

Figure 5: Page load time when visiting each of Alexa top 100 US websites under Content Analysis Only Configuration (CAOC), i.e., when TrackMeOrNot does not switch the browsing context. Overall, TrackMeOrNot imposed 39.56 ms (1.93%) extra load time on average compared to vanilla Chromium.

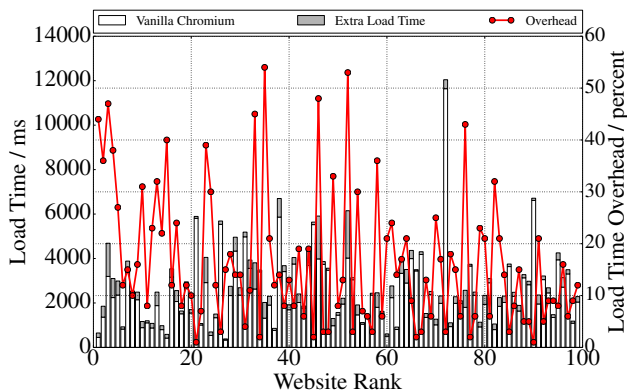


Figure 6: Page load time when visiting each of Alexa top 100 US websites under Browsing Context Switching Configuration (BCSC), i.e., when TrackMeOrNot performs switching to the persistent browsing context. Overall, TrackMeOrNot imposed 340.33 ms (16.40%) extra load time on average. Although this extra overhead may seem significant, this would not be easily observable to users in practice due to the natural inconsistent network latency.

reduce overhead in page load time introduced by TrackMeOrNot. We leave this implementation optimization as our future work.

5.2 Memory

TrackMeOrNot may require more memory in runtime because it includes 78 classification models (including a large vocabulary of features) in our implementation. In addition, if a browsing context switch is requested, TrackMeOrNot needs to create new renderer process which may also increase its memory usage. For these reasons, we measured the peak memory usage of TrackMeOrNot and vanilla chromium for 15 seconds in each of the 3 visits to a web page.

Figure 8 and Figure 9 show the peak memory usage of vanilla Chromium and the extra peak memory usage of TrackMeOrNot when visiting the main pages using Content Analysis Only Configuration (CAOC) and Browsing Context Switching Configuration (BCSC), respectively. The memory overhead is the ratio of extra peak memory usage of TrackMeOrNot to the peak memory usage of vanilla Chromium. For both configurations, the memory overheads are between -15% and 22%. The means are 3.06%

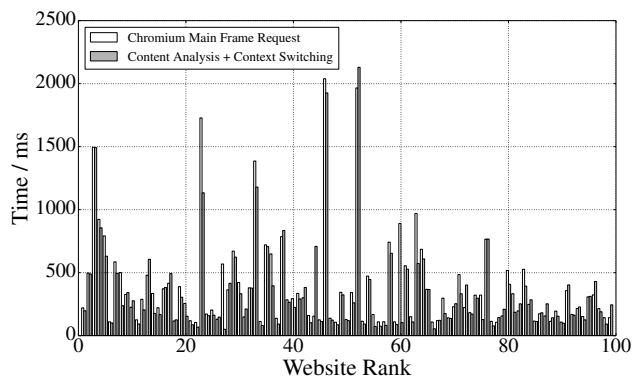


Figure 7: Main frame HTML source load time (marked as white boxes) v.s. extra page load time in TrackMeOrNot (marked as black boxes) when visiting each of Alexa top 100 US websites.

