

Lecture 14

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1 Simplex Issues: Number of Pivots

Question: How many pivots does the simplex algorithm need to take to find an optimal solution?

Answer: If we use a pivot rule that prevents cycling, like Bland’s rule, we know that the simplex algorithm never revisits a basis. Therefore the number of pivots is bounded by the number of basis, which is no larger than $\binom{n}{m}$. In practice, however the simplex algorithm seems to perform $O(m)$ pivots.

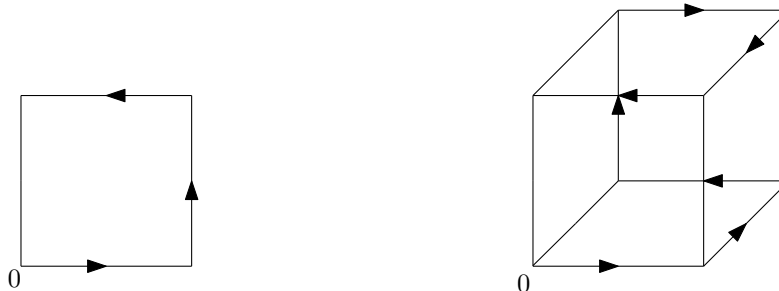
For most known pivot rules, there have been examples devised where $2^n - 1$ pivots are taken. This work was started by Klee and Minty (1970).

Idea: Consider n -dimensional cube

$$0 \leq x_i \leq 1, \forall i = 1, 2, \dots, n$$

There is a *Hamiltonian path* in any n -dimensional cube. This path starts at $x = 0$ and visits every vertex exactly once.

Examples:



The idea now is to perturb the costs and the constraints slightly so that the simplex algorithm follows the Hamiltonian path. Thus it performs $2^n - 1$ pivots. Observe, however that in such a case, only one pivot is necessary to reach the optimal solution!!!

Most pivoting rules used in practice have been shown to have an exponential number of pivots in the worst case by an example similar to the ones given by Klee and Minty (often called *Klee-Minty cubes*). Until recently, two exceptions to this were Zadeh’s rule and randomized pivoting rules. Zadeh’s rule chooses the entering variable that has entered the basis the least often so far. It was shown by Friedmann (IPCO 2011) that this rule can also take an exponential number of pivots

to reach the optimal solution. Randomized pivoting rules choose the entering variable randomly, and certain classes of this rule have also been shown to be exponential by Friedmann, Hansen, and Zwick (STOC 2011).

Suppose now that P is a bounded polyhedron and we have two vertices of P , x and y . Let $d(x, y)$ be the least number of nondegenerate pivots needed to go from x to y . Let

$$D(P) = \max_{\text{vertices: } x, y} d(x, y)$$

be the diameter of P . Let

$$\Delta(n, m) = \max_{P \in S} D(P),$$

where S is the set of all bounded polyhedra in \mathbb{R}^n with m constraints. Note that $\Delta(n, m)$ gives a lower bound on the number of pivots we might need for a bounded polyhedron with n variables and m constraints (assuming we start at the worst-case x and the optimal is at the worst-case y). The following was conjectured by Hirsch in 1957.

Claim 1 (*Hirsch Conjecture*): $\Delta(n, m) \leq m - n$

The conjecture is now known to be false. Santos (2011) showed that $\Delta(43, 86) > 43$, and in general, $\Delta(n, m) \geq \frac{21}{20}(m - n)$ for n and m sufficiently large. Kalai and Kleitman (1992) showed the bound $\Delta(n, m) \leq m^{2+\log_2 n}$, and the best upper bound known is $\Delta(n, m) \leq (m - n)^{\log_2 n}$ (Todd 2014).

2 Types of Simplex Method

2.1 Revised Simplex Method

This is an implementation of the simplex algorithm in which we maintain a basis B and compute all other information from it during each iteration. What we have called the simplex method throughout the semester thus far.

2.2 Standard Simplex Method

In this implementation of the simplex algorithm, we maintain a full tableau throughout the algorithm.

Tableau:

$-b(A_B^T)^{-1}c_B$	$c - A^T(A_B^T)^{-1}c_B$
$A_B^{-1}b$	$A_B^{-1}A$

- The top left hand corner has the negative value of the objective function. Recall that $\bar{c}x = c^T x - b^T y = c^T x - b^T (A_B^T)^{-1} c_B$. But $\bar{c}x = 0$, since $\bar{c}_B = 0$ and $x_N = 0$. Therefore $c^T x = b^T (A_B^T)^{-1} c_B$.
- The bottom left hand corner has the values of the basic variables.
- The top right hand corner has the reduced cost vector.
- The bottom right hand corner has a modified constraint matrix with the property that the submatrix consisting of the columns indexed by B is the identity I

