

Last class: For every graph  $G=(V,E)$  (with  $n=|V|$   
 $m=|E|$ ) <sup>wednesday 8/27/14</sup>  
there exists a cut  $S \leftrightarrow \bar{S}$  of size  $\geq \frac{m}{2}$ .

How did we prove it?

Look at a random partition  $S, \bar{S}$ .

Let  $X = \#$  of edges crossing  $S \leftrightarrow \bar{S}$ .

We showed that  $E[X] = \frac{m}{2}$ .

Hence there exists at least one cut of size  $\geq \frac{m}{2}$ .

Can we find such a cut?

Yes using method of conditional expectations.

$X$  is a random variable taking values  
in the range  $\{0, 1, 2, \dots, m\}$

Let  $V = \{v_1, v_2, \dots, v_n\}$

In order  $v_1, v_2, \dots, v_n$ , we'll assign each vertex  $v_i$  to  $S$  or  $\bar{S}$ .

When we assign  $v_i$  we'll use  $z_i$  to denote the assignment.

$$\text{let } z_i = \begin{cases} +1 & \text{if } v_i \in S \\ -1 & \text{if } v_i \in \bar{S} \end{cases}$$

We'll assign  $v_1, \dots, v_i$  in such a way that given this assignment for  $v_1, \dots, v_i$  then for a random assignment for  $v_{i+1}, \dots, v_n$  we have that the expected cut size  $\geq \frac{m}{2}$ .

This means that at the end when  $i=n$ , there's no randomness left & we have constructed a cut of size  $\geq \frac{m}{2}$ .

More formally, we want to assign  $z_1, \dots, z_i$  so that:

$$E[X \mid z_1, \dots, z_i] \geq \frac{m}{2} \quad (*)$$

Note for  $i=0$ , (\*) says:  $E[X] \geq \frac{m}{2}$   
which we showed last class. (3)

And the case  $i=1$  also holds:

$v_i$  is assigned to  $S$  or  $\overline{S}$ , we might as well label the set containing  $v_i$  as  $S$ , then  $z_i = +1$ , and we still have:

$$E[X | z_i] \geq E[X] \geq \frac{m}{2}.$$

For  $i > 1$  we'll aim to assign  $v_i$  so that:

$$E[X | z_1, \dots, z_i] \geq E[X | z_1, \dots, z_{i-1}] \quad (**)$$

then by induction we'll have that:

$$E[X | z_1, \dots, z_{i-1}] \geq \frac{m}{2}$$

& hence:

$$E[X | z_1, \dots, z_i] \geq \frac{m}{2}$$

So we'll be done.

How do we assign  $v_i$  to maintain (\*\*).

We need to factor  $E[X]$  to condition on the possible values of  $z_i$ .

First, let's look at the definition of conditional expectation.

$$E[X] = \sum_{j=0}^m j \Pr(X=j).$$

for event  $E$ ,

$$E[X|E] = \sum_{j=0}^m j \Pr(X=j|E)$$

So for the event that  $z_1=+1, z_2=-1$  then:

$$E[X|z_1, z_2] = \sum_{j=0}^m j \Pr(X=j|z_1, z_2)$$

Recall,

$$\begin{aligned} \Pr(X=j) &= \Pr(z_1=+1) \Pr(X=j|z_1=+1) + \Pr(z_1=-1) \Pr(X=j|z_1=-1) \\ &= \frac{1}{2} \Pr(X=j|z_1=+1) + \frac{1}{2} \Pr(X=j|z_1=-1) \end{aligned}$$

and

$$\begin{aligned} E[X] &= \sum_{j=0}^m j \Pr(X=j) = \frac{1}{2} \sum_{j=0}^m j \Pr(X=j|z_1=+1) + \frac{1}{2} \sum_{j=0}^m j \Pr(X=j|z_1=-1) \\ &= \frac{1}{2} E[X|z_1=+1] + \frac{1}{2} E[X|z_1=-1] \end{aligned}$$

As we already discussed, assigning  $z_1$  doesn't affect  $E[X]$  thus: (5)

$$E[X|z_1=+1] = E[X|z_1=-1] = E[X] \geq \frac{m}{2}.$$

But after we set  $z_1$  what about assigning  $z_2$ ?

We again have that:

$$E[X|z_1] = \frac{1}{2} E[X|z_2=+1, z_1] + \frac{1}{2} E[X|z_2=-1, z_1]$$

thus,

$$\max \{ E[X|z_2=+1, z_1], E[X|z_2=-1, z_1] \}$$

$$\geq E[X|z_1]$$

& we know this  $\uparrow E[X|z_1] \geq \frac{m}{2}$ .

