

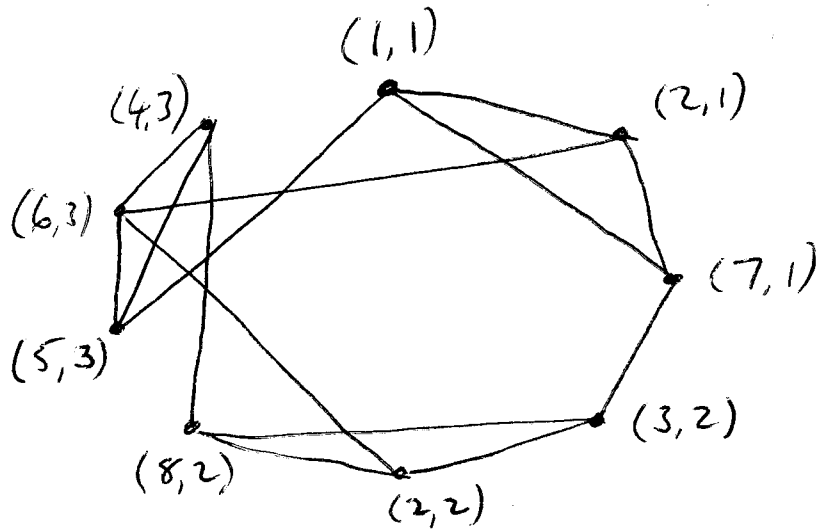
Reducing 3-SAT to UNWEIGHTED NODE PACKING:

$$C_1: x_1 + x_2 + \bar{x}_3$$

$$C_2: x_2 + x_3 + \bar{x}_4$$

$$C_3: \bar{x}_1 + \bar{x}_2 + x_4$$

~~⊗~~



Want a node packing of size ≥ 3 .

$(1,1), (2,1), (7,1)$ correspond to clique C_1 ,

— at most one of these in a packing

$(2,2), (3,2), (8,2)$ correspond to clique C_2 ,

and $(5,3), (6,3), (4,3)$ correspond to clique C_3 .

$(1, i)$ is linked to $(5, j)$:

taking $(1, i)$ corresponds to setting $x_1 = \text{true}$,

so cannot have $(5, j)$ ~~to~~ simultaneously, because

that would correspond to $x_1 = \text{false}$.

Packing $(1,1), (3,2), (6,3)$ shows instance is satisfiable:

$x_1 = \text{true}, x_3 = \text{true}, x_2 = \text{false}, x_4 = \text{anything}$.

Unweighted node packing (also independent set)

Given a graph $G = (V, E)$, is there a $U \subset V$ such that $|U| \geq k$ and U is a node packing? i.e. if v_i, v_j are in U then $(v_i, v_j) \notin E$

Then The lower bound feasibility problem for unweighted node packing is NP-complete

Proof Problem is a special case of 0-1 ~~linear programming~~ so it is in NP.

To show NP-complete:

Reduce SAT to node packing:

Let $C_i = (C_i^+, C_i^-)$ be a clause, so C_i^+ is the literals in C_i which are not negations, C_i^- are those that are negations.

For C_i , we construct a clique with one vertex for each literal in C_i : ~~Label vertices by (j, i)~~

$$\text{Let } V_i^+ = \{(j, i) : j \in C_i^+\}, V_i^- = \{(n+j, i) : j \in C_i^-\}$$

$$V_i = V_i^+ \cup V_i^-$$

Each pair of nodes in V_i is connected by an edge, so any packing includes at most one ~~edge~~ vertex for V_i .

~~In addition~~

Node in packing \iff literal being true.

In addition, ~~constant edges~~ between need to link cliques together, so that a variable can't have different values in

Different cliques.

So ~~do~~ join (j, k) to $(n+j, k)$ for $j=1, \dots, n, k \neq 1$.

Look for a packing of size at least n .

