

MS-E2122 - Nonlinear Optimization

Lecture 10

Fabricio Oliveira

Systems Analysis Laboratory
Department of Mathematics and Systems Analysis

Aalto University
School of Science

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Outline of this lecture

Barrier functions

Barrier method

Interior point method for LP/ QP

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Interior point method for LP/ QP

Barrier functions

Same idea as in penalty methods: turn constrained optimisation unconstrained and solve them iteratively.

Main difference: **barrier functions** prevent the search from **leaving the feasible region**. Consider the primal problem P

$$\begin{aligned}(P) : \quad & \min. \quad f(x) \\ & \text{subject to: } g(x) \leq 0 \\ & x \in X.\end{aligned}$$

$$f(x) = \frac{1}{x}$$

$$\hookrightarrow x > 0$$

Barrier functions

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$$\begin{aligned}(P) : \quad & \min. \quad f(x) \\ & \text{subject to: } g(x) \leq 0 \\ & \quad \quad x \in X.\end{aligned}$$

We define the **barrier problem** BP as

$$\begin{aligned}(BP) : \quad & \inf_{\mu} \theta(\mu) \\ & \text{subject to: } \mu > 0,\end{aligned}$$

where $\theta(\mu) = \inf_x \{f(x) + \mu B(x) : g(x) < 0, x \in X\}$ and $B(x)$ is a **barrier function**.

Barrier functions

The barrier function $B : \mathbb{R}^m \rightarrow \mathbb{R}$ is such that

$$B(x) = \sum_{i=1}^m \phi(g_i(x)), \text{ where } \begin{cases} \phi(y) \geq 0, & \text{if } y < 0; \\ \phi(y) = \infty, & \text{when } y \rightarrow 0^-. \end{cases}$$

$$g(x) \leq 0$$




Barrier functions

The barrier function $B : \mathbb{R}^m \rightarrow \mathbb{R}$ is such that

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Some common alternatives include

- ▶ $B(x) = -\sum_{i=1}^m \frac{1}{g_i(x)}$  $g_i(x) < 0$
- ▶ $B(x) = -\sum_{i=1}^m \ln(\min\{1, -g_i(x)\})$.

Perhaps the most important is **Frisch's log barrier function**

$$B(x) = -\sum_{i=1}^m \ln(-g_i(x)).$$

Barrier functions

Ideally, $B(x)$ would serve as an **indicator function**

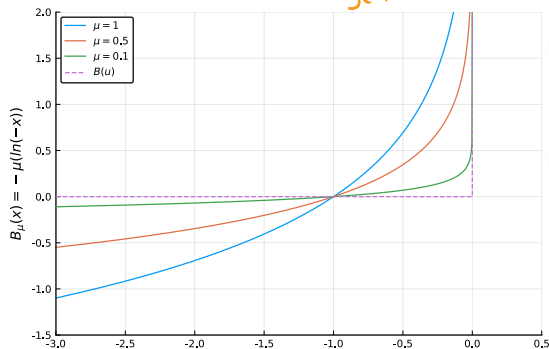
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To avoid numerical issues, the shape of $B(x)$ is controlled by μ .



- ▶ As $\mu \rightarrow 0^+$, $B(x)$ becomes closer to an **indicator function**.
- ▶ Notice that $B(x) > 0$ is not required for all feasible points, but must be so for those near $g(x) \leq 0$.

Barrier functions

We will proceed by repeatedly solving $\theta(\mu)$ and **iteratively reducing** the value of μ . For that to work, we need the following result.

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Theorem 1 (Convergence of barrier methods)

$$l \leq x \leq u$$

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$ be continuous functions and $X \in \mathbb{R}^n$ a nonempty closed set in problem P . Suppose $\{x: g(x) < 0, x \in X\}$ is not empty. Let \bar{x} be the optimal solution of P such that, for any neighbourhood $N_\epsilon(\bar{x}) = \{x: \|x - \bar{x}\| \leq \epsilon\}$, there exists $x \in X \cap N_\epsilon$ for which $g(x) < 0$. Then

$$\min \{f(x) : g(x) \leq 0, x \in X\} = \lim_{\mu \rightarrow 0^+} \theta(\mu) = \inf_{\mu > 0} \theta(\mu).$$

BP

$$\lambda < \mu$$

$$1) B(x_\lambda) \geq B(x_\mu)$$

Letting $\theta(\mu) = f(x_\mu) + \mu B(x_\mu)$, where $B(x)$ is a barrier function observing (1), $x_\mu \in X$, and $g(x_\mu) < 0$, the limit of $\{x_\mu\}$ is optimal to P and $\mu B(x_\mu) \rightarrow 0$ as $\mu \rightarrow 0^+$.

