THE UNIVERSITY OF TEXAS
AT AUSTIN

EE381V LARGE SCALE OPTIMIZATION

Problem Set 1

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Part I
Matlab and Computational Assignment

1 Gradient Descent on three matrices

Command to get executed:

```
>> gd_run_script()
```

1.1 $X1$, $b1$

- Range of γ that leads to convergence: $(0, 2)$
- Range of γ that leads to divergence: $(2, +\infty)$
- Explanation: if $\gamma = 2$, the program indicates that

$$\forall k, \ f(x^{k+1}) = f(x^k)$$

  Since the above equation is constantly true (independent of the minima), we can conclude that gradient descent with $\gamma = 2$ goes to the opposite side of that quadratic curve. Intuitively, the program will diverge if we set larger ($\gamma > 2$) and converge if we set smaller ($\gamma < 2$).

- Two illustrative examples: $\gamma = 0.5$ and $\gamma = 3.0$

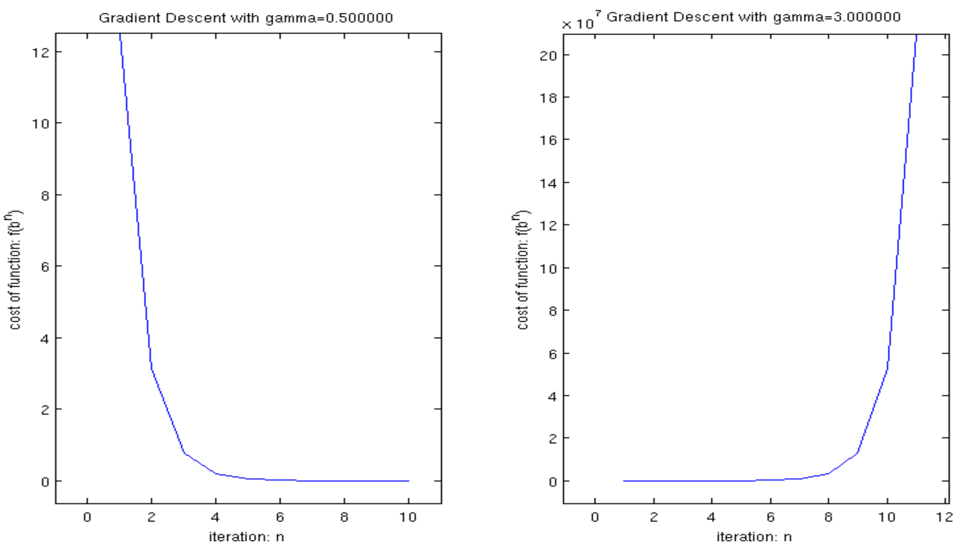

Figure 1: Illustration for gradient descent on $X1$, staring with $b1$ by $\gamma = 0.5$ and 3.0

1.2 $X2$, $b2$

- Range of γ that leads to convergence: $(0, 2)$
- Range of γ that leads to divergence: $(2, +\infty)$
- Explanation: if $\gamma = 2$, the program indicates that

$$\forall k, \ f(x^{k+1}) = f(x^k)$$

Since the above equation is constantly true (independent of the minima), we can conclude that gradient descent with $\gamma = 2$ goes to the opposite side of that quadratic curve. Intuitively, the program will diverge if we set larger ($\gamma > 2$) and converge if we set smaller ($\gamma < 2$).

