

## Linear least-squares problem:

```
X = [1, 274, 2450; ...  
     1, 180, 3254; ...  
     1, 375, 3802; ...  
     1, 205, 2838; ...  
     1, 86, 2347];  
Y = [162; ...  
     120; ...  
     223; ...  
     131; ...  
     67];
```

### Solution using Cholesky algorithm

```
R = chol(X'*X);  
z = X'*Y;  
p = R'\z;  
beta_hat_chol = R\p
```

```
beta_hat_chol = 3×1  
    7.0325  
    0.5044  
    0.0070
```

### Solution using QR factorization

```
[Q, R] = qr(X);  
z = Q'*Y;  
beta_hat_qr = R\z
```

```
beta_hat_qr = 3×1  
    7.0325  
    0.5044  
    0.0070
```

### Solution using SVD approach

```
[U, S, V] = svd(X);  
b = U'*Y;  
z = S\b;  
beta_hat_svd = V*z
```

```
beta_hat_svd = 3×1  
    7.0325  
    0.5044  
    0.0070
```

## Nonlinear least-squares problem

$$y = \theta_1 e^{\theta_2 x}$$

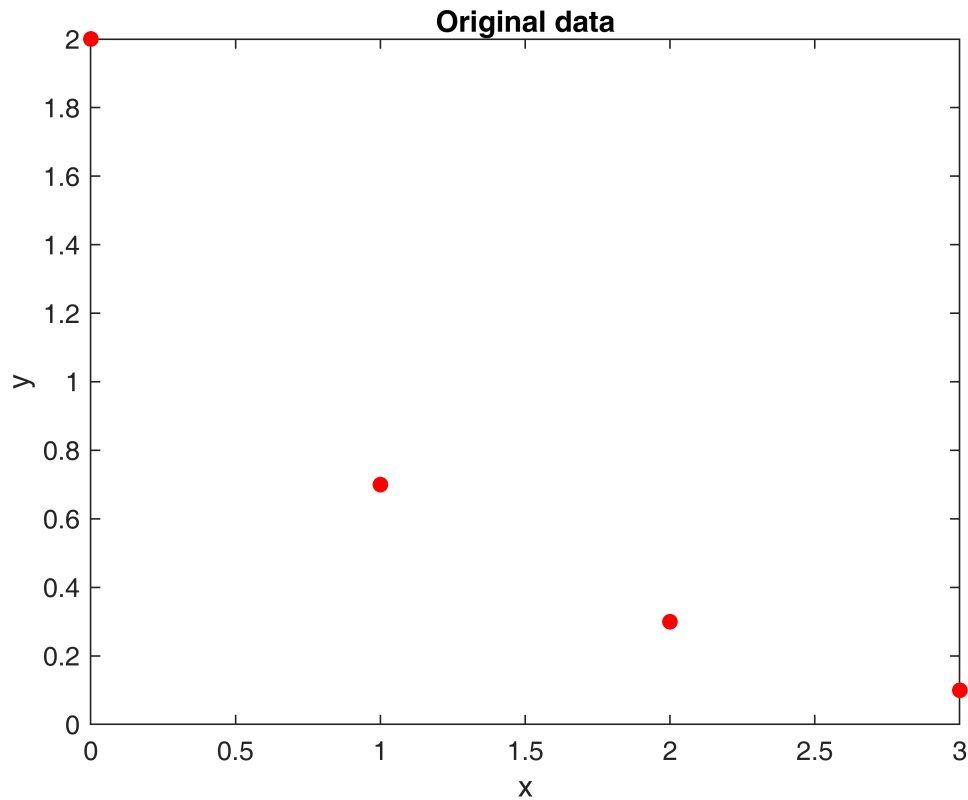
Original data

```
x = [0, 1, 2, 3]';
```

```

y = [2, 0.7, 0.3, 0.1]';
figure()
plot(x,y, '.r', 'markersize', 20)
xlabel("x")
ylabel("y")
title("Original data")

```



## Newton's method

Define residual function

```

syms theta_1 theta_2
residual = y - theta_1*exp(theta_2*x);
residual_func = matlabFunction(residual);

```

Define Jacobian

```

Jacobian = jacobian(residual, [theta_1, theta_2]);
jacobian_func = matlabFunction(Jacobian);

```

Gradient function

```

Gradient = Jacobian'* residual;
gradient_func = matlabFunction(Gradient);

```

Hessian

```

hessian_second_term = zeros(2,2);

