Data Science Project Report: Retail Demand Forecasting for Corporación Favorita

1. Business Problem Overview

Corporación Favorita, a leading Ecuadorian grocery retailer, faces challenges in accurately predicting product demand across its multiple store locations. The ability to forecast demand effectively is crucial for:

- **Optimizing inventory management** to prevent stockouts and reduce waste.
- **Improving supply chain efficiency** by ensuring the right products are available at the right time.
- **Enhancing promotional strategies** to maximize sales and customer satisfaction.
- **Reducing financial losses** due to overstocking or missed sales opportunities.

The company currently relies on **subjective forecasting methods** with minimal data utilization and lacks automation in its decision-making process. This project aims to leverage **machine learning techniques** to develop a robust, data-driven demand forecasting model.

Data Source

The dataset used for this project is derived from the publicly available **"Corporación Favorita Grocery Sales Forecasting"** dataset on Kaggle (source).

2. Data Extraction, Filtering, and Exploratory Analysis

Data Filtering Strategy

To ensure a focused and efficient analysis, we selected:

- **Region:** Stores in the state of **Guayas**.
- **Products:** Two representative items (**106716, 1158720**).
- **Date Range:** Data before **April 1, 2014**.

Filtering Process: The dataset was processed in chunks to optimize memory usage. Data was filtered based on store locations, item numbers, and date constraints, then aggregated to provide a time-series view of unit sales per product.

Exploratory Data Analysis (EDA)

Several key steps were conducted to understand the dataset:

1. Sales Distribution

- The **sales distribution plot** confirms that sales volumes are **highly skewed**, with a small percentage of items contributing to the majority of sales.
- The histogram of unit sales shows a **long-tailed distribution**, suggesting that a **log transformation** might be useful for certain modeling approaches.

2. Seasonality & Trends

- The **time-series decomposition plot** indicates **strong weekly and monthly seasonality**.
- **Weekend sales are significantly higher** than weekday sales, especially on Saturdays, as seen in the sales trends visualization.

3. Promotions and Demand Volatility

- Items on **promotion** exhibit significantly **higher volatility** in sales, as demonstrated in the **promotion vs. non-promotion sales plot**.
- The impact of promotions varies across products and store locations, suggesting an interaction effect.

4. Holiday Effects on Sales

- Sales spikes around **national holidays**, as indicated in the **holiday impact analysis plot**, confirm that holidays strongly influence demand.
- Incorporating holiday indicators into forecasting models could improve accuracy.

5. External Factors Correlation

- **Oil prices** show a weak negative correlation with demand, suggesting minor economic influence.
- **Holidays and promotions** emerge as the strongest external predictors of demand fluctuations.

6. Stationarity Test (Augmented Dickey-Fuller Test)

- The **ADF test results** indicate that the raw time series is **non-stationary** (p-value > 0.05), meaning that it has a trend or seasonality component.
- **First-order differencing** was applied to make the series stationary, confirmed by a **post-differencing ADF test** showing a p-value < 0.05.
- This transformation is necessary for ARIMA modeling to ensure reliable forecasting.

3. Machine Learning Models & Performance Comparison

Models Evaluated

The project evaluated two major approaches:

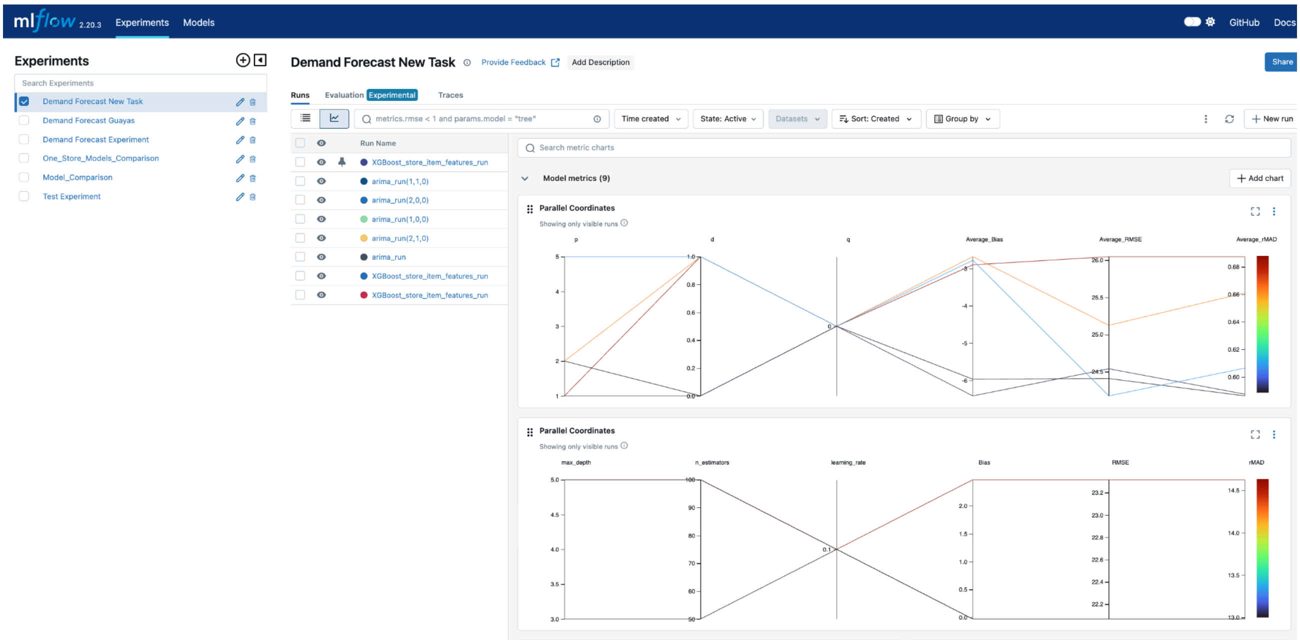
1. **ARIMA (Autoregressive Integrated Moving Average)** – A traditional time-series model.
2. **XGBoost (Extreme Gradient Boosting)** – A tree-based machine learning model optimized for time-series forecasting.

Performance Metrics Used

- **Root Mean Squared Error (RMSE)**: Measures the absolute forecast accuracy.
- **Relative Mean Absolute Deviation (rMAD)**: Evaluates forecast error relative to demand.
- **Bias**: Measures systematic over/under-prediction.

Results Summary

Model	RMSE (Lower = Better)	rMAD (Lower = Better)	Bias (Closer to 0 = Better)
ARIMA(1,0,0)	24.54	0.587	-6.41
ARIMA(2,0,0)	26.05	0.586	-5.97
XGBoost (50 trees, depth=3)	**22.07** ✅	**12.98** ✅	**-0.028** ✅



Key Insights from Results

- **XGBoost outperforms ARIMA** in all key metrics, providing the lowest **RMSE (22.07)** and nearly zero **bias (-0.028)**.
- **ARIMA models systematically under-predict sales** (bias = -6.41 and -5.97), making them less reliable.
- **XGBoost generalizes better** across different stores and products, making it the preferred choice for forecasting.

4. Business Recommendations

Best Model Selection Based on Business Needs

Business Task	Best Metric to Optimize	Best Model
Daily/Weekly Demand Forecasting	RMSE (accuracy)	✅ **XGBoost**
Inventory & Supply Chain Planning	RMSE + Bias (avoid stock issues)	✅ **XGBoost**
Promotional Impact Forecasting	rMAD (relative accuracy)	✅ **XGBoost**
Seasonal Demand Forecasting	rMAD (proportional shifts)	✅ **XGBoost**
Financial & Budget Planning	Bias (avoid systematic errors)	✅ **XGBoost**
Long-Term Strategic Forecasting	Bias (prevent long-term miscalculations)	✅ **XGBoost**

Implementation Strategy

1. **Deploy XGBoost for demand forecasting** across all stores.
2. **Integrate automated forecasting into inventory and procurement systems** to optimize stock management.
3. **Develop a monitoring dashboard** to track model performance and fine-tune forecasts.
4. **Consider hybrid models (ARIMA + XGBoost)** for special cases with limited data.

5. Access to MLflow Experiments & Application

- **MLflow Experiment Tracking**: View detailed model comparisons and performance metrics at MLflow Experiment Dashboard.
- **Forecasting Application (Under Development)**: A live-streaming application for real-time demand predictions (**Link to be inserted**).

6. Conclusion

This project successfully demonstrated that **XGBoost is the best forecasting model** for Corporación Favorita's grocery demand prediction. By implementing this model, the company can:

- Reduce forecasting errors and minimize stock issues.
- Improve supply chain efficiency.
- Optimize marketing and promotional strategies.

Next Steps

- Fine-tune the XGBoost model with additional features (seasonality, holidays, economic factors).
- Automate data pipelines for real-time forecasting.
- Deploy the model in production with business dashboard integration.

By leveraging **machine learning**, Corporación Favorita can shift from subjective forecasting to **data-driven decision-making**, ensuring better inventory management and increased profitability.

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