sciendo

Time Series Analysis of Bikes Sales Dataset in JASP

Julian VASILEV*
University of Economics Varna, Varna, Bulgaria
**Corresponding author, vasilev@ue-varna.bg*

Teodora DANEVA
University of Economics Varna, Varna, Bulgaria
teodora.daneva@ue-varna.bg

Silvia MOMCHEVA
University of Economics Varna, Varna, Bulgaria
silvia.momcheva@ue-varna.bg

Abstract. *This study examines the application of time series analysis to predict future bike sales, focusing on two categories: road and mountain bikes. Using the Prophet module in JASP, the research explores trends and weekly seasonality in sales data to derive insights into potential future performance. The study aims to enhance decision-making for inventory management and marketing strategies. A quantitative methodology underpins the research, relying on historical data and the Prophet forecasting tool. The findings reveal no seasonal patterns, different trends for each bike category, enabling targeted business strategies. Practical implications include improved forecasting accuracy and resource allocation. While limited to two bike categories and reliant on the dataset's quality, the research demonstrates the utility of time series forecasting for retail applications. The originality lies in applying modern forecasting tools to a specific retail context, contributing to both academic literature and industry practice. Our expectations are to have peak sales during weekends when customers have more free time for sports and recreation for both categories, albeit with varying intensities. But weekly patterns are not revealed. The MAPE values (for both categories-mountain and road bikes) are quite high and they do not increase slightly within the time frame of the forecast period. The conclusion is that if a trend was identified the forecast would not be reliable.*

Keywords: time series analysis, forecasting, Prophet, JASP, bike sales dataset.

Acknowledgments

This paper is written and financed within the project "PNI-KC24-05-BUC-TAI" – "High performance business forecasting use cases with time series data and AI".

Introduction

Understanding and predicting bike sales trends is essential for effective business operations in the retail industry. Time series analysis provides a structured approach to uncovering patterns in historical data, which can inform inventory management, marketing campaigns, and production planning. This study focuses on applying the Prophet module in JASP to forecast sales for two specific bike categories: road and mountain bikes. By analyzing trends and weekly seasonality, this research seeks to enhance the predictive accuracy of sales forecasts, thereby enabling more informed decision-making.

The objectives of this study include identifying the key trends and seasonal patterns in bike sales, assessing the forecasting capabilities of the Prophet module, and evaluating its practical

DOI: 10.2478/picbe-2025-0085

implications for retail management. This research addresses a critical gap in the application of advanced forecasting methods to retail sales data, with a specific focus on bike sales.

Literature review

Time series analysis has been widely employed in retail forecasting to understand sales dynamics and improve decision-making. Simeonidis et al. (2024) explored the role of trend and seasonality in predicting retail sales, demonstrating that incorporating these factors significantly enhances forecast accuracy. This aligns with the objectives of the current study, which emphasizes the importance of trend and seasonality in understanding bike sales. Furthermore, Sulova et al. (2022) highlighted the relevance of machine learning approaches in retail forecasting, suggesting that hybrid models outperform traditional methods. Their findings provide a foundation for the current study's use of Prophet, a state-of-the-art forecasting tool.

Research on time series forecasting tools has also focused on their applicability across various domains. Stoyanova (2020) examined the use of the Prophet module for forecasting in e-commerce, noting its flexibility in handling complex seasonal patterns. Similarly, Ramona et al. (2020) emphasized the importance of user-friendly tools like Prophet for non-technical users, which supports its selection for this study. However, Sulova and Marinova (2024) cautioned against over-reliance on any single tool, underscoring the need for critical evaluation of forecasting results.

From a practical perspective, recent studies conducted by researchers at the University of Economics Varna have provided valuable insights into time series forecasting. Parusheva and Pencheva (2021) examined retail sales forecasting in small and medium-sized enterprises, highlighting the importance of reliable data preprocessing. Armyanova and Aleksandrova (2023) focused on the role of seasonality in sales forecasting, which resonates with the current study's emphasis on weekly patterns. Kuyumdzhiev and Petrov (2024), Todoranova et al (2020) investigated the challenges of applying advanced forecasting tools in the retail sector, providing practical considerations for this research. Mileva (2024) studied seasonal fluctuations in marine traffic data. Bike sales may have regional specifics Georgieva (2024).

Machine learning methods are useful for advanced forecasting (Aleksandrova & Armianova 2022) but for predicting bike sales it is difficult to adapt them in practice. The digital transformation opens new opportunities (Georgescu et al., 2022) but sales forecasting stays in some cases apart from the forecasting. Blockchain technologies are innovative (Petrov et al., 2020; Stoyanova, 2021). Some structural changes (Raychev, 2018, 2020) in the sales may occur. Marketing and AI is a widely discussed topic (Boychev, 2020, 2021, 2024).

Marketing strategies require accurate estimation of future sales to manage inventory and match supply with demand. Thus, sales forecasting has become crucial for businesses to manage their inventory, make decisions, and increase their profits effectively. By applying time series analysis in retail, marketers can forecast the demand of products at certain times of the year or during specific promotions to avoid stockouts or overstocking. In a strategic perspective, the findings from the time series analysis can be used in the high-level decision making process.