```

```

for i = 1:length(x)
    hessian_second_term = hessian_second_term + residual(i)* hessian(residual(i),...
        [theta_1, theta_2]);
end
Hessian = Jacobian'*Jacobian + hessian_second_term;
hessian_func = matlabFunction(Hessian);

```

Applying Newton's algorithm:

The function can be found at the end of this document. Note that this function is custom made for this example. When the number of variable changes, we have to modify the function before applying it the problem.

```

initial_theta = [1;0];
[theta_newton, residual_norms, succ_approx_newton] = Newton_method(residual_func,...
    gradient_func, hessian_func, initial_theta, 0.05, 500, 1e-6);
theta_newton

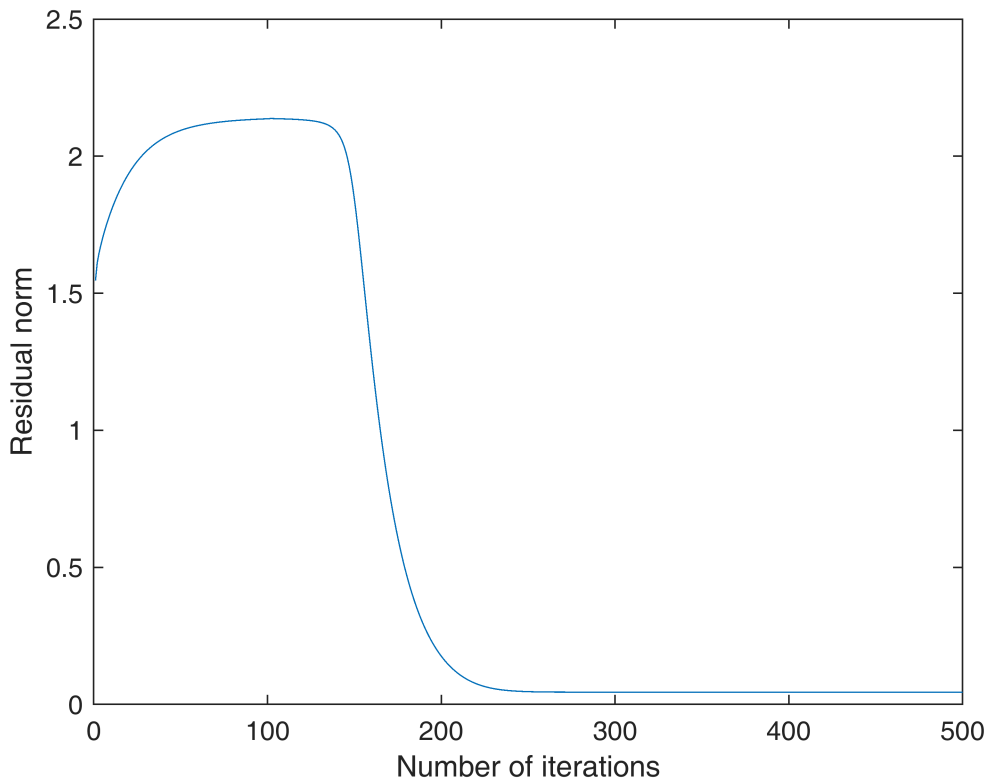
theta_newton = 2x1
    1.9950
   -1.0095

```

```

figure()
plot(residual_norms)
xlabel("Number of iterations")
ylabel("Residual norm")

