A Comprehensive Exploration of Machine Learning Models for Predicting Online Auction Prices

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Abstract

The transformative impact of traditional commerce by online marketplaces is exemplified through eBay, a global platform that facilitates diverse transactions via auctions. In this research, the dynamics of eBay auctions, crucial for buyers, sellers, and researchers, are delved into. The central inquiry revolves around the key factors shaping auction outcomes, examining bid behaviors and types. The study leverages a robust dataset from eBay, meticulously curated to encompass auction identifiers, bid details, pricing information, auction types, and temporal aspects. A comprehensive approach involves data preprocessing, ensuring reliability by addressing missing values and outliers. Rigorous exploration and validation validate the dataset's integrity. Machine Learning Techniques, including MLP, SVR, Linear Regression, Extra Trees, and Gradient Boosting, form the analytical backbone. Model evaluation reveals top-performing candidates, such as MLP Regressor (0.8084), SVR (0.8210), and Linear Regression (0.8173), exhibiting superior accuracy and reliability. These models are identified for adoption in future work, emphasizing nuanced predictions in eBay auctions. This research contributes to understanding online auction dynamics, offering practical insights for eBay users and the broader e-commerce community. The models identified pave the way for enhanced predictive capabilities and continuous refinement in deciphering factors influencing auction outcomes.

Keywords: Online Auctions; Auction Dynamics; Machine Learning, MLP Regressor; SVR, Linear Regression; Extra Trees; Gradient Boosting.

1. Introduction

The commerce landscape has been profoundly transformed by the advent of online marketplaces, marking an era where traditional buying and selling practices are increasingly being replaced by

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digital alternatives. At the forefront of this evolutionary wave is eBay, a global platform that has not only embraced this shift but has also become a pivotal player in facilitating diverse transactions, primarily through the innovative mechanism of online auctions [1]. The dynamics inherent in eBay auctions offer a unique and intricate backdrop for delving into the behaviors exhibited by both buyers and sellers within the expansive realm of virtual marketplaces. In the context of this digital commerce evolution, the understanding of the intricacies of eBay auctions emerges as a matter of paramount importance for various stakeholders. For buyers, the platform serves as a dynamic arena where strategic bidding becomes a means to optimize their chances of securing desired items at the most favorable prices. [2] On the other hand, sellers find themselves grappling with the challenge of strategically setting initial prices that attract competitive bids and maximize their returns. Amidst these considerations, researchers find that they are presented with a compelling opportunity to contribute to the broader understanding of online auction dynamics, as shown in figure 1. This contribution is made possible through the meticulous analysis of patterns discerned within the vast datasets generated by the myriad transactions on the eBay platform [3].

Figure 1: eBay Auction Process Infographic.

As this journey of exploration is embarked upon, the subsequent sections of this paper will delve into a comprehensive review of existing literature, providing a foundation that contextualizes our research within the broader landscape of online auctions and e-commerce dynamics. This literature review aims to assimilate critical concepts, theories, and findings from prior research, establishing a framework that informs and guides our analytical endeavors.
As we progress, the core focus of our study revolves around three pivotal research questions:

- What are the key factors influencing auction outcomes on eBay?
- How are final prices achieved in eBay auctions impacted by bid behaviors?
- In what ways are overall results and final prices influenced by different auction types on eBay?

These research questions encapsulate the central thrust of our investigation. As shown in figure 2, our overarching objective is to unearth underlying patterns, identify discernible trends, and pinpoint the influential factors that play a pivotal role in shaping successful auction outcomes. A data-driven approach, firmly rooted in both exploratory data analysis and advanced machine learning techniques, is adopted to achieve this. By combining these methodologies, valuable insights that extend beyond

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the realms of academia and directly benefit eBay users, academic researchers, and the broader e-commerce community are aimed to be extracted.

