

# Retail Sales Forecasting — Store-Level Demand Planning

## Executive Forecasting Assessment (M5 Dataset)

**Consultant-Grade Predictive Analytics Report (Retail Sector)**  
**Hybrid Project – Business Sector**

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### Executive Summary

This report presents a store-level retail sales forecasting assessment using historical Walmart sales data from the **M5 Forecasting Competition**. The objective was to evaluate how accurately **weekly sales demand** can be forecasted using different modeling approaches and to assess their **practical suitability for retail decision-making**.

Three forecasting models were evaluated under **identical experimental conditions**:

- **SARIMA** — Statistical baseline
- **Prophet** — Business-oriented forecasting model
- **LSTM** — Deep learning time-series model

All models were trained on the same historical window, evaluated on the same out-of-sample period, and compared using standard forecasting error metrics. This ensures a **fair, transparent, and reproducible comparison** suitable for business and technical stakeholders.

### Business Context

Accurate demand forecasting is a core capability in retail operations. Reliable weekly sales forecasts enable organizations to:

- Plan inventory replenishment more effectively
- Reduce stock-outs and excess inventory

- Optimize workforce scheduling
- Improve revenue planning and promotional timing

This analysis focuses on **weekly store-level sales**, aligning directly with operational planning cycles commonly used in retail supply chain and store operations. Forecast accuracy directly influences service levels, cost control, and margin stability.

## Data Overview

### Data Source

M5 Forecasting – Accuracy dataset (Kaggle)

### Key Characteristics

- Daily unit sales from Walmart stores across the United States
- Hierarchical structure: *state* → *store* → *category* → *item*
- Approximately five years of historical data

### Scope of Analysis

- Daily sales aggregated to weekly frequency
- Store-level forecasting
- Example store analyzed in detail: **CA\_1**

## Methodology Overview

### 1. Exploratory Trend & Seasonality Analysis

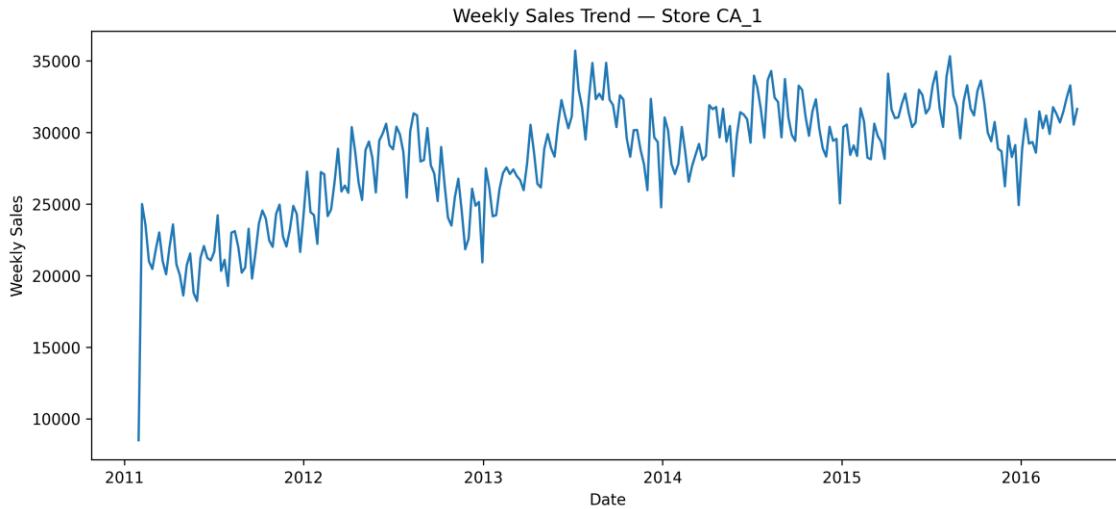
Daily sales were aggregated into weekly totals to match operational planning horizons.

