Duality in linear optimization

15.093: Optimization

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Dual problem: motivation and formulation

Lagrangian relaxation and duality

Consider a linear optimization problem, and relax the constraints
 → Assign a cost p_i to violating each constraint a_i^T x = b_i

$$(LO)$$
 min $oldsymbol{c}^ op oldsymbol{x}$ \longrightarrow $g(oldsymbol{p}) = \min$ $oldsymbol{c}^ op oldsymbol{x} + oldsymbol{p}^ op (oldsymbol{b} - oldsymbol{A} oldsymbol{x})$ s.t. $oldsymbol{A} oldsymbol{x} = oldsymbol{b}$ s.t. $oldsymbol{x} \geq oldsymbol{0}$

The relaxed problem provides a lower bound of the optimal cost

$$g(p) \leq c^{ op} x^* + p^{ op} \underbrace{(b - A x^*)}_{\text{O}} = c^{ op} x^*$$
 where x^* solves (LO)

 \rightarrow Seek the tightest possible lower bound: $\max g(\boldsymbol{p})$

$$g(\boldsymbol{p}) = \boldsymbol{p}^{\top} \boldsymbol{b} + \underbrace{\min_{\boldsymbol{x} \geq \boldsymbol{0}} \left((\boldsymbol{c}^{\top} - \boldsymbol{p}^{\top} \boldsymbol{A}) \boldsymbol{x} \right)}_{\boldsymbol{x} \geq \boldsymbol{0}} \longrightarrow \underbrace{\max_{\boldsymbol{x} \geq \boldsymbol{0}} \left((\boldsymbol{c}^{\top} - \boldsymbol{p}^{\top} \boldsymbol{A}) \boldsymbol{x} \right)}_{\boldsymbol{p} : \boldsymbol{p}^{\top} \boldsymbol{A} \leq \boldsymbol{c}^{\top}} \bigoplus_{\boldsymbol{dual problem}} \underbrace{p : \boldsymbol{p}^{\top} \boldsymbol{A} \leq \boldsymbol{c}^{\top}}_{\boldsymbol{dual problem}} \left(\boldsymbol{p} \right)$$

Dual formulation

Formulation (Dual of standard form problem)

Primal problem

$$\min \quad \boldsymbol{c}^{\top} \boldsymbol{x}$$

s.t.
$$Ax = b$$

$$x \ge 0$$

Dual problem

$$\max \ \mathbf{p}^{\top} \mathbf{b}$$

s.t.
$$\boldsymbol{p}^{\top} \boldsymbol{A} \leq \boldsymbol{c}^{\top}$$

Formulation (General form of the dual for minimization problems)

Primal problem

 $\min \ \boldsymbol{c}^{\top} \boldsymbol{x}$

s.t.
$$\boldsymbol{a}_i^{\top} \boldsymbol{x} \geq b_i, \ \forall i \in \mathcal{M}_1$$

$$\boldsymbol{a}_i^{\top} \boldsymbol{x} \leq b_i, \ \forall i \in \mathcal{M}_2$$

$$\boldsymbol{a}_i^{\top} \boldsymbol{x} = b_i, \ \forall i \in \mathcal{M}_0$$

$$x_j \ge 0, \ \forall j \in \mathcal{N}_1$$

$$x_j \le 0, \ \forall j \in \mathcal{N}_2$$

$$x_j$$
 free, $\forall j \in \mathcal{N}_0$

Dual problem

 $\boldsymbol{p}^{\top}\boldsymbol{b}$ max

s.t.
$$p_i > 0, \forall i \in \mathcal{M}_1$$

$$p_i \le 0, \ \forall i \in \mathcal{M}_2$$

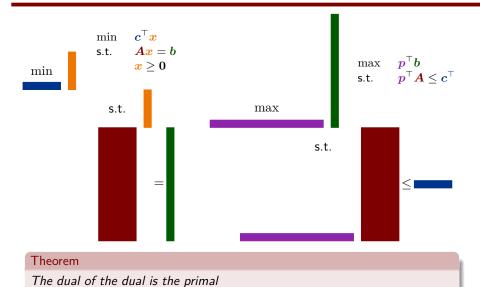
$$p_i$$
 free, $\forall i \in \mathcal{M}_0$

$$\boldsymbol{p}^{\top} \boldsymbol{A}_{j} \leq c_{j}, \ \forall j \in \mathcal{N}_{1}$$

$$\boldsymbol{p}^{\top} \boldsymbol{A}_j \geq c_j, \ \forall j \in \mathcal{N}_2$$

