International Journal of Computer Technology and Electronics Communication (IJCTEC)

| ISSN: 2320-0081 | www.ijctece.com | A Peer-Reviewed, Refereed and Bimonthly Journal|

|| Volume 5, Issue 6, November – December 2022 ||

DOI: 10.15680/IJCTECE.2022.0506020

High-Performance Data Pipeline Optimization for Retail Demand Forecasting

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ABSTRACT: A high-performance data pipeline is critical for achieving data-driven goals in retail demand forecasting and is particularly important for online algorithms. This work outlines best practices for building optimally responsive data pipelines that meet, in the least possible time, the fault-tolerance needs of the retail domain and improve forecast accuracy. Data-flow architecture, data ingestion, processing and transformation methods, storage systems, model deployment, and online inference are covered.

Demand forecasting is essential to retail operations, yet accurate forecasting is challenging due to the complexity of customer behaviour and the multitude of signals that impact demand. Data-driven forecasts that harness these signals require high-performance data pipelines that smoothly ingest large volumes of data, apply complex feature engineering, and support online inference. These pipelines must balance three interrelated dimensions: scalability, latency, and reliability. Scalable architectures can grow without degradation; low-latency systems respond rapidly to the arrival of new data; and fully fault-tolerant systems provide the right answers in the face of storage and computation failures. In retail, where the cost of data storage is essential but the need for data freshness is great, certain compromises in fault tolerance can be afforded.

KEYWORDS: Retail Demand Forecasting, High-Performance Data Pipelines, Online Learning Algorithms, Real-Time Forecast Inference, Scalable Data Architectures, Low-Latency Data Processing, Fault-Tolerant Retail Systems, Feature Engineering at Scale, Data Ingestion and Transformation Frameworks, Cloud-Native Forecasting Infrastructure, Online Model Deployment, Data Freshness Optimization, Stream Processing in Retail Analytics, Reliability–Latency Trade-Offs, Data-Driven Retail Operations.

I. INTRODUCTION

Data pipeline architectures developed for Machine Learning, real-time analytics and Stream Processing Systems are essential for enabling scalable, low-latency and fault-tolerant retail demand forecasting solutions. A high-performance data pipeline architecture integrates performance and fault-tolerance data ingestion and data integration patterns, a comprehensive data processing and transformation approach, an appropriate storage solution, scalable model deployment and online inference mechanisms.

Retail demand forecasting is central to the operations of multiple companies, such as retailers, consumer-package-goods manufacturers and logistics operators. Accurate demand forecasts enable optimization of multiple business processes, from managing inventory and warehouse space to workforce planning and logistic operations. The potential impact of accurately forecasting demand is enormous. It has been estimated that a mere improvement of 3% in forecasting accuracy translates into a cost reduction of over US$ 70 billion for US retailers alone.

A high-performance data pipeline is the spine of a successful retail demand forecasting solution. The data pipeline defines how data is ingested, integrated, processed and stored; and how the trained demand-forecasting model is deployed and made available for real-time inference. The high-performance nature of the data pipeline comes from the integration of low-latency, highly scalable Fault-tolerant Data Ingestion Patterns, a comprehensive Data Integration Strategy covering Data Quality, Data Governance, Data Lineage and Data Validation; the selection of a Data Processing Framework suited for the problem requirements, a Data Storage solution optimized for enabling demand-forecasting and a Data Pipeline Orchestration Strategy, which defines the data-flow between the different data-pipeline components.

1.1. Purpose and Scope of the Study

Retail demand forecasting remains challenging due to unpredictable consumer behaviour across many product categories, necessitating accurate predictions for inventory management and supply chain planning. A high-

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performance data pipeline capable of supporting low-latency demand forecasting for car spare parts serves as a potential solution. Demand forecasts for key product lines should be generated in near real time to meet an identified latency goal of less than 2 days. Altogether, these developments should help position the organization's information technology function as a key enabler of business performance.

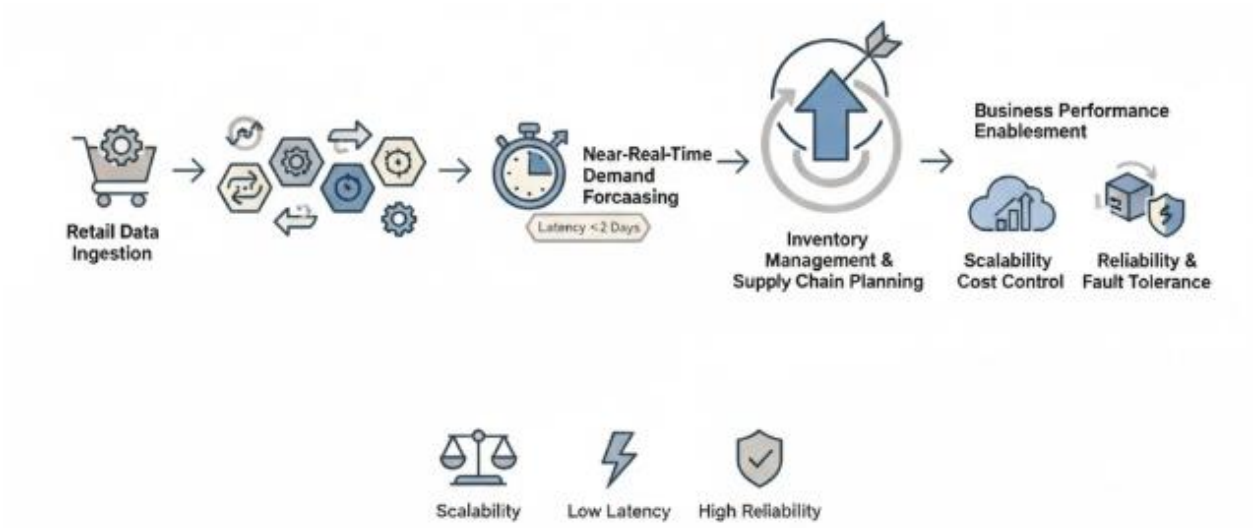

Fig 1: Scalable Low-Latency Pipelines for Near-Real-Time Retail Demand Forecasting: A Fault-Tolerant Framework for Industrial Spare Parts Logistics

To advance this agenda, a high-performance data pipeline has been designed that meets three critical criteria: it should have high scalability with cost control, extremely low latency for real-time to near-real-time demand forecasting, and high reliability with fault-tolerant mechanisms and no or very low downtime. Specifically, a high-performance data pipeline framework is proposed—addressing data ingestion, integration, processing, transformation, storage, model deployment, and online inference quality and performance—that enables near-real-time demand forecasting with offline capabilities at scale. The investigation aligns with best practices and seeks to answer a set of questions concerning the data-processing approach, design choices, and the various steps in the predictive-scoring process, ultimately seeking to establish the most efficient ways to generate predictions that will aid inventory management and supply chain planning.

