Demand Forecasting to Maximize Sales

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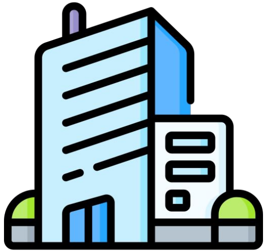
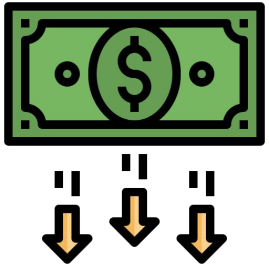
NEXT

This is you!



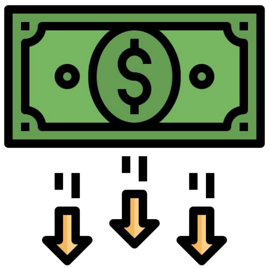
You are the owner of a medium-size grocery

You notice that sometimes you order too much stock, and sometimes too little



You’re losing money and customers are unhappy

Your current forecasting model is causing a loss



Your current model is costing you $10.8M in losses annualized*

Your customers are unhappy and leaving, and you are not maximizing your sales potential

You’re wasting a lot of products and you’re doing a lot of bad for the environment

*Based on naive model

You try our forecasting model and notice that:

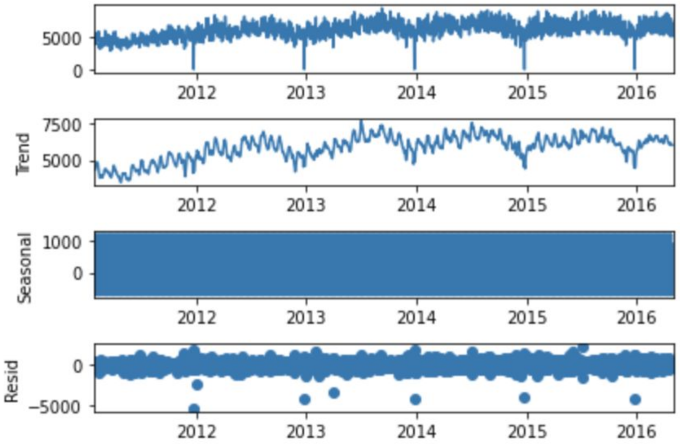
1. **Customer satisfaction has increased.**
   When customers come into the store, the product they are looking for is available.

2. **You don't overstock as often**
   Some items, like food, are perishable, so minimizing the chance of overstocking reduces cost and waste.

3. **You can plan better financially.**
   More accurate revenue and profit projections.

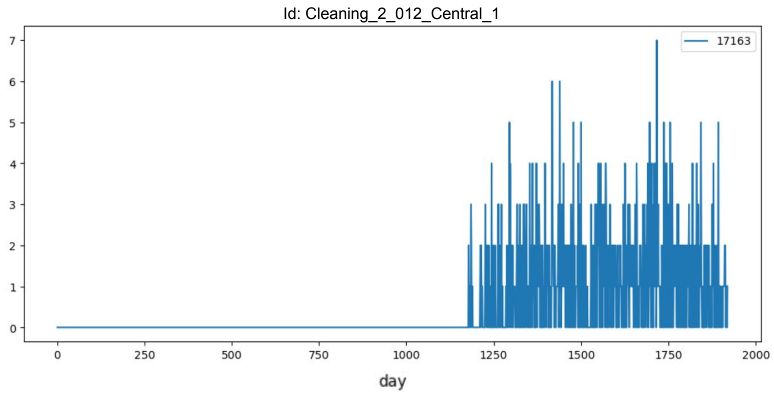
What did we notice?

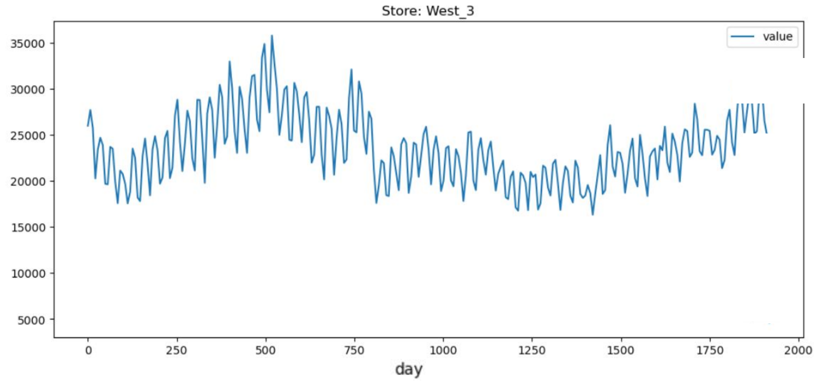
- Positive trend overtime
- High correlation between a day and the previous day's sales
- Seasonality every 7 days across stores and subcategories

