TLSH - A Locality Sensitive Hash

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Also see Oliver, J., Forman, S., and Cheng, C.: Using Randomization to Attack Similarity Digests. ATIS 2014, Nov, 2014, pages 199-210. https://github.com/trendmicro/tlsh/blob/master/Attacking_LSH_and_Sim_Dig.pdf

Contents

Abstract—Cryptographic hashes such as MD5 and SHA-1 are used for many data mining and security applications – they are used as an identifier for files and documents. However, if a single byte of a file is changed, then cryptographic hashes result in a completely different hash value. It would be very useful to work with hashes which identify that files were similar based on their hash values. The security field has proposed similarity digests, and the data mining community has proposed locality sensitive hashes. Some proposals include the Nilsimsa hash (a locality sensitive hash), Ssdeep and Sdhash (both Ssdeep and Sdhash are similarity digests). Here, we describe a new locality sensitive hashing scheme the TLSH. We provide algorithms for evaluating and comparing hash values and provide a reference to its open source code. We do an empirical evaluation of publically available similarity digest schemes. The empirical evaluation highlights significant problems with previously proposed schemes; the TLSH scheme does not suffer from the flaws identified.

Keywords—locality sensitive hash; fuzzy hashing; data fingerprinting; similarity digests; Ssdeep; Sdhash; Nilsimsa; TLSH.

There are many problems in data mining where identifying near duplicates and similar files is useful. This is especially true in the area of computer security where it is required to identify malware samples with similar binary file structure, identify variants of spam email, etc. In some of these problems, files or information is modified by accident, for example file corruption. In many applications, the file is deliberately changed by an adversary. For example, in spam outbreaks, spammers will go to significant effort to make sure that each spam email is unique - to avoid being matched to other spam emails by the use of cryptographic hash functions.

Similarity digests [2, 3, 5] are an approach to solving these problems. Similarity digests attempt to solve a nearest neighbour problem using a digest that is superficially similar to a cryptographic hash. Approaches to this include schemes based on feature extraction [5], Locality Sensitive Hashing (LSH) schemes [2, 10] and Context Triggered Piecewise Hashing (CTPH) schemes [3]. All these similarity digest schemes have the property that a small change to the file being hashed results in a small change to the hash. In this paper, we restrict the schemes we consider to those where the digest can be encoded as a digest and stored in a central repository. The bit sampling approaches [2, 10] are amenable to the creation of digests. For example, the random projection methods that approximate the cosine distance between two feature vectors [7] are less amenable to the creation of digests. For the methods which allow the creation of digests, the similarity between two files can be measured by comparing the digests of the documents under consideration.

These schemes have been released as open source code: Ssdeep [3], Sdhash [5] and Nilsimsa [2, 10]. In the area of malware analysis, the de facto standard is the Ssdeep hash [8]. For example, NIST supports Ssdeep [11] and Ssdeep is currently the only similarity digest supported by Virus-Total [13].

The Ssdeep scheme [3, 1] is a CTPH which segments the file, evaluates a 6 bit hash value for each segment. Ssdeep calculates the edit distance between digests as the similarity measure. Sdhash [5, 6] creates a similarity digest by identifying features with low empirical probability, hashing these features into a bloom filter, and encoding the bloom filter as the output digest. Sdhash uses a similarity score by calculating a normalized entropy measure between the two digests. The Sdhash scheme is close in spirit to a random projection method of LSH schemes where the distance between two feature vectors is the cosine distance between the feature vectors. The Nilsimsa scheme [2, 10] is a bit sampling LSH which uses the hamming distance between the digests as the similarity measure.

Previously, limitations of Ssdeep for practical applications have been raised [1, 6]. Roussev concludes that Sdhash consistently outperforms Ssdeep for the experiments performed [6].

This paper is organized as follows. Sections 2 and 3 give details of the TLSH scheme, including details on construction of TLSH digests and scoring the distance between two digests. Section 4 gives an empirical comparison of the TLSH scheme with the Ssdeep and Sdhash schemes. This evaluation confirms the limitations which were raised in [1, 6], and identifies limitations of the Sdhash method which have not been previously identified.

