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AI-Driven Cloud Data Orchestration for Real-Time Enterprise Decision Intelligence Systems

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ABSTRACT: Decision Intelligence goes beyond traditional Business Intelligence by providing organizations with all the data they need in a timely manner. Decision Intelligence Systems are built on Streaming Analytics and Event-Driven Architectures, ensuring that data is available for timely analysis and action. Recent data processing advancements are helping to develop the required Decision Intelligence Data Layer and its Supporting Resources and Services. First, data ingestion, normalization, and enrichment are being built at scale, applying Data Quality Frameworks for automated sanitization, Data Confidence Scoring systems for Intelligent Quality Control, and provenance information for interpretability. Next, patterns of orchestration for real-time pipelines are classified, Techniquestog and Techniquestog parameters supporting resilient handling of dynamic situations, thus aiding the Definition, Management, and Scheduling of Event Processing Pipelines. Finally, investigations are taking the first steps towards automatic provisioning of resources and orchestration of complex streaming convergences.

These developments are helping to complement the current step-wise, batch-oriented Operation Models of Data-Powered Enterprises with more responsive systems in charge of Dynamic Decision Intelligence, targeting niche applications such as Operational Intelligence, Situational Awareness, or Anomaly Detection Enablement. Decision Intelligence goes beyond traditional Business Intelligence by providing organizations with all the data they need in a timely manner. Decision Intelligence Systems are built on Streaming Analytics and Event-Driven Architectures, ensuring that data is available for timely analysis and action. Recent data processing advancements are helping to develop the required Decision Intelligence Data Layer and its Supporting Resources and Services. First, data ingestion, normalization, and enrichment are being built at scale, applying Data Quality Frameworks for automated sanitization, Data Confidence Scoring systems for Intelligent Quality Control, and provenance information for interpretability.

Keywords : AI; analytics; artificial intelligence; cloud; cloud computing; confidence scoring; data engineering; data governance; data in motion; data quality; decision intelligence; decision modeling; event processing; event-driven architecture; event-stream; fault tolerance; frontend protection; hybrid cloud; identity management;Infrastructure as a code; latency; low-code; MLOps; model monitoring; model reliability; model security; observability; Pipelines management; privacy; provenance; real-time; reliability; replicated data; role management; security; software development; Software as a Service; zero trust management.

I. INTRODUCTION

A growing number of digital-savvy enterprises are witnessing a steady deterioration of decision making quality attributed to lower levels of information access and increasing speed of change. Consequently, various organizations are collectively investing billions of dollars on the digitalization of business processes with the aim of increasing accessibility and speed of operation– supported by a large number of smart devices and Cloud technologies. However, these investments have not been repaid by a proportional improvement in decision quality. A possible explanation is the lack of a coherent framework that integrates several strands of research associated with Decision Intelligence (DI) systems in a unified manner. DI systems can be defined as cloud decision support environments allowing business users to combine human and machine intelligence, and seamlessly analyze information coming from a wide range of external and internal sources. They are complex systems designed to support strategic decision-modeling, support operational decision orchestration, and stimulate operational decisions, rather than supporting isolated operational decisions only.

Successful Digital Decision Intelligence Systems (DDISs) minimize the time lag between information generation and operational decision taking by deploying Digital Operations (DO) – which are intelligent, automatic, technology-

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enabled processes in a Cloud or hybrid environment that orchestrate routine operations following rules that reflect digital decision models. The time lag is controlled by the design and execution of Real-Time Pipelines for Data-Oriented Applications, which ensure verification of the information quality before triggering Digital Operations. These pipelines involve novel concepts like Data-Cleansing-as-a-Service and that of real-time Data Quality Flows and Frameworks. Such architectural patterns constitute information-driven ensembles of accessibility and speed of change.

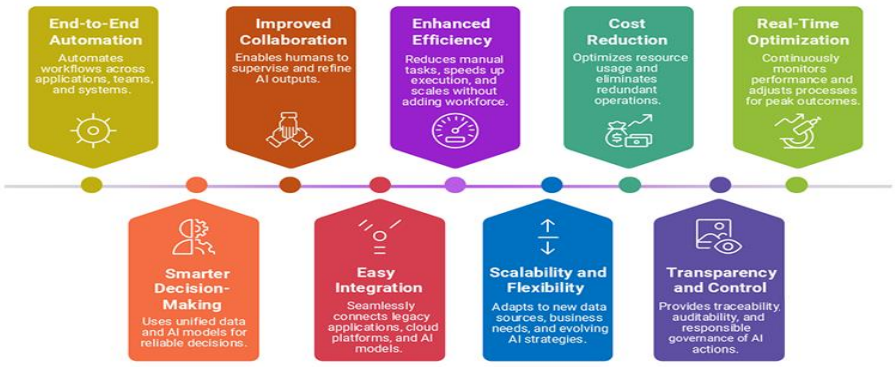

Fig 1: AI Orchestration

1.1. Research design

A structured overview of the research is provided, including research questions, the significance of the study, and a summary of major contributions. The need for an integrated approach to resourcing, security, compliance, and governance of cloud-based architectures for real-time Decision Intelligence Systems is established. Major gaps addressed include the need to accommodate data-layer processes such as cleansing and validation as an integral part of the real-time orientation, to formalize orchestration patterns, and to allow for automatic resource provisioning of the compute layer based on discovery-and-assessment AI.A Decision Intelligence System is a network-based—and typically cloud-hosted—software architecture that delivers a continuous stream of decision support to an organization. Such Systems use streaming analytics to process events as they arrive through a data source and make decisions by passing events through one or more Decision Models (support addressed through the application of Decision Modeling Technology) with the scheduling frequency set to minimize lag. Data cleansing, validation, and other quality-oriented processes are fundamental to the system that runs in near real-time; yet, elements such as cleansing pipelines are often considered outside the Machine Learning focus of the research community and consequently are not treated in a similarly urgent manner or with equal levels of resourcing.

Equation 1: End-to-end latency equation

Let

- t_{pub} = time a record is published
- t_{con} = time the same record is consumed/output

Then by definition,

$$L = t_{con} - t_{pub}$$

Now decompose the pipeline into stages:

- ingestion delay L_{ing}
- cleansing delay L_{cln}
- ETL/transform delay L_{etl}
- validation delay L_{val}
- model serving/evaluation delay L_{mdl}
- output/actuation delay L_{out}

Since total elapsed time across serial stages is the sum of stage times,

$$L = L_{ing} + L_{cln} + L_{etl} + L_{val} + L_{mdl} + L_{out}$$

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Step-by-step derivation
Start from timestamps:

$$L = t_{\text{con}} - t_{\text{pub}}$$

Insert intermediate timestamps:

- $t_0 = t_{\text{pub}}$
- t_1= after ingestion
- t_2= after cleansing
- t_3= after ETL
- t_4= after validation
- t_5= after model serving
- $t_6 = t_{\text{con}}$

Then

$$L = t_6 - t_0$$

Add and subtract the intermediate times:

$$L = (t_6 - t_5) + (t_5 - t_4) + (t_4 - t_3) + (t_3 - t_2) + (t_2 - t_1) + (t_1 - t_0)$$