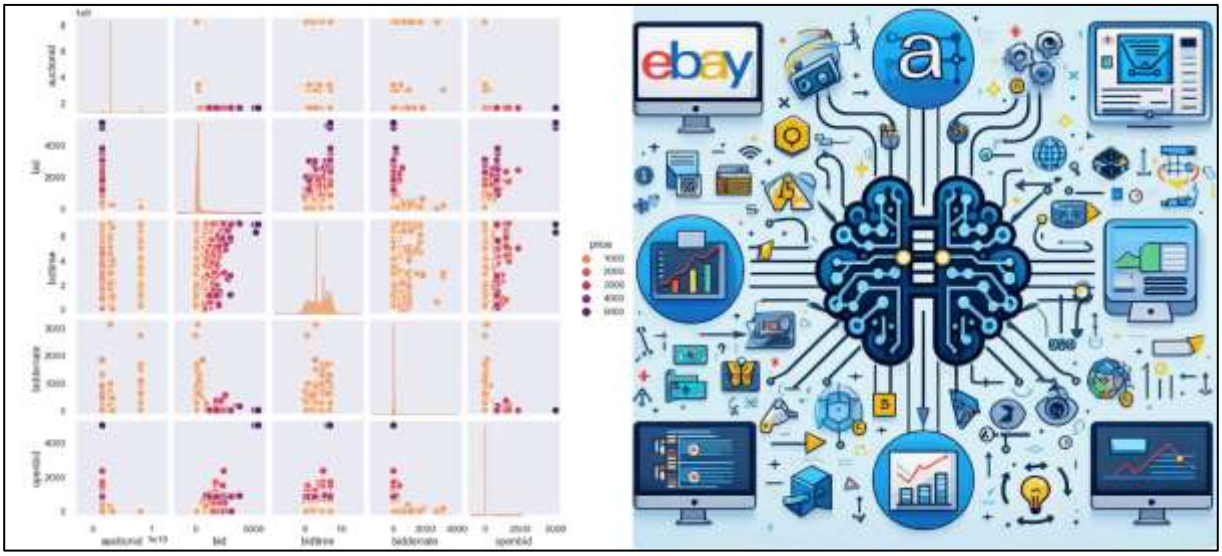

Figure 2: Integration of AI in eBay Auction.

2. Literature Review

The literature review explores the reliable estimation of online auction prices, remarkably the final price, in a study [4]. The study introduces a dynamically integrated regression model that sets itself apart by incorporating previous price data and bidding process duration. Notably, including integrated bidding time data enhances forecast accuracy compared to current methodologies. The study utilizes B-spline approximation to estimate and infer parameters and nonparametric functions within the model. A minimax convergence rate for prediction risk and large-sample outcomes, covering consistency and asymptotic normality, is established. Simulation experiments validate the model's accuracy and robustness, further evidenced by its practical application in predicting ultimate prices in a seven-day iPhone 6s auction. Another study [5] addresses challenges in establishing competitive equilibrium values from various cloud computing centers by examining cloud computing resource trading through double auctions. Learning models are deemed necessary for bidding strategies. The study focuses on challenges arising from individual restricted rationality and insufficient information in double auctions. Conventional models are employed, including Linear Regression, Random Forest, Decision Tree, and Artificial Neural Network. The Artificial Neural Network model outperforms existing models with a 97% accuracy rate, increasing revenues for consumers and service providers while reducing resource inefficiencies. The learning model effectively forecasts final prices for buyers and sellers.

The identification of automated bidding systems in online auctions is the objective of a study [6] employing machine learning approaches. The study addresses concerns about the potential unfairness introduced by automated bidding robots and programs. It assists website owners in locating and eliminating such automated programs to maintain a fair auction environment. Feature extraction, selection, model integration, and classification processes are crucial, with the Random Forest model demonstrating exceptional performance, as indicated by its ROC score of 0.954. In a study focusing on the demand-side platform (DSP) within the real-time bidding (RTB) ecosystem [7], advertisers use a second-price auction to purchase ad impressions. Accurate estimating of the winning price is crucial for optimizing bid values, aiding campaign planning, and transferring traffic. Challenges arise from the skewed distribution of winning prizes due to censorship, where the DSP only reveals successful auction prices. The study introduces a gradient boosting strategy to learn from visible and censored data, demonstrating improved performance compared to conventional linear censored regression.

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Explicitly exploring the real-time bidding (RTB) system [8], a study analyses keyword advertising bidding using Korean search engine Naver data. The study highlights the relevance of keyword ranking on websites and its impact on bidding expenses. Suggesting a methodology for predictive modeling that relies on the ranks of search terms., the study applies feature engineering and machine learning techniques to construct a prediction model for efficient bid prices and advertising ranks on online sites. Furthermore, the study [9] optimizes bid selection to increase traffic and advertiser income. Machine learning is employed to build regression models using real-world data, considering relationships between bid amount, ad spots, position relative to cost-per-click (CPC), and ad clicks. The models uncover hidden patterns in ad quality ratings and competitor bidding behavior, contributing to constructing optimal bidding strategies.