Construction of the TLSH DIGEST

In this section, we describe how to construct a TLSH value from a byte string. The various parameters and choices that were made are justified in Section 2(F). Source code which implements the algorithms described here has been released as open source code [12].

We consider a byte string of length len:

```
Byte[0], Byte[1], Byte[2] … Byte[len-1]
```

The TLSH digest of the byte string is evaluated as the following steps

1. Process the byte string using a sliding window of size 5 to populate an array of bucket counts
2. Calculate the quartile points, q1, q2 and q3
3. Construct the digest header values
4. Construct the digest body by processing the bucket array

Steps 1, 2 and 4 combine to use a modified bit sampling method; instead of bit sampling these steps are sampling pairs of bits. The sampling process is done to a finite precision so as to have a fixed length digest. Step 3 constructs innovative features based on the approach used to get a fixed length digest.

Step 1. Process the byte string with a sliding window

The byte string is processed using a sliding window of size 5 to populate an array of bucket counts using the following process:

```
For ew = 4 to len-1 {
        // sw is the start of the window
        sw = ew - 4
        For tri = 1 to 6 {
                (c1,c2,c3)=Triplet(tri,Byte[sw..ew])
                bi = b_mapping(c1, c2, c3)
                bucket[ bi ] ++
        }
}
```

Step 2. Calculate the quartile points

After step 1 has been performed we have an array of bucket counts. We calculate the quartiles of this array such that:

```
75% of the bucket counts are >= q1

50% of the bucket counts are >= q2

25% of the bucket counts are >= q3
```

Step 3. Construct the digest header

The first 3 bytes of the hash are a header. The first byte is a checksum (modulo 256) of the byte string. The second byte is a representation of the logarithm of the byte string length (modulo 256). The third byte is constructed out of two 16 bit quantities derived from the quartiles: q1, q2 and q3:

```
q1_ratio =  (q1*100/q3) MOD 16

q2_ratio =  (q2*100/q3) MOD 16
```

Step 4. Construct the digest body

1. The remainder of the digest is constructed using the bucket array using the following procedure:

```
For bi = 0 to 127 {

    if bucket[bi] <= q1       Emit(00)

    else if bucket[bi] <= q2 Emit(01)

    else if bucket[bi] <= q3 Emit(10)

    else                      Emit(11)

}
```

Putting the digest together

The final TLSH digest constructed from the Byte string is the concatenation of:

- the hexadecimal representation of the digest header values from step 3, and
- the hexadecimal representation of the binary string from step 4.

Choices in the Construction Algorithm

A number of choices have been made in the algorithm used to construct a digest from a byte string. We first list the choices, and offer an explanation for each choice below:

- A sliding window of size 5.
- We choose to extract triplets from the sliding window, and we selected 6 of the possible 10 triplets.

- The use of the Pearson hash as the bucket_mapping function.
- The use of quartiles instead of average or median.
- The use of a checksum and a length factor in the header.
- The form of the q_ratio parameters.

We selected a window size of 5 and to extract triplets from the sliding window because it had previously been used in the Nilsimsa hash, and it had proved effective.

We selected 6 triplets of the 10 possible triplets for the following reason. There are 10 possible triplets of bytes from a window of 5 bytes (A, B, C, D, E). The possible triplets are:

```
1.  A B C
2.  A B   D
3.  A B     E
4.  A   C D
5.  A   C   E
6.  A     D E
7.    B C D
8.    B C   E
9.    B   D E
10.     C D E
```

We excluded triplets 7 to 10 because they result in duplicated counting of triplets; each triplet from 7 to 10 will be processed in a subsequent iteration of moving the sliding window.

Implementation details: the source code that has been open sourced reverses each window of characters before the 6 triplets are extracted and had the Pearson hash applied.

We selected the Pearson hash [4] as the bucket mapping function because it has a long history, and is well respected.

We selected the quartile points rather than the average used by the Nilsimsa hash for a similar purpose to make the scheme work well on binary data such as binary files and on images.

