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ASYMMETRIC ACCURACY METRICS IN FOOD RETAIL SALES FORECASTING: AN EMPIRICAL COMPARISON

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ASYMMETRIC ACCURACY METRICS IN FOOD RETAIL SALES FORECASTING: AN EMPIRICAL COMPARISON[3]

This study covers the application of asymmetric accuracy metrics in the daily retail sales prediction problem. The paper is focused on the empirical validation of an accuracy metric derived from the newsvendor model. We scrutinize the accuracy metric's advantages and describe its properties. This paper uses two main accuracy metrics: quantile-weighted and mean absolute error. We compare the economic effect of accuracy metrics for different models trained on food retail chain data. The results show that the asymmetric loss based on quantile-weighted absolute loss leads to lower business costs than the mean absolute error. The research is of interest to store managers, inventory management specialists, and logistics specialists in retail and restaurant chains. Our findings provide a better understanding of how to implement forecasting methods in order to obtain more accurate sales predictions that meet practitioner expectations.

JEL Classification: D12, C52, C53

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1. Introduction

The problem of daily retail sales forecasting is an important area of research in management. A huge amount of transaction data is collected in retail chains, giving the opportunity to employ them in a wide variety of different business problems: sales volume predictions, optimal assortment management, supply planning, inventory management, labor scheduling, and others. Much research in economics and machine learning (Klassen & Flores, 2001) has investigated various approaches to forecasting in order to improve prediction accuracy. Accurate sales forecasts significantly improve retail chain profits and operations (Chen *et al.*, 2014). Sales forecasting is the cornerstone of data-driven retail revenue management.

However, few studies have been done on the importance of the accuracy metric in retail sales forecasting and, in particular, in food retail. A symmetric accuracy metric is employed to predict sales volumes in the retail sector, yet, the accuracy metric creates sales forecasts that are underestimated compared to an optimal one. From a practitioner's standpoint, forecasts should be accurate enough to avoid the shortage and excess that results in potentially lower profits. Often a symmetric accuracy metric is used without any elaboration on its properties and thus their significance (Pierdzioch *et al.*, 2013); an issue that lacks representation in the field of management (Wang *et al.*, 2009). Researchers strive to create a forecast that is the most accurate on average and focuses on the needs of business. As a result, sales predictions based on applying symmetric accuracy metrics are rarely used in the context of the profit maximization problem. Asymmetric accuracy metrics are explained from a technical viewpoint mostly in economic problems (for instance, in value-at-risk computing).

Döpke *et al.* (2009) emphasize that asymmetric accuracy metrics should be implemented in different fields, including management. Wang *et al.* (2009) show asymmetric loss, and the quantile regression function derived from it, allows interval forecasting that has benefits for daily retail sales predictions (Taylor, 2007). However, previous authors have not suggested a methodology to estimate the most appropriate quantile level. In this study, we derive the optimal quantile level based on the profit maximization assumption for a firm producing perishable goods. We show how to calculate the optimal quantile from a given cost structure and provide empirical verification of the required quantile regression forecast properties.

We consider a symmetric accuracy metric from the management standpoint and discuss how to construct a retail sales prediction model with an asymmetric accuracy metric in order to solve the problem of systematic underestimation. We discuss what input variables are necessary for retail sales forecasting and how to construct the prediction model. Then we describe and compare the models which are most frequently used in retail sales forecasting and pay attention to the model's robustness to bias in a statistical sense. We then we focus on the asymmetric accuracy metric, show how to implement it for the chosen models and identify major changes in such model predictions. Finally, we apply the described techniques to actual SKU-level daily sales data and show that models estimated using asymmetric loss functions with a pre-calculated optimal quantile level parameter provide the highest economic effect.

2. Literature review

This section analyzes theoretical and empirical studies in retail forecasting and address two crucial aspects. First, selecting the input variables for a prediction model, and secondly, issues about methods of comparing forecast accuracy.

