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Lecture 12

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1 Finding an initial basic feasible solution

Recall our discussion from last time about how to find an initial basic feasible solution of a linear program. Suppose we want to find a basic feasible solution of

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0. \end{aligned}$$

We modify the LP so that there is an easy choice of basic solution. We start by solving

$$\begin{aligned} \min \quad & e^T z \\ \text{s.t.} \quad & Ax + Iz = b \\ & x \geq 0 \\ & z \geq 0, \end{aligned}$$

where e is the vector of all ones, and $b \geq 0$ (if not, then we can multiply the constraints by -1 to achieve this). The z variables are called *artificial variables*, and the x's are called *real variables*. Define $x' := [x\ z]^T$ and $A' := [A\ I]$ so that the constraints of the modified LP can be written as $A'x' = b$, $x' \geq 0$.

Let B be the indices of the artificial variables. Then B is a basis, since the corresponding columns of A' are I, the identity, and thus linearly independent. The corresponding basic feasible solution is $x = 0$, $z = b$. We use this to initialize the simplex algorithm.

The simplex method can be one of two possible results (note that the modified LP is never unbounded: since $z \geq 0$, the objective function is bounded from below by 0.)

Case (1): The value of the LP is non-zero (and thus strictly greater than zero). Then there are no feasible solutions for the original LP, i.e., there are no x such that $Ax = b$. Indeed, if there were, we could take $z = 0$ and thus obtain a new feasible solution to the modified LP with value 0, a contradiction.

Case (2): The value of the LP is zero. Then there are two subcases:

(i) The Good Case: All artificial variables are non-basic. Then $A'_B = A_B$, so that B is a basis also for the original problem: $x'_B = (A'_B)^{-1}b$, $x'_N = 0$ is feasible, so $x_B = A_B^{-1}b$, $x_N = 0$ is a basic feasible solution. for $Ax = b$.

We can now run the simplex method for the original problem, starting with the basis B.

(ii) The Bad Case: Some artificial variables are in the basis.

In the bad case, we know that all the artificial variables $z_i = 0$. Therefore, the idea is that we should perform pivots, taking artificial variables out of basis, putting "real" variables in.

Recall: $\bar{A}' = (A'_B)^{-1} A'_N$

Now we again have two cases. First, suppose there exists a "real" variable $j \in N$ such that $\bar{A_{ij}} \neq 0$ for artificial variable $i \in B$. Consider pivot $\hat{B} \leftarrow B - \{i\} \cup \{j\}$.

Claim 1 *Current solution x' is also a solution associated with $\hat{B}$*

Proof: All we need to show is that x' satisfies $A'x' = b$ and $x'_k = 0 \;\; \forall k \notin \hat{B}$. $A'x' = b$ since no change to x'. $x'_k = 0 \;\; \forall k \notin \hat{B}$ since either $k \notin \hat{B}$ or $k = i$. For $k \notin \hat{B}$, $x'_k = 0$ (same as before). For $k = i$, $x'_i = 0$ (since i an artificial variable). $\square$

Claim 2 *$\hat{B}$ is a basis*

Proof: We use the same proof we used to show that a pivot leads to a new basis. We have

$$A'_{\hat{B}} = A'_B \begin{bmatrix} 1 & & \begin{pmatrix} \bar{A'_{1j}} \\ \bar{A'_{2j}} \\ \vdots \\ \end{pmatrix} & & \\ & 1 & & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix}$$

$$\uparrow$$
$$i^{th} \text{ column}$$

where A'_B is non-singular (it was a basis), and the next matrix is also non-singular (because its determinant value is $\bar{A_{ij}} \neq 0$ by assumption. $\square$

Now we suppose for artificial variable $i \in B$, for all real $j \in N$, $\bar{A'_{ij}} = 0$. Let α_i be i^{th} row of $(A'_B)^{-1}$. Then for each real $j \in N$

$$\alpha_i A'_j = \bar{A_{ij}} = 0. \qquad (A'_j : j^{th} \text{ column of } A')$$

For each real $j \in B$

$$\alpha_i A'_j = 0$$

since $(A'_B)^{-1} A_B = I$, and $i \neq j$ since j real and i artificial. So then, $\alpha_i A = 0$, which implies that the rows of A not linearly independent. Either this violates an assumption (if we assumed that A has linearly independent rows) or we can find a linearly dependent row and eliminate it. Get rid of constraints linearly dependent on others and continue.

