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BACKGROUND

Reserve Price Optimization (RPO) is a core service of most Supply-side Platforms. In some examples, RPO can be performed by applying machine learning to overall auction outcomes for particular segments of inventory (e.g., advertisements). However, with this approach, much of the bidder-specific price insights are not available as factors in the auction before applying a machine learning model for the auction.

Demand-side platform (DSP) systems can use machine learning to provide prices for their bids in auctions, and thus, behavior of the DSPs can be smooth and modeled relatively accurately by a feedforward neural network. However, DSPs can also tend to vary quite widely in their valuation approach, so raw auction outcomes can appear very noisy and difficult to model. Supply-side platform (SSP) systems are not optimizing the auction by not including individual bidder behavior when estimating auction outcomes.

SUMMARY

This document describes a RPO system that individually determines (e.g., reverse engineers) the bidding behavior of each DSP. In some cases, the RPO system can conduct a simulated auction to generate the reserve price and a safety bias. The individual bidder models can be feedforward neural networks trained with backpropagation, using bid requests as inputs and bids as supervised training results. A small neural network can also be trained to generate a safety bias which is subtracted from the predicted price outcome to maximize the overall expected auction outcome. This model is trained on bid requests, auction outcomes, and predicted prices from the bidder model auction.
In some cases, the RPO system can apply a Mixture of Experts (MoE) layer to the collection of bidder models to predict the price outcome.

DESCRIPTION OF DRAWINGS

Figure 1 is a diagram of an example auction modeling system for an auction between bidders.

DETAILED DESCRIPTION

Publishers of advertisements have historically manually set auction floors, which often can act as the second price in the event that there is not a bid during an auction that is unable to second price the top bid. However, publishers want to maximize the auction floor price, while also not surpassing the bid of the top bidder as doing such will not allow the auction to clear. Thus, auction floor modeling on an individual bidder basis can be performed to optimize the auction floor price.

FIG. 1 illustrates an example auction modelling system 100 for an auction between bidders. The system 100 includes individual bidder models 104a, 104b, 104c (collectively referred to as individual bidder models 104) that are associated with, respectively a bidder. However, the system 100 can include any number of individual bidder models 104 for any number of bidders. Each of the bidders can also be associated with bidder specific data 108. The bidder specific data 108 can include bidding history of the respective bidder. The bidding history can include, for each bid made by the respective bidder, parameters of the auction associated with the bid. That is, for each bid made by the respective bidder, the amount of the bid, as well as features of the auction – e.g., location, browser type, user identifying information (cookie), etc.
The system 100 further includes an auction model 106 in communication with the each of the individual bidder models 104.

Each of the individual bidder models 104 generates an estimated auction clearing price for a pseudo-auction. Specifically, each of the individual bidder models 104 receives as input auction data 110 that, for a specific auction, parameters associated with the auction. Such input auction data 110 can include location, browser type, user identifying information (cookie), etc. Each of the individual bidder models 104 also receives as input the respective bidder specific data 108 (e.g., bidder “behavior”). Each of the individual bidder models 104 processes the input
auction data 110 and the respective bidder specific data 108 and estimates the bid 112 of the respective bidder (e.g., bids 112a, 112b, 112c output by models 104a, 104b, 104c, respectively). In some examples, the individual bidder models 104 can include machine learning or neural networks to estimate the bid 112 of the respective bidder.

Thus, for each individual bidder model 104, the estimated bid 112 is based on a correspondence between the parameters of the auction data 110 and the bidder specific data 108. For example, as more parameters of the bidder specific data 108 correspond (align) to more parameters of the auction data 110, the higher the estimated bid 112 will be. For example, the bidder typically provides bids to auctions that are associated with a location of Copenhagen – the corresponding bidder specific data 108 reflects such. Additionally, for a particular auction, the location parameter includes Copenhagen, and the auction data 110 also reflects such. The individual bidder model 104 takes into consideration the location data from each of the user historical data 108 and the auction data 110, and determines correspondence (e.g., match) between such when generating the estimated bid 112.

The auction model 106 (MoE layer) receives each of the estimated bids 112, and based on the estimated bids 112, generates an auction floor estimate 114. In some examples, the auction floor estimate 114 can be the maximum of the estimated bids 112. In some examples, the auction floor estimate 114 can be the maximum of the estimated bids 112 with a safety bias applied.

Specifically, a safety bias can be a percentage discount that is applied to the auction floor estimate 114. By applying the safety bias to the auction floor estimate 114, the likelihood of the auction floor estimate 114 surpassing the actual bid of the top bidder decreases. In some examples, the safety bias is a few percentage points – 3% to 10%.
In some examples, the safety bias can be auction-independent. That is, the safety bias is a predetermined percentage applied to all auctions, independent of any factors relating to the auction. In some examples, the safety bias is auction dependent. That is, the safety bias is determined for each auction, and the factors associated with the auction. In some examples, the safety bias is bidder dependent. That is, the safety bias is determined for each bidder for each auction. That is, the respective individual bidder models 104 determines the safety bias for each bidder, and provide such determined safety bias to the auction model 106. The auction model 106 selects the appropriate safety bias based on the identified estimated bid 112 used as a basis for the auction floor estimate 114 (e.g., the maximum estimated bid 112).

In some examples, the parameters associated with the auction data 110 and/or the bidder specific data 108 can include user identifying information (e.g., cookie presence). Specifically, the individual bidder models 104 can incorporate, as a parameter, the presence or not of user identifying information in determination of the estimated bid 112. For example, when the auction data 110 includes the presence of a particular user identifying information, and the bidder specific data 108 includes a parameter indicating the same particular user identifying information, the estimated bid 112 reflect such (e.g., is increased).
ABSTRACT

A reserve price optimization (RPO) system estimates bids of individual bidders for an auction based on bidding information specific to the individual bidder. Auction data and bidder specific information are input to a model (e.g., neural network) that determines an estimated bid. Each of the estimate bids for each of the individual bidders of an auction are used as inputs in determination of an auction floor estimate optimization for a current auction. The auction floor estimate can be discounted by a safety bias to decreases likelihood of the auction floor estimate surpassing an actual top bid of the bidders.