INVENTORY SCHEDULER POC

What’s in it ?

PROBLEM STATEMENT & OBJECTIVE

DATA & ASSUMPTIONS

APPROACH/METHODOLOGY

OUTPUTS & RECOMMENDATIONS

APPENDIX

Problem Statement

With limited Warehouse space & fluctuating demand, proper forecast is the need of the hour to optimally replenish the inventory to meet customer needs and operational efficiency

Objectives

To forecast orders for each product

Devise a strategy to optimize the Inventory Replenishment Cycle

Optimize the Inventory space and reduce the non-availability of products

Outputs : Inventory Schedule (16 weeks)

Product	ProductA		ProductB		ProductC		ProductD		ProductE	
Date	Orders	Inventory Sch	Orders	Inventory Sch	Orders	Inventory Sch	Orders	Inventory Sch	Orders	Inventory Sch
06-12-2020	40	0	6	0	25	0	27	0	12	0
13-12-2020	41	0	6	0	26	0	29	0	11	0
20-12-2020	44	50	6	0	30	0	27	0	12	0
27-12-2020	43	50	6	0	30	50	29	0	12	0
03-01-2021	36	0	6	0	22	0	29	0	10	25
10-01-2021	36	50	7	0	22	0	30	50	10	0
17-01-2021	35	50	6	0	22	50	29	50	9	0
24-01-2021	35	0	6	0	22	0	30	0	9	25
31-01-2021	36	50	6	0	22	50	29	50	9	0
07-02-2021	35	50	6	25	22	0	30	0	9	0
14-02-2021	35	50	5	0	22	50	29	50	9	25
21-02-2021	35	0	6	0	22	0	30	50	9	0
28-02-2021	35	50	6	0	22	0	29	0	9	25
07-03-2021	37	50	6	0	26	50	30	50	10	0
14-03-2021	37	50	6	25	26	50	29	0	10	0
21-03-2021	37	0	7	0	26	0	30	50	10	25

Benefits

Forecasted Inventory Cycle				
Date	Orders	Inventory -EOW	InventoryReplenished	Cost of Inventory
06-12-2020	40	81	0	
13-12-2020	41	40	0	20
20-12-2020	44	46	50	23
27-12-2020	43	53	50	26.5
03-01-2021	36	17	0	8.5
10-01-2021	36	31	50	15.5
17-01-2021	35	46	50	23
24-01-2021	35	11	0	5.5
31-01-2021	36	25	50	12.5
Total			250	$134.50

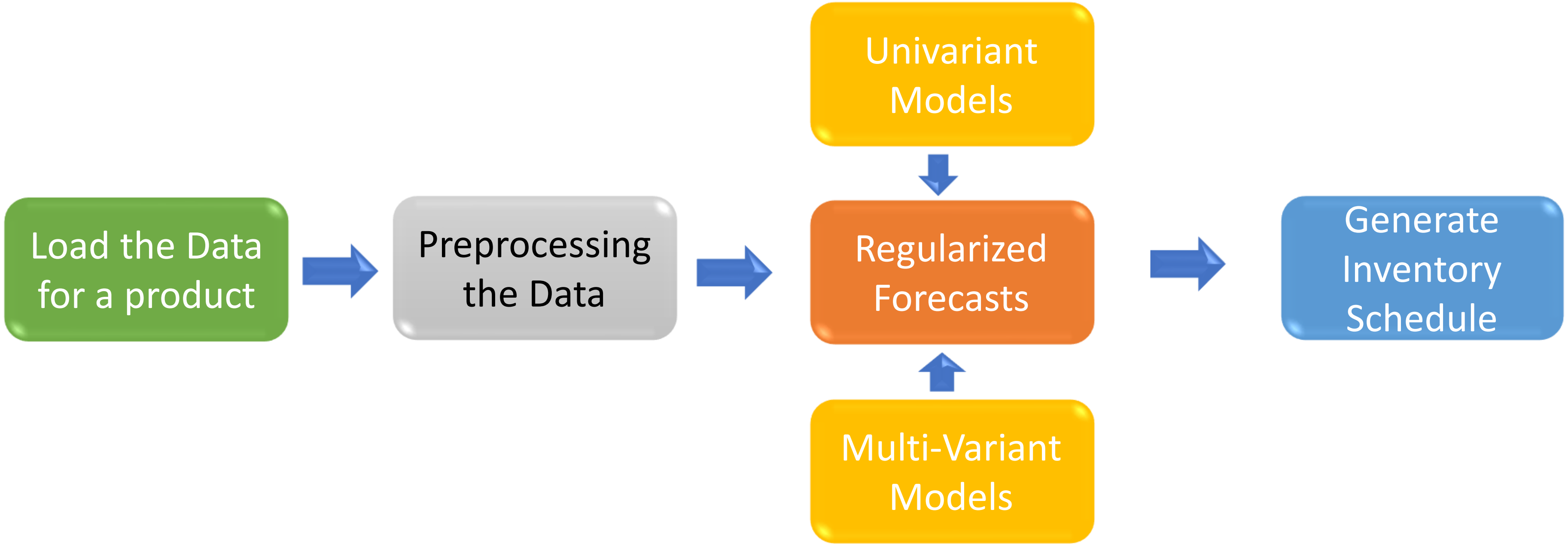
Actual Inventory cycle				
Date	Orders	Inventory -EOW	InventoryReplenished	Cost of Inventory
28-06-2020	33	68	50	
05-07-2020	38	231	201	115.5
12-07-2020	32	199	0	99.5
19-07-2020	36	163	0	81.5
26-07-2020	22	141	0	70.5
02-08-2020	27	114	0	57
09-08-2020	21	93	0	46.5
16-08-2020	31	62	0	31
23-08-2020	28	34	0	17
Total			251	$518.50

Base Assumptions

- It costs 0.5 CAD per product per week
- No. of Products spent in Inventory idle = Previous Week's End Inventory + Current Week Inventory Replenished– total orders executed in this week
- Example : No. of Products spent in Inventory idle => Previous Week's End Inventory **(46)** + Current Week Inventory Replenished (50) – total orders executed in this week (43) = (53)
- Cost = No. of Products spent in Inventory idle * 0.5 = **26.5 CAD**

Using Proper Inventory scheduling, we can save up to 74% of the cost (based on the above example)

Technical Approach



- Preprocessing Steps include adding external event variables to the data and performing statistical tests to check the stationarity and to estimate model parameters (more details are in the foot-note)

