

# Advanced Randomization

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# Hello

- ▶ More stories about Xiaoqiang and Ameba!

# Recovering Linear Function

- ▶ mod 2
- ▶  $f(x_1, x_2, \dots, x_n) = x_1 \oplus x_2 \oplus x_5$
- ▶ given access to a noisy version of  $f$
- ▶  $\tilde{f}(x) = f(x) \oplus g(x)$
- ▶  $g$  is non-zero on only 30% inputs
- ▶ can you recover  $f$ ?

# Little Secret

- ▶ Familiar?
- ▶ If you only have **random** samples
- ▶ Last year's CTSC. Collision + FFT, time complexity is
- ▶  $O(n\gamma^{-2^{\frac{n}{\log m}-1}})$
- ▶ where the noise ratio is  $1/2-\gamma$
- ▶ not polynomial
- ▶ let's forget about it

# Little Secret

- ▶ If we can query arbitrary point
- ▶  $\tilde{f}(x)$
- ▶ can we do better?
- ▶ Polynomial?

# Yes

- ▶ The answer is Goldreich-Levin
- ▶ One of the most amazing algorithm (at least in theory)

# Another Application

- ▶ Given **black box** access to a function
- ▶ You want to decide whether it only depends on only a few parameters
- ▶  $f(x_1..n)=h(x_3,x_5,x_8)$
- ▶ or, whether it is close to such a thing
- ▶  $\tilde{f}(x_1..n)=h(x_3,x_5,x_8)\oplus g(x)$

# When do we encounter Black Box?

- ▶ complied binary



科技  
资格：

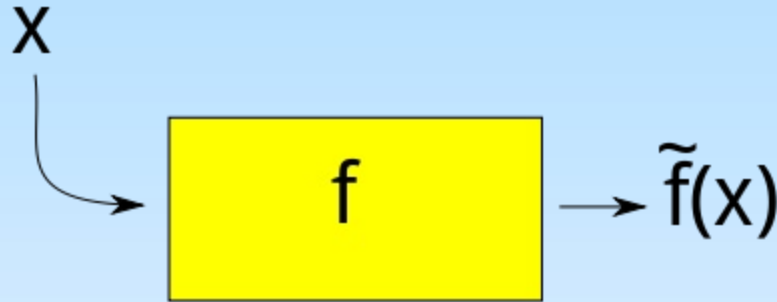
1. 本科及以上学历
2. 有软件破解、逆向工程经验
3. 有跨平台软件编写经验，精通C，熟悉
4. 熟悉x86/x64汇编，熟悉ARM汇编优先

- ▶ obfuscation v.s. reverse engineering



# Goldreich-Levin

- ▶ Let's only talk about the science part
- ▶ Given black-box and noisy access to a function,



- ▶ can you reverse-engineer it?

# Fourier Analysis

- ▶ the linear attack
- ▶ any (boolean) function can be written as a weighted combination of linear (mod 2) functions
- ▶  $a \wedge b = 0.5 a + 0.5 b - 0.5 a \oplus b$
- ▶  $a \vee b \vee c = 0.25 a + 0.25 b + 0.25 c - 0.25 a \oplus b - 0.25 a \oplus c - 0.25 b \oplus c + 0.25 a \oplus b \oplus c$

# Know How

- ▶ How do you find the coefficients?
- ▶  $\neg a \vee (b \wedge c)$   
 $= -0.75 a + 0.25 b + 0.25 c$   
 $-0.25 a \oplus b + 0.25 b \oplus c - 0.25 a \oplus c$   
 $+ 0.25 a \oplus b \oplus c$   
 $+ 1$
- ▶ Fourier Coefficients

# Fourier Coefficients

- ▶  $f(a,b,c)=\dots$  **-0.25**  $a \oplus b$  + ...
- ▶ There are totally  $2^n$  potential Fourier Coefficients, one for each frequency
- ▶  $2^n$  equations and  $2^n$  unknowns
- ▶ more insightful explanation:
- ▶ correlation coefficient
- ▶  $2 \left( \frac{1}{2^3} \sum_{a,b,c} [f(a, b, c) = a \oplus b] \right) - 1$

# Check it

a	b	c	$f(a,b,c)$	$a \oplus b$
0	0	0	1	0
0	0	1	1	0
0	1	0	1	1
0	1	1	1	1
1	0	0	0	1
1	0	1	0	1
1	1	0	0	0
1	1	1	1	0
			$a \oplus b = 0$	$a \oplus b = 1$
$f(a,b,c)=0$			1	2
$f(a,b,c)=1$			3	2

$$3/8 * 2 - 1 = -0.25$$

# Fourier Transform

- ▶ For each possible frequency (variable subset), compute

- ▶ 
$$\hat{f}(S) = \frac{1}{2^n} \sum_x f(x) (-1)^{\sum_{i \in S} x_i}$$

- ▶ e.g.

$$\hat{f}(\{1, 2\}) = \frac{1}{2^3} \sum_{x_1, x_2, x_3} [f(x_1, x_2, x_3) \cdot (-1)^{x_1 + x_2}]$$

