# Lecture # 12

Lecturer: Prof. Allan Borodin

Scribe: Yeleiny Bonilla

## Agenda:

- I. Finish discussion of Vector Program Relaxation for Max-Cut problem.
- II. Briefly discuss same approach for Max-2-Sat.
- III. The constructive Lovasz Local Lemma (LLL).
- IV. The Miller Rabin primality testing.
- V. Multiplicative update.

## I. Vector Program Relaxation for Max Cut problem

We can write the Max Cut problem as:

 $\begin{array}{l} \mbox{maximize } \sum_{i,j\in E} w_{ij} \ 1/2(1\mbox{-}v_iv_j) \ \ (1) \\ \mbox{subject to } \|v_i\|^2 = \ 1 \\ v_i \in R^n \end{array}$ 

Consider the vectors are in a sphere



We are going to take a random unit vector  $r \in R^n$ . Set  $y_i = +1$  if  $(v_i r \ge 0)$ 

As the inner product of two vectors is equal  $v_i v_j = \cos(\theta_{ij})$  and  $0 \le \theta \le \pi$ . Then substituting in equation (1), we can re-write the problem as:

maximize 
$$\sum_{i,j\in E} w_{ij} 1/2(1 - \cos(\theta_{ij}))$$

Where  $\cos (\pi) = -1$  $\cos (\pi/2) = 0$  $\cos (0) = 1$ 

<u>Claim</u>: The expected value of the rounded solution will be E [rounded solution]  $\geq \alpha \sum_{i,j \in E} w_{ij} 1/2(1 - \cos(\theta_{ij}))$  <u>Main Claim</u>: Prob<sub>r</sub> [v<sub>i</sub> and v<sub>j</sub> are separated by r] =  $\theta_{ij} / \pi$  (Proof by picture above \*)

→ To get the desired expectation we want  $\theta_{ij}/\pi \ge \alpha ((1 - \cos(\theta_{ij}))/2)$  $\alpha = \min_{0 \le \theta \le \pi} 2/\pi * (1 - \cos(\theta))/\theta) \ge 0.87856$ 

## II. Vector Program Relaxation for Max-2-Sat problem

 $\begin{array}{l} y_0 \ \ldots \ y_i \in _{0 \leq i \leq n} \{ +1, \text{-} 1 \} \\ y_i \ \sim \text{propositional } x_i \end{array}$ 

 $\begin{array}{l} \textit{Interpretation: } x_i = \{ true \ if \ y_i = y_0 \\ false \ if \ y_i = - \ y_0 \} \end{array}$ 

We are trying to maximize:

maximize  $_{\tau} \sum_{C} \operatorname{val}_{\tau} (C)$ 

 $\label{eq:val} \begin{array}{l} val(C) \mathrel{\mathop{\rightarrow}} \{1 \mbox{ if } C/\ \tau = true \\ 0 \mbox{ if } C/\ \tau = false \} \end{array}$ 

If  $C = x_i$  then  $val(C) = (1 + y_i y_0) / 2$ 

If  $C = \bar{x}_i$  then  $val(C) = 1 - (yi y_0)/2$ 

And if  $C = x_i v x_j$  then

 $\begin{aligned} val(C) &= 1 - val \; (\bar{x}_i) * val \; (\bar{x}_j) \\ &= a \; ((1 + y_i \; y_0) \; / 2) + b \; ((1 - y_i \; y_0) \; / 2) \end{aligned}$ 

maximize  $\sum_{i \in j} a_{ij} (1 + y_i y_j) + b_{ij} (1 - y_i y_j)$ 

Relaxing yi y<sub>j</sub> to  $v_i \cdot v_j$ , with  $v_i \in \mathbb{R}^{n+1}$ ,  $||v_i|| = 1, 0 \le i \le n$ .

Doing the calculations we get the same  $\alpha \sim 0.87856$  approximation.

## III. The constructive Lovasz Local Lemma (LLL)

Having a series of events E<sub>1</sub>,...., E<sub>m</sub>

Prob  $[E_i] = p < 1$ 

Prob  $[\bar{E}_1 \wedge \bar{E}_2 \wedge \dots \wedge \bar{E}_m] > 0$ , if all  $E_i$  are independent

Suppose that each  $E_i$  occurs with probability at most p, and such that each event is independent of all the other events except for at most d of them.

$$ep(d+1) \le 1$$

(Where e = 2.718... is the base of natural logarithms), then there is a nonzero probability that none of the events occurs.

Consider an instance of the LLL,

$$\mathbf{F} = \mathbf{C}_1 \wedge \mathbf{C}_2 \wedge \ldots \wedge \mathbf{C}_m$$

F in an exactly K - CNF,

 $E_i = C_i$  is not satisfied by a random  $\tau$ , then

Prob  $[E_i] = 1/2^k$ 

 $\bar{E}_{\,i}\,$  means  $\,C_{i}\,$  is satisfied, then

Prob  $[\bar{E}_1 \wedge \bar{E}_2 \wedge \dots \wedge \bar{E}_m] = \text{Prob}_{\tau} [F/\tau \text{ is satisfied}] > 0$ 

Let d be the number of clauses that share a variable (with a given clause C), then to apply the LLL we want:

 $d + 1 \le 2^k / e$  which implies that  $d < 2^k / e$ .

