Demand Forecasting for Materials to Improve Production Capability Planning in BASF

Team 6
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Executive Summary

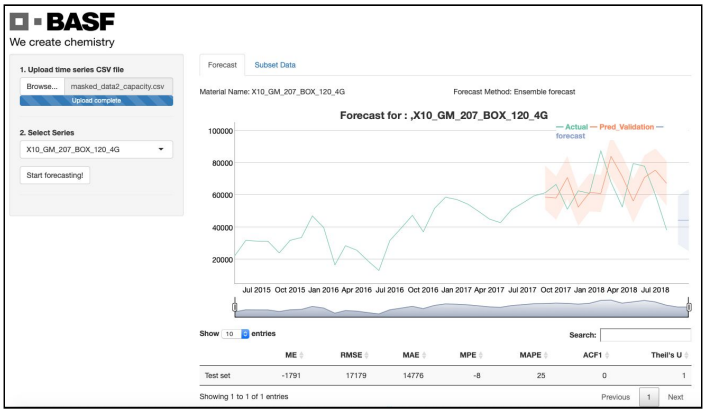
BASF is the currently the world largest chemical company. In 2017, BASF posted sales of €64.5 billion and income from operations before special items of approximately €8.3 billion. They have broad portfolio ranges from chemicals, plastics, performance products and crop protection products to oil and gas.

Every day, the production division in BASF need to deal with the incoming new demands, and they need ensure that it's always able to meet those demands in time. This situation become very complicated since they have thousands of products to offer. Furthermore, since they have limited production capacity so that they need to anticipate future demand in advance to optimize their capacity. Forecasting material demand is really a big challenge for BASF.

In this project, our forecasting goal is to create monthly forecast the demand of each materials for two-months ahead. The forecast should be able to be updated when they have new data. In addition our forecasting goal is two-months. When the new data in coming, we update the forecast by roll-forward for every month. In total, we forecast demand data of 826 materials.

Our forecasting approach is to classify each time series of the material into groups and analyze them to find out optimal forecasting methods for each group. After analyzing and comparing accuracy performance, we divided 826 series into 5 groups: Naive, zero-forecast, Arima, ETS and Ensemble. The predicted performance of each group is benchmarked with the Naive method. The results show that accuracy performance of each group is significantly improved compared to the Naive Method. In addition, we design a application that can be used by production executive to quickly see the forecast result of each materials.

Due to the volatility of the time series of each materials, creating very accurate forecast remained a challenge for the future works. We suggest several considerations such as find better way to classify the materials into groups, explore more advanced forecast technique, include price to estimate actual forecast impact, preprocessing negative value stored in the dataset in a more intelligent way.



1. Problem Description

Business goal: Optimization of production capacity line.

- Client: Business Analytics Team
- Stakeholders: Production Executive
- Humanistic implication: At one hand, over-forecasting might waste financial resources because production will likely produce material than needed. In results, they will spend more financial resources for raw materials, human labour, as well as warehouse. However, over-forecasting suppresses the likelihood of the failure meet the demand on time. On the other hand, under-forecasting may lead to insufficient product quantity to meet demand on time, which in result it can hurt BASF's brand image. For very big company as BASF, we argue that brand image is very important to protect since they are the largest in the chemical market. The leftover material due to over-forecasting still can be included in another demand. Hence, over-forecast is prefered.
- Opportunity: Time-series forecasting provides more accurate forecasts which helps production executive to make decision making.
- Challenges: There are no seasonality in the BASF's demand historical data, and there are a lot of intermittent and sporadic time series that make it very hard to forecast.

Forecasting goal: Forecast the demand of each materials for two-months ahead.

The forecast should be able to be updated when they have new data. In addition our forecasting goal is two-months ahead and we use one year in our validation period. When the new data in coming, we update the forecast by roll-forward for every month.

t = monthly
Y_t = denotes the actual number of demand for each materials at the time t
F_t = denotes the forecast number of demand for each materials at the time t
k = 1, 2 (two months ahead)

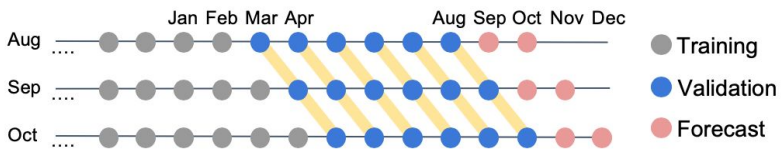


Figure 1. Roll-fordward illustration

2. Data Description

The raw data is contained BASF daily transaction of each material demand for each customer with time range from October of 2012 to October of 2018, containing 108,324 daily demands order records from 826 materials. We got the data from BASF business analytic division. In total, the historical data contains 108,324 rows with 7 columns which are (1) date, (2) company, (3) desc, (4) demand, (5) ship2, (6) material2, (7) capacity respectively. Figure 2 is showed the sample set of raw data and Figure 3 is the sample of demand time series measured by monthly.