Brykin (2024) compared the classic forecasting techniques such as ARIMA and ETS models with the new approaches like the Prophet model in sales forecasting. While ARIMA models are suitable for time series data with a linear structure, they fail to capture complex seasonality and non-linear trends in the data (Brykin, 2024). Also, Kwarteng and Andreevich (2024) investigated ARIMA, SARIMA, and Prophet models, stating that Prophet is better at handling gaps and seasonalities. Additionally, the rise of the machine learning models such as Recurrent Neural

Networks (RNN), and Long Short Term Memory (LSTM) networks have improved the ability to model non-linear and complex temporal dynamics (Hasan et al. 2022). These models are good in capturing long-term dependencies and are most useful in case of high frequency sales data. However, unlike the Prophet model, they often need a lot of data and are not very interpretable. Zunic et al. (2020) applied Prophet in sales forecasting and found that Prophet could benefit marketers in their decision-making processes concerning inventory and resource management. For instance, in the Prophet model of sales, trends can be used to inform product introductions, marketing strategies, and even prices. This enables marketers to develop strategies based on data, which in turn helps in avoiding the risks that incur while entering or expanding in the market.

Time series forecasting can provide marketers with more precise budget forecasts for marketing spend to match expected sales. Sales Forecasting and Demand Planning: The Prophet model assists marketers in sales trends forecasting, improving inventory management, and optimizing the utilization of resources (Zunic et al., 2021). Budgeting and Financial Planning: Marketing budgets can be aligned to expected sales performance using time series analysis, which is particularly helpful in seasonal markets (Kwarteng & Andreevich, 2024).

Campaign Performance Analysis: Marketers can determine the effectiveness of past campaigns by analyzing historical sales data (Brykin, 2024). Customer Segmentation and Personalization: Time series data can be used to recognize particular customer purchasing patterns for targeted marketing strategies (Albeladi et al., 2023). Market Trend Analysis: Marketers can use Prophet's trend analysis tools to determine changes in consumer behavior and modify their marketing strategies accordingly (Zunic et al., 2020).

Even though there have been improvements, in predicting time series data over the years according to study findings; there are still some hurdles when it comes to putting these methods into real-world use effectively. From the research by (Miryanov and Chalakova 2019) it is highlighted that the accuracy of forecasts can be greatly influenced by the quality of the data input which may contain values and noise issues, stressing how crucial it is to perform thorough data preprocessing to guarantee the reliability of predictive models. Their study (Nikolaev et al. 2018) delve into the impact of influences like downturns and changes in consumer trends on forecast accuracy emphasizing the importance of models being able to adjust to fluctuating market dynamics. These obstacles underscore the essentiality of assessing forecasting methods and guaranteeing their versatility, in retail industry applications.

Methodology

The dataset is a real dataset with anonymized data for bike sales. The dataset contains 15,645 rows. The columns are order_date, order_id, order_line, quantity, price, total_price, model, category_1, category_2, frame_material, bikeshop_name, city, and district. ETL procedures are carried out. The dataset is filtered by category of bike and by year (only the sales for year 2023 are analyzed). Then pivot tables are used for grouping the data by date and summarizing the quantities sold. Two data marts are created—for mountain bikes and for road bikes. Each case in the data mart has one row for each date. These data are treated as time series data.

Using JASP, several steps are carried out. History plots are visualized with a line. The models are tested with 2 and 3 change points. The estimation is "Markov chain Monte Carlo". Seasonalities on a weekly basis are checked. The prediction is for 14 days. The evaluation of the model includes: cross-validation for 14 days, visualizing the table with performance metrics: Mean absolute percentage error (MAPE).

The study employs time series analysis to forecast bike sales using the Prophet module in JASP. Prophet is an open-source forecasting tool designed for simplicity and flexibility, allowing for the incorporation of trend and seasonal components. The dataset comprises historical sales data for road and mountain bikes, segmented into weekly intervals.

The analysis involves three key steps: data preprocessing, model development, and forecast generation. During preprocessing, missing values are addressed, and the data is transformed into a suitable format for Prophet. The model incorporates both trend and weekly seasonality components, reflecting the study's focus on these factors. Forecasts are generated for a future period of six months, with separate models developed for road and mountain bikes.

Results and discussions

The analysis is based on real-world data, with quantities and prices adjusted for the purpose of the study. The dataset contains a total of 15,645 records, with sales aggregated on a daily basis. This format allows for the identification of long-term trends and seasonal patterns. Sales data is aggregated on a daily basis to facilitate a more accurate identification of long-term patterns and seasonal trends.

Our expectations are to have peak sales during weekends when customers have more free time for sports and recreation for both categories, albeit with varying intensities. But weekly patterns are not revealed.

The analyzed weekly seasonality confirms that sales of mountain bikes are highest during the weekends when customers have more free time for sports and recreation.

The data analysis is separated into two parts according to the category of bikes: road bikes and mountain bikes.

Results on mountain bikes

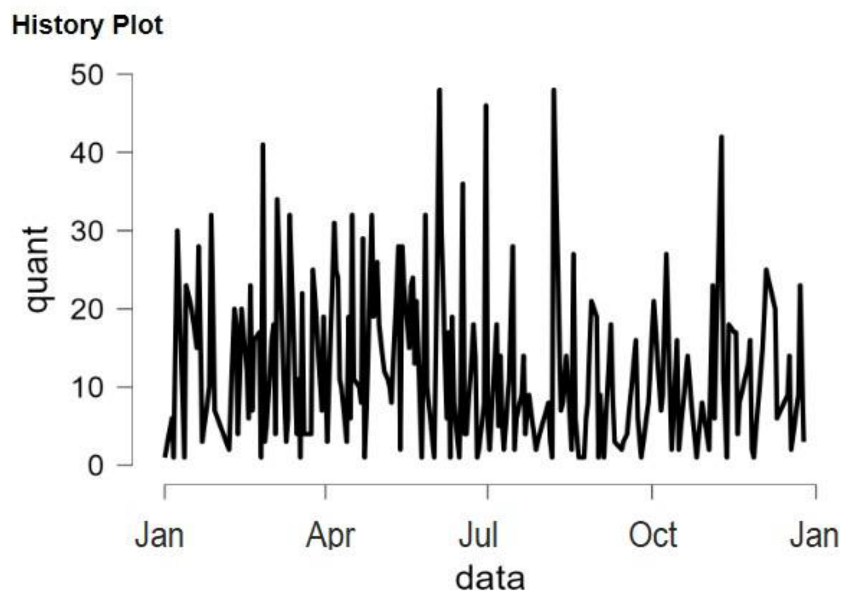

Figure 1. History plot for mountain bikes sales (2023)

Source: Own elaboration in JASP.