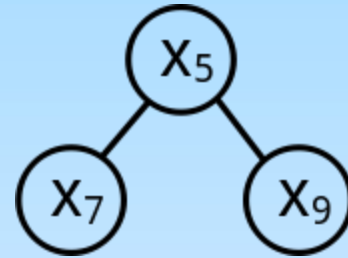
- ▶ Then  $2^{\hat{f}(\{1, 2\})}$  will be the coefficient behind  $x_1 \oplus x_2$

# Fourier Coefficients

- ▶  $a \wedge b = 0.5 a + 0.5 b - 0.5 a \oplus b$
- ▶ The sum of square of the coefficients  $\leq 1$   
(Parseval's Inequality)
- ▶ If we want to find all coefficients  $\geq 0.25$ , there will be at most 16 of them
- ▶ If the function only depends on a few variables, the Fourier coefficients will be sparse.

# Fourier Coefficients

```
int f(int x[]){  
    if (x[5]){  
        if (x[7]) return 0;  
        else return 1;  
    }else{  
        if (x[9]) return 1;  
        else return 0;  
    }  
}
```



- ▶ Possible non-empty frequencies:
- ▶  $x_5, x_7, x_5 \oplus x_7, x_9, x_5 \oplus x_9$



# So

Theoretically

- ▶ How to reverse-engineer a (simple) function
- ▶ S1: Somehow find the frequencies  $a$ ,  $b$ ,  $a \oplus b$
- ▶ S2: Compute correlations  $\Pr[f(a,b,\dots) \neq a \oplus b] \cdot 2^{-1}$
- ▶ S3: Write the original function as a linear combination

# Example

- ▶ Black box  $f(x[1..100])$ . We somehow know the non-empty frequencies are  $x_2$ ,  $x_1 \oplus x_2$ ,  $x_3$ ,  $x_1 \oplus x_3$ .

- ▶ Randomly choose 10000 samples, compute the correlations

- ▶  $\Pr[f(x)=x_2]=0.675$

$$\Pr[f(x)=x_1 \oplus x_2]=0.675$$

$$\Pr[f(x)=x_3]=0.675$$

$$\Pr[f(x)=x_1 \oplus x_3]=0.375$$

- ▶ Now we know that the function is

$$0.25 x_1 + 0.25 x_1 \oplus x_2 + 0.25 x_3 - 0.25 x_1 \oplus x_3$$

This is  $x_1 \oplus x_2 \oplus x_3$

# Now comes the key part

- ▶ How to find the non-empty frequencies?
- ▶ Goldreich-Levin
- ▶ Polynomial time complexity
- ▶ (but does not directly work in practice)

# The key

- ▶ Consider what is
- ▶  $g(x_2, x_3, \dots) = (f(0, x_2, x_3, \dots) + f(1, x_2, x_3, \dots)) / 2.0$
- ▶ For  $f$ 's Fourier component  $\alpha x_a \oplus x_b \oplus \dots$
- ▶ If  $x_1$  is inside the frequency, it disappears
- ▶  $(0 \oplus x_b \oplus x_c + 1 \oplus x_b \oplus x_c) / 2 = 0.5 \leftarrow \text{constant}$
- ▶ Otherwise, it is untouched
- ▶  $(x_a \oplus x_b \oplus x_c + x_a \oplus x_b \oplus x_c) / 2 = x_a \oplus x_b \oplus x_c$
- ▶ So,  $g$  retains a subset of all frequencies.

# The filter

▸ What is

▸  $g(x_4, \dots) =$

**+0.125**  $f(0,0,0,x_4,\dots)$  **-0.125**  $f(0,0,1,x_4,\dots)$

**-0.125**  $f(0,1,0,x_4,\dots)$  **+0.125**  $f(0,1,1,x_4,\dots)$

**+0.125**  $f(1,0,0,x_4,\dots)$  **-0.125**  $f(1,0,1,x_4,\dots)$

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▶  $x_4 \oplus x_5 \oplus x_6$

# The filter

- ▶ What is
- ▶  $g(x_4, \dots) =$ 

$$\begin{aligned}
 &+0.125 f(0,0,0,x_4,\dots) -0.125 f(0,0,1,x_4,\dots) \\
 &-0.125 f(0,1,0,x_4,\dots) +0.125 f(0,1,1,x_4,\dots) \\
 &+0.125 f(1,0,0,x_4,\dots) -0.125 f(1,0,1,x_4,\dots) \\
 &-0.125 f(1,1,0,x_4,\dots) +0.125 f(1,1,1,x_4,\dots)
 \end{aligned}$$
- ▶  $x_1 \oplus x_2 \oplus x_3 \oplus x_4 \oplus x_5 \oplus x_6$