date	company	desc	demand	ship2	material2	capacity
6/2/2016	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	10395	143	333	938265.4777
6/6/2016	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	24255	143	333	938265.4777
6/13/2016	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	39501	143	333	938265.4777
6/16/2016	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	38115	143	333	938265.4777
8/30/2016	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	-4272	143	333	938265.4777
12/28/2012	BASF Polyurethane Sp	BUM-STO-357-412-303-F-MHK-45	768	25	333	938265.4777

Figure 2. sample of daily demand from the BASF dataset

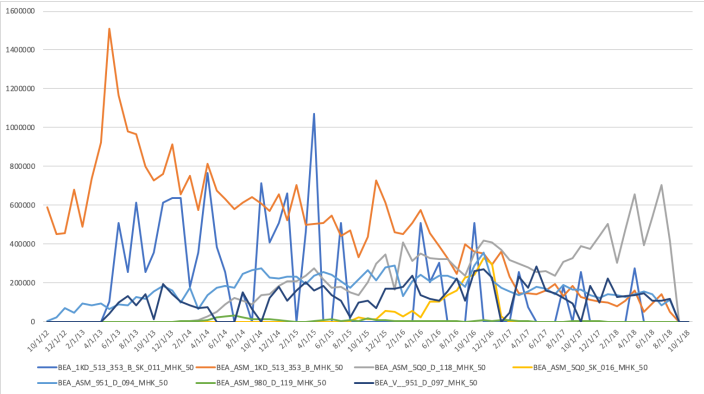


Figure 3. time series visualization for some materials

As we can see on figure 3, first, the pattern of each demand looks different compared to each other. second, some of materials demand orders might not have any demand within a month which causes an intermittent or sporadic time series that hard to forecast. Furthermore, some of materials, the time length of demand orders series is not sufficient to detect seasonality component.

3. Data Preparation

In overall, we remove all of negative value in the dataset and aggregate the demand into monthly and material. The process as below describe how we build a pipeline manipulating each step of data states. The negative value issue is described in appendix 1.

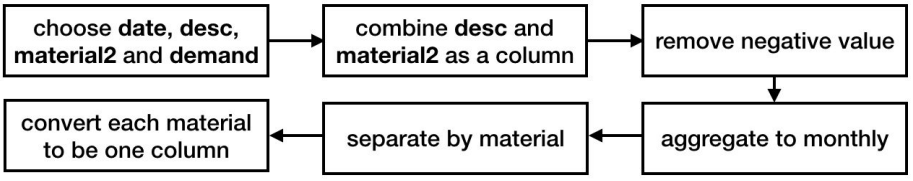


Figure 4. sample of monthly demand time series

4.Forecasting solution

4. 1. Short series forecast and Zero forecast

After exploring all 826 series corresponding, we separate 175 short series (series which contains less than 18 months data) and 329 zero-forecast series with our zero-forecast condition (All 0 in last 6 months; Sum of last 12 months <1000; Zero percentage count > 50%). The rest includes 322 series. For more detail, see appendix 2.

4.2. Analyze data and evaluate accuracy performance

Q1: ***Are there different optimal forecasting methods for each series?***

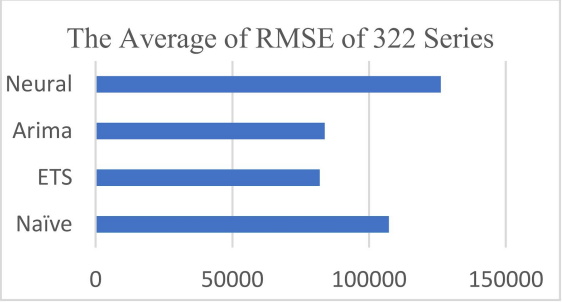


Figure 5. Average RMSE of 322 Series

We compare RMSE of various forecasting methods using the last 6 months validation periods and roll-forward. In average, the ETS is the best method while Neural Nets perform worst. However, if we compare RMSE in each series, we found that every series has different optimal forecast method which can separate into 4 groups: Neural Nets (45), Arima(113), ETS (114) and Naïve(50).

Question 2: ***Does the Auto Model selection method give the best results?***

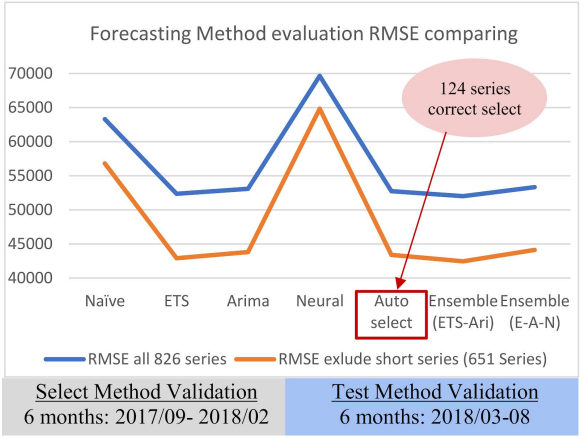


Figure 6. Forecast Evaluation Comparison

We test the *Auto Model selection method by separate* the last 12 months into 2 periods: *Select Method Validation* and *Test Method Validation*. First step, we run different forecast methods for every series and base on the "*Select method Validation*" to choose best method for each series. Second step, we check whether this ***best method*** *in "Select method Validation"* is ***still the best*** *method in "Test method Validation"*. As a result, only 124 series (81 ETS and 43 Arima) have the same best forecasting method in both periods**.**

Comparing average RMSE, we found that the *Auto Model selection method* does not produce good results. The Ensemble method between Arima and ETS gives the best results in average (but only higher than ETS a little bit). Moreover, when remove short series (the yellow line), the average of RMSE decrease means that short series group has higher RMSE than others in average.

