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Comparison of Demand Forecasting Methods for Global and Local Demand: The Case of Classic Literature Demand Forecasting

Abstract. *Forecasting is an integral part of entrepreneurship. The aim of this paper is to use Google Trends data to predict the local demand for books in the Czech Republic and compare it with the global demand. The forecasting will be done with data by Google Trends and by book purchases. Both approaches will be compared. It will also be evaluated whether the use of multiple measures of accuracy will lead to different results. The methods chosen for forecasting were seasonal naive method, ARIMA and ARFIMA method, ETS method, Holt and HoltWinters method. The calculations will be completed with BATS and artificial neural network methods and Hybrid method. For the GT data, the extent to which the search-based model accurately matches the actual purchases was quantified. It is an innovative concept. From the results, it can be concluded that all methods on the data for the Czech Republic, and on both sets of data, predict demand stagnation. For the global comparison, the results are different. Furthermore, it is clear that the calculation by search I purchases data gives similar results.*

Keywords: *demand forecasting, ARIMA models, ETS models, neural networks, hybrid model, accuracy, Google Trends data.*

JEL Classification: M21, M15, C53.

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1. Introduction

In today's world, the economy is undergoing constant changes that also affect individual companies operating in these conditions, for example, we can see the increasing integration of artificial intelligence into their internal processes. However, a company's success is often linked to its ability to adapt to these changes and make accurate predictions. The demon driven adaptive enterprise appears to be a modern functional concept (Ptak, 2018).

The aim of this paper is to predict the local demand for books in the Czech Republic based on Google Trends data and to compare it with the global demand. The forecasting will be done by searching the topic literature and using book purchases through Google. Both approaches will be compared. It will also be evaluated whether the use of multiple measures of accuracy will lead to different results. Previous research suggests (Kolkova, 2020) that using different accuracies should not lead to different results. Existing research on predictions based on

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searches and purchases does not produce clear results. Search should cross over to purchase; however, the length is still under-researched.

2. Literature review

Forecasting is an integral part of all enterprises. Larger enterprises also use forecasting analytics tools (Shafique et al., 2024). Forecasting is used in the hotel industry (Zhang et al., 2021), electricity consumption (Dudek et al., 2022) and (Wu et al., 2023), biofuel demand (Paula et al., 2022), bicycle demand (Kolkova & Macurova, 2022), automotive demand during the covid pandemic (Ramírez et al., 2021), tourism in Croatia (Cuhadar, 2020), and many other business drivers.

In current business practice, according to research (Kolkova et al., 2022), forecasting is the area that entrepreneurs require most to undergo scientific research. Thus, predictive analytics is becoming the field with the greatest scientific potential for business.

Forecasting methods nowadays rely more on quantitative methods. Statistical methods are still the methods used, but they are often supplemented by I modern methods based on artificial intelligence (Kolková & Ključnikov, 2022), (Alghalith, 2019), (Kolková & Navrátil, 2021). Artificial neural network methods are also coming to the fore. New methods are emerging both in academia (Hyndman & Athanasopoulos, 2021) and in the business sector (Shaub, 2020), (Montero-Manso et al., 2020), (Smyl, 2020). Closely related to the use of methods is the evaluation of their performance (Hyndman & Koehler, 2006; Kolkova, 2020). There are many methods of performance evaluation (Hyndman & Athanasopoulos, 2021). In this paper, methods ME, RMSE, MAE, MPE, and MAPE are used.

The methods utilised in this paper are both statistical methods according to basic calculations (Hyndman & Athanasopoulos, 2021) and methods based on artificial neural networks, according to (Hyndman & Khandakar, 2008). However, hybrid methods are also used, which are created by combining both of the above approaches (Shaub & Ellis, 2018).

3. Model specification

3.1 Data extrapolation analysis

Google Trends data is used for the forecast. Namely, data on searches for the key term "classic literature". Searches for this term are likely to be closely related to data on actual purchases of classic literature and can therefore be used to forecast demand for the same commodity. In addition, data on historical purchases of books in the field of classic literature through e-shops are applied, again according to Google trends data.

