HW8

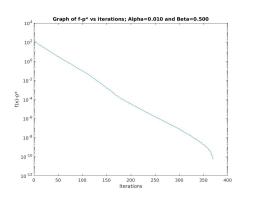
${\it Carl Mueller} \\ {\it CSCI 5254 - Convex Optimization}$

May 3, 2018

8.16

a)

Gradient Method



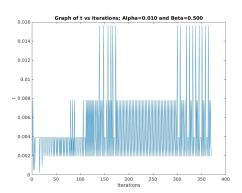
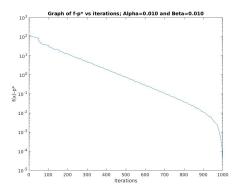


Figure 1: ALPHA=.01, BETA=.5



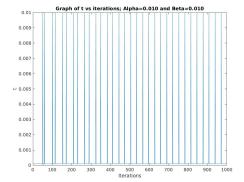
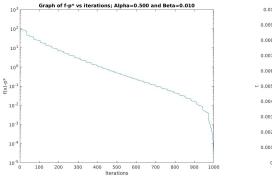


Figure 2: ALPHA=.01, BETA=.01



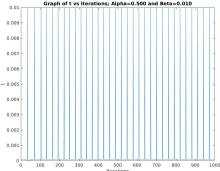
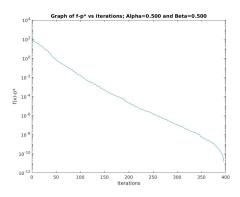


Figure 3: ALPHA=.50, BETA=.01



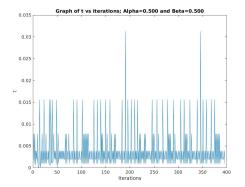


Figure 4: ALPHA=.50, BETA=.50

```
iter = 1000;
nu = .0001;
beta = .01;
alpha = .5;
n = 100;
m = 200;
x = zeros(n, 1);
A = randn(m, n);
V =
I = []
T = []
for i = 1:iter
    % function evaluation
    f = -sum(log(1-A*x)) - sum(log(1+x)) - sum(log(1-x));
    % gradient
    \operatorname{grad} = A'*(1./(1-A*x)) - 1./(1+x) + 1./(1-x);
    % breaking criterion using nu as threshold
```

```
if norm(grad) < nu
        break
    end
    % Gradient direction.
    dir = -grad;
    % second compoenent of backtracking
    fprime = grad '* dir;
    t = 1;
    while ((\max(A*(x+t*dir)) >= 1) \mid (\max(abs(x+t*dir)) >= 1))
        t = beta*t;
    end
    % backtracking algorithm
    while (-\sup(\log(1-A*(x+t*dir))) - \sup(\log(1-(x+t*dir).^2)) > f + alpha*t
        t = beta*t;
    end
    % update step
    x = x+t*dir;
    T = [T; t]
    V = [V; f];
    I = [I ; i]
end
f_minus_p = [];
for i = 1: length(V)
    diff = V(i) - f
    f_{\min us_p} = [f_{\min us_p}; diff]
end
f_minus_p
f
figure (1)
plot(I, f_minus_p);
set(gca, 'yscale', 'log');
titlestr = "Graph of f-p* vs iterations; Alpha=\%0.3f and Beta=\%0.3f";
str = sprintf(titlestr, alpha, beta);
title (str);
xlabel("Iterations");
ylabel("f(x)-p*");
figure (2)
plot(I,T);
titlestr = "Graph of t vs iterations; Alpha=\%0.3f and Beta=\%0.3f";
str = sprintf(titlestr, alpha, beta);
title(str);
xlabel("Iterations");
ylabel("t");
```

b)

Newton's Method

This approach clearly takes many less iterations and is always terminated based on the quit criteria rather than the max number of iterations.

