

Aug 10th, 12:00 AM

## **Making the Newsvendor Smart – Order Quantity Optimization with ANNs for a Bakery Chain**

Franz Seubert

*Lehrstuhl für Betriebswirtschaftslehre und Wirtschaftsinformatik, franz.seubert@uni-wuerzburg.de*

Nikolai Stein

*Julius-Maximilians-University, nikolai.stein@uni-wuerzburg.de*

Fabian Taigel

*Lehrstuhl für Logistik und quantitative Methoden in der Betriebswirtschaftslehre, fabian.taigel@uni-wuerzburg.de*

Axel Winkelmann

*University of Würzburg, axel.winkelmann@uni-wuerzburg.de*

Follow this and additional works at: <https://aisel.aisnet.org/amcis2020>

---

Seubert, Franz; Stein, Nikolai; Taigel, Fabian; and Winkelmann, Axel, "Making the Newsvendor Smart – Order Quantity Optimization with ANNs for a Bakery Chain" (2020). *AMCIS 2020 Proceedings*. 37. [https://aisel.aisnet.org/amcis2020/data\\_science\\_analytics\\_for\\_decision\\_support/data\\_science\\_analytics\\_for\\_decision\\_support/37](https://aisel.aisnet.org/amcis2020/data_science_analytics_for_decision_support/data_science_analytics_for_decision_support/37)

This material is brought to you by the Americas Conference on Information Systems (AMCIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in AMCIS 2020 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

# **Making the Newsvendor Smart – Order Quantity Optimization with ANNs for a Bakery Chain**

*Completed Research*

**Franz Seubert**

University of Würzburg  
franz.seubert@uni-wuerzburg.de

**Fabian Taigel**

University of Würzburg  
fabian.taigel@uni-wuerzburg.de

**Nikolai Stein**

University of Würzburg  
nikolai.stein@uni-wuerzburg.de

**Axel Winkelmann**

University of Würzburg  
axel.winkelmann@uni-wuerzburg.de

## **Abstract**

Accurate demand forecasting is particularly crucial for products with short shelf life like bakery products. Over- and underestimation of customer demand affects not only profit margins of bakeries but is also responsible for 600,000 metric tons of food waste every year in Germany. To solve this problem, we develop an IT artifact based on artificial neural networks, which is automating the manual order process and capable of reducing costs as well as food waste. To test and evaluate our artifact, we cooperated with an SME bakery chain from Germany. The bakery chain runs 40 points of sale (POS) in southern Germany. After algorithm based reconstructing and cleaning of the censored sales data, we compare two different data-driven newsvendor approaches for this inventory problem. We show that both models are able to significantly improve the forecast quality (cost savings up to 30%) compared to human planners.

## **Keywords**

Inventory, Newsvendor, Retail, Machine Learning, Forecast, Perishable Goods, Unobservable Lost Sales

## **Introduction**

Bread and buns are some of the favorite groceries in Germany. These products are produced in over 12,000 bakeries nationwide. Most of them are small and medium-sized enterprises (SME) (Jaeger 2018). In Germany, 63% of the bakeries have an annual revenue of less than 500,000€ per year<sup>1</sup>. In 2015, approximately 4.5 Mio metric tons of baked goods were produced in Germany, of which bakeries disposed around 600,000 metric tons (13.3%) due to overstocking (Jaeger 2018). This food waste is due to the uncertainty about the real demand. The increasing deployment of information systems (IS) and, therefore, the availability of data is paving the way for data-driven decision-making, even in SMEs. In this study, we cooperate with a mid-sized German bakery chain to tackle this problem. Every day each store must order products that are delivered the next morning. Due to production time and logistics, reordering during the day is not possible. Most of the products have a shelf life of just one day. Therefore, the leftovers are wasted while stock-outs lead to lost sales and unsatisfied customers.

Based on this real-world problem, we derive our guiding research question:

---

<sup>1</sup> Zentralverband des deutschen Bäckerhandwerks 2019. Umsatzverteilung im Bäckerhandwerk in Deutschland nach Umsatzgrößenklassen im Jahr 2017. <http://www.baeckerhandwerk.de/baeckerhandwerk/zahlen-fakten/umsatzentwicklung-und-verteilung/>.