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Outline of this lecture

Barrier functions

Barrier method

Interior point method for LP/ QP

Barrier method

Algorithm Barrier method

- 1: **initialise.** $\epsilon > 0, x^0 \in X$ with $g(x^k) < 0, \mu^k, \beta \in (0, 1), k = 0$.
 - 2: **while** $\mu^k B(x^k) > \epsilon$ **do**
 - 3: $\bar{x}^{k+1} = \arg \min \{f(x) + \mu^k B(x) : x \in X\}$ *\rightarrow unc. optimisation.*
 - 4: $\mu^{k+1} = \beta \mu^k, k = k + 1$
 - 5: **end while**
 - 6: **return** x^k .
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Barrier method

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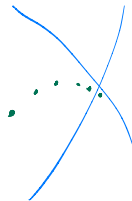
$$\bar{x}^{k+1} \Rightarrow d^{k+1} = \bar{x}^{k+1} - \bar{x}^k$$

$$\bar{x}^{k+1} = \bar{x}^k + d^{k+1}$$

$\lambda=1$

Remarks:

1. Notice that, starting with $x^0 \in X$ with $g(x^0) < 0$, x^k for all $k > 1$ satisfies $g(x^k) < 0$ due to the barrier function.
2. However, applying the barrier method using a fixed step size may cause infeasibility issues.
3. Due to 1., these methods are called **interior point methods**.



Barrier method

Example 1: $P = \min. \{ \underbrace{(x+1)^2}_{f(x)} : \underbrace{x \geq 0}_{g(x) = -x} \}$ with $B(x) = -\ln(x)$

$$\text{BP: } (x+1)^2 - \mu \ln(-x) =: f_\mu(x)$$

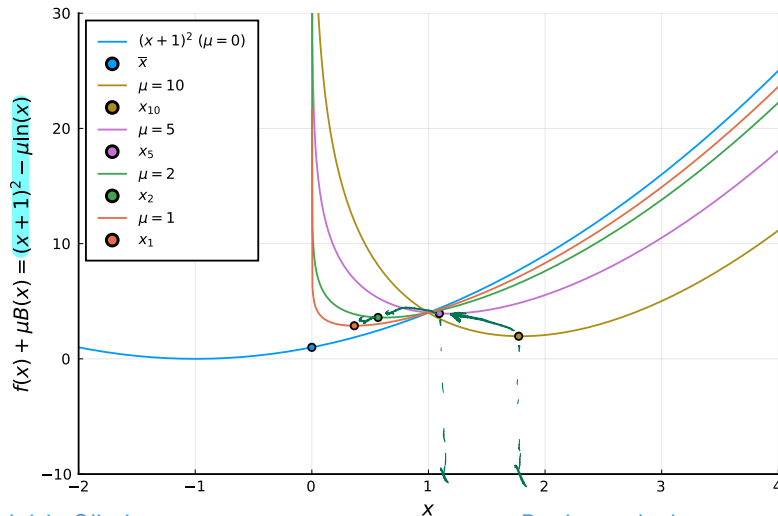
$$f'_\mu(x) = 0 \Rightarrow 2(x+1) - \frac{\mu}{x} =$$

$$2x^2 + x - \mu = 0 \Rightarrow x_\mu = -\frac{1}{2} + \frac{\sqrt{4+8\mu}}{4}$$

$$\mu \rightarrow 0^+ \Rightarrow x_\mu = 0$$

Barrier method

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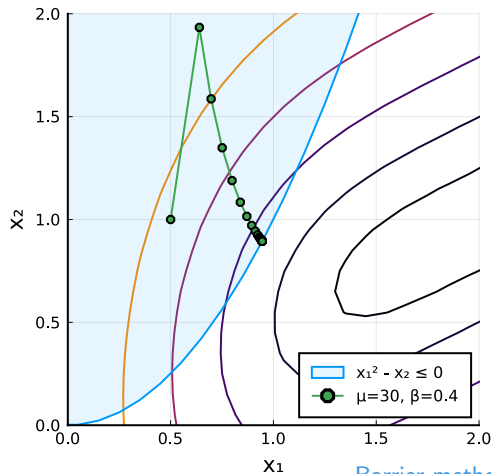
Barrier method