The data used represents the relative interest in searching and buying relative to the highest point on the graph for a given area and time. A value of 100 represents the highest popularity of the term and the highest number of purchases. A value of

50 means that the term had half the popularity. A score of 0 means that not enough data was collected for the term or there was minimal interest in searching for the term.

Before the actual forecasting, the data must be thoroughly analysed and statistical descriptions made. The data represent web searches or purchases for the term from 2008 to July 2020, and the data are monthly. Figure 1 is a line graph of the number of searches for the term "classic literature" in Google searches in the Czech Republic. Figure 2 then shows the same trend, but globally. When constructing the line graph, it is already evident that there is likely to be some seasonal component and trend in the searches.

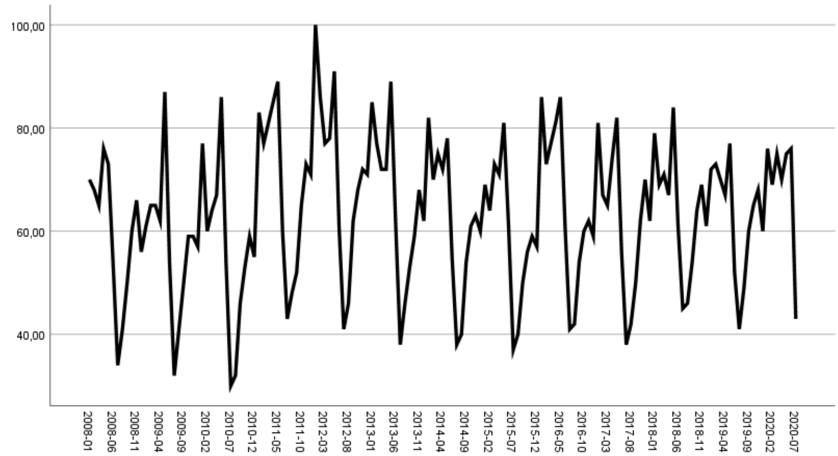

Figure 1. Search for "classical literature" in Czech Republic
Source: Authors' own creation.

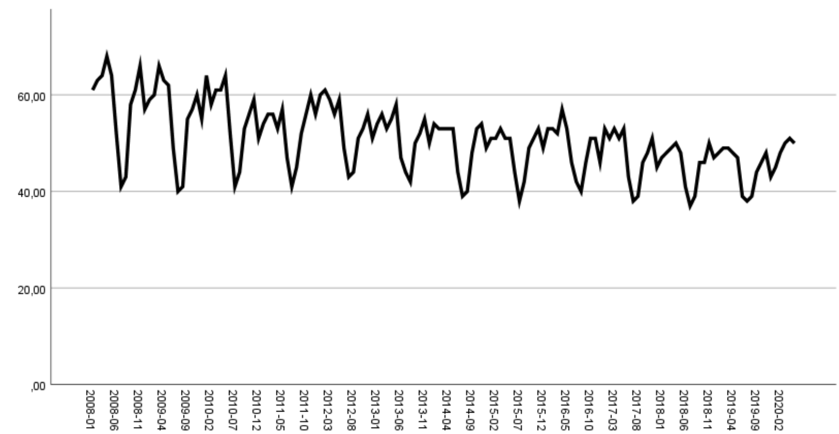

Figure 2. Search for "classical literature" worldwide
Source: Authors' own creation.

Some cyclical fluctuations can be seen in these figures. It is also possible that searches for the key term "classical literature" do not show any clear trend. In order to confirm the claim of trend or non-trend of this search, a decomposition will be performed in the next part of the data description.

For the analysis of purchases of classical literature in the Czech Republic and worldwide, purchases recorded via the Google browser were used. These data have been collected or published on Google since 2008, and again the data are monthly. The data used also represent relative interest to the highest point on the graph for a given area and time.

