Lecture 22: Linear Programming

Jessica Sorrell

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601.433/633 Introduction to Algorithms

Slides by Michael Dinitz

Introduction

Today: What, why, and juste a taste of how

- Entire course on linear programming over in AMS. Super important topic!
- Fast algorithms in theory and in practice.

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- Entire course on linear programming over in AMS. Super important topic!
- Fast algorithms in theory and in practice.

Why: Even more general than max-flow, can still be solved in polynomial time!

- Max flow important in its own right, but also because it can be used to solve many other things (max bipartite matching)
- Linear programming: important in its own right, but also even more general than max-flow.
- Can model many, many problems!

Example: Planning Your Week

168 hours in a week. How much time to spend:

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- Partying ($\boldsymbol{P}$)
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Constraints:

- $E \geq 56$ (at least 8 hours/day sleep, shower, etc.)
- $P + E \geq 70$ (need to stay sane)
- $S \geq 60$ (to pass your classes)
- $2S + E - 3P \geq 150$ (too much partying requires studying or sleep)

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Question: Suppose "happiness" is $\boldsymbol{2P + 3E}$. Can we find a feasible solution maximizing this?

Linear Programming

Input (a "linear program"):

- n variables $x_1, \ldots, x_n$ (take values in $\mathbb{R}$)
- m *non-strict linear inequalities* in these variables (constraints)
  - E.g.: $3x_1 + 4x_2 \leq 6$, $\quad 0 \leq x_1 \leq 3 \quad x_2 - 3x_3 + 2x_7 = 17$
  - Not allowed (examples): $x_2 x_3 \geq 5$, $\quad x_4 < 2$, $\quad x_5 + \log x_2 \geq 4$
- Possibly a *linear* objective function
  - $\max 2x_3 - 4x_5$, $\quad \min \frac{5}{2} x_4 + x_2$, $\quad \ldots$

Goals:

- Feasibility: Find values for x's that satisfy all constraints
- Optimization: Find feasible solutions maximizing/minimizing objective function

Both achievable in polynomial time, reasonably fast!

Planning your week as an LP

Variables: $\boldsymbol{P}, \boldsymbol{E}, \boldsymbol{S}$

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$$\mathbf{max} \quad \boldsymbol{2P + E}$$

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$$\begin{aligned} \textbf{max} \quad & \mathbf{2}\boldsymbol{P} + \boldsymbol{E} \\ \text{subject to} \quad & \boldsymbol{E} \geq \mathbf{56} \\ & \boldsymbol{S} \geq \mathbf{60} \\ & \mathbf{2}\boldsymbol{S} + \boldsymbol{E} - \mathbf{3}\boldsymbol{P} \geq \mathbf{150} \\ & \boldsymbol{P} + \boldsymbol{E} \geq \mathbf{70} \end{aligned}$$

Planning your week as an LP

Variables: P, E, S

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& P + S + E = 168 \\
& P \geq 0 \\
& S \geq 0 \\
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$$

When using an LP to model your problem, need to be sure that *all* aspects of your problem included!

Operations Research-style Example

Four different manufacturing plants for making cars:

	labor	materials	pollution
Plant 1	2	3	15
Plant 2	3	4	10
Plant 3	4	5	9
Plant 4	5	6	7

Operations Research-style Example

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- Need to produce at least **400** cars at plant 3 (labor agreement)
- Have **3300** total hours of labor, **4000** units of material
- Environmental law: produce at most **12000** pollution
- Make as many cars as possible

OR example as an LP

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$$x_3 \geq 400$$

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$$2x_1 + 3x_2 + 4x_3 + 5x_4 \leq 3300$$