II. BACKGROUND AND FOUNDATIONS

Retail demand forecasting is a critical business function that benefits from an extensive and high-quality set of predictive features extracted from historical and real-time data repositories. To be beneficial, a data pipeline that generates these features must perform at scale, delivering insights with low latency while maintaining high levels of service reliability. A theoretical and practical framework that connects the concepts of scalability, latency, and reliability creates a foundation for high-performance pipeline implementation and optimization.

The accuracy of retail demand forecasts is driven by the quality of the features used. To be beneficial, the feature engineering pipeline must assemble an extensive high-quality set of predictive features and deliver them in a timely manner. In particular, the pipeline that generates features for prediction should perform at scale, supporting an extensive ensemble of models; deliver insights with low latency, making the predictions actionable; and maintain high levels of service reliability, preventing the interruption of business operations dependent on the forecasts. A theoretical and practical foundation that connects the concepts of scalability, latency, and reliability provides the means for the definition, implementation, and optimization of a feature engineering data pipeline able to satisfy these constraints.

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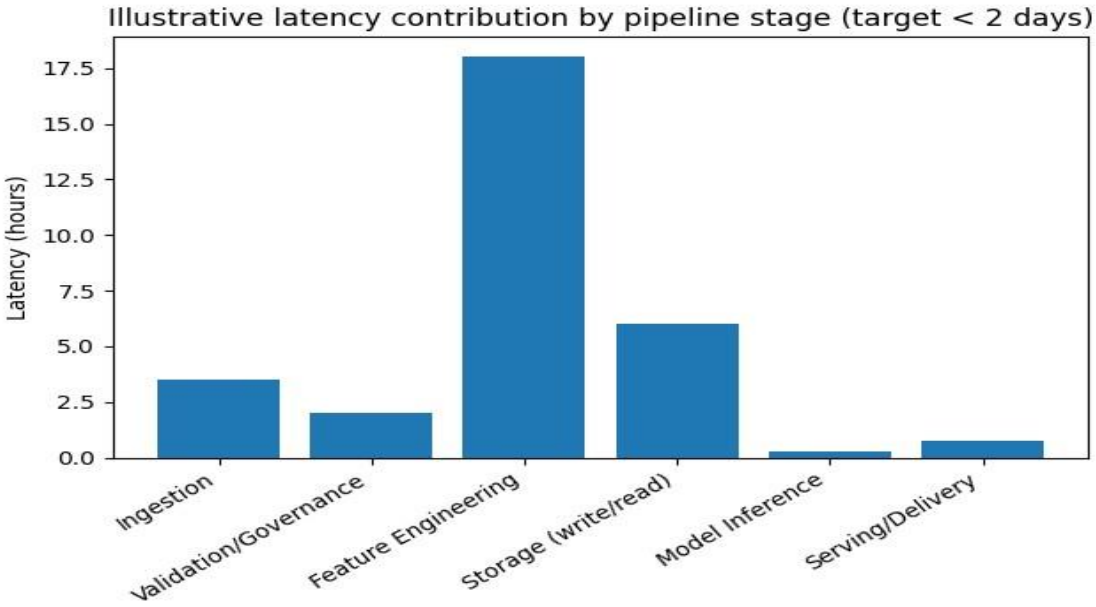

Equation 1) End-to-end pipeline latency (meeting the "< 2 days" target)
Step-by-step derivation
1. Break the pipeline into ordered stages (as described across ingestion → processing → storage → deployment/inference):

$$\text{Stages} = \{1,2,\dots,K\}$$

2. Let L_k be the latency contributed by stage k.
3. End-to-end latency is the sum (critical path):

$$L_{\text{E2E}} = \sum_{k=1}^{K} L_k$$

4. If the SLA is "< 2 days", convert to hours: $2 \text{ days} = 48$ hours. Requirement:

$$\sum_{k=1}^{K} L_k < 48 \text{ hours}$$

5. If some stages are parallelizable (e.g., feature generation via distributed processing), then the latency becomes:

$$L_{\text{E2E}} = L_{\text{serial}} + \max_{p \in \text{parallel groups}} L_p$$

("sum of unavoidable serial parts + the slowest parallel branch".)

2.1. Retail Demand Forecasting Overview

Retail demand forecasting quantifies anticipated future demand for a defined set of goods across one or more planning horizons. The consummate goal is use of real-time market data to generate continuously updated short-term (one- to six-week horizon) demand forecasts that accurately capture local demand for every item in the retailer's assortment in sufficient time for order placement. Demand forecasting is influenced by short-term shifts in local shopping behavior and supported by marketing or trading activities. During key promotional phases, demands can be affected by new product introductions, regional events, weather conditions, and the level of availability of competing products. Demand forecast accuracy is paramount, as errors will have a significant impact on decisions related to supply chain execution and demand fulfillment, margin management and sustainability, and ultimately customer satisfaction.

The retail demand forecast must be generated daily at a local level for store spaces typically containing more than 10,000 stock-keeping units (SKUs). Meeting these accuracy and execution requirements means providing reliable forecasts at the most granular level in a combination of replication and fresh data that reflects the most recent sales behavior. Recent studies in the field confirm that an accurate high-frequency demand forecast drives essential retail decision-making. However, modelling implementation and operational execution remain critical challenges for the formulation of a reliable demand-fresh forecast at the local level.

