Evaluating Quality Score of New Ads

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***Abstract*—Online or web advertisement(ad) is the prime source of income for search engines. Revenue generated through web advertisement depends on the number of times user clicks on ads. To increase revenue search engine selects best ad from pool of ads. So, ads of good quality score has more chances of getting selected by search engine. It is very difficult to calculate quality of new ads as they have no historic information related of their performance. Hence, evaluation of quality score is crucial. In this paper, we have proposed straightforward yet efficient method in terms of computation and space requirement to evaluate quality score of new ad. And also values of dominant parameters are computed empirically, that quality web page should possess.**

Keywords*—*GSP, online ad, new advertisements, web advertisement, quality score.

I. Introduction

Web advertisement is the type of advertisement in which ads are displayed on the websites and search engines or more formally on the web. Web advertisement is indispensable way to earn money. According to Gartner Survey, top notch search engine Google has witnessed $43 billion from advertisement in 2012 which is more than that of 2011. Web advertisement can be done in numerous ways viz. sponsored search advertising, contextual advertising, display advertising and banner ads. As far as online advertising system is considered sponsored search advertisement is evolved as most important business models for search engines [1], [2]. In sponsored search advertisement, advertiser chooses some keywords for which his ads would get displayed when words from users query get matched with keywords of advertisement. CTR is indispensable metric in evaluating quality of ad. CTR is the ratio of number of times ad is clicked to the number of times ad is displayed, i.e. if ad is displayed 1000 times on search result page, while it was clicked only 20 times then CTR of that ad is .02. In case of new ads, evaluation of CTR is Cumbersome as it was not displayed earlier. So, to predict CTR of new ad some alternative mechanism is required. CTR of ads decreases substantially with the position i.e. from top to bottom. It has been found that ads with top most position has highest probability of getting clicked. We have employed essence of GSP (Generalized Second Price) auction in our work. GSP is one of the most widely used auction mechanism in todays industries [3] .In GSP, ad rank is assigned to advertiser; on the basis of ad-rank ads got the position on search engine result page. Advertising order and rate are decided by GSP only. Though numerous auctions are available in literature but due to its much flexibility and user friendliness it is used. It has been found empirically that top most ads are more likely to receive large number of clicks and number of clicks varies drastically from top to bottom. Probability of ad with top most position has 50% probability to get clicked and it get decreased to 40%, 30%, 20%, and 20% at the 2nd 3rd 4th position respectively [4]. There is stiff competition between advertisers to get top slots.

The remainder of the paper is organized as follows: related work is explained in section II. Overall proposed method is discussed in subsequent section III. In section IV we describe the implementation part of proposed method. In next section V we evaluate our approach, present experimental results. Finally we conclude our paper with a conclusion and future work.

II. Related Work

A new advertisement auction mechanism based on GSP is proposed in [4] which consider the value of advertisement. And with experimental results it is proved that for certain environment given approach yields good revenue. Prior work nearest to proposed method is [5] that is mainly focused on new ads. Problem of estimating of CTR of new ads is addressed. Approach is divided into two phase: finding of similar ads and prediction of quality score. Two lists based on semantic and feature of ads are maintained. Eventually a final list is maintained which consists of sorted rank in descending order. Similarity between two ads is calculated using Euclidian distance. Jun Feng et.al [6] incorporates machine learning approach to predict the clicks on ads. A sampling algorithm is introduced which helps in learning and training the model in order to predict more accurate click prediction. Richardson et.al [7] used the general features of ads, advertiser and terms to predict real value of CTR. Their work solely focused on the performance and convergence of system. A new advertisement auction mechanism is proposed based on GSP, comparison between normal GSP, VCG(Vickrey Clarke Mechanism) and proposed mechanism is done, features, advantages and effects of new mechanism is discussed in [4]. Considerable work has been done in the area of fair transaction (e.g. [8]); in-order to sustain long business relationship search engine and advertiser should have vivid payment mechanism. An efficient and fair metering scheme is proposed which allows clients to use intelligent devices to obtain services round the clock. In [4], [9] advertisements are considered to possess co-relationship with other ads. It also considers cost of ad which is ignored by most of the researcher. Total revenue gets decreased when ads are considered to be independent.Yosuke et.al [10] focuses on particular situation of advertiser related to cost of advertisement. Ad performance of group of ads that display together on the search engine is studied in [9], [11]. They explored different aspects like interactive influence; depth etc. work is more focused on the prediction of CTR of group of ads for sponsored ads. In another related work [12], authors proposed

