Одиннадцатая международная научно-практическая конференция BIG DATA and Advanced Analytics, Минск, Республика Беларусь, 23-24 апреля 2025 год

УДК 004.67

LEVERAGING BIG DATA AND MACHINE LEARNING FOR OPTIMIZING BUSINESS DECISIONS IN E-COMMERCE

Eugene Alooeff
R&D Engineer ATEK,
Bachelor of Computer Science
alooeff@atek.dev

Mariia Bulycheva
Engineer Zalando SE,
Master of Mathematics
mbulytcheva@gmail.com

E.A. Alooeff
Bachelor of Computer Science, Electronic Information Systems department of Brest State Technical University. Scientific interests: cloud technology, machine learning and multi-agent modeling.

M.V. Bulycheva
Master of science in mathematics, mechanics-mathematics department of Lomonosov State University, Moscow. Scientific interests: machine learning, large scale optimization and forecasting

Abstract. In today's digital economy, e-commerce companies face increasing pressure to remain agile and competitive in a rapidly evolving marketplace. The explosion of data from online transactions, customer interactions, and external sources has opened new opportunities for data-driven decision-making. This paper explores how companies can leverage big data, advanced analytics, and machine learning - particularly deep learning techniques such as transformer-based architectures - to optimize pricing, discounting, and demand forecasting strategies. By analyzing historical sales data alongside customer behavior, competitor pricing, and seasonal trends, businesses can implement dynamic and personalized pricing strategies that enhance profitability, improve customer satisfaction, and streamline operations. The paper also highlights the technical foundations of modern demand forecasting models, best practices for model training and evaluation, and the real-world challenges businesses face in implementing these solutions. Ultimately, the integration of AI and big data technologies represents a powerful shift in how strategic business and production decisions are made in the e-commerce sector.

Keywords: Big Data, E-Commerce, Pricing Optimization, Demand Forecasting, Price Elasticity, Customer Segmentation, Personalized Pricing, Transformer-Based Models, Deep Learning, Time-Series Forecasting.

Introduction. In the era of digital transformation, businesses are generating an unprecedented volume of data daily. This surge is fueled by the wide spreading of IoT devices, the explosion of social media interactions, and the ever-increasing number of online transactions. From sales transactions and customer interactions to supply chain operations and market trends, data has become a valuable asset for companies seeking to optimize decision-making. The ability to extract actionable insights from historical data enables firms to improve operational efficiency, enhance customer experience, maximize profitability, and gain a significant competitive edge. This data can be monetized, used for product development, and provides deep insights into customer behavior, all of which are crucial for strategic planning.

One of the key areas where big data and machine learning play a crucial role is in pricing and discounting strategies for e-commerce companies [1]. This area is central to revenue management and overall business strategy. By leveraging historical sales, prices, discount levels data, specific product attributes, and external factors, businesses can make data-driven pricing decisions that balance profitability and growth and succeed in delivering their promises to shareholders while remaining competitive [2]. Effective pricing strategies are essential for maximizing revenue, optimizing inventory, and responding to market dynamics.

The role of big data in pricing and discounting decisions. Traditionally, pricing decisions were based on simple cost-plus models or competitor benchmarking. However, with the advent of big data and machine learning, companies can now implement dynamic pricing strategies that adapt to market conditions in real time [3].

Historical sales data is one of the most valuable assets for pricing optimization. It provides a rich source of insights that help businesses understand demand patterns, customer behavior, and price sensitivity over time. Companies use data-driven pricing strategies to maximize profitability while maintaining competitiveness. Below, we explore the key components of leveraging historical sales data for pricing optimization.

Key data sources for pricing optimization. To optimize pricing decisions, companies gather and analyze various types of historical data:

Table 1. Data types

Data type	**Description and use case**
Transactional Data	Past sales volumes, including date, time, price and discount applied, and quantity sold. Used to track demand fluctuations and measure price elasticity.
Customer Data	Purchase history, segmentation, and price sensitivity. Helps in personalized pricing and targeted discounts.
Competitive Pricing Data	Market prices from competitors, collected via web scraping or third-party data providers. Enables dynamic pricing adjustments, helps the companies stay competitive at strategically important positions.
Promotional Data	Historical impact of discounts and special offers. Helps in assessing promotion campaigns’ effectiveness.
Seasonality & External Factors	Data on holidays, weather patterns, and economic conditions affecting demand. Used for forecasting price-sensitive time periods.

