Continuous	O.	ptimization:	\mathbf{A}	ssigni	nent	9

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Exercise 1

The problem of finding the clostest point to another point can be formulated as

$$\min_{x \in \mathbb{R}^3} ||x - p||^2 \quad \text{s.t.} \quad ||x||^2 = 4$$

while the problem of finding the farthest point can be formulated as

$$\max_{x \in \mathbb{R}^3} ||x - p||^2 \quad \text{s.t.} \quad ||x||^2 = 4$$

which is equivalent to

$$\min_{x \in \mathbb{R}^3} -||x - p||^2 \quad \text{s.t.} \quad ||x||^2 = 4$$

where $p = (2, 4, 2)^{\top}$

Closest Point

We want the constraint levelset to be tangent to the curve of the objective function at the optimal point i.e.

where $f(x) = ||x - p||^2$ and $g(x) = ||x||^2$ satisfying g(x) = 4. After calculating the gradients, we have

$$2(x - p) = 2\lambda x$$
$$x - p = \lambda x$$
$$x = \frac{1}{1 - \lambda} p$$

x still has to satisfy the constraint $||x||^2 = 4$.

$$\frac{1}{(1-\lambda)^2}||p||^2 = 4$$
$$\frac{24}{(1-\lambda)^2} = 4$$
$$\frac{6}{(1-\lambda)^2} = 1$$
$$1 - \lambda = \pm\sqrt{6}$$
$$\lambda = 1 \pm\sqrt{6}$$

We have two solutions for x:

$$x = \pm \frac{1}{\sqrt{6}}p$$

The Langrange multiplier method gives us only the stationary points and we have to determine the minimum by checking which solution results in a smaller objective function value.

$$||x-p||^2 = \frac{1+\sqrt{6}}{-\sqrt{6}}||p||^2 \text{ or } \frac{1-\sqrt{6}}{\sqrt{6}}||p||^2$$

Apparently, the latter is smaller.

Thus, the closest point is $-\frac{1}{\sqrt{6}} \begin{pmatrix} 2\\4\\2 \end{pmatrix}$.

Farthest Point

Similarly, we have

$$2(x - p) = -2\lambda x$$
$$x - p = -\lambda x$$
$$x = \frac{1}{1 + \lambda} p$$

with constraint

$$||\frac{1}{1+\lambda}p||^2 = 4$$
$$\frac{24}{(1+\lambda)^2} = 4$$
$$\lambda = -1 \pm \sqrt{6}$$

We have two solutions for x:

$$x = \pm \frac{1}{\sqrt{6}}p$$

Which is the same as the ones we calculated for the closest point. Thus, the farthest point is $\frac{1}{\sqrt{6}} \begin{pmatrix} 2\\4\\2 \end{pmatrix}$.

Exercise 2

The minimization problem is given by

$$\min_{x \in \mathbb{R}^n} ||x||^2 \quad \text{s.t.} \quad Ax = b$$

It is equivalent to

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} ||x||^2 \quad \text{s.t.} \quad Ax = b$$

Let $f(x) = \frac{1}{2}||x||^2$ and $c_i(x) = a_i^{\top}x$ where a_i is the *i*-th row of A.

The constraints Ax = b can be rewritten as m smaller constraints: $c_i(x) = b_i$ for i = 1, ..., m.

Using the Lagrange multiplier method, we compose such equation:

$$\nabla f(x) = \sum_{i=1}^{m} \lambda_i \nabla c_i(x)$$
$$x = \sum_{i=1}^{m} \lambda_i a_i$$
$$x = A^{\top} \lambda$$

where λ_i is the Lagrange multiplier for the *i*-th constraint and λ is a column vector consists of all multipliers. We also have the constraint level sets:

$$Ax = b$$

$$AA^{\top}\lambda = b$$

$$\lambda = (AA^{\top})^{-1}b$$

$$\Rightarrow x = A^{\top}(AA^{\top})^{-1}b$$

Exercise 3

We have the following optimization problem:

$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{s.t.} \quad g(x) = 1$$

with $f(x) = c^{\top}x + \frac{1}{2\tau}||x - \bar{x}||^2$ and $g(x) = \sum_{i=1}^n x_i$ where x_i is the *i*-th element of x.

Using the Lagrange multiplier method, we have

$$\nabla f(x) = \lambda \nabla g(x)$$

$$c + \frac{1}{\tau}(x - \bar{x}) = \lambda \mathbf{1}$$
 observe that $\nabla g(x) = \mathbf{1}$ which is a column vector of 1s
$$x = \tau(\lambda \mathbf{1} - c) + \bar{x}$$

Plug x back into the constraint g(x) = 1, we have

$$g(\begin{pmatrix} \tau\lambda - c_i + \bar{x}_i \\ \vdots \\ \tau\lambda - c_n + \bar{x}_n \end{pmatrix}) = 1$$

$$\sum_{i=1}^n \tau\lambda - c_i + \bar{x}_i = 1$$

$$n\tau\lambda - \sum_{i=1}^n c_i + \sum_{i=1}^n \bar{x}_i = 1$$

$$n\tau\lambda - g(c) + g(\bar{x}) = 1$$

$$\lambda = \frac{1 + g(c) - g(\bar{x})}{n\tau}$$

Now that λ is determined, we can calculate x with the formula we derived earlier.