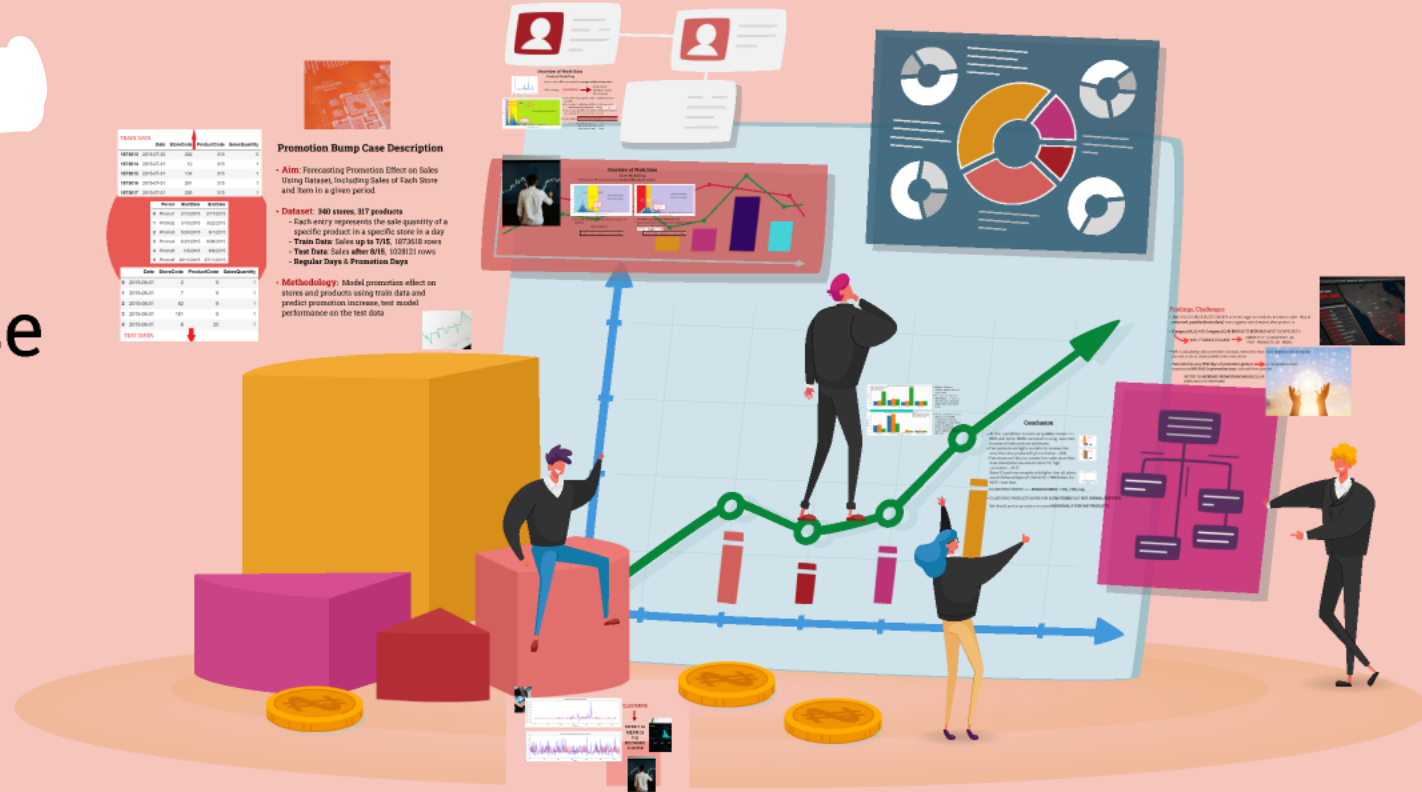


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Promotion Bump Case

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TRAIN DATA

	Date	StoreCode	ProductCode	SalesQuantity
1873613	2015-07-30	292	315	0
1873614	2015-07-31	12	315	1
1873615	2015-07-31	104	315	1
1873616	2015-07-31	261	315	1
1873617	2015-07-31	295	315	1

	Period	StartDate	EndDate
0	Promo1	2/10/2015	2/17/2015
1	Promo2	3/15/2015	3/22/2015
2	Promo3	5/24/2015	6/1/2015
3	Promo4	6/21/2015	6/28/2015
4	Promo5	1/9/2015	6/9/2015
5	Promo6	20/11/2015	27/11/2015

	Date	StoreCode	ProductCode	SalesQuantity
0	2015-08-01	2	9	1
1	2015-08-01	7	9	1
2	2015-08-01	62	9	1
3	2015-08-01	181	9	1
4	2015-08-01	6	20	1

