## Convex Optimization

Exercise 1 (100/500)

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1. (a) Let  $f: \mathbb{R}_+ \to \mathbb{R}$ , with  $f(x) = \frac{1}{1+x}$ . Let  $x_0 \in \mathbb{R}_+$ , the first- and second- order Taylor approximations of f at  $x_0$  are

$$f'(x) = \frac{\partial(\frac{1}{1+x})}{\partial x} = \frac{-\frac{\partial}{\partial x}(1+x)}{(1+x)^2} = -\frac{1}{(1+x)^2},$$
$$f_{(1)}(x) = f(x_0) + f'(x_0)(x-x_0) = \frac{1}{1+x_0} - \frac{1}{(1+x_0)^2}(x-x_0) = \frac{1-x+2x_0}{(1+x_0)^2}$$

$$f''(x) = \frac{\partial(\frac{-1}{(1+x)^2})}{\partial x} = \frac{\partial(\frac{-1}{(1+x)^2})}{\partial x} = \frac{2(1+x)}{(1+x)^4} = \frac{2}{(1+x)^3}$$

$$f_{(2)}(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(x_0)(x - x_0)^2 = \frac{1 - x + 2x_0}{(1+x_0)^2} + \frac{1}{2}\frac{2}{(1+x)^3}(x - x_0)^2 = \frac{1 - x + 2x_0 + x_0 - x_0x + 2x_0^2 + x^2 - 2x_0x + x_0^2}{(1+x_0)^3} = \frac{1 + 3x_0^2 + 3x_0 - 3x_0x - x + x^2}{(1+x_0)^3}$$

(b) Figure 1 shows some common plots of f(x),  $f_{(1)}(x)$  and  $f_{(2)}(x)$  for various  $x_0$ . It is evident just by looking at the plots that the first order Taylor approximation of the convex function f at  $x_0$  is a global underestimator of f. Moreover close to  $x_0$  the first order Taylor approximation is very similar to f. The second order Taylor approximation of f at the same point is not a global underestimator of f but it approximates f more accurately in the vicinity of  $x_0$ .

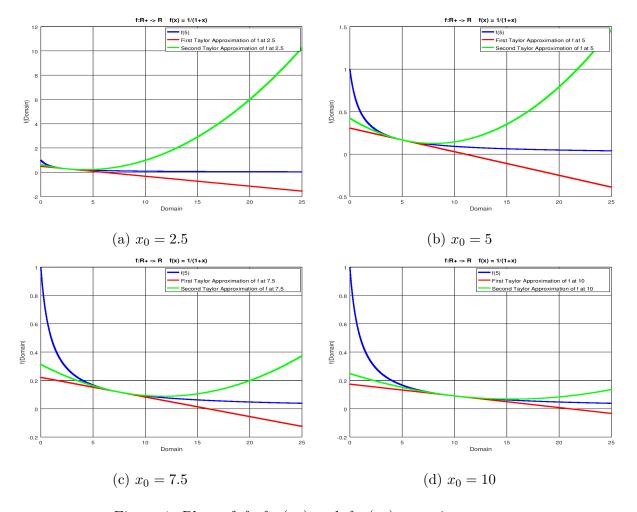


Figure 1: Plots of f,  $f_{(1)}(x_0)$  and  $f_{(2)}(x_0)$  at various  $x_0$ .

- 2. Let  $f: \mathbb{R}^2_+ \to \mathbb{R}$ , with  $f(x_1, x_2) = \frac{1}{1 + x_1 + x_2}$ .
  - (a) The plot of the convex function f for  $x1, x2 \in [0, x_*]$ , with  $x_* > 0$  is shown in Figure 2 (a).
  - (b) The level sets of f are shown in figure 2 (b). The brighter the regions are the higher the value of the function. In each contour the value of the function is the same.

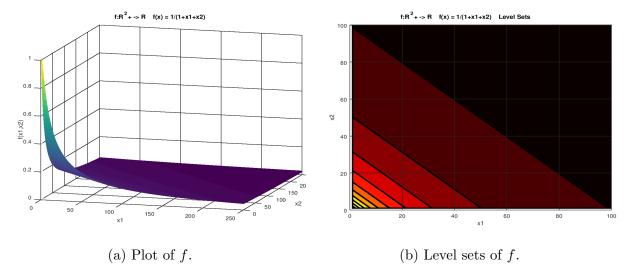


Figure 2: Plot and level sets of f.