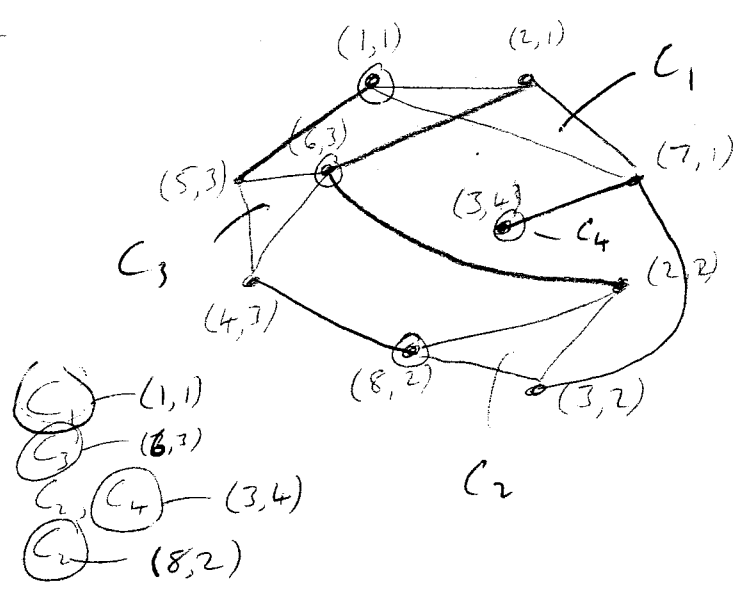
If SAT is true, then there is an assignment such that at least one literal in each clause is true; picking the corresponding vertices gives a node packing.

Given a node packing of size k , have exactly one vertex from each clique; can set corresponding literal to be true.

Eg

i	C_i^+	C_i^-
1	{1, 2}	{3}
2	{2, 3}	{4}
3	{4}	{1, 2}
4	{3}	\emptyset

- $x_1 = \text{true}$
- $x_2 = \text{~~true~~ false}$
- $x_3 = \text{true}$
- $x_4 = \text{~~true~~ false}$



Knapsack feasibility / low bounds problem

Q: Given a, b, c, z integers, does \exists binary x with $c^T x \geq z, a^T x \leq b$?
~~as $a, c \in \mathbb{Z}^n, b, z \in \mathbb{Z}$.~~

Thm The ~~low~~ knapsack feasibility with low bounds problem is NP-complete.

(No proof)

(RS, p. 274)

(NW, p. 137)

Thm $\exists O(ab)$ algorithm for the knapsack problem

(No proof)

(RS, p. 287)

not better than
 general knapsack

So knapsack is somewhat "close" to being polynomial - only reason it's not polynomial is because b requires only $\log b$ storage and $b = 2^{\log b}$.

The $O(ab)$ algo for knapsack is a pseudopolynomial algorithm

Defn An algo runs in pseudopolynomial time if its running time is a polynomial function of the length of the data encoded in binary (or one-symbol alphabet) (or poly in length of data and largest number in problem formulation)

Defn Let $\text{number}(D)$ be the size of the largest number appearing in the formulation of instance D of feasibility problem X . Let X_p denote X restricted to instances D for which $\text{number}(D) \leq p(|D|)$. Here $|D|$ is length of encoding of instance D . **X** is strongly NP-complete if X_p is NP-complete for some polynomial $p(n)$. Eg clique, sat (with ones?).

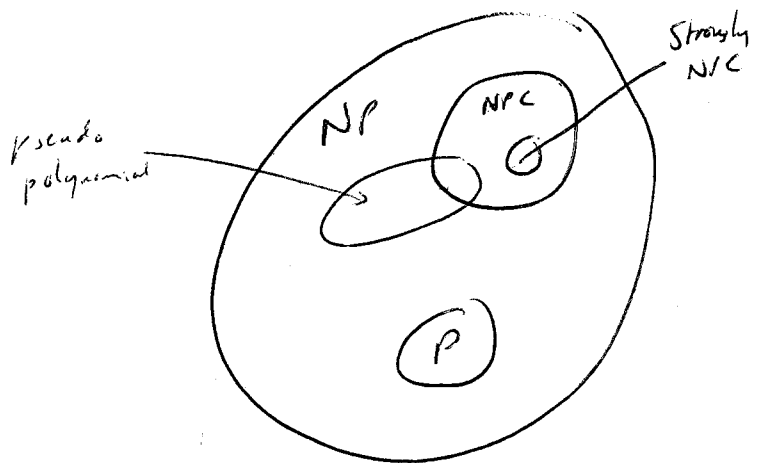
NP, P is defined for feasibility problems.

