CS675: Convex and Combinatorial Optimization
Spring 2018
The Simplex Algorithm

Instructor: Shaddin Dughmi

Algorithms for Convex Optimization

- We will look at 2 algorithms in detail: Simplex and Ellipsoid.
- If there is time, we might also look at interior point methods (e.g. gradient descent and variants). These are important in practice.

History and Basics of the Simplex Algorithm

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- In 1972, Klee and Minty exhibited worst-case examples that take exponential time, at least for some of the most popular simplex pivot rules
- This spurred development of the Ellipsoid method, interior point methods, . . .

Outline

1. Description of The Simplex Algorithm
2. Properties
3. Initialization

Linear Programming

We consider a standard form LP written as follows for convenience

$$\begin{array}{ll} \text{maximize} & c^\intercal x \\ \text{subject to} & Ax \preceq b \end{array}$$

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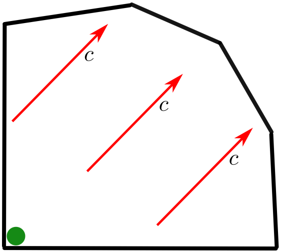
- Incidentally, algorithm will produce optimal dual y^* as well.

Recall: Physical Interpretation of LP



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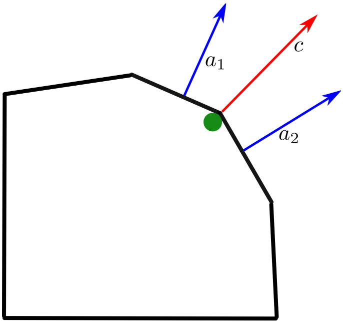

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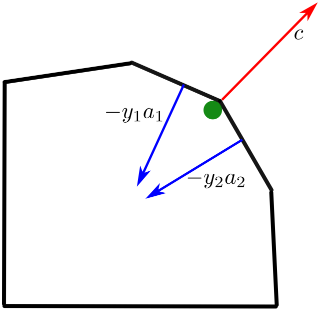

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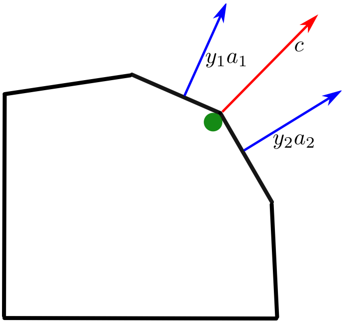

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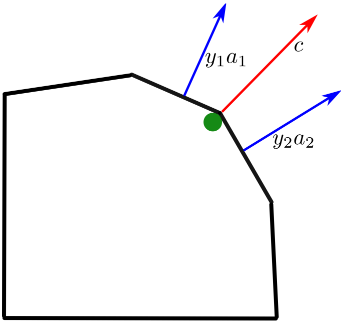

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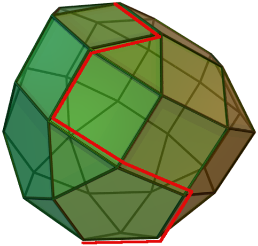
- Wall $a_i x \leq b_i$ applies some force $-y_i a_i$ to the ball for some $y_i \geq 0$
- Since the ball is still, $c^T = \sum_i y_i a_i = y^T A$.
- At optimality, only the walls adjacent to the ball push (Complementary Slackness)
    - Necessary and sufficient for optimality, given dual-feasible y

Informal Description



- Starts at initial vertex $x = x_0$
- While x is not optimal, move to a neighbouring vertex x' with $cx' > cx$.

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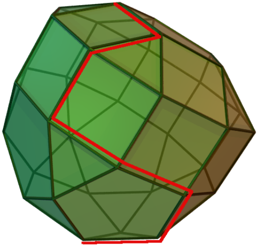

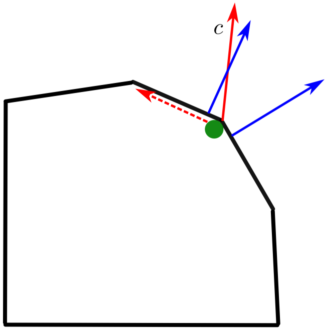

- Starts at initial vertex $x = x_0$
- While x is not optimal, move to a neighbouring vertex x' with $cx' > cx$.
  - Either c is in the cone defined by tight constraints at x, in which case x is optimal by complementary slackness
  - Or else can improve cx by moving along an edge (1-d face)

Simplex Method

- **Input:** vertex $x = x_0$
- **Output:** Optimal vertex x^* and complementary dual y^*, or unbounded

Repeat the following:

1. Write $c^\intercal = y^\intercal A$, where $y_i \neq 0$ only for n tight constraints $a_i x = b_i$.
2. If $y \geq 0$ then **stop and return** (x, y), else
3. Choose i with $y_i < 0$, and let $\vec{d}$ be s.t. $A_{T\setminus\{i\}} d = 0$ and $a_i d = -1$.
4. If $x + \lambda d$ feasible for all $\lambda \geq 0$, **stop and return unbounded**, else
5. $x \leftarrow x + \lambda d$, for largest $\lambda \geq 0$ maintaining feasibility

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- Let T be set of tight rows. $y_T^\intercal A_T = c^\intercal$
- Gaussian elimination

