The Time has Come – Application of Artificial Intelligence in Small- and Medium-Sized Enterprises

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Abstract. Artificial intelligence (AI) is not yet widely used in small- and medium-sized industrial enterprises (SME). The reasons for this are manifold and range from not understanding use cases, not enough trained employees, to too little data. This article presents a successful design-oriented case study at a medium-sized company, where the described reasons are present. In this study, future demand forecasts are generated based on historical demand data for products at a material number level using a gradient boosting machine (GBM). An improvement of 15% on the status quo (i.e. based on the root mean squared error) could be achieved with rather simple techniques. Hence, the motivation, the method, and the first results are presented. Concluding challenges, from which practical users should derive learning experiences and impulses for their own projects, are addressed.

Keywords: *artificial intelligence, demand forecasting, small- and medium-sized enterprises, supply chain management, case study*

1 Introduction

Not only large companies or digital pioneers can use AI successfully. Although these are usually diversified and have data science departments, positive developments in the last decade made an impact on the accessibility of AI [1].

The time has come for AI in SMEs. A democratization of AI is gradually taking place [1]. This is based on the strong development and publication of open-source software packages, such as scikit-learn [2], TensorFlow [3], and PyTorch [4], as well as auto machine learning (ML) packages like AutoGluon [5]. Furthermore, based on Moore's Law [6], a suitable computing power became affordable. Hence, existing IT can be used, easily be bought, or utilized on demand via cloud services, even if there are inhibitions regarding data security among some SMEs. [7].

Optimizing purchasing decisions and thus improving demand forecasting is a problem faced by many SMEs. Therefore, the first results of this case study are of interest to a broad spectrum, as they are transferable. It becomes clear that for initial successes, one should concentrate on a smaller sub-focus area. The first results are promising, as improvements in the 7-digit € range are already possible with the first pilot. Furthermore, concluding challenges are addressed from which practical users should derive learning experiences and impulses for their own projects.

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2 Improving Demand Forecasting with AI in an SME

This article presents a design-oriented study regarding an AI project. The project consists of a research group of a university and an SME. The objective is to develop a decision support for the purchasing employees regarding the quantity to be procured as well as the timing. The project has a duration of 1.5 years.

2.1 SME Description and Motivation

The company is a B2B distributor of technical products, such as bearings. It has about 250 employees, sales of over 50 million €, and over 140,000 products – on stock and on demand. A short delivery time is as important as minimizing the inventory costs and optimizing the cash flow. Thus, purchasing decisions are critical.

The status quo of demand forecasting: Purchasing decisions have mostly been based on historical data. In most cases, a moving average of the last twelve months is used, which can get subsequently adjusted by the employees based on their expertise.

Recent literature supports the argument that AI algorithms can be beneficial in purchasing [8]. Compared to a recent demand forecasting challenge (M4 [9]), with more than 61 forecasting models, the number of possible AI models may seem daunting for an SME at first glance. At the same time, research regarding the application of ML in SMEs identified cooperation with universities as a critical factor [10, 11].

2.2 Methodological Approach and Results

For the pilot about 8.500 products, accounting for almost 80% of the revenue, were selected. Their time series shows different patterns. They differ in recording length and in sales behavior (seasonality, trends, etc.). According to [12], demand can be classified as intermittent, lumpy, erratic, and smooth patterns.It can be assumed that a uniform forecast model for all items makes limited sense. Therefore, a univariate forecasting model was chosen, as there was also no availability of further causal data.

Depending on aggregation, evaluation metric, and classified demand pattern of time series, it is unclear which algorithm is the best [13]. In future, clustering, such as dynamic time-warping [14], Syntetos [12] categories, or domain experts may be helpful to create global unified models. However, as a first step we present that an improvement with a rather simple AI model could be achieved. We used a GBM variant, which reached second place in the recent M5 forecasting competition. The histogram-based gradient boosting implementation of scikit-learn [2] was implemented. Selected hyper-parameters were loss: least squares regression, learning_rate: 0.01, criterion: mse, max_features: auto, rest: default. As suggested by Bergmeir et al. [15], we evaluate the demand forecasts from the models on a rolling basis. Validation is based on a three-fold cross validation. The root mean square error (RMSE) served as the evaluation measure.

Table 1 shows the result of the GBM compared to the benchmark of the company. It is evident that the ML algorithm reduced the RMSE by roughly 15%.

According to an initial estimate, the company can reduce the tied-up capital in inventory by 6.1% (~ € 1.8 million), while maintaining the service level. It is expected that the improved inventory level will lead to higher sales in the long term.

Table 1. Comparison of the SME's status quo demand forecast with the GBM model

	Ø RMSE	Δ
Status quo	8,851.34	
GBM	7,466.58	-15.64 %

2.3 Challenges and Learnings from the Pilot

During the pilot phase, we faced repeated challenges and derived together with the SME learnings and impulses for practitioners:

Data

- Quality: Data was missing or incorrectly aggregated over the years, due to enterprise resource planning system changes. This data must be corrected before usage.
- Variety: Due to the high number of products, a focus on a limited selection of products was needed e.g., through an ABC analysis
- Causal data: Causal data influencing orders and purchases, were not available. It is planned to use sales data as well as to integrate marketing campaigns.

Organization

- Acceptance of the project: Employees were very skeptical at the beginning of the project regarding job cuts. It was crucial to make clear that the goal is not to cut jobs.
- Domain experts: Certain processes and time series did not seem to make sense at first glance, prediction was poorly. Here, clarification with domain experts is crucial.
- Processes: A workflow with the employees which enables integration in existing systems was helpful - no media breaks.

Models

- Pragmatism: Several simple as well as complex algorithms were tested. Interpretability is more important than predictive power. Feature importance was used to analyze the GBM. More complex neural networks are a black box. Being able to explain the employees what a model considered important for a decision increased the acceptance.
- Centricity: Improving data quality generates the biggest improvements. Complex algorithms and hyper-parameter optimizations should only take place thereafter.
- Evaluation: It is imperative that goals(-measurements) are defined at the beginning of the project. A status quo and an evaluation metric that fits the goals are crucial.

3 Conclusion and Future Work

The first results of the pilot are promising with an estimate of ~ € 1.8 million decrease in tied up capital. This study with an SME demonstrates that AI can already be applied advantageously with relatively simple tools. Highlights can be summarized as follows:

- Lightweight AI applications are possible for SMEs.
- SMEs benefit from cooperation with universities, which is supported by research.
- Data centricity - the focus should be on the data not the AI model.

Next step in the project is the improvement of the data base by integrating further causal data like marketing campaigns. We assume that the forecasts can also be improved through additional external data like industry indices. Ensembles, hybrid models but also more complex AI models, such as transformer neural networks, will be tested.

The time has come for SMEs to get started with AI.

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