Users' Fingerprinting Techniques from TCP Traffic

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Luca Vassio
Politecnico di Torino
luca.vassio@polito.it

Danilo Giordano
danilo.giordano@polito.it
Politecnico di Torino

Martino Trevisan
Politecnico di Torino
martino.trevisan@polito.it

Marco Mellia
Politecnico di Torino
marco.mellia@polito.it

Ana Paula Couto da Silva
Universidade Federal de Minas Gerais
ana.coutosilva@dcc.ufmg.br

ABSTRACT

Encryption at the application layer is often promoted to protect privacy, i.e., to prevent someone in the network from observing users' communications. In this work we explore how to build a profile for a target user by observing only the names of the services contacted during browsing, names that are still not encrypted and easily accessible from passive probes. Would it be possible to uniquely identify a target user from a large population that accesses the same network?

Aiming at verifying if and how this is possible, we propose and compare three methodologies to compute similarities between users' profiles. We use real data collected in networks, evaluate and discuss performance and the impact of quality of data being used. To this end, we propose a machine learning methodology to extract the services intentionally requested by users, which turn out to be important for the profiling purpose. Results show that the classification problem can be solved with good accuracy (up to 94%), provided some ingenuity is used to build the model.

CCS CONCEPTS

• **Networks** → **Network privacy and anonymity**; *Network measurement*; • **Security and privacy** → *Privacy protections*;

KEYWORDS

Passive Measurements, Machine Learning, Privacy, User Fingerprint, User Profiling.

1 INTRODUCTION

Privacy and user tracking are hot topics that impact everyone who uses the Web. When online, we offer information about our interests, habits, system configuration, etc., and someone able to eavesdrop the traffic that our devices exchange with the network could invade our privacy. End-to-end encryption – HTTPS – limits access to exchanged information, thus mitigating the problem. Yet, some traffic is transmitted without encryption, such as network and transport layer data.

In this work we explore different techniques for profiling and fingerprinting users leveraging the *set of domains*[1]. contacted during web navigation. Indeed, domain names are typically exchanged in clear text, i.e., when resolving a domain via DNS queries because DNS traffic is not encrypted (even DNSSEC does not guarantee confidentiality). Would it be possible to then build a user profile by simply considering the set of domains she visits during her browsing session? And would it be possible to re-identify her in a future time, e.g., when she is connected in a different network? Real-case scenarios include applications for tracking users in different networks, e.g., tracking users from both mobile and house traffic from a certain area, in which we may want to associate the two datasets. Or, when users change their IPs due to dynamical assignment.

Armed with two large datasets containing traffic summaries of ≈7 500 anonymized users during 4 weeks in 2017, we answer the previous questions. A big data approach must be considered when creating meaningful fingerprints. We investigate the use of three metrics, considering simple *Jaccard index*, an information theory *Maximum Likelihood* approach [9], and a text mining methodology based on *TFIDF* (Term Frequency - Inverse Document Frequency [8]). We evaluate their performance, highlighting their strengths, weaknesses and trade-offs. Results unveil that TFIDF offers overall the best performance, identifying a given user in different scenarios with up to 94% of accuracy. The rationale of this surprising result is the fact that among the hundreds of domains visited during few days, many are persistent in time and create a peculiar and unique mix of traffic.

The creation of fingerprints to profile users is a problem widely studied in literature under different perspectives. Here we briefly list those works where a limited set of features are considered. Authors in [6] collected volunteers' web browsing histories (i.e., full URLs), discovering that for 97% of the users, as little as 4 web pages uniquely distinguish them. Authors in [4] used the DNS traffic to build user fingerprints, reaching accuracy up to 74% in recognition of users in real world traces. Authors in [5] tackle the user tracking and recognition problem exploiting HTTP, HTTPS and SSH protocols, achieving a 50% accuracy. Differently from previous works, we rely on large flow level datasets in which we only consider the name of the contacted server as feature, comparing different methodologies. This work extends our previous work [3] where we evaluated the usage of the DNS requests to create a fingerprint and track the users over time, discovering that with the simple Jaccard

[1]We use the term domain informally throughout the paper, meaning Fully Qualified Domain Name (FQDN)

similarity method and one day of traffic only 60% of users can be correctly identified in the future.

