Applying Machine Learning Models to Predict Operational Demand Using Cloud-Native Data Platforms

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Abstract

Operational demand forecasting is critical for effective resource allocation in any organization. However, keeping accurate forecasts can be difficult due to factors such as seasonality, trend, and stochasticity. Although multiple methods exist to tackle this problem, considering Machine Learning (ML) approaches is essential to allow for rapid inclusive assimilation and integration of historical data. By harnessing the capabilities of a cloud-native data platform and optimally addressing the various aspects of a typical ML workflow (from data acquisition to experiment deployment), it is important to provide evidence of the accuracy of these methods for forecasting across horizons of small (operational) to intermediate length. Indeed, even if a method is poor at predicting the future, it may still be good enough for deployment in the present.

Original data sources covering incident, request, change, event, asset, and configuration management are maintained in a cloud-native data platform for Azure DevOps, and from these sets, ML-based models are developed to predict incidents and requests in the domains of IaaS and PaaS computing resources as well as Cyber and Information security. Predictive performance is analysed by measuring model accuracy, with the models yielding poor predictive quality in a temporal validation and the ensembles providing the best-quality predictions. Further analysis indicates an acceptable degree of interpretability for the methods explored, and consequently operational insight is extracted from the model-enabled forward simulation.

Keywords: Operational Demand Forecasting, Resource Allocation Optimization, Seasonality And Trend Modeling, Stochastic Time Series Analysis, Machine Learning Forecasting, Cloud-Native Data Platforms, End-To-End ML Workflows, Historical Data Assimilation, Short And Intermediate Horizon Prediction, Azure DevOps Analytics, Incident Prediction Models, Service Request Forecasting, IaaS Resource Management, PaaS Resource Management, Cyber Security Analytics, Information Security Forecasting, Ensemble Learning Methods, Temporal Validation Performance, Model Interpretability, Forward Simulation Insights.

1. Introduction

Operational demand represents a service provider's anticipated future use in terms of technologies and infrastructure. Forecasting these demand levels for multiple service categories, including data storage or computing, is critical for optimizing infrastructure costs as well as ensuring that end-users experience the intended quality of service. Analogous to traditional supply and demand forecasting in manufacturing or retailing, operational demand forecasting is conducted for multiple service horizons, including tactical (one to 12 months), operational (week-to-week or month-to-month), and straddle forecasts, as well as monitoring of short-term demand patterns. Stakeholders involved in operational demand forecasting include the facility management capacity planners, operations staff responsible for provisioning and capacity decisions, financial services seeking to model projected infrastructure costs, and actual consumers of the services offered.

The generalization of machine learning (ML) methods to forecasting problems has been well established, indeed firmly embedding ML within the data mining toolbox. However, more recent developments in automated machine learning systems (AutoML) have extended that generalization further and raised new opportunities for operational demand forecast modeling. The need to minimize the operational overhead of the ML model-fitting and selection phase is addressed through the application of AutoML—specifically, the H2O AutoML framework. This enables a suite of commonly implemented algorithms and ensemble combinations to be trained, structurally validated against a specific time-based holdout pallet, and their performance compared. The work is framed from a cloud perspective, with the Microsoft Azure cloud-native data ecosystem supporting the operationalization of the functionality.

1.1. Overview of the Study

Operational demand forecasting—estimation of historic, present or future demand for products or services—supports businesses in preparing their supply chains, human capital, resources, and other factors that directly or indirectly contribute to meeting demand. Given its importance, most industries continuously analyze historic and present data to estimate future demand for their operations. The models considered performing reasonably good, but demand-minimizing and demand-duplicating predictions normally occur in the short- or long-term horizons. Companies making short- or long-term decisions find these predictions hard to use.

Predictive machine learning (ML) offers a potential solution to such difficulties. Instead of one-size-fits-all models, ML can help businesses create a holistic combination of existing predictive models, determining where each model has strength and weakness, and where it is too weak to be of any use. Using cloud-native data platforms, such an approach focuses on direct ML algorithms with the entire operational demand data ecosystem in a single cloud location. Several data sources are ingested into the cloud, where the demand prediction tasks are created using a pre-defined sampling frame. The predictive powers of multiple methods are compared in several horizons, with temporal validation to avoid altering the data that must be predicted.