# The filter

► What is

►  $g(x_4, \dots) =$

**+0.125**  $f(0,0,0,x_4,\dots)$  **-0.125**  $f(0,0,1,x_4,\dots)$

**-0.125**  $f(0,1,0,x_4,\dots)$  **+0.125**  $f(0,1,1,x_4,\dots)$

**+0.125**  $f(1,0,0,x_4,\dots)$  **-0.125**  $f(1,0,1,x_4,\dots)$

**-0.125**  $f(1,1,0,x_4,\dots)$  **+0.125**  $f(1,1,1,x_4,\dots)$

►  $x_1 \oplus x_2 \oplus x_3 \oplus \dots$



# The Filter

- ▶ If we want to know whether  $f$  contains a (large) frequency with prefix  $x_a \oplus x_b \oplus \dots \oplus x_d$
- ▶ We just need to see if
 
$$g(x_k, \dots) = E_{x_1, x_2, \dots, x_{k-1}} [f(x) (-1)^{x_a \oplus x_b \oplus \dots \oplus x_d}]$$
 is (close to) constant
- ▶ The extremely clever reformulation
- ▶  $E_{x, x'_{1..k}} [f(x) f(x'_{1..k} x_{k+1..n}) \chi_S(x_{1..k}) \chi_S(x'_{1..k})]$
- ▶  $\chi_S$  is the "mask"

# Goldreich-Levin

- ▶ Binary search
- ▶ see if there are frequencies beginning with 0
- ▶ see if there are frequencies beginning with 00
- ▶ see if there are frequencies beginning with 000
- ▶ .....
- ▶  $E_{x, x'_{1..k}} [f(x)f(x'_{1..k}x_{k+1..n}) \chi_S(x_{1..k})\chi_S(x'_{1..k})]$

# GL

- ▶ Very good in theory. Used to prove Goldreich and Levin's Hard Core Predicate.
- ▶ Not useful in (OI) practice because of its huge constant factor.
- ▶  $O(n\epsilon^{-6}\log(n/\epsilon))$

# However

- ▶ It can be optimized in practice.
- ▶ And we need randomization to do it.

# Hashing

- ▶ Suppose the frequencies' first three digits are all different
- ▶ 000???
- ▶ 001???
- ▶ ...
- ▶ 110???
- ▶ 111???
- ▶ Then we can dig them out one by one

# Isolating

- ▶ define  $g(x_4, \dots) = (f(0, 0, 0, x_4, \dots) + f(0, 0, 1, x_4, \dots) + f(0, 1, 0, x_4, \dots) + f(0, 1, 1, x_4, \dots) + f(1, 0, 0, x_4, \dots) + f(1, 0, 1, x_4, \dots) + f(1, 1, 0, x_4, \dots) + f(1, 1, 1, x_4, \dots)) / 8$
- ▶ If we are lucky,  $g$  will be (close to) **linear**

# Isolating

- ▶ How to recover a linear function's coefficients
- ▶ at the presence of a tiny amount of noise?
- ▶ Influence
- ▶  $\Pr[g(x_1, \dots, x_{k-1}, 0, x_{k+1}, \dots, x_n) \cdot g(x_1, \dots, x_{k-1}, 1, x_{k+1}, \dots, x_n) < 0]$
- ▶ So long as  $< 0.25$  of all  $g$ 's sign are reversed, we will be able to decide if the uncorrupted  $g$  depends on  $x_k$

# And

- ▶  $g(x_4, \dots) = (f(0, 0, 0, x_4, \dots) - f(0, 0, 1, x_4, \dots) + f(0, 1, 0, x_4, \dots) - f(0, 1, 1, x_4, \dots) - f(1, 0, 0, x_4, \dots) + f(1, 0, 1, x_4, \dots) - f(1, 1, 0, x_4, \dots) + f(1, 1, 1, x_4, \dots)) / 8$
- ▶ selects the 101??? frequency out
- ▶ and so on



# One Issue

- ▶ What if the frequencies only differ at the last digits?
- ▶ ???000  
???001  
???010  
...  
???111
- ▶ We should somehow transform them to the "good cases"

# Randomization

- ▶ Randomly choose a (reversible) linear substitution
- ▶  $y_1 = x_2 \oplus x_3$
- ▶  $y_2 = x_1$
- ▶  $y_3 = x_1 \oplus x_3$
- ▶  $f(x_1, x_2, x_3) = u(y_1, y_2, y_3)$
- ▶ Find the Fourier components of  $u$ , then do back substitution
- ▶  $u$  will (probably) be good

# Optimization?

- ▶ Works when the noise is small enough
- ▶ Now talk about implementation details

```

vector<vec> genFreq(){
    vec U[MMax],V[MMax];
    getOrthBasis(U,V);
    int pt=0;
    for (int i=0;i<N;i++){
        for (int j=0;j<RMax;j++){
            vec u;
            for (int k=0;k<N;k++)u[k]=rand()&1;
            for (int z=0;z<=1;z++){
                u[i]=z;
                for (int l=0;l<(1<<M);l++){
                    vec x=u;
                    for (int m=0;m<M;m++)if ((1<<m)&l)x=x^V[m];
                    int key=0;
                    for (int m=0;m<M;m++)
                        key|=dotproduct(U[m],x)<<m;
                    trials[pt+key]=x;
                }
                pt+=(1<<M);
            }
        }
    }
    evaluatetrials(trials,trialresults,N*RMax*2*(1<<M));
}

