How to improve your Demand Planning Process with SAP Integrated Business Planning for demand

Tod Stenger and Rainer Moritz, SAP
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Introduction

Key Demand Planning Functionality

Current Coronavirus Use Case

Q&A
Plan and Respond with
SAP’s Integrated Business Planning Solution

Supply Chain Control Tower
Exception Handling and Business Network Collaboration

Sales & Operations
Strategic and Tactical Decision Processes

Demand
Statistical Forecasting, Consensus Planning & Demand Sensing

Inventory
Multi-Stage Inventory Optimization & DDMRP

Response & Supply
Allocations & Deployment Planning, Order Rescheduling
Unconstrained & Constrained Supply Planning

SAP HANA
Key Demand Planning Functionality
Full Value – A Streamlined Approach to Demand Planning
Cluster and Organize Your Demand Planning Process

Segmentation
Quarterly/Yearly

Time Series Analysis
Quarterly

Consensus Demand Planning

Statistical Forecasting
Weekly/Monthly

Management by Exception*
Daily/Weekly

Manual Input by Planners

Forecast Accuracy Calculation
Monthly

Monitoring & Controlling of the Planning Process*

*Additional licensing may apply
Full Value – A Streamlined Approach to Demand Planning
Cluster and Organize Your Demand Planning Process

Monitoring & Controlling of the Planning Process*

- Process Step 1
- Process Step 2
- ...
- Process Step n

Consensus Demand Planning

- Statistical Forecasting
- Management by Exception*
- Manual Input by Planners

Time Series Analysis

- Quarterly

Segmentation

- Quarterly/Yearly

Forecast Accuracy Calculation

- Monthly

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### Demand Segmentation

**Configure & Calculate Your Segments**

<table>
<thead>
<tr>
<th>PRODUCT IMPORTANCE / PROFITABILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PRODUCT VOLATILITY / FORECASTIBILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
</tr>
</tbody>
</table>

#### Define ABC and/or XYZ calculation rules
Example: Based on Revenue or QTYs?

#### Run segmentation jobs regularly
e.g. monthly or quarterly

#### Define planning strategies based on segmentation results
Full Value – A Streamlined Approach to Demand Planning
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Time Series Analysis

Example

Automated analysis of historical sales data via statistical tests

Demand pattern identified by the analysis

Resulting Demand properties to be stored as attribute values

- Constant
- Seasonal
- Sporadic
- Trend
Full Value – A Streamlined Approach to Demand Planning
Cluster and Organize Your Demand Planning Process

Monitoring & Controlling of the Planning Process*
- Process Step 1
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Consensus Demand Planning
- Statistical Forecasting Weekly/Monthly
- Management by Exception* Daily/Weekly
- Manual Input by Planners Daily/Weekly
- Forecast Accuracy Calculation Monthly

Segmentation
- Quarterly/Yearly

Time Series Analysis
- Quarterly

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Full Value – A Streamlined Approach to Demand Planning

Cluster and Organize Your Demand Planning Process

Monitoring & Controlling of the Planning Process*

Process Step 1 ➔ Process Step 2 ➔ ... ➔ Process Step n

Consensus Demand Planning

Segmentation

Time Series Analysis

Statistical Forecasting

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Monthly

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Data Cleansing
Create Baseline Sales History as Foundation for a Good Forecast

Cleansed Data ➔ Reliable Data ➔ Better Forecasting Results

Substitute Missing Values
Outlier Correction
Promotion Sales Lift Elimination

Automated Data Cleansing
Define „pre-processing algorithms“ that automatically cleanse the data before the actual forecasting run

Manual Data Cleansing
Via Microsoft Excel, e.g. by calculating standard variations. The data can then be changed directly in the planning view

