Dynamic Ad Layout Revenue Optimization for Display Advertising

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ABSTRACT

Display advertising has been growing rapidly in recent years, with revenue generated from display ads placed on spaces allocated on publisher's web pages. Traditionally, the design and layout of ad spaces on a web page are predetermined and fixed for the publisher. The objective of this work is to investigate the revenue opportunities of changing the ad layout dynamically for the publisher. A dynamic ad layout revenue optimization framework is developed for display advertising, in terms of both guaranteed and non-guaranteed advertising. The system automatically selects the ad layout template with the highest potential revenue yield for each single web page presented to the user. Forecasting algorithms are developed to predict the revenue of each ad opportunity. Two objectives are explored for the forecasting algorithms of ad layout optimization, the expected revenue and actual revenue. Promising results are obtained in offline simulation on real data collected from a Yahoo! property. The dynamic ad layout optimization system is further tested on real-time traffic and a significant revenue gain is observed compared with a static ad layout serving method.

Categories and Subject Descriptors

H.3.5 [**Online Information Services**]: Commercial Services; H.4.m [**Information Systems**]: Miscellaneous; I.5.2 [**Design Methodology**]: Classifier Design and Evaluation

Keywords

Ad Layout Optimization, Display Advertising, Revenue, Forecasting

1. INTRODUCTION

Online display advertising is a multi-billion dollar business with revenue generated for publishers by placing display ads on their web pages. The state-of-the-art display advertising is sold in two different business models [2], guaranteed delivery (**GD**) and non-guaranteed delivery (**NGD**). Publishers usually sell their high premium ad inventories to the highest-paying advertisers through a guaranteed contract of delivery (GD), which ensures that publishers must deliver their ad inventories consistently to advertisers until the desired impression goal is reached. The remaining ad inventories are usually sold on a non-guaranteed basis (NGD), typically in a spot market running on a per-impression auction, where the advertiser with the highest bid wins the ad opportunity.

Despite the underlying auction mechanism, small publishers or properties of large publishers usually sell single or multiple ad spaces with fixed positions and sizes on their web pages for display advertising. This static ad layout serving method is easy for managing and tracking. However, it ignores the opportunities to explore other ads with different sizes and positions for all the page views, limiting the revenue generated from other advertisers for the publishers. This problem can be alleviated by allowing multiple ad layout templates, consisting of ad slots with different sizes and positions, for the publishers. In this work, we investigate the revenue gain opportunities of using multiple ad layout templates with respect to both GD and NGD display advertising. Furthermore, a dynamic ad layout optimization framework is proposed to maximize the revenue for publishers by automatically selecting the ad layout template with the highest revenue yield for each page view.

To optimize the NGD revenue for publishers, a natural idea is to automatically select the ad layout template with the highest potential revenue for each ad opportunity. This method can significantly boost the NGD revenue of publishers for a number of reasons.

First, not all ads in the NGD marketplace are available in all ad sizes, therefore not all ads are valid candidates for all ad auctions. Each auction is run for one ad slot alone. Allowing templates of different ad sizes to be considered in one auction will likely increase the number of competing ads, hence resulting in higher prices. Second, different users may have different preferences on the ad slot arrangements on different pages. For example, some users may pay more attention to the ads on the left and others may respond to the ads on the right better. Capturing user's preferences better should result in more clicks/conversions on ads, thus more revenue. Third. dynamic ad layout optimization is capable of adapting to changes in the underlying ad inventory. When the ad inventory for one size shrinks, the revenue premium starts to drop due to decreasing number of competing ads. Dynamic ad layout optimization can automatically switch to another template which uses ad sizes with enough remaining ad inventory.

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The ad layout revenue optimization for GD advertising is even more challenging than the NGD advertising. This is because GD impressions have already been booked in pre-negotiated GD contracts between advertisers and publishers. That means the publisher revenue is guaranteed in advance in GD advertising. All the revenue will be realized sooner or later if all the GD contracts are delivered satisfactorily. Changing the ad layout for each page view only modifies the revenue realized in short term. Ad layout optimization is meaningful only for contracts that are under-delivered. Under delivery happens when there is not enough traffic to realize all the booked ad impressions. Not only the revenue booked in advance will be lost in under-delivery, publishers will also likely incur additional penalties as specified in their contracts with the advertisers. To reduce the ratio of under-delivery contracts for publishers in GD system, ad layout revenue optimization needs to shift the ad opportunities to fulfill the under-delivered GD contracts. This is achieved in this work by developing an algorithm to automatically assign the ad layout template with the highest potential under-delivered GD revenue to each page view. In a unified marketplace where both GD and NGD advertising exists, the NGD revenue and GD under-delivery revenue can be combined together as the objective of the ad layout revenue optimization process.

In order to select an ad layout template dynamically for revenue optimization, we need to forecast the potential revenue of all the ad layout templates for every single page view. In this paper, two objective functions are evaluated to estimate the potential revenue per template. One is expected revenue, which is a metric used in GD and NGD systems to measure the predicted revenue of various ad campaigns in a unified currency before the ads are actually shown. The other is the actual revenue, the actual money paid to the publishers. Forecasting models are built on top of numerical features extracted from the revenue data aggregated from the historical data as well as the category features extracted on-the-fly from user, publisher and advertiser side for every single page view. The proposed approaches are first evaluated offline and then online, in a live experiment. Both sets of results suggest that dynamic ad layout optimization can produce significant lifts in publisher revenue compared to the traditional systems with fixed ad layouts.

