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Online Auction Forecasting Precision: Real-time Bidding Insights and Price Predictions with Machine Learning

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Abstract: Fast-paced internet auctions require smart choices and real-time bidding. Both buyers and sellers in online auctions need price prediction. Accurate estimates let suppliers list products at the right time and type, and bidders choose. Data-driven decision-making requires advanced analytics. Selling prices are calculated first because auctions are dynamic markets with uncertain bid-by-bid evolution. Traditional papers focus on final sale prices, although interim bidding can aid. Strategic knowledge, value perception, and market enthusiasm drive bids. Bidder values and market interest determine bidding. The entire auction price prediction system that shows sophisticated bid history in this research fills this gap. Use a certified online auction dataset. To predict the auction form's eventual price and buyer bids, imported data must be cleansed and preprocessed to remove noise. Strong Z-scores eliminate outliers, ensuring bid progression analysis accuracy. Auction data comprises item, length, and open price. K-Fold cross-validation improves models across datasets. Assessors use bid forecast precision measure RMSE. The statistical basis predicts accurately, and sophisticated visualizations help stakeholders understand auction behavior. Finally, the bids are compared to historical data from auctions with the same number of bids to validate the system. To assure auction behavior, the paper evaluates predictions and bids. The bid value standard deviation is used to evaluate bids. These phases compare bids to auction history. Bids are visualized against auction data. Box and line graphs are popular. Compare produced bids to past auction data to understand bid distribution and dynamics. Auction players gain from its real-time predictions over other systems. The paper's holistic approach beats auction analytics. This paradigm provides a complete toolkit for forecasting bid-by-bid dynamics, interpretation, and visualization, not selling prices.

Keywords: Root Mean Squared Error (RMSE); Online Auctions; Predictive Analytics; XG Boost; Linear Regression; Bid Progression; K-Fold Validation; Data-driven Decision-Making; Machine Learning; Strategic Bidding; Bid Trajectory Forecasting.

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1. Introduction

Online auctions have become increasingly popular in recent years by being an omnipresent and revolutionary force in commerce, representing a paradigm shift from traditional auction houses to virtual platforms. These virtual markets are not limited by location, allowing users to bid in real-time on a wide variety of products and services worldwide [3]. Online auctions provide a dynamic environment where prices change in response to immediate bids and encourage competition by providing

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transparency through thorough descriptions and historical bid data. The importance of comprehending all aspects of these online auction dynamics extends to sellers optimizing their offerings in the constantly changing digital marketplace and strategic bidders seeking advantages. It provides a convenient and efficient way for buyers and sellers to transact goods and services. These platforms are becoming more common, which has created a wealth of data and opened up opportunities for advanced analytics to identify trends, improve methods, and improve participant and auctioneer decision-making.

Generally, Internet bidding consists of three types of information constraints: static (product brand, auction length), time-varying (the number of bids), and dynamic (rate of speed at which the auction happens) [1]. Key elements shaping the dynamics of online auctions include bid strategies, real-time bid tracking, auction duration, and the influence of auction types on bidder behavior, which can lead to increased efficiency and profits. Ultimately, the main goal of both buyer and seller is to finalize the bidding closing price of the product being auctioned. It could pave the way for the bidder so that advantage could be taken for price-prediction models to make well-informed decisions on when to bid on an item and how much to bid and as well as, to be more competitive, sellers can leverage bid-price prediction models to determine more optimal reserve prices. Predicting the end price depends on many factors, such as item type, type of auction, quantity available, opening price, number of bidders, average bid amount, etc. [2]. This could emerge into applications in various industries, including e-commerce, finance, and supply chain management, which can lead to increased efficiency and profits in their respective industries. For example, in the e-commerce industry, eBay offers millions of items for sale [3][4], incorporating a price prediction model would drastically change the efficiency and fairness that may ensure that both buyers and sellers can get the greatest bargains and that sellers can get the best price for their goods.

However, predicting the bid price of an item in an online auction can be challenging due to several factors, such as the item's condition, rarity, and the number of interested buyers. To overcome this challenge, several machine-learning algorithms and data mining methods are put into action for the prediction of the end price of the auction [4][9]. Among them, popularly and recently used machine learning techniques involve multiple linear regression in predicting the end price with improved accuracy using less training data [9] and the XG Boost (Extreme Gradient Boosting) algorithm that uses a tree-based ensemble model that combines the predictions of multiple decision trees to produce a final output. It is known for its high accuracy, speed, and efficiency [10], which serve as a solution for supervised learning problems such as classification and regression. Enhancing the use of two robust ML techniques, Linear regression and XG Boost, with the hybrid of the K-fold cross-validation technique delves into the comprehensive approach of this paper [11]. Here, the bid features models are trained with two techniques separately and evaluated with RMSE (Root Mean Squared Error). The lower the Root Mean Squared Error value, the better the model [12].

While many auction-related analytics have traditionally focused on predicting final sale prices, a critical piece of the puzzle is often overlooked the intricate sequence of bids that leads to those final prices [13]. Amidst the plethora of models geared toward forecasting auction outcomes, there remains a distinct void in models dedicated to elucidating the granular trajectory of bids, leading to the ultimate closing price [14]. It is this void that our paper seeks to fill. Hence, the proposed approach relies on robust Z-scores for outlier detection, real-time forecasting of bid progression using XG Boost and linear regression, K-fold cross-validation to enhance model robustness, and RMSE (Root Mean Squared Error) for model evaluation [15]. In doing so, we shed light on the often-overlooked intricacies of auction dynamics, bestowing stakeholders with a more profound and detailed understanding of auction behavior [16]. The application of these advanced methodologies extends beyond the realm of auction platforms; it presents an innovative approach to comprehending complex marketplaces, strategic decision-making, and subtle markers of enthusiasm [17]. This paper's far-reaching implications encompass diverse industries where predictive models inform strategies and decision-making processes, resulting in more informed approaches and a deeper grasp of market dynamics. In an era fueled by data-driven insights, this research not only enriches the auction domain but also significantly contributes to the broader fields of data analytics and market research [18].

2. Existing System

Machine learning plays a crucial role in various fields and applications due to its ability to analyze and learn patterns from data, make predictions, and adapt to changing environments. Because machine learning and data mining techniques are so good at identifying complex patterns and relationships in huge amounts of data, these techniques are excellent at handling multidimensional data and adjusting to changing conditions. This is especially important in situations involving dynamic and non-linear auction environments. The adaptability of machine learning models to evolving data and dynamic scenarios is crucial in domains where patterns may change over time. Predictive analytics facilitated by machine learning contributes significantly to decision-making processes, enabling foresight into future trends and outcomes. As a result, a wide range of factors influencing auction prices, including item characteristics, bidder behavior, and market conditions, can be effectively analyzed.