After this visual analysis, it is necessary to perform a more detailed description using statistical description analysis. The minimum, maximum, mean, median, and 1st and 3rd quartile statistics are quantified for all datasets. The results are presented in Tables 1 and 2.

Table 1. Descriptive characteristics of datasets searching for "classical literature"

	Min.	1st quartile	Median	Mean	3st quartile	Max.
Czech Republic	1	21	31	29,55	39	56
Worldwide	1	13	18	20,3	26	53

Source: Authors' processing.

Table 2. Descriptive characteristics of purchase datasets

	Min.	1st quartile	Median	Mean	3st quartile	Max.
Czech Republic	1	21	28	28,44	38	53
Worldwide	1	13	21	20,34	26	42

Source: Authors' processing.

3.2 Time-series decomposition

We use the automatic function decompose a in R, from the forecast package. Figure 3 is for the time series of searches; Figure 4 is for the time series of purchases of classic literature on the Internet. First, it is necessary to create a time series from the data in R using the *ts* code. Using the simple decompose function with automatically generated graphs with simple code for the historical time series of purchases in the Czech Republic:

```
sale_cr<-ts(sale_cr,frequency=12)
dekomposition_salecr=decompose(sale_cr)
plot(dekompozice_salecr)
```

The first part shows the actual time series, the second the trend, followed by the seasonality, and the last graph shows the random component. The additive decomposition was chosen as the most appropriate.

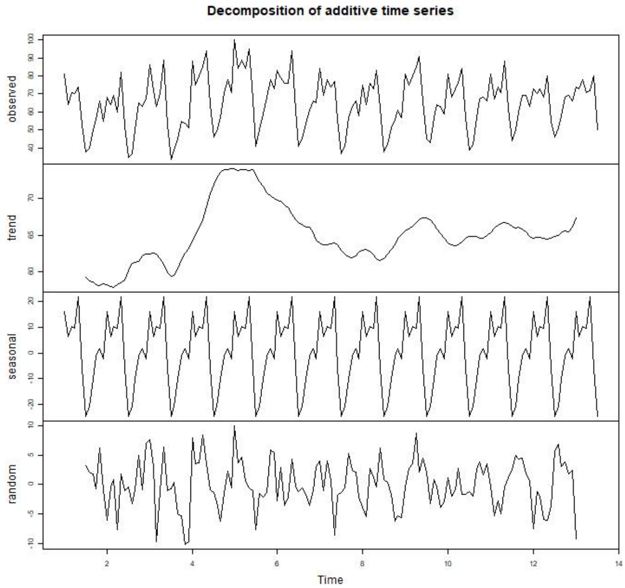

Figure 3. Decomposition searching for "classical literature" in Czech Republic
Source: Authors' own creation.

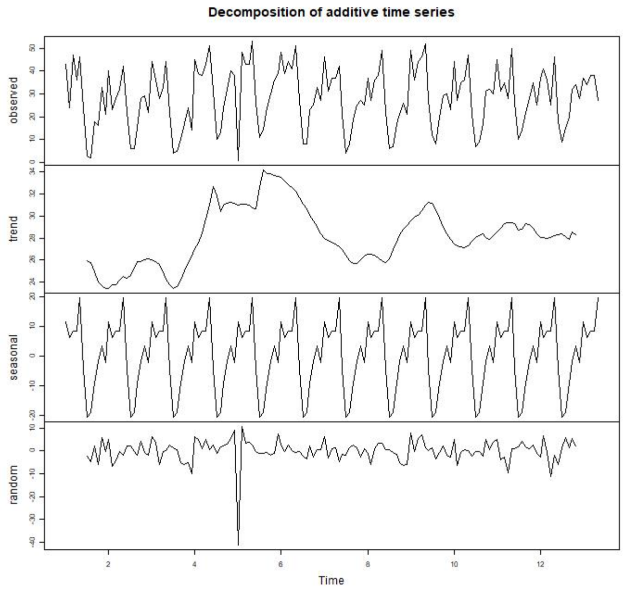

Figure 4. Decomposition searching for "classical literature" worldwide
Source: Authors' own creation.

