Abstract—Cost per click is a common metric to judge digital advertising campaign performance. In this paper we discuss an approach that generates a feature targeting recommendation to optimise cost per click. We also discuss a technique to assign bid prices to features without compromising on the number of features recommended.

Our approach utilises impression and click stream data sets corresponding to real time auctions that we have won. The data contains information about device type, website, RTB Exchange ID. We leverage data across all campaigns that we have access to while ensuring that recommendations are sensitive to both individual campaign level features and globally well performing features as well. We model Bid recommendation around the hypothesis that a click is a Bernoulli trial and click stream follows Binomial distribution which is then updated based on live performance ensuring week over week improvement.

This approach has been live tested over 10 weeks across 5 campaigns. We see Cost per click gains of 16-60% and click through rate improvement of 42-137%. At the same time, the campaign delivery was competitive.

I. INTRODUCTION

For anyone accessing the internet, Digital marketing is not a new term as you are targeted with advertisements on multiple platforms where businesses try to reach the right audience interested in buying different products and services. Digital marketing is an umbrella where all marketing channels like TV, Desktop and mobile are used to reach out to a particular audience. Digital marketing industry size in 2019 was around $300-310 billions and is expected to grow in 2021 at 15-20%. Digital marketing houses run primarily by agencies do look for proven data science and machine learning methods to strike the right balance between relevancy and growth. Online advertising is driven by the demand side and supply side of the business primarily governed by real time bidding exchange where real time auction takes place. Demand side is dominated by agencies and clients who are looking for an audience interested in their products and service. Publishers and sellers on the other hand dominate the Supply Side. Supply side parties have a placeholder for advertisements to be shown on their websites and mobile apps where traffic of relevant audience arrives and are thus redirected to websites of clients ending up purchasing their products and services.

Advertising on display and videos have been in the industry for long and people do look for ways to innovate it. Although the industry is led by solution owners or programmatic traders with their own assumptive intuition, Data Science practices have opened doors for people to dig deep and dive in further to bring the best value out of any click or conversion happening. With the algorithmic approach, it has gone wide to help the media industry quickly. Targeting the right audience for an advertisement does involve looking at a lot of factors and that can be solved using a model based approach. One of the most common business KPI that marketers look for when they want to call a managed campaign successful is CTR - click through rate. Click Through Rate is a KPI which looks at ratio of users who click the advertisement with respect to people shown an advertisement. In marketing campaigns, you would observe a click through rate of 0.03% while through our methods, we tend to increase the performance of the campaigns by 1.5X to 2X making sure the other media related constraints are satisfied. Technically a good click through rate depends on various factors including the platform. A good CTR for adword’s search page could be different from those of Facebook’s and would be largely different from media campaigns. It also normally varies from one vertical to another, the place an advertisement is placed, size of the advertisement creative and also the location where an advertisement is targeted.

With this paper, we are looking at data driven techniques to optimise click through rate. While looking at multi-level features selected for better clicks based on initial exploration serves as an initial component, other important aspects that we cover in this paper is the pipeline that allows us to scale our solution to over a Billion rows.

Another form of scale relevant to this paper is scale of impressions. Getting enough scale for any active campaign and at the same time making sure the cost spent on getting those clicks while keeping the cost minimal is the problem we are trying to solve in this paper.

II. DATA AND EXPERIMENTAL CONTEXT

A. Experimental Context

Before we proceed with the discussion of our approach, the experimental context and use-case of the final result needs to be addressed to better explain the practical restrictions governing use of results obtained via the approach outlined in this paper.

Many publications discuss approaches that can be utilised for modelling Click Through Rate. Typical approach is modelling for \( P(x = 1) \) using a classification model. Neural Networks, SVMs, Decisions Trees, Random Forests, and various boosted tree approaches have been shown to work for this task.
However, our setting and requirement are different from these existing solutions. Typical approaches usually are not very sensitive to the tail end of input features. In practice, we have seen that for our campaigns the highest performing features typically form the tail end of the distribution. It is well known that optimising a model for tail end values is an uphill task. Hence, we need an approach that optimises reasonably well for such features.