Addressing uncertainties in online group buying, a study [10] predicts the effectiveness of group purchasing auctions using a classification approach. Thirteen factors and five dimensions derived from previous research are used for success prediction. Experimental results on a real-world group purchasing platform demonstrate the effectiveness of the proposed strategy, outperforming a social propagation model in prediction accuracy, recall rate, and F1 score. Additionally, the study [11] delves into detecting fraudulent activity in online auctions by examining users' social networks. Fraudsters, intending to raise auction prices artificially, often collaborate with merchants. The study employs a graph-based, semi-supervised learning approach, leveraging social connections to identify fraudsters. Weighted degree centrality is a significant factor in distinguishing between fraudulent and authentic users. Incorporating real-world data into the model improves the accuracy of fraud detection.

3. Proposed Methodology

A. Dataset

The bedrock of our research is established through the scrupulous curation and analysis of an extensive dataset sourced from Kaggle [12], a preeminent global online marketplace. This dataset forms the nucleus around which our investigation into the intricate dynamics of eBay auctions revolves. The depth and diversity inherent in the dataset empower us to unravel patterns, identify trends, and elucidate the pivotal factors influencing auction outcomes.

1. Data Collection:
Our study hinges on a painstakingly curated dataset extracted from eBay, a global online marketplace of paramount significance. This dataset is the linchpin of our research, encompassing a diverse spectrum of auction transactions. Key attributes embraced by this dataset include auction identifiers, bid details, pricing information, auction types, and temporal nuances such as bid times.

2. Data Preprocessing:
An indispensable phase in our research involves meticulous dataset preprocessing before subjecting it to in-depth analysis [13]. This pivotal step involves handling missing values, addressing outliers, and ensuring data consistency. By undertaking these measures, we strive to augment the reliability of the dataset, mitigating potential biases and inaccuracies.

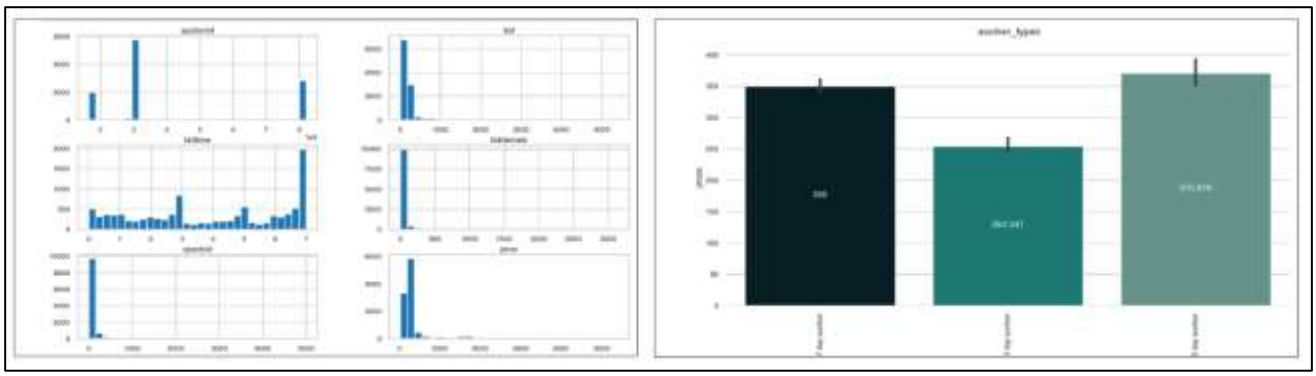

Figure 3: Dataset Exploration.

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3. Data Exploration and Validation:
In tandem with preprocessing, we undertake a comprehensive exploration of the dataset, as shown in figure 3, meticulously validating its integrity and relevance. This entails cross-checking data entries, ensuring the precision of auction details, and validating temporal aspects to fortify the dataset's robustness.

B. Exploratory Data Analysis

The foundation of our research, rooted in the meticulous curation and analysis of a comprehensive eBay dataset, extends seamlessly into the realm of Exploratory Data Analysis. This pivotal phase represents a critical juncture in unraveling the intricate patterns and trends inherent in the dynamics of eBay auctions [14]. Our journey through EDA initiates with an in-depth statistical summarization of key variables within the dataset. This involves the application of descriptive statistics, central tendencies, and measures of dispersion to provide a concise overview of the distribution and characteristics of crucial auction-related parameters. This statistical foundation forms the bedrock for subsequent analytical endeavors.