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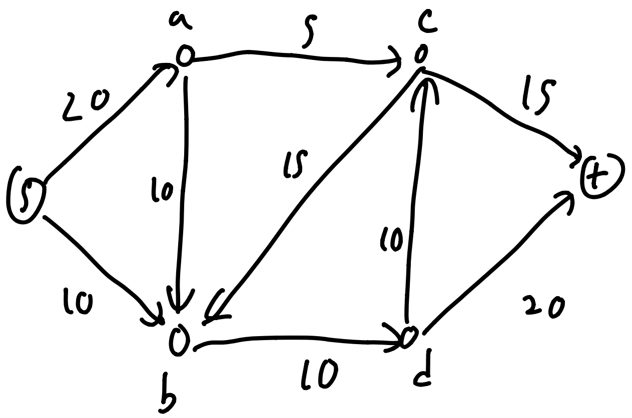
Max Flow as LP



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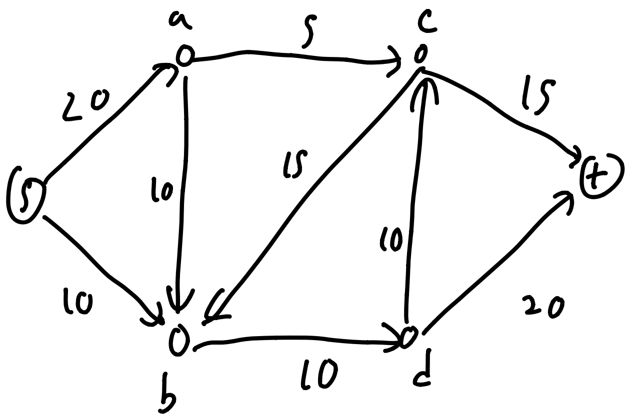

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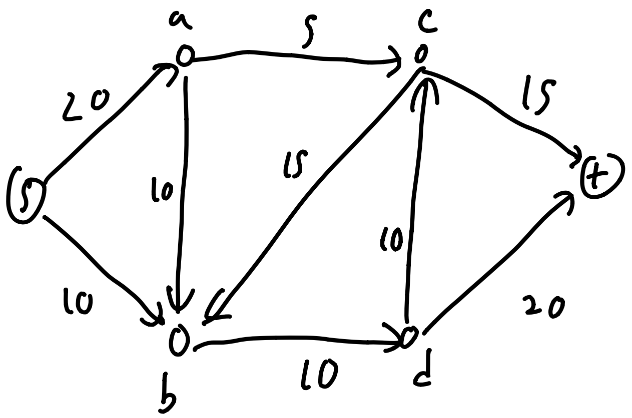

Variables: $f(e)$ for all $e \in E$

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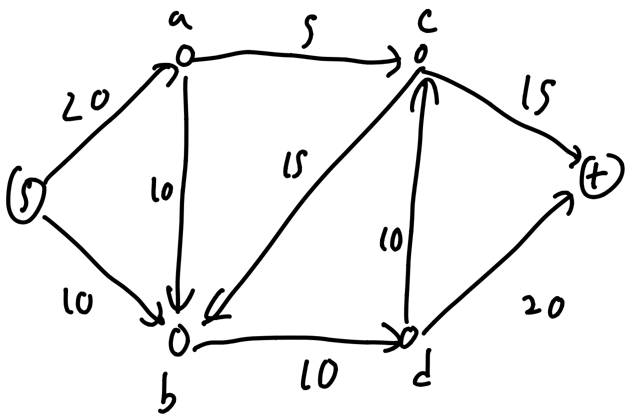

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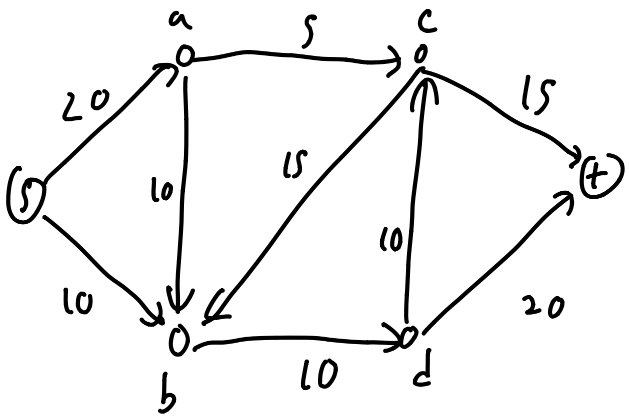