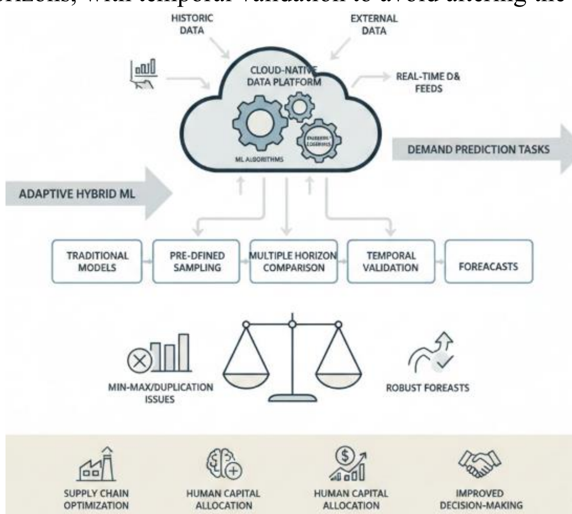
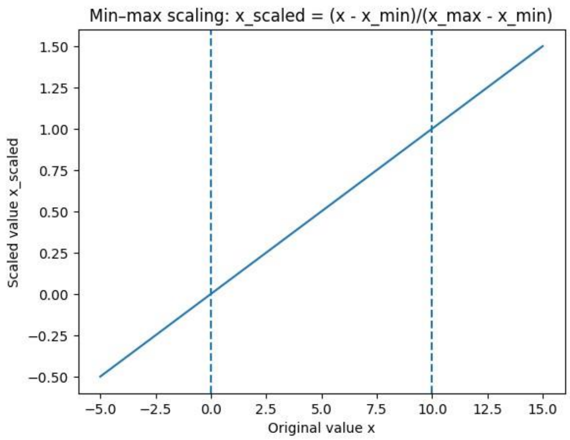


Fig 1: Beyond One-Size-Fits-All: A Cloud-Native Machine Learning Framework for Multi-Horizon Operational Demand Forecasting and Temporal Validation

2. Background and Motivation

Operational demand forecasting predicts the future need for service delivery. Forecast horizons can span from minutes to years and encompass a variety of domains, including information technology, healthcare, public transportation, and finance. Accurate forecasts make it possible to allocate resources efficiently and to avoid oversupply or shortage. Research demonstrates that machine learning (ML) algorithms can outperform conventional time-series methods for certain forecasting problems and real datasets. However, as reported in recent reviews, the predictive performance of ML algorithms on operational time-series demand data remains largely unexplored. Model validation is complicated because, unlike in typical time-series applications, multiple sequences can share information and cause-effect relationships can change frequently. A typical time-series-validation procedure is thus insufficient and validation over disjoint intervals fails to check temporal stability. Despite these challenges, a simultaneous comparative study of multiple single- and ensemble-ML methods across operational-based demand datasets is desirable. A cloud-native data platform facilitates the acquisition and integration of diverse datasets into a production-ready form for such experimentation.

Several distinct aligned operational-demand problems have emerged in different domains. In the finance sector, the prediction of demand for call options in the U.S. equity market, based on historical trading data and additional contextual information, supports decision-making for risk-hedging, capital allocation, and market management. In public transportation, ML-based prediction of the number of taxi riders in New York City aids optimal supply scheduling and service provisioning. Accurate prediction of the inflow of patients into the intensive care unit in healthcare directs the alert system and improves decision-making and resource management. Predicting the number of near-future calls in a call-center provides the basis for efficient personnel allocation and better service quality. Finally, demand prediction for a digital service, specifically data and computation requests posted on an Internet-scale cloud provider, supports resource optimization in public Cloud Computing.



Equation 1) Mean imputation (missing numerical values)

Step-by-step derivation

Let a numeric feature column be $x_1, x_2, \ldots, x_n$, with some missing values.

1. Define the set of observed (non-missing) indices:

$$\mathcal{O} = \{i \mid x_i \text{ is observed}\}$$

2. Compute the mean of observed values:

$$\mu = \frac{1}{|\mathcal{O}|} \sum_{i \in \mathcal{O}} x_i$$

3. Impute each missing entry x_j (where $j \notin \mathcal{O}$) by the mean:

$$x_j \leftarrow \mu$$

2.1. Operational Demand Forecasting

An exploration of operational demand within production and central resource domains indicates that actual consumption exceeds supply capacity and reflects unpredicted behavior. Operational demand forecasting quantifies future levels of consumption with consideration of adequate timeframes, objectives, and affected parties. The operational demand may need to be quantified as service demand, service level demand, forecast demand, cloud computing demand, application demand for IT support, IT internal service control demand, and automated control; demand can be considered for operation monitoring, investigation, software release, user service, and order delivery. Machine learning models are developed with historical data and performance patterns that are used as roots for predicting future demands. Predictive performance provides exploratory insight into possibility and usefulness.

