning model to a production environment. It is designed to switch with ease to other deep learning platforms and is capable of use inside Real-Time analytics with the help of APIs. Other services like Azure ML, SageMaker, Bento ML, and Kubeflow provide end-to-end solutions for deploying machine learning models. Each of the tools mentioned has similar platforms built into them.

10.5.1. Docker and Kubernetes

In the course of achieving a real-world AI deployment, the sysadmin will deploy the code developed by the research team in a production environment. This implies that the production code must be packaged as a common Unix tool or as commonly used packages so that the sysadmin can easily manage the code once he takes responsibility. Thus, we use containerizing tools such as Docker. Tools like Kubernetes orchestrate the lifecycle of these containers, thus providing an efficient way to deploy, maintain, and scale the number of containers.

Docker and Kubernetes have gained popularity for deploying AI models. Docker containers are popular since they package an application with all its dependencies, such as system libraries and other binaries. Docker provides an abstraction for applications and running services by providing an isolated environment from the host system. Kubernetes is an open-source platform for automatic deployment, scaling, and layer networking of containerized applications. Kubernetes allows administrators to run large clusters on multiple machines. It has resource management abilities in terms of collective physical and virtual resources and makes the entire cluster a single "compute node." A pod constitutes one or a set of containers each for a deployed Docker container. It acts as an atomic unit that can be scheduled on any of the Kubernetes nodes of the cluster. With enough computation and memory resources tailored for an AI model execution, deployment of models packaged as a pod can also leverage Kubernetes advantage by efficiently managing resources, performing

load balancing, re-creation of containers in case of failure, automated rollbacks, and continuous deployment since it comes with ready to use infrastructure, etc.

10.5.2. AWS Sagemaker

Amazon Web Services provides a new, convenient way to deploy and manage trained machine learning models. The goal is to simplify the deployment and lifecycle management of models on the AWS infrastructure. The Sagemaker ecosystem features common operations and some best practices aimed at easing development and operational concerns. The results are accelerated model development, elimination of model management complexity, high-performance model training, security, and support for continued model innovation.

Sagemaker offers a set of algorithms in its platform which may be used directly or customized with custom parameters. The algorithms include the training and inference components and are complete packages, supporting use in experiments, training, and prediction. While machine learning models must be trained before making predictions, Sagemaker provides model hosting in a production target endpoint. All Sagemaker algorithms, including those created and uploaded by Sagemaker, are trained as a part of the training workflow. Training runs of algorithms are called Jobs and they are versions of the produced models. The model must be trained, and the endpoint exposed, before models from Sagemaker can be consumed by applications. Thus, Sagemaker includes the tooling and monitoring necessary to track and manage endpoint performance. AWS provides Sagemaker Studio, the first fully integrated development environment (IDE) to build ML, data science, and deep learning applications. The platform is built for Amazon SageMaker, providing a single, web-based visual interface where developers can write code, track experiments, visualize data, and perform a variety of other tasks.

10.5.3. Google Cloud AI Platform

Google Cloud AI Platform is a comprehensive package of pre-trained models for common use cases, automated data preparation capabilities, and an extensive set of services for building, training, and deploying your machine learning models at scale. It includes an extensive set of tools for building, training, and deploying machine learning models. The AI Platform provides secure and flexible infrastructure and tools to build and deploy machine learning models at scale. The latest AI Platform is aimed to enhance the development of AI-

enabled apps for developers and includes valuable features including client libraries and APIs, an integrated development environment, automatic services, and development tools. It also provides capabilities that enable deep learning, such as sophisticated algorithms and processors that have been immensely essential for the advancement of deep learning technology. The models available in the Google Cloud AI Platform are best suited for organizations that are looking to use custom learnings from their data to impact their business or industry.

Key Features:

1. Google AI Platform training and prediction services 2. Framework for building, training, and serving models using machine learning from open-source libraries 3. Built-in machine learning libraries 4. Integration for data storage with Google BigQuery and isolation to store data within the region 5. Data splitting capability to randomly shuffle your data to split it into two distinct sets 6. Early stopping to halt the training of the model or use all data 7. Flexible software environment to support all popular machine learning frameworks 8. Ability to build a model starting from scratch or modify a pre-built model 9. Models can be trained in batch or online mode.

10.6. Challenges and Ethical Considerations in AI Model Deployment

There are numerous challenges related to deploying AI models. Unfair or biased models can potentially lead to significant consequences, such as legal action or negative public backlash. Developers strive to ensure the quality, accuracy, and safety of their models, but there is still the risk of unintended discrimination. Furthermore, "fairness" is defined largely relative to society's values and involves values about individual rights and group protections. Exploring and deciding the values that should be included and the balance that should be struck are areas that need further research.

Algorithms and models may reflect societal biases, and we need to be vigilant about designing algorithms that are mindful of these implications. For example, face recognition tools have been found to yield different error rates as a function of whether those faces are located near the equator or the North Pole. We can use "fairness" metrics like equality of opportunity to identify whether our model is fair. For instance, in the aforementioned example, we can assess the model has equality of opportunity if it commits relatively equal numbers of

errors in its predictions of African-American and Caucasian faces. Now, to assume that the aforementioned definition of fairness is the expectation of society may be true; however, the issue becomes a question of values and where to draw the line. Should the expectation of society be at best the machine respects the equality of opportunity? Alternatively, should it be 'error rates for every race group residing in the Equator must be equal'?

Turner explores these ideas with the example of discrimination against black people in which "white Ceilts discriminated against white Nob Ceiling". The Noble in this sentence refers to wealth and not to social status. Turner poses a plethora of questions about the depth to which our models should be fair. Among a list of questions, he asks: Could we reasonably expect a new algorithm to perform at least as well as in a setting where the old algorithm was deemed to be an 'acceptable standard'? What should we regard as 'an acceptable standard' of performance? Additionally, deploying biased models that are prejudiced against a particular individual or group of people poses significant risks (e.g. - being rejected for a loan or visa for reasons of gender or race).

10.6.1. Bias and Fairness

We now look at challenges related to deployment. Although AI is often viewed as "training models," what we are ultimately doing is deploying models to perform tasks in the real world. It's the performance of models when deployed, either alone or as part of a larger system and/or alongside human decision-making, and when used in production as intended, that are ultimately of interest.

Research shows that models that perform well on average often do not perform equally well across all user communities. Lack of equal performance can be caused by missing or unrepresentative training data or due to a model's behavior that reflects existing historical biases in the data. Biases identified as a lack of fairness in a model can sometimes occur due to human error in labeling and the underlying historical data, but can also occur due to something as simple as using binary measurements to define success (e.g., accuracy), which would lead to poor generalization to unmodeled sub-populations.

While fairness has achieved considerable interest in the AI literature, our focus on performance in deployment provides a slightly different context.

Several approaches have been developed to try to identify, mitigate, and in some cases monitor for fairness and bias in both data and models. In data, some authors have argued for a shared definition of fairness to guide our conception and measurement of bias in data. Such shared fairness should guide attempts to make datasets more representative of the population in general. In models, many disparate algorithms and methods to mitigate biases have been proposed. Some propose (post-doc) attempts to train a model so that prediction errors are equally distributed across groups. Other methods try to re-sample or balance training data in such a way that group errors in the model's proximity space are reduced. Finally, some authors advocate (in-processing) work on the fundamental structure of a model's predictive landscape, e.g., changing the loss function, to encourage fairness. Many even broader options have been posed for fairness: some argue against mitigating ambiguous metrics like harms well, while others have developed methods to "de-bias" the model outputs directly.

Besides raising many technical and conceptual challenges, bias and fairness represent significant ethical and practical concerns, as they can lead to biased and unfair predictions in AI. To assess an algorithm's vulnerability to these biases, we introduce a set of benchmark tasks aimed at capturing these violations of generalization.

10.6.2. Data Privacy and Security

Data privacy and security concerns are central to the enterprise AI model deployment vision. The interaction between ethics and privacy-preserving techniques has led to the convergence of AI development and AI model deployment. The primary focus is on improved representation learning using minimized labeled data, while also ensuring fair, explainable, and reliable representations of the data. The same best practices shared in Section 2 are considered vital in the context of AI model deployment, where the incentives to use AI are greater due to data visibility and breaches. Other best-practice ways for AI model deployment that capture privacy and security include regulatory path compliance via checking for data loss concerns in deployable AI design, and ensuring ethical concerns are met with ethical use of explicit consent and domain safety constraints.

Given the "creep" of sensitive data in and near technical systems and the potential for deployment to serve multiple ends (where use in specifically focused ends could be ethically acceptable), we do not presume that sensitive data is absent from the deployment data. Ethical consumer vulnerability due to the triggering of privacy concerns warrants careful review,

discussion, and intervention from privacy and technology due to the strong behavioral and social roots, connection with privacy and related laws, handling of data and related insights, and the ethical implications of such insights. For software AI tools that owe their success in part to responsible AI model training approaches, there is a multi-stakeholder interest in ensuring that these parameters are also maintained in AI model deployment. In this section, we highlight features and AI model deployment development that Zoom AI developers contend promote such responsible AI systems handling data innovation at scale.

10.7. Case Studies and Examples

In this section, we present several different ways that AI models are developed, deployed, or used in the real world in case studies and examples. While these case studies are not all directly related to criminal justice applications, they aim to showcase a variety of examples from different domains and illustrate concrete ways that models can be used to assist human decision-makers. Essentially, they are small-scale demonstrations of what Model Cards or a Datasheet could look like for a particular model under development or in deployment. We include case studies in risk assessment, image recognition, and language processing that touch on a variety of key issues that developers, users, and the general public may be interested in. We hope to demonstrate that AI models can be made comprehensible in concrete ways for different users and designers.

