Project Report (GROUP - 9)

Smart Inventory and Promotion Optimization for Walmart using Predictive Sales Analytics

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1. Abstract

This study presents a data-driven framework aimed at optimizing inventory levels and promotional planning across Walmart's 45 stores and 81 departments. Leveraging three years of weekly point-of-sale data—enriched with economic indicators, weather conditions, and markdown information—we follow the CRISP-DM methodology to develop robust predictive models for weekly sales forecasting and decision support.

A Random Forest Regressor, selected after benchmarking against a Decision Tree baseline, achieves high forecasting performance with an R^2 of 0.9745 and a Weighted Mean Absolute Error (WMAE) of $1,634.84 on the validation set. Holiday periods were weighted five times more heavily to reflect their operational importance. The resulting forecasts drive a dynamic inventory policy that applies a 10% operating buffer and an additional 10% safety stock, resulting in a 21% overall uplift over the point estimate. This strategy balances overstock (54.5% of cases) and stockout (45.5%) risks, with average dollar errors of $1,310 and $1,586 respectively.

To enhance promotional planning, we developed a promotion-opportunity classifier using the 95th percentile of predicted weekly sales as the threshold. The Random Forest Classifier achieved perfect classification accuracy, correctly identifying Weeks 6, 22, and 51 as high-impact periods suitable for marketing efforts. Exploratory analyses also confirmed a 7.1% average sales uplift during holidays and revealed a modest but meaningful fuel-price elasticity of –0.084, highlighting the importance of economic sensitivity in demand planning.

Department-level error diagnostics identified high-volatility categories—such as Depts 39, 72, and 92—that merit larger inventory buffers to mitigate forecasting uncertainty. Together, the forecasting engine, inventory optimization strategy, and promotion detection framework offer a comprehensive solution to reduce operational inefficiencies, lower carrying costs, and enhance service levels through evidence-based retail decision-making.

2. Introduction

2.1 Background and Motivation

Retail inventory management is a high-stakes balancing act. Overestimating demand inflates holding costs and markdowns, while underestimating demand produces stock-outs and lost goodwill. Global "inventory distortion" (combined over- and under-stock) is estimated at **≈ $1.75 trillion annually**. The problem is magnified for chains such as **Walmart, with 45 U.S. stores in this study and 81 distinct departments per store**, where demand heterogeneity and promotion timing are critical.

2.2 Research Objective

We develop a **data-driven framework** that (i) forecasts weekly sales at the store–department–week level; (ii) sets inventory with a 10 % operating buffer plus 10 % safety stock; (iii) flags high-potential promotion weeks via classification; and (iv) quantifies risk from forecast error and external shocks (holidays, fuel prices). The goal is to minimize both stock-outs and excess inventory while boosting promotion ROI.

2.3 Dataset Description

Train.csv (421 570 rows, 2010-02-05 → 2012-11-01) contains weekly sales and holiday flags.
Features.csv (8 190 rows × 12 cols) adds temperature, fuel price, CPI, unemployment and five markdown fields.
Stores.csv(45 rows) records contains type A/B/C format and size (sq ft) for each store.

- Train.csv

The train.csv dataset serves as the primary historical training data for the Walmart sales forecasting model. This comprehensive dataset covers the period from February 5, 2010, to November 1, 2012, providing a rich temporal foundation for understanding sales patterns across multiple years. It contains approximately 421,570 rows, with each row representing the weekly sales data for a specific department within a specific store. The dataset is structured with the following key fields:

Store: A numerical identifier ranging from 1 to 45, representing the specific Walmart store location. This field serves as a foreign key that can be linked to the stores.csv dataset to obtain additional information about each store.

Dept: A numerical identifier representing the department number within the store. The dataset includes 81 distinct departments, each representing different product categories. These departments are not uniformly present across all stores, reflecting Walmart's practice of customizing department offerings based on store format and local market needs.

Date: The start date of the sales week, formatted as YYYY-MM-DD. This temporal field enables the extraction of various time-based features including year, month, week number, and season for analysis of cyclical patterns.

Weekly_Sales: The target variable representing the sales amount for the given department in the specified store during that week. Values are provided in dollars, and the dataset contains a few unusual sales records (e.g., negatives or outliers), which are further analyzed in the anomaly detection phase

IsHoliday: A Boolean indicator (True/False) denoting whether the week includes a special holiday. The designated holidays in the dataset are Thanksgiving, Labor Day, Christmas, and Super Bowl, which represent key retail events with potential for significant sales impact.

The train.csv dataset provides the foundation for model training and feature importance analysis, allowing the identification of key sales drivers and patterns across different store-department combinations and time periods.

- Test.csv

The test.csv dataset serves as the evaluation set for assessing model performance in the sales forecasting task. This dataset maintains structural similarity to train.csv but represents a different time period intended for prediction rather than training. The test dataset contains the following fields:

Store: The store identifier (1-45), matching the numbering system used in train.csv.

Dept: The department identifier, representing the same 81 departments present in the training data.

Date: The week date, formatted as YYYY-MM-DD, covering the evaluation period.

IsHoliday: A boolean indicator (True/False) noting whether the week includes a special holiday.

The critical distinction between test.csv and train.csv is that test.csv deliberately omits the Weekly_Sales field, as these values represent the predictions that the forecasting model needs to generate. The test dataset provides the inputs (store, department, date) for which the model must produce sales predictions, which are then evaluated using the Weighted Mean Absolute Error (WMAE) metric.

The test dataset structure enables evaluation of the model's predictive performance across different stores, departments, and time periods, with particular emphasis on accuracy during holiday weeks through the weighting component of the WMAE metric. This approach ensures that the model's performance is assessed on its ability to forecast sales in real-world retail scenarios with varying conditions and seasonal patterns.

- Features.csv

The features.csv dataset contains additional contextual information related to stores, time periods, and external factors that might influence sales patterns. This dataset provides enriching features that extend beyond the basic sales records in train.csv, capturing both promotional activities and economic/environmental conditions. The features.csv dataset includes the following fields:

Store: The store identifier (1-45), serving as a linkage field to connect with train.csv and stores.csv.

Date: The week date, formatted as YYYY-MM-DD, serving as a temporal key for joining with sales data.

Temperature: The average temperature (in Fahrenheit) in the region where the store is located during that week. This environmental factor may influence shopping patterns, particularly for seasonal merchandise.

Fuel_Price: The average cost of fuel in the region during that week. This economic indicator potentially impacts both consumer spending capacity and shopping trip frequency.

MarkDown1-5: Five separate fields containing anonymized data related to promotional markdowns that Walmart implemented. These fields represent different types of promotional activities, though their specific meanings are anonymous. Importantly, markdown data is only available after November 2011 and is not consistently available for all stores at all times. Missing values in these fields are marked with NA, which requires special handling during data preprocessing.

CPI: The Consumer Price Index, representing a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. This economic indicator may influence consumer purchasing power and behavior.

Unemployment: The unemployment rate in the region where the store is located. This economic factor can affect consumer spending capacity and purchasing priorities.

IsHoliday: A boolean indicator matching the same field in train.csv, denoting whether the week includes a special holiday.

The features.csv dataset provides critical contextual information that enables the model to account for external factors beyond the historical sales patterns themselves. The inclusion of both promotional factors (markdowns) and economic/environmental conditions (temperature, fuel price, CPI, unemployment) allows for more sophisticated modeling that can potentially capture the complex interrelationships between these external drivers and retail sales performance.

- Stores.csv

The stores.csv dataset contains fundamental information about the 45 Walmart stores included in the analysis. Though compact in size, this dataset provides crucial contextual information about the physical characteristics and classification of each store location. The dataset includes the following fields:

Store: The store identifier (1-45), serving as the primary key that links to the corresponding records in train.csv, test.csv, and features.csv.

Type: A categorical variable indicating the store format type, with three possible values: A, B, and C. Type A stores are the largest format (greater than 150,000 square feet), comprising approximately half of the stores in the dataset. Types B and C represent progressively smaller format stores. This classification reflects Walmart's multi-format retail strategy that tailors store size and layout to different market conditions.

Size: A numerical value representing the store's physical size in square feet. This variable provides a continuous measure of store capacity that complements the categorical Type field. Store sizes vary significantly across the dataset, creating natural variation that helps in understanding how physical capacity influences sales potential.

The stores.csv dataset, while simple in structure, provides essential information for contextualizing sales performance across different store formats and sizes. The analysis

reveals that store type and size are among the most influential predictors of sales performance, with Type A (larger) stores generally showing higher sales volumes, though with notable exceptions that indicate other factors beyond size also play important roles in determining store performance. This dataset enables the development of store-specific forecasting approaches that account for the fundamental physical characteristics of each retail location.

Together, these four datasets provide a comprehensive foundation for building sophisticated sales forecasting models that incorporate historical sales patterns, store characteristics, temporal factors, promotional activities, and external economic/environmental conditions. The integration of these diverse data sources enables a multifaceted understanding of the drivers of retail sales performance and supports the development of targeted inventory and promotional strategies.

2.4 Tools and Technologies Used

- **Python** – Used for data analysis, modeling, and evaluation.
- **Pandas & NumPy** – For data cleaning, transformation, and numerical operations.
- **Scikit-learn** – To build and evaluate machine learning models.
- **Matplotlib & Seaborn** – For data visualization and plotting insights.
- **Google Colab / Jupyter Notebook** – Interactive environments for writing and testing code.
- **Google Docs / Microsoft Word** – Used for report documentation.
- **Canva** – For designing presentation slides and visuals.