Define each difference as its stage latency:

$$L_{\text{out}} = t_6 - t_5, L_{\text{mdl}} = t_5 - t_4, L_{\text{val}} = t_4 - t_3,$$
$$L_{\text{etl}} = t_3 - t_2, L_{\text{cln}} = t_2 - t_1, L_{\text{ing}} = t_1 - t_0$$

Hence,

$$\boxed{L = \sum_i L_i = L_{\text{ing}} + L_{\text{cln}} + L_{\text{etl}} + L_{\text{val}} + L_{\text{mdl}} + L_{\text{out}}}$$

1.2. Background and Significance

Billions of devices and sensors continuously generate high-frequency data streams, which organizations and industries can harness to improve business and management processes. For many real-time enterprise decision intelligence systems, decision-making can often be improved dramatically if statistical or machine-learning models are trained and continuously updated for decision-evidence generation. However, automating and scaling appropriate data-science processes with continuous, automatic streaming-data ingestion and provisioning to models at training, validation, and inference times represents a complex technical and engineering challenge—the potential to make faster, wiser decisions can be a double-edged sword for the enterprise. Hasty decisions based on erroneous or poor-quality data serve no one, and in real-time enterprise decision intelligence systems, failure at the data layer propagates up through the compute and presentation stack.

Well-known data quality dimensions—accuracy, completeness, consistency, timeliness, and uniqueness—apply to all data, whether batch or streaming formats. Modern data-cloud architectures enable almost limitless horizontal scaling of compute jobs for data ingestion, cleansing, and processing without needing home-grown solutions. Off-the-shelf time-series and streaming data stores can scale to handle data ingestion and provisioned storage created by the world's largest organizations. Proven AI models can be continuously retrained and automatically exposed to support model serving and inference. A mix of managed cloud services can be orchestrated to implement real-time streaming-data pipelines while complying with established data quality frameworks.

II. FOUNDATIONS OF REAL-TIME DECISION INTELLIGENCE

Various factors are accelerating the demand for real-time analytical capabilities. New sources of data are emerging from the Internet of Things (IoT) and social media platforms, while the dynamic nature of modern business conditions creates a thirst for fresh data and predictive capabilities to mitigate risk and seize opportunities. Historical data alone can be misleading and decision-makers often require up-to-the-minute analysis that can only be delivered through a dedicated analytics infrastructure. Such capabilities can predict undesirable future events and ultimately support decision automation or, at the very least, allow decision-makers to act with greater confidence. However, for many organizations, the lack of expertise in new processing paradigms such as event processing and streaming analytics is hindering progress.Real-time intelligence systems continuously collect and analyze data streams and produce insights

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tailored for increasing the velocity, volume, frequency, and precision of business decisions and actions. Decision intelligence, however, is a new field which extends beyond DWBI and enables business leaders to discover new ways to make their decisions supported by AI-driven advice. Decision-intelligence-driven data orchestration provides the means to automatically drive data-sourcing and analytics-driven AI decision pipelines in the cloud while meeting data quality, reliability, performance, cost, and compliance requirements. The reverse of real-time data-driven decisions is also important; they are an essential part of organizational feedback loops.

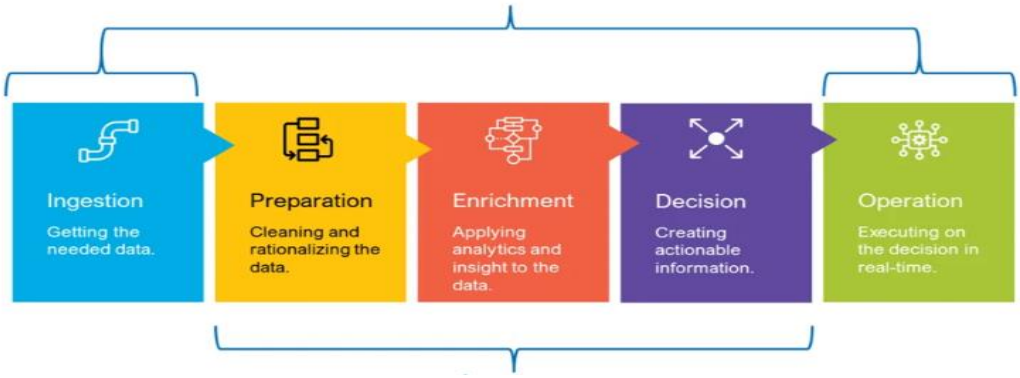

Fig 2: Real-Time Decision Intelligence

2.1. Definitions and Scope

Real-time decision intelligence (RTDI) involves decision-making operations based on the continuous analysis of data from multiple sources that is being ingested, transformed, processed, and modeled in a timely fashion. This constant flow of decision-ready insights helps organizations respond rapidly to changes in their operating environment and capitalize on fleeting opportunities. Ad-hoc RTDI is carried out using interactive analytics but because of the high level of uncertainty and dynamic nature of the business environment, organizations are moving toward end-to-end RTDI systems. While a data pipeline provides continuous delivery of data needed for decision-making, RTDI implements the decision logic and exploration of the decision space optimally. RTDI is not merely a collection of real-time models but comprises the orchestration logic and various aspects of DDL framework that turns the real-time decision-making capability into a repeatable setup. In essence, RTDI represents a "wheel" that keeps rolling by taking advantage of the flow physics of water resources, rather than a "bicycle" that relies on the physical power of a series of gears to create energy.

The enabling set of technologies includes streaming analytics, event processing, complex event processing (CEP), and real-time decisioning. While streaming analytics deals with the processing of high-velocity data streams, event processing represents a higher level of abstraction. Events can be produced manually by the user or automatically by a business application, monitored by a CEP engine that detects specific situations as defined by rules, and take actions through internal processes, APIs, or mail.

Equation 2: Throughput equation

Let

- N= number of records processed
- Δt= observation time

Then throughput is

$$T = \frac{N}{\Delta t}$$

Step-by-step derivation

Rate always means “amount per time”:

$$\text{rate} = \frac{\text{quantity}}{\text{time}}$$

Here, quantity is number of records processed:

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$$\text{quantity} = N$$

Time interval is:

$$\text{time} = \Delta t$$

Therefore,

$$\boxed{T = \frac{N}{\Delta t}}$$

If the average latency per record is L, and the system behaves like a single serial processor, then roughly

$$T \approx \frac{1}{L}$$

If there are $m$parallel workers, each with average service time L_s,

$$T \approx \frac{m}{L_s}$$

2.2. Architectural Principles

Enterprises utilize real-time decision intelligence capabilities for ad-hoc, streaming, and complex event processing across multiple business functions such as marketing, sales, risk and fraud detection, service delivery, and manufacturing support. Providing enterprises with real-time decision intelligence systems and pipeline-as-code capabilities requires a systematic approach to ingesting, cleansing, and processing vast amounts of data in a scalable, dependable, and maintainable manner. The flow of data through various pipelines must be orchestrated, scheduled, and continuously monitored to meet user-defined service-level objectives.

Real-time data orchestration ensures that data is ingested and processed when required to enable advanced analytics use cases. It generates, updates, and deletes datasets for end-user analytics via interactive dashboards and reports. It also predicts non-compliance with business rules or service-level agreements that require attention for pre-emptive action by business users. Unlike traditional data-in-motion patterns, modern systems support long-running interactions such as the orchestration of an autonomous supply chain model and a decision intelligence system that proactively identifies potential supply-chain disruptions.

