

CIS4930 - Math for Machine Learning

## **Homework 3**

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### Question 1

Use the Lagrange multiplier (parameter) approach to solve the following problems:

1.  $f(x) = \|x\|_2^2, h(x) = \sum_{i=1}^n x_i - 1$ .
2.  $f(x) = \sum_{i=1}^n x_i, h(x) = \|x\|_2^2 - 1$ .
3.  $f(x) = \|x\|_2^2, h(x) = x^T Q x - 1$ , where  $Q$  is positive definite (symmetric with all eigenvalues greater than zero).

**Solution:**

**1. Solve for:**

$$\begin{aligned} L(x, \lambda) &= \|x\|_2^2 + \lambda \left( \sum_{i=1}^n x_i - 1 \right) \\ &= \|x\|_2^2 + \lambda (1^T x - 1) \\ &= x^T x + \lambda 1^T x - \lambda \end{aligned}$$

Apply theorem,  $\nabla_x L = 0$

$$\begin{aligned} \nabla_x L &= \nabla_x (x^T x + \lambda 1^T x - \lambda) = 0 \\ 0 &= 2x + \lambda 1^T I \\ &= 2x + \lambda \end{aligned}$$

Therefore,  $x = -\lambda/2$ . Going back to the constraint:

$$\begin{aligned} h(x) &= \sum_{i=1}^n x_i - 1 \\ 0 &= 1^T x - 1 \\ 0 &= -\lambda/2 - 1 \end{aligned}$$

Therefore,

$$\lambda = 2 \quad \ominus$$

**2. Solve for:**

$$\begin{aligned} L(x, \lambda) &= \sum_{i=1}^n x_i + \lambda (\|x\|_2^2 - 1) \\ &= 1^T x + \lambda (x^T x - 1) \end{aligned}$$

Apply theorem,  $\nabla_x L = 0$

$$\begin{aligned} \nabla_x L &= \nabla_x (1^T x + \lambda (x^T x - 1)) = 0 \\ 0 &= 2x\lambda \end{aligned}$$

Therefore,

$$\lambda = 0 \quad \ominus$$

**3. Solve for:**

$$\begin{aligned}L(x, \lambda) &= \|x\|_2^2 + \lambda(x^T Q x - 1) \\ &= x^T x + \lambda x^T Q x - \lambda\end{aligned}$$

Apply theorem,  $\nabla_x L = 0$

$$\begin{aligned}\nabla_x L &= \nabla_x (x^T x + \lambda x^T Q x - \lambda) = 0 \\ 0 &= 2x + \lambda 2Qx\end{aligned}$$

Isolate for  $\lambda$ :

$$\begin{aligned}0 &= 2x + \lambda 2Qx \\ -2x &= 2x * \lambda Q \\ -1 &= \lambda Q \\ -Q^{-1} &= \lambda\end{aligned}$$

Therefore,

$$\lambda = -Q^{-1} \quad \ominus$$

## Question 2

Arithmetic-Geometric Mean Inequality:

Let  $\alpha_1, \dots, \alpha_n$  be positive scalars with  $\sum_{i=1}^n \alpha_i = 1$ . Use a Lagrange multiplier to solve the problem

$$\min_x \sum_{i=1}^n \alpha_i x_i$$

subject to

$$\prod_{i=1}^n x_i^{\alpha_i} = 1, x_i > 0 \forall i.$$

Establish the arithmetic-geometric mean inequality

$$\prod_{i=1}^n x_i^{\alpha_i} \leq \sum_{i=1}^n \alpha_i x_i$$

for a set of positive numbers  $x_i, \forall i \in \{1, \dots, n\}$ . Hint: Use a change of variables  $y_i = \log(x_i)$  where log is  $\ln$ .

**Solution:**

$$\prod_{i=1}^n x_i^{\alpha_i} = 1$$

$$x_1^{\alpha_1} \cdot x_2^{\alpha_2} \cdot \dots \cdot x_n^{\alpha_n} = 1$$

$$\alpha_1 \ln(x_1) + \alpha_2 \ln(x_2) + \dots + \alpha_n \ln(x_n) = 0$$

Taking the natural logarithm on both sides

$$\sum_{i=1}^n \alpha_i \ln(x_i) = 0$$

$$\sum_{i=1}^n \alpha_i y_i = 0$$

Therefore,

$$L(y, \lambda) = \sum_{i=1}^n \alpha_i x_i + \lambda \sum_{i=1}^n \alpha_i y_i$$

$$0 = \sum_{i=1}^n \alpha_i e^{y_i} + \lambda \sum_{i=1}^n \alpha_i y_i$$

$$0 = \alpha_i e^{y_i} + \lambda \alpha_i$$

Derivative on  $y_i$

$$0 = e^{y_i} + \lambda$$

$$e^{y_i} = -\lambda$$

$$y_i = \ln(-\lambda)$$

$$y_i = \ln(\lambda)$$

Additionally,

$$\sum_{i=1}^n \alpha_i y_i = 0$$

$$\sum_{i=1}^n \alpha_i \ln(\lambda) = 0$$

$$\ln(\lambda) = 0$$

for all  $i$ .

