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Leveraging AWS for Predictive Inventory Management in Auto Parts Retail

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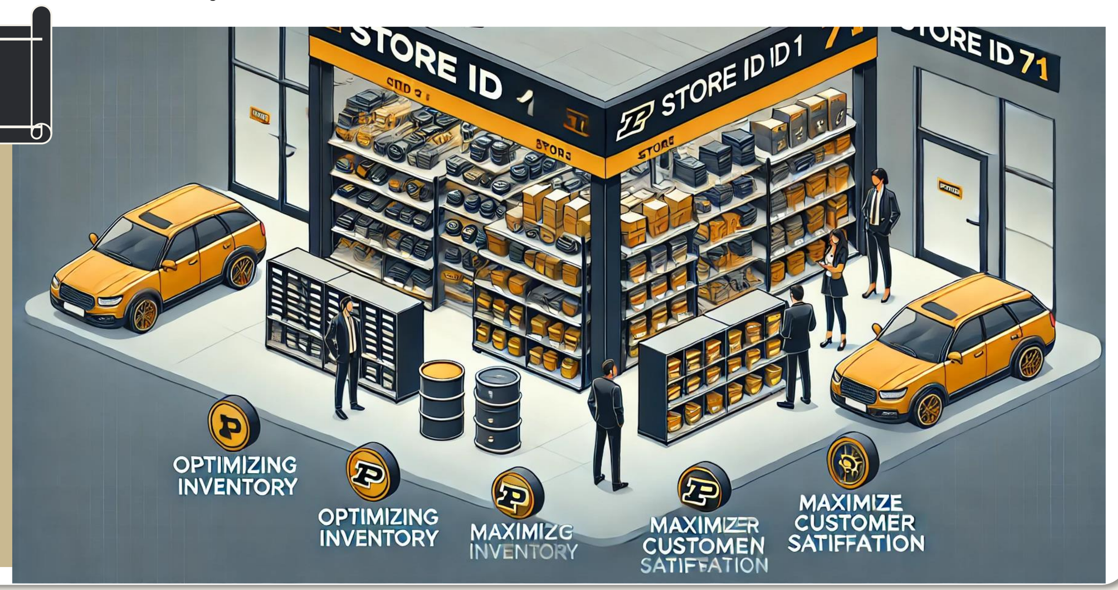
BUSINESS PROBLEM

The auto parts retailer faces a significant challenge in managing its inventory, specifically in ensuring the availability of the right parts in its stores. Customers typically visit these stores only when they need specific parts, which might occur infrequently, often just once or twice a year. The consequence of not stocking the required part can lead to lost sales and decreased customer loyalty, as customers may choose to visit competitors who have the parts they need. The primary objective of this project is to develop an optimized assortment of auto parts for Store ID 71, addressing the challenge of space constraints while maximizing customer satisfaction. By aligning the stocked inventory with customer demand, the retailer aims to enhance sales performance and improve overall operational efficiency.

OBJECTIVES

- Predict the optimal assortment of parts for Store ID 71
- Develop a scalable solution applicable to other stores



ANALYTICAL SOLUTION

Goal

- The main goal is to figure out which auto parts will be needed the most, so the store can stock them and meet customer demand effectively

How?

- Use Historical Data: Look at past sales and product details to build models that predict future demand.
- Create Models: Use statistical techniques to predict which items will sell and in what quantities.
- Optimize Stocking: Use an optimization approach to make sure the most important items are stocked within the limited shelf space.