Finding an initial basic feasible solution an associate basis is called *Phase I* of the simplex method. Finding an optimal solution given the initial basic feasible solution is called *Phase II.*

2 The complexity of a pivot

We now turn to thinking about the complexity (number of arithmetic operations) needed to perform a single pivot. Assume we have a basic feasible solution x and associated basis B. Recall the steps of a pivot:

- **Step 1**: Solve $A_B x_B = b$ for x_B.
- **Step 2:** Solve ${A_B}^T y = c_B$ for y.
- **Step 3:** Compute $\bar{c} = c - A^T y$. If $\bar{c} \geq 0$, stop. Else find $\bar{c_j} < 0$
- **Step 4:** Solve $A_B d = A_j$ for d. This computes column $\begin{pmatrix} \bar{A_{1j}} \\ \vdots \\ \bar{A_{mj}} \end{pmatrix}$ of $\bar{A} = ({A_B}^{-1})A_N$.
- **Step 5:** Compute max $\epsilon \quad$ s.t. $\epsilon d \leq \bar{b} = x_B$
- **Step 6:** Update solution to $\hat{x}$ where $\hat{x_j} = \epsilon$. $\hat{x_B} = x_B - \epsilon d$, Basis $\hat{B} = B - \{i^*\} \cup \{j\}$

Let's now consider the total work involved:

- Step 1,2, and 4: need to solve $m \times m$ system of equations. : $O(m^3)$ (this is faster if A_B is sparse, lots of zeros)
- Step 5 and 6: check $O(m)$ inequalities: $O(m)$ work
- In Step 3, to compute any component of $\bar{c}$ is $O(m)$ work, but there are n of them. Overall, $O(mn)$ times if we look through all entries.

Therefore, the overall work involved is $O(m^3 + mn)$ per pivot.

Suppose initially $A_B = I$. (If not true, we can multiply the constraints by ${A_B}^{-1}$ to make it true). Suppose $B_0, B_1, B_2, \cdots B_k$ be bases in a sequence of k pivots.

Recall that

$$A_{B_{i+1}} = A_{B_i} \begin{bmatrix} 1 & & & & \\ & 1 & \begin{pmatrix} \\ d \\ \\ \end{pmatrix} & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix}$$

↖ called an eta matrix

Let E_i be i^{th} eta matrix. Given that this, is the case how hard is it to solve the systems

$$A_{B_1} x = b \quad \text{for } x$$

$${A_{B_1}}^T y = c_{B_1} \quad \text{for } y$$

$$A_{B_1} d = A_j \quad \text{for } d$$

We know that $A_{B_1} = E_1$ for E_1 an eta matrix. So $A_{B_1}x = b$ is equivalent to

$$\begin{bmatrix} 1 & & & & \\ & 1 & \left(\begin{matrix} \\ d \\ \\ \end{matrix}\right) & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix} \begin{bmatrix} \\ x \\ \\ \end{bmatrix} = \begin{bmatrix} \\ b \\ \\ \end{bmatrix}$$

$$j^{th}$$

This implies

$$x_i + d_i x_j = b_i \quad (i \neq j) \qquad \text{and} \qquad d_j x_j = b_j \quad (i = j).$$

Then to solve this system, set $x_j = \frac{b_j}{d_j}$, and then $x_i = b_i - \frac{d_i b_j}{d_j}$. Solving this then takes $O(m)$ time.

Now consider solving ${A_{B_1}}^T y = c_{B_1}$ for y. Then

$$\left[\begin{array}{ccccc} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \hline & & d & & \\ \hline 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{array}\right] \begin{bmatrix} \\ y \\ \\ \end{bmatrix} = \begin{bmatrix} \\ c_{B_1} \\ \\ \end{bmatrix}$$

This implies

$$y_i = c_i \qquad i \neq j \qquad \text{and} \qquad \sum_{i=1}^{n} d_i y_i = c_j,$$

which we can easily solve in $O(m)$ time.

In the general case, we want to solve equations of the form $A_{B_k}x = b$. Note that we can solve $(A_{B_0}E_1E_2...E_k)x = b$ if we solve $(E_1E_2...E_k)x = b$. Let x_1 denote the product $E_2 \cdots E_k x$ (where we still don't know x). Then $E_1 x_1 = b$. We can solve this system for x_1 in $O(m)$ time. Now we iteratively solve $E_2 \ldots E_k x = x_1$ for x. Thus we can solve for x in $O(km)$ time.

Hence in general, after k pivots, we can perform a pivot in $O(km + mn)$ time. Note that this running time gets larger after we have performed a large number of pivots, so in practice, after some number of iterations, we recompute ${A_B}^{-1}$, make the current basis I, and start over again.