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2.2. Data Pipeline Architecture

Data pipelines consist of interconnected workflow elements responsible for changing the state of data in various ways from its original form at the source to the format required by end-users or applications. The architecture of a data pipeline involves routing data between these elements, the lineage of the data (i.e., the ordering of its travel across the pipeline), the fault-tolerance of the system (i.e., the handling of failures at any element of the pipeline), and the orchestration of the end-to-end process (i.e., the monitoring and scheduling of pipeline activities).

While many different applications are possible, this discussion focuses on high-performance data pipelines for retail demand forecasting, with speed, scalability, quality, and fault tolerance among the key considerations. Speed is especially important in machine learning, where predictive model training is highly resource-intensive and data features should therefore be generated as rapidly as possible. In most retail contexts, data pipelines should also be designed not just for traditional batch prediction but for real-time prediction and generation of demand forecasts.

III. DATA INGESTION AND INTEGRATION

Pipeline efficiency relies on thoughtful data ingestion and integration design. An ingestion approach is selected for each data source to satisfy latency, freshness, and availability needs, while integration blends data sourced from different origins. Retail demand predictions depend on historical sales data, enriched with additional data types to improve forecast quality, including high-resolution weather forecasts and competing product information.

Nine data sources deliver over eighty input features, supporting an average seventy percent forecast accuracy for twelve product categories. Data collection necessitates optimal support for data quality, governance, and lineage, along with robust validation procedures to ensure data correctness and usefulness. Batch ingestion portends the relative freshness of these data sources under the previously outlined latency and robustness constraints. Other data types require lower latency, prompting adoption of an unstructured data-store and Scikit-Monitor integration for streaming discovery of consumption demand as live demand-signal updates.

Pipeline stage	Latency (hours)	Cumulative latency (hours)	Cumulative latency (days)
Validation/Governance	2.0	5.5	0.22916666666666666
Feature Engineering	18.0	23.5	0.9791666666666666
Storage (write/read)	6.0	29.5	1.2291666666666667
Model Inference	0.25	29.75	1.2395833333333333
Serving/Delivery	0.75	30.5	1.2708333333333333

3.1. Data Sources and Quality Assurance

The data sources that feed the demand forecasting pipeline have varying constraints regarding the quality, architecture, drops, and historical coverage of the raw data. Demand and supply are tightly coupled and thus serve as the main source of validation. The pipeline has a source that provides daily downtimes of all the stores and online channels for the past years. The SKU-text categorization service ensures that no seasonal mistakes slip into the pipeline. Metadata governance assigns domain owners for each data product, who are responsible for maintaining data quality in conjunction with the data quality operations team. Initial monitoring, alerts, and remediation of bad data flow to these owners to ensure proper governance.

The forecasted products are stored as time series in the data lake. To predict these time series, the pipeline needs to establish the quality constraints that enable proper demand forecasting. The quality and availability of the source data flow determine how accurate the demand forecast can be. The source systems are all parts of various Data Meshes, and the quality and availability constraints are maintained utilizing the data quality framework. For example, check constraints ensure that for each of the SKUs that the channel is monitoring, dummy downtimes are provided. In addition, a Data Quality team is available when inadequate data lands in the mesh to take recompense action.

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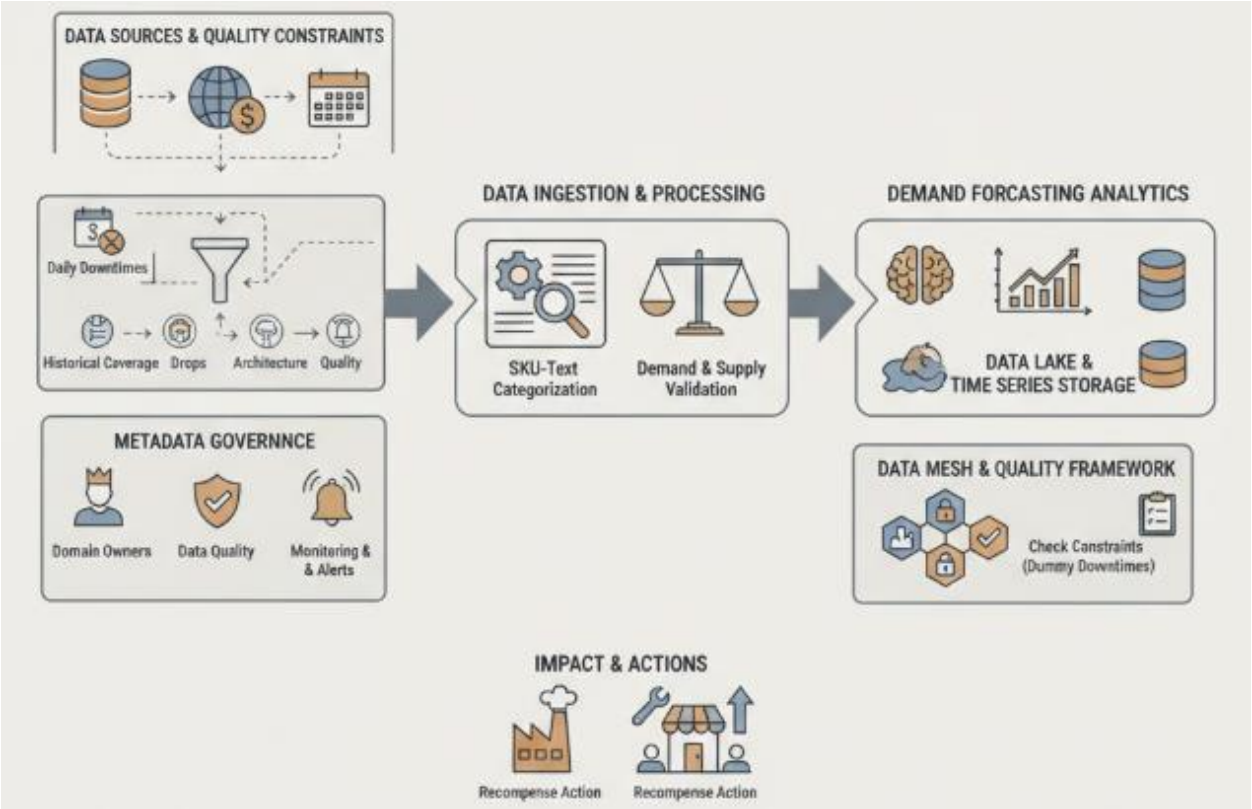

Fig 2: Governance-Centric Demand Forecasting: Integrating Data Mesh Architectures and Metadata Stewardship for Robust Time-Series Analytics

3.2. Streaming versus Batch Ingestion

Streaming-based ingestion is the preferred mode for real-time applications where latency is critical and freshness of information is paramount. In almost real-time ingest applications, such as demand forecasting for retail, there are generally business policies defined for how up to date information is in downstream applications. The data flows could be defined based on these freshness requirements, for example, the product and store data could be streamed in and processed on an individual mode, the sales data could come in an almost real-time mode so that the forecasting pipelines backstage can be ready all the time, and the other sources could be handled in batch mode.