- Two illustrative examples: $\gamma = 1.5$ and $\gamma = 3.0$

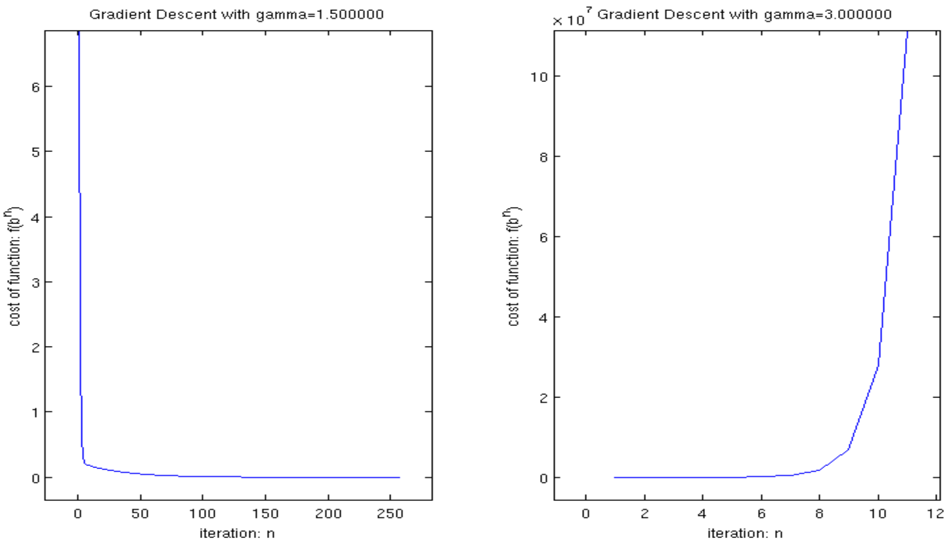

Figure 2: Illustration for gradient descent on $X2$, starting with $b2$ by $\gamma = 1.5$ and 3.0

1.3 $X3$, $b3$

- Range of γ that leads to convergence: $(0, 0.02)$
- Range of γ that leads to divergence: $(0.02, +\infty)$
- Explanation: if $\gamma = 0.02$, the program indicates that

$$\forall k,\ f(x^{k+1}) = f(x^k)$$

  Since the above equation is constantly true (independent of the minima), we can conclude that gradient descent with $\gamma = 0.02$ goes to the opposite side of that quadratic curve. Intuitively, the program will diverge if we set larger ($\gamma > 0.02$) and converge if we set smaller ($\gamma < 0.02$).

- Two illustrative examples: $\gamma = 0.005$ and $\gamma = 0.05$

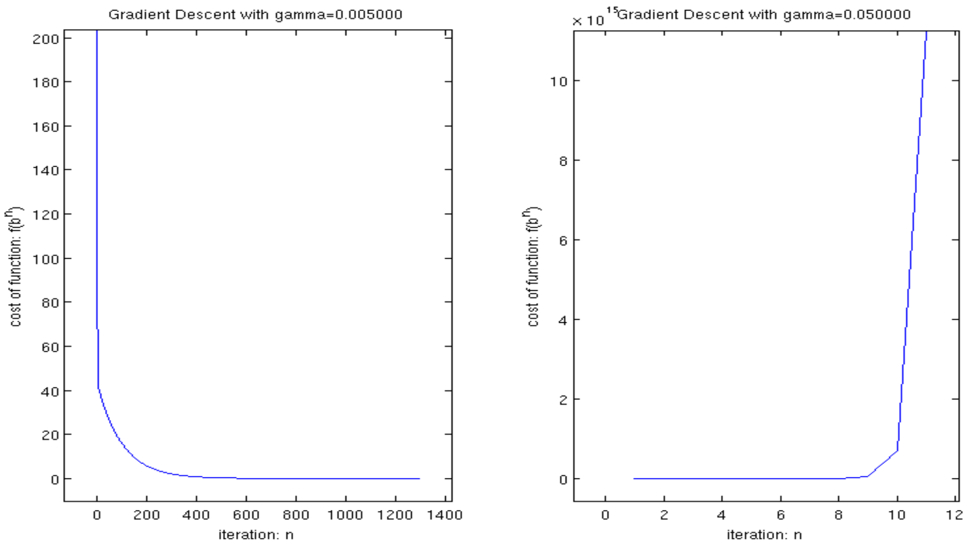

Figure 3: Illustration for gradient descent on $X3$ staring with $b3$ by $\gamma = 0.005$ and 0.05

2 $\gamma = 1$ for the second matrix

Command to get executed:

```
>> gamma = 1;
>> [b2_opt, iters, all_costs] = gd (X2, b2, gamma);
```

Plotting: figure for $\gamma = 1$

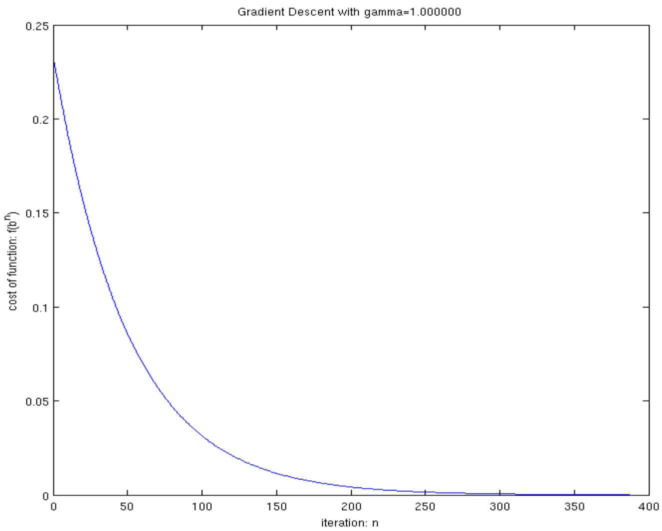

Figure 4: Plotting figure for gradient descent with $\gamma = 1$ on the second matrix

