

ex) Max-SAT

Input: CNF formula $F = C_1 \wedge C_2 \wedge \dots \wedge C_m$ on n vars x_1, \dots, x_n

Goal: Find assignment $x \in \{0, 1\}^n$ maximizing the # of SAT clauses.

For clause $C = \bigvee_{i \in S} x_i \vee \bigvee_{j \in T} \bar{x}_j$ let $\tilde{C}_i = \sum_{i \in S} x_i + \sum_{j \in T} (1 - x_j)$

Integer Linear Program

$$\begin{aligned} \max \quad & \sum_{i=1}^m c_i \\ \text{s.t.} \quad & \tilde{C}_i \geq c_i \quad \forall i=1 \dots m \\ & 0 \leq x_j \leq 1 \quad \forall j=1 \dots n \\ & 0 \leq c_i \leq 1 \quad \forall i=1 \dots m \\ & x_j, c_i \in \mathbb{Z} \end{aligned}$$

↑

- Represents Max-SAT exactly

- NP-Hard to solve

LP Relaxation

$$\begin{aligned} \max \quad & \sum_{i=1}^m c_i \\ \text{s.t.} \quad & \tilde{C}_i \geq c_i \quad \forall i=1 \dots m \\ & 0 \leq x_j \leq 1 \quad \forall j=1 \dots n \\ & 0 \leq c_i \leq 1 \quad \forall i=1 \dots m \\ & \cancel{x_j, c_i \in \mathbb{Z}} \end{aligned}$$

↑

- Doesn't represent Max-SAT exactly

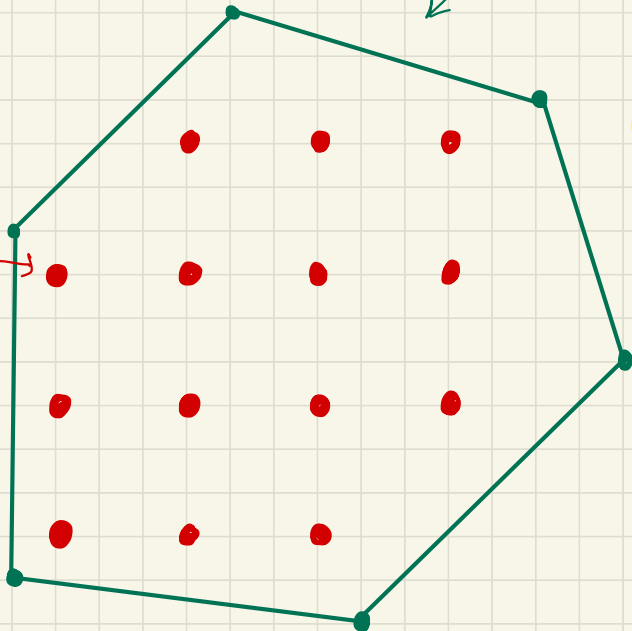
- Can be solved in poly time!

Geometric Picture

LP relaxation

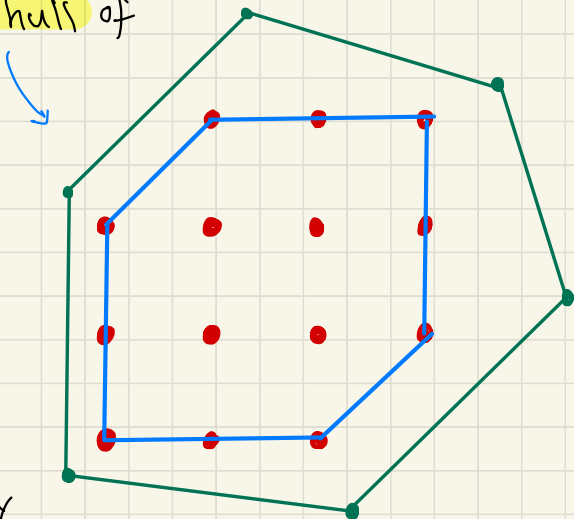
We want the optimal integral point, can only get the optimal fractional point.

Integral Points



Q. Is there a linear program that solves Max-SAT exactly?

A. Yes! Take the convex hull of integral points



Problems

(1) How do we get it?

A: Sherali-Adams

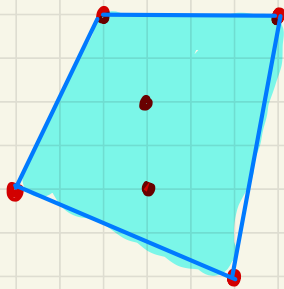
(2) There might be exponentially many inequalities in any description.

Today we focus on finding the integral hull using the SA hierarchy.