With the development of new technologies, there are always demands for new fresh features to improve model accuracy. Most of the time it requires exploring candidate factors, ensuring that the external data are completely evaluated, and giving predictive value to the models. These external factors need to be dynamically available. The models that have used the external factors normally only ingested them in the batch process. In those cases streaming was never an option, as the ingestion process can be complex, taking data through many applications.

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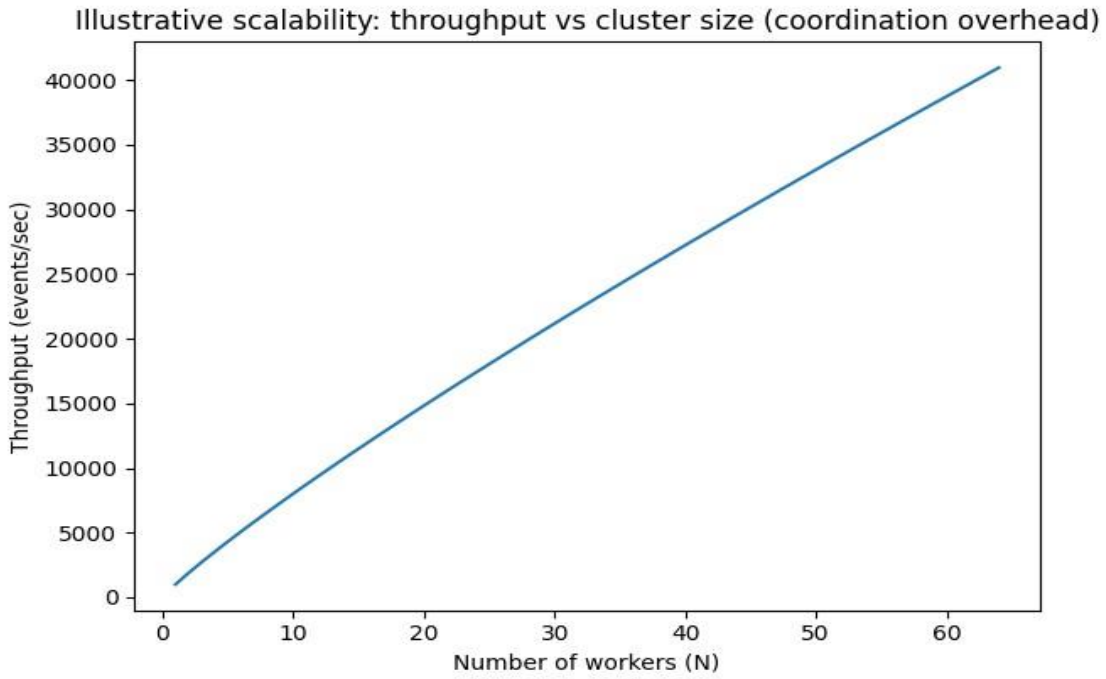

Equation 2) Data freshness vs batch/stream ingestion
Step-by-step derivation (freshness)

2. Let data item i be generated at time t_i^{src} and becomes available downstream at t_i^{avail}.
3. Define "staleness / freshness delay":

$$D_i = t_i^{\text{avail}} - t_i^{\text{src}}$$

3. For **batch ingestion** with batch interval B, worst-case waiting before pickup is almost B, average is $B/2$:

$$\mathbb{E}[D_{\text{pickup}}] \approx \frac{B}{2}, \quad D_{\text{pickup,max}} \approx B$$

5. End-to-end average delay for batch:

$$\mathbb{E}[D_{\text{batch}}] \approx \frac{B}{2} + L_{\text{process}} + L_{\text{serve}}$$

6. For **streaming**, pickup delay is near 0 (bounded by buffering/windowing):

$$\mathbb{E}[D_{\text{stream}}] \approx L_{\text{process(stream)}} + L_{\text{serve}}$$

IV. DATA PROCESSING AND TRANSFORMATION

A high-performance data pipeline for retail demand forecasting encompasses components from data ingestion to model inference. Data processing and transformation steps shape the information driving the prediction model. While data integration and feature engineering are primarily focused on forecast accuracy, other components—such as storage and deployment—affect the pipeline in more indirect ways.

Feature engineering greatly influences the quality of demand forecasts, and the competition for limited real-time forecasting resources calls for careful selection of features. Lag features, seasonality, weather, promotions, and external signals (such as COVID cases or gas prices) are common candidates in this domain. Covering all these aspects becomes a key part of the feature engineering workload. Parallel processing can make use of horizontally scalable, fault-tolerant solutions such as Apache Spark, Dask, or Flink, but the latency requirements of streaming systems can be difficult for Spark to fulfil due to its batch-oriented architecture. Light-weight feature transformations—such as encoding categorical variables or applying model-based imputations—can also be done closer to the model serving cluster.