TEST DATA

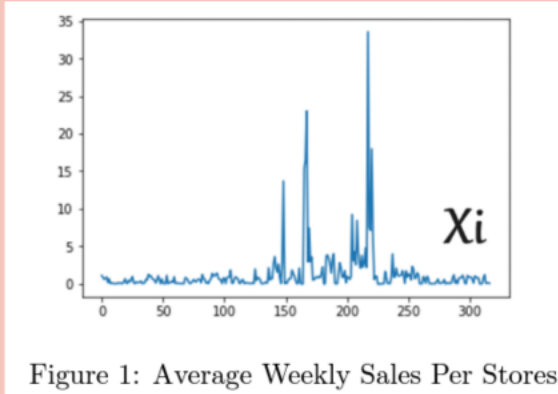
Promotion Bump Case Description

- **Aim:** Forecasting Promotion Effect on Sales Using Dataset, Including Sales of Each Store and Item in a given period
- **Dataset:** 340 stores, 317 products
 - Each entry represents the sale quantity of a specific product in a specific store in a day
 - **Train Data:** Sales up to 7/15, 1873618 rows
 - **Test Data:** Sales after 8/15, 1028121 rows
 - **Regular Days & Promotion Days**
- **Methodology:** Model promotion effect on stores and products using train data and predict promotion increase, test model performance on the test data



Overview of Work Done

Product Modelling



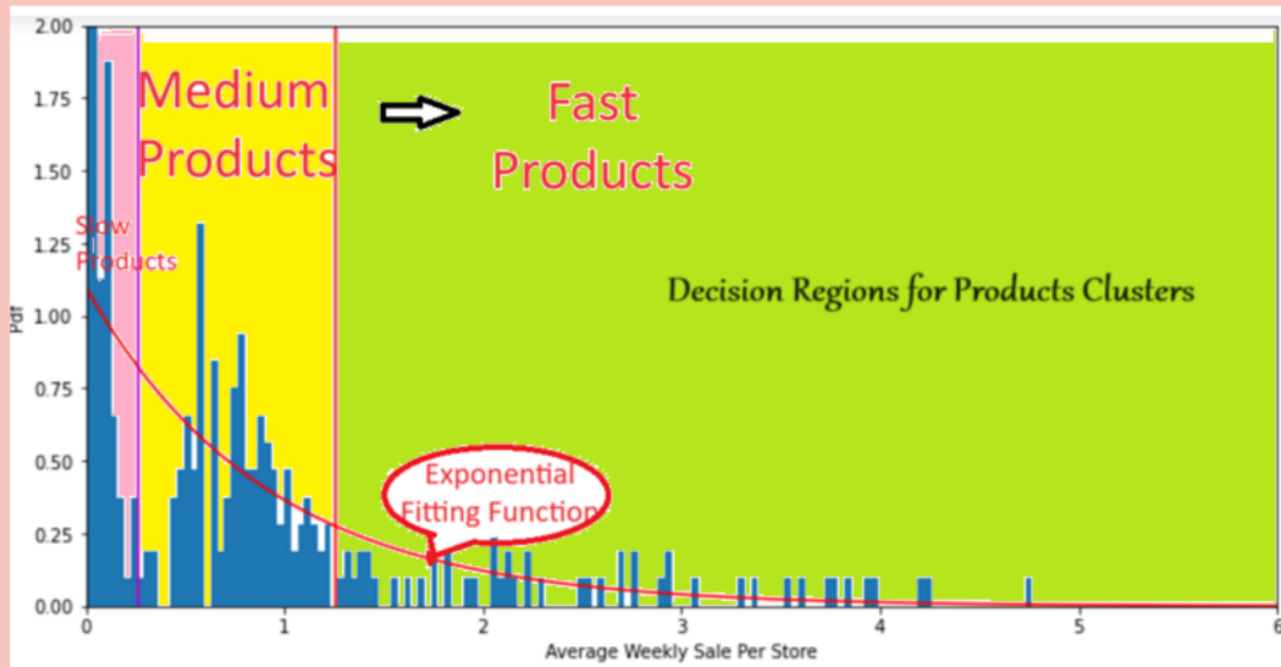
- Each product X_i is represented by **average weekly sale per store**

- Our strategy: **CLUSTERING** 
 - {Fast Items}
 - {Medium Items}
 - {Slow Items}