(c) 
$$\frac{\partial f(x1, x2)}{\partial x_1} = \frac{\partial (\frac{1}{1+x_1+x_2})}{\partial x_1} = \frac{-\frac{\partial (1+x_1+x_2)}{\partial x_1}}{(1+x_1+x_2)^2} = -\frac{1}{1+x_1+x_2}$$

$$\frac{\partial f(x1, x2)}{\partial x_1} = \frac{\partial f(x1, x2)}{\partial x_2}$$

$$\nabla f(x1, x2) = \begin{bmatrix} \frac{\partial f(x1, x2)}{\partial x_1} \\ \frac{\partial f(x1, x2)}{\partial x_2} \end{bmatrix} = \begin{bmatrix} -\frac{1}{1+x_1+x_2} \\ -\frac{1}{1+x_1+x_2} \end{bmatrix}$$

$$f_{(1)}(x) = f(x_0) + \nabla f(x_0)^T (x - x_0) =$$

$$= \frac{1}{1+x_{0,1}+x_{0,2}} + \left[ -\frac{1}{1+x_{0,1}+x_{0,2}} - \frac{1}{1+x_{0,1}+x_{0,2}} \right] \begin{bmatrix} x_1 - x_{0,1} \\ x_2 - x_{0,2} \end{bmatrix} =$$

$$\frac{1}{1+x_{0,1}+x_{0,2}} - \frac{x_1 - x_{0,1}}{(1+x_{0,1}+x_{0,2})^2} - \frac{x_2 - x_{0,2}}{(1+x_{0,1}+x_{0,2})^2} = 1 - \frac{(x_{0,1}+x_{0,2})^2 + x_1 + x_2}{(1+x_{0,1}+x_{0,2})^2}$$

$$\nabla f^{2}(x1, x2) = \begin{bmatrix} \frac{\partial^{2} f(x1, x2)}{\partial x1^{2}} & \frac{\partial^{2} f(x1, x2)}{\partial x1x2} \\ \frac{\partial^{2} f(x1, x2)}{\partial x2x1} & \frac{\partial^{2} f(x1, x2)}{\partial x2^{2}} \end{bmatrix} = \begin{bmatrix} \frac{\partial \frac{-1}{(1+x1+x2)^{2}}}{\partial x1} & \frac{\partial \frac{-1}{(1+x1+x2)^{2}}}{\partial x1} & \frac{\partial \frac{-1}{(1+x1+x2)^{2}}}{\partial x2} \\ \frac{\partial \frac{-1}{(1+x1+x2)^{2}}}{\partial x1} & \frac{\partial \frac{-1}{(1+x1+x2)^{2}}}{\partial x2} \end{bmatrix} = \begin{bmatrix} \frac{2}{(1+x1+x2)^{3}} & \frac{2}{(1+x1+x2)^{3}} \\ \frac{2}{(1+x1+x2)^{3}} & \frac{2}{(1+x1+x2)^{3}} \end{bmatrix}$$

$$f_{(2)}(x) = f(x_0) + \nabla f(x_0)^T (x - x_0) + \frac{1}{2} (x - x_0) \nabla^2 f(x_0)^T (x - x_0) =$$

$$= 1 - \frac{(x_{0,1} + x_{0,2})^2 + x_0 + x_0}{(1 + x_{0,1} + x_{0,2})^2} +$$

$$+ \frac{1}{2} \left[ x_0 - x_{0,1} \quad x_0 - x_{0,2} \right] \begin{bmatrix} \frac{2}{(1 + x_{0,1} + x_{0,2})^3} & \frac{2}{(1 + x_{0,1} + x_{0,2})^3} \\ \frac{2}{(1 + x_{0,1} + x_{0,2})^3} & \frac{2}{(1 + x_{0,1} + x_{0,2})^3} \end{bmatrix} \begin{bmatrix} x_0 - x_{0,1} \\ x_0 - x_{0,1} \end{bmatrix} =$$

$$= 1 - \frac{(x_{0,1} + x_{0,2})^2 + x_0 + x_0}{(1 + x_{0,1} + x_{0,2})^2} + \frac{(x_0 - x_0)^2 + x_0 + x_0}{(1 + x_0)^2} + \frac{(x_0 - x_0)^2 + x_0}{(1 + x_0)^2}$$

- (d) The plot of f along  $f_{(1)}$  can be seen in Figure 3 (a).
- (e) The plot of f along  $f_{(2)}$  can be seen in Figure 3 (b).

