Keyword Performance Prediction in Paid Search Advertising

Sakthi Ramanathan[1], Lenord Melvix[2] and Shanmathi Rajesh[3]

Abstract— **In this project, we explore search engine advertiser keyword bidding data over a period of 4 months released by Yahoo! to study the effects of bidding strategies in keyword performance defined by advertisement rank and click through rate. Empirical studies have shown that pulse bidding strategies significantly improve keyword performance at lower cost compared to fixed bidding strategies. Advertisers make use of keyword performance feedback given by search engine to optimize their subsequent bid to meet their marketing goals. Strategies adopted in this bidding process are trade secrets that estimate search engines evaluation of advertisement and competitor bidding strategies. As a part of this project, we have designed a regression model that predicts keyword performance for advertisers bid to aid him in evaluating whether the predicted performance is sufficient to meet his marketing goals. To achieve this goal, we engineered a Gradient Boost Regressor built with features based on historical keyword performance of advertiser, competitiveness of keyphrases and bid pulsing strategies. Our prediction model achieved a mean absolute error of 1.99947 for rank prediction task and 0.010386 for click through rate prediction task.**

I. INTRODUCTION

Search Engine Marketing is a form of Internet marketing that involves the promotion of websites by increasing their visibility in search engine results pages primarily through paid advertising. Search engine marketing has taken hold of a major percentage of the advertising market since its introduction in 1996. In 2007, U.S. advertisers spent US $24.6 billion on search engine marketing.In Q2 2015, Google (73.7%) and the Yahoo/Bing (26.3%) partnership accounted for almost 100% of U.S. search engine spend.

Keyword advertising uses specific words and phrases to target consumers. Advertisers bid on these keywords or phrases so their ads will be displayed to consumers when the keywords or phrases are used. For example, if a consumer searches a particular keyword, targeted advertising banners will be displayed based on the searched keyword. The search engine will then display the list of the paid advertising links based on the relevant bid price, ad content, and quality score of the landing pages. Every time a consumer clicks on a sponsored link, the corresponding advertisers account is billed.

Advertisers determine the bid value based on a number of factors, such as keyword performance (the number of exposures, the rankings, and the number of clicks the ad link receives), conversion rate, the revenue generated by clicks, and the resources and effort required to manage the bidding process. Advertisers can choose a set and forget fixed bidding amount (Fixed Bidding Strategy), or they can change the bid value based on certain types of rules (Pulse Bidding Strategy) to optimize performance whenever necessary. Other contributing factors such as keyword choice, ad content, and landing page design, can also be adjusted but for the sake of this project we assume that the other factors are maintained constant and pulsing is motivated purely based on search engines evaluation and competitor performance.

Two most common keyword auction formats adopted in the market include generalized first price (GFP) and the generalized second price (GSP) auctions. In both formats, the advertiser with the highest bid is likely to receive the highest rank and the most exposures (which in general will lead to a higher click-through rate). The only difference is the cost of each click. In the GFP auction, the advertiser will pay the price the advertiser bid; in the GSP auction, the advertiser will pay the price of the next-highest bid. Studies have shown that the GFP auction is naturally unstable featuring a sawtooth pattern of bid value and so GSP has been more widely adopted.

Yahoo! Webscope data collected under the GSP format for this project indicate that around 60 percent of advertisers indulge in bid pulsing strategies throughout the entire period. Various drivers of such dynamic bidding have been discussed in the literature: for instance, the previous ads rank and click-through rate, the search engines evaluation of the site, and competitors bidding behavior will all contribute to bid value variations. In this paper, we will explore the effect of various factors that affect keyword performance and design a regression model to predict keyword performance in terms of rank and click through rate based on identified contributing factors.

II. LITERATURE SURVEY

There is a size-able chunk of research literature on click-through-rate prediction and analysis of bidding strategy models in the search engine advertising industry. Notably [3], [4] and [5] discuss models that advertisers employ to optimize their bid prices, and how their bid strategies influence the performance of their advertisement during the search engine keyword auctions. With cross-sectional and longitudinal analyses on the Yahoo! Search advertising data [1] (that we have used), [2] addresses the impact of fixed bidding & pulse-bidding strategy on keyword performance in terms of ranks, impressions and clicks of an ad. This study empirically measures the differences between the two

*This work was prepared as coursework project for CSE258 at UCSD

[1]Sakthi is a Masters in Computer Engineering student at UC San Diego specializing in Embedded Computing, srsivara@eng.ucsd.edu

[2]Lenord is a Masters in Computer Science student at UC San Diego specializing in Machine Learning lmelvix@ucsd.edu

[3]Shanmathi is a Masters in Computer Science student at UC San Diego specializing in Artificial Intelligence shrajesh@eng.ucsd.edu

strategies in terms of their influence on their performance measures.