Reviews of AI deployment have shown that while individual case studies can illustrate the benefits of particular AI models and predict how an AI model will perform at deployment, it is very challenging to run perception studies or survey how the general public feels about model deployment. Nevertheless, we encourage developers and users of AI models to test their assumptions about model performance, the environment of deployment, and the likely progress of deployment. Given the high bar for predicting user satisfaction and developer understanding, internal testing should be a core part of any deployment. Using tools throughout the process, such as the ones in this document, to enable continuous, evolving testing is a key opportunity for improvement in the deployment process.

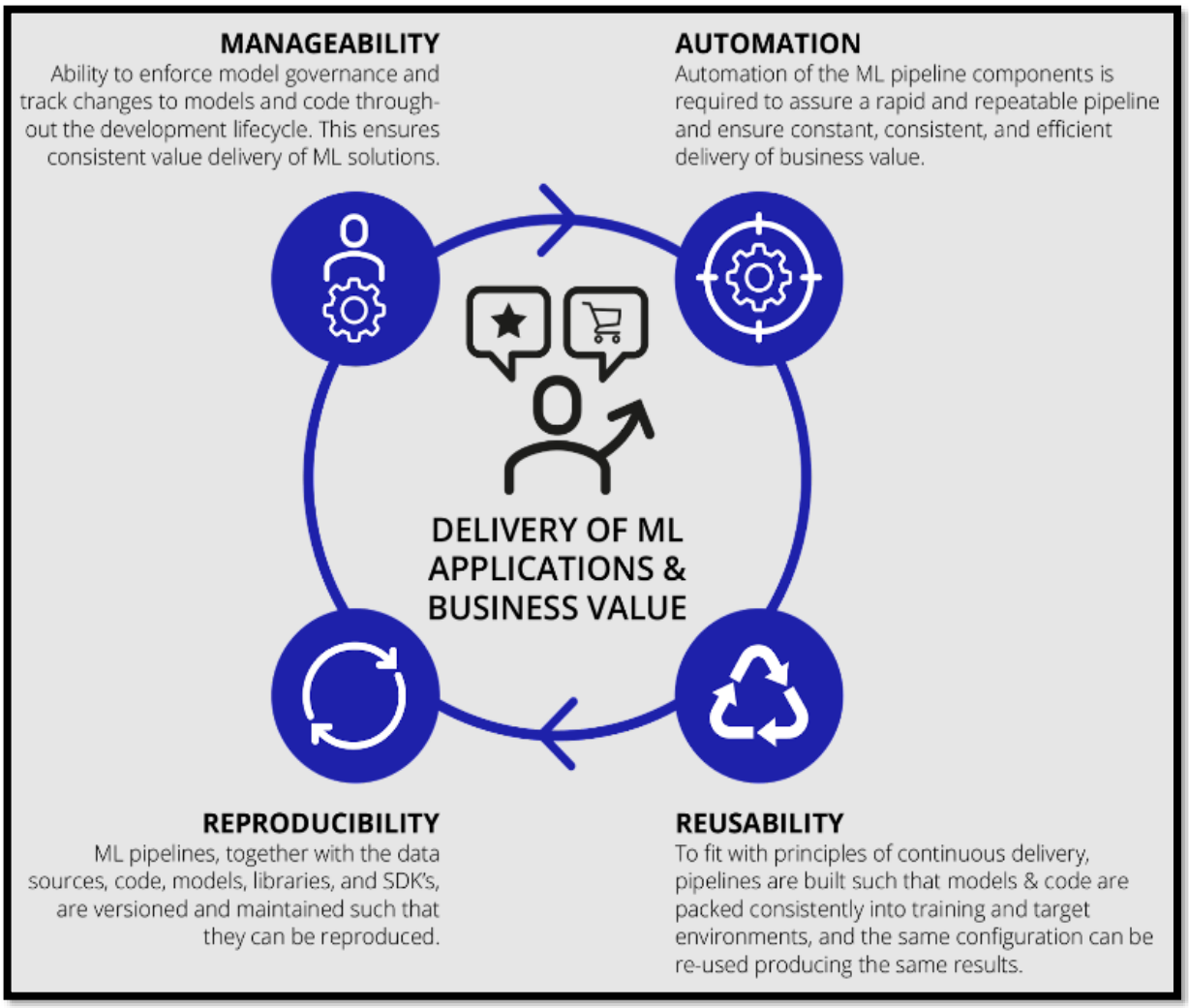

Fig 10 . 3 : Deploying AI Models in Production

10.7.1. Real-world Applications of AI Models

Real-world applications of AI models

AI models have proven to be an effective tool across a variety of domains. For instance, in material science, AI models can accurately predict material properties several orders of magnitude faster than physics-based approximations. These physics-informed heteroscedastic emulators have improved the design of aero-inertia for spacecraft by several percentages, saved thousands of hours in computational time, and potentially millions of dollars in simulation costs.

In energy, production models that can forecast loads and optimize power usage at large data centers have a growing impact given the accelerating demand for cloud data storage. In

smart and sustainable cities, AI models help public transport agencies, in an intuitively intuitive way, optimize service operations, and improve the passenger experience.

In biology, AI models can enable faster data-driven drug discovery and development. In climate and environmental science, long-term predictions and simulations extended by AI can forecast the short- and medium-term effects of anthropogenic climate change and natural disasters.

In healthcare, AI can assist as well as improve both diagnostic and prognostic accuracy. Although most AI models are benchmarked on simulated or public domain data, models that have been deployed and used in the real world can provide valuable insight into the difficulties of data acquisition and model deployment, as well as the impact of these models on their intended domain. These deployed models in limited domains such as industrial and medical applications have achieved remarkable predictive performance. They have been shown to improve engineer productivity, optimize the scheduling, resource allocation, and operation of complex and high throughput benchtop experiments, provide scalable quality control through automated anomaly detection in large-scale healthcare operations, and enable timely, individual therapy decisions.

10.8. Conclusion

This research paper has examined best practices for the development and deployment of AI models, in addition to the tools that can enhance these processes. To sum up, ensuring best practices are adhered to when developing AI models is extremely important, as is utilizing tools that can help to ensure adherence to these best practices, improve the interpretation of models, and stop individuals from abusing AI models. It is also essential to be aware of and stick to ethical considerations when working with data – particularly when AI models or machine learning are involved. An awareness of these ethical considerations is important, even in instances where the content exists in the public domain.

Several tools exist which enable the design of high-quality AI models. The tools available have varying purposes; some assess the usability and functionality of an AI model, while others help developers understand the interpretability of a model. These tools exist to make AI-based systems more secure and trustworthy, and also prevent opportunities for abuse that may affect products or individuals. In closing, ensuring that the best practices for AI model

development are followed, and making use of tools to enhance the model development process, will increase the possibility that the AI model will be secure, safe, and trusted. Ethical considerations also need to be kept in mind when developing an AI system.

10.8.1. Summary of Key Points

• Developing and deploying AI models at scale requires careful attention to a variety of best practices, particularly around model management strategy, reproducibility infrastructure, reproducible production workflows, and model maintenance and governance. • Despite advances in tooling, open challenges remain around model versioning, auditability and provenance, and creating and maintaining canonical model datasets. • Reinventions and reimplementations of the same core AI models and systems are still common. • Large, complex machine learning models and hardware accelerators have combined to make hardware requirements prevalent. Current tools and best practices have a lot of challenges in providing a good experience in response. • Current practice is to refactor large models into smaller parts for different tasks, but no tools for this have been developed in the architecture/system and AI/ML stack until now. • Challenges around datasets are straightforward, but datasets are often not treated as infrastructure within large research and production organizations, leading to incorrect or insufficient resources allocated. • Once the AI model is developed and the AI datasets and training system are deployed, there exist databases and AI development and tooling tools. DB administration (as with any service administration) can also be monitored for data biomedical surveillance. There are a variety of tools for model serving and model monitoring in production. • AI model development should include six stages of AI data workflow, including approvers for AI model training and deployment. AI model users can include a variety of actors, and successful deployments include notifying them of potential issues in AI model validation and deployment and making error explanations widely available. Model development presents a variety of challenges. Model management and deployment solutions also make compromises for the convenience and resources of the organization developing the AI model.

10.8.2. Future Directions in AI Model Development and Deployment

A new general-purpose software engineering platform

In this chapter, we offered recommendations for good practice across the entire spectrum of activities involved in developing and deploying AI models. The specific tools and workflows we discussed are all subject to change, especially as they are based on research that is still ongoing and comparing state-of-the-art methods. We highlighted that this field of research is still maturing, and the recommendations we presented reflect this. As NLP and Big Data research advances, both the models we create and the underlying software we use to create them will become more sophisticated. Further research is needed into the following open problems.

1. Automated deployment. Although there are tools that can make it easier, currently even provisionally deployed ML models require quite a lot of boilerplate code. When we deploy models to a testbed to finish the research, this overhead can quickly accumulate. Developing or improving upon models such as FloydHub and Cortex's is becoming gradually more common; however, being able to go one layer lower (i.e., to hidden channels in Kubernetes and Presto) may have more widespread advantages. Developing an interface between standard numerical computing Python (numpy, pandas, etc.) and TensorFlow could have an impact similar to Pandas or Apache Arrow by permanently lowering the barrier of entry for ML model deployment once deployed. Alternatively, we could explore tools that can be run on any server in which a city has the spare capacity (i.e., Tensor-comprehensions). Both of these examples can be seen as lower-level primitives and are domain-agnostic; they have the same potential to transform deployment as the individual parts that make up our architecture. Given the rapid pace of this field's development, we believe that in around 5 years we will be able to host ML model deployment meetings in the same way that we currently host RAPIDS, Koalas, and Apache Arrow meetings, all of which provide ML practitioners with a more powerful interface for the same domain.

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Chapter 11

FUTURE TRENDS: EMERGING TECHNOLOGIES SHAPING THE CLOUD LANDSCAPE

11.1. Introduction

The late 2010s and early 2020s have seen the decade fundamentally reshape the cloud computing landscape. And with the COVID-19 pandemic enriching the cloud market, various technologies have been heavily shaping and are set to shape the cloud landscape for the foreseeable future. In this essay, I will be discussing the importance of interconnected hybrid architectures, solid-state drives achieving price-performance parity with hard-disk drives, and the new edge computing services offered by hyperscalers and the emergence and bright future of niche serverless CaaS offerings.

