Inventory Manager

DEPI AI & Data Science - Data Engineer Track

Fall 2024

DEPI-CAI- AIS4-S5e

Project Team: Group 4

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Abstract

This project develops an end-to-end Azure Data Engineering solution for managing retail inventory and sales. It integrates a SQL database for tracking products, orders, and inventory, a data warehouse for storing historical data, and machine learning models for sales forecasting.

The project is structured into four phases: designing a SQL database, setting up an Azure Synapse Analytics data warehouse, developing machine learning models to predict sales, and deploying these models using MLOps and MLflow. Python-based ETL processes automate the flow of data, while Power BI dashboards provide real-time insights into inventory and sales and a website to interface with the database and use it to order items from the inventory and predict sales per quartile in some countries where the inventory exists.

Overall, this system optimizes inventory management for small businesses, automates reporting, and enhances decision-making through accurate demand forecasting.

Introduction & Overview

The goal of this project is to build a comprehensive, end-to-end data engineering solution for inventory management and sales forecasting using Azure. The solution includes a website interface that provides ease of access for the end user to order items and view product details.

Objectives & Project Phases

The project is structured into four distinct phases, each aimed at achieving specific objectives:

- **Phase 1: SQL Database Design and Implementation**
  - Design a robust relational database schema to manage products, customers, orders, and inventory.
  - Implement SQL queries and stored procedures for automated inventory tracking and sales reporting.
- **Phase 2: Data Warehousing and Python Integration**
  - Set up an Azure Synapse Analytics data warehouse to store historical sales and inventory data.
  - Automate the ETL process using Python, ensuring regular loading of data into the warehouse.
- **Phase 3: Forecasting Models and Azure Integration**
  - Develop machine learning models to predict sales trends in different regions based on historical sales data.
  - Integrate the forecasting models with Azure for streamlined data processing.
- **Phase 4: MLFlow, Model Deployment & Website**
  - Deploy the forecasting models and automate the retraining and monitoring of machine learning models using MLOps.
  - Create interactive dashboards for business users to visualize sales and inventory data, providing actionable insights.

Project Scope & Technology Stack

This project focuses on building an end-to-end Azure Data Engineering solution for managing inventory and sales within a retail business. It covers all aspects from database design and ETL processes to demand forecasting and automated reporting.

Key Technologies Used:

- SQL Server
- Azure Data Factory
- Azure Databricks
- Azure Synapse Analytics

- Website for interfacing
- Python
- MLflow
- Power BI

Problem Analysis

Business Problem:

Managing inventory and sales in a retail business is a complex task, particularly due to the large volumes of data generated from multiple sales channels, locations, and suppliers. Retailers face several key challenges that hinder efficient operations:

- **Demand Forecasting**: Accurately predicting customer demand is essential to meet customer needs while avoiding overstocking or stockouts.
- **Supplier Management**: Monitoring supplier performance and ensuring timely restocking is crucial for maintaining smooth inventory flow and avoiding delays.
- **Sales Reporting**: Retailers require daily, weekly, and monthly sales reports to make informed business decisions, but manually tracking and analyzing sales data can be time-consuming.
- **Manual Processes**: Many of these tasks are handled manually, increasing the likelihood of errors, inefficiency, and delays in decision-making, which can impact business performance.

Solution:

To address these challenges, an automated system is required that can:

- **Track inventory levels in real-time** across multiple locations, providing up-to-date information on stock availability.
- **Forecast future demand** using machine learning models to help retailers anticipate Sales and adjust inventory accordingly.
- **Generate automated sales and inventory reports**, allowing business owners to make timely, data-driven decisions and streamline operations.

Key Deliverables:

- A robust **database schema** to manage inventory and sales data.
- Automated **ETL processes** for seamless data flow.
- **Forecasting models** to predict future sales and demand.
- A **website interface** for easy interaction with the system and ML model interfacing
- A **Power BI dashboard** for real-time insights into inventory and sales.

Project Phases & Implementation

Phase 1: SQL Database Design and Implementation

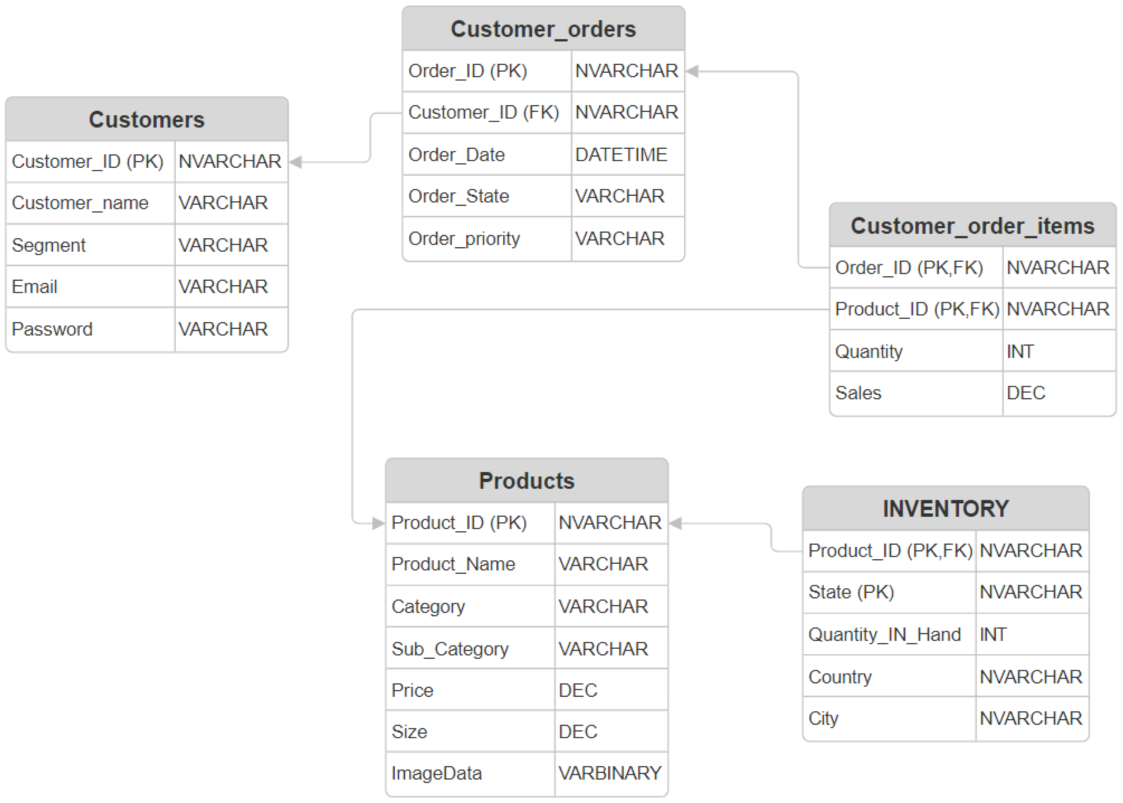
- **Database Design**

Identify key entities such as products, suppliers and sales.