The history plot reveals great variations in sales. No stable trend is identified.

DOI: 10.2478/picbe-2025-0085, pp. 1072-1087, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

Posterior Summary Table

Parameter	Mean	SD	95% CI Lower	95% CI Upper	R-hat	ESS (bulk)	ESS (tail)
Growth rate (k)	0.005	0.039	-0.079	0.078	1.021	514	347
Offset (m)	0.051	0.029	0.017	0.132	1.016	300	351
Residual variance (sigma)	0.218	0.012	0.196	0.243	1.003	1393	806

Figure 2. Posterior Summary (mountain bikes; 2023)

Source: Own elaboration in JASP.

The growth rate of 0.005 means for 200 days we may expect a slight increase with 1 bike. The R-hat value is near 1 which means the forecast may be made. But the ESS is below 1000 which means that the forecast lacks precision.

Changepoint Posterior Summary Table

Changepoint	Change in growth rate (δ) Mean	SD	95% CI Lower	95% CI Upper
2023-04-07	-0.032	0.046	-0.132	0.046
2023-06-23	-0.008	0.038	-0.083	0.065
2023-09-25	0.044	0.050	-0.042	0.155

Figure 3. Changepoint Posterior with 3 change points (mountain bikes; 2023)

Source: Own elaboration in JASP.

The identified change points include:

The table provides insights into how the growth rate of mountain bike sales has changed at specific points in 2023. Each changepoint represents a shift in the trend, showing whether sales growth slowed down or picked up.

On April 7, 2023, there was a decline in the growth rate of mountain bike sales by -0.032. This means sales were slowing down. Assuming a linear trend, this suggests a decrease of 1 unit every 30 days (since 1 ÷ 0.032 ≈ 30 days). While the confidence interval ranges from -0.132 to 0.046, indicating some uncertainty, the overall trend points toward a slowdown in sales.

On June 23, 2023, the growth rate saw a slight drop of -0.008. This change is minimal and doesn't significantly impact the overall trend. Sales remained relatively stable, with only a minor negative shift.

Looking at the final changepoint (September 25, 2023), we can expect sales to increase by 1 unit every 25 days. While this is a positive change, it's not a significant surge, indicating a gradual but stable trend rather than rapid growth.

Another experiment is done—trying to see the trend of mountain bikes with 2 change points.

Changepoint Posterior Summary Table

	Change in growth rate (δ)		95% CI	
Changepoint	Mean	SD	Lower	Upper
2023-05-14	−0.038	0.037	−0.117	0.024
2023-09-25	0.048	0.047	−0.031	0.154

Figure 4. Changepoint Posterior with 2 changepoints (mountain bikes; 2023)

Source: Own elaboration in JASP.

The identified 2 changepoints include:

The table provides insights into how the growth rate of mountain bike sales has changed at specific points in 2023. Each changepoint represents a shift in the trend, showing whether sales growth slowed down or picked up.

On May 14, 2023, the growth rate of mountain bike sales declined by -0.038, indicating a slowdown in sales. Assuming a linear trend, this suggests a decrease of 1 unit every approximately 26 days (since 1 ÷ 0.038 ≈ 26 days). The confidence interval ranges from -0.117 to 0.024, showing some uncertainty but suggesting that the overall trend leans toward a decline.

On September 25, 2023, the growth rate increased by 0.048, meaning sales started to pick up. Using the same logic, we can expect sales to rise by 1 unit every 21 days (1 ÷ 0.048 ≈ 21 days). While this is a positive shift, it's not a dramatic surge; rather, it suggests a gradual but steady upward trend in sales.

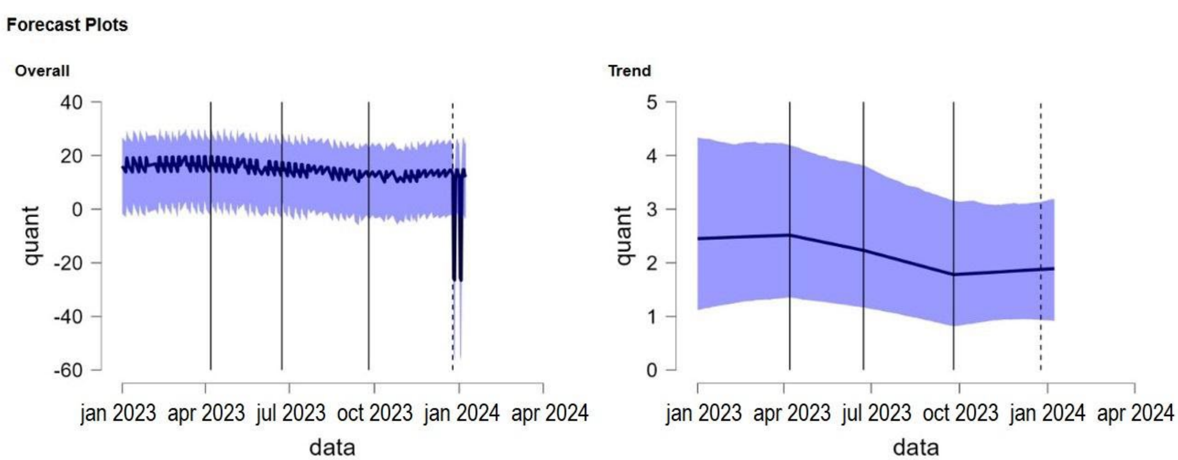

Figure 5. Forecast Plots on 3 changepoints (mountain bikes; 2023)

Source: Own elaboration in JASP

The graphical presentation of the change points and the trend shows that we cannot expect a sudden increase or decrease in sales (as a whole).

