Retail Demand Forecasting

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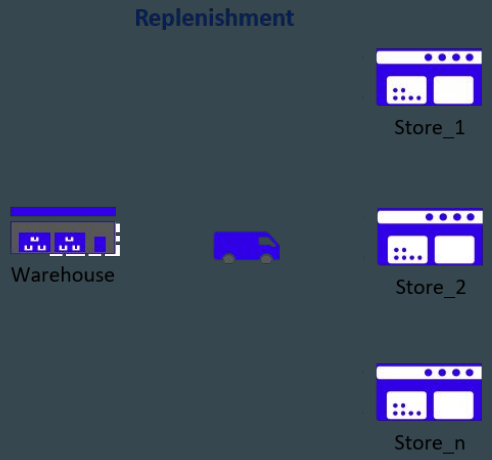
Demand Planning Optimization

For many retailers, demand planning systems follow a traditional rule-based approach to forecast and replenish orders. Such an approach is adequate for stable and predictable product categories, however, it is limited for optimization. This is especially true for products with a high stockout cost.

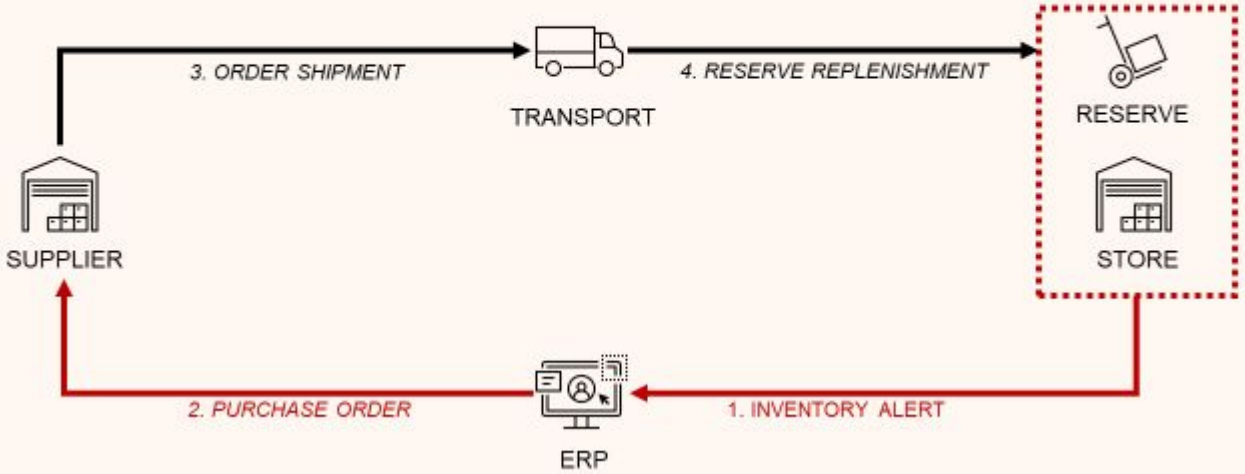


Sales

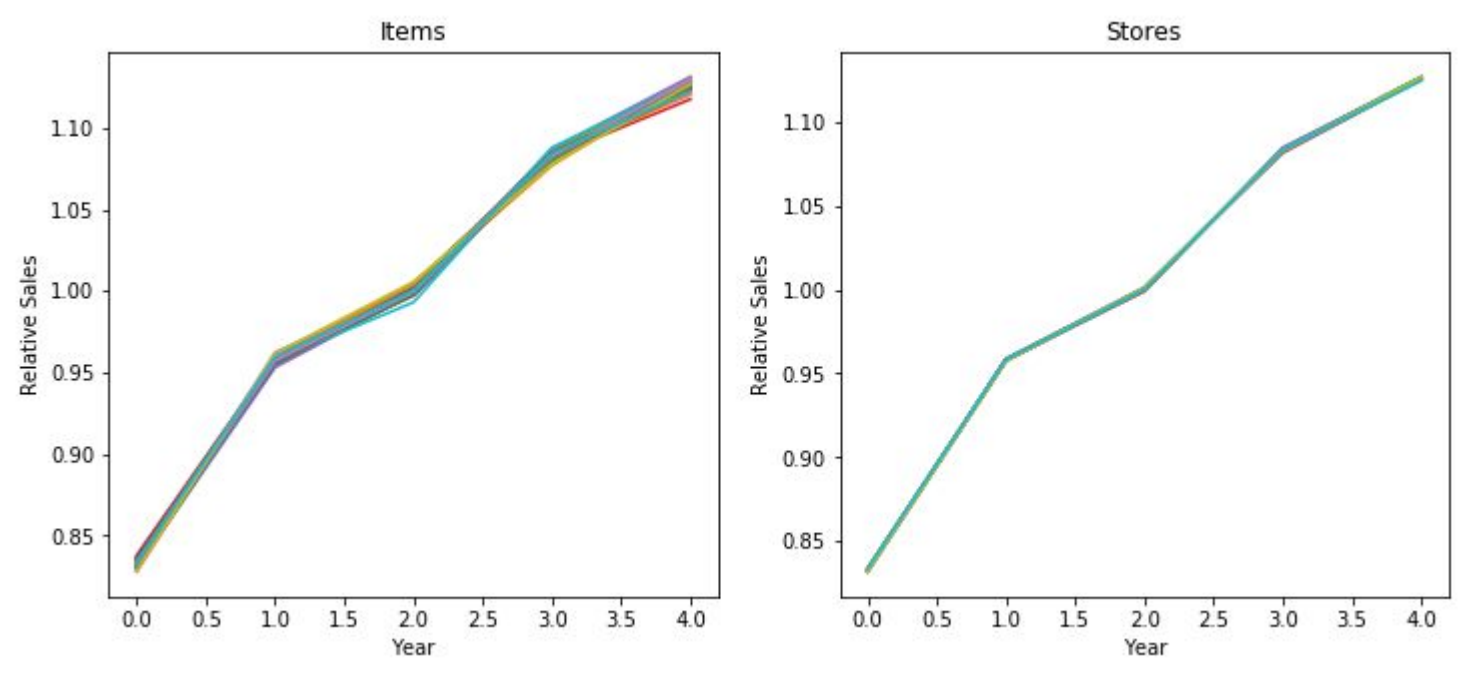
