Sales Volume Forecasting

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Set

Background

* Client: Product distributor who purchases office products from manufacturers, holds them and then resells them to its business customers

* Improve the inventory planning process for the product distributor

* Create a model that makes predictions about the sales volume for different product categories

Value of model

* Meet customer demand and ensure customer satisfaction

* Avoid having too much inventory which can lead to unnecessary storage costs, handling costs and cash-flow pressures

* Avoid stockouts which can result in loss of sales and/ or fines

* Maintain high profitability

Target Audience

* Product distributor whose data was analyzed

* All product sales planning, supply chain, and procurement professionals

Data Source

* The data used for this project comes in the form of CSV files obtained from the product distributor.

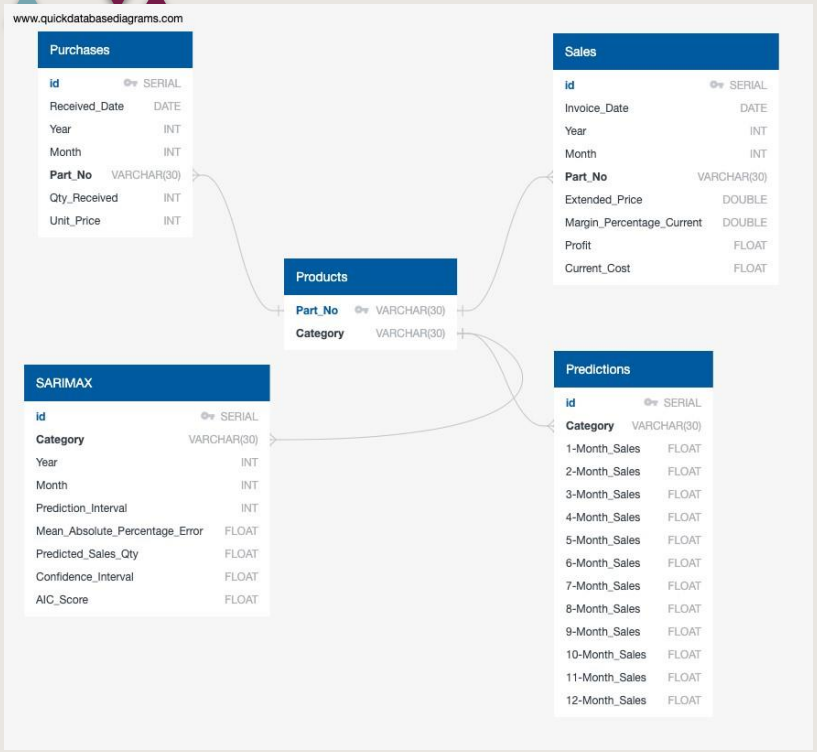
* The CSVs have 5-years worth of data (2018 to 2022) for Purchase, Sales and Product Details.

Data Hosting

* The raw CSV data files are hosted on an S3 Bucket through Amazon AWS.

* The database schema was stored in the Databricks File System (DBFS) through a Databricks Community Edition Account. This file system is ultimately hosted on AWS without charges for computing.

