

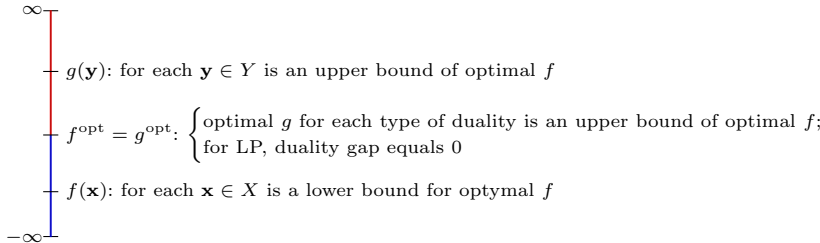
LP duality:

Primal problem	Dual problem
\max s.t.: $X = \{\mathbf{Ax} \leq \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$	\min s.t.: $Y = \{\mathbf{A}^T \mathbf{y} \geq \mathbf{c}, \mathbf{y} \geq \mathbf{0}\}$
Goal function (max \mathbf{cx})	Right-hand side \mathbf{c}
Right-hand side \mathbf{b}	Goal function (min \mathbf{by})
\mathbf{A} : matrix of constraints	\mathbf{A}^T : matrix of constraints
Unbounded	Infeasible
Infeasible	Unbounded or infeasible

Weak duality: $\forall \mathbf{x} \in X \forall \mathbf{y} \in Y \mathbf{cx} \leq \mathbf{by}$

Strong duality (duality principle): $f^{\text{opt}} = g^{\text{opt}}$

Bounds (primal problem is neither infeasible nor unbounded):



Lagrangian dual:

Primal problem: $\max z = F(\mathbf{x}), h_i(\mathbf{x}) = 0, i = 1, \dots, k, g_j(\mathbf{x}) \geq 0, j = 1, \dots, m, \mathbf{x} \in X$ (X can be itself defined with a set of equalities and inequalities).

Lagrangian function: $L(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\lambda}) = F(\mathbf{x}) + \sum_i \mu_i h_i(\mathbf{x}) + \sum_j \lambda_j g_j(\mathbf{x})$

Dualization of constraints: equalities $h_i(\mathbf{x}) = 0, i = 1, \dots, k$ and inequalities $g_j(\mathbf{x}) \geq 0, j = 1, \dots, m$

Dual variables (defined so that a proper relaxation is obtained): $\mu_i \in \mathbb{R}, \lambda_j \in \mathbb{R}, \lambda_j \geq 0$

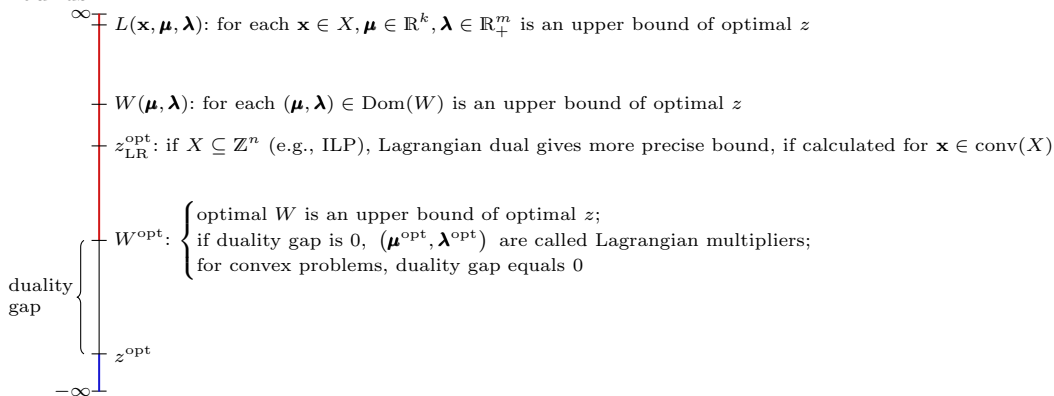
Lagrangian relaxation: $\max L(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\lambda}), \mathbf{x} \in X, \boldsymbol{\mu} \in \mathbb{R}^k, \boldsymbol{\lambda} \in \mathbb{R}_+^m$

Dual function: $W(\boldsymbol{\mu}, \boldsymbol{\lambda}) = \max_{\mathbf{x} \in X} L(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\lambda})$

Domain of a dual function: $\text{Dom}(W) = \{(\boldsymbol{\mu}, \boldsymbol{\lambda}) \mid \boldsymbol{\mu} \in \mathbb{R}^k, \boldsymbol{\lambda} \in \mathbb{R}_+^m, W(\boldsymbol{\mu}, \boldsymbol{\lambda}) < \infty\}$

Lagrangian dual: $\min W(\boldsymbol{\mu}, \boldsymbol{\lambda}), (\boldsymbol{\mu}, \boldsymbol{\lambda}) \in \text{Dom}(W)$

Bounds:



For a convex problem:

- X : convex set,
- h_i : linear functions,
- g_j : functions convex on X ,
- $\min F$ (F : convex on X) or $\max F$ ($-F$: convex on X).

we have the following properties:

- duality gap equals 0,
- complementary slackness,
- saddle point: $W(\boldsymbol{\lambda}^{\text{opt}}) = L(\mathbf{x}^{\text{opt}}; \boldsymbol{\lambda}^{\text{opt}})$.