The rest of the paper is organized as follows. Section 2 introduces additional background on display advertising. Section 3 proposes the main ad layout optimization framework. The revenue forecasting algorithms developed for the ad layout optimization system are presented in Section 3. Both offline and online results are summarized in Section 5. Finally we draw our conclusions and point out some future research directions in Section 6.

2. DISPLAY ADVERTISING SYSTEM

Display advertising is a complex advertising mechanism on the World Wide Web that allocates display ads next to the content of publisher's web pages, emails, messages etc. Many premium publishers sell display advertising initially via guaranteed contracts. Guaranteed contracts, as the name suggests, are guaranteed deals in which publishers will deliver a certain number of impressions matching all the targeting constraints in a specific period of time at a predetermined price per impression to the advertisers. Guaranteed display advertising (**GD**) has the advantage of generating predictable revenue to hedge uncertainty in the future demand of ad impressions. If the supply of ad inventory for large online publishers exceeds the demand for it, the publishers can potentially make more money by selling them in an auction based sales model, which is called non-guaranteed display advertising (**NGD**). When an ad opportunity from a web page is presented in a NGD market, such as Yahoo's Right Media Exchange [10], a large number of candidate ads with satisfied targeting requirement will participate in the auction process and only the winning ad with the highest bid will be delivered to the user.

2.1 GD display advertising

In GD display advertising, advertisers book the desired high premium impressions from publishers with guaranteed contracts at a flat price in terms of cost-per-thousand (**CPM**). Given an ad opportunity, all the GD contracts with different profiles are matched using targeting techniques such as contextual targeting, behavior targeting, geo targeting etc. The eligible contracts are further processed with the current GD allocation plan (**AP**), which is calculated from the forecasted future supply and demand in the next delivery window to obtain the probabilities of allocation of the supply to the demand [11, 12], to get their allocation probabilities. Let the probability of the ith matched contract be noted as $p(GD_i)$, $\sum_{i=1}^{n} p(GD_i)$ is the total probabilities of the ad opportunity going into a GD market place. The GD allocation plan also estimates the number of remaining ad impressions that can be allocated for each contract at current time, which is called planned impressions. When the planned impressions are the same as the remaining booked impressions, the contract is well delivered and the contract tends to execute as promised. However, in the case when the planned impressions are less than the remaining booked impressions, the contract will likely be under delivered. Under-delivery will enforce revenue penalties to the publishers as termed in the GD contract by the advertisers, which may cause significant revenue losses given that the price of GD impressions are usually higher than NGD. In a unified marketplace, GD allocation plan also calculates the probability of an ad opportunity going to the NGD market place as $1 - \sum_{i=1}^{n} p(GD_i)$.

2.2 NGD display advertising

In NGD display advertising, advertisers use different pricing models to sell their ad campaigns. They mostly fall into three categories, cost-per-thousand (**CPM**), cost-per-click (**CPC**) and cost-per-action (**CPA**).

- CPM model pays publishers at a flat price per thousand impressions. In this case, advertisers take all the risk since they pay no matter how the ad performs.
- CPC advertisers shift some of the performance risk to publishers by paying only when there is a click on their ad. It would be in the publishers' best interest to maximize the probability of ads getting clicked on their pages.
- CPA offers the least risk for advertisers since they only pay when user has performed a specific action that the advertiser considers a "conversion". This action could be registering to an email list, submitting requested information or purchasing an item. CPA campaigns can