*How can we use censored sales data to improve inventory planning for an SME bakery chain?*

This paper intends to develop an IT artifact, which can support decision-makers in these kinds of newsvendor planning problems. Therefore, we combine sales, delivery, and return data from different information systems within the company. In total, we gather more than 5.5 Mio. data points. We develop a data pipeline for cleaning and reconstruction censored sales data to compare two different approaches to determine the optimal order quantity on real demand data. Ordering fast-moving perishable consumer goods is always challenging. One must balance product availability against leftovers and food waste. Therefore, our Artifact can be used for both objectives, cost minimization and waste prevention. Besides, the IS community demand forecasting of perishable goods is also an essential topic for society concerning sustainability (Sakoda et al. 2019)

The structure of the remaining paper is as follows: We give an overview of related planning problems and solution approaches in the related scientific work in the next section. Subsequently, we describe the problem in detail and outline our research methodology. Next, we describe the data collection and preparation process for our study. Leveraging the available data, two different planning approaches are developed and compared with the current inventory planning of the human decision-makers. Finally, we provide an outlook on future research opportunities.

## Related Work

Predicting future demand and deriving optimal inventory levels is a well-studied problem spanning multiple research fields. To determine optimal stock levels for perishable goods Edgeworth (1888) and Arrow et al. (1951) put forward the newsvendor model. While this model provides cost-optimal inventory policies for normally distributed data, it is not able to integrate forecasts into the planning procedure. However, business information systems allow companies to leverage an increasing amount of historical and real-time data enabling better forecasting that has to be considered during the planning (Mann et al. 2018). The scientific literature proposes two different approaches to tackle this single period problem (SPP).

On the one hand, a sequential approach (SEO) consisting of a forecasting and a subsequent optimization step can be used. Here, future demand is predicted using either statistical time series forecasts or machine learning algorithms. To this end, Liu et al. (2001) study demand forecasting for casual restaurants and implement an automatic outlier detection using an ARIMA model. Huber et al. (2017) focus on a similar problem setting in a bakery chain. They use an ARIMA model to estimate future demand based on point of sale (POS) data. Wang et al. (2018) use machine learning models such as Random Forests and Support Vector Machines to forecast the demand for fresh agricultural products taking weather data into account. Subsequently, safety buffers are added to the forecasts to determine inventory levels.

On the other hand, an integrated approach (JEO) can be used. Here, the forecasting and the inventory planning problem are solved jointly. Ban and Rudin (2019) use sample average approximation to determine optimal stock levels and show that their approach outperforms a SEO approach in a nurse staffing setting. Taigel and Meller (2018) compare the SEO and JEO concept in a fast-casual restaurant setting. They show that the JEO approach outperforms the respective SEO counterpart, especially in settings with high demand heteroscedasticity. Oroojlooyjadid et al. (2019) implement the newsvendor cost function as a loss function for an artificial neural network and show that the JEO approach can outperform SEO approaches in a numerical study. Huber et al. (2019) use bakery data to compare an SEO newsvendor model assuming a parametric demand distribution with a data-driven (JEO) approach leveraging ANNs.

As shown above, demand forecasting and inventory optimization for fresh perishable groceries is an important and active field of research, which has the potential to reduce operational costs as well as food waste. However, existing research in the field of operations research mainly focuses on the development of new planning policies. In contrast, research in the field of information systems focuses on the extraction and preprocessing of the data as well as the training of predictive models. To the best of our knowledge, a practical implementation of an information system for data-driven inventory planning that takes the shortcomings associated with real-world data, such as censored demand and outliers, into account has not been published in the IS literature yet.

## Problem description and research methodology

The goal of our research is to develop an IT artifact that supports inventory decision making. To illustrate the development and usage of the proposed artifact, we leverage a real-world dataset provided by an SME bakery chain in Germany. The company bakes all its products in a single production facility and sells them in 40 stores across the mid-south of Germany. The product range includes about 40 to 50 daily products. All products are baked every night in the production facility. To this end, the company has to solve two planning problems under uncertainty:

1. Every morning, at 6 AM the production planner has to decide how much of each product should be produced for the next day. However, the POS send their orders at 4.30 PM to wait for potential customer orders during the day. Therefore, production quantities are determined based on the planner's experience.
2. Every evening, the staff in the stores has to place the orders for the next day. They have to estimate customer demand for each product for the next day.

Currently, as in many SMEs, both planning problems are solved based on experience and without any software-based decision support. Therefore, the resulting order decision are made by staff members based on their experience and gut feeling. Hence, manual orders show a high volatility. The proposed IS artifact can support both tasks by forecasting demand and providing an integrated planning solution 24 hours ahead.

As our research aims at building an information system supporting the inventory planning of small and medium enterprises, we follow the Design Science Research (DSR) paradigm, which is particularly concerned with the development of useful artifacts (Baskerville et al. 2018). Such an artifact can either (i) extend existing solutions to new problems, (ii) invent new solutions for new problems, or (iii) develop new solutions for known problems (Gregor and Hevner 2013). As we want to enrich the known domain of inventory planning with an innovative information system, we consider our artifact as a new solution for a known problem. Gregor and Hevner (2013) refer to such artifacts as an improvement.