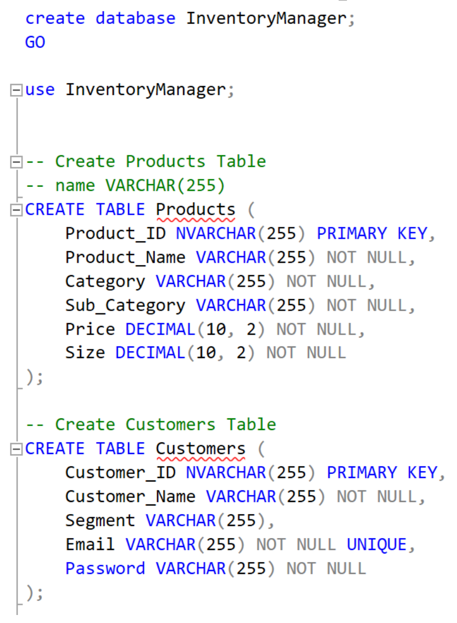
Schema Design (normalized to 3NF):

- **Products**: Product_ID (PK), Product_Name, Category, Sub_Category, Price, Size.
- **INVENTORY**: Product_ID (FK), State (PK), Quantity_in_hand, Country, City.
- **Customers**: Customer_id (PK), Customer_name, Segment, Email, Password.
- **Customer_orders**: Order_id (PK), Customer_id (FK), Order_date, Order_status, Order_priority.
- **Customer_order_items**: Order_id (FK), Product_ID (FK), Quantity, Sales.

ER Diagram

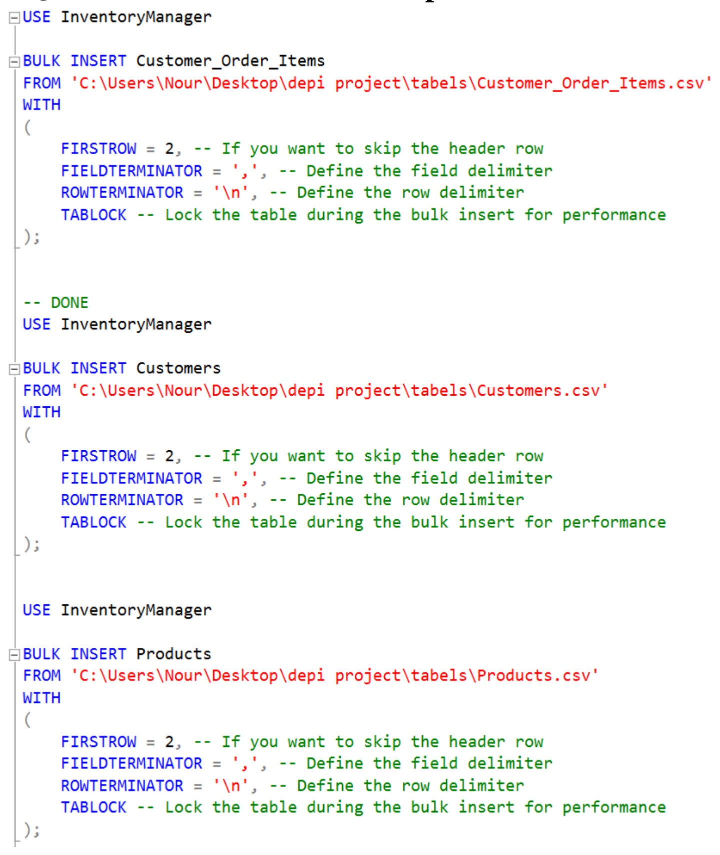


- **SQL Table Implementation**
  - **SQL Table Creation Script:**



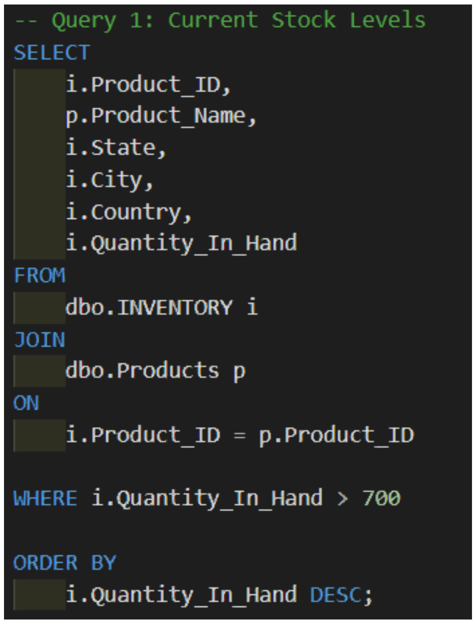
```sql
create database InventoryManager;
GO

use InventoryManager;


-- Create Products Table
-- name VARCHAR(255)
CREATE TABLE Products (
    Product_ID NVARCHAR(255) PRIMARY KEY,
    Product_Name VARCHAR(255) NOT NULL,
    Category VARCHAR(255) NOT NULL,
    Sub_Category VARCHAR(255) NOT NULL,
    Price DECIMAL(10, 2) NOT NULL,
    Size DECIMAL(10, 2) NOT NULL
);

-- Create Customers Table
CREATE TABLE Customers (
    Customer_ID NVARCHAR(255) PRIMARY KEY,
    Customer_Name VARCHAR(255) NOT NULL,
    Segment VARCHAR(255),
    Email VARCHAR(255) NOT NULL UNIQUE,
    Password VARCHAR(255) NOT NULL
);
```

  - **SQL Table Data Insertion Script:**

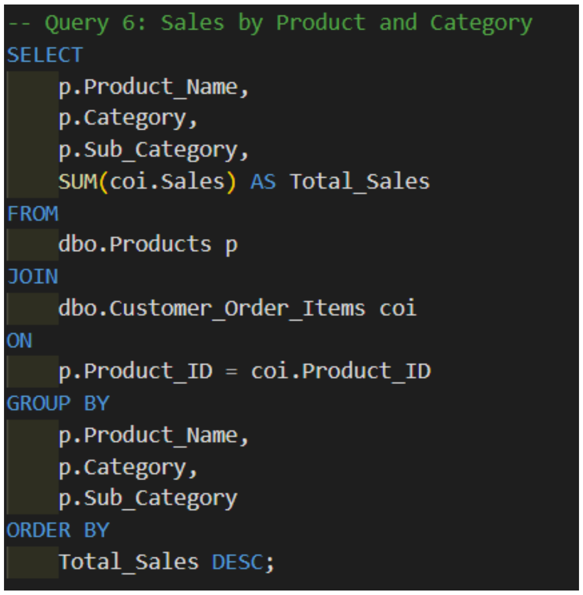


```sql
USE InventoryManager

BULK INSERT Customer_Order_Items
FROM 'C:\Users\Nour\Desktop\depi project\tabels\Customer_Order_Items.csv'
WITH
(
    FIRSTROW = 2, -- If you want to skip the header row
    FIELDTERMINATOR = ',', -- Define the field delimiter
    ROWTERMINATOR = '\n', -- Define the row delimiter
    TABLOCK -- Lock the table during the bulk insert for performance
);


-- DONE
USE InventoryManager

BULK INSERT Customers
FROM 'C:\Users\Nour\Desktop\depi project\tabels\Customers.csv'
WITH
(
    FIRSTROW = 2, -- If you want to skip the header row
    FIELDTERMINATOR = ',', -- Define the field delimiter
    ROWTERMINATOR = '\n', -- Define the row delimiter
    TABLOCK -- Lock the table during the bulk insert for performance
);


USE InventoryManager

BULK INSERT Products
FROM 'C:\Users\Nour\Desktop\depi project\tabels\Products.csv'
WITH
(
    FIRSTROW = 2, -- If you want to skip the header row
    FIELDTERMINATOR = ',', -- Define the field delimiter
    ROWTERMINATOR = '\n', -- Define the row delimiter
    TABLOCK -- Lock the table during the bulk insert for performance
);
```