Explanation: Through the smooth plotted curve, we guess that the gradient descent method got linear convergence when $\gamma = 1$ on X_2. Hence, we trace convergence rate conv_rate $= f(x^k)/f(x^{k-1})$ as follows:

```
Iter: 2, Cost: 2.254428e-01, Conv_Rate: 0.980100
Iter: 3, Cost: 2.209565e-01, Conv_Rate: 0.980100
Iter: 4, Cost: 2.165594e-01, Conv_Rate: 0.980100
Iter: 5, Cost: 2.122499e-01, Conv_Rate: 0.980100
Iter: 6, Cost: 2.080261e-01, Conv_Rate: 0.980100
Iter: 7, Cost: 2.038864e-01, Conv_Rate: 0.980100
...
...
Iter: 381, Cost: 1.107934e-04, Conv_Rate: 0.980100
Iter: 382, Cost: 1.085886e-04, Conv_Rate: 0.980100
Iter: 383, Cost: 1.064277e-04, Conv_Rate: 0.980100
Iter: 384, Cost: 1.043098e-04, Conv_Rate: 0.980100
Iter: 385, Cost: 1.022340e-04, Conv_Rate: 0.980100
Iter: 386, Cost: 1.001996e-04, Conv_Rate: 0.980100
Iter: 387, Cost: 9.820558e-05, Conv_Rate: 0.980100
Converged to zeros!
```

In terms of above dumps and the fact that $f(x^*) = 0$, we can conclude that when $\gamma = 1$

$$f(x^{k+1}) - f(x^*) = 0.9801 \cdot \left(f(x^k) - f(x^*)\right)$$

which supports our previous guess that

Gradient Descent with $\gamma = 1$ on second matrix leads to **linear convergence**.

Part II
Written Problems

1 Othorognal Subspace

(a) Show that if U is a subspace, then so is $U^{\perp}$

Proof. Since U is a subspace, then we have U satisfying all three properties shown below:

- $\mathbf{0} \in U$
- $\forall \mathbf{u}_1, \mathbf{u}_2 \in U, \mathbf{u}_1 + \mathbf{u}_2 \in U$
- $\forall \mathbf{u} \in U, \alpha \in \mathbb{R}, \alpha\mathbf{u} \in U$

Now we show that $U^{\perp}$ is also a subspace by indicating $U^{\perp}$ satisfies all three properties as above U do.

- Since $\forall \mathbf{u} \in U, \langle \mathbf{0}, \mathbf{u}\rangle = 0$ and $\mathbf{0} \in V$ $(\mathbf{0} \in U \subseteq V)$, then it turned out that $\mathbf{0} \in U^{\perp}$.
- Let $\mathbf{u}$ be arbitrary vector s.t. $\mathbf{u} \in U$, and $\mathbf{x}_1$, $\mathbf{x}_2$ to be distinct vector s.t. $\mathbf{x}_1 \in U^{\perp}$ and $\mathbf{x}_2 \in U^{\perp}$. By definition of $U^{\perp}$, we have $\langle \mathbf{x}_1, \mathbf{u}\rangle = 0$ and $\langle \mathbf{x}_2, \mathbf{u}\rangle = 0$. Then it is obvious that $\langle \mathbf{x}_1 + \mathbf{x}_2, \mathbf{u}\rangle = 0$. That is $\mathbf{x}_1 + \mathbf{x}_2 \in U^{\perp}$. Therefore, $\forall \mathbf{x}_1, \mathbf{x}_2 \in U^{\perp}, \mathbf{x}_1 + \mathbf{x}_2 \in U^{\perp}$ was proved.
- Let $\mathbf{x}$ be arbitrary vector s.t. $\mathbf{x} \in U^{\perp}$, $\mathbf{u}$ be arbitrary vector s.t. $\mathbf{u} \in U$ and arbitrary $\alpha \in \mathbb{R}$. By definition of $U^{\perp}$, we have $\langle \mathbf{x}_1, \mathbf{u}\rangle = 0$. Since inner product is linear operator, it is obvious that $\langle \alpha\mathbf{x}_1, \mathbf{u}\rangle = 0$. That is $\alpha\mathbf{x}_1 \in U^{\perp}$. Therefore, $\forall \mathbf{x} \in U^{\perp}, \alpha \in \mathbb{R}, \alpha\mathbf{x} \in U^{\perp}$ was proved.

