

# Algorithms - Spring '25

LPs - Duality



## Recap:

- Make sure to sign up for HW8 grading slot!
- Practice final is posted
- CIFS are live, & feedback is appreciated
- Block off time 2 days before final — keep an eye of web page & slack

A moment of honesty to start  
lecture.



To deal with a 14-dimensional space,  
visualize a 3-D space and say  
'fourteen' to yourself very loudly.  
Everyone does it.

— Geoffrey Hinton —

AZ QUOTES

# Linear optimization: Example

$n$  foods,  $m$  nutrients

Let  $a_{ij}$  = amount of nutrient  $i$  in food  $j$   
 $r_i$  = requirement of nutrient  $i$   
 $x_j$  = amount of food  $j$  purchased  
 $c_j$  = cost of food  $j$

Goal: Buy food so you satisfy nutrients  
while minimizing cost

Can view as matrix  $\rightsquigarrow$



$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ a_{ij} & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$i$   $j$

$m$   $n$

$$\vec{r} = (r_1, r_2, \dots, r_m)$$

$$\vec{x} = (x_1, \dots, x_n)$$

$$\vec{c} = (c_1, \dots, c_n)$$

So: minimize

s.t.

$$\sum_{i=1}^n c_i x_i = \vec{c} \cdot \vec{x}^T$$

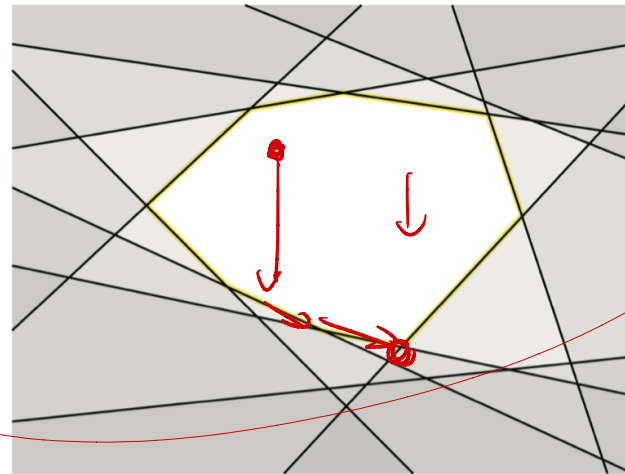
$\begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}$ 
 $\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$

$$A\vec{x} \leq \vec{r}$$

In general, get systems like this:

$$\begin{aligned} & \text{maximize } \sum_{j=1}^d c_j x_j \\ & \text{subject to } \sum_{j=1}^d a_{ij} x_j \leq b_i \quad \text{for each } i = 1 \dots p \\ & \sum_{j=1}^d a_{ij} x_j = b_i \quad \text{for each } i = p+1 \dots p+q \\ & \sum_{j=1}^d a_{ij} x_j \geq b_i \quad \text{for each } i = p+q+1 \dots n \end{aligned}$$

Geometric picture:



A two-dimensional polyhedron (white) defined by 10 linear inequalities.

# History

Dates back to 1800's where studied by Fourier.

By 1940's: serious study, due to business/optimization demand

- Not known to be NP-Hard ↪ 60's  
(Karp actually listed it as key open question in original paper on NP-Hardness)

Canonical form:

Avoid having both  $\leq$  and  $\geq$ .

Why?

So get something more like our first example:

$$\begin{aligned} &\text{maximize } \sum_{j=1}^d c_j x_j \\ &\text{subject to } \sum_{j=1}^d a_{ij} x_j \leq b_i \quad \text{for each } i = 1 \dots n \\ &\quad \quad \quad x_j \geq 0 \quad \text{for each } j = 1 \dots d \end{aligned}$$

Or, given a vector  $\vec{c}$ , matrix  $A$  & vector  $\vec{b}$ :

$$\begin{aligned} &\text{max } \vec{c} \vec{x} \\ &\text{s.t. } A \vec{x} \leq \vec{b} \end{aligned}$$

Anything can be put into  
canonical form

The reduction:

① Avoid =:

$$\sum a_i x_i \geq b$$

2 eqn  $\hookrightarrow$

$$\sum a_i x_i \leq b \text{ and } \sum a_i x_i \geq b$$

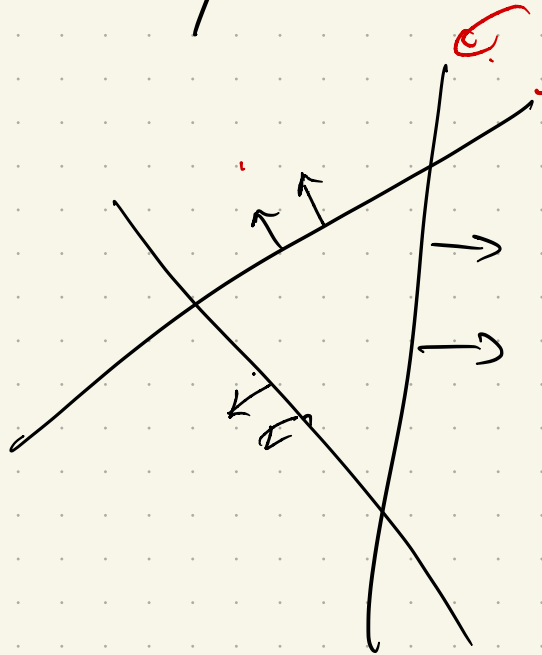
② Avoid  $\neq$ :

$$(-1) \cdot \left[ \sum a_i x_i \geq b \right]$$

$$\sum -a_i x_i \leq -b$$

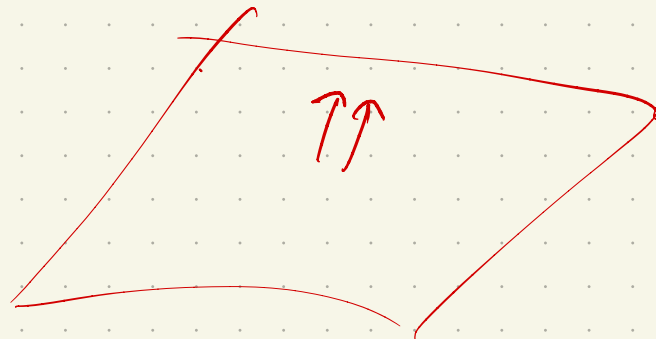
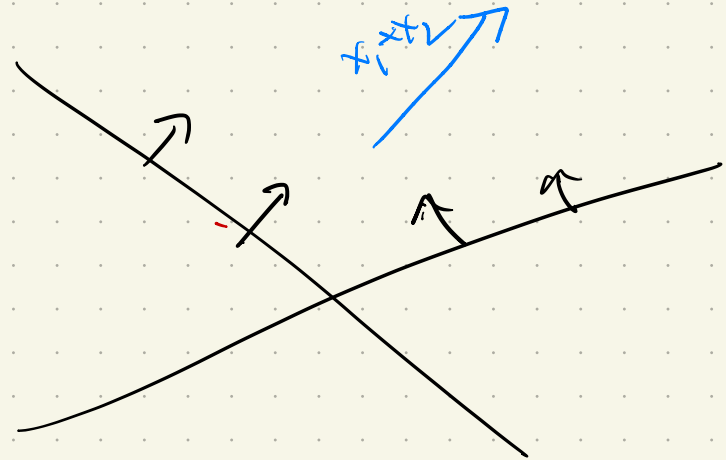
How could these not have a solution?

2 ways: 2d



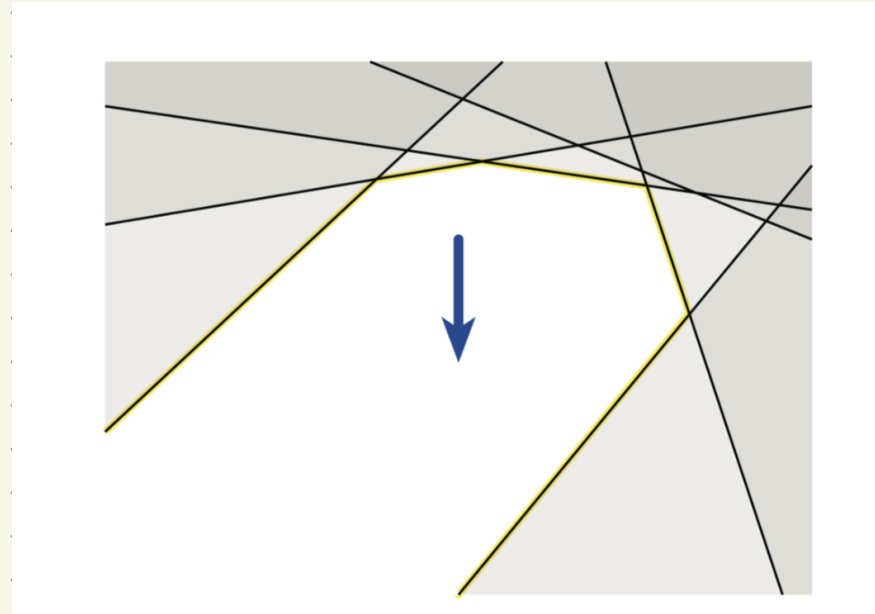
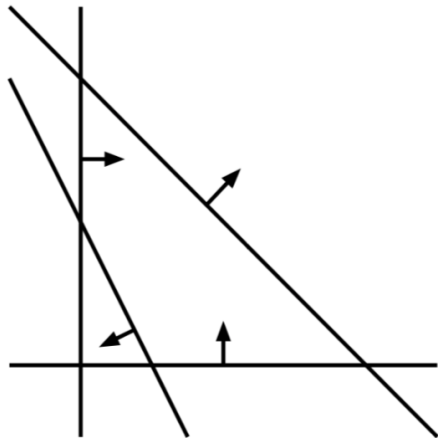
or

