

# MAX-SAT: (Lecture 17: Derandomization)

Given a ~~2-SAT~~ SAT formula  $\phi$ , with  $n$  variables,  $m$  clauses, and non-negative weights  $w_c$  on clauses, find an assignment that maximizes weight of satisfied clauses. ~~[It's assumed each clause has  $\geq 1$  variable]~~

Randomized algo: Set each variable  $X_i$  to T or F w/ equal prob.

~~Then  $E$  [wt. of satisfied clauses]~~

Let  $Y_c = +1$  if clause  $C$  is satisfied,  $= -1$  o.w.

$$\text{Then } E \left[ \sum_c w_c Y_c \right] = \sum_c w_c E[Y_c]$$

If  $C$  has  $k$  variables,  $P_r[Y_c = 1] \Rightarrow 1 - \frac{1}{2^k}$

Hence exp. wt. of satisfied clauses  $\geq \sum_c w_c / 2 \geq \text{OPT} / 2$ .

Now suppose we want a deterministic algo that has this guarantee. We will show how to derandomize this algorithm.

A key step will be to evaluate conditional probabilities:

$$E \left[ \sum_c w_c Y_c \mid X_1 \dots X_i \right] = \sum_c w_c P_r[Y_c = 1 \mid X_1 \dots X_i] \leftarrow \text{can be easily evaluated.}$$

using shorthand, not a r.v.

$$= E \left[ \sum_c w_c Y_c \mid X_1 \dots X_i = b_1 \dots b_i \right]$$

↑  
some string of  $\{T, F\}^i$

To evaluate  $P_r[Y_c = 1 \mid X_1 \dots X_i = b_1 \dots b_i]$

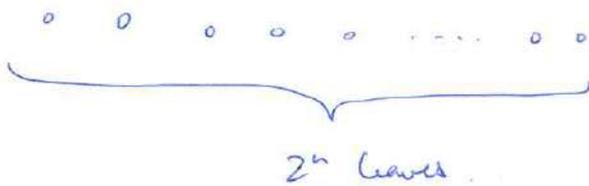
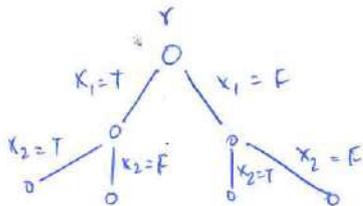
For each  $j \leq i$   
if

If  $C$  is already satisfied, by the setting of  $X_1 \dots X_i$ , then  $Y_c = 1$ . Else if  $C$  has  $r$  variables from  $X_{i+1} \dots X_n$ , then  $P_r = 1 - \frac{1}{2^r}$ .

So how do we derandomize the algo?

We will choose values for  $x_1, x_2, \dots$  in sequence, ensuring that when we've chosen  $(x_1, \dots, x_i)$ ,  $\mathbb{E}[\sum_c w_c Y_c | x_1, \dots, x_i] \geq \sum_c w_c / 2$ .

We can think of the algorithm as descending a tree:



For a node  $v$  at height  $i$ , we've chosen values for  $x_1, \dots, x_i$ , and the node stores  $\mathbb{E}[\sum_c w_c Y_c | x_1, \dots, x_i]$

Suppose at a leaf,  $\mathbb{E}[\sum_c w_c Y_c | x_1, \dots, x_n = b_1, \dots, b_n] \geq \sum_c w_c / 2$ . But then it must be true that, for  $x_1, \dots, x_n = b_1, \dots, b_n$ ,  $\frac{\sum w_c}{2}$  wt. of satisfied clauses is at least  $\sum_c w_c / 2$ .

At a node  $v$ , let  $E_v = \mathbb{E}[\sum_c w_c Y_c | x_1, \dots, x_i = b_1, \dots, b_i]$  at height  $i$

If node  $v$  has children  $b, c$ , then  $E_v = \frac{1}{2} E_b + \frac{1}{2} E_c$ , hence

Thus if  $E_v \geq \frac{\sum w_c}{2} \geq \text{OPT}/2$ , then either  $E_b \geq \text{OPT}/2$  or  $E_c \geq \text{OPT}/2$ .  $\max\{E_b, E_c\} \geq E_v$

Starting from the root, we evaluate  $E_b, E_c$  for both children, and choose  $x_i$  accordingly. We reach a leaf, and this gives us  $x_1, \dots, x_n$ .

## Set Balancing

Given:  $A$  is an  $n \times n$  0-1 matrix

$A_i$  is the  $i$ th row of  $A$ ,  $A_{ij}$  are entries.