Figure 3 shows that the trend appears to be stagnant. After a wave of increasing interest in classical literature around 2010, there is no clear decline or growth in interest in searching for the term on the Internet. This trend is very similar for the time series of purchases of classical literature on the Internet, which can be seen in Figure 4.

In Figure 5 and Figure 1 we see global data, and here we see an interesting fact, namely that the trend around the world is decreasing. The seasonal component roughly corresponds to the data in the Czech Republic.

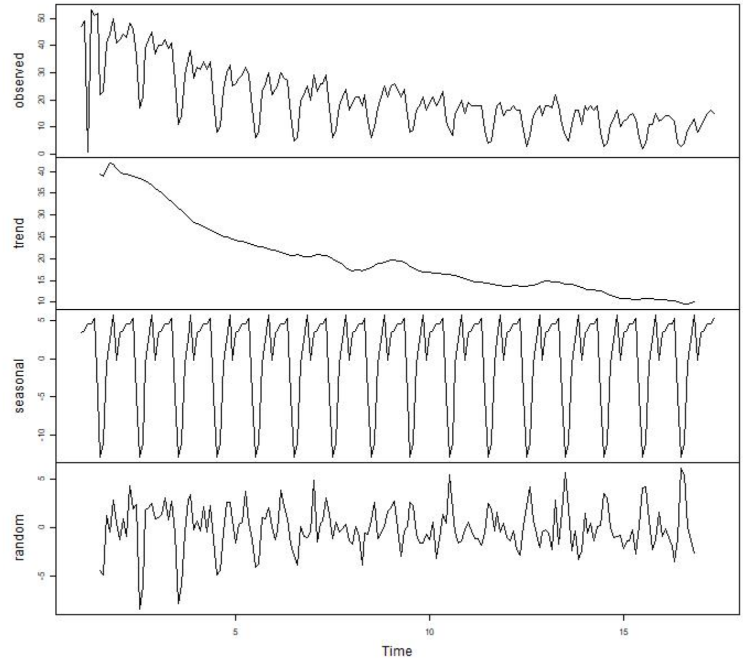

Figure 5. Decomposition purchase "classical literature" in Czech Republic
Source: Authors' own creation.

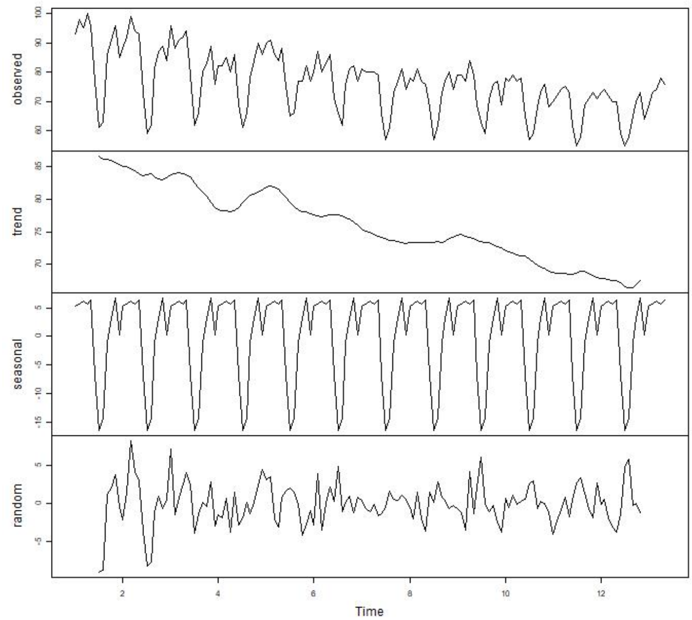

Figure 6. Decomposition purchase "classical literature" worldwide
Source: Authors' own creation.