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Forecasting Algorithms

<table>
<thead>
<tr>
<th>Product</th>
<th>Common Demand Patterns</th>
<th>Demand Properties</th>
<th>Algorithms Used</th>
<th>Forecast Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td></td>
<td>Adaptive Response Rate Single Exponential Smoothing</td>
<td>78%</td>
</tr>
<tr>
<td></td>
<td>Seasonal</td>
<td></td>
<td>Automated Exponential Smoothing</td>
<td>80%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Auto-ARIMA/SARIMA</td>
<td>78%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Brown Exponential Smoothing</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Croston Method</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Double Exponential Smoothing</td>
<td>70%</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Multiple Linear Regression</td>
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<td></td>
<td></td>
<td></td>
<td>Simple Average</td>
<td>70%</td>
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<td></td>
<td></td>
<td>Simple Moving Average</td>
<td>65%</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Single Exponential Smoothing</td>
<td>85%</td>
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<td></td>
<td></td>
<td></td>
<td>Triple Exponential Smoothing</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Weighted Average</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Weighted Moving Average</td>
<td>75%</td>
</tr>
</tbody>
</table>

Time Series Analysis identifies which demand pattern fits for which product. Only algorithms which fit the identified demand pattern are considered by system. Best Fit selects the algorithm with the best accuracy based on Model Fit Error.
Statistical Forecasting Algorithms

Data Cleansing
- Outlier Correction
- Substitute Missing Values
- Promotion Sales Lift Elimination

Constant Models
- Automated Exponential Smoothing
- Single Exponential Smoothing
- Adaptive-Response-Rate Single Exponential Smoothing
- Simple Moving Average
- Simple Average
- Weighted Moving Average
- Weighted Average

Trend Models
- Automated Exponential Smoothing
- Double Exponential Smoothing
- Brown's Linear Exponential Smoothing
- Auto-ARIMA

Seasonal Models
- Automated Exponential Smoothing
- Triple Exponential Smoothing
- Auto-SARIMA
- Seasonal Linear Regression

Sporadic Demand Models
- Croston's Method

Regression Models
- Multiple Linear Regression
- Seasonal Linear Regression
- Auto-ARIMAX/Auto-SARIMAX
- Demand Sensing

Machine Learning Models
- Gradient Boosting
- Demand Sensing

Naïve Models
- Copy Past Periods

This is the current state of planning and may be changed by SAP at any time.
Statistical Forecasting Algorithms

**Data Cleansing**
- Outlier Correction
- Substitute Missing Values
- Promotion Sales Lift Elimination

**Constant Models**
- Automated Exponential Smoothing
- Single Exponential Smoothing
- Adaptive-Response-Rate Single Exponential Smoothing
- Simple Moving Average
- Simple Average
- Weighted Moving Average
- Weighted Average

**Trend Models**
- Automated Exponential Smoothing
- Double Exponential Smoothing
- Brown’s Linear Exponential Smoothing
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**Sporadic Demand Models**
- Croston’s Method

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**Machine Learning Models**
- Gradient Boosting
- Demand Sensing

**Naïve Models**
- Copy Past Periods

Available with IBP for sales and operations license

This is the current state of planning and may be changed by SAP at any time.
Demand Sensing – Next Level of Forecasting
Enhance and disaggregate Forecast based on short term Demand Signals

“Internal” Demand Signals like Deliveries, Sales Orders, Promotions and Open Orders

“External” Demand Signals like PoS or Weather* data

Demand Sensing
Time Horizon: 4-8 Weeks
Granularity: Days

Consensus Demand Plan

Short Term Forecast

Drive operational supply planning processes:
- Deployment
- Transportation planning
- Production and packaging sequences
- Purchasing Decision
- Inventory Optimization

* Future Direction
A robust predictive model is the one that has low training error and low test error.
Error Measures / Forecast Error KPIs
IBP for Demand

Post-Processing steps in IBP calculate various standard error measures. These define the difference (absolute, percent) from the historic values towards the ex-post forecast.

