

## Problem 1

### question1

The number of iterate steps is 1000. And the learning rate  $\alpha$  is 0.0005.

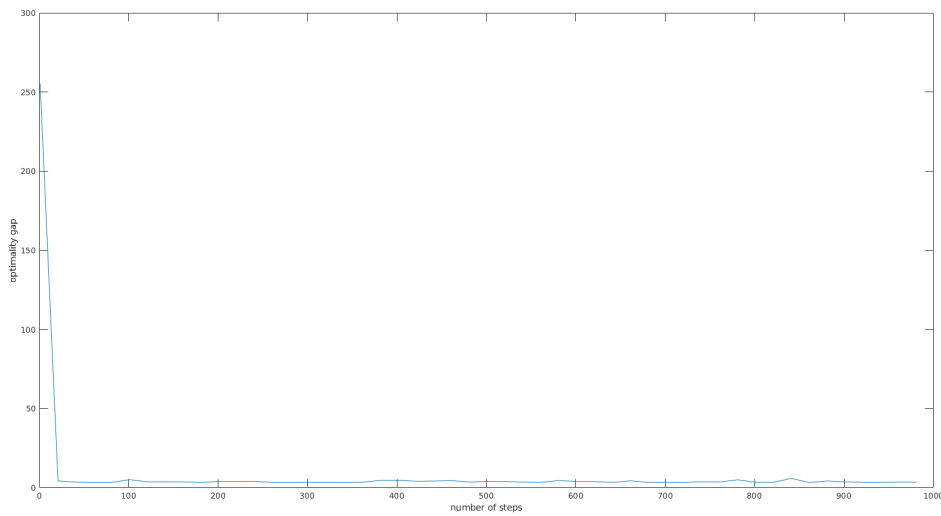


Figure 1: SGD method

### question2

As the  $\alpha$  increases, the optimality gap increases.

