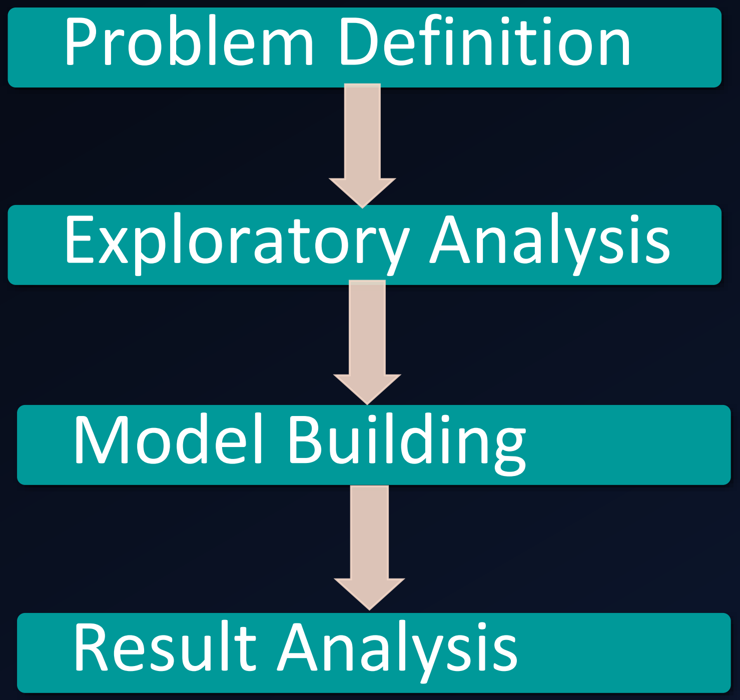
Analytical Approach and Methodology

- Current State Insight
  - Performance Analysis
  - Problem Identification
- Proof of Concept
  - Introduction
  - Feature Engineering
  - Result Analysis
- Recommendation