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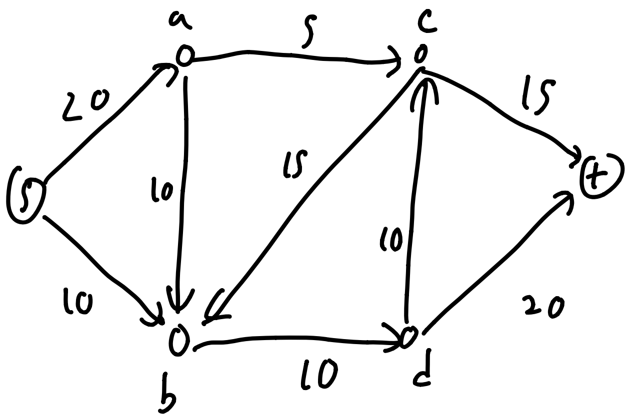

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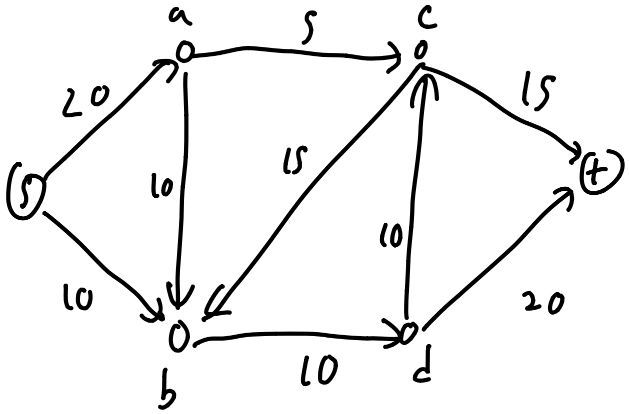

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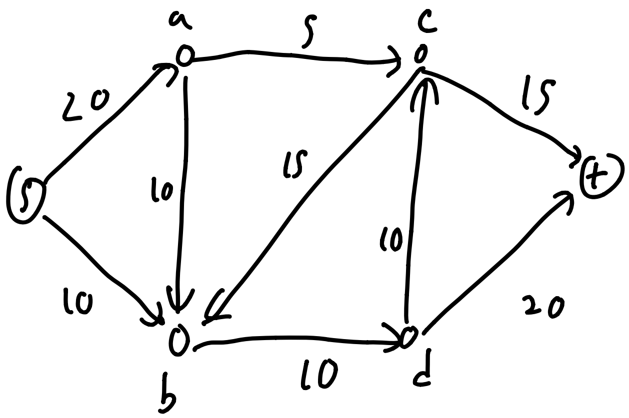

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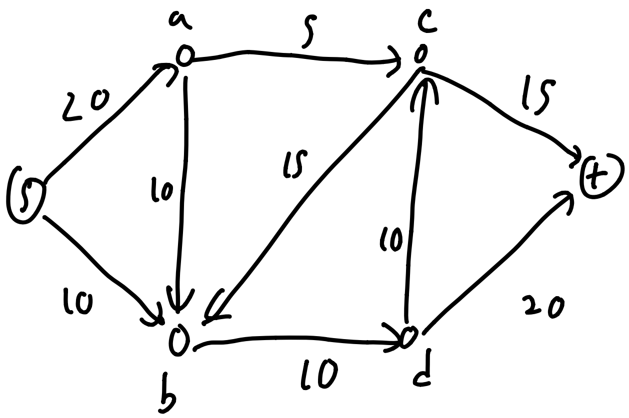

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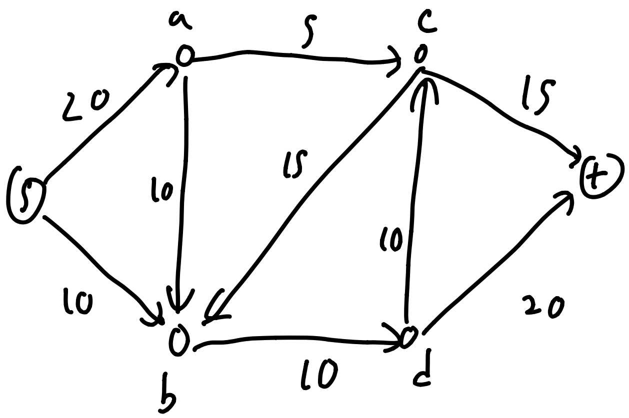