maximize  $x_1 + x_2$   
s.t.



Better pictures (still 2d):

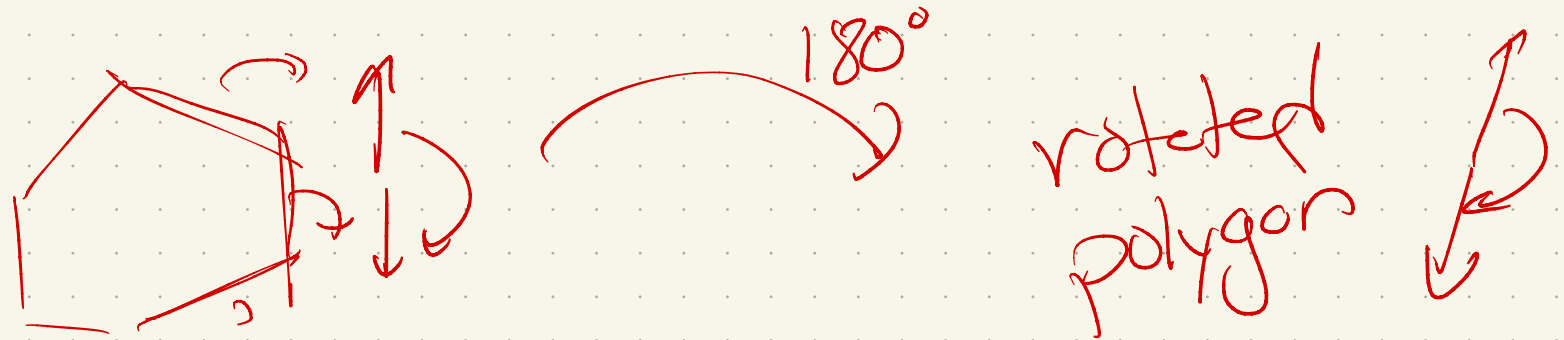
maximize  $x - y$   
subject to  $2x + y \leq 1$   
 $x + y \geq 2$   
 $x, y \geq 0$



Note:

- ① Multiplying by  $-1$  turns any maximization problem into a minimization one:

why?



- ② Can turn inequalities into equalities via slack variables:

$$\sum_{i=0}^n a_i x_i \leq b \Rightarrow$$

$$\sum_{i=0}^n a_i x_i + s = b$$

adds one  
dim (new  
variable)



(3) Can change equalities into inequalities, also!

$$\sum_{i=1}^n a_i x_i = b$$

$\Downarrow$

# Modeling Problems: Flows & Cuts

Input: directed  $G$  w/ edge capacities  $c(e)$   
&  $s, t \in V$

Goal: Compute flow  $f: E \rightarrow \mathbb{R}$  s.t.

①  $0 \leq f(e) \leq c(e)$  ✓

edge constraints

②  $\forall v \neq s, t,$

$$\sum_u f(u \rightarrow v) = \sum_w f(v \rightarrow w)$$

vertex constraints  
x\_i's flow on edge i

Make an LP: Maximize

s.t. ①  $x_i \geq 0$   
 $x_i \leq c(e_i)$

② Flow in = flow out at each vertex

$$\sum_{v \in V} f(s \rightarrow v)$$

Create  $x_i$  for each edge  $e_i = (u, v)$

② for each vertex  $v$

$$\sum_{(u,v)=e_i} x_i - \sum_{(v,w)=e_j} x_j = 0$$

Conversion:  $V$  vertices,  $E$  edges

↳  $E$  variables (or dimensions)

