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Business Analytics Using Forecasting

Enhance supply chain efficiency through demand forecasting for NIVEA

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EXECUTIVE SUMMARY

Problem Description: Due to long lead time in the supply chain, Nivea Taiwan faces issues to accurately predict their sales in advance and adequate the inventory level for their online e-commerce platforms in China. Therefore, our mission with the study from the business perspective is "**to optimize the efficiency of the downstream supply chain in Cross-Border E-commerce Department of Nivea Taiwan".** On the other hand, from the forecast perspective, the study focuses on forecasting sales quantity of hero products of Nivea Tmall[1] flagship store.

Data Description: Weekly sales data is generated from Tmall on every Monday. There is a total of 118 SKU's on shelf and 15 hero SKUs contributing the most are selected to be the forecasting time series. The time series contain 60-week data from November 1, 2017 to December 23, 2018.

Data Preparation: Data has been rearranged from the original sales report to another source file for R programming. Dummy variables are created to indicate promotional periods. Averaging is applied to the weeks of "Double 11" to remove outliners occurred in big promotion periods. Sales quantity and dummy variables are aggregated from weekly basis to 8-week basis.

Forecasting Solution: Naïve forecasts are used as the benchmark. Different forecasting methods are tested, including Simple Exponential Smoothing, Linear regression with External Information, Linear Regression, Moving Average, ARIMA, and ENSEMBLE. Considering the desirable over-forecasted results and the performance measures, ENSEMBLE model, averaging the forecasts among SES, MA and ARIMA, is used as the final forecasting solution.

Future Forecasts: Based on the ENSEMBLE model, forecasted sum of 8-week sales quantity from week 52 of 2018 to week 7 of 2019 for "80105", "81288", "83807", "83921" and "83922" [2] are 1550, 218, 3209, 1199 and 482 pcs respectively.

Conclusions: This forecasting project not only provides indicators of an appropriate timing to place an order to distributor, but also allows managers to adjust marketing strategies base on supply and demand. Based on the assumption of sufficient inventory in distributor's warehouse, managers should keep an eye on the upstream supply chain before adopting this forecast. It is recommended to maintain sales data with high quality for further studies.

[1] formerly Taobao Mall, is a Chinese-language website for business-to-consumer (B2C) online retail, spun off from Taobao, operated in China by Alibaba Group. It is a platform for local Chinese and international businesses to sell brand-name goods to consumers in mainland China, Hong Kong, Macau and Taiwan. Being the world's second second-biggest eCommerce website after Taobao, it has over 500 million monthly active users, as of February 2018.
[2] These numbers refer to the identification code for each product.

1. PROBLEM DESCRIPTION

Business Goal: NIVEA is a German personal care brand that specializes in body-care, owned by the Hamburg-based company Beiersdorf Global AG. During the 1980s, the NIVEA brand expanded into a wider global market including Taiwan. Apart from the local market, Nivea Taiwan is also in charge of part of the Chinese market by establishing cross boarder ecommerce department in 2015.

Since all products are imported from overseas and distributed to the sales channels in China, timing and vertically integrating along the whole supply chain is a key factor for the success of the business operation. For a short description, it takes 1 month to place an order, 3 months to manufacture, 2 months to ship to Hong Kong, 2 weeks to ship to China, and 4 weeks to go through the Chinese formal inspection and legal procedures until finally makes its way to the warehouse in free trade zone (FTZ). The problem for the company is the impossibility to predict in advance when to order new shipments because many issues are out of the company's control. External uncertainty factors, such as natural phenomena and governmental bureaucratic barriers, represent a major obstacle to control the appropriate order timing. For example, typhoons or extra inspections in the Chinese Custom might delay the shipment to FTZ.

Hence, considering the major possible complications, the business Goal of our forecasting study is **"to optimize the efficiency of the downstream supply chain in Cross-Border E-commerce Department of Nivea Taiwan."**

Forecasting goal: In order to estimate the next order shipment from distributor to FTZ, we choose 8 weeks as the forecasting horizon, which is considered the average 6 weeks shipping time plus 2 weeks buffering time. The study is to forecast from the present week to the upcoming 7 weeks' quantity sales for each product identified by its Stock Keeping Unit (SKU), that takes the total aggregation of the 8 weeks and compares with the current inventory level in FTZ. If the forecast equals or exceeds the stock level, it means that all the stock is expected to sell out 8 weeks later and the manager should place a delivery order this week. Otherwise, if the forecast is below the current stock level, the manager can wait for the next week when a new forecast is made. The ongoing forecasting tasks are being conducted every Monday once the manager receives the weekly sales report from retailers. (See Appendix A)

Hence, the forecasting goal is **"to forecast the sales quantity of specific hero products to Nivea Tmall flagship store"**

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2. DATA DESCRIPTION

The data is collected from Tmall platform's statistical system, that is collecting the sales data for all the Nivea products. The data are updated by appending the recent sales figures on a weekly basis. However, the main currently encountered problem is that the data series is short, which limits the data forecasting tools to be fully utilized. The given data series starts in November 2017, with a total data length of 60 weeks until December 24th, 2018. (See Appendix B)

Additionally, due to the unstable consumer purchasing behaviors and promotions, is hardly possible to find any trend or seasonality in the series. (See Appendix C)

3. DATA PREPARATION

As mentioned, the series doesn't have any trend or seasonality but shows strong peaks occasionally. In addition, the dataset also combines the last week of each month with the first week of next month in order to complete the weekly sales in round numbers. In order to perform forecasting, the raw data was prepared as described next:

1. The data is rearranged from the original sales report to our source file for R programming;
2. Dummy variables are created to indicated all promotional periods on Tmall platform;
3. Outliers are removed by averaging neighboring values for the week of "Double 11";
4. Sales quantity and dummy variables are aggregated from weekly basis to 8-week basis.

4. FORECASTING SOLUTION

First, due to the business nature and management perspective, Over-forecast is more desirable than under-forecast, considering the consequence of product shortage and overall associated costs of inventory.

Methods used: To compare the performance of the forecast results, the Naive model was used as the benchmark. The main methods include Simple Exponential Smoothing, Linear regression with External Information, Linear Regression, Moving Average, ARIMA, and ENSEMBLE. The main reason for using these methods come from the fact that the series doesn't have much trend and seasonality, which takes away the possibility to apply some other methods where trend and seasonality are a must, for such cases the simple versions of Moving Averages and Exponential Smoothing were chosen.

As mentioned before, the series doesn't have some basic elements of a typical time series, such as trend nor seasonality. Therefore, most models are having overfitting issues, that perform worse than the simple Naive model. Among all, the Simple Exponential Smoothing (ANN) model with alpha 0.2 has a better performance with the lowest RMSE.

When applying the linear regression model, the default settings are used because it provides better performance compared to more complex settings. For linear regression with external predictors, the promotions are presented by binary numbers, 1 for promotion and 0 for none. It's important to include external information to the models in the research.

Another method was ensemble which includes all methods previously mentioned. However, the result didn't seem to be good enough to beat the Naive forecasting. After deleting some methods that are believed to be aggravating the performance, the remaining set of methods include ARIMA, SES, and MA in the ensemble. Surprisingly, the new ensemble shows good performance, in some cases, it's as good as the NAIVE or ARIMA.

Performance evaluation: The primary criteria is to compare the actual values and forecasted values by visualization; the secondary criteria is to examine the accuracy measures, particularly RMSE. After analyzing the forecasting results, the resume table (with the performance indicators) shows that for most of the cases, RMSE in the test set is a lot bigger than the training set. Thus, this is a clear signal of model overfitting. However, there are 3 key factors preventing further modifications for better forecasting performance, such as changing the length of the training and the validation period.