Question 3: ***What is the best forecast method for each group of series?***

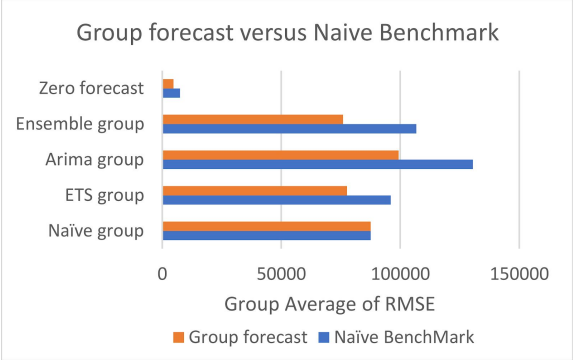


Figure 7. Group forecast versus Naive

We separate 322 series into groups and use optimal forecasting methods for each group. The 124 series which still best forecast method in both "6 months periods" is separate to ETS and Arima group. The remaining 198 series are allocated to Ensemble groups (Ensemble of Arima and ETS). Neural Nets method was eliminated because of the bad performance and unstable.

Combined with Zero forecast and Naive group (sort series), we have a total of 5 groups. To evaluate accuracy performance, the average of the RMSE of each group in the last 6 months validation period was compared with Naive forecast method. The Benchmark results showed that using different forecasting methods provide better RMSE when compared with Naive forecast. RMSE of Zero-forecast group is also better than Naïve forecast.

4.3. Propose forecasting solution

Our prediction solution is to separate all series into 5 groups (Arima, ETS, Ensemble, Zero-forecast and Naïve) and use different forecast method corresponding to each group. To evaluate the effectiveness of the solution, we recalculated the average of RMSE of the *last 12 months validation period* using *2 months ahead roll-forward forecast*. To evaluate the overfitting problem, we perform RMSE comparisons between training and validation period. To benchmark the

solution, we compare with Naive forecast. The results show that Arima, ETS and Ensemble method are better than Naive forecast. The Time plot of typical series with future forecasts for each of the 5 group are showed in the appendix 3.

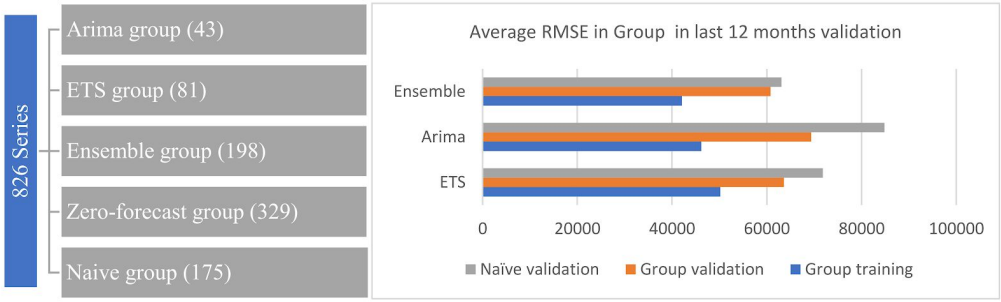


Figure 8. Average RMSE in Group in the last 12 months validation

5. Conclusions

In this project, our forecasting goal is to forecast the demand of each materials for two-months ahead. Good forecast accuracy is important so production executive could use this as reference to make effective decision. Our study employed different forecasting methods for 5 group of series to forecast 2 months ahead. The accuracy performance is determined base on RMSE. We suggest the use of different method for each group would give higher accuracy. We identify several limitations in our forecast project:

1. Since we don't have knowledge on the product price, we use low quantity rule (last 12 months <1000) which not be good the best design.
2. Many time series have enormous volatility and the number of materials make hard to forecast.