2.1 Sales determinants

We select input variables for a model following the Lasek, Cercone and Saunders approach (2016). The authors suggest using sales determinants as input variables for the model. This study identifies a few general groups of such determinants, provides an explanation of their importance and highlights the need for including additional variables from the research field. We analyze classical sales determinants and suggest, by reviewing the work in food retail, industry-specific determinants.

The studies (Lasek *et al.*, 2016; Jin *et al.*, 2015; Žliobaitė *et al.*, 2012) have shown that sales patterns are explainable by classical time-series determinants such as lagged values or moving averages as an example of aggregates. Lagged sales are sales that have their value coming from an earlier point in time and additionally reflect sales patterns (Jin *et al.*, 2015). Aggregate sales are the sum, average, or another aggregation function over lagged sales for a specific period in the past. Studies exploring the retail industry (Ehrenthal *et al.*, 2014) recommend conducting autocorrelation analysis and pay attention to sales with 1-, 2-, 3- and 4-week lags. As for aggregates, it is possible to check some smoothing parameters using correlation analysis.

The analysis of the food retail sector shows that there are additional important sales determinants, however, we suppose they are insignificant for 1-day forecasting. Kimes *et al*. (1998) presents an extensive discussion of food retail sales determinants. They give evidence that competitive points and location issues, and changes in the pricing policy or product management significantly influence the overall contribution to sales. Nevertheless, we suppose that the determinants are correlated to sales with a considerable lag, and, hence, the described determinants do not explain the short-term changes in retail sales that we investigate. The authors also suggest choosing the most relevant short-term forecasting groups of determinants: holiday factors, weather conditions, and marketing activities.

We provide a summary explanation of the relationship between seasonal characteristics and sales time characteristics and holiday factors that allow us to consider seasonality (Ehrenthal *et al.*, 2014). For instance, intra-week seasonality is observed as the distinction between sales volumes on weekdays and weekends. Weatherford *et al.* (2001) found important seasonal characteristics that are dependent on the forecast time-horizon: the day of the week, the day of the month and the. These are important in the analysis of the composite variables which we explain in more detail.

The second group of food retail-specific sales determinants are weather conditions. Weather characteristics have a significant influence on retail sales by affecting consumer behavior; in particular, their willingness to go to a store or a restaurant (Nenni *et al.*, 2013). We include the most frequently used characteristics, such as: daily temperature, air pressure, wind speed, precipitation. The authors emphasize that weather-based prediction accuracy is strongly dependent on the accuracy of the weather forecast. We overcame this obstacle in the further analysis through the investigation of historical weather data since it limits the predictive model in practice.

The last group of retail sales determinants explains the influence of marketing on consumer behavior. Promotions and price changes have a great impact on sales. An estimation of this impact depends on the marketing strategy and consumer features; its analysis goes beyond the scope of this research. Generally, variables indicating what activities take place on what days are marketing determinants.

Overall, a precise list of sales determinants depends on business specifics, country and region specifics, consumer behavior and other factors that differ from place to place. It is necessary to include the classical determinants from the literature and the specific determinants of the business being analyzed.

2.2 Accuracy metric

In addition to the input variables, the accuracy metric significantly influences the model's predictions. The main idea of accuracy evaluation in sales predictions is the measurement of the deviations of the predicted value of sales from the actual one. From the point of view of modeling, such a deviation is a forecasting error and it is minimized using a prediction model. Then, the quality of the model is evaluated as a function of errors, which is called the accuracy metric. The accuracy metric provides a qualitative measure of the model quality which is crucial in further analysis.

We pay special attention to the choice of the accuracy metric in this research. Armstrong & Collopy (1992) compared the classical symmetric evaluation metrics for time-series analysis and showed that the most preferred metric in terms of its reliability, outlier protection, and sensitivity is different for different depths and properties of the data. They show that the mean absolute error metric often has advantages over other symmetric metrics in similar time-series forecasting problems. Therefore, we use this metric in the analysis as an example of a symmetric metric.

