

How Unique and Traceable are Usernames?

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ABSTRACT

Suppose you find the same username on different online services, what is the probability that these usernames refer to the same physical person? This work addresses what appears to be a fairly simple question, which has many implications for anonymity and privacy on the Internet. One possible way of estimating this probability would be to look at the public information associated to the two accounts and try to match them. However, for most services, these information are chosen by the users themselves and are often very heterogeneous, possibly false and difficult to collect. Furthermore, several websites do not disclose any additional public information about users apart from their usernames (e.g., discussion forums or Blog comments), nonetheless, they might contain sensitive information about users.

This paper explores the possibility of linking users profiles only by looking at their usernames. The intuition is that the probability that two usernames refer to the same physical person strongly depends on the “entropy” of the username string itself. Our experiments, based on crawls of real web services, show that a significant portion of the users’ profiles can be linked using their usernames. To the best of our knowledge, this is the first time that usernames are considered as a source of information when profiling users on the Internet.

1. INTRODUCTION

Online profiling is a serious threat to users privacy. In particular, the ability to trace users by linking multiple identities from different public profiles may be of great interest to profilers, advertisers and the like. Indeed, it might be possible to gather information from different online services and combine it to sharpen the knowledge of users identities. This knowledge may then be exploited to perform efficient social phishing or targeted spam, and

might be as well used by advertisers or future employers seeking information. As it has been colloquially put by a judge of the US Supreme Court in a recent case about warrantless GPS tracking¹: “When it comes to privacy, the whole may be more revealing than its parts.”

Recent works [4, 3] showed how it is possible to retrieve users information from different online social networks (OSN). All of these works mainly exploit flaws in the OSN’s API design (e.g., Facebook friend search). Other approaches [17] use the topology of social network friend graphs to de-anonymize its nodes.

In this paper, we propose a novel methodology that uses usernames -an easy to collect information- rather than social graphs to tie user online identities. Our technique only assumes knowledge of usernames and it is widely applicable to all web services that publicly expose usernames. Our purpose is to show that users’ pseudonyms allow simple, yet efficient tracking of online activities.

Recent scraping services’ activities illustrate well the threats introduced by the ability to match up user’s pseudonyms on different social networks [2]. For instance, PeekYou.com has lately applied for a patent for a way to match people’s real names to pseudonyms they use on blogs, OSN services and online forums [14]. The methodology relies on public information collected for an user, that might help in matching different online identities. The algorithm empirically assigns weights to each of the collected information so as to deem different identities to be the same. However, the algorithm is ad-hoc and not robust to false or mismatching information. In light of these recent developments, it is desirable that the research community investigates the capabilities and limits of these profiling techniques. This will, in turn, allow for the design of appropriate countermeasures to protect users’ privacy.

In general, profiling unique identities from multiple public profiles is a challenging task, as information from public profiles is often incorrect, misleading or altogether missing [11]. Techniques designed for the purpose of profiling need to be robust to these occurrences.

Contributions.

The contributions of this paper are manifold. First, we introduce the problem of linking multiple online iden-

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¹<http://www.eff.org/press/archives/2010/08/06-0>

ties relying only on usernames. Second, we devise an analytical model to estimate the *uniqueness* of a username, which can in turn be used to assign a probability that a single username, from two different online services, refers to the same user. Based on language models and Markov Chain techniques, our model validates an intuitive observation: usernames with low “entropy” (or to be precise *Information Surprisal*) will have higher probabilities of being picked by multiple persons, whereas higher entropy usernames will be very unlikely picked by multiple users and refer in the vast majority of the cases to unique users.

Third, we extend this model to cases when usernames are *different* across many online services. In essence, given two usernames our technique returns the probability that these usernames refer to the same user, and allows then to effectively trace users identities across multiple web services using their usernames only. While we acknowledge that our technique cannot trace users that choose unrelated usernames on purpose, experimental data shows that users tend to choose closely related usernames on different services. Finally, by applying our technique to subsets of usernames we extracted from real cases scenarios, we validate and discuss our technique in the wild.

We envision several possible uses of these techniques, not all of them malicious. In particular, users might use our tool to test how unique their username is and, therefore, take appropriate decision in case they wish to stay anonymous. To this extent we provide an online tool that can help users choose appropriate usernames by measuring how unique and traceable their usernames are. The tool is available at <http://planete.inrialpes.fr/projects/how-unique-are-your-usernames>.

Paper organization.

In Section 2, we overview the related work on privacy and introduce the machine learning tools used in our analysis. In Section 4, we introduce our measure to estimate the uniqueness of usernames and in Section 5, we extend our model to compute the probability that two usernames refer to the same person and validate it using the dataset we collected from eBay and Google (Section 3). Different techniques are introduced and evaluated. Finally, in Section 7 we discuss potential impact of our proposed techniques and present some possible countermeasures.

2. RELATED WORK AND BACKGROUND

2.1 Related Work

Tracking OSNs users.

In [11] the authors propose to use what they call the *online social footprint* to profile users on the Internet. This footprint would be the collection of all little pieces of information that each user leaves on web services and OSNs. While the idea is promising this appears to be only a preliminary work and no model, implementation or validation is given.

Similarly in [4], Bilge et al. discuss how to link the membership of users to two different online social networks. Noticing that there might be discrepancies in the information provided by a single user in two social networks, the authors rely on Google search results to decide the equivalence of selected fields of interest (as for assigning uniqueness of a user). Typically, the input of their algorithm is the name and surname of a user, that is augmented by the education/occupation as provided in two different social networks. They use such input to start two separate Google searches, and if both appear in the first top three hits, these are deemed to be equivalent. The corresponding users are consequently identified as a single user on both social networking sites. Bilge et al.’s work illustrates well how challenging the process of identifying users from multiple public profiles is. Despite the usage of customized crawler and parser for each social network, the heterogeneity of information as provided by users (if correct) makes the process hard to deploy, if not unfeasible, at a large scale.

