

Internet advertising and ad-blocking software

A game theoretic perspective

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Abstract

We propose two models - a simultaneous game and a sequential game with imperfect information - for the topical conundrum of Internet advertising and ad-blocking software. We discuss the implications of the models and analyze them to arrive at the equilibrium profiles.

1 Introduction

The Internet is a complex collection of various agents, each involved in a multitude of complicated interactions involving numerous services. More often than not, there is some kind of payment model involved in such interactions. From a general consumer's perspective, interactions are of an explicit financial nature, for example e-commerce services including B2B (Alibaba [1]), B2C or online retail (Amazon, Tmall) and C2C (Craigslist, eBay, Taobao). However, a significant chunk of revenue flow is involved in the latent field of Internet advertising [2]. Major Internet giants like Google derive substantial share of their revenue from Internet advertising [3]. Most of the times, the delivery method and the background processing of such advertisements give rise to various issues for the users. Users are mainly bothered by the distraction and disruption in their normal browsing experience [4]. More and more, users are starting to realize the privacy concerns associated with curated content and tailored ads [5]. Increasing awareness of the downsides associated with Internet advertisements has led to a rise in the usage of various off-the-shelf ad-blocking software available widely. Such software are available in proprietary (Adblock Plus) and open-source (uBlock) forms. Recently, major hardware and software giants like Microsoft [6], Apple [7] and Opera [8] have lent their support to this growing voice of concern by either providing ad-blocking tools on their platforms or by supporting third party applications ad-blocking. A key outcome of widespread usage of ad-blocking software is its devastating effect on original content creators and websites, which depend on Internet advertisements for their livelihood [9]. The dynamics of this issue are further complicated by introduction of options like 'Do Not Track' (a way for the users to signal their preference of not revealing their personal data to trackers in ads) [10] and subscription based models to remove ads [11, 12].

In this paper, we will build game theoretic models of the setting of Internet advertising and ad-blocking software. We will then analyze these models to get to the equilibrium profiles.

2 Simultaneous game

As discussed in [13], this setting can be modelled in a way similar to a simultaneous n-player *Prisoners' Dilemma* game. However, [13] do not mention a formulation of the game; they just mention the constraints that the game will follow. Inspired by a variant of the *Stag Hunt* game in [14, p. 28], we now present the game model.

2.1 Game model

The model is a simultaneous game with complete information. We make some simplifying assumptions in this setting. We consider the interaction between n users (and implicitly, the Internet). Thus the set of players in this game is $U = \{u_1, \dots, u_n\}$. Each user u_i has two strategies $S_i = \{B, N\}$, with B corresponding to usage of ad-blocking software and N corresponding to not using ad-blocking software. The payoffs for various users depend on a key metric k . Essentially, k (where $0 < k < n$) is the *cutoff* on the number of users who use ad-blocking software, such that the Internet can absorb the financial damage caused by usage of ad-blocking software by m number of users, where $m \leq k$. Thus, if m is the number of users from u who are playing B is such that $m \leq k$, then every user will benefit by playing B instead of N . However, if $m > k$, then every user incurs significant loss compared to their previous state. They then prefer playing N over B , since they would have preferred an ad-free Internet and would like to do their part to revert it to its original position.

The payoff matrix for the users in u are represented as follows:

		u_{-i}	
		$m_{-i} < k$	$m_{-i} \geq k$
u_i	B	2	0
	N	1	-1

Here, u_{-i} refers to all the other players and m_{-i} refers to the number of players in $U \setminus \{u_i\}$ playing B . Note that this payoff matrix is similar to that of Prisoners' Dilemma. Also, the values are only indicative of the preference order, the exact values can be changed.

2.2 Analysis

In the model defined earlier, we now try to find the Nash equilibrium strategy profile. If $m < k$, then the best response of every user playing B will be to keep playing B , while best response of every player playing N will be to switch to B unilaterally. Thus in Nash equilibrium, $m \geq k$. Since we are dealing with an incremental situation where the m is slowly increasing, we will consider the case where $m = k$. In this case, no user playing B has a profitable deviation. Similarly, no user playing N will switch, since doing so will lead to monetization of the content. Hence, this is a Nash equilibrium profile. For all $m > k$, the

every player playing B will want to unilaterally deviate to N , since he gets better payoff. Thus the only Nash equilibrium profile is for $m = k$.