However, an interconnected hybrid cloud represents the reality of infrastructure. Enterprises today use a mix of services from public cloud vendors like AWS, Azure, and Google Cloud, while also having custom architectures serving private clouds and their data centers. Although everybody knows that the future of 'Cloud Computing' is the 'Hybrid Cloud', it is just a lazy industry consensus. Enterprise data integration today requires a new practically feasible paradigm of an interconnected hybrid infrastructure. Solid-state flash storage, in our opinion, is another underlying technology that has been influencing the cloud landscape and is going to shape it even further. The advent of ultra-low latency storage devices (Intel Optane - 150 µs) and hyper-converged solid-state storage systems has made one of the bottlenecks of cloud storage, which is the storage I/O on the edge, irrelevant - it now literally scales and performs linearly with every single container. But then what is the real bottleneck? Is it even the hyper-speed of RDMA networking provided; the ability to directly read/write to the storage subsystem using the kernel? It may be a bottleneck over the next couple of years. Use cases that not only require higher performance but also the infinite scalability of cloud storage will start to look elsewhere. That is the topic for the next trend.

11.1.1. Background and Significance

Cloud computing has grown by leaps and bounds over the last decade. Several tech-savvy firms and organizations have adopted the cloud system due to its potential for scalability and the removal of size-associated boundaries. Over time, more and more business consumers have adopted cloud technology to facilitate everything from AI and machine learning to data analysis and big data storage. These technological developments have sparked a significant increase in cloud computing capacity. Thus, it is essential to examine the development in the cloud field and evolving technologies and trends that have the potential to shape its future.

Security in the virtual world was once a luxury and is now essentially a necessity. We have deep trust in the cloud in terms of data security and privacy invasion concerns. When it comes to accessing resources on multiple devices, cloud technology has evolved as an integrated environment. Since developed software encompasses both large and small companies, cloud technology offers access to flexible, low-cost techniques for new business startups. Organizations generated greater revenue and further acceptability for consulting on cloud engineering and business strategies. Besides, there has been an increase in demand for cloud-based storage resources and analytics data to help aid new product-based, financial (including monetized), and token-oriented goals, among others.

11.2. Evolution of Cloud Computing

Act I - The Advent of Cloud Computing

If one were to take their GPS and lead in only one direction, navigating the business landscape in the late 1990s and onwards from the new millennium into the First Decade, they would surely end up in the Cloud, sometime after the turn of the century. The child of service locals, which matured in the 1960s in the supercomputer mainframes of the Time-Sharing period, Cloud Computing is as much an evolution in leveraged hardware systems as it is an archetype, defining a virtualization – or "abstractive" – method of delivering software.

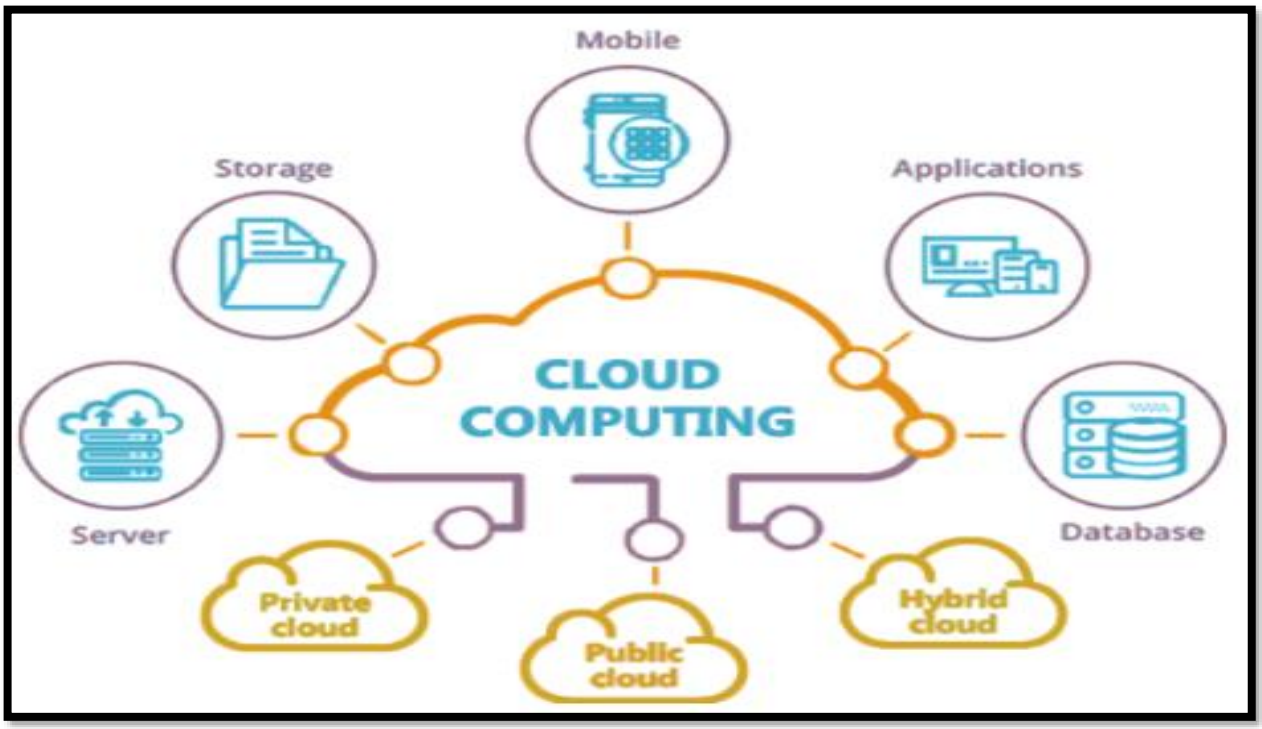

Fig 11. 1 : Evolution of Cloud Computing

More than a branded utility, "the cloud" as a concept means something different to the same potential services, originally used as an abstraction for the complex infrastructure it represents. In philosophy, it is atop Maslow's Hierarchy that "The Cloud" resides – as a container meta platform laying upon a tower of first levels in the Internet of Things (IoT) pyramid: the foundational network infrastructure & connectivity layer, then the interconnected device and communication models upon it. The IoT itself has thrived as a noun and will almost definitely persist in the evolving vernacular, where the Internet of Everything remained more speculative, as a suggestion for improved technological consolidation than any actualized proposition for unified system behavior. The Cloud employs a similar metaphor to the IoT for the larger space of FasT-TixT systems, as mentioned earlier, and the IoT of Systems. More than a system of connected systems, the Cloud operates as connectors of IT connectors – "meta platforms" in ever-encasing layers of Bacon's great, or Pythagorean, Theorems.

11.2.1. Historical Overview

Acknowledgments of cloud computing date back to the 1960s when some visionary thinkers expressed their wildest imaginations in various forms. One prominent example is Licklider and Taylor in "The Computer as a Communication Device." Remarkably, the early

stage industry language and the symbolic notations changed with cloud adoption. It started becoming universal with the invention of computing grids - for scientific networking and distributed infrastructure grids for infrastructure and utility computing - and the relative social messaging in the late 1990s, marking the birth of cloud computing. This was swiftly followed by several contributors, including AWS during the noughties, which ultimately accelerated public clouds. A few key advancements occurred between 2010 and now, including shared, scalable, and stored resources such as data centers, computer networks, servers, storage, application platforms, and services that permit access to services. Some of the major instances of improvement, design, and document machine learning models related to data centers, clouds, data, file systems, data warehousing, access analytics, and Hadoop insights have repeatedly reshaped the industry.

Firstly, we saw the innovation in 2006 of Amazon Web Services (AWS) Elastic Compute Cloud (EC2), enhancing systems administration to be automatic, provisioning, DevOps, automatic configuration, automated blocking of brute-forcing, and automated unobtrusive security in provisioning. Next, in 2008, Eucalyptus emerged as the first system that enabled enterprises to build private clouds using Amazon Web Services (AWS) APIs. Google's Bigtable and IBM's Cloud BLEU escorted in 2012, an open reusable cloud data repository. This was swiftly followed by POLOMINT (2014) which united management and dissemination of distributed huge-scale physical datasets in federated data depositories as well as a usable mechanism for storing heterogeneous global environmental datasets. In 2015, we saw YARN (Yet Another Resource Negotiator) ship as a resource manager for Hadoop 2 clusters, achieving a significant improvement in resource utilization across the clusters. In 2017, Fortissimosecoma created mimicry net, a deep-learning solution that predicts network throttle points by examining a few seconds of communication data.

11.2.2. Key Concepts and Definitions

Cloud: A 'highly available collection of computational resources hosted in clustered server-farms and distributed over the Internet'. Cloud offerings can be classified as Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS).

Cloud Computing: 'The use of the Internet as a platform for the consumption of IT resources'. Cloud-based solutions can take advantage of virtualization techniques to partition and abstract the physical resources from the users of the cloud. In these solutions, the cloud

providers can offer shared, private, dedicated, and high-performance hosting for their solutions. In other words, cloud-based solutions provide a value proposition for the consumption needs to be backed by strategic alliance opportunities.

Grid Computing: 'A type of parallel and distributed system that enables the sharing, selection, and aggregation of geographically distributed resources dynamically at the time of their use'.

Resource Virtualization: 'The process of taking one physical computing resource and making it look like many, potentially smaller, virtual resources'.

Elasticity. 'The ability of a solution to grow and contract available resources to optimally meet the demand at hand'. To address constraints; for example, performance, scalability, and privacy; various investigation models, control mechanism models, and decision-support systems and methodologies were developed. In the context of such work, only a few general open issues and principles can be identified, such as the need for care and the significance of the monitoring, virtualization, and provisioning techniques of the cloud service offering.