Problem: Find  $b \in \{-1, 1\}^n$  to minimize

$$\|Ab\|_{\infty} = \max_{i \in [n]} |A_i b|$$

we won't optimize, but will give bounds on how ~~small~~ large  $\min \|Ab\|_{\infty}$  can be, for any  $A$ .

Randomized algo: for each  $j \in [n]$ , let  $b_j \sim \{-1, 1\}$  <sup>independently</sup> with equal probability.

Clearly, for each row  $i$ ,  $E[A_i b] = 0$

$$\text{(since } E[A_i b] = E\left[\sum_j A_{ij} b_j\right] = \sum_j E[A_{ij} b_j] = 0)$$

But this does not mean that  $E[|A_i b|] = 0 \dots$  (why?)

To get a bound on  $E[|A_i b|]$ , we will use Hoeffding's inequality

Hoeffding's Inequality: Let  $Y_1, \dots, Y_n$  be independent r.v.'s, with bounded support  $[l_i, u_i]$ , and let  $Y = \sum_i Y_i$ . Then:

$$P(|Y - E[Y]| > \delta) \leq 2e^{-2\delta^2 / \sum_i (u_i - l_i)^2}$$

In our case, let  $Y_{ij} = A_{ij} b_j$ , and  $Y_i = \sum_j A_{ij} b_j$ .

Then each  $Y_{ij} \in \{-1, 0, +1\}$ ,  $E[Y_{ij}] = 0$ ,  $E[Y_i] = 0$ , and

hence:  $Pr[|Y_i| > \delta] \leq e^{-2\delta^2/4n}$

Suppose we choose  $\delta = 2\sqrt{4n \ln n} = 2\sqrt{n \ln n}$

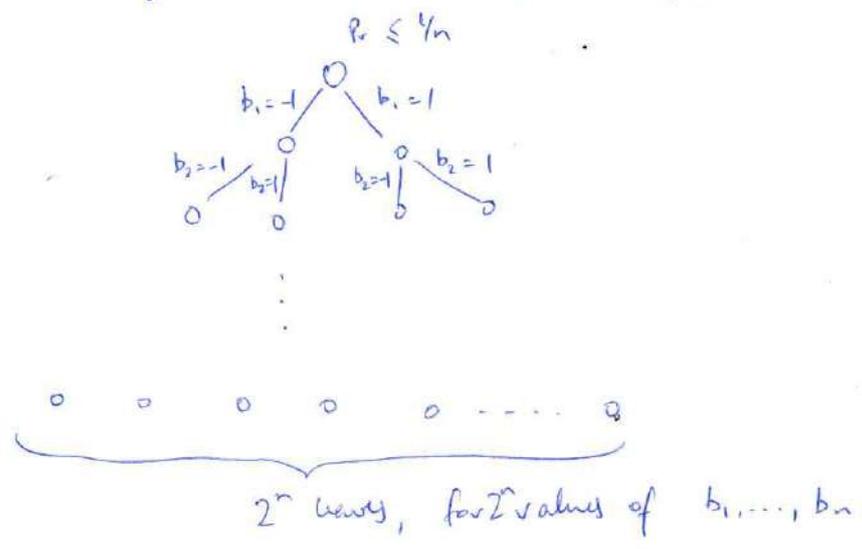
Then  $Pr[|Y_i| > \delta] \leq e^{-4n \ln n / 4n} = \frac{1}{n^2}$

Hence,  $Pr[\exists i: |Y_i| > \delta] \leq \frac{1}{n}$

Thus by choosing each entry  $b$  uniformly from  $+1, -1$ , we can obtain that  $\|Ab\|_\infty \leq 2\sqrt{n \ln n}$  w.h.p.

Can we do this with certainty? Can we derandomize this algorithm?

Again, we consider of the randomized algo as a tree, with  $n$  levels. A node at height  $j$  corresponds to a setting of  $b_1, \dots, b_j$ , and stores  $Pr[\|Ab\|_\infty > 2\sqrt{n \ln n} \mid b_1, \dots, b_j]$ .



~~Since each leaf is equally likely, we know that at~~

Consider a leaf (corr. to some choice of  $b_1, \dots, b_n$ ) s.t.

the value of the leaf is  $< 1$ .

(3)

Then  $P_r [\|A_b\|_\infty > 2\sqrt{n \ln n} \mid b_1, \dots, b_n] < 1$

But then there is no randomness at the leaf, since all values are already chosen. Hence for this choice of  $b_1, \dots, b_n$ , it must be true

(w.p. 1) that  $\|A_b\|_\infty \leq 2\sqrt{n \ln n}$ .

