Demand Forecast

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Introduction

The project is focused on SKU (Stock Keeping Unit) demand forecasting, which is a critical aspect for any generic medicine making company. As we all know, accurate demand forecasting is essential for ensuring that we have the right amount of stock at the right time. This is particularly important for our generic medicine manufacturing hub, where we produce a wide range of medicines that are used to treat a variety of illnesses.

Our project aims to develop a robust SKU demand forecasting system that takes into account various factors such as seasonality, market trends, and historical sales data. By doing so, we can ensure that we always have the right amount of stock on hand, minimizing the risk of stock outs or overstocking. By accurately forecasting demand, we can optimize our production schedule, reduce waste, and ensure that we meet the needs of our customers in a timely and efficient manner.

Objective

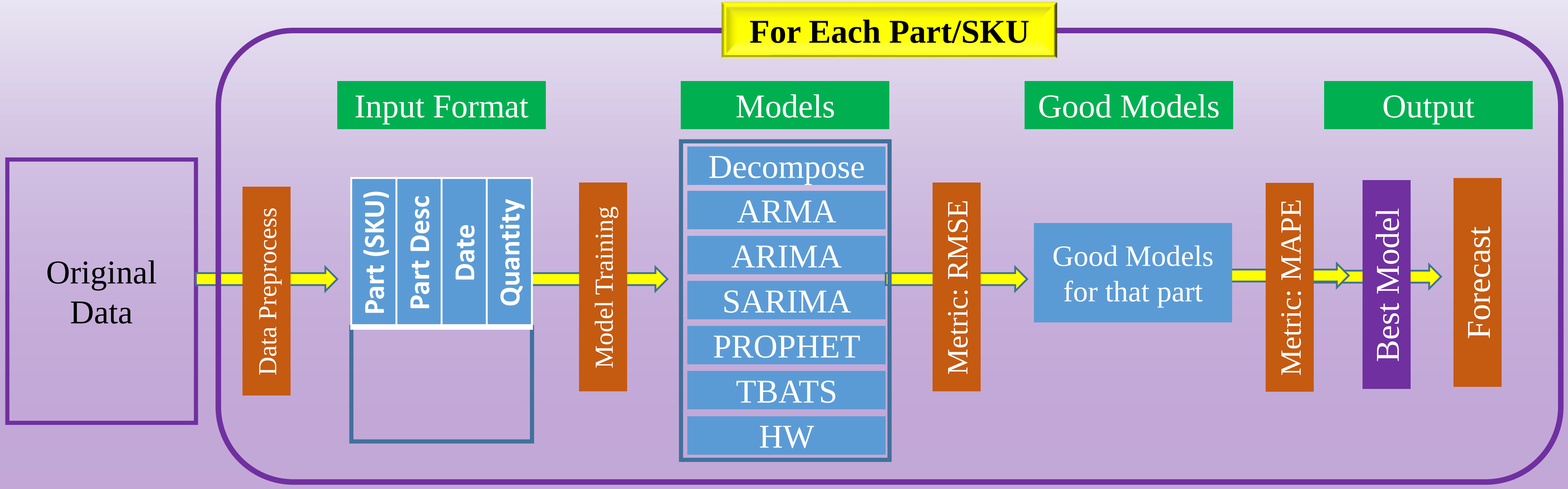
- Our main objective is to develop a demand forecasting model for each SKU using historical sales data and external factors such as market trends and seasonality.
- This will help the hub to optimize their inventory management, reduce waste, and improve production planning.
- Our secondary objective is to develop a dashboard for the hub to monitor SKU demand and inventory levels in real-time.

Data Overview

Part	Desc	Date	Sales	Market	Country	…..	Marketing Team
123456	Medicine 1	Jan’18	23456	Market 1	India	….	Team 1
123456	Medicine 1	Feb’18	23000	Market 1	India	….	Team 1
….	….	….	….	….	….	….	….
123456	Medicine 1	Mar’23	24567	Market 1	India	….	Team 1
654321	Medicine 1	Jan’13	23573	Market 10	Russia	….	Team 1
654321	Medicine 1	Feb’13	37893	Market 10	Russia	….	Team 1
….	….	….	….	….	….	….	….
654321	Medicine 1	Mar’23	967543	Market 10	Russia	….	Team 1

* It’s just a blueprint

Pipeline


For Each Part/SKU
Original Data
Data Preprocess
Input Format
Part (SKU)
Part Desc
Date
Quantity
Model Training
Models
Decompose
ARMA
ARIMA
SARIMA
PROPHET
TBATS
HW
Metric: RMSE
Good Models
Good Models for that part
Metric: MAPE
Output
Best Model
Forecast