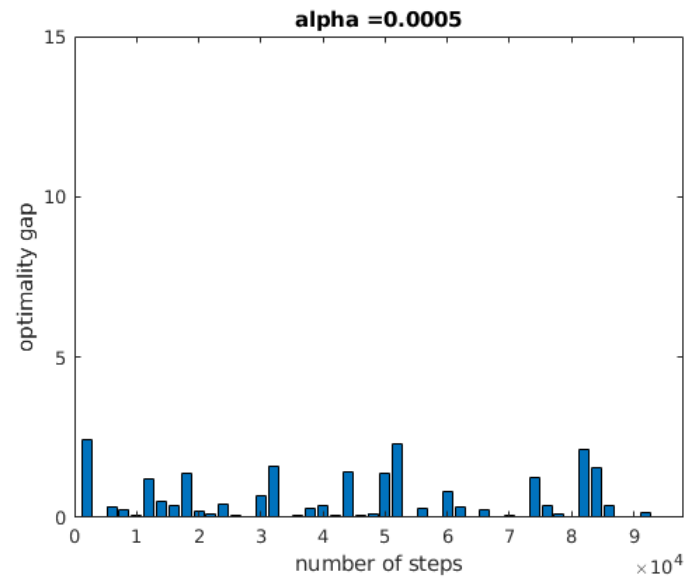


Figure 2: SGD method changing  $\alpha$

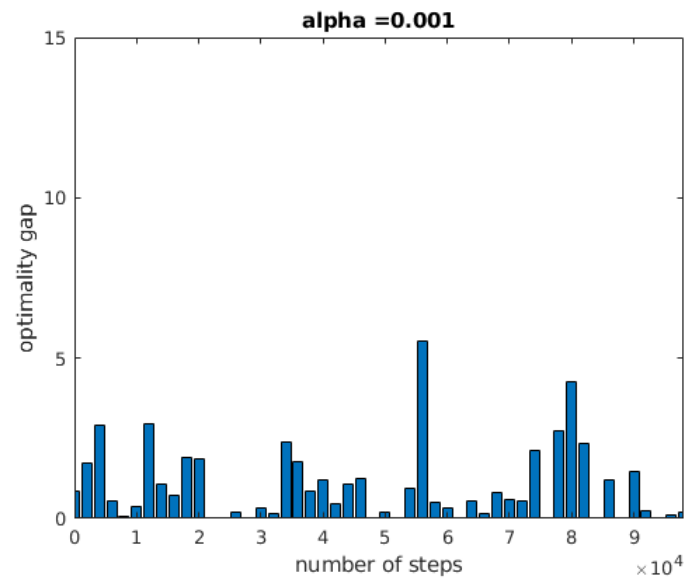


Figure 3: SGD method changing  $\alpha$

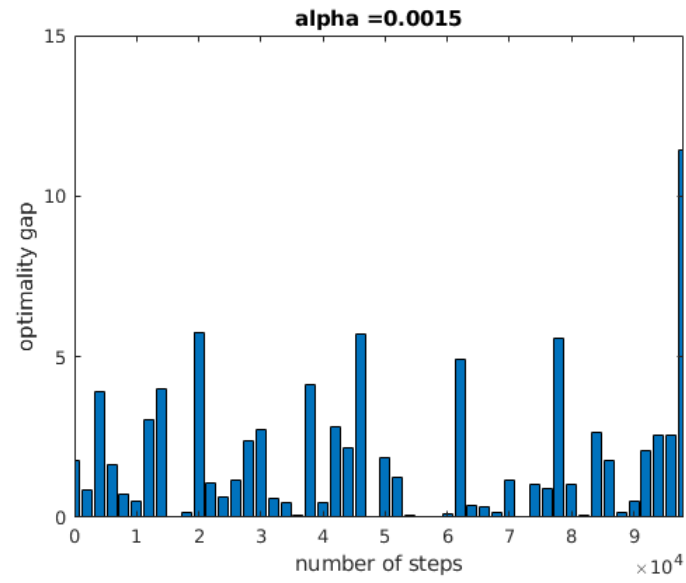


Figure 4: SGD method changing  $\alpha$

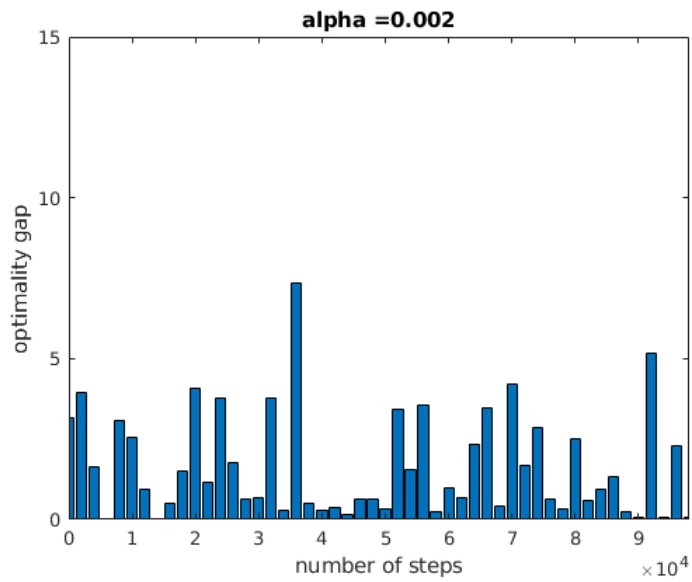


Figure 5: SGD method changing  $\alpha$

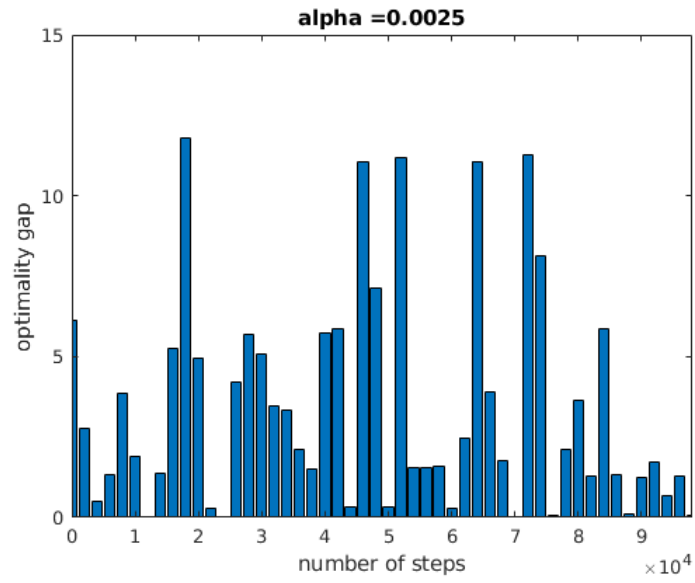