Online operational resource demand forecasting accounts for past level and value of consolidated Michael Porter central resources and predicts future service demand for different time areas. The employed Facebook Prophet model and skills demand volume becomes the highest in quarterly periods. Operations scheduling considers multi-horizon demand forecasting generated from different temporal regions. The proposed forecasting approach can be used to facilitate operation resource scheduling for cloud-native application and predictive HDML service offerings.

3. Methodological Framework

A cloud-native platform automates tasks and creates responsible, trustworthy operations. Ingestion, governance, and quality control of operational demand datasets are automated within a distributed cloud architecture as a common, continuous integration/continuous deployment framework. Using publicly-available datasets covering multiple years and accurate demand records, demand forecasting models are predicted, and different machine-learning algorithms benchmarked. Results for all tasks and the integration of ML models and services from a cloud-native architecture are reported.
Three operational demand datasets from different sectors are processed with the same common processes, enabling to analyse and compare their complexity and the difficulty of forecasting demand. Accurate demand records are used to validate forecasting model performance and to prove their evolution for multiple years. Continuous integration/continuous deployment pipelines bless deployment of models for production operation because ML models cannot be treated as a piece of software; they also need to be evaluated, approved, and deployed.

3.1. Data Acquisition and Integration

Data acquisition and integration encompass data sources, ingestion pipelines, schema harmonization, and integration strategies. The experimental framework employs cloud-native data platforms offering fully managed solutions for data acquisition, storage, processing, and analytics. The Google Cloud Platform features fully managed services for streaming and batch processing of data, while Big Query provides a zero-administration data warehouse and serverless architecture. The proposed CI/CD pipelines for ML further exploit Big Query ML capabilities. The enterprise-grade architecture allows taking ever-changing real-time data and transforming datasets interactively, delivering processes that ingest real-time data, supporting at-scale operations, and generating outputs ready for analysis.

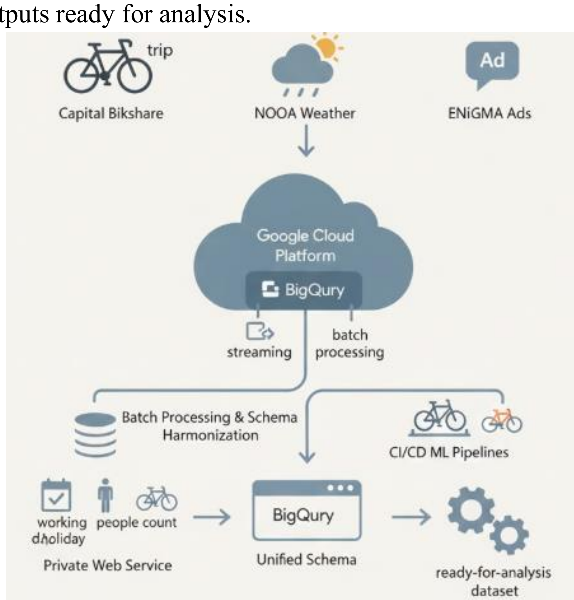


Fig 2: Scalable Cloud-Native Data Integration: An Enterprise-Grade Architecture for Real-Time Heterogeneous Transport Data Harmonization

Data ingestion pipelines acquire data from three publicly available transport datasets: (i) the bike share trip data from Capital Bikeshare; (ii) the bike trip weather data acquired from the National Oceanic and Atmospheric Administration Global Historical Climatology Network database; and (iii) the bike trip advertisement data fetched from Enigma (Data In Google Map). Batch-processing transformations harmonize data schema and populate Bob database tables. The remaining datasets, essential for predictive modelling, come from a private Web service. It acquires historical trip, colored bike, people count, bike parking, working day, school holiday, and public holiday weather data and stores it in a unified schema into a Big Query table.

