



# Supply Chain Demand Forecasting

Predictive Analytics for Inventory Management

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# About Me

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# Project Overview

## Business Use Case:

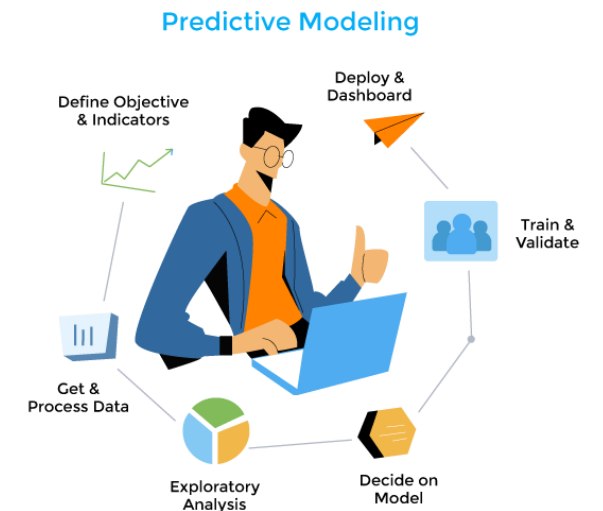
MegaHive retailer has 5 stores, 2 distributions centers and 50 different items. They use traditional SAP ERP software to predicted monthly demand for a class of product at market level or distribution level. Using the forecasted results, they allocate units for a specific class product for the upcoming month. MegaHive's supply chain operations, but their existing forecasting techniques lags today's competitive landscape of macro volatility and does not reflect the dynamics of different product demands at different locations at different times.

MegaHive seek improvements to their inventory management via big data analytics and machine learning in order to reduce costs, free up working capital and create a foundation for omnichannel innovation. The challenge now is to produce these forecasts in a timely manner and at a level of granularity that allows them to make precise adjustments to product inventories.



# Proposed Solution

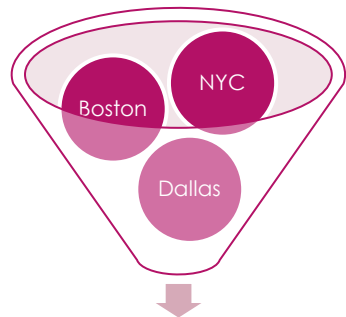
- ▶ Accurate demand forecasting relies on granular analysis, therefore we need to build a localized model that provides a fine-grained forecast at store-item level. These fine-grain demand forecasts can capture the patterns that influence demand closer to the level at which that demand must be met.
- ▶ As we increase scale and granularity while moving faster to respond to real-time conditions at the local level, we can optimize profitability and capital allocation by stocking the right items without wasting space on items that need to be discounted or disposed.



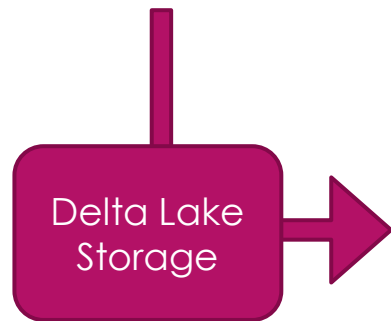
# Tech Stack

Service/Tool	Use	Benefits
Storage	Azure Delta lake	<ul style="list-style-type: none"><li>• Cheap storage with ACID properties</li></ul>
Processing/Compute	Databricks Spark for distributed computational processing	<ul style="list-style-type: none"><li>• Databricks provide a highly performant architecture using Delta Lake to optimize data for querying and distributed power of Apache Spark to scale our computational jobs</li><li>• Scale iterations by 100x in less time, providing faster and accurate results</li></ul>
Modeling	Time Series Analysis using Prophet	<ul style="list-style-type: none"><li>• Forecast time series data based on an additive model</li><li>• Robust in handling seasonality, holiday effects and outliers</li></ul>