- **Queries and Reporting**
  - **Inventory Monitoring Queries & Sales Reporting Queries (sample)**:

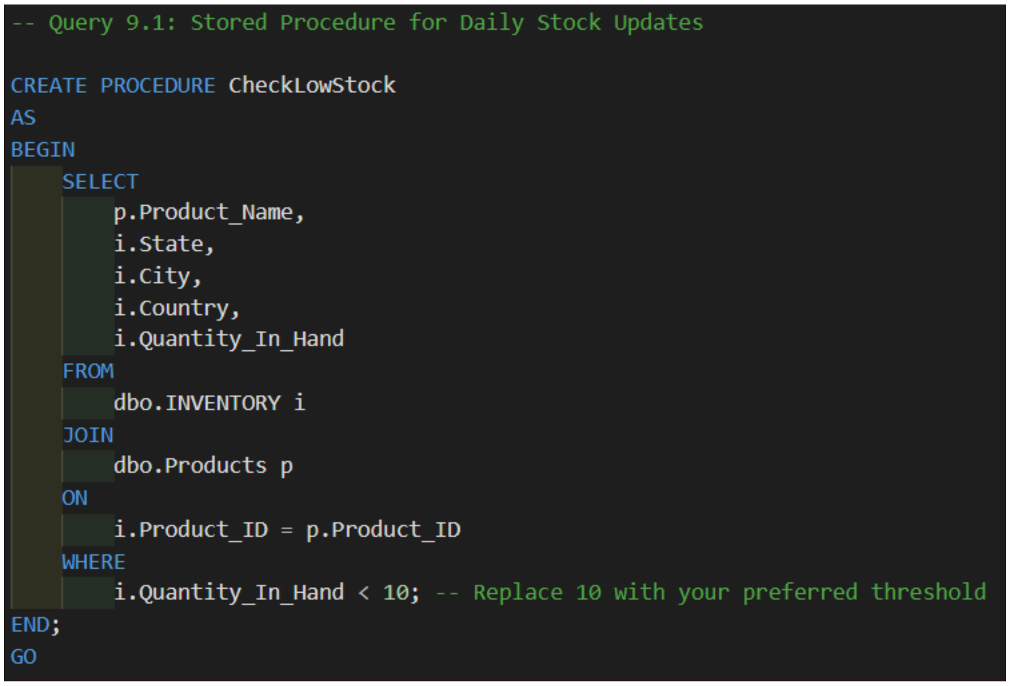


```sql
-- Query 1: Current Stock Levels
SELECT
    i.Product_ID,
    p.Product_Name,
    i.State,
    i.City,
    i.Country,
    i.Quantity_In_Hand
FROM
    dbo.INVENTORY i
JOIN
    dbo.Products p
ON
    i.Product_ID = p.Product_ID

WHERE i.Quantity_In_Hand > 700

ORDER BY
    i.Quantity_In_Hand DESC;
```



```sql
-- Query 6: Sales by Product and Category
SELECT
    p.Product_Name,
    p.Category,
    p.Sub_Category,
    SUM(coi.Sales) AS Total_Sales
FROM
    dbo.Products p
JOIN
    dbo.Customer_Order_Items coi
ON
    p.Product_ID = coi.Product_ID
GROUP BY
    p.Product_Name,
    p.Category,
    p.Sub_Category
ORDER BY
    Total_Sales DESC;
```

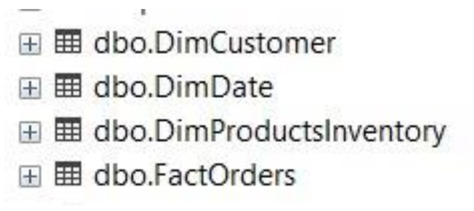
  - **Stored Procedures (sample)**:



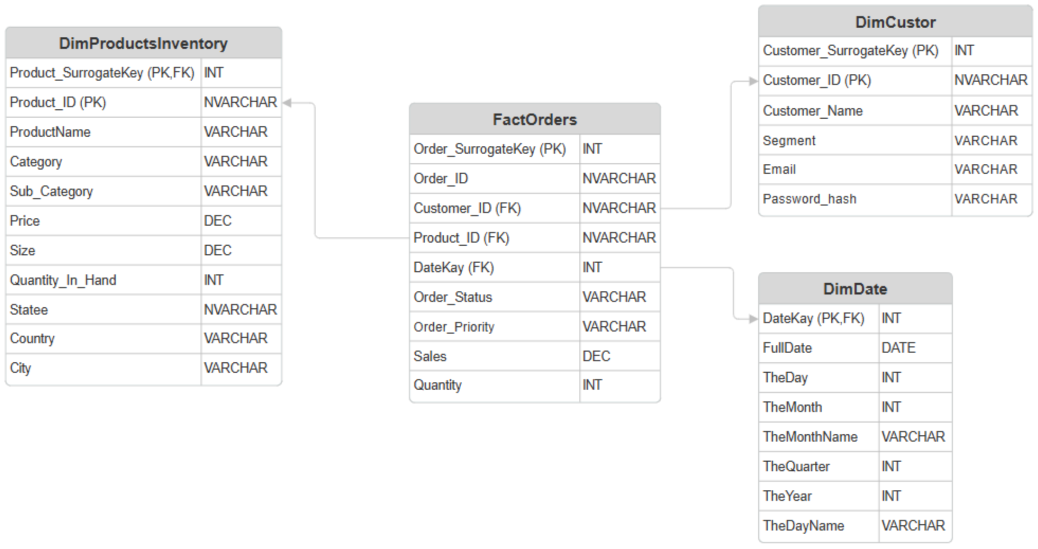
```sql
-- Query 9.1: Stored Procedure for Daily Stock Updates

CREATE PROCEDURE CheckLowStock
AS
BEGIN
    SELECT
        p.Product_Name,
        i.State,
        i.City,
        i.Country,
        i.Quantity_In_Hand
    FROM
        dbo.INVENTORY i
    JOIN
        dbo.Products p
    ON
        i.Product_ID = p.Product_ID
    WHERE
        i.Quantity_In_Hand < 10; -- Replace 10 with your preferred threshold
END;
GO
```