4. Results and discussion

4.1 Results

The calculation starts by dividing the data into training data and test data. According to the theoretical background (Hyndman & Athanasopoulos, 2021), the 150 values are divided into thirds. The first two thirds, that is, 100 data represent the training data. A model is built on these data, which is then applied to the 50-test data. The accuracy of the model is of course verified on both sets of data.

First, the complete forecast is performed on the benchmark, and this is the naive forecast. The variable expressing sales in the Czech Republic was named *sale_cr*, and the variable expressing searches *search_cr*. For this forecast a simple code has been applied in R, thanks to the forecast package, this is shown in follow codes.

```
G_Na_ncr<-naive(sale_cr[1:100,1],h=50)
accuracy(G_Na_ncr,sale_cr[101:150,1])
```

The ME, RMSE, MAE, MPE and MAPE methods were used to calculate the accuracy measures. It is natural that the accuracy rate is lower on the test data than on the training data. This was also confirmed in this study. However, the accuracy rates in the test data tell us more about the real possibility of using the model in practice.

Accuracy rates for pronunciations on the key term retrieval data were not quantified using the retrieval data. Measuring how accurately people search for key phrases on the Internet has no predictive power. It is completely useless for demand forecasting; here, it is necessary to know how searches ultimately led to purchases. Therefore, it was quantified how closely the search-based model matches the actual purchases in the test data. This is an innovative concept and has not been applied before. The code is as follows:

```
G_Na_cr<-naive(search_cr[1:100,1],h=50)
accuracy(G_Na_cr,sale_cr[101:150,1])
```

Figure 7 graphically shows the resulting search-based forecast and the accuracy rate then assessed using actual purchases. It can be seen that, according to this method, despite the unfavourable pandemic situation in the spring months, a stagnation in the development of demand for classic literature is forecast. This forecasting was used as a benchmark for other forecasts.

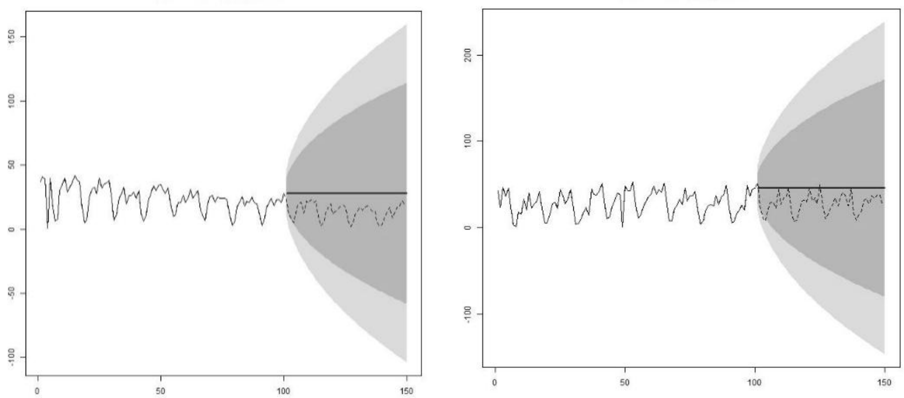

Figure 7. Forecast according to the naive method in the Czech Republic and worldwide

Source: Authors' own creation.

Based on the results of this method, the other methods will also be assessed. If the results are better, or their accuracy rates show lower error rates than the error rates in this naive forecast, these methods can be adopted for further use.

More complex statistical methods are more demanding on the knowledge of the researcher and on the software. In contrast, the naive method does not require any sophisticated software. It is therefore completely inconvenient for practical applications in enterprises to invest funds in more demanding hardware and software, or in the computing capacity of computer equipment, when a simple naive method could achieve the same or better results. There would certainly be no economic justification for using complex statistical methods, or methods based on artificial intelligence, if a method based on historical values alone would be more accurate.