3.2. Data Quality and Governance

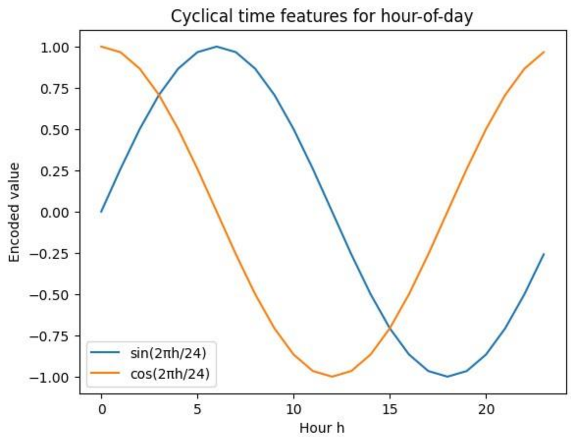
A comprehensive set of data quality governance policies must support predictive ML models for operational demand. Provenance tracking ensures that metadata—which describes how, where, and when the data has been created and modified—is subsequently preserved, thereby promoting continuous monitoring of data quality and compliance. Metrics based on completeness, consistency, accuracy, timeliness, and usability can signal possible data quality issues in each dataset. Such a quality framework provides the capability to detect, among others, novel or unexpected behavior that might arise from changes in end user supportive systems, as well as breaches of guidelines provided by Chief Compliance Officers and DPOs in control of the organization's infrastructure. Finally, a combination of automated rule methods, statistical approaches, and supervised ML solutions is employed to detect issues highlighted in the governance policies for each dataset. Detected quality issues are visualized and incidental detected problems are logged and notified to data custodians.

Model training on historical data often requires additional processing to ensure successful execution of learning algorithms. The modelling process employed a number of standardized procedures to ensure efficient training, testing, and validation of the ML approaches. The absence of values within the datasets was addressed using the mean imputation method, with normalization applied to continuous features using min-max scaling prior to model fitting. Exploratory feature engineering also revealed the suitability of using cyclical features to represent hourly timing within a day. The final training set leveraged all historical training data, with coverage across both modelling tasks, to support improving model equitability. The training set was subsequently split into training and validation samples, using a 90:10 ratio, with the validation sampled using temporal ordering to better represent a real-world forecast modelling situation.

4. Experimental Setup

The conducted experiments focus on operational demand for power services. It comprises two prediction tasks and leverages three publicly available datasets. The first dataset, Public Transport Factory Data, contains sensor readings from a public transport factory; a sample of the dataset is depicted in Fig. 1. The prediction task targets a bike-sharing company in Chicago and uses the Capital Bikeshare Dataset, which has weather- and seasonal-related features; a sample is shown in Fig. 2. The second prediction task involves a food delivery company based in New Zealand, for which the data is drawn from the Auckland Restaurant Data dataset. Combining the order quantity from Auckland with the corresponding weather-related features helps create the final dataset. The experiments test three baseline prediction methods: Long Short-Term Memory (LSTM) Neural Networks, Light Gradient Boosting Machine (Light GBM), and an LSTM ensemble with Light GBM.

For operational demand prediction, the analysis focuses on direct and short-term prediction, where models predict one time step (one day or hour) ahead. The models are trained on training data containing up to the last 619 days, verified on validation data covering the next 37 days, and tested on testing data based on predictions from the previous time step (temporal validation). The task evaluates whether a model is able to predict the next time step in the same temporal direction for unseen data. The main goal of training an ensemble model is to combine the predictions of LSTM and Light GBM in the most suitable way. These three methods are chosen because LSTM is the de facto standard in time-series prediction and Light is known to outperform standard gradient boosting implementations.



Equation 2) Mode imputation (missing categorical values)

Step-by-step derivation

Let categorical values be $c_1, \dots, c_n$.