DOI: 10.2478/picbe-2025-0085, pp. 1072-1087, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

Simulated Historical Forecasts Table

Horizon	MAPE
3	310.833 %
4	131.264 %
5	215.312 %
6	319.179 %
7	254.041 %
10	331.225 %
11	129.904 %
12	203.869 %
13	336.501 %
14	257.747 %

Figure 6. Simulated Forecasts (mountain bikes, 2023)
Source: Own elaboration in JASP.

The MAPE values are quite high, and they do not increase slightly within the time frame of the forecast period. The conclusion is that if a trend was identified, the forecast would not be reliable.

The high MAPE values indicate that the forecasting accuracy is limited, especially for short-term predictions. The best-performing forecast horizon is 11 days, suggesting Prophet performs better with medium-term projections. Further analysis of the rate means, which is 0.005 (or 5 thousandths), suggests a very small increase in sales. When dividing 1 by 0.005, the result is 200 days, meaning the expected growth is one additional sale every 200 days. This reflects a stable but slow growth rate.

Additionally, the ESS (bulk) value, which should ideally be close to 1000 to ensure reliable forecasting, is slightly lower in this case. This may impact the precision of the predictions. Another important metric, R-hat, measures how well the model has converged. A value close to 1 indicates a well-calibrated model, while higher values suggest potential instability. Overall, the data does not indicate a strong upward or downward trend in sales but rather a stable performance with seasonal variations.

Results on road bikes

The analysis continues with the second category: road bikes for the year 2023.

DOI: 10.2478/picbe-2025-0085, pp. 1072-1087, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

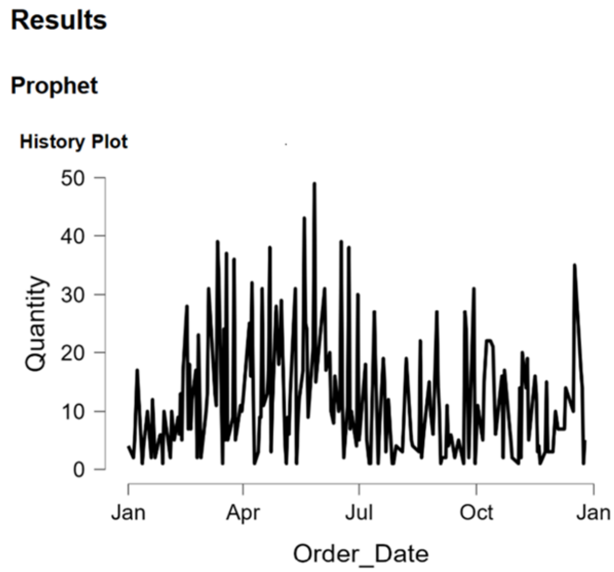

Figure 7. History plot for road bikes sales (2023)

Source: Own elaboration in JASP.

Over the period under review, sales of road bikes have been quite volatile. There is no clear upward or downward trend in the data; rather, road bike sales are cyclical, peaking at some times and plummeting at others. This variability can be attributed to factors like seasonal demand, promotional activities, and broader economic conditions.

Posterior Summary Table

Parameter	Mean	SD	95% CI Lower	95% CI Upper	R-hat	ESS (bulk)	ESS (tail)
Growth rate (k)	0.056	0.027	0.013	0.119	1.004	786	702
Offset (m)	0.021	0.011	0.007	0.050	1.005	656	479
Residual variance (sigma)	0.202	0.011	0.182	0.224	1.001	1351	1123

Figure 8. Posterior summary for with 2 change points (road bikes, 2023)

Source: Own elaboration in JASP.

This result shows that the growth rate (k) is 0.056, indicating a moderate increase in sales over time. This linear interpretation indicates that on average, sales rise by one unit roughly every 18 days (18 is approximately 1 divided by 0.056). This is a slow but regular increase. However, the 95% confidence interval (CI) of (0.013−0.119) indicates some uncertainty as to the real growth trend.

The offset (m) with a mean of 0.021 is a small baseline effect, which suggests little or no shift from the initial state of the forecast. The confidence interval for this offset is between 0.007 and 0.050, which also suggests small and rather stable values. However, the Residual Variance (σ) is 0.202 with a narrow confidence range of 0.182 to 0.224, indicating a lot of noise in the data. This high variance, however, means that short-term sales predictions may not be very accurate as they are given by historical trends, as external factors can cause a large shift in demand.

The R-hat values of all parameters are almost equal to 1 (range from 1.001 to 1.005) which indicates that the Markov Chain Monte Carlo (MCMC) simulations have converged, and the model is stable. However, the ESS values are less than 1000 for both the growth rate and the offset, bulk

DOI: 10.2478/picbe-2025-0085, pp. 1072-1087, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

ESS values are 786 and 656 respectively. This means that, although the estimates are useful, they may not be very precise. This highlights the necessity of incorporating external explanatory variables like promotional activities, competitive pricing, and seasonal demand trends to enhance the predictive model's accuracy.