The next section will quantify the seasonal naive method, both the ARIMA and ARFIMA methods, the ETS method, and the sub-methods of exponential smoothing, Holt, and the HoltWinters method. The calculations will be completed with BATS and artificial neural network methods. The final comparison will evaluate whether or not these methods have outperformed the simple naive method. By logic, the methods should outperform the naive forecast, if only because their computation is more complex. However, this is often not the case in practice. This is mainly due to the specific nature of data in the corporate economy.

Another method examined is seasonal naive forecasting. This time, the calculation in R was implemented using the code *snaive* from the *forecast* package. From the results of this forecast, it is obvious that according to this method we can assume a stagnation of demand for classic literature in the Czech Republic.

The third method is the ARIMA method. This time, the calculation in the R language was implemented using the code *arima* from the same package. Method ARFIMA shows a similar evolution to that of the ARIMA method, indicating the similarity of these methods. The code *arfima* was used for the calculation in the R language. The results of the ETS method report again a stagnation in the demand for classic literature. The code in R is again quite intuitive *ets*. Subsequently, the simple exponential equalization method, abbreviated SES, is used, with the code *ses*. Another of the ETS group of methods is the Holt method, using the code *holt*. The last of the group of ETS models is the HoltWinters model, which attempts to eliminate the shortcomings of the Holt model. The forecast *HoltWinters* code was used.

Another method used is an artificial intelligence-based method, namely a method inspired by the processes in the human brain artificial neural network. This method has been quantified to show large differences in accuracy on training data and on test data. On training data, which is what this method is actually built on, it usually shows high accuracy. However, this is often outperformed on test data; this has also been the subject of previous research (Kolková, 2019). The code used for the calculation in R has now been *nnetar*. The code *bats* were used for the applying the method BATS.

Thetam model is calculated by the *forecastHybrid* package. The results show that the Thetam method will not be among the most accurate methods in this case, although it outperformed the benchmark. The last method is the hybrid method, again based on the *forecastHybrid* package, processed in R. Within this hybrid method, the ARIMA, ETS, Thetam and Tbats models were applied with a weight of 0.2, supplemented by an artificial neural network model, which was also assigned a weight of 0.2. In Figure 22, it can be seen that the forecast is no longer so clearly stagnant. Indeed, according to the dashed line, which shows the actual data obtained ex post, the forecast suggests an initial decline followed by an increase.

The best method is the neural networks method named nnetar. Figure 8 shows the forecast. The solid line here shows the forecast based on searches, and the dashed line shows the actual purchases. It can be seen that the forecast really copies the actual purchases. According to this method, the expected development of demand will reflect cyclical development and individual cycles will repeat with the current trend.

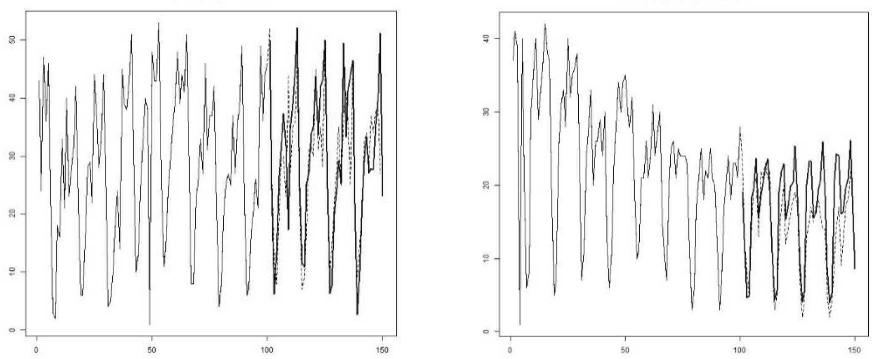

Figure 8. Forecast according to the neural network's method in the Czech Republic and worldwide
Source: Authors' own creation.

4.2 Discussion

Table 3 shows a comparison of the individual methods used with the benchmark. This is the naive method. The table shows that far from all methods exceeded this benchmark. Of the methods analysed, only ARIMA, ARFIMA, artificial neural networks, BATS, Thetam, and the hybrid model exceeded the benchmark on both test and training data. When forecasting based on historical purchases, the ETS method still exceeded the benchmark. Even for these methods, we see large differences between the evaluation of success on test data and training data.