Data Summary

	Product A	Product B	Product C	Product D	Product E
Orders per Week (Min, Avg, Max)	0, 30, 100	1, 7, 18	15, 26, 46	0, 25, 47	3, 9, 20

Data Summary

- Data Duration : ~ 1 year (2019-12-08 - 2020-11-29)
- Frequency : Weekly (52 Observations)
- Products : A,B,C,D,E (5 products)
- Forecasted Days : 16 weeks (4 months)

Assumptions

- Minimum Order Quantity : 50(A,C,D) & 25(B,E)
- Buffer Inventory : 0.3 (Need to be validated and updated)
- Event Variables: Black Friday, Christmas Eve, Back To School, Spring & Winter Season

Data Characteristics

Variable	Description
week	Starting date of the week represented in MM/DD/YYYY
product	Name of the product
orders	Number of orders placed for that product in that week
brand	Brand of the product
views	Number of page views for the product
cart_adds	Number of customers who added the product to their cart
price	Price of the product listed for that week
inventory	Available inventory of the product at the end of that week

Assumptions

- Products given are not volatile products (like electronics – frequent updated versions)
- Considered external events like Black Friday, Christmas Eve, Back To School, Spring & Winter Season (its predominant in CA). Covid-19 impact is not considered in analysis, since the data availability is limited in its spread.
- Assumed Minimum Order Quantity for the product for Best buy to purchase the product from suppliers.
- Buffer Inventory of 30% is considered, keeping the randomness in demand of the products. (it needs to be validated and updated). In future, confidence interval of the forecast can be used to estimate the buffer stock
- Orders are placed on the availability of product, but at the same time, Inventory should be maintained based on the probable order inflow.
- In E-commerce environment, one of the strategy for the sale of the product is Views -> Cart_Adds -> Orders.
- Based on the above two assumptions, Orders are forecasted to guide Inventory Analysts, since it has direct relation with product availability.
- Selection of models generally depends on its performance on cross-validation in validation environment, given the POC nature of analysis, models are selected based on the forecasted trend.
- Lead time for the inventory analyst to raise a purchase order for getting the product into warehouse at the start of the week based on our forecasted results is taken into consideration.
- After doing closeness match between products, we didn’t find any significant match. So, I dropped the idea of combined forecast.

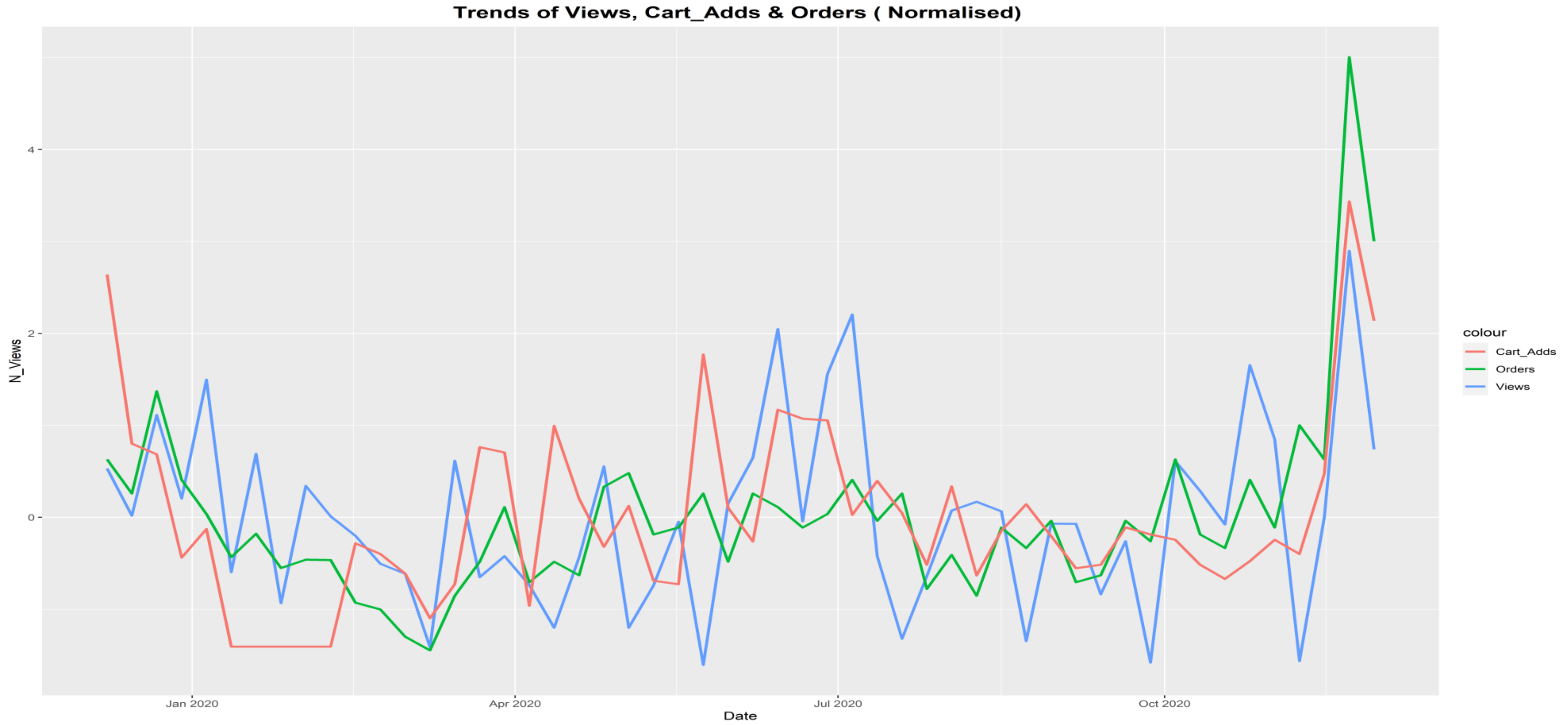
Next Steps

- Because of POC nature of assignment, external events should be accurately captured.
- Need to understand, we can’t predict what each individual customer is thinking.
- Instead of 30% more of our predicted value, we can do confidence estimation of orders.
- Code is not production ready as assertions are not regulated.

- Join Bestbuy !!