To get more insights, we investigate which domains are more useful for such purpose, in particular considering those intentionally visited by the users, that we call *Core domains*, or those contacted by the browser to fetch objects that compose a web page or by other background applications, that we call *Support domains*. To automatically identify them, we propose a methodology based on machine learning, and, more specifically, on decision trees. Results show that the intentionally visited web-services prove to better characterize the user than Support domains; however users are better re-identified when all the traffic is taken into account, suggesting that even Support domains help in characterizing users.

Our study, although preliminary, shows on the one hand how complicated is to protect our privacy when online; on the other hand, the potentiality of good similarity metrics and machine learning applications linked to, e.g., forensic. To foster new studies and permit results reproducibility, we contribute our dataset to the community.[2]

2 METRICS FOR SIMILARITY

In this section we provide a description of the three different methodologies upon which we base our profiling and identification techniques. Consider a user $u \in U$ in our collection of users U. In a time period ΔT_1 she visits a set of domains $D_{u,\Delta T_1}$. Let us call $\hat{D}$ the set of all the domains seen by the population at time ΔT_1, i.e., $\hat{D} := \cup_{u \in U} D_{u,\Delta T_1}$. Given the profiles $D_{u,\Delta T_1}$ for all $u \in U$ in a certain ΔT_1, we suppose to have the set $D_{v,\Delta T_2}$ in a future ΔT_2 only for user v, but without knowing the identity of user v in ΔT_2. Our goal is to correctly identify the user v among the profiles of users in U built in the past. The underlying hypothesis is that there is a positive-correlation among the domains retrieved by a user in different time windows.

2.1 Jaccard Index

The Jaccard index measures similarity between two finite sets. It is defined as the size of the intersection divided by the size of the union of the two sample sets:

$$Jac(D_{u,\Delta T_1}, D_{v,\Delta T_2}) := \frac{|D_{u,\Delta T_1} \cap D_{v,\Delta T_2}|}{|D_{u,\Delta T_1} \cup D_{v,\Delta T_2}|} \tag{1}$$

Jaccard index is in $[0, 1]$, and it is equal to 0 when there is no common element between the two sets, while if the two sets contain same elements, the index equals 1.

2.2 Maximum Likelihood Estimation

For this method, we assume a simple behavioral model for the visited domains in which a user's likelihood of visiting a certain domain is governed by the domain overall popularity and whether this domain already appeared in her previous domains set. Then, for each user $u \in U$, we compute her likelihood of generating the domain set $D_{v,\Delta T_2}$ under the imposed model. This method, with few modifications, has been already proposed in [9], where the proof can be found.

[2] Anonymized sets of domains are available to the public at http://bigdata.polito.it/content/domains-web-users

Let us suppose that each domain $d \in \hat{D}$ has a certain likelihood $p(d)$ of being picked in ΔT_2, independently from the user, given its popularity in ΔT_1:

$$p(d) := \frac{|u : d \in D_{u,\Delta T_1}|}{|U|}$$

We suppose a user is more likely to visit a domain she already visited in the past. For any $u \in U$ and parameter $r \geq 0$ we define a random variable $H(u, r)$ s.t.:

$$Pr(H(u,r) = d) := \begin{cases} r \cdot p(d)/z & \text{if } d \in D_{u,\Delta T_1} \\ p(d)/z & \text{otherwise} \end{cases} \tag{2}$$

where z is a normalizing factor. Then, given a number equal to $|D_{v,\Delta T_2}|$ of i.i.d. draws of $H(u, r)$, the Maximum Likelihood Estimation $(\hat{u}, \hat{r})$ of the underlying parameters for producing the set $D_{v,\Delta T_2}$ are:

$$\hat{u} = \underset{u \in U}{\text{argmax}} \left\{ q_u \log \frac{q_u}{s_u} + (1 - q_u) \log \frac{1 - q_u}{1 - s_u} \right\}$$

$$\hat{r} = \left(\frac{q_{\hat{u}}}{1 - q_{\hat{u}}} \right) \Big/ \left(\frac{s_{\hat{u}}}{1 - s_{\hat{u}}} \right)$$