Record linkage.

Record linkage (RL) (or alternatively Entity Resolution) [9, 5] refers to the task of finding records that refer to the same entity in two or more databases. This is a common task when databases of users records are merged. For example, after two companies merge they might also want to merge their databases and find duplicate entries. Record linkage is needed in this case if there are no unique identifiers available (e.g., social security numbers).

In RL terminology two records that have been matched are said to be *linked*. For the purpose of linking profiles using usernames, we test several RL techniques and compare their performance to the ones introduced in this paper. However, differently from the record linkage problem, in our setup a complete match of two different usernames does not necessarily indicate a positive identification. Furthermore, the application of record linkage techniques to link public online user profiles is novel to the best of our knowledge and presents several challenges of its own.

Tracking browsers across sessions.

Another related problem is the fingerprinting of web clients. Usually, ad servers set unique cookies on the browsers to allow for easy tracking of users between HTTP requests. A simple and straightforward practise on browsers to limit the risk of re-identification is to restrict or disable the use of third-party cookies. However, recent research [8] has shown that different browser installations might contain enough unique features or “entropy” to allow for re-identification even in the absence of long lived unique identifiers like cookies.

De-anonymizing sparse database and graph data.

[17] proposes an identification algorithm targeting anonymized social network graphs. The main idea of this work is to de-anonymize online social graph based on information acquired from a secondary social network users are known to belong to as well. Similarity identified

in the network topologies of both services allows then to identify users belonging to the anonymized graph.

2.2 Background

2.2.1 Information Surprisal

Self-information or Information Surprisal measures the amount of information associated to a specific outcome of a random variable. If X is a random variable and x one possible outcome, we denote the information surprisal of x as $I(x)$. Information Surprisal is computed as $I(x) = -\log_2(P(x))$ and hence depends only on the probability of x . The smaller the probability of x the higher is the associated surprisal. Entropy, on the other hand, measures the information associated to a random variable (regardless of any specific outcome), denoted $H(X)$. Entropy and Surprisal are deeply related as entropy can be seen as the expected value of the information surprisal, $H(X) = E(I(X))$. Both are usually measured in bits.

Suppose there exists a discrete random variable that models the distribution of usernames in a population, call this variable U . The random variable U follows a probability mass function P_U that associates to each username u a probability $P(u)$. In this context, the information surprisal of $P(u)$ is the amount of identifying information associated to a username u . Every bit of surprisal adds one bit of identifying information and thus allows to cut the population in which u might lie in half.

If we assume that there are W users in a population, then a username u identifies *uniquely* a user in the population if $I(P(u)) > \log_2(W)$. In this sense, information surprisal gives a measure of the “uniqueness” of a username u and it is the measure we are going to use in this work. The challenge lies in estimating the probability $P(u)$, which we will address in Section 4.

Our treatment of information surprisal and its association to privacy is similar to the one recently suggested in [8] in the context of fingerprinting browsers.

3. THE DATASET

Our study was conducted on several different lists of usernames: (a) a list of 3.5 million usernames gathered from public Google profiles; (b) a list of 6.5 million usernames gathered from eBay accounts; (c) a list of 16000 thousand username gathered from our research center LDAP directory; (d) two large username lists found online used in a previous study from Dell’Amico et al. [7]: a “finnish” dataset and a list of usernames collected from Myspace.

The “finnish” dataset comes from a list publicly disclosed in October 2007². The dataset contains usernames, email addresses and passwords of almost 79000 user accounts. This information has been collected from -most likely by hacking- the servers of several Finnish web forums. The MySpace dataset comes from a phishing attack, setting a fake MySpace login web page. This data has been disclosed in October 2006 and it contains more than 30000 unique usernames.

²<http://www.f-secure.com/weblog/archives/00001293.html>

The use we made of these datasets was threefold. First, we used the combined list of 10 million usernames (from eBay and Google) to train our Markov Chain model needed for the probability estimations. Second, we used the information on Google profiles to gather ground truth evidence and test our technique to link multiple public profiles even in case of slightly different usernames (Section 5). Third, we used all the datasets to characterize username uniqueness and depict Surprisal information distributions as seen in the wild. Our objective here is to validate our techniques on several datasets, where users come from widely distributed locations and may have different habits as for web services usage and usernames’ choices.

Notably, a feature of Google Profiles³, allowed us to build a *ground truth* we used for validation purposes. In fact, users on Google Profiles can optionally decide to provide a list of their other accounts on different OSNs and web services. This provided us with a ground truth, for a subset of all profiles, of linked accounts and usernames.

In our experiments we observed that web services differ significantly in their username policies. However, almost all services share a common alphabet of letters and numbers. Analyzing our most complete set of 10 million distinct usernames it appears clear that 85% of the users choose alphanumerical *only* usernames that thus comply to all username policy. This fact is of interest when evaluating the applicability of the techniques explained in this work.

4. ESTIMATING USERNAME UNIQUENESS

As we explained above, we would like to have a measure of username *uniqueness*, which can quantify the amount of identifying information each username carries. Information Surprisal is a measure, expressed in bits, that serves this purpose. However, in order to compute the Information Surprisal associated to usernames, we need a way to estimate the probability $P(u)$ for each username u .

A naive way to estimate $P(u)$, given a dataset of usernames coming from different services, would be to use Maximum Likelihood Estimation (MLE). If we have N usernames then we can estimate the probability of each username u as $\frac{\text{count}(u)}{N}$, if u belongs to our dataset, and 0 otherwise. Where $\text{count}(u)$ is simply the number of occurrences of u in the sample. In this case we are assigning maximum probability to the observed samples and zero to all the others. This approach has several drawback, but the most severe is that it cannot be used to give any estimation for the usernames not in the sample. Furthermore, the estimation given is very coarse.