$$\mathbf{p}^{\top} \mathbf{A}_i = c_i, \ \forall j \in \mathcal{N}_0$$

Dual transformations



Example: manufacturing problem

Formulation (Primal problem)

$$\max \quad \pi_1 x_1 + \dots + \pi_n x_n$$
s.t.
$$a_{11} x_1 + \dots + a_{1n} x_n \le b_1$$

$$a_{21} x_1 + \dots + a_{2n} x_n \le b_2$$

$$\dots$$

$$a_{m1} x_1 + \dots + a_{mn} x_n \le b_m$$

$$x_1, \dots, x_n \ge 0$$

Formulation (Dual problem)

$$\min \quad b_1 p_1 + \dots + b_m p_m$$

$$s.t. \quad a_{11} p_1 + \dots + a_{m1} p_m \ge \pi_1$$

$$a_{12} p_1 + \dots + a_{m2} p_m \ge \pi_2$$

$$\dots$$

$$a_{1n} p_1 + \dots + a_{mn} p_m \ge \pi_n$$

$$p_1, \dots, p_m \ge 0$$

- Reminder on the manufacturing problem
 - Decisions: quantities of each of n products to manufacture
 - Maximize profit, subject to limited availability of m resources
- Dual formulation: perspective of a procurement division
 - Decision: amount paid for acquiring each resource
 - Minimize total spend, while ensuring that the supplier does not have incentives to sell products directly to your customers

Example: transportation problem

Formulation (Primal problem)

$$\min \quad \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

$$s.t. \quad \sum_{i=1}^{m} x_{ij} \ge d_{j}, \quad \forall j = 1, \cdots, n$$

$$\sum_{j=1}^{n} x_{ij} \le s_{i}, \quad \forall i = 1, \cdots, m$$

$$x_{ij} \ge 0, \quad \forall i, j$$

Formulation (Dual problem)

$$\max \quad -\sum_{i=1}^{m} s_i u_i + \sum_{j=1}^{n} d_j v_j$$
s.t.
$$v_j - u_i \le c_{ij}, \ \forall i, j$$

$$u_i \ge 0, \ \forall i$$

$$v_j \ge 0, \ \forall j$$

- Reminder on the transportation problem
 - Decisions: shipments from each of n factories to each of m markets
 - Minimize cost, subject to capacity restrictions and demand requirements
- Dual formulation: perspective of a third-party provider
 - Decision: price collected at destination (v_i) , amount paid at origin (u_i)
 - Maximize profit, as long as the company will not internalize shipping

Duality in linear optimization Duality theory

Duality theory

Weak duality

Theorem (Weak duality)

If x is primal feasible and p is dual feasible, then $p^ op b \leq c^ op x$

 $\bullet \ \, \mathsf{Proof:} \,\, p^\top b = p^\top (Ax) = (p^\top A)x \leq c^\top x \,\,\mathsf{since} \,\, p^\top A \leq c^\top \,\,\mathsf{and} \,\, x \geq 0$

Corollary

The optimal dual value is less than the optimal primal cost.

Corollary

If x is primal feasible, p is dual feasible, and $p^{\top}b = c^{\top}x$, then x is optimal in the primal and p is optimal in the dual.

$$\max p^{\top}b \longrightarrow \min c^{\top}x$$

Strong duality

Primal problem

$$\min \ \ oldsymbol{c}^ op oldsymbol{x}$$
 s.t. $oldsymbol{A} oldsymbol{x} = oldsymbol{b}$

 $x \ge 0$

Dual problem

$$\max \ \boldsymbol{p}^{\top} \boldsymbol{b}$$

s.t.
$${m p}^{ op}{m A} \leq {m c}^{ op}$$

Theorem (Strong duality)

If (LO) has an optimal solution, so does the dual, and the optimal dual value is equal to the optimal primal cost.

- Proof of strong duality
 - ullet Basic feasible solution: $oldsymbol{x} = [oldsymbol{x}_B \ oldsymbol{x}_N]$ with $oldsymbol{x}_B = oldsymbol{B}^{-1}oldsymbol{b}$, $oldsymbol{x}_N = oldsymbol{0}$
 - Optimality conditions from the simplex: $\bar{c}_i = c_i c_R^{\top} B^{-1} A_i > 0, \forall i$
 - Define $\boldsymbol{v}^{\top} = \boldsymbol{c}_{\scriptscriptstyle B}^{\top} \boldsymbol{B}^{-1}$
 - p is a feasible solution of the dual problem: $p^{\top} A_i = c_B^{\top} B^{-1} A_i \leq c_i$
 - Moreover, x and p achieve the same objective value:

$$oldsymbol{p}^{ op}oldsymbol{b} = oldsymbol{c}_B^{ op}oldsymbol{B}^{-1}oldsymbol{b} = oldsymbol{c}_B^{ op}oldsymbol{x}_B = oldsymbol{c}^{ op}oldsymbol{x}$$

ightarrow By weak duality, $m{x}$ and $m{p}$ optimal

Four possible outcomes in linear optimization

1. The primal problem is infeasible and the dual problem is infeasible

$$\max \ p^{\top} b = -\infty$$
 $\min \ c^{\top} x = +\infty$

2. The primal problem is unbounded and the dual problem is infeasible

$$\max \ \boldsymbol{p}^{\top}\boldsymbol{b} = -\infty \ \longleftarrow \quad \min \ \boldsymbol{c}^{\top}\boldsymbol{x}$$

3. The primal problem and the dual problem have the same optimal values

$$\max p^\top b \xrightarrow{\qquad} \min c^\top x$$

4. The primal problem is infeasible and the dual problem is unbounded

$$\max p^{\top}b \longrightarrow \min c^{\top}x = +\infty$$

Complementary slackness

Primal problem

$$egin{array}{ll} \min & oldsymbol{c}^ op oldsymbol{x} \ ext{s.t.} & oldsymbol{A} oldsymbol{x} \geq oldsymbol{b} \ & oldsymbol{x} \geq oldsymbol{0} \end{array}$$

Dual problem

$$egin{array}{ll} \max & oldsymbol{p}^{ op} oldsymbol{b} \ & ext{s.t.} & oldsymbol{p}^{ op} oldsymbol{A} \leq oldsymbol{c}^{ op} \ & oldsymbol{p} \geq oldsymbol{0} \end{array}$$

Theorem

Let x primal feasible and p dual feasible. x and p are optimal if and only if

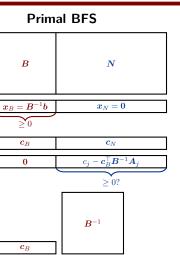
$$x_j(c_j - \boldsymbol{p}^{\top} \boldsymbol{A}_j) = 0, \ \forall j = 1, \cdots, n$$

 $p_i(\boldsymbol{a}_i^{\top} \boldsymbol{x} - b_i) = 0, \ \forall i = 1, \cdots, m$

- Interpretation
 - If a solution is non-zero, then its reduced cost is zero; vice versa, if a reduced cost is non-zero, then the solution is zero
 - If a dual price is non-zero, then the constraint is active (or binding); if a constraint is not active (or not binding), then the dual price is zero

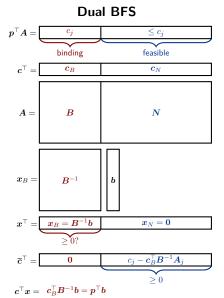
Primal feasibility, dual feasibility, and optimality

Standard form: primal and dual feasibility



 $c_B^{\top} B^{-1} A$

 $\leq c_j$?



binding

 $\boldsymbol{c}_B^{\top} \boldsymbol{x}_B$

A =

 c^{\top}

 $ar{c}^{ op}$

 $p^{\top}b =$

Standard form: feasibility and optimality conditions

Primal problem

 $egin{array}{ll} \min & oldsymbol{c}^{ op} oldsymbol{x} \ ext{s.t.} & oldsymbol{A} oldsymbol{x} = oldsymbol{b} \ & oldsymbol{x} \geq oldsymbol{0} \end{array}$

Basic solution:

$$\boldsymbol{x} = [\boldsymbol{x}_B \ \boldsymbol{x}_N], \quad \boldsymbol{x}_B = \boldsymbol{B}^{-1} \boldsymbol{b}$$

• Feasibility condition

$$\boldsymbol{B}^{-1}\boldsymbol{b} \geq \boldsymbol{0}$$

• Optimality condition:

$$\overline{oldsymbol{c}}^{ op} = oldsymbol{c}^{ op} - oldsymbol{c}_B^{ op} oldsymbol{B}^{-1} oldsymbol{A} \geq oldsymbol{0}^{ op}$$

- A primal BFS x defines a dual basic solution p
- If p is dual feasible, x is primal optimal and p is dual optimal

Dual problem

 $egin{array}{ll} \max & oldsymbol{p}^{ op} oldsymbol{b} \ & ext{s.t.} & oldsymbol{p}^{ op} oldsymbol{A} \leq oldsymbol{c}^{ op} \end{array}$