Other researchers investigate asymmetric metrics. For instance, Döpke, *et al*. (2009) gives an example of business cycles in which short-term sales forecasting using classical symmetric metrics has serious negative consequences. The key finding is that symmetric metrics are biased, and the average prediction differs from the actual value. Similar conclusions have been provided for the energy resource market (Pierdzioch *et al*., 2013). Taylor (2007) analyzes shortage in supermarket chains and highlights that high volatility in retail raises doubts about the classical assumptions and properties of point forecasting. As a sales series is bounded below by zero and its mean is non-representative, quantile estimation accommodates such a distribution as it avoids the need for assumptions regarding the spread and shape of the distribution. However, a quantile regression function requires a quantile value that represent the degree of confidence in terms of interval forecasting. Taylor proposes standard 75% or 25% quantiles while she emphasizing that the correct choice of the quantile guarantees a more accurate prediction.

Discussion about the advantages of asymmetric metrics are based on the irrelevance of the classical metric assumption. The core assumption of symmetric metrics in the sales prediction problem is that the costs of shortages and excesses are equal. However, in practice such an assumption does not often hold. Therefore, we conclude that the larger the difference between two types of costs, the higher the metric's bias. We explore the specific needs of practitioners in retail sales forecasting in order to choose the most appropriate accuracy metric for retail sales forecasting.

Retail specifics are analyzed for the different costs of shortage and excess, so practitioners require a forecast taking these into account. The difference in shortage and excess costs is widely discussed from a management standpoint (Wang *et al*., 2009). For this, we refer to the newsvendor model which analyzes manager behavior in sales forecasting from the point of view of operational management.

Schweitzer and Cachon (2000) show that an optimal order quantity may differ from the mean and median of the sales distribution in the newsvendor model. In the sales prediction problem, ordering too much generates costs of excess or production costs (crucial for perishable commodities), while ordering to little generates opportunity costs.

Based on this result, we analyze how managers make ordering decisions according to the suggested sales forecasts. Schweitzer & Cachon (2000) suggests that choosing the size of an order is based on the solution to an expected profit maximization problem in which underestimated opportunity costs and production costs are balanced. Suppose Q be one SKU order quantity, which the manager chooses according to the sales forecast and let *p* and *c* be the selling price and the production costs of each unit respectively. Then if Q^*, the actual value of sales in the next period, is unknown in advance for manager, we face with three alternatives depending on the Q/Q^* ratio, equation 1 shows profit (π) for each of three cases.

$$\pi = \begin{cases} Q(p-c) = Q^* * (p-c) - (Q^* - Q)(p-c) \; if \;\; Q < Q^* \\ Q(p-c) \; if \;\; Q = Q^* \\ Q^*p - Qc = Q^* * (p-c) - (Q - Q^*)c \; if \;\; Q > Q^* \end{cases}, \tag{1}$$

The equation shows that, in cases when Q and Q^* are not equal, profit is less than when $Q = Q^*$. These values are the costs of shortage and excess. They are constructed as a product of the value of the order error ($|Q - Q^*|$) and an appropriate constant value: the marginal value of sales (*p*-*c*) or c.

This theoretically proves that in the retail sales prediction task the appropriate accuracy metric should provide different but constant weights to the costs of shortage and excess. The paper also shows that, if *(p-c)* > *c*, which is a common assumption in business, the optimal choice of Q is higher than Q^* even if $Q^*$is known due to different costs of shortage and excess. Therefore, the symmetric metric provides a biased prediction which does not correspond to actual manager behavior, which is in line with the discussed model according to the authors' experiments.

3. Methodology

As we have shown in the literature review, an asymmetric accuracy metric gives unbiased retail sales forecasts and allows for unbiased prediction model quality estimation. We verify this result empirically by comparing forecasts created under different accuracy metrics. In order to get a better understanding of model quality, we compare the predictive power of models using the mean absolute percentage error (MAPE) as an example of a mean absolute error accuracy metric. MAPE gives the averaged absolute error value of the model as a percentage of the average value of the target variable. MAPE is calculated as:

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{\sum_{t=1}^{Ti}\left|Y_{it} - \hat{Y}_{it}\right|}{\sum_{t=1}^{Ti}Y_{it}}, \tag{2}$$

where: m is the total number of objects, T_i is the period of sales for object i, Y_{it} is the sales of object i at time t, $\hat{Y}_{it}$ is the prediction of sales of object i at time t.