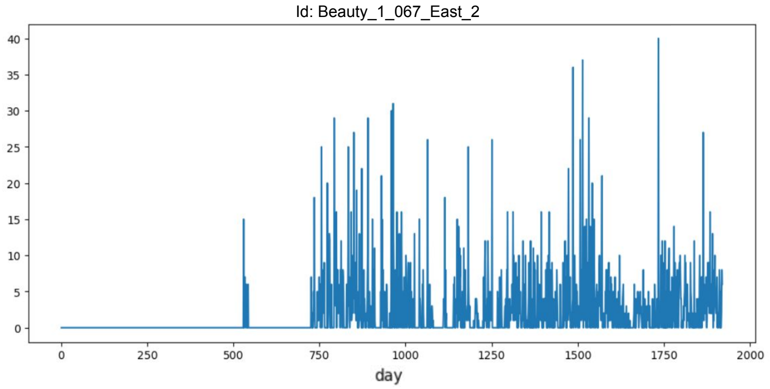


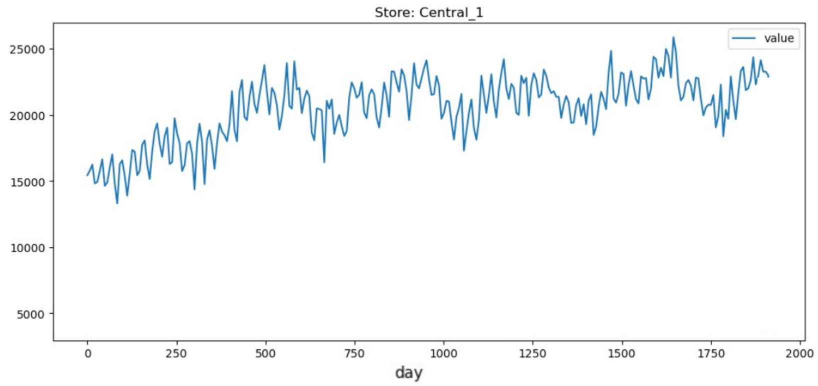
Decomposition for store_id: "East_3" with lag 210