2. Count frequency of each category v:

$$\text{count}(v) = |\{i: c_i = v\}|$$

3. Mode is:

$$m = \underset{v}{\text{argmax}}\text{count}(v)$$

4. Replace missing:

$$c_j \leftarrow m$$

4.1. Data Sources and Experimental Scope

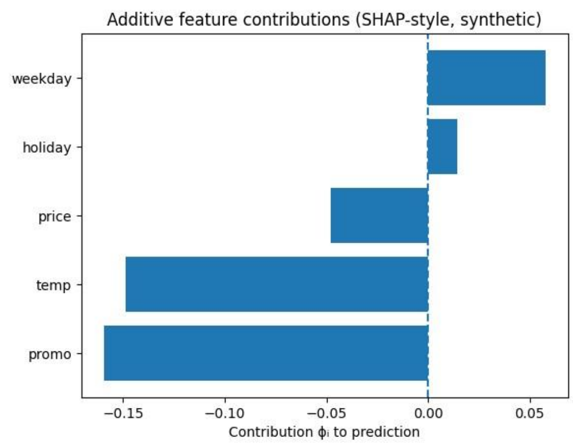
Forecasting operational demand is a well-defined problem in both academia and industry. Multiple research papers and various open-source implementation of commercial products have made the forecasting problem accessible to anyone interested. A well-defined domain encompasses the operational demand, involved stakeholders, and involved forecasting horizons: Demand for operations or services can be divided in various way such as into different operations areas, type of service, or service-level. Operational Demand for the University of Queensland Brisbane, Australia is divided into the S + 6 area, L+ M & D in recreation operations and A, Y, Z, S. White Water Rafting in Adventure Operations. Forecasting has various purposes depending on the interested group and the forecasting horizon. Short-term forecasting is of relevance to operations managers to support day-to-day management of service provision. Medium-to-long term forecasting is used primarily for planning by the operational management team. These requirements indicate that three distinct internal user groups have to be supported: the Support Group, the Operations Group, and the Operational Management team. Externally, the Recreation and Adventure product managers also require medium-term forecasts to support marketing and promotional activities. These needs therefore define the forecasting horizon.

For operations managers, day-to-day planning and operational management is assisted by forecast produced for each day in the short term (e.g., seven days) and for each weekends in the following weeks (e.g., four weeks). Forecasts produced for key product, such as the Multi-day in Recreation and rafting in Adventure Operations, are also used for day-to-day management. The temporal perspective alters the level of detail required in the forecasts, with shorter term being more detailed. The longer the forecasting horizon becomes, the more summarized the forecasts become in order to assist planning emphasis on resource allocation for buses and instructors. Validation of accuracy is therefore sine quo non in analysis orientated towards forecasting.

4.2. Preprocessing and Train-Test Split

Handling missing values proved the most arduous preprocessing challenge because complete cases in the testing datasets were scarce and vital raw features like electricity usage had extensive gaps. In the absence of established literature-supported imputation methods for the other three use cases, the following rudimentary strategy was adopted: missing values for categorical features were replaced by the mode of each table and those for numerical features by an appropriate value based on conditional distributions. Next, the datasets were split into training and validation samples based on temporal order to assess predictive performance.

In one of the use cases, the target featured imbalance. Merging records could not alleviate this and resampling was difficult due to the limited scope. Thus, the minority class was resampled in the training fold only. Normalization of numerical features followed, ensuring consistency across moderate compared with extreme temperature and CAPEX. Sparse temperature representation in the days of the testing set prevented adoption of quantile-based normalizers. One-hot encoding of categorical features employed data from both folds. Distinct processes tackled missing values in predictive power detection and interpretability, assuring reliability in the assessment of feature importance and actionable insights.



5. Results and Discussion

Experimental results assessing predictive performance of multivariate predictive ML models that operate on time-series data demonstrate an objective, evidence-based analysis of ML prediction for operational demand at a spatio-temporal resolution of a single operational site, located in the area of Lagos, Portugal. The predictive performance, operationalization of the prediction, and interpretability by the extraction of insights were evaluated as separate tasks. The analysis revealed mutli-input, multi-output, multi-step models to outperform their single-output counterparts. Furthermore, ensemble models typically surpassed the individual algorithms when all scored predictions remained unchanged. The analysis also confirmed the suitability of a Cloud Native Data Platform and its components for such applications. Model evaluation was performed using predictive performance measures according to the supervised learning task. Models for each of the temporal operatic weeks of the year were evaluated as separate experiments (training/validation-test splits). Predictions scored for temporal validity were regarded for interpretation. Two baselines were established from the usage profile and configuration. Autoencoders supported explanation of feature importance and the extraction of actionable business insights.