Date	Store	Item	Qty
XX/XX/XXXX	Store 1	Item 1	1
XX/XX/XXXX	Store 2	Item 13	23
XX/XX/XXXX	Store 3	Item 32	2
XX/XX/XXXX	Store 4	Item 43	3
XX/XX/XXXX	Store 5	Item 25	1
XX/XX/XXXX	Store 6	Item 18	5
XX/XX/XXXX	Store 7	Item 34	1
XX/XX/XXXX	Store 8	Item 46	1
...			
...			
XX/XX/XXXX	Store 1	Item 10	11
XX/XX/XXXX	Store 1	Item 30	9

Procurement Strategy Problem

What is the optimal quantity for your store replenishments?



Exploring Data



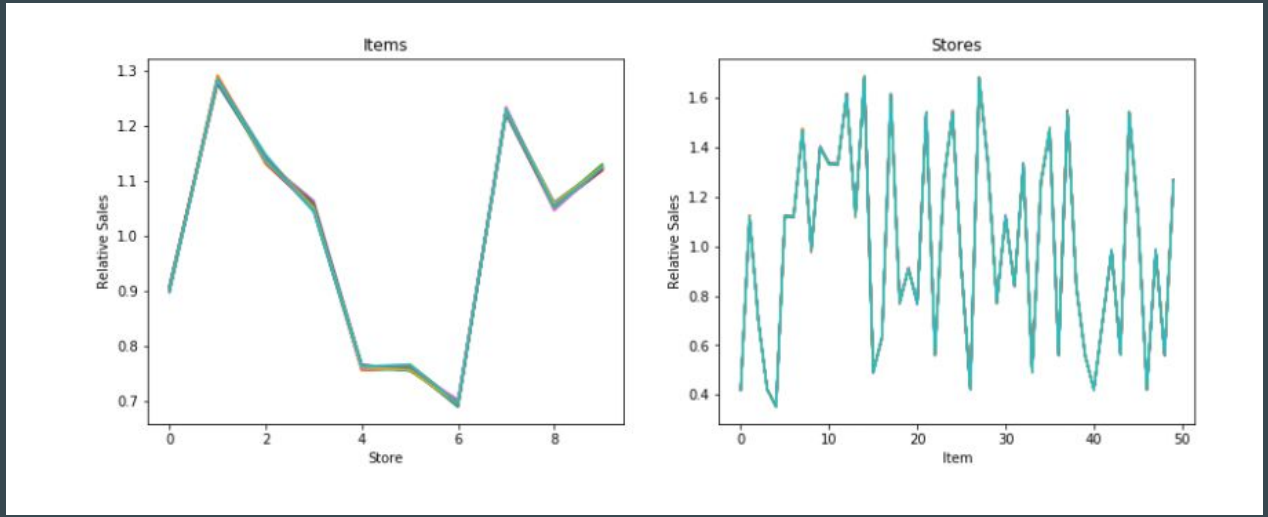
Benefits

Why embrace machine learning models to forecast demand?