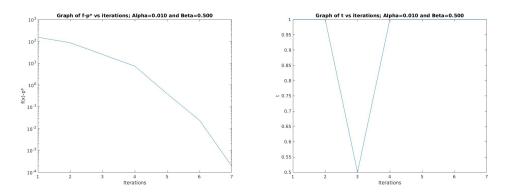


Figure 5: ALPHA=.01, BETA=.5

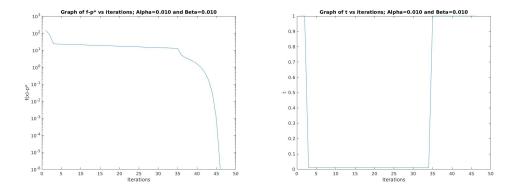


Figure 6: ALPHA=.01, BETA=.01

```
iter = 1000;
nu = .00000001;
beta = .01;
alpha = .50;
n = 100;
m = 200;
x = zeros(n, 1);
A = randn(m,n);
```

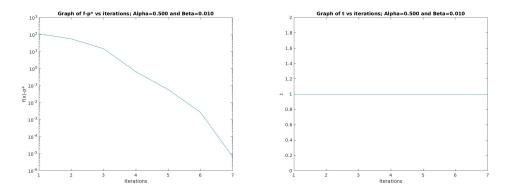


Figure 7: ALPHA=.50, BETA=.01

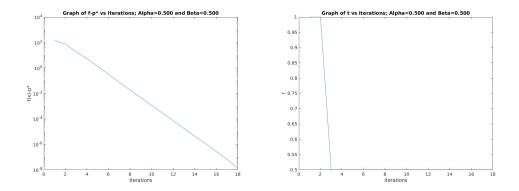


Figure 8: ALPHA=.50, BETA=.50

```
V = []
I = []
T = []
for i = 1:iter
     f = -sum(log(1-A*x)) - sum(log(1+x)) - sum(log(1-x));
     d = 1./(1-A*x);
    % first order derivative
     \operatorname{grad} = A' * d - 1./(1+x) + 1./(1-x);
    \% second order derivative i.e. hessian
     hessian = A'* \operatorname{diag}(d.^2)*A + \operatorname{diag}(1./(1+x).^2 + 1./(1-x).^2);
    % direction
     dir = -hessian \backslash grad;
    \% lambda^2 i.e decrement
     lambda_2 = grad * dir;
     while ((\max(A*(x+t*dir)) >= 1) \mid (\max(abs(x+t*dir)) >= 1))
          t = beta*t;
     end
```

```
% breaking criteria
    if abs(lambda_2) < nu
        break;
    end
    % backtracking algorithm
    while (-sum(log(1-A*(x+t*dir))) - sum(log(1-(x+t*dir).^2)) > f + alpha*t
        t = beta*t;
    end
    % update step
    x = x+t*dir;
    V = [V; f];
    I = [I ; i];
    T = [T; t];
end
f_minus_p = [];
for i = 1: length(V)
    diff = V(i) - f
    f_{minus_p} = [f_{minus_p}; diff]
end
f_minus_p
f
figure (1)
semilogy(I, f_minus_p)
titlestr = "Graph of f-p* vs iterations; Alpha=\%0.3f and Beta=\%0.3f";
str = sprintf(titlestr, alpha, beta);
title(str);
xlabel("Iterations");
vlabel("f(x)-p*");
figure (2)
plot(I,T);
titlestr = "Graph of t vs iterations; Alpha=\%0.3f and Beta=\%0.3f";
str = sprintf(titlestr, alpha, beta);
title(str);
xlabel("Iterations");
ylabel("t");
```