Example 2: $P = \min. \{ \underbrace{(x_1 - 2)^4 + (x_1 - 2x_2)^2}_{f(x)} : x_1^2 - x_2 \leq 0 \}$
with $B(x) = -\frac{1}{x_1^2 - x_2}$.

$$f_{\mu}(x) = \frac{f(x)}{f(x)} - \mu \cdot \left(\frac{1}{(x_1^2 - x_2)} \right)$$

Barrier method

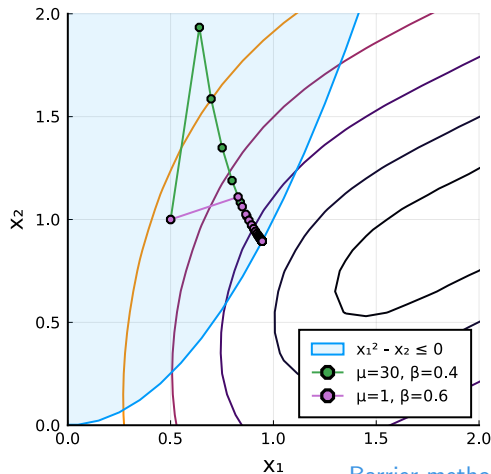
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$$f_{\mu}(x) = f(x) + \mu B(x)$$

Barrier method

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Interior point methods for LP/QP

Consider the following LP and its dual

$$(P) : \min. \quad c^\top x$$

$$\text{subject to: } Ax = b \quad : v$$

$$x \geq 0 \quad : u$$

$$(D) : \max. \quad b^\top v$$

$$\text{subject to: } A^\top v + u = c$$

$$u \geq 0, v \in \mathbb{R}^m.$$

Interior point methods for LP/QP

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$$u \geq 0, v \in \mathbb{R}^m.$$

The optimal solution $(\bar{x}, \bar{v}, \bar{u}) = \bar{w}$ satisfies KKT conditions of P :

$$Ax = b, \quad x \geq 0$$

$$A^\top v + u = c, \quad u \geq 0, \quad v \in \mathbb{R}^m$$

$$u^\top x = 0.$$

$$c^\top x + (b - Ax)^\top v - v^\top x$$

Let us consider the **barrier problem** for P by using the logarithmic barrier function.

Interior point methods for LP/QP

The barrier problem is given by:

$$(BP) : \min. \quad c^T x - \mu \sum_{i=1}^n \ln(x_i)$$

subject to: $Ax = b$.

$$g(x) = -x$$

$$\min \quad c^T x$$

$$\bar{A}x \leq \bar{b}$$

$$Ax \leq b$$

$$x \geq 0$$

$$\Downarrow$$

$$\bar{A}x + s = \bar{b}$$

$$Ax = b$$

$$x, s \geq 0$$

$$\begin{array}{l} \bar{A}\bar{x} = \bar{b} \\ \bar{x} \geq 0 \end{array} \xrightarrow{\Downarrow} \begin{bmatrix} \bar{A} \\ A \end{bmatrix} \begin{bmatrix} \bar{x} \\ x \end{bmatrix} = \begin{bmatrix} \bar{b} \\ b \end{bmatrix}$$

Interior point methods for LP/QP

The barrier problem is given by:

$$(BP) : \min. \quad c^\top x - \mu \sum_{i=1}^n \ln(x_i)$$

subject to: $Ax = b$.

The KKT conditions of BP are

$$Ax = b, \quad x > 0 \quad \Bigg| \quad A^\top v = c - \mu \left(\frac{1}{x_1}, \dots, \frac{1}{x_n} \right).$$

Notice that since $\mu > 0$ and $x > 0$, $u = \mu \left(\frac{1}{x_1}, \dots, \frac{1}{x_n} \right)$ serve as an estimate for the Lagrangian dual variables.