We selected a 1 byte check sum for false positive avoidance. Sometimes very similar long files (for example, with only one byte difference) can get collisions and near collisions using LSH techniques. In the open source software [12], this option is configurable.

We selected a 1 byte length description so that we can identify strings w hich have similar characteristics, but are very different in size. In the open source software [12], this option is configurable.

The q_ratio parameters were determined through experimentation, and found to be useful.

Scoring the Distance Between two TLSH Digests

The Ssdeep [3] and Sdhash [5] schemes provide a similarity score between two digests which ranges from 0 to 100, where 0 is a mismatch and 100 is a perfect match (or a near perfect match). The results in Section 4 highlight problems with the approach; and therefore the TLSH scheme uses a distance score. The TLSH scheme scores the distance between two digests - a distance score of 0 represents that the files are identical (or nearly identical) and scores above that represent greater distance between the documents. A higher score should represent that there are more differences between the documents.

In this section, we describe how to score the distance between two TLSH digests. Source code which implements this functionality is included in the open source code [12].

We define the mod_diff(X, Y, R) which is the minimum number of steps between X and Y on a circular queue of size R:

```
mod_diff(X,Y,R) = MIN((X-Y) mod R, (Y-X) mod R)
```

For example, the mod_diff(15, 3, 16) = 4 because it requires 4 steps to go from position 15 to position 3 on a circular queue of size 16. The steps are:

```
15 → 0 → 1 → 2 → 3
```

We now calculate the distance score between two digests, tX and tY. Each of these digests is a hexadecimal string, and we can extract the checksum, the lvalue, the q1ratio, the q2ratio from the first 6 hexadecimal digits. The distance score between the tX and tY digests is defined as the sum of the distance of the headers (as given by the `distance_headers` function below) and the distance of the digest bodies (as given by the `distance_bodies` function below).

```
Function distance_headers(tX, tY)
int diff=0
ldiff = mod_diff(tX.lvalue, tY.lvalue, 256);
If ldiff <= 1
        diff = diff + ldiff
else
        diff =  diff + ldiff * 12;
q1diff = mod_diff(tX.q1ratio, tY.q1ratio, 16);
        If q1diff <= 1
                diff = diff + q1diff
        else
                diff =  diff + (q1diff-1) * 12;
q2diff = mod_diff(tX.q2ratio, tY.q2ratio, 16);
        If q2diff <= 1
                diff = diff + q2diff
        else
                diff =  diff + (q2diff-1) * 12;
If tX.checksum <> tY.checksum
        diff = diff + 1
return(diff)
```

```
Function distance_bodies(tX, tY)
int diff=0
For I = 1 to 64 {
        x1 = tX.hex[i+5] / 4
        x2 = tX.hex[i+5] % 4
        y1 = tY.hex[i+5] / 4
        y2 = tY.hex[i+5] % 4
        d1 = abs(x1 - y1)
        d2 = abs(x2 - y2)
        if (d1 == 3)
                diff = diff + 6
        else
                diff = diff + d1
        if (d2 == 3)
                diff = diff + 6
        else
        diff = diff + d2
}
return(diff)
```

This distance calculated by the distance_bodies(tX, tY) function is very similar to the methods used by previous LSH methods that used a bit sampling method [10, 14]. The function calculates an approximation to the hamming distance between two digest bodies. The difference between the method in the `distance_bodies()` and using the hamming distance is the parameter 6 for the occasions when a bucket count in the tX and tY are at the extreme points – that is for one of the digests the bucket count was in the top quartile, and the other digest was in the bottom quartile.

Without loss of generality, consider the situation of x1=0 and y1=3. We derive the parameter 6 by considering the binomial situation when p=.25 and n=3. The probability of getting an event is

$$Prob(k=3 \mid n=3; p=0.25) = \binom{n}{k} p^k (1 - p)^{n-k}$$
$$=0.0156$$

As noted in [2], the scoring of the hamming distance is equivalent to the negative logarithm to base two of the probability of the events.

$$-log2(Prob(k=3 \mid n=3; p=0.25)) = 6$$

And hence the parameter in the `distance_bodies()` function for the situation is 6.

