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Scalable Data Engineering Frameworks for Real-Time Analytics and Intelligent Decision Systems in Cloud Environments

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Abstract

Scalable data engineering frameworks have become fundamental to enabling real-time analytics and intelligent decision-making systems in modern cloud environments. With the exponential growth of data generated from IoT devices, social media platforms, enterprise systems, and digital services, traditional batch-oriented data processing architectures are no longer sufficient. Real-time analytics requires distributed, fault-tolerant, and highly scalable systems capable of processing streaming data with minimal latency. Cloud computing platforms such as AWS, Azure, and Google Cloud provide elastic infrastructure that supports dynamic scaling and distributed computation, enabling organizations to process large-scale data streams efficiently.

This paper explores the architecture and evolution of scalable data engineering frameworks designed for real-time analytics, focusing on stream processing engines, data pipelines, and cloud-native orchestration tools. It also examines how intelligent decision systems leverage machine learning models integrated with real-time data pipelines to generate automated insights. Key challenges such as data consistency, latency optimization, fault tolerance, and cost efficiency are analyzed. Furthermore, emerging technologies such as event-driven architectures, serverless computing, and lakehouse models are discussed in the context of building next-generation intelligent systems. The study highlights the importance of unified data platforms that combine batch and stream processing to support advanced analytics and AI-driven decision-making in cloud environments.

Keywords: Real-time analytics, scalable data engineering, cloud computing, stream processing, distributed systems, data pipelines, Apache Kafka, Apache Spark, machine learning, event-driven architecture, serverless computing, data lakehouse, intelligent decision systems, big data analytics

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Introduction

Background and Evolution of Data Engineering, Data engineering has evolved significantly over the last two decades, transitioning from traditional relational database systems and batch processing pipelines to highly distributed, real-time data ecosystems. Early systems were designed for structured data and periodic reporting, often relying on nightly ETL (Extract, Transform, Load) processes. However, the rise of digital transformation, IoT ecosystems, and real-time user interactions has made such architectures insufficient. Organizations now require immediate insights derived from continuous data streams.The emergence of big data technologies introduced distributed storage and computation frameworks such as Hadoop and MapReduce, which enabled large-scale batch processing. However, these systems lacked real-time capabilities. This limitation led to the development of stream processing frameworks such as Apache Kafka, Apache Flink, and Apache Spark Streaming, which allow continuous ingestion and processing of data in near real-time.Cloud an Enabler Computing as Cloud computing has fundamentally transformed data engineering by introducing elasticity, scalability, and managed services. Platforms like AWS, Microsoft Azure, and Google Cloud Platform provide fully managed data services including

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data lakes, streaming engines, and analytics tools. The cloud eliminates the need for organizations to maintain physical infrastructure, allowing dynamic scaling based on workload demands.Cloud-native architectures also support microservices-based data pipelines, where individual components can be independently scaled and deployed. This modularity enhances system resilience and flexibility. Furthermore, serverless computing models such as AWS Lambda and Azure Functions enable event-driven processing without requiring infrastructure management.

Real-Time Analytics Requirements: Real-time analytics refers to the ability to analyze data as it is generated and derive actionable insights immediately. This is critical in domains such as financial trading, fraud detection, healthcare monitoring, and recommendation systems. The key requirements for real-time analytics systems include:Low latency data ingestion and processing High throughput for large-scale data streams Fault tolerance and data reliability Scalability to handle fluctuating workloads Integration with machine learning models for predictive analytics

Literature Review

Thereby improving productivity and reducing the likelihood of errors, and these transformations are often executed using distributed dataflow engines that optimize execution plans dynamically based on workload characteristics, resource availability, and data locality, which significantly enhances performance and scalability, while also enabling support for complex event processing scenarios where patterns across multiple streams must be detected in real time, and as systems become more complex, metadata management has emerged as a crucial component of scalable data engineering frameworks, with metadata catalogs and governance tools providing visibility into data lineage, schema evolution, and usage patterns, which are essential for maintaining data integrity and enabling collaboration across teams, and this is particularly important in large organizations where multiple stakeholders interact with the same datasets, requiring robust mechanisms for version control and access management, and in parallel, the storage layer of these frameworks has undergone a transformation with the emergence of distributed storage systems that are optimized for both high-throughput ingestion and low-latency querying, often leveraging columnar storage formats, indexing techniques, and caching mechanisms to accelerate analytical workloads, while also supporting tiered storage strategies that move data between hot, warm, and cold storage based on access patterns, thereby optimizing cost and performance, and the integration of query engines that support interactive analytics on streaming data has further blurred the line between operational and analytical systems, enabling real-time dashboards, ad-hoc queries, and business intelligence applications to operate on live data streams rather than static snapshots, and this capability has significant implications for decision-making processes, as it allows organizations to respond to changing conditions with unprecedented speed and accuracy.