First, the huge 11/11 promotion creates distortion, making the models overfit the training set. Even though the rational solution would be to add another 8 or 16 weeks to forecasting horizon to gain performance, when we apply the solution, the performance turned out to be worse. Second, the required forecast goal is set according to the company business needs, increasing or decreasing the number of weeks of the forecasting horizon would violate the requirement. After all, the length of the actual time series is just too short.

After running the new ENSEMBLES model to the data, it is noticeable that the model is performing better than the ARIMA in the training set of all series and beating the NAIVE with a close margin. However, as shown the detailed table in Appendix D**,** RMSE of all models perform in the validation set is worse than in the training set, meaning that all models are overfitting. Considering the performance in the validation set as the final result among the 15 time series data, the MA model performs better in 2 products, SES in 3 products, and ARIMA in 2 products. Comparing the other models, the ENSEMBLES provides good performance overall. For example, when comparing to ARIMA, in most cases, even the ENSEMBLE model cannot beat the ARIMA in the training set, but it reduces the error in the validation. In fact, the ENSEMBLES is in the top 3 best methods in 12 product time series, that has the lowest RMSE on average. (See Appendix D: Summary table)

To sum up, the ENSEMBLE model is selected to be the final forecasting method. Appendix E shows the time plots of forecasts based on ensemble model, with naïve forecasts as benchmark.

5. Future forecasts

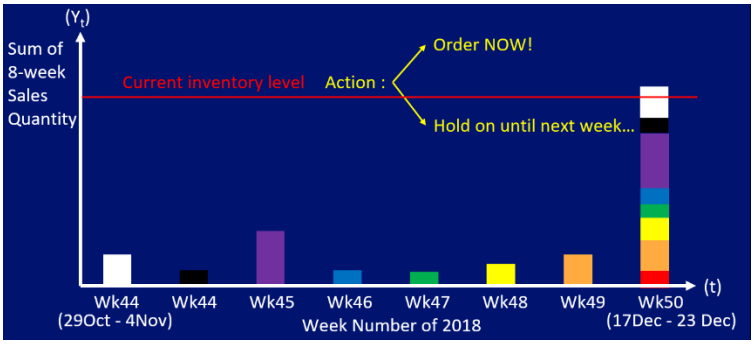
Based on the ensemble model, forecasted sum of 8-week sales for “80105”, “81288”, “83807”, “83921” and “83922” are 1550, 218, 3209, 1199 and 482 pcs respectively, which are below the inventory, indicating sufficient stocks from week 52 of 2018 to week 7 of 2019. (See Appendix F)

6. Conclusions

Based on the assumption that the distributor can fulfill immediate orders from Tmall, it is important to keep an eye on the upstream supply chain and ensure sufficient inventory in the distributor’s warehouse. Besides, managers should take domain knowledge and safety inventory level into concern even if the forecasted sales are below inventory, especially before any promotions on Tmall. On the other hand, if the inventory is far beyond the forecasted sales, managers can adjust marketing strategies base on supply and demand. Lastly, it is highly recommended to keep a good data maintenance for further studies which would allow to nicely capture seasonality with more data in a longer series.

APPENDIX A: ILLUSTRATION OF FORECASTING GOAL

Following the forecasting goal, the accumulated inventory of 8 weeks sets the control point for the company to decide if make or no a new order.



Data series (Y_t) : Sum of 8-week sales quantity of each product until current period

Time period (t) : Weekly, t_1 is the first week in the time series

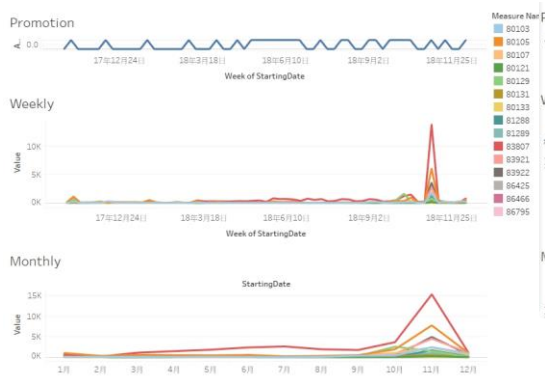
Forecast horizon (k) : 8 weeks, k=8

Forecasts (F_{t+k}) : Weekly forecast of sum of 8-week sales quantity of each product

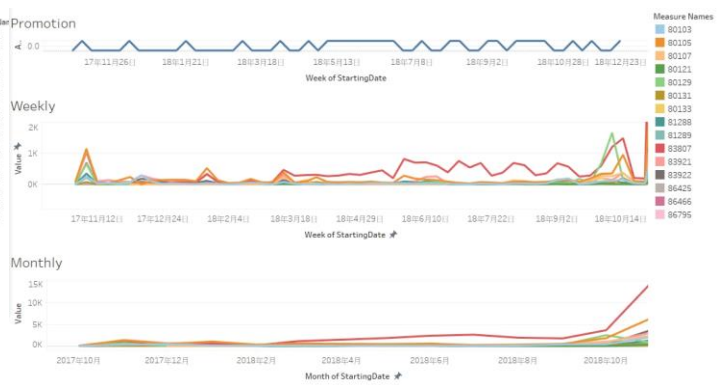
APPENDIX B: RAW DATA

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	StartingDate	WeekNo	Promotion	Theme	83807	80105	83921	83922	81288	80103	81289	80131	80129	86795	86466	86425	80107	80133	80121
2	30/10/2017	44	0		1	103	13	57	1	0	1	0	42	4	0	0	#N/A	#N/A	#N/A
3	6/11/2017	45	0	Double 11	12	67	58	58	6	17	7	2	28	8	1	1	#N/A	#N/A	#N/A
4	13/11/2017	46	0		23	30	102	58	11	33	12	4	14	11	1	1	#N/A	#N/A	#N/A
5	20/11/2017	47	0		21	43	137	53	6	51	19	11	24	19	1	1	#N/A	#N/A	#N/A
6	27/11/2017	48	0		21	133	96	89	12	27	15	11	6	9	0	0	#N/A	#N/A	#N/A
7	4/12/2017	49	0		28	239	81	46	8	58	13	8	0	12	0	1	0	0	0
8	11/12/2017	50	1	Double 12	87	0	292	180	49	283	60	46	0	40	4	6	0	0	0
9	18/12/2017	51	0		57	123	186	145	25	92	33	17	0	21	1	4	0	0	0
10	25/12/2017	52	0		35	142	129	77	9	20	24	8	0	12	3	0	0	0	0
11	1/1/2018	1	0		66	149	135	44	7	38	16	8	0	22	1	0	0	0	0

APPENDIX C: DATA VISUALIZATION



(Original data)



(After removing outliners)

APPENDIX D: PERFORMANCE MEASURES (SUMMARY TABLE & DETAILS)

Method	Training set	Test set
MA	166.31	335.35
Naïve	85.47	351.51
SES	170.87	324.26
LR	179.44	506.79
ARIMA	78.49	447.21
EXT	172.61	447.08
ENSEMBLE	132.97	322.71

(**Summary table:** Average RMSE of all methods)