where $q_u = |D_{u,\Delta T_1} \cap D_{v,\Delta T_2}| / |D_{v,\Delta T_2} \cap \hat{D}|$ and $s_u = \sum_{d \in D_{u,\Delta T_1}} p(d)$. q_u is the fraction of domains of $D_{v,\Delta T_2}$ that are in a previous set $D_{u,\Delta T_1}$. s_u is the generalized size of $D_{u,\Delta T_1}$, where it accounts both for the total number of domains in $D_{u,\Delta T_1}$ and the popularity of those items. Intuitively, $\hat{u}$ is a user for which q_u is large and s_u is small; that is, $D_{\hat{u},\Delta T_1}$ is not too big, but contains many of the domains in the observed history $D_{v,\Delta T_2}$. The model allows for $r < 1$, in which case $D_{\hat{u},\Delta T_1}$ is an anti-recommendation set. However, in our case we consider here only the cases where $r > 1$. If such r does not exists, we consider $\hat{u}$ for which r is bigger.

2.3 Cosine similarity based on TFIDF

TFIDF is the product of two statistics, Term Frequency and Inverse Document Frequency, and it is widely used in information retrieval. TFIDF reflects how important a domain d is for a user $u \in U$, with respect to the set of all users U.

Term Frequency (TF) measures the importance of domains for user u. Differently from the classic version of TF, since we are using just sets of domains it will be independent of a particular domain:

$$TF(u) := \frac{1}{|D_{u,\Delta T} \cap \hat{D}|}$$

IDF measures how important a domain is in the whole collection of users, in ΔT_1. While computing TF, all domains are considered equally important. However certain domains may be very popular and therefore have little importance. Thus, we weight less the frequent domains while scale up the rare ones.

Notice that for a user in ΔT_2, we are removing the domains never seen by the population at time ΔT_1, because such new domains will not have an Inverse Document Frequency (IDF) – remind that $\hat{D}$ is built at ΔT_1.

IDF is defined as:

$$IDF(d) := \log \frac{|U|}{|u : d \in D_{u,\Delta T_1}|}$$

Hence $IDF(d)$ is the logarithm of the total number of users divided by the number of users having seen domain d in ΔT_1. Finally, TFIDF is the product of the two, i.e., $TFIDF(d,u) := TF(u) \cdot IDF(d)$. Then we compare how similar two domain sets $D_{u,\Delta T_1}$ and $D_{v,\Delta T_2}$, computing the cosine distance of the two multi-dimensional arrays:

$$Cos(D_{u,\Delta T_1}, D_{v,\Delta T_2}) := \frac{\sum_{d \in \hat{D}} TFIDF(d,u) \cdot TFIDF(d,v)}{||TFIDF(d,u)|| \cdot ||TFIDF(d,v)||}$$

with $|| \cdot ||$ indicating the usual Euclidean norm. The resulting similarity ranges from 0, meaning no elements in common, to 1, meaning all the entries being exactly the same.

2.4 Complexity

Assuming to compute a similarity between a single user and other M users, each with $\approx N$ domains, Jaccard index computation costs at most $O(M \cdot N^2)$. If P is the total number of domains seen by all the M users, with $N \leq P \leq M \cdot N$, TFIDF and MLE methodologies cost at most $O(M \cdot N \cdot P)$. This is due to the fact that TFIDF and MLE make comparisons in the larger set of all domains.

Hashing methodology such as MinHash could be used on top of our computation to speed-up the process. With a smart implementation using hash functions, the computation cost could decrease to $O(M \cdot N)$ for Jaccard and $O(M \cdot P)$ for MLE and TFIDF.

In the user tracking problem, N should be relatively small (up to few thousands), while M and, by consequence, P, could range from few users to millions of them, depending on the application. In case of very large M, it is therefore much faster to use the simpler Jaccard similarity.

3 IDENTIFICATION OF CORE DOMAINS

When a browser visits a Web page, it first downloads the main HTML document and then fetches all the objects of the page (images, scripts, advertisements, etc.). These are often hosted on external servers (e.g., CDNs) having different domains. We call *Core domain* a domain originally contacted to download the main HTML document of a page. Core domains are important since they are visited intentionally by users, like `www.facebook.com` and `en.wikipedia.org`. Instead, we call *Support domains* all the remaining ones, i.e., the ones automatically triggered by a visit to a website, or contacted by background applications, like `static.xx.fbcdn.net` and `dl-client.dropbox.com`. Support domains do not contain useful information about user intention. When analyzing network traffic, having a list of all possible Core domains is important to make user behavior emerge. Are Core domains important also for user tracking and identification?