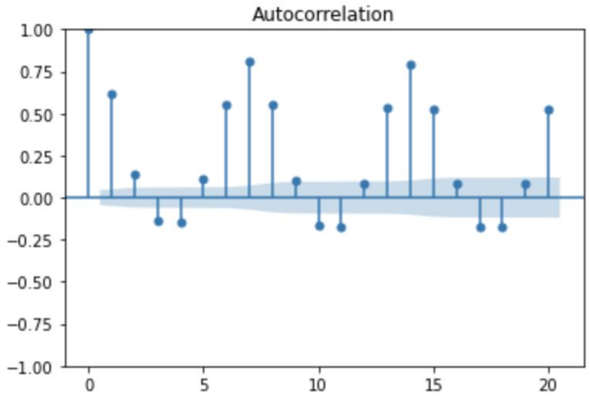
Time series of stores vs. item ids



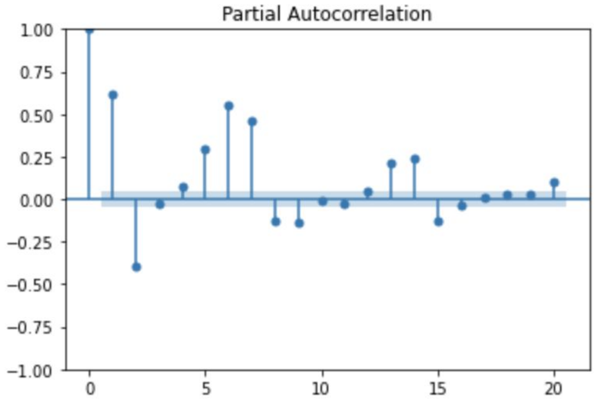




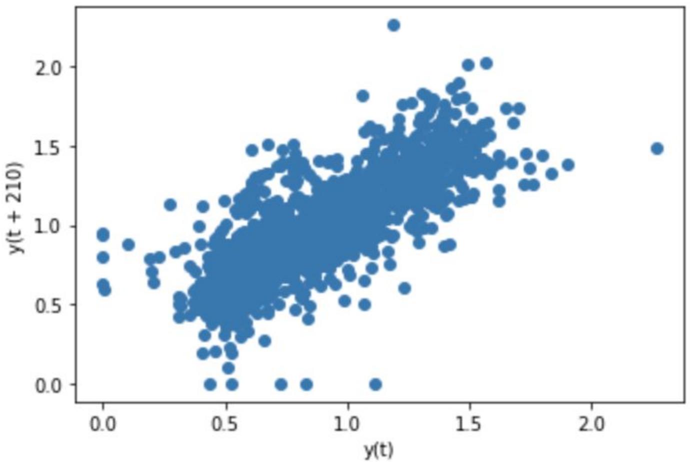




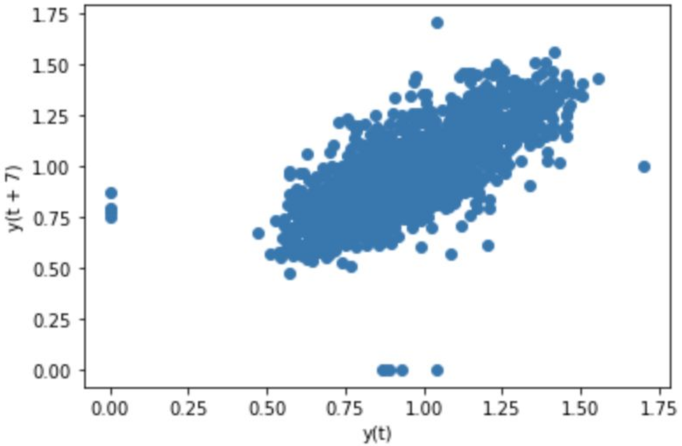
Autocorrelation plot for store_id: “East_1” - notice spike every 7 days



Partial autocorrelation plot for store_id: “East_1” - notice spike every 7 days



Lag plot for store_id: “West_1” with lag 210



Lag plot for store_id: “Central_1” with lag 7

Baseline - Naive Sales Model

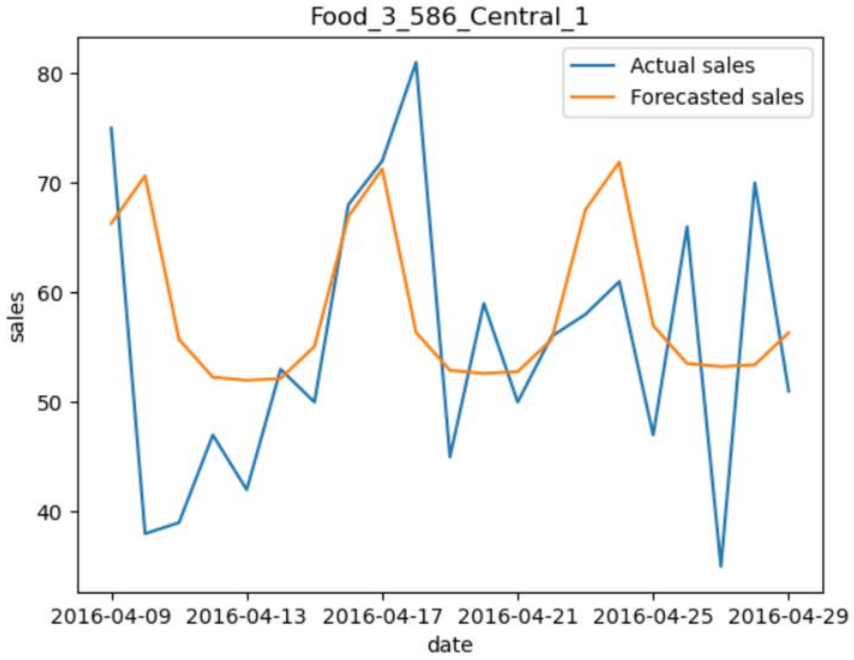
- Let's assume your business currently forecasts sales by taking the average number of goods sold in the past.
- An overprediction of sales results in **extra costs.**
- An underprediction of sales results in **lost potential profit.**