The results from a business perspective indicate that although the road bike sales are positive, the high residual variance and low ESS values mean that the short-term forecasts should be used with caution. This means that decision-makers should concentrate on quarterly sales planning rather than depend too much on the short-term predictive models. The moderate growth rate indicates the necessity of strategic marketing activities in order to maintain and enhance the demand during times of uncertainty. Future forecast improvements should be made by using hybrid models that incorporate historical trends along with real-time market signals to create more responsive and dynamic sales strategies.

Posterior Summary Table

Parameter	Mean	SD	95% CI Lower	95% CI Upper	R-hat	ESS (bulk)	ESS (tail)
Growth rate (k)	0.100	0.044	0.032	0.206	1.002	694	528
Offset (m)	0.017	0.012	0.001	0.048	1.002	894	728
Residual variance (sigma)	0.202	0.011	0.183	0.224	1.003	1531	1265

Figure 9. Posterior summary for 3 change points (road bikes, 2023)

Source: Own elaboration in JASP.

This moderate increase in sales overtime is shown by a growth rate of 0.100. Translated into linear terms, this means sales increase by 1 unit every 10 days, as 1 divided by 0.100 equals 10 days. This represents a faster growth rate than mountain bikes, which saw a growth rate of 0.005 and increased by one unit every 200 days. The R-hat value, which should be near one for the model to have trained well and be appropriate for prediction, supports this. Non-speaking However, with an Effective Sample Size (ESS) below 1,000, the forecast is not very accurate and should not be considered completely trustworthy. This suggests that while there is a high level of randomness in the short-term predictions, perhaps the longer trends are more reliable. Moreover, the high residual variance ($\sigma = 0.202$) suggests that the model has a hard time capturing the short-term variability. This might happen due to factors outside the model, like marketing activities, weather, or other seasonal patterns that have not been captured by the model. The table below provides insights into how the road bike sales growth rate has changed at specific points in 2023. Each changepoint represents a significant shift in the trend, indicating whether sales growth slowed down or picked up.

Changepoint Posterior Summary Table

Changepoint	Change in growth rate (δ) Mean	Change in growth rate (δ) SD	95% CI Lower	95% CI Upper
2023-04-06	-0.132	0.063	-0.280	-0.030
2023-06-24	-0.004	0.037	-0.080	0.067
2023-10-02	0.027	0.040	-0.049	0.114

Figure 10. Changepoint Posterior with 3 change points (road bikes 2023)

Source: Our own elaboration in JASP.

DOI: 10.2478/picbe-2025-0085, pp. 1072-1087, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

From January to December 2023, our changepoint analysis reveals variable growth rates in road bike sales, indicating changes in demand patterns. Sales declined by one unit per eight days starting April 6, 2023, up to the next measurement. During this time, the confidence interval between -0.280 and -0.030 confirmed the existence of this downturn. The drop might have happened because of seasonal factors or demand reduction after winter along with price changes. From June 24, 2023, forward, sales growth showed a limited change at -0.004 with a confidence interval of -0.080 to 0.067. The summer months saw stable sales because consumer attention remained consistent. Sales growth reached 0.027 on October 2, 2023, marking the biggest recovery with one-unit increases every 37 days. Although the confidence interval of -0.049 to 0.114 shows some ambiguity in this result, the upward trend might link to autumn promotions alongside pre-winter purchases and increased market interest. These findings demonstrate how seasonal forecasting combined with strategic marketing initiatives can help manage downturns and exploit growth opportunities. The decline during April demands special marketing strategies to prevent inventory build-up, while the stable demand in June allows for consistent product planning. During October, staff concentration increased alongside higher customer arrival rates, which produced effective service levels.

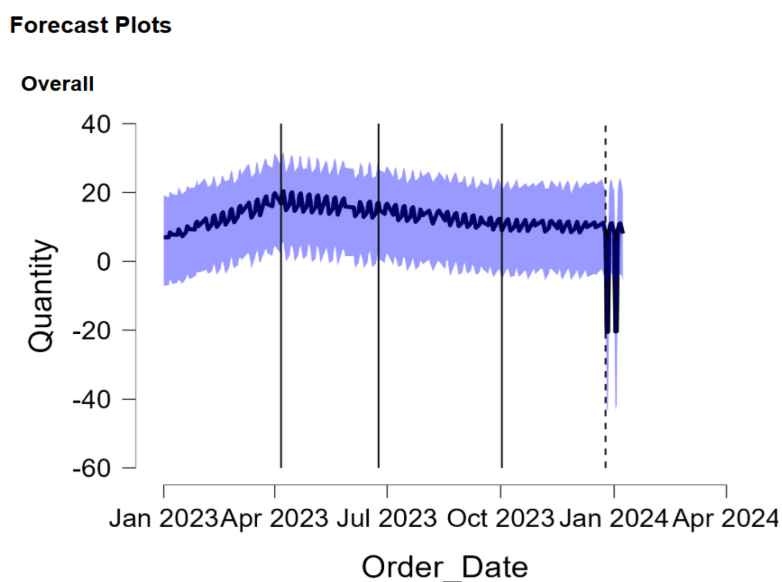

Figure 11. Forecast Plots on 3 changepoints (road bikes; 2023)

Source: Own elaboration in JASP.