In the literature, previous works tackled the problem of identifying intentionally visited domains, also called *user actions*. Authors of [12] exploit the *referer* field in HTTP requests to reconstruct web page structures from HTTP traces, while machine learning techniques are used by authors of [11] to automatically build rules for such purpose. However, an important fraction of traffic is becoming encrypted, making the above approaches ineffective and leaving passive probes with no visibility on HTTP fields. Few efforts have been put in identifying user actions from encrypted traffic; authors of [2] exploit machine learning techniques to identify user actions in Android devices, where most of the traffic is TLS, while those of [7] build traffic fingerprints for mobile applications. All these works aim at identifying user actions from flow level measurements examining traffic at runtime. Here, on the contrary, all we need is to build a pre-computed list of domains that typically contain user actions since they host actual Web services.

Given a domain, deciding if it is a Core or Support domain is a classification problem. Instead of building a custom heuristic to solve the problem, we opt for a machine learning approach by means of a decision tree classifier. First, we need to define the set of features to use: we consider an extensive list guided by domain knowledge, and let the classifier choose the ones that better allow us to separate Core and Support domains. Features include the length and the content type of the main HTML document (if present); the number of objects of the page and domains contacted by the browser to fetch all objects; HTTP response code (e.g., 2xx, 3xx and 4xx); and whether the browser has been redirected to an external domain. To get the set of features, we use active crawling, and visit the home page of each domain by means of Selenium automatic browser to extract page features.[3]

To train the classifier, we build a labeled dataset that we use for training and testing. For this experiment, we consider a list of 500 Core and 500 Support domains. More in detail, we picked the list of domains found in the Campus trace (see next Section for details), sorted by number of visits. Then, we manually visited each home page (if existing) corresponding to the domain name. We label such domain as a Core or a Support domain by looking at the rendered web page. We stop the labeling process when we reach 500 items for each class. We obtain a balanced labeled dataset that we make publicly available.[4] For the decision tree, we opt for the J48 implementation of the C4.5 algorithm offered by Weka.[5]

Interestingly, the final decision tree results in a very simple, efficient, and descriptive model which reads as: a) the main HTML document size must be bigger than 3357B and b) the browser must not be redirected to an external domain. Intuitively, support domains typically lack of real home page, and reply with a raw and simple text message. In some cases, Support domains redirect visitors to the service's home page (e.g., `fbcdn.net` redirects on `www.facebook.com`).

Despite its simplicity, overall accuracy is higher than 96% when tested against 1000 labeled domains, using 10–fold cross validations.

4 DATASETS FOR EXPERIMENTS

For our analysis we mainly rely on a dataset collected in our University Campus, where we consider the traffic of approximately 2 500 users. Users are faculty members whose terminals are directly connected to the Internet via wired Ethernet, using fixed IP addresses that we use as identifier of the terminal itself. Hence we assume each IP address is associated with one and only one user.

We rely on Tstat [10] to perform passive measurements. Tstat monitors each TCP connection, exposing information about more than 100 metrics, from IP addresses and port numbers, to fields coming from the DPI module. Here, we are interested in retrieving the domain of the server being contacted. Tstat implements three

[3] http://www.seleniumhq.org/
[4] http://bigdata.polito.it/content/domains-web-users
[5] http://www.cs.waikato.ac.nz/ml/weka/

Table 1: Overview of our datasets.

Trace	Log Size	Volume	Client IPs	Domains	2nd-lvl
Campus	229 GB	113 TB	≈2 500	404 k	136 k
ISP	440 GB	232 TB	≈5 000	611 k	204 k

techniques to get it. For plain HTTP flows, the Host header is extracted from HTTP request. In case of TLS, the DPI module provides the Server Name Indication (SNI) field in Client Hello message.[6] At last, it reports the domain name clients resolved via DNS queries prior to flows [1]. We combine these three sources to label each flow with a domain indication, giving higher priority to Host/SNI fields where more than one is present.

First row of Tab. 1 summarizes the characteristics of Campus dataset. In total, we observed about 404 k unique domains, corresponding to more than 136 k unique second level domains. In total, 691 millions flows have been observed during 4 weeks between January and February 2017; no holidays or festivities occurred during this period. We load and process the logs using Apache Spark in a 20-machine Hadoop cluster, capable of reading from disk and processing the Campus dataset in about 20 minutes. With the same machine, it took about 1 hour for classifying 404 k domains as Core or Support domains. The Internet access speed (1Gbps in our case) was the main bottleneck.

