

Minimizing stock costs for Proximus shops

Vlerick Business School
Group 7

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Meet the Team



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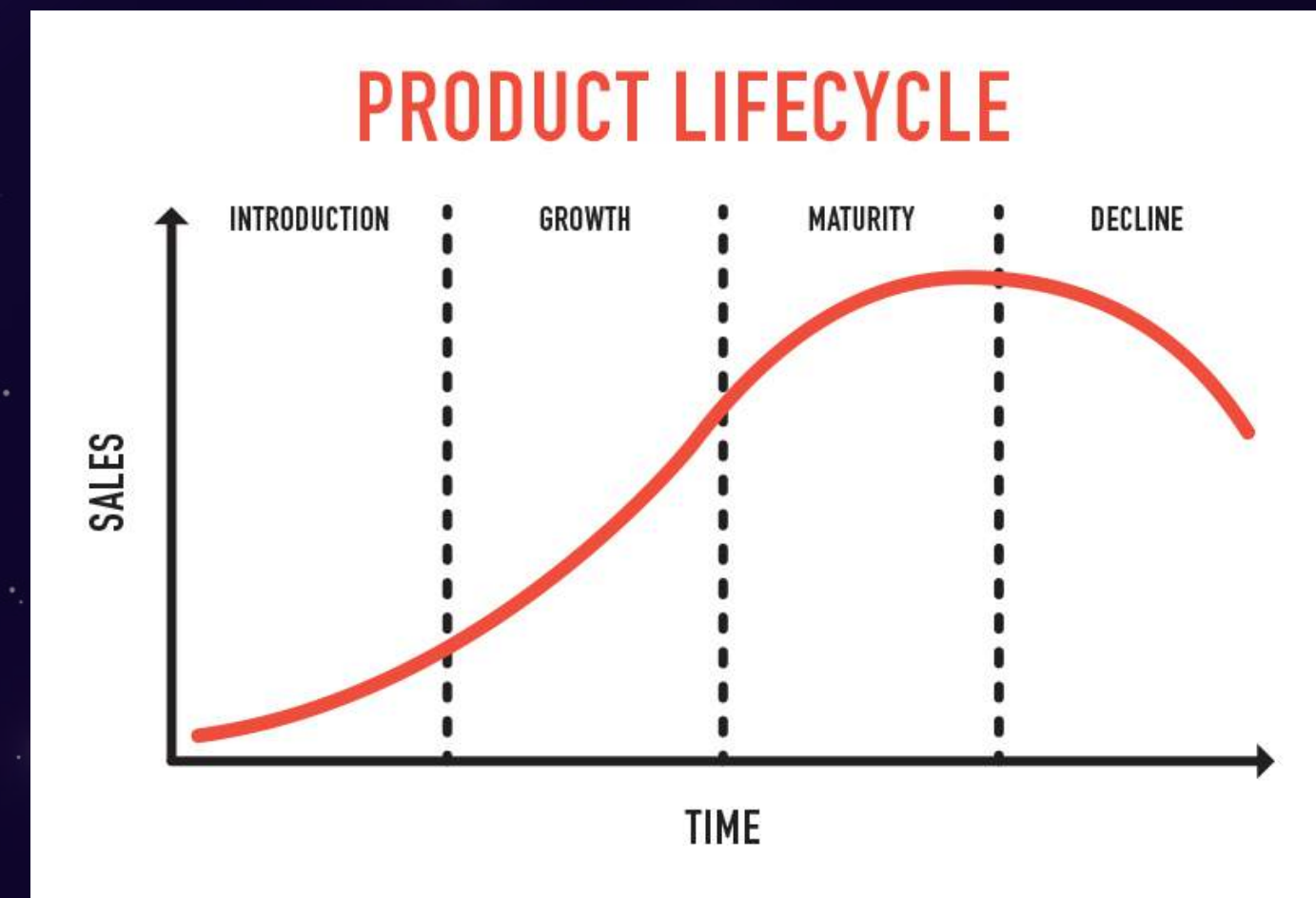


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Challenge:

Optimizing Proximus' product distribution across stores.

- **High Stakes:** Short product lifecycles and limited data make it difficult to ensure the right products are in the right stores at the right time.
- **Impact:** Lost sales, frustrated customers, and inefficient inventory management



Sample data = 9 products with 80+ shops

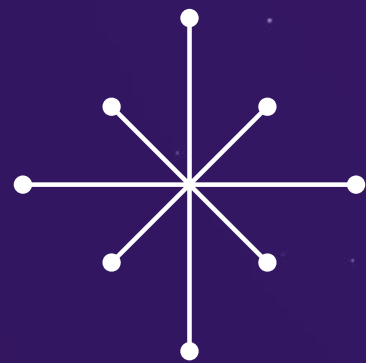
Our Solution



Improved demand forecast accuracy **by 52%**
using new forecast model



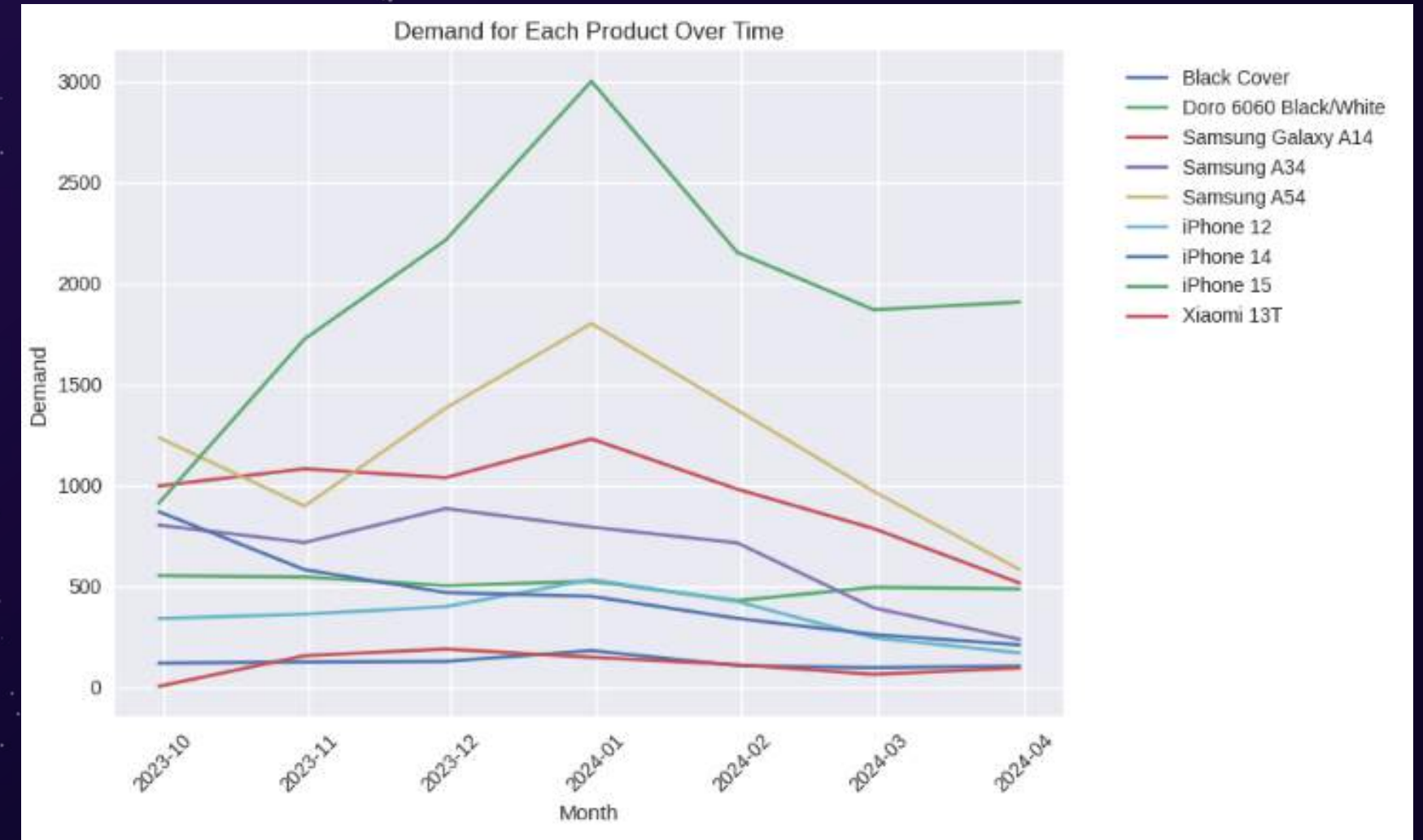
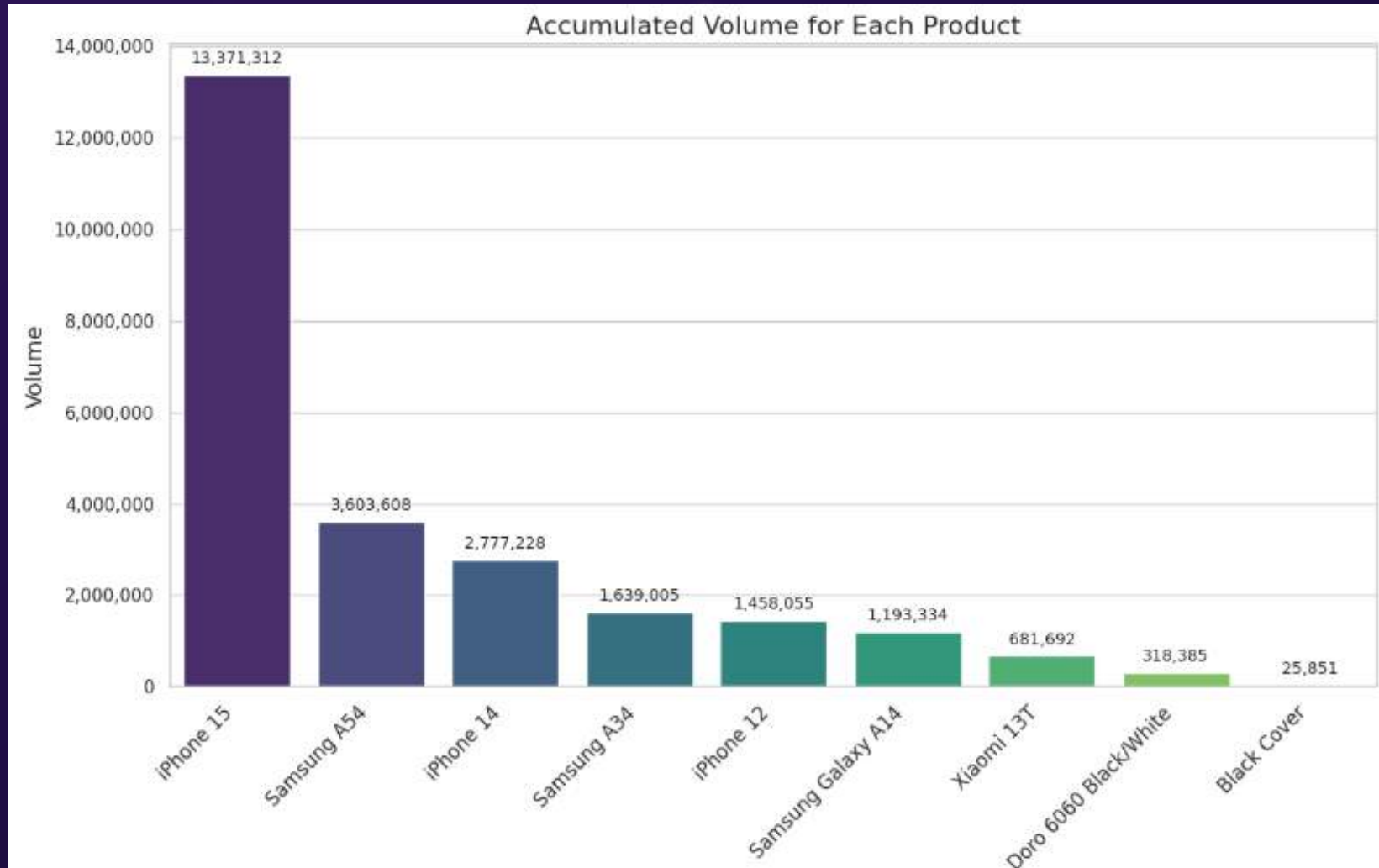
Optimized total cost **by 56%**
using our new policy optimization



