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Hybrid Cloud and AI Integration for Scalable Data Engineering: Innovations in Enterprise AI Infrastructure

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Abstract:

Training and deploying Deep Learning models in real-world applications often involve processing large amounts of data. There is an active research community working on building software and hardware infrastructure to address these big data challenges, particularly focusing on building highly optimized solutions and large footprints of parallel computers. Hyper focuses on the complementary set of problems in the Deep Learning ecosystem to lower the barrier of entry to the field. Hyper proposes a hybrid distributed cloud framework that simplifies the hardware and software infrastructure for large-scale distributed computing tasks.

The Hyper framework offers a unified view to multiple clouds and on-premise infrastructure for processing tasks using both CPU and GPU compute instances at scale. In the proposed system, the researcher implements a distributed file system and a failure-tolerant task processing scheduler, which are independent of the language and Deep Learning framework used. As a result, the framework assists researchers in exploiting the unused and cheap resources that are prone to become statistically more powerful tools in the community. To clearly demonstrate the cost-efficiency of the system, the researcher provides a detailed table showcasing the quantitative evaluation of Hyper usage costs. In real-world applications, deploying Deep Models is often non-trivial and can include multiple steps ranging from extensive post-processing of the obtained scores to the containment of the numerous pre-processing transformations of the data. The portability and generality of the framework is demonstrated by discussing the scalability of different and non-trivial real-life setups. These tasks include pre-processing, distributed training, hyperparameter search, and large-scale inference tasks, showcasing usage costs and total running times.

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1. Introduction

Enterprises use an average of 1,427 cloud services, an increase of 28.5% from the beginning of 2021 which is escalating the complexity to build and operate data services to support large workloads. Despite the cloud providers' ongoing efforts to make building infrastructure easier for cloud customers, there is still a huge gap

between how cloud providers build scalable AI infrastructure and how traditional enterprises deploy their AI, ML workloads and products. There is an increasing interest in AI infrastructure research that democratizes the creation of AI products. Most advances in AI infrastructure democratization are inspired by the microservice design pattern. In cloud environments, these advances are mostly customized orchestration engines or operators for a certain type of job or infrastructure as code with a specific domain-specific language for ML workloads.

With the increasing size of AI models, AI infrastructure democratization has become more challenging. First, with 3D Transformer models such as GPT-3 and other large-scale models introduced by T5, enterprise users desire AI infrastructure to be scalable for running deep learning training jobs across hybrid cloud and on-prem environments. Second, data engineering and preparation before training deep learning models deserve as much attention because they exacerbate the complexity of training models. It is driven by the need to parallelize data processing and model training to expedite model iteration. Third, complex data projects usually span various (at least two) workloads across granular partitions of data.

