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.

Lucking-Reiley et al. (2007) explored a dataset extracted from eBay with parameters including ing 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.

While online wine auction of Sotheby's is still relatively recent and has not been widely explored yet, previous research did investigated virtual wine auctions as well as factors affecting transaction price 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.

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.

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.

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.

While most research treat data from online auctions as cross-sectional and consequently ignore the changing dynamics that occur during an auction, there are recent papers focuses on the impact of price dynamics on closing prices.

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 tradition 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.

Schapire et al. (2002) proposed the concern about the dynamics associated with ongoing auctions of associated or similar items in predicting the closing prices of auctions. To address this concern, 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. This paper is useful in estimating the final price of an auction if auctions of multiple interacting goods are held simultaneously.

Reddy and Dass (2006)

This is very useful in using bidding history and historical closing prices of similar items to predict auction results. Penalized smoothing spline technique can be used in recovery of functional objects, converting the data into curves. This technique chooses important knots (datapoints) and measured penalty (degree of departure) of each knots.

Finally, when analyzing the closing price, a common way is to predict the accurate price, which is a continuous price prediction. I have looked at several papers using different datasets and technique, and continuous price prediction is not accurate as expected.

Another more accurate way is discrete price prediction, which I will be talking about in next slide. This is a multi-class classification task discretizing the final prices into several intervals depending on the actual price range.

I will employ discrete price prediction in my research using functional regression.
Functional regression views bidding history as a continuous event happening at different times, while conditional density estimation tries to predict the closing price at each time point and using all predictions to come up with a final one. I think conditional density estimation is less accurate than functional regression.

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