Data Preprocessing

- ❑ Removing NaN and zero before starting any non-zero sales value
- ❑ Internal NaN, negative and zero sales imputation.
  - ✓ Mean, Median impute
  - ✓ Average of pre-post value
  - ✓ Forward and backward fill
- ❑ Treatment for peak and trough
  - ✓ Winsorization
  - ✓ Lowess Smoothing

Models

- Decompose
- ARIMA

- Holt Winter (Additive)

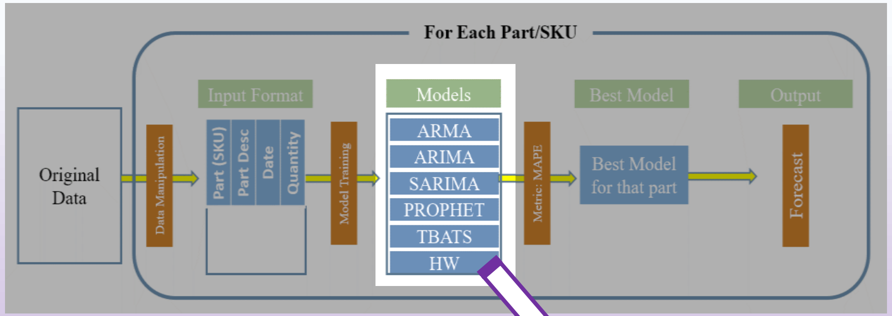
$$\hat{y}_t = L_t + T_t + S_{t-m+1}$$

$$Level: \quad L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} - T_{t-1})$$

$$Trend: \quad T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

$$Seasonal: \quad T_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m}$$

Model Training



Grid Search for each of the model

MODEL	Parameters	Considered Parameter Combinations
Decompose	Auto arima from pmdarima package	
ARMA	(p, q)	(0-6) x (0-6)
ARIMA	(p, d, q)	(0-6) x (0/1) x (0-6)
SARIMA	(p, d, q) (P, D, Q, s)	$p, q, P, Q \in (0,3);\ d, D \in \{0\ or\ 1\}; s \in \{6, 12\}$
TBATS	(s_p)	$s_p \in \{6, 12\}$
Holt Winter	(α, β, γ)	$(\alpha, \beta, \gamma) \in$ (0.1, 0.2, 0.3)

Evaluation Metrics

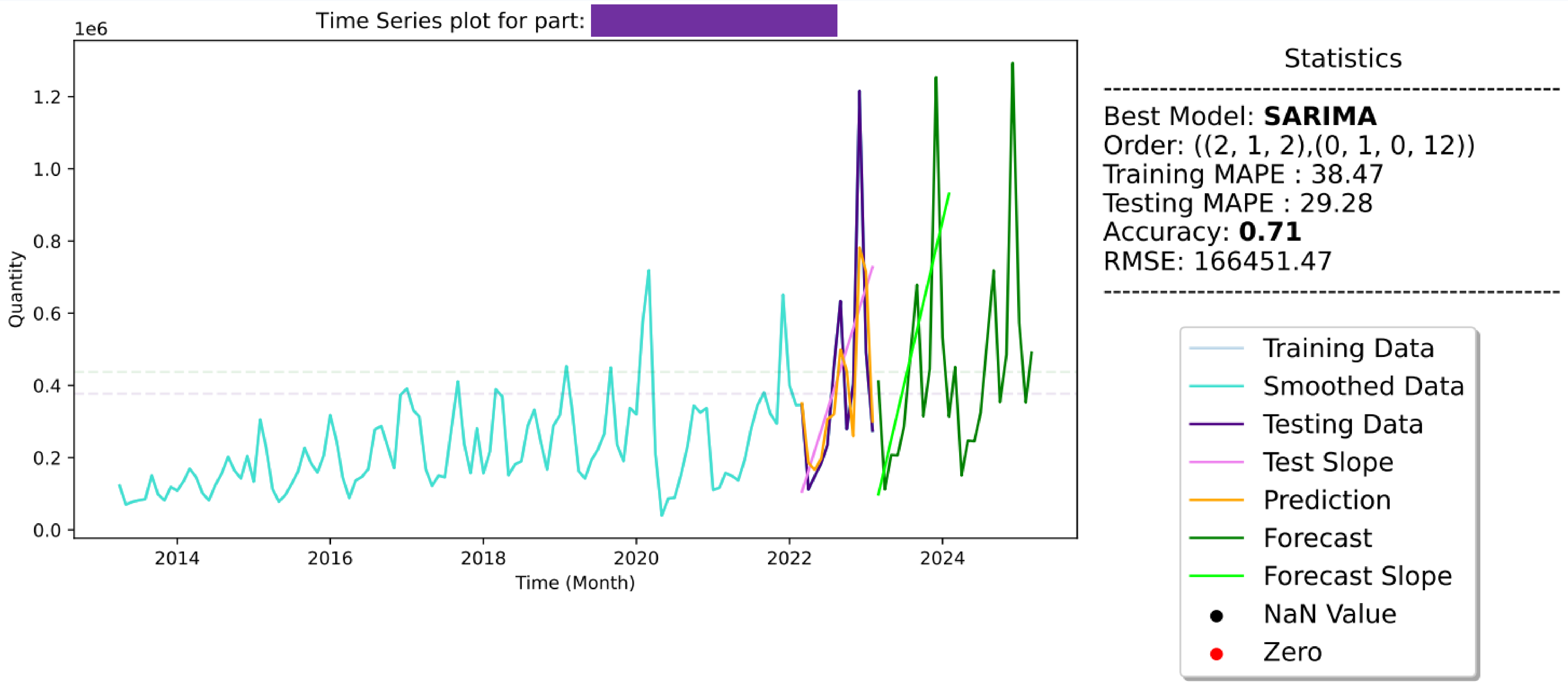
- RMSE (Root Mean Square Error) $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(A_t - F_t)^2}$
- MAPE (Mean Absolute Percentage Error) $MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{A_t - F_t}{A_t}\right|$
- MAP (Mean Absolute Percentage Error) $MAP = \frac{1}{T}\sum_{t=1}^{T}\frac{|A_t - F_t|}{A_t}$
- MASE (Mean Absolute Scaled Error) $MASE = \frac{MAP_{Model}}{MAP_{Naive\ Model}}$
- Accuracy $Accuracy = 100 - MAPE$