Prelims

- If $\vec{y}_1, \dots, \vec{y}_m \in \mathbb{R}^n$ then a convex combination of the y_i s is any point of the form
$$\sum_{i=1}^m \alpha_i \vec{y}_i \quad \alpha_i \geq 0, \quad \sum \alpha_i = 1$$
- If $C \subseteq \mathbb{R}^n$ then $\text{conv}(C) \subseteq \mathbb{R}^n$ is all convex combos of points in C .

ex) $C \rightsquigarrow$



C red points
 $\text{conv}(C)$ blue points

- If $C \subseteq \mathbb{R}^n$ then $\text{hull}_{\mathbb{Z}}(C) := \text{conv}(C \cap \mathbb{Z}^n)$

- We're given polytope $P \subseteq [0,1]^n$ i.e. the constraints

$$0 \leq x_i \leq 1 \text{ are in } P.$$

- We want to describe $\text{hull}_{\mathbb{Z}}(P)$.
- Since $P \subseteq [0,1]^n$, every point in $\text{hull}_{\mathbb{Z}}(P)$ can be written as

$$\alpha \in \text{hull}_{\mathbb{Z}}(P) \Rightarrow \alpha = \sum_{x \in \{0,1\}^n} \lambda_x x, \quad \lambda_x \geq 0, \quad \sum \lambda_x = 1$$

- Equivalently: $\alpha \in \text{hull}_{\mathbb{Z}}(P)$ represents a probability distribution of

$$x \in P \cap \{0,1\}^n$$

- For each α let $\mu^{(\alpha)}: \{0,1\}^n \rightarrow \mathbb{R}$ s.t.

$$\mu^{(\alpha)}(x) = \lambda_x$$

so $\mu^{(\alpha)}$ is a prob. dist. over $\{0,1\}^n \cap P$

Observation If we can test if $\alpha \in \mathbb{R}^n$ represents a valid prob. dist. over $P \cap \{0,1\}^n$ then $\alpha \in \text{hull}_{\mathbb{Z}}(P)$!

So: how do we test if α represents a probability distribution?

$$\mu: \{0,1\}^n \rightarrow \mathbb{R} \quad \mu(x) \geq 0 \quad \text{and} \quad \sum \mu(x) = 1$$

We modify this by adding more tests to verify that we are in \mathcal{P} .

Sufficient to show μ is dist over $\{0,1\}^n$.

Not for $\{0,1\}^n \cap \mathcal{P}$

Specific: Test the **marginal distributions** of μ .

If $S \subseteq [n]$ then

$$\mu_S : \{0,1\}^S \rightarrow \mathbb{R}$$

is defined by $\mu_S(\alpha) := \sum_{\substack{x \in \{0,1\}^n \\ x \upharpoonright S = \alpha}} \mu(x)$.

(if μ is a real prob. dist then

$$\mu_S(\alpha) = \Pr_{x \sim \mu} [\forall i \in S : x_i = \alpha_i])$$

Lemma $\mu : \{0,1\}^n \rightarrow \mathbb{R}$ is a prob. dist on $\{0,1\}^n$

iff

$$\forall S \subseteq T \subseteq [n], \forall \alpha \in \{0,1\}^S$$

$$(1) \mu_S(\alpha) = \sum_{\substack{\beta \in \{0,1\}^T \\ \beta \upharpoonright S = \alpha}} \mu_T(\beta) \quad \text{marginals agree}$$

$$(2) \mu_S(\alpha) \geq 0$$

non-negativity

$$(3) \mu_\emptyset = 1$$

normalizing

← explains $1 \geq 0$

Pf (\Rightarrow) Easy

(\Leftarrow) Define $\Pr_{x \sim \mu} [x=y] := \mu(y)$

$$\mathbb{1} = \mu_{\emptyset} \stackrel{(1)}{=} \sum_{x \in \{0,1\}^n} \mu(x) \quad \square$$

Answer: Where do non-negative juntas come from?

$y \in \{0,1\}^S$, let $S = T \cup U$ so that

$$\mu_S(y) \quad y_i = \begin{cases} 1 & i \in T \\ 0 & i \in U \end{cases} \quad \swarrow \mathcal{J}_{T,U}$$

$$\Pr_{x \sim \mu} [x|_S = y] = \Pr_{x \sim \mu} \left[\prod_{i \in T} x_i \prod_{j \in U} (1-x_j) = 1 \right]$$

Non-negative juntas are **random variables** that describe the **marginals** of probability distributions over $\text{hull}_Z(P)$.

This lemma is going to give a (somewhat crazy) LP for $\{0,1\}^n$.