Various data sets and models have been used in the past to examine the keyword bidding strategy. For example, Jansen et al. [7] investigated the keyword performance and the use of brand terms and found that matching brand terms in key phrases and ads will significantly improve the effectiveness and efficiency of keyword advertising. Ghose and Yang [6] modelled the impact of keyword characteristics, ad position, and landing pages quality score on advertisers bid price, consumers search and click behavior, and the search engines ranking decision.

Most empirical studies on search engine advertising focus on the factors of dynamic bidding, including advertisers previous positions (rank), click-through rate, the search engines evaluation of the site, and competitors. In our predictive model, in addition to these definite factors, we have also incorporated pulse-bidding features like pulsing strength (relative change in bid value) and modeled indirect features like consumers clicking behavior and search engines ranking scheme using the previous days' data, to get a better estimate of the performance measures for an ad.

III. Data Exploration

We designed our keyword prediction model using open sourced keyword auction data released by Yahoo! Webscope [1]. The dataset contains a record of 77,850,272 daily bidding activities of 16,268 advertisers, spanning over a period of 4 months in 2008. Each advertiser (bidder) is assigned a unique anonymous ID to be tracked across days and keywords (also anonymized). The dataset also contains the advertisers bid value for a keyphrase (combination of keywords), rank, number of impressions and clicks. A new bid data is available for an advertiser-keyphrase pair each time its rank is changed in the auctions on that day.

A. Dataset Description

Each data point consists of the following fields :

- Day of bidding activity
- Anonymized account id of advertiser
- Rank given to the advertisement
- Anonymized keyphrase for which advertiser is bidding
- Bid placed by advertiser
- Number of impressions allotted
- Number of clicks the advertisement received

B. Data Exploration

We analysed different advertiser behavior and keyword performances in the dataset and found that majority advertisers frequently adjust their bid prices according to feedback received on their keyword performances, while some advertisers hold on to fixed bidding technique. Interestingly, we observed that most advertisers involved in bidding for highly competitive keyphrases pulsed their bid at higher frequency. Figure 1 demonstrates pulse bidding activity of randomly chosen advertiser for a highly competitive keyphrase in

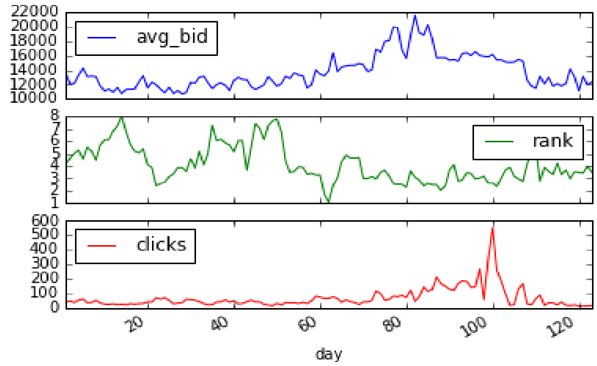

Fig. 1. Pulse bidding activity based on Keyword performance

correspondence to keyword performance via ranks and clicks over a period of 120+ days.

Advertisers seem to determine their bid prices heavily based on rank, impressions and clicks of the advertisement. Figure 1 shows how the rank and click count of an advertisement varies as its bid changes over 4 month period. From the figure, we can see that as the average bid is improved, the performance (rank/clicks) of the ad improves proportionately.

Yet another interesting observation on the bidding strategy is that as the number of clicks reaches peak, advertiser pulls down his bid value but still continues to enjoy higher rank and greater impressions as a result of better evaluation by Yahoo! thus saving on his overall bid pricing.

This could be because the search engine advertising auction algorithm calculates the rank of an advertisement not just based on the bid value, but also on the ad relevance, its click through rate (CTR), and landing page experience, in short – based on its past performance.

