

Optimization Technique

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December 4, 2018

$$\mathbf{f}(\mathbf{x}) = x - 1 - \ln(x) \quad (1)$$

Initially for the given Tolerance (0.001) and epsilon (0.0001) the number of iterations occurred for convergence is 13 and the precision obtained is 1.0004.

The varied tolerance range is from 10^{-7} to 10^{-4} and the number of iterations decreases as tolerance value increases as shown below in the figure.

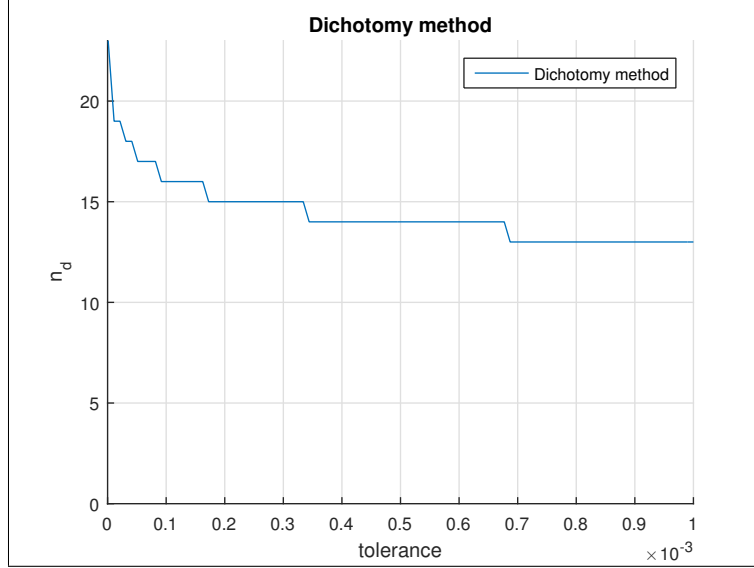
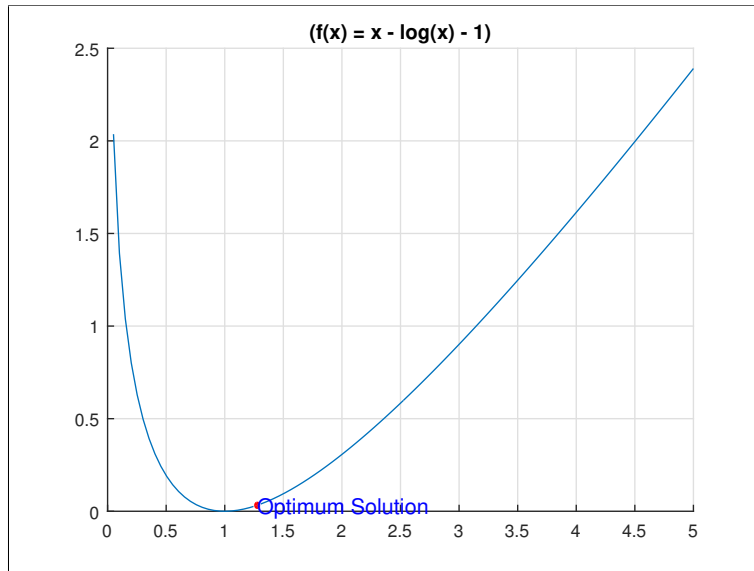