The confidence bands show a significant increase in width starting from the end of 2023 which implies that the model has a low accuracy in predicting sales in the subsequent periods. This is because the category “road bikes” may have a limited ability to capture factors that may affect road bike sales in the future, including seasonal patterns, promotional activities, competitors’ pricing strategies, and overall economic conditions that are not captured by the historical data used in the model. In addition, there is a sharp fluctuation at the end of the forecast period which supports the difficulties in making accurate long-term predictions.

This from a business perspective means that short-term forecasts should be treated with some caution and that real-time monitoring of sales trends is required in order to make the necessary adjustments to the inventory and marketing strategies in a timely manner. The downward trend that has been observed after the midyear period means that businesses should prepare some promotional activities or change the pricing strategy to reduce the possible decline in sales revenue. As a result of increasing uncertainty, other forecasting techniques, such as hybrid models that include macroeconomic indicators, competitor analysis, and consumer sentiment data, may be useful to enhance the accuracy of predictions and thus offer a better basis for decision-making.

Simulated Historical Forecasts Table

Horizon	MAPE
3	258.919 %
4	199.534 %
5	212.463 %
6	359.871 %
7	312.132 %
10	247.921 %
11	189.172 %
12	224.607 %
13	418.654 %
14	259.459 %

Figure 12. Simulated Historical Forecasts (road bikes; 2023)

Source: Own elaboration in JASP.

With the help of the MAPE analysis in the JASP, the predictive accuracy of the Prophet model for road bike sales is found to be very low for all the forecast horizons. The MAPE values are always very high and do not decrease with increasing forecasting horizon, meaning that the predicted and actual sales are very different. The lowest error is found at the 11-week horizon (189.17%) which can be interpreted as the model being only slightly better at forecasting for the middle term. Both the shorter- and longer-term forecasts are rather inaccurate. Also, the very high MAPE values at some time horizons, for instance, 418.65% in 13 weeks show that the model is not very stable and is not very effective in modeling real-world demand fluctuations.

High volatility coupled with external influences not captured by the model makes elevated error rates reasonable. Seasonal patterns together with rapid market changes and consumer preferences and overall economic factors like interest rates and available buying money may worsen these errors. In addition, the model not capturing weekly seasonality makes it difficult for the model to be used for short-term forecasting with accuracy. The increasing variation in errors across different time horizons makes it problematic to rely solely on the Prophet model for accurate sales predictions in a retail context.

These results have important implications for business practitioners as they suggest that time series models should be complemented with additional data sources and analysis techniques. Because there is low short-term accuracy it is important that organizations use real-time monitoring and adaptive forecasting models that include machine learning techniques as well as competitive intelligence and external economic indicators to improve the accuracy of the forecasts. Since the mid-term forecasts for the 11-week horizon are reliable it means that inventory management should be done on quarterly planning cycles while the short-term demand should be adjusted dynamically according to the actual sales and the market situation. In conclusion these findings highlight the weakness of the standalone statistical forecasting models and the need to adopt a systemic predictive approach for enhancing decision-making in road bike sales.

Discussion

The findings align with previous research emphasizing the significance of trend and seasonality in retail forecasting. For instance, the observed weekend peaks correspond to insights from Sulova and Marinova (2024), who identified similar patterns in seasonal sales data. Moreover, the upward trend in road bike sales corroborates Ramona et al. (2020) findings on the impact of long-term trends on forecast accuracy.

This study contributes new knowledge by demonstrating the practical applicability of Prophet in retail forecasting. Unlike traditional models, Prophet's ability to handle complex seasonality and trends makes it particularly suited for the dynamic retail environment. However, the findings also highlight the limitations of relying solely on historical data. This analysis aligns with the caution expressed by Penchev (2024), emphasizing that time series models should be augmented with additional external variables, such as macroeconomic indicators, competitive pricing data, and weather conditions to enhance predictive performance.

Additionally, data analysis may be made with AI and cloud solutions (Hristova 2024). According to Nacheva (2024) additional information about user experience and emotions may reveal better forecasting for bike sales. To further refine the analysis of road bike sales forecasting, additional marketing mix data should be incorporated to capture the external factors influencing demand.

According to Zhechev (2024) contemporary marketing trends place consumer sentiment analysis, competitor pricing strategies, promotional campaigns, and digital engagement metrics as critical for influencing purchasing behavior. Analyzing the effects of seasonal promotions, discounts and advertising expenditures on demand can provide valuable insights into fluctuations not fully captured by historical data. Moreover, the regular monitoring of customer characteristics, brand loyalty, and online search patterns can help to detect changes in consumer preferences that affect long-term sales trends. The use of macroeconomic indicators such as inflation rates, disposable income, and interest rates will improve the sales forecasting accuracy by considering the larger economic context. Additionally, data from social media interactions, product reviews, and influence partnerships can highlight emerging consumer preferences and potential demand surges. These marketing variables can be incorporated into predictive models to significantly enhance the accuracy of sales forecasts that in turn can support more effective inventory management and promotional strategies.

Conclusion

This study underscores the utility of time series analysis in forecasting bike sales, providing actionable insights for retail management. The use of the Prophet module in JASP proves effective in capturing trends and seasonal patterns, enabling more accurate predictions. While the research is limited to two bike categories (mountain bikes and road bikes) and specific seasonal components, the methodology offers a robust framework for future studies. Practical implications include improved inventory management and targeted marketing strategies.

This research is focused on two categories visible in the category_1 variable. Future work may be focused on filtering the dataset by a specific bike shop or specific city or specific category_2 and making a similar analysis. The filtered dataset by city may show some regional specifics which may be useful for inventory replenishment, manufacturing planning, and sales forecasting.