Demand prediction and price elasticity. One of the fundamental principles of pricing optimization is price elasticity, which measures how demand for a product changes in response to price adjustments.

1 Elastic demand: A small price decrease leads to a significant increase in sales volume. Common in price-sensitive markets (e.g., consumer electronics, fast fashion). Example: If the price of a popular brand of headphones decreases by 10%, sales might increase by 30%.

2 Inelastic demand: Price changes have little effect on sales volume. Common for premium brands or necessity goods (e.g., prescription drugs, luxury items). Example: Even if the price of a life-saving medication increases, demand will likely remain stable.

Techniques Used:

1 Regression Analysis – Models how changes in price affect sales volume. Example: Linear regression can be used to create a model that predicts sales based on price changes, while multiple regression can incorporate other factors like advertising spend.

2 A/B Testing – To test different pricing strategies, companies conduct A/B tests to measure the impact of price changes on sales and customer behavior. By splitting customers into two groups and offering different prices, businesses can analyze which pricing strategy yields higher conversions and revenue. For instance, subscription-based services like Netflix and Spotify experiment with different pricing tiers to determine the optimal balance between customer

acquisition and retention. Another approach involves segmenting similar products, also known as substitute goods, into distinct groups and applying tailored pricing strategies to each segment (if the local legislation does not allow price discrimination).

3 Demand Forecasting Models using statistical times series forecasting – Uses historical data to predict future responses to pricing changes. Example: Using ARIMA or other time-series models to forecast demand based on past sales and seasonal trends.

The utilization of deep neural networks, particularly transformer-based architectures, represents a significant leap forward in demand forecasting. To understand this powerful methodology in detail, we will explore it in the following section.

Demand forecasting with deep learning. Demand forecasting is a critical component in various industries, ranging from retail and e-commerce to manufacturing and logistics. Accurate predictions enable businesses to optimize inventory management, pricing strategies, and supply chain efficiency. Traditional statistical models and machine learning techniques have been widely used for demand forecasting. However, recent advances in deep learning, particularly transformer-based architectures, have demonstrated superior performance in capturing complex patterns and dependencies within time-series data.

Why use transformers for demand forecasting? Transformers are a type of deep neural network architecture originally designed for sequence-to-sequence modeling tasks in natural language processing [4]. They rely heavily on a mechanism called self-attention, which allows the model to weigh the importance of different elements in an input sequence when generating an output sequence. Unlike recurrent architectures, transformers process all elements in a sequence simultaneously, enabling them to model long-range dependencies more efficiently and without the limitations of sequential computation. The main idea behind using a transformer-based architecture for demand forecasting is that demand data forms a time series—and a time series is, fundamentally, a sequence. This allows us to feed a sequence of past demand values into the model and train it to output a corresponding sequence of future demand values, not just a single point forecast but an entire forecast horizon covering a specified time period [5].

Key advantages of using transformers for demand forecasting include:

1 Handling large-scale data: Transformers can process vast amounts of time-series data across multiple products and markets.

2 Capturing complex dependencies: The self-attention mechanism allows the model to focus on relevant past information when making predictions.

3 Scalability and efficiency: With parallel processing, transformers can handle high-dimensional time-series data more efficiently than RNN-based models.

Data preparation for transformer-based forecasting. Before training a transformer model for demand forecasting, proper data preparation is crucial. The key steps include:

1 Time-Series Aggregation: Demand data is collected at different granularities (daily, weekly, or monthly) and aggregated accordingly.

2 Feature Engineering: Additional covariates such as price discounts, stock levels, product attributes, holidays, and weather conditions can enhance predictive accuracy.

3 Handling Missing Data: Techniques such as interpolation or imputation can be used to fill gaps in historical data.

4Sales to Demand Translation: In cases where stock-outs occur, observed sales may not reflect actual demand. Estimating lost demand due to stock unavailability is important for accurate forecasting.

Transformer-based demand forecasting model. A typical transformer-based forecasting model consists of the following components [6][7]:

1 Encoder-Decoder Architecture: The encoder processes historical demand data, while the decoder generates future demand predictions. The attention mechanism helps identify important dependencies across time steps.

2 Positional Encoding: Since transformers do not inherently process sequential data, positional encoding is added to represent time-series order.

