8 Seidels LP-algorithm

- Suppose we want to solve $\min\{c^T x \mid Ax \geq b; x \geq 0\}$, where $x \in \mathbb{R}^d$ and we have m constraints.
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Setting:

- We assume an LP of the form

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

- We assume that the LP is bounded.

Ensuring Conditions

Given a standard minimization LP

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

how can we obtain an LP of the required form?

- **Compute a lower bound on $c^T x$ for any basic feasible solution.**

Computing a Lower Bound

Let s denote the smallest common multiple of all denominators of entries in A, b.

Multiply entries in A, b by s to obtain integral entries. This does not change the feasible region.

Add slack variables to A; denote the resulting matrix with $\bar{A}$.

If B is an optimal basis then x_B with $\bar{A}_B x_B = \bar{b}$, gives an optimal assignment to the basis variables (non-basic variables are 0).

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Theorem 2 (Cramers Rule)

Let M be a matrix with $\det(M) \neq 0$. Then the solution to the system $Mx = b$ is given by

$$x_i = \frac{\det(M_j)}{\det(M)} ,$$

where M_i is the matrix obtained from M by replacing the i-th column by the vector b.

Proof:

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- Define

$$X_i = \begin{pmatrix} | & & | & | & | & & | \\ e_1 & \cdots & e_{i-1} & x & e_{i+1} & \cdots & e_n \\ | & & | & | & | & & | \end{pmatrix}$$

  Note that expanding along the i-th column gives that $\det(X_i) = x_i$.

- Further, we have

$$MX_i = \begin{pmatrix} | & & | & | & | & & | \\ Me_1 & \cdots & Me_{i-1} & Mx & Me_{i+1} & \cdots & Me_n \\ | & & | & | & | & & | \end{pmatrix} = M_i$$

- Hence,

$$x_i = \det(X_i) = \frac{\det(M_i)}{\det(M)}$$

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Bounding the Determinant

Let Z be the maximum absolute entry occuring in $\bar{A}, \bar{b}$ or c. Let C denote the matrix obtained from $\bar{A}_B$ by replacing the j-th column with vector $\bar{b}$ (for some j).

Observe that

$$|\det(C)|$$

Here $\mathrm{sgn}(\pi)$ denotes the sign of the permutation, which is 1 if the permutation can be generated by an even number of transpositions (exchanging two elements), and -1 if the number of transpositions is odd.
The first identity is known as Leibniz formula.

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Observe that

$$|\det(C)| = \left| \sum_{\pi \in S_m} \operatorname{sgn}(\pi) \prod_{1 \le i \le m} C_{i\pi(i)} \right|$$

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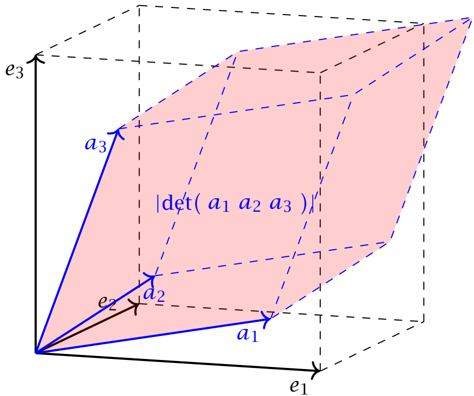
|\det(C)| &\le \prod_{i=1}^{m} \|C_{*i}\| \le \prod_{i=1}^{m} (\sqrt{m}Z) \\
&\le m^{m/2} Z^m \enspace .
\end{aligned}
$$

Hadamards Inequality



Hadamards inequality says that the volume of the red parallelepiped (Spat) is smaller than the volume in the black cube (if $\|e_1\| = \|a_1\|$, $\|e_2\| = \|a_2\|$, $\|e_3\| = \|a_3\|$).

Ensuring Conditions

Given a standard minimization LP

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

how can we obtain an LP of the required form?

- **Compute a lower bound on $c^T x$ for any basic feasible solution.** Add the constraint $c^T x \geq -dZ(m! \cdot Z^m) - 1$. Note that this constraint is superfluous unless the LP is unbounded.

Ensuring Conditions

Compute an optimum basis for the new LP.

- If the cost is $c^T x = -(dZ)(m! \cdot Z^m) - 1$ we know that the original LP is unbounded.
- Otw. we have an optimum basis.

In the following we use $\mathcal{H}$ to denote the set of all constraints apart from the constraint $c^T x \geq -dZ(m! \cdot Z^m) - 1$.

We give a routine SeidelLP$(\mathcal{H}, d)$ that is given a set $\mathcal{H}$ of explicit, non-degenerate constraints over d variables, and minimizes $c^T x$ over all feasible points.

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if $\hat{x}^* =$ infeasible **then**
    return infeasible
else
    add the value of x_ℓ to $\hat{x}^*$ and return the solution

8 Seidels LP-algorithm

Note that for the case $d = 1$, the asymptotic bound $\mathcal{O}(\max\{m, 1\})$ is valid also for the case $m = 0$.

- If $d = 1$ we can solve the 1-dimensional problem in time $\mathcal{O}(\max\{m, 1\})$.
- If $d > 1$ and $m = 0$ we take time $\mathcal{O}(d)$ to return d-dimensional vector x.
- The first recursive call takes time $T(m-1, d)$ for the call plus $\mathcal{O}(d)$ for checking whether the solution fulfills h.
- If we are unlucky and $\hat{x}^*$ does not fulfill h we need time $\mathcal{O}(d(m+1)) = \mathcal{O}(dm)$ to eliminate x_ℓ. Then we make a recursive call that takes time $T(m-1, d-1)$.
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This gives the recurrence

$$T(m,d) = \begin{cases} \mathcal{O}(\max\{1,m\}) & \text{if } d = 1 \\ \mathcal{O}(d) & \text{if } d > 1 \text{ and } m = 0 \\ \mathcal{O}(d) + T(m-1,d) + & \\ \frac{d}{m}(\mathcal{O}(dm) + T(m-1,d-1)) & \text{otw.} \end{cases}$$

Note that $T(m,d)$ denotes the expected running time.

8 Seidels LP-algorithm

Let C be the largest constant in the $\mathcal{O}$-notations.

$$T(m,d) = \begin{cases} C\max\{1,m\} & \text{if } d = 1 \\ Cd & \text{if } d > 1 \text{ and } m = 0 \\ Cd + T(m-1,d) + & \\ \frac{d}{m}(Cdm + T(m-1,d-1)) & \text{otw.} \end{cases}$$

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8 Seidels LP-algorithm

Let C be the largest constant in the $\mathcal{O}$-notations.

We show $T(m,d) \leq Cf(d)\max\{1,m\}$.

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if $f(d) \geq df(d-1) + 2d^2$.

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since $\sum_{i\geq 1}\frac{i^2}{i!}$ is a constant.

$$
\sum_{i\geq 1}\frac{i^2}{i!} = \sum_{i\geq 0}\frac{i+1}{i!} = e + \sum_{i\geq 1}\frac{i}{i!} = 2e
$$