

CS648 Assignment 2

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1. 2-Dimensional Pattern Matching

1.

Notations : Let T be the text bit-string and P the pattern bit-string. Size of T is n and P is m .

$M(P)$ is mapping of the pattern P to a 2×2 matrix as given in the problem statement.

$M(P)^{-1}$ is the inverse matrix to $M(P)$. Let l and r be two indices in T s.t. $1 \leq l \leq r \leq n$.

$T[l, r]$ is the substring starting at index l and ending at r .

Consequently, $M(T[l, r])$ is mapping of $T[l, r]$ to 2×2 matrix as given in the problem statement.

$$M(\epsilon) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad M(0) = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \quad M(1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \quad M(0)^{-1} = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix} \quad M(1)^{-1} = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$$

Algorithm : Basically, we will compare $M(P)$ with $M(T[i, i + m - 1]) \forall i$ in $[1, n - m + 1]$.

We will calculate $M(P)$ by right multiplying corresponding $M(P[i])$ for i from 1 to m to an identity matrix. Similarly, we will calculate $M(T[1, m])$. After that to get, $M(T[i, i + m - 1])$ for $i > 1$, we will take $M(T[i - 1, i + m - 2])$, right multiply $M(T[i + m, i + m])$ and left multiply $M(T[i - 1, i - 1])^{-1}$ to it.

The following pseudo code formalize the above algorithm.

```
pattern ← M(P);
current ← M(T[1, m]);
for i = 1 to n - m + 1
    if pattern == current
        print "Pattern present at index i";
    if i < n - m + 1
        current = multiply(current, M(T[i + m, i + m]));
        current = multiply(M(T[i, i]), current);
```

Order Analysis :

Calculating $M(P)$ takes $O(m)$ time

Calculating $M(T[1, m])$ takes $O(m)$ time

Loop Runs $n - m + 1$ times and at each iteration we do a $O(1)$ computation. Hence loop takes $O(n - m + 1)$ time.

Overall Complexity = $O(n + m)$ time.

2.

Notation :

Let M be a matrix then $M \bmod p$ denotes a matrix in which all entries of M are replaced by their modulo with p .

Hence, We perform the above algorithm but at each step, while multiplying two matrices, we take modulo with p .

Let $M(A)$ and $M(B)$ be two matrices which are mapping of string A and B of size m .

$\pi(t)$ = number of primes less than equal to t .

Now, if $M(A) == M(B)$ then $M(A) \bmod p == M(B) \bmod p$ then $A == B$ which is true.

But if $A != B$ and then $M(A) != M(B)$ then it might be possible that $M(A) \bmod p == M(B) \bmod p$. which will imply that $A == B$ which is not true.

Hence, this algorithm will fail iff $M(A) != M(B)$ and $M(A) \bmod p == M(B) \bmod p$.

Let $D = M(A) - M(B)$

$M(A) \bmod p == M(B) \bmod p$

$\Rightarrow M(A) - M(B) \bmod p == 0$ (where 0 is 2×2 null matrix)

$\Rightarrow D \bmod p == 0$

Hence, every entry of D is multiple of p , or conversely p is factor of every entry of D .

Now, take any entry of D (say x). Now, x is bounded by m^{th} Fibonacci number which is bounded by 2^m ;

Now, any number N has at most $\log N$ factors hence x has at most m factors or at most n factors ($m \leq n$).

Let say we choose p uniformly randomly from range $[2, t]$ then probability that a factor of x was chosen was $\frac{n}{\pi(t)}$

There are four elements of D and event that p is a factor of one of the element is independent of the event that p is a factor of other element of D .

Hence probability that p was a factor of all of the element $\leq (\frac{n}{\pi(t)})^4$.

We want this probability to be less than $\frac{1}{n^4}$.

Hence, we want $\frac{n}{\pi(t)}$ to be less than $\frac{1}{n}$.