For future forecast project, we would like to give several recommendations show as follows:

1. The selection of predictive models for each group should be based on careful analysis of each group's data, we cannot trust on "Automatic Model Selection" methods.
2. Negative demand should not be carelessly removed. As we mentioned in our data preparation step, we convert all negative value to zero. In fact, removing negative value without looking at its context might impact real demand as well as the forecast result.
3. Improve the categorization of the materials into group (e.g. Products categories, ABC-XYZ analysis). If we can classify products with similar characteristics in groups and find optimal forecasting methods for each group. ABC-XYZ analysis is a potential option. However in this study we do not have *sales data* so we cannot perform ABC-XYZ analysis.
4. We recommend using price of the materials and calculate the actual profit/loss from forecast result. Price can give us different perspective in which materials which should focus more. For instances, some material could be very expensive, so accuracy is very important in those material.
5. While we found that Neural Network is perform worst, still, it might wort to experiment with more advanced deep learning methods such as LSTM Keras in R programming.
6. For better user experience, business analytics team can further integrate with the Shiny applications with company database for better user experience so that they don't need to upload data everytime they use the apps. In addition, business analytics team can wrap the Shiny applications into desktop app using Electron package. By doing this, the app can be run from any computer without any installation (e.g: R Studio). The description of our developed shiny applications can be found on appendix 5.

APPENDIX

1. Negative Value Issue in the Dataset

We identified that there are many negative demand values and this created issues for forecasting. Normally, negative value means returns but this case may have several problems with it. Besides returns, manual recording is one of reasons resulting in this fault. Another reason is customers' mistake when ordering. Customers may correct the number after ordering, but it is not allowed for BASF to correct the original records in ERP, so BASF must update new negative records in database to make balance on numbers. Three situations above result in negative value appearing. This is one of data problems needed to be preprocessed before analyzing. However, we don't have any enough knowledge to treat this issues carefully. So, future project can considering this issue to be addressed in more appropriate manner.

To further dig in, we present several cases that might be better if we can address this issues in appropriately **Case 1** – Is it the case where the customer returns the product after one month? Is it possible? (return demand)

4/16/2013	BASF Polyu	PRO-PAR-CEL-BUM-RUB	1065	162	264	NA
4/18/2013	BASF Polyu	PRO-PAR-CEL-BUM-RUB	60	164	264	NA
4/18/2013	BASF Polyu	PRO-PAR-CEL-BUM-RUB	3870	21	264	NA
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5/30/2013	BASF Polyu	PRO-PAR-CEL-BUM-RUB	-3870	21	264	NA
5/31/2013	BASF Polyu	PRO-PAR-CEL-BUM-RUB	15000	30	264	NA

Product Return?

Case 2 – This is a case where you took a part of other customer order and give it to another customer? (channeling)

date	company	desc	demand	ship2	material2	capacity
12/2/2014	BASF Polyu	PRO-PAR-CEL-BUM-RUB	30	83	264	NA
12/5/2014	BASF Polyu	PRO-PAR-CEL-BUM-RUB	1260	77	264	NA
12/9/2014	BASF Polyu	PRO-PAR-CEL-BUM-RUB	9732	125	264	NA
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
12/23/2014	BASF Polyu	PRO-PAR-CEL-BUM-RUB	-1572	125	264	NA
12/23/2014	BASF Polyu	PRO-PAR-CEL-BUM-RUB	1572	150	264	NA

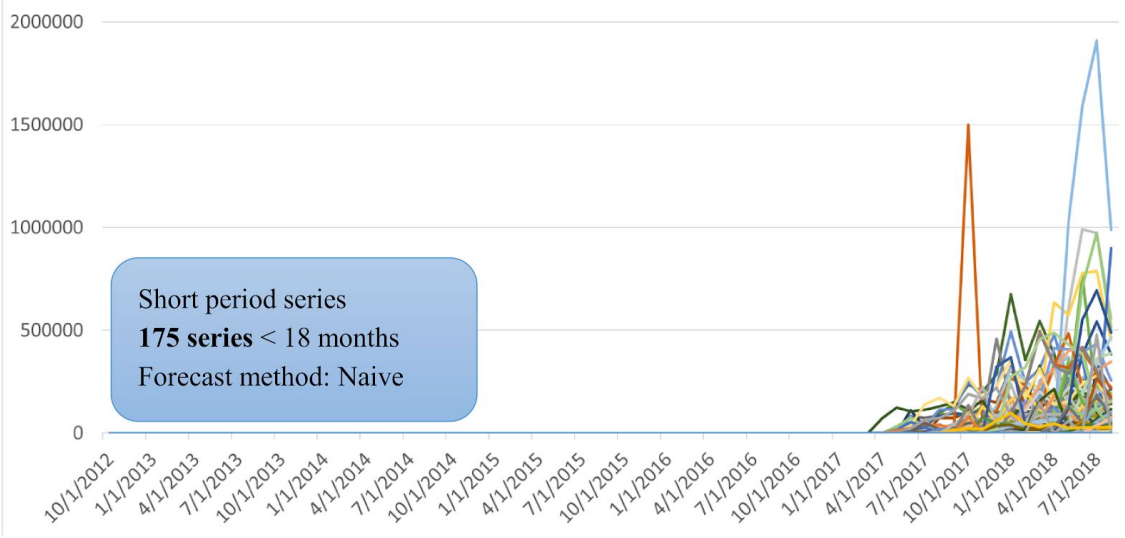
Case 3 - This look suspicious that customer '14' did a lot of negative demand for material 264, a couple months after the order.