Other transformations must follow the forecast horizon. External data sources—such as promotion schedules or planned advertising campaigns—should be merged to form a single table, separated into distinct tables for the model-serving layer, and loaded through a reliable process that guarantees data integrity and quality on each forecast run. For

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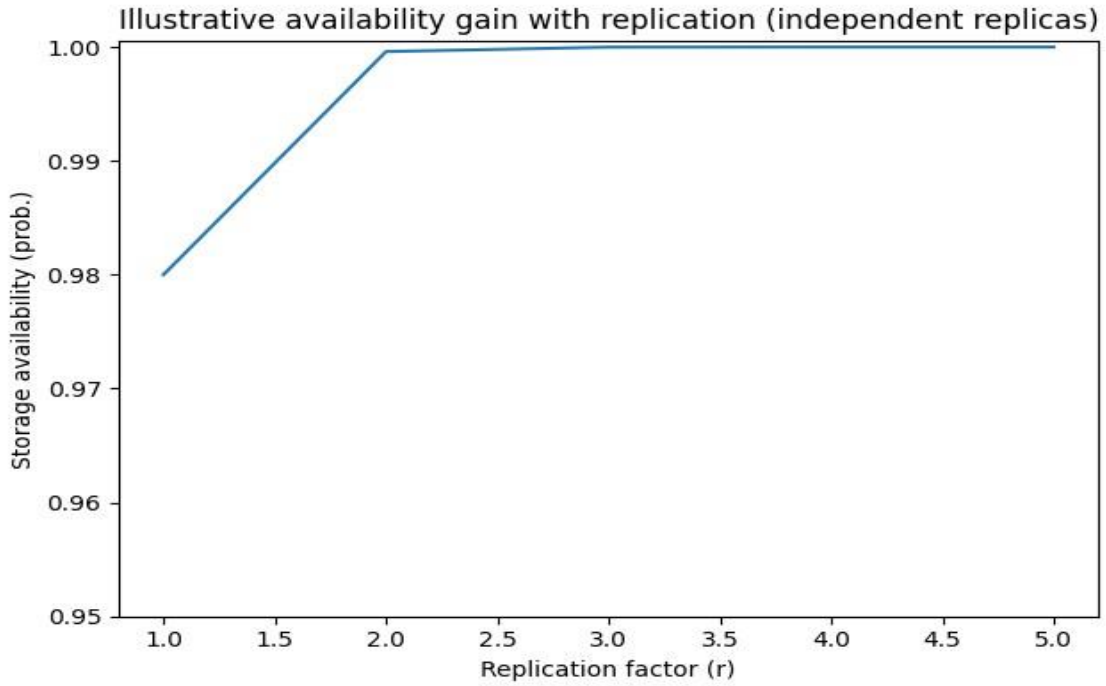
inference in the Amazon cloud, the best options are AWS Lambda for light-weight, latency-sensitive transformations and AWS Glue for more resource-intensive tasks that satisfy less stringent latency requirements.

4.1. Feature Engineering for Forecasting

Demand forecasting is a challenging task due to the large number of influencing factors. Feature engineering is the process of constructing additional and/or new features for learning algorithms. It is done primarily based on domain knowledge about the problem or data. There are several techniques to be applied depending on the attributes of the dataset.

Lag features enable the model to see the previous values which may affect future values. By knowing how many timesteps in the past to consider, a lag can be created using the predefined function using Pandas library in Python with the name of shifting.

Promotions, as a marketing technique, are considered a temporary push to increase the sales of a product for a limited period. Creating a feature that can identify when a new promotion for a particular product is on offer can aid the model. It is common to see sudden spikes or drops in demand due to factors other than seasonality and trend in time series. These spikes or drops can be due to component breakdown causing unavailability of products or refund orders. These can be incorporated using external signals.



Equation 3) Scalability (throughput vs cluster size)

Step-by-step derivation

4. Let each worker process at baseline rate r (events/sec). With N workers, ideal throughput:

$$T_{\text{ideal}}(N) = rN$$

4. Real systems have coordination/serialization overhead. Model overhead fraction as $o(N)$ (increasing with N):

$$T(N) = rN\left(1 - o(N)\right)$$

4. A simple (common) overhead assumption is logarithmic coordination:

$$o(N) = c\log_2(N)$$

6. Then:

$$T(N) = rN\left(1 - c\log_2(N)\right)$$

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4.2. Distributed Computing Frameworks

When demand forecasting requires large amounts of data processing, a framework that provides large-scale distributed computing with a simple programming model and supports dynamic workloads can help satisfy processing time constraints while ensuring efficiency, fault tolerance, and scalability. All three leading frameworks, Apache Hadoop, Apache Spark, and Apache Flink, provide suitable solutions, with their appropriateness being determined by whether the workload can be performed in batch mode.

Apache Hadoop enables distributed batch processing of large data sets using a simple programming model. Hadoop Common provides basic file system functions, Hadoop Distributed File System supplies high-throughput access to the application data, MapReduce supports a distributed computing model, and YARN provisions cluster resources. Data pipelines that use the Hadoop framework typically ingest and integrate data in real time, but perform demand forecasting with MapReduce in batch mode. Such a processing strategy is appropriate when the demand for forecasts is low or the cluster is underutilised.

Apache Spark offers Hadoop-like batch processing but is capable of managing and processing streaming data in near real-time. Spark can also support other workloads defined by libraries like MLlib (machine learning), GraphX (graph processing), and Spark SQL (interactive queries). With its resilient distributed datasets in memory, Spark can utilise a cluster for interactive queries or machine learning on large data sets.

Apache Flink was developed for streaming workloads, but supports batch processing and other workloads through a rich set of libraries. By being designed specifically for streaming and for cloud execution, it features truly low latencies, and supports efficient scaling and elasticity, enabling under-utilised resources to be reclaimed and more resources to be provisioned when workloads require additional capacity.

V. STORAGE SYSTEMS AND DATA MODELING

Choosing an appropriate storage system and data model is essential for the retail demand forecasting pipeline. The requirements of forecasting models drive the evaluation of different storage systems and associated data models. Demand predictions can turn into an intermediary product in supply chain management, where the next logical step is to decide how this demand prediction will be captured and archived.

The primary tension lies in choosing between a data lake or a data warehouse. A data lake allows data to be stored quickly in its native format. The simplicity of governance and access control ensures that data remains easily available for all novel analyses the business requires. Both technologies rely on different trade-offs to solve the same different problems: for a data lake, the primary problem is the speed at which structured or semi-structured information can be stored, while for a data warehouse, data governance and structured information completeness must be guaranteed. Retail businesses are in a unique position: on the one side, they collect 10–100 times more structured data than other business segments, and on the other side, they require unique analysis on this data. This creates a demand for built-in governance and security systems. In the case of demand forecasting, this also introduces a problem. The nature of retail is that demand data is naturally partitioned, either by item or store or both. The natural solution for a partitioning strategy therefore is to partition incoming demand signals by item or store or both. As these signals are naturally partitioned, they evolve, expand, and shatter response (the distribution of responses changes shape) each week. Capturing demand prediction therefore becomes capturing time-series data. Standard compression algorithms apply to these signals. Retail is also one segment where the demand prediction market is maturing. Schema evolution capabilities to accommodate the natural evolution of the underlying business drivers are also available. Handling information that does not fit the common schema ensures that built-in system will not be the limiting element in the speed at which the system can store incoming demand signals.