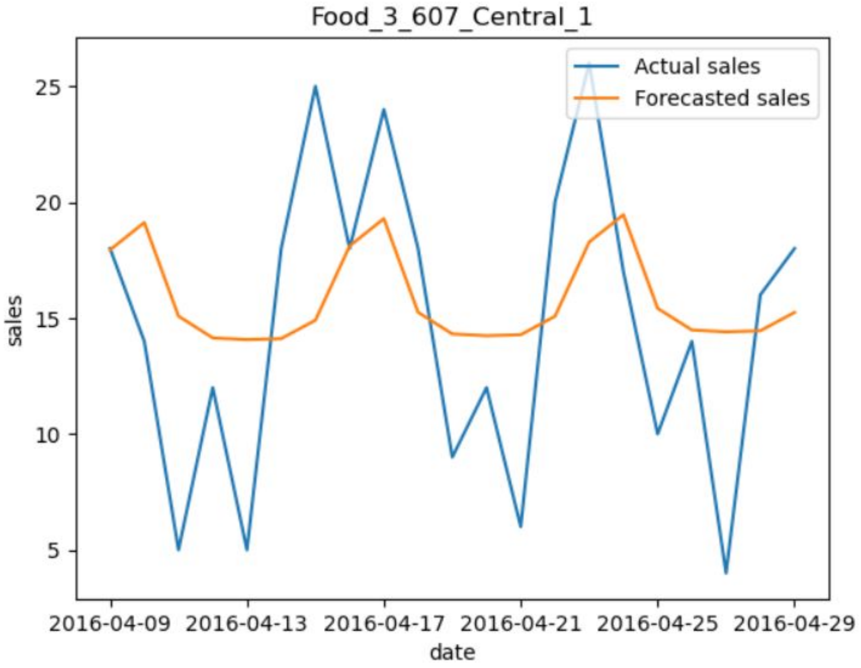
Pros	Cons
• Easy to understand • Easy to implement	• Can't predict spikes

Our model:
Error-Trend-Seasonality

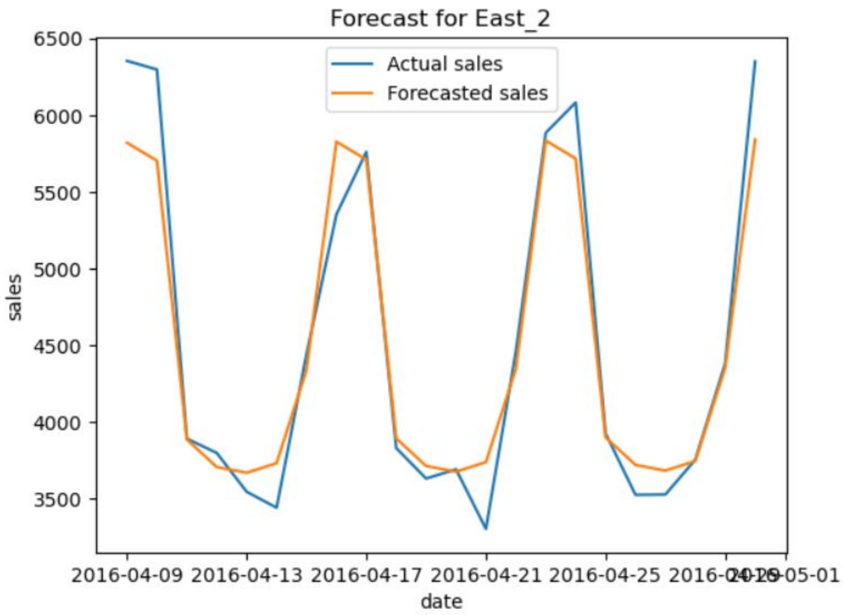
- Considers the trends of the sales of each store
- Takes into account that there is a repeating pattern every 7 days
- Uses the proportion of an item of total sales from the last week in the data
- Results imply ~$6m saved annually compared to baseline