Database Creation



Data Cleaning

01 Load and merge DataFrames

02 Select and filter the columns to be used

03 Convert the columns to the appropriate data type

04 Group the data to get yearly and monthly aggregates

Data Model Description

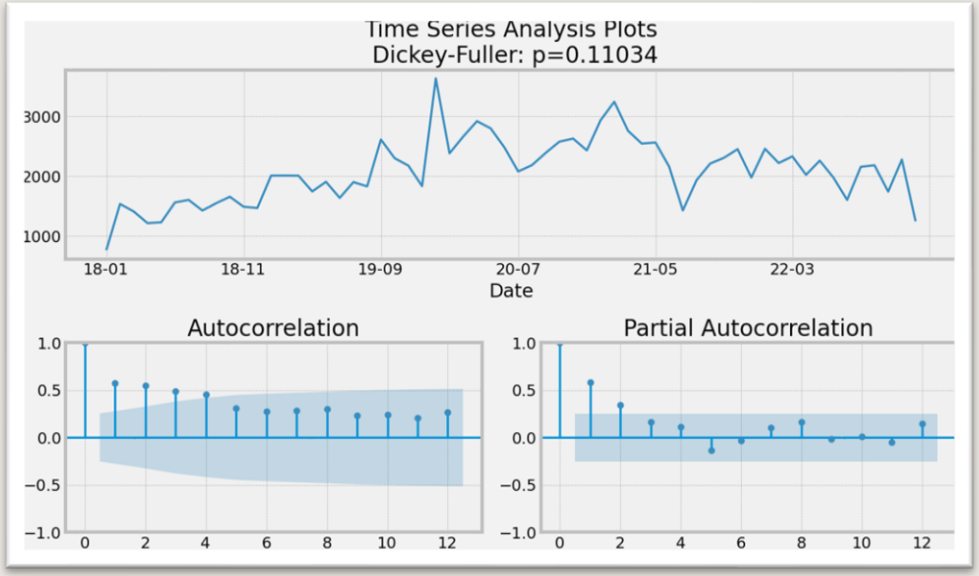
SARIMAX Model

* Time Series Analysis for Sales Volume predictions
* Trained On 4-years (2018-2021)

* Parameters:

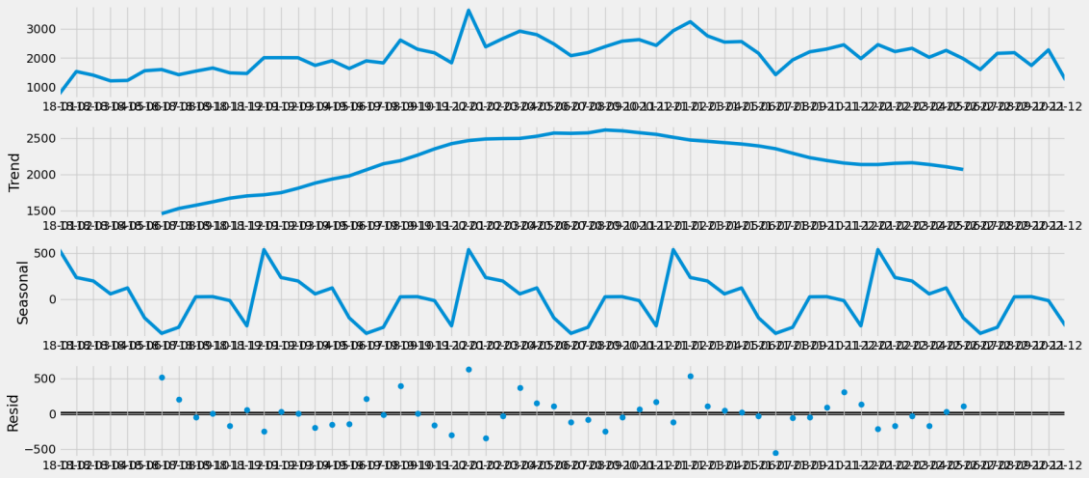
p - order of the autoregressive part
d - degree of first differencing involved
q - order of the moving average part
P, D, Q - all previous characteristics with seasonal factors
s - seasonal length in the data