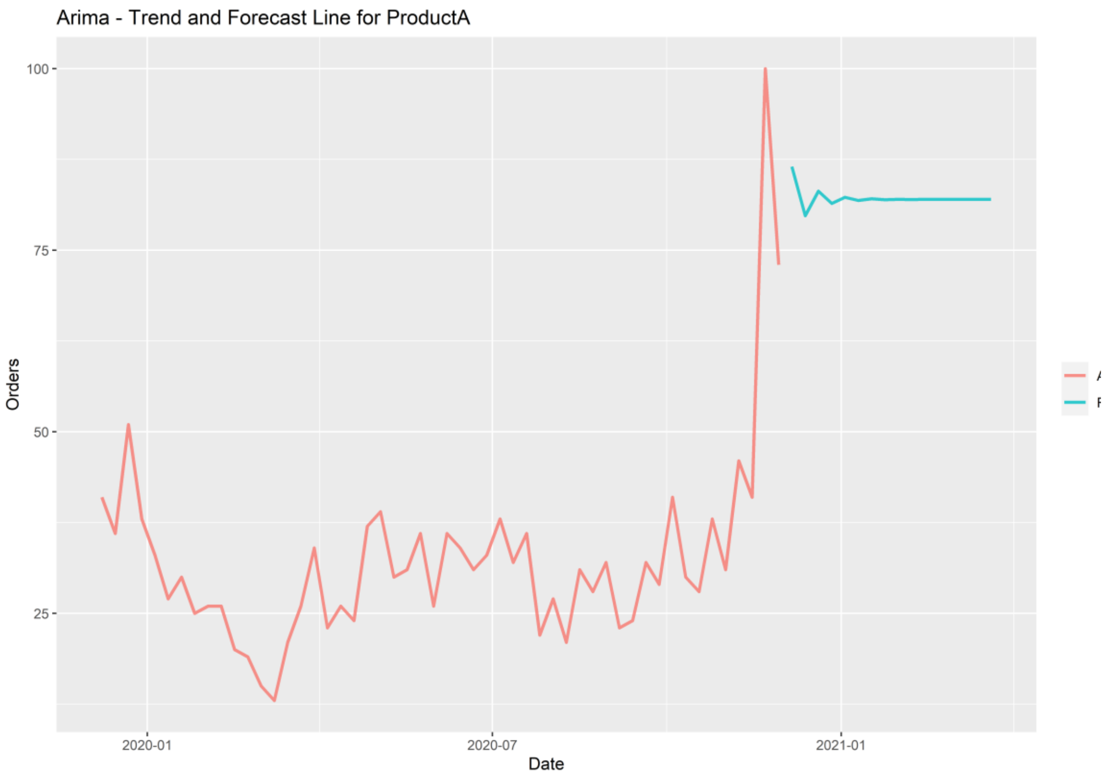
Appendix

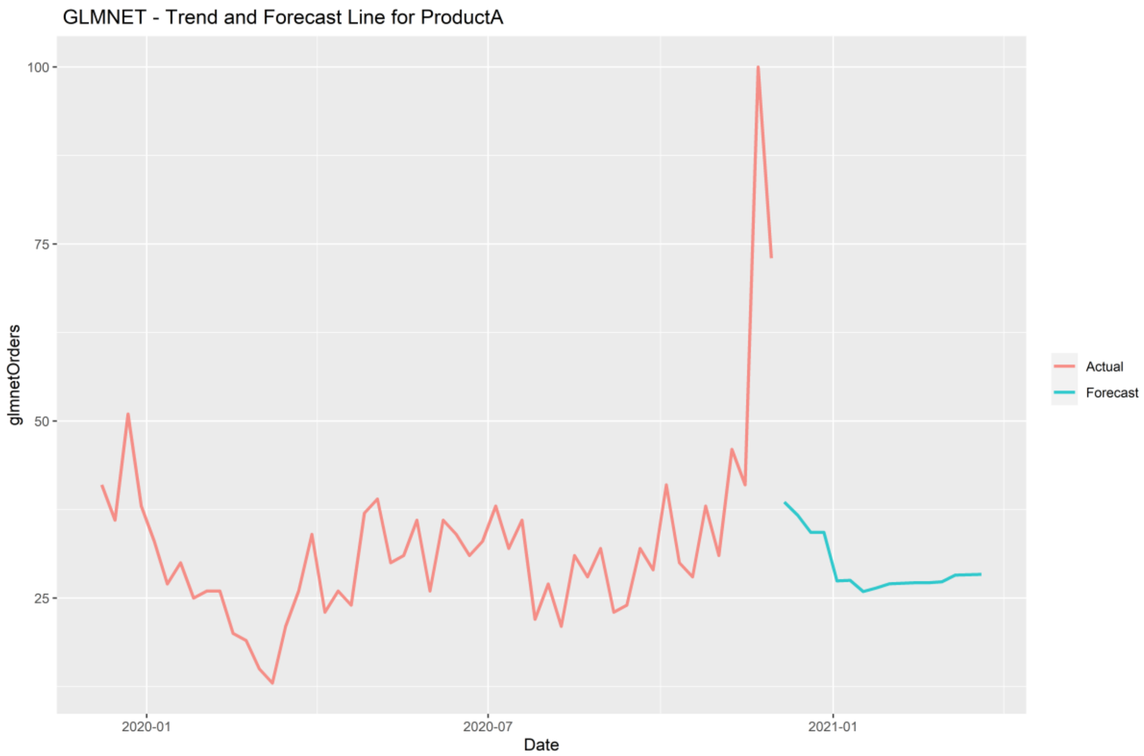
Similarity in Views, Cart_Adds & Orders



This plot helps us in understanding the trend correlation between views, cart_adds and orders. Given that all are in proximity and our assumption of taking Orders as our forecasted value is valid. All the values are normalized.