Scalable to all products and plants

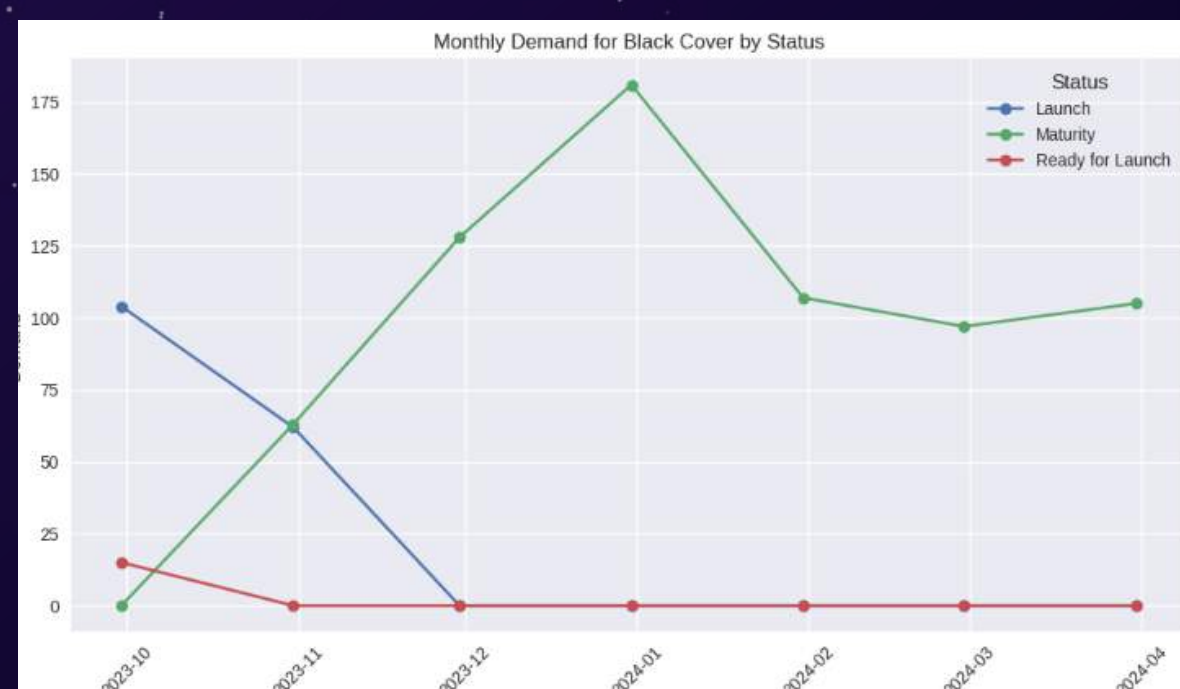
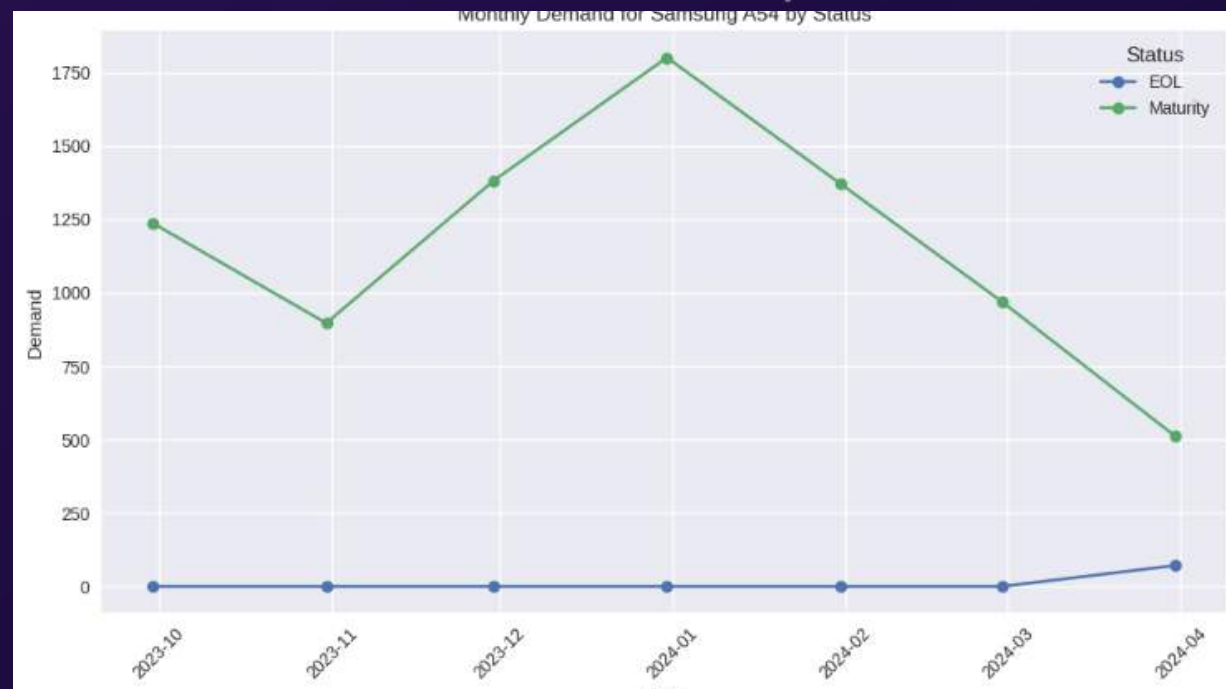
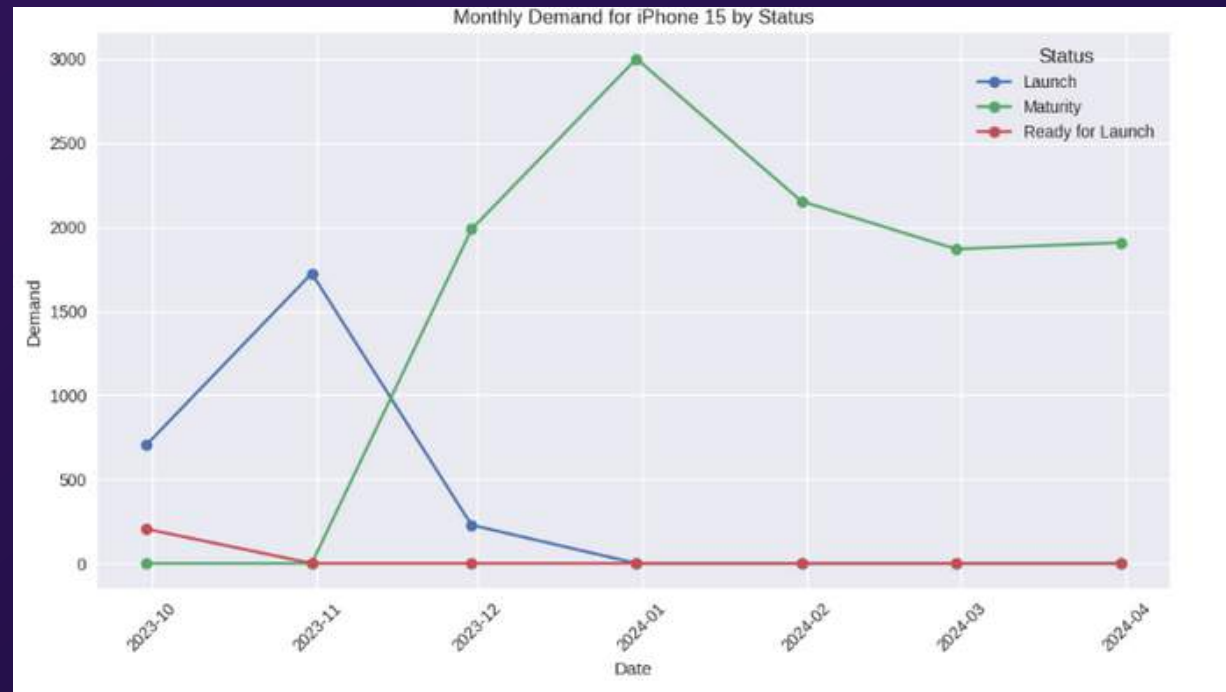
Data Exploration