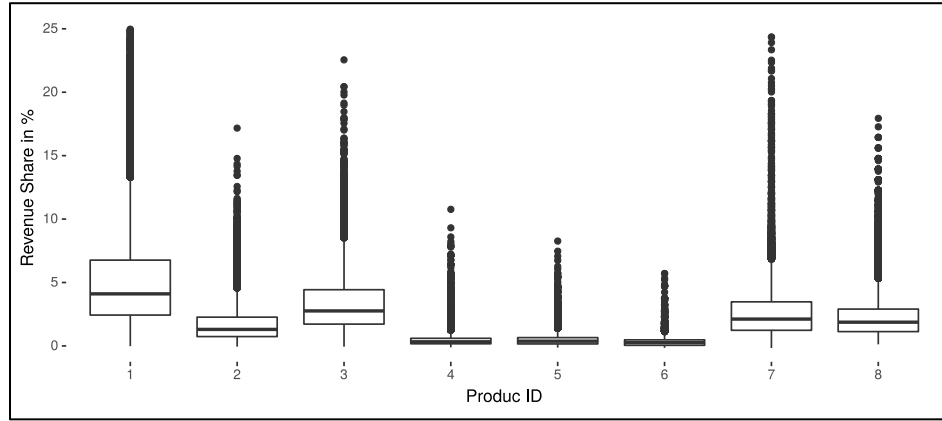
We follow the guidelines put forward by Hevner et al. (2004) to design the artifact and carry out our study.

- **Problem Relevance:** Apart from the obvious financial savings a company can obtain by ordering the “right” amount of goods, there are also improvements regarding sustainability and food waste reduction (Jaeger 2018; Sakoda et al. 2019). Furthermore, even on an organizational level, potential savings can be made due to the high reorder rate of perishable goods and lack of an appropriate implementation in business information systems (Huber et al. 2017).
- **Research Rigor:** We use state-of-the-art algorithms rooted in the information systems, machine learning, and operations research literature. The modules of the artifact are implemented in R and leverage the Keras API of TensorFlow.
- **Design as a Search Process:** Our artifact is based on different existing models and research articles (e.g. Huber et al. (2017), Huber et al. (2019), Taigel and Meller (2018), Ban and Rudin (2019). Furthermore, the designed artifact can serve as a base for practical implementation and further research.
- **Design as an Artifact:** We design an IT artifact with two different planning model implementations. Both are described in detail and implemented using R.
- **Design Evaluation:** We assess the artifact using real-world data by training and testing it with more than three years of sales data provided by a bakery chain.
- **Research Contribution:** Develop IS to plan optimal stock levels for perishable goods based on censored demand data and additional features.
- **Research Communication:** This research informs technical as well as managerial audiences and especially practitioners from SME. While the implementation and comparison of the models may primarily appeal to the audience with a more technical focus, the financial results address managers, and the insights of the real-world implementation are highly relevant for the practitioners.

## Data collection & Data preparation

We leverage several data sources to compose our final dataset. First, we extract sales transactions for eight different products for more than three years (January 2016 to April 2019) from the POS-system. For our approach, it is essential to have sales data on a single receipt level including a time stamp. The initial data export from the POS system was a 500 Mio line text file that first had to be formatted and imported to a database. We combine this data with delivery and return data from the production facility stored in an ERP-system. The resulting dataset consists of over 5.5 million data points.

As the quality of subsequent modeling efforts is constrained by the quality of the dataset, we start with data cleaning prior to any modeling activities (Stein et al. 2018; Zhang et al. 2003). Inspecting the transaction data shows that revenues per receipt exhibit severe outliers. To identify these outliers, we use isolation forest (iForest) developed by Liu et al. (2012) and its R implementation provided in the H2O.ai-Package (H2O.ai 2019). The iForest algorithms builds on two main assumptions: (1) outliers in the dataset are rare, and (2) their attribute values diverge significantly from the typical values (Liu et al. 2012). We identified around 3.2% of the data points as outliers and remove them from the data accordingly. The distribution of the cleaned revenues between the 8 different products across the different shops is summarized in Figure 1.