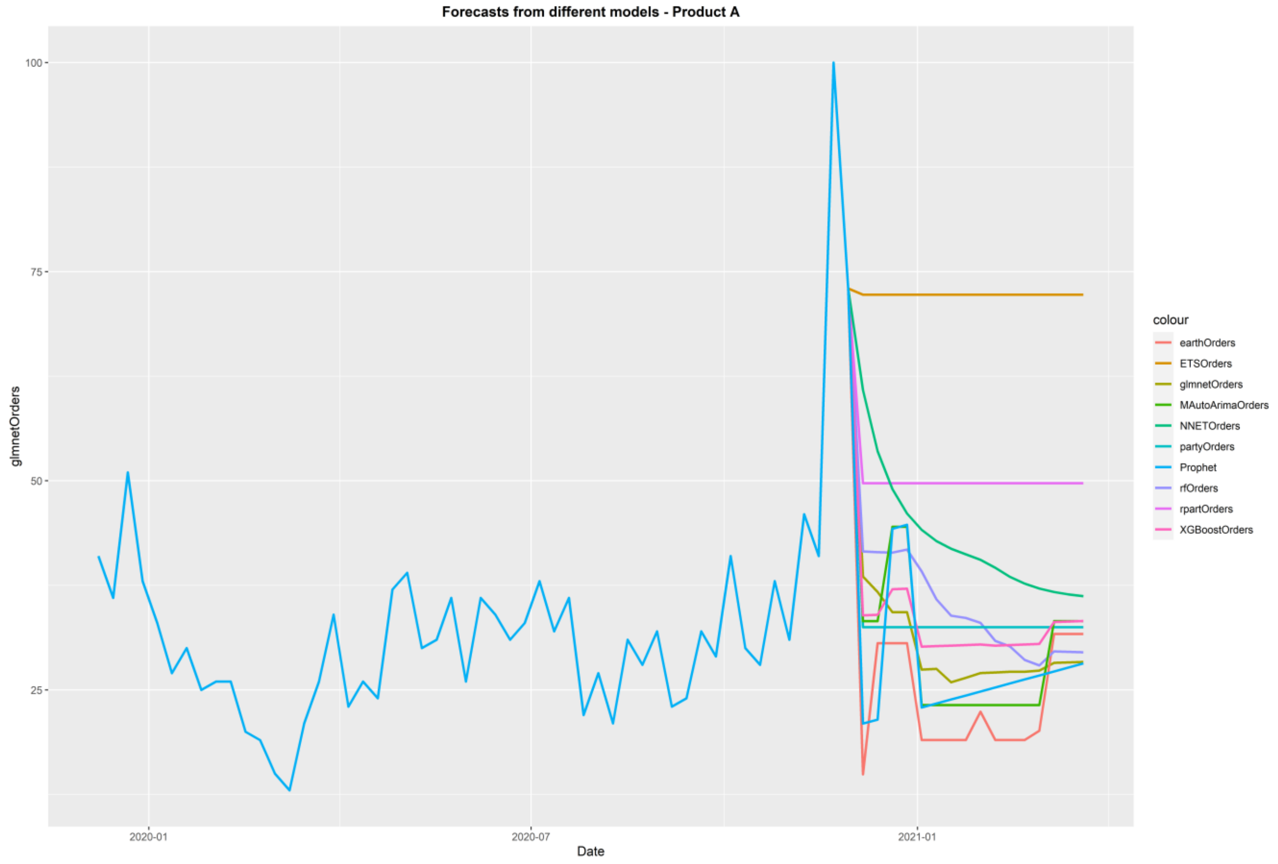
Why Multi-Variant ?

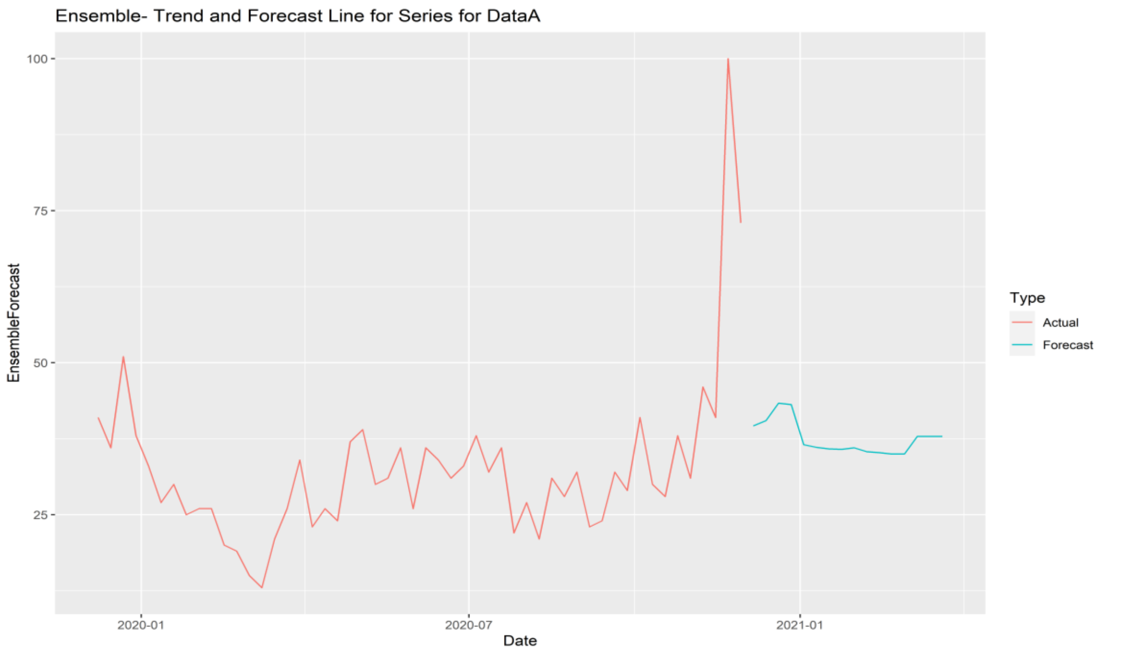


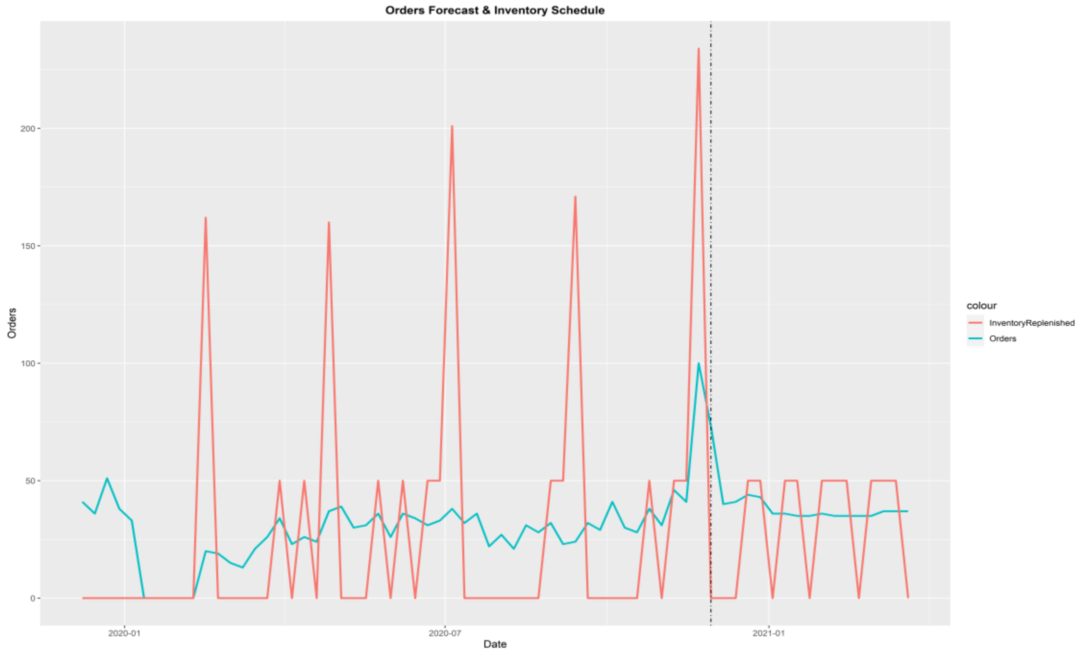


If the data is not sufficient or the data doesn't have significant auto-correlation with the previous day orders or the seasonal orders, then they tend to converge at the recent constant. Because of this reason, I used Multivariant analysis to obtain good forecasts