Evaluation Metrics

- ❑ Bias $MAP = \frac{1}{T}\sum_{t=1}^{T}\frac{A_t - F_t}{A_t}$
- ❑ Coefficient of Variation $CV = \frac{SD}{\mu}$
- ❑ Darbin Watson Test p-value $DW = \frac{\sum_{i=1}^{n-1}(r_{i+1} - r_i)^2}{\sum_{i=1}^{n} r_i^2} \sim N\left(2, \frac{2(1-\rho)}{n}\right)$

  Null hypothesis: Residuals are uncorrelated i.e. no autocorrelation.
- ❑ Mean Comparison between test and forecast phase
- ❑ Trend Comparison between test and forecast phase

Example


Time Series plot for part: [redacted]
1e6
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Quantity
2014
2016
2018
2020
2022
2024
Time (Month)
Statistics
Best Model: **SARIMA**
Order: ((2, 1, 2),(0, 1, 0, 12))
Training MAPE : 38.47
Testing MAPE : 29.28
Accuracy: **0.71**
RMSE: 166451.47
Training Data
Smoothed Data
Testing Data
Test Slope
Prediction
Forecast
Forecast Slope
NaN Value
Zero

Script Output

For each model (Based on RMSE)

Good Model Prediction | Good Model Forecast | Good Model Summary

× **Number of Models**

Accumulate the above results (Based on MAPE)

Best Model Prediction | Best Model Forecast | Best Model Summary

→ **Supply Chain Unit**

Problem and Proposal

Overfitting

Reason

- ❑ Sometimes high Test Accuracy.
- ❑ Drastic consecutive ups and downs.
- ❑ NaN value in the testing period.

Proposal

- ❑ Cluster basis different treatments.
- ❑ Changes in train test spilt ratio.
- ❑ Special treatments for bad performing SKU.

Hyper Parameter Tuning

Reason

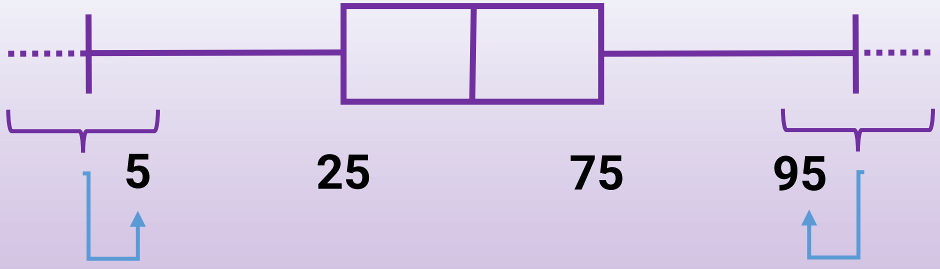
- ❑ Forecasts are not inline.
- ❑ Number of seasonal parameter values should be less during training.
- ❑ Model only captures the behavior of last few data points and forecasts accordingly.