However, our exploration continues beyond numerical summaries. It extends to the vivid realm of visualization techniques, as shown in figure 4, where a diverse array of graphs, charts, and plots is employed to portray intricate relationships between variables visually. Heatmaps, scatter plots, and histograms are tools to intuitively capture patterns and trends, fostering a more profound understanding of stakeholders. Temporal analysis is a pivotal aspect of our EDA, scrutinizing bidding behavior over time. Identifying peak periods and temporal patterns provides profound insights into the time-sensitive dynamics inherent in eBay auctions. This temporal exploration is crucial for understanding how time influences bidding activities and auction outcomes.

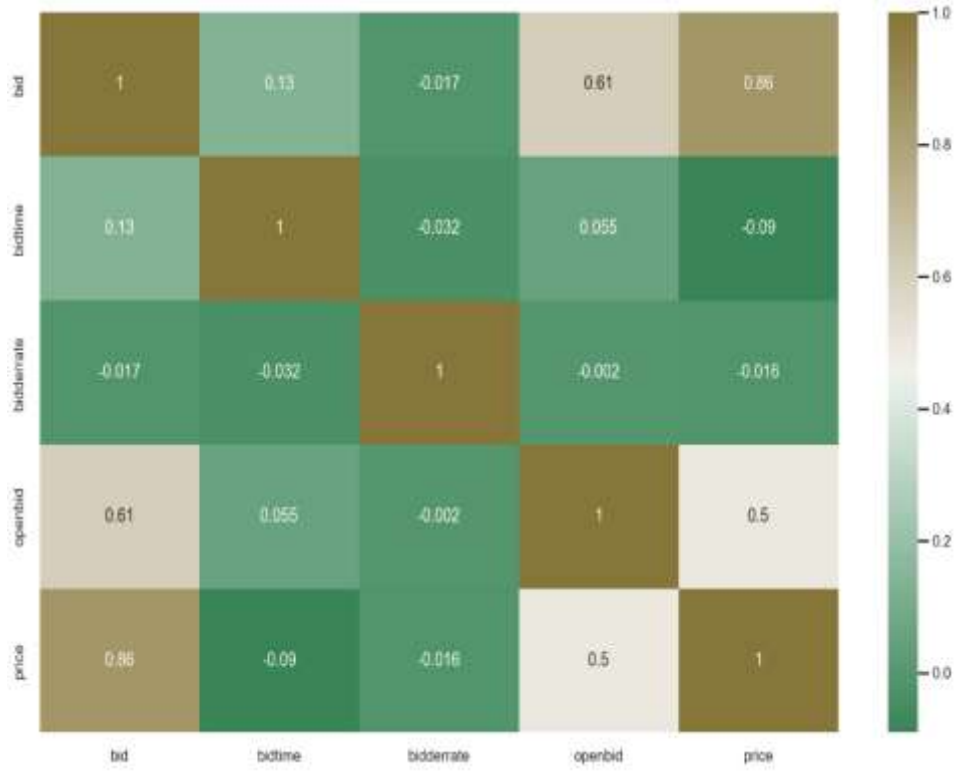

Figure 4: Heat Map as a Visualization Technique.

Our EDA delves into bid behaviors, exploring correlations between bidding patterns and auction outcomes. By discerning how bid amounts, frequencies, and temporal factors interplay, we aim to uncover influential factors that shape successful auction results. This bid-behavior correlation is integral to identifying strategies that contribute to favorable outcomes for buyers and sellers, and the

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EDA serves as a crucial bridge between data collection and subsequent modeling. It offers nuanced insights that pave the way for a comprehensive understanding of eBay auction dynamics, setting the stage for the subsequent phases of our research.