Product name/Method	Train/Valid	Performance Indicadors					Best individual		
1. 83807		ME	RMSE	MAE	MPE	MAPE		ACF1	Theil's U
MA	Training set	370.75	628.83	531.44	15.02	19.08		0.82	1.77
	Test set	-462.88	1103.48	848.88	-22.41	30.69		0.67	2.96
Naïve	Training set	114.25	307.43	214.02	5.99	9.26		0.17	NA
	Test set	-1489.38	1794.90	1489.38	-51.97	51.97		0.67	4.65
SES	Training set	437.64	696.75	543.34	13.58	25.21		0.82	NA
	Test set	-679.76	1210.57	848.88	-28.66	32.26		0.67	3.28
LR	Training set	0.00	608.79	454.09	-7.05	21.43	MA	0.89	NA
	Test set	-2052.43	2406.19	2052.43	-70.41	70.41	SES	0.67	6.17
ARIMA	Training set	0.00	282.22	207.09	-2.36	9.99	ENSEMBLE	0.17	NA
(0,1,0)with drift	Test set	-2003.50	2359.79	2003.50	-68.92	68.92		0.67	6.07
EXT	Training set	0.00	536.67	418.57	-7.72	18.82		0.79	NA
	Test set	-1354.26	1594.22	1354.25	-46.55	46.55		0.56	4.16
ENSEMBLE	Training set	297.29	515.20	414.48	11.12	14.12		0.72	1.45
	Test set	-1048.71	1507.22	1069.70	-40.00	40.43		0.67	4.06
2. 80105									
MA	Training set	46.37	333.21	219.96	-3.16	21.57		0.74	1.73
	Test set	638.00	784.49	676.63	28.73	32.06		0.67	2.49
Naïve	Training set	35.30	195.96	119.75	1.35	11.18		0.14	NA
	Test set	-406.25	611.08	418.50	-30.97	31.49		0.67	3.41
SES	Training set	46.68	335.88	217.81	-3.36	21.05		0.72	NA
	Test set	478.14	661.06	596.70	19.59	29.76		0.67	2.17
LR	Training set	0.00	369.40	257.89	-11.69	27.76	ARIMA	0.72	NA
	Test set	885.54	995.60	885.54	42.90	42.90	ENSEMBLE	0.67	3.20
ARIMA	Training set	10.93	190.98	113.18	-1.78	10.79	Naïve	0.03	NA
(1,0,1)with non zero mean	Test set	65.28	314.05	274.62	-1.29	16.62		0.64	1.46
EXT	Training set	0.00	367.26	250.82	-11.73	27.34		0.72	NA
	Test set	789.10	942.90	795.94	36.45	37.05		0.68	2.97
ENSEMBLE	Training set	31.83	277.80	176.10	-3.30	17.10		0.66	1.43
	Test set	393.81	563.13	515.98	15.68	26.15		0.67	1.91
3. 83921									
MA	Training set	-35.69	210.07	177.73	-13.15	30.81		0.79	1.95
	Test set	563.13	567.70	563.13	45.90	45.90		0.33	7.22
Naïve	Training set	2.86	128.07	89.50	-1.57	13.49		0.15	NA
	Test set	131.13	149.56	131.13	10.43	10.43		0.33	1.95
SES	Training set	-34.76	204.08	170.96	-13.30	28.40		0.72	NA
	Test set	487.94	493.22	487.94	39.72	39.72		0.33	6.29
LR	Training set	0.00	226.27	181.10	-11.94	30.29	Naïve	0.76	NA
	Test set	797.47	801.57	797.47	65.11	65.11	ARIMA	0.33	10.21
ARIMA	Training set	2.82	126.64	87.53	-1.53	13.19	ENSENBLE	0.15	NA
(0,1,0)	Test set	131.13	149.56	131.13	10.43	10.43		0.33	1.95
EXT	Training set	0.00	225.43	176.12	-11.81	29.52		0.75	NA
	Test set	844.77	849.99	844.77	69.00	69.00		0.46	10.85
ENSEMBLE	Training set	-32.57	171.89	144.01	-10.87	24.61		0.68	1.50
	Test set	394.06	400.58	394.06	32.02	32.02		0.33	5.12

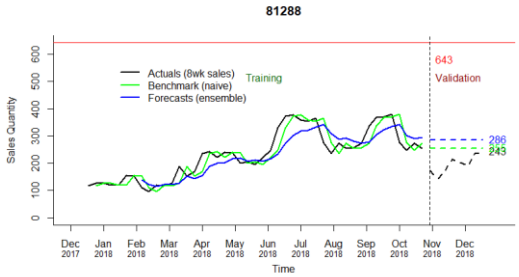
4. 83922									
MA	Training set	-12.86	124.31	104.01	-13.33	35.33		0.90	1.95
	Test set	-20.50	53.75	37.25	-5.79	9.02		0.24	0.85
Naïve	Training set	-1.75	54.00	38.02	-1.63	11.95		0.39	NA
	Test set	-145.00	153.28	145.00	-32.97	32.97		0.24	2.28
SES	Training set	-17.96	126.03	102.14	-17.79	35.93		0.88	NA
	Test set	-2.41	49.75	37.29	-1.84	8.72		0.24	0.78
LR	Training set	0.00	170.16	148.79	-32.67	59.12	SES	0.89	NA
	Test set	265.89	270.64	265.89	56.80	56.80	MA	0.17	3.90
ARIMA	Training set	4.35	49.60	31.83	2.59	9.67	ENSEMBLE	-0.01	NA
(1,2,1)	Test set	-258.69	271.32	258.69	-58.03	58.03		0.61	4.19
EXT	Training set	0.00	164.30	141.91	-28.96	53.81		0.84	NA
	Test set	158.39	185.61	161.14	32.49	33.26		0.55	2.41
ENSEMBLE	Training set	-11.30	92.61	77.53	-10.68	26.85		0.82	1.51
	Test set	-93.87	109.03	93.87	-21.88	21.88		0.41	1.71
5. 81288									
MA	Training set	13.76	56.14	47.38	2.88	18.02		0.74	1.34
	Test set	-116.50	120.76	116.50	-63.62	63.62		0.46	3.96
Naïve	Training set	3.11	35.63	25.52	0.55	11.36		0.17	NA
	Test set	-58.00	66.14	58.00	-33.09	33.09		0.46	2.21
SES	Training set	17.78	52.98	41.76	4.80	16.51		0.70	NA
	Test set	-93.29	98.56	93.29	-51.51	51.51		0.46	3.25
LR	Training set	0.00	52.23	41.97	-5.13	18.31	Naïve	0.74	NA
	Test set	-178.12	179.51	178.12	-94.89	94.89	ARIMA	0.22	5.86
ARIMA	Training set	3.05	35.23	24.96	0.54	11.11	ENSEMBLE	0.17	NA
(0,1,0)	Test set	-58.00	66.14	58.00	-33.09	33.09		0.46	2.21
EXT	Training set	0.00	49.25	41.42	-4.73	18.31		0.70	NA
	Test set	-135.86	143.39	135.86	-74.70	74.70		0.65	4.79
ENSEMBLE	Training set	12.28	46.12	37.85	2.78	14.66		0.60	1.15
	Test set	-89.26	94.76	89.26	-49.41	49.41		0.46	3.13
6. 80103									
MA	Training set	9.96	140.60	99.57	-12.23	35.53		0.86	2.11
	Test set	224.13	281.11	231.75	24.53	25.94		0.65	1.85
Naïve	Training set	5.50	65.26	38.00	-1.37	13.70		0.39	NA
	Test set	-7.38	169.83	146.13	-6.04	20.11		0.65	1.30
SES	Training set	7.26	143.37	102.68	-14.45	35.76		0.86	NA
	Test set	229.64	285.52	235.88	25.26	26.41		0.65	1.88
LR	Training set	0.00	197.40	172.07	-38.02	66.30	NAÏVE	0.86	NA
	Test set	475.84	505.05	475.84	57.78	57.78	ARIMA	0.65	3.44
ARIMA	Training set	-2.59	57.39	39.14	-4.50	14.56	ENSEMBLE	0.03	NA
(1,0,1)with non zero mean	Test set	101.83	229.24	201.00	7.38	24.55		0.68	1.53
EXT	Training set	0.00	197.40	172.07	-38.02	66.30		0.86	NA
	Test set	475.80	505.01	475.80	57.78	57.78		0.65	3.44
ENSEMBLE	Training set	2.64	110.33	79.69	-11.98	28.90		0.80	1.60
	Test set	185.20	259.24	214.04	19.06	24.27		0.66	1.70
7. 81289									
MA	Training set	-1.18	31.45	27.27	-5.61	22.41		0.80	1.80
	Test set	32.13	46.49	34.19	14.53	15.90		0.40	1.37
Naïve	Training set	0.93	18.55	13.07	-0.50	9.98		0.24	NA
	Test set	-10.63	35.24	32.88	-8.56	17.58		0.40	1.08
SES	Training set	-0.62	28.49	23.30	-4.72	18.71		0.74	NA
	Test set	29.67	44.82	32.35	13.20	14.99		0.40	1.32
LR	Training set	0.00	31.35	26.54	-5.45	20.62	NAÏVE	0.77	NA
	Test set	57.95	67.20	57.95	28.44	28.44	SES	0.41	2.01
ARIMA	Training set	-0.08	16.63	11.95	-1.64	9.15	MA	0.03	NA
(2,0,0)with non zero mean	Test set	34.25	57.55	44.87	14.78	21.46		0.53	1.72
EXT	Training set	0.00	31.29	26.43	-5.43	20.53		0.77	NA
	Test set	62.62	72.34	62.62	30.79	30.79		0.45	2.17
ENSEMBLE	Training set	-1.99	24.35	20.90	-5.08	17.18		0.67	1.35
	Test set	32.02	49.20	35.76	14.17	16.67		0.46	1.47