Rank fluctuations for a competitive keyword An advertisement has a better click probability when it is placed at higher position which is determined by the rank. The ad rank is recalculated each time the ad is eligible to appear and competes in an auction, so the ad rank (and hence the ad position) can fluctuate each time depending on the keyword competition at that moment. Figure 2 shows the fluctuations in the auction performance on a highly competitive keyword.

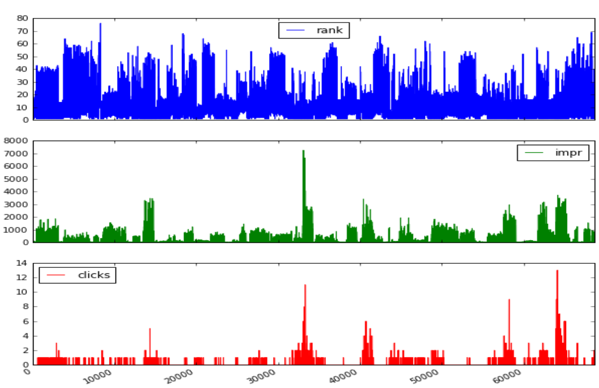

Fig. 2. Fluctuations in performance parameters on a single day

As these fluctuations are caused due to its competitors, these metrics can be potentially used to model effect of competitor on keyword performance. As can be seen in the figure, there are so many fluctuations in rank. These are insignificant for most times when the impression share (percentage of impressions that the ad receives compared to the total number of impressions possible) is considerably low, considering low chances of auctions where the ad is competitive enough to be shown.

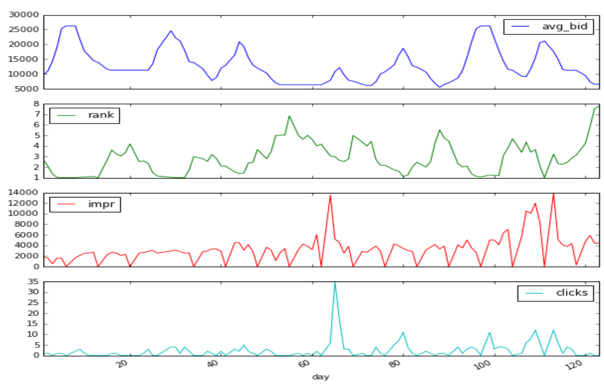

Fig. 3. Impact of bid pricing on keyword performance

Bid pricing effect on ad performance The figure shows the keyword auction bid values of an ad over 4 months by a competitive advertiser (who maintains his rank in top 10 over the 4 months period) and the corresponding performance values. Higher bid prices improve the impression shares with respect to the other competitors of the key word, and this leads to the ad landing up at higher positions in the search engine, thus increasing the possibility of getting seen and clicked. And this in turn increases the rank due to its past performance & bid value as can be seen in the Figure 3.

C. Limitations of Dataset

Dataset released by Yahoo on keyword bidding activity could contain real-world advertisers with different levels of budget constraints, marketing goals, campaign goals and target customer groups that could not be categorized as the account and keyphrase had been anonymized to protect their privacy. This limits from categorizing advertisers or keyword groups. However, competitiveness of keywords and advertiser groups competing for same keyword occurring in multiple keyphrase gives us a fair idea about potential clustering of advertisers and keyword categories that can be exploited for our prediction model.

Yahoo! evaluation metric in granting rank and impression not just depends on historical performance and bid value but also on the quality of landing page and relevance of advertisement to user group. Since these metrics are not available to us and it is highly improbable for an advertiser to frequently change quality of his landing page – we assume these metrics have an insignificant influence in determining keyword performance computed in near real time rate.

Yet another key limiting factor that limits bid pricing of an advertiser is his budgeting constraints and marketing goals that are trade secrets but could be better used by advertiser when the prediction model is used internally.

IV. Prediction Task Identification

Exploratory analysis of dataset to visualize various aspects of the data reveals a complex inter-relationship between bid pricing and keyword performance. This is governed by bidding strategies, search engine evaluation and competitive environment. Given the budget constraints and drive to optimally price the bid in order to achieve marketing goals - it is crucial for advertisers to predict potential performance of keyword for the bid to be placed.

This considering the bidding environment as a black box that receives bid price from advertiser and provides feedback in form of keyword performance - predicting keyword performance for a bid inherently tries to model the bidding environment and search engines evaluation algorithm.

We believe we have sufficient information to perform this prediction task and such a system can be very helpful for advertising companies in evaluating / optimizing their bidding strategies.