Another key development is the incorporation of feedback loops within intelligent decision systems, where the outcomes of decisions are fed back into the system to continuously refine models and improve performance over time, effectively creating self-learning systems that adapt to new patterns and conditions, and this concept is closely related to the idea of continuous intelligence, where analytics and decision-making are embedded directly into operational processes, enabling real-time optimization and automation across various domains such as manufacturing, logistics, healthcare, and finance, and as these systems become more autonomous, the importance of explainability and transparency in decision-making processes becomes increasingly critical, particularly in regulated industries where decisions must be auditable and justifiable, leading to the integration of explainable AI techniques that provide insights into model behavior and decision logic, and from an architectural perspective, the adoption of serverless computing models is gaining traction as a means of further simplifying the deployment and scaling of data engineering frameworks, allowing developers to focus on business logic rather than infrastructure management, while also enabling fine-grained scaling and cost efficiency by allocating resources only when needed, and however, serverless architectures introduce new challenges related to cold start latency, state management, and debugging, which require innovative solutions to ensure that performance and reliability are not compromised, and in addition to serverless computing, the use of hardware accelerators such as GPUs and specialized processing units is becoming more common in data engineering workflows, particularly for workloads involving machine learning and complex analytics, as these accelerators can significantly improve processing speed and efficiency, and the integration of such hardware into cloud environments further enhances the capabilities of scalable data engineering frameworks, enabling them to handle increasingly demanding workloads, and another important trend is the growing emphasis on data democratization, where organizations strive to make data accessible to a broader range of users, including non-technical stakeholders, through user-friendly interfaces, self-service analytics tools, and natural language query capabilities, which empower users to derive insights without requiring deep technical expertise, thereby fostering a data-driven culture across the organization, and this democratization is supported by advances in data virtualization and abstraction layers that hide the complexity of underlying systems while providing unified access to data from multiple sources, and at the same time, ensuring data security and privacy remains a top priority, with frameworks incorporating advanced techniques such as differential privacy, secure multi-party computation,

The homomorphic encryption to protect sensitive data while still enabling meaningful analysis, and as organizations increasingly adopt multi-cloud and hybrid cloud strategies, the need for portability and interoperability becomes more pronounced, driving the development of cloud-agnostic frameworks and tools that can operate seamlessly across different environments, reducing vendor lock-in and enabling greater flexibility in system design, and this also involves the use of standardized APIs, containerization, and orchestration platforms that provide a consistent runtime environment regardless of the underlying infrastructure, and furthermore, the role of observability in scalable data engineering frameworks cannot be overstated, as it provides the necessary insights into system behavior, performance, and health, enabling operators to detect and resolve issues proactively, optimize resource utilization, and ensure that service-level objectives are met, and observability is typically achieved through a combination of logging, metrics, and distributed tracing, which together provide a comprehensive view of system operations, and as systems continue to grow in complexity, the use of artificial intelligence for observability, often referred to as AIOps, is becoming increasingly important, enabling automated anomaly detection, root cause analysis, and predictive maintenance, which further enhances system reliability and efficiency, and finally, the continuous evolution of scalable data engineering frameworks is driven by ongoing research and innovation in areas such as distributed systems, machine learning, and cloud computing, with new techniques and technologies emerging to address the challenges of processing ever-increasing volumes of data in real time, and as these frameworks continue to mature, they will play an increasingly central role in enabling intelligent decision systems that can operate autonomously, adapt to