```

```

vector<vec> found;
for (int i=0;i<(1<<M);i++){
    vec freq;
    for (int j=0,pt=0;j<N;j++){
        int s=0;
        for (int k=0;k<RMax;k++){
            int t[2]={0,0};
            for (int z=0;z<2;z++){
                for (int l=0;l<(1<<M);l++){
                    if (__builtin_popcount(l&i)&1)
                        t[z]-=trialresults[pt++];
                    else t[z]+=trialresults[pt++];
                }
            }
            s+=((t[0]>0)!=(t[1]>0));
        }
        freq[j]= s*2-RMax > 0;
    }
    for (int j=0;j<M;j++)if ((1<<j)&i)freq^=U[j];
    int mcnt=0;
    for (int j=0;j<TMax;j++)
        mcnt+=(testresults[j]==dotproduct(testset[j],freq));
    if (abs(mcnt*2-TMax)>=TMax*0.040)
        found.push_back(freq);
}

```

# Implementation Detail

- ▶ How to generate orthogonal basis?
- ▶ Brute-force is OK

```

while (true){
    for (int i=0;i<M;i++)for (int j=0;j<N;j++)U[i][j]=rand()&1;
    bitset<MMax> found;
    for (int i=0;i<3*M*(1<<M);i++){
        vec x;
        for (int j=0;j<N;j++)x[j]=rand()&1;
        int s0=0,s1=0;
        for (int j=0;j<M;j++)
            if (dotproduct(U[j],x))
                s0++,s1+=j;
        if (s0==1 && !found[s1]){
            found[s1]=1;
            V[s1]=x;
            if (found.count()==M)break;
        }
    }
    if (found.count()==M)break;
}

```

# Implementation Detail

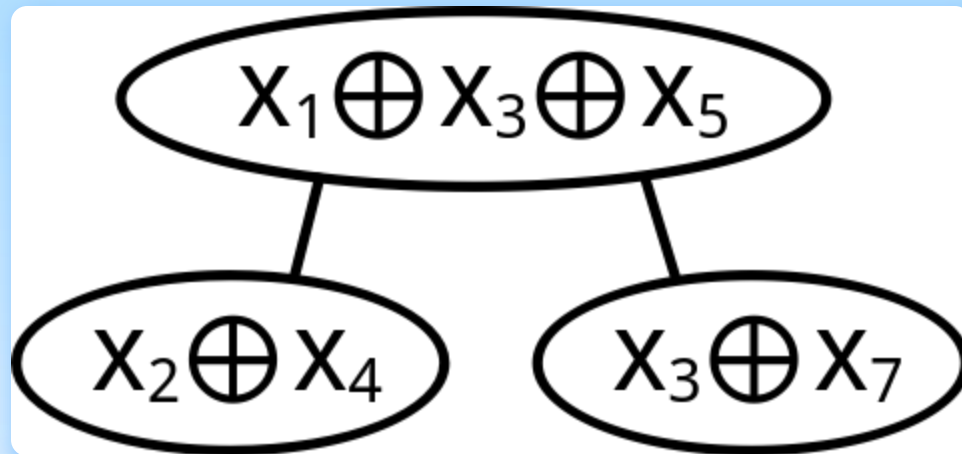
```
typedef bitset<NMax> vec;  
int dotproduct(const vec & a, const vec & b){  
    return (a&b).count()&1;  
}
```

- ▶ Run multiple times until enough energy is collected
- ▶ How large should the test set be?
- ▶  $O(\epsilon^{-2} \log n)$

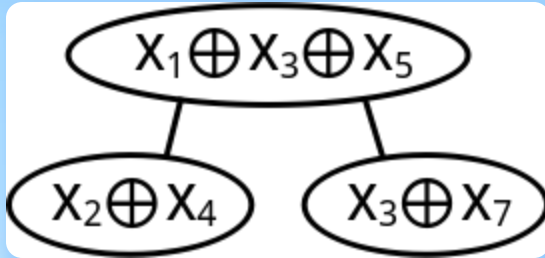


# Application

- ▶ Reverse a depth 2 Parity Decision Tree



# Application



▶ discovered frequencies

▶  $x_1 \oplus x_3 \oplus x_5$

$x_1 \oplus x_3 \oplus x_5 \oplus x_2 \oplus x_4$

$x_2 \oplus x_4$

$x_1 \oplus x_3 \oplus x_5$

$x_1 \oplus x_5 \oplus x_7$

$x_3 \oplus x_7$

# Application

- ▶ Discovered a 3-dim subspace, totally 8 possible frequencies
- ▶ brute force search  $8^3$  possible trees

# Enough about it

- ▶ Let's talk about something fun

# Interactive Proof

- ▶ How to prove that two graphs are isomorphic?