To summarize, the prediction task here is a regression problem that includes prediction of ad rank and CTR. These have been identified as metrics that best represent keyword performance.

Ad rank is computed by the search engine and is used to determine the ad position on the search page and determines the visibility of the advertisement.

CTR is the ratio of number of clicks that an ad receives to the number of times the ad is displayed.

A. Assumptions

Given the limitations of dataset and anonymization of data - we are forced to make some assumptions on the bidding environment and feature metrics in order to perform this prediction task. Some of major assumptions under which we have modelled our prediction system include :

- **Greedy bidding strategy :** One among the bidding strategies described in [2] assumes a greedy approach where the bid pricing is made purely based on keyword performance irrespective of competitor performance. Since competitor pricing strategies are trade secrets and mathematically estimating them is beyond the scope of this project - we have assumed a greedy bidding strategy.
- **Keyword performance feedback does not affect landing page quality :** As mentioned in the introduction, keyword performance data not only affects advertisers bid but also helps him optimize his advertisement, choice of keywords and quality of landing page. Since we are not given these information and in realistic scenario optimizing advertisements in real time is extremely hard we have assumed that keyword performance solely affects his bid in a static advertising environment.

Having stated these assumptions, we would also like to point out that in real world scenario - advertisers would have

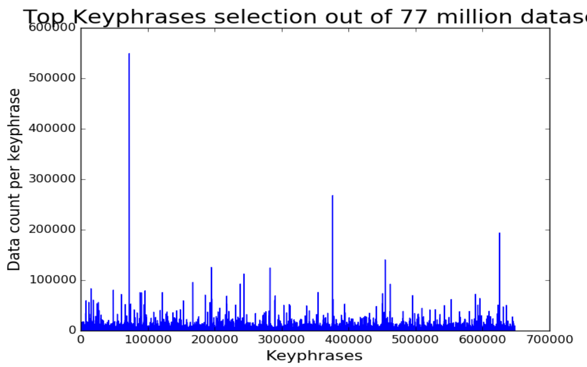

Fig. 4. Datapoints count for unique keyphrases

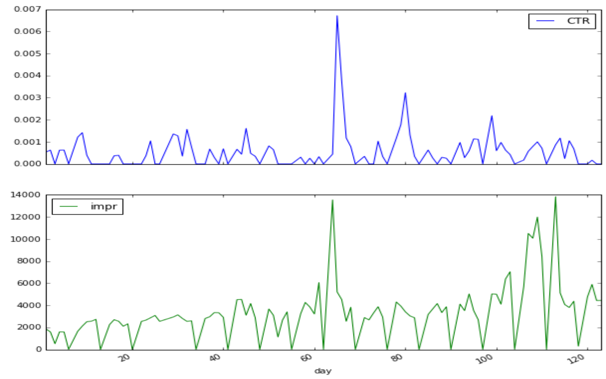

Fig. 5. Comparison between CTR and Impressions

additional to information to cross-validation or replace these assumptions with corresponding feature vectors to better perform the keyword performance prediction task.

V. Data Pruning

Due to compute power limitations to process 77 million data points (approximately 4Gb) we reduced dataset to model keyword performance for only top 20% of keyphrases with more than 2 competitors. Under the assumption that the budget allocation for each keyphrase marketing goal is independent - Inter-keyphrase competition could be significantly less thus we dont lose significant amount of information for the filtering keyphrases in this technique. Figure 4 shows distribution of keyphrases with maximum information from which top 20% was filtered for prediction. This truncation does not compromise the analysis as the data are inherently truncated at some level, in the sense that we have access to their bids only over 4 months of time, and these keyphrases could have been more competitive in timespan outside these 4 months. We also filtered out fixed bidders with standard deviation in bid less than 0.01 to permit tractable analysis. This also does not affect our prediction task as we are interested in the region of higher competitive auction performances where most advertisers use pulse-bidding to optimize their return-on-investment (ROI).

VI. Feature Engineering

We have engineered the following set of features to fit our keyword performance prediction model.

Average Bid : Running average of Bid amount placed by the advertiser for the keyword. This could give information about search engines prior knowledge about advertisers bidding activity and mitigate his bid pulsing tactics.

Mean Rank : Average rank given for the advertiser historically could give information about search engines evaluation of advertiser and his bidding position among competitors.