Since $U^{\perp}$ contains $\mathbf{0}$, and is closed under addition and scalar multiplication, it turned out that $U^{\perp}$ is a subspace. Therefore, the statement that if U is a subspace, then so is $U^{\perp}$ was proved. □

(b) Show that $(U^{\perp})^{\perp} = U$

Proof. By contradiction. Assume that $(U^{\perp})^{\perp} \neq U$ and then show the contradiction. By definition of $U^{\perp}$, we have $U^{\perp} = \{\forall \mathbf{v} \in V, \langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U\}$ and $(U^{\perp})^{\perp} = \{\forall \mathbf{x} \in V, \langle \mathbf{x}, \mathbf{v}\rangle = 0, \forall \mathbf{v} \in U^{\perp}\}$. Since $(U^{\perp})^{\perp} \neq U$, then we can say that $\exists \mathbf{x} \notin U, \langle \mathbf{x}, \mathbf{v}\rangle = 0, \forall \mathbf{v} \in U^{\perp}$. That is to say, $\exists \mathbf{x} \in V$ *but* $\notin U, \langle \mathbf{x}, \mathbf{v}\rangle = 0, \forall \mathbf{v}\ s.t. \langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U$. However, such $\mathbf{x}$ does not exist. Hence, we reject initial assumption and conclude that $(U^{\perp})^{\perp} = U$. □

(c) Show that if $U, W \subseteq V$ are subspaces of V, then $U \subseteq W \Leftrightarrow U^{\perp} \supseteq W^{\perp}$

Proof of $U \subseteq W \Rightarrow U^{\perp} \supseteq W^{\perp}$. $U^{\perp} = \{\forall \mathbf{v} \in V, \langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U\}$ and $W^{\perp} = \{\forall \mathbf{v} \in V, \langle \mathbf{v}, \mathbf{w}\rangle = 0, \forall \mathbf{w} \in W\} = \{\forall \mathbf{v} \in V, \langle \mathbf{v}, \mathbf{w}\rangle = 0, \forall \mathbf{w} \in W$ and $\langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U\}$ (This is valid because $\forall U \subseteq W$ and then $\mathbf{u} \in W$). Now since membership of $W^{\perp}$ requires one more condition, then it is obvious that $\mathbf{v} \in W^{\perp} \Rightarrow \mathbf{v} \in U^{\perp}$, and $\mathbf{v} \in U^{\perp} \not\Rightarrow \mathbf{v} \in W^{\perp}$ hold for arbitrary $\mathbf{v}$. Therefore, we can conclude that $U^{\perp} \supseteq W^{\perp}$. □

Proof of $U^{\perp} \supseteq W^{\perp} \Rightarrow U \subseteq W$. By definition, we have $U^{\perp} = \{\mathbf{v} \in V | \langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U\}$ and $W^{\perp} = \{\mathbf{v} \in V | \langle \mathbf{v}, \mathbf{w}\rangle = 0, \forall \mathbf{w} \in W\}$. Since $U^{\perp} \supseteq W^{\perp}$, then we have $U^{\perp} \cap W^{\perp} = W^{\perp}$. Then $U^{\perp} \cap W^{\perp} = \{\mathbf{v} \in V | \langle \mathbf{v}, \mathbf{u}\rangle = 0, \forall \mathbf{u} \in U$ and $\langle \mathbf{v}, \mathbf{w}\rangle = 0, \forall \mathbf{w} \in W\} = \{\mathbf{v} \in V | \langle \mathbf{v}, \mathbf{x}\rangle = 0, \forall \mathbf{x} \in W \cup U\} = W^{\perp}$ Then we have $W \cup U = W$, which naturally derives $U \subseteq W$. □

(d) Show that $X^\perp$ makes sense, $X^\perp$ is a subspace and $(X^\perp)^\perp \supseteq X$