Shu Zang introduced the K-nearest neighbors forecaster, which is a mixture of functional and non-functional distances and shows improved predictive performance over several competing models [1]. Khadge and Kulkarni [3] proposed Naive Bayes in determining whether the item will sell or not. Along with that, machine learning algorithms such as logistic regression [5] introduced by Kim take the heterogeneity of multi-round into account and perform better than a one-layered neural network, Khadge and Kulkarni inculcated Support vector machine(SVM) to predict whether an item maximizes profit or not, decision trees [7], Nicholas uses Bayesian linear regression [6] to accurately predict hourly PM2.5 concentrations in Santiago de Chile, and even deep recurrent neural networks [8] are being incorporated for prediction of results, yet find it difficult to correct the limitations.

One significant obstacle to accurately predicting bid prices in online auctions is the sensitivity of existing machine learning-based methods to outliers. Outliers are extreme values that significantly deviate from the majority. In the context of online auctions, where bid prices can vary greatly, the presence of outliers can adversely affect model training and jeopardize prediction accuracy [19]. These anomalies, which are frequently connected to uncommon or rare items that set off odd bidding patterns, could lead to erroneous conclusions about underlying trends in the model [20]. As a result, the model might give these extreme values disproportionate weight, impairing its ability to make useful generalizations. In order to overcome this limitation, bid-price prediction models must be carefully preprocessed using methods like outlier detection and robust modeling [21]. This will increase the models' accuracy and resilience in various dynamic auction situations. The complex and multidimensional nature of the data makes feature engineering a difficult task when it comes to online auction bid-price prediction [22]. It entails choosing, altering, or producing features accurately capture the primary variables affecting bid prices. The multifaceted nature of auction data, incorporating textual, numerical, and categorical information, necessitates careful consideration of feature types and encoding methods. Addressing missing data, accommodating non-linear relationships, and handling high-dimensional spaces are crucial considerations [23].

Another paramount hindrance is the lack of standardized evaluation metrics. Without well-defined and widely accepted evaluation criteria, measuring the accuracy, reliability, and generalizability of different machine learning models across diverse datasets becomes challenging [24]. This absence of standards hampers the ability to conduct fair and comprehensive comparisons between various approaches, hindering the identification of the most effective models for real-world auction scenarios [25]. Therefore, establishing standardized evaluation metrics is crucial for advancing the field, enabling a more systematic and reliable comparison of bid-price prediction models and fostering the development of approaches that perform consistently well across various auction scenarios [26]. By compromising all the hindrance factors, evolving an efficient and affordable approach is essential and the foremost plan to instigate online auction price prediction [27].

3. Proposed System

In response to these challenges, the main purpose is the introduction of an innovative predictive algorithm that not only forecasts final auction prices but also provides insights into the bid-by-bid trajectory leading to those outcomes. By bridging the gap between price prediction models and the intricate strategic elements of auction dynamics, this research significantly contributes to the field of auction analytics, enhancing our understanding of auction behavior and aligning with evolving data ethics standards. Harnessing the wealth of online auction data from any source, mostly from e-commerce websites like eBay, which consists of various general features like opening price, closing price, auction item, length of auction, and so on, is extracted. This extraction would be unstructured, which must undergo data cleaning where the missing values are mainly handled effectively and Z-score normalization is carried out for outlier detection.

The pre-processed data moves to the feature engineering phase, where each feature leverages advanced machine learning techniques such as linear regression and XG Boost, and the system provides a dynamic bid-by-bid forecast. The main specialty of the predictive algorithms is that they not only foresee the eventual auction price, considering variables like the initial bid, auction item, and duration, but also shed light on the papered sequence of bids leading to that outcome. The architecture includes models for separate trajectory processes involving bid number prediction, auction closing price estimation, bid rate and time prediction, bid value prediction, bid closing price estimation, and final auction price prediction. Each model is trained on historical auction data and validated using k-fold cross-validation, ensuring robust performance across diverse datasets. In contrast to all the existing systems, every bid trajectory model is evaluated using a robust metric, Root Mean Squared Error (RMSE), to choose better prediction accuracy between the linear regression developed model and the XG booster developed model [28]. Lower RMSE values indicate a higher degree of accuracy, emphasizing the reliability of our bid predictions. Finally, the generated bids are presented through visualizations that comprehensively understand how they compare to historical auction data [29]. These visualizations through box plots and line plots highlight bid distribution and dynamics, providing valuable insights that can inform decision-making [30].

To sum up, our approach is based on the research paper being developed by surveying various previous works that use datasets from Kaggle, the online auction dataset. This paper uses that dataset as input and provides granular details of the bidding process as output [31]. The whole purpose of the paper is to give a basic idea of how the proposed machine learning algorithm uses the techniques mentioned above to predict the number of bids and the final auction price estimation [32]. It is crucial to address data privacy and fairness throughout the paper [33]. Furthermore, we provide stakeholders with valuable insights into the anticipated progression of bids leading to the final culmination. Stakeholders, be they sellers, buyers, or market analysts, stand to benefit from this richer and more detailed portrayal of auction behavior [34]. The predictive algorithm thus acts as a powerful tool, enhancing decision-making processes by offering a comprehensive understanding of the intricate interplay between various auction parameters and bidding activities [35].

4. Methodology

The research's methodology is carefully developed to capture online auctions' intricate mechanics and build a reliable predictive algorithm for bid progression and auction prices. In online auctions, where numerous factors influence bidding behaviors, traditional analytical methods often fall short of capturing the complexity of user interactions and market dynamics. ML models, particularly XG Boost and linear regression, excel in learning from historical auction data and discerning non-linear relationships, enabling the algorithm to generate accurate predictions. The following Figure 1 depicts the architecture diagram. All the codes implemented for the whole paper are done by importing required libraries in Python for storing and working with data involved in Machine learning applications and for visualizing data [36]. The initial phase systematically collects data from various online auction platforms, encompassing crucial variables such as the open bid, auction item, and auction duration. Then, it moves to clean to ensure the dataset's quality, which involves handling the missing values [37]. The Z-score normalization technique is applied to identify and address outliers, maintaining the integrity of the information [38].