**Figure 1: Revenue per product and shop**

In addition to the transaction data, we also have to identify over- as well as understocking. Overstocking is represented in the dataset as returns at the end of each day. Over the examined period, the total returns rate across all products is about 19%. In contrast, understocking is not directly visible in the data as stock-outs censor customer demand in POS data (Conrad 1976). Frequent stock-outs are one of the biggest nuisances for customers and can significantly reduce customer loyalty (Ehrenthal and Stölzle 2013). Following Ehrenthal and Stölzle (2013), the reason for stock-outs are almost always wrong order decisions. Hence, reconstruction of the “real” customer demand from censored sales data is essential for inventory decisions (Sachs 2015). The scientific literature proposes different approaches to handle censored demand data.

Several authors propose to fit parametric demand distributions on the uncensored values (days without stock-outs can be identified based on the returns). Lu et al. (2008) and Huh et al. (2011) use Bayesian statistics or a Kaplan–Meier estimator. Ding et al. (2002) and Negoescu et al. (2008) optimize the tradeoff between short-term costs for overstocking and long-term savings due to more information obtained by ultimately fulfilling the customer demand. However, Sachs (2015) argues that it is questionable if real-world customer demand can be fitted to a theoretical distribution. Against this backdrop, we leverage the parameter free approach described by Lau and Hing-Ling Lau (1996) that is also used for similar problems by Sachs (2015) and Huber et al. (2019). To reconstruct the censored sales data, we first split our data set into days with occurrence of stock outs and without. For the next steps, we used the uncensored data. Additionally, we divide every day into discrete intervals (hourly). In the next step, we calculate the cumulative distribution function (CDF) of every product/POS/weekday combination on an hourly basis. With the calculated CDF, we can reconstruct the intraday lost sales after a stock out occurred. The

underlying assumption of this method is that the hourly proportion of sales volume for every combination is stable over time and not dependent on absolute sales numbers.

To test our implementation, we randomly censor 50 data points of every combination and calculated the root mean squared error (RMSE) and mean absolute percentage error (MAPE). Table 1 summarizes these results and shows the different products, company-wide sales and revenues, as well as the number of stockouts (OOS) and the OOS portion. The partial high MAPE is due to the relatively low sales numbers.

Article No	Product	Mean Sales*	Mean Revenue (€)*	OOS*	OOS (%)*	MAPE**	RMSE**
1	Bread roll	7,489	1,797.43	3,443	0,9%	26%	180,76
2	Multigrain bread roll	1,167	607.30	9,835	3,8%	30%	14,18
3	Pretzel	2,220	1,152.02	9,956	2,9%	18%	20,84
4	Rye bread	86	160.49	19,308	21,2%	42%	2,22
5	Sourdough bread	90	189.32	19,976	21,8%	61%	4,21
6	Whole grain bread	54	123.17	18,292	29,0%	62%	1,87
7	Butter croissant	1,269	944.86	11,595	4,3%	34%	18,81
8	Chicken sandwich	341	737.22	25,450	18,3%	43%	8,01

\* = mean is calculated per day for POS / \*\* means are calculated per day and POS

**Table 1: Demand reconstruction and error**

## Data Analysis and Planning

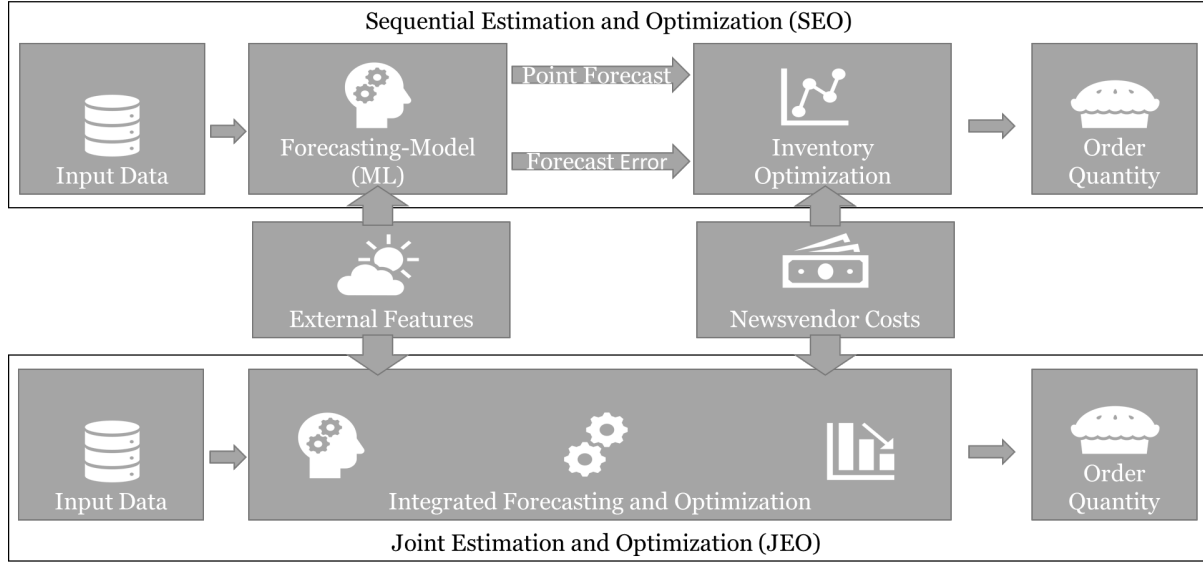
Having extracted, cleaned, and reconstructed the true demand data, we have to determine optimal production and inventory levels. As stated in the related work section, this task can be formalized in the sense of a newsvendor problem. Here, a decision-maker has to find the order quantity  $y$  that minimizes the expected total costs  $C$  depending on the demand  $D$ . Even though there exist many different newsvendor models e.g. multi period and /or multi product settings, we focus on the SPP due to the short shelf life (1 day) of the investigated products. The total costs consist of overstocking costs (overage costs  $c_o$ ) and of understocking costs (underage costs  $c_u$ ). The objective is formalized in Equation 1.