To compare the quantile and mean absolute error accuracy metrics, we evaluate different models using different loss functions depending on the chosen accuracy metric. MAPE corresponds to the L1 loss function which minimizes the absolute errors in the model evaluation, in other words, the absolute difference between the predicted values of sales and the actual value. We choose the quantile metric as an example of an asymmetric accuracy metric as the most suitable to the newsvendor problem. We show that the costs of over-predicting one unit equal the costs of producing one unit while costs of under-predicting equal the underestimated opportunity costs *(p-c)*. We represent both accuracy metrics in Figure 1 with different ratios *(p-c)/c* for quantile metric: ⅔ and ⅓.

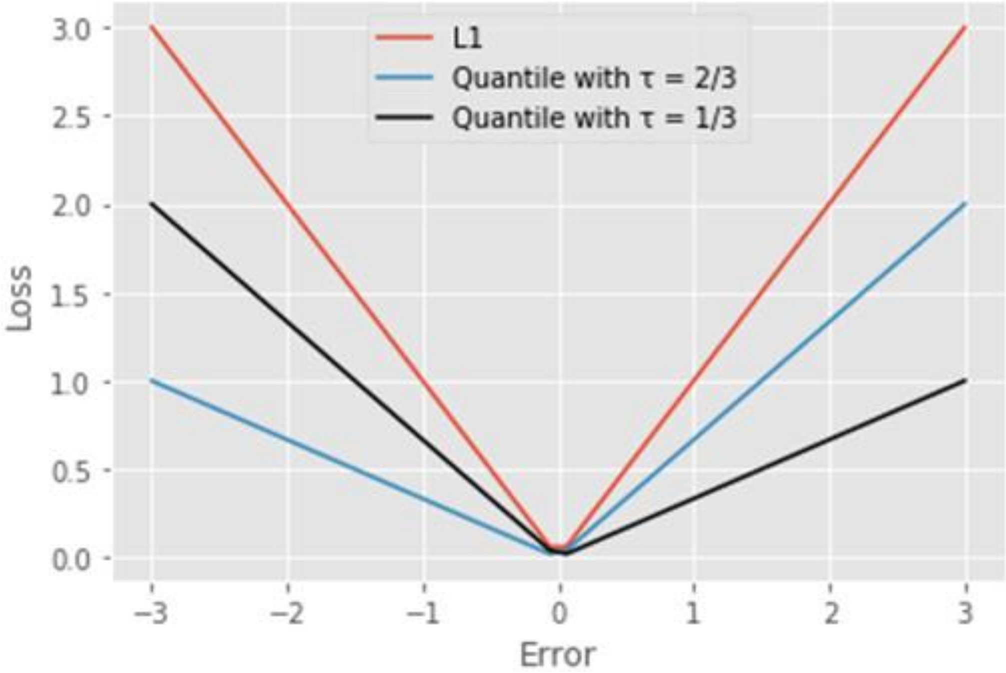

Fig.1 L1 and quantile loss functions

Figure 1 depicts different slopes of the quantile accuracy metric functions at different intervals of the predicted variable. Therefore, we define mean quantile error (*MQE*) accuracy metric according to equation (3).

$$MQE = \frac{1}{m}\sum_{i=1}^{m} c(Q_i - Q_i^*)I(Q_i > Q_i^*) + (p-c)(Q_i^* - Q_i)I(Q_i < Q_i^*) \quad , \tag{3}$$

where $I(Q_i > Q_i^*)$ is an indicator function equaling 1 if $Q_i > Q_i^*$, and 0 otherwise.