The distance calculated by the `distance_headers()` function also has a parameter. This time the range of the binomial trials implied by the mod_diff() function is 16 for the qratios and 256 for the length. It is not clear which distribution these parameters will follow – it will depend on the security application under consideration. We considered two approaches for deciding the parameters to use in the `distance_header()` function. The first approach was to extend the binomial argument used above to the case of n=15 and p=1/16. This leads to a multiplier parameter of 3. The second approach was to plot the relative occurrence of similar files having different qratios and lvalues. Inspecting the plots resulted in us selecting a multiplier parameter of 12. Ideally, the multiplier parameter should be selected based on trials for the data under consideration. For example executable files, image files, text files and source code have a different distribution for the qratios and the lvalues. Based on the results in the next section, a choice of 12 for the multiplier parameter is fairly robust. We also note that the open source software [12] allows the user to select options such as turning off any penalty for different lvalues.

The use of the checksum in the `distance_headers()` function was to make sure that digests from near collisions have a distance score greater than 0.

The computation of this score can be significantly sped up by the use of pre-calculated tables, which is implemented in the software [12].

Results

The TLSH scheme described has been implemented and source code has been made available online [12]. Here we present some comparisons with Ssdeep [3], Sdhash [5] and Nilsimsa [10].

ROC Analysis

We collected a set of files that we knew were distinct: 109 binary malware files from different malware families, 290 randomly constructed HTML fragments, 100 pieces of random text selected from the Unix dictionary (with no overlap) and 79 distinct text files about different topics.

We collected a set of files where we knew that the files are similar. This set included 20 binary files from the TROJ_DROPPER malware family, 20 binary files from the TROJ_ZLOB malware family, 20 binary files from the WORM_SOBER malware family. We took each of the 79 distinct text files and mutated it into 14 variations for a total of 15 similar files. Five of the 14 variations had a word selected and globally replaced by another random word selected from the text files. Three variations were created by using the Unix fmt command changing the formatting of the text file to have a width of 40, 60 and 80 characters. Five further variations were created by reformatting the file, and then globally replacing a random word with another random word selected from the text files. One of the 14 variations was constructed by using the Unix "sort --random-sort" to randomly sort the lines of the file.

The gold standard for this data set was a total of 8766 similar file comparisons and a total of 55822 different file comparisons. Ssdeep, Sdhash, Nilsimsa and TLSH were used to determine the similarity and distance scores for the respective methods. Tables 1 and 2 give a range of thresholds and the false positive rate and detection rate for each of the schemes.

The size of the data sets is relatively modest because it was important to check many of the pairs of files by hand; to ensure that errors had not crept into the analysis.

Sdhash			Ssdeep		
Score	FP rate	Detect rate	Score	FP rate	Detect rate
> 0	0.04711%	37.1%	> 0	0.09966%	31.2%
> 5	0.02718%	36.6%	> 5	0.09785%	31.2%
> 10	0.02174%	36.1%	> 10	0.09603%	31.2%
> 20	0.01812%	35.4%	> 20	0.09422%	31.2%
> 30	0.01268%	34.4%	> 30	0.05617%	30.9%
> 40	0.00544%	32.7%	> 40	0.01812%	29.3%
> 50	0.00362%	29.7%	> 50	0.00362%	27.3%
> 60	0.00362%	26.0%	> 60	0.00362%	25.9%
> 70	0.00181%	18.8%	> 70	0.00181%	23.1%
> 80	0.00181%	12.4%	> 80	0.00000%	16.2%
> 90	0.00181%	4.6%	> 90	0.00000%	8.8%
> 99	0.00000%	1.0%	> 99	0.00000%	3.5%