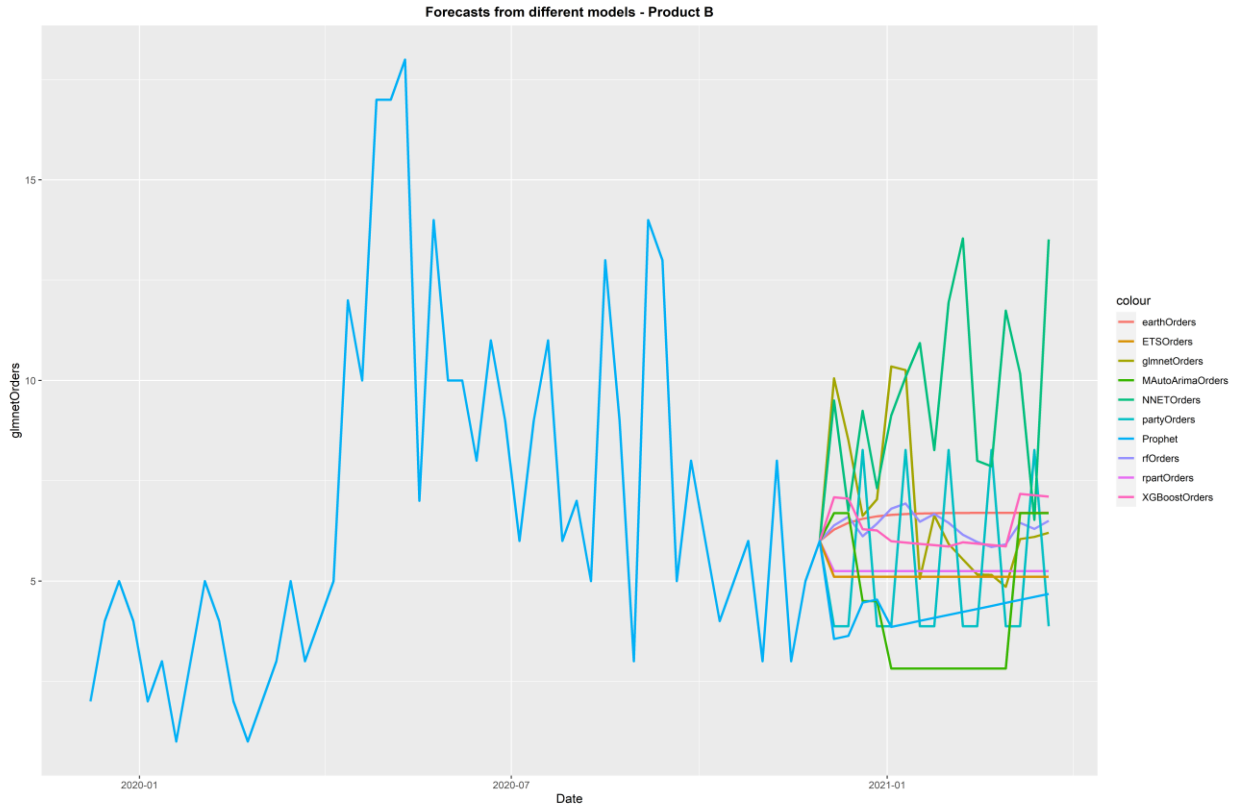
Outputs – Product A

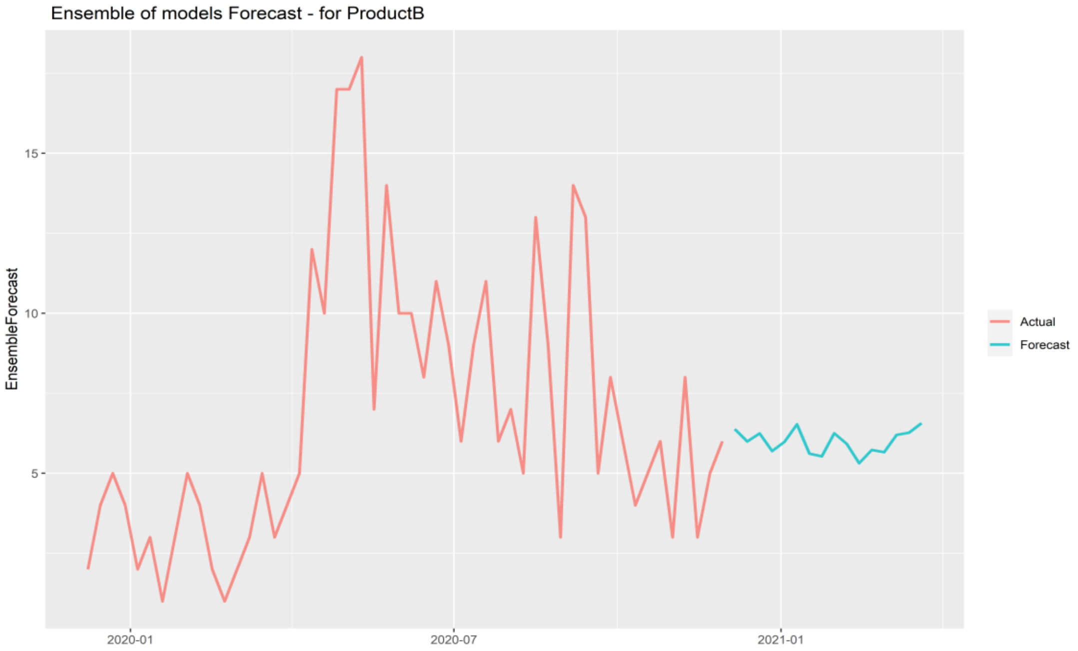


