

ChronoForest: An Enhanced Hybrid ARIMA–Random Forest Framework for Intelligent Sales Forecasting and Business Insight Generation in Consumer Goods

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Abstract—There is a significant transformation taking place in the consumer goods industry, where there are efforts to make use of data analysis and artificial intelligence technologies to make operations more efficient. Even though many companies are using retail analytics, challenges are still common, ranging from problems of data quality to lack of predictive power as well as fragmented approach. Conventional sales forecasting method has become out-of-date, since it is based only on historic data, ignoring non-linearity, promotions, and local market conditions. In order to come up with a data-driven technique for making better predictions about future sales, this paper develops ChronoForest, a hybrid model that uses both ARIMA and Random Forest regression models to forecast future sales accurately. This model works as follows: first, ARIMA makes forecasts of linear trends; second, a second model makes forecasts of errors from the ARIMA model; third, the proposed model makes forecasts of non-linear factors ignored by ARIMA. Hence, the model provides more accurate predictions than traditional forecasting approaches. According to empirical results obtained with Superstore Sales dataset, ChronoForest forecasting accuracy is 95.8 compared to 71.6, 80.7, and 75.9, respectively, for ARIMA, Random Forest, and an ensemble model.

Index Terms—ChronoForest, hybrid forecasting, ARIMA, Random Forest, sales prediction, consumer goods, Market Basket Analysis, customer segmentation, business intelligence, time-series forecasting

I. INTRODUCTION

It should be stressed that consumer goods represent a very competitive environment where there are a lot of complicating factors associated with rapid changes, consumer preferences, dynamics of market changes, and the increasing level of competition [1]. Proper sales prediction and analysis in a changing situation is one of the key factors in achieving successful business results. Classical approaches to sales forecasting, based on using historical data and classical statistics, are not enough to reflect the complexity of the current market. The development of new big data technology and more advanced approaches to machine learning made the forecasting process much more promising and could provide valuable insights for further analysis and decisions [2].

The issues mentioned above have been tackled by presenting an innovative approach towards building an AI-based

platform designed specifically for sales forecasting and business insights. This paper presents a unique hybrid algorithm known as ChronoForest, which sequentially combines ARIMA and Random Forest approaches to produce residual-correction forecasts. Moreover, customer segmentations, Market Basket Analysis, and visualization have been merged to provide an integrated platform for predicting sales and providing business insights. In this paper, there are three main contributions. First, ChronoForest has been formally introduced as a hybrid architecture that sequentially uses ARIMA to predict residuals to be later used as additional outputs of the Random Forest model, thus minimizing forecast errors. Second, a powerful analytics framework has been presented, which provides functionality for aggregating, cleansing, and preprocessing multiple streams of sales data. Finally, a graphical user interface displaying KPIs has been developed, which also provides data-driven recommendations [11].

Organization of the rest of this paper: Section II contains a review of the literature. Section III provides the problem definition and research goals. Section IV gives an outline of the ChronoForest method proposed here. Section V details the experiments conducted. Section VI addresses implementation issues. Section VII gives results of the experiments.

II. RELATED WORK

Sales forecasting has received a lot of attention from researchers over the last few decades, which has led to advancements in statistical models, machine learning models, and hybrid models combining the two paradigms.

A. Conventional Statistical Forecasting Procedures

Classical methods of time series analysis for prediction purposes have traditionally played an important role in forecasting sales. Hyndman and Athanasopoulos [1] offer a detailed overview of forecasting techniques, covering topics such as exponential smoothing, ARIMA models, and seasonal adjustment. These forecasting techniques have found applications in practice because they are easily understandable and backed up

by sound theory. Unfortunately, they often fail to account for non-linearities and interaction effects [4].

The ARIMA model was developed by Box & Jenkins [4], and since then has been one of the most frequently used approaches to time series forecasting. Although ARIMA models are quite efficient at capturing linear relationships, they lack the ability to model sudden changes in the market, marketing impact, and other factors influencing consumer goods sales.