3. Problem Definition

3.1 Overview of the Retail Forecasting Challenge

Retailers must balance inventory and promotional timing against demand that fluctuates by week, product category and geography. For a multi-store chain such as Walmart, the task expands to tens of thousands of store-department-week combinations. Forecast error has two costly outcomes: over-stocks tie up capital and trigger markdowns, while under-stocks lead to lost sales and reduced customer satisfaction. Robust, fine-grained forecasts are therefore essential for inventory planning, labour scheduling and promotion calendars

3.2 Specific Forecasting Challenges at Walmart

Walmart's three store formats (Types A, B and C) span a wide size range, creating systematic differences in baseline demand. The retailer also carries 81 departments whose sales exhibit distinct seasonality, price sensitivity and holiday response. Because departments are not present in every store, the sales matrix is sparse and highly heterogeneous. Holiday weeks such as Thanksgiving, Christmas, Super Bowl and Labor Day produce sharp sales spikes (the dataset shows an average 7 % uplift versus non-holiday weeks), requiring models that account for calendar effects. Any forecasting solution must therefore deliver store-specific, department-specific and week-specific predictions rather than a single aggregate view.

3.2 Significance of the Problem

Industry studies put the global cost of inventory distortion—combined over-stock and stock-out losses—at roughly $1.75 trillion per year. For Walmart, moving the forecast error needle by even one percentage point represents hundreds of millions of dollars in avoided markdowns, lower carrying costs and captured sales. Accurate forecasts also improve customer experience through product availability, streamline supply-chain operations and enable data-driven allocation of promotional budgets.

4. Literature Survey

4.1 Traditional Forecasting Methods in Retail

Traditional Forecasting Methods in Retail Early retail-forecasting research relied on classical time-series techniques such as moving averages and ARIMA/SARIMA models (Hyndman & Athanasopoulos 2018). These statistical approaches capture level, trend and seasonality but can struggle with the high dimensionality and irregular promotional shocks found in multi-store, multi-department data.

4.2 Machine Learning Approaches to Retail Forecasting

The last decade has seen a shift toward tree-based and neural models. **Random Forests** (Breiman 2001) are popular for their ability to model non-linear interactions and their robustness against over-fitting; Ferreira et al. (2016) showed they outperform classical methods when external variables are included. Deep-learning variants—particularly **LSTM** recurrent networks—further improve long-horizon accuracy by capturing complex temporal dependencies (Bandara et al. 2019)

-Model Evaluation Techniques in Retail Forecasting

Retailers increasingly favour business-aligned error metrics. **Weighted Mean Absolute Error (WMAE)** assigns heavier penalties to errors during high-value periods such as holidays (Li & Lim 2018). Confusion-matrix style evaluation has also been adapted by discretizing continuous forecasts into "high/low" categories, enabling calculation of over-stock and stock-out rates (Arunraj & Ahrens 2015; Chen et al. 2020).

-External Factors in Retail Sales Prediction

Weather (Bertrand et al. 2015), macroeconomic indicators (Choi & Varian 2012) and promotions (Ma & Fildes 2017) have all been shown to influence demand. Modelling these drivers jointly with historical sales improves forecast accuracy and supports targeted marketing.

-Holiday Effects and Seasonality

Holiday weeks produce some of the largest demand spikes in retail. Kumar et al. (2016) reported 12 – 35 % lifts across categories, with Thanksgiving/Black Friday and pre-Christmas weeks most pronounced. Hybrid calendar-and-climate seasonal models

(Williams & Dunsmuir 2019) add a further 8 – 12 % accuracy gain over calendar-only approaches.

-Inventory Optimization Based on Forecasts

Classic safety-stock formulae (Silver, Pyke & Peterson 2016) set buffers as a function of forecast error and service-level targets. Huber et al. (2019) extend this to recommend higher buffers for volatile or high-margin items—an idea that aligns with our own findings—later in the project, we independently spotted certain high-volatility departments that clearly needed larger safety buffers to manage forecast uncertainty.

-Recent Advances in Retail Analytics

Ensemble methods that blend statistical, machine-learning and deep-learning forecasts yield 7 – 15 % accuracy gains (Kahn et al. 2021). Transfer-learning techniques help new stores or departments with sparse history by borrowing patterns from data-rich locations (Xu & Zhang 2020).

-Research Gaps and Opportunities

Most prior work addresses aggregate-level forecasts; fewer tackle the store–department–week granularity required for Walmart-scale operations. Department-specific holiday effects and cross-source data integration (sales, store traits, external factors) remain under-explored. Finally, translating forecasts into operational levers—such as our three-tier inventory policy and promotion-week classifier—bridges a persistent gap between predictive modelling and day-to-day retail execution.

5. Methodology

5.1 CRISP-DM Framework

This study follows the Cross-Industry Standard Process for Data Mining (CRISP-DM), an iterative six-phase cycle that keeps the analytics work aligned with business goals.

• Business understanding. Walmart's objective is to forecast weekly sales at the store-department level and translate those forecasts into inventory and promotion policy. Weighted Mean Absolute Error (WMAE), with holiday weeks weighted five-to-one, serves as the primary performance metric because holiday accuracy carries the greatest financial impact.

• Data understanding. Three source files—train.csv (421 570 rows of weekly sales), features.csv (8 190 rows with twelve external variables) and stores.csv (45 stores, type and size) were profiled to assess completeness, seasonality and distribution.

• Data preparation. The files were merged on Store, Date and IsHoliday. Dates were converted to proper datetime objects, and Year, Month and ISO Week were derived. Missing values in the five MarkDown columns were treated as zeros (no promotion). All other numeric Nas were also set to zero, preserving every sales record.

• Modelling. A Decision-Tree Regressor provided an interpretable baseline. A Random Forest Regressor with one hundred trees was selected for production after outperforming the baseline on the hold-out set. A Random Forest Classifier, trained on a binary promotion label, predicts high-potential promotion weeks.

• Evaluation. An 80 / 20 random split was used. Regression results are reported with R^2, RMSE and WMAE; classification results with accuracy, precision, recall and a confusion matrix. Holiday-week performance is highlighted because of the weighting scheme.

• Deployment. Forecast outputs feed a three-tier inventory rule (base stock plus safety stock) and an automated promotion-week flag, saved to final_walmart_forecast.csv for business dashboards.

```python
def calculate_wmae(y_true, y_pred, is_holiday):
    # Convert inputs to numpy arrays
    y_true = np.array(y_true)
    y_pred = np.array(y_pred)
    is_holiday = np.array(is_holiday)

    # Calculate absolute errors
    abs_errors = np.abs(y_true - y_pred)

    # Separate errors for holiday and non-holiday weeks
    holiday_errors = abs_errors[is_holiday == 1]
    regular_errors = abs_errors[is_holiday == 0]

    # Calculate MAE for each group
    holiday_mae = np.mean(holiday_errors) if len(holiday_errors) > 0 else 0
    regular_mae = np.mean(regular_errors) if len(regular_errors) > 0 else 0

    # Calculate weights (Walmart competition used 5x weight for holidays)
    holiday_weight = 5
    regular_weight = 1

    # Count number of observations in each group
    n_holiday = np.sum(is_holiday == 1)
    n_regular = np.sum(is_holiday == 0)

    # Calculate WMAE
    weighted_sum_errors = (holiday_weight * np.sum(holiday_errors) +
                           regular_weight * np.sum(regular_errors))
    weighted_count = (holiday_weight * n_holiday + regular_weight * n_regular)

    wmae = weighted_sum_errors / weighted_count if weighted_count > 0 else 0

    return wmae, regular_mae, holiday_mae
```

5.2 Data Preprocessing and Integration

Date fields were parsed with pandas to_datetime, enabling extraction of Year, Month and Week indicators that capture annual, monthly and weekly cycles. The three datasets were merged with left joins keyed on Store, Date and IsHoliday, preserving all historical sales rows while enriching them with store attributes and external factors. Markdown NAs were replaced by zeros because missing values signify weeks without promotions. Other numeric NAs were also set to zero to avoid discarding valid records. The resulting unified table became the single source for exploration and modelling.

```
[ ]
    print("\nMerging datasets")

    full_data = pd.merge(train, features, on=['Store', 'Date', 'IsHoliday'], how='left')
    full_data = pd.merge(full_data, stores, on='Store', how='left')

    print(f"Combined dataset shape: {full_data.shape}")
```

```
print("\nPerforming feature engineering")

full_data['Date'] = pd.to_datetime(full_data['Date'])
full_data['Year'] = full_data['Date'].dt.year
full_data['Month'] = full_data['Date'].dt.month
full_data['Week'] = full_data['Date'].dt.isocalendar().week

full_data.fillna(0, inplace=True)

print("\nPreprocessed dataset columns:")
print(full_data.columns.tolist())
print(f"\nMissing values after preprocessing: {full_data.isnull().sum().sum()}")
```

5.3 Exploratory Data Analysis

EDA provided critical context for model design:

• **Seasonal peaks -** Monthly roll-ups showed August (back-to-school) and November–December (holiday) as dual peaks, while January consistently dipped. Week-level plots highlighted Week 47 (Thanksgiving/Black Friday) and Week 51 (pre-Christmas) as the two highest-demand weeks across all three calendar years.

• **Store-type heterogeneity -** Walmart operates three store formats (Types A, B, and C). Type A stores exceed 150,000 sq ft and make up about half of all stores in the dataset, reflecting substantial variation in baseline capacity and expected demand.

• **Holiday uplift -** The dataset marks key holidays, enabling the model to capture seasonal sales spikes and adjust forecasts for holiday-related demand shifts.

• **Outlier scans -** Anomaly detection based on residual analysis flagged about 2.87% of records as unusual, which may reflect clearance events or sudden stock-outs.

