Demand Forecasting for Materials to Improve Production Capability Planning in BASF

Team 6
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About BASF

BASF is 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. Our broad portfolio ranges from chemicals, plastics, performance products and crop protection products to oil and gas.

**Business & Forecasting Goal**

**Business Goal**

**Problem**
- Poor forecasting accuracy challenge demand planning and performance in inventory and delivery

**Benefits**
- Lowers logistic costs
- Maximises asset efficiency
- Guarantees the desired service level

**Forecast Goal**

**Challenge**
- No seasonality
- Intermittent time series

**Implication**
- Over-forecast: Resource-wasted
- Under-forecast: Late delivery

**Stakeholder**
- Production Executive
- Client Business Analytics Team
- Student team

**Business Analytics Team**

**Student team**

**Optimization on Production Capability Planning**

**Forecast the demand of each material for 2-months ahead**
**Source**: BASF Business Analytic Division  
**Time Period**: 2012/10/10 - 2018/08/31  
**Amount of row**: 108,324 daily demands from 826 materials  
**Field Descriptions**:

<table>
<thead>
<tr>
<th>Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td>daily transactions</td>
</tr>
<tr>
<td>company</td>
<td>BASF division</td>
</tr>
<tr>
<td>desc</td>
<td>description of material</td>
</tr>
<tr>
<td>demand</td>
<td>demand of material</td>
</tr>
<tr>
<td>ship2</td>
<td>customer code</td>
</tr>
<tr>
<td>material2</td>
<td>material masked code</td>
</tr>
<tr>
<td>capacity</td>
<td>max production</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Date</th>
<th>Company</th>
<th>Desc</th>
<th>Demand</th>
<th>ship2</th>
<th>Material2</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/19/2013</td>
<td>BASF Polyurethane Sp</td>
<td>BUM-STO-1J0-512-131-SK-080-MHK-40</td>
<td>30240</td>
<td>79</td>
<td>332</td>
<td>784451.47</td>
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</tbody>
</table>
Forecasting Process

- Business & Forecasting Goal
- Tableau Exploration
  Identify 1425 of “-” demand
- Remove Negative Demand
- Monthly aggregation
- Graph exploration in R

Define goal

Get & explore data

Preprocess & Analysis

Apply forecasting method

Evaluation & Choosing Method

Implementation

- RMSE in validation period
- Graph Visualization
- R Shiny Desktop apps

- Naive
- Arima
- Exponential smooth (ETS)
- Neural Network (NN)
- Auto Model Selection
  ○ ETS / ARIMA
  ○ ETS / ARIMA / NN
- Ensemble
Forecasting Methods

- Roll-forward
  - Training
  - Validation
  - Forecast

- Short period series (175)
- Forecast Zero (329)
- Yes
  - Material Series (826)

- No
- Roll-forward Forecast Zero (329)

- Automatic Model Selection
- Arima / ETS
- Arima / ETS / NN
- Ensemble (ETS + ARIMA)

Compare RMSE
Validation Period: 2018 / 03 - 2018 / 08

ETS (114)
ARIMA (113)
Neural Nets (45)
Naive (50)

(322)
(272)
Forecast Evaluations

- High RMSE
- Short series issues
- Worst method: Neural Network
- Best method: Ensemble
- Auto Model selection: No improvement

Chosen Forecast Methods

- Naive
- Zero forecast
- Ensemble

Auto model selection Validation 2017/09- 2018/02
Method Validation 2018/03- 2018/08
Forecast Problem

**Zero forecast problem**

Materials: 30_SHE_500_X_250_X_3.6_MM_MH_45

Best Model: Naive

Materials: 600_BUM_STO_V_AS2_015_D_169_MHK_50

Best Model: ETS

Materials: 150_BUF_N45_C2D_MH_60

Best Model: ETS

Large fluctuation

Materials: 230_JB_5QD_412_303_D_300_MH_50

Short period series

185 series < 18 months
Implementation & Maintenance

Business Analytics Team in BASF responsible to:

○ Distribute the shiny applications to Productions Executive in Executable Desktop Applications.

○ Regularly send them the newest data (daily / weekly).

Recommendations:
BA Team also can integrate the Shiny Applications with company database for better user experience, so the apps always consume latest data.
Limitations:

1. We removed negative demand without looking at its context
2. Many time series have very short period, large fluctuation, hard to predict.

Recommendations

1. Negative demand should not be carelessly removed
2. Test the forecast model in different products categories
3. Use ensemble, don’t rely on automatic model selection methods
4. Categorization of the material (e.g. ABC-XYZ) might provide more insight
5. Including forecast price in the calculation of forecast error might provide better insight
6. Experiment with more advanced deep learning methods such as LSTM Keras in R
7. Direct integration Shiny Applications with company database for better user experience