$$\min C(y) = E_D [c_u(D - y)^+ + c_o(y - D)^+] \quad (1)$$

Without loss of generality, we define  $c_u$  as the lost profit (selling price – variable production cost) due to stock-outs and  $c_o$  as variable production costs. Note that we currently exclude substitution behavior and customer satisfaction. Without using additional forecast information and with a known demand distribution, the optimal order quantity  $y^*$  can be determined as

$$y^* = F^{-1} \left( \frac{c_u}{c_u + c_o} \right). \quad (2)$$

However, as already stated above and emphasized by Huber et al. (2019), the assumption of a known demand distribution is not realistic in most real-world settings. Therefore, we leverage and compare two different data-driven approaches (SEO and JEO). In comparison, most other existing publications (Bertsimas and Thiele 2005; Huber et al. 2019; Oroojlooyjadid et al. 2019) compare only one of the data-driven approaches to the classical newsvendor solution. The concepts behind both data-driven approaches are visualized in Figure 2.



**Figure 2: SEO vs. JEO**

### **Model selection and feature engineering**

Both approaches leverage the available data to train a predictive model. We follow state of the art research (Huber et al. 2019; Oroojlooyjadid et al. 2019; Tsoumakas 2019) and rely on artificial neural networks (ANN) to forecast future demand. Following the authors ANNs are more flexible than standard statistic approaches and able to capture complex time series patterns. The fully connected feed forward ANN has two hidden layers. We perform a train-test-validation split to train and evaluate the model. The first two years of data are split into 80% training data and 20% validation data that is used to avoid overfitting. The remaining year serves as test set.

As pointed out by Zheng and Casari (2018), proper feature selection and engineering are crucial to achieve good forecasting results. However, most newsvendor planning problems are still solved without the integration of external features such as weather, holidays, or special promotion activities (Ban and Rudin 2019). To ensure high predictive power, we base our feature selection on Huber et al. (2019) and adopted it to our use-case. The selected features are summarized in Table 2. Categorical features are encoded using one-hot encoding (Potdar et al. 2017). Numerical values are standardized to improve the learning quality (Géron 2019) and training time (Wong and Guo 2013).

Feature	Description
POS ID	ID of the point of sale
Promotion	Binary feature indicating if there is a special advertising in the same or in the last week
Discount	Binary feature indicating if the price was discounted this or last week
Calendar data	Day of the week, month of the year, calendar week, school holidays, public holidays
Weather	Min, max , mean temperature, precipitation
Historic Sales data	Historic daily sales data for the last 60 day of each product and POS combination

**Table 2: Features**

## Inventory planning

The model architecture described above is identical for both the SEO and the JEO approach. In the SEO approach, the ANN serves as our forecasting module and is therefore trained to predict future demand. Hence, we use the mean absolute error (MAE) as loss function. To derive optimal inventory levels from the resulting point forecast  $\hat{y}$ , we have to take costs (over- and understocking) and uncertainty (model quality) into account. To do so, we follow Ban and Rudin (2019) and Huber et al. (2019) and select the service level quantile  $\left(\frac{c_u}{c_u + c_o}\right)$  of the empirical distribution of the forecast errors (calculated separately for every product/sales point combination) as a safety buffer. As formalized in Equation 3 the optimal inventory level  $y^*$  is determined by adding the safety buffer to the point forecast.

