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ME598/494 Homework 1

1. Solve the following problem using [Python SciPy.optimize](#). Please attach your code and results. Specify your initial guesses of the solution. If you change your initial guess, do you find different solutions? (30 points)

$$\begin{aligned} \text{minimize:} \quad & (x_1 - x_2)^2 + (x_2 + x_3 - 2)^2 + (x_4 - 1)^2 + (x_5 - 1)^2 \\ \text{subject to:} \quad & x_1 + 3x_2 = 0 \\ & x_3 + x_4 - 2x_5 = 0 \\ & x_2 - x_5 = 0 \\ & -10 \leq x_i \leq 10, \quad i = 1, \dots, 5 \end{aligned}$$

Note: Please learn how to use **break points** to debug. You can use Python on [Google Colab](#).

2. Let x and $b \in \mathbb{R}^n$ be vectors and $A \in \mathbb{R}^{n \times n}$ be a square matrix. Define $f : \mathbb{R}^n \rightarrow \mathbb{R}$ as $f(x) = b^T x + x^T A x$. (50 points)
 - (a) What is the gradient and Hessian of $f(x)$ with respect to x ?
 - (b) Derive the first and second order Taylor's approximations of $f(x)$ at $x = 0$. Are these approximations exact?
 - (c) What are the necessary and sufficient conditions for A to be positive definite?
 - (d) What are the necessary and sufficient conditions for A to have full rank?
 - (e) If there exists $y \in \mathbb{R}^n$ and $y \neq 0$ such that $A^T y = 0$, then what are the conditions on b for $Ax = b$ to have a solution for x ?
3. Due to the recent inflation, let's reconsider the [Stigler diet](#) problem proposed by Nobel laureate George Stigler after the second World War: Consider that the grocery store offers N types of food of your interest, and each food contains the same M types of nutrition. Denote a_{ij} as the quantity of nutrition type j of food type i for $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, M$, c_i the unit price of food type i , and b_j the necessary

quantity of nutrition type j for a month. Formulate an optimization problem to determine the minimum grocery cost to satisfy the nutrition needs. **(20 points)**

Problem-1

```
In [73]: from scipy import optimize
```

```
In [74]: # Function
fx = lambda x: (x[0] - x[1])**2 + (x[1] + x[2] - 2)**2 + (x[3] - 1)**2 + (x[4] - 1)**2
```

```
In [75]: # Constraints
c = ({'type': 'eq', 'fun': lambda x: x[0] + 3 * x[1]},
     {'type': 'eq', 'fun': lambda x: x[2] + x[3] - 2 * x[4]},
     {'type': 'eq', 'fun': lambda x: x[1] - x[4]})

# Upper and Lower Bounds
b = ((-10, 10), (-10, 10), (-10, 10), (-10, 10), (-10, 10))

# Results
r = optimize.minimize(fx, (0.5, 2, 1, -0.5, 1), method='SLSQP', bounds=b, constraints=c)

# Minimal Value of Function
r.fun
```

```
Out[75]: 4.093023255813957
```

```
In [76]: # X
r.x
```

```
Out[76]: array([-0.76744188,  0.25581396,  0.62790694, -0.11627902,  0.25581396])
```

Problem 2

$$x \text{ \& } b \in \mathbb{R}^n, A \in \mathbb{R}^{n \times n}$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R} \text{ as } f(x) = b^T x + x^T A x$$

(a) Gradient \& Hessian

$$\text{Let } f(x) = f(a) + f(b) \quad - (1)$$

$$f(a) = b^T x$$

$$f(b) = x^T A x$$

for $f(a) = b^T x$

$$f(a) = b^T x = \sum_{j=1}^n b_j x_j$$

$$\frac{\partial f(a)}{\partial x} = \nabla f(a) = \begin{bmatrix} \frac{\partial b_1 x_1}{\partial x} \\ \vdots \\ \frac{\partial b_n x_n}{\partial x_n} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} =$$

$$\therefore \nabla f(a) = \underline{b} \quad - (2)$$

$$H(a) = \frac{\partial^2 f(a)}{\partial x^2} = \underline{\frac{\partial b^T x}{\partial x} = 0} \quad - (3)$$