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a new mechanism for sponsored auction called OPT against of most commonly used GSP and VCG auction. Albeit, OPT uses features of both above mentioned mechanism. Proposed model achieved Bayesians incentive compatibility and rationality of advertiser. From the results they tried to depict that revenue generated from there mechanism is more than that of other two. Among other work in this domain is the work of [13], where authors try to minimize the revenue loss in GSP, they inherit the concept from English auction which is not decreasing, in which once bid is submitted cant be reduced. They consider both advertisers cost and search engine revenue in their work. They tried to explain how their work speeds up the convergence of search engines and user behavior. Other interesting and entirely different work in this area is done by [14], authors proposed a secure keyword auction mechanism in which bidding price is hidden from advertiser. They employed cryptographic technique in-order to hide bidding amount from advertiser and provide a model for simple payment rule.

III. Proposed Method

In this section proposed method has been explained in detail. Our method calculates the quality score of new ads by checking certain parameters of advertisers landing page and advertisers advertisement, parameters are elaborated subsequently. Unlike other methods, proposed method does not involve finding of similar ads [5], eventually other method sometimes results in faulty prediction of ad which has adverse impact on search engines revenue and popularity. First of how GSP is used in our work is explained.

A. Role of GSP

GSP is repetitive auction which executes every time when the users query word gets matched with advertisers keyword. Due to its flexibility, it allows advertiser to decide period on which its advertisement should take part in auction and he can set up the interval. So, advertiser can change his bid amount according to his budget [4]. When the amount to be paid by advertiser crosses the mark then his ad is not considered to take part in auction mechanism irrespective of best quality it possesses.

$$Adrank = CPC * QualityScore \tag{1}$$

Where, CPC is the cost per click, decided by advertiser and quality score constitutes of several parameters including click through rate, which is the ratio of number of times ad clicked to the number of time ad displayed [5]. Usually its magnitude is very small and ideally its value is 1. Basically, quality score comprises of three main components, click through rate, landing page quality and relevance.

$$P_i * Q_i = B_{i+1} * Q_{i+i} \tag{2}$$

$$P_i = B_{i+1} * (Q_{i+i})/Q_i \tag{3}$$

B_{i+1} is the bid amount of i+1th advertiser, P_i is the actual amount to be paid by ith advertiser, $Q_{i+1}$is the quality score of i+1th advertiser, Q_i is the quality score of ith advertiser. So, amount to be paid by advertiser much depends on its quality score. So to minimize the amount, quality of ad must be good enough otherwise bid amount gets equal to actual amount [5]. Advertisements slots are very few, as shown in Fig. 1 L.Adi is the ads that display just below the search box. R.Adj is the ad that is shown on right most side of search engine. Count of L.Adi is shown as

$$c.l = \sum_{i=0}^{\varphi} L.Adi \tag{4}$$

Where, c.l is the number of ads on left side of search engine and ads on right side of search engine is given as:

$$c.r = \sum_{j=0}^{\rho} R.Adj \tag{5}$$

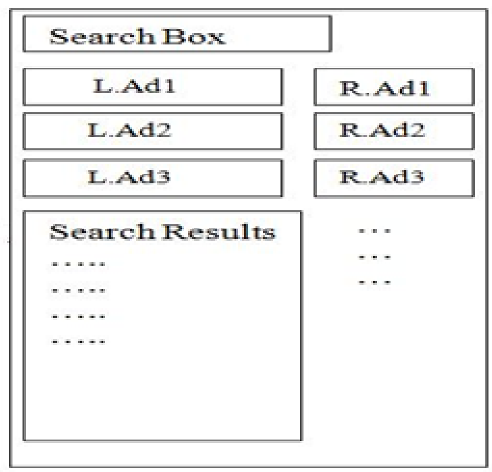

Fig. 1. Layout of Search Page of Search Engines

Where, (φ) and (ρ) are not fixed and depends on various parameter like damping factor, bid amount and total number of advertisers, explained in coming section of paper. It is not essential that ads would be displayed on every query. It all starts with users query. It might be possible that on particular query one ad A_i is displayed on the top while on the same query same ad A_i displayed on the last position. So, it can be concluded that GSP auction processes for every user query; advertiser can change their bid amount in-order to retain best position [15].