Proposal

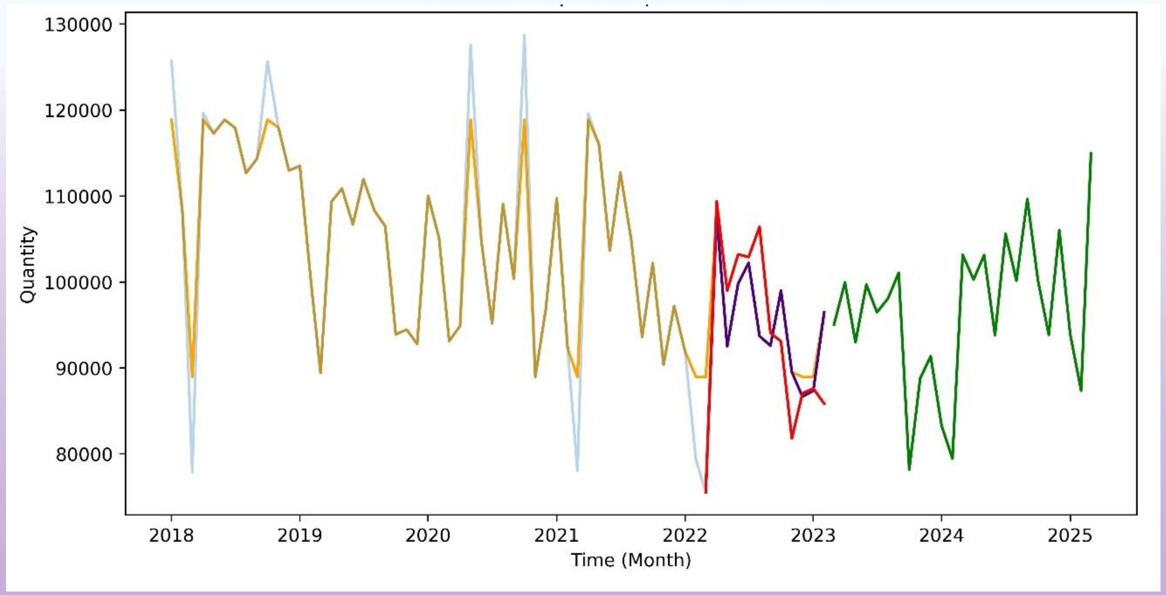
- ❑ For Holt-Winters, smoothing coefficients (α, β, γ) should have suitable upper bound.
- ❑ For ARMA & ARIMA, we should fix the upper bound of trend order p & q.
- ❑ For ARIMA & SARIMA, we should not keep a bound for trend differencing order (d)

Peak and Trough

Winsorization

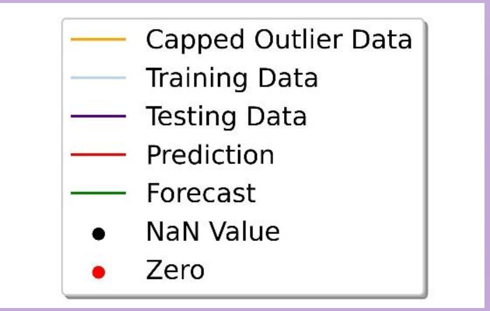


- ✓ Winsorization is the technique, which modifies the sample distribution of random variables by removing outliers. For example, 90% winsorization means all data below the 5th percentile is set at 5th percentile and all the data above the 95th percentile is set at 95th percentile.



Statistic

Best Model: **Decompose**
Order: (2, 0, 2)
Training MAPE : 7.61
Testing MAPE : 4.51
Accuracy: **95.49**
RMSE: 5971.97

