

SAT

SAT

- $x_1, \dots, x_n$ Boolean variables.
- Clause is an “OR” of Boolean variables or their negations $x_a \vee \neg x_b \vee \neg x_c \dots$
- Goal: Given a set of m clauses, compute an assignment that satisfies the largest fraction of clauses.

- Algorithm

1. For each $i \in [n]$, independently set x_i to be *true* or *false* with probability $\frac{1}{2}$.

- Fix a clause $C_i = x_{i_1} \vee \neg x_{i_2} \vee \dots \vee \neg x_{i_k}$.

$$\Pr[C_i \text{ is satisfied}] = 1 - \frac{1}{2^k}$$

SAT

$$\mathbb{E}[\text{number of clauses satisfied}] = \sum_{i \in [m]} \left(1 - \frac{1}{2^{|C_i|}}\right)$$

- k -SAT: each clause has exactly k variables.

$$\mathbb{E}[\text{number of clauses satisfied}] = \sum_{i \in [m]} \left(1 - \frac{1}{2^{|C_i|}}\right) = m \left(1 - \frac{1}{2^k}\right)$$

- Since $OPT \leq m$, this gives a $\left(1 - \frac{1}{2^k}\right)$ -approximation for k -SAT.
- In general, $|C_i| \geq 1$. Therefore,

$$\mathbb{E}[\text{number of clauses satisfied}] = \sum_{i \in [m]} \left(1 - \frac{1}{2^{|C_i|}}\right) \geq \sum_{i \in [m]} \left(1 - \frac{1}{2}\right) = \frac{m}{2}.$$

- Therefore $\frac{1}{2}$ approximation for SAT.

Integer Program

- Introduce variable y_i to indicate the value of x_i , i.e. $y_i = \begin{cases} 1 & \text{if } x_i \text{ is true} \\ 0 & \text{if } x_i \text{ is false} \end{cases}$.
- Introduce variable z_j to indicate whether clause C_j is satisfied.
- For a clause C_j , let P_j be the set of indices of variables that occur positively and let N_j be the set of indices of variables that occur negated. $C_j = \bigvee_{i \in P_j} x_i \bigvee_{i \in N_j} \neg x_i$. Add constraint

$$z_j \leq \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i)$$

$$\begin{aligned} & \max \sum_{j \in [m]} z_j \\ & \text{subject to} \\ & z_j \leq \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \quad \forall j \in [m] \\ & z_j \in \{0,1\} \quad \forall j \in [m] \\ & y_i \in \{0,1\} \quad \forall i \in [n] \end{aligned}$$

Randomized Rounding

$$\begin{aligned} & \max \sum_{j \in [m]} z_j \\ \text{subject to} \\ & z_j \leq \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \quad \forall j \in [m] \\ & 0 \leq z_j \leq 1 \quad \forall j \in [m] \\ & 0 \leq y_i \leq 1 \quad \forall i \in [n] \end{aligned}$$

- Algorithm-2

1. For each i , independently set x_i to *true* with probability y_i and *false* with probability $1 - y_i$.

- Fix a clause C_j and let $k = |C_j|$.

$$C_j = \bigvee_{i \in P_j} x_i \bigwedge_{i \in N_j} \neg x_i$$

$$\begin{aligned} \text{Pr}[C_j \text{ is not satisfied}] &= \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} (1 - (1 - y_i)) \\ \text{AM} \geq \text{GM} &\leq \left(\frac{1}{k} \left(\sum_{i \in P_j} (1 - y_i) + \sum_{i \in N_j} (1 - (1 - y_i)) \right) \right)^k = \left(1 - \frac{1}{k} \left(\sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \right) \right)^k \leq \left(1 - \frac{z_j}{k} \right)^k \end{aligned}$$

- Therefore, $\text{Pr}[C_j \text{ is satisfied}] \geq 1 - \left(1 - \frac{z_j}{k} \right)^k$.

- Lemma: $\forall x \in [0,1], 1 - \left(1 - \frac{x}{k}\right)^k \geq \left(1 - \left(1 - \frac{1}{k}\right)^k\right) x$
- Lemma implies $\Pr[C_j \text{ is satisfied}] \geq 1 - \left(1 - \frac{z_j}{k}\right)^k \geq \left(1 - \left(1 - \frac{1}{k}\right)^k\right) z_j \geq \left(1 - \frac{1}{e}\right) z_j$

$$\begin{aligned} \mathbb{E}[\text{number of clauses satisfied}] &= \sum_{j \in [m]} \Pr[C_j \text{ is satisfied}] \geq \left(1 - \frac{1}{e}\right) \sum_{j \in [m]} z_j \\ &= \left(1 - \frac{1}{e}\right) LP \end{aligned}$$

- Therefore, Algorithm-2 is a $\left(1 - \frac{1}{e}\right)$ -approximation algorithm.