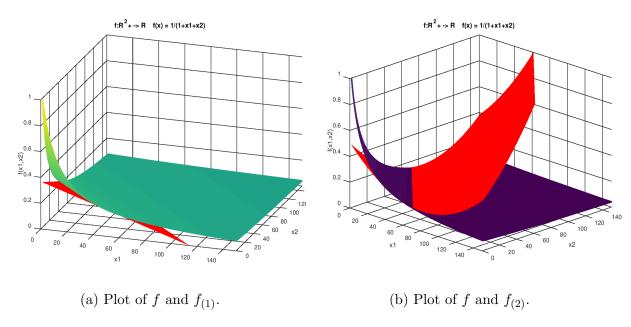


Figure 3: Plots of f along with its approximations  $f_{(1)}$  and  $f_{(2)}$ .

- 3. Let  $\mathbb{S}_{\mathbf{a},b} = \{ \mathbf{x} \in \mathbb{R}^n \, | \, \mathbf{a}^T \mathbf{x} \leq b \}.$ 
  - (a) Suppose  $x1, x2 \in S_{a,b}$  and  $0 \le \theta \le 1$ .

$$a^{T} x_{1} \leq b \Leftrightarrow \theta a^{T} x_{1} \leq \theta b$$

$$a^{T} x_{2} \leq b \Leftrightarrow (1 - \theta) a^{T} x_{2} \leq (1 - \theta) b$$

By adding the two inequalities we get

$$\theta a^T x_1 + (1 - \theta) a^T x_2 \le \theta b + (1 - \theta) b$$
$$a^T (\theta x_1 + (1 - \theta) x_2) \le b$$
$$a^T x_* < b$$

Where  $x_*$  is any convex combination of any  $x_1, x_2 \in S_{a,b}$ . Hence  $S_{a,b}$  is convex.

(b) In order for a set to be affine it must contain all the points of a line that connects any two of its points. Suppose  $x_1, x_2 \in S_{a,b}$ . The line connecting these two points is  $\theta x_1 + (1 - \theta)x_2$ . Now suppose that  $\theta > 1$  and  $x_1$  lies on the boundary of the halfspace(i.e  $a^T x_1 = b$ ). Then

$$a^{T}x_{1} = b \Leftrightarrow \theta a^{T}x_{1} = \theta b$$

$$a^{T}x_{2} \leq b \Leftrightarrow (1 - \theta)a^{T}x_{2} \geq (1 - \theta)b$$

By adding the two inequalities we get

$$\theta a^T x_1 + (1 - \theta) a^T x_2 \ge b$$
  
 $a^T (\theta x_1 + (1 - \theta) x_2) > b$ 

Hence  $S_{a,b}$  is not affine.

For a hyperplane  $H_{a,b} := \{x \in \mathbb{R}^n | a^T x = b\}$  we want to find a point  $x_*$  that is co-linear with a and lies on the hyperplane  $H_{a,b}$ .

$$x = ca, c \in \mathbb{R}$$

$$a^T x_* = b$$

Combining the above relations we get

$$ca^T a = b$$

$$c||a||_2^2 = b$$

$$c = \frac{b}{||a||_2^2}$$

Hence the point  $x_*$  is the

$$x_* = \frac{b}{||a||_2^2} a$$

- 5. (a)  $f: \mathbb{R}_+ \to \mathbb{R}$ ,  $f(x) = \frac{1}{1+x}$ . The domain of f is a convex set. Moreover f is differentiable within that domain. The second derivative of f, that was calculated in the first exercise, is  $f''(x) = \frac{2}{(1+x)^3}$ .  $f''(x) \ge 0$  for  $x \in \mathbb{R}_+$  hence f is convex.
  - (b)  $f: \mathbb{R}^2_+ \to \mathbb{R}$ ,  $f(x_1, x_2) = \frac{1}{1+x_1+x_2}$ . The domain of f is a convex set. Moreover f is differentiable within that domain. The second derivative of f, that was calculated in the first exercise, is  $\begin{bmatrix} \frac{2}{(1+x_1+x_2)^3} & \frac{2}{(1+x_1+x_2)^3} \\ \frac{2}{(1+x_1+x_2)^3} & \frac{2}{(1+x_1+x_2)^3} \end{bmatrix}$ . Suppose  $h \in \mathbb{R}^2$ .