What about optimization problems?

A problem is called NP-hard if there is an NP-complete problem that can be reduced to it.

So NP-hard problems are at least as difficult as NP-complete problems.

CoNP.



CoNP

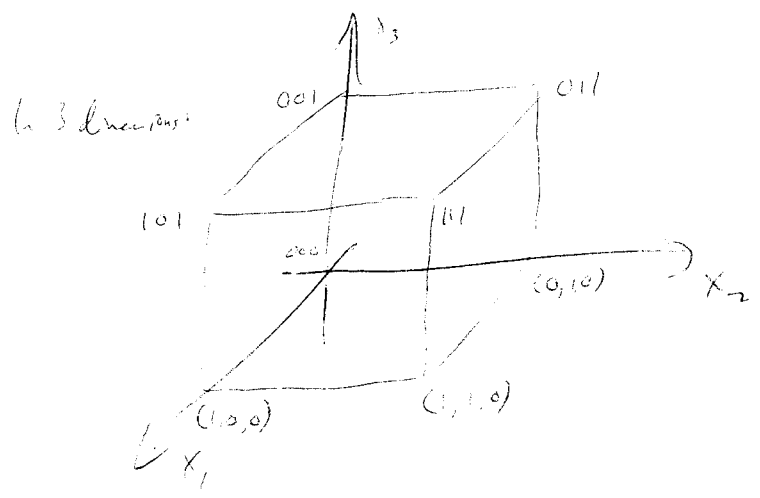
Exam - NP diff?

How good is the simplex algorithm?

Worst case behaviour is exponential (for all known pivot rules)

Klee-Minty cube example:

Consider d dimensional unit cube:



Described by

$$0 \leq x_1 \leq 1$$

$$0 \leq x_2 \leq 1$$
~~$$0 \leq x_3 \leq 1$$~~

$$0 \leq x_d \leq 1$$

$2d$ inequalities, d variables, 2^d extreme points.

So number of vertices is exponential in number of constraints and variables

Consider perturbed cube slightly: $(0 < \epsilon < 1)$

~~$$0 \leq x_1 \leq 1$$~~

$$2x_{j-1} \leq x_j \leq 1 - \epsilon x_{j-1} \quad j=2,3,\dots,d$$

For $\epsilon=0$, this is the original cube.

In three dimensions, extreme points are

- $(0, 0, 0)$
- $(1, \epsilon, \epsilon^2)$
- $(1, 1-\epsilon, \epsilon(1-\epsilon))$
- $(0, 1, \epsilon)$
- $(0, 1, 1-\epsilon)$
- $(1, 1-\epsilon, 1-\epsilon(1-\epsilon))$
- $(1, \epsilon, 1-\epsilon^2)$
- $(0, 0, 1)$

} Each point is adjacent to
 to ^{ones} ~~two~~ on either side
 of it.

~~These are adjacent +~~
 Obj. fun. $\max x^d$

The the objective function increases as we move down the list (0 < epsilon < 1)

So could visit all vertices while always improving objective function value

To make Dantzig's rule ^(close one with max value of 10 2.482) ~~can~~ every vertex to be visited,
 need slightly more severe permutation of cube;
 see Schrijver for details.

Expected behaviour: $O(n)$ for n smaller of # rows, # columns
 Borgwardt, Karmarkar.

How good is the simplex algorithm?

Can visit every bfs on the way to the optimal soln —
Klee-Minty, 1972.

$$\min -\sum_{j=1}^n 10^{n-j} x_j$$

$$\text{s.t. } \left(2 \sum_{j=1}^{i-1} 10^{i-j} x_j \right) + x_i \leq 100^{i-1} \quad i=1, \dots, n$$

$$x_j \geq 0$$

Simplex method takes $2^n - 1$ iterations.