In IBP for Demand, we calculate:
- Mean Percentage Error (MPE)
- Mean Absolute Percentage Error (MAPE)
- Mean Square Error (MSE)
- Root of the Mean Square Error (RMSE)
- Mean Absolute Deviation (MAD)
- Error Total (ET)
- Mean Absolute Scaled Error (MASE)
- Weighted Mean Absolute Percentage Error (WMAPE)
Managing Product Lifecycle

Key Functionality

- Assign dates for phase-in and phase-out periods, including launch dimension (if used)

- Assign like products to use for history

- Assign ramp-up curve to shape forecast during phase-in period

- Assign ramp-down curve during phase-out period
Manage Global Product Launch

Example

Phase-In: July 2018
Phase-Out: April 2022

Phase-In: September 2018
Phase-Out: July 2022

Phase-In: September 2018
Phase-Out: July 2023

Phase-In: July 2018
Phase-Out: April 2025

Phase-In: December 2018
Phase-Out: May 2026
Manage Product LifeCycle App
Full Value – A Streamlined Approach to Demand Planning
Cluster and Organize Your Demand Planning Process

Consensus Demand Planning

Monitoring & Controlling of the Planning Process*

- Process Step 1
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Segmentation
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Daily/Weekly

Forecast Accuracy Calculation
Monthly

Manual Input by Planners

*Additional licensing may apply
Manual Input & Refinement by Planners, Example

Refine an Automated Process

Example:

Statistical Forecast

Manual Sales Input

Manual Marketing Input

Manual Demand Planner Input

Final Consensus Demand Plan
Full Value – A Streamlined Approach to Demand Planning
Cluster and Organize Your Demand Planning Process

Monitoring & Controlling of the Planning Process*

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Consensus Demand Planning
- Statistical Forecasting
  - Weekly/Monthly
- Management by Exception*
  - Daily/Weekly
- Manual Input by Planners

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Forecast Accuracy Calculation
- Monthly

*Additional licensing may apply
Forecast Accuracy Calculation
Measure the Quality of the Forecasting Process

What it Does:

- **Accuracy Analysis**: Compares the different forecasts to the actual historical sales data.
- **Bias Analysis**: Compares forecast tendencies to historic sales trend.
- **Value Add Analysis**: Measures quality of different forecasting steps.

What it Means:

- Identify areas with planning issues
- Identify trends over time
- Identify areas suitable for automation

Short Term Improvements

Long Term Improvements
Forecast Accuracy & Bias: Example Analytics

Statistical vs. Demand Plan Forecast Accuracy & Bias (Lag 3)

Demand Planning Accuracy (%) Plan vs. Target
Forecast Accuracy Value Add: Example Analytics

A Segment: Forecast Value Add by XYZ (last 3 Months, Lag 1)

Forecast Value Add by Demand Pattern (last 3 Months, Lag 1)
Forecast Accuracy Calculation: Bias Analysis

Example of Same Accuracy, Different Bias

Accuracy: 70%

Negative Bias = Under-forecasting

Unbiased
Forecast Accuracy Calculation: Value Add

Example

**Statistical Forecast**
Accuracy: 70%

**Sales Input**
- Accuracy Change: ∆ +5%

**Sales Input**
- Accuracy Change: ∆ -5%

**Sales Input**
- Accuracy Change: ∆ +0%

**Marketing Input**
- Accuracy Change: ∆ -6%

**Demand Planner Input**
- Accuracy Change: ∆ +0%

**FINAL CONSENSUS DEMAND PLAN**
Cluster and Organize Your Demand Planning Process

Monitoring & Controlling of the Planning Process*

Segmentation

Time Series Analysis

Consensus Demand Planning

Statistical Forecasting

Management by Exception*

Forecast Accuracy Calculation

*Additional licensing may apply
Exception Handling & Case Management

- Real-time alerting on critical situations
- Understand the root causes
- Drive collaborative actions
- What-if simulation capabilities
**Consensus Demand Planning Process**