- Inventory Optimization: matching store inventory with actual needs to reduce storage space needed (Rental Costs)
- Replenishment Optimization: optimizing replenishment quantity per order to minimize the number of replenishments between warehouse and stores(Warehousing & Transportation Costs)

Example/Data

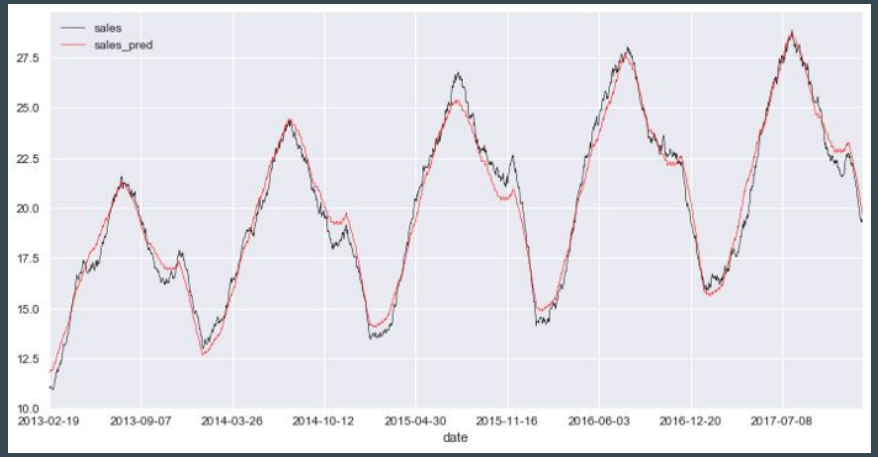
- Transactions from 2013-01-01 to 2017-12-31
- 913,000 Sales Transactions
- 50 unique SKU
- 10 Stores

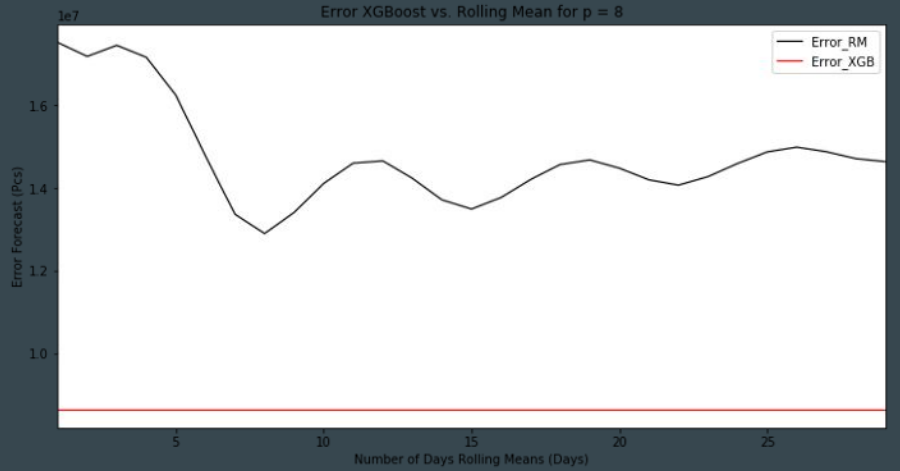


Rolling Mean vs. XGBoost

Rolling mean: Forecasts demand of previous sales at the end of the day. Forecast average demand across 8 days (most accurate amount).

XGBoost: simulation model to improve demand planning for store replenishment.





Conclusion and Next Steps

Using the Rolling mean method for demand forecasting, we can reduce forecast error by 35% with x(8) days.

XGBoost forecast can provide even better performance by replacing rolling mean by XGBoost forecast to predict day n, day n+1 and day n+2 demand reducing error by 32%.

Next Step: reduce order frequency using this forecasting model to match order quantity with demand.