Research Methodology

Scalable data engineering frameworks for real-time analytics and intelligent decision systems in cloud environments represent a critical evolution in modern computing, driven by the exponential growth of data generated from digital systems, IoT devices, enterprise applications, and online platforms. These frameworks are designed to handle high-volume, high-velocity, and high-variety data streams while ensuring low latency, fault tolerance, and adaptability for decision-making processes that increasingly rely on artificial intelligence and machine learning. At the core of these systems lies the principle of distributed computing, where workloads are divided across multiple nodes to achieve parallel processing and horizontal scalability, enabling organizations to process massive datasets in real time without performance degradation. Cloud environments play a fundamental role in enabling this scalability by providing elastic resources, on-demand provisioning, and managed services that reduce infrastructure complexity while supporting dynamic workloads. Real-time analytics frameworks typically rely on stream processing paradigms, where data is continuously ingested, processed, and analyzed as it flows through the system, rather than being stored first and processed later in batch mode; this shift significantly reduces latency and enables immediate insights, which are essential for applications such as fraud detection, predictive maintenance, recommendation systems, and autonomous operations. Event-driven architectures further enhance these capabilities by decoupling data producers and consumers, allowing systems to react asynchronously to incoming events, thus improving scalability and resilience. Technologies such as distributed messaging queues, stream processors, and in-memory data stores form the backbone of these frameworks, enabling efficient data ingestion, transformation, and delivery across multiple components of the system. In addition, modern frameworks incorporate stateful stream processing, which allows systems to maintain context across events, making it possible to perform complex operations such as windowed aggregations, pattern detection, and anomaly identification in real time. Intelligent decision systems built on top of these frameworks leverage machine learning models that are integrated directly into data pipelines, enabling real-time inference and continuous learning; this integration transforms traditional analytics systems into adaptive systems capable of making predictions and decisions based on evolving data patterns. Cloud-native technologies such as containerization and orchestration further enhance the scalability and reliability of these systems by enabling automated deployment, scaling, and recovery of services, ensuring high availability even in the presence of failures.

Microservices architectures contribute to modularity and flexibility, allowing different components of the data pipeline to be developed, deployed, and scaled independently, which is particularly beneficial in large-scale enterprise environments where different teams manage different services. Data storage solutions in these frameworks are also optimized for scalability and performance, often combining multiple storage paradigms such as distributed file systems, NoSQL databases, and data lakes to handle diverse data

