

16.1 MAXSAT

Problem definition:

- ▶ n Boolean variables
- ▶ m clauses C_1, \dots, C_m . For example

$$C_7 = x_3 \vee \bar{x}_5 \vee \bar{x}_9$$

- ▶ Non-negative weight w_j for each clause C_j .
- ▶ Find an assignment of true/false to the variables such that the total weight of clauses that are **satisfied** is maximum.

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Terminology:

- ▶ A variable x_i and its negation \bar{x}_i are called **literals**.
- ▶ Hence, each clause consists of a set of literals (i.e., no duplications: $x_i \vee x_i \vee \bar{x}_j$ is not a clause).
- ▶ We assume a clause does not contain x_i and \bar{x}_i for any i .
- ▶ x_i is called a **positive literal** while the negation \bar{x}_i is called a **negative literal**.
- ▶ For a given clause C_j the number of its literals is called its **length** or **size** and denoted with ℓ_j .
- ▶ Clauses of length one are called **unit clauses**.

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MAXSAT: Flipping Coins

Set each x_i independently to **true** with probability $\frac{1}{2}$ (and, hence, to **false** with probability $\frac{1}{2}$, as well).

Define random variable X_j with

$$X_j = \begin{cases} 1 & \text{if } C_j \text{ satisfied} \\ 0 & \text{otw.} \end{cases}$$

Then the total weight W of satisfied clauses is given by

$$W = \sum_j w_j X_j$$

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MAXSAT: LP formulation

- ▶ Let for a clause C_j , P_j be the set of positive literals and N_j the set of negative literals.

$$C_j = \bigvee_{i \in P_j} x_i \vee \bigvee_{i \in N_j} \bar{x}_i$$

$$\begin{array}{ll} \max & \sum_j w_j z_j \\ \text{s.t.} & \forall j \quad \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \geq z_j \\ & \forall i \quad y_i \in \{0, 1\} \\ & \forall j \quad z_j \leq 1 \end{array}$$

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MAXSAT: Randomized Rounding

Set each x_i independently to **true** with probability y_i (and, hence, to **false** with probability $(1 - y_i)$).

Lemma 3 (Geometric Mean \leq Arithmetic Mean)

For any nonnegative a_1, \dots, a_k

$$\left(\prod_{i=1}^k a_i \right)^{1/k} \leq \frac{1}{k} \sum_{i=1}^k a_i$$

Definition 4

A function f on an interval I is **concave** if for any two points s and r from I and any $\lambda \in [0, 1]$ we have

$$f(\lambda s + (1 - \lambda)r) \geq \lambda f(s) + (1 - \lambda)f(r)$$

Lemma 5

Let f be a concave function on the interval $[0, 1]$, with $f(0) = a$ and $f(1) = a + b$. Then

$$f(\lambda)$$

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$$\begin{aligned} f(\lambda) &= f((1 - \lambda)0 + \lambda 1) \\ &\geq (1 - \lambda)f(0) + \lambda f(1) \\ &= a + \lambda b \end{aligned}$$

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$\Pr[C_j \text{ not satisfied}]$

$$\Pr[C_j \text{ not satisfied}] = \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} y_i$$

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

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

The function $f(z) = 1 - (1 - \frac{z}{\ell})^\ell$ is concave. Hence,

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$f''(z) = -\frac{\ell-1}{\ell} \left[1 - \frac{z}{\ell}\right]^{\ell-2} \leq 0$ for $z \in [0, 1]$. Therefore, f is concave.

$E[W]$

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MAXSAT: The better of two

Theorem 6

Choosing the better of the two solutions given by randomized rounding and coin flipping yields a $\frac{3}{4}$ -approximation.

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$E[\max\{W_1, W_2\}]$$

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$\begin{aligned} E[\max\{W_1, W_2\}] \\ \geq E[\frac{1}{2}W_1 + \frac{1}{2}W_2] \end{aligned}$$

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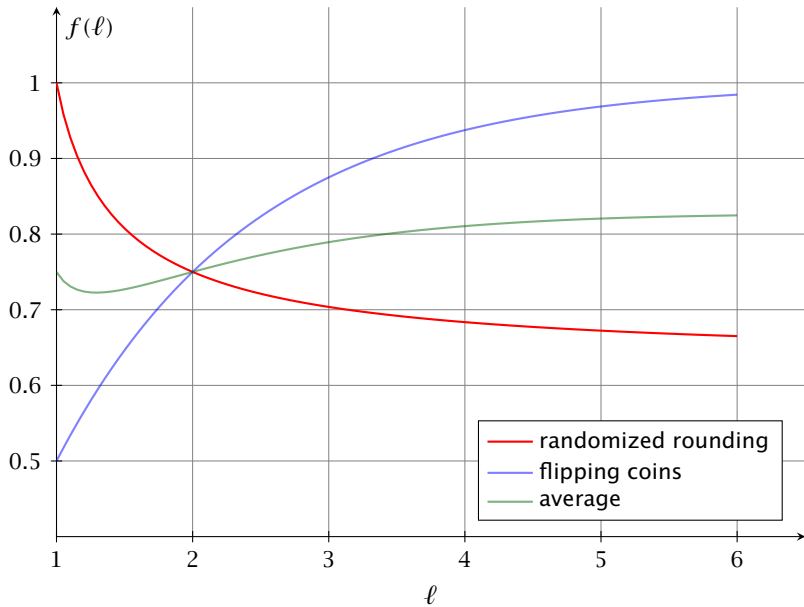
$$\begin{aligned} E[\max\{W_1, W_2\}] &\geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2] \\ &\geq \tfrac{1}{2} \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j} \right] + \tfrac{1}{2} \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \end{aligned}$$