Table 1. False positive and detection rates for Sdhash and Ssdeep

TLSH			Nilsimsa		
Score	FP rate	Detect rate	Score	FP rate	Detect rate
< 300	79.30%	98.8%	> 120	99.86%	100.0%
< 250	69.06%	98.8%	> 130	99.20%	100.0%
< 200	50.10%	98.8%	> 140	98.11%	100.0%
< 150	24.33%	98.1%	> 150	96.98%	100.0%
< 100	6.43%	94.5%	> 160	94.26%	100.0%
< 90	4.49%	92.3%	> 170	89.52%	100.0%
< 80	2.93%	89.0%	> 180	81.38%	100.0%
< 70	1.84%	83.6%	> 190	69.69%	99.7%
< 60	1.09%	76.0%	> 200	54.45%	98.8%
< 50	0.52%	65.3%	> 210	36.73%	96.4%
< 40	0.07%	49.6%	> 220	18.29%	91.9%
< 30	0.00181%	32.2%	> 230	5.52%	72.0%
< 20	0.00181%	17.3%	> 240	1.26%	35.2%
< 10	0.00181%	6.4%	> 250	0.49%	9.5%

Table 2. False positive and detection rates for tlsh and the Nilsimsa hash

We note the following from the tables:

- The schemes have different scoring ranges. TLSH distance scores go up to 300 (and can potentially go up to over 1000). Sdhash and Ssdeep similarity scores are restricted to the range 0-100.
- The Nilsimsa hash typically gives scores in the range 128-256 – and rarely goes below 128. A Nilsimsa score of 128 can be interpreted as meaning the files are completely different, while a score of 256 means the files are very similar.
- The Sdhash and Ssdeep schemes have very low false positive rates for all sensible thresholds, but have a significantly lower range for their detection rate.
- The TLSH scheme has very low false positive detection capabilities at thresholds <= 30 and very high detection rates for thresholds closer to 100. Of the four schemes, it is the only scheme which allows for the user to select a threshold which enables tradeoffs to be made between false positive rates and detection rates.
- The Nilsimsa scheme has very strong capabilities for detecting similar files, but suffers from significantly higher false positive rates. We note that the results of the Nilsimsa scheme are strictly worse than the TLSH scheme – so we drop the Nilsimsa scheme from further consideration.

We took the false positive and true positive rates for three of the schemes and created a ROC curve (for clarity we have removed the Nilsimsa scheme since it is not a competitive scheme). Fig. 1 shows the ROC curve where the scoring threshold was systematically varied to determine whether two files were a match or not.

The ROC curve highlights a deficiency in the Sdhash and Ssdeep schemes. Limiting the scoring to 0-100 has resulted in schemes where there is no available threshold for many useful cases.

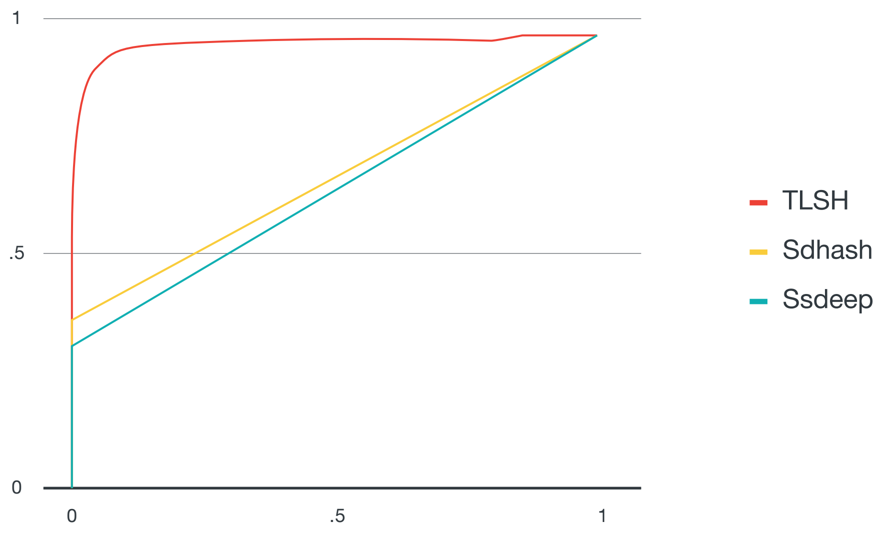


Figure 1. ROC Curve

For the Sdhash and Ssdeep schemes, this results in a ROC curve which abruptly changes in nature once the threshold hits the score of 1. It is not a sensible use of these schemes to use a threshold of 0 – since that is equivalent to asserting that all files are similar. From Table 1, we see that at a threshold of 1, Sdhash has a false positive rate of 0.047% and a detection rate of 37.1%. At a threshold of 0, Sdhash has a false positive rate of 100% and a detection rate of 100%. There are no thresholds available between these extremes. We have drawn in this point on the ROC diagram so that we can calculate the ROC area.

