# Optimizing Sales Predictions in Superstore Retail: A Comparative Study of ARIMA and TBATS Models

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**Abstract.** Sales forecasting is a necessary tool for effective inventory management and strategic decision-making in retail. We explore the forecasting efficacy of two state-of-the-art time series models, Auto Regressive Integrated Moving Average (ARIMA) and Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components (TBATS), on real-world Superstore retail data. This dataset works like a replica to an existing store's data in the real world, allowing us to analyze what works best for them. Preprocessing steps were taken to handle inconsistencies. We fit ARIMA and TBATS models to this data and assess their performance with short and medium-term (metric-wise) forecasting using RMSE, MAE, and MAPE. This research is an attempt to pinpoint the pros and cons of both models over a range of prediction horizons and provide relevant guidance to those retailers with specific market requirements.

**Keywords:** Sales Prediction, ARIMA, TBATS, Forecasting models, Inventory Management

## 1 INTRODUCTION

The profits earned within the commerce domain is clearly noticeable in today's fast paced world. Yet, businesses and entrepreneurs must find ways to optimize sales with respect to the dynamic changes seen in the market today. Thus, to see growth and to sustain their revenue stream, it is pertinent to analyze and understand consumer needs and market demands. The Superstore sales dataset offers good information on sales volumes and profit margins. Accurate sales forecasting is necessary for strategic decision-making, helping retailers predict demand, optimize promotions, and adapt to market shifts. This project explores two forecasting methods, ARIMA and TBATS, analyzing their behaviors in Superstore retail operations. Understanding these models against benchmarked criteria can help retailers identify the significance of each to meet respective goals and market demands.

## 2 DATASET

In this study, the Superstore Sales dataset was used, which contains a total of 9,994 records. Each dataset entry has a Row ID, which is the unique identifier for the sales records. The dataset contains various attributes capturing multiple angles of the sales records. Few of the main features include the ID and Date of an order, and the Shipment Date and Mode, which provide insights into product delivery logistics.

It also records customer details, especially the ID and Name of the customer, and address details, providing a comprehensive sight of customer demographics and purchasing behavior. Data related to the Product is well-defined by fields such as ID, Category and Sub-Category, Name of the Product, and quantitative variables like Sales, Quantity, Discount, and Profit. This enables a more detailed review of product performance and profitability.