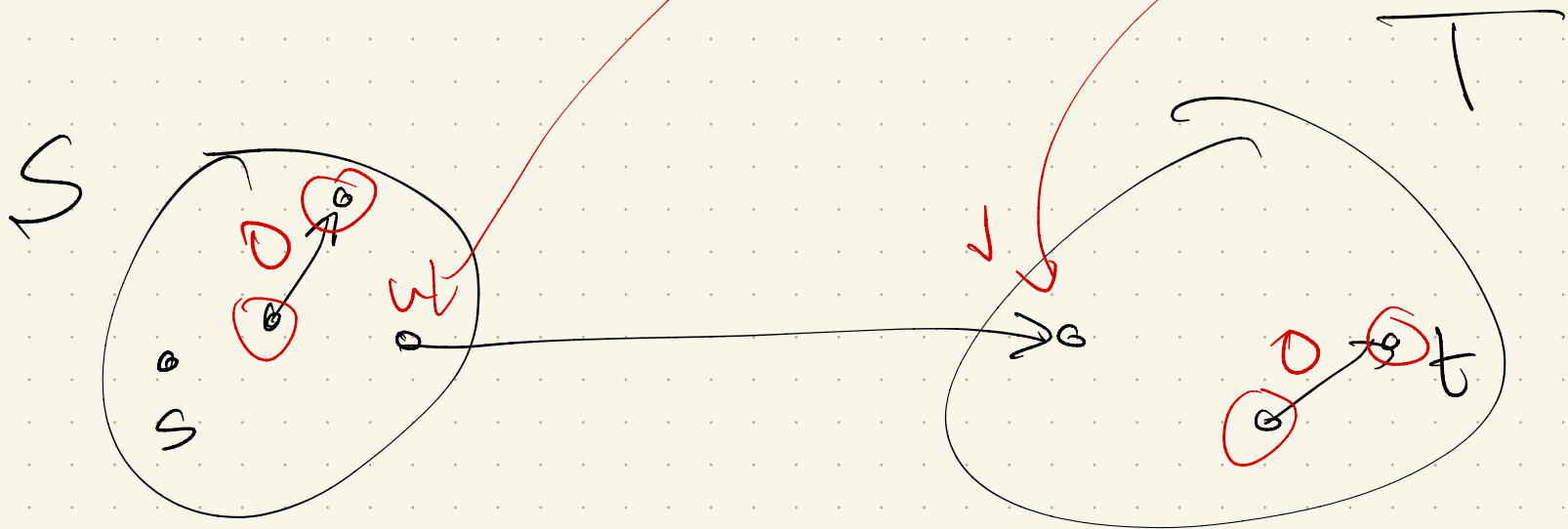
2 eqns per edge  
1 eqn per vertex }  $O(V+E)$

Related: Min cuts (S,T)

Use indicator variables: (ILP)

$S_v = 0$  or  $1$   $\leftarrow$  on  $s$  side or  $t$  side

goal:  $X_e = X_{(u \rightarrow v)} = 1$  if  $u \in S$  and  $v \in T$



The LP:

Minimize  $\sum_{u \rightarrow v} C_{u \rightarrow v} \cdot X_{u \rightarrow v}$

*if in cut*  
 $\nwarrow$  want few edges

s.t.

$X_{u \rightarrow v} + S_v - S_u \geq 0 \quad \forall u \rightarrow v$   
*can be 0*  
*if on same side*

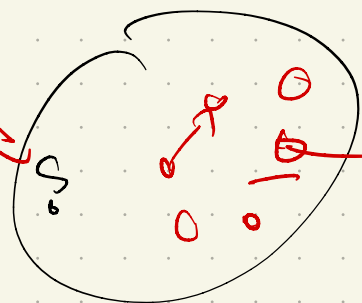
$X_{u \rightarrow v} \geq 0 \quad \forall u, v$

Which are forced?

$S_s = 1$

$S_t = 0$

*negative if cut edge*



Cuts: input - graph  $G$

$V + E$  variables

$2E$  equations  
+ 2

Note:

For flow/cuts, a solution would yield optimal LP solution.

The reverse is not obvious!

LP might have strange fractional answer which doesn't describe a cut.

It can be shown that this won't happen

↳ but not obvious...

# Duality:

Recall our chocolate:

$$\text{LP: } \max x_1 + 6x_2$$

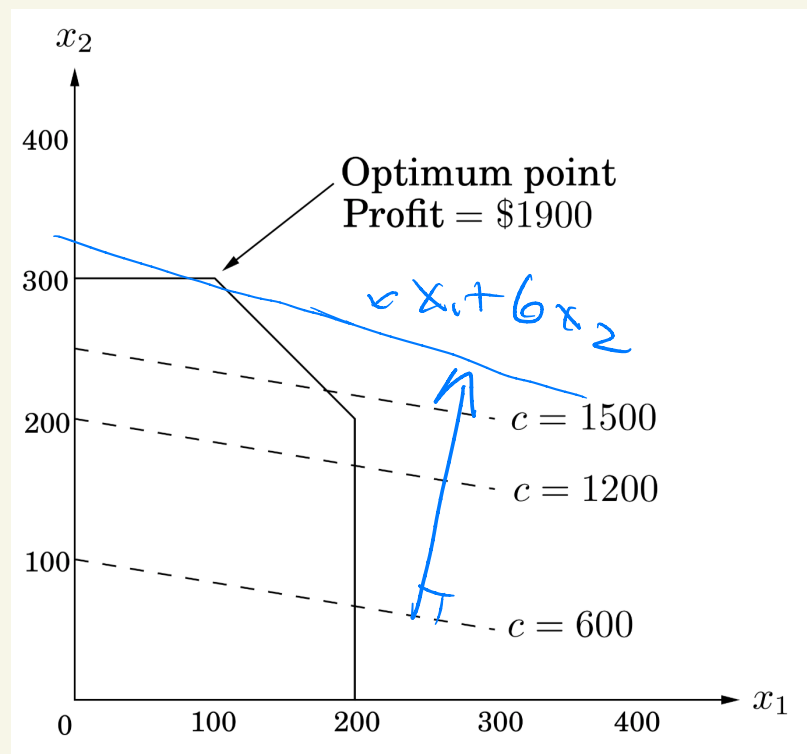
s.t.

$$x_1 \leq 200$$

$$x_2 \leq 300$$

$$x_1 + x_2 \leq 400$$

$$x_1, x_2 \geq 0$$





Can we check that this is best?

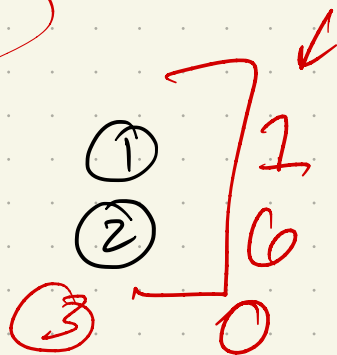
s.t. max  $x_1 + 6x_2$

$\rightarrow x_1 \leq 200$

$\rightarrow x_2 \leq 300$

$x_1 + x_2 \leq 400$

$x_1, x_2 \geq 0$



Play w/ inequalities:

① +  $6 \cdot$  ② :

$x_1 + 6x_2 \leq 200 + 6 \cdot 300$

$x_1 \leq 200$   
 $6x_2 \leq 1800$

$\downarrow$   
 $2000$

Interesting!

These 2 inequalities tell us that we couldn't ever beat \$2000.

But recall soln was \$1900—

Can we get a better combo?

$$\max x_1 + 6x_2$$

s.t.

$$x_1 \leq 200$$

$$x_2 \leq 300$$

$$x_1 + x_2 \leq 400$$

$$x_1, x_2 \geq 0$$

$$\textcircled{1} \times 0$$

$$\textcircled{2} \times 5$$

$$\textcircled{3} \times 1$$

$$\text{Play: } 0 \cdot \textcircled{1} + 5 \cdot \textcircled{2} + 1 \cdot \textcircled{3}$$

$$5x_2 \leq 1500$$

$$x_1 + x_2 \leq 400$$

$$\text{add} \Rightarrow x_1 + 6x_2 \leq 1900$$

These multipliers,  $(0, 5, 1)$ , are a certificate  
of optimality.  
↳ No valid solution can ever beat \$1900

But

How do we find these magic values??

In this, we had three " $\leq$ " inequalities

↳ so goal is to find the right 3  
multipliers:  $y_1$ ,  $y_2$ , and  $y_3$

Let's try to rewrite...

Multiplier

Inequality

$$\begin{array}{lcl} y_1 & \times & (x_1 \leq 200) \\ \rightarrow y_2 & \times & (x_2 \leq 300) \\ y_3 & \times & (x_1 + x_2 \leq 400) \end{array}$$

Result

$$\underline{y_1 x_1 + y_2 x_2 + y_3 (x_1 + x_2)} \leq 200y_1 + 300y_2 + 400y_3$$
$$\hookrightarrow (y_1 + y_3)x_1 + (y_2 + y_3)x_2 \leq 200y_1 + 300y_2 + 400y_3$$

Rewrite: Make left side look like the original max/min goal, so right will be an upper bound

So here:

$$(y_1 + y_3)x_1 + (y_2 + y_3)x_2 \leq 200y_1 + 300y_2 + 400y_3$$

Means:

$$1x_1 + 6x_2 \leq 200y_1 + 300y_2 + 400y_3$$

if :  $\begin{cases} y_1, y_2, y_3 \geq 0 \end{cases}$  b/c if negative, inequalities flip!

$$\begin{cases} y_1 + y_3 \geq 1 \\ y_2 + y_3 \geq 6 \end{cases} \text{ b/c original eqn.}$$

Any  $y_i$ 's would give an upper bound!