11.3. Emerging Technologies in Cloud Computing

As cloud computing emerges as the new norm in enterprise architecture, new trends and methods are pushing IT further into the strategic direction in which it deserves to be. The landscape of servers, cloud platforms, and systems will change as these changes unfold, and so will the supervisory function to ensure that the amount of data collected remains usable. The exponential growth of IT in the future will make it necessary to handle the increased analytical and computing capabilities associated with advanced analytics and strategic themes such as artificial intelligence, machine learning, the Internet of Things, and blockchain.

Artificial intelligence and machine learning are currently some of the most proven technologies that will drive our future. I predict that we will see an increase in homes or businesses that use a smart interface such as Amazon Alexa, Google Home, or Siri. Companies will invest more in machine learning algorithms designed to root out fraud, waste, and other abuse. We are also starting to see interactions with smart machine-learning help desks, which will have the ability to learn customers' support issues and provide faster, more efficient responses to those customers. Cloud-based AI and machine learning are opening up a new era

of innovation to their users and are quickly moving from experimentation to a host of mainstream, worldwide technologies. Over the next several years, businesses that adopt cloud-based AI and machine learning infrastructures will be able to save on costs due to automating tasks and getting machines to do the work, rather than doing things manually. As a rule, the speed and agility of the cloud is advantageous. This mentality bleeds into edge computing.

11.3.1. Artificial Intelligence and Machine Learning

Artificial intelligence (AI) and machine learning (ML) are revolutionizing cloud computing, driving innovation in a variety of applications and services. In cloud computing platforms, they automate traditional manual processes, enabling better and faster IT operations. AI and ML can develop business activities, including using data for cognitive computing applications such as data processing and machine learning. This technology allows for powerful processing and data analytics capabilities at lower costs. It also helps with security, making identities more difficult to fake, keeping sensitive data secure, and improving cryptography and password security. AI improves data center management, making more intelligent systems that can detect server failure or trend analysis. It cuts the time it takes to query data, allows companies to save and analyze data automatically, and increases diagnostic accuracy by parsing feedback on failed services.

Combined, AI and machine learning technologies help to look at all the possible combinations out there in computing and be able to assess not only what combination is the best and most efficient, but also what is the most cost-effective. Since these systems increase automation, AI will have a very significant role in system self-repair, especially in terms of proactive system error detection. AI turns the traditional concept of infrastructure on its head. Originally, hardware was the important part, and software was developed afterward. But in AI, software informs hardware. There is a tailored standardization of hardware to software in AI. For businesses in the cloud space, the power to automate is a key advantage of AI. They can push out new machines or databases to their cloud services quickly and at a much lower cost than traditional services. Traditionally, deploying a new front end was always a manual task. It required creating various image files, releasing the image to hardware, and then configuring and setting up the frontend server. But AI and ML automate contrast checking, speeding up the process significantly.

11.3.2. Edge Computing

In different ways, cloud computing is evolving due to cloud-based features and technologies. One of those prominent trends is edge computing. Recent developments in edge technologies indicate a significant migration of computation away from the cloud centers towards the edge. Not only do edge computing characteristics reduce travel time and data latency, but they also have the potential to address many of the resource bottlenecks that drive performance and efficiency tradeoffs faced by data centers and edge devices today.

Most importantly, the edge is likely to break the level of control granularity associated with cloud data centers today because of federated edge architectures and a potentially vast distribution of edge resources. This will require much more automation within the system and may introduce novel applications related to intermediate control over parts of the network. Therefore, edge will require integration with cloud orchestration, and accelerated development resulting in cloud-edge fusion. This fusion will strongly shape the future of the cloud, breaking centralization trends into a heavily decentralized architecture that shares common cloud principles. Cloud architecture is compactly regionally distributed: the spread of microlevel edge servers from metropolitan to building or data center edge reflects the deeper interconnection between computation, storage, control, and data within computer systems today. Edge and cloud data move back and forth, optimizing routing on a per-application basis. Cloud-edge control will increasingly need interconnection on sub-metropolitan to city-level scales. Public edge and private edge merge with the city, exploit the economy of scale, subversion of data silos, and deep integration with edge services.

11.3.3. Quantum Computing

While one of the latest and most hyped industry trends, quantum computing can be a gray area for businesses. Most news in this field has reflected visionary or theoretical advances and just a few announcements about practical use. However, quantum computing is and will continue to be one of the most influential fields in computer science. A quantum computer can be a vast resource of computation hardware working with millions of parallel processes that can cover each combination of all the data. Although the core part of cloud service, data center capabilities such as Amazon EC2, are only emulations of the latest digital computers. Users can gain access to the most sophisticated computation capabilities. The fusing of cloud services and quantum computing will be a breakthrough in the computer world. Indeed, the

negative NP-solved problems widely known to have factorial solutions can be solved easily with the right estimation of quantum service.

We look forward to using a quantum cloud virtualization service that conceals quantum problem formulation and estimation. Although quantum cloud services are not close to real-world markets, they promise an unprecedented transformation in quantum computing generations. Quantum computing can get hold of a higher computational precision rate and capacity. The most exciting quantum achievement in computer science is the quantum computation power based on its unique and bizarre quantum mechanics specifications, transforming them into potential intrusive assets. Since destructive interference helps quantum computation further, quantum computing became so influential because of the massive number of possibilities that can be explored and usually speeds up the main source of parallelism. Sometimes it is also the uncertainty of atoms that allows quantum computers to work.

11.4. Impact of Emerging Technologies on Cloud Landscape

Emerging technologies impact on the cloud landscape

Scalability & Performance: In-memory computing, cloud computing capacity is enhanced directly in the amount of memory required and also because in-memory computing systems can have multiple processor cores. This increases processing power as a function of the capacity and additionally increases the speed of the data that can be processed. As of now, many cloud service models such as IaaS, PaaS, and SaaS can easily be integrated with this technology for performance improvement. In addition, with technology such as blockchain as data, decryption techniques using machine learning are also considerable for improvement in data privacy and data security, and cloud computing only.

Security and Privacy: This becomes important every day as more and more data is processed in the cloud. In addition, security affects all cloud models, from a small one like Sensor as a Service to a Hybrid Cloud model. The use of blockchain technology will be growing which makes our result a heavyweight of privacy protection, which are essential characteristics of cloud service operations because it is a decentralized service system where there is a secure distribution of blockchain creator transactions and documented periodically.

By being aware of its advantages and the role of emerging technologies, cloud service providers gain an optimistic apprehension for future trends. These technologies are expected to change the landscape of the cloud and make it more efficient and reliable.

Fig 11 . 2 : Technological Trends Shaping the Future

11 4.1. Scalability and Performance

The problems of scalability and performance have been identified as essential in cloud systems. Scalability in system design usually describes the possibility of the system to cope with additional charges with no deterioration. However, different types of scalability improve the general scalability of an ecosystem. They embrace the dimensions - horizontal, vertical, functional, and procedural - of scalability. Different forms of scalability enhance the overall performance of the system. For example, smooth upscaling or downscaling of the system regarding work or demand is one explanation of scalability. Moreover, pushing the next

responsibilities to future services or diverting obligations to specialized servers or systems is shown to be another measure. In addition to present scalability problems, cloud systems will experience significant new challenges triggered by emerging technologies. The large number of new applications or markets that traditional commercial or educational data centers host becomes a sensitive issue of safety.

Cloud hosts will increasingly deploy machine learning to forecast workload metrics which, for newly arriving use cases, can improve power consumption and network co-flow suggestions. Lastly, cloud suppliers continue to develop and explore new fabric architectures and standards. These fabrics use fast, security-coupled flexible next-generation network devices to help create cloud networks with absolute wire speed. They possess terabit bisection mutation-selected fabrics that use only 3.8 mW per port. Achieving this in an interoperable way requires innovative and rapid systems of scheduling that can balance the possibilities of a neighborhood for congestion. As networks continue to raise the costs of shifts across hops, port-to-port speeds are predicted to rise. Shopify, Amazon, and Google are entering the 400 Gbps fabric hardware. With the potential for subsequent hops to flee congested locations, every spine and aggregation swap nearest hops could feasibly take advantage of any further additional local potential that the furthest ports of every trade packet need. Additionally, this propels towards a bimodal workload, requiring a low skyline atop saturation. At once, many jobs still see congestion end-to-end and require a quality responsible set of rules 100. Multiple hypotheses predict that certain bisection network powers would not change, as these works result in a similar amount of backbone impairments with lower, network-imposed congestion levels.

11.4.2. Security and Privacy

Security and privacy. Legal and social norms must be considered in the context of smart communities, where co-bots will have easily identifiable physical features and act near individuals. The EY report defines the cloud environment as being an ecosystem of providers within the channel supply from a customer to an application. In South Africa, we currently see multiple defensive strategies utilized (as in the US environment); however, the threat community is focused, creative, well-resourced, and intelligent, therefore our national and business security risks are high.

Risks to individual Heart Rate Monitors (HRMs) are currently low in South Africa; however, as the technology becomes more affordable and accessible, as well as integrating seamlessly with other technology such as the TV or smart home systems, the risk would likely increase. Deploying cryptographic security controls onto a smart object might help diminish some of the exposure; however, the pace at which threats are evolving does not indicate a long-term benefit. Any acquisition of personal data and use thereof in Smart Computing needs to be in line with the Regulation of Interception of Communications and Provision of Communication-Related Information Act (RICA) and applicable Privacy Legislation, such as POPIA. Application programmers not only need to have a credentials-checking function but must also determine whether a request for secure access is appropriate given the requestor's role by "least-privilege" principles.

11.5. Future Trends and Predictions

Hybrid cloud is espoused to be the future cloud landscape as it holds the potential to improve cloud computing reliability and predictability not only for broad sections of industry, healthcare, and education but also for IT and cloud infrastructure providers. Hybrid clouds ease software complexity, permit cost reduction strategies for access to wider resource pools such as volunteer or contributor clouds, provide disaster recovery services across clouds, eco-system multi-tenancy, and provide user-friendly cloud access via cloud workload managers. Such enablers will permit cloud infrastructure providers to offer guarantees that span not only financial aspects but also explicit QoS, Volunteered and Effective Service Durability, and Disaster Recovery. Confidence in the cloud is what will drive adoption and hybrid cloud computing is set to ensure it.