Phase 2: Data Warehousing and Python Integration

- **Data Warehouse Design**
  - Design the data warehouse schema (used star schema)
  - Fact and dimension tables used Date in customers_order table after Denormalization of tables of the original Database



dbo.DimCustomer
dbo.DimDate
dbo.DimProductsInventory
dbo.FactOrders



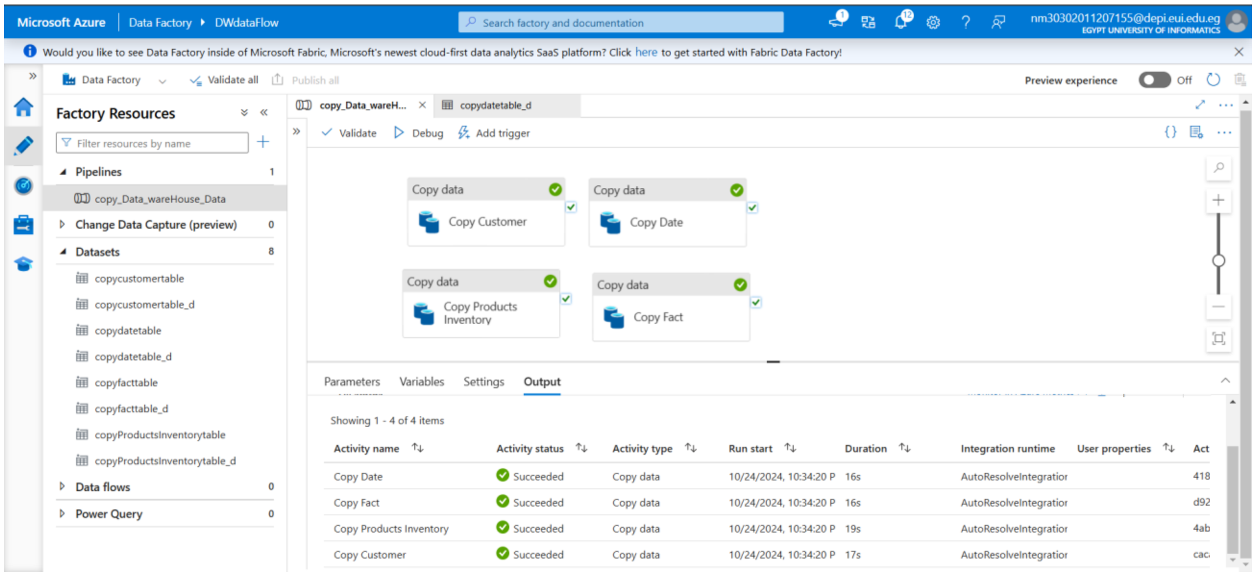
DimProductsInventory	
Product_SurrogateKey (PK,FK)	INT
Product_ID (PK)	NVARCHAR
ProductName	VARCHAR
Category	VARCHAR
Sub_Category	VARCHAR
Price	DEC
Size	DEC
Quantity_In_Hand	INT
Statee	NVARCHAR
Country	VARCHAR
City	VARCHAR

FactOrders	
Order_SurrogateKey (PK)	INT
Order_ID	NVARCHAR
Customer_ID (FK)	NVARCHAR
Product_ID (FK)	NVARCHAR
DateKay (FK)	INT
Order_Status	VARCHAR
Order_Priority	VARCHAR
Sales	DEC
Quantity	INT

DimCustor	
Customer_SurrogateKey (PK)	INT
Customer_ID (PK)	NVARCHAR
Customer_Name	VARCHAR
Segment	VARCHAR
Email	VARCHAR
Password_hash	VARCHAR

DimDate	
DateKay (PK,FK)	INT
FullDate	DATE
TheDay	INT
TheMonth	INT
TheMonthName	VARCHAR
TheQuarter	INT
TheYear	INT
TheDayName	VARCHAR

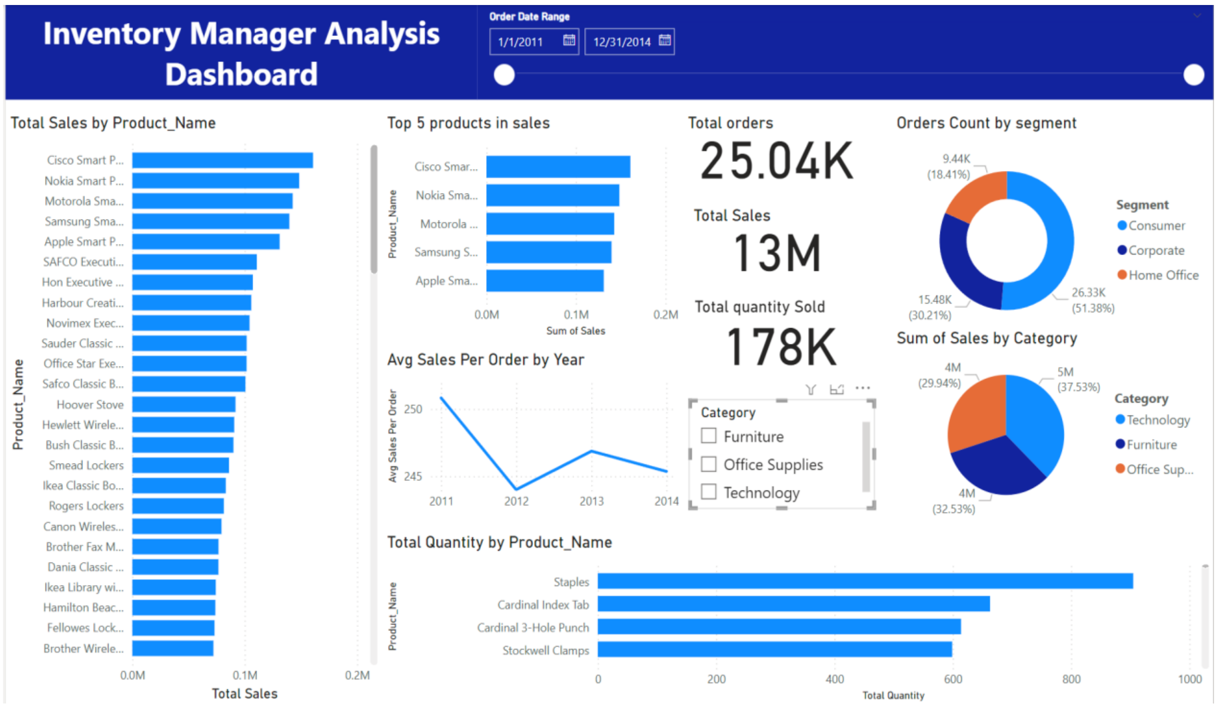
- **ETL Process Using Python**
  - **Extract Data from SQL Database** using python