$$B_a >= B_{aa} \tag{6}$$

Here B_a is bid amount that is provided to search engine to get a place on the result page, while B_{aa} is the actual amount which is generally less than bid amount.

B. Steps to Calculate the Quality Score of New Ads

1) Extract words Wi from users query where 1<=i<=20.
2) Remove stop words(pronouns, auxiliary verbs) from query.

3) Make a cluster C_k of all advertisers whose keywords matched with the query words (Cluster can be of any size).
4) Process all web pages WP_i in cluster C_k, for every web page perform steps given below:
    a) Check words from query in title of web page.
    b) Count the occurrence of query words in keywords of web page.
    c) Check whether query word comes in anchor tag.
    d) Count the number of anchor tags in web page.
    e) Count the number of lines in web page.
5) Certain value is fixed for every step, so sum up the values, this sum is called Quality Score.
6) Compute the ad rank as done in GSP mechanism and stored it in list along with web page URL (to uniquely identify it).
7) Now, we have multidimensional list consisting of web page URL and ad rank. Sort the whole list in descending order with respect to ad rank.
8) Now, once again employ GSP and find out the actual amount to be paid by bidder.
9) Pick top eight ads. Embed 3 ads on top left of the search engine page and remaining on top to down on right side on search engine web page.

C. Assumptions

1) Value of bid varies from 1 to 10 $.
2) We have formed a cluster of same web pages containing laptop.
3) Number of bidder is always more than slots available on search engine.
4) Strategy based on Pay per Click (PPC) Payment model.

IV. Implementation

In this section how proposed method is implemented is explained.

A. Data Set

Our method is designed for new ads which is less in number than the ads that were existing in the system for long time. We have collected a data set from well known search engine Google. Keywords along with web pages are provided for scholars for experimental purpose and data is real time, available at [16]. Nearly 8000 web pages are processed for a set of keywords.

B. List of Parameters

This section comprised of explanation of parameters that are considered in calculating quality score of new ad. These parameters help in calculating quality score of new ad as well as aid in making web page of good quality. Here web page of good quality is the web page that has the high probability of getting clicked. Some most important parameters are stated below. Almost all parameters are somewhat related to keywords of web page. In brief, keywords are crux of web page because they tell a lot about web page and advertisement. Keywords are decided by advertiser, and if words from users query get matched with keywords then that ad is eligible to be processed in auction. For e.g. in advertisement of laptop, generally advertiser would select keywords as: cheap laptop, second hand laptop, light weight laptop, latest laptop etc.

1) Matching of Title(α): This is most important parameter which tells a lot about quality of landing page. It refers to matching of keywords of web page to the title of web page. Positive value of this parameter signifies about good quality of web page.

2) URL of Landing Page(β): When advertisement is clicked it is redirected to some other page that has more details about advertisement. This web page is called landing page. If keyword occurs in URL of landing page then that page is of high quality.

3) Ratio of count of keywords matched in title to the total number of words in title (γ): This metric is enhanced version of first parameter, here ratio is calculated. Although ratio is always less than 1 but higher magnitude is desirable.

4) Length of ad (Ω): Length of ad play vital role in evaluation of quality of web page. It is found that smaller ad is more focused, relevant and of more quality [11].

5) Number of keywords matched (λ): This parameter is slightly different from above one. Here whole web page is traversed and keywords are checked. And count is maintained. Naturally, more is the desirable.

6) Count of anchor tags (η): Count of number of anchor tag has good role in determining quality of web page. Because more the number of anchor tag greater will be the probability of redirecting to another page.