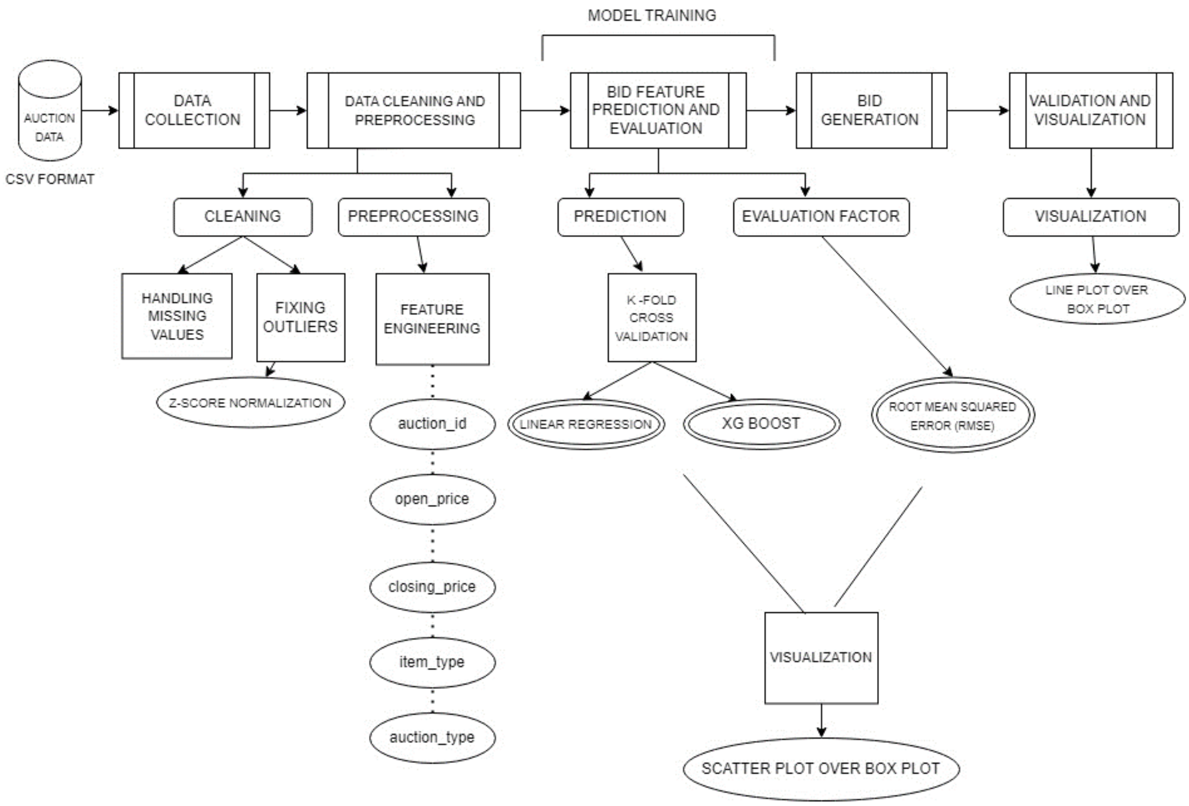

Figure 1: Architecture Diagram

Preprocessing involves feature selection by investigating correlation using a pair-plot matrix and removing unwanted features that do not have a defined correlation. Here, the finalized features are open price and closing price, ... according to the dataset imported from Kaggle [39]. Then, the processed data undergoes model training, which uses predictive algorithms that integrate sophisticated machine learning models, notably XG Boost and linear regression. These models undergo a thorough training process using historical auction data, fine-tuning their parameters to optimize predictive performance. K-Fold Validation is employed to strengthen the models' reliability and generalizability, subjecting the algorithm to diverse datasets for comprehensive validation [40]. This step ensures that the predictive capabilities extend beyond specific instances to provide robust insights across various scenarios. The efficacy of the developed algorithm is rigorously evaluated using prominent metrics, with a primary focus on Root Mean Squared Error (RMSE). RMSE is a critical measure of accuracy, assessing the disparity between predicted and observed values [41]. The bid generation phase uses the machine learning models developed in the previous step to predict individual bids and closing prices [42]. Finally, validation involves comparing the generated bids with historical data from auctions with the same number of bids. By doing this, the paper ensures that the generated bids are consistent with actual auction behavior [43]. It validates the predictions' accuracy, and visualization represents the generated bids using box plots and line plots [44]. Figure 2 below summarizes the process as mentioned earlier in a simplified way to depict the step-by-step methods.

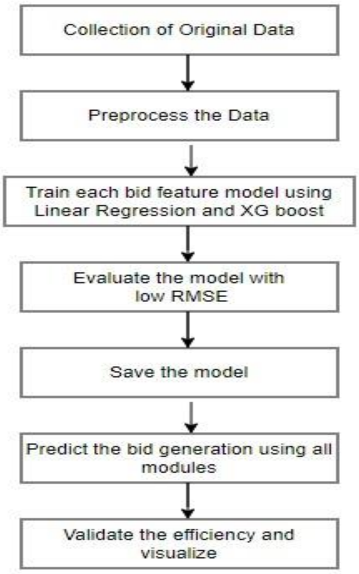

Figure 2: Workflow Diagram

5. Module Description

The entire process is divided into five major modules.

5.1. Module 1: Data collection

This module involves collecting historical auction data from various online platforms, which serves as the foundation for the paper [45]. In this paper, data has been imported from Kaggle, an online auction data set. The datasets contain eBay auction information on Cartier wristwatches, Palm Pilot M515 PDAs, and Xbox game consoles [46]. Through this dataset, we could infer the relationship between bids, bid time, and the closing price for each item and whether the relationship differs by the length of the auction, opening bid, or bidder rating (Figure 3).

1	auctionid	bid	bidtime	bidder	bidderrate	openbid	price	item	auction_type
2	1.64E+09	175	2.230949	schadenfr	0	99	177.5	Cartier wr	3 day auction
3	1.64E+09	100	2.600116	chuik	0	99	177.5	Cartier wr	3 day auction
4	1.64E+09	120	2.60081	kiwisstuff	2	99	177.5	Cartier wr	3 day auction
5	1.64E+09	150	2.601076	kiwisstuff	2	99	177.5	Cartier wr	3 day auction
6	1.64E+09	177.5	2.909826	eli.flint@f	4	99	177.5	Cartier wr	3 day auction
7	1.64E+09	1	0.355856	bfalconb	2	1	355	Cartier wr	3 day auction
8	1.64E+09	1.25	0.484757	sbord	1	1	355	Cartier wr	3 day auction
9	1.64E+09	1.5	0.492639	bfalconb	2	1	355	Cartier wr	3 day auction
10	1.64E+09	25	0.49463	sbord	1	1	355	Cartier wr	3 day auction
11	1.64E+09	2	0.511169	bfalconb	2	1	355	Cartier wr	3 day auction
12	1.64E+09	5	0.511308	bfalconb	2	1	355	Cartier wr	3 day auction
13	1.64E+09	10	0.511458	bfalconb	2	1	355	Cartier wr	3 day auction
14	1.64E+09	20	0.511644	bfalconb	2	1	355	Cartier wr	3 day auction
15	1.64E+09	50	0.511759	bfalconb	2	1	355	Cartier wr	3 day auction
16	1.64E+09	30	0.772928	veuvenoir	1	1	355	Cartier wr	3 day auction
17	1.64E+09	50	1.39353	norcal_da	15	1	355	Cartier wr	3 day auction
18	1.64E+09	100	1.393623	norcal_da	15	1	355	Cartier wr	3 day auction
19	1.64E+09	75	1.516979	kat2911	0	1	355	Cartier wr	3 day auction