Interior point methods (IPM) for LP/QP

Let $X \in \mathbb{R}^{n \times n}$ and $U \in \mathbb{R}^{n \times n}$ be defined as

$$X = \mathbf{diag}(x) = \begin{bmatrix} \ddots & & \\ & x_i & \\ & & \ddots \end{bmatrix} \text{ and } U = \mathbf{diag}(u) = \begin{bmatrix} \ddots & & \\ & u_i & \\ & & \ddots \end{bmatrix}$$

and let $e = [1, \dots, 1]^\top$ be a vector of ones of suitable dimension.

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We can rewrite the KKT conditions of BP as

$$\begin{aligned} X^{-1} &= \begin{bmatrix} \frac{1}{x_1} & & \\ & \ddots & \\ & & \frac{1}{x_n} \end{bmatrix} & Ax = b, \quad x > 0 & (2) \\ & A^\top v + u = c & (3) \\ u = \mu X^{-1} e & \Rightarrow XUe = \mu e & (4) \end{aligned}$$

$$\begin{aligned} Ax &= b \\ A^\top v + u &= c \\ X^\top u &= 0 \end{aligned}$$

Remark: condition (3) is called relaxed complementarity condition with 0 replaced by μ . This is known as the **perturbed KKT system**.

Interior point methods (IPM) for LP/QP

According to [Theorem 1](#), $w_\mu = (x_\mu, v_\mu, u_\mu)$ approaches the optimal primal-dual solution of P as $\mu \rightarrow 0^+$.

Remarks:

1. The trajectory formed by successive solutions $\{w_\mu\}$ is called a **central path** due to its interiority forced by the barrier function.

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2. Notice that $XUe = \mu e \Rightarrow u_i x_i = \mu$ for all $i = 1, \dots, n$.
3. $c^T x - b^T v = u^T x$ measures the **duality gap** for the current μ .

$$\begin{aligned} c^T x &= (A^T v + u)^T x \\ &= (A^T v)^T x + u^T x \\ &= v^T (\underbrace{Ax}_b) + u^T x \end{aligned}$$

$$\begin{aligned} c^T x - v^T b &= u^T x \\ &= \sum_{i=1}^n u_i x_i \\ &= \sum_{i=1}^n \frac{\mu}{x_i} \cdot x_i \Rightarrow n \cdot \mu \end{aligned}$$

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2. Notice that $XUe = \mu e \Rightarrow u_i x_i = \mu$ for all $i = 1, \dots, n$.
3. $c^\top x - b^\top v = u^\top x$ measures the **duality gap** for the current μ .
4. Also, $u^\top x = \sum_{i=1}^n u_i x_i = n\mu$ is equal to the total **slack violation** and can be used as a stopping condition.

The notion of interiority

For large enough μ , the solution of the barrier problem is close to the **analytic centre** of the feasibility set.

The notion of interiority

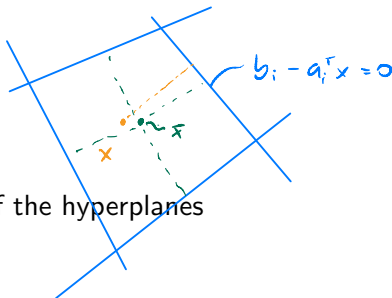
For large enough μ , the solution of the barrier problem is close to the **analytic centre** of the feasibility set.

The analytic centre of a polyhedral set $S = \{x \in \mathbb{R}^n : Ax \leq b\}$ is given by the solution of

$$\max_x \prod_{i=1}^m (b_i - a_i^\top x)$$

subject to: $x \in X$,

i.e., finding $\bar{x} \in S$ of **maximum distance** to each of the hyperplanes $a_i^\top x = b_i$.



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i.e., finding $\bar{x} \in S$ of **maximum distance** to each of the hyperplanes $a_i^\top x = b_i$. This is equivalent to

$$\min_x \sum_{i=1}^m -\ln(b_i - a_i^\top x)$$

subject to: $x \in X$.

~~$c^\top x - \mu \ln(x)$~~ $\left(\begin{array}{l} a_i^\top x + s = b_i \\ \bar{a}_i^\top \bar{x} = \bar{b}_i \end{array} \right)$

IPM for LP/QP: primal/dual method

Primal/dual path following method is a specialisation of IPM to linear and quadratic problems.

It combines BP with one “additional trick”: instead of solving BP to optimality, perform a single Newton step for each μ .