Filtering by bike shop may outline specific customer features. If the dataset is filtered by model and city customer profiles may be created. Additional data on the age of the customer may reveal in-depth customer profiling. Moreover, this dataset after grouping by categorical variables and summing in a variable on an interval scale may reveal additional regional and model characteristics. Additional info on customer satisfaction or customer user experience combined with transactional data analysis may outline future marketing strategies and better politics for new product pricing. Customer segmentation may be done within the STP (segmentation targeting positioning) process. The dataset may be used for creating a better marketing plan. Additional data on customers may help customer personalization.

Future research in time series forecasting could enhance marketers' ability to develop more accurate budget projections, ensuring marketing expenditures align with anticipated sales. Advancements in sales forecasting and demand planning may further refine the capabilities of models like Prophet, enabling more precise predictions of sales trends, improved inventory management, and optimized resource allocation. Additionally, future developments in budgeting and financial planning could leverage time series analysis to create more adaptive budgeting strategies, particularly for industries affected by seasonality.

Further exploration in campaign performance analysis may lead to more sophisticated methods for assessing past marketing efforts and enhancing strategic decision-making. In customer segmentation and personalization, future studies could refine techniques for identifying nuanced purchasing behaviours, leading to more targeted and effective marketing strategies. Finally, continued innovation in market trend analysis may allow for more dynamic adjustments to shifts in consumer behaviour, ensuring that marketing strategies remain responsive and data-driven.

References

Albeladi, K., Zafar, B., & Mueen, A. (2023). A Novel Deep-learning based Approach for Time Series Forecasting using SARIMA, Neural Prophet, and Fb Prophet. *arXiv preprint arXiv:2111.15397*

Aleksandrova, Y., & Armianova, M. (2022). Evaluation of cost-sensitive machine learning methods for default credit prediction. *International Conference Automatics and Informatics, ICAI 2022 - Proceedings*, 89–94. https://doi.org/10.1109/ICAI55857.2022.9960023

Aleksandrova, Y. (2019). Predicting students performance in Moodle platforms using machine learning algorithms. In *Conferences of the department Informatics* (No. 1, pp. 177-187). Publishing house Science and Economics Varna.

Ana-Maria Ramona, S., Marian Pompiliu, C., & Stoyanova, M. (2020). Data mining algorithms for knowledge extraction. In Challenges and Opportunities to Develop Organizations Through Creativity, Technology and Ethics: The 2019 Griffiths School of Management *Annual Conference on Business, Entrepreneurship and Ethics (GSMAC)* (pp. 349-357). Springer International Publishing.

Armyanova, M., & Aleksandrova, Y. (2023, December). Design patterns in machine learning. In *AIP Conference Proceedings* (Vol. 2938, No. 1). AIP Publishing.

Boychev, B. (2020). Organizational and Methodological Issues of Using Infrastructure as a Service. *Monographic Library "Knowledge and Business" Varna*. https://ideas.repec.org/b/kab/monogr/7.html

Boychev, B. (2021). Marketing aspects of dark tourism. *Monographic Library "Knowledge and Business" Varna*. https://ideas.repec.org/b/kab/monogr/16.html

Boychev, B. (2024). Marketing Tools With Artificial Intelligence. *Conferences of the Department Informatics, 2024•informatics.Ue-Varna.Bg*, 71–75. https://informatics.ue-varna.bg/conference/Proceedings2024.pdf#page=72

Brykin, D. (2024). Sales Forecasting Models: Comparison between ARIMA, LSTM, and Prophet. *Journal of Computer Science*, 20(10), 1222-1230

Döring, L., Grumbach, F., & Reusch, P. (2024). Optimizing Sales Forecasts through Automated Integration of Market Indicators. *arXiv preprint arXiv:2406.07564*.

Georgescu, M. R., Stoica, E. A., Bogoslov, I. A., & Lungu, A. E. (2022). Managing Efficiency in Digital Transformation - EU Member States Performance during the COVID-19 Pandemic. *Procedia Computer Science*, *204*, 432–439. https://doi.org/10.1016/j.procs.2022.08.053

Georgieva, H. (2024). Characteristics and analysis of the Culture and Arts sector, specifically the Performing dance sector in Bulgaria. *Business & Management Compass*, 68(1), 5-13.

Hasan et al (2022). A Comparative Study on Forecasting of Retail Sales. *arXiv preprint arXiv:2203.06848*. (arxiv.org)

Hristova, I. (2024). *Optimizing Cloud Data Management With Ai-Driven Solutions.* In Conferences of the department Informatics (No. 1, pp. 162-168). Publishing house Science and Economics Varna. Retrieved from https://informatics.ue-varna.bg/ICTBE2024/ICTBE2024_162-168.pdf

Kuyumdzhiev, I., & Petrov, P. (2024). Virtualization and Online Engineering of the Administrative Services in Universities. *International Journal of Online & Biomedical Engineering*, 20(1).

Kwarteng, S. B., & Andreevich, P. A. (2024). Comparative Analysis of ARIMA, SARIMA, and Prophet Model in Forecasting. *Research & Development*, 5(4), 110-120.

Mileva, L. (2024). Big data predictions of Seasonal Fluctuations in Marine Traffic (using AIS data) by monitoring idle ships. *Business & Management Compass*, 68(4), 5-22. Retrieved from https://bi.ue-varna.bg/ojs/index.php/bmc/article/download/83/22/457

Miryanov, R., & Chalakova, K. (2019). One Type of Problems with Infinite Number of Cube Roots. *Math. Inform*, *62*, 284-289.