Instead, we would like to have a probability estimation that allows us to give estimate probabilities for usernames we have never encountered. Markov-Chains have been successfully used to extrapolate knowledge of human language from small corpuses of text. In our case, we apply Markov Chain techniques on usernames

³<http://www.google.com/profiles>

to estimate their probability.

4.1 Estimating username probabilities with Markov Chains

Markov models are successfully used in many machine learning techniques that need to predict human generated sequences of words, as in speech recognition [15]. In a very common machine learning problem, one is faced with the challenge of predicting the next word in a sentence. If for example the sentence is “*The quick brown fox*”, the word *jumps* would be a more likely candidate than *car*. This problem is usually referred to as *Shannon Game* following Shannon’s seminal work on the topic[18]. This task is usually tackled using Markov-Chains and modeling the probability of the word *jumps* depending of a number of words preceding it.

In our scenario, the same technique can be used to estimate the probability of username strings instead of sentences. For example, if one is given the beginning of a username like *sara*, it is possible to predict that the next character in the username will likely be *h*. Notably Markov-Chain techniques have been successfully used to build password crackers [16] and analyse the strength of passwords [7].

Without loss of generality, the probability of a given string c_1, \dots, c_n can be written as $\prod_{i=1}^n P(c_i | c_1, \dots, c_{i-1})$. In order to make calculation possible a Markovian assumption is introduced: to compute the probability of the next character, only the previous k characters are considered. This assumption is important because it simplifies the problem of learning the model from a dataset. The probability of any given username can be expressed as:

$$P(c_1, \dots, c_n) = \prod_{i=1}^n P(c_i | c_{i-k+1}, \dots, c_{i-1})$$

To utilize Markov-Chain for our task we need to estimate, in a learning phase, the model parameters (the conditional probabilities) using a suitable dataset. In our experiments we used the database of approximately 10 million usernames populated by collecting Google public profiles and eBay user accounts (see Section 3).

In general, the conditional probabilities are computed as:

$$P(c_i | c_{i-k+1}, \dots, c_{i-1}) = \frac{\text{count}(c_{i-k+1}, \dots, c_{i-1}, c_i)}{\text{count}(c_{i-k+1}, \dots, c_{i-1})}$$

by counting the number of n -grams that contain character c_i and dividing it by the total number of $n - 1$ -grams without the character c_i . Where an n -gram is simply a sequence of n characters.

Markov-Chain techniques benefit from the use of longer n -grams, because longer “histories” can be captured. However longer n -grams result into an exponential decrease of the number of samples for each n -gram. In our experiments we used 5-grams for the computation of conditional probabilities.

Once we have calculated $P(u)$, we can trivially compute the information surprisal of u as $-\log_2(P(u))$.

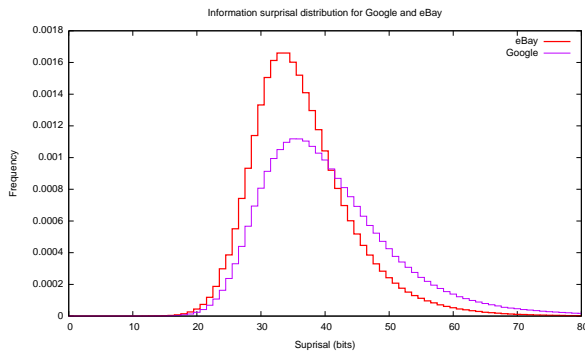


Figure 1: Surprisal distribution for eBay and Google usernames

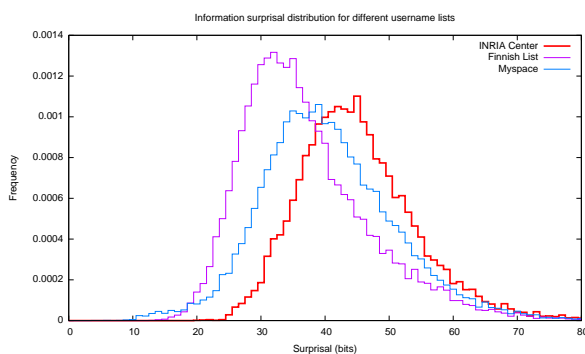


Figure 2: Surprisal distribution for other services

In Appendix 8 we give a different, yet related, probabilistic explanation of username uniqueness.

4.2 Experiments

We conducted experiments to estimate the surprisal of the usernames in our dataset and hence how unique and identifying they are. As explained above, our Markov-Chain model was trained using the combined 10 million usernames gathered from eBay and Google. The dataset was used for both training and testing by using leave-one-out cross validation. Essentially, when computing the probability of a username u using our Markov-Chain tool, we *excluded* u from the model the occurrence counts. This way, the probability estimation for u depended on all the other usernames but u .

We computed information surprisal for all the usernames in our dataset and the results are shown in Figure 1. The entropy of both distributions is higher than 35 bits which would suggest that, on average, usernames are extremely unique identifiers.

Notice the overlap in the distributions that might indicate that our surprisal measure is stable across different services. Notably, the two services have largely different username creation policies, with eBay accepting usernames as short as 3 characters from a wider alphabet and Google giving more restrictions to the users. Also, the account creation interfaces vary greatly across the two

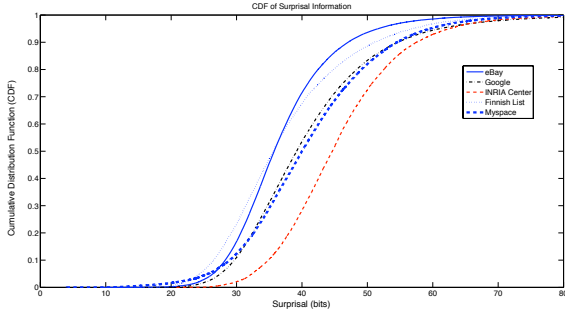


Figure 3: Cumulative distribution function for the surprisal of all the services

services. In fact, Google offers a feature that suggests usernames to new users derived from first and last names. Probably this is the reason why Google usernames have a higher Information Surprisal (see Figure 3). It must also be noted that both services have hundreds of millions of reported users. This raises the entropy of both distributions: as the number of users increases they are forced to choose usernames with higher entropies to find *available* ones. Overall it appears clear that usernames constitute highly identifying piece of information, that can be used to track users across websites.