Assumptions

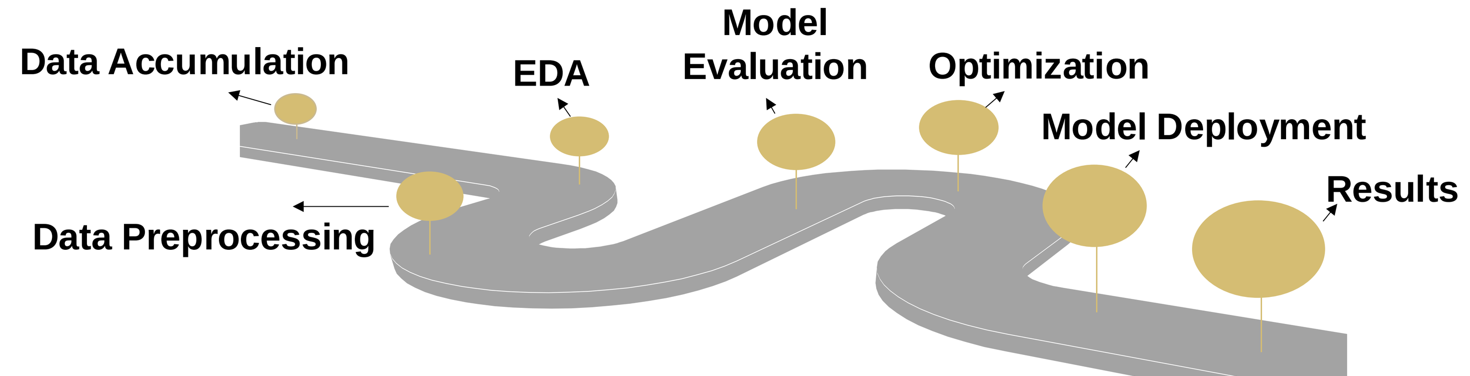
- **Stable Market Conditions:** We assume that the market won't change drastically, and customers will keep buying parts in the same way.
- **Consistent Customer Behaviour:** We believe that customers will continue to buy parts in similar patterns as they have in the past.

Success Metrics

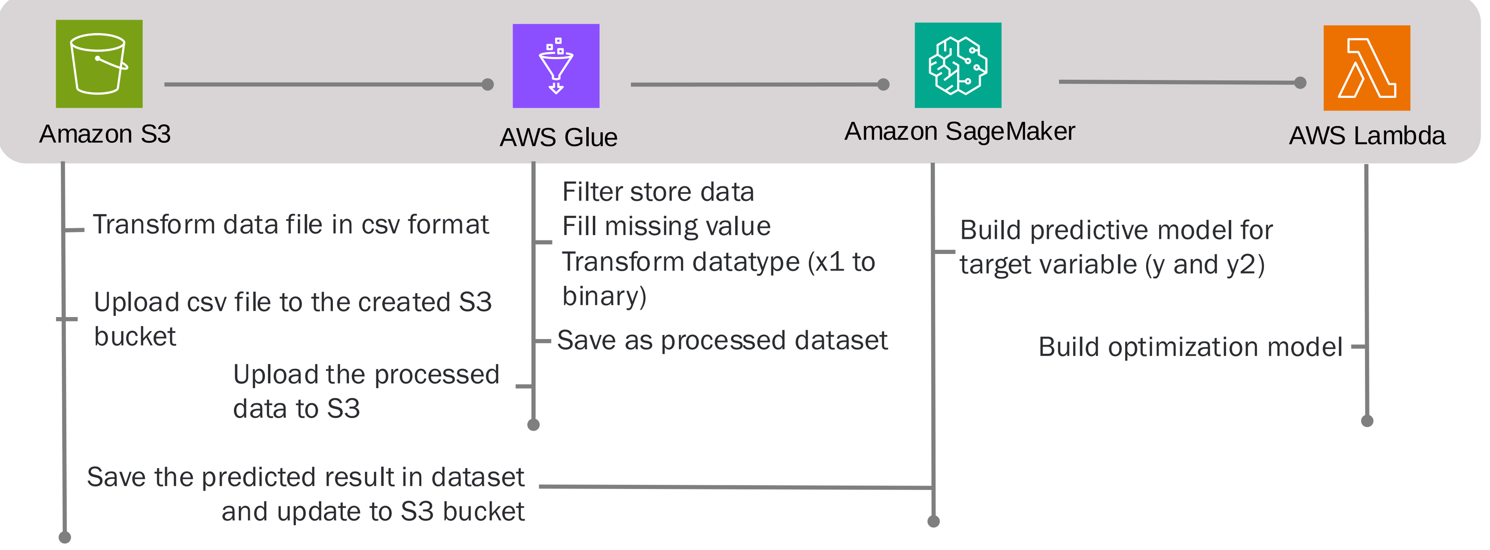
- RMSE – Linear and Logistic Regression models
- Cross Validation - Mean and Standard Deviation
- Total Revenue generated from the optimized assortment