Five years from now, Infrastructure as a Service (IaaS), mostly based on virtualization, will continue to be popular for batch processing applications in bio and pharmaceutical research and other industries. However, serverless computing will emerge as the next cloud service computing paradigm where the unit of assignment becomes computing functions and is predicted to become the dominant architecture in the next five to ten years. Serverless computing applies to a wider array of applications including Human Genome Project distributed computes, compute QoS assisted multiplex testing Virtual Laboratories, lightweight cloud applications for desktops, laptops, and sub-netted appliances, and individual and/or group desktop and server appliances for federated cloud sharing of resources, work tools, and applications.

11.5.1. Hybrid Cloud Adoption

The cloud computing environment has evolved from inception with IaaS services to encompass various service models as well as deployment models. One of the primary cloud deployment models is a hybrid cloud, also referred to as a 'paired' cloud, due to the integration of two or more cloud infrastructures, ideally public and private. For this study, we define a hybrid cloud as a mixture of multiple deployment models, primarily public and private clouds, as per the official definition by the National Institute of Standards and Technology (NIST). Hybrid cloud is considered an emerging trend in the future because an increasing number of organizations are combining their offsite running cloud applications (public cloud) and resources located within their corporate infrastructure.

Key Benefits: Various fundamental benefits of the hybrid cloud can be categorized as primary and secondary. For example, the key primary benefits of a hybrid cloud include, but are not limited to, partial data and processing migration to the public cloud, workload flexibility, improved uptime through offsite resources, and enhanced redundancy. Hybrid cloud concerns, challenges, and requirements suggest that adoption implicates operational impact related to data protection, security, network quality, interoperability between environments, quality of service, cost control, and legal compliance with regulations. The decision to adopt a hybrid cloud is dependent on numerous pros and cons. Although it provides many benefits, it also implies some restrictions, controls, oversight, and constraints that need to be addressed. As we will discuss briefly in the following sections, in integrating these infrastructures for large businesses, the primary action is the opening of the private cloud network to interoperate with the public cloud deployments.

11.5.2. Serverless Computing

Serverless computing (even though servers are still there keeping up the service) that is also known as Function as a Service (FaaS) has proven to be a platform of choice for running event-driven services in the cloud. With serverless programming for cloud computing, one can reduce 90% of managing complexity and significantly reduce costs. A typical startup is saving 15%–20% of their cloud expenses by using serverless for their infrastructure over conventional computing. Serverless computing shifts the responsibilities of managing the server to the cloud provider. We just need to write our code and deploy it on the serverless

platform, let the platform deliver the services we have written, and then scale for us when our function starts to be executed.

New development practices are a key benefit as serverless architecture means that you typically break one application down into many small functions. With serverless computing, functions are autonomous and only execute when triggered. Each function is a microservice architecture and is quite isolated from the other functions. It provides both business and development advantages that are attractive for cloud-native enterprises. Production-level serverless cloud platforms are now available from the main cloud providers such as Amazon, Google, and Microsoft, as well as emerging platforms like Serverless, Platform9 Fission, and Vercel. Several tools are now emerging to abstract away different cloud serverless providers and provide a fully managed platform for all the major cloud providers. Historically, cloud providers fragment options in standard platform offerings, positioning them to remove such fragmentation across providers, distinct architectures, or multi- or single cloud.

11.6. Conclusion

The advent of emerging technologies, such as hardware accelerators, quantum computing, low-power devices, and smart materials, among others, is collectively set to exert both incremental and transformative effects on the cloud in the next years and a decade. From AI, going faster and even at the edge, through security to cost-effectiveness, an enriched cloud landscape will likely not even be carried out on traditional commercial platforms and infrastructures themselves. By challenging today's core technologies and informing computer systems design both by academia and industry, the seven key drivers of the cloud landscape's unofficial roadmap inevitably raise intertwined scientific and engineering questions. They push toward the conception of protocols, interfaces, and systems, knocking down prior personal, technological, and design choices.

The exploration and adoption are envisioned to deeply connect industrialists and researchers alike, to the greatest benefit of the outcome, the 'users' (though we have proposed to bear in mind both people and the entire planet as such). Some recent announcements have officially unveiled, in parallel, designers' work on quantum-inspired hardware, domain-specific processors, and hybrid prototype computers, just to cite a few. The cloud landscape is about to change also. Now we are looking at this new class of computing both as an opportunity and a challenge conveying pragmatic industrialism and scientific interest.

11.6.1. Summary of Key Findings

As these six technologies emerge and intersect, the cloud computing landscape changes, expanding the range of specific capabilities and interfaces across the service scope to include edge computing for data analysis and machine learning, universal quantum computing and quantum machine learning, or specialized distributed permissionless ledger. New market-shaping capabilities being developed will lead to the growth of AI as the big game changer of the next two decades. Edge-powered cloud robotics and AR/VR/MR games will drive consumers to early 5G adoption.

The privacy of individuals and digital identity protection, using context-aware behavioral biometrics or with fully homomorphic encrypted query capability, is a key enabler of the privacy-preserving analytics, transparent provenance of product, process, and service life-cycle with efficient secure supply chains, emerging from technology gateways for distributed uncommissioned ledgers (DUTL/Blockchain). Cloud edge-powered digitized twins will gather data from the real product and associated services and fortune-tell them in dynamic, value-based predictive and prescriptive digital business operation outcomes in life-cycle based services systems of systems, product-service bundle providers to be vital creators within security-focused ZERO trust management systems. Quantum computers that obey strong quantum supremacy shortly will trigger a variety of necessary technological developments, including quantum communication, post-quantum encryption, and quantum clock signals. Other technology development vectors such as practical automated ML/Quantum ML (QML), quantum encryption, and blockchain-inspired large-scale DLT infrastructure construction may also benefit from the prosperity. Another driving force of quantum computing-related technology growth is the specific requirements from smart and sustainable services and forums for future social values on quality, AI ethics, digital twins, and quantum computing.

11.6.2. Implications for Industry and Research

This may trigger the development of more decentralized and privacy-preserving cloud platforms. There might be a potential for a space where blockchain and cloud can play to each other's strengths, which goes in line with the current move by the three research communities (decentralized systems, cloud computing, and big data) to come up with Edge and Fog computing paradigms that share the computational load across the network from resource-

constraint IoT devices (the 'edges') to powerful servers (the 'fog of the cloud'). This space of decentralized and privacy-preserving cloud platforms might in the future converge with "Privacy-Enhancing Computation" which includes privacy-preserving data analysis in federated learning, homomorphic encryption, and secure multi-party computation. Companies can explore these alternative paradigms in the future, especially with ephemeral storage that could render migration attacks impossible.

Security must be solved for many of these technologies, but this is also an opportunity for future work. With the increasing move of some businesses towards the security cloud, like banks, innovation is a necessity as the next attacker's wealth will include the stealing of encryption keys. Authentication arising from bad use of new technologies such as the spread of user-monthly 2-factor authentication via an SMS message can also be weakened with SIM-jacking vulnerabilities exploited by malicious people. Further research must be done to fully understand how these technologies can help or hinder developments in cloud computing and cloud services. Moreover, standardization bodies are working on standardizing these technologies. The respective IETF Working Groups are working on transport encryption (quic), the applied cryptography protection feature "Token Binding" (tcg), and developing privacy-preserving protocols like a payoff.

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Chapter 12

STRATEGIC ROADMAP: IMPLEMENTING AI AND ML FOR FUTURE-PROOF CLOUD SOLUTIONS

12.1. Introduction

Strategizing the traditional software development lifecycle, right from the requirements gathering to development, testing, monitoring, and roll out to the consumer markets, opportunities need to be brought in to make these solutions future-proof. Cloud solutions packaged as containers in a K8s cloud infrastructure are trending at the moment. While this architecture has solved numerous issues related to high availability and zero downtime, one critical problem to solve is how to equip existing cloud platforms to think forward and integrate AI and ML right into the core platform.

The purpose of this strategic roadmap is to reflect on what is almost a business plan to introduce AI and ML into a software portfolio. This current cloud and DevOps initiative will provide the early win, incentivizing higher management to open the funds for a longer-term future-proofing plan. This paper orients to integrate core AI/ML technologies into cloud infrastructure. The future-proof agenda we speak of, contingent on immediate success, is to integrate automation in the cloud as a part of its control plane. This control plane capability is further exported out in the form of more automated platforms, which will dissipate into actions in the data plane. The cloud will become a more autonomous platform, focusing on meeting the service level objectives rather than getting the system to a consistent state, since the chance of an undesirable state will shrink as we integrate AI and ML for operations. Since AI and ML training have to run on a huge scale, these operations need to move to the cloud itself and eventually into high-powered quantum machines.

12.1.1. Background and Significance

Artificial intelligence (AI) and machine learning (ML) are the cutting-edge technologies in today's world, driving most of the present applications in industries. From beating the game of 'Go' to driving autonomous vehicles, AI has brought a revolution in the field of technology. AI, along with the help of ML, enhances applications and functionalities of systems currently implemented in different fields.

Cloud computing has been revolutionizing many fields by offering many services and advantages through virtualization and scaling technologies. With the present growth of cloud technology and its capabilities, it is important to leverage AI and ML to offer more advanced and scalable cloud solutions. The focus of the presentation is to provide a strategic roadmap discussing the implementation of AI and ML in future-proof cloud solutions.

The plan is to start by delivering the importance of AI and ML in cloud computing, along with a discussion of the importance and growth of cloud solutions. The presentation further explains the AI and ML technologies in cloud computing and provides a brief categorization of the AI-based advancements in cloud solutions. A cursory view of the benefits of AI and ML on cloud solutions is given. The presentation ends with the necessity of releasing this information as a white paper.