Equation 4 presents the general structure of the quantile loss function. Let quantile *t* be $(\frac{c}{p})$ and *the* error *e* be $(Q_i - Q_i^*)$, then the usage of such loss functions in sales forecasting leads to the solution of the newsvendor problem. As a result, we evaluate sales forecast accuracy using the profit equation from the newsvendor problem.

$$L = f(e,t) = \begin{cases} t * e \; if \; e \geq 0 \\ -(1-t) * e \; if \; e < 0 \end{cases} = \quad , \tag{4}$$

$$= t * e * I(e \geq 0) - (1-t) * e * I(e < 0)$$

This equals the quantile regression function for sales estimation where the quantile level is *1-t*, in terms of costs the optimal quantile equals ($\frac{p-c}{p}$), the ratio of marginal profit of one unit to the selling cost when $p > c$.

Another important issue in retail sales forecasting is the practicality of the prediction model. The literature (Lasek *et al.*, 2016) contains many different techniques, including the empirical comparison of models and theoretical comparisons of their advantages and disadvantages. Researchers have steadily developed new techniques with better predictive power. Darbellay & Slama (2000) emphasizes that there is no universal solution, so it is necessary to choose the most appropriate for the data and the business.

For our study, we chose the most frequently used models in recent works. First, we use a naive model as a baseline method. We define the naive model according to the forecasting strategy used in practice: using sales 7 days prior as a forecast. Then we include the classical ordinary least squares linear model (LM) that appears in almost all analyzed papers as the model is distinguished by the interpretability of the results. Another classical model in the machine learning field is support vector regression (SVR). There are a variety of reasons for selecting SVR as a method of forecasting, for instance, the ability to reveal complex non-linear relations between variables by selecting the kernel function, and its generally high performance (Bajari *et al.*, 2015). The final group of models includes ensembles based on regression trees, which reveal the non-linear relationships between independent variables and are robust to outliers, however, they are unsustainable (Zhang & Suganthan, 2014). To address this shortcoming, we examine the random forest model (RF) and the gradient boosting tree-based model (GB). Each model has its own advantages and disadvantages, and the suitability depends on the dataset.

Conducting such a comparative analysis requires special techniques of dataset splitting. The prediction process starts with model tuning. We search for the optimal hyperparameters via a 5-fold cross-validation. Bergmeir and Benítez (2012) analyzed the problem of cross-validation for time series and showed that in large enough datasets the main properties of cross-validated accuracy results (mainly, robustness) are maintained and the dependencies in the data due to the time structure of observations do not prevent the use of classical cross-validation techniques in time series and panel data analysis. Following their approach, we use 40% of the observations to validate the hyperparameter tuning, the next 40% as the training part for model evaluation and the remaining 20% for forecasting and accuracy estimation.

4. Data

For result verification, we collect sales transactions data from a food retail chain from 14 January 2019 to 31 December 2019 without gaps. The data contain information about the top-5 restaurants located in a large Russian city, where the food market is highly competitive. During the period under review, the restaurants' price policy remained unchanged and the average restaurant revenue grew from 0.9 million 1.12 million rubles per month. The chain's distinctiveness is that more than half of the products are perishable goods with an expiry period of 1 day.

The data structure is an unbalanced panel due to the differences in the assortment between days and restaurants. The dataset contains over 700 unique SKU, resulting in 251,283 daily observations. The unit of observation is the volume of sales of an SKU per restaurant per day. Following the literature, we include 6 groups of explanatory factors: the lagged values of sales, lagged sales aggregates, holidays and seasonal indicators, weather characteristics, marketing activity indicators, and dish categories.

Based on the partial autocorrelation function, the following statistically significant lags are selected: 1, 2, 3, 4, 7, 14 and 21 days. Average sales for the last 1, 2 and 3 weeks are also selected as important factors. Holidays factors contain dummy variables of 18 national holidays, seasonal indicators represent weekdays and days of the month. Weather characteristics describe the average daily temperature, the humidity level, pressure, wind speed, and precipitation. Data are taken from rgw open source openweathermap.org. Marketing activities in the restaurant chain are described by average daily selling price on each SKU as each activity is characterized by discounts. Hence, the data contains 19 explanatory variables.