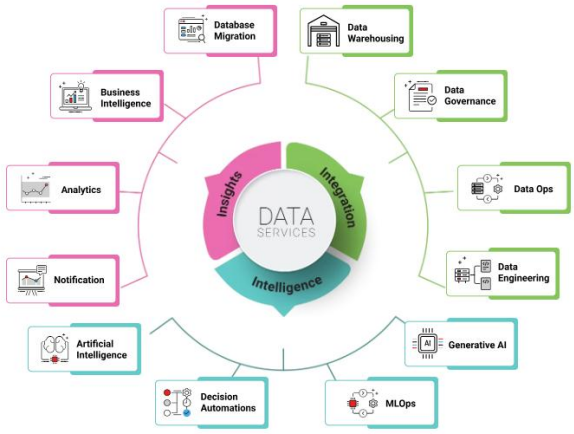

Fig 1: Hybrid Cloud and AI Integration for Scalable Data Engineering

1.1. background and Significance Data Engineering is at the core of a Data-Centric AI strategy. Data consists of raw information in need of extraction, flatting, aggregation, merging, filtration, denoising, imputing, structuring, locating, anonymizing, normalizing, arranging according to domain-specific sequencing/organization practices. Moreover, there is a host of analyses and computations, such as detection, unique counting, binary aggregation, time-window statistics, graph traversal, regressions, clustering, some of which can be expressed through domain-specific sequences of operations of increasing complexity. Data Engineering is the systematic programming of these operations at scale testifying hybrid knowledge of the nature of operations and tools, and domain-specific understanding of the data. Pre-dating the AI revolution, Data Science emphasized statistical experimental methodologies to segment, cluster, or classify indicative properties of information, with the interest of generating a data-rich environment leading to question-driven hypotheses. However post-AI revolution, the focus is on a simplified presentation and management of feature-sets and computational resources. Data-driven invariances-of-interest are ignored. Presently, the availability of new Enterprise AI infrastructure and ecosystems extends the complexity potential of developed models. This translates into one or several components whose nature is agnostic to input features, with connections of a non-Euclidean geometry that can be arbitrarily deep and wide. Consequently, exploiting modules, or similar piecewise symbolic controllers, evolves into simply the string connection of classical learnable blocks, which resemble usual optimized architectures, of which the parameters rather than the architecture are learned.

Equ 1: Scalable Data Storage in Hybrid Cloud

$$D_{total} = D_{on-prem} + D_{cloud}$$

Where:

- D_{total} is the total data storage required.
- $D_{on-prem}$ is the storage available on on-premises
- D_{cloud} is the cloud-based storage.

2. Understanding Hybrid Cloud Architecture

Abstract: Assembled applications can perform their operations transparently and uniformly, without being affected by their operational environment. In order to manipulate a large variety of components offering different types of services, these applications sacrifice efficiency for abstract usability and need a complex interface and operation orthogonal to their primary purpose. Platform-based applications however, assist their operation with a dedicated runtime infrastructure. The proposed platform encompasses execution venues, resource management and virtualization and relies on a minimal, abstract interface. The platform accommodates these services in a scale-proportional manner. Commercial applications are fixed constructs executing transparently. For a broad range of applications, such runtime support is key for cloud execution. These components, which are at a higher collection of mainly scientific applications can be parameterized. However, a prototype implementation provides an indicative implementation.

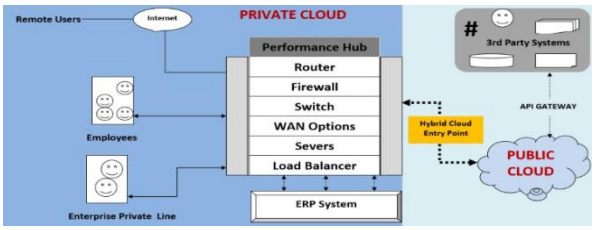

Fig 2: Hybrid Cloud Architecture

2.1. Definition and Key Components This section provides an overview of a hybrid cloud and AI-integrated data engineering service framework as an innovation in enterprise data engineering infrastructure to accommodate next-scale data supply chains in the era of data capitalism. It considers the following way of innovating a frontier data engineering infrastructure: A modern data engineering infrastructure is developing as an ecosystem fed by a fast-growing group of startup vendors to optimize the job processing performance. However, there is a lack of academic work for understanding this emerging technology. In this section, the research develops proprietary ML-driven workload and infrastructure awareness and optimization technology. This technology consists of an ensemble of time series forecasting models for predicting job queue length and runtime, multi-armed bandit optimization for job configuration tuning, hyper-parameter optimization, and a gradient boosting machine (GBM) model for resource tuning of the data engineering service.

By keeping close collaboration with industry practitioners, this research brings two innovations in technology development. First, a cloud-native data engineering service is jointly developed to provide a low entry barrier for small-medium industry adopters in developing advanced data engineering pipelines. Second, an encapsulation framework is developed to package the ML-driven infrastructure awareness and optimization technology as a cloud-native service.

The encapsulation technology, together with the cloud-native data engineering service, is now open sourced for benefiting academic teaching, researching and developing. This research not only contributes to understanding modern data engineering infrastructure development but also bridges the gap between academic research work and the technology developed by industry startups and vendors. This paper keeps a consistent time period within different research objectives for robust model training and testing. The forecasted job queue length from proprietary models is normalized and applied to find the job placement opportunity in a central scheduler-managed cluster.