The ROC area for each of the methods is shown in Table 3. We list the areas under the curves as a standard part of a ROC analysis, while noting that the areas for the Sdhash and Ssdeep schemes were dominated by the limitation on thresholds noted above.

	TLSH	Sdhash	Ssdeep
Area under ROC curve	0.9775	0.6855	0.6555

Table 3. Area under ROC curve

The value in doing the ROC analysis was twofold:

1. It established that the various choices about the algorithm and parameters made in Sections 2 and 3 created a robust scheme.
2. It identified that using a scoring range of 0-100 created limitations for the Sdhash and Ssdeep schemes.

Systematically Changing a File

We started with the first 500 lines of Pride and Prejudice (pg1342.txt from [9]). We created 500 versions of this text, each one more `different` from the original text than the previous.

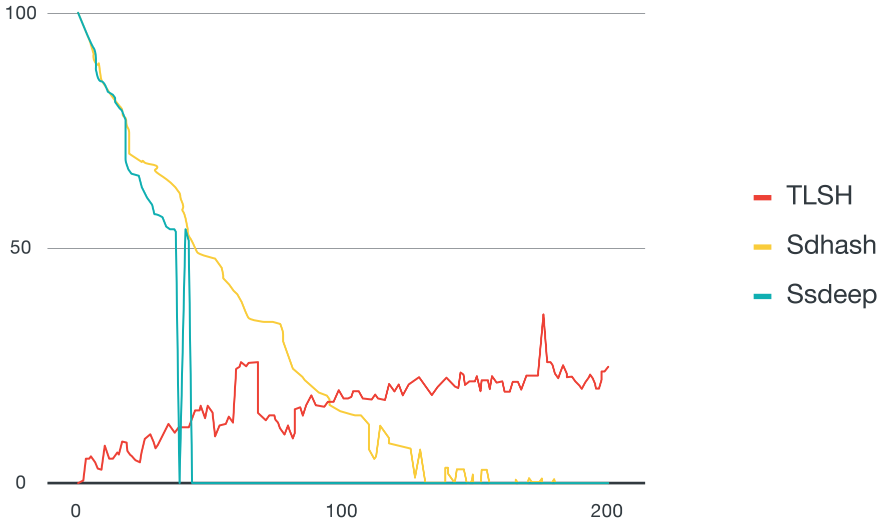


Figure 2. The scores on mutations of the first 500 lines of Pride and Prejudice.

The changes we introduced were random, and consisted of performing one of the following changes:

1. inserting a new word,
2. deleting an existing word,
3. swapping two words,
4. substituting a word for another word,
5. replacing 10 occurrences of a character for another character, or
6. deleting 10 occurrences of a character.

The scores comparing the original text with the files generated by this process for Ssdeep, Sdhash and TLSH are shown below in Fig. 2.

We then applied the same approach to the entire text of Pride and Prejudice (13426 lines containing 704,146 bytes). We again iteratively applied changes. Due to the size of the book, at each iteration we would do one of the following transactions:

A. apply 40 of the changes (1-6) described above,
B. swap two sections containing 5-25 lines, or
C. delete 5-25 lines.

The scores comparing the original text with the files generated by this process for Ssdeep, Sdhash and TLSH are shown below in Fig. 3.