Figure 1: Tolerance vs iterations

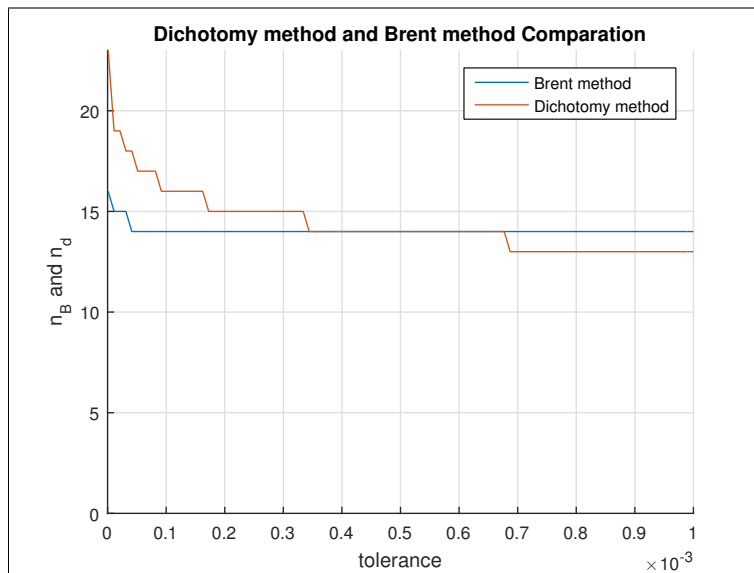
when we increase the tolerance, the soon the convergence is occurred decreasing the number of iterations but, it decreases the precision. For the smaller tolerance the minimal obtained is 1.0000 and for the larger tolerance the precision obtained is 1.0004.

By choosing the larger epsilon (0.2), we exclude the larger region of search and we might also reject the minima and precision is not obtained. For example, choosing $e = 0.2$ and by varying tolerance. For smaller and larger tolerance, the minima obtained is 1.0938 and the iterations occurred are 5.

By choosing very smaller epsilon value, the number of iterations may increase or decrease, but it might exceed the maximum number of iterations and terminates with wrong precision values. For example, by choosing epsilon as $\text{tolerance}(i)/10^9$.



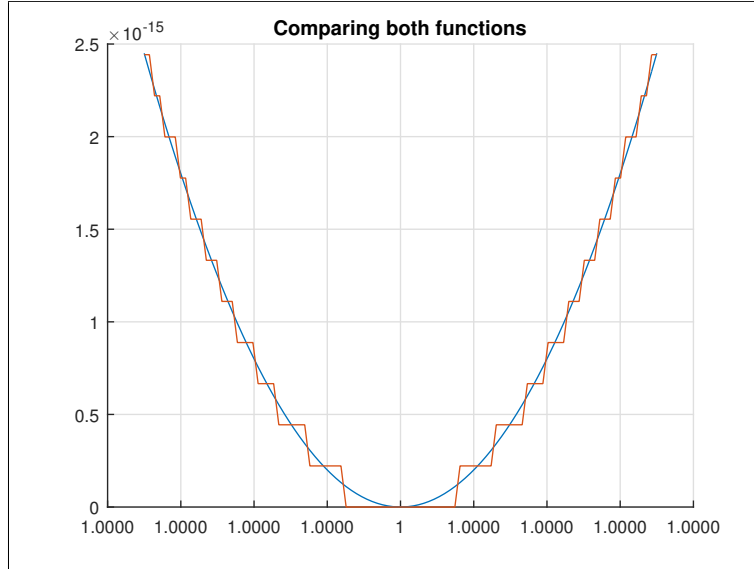
Now we compare both the methods by varying tolerance and plot tolerance vs iterations.



For the function

$$\mathbf{f}(\mathbf{x}) = x - \ln(x) - 1 \quad (2)$$

, which is same as the first function, but as matlab reads the function from left to right, it appears to be a different function. The obtained results are same with same precision.



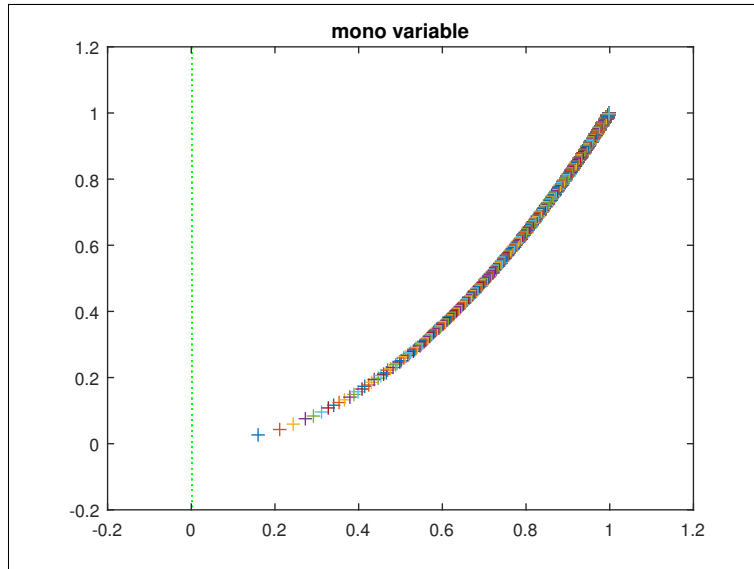
1 Rosenbrook function Minimization :

