

$$1. \min f(x) = \frac{1}{2} x^T P x + q^T x$$

$$\text{s.t. } Ax = b$$

$$\text{最优性条件 } \begin{cases} Ax^* = b \\ Px^* + q + A^T v^* = 0 \end{cases}$$

infeasible start 的牛顿法.

$$\begin{pmatrix} P & A^T \\ A & 0 \end{pmatrix} \begin{pmatrix} \Delta x_{pd} \\ \Delta v_{pd} \end{pmatrix} = - \begin{pmatrix} Px + q + A^T v \\ Ax - b \end{pmatrix}$$

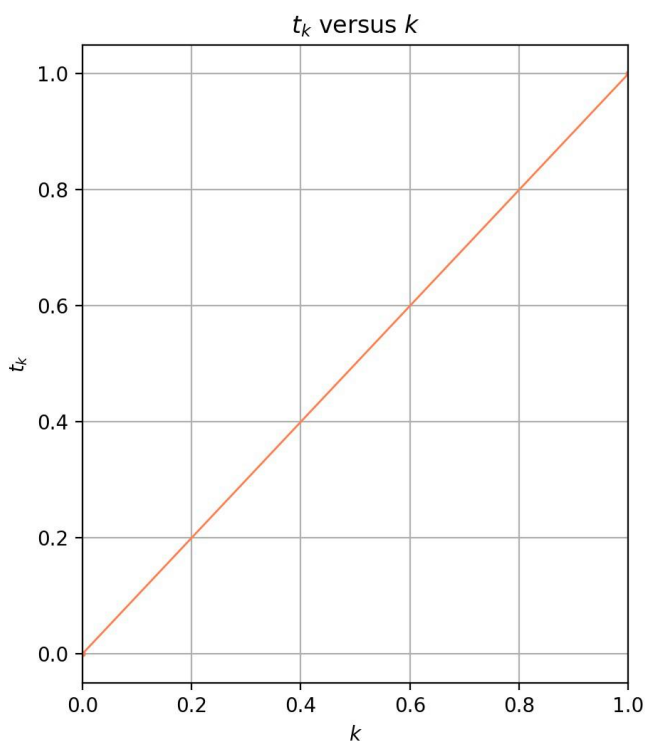
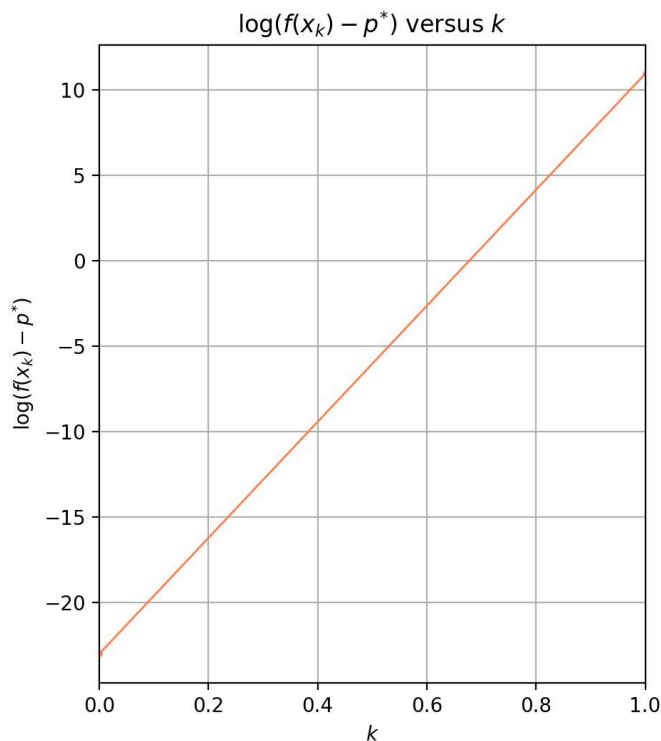
$$r(x, v) = \begin{pmatrix} Px + q + A^T v \\ Ax - b \end{pmatrix} = \begin{pmatrix} r_{dual} \\ r_{pri} \end{pmatrix}$$

$$\text{终止条件 } \lambda^2(x) = \Delta x_{int}^T \nabla^2 f(x) \Delta x_{int} < 10^{-5}$$

$$\text{超参数 } \alpha = 0.4, \beta = 0.5$$

$$\text{初值 } x^{(0)} = \mathbf{1}^{200}, v^{(0)} = \mathbf{1}^{100}.$$

图像如下:



原问题最优解 x^* 、对偶问题最优解 v^* 、函数最优值 p^* 见 [./results/T1.txt](#)

$$2. \min f(x) = \frac{1}{2} x^T P x + q^T x$$

$$\text{s.t. } Ax = b$$

$$x \geq 0.$$

①. 障碍函数法.