Thus we want to assign  $z_2$  to the best of these two

Choose  $z_2$  to maximize  $E[X|z_1, z_2]$

Suppose we set  $z_1 = z_2 = +1$  so  $v_1, v_2 \in S$ . (6)

Then the edge  $(v_1, v_2)$  if it exists doesn't count.

For all other edges, they have Prob.  $\frac{1}{2}$  of crossing  $S \leftrightarrow \bar{S}$ .

$$\text{Thus, } E[X | z_1 = z_2 = +1] = \frac{m - \#\text{edges between } v_1, v_2}{2}$$

Similarly for  $z_1 = +1, z_2 = -1$ ,

$$E[X | z_1 = +1, z_2 = -1] = \frac{m + \#\text{edges between } v_1, v_2}{2}$$

So we can compute the assignment for  $v_2$  to maximize  $E[X | z_1, z_2]$ .

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More generally, if we fix the assignment for  $v_1, \dots, v_i$   
(so we assign  $z_1, \dots, z_i$ ) then we  
can compute  $E[X | z_1, \dots, z_i]$  by:

- Counting the edges with both endpoints in  $v_1, \dots, v_i$  that are crossing the cut. ~~not~~
- Plus we get every other edge with Prob.  $\frac{1}{2}$

So given  $z_1, \dots, z_{i-1}$

we assign  $z_i$  by trying  $z_i = +1$  &  $z_i = -1$   
& choosing the one maximizing the following:

Look at edges with both endpoints fixed  
(so both endpoints in  $v_1, \dots, v_i$ )

- Keep those crossing  $S \leftrightarrow \bar{S}$
- Discard those contained wholly in  $S$   
or wholly in  $\bar{S}$ .

For unfixed edges:  
add  $\frac{1}{2}$  for each

Take larger of these 2 counts.

(5)

This algorithm has a simple greedy form:

Let  $d_i = \text{degree of vertex } v_i$

Assign  $v_1$  to  $S$ .

For  $i=2 \rightarrow n$ :

let  $j = \#$  of neighbors of  $v_i$  assigned to  $S$   
so far.

$k = \#$  of neighbors of  $v_i$  assigned to  $\overline{S}$ .

We know  $j+k \leq d_i$

Assigning  $v_i$  to  $S$ :

we gain  $k$  edges & lose  $j$   
& get  $\frac{1}{2}$  of  $d_i - (k+j)$ .

Assigning  $v_i$  to  $\overline{S}$ :

we gain  $j$  & lose  $k$   
& get  $\frac{1}{2}$  of  $d_i - (k+j)$ .

Thus, if  $j < k$  assign  $v_i$  to  $S$

if  $j \geq k$  assign  $v_i$  to  $\overline{S}$ .

(So we place  $v_i$  on side with fewer neighbors so far)



Greedy algorithm:

For  $i=1 \rightarrow n$ :

Assign  $v_i$  to  $S$  or  $\bar{S}$  to maximize  
its neighbors in the other set  
(only considering neighbors assigned earlier)

Why do we say this is a  $\frac{1}{2}$ -approximation algorithm?

For a graph  $G$ , let  $OPT$  denote the size of its max cut.

Let  $OUT$  denote the size of the cut output by our algorithm.

We say an algorithm is an  $\alpha$ -approximation algorithm if

$$\min_G \frac{OUT}{OPT} \geq \alpha.$$

What about for MAX-SAT?

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Formula  $f$ ,  
Variables  $x_1, \dots, x_n$

Clauses  $C_1, \dots, C_m$

For a random assignment,

let  $Y = \#$  of satisfied clauses

We showed that  $E[Y] \geq \frac{M}{2}$

~~For~~

Given an assignment for  $x_1, \dots, x_{i-1}$

want to assign  $x_i$  to T or F so that:

$$E[Y | x_1, \dots, x_i] \geq E[Y | x_1, \dots, x_{i-1}] \geq \frac{M}{2}$$

As before:

$$\max \left\{ E[Y | x_i = T, x_1, \dots, x_{i-1}], E[Y | x_i = F, x_1, \dots, x_{i-1}] \right\} \\ \geq E[Y | x_1, \dots, x_{i-1}]$$

So try both

Given an assignment to  $x_1, \dots, x_{i-1}$ :

- try  $x_i = T$  &  $x_i = F$  and for each:

- fix the assignments to  $x_1, \dots, x_i$  in  $f$
- Count the satisfied clauses
- Drop those clauses with all literals fixed to unsatisfied
- add  $\frac{1}{2}$  for each remaining clause

- Take the better of the two cases  
 $x_i = T$  or  $x_i = F$ .