For the given function (Rosenbrook function) defined as

$$f(x_1, x_2) = 100(x_1^2 - x_2)^2 + (1 - x_1)^2 \quad (3)$$

1.1 Monovariate Method

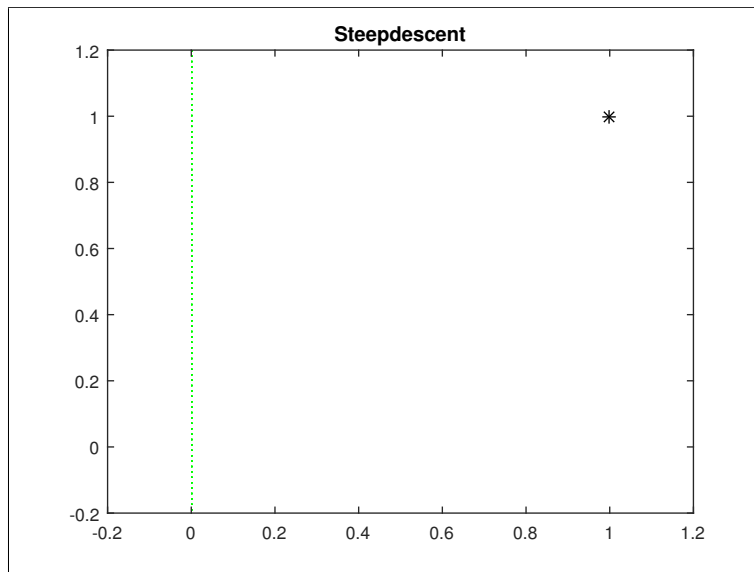
For a multivariable problem, each variable searches in all the directions, while the other variable is kept constant, similarly the second variable finds minimum in all directions, while first variable is kept constant. Successive iterations are carried out to find the minimum.



1.2 Steepest descent method

Steepest descent method uses the concept of Gradient, that is the direction towards the maximum function value, so the negative of the gradient is chosen for the minimum function value and with appropriate step length from the initial point. The step length is chosen as $\lambda_i = S_i^T * S_i / S_i^T * A * S_i$

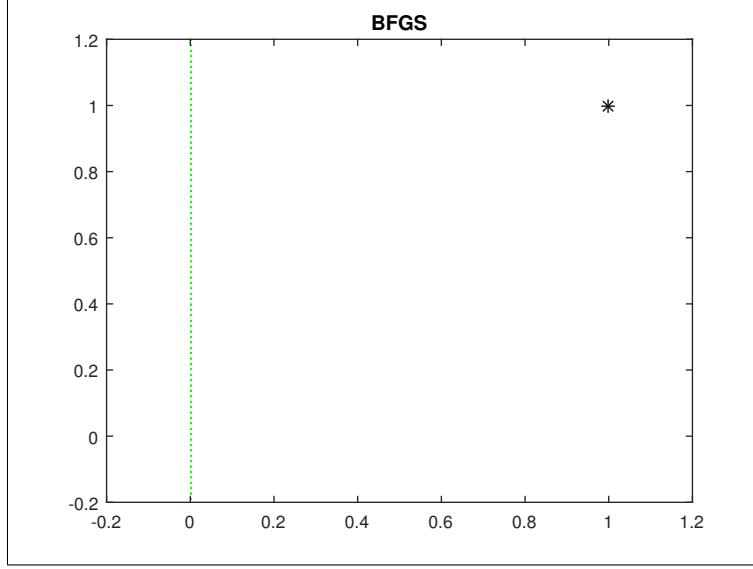
In above example we are getting the optimal point in only 1 iteration.