$$y^* = \hat{y} + \inf \left\{ p: \frac{1}{n} \sum_{i=1}^n \mathbb{1}(\epsilon_i \leq p) \geq \frac{c_u}{c_u + c_o} \right\} \quad (3)$$

In contrast, the JEO approach solves the forecasting and optimization in a single integrated step. To this end, we use the same setting (identical configured ANN) as described before. However, we modify the loss function and replace the standard MAE with the newsvendor cost function:

$$C_i = \begin{cases} c_u(d_i - y_i), & \text{if } y_i < d_i \\ c_o(y_i - d_i), & \text{if } d_i \leq y_i \end{cases} \quad (4)$$

After training the ANN using the newsvendor loss, the model predicts cost minimizing inventory levels instead of demand forecasts. In the next section, we compare the results of the SEO and the JEO models with the historic real-world planning data from the bakery chain.

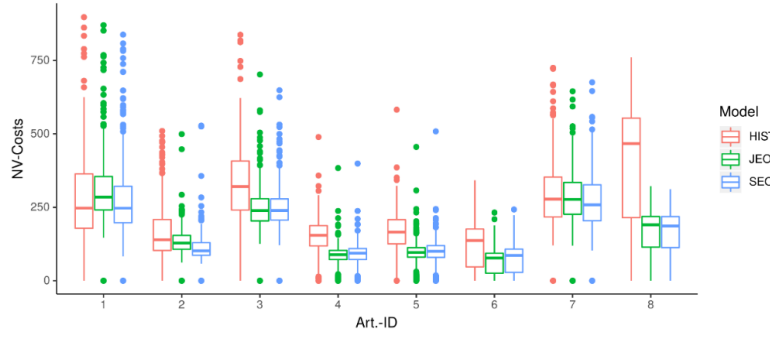
## Result Interpretation & Evaluation

We evaluate the performance of the different models and the human planner (HIST) based on the total realized cost. We choose this metric due to its generalizability as a universal unit of measurement in business context. As summarized in Table 3, using data-driven planning approaches enables the company to realize significant savings. Even though both models outperform the human planner, the SEO approach performs slightly better in the problem setting at hand.

	HIST	SEO	JEO
Total Costs	749,548.80€	525,243.90€	547,554.30€
Abs. Savings	0	224,304.90€	201,994.50€
Savings in %	0	30%	27%

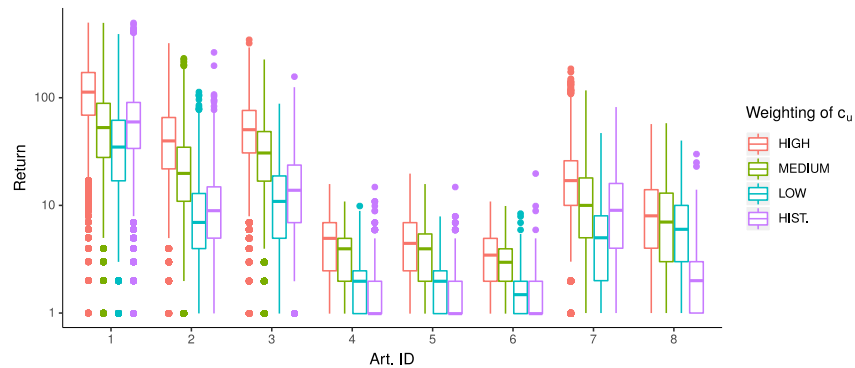
**Table 3: Cost Comparison**

Next, we compare the performance of the model on a less aggregated level. Figure 3 shows the distribution of the total costs for each product across the different shops. The smaller interquartile ranges of both data-driven models show that these approaches plan much more consistently compared to the human planner. We can achieve significantly lower costs for almost all products.



**Figure 3: Daily NV Cost per Product**

This first evaluation shows, that the information system allows significant cost decreases for the planner. However, the lower costs come at the cost of increased returns. Due to the high gross margin for bakery products, a stock out is much more costly for the bakery than lost sales. Next, we want to evaluate the impact of the system on food waste (returned products). To include a penalty for food waste into the model, we assume that returning (and disposing) food becomes more expansive compared to having stock outs. Figure 4 shows the absolute number of returns for several cost scenarios (high: 100% underage costs, medium: 60% underage costs, low: 20% underage costs). We see that the data-driven approaches are able to reduce food returns compared to the human planner for 4 of the 8 products. For the other 4 products median returns of the human planner are lower as the company follows a “no waste” policy for these items. However, using the waste minimizing parametrization (“low”), the data-driven approach is able to reduce total food waste by 55% while simultaneously reducing the total costs. A detailed comparison of food return quotes and cost differences is summarized in Table 4.