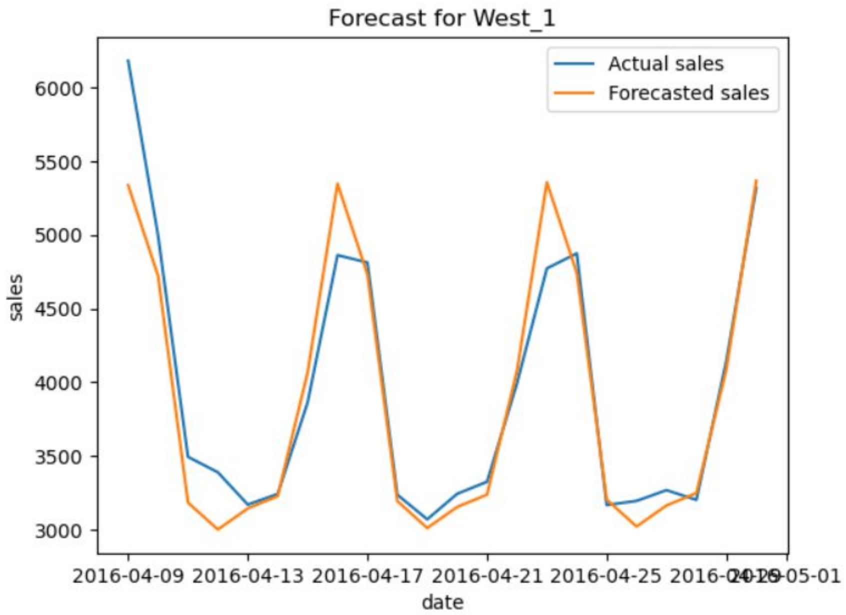
Performance of our model





Performance of our model





There are some limitations

- It might be preferable to be **conservative** or **aggressive** in how much we stock depending on the *kind* of good that we are considering
    - ie. for perishable goods, you may decide to understock rather than overstock (because overstocked goods may expire)
- Inability to account for various levels of errors for different categories
- Inability to handle **seasonality variations**
- Difficulty in forecasting for **long horizons**
- Inability to handle **external factors**
- Inability to account for other potentially **important predictors** such as price of the goods
- Limited ability to capture **sudden changes** in demand

Immediate next steps

- Be more or less conservative with predictions for different types of items
- Incorporate more data that may allow us to build a model that gives insight on what influences sales
    - Regional statistics/features
    - Customer statistics

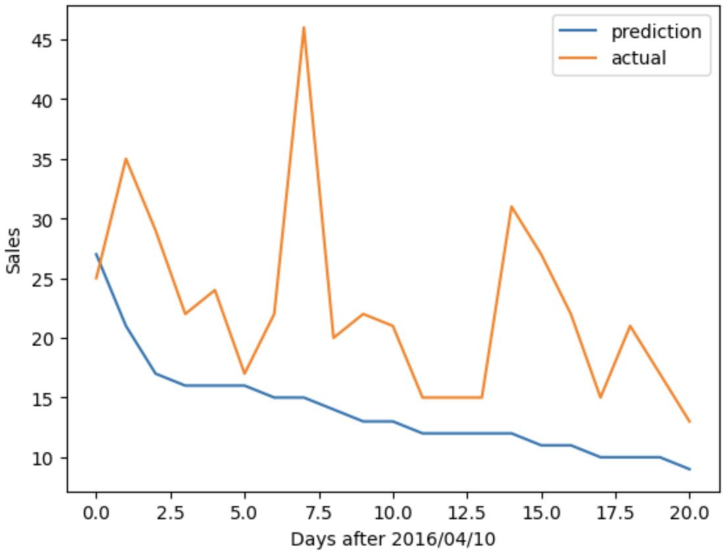
Thank you

Appendix

Performance of our other models

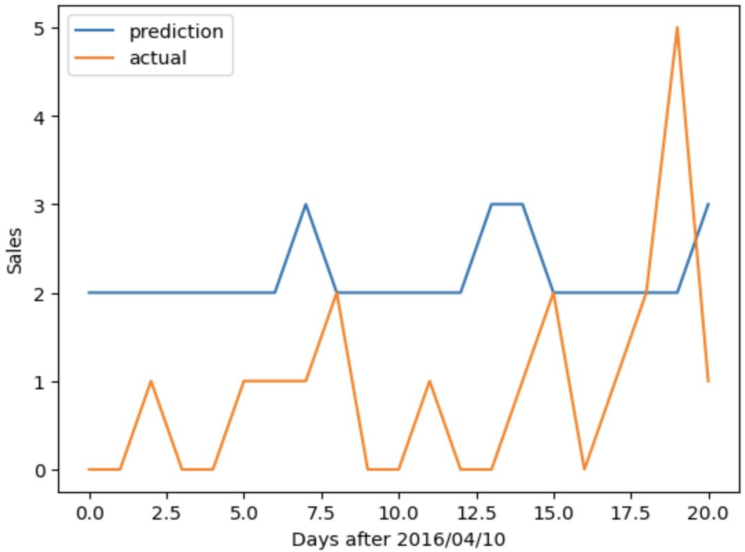
Arima

item: Food_1_122_West_1



XGBoost

item: Food_2_274_East_3



* *predicted sales using Arima and XBoost versus actual predicted sales*