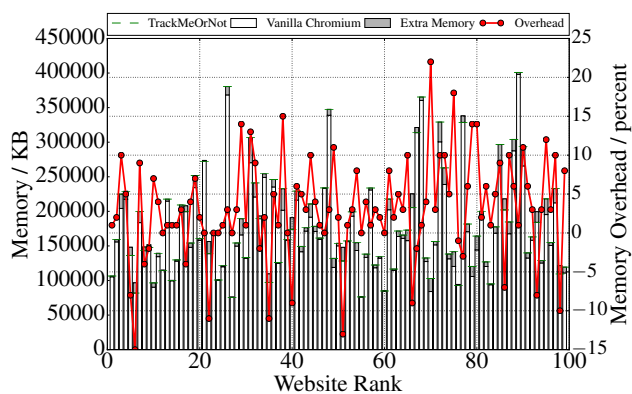


Figure 8: Peak memory usage when visiting each of Alexa top 100 US websites under Content Analysis Only Configuration (CAOC). TrackMeOrNot imposed 3.06% overhead on average.

(CAOC) and 1.68% (BCSC), respectively. We observe that sometimes TrackMeOrNot consumed less memory than vanilla Chromium, which might be attributed to that smaller dynamic contents were loaded when using TrackMeOrNot to visit those web pages. Similarly, the memory over consumed by TrackMeOrNot may also due to the dynamics of web contents. As a result, TrackMeOrNot did not significantly require more memory than the vanilla build.

6. ANTI-TRACKING EVALUATION

As is mentioned in §3, TrackMeOrNot allows users to specify unwanted page visits based on web content category. Our implementation of TrackMeOrNot includes 78 classifiers for categorizing the web pages that users visit. TrackMeOrNot compares the output of the classification models with user specified needs and switch a browsing session between different browsing contexts. In this section, we demonstrate how effectively TrackMeOrNot uses the classifiers to conceal users' privacy sensitive visits. In particular, we first describe our experimental design. Then, we evaluate how effectively the classifier satisfies user's privacy needs.

6.1 Experimental Design

To evaluate the effectiveness of TrackMeOrNot on hiding sensitive web browsing activities – such as browsing pornographic web pages and health related forums – we need to simulate a series of web page visits and then examine if TrackMeOrNot can accurately

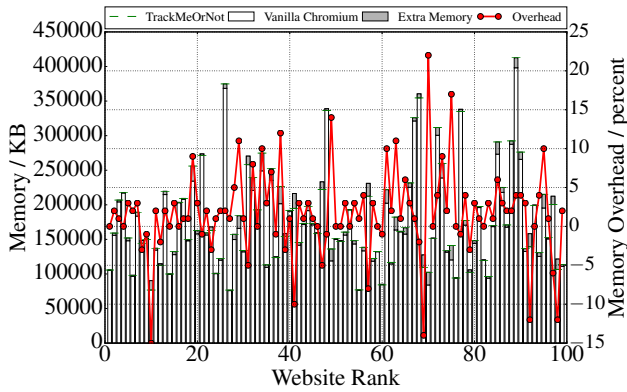


Figure 9: Peak memory usage when visiting each of Alexa top 100 US websites under Browsing Context Switching Configuration (BCSC). TrackMeOrNot imposed 1.68% overhead on average.

conceal user specified privacy sensitive visits when visiting these web pages. As a user may specify any category of visits as privacy sensitive browsing activities, we need a sequence of page visits that covers all spectrums of categories. We selected web pages that had not been used for training any classifier from the AOL data set discussed in §4 as our evaluation web page corpus, which contains 43,807 English web pages in 78 unique categories.

To examine the effectiveness of TrackMeOrNot on hiding privacy sensitive visits, we also need to know users’ needs to browsing privacy. In other words, we need to know the page categories in which a user is (or not) willing to disclose his or her visits to vendors. To obtain the users’ needs to browsing privacy, we conducted an online survey through Amazon Mechanical Turk. The survey was approved by the IRB of our institute. We presented all 78 categories to participants and asked them to choose the page categories in which they are not comfortable to disclose their visits. In addition, participants were asked to choose the page categories in which they are comfortable to share their visits. Ultimately, we collected 145 valid responses. The demographic distribution of the 145 subjects is shown in Table 1. Table 2 and Table 3 show the top categories of web pages that users specified as blacklist rules or whitelist rules, respectively. In other words, they represent the page categories on which users want to hide or disclose their browsing activities from or with online vendors. From our collected questionnaires, we found 14 participants who expressed strong privacy concern and did not want to share any of their visits with vendors. We also observed 2 participants who stated that they were not concerned with privacy and wanted to offer all of their footprints to vendors. Overall, we obtained 129 unique privacy needs from all the participants.