Showing 1 - 4 of 4 items

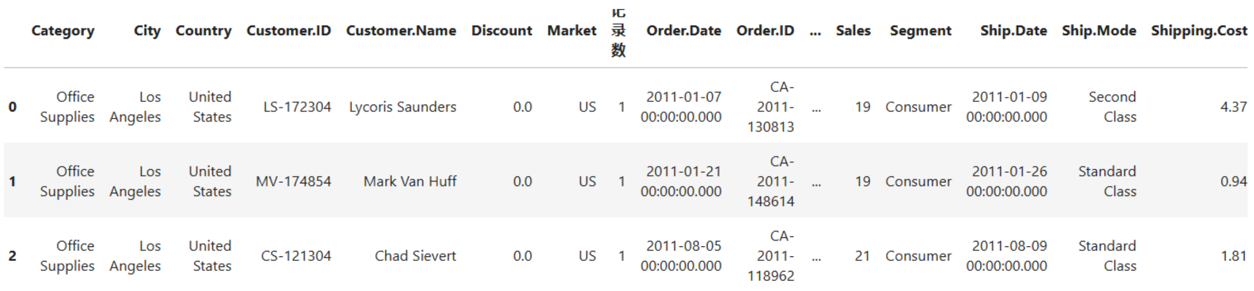
Activity name	Activity status	Activity type	Run start	Duration	Integration runtime	User properties	Act
Copy Date	✓ Succeeded	Copy data	10/24/2024, 10:34:20 P	16s	AutoResolveIntegratior		418
Copy Fact	✓ Succeeded	Copy data	10/24/2024, 10:34:20 P	16s	AutoResolveIntegratior		d92
Copy Products Inventory	✓ Succeeded	Copy data	10/24/2024, 10:34:20 P	19s	AutoResolveIntegratior		4ab
Copy Customer	✓ Succeeded	Copy data	10/24/2024, 10:34:20 P	17s	AutoResolveIntegratior		cac

- **Automation Using Azure Data Factory**
  - **Pipeline Overview**: Automate the ETL process using Azure Data Factory to extract, transform, and load data into Azure Synapse Analytics.
  - **Scheduling ETL Jobs**: Schedule ETL jobs using ADF to regularly preprocess new data for retraining.
  - **Load** New Data to PowerBI to be included in the data visualization and providing insights on it.

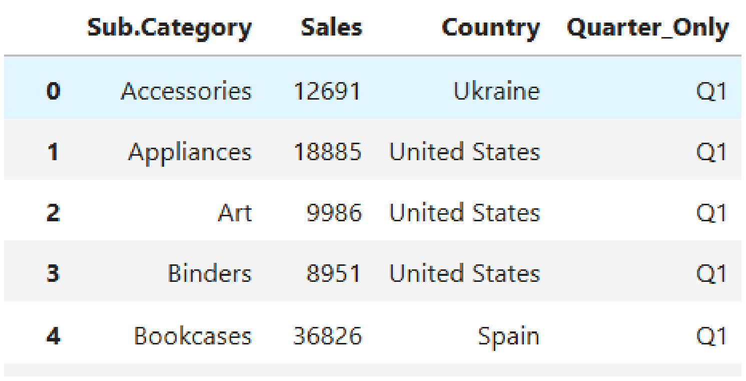


Phase 3: Forecasting Models and Azure Integration

- **Forecasting Models**
  - **Historical Data Collection**:
    Use sales data extracted from the data warehouse\ historical data in the database to train forecasting models.
  - **Data Preprocessing**: applied grouping to sub-categories per quartile

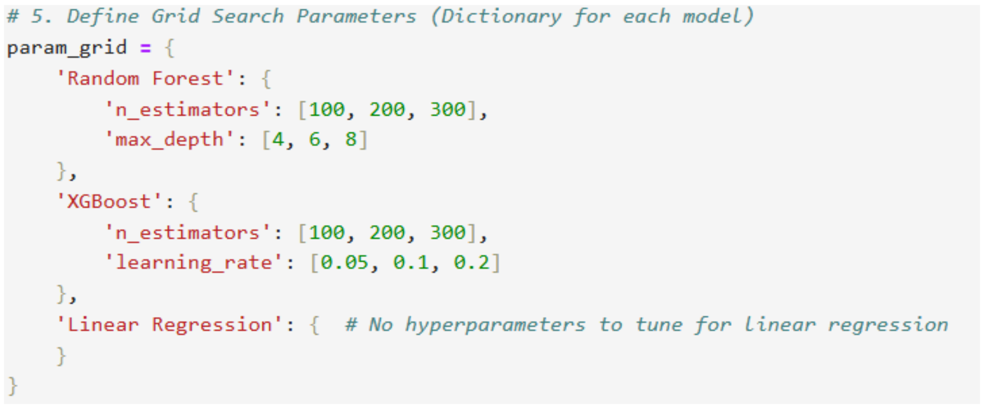


	Category	City	Country	Customer.ID	Customer.Name	Discount	Market	记录数	Order.Date	Order.ID	...	Sales	Segment	Ship.Date	Ship.Mode	Shipping.Cost
0	Office Supplies	Los Angeles	United States	LS-172304	Lycoris Saunders	0.0	US	1	2011-01-07 00:00:00.000	CA-2011-130813	...	19	Consumer	2011-01-09 00:00:00.000	Second Class	4.37
1	Office Supplies	Los Angeles	United States	MV-174854	Mark Van Huff	0.0	US	1	2011-01-21 00:00:00.000	CA-2011-148614	...	19	Consumer	2011-01-26 00:00:00.000	Standard Class	0.94
2	Office Supplies	Los Angeles	United States	CS-121304	Chad Sievert	0.0	US	1	2011-08-05 00:00:00.000	CA-2011-118962	...	21	Consumer	2011-08-09 00:00:00.000	Standard Class	1.81



	Sub.Category	Sales	Country	Quarter_Only
0	Accessories	12691	Ukraine	Q1
1	Appliances	18885	United States	Q1
2	Art	9986	United States	Q1
3	Binders	8951	United States	Q1
4	Bookcases	36826	Spain	Q1

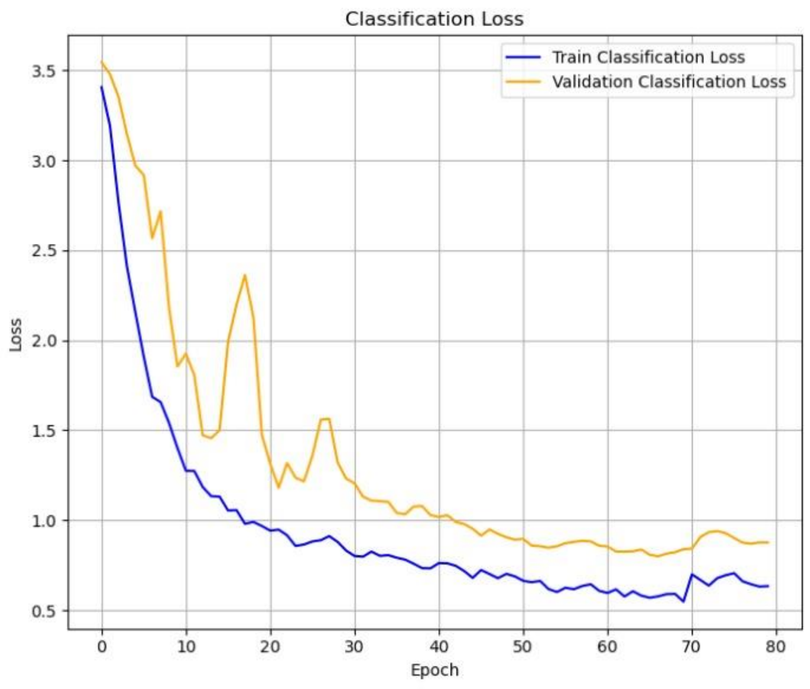
  - **Hyperparameter Tuning and Model Optimization:** Pre-Training for accuracy and efficiency
  - **Model Selection**: used grid search on multiple models with different hyperparameters such as (Linear regression- Random Forest- XGBoost) to find the best model



```python
# 5. Define Grid Search Parameters (Dictionary for each model)
param_grid = {
    'Random Forest': {
        'n_estimators': [100, 200, 300],
        'max_depth': [4, 6, 8]
    },
    'XGBoost': {
        'n_estimators': [100, 200, 300],
        'learning_rate': [0.05, 0.1, 0.2]
    },
    'Linear Regression': {  # No hyperparameters to tune for linear regression
    }
}
```