Example of the standard Simplex Method

$$\begin{array}{rllllll}
 \min & -x_1 & +2x_2 & -x_3 & & & & \\
 \text{s.t.} & x_1 & & & + x_4 & & & = 4 \\
 & & x_2 & & & + x_5 & & = 4 \\
 & x_1 & +x_2 & & & & + x_6 & = 6 \\
 & -x_1 & & + 2x_3 & & & & + x_7 = 4 \\
 & & & & x_1, \dots, x_7 & \geq 0 & &
 \end{array}$$

0	-1	2	-1	0	0	0	0
$x_4=4$	1	0	0	1	0	0	0
$x_5=4$	0	1	0	0	1	0	0
$x_6=6$	1	1	0	0	0	1	0
$x_7=4$	-1	0	2	0	0	0	1

During this iteration, x_1 enters the basis and x_4 leaves the basis. To do an update take row defining the pivot, do Gaussian elimination to make the new basis submatrix into the Identity matrix. Also use this row to eliminate x_1 from the reduced costs.

$$\begin{array}{c|cccccc}
 4 & 0 & 2 & -1 & 1 & 0 & 0 & 0 \\
 \hline
 x_1=4 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
 x_5=4 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
 x_6=2 & 0 & 1 & 0 & -1 & 0 & 1 & 0 \\
 x_7=8 & 0 & 0 & 2 & 1 & 0 & 0 & 1
 \end{array}$$

During this iteration, x_3 enters the basis and x_7 leaves.

$$\begin{array}{c|cccccc}
 8 & 0 & 2 & 0 & 1.5 & 0 & 0 & 0.5 \\
 \hline
 x_1=4 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
 x_5=4 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
 x_6=2 & 0 & 1 & 0 & -1 & 0 & 1 & 0 \\
 x_3=4 & 0 & 0 & 1 & 0.5 & 0 & 0 & 0.5
 \end{array}$$

We found the optimal solution, since the reduced costs vector has nonnegative entries. The value of the LP is -8 and the optimal solution is $[4,0,4,0,4,2,0]$.

2.3 Capacitated Simplex

We consider an LP of the following form.

$$\begin{array}{ll}
 \min & c^T x \\
 \text{s.t.} & Ax = b \\
 & l \leq x \leq u
 \end{array}$$

Question: How do we solve such an LP?

Idea 1: Put into standard form. Let $z = x - l$ and $\tilde{b} = b - Al$. The new LP is

$$\begin{array}{ll}
 \min & c^T z \\
 \text{s.t.} & Az = \tilde{b} \\
 & 0 \leq z \leq u - l
 \end{array}$$

Now we can convert $z \leq u - l$ to equality constraints by adding slack variables. Thus the number of constraints in the constraint matrix and the number of variables are increased by n . Since we typically have that $n \gg m$, this alteration could cause the complexity of the algorithm to increase significantly.

Idea 2: Modify the Simplex Method! We will maintain three sets of variables: B (basic), L , and U . Then

$$\begin{array}{l}
 j \in L \implies x_j = l_j \\
 j \in U \implies x_j = u_j
 \end{array}$$

If we take the dual of the original LP, we get

$$\begin{array}{ll}
 \max & b^T y - u^T v + l^T w \\
 \text{s.t.} & A^T y - v + w = c \\
 & v, w \geq 0
 \end{array}$$

Notice that for any y , there exists a dual feasible solution; namely

$$v = \max(0, A^T y - c)$$

$$w = \max(0, c - A^T y)$$

We can set $y = (A_B^T)^{-1} c_B$ as usual and compute reduced costs, $\bar{c} = c - A^T y$. Let's now consider a solution to the primal, x .

$$A_B x_B + A_L x_L + A_U x_U = b$$

$$A_B x_B = b - A_L x_L - A_U x_U$$

$$x_B = A_B^{-1} b - A_B^{-1} A_L x_L - A_B^{-1} A_U x_U$$

If x satisfies the above equation and $l_B \leq x_B \leq u_B$, then it is primal feasible. Furthermore, it is optimal if it is primal feasible and $\bar{c}_j \geq 0$ for all $j \in L$, and $\bar{c}_j \leq 0$ for all $j \in U$. This follows since if $\bar{c}_j \geq 0$ then $A_j^T y \leq c_j \implies v_j = 0$ and $w_j \geq 0$. Therefore complementary slackness is obeyed since $w_j > 0 \implies x_j = l_j$. If $\bar{c}_j \leq 0$ then $A_j^T y \geq c_j \implies w_j = 0$ and $v_j \geq 0$. Therefore complementary slackness is obeyed since $v_j > 0 \implies x_j = l_j$.

Suppose these optimality conditions did not hold, i.e., either $\bar{c}_j < 0$ for some $j \in L$ or $\bar{c}_j > 0$ for some $j \in U$. This would motivate increasing or decreasing x_j , respectively.

The rest of the details of the capacitated simplex method will be given as a homework problem.