

# Semester project TMA4215

Candidate number one  
and  
Candidate number two

25.09.2011

# 1 Task

We consider minimization problems of the type

$$\min_{\mathbf{x} \in \mathbb{R}^n} g(\mathbf{x}), \quad g(\mathbf{x}) := -\mathbf{b}^T \mathbf{x} + \frac{1}{2} \mathbf{x}^T H \mathbf{x} + \frac{1}{12} \mathbf{x}^T C(\mathbf{x}) \mathbf{x},$$

here  $\mathbf{b} \in \mathbb{R}^n$  and,  $H$  is a  $n \times n$  symmetric and positive definite matrix and  $C(\mathbf{x})$  is a diagonal matrix with diagonal entries  $c_i x_i^2, i = 1, \dots, n$ . Here  $c_i > 0$  are the components of a vector  $\mathbf{c} \in \mathbb{R}^n$  and  $x_i$  are the components of  $\mathbf{x}$ .

## 2 Generation of the data

The data is generated in the function **data**.  $\mathbf{b}$  and  $\mathbf{c}$  should be of the same dimension and  $H$  should be a symmetric matrix which fits to the vectors. Line 6 can be used to check the dimensions of the input data, but this costs a lot of resources, because **data** is often called.

```
1 function [b, H, c] = data
2     b = [1; 0];
3     c = [1; 1];
4     H = [1, 1;
5         1, 1];
6     % b' * H * c;
7 end
```

## 3 Function, gradient and Hessian of $g$

```
1 function [ g ] = ( X )
2     [ b, H, c ] = data;
3     dim = size(H,1);
4     C = zeros ( dim, dim );
5     for i = 1 : dim
6         C(i,i) = c(i) * X(i) * X(i);
7     end
8     g = - b' * X + 0.5 * X' * H * X + 1/12 * X' * C * X;
9 end
```

$$\nabla g = -\mathbf{b} + H\mathbf{x} + \frac{1}{3}C\mathbf{x} \quad (1)$$

```
1 function [ nablG ] = grad( X )
2     [ b, H, c ] = data;
3     dim = size ( H, 1 );
4     for i = 1 : dim
5         C(i,i) = c(i) * X(i) * X(i);
6     end
7     nablG = - b + H * X + 1/3 * C * X;
8 end
```

$$\nabla^2 g = H + C \quad (2)$$

```

1 function [ HessG ] = hessian( X )
2     [ ~, H, c ] = data;
3     dim = size ( H, 1 );
4     C = zeros ( dim, dim );
5     for i = 1 : dim
6         C(i,i) = c(i) * X(i) * X(i);
7     end
8     HessG = H + C;
9 end

```

## 4 Existence of minimum

Let  $u \in R^n$  be an arbitrary vector, except  $\vec{0}$  then

$$u(\nabla^2 g(x))u = u(H + C)u = uHu + uCu = uHu + \sum_{i=1}^n c_i u_i^2 x_i^2.$$

Since  $H$  is positive definite,  $uHu > 0$  and because  $c_i > 0$ ,  $uCu > 0$ , so

$$u(\nabla^2 g(x))u > 0$$

That means that the Hessian of  $g$  is positive definite.

## 5 Plot for $n = 2$

## 6 Steepest decent method

```

1 function [ iterations , X, Y, Z ] = steepest( Xk, alpha )
2     tol = 1e-6;
3     maxiterations = 1000;
4     [~,H,~] = data;
5     dim = size(H, 1);
6     X1 = zeros(1, maxiterations);
7     X2 = zeros(1, maxiterations);
8     Y = zeros(1, maxiterations);
9     Z = zeros(1, maxiterations);
10    X1(1) = Xk(1);
11    X2(1) = Xk(2);
12    condition = 1;
13    norm_old = norm ( grad ( Xk ) );
14    Y(1) = norm_old;
15    Z(1) = problem(Xk);
16    while condition
17        maxiterations = maxiterations - 1;
18        Xk = Xk - alpha * grad ( Xk );
19        if dim == 2
20            X1(1000-maxiterations+1) = Xk(1);
21            X2(1000-maxiterations+1) = Xk(2);
22        end
23        residual = norm ( grad ( Xk ) ) / norm_old;
24        Y(1000-maxiterations+1) = residual;
25        Z(1000-maxiterations+1) = problem(Xk);
26        condition = (maxiterations > 0) && ( residual > tol);
27    end
28    X1 = X1(1:1000-maxiterations+1);
29    X2 = X2(1:1000-maxiterations+1);

```

```

30     X = [X1;X2];
31     iterations = (1:1:1000-maxiterations+1);
32     Z = Z(1:1000-maxiterations+1);
33     Y = Y(1:1000-maxiterations+1);
34 end

```

## 7 Equivalence of steepest decent method and forward Euler method

No idea.

## 8 Improved steepest decent method

To find the optimal  $\alpha$ ,

$$g(\mathbf{x}^{(k+1)}) = g(\mathbf{x}^{(k)} - \alpha^{(k)} \nabla g(\mathbf{x}^{(k+1)}))$$

has to be minimal, so  $\frac{\partial}{\partial \alpha} g(\mathbf{x}^{(k+1)})$  has to be zero. This leads to the equation

$$\begin{aligned} & \left( \mathbf{b} \nabla g - \mathbf{x} H \mathbf{x} - \frac{1}{3} \mathbf{x} H \nabla g \right) + ((\nabla g)(H + C) \nabla g) \alpha \\ & + \left( - \sum_{i=1}^n c_i x_i (\nabla g)_i^3 \right) \alpha^2 + \left( \sum_{i=1}^n c_i (\nabla g)_i^4 \right) \alpha^3 = 0 \end{aligned}$$

## 9 Newton method

## 10 Combination of steepest decent methode and Newton method