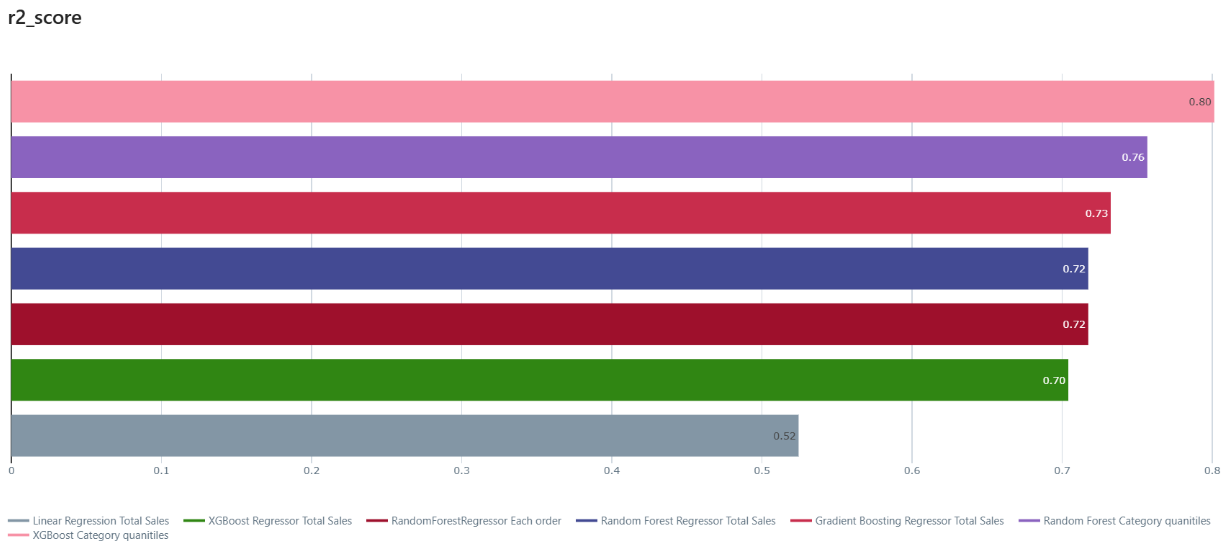
- **Model Training:** Trained the model on the following features (date quartiles – subcategory-country) to predict sales per quartile in a certain country

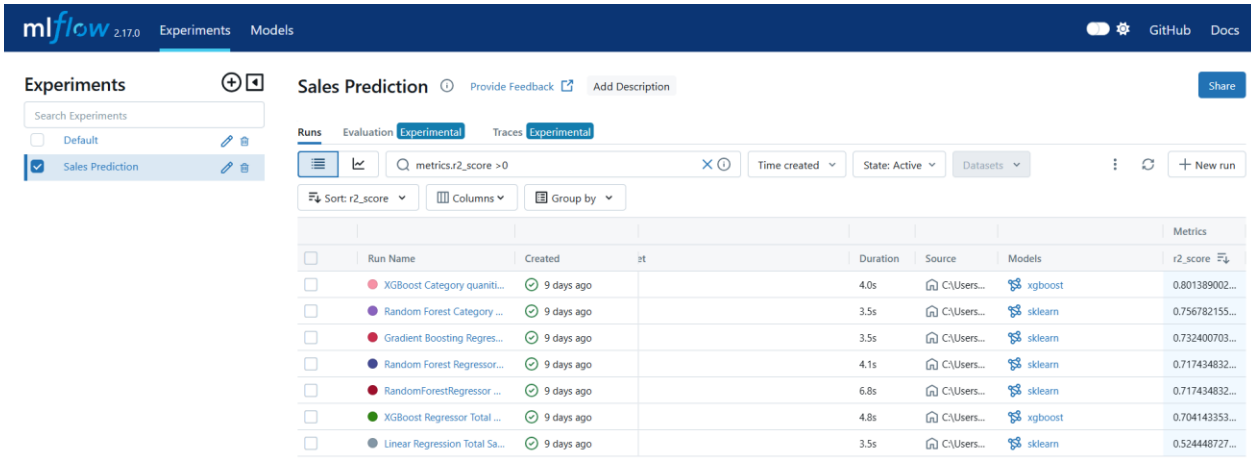
- **Computer Vision Model for Inventory Security**
  - Implemented a computer vision model to safeguard inventory.
  - Model analyzes images of items and compares them to a database of authentic pieces.
  - System triggers alerts for any discrepancies, preventing potential theft or loss.



Phase 4: MLFlow, Model Deployment & Website

- **Model Selection & Evaluation**: used R2-Score to evaluate each model and we choose XGBoost as it gave optimal performance through MLFlow.