7) Count of matched keywords in anchor tag (σ): Here occurrence of keywords in anchor tag is maintained. If keywords lie in anchor tag then it means redirect page belongs to same domain.

8) Length of Landing page (ζ): Length of landing page refers to number of lines it has. Quality of web page is more likely to get affected by value of more value of ζ. We have empirically found out the most appropriate value of these parameters for ad of good quality.

Values of all parameters are stated in Table I. These values are derived empirically.

TABLE I. **Parameters of Quality Score**

Parameter	Multiplier
α	.35
β	.15
γ	.10
Ω	.10
λ	.10
η	.05
σ	.02
ζ	.001

Here multiplier is the value with which count of particular parameter is multiplied.

$$Q.S = \sum((\alpha, \beta, \gamma, \Omega, \lambda, \eta, \sigma, \zeta) * (\sum_{i=1}^{8} \upsilon_i)) \tag{7}$$

Where, υ_i is the value of i^{th} parameter. Q.S is the quality score of advertisement which would require in calculating ad rank using GSP. Damping factor (ω) is added in quality score, as GSP converges on Locally Envy Free equilibrium [17], [18]. Due to extreme sparseness in clicks, CTR computed on random sampled data is not distinct with CTR computed on real world data. Relative difference is computed to measure change in CTR in both cases:

$$\triangle_{(q_i,a_i)} = \frac{|\,(CTR_i^w) - (CTR_i^s)\,|}{CTR_i^w} \quad (8)$$

$$\omega = \begin{cases} 0 & \triangle < \xi \\ \triangle & \triangle >= \xi \end{cases}$$

Where $\triangle$ is the relative difference of CTRs, where CTR_i^w is the CTR on whole data while CTR_i^s is the CTR on sampled data and (ξ) is the threshold value [18]. Damping factor is ignored if relative difference is less than threshold while damping factor will be equal to relative difference when threshold is less than relative difference [9].

C. Detailed Explanation of Component of Proposed Method

Here, we have tried to elucidate every component of proposed method in a more crystal clear way:

1) Extracting and Finding Keyword in Ads Dataset: User enters query in search engine and expect some results. First and foremost query is fragmented into words. Thereupon stop words are removed from fragmented words. Now, remaining words are searched into database of search engine. For advertisement there is separate database where all keywords of ads are stored. So, words from query are searched into ad database and matched ads are retrieved.

2) Retrieve Quality Score of old ads and new ad: Basically there are two types of ads that are a part of system:Old ads that are in system for long time, performance realted historical information of these ads are available. So its very easy to calcualte quality score of these ads. Usually search engine pre computes these information. In case of new ads, no historic information is available. Basically new ads are the ads that are going to display very first time. So, in this case proposed method is processed, which calculates the quality score of news ads in simplified way.

3) Merge List in descending order: After retrieving both quality score of new ads and old ads. Both lists are merged in descending order. As most of the search engine focusses on quality, so on the basis of quality, sorting is performed. And top few ads are remain intact while others are discarded. Count of these ads vary from search engine to searche engine.

4) Perform GSP: In GSP, ad rank is calculated with the help of bid amount. Bid amount is one of the important metric in calculating ad rank. So, after performing GSP, lists of advertisements are sorted in descending order. Reason behind this sorting is equation 1,2,3.

5) Embed ads in result page: This is the last step that is performed in system, ads are embedded into search engine result page and send to user. Here number of ads embedded in result page vary from search engine to search engine and also on the quality of advertisements. In short there is no fixed value for number of advertisements.

D. Working

Abstract view of proposed method is shown in Fig. 2.