Fig. 1 shows the number of unique domains (Core and Support domains) seen in the whole dataset. New domains are continuously discovered, reaching ≈ 404 k after 4 weeks, of which Core domains are ≈115 k (left y-axis). Next, we observe the number of active users creating some traffic for each hour; they vary from 400 at night to almost 1 400 at midday. We plot the median over the users of unique domains discovered over time (right y-axis). Ratio between Support and Core domains increases, with a median of 662 Support and 70 Core domains after 4 weeks. Domain popularity is unbalanced: a very small portion of domains are popular and just 634 domains out of the 400 000 are contacted by 10% or more of the users. Core domains are about 32% of the total; however, only 4% of the top 1 000 most popular domains are Core domains.

Finally, in the experiment in Sec. 5.5 we use a second trace. We deployed Tstat during the same period in a PoP of an European ISP where the traffic of ≈5 000 ADSL and Fiber households is aggregated. All households have a fixed IP address which identifies a home gateway acting as NAT router, behind which multiple user devices may be connected to the Internet. Therefore a single identifier (i.e., the client IP address) can actually hold more than one user. Second row of Tab.1 reports the dataset statistics.

4.1 Ethical and privacy implications

Both the data collection process and the collected data have been discussed, reviewed and approved by the ethical board of our University. We took all possible actions to protect leakages of private information from users. In particular, we anonymized the IP addresses of clients using a technique based on irreversible hash functions, only retaining the data that is strictly needed for our study. More in detail, we limit the data to i) the anonymized client IP address, ii) the name of the contacted server, iii) the timestamp of the TCP connection. We further anonymized the server name in the datasets that we contribute to the community which contains data collected from our campus.

Considering the data collection process in the ISP, the same precautions have been implemented, and the data collection process has been reviewed and approved by the ISP security board. In this second scenario, we have no information at all about the ISP customers.

[6]SNI is a TLS extension by which the client indicates the domain of the server that is trying to contact.

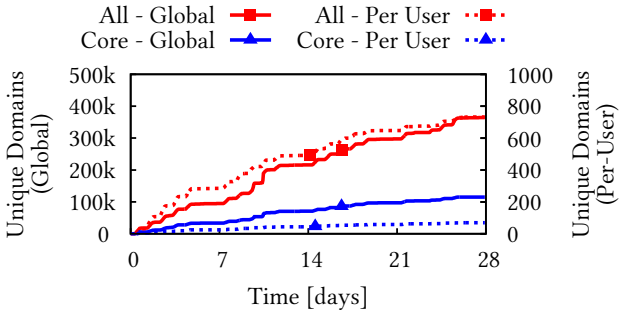


Figure 1: Discovery of domains over time (Campus trace).

5 USER FINGERPRINT AND IDENTIFICATION

In this section, we show different case studies for defining a user fingerprint. Our main task is to identify a user, by tracking her visited domains. In the first phase, we *profile* the users creating *fingerprints*, while in a second phase, we try to *identify* a given user in a later trace. All clients are provided with a public and fixed IP address that we use as identifier to build the ground truth. We consider 1 205 users that were active during the period of time of data collection. The constraints used for choosing the 1 205 users are written in each experiment. When otherwise stated, the 1 205 users are chosen randomly. Performance of each similarity metric is measured by the percentage of users correctly identified. The results can be meaningfully compared since they are always related to 1 205 possible cases.

5.1 Role of number of domains

The first set of results aims at assessing the importance of the number of Core and Support domains for the profiling and identification tasks. We collect the domains visited by users and generate a profile $D_{u,\Delta T_1}$ for each $u \in U$. In the next step, we associate user v with profile $D_{v,\Delta T_2}$ to the most likely user $u \in U$. If $u = v$ we have a positive match. Fig. 2 shows the percentage of users that were correctly identified, versus the number of Core and Support domains used in the profile generation phase. For equal user number, the larger is the data, the better is the identification. For low number of both Core and Support domains, it is hard to identify users; in fact, just up to 23.8% were correctly identified with 10 domains.

