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Batch Gradient descent

This is the script for batch gradient descent algorithm using polynomial base function

```
clc;
clear;
close all;
```

Generate data: generate t0 from x0

```
x0=[0.0050:0.0050:10.0000]';
noise=0.2.*randn(1,2000)';
t0=sin(x0)+noise;
% plot(x0,t0);
% hold on

% Min-max norm
x=(x0-min(x0))/(max(x0)-min(x0));
t=t0;
```

Split data into train set and test set

```
idx=crossvalind('Kfold',size(x0,1),5);
test_idx = find(idx==1);
train_idx = find(idx~=1);
train_x=x(train_idx,:);
train_t=t(train_idx,:);
test_x=x(test_idx,:);
test_t=t(test_idx,:);
```

Training params

- Below is the equation for Batch Gradient Descent. Here i is the iteration number, j is the power of corresponding w , n iterates through all data points. η is the learning rate for each iteration. $W_j^{i+1} = W_j^i - \eta \sum_{n=1}^N (y(x_n, W) - t_n) * x^j$

```
M=4; % Maximum power of x
max_iter=100000;
eta=0.7;
W=zeros(M+1,1);
```

```
W_threshold = repmat(0.0001, M+1, 1);
err_threshold = .0001;
```

Training

Here comes the base matrix with power 4

```
x_pol=[ones(size(train_x,1),1) train_x train_x.*train_x train_x.*train_x.*train_x ...
        train_x.*train_x.*train_x.*train_x];
% size(x_pol)
for iter = 1:max_iter
    W_prev = W;
    fx = x_pol*W;
    W = W - eta*1/size(train_x,1)*sum(repmat(fx - train_t,1,M+1).*x_pol)';

    % Sum square error on training
    err(iter,1) = 1/2*sum((fx - train_t).^2);

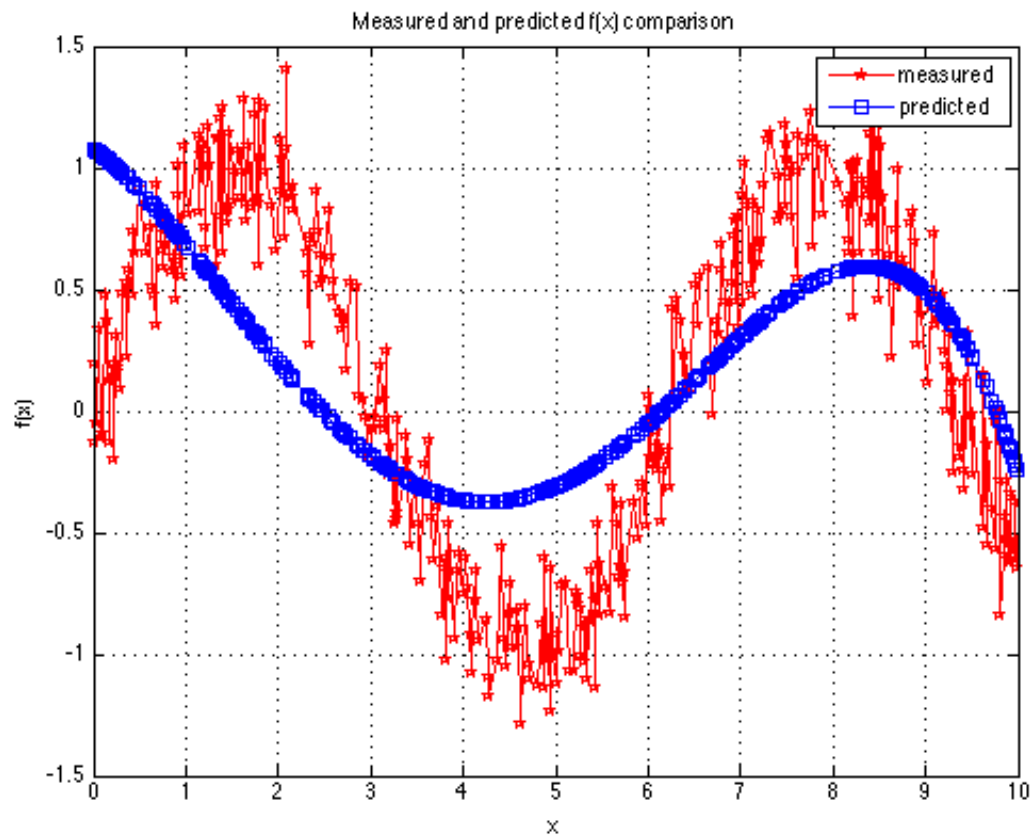
    % check for termination conditions
    if abs(W_prev - W) < W_threshold
        break;
    elseif iter>1 && abs(err(iter-1,1)-err(iter,1))< err_threshold
        break;
    end
end
```

