Literature Review
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As online auctions has grown at a tremendous rate, a wide variety of algorithms have been proposed to predict the ending prices of auctions of different forms. Past studies have either choose to focus on one auction dynamics, bidding dynamics or dynamics of other ongoing auctions, or completely ignore the dynamics and uncertainties of an auction in predicting the ending prices. In order to answer the question that would incorporating factors related to the two auction dynamics significantly improve the accuracy of predicting closing prices of auctions, this research focuses on datasets extracted from eBay and Sotheby's online wine auctions and their associated dynamics respectively.

<u>EBay and Sotheby's Wine Auctions</u>

EBay is the most well-known online auction platform, and it employs second-price auction. Previous research have widely studied datasets from eBay online auctions, and variables affecting the ending prices was also explored extensively. Lucking-Reiley et al. (2007) explored a dataset extracted from eBay with parameters including last bid (if any), opening and closing time and date, seller's ID and rating, minimum bid, number of bids, and a listing of bid history, which contains buyer's ID and ratings, time of biddings, and the price of each bid. While they did not extensively examined the listing of bid history to evaluate the impact of jump bids or snapping bids on ending prices, Lucking-Reiley et al. (2007) presented that regressions showed that seller reputation, especially the negative ratings, lasting time of auctions, minimum bids, and reserve prices affect the closing prices significantly. This research will employ their results in identifying vital parameters, including lasting time, buyer's rating, reserve price, minimum bid, and bid history to predict the ending prices of auctions.

While online wine auction of Sotheby's is still relatively recent and has not been widely explored yet, previous research did investigate virtual wine auctions as well as factors affecting transaction prices of wine. Ashenfelter (1989) collected and studied a dataset on wine auctions, and his result proposed that when identical wines are sold in a single auctions, the price is likely to decline. Ashenfelter (1989) also found that the price estimated from auction houses are very highly correlated with the price fetched and ending prices. Moreover, Lecocq et al. (2006) examined objective and sensory characteristics determining wine prices. In this study, a wine dataset from the Institut National de la Consommation (INC) on Bordeaux was employed, and the correlation between the actual sold price and objective variables, which includes ranking, vintages, and bordeaux groups, as well as sensory variables, which includes firmness of attack, if well concentrated, and if needs keeping, are examined using a hedonic price equation. Lecocq et al. (2006) concluded that objective characteristics explained the major part of price differences among wines, while sensory variables appears to be relatively unimportant.

According to Ashenfelter (1989), the mean price estimate for each lot will be used for reference in predicting the closing price. Then based on the result of Lecocq et al. (2006), this research will categorize wines according to the ranking, vintage, and bordeaux group information provided, and auctions of same-categorized items can be used as historical information. Note that since bidding history is not available for Sotheby's online wine auctions, only dynamics of related items would be explored in this paper. However, since Sotheby's employs English auction, bidders must pay their own bid if they win, so snapping or jump bids are less motivated.

Therefore, less uncertainties arise, and price evolution during an auction is as influential as in second-price auctions on eBay platform.

Predicting Ending Prices

Most research treat data from online auctions as cross-sectional and consequently ignore the changing dynamics that occur during an auction. While the goal of this research is to investigate the impact of auction dynamics in predicting the closing prices, it is still useful to look at the approaches and accuracy of previous research disregarded the dynamics.

Ghani and Simmons (2004) explored the possibility and accuracy of using machine learning algorithms to predict the ending price of given auctions using feature known prior to the start of the auctions. They have also used a dataset from eBay online auctions of Palm Zire 21 over a two-month period, which contains information about sellers, the auction item, recent auction results, and the auction. Ghani and Simmons (2004) evaluated the accuracy of three machine learning algorithms, simple regressions, multi-class classification, and multiple binary classification approach, in predicting the closing prices of auctions, and he found that classification approach, using decision trees and neural networks, yielding the $5 price range of the predicted closing price is far better than the regression approach predicting the exact final price. Based on the result of Ghani and Simmons (2004), this research will employ discrete price prediction, a multi-class classification task discretizing the final prices into several intervals depending on the actual price range. The discrete price prediction approach outperforms simple continuous price prediction.

There are recent papers focuses on the impact of one of the two price dynamics, dynamics of current auction and auctions of related items, on closing prices. It is helpful to consult their approaches in capturing the dynamics in dataset and ways to utilize the dynamics in closing-price predictions.

Wang et al. (2012) and Li et al. (2014) proposed different approaches in addressing the dynamics of prices that occurs during an auction. Wang et al. (2012) developed a dynamic forecasting system to predict the price of an ongoing auction. Dataset were collected from 190 7-day eBay online auctions of Microsoft Xbox gaming system, which contains bidding history, auction format, product characteristics, and bidder and seller attributes. Bidding history was recovered to a functional object, which is a curve, for functional object regression and treated as the core of the dynamic forecasting system built. Wang et al. (2012) concluded that their system models the auction's price velocity and acceleration using bidding history, and significantly outperformed standard forecasting methods utilizing only information available at the start of an auction. Li et al. (2014) also focused on the price evolution that occur during an auction, but they employed a different approach in treating the dataset. This paper used attribute construction, which transform the one to many relationship between auction and bids to a one-to-one relationship, in data preprocessing, and thus enables traditional machine learning algorithms and statistical analysis methods to be used to predict the closing prices. They also concluded that incorporating the dynamics into machine algorithms improves the accuracy of prediction. While the attribute construction approach appears to be more convenient since traditional machine learning algorithms can be applied after data preprocessing, functional regression analysis better captures the velocity and acceleration of the bidding history. This research will employ functional regression analysis in resolving the price dynamics, and penalized smoothing spline technique can be used in recovery of functional objects, converting the data into curves.

Another dynamics to be concerned is the dynamics of ongoing auction of related items. Previous literature has found that this dynamics is vital in improving the accuracy of final-price predictions. Lim et al. (2008) compared the accuracy of artificial neural network and the grey system approach in predicting closing prices of auctions. Using dataset from electronic simulated marketplace of English, Dutch, and Vickrey auctions, this paper shows that while the accuracy rate for both approaches are high, using moving historical data capturing the dynamics of ongoing auctions of similar items as well as past closing auctions yielded higher accuracy rate than using fixed historical data containing only information of closed auctions in both approaches. Motivated by Lim et al. (2008), this research aims to resolve the dynamics of related auctions as well as the price evolution of the predicted auction itself.

Schapire et al. (2002) proposed an approach to address the concern about the dynamics associated with ongoing auctions of related items in final-price prediction using boosting-based conditional density estimation. They collected data from closed auctions and currently open auctions of similar items, and then used a boosting-based algorithms to estimate the the closing price based on historical data (past auction results) and current status of game (currently open auctions and information about the predicting auction). The idea to to predict the how much the price would increase until closing from current time point, instead of the actual closing price. The result of Schapire et al. (2002) is useful in estimating the final price of an auction if auctions of multiple interacting goods are held simultaneously, such as in the eBay dataset this research will explore. Boosting-based conditional density estimation can capture the dynamics of related auctions perfectly.

Based on past literatures, correlated parameters from eBay online auctions datasets and Sotheby's online wine auctions can be identified in predicting the final prices. Furthermore and most importantly, by combining discrete price prediction, functional object regression, and boosting-based conditional density estimation, which have been evaluated to be accurate in auction price prediction, this research can appropriately capture the dynamics of price evolution and related auctions in final-price prediction, and thus the impact of these dynamics in accuracy of prediction can be assessed. This study will contribute to past literature in this field as a more extensive study on the impact of dynamics in final-price prediction, as no previous study have addressed both dynamics in any online auction platform.

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