IN 101: Bachelor Project #1

Due on Monday, January 1, 2012

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Introduction

The motivation of this project is first and foremost to improve the Linear attack on the Hill cipher, by changing the recovery of the key modulo 26 and then see the possible algorithm to improve the FFT.

Let's briefly recall how this attack works.

You get the plaintext into modulo 2, then with the aid of vectors, and bias

bias(X)= $\varphi_X(\frac{2\pi}{p})$ in $\mathbb{Z}/26\mathbb{Z}$

With the fact that the plain text is of length d , we can write λ X that represent the plain text , where X is a vector column.

Then thanks to the bias , we found correspondence between λ and μ (which is the same vector but for the cipher text). Wa actually get $\mu = (K^T)^{-1} \times \lambda$

Then with this formula and the approximation of all the vector μ , we get the column of the key matrix.

Then we need to find the correct order in the key matrix , we use algorithm 1

Key recover modulo 26

So now that we have the key matrix in $\mathbb{Z}/2\mathbb{Z}$, we can have the plain text in $\mathbb{Z}/2\mathbb{Z}$ using the linearity of the cipher.

To get the key matrix in $\mathbb{Z}/26\mathbb{Z}$, we can use the Chinese Reminder Theorem, but we would get a complexity of $O(13^d)$. In the previous paper, it was believed that it's possible to get the key matrix in $\mathbb{Z}/26\mathbb{Z}$ without considering $\mathbb{Z}/13\mathbb{Z}$.

First of all , we create a hash table using long text , and search mapping between segments of reference text and plain text modulo 2

#(seg in reference) = len(reference text) - n + 1, with n the segment size.

Indeed, if you take the following text: this is a test, with n = 5, you get the following segment:

thisi, hisis, isisa, sisat, isate, sates, atest which is 7 segments 11 - 5 + 1 = 7

We get the same thing for #(str in plain) = len(plain text) - n + 1, with n the string size.

Then we define the good mathcings: segments are equals before and after modulo 2, and bad matching segment are not equal but they are equal modulo 2.

We use Rnyi entropy to get the good matching and all matching as it find the collision , with the following formula :

 $H_{\alpha}(X) = \frac{1}{1-\alpha}log_2(\sum_{i=1}^n Pr(X=i)^{\alpha})$, then when alpha has the value 2, we just get $-log_2(\sum_{i=1}^n Pr(X=i)^2)$ that gives us the probability that a segment equals another one.

For good matchings, we have $E(\# \text{ good matchings}) = (\# \text{ segments in reference}) \times (\# \text{ segment in plaintext}) \times 2^{-H_2(X)}$, as the number of good matching is actually the collision between segment in plaintext and segment in reference text time the entropy of rnyi where two segments are the same.

Then you do the same for E(# all matchings), the difference is that you do it this way: $E(\# \text{ good matchings}) = (\# \text{ segments in reference}) \times (\# \text{ segment in plaintext}) \times 2^{-H_2(X mod 2)}$. And indeed you understand that if X modulo 2 are equals the X are not always equals.

The previous part assumed that $H_2(Xmod2)$ was equals to n , but i did these maths again and it seems good.

Then to have an idea of the complexity, you do the ratio $\frac{E(\#goodmatchings)}{E(\#allmatchings)}$, you generally found $\frac{1}{8^n}$. In the following parts, I did the calculation again to check if it's really correct

But to have a better complexity, we need to increase this ratio: E(# all matchings) can't be changed so we can only try on E(# good matchings), with different assumptions and calculations.

Experiment

from wiki:

Probabilite de la 1ieme lettre de l'aphabet 0.08167 Probabilite de la 2ieme lettre de l'aphabet 0.01492 Probabilite de la 3ieme lettre de l'aphabet 0.02782 Probabilite de la 4ieme lettre de l'aphabet 0.04253 Probabilite de la 5ieme lettre de l'aphabet 0.12702 Probabilite de la 6ieme lettre de l'aphabet 0.02228 Probabilite de la 7ieme lettre de l'aphabet 0.02015 Probabilite de la 8ieme lettre de l'aphabet 0.06094 Probabilite de la 9ieme lettre de l'aphabet 0.06966 Probabilite de la 10ieme lettre de l'aphabet 0.00153 Probabilite de la 11ieme lettre de l'aphabet 0.00772 Probabilite de la 12ieme lettre de l'aphabet 0.04025 Probabilite de la 13ieme lettre de l'aphabet 0.02406 Probabilite de la 14ieme lettre de l'aphabet 0.06749 Probabilite de la 15ieme lettre de l'aphabet 0.07507 Probabilite de la 16ieme lettre de l'aphabet 0.01929 Probabilite de la 17ieme lettre de l'aphabet 9.5E-4 Probabilite de la 18ieme lettre de l'aphabet 0.05987 Probabilite de la 19ieme lettre de l'aphabet 0.06327 Probabilite de la 20ieme lettre de l'aphabet 0.09056 Probabilite de la 21ieme lettre de l'aphabet 0.02758 Probabilite de la 22ieme lettre de l'aphabet 0.00978 Probabilite de la 23ieme lettre de l'aphabet 0.02361 Probabilite de la 24ieme lettre de l'aphabet 0.0015 Probabilite de la 25ieme lettre de l'aphabet 0.01974 Probabilite de la 26ieme lettre de l'aphabet 7.4E-4