$$h^{T} \begin{bmatrix} \frac{2}{(1+x_{1}+x_{2})^{3}} & \frac{2}{(1+x_{1}+x_{2})^{3}} \\ \frac{2}{(1+x_{1}+x_{2})^{3}} & \frac{2}{(1+x_{1}+x_{2})^{3}} \end{bmatrix} h = \begin{bmatrix} h_{1} & h_{2} \end{bmatrix} \begin{bmatrix} \frac{2(h_{1}+h_{2})}{(1+x_{1}+x_{2})^{3}} \\ \frac{2(h_{1}+h_{2})}{(1+x_{1}+x_{2})^{3}} \end{bmatrix} =$$

$$= \frac{2h_{1}^{2} + 4h_{1}h_{2} + 2h_{2}^{2}}{(1+x_{1}+x_{2})^{3}} = \frac{(2h_{1} + 2h_{2})^{2}}{(1+x_{1}+x_{2})^{3}} \ge 0$$

$$\forall x_{1}, x_{2} \in dom f$$

$$\forall h \in \mathbb{R}^{2}$$

$$\forall h \in \mathbb{R}^2$$

Hence f is convex.

(c) 
$$f: \mathbb{R}_{++} \to \mathbb{R}, f(x) = x^a$$
.

$$f'(x) = ax^{a-1}$$
  
 $f''(x) = a(a-1)x^{a-2}$ 

For  $a \ge 1$  or  $a \le 0$  and  $x \in \mathbb{R}_{++}$ ,  $f''(x) \ge 0$  hence f is convex. For  $0 \le a \le 1$  and  $x \in \mathbb{R}_{++}$ ,  $f''(x) \le 0$  hence f is concave.

(d) 
$$f: \mathbb{R}^2 \to \mathbb{R}, f(x) = ||x||_2$$
.

Suppose  $x_1, x_2 \in dom f$  and  $\theta \in \mathbb{R}$  with  $0 \le \theta \le 1$ .

$$f(x) = ||\theta x_1 + (1 - \theta)x_2||_2$$

$$\leq ||\theta x_1||_2 + ||(1 - \theta)x_2||_2 = |\theta|||x_1||_2 + |(1 - \theta)|||x_2||_2 =$$

$$= \theta||x_1||_2 + (1 - \theta)||x_2||_2 = \theta f(x_1) + (1 - \theta)f(x_2)$$

So f is convex. We used the triangle inequality and the homogeneity of a norm.

6. Consider the composition of scalar functions  $f(x_0) := (hog)(x) = h(g(x))$  with  $f, g, h : \mathbb{R} \to \mathbb{R}$ , where h and g are smooth functions.

$$f'(x) = h'(g(x))g'(x)$$
$$f''(x) = h''(g(x))g'(x)^{2} + h'(g(x))g''(x)$$

- (a) If h is convex and non-decreasing, and g is convex, then f is convex. This is because  $h''(g(x)) \ge 0$  as h is convex,  $g'(x)^2 \ge 0$ ,  $h'(g(x)) \ge 0$  as h is non-decreasing and  $g''(x) \ge 0$  as g is convex. An example of h is  $e^x$  and of g the  $||x||_2$ .
- (b) If h is convex and non-increasing, and g is concave, then f is convex. This is because  $h''(g(x)) \ge 0$  as h is convex,  $g'(x)^2 \ge 0$ ,  $h'(g(x)) \le 0$  as h is non-increasing and  $g''(x) \le 0$  as g is concave. An example of h is  $-\log x$  and of g the  $\log x$ .