Step 1: Identified the stationarity of the time series



P-Value > 0.05 implies data is not stationary

Step 2: Suggested the initial parameters



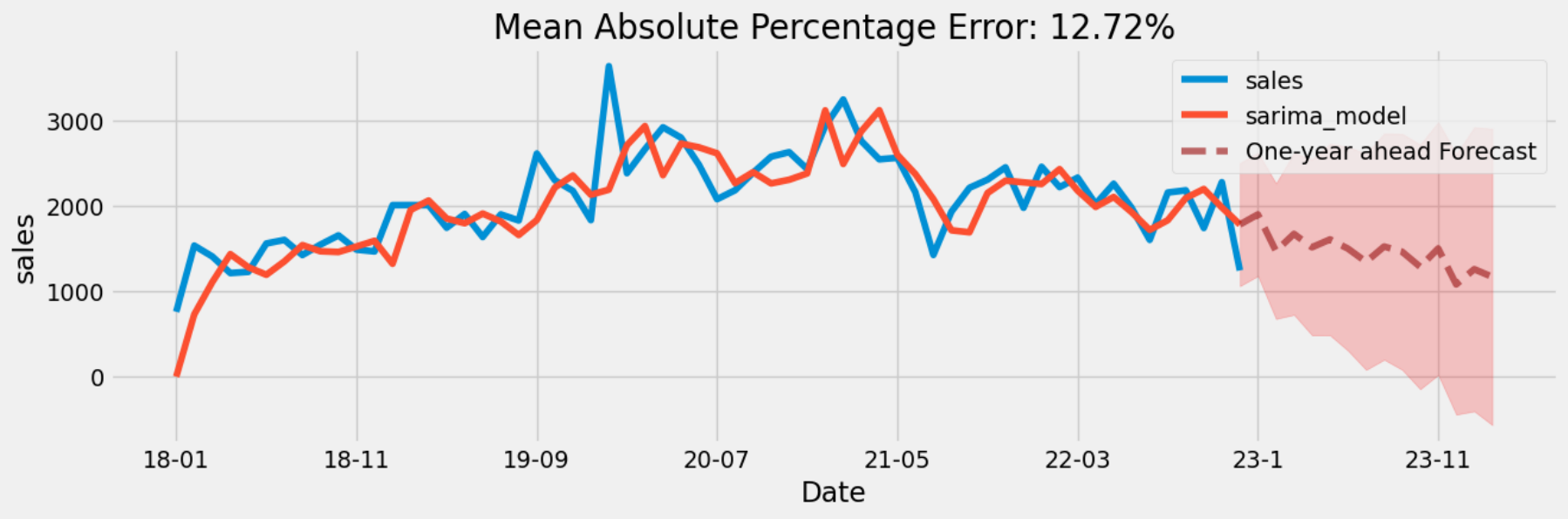
Applied differencing analysis if needed

	parameters	aic
0	(2, 0, 0, 2, 0, 1)	182.932220
1	(0, 1, 1, 0, 0, 1)	697.156454
2	(0, 1, 1, 1, 0, 0)	697.705893
3	(0, 1, 1, 2, 0, 0)	699.072669
4	(1, 1, 1, 0, 0, 1)	699.142650
5	(0, 1, 2, 0, 0, 1)	699.143229
6	(0, 1, 1, 1, 0, 1)	699.156443
7	(0, 1, 2, 1, 0, 0)	699.699439
8	(1, 1, 1, 1, 0, 0)	699.699695
9	(2, 1, 0, 0, 0, 1)	700.852337

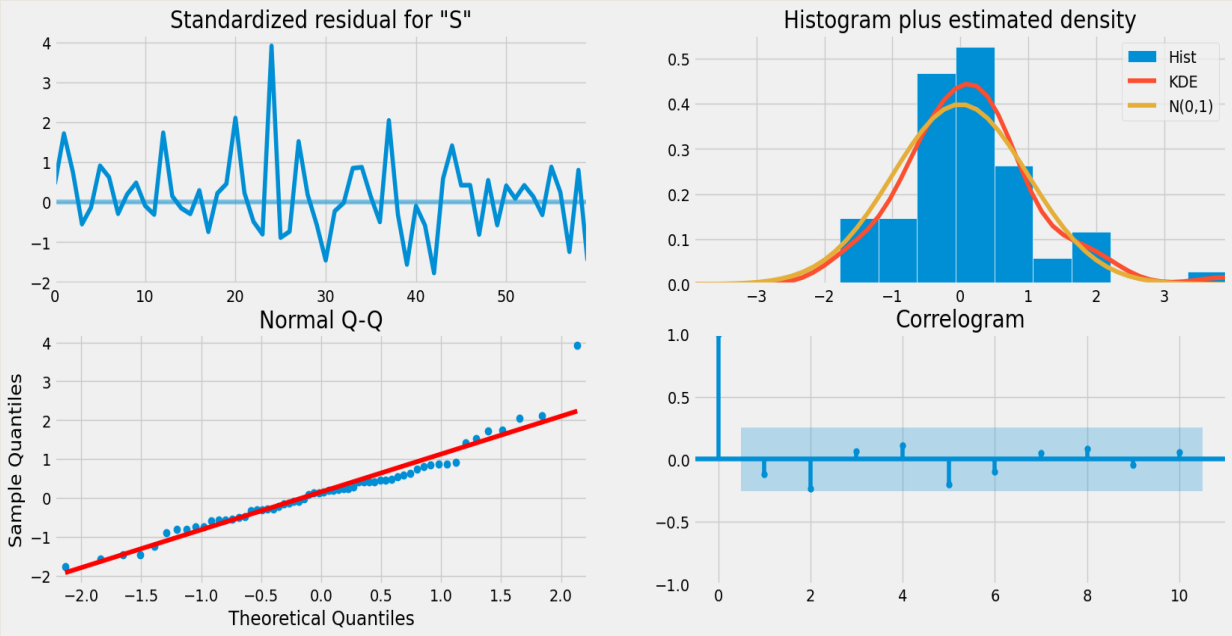
Step 3: Generated the final parameters for the model