**Recap**

**Input**
- Derived from ERP Backend System
- Sales Orders
- Shipments

**Data Cleansing of Sales History**
- Substitution of missing values
- Correction of Outliers
- Elimination of Promotion Sales

**Manual Input from:**
- Sales Department
- Marketing Department
- Demand Planners

**Automated Cleansing based on algorithms**
- Manual Cleansing in MS Excel Planning View

**Different forecasting algorithms are used to accurately predict future demand based on historic data**

**Output**

**Consensus Unconstrained Demand Plan**
- Measure Forecast Accuracy & Bias at end of Forecasted Period

**Statistical Forecasting**
- Combine algorithms in one forecast model
- System computes the „best fit“ per planning object based on the best forecast error

**E.g. additional Sales Opportunities, Realization Probabilities, Price Discounts, Predicted Sales Spikes**

**Sales History**
Current Coronavirus Use Case
How to handle Events like COVID-19 in IBP Forecasting
Problem and Solution Ideas

Purpose of this document:

- Explain the issues of COVID-19 for forecasting
- Provide some ideas how the problem could be tackled within IBP

Customer specific investigations and tests are required
Examples are simplified to illustrate the logic
Impact of COVID-19 on Forecasting
Impact on Sales Quantity

Depending on the product and industry, COVID-19 can have huge impact on sales.

Illustration of sales drop (simplified):
Impact of COVID-19 on Forecasting
Impact during and after the Pandemic

Two main phases exist during which COVID-19 causes issues in forecasting:

**Phase 1: COVID-19 impact on sales is “active”**
- Sales do not follow any pattern of the past
- Huge increase (e.g. noodles) or drop (e.g. cars) in sales
- Statistical methods used so far are not able to handle the situation properly/at all

**Issue:** How to create an acceptable forecast for the periods with ongoing COVID-19 impact?

**Phase 2: No/small COVID-19 impact on sales anymore**
- Sales are somehow back to “normal”
- Sales history of the previous periods is “messed up”
- “Messed up” sales history may impact forecast results for years if not treated properly

**Issue:** How to properly handle the “messed up” sales history?
Impact of COVID-19 on Forecasting
Impact during and after the Pandemic

Two main phases exist during which COVID-19 causes issues in forecasting:

![Sales Qty: significant drop + catch-up](image)

Phase 1
Phase 2

How to create an acceptable forecast for the periods with ongoing COVID-19 impact?
Impact of COVID-19 on Forecasting
Impact during and after the Pandemic

Two main phases exist during which COVID-19 causes issues in forecasting:

Phase 1 can further be split into:
• Phase 1a: Down (Up) turn phase
• Phase 1b: Recovery phase
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

1. Manual forecasting ("interactive"):  
   - Planners adjust forecast manually by estimating the demand drop/uplift by e.g. product group and country  
   - Regular manual updates according to new insights on COVID-19 impact

2. Using statistical forecasting methods ("Batch job"):  
   a. Classical time series forecasting methods:  
      Use only/mainly the latest sales history and forecasting methods which work with such data (like Simple Moving Average or the difference available flavors of Exponential Smoothing algorithms)  
   b. Use advanced forecasting algorithms which can react on the changes more easily:  
      MLR or (S)ARIMAX considering change points (planned with IBP 2005)  
   c. Use advanced forecasting algorithms which can use COVID-19 specific information:  
      MLR, (S)ARIMAX or Gradient Boosting using a key figure as kind of indicator for COVID-19
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with on going COVID-19 impact

- Some forecasting examples based on this sales pattern:
  - Pretty stable sales around 1000 pieces
  - COVID-19 causing sales drop starting in Oct 19 (assumption for this example only)
  - Current period: April 2020

=> Examples for forecasting during phase 1a
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with on going COVID-19 impact

Simple Moving Average using past 12 sales periods:

Using short sales history horizon may work during this phase. But it’s not a good solution during the “recovery” phase.