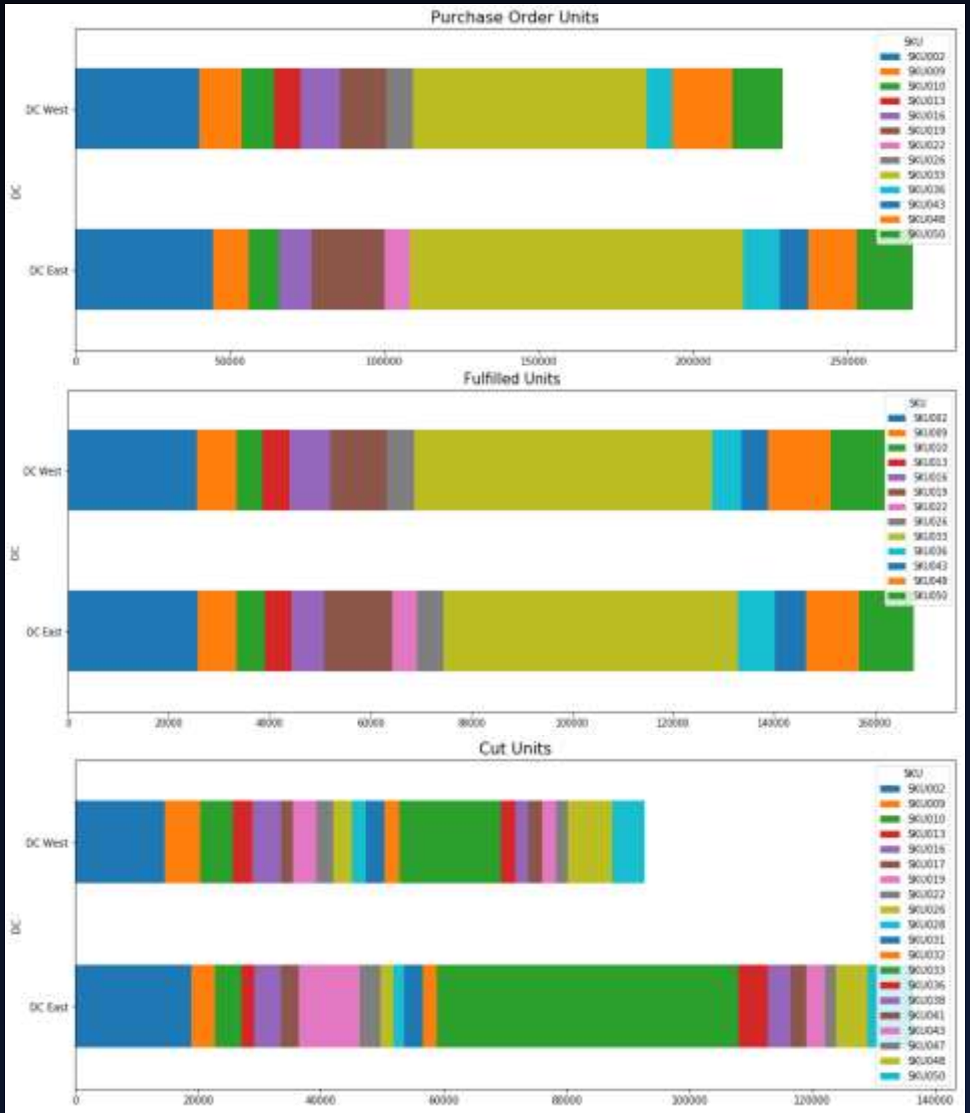


1 Current State Analysis

- **Current supply chain capabilities shows interesting behavior involving distribution center**
  - **Purchase order quantity:** DC-West < DC-East
  - **Fulfilled units capacity:** DC-West = DC-East
  - **Cut Units:** DC-West = DC-East
- **Overall product demand is higher at DC East, and the supply capacity involved at both center is completely similar. This can be seen by the plots.**
- **These creates a necessary void for demand satisfaction at DC East. Therefore we are seeing more order cuts at DC East.**

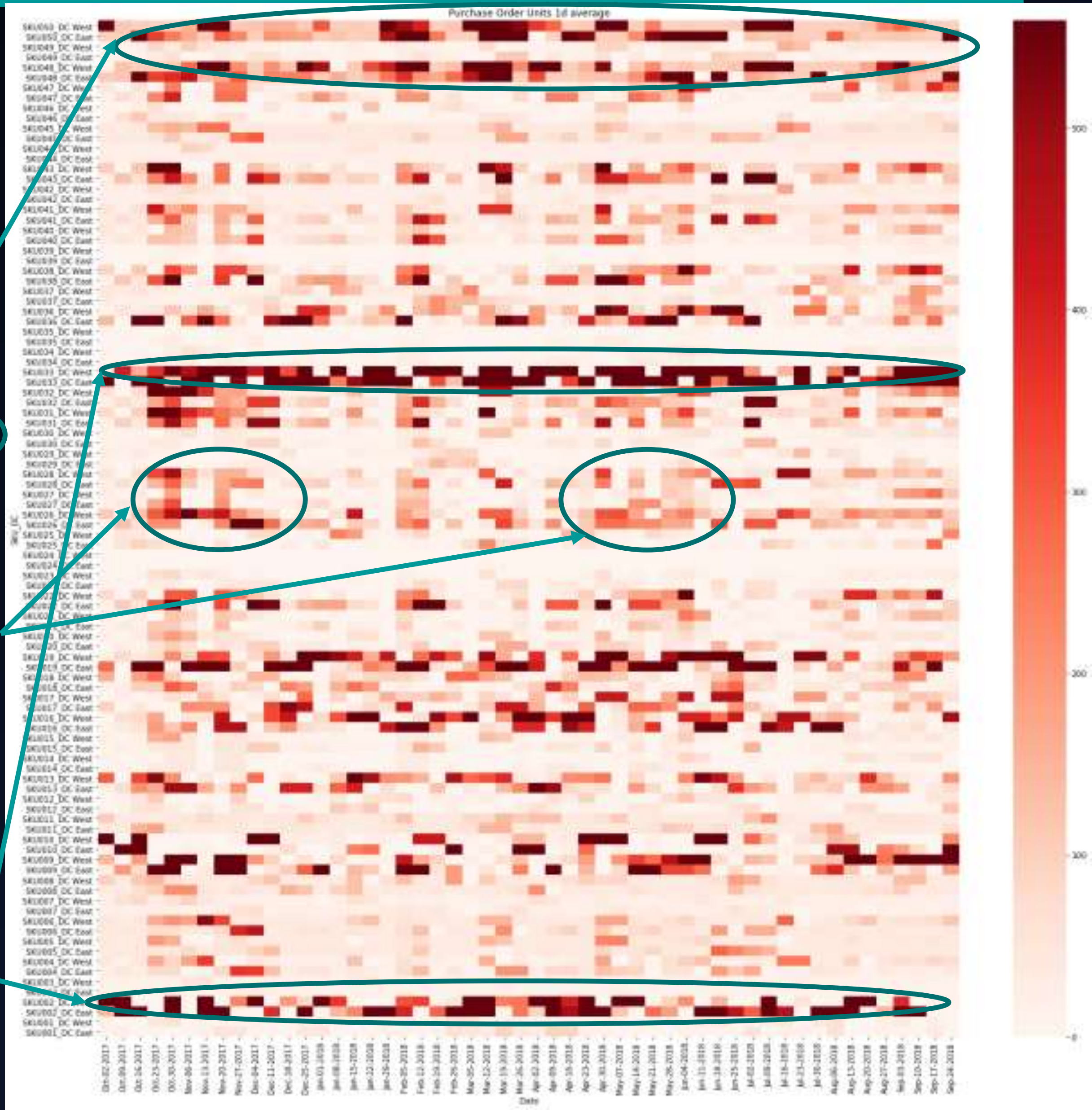
➢ Recommendation:

Optimize Resource Utilization at distribution center according to market need



Current State Analysis -2

- It is very necessary to understand the buying behavior of the products by the Pazzo
- The Buying behavior has multiple pattern associated with different product.
  - Cyclical buying across DC
  - Seasonal buying
  - Somewhat Constant Demand



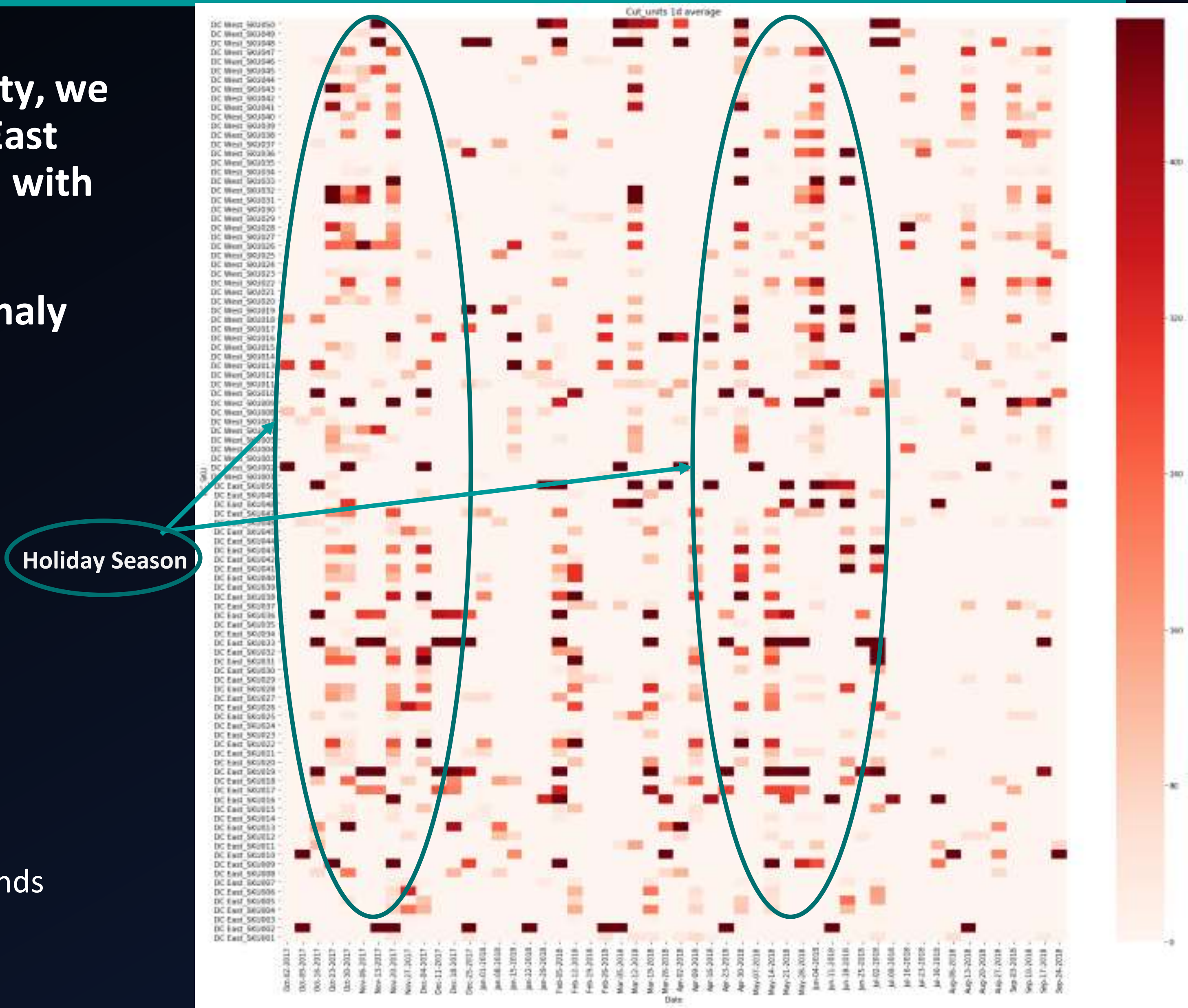
➢ Recommendation:

Necessary understanding of buying/demand behavior

Current State Analysis - 3

- If we look at the cut order quantity, we also see similar pattern in it. DC East has more anomaly cut associated with it.

