Selling Futures Online Advertising Slots via Option Contracts

Jun Wang and Bowei Chen
Department of Computer Science
University College London
{j.wang, bowei.chen}@cs.ucl.ac.uk

ABSTRACT

Many online advertising slots are sold through bidding mechanisms by publishers and search engines. Highly affected by the dual force of supply and demand, the prices of advertising slots vary significantly over time. This then influences the businesses whose major revenues are driven by online advertising, particularly for publishers and search engines. To address the problem, we propose to sell the future advertising slots via option contracts (also called *ad options*). The ad option could give its buyer the right to buy the future advertising slots at a prefixed price. The pricing model of ad options is developed in order to reduce the volatility of the income of publishers or search engines. Our experimental results confirm the validity of ad options and the embedded risk management mechanisms.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioural Science–Economics; J.1 [**Computer Applications**]: Administrative Data Processing–Financial

General Terms

Theory, Algorithms, Experimentation

Keywords

Online Advertising, Ad Option, Risk Management

1. INTRODUCTION AND MOTIVATION

In the online advertising markets, most of the publishers and search engines choose to auction off their online advertising slots to advertisers. In the bidding campaigns, two interesting points should be stated here.

Firstly, as shown in Figure 1, affected by the dual force of supply and demand, the prices of an advertising slot often exhibit abrupt and extreme changes over time. This makes the advertising costs (for advertisers) and the advertising incomes (for publishers or search engines) unpredictable. Secondly, there are increasing needs for new advertising contracts that could not only enable advertisers guarantee the future advertising slots but also help publishers or search engines to manage their future advertising income smoother, less volatile and be easy to predict.

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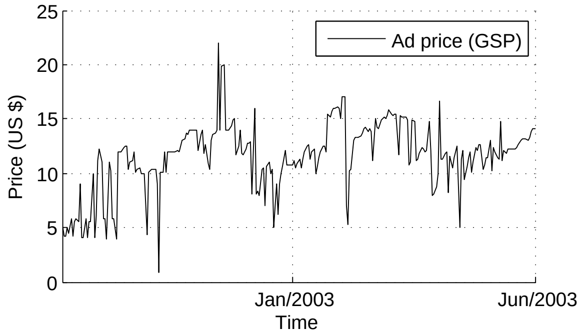

Figure 1: Plot of generalised second-prices (GSPs) of a Yahoo! online advertisement from 2002 to 2003.

2. AD OPTION AND ITS PRICING

By borrowing ideas from finance [1, 2], we introduce the concept of option contracts into online advertising. An *online advertising option*, shortly *ad option*, is defined as a contract signed by advertisers and publishers or search engines. The ad option can give its buyer, normally advertisers, the right to buy a certain amount of advertising impressions or clicks from its seller, normally publishers or search engines, in the future time at a prefixed price. At the current time, the ad option buyer needs to pay its seller an upfront fee, which is called the *ad option price*.

In discussing ad options, the most important question is: "How much of an ad option price should be?" This question leads us to study the pricing model of ad options. Let us now consider a basic ad option pricing model for the online advertisements with impression-based pricing scheme.

At the current time t, let A_t be the final agreed price of an advertising slot and a publisher would like to sell the advertising slots of the future time $t + \Delta t$ through ad options, where each option contract corresponds to the right to buy 1000 impressions at a prefixed price K. Assume there are M total impressions to sell at the future time and also assume that the publisher has sold $\alpha M/1000$ number of future advertising impressions at the current time.

We then employ the binomial tree model [2] to set up the framework for analysing the possible situations of the future advertising slot prices under uncertainty. That means, if the advertising slot price goes up the value of the publisher's income will be

$$I^u_{t+\Delta t} = \frac{A^u_{t+\Delta t} M}{1000} - \frac{\alpha M}{1000} \max\Big\{A^u_{t+\Delta t} - K, 0\Big\}. \quad (1)$$

Similarly, we could have the value of the publisher's income when the advertising price goes down at time $t + \Delta t$. This confirms our statement in the introduction: the uncertain and volatile advertising slot prices influence the income of publishers or search engines.

Now the question is: "What is the best amount of sold future impressions $\alpha M/1000$ for the publisher so that he could manage his future income to be more stable?" An extreme case is that if we let the publisher's upside and downside incomes equal, that is

$$I^u_{t+\Delta t} = I^d_{t+\Delta t}, \qquad (2)$$

we then have a value of α, which gives out the percentage of the future impressions to sell at the current time and whose range should be $[0, \infty)$. If we further let the discounted future income of the publisher equal to his current advertising income, the ad option price at time t can be obtained.