Product level Demand



iPhone 15 is the highest value product (price * volume) followed by Samsung A54 and iPhone 14. Peak in demand in the month of January for almost all products.

Demand View by Status

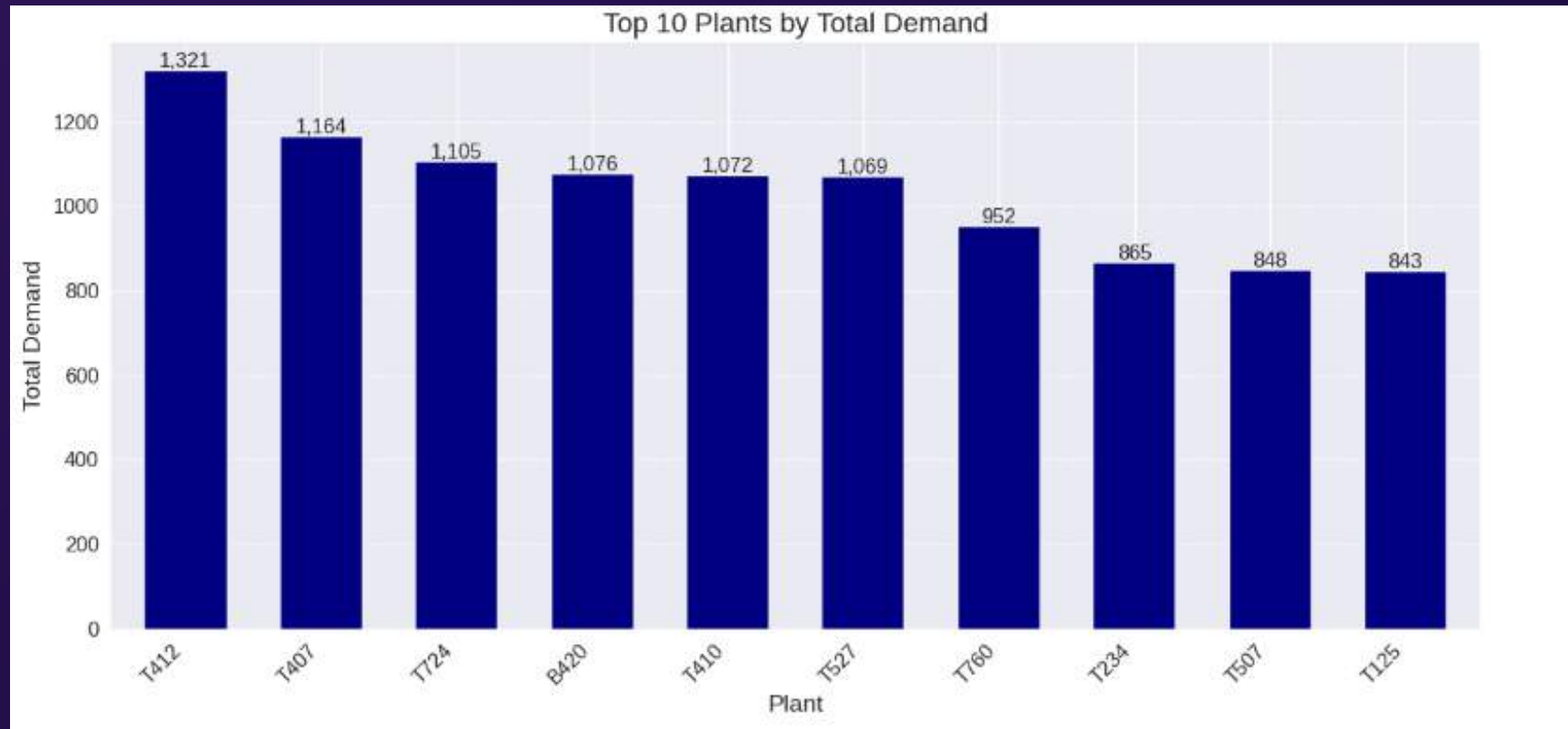


Multiple products have different 'Status' at any given time - Varied Product life cycle stage simultaneously

Most products are in **maturity** stage and naturally Demand in 'maturity' stage is higher than in other stages.