In case  $y_1 = y_2 = \dots = y_n = 0$ ,

$$\alpha_i e^{y_i} + \alpha_i e^{y_i} + \dots + \alpha_i e^{y_i} = 1$$

This can only mean,

$$\begin{aligned} \alpha_i e^{y_i} + \alpha_i e^{y_i} + \dots + \alpha_i e^{y_i} &\geq 1 \\ \alpha_i e^{y_i} + \alpha_i e^{y_i} + \dots + \alpha_i e^{y_i} &\geq x_1^{\alpha_1} \cdot x_2^{\alpha_2} \cdot \dots \cdot x_n^{\alpha_n} \\ \sum_{i=1}^n \alpha_i x_i &\geq \prod_{i=1}^n x_i^{\alpha_i} \quad \odot \end{aligned}$$

### Question 3

Consider the optimization problem

$$\min_{x,y} f(x,y) = \frac{1}{2} ((x - x_0)^2 + (y - y_0)^2)$$

with  $(x_0, y_0)$  fixed and subject to

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1.$$

- Write out the Lagrangian for this problem.
- Solve for  $x, y$  in terms of the Lagrange parameter.
- Rewrite the ellipse constraint in terms of the Lagrange parameter.
- Show that this leads to a quartic. Can a general quartic be solved using radicals?

**Solution:**

Lagrangian:

$$L(x, y, \lambda) = \frac{1}{2}(x^2 - 2xx_0 + x_0^2) + \frac{1}{2}(y^2 - 2yy_0 + y_0^2) + \lambda\left(\frac{x^2}{a^2} + \frac{y^2}{b^2} - 1\right)$$

$$\nabla_x L = x - x_0 + \lambda \frac{2x}{a^2} = 0 \rightarrow x = \frac{a^2 x_0}{a^2 + 2\lambda} \rightarrow \lambda = \frac{a^2(x_0 - x)}{2x} \quad (1)$$

$$\nabla_y L = y - y_0 + \lambda \frac{2y}{b^2} = 0 \rightarrow y = \frac{b^2 y_0}{b^2 + 2\lambda} \rightarrow \lambda = \frac{b^2(y_0 - y)}{2y} \quad (2)$$

Rewriting the ellipse function:

$$\begin{aligned} \frac{x^2}{a^2} + \frac{y^2}{b^2} &= 1 \\ \frac{\left(\frac{a^2 x_0}{a^2 + 2\lambda}\right)^2}{a^2} + \frac{\left(\frac{b^2 y_0}{b^2 + 2\lambda}\right)^2}{b^2} &= 1 \\ \frac{a^2 x_0^2}{(a^2 + 2\lambda)^2} + \frac{b^2 y_0^2}{(b^2 + 2\lambda)^2} &= 1 \\ a^2 x_0^2 (b^2 + 2\lambda)^2 + b^2 y_0^2 (a^2 + 2\lambda)^2 &= (a^2 + 2\lambda)^2 (b^2 + 2\lambda)^2 \\ (a^2 + 2\lambda)^2 (b^2 + 2\lambda)^2 - a^2 x_0^2 (b^2 + 2\lambda)^2 - b^2 y_0^2 (a^2 + 2\lambda)^2 &= 0 \end{aligned}$$

**Conclusion:**  $(a^2 + 2\lambda)^2 (b^2 + 2\lambda)^2$  will lead to a  $\lambda^4$ . A quartic. They can be solved using radicals, but it is extremely difficult to solve by hand. ☹

#### Question 4

You are given the least squares problem

$$E(\mathbf{w}) = \left\| \mathbf{y} - \sum_{k=1}^K w_k \mathbf{x}_k \right\|_2^2$$

where  $\mathbf{w} \in \mathbb{R}^K$  and  $\mathbf{x}_i, \mathbf{y} \in \mathbb{R}^D$ .

- Write the Lagrangian for this problem when supplied with the constraint  $\sum_{k=1}^K w_k = 1$ .
- Solve for the Lagrange parameter explaining all steps.
- Solve for  $\mathbf{w}$  while satisfying the constraint.
- Describe the criteria for solutions to exist for this problem.

