

## Approximation Algorithm

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Lecture 35

Lecture 35 : Randomized Rounding Based  $(1-1/e)$  Factor Approximation Algorithm for MAX-SAT

welcome. So, in the last class we have seen a  $\frac{\sqrt{5}-1}{2}$  factor approximation algorithm for MAX-SAT problem. So, in this class we will see a randomized rounding based algorithm for the same problem with better approximation guarantee. So, today's topic is rounding of LP's for MAX-SAT. So, we first write a linear programming relaxation, first let us write the integer linear program and then we will relax the integrality constraints. So, for each clause  $C_j$  we have a variable  $z_j$  which takes value 1 if  $C_j$  is satisfied.

and 0 otherwise ok. So, with this the objective function is easy to write, hence the objective maximize  $\sum w_j z_j$ . Next for every variable for every variable of the MAX-SAT formula we have a variable in linear program which will be set to true if the which will be set to 1 if the variable is set to true. So, for each Boolean variable  $x_i$  of max set, we have a variable  $y_i$  which takes value 1 if  $x_i$  is set to true and 0 otherwise.

So, now let us we will write the constraints. So, let us write down the integer linear programming formulation maximize  $\sum w_j z_j$  subject to Now consider the  $j$ -th variable. So, for each variable we will have a constraint which basically says that is set to 1 only if at least one of its literals are set to true. So, let  $p_j$  be the set of variables appearing positively in clause  $C_j$  and  $n_j$  the set of variables appearing negatively. in clause  $C_j$  ok.

So,  $C_j$  will be satisfied if one of its variable which are appearing positively is set to true or any of its variable which is appearing negatively is set to true set to false. So, then only  $z_j$  will be allowed to take value 1. So, here is the constraint that I sum over  $y_i$ 's  $i$  in  $p_j$  ok and  $\sum 1 - y_i$  see if any of the variable appearing positively and it is said to true in the corresponding  $y_i$  will be value will take value 1 or if any of the variable which are appearing negatively in  $n_j$ . are set to false then that  $y_i$  will be set to 0 and that  $1 - y_i$  this

value will be 1.

So, this sum will take value 1 if or at least 1 if  $C_j$  is satisfied otherwise it take value So,  $z_j$  should be allowed to take value 1 if and only if this sum is greater than equal to 1. So, this is  $z_j$  ok yeah. Now, what are the  $y_i$ 's?  $y_i$ 's belong to  $\{0,1\}$ . for all  $i \in [n]$  ok. Now, here is a little problem I want  $z_j$  also to take  $\{0,1\}$  values, but you know if say 2 variables which are appearing positively in a clause  $C_j$  is said to true then the value of this sum is greater than equal to 2.

that will allow this that will allow to set  $z_j$  to value more than 1 and that is fine because that will even increase the objective function which we are trying to maximize. So, to prevent that we can make another constraint that  $z_j$  should take value less than equal to 1 and of course, it is greater than equal to 0 ok. So, this is the ILP formulation. Now, to go to the LP formulation, we relax this integrality constraint, we replace this integrality constraints with inequalities instead of demanding  $y_i$  to take value 0 or 1, we insist that  $y_i$  take value in between 0 and 1. So, this is the relaxed LP ok.

So, what we have is opt equal to ILP of integer linear program with the constraints that  $y_i$  takes value either 0 and 1 and once we relax it we have a larger search space and hence the maximum value can only increase. So, this is less than equal to LP opt. So, LP opt is a upper bound on opt ok good. Now, what we do? for any rounding based algorithms what we first solve this relaxed LP get the optimal solution and use that as a guide to design a good approximation algorithm. So, solve the relaxed LP, let  $(y^*, z^*)$  be an optimal solution.

of this LP and before that before see how it can be used let us recall some inequalities which we will be needing. First I am writing them as fact, first is arithmetic geometric mean inequality AM-GM inequality. It says that for any n non-negative real numbers  $a_1, \dots, a_n$  the geometric mean which is product of  $a_i$ , i equal to 1 to n and then you take the nth root geometric mean is less than equal to arithmetic mean  $\frac{1}{n} \sum_{i=1}^n a_i$  ok.

So, this we will use crucially and another fact if a function  $f(x)$ .  $f(x)$  is concave on the interval closed interval  $[0,1]$  what does that mean ok we will see and  $f(0)=a$   $f(1)=b+a$ , then  $f(x) \geq a+bx$  for all  $x \in [0,1]$ . ok what is concave mean? So,  $f(x)$  is concave on say  $[0,1]$ . The idea is you take an interval suppose this is  $[0,1]$  take the function values at 0 take the function value at 1 and you draw this line.

If the graph of the function lies above it then it is concave function if this is a and this is

b if  $f(x) \geq a + bx$  and this not only for this function. So, this there is some problem with this picture. So, it should look like this. So, what is important is for any two point  $x_1, x_2$  the graph of the function lies above it. So, if correct it if for all  $0 \leq x_1 \leq x_2 \leq 1$ .