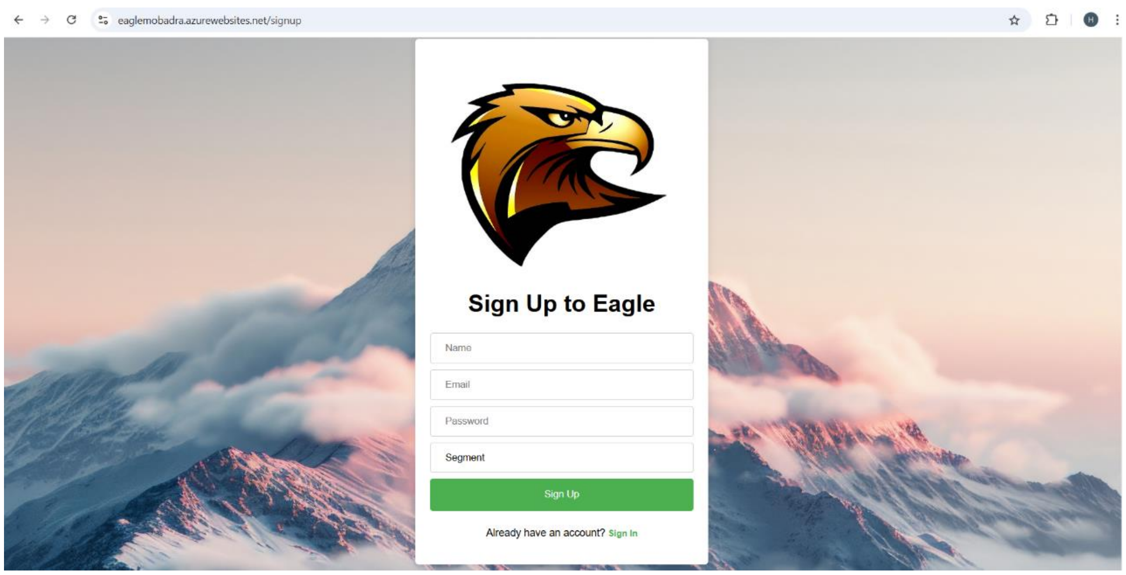
metrics.r2_score >0

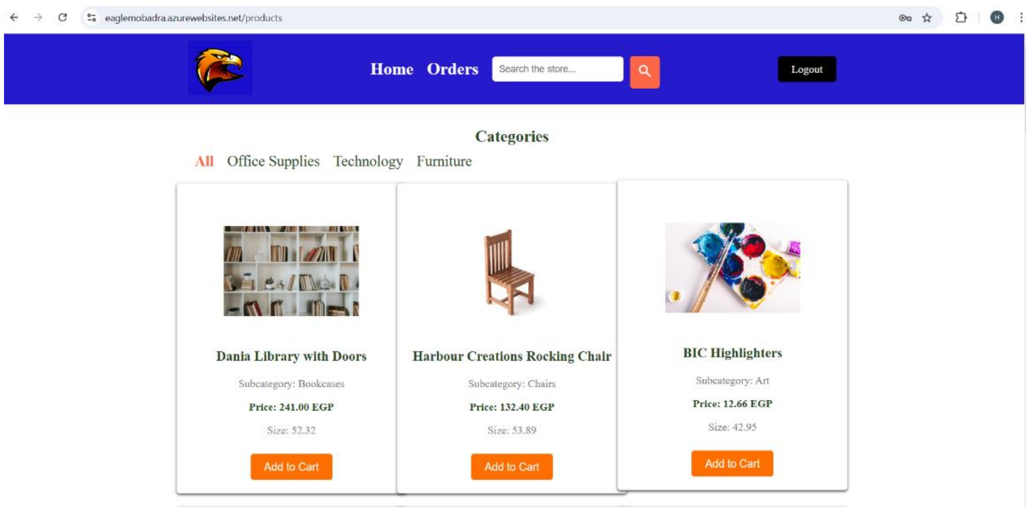
	Run Name	Created	Duration	Source	Models	Metrics r2_score
	● XGBoost Category quaniti...	9 days ago	4.0s	C:\Users...	xgboost	0.801389002...
	● Random Forest Category ...	9 days ago	3.5s	C:\Users...	sklearn	0.756782155...
	● Gradient Boosting Regres...	9 days ago	3.5s	C:\Users...	sklearn	0.732400703...
	● Random Forest Regressor...	9 days ago	4.1s	C:\Users...	sklearn	0.717434832...
	● RandomForestRegressor ...	9 days ago	6.8s	C:\Users...	sklearn	0.717434832...
	● XGBoost Regressor Total ...	9 days ago	4.8s	C:\Users...	xgboost	0.704143353...
	● Linear Regression Total Sa...	9 days ago	3.5s	C:\Users...	sklearn	0.524448727...

- **MLflow**
  - **Model Tracking &Versioning**: Saved multiple models trained and picked the best score of accuracy model to be used
  - **Deployment of Forecasting Models**

- **Website**
  - **Interactive Dashboards**:
    a website to provide the predictions once the user enters the needed parameters to evaluate a prediction

- **Website features**:
    - User: searching, tracking & ordering/buying of products
    - Admin: track, modify products, forecast product sales per quartile in a certain country (using quartile, country and subcategory)
    - Data Integrity: Logins are secure.

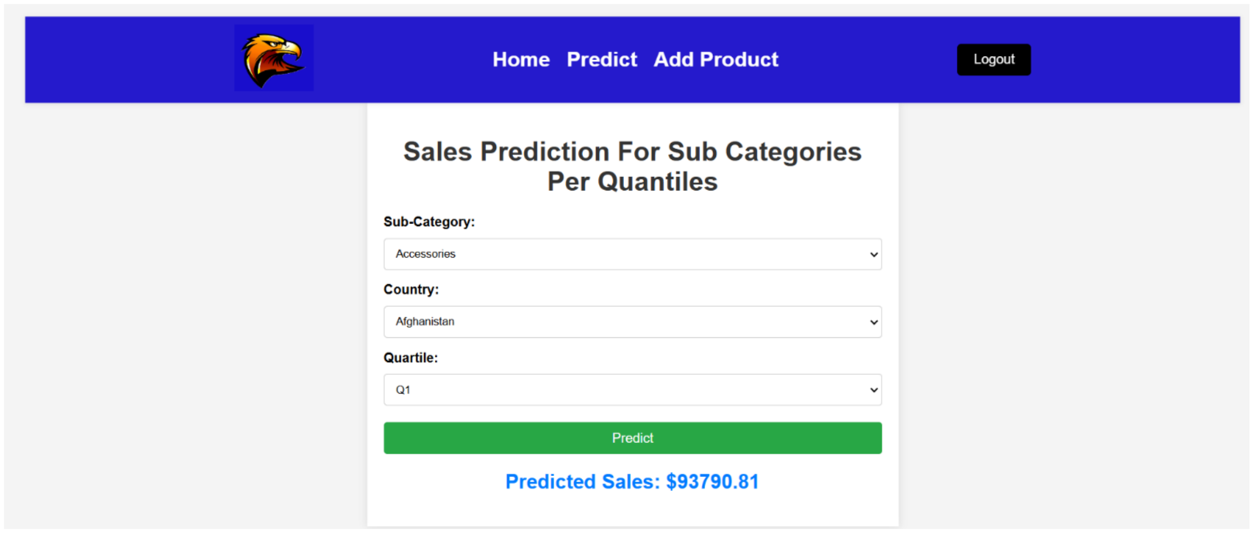

eaglemobadra.azurewebsites.net/signup
Sign Up to Eagle
Name
Email
Password
Segment
Sign Up
Already have an account? Sign In



Dania Library with Doors
Subcategory: Bookcases
Price: 241.00 EGP
Size: 52.32

Harbour Creations Rocking Chair
Subcategory: Chairs
Price: 132.40 EGP
Size: 53.89

BIC Highlighters
Subcategory: Art
Price: 12.66 EGP
Size: 42.95



Sales Prediction For Sub Categories Per Quantiles

Sub-Category: Accessories

Country: Afghanistan

Quartile: Q1

Predicted Sales: $93790.81

Challenges and Solutions

- **Data Inconsistencies**:
  - **Challenge**: During the ETL process, data inconsistencies (e.g., missing or inaccurate values) were encountered.
  - **Solution**: Data validation checks were applied, and the data was cleaned before loading into the warehouse, ensuring consistent and accurate data in the system.
- **Schema Normalization to 3NF**:
  - **Challenge**: Designing a database schema that is fully normalized to 3NF without redundancy was challenging, especially when managing interrelated entities such as products, inventory, and sales.
  - **Solution**: The use of an Entity-Relationship (ER) Diagram helped visualize relationships between entities, ensuring a well-structured and optimized schema that reduced redundancy and improved query performance.