2.2. Benefits of Hybrid Cloud Solutions As IT inevitably continues to expand and transform, escalating pressure is being placed on traditional data engineering systems to deliver on new deployment expectations. Simplified scalability, portability between infrastructure environments, and scalability are several of the benefits. Because scalable data engineering is a foundational part of Enterprise AI infra operation, the choice for underlying scalable data engineering systems determines if the overall system is adaptable, open, and ready for the expected upsurge in challenges. One promising strategy is to pursue the separation of compute and storage structures, a purpose shared by the opening and embodiment of many cloud-native tasks and scalable

data engineering systems. Many businesses embracing distributed machine learning systems are establishing new, cloud-based solutions to encapsulate and expedite the deployment and operation of these systems on top of the distributed-filing and orchestration platforms. Each of the large cloud providers has inaugurated their respective hybrid cloud solutions, all of which are re-engineering distributed cloud processing to provide micro-services on pre-configured on-premise racks that can be linearly expanded to the cloud or other facilities.

Bringing scalable data engineering on-premise is a must for many enterprises dealing with large data sets and ML models in order to address compliance and performance or monetization aspects. But while the total tally of data transferred out of the cloud costs, network is traced and in-cloud data transfer is complimentary, unexpected charges combine mosquito-tier cloud bills that don't last long. Thus, those cloud costs are scrutinized, optimizing for the most price-efficient configuration. There is no privacy concern as network cost tracking only requires access to the cloud provider billing data. The motivation for cloud and cost model size choice can easily be visualized and halted and the effect of these choices on efficiency assessed. Data that should only be transferred between DC and cloud, and the cost threshold that the task can be carried out in compliance with an on-premise data transfer budget is also proposed. Hyper is a distributed cloud work service created specifically to save AIOps time, cloud costs and simplify cloud on-premise data and model transfers for large-scale.

3. The Role of Artificial Intelligence in Data Engineering

Artificial intelligence (AI) systems together with machine learning (ML) models have proven efficient in the automation of various data engineering tasks, such as data cleaning, pre-processing or transformation. Thus, a rapidly growing data engineering ecosystem around AI technologies has formed, driven by software companies and open-source projects offering data engineering platforms with integrated AI functionalities for building ML models on large-scale datasets. Also, the creation of ML models requires handling large-scale datasets, the characterization of the training data and the dataset distribution, as well as ensuring the reproducibility and interpretability of the entire training procedure. In this context, a new research discipline at the intersection of AI, machine learning and data engineering has recently emerged to optimize and facilitate the ML model learning process: Optimized Data Engineering for ML. Major AI tech companies have been using these systems to train ML models efficiently at a large scale. These developments have motivated the adaptation and adoption of a similarly efficient data engineering ecosystem around AI technologies, also in a non-tech industry-specific domain, often referred to as Enterprise AI.

There are several reasons to argue the importance of a scalable data engineering systems ecosystem around AI-technologies in a rise of data-centric AI. First, the technical complexity of using large-scale datasets on ML model creation for non-data scientists: Data-centric AI differs the most from the traditional big-data analytics research field. It usually requires a tight collaboration between domain experts, often with a weak machine learning or AI background, and data scientists. At the same time, a large amount of data preparation is needed before a ML model can be built. Already a widely used cloud-based data engineering platform with AI functionalities can facilitate and smoothen the conventional data-to-AI workflow, and thus significantly decrease the entry barrier to start AI projects for data-engineers. Second, the lack of data-centric AI related knowledge or general awareness within non-data scientist teams working on AI project teams. However, these use-cases are typically not recognized a-priori as company's products, but rather project-based tasks that individual teams would like to explore. This would require a broader technological background and an understanding of what can be feasibly achieved. Unfortunately, the rapidly growing data engineering ecosystem aimed at increasing the efficiency of the data-to-AI workflow consists mainly of specialized tech knowledge and thus remains overlooked by a non-data scientist organization.

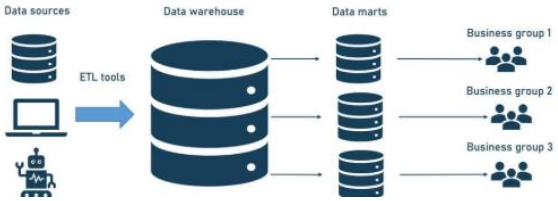

Fig 3: Data Engineering

3.1. AI Techniques for Data Processing AI's rapid advances promise groundbreaking improvements in many areas, including medicine, cybersecurity and customer service, among others. However, in practice, AI-driven initiatives often face challenges to bring those gains to reality, such as time-consuming manual work required for data collection, preparation and labelling. These essential tasks become particularly onerous when data grows in size and complexity.

