Ad Blocking and Counter-Ad Blocking: Analysis of Online Ad Blocker Usage

Emergent Research Forum papers

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Abstract

Compared with online advertising industry, there is an even faster increase of ad blocker usage, which influence badly on publishers' and advertisers' business. Thus more and more companies initialize their counter-ad blocking strategies, in which customers choose to either disable their ad blockers or leave without seeing the content. There are also companies which abandon their counter-ad blocking strategies after conducting them for a while due to insufficient understanding of users' ad blocking behavior. In this study, we employed a quasi-experiment framework and collected a large-size data with the cooperation with Forbes Media. We aim to identify factors influencing ad blocker usage. Furthermore, we will model the interaction effects among user profile, online behavior patterns, device features on ad blocker usage propensity. Our study contributes the literature of understanding ad blocker usage by evaluating those principles using big amount of real-world data.

Keywords

online advertising, big data analytics, ad avoidance, ad blocker

Introduction

Digital technologies and the Internet have dramatically changed the content publishing industry whose major product is information goods. Most content in the internet is free to read and the publishers make profits through digital advertising. There is a striking growth of online advertising industry. According to reports of Interactive Advertising Bureau (IAB), online display advertising has emerged as the largest medium after surpassing TV broadcast advertising since 2013 (IAB 2014). The revenue of digital advertising in 2015 reached to 59.6 billion dollars in United States, 20.4% higher than in 2014 (IAB 2016). Online advertising aims at increasing sales by making viewers to notice their advertised products when they are viewing the publishers' content, so as to entice them to buying the products (Danaher and Mullarkey 2003). Typically, there are three basic stakeholders in online advertising market, i.e., readers, publishers and advertisers. A publisher integrates ads into its online content. An advertiser provides the ads and pay publishers for displaying the ads. Readers are the consumers of the content and the ads.

However, ad blockers have gained wide usage rapidly. An ad blocker is a tool, most likely a browser plugin, to remove ads while a user is reading online content. As a result, the advertisers fail to make the marketing via online ads and publisher suffers from the decrease of online ads revenue. According to a 2015 report by PageFair on ad blocking, the number of ad blocker users has increased steadily by 41% year over year and ad blocking is estimated to strip about 1/3 of the revenue of digital advertising in 2015. (PageFair 2015 Report).

To address this, nowadays more and more online publishers launch their anti-ad blocker project, for example, RateMyProfessor, Wired, Forbes, and Digiday. By analyzing JavaScript codes on the websites, Rafique et al. (2016) found that anti-adblocking scripts were used by 16.3% of the 1,000 domains they crawled. They adapted similar strategies: they ban users who try to view their content with active ad blockers. If the website detects a user has an ad blocker, it would pop up a message to request the user to turn off or at least pause the ad blocker, i.e. whitelist, in order to view the content. If the user rejects to whitelist, s/he would be forbidden to access the content they intend to view.

As "counter-ad blocking wall" prevents users to read the content without ads, it can result in loss of readers and the web traffic to their websites. Thus some publishers abandon their counter-ad blocking strategies after conducting for a while. Some other publishers decide to provide incentive to encourage customers to whitelist them, for example, a "less-ads" promise. Lacking of good solutions, both publishers and advertisers have great interests in understanding the usage of ad blockers and the impact of "counter-ad blocking wall" to user behaviors, however, which is an open question.

Thanks to the technological advancements in digital advertising, publishers and advertisers can analyze consumers' digital footprints at a more granular level, at a large scale easily. In this study, we employed a quasi-experiment framework in cooperation with Forbes Media and collected a large size of real-life data. With the abundant behavior data, we can study customers' usage of ad blockers and activities detailed. For example, we are able to measure environmental factors (like device, traffic origins) of each web visit, which is infeasible to obtain through traditional survey methods. The research questions we aim to answer in this study are the following:

1. What are the factors influencing the usage of ad blockers?

2. What is interaction effects among user profile, browsing behavior patterns, device features on ad blocker usage propensity?

3. Publishers want more ad blocker users to be converted to non-ad blocker users through their anti-ad blocking strategies. But is it effective? What are user behavior changes after the websites' anti-ad blocking strategies?

In this paper, we present some preliminary results of studying the first question. To the best of our knowledge, this is the first empirical study of ad blocking based on publishers' real-life data. The insights from this study will help publishers and advertisers to their decision making process about counter-ad blocking strategies.

Related Work

Our study builds on the following two streams of research.