III. RESEARCH SUMMARY

Across many industry sectors, organizations have become accustomed to the capabilities made possible by Massive Online Open Courses (MOOCs). The search engines, the rises of social networks and hundreds of applications have all provided users and consumers with more information than they care to deal with, made instant communication effortless and intuitive, instant gratification even easier and democratised the consumption of music and much more, but it has not yet transformed the way businesses work. Enterprise businesses are not yet able to make instant data-based decision in real-time, at least in volume and at scale. In fact, when news breaks, these organizations need to wait hours, sometimes days and VERY rarely in minutes or seconds for their own data to deliver mission critical insights to business leaders. The realities of development, testing, deployment time of models to serve this need for real-time decision intelligence into the market remains ever-present. Real-time companies are often the first to know and the first to profit.

This section examines how in the next frontier of information technology, the intelligence and automotive world, all of the tasks performed by dedicated specialists in forecasting cannot fully automate – deploying and maintaining models and pipelines, monitoring business dimensions month-on-month, ensuring alerts trigger in and create the right automations, performing sensitivity analysis on dimensional shifts. All of these elements can and should be automated. AI could and should exploit the full potential of being real-time – adapting models, responses, calibration scores, predictions and decisions for each new row added, not being trained in batch at a lag of hours, days and weeks and requiring multi-week testing. The logical orchestration to serve the real-time demands of today's business world then becomes akin to the tactical decision-making a football coach must orchestrate in response to constant situational changes in a match on the field. Such is the potential of real-time Business Intelligence.

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3.1. Data Ingestion and Cleansing at Scale

Data ingestion is the process of gathering and storing information from various data sources into a central repository—a specialized storage system (such as a database) that is used for further processing, analysis, or machine learning model training and evaluation. Cloud computing platforms provide data ingestion and cleansing services that can be operated in a massively parallel way. The amount of ingested data, often referred to as data throughput or ingestion throughput, is frequently expressed in terabytes (TB) or petabytes (PB) per day. The strategies for data ingestion and cleansing can be classified into the following categories: Data ingestion at scale involves ingesting data that are generated around enormous data volume in a real-time fashion or in near real-time. The ingestion and cleansing process can include the provisioning of compute resources, such as containers or serverless functions, that are required to complete the tasks and the delivery of collected (cleansed) data into datastores on the cloud.

Data quality plays an important role in building AI models used for real-time decision processes. It is composed of accuracy, consistency, completeness, validity, reliability, and timeliness. Data quality frameworks for transit data, such as monitoring the quality of traffic flow index and data quality evaluation of groundwater, ensure the completeness of highways and operating conditions of vehicle networks. To improve data quality in data ingestion and cleansing, data confidence scoring techniques are used to provide a measure of certainty or doubt surrounding the correctness, reliability, or creditability of data streams processed by the system. The confidence scoring process can be realized by adding a confidence layer into the data layer and can systematically support the interpretability of AI pipelines.

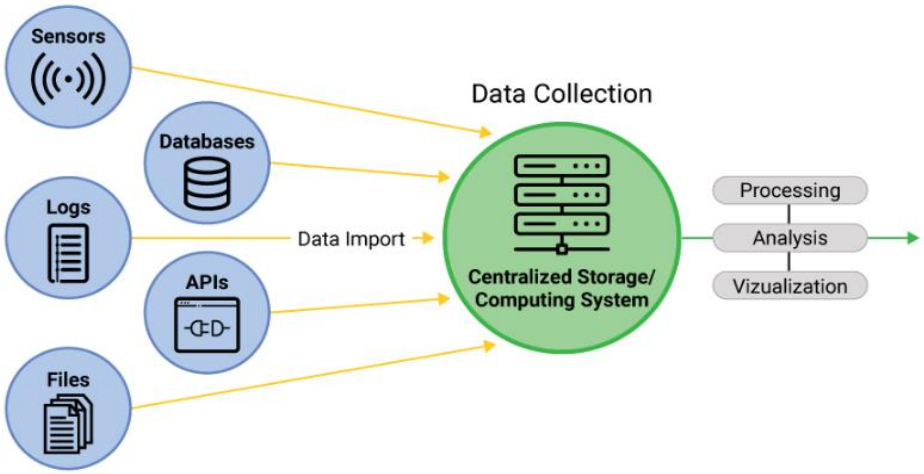

Fig 3: Data Ingestion and Cleansing at Scale

3.2. Orchestration Patterns for Real-Time Pipelines

Rapid expansion in the volumes and variety of data being ingested and processed—resulting in huge spikes in data quantity, velocity, and variability—has made real-time data-and-decision-intelligence systems far more sophisticated than batch-processing systems. The patterns introduced by domain experts have made it possible to deploy real-time data pipelines for ingestion of streaming or continuous data using popular event-processing and/or message broker technologies. The introduction of such patterns has broadened the applicability of existing frameworks such as Airflow, Luigi, or Stateflow, which were originally developed for orchestrating batch jobs to support real-time data pipelines as well.

Increasing numbers of organizations are relying on real-time data-and-decision-intelligence systems, since relying solely on historical data to train and operationalize analytic models often turns into a blind spot because of the delay associated with both the training and operationalization of the models and the inability of the models to adapt to the latest changes in data patterns. A data-and-decision-intelligence system is primarily composed of four parallel layers, which capture different aspects of the AI life cycle. The data layer manages the continuous ingestion and storage of data, ensuring data quality throughout the ingestion and storage processes and continuously generating new data that brings value to the organization. The compute layer is responsible for scaling the processing of any data consumed either for training purpose or real-time inference, regardless of whether it is a volume, variety, or velocity problem.

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3.3. Resource Management and Scheduling with AI

Dynamic service provisioning and resource scaling for complex AI pipelines requires sophisticated orchestration. In many enterprise use cases, training and serving datasets for models trained on laboratory conditions possess concept drift. Other geospatial dimensions of data also vary in their complexity and load patterns during peak processing times. Intelligent and disaster-aware provisioning of resources for model training and serving should be based on anticipated workload and quality of the ongoing serving latency.

Continual Learning, situated in the intersection of Machine Learning and AI, develops algorithms that can learn data and tasks sequentially. With a parallel focus of accumulating knowledge without end-to-end retraining, Low-Cost Continual Learning aims at minimizing training costs and is relevant when resource provisioning of the model pipeline depends on cost-effectiveness for enterprise deployment. In areas of low data density, the economic cost of high-quality prediction should be suitably reduced.