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So can solve max-flow and min-cut (slower) by using generic LP solver

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Generalization of max-flow with multiple commodities that can't mix, but use up same capacity

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- k source-sink pairs $\{(s_i, t_i)\}_{i \in [k]}$

Goal: send flow of commodity i from s_i to t_i, max total flow sent across all commodities

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Concurrent Flow

Multicommodity flow, but:

- Also given *demands* $\boldsymbol{d} : [\boldsymbol{k}] \to \mathbb{R}_{\geq \mathbf{0}}$
- Question: Is there a multicommodity flow that sends at least $\boldsymbol{d}(\boldsymbol{i})$ commodity-$\boldsymbol{i}$ flow from $\boldsymbol{s_i}$ to $\boldsymbol{t_i}$ for all $\boldsymbol{i} \in [\boldsymbol{k}]$?

Concurrent Flow

Variables: $f_i(e)$ for all $e \in E$ and for all $i \in [k]$.

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Constraints:

$$\begin{aligned}
\sum_v f_i(v,u) - \sum_v f_i(u,v) &= 0 && \forall i \in [k],\ \forall u \in V \setminus \{s_i, t_i\} \\
\sum_{i=1}^{k} f_i(e) &\leq c(e) && \forall e \in E \\
f_i(e) &\geq 0 && \forall e \in E,\ \forall i \in [k] \\
\sum_v f_i(s_i, v) - \sum_v f_i(v, s_i) &\geq d(i) && \forall i \in [k]
\end{aligned}$$

Maximum Concurrent Flow

If answer is no: how much do we need to scale down demands so that there is a multicommodity flow?

Maximum Concurrent Flow

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Variables:

- $f_i(e)$ for all $e \in E$ and for all $i \in [k]$.
- λ

Objective: $\max \lambda$

Constraints:

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$$\sum_{i=1}^{k} f_i(e) \le c(e) \qquad \forall e \in E$$

$$f_i(e) \ge 0 \qquad \forall e \in E,\ \forall i \in [k]$$

$$\sum_v f_i(s_i,v) - \sum_v f_i(v,s_i) \ge \lambda d(i) \qquad \forall i \in [k]$$

Shortest $s-t$ path

Very surprising LP!

Variables: d_v for all $v \in V$: shortest-path distance from s to v

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Inductive step: $d_{v_i}^* \leq d_{v_{i-1}}^* + \ell(v_{i-1}, v_i) \leq d(s, v_{i-1}) + \ell(v_{i-1}, v_i) = d(s, v_i)$

Algorithms for LPs

Geometry

To get intuition: think of LPs *geometrically*

- Space: $\mathbb{R}^n$ (one dimension per variable)
- Linear constraint: halfspace (one side of a hyperplane)
- Feasible region: intersection of halfspaces. *Convex Polytope* (usually just called a *polytope*)