Nacheva, R. (2024). *An Emotions Mining Approach To Support Artificial Intelligence Systems.* In *Conferences of the department Informatics* (No. 1, pp. 92-104). Publishing house Science and Economics Varna. Retrieved from https://informatics.ue-varna.bg/ICTBE2024/ICTBE2024_92-104.pdf

Nikolaev, R., Milkova, T., & Miryanov, R. (2018). A New Meaning of the Notion "Expansion of a Number". *Mathematics and Informatics*, *61*(6), 596-602.

Parusheva, S., & Pencheva, D. (2021). Modeling a Business Intelligent System for Managing Orders to Supplier in the Retail Chain with Unified Model Language. In *Digital Transformation Technology: Proceedings of ITAF 2020* (pp. 375-393). Singapore: Springer Singapore.

Penchev, B. (2024). A Study On The Usage Of M-Learning Applications Within Bulgarian Schools. *Business & Management Compass*, 68(1), 45-53.

Petrov, P., Ivanov, S., Aleksandrova, Y., Dimitrov, G., & Ovacikli, A. K. (2020). Opportunities to use virtual tools in start-up fintech companies. 20th International Multidisciplinary Scientific GeoConference Proceedings SGEM 2020, Informatics, Geoinformatics and Remote Sensing, 20, 247–254. https://doi.org/10.5593/sgem2020/2.1/s07.032

Raychev, T. (2018). Assessment of canceled and problematic concession projects in the water supply and sewerage sector worldwide (in Bulgarian). Journal of the Union of Scientists, 7(3), 184–195.

Raychev, T. (2020). Assessment of structural changes of concessions in the water and sewerage sector. Economics and Computer Science, 6(1), 92–123

Simeonidis, D., Petrov, P., Penchev, G., Petrova, S., Dimitrov, G., & Petrivskyi, V. (2024, October). Performance and Accuracy Assessment of Detecting Network Intrusions with eSOM-Based Techniques. In *2024 International Conference Automatics and Informatics* (ICAI) (pp. 586-591). IEEE.

Stoyanova, M. (2020). Good practices and recommendations for success in construction digitalization. *TEM Journal*, 9(1), 42-47.

Stoyanova, M. (2021). Potential Applications of Blockchain Technology in the Construction Sector. *Data Science in Engineering and Management*, 35–48. https://doi.org/10.1201/9781003216278-4/POTENTIAL-APPLICATIONS-BLOCKCHAIN-TECHNOLOGY-CONSTRUCTION-SECTOR-MIGLENA-STOYANOVA

Sulova, S. (2016). An approach for automatic analysis of online store product and services reviews. *Izvestiya*. Journal of Varna University of Economics, 60(4), 455-467.

Sulova, S., Aleksandrova, Y., Stoyanova, M., & Radev, M. (2022, June). A Predictive Analytics Framework Using Machine Learning for the Logistics Industry. In *Proceedings of the 23rd International Conference on Computer Systems and Technologies* (pp. 39-44).

Sulova, S., & Bankov, B. (2019). Approach for social media content-based analysis for vacation resorts. *Journal of Communications Software and Systems*, 15(3), 262-271.

Sulova, S., & Marinova, O. (2024). Metadata Management Framework For Business Intelligence Driven Data Lakes. *Business Management/Biznes Upravlenie*, (2).

Todoranova, L., Nacheva, R., Sulov, V., & Penchev, B. (2020). A model for mobile learning integration in higher education based on students' expectations. *International Journal of Interactive Mobile Technologies (iJIM)*, Wien: International Association of Online Engineering (IAOE), 14, 2020, 11, 171 - 182.

Zhechev, V. (2024). A dive into the marketing trends of 2024: insights to unlocking potential. *Business & Management Compass*, 68(1), 54-65.

Zunic, E., Korjenic, K., Hodzic, K., & Donko, D. (2020). Application of Facebook's Prophet Algorithm for Successful Sales Forecasting Based on Real-world Data. *International Journal of Computer Science & Information Technology*, 12(2), 23-34

Zunic et al (2021). Comparison Analysis of Facebook's Prophet, Amazon's DeepAR+ and CNN-QR Algorithms for Successful Real-World Sales Forecasting. *arXiv preprint arXiv:2105.00694*

Appendix

Appendix 1. A fragment from the dataset

order_date	order_id	order_line	quantity	price	total_price	model	category_1	category_2
2019-01-07 00:00:00 UTC	1	1	1	6070	6070	Jekyll Carbon 2	Mountain	Over Mountain
2019-01-07 00:00:00 UTC	1	2	1	5970	5970	Trigger Carbon 2	Mountain	Over Mountain
2019-01-10 00:00:00 UTC	2	1	1	2770	2770	Beast of the East 1	Mountain	Trail
2019-01-10 00:00:00 UTC	2	2	1	5970	5970	Trigger Carbon 2	Mountain	Over Mountain
2019-01-10 00:00:00 UTC	3	2	1	3200	3200	Jekyll Carbon 4	Mountain	Over Mountain
2019-01-11 00:00:00 UTC	5	1	1	480	480	Catalyst 3	Mountain	Sport
2019-01-11 00:00:00 UTC	5	2	2	11190	22380	F-Si Black Inc.	Mountain	Cross Country Race
2019-01-11 00:00:00 UTC	5	4	1	2060	2060	F-Si 2	Mountain	Cross Country Race
2019-01-11 00:00:00 UTC	6	3	1	2340	2340	Habit 5	Mountain	Trail
2019-01-12 00:00:00 UTC	7	4	1	3200	3200	Scalpel 29 4	Mountain	Cross Country Race

Source: Anonymized dataset.