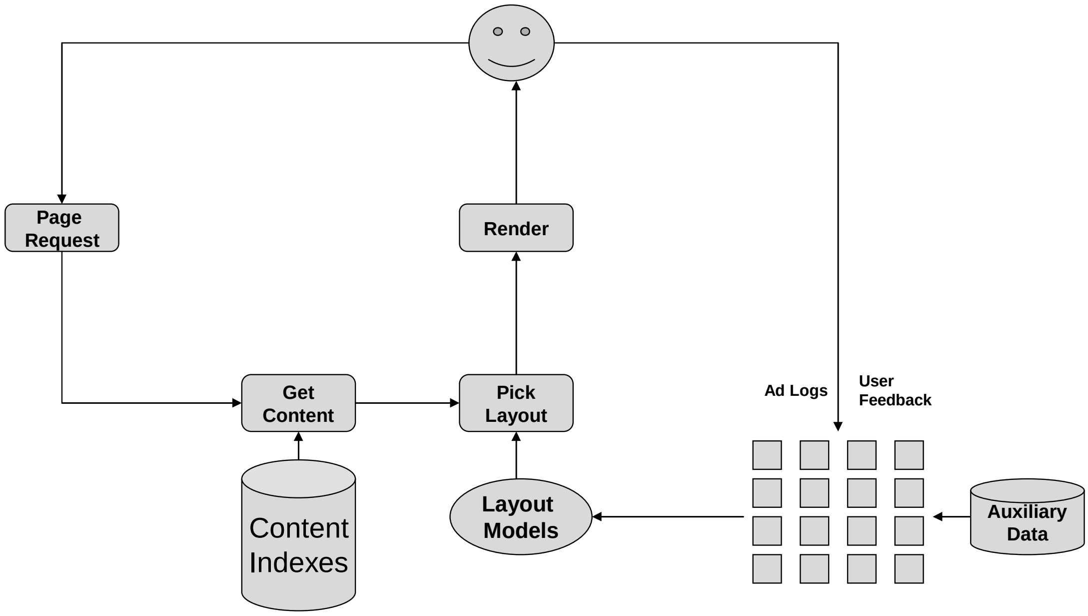

Figure 1: Ad Layout Optimization Work Flow

be further divided into post view conversion and post click conversion. In post click conversion, the advertiser only pays when the user clicks on that particular ad before the conversion action. In post view conversion, the advertiser pays for every conversion of the user who was exposed to that particular ad, regardless of there being a click in between.

One variation of the CPM ad is dynamic CPM (**dCPM**), which runs on CPM basis but has a CPC or CPA target that advertiser wants to meet. dCPM prices every impression to reflect its actual value to the advertiser by discounting the CPM with the predicted probability of click or conversion, depending on the specified target.

In NGD display advertising, all the candidate ads meeting the targeting requirements of the ad opportunity participate in a single auction, where their values are measured in a unified currency as **eCPM** (expected CPM). It is clear that eCPM is equivalent to the CPM for CPM ads. The value of a CPC ad not only depends on its bid but also its probability of being clicked when shown to the user. The actual value of CPC ad is thus formulated as:

$$eCPM_{CPC} = p(click) * bid \tag{1}$$

where $p(click)$ is the predicted probability of the ad to be clicked by the user [9]. The eCPM of CPA ads is calculated similarly as:

$$eCPM_{CPA} = p(conversion) * bid \tag{2}$$

where $p(conversion)$ is the probability of the ad view leading the user to an advertiser desired action. During the auction, the ad with the highest eCPM is selected to fulfill the ad opportunity and presented to the user. The estimation of $p(click)$ and $p(conversion)$ typically relies on machine learning models [6] trained using various features extracted from users, publishers and advertisers.

3. AD LAYOUT OPTIMIZATION SYSTEM

Publishers receive revenue from advertisers by selling ad spaces on their web pages. An ad slot on a web page is a space with a standardized ad size allocated by publishers to advertisers. Given a set of different ad slots, S, an ad layout template is designed as a combination of single or multiple ad slots $s_i \in S$ with corresponding positions p_i, $T = \{(s_1, p_1) \cdots (s_{|T|}, p_{|T|})\}$. Note that two ad layout templates with the same set of ad slots are regarded as different templates if at least one of the ad slots is positioned differently on the web page. Different ad layout templates perform differently in terms of revenue for a number of reasons. First, large ads are usually more valuable than small ads. Second, ads on a better position that attract more user attention will receive more clicks and conversion, which in turn will result in more revenue. Given a set of ad layout templates $\{T_1 \cdots T_N\}$, revenue based dynamic ad layout optimization picks the template with the highest predicted revenue for every page view.

There has been some previous work in the literature studying the problem of ad layout optimization such as [1, 14]. However these papers focus on the problem of ad space allocation optimization for a small set of ads. To the best of our knowledge there has not been any published work that integrates an ad layout optimization algorithm with an advertising system which is proven to scale to real applications. In this work, we present an innovative ad layout optimization framework integrated with a real advertising system, and provide results of live experiments using this framework.

Figure 1 shows the proposed ad layout optimization system. Impression logs from both GD and NGD marketplaces with actual revenue information and user feedback are collected, aggregated and processed using a large scale computation platform (grid). A revenue forecasting model is built on top of the aggregated data. The model is refreshed periodically to incorporate the latest information available. When a new web page is requested by a user, the latest model is utilized to predict the potential revenue for all the ad opportunities. The potential revenue for each candidate ad layout template is estimated by summing up the forecasted revenue of all the ad opportunities on that template. The candidate ad layout template with the highest forecasted revenue wins the serving opportunity. The ads selected for the corresponding ad slots on the winning template will be delivered to the user along with the page content.

The most challenging part of the system is to produce an accurate estimation of the potential revenue for each ad opportunity. In this work we investigate and provide results for two strategies based on the Yahoo! display advertising system.

4. REVENUE FORECASTING FOR AD LAYOUT OPTIMIZATION

Given an ad opportunity on a web page visited by a user, the revenue forecasting algorithm tries to estimate the potential revenue that could be produced from the underlying advertising system. As we introduced in Section 2, eCPM is a unified currency in display advertising representing the expected revenue for various types of ads shown on the web page. It can naturally be used as the objective in our revenue forecasting algorithm. Now the problem is to estimate the eCPM for each ad slot, which will be further aggregated to produce the eCPM estimate for each template. A straightforward way to get the eCPM for all the ad opportunities on a page view is to make a call to the ad server multiple times, once per ad slot. This is quite expensive in terms of front end latency considering we have multiple ad slots per templates and multiple templates to evaluate. Instead, a lightweight machine learning model is built in this work to forecast the eCPM for each ad opportunity. The forecasted eCPM is utilized as the criteria for selecting the ad layout template with the highest expected revenue yield. In this section, we present the revenue forecasting algorithms for ad layout optimization for both NGD and GD advertising systems.