Selected parameters based on AIC Scores

Step 4: Ran the SARIMAX model



Error Analysis



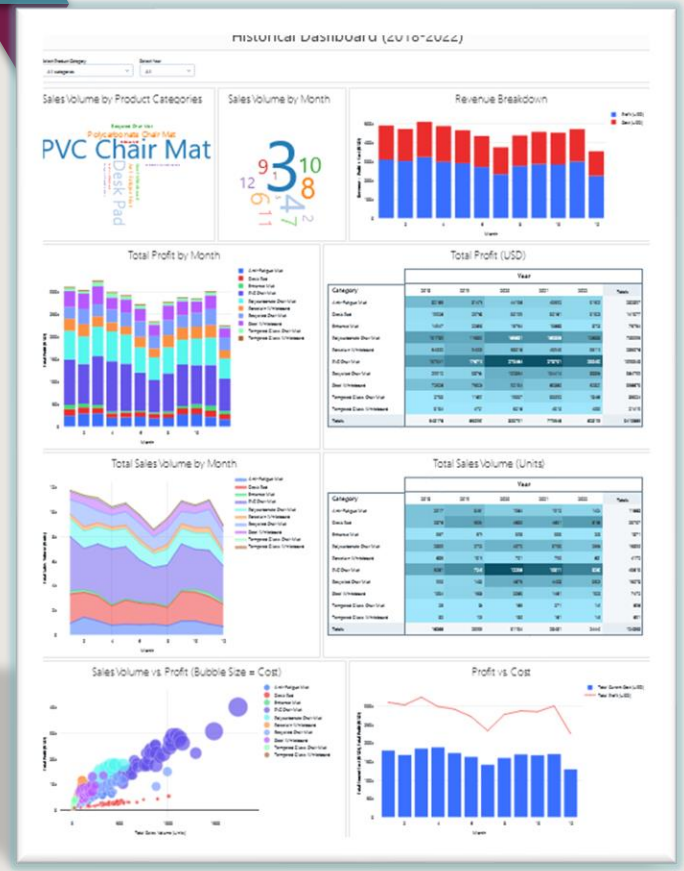
Attempt to Optimize the Model

Product Category	Mean Absolute Percentage Error (Attempt 1)	Mean Absolute Percentage Error (Attempt 2)
All categories	14.09%	12.28%
Anti-Fatigue Mat	39.86%	34.19%
Desk Pad	32.62%	37.37%
Entrance Mat	43.63%	42.40%
Polycarbonate Chair Mat	25.91%	21.24%
Porcelain Whiteboard	42.87%	48.14%
PVC Chair Mat	19.99%	20.31%
Recycled Chair Mat	41.50%	41.50%
Steel Whiteboard	31.49%	34.42%
Tempered Glass Chair Mat	41.95%	46.20%
Tempered Glass Whiteboard	44.48%	47.31%