# 3 PROPOSED WORK

## 3.1 System Architecture

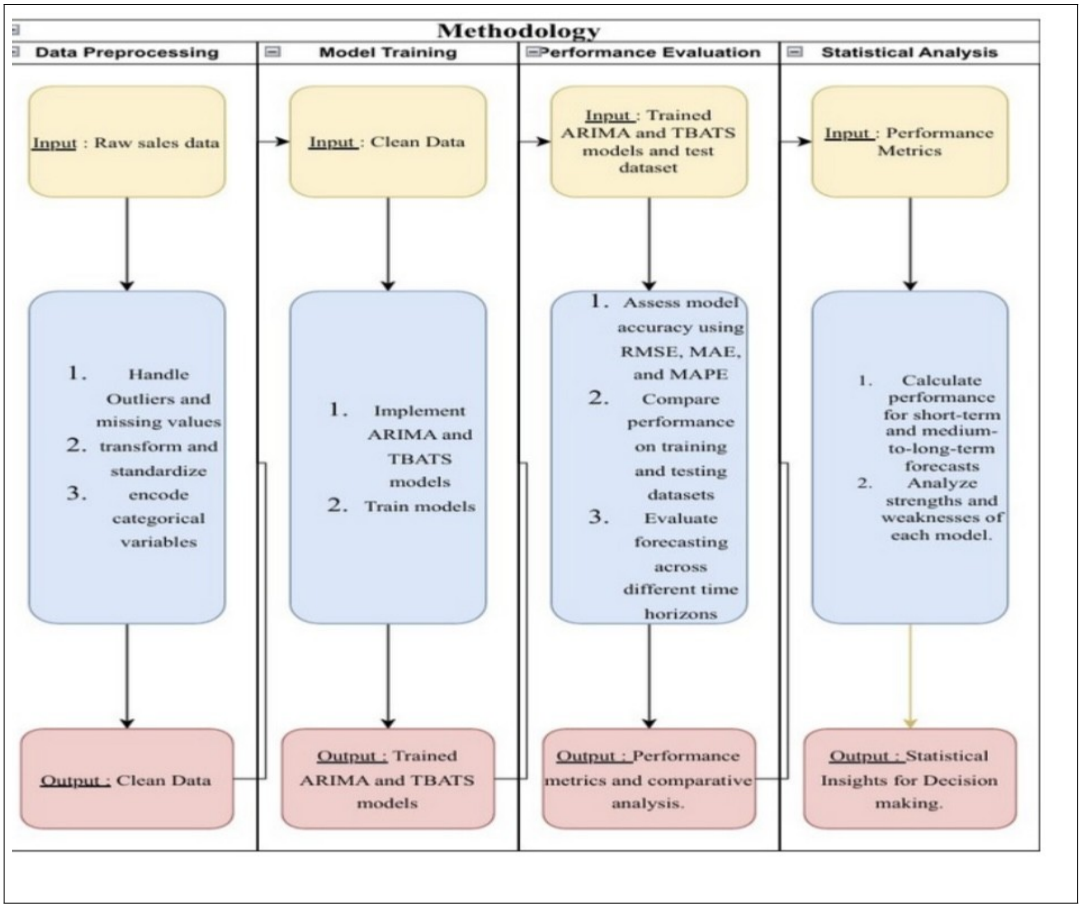



Fig. 1: System Architecture of the Proposed Framework

The framework has four stages: Data Preprocessing, Model Training, Performance Evaluation, and Statistical Analysis. Raw sales data is cleaned and transformed, followed by ARIMA and TBATS model training. Performance is assessed using RMSE, MAE, and MAPE across datasets and time periods. Statistical analysis will then establish each model’s strengths and weaknesses.