1.3 Quasi-Newton BFGS method

The main difference in this method with respect to other method is, in this we keep updating the Hessian matrix with B matrix, in the absence of additional information, B is chosen as identity matrix. The direction is given as $S_i = -[B_i]\nabla f_i$

In the above example the optimal step length and direction is obtained in only one iteration.



2 Estimation :

A exponential noisy series is given as

$$y_k = a_0 b_0^{(k-1)} + w_k \quad (4)$$

where w_k is a series of white Gaussian noise of variance 1

we want to estimate a_0 and b_0 by minimizing the least square criteria which is given as

$$J(a, b) = \sum_{k=1}^{40} (y_k - ab^{(k-1)})^2 \quad (5)$$

for the stimulation we take $a_0 = 10$, $b_0 = 0.9$.

2.1 Monovariate :

Rewriting the minimization criteria of J w.r.t to one of the variable.

$$\frac{\partial J}{\partial a} = 0 \quad (6)$$

if we implement this on equation 4 we get

$$J(b) = \sum_{k=1}^{40} \left(y_k - \frac{\sum_{i=1}^{40} b^{i-1} y_i}{\sum_{i=1}^{40} (b^{i-1})^2} (b^{(k-1)})^2 \right)^2 \quad (7)$$

The above equation is the the new criteria which should be used in order to minimize the given function.

2.2 Comparing :(Mono and BFGS)

By applying the above criteria's we got the following solution's :

As we use random numbers we can run the program n number of times and study/compare the methods and study the behaviour.

For the first time :

Mono-variable :

a = 10.4697
b = 0.9035
i = 14
duration = 0.9531

BFGS :

a = 10.4698
b = 0.9035
i = 22
duration = 0.8750

For the second time :

Mono-variable :

a = 10.0150
b = 0.8999
i = 14
duration = 1

BFGS :

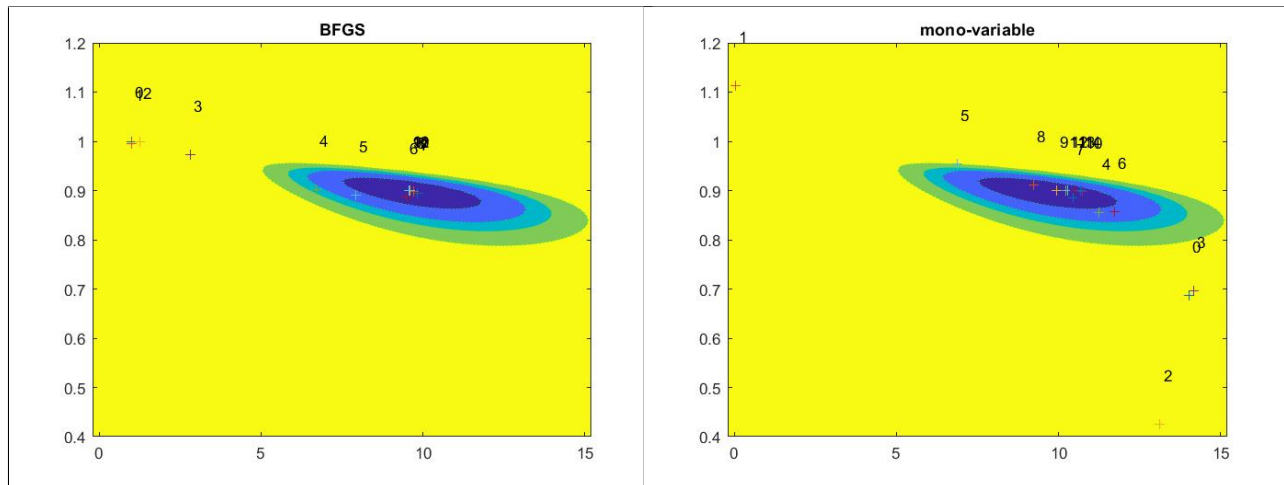
a = 10.0151
b = 0.8999
i = 12
duration = 0.8594

From the above results we can see that the time taken to calculate the minimum is best in **BFGS** i.e the result is obtained much **faster** when compared to the Mono-variable **even when the number of iterations were more in BFGS**.