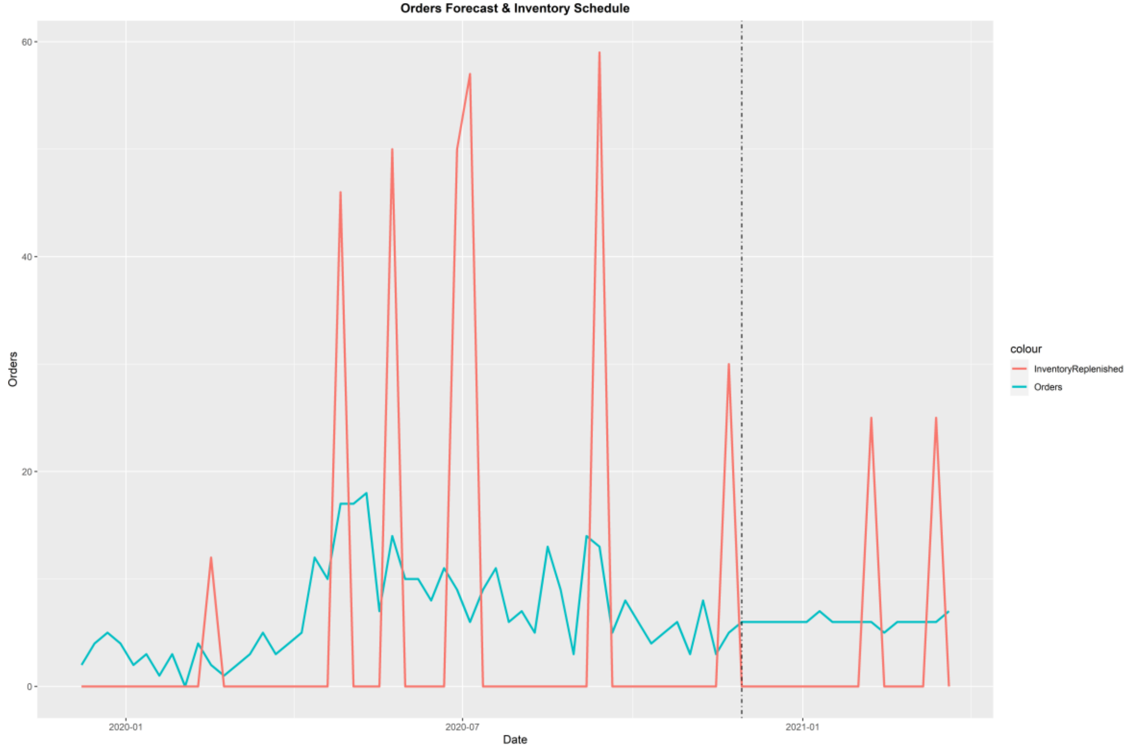




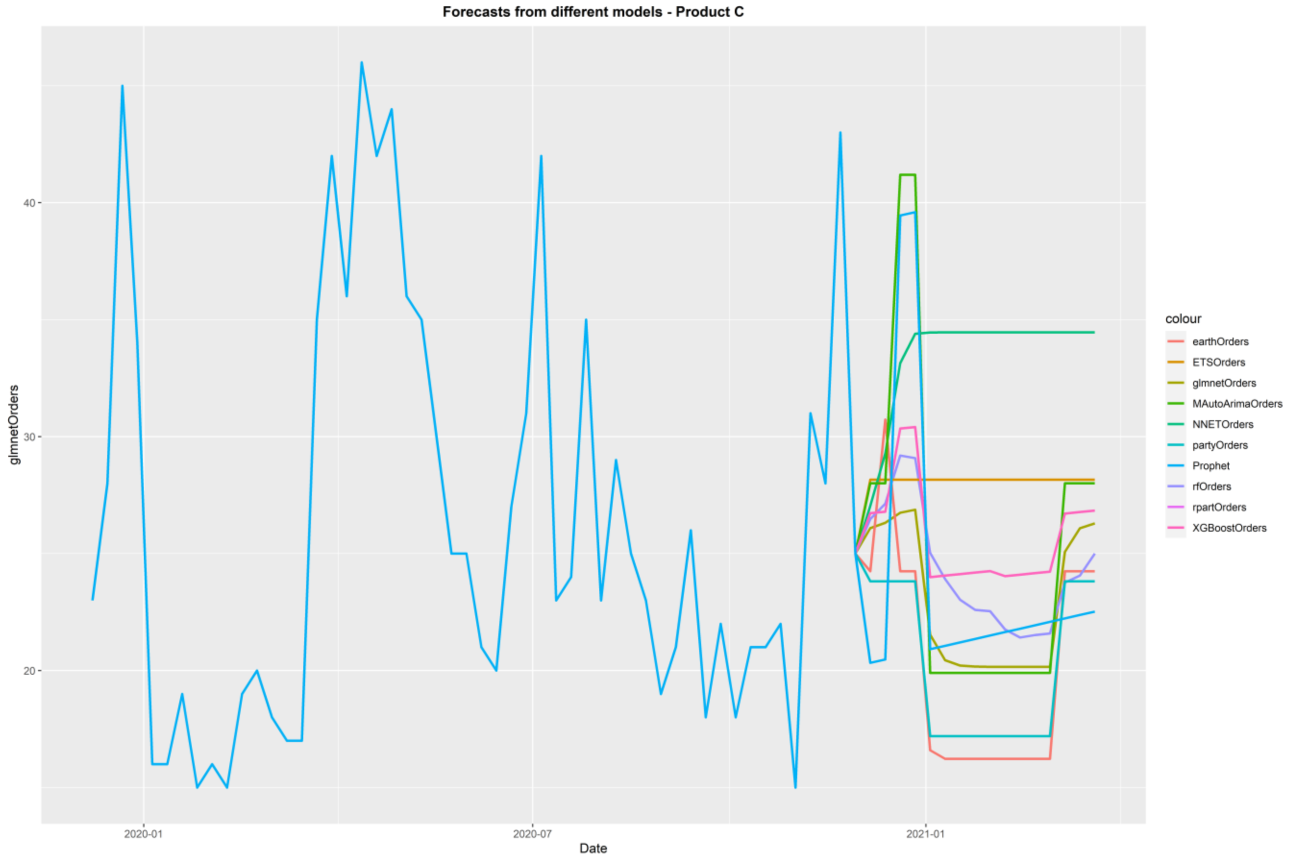
Outputs – Product B

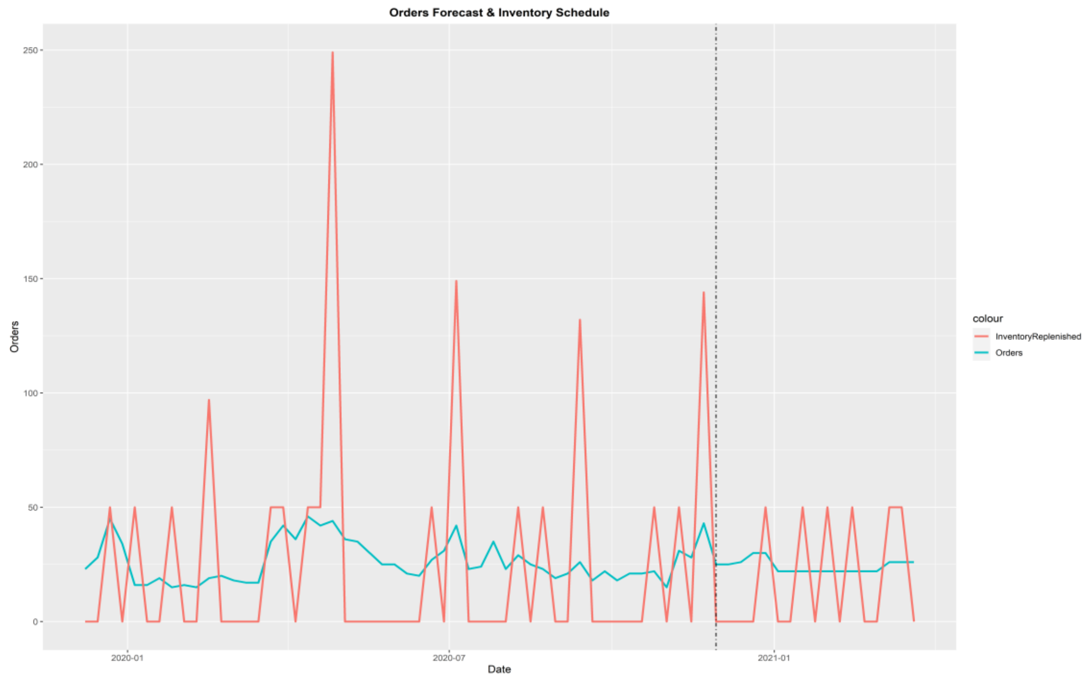