3 Multi-Head Attention Mechanism: This mechanism enables the model to attend to multiple relevant past points in time simultaneously.

Training and optimization. Training a transformer model involves several steps:

1 Loss Function Selection: Mean squared error (MSE) or custom weighted loss functions tailored to business objectives (e.g., profit maximization) are commonly used.

2 Regularization Techniques: Dropout, layer normalization, and batch normalization help prevent overfitting.

3 Hyperparameter Tuning: Parameters such as number of attention heads, hidden layers, and learning rates need to be optimized for the best performance.

4 Retraining Frequency: Regular retraining ensures that the model adapts to shifts in demand trends and external factors.

Model evaluation. To measure forecasting accuracy, businesses typically use metrics such as:

1 Root Mean Squared Error (RMSE): Measures the difference between predicted and actual demand.

2 Mean Absolute Percentage Error (MAPE): Evaluates the percentage deviation of forecasts.

3 Demand Bias: Identifies whether the model consistently overestimates or underestimates demand.

Applications of transformer-based demand forecasting.

1 Retail and E-commerce: Predicting product demand for dynamic pricing and inventory management.

2 Supply Chain Optimization: Anticipating material requirements to prevent supply disruptions.

3 Manufacturing: Forecasting raw material needs to streamline production schedules.

4 Logistics and Transportation: Demand predictions for optimizing fleet management and delivery planning.

Time-based & seasonal pricing. Historical data often reveals strong seasonal trends that affect demand. Businesses use these patterns to optimize prices dynamically [8].

Example: A fashion retailer sees a spike in sales of winter coats from October to February based on past sales data. They optimize pricing by:

1 Maintaining premium prices in October-November when demand is naturally high.

2 Gradually reducing prices in December-January as customers expect post-holiday discounts.

3 Applying deep discounts in February to clear remaining stock.

Techniques Used:

1 Statistical time-series forecasting (e.g. ARIMA) – Predicts seasonal demand fluctuations.

2 Moving Averages – Identifies cyclical trends in sales.

3 Fourier Transform & Decomposition – Extracts seasonal patterns from noisy sales data.

NLP & sentiment analysis for pricing insights. Companies also use Natural Language Processing (NLP) to analyze customer sentiment and predict price sensitivity [12][13].

Example: A retailer collects customer reviews and social media mentions to assess perceived value of products. If negative sentiment increases due to high prices, they adjust pricing accordingly.

Techniques Used:

1 Sentiment Analysis (BERT, VADER, TextBlob) [14] – Measures customer opinions on pricing.

2 Topic Modeling (LDA, Word2Vec) [15] – Identifies pricing-related discussions.

Challenges & best practices Despite the advantages, pricing optimization based on historical data has challenges:

Table 2. Challenges and solutions

Challenge	**Solution**
Data Quality and Integration	Businesses must ensure that historical sales data is clean, consistent, structured and integrated across multiple sources
Customer Backlash Against Dynamic Pricing	Use transparent pricing policies and ensure fairness. Frequent price changes can lead to customer dissatisfaction if not implemented transparently
Overfitting in Machine Learning Models	Regularize models and test on unseen data to prevent overfittings.
Regulatory Compliance	Ensure compliance with antitrust laws and ethical pricing practices. In some industries, dynamic pricing is subject to legal and ethical scrutiny (e.g., price discrimination concerns).
Computational Complexity	Advanced AI models require significant computational power and expertise to maintain.

Conclusion. The use of big data, advanced analytics, and machine learning has transformed pricing and discounting strategies across industries. By leveraging historical sales data, companies can optimize pricing in real time, enhance customer segmentation, and improve demand forecasting. By integrating machine learning, demand forecasting, and dynamic pricing algorithms, companies can increase revenue, improve customer satisfaction, and enhance operational efficiency. However, ethical considerations and transparency must remain central to avoid consumer distrust.

As technology evolves, the future of pricing strategies will increasingly rely on automated AI systems, personalized pricing models, and real-time market intelligence. Companies that invest in data-driven pricing solutions today will be better positioned to thrive in the dynamic and competitive business landscape of tomorrow.

The future of pricing optimization will likely see more automated, real-time AI systems, ensuring that businesses can stay competitive in an increasingly data-driven marketplace.