Proof. $X^\perp$ also makes sense. $\square$

(e) Show that any $v \in V$ can be written uniquely as $v = u + u^\perp$

2 Boyd and Vandenberghe, Ex. 2.10

(a) Show that if $A \in \mathbb{S}_+^n$ then the set C is convex

Proof. Assume that $A \in \mathbb{S}_+^n$. Let $\mathbf{x}_1$, $\mathbf{x}_2$ to be arbitrary vector such that $\mathbf{x}_1 \in C$, $\mathbf{x}_2 \in C$ and $\mathbf{x}_1 \neq \mathbf{x}_2$. Then we show arbitrary linear combination $\mathbf{x}_* = \lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2,\ \lambda \in [0,1]$ also belongs to the set C. According to the definition of set C, we have

$$\mathbf{x}_1^T A\mathbf{x}_1 + b^T\mathbf{x}_1 + c \leq 0 \tag{1}$$
$$\mathbf{x}_2^T A\mathbf{x}_2 + b^T\mathbf{x}_2 + c \leq 0 \tag{2}$$

By positive semidefiniteness of A, we have

$$\mathbf{x}^T A\mathbf{x} \geq 0,\ \forall\mathbf{x} \tag{3}$$

That is

$$\mathbf{x}_1^T A\mathbf{x}_1 \geq 0 \tag{4}$$
$$\mathbf{x}_2^T A\mathbf{x}_2 \geq 0 \tag{5}$$
$$(\mathbf{x}_2 - \mathbf{x}_1)^T A(\mathbf{x}_2 - \mathbf{x}_1) \geq 0 \tag{6}$$

Besides,

$$\lambda \geq 0 \tag{7}$$
$$1 - \lambda \geq 0 \tag{8}$$
$$\lambda - 1 \leq 0 \tag{9}$$

Then we investigate the property of $\mathbf{x}_*^T A\mathbf{x}_* + b^T\mathbf{x}_* + c$.

$$\begin{aligned}
&\mathbf{x}_*^T A\mathbf{x}_* + b^T\mathbf{x}_* + c && (10)\\
&= (\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2)^T A(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) + b^T(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) + c && (11)\\
&= \lambda^2\mathbf{x}_1^T A\mathbf{x}_1 + (1-\lambda)^2\mathbf{x}_2^T A\mathbf{x}_2 + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) + \lambda b^T\mathbf{x}_1 + (1-\lambda)b^T\mathbf{x}_2 + c && (12)\\
&= \lambda^2\mathbf{x}_1^T A\mathbf{x}_1 - \lambda\mathbf{x}_1^T A\mathbf{x}_1 + (1-\lambda)^2\mathbf{x}_2^T A\mathbf{x}_2 - (1-\lambda)\mathbf{x}_2^T A\mathbf{x}_2 \\
&+ \lambda(\mathbf{x}_1^T A\mathbf{x}_1 + b^T\mathbf{x}_1 + c) + (1-\lambda)(\mathbf{x}_2^T A\mathbf{x}_2 + b^T\mathbf{x}_2 + c) + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) && (13)\\
&\leq \lambda(\lambda-1)(\mathbf{x}_1^T A\mathbf{x}_1 + \mathbf{x}_2^T A\mathbf{x}_2) + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) && (14)\\
&= \lambda(\lambda-1)((\mathbf{x}_2 - \mathbf{x}_1)^T A(\mathbf{x}_2 - \mathbf{x}_1)) && (15)\\
&\leq 0 && (16)
\end{aligned}$$

Then, it is obvious that

$$\mathbf{x}_* \in C \tag{17}$$

Since $\mathbf{x}_*$ is arbitrary convex combination of $\mathbf{x}_1$ and $\mathbf{x}_2$, then

$$C \text{ is convex set.} \tag{18}$$

Hence, it is proved that

$$A \in \mathbb{S}_+^n \Rightarrow C \text{ is convex.} \tag{19}$$

□

(b) Show that C_1 is convex if there exists $\lambda \in \mathbb{R}$ such that $(A + \lambda gg^T) \in \mathbb{S}_+^n$

Proof. Assume that there exists $\lambda \in \mathbb{R}$ such that $(A + \lambda gg^T) \in \mathbb{S}_+^n$. Let λ^* be the λ that satisfies $(A + \lambda gg^T) \in \mathbb{S}_+^n$. Now we show that

$$\begin{aligned} C_1 &= C \cap \{\mathbf{x} \in \mathbb{R}^n : g^T\mathbf{x} + h = 0\} &(20)\\ &= \{\mathbf{x} \in \mathbb{R}^n : \mathbf{x}^T A\mathbf{x} + b^T\mathbf{x} + c \le 0 \text{ and } g^T\mathbf{x} + h = 0\} &(21)\end{aligned}$$