We want the best one

↳ ie minimize another LP!

# Duality:

$$\begin{array}{ll} \text{s.t. max} & x_1 + 6x_2 \\ & x_1 \leq 200 \\ & x_2 \leq 300 \\ & x_1 + x_2 \leq 400 \\ & x_1, x_2 \geq 0 \end{array} \quad \text{dual} \quad \Longleftrightarrow \quad \begin{array}{ll} \text{min} & 200y_1 + 300y_2 + 400y_3 \\ \text{s.t.} & y_1 + y_3 \geq 1 \\ & y_2 + y_3 \geq 6 \\ & y_1, y_2, y_3 \geq 0 \end{array}$$

*Red arrows indicate the mapping of constraints to dual variables:  $y_1$  to  $x_1 \leq 200$ ,  $y_2$  to  $x_2 \leq 300$ , and  $y_3$  to  $x_1 + x_2 \leq 400$ .*

Any solution to bottom is upper bound to top LP.

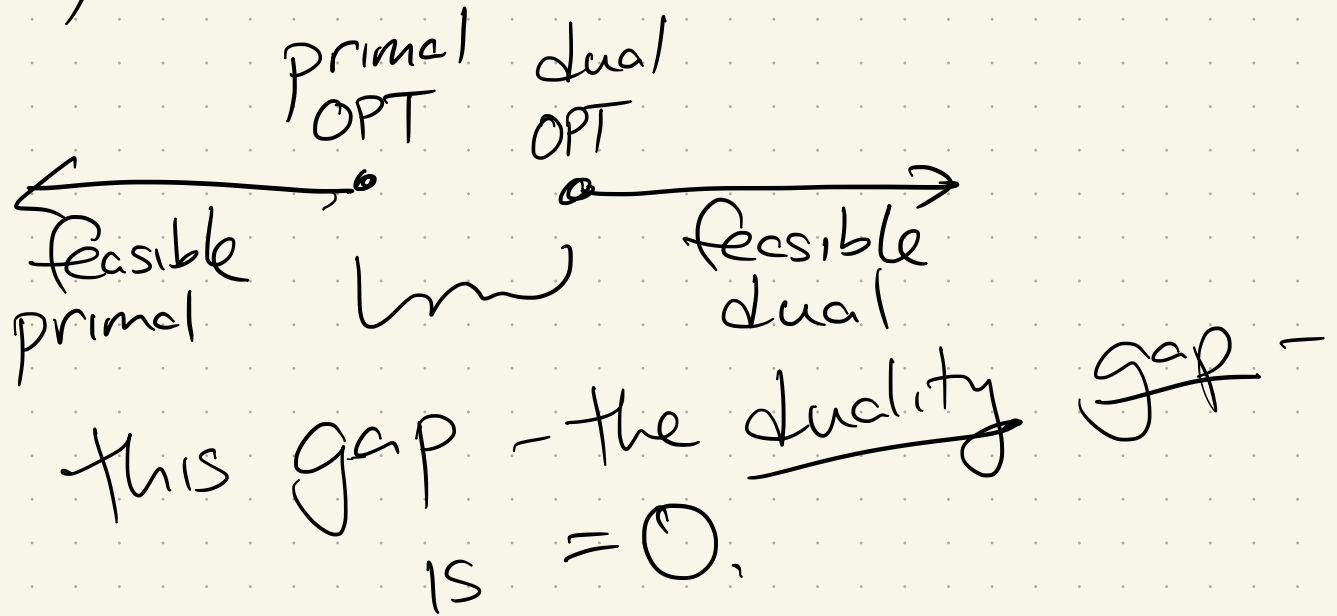
$\Rightarrow$  If we can find primal/duals that are equal, both are OPT

Here, 1900: primal  $(x_1, x_2) = (100, 300)$

Dual:  $(y_1, y_2, y_3) = (0, 5, 1)$

This is just like max flow / min cut duality, in a way.

Works for any LP:



For ILP  $\rightarrow$  can be  $> 0$ .

