

HOMEWORK 5

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PROBLEM 0: Homework checklist

I worked alone.

PROBLEM 1: Steepest descent

(Nocedal and Wright, Exercise 3.6) Let's conclude with a quick problem to show that steepest descent can converge very rapidly! Consider the steepest descent method with exact line search for the function $f(x) = (1/2)x^T Qx - x^T b$. Suppose that we know $x_0 - x^*$ is parallel to an eigenvector of Q . Show that the method will converge in a single iteration.

If we know that $x_0 - x^*$ is parallel to an eigenvector of Q , this means that

$$x_0 - x^* = \mu v$$

Where

$v \in \mathbb{R}^n$ is an eigenvector of Q

$\mu \in \mathbb{R}$ is a scalar

As v is an eigenvector of Q

$$Qv = \lambda v$$

where λ is the eigenvalue of Q for the eigenvector v

After explaining the supposition, let's show that the steepest descent can converge in a single operation

Steepest descent begins with some prescribed point x_0 . At each step, it considers a linear approximation $f(x)$ in the direction of the negative gradient.

$$x_{k+1} = x_k - \alpha_k g_k.$$

So, the first iteration is computing as follows:

$$x_1 = x_0 - \alpha_0 g_0$$

Let's compute α_0 and g_0 in order to compute x_1

Firstly, let's compute g_0

$$g_0 = Qx_0 - b$$

as we know that $x_0 - x^* = \mu v$, we can say that $x_0 = \mu v + x^*$

So, let's substitute x_0 by $\mu v + x^*$:

$$g_0 = Q(\mu v + x^*) - b = \mu Qv + Qx^* - b$$

As $Qv = \lambda v$:

$$g_0 = \mu \lambda v + Qx^* - b$$

Note that $Qx^* - b$ is the gradient at the optimum, $g^* = Qx^* - b$. The gradient at the optimum is 0, so

$$g^* = Qx^* - b = 0 \text{ and:}$$

$$g_0 = \mu \lambda v$$

Now, let's compute α_0

We know from class that

$$\alpha = \frac{\|g_k\|^2}{g_k^T Q g_k},$$

So:

$$\alpha_0 = \frac{\|g_0\|^2}{g_0^T Q g_0} = \frac{\mu^2 \lambda^2 v^2}{(\mu \lambda v)^T Q \mu \lambda v} = \frac{1}{\lambda}$$

because $Qv = \lambda v$

Now, let's compute x_1

$$x_1 = x_0 - \alpha_0 g_0 = x_0 - \frac{1}{\lambda} \cdot \mu \lambda v = x_0 - \mu v$$

As $x_0 - x^* = \mu v$, $x^* = x_0 - \mu v$

So :

$$x_1 = x_0 - \mu v = x^*$$

So, the method converges in a single iteration.

PROBLEM 2: LPs in Standard Form

Show that we can solve:

$$\text{minimize } \sum_i \max(a_i^T x - b_i, -0.5)$$

by constructing an LP standard form

The standard form for a linear program is

$$\begin{array}{ll} \underset{x}{\text{minimize}} & c^T x \\ \text{subject to} & Ax = b \text{ and } x \geq 0 \end{array}$$

In the previous hw (hw 4), we reformulated this as a constrained optimization problem:

Notice that: $\forall i \in \{1, 2, 3, \dots, n\}, a_i^T x - b_i \geq -0.5 \rightarrow \max(a_i^T x - b_i, -0.5) = a_i^T x - b_i$

$$\begin{array}{ll} \underset{z}{\text{minimize}} & e^T z \\ \text{subject to} & z = a_i^T x - b_i \text{ and } z \geq -0.5. \end{array}$$

Let's define $\hat{c}, \hat{x}, \hat{A}$ and \hat{b} in order to write our problem in LP standard form

$$\hat{c} = (0, 0, e, -e, 0)^T$$

$$\hat{x} = (x^+, x^-, z^+, z^-, s)$$

$$\hat{b} = (b, 0.5)$$

$$\hat{A} = \begin{bmatrix} A & -A & -I & I & 0 \\ 0 & 0 & 0 & I & I \end{bmatrix}$$

So, we get from

$$\hat{A}\hat{x} = \hat{b} :$$

2 equalities

The first one is:

$$Ax^+ - Ax^- - z^+ + z^- = b$$

because we want $z = a_i^T x - b$, so $-z + a_i^T x - b = 0$ and as x is unconstrained in sign $-z + a_i^T x^+ - a_i^T x^- - b = 0$. We include z^+ and z^- because z can be a value in $[-0.5, +\infty)$

The second one is:

$$z^- + s = 0.5$$

because we want $z \geq -0.5$, so $-z^- + 0.5 - s = 0$

And from $c^T x$, we get:

$$c^T x = e^T z^+ - e^T z^-$$

As we will say that $\hat{x} \geq 0, x^+, x^-, z^+, z^-, s \geq 0$

So, the problem can be written in LP standard form as follows:

$$\begin{aligned} & \underset{\hat{x}}{\text{minimize}} && \hat{c}^T \hat{x} \\ & \text{subject to} && \hat{A}\hat{x} = \hat{b} \text{ and } \hat{x} \geq 0 \end{aligned}$$

Thus, we have shown that we can solve the given problem using an LP standard form.