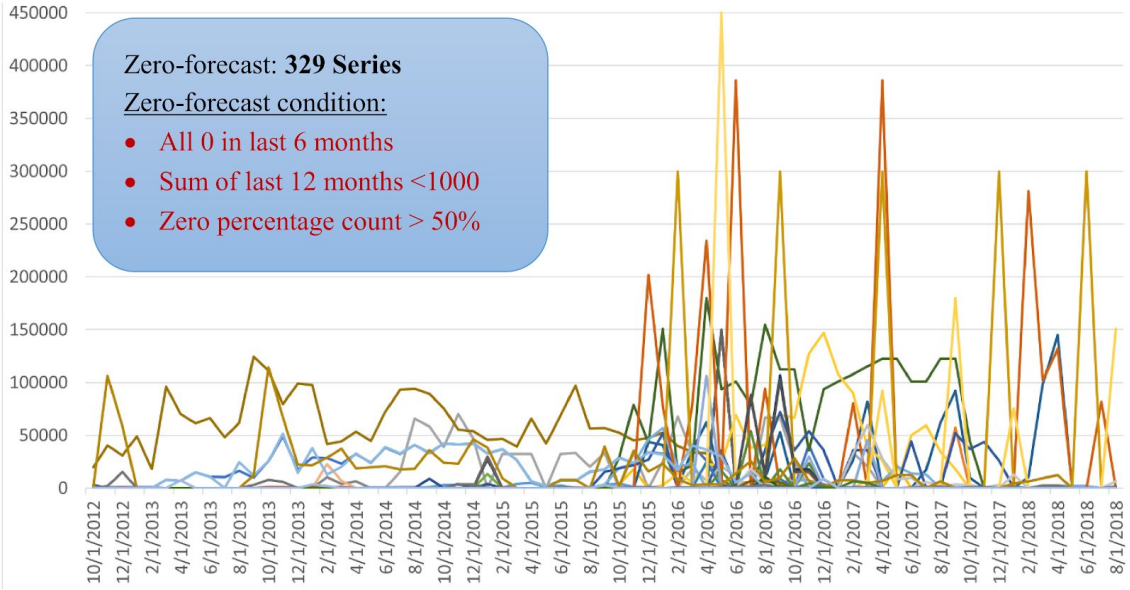
date	company	desc	demand	ship2	material2	capacity
7/19/13	BASF Polyure	PRO-PAR-CE	18000	14	264	NA
7/24/13	BASF Polyure	PRO-PAR-CE	6750	14	264	NA
12/10/14	BASF Polyure	PRO-PAR-CE	-1500	14	264	NA
12/11/14	BASF Polyure	PRO-PAR-CE	-2127	14	264	NA
12/17/14	BASF Polyure	PRO-PAR-CE	-1440	14	264	NA
12/23/14	BASF Polyure	PRO-PAR-CE	-726	14	264	NA
12/29/14	BASF Polyure	PRO-PAR-CE	-960	14	264	NA
1/12/15	BASF Polyure	PRO-PAR-CE	-1587	14	264	NA
1/15/15	BASF Polyure	PRO-PAR-CE	-6	14	264	NA
1/30/15	BASF Polyure	PRO-PAR-CE	-6318	14	264	NA
2/10/15	BASF Polyure	PRO-PAR-CE	-4320	14	264	NA
1/15/15	BASF Polyure	PRO-PAR-CE	24	14	264	NA
2/4/15	BASF Polyure	PRO-PAR-CE	6318	14	264	NA
9/7/15	BASF Polyure	PRO-PAR-CE	-840	14	264	NA
9/9/15	BASF Polyure	PRO-PAR-CE	-3336	14	264	NA
9/9/15	BASF Polyure	PRO-PAR-CE	-372	14	264	NA
10/9/15	BASF Polyure	PRO-PAR-CE	-120	14	264	NA
11/23/15	BASF Polyure	PRO-PAR-CE	-180	14	264	NA

2. Short series forecast and Zero forecast

There are all 826 series corresponding to 826 materials. Firstly, we sort out the series for less than 18 months. In case the series has too little data, there will not be enough data to divide into training and validation period. We choose the Naive forecast method for a total of 175 short series.

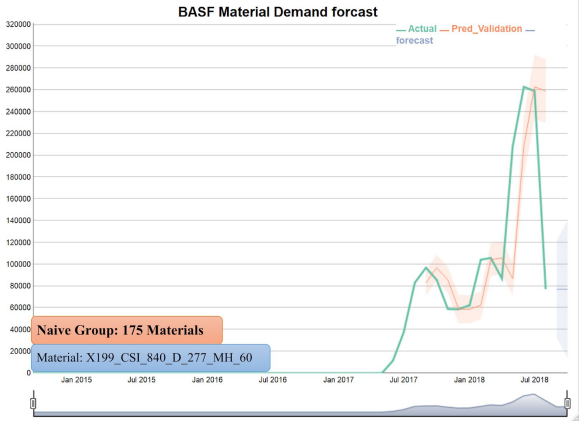
After plotting and checking the remain series, we found that there are many intermittent time series, in which data only appears for several months. In addition, there are many series almost no data in the last 12 months. Using our zero-forecast condition (All 0 in last 6 months; Sum of last 12 months <1000.; Zero percentage count > 50%), we found a total of 329 series. After removing 175 short series and 329 zero-forecast series. The rest includes 322 series. The next step is to find the optimal forecasting method for these 322 series.