C. Machine Learning Techniques

In the realm of predictive analytics, the application of Machine Learning Techniques signifies a pivotal stage where descriptive insights are transcended to anticipatory capabilities. At this critical phase, models are meticulously selected, each chosen for its unique strengths in unraveling the complexities inherent in eBay auction dynamics. The selection of models represents a diverse array, with each model contributing a distinct approach to capturing patterns and relationships within the eBay auction dataset. The Multi-layer Perceptron (MLP), recognized for its proficiency in discerning intricate patterns, navigates complex relationships embedded in the dataset, extracting nuanced insights from auction transactions. Support Vector Regression (SVR) is harnessed for its adeptness in handling non-linear relationships, emerging as a potent tool in our predictive toolbox. Its ability to navigate intricate bidding dynamics contributes to a more accurate representation of auction outcomes. Linear regression, as a fundamental model, provides a baseline for comparison and interpretation. Its simplicity allows for a clear understanding of the linear relationships within the auction data, offering valuable insights into pricing determinants [15-17].

Extra Trees (ET), embraced for its ensemble nature and robustness, capture complex data relationships. By leveraging a multitude of decision trees, it excels in uncovering hidden patterns and contributes to a holistic understanding of auction dynamics. Gradient Boosting (GB), operating as an algorithmic powerhouse, sequentially builds a series of weak learners, progressively refining predictive accuracy. Its iterative approach enhances the model's ability to adapt to evolving bidding patterns, providing a comprehensive view of auction outcomes. This diversified lineup of models collectively forms a robust framework poised to extract actionable insights from the eBay auction dataset. The combined strengths of these models ensure a comprehensive understanding of auction dynamics, empowering stakeholders with the knowledge needed for informed decision-making and strategic maneuvering in the dynamic digital marketplace [18-21].

D. Model Evaluation and Selection

[In model evaluation for our eBay auction dynamics study, the choice and application of evaluation metrics play a paramount role in scrutinizing the predictive performance of the selected models. As shown in table 1, a diversified set of metrics is employed to encompass various facets of model accuracy, precision, and generalization [22].

Table 1: Criteria for evaluating regression result.

Metric	Formula
RMSE	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\grave{V}_n - V_n\right)^2}$
RRMSE	$\frac{RMSE}{\sum_{n=1}^{N}\grave{V}_n} \times 100$
MAE	$\frac{1}{N}\sum_{n=1}^{N}\left\|\grave{V}_n - V_n\right\|$
MBE	$\frac{1}{N}\sum_{n=1}^{N}\left(\grave{V}_n - V_n\right)$
NSE	$1 - \frac{\sum_{n=1}^{N}\left(V_n - \grave{V}_n\right)^2}{\sum_{n=1}^{N}\left(V_n - \bar{\grave{V}}_n\right)^2}$
WI	$1 - \frac{\sum_{n=1}^{N}\left\|\grave{V}_n - V_n\right\|}{\sum_{n=1}^{N}\left\|V_n - \bar{V}_n\right\| + \left\|\grave{V}_n - \bar{V}_n\right\|}$

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R^2	$1 - \frac{\sum_{n=1}^{N}\left(V_n - \grave{V}_n\right)^2}{\sum_{n=1}^{N}(\sum_{n=1}^{N} V_n) - V_n)^2}$
r	$\frac{\sum_{n=1}^{N}\left(\grave{V}_n - \bar{\grave{V}}_n\right)\left(V_n - \bar{V}_n\right)}{\sqrt{\left(\sum_{n=1}^{N}\left(\grave{V}_n - \bar{\grave{V}}_n\right)^2\right)\left(\sum_{n=1}^{N}\left(V_n - \bar{V}_n\right)^2\right)}}$

The following metrics are critical components of our comprehensive evaluation framework:

1. **MSE (Mean Squared Error)** measures the average squared difference between the observed and predicted values. A lower MSE indicates better model performance.
2. **RMSE (Root Mean Squared Error):** It is the square root of the MSE and measures the average magnitude of the errors. Like MSE, a lower RMSE is desirable.
3. **MAE (Mean Absolute Error)** calculates the average absolute differences between the observed and predicted values. It gives a sense of the average error magnitude.
4. **MBE (Mean Bias Error)** represents the average differences between predicted and observed values. Positive values indicate overestimation, while negative values indicate underestimation.
5. **R (Correlation Coefficient)** measures the strength and direction of a linear relationship between two variables. A value close to 1 indicates a strong positive correlation.
6. **R^2 (Coefficient of Determination)** represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s). A higher R^2 suggests a better fit of the model.
7. **RRMSE (Relative Root Mean Squared Error)** is expressed as a percentage of the range of the observed values. It provides a normalized measure of prediction accuracy.
8. **NSE (Nash-Sutcliffe Efficiency):** It assesses the accuracy of the model predictions compared to the mean observed value. Values closer to 1 indicate better model performance.
9. **WI (Willmott Index):** It evaluates the agreement between observed and predicted values. A WI value 1 indicates perfect agreement, while 0 indicates no agreement.
10. **Fitted Time:** It represents the time taken for the model to be fitted or trained on the dataset. Lower values are preferable for efficiency.