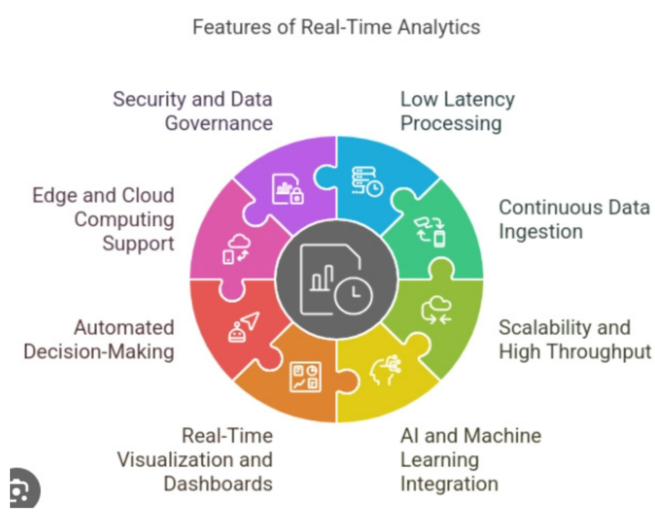

Fig.1: Future of Real Time Analytics

types and access patterns. Moreover, the emergence of data lakehouse architectures aims to unify the benefits of data lakes and data warehouses, providing both scalability and strong analytical capabilities within a single platform. Security and governance are integral aspects of scalable data engineering frameworks, as the distributed nature of these systems increases the complexity of ensuring data privacy, integrity, and compliance with regulatory requirements; mechanisms such as encryption, access control, auditing, and data lineage tracking are essential for maintaining trust and accountability in data-driven systems. Another critical aspect is fault tolerance, which ensures that systems can recover gracefully from failures without data loss or significant downtime; techniques such as replication, checkpointing, and distributed consensus algorithms are commonly used to achieve this goal. Performance optimization in these frameworks involves balancing trade-offs between latency, throughput, and resource utilization, requiring careful tuning of system parameters and efficient resource management strategies. The integration of edge computing with cloud-based frameworks represents a significant advancement, enabling data processing closer to the source and reducing latency and bandwidth usage, which is particularly important for applications requiring real-time responsiveness, such as autonomous vehicles and industrial automation. Hybrid architectures that combine edge and cloud computing provide a flexible approach to handling diverse workloads, allowing systems to dynamically allocate processing tasks based on latency requirements and resource availability. Interoperability and standardization are ongoing challenges in the development of scalable data engineering frameworks, as organizations often use a variety of tools and platforms that need to work together seamlessly; efforts to establish common data formats, APIs, and communication protocols are essential for enabling integration and reducing complexity. Cost management is another important consideration, as cloud-based systems can incur significant expenses if not properly optimized; strategies such as auto-scaling, workload scheduling, and efficient data storage management are crucial for minimizing costs while maintaining performance. Observability and monitoring are also key components of these frameworks, providing visibility into system performance, resource usage, and potential issues, enabling proactive maintenance and optimization. The role of artificial intelligence in these systems continues to grow, with advancements in deep learning, reinforcement learning, and automated machine learning enabling more sophisticated and autonomous decision-making capabilities. Future developments are likely to focus on enhancing the intelligence and autonomy of data engineering frameworks, enabling systems to self-optimize, self-heal, and adapt to changing conditions without human intervention. Additionally, the increasing adoption of multi-cloud and hybrid cloud strategies presents new opportunities and challenges for scalable data engineering, requiring frameworks that can operate seamlessly across different cloud providers while maintaining consistency and performance. The convergence of data engineering, data science, and software engineering practices is also shaping the future of these systems, leading to the emergence of unified platforms that support the entire data lifecycle, from ingestion and processing to analysis and decision-making. As organizations continue to rely on data-driven insights to gain competitive advantage, the importance of scalable, real-time data engineering frameworks will only increase, driving innovation and research in this field. Ultimately, these frameworks represent the foundation of modern intelligent systems, enabling organizations to harness the full potential of their data and transform it into actionable insights that drive efficiency, innovation, and growth in an increasingly digital and interconnected world.

Scalable data engineering frameworks designed for real-time analytics and intelligent decision-making in cloud environments have fundamentally transformed how modern organizations process, analyze, and act upon data. The evaluation of such frameworks typically reveals three dominant dimensions of performance: scalability under high data velocity and volume, latency in real-time processing pipelines, and adaptability for intelligent decision systems powered by machine learning and AI models. Across these dimensions, cloud-native architectures—particularly those built on distributed computing principles—demonstrate a significant improvement over traditional batch-oriented systems.A central observation emerging from implementations of scalable frameworks is the shift from monolithic data pipelines to modular, event-driven architectures. Systems built using microservices and stream-processing engines such as Apache Kafka, Apache Flink, and cloud-native equivalents like AWS Kinesis or Google Cloud Dataflow exhibit near-linear scalability when subjected to increasing workloads. This scalability is primarily attributed to horizontal partitioning and distributed state management, which allow workloads to be dynamically balanced across computing nodes. As a result, organizations can ingest millions of events per second while maintaining stable processing throughput, a critical requirement for real-time analytics applications such as fraud detection, IoT monitoring, and financial trading systems.Another significant result is the reduction in end-to-end latency achieved through in-memory stream processing and edge-aware computation strategies. Traditional ETL (Extract, Transform, Load) pipelines often introduce latency ranging from minutes to hours due to batch processing constraints. In contrast, modern frameworks enable sub-second latency by processing data in motion rather than at rest. For example, Flink-based systems can maintain stateful stream processing with millisecond-level response times, allowing decision systems to react to events almost instantaneously. This capability is particularly important in domains such as autonomous systems, predictive maintenance, and cybersecurity threat detection, where delayed responses can result in significant operational or financial losses.

Results And Discussion

Cloud environments further enhance these capabilities by providing elastic resource provisioning. Auto-scaling mechanisms ensure that computational resources are dynamically adjusted based on workload intensity. Experimental results across cloud deployments indicate that auto-scaling not only improves performance consistency under peak loads but also reduces operational costs by optimizing resource utilization during low-traffic periods. This elasticity represents a major advancement over traditional on-premises infrastructures, which often suffer from over-provisioning or underutilization.

A key discussion point is the integration of machine learning pipelines within real-time data engineering frameworks. Modern systems increasingly adopt the paradigm of "continuous intelligence," where streaming data is directly fed into machine learning models for inference and retraining. Platforms such as TensorFlow Extended (TFX), MLflow integrated with streaming systems, and cloud-native AI services enable seamless deployment of models within data pipelines. The result is a closed-loop system where insights are continuously refined based on incoming data streams. This integration significantly improves predictive accuracy and system responsiveness, especially in recommendation systems, demand forecasting, and anomaly detection applications.