Figure 6: SGD method changing  $\alpha$

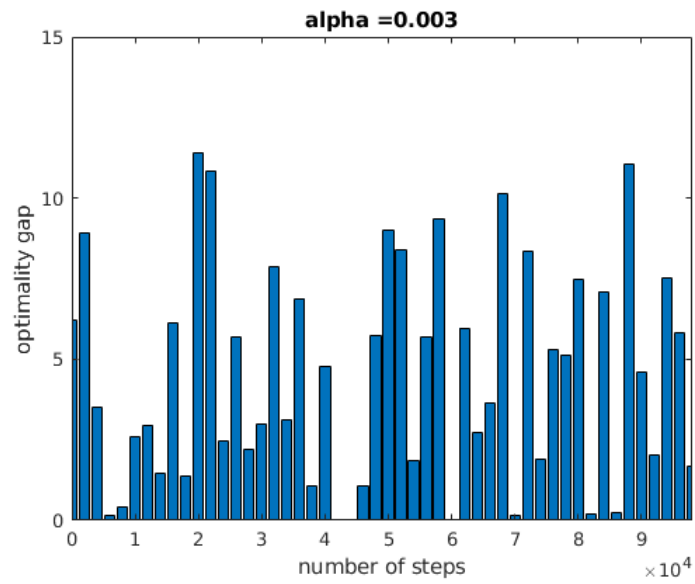


Figure 7: SGD method changing  $\alpha$

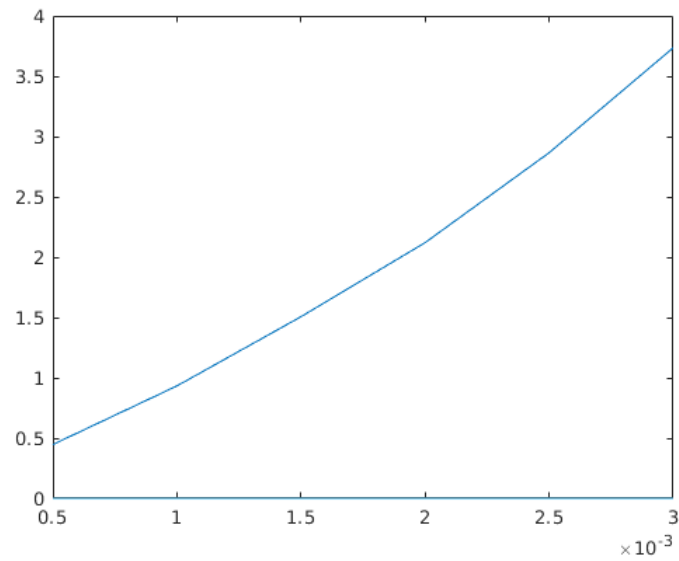


Figure 8: mean optimality gap v.s.  $\alpha$

## Problem 2

### question1

$$\log \rho(I) = 6.6613e - 16$$

### question2

With the sample sizes increases, the  $\log \rho(G)$  decreases.(almost linearly)