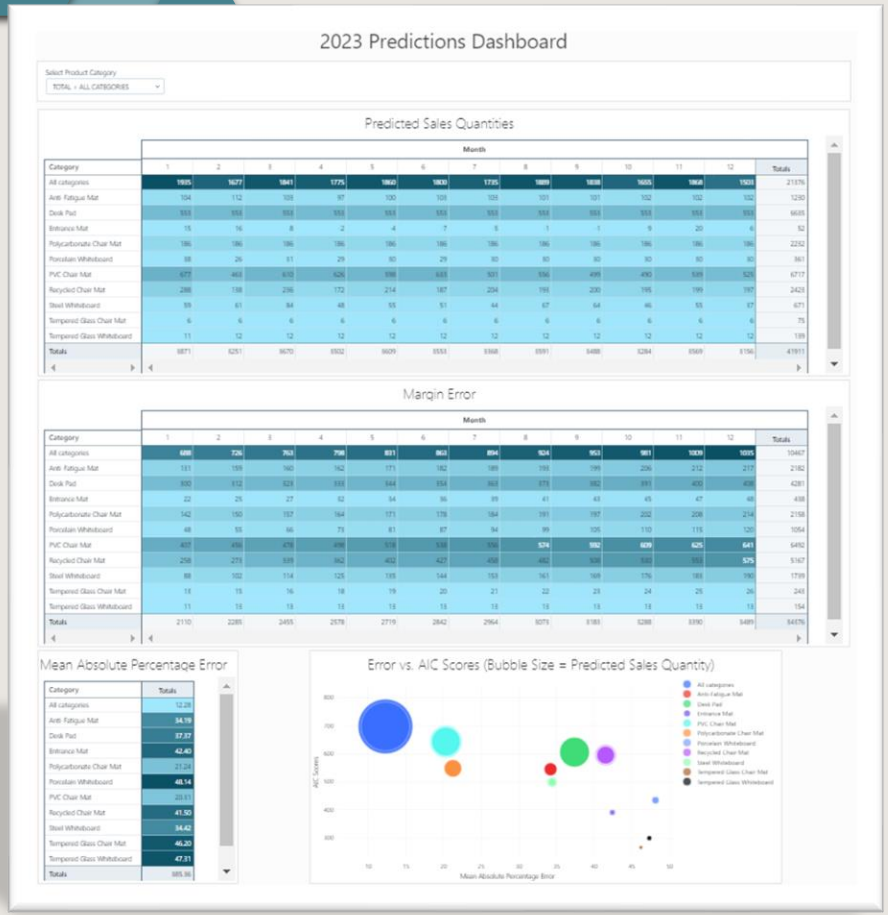
Visualizations and Dashboards

* Used Databricks Dashboards

* Created filters in the Databricks Notebooks



Historical Dashboard (2018-2022)

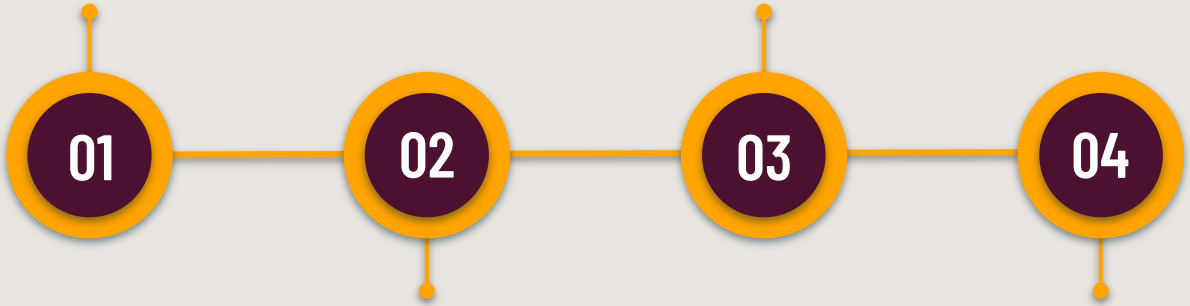


Predictions Dashboard (2023)

Limitations and Assumptions

134 different product SKUs within the original dataset

Unlimited resources and budget



Unlimited warehouse space to store the products

No minimum order quantities

Challenges

* The clusters on Databricks Community Edition reset after 2 hours of inactivity.

* ETL was processed in Databricks and it was truncating the data to 10,000 rows.

* The dashboards in Databricks do not have a default option for adding filters to visualizations.

* The filters on the Databricks dashboards do not carry over to the HTML file.

Conclusions

* Predictions show a slight decline in sales volume in the next year for overall sales but stable sales for some categories.

* Sales predictions are helpful but additional models incorporating special dimensions of warehouse, and budget constraints could help make more applicable predictions.

* Margin Error increases for longer time periods. This makes it more appropriate for Just-In-Time distributors.

Thank you for listening!

Any Questions?