For each unique privacy need, we encode it by converting it into blacklist and whitelist rules as discussed in §3.2. We illustrate the number of blacklist and whitelist rules across 129 unique privacy needs in Figure 10. Note that, for those page categories that a user does not specify as “comfortable to reveal” or “reluctant to disclose”, we convert them into either whitelist rules or blacklist rules by assuming the users had specified *persistent* or *anonymous* as their fallback browsing context, respectively. Thus, we have two different rule sets across 129 unique privacy needs (see Figure 11 and Figure 13).

Including two special whitelist and blacklist rule pairs that indicate “do not disclose any visits” and “reveal all visits”, we configure TrackMeOrNot using the 256 whitelist and blacklist rule pairs shown in Figure 11 and Figure 13. Then, we simulate the visits to the aforementioned 43,807 web pages using TrackMeOrNot. We ex-

Table 1: Distribution of demographics of survey subjects.

| Age | 18-24 | 25-34 | 35-44 | 45-54 | 55+ |
|-----------|---------------------|--------|------------|--------------------|--------|
| | 8 | 58 | 34 | 29 | 16 |
| | 5.52% | 40.00% | 23.45% | 20.00% | 11.03% |
| Gender | Male | | Female | | |
| | 60 | | 85 | | |
| | 41.38% | | 58.62% | | |
| Education | High school or less | | Associates | Bachelor or higher | |
| | 32 | | 25 | 88 | |
| | 22.07% | | 17.24% | 60.69% | |

Table 2: The top-10 page categories in which users do not want to disclose their visits to vendors.

| Category | % of votes |
|--|------------|
| society/sex | 78.67 |
| finance | 58.67 |
| society/dating | 58.67 |
| health and fitness/disorders | 52.67 |
| society/crime | 51.33 |
| law, govt and politics/armed forces | 50.00 |
| law, govt and politics/legal issues | 50.00 |
| religion and spirituality | 47.33 |
| law, govt and politics/government | 47.33 |
| health and fitness/disease | 47.33 |
| law, govt and politics/law enforcement | 46.00 |

amine the accuracy of hiding blacklist visits and disclosing whitelist visits. In addition, we study the False Negative Rate (FNR) and False Positive Rate (FPR) of our TrackMeOrNot. Specifically, a page that needs to be browsed in an anonymous browsing context is a positive sample in our evaluation. The false negative rate is the ratio of number of false negatives (incorrectly predicted as negative) to the number of positives (including false negatives and true positives). The false positive rate is the ratio of number of false positives (incorrectly predicted as positive) to the number of negatives (including false positives and true negatives). The system would mistakenly disclose many privacy sensitive visits to vendors when the false negative rate is high. Similarly, the system may hide many visits that the user feels OK to share with vendors when the false positive rate is high. We present the evaluation results in the next subsection.

6.2 Evaluation Result

Figure 12 and Figure 14 show the performance of TrackMeOrNot in terms of accuracy, false positive rates and false negative rates for persistent and anonymous fallback tracking preferences, respectively. We observed that TrackMeOrNot achieved 0.86 accuracy in hiding and disclosing user visits on average for both persistent and anonymous fallback tracking preferences. The minimum accuracies were 0.69 and 0.74 for the two different settings, respectively, where the maximum accuracy was 1.00. The results indicate TrackMeOrNot can effectively cloak user specified privacy sensitive visits and disclose a certain amount of footprints regardless of the fallback browsing context.