Ad Avoidance

Ad avoidance can be defined as "all actions by media users that differentially reduce exposure to ad content" (Speck and Elliott, 1997). They conducted a national survey of 946 adults to examine the predictors of ad avoidance in magazines, newspapers, radio, and television in 1997. They found that ad avoidance is related to some demographic features of users. Their studies provide ground work for the following research of ad avoidance. After that, researchers found ad avoidance in online environment is quite different. Compared with traditional advertising, online customers are more goal-oriented or task-oriented (Li et al. 2002). Second, Internet users concern about the speed of data access and retrieval. Third, the Internet involves more two-way interactivity actions from consumers (Cho and Cheon 2004). By analyzing consumer activities through online services, Cho and Cheon (2004) developed and tested a model that explains why people avoid advertising on the Internet. They found that perceived goal impediment, perceived ad clutter, and prior negative experiences can explain avoidance of ads on the Internet. Recently Seyedghorban et al. (2016) replicated and extended Cho and Cheon's advertising avoidance model and their extension of the study suggested that user mode moderates the relationship identified in the original model. Tang et al. (2013) studied the effects of ad design on consumers' behavioral response on different ad avoidance approaches. There are three types of ad avoidance (behavioral, cognitive, and mechanical) and ad blocker usage belongs to the mechanical type (Seyedghorban et al. 2016). Compared with other two approaches of ad avoidance, the usage of ad blocker is more like a long-term preference instead of temporal choice. Thus ad blocker usage cost more benefits of publishers and advertisers.

However, all of the above work used survey method to measure the user attitude and intention of ad avoidance. Compared with their work, our study is based on the analysis of large-size real-life data, which provides more details on user behaviors. Also, our study will provide empirical rigorousness for and extend the previous theories of ad avoidance. In addition, we plan to study the interactions among factors and study the behavior changes after the websites' anti-ad blocking strategies.

Ad Blocking and Counter-Ad Blocking

The predominant Internet ad blocking tool is Adblock Plus, which is a free extension for various browsers. Wills and Uzunoglu (2016) found that it has an 85% share of the ad blocking tool market based on App stores download times. A mainstream research of ad blocking and counter-ad blocking is the mechanism. Rafique et al. (2016) and Nithyanand et al. (2016) studied the current technology of ad blocking and counter-ad blocking. They focus on the ad blocking mechanism, i.e., how to technically block internet ads and industry practices of ad blocking. In contrast, our work focuses on understanding the factors impacting on ad blocker usage and the behaviors.

Online users block ads for various kinds of reasons. Singh and Potdar (2009) summarized the main reasons used by internet users to block online ads. They listed 7 main reasons such as preventing malware infection, psychological impacts, intrusiveness and misleading users. However, most of the reasons were obtained from surveys and they do not study characteristics of user demographics and the environmental factors, such as operating systems and traffic sources. In addition, most of the factors summarized by Singh and Potdar (2009) are perceived attitude and intention of users. The factors which we study in this paper are objective factors and easy to acquire, which publishers and advertisers can make decision more conveniently according to.

Data

Our data set is collected in collaboration with Forbes Media, a large online publisher. We employed a quasi-experiment method that avoids the self-selection and other treatment selection biases. Forbes blocks ad-blocker users to access the site. We collected the data for one week in August 2016. During the experiment period, we use a JavaScript program to detect the existence of ad blockers. All users who enter the website for the first time would be forwarded to a welcome page. For non-ad blocker users, they can view the content directly after the welcome page. If the website detects an ad-blocker, the welcome page will pop up a message "Adblock Detected" to inform the current user to pause or turn off the ad blocker in order to view the content of that website. Once an ad blocker is disabled, users would receive a message "Thank you" and they are promised the "Adlight experience" for 30 days, with fewer ads, and ads that typically load faster. If a user rejects to disable the ad blocker, s/he will be prevented from viewing any online content in that website.

The data includes two parts: (1) user profile data, (2) user behavior data. The user profile data includes user ID, gender, age, location, interest, and whether s/he is an ad blocker user. The behavior data is browsing sessions. It includes session ID, device type, traffic source (referred URL, search engine, social media), page/session duration and all behaviors on pages (text selection, video play, scroll, etc.). The data set has 26,777,221 sessions, 21,889,698 unique users. Users comprise ad blocker user and non-ad blocker users.

