Probabilistic Models for Ad View ability using Prediction on the Web

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Abstract - *Nowadays, we see online display advertising has become a billion-dollar industry and it keeps growing day by day. Advertisers send marketing messages to attract and capture potential customers by using online graphic banner ads on webpages. Advertisers are charged customers for each view of a page that delivers their online display ads. However, recent studies have found that more than half of the online ads are never shown on users' screen due to insufficient scrolling. Thus, advertisers are wasting a great amount of money and time on these ads that do not bring any return on their investment. The IAB (Interactive Advertising Bureau) does call for a shift towards charging by viewable impressions, i.e., charge for online ads that are viewed by the users. It is helpful to predict the viewability of an online ad with this new pricing model. By using the PLC Models (i.e. Probabilistic Latent Class Models) that predict the viewability of any given scroll depth for a user page pair, we have built the web model to represent that how the scroll depth technique is used to charge from the customers.*

Key Words: **Online Advertising, Viewability Prediction, User Behavior, Probabilistic Latent Class, Prediction Model, etc.**

1. INTRODUCTION

Our problem is to estimate how likely a user will scroll down to a target scroll depth of a webpage. Exactly, the prediction should be personalized to individual user and webpages. The proposed approach is a supervised learning technique. The inputs of the training module are historical user logs that contain the context of page views. The output is our viewability prediction model. The inputs of the prediction model are a target page depth *X* and a given pair of user *u* and webpage *a*, while the output is the viewability probability of *X* in the page view. Online display advertising has emerged as one of the big popular forms of advertising. Studies show that display advertising has generated earnings of over $63.2 billion in 2015. Online display advertising involves a publisher, who integrates ads into its online content and an advertiser, who provides ads to be shown. Displayed ads can be seen in a wide range of various formats and contain items such as text, images, flash, videos, and audios. In online display advertising, the advertisers pay to a publisher for space on webpages to display a banner during page views in order to catch up and attract visitors that are interested in its products. A page view happens each time a webpage is requested by a user and shown in a browser. One display of an ad in a page view is called ad impression, and it is assumed the basic unit of ad delivery. Advertiser pays for ad impressions with the expectation that their ads will be viewed, clicked on, or converted by users (e.g., ad results in a purchase). Traditional online display ad compensation is mainly based on user clicks because they bring profits to the advertisers. Much more research has been done for predicting click rate and conversion rate, bid optimization and auctions..

1.1 Motivation

Recently, there is growing interest by advertisers to use online display ads to raise brand awareness and to promote the visibility of companies and their products. Indeed, users like to buy products from the brands that they know and believe. Display ads can create an emotional experience that gets users excited about a brand and builds trust. However, user does not typically click this type of ads, rendering the traditional form of pricing structure based on clicks to be ineffective. To overcome this problem, a different pricing model, which pays ads by the number of impressions that a publisher being served, has become popular in the online advertising market. However, a recent study shows that more than half number of the impressions is actually not viewed by users because they do not scroll down a page enough to view the ads. Low view ability leads to ineffective brand promotion. Therefore, a new pricing model is introduced: pricing ads by the no. of impressions that can be viewed by the users, instead of just letting served. This ignores the irritation of advertisers, who worry about paying for ads that were served and not seen by users. Ads placed at different page depths have different prospects of being viewed by a user. Therefore, it is important to predict the probability that an ad at the given page depth which will be shown on a screen of the user and thus can be considered as viewed. The vertical page depth that a user scrolls to is defined as the scroll depth.

2. LITERATURE SURVEY

Ad click through rate (CTR) prediction is to estimate CTR with click chart, which is impacted by the page information, the position, the user properties, the nature features of ad and some other factors. The best ads for the query and the order they are displayed nicely affects the revenue the company gets from these ads. Therefore, it is important to be able to estimating CTR accurately with click log in sponsored search advertising systems. We represent a useful CTR prediction model for ads of abundant history data. We also show that using our model enhances the performance of the advertising system. We present a simulation model to determine the optimal budget allocation strategies for the real time bidding (RTB) based online display advertising. A common challenge across RTB exchanges is to optimize both budget spend and performance attainment. Our simulation model uses the assumptive dynamic programming approach based budget allocation to determine budget for each time instant. We report on results from a real-world pilot in which our approach delivered an average 18% performance gain.