# Interactive Proof

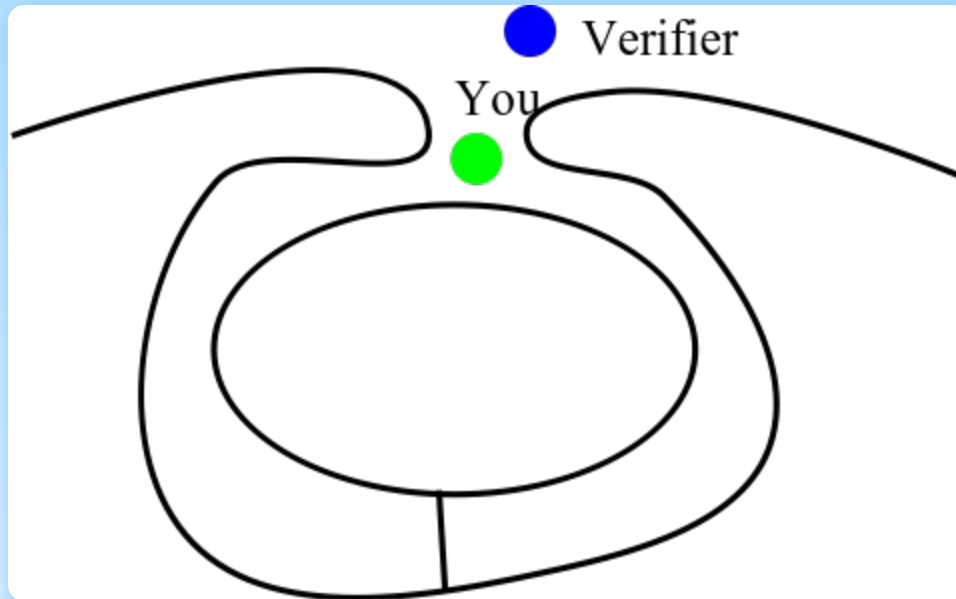
- ▶ How to prove that two graphs are not isomorphic?

# Interactive Proof

- ▶ Zero knowledge proofs
- ▶ Prove to someone (verifier) that you know something without revealing it

# One Example

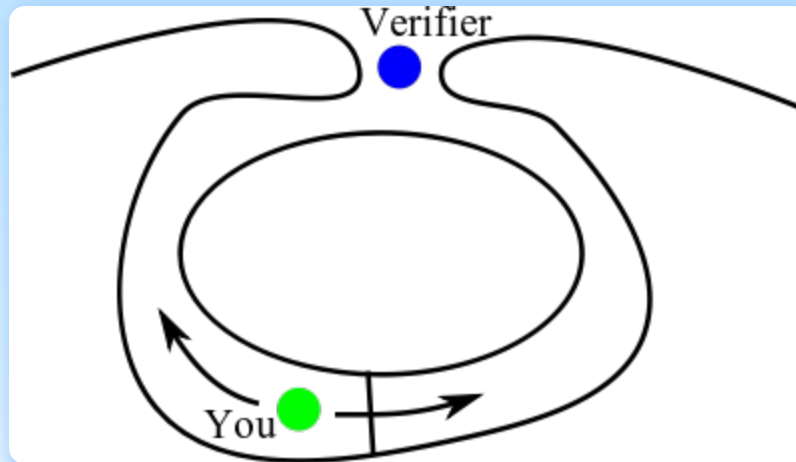
- ▶ How to prove that you can cross a wall?





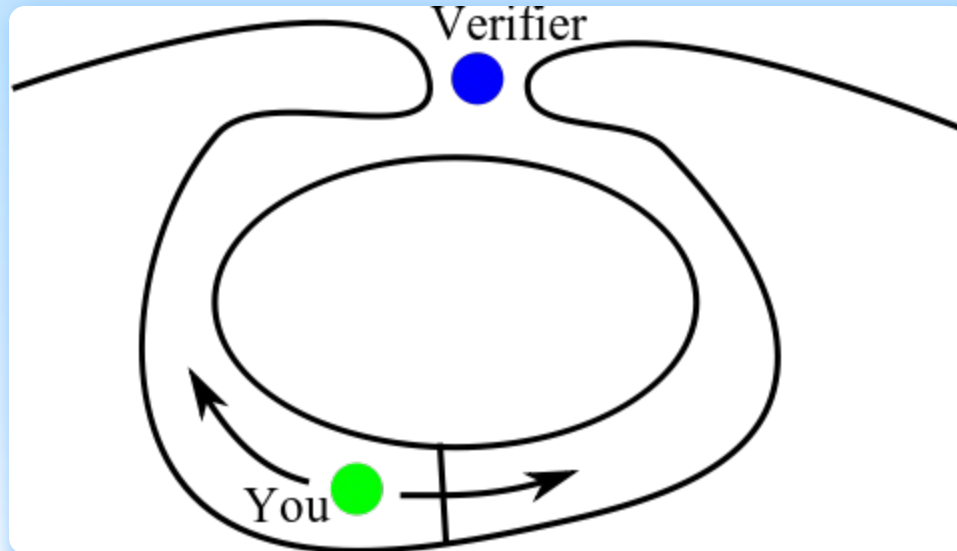
# One Example

- ▶ The prover goes into the cave, chooses a direction and goes into it
- ▶ The verifier goes into the cave, requests the prover comes from one of the directions.



# One Example

- ▶ Zero knowledge: The verifier cannot even prove to others that he knows the prover can do this.
- ▶ He can make the video record himself



# Discrete Logarithm

- ▶ how to prove that you know an  $x$  such that  $g^x \bmod p = C$

# Discrete Logarithm

- ▶  $g^x \bmod p = C$
- ▶ **prover** randomly chooses  $r$ , sends  $k = g^r \bmod p$  to verifier
- ▶ **verifier** either requests prover to send  $r$  or  $(x+r) \bmod p-1$  and checks this
- ▶  $g^{(x+r) \bmod p-1} = kC$

# Sudoku

- ▶ How to prove that you have solved a Sudoku?