See example for $n=3$.

This example is for the largest reduced cost entering rule.

But, for all proposed rules, similar examples have been constructed.

In practice: for $\min c^T x$ $Ax = b$ $x \geq 0$ $A \ m \times n$,

$$\# \text{ itns} \approx \frac{3m}{2}$$

Expected behaviour: (Bergwaldt 1982) (Hammond 1983)

$$\text{Expected } \# \text{ itns} \approx \min \left\{ \frac{1}{2}n, m \right\}$$

Klee-Minty cube for $n=3$

0. min $-100x_1 - 10x_2 - x_3$

s.t. $\begin{matrix} \textcircled{x_1} & & & +x_4 & & & = 1 \\ 20x_1 & +x_2 & & & +x_5 & & = 100 \\ 200x_1 & +20x_2 & +x_3 & & & +x_6 & = 10000 \\ x_i \geq 0 \end{matrix}$

1. x_1 enters, x_4 leaves:

min $-10x_2 - x_3 + 100x_4$ -100

s.t. $\begin{matrix} x_1 & & & +x_4 & & & = 1 \\ \textcircled{x_2} & & & -20x_4 & +x_5 & & = 80 \\ 20x_2 & +x_3 & & -200x_4 & & +x_6 & = 9800 \\ x_i \geq 0 \end{matrix}$

2. x_2 enters, x_5 leaves:

min $-x_3$ -900

s.t. $\begin{matrix} x_1 & & & \textcircled{+x_4} & & & = 1 \\ & x_2 & & -20x_4 & +x_5 & & = 80 \\ & & x_3 & +200x_4 & -20x_5 & +x_6 & = 8200 \\ x_i \geq 0 \end{matrix}$

3. x_4 enters, x_1 leaves:

min $100x_1$ -1000

s.t. $\begin{matrix} x_1 & & & +x_4 & & & = 1 \\ 20x_1 & +x_2 & & & +x_5 & & = 100 \\ -200x_1 & & \textcircled{+x_3} & & -20x_5 & +x_6 & = 8000 \\ x_i \geq 0 \end{matrix}$

4. x_3 enters, x_6 leaves:

$$\begin{array}{rcll}
 \text{min} & -100x_1 & & -9000 \\
 \text{s.t.} & \textcircled{x_1} & & \\
 & 20x_1 + x_2 & +x_4 & = 1 \\
 & -200x_1 & +x_3 & = 100 \\
 & & & -20x_5 + x_6 = 8000 \\
 & & & x_i \geq 0
 \end{array}$$

5. x_1 enters, x_4 leaves:

$$\begin{array}{rcll}
 \text{min} & & 100x_4 - 10x_5 + x_6 & -9100 \\
 \text{s.t.} & x_1 & & = 1 \\
 & & +x_4 & = 80 \\
 & x_2 & -20x_4 & \textcircled{+x_5} \\
 & & +200x_4 & -20x_5 + x_6 = 8200 \\
 & & & x_i \geq 0
 \end{array}$$

6. x_5 enters, x_2 leaves:

$$\begin{array}{rcll}
 \text{min} & & 10x_2 & -100x_4 & +x_6 & -9900 \\
 \text{s.t.} & x_1 & & +x_4 & & = 1 \\
 & & x_2 & -20x_4 & +x_5 & = 80 \\
 & & 20x_2 + x_3 & -200x_4 & +x_6 & = 9800 \\
 & & & & & x_i \geq 0
 \end{array}$$

7. x_4 enters, x_1 leaves:

$$\begin{array}{rcll}
 \text{min} & 100x_1 + 10x_2 & & +x_6 & -10000 \\
 \text{s.t.} & x_1 & & +x_4 & = 1 \\
 & 20x_1 + x_2 & & +x_5 & = 100 \\
 & 200x_1 + 20x_2 + x_3 & & +x_6 & = 10000 \\
 & & & & x_i \geq 0
 \end{array}$$

Optimal.