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Suppose we start with a $\bar{\mu} > 0$ and a $w^k = (x^k, v^k, u^k)$ sufficiently close to $w_{\bar{\mu}}$. Then, for a sufficiently small $\beta \in (0, 1)$, $\beta\bar{\mu}$ will lead to a w^{k+1} sufficiently close to $w_{\beta\bar{\mu}}$.

Remark: β is typically related to **convergence results**. Values like $\mu^0 = (x^\top u)/n$ and $\beta \in [0.1, 0.5]$ are often used in practice.

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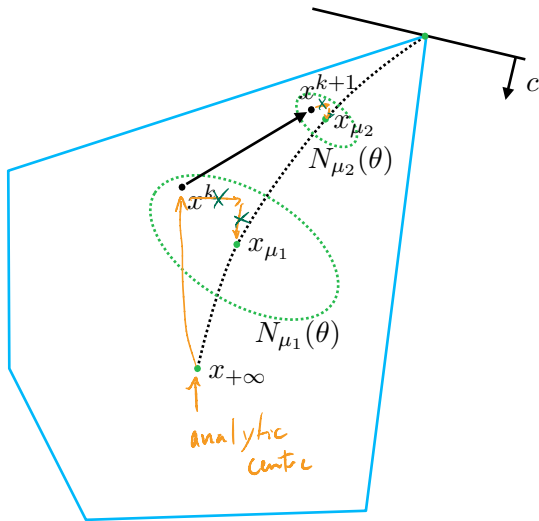
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For example, let $N_\mu(\theta) = \|X_\mu U_\mu e - \mu e\| \leq \theta\mu$. Then, by selecting $\beta = 1 - \frac{\sigma}{\sqrt{n}}$, $\sigma = \theta = 0.1$, and $\mu^0 = (x^\top u)/n$, successive Newton steps **are guaranteed to remain** within $N_\mu(\theta)$.

Further reading: see this reference ([link](#)) for more details.

IPM for LP/QP: primal/dual method



IPM for LP/QP: primal/dual method

Let the perturbed KKT system (2) – (4) for each $\hat{\mu}$ be denoted as $H(w) = 0$. Let $J(\bar{w})$ be the **Jacobian** of $H(w)$ at \bar{w} .

Applying **Newton's method** to solve $H(w) = 0$ for \bar{w} , we obtain

$$J(\bar{w})d_w = -H(\bar{w}) \quad (5)$$

where $d_w = (w - \bar{w})$.

$$H(w) = \begin{vmatrix} Ax - b \\ Av + u - c \\ Xu - \mu e \end{vmatrix}$$

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where $d_w = (w - \bar{w})$. By rewriting $d_w = (d_x, d_v, d_u)$, (5) can be equivalently stated as

$$\begin{aligned} Ad_x &= 0 \\ A^\top d_v + d_u &= 0 \quad \beta/\hat{\mu} \\ \bar{U}d_x + \bar{X}d_u &= \hat{\mu}e - \bar{X}\bar{U}e. \end{aligned}$$

$\bar{v} \quad \uparrow \quad \uparrow \quad \bar{x}$

The algorithm proceeds by **iteratively solving** the above system with $\mu^{k+1} = \beta\mu^k$ with $\beta \in (0, 1)$ until $n\mu^k$ is **small enough**.

IPM for LP/QP: primal/dual method

Remark: Notice that **primal feasibility conditions** are included in the system $H(w) = 0$. This is typically referred to as the **equality constrained Newton's method** with “Newton system”

$$J(w) = \begin{bmatrix} A & 0^\top & 0 \\ 0 & A^\top & I \\ \overline{U} & 0^\top & \overline{X} \end{bmatrix} \begin{bmatrix} d_x \\ d_v \\ d_u \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \hat{\mu}e - \overline{X}\overline{U}e \end{bmatrix}. \quad (6)$$

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In practice, updates **incorporate primal and dual infeasibility**, which can be shown to **vanish** as the algorithm progress. Updates become

$$\begin{bmatrix} A & 0^\top & 0 \\ 0 & A^\top & I \\ U^k & 0^\top & X^k \end{bmatrix} \begin{bmatrix} d_x^{k+1} \\ d_v^{k+1} \\ d_u^{k+1} \end{bmatrix} = - \begin{bmatrix} Ax^k - b \\ Av + u - c \\ X^k U^k e - \mu^{k+1} e \end{bmatrix}, \quad (7)$$

Handwritten notes: "primal inf" above $Ax^k - b$; "dual inf" next to $Av + u - c$ and $X^k U^k e - \mu^{k+1} e$.

where $\mu^{k+1} = \beta\mu^k$.

