

### Challenge

This test of the forecast accuracy of our product deepRetail is based on data from 17 companies in the German textile trade.

ERP-systems often only describe the **current status from the past to the present**, but **do not provide effective tools for managing the supply chain through forecasts**. This raises the question of how precisely artificial intelligence systems are able to predict sales numbers.

Due to the diverse assortment of goods per company, forecasts were created by product group and brand - in addition to comprehensive overall forecasts. Almost 500 models were created for the most diverse scenarios, with scenarios such as *Company A | Manufacturer B | Ladies blouses, company X | Brand Y | Men's jackets* etc.

Three tested forecast horizons:

- A shorter **1-month** forecasting period, which allows to **avoid potential out-of-stock** situations.
- A medium forecast period of **3 months**, which allows the **reduction of overstock**, e.g. by price control.
- A longer **9-month forecasting period**, which advises in **seasonal purchasing** and creating sound purchasing budgets.

Provided data:

30 GB of sales data from approximately **10 million transactions** over a **4-year period**, from **17 retailers** with **62 stores** - with a total turnover of € 250 million.

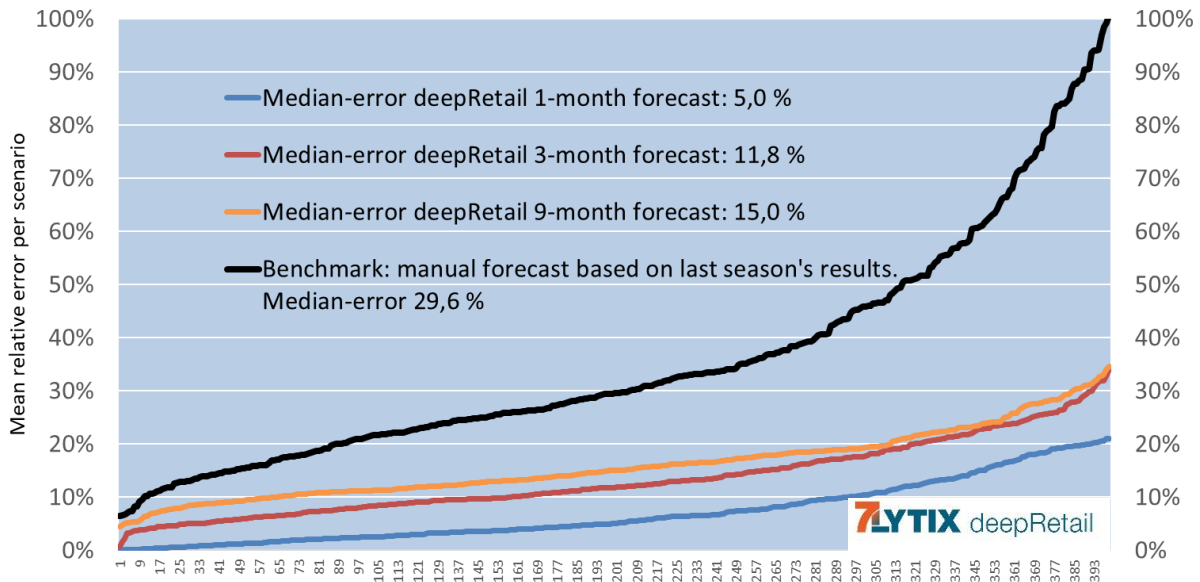
Overall, the data contained 500,000 different articles, 744 brands, and 730,000 loyalty cards.

### Result

The forecast accuracy of all scenarios was measured by comparing the actual values against predicted values. The lower the mean relative error between forecast and actual sales, the better the model.

Furthermore, for the 9-month forecast, the error which results from the frequent use of the previous year's results as the basis for a seasonal estimate was measured.

**Accuracy distribution of our forecasts is vastly better than the conventional benchmark**



400 time series models of different scenarios  
(Company / Brand / Product Category)

The models are sorted by performance, with the better performing / lower error models appearing toward the left side. For every scenario of *Company | Manufacturer | Product category*, three different forecast periods were created (1 month, 3 months and 9 months).

The longer the forecast period, the greater the forecast error. Examination of the forecasts with the worst results shows **two major sources of error: poor data quality and low data density due to low sales figures** of infrequently purchased products.