In Figure 2 we plot information surprisal for three datasets gathered from different services. This graph is motivated by our need to understand how much surprisal varies across services.

The results are similar to the ones obtained for eBay and Google usernames. The Finnish list is noteworthy, these usernames come from different Finnish forums and most likely belong to Finnish users. However, Suomi (the official language in Finland) shares almost no common roots with Roman or Anglo-Saxon languages. This can be seen as a good representative of the stability of our estimation for different languages.

Furthermore, notice that the dataset coming from our own research center (INRIA) has a higher surprisal than all the other datasets. While there are a possible number of explanations for this, the most likely one comes from the username creation policies in place that require usernames to be the concatenation of first and last name. The high surprisal comes despite the fact that the center has only around 16000 registered usernames and lack of availability does not pressure users to choose more unique usernames.

Comparing the distributions of Information surprisal of our different datasets is enlightening, as illustrated in Figure 3. This confirms that usernames collected from the INRIA center exhibit the highest information surprisal, with almost 75% of usernames with a surprisal higher than 40 bits. We also observe that both Google and MySpace CDF curves closely match. In all cases, it is worth noticing that the maximum (resp. the minimum) fraction of usernames that do exhibit an information surprisal less than 30 bits is 25% (resp. less than 5%). This shows that a vast majority of users from our datasets can be uniquely identified among a population of 1 billion

users, relying only on their usernames.

5. USERNAME COUPLES LINKAGE

The technique explained above can only estimate the uniqueness of a single username across multiple web services. However, there are cases in which users, either willingly or forced by availability, decide to change their username.

We would like to know whether users change their usernames in any predictable and traceable way. In Figure 4(a) and 4(b) is plotted the distribution of the Levenshtein (or Edit) Distance for username couples. In particular, Figure 4(a) depicts the distribution for 10^4 username couples we can verify to belong to single users (we call this set L for *linked*), using our dataset. On the other hand, Figure 4(b) shows the distribution for a sample of random username couples that do not belong to a single user (we call this set NL for *non-linked*). In the first case the mean distance is 4.2 and the standard deviation is 2.2, in the second case the mean Levenshtein distance is 12 and the standard deviation is 3.1. Clearly, linked usernames are much closer to each other than non linked ones. This suggests that, in many occurrences, users choose usernames that are related to each other. The difference in the two distributions is remarkable and so it might be possible to estimate the probability that two different usernames are used by the same person or, in record linkage terminology, to *link* different usernames.

However, as illustrated in Section 4, and differently from record linkage, an almost perfect username match does not always indicate that the two usernames belong to the same person. The probability that two usernames, let's say *sarah* and *sarah2*, are linked (we call it $P_{same}(sarah, sarah2)$) should depend on:

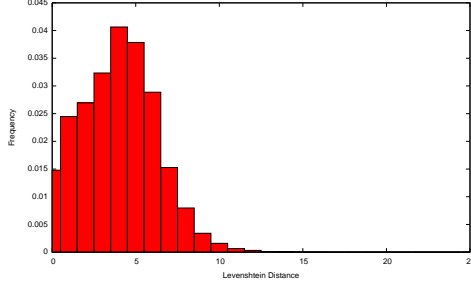
1. how much ‘information’ there is in the common part of the usernames (in this case *sarah*) and,
2. how likely is that a user will change one username into the other (in this case the addition of a 2 at the end).

We will show two different novel approaches at solving this problem. The first approach uses a combination of Markov Chains and a weighted Levenshtein Distance using probabilities. The second approach makes use of the theory and techniques used for information retrieval in order to compute document similarity, specifically using TF-IDF.

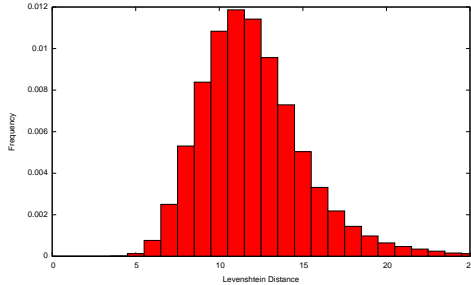
We compare these two techniques to record linkage techniques for a base-line comparison. Specifically we use string-only metrics like the normalized Levenshtein Distance and Jaro distance to link username couples.

Method 1: Linkage using Markov-Chains and LD.

First of all, we need to compute the probability of a certain username u_1 being changed into u_2 . We denote this probability as $P(u_2|u_1)$. Going back to our original example, $P(sarah2|sarah)$ is equal to the probability of adding the character 2 at the end of the string *sarah*. This same principle can be extended to deletion and substitution. In general, if two strings u_1 and u_2 differ



(a) Levenshtein distance distribution for linked username couples (set L , $|L| = 10^4$)



(b) Levenshtein distance distribution for non-linked username couples (set NL , $|NL| = 10^4$)

Figure 4: Levenshtein distance distribution for username couples gathered from 3 million Google profiles

by a sequence of basic operations o_1, o_2, \dots, o_n , we can estimate $P(u_2|u_1) = P(u_1|u_2) = p(o_1)p(o_2)\dots p(o_n)$.

In order to estimate the probability that username u_1 and u_2 belong to the same person, we need to consider that there are two different possibilities on how u_1 and u_2 were chosen in the first place. The first possibility is that they were picked independently by two different users. The second possibility is that they were picked by the same user, hence they are not independent.