4.1 Features

For the ad layout optimization problem, many features can be derived from information extracted from the users, publishers and advertisers. On the user side, user profile information such as age, gender and their geographical location are typical features widely used for targeting. These features are also quite useful for ad layout optimization. First, they capture user's preference on ad layout template. Second, they provide the page view with high premium ads which are targeted on specific user segment such as demographics or location. On the publisher side, a series of id's identifying the page in a hierarchical manner can be used as features such as site id, publisher id, property id, section id, page url or page domain. These features capture how different ad layout templates perform on various publisher pages with different content. From the advertiser side, the most important feature is the ad size. It is expected that ad slots with similar ad sizes are likely to be priced similarly and large ad slots cost more than small ad slots. The features from the actual pool of candidate ads are not explored in ad layout optimization for two reasons. First it is quite expensive to fetch and process a large number of ads. Second, the pool of candidates has been processed by the underlying advertising system (e.g. auction in NGD) and only the final selected ad is used to determine the value of an ad slot in an ad layout template. Contextual information such as 'hour of the day' or 'day of the week' can also be used as features in ad layout optimization. These features are mostly category features that can be extracted on the fly.

For the revenue forecasting algorithm, another set of important features are extracted from the historical revenue data. Using historical revenue data for future revenue forecasting relies on the observation that ads performing well in the past will likely perform well in the future. The historical revenue data can be aggregated at different levels, for example (user,publisher,ad size), to capture revenue variations at different granularities. Statistics from the historical revenue aggregation data such as mean and standard deviation can be utilized as features for revenue forecasting. When using historical revenue information as features for forecasting, we need to take into account seasonality, trends and holiday effects to avoid biased forecasting result. Furthermore, these features need to be refreshed periodically to reflect an up-to-date view. A proper data structure should also be designed to store and update the data for feature extraction and feature look ups.

4.2 NGD Revenue Optimization

In this work, we utilize a NGD forecasting algorithm similar to the one introduced in [3] for our NGD eCPM revenue forecasting task. The system consists of an offline process and an online serving component. The offline pipeline collects historical revenue data, extracts features, builds history indexes and trains the forecasting model. The revenue data in a sliding window of historical logs, which contains all ad impressions and user responses, is aggregated at different levels of granularity such as (user, publisher, ad size). A star tree [3] is built on top of the aggregated data for fast lookup and updates. The category features as well as the statistics of the historical revenue aggregation data are extracted as features and further processed by a feature selection process [8, 13] based on mutual information. The data collected in the following month of the historical sliding window is used to construct the training set $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$, where $x_i \in \Re^d$ represents the a d dimension feature vector for $i_t h$ sample in the training data and $y_i \in \Re$ represents its target eCPM. A regression function $f : x \rightarrow y$ is learned using gradient boosting decision trees (GBDT) [4, 5, 7] by minimizing the expected value of specific prediction loss as:

$$f^*(x) = arg \min_f E(L(f(x), y)) \tag{3}$$

where $L()$ is a loss function. In our work, the GBDT algorithm learns the prediction function f through an ensemble of a sequence of simple decision trees as base learner, which performs least-squares residual fitting with a square-error loss function.

The online serving part predicts the eCPM using the learned regression model f for any given ad opportunity, where the category features such as age, gender, ad size etc. are constructed on the fly and the historical revenue features are extracted by querying the historical revenue aggregation data stored in the form of a star-tree. The eCPM history aggregation pipeline has to be continuously maintained for online data lookup and feature extraction to capture latest information. The newest model trained from the latest historical revenue feature is then applied to forecast the eCPM for all the ad opportunities on the requested page. The predicted eCPMs of corresponding ad slots in each template are combined together to produce the eCPM estimation for the entire page view. The template with the highest total eCPM is selected to serve the web page in dynamic ad layout optimization system.

4.3 GD Revenue Optimization

Ad layout optimization for GD is more complex than NGD in terms of the objective of optimization. In the NGD marketplace, ad layout optimization algorithm picks the template with the highest total winning bid from the all advertisers. The additional revenue generated by optimizing the ad layout selection in NGD marketplace is the actual revenue gain. However, the story is different in the GD marketplace. All the ad impressions have already been booked in advance at a fixed price and the GD system is only responsible to deliver them systematically to the advertisers. Picking the ad layout template with higher expected revenue only increases the revenue in the short term. This is because the payout from advertisers is not subject to change if all the booked impressions will be delivered in the end. However, a penalty to publishers is incurred in the case when some contracts are under delivered, resulting in significant revenue loss. Under-delivery can be caused by multiple reasons: decreasing traffic for certain targeting profiles; bad forecasting or planning of future supply of ad impressions etc. As a result, the objective of the ad layout revenue optimization in the GD marketplace is to reduce the under delivery rate. Instead of shifting the traffic to the ad layout template with higher winning bid as in NGD, the ad layout optimization for GD achieves revenue boosting by shifting the traffic to fulfill the under-delivery contracts.