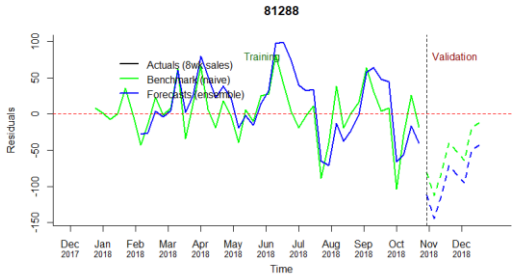
8. 80131									
MA	Training set	19.03	47.73	34.42	4.67	17.23		0.48	1.01
	Test set	64.38	102.85	98.50	12.32	27.27		0.60	1.69
Naïve	Training set	7.80	40.78	22.25	1.68	11.86		0.00	NA
	Test set	-80.38	113.55	80.38	-30.37	30.37		0.60	2.87
SES	Training set	21.73	50.30	33.46	6.57	16.71		0.45	NA
	Test set	53.88	96.62	93.25	9.23	26.47		0.60	1.66
LR	Training set	0.00	44.32	31.74	-3.87	19.19	ENSEMBLE	0.46	NA
	Test set	50.67	103.21	98.95	7.52	28.63	SES	0.62	1.83
ARIMA	Training set	7.62	40.33	21.76	1.64	11.60	MA	0.00	NA
(0,1,0)	Test set	-80.38	113.55	80.38	-30.37	30.37		0.60	2.87
EXT	Training set	0.00	43.50	32.28	-3.79	19.72		0.43	NA
	Test set	30.07	106.66	96.82	0.54	29.68		0.64	2.11
ENSEMBLE	Training set	17.24	45.52	29.77	4.27	14.56		0.33	0.98
	Test set	12.63	81.20	72.63	-2.94	23.31		0.60	1.75
9. 80129									
MA	Training set	182.72	530.73	206.72	-Inf	Inf		0.78	0.00
	Test set	369.38	1218.35	1187.75	-182.47	242.48		0.69	8.14
Naïve	Training set	61.80	268.27	76.61	-Inf	Inf		0.39	NA
	Test set	-1169.13	1647.66	1169.13	-518.19	518.19		0.69	19.17
SES	Training set	166.78	525.90	190.60	-Inf	Inf		0.78	NA
	Test set	110.44	1166.25	1123.02	-238.98	285.98		0.69	9.98
LR	Training set	0.00	565.47	359.59	Inf	Inf	SES	0.76	NA
	Test set	597.09	1359.81	1298.26	-146.38	219.71	MA	0.69	7.19
ARIMA	Training set	0.64	233.40	101.06	-Inf	Inf	ENSEMBLE	-0.03	NA
(0,1,1)(0,0,1)52 with drift	Test set	-1580.55	2044.70	1580.55	-638.33	638.33		0.69	23.62
EXT	Training set	0.00	563.50	354.09	Inf	Inf		0.76	NA
	Test set	482.64	1384.32	1333.28	-186.82	256.47		0.70	8.63
ENSEMBLE	Training set	131.00	414.39	157.23	-Inf	Inf		0.71	0.00
	Test set	-366.91	1260.71	1075.91	-353.26	379.40		0.69	13.89
10. 86795									
MA	Training set	-3.98	25.16	22.79	-11.13	29.71		0.84	1.75
	Test set	-4.38	16.12	14.03	-6.47	14.14		0.12	0.77
Naïve	Training set	0.20	15.81	10.98	-1.81	13.00		0.12	NA
	Test set	-28.25	32.23	28.25	-29.76	29.76		0.12	1.52
SES	Training set	-3.10	25.85	22.93	-11.85	29.33		0.78	NA
	Test set	-3.86	15.99	13.90	-5.97	13.95		0.12	0.76
LR	Training set	0.00	32.72	27.16	-15.75	36.31	SES	0.85	NA
	Test set	34.78	38.54	34.78	31.62	31.62	MA	0.19	1.75
ARIMA	Training set	0.20	15.64	10.74	-1.77	12.71	ENSEMBLE	0.12	NA
(0,1,0)	Test set	-28.25	32.23	28.25	-29.76	29.76		0.12	1.52
EXT	Training set	0.00	32.71	26.98	-15.77	36.15		0.85	NA
	Test set	36.64	40.43	36.64	33.42	33.42		0.23	1.85
ENSEMBLE	Training set	-3.82	20.68	18.42	-9.87	24.43		0.71	1.43
	Test set	-12.16	19.71	17.21	-14.07	18.03		0.12	0.94
11. 86466									
MA	Training set	1.29	5.54	4.57	3.05	17.91		0.81	1.49
	Test set	0.00	8.93	7.94	-13.98	35.89		0.65	1.14
Naïve	Training set	0.41	3.44	2.36	1.62	10.13		0.05	NA
	Test set	2.25	9.21	8.50	-4.91	35.02		0.65	1.06
SES	Training set	1.91	5.98	4.46	5.07	18.50		0.79	NA
	Test set	0.06	8.93	7.95	-13.74	35.87		0.65	1.13
LR	Training set	0.00	7.28	5.32	-10.39	25.15	MA	0.86	NA
	Test set	-12.86	14.97	12.86	-64.08	64.08	SES	0.62	2.14
ARIMA	Training set	0.40	3.40	2.31	1.58	9.91	ENSEMBLE	0.05	NA
(0,1,0)	Test set	2.25	9.21	8.50	-4.91	35.02		0.65	1.06
EXT	Training set	0.00	6.34	4.98	-8.17	23.33		0.73	NA
	Test set	-4.20	14.04	12.69	-36.99	60.39		0.71	1.92
ENSEMBLE	Training set	1.25	4.81	3.80	3.04	15.06		0.66	1.29
	Test set	0.77	8.96	8.13	-10.88	35.59		0.65	1.10