Equation 3: Data quality / confidence score equation

Let normalized quality dimensions be:

- a= accuracy
- c= consistency
- p= completeness
- v= validity
- r= reliability
- τ= timeliness

Assume each is scaled to $[0, 1]$, and weights $w_i$sum to 1:

$$w_a + w_c + w_p + w_v + w_r + w_\tau = 1$$

Then a natural confidence score is the weighted sum:

$$C = w_a a + w_c c + w_p p + w_v v + w_r r + w_\tau \tau$$

Step-by-step derivation

A weighted average of factors $x_1, \dots, x_n$is

$$\bar{x}_w = \sum_{i=1}^{n} w_i \, x_i \text{with} \sum_{i=1}^{n} w_i = 1$$

Apply that general formula to the six quality dimensions:

$$C = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$$

Now substitute:

$$x_1 = a,\ x_2 = c,\ x_3 = p,\ x_4 = v,\ x_5 = r,\ x_6 = \tau$$

So

$$\boxed{C = w_a a + w_c c + w_p p + w_v v + w_r r + w_\tau \tau}$$

If all dimensions are equally important, each weight is $1/6$, giving

$$\boxed{C = \frac{a + c + p + v + r + \tau}{6}}$$

IV. OBJECTIVE OF THE STUDY

The design of a real-time decision intelligence solution inherently relies on a cloud-based system provided by a major cloud vendor. Therefore, a real-time decision intelligence solution, suitable for deployment in a public cloud environment, cannot be created in isolation and must therefore be defined along three intertwined layers: data and storage; compute; and model serving and inference. Furthermore, within the context of the designated cloud environment, reliability and efficiency are essential characteristics of any solution. Delivering both requires the execution of the model serving pipelines---including provision, life-cycle management, and orchestration of all AI

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models, including the AI models for confidence scoring, interpretability, auditing, and provenance of the AI predictions---and the data layer, which provide services to the serving pipelines, to operate in continuous integration and continuous delivery mode.

These continuous processes must ensure that any change, whether data, model, or configuration update in the data layer, is reflected in the serving pipelines as promptly as possible. The remaining operational tasks must assure that the models within the serving pipelines are constantly performing their function as defined by the orchestrating logic and that the correct models are executed against the appropriate data. These two sets of operations are tightly related to the secure, private, and compliant use and storage of all data within the cloud environment and, most importantly, to the speeding up and management of the DavOps for the data orchestration layer of a real-time decision intelligence solution.

Equation 4: Predictive confidence interval equation

Let

- $\hat{y}$= predicted value
- error variance $= \sigma_e^2$
- error standard deviation $= \sigma_e$

For a normal-error approximation, a $100(1-\alpha)$%confidence interval is

$$\hat{y} \pm z_{\alpha/2}\sigma_e$$

So the interval is

$$\boxed{[\hat{y} - z_{\alpha/2}\sigma_e,\ \hat{y} + z_{\alpha/2}\sigma_e]}$$

Step-by-step derivation

Suppose the forecast error is

$$e = y - \hat{y}$$

Assume

$$e \sim \mathcal{N}(0, \sigma_e^2)$$

Standardize the error:

$$Z = \frac{e}{\sigma_e}$$

Then $Z \sim \mathcal{N}(0,1)$. For a two-sided confidence level $1-\alpha$,

$$P(-z_{\alpha/2} \le Z \le z_{\alpha/2}) = 1 - \alpha$$

Replace Z:

$$P\left(-z_{\alpha/2} \le \frac{y - \hat{y}}{\sigma_e} \le z_{\alpha/2}\right) = 1 - \alpha$$

Multiply through by σ_e:

$$P\left(-z_{\alpha/2}\sigma_e \le y - \hat{y} \le z_{\alpha/2}\sigma_e\right) = 1 - \alpha$$

Add $\hat{y}$to all terms:

$$P\left(\hat{y} - z_{\alpha/2}\sigma_e \le y \le \hat{y} + z_{\alpha/2}\sigma_e\right) = 1 - \alpha$$

Hence the prediction interval:

$$\boxed{[\hat{y} - z_{\alpha/2}\sigma_e,\ \hat{y} + z_{\alpha/2}\sigma_e]}$$

For 95% confidence, $z_{0.025} \approx 1.96$, so

$$\boxed{\hat{y} \pm 1.96\,\sigma_e}$$

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4.1. Data Layer and Storage Strategies

The question of where to store the data, how to structure the data, and under what technology to store it is an important one. First and foremost, attention needs to be paid to what data is actually required for downstream analytics, as retaining previous datasets not only occupy space, but also increases the complexity of cleaning. Since the process of data pipelining is highly complex and relies on different components, frameworks, and technologies, factors including data integrity, consistency, and quality must also be maintained throughout the pipeline process. Although real-time data streaming pipelines do not allow for re-running experiments or repairing issues in a conventional manner, high levels of data pipeline reliability can be achieved by employing data quality monitoring frameworks.

Data quality and integrity are important factors supporting enterprise decision-making, as inaccuracies in large pipelines will impact the model outputs observed. Confidence scores related to migration are useful data quality measures for determining whether the decision model assigned a proper match to the signal event, and uncertain signals should preferably be classified as hard negatives if feasible. Spurious spikes in a time series may originate from a range of causes, including sensor failure, sensor redundancy in the environment, hardware failure, problems at the data collection point, or data transmission. These could be detected automatically and, where possible, tagged during the data cleaning and preparation stage itself, so that they could be taken care of in the inference pipeline.

For specific algorithms (e.g., K-Means), the service offers direct support for model building and serving, enabling advanced managed capabilities such as resource allocation for model training. For some processes, mainly data ingestion, managed services might induce a lock-in with the provider. For models that need to be served in real time, dedicated computation layers must be created. These could be relayed directly from essentially any cloud compute service at optimal resource utilization.

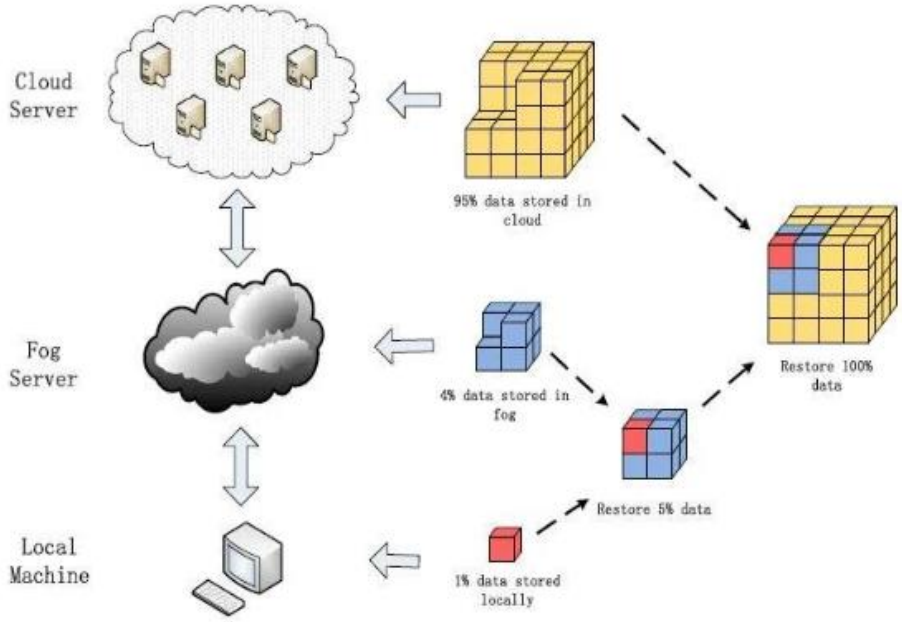

Fig 4: Data Layer and Storage Strategies

4.2. Compute Layer and Scalability

The implementation of scalable data pipelines also depends on the compute layer. Several cloud providers offer an abstraction service over well-known functions (e.g., execution of Python functions), so a horizontal scaling and load balancing layer is added. Several of these products allow the execution of processing functions that adhere to a well-defined signature. These services typically scale automatically based on usage and isolate calls, allowing concurrent execution with no fragment share.

