Sales Forecasting Report: Weekly Product Demand Prediction for Store (89888)

Objective

To develop a data-driven model that accurately forecasts weekly product sales quantities, supporting better inventory planning, pricing strategy, and promotional targeting.

Approach & Methodology

1. Data Preparation

- **Handle Missing Values**: No missing value found
- **Handle Outliers**: Using Interquartile Range(IQR), Winsorization to cap extreme value at a define percentile
- **Feature Extraction**: Extract "*Month*" and "*Week*" from "*Sales_Week*" given

2. Feature Engineering

- Revenue-based features: reflect business value, capture price impact
- Aggregated features (mean, median, sum, count) for price and sales
- Lag-based features & rolling averages for time series: to capture temporal dependencies

3. Development

- **Train-test split**: train on historical data, 80/20 split
- **Regression-based Model**: XGBRegressor
- **Sample weights**: Add weights to *y_train* to reduce the imbalanced of low-volume samples
- **Gain-based Feature Importance**: Identified historical product performance as the strongest driver of future sales
- **Hyperparameter Tuning**: Used *RandomizedSearchCV* rather than *GridSearchCV*, allowed faster experimentation across a broader range of values

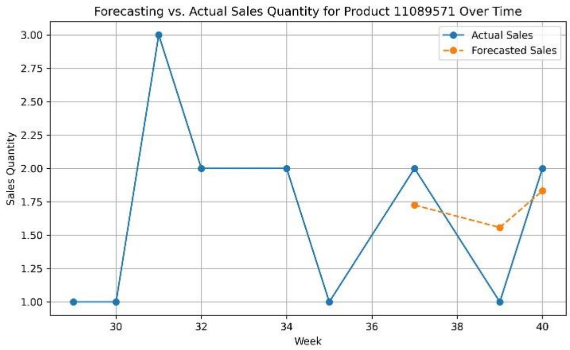
4. Model Evaluation & Visualization

- **Evaluation Metrics**
    - **Mean Absolute Error (MAE):** The average prediction error is **16.21%** of **weekly average sales**, showing high practical accuracy
    - **Mean Absolute Percentage Error (MAPE):** Predictions are off by **45.62%**, which indicates rooms for improvement, possibly due to outliers or volatile sales weeks. Performs very well with **2.56% target grouping MAPE**, suggesting better aggregated forecasting accuracy
    - **R^2 score**: The model explain **87%** of the variance in weekly quantity sales, captures most patterns and trends in data, indicating reliable predictions

- **Error Distribution Plot (*y_test-y_pred*):** The model prediction errors are tightly clustered around zero, with minimal bias and few extreme deviations, indicating strong and reliable performances.

- Comparison using **Baseline (4-weeks moving average):** XGBoost significantly outperformed this baseline in R^2, MAPE and MAE.

- **Forecasting vs Actual Sales Quantity** over time chart: The model closely tracks actual sales across weeks, accurately capturing fluctuations and seasonal patterns. This indicates strong generalization ability and reliability for forward-looking sales quantity forecasting.



- **Compare metrics performance** with other Regression-based Model**:**
  XGBoost provides the best balance of accuracy, flexibility, and explainability.

  - Its ability to model complex sales behaviour, capture non-linearity
  - Robust to handle imbalances, missing values and outliers
  - Deliver actionable feature importance made it the suitable choice for sales prediction

Metrics	XGBoost	Random Forest	Linear Regression	Baseline (4-weeks MA)
MAE (% of avg sales weekly)	16.21%	38.56%	13.14%	22.48%
MAPE (Overall)	45.62%	51.68%	52.13%	58.71%
MAPE (Target Grouping)	2.56%	6.06%	2.06%	3.52%
R^2 SCORE	0.87	0.85	0.84	0.78

Model Accuracy: XGBoost > RandomForest > Linear Regression

Key Findings

- **Weekly-level** features and aggregation help reduced error metrics significantly
- The model closely tracks actual sales across weeks, accurately capturing fluctuations and seasonal pattern
- **Limitations:**
  - **Overfitting Risk**
  - **Features Sensitivity:** Performances heavily depends on input features' quality, may not generalize well if external factors change (not include promotions or holidays in training)
  - **Computational Cost**: Require more resources for training or tuning