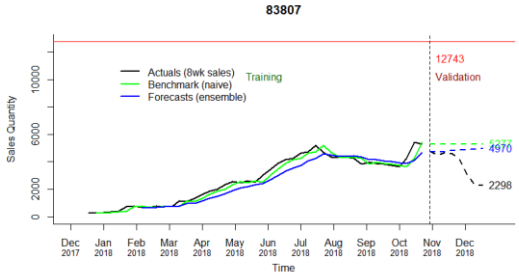
12. 86425									
MA	Training set	-1.02	4.22	3.58	-28.86	46.66		0.84	2.00
	Test set	2.63	3.66	3.00	25.55	34.92		0.72	1.92
Naïve	Training set	-0.23	2.55	1.59	-7.03	19.25		0.04	NA
	Test set	3.38	4.23	3.38	37.30	37.30		0.72	2.26
SES	Training set	-0.88	4.20	3.56	-30.63	47.34		0.79	NA
	Test set	2.14	3.33	2.82	18.01	34.55		0.72	1.76
LR	Training set	0.00	4.83	4.03	-26.19	50.62	LR	0.86	NA
	Test set	1.21	3.09	2.86	1.45	40.93	SES	0.72	1.77
ARIMA	Training set	0.12	2.53	1.66	-3.48	19.55	MA	0.05	NA
(1,0,0)with zero mean	Test set	3.84	4.72	3.84	43.30	43.30		0.72	2.53
EXT	Training set	0.00	3.33	2.58	-10.86	36.60		0.51	NA
	Test set	9.71	13.17	10.00	100.93	108.01		0.68	6.53
ENSEMBLE	Training set	-0.80	3.49	2.89	-24.10	38.14		0.68	1.56
	Test set	2.87	3.88	3.17	28.95	36.52		0.72	2.04
13. 80107									
MA	Training set	131.71	238.87	206.84	-Inf	Inf		0.90	0.00
	Test set	404.75	416.55	404.75	27.39	27.39		0.18	3.15
Naïve	Training set	39.05	93.75	58.18	-Inf	Inf		0.42	NA
	Test set	-63.38	117.07	89.88	-4.83	6.46		0.18	0.93
SES	Training set	125.13	250.28	194.48	-Inf	Inf		0.87	NA
	Test set	397.21	409.22	397.21	26.87	26.87		0.18	3.10
LR	Training set	0.00	276.16	230.11	NaN	Inf	Naïve	0.88	NA
	Test set	474.74	490.20	474.74	32.16	32.16	ENSEMBLE	0.44	3.59
ARIMA	Training set	9.46	76.01	49.50	Inf	Inf	SES	-0.03	NA
(0,2,1)(0,0,1)52	Test set	-626.39	701.34	626.39	-43.80	43.80		0.66	5.79
EXT	Training set	0.00	264.58	217.97	NaN	Inf		0.77	NA
	Test set	453.40	482.99	453.40	30.68	30.68		0.41	3.41
ENSEMBLE	Training set	100.29	179.33	149.84	-Inf	Inf		0.84	0.00
	Test set	58.52	157.46	138.05	3.49	9.50		0.54	1.13
14. 80133									
MA	Training set	47.82	104.71	87.05	13.33	33.20		0.87	1.67
	Test set	-150.13	230.19	189.09	-427.15	435.37		0.70	3.55
Naïve	Training set	12.56	46.29	30.41	8.13	16.40		0.37	NA
	Test set	-242.75	298.96	243.75	-550.02	550.22		0.70	4.65
SES	Training set	46.07	99.26	76.29	-Inf	Inf		0.85	NA
	Test set	-168.33	242.46	196.54	-451.30	457.18		0.70	3.76
LR	Training set	0.00	94.48	80.70	-Inf	Inf	MA	0.88	NA
	Test set	-230.91	301.91	243.43	-551.25	553.78	SES	0.70	4.79
ARIMA	Training set	7.16	41.46	26.40	6.04	14.44	ENSEMBLE	-0.07	NA
(1,1,0)	Test set	-238.93	295.61	240.55	-544.57	544.90		0.70	4.60
EXT	Training set	0.00	93.11	79.32	-Inf	Inf		0.86	NA
	Test set	-235.23	307.55	250.27	-549.12	552.17		0.69	5.09
ENSEMBLE	Training set	38.60	77.64	62.76	11.41	23.51		0.76	1.35
	Test set	-185.80	254.79	205.13	-474.34	478.34		0.70	3.97
15. 80121									
MA	Training set	8.61	13.12	11.69	16.92	31.51		0.83	2.37
	Test set	62.25	75.90	62.25	37.52	37.52		0.55	1.68
Naïve	Training set	2.21	6.33	4.21	8.87	15.92		0.02	NA
	Test set	54.50	69.68	55.50	31.33	32.55		0.55	1.53
SES	Training set	8.78	13.65	11.36	-Inf	Inf		0.80	NA
	Test set	64.29	77.58	64.29	39.14	39.14		0.55	1.72
LR	Training set	0.00	10.69	9.37	NaN	Inf	ARIMA	0.84	NA
	Test set	51.20	64.34	51.20	29.94	29.94	EXT	0.52	1.44
ARIMA	Training set	0.00	5.86	3.89	-Inf	Inf	LR	0.02	NA
(0,1,0)with drift	Test set	44.58	59.13	47.63	24.69	28.28		0.52	1.32
EXT	Training set	0.00	10.49	9.14	NaN	Inf		0.77	NA
	Test set	50.65	63.56	50.65	29.65	29.65		0.54	1.43
ENSEMBLE	Training set	6.75	10.44	8.99	13.32	23.83		0.66	1.77
	Test set	57.04	70.76	57.04	33.78	33.78		0.54	1.57

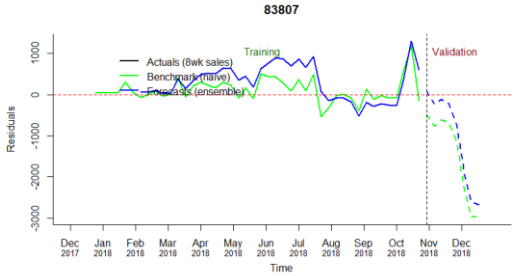
APPENDIX E: TIME PLOTS & RESIDUALS PLOTS IN THE TRAINING & VALIDATION PERIODS

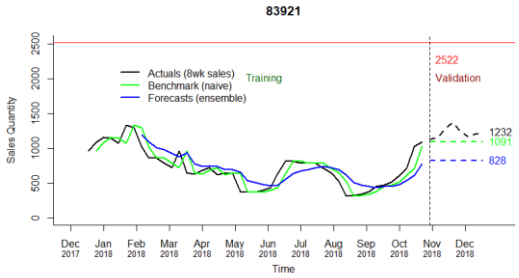
(Actuals vs Forecasts) (Residuals)

