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# COMPARATIVE ANALYSIS OF MODERN MACHINE LEARNING MODELS FOR RETAIL SALES FORECASTING

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## ABSTRACT

Accurate forecasting is key for all business planning. When estimated sales are too high, brick-and-mortar retailers may incur higher costs due to unsold inventories, higher labor and storage space costs, etc. On the other hand, when forecasts underestimate the level of sales, firms experience lost sales, shortages, and impact on the reputation of the retailer in their relevant market. Accurate forecasting presents a competitive advantage for companies. It facilitates the achievement of revenue and profit goals and execution of pricing strategy and tactics. In this study, we provide an exhaustive assessment of the forecasting models applied to a high-resolution brick-and-mortar retail dataset. Our forecasting framework addresses the problems found in retail environments, including intermittent demand, missing values, and frequent product turnover. We compare tree-based ensembles (such as XGBoost and LightGBM) and state-of-the-art neural network architectures (including N-BEATS, NHITS, and the Temporal Fusion Transformer) across various experimental settings. Our results show that localized modeling strategies especially those using tree-based models on individual groups with nonimputed data, consistently deliver superior forecasting accuracy and computational efficiency. In contrast, neural models benefit from advanced imputation methods, yet still fall short in handling the irregularities typical of physical retail data. These results further practical understanding for model selection in retail environment and highlight the significance of data preprocessing to improve forecast performance.

**Keywords** Retail Sales Forecasting, Time-Series Analysis, Machine Learning, Deep Learning, Gradient-Boosted Decision Trees, Neural Networks, Predictive Analytics, Retail Analytics

## 1 Introduction

Accurate sales forecasting is indispensable in retail, enabling better inventory planning, resource allocation, and achieving revenue and profit goals. The choice of the best possible forecasting model to use is of the essence as retailers aim to gain a competitive advantage in the context of irregular demand and limited historical sales data in various product categories. While classical approaches such as ARIMA [1] have historically formed the backbone of retail forecasting, they often fall short in capturing modern retail complexities and operational nuances. Recent advances in machine learning and deep learning present significant opportunities for retailers to improve their sales predictions and operational efficiencies with new alternatives, such as tree-based models like XGBoost [2] and LightGBM [3], as well as neural architectures such as N-BEATS [4], NHITS [5], TFT [6], and others [7, 8, 9, 10, 11].

Recent comparative evaluations of forecasting models have shown mixed results across domains. Studies such as [12, 13, 14, 15, 16, 17] have explored the performance of neural networks versus gradient boosting models and highlighted that deep learning does not consistently outperform tree-based approaches, especially on tabular, sparse, or highly intermittent retail data. These findings align with results from the M5 forecasting competition [18], which used Walmart’s highly granular retail sales data consisting of daily item-store records. While some series exhibited

intermittent demand patterns, the dataset primarily featured dense, continuous observations with limited explicit missingness. Despite this, LightGBM-based ensembles outperformed deep learning models, including those developed by Amazon’s forecasting team [19]. On the other hand, recent findings from Zalando suggest that transformer-based models exhibit scaling laws in retail forecasting: as the volume of training data increases, demand forecasting error decreases in a predictable manner [20]. These understandings motivate a closer investigation into the conditions under which different forecasting paradigms perform best.

Much of the recent deep learning success has been in large-scale online retail settings, where companies like Amazon [21] and Zalando [20] operate centralized warehouses and enjoy the benefits of aggregated demand and operational homogeneity. In contrast, brick-and-mortar (B&M) retail is far more fragmented: sales occur across thousands of physical stores, each with limited shelf space, store-level variability, and frequent changes in product assortment. These conditions lead to noisy, intermittent demand signals known to affect neural forecasting models [22, 23, 24, 25, 26].

In this study, we conducted a large-scale evaluation of forecasting models in the context of B&M retail, using real-world data from a major South-East Europe (SEE) retailer. The forecasting goal was to provide the best sales prediction possible for daily demand 365 days into the future for products in the hygiene product category based on their daily demand data. The retailer in this study operates on an annual planning cycle. Models deployed by the research team are benchmarked for their ability to handle operational realities of physical retail, including intermittent, missing, and product censorship due to assortment shifts and other changes in the retail environment. Our work builds on lessons from both academic literature and industrial benchmarks, including the Rossmann case study [27] and the M5 competition [18], and provides new insights into evaluation of model performance.

**Our main contributions are as follows:**

- We describe an end-to-end modeling pipeline for long-horizon retail forecasting.
- We provide empirical results comparing state-of-the-art forecasting models, including statistical, machine learning, and neural approaches, on a real-world, high-resolution B&M retail dataset.
- We highlight the limitations of neural models under operational constraints typical of physical retail and provide insights on how to improve forecasting accuracy in the B&M environment, offering practical guidance for academics studying performance of forecasting models in the retail environment as well as retail practitioners.

## 2 Dataset

### 2.1 Data analysis

The dataset includes daily retail sales information with multiple dimensions, including time, store characteristics, product attributes, prices, promotional activities, and inventory changes. Each observation represents a daily record for a specific product-store combination, making the dataset well-suited for longitudinal analysis across multiple hierarchical levels.

Each store is assigned a strategic zone, not geographically defined, but based on business strategy, which determines the price structure of products. Products themselves follow a two-level hierarchy: individual items are first organized into subcategories called “groups,” and within each group, related products are further clustered into units-of-need (UoNs). This ordering, groups first, then UoNs, enables precise, granular modeling and targeted price strategies.

Product metadata includes category, group, unit pricing (with and without tax), and cost of goods sold. Promotions are extensively captured through binary and count features indicating tactical promotions and various loyalty initiatives. Inventory data is tracked comprehensively, including physical stock levels, incoming shipments, and reserved or frozen quantities.

The daily time series in this dataset, as can be seen in Table 1, display highly irregular temporal patterns, with over 70% classified as intermittent and most of the remainder falling into lumpy or erratic categories, while smooth series are rare. This irregularity, combined with an average coverage ratio of 63% and 50% missingness in the training set, presents challenges for traditional forecasting methods. The series’ forecastability classification is done using the Syntetos-Boylan method [28]. The product sales of the company studied can be described by a dynamic environment with shifting demand, changes in competition, and differences in turnover across products resulting in dynamic impacts on sales, and assortment changes in the stores. For example, many product series are censored, observed for only part of the total time window, typically around six months, due to frequent product introductions and discontinuations. A typical example of a censored product would be seasonal items, such as decorative napkins for Easter or Christmas.

Classification	Total Count	Percentage (%)	Metric	Train	Valid
Erratic	2345	3.11	Series Count	70201	54454
Intermittent	52816	70.06	Global Average Missingness	0.50	0.30
Lumpy	17704	23.48	Global Average Coverage Ratio	0.63	0.82
No Demand	692	0.92	Eliminated/New Products Count	20933	5186
Smooth	1830	2.43	Eliminated/New Ratio	0.30	0.10
Table 1: Series Demand Classification			Series with More Than 730 Data Points	6966	—
			Imputed Series with More Than 730 Data Points	69442	—
			Table 2: Train vs Valid Series Statistics		

This limits historical visibility and can bias modeling efforts if not addressed a priori. Around 30% of products were eliminated during training and 10% are newly introduced in validation.

The dataset structure and challenges are comparable to those reported in major demand forecasting benchmarks such as the M5 Competition[18] or Rossman study case [27] and industry-specific datasets from companies like Zalando [20] and Amazon[21]. However, unlike some e-commerce datasets which benefit from smoother, denser demand signals, B&M retail environments such as the one studied here are more exposed to changes in consumer demand, localized promotions, and physical differences across stores, which further drive stability of consumer demand.

Together, these characteristics highlight the need for robust forecasting models that can handle intermittent demand, assortment volatility, and varying data coverage challenges common in real-world retail but often underrepresented in more sanitized datasets in academic research.

## 2.2 Data Preprocessing

To ensure high-quality inputs for forecasting, a structured data preprocessing pipeline was implemented, including enrichment, imputation, transformation, and formatting steps appropriately adjusted for time series models.

**Competitive and Macroeconomic Environment.** The point of sale store specific data was augmented with relevant competitive and macroeconomic indicator data. In order to control for the level of competition in the relevant geographic market, the count of competitors within a 1-kilometer radius and their prices for comparable items were added to the dataset. Further, macroeconomic environment variables from the National Statistical Office, such as Consumer Price Index (CPI), average salaries (national and regional), and population estimates within specific geographies, were included in order to control for the purchasing power and the size of the market.

**Handling Missing Values.** Basic imputation strategies were applied first, including forward and backward fills for time-continuous numeric variables, and mode imputation for categorical fields. These methods were chosen for fields with stable or slowly changing, predictable behavior. In addition, we conducted a separate experiment with a deep learning-based imputation model to assess its impact on downstream predicting accuracy. Specifically, we used the SAITS model [29], implemented via the PyPOTS library [30], to impute missing values in the training and validation sets. This approach aimed to restore temporal consistency in volatile variables and evaluate whether improved continuity would benefit model performance. Figure 1 illustrates a representative example of the imputation process, demonstrating how the applied methods restore temporal consistency in the data.

**Feature Engineering.** Several engineered features were introduced to enrich the temporal signal. Lag and rolling-window statistics for sales and promotional indicators were created to capture historical dynamics, particularly beneficial for models like XGBoost and LightGBM that treat each row independently. All nominal prices were converted into real prices using CPI, and relative pricing metrics were computed: one measuring the chain’s pricing advantage or disadvantage versus competitors (out-store metrics), and another capturing intra-store product positioning within the same UoN.

**Feature Selection.** Key variables used in the demand forecasting models predicted by the economic theory were retained. To reduce model complexity and improve generalization, we applied a filtering procedure on additional predictors based on feature importance. We used the Boruta algorithm [31] with LightGBM as the background model to identify and keep only features with proven predictive value. Features with excessive missingness, low variance, or multicollinearity were discarded to enhance efficiency and stability.

**Train-Validation Split.** A time-based cutoff was used to divide the dataset into training and validation periods. For ensemble models, we retained only series with observations in both periods, while for neural models, we further restricted to series having at least 730 training points.

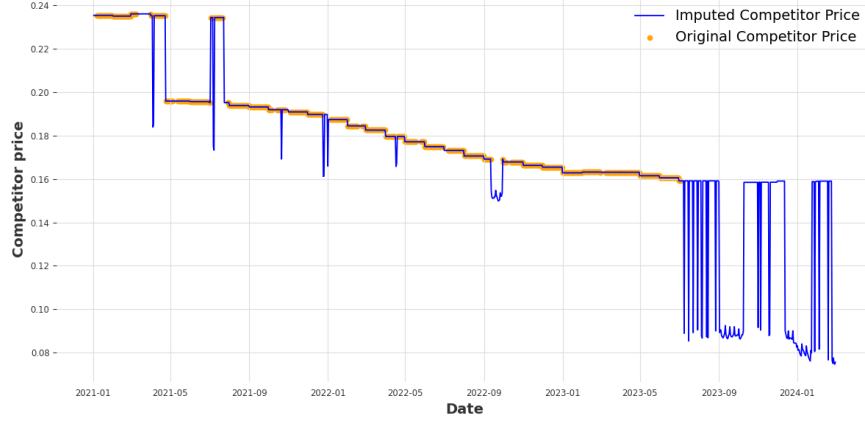


Figure 1: Competitor Price Feature Values Real and Imputed

**Categorical Encoding.** Categorical variables were encoded using the CatBoost encoder [32] from the package `category_encoders`.

**Final Time-Series Transformation.** For neural forecasting models, data was organized into time-series objects by grouping over product and store identifiers. For scalability sake, numerical fields were downcast to lighter data types to optimize memory usage during model training on large datasets.

### 3 Overview of Forecasting Models and Implementation

This study evaluates performance results of a range of forecasting models commonly applied in time-series prediction. These models include tree-based ensembles, neural networks, and classical statistical approaches. Although the theoretical foundations of these models are well-established in the literature, our emphasis lies on their implementation, training configurations, and evaluation setup tailored to the demands of long-term brick-and-mortar retail forecasting.

All neural network models were implemented using the Darts library, which supports modular time-series architectures and standardized training workflows. Each model was trained across four experimental setups: (1) training on each product group independently using nonimputed data; (2) training on each product group using imputed data; (3) training across all product groups jointly on nonimputed data; and (4) training jointly using the imputed dataset. This design allowed us to assess the impacts of imputation and group-level modeling on sales forecasting results.

To optimize model performance, a hyperparameter search was conducted using the HEBO algorithm [33], a scalable Bayesian optimization method. Due to computational constraints, hyperparameter tuning was conducted on a randomly sampled 10% subset of nonimputed data points for ensemble models, and on a random 10% subset of time series with at least 730 observations for neural models. This subset was chosen to be representative of the overall data distribution, ensuring that optimized hyperparameters would generalize between training setups that are group-specific and full-category. The feature set used for all experiments was restricted to the subset identified as relevant through Boruta feature selection.

The naive mean model is used as a benchmark. It predicts the mean of each series for items present in the training set, and the group-level mean for items not seen during training.

By standardizing the implementation pipeline across models and varying experimental conditions, this setup provides a robust empirical basis for comparing forecasting approaches in a B&M retail setting.

#### 3.1 Evaluation Metrics

In addition to standard evaluation metrics, we measured financial performance by computing demand error and bias [20] and WMAPE for both revenue and profit. True revenue was calculated as actual sales multiplied by the CPI-adjusted price, and true profit as actual sales multiplied by the unit margin (CPI-adjusted price minus cost of goods sold plus any rebate). Predicted revenue and profit were obtained by applying the same price and margin calculations to the model’s sales forecasts. The WMAPE itself was computed as the sum of absolute errors divided by the sum of true values, yielding separate error rates for revenue and profit.

For the group-level evaluation, we aggregated both true and predicted revenue and profit by store zone and product group. For the series-level evaluation, we performed an analogous process at the individual product level. True and predicted revenue and profit were summed for each unique product identifier, WMAPE was computed for each series, and the final series-level performance was reported as the average of all per-series WMAPE values.