Dual basic solution:

$$oldsymbol{p}^ op = oldsymbol{c}_B^ op oldsymbol{B}^{-1}$$

Feasibility condition

$$\overline{\boldsymbol{c}}^{\top} = \boldsymbol{c}^{\top} - \boldsymbol{c}_{B}^{\top} \boldsymbol{B}^{-1} \boldsymbol{A} \geq \boldsymbol{0}^{\top}$$

• Optimality condition:

$$oldsymbol{B}^{-1}oldsymbol{b} \geq oldsymbol{0}$$

- ullet A dual BFS p defines a primal basic solution x
- If x is primal feasible, x is primal optimal and p is dual optimal

Summary and visualization

Primal problem **Dual problem** $\max p^{\top}b$ primal feasible, dual infeasible dual feasible, primal feasible dual feasible, primal infeasible $\min \ \boldsymbol{c}^{\top} \boldsymbol{x}$

Problem in general form

Primal problem

$$\min \ oldsymbol{c}^ op oldsymbol{x}$$

s.t.
$$\boldsymbol{a}_i^{\top} \boldsymbol{x} \geq b_i, \ \forall i = 1, \cdots, m$$

Dual problem

$$\max \quad \boldsymbol{p}^{\top}\boldsymbol{b}$$

s.t.
$$\sum_{i=1}^m p_i \boldsymbol{a}_i = \boldsymbol{c}$$

$$oldsymbol{p} \geq oldsymbol{0}$$

• Consider a non-degenerate basic feasible solution x^I :

$$m{a}_i^{ op} m{x}^I = b_i, i \in I, \quad \text{with } |I| = n \text{ and } \{ m{a}_i : i \in I \} \text{ linearly independent}$$

• Let $p \in \mathbb{R}^m$; what does it take for x^I and p to be optimal?

Primal feasibility

Comp. slackness

Dual feasibility

$$\boldsymbol{a}_i^{\top} \boldsymbol{x}^I \geq b_i, \forall i \in I$$

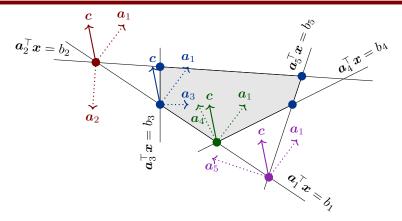
$$p_i = 0, \ \forall i \notin I$$

$$p_i = 0, \ \forall i \notin I$$

$$\sum_{i \in I} p_i \boldsymbol{a}_i = \boldsymbol{c}, \ \boldsymbol{p} \geq \boldsymbol{0}$$

- \rightarrow Primal feasibility: x^I on the "correct side" of all hyperplanes $a_i^\top x \geq b_i$
- \rightarrow Dual feasibility: the cost vector c can be written as a non-negative linear combination of vectors defining active constraints

Geometry of duality



- Solution that is primal infeasible and dual infeasible
- Solution that is primal feasible and dual infeasible
- Solution that is primal infeasible and dual feasible
- Solution that is primal feasible and dual feasible, hence optimal

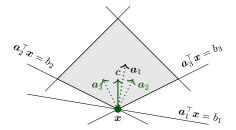
Duality and degeneracy

- A non-degenerate primal solution defines a unique dual solution
 - $m{x}$ is defined by a unique subset I such that $m{a}_i^{ op} m{x} = b_i, \ orall i \in I$
 - o $m{x}$ is associated with a unique dual solution $m{p}$, such that $\sum_{i \in I} p_i m{a}_i = m{c}$
- Now, what if x is a degenerate solution?
 - There exist several subsets I such that $\boldsymbol{a}_i^{\top} \boldsymbol{x} = b_i, \ \forall i \in I$
 - ullet Each subset I induces a dual solution $oldsymbol{p}^I$, such that $\sum_{i\in I} p_i^I oldsymbol{a}_i = oldsymbol{c}$
 - ullet x is optimal as long as \emph{one} of the p^I solutions is dual feasible

Dual infeasible solution

a_2^{\uparrow} b_2 a_3^{\uparrow} a_2 a_1^{\uparrow} a_2 a_1^{\uparrow} a_2 a_1^{\uparrow} a_2 a_1^{\uparrow} a_2

Dual feasible solution



Conclusion

Summary

Takeaway

Dual formulation: one dual variable per primal constraint, one dual constraint per primal variable, with appropriate dual transformations

Takeaway

A feasible dual solution yields a lower bound to the primal problem.

Takeaway

There is no "duality gap" in linear optimization: if the problem admits an optimal solution, so does its dual and both optimal values coincide.

Takeaway

Each basis defines a basic primal solution and a basic dual solution. If both solutions are feasible, then they are both optimal.