Anti-Ad Blocking Strategy: Measuring its True Impact

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Presenter – Deepak Pai (Adobe)
Outline

- What is Ad-blocking?
- What is Anti-ad blocking?
- What is the research problem?
- Method
- Solution
- Evaluation
Online Advertisements
Meet the Blocker!

AdBlock
Ad-Blocking is on a Rise

- **198 million** active ad-block users globally as on June'15
- Ad blocking **grew by 41%** globally in 2014-15.
- US ad blocking **grew by 48%** to reach 45 million users
- UK ad blocking **grew by 82%** to reach 12 million users

Source: The cost of ad blocking, PageFair and Adobe 2015 ad blocking report
Effect of Ad-Blocking on:

**Publisher**
Ad revenue loss, the main source of income for most of them

**User**
Threat to existence of favorite sites and free internet content

**Advertiser**
Potential views on ads get limited

- Resources like bandwidth are still costing money
- The estimated loss of global revenue in 2015 was $21.8B

Source: The cost of ad blocking, PageFair and Adobe 2015 ad blocking report
What is the response?

Enter Anti-ad Blocking Actions
We’re committed to hosting safe ads and respecting your privacy.

To keep reading, please disable your ad blocker.
The Reactions...

**FINANCIAL TIMES**

Axel Springer says it is winning fight against adblockers

Bild readers stop blocking adverts when asked to buy subscription

![Image](image_url)

**Would switch off ad blocker if requested by site to access content**

<table>
<thead>
<tr>
<th>Type of Access</th>
<th>All</th>
<th>18-24s</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Net&quot; would switch off</td>
<td>54%</td>
<td>73%</td>
</tr>
<tr>
<td>Only on favourite/frequently used sites</td>
<td>31%</td>
<td>46%</td>
</tr>
<tr>
<td>On some websites</td>
<td>19%</td>
<td>26%</td>
</tr>
<tr>
<td>On all sites</td>
<td>3%</td>
<td>1%</td>
</tr>
</tbody>
</table>

**Source:** Would you switch off your ad blocker? (IAB)
A Hit on traffic.. Drop in Alexa Rankings

- Denial of access to ad blockers
  - Ranking based on reach and page view calculated daily.

Source: Sites that block ad-blockers seem to be suffering (The Stack)
Research Question

Context: Anti-ad blocking actions are implemented site-wide

All adblockers in treatment group
(Every adblock user inflicted by action)

Questions:

a) How to measure effectiveness of Anti-ad blocking actions?

b) How effectiveness varies by different ad blocking tendencies?
True Effectiveness

Measurement is challenging

- Any site-wide action suffers from lack of natural control group (not subjected to action)
- Before – After measure, widely used, subject to sampling bias due to group differences
- Choice of time period for comparison contributes to sampling bias
- Difference in differences (DiD) could potentially be used
  - But, which group(s) to use as control ??
  - Data from other comparable websites are not forthcoming !
Our Approach

- Ex post, that is, uses only past, observational data
  - without running new, costly experiments.
- Allows endogenous selection of the control group from the available data, going back in time.
  - Ad blockers from a previous time
  - (Multiple experiments to find the appropriate control group)
- Allows endogenous selection of clusters of visitors within the DiD framework
  - recognizing heterogeneity in ad blocking tendencies
- Shows to quantify the effect of anti-ad blocking action the Negative Binomial regression model performs better than Poisson regression.
Data

- Unnamed online-only publisher
- Data span three days after anti-ad blocking action
- Prior to action two months of data are available
- Hit level data of clicks
- Aggregate data of outcome metrics like pageviews, time spent,

22,000 users
Featuring: Features

<table>
<thead>
<tr>
<th>Hit Level Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Content Tags (10 major)</td>
</tr>
<tr>
<td>Browser (5 major)</td>
</tr>
<tr>
<td>Geolocation</td>
</tr>
<tr>
<td>Script Versions</td>
</tr>
<tr>
<td>Total Time Spent</td>
</tr>
<tr>
<td>User page tag sequence</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>User Level Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency of each tag in user sequence</td>
</tr>
<tr>
<td>Time spent on Ti</td>
</tr>
<tr>
<td>Freq(Ti)</td>
</tr>
<tr>
<td>Capture co-occurrence of tags in page sequence</td>
</tr>
<tr>
<td>Bigrams and Trigrams</td>
</tr>
<tr>
<td>How updated is the Browser / OS version</td>
</tr>
<tr>
<td>Browser &amp;OS</td>
</tr>
</tbody>
</table>

Engineered Features

- Empty data fields
- Web crawlers
- Mobile Devices

Unsupervised Scheme: Clustering

- K-means Clustering\(^{[1]}\)
  - Euclidean distance
  - Scaled data columns
  - Gave stable clusters
  - Interesting insights in user segmented clusters

Algorithm – at cluster level

Time series of metrics, treatment date ($D$)

Choose $d_1, d_2$ (number of days)
Pre treatment: $[D - d_1, D)$,
Post treatment: $(D, D + d_2)$

Choose $k$, for control:
$[D - 7k - d_1, D - 7k) \cup$ 
$(D - 7k, D - 7k + d_2)$

Select the best $k$
using Wilcoxon Test

Negative Binomial regression
on pre treatment and corres-
ponding control period

Output $d_1, d_2, k$ of model with min AIC

Figure 1: Summary of Effectiveness algorithm
Control group selection – at cluster level