Mean Impressions : Average impressions given for the advertiser historically could give information about search engines evaluation of advertiser, his success rate and his budget potential if he has subscribed for pay-per-impression mode. This correlation can be seen in Figure 5.

Mean Click : Average clicks given for the advertiser historically could give information about his success rate, relevance of keyphrase to the advertiser and his popularity.

Current Bid : Current bid placed by the advertiser for which performance has to be predicted. This has a strong correlation with the performance as supported by the data analysis.

Pulsing Strength : Empirical analysis presented in [2] clearly demonstrates an improvement in keyword performance with increase in pulsing strength. So in real-time bidding , pulsing strategies become an inherent technique for advertisers to improve their ad performance. Figure 6 shows a plot capturing the pulsing behavior of the bids in the dataset for a keyword-advertiser pair over 4 months. It can be noticed that greater the pulsing strength, the larger the level of improvement in the rank, impressions, and clicks.

Maximum Bid, Minimum Bid, Bid Deviation : Gives information about potential range of advertisers bid which could be used by search engine evaluator to greedily favour an advertiser or force the advertiser to bid better.

Previous Rank : Most recent performance information proves to have a significant effect on subsequent evaluation as shown by data.

Number of Keywords : Greater the number of Keywords in the keyphrase, better the rank was. This could be due to the

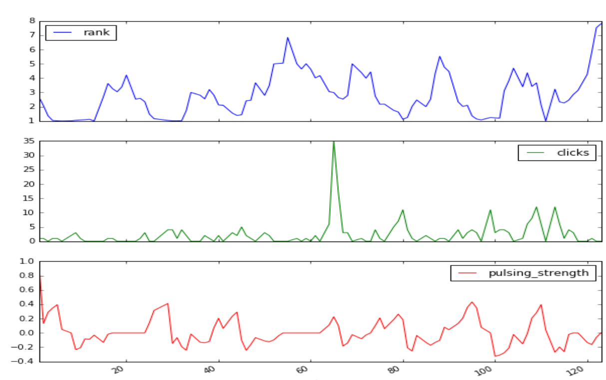

Fig. 6. Pulsing Strength and Keyword Performance comparison

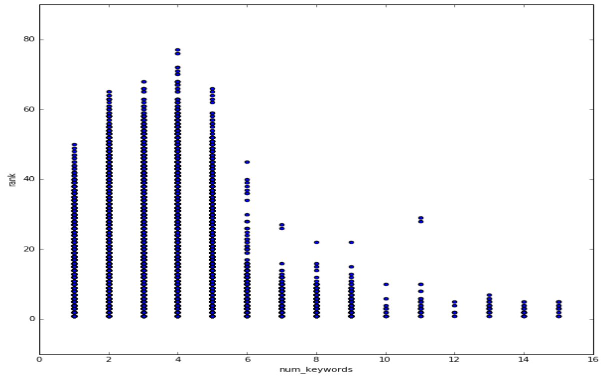

Fig. 7. Effect of Number of Keywords on Rank

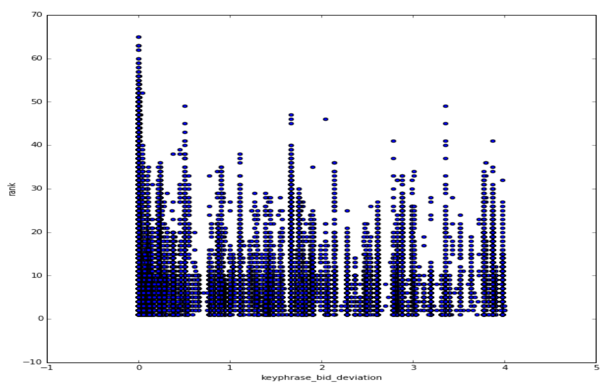

Fig. 8. Effect of Bid Deviation on Rank

reason that a particular phrase was a part of an advertisers campaign goal that did not have other competitors bidding on it, thereby giving the advertiser a better performance as shown in Figure 7.

Number of Keyphrase Competitors : More the number of competitors, competitors' bidding strategies will have a significant impact on the keyphrase performance and affects our underlying assumption of greedy bidding environment.

Deviation from average bid for Keyphrase : More the advertiser is willing to pay for a keyphrase from what is quoted on an average - better is his performance. This can be noticed from the Figure 8.