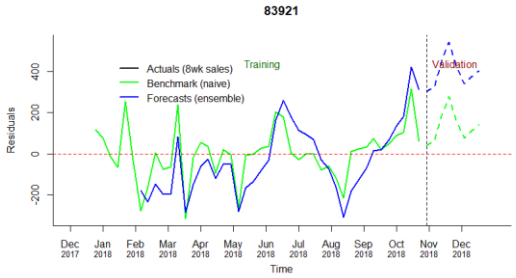


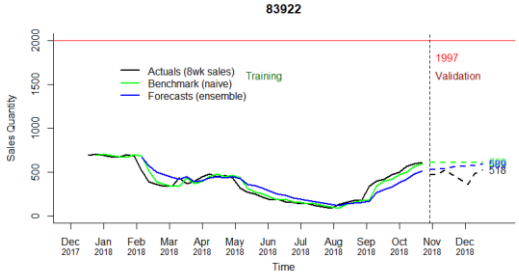


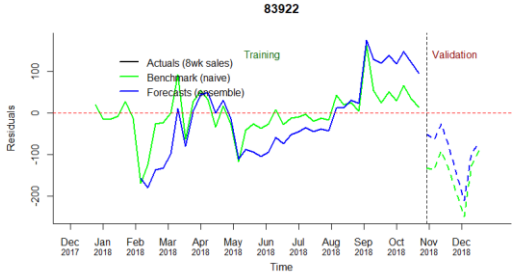


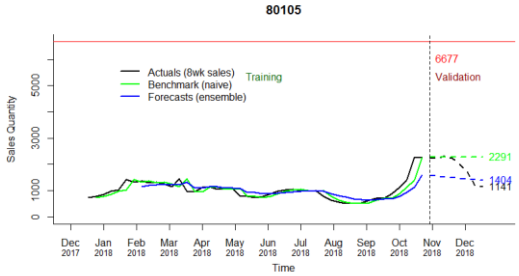


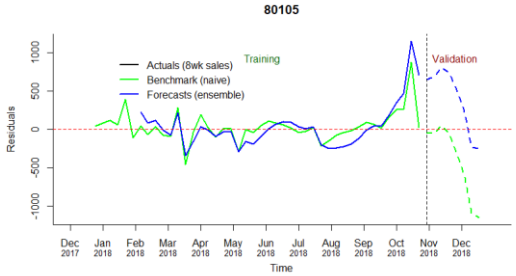






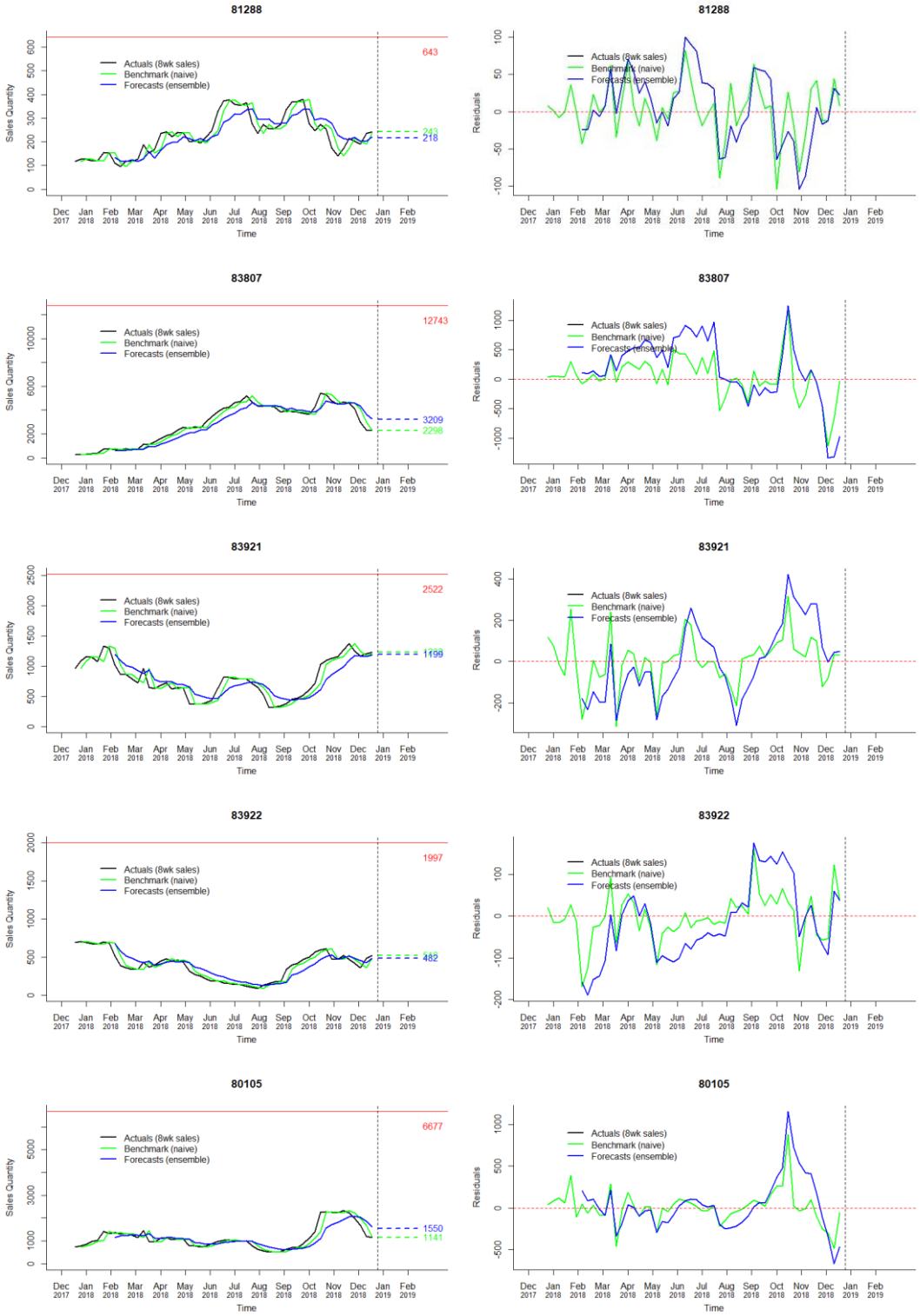






APPENDIX F: TIME PLOTS & RESIDUALS PLOTS FOR THE ENTIRE TIME SERIES

(Actuals vs Forecasts) (Residuals)