<u>The Constructive Proof:</u> (Proof by Moser and Gabor, Tardos + Moser)

Chose any random  $\tau$ 

Solve,

while there exists a clause C not satisfied by  $\tau$ Call Fix(C) end while

Fix(C)

Randomly set the bits in C While there is a neighboring clause D that is unsatisfied Call Fix (D) End while

<u>Theorem:</u> Let r be the size of neighborhood. If r is not to big:  $r \le 2^k/8$ , then with high probability the algorithm terminates in O (mlogm) calls to Fix(C) and hence found a satisfying assignment.

Proof:

Suppose the algorithm takes at least *s* recursive calls to fix,

If

 $n + s^{*k}$  bits describes algorithm up to the  $s^{th}$  cell at which time we have some true assignment  $\tau$ '.

Using Kolmogorov complexity, we state the fact that most random strings cannot be compressed.

Now we say that if r is sufficiently small  $k - \log v - c > 0$ 

Then we can describe these n + s \* k bits in a compressed way.

n bits to describe  $\tau^{\prime}.$  s calls to fix  $C_1 \hdots C_s \mbox{ clauses being fixed.}$ 

<u>Claim:</u> Solve has at most *m* clauses.

Any C' satisfied before Fix(C) that is called in Solve remains satisfied.

<u>Claim:</u> We can recover original  $n + s^*k$  bits using

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n + m \log m + s (\log r + c) \ge n + s^*k
(for \tau') (calls to fix

in solve)
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 $m \log m \ge s (k - \log r - c)$ 

(Note: Here it is not proved, but the algorithm does not always terminates)

## IV. Primality testing

Some background in primality tests and authors:

- The Solovay–Strassen primality test, developed by Robert M. Solovay and Volker Strassen, is a probabilistic test to determine if a number is composite or probably prime. It has been largely superseded by the Miller–Rabin primality test, but has great historical importance in showing the practical feasibility of the RSA cryptosystem.
- The Miller–Rabin primality test or Rabin–Miller primality test is in an algorithm which determines whether a given number is prime, similar to the Fermat primality test and the Solovay–Strassen primality test. Its original version, due to Gary L. Miller, is deterministic, but the determinism relies on the unproven generalized Riemann hypothesis; Michael O. Rabin modified it to obtain an unconditional probabilistic algorithm.

In general those authors gave a one sided randomized algorithm.

Prob[ ALG says N prime | N composite ]  $\leq \frac{1}{2}$ 

Prob [ALG says N composite | N prime] = 0

→ Composite testing  $\in$  RP

Except for a very small (but still infinite) class of numbers, there is a very simple randomized algorithm:

→ Fernat's little theorem: N prime implies  $a^{N-1} = 1 \mod N$ , where gcd(a,N) = 1

Lagrange's Theorem: If S is a subgroup of a group G, then |S| divides |G|.

Our group:  $Z_N^* = \{a \mid gcd(a,N) = 1, under mullt' \mod N\}$ 

 $S = \{a \mid gcd(a,N) = 1 \text{ and } a^{n-1} \text{ mod } N = 1, 1 \leq a \leq n-1 \} \text{ is a subgroup.}$ 

*False test:* choose  $a \in Z^*_N$  randomly.

If  $a^{k-1} \mod N = 1 \rightarrow Output prime$ 

Else -> Output composite

#### Carmichael number (AKA false primes):

For all  $a \in Z_{N}^{*}$ ,  $a^{k-1} \mod N = 1$ , and N is composite.

N- Carmichael -> N=N<sub>1</sub>N<sub>2</sub>N<sub>3</sub>, N<sub>i</sub> square free. Gcd (N<sub>i</sub>, N<sub>J</sub>) = 1

- If N is prime, then  $Z_N^*$  is a field, and 1 has exactly 2 square roots  $\{-1, +1\}$
- If N is odd then N-1 is even  $> N-1 = 2^{t}u$ , with u odd

### Algorithm:

Choose  $a \in Z^*_N$  randomly,

 $x_0 = a^u \; mod \; N \;$  ,  $x_t = a^{N\text{-}1} \; mod \; N$ 

for i=1 until t

 $x_i = x_{i-1}^2 \mod N$ 

if  $x_i$  does not belong to  $\{-1, +1\}$  then output composite.

end for

if  $x_i \neq 1$  then output composite

else output prime.

#### Chinese remainder theorem (CRT):

 $gcd(N_1N_2) = 1$  then for all u, v,  $N = N_1N_2$ 

Exist  $\lambda$ :  $\lambda = u \mod N_1$ 

 $\lambda = v \text{ mod } N_2 \text{ and } 0 \leq \lambda < N_1 N_{2.}$ 

# V. Multiplicative update

Suppose we have n experts who every day are predicting the value of a  $\{0, 1\}$  event.

Let m<sup>t</sup><sub>i</sub> be the number of errors by experts i in first t days. We want an algorithm that will do well compared to the best expert.

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w_i will be the weight of i<sup>th</sup> expert. Initially w_i^0 = 1.
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Algorithm:

For j=1 until t (for each day)

For each  $\mathbf{i}$ 

if prediction of expert **i** on day **j** is wrong then  $w_{i}^{j} = w_{i}^{j-1}$  (i-  $\mathcal{E}$ )

else  $w_i^j = w_i^{j-1}$ 

end for

end for

Output: the weighted majority of the expert predictions.

<u>Claim</u>: Let  $m^t$  be the number of errors the algorithm make. Then  $m^t \le 2\ln n/\epsilon + 2(1+\epsilon)m_{i}^t$ , for all i.