AI technologies have been used to automate a wide variety of jobs. A tailored solution widely used in the context of data analytics is the collection and analysis of performance or monitoring data such as log files. Modern AI-powered data analysis solutions promise vast improvements in accuracy and efficiency, enabling organizations to locate and fix potential issues before they happen. However, commercial data engineering practices generally overlook vast swathes of their data for monitoring since collecting, preparing and manually annotating large datasets is an onerous process. The exponential growth of data volumes faced by many industries exacerbates these challenges. Even when such monitoring systems are in place, companies often analyze just a small fraction of their data due to current limitations in human-aware techniques.

3.2. Machine Learning Models in Data Engineering The role of Machine Learning (ML) in data processing is growing and the scale of inference is a function of the scale of data generation. However, large ML models are complex systems. For ease of development, different functionality is implemented in separate independent models. Thus, it naturally separates the tasks of loading and serving data and the ML model itself. However, the development process is far from easy — the possibility of inference (online) deployment often is not apparent, and the code that processes the data for the model becomes the main requirement for training and inference. Moreover, conditions of operation often differ from each other. Separation processes featuring pre-calculate the features of the model, storage of the calculated characteristics of the model, and making predictions based on the stored characteristics of the model today have taken its place in the industry shemoproizvodstveus. The design of such a model is atypical for ordinary models and is possible only for some libraries.

Regardless of the design of the model, a great place in the final realization is occupied by the choice of interfaces and use cases for the model. If the prepared data is in the form of a DataFrame or in the form of a database ROW, then organizing the prediction of a one-time sample leads to an unreasonably heavy load on the system. Moreover, the user code that executes the prediction must be protected from "train-time information leakage". The code for ML models is usually run isolated from user code on a different instance, different hardware, etc. On the other hand, typical data preparation usually excludes a priori Dask. At the same time, some use cases, e.x. serving a web server or model, serving a large number of predictions at a single request. In this context, the idea appeared of making a package that collapses the DataFrame to the list of events and connects directly to the interface of Dask.delayed. Such a package would allow to smoothly adapt the "user" code to the format accepted in the industry, while maintaining the original sample type.

Equ 2: Scalable Data Processing Power for AI Models

$$P_{total} = \gamma P_{on-prem} + (1-\gamma) P_{cloud}$$

Where:

- P_{total} is the total processing power.
- $P_{on-prem}$ is the processing power available on-premises.
- P_{cloud} is the processing power from cloud resources.
- γ is a factor that adjusts the proportion of resources allocated

4. Integration of AI and Hybrid Cloud

This paper describes Hyper, a prototype distributed cloud infrastructure designed for processing deep learning workloads at a large scale. Hyper is based on a combination of three key ideas. First, Hyper introduces a common DSL for the workload description. Second, for a given workload specification, it searches for the optimal combination of available resources across multiple heterogeneous clouds and on-prem. Finally, it minimizes the data movement between the resources by co-writing and partitioning into shards. The results

show that implemented Hyper infrastructure allows to scale the deep learning tasks to up to 300 GPUs and over 10,000 CPU cores on an unprecedented scale, running workloads involving 100TB+ size datasets.

The growing volume and complexity of AI workloads pose scalability and resource utilization challenges even for large GPU clouds. Rapid progress in the development of large models and datasets indicates the significance of adequate scaling infrastructure. As an example, depending on the batch size, it takes several hours to train a modern image classification model. The latest techniques in model research extend this time to dozens of days. As a consequence, the cost of experiments in the model architecture study grows rapidly.

In recent years, widespread AI capabilities and research achievements in developing new models have rapidly accelerated a wide variety of tasks. The non-trivial issue is the likelihood to deploy new models in industry. To support this scenario, an experiment that used large and very large pre-trained models flowed into end-transformers. The results of the experiment showed that the models grew significantly in scale, but also brought an improvement in the quality of the final results.