Figure 3: Sample input imported for Data Collection

Ten thousand six hundred eighty-one rows of auction data of items are saved in a CSV (comma-separated values) file [47]. This is the input for our paper, which includes the following:

auction.csv includes nine variables:

- auctionid: unique identifier of an auction
- bid: the proxy bid placed by a bidder
- bidtime: the time in days that the bid was placed, from the start of the auction
- bidder: eBay username of the bidder
- bidderrate: eBay feedback rating of the bidder
- openbid: the opening bid set by the seller
- price: the closing price that the item sold for (equivalent to the second highest bid + an increment)
- item: auction item
- Cartier wristwatch
- Palm Pilot M515 PDA
- Xbox game console
- auction_type
- 7-day auction
- 5-day auction
- 3-day auction

5.2. Module 2: Data Cleaning and Preprocessing

5.2.1. Data cleaning module:

Data cleaning is essential in data preparation, ensuring the data is accurate, complete, consistent, and formatted correctly for analysis. It can make data easier to work with and analyze. It includes techniques such as handling missing values and fixing outliers [48]. Handling Missing Values: Missing values can occur when data is unavailable for a particular observation. In this sample input, we employed several techniques to handle missing values in the online auction dataset. Initially, we identified missing values in the 'bidder' and 'bidderrate' columns [49]. To address this, we filled missing 'bidderrate' values with the average bidder rate per item, ensuring a reasonable estimation based on existing data. We strategically filled missing values for the 'bidder' column by randomly selecting non-missing values from the same column [50]. This approach maintains the integrity of the bidder information while ensuring the completion of the dataset [51]. After these procedures, we checked the dataset for missing values again and successfully eliminated missing values in both the 'bidder' and 'bidderrate' columns [52]. The resulting dataset is ready for further analysis without missing data points. Figure 4 shows the values missing before and after the procedure.

auctionid	0	auctionid	0
bid	0	bid	0
bidtime	0	bidtime	0
bidder	16	bidder	0
bidderrate	11	bidderrate	0
openbid	0	openbid	0
price	0	price	0
item	0	item	0
auction_type	0	auction_type	0
dtype: int64		dtype: int64	

Figure 4: Before and After data cleaning

Fixing Outliers: Outliers are data points significantly different from the rest. They can skew the analysis results and make it difficult to identify patterns and trends. Here, we use the z-score normalization in data mining to analyze the data efficiently and use a Z-score value to understand how far the data point is from the mean. Technically, it measures the standard deviations below or above the mean [53]. It ranges from -3 standard deviation up to +3 standard deviation. In the given data set, for the 'price' column, we utilized the z-score method, removing values beyond a z-score of 3. This process resulted in the removal of 370 outliers. Similarly, for the 'openbid' column, we applied the z-score technique, removing 160 outliers [54]. To address outliers in the 'bidderrate' column, we used the Interquartile Range (IQR) method. Values outside the boundaries defined by 1.5 times the IQR were clipped, and normalization was applied to maintain consistency [55]. The 'bidtime' column was normalized, as it did not exhibit outliers [56]. Figure 5 shows the removed outliers that are visualized with the help of a box plot imported from the Seaborn library -Python.

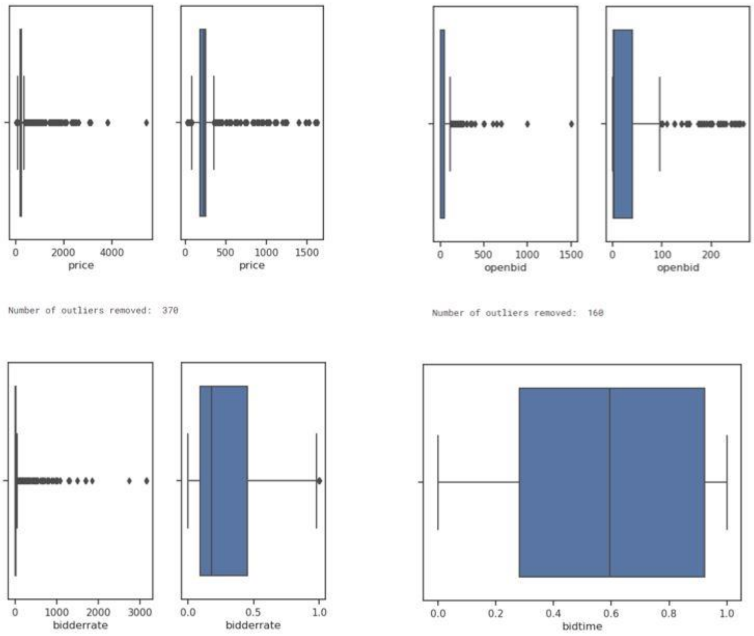

Figure 5: Fixing outliers

5.2.2. Data preprocessing module:

In the data preprocessing phase, we strategically selected and engineered features to enhance the predictive power of our models through the feature engineering process. The objective was to identify and retain the most relevant features while discarding redundant or less impactful ones. Initial exploration through a pair plot matrix revealed correlations between various features. To handle this, categorical values were encoded using label encoding, and shuffling was applied to remove potential correlations, ensuring a more balanced dataset. Further, after the outliers' removal, the resulting pairplot matrix displayed meaningful correlations, offering a more balanced and representative dataset. Figure 6 provides you with the pair plot after outlier removal.

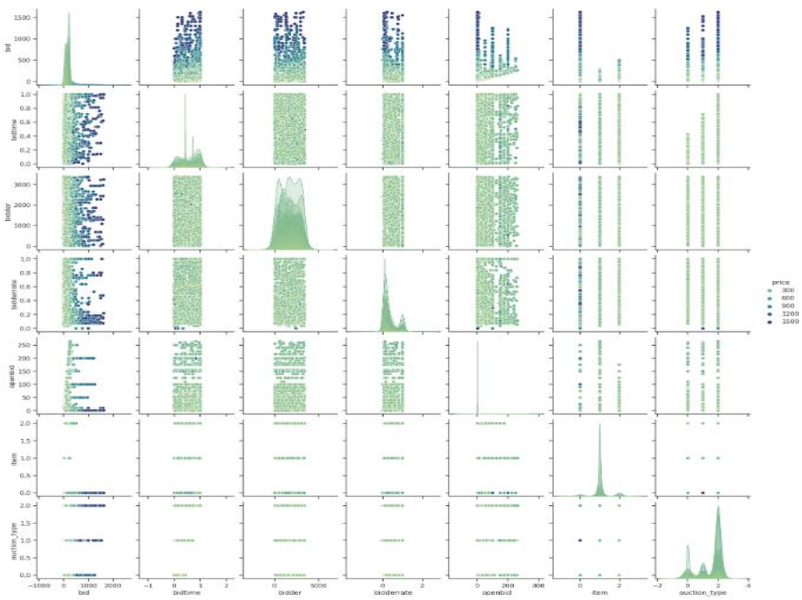

Figure 6: Pairplot after outlier removal

To streamline the dataset, column names were standardized, and a checkpoint was saved for reference. Subsequently, a base auction data frame was created, grouping data by essential features 'auction_id', 'open_price', 'closing_price', 'item_id', and 'auction_type'. This data frame was pivotal for subsequent actions.