- Possible Reasons for having anomaly demand
  - Discount offered by the customer
  - Holidays
    - Thanksgiving
    - Christmas etc.
  - Competitor's Effect



➢ Recommendation:

Necessary understanding of Anomaly Demands

2 Proof of Concept

Problem Definition

- Better understanding of buying pattern
- Predicting anomaly demand
- Optimum resource utilization by distribution center

Assumptions

- TDF will fulfil the order up to 100% predicted demand
- Because of these, cut units is not used as a feature.
- Pazzo's consumer end buying pattern remains same in future years.

Solution

- Building Knowledge based around buying behavior associated with Pazzo.
- These knowledge can be translated into machine learning regression model.
- Incorporating these behavior to predict next week's order by SKU/DC.
- For this We can utilize Pazzo's consumer end data.

Next week's Purchase Order $\longrightarrow Y_{t+1} = F(X)$

Model

Features

Feature Engineering

Feature Type	Feature Name	Feature Description	Feature Value
Lag Based Features	N_week_before_purchase_unit	Purchase quantity N week before the future week by SKU/DC	Continuous
Effect of Previous Purchase Quantity	gradient purchase units	Slope of current 1 week order quantity. Help to understand the past trend to forecast future trend	Continuous
	past_other_dc avg_order	Quantifying type of change in future quantity order: positive(1), negative(-1) or no effect(0) if current week's DC West order is higher than DC East or vise-versa	-1,0,1
	past_other_dc comp_order	Quantifying type of change in future quantity order: positive(1), negative(-1) or no effect(0) if current week's DC West order is higher than DC East or vise-versa	-1,0,1
Demand Distribution	mean purchase order by N week	Estimating future demand distribution by purchase order quantity N week before. Here estimating average future purchase order by binning past N week's purchase order into 5/4/3/2 bins and calculating average in that bin	Continuous Category
	Std purchase order by N week	Estimating fluctuation in future purchase demand by binning past N week's purchase order into 5/4/3/2 bins and calculating std deviation in that bin	Continuous Category

Feature Engineering - 2

Feature Type	Feature Name	Feature Description	Feature Value
Product Based (Calculated from Pazzo data)	Low Price Product /Low Std Price Product	High avg price or high standard deviation in the price based product categorization	1,0
	High Price Product/ High Std Price Product	Low avg price or low standard deviation in the price based product categorization	1,0
	High/Low Demand Product	High/ Low Demand based on quantity order	1,0
	High/Low Std Demand Product	Fluctuation in demand based on the quantity order	1,0
	Seasonal/Constant demand	Based on purchase quantity standard deviation over time	1,0
	Commodity /Luxury /CashCow	High Demand & Low Price = Cash Cow Low Demand & High Price = Luxury High Demand & High Price =CashCow	1,0
	ratio sell by stock	Ratio between consumer order units to on hand inventory	Continuous Category
Specific Event Based	Holiday	If the next week contains holiday in it.	1,0

Modeling & Result Analysis

Data

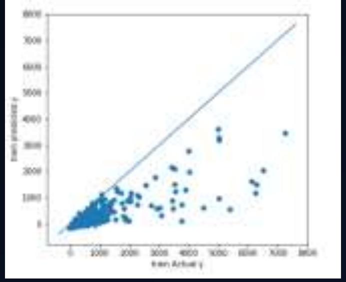
- Final data consist of 29 features
- Training on 8 months of data and testing on 4 months of data
- Assumption - Anomaly demand range presented in testing and training is similar