Demand sees a big drop after the peak in **January** irrespective of the Status/Stage

Shop Level View



Shop **T412** has the highest demand followed by **T407** & **T724**

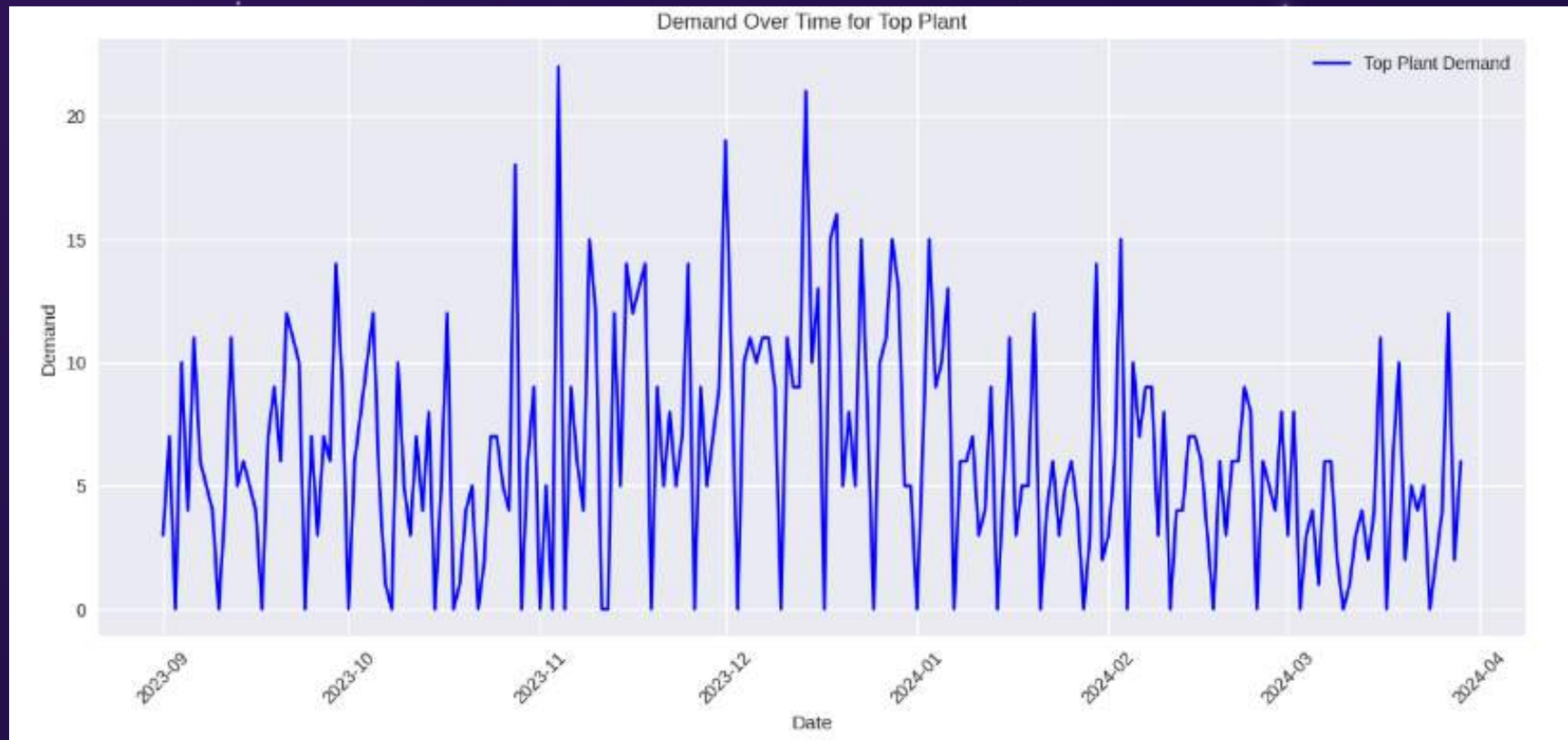
- Contribute to ~ **23%** of the total demand
- T412 has the highest demand with **1,321** units



Shop **T237**, **T348** & **T146** have the least demand

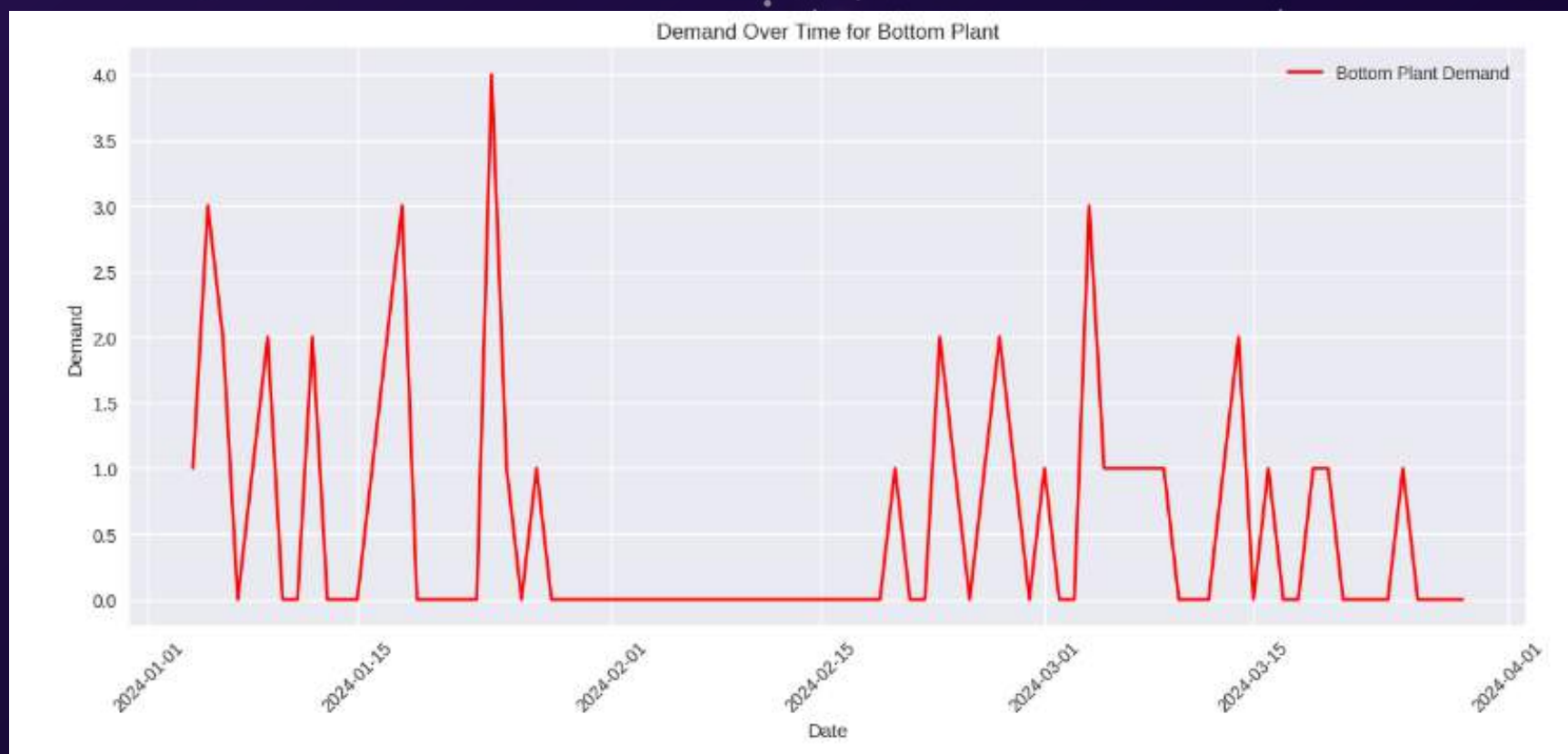
- Contribute to ~ **3.5%** of the total demand
- T237 has the lowest demand with **47** units

Shop Level - Demand over Time



The demand for the top shop remained mostly within the range of **5-15** units

Though there are some **outliers** in the month of November & December 2023.



A lot more **inconsistent** demand with frequent **spikes** for the bottom shop

Demand peaked at **4** but also remained **zero** quite often



Finding a Policy

Baseline Dummy

When stock reaches a certain
ordering point:

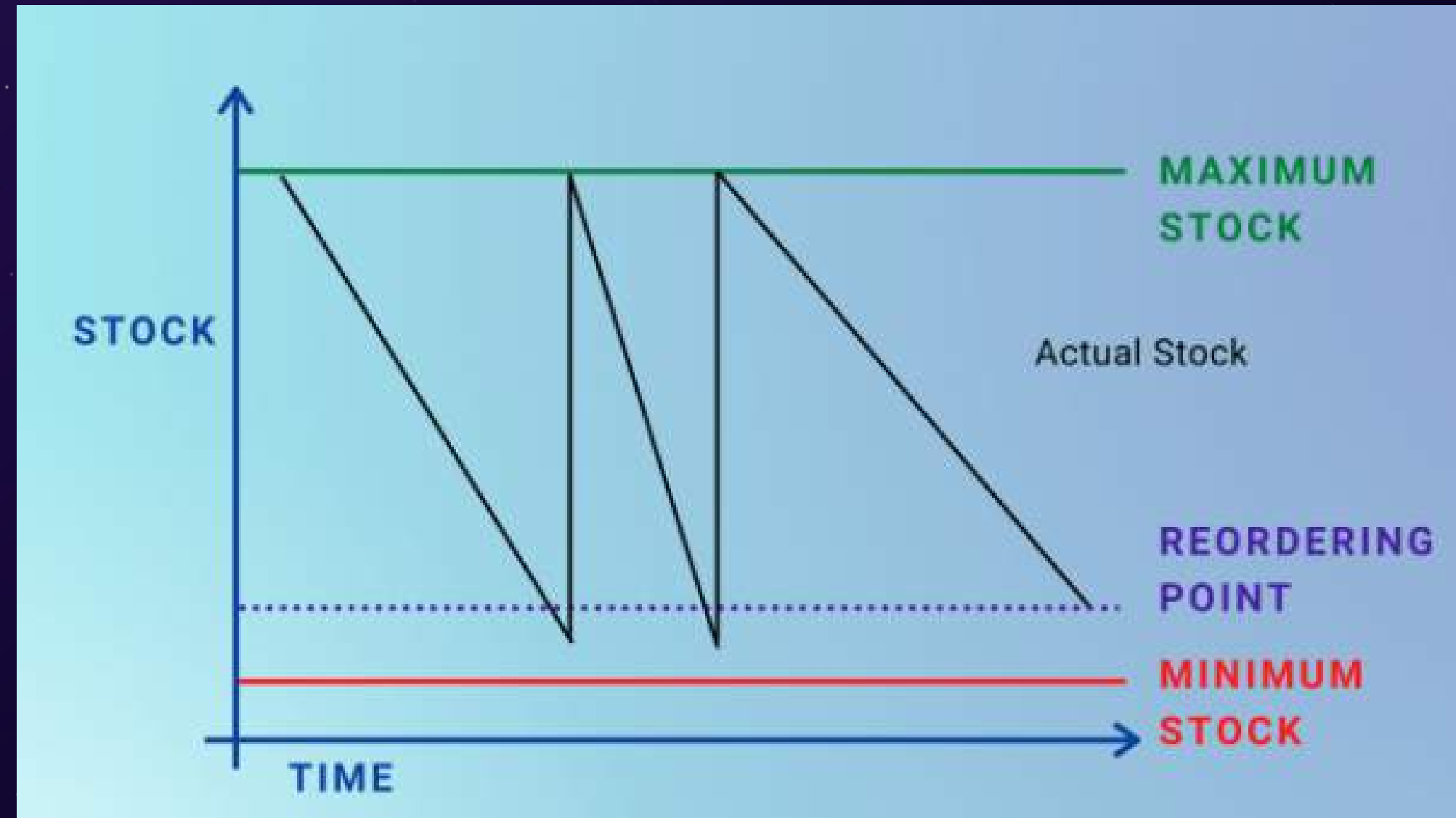
- Order up to a **defined stock level** for all plants

For the iPhone 14 across all 88 plants
September to March:

ROP = 0, level = 1: **\$226 856**

After making it more anticipatory and
optimizing:

ROP = 1, level = 2: **\$197 517**



*Benchmark to beat



Why order up to a certain level if you can anticipate demand?

Leverage our **forecasting figures** to determine how much to order



Demand Anticipating Policy

Cost of shortage is 5000X more than an overstock

- Therefore, aim to have a **buffer inventory**.

Aim to achieve a **specified inventory level** after the lead time.

Takes orders in the pipeline and forecasted demand into account during the lead time.

