

University of New Orleans
Department of Computer Science

Spr 2019: CSCI 6990 Homework # 1

Machine Learning - I

Submitted to:
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PART (A)

Rewrite the CG for minimizing MSE (mean square error) in terms of β . Replace, ∇f , P , d and Q from the CG algorithm with y_i , x_i , β , X , Y , β etc. as needed. Show your derivation(s) (if any).

SOLUTION:

Here,

$$\begin{aligned}\text{Mean Square Error (MSE)} &= \frac{1}{N} \text{RSS}(\beta) \\ &= \frac{1}{N} \sum_{i=1}^N (y_i - x_i \beta)^2 \quad \text{----- (i)}\end{aligned}$$

In order to perform square operation in (i), we can write it as:

$$= \frac{1}{N} (Y - X\beta)^T (Y - X\beta) \quad (\text{since } A^2 = A^T A),$$

where, X is a $N \times p$ matrix including each input and Y is a N vector output

$$\begin{aligned}&= \frac{1}{N} (Y^T (X\beta)^T) (Y - X\beta) \\ &= \frac{1}{N} (Y^T Y - Y^T X\beta - (X\beta)^T Y + (X\beta)^T X\beta) \\ &= \frac{1}{N} (Y^T Y - (X\beta)^T Y - (X\beta)^T Y + \beta^T X^T X\beta) \\ &\quad (\text{since, } A^T B = B^T A \text{ and } (AB)^T = B^T A^T) \\ \text{MSE} &= \frac{1}{N} (Y^T Y - 2\beta^T X^T Y + \beta^T X^T X\beta) \quad \text{----- (ii)} \\ &= \frac{Y^T Y}{N} - \frac{2\beta^T X^T Y}{N} + \frac{\beta^T X^T X\beta}{N}\end{aligned}$$

Now, CG can be derived from steepest descent method by converging it quadratically

We know, the quadratic equation is given by:

$$f(X) = \frac{1}{2} X^T Q X - b^T X + C \quad \text{----- (iii)}$$

equation (ii) can be re-written as:

$$\text{MSE} = \frac{1}{2} * 2 \beta^T \frac{X^T X}{N} \beta - \beta^T \frac{2X^T Y}{N} + \frac{Y^T Y}{N}$$

$$\text{MSE} = \frac{1}{2} * 2 \beta^T \frac{X^T X}{N} \beta - \left(\frac{2X^T Y}{N} \right)^T \beta + \frac{Y^T Y}{N} \text{----- (iv)}$$

$$(\text{since, } A^T B = B^T A)$$

Comparing (iii) and (iv), we get:

$$Q = \frac{2X^T X}{N}$$

$$b = \frac{2X^T Y}{N}$$

$$C = \frac{Y^T Y}{N}$$

Differentiating equation (ii) with respect to β , we get

$$\begin{aligned} \text{RSS}'(\beta) &= \frac{1}{N} * \left[\frac{\partial}{\partial \beta} (Y^T Y - 2\beta^T X^T Y + \beta^T X^T X \beta) \right] \\ &= \frac{1}{N} * \left[\frac{\partial}{\partial \beta} (Y^T Y) - 2X^T Y \frac{\partial}{\partial \beta} (\beta^T) + \left(\beta^T X^T X \frac{\partial}{\partial \beta} (\beta) + X^T X \beta \frac{\partial}{\partial \beta} (\beta^T) \right) \right] \\ &= \frac{1}{N} * [0 - 2X^T Y + \beta^T X^T X + X^T X \beta] \\ &= \frac{1}{N} * [-2X^T Y + 2X^T X \beta] \quad (\text{since } B^T A^T = (AB)^T \text{ and } (A)^T B = (B)^T A) \\ &= \frac{1}{N} * [2X^T X \beta - 2X^T Y] \end{aligned}$$

Therefore, the given CG algorithm can be rewritten as follows:

BEGIN

STEP 1: Set $i=0$; select the initial point as $\beta(0)$

STEP 2: If $\nabla f(\beta(0)) = 0$, STOP; else set $d_0 = -\nabla f(\beta(0))$

STEP 3: Compute: $\alpha_i = -\frac{\nabla f d_i}{d_i^T Q d_i}$

STEP 4: Compute: $\beta_{(i+1)} = \beta_{(i)} + \alpha_i d_i$

STEP 5: Compute: $\nabla f(\beta_{(i+1)})$. If $\nabla f(\beta_{(i+1)}) = 0$, STOP

STEP 6: Compute: $\gamma_i = \frac{\nabla f(\beta_{i+1})^T Q d_i}{d_i^T Q d_i}$

STEP 7: Compute: $d_{i+1} = -\nabla f(\beta_{(i+1)}) + \gamma_i d_i$

STEP 8: Set $i=i+1$; go to STEP 3.

END

PART (B)

Draw the space of the equation (in MATLAB): $f(x_1, x_2) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2$, twice for the following two cases:

(i) on the space-figure, superimpose iteratively obtained all the points starting from

$X_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ to X_6 using steepest descent algorithms. Then sequentially connect those points: $\{X_0, \dots, X_6\}$ using lines. Appropriately, label your figure.

SOLUTION

MATLAB Code:

```
%initializing at origin
X = [0;0];
x1_plot = [0];
x2_plot = [0];
y_plot=[0];

i=0; %for counting iteration
while i<6

%the differentiation of given quadratic equation wrt to x1 is 1+4x1+2x2 and that wrt to x2 is -
1+2x1+2x2

%now substituting values of each x1 and x2 for new iteration, we have
val_x1 = 1+4*X(1)+2*X(2);
val_x2 = -1+2*X(1)+2*X(2);

%since direction is negative matrix of obtained differentiation value
direction = [-val_x1; -val_x2];
a=sym(a);
a_x = X(1)+(a*direction(1));
a_y = X(2)+(a*direction(2));

%substituting the x and y coordinates of alpha to the function, we get
func = (a_x)-(a_y)+(2*a_x*a_x)+(2*a_x*a_y)+(a_y*a_y);
diff_func =diff(func,a);
alpha_val=solve(diff_func,a);
```

```

X_update = X+(alpha_val.*direction);

%generating values of Y for corresponding values of x1 and x2
y = X_update(1) - X_update(2) + 2*X_update(1)*X_update(1) + 2*X_update(1)*X_update(2) +
X_update(2)*X_update(2);

%computing updated values of x1 and x2
x_plot = [x_plot X_update(1)];
y_plot = [y_plot X_update(2)];

X= X_update;
i= i+1;
end

%displaying of the final points

disp(x1_plot);
disp(x2_plot);
disp(y_plot);

%for calculated values of x1, x2, and y, the graph can be plotted as:
Plot3(x1_plot,x2_plot,y_plot);
title('Superimosing values using Steepest Descent Algorithm');
xlabel('X1 points');
ylabel('X2 points');
zlabel('Y points');

```

OUTPUT:

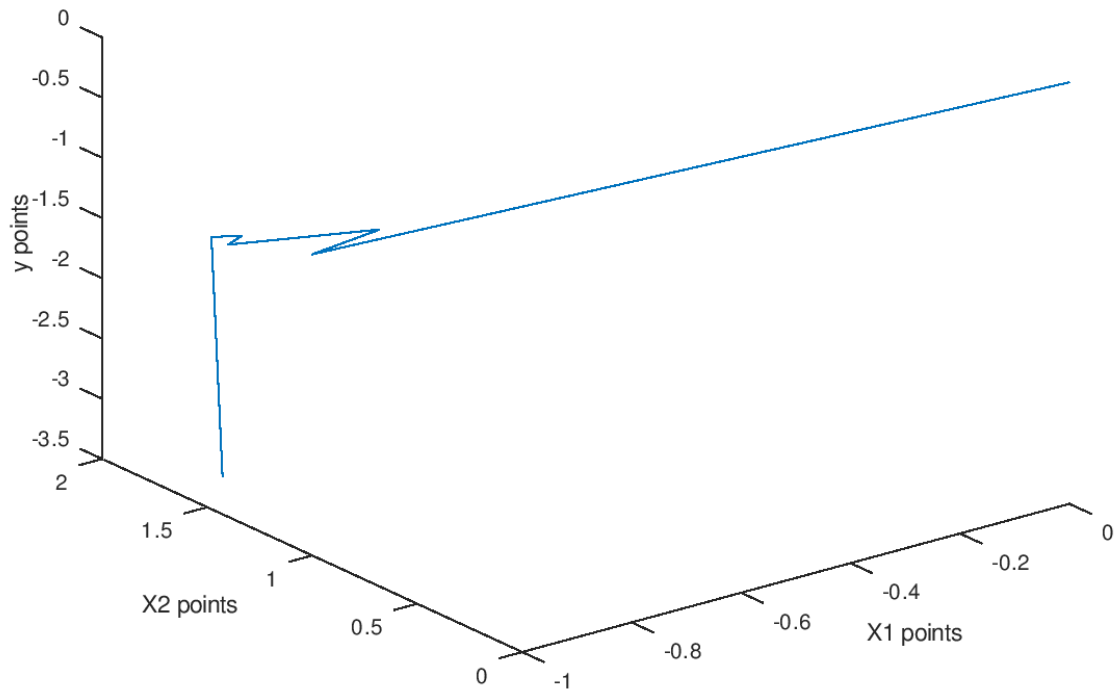
```

[ 0, -1, -0.8, -1, -0.96, -1, -0.992]
[ 0, 1, 1.2, 1.4, 1.44, 1.48, 1.448]
[0, -1, -1.2, -1.24, -1.248, -1.24, -3.216]

```

GRAPH:

Superimposing values using Steepest Descent Algorithm



(ii) Similarly, for the same equation-space (but in a separate figure), place and connect the points sequentially obtained by conjugate gradient approach. Appropriately, label your figure.

SOLUTION

MATLAB CODE:

```
%initialing Q from given equation and starting point as origin
```

```
X=[0;0];
```

```
Q=[4 2;2 2];
```

```
x1_plot=[0];
```

```
x2_plot=[0];
```

```
y_plot=[0];
```

```
i=0; %setting variable for iteration
```

```
%the differentiation of given quadratic equation wrt to x1 is 1+4x1+2x2 and that wrt to x2 is -1+2x1+2x2
```

```
%now substituting values of each x1 and x2 for new iteration, we have
```

```
val_x1=1+(4*X(1))+(2*X(2));
```

```
val_x2=(2*X(1))+(2*X(2))-1;
```

```

func=[val_x1; val_x2];
dir=[-val_x1; -val_x2];

while i<2

%computing transpose function
func_t=func.';
dir_T=dir.';

%calculating the value of alpha
a=-dot(func_t,dir)/dot(dir_T,(Q*dir));

%compute X values
X_update=X.'+a*dir_T;
X_update=X_update.';

dir_x1=1+(4*X_update(1))+(2*X_update(2));
dir_x2=(2*X_update(1))+(2*X_update(2))-1;
func=[dir_x1; dir_x2];

%computing the value for beta
b=dot(func.',(Q*dir))/dot(dir_T,(Q*dir));
dir_update=-func+b.*dir;
dir=dir_update;

%generating values of Y for corresponding values of x1 and x2
y = X_update(1) - X_update(2) + 2*X_update(1)*X_update(1) + 2*X_update(1)*X_update(2) +
X_update(2)*X_update(2);

x_plot=[x_plot X_update(1)];
y_plot=[y_plot X_update(2)];

%updating the matrix X

X=X_update;
i=i+1;
end

%displaying of the final points
disp(x1_plot);
disp(x2_plot);
disp(y_plot);

%for calculated values of x1 and x2, the graph can be plotted as:
Plot3(x1_plot,x2_plot,y_plot);
title('Superimosing value using Conjugate Gradient Algorithm');

```

```
xlabel('X1 points');  
ylabel('X2 points');  
zlabel('Y points');
```

OUTPUT:

```
0 -1 -1  
0.00000 1.00000 1.50000  
0.00000 -1.00000 -1.25000
```

GRAPH:

Superimposing values using Conjugate Gradient Algorithm