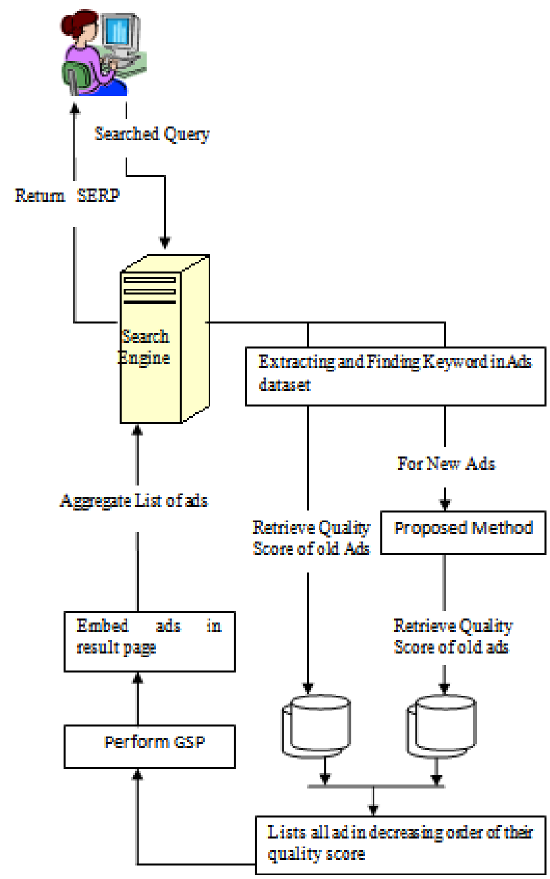

Fig. 2. Block Diagram of Proposed Method

V. Experimental Results and Analysis

Values of parameters are computed on large data set and normalized value has been found out by calculating average. Fig. 3 represents normalized value of every parameter. Here, shaded value is desirable value that quality web page should Possess.From Fig. 3 it can be stated that (α) is the most important parameter in determining quality of web page and (ζ) has least value but it is significant importance.

Fig.4 shows the performance of proposed method over model that has addressed the same problem. Graph is drawn between bid amount and quality score.

Bid amount is taken on X-axis while its counterpart on Y-axis. In given graph, quality score is normalized to less than

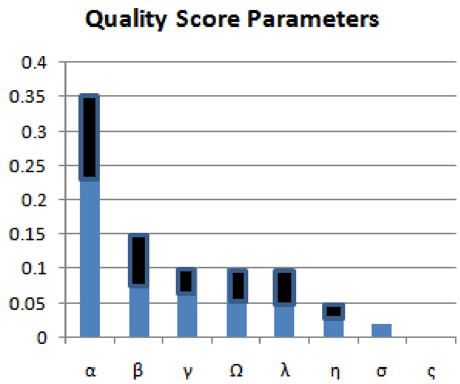

Fig. 3. Range of Parameters

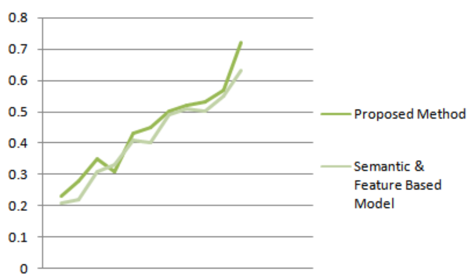

Fig. 4. Model analysis

1. So, normalized range of quality score is 0 to 1. And bid amount lies in the bracket of 1 to 10. This graph is plotted after processing large set of advertisements and it deduce that proposed approach performs better than semantic and feature based model.

Table II shows the comparison done on the randomly picked advertisements from large pool of ads. To bring more fairness, bid amount is kept same for both the approaches. Quality score is generated and arranged in tabular format. From the table, it can be deduced that given approach also performs better on the random inputs.

TABLE II. **Comparison of Proposed Method with other Method with Constant bid amount**

	Bid Amount	Quality Score
Proposed Method	5	.457
	7	.524
	9	.599
Semantic and Feature Based Model	5	.413
	7	.512
	9	.577

VI. Conclusion and Future Work

In this paper we made an effort to address the problem of determining quality score of new ads. Proposed approach doesnt consider similar related advertisements. Several parameters are considered related to advertisers advertisement and landing page in evaluating quality score. And their approximate value is also calculated empirically. It has been found that given approach evaluate quality score of new ads in very simplified way yet efficient way. As the proposed work is confined to only new advertisements so, in future we will focus our work on broader domain i.e. on both new and olds advertisements.

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