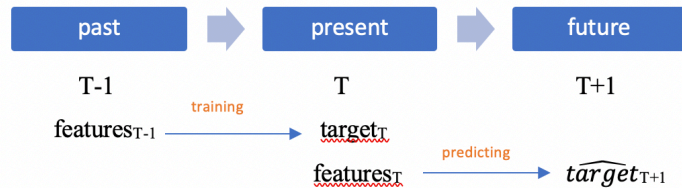


OBJECTIVE

Forecasting the online auction outcome

Background – Online auction has been one of the most popular methods to buy and sell items online. Forecasting the auction outcome is beneficial to all auction parties.



RESULTS

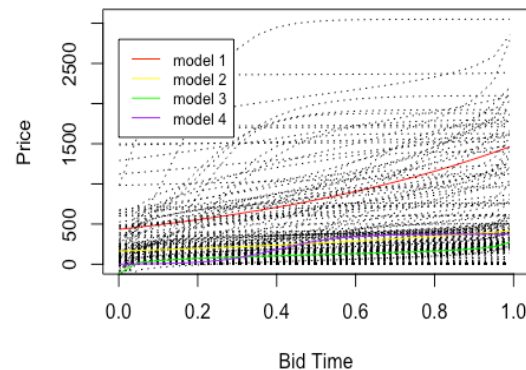
$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n}$$

Feature	Method	Testing MAE
Static features	Multiple Linear Regression	110.296938
	KNN	89.9072
Static features+Dynamic features	Multiple Linear Regression	67.37456
	KNN	85.78306
	XGBoost	11.8855213
	LSTM Neural Network	102.7578

DATA CURATION AND ANALYSIS

The dataset contains both time series and cross-sectional data.

- Each auction has a sequence of bidding history
- 10681 observations and 9 variables, 627 auctions in total
- The timestamp is generated by user activities, where events are not equally spaced
- Auction price- second highest bid+ increment
- Static information vs evolving information
- Modeling discrete bidding price to a smoothing curve using methods such as Spline, GAM



CONCLUSIONS

Model: "sequential_88"		
Layer (type)	Output Shape	Param #
lstm_77 (LSTM)	(1, 128)	66560
dense_115 (Dense)	(1, 32)	4128
dropout_28 (Dropout)	(1, 32)	0
dense_116 (Dense)	(1, 1)	33
Total params: 70,721		
Trainable params: 70,721		
Non-trainable params: 0		

Follow On Work/Lessons Learned:

- Our baseline model using ML models to predict the end-price with static features did not perform satisfactorily with a testing MAE of 110.29693. Adding the on-going information can reduce the MAE to 11.8855213.
- The LSTM Neural Network did not return the best result.
- An ensemble of unsupervised clustering results and linear regression might have higher predictive capabilities. My future works also includes the practical application of auction predicting models that helps the buyers making bidding decisions.