For experiments involving imputed data, evaluation was performed exclusively on the original (non-imputed) validation data points to ensure a fair comparison across models.

All experiments were executed on a workstation equipped with an AMD Ryzen Threadripper PRO 7985WX 64-core CPU, 256 GB of RAM, and 2xNVIDIA RTX 4080 GPUs.

## 4 Results

Model	RMSSE	MASE	MSE	RMSE	MAE	R2	ME	MFB	Theils Bias	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias
<b>Case A: Individual Groups</b>															
LGBM	<b>0.758</b>	0.847	<b>2.073</b>	<b>1.440</b>	0.605	0.507	-0.024	-0.036	0.000	<b>0.069</b>	0.231	0.117	0.252	0.670	-0.018
NH	0.930	1.205	3.203	1.790	0.882	0.209	0.001	0.002	0.000	0.192	0.337	0.201	0.343	0.840	0.017
NB	0.951	1.230	3.350	1.830	0.900	0.172	0.009	0.010	0.000	0.221	0.377	0.226	0.382	0.860	0.030
TFT	0.952	1.250	3.354	1.831	0.915	0.171	-0.013	-0.015	0.000	0.194	0.364	0.214	0.391	0.845	<b>-0.001</b>
XGB	0.759	<b>0.837</b>	2.076	1.441	<b>0.597</b>	0.506	-0.054	-0.081	0.001	0.072	<b>0.215</b>	0.096	0.231	0.670	-0.067
<b>Case B: Whole Category</b>															
LGBM	0.773	0.877	2.156	1.468	0.626	<b>0.511</b>	-0.070	-0.100	0.002	0.096	0.220	0.086	0.231	<b>0.665</b>	-0.087
XGB	0.784	0.879	2.215	1.488	0.628	0.498	-0.080	-0.114	0.003	0.112	0.218	0.082	<b>0.230</b>	0.675	-0.104
NH	1.463	1.648	7.716	2.778	1.176	-0.323	-0.062	-0.080	0.000	0.935	1.316	1.118	1.646	1.102	0.017
NB	1.482	1.649	7.920	2.814	1.177	-0.358	-0.073	-0.093	0.001	0.907	1.326	1.075	1.653	1.112	-0.006
TFT	1.319	1.493	6.274	2.505	1.066	-0.076	-0.101	-0.131	0.002	0.797	1.078	0.917	1.313	0.990	-0.073
<b>Case C: Individual Groups, Imputed Train Data</b>															
LGBM	1.205	1.504	5.341	2.311	1.095	-0.242	0.424	0.619	0.034	0.928	1.259	1.140	1.408	1.093	-0.294
NH	0.876	0.896	2.823	1.680	0.652	-0.018	-0.181	-0.330	0.012	0.286	0.452	0.150	0.410	0.981	-0.294
NB	1.083	1.084	4.316	2.077	0.789	-0.004	-0.153	-0.223	0.005	0.210	0.422	<b>0.040</b>	0.400	0.963	-0.214
TFT	1.076	1.253	4.264	2.065	0.912	0.008	<b>-0.000</b>	<b>-0.000</b>	0.000	0.153	0.456	0.248	0.544	0.936	0.042
XGB	0.831	0.878	2.540	1.594	0.639	0.409	-0.128	-0.187	0.006	0.219	0.386	0.166	0.378	0.746	-0.214
<b>Case D: Whole Category, Imputed Train Data</b>															
LGBM	1.010	1.144	3.679	1.918	0.816	0.144	-0.033	-0.048	0.000	0.311	0.685	0.322	0.788	0.878	-0.082
XGB	0.847	0.884	2.588	1.609	0.631	0.398	-0.197	-0.288	0.015	0.335	0.428	0.280	0.419	0.752	-0.304
NH	1.026	1.074	3.795	1.948	0.767	0.117	-0.172	-0.251	0.008	0.325	0.566	0.262	0.577	0.905	-0.266
NB	1.031	1.039	3.829	1.957	0.742	0.110	-0.218	-0.319	0.012	0.333	0.566	0.242	0.567	0.908	-0.330
TFT	0.992	1.114	3.549	1.884	0.795	0.174	-0.019	-0.028	0.000	0.252	0.421	0.259	0.474	0.856	-0.037

Table 3: Summary Statistics. Abbreviations: TFT: Temporal Fusion Transformer; NH: NHITS; NB: NBEATS; LGBM: LightGBM; Best Results are Bolded and Second Best Underlined

We report both demand- and sales-based accuracy measures. The demand metrics follow standard forecasting practice, but our primary emphasis is on the sales metrics since accurate sales forecasts directly feed into the downstream pricing optimization.

In Table 3, the ensemble models, particularly LightGBM and XGBoost, exhibit strong performance in both individual-group raw data (Case A) and whole-category raw data (Case B) settings. When focusing on group-level evaluation metrics, specifically, group revenue and group profit WMAPE, which are critical for improved operational efficiency and financial results, ensemble methods demonstrate robust predictive capabilities. For example, in Case A, LightGBM achieves a group revenue WMAPE of 0.069 while XGBoost reports a competitive group profit WMAPE of 0.096. In the whole-category configuration (Case B), both LGBM and XGBoost maintain robust performance. Interestingly, an unexpected strong result is observed for NBEATS in the imputed individual-group setting (Case C), with a best-in-class group profit WMAPE of 0.040, though overall ensemble methods remain reliable across multiple metrics. These findings indicate that, depending on the metric prioritized by practitioners, ensemble models provide a reliable forecasting solution in both localized and aggregated settings.

For neural network-based models (including NBEATS, NHITS, and the Temporal Fusion Transformer), the use of imputed data (Cases C and D) makes a significant difference. These models exhibit marked improvements, with reduced error rates compared to their nonimputed counterparts. This indicates that the imputation process, by restoring temporal continuity and mitigating the impact of missing values, is especially beneficial for complex architectures that are more sensitive to noise. Despite these gains, the best overall forecasting performance remains with the ensemble methods using the individual-group configuration.

An additional observation comes from the analysis of the demand bias metric. Although the bias is slightly negative for most models, including NBEATS (WC, non-imputed data), indicating a general tendency to underestimate actual demand, the aggregated predictions for the whole category in Figure 2 reveal a mild positive bias. This apparent discrepancy can be explained by the distribution of products: while the model tends to underestimate demand for

higher-priced items, it tends to overestimate for lower-priced items, which are more prevalent in the dataset. As a result, the overall effect skews the aggregate predictions toward a positive bias, despite localized underpredictions for premium products. Government interventions in pricing may further contribute to this imbalance by introducing systematic shifts in demand behavior and distorting historical patterns the model relies on.

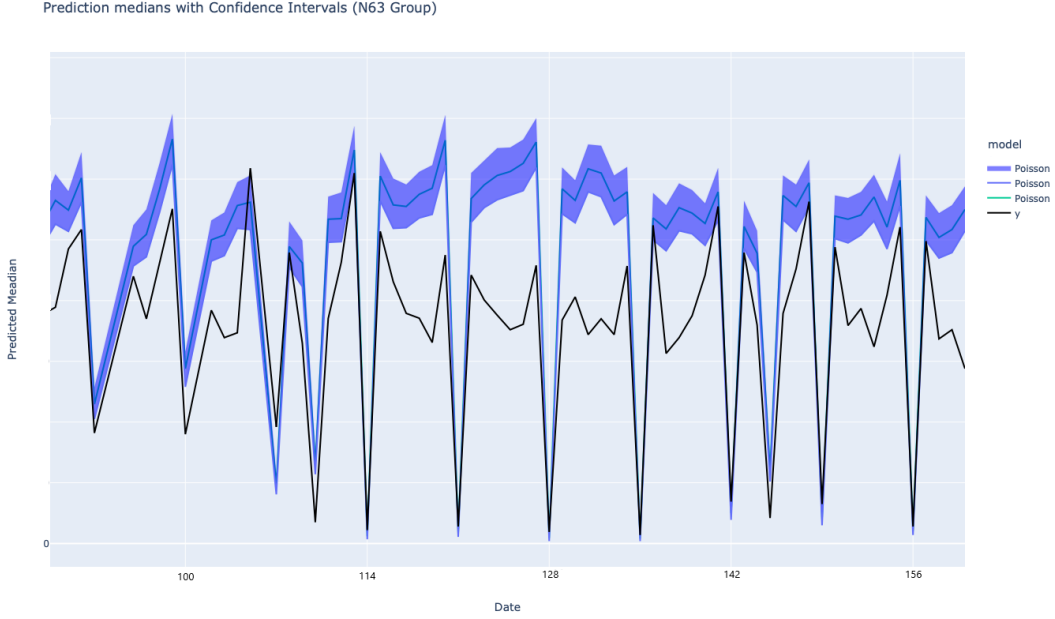
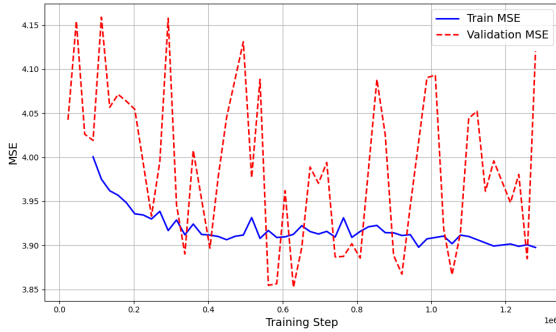
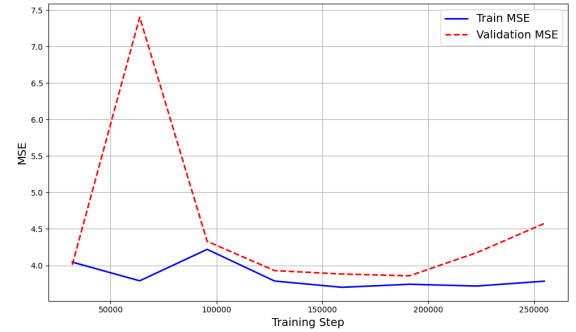


Figure 2: Prediction Medians with Confidence Intervals for NBEATS (WC, Non-Imputed Data) Model on N63 Group



(a) N-BEATS (WC, imp): Train vs. Validation MSE



(b) TFT (WC, raw): Train vs. Validation MSE

Figure 3: Comparison of Training and Validation MSE for N-BEATS and TFT models.

Beyond predictive accuracy, computational efficiency is another key factor used to evaluate forecasting models for practical use. Table 4 provides a detailed comparison of training times in the whole category setting for nonimputed and imputed data. The results make it evident that ensemble approaches, especially XGBoost, are highly efficient: they require considerably less memory and train much faster than neural network approaches. In contrast, neural models such as NBEATS and NHiTS demand significantly more resources, while the Temporal Fusion Transformer (TFT) incurs an even higher computational cost, particularly when trained on imputed data (which is expected since there are approximately ten times more training series for imputed data). For real-world applications where speed and accuracy matter, the lower computational footprint of the ensemble methods represents a clear advantage.

Model	Mean	Min	Max
NB (WC, imp)	171.555	171.555	171.555
NB (WC, raw)	15.818	15.818	15.818
NH (WC, imp)	114.340	114.340	114.340
NH (WC, raw)	10.000	9.986	10.014
TFT (WC, imp)	14678.233	14678.233	14678.233
TFT (WC, raw)	750.909	202.400	1299.418
LGBM (WC, imp)	35.566	31.047	42.010
LGBM (WC, raw)	11.237	7.383	15.533
XGBoost (WC, imp)	14.542	13.877	15.700
XGBoost (WC, raw)	6.191	5.486	8.041

Table 4: Training Time Statistics (in Minutes) Per epoch for neural networks, total for LGBM and XGB

## 5 Discussion

The preliminary findings presented in the Results section offer several important insights into retail sales forecasting using modern machine learning models. Notably, ensemble models such as LightGBM and XGBoost exhibit robust performance in both localized (individual-group) and aggregated (whole-category) configurations when using nonimputed data. These models consistently achieve lower error rates across multiple metrics, particularly in group revenue and group profit measures that are pivotal for pricing optimization, while also demonstrating a significant advantage in training time compared to more computationally intensive neural network approaches. This performance advantage aligns well with the broader literature on tabular data. For instance, Borisov et al. [14] highlight that despite the recent surge in deep learning innovations, gradient-boosted decision tree (GBDT) ensembles often remain the state-of-the-art for heterogeneous tabular data due to their robustness and lower sensitivity to data irregularities.

A key takeaway from our study is the importance of tailoring the modeling approach to the characteristics of the dataset. When data is segmented into individual groups and they do not share too much information between them, localized modeling can capture unique patterns more effectively. In contrast, training on the whole category does not introduce enough inter-group information to bring improvements, a phenomenon that resonates with the observations by McElfresh et al. [12], who note that differences in dataset properties, such as skewed feature distributions and irregularities, can diminish the relative advantage of complex neural network architectures over simpler, well-tuned tree-based methods.

Furthermore, experiments with imputed versus only processed data underscore the critical role of data quality and preprocessing. Deep neural networks, as discussed by Ramesh and Usman [13], tend to be more sensitive to inherent noise and missing values in tabular datasets. In our study, while imputation improved the performance of neural network models by restoring temporal continuity, ensemble methods on raw data still emerged as the best performers overall.

While recent work by Zalando [20] has demonstrated the presence of scaling laws for transformer-based models, where forecasting accuracy improves as training data size increases, such advantages were not observed in our experiments. This is likely due to the comparatively smaller scale of our dataset and the absence of centralized, high-density demand signals typical of e-commerce platforms. As a result, we did not observe a trade-off between computational cost and accuracy in favor of deep learning models. In our setting, ensemble methods remained both more efficient and more accurate, reinforcing their suitability for brick-and-mortar retail forecasting tasks characterized by fragmentation, intermittency, and limited historical coverage.