Our goal here is to recommend a feature combination along with a reasonable bid value so that the aggregate cost per click is improved. Feature combination is a set of contextual features that define where an impression can be delivered. For example the following table shows a few valid feature combinations:

| Site Domain     | Device Type | Size  | Fold |
|-----------------|-------------|-------|------|
| analyticsindiamag.com | Mobile      | 300x50 | 1    |
| yahoo.com       | Desktop     | 300x250| 0    |

Along with such feature combinations (sometimes referred to as context), we need to send bid prices that we are willing to pay for an impression served at each such context. We however have no way of specifying the exact number of impressions that we wish to win for a particular feature combination. That control is not available. Thus bid prices are the only other parameter that we can control. Various methods exist that allow modelling of number of impressions vs a bid price. However, all of them require auction level level censored data that is not available to us. Therefore, the approach discussed in this paper focuses on assigning maximum bid price which is also the price at which the expected CPC is equal to or lower than our target.

Digital advertising campaigns are very dynamic leading to varying week over week performance of same feature sets. Any approach that is chosen for the task should allow for constant feedback and iterative improvement. In case of ill-performing feature set, the approach should be quick in updating its recommendation.

At the same time the approach had to be compliant to GDPR, a European law outlining privacy honouring requirements of data collection and processing. Therefore, our approach does not use user level identifiers and operates at aggregated feature level.

Our chosen approach fulfils all these requirements.

### B. Data

We use impression stream and click stream at the organisation level as the input to our process. An impression stream data consists of all impressions that we were able to serve at the account level. Similarly, click stream data consists of every click that happened as a result of an advertisement shown by us.

Along with the information of an impression event or a click event, these streams provide us information about the context of the ad impression. Typical row from this data set contains information about the site domain where the ad impression took place, time stamp of ad impression, device type, geographical information like Zip code, Internet service provider etc. The complete data dictionary contains well over 30 columns of which 7 columns that contain information about price and targeting are of interest to us.

Three types of columns are present in our data set which convey

1) Context of ad slot
2) Cost of ad slot
3) Non Context information

Context information indicates where the ad impression was shown and can be directly used for targeting. This includes the following columns:

- **Timestamp**: Time stamp of click or impression
- **Height**: Height of the image required by the ad slot
- **Width**: Width of the image required by the ad slot
- **Device Type**: Type of device Desktop, Mobile, or Tablet that this ad impression was shown
- **Operating System**: Operating system of device
- **Browser**: Browser type and version where this ad impression was shown
- **Fold Position**: Above fold or below fold. Indicates if the advertisement is visible on page load or after scrolling down the page
- **Geo Country**: Country where this ad impression was shown
- **Geo Region**: DMA
- **Seller Member ID**: Seller via whom the inventory is made available
- **Tag ID**: Unique ID of ad location on a website
- **Publisher ID**: Unique ID of website owner
- **Site Domain**: Mobile Application or Website

Non Context information includes following columns

- **Insertion Order ID**: Advertising campaign identifier
- **Advertiser ID**: ID of Advertiser a particular impression or click belongs to
- **Is Click**: 0 if not click, 1 if click

Cost information contains following columns:

- **Media Cost**: Cost of the impression in USD
- **Data Cost**: Per impression cost of third party data used

Due to the targeting restrictions of our upstream provider, we combine Height and Weight and create Size. Similarly, Geo country and Geo Region are combined to form Geo targeting column. Actual realised cost of an ad impression is $\text{MediaCost} + \text{DataCost}$. We use the aggregated amount for further analysis and modelling.

From the click and impression stream, we prepare two data sets campaign level, and network level with minor differences. Campaign level data contains all the columns mentioned above that we filter from the larger data set. Network level data however is not processed at campaign level. For this data set, we remove the following columns:

- **Insertion Order ID**
III. Modelling

An ad-impression can lead to two states that are relevant to this discussion. It can either lead to a click or not lead to a click. We can thus say that a Click is a binary random variable where the value 0 represents a non-click event and 1 represents a click event. We are treating clicks, and impressions as independent events.