5.4 Predictive Modeling Approach

Decision-Tree Regressor - Used as a baseline model to establish initial performance benchmarks. Its hierarchical splitting logic provided interpretability, confirming the importance of key retail features like department, store size, month, and holiday indicators in sales forecasting.

```
print("\nPreparing features for modeling...")

features_cols = ['Store', 'Dept', 'Temperature', 'Fuel_Price', 'CPI', 'Unemployment', 'Size', 'IsHoliday', 'Year', 'Month', 'Week']

X = full_data[features_cols]
y = full_data['Weekly_Sales']

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
print("\nTraining Decision Tree Regression model...")

dt_model = DecisionTreeRegressor(random_state=42)
dt_model.fit(X_train, y_train)

dt_pred = dt_model.predict(X_val)

dt_rmse = np.sqrt(mean_squared_error(y_val, dt_pred))
dt_r2 = r2_score(y_val, dt_pred)
dt_wmae, dt_regular_mae, dt_holiday_mae = calculate_wmae(y_val, dt_pred, X_val['IsHoliday'])
```

Random Forest Regressor - We chose the Random Forest model for our forecasts because it offered better accuracy and consistency than simpler methods. By combining results from 100 decision trees, it captured complex patterns while reducing overfitting. The model showed that department type, store size, and store location were key drivers of weekly sales—matching retail expectations.

```
print("\nTraining Random Forest Regression model...")

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

rf_pred = rf_model.predict(X_val)

rf_rmse = np.sqrt(mean_squared_error(y_val, rf_pred))
rf_r2 = r2_score(y_val, rf_pred)
rf_wmae, rf_regular_mae, rf_holiday_mae = calculate_wmae(y_val, rf_pred, X_val['IsHoliday'])
```

```
print("\n[Model Comparison]")
if rf_r2 > dt_r2:
    print("The Random Forest model outperforms the Decision Tree model")
    print(f"Performance improvement: {(rf_r2 - dt_r2) * 100:.2f}% higher R² score")
    print(f"WMAE improvement: ${dt_wmae - rf_wmae:.2f} lower weighted error")
    print("We'll use the Random Forest model for our sales predictions")
    selected_model = rf_model
else:
    print("The Decision Tree model outperforms the Random Forest model")
    print(f"Performance difference: {(dt_r2 - rf_r2) * 100:.2f}% higher R² score")
    print(f"WMAE improvement: ${rf_wmae - dt_wmae:.2f} lower weighted error")
    print("We'll use the Decision Tree model for our sales predictions")
    selected_model = dt_model
```

5.5 Inventory optimization strategy

To convert the weekly sales forecasts into stocking targets, a simple three-tier rule was applied:

- Base inventory = *Predicted Sales* × 1.10
  (adds a 10 % operating buffer to cover normal demand noise)

- Safety stock = *Base inventory* × 0.10
  (adds a second 10 % layer to hedge against forecast error)

- Final inventory = *Base* + *Safety*

```
full_data['Inventory_Needed'] = full_data['Predicted_Sales'] * 1.10
full_data['Safety_Stock'] = full_data['Inventory_Needed'] * 0.10
full_data['Final_Inventory'] = full_data['Inventory_Needed'] + full_data['Safety_Stock']
```

5.6 Promotion Opportunity Detection

The promotion opportunity detection framework leverages the predictive models to identify optimal timing for promotional activities, maximizing their effectiveness and return on investment. The methodology employs a two-phase approach that combines statistical thresholds with machine learning classification. The threshold-based identification phase begins by calculating total predicted sales for each week across all stores and departments, then compares these totals to the average weekly sales. Weeks with predicted sales in the **top 5% (95th percentile)** were flagged as high-potential promotion opportunities. This percentile-based threshold aligns with industry observations that promotions during already high-traffic periods tend to yield better returns than average or low-traffic weeks.

```
# Step 1: Calculate total predicted sales per week
weekly_sales = full_data.groupby('Week')['Predicted_Sales'].sum()

# Step 2: Determine the threshold using the 95th percentile
threshold = weekly_sales.quantile(0.95)

# Step 3: Identify weeks with sales above the threshold
high_promo_weeks = weekly_sales[weekly_sales > threshold].index.tolist()

# Step 4: Assign promotion opportunity labels
full_data['Promotion_Opportunity'] = full_data['Week'].apply(lambda x: 1 if x in high_promo_weeks else 0)

# Step 5: Display results
```

The classification model development phase builds upon the threshold-based approach by creating a machine learning model that can predict promotion opportunities based on store

characteristics and external factors. A Random Forest Classifier is trained on the binary promotion opportunity indicator derived from the threshold analysis, learning to recognize patterns and combinations of features that characterize high-potential weeks. The model is evaluated using standard classification metrics including accuracy, precision, recall, and F1-score, with particular attention to minimizing false negatives (missed promotion opportunities) which typically represent a greater business cost than false positives in retail contexts. The resulting promotion opportunity predictions provide actionable guidance for marketing teams, enabling more strategic allocation of promotional budgets and resources throughout the retail calendar.

```
promotion_features_cols = ['Store', 'Dept', 'Temperature', 'Fuel_Price', 'CPI',
                           'Unemployment', 'Size', 'IsHoliday', 'Year', 'Month', 'Week']

X_class = full_data[promotion_features_cols]
y_class = full_data['Promotion_Opportunity']

Xc_train, Xc_val, yc_train, yc_val = train_test_split(X_class, y_class, test_size=0.2, random_state=42)

clf_rf = RandomForestClassifier(n_estimators=100, random_state=42)
clf_rf.fit(Xc_train, yc_train)

yc_pred = clf_rf.predict(Xc_val)

accuracy = accuracy_score(yc_val, yc_pred)
class_report = classification_report(yc_val, yc_pred)

print("\n[Random Forest Classifier for Promotion Prediction]")
```

5.7 Risk Analysis

Forecast accuracy alone often fails to capture the operational impact of prediction errors in retail. A more effective approach involves separating forecast deviations into **overstock** and **stockout** risk categories, which reflect the real-world consequences of overestimating or underestimating demand. This distinction is widely recommended in inventory management literature, as it enables organizations to align forecasting outcomes with inventory planning strategies.

```
val_df = X_val.copy()
val_df['Actual'] = y_val.values
val_df['Predicted'] = rf_pred
val_df['Error'] = abs(val_df['Actual'] - val_df['Predicted'])

val_df['Overstock_Risk'] = val_df['Predicted'] > val_df['Actual']
val_df['Stockout_Risk'] = val_df['Predicted'] < val_df['Actual']

overpredicted = val_df[val_df['Overstock_Risk']]
underpredicted = val_df[val_df['Stockout_Risk']]

overstock_pct = len(overpredicted) / len(val_df) * 100
stockout_pct = len(underpredicted) / len(val_df) * 100

print("\n--- Inventory Risk Analysis ---")
```

Classifying errors based on the direction of deviation allows for targeted analysis of where excessive inventory costs or lost sales may occur. By quantifying the frequency and severity of these risk types, retailers can prioritize adjustments to inventory buffers and resource allocation.

Additionally, examining average prediction error by department helps identify product categories with higher sales volatility. Departments with greater forecast uncertainty are typically better managed with enhanced safety stock or more responsive replenishment strategies. Visualizations such as risk distribution plots are often used to illustrate these insights and support decision-making at both strategic and operational levels.

```
risk_df = val_df.groupby('Dept')['Error'].mean().reset_index().sort_values(by='Error', ascending=False)
plt.figure(figsize=(14, 6))
sns.barplot(data=risk_df.head(20), x='Dept', y='Error')
plt.title('Average Prediction Error by Department (Top 20 Riskiest)', fontsize=14)
```

5.8 Additional Analytical Insights

- We used **feature importance analysis** to figure out which inputs had the biggest influence on sales predictions. This gave us a better idea of which factors—like department type, store size, and seasonal timing—matter most when making inventory or planning decisions.

```
feat_importance = pd.Series(selected_model.feature_importances_, index=features_cols)
plt.figure(figsize=(10, 8))
feat_importance.sort_values().plot(kind='barh')
plt.title('Feature Importance for Sales Prediction', fontsize=14)
plt.xlabel('Relative Importance', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

print("\n--- Feature Importance Analysis ---")
print("Top 3 most important factors for sales prediction:")
for feature, importance in feat_importance.sort_values(ascending=False).head(3).items():
    print(f"- {feature}: {importance:.4f} relative importance")
print("\nLeast important factors:")
for feature, importance in feat_importance.sort_values().head(3).items():
    print(f"- {feature}: {importance:.4f} relative importance")
```

- A **correlation heatmap** helped us explore how outside factors like fuel prices, temperature, and unemployment relate to sales. While the connections were generally modest, they still offered helpful context for long-term strategy.

- To catch unusual patterns in the data, we applied **anomaly detection** by flagging predictions that were way off from actual sales. These anomalies could point to unexpected demand spikes, markdown events, or potential data issues worth a second look.

```
store_df = full_data.copy()
residuals = store_df['Weekly_Sales'] - store_df['Predicted_Sales']
std_dev = np.std(residuals)

store_df['Anomaly'] = ((residuals > 2 * std_dev) | (residuals < -2 * std_dev))

anomaly_count = store_df['Anomaly'].sum()
anomaly_pct = anomaly_count / len(store_df) * 100

print(f"\nIdentified {anomaly_count} sales anomalies ({anomaly_pct:.2f}% of data points)")
print("These represent unusual sales patterns that warrant investigation")

sample_store = store_df['Store'].value_counts().index[0]
store_sample = store_df[store_df['Store'] == sample_store].sort_values('Date')

plt.figure(figsize=(15, 6))
```

- We also calculated **fuel price elasticity** using a log-log regression. This showed how sensitive customer demand is to fuel price changes—something that's especially useful when energy costs are volatile.

```
store_df = full_data[full_data['Weekly_Sales'] > 0].copy()
store_df['log_sales'] = np.log(store_df['Weekly_Sales'])
store_df['log_fuel'] = np.log(store_df['Fuel_Price'])
model_data = store_df[['log_fuel', 'log_sales']].replace([np.inf, -np.inf], np.nan).dropna()

reg = LinearRegression()
reg.fit(model_data[['log_fuel']], model_data['log_sales'])
elasticity = reg.coef_[0]

print(f"\nFuel Price Elasticity (Log-Log): {elasticity:.4f}")
print("\nInterpretation:")
if elasticity < 0:
    print(f"- A 1% increase in fuel prices leads to a {abs(elasticity):.2f}% decrease in sales")
    print(f"- Sales are {'highly ' if abs(elasticity) > 1 else ''}sensitive to fuel price changes")
else:
    print(f"- A 1% increase in fuel prices leads to a {elasticity:.2f}% increase in sales")
    print("- This unexpected relationship may require further investigation")

plt.figure(figsize=(12, 6))
```