PROBLEM 3: Duality

Show that the these two problems are dual by showing the equivalence of the KKT conditions:

$$\begin{aligned} & \underset{x}{\text{minimize}} && c^T x \\ & \text{subject to} && Ax \geq b, x \geq 0 \end{aligned}$$

and

$$\begin{aligned} & \underset{\lambda}{\text{maximize}} && b^T \lambda \\ & \text{subject to} && A^T \lambda \leq c, \lambda \geq 0 \end{aligned}$$

Let's see the KKT conditions of both problem in order to see if they are equivalent

KKT conditions for problem 1

Problem 1 is the standard form for a linear programming and we know from class that the KKT conditions are the following ones:

$$\begin{aligned} A^T \lambda + s &= c \\ Ax &= b \end{aligned}$$

$$\begin{aligned}
 x &\geq 0 \\
 s &\geq 0 \\
 x^T s &= 0
 \end{aligned}$$

KKT conditions for problem 2

$$\begin{aligned}
 &\underset{\lambda}{\text{maximize}} && b^T \lambda \\
 &\text{subject to} && A^T \lambda \leq c, \lambda \geq 0
 \end{aligned}$$

is the same as

$$\begin{aligned}
 &\underset{\lambda}{\text{minimize}} && -b^T \lambda \\
 &\text{subject to} && A^T \lambda \leq c, \lambda \geq 0
 \end{aligned}$$

So, The Lagrangian is

$$L = -b^T \lambda - x^T (c - A^T \lambda)$$

And

$$\frac{\partial L}{\partial \lambda} = -b + Ax = 0$$

So, the KKT conditions are:

$$Ax = b$$

$$A^T \lambda \leq c$$

$$x \geq 0$$

$$x^T (c - A^T \lambda) = 0$$

And if we include the condition $c - A^T \lambda = s$, the KKT conditions are the following ones:

$$A^T \lambda + s = c$$

$$Ax = b$$

$$x \geq 0$$

$$s \geq 0$$

$$x^T s = 0$$

So, the KKT conditions of both problems are equivalent

PROBLEM 4: Geometry of LPs

(Griva, Sofer, and Nash, Problem 3.12) Consider the system of constraints $Ax = b, x \geq 0$ with

$$A = \begin{bmatrix} 1 & 4 & 7 & 1 & 0 & 0 \\ 2 & 5 & 8 & 0 & 1 & 0 \\ 3 & 6 & 9 & 0 & 0 & 1 \end{bmatrix}, \text{ and } b = \begin{bmatrix} 12 \\ 15 \\ 18 \end{bmatrix}$$

Is $x = [1 \ 1 \ 1 \ 0 \ 0 \ 0]^T$ a basic feasible point? Explain your answer precisely in terms of the definition.

Fistly, let's see if x is a feasible point.

In order to be a feasible point the following conditions have to be satisfied:

$$x \geq 0$$

$$Ax = b$$

First condition: $x \geq 0$

It is satisfied since all entries of x are non-negative\

Second condition: $Ax = b$

$$Ax = \begin{bmatrix} 1 & 4 & 7 & 1 & 0 & 0 \\ 2 & 5 & 8 & 0 & 1 & 1 \\ 3 & 6 & 9 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 12 \\ 15 \\ 18 \end{bmatrix} = b$$

So, the second condition is also satisfied and x is a feasible point

Now, let's see if x is a basic feasible point.

The indices corresponding to the non-zero entries of x are 1,2 and 3.

We have to see if the columns of A corresponding to indices 1,2 and 3 are linearly independent in order to see if this set forms a basis for A

In order to see if the columns corresponding to indices 1,2 and 3 are linearly independent, we create a new matrix B whose columns are the 3 first column of A and we compute its determinant.

$$B = \begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix}$$

Its determinant is:

$$|B| = 0$$

As $|B| = 0$, the first 3 columns of A are linearly dependent and indices 1,2 and 3 does not form a basis for A .

So, $x = [1 \ 1 \ 1 \ 0 \ 0 \ 0]^T$ is not a basic feasible point in this case

PROBLEM 5: USING THE GEOMETRY

(Griva, Sofer, and Nash, Section 4.3, problem 3.13. Suppose that a linear program originally included a free variable x_i where there were no upper-and-lower bounds on its values. As we described in class, this can be converted into a pair of variables x_i^+ and x_i^- such that $x_i^+, x_i^- \geq 0$ and x_i is replaced with the difference $x_i^+ - x_i^-$. Prove that a basic feasible point can have only one of x_i^+ or x_i^- different from zero. (Hint: this is basically a one-line proof once you see the right characterization. I would suggest trying an example.)

Suppose we have a basic feasible point with both x^+ and x^- non-zero. We express $x = x^+ - x^-$.

A basic feasible point is a vertex of the feasible region, where at least n linearly independent constraints are active. In the case of linear programming problems in standard form, the constraints are of the form

$Ax = b, x \geq 0$, where A is an $m \times n$ matrix and b is a vector of length m .

If we suppose that there is a basic feasible point x with both x^+ and x^- non-zero, the columns of A corresponding to x^+ and x^- are opposite vectors, so the rows of B are linearly dependent, and B is non-invertible.

Therefore, a basic feasible point can have only one of x^+ or x^- different from zero, because if not B would be non-invertible.