9.31

Delayed Hessian Update:

```
Code: clear all;
```

```
iter = 1000;
nu = .00000001;
beta = .5;
alpha = .01;
n = 100;
m = 200;
x = zeros(n, 1);
A = randn(m, n);
GD = []
step = [1, 5, 10, 20]
for N = 1: length (step)
    V = [];
    I = [];
    T = [];
    for i = 1: iter
         f = -sum(log(1-A*x)) - sum(log(1+x)) - sum(log(1-x));
         d = 1./(1-A*x);
         % first order derivative
         \operatorname{grad} = A' * d - 1./(1+x) + 1./(1-x);
         % second order derivative i.e. hessian
         if i = 1 \mid \mod(i, N) = 0
              hessian = A'* \operatorname{diag}(d.^2)*A + \operatorname{diag}(1./(1+x).^2 + 1./(1-x).^2);
         end
         % direction
         dir = -hessian \backslash grad;
         % lambda^2 i.e decrement
         lambda_2 = grad' * dir;
         t = 1;
         while ((\max(A*(x+t*dir)) >= 1) \mid (\max(abs(x+t*dir)) >= 1))
              t = beta*t;
         end
         % breaking criteria
         if abs(lambda_2) < nu
              break;
         end
         % backtracking algorithm
         while (-\sup(\log(1-A*(x+t*dir))) - \sup(\log(1-(x+t*dir).^2)) > f + alp
              t = beta*t;
         end
         % update step
         x = x+t*dir;
         V = [V; f];
```

```
I = [I ; i];
        T = [T; t];
    end
    f_{\min us_p} = [];
    for i = 1: length(V)
         diff = V(i) - f
         f_{\min us_p} = [f_{\min us_p}; diff]
    end
    GD = [GD ; \{f, f_minus_p, V, I, T\}]
    x = zeros(n, 1);
end
figure (1)
D = GD(1, :)
semilogy (D\{4\}, D\{2\})
hold on
D = GD(2, :)
semilogy (D\{4\}, D\{2\})
hold on
D = GD(3, :)
semilogy (D\{4\}, D\{2\})
hold on
D = GD(4, :)
semilogy (D\{4\}, D\{2\})
hold off
titlestr = "Graph of delayed Hessian Update for Netwon's method";
str = sprintf(titlestr, alpha, beta);
title(str);
xlabel("Iterations");
vlabel("f(x)-p*");
legend ("Newton", "N=5", "N=10", "N=20")
0.0.1
     b)
9.31
Delayed Hessian Update:
  Code:
. . .
for i = 1: iter
```

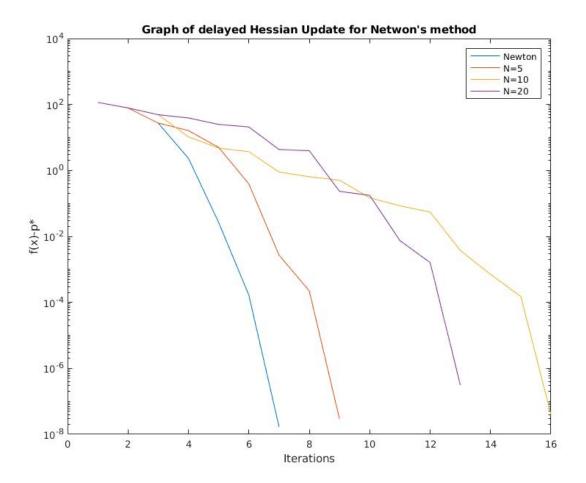


Figure 9: Different iterations counts N until Hessian update.

```
\begin{array}{lll} f = -sum(\log(1-A*x)) - sum(\log(1+x)) - sum(\log(1-x)); \\ d = 1./(1-A*x); \\ \% & \text{first order derivative} \\ \text{grad} = A'*d - 1./(1+x) + 1./(1-x); \\ \% & \text{diagnal of the second order derivative i.e. hessian} \\ \text{hessian} = \text{diag}(\text{diag}(A'*\text{diag}(d.^2)*A + \text{diag}(1./(1+x).^2 + 1./(1-x).^2))); \end{array}
```

. .