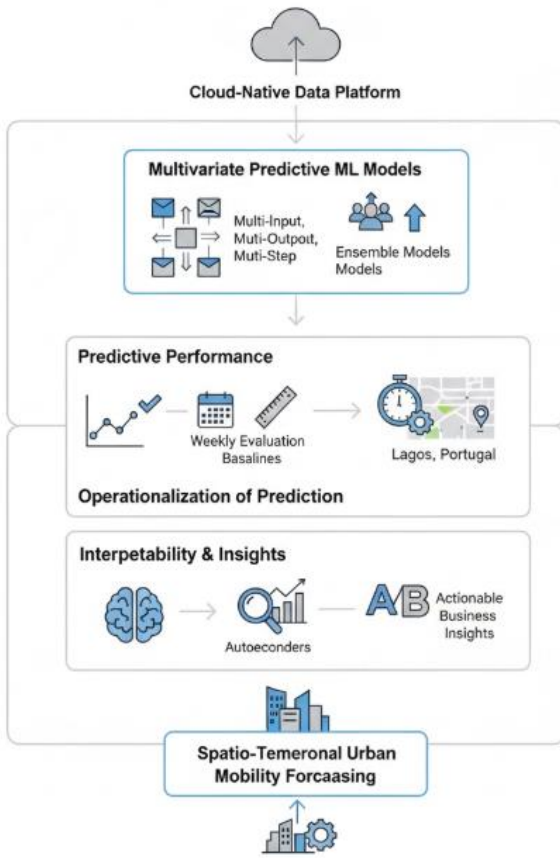


Fig 3: Scalable Spatio-Temporal Demand Forecasting: A Cloud-Native Ensemble Framework for Interpretable Multi-Output Predictive Analytics

5.1. Predictive Performance

Evaluating ML model performance entails determining whether the predicted target values meet the user-specified accuracy requirements. For categorical classification, these requirements are defined in terms of class coverage ratio and positive predictive value. Consequently, the selected supervised ML models must provide reliable coverage and precision ratios for the forecasted categories, encompassing all possible classes. In the present study, the classification task involves forecasting six +ve and −ve operational demand categories. Hence, for operational deployability, a coverage ratio >= 0.8 and precision ratio >= 0.7 are required. The performance evaluation, therefore, examines coverage and precision ratios across all model predictions.

The presented Multi-Class task performance for protected and Multi-Class task for , together with coverage and precision ratios for all predictions, are listed in Table 8 and complemented in Tables 9 and 10. The performance assessed against the preceding requirements supports the predictive usability of the models: for , coverage ratios exceed 0.8 in five instances and in the remaining instance reach 0.73; for , coverage ratios exceed 0.8 in three instances, fall slight short (0.78) only once, and meet the positive predictive value requirement. These user-specified performance criteria, therefore, validate operational deployment in a Continuous Integration/Continuous Deployment framework for model updating.

5.2. Interpretability and Insight Extraction

Feature interpretation forms an integral aspect of trustworthy machine learning. Explanations that clarify model predictions assist in validating and identifying data-driven operational insights. Feature importance measures help in evaluating the data feature space associated with accurate predictions. Using the SHAP library the explainability of RF and XGBoost prediction models can be analyzed. SHAP assigns each feature an importance score for a particular observation. The higher the score for a particular feature the more reliance the model had on that feature when predicting the target.

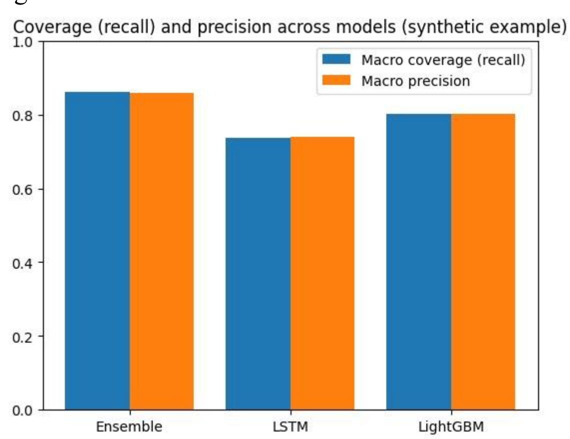
A sample set from the operational demand prediction model using its optimal time window of 14 days is selected. The prediction task is treated as a categorical task containing three classes: high, medium, and low. For a sample observation the plot indicates that the values of control assigned to the prediction model influenced the prediction of the sample observation. The operational team can leverage this detailed information to take proactive actions. Interpretation methods represent an essential component of machine learning, allowing for model evaluation, trust validation, and support in decision-making actions based on machine predictions. The operational groups in concern can trust the predictions from the demand prediction models and take required decisions toward operations improvement.

