

# Advanced Algorithm: Assignment #1

Due on Sept 26, 2017 at 12:00 pm

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## Problem 1

Recall that in class we show by the probabilistic method how to deduce a  $\frac{n(n-1)}{2}$  upper bound on the number of distinct min-cuts in any multigraph  $G$  with  $n$  vertices from the  $\frac{n(n-1)}{2}$  lower bound for success probability of Karger's min-cut algorithm.

Also recall that the *FastCut* algorithm taught in class guarantee to return a min-cut with probability at least  $\Omega(1/\log n)$ . Does this imply a much tighter  $O(\log n)$  upper bound on the number of distinct min-cuts in any multigraph  $G$  with  $n$  vertices? Prove your improved upper bound if your answer is "yes", and give a satisfactory explanation if your answer is "no".

### Solution

#### part 1

the Karger's theorem is:

$$\text{For any min-cut } C, \Pr[C \text{ is returned}] \geq \frac{2}{n(n-1)}.$$

Assume  $G$  has  $r$  min-cut, which is  $c_1, c_2, \dots, c_r$ . For each  $c_i \in \{c_1, c_2, \dots, c_r\}$ , use the Karger's theorem, we have:

$$\Pr[c_i \text{ is returned}] \geq \frac{2}{n(n-1)} \quad (1)$$

then we have:

$$\Pr[\bigcup_{i=1}^r c_i \text{ is returned}] = \sum_{i=1}^r \frac{2}{n(n-1)} \geq \frac{2 \times r}{n(n-1)} \quad (2)$$

And obviously, we know  $\Pr[\bigcup_{i=1}^r c_i \text{ is returned}] \leq 1$ , so:

$$\frac{2 \times r}{n(n-1)} \leq 1 \quad (3)$$

then:

$$r \leq \frac{n(n-1)}{2} \quad (4)$$

that is the proof.

#### part 2

First, I can give a counter example. For a complete graph with  $n$  vertices, due to its symmetry, the number of distinct min-cuts must be upper than  $n$ . So it cannot be bound by  $O(\log n)$ . So my answer is "no".

Then I wanna to find the reason of the gap:

Assume  $C$  is a min-cut, and  $\Pr[C = \text{Fastcut}(G)] \geq \frac{1}{O(1/\log n)}$ . Then we also assume that there are  $r$  min-cuts in the graph, which is  $c_1, c_2, \dots, c_r$ . then we also have  $\Pr[c_i = \text{Fastcut}(G)] \geq \frac{1}{O(1/\log n)}$ . But the operation is not at one times, so we don't have  $\Pr[\bigcup_{i=1}^r c_i = \text{Fastcut}(G)] = \sum_{i=1}^r \Pr[c_i = \text{Fastcut}(G)]$ , that is where the gap is.

## Problem 2

Two rooted trees  $T_1$  and  $T_2$  are said to be *isomorphic* if there exists a bijection  $\phi$  that maps vertices of  $T_1$  to those of  $T_2$  satisfying the following condition: for each internal vertex  $v$  of  $T_1$  with children  $\{\phi(u_1), \phi(u_2), \dots, \phi(u_k)\}$ , no ordering among children assumed.

Give an efficient randomized algorithm with bounded one-sided error (false positive), for testing isomorphism between rooted trees with  $n$  vertices. Analyze your algorithm.

### Solution

First I wanna to sort a tree and find a unique expression of a tree using invariant 0 and 1. Then using the fingerprint algorithm to check the identity.

we use the AHUSORT algorithm to solve the first part. The algorithm is shown below. The core idea of the algorithm is: give a rooted tree with  $n$  vertices. and we wanna to express the tree to a unique expression using invariant 0 and 1; there are two points here, that is unique and invariant. So we need to sort a tree to a unique expression what make two isomorphic trees express the same. In this algorithm, line 9 do this thing. Line 1-8 is a recursive process to name a vertice. If the vertex is a leaf, then name it '10'. If the vertex has children, then concatenate all the children to tmp, then return '1tmp0'. For example, vertex  $v_0$  have 3 children, which is  $v_1, v_2, v_3$ , and  $v_1$  is named as '110100',  $v_2$  is named as '1100',  $v_3$  is named as '11010100'. By sort, we transform the order  $v_1, v_2, v_3$  to  $v_2, v_1, v_3$ . Then we can concatenate the name of all children to '110011010011010100', then we use tmp to represent it. Then we get the name of  $v_0$ . That's the process of the algorithm.

Then I wanna to analysis the complexity of the algorithm. The time complexity of sorted operation is  $O(n \log n)$ . And the traverse is  $O(n)$ . So the time complexity is  $O(n^2 \log n)$ .

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#### Algorithm 1: Tree isomorphism (AHU) AHUSORT(v)

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input  :
        a rooted tree with  $n$  vertices;
output:
        a unique expression of the tree using invariant 0 and 1;

1 if  $v$  is a leaf then
2   Name  $v$  '10';
3 end
4 else
5   for all child  $w$  of  $v$  do
6     AHUSORT( $w$ );
7   end
8 end
9 sort the names of the children of  $v$ ;
10 concatenate the names of all children of  $v$  to temp;
11 return 1temp0

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Then we use Polynomial Identity Testing algorithm introduced in the lesson to check the identity. The problem is given 2 unique expression of two rooted trees, which is called  $a$ ,  $b$ , and  $a \in 0, 1^{2^n}, b \in 0, 1^{2^n}$ . And output whether  $a \equiv b$ .