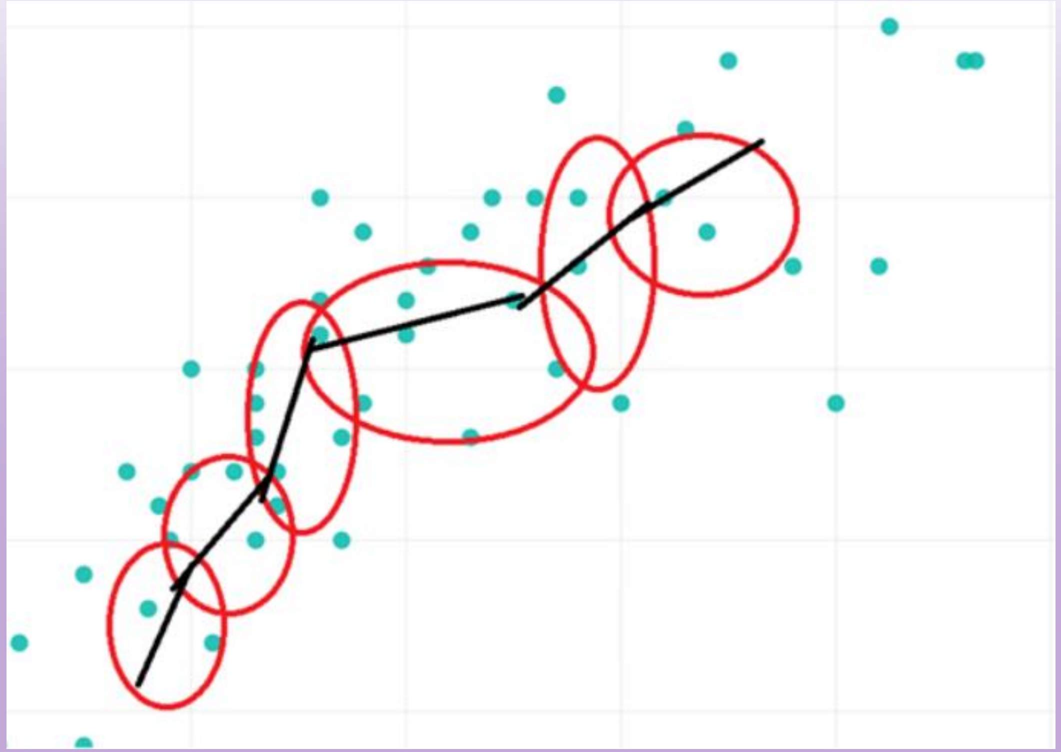


Peak and Trough

Lowess Smoothing

Locally Weighted Scatterplot Smoothing

- ✓ Choosing fixed window size k or smoothing parameter f
- ✓ If f provided, then $k = \lfloor f \times n \rfloor$, n be the total number of point
- ✓ For each point select k nearby points
- ✓ Apply weights using $W(d) = (1 - |d|^3)^3$, d is the distance between point of interest and neighbouring point
- ✓ Fit a linear regression using weighted data
- ✓ Repeat the above steps to get smoothed data for all points



Results Summary

All SKU

Market	Avg. Train (MAPE)	Avg. Test (MAPE)	Avg. Accuracy	Avg. Bias	Avg. RMSE	Avg. MASE
1	2219.86	2591.82	-24.92	-25.63	25812.96	0.999995
2	108.18	47.55	0.52	-0.07	1902.05	0.99854
3	177.70	27.84	0.72	-0.17	9834.67	0.99820
4	268.04	121.97	-0.21	-0.88	1037.21	0.99893

Proper SKU

Market	Avg. Train (MAPE)	Avg. Test (MAPE)	Avg. Accuracy	Avg. Bias	Avg. RMSE	Avg. MASE
1	270.14	12.71	0.87	-0.02	28857.94	0.999990
2	60.55	16.71	0.83	-0.03	1624.08	0.99810
3	176.61	10.67	0.89	-0.01	9649.66	0.99810
4	205.31	22.41	0.78	-0.02	911.49	0.998377

Distribution of Models

Market	ARIMA	ARMA	Decompose	HW	PROPHET	SARIMA	PROPHET	Flatline
1	8%	10%	1%	16%	21%	24%	20%	0%
2	5%	11%	3%	1%	42%	18%	7%	13%
3	4%	16%	2%	10%	30%	21%	7%	11%
4	10%	21%	9%	8%	26%	12%	5%	9%

Future Work

- Implement some advanced imputation technique for NaN and zero/negative sales.
- Clustering SKUs based on the past behavior and market features.
- Use of cluster specific smoothing technique.
- Finding best evaluation metrics for generalization.

Appendix

Packages

- ❑ warnings, tqdm, logging
- ❑ numpy, pandas, scipy, matplotlib
- ❑ stamodels, pdmarima, tsmoothie

System

- ❑ Acer Laptop, i5-10 Gen, Intel Processer
- ❑ Google Cloud Platform (GCP) Access, Unlimited Runtime
- ❑ Use of other team member's laptops

Thank You