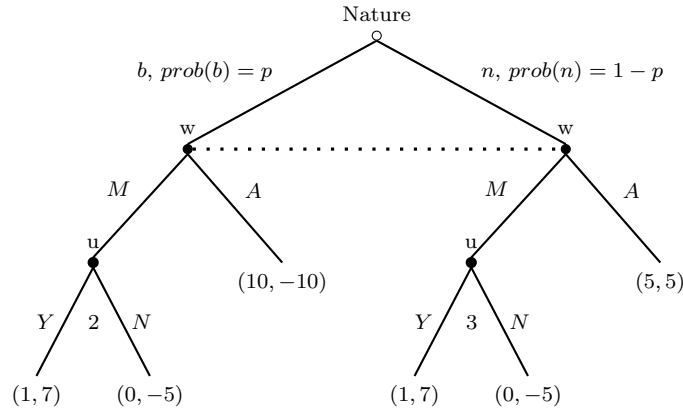
[13] note that such an equilibrium is bound to be achieved at some point of time, after which, the content creators will put subscription fees on their content.

3 Sequential game with imperfect information

A shortcoming of the model defined in the previous section is that it deals with bulk of the users and the equilibrium profile is coupled for the users. Another shortcoming in the model is that the user and the website play simultaneously. These are highly unrealistic assumptions. This situation will be better analyzed if we deal with the interaction of the website with a single user, with sequential information revelation. [15] consider a setting where the website w invests in technology to detect the presence of ad-blocking software on the user u 's device. They then proceed to analyze the subsequent game, with the assumption that it is costly to get such technology. The methods mentioned to detect ad-blocking software which are mentioned in [15] are quite easy and inexpensive to implement [16, 17]. While this does not undermine the need to include the cost of implementing such detection tools, a more important criterion to consider here is what is the confidence level with which the detection tool detects the use of ad-blocking software. We create a model which includes this uncertainty in this formulation.

3.1 Game model

We consider an interaction between the website w and the user u . The user u is of two types, either she uses ad-blocking software, giving her type b or she does not use any ad-blocking software, giving her type n . The website w has some detection software which tells it that the probability with which u is of type b is p (and $1 - p$ for type n). w then decides to either monetize the content (by playing M) or give ad-supported content for free (by playing A). If w plays A , the game ends. However, if w plays M , u either accepts (Y) or rejects (N) the subscription. An important and valid assumption is that u is aware of her type. The corresponding payoffs are written as below (payoffs for a particular terminal history ϕ are given in the form of $(v_u(\phi), v_w(\phi))$):



In case u has ad-blocking software (u is of type b), w 's first preference is to monetize (play M) and that u accept (u play Y) subsequently, second preference is to monetize (play M) and that u reject (u play N) subsequently. w prefers giving ad-supported content the last in this case, since u is blocking the ads and w will get no revenue. In case u does not have ad-blocking software (u is of type n), w 's first preference is to monetize the content (play M) and that u accept (u play Y) subsequently. The second preferred outcome for w is to give ad-supported content (playing A), since u is not blocking the ads. However, in this case, w prefers monetizing (play M) and that u reject (u play N) subsequently, the last. The payoffs in the game tree correspond to these constraints.

The exact value of z depends on the user's preferences. Also, the values are only indicative of the preference order, the exact values can be changed. However, the payoffs in case w plays A are do matter, since they determine the outcome. For u , the least preferred outcome is to not view the content (play N) in the case that w has monetized it (played M). The second least preferred outcome is to pay and view the monetized content (play Y after w played M). The payoff on consuming ad-supported content depend on the type of the user. A b type user gets much better payoff on watching ad-supported content as compared to an n type user. However, both these payoffs will be higher as compared to paying for content.

3.2 Analysis

We use the concept of Perfect Bayesian Equilibrium (PBE) in this setting. Since a PBE profile is sequentially rational, u will play play Y in subgames 2 and 3. Thus the whole game now reduces to a single player game for w . In this game, w gets no signal with which it can update its belief p about u . Hence, the expected payoff is calculated using the belief p . Hence, $v_w(M) = 7p + 7(1 - p) = 7$ and $v_w(A) = 10p + 5(1 - p) = 5 + 5p$. Clearly, A gives better payoff for $p < \frac{2}{5}$ and M gives better payoff for $p > \frac{2}{5}$. Thus, there are different Perfect Bayesian Equilibria, depending on the confidence level that w has about u 's ad-blocking habits: (Y, A) for belief level $p \leq \frac{2}{5}$ and (Y, M) for belief level $p \geq \frac{2}{5}$.