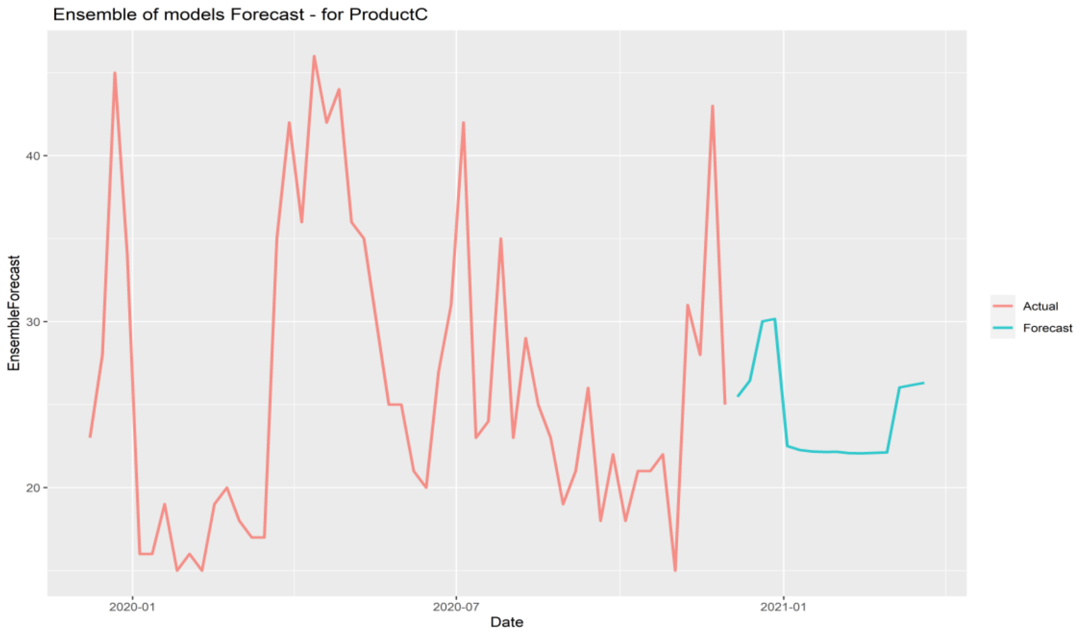




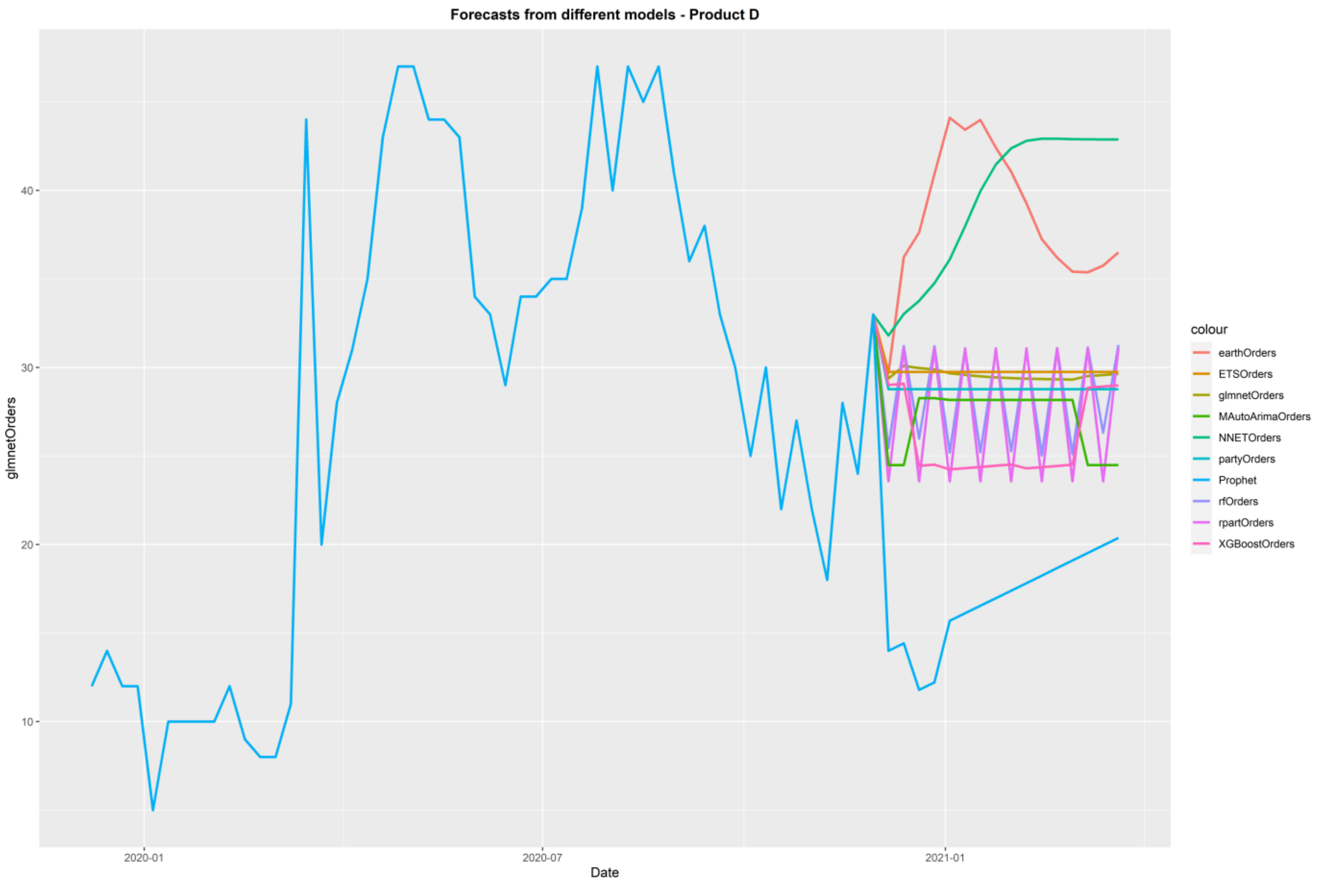
Outputs – Product C