We observed some interesting patterns of false positive rates and false negative rates in regards to the number of blacklist rules in the tracking preference. As is evident in Figure 12 and Figure 14, the false positive rates increased when a user specified more page categories as his or her blacklist rules. On the other side, we also observed the decrease in false negative rates as more categories were specified in blacklist. The reason behind these patterns are that with

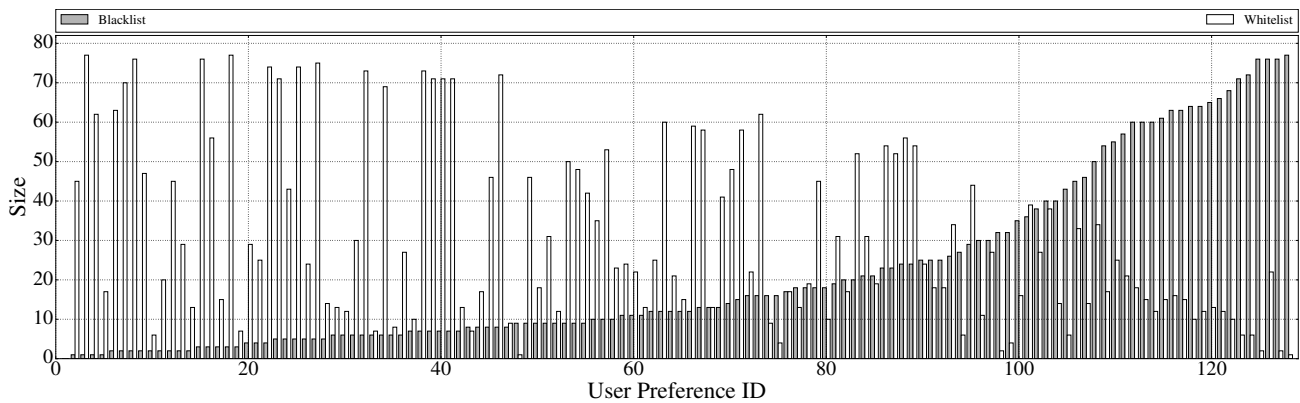


Figure 10: The number of whitelist and blacklist rules across 129 distinct privacy needs.

Table 3: The top-10 page categories in which users are comfortable to share their visits with vendors.

| Category | % of votes |
|------------------------|------------|
| arts and entertainment | 64.00 |
| food and drink | 54.00 |
| hobbies and interests | 50.67 |
| sports | 45.33 |
| pets | 45.33 |
| shopping | 44.00 |
| travel | 42.67 |
| home and garden | 42.67 |
| news | 42.00 |
| education | 39.33 |

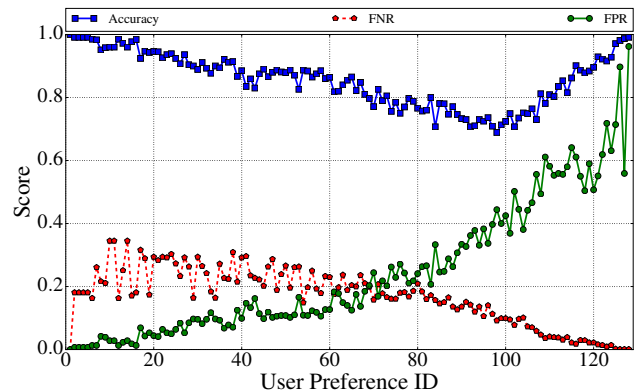


Figure 12: Evaluation results on 129 tracking preferences with persistent fallback browsing context.

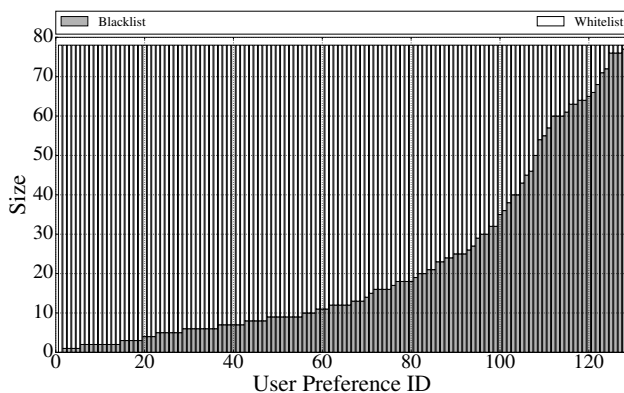


Figure 11: Tracking preferences using persistent fallback browsing context.

more categories that are specified as blacklist rules, TrackMeOrNot relies on more binary classifiers to examine blacklist visits, and consequently a web page is more likely to be classified as positive.