- For each $S \subseteq [n]$ let $y_S \in \mathbb{R}$ be a variable for S .

$$\text{Intuitively: } y_S = \mu_S(\vec{\mathbb{1}}) = \Pr_{x \sim \mu} [x_i = 1 \forall i \in S]$$

$$= \mathbb{E}_{\mu} \left[\prod_{i \in S} x_i \right] \quad \leftarrow \text{moment for } S$$

Define an LP on $\{y_S \mid S \subseteq [n]\}$, with constraints

$$(a) y_\emptyset = 1$$

$$y_{\{i\}} = x_i^0$$

$$(b) \forall S \subseteq [n], \forall T \cup U = S, T \cap U = \emptyset$$

$$\sum_{U' \subseteq U} (-1)^{|U'|} y_{U' \cup T} \geq 0 \quad (1 \geq 0)$$

Claim (1), (2) \Rightarrow (b)

$$S \subseteq T$$

$$(1) \mu_S(d) \geq 0 \quad (2) \mu_S(d) = \sum_{\substack{\beta \in \{0,1\}^T \\ \beta|_S = d}} \mu_T(\beta)$$

$$\stackrel{(1)}{0} \leq \mu_S(d) \stackrel{(2)}{=} \Pr_{x \sim \mu} [x|_S = d] \quad \text{let } d_i^0 = \begin{cases} 1 & \text{if } i \in T \\ 0 & \text{if } i \in U \end{cases}$$

$$= \Pr \left[\prod_{i \in T} x_i \prod_{j \in U} (1 - x_j) = 1 \right]$$

$$= \mathbb{E} \left[\prod_{i \in T} x_i \prod_{j \in U} (1 - x_j) \right]$$

$$= \sum_{U' \subseteq U} \mathbb{E} \left[(-1)^{|U'|} \prod_{i \in U' \cup T} x_i \right]$$

$$= \sum_{U' \subseteq U} (-1)^{|U'|} y_{U' \cup T}$$

How to include constraints from P ?

Write P as

$$Ax \leq b = \begin{cases} a_1 \cdot x \leq b_1 \\ a_2 \cdot x \leq b_2 \\ \vdots \\ a_m \cdot x \leq b_m \end{cases}$$

$$0 \leq x \leq 1$$

$$\text{Let } Q = \{b_1 - a_1 x \geq 0, \dots, b_m - a_m x \geq 0\} \cup \{1 \geq 0\}$$

Defn The degree- d Sherali-Adams tightening of Q is obtained by the following two steps

(1) For each inequality $q_i \geq 0$ in Q add

$$\sum_{S,T} q_i \geq 0$$

$$\leftarrow \sum_{i \in S} x_i \prod_{j \in T} (1-x_j)$$

to Q where $|S \cup T| \leq d, S \cap T = \emptyset$

(2) For every inequality $p_i \geq 0$ created in the last step, linearize p_i by

- Replace each x_i^c term with x_i

- For every monomial $\prod_{i \in S} x_i$, replace it with y_S .

Lemma (Next class) The degree- n Sherali-Adams tightening is exactly $\text{hull}_{\mathbb{Z}}(P)$.

ex) Max-SAT

$$\text{Let } F = (x_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1)$$

LP Relaxation

constraints: $x_1 + x_2 \geq x_3$

$$x_1 + (1 - x_2) \geq x_4$$

$$(1 - x_1) \geq x_5$$

The degree-2 SA tightening would add

$$y_{\{i,j\}} \geq 0 \quad (1 - y_{\{i,j\}}) \geq 0 \quad \forall i, j \quad i \neq j$$

$$y_i(1 - y_j) \geq 0 \quad y_i y_j \geq 0$$

↓

↓

$$y_i - y_{\{i,j\}} \geq 0 \quad y_{\{i,j\}} \geq 0$$

Then, we multiply each constraint in the LP by a non-neg junta and linearize

ex) $x_1 + x_2 \geq x_4 \rightsquigarrow x_i^0 (x_1 + x_2 - x_4) \geq 0$

$$(1 - x_i^0) (x_1 + x_2 - x_4) \geq 0$$

$$\forall i, j \quad x_i^0 x_j^0 (x_1 + x_2 - x_4) \geq 0$$

$$i \neq j \quad x_i^0 (1 - x_j^0) (x_1 + x_2 - x_4) \geq 0$$

$$(1 - x_i^0) (1 - x_j^0) (x_1 + x_2 - x_4) \geq 0$$

$$x_i^0 (x_1 + x_2 - x_4) \geq 0$$

↓

$$y_{\{i,1\}} + y_{\{i,2\}} - y_{\{i,4\}} \geq 0$$

$$z_m \binom{n}{\leq d} = m n^{o(d)}$$