# Sudoku

- ▶ write numbers on chess pieces and put them upside-down on a board
- ▶ the **verifier** chooses a row/column/block
- ▶ the **prover** picks those pieces up from the board, shuffle them and give them to the verifier
- ▶ repeat for many rounds

# 3 coloring

- ▶ How to prove that you know a 3-coloring of a graph?
- ▶ Of particular interest because graph coloring is NP-hard.

# graph coloring

- ▶ randomly shuffle your coloring
- ▶ cover them with chess pieces
- ▶ verifier requests to reveal two adjacent pieces
- ▶ repeat



# Bit Commitment

- ▶ How to do the choose-and-reveal step?
- ▶ prover sends  $\text{hash}(c_i, \text{salt}_i)$  for all  $i$
- ▶ verifier requests  $c_u, c_v, \text{salt}_u, \text{salt}_v$  for adjacent  $u$  and  $v$

# NP-hard?

- ▶ The implication of NP-hardness
- ▶ Any NP problem can be reduced to it
- ▶ Especially, you can prove that you know a proof to a math theorem
- ▶ because  $\text{MATH} \in \text{NP}$

# More on cryptography

- ▶ randomness + hardness assumption + interaction

# Flip a coin through telephone

- ▶ How to flip a coin through a telephone line?
- ▶ "I guess your coin is head"
- ▶ "Let me see... Sorry, it is tail"

# Quadratic Residual

- ▶ Alice chooses  $p, q$ , sends  $m=pq$  to Bob
- ▶ Bob chooses  $x_1$ , sends  $y=x_1^2 \bmod m$
- ▶  $y=x^2 \bmod m$  has two roots  $x_1$  and  $x_2$

# How to compute square root

- ▶ How to compute square root of  $y \bmod pq$ ?
- ▶ compute the square root of  $y \bmod p$  and  $\bmod q$ , then CRT
- ▶ How to compute square root of  $y \bmod p$ ?
- ▶ Tonelli Shanks / Cipolla
- ▶  $\left(a + \sqrt{a^2 - y}\right)^{(p+1)/2} \bmod p$
- ▶ All operations are  $\bmod p$ .  $a^2 - y$  is chosen so that it is not a quadratic residual.

# Flip Coin

- ▶ Alice sends  $t = x_1^2 \bmod m$  to Bob
- ▶ Bob knows how to compute sqrt of  $t$ , but he does not know which root is Alice's
- ▶ He arbitrarily chooses one and sends it to Alice.
- ▶ If he happens to send  $x_2$  to Alice, Alice now knows the factorization of  $m$
- ▶  $x_1^2 - x_2^2 = 0 \bmod m$
- ▶ Otherwise, Alice still does not know how to factor  $m$
- ▶ A fair coin flip

# Do you want more cryptography?

- ▶ Perhaps not
- ▶ Then let's move back to proofs
- ▶ The PCP Theorem
- ▶  $\text{NP} = \text{PCP}(O(\log n), O(1))$



# PCP Theorem

- ▶ Any NP language admits polynomial length proof
- ▶ that can be checked **probabilistically** by looking at only constant number of bits
- ▶ "New Short Cut Found For Long Math Proofs"
- ▶ 1992 April 7, New York Times

# How it works

- ▶ A certificate of an instance belonging to a language
- ▶ A randomized verifier only looks at constant number of bits in the proof
- ▶ and has constant probability of rejecting fake proofs

# The PCP Theorem

- ▶ I'll cheat you a little bit
- ▶ Only prove that  $\text{NP} = \text{PCP}(\text{poly}(n), O(1))$   
because it is much easier but still interesting
- ▶ Heavily relies on randomization

# NP-Hard

- ▶ Solving quadratic boolean equations is NP-Hard
- ▶  $x_2x_3 + x_1x_1 = 0 \pmod 2$   
 $x_1x_2 + x_1x_3 + x_2x_3 = 1 \pmod 2$   
.....
- ▶ Now I'll give a  $2^{n^2}$  length **P**robabilistically **C**heckable **P**roof to it.

# The proof

- ▶ computes  $x_i x_j$  for all  $i, j$
- ▶ writes all linear combinations of them in the proof
- ▶ totally  $2^{n^2}$  bits
- ▶ how should I check it?