Simple Moving Average using past 4 sales periods:
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

**Single Exponential Smoothing** using past 24 sales periods and high alpha coefficient of 0.5:

Due to parameter optimization, a high alpha coefficient is used automatically.

**Automated Exponential Smoothing (AES)** using past 24 sales periods:

High alpha coefficient means high weight of the latest historical periods.
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

MLR or (S)ARIMAX using change point information:
- Change point detection is available since IBP 1911
- Structural changes in sales pattern can be identified

Change points detected in our example

<table>
<thead>
<tr>
<th>Planning ID</th>
<th>Customer Country</th>
<th>Number of Change Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>ConsumersChoice Mobile Phones</td>
<td>Germany</td>
<td>1</td>
</tr>
</tbody>
</table>
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

MLR using past 24 sales periods **AND change point** information (planned for IBP 2005):

![Graph showing MLR with change point information](image1)

MLR using past 24 sales periods **but NO change point** information:

![Graph showing MLR without change point information](image2)
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

**SARIMAX** using past 24 sales periods **AND change point** information (planned for IBP 2005):

**SARIMAX** using past 24 sales periods **but NO change point** information:
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

Gradient Boosting (GB) using past 24 sales periods and “COVID-19 Indicator” key figure:

COVID-19 Indicator:
- New Key Figure
- Maintained on higher level, e.g. country, with values 0 or 1
- Additional input to GB

COVID-19 Indicator:
- New Key Figure
- Maintained on higher level, e.g. country, with values between 0 and 1
- Additional input to GB
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

- Some forecasting examples based on this sales pattern:
  - Pretty stable sales around 1000 pieces
  - COVID-19 causing sales drop starting in Aug 19 (assumption for this example only)
  - Current period: April 2020

=> Examples for forecasting during phase 1b (“Recovery”)
Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

Simple Moving Average using past 4 sales periods:

Automated Exponential Smoothing (AES) using past 24 sales periods:

OK during phase 1a but not for phase 1b during “recovery”.

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Phase 1: Impact of COVID-19 on Forecasting
How to create an acceptable forecast for the periods with ongoing COVID-19 impact

MLR using past 24 sales periods **AND change point** information (planned for IBP 2005):

Not good in this concrete example as only one change point was detected.

Using change points works much better when forecasting in weekly time buckets as identification of change point works better in weekly than monthly buckets.

=> MLR and (S)ARIMAX using change points is a valid option when forecasting in weekly granularity.
Phase 1: Impact of COVID-19 on Forecasting

How to create an acceptable forecast for the periods with ongoing COVID-19 impact

Gradient Boosting (GB) using past 24 sales periods and “COVID-19 Indicator” key figure:
Impact of COVID-19 on Forecasting
Impact during and after the Pandemic

Two main phases exist during which COVID-19 causes issues in forecasting:

![Graph showing Sales Qty: significant drop + catch-up from periods 1 to 24 with Phase 1 and Phase 2 indicated]

How to properly handle the “messed up” sales history?
Phase 2: Impact of COVID-19 on Forecasting

How to properly handle the “messed up” sales history

1. Use statistical forecasting as before BUT only use sales history up to start of COVID-19 crisis

2. Process to “clean” the sales history of phase 1
   - Clean the sales history via batch process for mass data

3. Manually “clean” the sales history

4. Use un-cleaned sales history AND advanced forecasting methods
   a. Automated Exponential Smoothing (or high alpha value for the other exp. smoothing algorithms)
   b. MLR + SARIMAX with change points
   c. MLR, SARIMAX, Gradient Boosting with COVID indicator key figure
Phase 2: Impact of COVID-19 on Forecasting