Preliminary Results

The study was designed to help in understanding which customer groups are likely to use ad blockers. The first phase is to examine the relationship between each studied factor and the usage of ad blockers. It is designed to partially examine the ad avoidance models mentioned before (Cho and Cheon 2004; Seyedghorban et al. 2016).

We have obtained some preliminary findings in the first phase. For example, figure 1 plots the proportion of users by gender. The numbers inside the pie chart are the percentage of female users and male users. The numbers outside the pie chart are the corresponding ad blocker rate for female users and male users.

More readers of Forbes are male users (66%). We can also see that 5.8% of male customers use ad blockers while that rate is 2.5% for female customers. We use odds ratios (OR) to measure the effect size between gender and ad blocker usage. OR is a measure of association between an exposure and an outcome. In our case, the exposure is being male (instead of being female) and the outcome is using ad blockers. After calculation, the OR is 2.3. It shows that male users have 2.3 times odds to use ad blockers compared with female users. Clearly there is a strong association between gender and ad blocker usage. The p value of chi-square test is 0.000 due to the sensitivity of chi-square to sample size, which may make a weak relationship statistically significant if the sample is large enough (Barrett 2007; Steiger 2007). We will not consider the significance test in our group-level analysis since that our sample size is very large (Beauducel and Wittmann 2005; Fan and Sivo 2005).

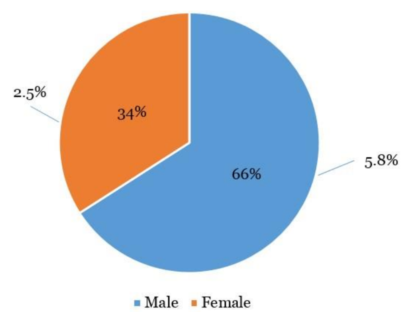

Figure 1: Gender Distribution

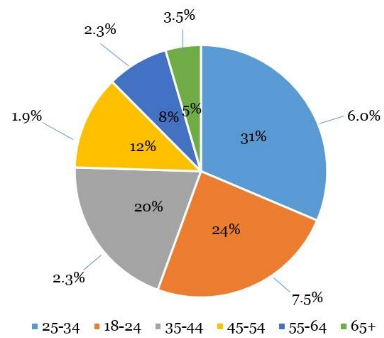

Figure 2: Age Distribution

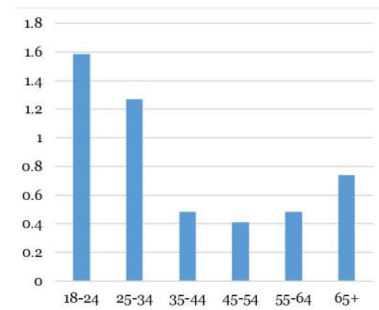

Figure 3: Odds Ratios of Age

Figure 2 plots the proportion of user by age and we can see that the largest age group is 25-34. Figure 3 plots the odds ratios of ad blocker rate for different age groups compared with the overall ad blocker average rate. We find that people who are younger than 34 are more likely to use ad blockers. The ad blocker rate is 6.0% and 7.5% for users who are within 25-34 and 18-24 groups respectively. Also the odds ratios of two age groups are at least 50% larger than the other age groups. The possible reason is that younger users are more strongly opinionated (Aaker and Bruzzeone 1985). They found that people under 40 exhibit stronger opinions about a selection of ads, and that younger people tend to be more irritated by certain product ads categories. Therefore, the ads may be perceived to be more annoying to young people. Another possible reason is that young people are more familiar with computer technology. And they know well how to install ad blocker plugins or software. As time flies, more and more young users will replace old users who are not familiar with technology. It explains why the rate of ad blocker usage is keeping growing quickly. An interesting finding is that we found customers who older 65 have a slight higher usage of ad blockers compared with mid-age customers. A possible reason is that the influence of age to ad blocker usage is interacted with another variable, for example, age. Maybe most of the users older than 65 of Forbes are male instead of female. And thus with that curiosity about aged customers, we will study the interaction between age and other factors in the second phase.

Future Research Agenda

The second phase is to study the interaction effects among user profile, browsing behavior patterns, device features on ad blocker usage propensity. Besides the interaction, dominance analysis (Budescu 1993) will be used for comparing the relative importance of predictors on ad blocker usage propensity, which is missing in previous study. In this phase, we will partially examine and extend the previous ad avoidance theories in the Internet (Cho and Cheon 2004; Seyedghorban et al. 2016). We can measure how customers are goal-oriented based on their page dwell time and scroll behavior. Strong goal-oriented customers are assumed to read faster and scroll more frequently.