Objective: minimize stockouts

	Day 1	Day 2	Day 3	Day 4
Inventory	6	2	0	3
Pipeline	0	3	x	x
Demand	4	2	0	1



Lead Time

$3 - 1 =$
buffer inventory

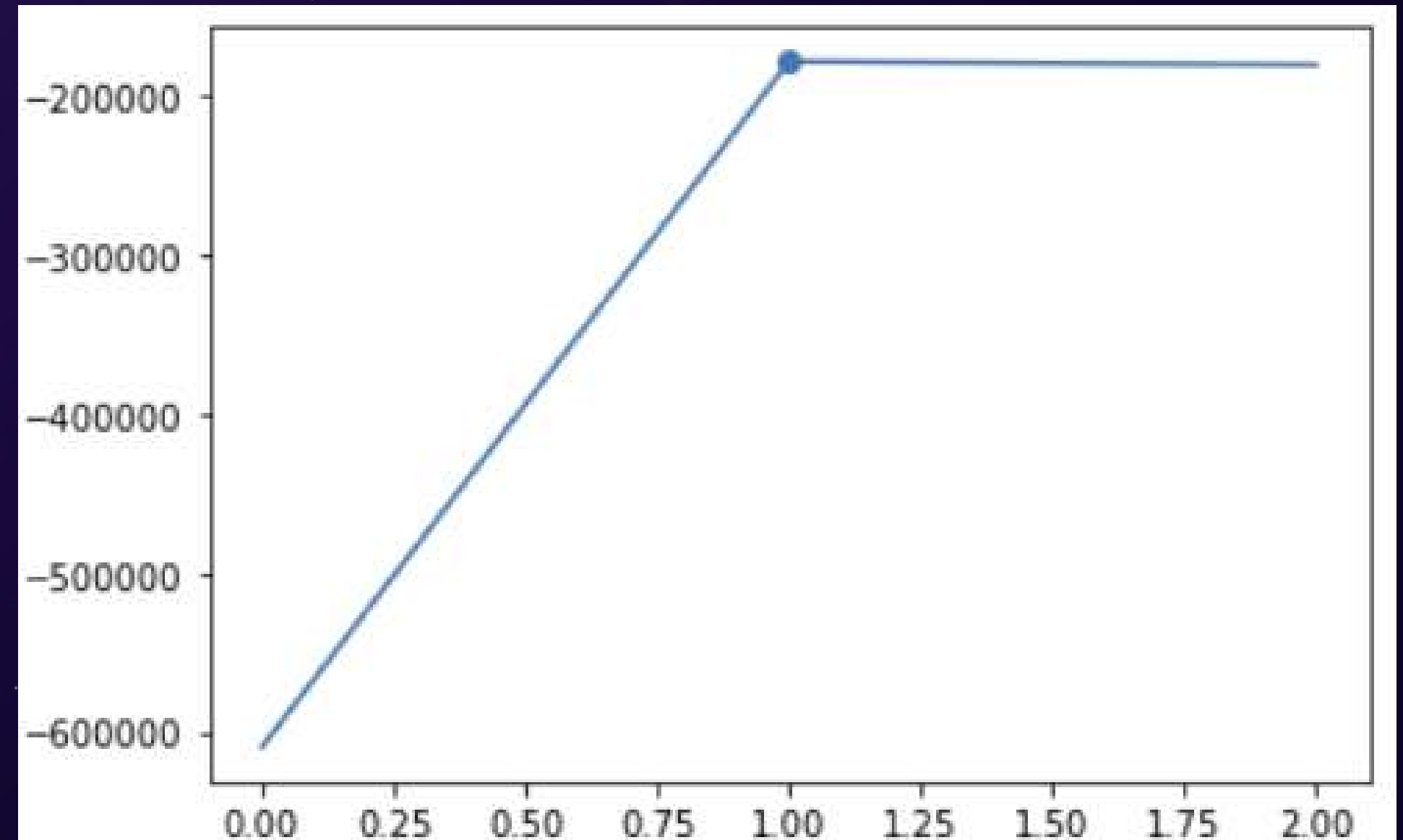
Demand Anticipating Policy

Optimize for the target level stock:
Safety Stock level = 1
Cost = \$178 372

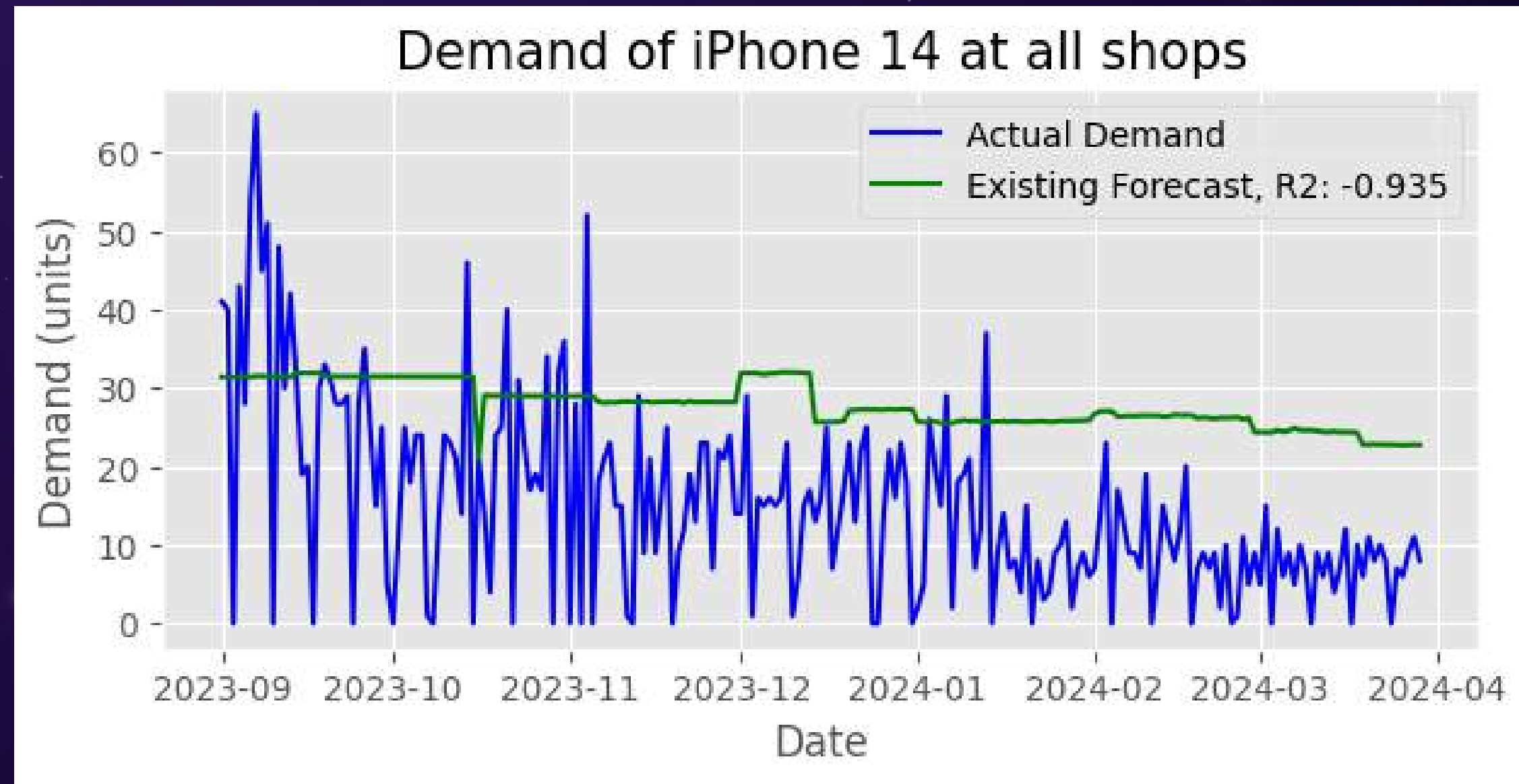
10% improvement in costs!

How to improve?

- Can start adding heuristics based on the data to better anticipate demand (from EDA)
- **OR** improve forecast



Current Forecast Accuracy



Improving the forecast

Step 1:

- **Segment** products based on features
- **Cluster** products within segments based on sales patterns (product lifecycles)

Step 2:

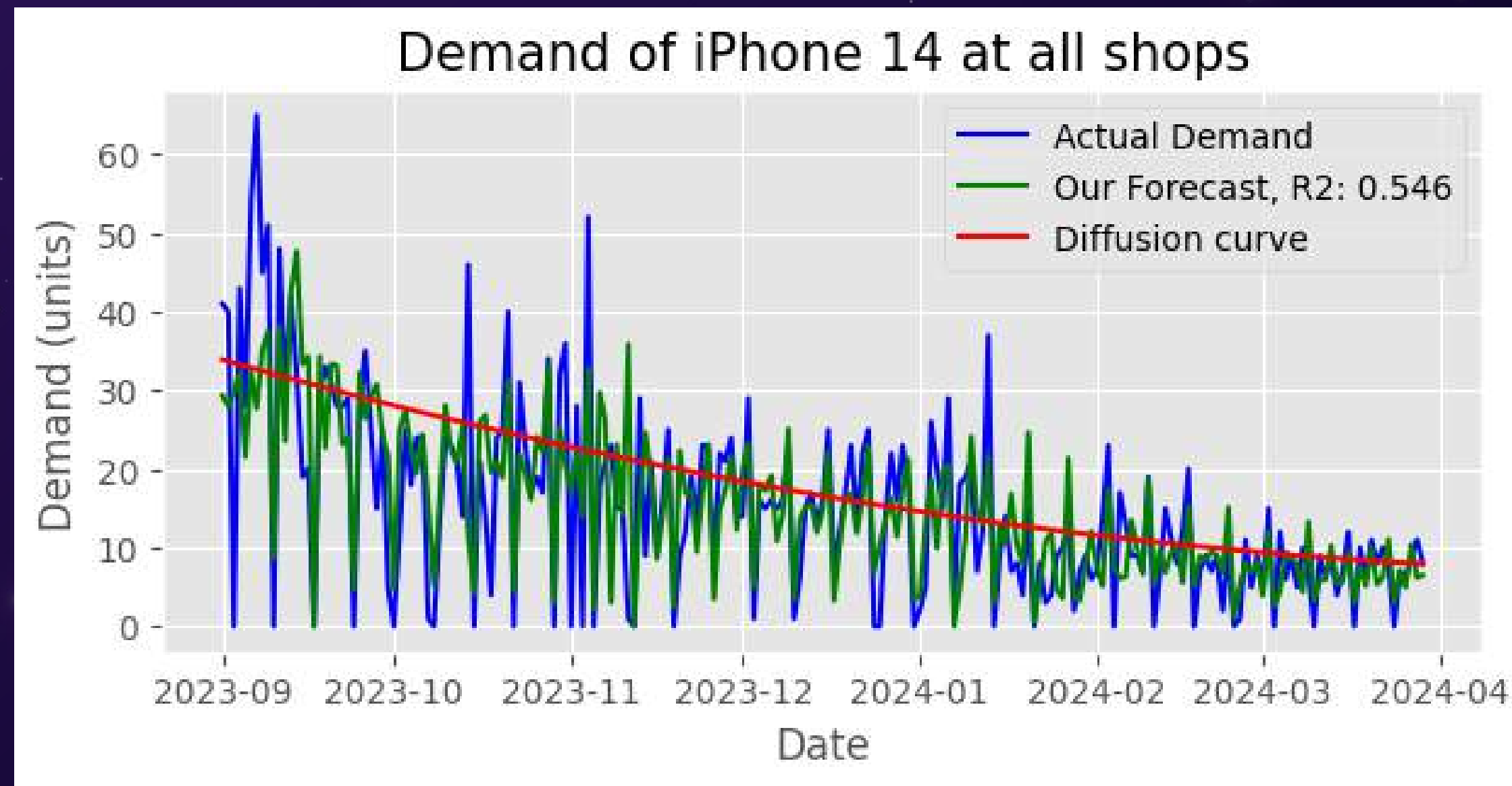
- Fit **Bass model** to estimate the product adoption curves and use for product clusters

Step 3:

- **Arma model** to capture more fine grained demand & seasonality (Sundays)



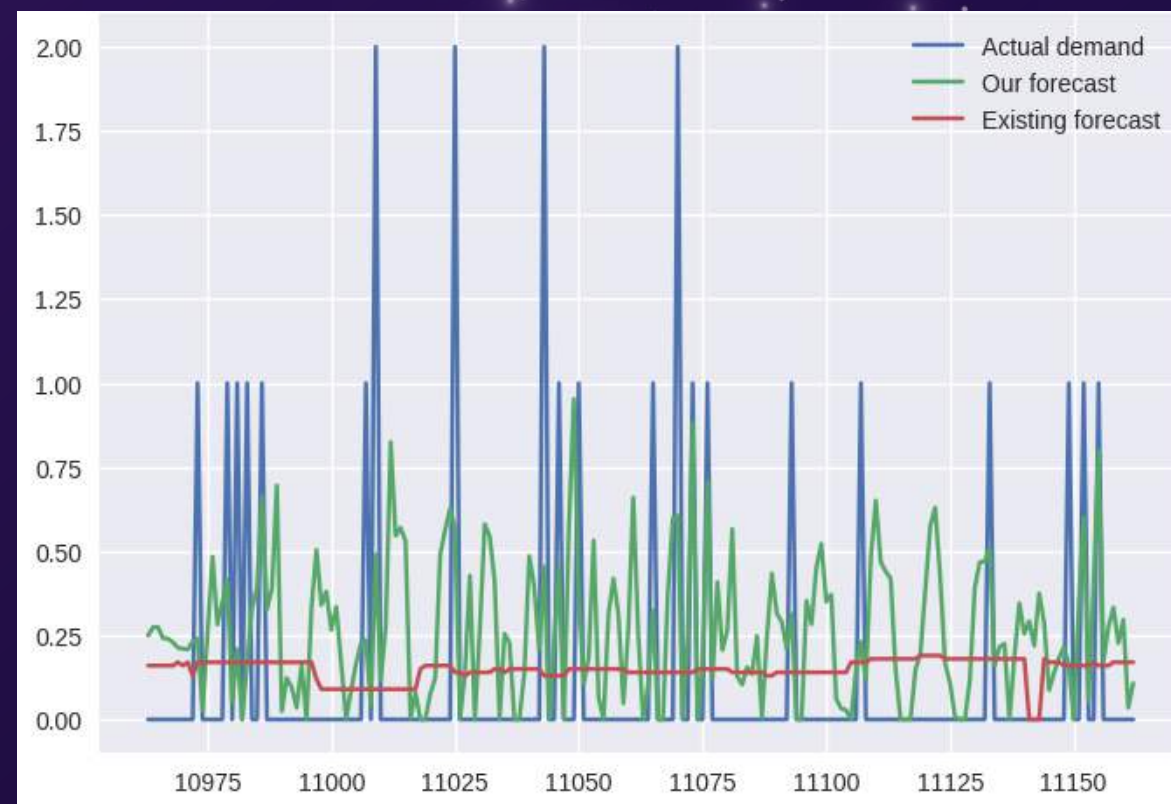
Forecast Improvement



Forecasts at product level

*Distribute forecasts to shops based on **historical sales contribution** per shop