METHODOLOGY

We employed a structured approach to address the retailer's stocking problem, starting with data preprocessing. The dataset, stored in S3 as cc2_case.csv, we grouped the store_id to extract observations for store_id=71. The dataset was loaded and cleaned. Exploratory Data Analysis (EDA) provided initial insights through descriptive statistics and visualizations, such as distribution plots and correlation heatmaps. For predictive modeling, we developed a logistic regression model to classify whether a product was sold (y) and a linear regression model to predict the quantity sold (y2). Both models were evaluated using K-Fold cross-validation, ensuring robust performance metrics. Additionally, we formulated an optimization problem using Mixed-Integer Linear Programming (MILP) to determine the optimal assortment of SKUs, with constraints on shelf space and predicted demand.



DEPLOYMENT



$$Profit\ rate = \frac{\sum(sold\ quantity \times price)}{\sum(sold\ quantity \times space)}$$

	Last year	Predicted
Total profit	1944.91	1532.18
Total storage space	962.05	464.24
Profit rate	**2.02**	**3.30**

The solution implemented AWS Cloud Services to ensure scalability and periodic updates. The deployment strategy involved setting up a data pipeline that ingests new data, updates predictions, and adjusts the inventory recommendations accordingly. The model's performance was continuously monitored and validated against actual sales data to ensure its effectiveness. This solution increase the revenue by increase the profit rate per storage inch. We increase the profit rate from **2.02** to **3.3**.