Model Result

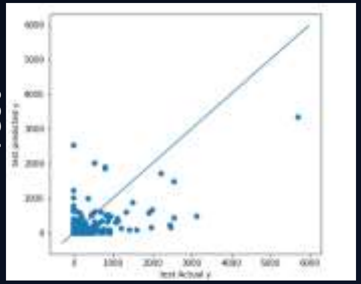
- Reduction in Percent Cut Order

  Train = 77% , Test = -93%

Train



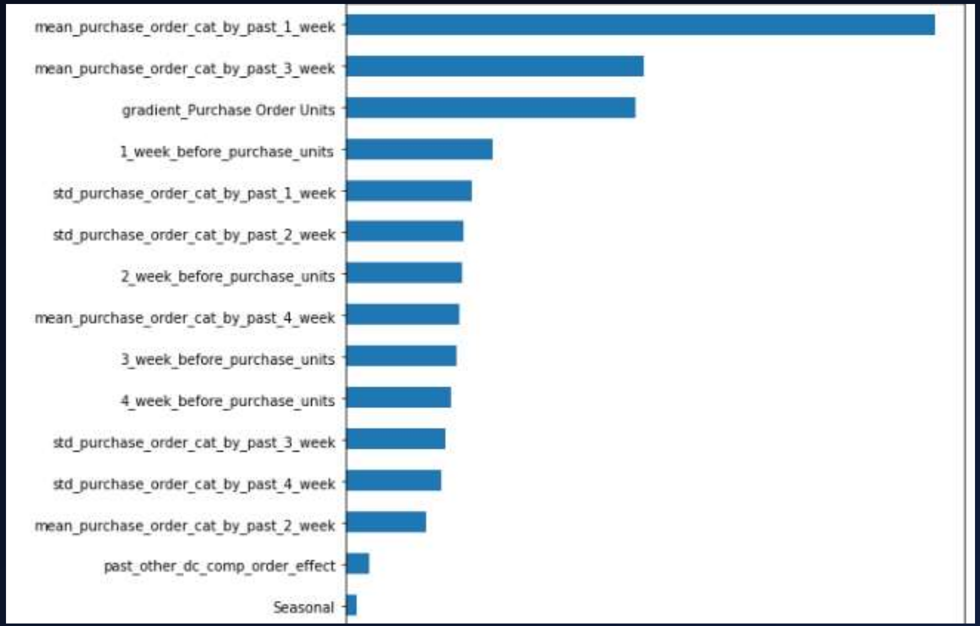
Test



ML Model

- Linear Regression
- **Decision Tree** - Best Performed Model
- Random Forest

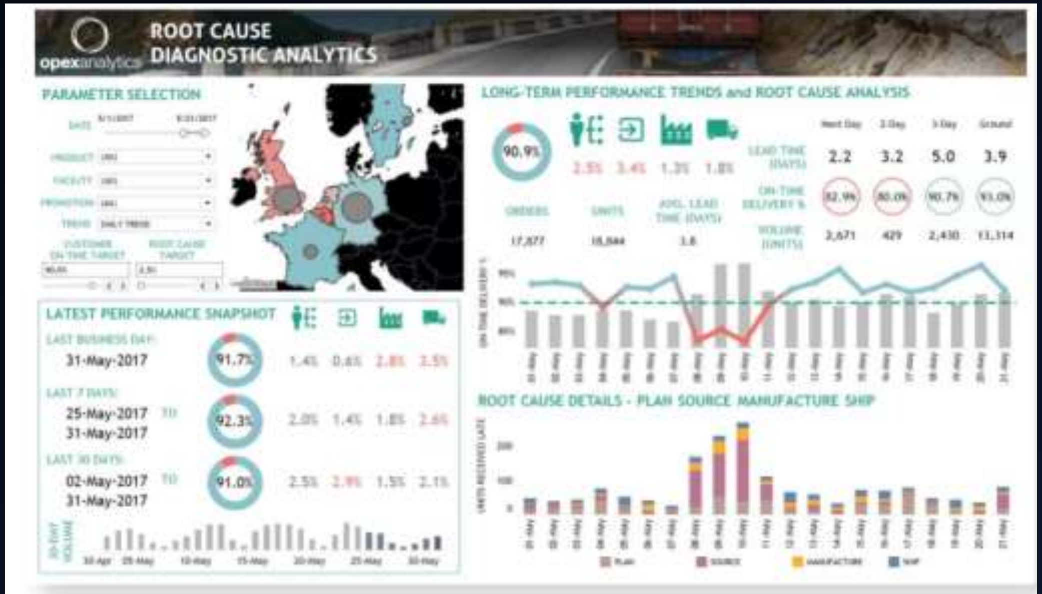
Feature Importance



3 Adoption Plan and Solution

Next Plan:

- **Building analytical dashboard for better understanding and prediction of future product demand.**
- **Inventory related KPI : Past Order Performance, Carrying Cost monitoring can help to plan for the future orders.**
- **Optimizing price of products based on demand**
- **Machine learning model prediction:**
  - **First Classification of future order anomaly and normal order and**
  - **Regression to predict next N week’s order.**



Additional Data:

- **Product life cycle data**
- **Quarterly Pazzo’s end consumer data (to continuously tune for the accurate prediction)**