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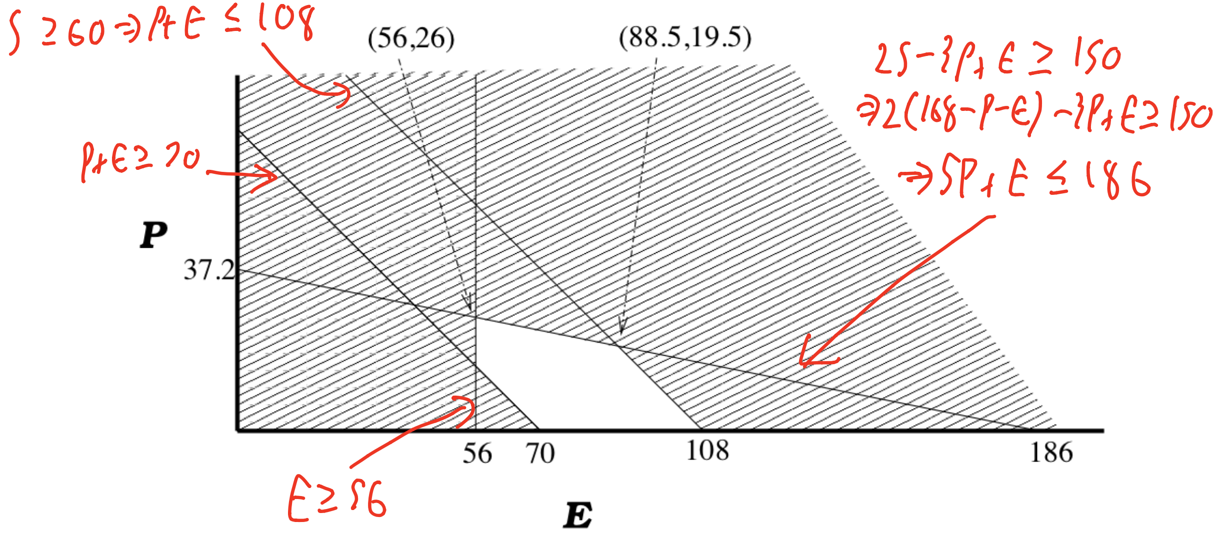
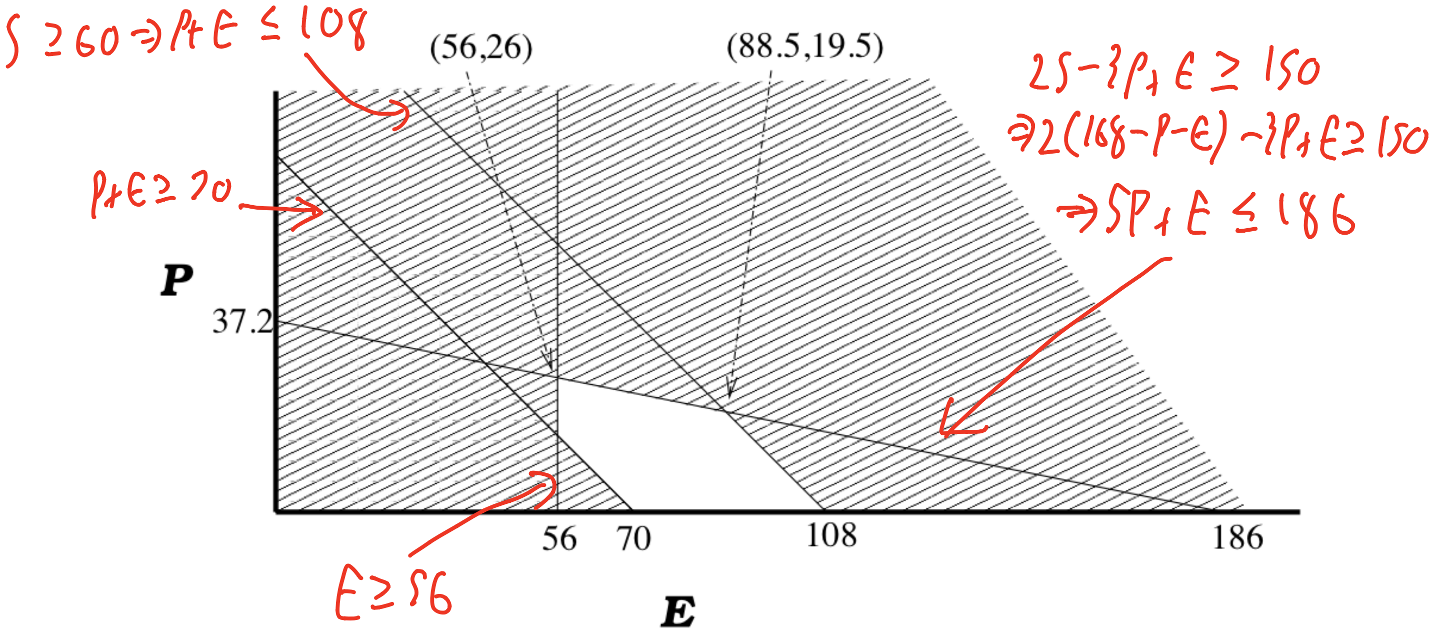
Example: planning your week