Besides these features, we also explored one-hot representation of keyphrase competitiveness, pulsing range, performance deviation, keywords bid by the advertiser and periodicity of bid pulsing activity. However, these features had detrimental effect on the prediction task and thus have not been included in the final model.

VII. Evaluation Metric

We employed Mean Absolute Error (MAE) as evaluation metric to benchmark our prediction engine. This metric is more robust to outliers that exist in dataset despite meticulous pruning as bidding strategies drastically vary across advertisers for different keyphrases.

VIII. Regression Model

We evaluated 14 regression models from linear, tree and ensemble categories to perform rank and CTR prediction tasks. Mean Absolute Error in prediction from models after fine tuning parameters have been tabulated in Table 1. It can be noticed Gradient Boost Regressor significantly outperforms other models closely followed by Huber Regressor.

TABLE I
Model Evaluation for Keyword Performance Prediction

Model	Rank Prediction	CTR Prediction
Linear	2.198010314	0.01110396648
Lasso	2.215933496	0.01126915063
ElasticNet	2.217617945	0.01128888461
TheilSen	3.147455712	0.1769128593
Huber	2.038764891	0.1769128593
RANSAC	2.317838229	Does not fit
Ridge	2.198013176	0.01110394989
Random Forest	2.065567292	0.0114166355
ExtraTrees	2.230450369	0.01137225712
KNeighbours	3.120195129	0.01049818238
DecisionTree	2.992233129	0.01288159789
Bagging	2.202136102	0.01171668549
AdaBoost	3.326263662	0.01933823867
GradientBoost	1.999473959	0.01038647007

Linear Regression : Simple model to minimize residual sum of squares in observed dataset. However, this model assumes independence of model terms to perform linear approximation. When terms are correlated, design matrix becomes singular and is highly sensitive random error producing large variance. The features used for this model have high probability of inherent correlation say for example - mean clicks could have a direct correlation with mean impressions despite uniquely defining the historical performance of advertiser-keyphrase pair. This could possibly explain the reason for poor performance of simple linear regressor in both rank and CTR prediction.

Ridge Regression : Additional L2 norm regularization employed to reduce over-fitting marginally reduced prediction performance in test set compared to linear regression. However, this would still be preferred over linear regression model given its ability to handle over-fitting issue.

Lasso Regression : This model is highly suitable for cases where redundant parameters ought to be suppressed by assigning sparse coefficients using L1 norm. We have meticulously engineered features to remove correlating features and believe poor performance of this model could be attributed to its penalizing criteria. Varying ranges of parameters could also be another reason why this technique performs poorly in efforts to minimize weights given to features.

ElasticNet Regression : This model uses both L1 and L2 norm regularization to pick multiple correlating features instead of just one among them like Lasso. This technique generally preferred to mitigate over-fitting suffers poorer performance probably due to penalizing weights to highly contributing features such as previous rank - identified when evaluating Gradient Boost Regressor.

RANSAC Regression : This model fails miserably in rank prediction and was not able fit a least squares model effective for CTR prediction task. This could be due to the nature of task we are handling. In this case, there is a time dependent correlation between data points which could be captured by linear regression models. Since RANSAC randomly samples data points to fit a model, it might not have picked effective set of data points that provide sufficient information to fit the model.

Thiel-Sen Regression : Non parametric method that makes no assumption of underlying distribution in dataset. This model is more suited to approximations on dataset with several outliers. Data pruning techniques employed before feature extraction would have effectively removed outliers and there is a clear correlation between features and rank/ctr which this model fails to take advantage of. This could be a potential reason why this model fails to CTR model.

Huber Regression : This technique outperforms majority of the models primarily due to the way it handles outliers by giving them lower weights instead of eliminating them like RANSAC. This could have effectively captured evaluation strategies by Yahoo and thereby contributed towards improved performance.

Decision Tree Regression : This model has poor performance probably due to over-fitting or fitting rules to features for regression might have failed to learn the complications in search engines evaluation of keyword performance.

K Neighbors Regression : This technique has the worst performance because the underlying distribution of data did not have spherical clusters along the hyperplane defined by the feature vectors.

Random Forest Regression : A tree is constructed by randomly choosing a sample and iteratively split until it cannot be better split for the given feature set. This ensemble technique performs relatively better probably because it was able to model the most dominant keyword performance evaluation strategy.