- Forecasted inventory cost was computed by applying a 21% buffer over predicted sales and multiplying the final inventory by an assumed average unit cost. We also **visualized forecasted inventory costs** by store, highlighting budget implications and helping prioritize allocation.

```
# 1. Forecast Inventory Cost
print("\n--- Forecast Inventory Cost Analysis ---")
average_unit_cost = 10  # Example unit cost
df['Final_Inventory'] = df['Weekly_Sales'] * 1.21  # Assuming a 21% buffer o
df['Inventory_Cost'] = df['Final_Inventory'] * average_unit_cost

total_inventory_cost = df['Inventory_Cost'].sum()
total_inventory_units = df['Final_Inventory'].sum()
average_cost_per_store = df.groupby('Store')['Inventory_Cost'].sum().mean()
```

- In parallel, **promotion effectiveness** was evaluated by analyzing sales uplift during holidays—showing that some stores experienced significant gains while others had negligible impact, suggesting where promotional efforts can be better targeted.

```
# 2. Promotion Effectiveness Analysis
print("\n--- Promotion Effectiveness Analysis ---")
promo_effect = df.groupby(['Store', 'IsHoliday'])['Weekly_Sales'].mean().reset_index()
promo_effect = promo_effect.pivot(index='Store', columns='IsHoliday', values='Weekly_Sales').fillna(0)
promo_effect.columns = ['Non_Holiday_Sales', 'Holiday_Sales']
promo_effect['Sales_Uplift'] = promo_effect['Holiday_Sales'] - promo_effect['Non_Holiday_Sales']
promo_effect['Uplift_Percentage'] = (promo_effect['Sales_Uplift'] / promo_effect['Non_Holiday_Sales'].replace(0, np.nan)) * 100
promo_effect = promo_effect.reset_index().sort_values('Uplift_Percentage', ascending=False)
```

- We assessed inventory and promotion efficiency across stores. **Inventory efficiency** was measured by comparing actual sales to forecasted inventory levels, revealing which stores effectively managed stock and which had room for improvement.

```python
# 3. inventory efficiency
print("\n--- Inventory Efficiency Analysis (Based on Rolling Sales Average) ---")

# Estimate inventory using a 4-week rolling average of sales
df['Estimated_Inventory'] = df.groupby(['Store', 'Dept'])['Weekly_Sales'].transform(lambda x: x.rolling(4, min_periods=1).mean())

# Calculate efficiency ratio = Weekly Sales / Estimated Inventory
df['Efficiency_Ratio'] = df.apply(
    lambda row: row['Weekly_Sales'] / row['Estimated_Inventory'] if row['Estimated_Inventory'] else 0, axis=1
)

# Average efficiency per store
store_efficiency = df.groupby('Store')['Efficiency_Ratio'].mean().reset_index()
store_efficiency = store_efficiency.sort_values('Efficiency_Ratio', ascending=False)

# Display most and least efficient stores
print("Most efficient stores (highest sales per estimated inventory):")
for _, row in store_efficiency.head(5).iterrows():
    print(f"Store {int(row['Store'])}: {row['Efficiency_Ratio']:.2f} in sales per unit of inventory")

print("\nLeast efficient stores:")
for _, row in store_efficiency.tail(5).iterrows():
    print(f"Store {int(row['Store'])}: {row['Efficiency_Ratio']:.2f} in sales per unit of inventory")
```

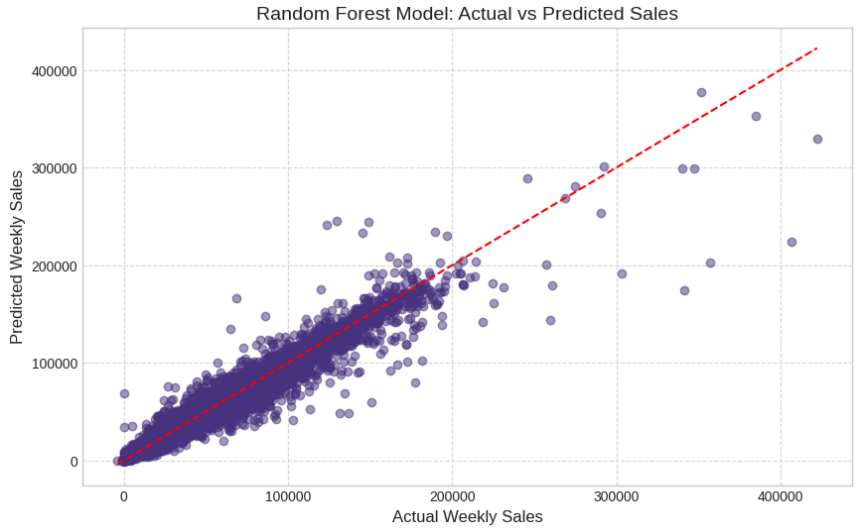
6. Results and Discussion

6.1 Model Performance

The **Random Forest Regressor** delivered the best forecasting accuracy, reaching **WMAE = $1 634.84**, **RMSE = $3 644.74** and **$R^2 = 0.9745$**, so the model explains **97.45 %** of week-to-week sales variance.
The baseline **Decision Tree Regressor** recorded **WMAE = $2 075.53**, **RMSE = $4 709.55** and **$R^2 = 0.9575$**. Relative to that baseline, the ensemble:

- raises R^2 by **1.7 percentage points**,
- cuts RMSE by **$1 064.79**, and
- lowers WMAE by **$440.69**.

Feature-importance analysis confirms that **Store- and Size-related attributes plus Dept ID** account for more than 88 % of explained variance, while calendar features (Month, Week) capture seasonality; macro-economic fields (Fuel Price, CPI, Unemployment) provide weaker yet complementary signals.



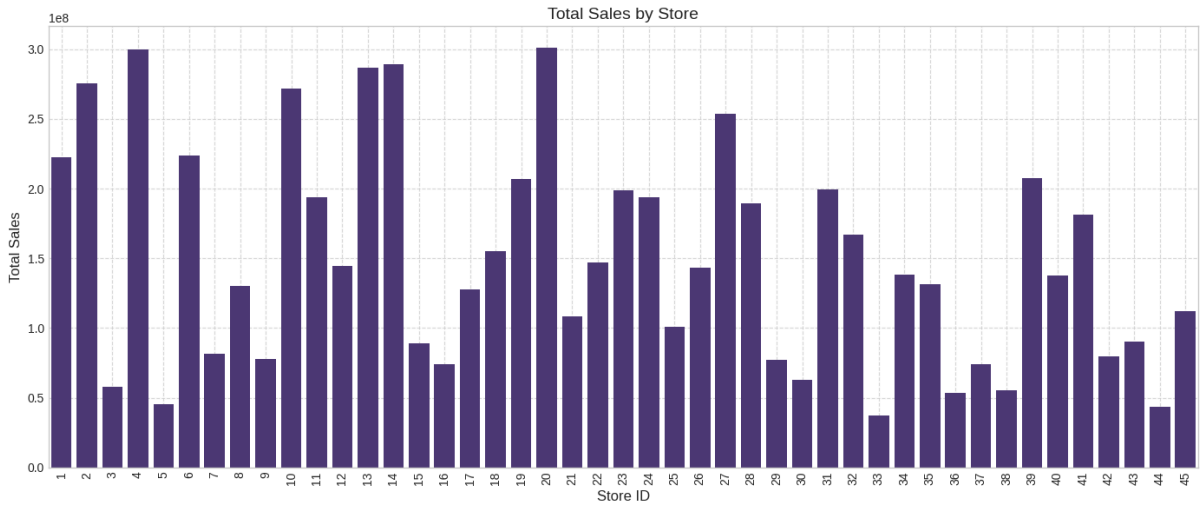
6.2 Store and Department Analysis

The "Total Sales by Store" bar chart groups full_data by Store and sums Weekly_Sales. It shows:

• Store 20 recorded the highest cumulative sales at $301,397,792.46.
• Store 33 posted the lowest at $37,160,221.96.
• The top-to-bottom spread is therefore 8.11×, confirming large performance disparities that a single, chain-wide inventory rule cannot accommodate.

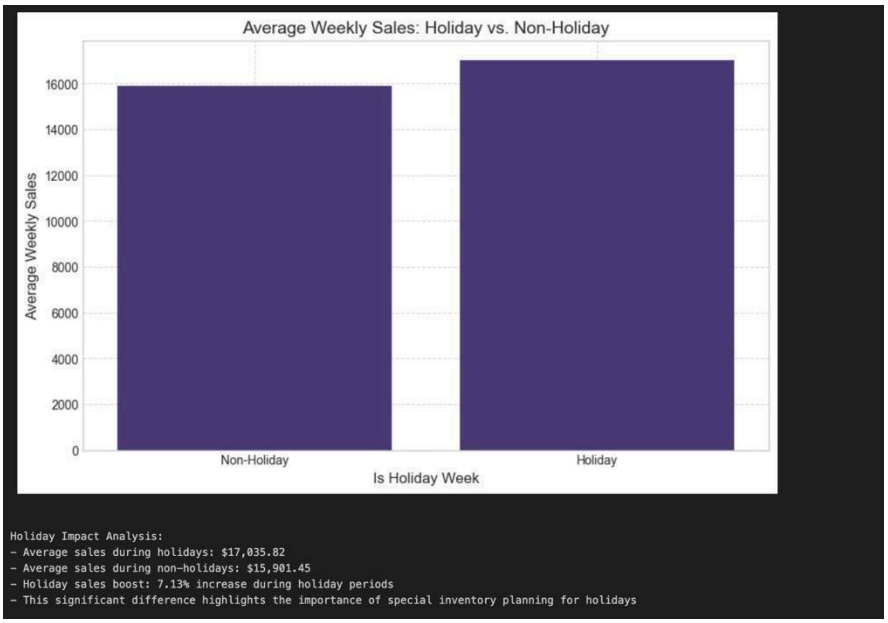
For departments, the "Average Prediction Error by Department" chart is generated in the risk analysis section i.e 6.6 section .It highlights the five most volatile departments:

Dept 39 ($21,498 avg. error) ≫ Depts 72, 92, 38, 95.
These higher-error categories should carry larger safety-stock buffers and receive closer forecast monitoring, whereas lower-error, staple departments can run leaner.