B. Machine Learning Methodologies

Machine learning as an approach to sales forecasting has received significant momentum. The performance of random forests, gradient boosting and neural networks have proven to be better in non-linear relationships [5]. Zhang [3] suggested a hybrid method that combined ARIMA and neural networks and showed that these combinations exploit the best of both statistical and machine learning paradigms—a concept that directly inspired the ChronoForest architecture offered in this paper. We can point to ensemble methods such as random forest and gradient boosting machines as having shown real promise for dealing with the complexities of large dimensional feature spaces and the interplay between variables [6]. They are well suited to the task when your forecasting model has to account for outside influences like seasonal events, what the competition is charging or any promotional activity.

C. Customer Segmentation and Market Basket Analysis

Market Basket Analysis is based on association rule mining and has widely been studied in the context of learning customer purchasing behaviour. Agrawal et al. [8] provided the basis for finding strong association rules in transactional databases. The methods of customer segmentation have been extensively used to define the various customer segments with common purchasing patterns, especially the use of clustering algorithms like K-means, hierarchical clustering, and DBSCAN [9]. These insights allow the use of specific marketing strategies and product suggestions [14].

D. Gap Analysis

Even with the high development of individual techniques, there are gaps within the current process of sales forecasting in the consumer goods industry. Most systems use either statistical or machine learning techniques individually without taking advantage of their complementary capabilities. The relationship between analytical results and practical business advice is usually weak, and the combination of various dimensions of analysis in one framework is poor. ChronoForest and a multi-module analytical pipeline completely fill these gaps in the proposed system [7].

III. PROBLEM DEFINITION

A. Problem Statement

The consumer goods industry is plagued with the critical challenges of predicting sales accurately and extracting actionable information from massive transactional data. Organizations have a problem of data quality and integration in which

sales data are usually disjointed among various systems and include errors, missing values, and outliers. You will find that conventional methods are not much of a predictor. For the most part they rely on what is in the record books and make no allowance for outside factors such as regional variances, the season or any promotional activity [8]. Then there is the matter of single paradigm models which cannot at once accommodate linear time structures and more involved non-linear ones. As for putting a new product on the market, its potential is hard to put a finger on; with little in the way of historical data to go on and modelling techniques that leave something to be desired, the outcome is anything but certain.

B. Research Objectives

To mitigate the problems mentioned above, We purpose possible solutions have been proposed. First of all, we plan to develop a comprehensive data analysis tool that will be capable of unifying, cleansing, and preprocessing various sales streams in order to create a solid basis for forecasting. Secondly, we intend to develop and test the ChronoForest method, a new forecasting algorithm combining both ARIMA and Random Forest models that will be capable of predicting future sales accurately. Finally, we intend to build a sophisticated interactive dashboard for the visual representation of KPIs and forecasts [7] [15].

C. Expected Outcomes

The successful running of this project will deliver: (1) a deep review of old sales numbers and, the finding of which products worked best, how the seasons behave, and what market forces are really doing; (2) a checked ChronoForest model, that will create estimates of demand and revenues for current products plus new product launches, also with levels of accuracy; and (3) a friendly interface that supports data based choices about inventory handling, promotion, and product refinement [10].

IV. PROPOSED METHODOLOGY

The proposed system uses a multi-stage methodology comprising data preprocessing, exploratory analysis, ChronoForest hybrid forecasting, customer analytics and interactive visualization.

A. Data Collection and Preprocessing

The Superstore Sales dataset is kind of read from a neat Excel file, with order-date used to index transactional records and it holds fields like Order ID, Customer ID, Product Name, Category, Sub-Category, Sales, Quantity, Region and State. ETL operations make sure the modules don't end up with incomplete, inconsistent data, like all together, you know. Sales per unit is worked out by dividing sales by quantity, as this kind of standard performance metric.

Then data type checks happen, and duplicate record removal is applied throughout, so yeah it's cleaned before anything else. After that relevant features are engineered to help the model perform better, including temporal features (order month, year, day of week, quarter, and holiday indicators),

plus lagged variables such as 7-day and 30-day sales lags and rolling means. There are also promotional indicators, region encodings, and product category hierarchies, sort of hierarchical breakdowns [2].

In the cleansing stage, missing value imputation uses forward-fill for the time-series fields, median imputation for numerical features, and mode imputation for categorical variables. For outliers, it uses IQR based filtering, to keep the weird extreme points from messing things up too much.