Lemma: $\forall x \in [0,1], 1 - \left(1 - \frac{x}{k}\right)^k \geq \left(1 - \left(1 - \frac{1}{k}\right)^k\right) x$

1. The function $f(x) = 1 - \left(1 - \frac{x}{k}\right)^k$ is concave in $[0,1]$.

$$f'(x) = \left(1 - \frac{x}{k}\right)^{k-1} \text{ and } f''(x) = -\frac{(k-1)}{k} \left(1 - \frac{x}{k}\right)^{k-2}. \text{ Therefore, } f''(x) \leq 0 \forall x \in [0,1].$$

2. $f(x)$ does not lie below the line segment joining $f(0)$ and $f(1)$ for $x \in [0,1]$.

$$f(x) \geq x(f(1) - f(0)) + f(0) \geq x \left(1 - \left(1 - \frac{1}{k}\right)^k\right)$$

- For clause C_j
 1. $\Pr[\text{Alg1 satisfies } C_j] = \left(1 - \frac{1}{2^k}\right)$
 2. $\Pr[\text{Alg2 satisfies } C_j] = \left(1 - \left(1 - \frac{1}{k}\right)^k\right) z_j$
- For “large” values of k , Alg1 is better and for “small” values of k , Alg2 is better.
- Algorithm 3
 1. Choose a random algorithm from $\{\text{Alg1}, \text{Alg2}\}$ and run it on the instance.

$$\begin{aligned}
 \Pr[\text{Alg3 satisfies } C_j] &= \frac{1}{2} \Pr[\text{Alg1 satisfies } C_j] + \frac{1}{2} \Pr[\text{Alg2 satisfies } C_j] \\
 &= \frac{1}{2} \left(1 - \frac{1}{2^k}\right) + \frac{1}{2} \left(\left(1 - \left(1 - \frac{1}{k}\right)^k\right) z_j \right) \\
 &\geq \left(\frac{1}{2} \left(1 - \frac{1}{2^k}\right) + \frac{1}{2} \left(1 - \left(1 - \frac{1}{k}\right)^k\right) \right) z_j
 \end{aligned}$$

3/4-approximation

k	$\left(1 - \frac{1}{2^k}\right)$	$\left(1 - \left(1 - \frac{1}{k}\right)^k\right)$	$\frac{1}{2}\left(1 - \frac{1}{2^k}\right) + \frac{1}{2}\left(1 - \left(1 - \frac{1}{k}\right)^k\right)$
1	1/2	1	3/4
2	3/4	3/4	3/4
≥ 3	$\geq 7/8$	$\geq 1 - 1/e$	$\geq 3/4$

$$\Pr[\text{Alg3 satisfies } C_j] \geq \left(\frac{1}{2} \left(1 - \frac{1}{2^k}\right) + \frac{1}{2} \left(1 - \left(1 - \frac{1}{k}\right)^k\right) \right) z_j \geq \frac{3}{4} z_j$$

Max 2SAT- Integer Program

- For each x_i , introduce variable $y_i \in \{+1, -1\}$ to “indicate” if x_i is true.
- clause $\neg x_a \vee x_b$ is not satisfied if $\frac{1}{4}(1 + y_a)(1 - y_b) = 1$.
- Therefore, $\neg x_a \vee x_b$ is satisfied if $1 - \frac{1}{4}(1 + y_a)(1 - y_b) = 1$.

- Introduce “one” vector v_0 .

- For clause $\neg x_a \vee x_b$

$$\begin{aligned}\text{val}(C_j) &= 1 - \frac{1}{4} \langle v_0 + v_a, v_0 - v_b \rangle \\ &= 1 - \frac{1}{4} (\langle v_0, v_0 \rangle + \langle v_0, v_a \rangle - \langle v_0, v_b \rangle - \langle v_a, v_b \rangle) \\ &= \frac{1}{4} (1 - \langle v_0, v_a \rangle) + \frac{1}{4} (1 + \langle v_0, v_b \rangle) + \frac{1}{4} (1 + \langle v_a, v_b \rangle)\end{aligned}$$

$$\begin{aligned}&\max \sum_{j \in [m]} \text{val}(C_j) \\ &\text{subject to} \\ &\quad y_i^2 = 1 \quad \forall i \in [n]\end{aligned}$$

$$\begin{aligned}&\max \sum_{j \in [m]} \text{val}(C_j) \\ &\text{subject to} \\ &\quad \|v_i\|^2 = 1 \quad \forall i \in [n] \\ &\quad \|v_0\|^2 = 1\end{aligned}$$

GW algorithm

1. Sample $g \sim \mathcal{N}(0,1)^{n+1}$ and let $S_g = \{i \in [n]: \langle v_i, g \rangle \text{ has same sign as } \langle v_0, g \rangle\}$.
 2. Set all variables in S_g to “True” and variables in $[n] \setminus S_g$ to “False”.
- $(1 - \langle v_0, v_a \rangle)$ gets rounded to 2 with probability θ_{0a}/π and $1 - \langle v_0, v_a \rangle = 1 - \cos \theta_{0a}$
 - $(1 + \langle v_0, v_b \rangle)$ gets rounded to 2 with probability $(\pi - \theta_{0b})/\pi$ and
 $1 + \langle v_0, v_b \rangle = 1 + \cos \theta_{0b} = 1 - \cos(\pi - \theta_{0b})$
 - Therefore, α_{GW} (≈ 0.878) approximation to Max 2SAT (H.W.).

- $\frac{7}{8}$ -approximation for Max-3SAT.
- NP-hard to do better than this [Hastad - 2001].