APPENDIX G: R CODE FOR FORECASTING THE TRAINING & VALIDATION PERIODS

```
# Load libraries
library(readxl)
library(forecast)
library(zoo)

# Read data from excel
NIVEA <- read_excel("NIVEA.xlsx", sheet = 2) #Sales quantity
NIVEA2 <- read_excel("NIVEA.xlsx", sheet = 3) #Inventory

# Run forecast with different models with a loop for all 15 SKUs
for(i in c(0:14)){

  if(i<12){

    # Define time series object
    hero.8wk <- ts(rollapply(na.omit(NIVEA[,i+5]), 8, sum), start = c(2017,
51), freq = 52)

    # Partition the data
    nValid <- 8
    nTrain <- length(hero.8wk) - nValid
    train.ts <- window(hero.8wk , start = c(2017, 51), end = c(2017, nTrain +
50))
    valid.ts <- window(hero.8wk , start = c(2017, nTrain + 51), end = c(2017,
nTrain + 50 + nValid))

    # Create a dummy variable for promotion
    dummy.ts <- ts(na.omit(NIVEA$HPromotion), start = c(2017, 51), end =
c(2019, 6), freq = 52)
    dummy.train.ts <- window(dummy.ts, start = c(2017, 51), end = c(2017,
nTrain + 50))
    dummy.valid.ts <- window(dummy.ts, start = c(2017, nTrain + 51), end =
c(2017, nTrain + 50 + nValid))

    # Moving average
    ma <- rollmean(train.ts, k = 8, align = "right")
    last.ma <- tail(ma, 1)
    pred.ma <- ts(rep(last.ma, nValid), start = c(2017, nTrain + 51), end =
c(2017, nTrain + 50 + nValid ), freq = 52)
  }
  else
  {
    # Define time series object
    hero.8wk <- ts(rollapply(na.omit(NIVEA[,i+5]), 8, sum), start = c(2017,
56), freq = 52) #5 missing values at the begining

    # Partition the data
    nValid <- 8
    nTrain <- length(hero.8wk) - nValid
    train.ts <- window(hero.8wk , start = c(2017, 56), end = c(2017, nTrain +
55))
    valid.ts <- window(hero.8wk , start = c(2017, nTrain + 56), end = c(2017,
nTrain + 55 + nValid ))
```

```
    # Create a dummy variable
    dummy.ts <- ts(na.omit(NIVEA$Promotion), start = c(2017, 51), end =
c(2019, 6), freq = 52)
    dummy.train.ts <- window(dummy.ts, start = c(2017, 56), end = c(2017,
nTrain + 55))
    dummy.valid.ts <- window(dummy.ts, start = c(2017, nTrain + 56), end =
c(2017, nTrain + 55 + nValid))

    # Moving average
    ma <- rollmean(train.ts, k = 8, align = "right")
    last.ma <- tail(ma, 1)
    pred.ma <- ts(rep(last.ma, nValid), start = c(2017, nTrain + 56), end =
c(2017, nTrain + 55 + nValid ), freq = 52)
  }

  #################### Forecasting ####################

  # Naive forecasts (the most recent actual data)
  pred.naive<- naive(train.ts, h = nValid)

  # Simple exponential smoothing
  ses <- ets(train.ts, model = "ANN", alpha = 0.2)
  pred.ses <- forecast(ses, h = nValid)

  # Linear regression model
  lm <- tslm(train.ts ~ trend)
  pred.lm <- forecast(lm, h = nValid)

  # ARIMA model
  arima <- auto.arima(train.ts)
  pred.arima <- forecast(arima, h = nValid)

  # Linear regression model with external variable
  ext <- tslm(train.ts ~ trend + dummy.train.ts)
  pred.ext <- forecast(ext, newdata = dummy.valid.ts, h = nValid)

  #Ensemble
  ensemble <- (ses$fitted + arima$fitted + ma)/3
  pred.ensemble <- (pred.ses$mean + pred.arima$mean + pred.ma)/3

  #################### Visualization ####################

  # Current inventory level
  inventory <- as.numeric(NIVEA2[,i+2])
  position <- max(hero.8wk, inventory, na.omit(pred.naive$fitted,
pred.ses$fitted, pred.lm$fitted, pred.arima$fitted, pred.ext$fitted, ma,
ensemble), pred.naive$mean, pred.ses$mean, pred.lm$mean, pred.arima$mean,
pred.ext$mean, pred.ma, pred.ensemble)

  if(i<12){
    plot(train.ts, ylim = c(0, position), xlim = c((2017+11/12),
(2018+12/12)), ylab = "Sales Quantity", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]), lwd=2)
    lines(pred.naive$fitted, col = "green", lwd=2)
    lines(ensemble, col = "blue", lwd=2)
```

```
    lines(valid.ts, lwd=2, lty=2)
    lines(pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(pred.ensemble, col = "blue", lwd =2, lty=2)
    text(2017 + (nTrain + 50+7)/52, valid.ts[8], round(valid.ts[8]), pos = 4)
    text(2017 + (nTrain + 50+7)/52, pred.naive$mean[8],
round(pred.naive$mean[8]), col = "green", pos = 4)
    text(2017 + (nTrain + 50+7)/52, pred.ensemble[8],
round(pred.ensemble[8]), col = "blue", pos = 4)
    abline(h = inventory, col = "red")
    text(2017 + (nTrain + 50)/52, inventory*0.9, inventory, col = "red", pos
= 4)

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+11/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec"))
    mtext((c("2017", rep("2018", 12))), side = 1, at = seq(2017+11/12,
(2018+11/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (nTrain + 50)/52), lty=2)
    text(2017 + (nTrain + 25)/52, position*0.8, "Training", col = "dark
green", pos = 4)
    text(2017 + (nTrain + 50)/52, position*0.8, "Validation", col = "dark
red", pos = 4)
    legend(2017 + length(hero.8wk)/52, position*0.9, c("Actuals (8wk sales)",
"Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black",
"green", "blue"), bty = "n")
  }
  else
  {
    plot(train.ts, ylim = c(0, position), xlim = c((2017+11/12),
(2018+12/12)), ylab = "Sales Quantity", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]), lwd=2)
    lines(pred.naive$fitted, col = "green", lwd=2)
    lines(ensemble, col = "blue", lwd=2)
    lines(valid.ts, lwd=2, lty=2)
    lines(pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(pred.ensemble, col = "blue", lwd =2, lty=2)
    text(2017 + (nTrain + 55+7)/52, valid.ts[8], round(valid.ts[8]), pos = 4)
    text(2017 + (nTrain + 55+7)/52, pred.naive$mean[8],
round(pred.naive$mean[8]), col = "green", pos = 4)
    text(2017 + (nTrain + 55+7)/52, pred.ensemble[8],
round(pred.ensemble[8]), col = "blue", pos = 4)
    abline(h = inventory, col = "red")
    text(2017 + (nTrain + 55)/52, inventory*0.9, inventory, col = "red", pos
= 4)

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+11/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec"))
    mtext((c("2017", rep("2018", 12))), side = 1, at = seq(2017+11/12,
(2018+11/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (nTrain + 55)/52), lty=2)
    text(2017 + (nTrain + 28)/52, position*0.8, "Training", col = "dark
green", pos = 4)
```

```
    text(2017 + (nTrain + 55)/52, position*0.8, "Validation", col = "dark
red", pos = 4)
    legend(2017 + length(hero.8wk)/52, position*0.9, c("Actuals (8wk sales)",
"Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black",
"green", "blue"), bty = "n")
  }

  #Residuals plot
  position_high <- max(na.omit(train.ts-pred.naive$fitted), na.omit(valid.ts-
pred.naive$mean),
                       na.omit(train.ts-ensemble), na.omit(valid.ts-
pred.ensemble))
  position_low <- min(na.omit(train.ts-pred.naive$fitted), na.omit(valid.ts-
pred.naive$mean),
                      na.omit(train.ts-ensemble), na.omit(valid.ts-
pred.ensemble))

  if(i<12){
    plot(na.omit(train.ts-pred.naive$fitted), col = "green", lwd=2, ylim =
c(position_low, position_high), xlim = c((2017+11/12), (2018+12/12)), ylab =
"Residuals", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]))
    lines(valid.ts-pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(train.ts-ensemble, col = "blue", lwd=2)
    lines(valid.ts-pred.ensemble, col = "blue", lwd=2, lty=2)
    abline(h=0, lty=2, col="red")

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+11/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec"))
    mtext((c("2017", rep("2018", 12))), side = 1, at = seq(2017+11/12,
(2018+11/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (nTrain + 50)/52), lty=2)
    text(2017 + (nTrain + 25)/52, position_high*0.8, "Training", col = "dark
green", pos = 4)
    text(2017 + (nTrain + 50)/52, position_high*0.8, "Validation", col =
"dark red", pos = 4)
    legend(2017 + length(hero.8wk)/52, position_high*0.9, c("Actuals (8wk
sales)", "Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2),
col=c("black", "green", "blue"), bty = "n")

  }
  else
  {

    plot(na.omit(train.ts-pred.naive$fitted), col = "green", lwd=2, ylim =
c(position_low, position_high), xlim = c((2017+11/12), (2018+12/12)), ylab =
"Residuals", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]))
    lines(valid.ts-pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(train.ts-ensemble, col = "blue", lwd=2)
    lines(valid.ts-pred.ensemble, col = "blue", lwd=2, lty=2)
    abline(h=0, lty=2, col="red")
```

```
    # Add notations
    axis(1, at = seq(2017+11/12, (2018+11/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec"))
    mtext((c("2017", rep("2018", 12))), side = 1, at = seq(2017+11/12,
(2018+11/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (nTrain + 55)/52), lty=2)
    text(2017 + (nTrain + 28)/52, position_high*0.8, "Training", col = "dark
green", pos = 4)
    text(2017 + (nTrain + 55)/52, position_high*0.8, "Validation", col =
"dark red", pos = 4)
    legend(2017 + length(hero.8wk)/52, position_high*0.9, c("Actuals (8wk
sales)", "Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2),
col=c("black", "green", "blue"), bty = "n")
  }
}
```