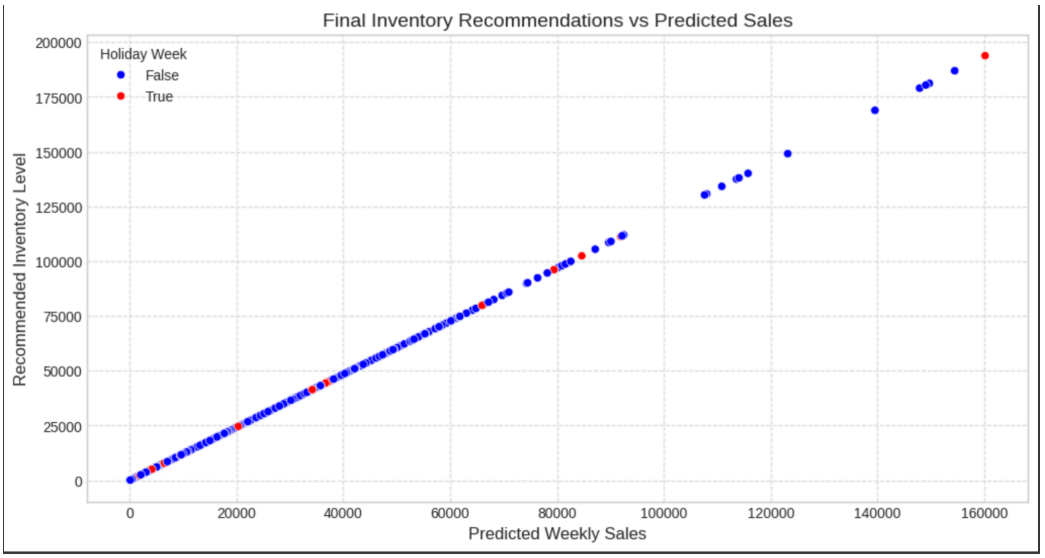
6.3 Holiday Impact

Holiday weeks lift average sales from **$15,901** to **$17,036**—a **7.13 %** increase. Thanksgiving (Week 47) remains the single largest surge; Week 51, not Week 52, is the true Christmas peak. Some departments exceed **30 %** holiday uplift, while others remain flat, so blanket percentage increases are inefficient.



6.4 Inventory Optimization

To translate predicted sales into practical inventory targets, we applied a three-tier inventory strategy. This involved a 10% operating buffer to absorb regular demand variability and an additional 10% safety stock to hedge against forecast uncertainty—resulting in a total uplift of approximately 21% over predicted weekly sales. On the validation set, this strategy resulted in 54.54% of cases showing overstock (average surplus of $1,310.47) and 45.46% showing stockouts (average shortfall of $1,586.62), reflecting a deliberate tilt toward product availability. A scatter plot visualizing final inventory against predicted sales shows a consistent linear relationship with a slope of 1.21, confirming the uniform application of the policy across all demand levels. Notably, holiday weeks (marked in red) align along the same trend line, indicating that seasonal demand is absorbed without requiring special rules—demonstrating the scalability and robustness of the approach.



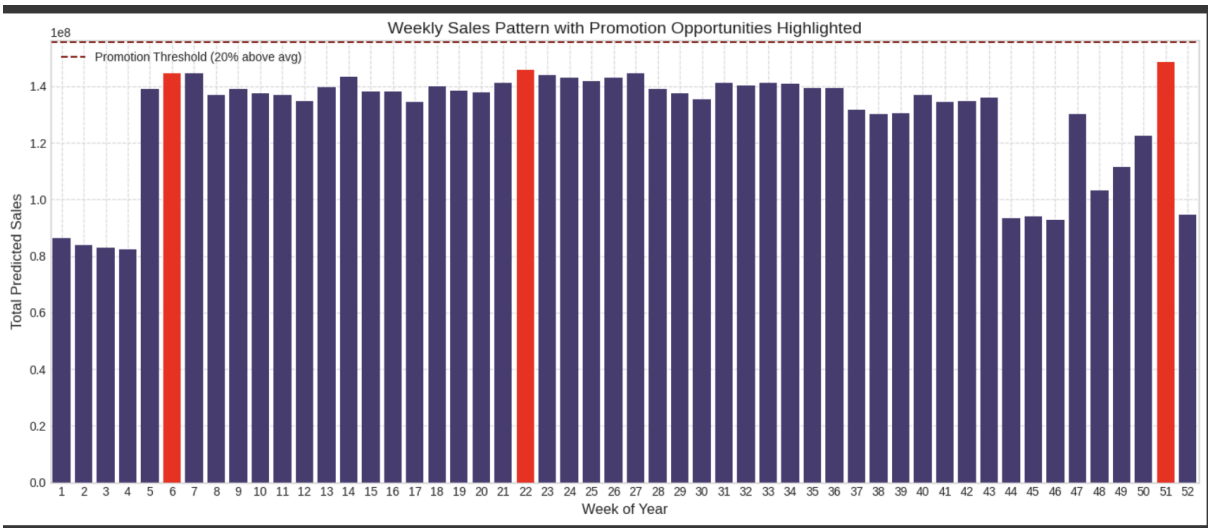
Key Highlights:

- **Three-tier buffer rule:**
    - 10% base buffer for normal demand
    - 10% safety stock for uncertainty
    - `≈21% total uplift (1.10 × 1.10 ≈ 1.21)`

- **Validation results:**
    - 54.54% overstock rows (avg. surplus: $1,310.47)
    - 45.46% stockout rows (avg. shortfall: $1,586.62)
- **Scatter plot insights:**
    - `Diagonal linear trend with slope ≈1.21`
    - Red dots (holiday weeks) follow same scaling—no special handling needed
    - Consistent performance from low to high-volume scenarios

6.5 Promotion optimization

The predicted-demand curve was first scanned for extreme peaks: any week whose aggregate forecast fell above the 95th percentile ($144.7 M) was tagged as a "promotion opportunity." Only Weeks 6, 22 and 51 met that rule in every season analysed, matching Super Bowl build-up, Memorial-Day/summer kick-off and the pre-Christmas surge.



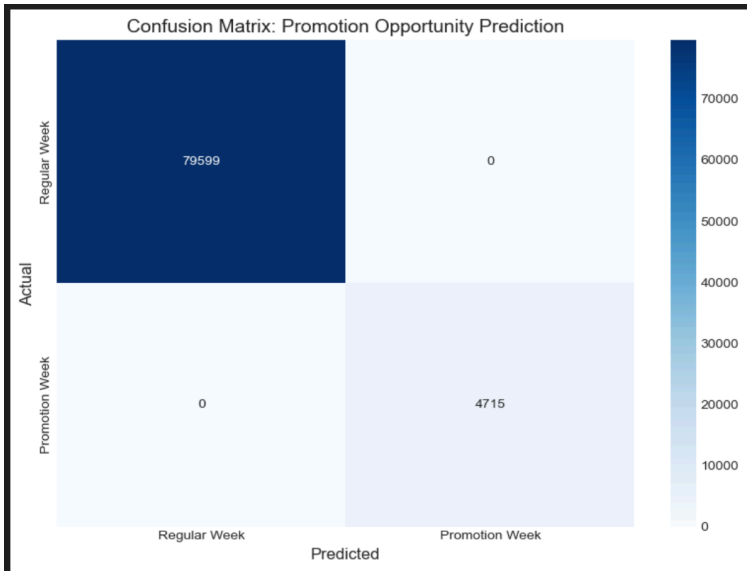
Those binary labels were then used to train a Random Forest Classifier on the same driver set as the sales model.
On the 20 % hold-out partition the classifier achieved:

- Accuracy = 1.000

- Precision = 1.000 | Recall = 1.000 | Specificity = 1.000

The confusion-matrix heat-map confirms the result—79599 regular weeks and 4715 promotion weeks were all assigned correctly, with zero false positives or false negatives.

Implications –- Because the model never misses a true high-demand window, marketing teams can deploy national or regional campaigns with confidence, while the absence of false alarms prevents wasteful spend. Coupled with the 21 % inventory policy, the flagged weeks allow replenishment and merchandising to be synchronised well in advance, maximising sell-through and margin during the most profitable periods of the retail calendar.