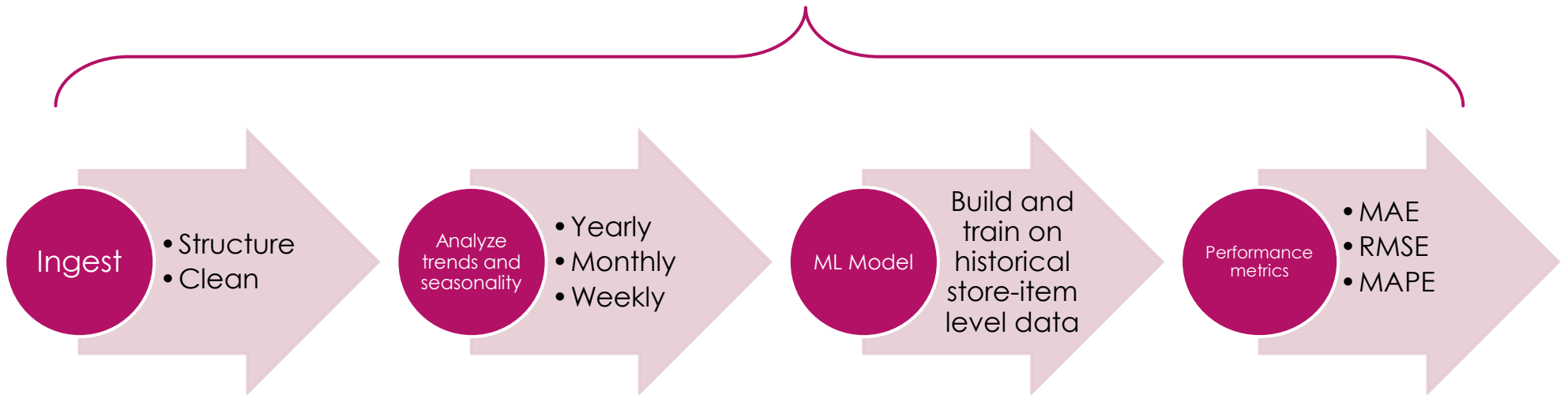
# Workflow



All Store Data

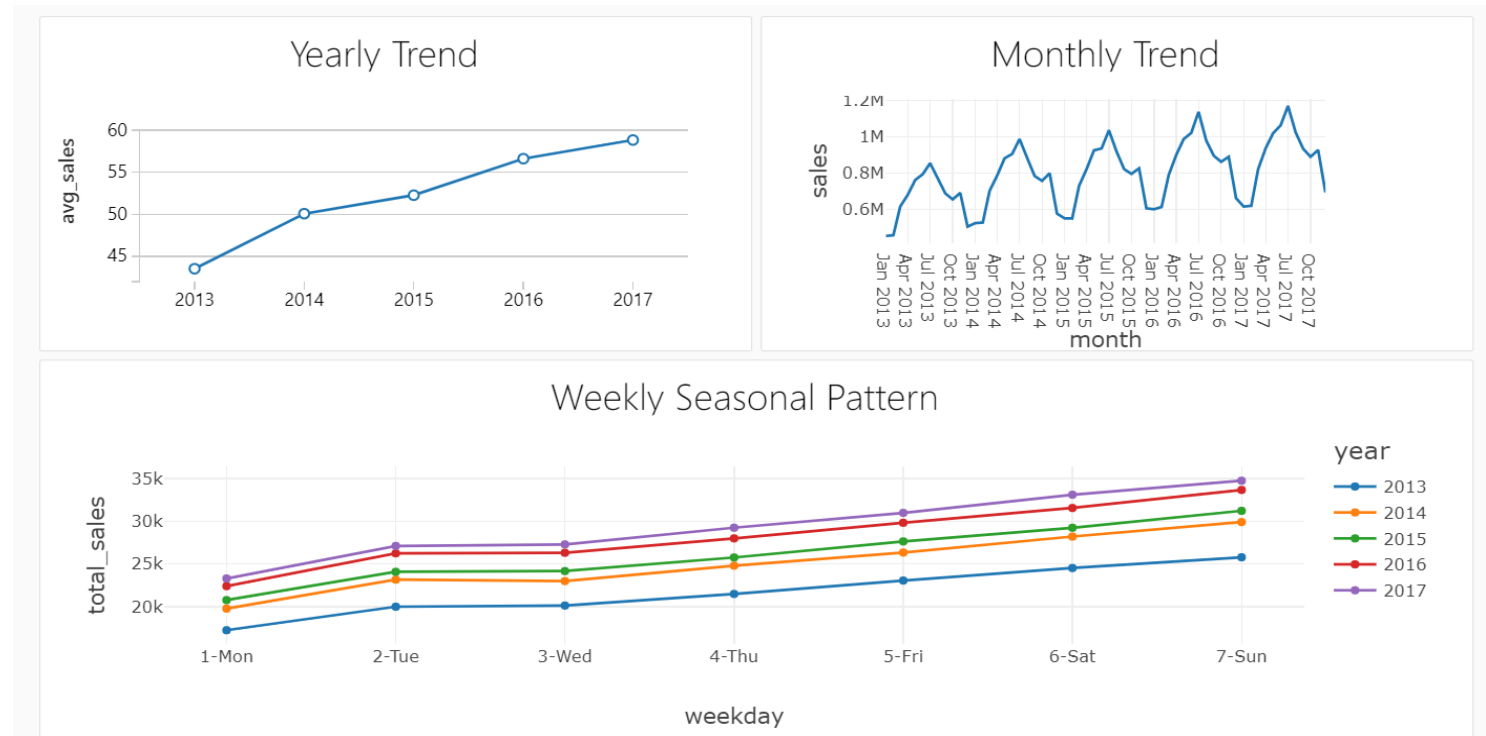


Databricks Apache Spark + Facebook Prophet



# Historical Data Exploration

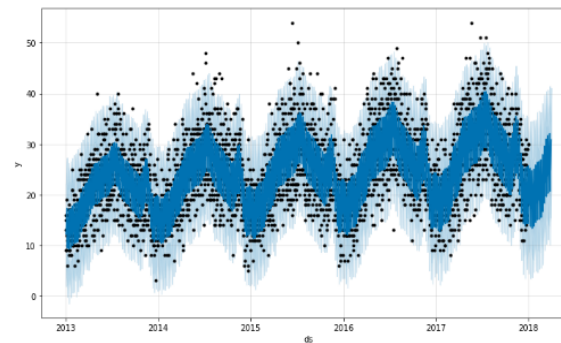
- ▶ **Figure 1:** Yearly upward trend in total unit sales across the stores
- ▶ **Figure 2:** Monthly trends shows a seasonal pattern which grows in scale with overall growth in sales
- ▶ **Figure 3:** Weekly seasonal pattern – low on Monday through Wednesday and spikes during weekends. Pattern is stable across all five years



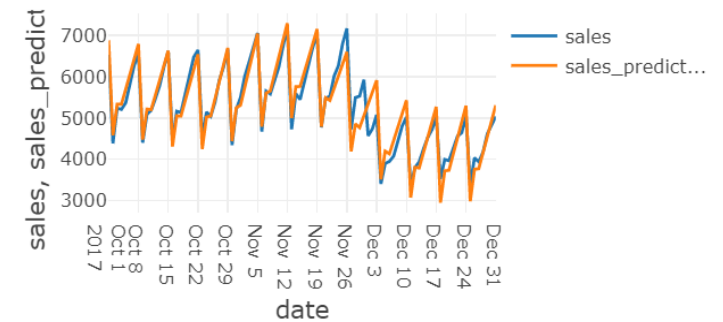
# Time Series Forecasting Analysis

- ▶ **Figure 1:** Black dots represent actuals, darker blue line representing predictions and the lighter blue band representing uncertainty interval
- ▶ **Figure 2:** Predictions and actuals comparison for year 2017
- ▶ **Figure 3:** Predictions for 3 different stores for one particular item