2.3 Level Curves :

The above obtained results can be plotted in the form of level curves i.e the evolution of the minimum in a plane (a,b) for both the methods.

The trajectory of the minimum in both the methods is as shown below :



(a) BFGS

(b) Mono-Variable

Figure 2: Trajectory

1 MATLAB Codes

1.1 Mono-variable minimization : comparison of dichotomy and Brent's method

Listing 1: Code for setting options/Brent's method/plotting

```

1
2 close all
3 clear all
4 clc
5
6 % Setting the limits for X
7 xmin = 0;
8 xmax = 5;
9 xmin2 = 0;
10 xmax2 = 5;
11
12 n_d = [];
13 n_d2 = [];
14 n_Brent = [];
15
16 % tolerance = linspace(2e-4,1e-6,100);
17 tolerance = linspace(1e-6,1e-3,100);
18
19
20 for i = 1: length (tolerance)

```



```

21
22 options = optimset('Display', 'iter', 'TolFun', tolerance(i),.....
23                 'TolX', tolerance(i)/11, 'MaxFunEvals', 200 , 'MaxIter', 100);
24
25 [X1(i), X2(i), n_d(i),n_d2(i)] = dichot(xmin, xmax, xmin2, xmax2, options);
26
27 % Brent's method
28
29 options.TolX = tolerance(i);
30
31 [x,fval,exitflag,output] = fminbnd(@objfun, xmin, xmax, options);
32
33 n_Brent = [n_Brent output.funcCount];
34
35 end
36
37 figure(1)
38 hold on
39 grid on
40 plot(tolerance, n_Brent, tolerance, n_d)
41 legend('Brent method','Dichotomy method')
42 title('Dichotomy method and Brent method Comparation')
43 xlabel('tolerance')
44 ylabel('n_B and n_d')
45 ylim([0 inf])
46
47
48
49 % Plotting
50 x_1 = linspace(xmin,xmax);
51 x_2 = linspace(xmin2,xmax2);
52
53
54 % Objective Function
55 for i = 1:length(x_1)
56     y_1(i) = objfun(x_1(i));
57 end
58
59 for i = 1:length(x_2)
60     y_2(i) = objfun2(x_2(i));
61 end
62
63 figure(2)
64 hold on
65 grid on
66 plot(x_1,y_1) % Function Plotting
67 viscircles([X1(1),objfun(X1(1))], 0.01); % Solution Plotting
68 title('(f(x) = x - 1 - log(x))');
69 txt = {'Optimum Solution'};
70 text(X1(1),objfun(X1(1)),txt,'Color','r','FontSize',12)
71

```

```

72 figure(3)
73 hold on
74 grid on
75 plot(x_2,y_2) % Function Plotting
76 viscircles([X2(1),objfun2(X2(1))], 0.01); % Solution Plotting
77 title('(f(x) = x - log(x) - 1)');
78 txt = {'Optimum Solution'};
79 text(X2(1),objfun2(X2(1)),txt,'Color','b','FontSize',12)
80
81 figure(4)
82 hold on
83 grid on
84 len=0.00000007;
85 x = linspace(1-len,1+len);
86 plot(x,objfun(x),x,objfun2(x))
87 title('Comparing both functions');

```

Listing 2: Code for Dichotomy

```

1
2
3 function [X1, X2, n_d, n_d2] = dicho(xmin, xmax, xmin2, xmax2, options)
4     iter = 0;
5
6     while (abs(xmax-xmin)>options.TolFun)
7
8         L = xmax + xmin; % Interval size
9
10        % Selecting smaller interval
11        x1 = (L - options.TolX)/2;
12        x2 = (L + options.TolX)/2;
13
14        % Checking the values of objfun on both limits
15        f1 = objfun(x1);
16        f2 = objfun(x2);
17
18        % Updating the interval for next iteration
19        if (f1<f2)
20            xmax = x2;
21        else
22            xmin = x1;
23        end
24        % Updating the State
25        iter = iter+1 ;
26    end
27
28    if(f1<f2)
29        X1 = x2;
30    else X1 = x1;
31    end
32    n_d = [iter];
33