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Hyper-parameter tuning or burst serving on demand can be performed with dedicated servers. Nevertheless, companies can achieve a cost-efficient setup by setting up model serving using the provider's offering during periods of lower demand and defining a burst rule based on metrics that indicate demand change, falling outside the default optimal resource. The burst triggering allows not-expensive word-of-mouth communication.

4.3. Model Serving and Inference Pipelines

Machine learning (ML) models of all types are gaining adoption by organizations for decision support and automation, as well as improvement of customer experiences through the delivery of relevant and timely services and content. Cloud service providers have built these model serving capabilities into their platforms. ML models for supervised learning problems are designed to predict a target variable given a feature vector. During the training process, these models learn the relationship between the target variable and the features based on the training data consisting of historical records of the target variable and the features. After training, the learned model can be used to automatically predict the target variable when a feature vector is provided.

In the case of functional models, these are not considered as classification or regression models. Model serving in functional models is providing some external feature vectors which are either application models doing business-critical jobs or are some service API which has to be reusable across application for different feature-vector inputs. These resources can be efficiently served through a function-as-a-service layer and should be capable of being called anytime. The requirement for serving these resources can also be dynamic. Therefore a thorough model serving layer need to be present for all kind of model serving need in enterprise-level decision intelligence systems.

V. METHODOLOGY

Real-time enterprise decision intelligence systems require a methodology that supports data ingestion, processing and model serving at a scale never before experienced in commercial systems. Streaming analytics offers a purpose-built framework for ingestion and processing and an event-based architecture for decision modeling and orchestration logic. Decision intelligence calls for a fundamentally different view on the two basic types of operation available within streaming analytics: stateful and stateless processing.

Real-time Decision Intelligence systems consume, process and produce a constant stream of events where each event is related to a certain state of the world. The event has sufficient context to allow for a semi-structured model to be built containing representative features of what they model in the world. Enterprise pipelines are therefore moving towards pink in Gartner's data pipeline colour-coding scheme, which underlines the increasing importance of stateful processing.

A stateful operation retains state across multiple incoming events, allowing the operator to compute aggregates on these events or produce a single output after processing a large number of inputs. Stateful operation out of the box faces a number of challenges such as unbounded memory growth, undecided output timings or processing ordering dependencies. Real-time Decision Intelligence retains these qualities while propositioning that Decision Intelligence Tasks leverage them for more efficient problem solving.

Equation 5: Availability / reliability equation

Let

- U= uptime
- D= downtime
- total observation time $= U + D$

Availability is the fraction of time the system is operational:

$$A = \frac{U}{U + D}$$

Step-by-step derivation

Availability means

$$\text{Availability} = \frac{\text{time available}}{\text{total time}}$$

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Available time is uptime U, total time is $U + D$. So

$$\boxed{A = \frac{U}{U + D}}$$

If expressed as a percentage,

$$\boxed{A(\%) = \frac{U}{U + D} \times 100}$$

If there are $n$serial components with independent availabilities $A_1, \ldots, A_n$, the end-to-end availability is

$$\boxed{A_{\text{sys}} = \prod_{i=1}^{n} A_i}$$

because the full pipeline is available only if all required serial components are available.
If there is active redundancy with two parallel identical services of availability A, then system availability is

$$A_{\text{parallel}} = 1 - (1 - A)^2$$

5.1. Streaming Analytics and Event Processing

Classic data management and analytics platforms rely on batch processing and offline analytical capabilities that operate both at a different scale and over a different time horizon than routine business transactions. Such operations are often powered by a data warehouse that enables analytical (OLAP) queries over non-volatile data, typically stored in a well-defined schema. By contrast, streaming analytics and event-processing systems typically operate in real time and take a more incremental approach to data analysis, where incoming new data can trigger decisions or statistics without requiring processing of a complete dataset. What counts as streaming data varies by context and specific application. In the context of enterprise decision intelligence systems, data is treated as a stream when incoming data requires real-time processing for the purposes of enabling rapid operational responses.

Enterprise decision intelligence systems integrate business operations, real-time analytics, and artificial intelligence into a Decisioning as a Service (DaaS) offering deployed and accessed through a Cloud as a Service (CaaS) delivery model. Critical to the success of such a system—especially for event-driven operations like fraud detection, churn prediction, and inventory demand forecasting—is the real-time availability of business data needed as input to the analytics. Many enterprise organizations are migrating their operations into the Cloud, deploying new applications in the Cloud and re-architecting existing systems as CaaS solutions. In the process, they identify opportunities to extract additional business value from their transaction systems by providing analytics-driven decisioning services.

5.2. Stateful versus Stateless Processing

The distinction between stateful and stateless processing is an important consideration that affects high-level architecture decisions. While stateless stream processing provides lower latency, stateful stream processing is required when the analytics solution needs to take important information such as all prior visits of a user into account. Some applications use a combination of both processing modes.

All users of a website, for example, can be processed in a stateless manner to determine whether they are demanding a service that has an acceptable wait time. At the same time, an active user can be processed in a stateful manner to check whether his or her activities make it necessary to inform a support user with a full history of the last actions carried out on the site. When this pattern emerges, the two paths are usually referred to as a north-bound and a south-bound analysis, respectively. Typically, the routing of information is handled by a Message-Oriented Middleware (MoM), an extremely reliable protocol along the lines of Zero Message Loss. The Decision Model in this case will specify explicitly what messages are north-bound and what ones are south-bound.

5.3. Decision Modeling and Orchestration Logic

Modeling the decision-making process using the right model family and algorithm for a specific task is an essential part of real-time DI platforms. Decision modeling frameworks bridge the gap between business verb statements and the business-as-usual model-solving capabilities offered by open-source model templates and engines. Some framework

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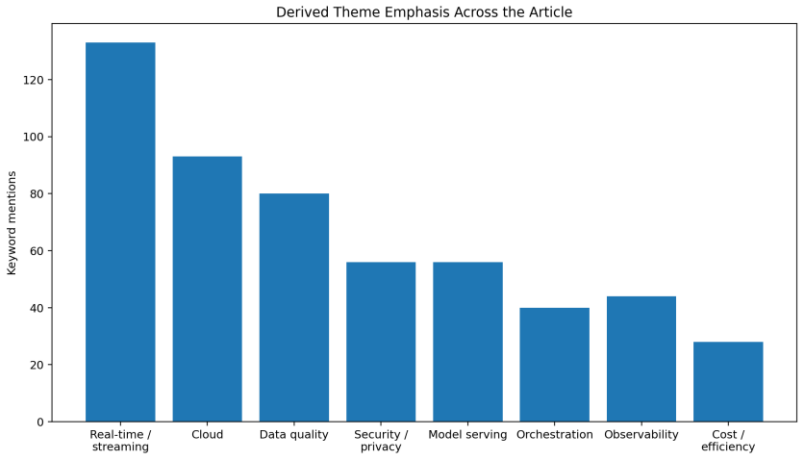
choices can be simple for vertical applications; for broader horizontal applications, these frameworks provide a family of best-fit mini templates for specialized decision-making users.