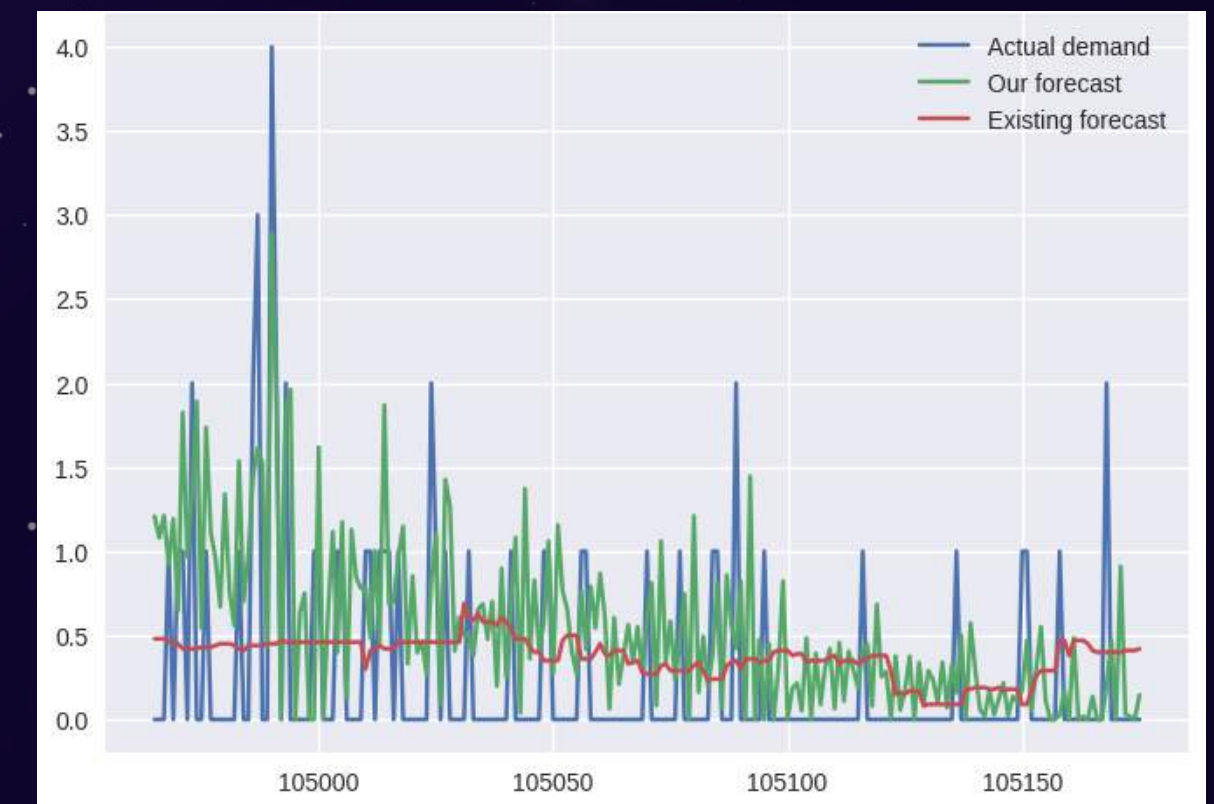
Forecasts included for all products at particular shop



Cover at shop T412



Xiaomi at shop B319



iPhone 15 at shop B412

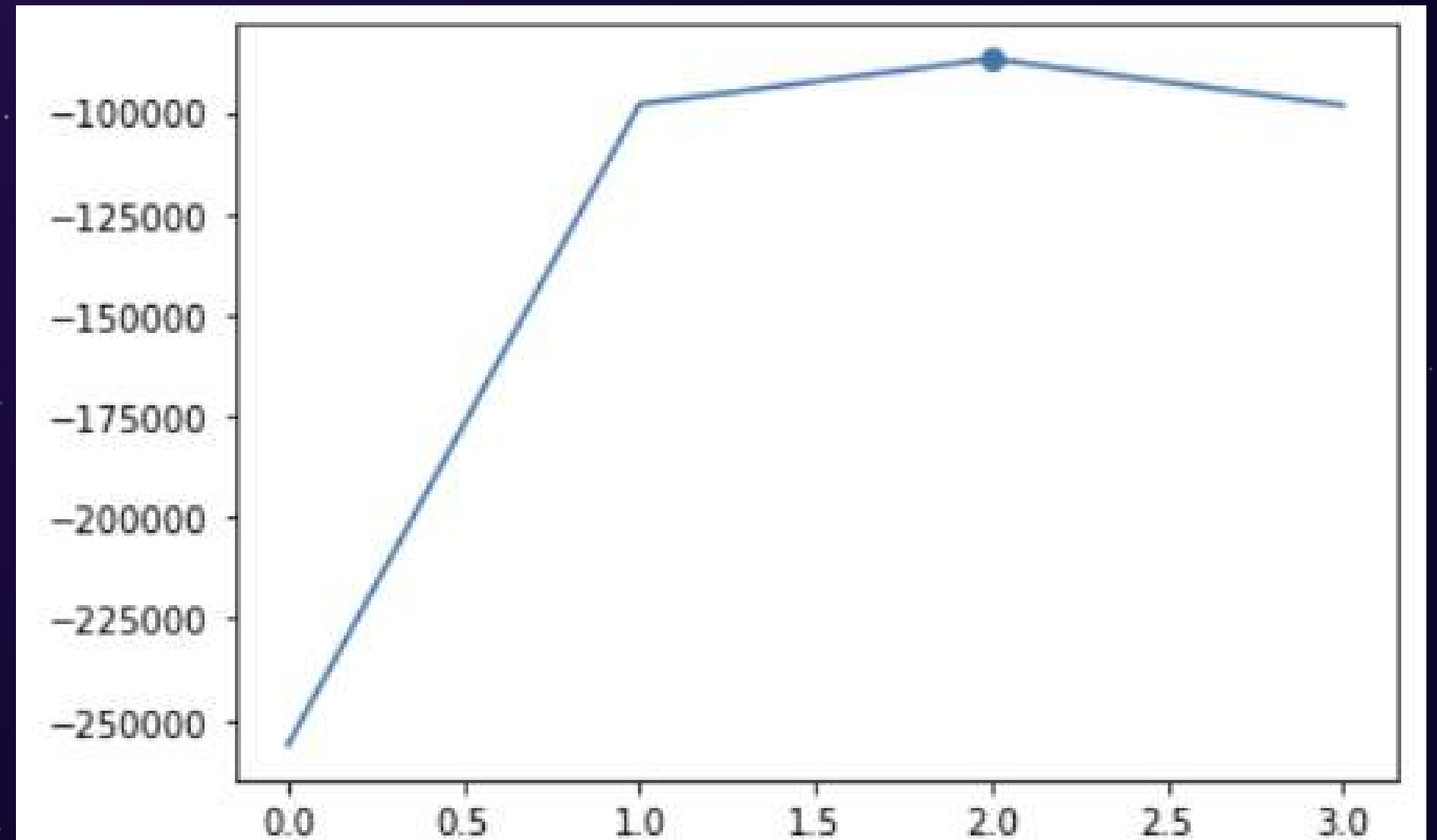
This technique allows us to optimize the safety stock level for all products

Demand Anticipating Policy: Improved

Optimize for the target level stock:
Safety Stock level = 2
Cost = \$86 935

56% improvement in costs!