5.3. Module 3: Bid Feature Prediction and Evaluation

We employ a robust approach to forecast critical bidding features within an auction environment in the Bid Feature Prediction and Evaluation module. The heart of the paper is predictive modeling. This module includes training models using XG Boost and Linear Regression. The models are trained to predict various aspects of online auction dynamics, such as the number of bids, bid rates, bid times, and more. The models were trained using the available bid data, emphasizing the importance of 'open_price', 'closing_price', 'item_id', 'auction_type', and 'num_bids' features identified during the feature engineering phase. Hyperparameter tuning is performed to optimize the model's performance.

Generally, to evaluate models in machine learning, there will be a machine learning model and some data, which need to be checked to determine whether the model can fit. So, the data is split into training and test sets. Train the model with the training set and evaluate the result with the test set. If the evaluated model is tested only once and wants to be evaluated multiple times to become confident about the model design, a Cross-validation technique should be implemented. K-fold cross-validation is one often used technique for this, and it takes the following approach:

- Divide a dataset into k roughly equal-sized groups, or "folds," randomly.
- Select a fold to serve as the holdout set or test set. Take the remaining groups as a training data set. On the remaining k-1 folds, fit the model. Determine the test RMSE (evaluation score metric used here) based on the observations in the held-out fold.
- Carry out steps k times, utilizing a different set as the holdout set each time.
- Assume that the average of the k-test RMSEs represents the overall test RMSE.

Incorporating machine learning models with k fold would be done as follows, a general idea for all the predicted models.

5.3.1. Linear Regression Model

Linear regression is initially used to predict the models evaluated entirely. The model is evaluated using K-fold cross-validation with five folds. Mean Root Mean Squared Error (RMSE) is the evaluation metric. Lower RMSE values indicate a higher degree of accuracy. The model performs reasonably well, with an acceptable mean RMSE.

5.3.2. XG Boost Model

XGBoost is then employed to enhance the features' accurate prediction even more, to check whether the mean RMSE value is lesser than that of the Linear regression model. The model demonstrates a marginal improvement over linear regression. The mean RMSE range for accurate predictions must coincide with the median in the IQR quartile, or else, at least, it must be within the IQR region, which would result in a slight deviation from precise accuracy. Multiple attempts are made with different hyperparameters if it is not in the acceptable region. Even further, if it is not around the IQR region, attempts are made to reduce outliers using the IQR method, and for a reduced data frame, model evaluation would be done. Then, finally, the XG Boost model is saved for future use. Data could be visualized using a scatter plot over the box plot to check the mean RMSE range. The boxplot provides insights into the distribution of the model, including median, quartiles, and outliers. At the same time, the scatter plot (here, a dot in orange) helps visualize the range within which the model's predictions deviate from the actual model. By using the above techniques, the predicted and saved XG boost models would be according to the sample dataset:

Number of bids per auction:

- Linear Regression: Mean RMSE: 3.25
- XG Boost: Mean RMSE: 2.93
- The RMSE score is within IQR, so we can use it for rough predictions.

Closing price per auction:

- Linear Regression: Mean RMSE: 168.48; Figure 7 helps to check the RMSE range.
- XG Boost: Mean RMSE: 31.32

While evaluating the XG boost for the first time, mean RMSE was even worse than linear regression, and then, after hyperparameters tuning, results were not accepted. Further, outliers were removed using the IQR method, and then, finally, the model was evaluated for an outlier-reduced data frame. Figure 8 shows the plot for a few features; this model is saved.

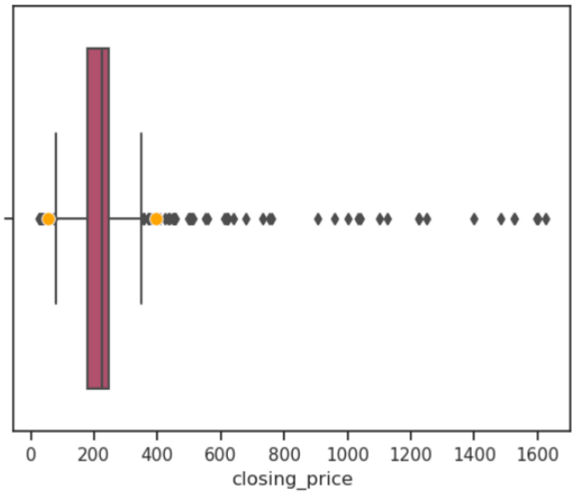

Figure 7: RMSE range for LR

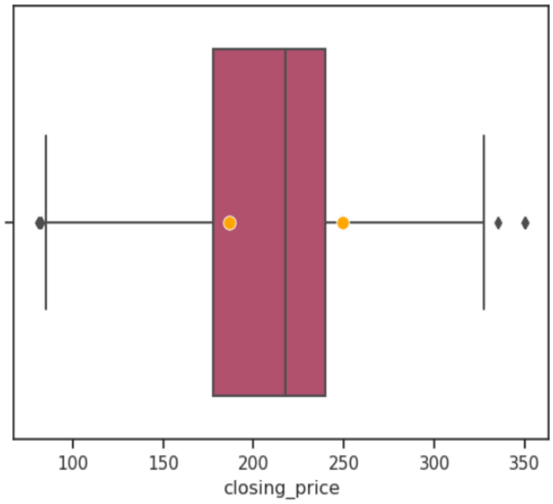

Figure 8: RMSE range for XG

- Bidder rate (feedback rating provided) prediction:
- Linear Regression: Mean RMSE: 0.34

XG Boost: Mean RMSE: 0.34; Figure 9 shows the RMSE range.