### Key findings

- A clear long-term sales trend is present
- Strong annual seasonality (52-week cycle) is evident
- Statistical seasonal decomposition confirms recurring seasonal structure

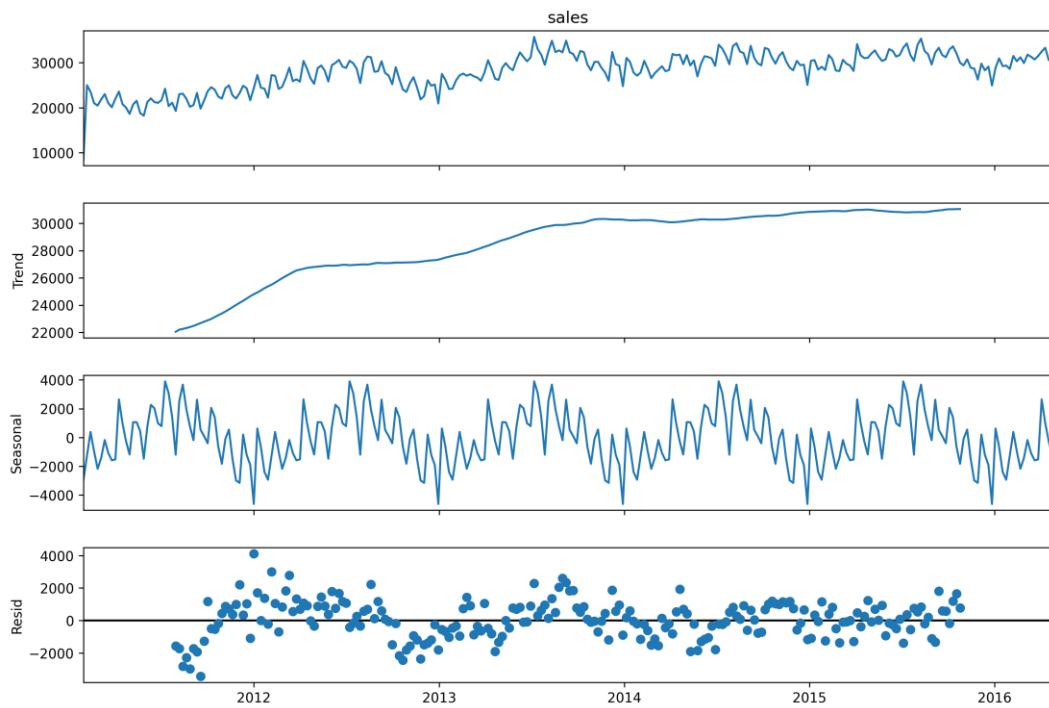
### Outcome

The data exhibits properties well suited for seasonal forecasting models.



**Figure 1. Weekly Sales Trend — Store CA\_1**

This figure displays aggregated weekly sales over time for Store CA\_1, illustrating the presence of a long-term sales trend and recurring fluctuations.



**Figure 2. Seasonal Decomposition of Weekly Sales (52-Week Period)**

Seasonal decomposition separates the observed series into trend, seasonal, and residual components, revealing a consistent annual (52-week) seasonal pattern.

## 2. SARIMA — Statistical Baseline Model

### Purpose

Establish a transparent and defensible statistical benchmark.

### Approach

- Seasonal ARIMA with annual (52-week) seasonality
- Time-aware train/test split (80% / 20%)

### Key Observations (Fact-Based)

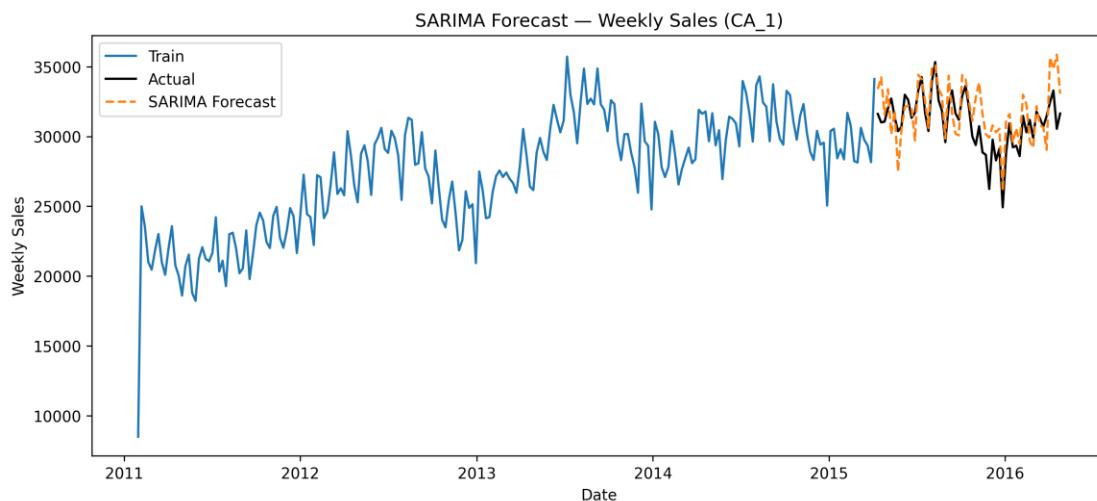
- Model converged successfully
- Residual diagnostics indicate no remaining autocorrelation
- Normality assumptions were not violated