How to properly handle the “messed up” sales history

1. Use statistical forecasting as before BUT only use sales history up to start of COVID-19 crisis

In our example don’t use the sales history of last 6 months

Pros:
- Pretty easy to do as “only” forecast model offset need to be adapted

⇒ Possible interim forecasting solution when COVID-19 impact is over until new process is ready
⇒ But in general no recommended approach

Cons:
- Forecast model offset need to be changed with each new period
- No path to get back to normal forecasting
- Bad forecast expected for items with seasonality or trend

⇒ Possible interim forecasting solution when COVID-19 impact is over until new process is ready
⇒ But in general no recommended approach
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

2. Process to “clean” the sales history of phase 1

Use forecast as “cleaned” sales history:

- Key figure representing “Corrected Sales History” required
- Create forecast using proper historical and forecast horizon
- Forecast result is stored in key figure “Corrected Sales History”
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

2. Process to “clean” the sales history of phase 1

Forecast model setup (example):

“Proper” forecast algorithm should be used:
• Same algorithm as before
• Copy past periods
• …
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

2. Process to “clean” the sales history of phase 1

Result of forecast run: “Cleaned” Sales History for phase 1
• To be used as input for statistical forecasting during phase 2

Pros:
• Sales history cleaning can be done for mass data via job
• As soon as cleaning was done once, no additional effort required
• At the end of COVID-19 crisis, forecasting is done as before

Cons:
• Cleaning quality depend on forecast accuracy

=> Possible long term solution for some items, e.g. products of segment X + Y
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

3. Manually “clean” the sales history

- Planners correct and adjust sales history manually
- Can be done on aggregated level, e.g. product group and country

Pros:
- Quality of cleaning is under control of planners
- As soon as cleaning was done once, no additional effort required
- At the end of COVID-19 crisis, forecasting is done as before

Cons:
- Cleaning quality depend on planers knowhow and time invested

=> Possible long term solution for some items, e.g. products of segments A/Y and A/Z
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

4. Use un-cleaned sales history AND advanced forecasting methods

a. Automated Exponential Smoothing (or high alpha value for the other exp. smoothing algorithms)

**Automated Exponential Smoothing** (AES) using past 24 sales periods:

- **PROs:**
  - No need to clean the sales history
  - Algorithm adapts automatically – no need change the forecast model setup

- **CONs:**
  - Change of forecasting method required for several years
  - Not good for seasonal items as seasonality is “destroyed”

=> Possible long term solution for some items, e.g. products with regular sales and without seasonality
Phase 2: Impact of COVID-19 on Forecasting
How to properly handle the “messed up” sales history

4. Use un-cleaned sales history AND advanced forecasting methods

b. MLR + SARIMAX with change points

Not good in our example as “only” two change points are detected
But valid option when forecasting in weekly buckets

MLR using past 24 sales periods AND change point information (planned for IBP 2005):
4. Use un-cleaned sales history AND advanced forecasting methods

C. MLR, SARIMAX, Gradient Boosting with COVID indicator key figure

**Gradient Boosting** (GB) using past 24 sales periods and “COVID-19 Indicator” key figure:

**PROs:**
- No need to clean the sales history
- Algorithm adapts automatically – no need change the forecast model

**CONs:**
- Change of forecasting method required for several years
- COVID Indicator key figure need to be added and maintained
- Longer runtime of forecast jobs

=> Possible long term solution for some items, e.g. A products with regular sales
How to handle Events like COVID-19 in IBP Forecasting

Recap

Different options are available depending

- on the time: phase 1a, phase 1b, phase 2
- on the product: like segment (ABC/XYZ) or sales pattern (seasonal, sporadic,…)
- Automated Exponential Smoothing is automatically adapting and one option worth to look into
- COVID-19 Indicator key figure together with advanced forecasting method can provide good results and enables simulations possibilities
- Cleaning sales history makes sense as otherwise there are issues in forecasting for years
Questions?
Thank you.

Contact information:

**Tod Stenger**  
Solution Manager, Digital Supply Chain  
Tod.stenger@sap.com