Tab. 1. Descriptive statistics of key variables

Variable	Min	Mean	Max	St.d.
Sales	0.1	2.7	12	2.1
Holiday	0	0.1	1	-
Weekday	0	3.0	6	-
Day	1	16.9	31	-
Average temperature	-19.0	11.0	29.6	9.7
Humidity	17.0	71.0	100.0	17.1
Wind speed	0.2	4.5	13.0	2.1
Pressure	974	1011	1039	11
Price	0	137.2	2000	205
Category: Bread	0	0.11	1	-
Category: Cakes	0	0.15	1	-

Category: Drinks	0	0.22	1	-
Category: Main courses	0	0.29	1	-
Category: Other	0	0.16	1	-

5. Results

Considering the conclusions from the previous section, we identified the model with the best predictive out-of-sample power (with the lowest accuracy metric MQE). We chose a quantile-in-quantile loss function t=0.67 as this reflects the average proportion between marginal profit and the production costs of one unit. The results of the model comparison and loss functions are presented in Table 2. MAPE is the error as a percentage of the average volume sales, MQE in the volume of sales, and the economic effect is in rubles.

The second row in Table 2 shows actual sales (without prediction errors); the row describes average sales in the sample and the economic effect in comparison to the baseline strategy of forecasting. The baseline row depicts a MAPE of about 20% and MQE 0.27 when the ordering volume equals sales a week ago. The actual strategy of ordering gives an economic effect of more than 1.2 million rubles per month over the baseline strategy. The economic effect column is the key to deciding which model better serves its aim.

Tab. 2. Comparison of techniques

Model	Loss function	$\overline{Y_{pred}}$	MAPE	MQE	Economic effect (in 5 locations per month)
Actual sales		2.71	0.0	0.0	1 244 064
Baseline		2.76	20.3	0.27	0
LM	MAE	2.71	16.74	0.23	180 499
	Quantile	2.97	17.73	0.19	330 900
SVR	MAE	2.77	16.93	0.22	224 569
	Quantile	2.94	17.80	0.20	304 836
RF	MAE	2.68	15.15	0.21	238 120
	Quantile	2.83	15.23	**0.18**	**376 205**
GB	MAE	2.68	15.13	0.21	266 477
	Quantile	2.90	15.70	**0.18**	**408 509**

The forecast constructed by the linear model using different loss functions provides different results. MAE loss function gives lower MAPE while the quantile loss function provides lower MQE as expected according to the theoretical results. The average prediction of the model is evaluated using the MAE loss function, providing the average forecast close to actual sales, while the average prediction of the linear model with the quantile loss function produces an overvalued forecast, as suggested in the theoretical analysis. This is also in line with the theory of optimal management behavior. For linear models, an overvalued prediction is obtained by the model evaluation with the quantile loss function, which allows almost double the economic effect of the prediction from 180,000 to 330,000 rubles. The quantile loss function is preferable in sales retail forecasting to the symmetric one.

Other models provide a similar pattern of lower MAPE for models estimated on MAE rather than the quantile loss function and lower MQE for the quantile loss function. Likewise, models evaluated using quantile loss functions provide a higher economic effect. The findings suggest that the sales prediction algorithm in retail should include an asymmetric loss function (for instance, quantile), as this provides a higher economic effect. It is also advised to assess the algorithm quality using an asymmetric accuracy metric.

6. Conclusion

This study investigates different accuracy metrics in retail sales prediction. We provide a comparative analysis of two of the most frequently used accuracy metrics in retail sales forecasting from a theoretical point of view and provide empirical validation.

For this, we chose linear, support vector regression, random forest, and gradient boosting models as prediction models and mean absolute error and quantile loss function for model evaluation. We described its relation to the forecasting problem and highlighted the possible advantages and disadvantages of their use. Finally, we empirically compared the economic effects from different accuracy metrics using sales transaction data from a Russian food retailer.