- **Efficient Data Population**:
  - **Challenge**: Populating large datasets into multiple tables while maintaining data integrity and handling foreign key constraints posed challenges.
  - **Solution**: Python scripts were developed to automate data insertion, ensuring data was inserted in the correct order without violating key constraints, streamlining the data population process.
- **Complex ETL Process**:
  - **Challenge**: Managing the ETL process across multiple sources with varying data formats, handling missing data, and ensuring consistency was complex.

    - **Solution**: Python and Pandas were used to preprocess and clean the data before loading it into the warehouse. The entire process was automated using Azure Data Factory, ensuring regular data updates and clean data across datasets.
- **Automating ETL with Azure Data Factory**:
    - **Challenge**: Setting up a reliable automated ETL pipeline that handled complex transformations and scheduled regular data loads was difficult.
    - **Solution**: Azure Data Factory was utilized to automate the ETL pipeline. Schedules and triggers were configured to ensure regular data processing, with detailed logging to resolve any issues during automation.
- **Model Performance and Hyperparameter Tuning**:
    - **Challenge**: Initial forecasting models did not perform well due to high variability in product sales. Hyperparameter tuning was time-consuming and required iterations to improve accuracy.
    - **Solution**: Automated hyperparameter tuning techniques such as grid search and cross-validation were employed, allowing faster and more accurate model optimization, leading to improved model performance.
- **Model Versioning and Tracking**:
    - **Challenge**: Managing multiple versions of forecasting models, while tracking hyperparameters, performance metrics, and changes, made version control difficult.
    - **Solution**: MLflow was used to track model versions, hyperparameters, and performance metrics, enabling easy comparison between versions and facilitating model rollbacks or updates.
- **System Scalability**:
    - **Challenge**: Managing large volumes of data and ensuring timely updates in the data warehouse posed scalability challenges.
    - **Solution**: Azure Synapse's built-in scalability features optimized data storage and query performance, ensuring that large volumes of data were handled efficiently.

Conclusion

Summary of Achievements:

- **Phase 1: SQL Database Design and Implementation**
  Successfully designed and implemented a robust SQL database to track products, inventory, orders, and customers. Automated SQL queries and stored procedures were developed to monitor inventory levels and generate sales reports, improving efficiency and data accuracy.

- **Phase 2: Data Warehousing and Python Integration**
  Set up a scalable data warehouse in Azure Synapse Analytics for storing historical sales and inventory data. The ETL process was automated using Python, ensuring timely and consistent data loading into the warehouse, reducing manual intervention.
- **Phase 3: Forecasting Models and Azure Integration**
  Developed and deployed a forecasting model using XGBoost to predict future sales in a given region.
- **Phase 4: MLFlow, Model Deployment & Website**
  Successfully deployed the forecasting models and used a website to interface with it

Conclusion:

Throughout the project, a variety of technical and operational challenges were encountered, from database design and data management to model deployment and automation. These challenges were successfully overcome through the use of robust automation tools, best practices for database architecture, and advanced frameworks for model tracking and deployment.

By leveraging technologies such as Python, Azure Synapse Analytics, MLflow, and Azure Data Factory, the project was able to deliver a scalable, efficient system. Schema design played a key role in maintaining data integrity, while automation tools streamlined the ETL process, ensuring minimal manual intervention. Advanced tracking and versioning tools facilitated seamless management of forecasting models, allowing for easy deployment and retraining.

The integration of data warehousing, machine learning, and automation not only ensured accurate forecasting models but also provided a flexible infrastructure capable of accommodating future updates and retraining needs. Overall, the project resulted in a well-structured and efficient system that meets the current needs of inventory and sales management while being scalable for future growth.

Future Enhancements

While the project successfully achieved its goals, there are several potential areas for future work that can optimize performance and expand the system's functionality:

1. **Scaling to Multiple Stores**
   The system can be expanded to manage inventory and sales data from multiple retail locations, providing a consolidated view of stock levels and demand forecasts across all stores.

2. **Advanced Forecasting Techniques**
   Incorporating more advanced forecasting models, such as machine learning algorithms like XGBoost, Random Forest, or even deep learning models, could further improve the accuracy of predictions, especially for products with highly fluctuating demand or large-scale data.
3. **Real-Time Data Integration**
   Implementing real-time data ingestion from point-of-sale (POS) systems or other sources would allow for instant updates to sales data and inventory levels, enhancing the responsiveness of forecasts and stock management.
4. **Supplier Performance Tracking**
   Adding features to track supplier performance, such as delivery times and product quality, could help optimize restocking strategies and improve relationships with suppliers, leading to better supply chain management.
5. **Scalable Cloud Infrastructure**
   As the system expands, increasing the scalability of the cloud infrastructure is essential to handle larger datasets, higher data frequencies, and more complex analyses. This ensures that the system remains performant as business needs grow.
6. **Enhanced Visualization**
   Expanding the use of advanced visualization tools in Power BI or other BI platforms could provide more interactive dashboards and reports, enabling a wider range of stakeholders to gain valuable insights and make informed decisions.
7. **Automated Model Retraining**
   Setting up a fully automated model retraining pipeline would ensure that models remain up-to-date and relevant as new data is ingested or as business environments change, improving overall forecast reliability.

Obtained Experience

Throughout the course of this project, significant technical and practical experience was gained in various areas, ranging from database design and machine learning to project management and cloud integration. Key experiences include:

1. **Database Design and Optimization**
   In-depth experience was gained in designing and optimizing a relational database

schema, ensuring proper normalization to 3NF. The project provided valuable insights into creating efficient relationships between tables and optimizing SQL queries for reporting and analysis.

2. **ETL Process and Data Warehousing**
   The process of extracting, transforming, and loading (ETL) data into a cloud-based warehouse provided hands-on experience in managing complex data pipelines. Using Python and Pandas for preprocessing, along with Azure Data Factory for automation, enhanced understanding of scalable data workflows and real-time data management.
3. **Forecasting Model Development and Evaluation**
   Significant experience was gained in selecting and tuning forecasting models, such as ARIMA and Prophet, and evaluating their performance using metrics like RMSE and MAE. This reinforced skills in model selection, hyperparameter tuning, and model performance evaluation in a production environment.
4. **MLFlow and Automation**
   Implementing MLOps principles, including model tracking, versioning, and automated deployment with MLflow and CI/CD pipelines, provided a deeper understanding of managing machine learning models in production. The project emphasized the importance of automation and lifecycle management for models.
5. **Cloud Integration and Scalability**
   Integrating data processing and model deployment with Azure services, such as Azure Synapse Analytics and Azure Data Factory, offered a deep dive into cloud-based architectures. Automating workflows and handling large datasets in the cloud enhanced knowledge of system scalability and performance.
6. **Collaborative Project Management**
   The project involved collaboration across various teams (data engineering, data science, DevOps), which helped strengthen communication, task coordination, and alignment of project objectives. Tools like Azure DevOps were used to manage timelines and deliverables effectively, improving overall project management skills.

This accumulated experience has not only strengthened technical skills but also provided valuable insights into building and deploying end-to-end data systems and machine learning models. These learnings will contribute significantly to future projects in data engineering, machine learning, and cloud computing.

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