As introduced in Section 2, GD allocation plan allocates an ad opportunity to each booked contract GD_i with matched targeting profile with a probability $p(GD_i)$. The expected revenue of the contract GD_i for the ad opportunity can be denoted as:

$$eCPM_i * p(GD_i) \tag{4}$$

The allocation plan calculates the number of planned impressions according to the ad impression supply and demand forecasts for the remainder of the contract period. Each contract also records the number of booked impressions left to be delivered. In this work, a contract GD_i with planned impressions PI_i and remaining booked impressions BI_i is treated as an under delivery contract when:

$$PI_i \leq \delta * BI_i \tag{5}$$

The parameter $\delta \in [0, 1]$ in the above equation can be adjusted to determine the level of under-delivery that we can tolerate. The larger the value of δ, the more contracts will be treated as under-delivery and more traffic is required to be shifted to these contracts to reduce under-delivery. The weighted eCPM of all the under delivered contracts are summed up to calculate the total GD under delivered revenue for each ad opportunity as:

$$eCPM_{UGD} = \sum_{i \in UGD} eCPM_i * p(GD_i) \tag{6}$$

where UGD is the set of matched GD contracts that are under delivered according to Equation 6. Any forecasting algorithm can be applied to this new objective of ad layout revenue optimization. In this paper, we try a simple aggregation method first, which uses the aggregated total eCPM in the history directly as the predicted eCPM. The ad layout template with the highest under-delivered GD revenue is picked to serve the page view.

4.4 GD+NGD Revenue Optimization

In a unified market place, an ad opportunity can be fulfilled by both GD and NGD ads. The allocation plan calculates the probability of an ad being assigned to each GD contract as $P(GD_i)$ as well as the probability of being forwarded to a NGD market place as:

$$p(NGD) = 1 - \sum_{i=1}^{|GD|} p(GD_i)$$

So in the GD+NGD ad layout optimization system, the total expected revenue for an ad opportunity is calculated by summing up eCPM of all the GD contracts and the NGD contract weighted by their allocation probabilities as:

$$\begin{aligned} eCPM_{UGD+NGD} &= \sum_{i=1}^{|UGD|} eCPM_i * p(GD_i) \\ &+ eCPM_{NGD} * p(NGD) \end{aligned} \tag{7}$$

Again we use a simple aggregation method to forecast the total NGD and UGD eCPM. The ad layout template with the highest under-delivered GD revenue and NGD revenue is picked to serve the page view.

4.5 Expected Revenue Versus Actual Revenue

In NGD, using eCPM as objective in the revenue forecasting algorithm assumes that eCPM is an accurate estimation of the real revenue, which is the ultimate value we want to maximize. As we introduced in Section 2, eCPM represents the actual bid only for CPM ads, while it relies on the accurate estimation of $p(click)$ and $p(conversion)$ for CPC and CPA ads by an underlying machine learning model. When CPC and CPA ads represent a large portion of the actual revenue, using eCPM as objective in the revenue forecasting algorithm might not be the best approach. To alleviate this problem, we developed an alternative revenue forecasting framework to estimate the actual revenue directly for all the ad layout templates. The same set of features and model described earlier in this section can be used in the actual revenue forecasting algorithm except that the eCPM is replaced with the actual revenue data.

5. EXPERIMENTAL RESULT

In this section, we present the offline and online experimental results for the proposed ad layout optimization framework.

5.1 Experiment Setup

Table 1: **Actual pixel dimensions of ad slots LREC, MREC, N and SKY**

Ad Slot	Size
LREC	300x250
MREC	300x100
N	728x90
SKY	160x600

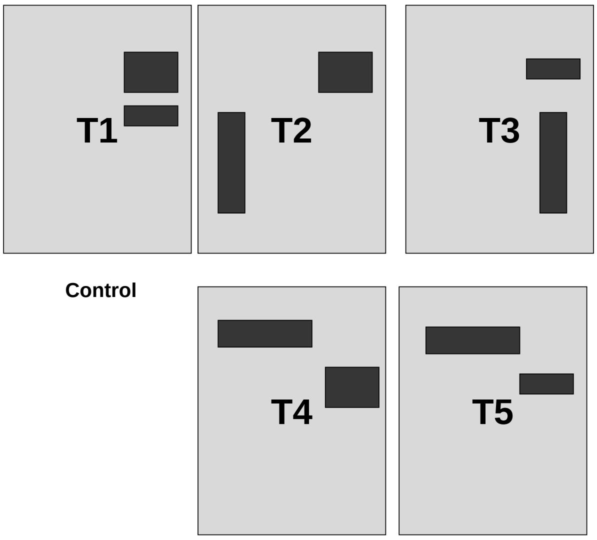

Figure 2: 5 Ad layout templates. T1:LREC+MREC, T2:LREC+SKY, T3: MREC+SKY, T4: LREC+N, T5: MREC+N.

We conducted our experiments on 10% of the traffic on a property of Yahoo! network (the actual name of the property is omitted to protect proprietary information). It represents approximately 0.33M views per day. 5 templates are designed for the experiment using 4 ad slots, LREC, MREC, N and SKY. Their actual dimensions in terms of the number of pixels are summarized in Table 1. LREC, N and SKY are all for large ads while MREC is relatively small. The control template (**T1**) is a LREC+MREC ad pair on the right side of the web page. Figure 2 shows the relative positions of these ad slots on a web page for all the 5 candidate ad layout templates. T1,T3 and T5 all consists of one large ad and one small ad while T2 and T4 both have two large ads. For our data collection purpose, the traffic is served by NGD ads only by turning off the GD ads in the system. This is because GD ads can be retrieved offline by matching the allocation plan with the contract database. Also all the GD ads are CPM based whose revenue is equivalent to eCPM, while a significant portion of NGD revenue comes from CPA or CPC ads, which require user's response (click or conversion) to measure.