The average false negative rates of TrackMeOrNot were about 0.17 and 0.12 and average false positive rates were about 0.24 and 0.36 when using persistent and anonymous fallback browsing context, respectively. As is shown in Figure 12 and Figure 14, the false negative and false positive rates are complementary. For users concerned more with privacy than personalized user experience, they may configure TrackMeOrNot to achieve a low false negative rate and a high false positive rate by specifying more blacklist rules. In contrast, users may configure TrackMeOrNot with a high false negative rate but a low false positive rate by trading her or his need for privacy for better usability.

7. RELATED WORK

In this section, we summarize various tracking technologies and analyze existing anti-tracking mechanisms.

Defense against HTTP cookie tracking. HTTP cookie tracking is a stateful tracking technology. It stores in a user’s browser a piece of data (including a unique identifier) set by an online vendor while the user is browsing a website that contains the vendor’s content. The cookie is automatically sent to the vendor whenever the user visits a website that contains the vendor’s content in the future. It can be used to analyze the user’s web browsing behavior. Tracking cookies are widely adopted by advertising networks for the purpose of serving up “interest-based” or “behaviorally targeted” ads. To stop them from tracking a person’s surfing habits, companies and non-profit organizations (*e.g.* abine [1], NAI [12] and DAA [7]) implement a cookie opt-out mechanism which enables users to block and prevent the advertising network from installing future tracking cookies. A recent study demonstrates many drawbacks of this approach including poor usability and unreliability [28]. As an alternative approach, user self-help anti-tracking tools are developed and implemented [2, 8, 33]. They defend trackers by blocking HTTP requests to corresponding vendors. For example, Adblock plus [2] and Ghostery [8] impede HTTP requests to advertising networks, and thus browsers cannot report user footprints to the advertising networks. Both cookie opt-out and self-help anti-tracking tools are designed for defending HTTP cookie tracking. Considering a number of online vendors have been discovered using advanced technologies to track users [4], the effectiveness of these approaches wanes. In this paper, our proposed anti-tracking mechanism not

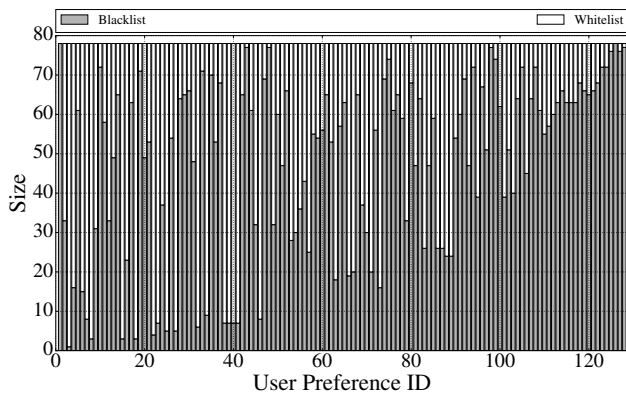


Figure 13: Tracking preferences using anonymous fallback browsing context.