So, for every interval  $[x_1, x_2]$  for all  $x \in [x_1, x_2]$   $f(x) \geq f(x_1) + (x_2 - x_1)f(x_2)$ . So, it basically says that if I take any point  $x_1, x_2$  on this graph and draw this straight line the graph in between  $x_1$  and  $x_2$  the graph of the function  $f(x)$  in between  $x_1$  and  $x_2$  should lie above it. An equivalent condition for concavity if  $f$  is double differentiable then this double derivative should be less than equal to 0. So, if  $f$  is double differentiable, then  $f$  is concave if and only if  $f'(x)$  is concave in say any range say  $[0, 1]$ , then  $f''(x) \leq 0$ , in  $[0, 1]$ .

So, with this now we will see a randomized rounding based technique for  $1 - \frac{1}{e}$  factor approximation algorithm for MAX-SAT. So, here is theorem. there is a randomized rounding based algorithm for MAX-SAT. which achieves an approximation factor of at least  $1 - \frac{1}{e}$ . So, in randomized rounding based technique whenever you have variables which take value in between 0 and 1, it is quite natural to treat those variables as probabilities and used as those probabilities effectively.

Here we want to set some values true and false to the variables of the SAT instance. for each such variable  $x_i$  I have a variable  $y_i$  in linear program programming relaxation which takes value in between 0 and 1. So, what I do I can a natural thing is that I can set  $x_i$  to true with probability  $y_i$ . So, our algorithm is set  $x_i$  to true with probability  $y_i$  and false with probability  $1 - y_i$  independent of everything else ok. So, what is the now again we will see the same analysis ALG is  $w_1 z_1 + \dots + w_m z_m$ .

So, expectation of ALG is expectation of  $w_1 z_1 + \dots + w_m z_m$  we apply linearity of expectation  $w_1 E[z_1] + \dots + w_m E[z_m]$  and again these are indicator random variables their expectations are the probabilities of the events. So, this is  $w_1$  probability that  $C_1$  is satisfied probability that  $C_m$  is satisfied. So, we need to give lower bounds on the probability that any clause  $C_j$  is satisfied. So, what is the probability that so, I have a  $j \in [m]$  probability that  $C_j$  is satisfied. Again you see the only way it is it can be unsatisfied is all its positive variables are set to false and all its negative variables are set to true.

So, this is 1 minus probability that  $C_j$  is not satisfied ok and this is nothing, but 1 minus product over the positive terms  $i \in P_j$  that they are said to false and all are all the negative

variables they are said to be true. So, this is the only way it can be unsatisfied. So, this is greater than or equal to 1 minus here I am using arithmetic geometric arithmetic mean AM-GM inequality that arithmetic mean is greater than or equal to geometric mean. So, if I replace this geometric means ok.

So, I will apply. So, this is suppose let  $l_j$  is number of literals in  $C_j$ . So, this is 1 by what is arithmetic mean of these terms  $\frac{1}{l_j} \sum_{i \in P_j} (1 - y_i^*)$  So, this should be  $y_i^*$  because I have started with an optimal solution of the linear program  $1 - y_i^*$  plus  $\sum_{i \in N_j} y_i^*$ . So, this is the arithmetic mean and in geometric mean there is a  $\frac{1}{l_j}$  term. Now, this  $\frac{1}{l_j}$  I raise it to the power here.

This is how I apply arithmetic mean geometric mean a m g m inequality ok good. this is same as  $1 - (1 - \frac{1}{l_j}) \sum_{i \in P_j} y_i^*$  plus  $\sum_{i \in N_j} 1 - y_i^*$ . So, if added and subtracted 1 in both side to the power  $l_j$  ok. Now, you see that this one this sum this is the LP constraint that this is greater than equal to  $z_j$ .

So, what we have is because there are 2 negative terms here is 1 and here is 1 the direction of inequality remains same  $(1 - \frac{1 - z_j}{l_j})^{l_j}$  ok. And now you consider the function  $f$  this is also  $z_j^*$  consider the function  $z_j^*$  to be  $(1 - \frac{1 - z_j}{l_j})^{l_j}$  ok. So, this is concave you check this is concave in or on interval  $[0, 1]$ , it is a function of  $z_j^*$  for every  $l_j \geq 1$ , every natural number  $l_j$ . So, then we use that fact and we can write that this probability at  $C_j$  is satisfied this is greater than equal to this whole thing is greater than equal to. So, if  $z_j$  equal to 0 then this is  $f(0)$  is what is  $f(0)$ ?  $f(0)$  is 0 and  $f(1)$  is  $1 - (1 - \frac{1}{l_j})^{l_j}$  ok.

So,  $f(z_j^*) \geq f(0) + f(1)z_j^*$ . So, this is greater than equal to  $(1 - \frac{1}{e})z_j^*$ . So, this is what we have got probability that  $C_j$  is satisfied is greater than equal to  $(1 - \frac{1}{e})z_j^*$ . Now, we put this here expectation of ALG. So, expectation of ALG is then greater than equal to  $1 - \frac{1}{e}$  and here we have  $w_1 z_1^* + \dots + w_m z_m^*$  ok.

this is LP opt because you see this is the optimization function and  $z^*$  is a

is an optimal solution. So, this is equal to  $(1 - \frac{1}{e})LP-opt$  which is greater than equal to  $(1 - \frac{1}{e})opt$ . hence it is a  $1 - \frac{1}{e}$  factor randomized approximation algorithm. Again this can be de-randomized using method of conditional expectation I leave that as a homework ok. Thank you.