### Important Limitation

- Some coefficients exhibit numerical instability (e.g., large seasonal MA terms, undefined standard errors)
- This is a known limitation when modeling long seasonal periods and **does not invalidate SARIMA as a forecasting benchmark**

### Interpretation

SARIMA is appropriate as a **baseline forecasting model**, but its parameters are not used for business interpretation.



**Figure 3. SARIMA Baseline Forecast vs Actual (Out-of-Sample)**

This visualization compares SARIMA out-of-sample forecasts against actual weekly sales, providing a baseline assessment of forecast accuracy and error behavior.

### **3. Prophet — Business-Oriented Forecasting Model**

#### **Purpose**

Provide a forecasting model that balances **accuracy, robustness, and interpretability**.

#### **Key Characteristics**

- Explicit modeling of trend and seasonality
- Automatic changepoint detection
- Robust to missing values and outliers

#### **Interpretation**

Prophet is well suited for operational forecasting contexts where **forecast stability, transparency, and communication with non-technical stakeholders** are critical.

### **4. LSTM — Deep Learning Model**

#### **Purpose**

Evaluate a high-capacity nonlinear model capable of learning complex temporal patterns.

#### **Key Characteristics**

- Sequence-based learning from historical sales
- Ability to capture nonlinear demand dynamics

#### **Interpretation**

LSTM models offer flexibility and expressive power but require:

- Larger data volumes
- Careful tuning and validation
- Ongoing monitoring in production environments

This introduces additional implementation and maintenance complexity compared to statistical or business-oriented models.

## **Model Evaluation Framework**

#### **All models were evaluated using:**

- Out-of-sample test data
- Identical forecast horizons
- Consistent error metrics

## Evaluation Metrics

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

## Summary of Results — Store CA\_1

Model	RMSE	MAE	Business Interpretation
SARIMA	1785.78	1431.01	Reliable statistical benchmark
<b>Prophet</b>	<b>1506.02</b>	<b>1185.88</b>	Stable and interpretable forecasts
LSTM	1831.50	1442.17	High-capacity but operationally complex

All metrics were computed on the same out-of-sample period. Detailed implementation steps and diagnostics are available in the technical notebooks to ensure full reproducibility.

## Key Insights

- Weekly retail sales exhibit strong annual seasonality
- A statistical baseline provides a meaningful performance reference
- Business-oriented models improve forecast stability and interpretability
- Increased model complexity introduces additional deployment and maintenance considerations

## Business Implications

### Based on the findings:

- Short- to medium-term planning can be effectively supported by **interpretable forecasting models**
- Operational teams benefit from models that balance **accuracy with transparency**
- Advanced models should be considered when organizational scale and data maturity justify the added complexity

## Limitations

- Results are based on a single example store
- External drivers (pricing, promotions, holidays) were not explicitly modeled

- Forecast performance may vary across stores and product categories

## Conclusion

This assessment demonstrates a **structured, defensible approach to retail sales forecasting**. By benchmarking statistical, business-oriented, and deep learning models under consistent conditions, decision-makers can select forecasting strategies aligned with their **operational needs, data maturity, and implementation constraints**.

## Disclaimer

This report is provided for **demonstration and portfolio purposes only**. It does not represent production forecasts or official Walmart analyses.