For a node  $v$  at level  $j$ , let  $P_v = P_r [\|A_b\|_\infty > 2\sqrt{n \ln n} \mid b_1, \dots, b_j]$

be the value stored at the node. Note that at the root,  $r$ ,

$P_r \leq \frac{1}{n}$ . For a node  $a$  <sub>at level  $j$</sub>  w/ children  $b, c$ , further

$$P_a = \frac{1}{2} P_b + \frac{1}{2} P_c.$$

$$\begin{aligned} \text{Since } P_a &= P_r [\|A_b\|_\infty > M \mid b_1, \dots, b_j] = P_r [\|A_b\|_\infty > M \mid b_1, \dots, b_{j+1} = +1] P_r [b_{j+1} = +1] \\ &\quad + P_r [\|A_b\|_\infty > M \mid b_1, \dots, b_{j+1} = -1] P_r [b_{j+1} = -1] \\ &= \frac{1}{2} P_b + \frac{1}{2} P_c \end{aligned}$$

Thus, in particular, either  $P_b$  or  $P_c \leq P_a$ .

~~From~~ Since  $P_r \leq 1$ , we just follow a path  $r, v_1, \dots, v_{n-1}$  where  $v_{n-1}$  is a leaf, and  $P_{v_{n-1}} \leq P_{v_{n-2}} \leq \dots \leq P_r < 1$ . Then at leaf  $v_{n-1}$ , for the corresponding choice of  $b$ ,  $\|A_b\|_\infty \leq M = 2\sqrt{n \ln n}$ .

However, this depends on being able to calculate  $P_r [\|A_b\|_\infty > M \mid b_1, \dots, b_j]$ , which we don't know how to do in polynomial time.

Instead, we use a "pessimistic estimator":

$$\hat{p}_v \geq p_v \text{ for each node } v. \text{ (hence pessimistic)}$$

~~Let  $\epsilon$  be the event that~~

$$\hat{p}_v = \sum_{j \in I} p_v [ |A_i b| > M ]$$

$$p_v = \sum_{i \in [n]} p_v [ |A_i b| > M \mid b_1, \dots, b_j ] \quad , \quad v \text{ is at level } j.$$

and this we can calculate; Further, we show that if  $v$  has

~~fix  $i, k$ . Then  $p_v [ |A_i b| > M \mid b_1, \dots, b_j ]$  Let  $S_i = \{$~~

~~the~~

children  $c, d$ , then  $\min \{ \hat{p}_c, \hat{p}_d \} < \hat{p}_v$ .

Since  $\hat{p}_v < 1$  (by our proof technique that shows  $p_v < 1$ ), we

can then follow the path downwards to obtain a leaf  $s.t.$   $\hat{p}_v < 1$ .

$$\sum \Pr [ |A_i b| > M ] \quad m \geq 0$$

$$= \Pr [ A_i b > M ] + \Pr [ A_i b < M ]$$

$$\text{let } k = \sum_{j \leq i} A_{ij}$$

$$\text{then } \Pr [ |A_i b|$$

$$\Pr [ |A_i b| > M ] = \sum_{R=M+1}^n \Pr [ |A_i b| = R ]$$

$$\text{now } \Pr [ |A_i b| = R ] = \Pr [ A_i b = R ] + \Pr [ A_i b = -R ]$$

$$\text{let } k = \sum_{j \leq i} A_{ij}, \quad S_i = \{ j' > j : A_{ij'} = 1 \}$$

$$\text{Then } \Pr [ A_i b = R \mid b_1, \dots, b_j ] = \Pr [ \sum_{j \in S_i} A_{ij} b_j = R - k ] = \Pr [ \sum_{j \in S_i} b_j = R - k ]$$

say in  $S_i$ ,  $n_1$  coordinates of  $b$  are +1,  
 $|S_i| - n_1$  " " " " are -1.

$$\text{Then } \sum_{j \in S_i} A_{ij} b_j = \sum_{j \in S_i} b_j = 2n_1 - |S_i| = R - k$$

$$\Rightarrow n_1 = \frac{1}{2}(R - k + |S_i|)$$

$$\text{and thus, } \Pr [ A_i b = R \mid b_1, \dots, b_j ] = \binom{|S_i|}{\frac{1}{2}(R - k + |S_i|)} \frac{1}{2^{|S_i|}}$$

we can thus obtain  $\Pr [ |A_i b| > M \mid b_1, \dots, b_j ]$  which is =  $\frac{\text{sum of binom. coeffs.}}{2^{|S_i|}}$