This allows us to model a click stream as a Bernoulli Trial

**A. Bernoulli Trial**

- Let probability of a click be $p_c$
- Then, Probability of no-click $p_n = 1 - p_c$
- $p_c + p_n = 1$

Since we treat each impression as a Bernoulli Trial, it follows that a series of such trials be modelled as a Binomial experiment where probability of getting $n$ clicks can be expressed as:

$$Pr(X = n) = \binom{i}{n} p_c^n (1 - p_c)^{i-n}$$

From data, we can calculate the ratio of clicks vs total impressions. However, consider a coin toss experiment. If we observe coin toss leading to 2 heads and 0 tails in two independent trials, does it follow that the coin only lands on Heads?

This question leads us to the Beta Distribution.

**B. Beta Distribution**

Beta distribution is the conjugate prior for Binomial and Bernoulli Distributions. Accordingly, we can write

$$f(p_c | n, n_i, i_i, i) \propto p_c^{n+n_i-1}(1-p_c)^{(i-n)+(i_i-n_i)-1}$$

where

- subscript $i$ indicates imaginary trials

The expectation of (2) will give us the expected probability of click $P_c$ from click vs non click data.

For this we leverage Bayesian inference [3] over Beta Distribution as mentioned in equation (3)

$$p(x = 1 | Data) = \frac{m + a}{m + a + l + b}$$

where

- $p(x = 1)$ is the probability of Success
- $m$ is prior clicks
- $a$ is real clicks
- $l$ is prior non clicks
- $b$ is real non clicks

This affords us a very simple and explainable approach that we can use to calculate expected click through rate or $P_c$ from the data.

Per the Bayesian approach, we can use the same equation with updated data of $a$ and $b$ to update our belief. This way, we can calculate the posterior probability of clicks by simply adding new data to our data-set without modifying any other part of the system.

**C. Final Approach**

Our final approach uses equation (3) to calculate expected Cost as well as expected Click through Rate. Along with this we use a heuristic measures to prevent under delivery and high cost.

We utilise data from Network level feed as well as campaign level feed as discussed in section [II-B] The reasons for this are twofold:

- Prevent under delivery by using feature combinations with wider reach extracted from network level data
- Bootstrap performance of campaign from known high performing features from network level data.

We first calculate network wide average impressions, and average number of clicks for all feature combinations. This forms the prior part of equation (3). For all feature combinations, we calculate adjusted click through rate by adding the prior to their actual performance.

We repeat this step for cost column to give us a prior cost. Both these steps allow us to handle feature combinations with few data points well.

The same steps are repeated for campaign level data where the prior is again calculated at campaign level. Adjusted Cost and CTR are then calculated for all campaign level features.

We then proceed with bid calculation targeting a specified CPC per the logic below.

$$CTR = \frac{Click}{Impressions}$$

$$CPC = \frac{Cost}{Click}$$

$$adjusted\_ctr = \frac{prior\_click + click}{prior\_imp + imp}$$

$$adjusted\_cost = prior\_cpm * prior\_imp + feature\_cpm * feature\_imp$$

$$adjusted\_cpm = \frac{adjusted\_cost}{adjusted\_imp} * 1000$$

$$CPM = CPC * CTR * 1000$$

Substituting CPC in equation (10) with a known target, we can calculate the max affordable CPM. By substituting CTR with adjusted_ctr in equation (10) we can calculate the highest bid price we can recommend given the expected CTR. In this step we introduce a parameter **optimization_fraction**. Since the goal of this approach is to optimise CPC, we
multiply this variable with the obtained CPM before recommending it to the users. This enables us to always push recommendations that would perform better than the rest of the campaign. Using aggressive value of \(\text{optimization\_fraction}\) leads to severe under delivery. Hence, it is advisable to test a few variations or modify this value automatically in a feedback loop.

**IV. Implementation Overview**

Any task in Digital Advertising industry has to handle at least a few terabytes of data. The approach in this paper is no different and needs to scale to ~24TB of raw input data. PySpark or in our case Databricks is the go to platform.