When forecasting based on classic literature purchase history data, the artificial neural network method was most successful on both test and training data. Thus, it can be described as the most successful and applicable in practice. Further results were not clear-cut. In the training data, the second-best method was the hybrid method, which is understandable given the success of artificial neural networks. The third best method on the training data was the BATS method, but it was not as successful on the test data. Here, it ranked as high as 5th place.

The second best on the test data was the ARFIMA method followed by the ARIMA method. The ETS method is the worst of the methods exceeding the benchmark, but the fact that it exceeded the benchmark makes it also a usable method.

When comparing based on Google searches of the classical literature, there are fewer methods that exceeded the benchmark. Neither on the training nor on the test data did the ETS method exceed the benchmark anymore. Thus, only ARIMA, ARFIMA, artificial neural network, BATS, Thetam and hybrid model are included in the methods exceeding the benchmark. Unsurprisingly, the artificial neural network-based method performed the best on the training data. However, on the test data, this method already showed the worst result. The hybrid model came in second on the training data.

The BATS method appears to be the best performing on the test data and, therefore , the most beneficial for practice. The ARIMA and AFRIMA methods share the second and third place. ARIMA performs slightly better on training data ARFIMA, as well as when using historical purchase data, on test data.

Thus, the results clearly show that it is not possible to identify a method that is generally suitable for the forecasting demand for classic literature. The most appropriate methods vary according to whether the data is searching data or historical purchase data. Although it can be traced that more complex statistical methods, AI-based and hybrid methods, were more successful than simple statistical methods when compared to the benchmark.

Table 3. Comparison of methods with respect to exceeding the benchmark on Czech Republic data

Method/data		**Forecasting based on key term searches**		**Forecast based on purchase history**	
		better than bench mark	**ranking**	**better than benchmark**	**ranking**
Naive		**Benchmark**			
sNaive	**Training data**	no		no	
	Test data	no		no	
ARIMA	**Training data**	yes	3.	yes	4.
	Test data	yes	3.	yes	3.
ARFIMA	**Training data**	yes	4.	yes	5.
	Test data	yes	2.	yes	2.
ETS	**Training data**	no		yes	6.
	Test data	no		yes	6.
SES	**Training data**	yes		yes	
	Test data	no		no	
Holt	**Training data**	yes		yes	
	Test data	no		no	
HoltWinters	**Training data**	no		no	
	Test data	no		no	
NNETAR	**Training data**	yes	1.	yes	1.
	Test data	yes	5.	yes	1.
BATS	**Training data**	yes	5.	yes	3.
	Test data	yes	1.	yes	5.
Thetam	**Training data**	yes	6.	yes	7.
	Test data	yes	6.	yes	7.

Method/data		Forecasting based on key term searches		Forecast based on purchase history	
		better than bench mark	ranking	better than benchmark	ranking
Hybrid model	Training data	yes	2.	yes	2.
	Test data	yes	4.	yes	4.

Source: Authors' processing.

If we use a purely AI-based method, namely the artificial neural network method, it achieves great success on the training data, but this is expected for this method. Somewhat surprisingly, the hybrid model is not a clear winner, although as expected, it outperformed the benchmark.

Table 4 summarises the comparison of the analysed methods with the benchmark, which, as in the comparison within the Czech Republic, was the naive method. Here again, we see differences in accuracy on the test and training data. However, the methods that exceeded the benchmark are different. Surprisingly, the benchmark was not exceeded by the BATS method, which always exceeded the success rate of the naive method on the Czech Republic data.