ExtraTrees Regression : In this case, the thresholds are the best among randomly chosen for the splitting rule used in Tree construction. This technique increases bias but mitigates this by averaging to reduce variance. However, this model performs poorly compared to Random Forest model which could probably be due to the bias that this model introduces.

Adaboost Regression : This model using multiple weak regressors - Decision Trees in this case performs performs poor probably due to the cumulative effect of over-fitting that is incurred by Decision Tree at each level.

Bagging Regression : This model builds multiple prediction models using sub-samples. Poor performance of this ensemble technique could be because the sampling technique might have not effectively captured distribution across several advertiser-keyphrase pair. As they are likely to have varying pulse bidding rules.

Gradient Boosted Regression : This model by performs the best after parameter tuning for both Rank prediction and CTR prediction tasks. Superior performance of this model could be attributed to its robustness to outliers and natural way of handling heterogeneous features. With 500 estimators minimizing over least squares error - this technique promises to be better model of all the models explored for this prediction task.

We also tried to fit individual Gradient Boosted Regression model for each keyphrase anticipating that Yahoo might have different evaluation criteria for different keyphrases or competitor effects might vary across keyphrases. But this model performs poorly for certain keyphrases and better for some – on average performs poor than overall Gradient Boosted Regression technique.

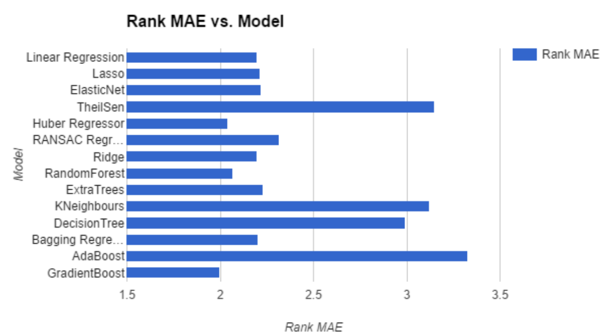

Fig. 9. Rank prediction performance for various Models

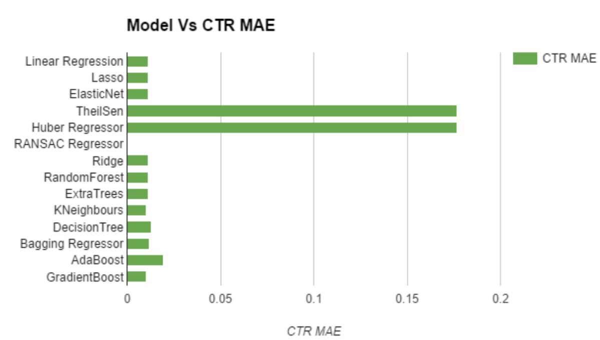

Fig. 10. CTR prediction performance for various Models

IX. Results and Discussion

A. Baseline Model

To our knowledge, keyword performance prediction model using Yahoo! Webscope advertisement dataset [1] that we have designed is the first of its kind. We couldnt find any literature on existing models using this dataset to benchmark our design. Hence we took a *naive linear regression model* designed using average rank, average CTR and current bid to make baseline prediction. This baseline model achieves a MAE of 3.49463563372 for rank prediction and 0.010934250553 for CTR prediction.

B. Model Evaluation

Gradient Boost Regression model that we have designed outperforms baseline model for Rank prediction by 42.3% and baseline model for CTR prediction by 5.008%. Figure 10 and 11 show importance of features in the Rank and CTR prediction models. It can be observed that previous rank and mean rank have the highest importance in making the rank prediction which shows the robustness of Search Engine evaluation engine to pulsing activities trying to maintain a uniform bidding environment unaltered by spurious bidding activities. Despite the robustness, it can still be noticed that pulsing behaviour has the next highest influence on prediction of rank thus validating the argument put forth in [2] on positive effect of pulse bidding in keyword performance.

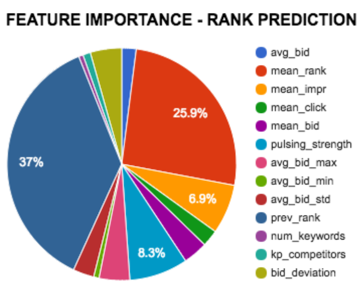

Fig. 11. Importance of features in Rank Prediction

Similar trend is observed in CTR prediction as well. Mean clicks could have been used by search engine to evaluate performance of an advertiser thereby granting him more impressions which in turn resulted in more CTR. Interestingly pulsing strength has very little effect on click through rate prediction probably due to greater influence of mean impressions and click which historically makes a brand better known to customers and thereby have better influence on CTR compared to bid pulsing behaviour which only have an indirect effect on click by increasing impressions.