4. Results

In this section, we present the outcomes of our machine learning models applied to the eBay auction dynamics dataset. The selected models were explicitly tailored to disentangle the intricate patterns and behaviors in auction transactions on the eBay platform. The evaluation metrics serve as benchmarks to assess the predictive capabilities of each model, providing valuable insights into their performance. Table 2 comprehensively outlines the performance of each model across various evaluation metrics, allowing for a detailed comparison of their effectiveness in predicting eBay auction outcomes.

Table 2: Regression result.

Models	**mse**	**rmse**	**mae**	**mbe**	**r**	**R2**	**RRMSE**	**NSE**	**WI**	**Fitted Time**
MLPRegressor	0.0047	0.0687	0.0382	0.0048	0.8991	0.8084	53.8120	0.8074	0.8250	5.2785
SVR	0.0048	0.0695	0.0351	0.0179	0.9061	0.8210	54.3913	0.8033	0.8390	0.5602
LinearRegression	0.0051	0.0716	0.0488	0.0194	0.9040	0.8173	56.0914	0.7908	0.7761	0.0253
ExtraTreesRegressor	0.0081	0.0899	0.0401	0.0106	0.8368	0.7002	70.4405	0.6700	0.8161	0.0156
GradientBoostingRegressor	0.0089	0.0945	0.0419	0.0107	0.8157	0.6654	74.0213	0.6356	0.8079	0.0000
CatBoost	0.0090	0.0946	0.0418	0.0153	0.8169	0.6674	74.1199	0.6347	0.8083	31.9602

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RandomForestRegressor	0.0090	0.0949	0.0470	0.0065	0.8164	0.6665	74.2876	0.6330	0.7846	0.7365
XGBoost	0.0098	0.0990	0.0451	0.0090	0.7968	0.6349	77.4998	0.6006	0.7931	25.7386
DecisionTreeRegressor	0.0099	0.0993	0.0492	0.0097	0.7861	0.6180	77.7844	0.5976	0.7744	0.2277
KNeighborsRegressor	0.0101	0.1007	0.0483	0.0191	0.8021	0.6434	78.8610	0.5864	0.7784	0.0351
pipeline	0.0161	0.1271	0.0575	0.0183	0.6091	0.3710	99.5221	0.3413	0.7365	0.1413

5. Conclusion

In conclusion, a wealth of valuable insights has been revealed through the comprehensive exploration of a rich dataset and the application of advanced machine learning techniques in unraveling the dynamics of eBay auctions. The curated dataset, meticulously sourced from eBay transactions, serves as the linchpin for the analysis, offering a diverse array of auction-related attributes.
The exploration, encompassing data preprocessing, validation, and in-depth exploratory data analysis (EDA), has ensured the integrity and relevance of the dataset. Machine learning techniques have been applied, introducing MLP, SVR, Linear Regression, Extra Trees, and Gradient Boosting models. This selection represents a strategic choice, considering the unique strengths of each model in unraveling the intricacies of eBay auction dynamics. Furthermore, the performance of these models is showcased through evaluation metrics. Three top-performing candidates—MLP Regressor, SVR, and Linear Regression—have been identified for future emphasis, exhibiting superior accuracy and reliability in predicting auction outcomes. These models offer a foundation for continued refinement and improvement in subsequent research endeavors.

As we move forward, adopting these models is expected to enhance predictive capabilities, providing a more nuanced understanding of the factors influencing eBay auction outcomes. This research contributes to the academic understanding of online auctions and holds practical implications for eBay users and the broader e-commerce community. In addressing the key factors influencing auction outcomes on eBay, the meticulous analysis of bid behaviors and auction types has revealed essential insights. Final prices in eBay auctions are impacted by bid behaviors in diverse ways, influencing the overall results of the auction process. Moreover, examining different auction types on eBay has highlighted their distinct influences on overall results and final prices. These findings collectively contribute to a comprehensive understanding of the multifaceted dynamics inherent in eBay auctions.

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