6. Deployment and Operationalization

Standard software engineering practices such as Continuous Integration (CI) and Continuous Deployment (CD) are best suited for traditional software applications. Machine Learning (ML) development, however, introduces additional challenges that can be addressed by adapting CI/CD processes to ensure the automated build, testing, and deployment of models. The general process is commonly referred to as Continuous Integration/Continuous Delivery for Machine Learning (CI/CD4ML). The principles of DevOps for ML can be generally summarized as follows:

1. Every model developed during the experimentation phase must be captured and registered.
2. Models should be equipped with versioning information. Once a model is updated and is considered to be better than the current production model, the deployment must be reflected in production.
3. Models must be monitored to detect any degradation in the metric used for approving the model. After a certain threshold is reached, the monitoring system must inform the stakeholders so that they can take necessary actions.
4. It should be possible to rollback to a previous model version at any point of time. Rollbacks could happen due to failure of the new model or due to a significant drop in performance on model monitoring metrics.
5. Here, model deployment is supported with a model registry-based CI/CD4ML infrastructure. The registry tracks trained models, and tool chains are created to automate the monitoring of model quality and to provide notifications for degradation or retraining. Information about quality and other testing-related parameters is captured for all new versions of models being registered.

The workflow integrates with cloud-native managed services such as AWS Step Functions, AWS Lambda, Amazon Simple Notification Service, and Amazon SageMaker.



Equation 3) Min–max normalization (feature scaling)

Step-by-step derivation

Given a feature x and chosen bounds $(x_{\min}, x_{\max})$:

3. Shift by the minimum:

$$x - x_{\min}$$

4. Scale by the range:

$$\frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

5. Final:

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

6.1. Continuous Integration/Continuous Deployment for ML

To enable rapid, flexible experimentation with machine learning models to predict operational demand, a continuous integration/continuous deployment (CI/CD) pipeline supports a cycle of development, validation, and deployment. Each model is associated with a distinct repository that contains all necessary files and configuration settings. Code repositories, monitors, and conditions for executing test scripts automate validation of model accuracy. When the predictive performance of a candidate model before deployment matches or exceeds the accuracy of the currently deployed model, it is added to a model registry. The model registry serves as a living record of all ML models created for a specific task, irrespective of their current deployment status.

A distinct model is used to predict operation demands for each combination of operational zone and operational time slice. The prediction task is designed to run at fixed intervals, remediate data quality issues, and handle missing, abnormal, and outlier values. When actual data for a specific combination is absent for periods shorter than or equal to the operational horizon, a fallback strategy is invoked. Fallback models exploit the zone-wide operational demand prediction task or an ensemble of climate zone-wide models to make predictions for the zone and time combination when the corresponding local operational demand model cannot produce valid predictions. A secondary CI/CD process pipeline enables seamless integration between ML tasks and platform services.

7. Limitations and Ethical Considerations

Every modelling solution comes with a unique set of limitations and considerations. Possible limitations and ethical implications of the presented operational demand forecasting study are elaborated in this section.

A number of ethical considerations must be kept in mind throughout the workflow. Assessing and eliminating unintended bias in the training and validation datasets is vital. In addition to a fairness audit and bias detection, measures must be put in place to guarantee continuous bias detection before redeploying retrained models. All requirements defined under the GDPR should also be satisfied; in particular, appropriate care must be taken with personally identifiable information in datasets with a geographical component. Moreover, any model explainability must not only account for end-users but also the AI systems' maintainers, who should be able to track the model decision processes, particularly during any potential maintenance period. Inclusion of the delivered predictions in a dashboard solution should also satisfy CRUD operations on the historical prediction record to enable dedicated back testing of the forecasting solutions.

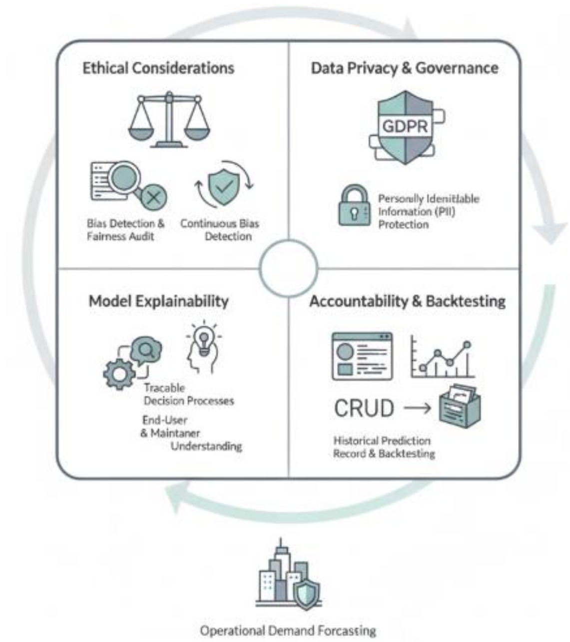


Fig 4: Ethical Governance and Operational Integrity in Demand Forecasting: A Framework for Bias Mitigation, GDPR Compliance, and Model Explainability