The release of this white paper is necessary to provide insight into AI and ML-based projects on cloud computing being done, and to also provide potential research fields for individually inclined researchers as well as industrial research labs.

12.1.2. Purpose of the Paper

This paper describes a set of best practices that primes the ecosystem for the adoption of future-proof, AI-enhanced cloud-based solutions. The strategic roadmap explicitly fuses cloud computing with AI technologies, moving away from the siloed approach taken by most cloud service providers (except the three leading cloud platforms) and other cloud initiatives around the globe. Our goal is to harmonize AI and cloud technologies, ensuring generic, extensible, and forward-looking strategies. To this end, this paper first sets out: a) how the horizon of AI applications has shifted from on-premises technology to cloud multi-tenancy, differentiating between customer-specific and general good practices; b) the evolving architecture of cloud systems that adapt to AI blending at various degrees of depth. These two

perspectives are crystallized into core focus areas that contain a further ten dimensions, embracing specific business planning, technical, security, and interaction considerations. We propose a unified action roadmap to assess, develop, implement, and accelerate the converging layers of AI-C cloud services. A series of adoption strategies – starting from the more contained side of the AI-C spiral and spiraling out to the full advantage of AI synergies – identify sound guidelines for future-proof service development and contribute to the ultimate goal of creating a future-proof European cloud, exemplified under the GAIA-X Initiative.

This paper is aimed at offering high-level guidelines and industry best practices to support a strategic roadmap that facilitates clear. We strongly believe that the AI-C convergence will ultimately make it impossible to separate the two technologies. The exact configurations are therefore diverse, sharing many interoperability and synergy traits, but should be developed following a clear strategy that has the future of the market in view. We argue that these insights will be highly valuable to a range of cloud stakeholders aiming to create AI-C-enhanced products while avoiding the pitfalls of lock-in.

12.2. Understanding AI and ML in Cloud Solutions

As paper topics related to artificial intelligence (AI) and machine learning (ML) become trends in research, defining these topics and understanding how they relate to cloud solutions is crucial. AI and ML are two fields generally projected in a broad sense because we apply them to our daily lives without realizing it. Cloud computing becomes the infrastructure for them to perform as we can implement cloud solutions as resources. Ad-hoc solutions can be embedded into software and applied at any time using cloud-enabled service models. The evolution of AI and ML, especially when embedded into a cloud environment, offers more value to a variety of services that should be considered in the strategic roadmap to companies' success and resilience.

Therefore, our long-term strategic vision explained in this paper is to apply AI and ML to implement cloud solutions that are simpler, more flexible, and easier to maintain by having the ability to learn from data and improve through experiences from the use of analytics. The paper discusses AI/ML in cloud solutions from four viewpoints that will enable a comprehensive strategic plan. Our planned cloud-based AI and ML include Chapters 2 and 3 concentrating on a primer on AI and ML function both from a big picture and technical perspective, and we cover the application of ML for cloud systems and our research to come.

12.2.1. Definitions and Concepts

In this section, we elaborate on some key concepts and terminology related to our strategic roadmap. Our motivation is to set the groundwork for the following discussion, as it sheds light on precisely what the following discussion is and is not about. We will start by defining the overarching concept of AI and, to distinguish between the different kinds of AI applications, elaborate on what machine learning entails and how it is related to the concept of true AI. Subsequently, we detail cloud solutions, to signpost some of the more novel state-of-the-art technologies that have been developed to form the core of a future-proof cloud solution.

Artificial intelligence refers to the science and engineering of making intelligent machines. An intelligent machine is a system that perceives its environment and takes actions in a manner that is optimized to reach its own goals. The concept of an intelligent machine forms the groundwork for the popular conception of AI, which is mostly characterized by its anthropomorphic (i.e., human-like) portrayal in literature and popular science. AI systems extend from simple, rule-based software programs to truer AI systems - the kind of AI that is characterized as agent-based, deliberative, learning, autonomous, social, rational, emotional, or any combination thereof. Historically, the most significant shift within AI has been the rise of machine learning (ML). ML concerns finding, extracting, and sampling patterns or regularities from specific data. A major commonality between AI and ML is the aspiration toward a real-world problem-solving capacity that extends beyond individual cases or narrowly defined tasks. The critical difference is that AI is about achieving this via intelligent reasoning and decision-making, while ML is about finding relevant patterns in information.

As of 2021, cloud computing has turned into a default method of delivering IT services in a modern, highly digitalized society; many public sector organizations have come to draw on either private- or hybrid-cloud services in delivering core operations. Cloud computing covers hardware and cloud system service. In a broad sense, cloud computing refers to the act of consuming any information or data resources over an internet connection instead of within a local network. One of the USP's of the cloud is that it continuously serves software and control to the customers on a pay-per-use period. One can visualize cloud computing as a step toward the goal of infinite computing. In its historical context, cloud computing as a computing model had its origins in centralized (time-share, data center) and distributed (client-server) computing paradigms; as well, it can be seen, in many ways, to be a reinvention of

utility computing, taking capacity-based pricing and business models either from the mainframe or broadband cable infrastructures to which they were an alternative.

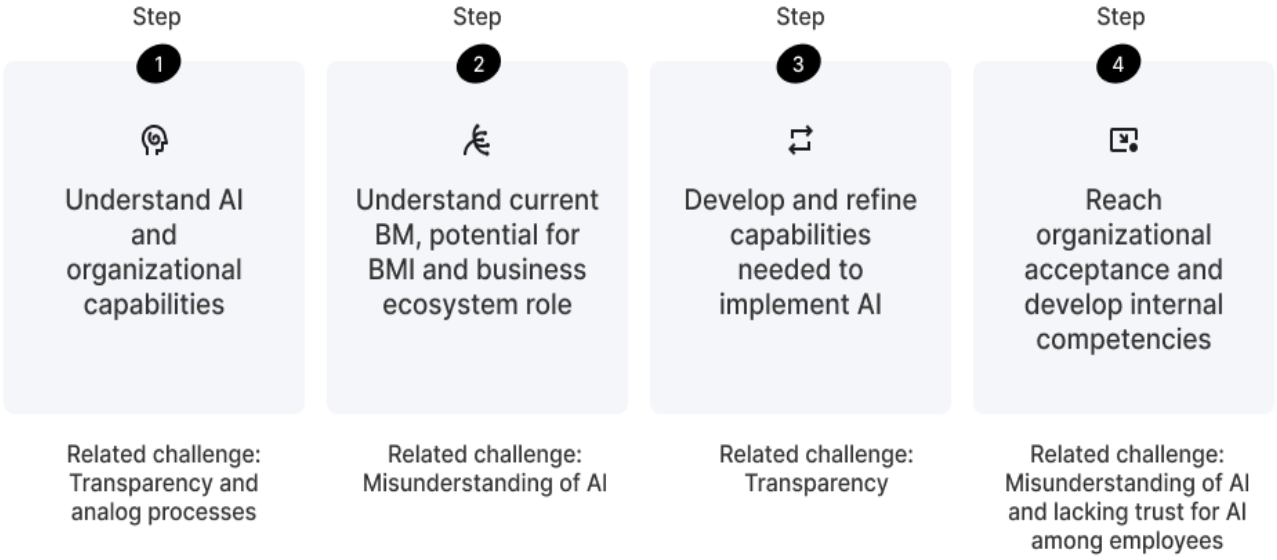

Fig 12 . 1 : AI Roadmap for No-Stress AI Implementation

12.2.2. Current Trends and Applications

There is a clear consumer and industry adoption of AI and ML, further exacerbated by the technical advancements made this decade. As such, real-world applications of AI and ML are becoming more prevalent in the consumer and technology markets, from general applications such as virtual personal assistants to highly specialized use cases in fields such as medicine and logistics. This section provides a compelling example of the possibilities of AI and ML within cloud solutions that uphold the potential for a wide-reaching strategic implementation.

Cloud-Native AI Services: This trend focuses on the integration of cloud computing services with AI and ML capabilities. These emerging platforms use cloud-hosted services to create a suite of APIs for AI developers to use, helping them to expand the usage and potential of their services without the need for expert knowledge in the field. For example, there is a wide array of AI services provided by Google Cloud, such as Google Cloud Vision, which enables the usage of the underlying AI models for image and video recognition. This enables functionalities such as Vision Product Search, which replaces traditional search functionality, allowing users to perform a search by submitting an image file. By including these

frameworks, it will enable a transition from traditional cloud solutions towards highly specialized, AI/ML powered, "future-proof" cloud offerings.

12.3. Benefits and Challenges of Implementing AI and ML in Cloud Solutions

The adoption of artificial intelligence (AI) and machine learning (ML) among IT researchers and experts has become a trending research, development, and operational task over the recent past in academia and professional bodies as well. At its core, AI is the capability of a digital computer to execute tasks or work patterns without the need for human involvement—characteristics that might relate to reasoning, learning, planning, and problem-solving. Even so, AI builds on ML, which is a set of processes that can be used to learn from data on some task to execute well on that job. In the future, these solutions will be in high demand for potential competitiveness and profound knowledge of cloud computing domains, which are not the predominant areas of scientific analysis.

Several possibilities may result from the synthesis and implementation of software tools and techniques execution between additional cloud solution segments as they have enlarged services since openings in the past. The strategic roadmap has given cloud computing further multidimensional difficulties that require continuous technical innovation in a variant function towards AI-ML operations with a high conductance system. Several benefits have been witnessed, such as energy and enjoyment, for collecting and making use of secure and secure information. Nevertheless, the challenges inherent in AI-ML's progress towards cloud solutions are well documented. Opportunities include strategic thinking to sustain various domains such as cloud analytics beyond the enhanced improvement of significant behavior. It nonetheless requires further conceptual and operational advancements that are accomplished subsequently.