### Practical Implications.

The demonstrated effectiveness of localized modeling using LightGBM or XGBoost indicates that segmenting retail data into individual product groups can lead to significant improvements in forecast accuracy. Retailers can leverage these insights to optimize inventory management, streamline supply chain operations, and design targeted marketing strategies. Additionally, the superior computational efficiency of tree-based methods makes them particularly well suited for real-time or near-real-time forecasting scenarios where fast turnaround is critical.

### Limitations and Future Research.

Despite the promising results, several limitations of this study warrant discussion. One potential limitation is the reliance on aggregated error metrics, which, while informative, may obscure variability in model performance across different retail segments or temporal conditions. In addition, the experiments were conducted on datasets with specific characteristics, and the findings may not generalize to all types of retail environments, particularly those with extremely sparse or highly volatile data. Future research should investigate hybrid approaches that integrate the interpretability

and efficiency of tree-based models with the representation learning capabilities of neural networks. Additionally, further exploration into advanced data preprocessing techniques, such as more sophisticated imputation methods and feature transformation strategies, could help bridge the performance gap observed between nonimputed and imputed data experiments. Expanding the study to include a broader range of datasets and real-world retail scenarios would also provide deeper insights into the robustness and scalability of the proposed methods.

Overall, the findings suggest that for retail sales forecasting, leveraging a localized modeling strategy with robust, efficient algorithms such as LightGBM is advantageous. However, the debate between neural networks and boosted trees is not entirely one-sided. In scenarios where the dataset exhibits lower irregularity, neural networks might narrow the performance gap. These insights not only advance the state-of-the-art in retail sales forecasting but also provide a roadmap for future research and practical implementation in the retail sector.

## 6 Conclusion

This study underscores the critical importance of selecting a forecasting model that aligns with the unique challenges of brick-and-mortar retail environments. Our evaluation demonstrates that ensemble methods, particularly LightGBM and XGBoost, outperform complex neural network architectures in terms of both forecast accuracy and computational efficiency when applied to localized, individual-group data. The individual group approach enables models to more effectively adapt to unique group-specific dynamics, in contrast to combined data, where limited cross-group information sharing obscures critical nuances.

Although deep learning models have the potential to extract complex patterns from data, their sensitivity to data irregularities, such as missing values and noise, makes them less effective in environments characterized by high intermittency. Even with sophisticated imputation techniques like the SAITS model, the performance gains for neural networks remained limited. This can be attributed to the extensive amount of missing data in our setting, rather than a few isolated gaps, many series contain large contiguous sections of missing values. As a result, the imputed values introduce uncertainty that can overwhelm the underlying signal. Consequently, models trained on these imputed sequences may focus disproportionately on noisy reconstructions, further limiting their effectiveness compared to more robust ensemble methods.

The practical implications of our findings are significant. Retailers facing operational constraints can benefit from adopting a localized modeling strategy that leverages the strengths of tree-based ensembles, ensuring scalability, efficiency, and improved forecast accuracy. Moreover, the insights obtained from this work provide a valuable foundation for future research. Prospective studies should explore hybrid approaches that combine the robustness of tree-based models with the representational power of neural networks and investigate further enhancements in data preprocessing and imputation techniques.

In general, our work contributes to the evolving literature on forecasting in brick-and-mortar retail settings. It offers a systematic performance analysis of various forecasting models under realistic and dynamic conditions. In addition, it provides information for academics and practitioners to improve their accuracy of forecasts. Finally, it offers a robust foundation for broader advanced analytics workflows, enabling retail professionals to improve demand and pricing models, ultimately leading to more informed decision making and more beneficial business outcomes.



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## A Implementation Details

For neural networks, we kept time series only with more than 730 entries due to Darts restrictions. Since these long series also need to be continued, basic forward fill values were added and a mask was introduced to prevent training on these artificially filled points.

### A.1 Libraries

The implementation was done in Python 3.10 using a combination of standard and specialized libraries. Neural time series models were implemented with darts, while pypots handled data imputation. pandas, numpy, and scikit-learn were used for general data processing and modeling.

Feature selection was performed with Boruta, and categorical variables were encoded using CatBoostEncoder from the category\_encoders package. Gradient boosting models were trained with LightGBM and XGBoost. Hyperparameter optimization was conducted via Ray Tune with the HEBO search algorithm.

## B Experimental Results per Group

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.321	1.149	0.548	-0.218	0.137	0.375	0.120	0.354	1.044	-0.033	1.111	1.207	-0.009	-0.024	0.000
N56	2.128	1.459	0.771	-0.197	0.293	0.353	0.273	0.343	0.991	-0.295	1.337	1.636	-0.167	-0.264	0.013
N63	8.620	2.936	1.764	-0.029	0.244	0.439	0.269	0.435	0.866	0.241	0.907	1.387	0.467	0.257	0.025
N70	5.314	2.305	1.063	0.331	0.245	0.346	0.226	0.362	0.769	-0.247	0.764	0.783	-0.261	-0.229	0.013
N80	2.385	1.544	0.678	0.018	0.039	0.259	0.020	0.268	0.962	-0.039	1.005	1.144	-0.033	-0.064	0.000
N48	0.510	0.714	0.359	-0.813	0.216	0.350	0.284	0.379	1.273	0.215	1.112	1.308	0.043	0.207	0.004
N52	0.512	0.716	0.358	-0.546	0.122	0.299	0.101	0.288	1.145	-0.124	1.257	1.494	-0.030	-0.125	0.002
N57	1.683	1.297	0.790	-0.782	0.733	0.830	0.845	0.916	1.242	0.727	1.161	1.341	0.290	0.657	0.050
N64	26.020	5.101	3.124	0.170	0.067	0.142	0.028	0.176	0.719	-0.071	2.030	2.443	-0.441	-0.100	0.007
N74	4.994	2.235	1.319	0.236	0.119	0.259	0.085	0.246	0.790	-0.121	1.206	1.431	-0.146	-0.102	0.004
X15	0.351	0.593	0.216	-0.187	0.216	0.495	0.141	0.466	1.048	-0.204	1.076	1.391	-0.027	-0.189	0.002
N49	0.611	0.782	0.414	-0.763	0.128	0.288	0.183	0.314	1.221	0.125	0.969	1.038	0.026	0.103	0.001
N53	0.320	0.566	0.223	-0.551	0.192	0.478	0.264	0.502	1.254	0.191	1.086	1.236	0.007	0.054	0.000
N58	2.659	1.631	1.056	-0.334	0.325	0.491	0.368	0.519	1.002	0.320	1.080	1.195	0.257	0.310	0.025
N65	1.601	1.265	0.687	-0.256	0.401	0.441	0.348	0.398	1.000	-0.403	0.688	0.735	-0.220	-0.389	0.030
N76	1.809	1.345	0.756	-0.066	0.049	0.300	0.058	0.308	0.971	0.046	1.282	1.406	-0.036	-0.058	0.001
X16	1.460	1.208	0.638	-0.275	0.087	0.308	0.123	0.315	1.043	0.087	1.212	1.440	0.041	0.091	0.001
N54	0.774	0.880	0.543	-0.858	0.171	0.384	0.232	0.388	1.240	0.171	2.354	4.667	0.024	0.070	0.001
N62	4.802	2.191	1.469	-0.009	0.187	0.248	0.185	0.248	0.785	-0.160	0.906	0.981	-0.289	-0.165	0.017
N78	8.580	2.929	1.515	0.084	0.359	0.458	0.344	0.455	0.857	-0.362	1.893	1.959	-0.615	-0.391	0.044
USO	0.451	0.671	0.270	-0.599	0.178	0.683	0.151	0.678	1.236	0.177	1.449	2.372	0.015	0.108	0.001
X17	0.014	0.118	0.010	-1.112	1.855	2.696	-0.979	-2.780	1.631	1.729	0.100	0.029	0.004	1.364	0.001

Table 5: Results for nbeats (IG, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.321	1.149	0.548	-0.218	0.137	0.375	0.120	0.354	1.044	-0.033	1.093	1.187	-0.009	-0.024	0.000
N56	2.128	1.459	0.771	-0.197	0.293	0.353	0.273	0.343	0.991	-0.295	1.299	1.570	-0.167	-0.264	0.013
N63	8.620	2.936	1.764	-0.029	0.244	0.439	0.269	0.435	0.866	0.241	0.884	1.308	0.467	0.257	0.025
N70	5.314	2.305	1.063	0.331	0.245	0.346	0.226	0.362	0.769	-0.247	0.712	0.726	-0.261	-0.229	0.013
N80	2.385	1.544	0.678	0.018	0.039	0.259	0.020	0.268	0.962	-0.039	0.916	1.012	-0.033	-0.064	0.000
N48	0.510	0.714	0.359	-0.813	0.216	0.350	0.284	0.379	1.273	0.215	1.110	1.278	0.043	0.207	0.004
N52	0.512	0.716	0.358	-0.546	0.122	0.299	0.101	0.288	1.145	-0.124	1.228	1.428	-0.030	-0.125	0.002
N57	1.683	1.297	0.790	-0.782	0.733	0.830	0.845	0.916	1.242	0.727	1.146	1.318	0.290	0.657	0.050
N64	26.020	5.101	3.124	0.170	0.067	0.142	0.028	0.176	0.719	-0.071	1.959	2.323	-0.441	-0.100	0.007
N74	4.994	2.235	1.319	0.236	0.119	0.259	0.085	0.246	0.790	-0.121	1.110	1.278	-0.146	-0.102	0.004
X15	0.351	0.593	0.216	-0.187	0.216	0.495	0.141	0.466	1.048	-0.204	1.128	1.416	-0.027	-0.189	0.002
N49	0.611	0.782	0.414	-0.763	0.128	0.288	0.183	0.314	1.221	0.125	0.943	0.991	0.026	0.103	0.001
N53	0.320	0.566	0.223	-0.551	0.192	0.478	0.264	0.502	1.254	0.191	1.072	1.194	0.007	0.054	0.000
N58	2.659	1.631	1.056	-0.334	0.325	0.491	0.368	0.519	1.002	0.320	1.057	1.153	0.257	0.310	0.025
N65	1.601	1.265	0.687	-0.256	0.401	0.441	0.348	0.398	1.000	-0.403	0.649	0.674	-0.220	-0.389	0.030
N76	1.809	1.345	0.756	-0.066	0.049	0.300	0.058	0.308	0.971	0.046	1.261	1.368	-0.036	-0.058	0.001
X16	1.460	1.208	0.638	-0.275	0.087	0.308	0.123	0.315	1.043	0.087	1.197	1.421	0.041	0.091	0.001
N54	0.774	0.880	0.543	-0.858	0.171	0.384	0.232	0.388	1.240	0.171	2.297	4.444	0.024	0.070	0.001
N62	4.802	2.191	1.469	-0.009	0.187	0.248	0.185	0.248	0.785	-0.160	0.866	0.919	-0.289	-0.165	0.017
N78	8.580	2.929	1.515	0.084	0.359	0.458	0.344	0.455	0.857	-0.362	1.759	1.762	-0.615	-0.391	0.044
USO	0.451	0.671	0.270	-0.599	0.178	0.683	0.151	0.678	1.236	0.177	1.508	2.610	0.015	0.108	0.001
X17	0.014	0.118	0.010	-1.112	1.855	2.696	-0.979	-2.780	1.631	1.729	0.108	0.044	0.004	1.364	0.001

Table 6: Results for nbeats (IG, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.417	0.646	0.393	0.178	0.008	0.247	0.021	0.244	0.838	0.002	0.625	0.865	-0.000	-0.001	0.000
N51	0.465	0.682	0.311	0.043	0.100	0.350	0.074	0.352	0.942	-0.094	0.722	0.871	-0.017	-0.088	0.001
N56	0.553	0.744	0.343	0.115	0.316	0.378	0.310	0.376	0.896	-0.315	0.682	0.727	-0.082	-0.305	0.012
N63	9.293	3.048	1.583	0.443	0.049	0.238	0.203	0.314	0.671	0.052	0.941	1.244	0.137	0.069	0.002
N70	4.707	2.170	1.172	0.535	0.051	0.188	0.045	0.187	0.620	-0.050	0.719	0.864	-0.046	-0.030	0.000
N80	1.363	1.168	0.511	0.275	0.122	0.201	0.120	0.201	0.819	-0.121	0.759	0.861	-0.052	-0.117	0.002
N48	0.201	0.448	0.235	0.103	0.115	0.236	0.095	0.232	0.913	-0.114	0.697	0.857	-0.020	-0.125	0.002
N52	0.166	0.407	0.219	0.102	0.152	0.252	0.148	0.250	0.899	-0.150	0.716	0.914	-0.023	-0.156	0.003
N57	0.662	0.813	0.447	0.331	0.212	0.267	0.172	0.246	0.762	-0.211	0.728	0.758	-0.097	-0.231	0.014
N64	3.565	1.888	1.006	0.483	0.088	0.300	0.075	0.364	0.653	-0.077	0.751	0.786	-0.150	-0.118	0.006
N74	2.298	1.516	0.916	0.514	0.089	0.154	0.072	0.141	0.637	-0.089	0.818	0.993	-0.094	-0.082	0.004
N85	0.170	0.412	0.094	-0.108	0.076	0.523	0.069	0.519	1.045	0.086	0.891	1.002	0.004	0.082	0.000
X15	0.080	0.283	0.078	0.111	0.496	0.600	0.526	0.614	0.932	-0.488	0.514	0.505	-0.027	-0.479	0.009
N49	0.333	0.577	0.358	0.258	0.024	0.180	0.056	0.187	0.827	0.024	0.715	0.898	-0.006	-0.021	0.000
N53	0.111	0.333	0.140	0.094	0.037	0.298	0.031	0.302	0.933	-0.030	0.640	0.778	-0.007	-0.080	0.000
N58	0.994	0.997	0.646	0.331	0.256	0.287	0.265	0.303	0.729	-0.254	0.661	0.731	-0.166	-0.238	0.028
N65	3.604	1.898	1.006	0.350	0.230	0.295	0.198	0.275	0.754	-0.230	1.032	1.075	-0.230	-0.211	0.015
N76	0.529	0.727	0.475	0.153	0.066	0.249	0.056	0.242	0.853	0.067	0.693	0.884	0.013	0.038	0.000
X16	0.860	0.927	0.409	0.143	0.116	0.226	0.112	0.229	0.879	-0.122	0.930	0.923	-0.046	-0.142	0.002
N50	0.075	0.274	0.105	0.013	0.085	0.375	0.113	0.382	0.979	0.075	0.665	0.882	0.007	0.127	0.001
N54	0.061	0.246	0.089	0.069	0.179	0.401	0.170	0.412	0.947	-0.178	0.658	0.766	-0.011	-0.201	0.002
N62	1.887	1.374	0.933	0.431	0.084	0.179	0.084	0.185	0.633	-0.005	0.568	0.623	-0.011	-0.009	0.000
N78	1.570	1.253	0.640	0.397	0.390	0.417	0.384	0.416	0.719	-0.389	0.810	0.828	-0.273	-0.388	0.048
USO	0.071	0.267	0.078	0.042	0.030	0.534	0.032	0.535	0.967	0.022	0.576	0.690	-0.000	-0.008	0.000
X17	0.025	0.157	0.018	-0.011	1.215	2.076	1.488	4.100	1.005	1.056	0.133	0.050	0.005	0.834	0.001