Putting $t = n^2 \log n$ and $\pi(t) = \frac{t}{\log t}$.
 We get this probability to be less $\frac{1}{n^4}$.

(As done in class)

3.

Notation :

Here we assume that all operation are accompanied by a modulo operation by p which is chosen in the begining.

Let S be 2-D bit-matrix and $S(i, j)$ denotes the element of i^{th} row and j^{th} column.

$PrefixProduct(i, j) = \text{Product of all the } M(S(k, j)) \text{ s.t. } 1 \leq k \leq i.$

i.e. $PrefixProduct(i, j) = M(S(1, j)) * M(S(2, j)) * \dots * M(S(i, j))$

$PrefixProductInverse(i, j) = \text{Matrix inverse of } PrefixProduct(i, j)$

i.e. $PrefixProductInverse(i, j) = M(S(i, j))^{-1} * M(S(i-1, j))^{-1} * \dots * M(S(1, j))^{-1}$

Now let us assume there is a matrix X of size $N \times M$ then we have map this matrix to 2×2 matrix $M(X)$

We define this map as follows:

If X is column matrix, cut this matrix into two submatrix by cutting at any row. Let U be upper column matrix and L be the lower one.

Then $M(X) = M(U) * M(L)$

If X is not a column matrix, cut this at any column, let L be the submatrix left of this line and R be the one right to it. Then

$M(X) = M(L) * M(R)$

Now we have defined the new mapping M, we can state our algorithm.

Algorithm : Let T be the text $n \times n$ 2-D bit-matrix and P be the pattern $m \times m$ 2-D bit-matrix. $T(i, j)$ is the element at the i^{th} row and j^{th} column.

First we show how to calculate $PrefixProduct(i, j)$ and $PrefixProductInverse$ for matrix T in $O(n^2)$ time.

$PrefixProduct(1, j)$ and $PrefixProductInverse(1, j)$ will be simply the M and M^{-1} of the corresponding element. To calculate them for other rows just use the $PrefixProduct$ and $PrefixProductInverse$ of previous row.

Following pseudocode describes our algorithm :

```

for j = 1 to n
    PrefixProduct(1, j) = M(T(1, j))
    PrefixProductInverse(1, j) = M(T(1, j))-1
for i = 2 to n
    for j = 1 to n
        PrefixProduct(i, j) = PrefixProduct(i-1, j) * M(T(i, j))
        PrefixProductInverse(i, j) = M(T(i, j))-1 * PrefixProductInverse(i-1, j)

```

Also we calculate $M(P)$ in $O(m^2)$ time.

Initialize $M(P) = I_{2 \times 2}$

for i = 1 to m

for j = 1 to m

$M(P) = M(P) * M(T(j, i))$

Now we have to calculate mapping of every submatrix of size m of matrix T. Let $M(T(i, j))$ is the mapping of submatrix of size m ending at (i, j) in T. $m \leq i, j \leq n$. We will calculate this mapping in $O(n^2)$ time as follows :

First we calculate $M_c(i, j)$ which is product of all the $M(T[k, j])$ such that $i-m+1 \leq k \leq i$, $m \leq i \leq n, 1 \leq j \leq n$

Also we will calculate $M_c(i, j)^{-1}$ with it. We can calculate these both in $O(n^2)$ as follows:

```

for i = m to n
    for j = 1 to n
        If i = m
             $M_c(m, j) = PrefixProduct(m, j)$ 
             $M_c(m, j)^{-1} = PrefixProductInverse(m, j)$ 
        else
             $M_c(i, j) = PrefixProductInverse(i-m, j) * PrefixProduct(i, j)$ 
             $M_c(i, j)^{-1} = PrefixProductInverse(i, j) * PrefixProduct(i-m, j)$ 