Rules specify the task to be performed and point to the model solver best suited for the job. Business logic expresses requirement semantics, such as "If X and Y, then do A"; "If Z, then stop"; or "As long as A, do B". These rules form a decision tree, prescribing a logical ordering of tasks. Decision orchestration applies these elements to temporal data coming through the decision pipeline, triggering task execution and completing tasks downstream.All decisions are time-stamped; an additional timestamp indicates the time by which downstream completion must occur. Non-time-consuming tasks are monitored at least by the trigger time. Trends forecast the time of completion for time-consuming tasks. Monitoring other temporal attributes indicates when to stop or suspend those tasks. Integration with cyber-physical systems helps with automation. External trigger events (e.g., arrival or departure of specified shipments) can also suspend operation and automatically resume operation.

VI. RESULT

Success in real-time decision intelligence requires rigorous approaches to data quality, confidence scoring, model explainability, monitoring and auditing. Building trust in a web of cloud-native, AI-enabled pipelines demands seeking to preserve data quality throughout the entire life cycle. Good quality initial data does not ensure perfect decision outcomes, as systems must be capable of dealing with noisy, misleading, and erroneous data. Confidence scoring evaluates the reliability of decision-making processes, while explainability seeks to make these processes human-understandable. Monitoring focuses on maintaining the systems, proactively identifying noises, and introducing safeguards and alerts.

Data quality frameworks typically define a set of rules that data must follow to be considered “fit for purpose.” Rule violations can be monitored to identify high- or low-confidence input observations and trigger mechanisms to take necessary precautions during the decision-making process. When confirmed, such violations can lead to model re-training. Confidence scoring quantifies the trustworthiness of a data input, its associated predictions, and the actions pursued based on these predictions. The interpretation of the different output scores can diverge, and several domains use expert knowledge to ascertain ranges and guidelines followed by humans or other models. Auditability establishes provenance, including input training data, as well as model characteristics and parameters feeding the decision outputs.



6.1. Data Quality Frameworks

Not all data is equally relevant, and not all data can be treated with the same confidence. A bank model predicting a customer’s propensity to repay a loan is based on rules like “High income = low probability to default” — therefore, should be used only when the customer’s income is recorded. If this information is missing it would be more trustworthy to revert to the default score provided by the bank. A data quality framework ground on the movement through levels of acceptable quality (availability, context, currency, dependability, granularity, precision, range, reliability, semantic consistency, is-ness, and timeliness) adds additional general data properties to take into consideration when creating the Relational Model for the Enterprise and that is useful to feed the decision model.

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These additional properties unambiguously reduce the quality of any data used, including historical ones, introducing delay and the chance of meaningful buffers (dependent on past events with respect to the time dimensions of the business) in making decisions affecting future actions. Data sources can have different data characteristics for different events: weather can be timely in forecasting frequent triggers (travelers in transit), can have a limited is-ness (melting snow block the view at the airport), context quality must be evaluated for every forecast, with its validity root in non-overlapping historic seasons, and information (temperature, snow forecast, drivers, car circle, airports, etc.) stops being dependability with the extreme advents like tsunami or tornado, can visibly nevertheless reveal the new route and the heavy rain radar in real time, etc.

6.2. Confidence Scoring and Interpretability

The lack of accuracy measures for advanced analytics solutions has hindered their adoption in business applications. Unlike the generalization of performance metrics like error rate, the accuracy of a specific prediction is rarely made explicit. Although it is often hard to quantify confidence due to interaction with unknown factors, those using predictive modeling techniques to support decision-making must develop a heightened awareness of limitations and potential problems. Confidence or probability scoring is a natural and often necessary by-product of a regression model, providing a predictive interval around the forecast based on variance of recent errors.

For rules-based recommendations, the number of conditions is an obvious measure of complexity. Neural networks, especially ensembles, are often seen as black boxes. Researchers have developed much work around providing explanations and visualizations to users to enhance trust. Computing data at different granularities — such as product granularity for demand forecasting but region granularity for supply chain recommendations — has proven effective for enabling better visualization or explanation of such complex decisions. The issue of confidence scoring naturally arises when decision models involve potentially conflicting signals from multiple sources.

6.3. Auditing and Provenance

Comprehensive audit trails that record when data arrives, how it is processed, and the identity of users accessing it are essential for ensuring compliance with legal and regulatory requirements. Providing end users with transparent explanations of the source and transformation of data empowers them to make informed decisions about the confidence with which to act on analytic results. Along similar lines, enabling organizations to detect abuse during model training and testing is also an important capability.

Provenance refers to the documentation of the history of data, including where it came from, how it was created, and what processes have been applied to it. Provenance queries, which provide insight into how a particular result was generated, are also needed to support the interpretability of machine learning models. Tracking both the provenance of decisions and any potential security violations is a critical requirement for real-time mission-critical AI-based decision support systems. In the data management domain, provenance capture involves logging metadata that describes the actions taken on data or the results expected from the application of a particular process. Provenance capture and storage for data ingestion, cleansing, and preprocessing is facilitated by automatically adding a logging step within the cloud infrastructure. This enables the direct storage of captured provenance data into a dedicated repository. Auto-generated tags can also be incorporated within the data in order to create a richer context around the provenance. Applications in data provenance typically fall into three groups: data management, security, and scientific research.

VII. SECURITY, PRIVACY, AND COMPLIANCE IN THE CLOUD

A cloud environment provides several capabilities such as flexibility, scalability, availability, and low-cost. However, it also brings security, privacy, and compliance concerns for organizations wishing to operate in the cloud. Organizations need to safeguard their data, applications, and services while operating in the cloud. The cloud vendor's security and privacy provision are insufficient. Organizations should enforce their internal security and privacy policies and controls on their files, folders, applications, and user accounts using cloud-native methods such as identity and access management (IAM) and encryption. IAM controls access to cloud services, while encryption protects sensitive data at rest, in transit, and in use. De-identification and data masking render the sensitive real data useless for intruders.

Organizations must also address their local regulations that mandate storing certain types of data (e.g., personal data) in specific geographical jurisdictions. Cloud providers operate their services across multiple regions, utilizing multiple data-residency techniques to satisfy the residency requirement of their customers. Creating a single cloud service is not

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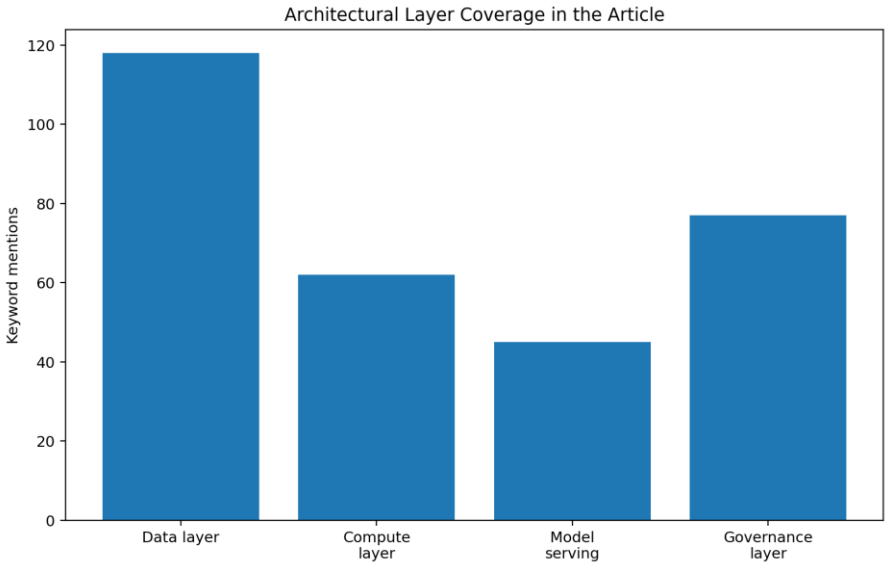
sufficient to meet the residency demand of all customers. Cloud and IT service providers must also have appropriate compliance framework policies and controls in place. Real-time updating of compliance frameworks among certifying agencies, governing bodies, and external and internal auditors is essential, enabling organizations to ensure compliance with fast-evolving industry and geographical regulations.