Actuals vs. Predictions

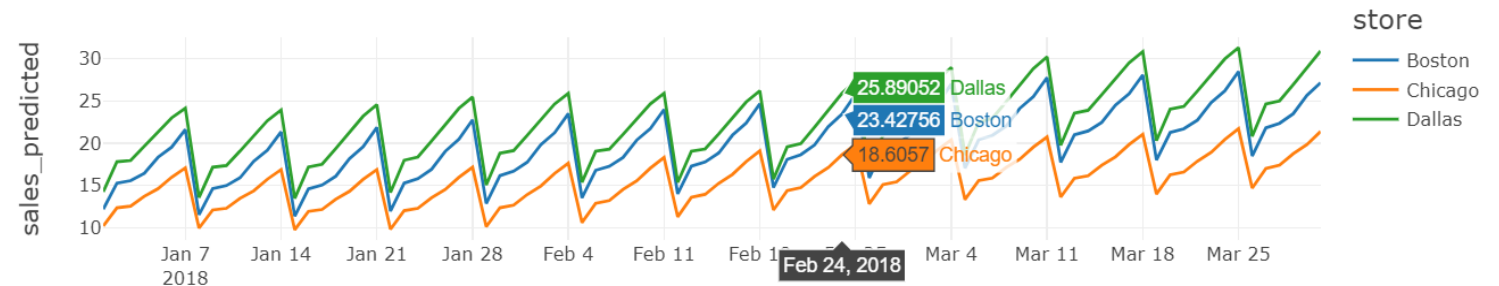


Actuals vs. Predictions for last 1 year



Aagreqated (by sum) in the backend.

Forecast for Item 'A' at 3 stores

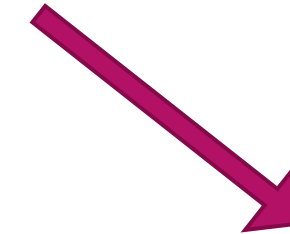
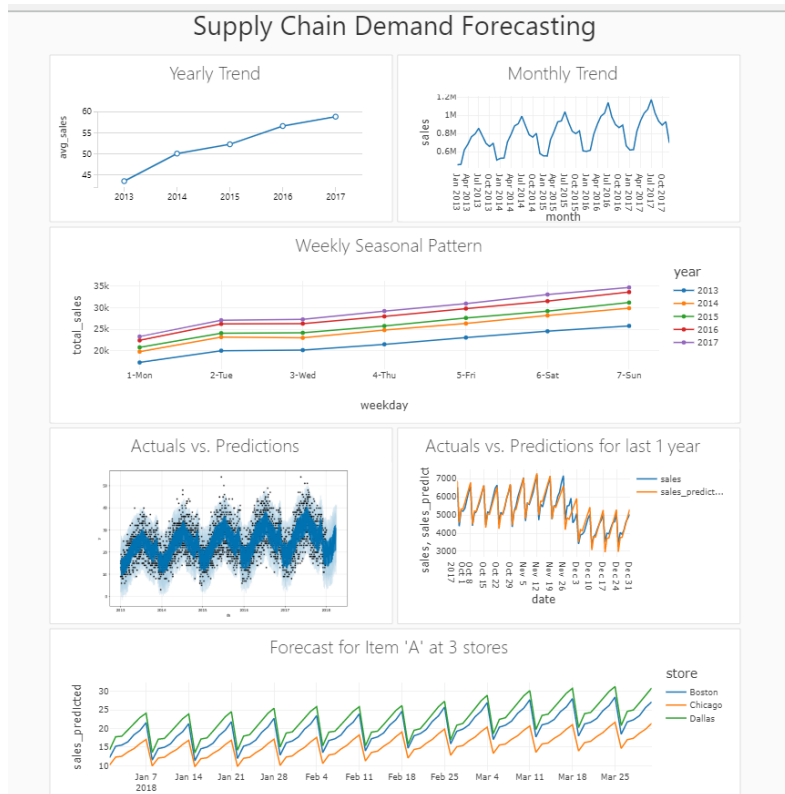




# Future Challenges

- ▶ Shifting from aggregate to high level of granularity forecasts, the number of forecasting and iterations increases exponentially. This requires huge processing power which is costly and out of reach for existing forecasting tools. This limitation leads to companies making tradeoffs in the number of categories being processed, or the level of grain in the analysis.
- ▶ The demand patterns that exist in aggregate may not be present when examining data at a finer level of granularity, making lower-level forecasts with techniques applicable at higher levels more challenging.
- ▶ At high granular levels, our dependent variables such as units sold, may become skewed, which might not be handled by simple transformations and may require advance forecasting techniques.

# View Dashboard





Thank You!