12.3.1. Benefits

3. Results and Benefits

3.1. Benefits

According to our survey, there are both transformative results and positive outcomes when incorporating AI and ML in the existing cloud solutions. One significant result is that an insightful 96% of experts agreed that AI and ML systems will add value for users of cloud

solutions. Among these experts, a notable 45% were strongly optimistic about the potential value. This conclusion is also confirmed by the user survey, where 80% of users think that AI and ML can be beneficial in future-proof cloud solutions. In addition, AI and ML technologies will better monitor, investigate, and ensure security controls, as mentioned by Delphi Expert 1. Furthermore, these results are in line with the findings in Reference [5], where all 9 contributing projects confirm that integrating AI and ML with existing cybersecurity mechanisms offers a strong potential for significantly better outcomes concerning security and privacy in four defined use cases.

AI and ML technologies should dramatically shift the cloud security perspective towards an improvement in risk analysis, which is in line with the increased variety of threats due to technology advancements, regulation, and big data. These changes encompass conservative models built on statistical data where static cybersecurity is now reactive due to the omnipresence of malware, to the modern models that anticipate and avoid attacks by learning individual entities, especially on data center workloads. Additionally, these new models will be able to better understand the environment and interpret and forecast multiple inter-relationships based on declarative properties, such as techniques less dependent on expert systems and black-box machine learning, which are not accurate for cloud systems.

Aided by ethnographic fieldwork, the following value commitment and benefits can be found in the user survey. It is more user-centric. Due to the stakeholders' influence on AI's perceptions and capabilities within the system's decision-making processes through the increasing social, regulatory, and corporate push, AI's presence in governance and collaboration makes the cloud system more adaptable and business-oriented.

12.3.2. Challenges

It is widely known that AI and machine learning (ML) are believed to be the technologies of the future. In combination with cloud solutions, they introduce smart and intelligent services. However, the intersection of cloud solutions, AI, and machine learning experiences high complexity and enormous challenges that need to be addressed to successfully design, select, and implement these solutions. Firstly, the selection of the proper AI and machine learning algorithms is not trivial. Proper selection and fine-tuning of the algorithm's hyperparameters significantly influence the final solution.

Furthermore, machine learning and AI solutions need to be evaluated using numerous key metrics, e.g., accuracy, precision, recall, F-score, ROC AUC, FPR, FDR, lift, g-index, GM measure, cosine similarity measure, Matthews correlation coefficient, True skill statistic. Observing these metrics allows for the selection of the best-performing AI/ML model that addresses a specific project's requirements. Lastly, AI and machine learning solutions often require vast amounts of data and sophisticated computational power. In addition to the infrastructural costs, computational power usage at scale is a key concern that may halt the deployment of machine learning applications in cloud solutions. All of the above challenges expose the vast complexity of employing AI and machine learning in the design and implementation of cloud solutions. However, these challenges present an opportunity for future research.

12.4. Developing a Strategic Roadmap

Building a roadmap for the successful incorporation of cutting-edge technologies such as AI and ML into modern cloud solutions is essential for organizations looking for that elusive competitive edge. Failure to dive into new and unknown domains rests upon the firm foundation of a practiced approach and requires a cleverly designed plan. Following a strategic roadmap to embrace AI and ML can help in two ways. First, it can act as a guide for stakeholders already prompting organizations on this journey. Second, it can also work as the foundation for newcomers and those looking to follow through shortly. It will also be useful in convincing founders and leaders to integrate cloud solutions with AI and ML. This section of the paper presents a strategic roadmap for embedding AI and ML in the cloud with a focus on future-proof cloud solutions. The roadmap has been developed based on earlier research work reviewed in the background section. Figures IA and IB present the roadmap for implementing AI and ML in the integration of cloud solutions and have been tested with domain experts and interested parties as well to check their effectiveness and practical implications.

The construction of a strategic roadmap consists of ten stages. The first step comes during the preparation phase. In it, the focal problem is identified with a specific purpose. The primary aim is to conceptualize the roadmap by stating deliverables, objectives, assumptions, and limitations. The problem at hand is that AI and ML win when it comes to current-day cloud solutions, and organizations are forced to adopt them to retain interest from potential customers, including cloud consumers, IaaS, SaaS, PaaS, and big data solutions. The future is

AI and ML and any organization with the help of cloud solutions will be able to provide efficient storage and computing, among other services. This integration should be able to cater to a variety of needs and expectations. The fusion of AI and ML easily fits current customers. Providing this is for cloud AI and ML capabilities, it fits cloud automation concepts and is achievable. However, the integration has to be built for the future by considering protocol evolution and catering to the number of years that an API capability has to stay maintained and relevant. In our travels from current features to the future, we also incorporate edge cloud concepts and backend reversing. The roadmap applies to all AI cloud computing domains and is deemed trustworthy by domain experts.

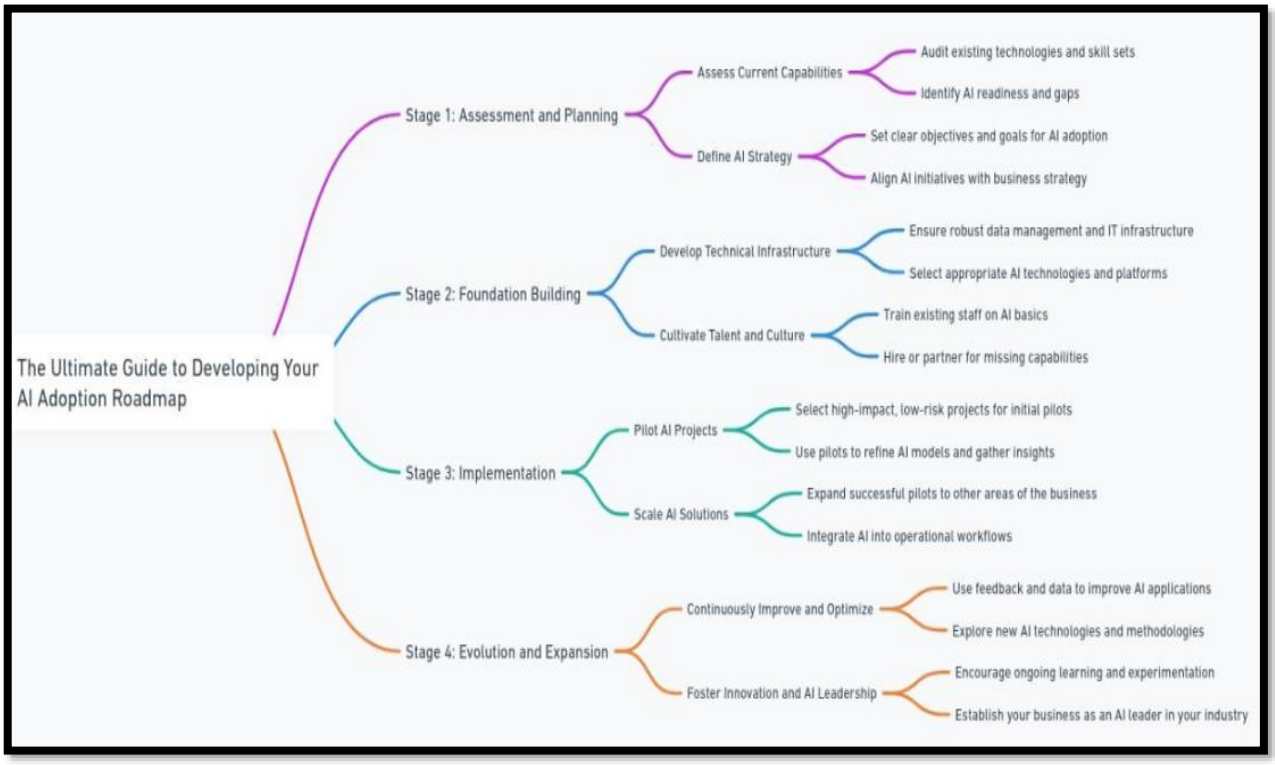

Fig 12 . 2 : Developing Your AI Adoption Roadmap

12.4.1. Key Components

To support the overall strategy of a company, a roadmap for future-proof cloud solutions is necessary. By analyzing the general roadmap taxonomy, it is noted that the steps and elements within need to be aligned with requirements and tailored outcomes. The overall roadmap includes and interlinks strategy components, main components, and a technological component. The latter aims at showcasing the technological way forward following the service management approach to align with customers in terms of resilience and sustainability. This

ensures the creation of a future-proof solution that epitomizes the strategy and applies to urging everyone's cloud-first policy. The roadmap focus is proposing a structured way of implementing artificial intelligence (AI) and machine learning (ML) in a European Organization for Nuclear Research (CERN) cloud implementation based on cloud utilization, optimization, and stocking for cost-effectiveness and transparent storage. The steps and elements within apply to cloud solutions in general for any infrastructure and interlink with CERN's overall strategy and technology roadmaps for computing services.

The roadmap is structured to include a main umbrella service with prioritization in clinical analysis versus the lack of prioritization. Both are seeing similar technical implementation in the short to medium term. Only the clinical data analysis component is a legal requirement. Therefore both the main umbrellas and prioritization help in providing the strategy alignment to then enhance the technological implementation. The roadmap further includes a categorization mechanism, bringing forward three different types: financial conditions, buying behavior, and patient conditions, while all maintaining the same framework for implementation. The roadmap's main elements are the AI service, implementing the AI technology, and thus the training and potential improvements, including a knowledge base, user representative group, training process, testing, deployment, and data collection for further training followed by a feedback loop to improve the service.

12.4.2. Best Practices

Given the lack of expertise in the field, strategic development and execution form a challenge for most of those that we work with. Once technical or business strategy decisions are made, often, stakeholders are asking to see the results. Concerning a strategic roadmap, we recommend fully investigating AI and ML capabilities, reviewing case studies and the competition, attending trade shows, and conversing with technology vendors. Based on broad findings, determining the best technologies to integrate along with the best AI partner is the next recommended step. Specifically, we advocate piloting an AI "Quick Win" as a means of proving its worth to key stakeholders. It will allow executive leadership to see: (1) clear ROI, (2) cloud compatibility, (3) improved access to and use of data, and (4) a vision of what the future state of the company could look like. This is very much like the "fail fast and pivot" model of strategic implementation that has worked for the best innovations in Silicon Valley. The final strategic product that we produce suggests a broad and scalable view of how AI and ML could be integrated into a smaller hosting or CSP as a future-proof business model in

addition to an organizational change management plan to support people, processes, and a cloud-first architecture.