4 Conclusion

The simultaneous model for the situation gives rise to an *equilibrium point*, which is a number of users using ad-blocking software. This is a critical point, beyond which ramifications of ad-blocking software will be immense. On the other hand, the sequential model gives rise to the equilibria outcome where monetizing is beneficial if the user is an ad-blocking software user with high probability and giving ad-supported content is beneficial if the user is an ad-blocking software user with low probability. There are various assumptions that we made in the sequential model, mostly relating to the payoffs of the website and the user, which can be relaxed. For example, we can contrast the payoffs assigned to the user on paying for content compared to consuming ad-supported content to get a more comprehensive model. A more detailed study with simulations of the topic can prove to be immensely helpful in helping shape the public policy, since our model are based on sound technical reasons.

References

- [1] B2b ecommerce market worth \$6.7 trillion by 2020: Alibaba & china the front-runners. <http://www.forbes.com/sites/sarwantsingh/2014/11/06/b2b-ecommerce-market-worth-6-7-trillion-by-2020>. Accessed: 2016-04-10.
- [2] Internet advertising. <http://www.pwc.com/gx/en/industries/entertainment-media/outlook/segment-insights/internet-advertising.html>. Accessed: 2016-04-10.
- [3] How does google make the big bucks? an infographic answer. <http://www.wired.com/2011/07/google-revenue-sources/>. Accessed: 2016-04-10.
- [4] Chang-Hoan Cho and University of Texas at Austin) is an as. Why do people avoid advertising on the internet? *Journal of advertising*, 33(4):89–97, 2004.
- [5] For online privacy, click here. <http://www.nytimes.com/2012/01/20/business/media/the-push-for-online-privacy-advertising.html>. Accessed: 2016-04-10.
- [6] Microsoft edge browser to support ad-blocking features. <http://gadgets.ndtv.com/apps/news/microsoft-edge-browser-to-get-built-in-ad-blocking-features-820213>. Accessed: 2016-04-10.
- [7] Apple ios 9 ad-blocking explained (and why it’s a bad move). <http://www.pcmag.com/article2/0,2817,2485827,00.asp>. Accessed: 2016-04-10.
- [8] Introducing native ad-blocking feature for faster browsing). <http://www.opera.com/blogs/desktop/2016/03/native-ad-blocking-feature-opera-for-computers/>. Accessed: 2016-04-10.
- [9] Why ad blocking is devastating to the sites you love. <http://arstechnica.com/business/2010/03/why-ad-blocking-is-devastating-to-the-sites-you-love/>. Accessed: 2016-04-10.
- [10] Protecting consumer privacy in an era of rapid change: A proposed framework for businesses and policymakers. http://donottrack.us/docs/FTC_Privacy_Comment_Stanford.pdf. Accessed: 2016-04-10.
- [11] Google contributor. http://donottrack.us/docs/FTC_Privacy_Comment_Stanford.pdf<https://www.google.com/contributor/>. Accessed: 2016-04-10.
- [12] Joacim Taag. Paying to remove advertisements. *Information Economics and Policy*, 21:245–252, 2009.
- [13] Ad-blocking software and game theory. <https://blogs.cornell.edu/info2040/2014/09/30/ad-blocking-software-and-game-theory/>. Accessed: 2016-04-10.

- [14] Martin J Osborne and Ariel Rubinstein. *A course in game theory*. MIT press, 1994.
- [15] Nevena Vratonjic, Mohammad Hossein Manshaei, Jens Grossklags, and Jean-Pierre Hubaux. Ad-blocking games: Monetizing online content under the threat of ad avoidance. In *WEIS*, 2012.
- [16] How to block adblock. https://thepcspy.com/read/how_to_block_adblock/. Accessed: 2016-04-10.
- [17] Detecting ad blockers on your website the easy way. <http://broadstreetads.com/blog/detect-ad-blocker/>. Accessed: 2016-04-10.