The emerging dynamics of the digital e-markets may create many opportunities with the vast growth and potential of the online services and mobile technologies. However, the sustainability of e-markets is unsure due to industries and operational risk. While industry threats extend to the rapidly shifting powers, fuzzy dynamics and fierce rivalry, this work examines the overlooked operational risks that relate to the facts present e-markets regularly constrain e-traders from strategic conduct. Such denial incites adverse reaction that causes e-market failure. Conveying strategies as rules may, also, accelerate the bidding lifecycles due to the automatic preference deduction of rules by the smart exchange. This work introduces the RBBL rule based bidding language which enables free expressions of strategic rules in bid structure during proposing the GSPM generalized second price truthful matching doubles auction that computes stable and efficient and tractable outcomes with the market profitability. The smart exchange which deliberates on the RBBL rules for the automatic select deduction while using the GSPM for winner determination, hence, improves sustainability with the rapid and stable e-trades, social efficiency, and self-prosperity of free choice.

3. Proposed System

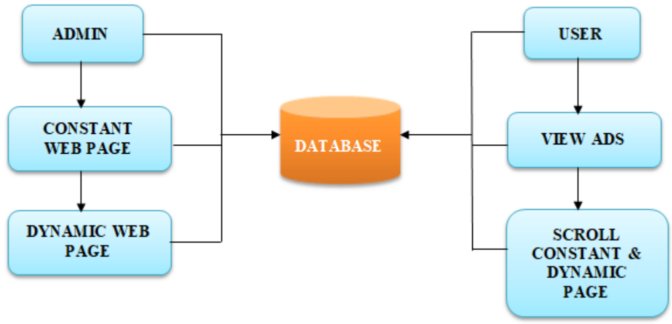

Fig1:- System Architecture

- **Implementation Details (Modules):**

Admin: Admin has the overall control of the system and can create the users, view the registered users, track their activities like visited ads web pages, scrolled percentage, etc.

User: User can login into the system by its user credentials and can visit the different ads web pages to see the ads or product information.

View Ads: In View Ads module, user can see the ads and product's image with detailed description.

Scroll Constant and Dynamic Webpage: Users who prefer to scroll far down on most web pages would have a higher probability to scroll down the current page. Also, features such as device type and geo-location are easy to be modeled.

Database: Database stores the overall data of the system.

Proposed Algorithm

Web pages can be utilized to improve the performance of max scroll depth prediction models. The users that prefer to scroll far down on very most web pages would have a highest probability to scroll down the current page. In this project we are using two proposed PLC models to perform the substantially better than the other models within this challenging interval

I. Prediction Model With Constant Memberships

Our task is to infer the max scroll depth of a page view, x_{ua}, where u is the user and a is the webpage. It is intuitive that the characteristics of individual users, client and web pages can be utilized to improve the high-performance of max scrolled-depth prediction models. Also, features such as the device type and geo-location are easy to be modeled.

II. Prediction Model With Dynamic Memberships

By computing offline the memberships of users and web pages belonging to latent user and webpage classes, PLC const. predicts the view ability of any target scroll depth in a page view. However, user and webpage memberships in reality can be dynamic during the online process, since user interests and page popularity keep changing. To grebe the dynamic nature of the memberships, we put up to represent the memberships by a function whose output value is determined in real-time. Meanwhile, the feature vectors should also be able to reflect the change of user, webpage, and context.

4. CONCLUSIONS

To the best of our knowledge, our research is the first to study the problem of predicting the view ability probability for the given scroll depth and the user/webpage pair. Solving this issue can benefit online advertisers to allow them to invest more effectively in advertising and can benefit publishers to increase their revenue. We presented two PLC models, i.e., PLC with constant memberships and PLC with dynamic memberships, that can predict the view ability for any given scroll depth where an ad may be placed. The experimental results show that both PLC models have substantially better prediction performance than comparative systems. The PLC with dynamic memberships can better adapt to the shift of user interests and webpage attractiveness and has less memory consumption.

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