```



```

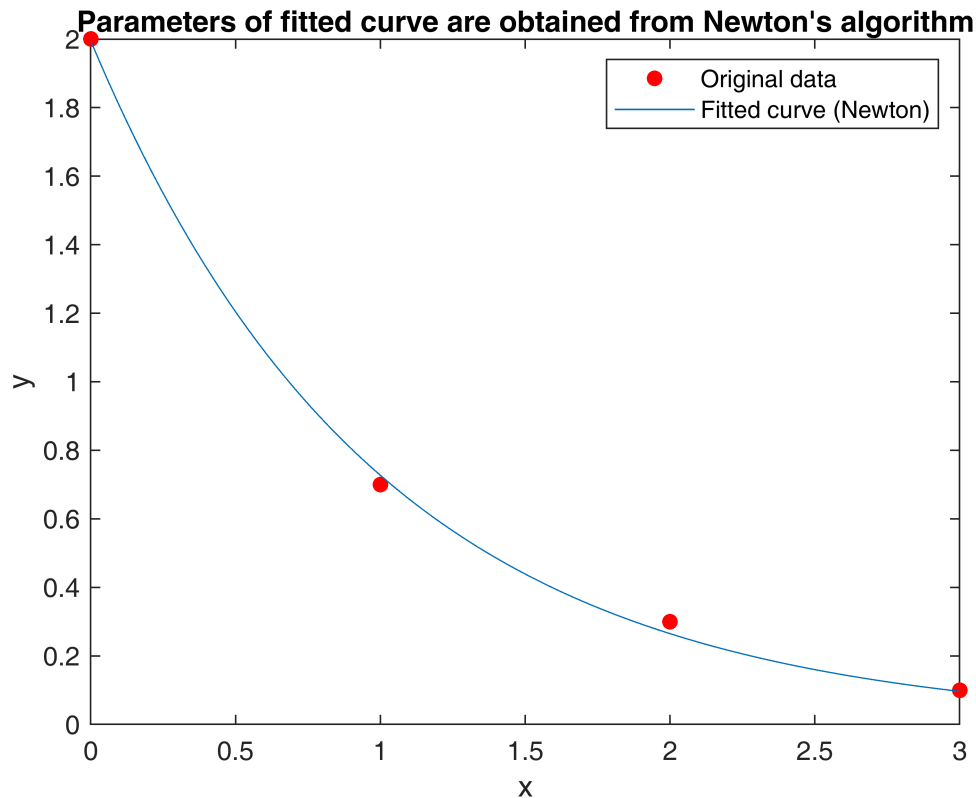
figure()
plot(x,y, '.r', 'markersize', 20); hold on
x_dat = linspace(0, 3, 100);

```

```

y_newton = theta_newton(1) * exp(theta_newton(2)*x_dat);
plot(x_dat, y_newton); hold off
xlabel("x")
ylabel("y")
legend("Original data", "Fitted curve (Newton)")
title("Parameters of fitted curve are obtained from Newton's algorithm")

```



## Gauss-Newton method

Our MATLAB codes for Gauss-Newton and Levenberg-Marquadrat algorithms are similar in line to the ones given at [this link](#). The function implementing Gauss-Newton method can be found at the end of this document.

```

initial_theta = [1;0];
[theta_gauss_newton, norm_squares, succ_approx_gauss_newton] = ...
    gauss_newton_method(residual_func, jacobian_func, initial_theta, 10, 1e-6);
theta_gauss_newton

```

```

theta_gauss_newton = 2×1
    1.9950
   -1.0095

```

```
norm_squares
```

```

norm_squares = 10×1
    2.3900
    0.2126
    0.0073
    0.0020
    0.0020
    0.0020
    0.0020

```



```
[theta_leven, objectives, residuals, succ_approx_leven] = leven_marq(residual_func,...
    jacobian_func, initial_theta, 1, 100, 1e-6);
theta_leven
```

```
theta_leven = 2×1
    1.9950
   -1.0095
```

### objectives

```
objectives = 14×1
    2.3900
    0.6220
    0.1606
    0.0364
    0.0082
    0.0029
    0.0021
    0.0020
    0.0020
    0.0020
    ⋮
    ⋮
```

### residuals

```
residuals = 14×1
    8.9822
    1.6781
    0.7007
    0.3187
    0.1314
    0.0491
    0.0165
    0.0049
    0.0013
    0.0003
    ⋮
    ⋮
```