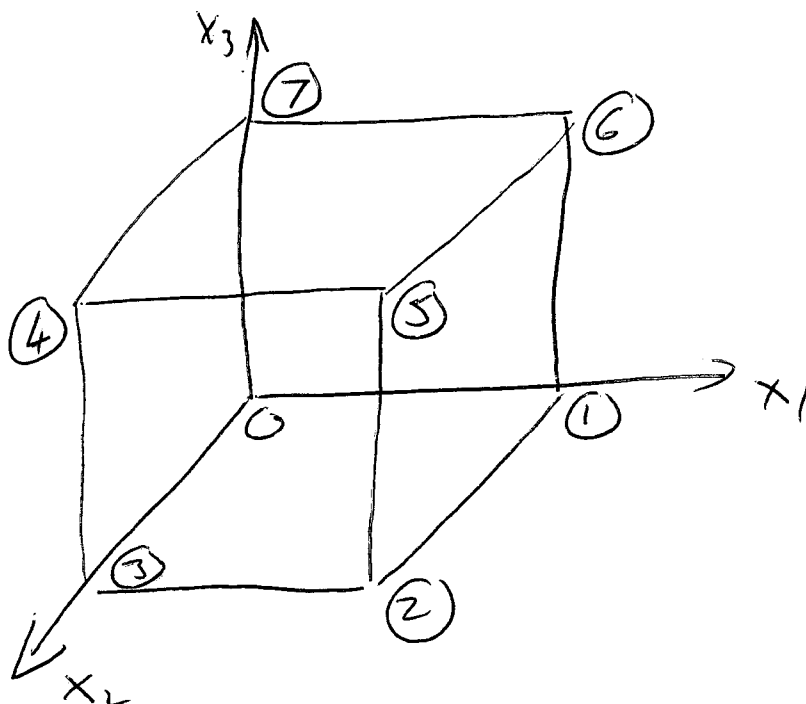
Notice: if x_3 had entered at Step 1 instead of x_1 , then we would have solved the problem in one step.

The constraints are approximately the cube

$$\begin{aligned} 0 \leq x_1 &\leq 1 \\ 0 \leq x_2 &\leq 100 \\ 0 \leq x_3 &\leq 10000. \end{aligned}$$

We start at the origin, then (approximately) visit the vertices

- ① $(1, 0, 0)$
- ② $(1, 100, 0)$
- ③ $(0, 100, 0)$
- ④ $(0, 100, 10000)$
- ⑤ $(1, 100, 10000)$
- ⑥ $(1, 0, 10000)$
- ⑦ $(0, 0, 10000)$ - optimal.



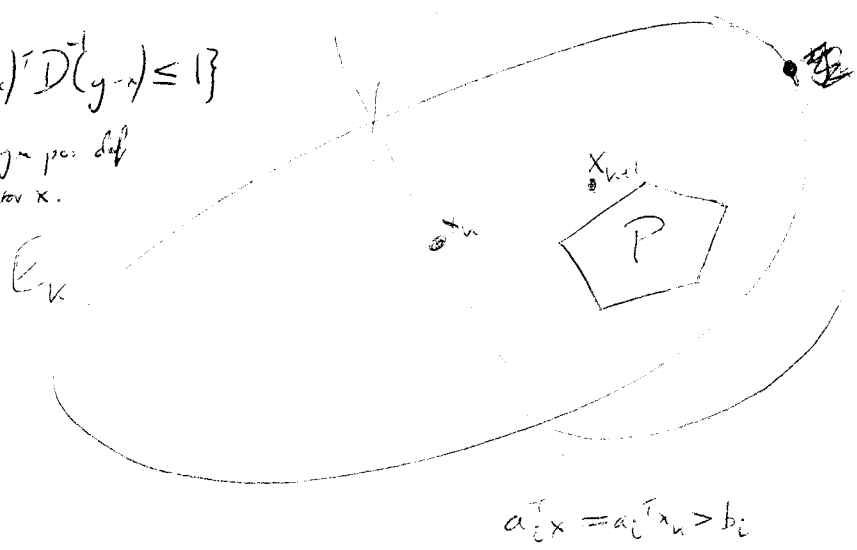
Ellipsoid algorithm (Brief outline) (See NW p. 147; PS p. 170)

Consider LP feasibility problem $Ax \leq b$? A is $n \times n$.
 Does $\exists x$ satisfying $Ax \leq b$?
 Denote i th row of A by a_i (column vector). Let $P = \{x : Ax \leq b\}$
 Assume P bounded.