for $f(b) = x^T A x$

$$f(b) = x^T A x = \sum_{j=1}^n \sum_{i=1}^n x_i a_{ij} x_j$$

$$= \sum_{i=1}^n \left(a_{ii} x_i^2 + \sum_{j \neq i} x_i a_{ij} x_j \right)$$

$$\nabla f(b) = \frac{\partial f(b)}{\partial x} = \begin{bmatrix} \sum_{j=1}^n x_j a_{j1} \\ \vdots \\ \sum_{j=1}^n x_j a_{jn} \end{bmatrix} + \begin{bmatrix} \sum_{j=1}^n a_{1j} x_j \\ \vdots \\ \sum_{j=1}^n a_{nj} x_j \end{bmatrix}$$

$$\therefore \nabla F(b) = \underline{(A^T + A)x}$$

$$H(b) = \frac{\partial^2 f(b)}{\partial x^2} = A + A^T$$

\therefore we have

gradient ($g(x)$)

hessian ($H(x)$)

$$\underline{g(x) = b + (A + A^T)x}$$

$$\underline{H(x) = A + A^T}$$

if system is symmetric i.e. $A = A^T$

$$g(x) = b + 2Ax$$

$$H(x) = 2A$$

(b) Taylor approximation at $x=0$

$$1^{st} \text{ order: } f(x) \approx f(x_0) + \nabla_x f \Big|_{x_0} (x - x_0)$$

$$2^{nd} \text{ order: } f(x) \approx f(x_0) + \nabla_x f \Big|_{x_0} (x - x_0) + \frac{1}{2} (x - x_0)^T H \Big|_{x_0} (x - x_0)$$

$$\therefore f(x) = b^T x + x^T A x$$

for $x=0$

$$\underline{f(0) = 0}$$

$$g(x) = (A + A^T)x + b$$

$$g(0) = b$$

$$H(x) = A + A^T$$

$$H(0) = A + A^T$$

\therefore 1st order

$$f(x) = f(0) + \nabla_x \Big|_{x_0} (x - x_0)$$

$$= 0 + b(x - 0) = bx$$

$$\therefore f(x) = b^T x$$

\therefore 2nd order

$$f(x) = f(0) + \nabla_x \Big|_{x_0} (x - x_0) + \frac{1}{2} (x - x_0)^T H \Big|_{x_0} (x - x_0)$$

$$= 0 + b(x - 0) + \frac{1}{2} (A + A^T)(x - 0)^2 = bx + \frac{(A + A^T)x^2}{2}$$

$$\therefore f(x) = b^T x + \frac{1}{2} x^T (A + A^T) x$$

The approximations are not exact.

(c) A to be positive definite

$$A \in \mathbb{R}^{n \times n}, A = A^T$$

$\lambda > 0$ means positive definite

The eigen value has to be greater than 0.

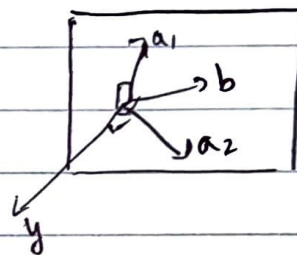
(d) A full rank when

- each of the rows are linearly independent \Rightarrow full row rank
- each of the columns are linearly independent \Rightarrow column full rank
- determinant is nonzero. $|A| \neq 0$

(e) $y \in \mathbb{R}^n$ $y \neq 0$ $A^T y = 0$

conditions on b for $Ax=b$ for x to have a solⁿ.

- y is also perpendicular to b (b is orthogonal to y)
- b should be in column space of A



Problem 3

Let x_i be the purchased amount of food type $i=1, 2, 3, \dots, N$

Let the function be $f(x) = A^T x$

The total nutrition j in purchased food = $\sum_{i=1}^N a_{ij} x_i \quad \forall j=1, 2, 3, \dots, M$

\therefore optimization problem : $\min_x A^T x \quad \text{s.t.} \quad \sum_{i=1}^N a_{ij} x_i \geq b_j \quad \forall j=1, 2, 3, \dots, M$

or s.t $Ax \geq b$

where

$$A = \begin{bmatrix} a_{11} & \dots & a_{1N} \\ \vdots & & \vdots \\ a_{M1} & \dots & a_{MN} \end{bmatrix} \in \mathbb{R}^{M \times N}, \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_M \end{bmatrix} \in \mathbb{R}^M, \quad x = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix} \in \mathbb{R}^N$$