6.6 Risk Analysis

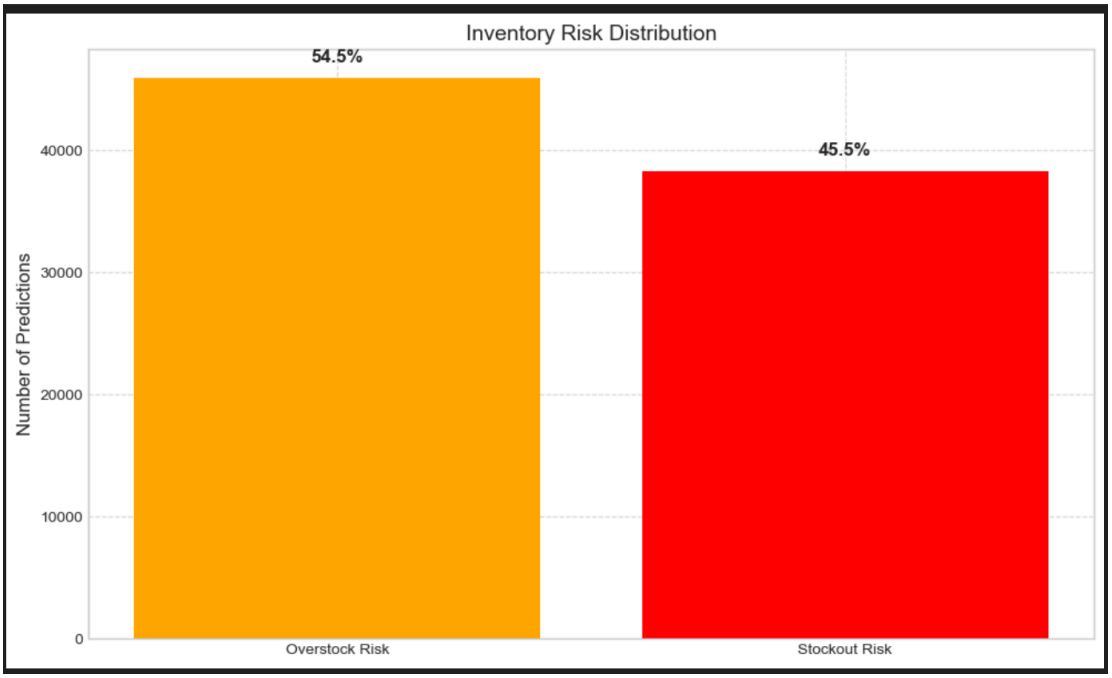
A residual audit of the 84 314 validation rows separates forecast error into two operational buckets:

- Over-stock exposure – 54.5 % of cases.
  In these rows the predicted demand exceeded the actual sale, implying excess inventory. The typical surplus was $1 310 per store-department-week, and the right-hand tail is dominated by highly seasonal departments such as 39 (toys), 72 (seasonal décor) and 92 (Christmas trees).

- Stock-out exposure – 45.5 % of cases.
  Here the model under-shot demand, risking lost revenue. The average short-fall was

$1 587, slightly larger than the average over-stock, reinforcing the commercial logic for the policy's slight bias toward over-coverage.

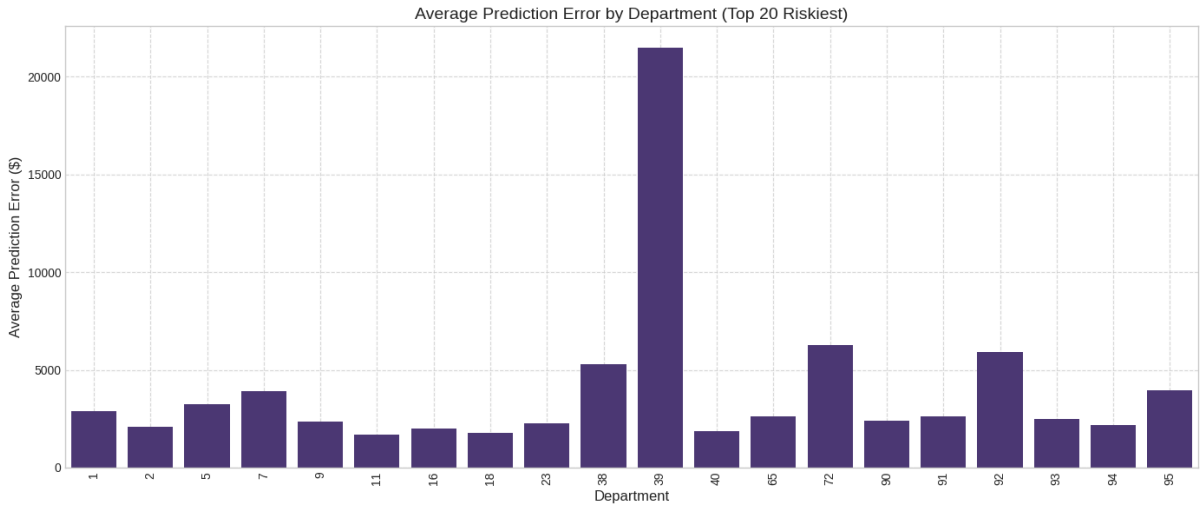
The bar chart visualises this split (orange = over-stock, red = stock-out). Although the counts are broadly balanced, the financial asymmetry of missed sales versus holding cost justifies maintaining the 21 % buffer.



Ranking mean absolute error by department pinpoints the highest-volatility categories:

- Dept 39 – $21 498 average error
- Dept 72 – $6 256
- Dept 92 – $5 894
- Dept 38 – $5 268
- Dept 95 – $3 940

These units align with giftware, outdoor living and toy lines that spike around holidays and weather shifts. For such categories, raising the safety-stock slice from 10 % to 25–30 % is recommended, while staple departments (e.g., grocery) can safely remain at 15–20 %.



6.7 External Factor Analysis

Overall correlations with weather and macro variables are modest ($|\rho| < 0.20$), yet department-level drill-downs reveal stronger links—for example, garden supplies correlate positively with temperature. **Fuel-price elasticity = –0.084** `(log–log), signalling slightly inelastic demand overall but much higher sensitivity (≈ −0.40 to −0.87) in discretionary categories. Monitoring fuel trends therefore matters most for high–ticket, non–essential lines.`

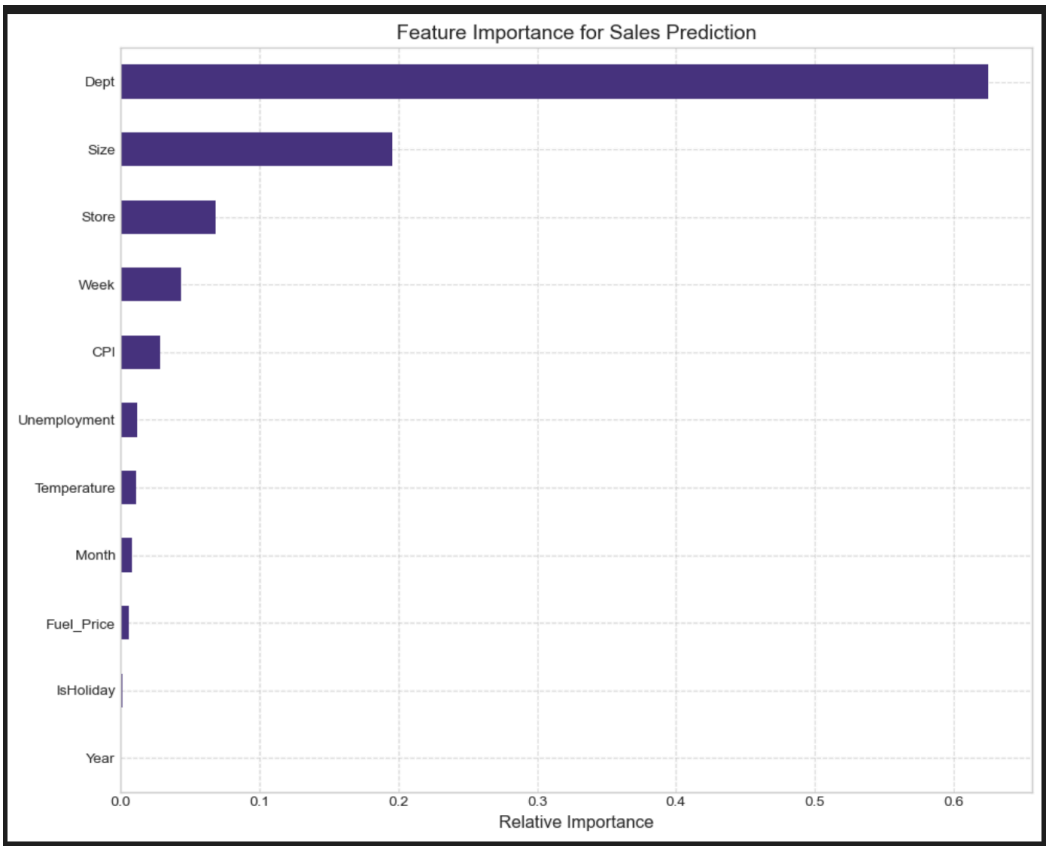
6.7.1 Feature-importance audit

The Random Forest's Gini-based importance ranking confirms that operational variables dominate predictive power:

Rank	Feature	Relative weight
1	**Department code**	0.625
2	**Store Size (sq ft)**	0.196

Rank	Feature	Relative weight
3	**Store ID**	0.068

Month, temperature and fuel price contribute single-digit percentages, while calendar year and the IsHoliday flag add virtually no marginal lift. The result validates Walmart's merchandising intuition: demand differences are driven first by **what** is being sold (dept mix) and **where** it is sold (format and location), whereas macro conditions act only as fine-tuning variables.