In the former case we can compute $P(u_1 \wedge u_2)$ as $P(u_1) * P(u_2)$ since we can assume independence. In the latter, $P(u_1 \wedge u_2)$ equals $P(u_1) * P(u_2|u_1)$ in case the user is the same. Note that using Markov Chains and the our estimation of $P(u_2|u_1)$, we can compute all the terms involved. Estimating the probability $P_{same}(u_1, u_2)$ is now a matter of estimating and comparing the two probabilities above.

The formula for $P_{same}(u_1, u_2)$ is derived from the probability $P(u_1 \wedge u_2)$ using Bayes' Theorem. In fact, we can rewrite the probability above as $P(u_1 \wedge u_2|S)$ where the random variable S can have values 0 or 1 and it is 1 if u_1 and u_2 belong to the same person and 0 otherwise. Hence without loss of generality:

$$P(S|u_1 \wedge u_2) = \frac{P(u_1 \wedge u_2|S)P(S)}{\sum_{S=0,1} (P(u_1 \wedge u_2|S) * P(S))}$$

which leads to $P(S = 1|u_1 \wedge u_2)$ equal to

$$\frac{P(u_1)P(u_2|u_1)P(S = 1)}{P(u_1)P(u_2)P(S = 0) + P(u_1)P(u_2|u_1)P(S = 1)}$$

where $P(S = 1)$ is the probability of two usernames belonging to the same person, regardless of the usernames. We can estimate this probability to be $\frac{1}{W}$, where W is the population size. Conversely $P(S = 0) = \frac{W-1}{W}$. And so we can rewrite $P_{same}(u_1, u_2)$ as $P(S = 1|u_1 \wedge u_2)$ equal to

$$\frac{P(u_1)P(u_2|u_1)}{W * P(u_1)P(u_2)\frac{W-1}{W} + W * P(u_1)P(u_2|u_1)\frac{1}{W}}$$

Please note that when $u_1 = u_2 = u$ then the formula above becomes

$$P_{same}(u, u) = \frac{1}{(W - 1)P(u) + 1} = P_{uniq}(u)$$

which is exactly the same estimation we devised for the username uniqueness in Appendix.

Method 2: Linkage using TF-IDF.

In this case we use a well known information retrieval tool called TF-IDF. However, TF-IDF similarity measures the distance between two documents (or a search query and a document), which are set of words.

The term frequency-inverse document frequency (TF-IDF) is a weight used to evaluate how important is a word to a document that belongs to a corpus [13]. The weight assigned to a word increases proportionally to the number of times the word appears in the corpus but the importance decreases for common words in the corpus.

If we have a collection of documents D in which each document $d \in D$ is a set of terms, then we can compute the *term frequency* of term $t_i \in d$ as: $tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$ where $n_{i,j}$ is the number of times term t_i appears in document d_j . The *inverse document frequency* of a term t_i in a corpus D is $idf_i = \frac{|D|}{c_i}$ where c_i is the number of documents in the corpus that contain the term t_i . The TF-IDF is computed as $(tf - idf)_{i,j} = tf_{i,j}idf_i$. The TF-IDF is often used to measure the similarity between two documents, say d and d' , in the following way: first the TF-IDF is computed over all the term in d and d' and the results are stored in two vectors v and v' ; then the similarity between the two vectors is computed, for example using a cosine similarity measure $sim(d, d') = \frac{v \cdot v'}{\|v\| \|v'\|}$.

In our case we need to measure the distance between usernames composed of a single string. The way we solved this problem is pragmatical: we consider all possible substrings, of size q , of a string u to be a document d_u . Where d_u can be seen as the *building blocks* of the string u . The similarity between username u_1 and u_2 is computed using the similarity measure described above. This similarity measure is referred to in the literature as q -gram similarity [19], however it has been proposed for fuzzy string matching in database applications and its application to online profiling is novel.

Method 3: String Only Similarity Metrics from Record Linkage.

The Levenshtein (or edit) distance (LD) measures the similarity between two strings of different or equal length. It is defined as the minimum number of basic operations (deletion, insertion and substitution) needed to edit one

string into another. The Levenshtein distance is a useful tool but its interpretation is not always clear in practice. For example, consider the case of the usernames `alice` and `malice`, in comparison to the couple `vonneumann` and `jvonneumann`. Both couples have a LD of 1 but in the latter case the two usernames are clearly more related than in the former. To cope with these cases a normalized Levenshtein distance (NLD) is used instead. While there are different methods used to normalize the LD between two strings, in our experimentations we use the following formula: $NLD = 1 - \frac{LD}{\max(\text{len}(u_1), \text{len}(u_2))}$. Note that a NLD is always a number between 0 and 1 since the LD can be at most equal to the length of the longest string. Note also that the longer u_1 or u_2 are the closer NLD approaches one.

The Jaro distance [12] is yet another measure of similarity between two strings and it is mainly used in the area of record linkage. The distance is normalized and goes from 0 to 1 with 1 indicating an exact match. We will use it as a base-line comparison with our novel approaches. However, because of lack of space, we will not explain it in detail.

5.1 Validation

Our goal is to assess how accurately usernames can be used to link two different accounts. For this purpose we design and build a classifier to separate the two sets L and NL , respectively of linked usernames and non-linked usernames.

For our tests the ground-truth evidence was gathered from Google Profiles and the size the number of linked username couples $|L|$ is 10000. In order to fairly estimate the performance of the classifier in a real world scenario we also randomly paired 10000 non-linked usernames to generate the NL set.

The username couples were separated, shuffled and a list of usernames derived from L and NL was constructed. The task of the classifier is to re-link the usernames in L maximizing the username couples correctly linked while linking as few incorrect couples as possible.