- X is modeled by exponentially distributed random variable.
- Exponential distribution is fitted to histogram by
 - estimating the parameter $\hat{\lambda}$ using $\hat{\mu}_{robust}$, $\hat{\sigma}_{robust}$
- 1st and 3rd quartiles are used for decision threshold respectively for Slow and Fast Products

Decision Region: $x_{slow} < 0.26 < x_{medium} < 1.26 < x_{fast}$

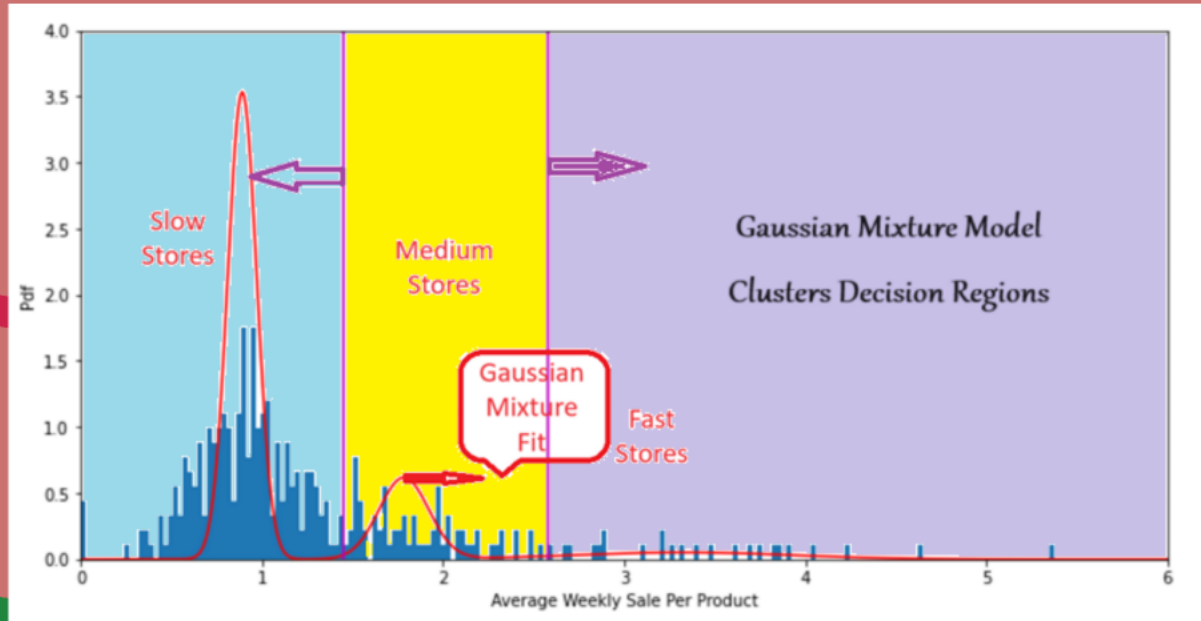
- | Fast Product Cluster | = 63
- | Medium Product Cluster | = 126
- | Slow Product Cluster | = 128



Overview of Work Done

Store Modelling

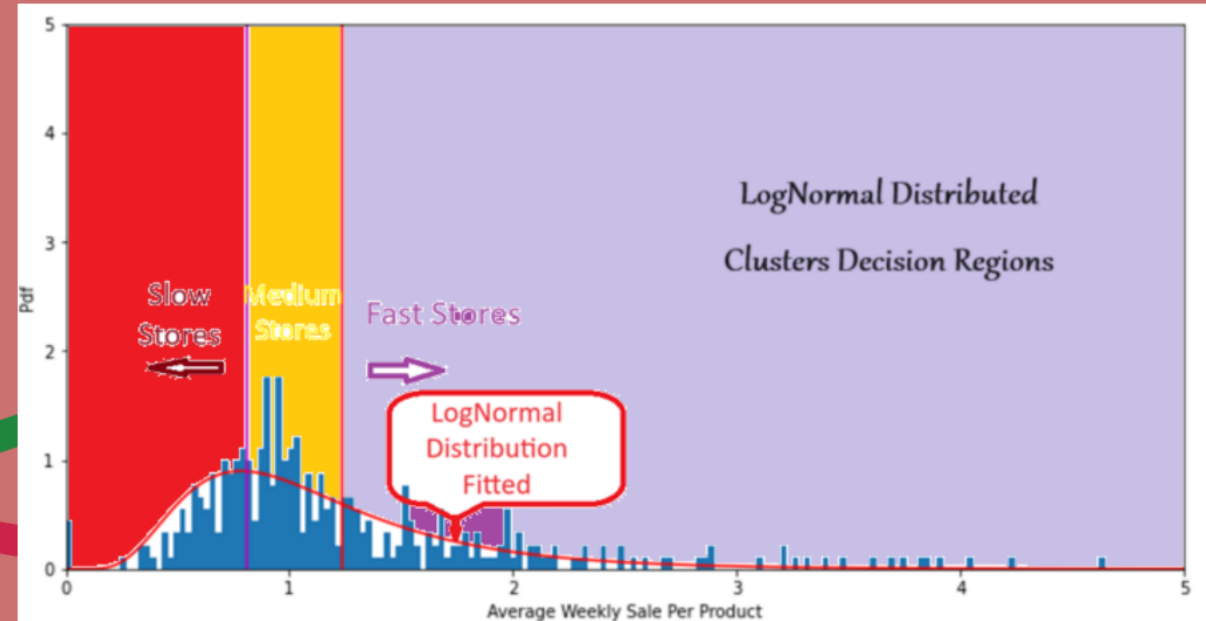
- Each product Y_i is represented by average weekly sale per product