### 3.2 Workflow

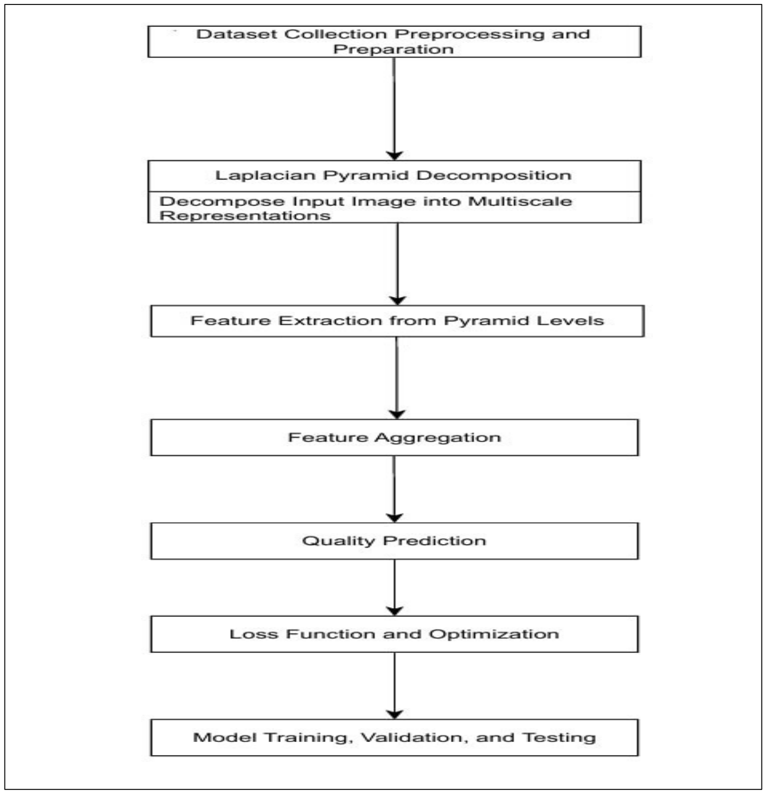
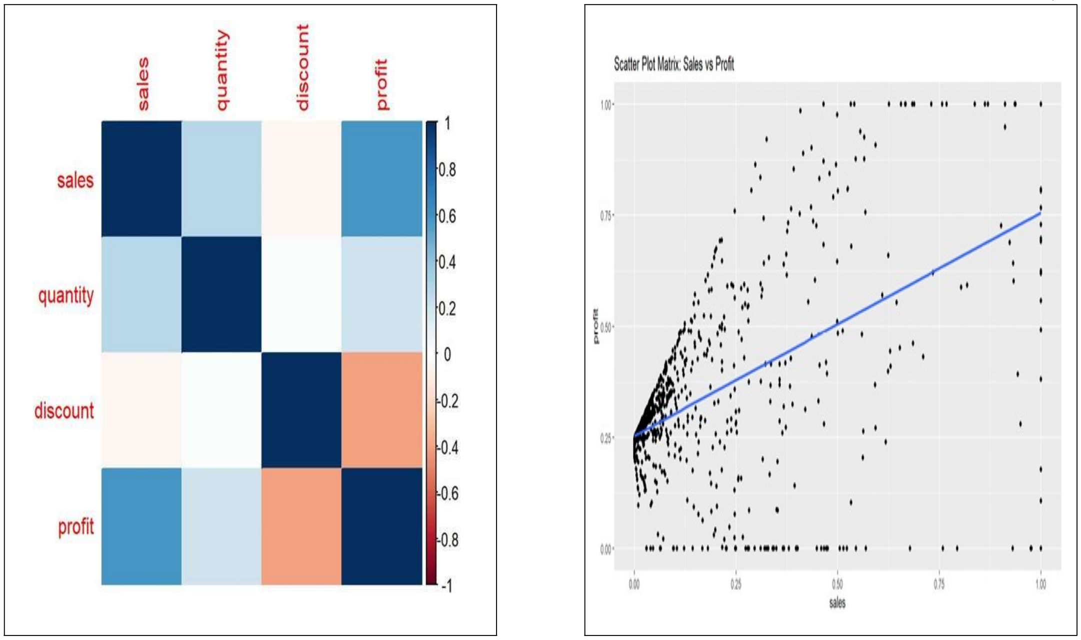



Fig. 2: System Architecture of the Proposed Framework

1. **Importing Libraries:** Main libraries used include **dplyr** for data manipulation, **forecast** for time series modelling, **tbats** for TBATS model implementation, and **ggplot2** for data visualization and metric evaluation (all packages are imported with respect to R studio).
2. **Loading the Data:** The SuperStore dataset is a publicly accessible retail store dataset from the United States. It is loaded in CSV format.
3. **Exploratory Data Analysis (EDA):** Exploring the Superstore Sales dataset involves examining its characteristics to get a better view of what we are dealing with and how to make sense of it. Using EDA, we plan to analyze data distributions, correlations, trends, and patterns, offering findings in sales patterns and customer approach.
4. **Data Preprocessing:** Data refining is an analytical step that requires careful attention to detail. It starts with organizing the data in an interpretable manner to make it easy.




(a) Heatmap

(b) Sales vs Profit

Fig. 3: Visualization of Data: Heatmap and Sales vs Profit Scatter Plot

This is followed by data cleansing, evaluating data validity and quality, and addressing noise such as values that are missing or extreme values that may cause disruption. “NaN” or “not a number” values are managed by imputing the average of a feature or using a unique placeholder value. Additionally, unrequired columns are removed to make the model training process simpler.