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$$\begin{aligned} & E[\max\{W_1, W_2\}] \\ & \geq E\left[\frac{1}{2}W_1 + \frac{1}{2}W_2\right] \\ & \geq \frac{1}{2} \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j} \right] + \frac{1}{2} \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\ & \geq \sum_j w_j z_j \underbrace{\left[\frac{1}{2} \left(1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right) + \frac{1}{2} \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \right]}_{\geq \frac{3}{4} \text{ for all integers}} \\ & \geq \frac{3}{4} \text{OPT} \end{aligned}$$



MAXSAT: Nonlinear Randomized Rounding

So far we used **linear** randomized rounding, i.e., the probability that a variable is set to 1/true was exactly the value of the corresponding variable in the linear program.

We could define a function $f : [0, 1] \rightarrow [0, 1]$ and set x_i to true with probability $f(y_i)$.

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We could define a function $f : [0, 1] \rightarrow [0, 1]$ and set x_i to true with probability $f(y_i)$.

MAXSAT: Nonlinear Randomized Rounding

Let $f : [0, 1] \rightarrow [0, 1]$ be a function with

$$1 - 4^{-x} \leq f(x) \leq 4^{x-1}$$

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Rounding the LP-solution with a function f of the above form gives a $\frac{3}{4}$ -approximation.

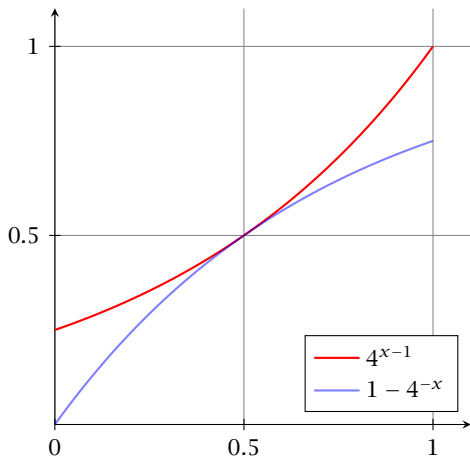
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Can we do better?

Not if we compare ourselves to the value of an optimum LP-solution.

Definition 8 (Integrality Gap)

The integrality gap for an ILP is the worst-case ratio over all instances of the problem of the value of an optimal IP-solution to the value of an optimal solution to its linear programming relaxation.

Note that the integrality is less than one for maximization problems and larger than one for minimization problems (of course, equality is possible).

Note that an integrality gap only holds for one specific ILP formulation.

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Lemma 9

Our ILP-formulation for the MAXSAT problem has integrality gap at most $\frac{3}{4}$.

$$\begin{array}{ll} \max & \sum_j w_j z_j \\ \text{s.t.} & \forall j \quad \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \geq z_j \\ & \forall i \quad y_i \in \{0, 1\} \\ & \forall j \quad z_j \leq 1 \end{array}$$

Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- ▶ any solution can satisfy at most 3 clauses
- ▶ we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
- ▶ hence, the LP has value 4.

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Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- ▶ any solution can satisfy at most 3 clauses
- ▶ we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
- ▶ hence, the LP has value 4.

MaxCut

Given a weighted graph $G = (V, E, w)$, $w(v) \geq 0$, partition the vertices into two parts. Maximize the weight of edges between the parts.

Trivial 2-approximation

Semidefinite Programming

$$\begin{array}{ll} \max / \min & \sum_{i,j} c_{ij} x_{ij} \\ \text{s.t.} & \forall k \quad \sum_{i,j} a_{ijk} x_{ij} = b_k \\ & \forall i, j \quad x_{ij} = x_{ji} \\ & X = (x_{ij}) \text{ is psd.} \end{array}$$

- ▶ linear objective, linear constraints
- ▶ we can constrain a square matrix of variables to be symmetric positive semidefinite

Vector Programming

$$\begin{array}{ll} \max / \min & \sum_{i,j} c_{ij} (v_i^t v_j) \\ \text{s.t. } \forall k & \sum_{i,j,k} a_{ijk} (v_i^t v_j) = b_k \\ & v_i \in \mathbb{R}^n \end{array}$$

- ▶ variables are vectors in n -dimensional space
- ▶ objective functions and constraints are linear in inner products of the vectors

This is equivalent!

Fact [without proof]

We (essentially) can solve Semidefinite Programs in polynomial time...

Quadratic Programs

Quadratic Program for MaxCut:

$$\begin{array}{ll} \max & \frac{1}{2} \sum_{i,j} w_{ij} (1 - y_i y_j) \\ \forall i & y_i \in \{-1, 1\} \end{array}$$

This is exactly MaxCut!