- 7. Let  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$ , and  $f : \mathbb{R}^n \to \mathbb{R}$ , with  $f(x) = ||Ax b||_2^2$ .
  - (a) Assume that the columns of A are linearly independent.

$$f'(x) = \frac{\partial((Ax - b)^T (Ax - b))}{\partial x} = \frac{\partial(x^T A^T Ax - x^T A^T b - b^T Ax + b^T b)}{\partial x} = \frac{1}{2} A^T Ax - 2A^T b$$

$$f''(x) = A^T A$$

 $A^TA$  is called the Gram matrix witch is always positive semi-definite. Because all the columns of A are linearly independent(equivalently, it is invertible with  $det A \neq 0$ ) the matrix  $A^TA$  is positive definite. Hence f is strictly convex.

(b) The function f takes its minimal value, which is zero, at the solution x. This can also be seen from the plot and level sets of f near its solution.

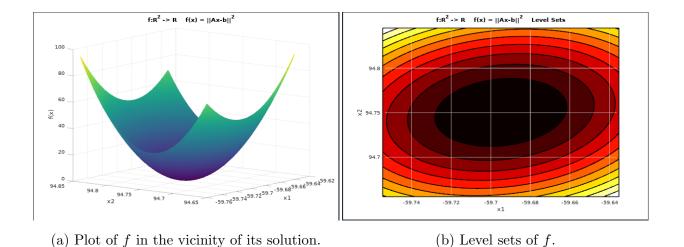


Figure 4: Plot and level sets of f.

By adding some noise to the vector  $\mathbf{b}$ , f is no longer minimized at x. The minimum is attained at a different point. Observe that f does not attain the zero value at its minimum.

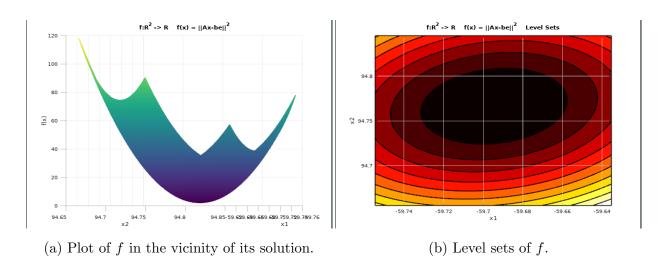


Figure 5: Plot and level sets of f.

## main.m

```
#Vissarion Konidaris
#Convex Optimization Course
# 9/3/2018

clc;
clear;
clc;
```

```
start = 0.;
finish = 25.;
```

```
domain = linspace(start, finish, precision);
func1 = 1./(1.+domain);
[FirstTaylor, SecondTaylor] = F1_Taylor_Appr(2.5, domain);
\% Plot the function along with its first and
\% second taylor approximations at point 2.5
figure (1);
pl = plot (domain, func1, 'linewidth', 2, 'b',
           domain, First Taylor, 'linewidth', 2, 'r',
           domain, SecondTaylor, 'linewidth', 2, 'g');
xlabel ('Domain');
ylabel ('f (Domain)');
title ('f:R+ -> R f(x) = 1/(1+x)');
legend ('f(5)', 'First Taylor Approximation of f at 2.5',
        'Second Taylor Approximation of f at 2.5');
grid on
[FirstTaylor, SecondTaylor] = F1_Taylor_Appr(5, domain);
% Plot the function along with its first and
\% second taylor approximations at point 5
figure (2);
pl = plot (domain, func1, 'linewidth', 2, 'b',
           domain, First Taylor, 'linewidth', 2, 'r',
           domain, SecondTaylor, 'linewidth', 2, 'g');
xlabel('Domain');
ylabel('f(Domain)');
title ('f:R+ \rightarrow R f(x) = 1/(1+x)');
legend ('f(5)', 'First Taylor Approximation of f at 5',
        'Second Taylor Approximation of f at 5');
grid on
[FirstTaylor, SecondTaylor] = F1_Taylor_Appr(7.5, domain);
```