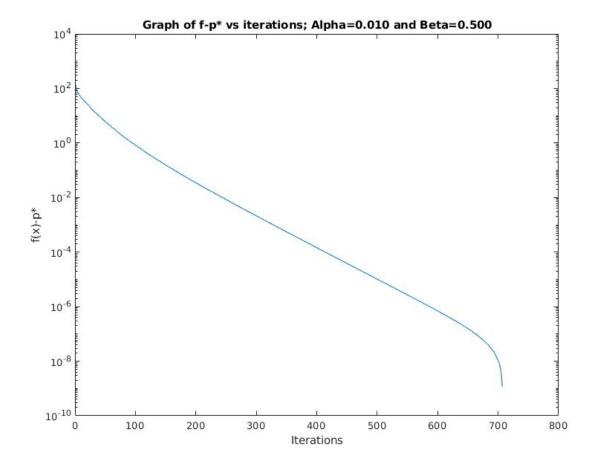


Figure 10: Using the diagonal of the hessian. There is a clear increase in the required number of iterations

11.1

We are given the minimization problem:

minimize
$$x^2 + 1$$

subject to $2 \le x \le 4$

We used the log barrier approximation as follows:

$$\hat{I}(x) = -\log(x-2) - \log(4-x)$$

Code:

$$t = [.01\,,\ .02\,,\ .04\,,\ .08\,,\ .16\,,\ .32\,,\ .64\,,\ 1.28\,,\ 2.56\,,\ 5.12\,,\ 10.80]$$
 figure (1) fplot (@(x) power (2,x)+1, [0,6]) hold on

```
\label{eq:formula} \begin{array}{lll} & \text{for } i = 1 \colon length\,(\,t\,) \\ & \text{fplot}\,(@(x) \ power\,(\,2\,,x\,) + 1 \ + \ (\,1/\,t\,(\,i\,)\,) * (\,-\log\,(x-2) - \log\,(4-x\,)\,)\,) \\ & \text{end} \\ & \text{hold off} \\ & \text{xlabel}\,(\,"\,x\,"\,) \\ & \text{ylabel}\,(\,"\,tunction \ value\,"\,) \\ & \text{title}\,(\,"\,Log \ Barrier \ of \ f \ for \ various \ t \ values\,.\,"\,) \\ & \text{legend}\,(\,"\,t = .01\,"\,,\,"\,t = .02\,"\,,\,"\,t = .04\,"\,,\,"\,t = .08\,"\,,\,"\,t = .16\,"\,,\,"\,t = .32\,"\,,\,"\,t = .74\,"\,,\,"\,t = 1.28\,"\,,\,"\,t = 5\,. \end{array}
```

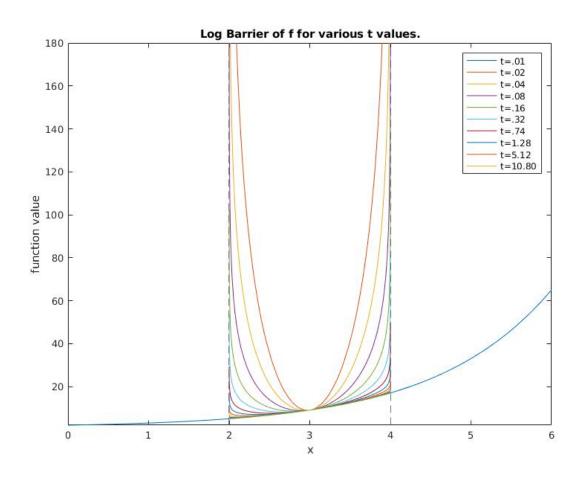


Figure 11: Log Barrier plotting verus f(x) for various t values.

11.22

We use the following optimization problem. We use the bounds of our x values of the constraints using u and l to constrain the log barrier of the rectangle.