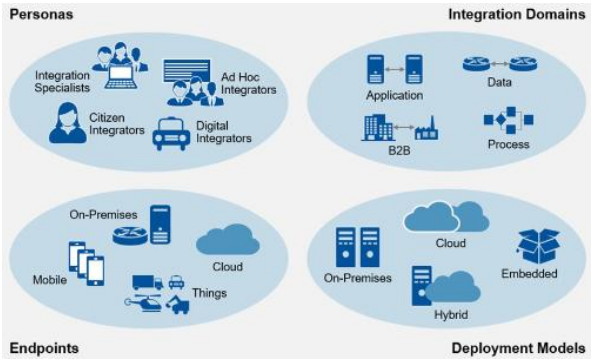

Fig 4: Hybrid Integration

4.1. Frameworks for Integration A distributed processing system for AI models is introduced that combines managing Docker containers with a dynamic Enterprise Message Bus and a fine-grained task management system. A prototype implementation used in the context of deep learning tasks is detailed, and the approach's flexibility illustrated by prototyping in other domains.

Let's integrate the two relevant innovations. The combination of AI-based services with data from a variety of sources — sensors, transactional data, microservices, batch jobs — leads to the aggregate production of AI models with complex pipelines. Such pipelines often require multiple processing steps with different requirements regarding the infrastructure. Moreover, as the number of models grows, separate processing is required for each component task per model.

Frameworks for building reusable AI models, compatible with hybrid and multi-cloud setups, are still at nascent stages.

Simply, a distributed processing system for AI models is used that aggregates running Docker containers with training scalers. Model and Data I/O are handled by a dynamic Enterprise Message Bus with a task-parallel backend, implemented using a parallel processing framework. A wide use-case is demonstrated for scalable deep learning tasks.

4.2. Case Studies of Successful Integrations Given the massive growth in on-premises data, edge processing, and cloud AI deployments, hybrid cloud-AI infrastructure will dominate data engineering architecture in the near future. However, there are not too many comprehensive and mature tools/frameworks in the current landscape. This text envisages future innovations which may advance as the common enterprise infrastructure technologies. Some early efforts towards these directions will also be presented. On-prem data tools can't natively communicate with cloud AI tools. It would be desirable that these tools take an "orchestration-as-a-service" approach. Data job A (e.g., ML model training) is usually done in the cloud. Job A needs to run many distributed tasks associated with large data. However, there may not be enough cloud resources for job A to directly process all the data. Luckily, part of that data coincides with the data from on-prem job B. This on-prem data may have been efficiently pre-processed via the aforementioned tools and is not

suitable to duplicate in the cloud. Convenient APIs & abstractions would be provided for job B to be triggered by job A and automatically adjust the data processing structure. Smart tricks would be pre-implemented inside the tools that understand the cloud job A (like automatically shuffling the on-prem data). Too many data tasks must be done in the cloud. As a result, it limits the agility/scalability of running on-prem KT pipelining. It is desired that common ETL or data copy primitives have the "parallelism matching" awareness.

5. Scalability in Data Engineering

A recent trend in Artificial Intelligence (AI) is the transformation of domain knowledge into solver programs. Modern Deep Learning (DL) based models typically consist of multiple layers and have been shown to outperform manual feature engineered algorithms in numerous domains. Trained models encode the gathered information about the data in the input features. The models can form complex dependencies and discover hidden patterns which the manual feature engineering does not encompass. Wide and Deep models can also be optimized for batch inference in an efficient way. The scalable transformer task consists in training, deploying and executing a large-scale transformer model on terascale unlabelled data. Randomly initialized fully connected Deep Neural Networks (DNNs) perform well for user-response and ad-click prediction. A Wide and Deep (WD) learning-based model has been introduced for this task to handle both categorical features with large sparsity and continuous features.

Recent production-ready models in Deep Learning (DL) are trained on large-scale labelled data with powerful hardware resources. Single machine with limited memory resources can not be used in training state-of-the-art powerful models. The client requires a distributed cloud-based solution for distributed processing. TensorFlow is a well-known and widely accepted DL framework. High-level API keras has been part of TensorFlow since the version 1.5 release. Scalability is a must for the developed solution. Distributed cluster processing is distributed across multiple machines to store and execute tasks simultaneously for high performance. compr is based on the RISELab's Ray framework which is a dynamic task-parallel framework. Task-parallel frameworks execute and coordinate tasks in a distributed manner.