References

[1] Cheung, Simchi-Levi, Wang (2018). Dynamic pricing and demand learning with limited price experimentation. Operations Research, 66(1), 144–162.

[2] Feng, Y., & Xiao, B. (2000). A Continuous-Time Yield Management Model with Multiple Prices and Reversible Price Changes. May 2000 Management Science 46(5):644-657.

[3] Kraus, M., Feuerriegel, S., & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications, and managerial implications. European Journal of Operational Research, 281(3), 628–641.

[4] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, Illia Polosukhin “Attention is all you need”

[5] Manuel Kunz, Adele Gouttes, Mateusz Koren, Tofigh Naghibi, Johannes Stephan, Mariia Bulycheva, Matthias Grzeschik, Armin Kekić, Kashif Rasul, Tim Januschowski. Deep Learning based Forecasting: a case study from the online fashion industry” (2023).

[6] Lim, B., Arik, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting. International Journal of Forecasting.

[7] Li, S., Jin, X., Xuan, Y., Zhou, X., Chen, W., Wang, Y. X., & Yan, X. (2019). Enhancing the Locality and Breaking the Memory Bottleneck of Transformer on Time Series Forecasting. Advances in Neural Information Processing Systems (NeurIPS).

[8] Bandara, K., Bergmeir, C., & Smyl, S. (2020). Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. Expert Systems with Applications, 140, 112896.

[9] Hassani, H., Huang, X., & Silva, E. S. (2020). Digitalisation and big data mining in banking. Big Data Cognitive Computing, 4(1), 5.

[10] Vellido, A., Lisboa, P. J., & Vaughan, J. (2012). Neural networks in business: A survey of applications (1999). Expert Systems with Applications, 39(12), 9290–9311.

[11] Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. Expert Systems with Applications, 36(2), 2592–2602.

[12] Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New avenues in opinion mining and sentiment analysis. IEEE Intelligent Systems, 28(2), 15-21.

[13] Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal, 5(4), 1093–1113.

[14] Feldman, R. (2013). Techniques and applications for sentiment analysis. Communications of the ACM, 56(4), 82-89.

[15] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. Journal of Machine Learning Research, 3(Jan), 993–1022.

Author's contribution

Eugene Alooeff – conducted a general overview and reference investigation.

Mariia Bulycheva – conducted a transformer-based architecture analysis and implementation.

ИСПОЛЬЗОВАНИЕ БОЛЬШИХ ДАННЫХ И МАШИННОГО ОБУЧЕНИЯ ДЛЯ ОПТИМИЗАЦИИ БИЗНЕС-РЕШЕНИЙ В ЭЛЕКТРОННОЙ КОММЕРЦИИ

Е.А. Алуев
Инженер-исследователь АТЕК,
Бакалавр технических наук

М.А. Булыева
Инженер Zalando SE,
Магистр математических наук

Аннотация. В современной цифровой экономике компании электронной коммерции сталкиваются с растущим давлением, чтобы оставаться гибкими и конкурентоспособными на быстро меняющемся рынке. Взрывной рост данных из онлайн-транзакций, взаимодействия с клиентами и внешних источников открыл новые возможности для принятия решений на основе данных. В этой статье рассматривается, как компании могут использовать большие данные, расширенную аналитику и машинное обучение, в частности методы глубокого обучения, такие как архитектуры на основе трансформеров, для оптимизации стратегий ценообразования, скидок и прогнозирования спроса. Анализируя исторические данные о продажах наряду с поведением клиентов, ценообразованием конкурентов и сезонными тенденциями, компании могут внедрять динамические и персонализированные стратегии ценообразования, которые повышают прибыльность, улучшают удовлетворенность клиентов и оптимизируют операции. В статье также освещаются технические основы современных моделей прогнозирования спроса, передовые методы обучения и оценки моделей, а также реальные проблемы, с которыми сталкиваются компании при внедрении этих решений. В конечном счете, интеграция технологий искусственного интеллекта и больших данных представляет собой мощный сдвиг в том, как принимаются стратегические деловые и производственные решения в секторе электронной коммерции.

Ключевые слова: Большие данные, Электронная коммерция, Ценовая оптимизация, Прогнозирование спроса, Эластичность цен, Сегментация клиентов, Персонализированное ценообразование, Модели на основе трансформеров, Машинное обучение, Прогнозирование временных рядов.