is convex.
Let $\mathbf{x}_1$ and $\mathbf{x}_2$ be arbitrary vector that $\mathbf{x}_1 \in C_1$, $\mathbf{x}_2 \in C_1$ and $\mathbf{x}_1 \neq \mathbf{x}_2$. Let $\mathbf{x}_*$ to be the arbitrary convex combination of $\mathbf{x}_1$ and $\mathbf{x}_2$ as $\mathbf{x}_* = \lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2$, and next we show that $\mathbf{x}_* \in C_1$.
By the definition of C_1 (See. (21)), we have

$$\begin{aligned} \mathbf{x}_1^T A\mathbf{x}_1 + b^T\mathbf{x}_1 + c \le 0 \text{ and } g^T\mathbf{x}_1 + h = 0 &\quad (22)\\ \mathbf{x}_2^T A\mathbf{x}_2 + b^T\mathbf{x}_2 + c \le 0 \text{ and } g^T\mathbf{x}_2 + h = 0 &\quad (23)\end{aligned}$$

Then we have

$$\begin{aligned} g^T\mathbf{x}_2 + h - (g^T\mathbf{x}_1 + h) = 0 &\quad (24)\\ g^T(\mathbf{x}_2 - \mathbf{x}_1) = 0 &\quad (25)\end{aligned}$$

Derivation for $g^T\mathbf{x}_* + h = 0$ is as follows:

$$\begin{aligned} &g^T\mathbf{x}_* + h &(26)\\ =\ &g^T(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) + h &(27)\\ =\ &\lambda g^T\mathbf{x}_1 + (1-\lambda)g^T\mathbf{x}_2 + h &(28)\\ =\ &\lambda(g^T\mathbf{x}_1 + h) + (1-\lambda)(g^T\mathbf{x}_2 + h) &(29)\\ =\ &0 &(30)\end{aligned}$$

Derivation for $\mathbf{x}_*^T A\mathbf{x}_* + b^T\mathbf{x}_* + c \le 0$ is as follows:

$$\begin{aligned} &\mathbf{x}_*^T A\mathbf{x}_* + b^T\mathbf{x}_* + c &(31)\\ =\ &(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2)^T A(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) + b^T(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) + c &(32)\\ =\ &\lambda^2\mathbf{x}_1^T A\mathbf{x}_1 + (1-\lambda)^2\mathbf{x}_2^T A\mathbf{x}_2 + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) + \lambda b^T\mathbf{x}_1 + (1-\lambda)b^T\mathbf{x}_2 + c &(33)\\ =\ &\lambda^2\mathbf{x}_1^T A\mathbf{x}_1 - \lambda\mathbf{x}_1^T A\mathbf{x}_1 + (1-\lambda)^2\mathbf{x}_2^T A\mathbf{x}_2 - (1-\lambda)\mathbf{x}_2^T A\mathbf{x}_2 \\ &+ \lambda(\mathbf{x}_1^T A\mathbf{x}_1 + b^T\mathbf{x}_1 + c) + (1-\lambda)(\mathbf{x}_2^T A\mathbf{x}_2 + b^T\mathbf{x}_2 + c) + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) &(34)\\ \le\ &\lambda(\lambda-1)(\mathbf{x}_1^T A\mathbf{x}_1 + \mathbf{x}_2^T A\mathbf{x}_2) + \lambda(1-\lambda)(\mathbf{x}_1^T A\mathbf{x}_2 + \mathbf{x}_2^T A\mathbf{x}_1) &(35)\\ =\ &\lambda(\lambda-1)((\mathbf{x}_2 - \mathbf{x}_1)^T A(\mathbf{x}_2 - \mathbf{x}_1)) &(36)\\ =\ &\lambda(\lambda-1)\Big((\mathbf{x}_2 - \mathbf{x}_1)^T(A + \lambda^* gg^T)(\mathbf{x}_2 - \mathbf{x}_1) - (\mathbf{x}_2 - \mathbf{x}_1)^T(\lambda^* gg^T)(\mathbf{x}_2 - \mathbf{x}_1)\Big) &(37)\\ \le\ &\lambda(1-\lambda)(\mathbf{x}_2 - \mathbf{x}_1)^T(\lambda^* gg^T)(\mathbf{x}_2 - \mathbf{x}_1) &(38)\\ =\ &0 &(39)\end{aligned}$$

Then we have

$$\mathbf{x}_*^T A\mathbf{x}_* + b^T\mathbf{x}_* + c \le 0 \text{ and } g^T\mathbf{x}_* + h = 0 \quad (40)$$