Table 7: Results for lgbm (IG, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.417	0.646	0.393	0.178	0.008	0.247	0.021	0.244	0.838	0.002	0.614	0.851	-0.000	-0.001	0.000
N51	0.465	0.682	0.311	0.043	0.100	0.350	0.074	0.352	0.942	-0.094	0.697	0.826	-0.017	-0.088	0.001
N56	0.553	0.744	0.343	0.115	0.316	0.378	0.310	0.376	0.896	-0.315	0.662	0.698	-0.082	-0.305	0.012
N63	9.293	3.048	1.583	0.443	0.049	0.238	0.203	0.314	0.671	0.052	0.917	1.173	0.137	0.069	0.002
N70	4.707	2.170	1.172	0.535	0.051	0.188	0.045	0.187	0.620	-0.050	0.670	0.801	-0.046	-0.030	0.000
N80	1.363	1.168	0.511	0.275	0.122	0.201	0.120	0.201	0.819	-0.121	0.692	0.761	-0.052	-0.117	0.002
USU	0.014	0.117	0.033	-0.174	1.620	2.287	1.544	2.233	1.074	1.634	0.233	0.333	0.015	1.674	0.017
N48	0.201	0.448	0.235	0.103	0.115	0.236	0.095	0.232	0.913	-0.114	0.696	0.837	-0.020	-0.125	0.002
N52	0.166	0.407	0.219	0.102	0.152	0.252	0.148	0.250	0.899	-0.150	0.699	0.873	-0.023	-0.156	0.003
N57	0.662	0.813	0.447	0.331	0.212	0.267	0.172	0.246	0.762	-0.211	0.719	0.745	-0.097	-0.231	0.014
N64	3.565	1.888	1.006	0.483	0.088	0.300	0.075	0.364	0.653	-0.077	0.725	0.748	-0.150	-0.118	0.006
N74	2.298	1.516	0.916	0.514	0.089	0.154	0.072	0.141	0.637	-0.089	0.753	0.887	-0.094	-0.082	0.004
N85	0.170	0.412	0.094	-0.108	0.076	0.523	0.069	0.519	1.045	0.086	0.886	0.982	0.004	0.082	0.000
X15	0.080	0.283	0.078	0.111	0.496	0.600	0.526	0.614	0.932	-0.488	0.539	0.514	-0.027	-0.479	0.009
N49	0.333	0.577	0.358	0.258	0.024	0.180	0.056	0.187	0.827	0.024	0.696	0.857	-0.006	-0.021	0.000
N53	0.111	0.333	0.140	0.094	0.037	0.298	0.031	0.302	0.933	-0.030	0.632	0.751	-0.007	-0.080	0.000
N58	0.994	0.997	0.646	0.331	0.256	0.287	0.265	0.303	0.729	-0.254	0.646	0.705	-0.166	-0.238	0.028
N65	3.604	1.898	1.006	0.350	0.230	0.295	0.198	0.275	0.754	-0.230	0.974	0.986	-0.230	-0.211	0.015
N76	0.529	0.727	0.475	0.153	0.066	0.249	0.056	0.242	0.853	0.067	0.682	0.860	0.013	0.038	0.000
USB	0.004	0.061	0.005	0.002	0.132	1.525	0.123	1.522	0.998	0.098	0.507	0.448	0.000	0.089	0.000
X16	0.860	0.927	0.409	0.143	0.116	0.226	0.112	0.229	0.879	-0.122	0.919	0.911	-0.046	-0.142	0.002
N50	0.075	0.274	0.105	0.013	0.085	0.375	0.113	0.382	0.979	0.075	0.702	0.947	0.007	0.127	0.001
N54	0.061	0.246	0.089	0.069	0.179	0.401	0.170	0.412	0.947	-0.178	0.642	0.729	-0.011	-0.201	0.002
N62	1.887	1.374	0.933	0.431	0.084	0.179	0.084	0.185	0.633	-0.005	0.543	0.583	-0.011	-0.009	0.000
N78	1.570	1.253	0.640	0.397	0.390	0.417	0.384	0.416	0.719	-0.389	0.752	0.745	-0.273	-0.388	0.048
USO	0.071	0.267	0.078	0.042	0.030	0.534	0.032	0.535	0.967	0.022	0.599	0.759	-0.000	-0.008	0.000
X17	0.025	0.157	0.018	-0.011	1.215	2.076	1.488	4.100	1.005	1.056	0.143	0.076	0.005	0.834	0.001

Table 8: Results for lgbm (IG, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.415	0.644	0.383	0.182	0.044	0.220	0.028	0.212	0.838	-0.044	0.623	0.843	-0.014	-0.051	0.000
N51	0.464	0.681	0.307	0.047	0.142	0.330	0.120	0.330	0.940	-0.140	0.720	0.859	-0.024	-0.120	0.001
N56	0.554	0.744	0.344	0.114	0.340	0.389	0.332	0.383	0.894	-0.339	0.682	0.729	-0.088	-0.329	0.014
N63	9.084	3.014	1.524	0.456	0.034	0.208	0.096	0.255	0.667	-0.031	0.931	1.198	-0.048	-0.024	0.000
N70	4.832	2.198	1.178	0.523	0.060	0.189	0.055	0.188	0.630	-0.059	0.729	0.868	-0.067	-0.043	0.001
N80	1.426	1.194	0.509	0.241	0.161	0.224	0.156	0.223	0.836	-0.160	0.777	0.859	-0.071	-0.159	0.004
N48	0.204	0.452	0.233	0.089	0.160	0.277	0.137	0.268	0.919	-0.160	0.703	0.849	-0.030	-0.189	0.004
N52	0.168	0.410	0.217	0.092	0.195	0.280	0.187	0.274	0.904	-0.194	0.720	0.909	-0.030	-0.202	0.005
N57	0.634	0.796	0.451	0.359	0.159	0.234	0.132	0.230	0.750	-0.158	0.712	0.765	-0.071	-0.170	0.008
N64	3.526	1.878	0.955	0.488	0.137	0.217	0.116	0.231	0.649	-0.136	0.747	0.747	-0.187	-0.147	0.010
N74	2.367	1.538	0.920	0.499	0.087	0.148	0.068	0.134	0.645	-0.086	0.830	0.997	-0.092	-0.080	0.004
N85	0.158	0.398	0.086	-0.034	0.198	0.556	0.208	0.559	1.010	-0.101	0.861	0.915	-0.005	-0.107	0.000
X15	0.082	0.286	0.082	0.089	0.440	0.601	0.444	0.592	0.940	-0.433	0.520	0.529	-0.025	-0.434	0.008
N49	0.334	0.578	0.360	0.255	0.019	0.174	0.052	0.182	0.829	0.020	0.717	0.903	-0.006	-0.022	0.000
N53	0.110	0.332	0.137	0.100	0.094	0.311	0.062	0.308	0.930	-0.092	0.638	0.760	-0.013	-0.153	0.002
N58	1.015	1.008	0.649	0.317	0.271	0.304	0.282	0.324	0.738	-0.270	0.668	0.734	-0.175	-0.251	0.030
N65	3.869	1.967	1.003	0.302	0.344	0.374	0.304	0.343	0.778	-0.344	1.070	1.072	-0.374	-0.343	0.036
N76	0.517	0.719	0.456	0.172	0.081	0.206	0.087	0.208	0.837	-0.081	0.685	0.848	-0.030	-0.085	0.002
X16	0.864	0.930	0.411	0.139	0.145	0.234	0.134	0.231	0.881	-0.148	0.933	0.927	-0.051	-0.159	0.003
N50	0.074	0.272	0.101	0.031	0.041	0.390	0.049	0.398	0.967	0.011	0.658	0.852	0.001	0.022	0.000
N54	0.061	0.246	0.087	0.066	0.241	0.432	0.214	0.433	0.949	-0.241	0.659	0.751	-0.014	-0.256	0.003
N62	1.908	1.381	0.931	0.424	0.048	0.179	0.048	0.186	0.636	-0.047	0.571	0.621	-0.058	-0.048	0.002
N78	1.629	1.276	0.647	0.375	0.410	0.436	0.403	0.433	0.733	-0.410	0.825	0.837	-0.285	-0.405	0.050
USO	0.072	0.268	0.079	0.035	0.066	0.494	0.071	0.493	0.971	0.008	0.578	0.698	-0.000	-0.007	0.000
X17	0.024	0.156	0.025	-0.003	1.849	2.612	2.952	5.632	0.999	1.622	0.133	0.069	0.012	1.859	0.006

Table 9: Results for xgboost (IG, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.415	0.644	0.383	0.182	0.044	0.220	0.028	0.212	0.838	-0.044	0.613	0.830	-0.014	-0.051	0.000
N51	0.464	0.681	0.307	0.047	0.142	0.330	0.120	0.330	0.940	-0.140	0.696	0.815	-0.024	-0.120	0.001
N56	0.554	0.744	0.344	0.114	0.340	0.389	0.332	0.383	0.894	-0.339	0.662	0.699	-0.088	-0.329	0.014
N63	9.084	3.014	1.524	0.456	0.034	0.208	0.096	0.255	0.667	-0.031	0.907	1.130	-0.048	-0.024	0.000
N70	4.832	2.198	1.178	0.523	0.060	0.189	0.055	0.188	0.630	-0.059	0.679	0.805	-0.067	-0.043	0.001
N80	1.426	1.194	0.509	0.241	0.161	0.224	0.156	0.223	0.836	-0.160	0.708	0.760	-0.071	-0.159	0.004
USU	0.012	0.107	0.027	0.008	1.017	1.671	0.970	1.646	0.994	1.024	0.214	0.278	0.009	1.038	0.008
N48	0.204	0.452	0.233	0.089	0.160	0.277	0.137	0.268	0.919	-0.160	0.702	0.829	-0.030	-0.189	0.004
N52	0.168	0.410	0.217	0.092	0.195	0.280	0.187	0.274	0.904	-0.194	0.703	0.869	-0.030	-0.202	0.005
N57	0.634	0.796	0.451	0.359	0.159	0.234	0.132	0.230	0.750	-0.158	0.703	0.752	-0.071	-0.170	0.008
N64	3.526	1.878	0.955	0.488	0.137	0.217	0.116	0.231	0.649	-0.136	0.721	0.710	-0.187	-0.147	0.010
N74	2.367	1.538	0.920	0.499	0.087	0.148	0.068	0.134	0.645	-0.086	0.764	0.891	-0.092	-0.080	0.004
N85	0.158	0.398	0.086	-0.034	0.198	0.556	0.208	0.559	1.010	-0.101	0.856	0.897	-0.005	-0.107	0.000
X15	0.082	0.286	0.082	0.089	0.440	0.601	0.444	0.592	0.940	-0.433	0.545	0.539	-0.025	-0.434	0.008
N49	0.334	0.578	0.360	0.255	0.019	0.174	0.052	0.182	0.829	0.020	0.697	0.862	-0.006	-0.022	0.000
N53	0.110	0.332	0.137	0.100	0.094	0.311	0.062	0.308	0.930	-0.092	0.629	0.734	-0.013	-0.153	0.002
N58	1.015	1.008	0.649	0.317	0.271	0.304	0.282	0.324	0.738	-0.270	0.653	0.709	-0.175	-0.251	0.030
N65	3.869	1.967	1.003	0.302	0.344	0.374	0.304	0.343	0.778	-0.344	1.009	0.984	-0.374	-0.343	0.036
N76	0.517	0.719	0.456	0.172	0.081	0.206	0.087	0.208	0.837	-0.081	0.674	0.825	-0.030	-0.085	0.002
USB	0.004	0.062	0.012	-0.021	3.332	3.968	3.333	3.970	1.010	3.318	0.513	1.151	0.008	3.352	0.016
X16	0.864	0.930	0.411	0.139	0.145	0.234	0.134	0.231	0.881	-0.148	0.921	0.915	-0.051	-0.159	0.003
N50	0.074	0.272	0.101	0.031	0.041	0.390	0.049	0.398	0.967	0.011	0.695	0.915	0.001	0.022	0.000
N54	0.061	0.246	0.087	0.066	0.241	0.432	0.214	0.433	0.949	-0.241	0.643	0.715	-0.014	-0.256	0.003
N62	1.908	1.381	0.931	0.424	0.048	0.179	0.048	0.186	0.636	-0.047	0.546	0.582	-0.058	-0.048	0.002
N78	1.629	1.276	0.647	0.375	0.410	0.436	0.403	0.433	0.733	-0.410	0.766	0.753	-0.285	-0.405	0.050
USO	0.072	0.268	0.079	0.035	0.066	0.494	0.071	0.493	0.971	0.008	0.601	0.768	-0.000	-0.007	0.000
X17	0.024	0.156	0.025	-0.003	1.849	2.612	2.952	5.632	0.999	1.622	0.142	0.104	0.012	1.859	0.006