#### **Solution:**

Lagrangian:

$$\begin{aligned} L(\mathbf{w}, \lambda) &= \left\| \mathbf{y} - \sum_{k=1}^K w_k \mathbf{x}_k \right\|_2^2 + \lambda \left( \sum_{k=1}^K w_k - 1 \right) \\ &= \|\mathbf{y} - \mathbf{w}\mathbf{x}\|_2^2 + \lambda(1^T \mathbf{w} - 1) && \text{- Acknowledging dot product and sum of elements of } \mathbf{w} \\ &= (\mathbf{y} - \mathbf{w}\mathbf{x})^T (\mathbf{y} - \mathbf{w}\mathbf{x}) + \lambda(1^T \mathbf{w} - 1) && \text{- } \|\mathbf{y} - \mathbf{w}\mathbf{x}\|_2^2 \text{ is the euclidean norm of the residual. } \|\mathbf{r}\|_2^2 = \mathbf{r}^T \mathbf{r} \\ &= \mathbf{y}^T \mathbf{y} - 2\mathbf{x}^T \mathbf{w}^T \mathbf{y} - \mathbf{x}^T \mathbf{w}^T \mathbf{w} \mathbf{x} + \lambda 1^T \mathbf{w} - \lambda && \text{- Expand} \\ \nabla_{\mathbf{w}} L &= -2\mathbf{x}^T \mathbf{y} - 2\mathbf{x}^T \mathbf{w} \mathbf{x} + \lambda = 0 && \text{- Take derivative w.r.t. } \mathbf{w} \\ 0 &= -2\mathbf{x}^T \mathbf{y} - 2\mathbf{x}^T \mathbf{w} \mathbf{x} + \lambda \end{aligned}$$

From that, you can derive:

$$\mathbf{w} = \frac{\lambda - 2\mathbf{x}^T \mathbf{y}}{2\mathbf{x}^T \mathbf{x}} \quad (3)$$

$$\lambda = 2\mathbf{x}^T (\mathbf{y} - \mathbf{x}\mathbf{w}) \quad (4)$$

- Observe on (4),  $\mathbf{y} - \mathbf{x}\mathbf{w}$  is the residual.
- In order for solutions to exist,  $K$  must be equivalent to  $D$ .

### Question 5

Write a program to roughly carry out the optimization problem inherent in  $\|A\|_2$ , namely

$$\max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$$

. The program should take an arbitrary  $m \times n$  matrix  $A$  and sample over 100000 random vectors  $x \in \mathbb{R}^n$  (and use Gaussian random numbers) to approximately pick the maximum. Compute and empirically show that the analytic solution is an upper bound for the search. For demonstration purposes, use  $m = 9$  and  $n = 6$ . The matrix entries can also be randomly chosen. Your program should contrast the empirical maximum with the analytically derived maximum to the optimization problem.

**Solution:** on Google Colab, Link:

<https://colab.research.google.com/drive/1aJ9PQJdT2-6eDrASEOfCzj7BqoZXXaA> ☺

### Question 6: BONUS

Consider the  $L_2$  norm of a matrix defined as  $\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$ . Is  $\|A\|_2 \geq \|A\|_F$  or is  $\|A\|_2 \leq \|A\|_F$  or is it neither where  $\|A\|_F$  is the Frobenius norm of the matrix? Give a clear mathematical explanation and justification for your choice (out of the three possible choices).

**Solution:**

We have  $\|A\|_F = \sqrt{\sum_{i,j} |a_{i,j}|^2}$ , where  $a_{i,j}$  is the entry in the  $i$ th row and  $j$ th column of  $A$ .

Let  $x$  be a unit vector such that  $\|Ax\|_2 = \|A\|_2$ . Then we have:

$$\begin{aligned} \|A\|_2 &= \|Ax\|_2 \\ &= \sqrt{\sum_{i=1}^m \left( \sum_{j=1}^n a_{i,j} x_j \right)^2} && \text{Definition of the 2-norm of a vector} \\ &\leq \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{i,j}|^2 \sum_{j=1}^n x_j^2} && \text{by Cauchy-Schwarz inequality} \\ &= \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{i,j}|^2} && \text{since } \|x\|_2 = 1. \end{aligned}$$

Therefore, we have  $\|A\|_2 \leq \|A\|_F$ . ☺

F.S.



**Note:-**

- Question 1
  - I. 2/5 Incomplete
  - II. 2/5 Incomplete
  - III. 5/10 Incomplete
- Question 2: 17/20 Not a general solution for the AM, GM Inequality
- Question 3: Correct
- Question 4: 10/20
- Question 5: Correct, but the proof is very clever and even though it needs a few more things to firm it up, the basic idea is great.