- Y is modeled by Gaussian Mixture Model, ie mixture of 3 Gaussians

Decision Regions:

$$x_{\text{slow}} < 1.45 < x_{\text{medium}} < 2.58 < x_{\text{fast}}$$



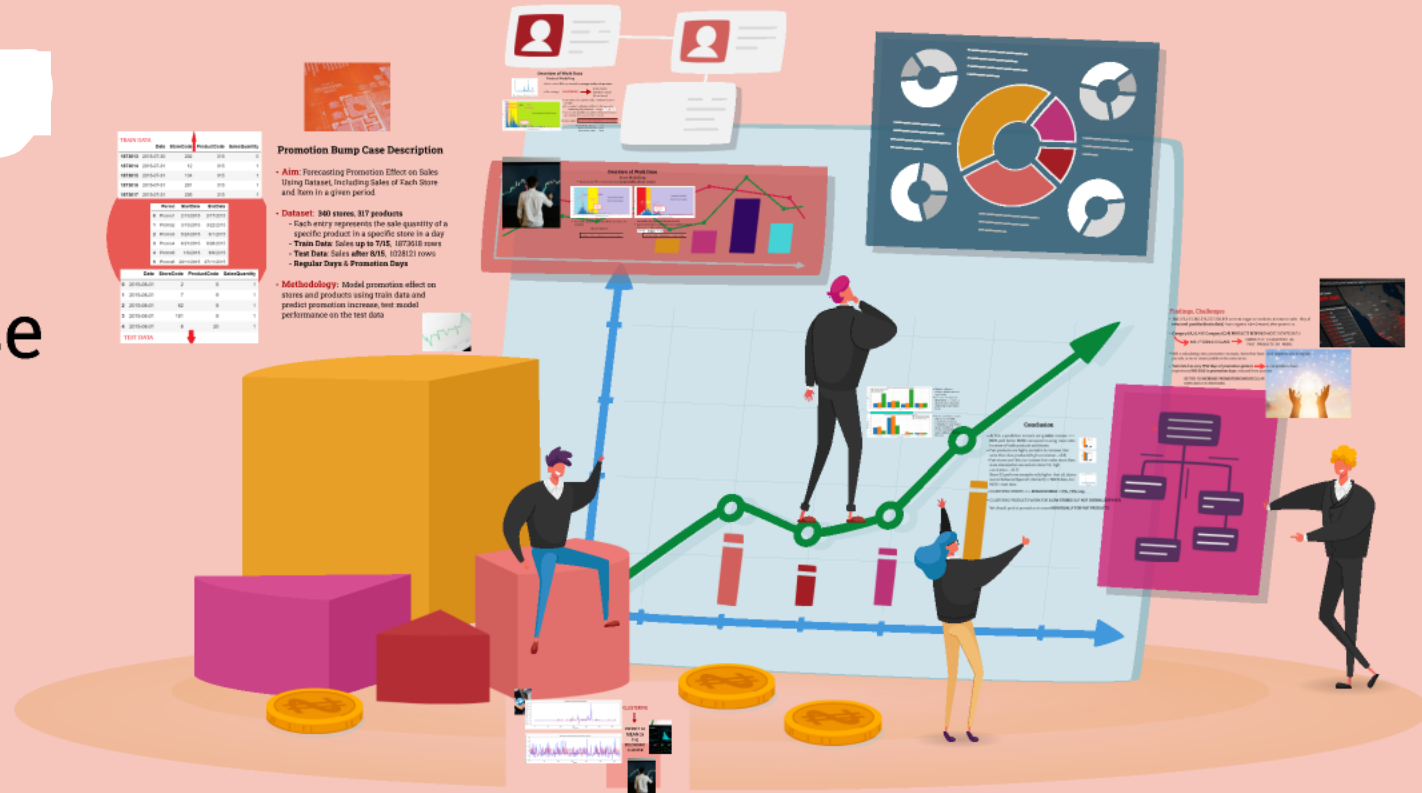
- Y is modeled by LogNormal Random Variable
- Lognormal distribution parameters are roughly estimated from mean, median and std as
- $\mu = 7e - 3$ and $\sigma = 0.5$