The concept of the strategic roadmap is built on the intentional integration of the business, technical, transformation, and stakeholder objectives under the financial and technical constraints of hosting providers and/or cloud service providers. Adapted from our experience in the industry, a strategic roadmap is intended to be a very high-level document specifying future goals, supported by stakeholders, and suggesting the features and initiatives in order of execution or effect most likely to achieve those goals. Its primary objective is to indicate the strategic vision of the company. The general approach usually involves a series of workshops with hosting/CSP executive leadership, data center/cloud services subject matter experts, and other impacted stakeholders such as marketing and sales teams. During these workshops, higher-level business and functional requirements are gathered, cost and technology constraints are addressed, and future technologies and business practices are evaluated. The finished product is similar to our strategic roadmap except for the fact that it connects stakeholder objectives with a prioritized list of desired initiatives and any necessary and associated out-year costs or internal resource expenditures for implementation. This is then built upon in our tactical roadmap and implementation plan.

12.5. Case Studies and Practical Applications

There are numerous real-world examples where AI and ML have been successfully deployed as part of a cloud solution. Two such examples will bring the discussion to this point to life.

IBM Watson provides a cloud-based image analysis service for dental practices. A webcam or an ordinary smartphone is set up to take a close-up picture of a patient's mouth. This image can then be uploaded to IBM's cloud where a trained convolutional neural network (CNN) analyzes it. The trained CNN can identify pathological features in the mouth and potentially aid in medical diagnosis. The London-based start-up Tractable was founded in 2014 and has developed an AI solution that automates appraisal and helps to settle car insurance claims. Their solution analyzes car damage images in the cloud and uses machine learning to generate rapid, accurate computer vision appraisals in real time.

While I worked for Hewlett-Packard (HP) across different domains, I was involved in several initiatives that applied AI, but one instance in particular stands out. I was part of an interdisciplinary team at HP Labs interested in the many ways AI could be deployed within the supply chain. This multinational initiative was the brainchild of the senior vice president of the logistics domain. We had software developers in Bangalore design and build customized AI solutions that were first given practical tests in the field and later rolled into production at various manufacturing sites across Asia. HP was able to use these practical tests to prove feasibility and refine our AI capabilities. I can vouch for the rest of the distinguished authors that we have also had AI and ML initiatives in production with high degrees of accuracy. Training an AI model occurs primarily with tools that leverage the power of the cloud.

12.5.1. Successful Implementations

Li et al. successfully utilized ML for cloud security intelligence by implementing a semi-supervised model to analyze cap files. The proposed solution achieved better performance compared to other ML techniques in the analysis of a dataset of 22,000 caps regarding the true positive rate. Furthermore, the clustering approach using K-means outperformed the DB-SCAN in terms of the average F1 score.

Xu et al., on the other hand, proposed a CNN-BLSTM-based malware analysis engine for the Google Cloud environment. The model SENSETECH was capable of identifying malware as it outperformed DRASTOX, a similar malware engine published in 2018. In addition, SENSETECH also generated the best TPR and the second-best TNR among many other malware analysis models in a study conducted by the National Institute of Standards and Technology (NIST). Finally, the model was also able to achieve an accuracy result slightly below 99% with a time consumption of under 30 seconds.

Dahad et al. developed a solution to detect attacks including scans, brute force, and dirty cow infiltrations on a cloud service within an RDBMS use case, showing a 50% reduction in computation time for analysis. Suiting et al. demonstrated a sequential redo-logging dataset of the operations occurring during the data loading processes from different sources to a Redshift cloud data warehouse. They trained three LSTM (RNN) models for predicting the next operations inside one type of load job, performing smoothing on all three models' data to reduce noise before model checking. The experimental outcome for results on the test was reported as precision, recall, F1 score, and MAE. They successfully identified the operations

in the current vulnerability detection tool, achieving results close to or above 99% in precision, recall, and F1 metrics.

12.5.2. Lessons Learned

Inspecting the implemented AI components at different horizons and different system levels provides a deeper view of the evolution over several years. During the first horizon, only a few cloud solution initiatives or products existed for AI and ML tasks. Sqlerate was considered the only large European project that used this technology on the HPC side of the cloud. Nowadays, in the second and third cloud horizons, currently existing AI and ML cloud initiatives that win the race while considered together in these pioneering times, are cited in the ELIXIR cloud strategy. On the one-to-one side, the AWS ecosystem (Amazon Sagemaker) was introduced, which currently holds the leading position in cloud computing for AI and ML operations.

Similarly, Google Cloud (GCP) introduced several dedicated cloud-based services for AI and ML tasks and enhanced them with hybrid solutions for on-premises computational workloads (especially related to HPC). IBM Cloud competes by providing cloud-based computing power for AI and ML and offers high-speed interconnections to connect between cloud or even cloud-to-on-premises data centers. Well-known cloud-centric platforms such as Azure or HPC solutions such as from Atos or Cray compete with other cloud actors in their solutions which offer support to work with Kubernetes and HPC solutions for AI and ML automation.

12.6. Conclusion

By summarizing the current informative article, the findings of the document, or the conclusions can be presented again. Doing so reinforces the importance of creating a strategic roadmap, particularly for AI and ML implementation in cloud solutions. Given the prominent market trends, their expected canvas, as well as the anticipated revenues, such a roadmap is necessary for the success and market tractability of the cloud solutions built. In conclusion, the strategic roadmap provided all the architects, especially cloud infrastructure developers, with an analysis to help them integrate AI and ML capacities into near-future products.

The implementation of AI and ML models, apart from the synchronization and deployment strategies, provided the cloud infrastructure developers and investors with stitch

dates to benefit from new services. The results have also introduced the new potential of more than five cloud-native service frameworks and listed the metrics with which the models' dependability can be analyzed for current and future trends. To articulate this study, an executive "user" journey is presented; this journey explains the implemented strategy and provides additional value to any professional in the cloud computing industry.

12.6.1. Summary of Key Findings

Chapter 6 (A.4) presents a critical review of the literature and summarizes the key findings as follows:

6.1. Summary of Key Findings 1. There is a strong rationale for cloud-based intelligent sensory systems for rural applications. However, the manufacturing of resource-constrained sensing devices with on-device AI has not been commercially viable. 2. The application of deep-learning methods for Betfair horse race classification is possible. However, due to the adversarial nature of providing empirical evidence for inaccurate predictions, it is difficult to provide. 3. A novel variant of a 1D convolutional neural network was applied to form classifications of images without the need to complete a full backpropagation in each training phase using foveated rendering. 4. Population-based training is an area of future work in reinforcement learning. Despite achieving high-performing agents on multiple games, in general, extinction and genetic algorithms struggled to converge. 5. Data from large-scale forestry analytics projects with machine learning, utilizing hyperspectral imaging from manned aircraft on a variety of tree species located in Ireland and the US, demonstrated successful segmentation of crowns for all species studied. In theory, the risk model computational time can be significantly reduced if we quantify the number of rings in an image from each species, as the RiskSIM core computations of tree growth are invoked at the resolution of radial coordinates.

6. ATV-IoT searches and reviews existing implementations of cognitive intelligent electronic surveillance to make recommendations in a roadmap to develop a next-generation system with 5G capabilities that is driven by AI & ML, which is designed for ATV carrier operations. It is noted that currently, few systems have AI & ML encompassed in the logical and physical layer functions. The only systems currently developed to encompass AI and ML are academic-based systems, with no ongoing research in this domain in the surveillance

community. Due to that, the literature review supports the targeted requirements to drive a surveillance system for Australian conditions.

12.6.2. Future Directions for Research and Practice

Adoption of the use of cognitive AI and ML training, utilizing shared cloud-based infrastructure, presents wider societal challenges and it could also further raise the profile of using covert data to train ML systems. Furthermore, the combination of AI and cloud services can facilitate more efficient training of ML models as well as democratize the use of more advanced AI techniques. For instance, federated learning where edge devices collaboratively train an ML model can alleviate some of the privacy concerns raised by centralized, large-scale machine training operations. However, future work could also consider how updates and new features to the model could be carried out securely. Furthermore, the authors elaborate on the first steps in developing a framework for practitioners, utilizing this promising technology within their cloud architecture. The computing industry is constantly evolving, and cloud technologies have moved from Infrastructure as a Service to Platform as a Service; applying AI services has the potential to shift to Insight as a Service. In particular, working in cooperation tools and virtualized reality services, both of which could also benefit from AI-driven cognitive learning from user interactions with surprising opportunities.

Building on the research reported here, and industry needs, which were co-developed, future work will seek to establish the requirements for implementing the framework produced within this paper. The work will map the six elements of our strategic roadmap with particular tools and technologies, including defining the AI workflows, pipeline, or process templates that should be developed with the addition of AI/ML-based services. Many cloud vendors have pre-existing services for such activities, templating AI/analysis is still in the early stages, but the ALA cloud research lifecycle provides a good starting point for creating AI/ML-based activities.

To deliver AI/ML-driven cognitive tooling that can be easily scalable, best practice for implementing and integrating the much-needed training environment is required. Finally, we aim to support practitioners and other researchers in the co-creation of cloud-based services and capabilities that truly meet their needs. This includes straightforward cloud vendor selection advice and maturity assessment tools to gauge if a vendor truly can meet their needs to deploy AI solutions on a cloud service for it to be capable of the evolution needed for the

future. We will create and deliver materials to support the UK's first Chartered Institute for Data Centre Professionals' new AI for IT Management course. The research presented in this paper, therefore, provides a measured approach to the combining of AI and ML with cloud solutions. The step-by-step approach when preparing an AI-enriched cloud architecture has been outlined and the benefits and risks of implementation presented. This should help inform current research, as well as guide implementation in practice.

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