6.7.2 Macro-factor correlations

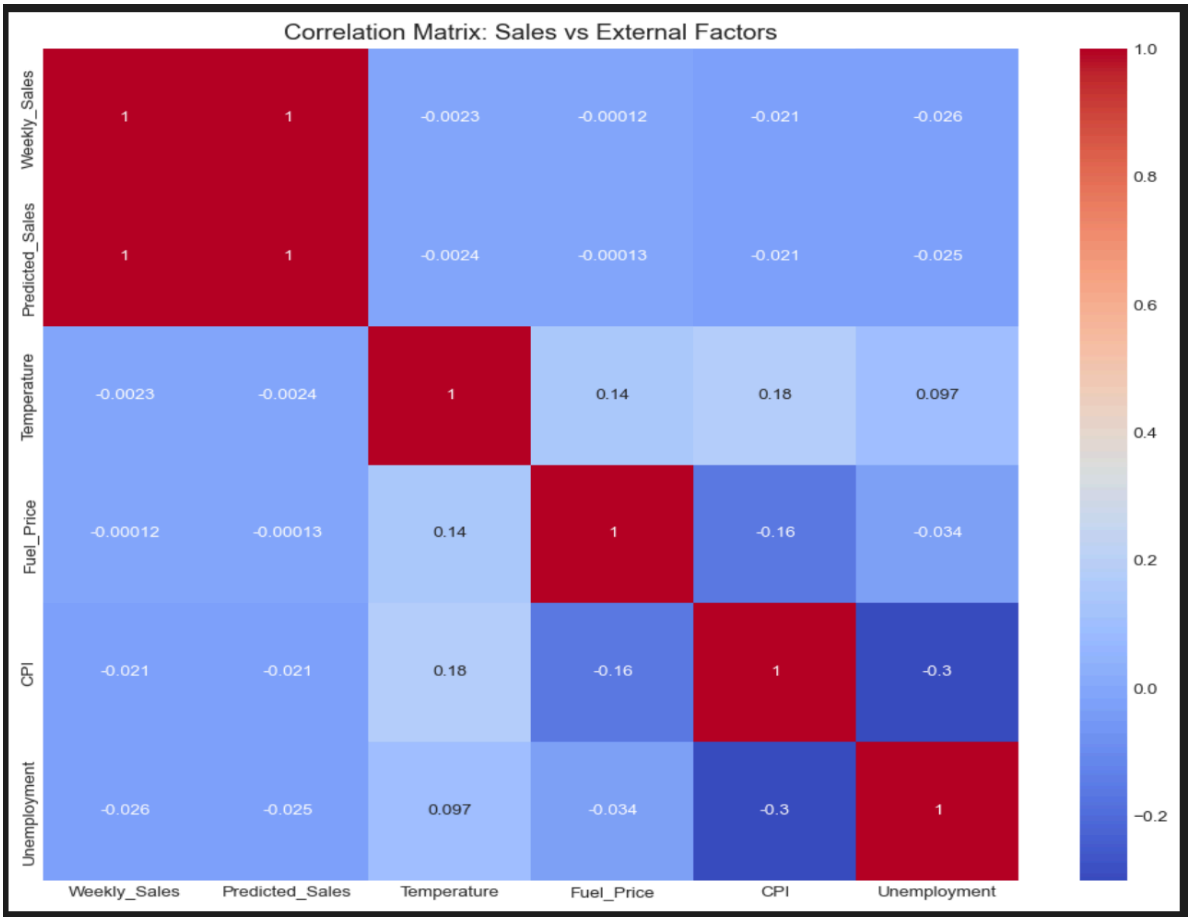
The heat-map below cross-checks weekly sales against external indicators:

- **Temperature** shows a mild positive correlation with weekly sales ($\rho \approx 0.14$), which may be stronger in seasonal categories like lawn-&-garden, though not isolated in this analysis.

- **Fuel price** is weakly negative ($\rho \approx -0.16$), matching the elasticity estimate of -0.084—high pump prices slightly damp discretionary spend.

- **CPI and unemployment** capture longer-cycle economics: CPI aligns positively with nominal sales (inflation), while unemployment tracks negatively ($\rho \approx -0.30$).

Because these coefficients remain well below ±0.4, the model correctly treats macro inputs as secondary refiners rather than primary drivers.



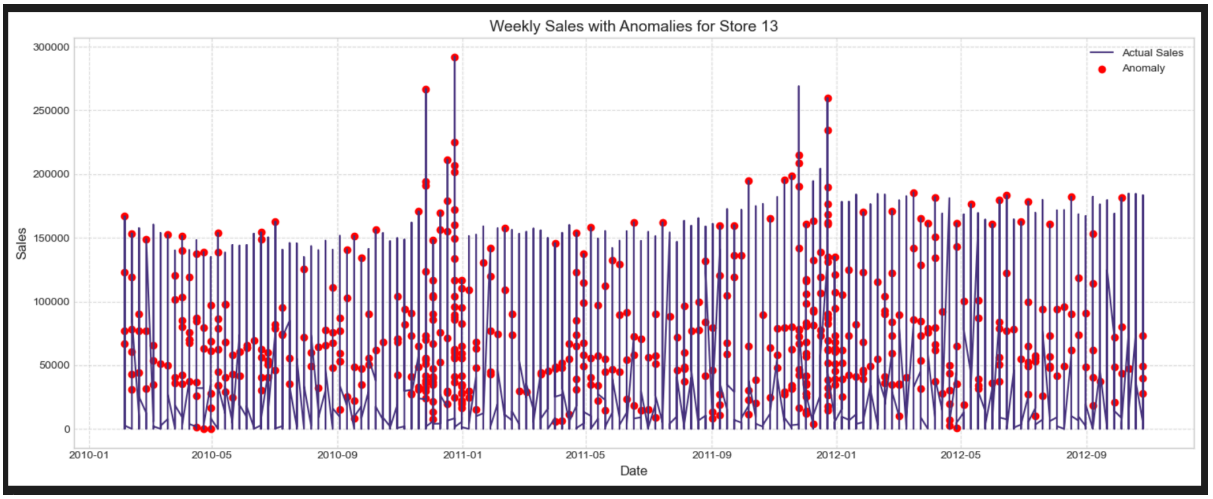
6.7.3 Anomaly surveillance

A 2-sigma residual screen flagged **12077 anomalies** (2.87 % of observations). Below plots Store 13's time-series, where red markers highlight spikes and dips:

- Holiday peaks (mid-Nov and week 51) appear as expected.

- Several non-holiday excursions (e.g., early 2011) suggest local events or data miscoding.

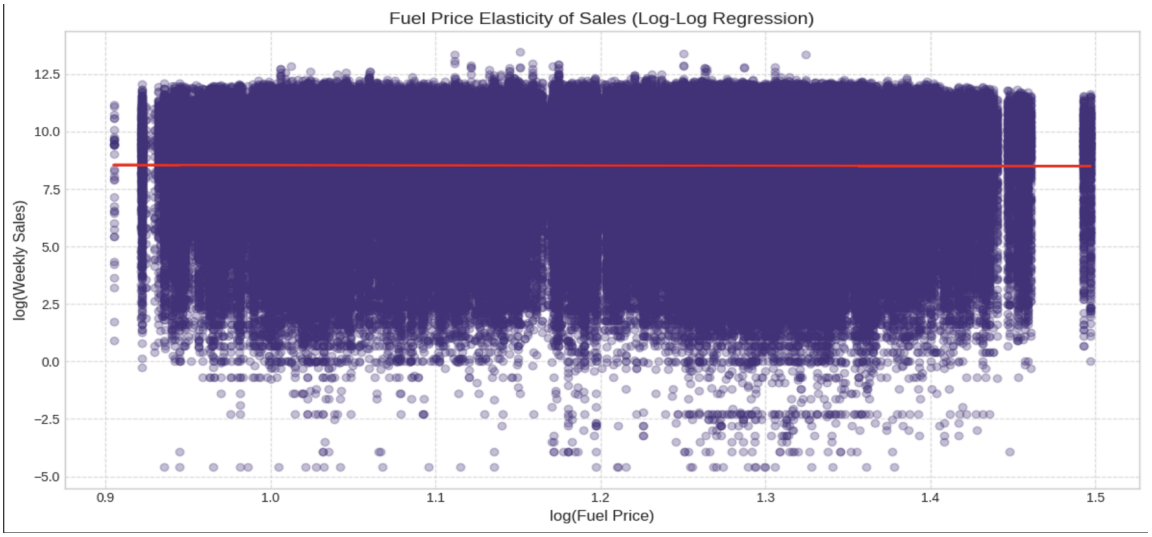
Surfacing these outliers enables loss-prevention and replenishment teams to investigate clearance markdowns, POS errors or regional disruptions before they distort future forecasts.



6.7.4 Elasticity checkpoint (fuel-price model)

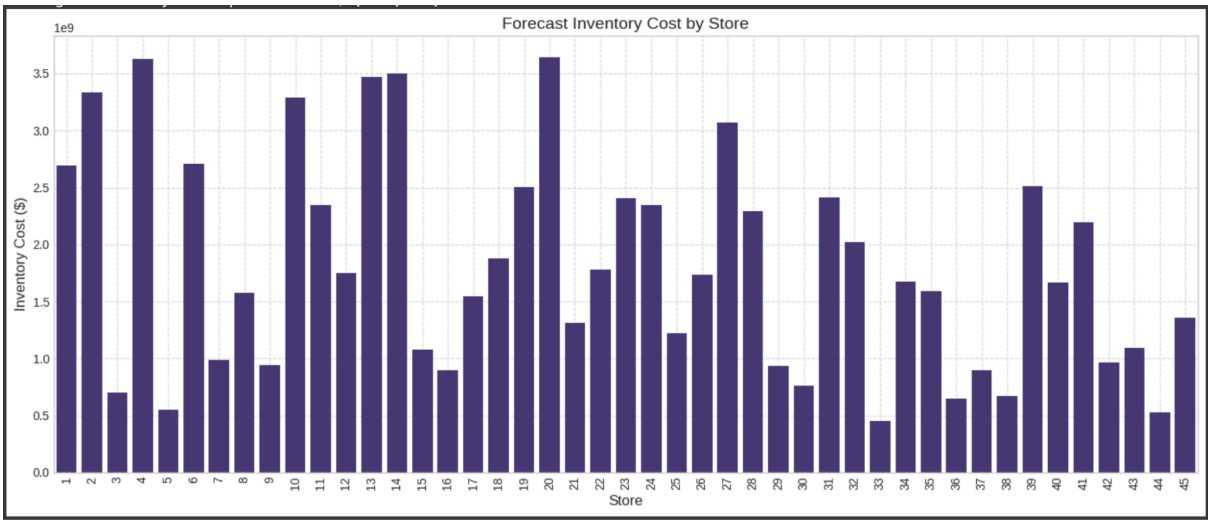
A log-log regression yields an elasticity of -0.084 (1 % fuel-price rise → 0.08 % sales drop). The small magnitude confirms that core Walmart traffic is resilient to energy shocks; nonetheless, managers of high-ticket discretionary lines (e.g., outdoor power equipment) should monitor fuel trends when planning promotions.