In practise for each username in the list our program computed the distance to any other username and kept only the link to the *single* username with highest similarity. If this value is above a threshold then the candidate couple is considered *linked* otherwise *non-linked*.

5.1.1 Measuring the performance of our binary classifier

Binary classifiers are primarily evaluated in terms of *Precision* and *Recall*, where precision is defined in terms of true positives (TP) and false positives (FP) as follows $precision = \frac{TP}{TP+FP}$ and recall takes into account the true positives compared to false negatives $recall = \frac{TP}{TP+FN}$. The recall is the proportion of usernames that were correctly classified as unique (TP) out of all unique usernames ($TP+FN$). In addition to those two measures, we will also use Accuracy defined, with the addition of true negatives (TN) as $accuracy = \frac{TP+TN}{TP+TN+FP+FN}$.

In our case, we are interested in finding usernames couples that are actually linked (true positives) while minimizing the number of couples that are linked by

mistake (false positives). Precision for us is a measure of exactness or fidelity and higher precision means less profiles linked by mistake. Recall measures how complete our tool is, which is the ratio of linked profiles that are found out of all linked ones. Precision and recall are usually shown together in a precision/recall graph. The reason is that they are often closely related: a classifier with high recall usually has sub-optimal precision while one with high precision has lower recall. An ideal classifier has both a high precision and recall of 1.

Our classifier looks for potentially matching usernames. Once a set of potential matches is identified our scoring algorithms are used to calculate how likely it is that the two usernames represent the same real identity. By using our labeled test data, score thresholds can be selected that yield a desired trade-off between recall and precision. Figure 5 shows the precision and recall of the two methods discussed in this paper and known string metrics (Jaro and NLD) at various threshold levels.

In general the metric based on Markov models outperforms the other metrics. Our Markov-Chain method has the advantage of having the highest precision values especially at recalls up to 0.71. Remember that a recall of 0.71 means that 71% of all matching username couples have been successfully linked. Depending on the application, one might favor TF-IDF based approach (method 2) which has good precision at higher recalls or the Markov chain approach (method 1) which has the highest precision up to recall 0.7.

The string metrics (NLD and Jaro) perform surprisingly well in the task of matching different usernames. This is probably because, as shown in Figure 4, non-linked usernames tend to have higher mean distances between themselves than linked usernames. Both of these string-only-metric tools assign a positive weight for close strings and normalize it according to the maximum length of the strings. Hence, one possible explanation of the performance of NLD and Jaro distances is that the string length models sufficiently well the surprisal of a string for the purpose of username linkage. Indeed, Figure 6 shows a scatter plot of the entropy as computed by our uniqueness metric in comparison to the length of the strings. The graph clearly shows a central area of correlation between the two metrics and this is reflected by a high Pearson correlation between the two samples of 0.801.

5.1.2 Discussion of Results

Our results show that it is possible, with high precision, to link accounts solely based on usernames. This is due to the high average entropy of usernames and the fact that users tend to choose usernames that are related to each other. Clearly users could completely change their username for each service they use and, in this case, our technique would be rendered useless. However, our analysis shows that users indeed choose similar and high entropy usernames. This phenomenon can be seen as related to the much more studied password reuse phenomenon [10] that plagues web services. Users tend to reuse a small subset of passwords on 3.9 services on average, which can be explained by the difficulty of remembering multiple passwords. The same might

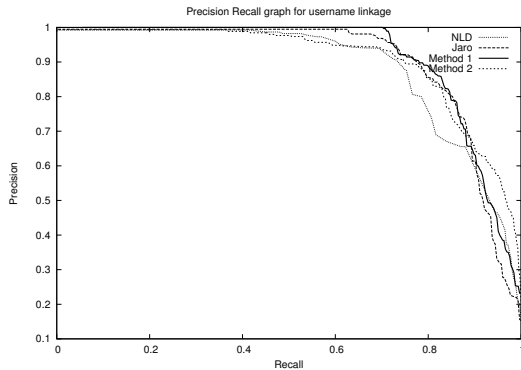


Figure 5: Precision and recall for username Linkage

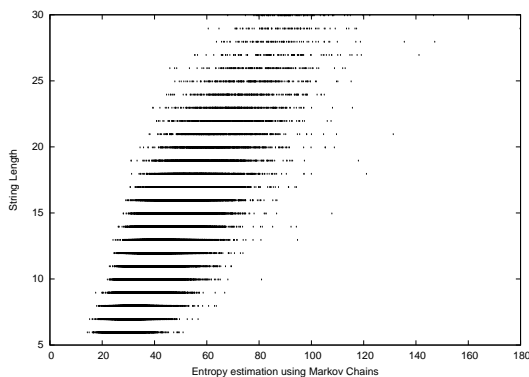


Figure 6: Scatter plot for the entropy estimation using Markov Chains and string length

hold true for usernames, with the notable exception that usernames can be freely written and do not have to be securely stored.

This technique might be used by profilers and advertiser trying to link multiple online identities together in order to sharpen their knowledge of the users. By crawling multiple web services and OSNs (a crawl of 100M Facebook profiles has already been made available on BitTorrent) profilers could obtain lists of accounts with their associated usernames. These usernames could be then used to link the accounts using the techniques underlined in the previous section.

5.1.3 Addressing Possible Limitations

The linked username couples we used as ground truth have been gathered from Google Profiles. We have shown how that, in this sample, the users tend to choose related usernames. However, one might argue that this sample might not be sufficiently representative of the whole population. Indeed Google Profiles users might be least concerned about privacy and show a preference of being traceable by posting their information on their Profiles.