7.1. Access Control and Identity Management

In a cloud environment, access control is the deliberated constraint of user access to, or use of, an enterprise's resources. This can be addressed by the well-established area of Identity and Access Management (IAM), responsible for managing who is authenticated (and authorized) to use services and resources in the enterprise, as illustrated in Fig. 26. In addition to the generic IAM services offered by the cloud provider (such as support for Security Assertion Markup Language (SAML) authentication to allow safe Single Sign-On (SSO) access via federation with on-premise Active Directory), cloud-native enterprise applications often need to manage their own users too. The Multi-Tenant User Module of IAM offers an isolated storage for tenants' user profiles and credentials. Cloud-native enterprise applications can manage their tenants' users with this module. There are different access levels between tenants' administrators and users. Each tenant's administrator can add and delete users of their tenant and assign privileges. With this module, end users can register and log into enterprise applications directly. After a tenant administrator's approval, each end user can log into their required enterprise application.

User access to the actual data being considered by the cloud-native enterprise application needs to be constrained as well, either directly through low-level data storage elements or indirectly through high-level data abstractions. Fine-grained access control governs users' access to the data by configuring policies on the data and their resources. It allows specifying Control List (ACL) information on cloud storage objects residing in Cloud Object Store (COS) or Alibaba Cloud Object Storage Service (OSS) and on tables residing in Cloud Table (CT) or Alibaba Table Store (TS). Such ACLs check whether the requesting user is allowed to access the resource in question before the access is executed. The component also enables the detection of relevant sensitive data for the enterprise, possibly in combination with third-party scanning engines.

7.2. Data Residency and Privacy Preserving Techniques

Residency restrictions are often a requirement for the safe processing and storage of data—co-location of data and processing is a necessity for true privacy-preserving systems. These complex constraints bestow on organizations the dual role of being both data controller and data processor. Subsequently, two common techniques for privacy preserving processing have emerged: differential privacy; and homomorphic encryption. Differential privacy guarantees that learning outcomes about any individual are so gentle that a data user is free to consider a population statistic that is flattering to any sub-group. Very generally, differential privacy guarantees can be cast as small

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perturbations of the data itself or as error terms added into the learning model. Both variants afford equivalent release-level privacy guarantees but are deployed under fundamentally different litigation and operational styling.

Homomorphic encryption achieves similar protection by encrypting the data and letting the user do useful processing with the data—on the encrypted data—without exposing the actual data to the user or any system-wide administrator. Communications-based solutions are equally beneficial because they allow relatively unrestricted data processing by data processors that do not actually see the data. An increasingly common approach is the utilization of XAPs. Like cloud vendors, XAPs-in-a-box offer inexpensive backups (bundled with pollution prevention for consequent re-deployment) but, uniquely, they also offer free form connection to an unknown number of geographically dispersed suppliers and users. Sensitive or secret document processing is efficiently handled on line with native vanishing-keys (the key for decoding the response drift is shared only after the decoding).

7.3. Compliance Frameworks and Certifications

No regulatory landscape is stable over the long term. Therefore, the deployment of a cloud platform is a challenge, for which cloud service providers continuously develop new controls and certifications. Certification programs allow both certification of cloud service providers based on compliance with best practices as well as validation of information security requirements demanded by users of cloud services.

Cloud customers need to understand these certification frameworks in detail to ensure that proper cloud providers are selected. Likewise, cloud service providers must support compliance with regulations that reflect the requirements of their customers. Cloud customers should demand compliance with the controls of international standards such as ISO 27001, ISO 27017, ISO 27018, and ISO 27036 to guarantee the effective application of the security lifecycle. A data security compliance framework provides high-integrity and nonrepudiation security for cloud services among multiple cloud service providers. Accumulated authenticator data generated in accessing different cloud-providers' services can be leveraged to facilitate compliance audits and provide user-centric control over who can use that data via an iris recognition cloud-computing service.

Cloud deployment brings compliance concerns that need careful assessment. The technical challenges associated with utilising a public cloud system while complying with the requirements of the General Data Protection Regulation (GDPR) are highlighted, with a focus on technical controls. A cloud deployment model with a multi-master and multi-slave solution map is introduced, which has a dynamic customer identity access and management module and uses products from three different enterprises. The studied research problem is summarised as follows: does the above cloud deployment model comply with the GDPR and other appropriate regulations when configured under the technical responsibility of a data controller or a data processor?

VIII. EVALUATION, METRICS, AND BENCHMARKING

High-level information about the evaluation of platforms for Real-Time Decision Intelligence Systems is provided below in the form of evaluation aspects and high-level metrics. Domain-specific benchmarks, where applicable, are provided as well.

The evaluation of cloud-based platforms for Decision Intelligence Systems concerns multiple aspects. Performance characteristics such as latency or throughput are therefore relevant. They also provide service non-functional properties for a Quality of Service (QoS) perspective. Other aspects concern reliability aspects of the environments and hence specifically availability of the Service Level Agreements provided by the cloud. These include Service-Level Indicators (SLIs) for fault tolerance as well as economic factors for cost effectiveness.

For cloud decision intelligence systems, specific platforms should include cost modelling as part of overall architecture and approach. This involves not only understanding the platforms' structure but also the proposed usage of the services. A data-centric view enables identification of service requirements – latency, throughput, SLA and cost associated with data costs, compute resources and storage. The accumulated costs at each stage together with required margins then enables setting a cost threshold for the wider systems.

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Layer	Primary role	Representative article concepts
Data layer	Ingest, cleanse, validate, enrich, and store event data	confidence scoring, data quality frameworks, storage strategies
Compute layer	Scale processing, scheduling, and resource provisioning	auto-scaling, workload-aware scheduling, burst provisioning
Model serving layer	Run decision models and expose inference services	real-time inference, function-as-a-service, decision models
Governance layer	Enforce security, privacy, compliance, audit, and provenance	IAM, encryption, data residency, certifications

Table: Architecture layers

8.1. Performance, Latency, and Throughput Metrics

The end-to-end performance of a real-time Decision Intelligence system is evaluated in terms of latency and throughput, with special consideration given to latency-sensitive components such as data ingestion and decision-model serving. Latency is evaluated as the time taken for a single input data record to be processed by the system, that is, the time between publish and consume operations on the exact same data. It can be further decomposed to identify sources of delays and their contribution to total latency. Components such as data cleansing, ETL, and decision model evaluation introduce latency when using orchestration patterns like materialize-validate-trigger-submit Combined Latency is evaluated across the system's decision pipelines to support SLA compliance monitoring.