```

```

34
35     iter2 = 0;
36
37     while (abs(xmax2-xmin2)>options.TolFun)
38
39         L2 = xmax2 + xmin2;           % Interval size
40
41         % Selecting smaller interval
42         x21 = (L2 - options.TolX)/2;
43         x22 = (L2 + options.TolX)/2;
44
45         % Checking the values of objfun on both limits
46         g1 = objfun2(x21);
47         g2 = objfun2(x22);
48
49         % Updating the interval for next iteration
50         if (g1<g2)
51             xmax2 = x22;
52         else
53             xmin2 = x21;
54         end
55         % Updating the State
56         iter2 = iter2 +1 ;
57     end
58
59     if(g1<g2)
60         X2 = x22;
61     else X2 = x21;
62     end
63
64     n_d2 = [iter2];
65 end

```

Listing 3: Code for objective function 1

```

1 function f = objfun(x)
2
3     f = x - 1 - log(x) ;
4
5 end

```

Listing 4: Code for objective function 2

```

1 function g = objfun2(x)
2
3     g = x - log(x) - 1 ;
4
5 end

```

1.2 Rosenbrook function minimization

Listing 5: Monovvariable/Steepest descent method/The quasi newton BFGS method

```

1
2 close all
3 clear all
4 clc
5
6
7 tolerance = 1e-6;
8 % [a,b]x[c,d]
9 a = -5;
10 b = 5;
11 c = -5;
12 d = 5;
13
14
15 [X,Y] = meshgrid(-0.2:0.001:1.2, -0.2:0.001:1.2);
16 f = 100*((X^2-Y)^2) + (1-X)^2;
17 v = [128,64,32,16,8,4,2,0.5,0.1,0.01];
18
19 fun = @(x) 100*((x(1)^2-x(2))^2) + (1-x(1))^2;
20 x2 = 0;
21 x1 = 0;
22 figure
23 contour(X,Y,f,v,':g');
24 hold on
25
26 options.TolX = tolerance;
27 i1=0;
28 i2=0;
29 i3=0;
30 n_Mon = 0;%nb of iterations using monovvariable method
31 n_s =0;%nb of iterations using steepest method
32 n_B=0;%nb of iterations using BFGS method
33 %method monovvariable
34 x1_prev = a;
35 x2_prev = c;
36 t1=cputime;
37
38
39
40 while (abs(x1 - x1_prev) > tolerance) & (abs(x2 - x2_prev) > tolerance)
41     x1_prev = x1;
42     x2_prev = x2;
43
44
45     [x1,fval,exitflag,output] = fminbnd(@(x1)fun([x1;x2]), a, b, options);
46     [x2,fval,exitflag,output] = fminbnd(@(x2)fun([x1;x2]), c, d, options);
47
48     hold on
49     plot (x1,x2,'+')
50 end

```

```

51
52 hold off
53 title 'mono variable'
54
55 n_Mon =output.funcCount;
56 i1=output.iterations;
57 x1_fminbnd = x1
58 x2_fminbnd = x2
59 tmon=cputime-t1;
60
61 %Steepest descent method
62 x0 = [x1, x2];
63 t2=cputime;
64 figure
65 contour(X,Y,f,v,':g');
66 hold on
67 fprintf('result-Steepdscent:');
68 options.HessUpdate = 'steepdesc';
69 x_Stepest = fminunc(fun,x0,options)
70 plot(x_Stepest(1),x_Stepest(2),'k*')
71 [x_Stepest,fval,exitflag,output]=fminunc(fun,x0,options)
72 n_s =output.funcCount;
73 i2=output.iterations;
74 tsteepest=cputime-t2;
75 hold off
76 title 'Steepdescent'
77
78 %Quasi - Newton BFGS method
79 x0 = [x1, x2];
80 t3=cputime;
81 figure
82 contour(X,Y,f,v,':g');
83 hold on
84 fprintf('result-BFGS:');
85 options.HessUpdate = 'bfgs';
86 x_BFGS = fminunc(fun,x0,options)
87 plot(x_BFGS(1),x_BFGS(2),'k*')
88 [x_BFGS,fval,exitflag,output]=fminunc(fun,x0,options)
89 n_B =output.funcCount;
90 i3=output.iterations;
91 tbfgs=cputime-t3;
92 title 'BFGS'