We were not able to test our tool in linking profiles

to certain types of web services in which users are more privacy aware, like dating and medical websites (e.g., WebMD). This was due to the difficulty of gathering ground truth evidence for this class of services. However, even if we assume that users choose completely unrelated usernames for different websites, our tool might still be used. In fact, it might be the case that a user is registered on multiple dating websites with similar usernames. Those profiles might be linked together with our tool and more complete information about the user might be found. For example, a date of birth on a website might be linked with a city of residence and a first name on another, leading to real world identification. We acknowledge that, without evidence, this is only speculation and a more thorough analysis is left for future work.

5.1.4 Possible Improvements

Finding linked usernames in a population requires time that is quadratic in the population size, as all possible couples must be tested for similarity. This might be too costly if one has millions of usernames to match. A solution to this problem is to divide the matching task in two phases. First, divide usernames in clusters that are likely be linked. For example, one could choose usernames that share at least one n -gram, thus restricting the number of combinations that need to be tried. Second, test all possible combinations within a cluster.

Another possible improvement is to use a hybrid approach in which different similarity metrics are combined to obtain a single similarity [5]. For instance one could use different similarity metrics (TF-IDF, Markov, Jaro, etc.) to compose a feature vector that can be then classified using machine learning techniques like SVMs [6]. Such hybrid approaches are known to perform better in the record linkage tasks [5]. However, we did not test or implement such approaches and their application to linking online identities is left as future work.

6. RELEVANT USERNAME STATISTICS

This section contains username statistics that complement the experiments we proposed and justify our technique in more practical scenarios.

How do people choose their username?

We now aim to exploit our Google profiles dataset to verify whether people use their real name to compose pseudonyms as usernames. If this the case an attacker might try to generate likely usernames for a victim and track the victim on multiple web services using the techniques explained above to determine username uniqueness and linkage. Our analysis is then based on first and last names as provided by users in their profiles. We discard from the original dataset names provided with strings containing non Latin characters. These names cannot be mapped to a username according to the Google policy and so we restrict our study to the Latin alphabet ($a-z$). For simplicity, we also considered names composed by two words (i.e. both first and last

names are provided). After this filtering, we ended up with 2.6M couples of names and usernames.

We decomposed the name into two words that we refer to as w_1 and w_2 . According to Google profiles policy, w_1 (resp. w_2) refers to the first name (resp. last name). We first performed a preliminary matching using Perl’s regular expressions to check whether usernames contain a combination of w_1 , w_2 and digits. Results are shown in Table 1.

Matching Condition	# Usernames	Percentage (%)
w_1 and w_2 and d	207K	7.93
w_1 and w_2	774K	29.63
w_1 and d	142K	5.47
w_2 and d	132K	5.06
w_1	241K	9.24
w_2	323K	12.38
Not matching	792K	30.3
Total	2,6M	100

Table 1: Usernames construction analysis matching first/last name of users: the first name (w_1) and/or last name (w_2) and digits (d).

The matching conditions are exclusive, following the order as presented in the table (e.g., a username matching w_1 and w_2 is counted in the second row and not in the w_1 and w_2 rows separately). One of the most remarkable results is that 70% of the usernames contain at least one of the two parts of the real name. In particular, 30% of the collected usernames are constructed by simply concatenating the first and last name without adding any digit. We also observe that more than 18% of the usernames are constructed adding digits to the provided first and last names. This is most likely a typical behavior of users, whose first chosen pseudonym (a variant of first and last name) is not available and that do add digits (e.g. birth year) to be able to register into the service.

After this preliminary analysis we want to understand how w_1 and w_2 are combined to build the exact username. In order to do that, we also consider the first character of each word, namely c_1 and c_2 respectively. Table 2 shows multiple ways to combine w_1 , w_2 , c_1 , c_2 and digits (d). We provide the percentage of usernames observed for each combination. The results show that more than 50% of usernames match exactly the patterns we tested. One can observe that the most common way usernames are generated from users’ real names is by *concatenating* the first and last name, in that specific order (almost 14%), or by adding a dot between both names (13%).

Pattern	%	Pattern	%	Pattern	%
$w_1 w_2$	13.99	$c_1 . w_2$	0.44	$w_2 d$	0.84
$w_2 w_1$	1.46	$w_2 c_1$	0.28	$w_1 w_2 d$	6.04
$w_1 . w_2$	12.95	$w_2 . c_1$	0.08	$w_1 . w_2 d$	1.86
$w_2 . w_1$	2.22	$c_2 w_1$	0.09	$w_2 w_1 d$	0.89
w_1	0.91	$w_1 c_2$	0.44	$w_2 . w_1 d$	0.49
w_2	0.99	$w_1 . c_2$	0.09	$c_1 w_2 d$	2.58
$c_1 w_2$	3.45	$w_1 d$	2.71	$w_1 c_2 d$	0.8

Table 2: Usernames exactly matching a pattern.

Again, because first-chosen usernames might be already in use, users typically choose to (or are suggested to by the online service itself) add a number as a postfix

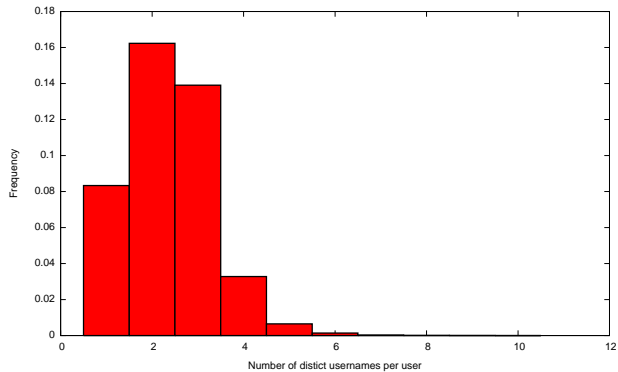


Figure 7: Number of distinct usernames per user distribution

of their desired username. In particular, we observe that in most of these cases, users add exactly respectively two or four numbers, in 40% of the cases and 20% respectively. These ending digits suggest then either the year of birth (full or simply the last two digits) or the birth date.