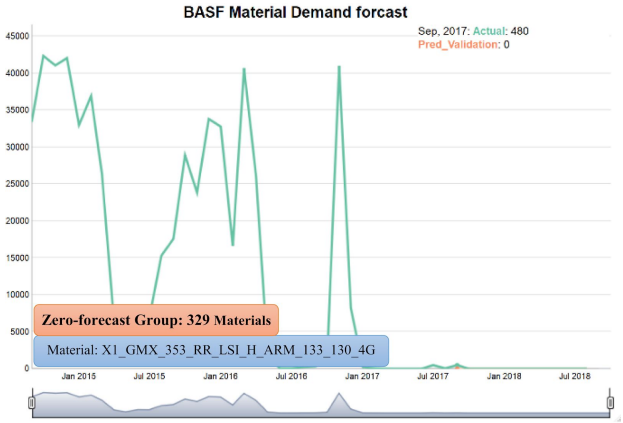


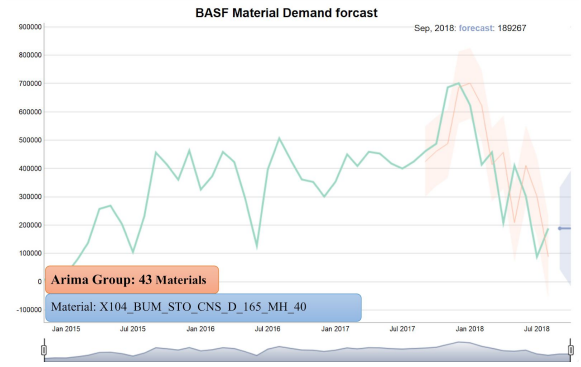


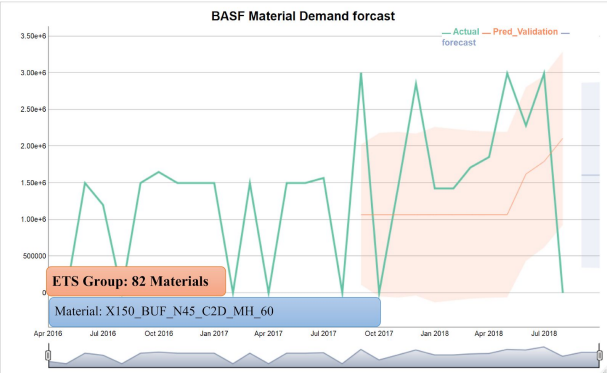
3. Time plot of series with future forecasts

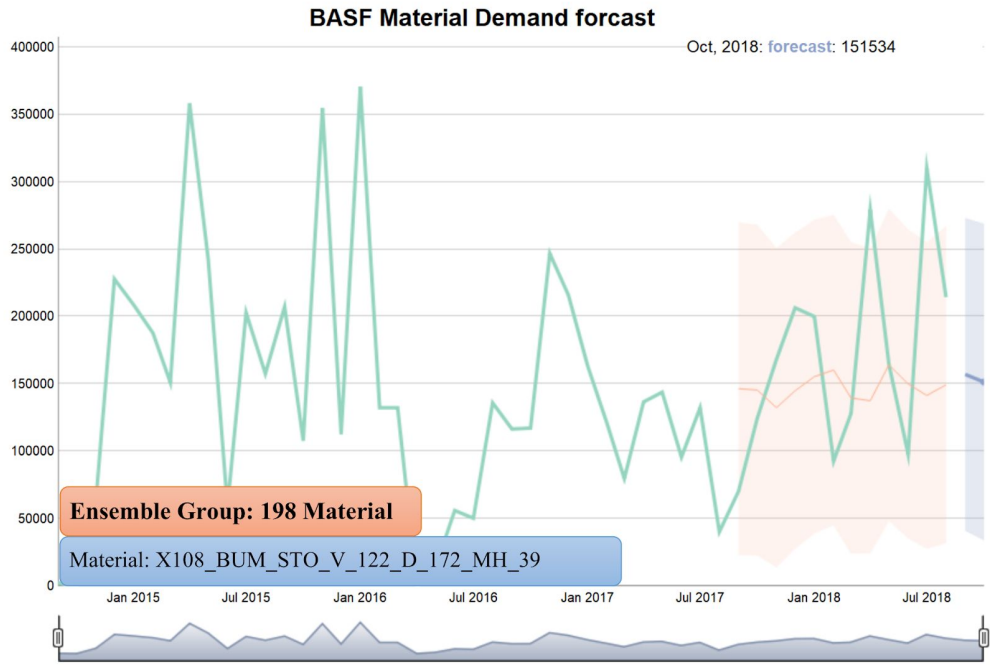
All 826 time series is separated into 5 group: Naïve, Zero- forecast, Arima, ETS and Ensemble which correspond with the 5 optimal forecasting method for each group.