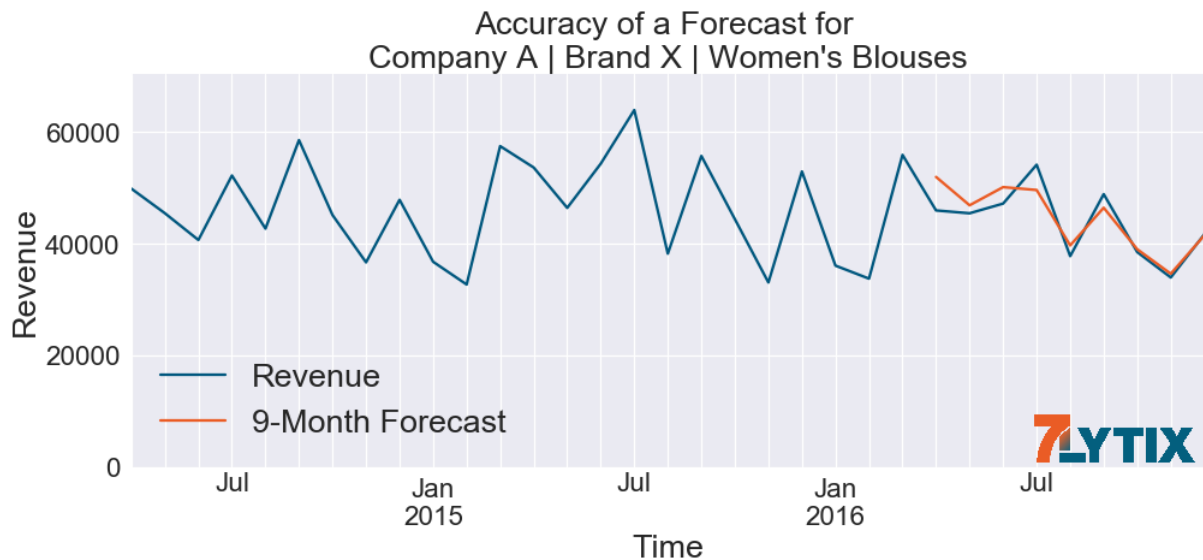
When compared against the actual sales values, around three quarters of the 1-month forecast models have below 10% mean relative error. Half of the 1-month forecast models have below 5% error.

Compared to using the previous year's results in manual calculations as the basis for a seasonal estimate, the error is halved by the use of deepRetail.

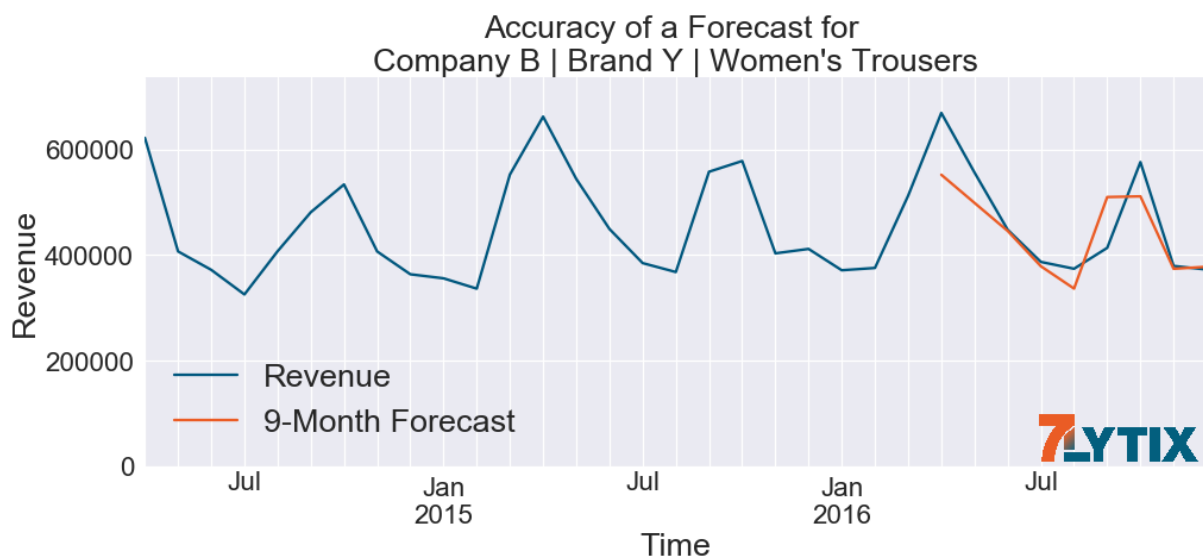
The short-term forecasting accuracy can further be increased by including weather data. The long-term accuracy can be improved by taking into account external influential factors (calendar information, major events, economic data, etc.).

### Example Scenarios

Women's blouses, forecast period 9 months: average forecast error 5%



Women's trousers, forecast period 9 months: average forecast error 8.5%



### Profitability of forecasts with deepRetail

According to our experience, the costs of deepRetail are 5-20% of the profit increase due to reduced sale discounts and reduction of out-of-stock situations.

### Technical details

The model calculations are run via the Microsoft Azure cloud. Only open source software (Python, neural networks, Deep Learning and machine learning libraries) is used. Data access is done through interfaces to the customer's ERP system or data warehouse.