That is to say, for arbitrary convex combination $\mathbf{x}_* \in C_1$. Then

$$C_1 \text{ is convex set.} \quad (41)$$

Hence, it is proved that

$$\exists\lambda \in \mathbb{R},\ (A + \lambda gg^T) \in \mathbb{S}_+^n \Rightarrow C_1 \text{ is convex.} \quad (42)$$

□

3 Boyd and Vandenberghe, Ex. 2.21

Proof. Let $(a_1, b_1) \in S$, $(a_2, b_2) \in S$ and $(a_1, b_1) \neq (a_2, b_2)$, then show that arbitrary convex combination $(a_*, b_*) = (\lambda a_1 + (1-\lambda)a_2, \lambda b_1 + (1-\lambda)b_2) \in S$.
By definition of set S, we have

$$a_1^T x \leq b_1 \ \forall x \in C, \text{ and } a_1^T x \geq b_1 \ \forall x \in D \tag{43}$$
$$a_2^T x \leq b_2 \ \forall x \in C, \text{ and } a_2^T x \geq b_2 \ \forall x \in D \tag{44}$$

Then we turn to discuss $a_*^T x_c$ as follows: let x_c be arbitrary vector in set C,

$$\begin{aligned} a_*^T x_c &= (\lambda a_1 + (1-\lambda)a_2)^T x_c && (45)\\ &= \lambda a_1^T x_c + (1-\lambda)a_2^T x_c && (46)\\ &\leq \lambda b_1 + (1-\lambda)b_2 && (47)\\ &= b_* && (48)\end{aligned}$$

and now let x_d be arbitrary vector in set D,

$$\begin{aligned} a_*^T x_d &= (\lambda a_1 + (1-\lambda)a_2)^T x_d && (49)\\ &= \lambda a_1^T x_d + (1-\lambda)a_2^T x_d && (50)\\ &\geq \lambda b_1 + (1-\lambda)b_2 && (51)\\ &= b_* && (52)\end{aligned}$$

Now since we have $a_*^T x_c \leq b_* \ \forall x_c \in C$ and $a_*^T x_d \geq b_* \ \forall x_d \in D$, then we can conclude that

$$(a_*, b_*) \in S \tag{53}$$

Hence, it is proved that

$$S \text{ is convex.} \tag{54}$$

□

7 $\{x : ||x - v_1|| \leq ||x - v_2||\} = \{x : c^T x \leq d\}$

Proof.

$$\begin{aligned} & ||x - v_1|| \leq ||x - v_2|| && (55)\\ \Leftrightarrow\quad & ||x - v_1||^2 \leq ||x - v_2||^2 && (56)\\ \Leftrightarrow\quad & (x - v_1)^T(x - v_1) \leq (x - v_2)^T(x - v_2) && (57)\\ \Leftrightarrow\quad & x^T x - x^T v_1 - v_1^T x + v_1^T v_1 \leq x^T x - x^T v_2 - v_2^T x + v_2^T v_2 && (58)\\ \Leftrightarrow\quad & -v_1^T x - v_1^T x + v_1^T v_1 \leq -v_2^T x - v_2^T x + v_2^T v_2 && (59)\\ \Leftrightarrow\quad & 2(v_2 - v_1)^T x \leq v_2^T v_2 - v_1^T v_1 && (60)\end{aligned}$$

Let $c = 2(v_2 - v_1)$ and $d = v_2^T v_2 - v_1^T v_1 = ||v_2||^2 - ||v_1||^2$, then

$$c^T x \leq d \tag{61}$$

where $c = 2(v_2 - v_1)$ and $d = ||v_2||^2 - ||v_1||^2$.
Hence, we can conclude that

$$\{x : ||x - v_1|| \leq ||x - v_2||\} = \{x : c^T x \leq d\} \tag{62}$$

□

8 Exists C such that $CA = B$

Proof. By Contradiction. Assume that there does not exist such C that $CA = B$. This means

$$\forall C,\ \nexists \mathbf{x}, CA\mathbf{x} = B\mathbf{x} \tag{63}$$

Let $\mathbf{x}_* \in \mathbb{R}^m$ such that $A\mathbf{x}_* = 0$. Since we already have

$$A\mathbf{x} = 0 \Rightarrow B\mathbf{x} = 0 \tag{64}$$

Then we have

$$B\mathbf{x}_* = 0 \tag{65}$$

Therefore, we find a $\mathbf{x}_*$ such that $CA\mathbf{x}_* = B\mathbf{x}_* = 0,\ \forall C$, which contradict the statement (63). Hence, the initial assumption should be rejected and then it is proved that

$$\exists C \text{ such that } CA = B \tag{66}$$

□

A Codes Printout

(a) Gradient Descent Routine

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Problem set 1: Standard Gradient Descent with fixed step size
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Usage:
%     [b, iter, all_costs] = gd (X, b_init, gamma)
% Parameters:
%     X: matrix in quadratic optimization
%     b_init: starting vector of variable b
%     gamma: fixed step size
% Note that stopping criteria is set by absolute eps = 10e-5.