5. **Splitting the Data for Training the Models:** The preprocessed data is used for model training. The training set is further divided into two parts-70% for training the models and the other 30% is used for testing/evaluating the models.
6. **Data Standardization:** It is important for data to be in a standard form. The features are standardized in a machine-learning pipeline. The Standard Scaler, boasting a mean of zero and a standard deviation of one (unit variance), masterfully normalizes the data, ensuring a standardized distribution that is both precise and consistent. To standardize the data points, the following mathematical formula can be used:

$$z = \frac{(x - u)}{s} \quad (1)$$

7. **Model Building:** The preprocessed data is then used to build machine learning models. In this study, two models are employed (ARIMA and TBATS). These models are deployed and then studied to observe how these algorithms perform under standardized and unscaled data. The ARIMA model is used as a reference criterion to check if the TBATS's capability which incorporates seasonal and trend components, exceeds expectations.
8. **Model Evaluation:** Finally, the models are validated against various performance metrics. This study uses the below key metrics:
   - **Mean Squared Error (MSE):** This metric quantifies the quality of a model's prediction capability by measuring how closely it aligns with the truth values.
   - **Root Mean Squared Error (RMSE):** RMSE is used for gauging prediction errors. It gives greater weight to larger errors, offering a more specific measure of a model's performance.
   - **Mean Absolute Percentage Error (MAPE):** MAPE is used to check out how far off the predictions are on an average.

# 4 RESULTS

## 4.1 Sales Forecast

This section presents the forecast results obtained the next 30 days, starting after the given last date. The error rates for both models are listed in the table below:

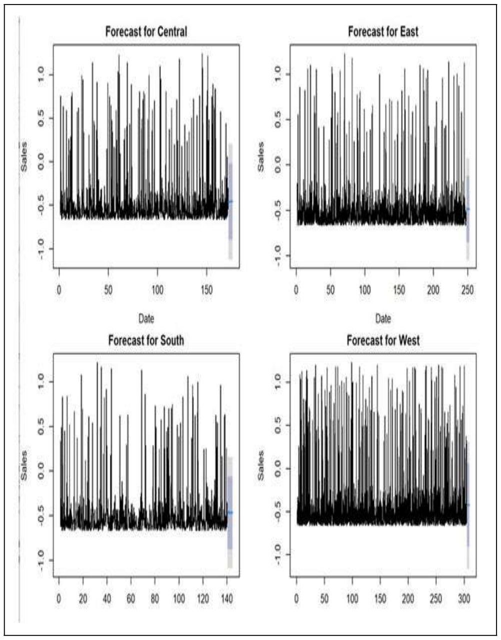
Table 1: Error Comparison

| Model | MSE | RMSE | MAPE |
|---|---|---|---|
| ARIMA | 0.12150 | 0.34857 | 42.0308 |
| TBATS | 0.12151 | 0.34858 | 42.0156 |

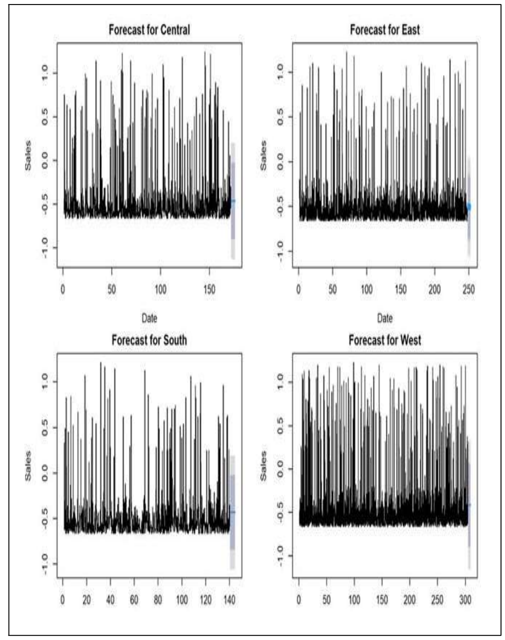
Both of them scored nearly indistinguishable on the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE) metrics. However, when looked at the Mean Absolute Percentage Error (MAPE), we observe a slight advantage in the case of the TBATS model, which recorded a MAPE of 42.01563 alongside to ARIMA's 42.03089. This difference implies that the TBATS model's forecasts, on average, are relatively closer to the actual sales values expressed as a percentage. This slight variation might be of a huge importance to businesses who severely depend on their forecasted values.