precision = 1000000;

```
% Plot the function along with its first and
% second taylor approximations at point 7.5
figure (3);
pl = plot (domain, func1, 'linewidth', 2, 'b',
        domain, First Taylor, 'linewidth', 2, 'r',
        domain, SecondTaylor, 'linewidth', 2, 'g');
xlabel('Domain');
vlabel('f(Domain)');
title ('f:R+ -> R f(x) = 1/(1+x)');
legend ('f(5)', 'First Taylor Approximation of f at 7.5',
      'Second Taylor Approximation of f at 7.5');
grid on
[FirstTaylor, SecondTaylor] = F1_Taylor_Appr(10, domain);
% Plot the function along with its first and
% second taylor approximations at point 10
figure (4);
pl = plot (domain, func1, 'linewidth', 2, 'b',
        domain, First Taylor, 'linewidth', 2, 'r',
        domain, SecondTaylor, 'linewidth', 2, 'g');
xlabel('Domain');
ylabel ('f (Domain)');
title ('f:R+ -> R f(x) = 1/(1+x)');
legend ('f(5)', 'First Taylor Approximation of f at 10',
      'Second Taylor Approximation of f at 10');
grid on
```

```
start = 0.;
finish = 20.;
precision = 250;
x1 = linspace(start, finish, precision);
x2 = x1;
[X,Y] = meshgrid(x1,x2);
func2 = 1./(1.+X.+Y);
\% Plot the 3d plot of the second function using mesh
figure (5);
mesh (func2, 'LineWidth', 2);
rotate3d on;
axis([0 100 0 100 0 1]);
title ('f:R^2+ -> R f(x) = 1/(1+x1+x2)');
zlabel('f(x1,x2)');
xlabel('x1');
ylabel('x2');
grid on
\% Plot the level sets of the second function using contour
figure (6);
contourf(func2, 'LineWidth', 2);
colormap hot
axis([0 100 0 100 0 1]);
xlabel('x1');
ylabel('x2');
grid on
[FirstTaylor, SecondTaylor] = F2_Taylor_Appr(2,2,X,Y);
% Common 3d plot of the second function with its
\% first Taylor Approximation at point (2,2)
figure (7); hold on
```

```
mesh (func2, 'LineWidth', 2);
surf(FirstTaylor, 'FaceColor', 'red', 'EdgeColor', 'none');
rotate3d on;
axis([0 150 0 150 0 1]);
title ('f:R^2+ -> R f(x) = 1/(1+x1+x2)');
zlabel('f(x1,x2)');
xlabel('x1');
ylabel('x2');
grid on
% Common 3d plot of the second function with its
\% second Taylor Approximation at point (2,2)
figure (8); hold on
mesh (func2, 'LineWidth', 2);
surf(SecondTaylor, 'FaceColor', 'red', 'EdgeColor', 'none');
rotate3d on;
axis([0 150 0 150 0 1]);
title ('f:R^2+ \rightarrow R f(x) = 1/(1+x1+x2)');
zlabel('f(x1,x2)');
xlabel('x1');
ylabel('x2');
grid on
[FirstTaylor, SecondTaylor] = F2_Taylor_Appr(5,5,X,Y);
\% Common 3d plot of the second function with its
% first Taylor Approximation at point (5,5)
figure (9); hold on
mesh (func2, 'LineWidth', 2);
surf(FirstTaylor, 'FaceColor', 'red', 'EdgeColor', 'none');
rotate3d on;
axis([0 150 0 150 0 1]);
title ('f:R^2+ -> R f(x) = 1/(1+x1+x2)');
zlabel('f(x1,x2)');
```

```
xlabel('x1');
ylabel('x2');
grid on
% Common 3d plot of the second function with its
\% second Taylor Approximation at point (5,5)
figure (10); hold on
mesh (func2, 'LineWidth', 2);
surf(SecondTaylor, 'FaceColor', 'red', 'EdgeColor', 'none');
rotate3d on;
axis([0 150 0 150 0 1]);
title ('f:R^2+ -> R f(x) = 1/(1+x1+x2)');
zlabel('f(x1,x2)');
xlabel('x1');
ylabel('x2');
grid on
start = 0.01;
finish = 25.;