# Step 1

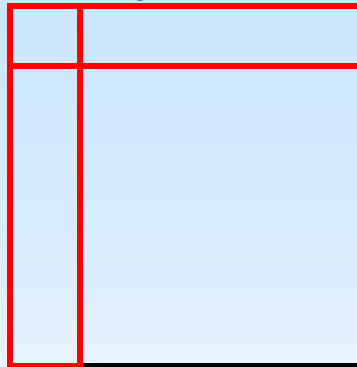
- ▶ check that the original equations are satisfied
- ▶ I cannot check the  $m$  equations one by one, because this requires reading more than  $O(1)$  bits
- ▶ randomly choose a subset of equations and check their sum
- ▶  $x_2x_3 + x_1x_1 = 0 \pmod{2}$   
 $x_1x_2 + x_1x_3 + x_2x_3 = 1 \pmod{2}$   
 .....
- ▶  $x_1x_1 + x_1x_2 + x_1x_3 = 1 ?$

# Step 1

- ▶ because the chosen subset is random
- ▶ if there are at least one unsatisfied equations
- ▶ my chance to detect it is  $\geq 0.5$
- ▶ 001000000001100000  
010100101010101101

# Step 2

- ▶ Check that  $x_i x_j$  is really  $x_i$  times  $x_j$
- ▶ The same trick
- ▶ randomly choose two subsets A,B
- ▶ checks if
$$\sum_{i \in A} x_i^2 \sum_{i \in B} x_i^2 = \sum_{i \in A, j \in B} x_i x_j$$
- ▶ at least 1/4 prob. to reject wrong proofs





# Step 3

- ▶ Check that the  $2^{n^2}$  bits encodes after all the linear combination of  $n^2$  variables.
- ▶ Equal to testing whether a function is linear
- ▶ 0011001100110011

# The linearity test

- ▶ Randomly choose  $a, b$
- ▶ Checks if  $f(a+b) = f(a) + f(b) \pmod{2}$
- ▶ probability of passing is  $\sum_S \hat{f}^3(S) \leq \max \hat{f}(S)$
- ▶ So the function is **close** to linear if it passes many random tests

# Are we done?

- ▶ Wait, there is one issue
- ▶ Independence

# Self Correcting

- ▶ Using the linearity test, we can use ?000 tests to ensure that the truth table is 0.999 close to **some** linear function (although we don't know which one it is)
- ▶ However, no guarantee is given on which bits are corrupted
- ▶ And the queries in Step 1,2 are not uniform

# Self Correcting

- ▶ It is possible that although only a small portion of bits are corrupted in the linear function
- ▶ but they are the bits that are queried in Step 1 and 2
- ▶ Solution: self correcting
- ▶  $f(x)=f(a)+f(x+a)$
- ▶ query  $f(a)$ ,  $f(x+a)$  whenever we want to get  $f(x)$  in later steps
- ▶ the queries are uniform now

# Putting everything together

- ▶  $NP = PCP(O(n^2), O(1))$
- ▶ Can be optimized to  $PCP(O(\log n), O(1))$  by using more advanced techniques
- ▶ enough about proofs!

# A New Page

- ▶ Let's talk about something interesting (and useful for OI)
- ▶ Advanced Randomization
- ▶ Sketching

# Sketch

- ▶ A short summary (hash) of a large object that (probabilistically) preserves some of its properties
- ▶ Randomization \*/+ Approximation



# Sketch of String Equality

- ▶ Suppose both you and your friend have a (long) 01 string
- ▶ You want to decide whether they are same
- ▶ by exchanging only 1 bit
- ▶ with accuracy requirement  $\geq 2/3$

# Which bit to send?

- ▶ The first bit?
- ▶ The last bit?
- ▶ The xor of all bits?

# 1 bit sketch

- ▶ Assume you have shared randomness
- ▶ randomly choose a subset of bits (must be the same subset for both of you)
- ▶ send the xor sum
- ▶ If not the same,  $\geq 1/2$  probability of detecting it

# 1 bit sketch

- ▶ same: 100% - 0%
- ▶ not same: 50% - 50%
- ▶ The trick: if the bits match, answer with  $\frac{2}{3}$  prob. that the strings are the same
- ▶ same: 67% - 33%
- ▶ not same: 67% - 33%

# Better Accuracy

- ▶ Just increase the number of bits
- ▶ by repeating this process
- ▶  $k$  bits  $\rightarrow 2^{-k}$  failure prob.

# Sketch of set size

- ▶ support union operation
- ▶ the MinHash algorithm
- ▶  $f(X) = \min((ax+b)\%p \text{ for } x \text{ in } X)$

# Review of MinHash

- ▶ pairwise independence, Chernoff bound, ...
- ▶ improved version: multi-scale buffer
- ▶ store a buffer of  $k^2$  items
- ▶ only store items whose hash values' last  $p$  digits are zero
- ▶  $\text{size} = \# \text{elements in buffer} * 2^p$
- ▶ relative error  $\leq O(1/k)$
- ▶ merge sort to merge two sets

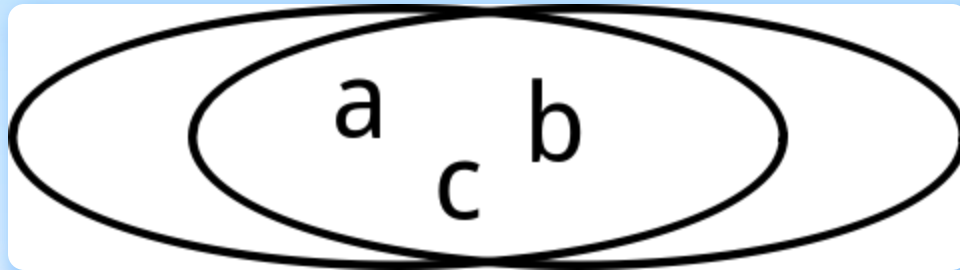
# BJOI

- ▶ maintain many sets
- ▶ each time, create a new set as the union of two previously created sets
- ▶ return the size of the newly created set
- ▶ probably ( $\geq 95\%$ ) approximately ( $\pm 25\%$ ) correct