Note: $A^{+} = max(A, 0)$ and $A^{-} = max(-A, 0)$

minimize
$$-\sum_{i=1}^{n} log(u_i - l_i)$$
subject to
$$A^+u - A^-l \leq b$$

$$l \leq u$$

$$\begin{split} \psi &= t - \sum_{i=1}^n log(u_i - l_i) - \sum_{i=1}^n log(b - A^+u_i + A^-l_i) \\ \nabla \psi &= t \begin{bmatrix} I \\ -I \end{bmatrix} diag(u - l)^{-1} \mathbf{1} + \begin{bmatrix} -A^{-T} \\ A^{+T} \end{bmatrix} diag(b - A^+u + A^-l)^{-1} \mathbf{1} \\ \nabla^2 \psi &= t \begin{bmatrix} I \\ -I \end{bmatrix} diag(u - l)^{-2} \begin{bmatrix} I \\ -I \end{bmatrix}^T + \begin{bmatrix} -A^{-T} \\ A^{+T} \end{bmatrix} diag(b - A^+u + A^-l)^{-2} \begin{bmatrix} -A^{-T} \\ A^{+T} \end{bmatrix}^T \end{split}$$

Code:

```
MAXITERS = 200;
ALPHA = 0.01;
BETA = 0.5;
NTTOL = 1e - 8;
% terminate Newton iterations if lambda^2 < NTTOL
MU = 20;
TOL = 1e-4;
n = 2
A = \begin{bmatrix} 0 & -1; & 2 & -4; & 2 & 1; & -4 & 4; & -4 & 0 \end{bmatrix}
b = ones(5,1)
m = 5
% terminate if duality gap less than TOL
Ap = \max(A, 0); Am = \max(-A, 0);
r = \max(Ap*ones(n,1) + Am*ones(n,1));
u = (.5/r)*ones(n,1); l = -(.5/r)*ones(n,1);
t = 1;
for iter = 1:MAXITERS
     y = b+Am*l-Ap*u;
     val = -t * sum(log(u-l)) - sum(log(y));
     grad = t * [1./(u-1); -1./(u-1)] + [-Am'; Ap'] * (1./y);
     hess = t * [diag(1./(u-1).^2), -diag(1./(u-1).^2); -diag(1./(u-1).^2), diag(1./(u-1).^2)]
     step = -hess \backslash grad;
     fprime = grad '* step;
```

```
if (abs(fprime) < NTTOL)
         gap = (2*m)/t;
         disp(['iter', int2str(iter), '; gap = ', num2str(gap)]);
         if (gap<TOL)
              break;
         end
         t = MU * t;
      else
         dl = step(1:n); du = step(n+[1:n]);
         dy = Am*dl-Ap*du;
         tls = 1;
         while (\min([u-l+tls*(du-dl); y+tls*dy]) \le 0)
              tls = BETA*tls;
         end
         while (-t*sum(log(u-l+tls*(du-dl))) - sum(log(y+tls*dy)) >= val + tls
              tls = BETA*tls;
         end
         l = l+tls*dl; u = u+tls*du;
    end
end
plotregion(-A,-b,[], [],
hold on
bbox = [1(1), 1(2), u(1), u(2)]
points = bbox2points(bbox)
plot\left(\,points\left(\,:\,,1\,\right)\,,\,points\left(\,:\,,2\,\right)\,,\quad '*-\,'\right);
hold off
```

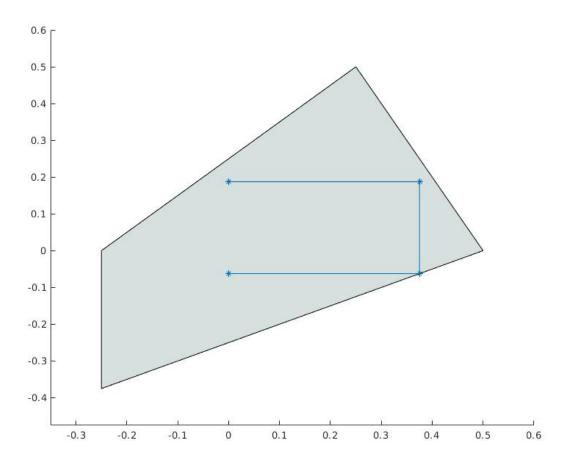


Figure 12: Inscribed box contained by polyhedron defined by constraints.