Visitors broken down by these **Control Variables**

- Browser
- Operating system
- Sections
- Language
- First touch marketing channel
- Page depth

5 options for control group

Hypothesis testing using Wilcoxon signed rank test on all **control variables**

Control group which matches on maximum number of control variables picked
Evaluation

- No ground truth available to us
  - Implementation site-wide
- Even if A/B testing is done, the implementation of either A or B is site-wide
  - Produces differences with testing results
- We perform indirect evaluation
Model free evidence

Control_1 is our method.
Control_2 is where the control group is same duration as the treatment group, selected from recent preceding time.
Control_3 is where multiple equivalent durations are selected going back in time and then averaged.

Figure 3: Real Life Data - Aggregate Statistics for Adblockers
## Model based evidence

### Table 3: Real Life Data - Cluster level model for Visitors

<table>
<thead>
<tr>
<th>Visitors</th>
<th>Cluster1</th>
<th>Cluster2</th>
<th>Cluster3</th>
<th>Cluster4</th>
<th>Cluster5</th>
<th>Cluster6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.09**</td>
<td>4.80**</td>
<td>5.21**</td>
<td>3.10**</td>
<td>2.62**</td>
<td>3.61**</td>
</tr>
<tr>
<td>timeperiod</td>
<td>0.46**</td>
<td>0.49**</td>
<td>0.44**</td>
<td>0.07</td>
<td>0.50**</td>
<td>0.27**</td>
</tr>
<tr>
<td>grouptype</td>
<td>0.25**</td>
<td>0.17**</td>
<td>0.19**</td>
<td>-0.20**</td>
<td>-0.16**</td>
<td>0.02</td>
</tr>
<tr>
<td>dummy_1</td>
<td>-1.22**</td>
<td>-1.18**</td>
<td>-1.21**</td>
<td>-0.81**</td>
<td>-1.17**</td>
<td>-1.04**</td>
</tr>
<tr>
<td>dummy_2</td>
<td>-0.05</td>
<td>0.05</td>
<td>-0.05</td>
<td>0.24**</td>
<td>0.05</td>
<td>0.21**</td>
</tr>
<tr>
<td>weekend</td>
<td>-0.43**</td>
<td>-0.45**</td>
<td>-0.40**</td>
<td>-0.44**</td>
<td>-0.31**</td>
<td>-0.56**</td>
</tr>
<tr>
<td>t:tg</td>
<td>-0.59**</td>
<td>-0.66**</td>
<td>-0.56**</td>
<td>0.11</td>
<td>-0.54**</td>
<td>-0.40**</td>
</tr>
</tbody>
</table>

Significance codes: * < 0.05, ** < 0.01

### Table 4: Cluster Details

<table>
<thead>
<tr>
<th>Visitors</th>
<th>(% of total)</th>
<th>Visits (of total)</th>
<th>End of Article Reached (%)</th>
<th>Viewed 5 Pages (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster1</td>
<td>32.44</td>
<td>32.41</td>
<td>8.45</td>
<td>0.35</td>
</tr>
<tr>
<td>Cluster2</td>
<td>22.51</td>
<td>22.24</td>
<td>90.22</td>
<td>0.04</td>
</tr>
<tr>
<td>Cluster3</td>
<td>34.69</td>
<td>34.63</td>
<td>11.47</td>
<td>0</td>
</tr>
<tr>
<td>Cluster4</td>
<td>2.18</td>
<td>2.15</td>
<td>92.72</td>
<td>29.17</td>
</tr>
<tr>
<td>Cluster5</td>
<td>1.94</td>
<td>1.90</td>
<td>56.52</td>
<td>0.56</td>
</tr>
<tr>
<td>Cluster6</td>
<td>6.24</td>
<td>6.66</td>
<td>26.57</td>
<td>1.56</td>
</tr>
</tbody>
</table>
Limitations and Future Work

- Do Direct Evaluation with suitable Data
- Extend analysis to other websites
- Compare actions across publishers
- Scrape tags from content
EXTRAS - EXTRAS - EXTRAS
Feature Buckets

Loyalty
- End of article reached
- Monthly user
- Visit number
- Total Hits

Interest
- Frequency of tags
- Avg. time per tag

Technology
- Browser Version
- OS version
- New/ Old
- Cookies enabled
- JavaScript Version

Geo-Segmentation
- Country
- Region
- City
Clustering Quality – Loyalty Set

- Number of clusters: Average Silhouette\(^2\) Width

\[
s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}
\]

\(a(i)\): average dissimilarity of \(i\) with all other data within the same cluster

\(b(i)\): lowest dissimilarity of \(i\) to any other cluster

Silhouette Score

Silhouette plot of (\(x = \text{km$\models$cluster, dist = dist(df)}\))

- Number of clusters: Average Silhouette\(^2\) Width

- Cluster Analysis

6 clusters \(C_i\)

1: 1201 | 0.35

2: 3764 | 0.81

3: 9979 | 0.76

4: 1067 | 0.29

5: 4208 | 0.45

6: 407 | 0.93

Average silhouette width: 0.67