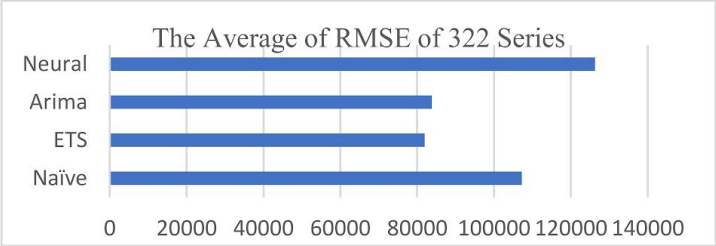
4. Analyze data and evaluate accuracy performance in detail

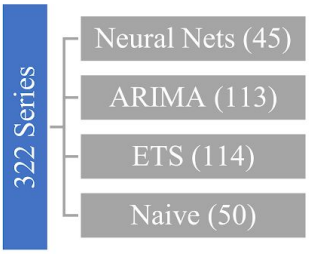
Question 1: ***Are there different optimal forecasting methods for each series?***

To answer question 1, we used various forecasting methods to make predictions and compare RMSE to find the best method for every series. The last 6 months is used as validation periods and we perform one months ahead roll-forward forecast. We used 1 months ahead forecast because the most recent month forecast has the greatest business significance. In average of 322 series, the ETS is the best method and Neural Nets is the worst.

However, if we compare RMSE in every series, we found that every series has the difference optimal forecast method. This suggests that although each series is highly volatile, there are still possible predictive methods for each series for better results with the Naive method. From the results of this preliminary analysis, we raised the question of whether it is possible to use past data to predict which method would be suitable for each series and then use this method to forecast the future value.

To answer this question, we build the "Auto Model Selection" method and check the accuracy performance of this method with traditional methods.





Question 2: ***Does the Auto Model Selection method give the best results?***

In order to check the accuracy "Auto Model Selection" method, We *separate* the last 12 months into 2 periods: (P1) *Select Method Validation* (6 months: 2017/09-2018-02) and (P2) *Test Method Validation* (6 months: 2018/03-2018/08).

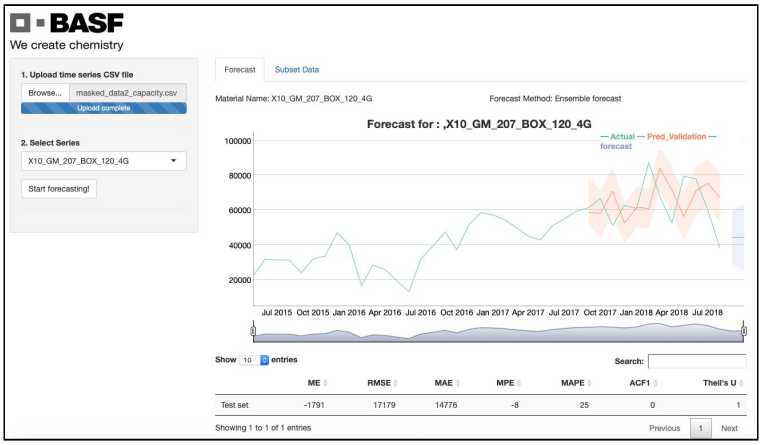
Step 1: Use P1 as validation period to forecast the best forecast method in P2

Step 2: Using P2 as a validation to compare the accuracy performance between "the best forecast method predicted" with other forecast methods.

We try to run two "Auto Model Selection" method: (1) Auto select (ETS, Arima, Neural Nets); (2) Auto select (ETS, Arima). Comparing based on the average RMSE, we find that the "Auto Select Method" **does not produce good results**. In addition, adding more methods to "Auto Model Selection" method, the accuracy performance is worse. This happens because more and more methods are used in "Auto Model Selection" method, the higher failure prediction rate of the optimal method forecasting for the next period. We also try with (3) Auto select (ETS, Arima, Neural Nets, Naive), the result is even worse. The accuracy performance of "Auto Model Selection" method comparing with other method is represented in the table below.

RMSE	Naïve	ETS	Arima	Neural	Ensemble (ETS-Ari)	Ensemble (ETS- Ari -Naïve)	Auto (Ets-Ari)	Auto (Ets-Ari-Neural)
All series	63309	52357	53092	69653	52008	53331	52742	54657
Exlude short series	56791	42894	43827	64839	42451	44131	43383	45813

5. Shiny Application Installation Guide

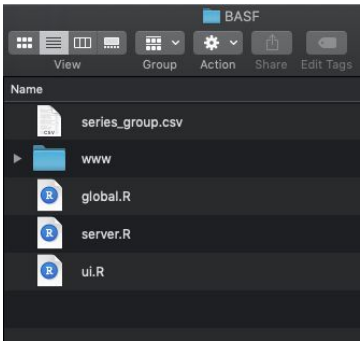


While provide the code for business analytics team to use our algorithm and put on their existing system, we also we developed an shiny application to support production executive to quickly see the forecast results of each materials. We describes the requirements, directories, and the workflow below.