Core domains are clearly better characterizing and more important for user identification than Support domains, for all the three

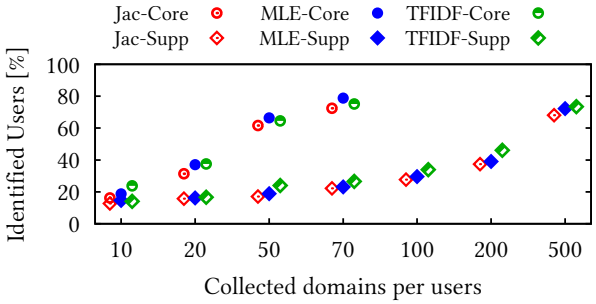


Figure 2: Identification of users considering different number of domains for profiling and identification.

metrics. With only 70 Core domains, the range of correctly identified users is equal to 72-79%. This percentage is higher than the range of correctly identified users when 500 Support domains are used (68-73%). Regarding to the performance of the three similarity metrics, Jaccard performs worst in all the cases; TFIDF has the best results in most of the experiments with Support domains, while MLE performs a slightly better with Core domains.

5.2 Role of observation time

We now focus our attention to study how observation time impacts on profiling and identifying users. The rate for discovering new domains differs from user to user, and we expect that the same number of domains is collected after a different amount of time. For instance, for discovering 50 Support domains it takes, in median, only 11 hours. For Core domains, instead, it takes about 3.5 days. 5 days are needed to obtain 70 Core domains, but only 3 days for 500 Support domains. This is mainly due to the large number of Support domains (see Sec. 4).

Here, we maintain constant the time of observations ΔT_1 and ΔT_2. We consider two consecutive weeks of traffic, taking into account only users that visited at least 20 Core domains per week, avoiding those that either disappeared or generated little traffic. We use the first week for profiling, and the second one for identification. Tab. 2 details results for the three similarity metrics considering Core, Support and All domains. The median number of domains per week per user is reported for completeness. Best results are in bold. We repeat the same experiment considering 2 consecutive days, with results in Tab. 3, where the median number of discovered domains decreases to about the half, and performance also drops. In both cases the large quantity of Support domains, about ten times the number of Core domains, helps in user identification.

As expected, performance decreases when scarce information is available, in particular moving from the two weeks experiment to the two days one. However, still 70% of users can be identified when observing them during one day only. Results of the three metrics are consistent to the ones showed in Fig. 2: Jaccard has always the worst performance, MLE seems less affected by the limited size of Core domains and TFIDF offers the overall best performance except when few Core domains are considered.

To give an intuition about the discriminative power of the profiles, we report in Fig. 3 the Cumulative Distribution Function (CDF) of TFIDF metric between the same user (called self-similarity) and between two different users, considering all the domains from the same two consecutive weeks of Table 2. Self-similarity is almost always higher than the similarity with a different user, thus allowing to correctly identify the target user.

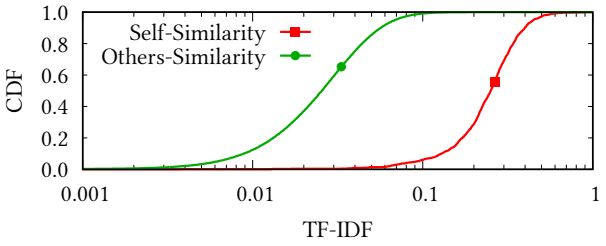


Figure 3: CDF of similarity in two consecutive weeks between the same user, or two different users.

Table 2: Identified users in two consecutive weeks.

	Median $\lvert D_{u,\Delta T}\rvert$	Jac	MLE	TFIDF
All	710	76.9%	79.6%	**82.3%**
Core only	69	67.2%	**70.9%**	70.8%
Support only	641	75.4%	78.3%	**80.7%**

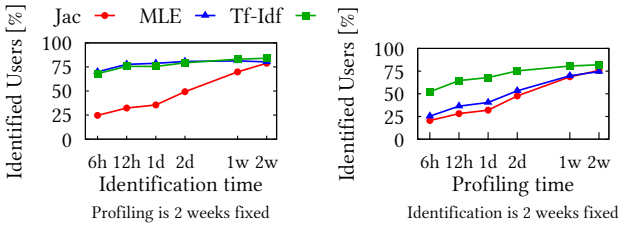
Table 3: Identified users in two consecutive days.