In the above ad option pricing, there are two fundamental assumptions. The first assumption is the risk aversion, that is, a publisher or search engine prefers stable income flow rather than high reward but volatile income. The second assumption is that the discounted future income of the publisher should be at least equal to the current income.

3. EXPERIMENTS

We now present our experimental results from both simulated and real market data, in which we aim at: 1) studying the impact of the model parameters; 2) testing if the developed ad option can reduce the volatility of a publisher's or search engine's income effectively.

In the experiments, we use Yahoo! online advertising dataset, which contains advertising slot bidding prices from 2002 to 2003. We split the dataset into one training, one development, and one test set. We also construct stochastic models and price the ad options based on the training data. The estimations given by the developed models are categorised into the development set. We then use the data in the test set to examine the priced ad option and its embedded risk management mechanism.

3.1 Impact of the Model Parameter

Geometric Brownian motion and mean-reverting process [4] are investigated to describe the movement of advertising slot prices. We randomly selected 100 sample from 1000 ads data and examine the accuracy of the stochastic models. Root mean square error (RMSE) is a metric employed to evaluate the difference (or "errors") between the estimations and the test data, by which we find the mean-reverting process gives more accurate description of the ad slot price movement.

We continue our study and test the impact of the parameter λ by using the mean-reverting models, where λ is defined as an adjusting parameter in the future advertising slot price forecasting. As shown in Figure 2, each line represents the means of RMSEs at a time point from 100 experiments. There is 41.1% probability that when $\lambda = 1.3$ that error has the minimum values at a fixed time point, followed by $\lambda = 1.2$ with 35.56% probability. When $\lambda \in [1, 1.3]$, there has 97.78% probability that the error achieves the minimum values cross time. Therefore, we shall carry on the remaining experiments by choosing λ equal to 1.3 under mean-reverting processes as default settings.

3.2 Risk vs. Reward

Let us now study how a publisher could use the priced ad options to manage his risk in selling the futures advertising

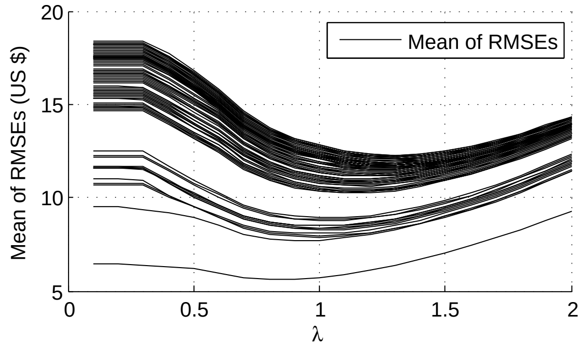

Figure 2: The impact of parameter λ on the accuracy of estimated ad option prices.

Table 1: Risk vs. reward of a Yahoo! online ad.

Time	0 options	$\frac{1}{2}\frac{\alpha M}{1000}$ options	$\frac{\alpha M}{1000}$ options
5	294.6 (116.5)	263.2 (67.2)	231.8 (18.9)
10	313.3 (104.4)	284.2 (60.2)	255.2 (32.4)
30	334.8 (127.9)	301.9 (87.9)	269.0 (57.9)
60	333.0 (122.1)	305.9 (81.3)	278.9 (52.7)

slots. Table 1 exhibits the statistics of a publisher's Yahoo advertising income, where the figures outside the brackets represent the moving average income up to the 5, 10, 30 and 60 days and the figures in the brackets represent the corresponding standard-deviations. It is obviously that when the number of ad options increases from zero to the estimated number of options, $\alpha M/1000$ (suggested by our pricing model), the volatility of the publisher's income is reduced substantially to a minimum value at each time point. These experimental results illustrate clearly that a publisher could adjust the number of ad options from zero to the number of ad options suggested by the pricing model to balance his risk and reward of the future income.

4. CONCLUSION

In this paper we show our first attempt to sell future advertising slots using option contracts. Moon and Kwon [3] recently studied the option contracts for online advertising, however, their research focused on the properties of the ad option contract other than its pricing and risk management mechanism. Our experimental results exhibit the proposed ad option pricing model is able to provide a useful and effective risk management mechanism to the online advertising businesses. Our work can be further improved by studying more accurate stochastic models for the movement of advertising slot prices, i.e., considering the jump-diffusion processes.

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