When considering system throughput, it represents the number of data records that can be processed over a defined time period, typically per second. More specifically, it gives a measure of the system's capacity to handle load and is complementary to latency; high throughput can compensate for higher latency in an application scenario. The throughput also depends on the processing pattern for the decision pipelines, with stateless and batch processing achieving higher throughput. The maximum throughput of the system may be limited by external sources or sinks such as data ingestion or model evaluation. Real-time Decision Intelligence systems need to sustainably scale beyond these points with increased load, to maintain low latency, low error rates and high throughput.

8.2. Reliability, Availability, and Fault Tolerance

Reliability, availability, and fault tolerance of cloud configurations are critical in enabling resilient data orchestration environments. Despite user confidence in data cloud providers and the joined efforts to minimize physical hardware failures, such incidents are inevitable. Software faults in the supporting infrastructure are more frequently encountered, offering greater opportunities for mitigation with redundant configurations. In well-designed data orchestration setups, user-defined data pipelines are isolated from each other. The key concern is the stability of the underlying cloud framework and achieving high availability. Standard metrics for assessing these properties of cloud configurations encompass uptime, incident history, review response time, and downtime duration, all of which can be monitored by service providers and published in compliance with open standards.

Redundant configurations at different levels of the stack enhance resilience. State-of-the-art cloud infrastructure combines geographically distributed availability zones, which host fault-isolated resources. To maximize reliability, sensitive cloud components, such as data ingress processes, storage systems, data egress processes, management components, and critical software services running entirely in the cloud, should be managed by control mechanisms that automatically switch to a backup if a primary fails. Services offered by external agents, such as authentication, can also be configured in a shape that permits automatic recovery by activation of an alternative agent if one of them becomes unreachable.

8.3. Economic Efficiency and Cost Modeling

Cost-efficiency models take into account the total cost of ownership of cloud-based services, including storage, network, and compute resources required by an enterprise. Public cloud services offer lower initial costs but may be

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more expensive in the long run as the scale of data growth increases. To ensure the availability of services while meeting cost requirements, a cost model is applied to budget all service stages and check continuously whether the consumption stays within the budget. Risk is modeled by applying copulas to align the sporadic failures seen in cloud providers: equipment mostly fails on a synchronous basis, forcing data recovery; flooding usually generates high consumption in a short time frame and is, therefore, modeled accordingly. The overall objective is to recreate the downtime behavior seen in practice with a low computational cost.

Cloud-based streaming services enable the distributed storage and processing of high-frequency, high-velocity data. Commercial services such as Amazon Kinesis Data Stream and Azure Event Hub allow clients to decouple data producers and consumers by providing a centralized broker. However, implementing such frameworks in a self-managed infrastructure requires a deeper understanding of lower-level stream- and event-processing concepts. A two-part analytic discussion is therefore presented. The first segment discusses stream processing and its architectural pillars. The second segment investigates event processing and the decision factors that influence the choice between a single-event basis or batch-processing approach.

IX. DEPLOYMENT STRATEGIES AND BEST PRACTICES

Real-time data pipelines are critical for many enterprise decision intelligence applications, yet tools and frameworks for managing real-time data stacks remain relatively immature. Just as other IT stacks have DevOps principles and tools for build and deployment, so too do data stacks require these same paradigms. The evolving area of data orchestration is focused on building and managing data infrastructure both for traditional ETL operations as well as for real-time streaming flows. Continuous integration and delivery of data pipelines, monitoring and observability standards, and other systems necessary to support DevOps for data allow organizations to validate that their pipelines remain functional and performant in production without requiring lab environments for testing such as those supporting Continuous Performance Engineering (CPE) of application code.

Real-time enterprise decision intelligence systems are run in the cloud and operate continuously with operational costs that are consumed at runtime. The continuous operation model changes the deployment paradigm of AI decision models from traditional practice, where careful preparation precedes roll-out, to a flow that requires CI/CD practices focused on managing quality at speed and economy at scale. All aspects of model deployment — data quality, confidence metrics, explanation and interpretation, auditing, and provenance — are scrutinized, with automation actively managing monitoring and testing of read-scored-predict pipelines serving business decision processes.

9.1. DevOps for Data Orchestration

Data-driven applications, machine learning pipelines, models, and workflows can be deployed and maintained in data orchestration platforms. Cloud service providers offer elements such as data sources, batch and streaming pipelines, data engineering pipelines, model training, serving, and hosting that are designed for simplified and managed operation. The overall process requires a combination of DevOps and DataOps principles for system operation, maintenance, and health. The controls, observability tools, and higher-level management built into the platform reduce the effort required to maintain these data pipelines and underlying elements.

DataOps processes can help improve the quality, responsiveness, and efficiency of data engineering pipelines. Continuous integration and delivery can be applied to traditional data engineering, batch-processing, and analytical pipelines. Continuous training and testing of model performance ensure that the best model is being used in the system. The infrastructure is also in place to automate continuous delivery of new models from training and testing. Continuous delivery of models is standard practice in many leading cloud services. The combination of model serving, counting, and triggering capabilities provides a complete environment for serving AI-driven systems in a production setting.

9.2. Continuous Integration and Delivery of AI Pipelines

Data orchestration is now a critical layer of the enterprise cloud stack, providing the real-time, complete and trusted data foundation for AI and analytics workloads across all lines of business—risk, compliance, fraud detection, detection of manufacturing defects, customer experience, revenue and sales forecasts, supply chain resilience, new product and service launches, and more. Continuous data integration (CDI), the discipline of data ingestion, cleansing, and movement across storage and processing systems combined with AI capabilities to continuously optimize cost and performance, has emerged as the DevOps for data pipelines. Just as organizations automate the testing and validation of

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software changes, large enterprises are adopting data quality frameworks to characterize the quality of data streams feeding mission-critical AI and analytics pipelines, enabling release gates that push changes into production only when ground-truth statistics are met.

DevOps for data pipeline creation requires significantly more than an additional level of integration testing. Organizations build real-time data pipelines to supply complete, fresh and trusted data to models that advise decisions taken by people and automated decision engines. Robert E. McElreath builds an insightful analogy in the book Statistical Rethinking: "Imagine world-class chess players designing a chess-playing program. They would begin with a brilliant evaluation function, proceed to use tree search, and end with a dozen clever pruning ideas. But the real world has engineers building chess programs, and smart programmers use a different order: tree search is the foundation, evaluation comes next, knowledge is added later, and pruning gets tacked on almost as an afterthought." Similarly, organizations build real-time data orchestration pipelines by addressing: (1) a streaming-latency-ready monitoring and alerting road map, (2) stress testing for attack-resilience detection and (3) well-architected decision trees with intelligent fallback strategies.

X. CONCLUSION

Data-driven decision making has proven beneficial, but drawbacks remain, especially when decisions rely on static and historical data. These sources, while valuable, are misleading when condition changes are rapid and dramatic.

Real-time decisions considering all sources—transactions, social media, market signals, sensor data—are feasible by implementing Real-Time Enterprise Decision Intelligence Systems, where patterns are detected, hypotheses formulated, decisions modeled, and a combination of simulation, optimization, evaluation, and explainability concepts employed to automatically call for the best decision based on a variety of new sources.

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