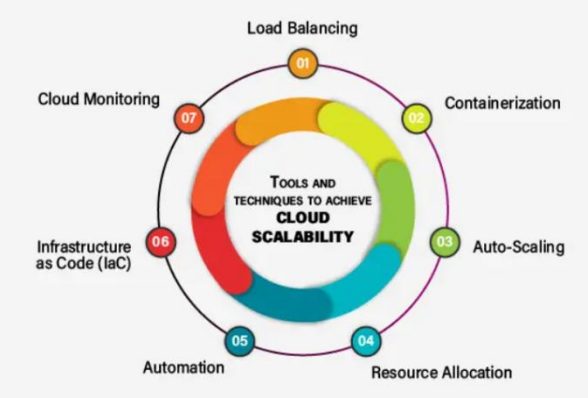

Fig 5: Scalability in Cloud Computing Explained

5.1. Techniques for Achieving Scalability Scalability of Hybrid Cloud and AI Integration aims to execute large-scale data engineering tasks. By definition of the Hybrid Cloud, the term scalability stands for the ability of an AI deployment to handle the increased workload of an entire enterprise. However, not every enterprise is easily scalable and grows without barriers. This section provides a set of innovations in Enterprise AI Infrastructure that achieve scalable data engineering. Furthermore, it examines techniques for evolving a typical Enterprise AI Infrastructure to a scalable one.

5.2. Performance Metrics for Scalable Systems The proposed research rests on analyzing the hybrid cloud and AI integration in the light of their significance to scalable data engineering for enterprise AI. The cloud and AI technologies have grown rapidly and they have brought various opportunities and expectations to serve machine learning and data analytics processes. There are several cloud-based scalable AI platforms in the market and one integrated platform has become popular as enterprise AI in diverse business areas. There is a timely need to explore and study such AI platforms oriented to enterprise businesses which have hybrid cloud

architectures as emerging AI infrastructure. This study aims to understand and explain such integration and discuss its implications in serving scalable data engineering for various data sources such as structured, unstructured, and real-time streaming data to be managed and analyzed with both batch and online processing.

The hybrid cloud and AI integration use centralized and distributed computing resources to manage and analyze both batch and streaming data in various data formats. The scalable AI platforms rely on the cloud technologies with the serverless execution capability to provide auto-scaling, monitoring, and integrating various ML models as microservice based architecture. Moreover, scalable AI platforms also consist of automated ML models as a service, hyper-parameter tuning, data transformation, validation, and model evaluation as meta learning to assist the data scientist process. Such AI platforms have interconnected with various scalable cloud storage and database services to adapt diverse data sources and computation resources. Scalable AI platforms are harmonized by the hybrid cloud technology between public clouds and cloud-on-premises.

Equ 3: Elastic Scaling for AI Workloads

$$R_{scaled} = R_{base} \times (1 + \lambda t)$$

Where:

- R_{scaled} is the scaled resource allocation (compute/storage).
- R_{base} is the base resource allocation.
- λ is the scaling factor (rate of increase in resources).
- t is the time or demand factor.

6. Conclusion

Continued investment in AI and machine learning research has resulted in advanced data engineering requirements for scaling the data, models, and embedding learning frameworks. As organizations look to innovate with AI at high velocity, existing challenges will become more profound. Recent technological advancements have transformed the way in which data and machine learning operations are managed in the cloud. However, optimizing machine learning is more difficult than optimizing data systems because it involves end-to-end lifecycle DAGs that combine data engineering workloads and ML training.

The majority of organizations will take a best-of-breed approach to build their own AI infrastructure systems. Such composed data engineering and model serving platforms require a consortium of interoperable technologies, allowing combinations of orchestration frameworks, databases, object storage systems, stream processing technologies, and model server design. Collaboration among industrial partners is needed to build the next generation of AI infrastructure that fully integrates the data and model life-cycles in a common platform. Such collaboration would allow organizations to more quickly and cost-effectively develop and deploy advanced AI systems in the cloud and operate them at scale thereafter.

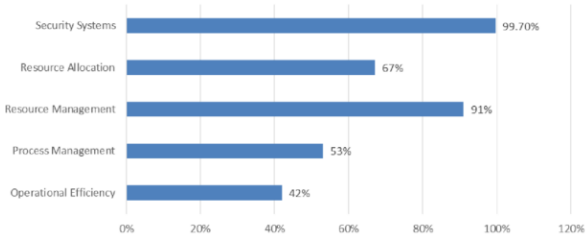

Fig : Innovative Cloud Architectures

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