Unlike rank prediction, CTR is dependent on several other factors such as demography of users, relevance of advertisement, season of advertisements, landing page quality, etc. This could be the reason for poor improvement in prediction performance compared to baseline predictor.

Decades of research work has gone into click through rate prediction based on several thousand features. We do not claim to have high accuracy in CTR prediction but have demonstrated the effect of bidding strategies in this performance measure. On the other hand, rank prediction shows a significant improvement with our model due to greater dependence on competitor bidding and search engines evaluation metric that are more sensitive to pulsing effects.

Yet another interesting aspect in data that we noticed was the correlation between rank and CTR. Figure 12 shows that

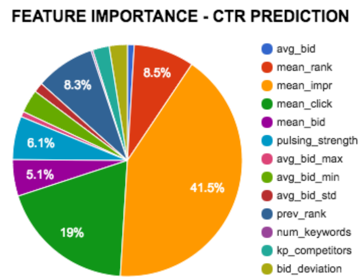

Fig. 12. Importance of features in CTR prediction

higher the rank, better is the click probability thus potentially increasing performance. This justifies the use of similar feature set for rank prediction & CTR prediction models.

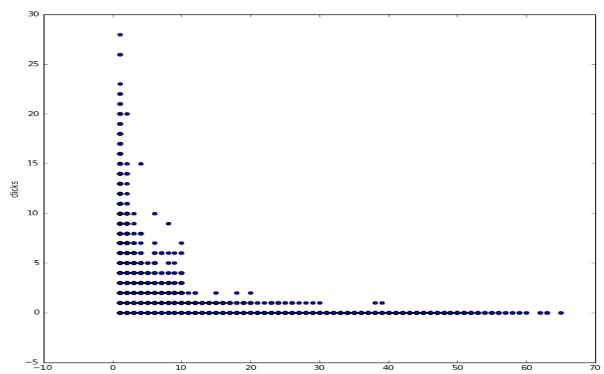

Fig. 13. Influence of Rank on CTR

X. Conclusion

In this project, we designed a Gradient Boost Regression model to predict Keyword performance for Search Engine advertiser based on Bidding activity data open sourced by Yahoo! Webscope. We engineered 13 features to model prediction engine and achieved an improvement of 42.3% in MAE for rank prediction and 5.008% for click-through-rate prediction that define the performance of keyword.

XI. Source Code

Source code for Designed Prediction Model can be found here: github link

References

[1] A3 - Yahoo! Search Marketing Advertiser Bid-Impression-Click data on competing Keywords, version 1.0 [data set], http://webscope.sandbox. yahoo.com/catalog.php?datatype=a.

[2] Savannah Wei Shi & Xiaojing Dong (2015) The Effects of Bid Pulsing on Keyword Performance in Search Engines, International Journal of Electronic Commerce, 19:2, 3-38.

[3] S. Athey and D. Nekipelov. A structural model of sponsored search advertising auctions., 2010.

[4] A. Broder, E. Gabrilovich, V. Josifovski, G. Mavromatis, and A. Smola. Bid generation for advanced match in sponsored search. In Proceedings of the fourth ACM international conference on Web search and data mining, WSDM 11, pages 515524, New York, NY, USA, 2011. ACM.
[5] M. Cary, A. Das, B. Edelman, I. Giotis, K. Heimerl, A. R.Karlin, C. Mathieu, and M. Schwarz. Greedy bidding strategies for keyword auctions. In EC 07 Proceedings of the 8th ACM conference on Electronic commerce. ACM Press., 2007.
[6] Ghose, A., and Yang, S. An empirical analysis of sponsored search performance in search engine advertising. Management Science, 55, 10 (2009), 16051622.
[7] Jansen, B.J.; Sobel, K.; and Zhang, M. The brand effect of key phrases and advertisements in sponsored search. International Journal of Electronic Commerce, 16, 1 (fall 2011), 77106.
[8] Haifeng Xu; Diyi Yang; Bin Gao; Tie-yan Liu, Predicting Advertiser Bidding Behaviors in Sponsored Search by Rationality Modeling.