precision = 1000000;
domain = linspace(start, finish, precision);
func1 = domain.^3;
func2 = domain. 0.25;
func3 = domain.^(-2);
% Plot the function along with its first and
% second taylor approximations at point 2.5
```

```
figure (11);
pl = plot (domain, func1, 'linewidth', 2, 'b',
         domain, func2, 'linewidth', 2, 'r',
         domain, func3, 'linewidth', 2, 'g');
xlabel('Domain');
ylabel ('f (Domain)');
title ('f:R++ -> R f(x) = x^a');
legend('a=3', 'a=0.25', 'a=-2');
axis([-0.5 \ 10 \ -2.5 \ 25]);
grid on
start = -20.;
finish = 20.;
precision = 500;
x1 = linspace(start, finish, precision);
x2 = x1;
[X,Y] = meshgrid(x1,x2);
norm2 = (X.^2.+Y.^2).^(1/2);
% Plot the 3d plot of the second function using mesh
figure (12);
mesh (norm2, 'LineWidth', 2);
rotate3d on;
title ('f:R^2 -> R f(x) = ||X||');
zlabel('f(x1,x2)');
xlabel('x1');
ylabel('x2');
grid on
```

```
A = 200*rand(3,2) - 100;
x = 200*rand(2,1)-100;
b = A*x;
precision = 15;
x1 = linspace(x(1,1) - abs(x(1,1))/1000, x(1,1) + abs(x(1,1))/1000, precision);
x2 = linspace(x(2,1) - abs(x(2,1))/1000, x(2,1) + abs(x(2,1))/1000, precision);
[X,Y] = meshgrid(x1,x2);
LeastSquares = (A(1,1)*X+A(1,2)*Y-b(1,1)).^2 ...
               +(A(2,1)*X+A(2,2)*Y-b(2,1)).^2 ...
               +(A(3,1)*X+A(3,2)*Y-b(3,1)).^2;
% Plot the 3d plot of the Least Squares Equation
figure (1);
mesh(X,Y,LeastSquares, 'LineWidth', 2);
rotate3d on;
title ('f:R^2 -> R  f(x) = ||Ax-b||^2');
zlabel('f(x)');
xlabel('x1');
ylabel('x2');
grid on
\% Plot the level sets of the Least Squares Equation
figure (2);
contourf(X,Y,LeastSquares, 'LineWidth', 2);
colormap hot
                   f(x) = ||Ax-b||^2 Level Sets');
title ('f:R^2 \rightarrow R
xlabel('x1');
ylabel('x2');
grid on
```

```
b=randn(3,1); % Adding Gaussian noise to the b vector
LeastSquaresE = (A(1,1)*X+A(1,2)*Y-b(1,1)).^2 ...
                +(A(2,1)*X+A(2,2)*Y-b(2,1)).^2...
                +(A(3,1)*X+A(3,2)*Y-b(3,1)).^2;
% Plot the 3d plot of the Least Squares Equation
figure (3);
mesh(X,Y,LeastSquaresE, 'LineWidth',2);
rotate3d on;
                   f(x) = ||Ax-be||^2;
title ('f:R^2 \rightarrow R
zlabel('f(x)');
xlabel('x1');
ylabel('x2');
\%xlim ([X(1,1)-10 X(1, size(X,2))+10]);
\%ylim ([Y(1,1)-10 Y(size(Y,1),1)+10]);
grid on
\% Plot the level sets of the Least Squares Equation
figure (4);
contourf(X,Y,LeastSquaresE, 'LineWidth', 2);
colormap hot
title ('f:R^2 -> R f(x) = ||Ax-be||^2 Level Sets');
xlabel('x1');
ylabel('x2');
grid on
disp('x')
disp(x)
disp('X')
disp(X)
disp('Y')
```

```
disp(Y)
disp ('LeastSquares')
disp (LeastSquares)
disp('LeastSquaresE')
disp (LeastSquaresE)
function [FirstTaylor, SecondTaylor] = F1_Taylor_Appr(Num, Dom)
  First Taylor = (1-Dom+2*Num)./(1+Num)^2;
  SecondTaylor = (1+3*Num^2+3*Num-3*Num.*Dom.-Dom.+Dom.^2)...
              ./(1+Num)^3;
  return
endfuncion
function [FirstTaylor, SecondTaylor] = F2-Taylor_Appr(Num1, Num2, X, Y)
  FirstTaylor = 1. - ((Num1+Num2)^2.+X.+Y)./(1+Num1+Num2)^2;
  SecondTaylor = FirstTaylor.+((X.-Num1.+Y.-Num2).^2)...
              ./(1+Num1+Num2)^3;
  return
endfuncion
```