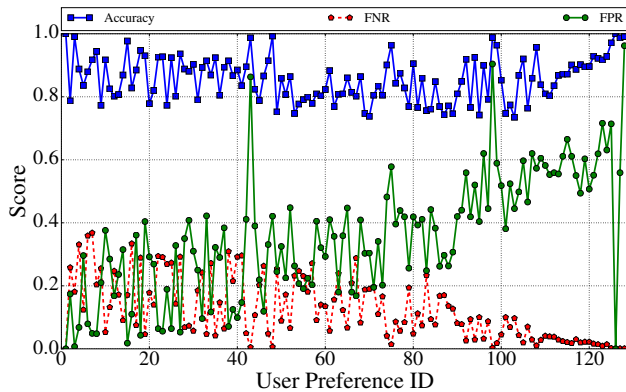


Figure 14: Evaluation results on 129 tracking preferences with anonymous fallback browsing context.

only can impede HTTP cookie tracking, but also defend many other previously known stateful tracking technologies, e.g., supercookies.

Defense against Supercookies. Apart from HTTP cookie tracking, another stateful tracking technology is supercookie tracking. Using this technology, online vendors can encode a globally unique identifier – supercookies – into a web browser. For example, vendors can abuse HTML5 local storage feature [9] or Flash Local Share Object [10] to store a unique identifier on a user’s hard drive for tracking the user’s digital footprints later on. To the best of our knowledge, there are only two approaches that can be adopted to impede such advanced tracking technologies. Private browsing [3] is one of these approaches, which does not store any local data that could be retrieved at a later date. Using private browsing, a user can therefore prevent vendors from using supercookies to track her surfing habits. Another defense against supercookies is TrackingFree [30], an anti-tracking browser that can impede supercookie tracking practice by partitioning a user’s visits into multiple isolation units based on URL. With this isolation, online vendors can still store supercookies but not correlate a user’s browsing activities across websites. One problem of this approach is that the system overhead linearly increases when a user browses more websites because TrackingFree maintains an isolated browser state for each unique website and OS needs to allocate a new memory space for each isolated browser state. Considering unexpected memory consumption can potentially jeopardize user experience, our proposed anti-tracking mechanism follows a lightweight design principle which constructs in-memory isolation units based on browser tabs. In addition, our proposed anti-tracking mechanism goes beyond the

mentioned two approaches by allowing users to instruct web browser to selectively block tracking activities. In addition to boosting profits, online vendors use information collected to personalize user experience. From the usability perspective, our anti-tracking mechanism therefore allows users to enjoy customized browsing experience without worrying about privacy invasion, while existing defense restrict data sharing completely and users cannot obtain any benefits from personalization.

Defense against Stateless Fingerprinting. Different from the stateful tracking technologies discussed above, a new class of web tracking technologies can use stateless information to identify users and report their surfing habits. This new class of tracking technologies neither stores nor retrieves data on user’s hard drive. Instead, it tracks a user by learning properties of her web browser and forming a unique or nearly unique identifier (*i.e.*, fingerprinting) [5]. To counteract such a tracking mechanism, anti-tracking technologies focus on making browser fingerprints non-deterministic across multiple browsing sessions [6, 18, 29]. This makes vendors difficult to link a user’s multiple visits. For example, Nikiforakis *et al.* designed and developed PriVaricator [29] that utilizes the power of browser fingerprint randomization to break vendors’ ability to connect the same fingerprint across multiple visits. Our anti-tracking mechanism is orthogonal to defense against stateless tracking. In this paper, we focus on building an anti-tracking mechanism that impedes stateful tracking based on user demand.

8. CONCLUSION

In this paper, we present TrackMeOrNot, a new anti-tracking mechanism that allows users to selectively sharing their online footprints with vendors for better user experience while shielding privacy sensitive browsing activities from online trackers. TrackMeOrNot provides a user with two browsing contexts – anonymous and persistent context – and a web browser can switch a user’s browsing session between the contexts based on user specified privacy needs. We demonstrate how a user can specify his or her privacy need and employ TrackMeOrNot to surf the web without disclosing privacy sensitive visits accordingly.

As TrackMeOrNot allows users to selectively disclose their online footprints, users can enjoy personalized online experience without worrying about privacy. From the perspective of online vendors, TrackMeOrNot may persuade users overly concerned with privacy to share footprints selectively for specific rewards, and vendors may use shared browsing habits to yield more profits.

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