```

1.3 Estimation

Listing 6: Main Script

```

1 close all
2 clear all
3 clc

```

```

4
5 a0 = 10;
6 b0 = 0.9;
7 tol = power(10, -5);
8
9 y = zeros(40,1);
10 for i = 1:40
11     y(i) = a0*power(b0,i-1)+randn(1);
12 end
13
14 X = 0.4:0.01:1.2;
15 Y = -0.2:0.01:15.2;
16 Z = zeros(length(X), length(Y))
17 for i=1:length(X)
18     for j=1:length(Y)
19         Z(i,j)=critere2([Y(j),X(i)],y);
20     end
21 end
22
23 v= [0.01,0.1,1.5,10,20,40,60,75,100];
24
25
26 %method monovariable
27 t=cputime;
28 figure
29 contourf(Y,X,Z,v,':g');
30 hold on
31 options = optimset('TolX',tol,...
32                     'MaxFunEvals',800,'MaxIter',200,'OutputFcn',@outfun2);
33
34 [b,fval,exitflag,output] = fminbnd(@(b) critere(b,y),0,1.8,options);
35 title 'mono-variable'
36 fprintf('result mono-variable')
37 b
38 i1 = output.iterations
39
40 a1 = 0;
41 a2 = 0;
42 for i = 1:length(y)
43     a1 = a1 + power(b,i-1)*y(i);
44     a2 = a2 + (power(b,i-1))^2;
45 end
46
47 a=a1/a2
48 duration1 = cputime-t
49
50 %method BFGS
51 t = cputime;
52 figure
53 contourf(Y,X,Z,v,':g');
54 options = optimset('TolX',tol,...

```

```

55         'MaxFunEvals',800,'MaxIter',200,'OutputFcn',@outfun);
56
57 [x,fval,exitflag,output] = fminunc(@(x) critere2(x,y),[1,1],options);
58 title 'BFGS'
59 fprintf('result-BFGS')
60 a_bfgs = x(1)
61 b_bfgs = x(2)
62 i2 = output.iterations
63
64 duration2 = cputime-t

```

Function - Critere :

```

1 function [J] = critere(b,y)
2 a1=0;
3 a2=0;
4 for i=1:length(y)
5 a1=a1+power(b,i-1)*y(i);
6 a2=a2+(power(b,i-1))^2;
7 end
8 a=a1/a2;
9 J=0;
10 for i=1:length(y)
11     J=J+power(y(i)-a*power(b,i-1),2);
12 end

```

Function - Critere2 :

```

1 function [J]=critere2(x,y)
2 J=0;
3 for i=1:length(y)
4     J=J+power(y(i)-x(1)*power(x(2),i-1),2);
5 end

```

Function - outfun :

```

1 function stop = outfun(x,optimValues,state)
2     stop=false;
3     switch state
4         case 'init'
5             hold on
6         case 'iter'
7             plot(x(1),x(2),'+');
8             text(x(1)+0.1,x(2)+0.1,num2str(optimValues.iteration))
9         case 'done'
10            hold off
11        otherwise
12            end
13    end

```

Function - outfun2 :

```

1  function stop = outfun2(b,optimValues,state)
2      stop=false;
3      switch state
4          case 'init'
5              hold on
6          case 'iter'
7              a0=10;
8              b0=0.9;
9              y=zeros(40,1);
10             for i=1:40
11                 y(i)=a0*power(b0,i-1)+randn(1);
12             end
13             a1=0;
14             a2=0;
15             for i=1:length(y)
16                 a1=a1+power(b,i-1)*y(i);
17                 a2=a2+(power(b,i-1))^2;
18             end
19             a=a1/a2;
20             plot(a,b,'+');
21             text(a+0.1,b+0.1,num2str(optimValues.iteration));
22         case 'cone'
23             hold off
24         otherwise
25             end
26     end

```