## 4.2 Forecast Performance Comparison

Here, we present the results obtained from our sales forecasting models using ARIMA and TBATS.




(a) ARIMA Region Forecast




(b) TBATS Region Forecast

Fig. 4: Comparison of Region Forecasts Using ARIMA and TBATS Models

1. **Training Performance Metrics**
   With a training RMSE of 0.0123, the ARIMA model shows a rather lower value than the TBATS model with an RMSE of 0.0126. Still, the two models' RMSE varies hardly at all. Likewise, both models show similar training MAE and MAPE values, so indicating similar accuracy in sales prediction on the training set. Consequently, training performance in the ARIMA and TBATS models is not much different.

Table 2: Training Performance Metrics

| Model | Training RMSE | Training MAE | Training MAPE |
|---|---|---|---|
| ARIMA | 0.0123 | 0.3342 | 0.1993 |
| TBATS | 0.0126 | 0.3343 | 0.2016 |

2. **Testing Performance Metrics**
   For testing data accuracy, the results for the ARIMA model is marginally preferred over the TBATS model. The ARIMA model is of higher quality TBATS model has RMSE approach 0.01229080, MAPE approach 0.1993290, TBATS RMSE approach 0.01264176, MAPE approach 0.2015699. On the other hand, RMSE and MAPE difference between two models is not statistically significant, thus means both models perform similarly on test set.

Table 3: Testing Data Metrics

| Model | RMSE | MAE | MAPE |
|---|---|---|---|
| ARIMA | 0.0122 | 0.3341 | 0.1993 |
| TBATS | 0.0126 | 0.3342 | 0.2015 |

3. **Short-Term Forecasting Performance Metrics**
   Both the ARIMA and TBATS models show stable forecasting performance in the short run, regardless of the forecast horizon. In terms of RMSE, the values of 1-day, 7-days, and 30-days forecasts using the two models are similar and seem accurate in capturing short term sales fluctuations. Third, the differences in RMSE between the ARIMA and TBATS models are small in all the forecast horizons.

Table 4: Short-Term Forecasting Performance Metrics

| Model | 1-Day Forecasting | 7-Day Forecasting | 30-Day Forecasting |
|---|---|---|---|
| ARIMA | -0.1038 | -0.1300 | -0.0783 |
| TBATS | -0.1031 | -0.1297 | -0.0779 |

4. **Medium to Long-Term Forecasting Performance Metrics**
   For the medium to long-term horizon forecasting of sales, ARIMA and TBATS models performed comparably. Having nearly identical RMSE values at 3-month, 6-month, and 1-year forecast intervals indicates that both models are able to capture trends and seasonality patterns quite well for longer time periods. In summary, the ARIMA and TBATS models perform comparably in predicting the future values of a time series, with no significant difference in forecasting accuracy until medium to long term horizons.

Table 5: Medium - Long Term Forecasting Performance Metrics

| Model | 3-Months | 6-Months Forecasting | 1-Year Forecasting |
|---|---|---|---|
| ARIMA | -0.1038 | -0.1300 | -0.0783 |
| TBATS | -0.1031 | -0.1297 | -0.0779 |

## 5 CONCLUSION AND FUTURE SCOPE

We conduct a comparison of TBATS and ARIMA models for anticipating sales in retail settings, in the presence of non-linear trends and strong seasonal variations. The two models performed quite similarly, with slight differences. In summary, both models are reasonable choices, and the selection depends on the trade-off between computational complexity, interpretability, and the characteristics of the data. Furthermore, integrating advanced models, such as machine learning algorithms, can enhance predictive capability. Dynamic model selection based on data characteristics could also be explored. Methods that accurately forecast and quantify uncertainty in real time would provide timely insights and enable evidence-based decision-making. Forecasting accuracy and operational efficiency can be improved by integrating optimization algorithms that support inventory management and long-term trend analysis.

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