Table 10: Results for xgboost (IG, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.197	1.094	0.487	-0.103	0.443	0.680	0.472	0.669	0.993	-0.444	1.058	1.072	-0.165	-0.455	0.023
N56	2.385	1.544	0.920	-0.341	0.150	0.433	0.195	0.461	1.050	0.144	1.415	1.951	0.084	0.132	0.003
N63	7.482	2.735	1.606	0.107	0.090	0.263	0.073	0.263	0.805	-0.082	0.845	1.262	-0.169	-0.093	0.004
N70	5.818	2.412	1.123	0.267	0.131	0.290	0.087	0.312	0.799	-0.121	0.800	0.827	-0.148	-0.129	0.004
N80	2.674	1.635	0.800	-0.101	0.324	0.484	0.365	0.521	1.017	0.327	1.064	1.348	0.128	0.248	0.006
N48	0.416	0.645	0.413	-0.479	0.576	0.705	0.693	0.786	1.145	0.576	1.004	1.505	0.111	0.538	0.029
N52	0.417	0.646	0.367	-0.260	0.166	0.580	0.160	0.590	1.037	-0.168	1.135	1.532	-0.044	-0.182	0.005
N57	1.372	1.171	0.759	-0.452	0.705	0.767	0.789	0.837	1.117	0.705	1.048	1.288	0.279	0.632	0.057
N64	39.219	6.262	4.236	-0.252	0.449	0.866	0.324	0.958	0.888	-0.452	2.492	3.313	-2.263	-0.511	0.131
N74	5.736	2.395	1.393	0.122	0.013	0.211	0.031	0.213	0.832	0.011	1.292	1.510	0.024	0.016	0.000
X15	0.382	0.618	0.300	-0.290	0.295	0.938	0.434	0.923	1.091	0.321	1.122	1.934	0.053	0.371	0.007
N49	0.487	0.698	0.456	-0.404	0.422	0.501	0.491	0.548	1.088	0.424	0.865	1.142	0.105	0.408	0.023
N53	0.292	0.541	0.296	-0.418	1.069	1.110	1.218	1.238	1.174	1.068	1.039	1.643	0.106	0.776	0.038
N58	2.054	1.433	0.944	-0.031	0.044	0.292	0.072	0.300	0.879	0.043	0.950	1.068	0.037	0.045	0.001
N65	1.491	1.221	0.640	-0.170	0.650	0.671	0.618	0.644	0.967	-0.652	0.664	0.684	-0.368	-0.651	0.091
N76	1.969	1.403	0.861	-0.161	0.424	0.555	0.427	0.571	0.998	0.422	1.337	1.601	0.184	0.298	0.017
X16	1.291	1.136	0.546	-0.128	0.550	0.658	0.530	0.650	0.979	-0.560	1.140	1.232	-0.246	-0.552	0.047
N54	0.503	0.709	0.427	-0.208	0.342	0.419	0.274	0.412	0.979	-0.342	1.898	3.673	-0.144	-0.410	0.041
N62	5.352	2.313	1.612	-0.125	0.212	0.268	0.217	0.273	0.829	-0.021	0.956	1.076	-0.050	-0.028	0.000
N78	7.727	2.780	1.546	0.175	0.159	0.411	0.134	0.424	0.816	-0.160	1.796	1.999	-0.306	-0.195	0.012
USO	0.506	0.712	0.427	-0.797	1.675	1.911	1.619	1.871	1.330	1.672	1.536	3.753	0.206	1.452	0.084
X17	0.013	0.114	0.046	-0.976	17.310	17.381	-8.348	-	1.558	16.403	0.097	0.128	0.040	12.804	0.121
									14.439						

Table 11: Results for tft (IG, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.197	1.094	0.487	-0.103	0.443	0.680	0.472	0.669	0.993	-0.444	1.040	1.055	-0.165	-0.455	0.023
N56	2.385	1.544	0.920	-0.341	0.150	0.433	0.195	0.461	1.050	0.144	1.375	1.872	0.084	0.132	0.003
N63	7.482	2.735	1.606	0.107	0.090	0.263	0.073	0.263	0.805	-0.082	0.823	1.190	-0.169	-0.093	0.004
N70	5.818	2.412	1.123	0.267	0.131	0.290	0.087	0.312	0.799	-0.121	0.745	0.767	-0.148	-0.129	0.004
N80	2.674	1.635	0.800	-0.101	0.324	0.484	0.365	0.521	1.017	0.327	0.970	1.193	0.128	0.248	0.006
N48	0.416	0.645	0.413	-0.479	0.576	0.705	0.693	0.786	1.145	0.576	1.002	1.470	0.111	0.538	0.029
N52	0.417	0.646	0.367	-0.260	0.166	0.580	0.160	0.590	1.037	-0.168	1.108	1.465	-0.044	-0.182	0.005
N57	1.372	1.171	0.759	-0.452	0.705	0.767	0.789	0.837	1.117	0.705	1.035	1.266	0.279	0.632	0.057
N64	39.219	6.262	4.236	-0.252	0.449	0.866	0.324	0.958	0.888	-0.452	2.406	3.150	-2.263	-0.511	0.131
N74	5.736	2.395	1.393	0.122	0.013	0.211	0.031	0.213	0.832	0.011	1.190	1.349	0.024	0.016	0.000
X15	0.382	0.618	0.300	-0.290	0.295	0.938	0.434	0.923	1.091	0.321	1.176	1.968	0.053	0.371	0.007
N49	0.487	0.698	0.456	-0.404	0.422	0.501	0.491	0.548	1.088	0.424	0.841	1.090	0.105	0.408	0.023
N53	0.292	0.541	0.296	-0.418	1.069	1.110	1.218	1.238	1.174	1.068	1.025	1.588	0.106	0.776	0.038
N58	2.054	1.433	0.944	-0.031	0.044	0.292	0.072	0.300	0.879	0.043	0.929	1.031	0.037	0.045	0.001
N65	1.491	1.221	0.640	-0.170	0.650	0.671	0.618	0.644	0.967	-0.652	0.626	0.627	-0.368	-0.651	0.091
N76	1.969	1.403	0.861	-0.161	0.424	0.555	0.427	0.571	0.998	0.422	1.315	1.557	0.184	0.298	0.017
X16	1.291	1.136	0.546	-0.128	0.550	0.658	0.530	0.650	0.979	-0.560	1.126	1.216	-0.246	-0.552	0.047
N54	0.503	0.709	0.427	-0.208	0.342	0.419	0.274	0.412	0.979	-0.342	1.852	3.497	-0.144	-0.410	0.041
N62	5.352	2.313	1.612	-0.125	0.212	0.268	0.217	0.273	0.829	-0.021	0.914	1.008	-0.050	-0.028	0.000
N78	7.727	2.780	1.546	0.175	0.159	0.411	0.134	0.424	0.816	-0.160	1.669	1.798	-0.306	-0.195	0.012
USO	0.506	0.712	0.427	-0.797	1.675	1.911	1.619	1.871	1.330	1.672	1.599	4.129	0.206	1.452	0.084
X17	0.013	0.114	0.046	-0.976	17.310	17.381	-8.348	-	1.558	16.403	0.104	0.192	0.040	12.804	0.121
									14.439						

Table 12: Results for tft (IG, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.308	1.144	0.534	-0.206	0.131	0.382	0.119	0.363	1.039	-0.090	1.106	1.175	-0.030	-0.084	0.001
N56	2.204	1.485	0.816	-0.240	0.134	0.297	0.109	0.294	1.008	-0.136	1.361	1.729	-0.065	-0.102	0.002
N63	7.657	2.767	1.658	0.086	0.181	0.337	0.211	0.338	0.820	0.178	0.854	1.303	0.314	0.172	0.013
N70	5.280	2.298	1.039	0.335	0.284	0.364	0.260	0.370	0.768	-0.286	0.762	0.765	-0.314	-0.275	0.019
N80	2.433	1.560	0.671	-0.001	0.089	0.289	0.063	0.297	0.969	-0.092	1.014	1.132	-0.067	-0.129	0.002
N48	0.530	0.728	0.373	-0.882	0.301	0.396	0.376	0.437	1.297	0.299	1.132	1.358	0.060	0.290	0.007
N52	0.544	0.738	0.378	-0.641	0.007	0.270	0.032	0.263	1.178	0.005	1.295	1.582	0.003	0.013	0.000
N57	1.480	1.217	0.722	-0.566	0.494	0.626	0.578	0.683	1.159	0.489	1.088	1.225	0.190	0.431	0.024
N64	24.745	4.974	3.207	0.210	0.001	0.203	0.128	0.289	0.702	-0.004	1.979	2.508	-0.221	-0.050	0.002
N74	4.898	2.213	1.318	0.250	0.056	0.213	0.035	0.200	0.784	-0.058	1.194	1.429	-0.047	-0.033	0.000
X15	0.391	0.626	0.259	-0.323	0.181	0.622	0.281	0.619	1.103	0.196	1.137	1.669	0.031	0.220	0.003
N49	0.607	0.779	0.416	-0.751	0.145	0.296	0.203	0.323	1.217	0.142	0.966	1.042	0.030	0.115	0.001
N53	0.324	0.569	0.228	-0.571	0.283	0.565	0.371	0.605	1.275	0.283	1.093	1.267	0.013	0.098	0.001
N58	2.660	1.631	1.069	-0.335	0.379	0.496	0.426	0.528	0.999	0.374	1.081	1.210	0.316	0.382	0.038
N65	1.593	1.262	0.680	-0.250	0.417	0.453	0.367	0.416	0.998	-0.419	0.686	0.727	-0.232	-0.409	0.034
N76	1.918	1.385	0.752	-0.130	0.093	0.276	0.095	0.288	0.981	-0.074	1.319	1.399	-0.059	-0.096	0.002
X16	1.619	1.272	0.706	-0.414	0.338	0.466	0.373	0.482	1.100	0.333	1.276	1.593	0.148	0.333	0.014
N54	0.616	0.785	0.433	-0.478	0.360	0.461	0.322	0.426	1.093	-0.360	2.099	3.723	-0.152	-0.435	0.038
N62	4.928	2.220	1.483	-0.035	0.189	0.279	0.185	0.278	0.795	-0.159	0.918	0.990	-0.287	-0.164	0.017
N78	7.762	2.786	1.441	0.172	0.326	0.381	0.315	0.378	0.817	-0.329	1.800	1.863	-0.551	-0.350	0.039
USO	0.457	0.676	0.278	-0.620	0.297	0.860	0.255	0.856	1.251	0.295	1.458	2.442	0.028	0.198	0.002
X17	0.011	0.105	0.007	-0.650	0.816	2.009	-0.365	-2.019	1.431	0.723	0.089	0.021	0.001	0.380	0.000

Table 13: Results for nhits (IG, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.308	1.144	0.534	-0.206	0.131	0.382	0.119	0.363	1.039	-0.090	1.087	1.156	-0.030	-0.084	0.001
N56	2.204	1.485	0.816	-0.240	0.134	0.297	0.109	0.294	1.008	-0.136	1.321	1.660	-0.065	-0.102	0.002
N63	7.657	2.767	1.658	0.086	0.181	0.337	0.211	0.338	0.820	0.178	0.833	1.229	0.314	0.172	0.013
N70	5.280	2.298	1.039	0.335	0.284	0.364	0.260	0.370	0.768	-0.286	0.710	0.710	-0.314	-0.275	0.019
N80	2.433	1.560	0.671	-0.001	0.089	0.289	0.063	0.297	0.969	-0.092	0.925	1.001	-0.067	-0.129	0.002
N48	0.530	0.728	0.373	-0.882	0.301	0.396	0.376	0.437	1.297	0.299	1.130	1.326	0.060	0.290	0.007
N52	0.544	0.738	0.378	-0.641	0.007	0.270	0.032	0.263	1.178	0.005	1.265	1.512	0.003	0.013	0.000
N57	1.480	1.217	0.722	-0.566	0.494	0.626	0.578	0.683	1.159	0.489	1.075	1.204	0.190	0.431	0.024
N64	24.745	4.974	3.207	0.210	0.001	0.203	0.128	0.289	0.702	-0.004	1.911	2.385	-0.221	-0.050	0.002
N74	4.898	2.213	1.318	0.250	0.056	0.213	0.035	0.200	0.784	-0.058	1.099	1.276	-0.047	-0.033	0.000
X15	0.391	0.626	0.259	-0.323	0.181	0.622	0.281	0.619	1.103	0.196	1.191	1.699	0.031	0.220	0.003
N49	0.607	0.779	0.416	-0.751	0.145	0.296	0.203	0.323	1.217	0.142	0.940	0.994	0.030	0.115	0.001
N53	0.324	0.569	0.228	-0.571	0.283	0.565	0.371	0.605	1.275	0.283	1.079	1.224	0.013	0.098	0.001
N58	2.660	1.631	1.069	-0.335	0.379	0.496	0.426	0.528	0.999	0.374	1.057	1.167	0.316	0.382	0.038
N65	1.593	1.262	0.680	-0.250	0.417	0.453	0.367	0.416	0.998	-0.419	0.648	0.667	-0.232	-0.409	0.034
N76	1.918	1.385	0.752	-0.130	0.093	0.276	0.095	0.288	0.981	-0.074	1.298	1.361	-0.059	-0.096	0.002
X16	1.619	1.272	0.706	-0.414	0.338	0.466	0.373	0.482	1.100	0.333	1.261	1.572	0.148	0.333	0.014
N54	0.616	0.785	0.433	-0.478	0.360	0.461	0.322	0.426	1.093	-0.360	2.048	3.545	-0.152	-0.435	0.038
N62	4.928	2.220	1.483	-0.035	0.189	0.279	0.185	0.278	0.795	-0.159	0.877	0.928	-0.287	-0.164	0.017
N78	7.762	2.786	1.441	0.172	0.326	0.381	0.315	0.378	0.817	-0.329	1.673	1.676	-0.551	-0.350	0.039
USO	0.457	0.676	0.278	-0.620	0.297	0.860	0.255	0.856	1.251	0.295	1.518	2.687	0.028	0.198	0.002
X17	0.011	0.105	0.007	-0.650	0.816	2.009	-0.365	-2.019	1.431	0.723	0.095	0.031	0.001	0.380	0.000