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- y is a dual satisfying complementary slackness with x
- Therefore both are optimal

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- Chosen so that moving in direction d preserves tightness of $T \setminus \{i\}$, and loosens i.
- A_T is full-rank, therefore $null(A_{T \setminus \{i\}})$ is a 1-dimensional subspace which is not normal to a_i
- Choose $d \in null(A_{T \setminus \{i\}})$ appropriately.
- Moving in direction d improves objective: $c^\intercal d = y^\intercal A d = y_i a_i d > 0$

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- i.e. $Ad \leq 0$

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- $\lambda = \min \left\{ \frac{b_j - a_j x}{a_j d} : j \in [m], a_j d > 0 \right\}$
- j achieving this minimum is a new tight constraint, replacing i.
- By nondegeneracy assumption, $\lambda > 0$

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Correctness

Claim

If the simplex algorithm terminates, then it correctly outputs either an optimal primal/dual pair or unbounded.

- Primal feasibility of x is maintained throughout
- Returns (x, y) only if y is dual feasible and satisfies complementary slackness
  - x and y are both optimal
- Returns unbounded only if there is a direction d with $c^\intercal d > 0$ and $Ad \leq 0$.

Termination in the Absence of Degeneracy

Claim

In the absence of degenerate vertices, the simplex algorithm terminates in a finite number of steps, at most $\binom{m}{n} \leq 2^m$.

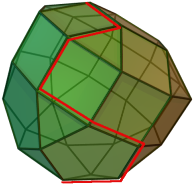
- There are at most $\binom{m}{n}$ distinct vertices in the polyhedron
- In the absence of degeneracy, the simplex algorithm does not repeat a vertex
  - In each iteration, moves along an edge in direction d, in total λd
  - We saw: $c^\intercal d > 0$, and $\lambda > 0$.
  - Objective <u>strictly</u> improves each iteration

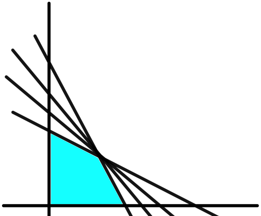
Pivot Rules

Note

The algorithm we presented was not fully specified

- When multiple neighboring vertices are improving, which one should we choose so as to terminate as quickly as possible?
- In the presence of degeneracy, how should we identify the next (geometric) vertex so as to guarantee termination?
  - We maintain n tight and linearly independent constraints T, to be thought of as an algebraic representation of a vertex (aka a basic feasible solution (BFS))
  - When many algebraic representations are possible of a single geometric vertex, unclear how to identify the next geometric vertex.





Pivot Rules

Both concerns are addressed by the use of a pivot rule, which determines the order in which we examine algebraic vertices.

Pivot rule

A rule for selecting which i leaves T, and which j enters T, when multiple choices are possible either because of multiple improving neighbors or degeneracy. Examples:

- Bland's rule: Choose lowest indexed i, then lowest indexed j
- Lexicographic: Maintain an order over rows, and move from T to the lexicographically smallest possible T'.
- Perturbation: perturb entries of b by a small value to remove degeneracy. This perturbation can be purely symbolic.

Runtime and Termination

- Many pivot rules, like the ones we mentioned, have been shown to never cycle over algebraic vertices
  - Guarantees termination in general, even in the presence of degeneracies
  - See book and notes for proofs.
- However, no pivot rules have been shown to guarantee a polynomial number of pivots
  - Even if no degeneracies.
- In 1972, Klee and Minty exhibited a family of examples that lead to exponential worst-case runtime for some widely-used pivot rules

Runtime and Termination

Nevertheless, one explanation as to the efficiency of the simplex algorithm in practice is through smoothed complexity

Theorem (Spielman & Teng '01)

The simplex algorithm has polynomial smoothed complexity.

- Model of input:
  - A, b, c chosen arbitrarily (worst case)
  - Then subjected to small gaussian noise with stddev σ (relative to largest entry of A, b, c)
  - Interpretation: measurement error
- More optimistic than worst case, but not quite as optimistic as average case.
- Expected runtime is polynomial in n, m and $\frac{1}{\sigma}$

Runtime and Termination

Open Question

Is there a pivot rule which guarantees a polynomial number of pivots of the simplex algorithm in the worst case?

Why is this important?

- Would yield a strongly polynomial algorithm for LP
- If true, resolves in the affirmative a classic open question in polyhedral combinatorics
  - Polynomial Hirsch Conjecture: Is the diameter of the edge-vertex graph of an m-facet polytope in n-dimensional space bounded by a polynomial in n and m?

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Initialization

Solving a Linear Program via the Simplex Method

- Phase I: Find a vertex x_0.
- Phase II: Run the simplex algorithm starting from x_0

- So far, we have looked only at phase II
- For phase I, we pose a different LP whose optimal solution is a vertex, if one exists

Phase I

$$\begin{array}{ll} \text{maximize} & c^\intercal x \\ \text{subject to} & Ax \preceq b \\ & x \succeq 0 \end{array}$$

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- An optimal vertex of new LP (with $z = 0$) will correspond to some vertex x_0 of original LP

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- Running simplex on new LP with starting vertex (x_0', z_0), we get starting vertex x_0 for original LP.