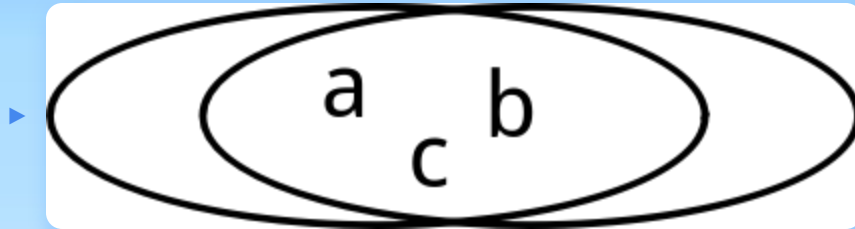


# Sketch of set intersection

- ▶ decide whether two sets are close enough to each other
- ▶ close : intersection / union is large
- ▶ MinHash
- ▶ the  $k$  smallest distinct hash values



# Sketch of set intersection



- ▶ k smallest hash values
- ▶ assume intersection  $\geq p$  union
- ▶ prob. of equal :  $p^k$

# Thu Training 2014

- ▶ Ameba mutation
- ▶ find similar N-element set pairs in  $2N^2$  subsets of a  $N^2$  universe
- ▶ randomly generated
- ▶ intersection of close pairs:  $N/2$
- ▶  $p=1/3$  for close pairs,  $1/N$  for irrelevant pairs
- ▶ choose  $k=2$
- ▶ #subsets shrinks by  $1/9$  after each iteration
- ▶  $O(N^2)$  false positives

# Implementation Detail

- ▶ do not explicitly choose  $k$
- ▶ randomly relabel the elements
- ▶ sort alphabetically, check adjacent pairs
- ▶ using a reverted index, this can be done in sub-linear time!
- ▶ Overall time complexity: linear

# Sketch of Hamming Distance

- ▶ sketch used to estimate the Hamming Distance of two 01 strings
- ▶  $d(x,y) \approx f(h(x), h(y))$
- ▶ randomly choose  $p$  bits, compute xor sum
- ▶ enumerate  $p=1,2,4,\dots,n/2,n$
- ▶ multiple runs
- ▶ multi-scale Equality sketch

# Multi-scale Equality Sketch

- ▶ assume the real Hamming distance is  $qN$
- ▶  $p$  bits: equal prob. =  $(1-q)^p$
- ▶  $O(1)$  distortion

# Nearest Neighbour Search

- ▶ In Hamming cube
- ▶ coarse-to-fine hashes based on sampling and Equality
- ▶ Efficient Search for Approximate Nearest Neighbour in High Dimensional Space
- ▶ Kushilevitz, Ostrovsky, Rabani

# Sketch of Edit Distance?

- ▶ Sketch of string's edit distance?
- ▶ Possible! Distortion  $2^{O(\sqrt{\log n \log \log n})}$
- ▶ patented, not very useful in OI (at least now)



# Sketch of frequency

- ▶ Implement a multiset that supports `count()`
- ▶ for the most frequent elements
- ▶ naive idea: randomly sample a population
- ▶ works if the portion of the element is high

# Sketch of frequency

- ▶ Improved idea
- ▶ Hash each element to a unit vector in  $k$ -dim sphere
- ▶ Record the sum, compute the dot product
- ▶ Works in expectation
- ▶  $1/\sqrt{N}, 1/N, 1/N, \dots, 1/N$
- ▶ better than the naive idea!

# Signal to Noise Ratio

- ▶ signal:  $x_i$
- ▶ noise:  $\sqrt{\sum_j x_j^2}$
- ▶ works if the portion of second-order moment is high
- ▶ always better for the most frequent element

# sketch of most frequent element

- ▶ hash the elements to  $k$  bins
- ▶ inside each bin, map each element to a unit vector (or just  $\pm 1$ ), compute the sum
- ▶ take the maximum absolute value
- ▶ linear sketch!

# sketch of second order moment

- ▶  $x_1^2 + x_2^2 + \dots + x_n^2$
- ▶ The amazing AMS algorithm
- ▶ map each element to  $\pm 1$
- ▶ compute the sum
- ▶ square it

# How it works

- ▶  $1+1+\dots+1=E[(\pm 1\pm 1\dots\pm 1)^2]$

# Let me analyze it

- ▶  $X = x_1 + \dots + x_n$
- ▶  $E[X^2] = x_1^2 + x_2^2 + \dots + x_n^2 = F_2$
- ▶  $E[(X^2 - F_2)^2] \leq E[X^4 + F_2^2] \leq 2F_2^2$
- ▶ Chebyshev bound
- ▶  $\varepsilon^{-2}$  repetitions
- ▶ 4-wise independence

# How to get 4-wise independence?

- ▶  $ax^3+bx^2+cx+d \bmod p$



# Sketch endless

- verification
- database search





Best is Endless.