Finally, figure 7 shows the distribution of the number of different usernames the users in our dataset utilize. The graph shows that most users have two or three different usernames. The mean number of usernames per user is 2.3.

7. DISCUSSION

Recently some governments and institutions are trying to pass laws and policies to force users to tie their digital identities with their real ones. For example, there is a current discussion in China and France [1] on laws that would require users to use their real names when posting comments on blogs and forums. Similarly, the company Blizzard had started an effort to tie real identities to the ones used to post comments on its video games forums.

This work shows that it is clearly possible to tie digital identities together and, most likely, to real identities in many cases only using ubiquitous usernames. We also showed that, even though users are free to change their usernames at will, they do not do it frequently and, when they do, it is in a predictable way. Our technique might then be used as an additional tool when investigating online crime. It is however also subject to abuse and could result in breaches in privacy. Advertisers could automatically build online profiles of users with high accuracy and minimum effort, without the consent of the users involved.

Spammers could gather information across the web to send extremely targeted spam, which we dub *E-mail spam 2.0*. For example, by matching a Google profile and an eBay account one could send spam emails that mention a recent sale. In fact, while eBay profiles do not show much personal information (like real names) they do show recent transactions indexed by username. This would enable very targeted and efficient phishing attacks. We argue that these targeted attacks might have higher click rates for spammers thus leading to

smaller spam campaigns that would be much harder for spam classifiers to recognize.

Finally, users could use our tool to assess how unique and linkable their usernames are. They can thus take an informed decision on whether to change their pseudonym for their online activity they wish to remain private. Paradoxically, it would be difficult for an user who decides to prevent the linking of her different usernames (particularly on OSNs), to choose usernames that are unlinkable without loosing some of the benefits of the various features of OSNs.

In the light of our results, an analysis on the nature and anonymity of usernames is needed. Historically usernames have been used to identify users in small groups, one such example are Unix usernames. In groups of dozens or few hundreds of people, usernames naturally tend to be not identifying and non unique⁴. As the online communities grow in size, so does the entropy of the usernames. Nowadays users are forced to choose usernames that have to be unique in online services that have hundreds of million of users. Naturally users had to adapt and choose higher entropy usernames to be able to find usernames that were not already assigned. This can allow for privacy breaches.

7.1 Countermeasures

On the user side.

Following this work users might change their username habits and use different usernames on different web services. We released our tool as a web application that users can access to estimate how unique their username is and thus take informed decision on the need to change their usernames when they deem appropriate (<http://planete.inrialpes.fr/projects/how-unique-are-your-usernames>).

For web services.

There are two main features that make our technique possible and exploitable in real case scenarios. First, web services and OSNs allow access to public accounts of their users via their usernames. This can be used to easily check for existence of a given username and to automatically gather information. Some web services like Twitter are built around this particular feature. Second, web services usually allow the user pages to be crawled automatically. While in some cases this might be a necessary evil to allow search engines to access relevant content, in many instances there is no legitimate use of this technique and indeed some OSNs explicitly forbid it in the terms of service agreements, e.g., Facebook.

While preventing automatic abuse of public content can be difficult in general, for example when the attacker has access to a large number of IPs, it is possible to at least throttle access to those resources via CAPTCHAs [20] or similar techniques. For example, in our study we discovered that eBay presents users with a CAPTCHA if too many requests are directed to their servers from

⁴ We compared the mean entropy of the usernames on a shared server in our lab with the ones gathered from Google and the difference is remarkable.

the same IP.

8. CONCLUSION

In this paper we introduced the problem of linking online profiles using only usernames. Our technique has the advantage of being almost always applicable since most web services do not keep usernames secret. Two family of techniques were introduced. The first one estimates the uniqueness of a username to link profiles that have the same username. We gather from language model theory and Markov-Chain techniques to estimate uniqueness. Usernames gathered from multiple services have been shown to have a high entropy and therefore might be easily traceable.

We extend this technique to cope with profiles that are linked but have different usernames and tie our problem to the well known problem of record linkage. All the methods we tried have high precision in linking username couples that belong to the same users.

Ultimately we show a new class of profiling techniques that can be exploited to link together and abuse the public information stored on online social networks and web services in general.

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APPENDIX

Username uniqueness from a probabilistic point of view

We now focus on computing the probability that only *one* users has chosen username u in a population. We refer to this probability as $P_{uniq}(u)$.

Intuitively $P_{uniq}(u)$ should increase with the decrease in likelihood of $P(u)$. However, $P_{uniq}(u)$ also depends on the size of the population in which we are trying to

estimate uniqueness. For example, consider the case of first names. Even an uncommon first name does not uniquely identify a person in a very large population, e.g. the US. However, it is very likely to uniquely identify a person in a smaller population, like a classroom.

To achieve this goal we use the $P(u)$ to calculate the expected number of users in the population that would likely choose username u . Let us denote by $n(u)$ the expected number of users that choose string u as a username in a given population W . The value of $n(u)$ is calculated based on $P(u)$ as:

$$n(u) = P(u) * W$$

where W is the total number of users in the population. In our case W is an estimation of the number of users on the Internet: 1.93 billions⁵.

In case we are sure there exists *at least one* user that selected the username u (because u is taken on some web service) then the computation of $n(u)$ changes slightly:

$$n(u) = P(u) * (W - 1) + P(u|u) = P(u) * (W - 1) + 1$$

where the addition of 1 comes from the fact that we are sure that there exists *at least one* user that choses u and $W - 1$ is there to account for the person for which we are sure of.

Finally we can estimate the uniqueness of a username u by simply considering the probability that our user is unique in the reference set determined by $n(u)$, hence:

$$P_{uniq}(u) = \frac{1}{n(u)}$$

⁵ <http://www.internetworldstats.com/stats.htm>