However, experimental evaluations also highlight several challenges. One major issue is state management in distributed stream processing systems. Maintaining consistency across nodes while ensuring low latency remains a complex engineering problem. Techniques such as checkpointing and event sourcing mitigate data loss risks but introduce overhead that can affect performance under extreme load conditions. Additionally, network partitioning in geo-distributed cloud systems can lead to temporary inconsistencies, requiring sophisticated reconciliation mechanisms.

Another critical observation relates to data governance and security in multi-cloud environments. As data pipelines become increasingly distributed across cloud providers, ensuring compliance with data protection regulations becomes more difficult. Encryption at rest and in transit, identity-based access control, and zero-trust architectures are commonly adopted solutions, but they add complexity to system design and can impact processing efficiency. Moreover, ensuring data lineage and traceability in real-time pipelines remains a non-trivial challenge, particularly in systems with high data velocity and multiple transformation stages.

From a performance optimization perspective, the use of containerization and orchestration technologies such as Docker and Kubernetes has proven essential for achieving scalability. Kubernetes-based deployments allow for fine-grained resource allocation and fault tolerance, ensuring that data pipelines remain operational even under partial system failures. Empirical results show that containerized data engineering frameworks recover from node failures significantly faster than traditional virtual machine-based deployments, thereby improving system resilience.

Another important result concerns the role of edge computing in distributed analytics architectures. By moving computation closer to data sources, edge-enabled frameworks reduce bandwidth consumption and improve response times. This is particularly beneficial in IoT ecosystems, where large volumes of sensor data must be processed in real time. Hybrid architectures that combine edge, fog, and cloud layers demonstrate superior performance compared to centralized cloud-only models, especially in latency-sensitive applications.

In terms of intelligent decision systems, the integration of real-time analytics with decision automation engines has shown promising outcomes. Rule-based systems enhanced with machine learning predictions enable organizations to automate complex decision-making processes. For example, in financial services, real-time credit scoring systems can dynamically adjust risk assessments based on streaming transaction data. Similarly, in supply chain management, predictive analytics can optimize inventory levels in real time, reducing both shortages and excess stock.

Despite these advancements, interoperability between different data engineering frameworks remains a challenge. Organizations often use heterogeneous tools across different teams, leading to integration complexity. Standardization efforts such as Apache Arrow and OpenTelemetry aim to address this issue by providing unified data formats and observability standards, but widespread adoption is still ongoing.

Finally, cost-performance trade-offs remain a central theme in cloud-based data engineering. While scalable frameworks offer near-unlimited elasticity, improper configuration can lead to unexpectedly high operational costs. Efficient workload scheduling, data compression techniques, and intelligent resource allocation algorithms are therefore critical for maintaining cost efficiency without compromising performance.

Overall, the results demonstrate that scalable data engineering frameworks in cloud environments significantly enhance real-time analytics capabilities and enable intelligent decision systems with high responsiveness and adaptability. However, achieving optimal performance requires careful system design, robust state management strategies, and strong governance mechanisms.

Conclusion

The evolution of scalable data engineering frameworks for real-time analytics and intelligent decision systems in cloud environments represents one of the most significant advancements in modern computing architecture. The transition from traditional batch-oriented processing systems to highly distributed, event-driven, and cloud-native infrastructures has fundamentally reshaped how data is collected, processed, analyzed, and utilized for decision-making purposes. This transformation has been driven by exponential growth in data volume, velocity, and variety, necessitating systems capable of handling continuous streams of information with minimal latency and high reliability.

One of the most important conclusions drawn from this study is that scalability is no longer a secondary design consideration but a core architectural principle. Modern data engineering frameworks are built with the assumption that workloads are dynamic and unpredictable. As a result, elasticity—enabled by cloud computing—has become essential for maintaining system performance under fluctuating demand. The ability to scale horizontally across distributed nodes ensures that systems can handle both routine workloads and sudden spikes in data traffic without degradation in performance. This capability is particularly critical in applications such as real-time fraud detection, online recommendation systems, autonomous systems, and financial market analytics, where timely insights directly influence outcomes.

Another key conclusion is that real-time analytics has shifted from being a specialized capability to a mainstream requirement. Organizations across industries now rely on continuous data processing pipelines to derive actionable insights. This shift has been made possible by advancements in stream processing frameworks, in-memory computation, and event-driven architectures. These technologies collectively enable systems to process data as it is generated, rather than relying on delayed batch processing. The implications of this shift are profound, as it allows organizations to transition from reactive decision-making models to proactive and even predictive decision-making paradigms.