The real time traffic is further divided into 3 buckets. Half of the traffic (5%) is used for random bucket, where 5 templates are randomly selected for each page view. The data collected from the random bucket is used to evaluate every template as well as to build models for ad layout optimization. Another two buckets with each 2.5% of the traffic are used to test the ad layout optimization with eCPM revenue

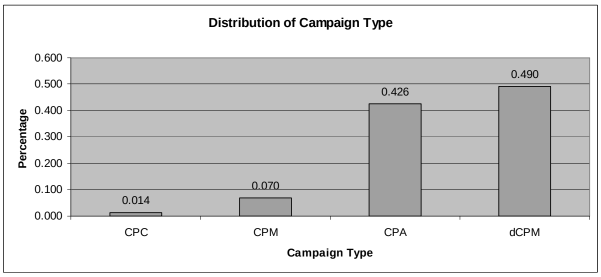

Figure 3: NGD ad campaign distribution for the tested property.

forecasting algorithm and actual revenue forecasting algorithm.

We use eCPM and actual revenue to evaluate different templates for revenue gains. The eCPM value is collected from the ad logs for every impression. Obtaining the actual revenue is more complex than eCPM especially for CPC and CPA campaigns. We need to attribute the click event to the right impression event for CPC campaigns and the conversion event to the right click or impression event for CPA campaigns.

5.2 Initial NGD Results on Random Bucket

To see whether the eCPM is the right criteria for revenue prediction, it is necessary to investigate the distribution of campaign types in the traffic. If the majority of the traffic is served with CPM ads, eCPM forecasting algorithm is enough for actual revenue prediction. Figure 3 shows the distribution of different ad campaign types. It shows that CPA and CPC accounts for more than 40% of all the impressions for the Yahoo! property we tested, which may encourage us to consider using actual revenue as forecasting objective instead of eCPM for revenue optimization.

In the random bucket, all the templates have the same probability to be selected for any page view and thus are evaluated fairly. The eCPM and actual revenue gains over the control template $T1$ for all the candidate templates are shown in Table 2. It is noteworthy that templates $T2$ and $T4$ have the largest gain over the control template $T1$. The eCPM of template $T2$ is 74.11% higher than the control template and the actual revenue is 79.11% higher than the control template. Similarly, template $T4$ is 81.05% higher in terms of eCPM and 79.70% higher in terms of actual revenue compared to $T1$. It is shown in Figure 2 that both $T2$ and $T4$ consists of two large ads, while the others all have one small ad slot (MREC). It seems that the bid for large ad slots is significantly higher than small ad slots, most likely because they capture users' attention more. It also suggests that there may be a large bias in terms of revenue optimization when there is a big difference in actual ad sizes between different ad layout templates. In contrast, the difference in eCPM and revenue among $T1$, $T3$ and $T5$ is much smaller, within 10%. We also see that there is quite a bit of inconsistency between eCPM and the actual revenue for these 3 templates. For example, $T3$ is 3.22% higher in terms of eCPM but 8.27% lower in terms of actual revenue. This is probably due to the bias of the click and conversion probability estimation algorithms for CPC and CPA ads.

Table 2: Revenue Comparison between 5 templates in the random bucket

model	eCPM	Revenue
T2	74.11%	79.11%
T3	3.22%	-8.27%
T4	81.05%	79.70%
T5	10.02%	4.05%

5.3 Offline Simulation for NGD Revenue Optimization

In this section, the simulation results for NGD ad layout optimization using the data collected from the random bucket is presented. As we showed in Section 5.2, there is a significant bias in revenue towards ad layout templates with more large ad slots. Optimizing over 5 templates may not give the other three templates $T1$,$T3$, $T4$ with small ad slots any chance to win. Furthermore, adding one more large ad compared to the control template brings more unknown risk in user experience. As a result, we decided to include only 3 templates in our optimization. Each of these 3 templates consists of one large ad and one small ad.

30 days of data were collected from the random bucket, with more than 1 million page views. A subset of the page views showing the 3 selected templates were reserved for the offline simulation. Given a revenue forecasting model, the template with the highest predicted revenue is assigned to each page view in the data during the simulation. Since the page views only have the eCPM and actual revenue recorded for the template that is actually shown in the random bucket. For each model in the simulation, we only keep the page views whose assigned template is exactly the same as the actual template assigned in the random bucket. The average eCPM and revenue are then calculated to evaluate the corresponding model.

Two revenue forecasting algorithms were tested in this simulation framework, the eCPM revenue forecasting algorithm (**EO**) and actual revenue forecasting algorithm (**RO**). The eCPM revenue forecasting algorithm uses an existing forecasting model built from 3 months of historical eCPM data over all the traffic. However, when it is applied to the real traffic, only one unique site id is used to look up the historical eCPM. The model is refreshed every month and the historical eCPM look up table is refreshed every day, with approximately a 14 days latency due to data source issues. The actual revenue forecasting algorithm (**RO**) tested in our work is much simpler. We aggregate the actual revenue for each template at the (age, gender, geo, hour of day, ad size) level using the data collected from the random bucket during the past 7 days. The average actual revenue for each template is calculated and the one with the highest revenue is assigned to the page views. In order to test whether eCPM is the right criteria for template selection, we also tested a cheating eCPM model (**CEO**) that uses aggregation of eCPM as the prediction for page views in the same day. This is a cheating experiment because we are using all the data from day d to predict the eCPM for day d. The eCPM and actual revenue gain produced by the cheating eCPM model serves as the upper bound of any forecasting algorithm using eCPM as objective.