$$x_{\text{slow}} < 0.8 < x_{\text{medium}} < 1.24 < x_{\text{fast}}$$

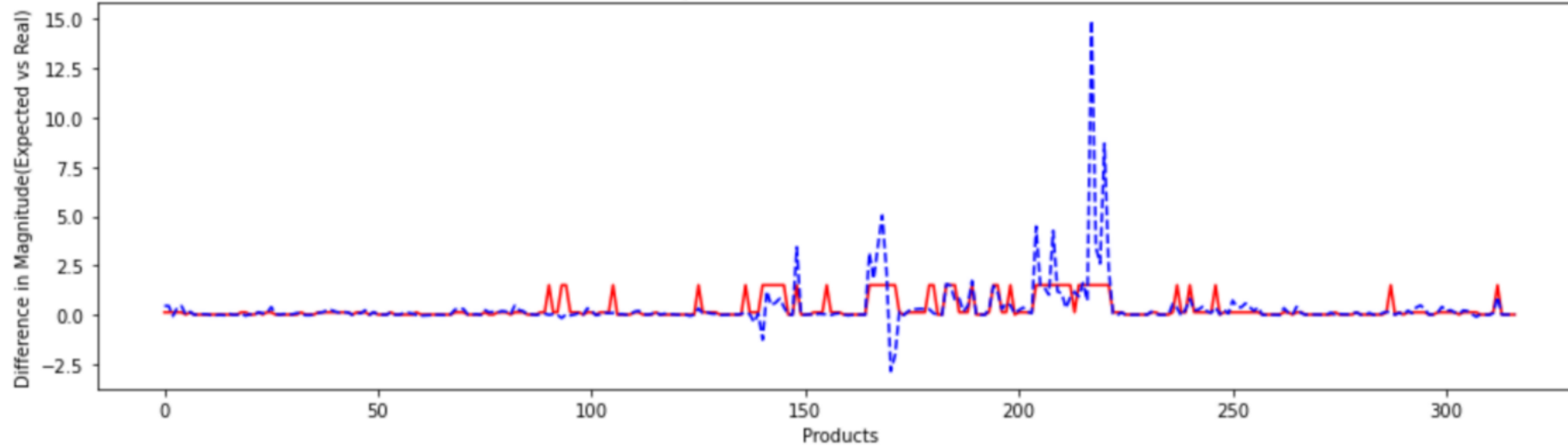
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Expected vs Real Promotion Effect