In general:

Primal LP

$$\begin{aligned} \max \quad & C^T x \\ \text{s.t.} \end{aligned}$$

$$A \vec{x} \leq \vec{b}$$

$$\vec{x} \geq 0$$

$\vec{c}, \vec{x}, \vec{b}$  vectors

Dual LP

$$\begin{aligned} \min \quad & y^T b \\ \text{s.t.} \end{aligned}$$

$$y^T A \geq c^T$$

$$y \geq 0$$

$\vec{c}, \vec{b}, \vec{y}$ , vectors

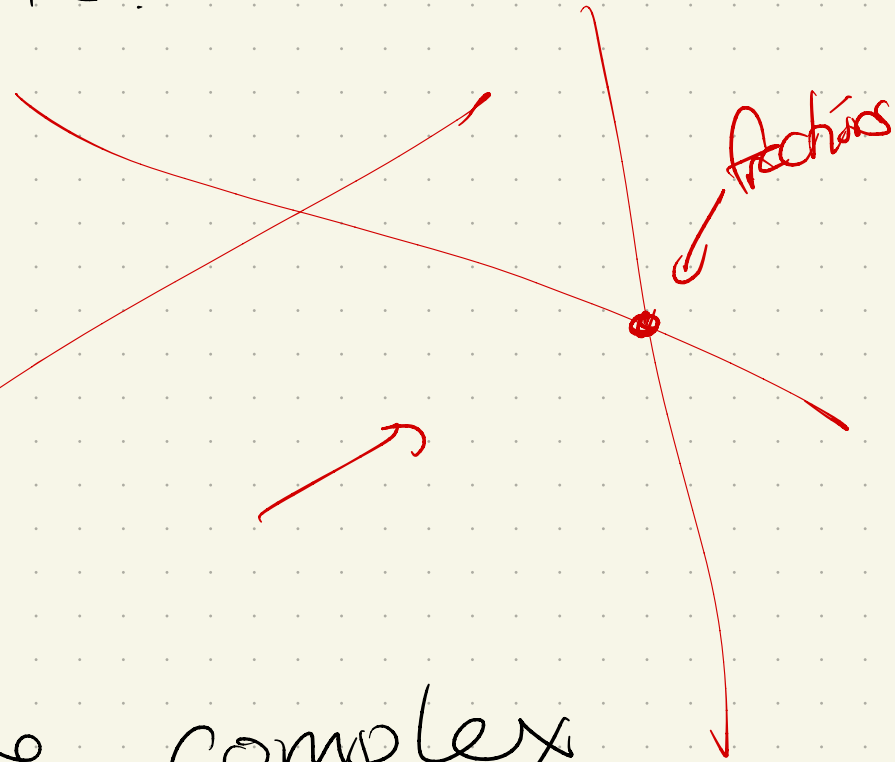


# Limits of LP:

Many things are not LPs!

Ex: Integer solutions

if eqns  
not on grid  
points:



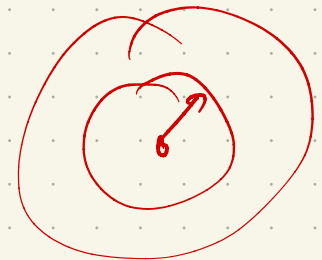
Ex: Quadratic or more complex constraints

distance func

$x_1, y_1$        $x_2, y_2$

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

not linear



Often other approaches could give a better runtime!

Ex: Flows & cuts!

Or  $\ln: O(VE)$  via a combinatorial approach

LP:

$E$  variables,

$V+E$  equations

$\Rightarrow$

• LP w/ simplex alg. is exponential

• with "better" algorithm (matrix multiply time (so  $\sim E^3$ ))

# The algorithm: Simplex (Dantzig 1947)

Assumes canonical form:

$$\text{maximize } \sum_{j=1}^d c_j x_j$$

$$\text{subject to } \sum_{j=1}^d a_{ij} x_j \leq b_i \quad \text{for each } i = 1 \dots n$$

$$x_j \geq 0 \quad \text{for each } j = 1 \dots d$$

So.