Another site:

Probabilite de la 1ieme lettre de l'aphabet 0.0808 Probabilite de la 2ieme lettre de l'aphabet 0.0167 Probabilite de la 3ieme lettre de l'aphabet 0.0318 Probabilite de la 4ieme lettre de l'aphabet 0.0399 Probabilite de la 5ieme lettre de l'aphabet 0.1256 Probabilite de la 6ieme lettre de l'aphabet 0.0217 Probabilite de la 7ieme lettre de l'aphabet 0.018 Probabilite de la 8ieme lettre de l'aphabet 0.0527

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Probabilite de la 9ieme lettre de l'aphabet 0.0724
Probabilite de la 10ieme lettre de l'aphabet 0.0014
Probabilite de la 11ieme lettre de l'aphabet 0.0063
Probabilite de la 12ieme lettre de l'aphabet 0.0404
Probabilite de la 13ieme lettre de l'aphabet 0.026
Probabilite de la 14ieme lettre de l'aphabet 0.0738
Probabilite de la 15ieme lettre de l'aphabet 0.0747
Probabilite de la 16ieme lettre de l'aphabet 0.0191
Probabilite de la 17ieme lettre de l'aphabet 9.0E-4
Probabilite de la 18ieme lettre de l'aphabet 0.0642
Probabilite de la 19ieme lettre de l'aphabet 0.0659
Probabilite de la 20ieme lettre de l'aphabet 0.0915
Probabilite de la 21ieme lettre de l'aphabet 0.0279
Probabilite de la 22ieme lettre de l'aphabet 0.01
Probabilite de la 23ieme lettre de l'aphabet 0.0189
Probabilite de la 24ieme lettre de l'aphabet 0.0021
Probabilite de la 25ieme lettre de l'aphabet 0.0165
Probabilite de la 26ieme lettre de l'aphabet 7.0E-4
```

```
proba sum = 0.99990000000000001
proba sum squared = 0.06609151
proba sum squared 0 = 0.5657 0.32001649
proba sum squared 1 = 0.4342 0.18852964
Ration of good matching and all matchings=0.12996168115565054
Donc 7,69457
```

Enhancement good matching's ratio

This section will be to increase the ratio found which is actually $\frac{1}{8^n}$

To do so , I'll now consider instead of independent letters , independent blocks of letter. With the help of a Java programm , i'm doing an heuristic search over a very very long text , with different block size.

With the program, we clearly see that there is no way to improve it considering that they are independent.

Study of Faster Fourrier Transform for Algorithm 1

lololo

Algorithm

You hash a reference text.

You take the key matrix that you get from algorithm 1, find plain text in $\mathbb{Z}/2\mathbb{Z}$, and create an array. find the list of all matchings: find all pairs(seg,str) such that seg is a segment of plaintext modulo 2 and str $\in hash(seg)$ and save it in a list.

repeat

select d matching form list (you'll get a dxd key matrix)

```
for each of these matchings (seg_i, str_i) extract block_i from seg_i and str_i' from str_i, then find ciphertext_i such that K^{-1} \times ciphertext_i \mod 2 = block_i solve ciphertext_i = K * str_i' for i=1 to d compute K^{-1}*ciphertext until it makes sense number of iteration is \frac{1}{ration^d} = 8^{nd}
```

The following algorithm is to recover the key matrix in $\mathbb{Z}/2\mathbb{Z}$ Part1:

```
You require Ciphertext Y_1, Y_2, ..., Y_n for all \mu do compute S_n(\mu) = \sum_{k=1}^n (-1)^{\mu \cdot y} \times n_y where n_y = \#\{k; Y_k = y\} endfor set all \mu to the d values of \mu with largest S_n(\mu) = bias(\mu \cdot Y)
```

Part2:

```
for all (i,i') do compute n_{00}(i,i') = \#\{k < n : (\mu_i.Y_k,\mu_i'.Y_{k+1}) = (0,0)\} endfor set (i_d,i_1) to the first pair with lowest n_{00}
```