**Figure 4: Returns per Article**

Weighting of $c_u$	Total Returns	Diff. to HIST	Diff. Cost
100%	3,314,349	+150%	-30%
60%	1,574,410	+19%	-25%
20%	599,933	-55%	0%

**Table 4: Returns on Different Cost Levels**

## Summary and Further Research

In this study we develop an IT artifact that supports data-driven inventory decision making. The proposed artifact is implemented and evaluated based on sales data provided by a German bakery chain. To this end, we implement a data-preprocessing module that cleans the real-world data and reconstructs censored demand. This kind of data driven demand forecasting is yet not integrated in IS software for bakeries. Based on the final dataset we show that the suggested approaches are able to outperform the human planner in terms of total costs as well as food waste reduction. In line with Huber et al. (2019), we cannot identify a clear superiority between SEO and the JEO and conclude that.

Beside the comparison of the SEO and JEO approach showcased that a SME bakery company could remarkably save costs with our model even without a huge integration effort. All data we used already existed within the IS of the company. This example of our data pipeline could be a blue print not just for bakeries but all kind and size of enterprises dealing with perishable goods.

Even though we chose a realistic example and picked a heterogenic group of eight products, this case is just an example, and further research is necessary. Primarily to obtain the “real” underage costs ( $c_u$ ), further research in customer behavior in stock out situations is necessary. Therefore, we have to investigate how customers substitute fresh products with short shelf life like bakery products. Additionally, the forecasts could be further improved if one considered a hierarchical forecast on product group level like Huber et al. (2017) did. Also, a broader scope of models (e.g., more advanced deep learning architectures) as well as a direct comparison with existing approaches should be employed to further increase and evaluate the planning performance of the proposed artifact. In addition, testing our approach with other real word SPP form other domains like greengrocers is needed to obtain further information about generalization abilities of our approach.

## REFERENCES

- Arrow, K. J., Harris, T., and Marschak, J. 1951. “Optimal Inventory Policy,” *Econometrica* (19:3), p. 250 (doi: 10.2307/1906813).
- Ban, G.-Y., and Rudin, C. 2019. “The Big Data Newsvendor: Practical Insights from Machine Learning,” *Operations Research* (67:1), pp. 90-108 (doi: 10.1287/opre.2018.1757).
- Baskerville, R., Baiyere, A., Gergor, S., Hevner, A., and Rossi, M. 2018. “Design Science Research Contributions: Finding a Balance between Artifact and Theory,” *Journal of the Association for Information Systems* (19:5), pp. 358-376 (doi: 10.17705/1jais.00495).
- Bertsimas, D., and Thiele, A. 2005. “A data-driven approach to newsvendor problems,” Working Paper, Massachusetts Institute of Technology.
- Conrad, S. A. 1976. “Sales Data and the Estimation of Demand,” *Journal of the Operational Research Society* (27:1), pp. 123-127 (doi: 10.1057/jors.1976.13).
- Ding, X., Puterman, M. L., and Bisi, A. 2002. “The Censored Newsvendor and the Optimal Acquisition of Information,” *Operations Research* (50:3), pp. 517-527 (doi: 10.1287/opre.50.3.517.7752).
- Edgeworth, F. Y. 1888. “The mathematical theory of banking,” *Journal of the Royal Statistical Society* (51:1), pp. 113-127.
- Ehrental, J. C.F., and Stölzle, W. 2013. “An examination of the causes for retail stockouts,” *International Journal of Physical Distribution & Logistics Management* (43:1), pp. 54-69 (doi: 10.1108/09600031311293255).
- Géron, A. 2019. *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*, Sebastopol, CA: O'Reilly Media, Inc.
- Gregor, S., and Hevner, A. R. 2013. “Positioning and Presenting Design Science Research for Maximum Impact,” *MIS Quarterly* (37:2), pp. 337-355 (doi: 10.25300/MISQ/2013/37.2.01).
- H2O.ai 2019. R Interface for 'H2O'. <https://github.com/h2oai/h2o-3>.
- Hevner, March, Park, and Ram 2004. “Design Science in Information Systems Research,” *MIS Quarterly* (28:1), p. 75 (doi: 10.2307/25148625).
- Huber, J., Gossmann, A., and Stuckenschmidt, H. 2017. “Cluster-based hierarchical demand forecasting for perishable goods,” *Expert Systems with Applications* (76), pp. 140-151 (doi: 10.1016/j.eswa.2017.01.022).