- $\mathbf{3}$ variables $\boldsymbol{S, P, E}$ so $\mathbb{R}^3$
- But $\boldsymbol{S + P + E = 168 \implies S = 168 - P - E}$
- Make this substitution, get $\mathbb{R}^2$



Geometry (cont'd)



Objective: feasible solution "furthest" along specified direction

- **max P: $(56, 26)$**
- **max $2P + E$: $(88.5, 19.5)$**

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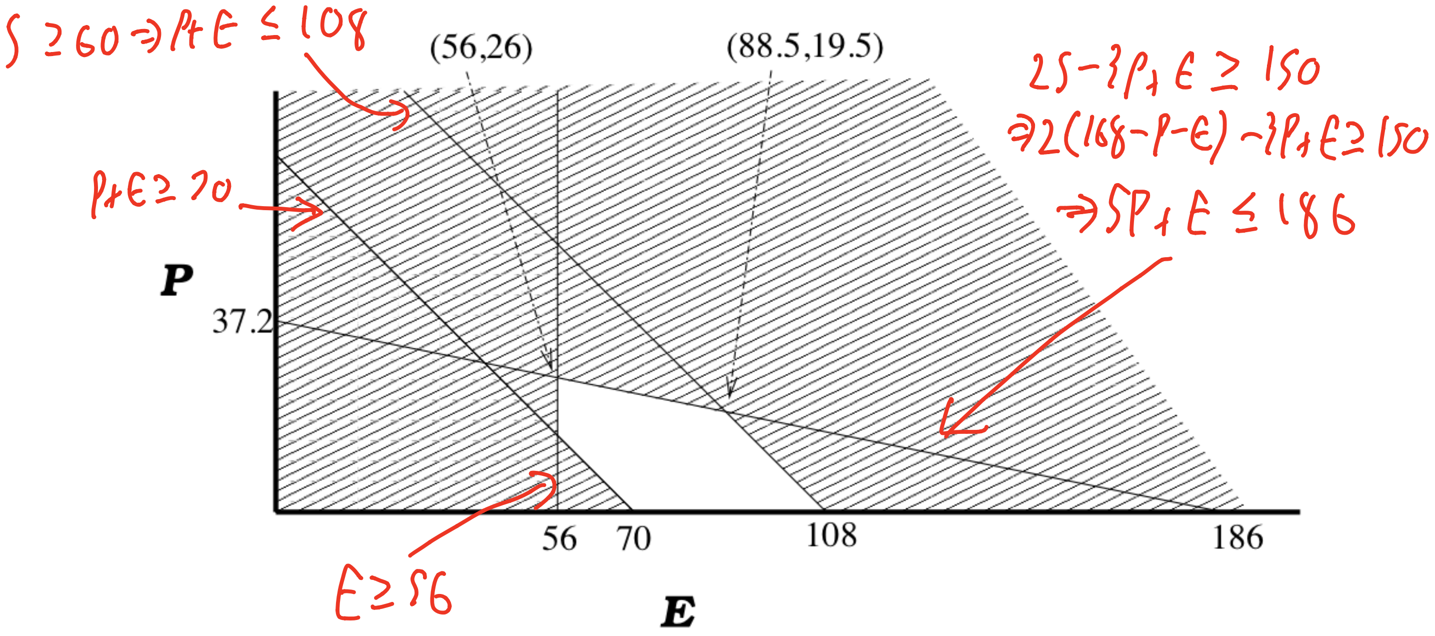