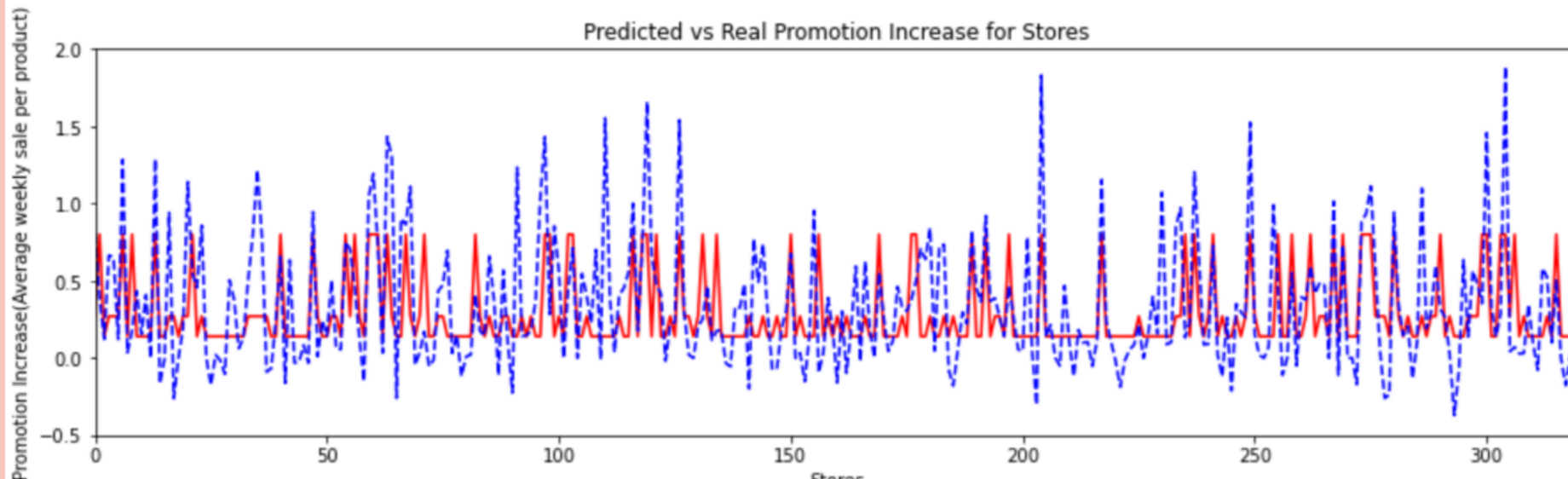


CLUSTERING

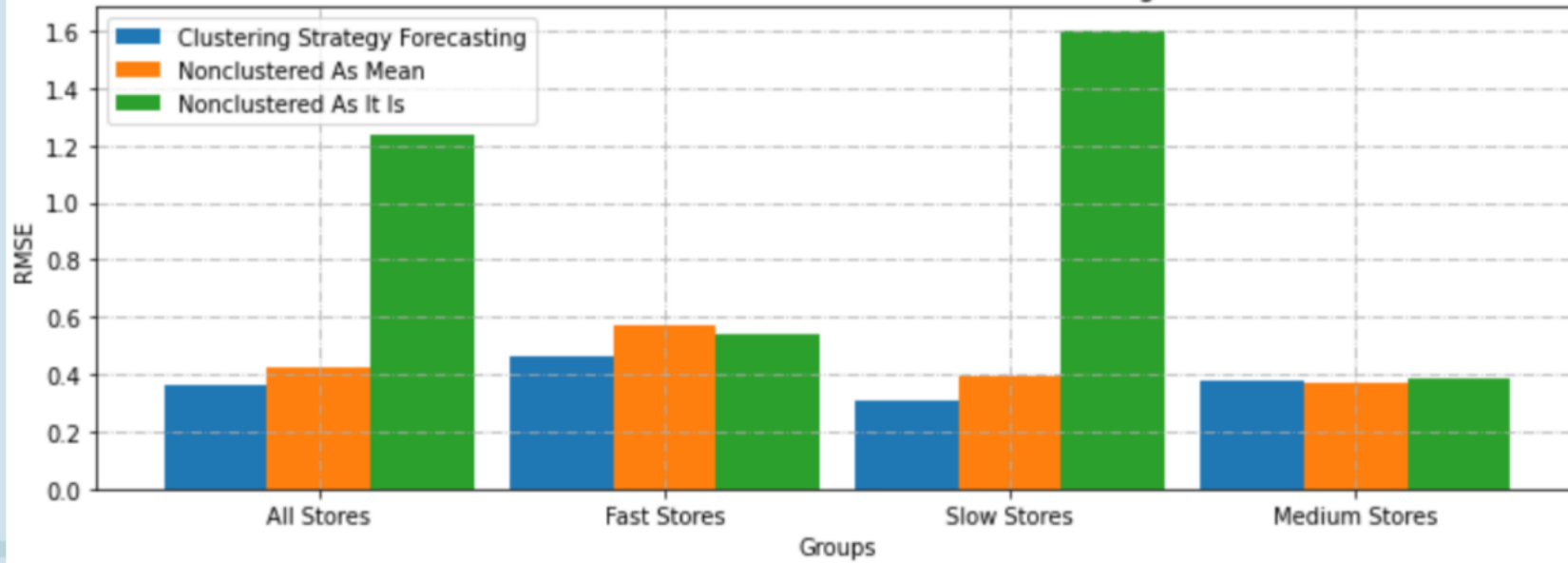


**PREDICT AS
MEAN OF
THE
BELONGING
CLUSTER**

Predicted vs Real Promotion Increase for Stores

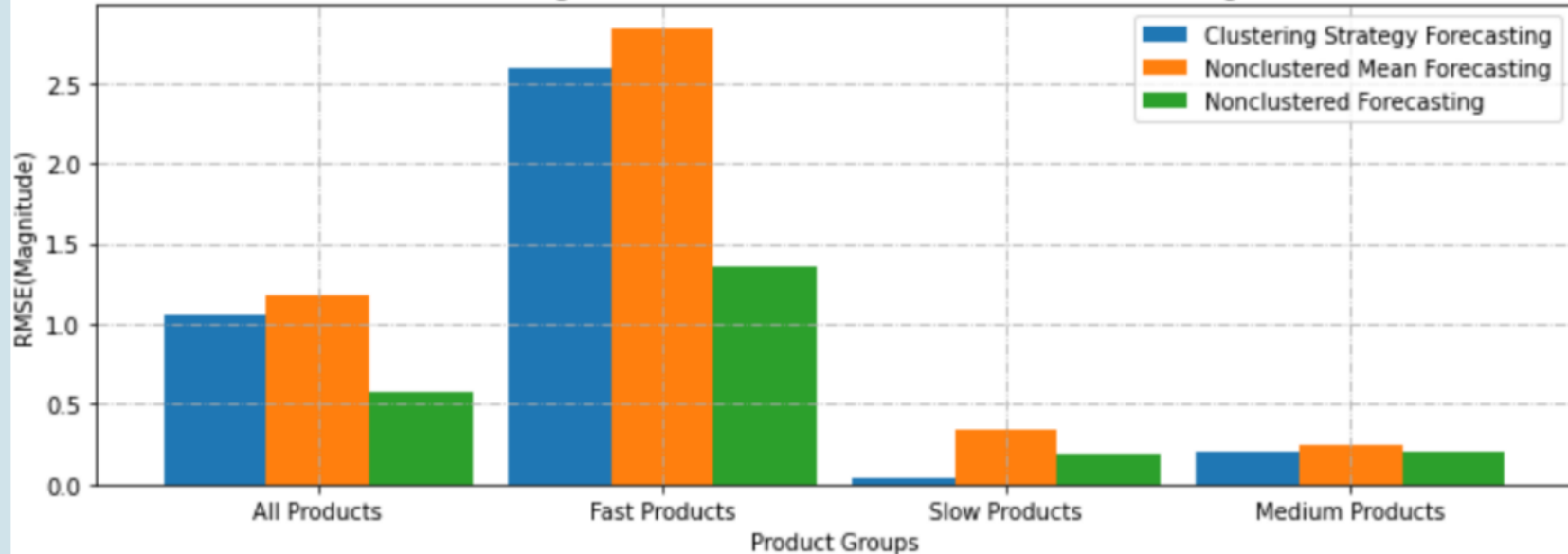


RMSE of Clustered and Nonclustered Forecastings



- Clustering Stores is efficient, ie RMSE reduced significantly.
- It is more meaningful for **Slow Stores**. It is better to determine Slow Stores for estimating the promotion bump.