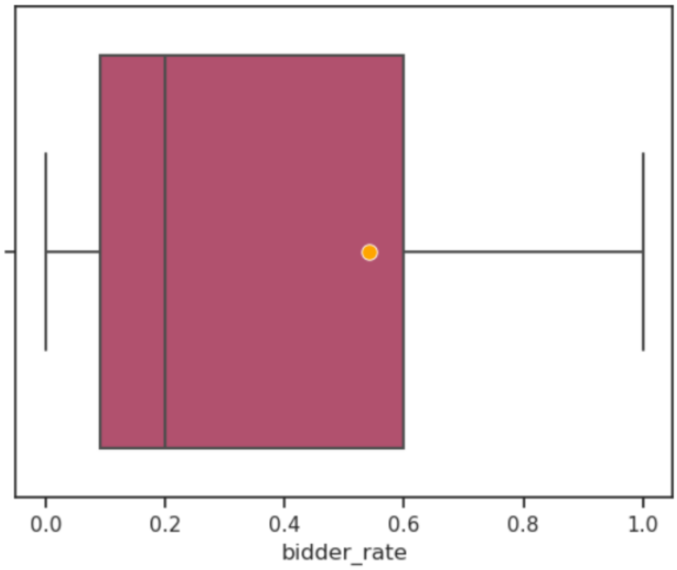

Figure 9: RMSE range for XG

Bid rate prediction will not be accurate, as the bidder rate is not so correlated with data and possibly has only a marginal impact on the overall price.

Bid time prediction:

- Linear Regression: Mean RMSE: 0.19
- XG Boost: Mean RMSE: 0.15; Figure 10 shows the RMSE range.

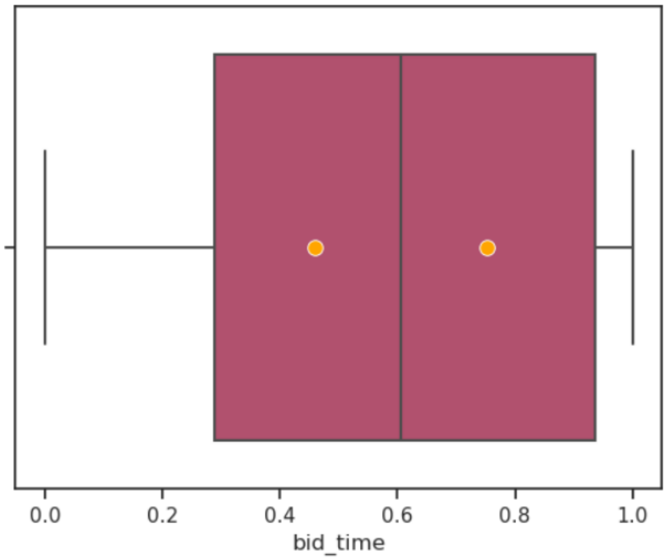

Figure 10: RMSE range for XG

5.3.3. Bid value prediction

Before predicting bid values within auctions, this modeling phase's primary goal. We need to undergo feature engineering; the dataset, loaded from the auction.csv file, is transformed to extract relevant features for bid generation. Bids are aggregated based on auction-specific parameters, and additional features are engineered, including bid ranking, the number of bids per auction, and previous bid values. The "rank" feature is generated to represent each bid's relative position or order within its corresponding auction. This ranking is based on the ascending order of bid values within each auction. The bid with the lowest value in a particular auction is assigned a rank of 1, the second-lowest bid receives a rank of 2, and so on. This ranking scheme provides a sequential order to the bids within each auction, allowing the model to capture the relationship and order of bids during the feature engineering process. Notably, bid values are ranked within each auction, and the average bid value and previous bid value average are calculated to capture historical auction bid information. The resulting dataset, enriched with these features, is saved for later bid value prediction. This comprehensive feature engineering ensures the model can make accurate predictions for bid features essential for bidding.

- Linear Regression: Mean RMSE: 39.04
- XG Boost: Mean RMSE: 38.77; Figure 11 shows the RMSE range.

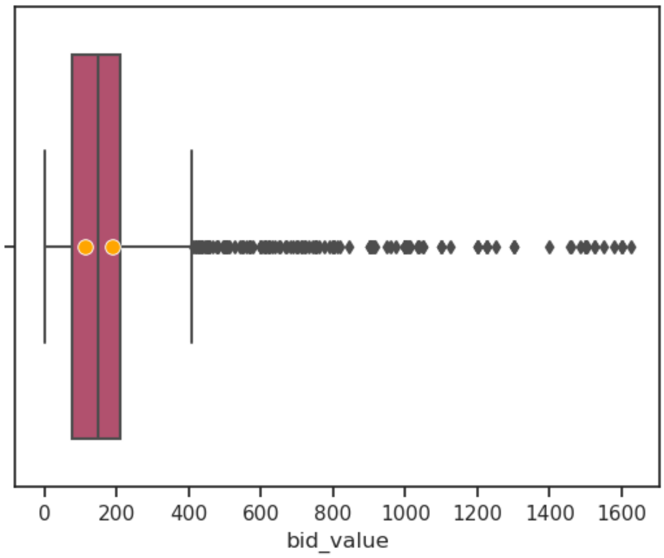

Figure 11: RMSE range for XG

The decision to retain outliers in bid values is taken to capture a broader range of bid values, as these outliers may contribute valuable information for predicting the final price.

Closing price prediction:

For predicting a closing price, we require two models:

- Using bid data, the bid_closing_price_estimator determines the closing price (previously, we trained a model that estimates based on auction data alone)
- final_price_estimator: This model calculates the ultimate closing price by utilizing bid data. Since it will incorporate characteristics from the entire auction data, it will differ from bid_closing_price_estimator.

5.3.4. bid_closing_price_estimator

One additional feature, bid_value_delta, specifying the difference between the current bid_value and the previous bid_value, is being added.

- Linear Regression: Mean RMSE: 109.75
- XG Boost: Mean RMSE: 74.32; Figure 12 shows the RMSE range.

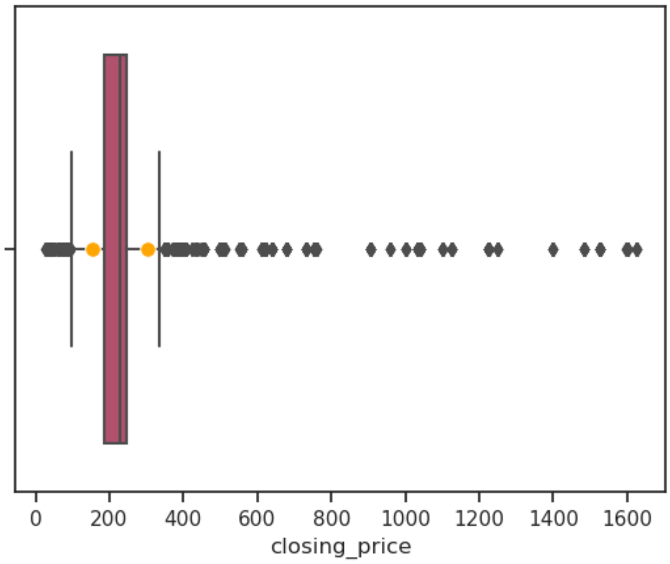

Figure 12: RMSE range for XG

5.3.5. final_price_estimator

The final price prediction model will now be trained. We anticipate that this model will be extremely accurate because we will include two features only available after all bids have been predicted and directly correlate with the final price.