Semidefinite Relaxation

$$\begin{array}{ll} \max & \frac{1}{2} \sum_{i,j} w_{ij} (1 - v_i^t v_j) \\ & \forall i \quad v_i^t v_i = 1 \\ & \forall i \quad v_i \in \mathbb{R}^n \end{array}$$

- ▶ this is clearly a relaxation
- ▶ the solution will be vectors on the unit sphere

Rounding the SDP-Solution

- ▶ Choose a random vector r such that $r/\|r\|$ is uniformly distributed on the unit sphere.
- ▶ If $r^t v_i > 0$ set $y_i = 1$ else set $y_i = -1$

Rounding the SDP-Solution

Choose the i -th coordinate r_i as a Gaussian with mean 0 and variance 1, i.e., $r_i \sim \mathcal{N}(0, 1)$.

Density function:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

Then

$$\begin{aligned} \Pr[r = (x_1, \dots, x_n)] &= \frac{1}{(\sqrt{2\pi})^n} e^{-x_1^2/2} \cdot e^{-x_2^2/2} \cdot \dots \cdot e^{-x_n^2/2} dx_1 \cdot \dots \cdot dx_n \\ &= \frac{1}{(\sqrt{2\pi})^n} e^{-\frac{1}{2}(x_1^2 + \dots + x_n^2)} dx_1 \cdot \dots \cdot dx_n \end{aligned}$$

Hence the probability for a point only depends on its distance to the origin.

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Rounding the SDP-Solution

Fact

The projection of r onto two unit vectors e_1 and e_2 are independent and are normally distributed with mean 0 and variance 1 iff e_1 and e_2 are orthogonal.

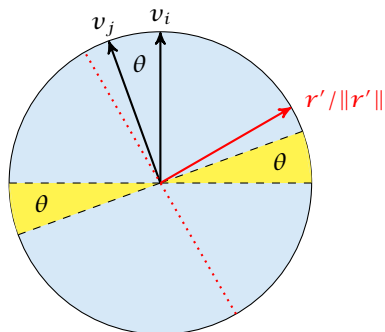
Note that this is clear if e_1 and e_2 are standard basis vectors.

Rounding the SDP-Solution

Corollary

If we project r onto a hyperplane its normalized projection $(r' / \|r'\|)$ is uniformly distributed on the unit circle within the hyperplane.

Rounding the SDP-Solution



- ▶ if the normalized projection falls into the shaded region, v_i and v_j are rounded to different values
- ▶ this happens with probability θ/π

Rounding the SDP-Solution

- ▶ contribution of edge (i, j) to the SDP-relaxation:

$$\frac{1}{2}w_{ij}(1 - v_i^t v_j)$$

- ▶ (expected) contribution of edge (i, j) to the rounded instance $w_{ij} \arccos(v_i^t v_j) / \pi$
- ▶ ratio is at most

$$\min_{x \in [-1, 1]} \frac{2 \arccos(x)}{\pi(1-x)} \geq 0.878$$

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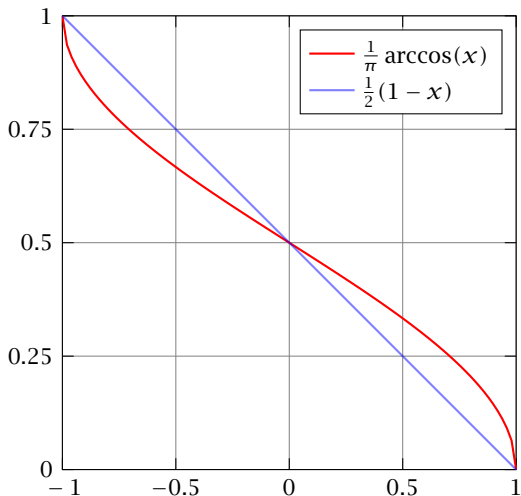
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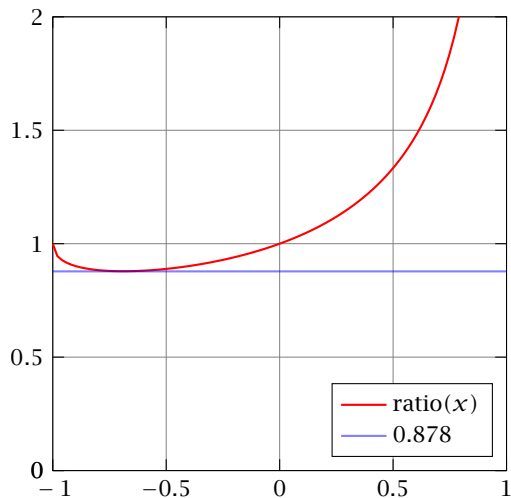
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Rounding the SDP-Solution



Rounding the SDP-Solution



Rounding the SDP-Solution

Theorem 10

Given the unique games conjecture, there is no α -approximation for the maximum cut problem with constant

$$\alpha > \min_{x \in [-1,1]} \frac{2 \arccos(x)}{\pi(1-x)}$$

unless $P = NP$.