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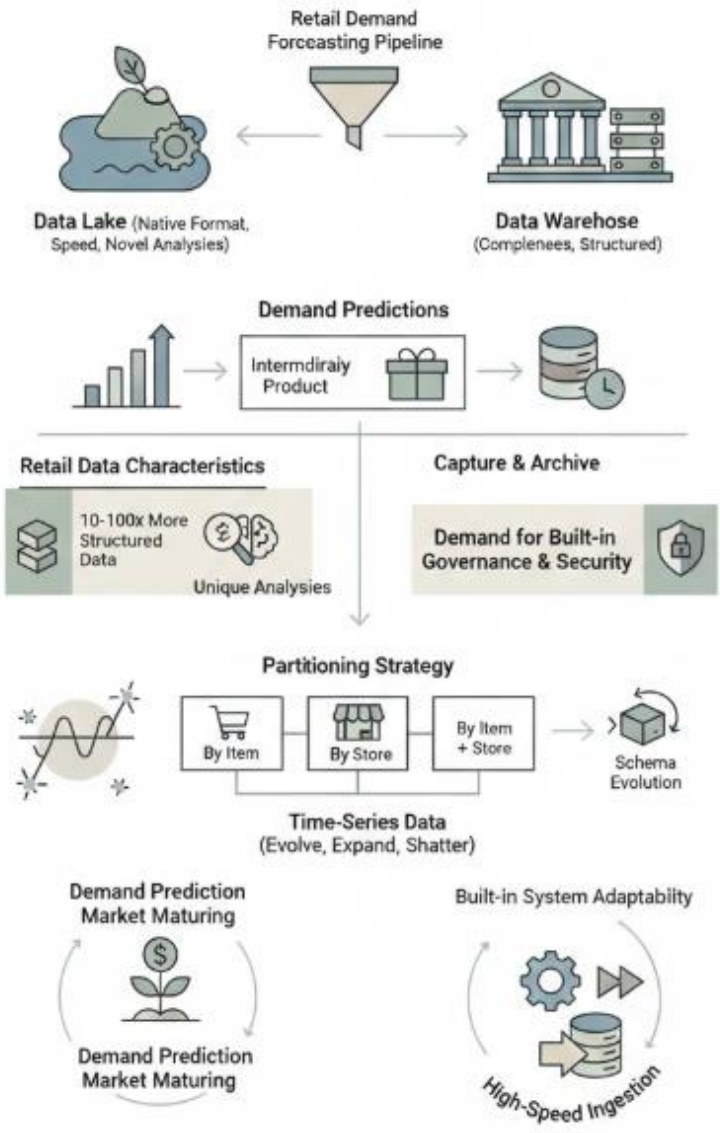

Fig 3: Navigating the Data Lake-Warehouse Tension: Optimized Partitioning Strategies and Schema Evolution for Scalable Retail Demand Forecasting

5.1. Data Lakes versus Data Warehouses

While data lakes offer elasticity and flexibility, especially for high-dimensional data with evolving schemas, they typically lack stringent security and governance controls. In contrast, data warehouses usually enforce schema-on-write, enabling tuning for specific workloads, while ensuring data quality and governance standards through a more rigid approval process.

Data location directly influences user access capabilities, adding another dimension for selection between data lakes and warehouses. Actions such as modeling or dashboarding require read access, whereas data science might demand write privileges.

Batch size	Latency (ms)	Relative cost (units)
1	50.0	1000.0
5	87.0820393249937	447.21359549995793
10	114.86832980505139	316.2277660168379
25	170.0	200.0

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Batch size	Latency (ms)	Relative cost (units)
50	232.13203435596427	141.4213562373095
100	320.0	100.0
250	494.34164902525686	63.245553203367585

5.2. Partitioning, Compression, and Schema Evolution

Both a data lake for raw data and a data warehouse for processed data are included in the architecture. Consequently, the requirements and properties of partitions, compression, and schema evolution are evaluated for both components. Partitioning of the data stored in the data lake is determined by the frequency at which new data arrives and by the logical organization and size of the data. For the data warehouse, partitioning is determined by the frequency at which new data arrives and the processing strategies used. Compression of the data depends on the nature of the data and the processing requirements. As retail is an evolving business, the processing architecture must support schema evolution via CDC or soft-deletes.

Ingest patterns laser prioritize partitioning and contrasting partition, compression, and schema evolution ideas. The sources comprise streaming data, which arrives unceasingly at a rapid rate, and static data, which changes sporadically. Streaming data that needs rapid processing is partitioned in small amounts to enhance manageability. Static data is partitioned into substantial volumes for efficiency, organized by logical groupings. Partitioning of these static data becomes crucial when changes in the data are detected and a separate processing phase is required. CDP-analysis enables the detection of changes in schema and special values in the static data, triggering the window operations on the streaming data. All sources can either spawn or be data quality control points, ensuring that quality issues are detected promptly, even in streaming scenarios, where there are some special considerations for data governance and monitoring.

VI. MODEL DEPLOYMENT AND ONLINE INFERENCE

Forecasting pipelines can be extended with real-time inference for upcoming time periods; these pipelines require additional monitoring capabilities and should provide low-latency availability guarantees. The need for real-time forecasting is determined by business needs and the time between data ingestion and prediction. Key non-functional requirements are availability and latency. Depending on the value of the target variable, a latency target should be set for the end-to-end pipeline. If the target variable has low product value, batching multiple requests is acceptable; if it has high product value, it should be made available to relevant business stakeholders with low latency. Monitoring capabilities are necessary for all real-time pipelines to oversee the availability percentile.