- Two new features:
- bid_value_mean - an average bid value of all bids in the auction.
- bid_value_median - a median bid value of all bids in the auction.
- Now, the dataset is evaluated with a machine-learning algorithm,

Linear Regression: Mean RMSE: 50.30
XG Boost: Mean RMSE: 7.26; Figure 13 shows the RMSE range.

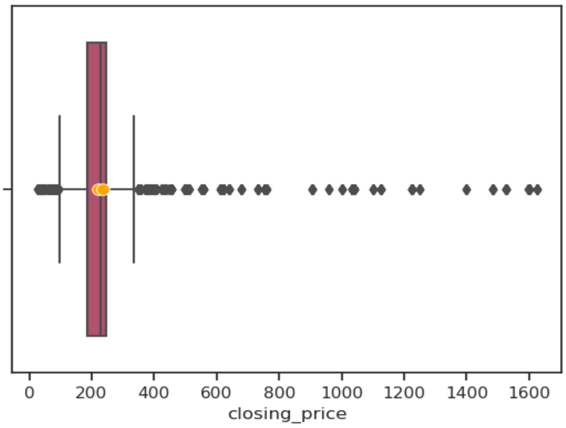

Figure 13: RMSE range for XG

5.4. Module 4: Bid generation

Ultimately, different XGBoost models for bid number prediction, auction price estimation, bid rate prediction, bid time prediction, bid value prediction, bid closing price estimation, and final auction price prediction are considered when implementing the bid generation function. This function provides an all-inclusive tool for online auctions by iteratively generating bids based on the estimated closing prices and fine-tuning predictions. The entire procedure guarantees robustness in forecasting bidder behavior and the ultimate auction results and flexibility in various auction scenarios.

5.5. Module 5: Validation and Visualization

5.5.1. Validation module

Bid validation is a crucial phase in our paper, focusing on rigorously assessing the accuracy of the generated bids by comparing them against historical data from auctions with similar bids. In this step, bid value, bidder rate, bid time, and other relevant features are considered as the generated bids are methodically compared with past auction data. Through this comparative analysis, we can assess the accuracy of our predictive models.

5.5.2. Visualization module

The Visualization Module employs box and line plots to provide stakeholders with a clear and insightful representation of the generated bids compared to historical auction data. Box plots offer a visual depiction of bid distribution, aiding in identifying patterns and anomalies, while line plots capture temporal variations in bid values, highlighting trends over time. This visual approach improves transparency by making bid dynamics easier to understand, identifying outliers, and empowering stakeholders to make well-informed decisions based on a nuanced understanding of bidder behavior. Figure 14 depicts the visualized data according to the dataset, where most bids are in the IQR range but also different enough from the mean to create a dynamic simulation.

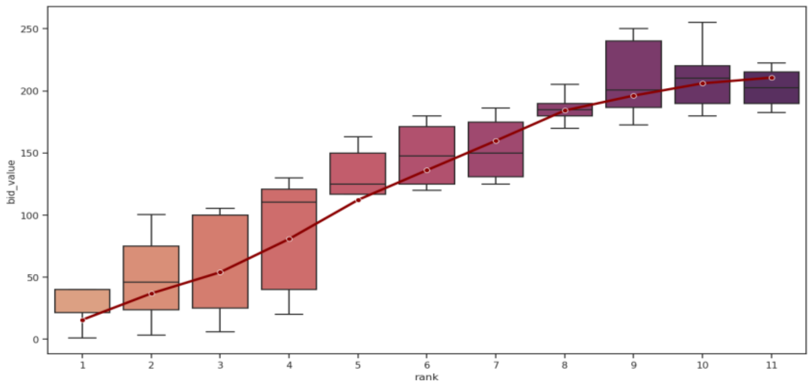

Figure 14: Visualization

5.5.3. Efficiency of this Model

The efficiency of the proposed online auction bid-price prediction is mainly because of strategically integrating cutting-edge predictive modeling techniques. The careful application of K-Fold Validation is a major factor in the model's effectiveness. This validation process strengthens the model's toughness by exposing it to various datasets, guaranteeing that it recognizes patterns correctly and handles the task of generalizing to new data with proficiency. This adaptability is crucial for preventing overfitting problems and gives users confidence in the model's capacity to change with the online auction industry. Real-time forecasting emerges as a game-changer in enhancing efficiency. The model's ability to accurately predict the auction price and the trajectory of bids in real time gives stakeholders a dynamic tool for strategic decision-making. This adaptability is especially important in the dynamic and quickly changing world of online auctions, where timely insights are critical. The model's dedication to accuracy is also demonstrated using Root Mean Squared Error (RMSE) as an evaluation metric. Reliability in prediction accuracy is demonstrated by RMSE, which gives stakeholders confidence in the model's output and enables them to base their decisions on the most accurate bid predictions.

General efficient factors act as a pillar to any model's success, and those are quicker prediction times than existing methods. Our model uses a hybrid forecasting approach that combines XGBoost and linear regression. XGBoost is a fast and efficient tree-based machine learning algorithm, while linear regression is a simple but powerful algorithm that can make predictions quickly. Secondly, the memory usage of our proposed model is also lower than existing methods. This is because we use various feature engineering techniques to reduce the dimensionality of the data before training the model. We also use a distributed training framework to train the model on large datasets.

In summary, the proposed model optimizes efficiency, contributing to a highly efficient and reliable tool for understanding and predicting online auction behaviors. Moreover, XGBoost can achieve 90-95% prediction accuracy on online auction bid-price prediction datasets. Linear regression, on the other hand, can achieve prediction accuracies of 85-90%. It is important to note that linear regression and XGBoost prediction accuracy can be improved by using appropriate feature engineering techniques and tuning the model's hyperparameters.