### succ\_approx\_leven

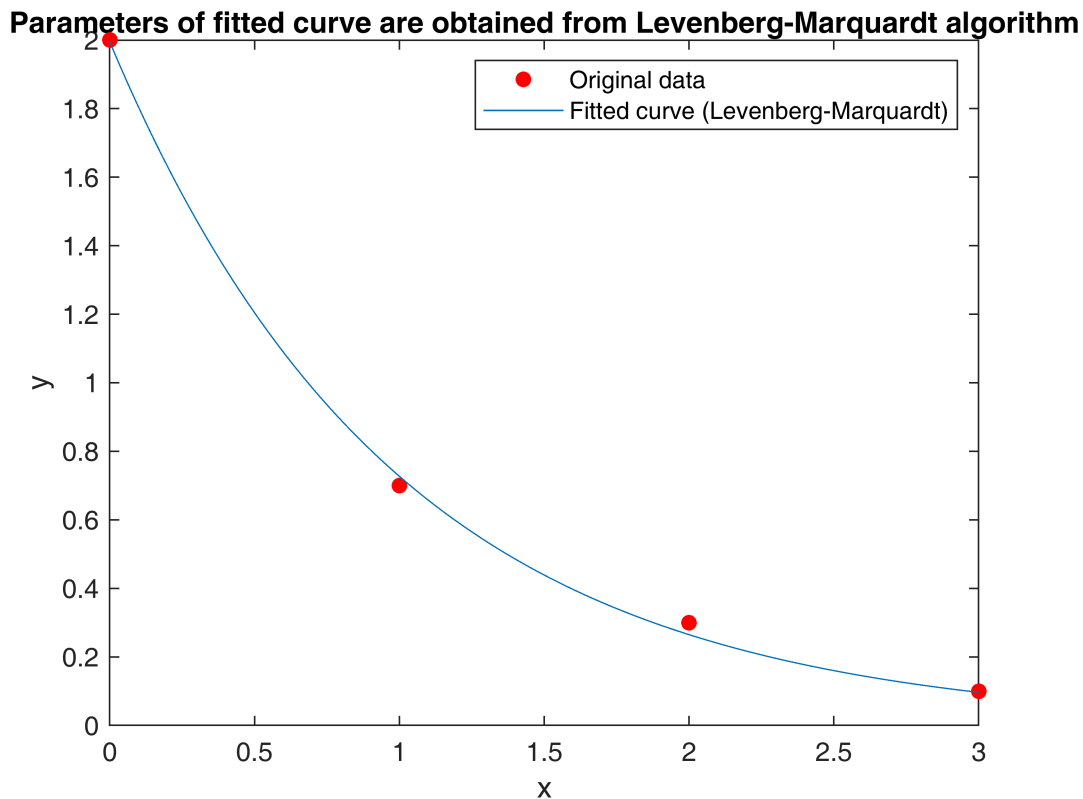
```
succ_approx_leven = 14×2
    1.0000     0
    1.3308   -0.4256
    1.6359   -0.7119
    1.8295   -0.8622
    1.9279   -0.9415
    1.9708   -0.9814
    1.9872   -0.9994
    1.9928   -1.0064
    1.9944   -1.0087
    1.9949   -1.0093
    ⋮
    ⋮
```

```
figure()
plot(x,y, '.r', 'markersize', 20); hold on
y_leven = theta_leven(1) * exp(theta_leven(2)*x_dat);
plot(x_dat, y_leven); hold off
xlabel("x")
ylabel("y")
```

```

legend("Original data", "Fitted curve (Levenberg-Marquardt)")
title("Parameters of fitted curve are obtained from Levenberg-Marquardt algorithm")