Real-time forecasting predictions can be obtained by extending the model deployment architecture shown in Fig. 4 before the target variable becomes a tuning parameter. The entire streaming inference architecture for real-time forecasting can be seen in Fig. 9. A defined batch size for the online model should fit well within the latency target. The batch size should be small enough to keep the latency low, but large enough to keep the cost low. Alternatively, external services can easily introduce A/B testing or rollback possibilities. Services like AWS SageMaker offer a separate layer for A/B testing and rollback implementation, but the decision remains in the application service layer. If the model is served as a single container, A/B testing and rollback capabilities need to be custom-built. The application service monitors the incoming requests stream; when a new model is deployed, the request stream is sent to both the old and new models and the predictions are stored. Once the negative prediction count reaches a threshold, the new model becomes the main model. If the count is negative for the new model, it is set as the backup model.

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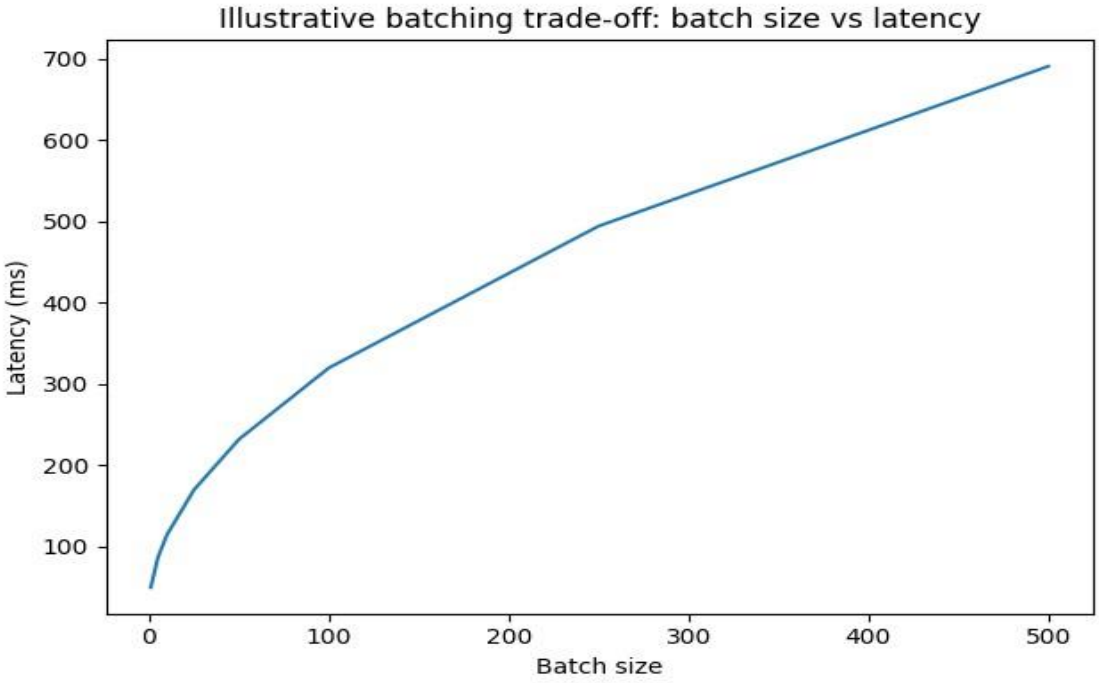

Equation 4) Reliability / availability (fault tolerance)
Step-by-step derivation (component availability)
5. Let a component have **MTBF** (mean time between failures) and **MTTR** (mean time to repair).
6. Availability A is:

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}}$$

Step-by-step derivation (end-to-end pipeline availability)
If the pipeline is a series system (any stage failure breaks service), with independent component availabilities $A_1, \ldots, A_K$:

$$A_{\text{pipeline}} = \prod_{k=1}^{K} A_k$$

Step-by-step derivation (replication improves availability)
If storage is replicated r times and service is available if **at least one replica** is up, with single-replica availability a:
1. Probability all replicas down:

$$P(\text{all down}) = (1-a)^r$$

5. So replicated availability:

$$A_{\text{rep}} = 1 - (1-a)^r$$

6.1. Real-Time Forecasting Pipelines
Real-time pipelines for demand forecasting produce predictions as new sales events occur, integrating model inference with the data stream to minimize end-to-end latency from ingestion to scoring. Architecture design requires careful consideration of target inference latency and intended use, balancing requirements against model reliability. For urgent predictions that support inventory movement or price adjustments, end-to-end latency may need to remain under 15 minutes. Directly streaming new sales events into model inference can achieve low latency, but incurs higher risk; a cascade of aggregate predictions with low-latency requirements, fault-tolerant joining and inclusion of additional external signals is a more robust choice. Other factors influence latency beyond the model design, such as low-latency ingestion and serving architectures, demand on model providers, computing capacity, and overall orchestration.

Three architectures for real-time forecasting pipelines are common: a streaming architecture with model inference deployed in-line, a hybrid of pipeline and model serving architecture that feeds predictions into a secondary stream, and a pipeline serving architecture that processes predictions separately. The most suitable option depends on the end-to-end latency requirements, the direction of forecasting and possible re-routing of traffic. A streaming architecture

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supports very low end-to-end latency at the cost of higher risk during periods of data scarcity. Consequently, pipelines targeting longer aggregation intervals rely on a hybrid or pipeline serving architecture that explicitly joins model predictions back into the event stream prior to routing. The ability to iterate on serving deployment patterns facilitates A/B testing of individual prediction requests with rollback option for being routed elsewhere if failure is detected.

6.2. Model Serving Architectures

Three model serving architectures are prevalent in production deployments. The first one is 'on-demand serving.' In this typical architecture, a model-training job creates the model artifact, stores it on an object store (usually a cloud-based remote artifact store), and a model-serving unit serves the model on demand. The serving unit retrieves the model artifact from the object store, calibrates the endpoint, and starts serving it to predictions for incoming requests. This architecture can be implemented in a batch mode where the endpoints are created one or more times a day to trigger the inference job in a scheduled manner. In this setup, model loading serves as a single-point bottleneck and makes the predictions slower than in other architectures. A model-A/B test differs from this architecture only in the way that it hosts several models that are not automatically loaded and unloaded based on traffic but need to be carefully orchestrated.