- Huber, J., Müller, S., Fleischmann, M., and Stuckenschmidt, H. 2019. "A data-driven newsvendor problem: From data to decision," *European Journal of Operational Research* (278:3), pp. 904-915 (doi: 10.1016/j.ejor.2019.04.043).
- Huh, W. T., Levi, R., Rusmevichientong, P., and Orlin, J. B. 2011. "Adaptive Data-Driven Inventory Control with Censored Demand Based on Kaplan-Meier Estimator," *Operations Research* (59:4), pp. 929-941 (doi: 10.1287/opre.1100.0906).
- Jaeger, S. 2018. "Unser täglich Brot: Von überschüssigen Brotkanten und wachsenden Brotbergen," WWF Deutschland (ed.).
- Lau, H.-S., and Hing-Ling Lau, A. 1996. "Estimating the demand distributions of single-period items having frequent stockouts," *European Journal of Operational Research* (92:2), pp. 254-265 (doi: 10.1016/0377-2217(95)00134-4).
- Liu, F. T., Ting, K. M., and Zhou, Z.-H. 2012. "Isolation-Based Anomaly Detection," *ACM Transactions on Knowledge Discovery from Data* (6:1), pp. 1-39 (doi: 10.1145/2133360.2133363).
- Liu, L.-M., Bhattacharyya, S., Sclove, S. L., Chen, R., and Lattyak, W. J. 2001. "Data mining on time series: an illustration using fast-food restaurant franchise data," *Computational Statistics & Data Analysis* (37:4), pp. 455-476 (doi: 10.1016/S0167-9473(01)00014-7).
- Lu, X., Song, J.-S., and Zhu, K. 2008. "Analysis of Perishable-Inventory Systems with Censored Demand Data," *Operations Research* (56:4), pp. 1034-1038 (doi: 10.1287/opre.1080.0553).
- Mann, H., Gullaiya, N., and Mann, I. J. S. 2018. "Consumer-driven Demand Estimation: Smart Storage IoT in SSCM of Perishables,"
- Negoescu, D., Frazier, P., and Powell, W. 2008. "Optimal learning policies for the newsvendor problem with censored demand and unobservable lost sales," URL: [http://people. orie. cornell. edu/pfrazier/pub/learning- newsvendor. pdf](http://people.orie.cornell.edu/pfrazier/pub/learning-newsvendor.pdf).
- Oroojlooyjadid, A., Snyder, L. V., and Takáč, M. 2019. "Applying deep learning to the newsvendor problem," *IIE Transactions* (226:3), pp. 1-20 (doi: 10.1080/24725854.2019.1632502).
- Potdar, K., S., T., and D., C. 2017. "A Comparative Study of Categorical Variable Encoding Techniques for Neural Network Classifiers," *International Journal of Computer Applications* (175:4), pp. 7-9 (doi: 10.5120/ijca2017915495).
- Sachs, A.-L. (ed.) 2015. *Retail Analytics*, Cham: Springer International Publishing.
- Sakoda, G., Takayasu, H., and Takayasu, M. 2019. "Data Science Solutions for Retail Strategy to Reduce Waste Keeping High Profit," *Sustainability* (11:13), p. 3589 (doi: 10.3390/su11133589).
- Stein, N., Meller, J., and Flath, C. M. 2018. "Big data on the shop-floor: sensor-based decision-support for manual processes," *Journal of Business Economics* (88:5), pp. 593-616 (doi: 10.1007/s11573-017-0890-4).
- Taigel, F., and Meller, J. 2018. "Data-Driven Inventory Management: Integrated Estimation and Optimization," *SSRN Electronic Journal* (doi: 10.2139/ssrn.3256643).
- Tsoumakas, G. 2019. "A survey of machine learning techniques for food sales prediction," *Artificial Intelligence Review* (52:1), pp. 441-447 (doi: 10.1007/s10462-018-9637-z).
- Wang, X., Lin, D., Fan, W., and Wang, T. 2018. "Research on Sales Forecast of Fresh Produce Considering Weather Factors,"
- Wong, W. K., and Guo, Z. X. 2013. "Intelligent sales forecasting for fashion retailing using harmony search algorithms and extreme learning machines," in *Optimizing decision making in the apparel supply chain using artificial intelligence (AI): From production to retail*, W.-k. Wong (ed.), Elsevier, pp. 170-195.
- Zhang, S., Zhang, C., and Yang, Q. 2003. "Data preparation for data mining," *Applied Artificial Intelligence* (17:5-6), pp. 375-381 (doi: 10.1080/713827180).
- Zheng, A., and Casari, A. 2018. *Feature engineering for machine learning: Principles and techniques for data scientists*, Beijing, Boston, Farnham: O'Reilly.