What Size Should a Mobile Ad Be?

Pengyuan Wang† Wei Sun§ Dawei Yin†
†Yahoo Labs, Sunnyvale, CA, USA
§Purdue University, West Lafayette, IN,USA
†{pengyuan, daweiy}@yahoo-inc.com §sun244@purdue.edu

ABSTRACT

We present a causal inference framework for evaluating the impact of advertising treatments. Our framework is computationally efficient by employing a tree structure that specifies the relationship between user characteristics and the corresponding ad treatment. We illustrate the applicability of our proposal on a novel advertising effectiveness study: finding the best ad size on different mobile devices in order to maximize the success rates. The study shows a surprising phenomenon that a larger mobile device does not need a larger ad. In particular, the 300*250 ad size is universally good for all the mobile devices, regardless of the mobile device size.

Categories and Subject Descriptors

G.3 [**PROBABILITY AND STATISTICS**]: Statistical Computing; J.1 [**ADMINISTRATIVE DATA PROCESSING**]: Business, Marketing

General Terms

Measurement, Experimentation

Keywords

Advertising, Mobile, Ad Size, Causal Inference

1. INTRODUCTION

In the current online advertising ecosystem, user are exposed to ads with diverse formats and channels, and user's behaviors are caused by complex ad treatments combining of various factors. The online ad delivery channels include search, display, mail, mobile and so on. Besides the multi-channel exposure, ad creative characteristics and context may also affect ad effectiveness [4]. Hence the ad treatments are becoming a combination of various factors mentioned above. The complexity of ad treatments calls for an accurate and causal measurement of ad effectiveness, i.e., how the ad treatment *causes* users' responses, such as whether or not the user clicks a link, searches for the brand or visits websites.

Ideally, the gold standard of accurate ad effectiveness measurement is the experiment-based approach, such as A/B test, where different ad treatments are randomly assigned to users. However, the cost of fully randomized experiments is usually very high and in some rich ad treatment circumstances, such experiments are even infeasible [1, 2]. It is critical and necessary to provide statistical approaches to estimate the ad effectiveness directly from observational data rather than experimental data. In observational data, typically the user characteristics may affect both the exposed ad treatment and the success tendency. For example, assume in an auto campaign all of exposed users are males and all of the non-exposed users are females. If the males generally have a larger success rate than females, the effectiveness of the campaign could be overestimated because of the confounding effects of the user characteristics—in this case, gender: It might just be that males are more likely to be exposed and perform success actions. Therefore, the evaluation framework needs to eliminate the confounding effect of user characteristics to reach fair measurement.

In this paper, we first describe a computationally efficient tree-based causal inference framework to provide fair evaluation of general ad effectiveness as in [8]. Our causal inference is fully general, where the treatment can be single- or multi-dimensional, and it can be binary, categorical, continuous, or a mixture of them. Compared to previous causal inference work [3, 7, 5], the proposed approach is more robust and highly flexible with minimal manual tuning. The framework is general and can be applied to aspects of ads that are of interest to the advertisers.

We then conduct a study with a mobile-based ad campaign to find the optimal ad size on different mobile devices by measuring the causality effect of ads with different sizes on users' success rates. It might be hypothesized that a larger screen needs a larger ad size, but the causality analysis shows that, the ad size 300*250 is universally good for all the mobile screen sizes in our study.

2. METHODOLOGY

The intuition can be described with the following roadmap. In order to obtain a valid causal inference of the treatment, we need to account for the confounding impact of user features (Figure 1). We employ a tree model to fit the ad treatment with user characteristics (features). Hence within each tree leaf, the users are homogeneous in terms of the potential ad treatments given user characteristics, which means the link between user features and treatment is cut off. So within each tree leaf node, the impact of the treatment on the outcome is the causal, without the confounding effect of user features (Figure 3). We then estimate the population-level treatment effect by a weighted average of the estimators from each leaf node.

We prove that the proposed tree-based causal inference estimation is unbiased under standard conditions. We further wrap the methodology with bootstrapping that provides uncertainty evaluation (i.e. standard error) for the results. For details of the method-

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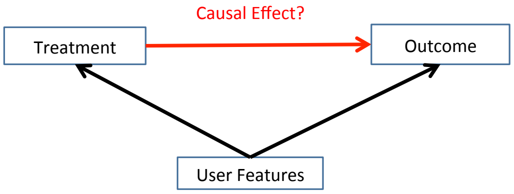

Figure 1: Confounding effect of user features.

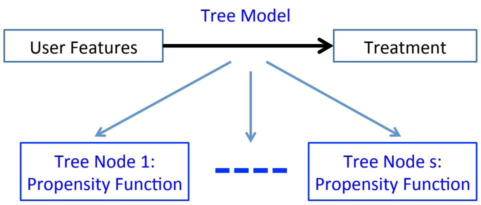

Figure 2: Estimate the propensity function via the proposed tree model.