Heuristics can work but the
forecasts will have the biggest
improvements on costs



Overview of policies and costs

Forecast type	Policy	Cost
None	Dummy policy	\$197,517
Existing forecast	Our policy with SS	\$178,372
Improved forecast	Our policy with SS	\$86,935

**For the iPhone 14*

Using this method for **all products** will drastically improve performance



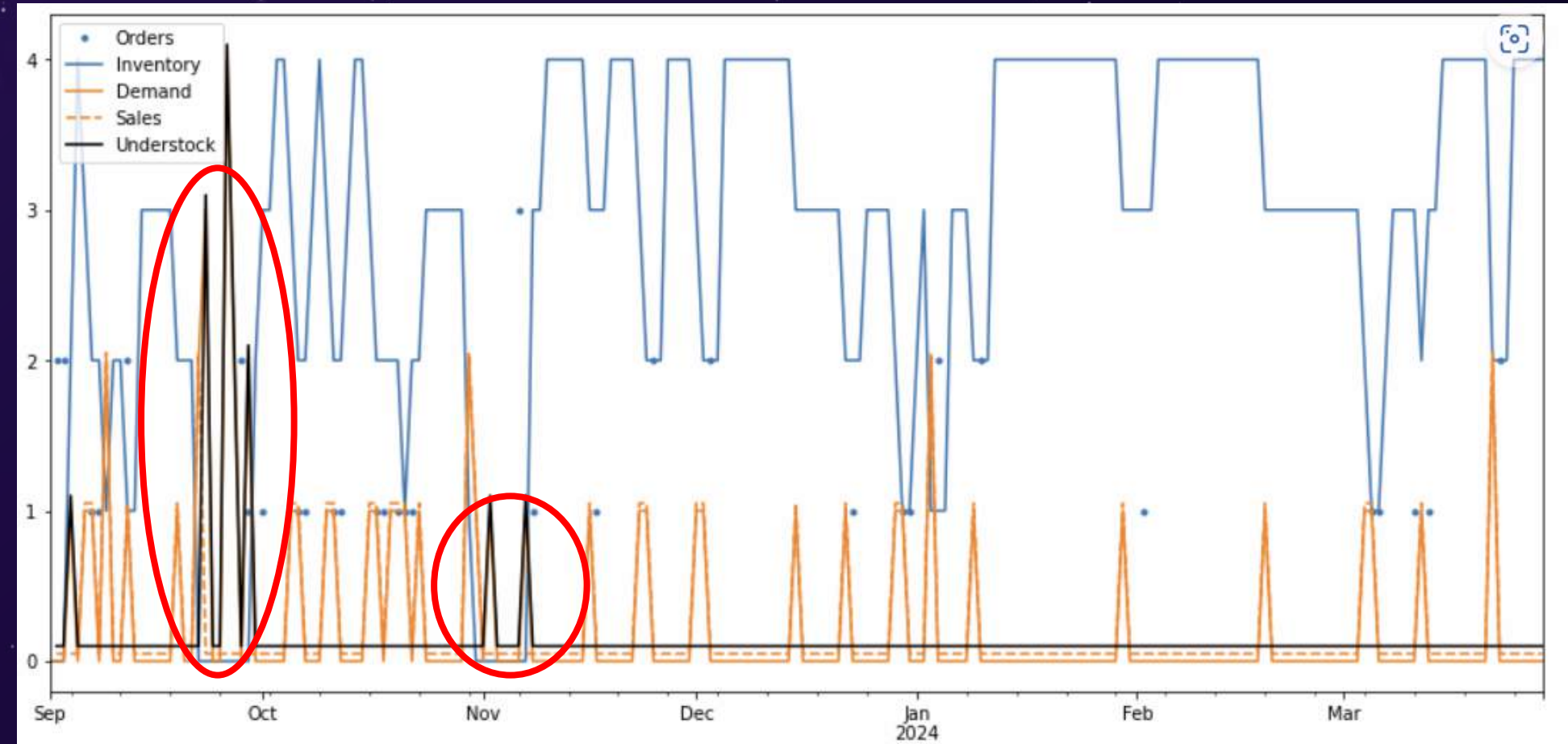
**Compute time limited company wide costs calculations*

SS = Safety Stock

Deep dive plant level - B319

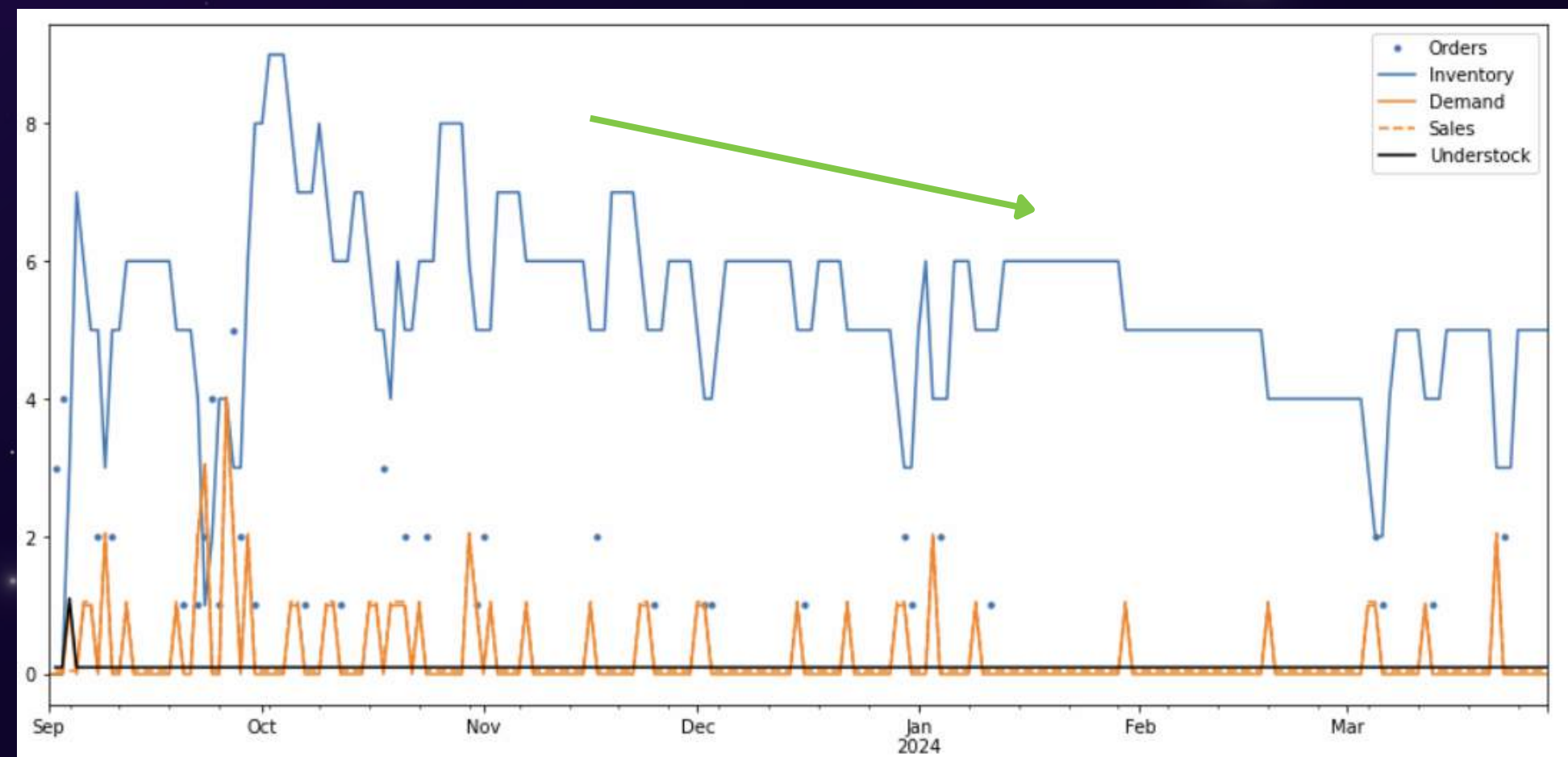
Original forecast:

- Bad forecast leads to no inclusion of trend and **stockouts**



Improved forecast:

- Forecast now takes **adoption rate** into account and less stockout



Insights and Takeaways

- Implementing policies based on heuristics (i.e. status and activity) is merely a reactive measure to compensate for inaccurate forecasts. It addresses the symptoms rather than the **root cause**.
- **Maintain minimum inventory levels (2 units for iPhone 14)**: Ensure enough inventory is across all shops, while still using data to predict demand. Avoiding high understock costs
- **Boost forecast accuracy**:
 - Segment and cluster products (improves forecasting for new items)
 - Utilize Bass diffusion model (predicts product adoption curves)
 - Leverage ARMA models (accounts for variation and seasonality)
- **Proactive approach benefits Proximus**: While these improvements fall outside the direct scope, they can significantly benefit the Proximus.

Thank you!

Workflow Overview and Q&A