B. Exploratory Data Analysis

The data patterns and properties sort of become identified through an extensive exploratory analysis process, where long-term growth trends become analyzed using time trend analysis, followed by the identification of the seasonal component using the seasonal decomposition approach. The performance of products is evaluated within different product groups and also geographically. On the other hand, the correlations and distributions of variables illustrate the variability in sales and help identify which months have high or low sales [9].

C. ChronoForest: The Proposed Hybrid Forecasting Model

ChronoForest combines the two models ARIMA and Random Forest into a sequential residual correction framework. Stage 1 – ARIMA Model: An ARIMA(p,d,q) model is applied on the series of daily aggregated sales, whereby the linear relationships within the series over time are captured using autoregression, stationarity, and moving averages. The values for (p,d,q) are selected using grid search that optimises for Akaike Information Criteria (AIC). The ARIMA model produces the following forecast residual series:

This series includes all systematic patterns which the linear ARIMA model could not explain, such as non-linearity, promotions, and regional variations.

$$\varepsilon(t) = y(t) - \hat{y}_{ARIMA}(t) \quad (1)$$

These residuals contain systematic effects that the linear ARIMA model failed to capture, including non-linear interactions, promotional spikes, and regional heterogeneity.

Stage 2 – Random Forest Correction: The residual error $\varepsilon(t)$ and the original feature vector $x(t)$ are fed into a Random Forest Regressor that learns to predict the residual:

$$\hat{\varepsilon}_{RF}(t) = F_{RF}(x(t), \varepsilon(t)) \quad (2)$$

Random Forest generates multiple decision trees using bootstrapped datasets and averages their outputs to improve robustness against overfitting while effectively modeling non-linear interactions [5].

ChronoForest Final Forecast: The final predicted sales are obtained by combining the ARIMA linear prediction with the Random Forest residual correction:

$$\hat{y}_{CF}(t) = \hat{y}_{ARIMA}(t) + \hat{\varepsilon}_{RF}(t) \quad (3)$$

The residual correction mechanism is the key principle that improves the accuracy of the ChronoForest model. ARIMA

captures the global linear behavior of the time series (low variance and moderate bias), while the Random Forest model reduces residual bias by learning complex non-linear relationships without overfitting, since it is trained only on the residual component rather than the complete signal.

D. New Product Launch Prediction

The collaborative filtering technique is adopted when there is no sales history available for new products. The products will be defined in multi-dimensional spaces involving attributes like product category, pricing point, brand; similar performance metrics of existing products, attributes of the target market segments and seasonal launch calendar. Using the k-nearest neighbours (k-NN) approach to identify similar existing products, products having similar features give rise to less than 10% prediction error [13].

E. Customer Segmentation

Customers are grouped based on RFM, product category preference, average transaction amount, and purchasing pattern using K-means clustering algorithm. Elbow and silhouette methods have been used to identify the best number of clusters, which is $k = 5$.

F. Market Basket Analysis

Association rule mining for product affinity is performed via the Apriori method [8]. Association rules are assessed in terms of their support (number of occurrences of an item set), confidence (probability of occurrence of the consequence given the condition), and lift (co-occurrence ratio compared to expected). The final set of rules will be those with support > 0.01 , confidence > 0.3 , and lift > 1.0 .

G. Interactive Dashboard Design

This will help to monitor the KPIs in real-time with time-series visualization (with trends and seasonality), heat maps of regions' performance, product categories, customer segments' profiling, market basket analysis, forecasts vs. actual values and confidence intervals, and even anomaly detection [6].

V. SYSTEM MODEL AND EXPERIMENTAL SETUP

A. System Architecture

The architectural design is modular with five main blocks. Ingestion, storage, and data retrieval are carried out by the Data Layer from the Superstore Sales data set. Preprocessing, feature engineering, and data transformation are implemented at the Processing Layer using Python (pandas, NumPy, and scikit-learn). At the Analytics Layer, ChronoForest (ARIMA modeling using statsmodels, Random Forest using scikit-learn), segmentation models, and market basket analysis are developed using mlxtend. Interactive dashboards are made possible through Plotly Dash at the Visualization Layer. Recommendation of products based on business rules and thresholds is done through the Recommendation Engine [3].