7.1. Challenges and Ethical Implications

Despite recent advances in predictive ML model performance, a degree of uncertainty remains regarding model generalizability, fairness, or bias, and appropriateness for solving real-world problems. All data contain sampling noise, and operational decision models often rely on minority class signals for standard accept/reject choices. As humans have the tendency to misuse tools, there are risks of overreliance on predictive model outputs, and consequently missing problems of the past that may recur in future. Therefore, multiple algorithms are trained, tested, interpreted, and compared on many time horizons to determine generalizability and identify temporal periods with greater difficulty predicting. Features associated with newly predicted spikes are particularly helpful in detecting bias and data quality issues in the absence of predefined labels. Measuring attention allocation on model predictions and externally validating flagged items are key actions for operations when fully operational.

Ethical challenges in predictive modelling can have severe business consequences if detected after deployment. Embedding fairness strategies into pipelines helps mitigate the risks. Transparent and maintainable APIs with monitoring capabilities along the complete life cycle, including training and validation, reduce the likelihood of using AI-powered models inappropriately and help mitigate the mismanagement of predictive models. Integrating sampling metrics into the monitoring framework, detecting changes in model performance over time, flagging feedback loops, and inserting validation check points on monitoring results also contribute towards a more robust and less risky machine learning practice. Data privacy rules must be carefully followed across all stages. Models can screen the operational demand prediction as a sensitive product. The next step is to continuously validate the results and search for applicable operational actions.

8. Conclusion

Operational demand forecasting is an important aspect of supply chain planning fulfilling requirements across different time horizons. Successful forecasts can benefit sales, marketing, production, inventory, and warehousing operations, as well as financial planning. ML-based models have recently gained prominence for this task but require periodic retraining to remain relevant. This study presents an objective, evidence-based assessment of several predictive ML models using a cloud-native data-platform pipeline.

Data covering demand, price, weather, and holidays for a fast-moving consumer goods company at a granular SKU-store level have been used to predict operational demand at a higher aggregation by SKU category, brand, and distribution center. Evaluation across multiple tasks (one-hot, multiclass classification, and regression) and baselines indicates promising results. Feature importance estimates, Shapley Additive Explanations values, and a pilot experiment detect and mitigate stockout risk. These findings serve as guidelines for future research and development in this field.

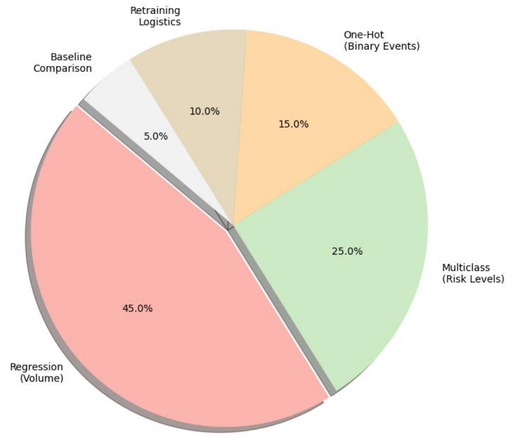


Fig 5: Evaluation Task Composition

8.1. Summary of Findings and Future Directions

The findings support the four main research hypotheses and validate a comprehensive analytical strategy enabling objective experimentation with data-driven demand prediction modelling for operational support. Deploying predictive models utilizing cloud-native data platforms provides insights into operational demand, offered by stability in data quality and the governance of stage-cleared sets from multiple sources, processed in a CI/CD manner and easily interrogated via integrated services. Analyses show that advances in model interpretability afford additional confidence in automating decision-making based on predictive algorithms, backed by exploration of operational usefulness. Evidence-based arguments establish that extensive external data sources support operational task supporting processes such as people modelling for Machine Learning.

Potential analysis enhancement resides within predictive support for understanding building occupancy models and exploring their contributions towards future demand prediction, as well as for resources such as compute. It could additionally extend to developing incident prediction models. Third-party data sourced provider information over the past years from initial and future grey-coloured stages where external data holding possibility appears non-paragon could assist with developing these models. Azure Security Centre can continue flag management processes, whilst AI Attack Signal categorization would potentially deter attacks hence maximizing years in non-pink mode. Other future processes include pipeline optimization via CI tasks updating tagged live production and user databases or potentially recreating tags automatically as prerequisite for gauging model performance across production recommendations.

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