```

Now with help of this we can calculate $M(T(i, j))$ in $O(n^2)$ as follows :

```

for i = m to n
  for j = m to n
    if j = m
      Initialize  $M(T(i, j)) = I_{2 \times 2}$ 
      for k = 1 to m
         $M(T(i, j)) = M(T(i, j)) * M_c(i, k)$ 
    else
       $M(T(i, j)) = M_c(i, j - m)^{-1} * M(T(i, j - 1)) * M_c(i, j)$ 

```

For $n - m + 1$ elements we take $O(m)$ time and for rest of the elements we take $O(1)$ time. Hence total time = $O(m * (n - m + 1)) + O((n - m + 1) * (n - m + 1)) = O(n^2)$
Hence we just go at each i, j s.t $m \leq i, j \leq n$, compare $M(P)$ with $M(T(i, j))$ in $O(1)$ time which take overall $O(n^2)$
Now, for the error probability, we again receive two 2×2 matrix and compare them in our algorithm. Hence, we can again choose prime as done in last part and get the same error probability i.e. $\frac{1}{n^4}$.

2. How well did you internalize the proof of Chernoff bound ?

1. Probability that number of coin tosses required to get n heads is greater than equal $2n(1 + \delta)$ is same as Probability of getting less than or equal $n - 1$ heads out $2n(1 + \delta) - 1$ coin tosses because otherwise we would have got greater than equal n heads in first $2n(1 + \delta) - 1$ tosses which clearly means we do not require greater than equal $2n(1 + \delta)$ tosses to get n heads
For given geometrically distributed random variable, we know that expected value is $\frac{1}{p}$ which is given 2 , hence $p = \frac{1}{2}$.

$$X_i = \begin{cases} 1 & \text{if head is obtained at } i^{th} \text{ iteration} \\ 0 & \text{otherwise} \end{cases}$$

$$E[X_i] = \frac{1}{2} * 1 + \frac{1}{2} * 0 = \frac{1}{2}.$$

$$X' = \sum_{i=1}^{2n(1+\delta)-1} X_i$$

Number of heads in $2n(1 + \delta) - 1$ tosses

$$E[X'] = \sum_{i=1}^{2n(1+\delta)-1} E[X_i] = n(1 + \delta) - \frac{1}{2}$$

By linearity of expectation

Assuming $n \gg \frac{1}{2}$, we get $E[X'] = n(1 + \delta)$

$$P(X' \leq (n - 1))$$

$$= P(X' \leq (n - 1) \frac{E[X']}{(1 + \delta)n})$$

$$= P(X' \leq (1 - \frac{n\delta+1}{n(1+\delta)}) * E[X'])$$

$$\leq P(X' \leq (1 - \frac{\delta}{\delta+1}) * E[X']) \quad (As \frac{n\delta+1}{n(1+\delta)} > \frac{\delta}{\delta+1})$$

$$= P(X' \leq (1 - \delta') * E[X']) \text{ By letting } \delta' = \frac{\delta}{\delta+1}$$

$$\leq (\frac{e^{-\delta'}}{(1-\delta')^{1-\delta'}})^{E[X']}$$

Putting value of δ' , we get

$$\leq ((1 + \delta)e^{-\delta})^n$$

2. According to Markov's Inequality

$$P(X \geq a) \leq \frac{E[X]}{a} \text{ if } X(\omega) \geq 0 \forall \omega \in \Omega$$

$$\because X(\omega) \in \mathbb{N}$$

$$P(X \geq (1 + \delta)\mu)$$

$$= P(e^{tx} \geq e^{(1+\delta)t\mu}) \leq \frac{E[e^{tx}]}{e^{(1+\delta)t\mu}}$$

$$\begin{aligned}
& E[e^{tX}] \\
&= E[e^{tX_1+tX_2+tX_3+\dots+tX_n}] \\
&= \prod_{i=1}^n E[e^{tX_i}] \\
& E[e^{tX_i}] = \frac{e^t}{2} + \frac{e^{2t}}{4} + \frac{e^{3t}}{8} \dots = \frac{e^t}{2(1-\frac{e^t}{2})} = \frac{e^t}{2-e^t} \quad (\text{Assuming } e^t < 2 \text{ so that sequence converges}) \\
& E[e^{tX}] = \prod_{i=1}^n E[e^{tX_i}] = \left(\frac{e^t}{2-e^t}\right)^n
\end{aligned}$$

$$\text{Now } \mu = \sum_{i=1}^n E[X_i] = 2n \quad \text{By linearity of expectation}$$

$$P(X \geq 2n(1+\delta)) \leq \left(\frac{e^t}{(2-e^t)e^{2t(1+\delta)}}\right)^n$$