function [b, iter, all_costs] = gd (X, b_init, gamma)
eps = 10e-5;
b = b_init;
last_cost = 0.5 * b' * X * b;
iter = 1;
all_costs = [];
while true,
    %% compute essential numerics and do gradient descent
    gradient = X * b;
    b = b - gamma * gradient;
    cost = 0.5 * b' * X * b;
    rate = (cost / last_cost);
    all_costs = [all_costs cost];
    %% output numeric information of this iteration
    disp(sprintf('Iter: %d, Cost: %e, Conv_Rate: %f',iter,cost,rate));
    %% quadratic optimization converges to zero
    if cost < eps,
        disp('Converged to zeros!')
        break
    end
    %% qudratic optimization diverges
    if cost >= last_cost && iter > 10,
        disp('Problem diverges!')
        break
    end
    %% prepare for next iteration
    last_cost = cost;
    iter = iter + 1;
end

%% uncomment following code for plotting individual gradient descent run
%plot f(b^(n)) with regard to n
%plot (1:iter, all_costs)
%title (sprintf ('Gradient Descent with gamma=%f', gamma))
%xlabel ('iteration: n')
%ylabel ('cost of function: f(b^n)')

end
```

(b) Running Script

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Running scripts for applying gradient descent
%%% on three given dataset
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% for X1, b1
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
gamma1_one = 0.5; gamma2_two = 3;
[b1_opt_one, iter1_one, costs1_one] = Gradient_Descent(X1, b1, gamma1_one);
[b1_opt_two, iter1_two, costs1_two] = Gradient_Descent(X1, b1, gamma2_two);
subplot (1, 2, 1)
plot (1:iter1_one, costs1_one)
axis ([-0.1*iter1_one 1.1*iter1_one -0.05*max(costs1_one) max(costs1_one)])
title (sprintf ('Gradient Descent with gamma=%f', gamma1_one))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')
subplot (1, 2, 2)
plot (1:iter1_two, costs1_two)
axis ([-0.1*iter1_two 1.1*iter1_two -0.05*max(costs1_two) max(costs1_two)])
title (sprintf ('Gradient Descent with gamma=%f', gamma2_two))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% for X2, b2
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
gamma2_one = 1.5; gamma2_two = 3;
[b2_opt_one, iter2_one, costs2_one] = Gradient_Descent(X2, b2, gamma2_one);
[b2_opt_two, iter2_two, costs2_two] = Gradient_Descent(X2, b2, gamma2_two);
figure()
subplot (1, 2, 1)
plot (1:iter2_one, costs2_one)
axis ([-0.1*iter2_one 1.1*iter2_one -0.05*max(costs2_one) max(costs2_one)])
title (sprintf ('Gradient Descent with gamma=%f', gamma2_one))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')
subplot (1, 2, 2)
plot (1:iter2_two, costs2_two)
axis ([-0.1*iter2_two 1.1*iter2_two -0.05*max(costs2_two) max(costs2_two)])
title (sprintf ('Gradient Descent with gamma=%f', gamma2_two))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% for X3, b3
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
gamma3_one = 0.005; gamma3_two = 0.05;
[b3_opt_one, iter3_one, costs3_one] = Gradient_Descent(X3, b3, gamma3_one);
[b3_opt_two, iter3_two, costs3_two] = Gradient_Descent(X3, b3, gamma3_two);
figure()
subplot (1, 2, 1)
plot (1:iter3_one, costs3_one)
axis ([-0.1*iter3_one 1.1*iter3_one -0.05*max(costs3_one) max(costs3_one)])
title (sprintf ('Gradient Descent with gamma=%f', gamma3_one))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')
subplot (1, 2, 2)
plot (1:iter3_two, costs3_two)
axis ([-0.1*iter3_two 1.1*iter3_two -0.05*max(costs3_two) max(costs3_two)])
title (sprintf ('Gradient Descent with gamma=%f', gamma3_two))
xlabel ('iteration: n')
ylabel ('cost of function: f(b^n)')
```