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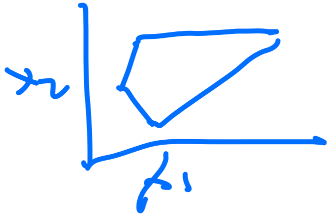
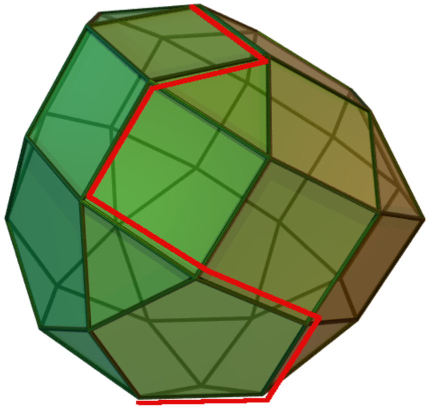
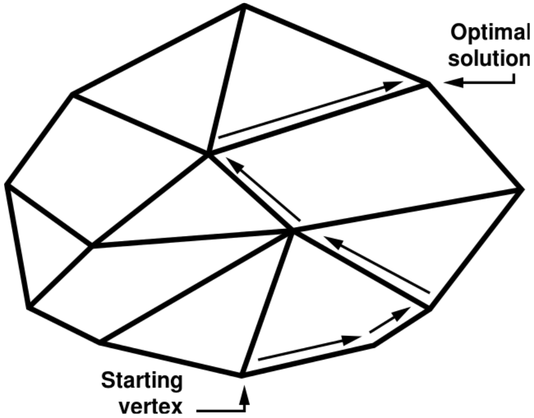
Main theorem: optimal solution is always at a "corner" (also called a "vertex")

Simplex Algorithm [Dantzig 1940's]

Initialize $\vec{x}$ to an arbitrary corner
while(a neighboring corner $\vec{x}'$ of $\vec{x}$ has better objective value) {
    $\vec{x} \leftarrow \vec{x}'$
}
return $\vec{x}$







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Theorem: Simplex returns the optimal solution.

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  - Much of AMS LP course really about simplex: traditionally favorite algorithm of people who want to actually solve LPs
- Some theory to explain discrepancy ("smoothed analysis")

Ellipsoid Algorithm [Khachiyan 1980]

First polytime algorithm!

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First polytime algorithm!

Designed to just solve feasibility question $\implies$ can also solve optimization

- Start with ellipsoid $\boldsymbol{E}$ containing feasible region $\boldsymbol{P}$ (if it exists)
- Let $\boldsymbol{x}$ be center of $\boldsymbol{E}$
- While($\boldsymbol{x}$ not feasible)
    - Find a hyperplane $\boldsymbol{H}$ through $\boldsymbol{x}$ such that all of $\boldsymbol{P}$ on one side
    - Let $\boldsymbol{E'}$ be the half-ellipsoid of $\boldsymbol{E}$ defined by $\boldsymbol{H}$
    - Find a new ellipsoid $\hat{\boldsymbol{E}}$ containing $\boldsymbol{E'}$ so that $\boldsymbol{vol}(\hat{\boldsymbol{E}}) \leq \left(1 - \frac{1}{n}\right) \boldsymbol{vol}(\boldsymbol{E})$
    - Let $\boldsymbol{E} = \hat{\boldsymbol{E}}$ and let $\boldsymbol{x}$ be center of $\hat{\boldsymbol{E}}$

Analysis

Extremely complicated!

Geometry of ellipsoids: can always find an ellipsoid containing a half-ellipsoid with at most $(1 - 1/n)$ of the volume of the original

- After t iterations, volume drops by $\left(1 - \frac{1}{n}\right)^t$ factor
- Absurdly useful inequality: $1 + x \leq e^x$
- $\left(1 - \frac{1}{n}\right)^t \leq (e^{-1/n})^t = e^{-t/n}$
- Crucial fact: if volume "too small", P must be empty. Let v a volume below which we can conclude P is empty.
- Then suffices to find t such that $(e^{-t/n})Vol(E) \leq v$, so taking $t \geq n \log(Vol(E)/v)$ suffices

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In practice: horrible.

Interior Point Methods (Karmarkar's Algorithm)

Fast in both theory and practice!