The actual revenue gains for all the models comparing every single template are summarized in Table 3. It is clear that the cheating eCPM forecasting model (CEO) has the highest revenue gain, which is 60.47% higher than the control template $T1$ and 20.25% higher than the best single template with the highest revenue yield $T5$. The simple revenue forecasting algorithm performs the second best. Its revenue is 37.92% higher than the control template $T1$ and 3.35% higher than the best template $T5$. The eCPM revenue forecasting algorithm is 32.42% higher than the control template but it performs slightly worse than template $T5$. The result indicates that an accurate prediction of eCPM has the potential to produce a significant revenue gain over other models, although the eCPM forecasting algorithm does not perform well compared with the best template. The simple revenue forecast algorithm produces a better revenue gain compared with the eCPM forecasting algorithm.

Table 3: Actual Revenue gain of 3 ad layout templates compared with control template $T1$ in offline simulation.

Model	T1	T3	T5
EO	32.42%	18.51%	-0.78%
CEO	60.47%	43.62%	20.25%
RO	37.92%	23.44%	3.35%

Table 4: Expected Revenue (eCPM) gain and Actual Revenue gain of two optimization algorithms over 3 ad layout templates.

Model	eCPM Gain	Revenue Gain
FT3	3.22%	-8.27%
FT5	10.02%	4.05%
EO	14.79%	0.61%
RO	11.91%	12.81%

5.4 Online Experimental Result for NGD optimization

Offline simulation using random data assumes that both the underlying ad supply and users' response does not change with different ad layout optimization models, which is actually not true in a real system. Therefore the eCPM and actual revenue forecasting algorithms were further tested using real time traffic. The same 3 templates were used in real time bucket testing. The eCPM model is updated daily by refreshing the historical data lookup table. The revenue model is also updated daily by collecting the logs from the random bucket. The bucket was ran for about one month.

The eCPM and revenue gains of both models are summarized in Table 4. Table 4 also includes the eCPM and revenue gains of fixed templates $T3$ and $T5$ compared with template $T1$ calculated using data from the random bucket. The eCPM model produces 14.79% higher eCPM compared with control template but the actual revenue is neutral, only

Table 5: Distribution of template assignments of the two optimization algorithms over 3 ad layout templates.

Template	EO	RO
T1	2.36%	19.12%
T3	39.45%	15.73%
T5	58.19%	65.15%

with a gain of 0.61%. The average eCPM of actual revenue forecasting algorithm is 11.91% higher than that of the control template. Its actual revenue is 12.81% higher than the control template. The actual revenue forecasting algorithm works much better than the eCPM forecasting algorithm in terms of actual revenue gain, which is probably due to the inconsistency between the eCPM and actual revenue. The template assignments of both algorithms are reported in Table 5. Note that the eCPM based model assigns 39.45% of the page views to template $T3$. From table 4 we see that eCPM of template $T3$ is 3.22% higher than eCPM of the control template but revenue is 8.27% lower than the control template, which explains why the eCPM based model produces higher eCPM but lower revenue. The actual revenue forecasting algorithm is more consistent than the eCPM based model in terms of actual revenue gain by assigning 65.15% to template $T5$.

5.5 Offline Simulation for NGD+GD Revenue Optimization

In this section, we include the GD ads in the ad layout optimization. Before discussing the actual simulation, let us take a look at the revenue and impression distribution of GD and NGD advertising at first. 30 days of data was collected from October and November in 2010 for this purpose. Each ad opportunity in the logs was matched with the GD contract database and a list of matched GD contracts were returned with recorded eCPM and allocation probability. Assuming that the sum of all the GD contracts' matching probability is g, $1-g$ is the probability of serving NGD ads in the unified market. The GD contracts whose planned impressions are less than 99% of the remaining booked impressions are treated as under-delivered GD contracts (UGD) and the rest are well-delivered GD contracts (WGD). By summing up all the probabilities of UGD, WGD and NGD contracts for all the impressions, we calculate the impression distribution for UGD, WGD and NGD. The eCPM distribution for UGD, WGD and NGD is calculated too using the eCPM recorded for each contract, weighted by the corresponding allocation probability. The impression and revenue distributions of UGD, WGD and NGD are summarized in Figure 4. We can see that although 19% of all the impressions are served with NGD, only 10% revenue is generated by NGD. Although the majority of revenue and impressions is served with WGD, there are still 27% of impressions and 23% of revenue served by under-delivered GD contracts, which is even higher than entire NGD share. The analysis shows optimizing over both UGD and NGD should produce more additional revenue gain.