Brief idea of algo:

$$E = \{y : (y-x)^T D (y-x) \leq 1\}$$

for some pos sym pos def matrix D , vector x .



Have ellipsoid E_k containing feasible region, if it is nonempty. Check corner of ellipsoid. If it is feasible, done. Otherwise, it violates some constraint $a_i^T x < b_i$

Can the cut off half of ellipsoid and ~~replace~~ construct a new ellipsoid E_{k+1} which contains important half of current ellipsoid.

How does size of E_{k+1} relate to size of E_k ?

Thm Consider ellipsoid E , center x , ~~regularity~~

Let $H = E \cap \{y : d^T y \leq d^T x\}$ - half ellipsoid.

Then H is contained in an ellipsoid E' with the property

$$\frac{\text{vol}(E')}{\text{vol}(E)} \leq e^{-\frac{1}{2n}}$$

(No proof)

So shrink ellipsoid at each iteration.

~~Eventually, ellipsoid center of ell,~~ a sphere of radius R , volume V

Initial ellipsoid is drawn large enough so that it ~~is bounded~~ contains P feasible solution ~~to~~ $Ax \leq b$, if one exists.

Also, if \exists soln to $Ax \leq b$, there is a sphere of positive radius r contained in the feasible region. This sphere has volume v .

So, ~~since~~ ~~all~~ since ellipsoid contains P shall contain a sphere of radius r if LP is feasible, will find solution before vol of ellipsoid decrease below vol of sphere of radius r .

Note that if the volume of our ellipsoid is less than v , and we still have not found a feasible point, then the LP is infeasible.

Since: ~~$v \leq \text{vol}(P)$, $P \subseteq \text{ellipsoid} \Rightarrow \text{vol}$~~

$$v > \text{vol}(\text{ellipsoid}) \geq \text{vol}(P) \quad \text{since } P \subseteq \text{ellipsoid}$$

$$\geq v \quad \text{provided } P \neq \emptyset.$$

✘

So we have a termination criterion.

Let ~~ϵ^*~~ $\epsilon^* = \sqrt{2(n+1)} (\log(V) - \log(v))$

Then what is volume of ϵ^* ellipsoid?

$$\begin{aligned}
 \text{vol}(E_{k^*}) &\leq e^{-\frac{1}{2k^*}} \text{vol}(E_{k^*-1}) \\
 &\leq \left[e^{-\frac{1}{2k^*}} \right]^{k^*} \text{vol}(E_0) \\
 &= e^{-\frac{k^*}{2k^*}} \text{vol}(E_0) \\
 &\leq e^{-(\log(V) - \log(v))} V \\
 &= e^{-\log\left(\frac{V}{v}\right)} V = \frac{v}{V} \cdot V = v
 \end{aligned}$$

So need at most k^* iterations.

See Prop 2.12,
p. 158, N&W.

$\log(V)$ and $\log(v)$ can both be taken polynomial in length of data.)

So algo takes a polynomial number of iterations.

Work at each iteration:

Need to calculate new ellipsoid.

Requires calculating square roots. So can not calculate everything exactly.

So some subtle analysis is required to show that algo ~~can~~ can be implemented to only require a polynomial amount of work each iteration.

Extend to optimization.

(Joe)

POLYNOMIAL EQUIVALENCE OF
SEPARATION & OPTIMIZATION.
Requires definition of the separation problem

Given convex set C , a point x ,
is $x \in C$? If not, provide separating
hyperplane.

(The ... method - MPL0 (1988) 59-93.)