```

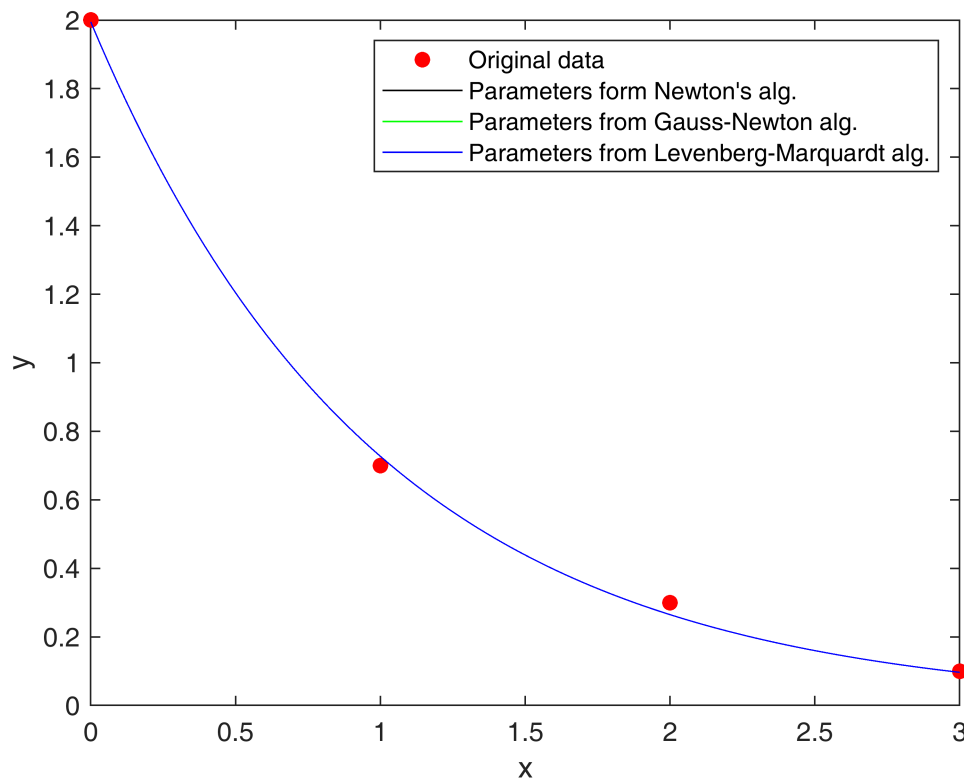


Finally, we will compare the curves obtained by using parameters of Gauss-Newton and Levenberg-Marquardt algorithms by plotting both the fits in a single figure along with the original data.

```

figure()
plot(x,y, '.r', 'markersize', 20); hold on
plot(x_dat, y_newton, 'k')
plot(x_dat, y_gauss_newton, 'g')
plot(x_dat, y_leven, 'b'); hold off
legend("Original data", "Parameters form Newton's alg.", ...
      "Parameters from Gauss-Newton alg.", ...
      "Parameters from Levenberg-Marquardt alg.")
xlabel("x"); ylabel("y")

```



As we can see, all the fits are indistinguishable. It can also be checked that parameters obtained from both the methods match till 6 digits after decimal point. We have run Gauss-Newton for a maximum of 10 iterations whereas Levenberg-Marquardt is run for 100 iterations.

```
function [theta, fnorms, succ_approx_newton] = Newton_method(f, grad, hess, ...
    initial_theta, alpha, kmax, tol)
theta = initial_theta;
fnorms = nan(kmax,1);
succ_approx_newton = [theta'; nan(kmax,2)];
for k = 1:kmax
    fk = feval(f, theta(1), theta(2));
    fnorms(k) = norm(double(fk));
    if fnorms(k) < tol
        break
    end
    theta = theta - alpha * (double(feval(hess, theta(1), theta(2))) \ ...
        double(feval(grad, theta(1), theta(2))));
    succ_approx_newton(k+1,:) = theta';
end
fnorms = fnorms(~isnan(fnorms));
if k ~= kmax
    succ_approx_newton = succ_approx_newton(1:k,:);
end
end
```



```

function [theta, fnorm_square, succ_approx_gauss_newton] = gauss_newton_method(f,...
    jacobian_func, theta_initial, kmax, tol)
theta = theta_initial;
fnorm_square = nan(kmax,1);
succ_approx_gauss_newton = [theta'; nan(kmax,2)];
for k = 1:kmax
    fk = feval(f, theta(1), theta(2));
    fnorm_square(k) = norm(double(fk))^2;
    if fnorm_square(k) < tol || (rank(double(feval(jacobian_func, theta(1), theta(2)))) ~=
        break
    end
    theta = theta - double(feval(jacobian_func, theta(1), theta(2))) \ ...
        double(feval(f, theta(1), theta(2)));
    succ_approx_gauss_newton(k+1,:) = theta';
end
fnorm_square = fnorm_square(~isnan(fnorm_square));
if k ~= kmax
    succ_approx_gauss_newton = succ_approx_gauss_newton(1:k,:);
end
end

```

```

function [theta, objectives, residuals, succ_approx leven] = leven_marq(f, ...
    jacobian_func, theta_initial, lambda1, kmax, tol)
n = length(theta_initial);
theta = theta_initial;
lambda = lambda1;
objectives = nan(kmax,1);
residuals = nan(kmax, 1);
succ_approx leven = [theta'; nan(kmax,2)];
for k = 1:kmax
    fk = double(feval(f, theta(1), theta(2)));
    jacobian_res = double(feval(jacobian_func, theta(1), theta(2)));
    objectives(k) = norm(fk)^2;
    residuals(k) = norm(2*jacobian_res'*fk);
    if residuals(k) < tol
        break
    end
    theta_t = theta - [jacobian_res; sqrt(lambda)*eye(n)] \ [fk; zeros(n,1)];
    if norm(double(feval(f, theta_t(1), theta_t(2)))) < norm(fk)
        lambda = 0.8 * lambda;
        theta = theta_t;
        succ_approx leven(k+1, :) = theta';
    else
        lambda = 2.0 * lambda;
    end
end
objectives = objectives(~isnan(objectives));
residuals = residuals(~isnan(residuals));
if k ~= kmax

```

```
    succ_approx_leven = succ_approx_leven(1:k,:);  
end  
end
```