We implemented three algorithms for the GD+NGD revenue optimization problem. The first algorithm is NGD ad layout revenue optimization algorithm (ngdO), which builds an eCPM aggregation model based on NGD data only. The predicted NGD eCPM for each template is used for dynamic ad layout assignment. Another algorithm (ugdO) is built on historical UGD data. The template with the highest forecasted under-delivery eCPM is selected for each page view. The last algorithm is a combination of UGD and NGD. From the historical data, we aggregate both UGD and NGD eCPM and then build a forecasting model based on their summation. The model is utilized to predict the total UGD and NGD revenue for each ad layout template and the template with the highest revenue is picked for each page view. To evaluate these models in different aspects, we measure the revenue gains in terms of NGD, UGD and UGD+NGD. We expect using models with different objectives will produce revenue gains in different portion of the marketplace.

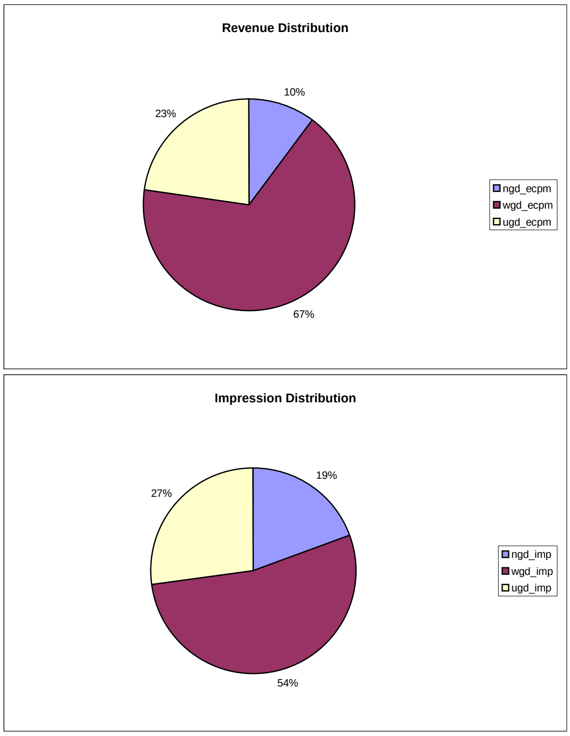

Figure 4: Revenue and Impression Distribution of Well-Delivered GD, Under-Delivered GD and NGD

Table 6 summarizes the results for the three algorithms tested on the collected data compared with 5 other serving strategies, all using fixed templates. Compared with the control template, the NGD-only algorithm improves NGD revenue by 107.89% but only 36.76% in terms of both NGD and UGD revenue. This is because the improvements produced by the NGD optimization algorithm on UGD revenue is only 21.47%. The UGD-only optimization algorithm generates the largest UGD revenue gain, 36.47%. In terms of both UGD and NGD revenue, the gain from the UGD optimization algorithm is 42.74%, better than the NGD-only optimization algorithm but worse than the NGD+UGD optimization algorithm. The algorithm using the summation of NGD and UGD eCPM as objective has the largest gain in terms of the combined UGD and NGD revenue, 45.87%, although its NGD revenue gain is worse than NGD-only optimization algorithm and its UGD revenue gain is slightly worse than the UGD-only optimization algorithm. This concludes that in order to obtain the best revenue performance for both NGD and UGD, both of them needs to be taken into account in the objective of the ad layout optimization algorithm.

6. CONCLUSIONS AND FUTURE WORK

In this work, we investigated the dynamic ad layout optimization problem for display advertising in both NGD and GD marketplaces. In the NGD marketplace, an ad layout

Table 6: Expected Revenue Gain for different serving model optimizing over 5 ad layout templates.

model	ngd_revenue	ugd_revenue	ugdngd_revenue
FT2	89.84%	33.79%	41.70%
FT3	13.64%	-22.15%	-11.47%
FT4	92.05%	31.70%	40.69%
FT5	-5.19%	-23.56%	-17.47%
ngdO	107.89%	21.47%	36.76%
ugdO	85.69%	36.47%	42.73%
ugdngdO	104.13%	35.63%	45.87%

optimization algorithm is proposed to maximize the NGD revenue by assigning the template with the highest predicted revenue to each page view. An ad layout optimization algorithm in the GD marketplace is developed to reduce the under-delivered revenue loss by shifting the traffic to the ad layout templates with more under-delivered contracts. Significant revenue gains were observed when testing the proposed ad layout optimization framework in both GD and NGD display advertising systems. We then presented a simple algorithm that combines both objectives which provided the best results for the unified marketplace. All proposed algorithms were implemented within the framework presented in this paper and tested with real-traffic. To the best of our knowledge ours is the first published work that provides experimental results for revenue optimization for the unified display marketplace.

We also found that there is an inconsistency between eCPM and actual revenue when they are used as objectives of the forecasting algorithm for the ad layout optimization. Experimental results suggest that actual revenue based forecasting algorithm produces more revenue gains in ad layout optimization, and that eCPM based forecasts can be even directionally wrong.

There are several promising directions for future research. First, the model proposed does not include the impact on user engagement metrics. We excluded certain templates from our experiments due to the high risk to user experience. However including a user engagement factor into our objective function is our ultimate goal. Second, it is also believed that dynamic ad layout optimization may affect the underlying ad supply. We were unable to address this concern in our live experiments since the traffic was limited and the experiment was run for a period which could be considered short for GD contracts.

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