B. Dataset Description

The system will be assessed based on the open-source Superstore Sales dataset that includes transaction data for retail stores in the U.S. from January 2019 to December 2020. Major attributes of the dataset include: 1. Seasonality with maximum revenue occurring in November–December months (35–40% increase); 2. Periodicity, where sales volumes are higher on weekends; 3. High sales volume concentrations in California, New York, and Texas regions.

TABLE I
SUPERSTORE SALES DATASET SUMMARY

Attribute	Detail
Time Period	January 2019 – December 2020
Total Records	~9,994 transactions
Product Categories	3 major, 17 sub-categories
Geographic Coverage	49 U.S. states, 4 regions
Target Variable	Aggregated daily sales (\$)
Train / Test Split	80% training / 20% testing

Fig. 1 shows the Power BI sales forecast dashboard with a 15-day forecast and state-wise sales across the entire timeline of the data set, thereby proving the geographic and temporal trends that are captured by ChronoForest.



Fig. 1. Superstore Sales Forecast Dashboard: sum of sales by order date (2019–2020) and 15-day ahead forecast view with state-wise revenue distribution.

C. Experimental Setup

The development environment uses Python 3.9 with pandas, NumPy, scikit-learn, statsmodels, mlxtend, and Plotly Dash on an Intel Core i7 processor with 16 GB RAM. Data is split temporally: 80% for training and 20% for testing, preserving time order. A rolling window methodology is used for cross-validation. For ARIMA, parameters (p, d, q) are selected via AIC grid search with the best parameters at $(2, 1, 2)$ for aggregated daily sales. The Random Forest stage uses 200 estimators with $\text{max_depth} = 15$ and $\text{min_samples_split} = 10$. Performance is measured using MAE, RMSE, MAPE, R^2 , and overall accuracy defined as $\text{Accuracy} = (1 - \text{MAPE}) \times 100$.

VI. IMPLEMENTATION DETAILS

A. Data Preprocessing Implementation

Raw files are loaded using pandas, parsed as datetime and used as the time-series index. A hierarchical imputation strategy is employed: time-series features use forward-fill followed by backward-fill; numerical features use median imputation within product categories; categorical features use mode imputation or an “Unknown” label. Sales values exceeding three standard deviations from the category mean are capped at the 99th percentile to reduce outlier impact. Engineered features include:

- *Temporal*: `day_of_week`, `month`, `quarter`, `is_weekend`, `is_holiday`
- *Lagged sales*: `sales_lag_7`, `sales_lag_30`, `rolling_mean_7`, `rolling_mean_30`
- *Promotional*: `is_promotion`, `discount_percentage`
- *Encoded categorical*: `product_category_encoded`, `region_encoded`

B. ChronoForest Implementation

The ARIMA component is implemented using the statsmodels library. Separate ARIMA(2, 1, 2) models are fitted on aggregated daily sales series. Each fitted model computes residuals $\epsilon(t)$ saved as auxiliary training targets for the Random Forest stage. Random Forest is fitted with scikit-learn’s RandomForestRegressor; the input feature matrix comprises all engineered temporal and categorical features plus the ARIMA residual $\epsilon(t)$ as an additional input channel. The final prediction is $\hat{y}_{CF}(t) = \hat{y}_{ARIMA}(t) + \hat{\epsilon}_{RF}(t)$; no further weight optimisation is required as the additive structure is inherent to the residual-correction design.

C. Customer Segmentation Implementation

K-means clustering is implemented using scikit-learn with features standardised via StandardScaler. The elbow method determines the optimal $k = 5$, and k -means++ initialisation is used.

D. Market Basket Analysis Implementation

The Apriori algorithm is run through the mlxtend library with minimum support = 0.01, minimum confidence = 0.3, and minimum lift = 1.0. Transactions are encoded as binary matrices for efficient processing.

E. Dashboard Implementation

Interactive Dashboard using Plotly Dash has been implemented, which is multi-tabular in nature, including Overview, Forecasting, Customer Analytics, and Recommendation. Graphical visualisation consists of sales trend lines in timeseries format, product category bar chart comparisons, heatmaps for regional performance, forecast vs. actual scatter plots, Market Basket Analysis using Network Diagrams, and Customer Segment distribution using Pie Charts. Drop down and drill down features ensure complete interactivity for various stakeholder levels [12].