RMSE(Magnitude) of Clustered and Nonclustered Forecasting

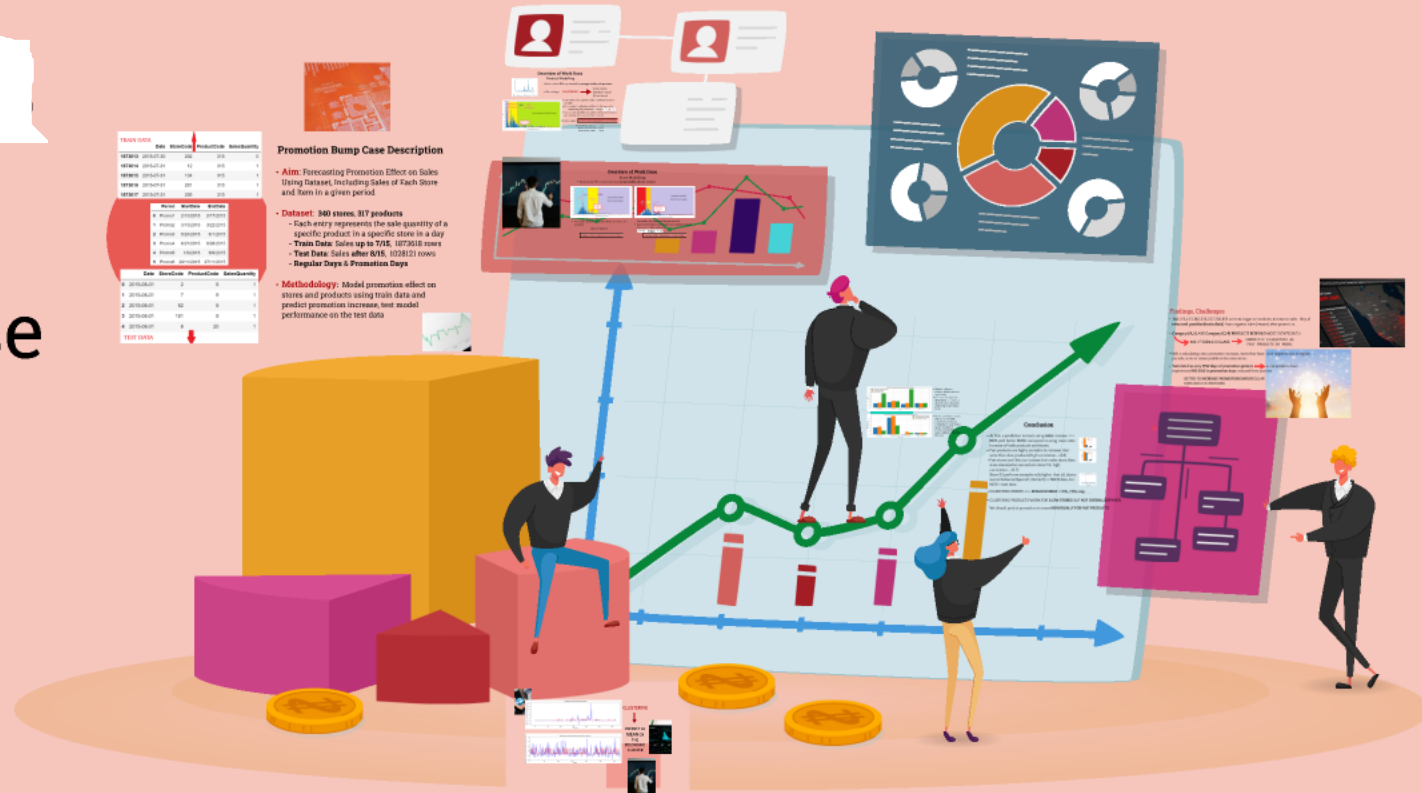


- Clustering Products has **not reduced** overall RMSE compared to predicting individually for each product
- Clustering Model of Products has **worked** for **Slow Products**, but not **Fast Products**

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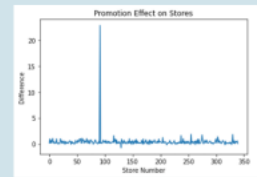
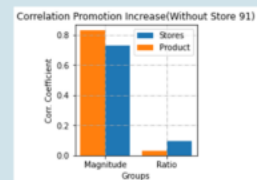
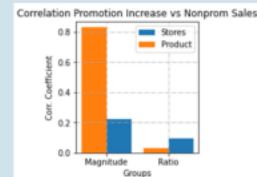
Promotion Bump Case

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Conclusion

- At first, a prediction is made using **ratio** increase ==> **NOT** yield better RMSE compared to using mean ratio increase of both products and stores.
- Fast products are highly probable to increase their sales than slow products (high correlation $\sim > 0.8$)
- Fast stores are likely to increase their sales more than slow stores (when we exclude store 92, high correlation $\sim > 0.7$)
- Store 92 performs exceptionally higher than all, above overall behavior (Special?, Outlier?) in TRAIN data, but NOT in test data
- CLUSTERING STORES ==> **REDUCED RMSE : 15%, 70% resp.**
- CLUSTERING PRODUCTS WORK FOR SLOW STORES BUT NOT OVERALL (ESP FAST)
- We should predict promotion increase **INDIVIDUALLY FOR FAST PRODUCTS**




Findings, Challenges

- 160,163,165,182,226,227,228,309 are total negative products, ie returns > sales. They all **returned positive(train data)** from negative sales(returns) after promotion.

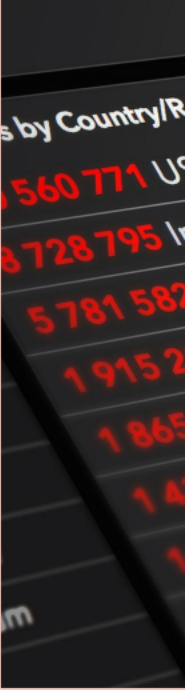
- **Category (A,5) AND Category (G,4) PRODUCTS RESPOND MORE SIGNIFICANTLY**

 **FAST PRODUCTS CLASS**  **CORRECTLY CLASSIFIED AS FAST PRODUCTS BY MODEL**

- While calculating ratio promotion increase, items that have total negative sale in regular periods, ie more return prohibits the calculation.

- **Test data has very FEW days of promotion periods**  **some products have experienced NO SALE in promotion days, reduced from positive**

BETTER TO INCREASE PROMOTION DAYS/REGULAR DAYS RATIO IN TEST DATA



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