- no min

- only  $\leq$

-  $x \geq 0$  for all variables

- fast in practice, but exponential in worst case

Klee-Minty, 1973: some feasible polytopes have  $O(n^{d/2})$  vertices

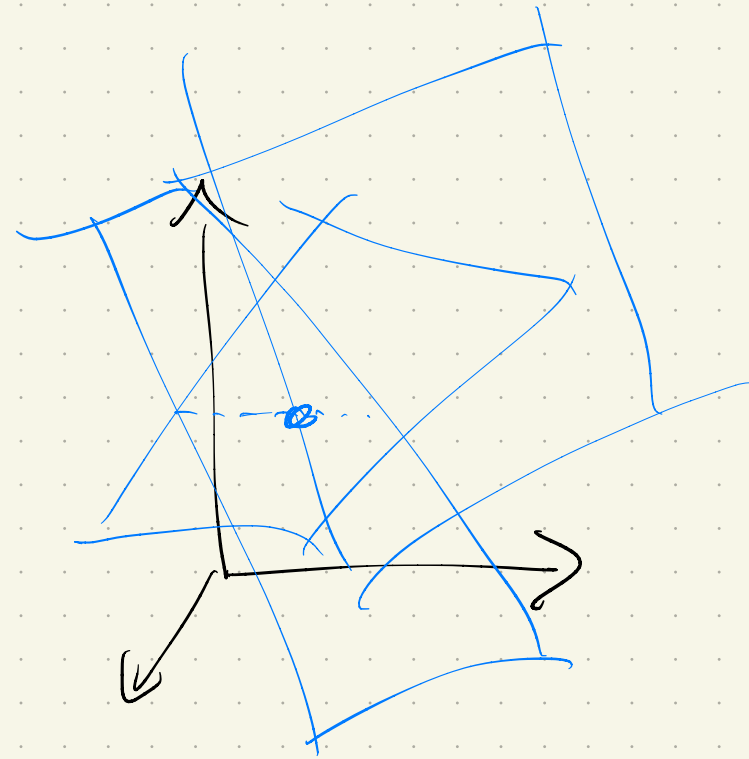
# Algorithm (Simplex):

Take any vertex  $v$  in feasible region  
while some neighbor  $v'$  is better

$$v \leftarrow v'$$

Details lacking!

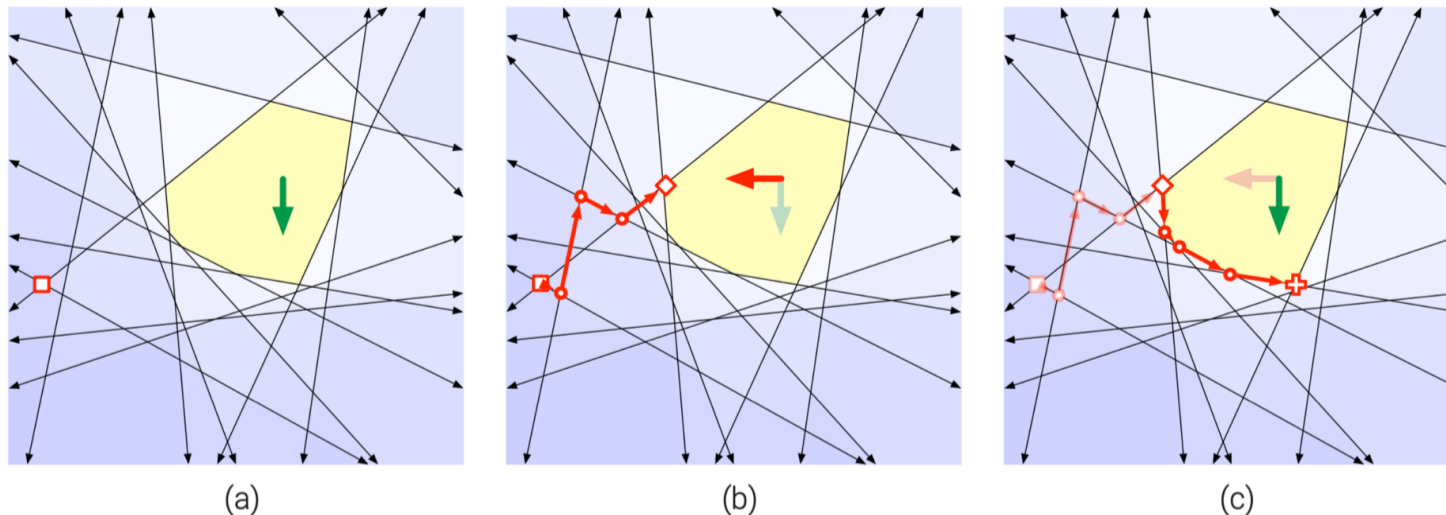
Step 1: find a vertex  
take  $d$   
hyperplanes:



Any  $d$  hyperplanes give a vertex:  
Loop through  $m-d$  others!

Either feasible for each  
Or Not

↳ use this new hyperplane



**Figure 1.2.** Primal simplex with dual initialization: (a) Choose any basis. (b) Rotate the objective to make the basis locally optimal, and pivot "up" to a feasible basis. (c) Pivot down to the optimum basis for the original objective.

How to pick where to move?

No ideal way!

Many proposed, but for almost every one, there is some input polygon that needs an exponential number of pivots.

## Ellipsoid algorithm, Khachiyan 1979

- (weakly) polynomial time
  - ↳ dependent of precision
- high level idea: compute smaller & smaller ellipses which contain solution

## Interior point Methods, Karmarkar 1984

- Move through polytope's interior:
- Still weakly polynomial
  - but - practical