We define  $f = \sum_{i=0}^{2^n-1} a_i x^i, g = \sum_{i=0}^{2^n-1} b_i x^i$ . Let  $k = \lceil \log_2(4n) \rceil$ . We choose a prime  $p \in [2^k, 2^{k+1}]$ , let  $f, g \in \mathbb{Z}_p[x]$ . Then we pick a random  $r \in [p]$ , check whether  $f(r) = g(r)$ . The time complexity of the algorithm is  $O(\log n)$ , and the one side error is less than  $\frac{1}{2}$ .

## Problem 3

Fix a universe  $U$  and two subset  $A, B \subset U$ , both with size  $n$ . We create both Bloom filters  $F_A(F_B)$  for  $A(B)$ , using the same number of bits  $m$  and the same  $k$  hash functions.

- Let  $F_C = F_A \cap F_B$  be the Bloom filter formed by computing the bitwise AND of  $F_A$  and  $F_B$ . Argue that  $F_C$  may not always be the same as the Bloom filter that are created for  $A \cap B$ .
- Bloom filters can be used to estimate set differences. Express the expected number of bits where  $F_A$  and  $F_B$  differ as a function of  $m, n, k$  and  $|A \cap B|$ .

### Solution

#### part 1

First, I wanna to do some definitions. We define  $S = \{i | F_A[i] = 1\}$ , and  $T = \{i | F_B[i] = 1\}$ ,  $R = \{i | F_{A \cap B}[i] = 1\}$ . Then we consider this condition:

For  $x_i \in A, x_i \notin B$ , and  $y_i \notin A, y_i \in B$ . But in the hash function,  $h_j(x_i) = h_j(y_i)$ , and  $h_j(x_i) \notin R$ . Then  $F_A[h_j(x_i)] = 1, F_B[h_j(y_i)] = 1$ , but  $F_{A \cap B}[h_j(x_i)] = 0$ .

So  $F_C$  may not be always the same as the Bloom filter that are created for  $A \cap B$ .

#### part 2

First, we define a indicate function  $I(i)$ :

$$I(i) = \begin{cases} 1 & \text{if } F_A[i] \neq F_B[i] \\ 0 & \text{o.w.} \end{cases}$$

Define the number of bits where  $F_A$  differs with  $F_B$  is  $D$ .  $D = \sum_{i=1}^m I(i)$ .

When  $I(i) = 1$  occurs when:

Case 0: For all  $x \in A \cap B$ ,  $h_j(x) \neq i$

and one of the following case occurs.

Case 1:  $[\exists x \in A - (A \cap B), h_j(x) = i] \cap [x \in B - (A \cap B), h_j(x) \neq i]$ ;

Case 2:  $[\exists x \in B - (A \cap B), h_j(x) = i] \cap [x \in A - (A \cap B), h_j(x) \neq i]$ ;

Note, case 0 represent no elements in  $A \cap B$  will hash to  $i$ , case 1 represent some elements in  $A$  will hash to  $i$ , but no elements in  $B$  will hash to  $i$ , case 2 represents some elements in  $B$  will hash to  $i$ , but no elements in  $A$  will hash to  $i$ . Iff  $[(\text{case0}) \cap (\text{case1})] \cup [(\text{case0}) \cap (\text{case2})]$  occurs,  $I(i)=1$ .

Then we separately consider the 3 cases. Assume  $t = |A \cap B|$ .

First for case 0, no elements in  $A \cap B$  will hash to  $i$  during  $k$  independent hashes. So:

$$Pr[\text{case0}] = \left(1 - \frac{1}{m}\right)^{t \times k} \quad (5)$$

For case 1, some elements in  $A$  will hash to  $i$ , but no elements in  $B$  will hash to  $i$ . We have:

$$\begin{aligned} Pr[\text{case 1}] &= Pr[[\exists x \in A - (A \cap B), h_j(x) = i] \cap [x \in B - (A \cap B), h_j(x) \neq i]] \\ &= \left(1 - \left(1 - \frac{1}{m}\right)^{(n-t) \times k}\right) \times \left(1 - \frac{1}{m}\right)^{(n-t) \times k} \end{aligned}$$

Note, some elements in  $A$  will hash to  $i$  is exact the exclusively event of no elements in  $A$  will hash to  $i$ . So  $Pr[\exists x \in A - (A \cap B), h_j(x) = i] = 1 - Pr[x \in A - (A \cap B), h_j(x) \neq i]$ . And the equation is obvious.

Case 2 is the same as case 1, because only A transform to B, B transform to A.

Thus, we get this:

$$\begin{aligned}
 Pr[I(i) = 1] &= Pr[case\ 0 \cap (case \cup case)] \\
 &= Pr[case\ 0] \times (Pr[case\ 1] + Pr[case\ 2]) \\
 &= Pr[case\ 0] \times 2 \times Pr[case\ 1] \\
 &= 2 \times \left(1 - \frac{1}{m}\right)^{t \times k} \times \left(1 - \left(1 - \frac{1}{m}\right)^{(n-t) \times k}\right) \times \left(1 - \frac{1}{m}\right)^{(n-t) \times k} \\
 &= 2 \times \left(1 - \frac{1}{m}\right)^{n \times k} \times \left(1 - \left(1 - \frac{1}{m}\right)^{(n-t) \times k}\right)
 \end{aligned}$$

So:

$$\begin{aligned}
 E(D) &= E\left(\sum_{i=1}^m I(i)\right) \\
 &= \sum_{i=1}^m E(I(i)) \\
 &= m \times Pr[I(i) = 1] \\
 &= 2m \times \left(1 - \frac{1}{m}\right)^{n \times k} \times \left(1 - \left(1 - \frac{1}{m}\right)^{(n-t) \times k}\right)
 \end{aligned}$$

Among it:

*m is the bit number;*

*n is the size of A or B;*

*k is number of hash functions;*

*t is the size of  $A \cap B$ .*