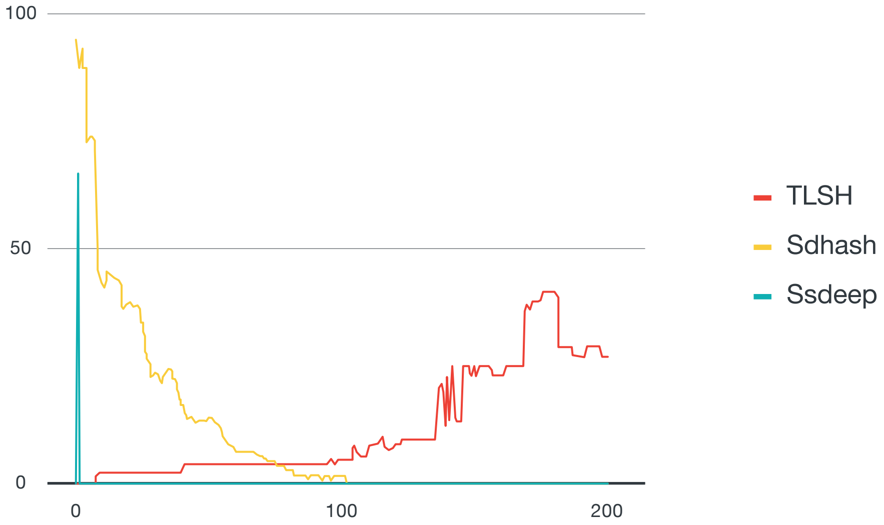
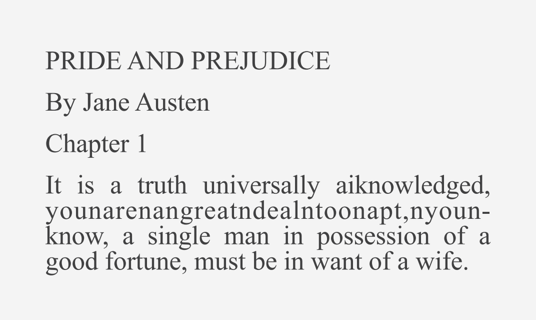


Figure 3. The scores on mutations of entire text of Pride and Prejudice.

In both Fig. 2 and Fig. 3, the Ssdeep and Sdhash similarity scores go down from 100 to 0, while the distance score for TLSH grows. In both graphs, well after the Ssdeep and Sdhash methods have scored the files as being distinct (a score of 0), the TLSH method is giving distance scores which can be interpreted as saying the files are `similar` (in the range of 10 to 40).

Alarmingly for the Ssdeep method, in Fig. 3, the Ssdeep score immediately goes to zero after the 2nd iteration of changes to the text. At this point the Unix diff command can determine that the files are very similar – only 153 changes have occurred and the first change does not occur until line 44 out of 13426 lines.

A visual inspection of the files agrees with the TLSH scores. After 150 iterations of the process, where both Sdhash and Ssdeep have failed to identify the files as being similar, a human reader can still say with confidence that the text is the start of Pride and Prejudice. The first paragraph of the 150th iteration of this process is shown in Fig. 4.



PRIDE AND PREJUDICE

By Jane Austen

Chapter 1

It is a truth universally aiknowledged, younarenangreatndealntoonapt,nyounknow, a single man in possession of a good fortune, must be in want of a wife.

Figure 4. The first paragraph of the 150th iteration of the mutation process.

Performance

We performed a comparison of the speed of the TLSH code. Table 4 below shows the TLSH performance on Ubuntu machine (Intel Pentium 4 CPU 3.40 GHz, 4G RAM) compared to MD5, SHA-1 and Ssdeep. The input data length is 4096 bytes, and the times were averaged over 10,000 computations of the hash.

Method	Average time (microsecond)
TLSH	286
MD5	38
SHA1	53
Ssdeep	265

Table 4. Average speed for calculating the digests

The speed of TLSH is about the same as Ssdeep.

Conclusion

This paper has described the TLSH approach based on Locality Sensitive Hashing for implementing similarity digests. The approach described here has been released as open source code [12].

The ROC analysis highlighted a significant problem with the range of values which the Sdhash and Ssdeep similarity score can take. Restricting this to a range of 0-100 limits the usefulness of the schemes.

The TLSH scheme described has outperformed available digest methods for identifying similar documents, especially for applications where missed detections are of concern and false alarms are acceptable. The TLSH method shows distinct advantages in the nature of its ROC curve, and therefore has a wider range of computer security applications. The empirical evaluation highlights significant problems with previously proposed schemes.

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