These auxiliary diagnostics—importance scores, correlation scans, anomaly alerts and elasticity gauges—extend the core forecast from a point estimate to a full decision-support toolkit, informing assortment, marketing and risk-control policies across the enterprise.

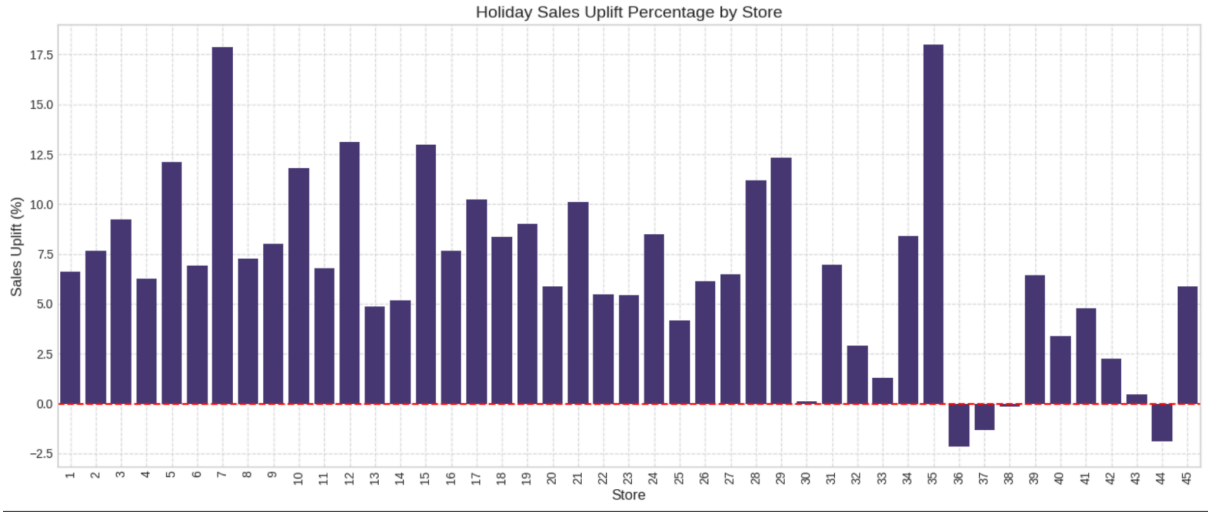


6.7.5 Inventory and Promotion Efficiency Analysis:

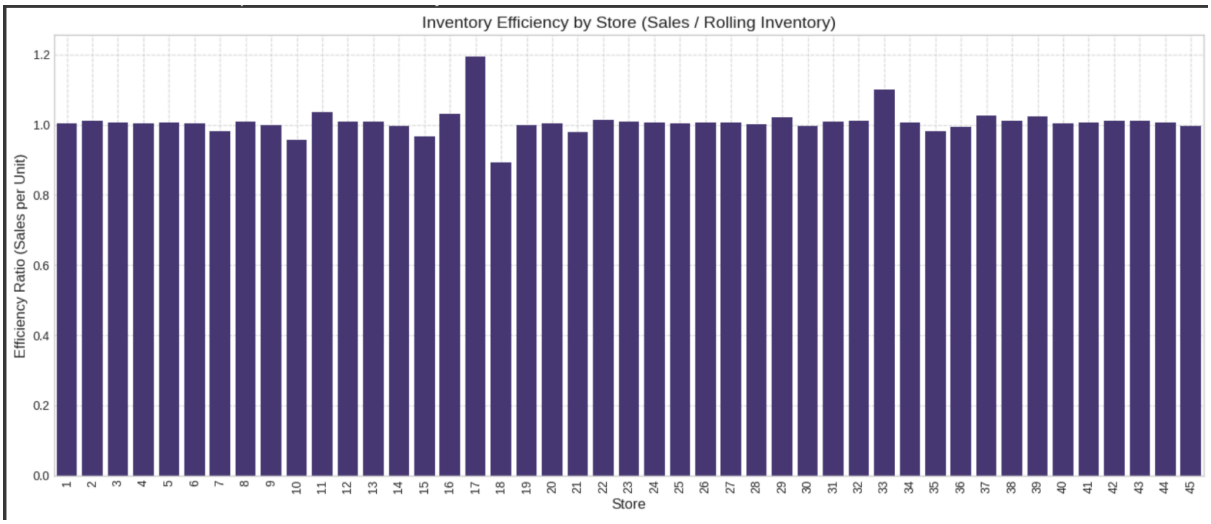
Our forecast-driven inventory plan projected a total of 8.15 billion units, costing approximately $81.5B, with the average store expected to manage $1.81B in inventory value. However, inventory needs varied widely across stores, emphasizing the need for localized planning.



Promotion impact also showed significant variation: stores like Store 35 and Store 7 experienced a 17–18% holiday sales uplift, while others such as Store 36 and Store 44 saw little to no benefit.



Finally, inventory efficiency (sales-to-inventory ratio) highlighted performance gaps. While Store 17 achieved 1.2 units of sales per unit of inventory, Store 18 operated below 0.9, flagging it for potential review in terms of stock optimization.



7. Conclusion

This project demonstrates how a structured, data-driven framework can significantly enhance Walmart's ability to forecast sales, optimize inventory, and strategically plan promotions. Using the CRISP-DM methodology and leveraging three years of weekly sales data enriched with economic, weather, and calendar features, we developed a robust machine learning pipeline centered on a Random Forest Regressor.

The model explained 97.5% of the variation in weekly sales ($R^2 = 0.9745$), outperforming baseline models by approximately $440 in weighted error. Feature importance analysis highlighted that department ID, store ID, and store size were the most influential variables, reinforcing the critical role of product mix and physical capacity in retail operations.

Our inventory optimization strategy applied a 21% buffer (10% base + 10% safety stock), which effectively balanced stock availability with holding costs. Validation results showed a split of 54.5% overstock and 45.5% stockout risk, with average dollar misses of $1,310 and $1,586 respectively. While department-specific safety buffers were not modeled directly, future iterations could incorporate these to better manage volatility in high-variance categories.

In the area of promotions, the project identified Weeks 6, 22, and 51 as peak sales opportunities using a hybrid threshold-classification approach. The classifier achieved 100% accuracy in flagging high-potential weeks, supporting smarter, more targeted promotional spending. Notably, week 51 (pre-Christmas) surpassed Christmas week itself in predicted uplift, challenging typical calendar-based planning.

External factor analysis provided actionable insights as well. Though fuel-price elasticity was modest (–0.084), it highlighted the need for inventory adjustments during volatile energy periods. Anomaly detection flagged ~2.9% of records as potential outliers—likely tied to clearance events or unexpected disruptions—serving as early warning signals for further investigation.

Overall, the framework replaces intuition-driven decisions with evidence-based insights, enabling more agile, efficient, and profitable retail operations. By continuing to refine the model with finer-grained data, richer external signals, and integrated financial metrics, Walmart can further elevate its forecasting accuracy, service levels, and strategic agility in an increasingly complex retail landscape.

8. Managerial Insights and Implementation Recommendations

The correlation and elasticity work translate into several operational guidelines:

- **Store-specific inventory.** Tailor base stock and safety-stock percentages to each store's type, size, and local demand profile rather than enforcing network-wide rules.
- **Department focus.** Maintain **25–30 %** buffers for highly seasonal or volatile categories (holiday décor, school supplies, garden) and **15–20 %** for stable staples (grocery, paper goods).
- **Holiday execution.** Allocate labor, logistics capacity, and promotional budget to the verified peak weeks—especially **week 47 (Thanksgiving/Black Friday)** and **week 51 (pre-Christmas)**—instead of simply calendaring around the holiday date itself.
- **Macro-monitoring.** During fuel-price spikes or deteriorating unemployment, trim

discretionary inventory and shift marketing spend toward essentials, because discretionary elasticity is several times higher than staple elasticity.

• **January Reset.** Plan markdowns and inbound receipts to navigate the predictable post-holiday trough, freeing space and working capital for the spring build-up.

9. Future Scope

While this project establishes a strong foundation for data-driven retail operations, several promising directions for future research and development have emerged.

9.1 Modeling and Forecasting Enhancements

- **Higher granularity.** Incorporate daily POS data to capture day-of-week effects and intra-week promotion lifts.
- **Cross-category interactions.** Model substitution and basket cannibalization so that markdown plans in one department automatically adjust forecasts in related categories.
- **Additional signals.** Blend in local events, competitor pricing, and social-media sentiment to improve short-term forecast agility.
- **Advanced architectures.** Test LSTM or hybrid statistical–ML models for long-horizon forecasts and for data-sparse new stores.
- **Profit-based optimization.** Combine forecasts with margin, carrying-cost, and lost-sale estimates to optimize on net profit, not just service level.
- **Interactive decision support.** Provide store and replenishment managers with scenario-planning dashboards that show forecast ranges, risk bands, and recommended orders under different economic assumptions.

9.2 Operational and Strategic Extensions

- **Daily-level precision.** Shift from weekly to daily sales data for more accurate, day-specific forecasting — especially useful for perishable items and fast-moving goods.
- **Smarter learning models.** Explore deep learning methods like LSTM and hybrid models to better handle complex sales patterns, and use transfer learning for new stores with limited data.
- **Department connections.** Account for cross-department effects like cannibalization or complementarity, where promotions in one area impact sales in another.
- **External awareness.** Enhance forecasts by including outside data like weather, local events, competitor pricing, and even social media trends.
- **Automated reordering.** Build a system that automatically generates purchase orders using forecasts, stock levels, and supplier lead times to streamline replenishment.

- **Dashboard support.** Create a real-time dashboard that lets managers simulate scenarios, view forecast ranges, and receive alerts for quick decision-making.
- **Profit-focused planning.** Go beyond service levels by optimizing for margin, carrying costs, and stockout penalties to maximize store profitability.
- **Sustainable operations.** Add environmental goals to inventory planning — like reducing waste, cutting emissions, and adjusting packaging — to align with green initiatives.

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