Figure [I] outlines the overall design of pipeline that we are currently using to generate recommendations. It is divided into 3 parts

- Request creation
- Aggregation and Generation of recommendation
- Activation

Jarvis is an internal tool that takes care of receiving requests for recommendation which is then processed in batch mode once or twice per week.

The bulk of processing happens on Databricks. The first step is to load the raw feeds from S3. For the purpose of these experiments, we loaded 7 days of impression and click stream feeds. Following are the steps that are performed on network level data:

- Filter for relevant Geographical region.
- Group by data with relevant fields
- Remove outliers outside 2 standard deviation
- Calculate average impression & click for use as prior
- Add prior to all feature combinations generated
- Sort by adjusted CTR
- Filter the feed for top 100K impressions with the highest adjusted CTR
- These features are common for all campaigns however bid values are different across each campaign

We perform similar step on campaign data. Prior impressions and clicks are calculated at per campaign level. Another difference is that we do not filter campaign data for top 100K impressions. All impressions and feature combinations are used albeit at lower bids. Once both feeds are individually processed, we proceed with a merger of recommendations from both these sources based on the requested scale of recommendation. Typically, 30% of scale is served from network level features.

Next step is to calculate the bid values using methods discussed in section [II]. Subsequent steps involve packaging these results into required format and uploading them to our upstream service provider.

We repeat this process twice every week to ensure that bad performing features are kept in check.

**A. Effectiveness of Feedback loop**

Our hypothesis is that every feature that is not optimally performing will eventually face reduced bids till it starts performing better.

Let’s assume a feature combination \(T\) that has only delivered 100 impressions so far and has received exactly 1 click. At this point there isn’t enough information about \(T\) to allow us to make an informed decision. Therefore, we add the prior values calculated from campaign data.

For the sake of argument let’s assume that the prior values are at 1 click and 1000 impression. After adding this to the data of \(T\), the effective CTR now becomes

\[
\text{adj\_ctr} = \frac{1 + 1}{100 + 1000} = 0.18\%
\]

This adjusted CTR value is very high and consequently \(T\) receives a very high bid value.

In the next iteration of the pipeline, there are 3 possible cases

1) \(T\) is performing really well
2) \(T\) is delivering a lot of impressions and thus costing us a lot without getting us a lot of clicks
3) \(T\) is not able to deliver at all. The delivery is stuck at 100 impressions.

Case 3 is trivial. The algorithm will arrive as bids same as the last time, and we will not see a lot of delivery again in the next week. This is OK as long as other features are delivering sufficient inventory.

Case 1 is also trivial. The algorithm will recalculate the adjusted CTR and increase the bids as applicable.

Case 2 is where we need to ensure that bad performing features stop delivering or deliver at a lower cost per thousand impressions thereby increasing the effective CPC. Let’s assume that the total impressions delivered by \(T\) in this case is 10,000 without any new clicks.

By calculating the adjusted ctr, we get

\[
\text{adj\_ctr} = \frac{1}{10000} = 0.009\%
\]

This time around, the algorithm will reduce the bid value allocated to feature combination \(T\) as governed by equation [10]. Since adjusted CTR is in the numerator of this equation, the effective bids allocated to \(T\) will be very low as required by the equally bad performance.

Hence, if a high bid value is assigned to a bad performing feature yet unknown to us, it is benign if it falls under case 3. If it falls under Case 2, we can be sure that the bids will be reduced in response. This dynamic nature of our approach make it responsive to bad performing features and ensures that campaign budget is not wasted.