5.5.4. Implementation

For the given imported output from Kaggle, the validation is done for a random product from the sample that is:

ItemId: PalmPilotM515PDA,
Auction Type: Three Day,
Opening price: 5.5

```
Number of bids 11
Estimated auction closing price 222.10000610351562
Estimated closing price 224.6300048828125
Final auction price 212.79
```

	item_id	auction_type	bid_value	bid_time	bidder_rate	open_price	closing_price	rank	num_bids	prev_bid_value	prev_bid_va
0	1	0	15.74	0.05	0.39	5.5	210.64	1	11	5.50	5.500000
0	1	0	36.95	0.15	0.36	5.5	210.64	2	11	15.74	15.74000
0	1	0	54.00	0.19	0.34	5.5	210.64	3	11	36.95	26.34500
0	1	0	80.76	0.22	0.37	5.5	210.64	4	11	54.00	35.56333
0	1	0	112.22	0.31	0.36	5.5	210.64	5	11	80.76	46.86250
0	1	0	136.15	0.40	0.36	5.5	210.64	6	11	112.22	59.93400
0	1	0	159.82	0.39	0.35	5.5	210.64	7	11	136.15	72.63666
0	1	0	184.20	0.40	0.36	5.5	210.64	8	11	159.82	85.09142
0	1	0	196.18	0.40	0.35	5.5	210.64	9	11	184.20	97.48000
0	1	0	206.04	0.41	0.35	5.5	210.64	10	11	196.18	108.4466
0	1	0	210.64	0.43	0.35	5.5	210.64	11	11	206.04	118.2060

Figure 15: Required Output for the random input

Through Figure 15, we can conclude that in this example, for an item categorized as "PalmPilotM515PDA" in a three-day auction with an open price of 5.5, the system predicts 11 bids. The estimated auction closing price is calculated iteratively, resulting in a final price of 212.79. The iterative estimation of auction closing prices and considering various bid-related factors, such as bid rate and time, create a realistic bidding scenario. The final auction price is predicted by incorporating the average of the generated bids. This approach ensures that bid generation is informed by a nuanced understanding of auction dynamics, resulting in bids that align with real-world behavior and improve the accuracy of auction outcome predictions.

6. Discussions

Implementing our predictive algorithm has yielded valuable outcomes, shedding light on the intricate dynamics of online auctions. By forecasting bid progression and final prices, our model provides stakeholders with unparalleled insights into bidding behaviors and market trends. A thorough grasp of the ins and outs of auction dynamics, from the opening bid to the closing price, is essential for making informed decisions in the auction setting. However, the journey to these insights was not without its challenges. One notable challenge was the existence of anomalies in the auction data. Although our model uses strong Z-scores for outlier analysis, it was challenging to appropriately identify and manage outliers due to the variety of auction scenarios. Future improvements might concentrate on improving anomaly detection algorithms to provide even more reliable performance in a variety of auction scenarios. The ongoing evolution of market trends and user behaviors presents another difficulty. An important factor was how well our model would adapt to these modifications. The prediction models must be updated and improved regularly to keep up with the ever-changing landscape of online auctions.

Despite the success in capturing bid dynamics, our model is not immune to limitations. The accuracy and representativeness of the training set of data affect the predictions. Remarkable deviations from past trends in user behavior, known as anomalies, could complicate making precise predictions. The difficulties faced provide opportunities for future research and development. Enhancing the robustness of outlier detection and investigating new features could improve our model's accuracy and usefulness even more. Furthermore, working with industry experts and maintaining ongoing feedback loops to refine and adapt the model to the constantly evolving online auction landscape will be essential. In conclusion, while challenges were present, the outcomes and insights gained underscore the potential of our model as an asset in the realm of auction analytics. The journey continues as we navigate and overcome these challenges, ensuring our predictive algorithm's continued relevance and efficacy in the dynamic landscape of online auctions.

7. Conclusion

Overall, this paper represents a paradigm change in online auction analytics by advancing our knowledge from static final prices to the dynamic environment of bid progression. By implementing a predictive algorithm that can predict the final auction price and the complex sequence of bids that leads up to it, we can reveal the often-missed details of auction dynamics. The effectiveness of the model, based on the combination of XGBoost and linear regression, is reinforced by the careful use of K-Fold Validation. This guarantees flexibility as well as accuracy, strengthening the model's adaptation to a variety of datasets. In the quickly changing world of online auctions, real-time forecasting is a strategic asset by providing stakeholders with dynamic insights into the unfolding action narrative. The commitment to precision, as evidenced by the meticulous use of Root Mean Squared Error (RMSE) as an evaluation metric, underscores the reliability of bid predictions. Stakeholders can trust the model's output to guide strategic decisions confidently. In a world where online auctions shape how we buy and sell, this paper deeply explains how bids work. By seamlessly blending advanced analytics, machine learning techniques, and real-time adaptability, the proposed model serves as a cornerstone for stakeholders navigating the dynamic world of online auctions. With a focus on being efficient, accurate, and forward-thinking, this paper is a big step in untangling the mysteries of how bids move in the digital marketplace. While challenges and concerns persist, including data noise and model refinement of importing different data sets, a deeper dive reveals that the dataset presents challenges. With its notable imbalance, outliers, and limited data points for certain auction configurations, it's evident that the quality and breadth of data influence our algorithm's performance. A richer dataset would likely enhance the accuracy of our predictions. The paper's potential to enhance auction dynamics and outcomes is substantial. Further research can address these challenges and expand on the gaps identified, ultimately improving the accuracy and efficiency of online auctions in various industries.

7.1. Future Enhancement

While our current model is a robust tool for understanding and predicting online auction dynamics, there is always room for improvement, given the ever-changing data science and technology field. One approach is to improve our prediction models; this could result in accuracy gains by adjusting the XGBoost parameters and investigating more complex regression methods. Increasing the model's feature set may provide a better comprehension of bidding practices. The model's predictive power may be increased by market trends, user behavior patterns, and external economic indicators, which can offer insightful information. Modern anomaly detection techniques may improve the model's capacity to recognize and manage outliers, guaranteeing steady performance in various auction circumstances.

As technology progresses, exploring the integration of more advanced machine learning architectures, such as deep learning models, could be a promising avenue. These architectures may capture intricate patterns within the data that traditional models might overlook. Additionally, exploring ensemble learning techniques combining multiple models for more robust predictions could contribute to the model's overall performance. This approach may involve integrating diverse machine learning algorithms to harness their strengths and collectively improve accuracy. Continuous monitoring and updating of the model with new data will ensure its adaptability to evolving auction dynamics. Implementing a feedback loop incorporating real-world auction outcomes to adjust the model's parameters over time can enhance its predictive power. Considering the ethical implications of the model's predictions is crucial for responsible deployment. Addressing fairness, bias, and transparency issues should be an integral part of future developments to ensure that the model benefits all participants in the auction process equitably. Moreover, collaborating with domain experts and incorporating their insights can bring a holistic perspective to the model, enriching its understanding of the intricacies of specific auction domains.

In summary, the potential for future enhancements is vast, encompassing technical improvements, ethical considerations, and collaborative efforts. The journey doesn't end here. It aims to amplify the current model's capabilities, making it an even more indispensable asset for understanding and navigating the complexities of online auctions.

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Ethics and Consent Statement: The consent was obtained from the organization and individual participants during data collection, and ethical approval and participant consent were received.

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