IPM for LP/QP: primal/dual method

Let the residuals (i.e., the amount of **infeasibility**) be

$$r_p(x, u, v) = Ax - b \text{ (primal); } r_d(x, u, v) = A^T v + u - c \text{ (dual).}$$

Let $r(w) = r(x, u, v) = (r_p(x, u, v), r_d(x, u, v))$. The optimality conditions (6) **require the residuals to vanish**, that is $r(\bar{w}) = 0$.

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Consider the first-order approximation for r at w for a step d_w

$$r(w + d_w) \approx r(w) + Dr(w)d_w,$$

where $Dr(w)$ is the derivative of r evaluated at w . The step d_w for which the residue vanishes is $Dr(w)d_w = -r(w)$ (cf. (7)).

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The **directional derivative** of $\|r(w + td_w)\|_2^2$ in the direction d_w is

$$\left. \frac{d}{dt} \|r(w + td_w)\|_2^2 \right|_{t \rightarrow 0^+} = 2r(w)^\top Dr(w)d_w = \overbrace{-2r(w)^\top r(w)}^{\approx 0} \leq 0$$

which is **strictly decreasing**.

$$= 2r(w + td_w) \cdot Dr(w + td_w) \cdot d_w$$

IPM for LP/QP: primal/dual method

Algorithm Interior point method for LP

- 1: **initialise.** primal-dual feasible w^k , $\epsilon > 0$, μ^k , $\beta \in (0, 1)$, $k = 0$.
 - 2: **while** $n\mu = c^\top x^k - b^\top v^k > \epsilon$ **do**
 - 3: compute $d_{w^{k+1}} = (d_{x^{k+1}}, d_{v^{k+1}}, d_{u^{k+1}})$ using (7) and w^k .
 - 4: $w^{k+1} = w^k + d_{w^{k+1}}$
 - 5: $\mu^{k+1} = \beta\mu^k$, $k = k + 1$
 - 6: **end while**
 - 7: **return** w^k .
-

IPM for LP/QP: primal/dual method

Algorithm Interior point method for LP

- 1: **initialise.** primal-dual feasible w^k , $\epsilon > 0$, μ^k , $\beta \in (0, 1)$, $k = 0$.
 - 2: **while** $n\mu = c^\top x^k - b^\top v^k > \epsilon$ **do**
 - 3: compute $d_w^{k+1} = (d_x^{k+1}, d_v^{k+1}, d_u^{k+1})$ using (7) and w^k .
 - 4: $w^{k+1} = w^k + d_w^{k+1}$ λ = 1
 - 5: $\mu^{k+1} = \beta\mu^k$, $k = k + 1$
 - 6: **end while**
 - 7: **return** w^k .
-

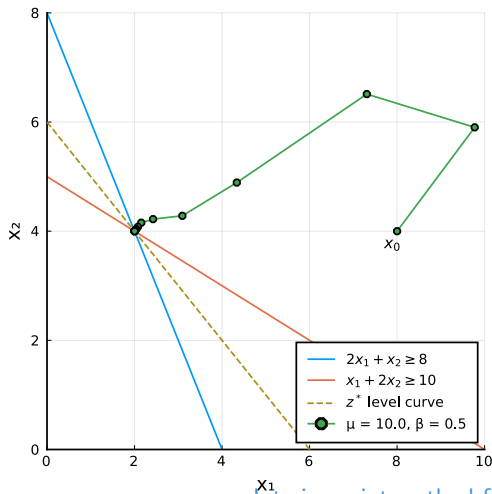
Remarks:

1. Notice that the step size is set to one. A **line search** could be performed between Lines 3 and 4.
2. This method has **polynomial complexity** which, under specific conditions, can be shown to be $O(\sqrt{n} \ln(1/\epsilon))$.

The primal-dual interior point (IP) method

Example:

min. $z = x_1 + x_2 : 2x_1 + x_2 \geq 8, x_1 + 2x_2 \geq 10, x_1, x_2 \geq 0$.



The primal-dual interior point (IP) method

Example:

min. $z = x_1 + x_2 : 2x_1 + x_2 \geq 8, x_1 + 2x_2 \geq 10, x_1, x_2 \geq 0.$