1. To able to run the shiny apps, the targeted computer should have R studio installed in the computer and install required package listed below:

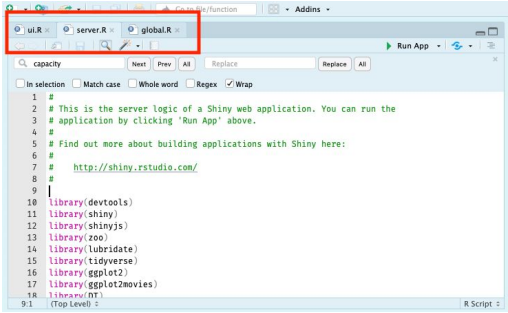
```
install.packages("devtools")
install.packages("shiny")
install.packages("shinyjs")
install.packages("zoo")
install.packages("lubridate")
install.packages("tidyverse")
install.packages("ggplot2")
install.packages("DT")
install.packages("forecast")
install.packages("plotly")
install.packages("dygraphs")
install.packages("shinycssloaders")
```

2. Copy shiny folder into desired directory, our shiny folder consist of several files:

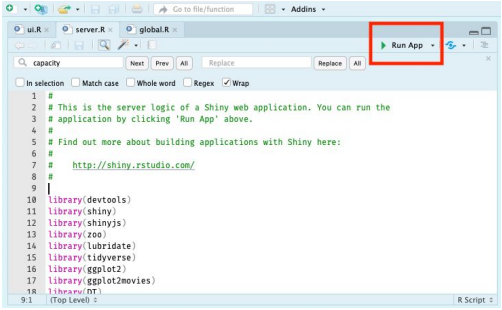


   a. global.R - this is where all of the forecast algorithm were stored
   b. server.R - this is where all of the system logic were stored
   c. ui.R - this is where all of the User Interface code were stored
   d. “www” folder - this is where basf logo were stored
   e. series_group.csv - this is preloaded files that contain grouping. BASF Team need to regularly updated the file using separated script that we developed to grouping the series.

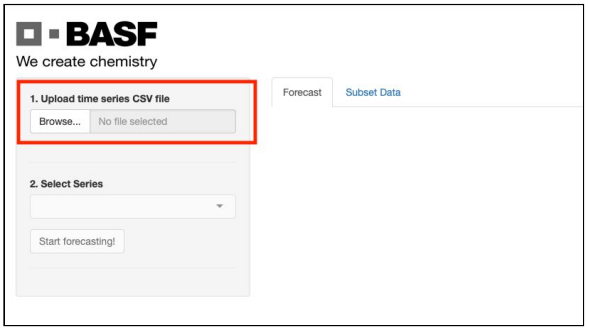
3. Open all of the files in the R studio



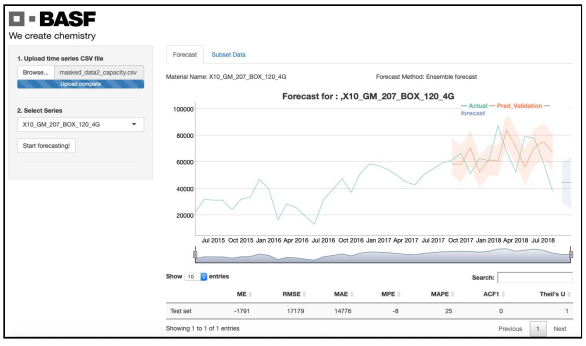
4. Run the applications



5. Load the files of “masked_data2_capacity” that BASF Business Analytics divison provided. The process may take couple of seconds as we simultaneously convert the wide format to long format format.



6. After the upload process is finished and success, you may choose which series you want to forecast and click “Start forecasting!”



5. Submit checklist and description

No	File name	Description
1	masked_data2_capacity.csv	The raw daily transaction data
2	BASF_series.csv	The time series data after “Data preparation” step in part 3 of this report.
3	Data_part_4.2_figure5.xlsx	Data and graph for part 4.2, question 1 in this report.
4	Data_part_4.2_figure6.xlsx	Data and graph for part 4.2, question 2 in this report.
5	Data_part_4.2_figure7.xlsx	Data and graph for part 4.2, question 3 in this report.
6	Data_part_4.3_figure8.xlsx	Data and graph for part 4.3 in this report.
7	series_group.csv	Series in 5 group (Naive, Zero-forecast, ETS, Arima and Ensemble).
8	BASF_accuracy peformance benchmark.R	R code for running the last 12 month validation with 2 months ahead roll-forward forecast and comparing RMSE of each group with Naive benchmark.
9	BASF_Shiny_app_demo.mp4	Demo Shiny forecasting application
10	BASF_Shiny_Application	Shiny forecasting application source code, which is described in appendix 5.