CS602 Applied Algorithms

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Feasibility \in co-NP and Feasibility \in NP. And if a problem is in NP and also co-NP, it mostly turns out to be in P.

Optimization(Duality)

Example: Consider the following linear program. Let P be a polyhedron given by the following set of linear constraints

$$x \geq 0 \tag{1}$$

$$y \geq 0 \tag{2}$$

$$x \leq 2 \tag{3}$$

$$y \leq 2 \tag{4}$$

$$x + y \le 3 \tag{5}$$

Suppose we have to maximise f(x,y) = 7x + 8y under these constraints. Let say the optimal value is w^* . Take any point in P. Let's pick $(1,1) \in P$, we can confirm that f(1,1) = 15. And hence, $w^* \ge 15$. Similarly, any feasible point of the LP will us a lower bound on the optimal value.

Observation 7.1 In the LP $\max\{w^Tx \mid Ax \leq b\}$ if α is a feasible point then $w^* \geq w^T\alpha$.

For example, (2,1) is a feasible point and it gives us $w^* \ge f(2,1) = 22$. Another point (1,2) gives a better lower bound: $w^* \ge f(1,2) = 23$.

Can we also get an upper bound on w^* somehow? To upper bound w^* we can try to express f(x,y) as positive linear combination of given linear constraints. Let us do it for the above example.

Attempt 1: Let us multiply (3) by 7 and (4) by 8, and add the two inequalites.

$$7 \times (x \leq 2)$$

$$8 \times (y \leq 2)$$

$$7x + 8y \leq 14 + 16$$

$$\implies f(x, y) \leq 30$$

This gives us an upper bound of $w^* \leq 30$ which is far from the lower bounds we saw. Let us try another possibility.

Attempt 2: Let us multiply (5) by 8 and (1) by -1, and add the two.

$$8 \times (x+y \leq 3)
-1 \times (x \geq 0)
\hline
 7x+8y \leq 24-0
\implies f(x,y) \leq 24$$

We get $w^* \leq 24$ which is close to the lower bound of 23, but there is still a gap.

Attempt 3: Let us multiply (5) by 7 and (3) by 1, and add the two.

$$7 \times (x + y \le 3)$$
$$1 \times (x \le 2)$$

$$7x + 8y \le 21 + 2$$

$$\implies f(x, y) \le 23$$

We get $w^* \leq 23$, which matches exactly with our best lower bound. Of course, we can not hope to further improve either the upper bound or the lower bound. Thus, it must be that $w^* = 23$ and (1,2) must be the optimal point.

Weak Duality Theorem

This way of upper bounding the optimal value can be expressed as another LP, which is called the dual LP.

Primal LP (LP) : maximise $f(x) = w^{\mathsf{T}}x$ such that $Ax \leq b$ where $A \in \mathbb{R}^{mxn}$, $b \in \mathbb{R}^m$, $w \in \mathbb{R}^n$.

Dual LP (LP*) : minimise $g(y) = b^{T}y$ such that $A^{T}y = w, y \ge 0$.

Theorem: if $(x_1, x_2,, x_n)$ is a feasible solution for the primal maximization linear program and $(y_1, y_2,, y_m)$ is a feasible solution for the dual minimization linear program, then the weak duality theorem can be stated as $\sum_{j=1}^n w_j x_j \leq \sum_{i=1}^m b_i y_i$.

Proof: Suppose α is feasible for LP and β is feasible for LP*

$$A\alpha \leq b$$

$$\beta^{\mathsf{T}} A\alpha \leq \beta^{\mathsf{T}} b \qquad (because \ \beta \geq 0)$$

$$w^{\mathsf{T}} \alpha \leq \beta^{\mathsf{T}} b \qquad (A^{\mathsf{T}} \beta = w)$$

$$\therefore f(\alpha) \leq g(\beta)$$

Strong Duality Theorem

If the LP is feasible and optimal value w^* is bounded then $\exists \beta^* \in \mathbb{R}^m$ such that $A^T\beta^* = w$ and $\beta^* \geq 0$ with $b^T\beta^* = w^*$, i.e., $\mathrm{OPT}(\mathrm{LP}) = \mathrm{OPT}(\mathrm{LP}^*)$.