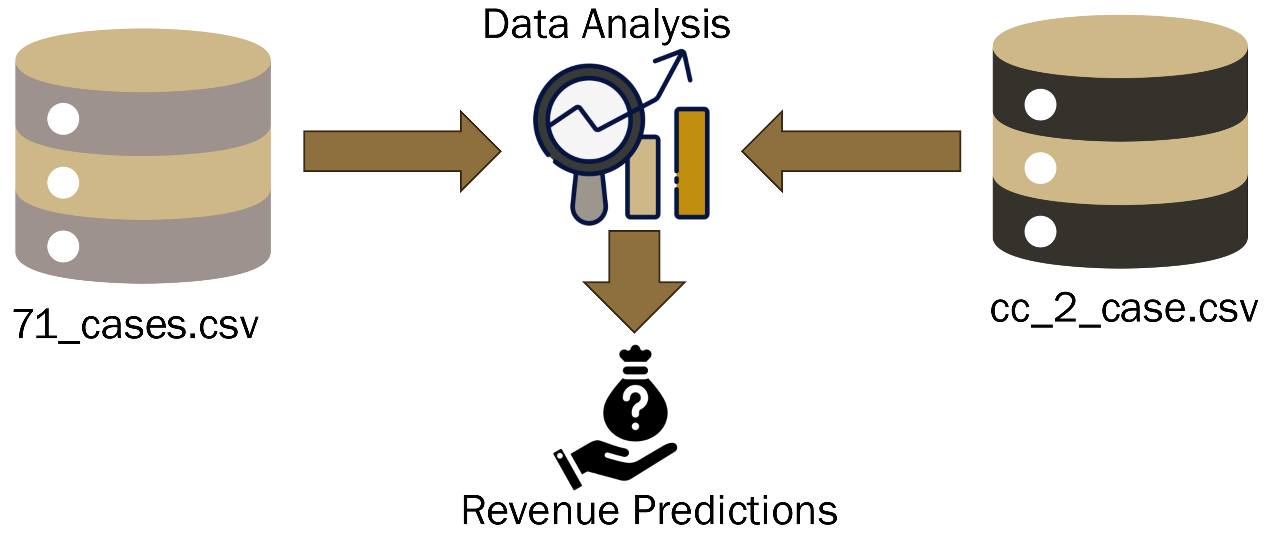
LITERATURE REVIEW

The solution was implemented using AWS cloud services, ensuring scalability and periodic updates. The deployment strategy involved setting up a data pipeline that ingests new data, updates predictions, and adjusts the inventory recommendations accordingly. The model's performance was continuously monitored and validated against actual sales data to ensure its effectiveness. This validation process provided critical feedback, enabling adjustments and improvements to the model as needed. The business impact of this deployment is significant, potentially increasing sales and customer satisfaction by ensuring the availability of high-demand products while optimizing inventory levels.

Study	AWS Services	Gurobi and Pyomo packages	Machine Learning	Optimaiztion concepts	AWS Academy Knowledge Checks
Data Science in Cloud Lectures & Notes (Purdue)	✓	✓	✓	✓	
AWS Academy Machine learning Modules & Labs	✓		✓	✓	✓
Machine Learning Lectures & Notes (Purdue)			✓		✓
Optimization Lectures & Notes (Purdue)			.	✓	✓

DATA

The project utilized a comprehensive dataset comprising historical sales data, product characteristics, and store-specific information, stored in files such as cc2_case.csv and 71_cases.csv. These data files were securely stored within an S3 bucket, ensuring easy access and scalability for analysis. We carried out the data analysis and model development using a Jupyter notebook within AWS SageMaker, leveraging the cloud platform's robust computational resources. Key variables included sku_id, price, cubic_in, and other attributes relevant to product features and sales performance. The data underwent rigorous preprocessing steps, including handling missing values, normalizing numerical data, and encoding categorical variables, to ensure accuracy and consistency. Descriptive statistics and initial data exploration provided valuable insights into patterns and trends, laying the foundation for subsequent modeling efforts.



Model Building

Predictive Model

y (Binary: 1 for demanded)
Logistic Regression
K-fold (21)
*Cross Validation **Accuracy** score: 0.75*
Standard Deviation: 0.17

Independent Variables (previous selling condition): x1, x2, …, x17

y2 (Continuous: demand quantity)
Linear Regression
K-fold (21)
*Cross Validation **RMSE** score: 1.78*
Standard Deviation: 1.23

y_pred

round to nearest non-negative integer: **y2_pred**

Optimization

$$maximize: Optimal\ Revenue = \sum_{i=1}^{n}(y_i \times price_i \times y\_pred_i)$$

Recognize the specific SKU is chose or not, not chosen (0) should have 0 revenue

Constraint:

Storage: $\sum_{i=1}^{n}(y_i \times cubic\_in_i) \leq \sum_{i=1}^{n} cubic\_in_i \times 0.65$

Optimal value: $0 \leq y_i \leq y2\_pred_i$

*n: number of unique SKU

*y_pred: predicted value of y (binary: 1 for selected, 0 for not selected)

*y: optimal value for each unique SKU

*cubic_in: storage space for SKU

*y2_pred: rounded value for predicted demand quantity

Sample Result:

SKU	y_pred	optimal value
1038	0	0
1169	1	5
1083	1	1

LIFE CYCLE MANAGEMENT

Maintaining the model's accuracy and accuracy over time is crucial for ongoing success. We established a framework for monitoring key performance metrics, such as prediction accuracy and model stability. This involves regular updates and recalibrations of the model using new data, ensuring it adapts to any changes in customer behavior or market conditions. Additionally, we outlined a future work plan that includes expanding the model's application to other stores and incorporating more diverse data sources, such as real-time sales data and external market trends. This proactive approach ensures the model remains a valuable tool for inventory management and strategic decision-making.