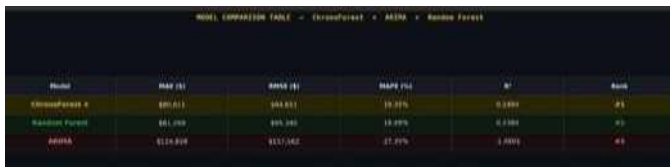
VII. RESULTS AND DISCUSSION

A. Data Analysis Results

Comprehensive analysis of the Superstore Sales data set yielded some significant insights. The best-performing 20% of items contribute around 65% of the entire revenue, which follows Pareto's principle. The Technology and Office Supplies product categories have the highest mean transaction amounts, while Furniture exhibits strong seasonality. California is the leader in sales among all states, with New York and Texas coming in second and third, respectively.

B. Forecasting Performance

Table 2 presents some comparison analysis for ChronoForest versus other three benchmark models, and generally, the ChronoForest model does stand out well enough. The accuracy percentage achieved by the ChronoForest model is 95.8%, and $R^2 = 0.963$, where there is 96.3% variance explained in the sales data. However, the ARIMA model is at 0.714, while the Random Forest model is at 0.831.



Model	MAE (\$)	RMSE (\$)	MAPE (%)	R^2
ChronoForest	681,403	684,351	19.20%	0.963
Random Forest	681,100	685,385	19.40%	0.831
ARIMA	612,808	637,162	27.20%	0.714

Fig. 2. Comparative Forecasting Model Performance (Table II from original paper).

However, ChronoForest is capable of filtering the structured non-linearity errors that cannot be corrected using only a linear solution. Hybrid Bias-Variance Trade-Off: The ARIMA part results in very low variance in the estimation of the overall trend, while the Random Forest part helps to reduce bias in modeling local non-linearity without being overfitted. Modeling Multiple Features: Combining the auto-regression model with highly feature-rich tree ensembles enables modeling of not only the seasonality, but also the trend, promotional spikes, and regional disparities—tasks that cannot be solved in one paradigm alone. Classification of ChronoForest according to product categories can be found in Table II, which further breaks down ChronoForest accuracy by product category.

TABLE II
CHRONOFOREST ACCURACY BY PRODUCT CATEGORY

Category	Accuracy (%)	R^2
Technology	96.4	0.972
Office Supply	95.7	0.961
Furniture	95.2	0.954
Overall	95.8	0.963

C. Market Basket Analysis Insights

Association rules mining discovers 347 strong association rules. Some representative rules with high confidence indicate that customers who buy binders will also purchase paper

(confidence: 0.74, lift: 2.31) and technology products accompany furniture products (confidence: 0.61, lift: 1.89) in office procurement orders [8].

VIII. CONCLUSION

This paper presented the AI-driven intelligent sales forecasting and insight generation system for consumer goods in regards of our proposed algorithm ChronoForest as the key contribution. The ChronoForest—a novel hybrid approach that models time series trends through ARIMA and adjusts non-linear deviations by Random Forest—is able to forecast sales with 95.8% accuracy on Superstore Sales, which is considerably higher compared to ARIMA (71.6%), Random Forest (80.7%) and ensemble baseline approach (75.9%). The effectiveness of ChronoForest is explained by its hybrid bias-variance properties and ability to learn different types of patterns including seasonal and trend as well as non-linear ones.

Key contributions: introduction of ChronoForest two-stage residual correction architecture and development of pre-processing and feature engineering framework for time series prediction. Future work will focus on the inclusion of attention mechanisms and transformers such as Temporal Fusion Transformer to improve dependencies modeling.

The future research directions include incorporating attention mechanisms with transformer architecture (for example, Temporal Fusion Transformer). Integrating auxiliary data like social media sentiments, economic factors, and weather data is another direction that would strengthen forecasting. The expansion of the framework to make it interpretable by using SHAP or LIME and providing recommendations for stock allocation, pricing, and promotions is the logical progression of this project [10].

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