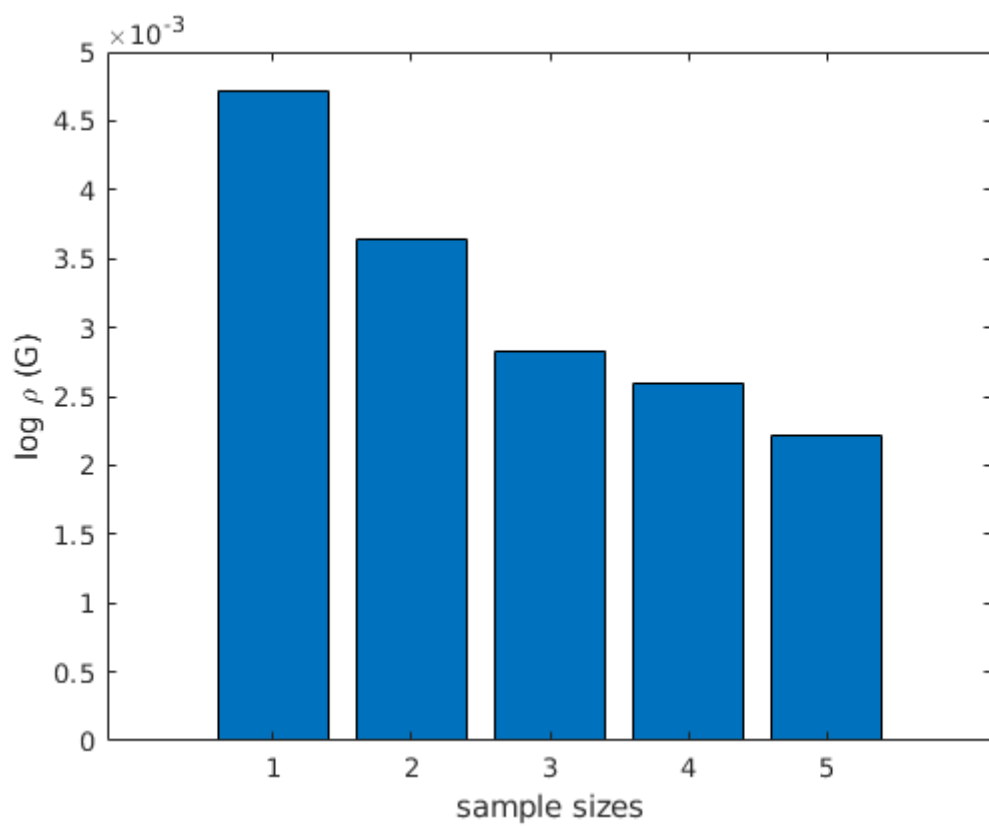


Figure 9: Gauss-Newton method

### Problem 3

The figure shows that Gauss-Newton method converges quicker than SGD method.

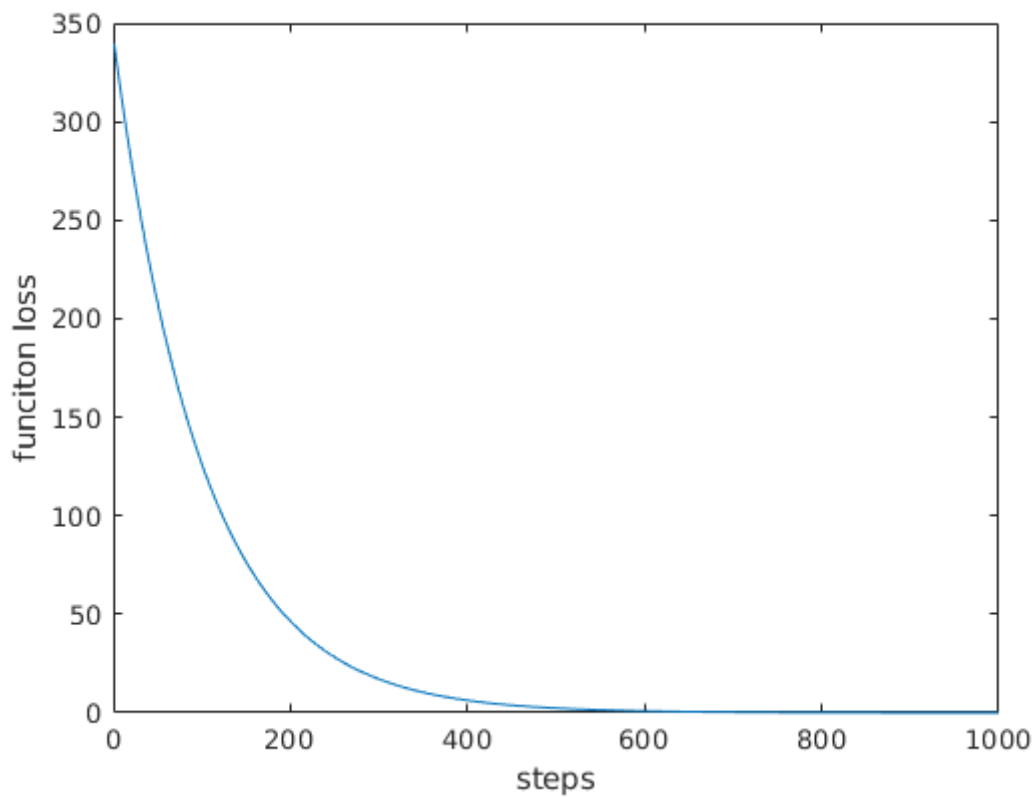


Figure 10: Gauss-Newton method

```
load('cricket.dat');
A = cricket(:,1);
b = cricket(:,2);

A = [A, ones(length(b), 1)];

% ===== initial ===== %

max_step = 1000;
alpha = 0.005;
c = 0.0003;
threshold = 1e-4;

len = length(b);
phi = 0;
tmp = A*x-b;
for i = 1:len
    phi = phi + exp(tmp(i)^2);
end
```

```

phi = phi - 1;
% ===== iterate ===== %

x = [0; 0];
errors = zeros(1, max_step);

for i = 1:max_step
    r = b - A*x;

    df = -2 * c * exp(c*r.^2).*r.*A;
    f = exp(c*r.^2) - 1;

    p = -(df'*df) \ (df'*f);
    x = x + alpha * p;

    errors(i) = 0.5 * (f' * f);

    if norm(df, 2) < threshold
        break;
    end
end

x_step = 1:max_step;
plot(x_step, errors);
xlabel('steps');
ylabel('funciton_loss');

```