The second architecture is 'online continuous inference.' In this model, the inference pipelines are executed continuously to serve the incoming request. The model-serving unit loads the model into the prediction-serving host and features with the incoming request are passed on to the model for prediction. In the third approach, a model-serving unit uses an in-memory cache to store the model feature inputs computed during the continuous-feeding pipeline. The prediction service frequently checks the cache for the incoming requests and serves the predictions by retrieving the feature inputs from the cache, avoiding a double computation of the same features from the gems with swallowing models.

VII. CONCLUSION

The analysis reveals that implementing proven strategies relative to scalability, latency, and reliability enables building, operating, and maintaining a data pipeline that meets the business requirements for retail demand forecasting. These decisions cover the entire data pipeline: from the sources and methods for ingesting and integrating the data to the processing, storage, model deployment, and online inference. Consequently, the supported forecasting models account for external signals, seasonality, trend, promotion activity, and highly granular temporal structure within the data, through the inclusion of lag features. The impact of each decision on the flow of data is evaluated, with a specific emphasis on forecast accuracy.

A working data pipeline that incorporates these aspects represents a strong step toward efficiently serving demand forecasts at Lowe’s or any other retailer with similar objectives. Nevertheless, it is essential to bear in mind the limitations of the current analysis, given that these practical implementations are often subject to the technologies, providers, services, and applications available at the moment, rather than strict theoretical justification. In future work, a service-oriented approach will be employed to further enhance the reliability of the data pipeline, by addressing A/B testing and rollback capabilities for model deployments, as well as the integration of prediction monitor services to improve forecasting accuracy and availability quality dimensions.

| ISSN: 2320-0081 | www.ijctece.com | A Peer-Reviewed, Refereed and Bimonthly Journal|

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DOI: 10.15680/IJCTECE.2022.0506020

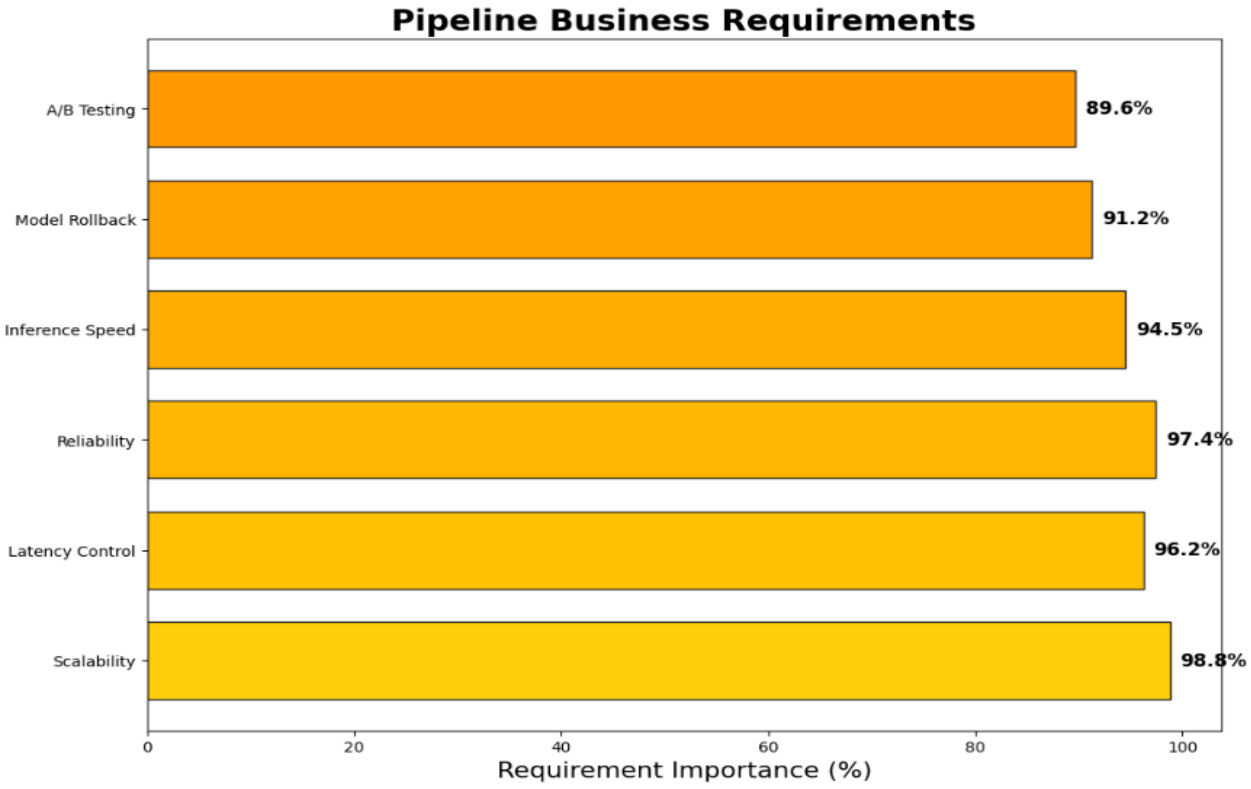

Fig 4: Pipeline Business Requirements

7.1. Final Thoughts and Future Directions

High-performance data pipelines are crucial for operational forecasting in demand-sensitive business domains, yet little academic literature addresses their design and construction, particularly in the retail sector. In addition, the work achieved sub-millisecond queries in the most complex retail demand forecasting task yet attempted. This approach effectively enables decomposition of the forecasting problem into smaller subtasks that can be modelled independently without negatively impacting the accuracy of the predictions.

Delving deeper into fulfilment-centre-specific demand from customers, high-performance pipelines can facilitate the integration of factors traditionally glossed over during modelling. To this end, the next logical step involves building a seamless pipeline from source databases through ingestion, preparation, and transformation to model deployment, with a particular focus on model-monitoring data ingestion. Ultimately, the goal is to build a complete data pipeline for operational demand forecasting capable of validating, augmenting, and retraining the entire demand-forecasting system. Such work naturally leads to an expansion of the pipeline from fulfilment-centre demand to operational demand at the store level.

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