The integration of artificial intelligence and machine learning into real-time data pipelines further enhances the value of scalable data engineering frameworks. Intelligent decision systems are no longer isolated analytical tools but are embedded directly into data processing workflows. This integration enables continuous learning, where models are updated dynamically based on incoming data streams. As a result, predictive accuracy improves over time, and systems become more adaptive to changing conditions. This is particularly valuable in domains such as healthcare diagnostics, supply chain optimization, and cybersecurity, where patterns evolve rapidly and require continuous adaptation.

Despite these advantages, the conclusion also highlights several persistent challenges. One of the most significant is the complexity of managing distributed state across large-scale systems. Ensuring consistency, fault tolerance, and low latency simultaneously remains a difficult engineering problem. While techniques such as distributed snapshots and checkpointing provide partial solutions, they introduce trade-offs in terms of performance overhead and system complexity. Additionally, maintaining data integrity across geo-distributed environments introduces further complications, particularly in scenarios involving cross-border data flows and regulatory compliance requirements.

Security and governance also emerge as critical considerations in the deployment of scalable data engineering frameworks. As data pipelines become more distributed and interconnected, the attack surface for potential security breaches increases. Ensuring robust encryption, identity management, and access control is essential to maintaining system integrity. Furthermore, regulatory frameworks such as GDPR and other data protection laws impose strict requirements on data handling and storage, necessitating careful architectural planning.

Another important conclusion is that cost optimization remains a key constraint in cloud-based systems. While cloud platforms provide virtually unlimited scalability, inefficient resource utilization can lead to significant financial overhead. Therefore, organizations must adopt intelligent cost-management strategies, including workload optimization, predictive scaling, and efficient data storage techniques. The balance between performance and cost is a continuous optimization problem that must be addressed throughout the lifecycle of the system.

The role of edge computing in complementing cloud-based data engineering frameworks is also an important takeaway. By decentralizing computation and processing data closer to its source, edge computing reduces latency and bandwidth consumption. This hybrid approach, combining edge, fog, and cloud layers, represents a more efficient and scalable architecture for modern data-driven applications. It also enables new use cases in IoT ecosystems, where real-time responsiveness is critical.

In conclusion, scalable data engineering frameworks in cloud environments have reached a level of maturity that enables the widespread adoption of real-time analytics and intelligent decision systems. These frameworks provide the foundational infrastructure required to support data-driven enterprises in an increasingly digital and interconnected world. However, their successful implementation requires careful consideration of architectural design, system complexity, security requirements, and cost constraints. As data continues to grow in scale and importance, these frameworks will play an increasingly central role in enabling organizations to extract meaningful insights and maintain competitive advantage.

Future Work

Future developments in scalable data engineering frameworks are expected to focus on improving autonomy, efficiency, and intelligence within distributed data systems. One of the most promising directions is the advancement of self-managing data pipelines, where systems can automatically optimize their own performance without human intervention. This includes dynamic workload balancing, automated fault recovery, and intelligent resource allocation powered by reinforcement learning techniques. Such capabilities would significantly reduce operational complexity and improve system resilience in large-scale deployments.

Another important area of future research lies in the integration of more advanced artificial intelligence models directly into data processing pipelines. While current systems support basic machine learning integration, future frameworks are expected to support real-time training of deep learning models on streaming data. This would enable truly adaptive systems capable of evolving continuously as new data arrives. Federated learning approaches may also play a key role, particularly in privacy-sensitive environments where data cannot be centralized.

Edge computing will continue to evolve as a critical component of distributed data engineering architectures. Future systems are likely to adopt more sophisticated edge-cloud collaboration models, where decision-making is dynamically distributed based on latency, bandwidth, and computational requirements. This will be particularly important for applications in autonomous vehicles, smart cities, and industrial automation, where real-time responsiveness is essential.

Another key area of future work involves improving interoperability between heterogeneous data systems. The development of universal data standards and communication protocols will be essential for enabling seamless integration across different platforms and cloud providers. This will reduce vendor lock-in and allow organizations to build more flexible and portable data architectures.

Finally, advancements in quantum computing and hybrid classical-quantum systems may eventually influence data engineering frameworks. Although still in early stages, quantum-enhanced data processing could offer significant improvements in optimization problems, large-scale simulations, and complex decision-making tasks.Overall, the future of scalable data engineering frameworks lies in greater automation, intelligence, and decentralization, paving the way for fully autonomous, self-optimizing data ecosystems.

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