Table 4. Comparison of methods with respect to exceeding the benchmark on global data

Method/data		Forecasting based on key term searches		Forecast based on purchase history	
		better than benchmark	ranking	better than benchmark	ranking
Naive		Benchmark			
sNaive	Training data	no		no	
	Test data	yes		yes	
ARIMA	Training data	yes		yes	
	Test data	no		no	
ARFIMA	Training data	yes	2.	yes	4.
	Test data	yes	2.	yes	2.
ETS	Training data	no		yes	
	Test data	yes		no	
SES	Training data	no		yes	
	Test data	yes		no	
Holt	Training data	yes	3.	yes	5.
	Test data	yes	3.	yes	3.
HoltWinters	Training data	no		no	
	Test data	no		no	

Method/data		Forecasting based on key term searches		Forecast based on purchase history	
		better than benchmark	ranking	better than benchmark	ranking
NNETAR	Training data	yes	1.	yes	1.
	Test data	yes	1.	yes	1.
BATS	Training data	no		no	
	Test data	yes		yes	
Thetam	Training data	no		yes	3.
	Test data	yes		yes	4.
Hybrid model	Training data	no		yes	2.
	Test data	yes		yes	5.

Source: Authors' processing.

Worldwide, five methods were the best for forecasting on purchase history data, namely ARFIMA, artificial neural networks, Thetam, the hybrid model, and the surprisingly simple statistical method Holt exponential equalisation.

On the keyword search data, the successful methods were considerably fewer, namely only ARIMA, artificial neural networks, and again Holt equalisation. Somewhat surprisingly, the Theta and hybrid methods outperformed the benchmark on the key term search test data, while failing to outperform on the training data.

The artificial neural network method was the most successful on these data, both for the key term search data and for the data based on historical purchases. The second most successful method, again for both the search-based data and the history-based data, was the ARFIMA method. Holt's method was the last one to outperform the benchmark.

5. Conclusions

In conclusion, it is appropriate to evaluate the resulting demand for classical literature both in the Czech Republic and worldwide. Methods usually predict the completion of an established trend. Since the historical data (both purchases and searches) ended in the pre-holiday period, it is likely that a decline in demand will follow based on decomposition and graphical assessment. This is caused by the cyclical fluctuation in the holiday months, when people typically both purchase and consider purchasing classic literature less.

If we assess the following main trend without taking this cyclical decline into account, the results of the methods that exceeded the benchmark are similar. For the Czech Republic, it can be seen that all methods, even on both sets of data, predict a stagnation in demand. For the global comparison, the results are different. While the ARFIMA method predicts stagnation, artificial neural networks also predict a stagnant cyclical trend, the Holt method predicts a worldwide decline in demand for classic literature.

Furthermore, this research verified that, despite using multiple measures of accuracy, these measures define the same outcome. Thus, in the overall context, it does not matter which measure is used to predict the demand for classic literature, they all recommend the same method. This is also consistent with the author's previous research.

In future research, it would be useful to test the ability of each prediction to be applied in practice using multi-criteria evaluation methods. After assigning weights to each method, it would be clear even on global data how demand is likely to evolve in the future. However, this requires a scientific decision as to which method has a higher weight and which a lower weight. This is not yet possible with the current level of scientific knowledge in the field of demand forecasting. Forecasting each demand is an individual process, and a different method may be appropriate for each demand. Perhaps the future in scientific research will give a clear answer; scientific research in this field is still important.

However, even from this simple verbal assessment, it is clear that while the demand for classical literature will not decline in the Czech Republic, it is possible worldwide. Of course, it is a question of what people in e-publishing companies, who group their books together, or people searching for the term on search engines, understand by classic literature. Sticking to the definition of the Institute for Czech and World Literature, we can consider classical literature to be: 'the designation of important artistic and scientific works of a particular national literature which have received universal national recognition and affection and which are characterised by high ideological and artistic value'. From this definition, in the context of the continuing demand for classical literature in the Czech Republic, we can deduce that the people of this nation are capable of reading titles of high ideological and artistic value, and are able to appreciate and even love national (and even world) works of art. Globally, there may be a decline in this appreciation. There is some hope, therefore, that the Czech nation will continue to recognise valuable works of literature and that its interest in the arts will not decline. This cannot be said with certainty about the worldwide interest.

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