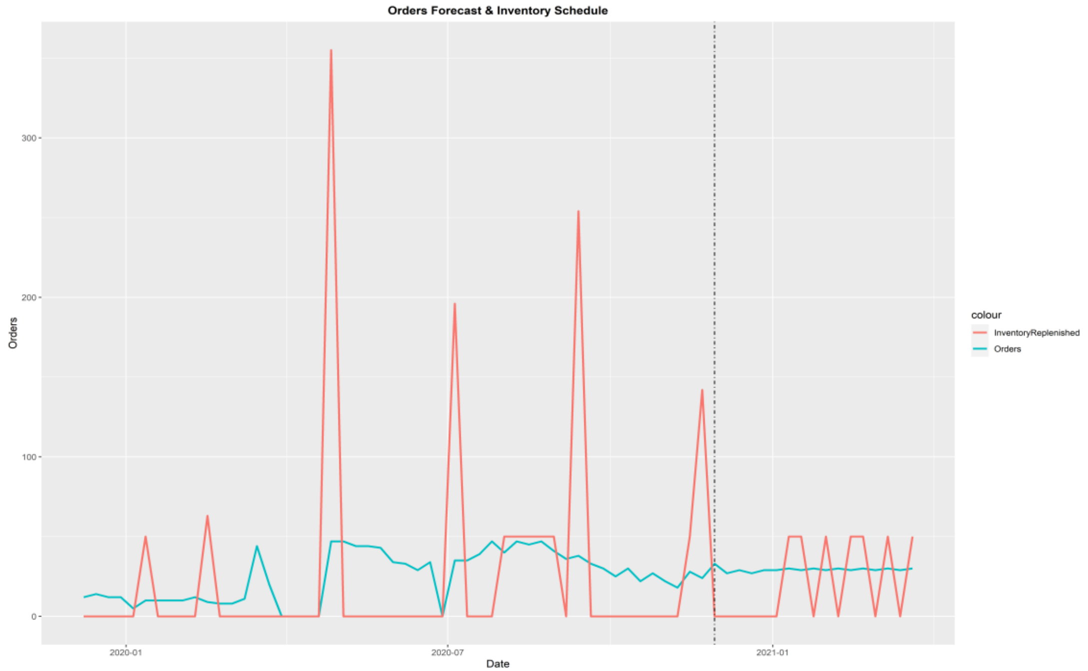


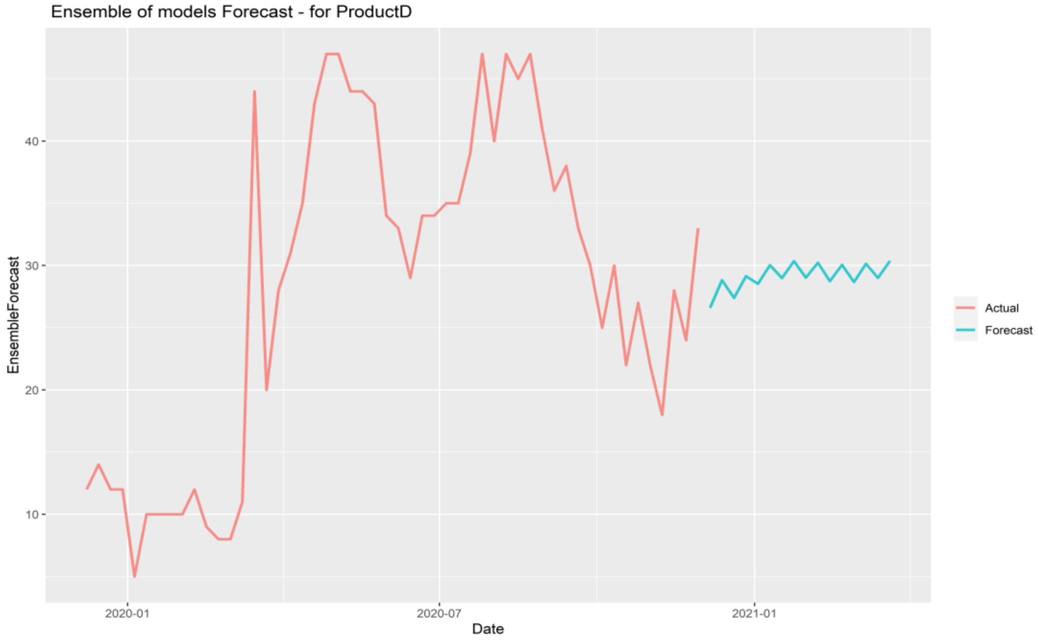




Outputs – Product D







Outputs – Product E