**V. Tests and Results**

We tested our approach on 5 live campaigns in the US Region across different verticals and campaign configuration for a duration starting from Late September to Early December. Within each of these campaigns, a new strategy (Line Item) was created and associated with our recommendations. Other strategies that were already delivering on these campaigns included ones optimising for Impressions, CPC, Viewability. No change was made to other line items of these test campaigns.
Fig. 1. High level pipeline architecture

### Table II

| Impressions | Daily Budget | Delivery % | Campaign | Impressions | LI Budget | Daily Delivery % |
|-------------|--------------|------------|----------|-------------|------------|------------------|
| C           | C            | C          | Type     | R           | R          |                  |
| 4626434     | 16170000     | 28.61%     | A        | 817478      | 2560000   | 31.95%           |
| 6537127     | 13914000     | 46.98%     | B        | 1124843     | 960000    | 117.17%          |
| 8077947     | 57446000     | 14.06%     | C        | 1201979     | 2860000   | 42.03%           |
| 3161197     | 6910000      | 45.75%     | D        | 170969      | 9600000   | 17.81%           |
| 2965780     | N/A          | N/A        | E        | 104277      | N/A       | N/A              |

### Table III

| Clicks | Media Cost | CPC | CPM | CTR | Campaign | Clicks | Media Cost | CPC | CPM | CTR |
|--------|------------|-----|-----|-----|----------|--------|------------|-----|-----|-----|
| C      | C          | C   | C   | C   | Type     | R      | R          | R   | R   | R   |
| 3900   | 8080       | 2.07| 1.75| 0.08%| A        | 1538   | 1693.233   | 1.00| 1.75| 0.09%|
| 3616   | 12486      | 3.45| 1.91| 0.06%| B        | 1019   | 1378.6872  | 1.35| 1.91| 0.09%|
| 5823   | 11472      | 1.42| 1.97| 0.07%| C        | 1204   | 1435.88    | 1.19| 1.97| 0.10%|
| 1882   | 6610       | 3.51| 2.09| 0.06%| D        | 336    | 321.96     | 0.99| 2.09| 0.20%|
| 5594   | 6626       | 1.42| 1.97| 0.07%| E        | 472    | 258.05     | 0.56| 2.48| 0.45%|

Tables II and III compare the result of existing strategies indicated by C against type with recommended strategies indicated by R against type. Campaign A to C had a greater geographical coverage. Campaign D was configured to deliver on a very restricted geographical area akin to a district. Campaign E was a geo-fence campaign using 3rd party data.

In table II, the Impressions column indicates the total number of advertisements show during the test period for a campaign. The daily budget column contains the sum of individual targets of each strategy. Typically, stakeholders over-allocate strategies to ensure campaign delivery. Therefore, we see the Delivery% column containing numbers much below 50%. In practice, the Delivery% of our recommendations should be comparable to corresponding existing strategies.

On the delivery front, we see that Campaigns A to C have a much higher delivery percentage for our recommendations. This percentage when higher indicates that we are able to deliver more than our fair share of the impressions. In campaign D our recommendation as only able to reach 17.81% delivery whereas existing strategies delivered 45.75%. We attribute this to the strict geographic requirement of the campaign.

On the KPI front in table III we see that campaigns that were able to fulfil delivery requirements also have 42.8% to 137.5% better Click through Rate(CTR) and at the same time have 16.19% to 60.86% better Cost Per Click(CPC).

CPM across all well delivering campaigns is lower except for campaign A where it is 18.28% higher than the corresponding strategies. However, this is more than made up by
the much better CTR allowing the line to achieve a lower CPC with respect to control lines.

Campaigns D and E under delivered and the corresponding delivery is much lower than required. However, even in such cases our approach resulted in much lower CPC and much higher CTR. Campaign D realised 233% improvement in CTR corresponding to 72% reduction in CPC. Campaign E realised 641% improvement in CTR corresponding to 60% reduction in CPC.

Thus far, our approach has been able to meet the primary goal of improving Cost per Click for each of the campaigns. After monitoring the week over week performance of these campaigns for the test duration, we can say that the approach is able to react quickly to performance changes, thus satisfying our requirement of responsiveness.

VI. CONCLUSION AND FUTURE WORK

In this paper we have discussed the effectiveness of modelling a Click event as a Bernoulli Trial. In digital advertising, many events like Converts, Views, Video completion are suitable candidates for application of this approach. We have seen certain edge cases like restrictive geographical targeting that have resulted in low impression delivery. We would like to explore variations to this approach that will enable us to guarantee delivery for such campaigns. A reinforcement learning approach to modify the parameters of our approach will reduce the manual intervention required in cases of extreme delivery.

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