Testing

```
pred_fx=[ones(size(test_x,1),1) test_x test_x.*test_x test_x.*test_x.*test_x ...
        test_x.*test_x.*test_x.*test_x]*W;
test_err = 1/2*sum((pred_fx - x(test_idx,:)).^2);
rmse = sqrt(2*test_err/size(test_idx,1));
```

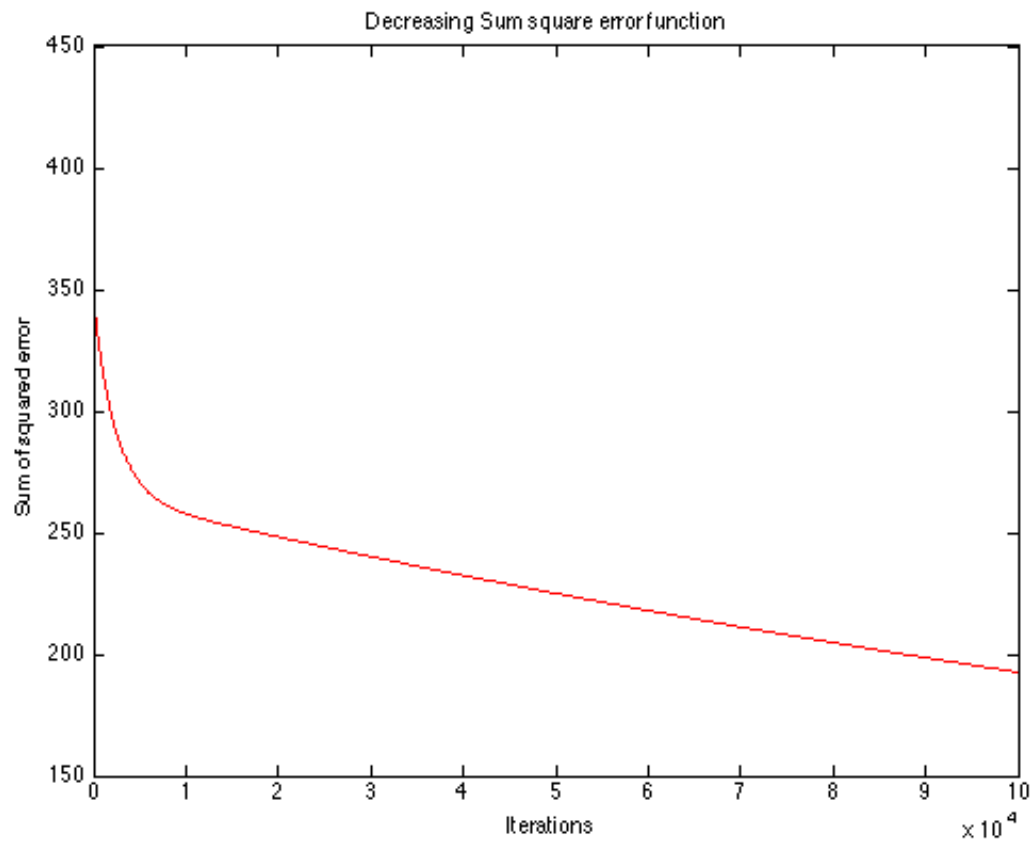
Results 1: Figure for predicted and actual comparison

```
fig1=figure(1);
plot(x0(test_idx),t0(test_idx),'rp-',x0(test_idx),pred_fx,'bs-');
legend('measured', 'predicted');
grid on;
xlabel('x');
ylabel('f(x)');
title('Measured and predicted f(x) comparison');
saveas(fig1,'ms_pred_cmp.jpg','jpg');
```



Result 2: Error curve with different iterations

```
fig2=figure(2);  
plot(err,'r');  
title('Decreasing Sum square error function');  
xlabel('Iterations');  
ylabel('Sum of squared error');  
saveas(fig2,'Sum_sqr_err.jpg','jpg');
```



Result 3: Final Root-Mean-Square Error and W

```
fprintf('\nRoot mean square error: ');
rmse
fprintf('\ncoefficient W:\n');
W
```

```
Root mean square error:
rmse =
```

```
0.6173
```

```
coefficient W:
```

```
W =
```

```
1.0791
-2.7606
-16.5728
48.1560
-30.1568
```