APPENDIX H: R CODE FOR FORECASTING THE ENTIRE TIME SERIES

```
# Load libraries
library(readxl)
library(forecast)
library(zoo)

# Read data from excel
NIVEA <- read_excel("NIVEA.xlsx", sheet = 2) #Sales quantity
NIVEA2 <- read_excel("NIVEA.xlsx", sheet = 3) #Inventory

# Run forecast with different models with a loop for all 15 SKUs
for(i in c(0:14)){

  if(i<12){
    # Define time series object
    hero.8wk <- ts(rollapply(na.omit(NIVEA[,i+5]), 8, sum), start = c(2017,
51), freq = 52)
    n <- length(hero.8wk)
    h <- 8 #forecast horizon

    # Create a dummy variable for promotion
    dummy <- ts(na.omit(NIVEA$HPromotion), start = c(2017, 51), freq = 52)
    dummy.ori <- window(dummy, start = c(2017, 51), end = c(2017, n + 50))
    dummy.new <- window(dummy, start = c(2017, n + 51), end = c(2017, n + 50
+ h))

    # Moving average
    ma <- rollmean(hero.8wk, k = 8, align = "right")
    last.ma <- tail(ma, 1)
    pred.ma <- ts(rep(last.ma, h), start = c(2017, n + 51), end = c(2017, n +
50 + h), freq = 52)
  }
  else
  {
```

```
    # Define time series object
    hero.8wk <- ts(rollapply(na.omit(NIVEA[,i+5]), 8, sum), start = c(2017,
56), freq = 52) #5 missing values at the begining
    n <- length(hero.8wk)
    h <- 8 #forecast horizon

    # Create a dummy variable
    dummy <- ts(na.omit(NIVEA$Promotion), start = c(2017, 51), end = c(2019,
6), freq = 52)
    dummy.ori <- window(dummy, start = c(2017, 56), end = c(2017, n + 55))
    dummy.new <- window(dummy, start = c(2017, n + 56), end = c(2017, n + 55
+ h))

    # Moving average
    ma <- rollmean(hero.8wk, k = 8, align = "right")
    last.ma <- tail(ma, 1)
    pred.ma <- ts(rep(last.ma, 8), start = c(2017, n + 56), end = c(2017, n +
55 + h), freq = 52)
  }

  #################### Forecasting ####################

  # Naive forecasts (the most recent actual data)
  pred.naive<- naive(hero.8wk, h = h)

  # Simple exponential smoothing
  ses <- ets(hero.8wk, model = "ANN", alpha = 0.2)
  pred.ses <- forecast(ses, h = h)

  # Linear regression model
  lm <- tslm(hero.8wk ~ trend)
  pred.lm <- forecast(lm, h = h)

  # ARIMA model
  arima <- auto.arima(hero.8wk)
  pred.arima <- forecast(arima, h = h)

  # Linear regression model with external variable
  ext <- tslm(hero.8wk ~ trend + dummy.ori)
  pred.ext <- forecast(ext, newdata = dummy.new, h = h)

  #Ensemble
  ensemble <- (ses$fitted + arima$fitted + ma)/3
  pred.ensemble <- (pred.ses$mean + pred.arima$mean + pred.ma)/3

  #################### Visualization ####################

  # Current inventory level
  inventory <- as.numeric(NIVEA2[,i+2])
  position <- max(hero.8wk, inventory, na.omit(pred.naive$fitted,
pred.ses$fitted, pred.lm$fitted, pred.arima$fitted, pred.ext$fitted, ma,
ensemble), pred.naive$mean, pred.ses$mean, pred.lm$mean, pred.arima$mean,
pred.ext$mean, pred.ma, pred.ensemble)
```

```
  if(i<12){
    plot(hero.8wk, ylim = c(0, position), xlim = c((2017+11/12),
(2018+14/12)), ylab = "Sales Quantity", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]), lwd=2)
    lines(pred.naive$fitted, col = "green", lwd=2)
    lines(ensemble, col = "blue", lwd=2)
    lines(pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(pred.ensemble, col = "blue", lwd =2, lty=2)
    text(2017 + (n + 50+7)/52, pred.naive$mean[8], round(pred.naive$mean[8]),
col = "green", pos = 4)
    text(2017 + (n + 50+7)/52, pred.ensemble[8], round(pred.ensemble[8]), col
= "blue", pos = 4)
    abline(h = inventory, col = "red")
    text(2017 + (n + 50+7)/52, inventory*0.9, inventory, col = "red", pos =
4)

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+13/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec", "Jan", "Feb"))
    mtext((c("2017", rep("2018", 12), "2019", "2019")), side = 1, at =
seq(2017+11/12, (2018+13/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (n + 50)/52), lty=2)
    legend(2017 + n/52, position*0.9, c("Actuals (8wk sales)", "Benchmark
(naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black", "green",
"blue"), bty = "n")
  }
  else
  {
    plot(hero.8wk, ylim = c(0, position), xlim = c((2017+11/12),
(2018+14/12)), ylab = "Sales Quantity", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]), lwd=2)
    lines(pred.naive$fitted, col = "green", lwd=2)
    lines(ensemble, col = "blue", lwd=2)
    lines(pred.naive$mean, col = "green", lwd=2, lty=2)
    lines(pred.ensemble, col = "blue", lwd =2, lty=2)
    text(2017 + (n + 55+7)/52, pred.naive$mean[8], round(pred.naive$mean[8]),
col = "green", pos = 4)
    text(2017 + (n + 55+7)/52, pred.ensemble[8], round(pred.ensemble[8]), col
= "blue", pos = 4)
    abline(h = inventory, col = "red")
    text(2017 + (n + 55+7)/52, inventory*0.9, inventory, col = "red", pos =
4)

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+13/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec", "Jan", "Feb"))
    mtext((c("2017", rep("2018", 12), "2019", "2019")), side = 1, at =
seq(2017+11/12, (2018+13/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (n + 55)/52), lty=2)
    legend(2017 + n/52, position*0.9, c("Actuals (8wk sales)", "Benchmark
(naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black", "green",
"blue"), bty = "n")
  }
```

```
  #Residuals plot
  position_high <- max(na.omit(hero.8wk-pred.naive$fitted), na.omit(hero.8wk-
ensemble))
  position_low <- min(na.omit(hero.8wk-pred.naive$fitted), na.omit(hero.8wk-
ensemble))

  if(i<12){
    plot(na.omit(hero.8wk-pred.naive$fitted), col = "green", lwd=2, ylim =
c(position_low, position_high), xlim = c((2017+11/12), (2018+14/12)), ylab =
"Residuals", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]))
    lines(hero.8wk-ensemble, col = "blue", lwd=2)
    abline(h=0, lty=2, col="red")

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+13/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec", "Jan", "Feb"))
    mtext((c("2017", rep("2018", 12), "2019", "2019")), side = 1, at =
seq(2017+11/12, (2018+13/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (n + 50)/52), lty=2)
    legend(2017 + n/52, position_high*0.9, c("Actuals (8wk sales)",
"Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black",
"green", "blue"), bty = "n")
  }
  else
  {
    plot(na.omit(hero.8wk-pred.naive$fitted), col = "green", lwd=2, ylim =
c(position_low, position_high), xlim = c((2017+11/12), (2018+14/12)), ylab =
"Residuals", xlab = "Time", bty = "l", xaxt = "n",
         main = colnames(NIVEA[,i+5]))
    lines(hero.8wk-ensemble, col = "blue", lwd=2)
    abline(h=0, lty=2, col="red")

    # Add notations
    axis(1, at = seq(2017+11/12, (2018+13/12), (1/12)), labels = c("Dec",
"Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov",
"Dec", "Jan", "Feb"))
    mtext((c("2017", rep("2018", 12), "2019", "2019")), side = 1, at =
seq(2017+11/12, (2018+13/12), (1/12)), line = 1.8, cex = 0.8)
    abline(v= (2017 + (n + 55)/52), lty=2)
    legend(2017 + n/52, position_high*0.9, c("Actuals (8wk sales)",
"Benchmark (naive)", "Forecasts (ensemble)"), lwd=c(2, 2, 2), col=c("black",
"green", "blue"), bty = "n")
  }

}
```