Table 14: Results for nhits (IG, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.658	0.811	0.377	-0.416	0.110	0.486	0.089	0.499	1.118	-0.111	0.785	0.830	-0.034	-0.132	0.002
N48	0.190	0.436	0.145	-0.616	0.454	0.740	0.458	0.758	1.210	-0.231	0.679	0.529	-0.005	-0.060	0.000
N49	5.915	2.432	1.229	0.143	0.158	0.487	0.061	0.602	0.847	-0.162	3.015	3.081	-0.275	-0.217	0.013
N50	1.818	1.348	0.524	0.006	0.280	0.396	0.266	0.396	0.961	-0.282	3.267	4.411	-0.130	-0.302	0.009
N51	0.313	0.560	0.225	-0.492	0.209	0.482	0.171	0.488	1.204	-0.210	0.592	0.630	-0.037	-0.251	0.004
N52	0.103	0.322	0.090	-0.656	0.108	0.718	0.092	0.733	1.286	-0.109	0.565	0.375	-0.010	-0.183	0.001
N53	4.492	2.120	1.005	0.105	0.388	0.459	0.350	0.432	0.895	-0.390	4.070	5.581	-0.441	-0.441	0.043
N54	0.283	0.532	0.162	-0.881	1.762	1.813	1.777	1.816	1.367	1.781	1.422	1.391	0.079	1.743	0.022
N56	0.593	0.770	0.373	-0.372	0.075	0.403	0.026	0.412	1.144	-0.077	0.706	0.791	-0.043	-0.158	0.003
N57	0.759	0.871	0.374	-0.287	0.186	0.474	0.169	0.467	1.078	-0.188	0.779	0.636	-0.040	-0.157	0.002
N58	8.599	2.932	1.451	0.133	0.353	0.527	0.305	0.527	0.859	-0.355	1.943	1.642	-0.508	-0.334	0.030
N62	0.145	0.381	0.107	-0.985	0.887	1.298	0.939	1.328	1.437	0.885	0.157	0.071	0.029	0.702	0.006
N63	0.160	0.399	0.129	-1.255	0.801	1.014	0.892	1.093	1.506	0.800	0.123	0.102	0.037	0.725	0.009
N64	1.177	1.085	0.519	-0.218	0.152	0.688	0.058	0.697	1.054	-0.154	0.432	0.406	-0.120	-0.295	0.012
N65	3.523	1.877	1.050	0.223	0.198	0.311	0.187	0.309	0.812	-0.201	1.021	1.122	-0.211	-0.189	0.013
N70	0.587	0.766	0.281	-0.241	0.292	0.475	0.274	0.476	1.074	-0.292	0.254	0.207	-0.049	-0.256	0.004
N74	1.808	1.344	0.781	-0.239	0.129	0.540	0.072	0.509	0.998	-0.132	0.725	0.847	-0.185	-0.272	0.019
N76	0.810	0.900	0.465	-0.335	0.154	0.316	0.146	0.316	1.067	-0.156	0.857	0.864	-0.052	-0.152	0.003
N78	0.158	0.397	0.112	-0.604	0.364	0.854	0.261	1.075	1.235	0.038	0.257	0.145	0.007	0.126	0.000
N80	0.305	0.552	0.237	-0.702	0.174	0.487	0.167	0.481	1.254	-0.016	0.359	0.399	-0.008	-0.058	0.000
N85	3.072	1.753	1.097	0.044	0.153	0.284	0.149	0.289	0.824	-0.127	3.793	11.723	-0.154	-0.132	0.008
USO	1.112	1.054	0.408	-0.139	0.284	0.475	0.280	0.483	1.029	-0.295	2.275	3.584	-0.108	-0.349	0.010
X15	16.315	4.039	1.957	-0.039	0.417	0.648	0.288	0.730	0.914	-0.420	7.338	12.623	-0.808	-0.421	0.040
X16	2.415	1.554	0.733	0.047	0.413	0.488	0.398	0.482	0.902	-0.415	1.559	1.654	-0.292	-0.424	0.035
X17	0.063	0.252	0.043	-1.510	2.987	3.747	4.991	7.701	1.506	2.718	0.214	0.119	0.029	4.133	0.013

Table 15: Results for nbeats (WC, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	2.601	1.613	0.787	-2.130	0.475	1.420	0.509	1.438	1.626	0.470	1.533	1.706	0.186	0.476	0.013
N48	0.894	0.945	0.499	-1.774	1.270	1.550	1.404	1.675	1.750	1.268	1.468	1.777	0.185	0.858	0.038
N49	4.617	2.149	1.006	-6.476	2.030	2.586	2.308	2.824	2.823	2.046	2.591	2.409	0.549	1.525	0.065
N50	3.410	1.847	0.921	-	20.587	21.152	22.860	23.372	6.918	20.569	4.726	8.320	0.862	20.179	0.218
N51	26.235	5.122	1.974	47.591	8.730	9.435	9.147	9.839	7.088	8.726	5.232	5.241	1.649	6.745	0.104
N52	0.736	0.858	0.450	40.295	1.620	1.883	1.670	1.933	1.921	1.620	1.471	1.796	0.221	1.437	0.066
N53	2.512	1.585	0.675	-2.910	8.872	9.128	9.508	9.727	5.488	8.865	3.003	3.625	0.517	4.685	0.106
N54	3.322	1.823	0.734	13.727	9.552	9.769	9.560	9.757	5.891	9.550	4.757	6.010	0.654	9.834	0.129
N56	1.693	1.301	0.653	-	0.411	0.968	0.425	1.003	1.209	0.220	1.158	1.329	0.080	0.213	0.004
N57	2.335	1.528	0.805	-0.628	0.181	0.986	0.178	1.078	1.219	0.075	1.350	1.344	-0.010	-0.018	0.000
N58	4.455	2.111	1.283	-0.661	0.584	1.111	0.541	1.287	1.255	0.019	1.368	1.401	-0.074	-0.080	0.001
N62	9.563	3.092	2.048	-0.867	0.598	0.792	0.597	0.801	0.957	-0.448	1.222	1.280	-0.922	-0.460	0.089
N63	40.563	6.369	3.018	-0.471	0.754	0.863	0.591	0.907	0.973	-0.755	1.917	2.238	-2.267	-0.750	0.127
N64	7.986	2.826	1.549	-0.197	0.354	1.656	1.259	2.388	1.459	0.303	1.085	1.152	0.047	0.051	0.000
N65	13.760	3.709	1.928	-1.211	0.156	1.164	0.117	1.176	1.123	-0.159	1.903	1.890	-0.913	-0.546	0.061
N70	15.646	3.956	1.895	-0.239	0.496	0.904	0.459	0.894	0.993	-0.498	1.222	1.295	-0.986	-0.566	0.062
N74	9.344	3.057	1.622	-0.197	0.104	0.999	0.128	0.992	1.173	-0.107	1.519	1.571	-0.229	-0.184	0.006
N76	3.816	1.953	1.041	-0.627	2.102	2.709	2.064	2.679	2.684	2.096	1.831	1.883	0.514	1.342	0.069
N78	9.642	3.105	1.617	-4.866	0.113	1.131	0.186	1.179	1.157	-0.118	1.864	1.881	-0.170	-0.150	0.003
N80	6.050	2.460	1.096	-0.600	0.271	1.100	0.349	1.082	1.135	-0.050	1.459	1.634	-0.055	-0.076	0.001
N85	0.114	0.338	0.088	-0.428	1.483	2.028	1.478	2.023	1.568	1.485	0.727	0.917	0.039	1.485	0.013
USB	2.107	1.451	0.745	-1.494	569.067	569.314	546.343	546.581	40.303	568.154	12.091	69.125	0.742	491.000	0.261
USO	1.805	1.343	0.600	1394.860	11.021	11.374	10.934	11.337	4.372	11.011	3.018	5.802	0.523	9.976	0.152
USU	1.234	1.111	0.401	-	58.961	59.208	57.036	57.360	11.610	57.767	2.213	4.095	0.392	55.287	0.124
X15	3.978	1.994	0.977	133.925	6.691	7.209	7.652	8.480	3.816	6.799	3.797	6.410	0.830	7.544	0.173
X16	4.327	2.080	0.897	-	0.706	1.335	0.634	1.401	1.221	0.187	2.061	1.998	0.089	0.173	0.002
X17	1.756	1.325	0.551	-0.590	183.177	183.399	-	-	16.442	151.207	1.206	2.314	0.545	124.693	0.169
				179.750			11861.120	14305.556							

Table 16: Results for nbeats (WC, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.702	0.838	0.509	-0.509	0.486	1.121	0.578	1.186	1.140	0.484	0.810	1.121	0.144	0.555	0.030
N48	0.326	0.571	0.286	-0.554	0.579	1.227	0.663	1.304	1.316	0.579	0.889	1.041	0.041	0.274	0.005
N49	0.540	0.735	0.421	-0.248	0.171	0.827	0.206	0.837	1.090	0.169	0.911	1.054	0.027	0.101	0.001
N50	0.229	0.478	0.228	-2.235	2.370	2.663	2.530	2.814	1.768	2.370	1.159	1.918	0.147	2.883	0.095
N51	0.625	0.791	0.402	-0.322	0.323	1.056	0.367	1.088	1.096	0.323	0.836	1.126	0.095	0.497	0.014
N52	0.275	0.524	0.288	-0.536	0.439	1.081	0.464	1.101	1.197	0.439	0.921	1.204	0.059	0.418	0.013
N53	0.228	0.478	0.220	-0.936	0.818	1.463	0.909	1.540	1.336	0.832	0.917	1.223	0.089	1.066	0.035
N54	0.298	0.546	0.306	-3.771	3.860	4.170	4.298	4.600	2.018	3.870	1.460	2.629	0.243	4.579	0.199
N56	0.864	0.930	0.465	-0.466	0.181	1.075	0.179	1.074	1.130	0.044	0.852	0.987	0.039	0.155	0.002
N57	0.941	0.970	0.551	0.026	0.376	0.665	0.317	0.668	0.931	0.108	0.868	0.936	0.064	0.157	0.004
N58	1.415	1.189	0.710	0.031	0.318	0.547	0.234	0.550	0.871	-0.320	0.788	0.804	-0.209	-0.308	0.031
N62	3.507	1.873	1.095	-0.092	0.619	0.662	0.630	0.668	0.876	-0.613	0.774	0.731	-0.718	-0.615	0.147
N63	13.986	3.740	1.845	0.110	0.256	0.538	0.181	0.595	0.853	-0.253	1.155	1.451	-0.475	-0.248	0.016
N64	5.493	2.344	1.209	0.204	0.170	0.516	0.158	0.657	0.820	-0.084	0.933	0.945	-0.180	-0.142	0.006
N65	4.240	2.059	1.081	0.156	0.047	0.652	0.102	0.661	0.879	-0.033	1.120	1.156	-0.200	-0.200	0.009
N70	9.812	3.132	1.741	0.011	0.259	0.706	0.222	0.726	0.899	-0.035	1.039	1.283	0.154	0.101	0.002
N74	3.728	1.931	1.016	0.178	0.388	0.503	0.389	0.500	0.815	-0.388	1.042	1.101	-0.466	-0.417	0.058
N76	0.619	0.787	0.434	-0.020	0.318	0.478	0.305	0.471	0.935	-0.320	0.749	0.806	-0.106	-0.314	0.018
N78	2.275	1.508	0.769	0.103	0.299	0.601	0.285	0.604	0.880	-0.302	0.975	0.994	-0.191	-0.278	0.016
N80	1.726	1.314	0.550	0.056	0.220	0.561	0.218	0.557	0.933	-0.221	0.855	0.927	-0.096	-0.223	0.005
N85	0.229	0.479	0.145	-0.525	1.349	1.718	1.344	1.709	1.225	1.350	1.036	1.554	0.061	1.351	0.016
USO	0.473	0.688	0.315	-5.485	5.172	5.547	4.777	5.190	2.479	5.173	1.485	2.772	0.250	5.991	0.133
X15	0.322	0.567	0.332	-2.276	3.361	3.796	3.111	5.671	1.678	3.411	1.030	2.139	0.248	4.364	0.191
X16	1.127	1.061	0.511	-0.154	0.016	0.773	0.093	0.816	1.009	0.034	1.065	1.153	0.060	0.193	0.003
X17	0.066	0.257	0.050	-1.615	7.194	8.262	10.122	15.212	1.920	6.658	0.218	0.140	0.037	5.292	0.021

Table 17: Results for lgbm (WC, imp)



Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.419	0.648	0.376	0.174	0.116	0.253	0.100	0.244	0.842	-0.115	0.616	0.814	-0.034	-0.123	0.003
N48	0.202	0.449	0.241	0.098	0.071	0.235	0.051	0.234	0.916	-0.055	0.698	0.857	-0.014	-0.090	0.001
N49	0.338	0.581	0.359	0.247	0.044	0.218	0.052	0.217	0.833	-0.033	0.701	0.860	-0.023	-0.081	0.002
N50	0.075	0.274	0.113	0.012	0.311	0.548	0.385	0.595	0.980	0.314	0.702	1.019	0.014	0.254	0.003
N51	0.463	0.680	0.298	0.049	0.218	0.323	0.196	0.315	0.939	-0.210	0.695	0.792	-0.042	-0.211	0.004
N52	0.167	0.409	0.221	0.095	0.144	0.254	0.134	0.246	0.902	-0.143	0.701	0.885	-0.023	-0.155	0.003
N53	0.112	0.334	0.151	0.087	0.155	0.480	0.214	0.499	0.940	0.157	0.634	0.809	0.001	0.017	0.000
N54	0.061	0.248	0.105	0.056	0.140	0.462	0.194	0.479	0.956	0.141	0.647	0.861	0.006	0.111	0.001
N56	0.553	0.744	0.354	0.115	0.277	0.359	0.271	0.355	0.892	-0.275	0.662	0.720	-0.073	-0.273	0.010
N57	0.628	0.793	0.461	0.365	0.110	0.249	0.080	0.244	0.748	-0.109	0.700	0.769	-0.061	-0.144	0.006
N58	0.970	0.985	0.647	0.348	0.199	0.239	0.196	0.245	0.718	-0.198	0.639	0.707	-0.124	-0.178	0.016
N62	2.010	1.418	0.901	0.393	0.236	0.257	0.238	0.261	0.653	-0.234	0.560	0.564	-0.282	-0.234	0.039
N63	8.935	2.989	1.494	0.465	0.083	0.217	0.042	0.249	0.662	-0.081	0.900	1.108	-0.156	-0.079	0.003
N64	3.238	1.799	0.939	0.530	0.094	0.158	0.052	0.167	0.623	-0.093	0.691	0.698	-0.137	-0.107	0.006
N65	3.312	1.820	1.012	0.402	0.100	0.195	0.078	0.187	0.729	-0.098	0.934	0.993	-0.097	-0.089	0.003
N70	4.838	2.200	1.165	0.523	0.067	0.184	0.060	0.180	0.627	-0.066	0.680	0.796	-0.098	-0.063	0.002
N74	2.351	1.533	0.909	0.502	0.149	0.189	0.130	0.174	0.643	-0.148	0.762	0.881	-0.156	-0.135	0.010
N76	0.518	0.720	0.446	0.170	0.144	0.222	0.142	0.220	0.837	-0.143	0.675	0.806	-0.055	-0.158	0.006
N78	1.538	1.240	0.658	0.409	0.302	0.344	0.294	0.342	0.710	-0.301	0.745	0.766	-0.219	-0.312	0.031
N80	1.419	1.191	0.517	0.245	0.132	0.223	0.122	0.224	0.834	-0.130	0.707	0.772	-0.064	-0.144	0.003
N85	0.153	0.391	0.089	0.001	0.048	0.412	0.050	0.412	0.992	-0.011	0.841	0.938	-0.001	-0.013	0.000
USO	0.074	0.271	0.090	0.009	0.329	0.682	0.337	0.685	0.985	0.330	0.609	0.873	0.011	0.249	0.002
X15	0.080	0.283	0.104	0.113	0.177	0.538	0.197	0.535	0.932	0.063	0.538	0.683	0.002	0.032	0.000
X16	0.847	0.920	0.425	0.156	0.093	0.233	0.078	0.228	0.873	-0.094	0.912	0.947	-0.030	-0.093	0.001
X17	0.025	0.159	0.027	-0.034	3.164	3.717	3.801	6.962	1.021	2.822	0.144	0.115	0.015	2.295	0.009

Table 18: Results for lgbm (WC, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.400	0.633	0.344	0.139	0.224	0.370	0.208	0.363	0.863	-0.224	0.632	0.859	-0.062	-0.238	0.010
N48	0.196	0.443	0.235	0.066	0.117	0.438	0.109	0.444	0.932	-0.037	0.808	1.133	-0.019	-0.128	0.002
N49	0.347	0.589	0.341	0.197	0.163	0.351	0.112	0.342	0.856	-0.163	0.751	0.960	-0.062	-0.229	0.011
N50	0.073	0.270	0.144	-0.030	1.146	1.342	1.285	1.462	1.002	1.149	0.789	1.556	0.051	1.006	0.036
N51	0.462	0.680	0.282	0.023	0.340	0.496	0.317	0.489	0.953	-0.329	0.932	1.196	-0.063	-0.331	0.009
N52	0.166	0.408	0.230	0.071	0.108	0.409	0.103	0.404	0.917	-0.046	0.791	1.063	-0.011	-0.080	0.001
N53	0.111	0.334	0.178	0.054	0.662	0.964	0.773	1.032	0.959	0.666	0.650	0.891	0.035	0.420	0.011
N54	0.062	0.248	0.134	0.012	0.798	1.120	0.939	1.210	0.978	0.800	0.613	0.872	0.039	0.725	0.024
N56	0.538	0.734	0.344	0.087	0.294	0.457	0.283	0.455	0.909	-0.295	0.839	1.084	-0.076	-0.298	0.011
N57	0.650	0.806	0.438	0.327	0.244	0.378	0.168	0.351	0.768	-0.244	0.956	1.231	-0.121	-0.297	0.023
N58	1.028	1.014	0.627	0.296	0.331	0.355	0.300	0.332	0.742	-0.331	1.036	1.615	-0.229	-0.337	0.051
N62	1.995	1.412	0.871	0.379	0.253	0.271	0.258	0.277	0.663	-0.250	0.842	1.176	-0.291	-0.249	0.043
N63	10.874	3.298	1.525	0.308	0.388	0.451	0.293	0.434	0.757	-0.386	1.119	1.932	-0.690	-0.360	0.044
N64	3.907	1.977	1.000	0.434	0.250	0.405	0.117	0.440	0.684	-0.248	1.008	1.386	-0.357	-0.281	0.033
N65	3.282	1.812	0.902	0.347	0.284	0.336	0.257	0.318	0.759	-0.283	1.294	1.697	-0.325	-0.325	0.032
N70	6.033	2.456	1.218	0.392	0.292	0.403	0.277	0.404	0.726	-0.290	1.001	1.648	-0.380	-0.250	0.024
N74	2.546	1.596	0.881	0.438	0.326	0.337	0.312	0.324	0.682	-0.325	1.000	1.330	-0.346	-0.310	0.047
N76	0.521	0.722	0.414	0.142	0.290	0.365	0.286	0.361	0.853	-0.290	0.771	0.995	-0.105	-0.311	0.021
N78	1.521	1.233	0.643	0.400	0.358	0.413	0.347	0.414	0.717	-0.357	0.950	1.229	-0.252	-0.366	0.042
N80	1.420	1.192	0.481	0.223	0.264	0.334	0.253	0.334	0.848	-0.264	0.985	1.177	-0.119	-0.277	0.010
N85	0.154	0.392	0.145	-0.023	1.339	1.517	1.344	1.517	1.005	1.348	1.035	2.034	0.060	1.328	0.024
USO	0.075	0.274	0.130	-0.031	1.446	1.654	1.460	1.673	1.008	1.446	0.730	1.294	0.053	1.277	0.038
X15	0.091	0.302	0.154	0.073	1.007	1.300	1.100	1.615	0.953	1.027	0.552	0.814	0.055	0.977	0.034
X16	0.847	0.920	0.388	0.132	0.297	0.405	0.291	0.407	0.887	-0.299	1.243	1.466	-0.096	-0.311	0.011
X17	0.037	0.192	0.115	-0.462	13.323	13.665	11.084	20.114	1.183	12.401	0.207	0.611	0.102	14.524	0.282

Table 19: Results for xgboost (WC, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.420	0.648	0.378	0.172	0.103	0.249	0.087	0.240	0.843	-0.103	0.616	0.819	-0.031	-0.112	0.002
N48	0.203	0.451	0.240	0.092	0.094	0.257	0.072	0.252	0.918	-0.084	0.700	0.853	-0.019	-0.121	0.002
N49	0.340	0.583	0.363	0.243	0.058	0.221	0.068	0.222	0.835	-0.011	0.703	0.869	-0.019	-0.066	0.001
N50	0.075	0.274	0.110	0.019	0.232	0.491	0.298	0.527	0.975	0.233	0.700	0.992	0.010	0.183	0.001
N51	0.462	0.679	0.298	0.051	0.223	0.298	0.203	0.288	0.938	-0.218	0.694	0.790	-0.042	-0.212	0.004
N52	0.169	0.411	0.218	0.085	0.197	0.284	0.184	0.274	0.907	-0.197	0.705	0.870	-0.031	-0.214	0.006
N53	0.112	0.335	0.147	0.082	0.084	0.463	0.142	0.477	0.941	0.086	0.635	0.788	-0.004	-0.050	0.000
N54	0.061	0.248	0.107	0.055	0.171	0.469	0.232	0.488	0.956	0.172	0.647	0.874	0.008	0.136	0.001
N56	0.555	0.745	0.358	0.112	0.260	0.343	0.252	0.339	0.893	-0.259	0.663	0.729	-0.068	-0.254	0.008
N57	0.644	0.802	0.460	0.349	0.133	0.260	0.106	0.249	0.755	-0.132	0.709	0.768	-0.071	-0.169	0.008
N58	0.973	0.987	0.645	0.346	0.206	0.231	0.205	0.236	0.719	-0.205	0.640	0.705	-0.131	-0.188	0.018
N62	2.029	1.424	0.915	0.388	0.145	0.200	0.142	0.200	0.655	-0.142	0.563	0.572	-0.176	-0.146	0.015
N63	9.210	3.035	1.493	0.448	0.109	0.214	0.001	0.246	0.673	-0.107	0.913	1.107	-0.221	-0.112	0.005
N64	3.279	1.811	0.926	0.524	0.106	0.147	0.086	0.154	0.626	-0.106	0.696	0.688	-0.144	-0.113	0.006
N65	3.338	1.827	0.994	0.398	0.149	0.199	0.127	0.186	0.730	-0.147	0.937	0.975	-0.159	-0.146	0.008
N70	4.985	2.233	1.174	0.508	0.078	0.181	0.076	0.178	0.639	-0.077	0.690	0.802	-0.092	-0.060	0.002
N74	2.454	1.566	0.909	0.481	0.187	0.212	0.170	0.198	0.654	-0.186	0.778	0.881	-0.207	-0.180	0.017
N76	0.520	0.721	0.450	0.167	0.110	0.201	0.108	0.199	0.839	-0.110	0.676	0.814	-0.045	-0.127	0.004
N78	1.567	1.252	0.662	0.399	0.300	0.340	0.291	0.338	0.716	-0.299	0.751	0.770	-0.218	-0.310	0.030
N80	1.466	1.211	0.518	0.220	0.158	0.239	0.147	0.239	0.847	-0.156	0.718	0.773	-0.076	-0.170	0.004
N85	0.153	0.391	0.101	-0.001	0.254	0.456	0.255	0.455	0.993	0.252	0.842	1.062	0.012	0.250	0.001
USO	0.074	0.271	0.091	0.010	0.330	0.640	0.335	0.643	0.985	0.329	0.609	0.878	0.011	0.256	0.002
X15	0.080	0.283	0.107	0.109	0.256	0.572	0.281	0.573	0.933	0.103	0.539	0.699	0.004	0.067	0.000
X16	0.852	0.923	0.427	0.151	0.077	0.217	0.057	0.211	0.876	-0.078	0.914	0.952	-0.027	-0.084	0.001
X17	0.026	0.161	0.045	-0.066	5.507	5.830	6.337	11.344	1.037	4.972	0.146	0.188	0.032	4.992	0.040

Table 20: Results for xgboost (WC, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.618	0.786	0.462	-0.329	0.407	0.575	0.442	0.593	1.077	0.406	0.760	1.017	0.101	0.390	0.017
N48	0.214	0.463	0.234	-0.819	1.414	1.458	1.541	1.573	1.308	1.432	0.721	0.851	0.104	1.244	0.050
N49	5.464	2.338	1.203	0.208	0.063	0.302	0.084	0.375	0.811	-0.064	2.898	3.016	-0.128	-0.101	0.003
N50	2.000	1.414	0.684	-0.094	0.387	0.494	0.410	0.517	1.011	0.388	3.427	5.753	0.146	0.340	0.011
N51	0.291	0.539	0.306	-0.386	0.758	0.815	0.840	0.892	1.178	0.758	0.571	0.856	0.079	0.531	0.021
N52	0.110	0.331	0.176	-0.758	1.809	1.850	1.966	1.992	1.300	1.812	0.582	0.735	0.093	1.743	0.078
N53	4.600	2.145	1.101	0.084	0.035	0.364	0.010	0.363	0.909	-0.034	4.118	6.115	-0.155	-0.155	0.005
N54	0.234	0.484	0.221	-0.557	3.146	3.192	3.157	3.199	1.242	3.168	1.294	1.901	0.142	3.124	0.086
N56	0.543	0.737	0.440	-0.255	0.467	0.579	0.582	0.658	1.086	0.468	0.675	0.934	0.081	0.299	0.012
N57	0.802	0.896	0.486	-0.360	0.521	0.616	0.550	0.634	1.108	0.521	0.801	0.825	0.131	0.517	0.022
N58	8.301	2.881	1.453	0.163	0.171	0.329	0.156	0.341	0.824	-0.171	1.909	1.644	-0.270	-0.178	0.009
N62	0.134	0.367	0.178	-0.842	2.655	2.659	2.637	2.644	1.333	2.655	0.152	0.119	0.107	2.569	0.086
N63	0.138	0.371	0.190	-0.947	2.219	2.253	2.364	2.395	1.406	2.226	0.115	0.149	0.105	2.050	0.079
N64	1.042	1.021	0.589	-0.079	0.339	0.547	0.535	0.677	0.994	0.340	0.406	0.460	0.085	0.210	0.007
N65	4.068	2.017	1.166	0.103	0.029	0.232	0.027	0.238	0.853	0.002	1.097	1.247	-0.006	-0.005	0.000
N70	0.711	0.843	0.444	-0.504	0.868	0.895	0.925	0.945	1.194	0.868	0.280	0.327	0.158	0.831	0.035
N74	1.816	1.348	0.873	-0.245	0.257	0.420	0.379	0.509	1.005	0.256	0.727	0.946	0.119	0.176	0.008
N76	0.816	0.903	0.552	-0.345	0.339	0.461	0.343	0.466	1.072	0.338	0.860	1.026	0.098	0.289	0.012
N78	0.160	0.400	0.184	-0.631	1.555	1.661	1.468	2.218	1.249	1.599	0.259	0.239	0.092	1.616	0.052
N80	0.264	0.514	0.303	-0.476	0.641	0.734	0.676	0.757	1.148	0.642	0.334	0.511	0.089	0.631	0.030
N85	3.691	1.921	1.248	-0.149	0.187	0.267	0.195	0.280	0.903	0.101	4.158	13.333	0.111	0.095	0.003
USO	1.131	1.063	0.519	-0.158	0.370	0.530	0.396	0.548	1.044	0.360	2.295	4.560	0.089	0.286	0.007
X15	14.146	3.761	1.843	0.099	0.212	0.391	0.083	0.414	0.846	-0.211	6.833	11.883	-0.405	-0.211	0.012
X16	2.257	1.502	0.815	0.110	0.102	0.308	0.101	0.321	0.873	-0.013	1.507	1.840	-0.023	-0.034	0.000
X17	0.044	0.209	0.078	-0.721	8.379	8.555	9.810	14.787	1.282	7.798	0.177	0.218	0.066	9.364	0.100