The main finding from the work is that the quantile loss function, as an example of an asymmetric accuracy metric, provides better prediction accuracy calculated as the economic effect of implementing the forecast, including the specifics of food retail: asymmetric costs with the prevalence of shortage costs over excess costs. We show a simple way to precisely calculate the optimal quantile level. A deeper analysis is required before model construction and evaluation in practice from the cost-benefit perspective. Our results help provide a better understanding of how to implement forecasting methods in order to create accurate sales predictions that meet practitioners' expectations.

References

1. Armstrong, J. S., & Collopy, F. (1992). Error measures for generalizing about forecasting methods: Empirical comparisons. *International journal of forecasting*, *8*(1), 69-80.

2. Bajari, P., Nekipelov, D., Ryan, S. P., & Yang, M. (2015). Machine learning methods for demand estimation. *American Economic Review*, *105*(5), 481-85.

3. Bergmeir, C., & Benítez, J. M. (2012). On the use of cross-validation for time series predictor evaluation. *Information Sciences*, *191*, 192-213.

4. Chen, Q., Liu, B., Zhang, Q., Liang, J., Suganthan, P., & Qu, B. (2014). Problem definitions and evaluation criteria for CEC 2015 special session on bound constrained single-objective computationally expensive numerical optimization. *Technical Report, Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou, China and Technical Report, Nanyang Technological University*.

5. Darbellay, G. A., & Slama, M. (2000). Forecasting the short-term demand for electricity: Do neural networks stand a better chance?. *International Journal of Forecasting*, *16*(1), 71-83.

6. Döpke, J., Fritsche, U., & Siliverstovs, B. (2009). Evaluating German business cycle forecasts under an asymmetric loss function (No. 5/2009). *DEP (Socioeconomics) Discussion Papers, Macroeconomics and Finance Series.*

7. Ehrenthal, J. C. F., Honhon, D., & Van Woensel, T. (2014). Demand seasonality in retail inventory management. *European Journal of Operational Research*, *238*(2), 527-539.

8. Jin, Y. H., Williams, B. D., Tokar, T., & Waller, M. A. (2015). Forecasting with temporally aggregated demand signals in a retail supply chain. *Journal of Business Logistics*, *36*(2), 199-211.

9. Kimes, S. E., Chase, R. B., Choi, S., Lee, P. Y., & Ngonzi, E. N. (1998). Restaurant revenue management: Applying yield management to the restaurant industry. *Cornell Hotel and Restaurant Administration Quarterly*, *39*(3), 32-39.

10. Klassen, R. D., & Flores, B. E. (2001). Forecasting practices of Canadian firms: Survey results and comparisons. *International journal of production economics*, *70*(2), 163-174.

11. Lasek, A., Cercone, N., & Saunders, J. (2016). Restaurant sales and customer demand forecasting: Literature survey and categorization of methods. In *Smart City 360°* (pp. 479-491). Springer, Cham.

12. Nenni, M. E., Giustiniano, L., & Pirolo, L. (2013). Demand forecasting in the fashion industry: a review. *International Journal of Engineering Business Management*, *5*, 37.

13. Pierdzioch, C., Rülke, J. C., & Stadtmann, G. (2013). Oil price forecasting under asymmetric loss. *Applied Economics*, *45*(17), 2371-2379.

14. Schweitzer, M. E., & Cachon, G. P. (2000). Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science*, *46*(3), 404-420.

15. Taylor, J. W. (2007). Forecasting daily supermarket sales using exponentially weighted quantile regression. European Journal of Operational Research, 178(1), 154-167.

16. Wang, C. X., Webster, S., & Suresh, N. C. (2009). Would a risk-averse newsvendor order less at a higher selling price?. *European Journal of Operational Research*, *196*(2), 544-553.

17. Weatherford, L. R., Kimes, S. E., & Scott, D. A. (2001). Forecasting for hotel revenue management: Testing aggregation against disaggregation. *Cornell hotel and restaurant administration quarterly*, *42*(4), 53-64.

18. Žliobaitė, I., Bakker, J., & Pechenizkiy, M. (2012). Beating the baseline prediction in food sales: How intelligent an intelligent predictor is?. *Expert Systems with Applications*, 39(1), 806-815.

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