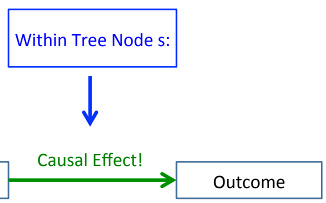

Figure 3: Obtain causal effect by conditioning on the propensity function estimated from each tree leaf node.

ology, please refer to [8].

3. APPLICATION

We apply the framework on a mobile-based ad campaigns to find the best ad size on mobile devices. We obtain the ad impression and conversion (defined as quote) data from an auto company's one-week mobile campaign on four devices: Andoid Phone, Android Tablet, IPhone and IPad. On each of the devices, we conduct the causal analysis of the relationship between ad size and the conversion rate. In this study the ad size is treated as a categorial variable that takes value on five categories (120×30, 300×250,728×90,300×250, and 300×600), and we fit the tree with a loss function defined as in [6].

We first calculate the naive conversion rates corresponding to each ad size on each mobile device as in Figure 4 with one standard error bars. The result suggests that a larger screen needs a larger ad for better conversion rates, for example, the optimal ad size for Android Tablet is larger than that for Android Phone, and the optimal ad size for IPad is larger than that for IPhone.

However, after considering the confounding effects of user characteristics, our causal estimator finds that 300*250 is universally good for all types of mobile devices, see Figure 5. It is optimal for Android Tablet, iPhone, iPad, and is close to the optimal for Android Phone with no statistical significant difference. Therefore, shrinking the overly large ads to such size can not only save space on the mobile web pages, but also yield more successes.

4. CONCLUSION AND DISCUSSION

This paper describes a tree-based causal inference framework for complex ad treatment measurement and applies it to a novel study on mobile ads. Our study shows a surprising phenomenon that a larger mobile device does not necessarily need a larger ad: the 300*250 ad size is universally good for all types of mobile devices in our study. This result inspires better usage of mobile webpages.

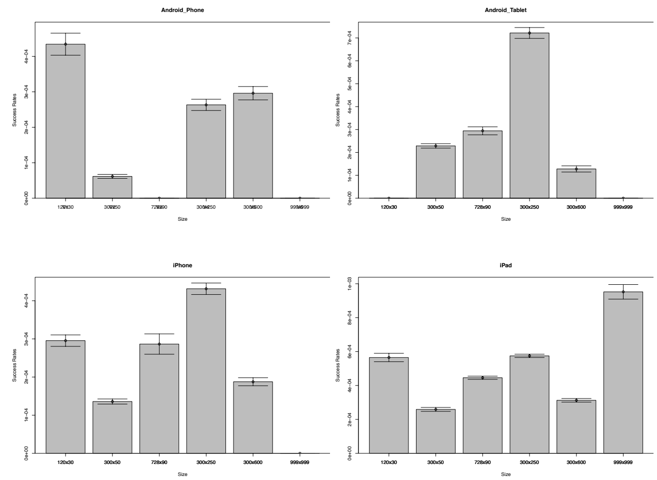

Figure 4: Success rates via the naive estimator. The top left plot is for Android phone, the top right one is for Android tablet, the bottom left one is for iPhone, and the bottom right one is for iPad. The x-axis shows various ad sizes (from left to right): 120×30, 300×250,728×90,300×250, and 300×600.

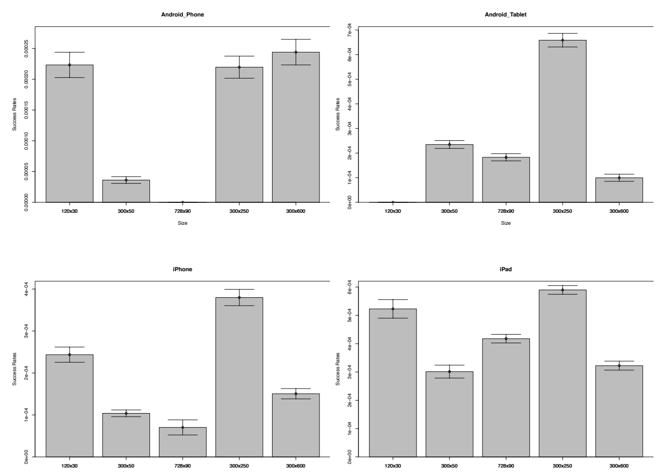

Figure 5: Success rates via our causal estimator. The top left plot is for Android phone, the top right one is for Android tablet, the bottom left one is for iPhone, and the bottom right one is for iPad.

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