Table 21: Results for tft (WC, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	1.553	1.246	0.715	-0.869	0.410	1.103	0.438	1.111	1.254	0.409	1.185	1.550	0.161	0.411	0.017
N48	0.755	0.869	0.536	-1.342	1.626	1.722	1.779	1.870	1.598	1.629	1.349	1.906	0.248	1.154	0.082
N49	2.082	1.443	0.820	-2.371	1.517	1.846	1.796	2.079	1.912	1.528	1.740	1.961	0.383	1.065	0.071
N50	1.560	1.249	0.691	-	15.117	15.301	16.780	16.935	4.727	15.147	3.197	6.244	0.629	14.712	0.253
N51	4.200	2.049	1.042	-5.610	3.694	4.252	4.018	4.565	2.791	3.698	2.093	2.766	0.698	2.856	0.116
N52	0.574	0.758	0.484	-2.051	2.061	2.195	2.143	2.278	1.713	2.068	1.300	1.932	0.281	1.828	0.137
N53	1.389	1.179	0.571	-7.147	6.706	6.830	7.272	7.366	3.941	6.721	2.234	3.066	0.423	3.836	0.129
N54	1.498	1.224	0.575	-	7.744	7.775	8.083	8.112	4.021	7.758	3.195	4.712	0.499	7.508	0.166
N56	1.552	1.246	0.699	-0.493	0.499	0.996	0.566	1.048	1.151	0.500	1.109	1.423	0.178	0.476	0.020
N57	1.800	1.341	0.784	-0.280	0.174	0.827	0.273	0.909	1.052	0.170	1.185	1.308	0.041	0.074	0.001
N58	3.621	1.903	1.209	-0.517	0.562	0.932	0.542	1.072	1.123	0.047	1.234	1.320	-0.036	-0.039	0.000
N62	8.083	2.843	1.924	-0.244	0.500	0.637	0.500	0.644	0.880	-0.377	1.123	1.203	-0.776	-0.388	0.075
N63	36.701	6.058	2.830	-0.083	0.693	0.769	0.529	0.788	0.928	-0.693	1.823	2.098	-2.077	-0.688	0.118
N64	5.169	2.274	1.291	-0.431	0.126	1.226	0.788	1.673	1.142	0.121	0.873	0.960	-0.056	-0.060	0.001
N65	11.987	3.462	1.824	-0.079	0.212	0.922	0.201	0.933	1.002	-0.196	1.776	1.789	-0.849	-0.508	0.060
N70	13.695	3.701	1.748	-0.047	0.516	0.748	0.477	0.738	0.920	-0.517	1.144	1.194	-0.975	-0.560	0.069
N74	7.191	2.682	1.426	-0.252	0.192	0.711	0.205	0.710	1.007	-0.192	1.332	1.382	-0.307	-0.247	0.013
N76	2.058	1.435	0.874	-2.165	1.351	1.719	1.370	1.749	1.349	1.345	1.581	0.388	1.013	0.073	0.073
N78	7.585	2.754	1.450	-0.258	0.199	0.872	0.139	0.893	1.023	-0.201	1.654	1.687	-0.265	-0.233	0.009
N80	5.035	2.244	1.026	-0.189	0.334	0.932	0.361	0.949	1.034	-0.056	1.331	1.531	-0.079	-0.109	0.001
N85	0.148	0.385	0.221	-2.232	6.796	6.796	6.785	6.785	1.785	6.812	0.828	2.312	0.177	6.812	0.212
USB	0.736	0.858	0.495	-	368.085	368.085	352.963	352.963	23.652	367.522	7.147	45.942	0.493	326.163	0.330
USO	1.032	1.016	0.522	-9.419	9.531	9.626	9.580	9.696	3.320	9.542	2.282	5.051	0.451	8.590	0.197
USU	1.291	1.136	0.520	-	77.192	77.407	74.160	74.433	11.750	76.372	2.263	5.307	0.516	72.810	0.206
X15	2.025	1.423	0.789	-8.167	5.269	5.643	5.769	6.514	2.808	5.442	2.709	5.180	0.643	5.842	0.204
X16	3.558	1.886	0.853	-0.307	0.725	1.154	0.675	1.193	1.121	0.244	1.869	1.900	0.084	0.164	0.002
X17	0.798	0.894	0.355	-	114.069	114.137	-	-	11.383	94.735	0.813	1.488	0.348	79.652	0.152
				81.182			7759.075	9697.216							

Table 22: Results for tft (WC, org)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	0.695	0.834	0.406	-0.494	0.068	0.521	0.107	0.539	1.153	0.066	0.806	0.895	0.007	0.026	0.000
N48	0.249	0.499	0.192	-1.115	0.569	1.010	0.612	1.080	1.386	0.373	0.777	0.699	0.050	0.603	0.010
N49	5.803	2.409	1.278	0.159	0.056	0.487	0.292	0.684	0.848	-0.019	2.986	3.204	-0.118	-0.093	0.002
N50	1.857	1.363	0.571	-0.016	0.103	0.384	0.104	0.397	0.976	-0.081	3.302	4.804	-0.050	-0.116	0.001
N51	0.363	0.603	0.264	-0.731	0.280	0.677	0.359	0.731	1.352	0.279	0.638	0.738	0.008	0.053	0.000
N52	0.162	0.402	0.139	-1.591	0.820	1.186	0.974	1.277	1.577	0.820	0.707	0.580	0.044	0.819	0.012
N53	4.535	2.129	1.027	0.097	0.310	0.448	0.270	0.419	0.904	-0.312	4.089	5.705	-0.395	-0.395	0.034
N54	0.374	0.612	0.231	-1.489	3.335	3.353	3.350	3.364	1.572	3.358	1.636	1.986	0.150	3.311	0.060
N56	0.638	0.798	0.406	-0.475	0.152	0.481	0.253	0.515	1.206	0.149	0.732	0.862	-0.000	-0.001	0.000
N57	0.829	0.911	0.426	-0.406	0.134	0.492	0.144	0.496	1.131	0.117	0.815	0.724	0.031	0.123	0.001
N58	8.335	2.887	1.446	0.159	0.319	0.490	0.273	0.495	0.848	-0.321	1.913	1.637	-0.455	-0.299	0.025
N62	0.214	0.463	0.162	-1.937	2.524	2.734	2.602	2.798	1.780	2.521	0.191	0.108	0.088	2.108	0.036
N63	0.202	0.449	0.164	-1.848	1.699	1.816	1.844	1.957	1.731	1.699	0.139	0.129	0.074	1.454	0.027
N64	1.232	1.110	0.562	-0.275	0.060	0.728	0.326	0.787	1.089	0.057	0.442	0.440	-0.050	-0.123	0.002
N65	3.644	1.909	1.074	0.196	0.171	0.308	0.160	0.309	0.820	-0.174	1.038	1.148	-0.206	-0.185	0.012
N70	0.670	0.819	0.339	-0.417	0.119	0.519	0.151	0.542	1.152	0.114	0.271	0.250	0.025	0.132	0.001
N74	1.916	1.384	0.830	-0.313	0.101	0.607	0.324	0.643	1.050	0.097	0.747	0.901	-0.052	-0.076	0.001
N76	0.857	0.926	0.497	-0.414	0.040	0.350	0.040	0.350	1.105	-0.005	0.882	0.925	-0.010	-0.031	0.000
N78	0.199	0.447	0.145	-1.030	0.715	1.212	0.547	1.645	1.403	0.747	0.289	0.188	0.044	0.775	0.010
N80	0.372	0.610	0.286	-1.075	0.456	0.697	0.521	0.726	1.393	0.455	0.397	0.483	0.054	0.381	0.008
N85	3.068	1.751	1.109	0.045	0.167	0.259	0.164	0.265	0.824	-0.093	3.791	11.850	-0.115	-0.098	0.004
USO	1.178	1.085	0.471	-0.207	0.103	0.437	0.090	0.440	1.065	0.026	2.342	4.139	-0.007	-0.024	0.000
X15	15.966	3.996	1.930	-0.016	0.426	0.632	0.273	0.671	0.906	-0.429	7.259	12.445	-0.817	-0.426	0.042
X16	2.431	1.559	0.770	0.041	0.318	0.472	0.297	0.478	0.907	-0.320	1.564	1.738	-0.233	-0.338	0.022
X17	0.090	0.300	0.065	-2.568	5.235	5.871	7.111	10.978	1.747	4.826	0.255	0.181	0.052	7.339	0.030

Table 23: Results for nhits (WC, imp)

Group	MSE	RMSE	MAE	R2	Group Rev- enue WMAPE	Series Rev- enue WMAPE	Group Profit WMAPE	Series Profit WMAPE	Demand Error	Demand Bias	RMSSE	MASE	ME	MFB	Theils Bias
N47	2.433	1.560	0.792	-1.927	0.518	1.379	0.556	1.396	1.577	0.514	1.483	1.715	0.202	0.517	0.017
N48	0.842	0.918	0.505	-1.614	1.315	1.491	1.451	1.618	1.688	1.313	1.425	1.799	0.196	0.912	0.046
N49	4.218	2.054	1.000	-5.829	2.068	2.532	2.352	2.767	2.704	2.085	2.476	2.394	0.556	1.544	0.073
N50	3.179	1.783	0.899	-	20.084	20.505	22.293	22.674	6.692	20.071	4.563	8.127	0.841	19.668	0.222
N51	28.463	5.335	2.114	44.294	9.455	10.059	9.925	10.517	7.391	9.451	5.449	5.611	1.797	7.348	0.113
N52	0.706	0.840	0.450	43.802	1.673	1.837	1.742	1.902	1.892	1.673	1.441	1.796	0.227	1.475	0.073
N53	2.411	1.553	0.705	-2.749	9.317	9.480	10.002	10.131	5.331	9.309	2.943	3.782	0.554	5.019	0.127
N54	6.170	2.484	0.918	13.139	-	11.939	12.084	11.624	11.747	7.873	11.936	6.483	7.518	0.843	0.115
N56	1.650	1.284	0.658	74.741	0.374	0.915	0.386	0.953	1.193	0.265	1.143	1.339	0.093	0.248	0.005
N57	2.308	1.519	0.821	-0.586	0.187	0.978	0.251	1.061	1.205	0.125	1.342	1.370	0.013	0.023	0.000
N58	4.460	2.112	1.298	-0.642	0.555	1.111	0.511	1.295	1.259	0.056	1.369	1.418	-0.059	-0.063	0.001
N62	9.317	3.052	2.026	-0.869	0.621	0.799	0.618	0.807	0.945	-0.480	1.206	1.267	-0.986	-0.492	0.104
N63	40.107	6.333	2.992	-0.434	0.752	0.850	0.587	0.886	0.968	-0.753	1.906	2.218	-2.265	-0.750	0.128
N64	6.949	2.636	1.497	-0.183	0.314	1.546	1.177	2.206	1.347	0.271	1.013	1.113	0.030	0.033	0.000
N65	13.799	3.715	1.949	-0.924	0.131	1.161	0.091	1.171	1.118	-0.134	1.906	1.911	-0.884	-0.529	0.057
N70	15.098	3.886	1.861	-0.242	0.510	0.878	0.468	0.868	0.973	-0.512	1.201	1.271	-1.007	-0.578	0.067
N74	9.142	3.024	1.582	-0.155	0.140	0.938	0.155	0.936	1.145	-0.144	1.502	1.532	-0.251	-0.202	0.007
N76	3.642	1.908	1.108	-0.592	2.442	2.922	2.403	2.891	2.560	2.435	1.788	2.004	0.618	1.616	0.105
N78	9.149	3.025	1.590	-4.599	0.122	1.104	0.160	1.147	1.128	-0.127	1.816	1.849	-0.187	-0.165	0.004
N80	5.803	2.409	1.079	-0.518	0.267	1.043	0.340	1.024	1.111	-0.064	1.429	1.609	-0.069	-0.096	0.001
N85	0.205	0.453	0.158	-0.370	4.297	4.297	4.287	4.287	2.099	4.303	0.974	1.653	0.112	4.303	0.061
USB	1.337	1.156	0.616	-3.472	462.005	462.005	442.017	442.017	31.692	461.244	9.633	57.218	0.614	406.375	0.282
USO	1.473	1.214	0.588	884.964	-	10.739	11.004	10.685	10.996	3.938	10.731	2.727	0.513	9.774	0.178
USU	1.152	1.074	0.432	13.876	64.285	64.510	62.360	62.645	11.270	63.000	2.139	4.408	0.423	59.702	0.155
X15	3.632	1.906	0.998	125.032	-	7.042	7.460	7.898	8.715	3.716	7.179	3.628	6.550	7.805	0.203
X16	4.030	2.008	0.896	15.442	0.724	1.298	0.655	1.363	1.185	0.228	1.989	1.995	0.098	0.192	0.002
X17	1.848	1.359	0.606	-0.481	205.450	205.616	-	-	17.386	169.447	1.237	2.541	0.600	137.227	0.195
				189.218			12206.406	15635.463							

Table 24: Results for nhits (WC, org)