	Median $\lvert D_{u,\Delta T}\rvert$	Jac	MLE	TFIDF
All	325	63.2%	67.6%	**71.2%**
Core only	26	45.8%	**55.1%**	50.1%
Support only	294	61.2%	65.6%	**70.3%**

5.3 Longer profiling or identification?

Differently from the previous results, here we consider all users in our dataset, allowing real cases in which users may disappear and generate little traffic. We consider two cases. First, we assume to have i-a) fixed and long profiling time, i.e., 2 weeks for each user, and ii-a) variable observation windows for identify them. Second, we assume to have i-b) a fixed amount of 2 weeks for identification, but ii-b) variable time profiling all the users. Figs. 4a and 4b depict the results for both aforementioned cases. Jaccard considers the two sets independently from the rest of the population; therefore such metric is symmetric with respect to the two sets and depends just on their sizes. This implies that Jaccard performs equally in a) and b) cases, reaching good performance only when the training and testing sets of domains are both large. TFIDF and MLE metrics account for the whole population when profiling, hence having large profiling sets for the population is much more important than having a single large identification set. This is why with a 2 weeks profiling time TFIDF and MLE show good performance even with just few hours of identification time. On the contrary, building profiles with few hours of traffic makes the large amount of data for identification much less useful.

In a nutshell, building better profiles for the whole population is much more important that having a lot of data for identification.



(a) Identification time **(b) Profiling time**

Figure 4: Accuracy varying the period of identification and profiling on traces.

5.4 Profiling aggregate traffic

Here we consider to build a profile from different *groups of users*, and then see if it would be possible to associate a user to her group. For this analysis, we consider the aggregate traffic produced by all people in the same University Department during one week, and build a profile for the active department. Medianly, each department profile contains ≈24 k domains, two orders of magnitude more than single user case. Next, we consider each user (from the following week of traffic) with the goal of assigning her to the correct department. Having our Campus 10 departments, a random unbiased method assigns correctly 10% of users.

Results show that Jaccard performs poorly, correctly associating only 8.7% of users: without weighting the popularity of domains, the traffic of the single user it is almost indistinguishable within the departments. TFIDF instead reaches a surprising 73.9% accuracy. Intuitively, TFIDF is able to identify the peculiar, per-department, domains, i.e., those with high IDF among the huge quantity of domains. MLE reaches 23.4%; its performance are biased from the fact that we assume a user will contact websites according to the model of Eq. 2, based more on the persistence of the traffic than on the peculiarity of domains for each user.

This experiment suggests also that users in the pool are quite similar, and thus harder to identify, e.g., it is easy to distinguish a electrical engineering department user from an architecture department professor, but harder to distinguish two electrical engineering department users.

5.5 ISP Case

We now repeat the experiments of Tab. 2 and 3 using the ISP trace, where users are possibly more heterogeneous. To compute results against the Campus Dataset, we randomly select 1 205 users, among the active ones. We profile them for one day (week), and identify using data from the second day (week). Results are in Tab. 4. Recall that here we have residential access, with possibly multiple devices multiplexed on the same public IP address that we use as identifier. This factor contributes to explain the high median number of domains. Identification accuracy tops to more than 86% (94%) with TFIDF, quite a surprising result. This, other than the bigger amount of data, is also due to the more heterogeneous navigation habits of residential users with respect to campus ones. In fact, 1 day of profiles in the ISP dataset has less median number of domains than 1 week of profiles in the Campus dataset (see Tab. 2), but reaches better performance.

Table 4: Users correctly identified in residential dataset.

	Median $\lvert D_{u,\Delta T}\rvert$	Jac	MLE	TFIDF
1 day	556	80.4%	84.1%	**86.6%**
1 week	1 785	93.6%	93.7%	**94.9%**

6 CONCLUSIONS

We explored techniques for users' fingerprinting and identification using only the domains of visited web-services. Results show that a simple approach like the TFIDF can be used to solve the identification problem in different scenarios, provided users are profiled for enough time. Web-services intentionally requested have proved to better characterize users.

We expect the probability of identification to decrease with respect to the user population size. Our conclusions could be over-optimistic with larger user-base, and we are planning to repeat the same experiments with larger datasets. We are also focusing on extending this approach to include more features e.g., the information coming from timing, or volume of data.

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