$\frac{n}{t}$ 次优的优化问题.

$$\min \quad t f(x) + \phi(x) = \frac{1}{2} t x^T P x + t q^T x - \sum_{i=1}^n \log(x_i)$$

$$\text{s.t. } Ax = b.$$

$$\nabla f(x) = Px + q, \quad \nabla^2 f(x) = P.$$

$$\nabla \phi(x) = \begin{pmatrix} -1/x_1 \\ \vdots \\ -1/x_n \end{pmatrix}, \quad \nabla^2 \phi(x) = \begin{pmatrix} 1/x_1^2 & & 0 \\ & \ddots & \\ 0 & & 1/x_n^2 \end{pmatrix}$$

infeasible start 的牛顿法 (第一个循环).

$$\begin{pmatrix} t \nabla f(x) + \nabla \phi(x) & A^T \\ A & 0 \end{pmatrix} \begin{pmatrix} \Delta x_{pd} \\ \Delta v_{pd} \end{pmatrix} = - \begin{pmatrix} t \nabla f(x) + \nabla \phi(x) + A^T v \\ Ax - b \end{pmatrix} = -r(x, v)$$

$$\text{终止条件 } \|r(x, v)\|_2 < 10^{-8}$$

feasible start 的牛顿法 (第二个及之后的循环)

$$\begin{pmatrix} t \nabla f(x) + \nabla \phi(x) & A^T \\ A & 0 \end{pmatrix} \begin{pmatrix} \Delta x_{nt} \\ w \end{pmatrix} = \begin{pmatrix} -t \nabla f(x) - \nabla \phi(x) \\ 0 \end{pmatrix}$$

$$\text{终止条件: } \frac{1}{2} \lambda^2(x) < 10^{-8}$$

$$\frac{n}{t} < \varepsilon = 10^{-8} \text{ 后, 退出循环.}$$

$$\text{解出 } x^* \text{ 后, } \lambda_i^* = -\frac{1}{t \cdot (-x_i)} = \frac{1}{t x_i}$$

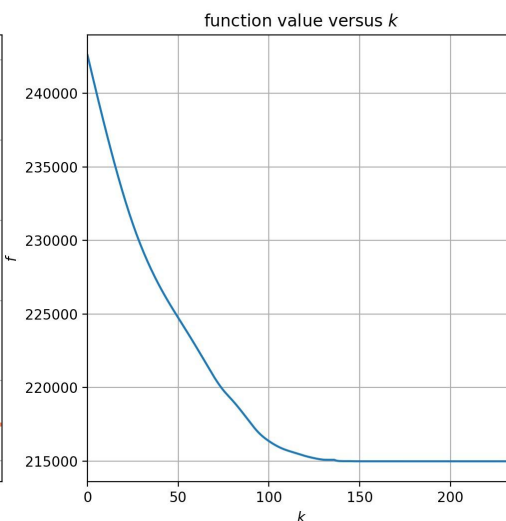
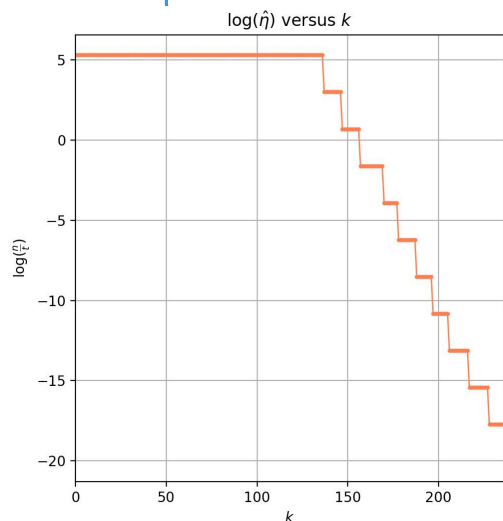
$$v_i^* = \frac{\hat{v}_i}{t} = \frac{w_i}{t}$$

回溯直线搜索 $\alpha = 0.1, \beta = 0.5.$

$$\mu = 10.$$

图像如下:

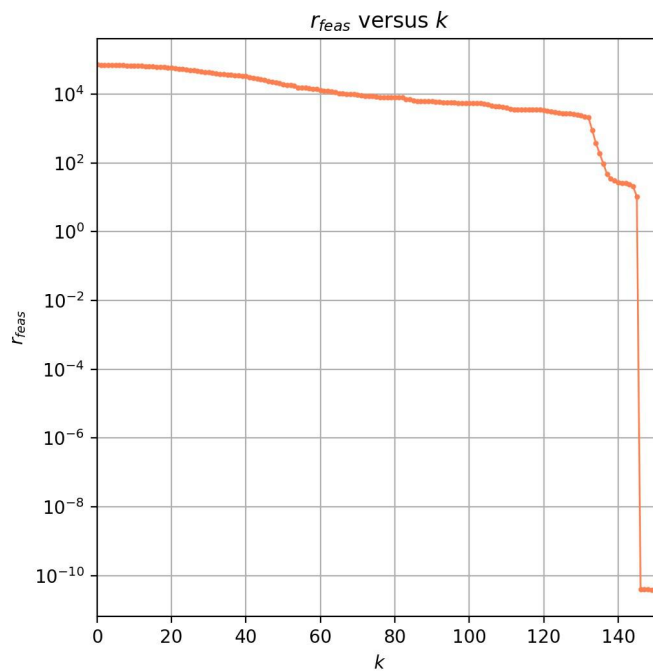
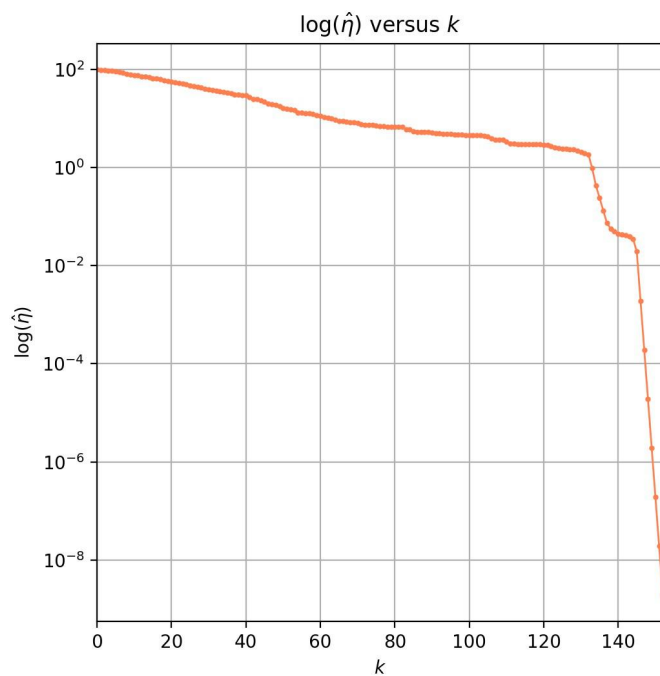
原问题最优解 x^* 、对偶问题最优解 λ^* 和 v^* 、函数最优值 p^* 见 ./results/T2_a.txt



②. 原对偶内点法.

$$\begin{pmatrix} \nabla^2 f(x) & -I_{200} & A^T \\ \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_{200} \end{pmatrix} & \begin{pmatrix} x_1 & 0 \\ 0 & x_{200} \end{pmatrix} & 0_{200 \times 100} \\ A & 0_{100 \times 200} & 0_{100 \times 100} \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta \lambda \\ \Delta v \end{pmatrix} = - \begin{pmatrix} p x + q - \lambda + A^T v \\ \text{diag}(\lambda) x - \frac{1}{t} \mathbf{1}_{200} \\ Ax - b \end{pmatrix}$$

图像如下:



原问题最优解 x^* 、对偶问题最优解 λ^* 和 v^* 、函数最优值 p^* 见 ./results/T2_b.txt

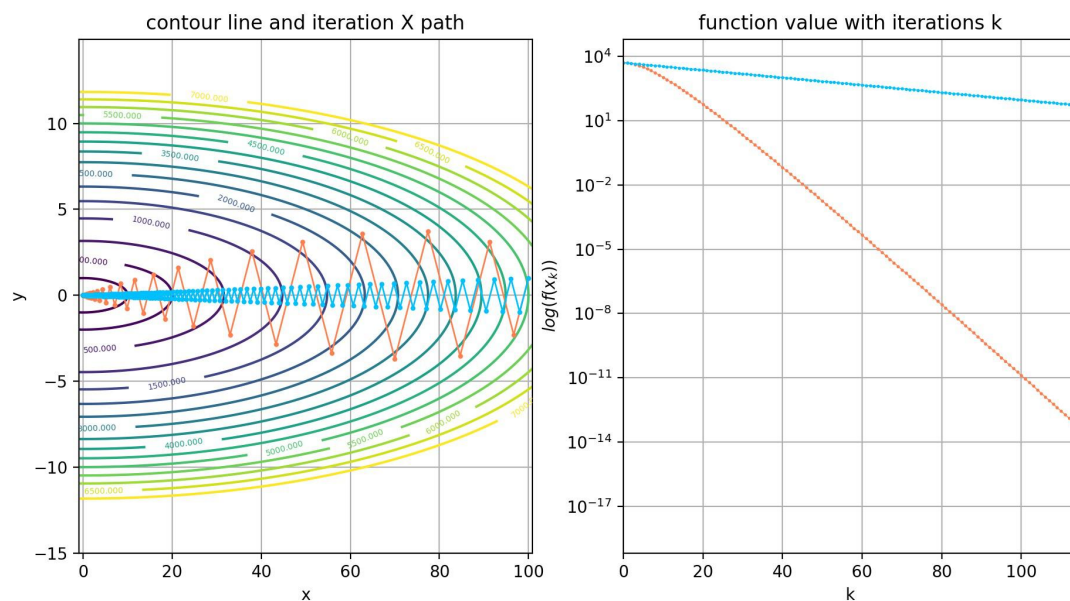
3. Heavy-Ball 算法.

$$x_{k+1} = x_k - \alpha \cdot A x_k + \beta (x_k - x_{k-1}),$$

Gradient Descent 算法.

$$\alpha = \frac{2}{101}.$$

图像:



蓝色曲线为梯度下降的结果；
红色曲线为Heavy-Ball加速的结果。