The third phase is to study the changes of user behavior after counter-ad blocking strategies being implemented. We found that on average non-ad blocker users read more webpages per session than ad blocker users who chose to turn off their ad blockers. This indicates Adlight service may increase user engagement. In the further, we will investigate more behavioral factors, such as session duration and user actions. To the best of our knowledge, identifying ad blocker users with real-life data is an open question and that has not been studied before. Our work will assist publishers and advertisers in decision making processes about counter-ad blocking strategies.

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REFERENCES

Aaker, D. A., and Bruzzone, D. E. 1985. "Causes of Irritation in Advertising," *Journal of Advertising (49:2)*, pp. 47-57

Beauducel, A., and Wittmann, W. 2005. "Simulation Study on Fit Indices in Confirmatory Factor Analysis Based on Data with Slightly Distorted Simple Structure," *Structural Equation Modeling (12:1),* pp. 41-75

Barrett, P. 2007. "Structural Equation Modelling: Adjudging Model Fit," *Personality and Individual Differences (42:5)*. pp. 815-824

Budescu, D. V. 1993. "Dominance Analysis: A New Approach to the Problem of Relative Importance of Predictors in Multiple Regression", *Psychological Bulletin (114:3)*, pp. 542-551.

Cho, C., and Cheon, H. J. 2004. "Why Do People Avoid Advertising on the Internet," *Journal of Advertising (33:4)*, pp. 89-97.

Danaher, P. J., and Mullarkey, G. 2003. "Factors Affecting Online Advertising Recall: A Study of Students," *Journal of Advertising Research (43:03)*, pp. 252-267.

Fan, X., and Sivo, S. A. 2005. "Sensitivity of Fit Indices to Misspecified Structural or Measurement Model Components: Rationale of Two-Index Strategy Revisited", *Structural Equation Modeling (12:3)*. pp. 343-367

IAB 2014, "Digital Ad Revenue Skyrockets, But Still Lags TV," *Retrieved from* http://blogs.wsj.com/cmo/2014/04/10/internet-ad-revenues-iab/

IAB 2016, "Digital Ad Spending Surges to Record High as Mobile and Social Grow More than 50%," *Retrieved from* http://adage.com/article/digital/iab-digital-advertising-generated-60-billion-2016/303650/

Li, H., Edwards, S. M., and Lee, J-H. 2002. "Measuring the Intrusiveness of Advertisements: Scale Development and Validation," *Journal of Advertising (31:2)*, pp. 37-47.

Nithyanand, R., Khattak, S., et al. 2016. "Adblocking and Counter-Blocking: A Slice of the Arms Race," *the 6th USENIX Workshop on Free and Open Communications on the Internet*, Austin, TX

PageFair and Adobe 2015 Ad Blocking Report, *Retrieved From* https://downloads.pagefair.com/wp-content/uploads/2016/05/2015_report-the_cost_of_ad_blocking.pdf

Rafique, M. Z., Goethem, T. V., Joosen, W., Huygens, and Nikiforakis, N. 2016. "It's Free for a Reason: Exploring the Ecosystem of Free Live Streaming Services," *The Network and Distributed System Security Symposim*, San Diego, CA

Singh, A. K., and Potdar, V. 2009. "Blocking Online Advertising – A State of the Art," *IEEE International Conference on Industrial Technology*, Gippsland, VIC, pp. 1-10.

Seyedghorban, Z., Tahernejad, H., and Matanda, MJ. 2016. "Reinquiry into Advertising Avoidance on the Internet: A Conceptual Replication and Extension," *Journal of Advertising (45:1),* pp. 120-129

Speck, P. S., and Elliott, M. T. 1997. "Predictors of Advertising Avoidance in Print and Broadcast Media," *Journal of Advertising (26:3)*, pp. 61-76

Steiger, J. H. 2007. "Understanding the Limitations of Global Fit Assessment in Structural Equation Modeling," *Personality and Individual Differences (42:5)*, pp. 893-898.

Tang, J., Zhang, P., and Wu, P. F. 2013. "Passive or Active: Understanding Consumers' Behavioral Responses to Online Advertising," *PACIS 2013 Proceedings*, 188.

Wills, C. E., and Uzunoglu, D. C. 2016. "What Ad Blockers Are (and Are Not) Doing," *the 4th IEEE Workshop on Hot Topics in Web Systems and Technologies*, Washing D.C., USA, pp. 72-77.