Now differentiating w.r.t t to get the *minima* we get

$$P(X \geq 2n(1+\delta)) \leq \left(\frac{(1+\delta)^{2(1+\delta)}}{(1+2\delta)^{1+2\delta}}\right)^n$$

3.

Claim : Bound obtained from 2nd part is better

Proof : Bound obtained in 1st part (say $b1$) = $\left(\frac{1+\delta}{e^\delta}\right)^n$

Bound obtained in 2nd part (say $b2$) = $\left(\frac{(1+\delta)^{2(1+\delta)}}{(1+2\delta)^{1+2\delta}}\right)^n$

To prove $\frac{b1}{b2} \geq 1$ $\frac{b1}{b2} = \left(\frac{(1+\delta)(1+2\delta)^{1+2\delta}}{((1+\delta)^{2(1+\delta)})e^\delta}\right)^n$

Taking \ln on both sides, we get

$$n(\ln(1+\delta) - \delta - 2(1+\delta)\ln(1+\delta) + (2\delta+1) * \ln(1+2\delta)) \geq 0$$

$$(2\delta+1)(\ln(\frac{1+2\delta}{1+\delta})) > \delta$$

$$\ln(\frac{1+2\delta}{1+\delta}) = \ln(1 + \frac{\delta}{1+\delta}) > \frac{\delta}{\delta+1} - \frac{\delta^2}{2(\delta+1)^2}$$

$$\text{LHS} > (2\delta+1)\left(\frac{\delta}{\delta+1} - \frac{\delta^2}{2(\delta+1)^2}\right) = \frac{\delta(2\delta+1)(\delta+2)}{2(\delta+1)^2} = \frac{\delta(2\delta^2+5\delta+2)}{(2\delta^2+4\delta+2)} > \delta$$

Hence proved.

3. Estimating biasness of a coin

Strategy: We toss the coin N times, Let H be the random variable denoting the number of heads in N coin tosses. We report \tilde{p} to be $\frac{H}{N}$.

Now, given ϵ , δ and a , we will estimate the value of N so that the following probability hold.

$$\Pr[|p - \tilde{p}| > p\epsilon] < \delta$$

$$\implies \Pr[\tilde{p} < p(1-\epsilon)] + \Pr[\tilde{p} > p(1+\epsilon)] < \delta$$

$$\implies \Pr[N\tilde{p} < Np(1-\epsilon)] + \Pr[N\tilde{p} > Np(1+\epsilon)] < \delta$$

$$\implies \Pr[H < E[H](1-\epsilon)] + \Pr[H > E[H](1+\epsilon)] < \delta$$

$$\text{Now } \Pr[H < E[H](1-\epsilon)] + \Pr[H > E[H](1+\epsilon)]$$

$$< e^{\frac{-N\epsilon^2 p}{2}} + e^{\frac{-N\epsilon^2 p}{4}}$$

$$< 2e^{\frac{-N\epsilon^2 p}{4}}$$

$$< 2e^{\frac{-N\epsilon^2 a}{4}}$$

If we have this term to be less than δ then our Probability condition will hold.

$$2e^{\frac{-N\epsilon^2a}{4}} < \delta$$

$$\implies \frac{-N\epsilon^2a}{4} < \ln(\frac{\delta}{2})$$

$$N > 4\frac{\ln(\frac{2}{\delta})}{a\epsilon^2}$$