

HW4 CS289A

Antonio Rohit De Lima Fernandes

Question 1:

4. Using a learning rate of 0.5

a. $\mu^{(0)} =$

0.9526

0.7311

0.7311

0.2689

b. $\beta^{(1)} =$

-1.0008

1.8101

-2.6092

c. $\mu^{(1)} =$

0.9438

0.8606

0.3102

0.1419

d. $\beta^{(2)} =$

-0.8722

2.2867

-3.6905

Question 2:

1. Code (bCourses)

2. Min Predicted Value: 1953.85

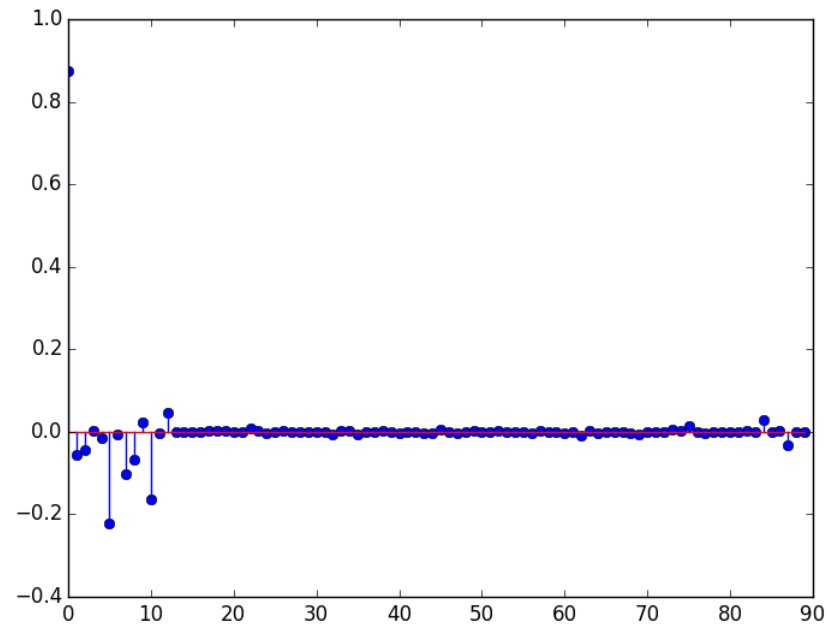
Max Predicted Value: 2045.55

They are close to what the values should be, but not exactly.

RSS: 467M

3. β_0 : 1951.12

Rest of β values:

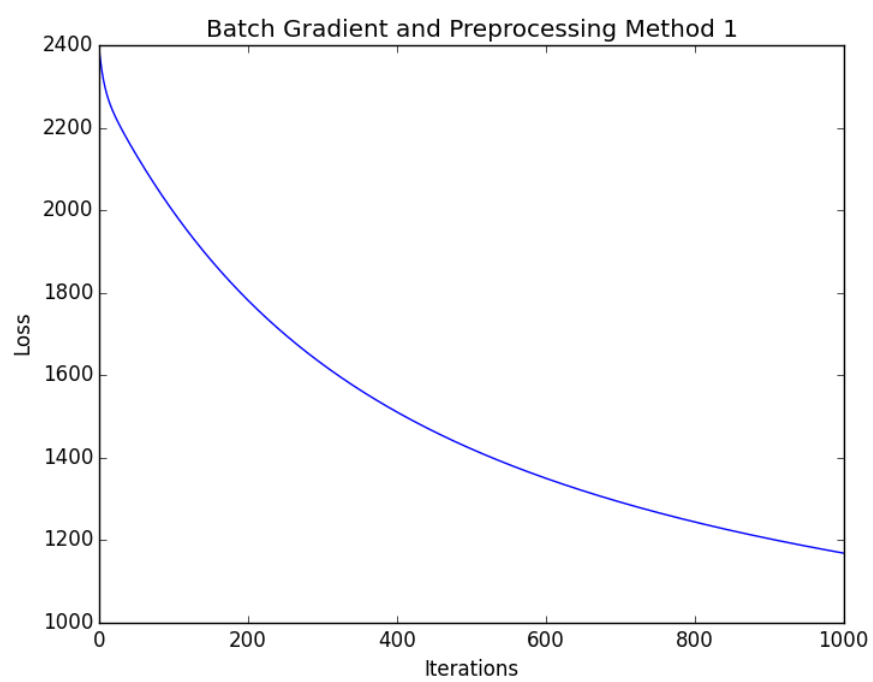
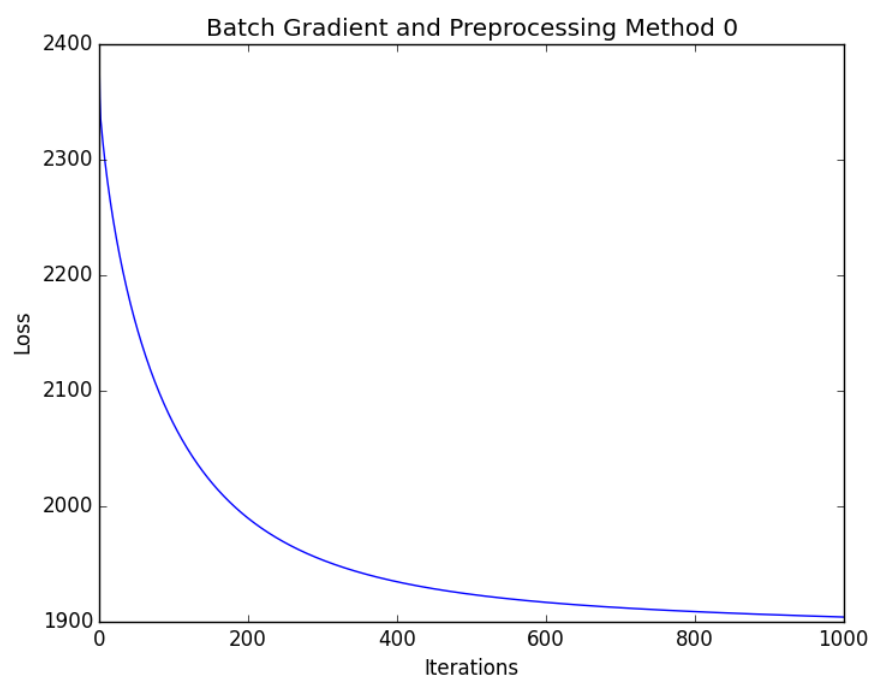


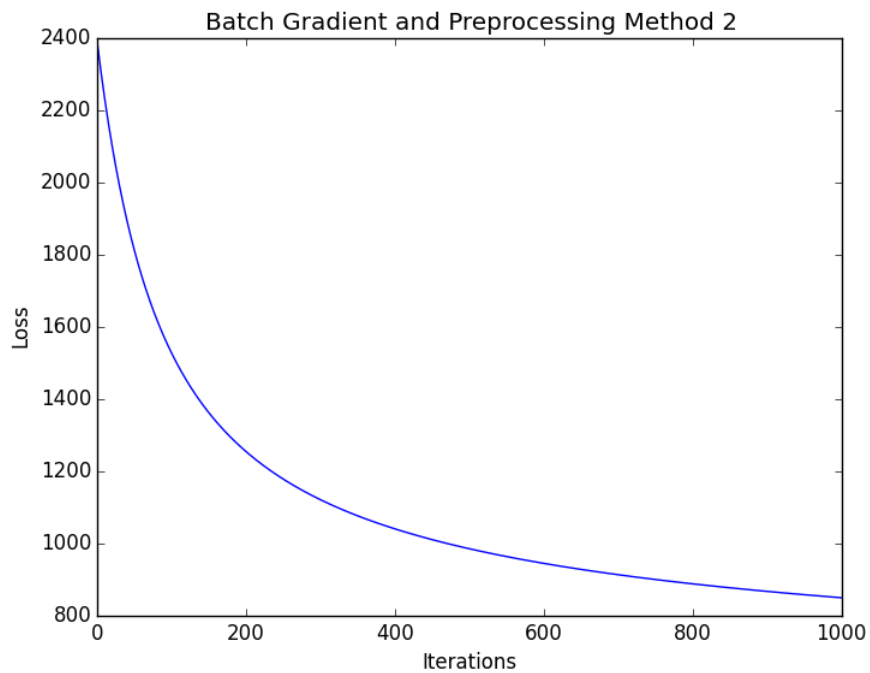
Question 3:

1. Batch Gradient Descent

$$\beta^{(t+1)} = \beta^{(t)} + \eta \nabla_{\beta} \ell(\beta^{(t)})$$

Using the gradient derived in question 1:

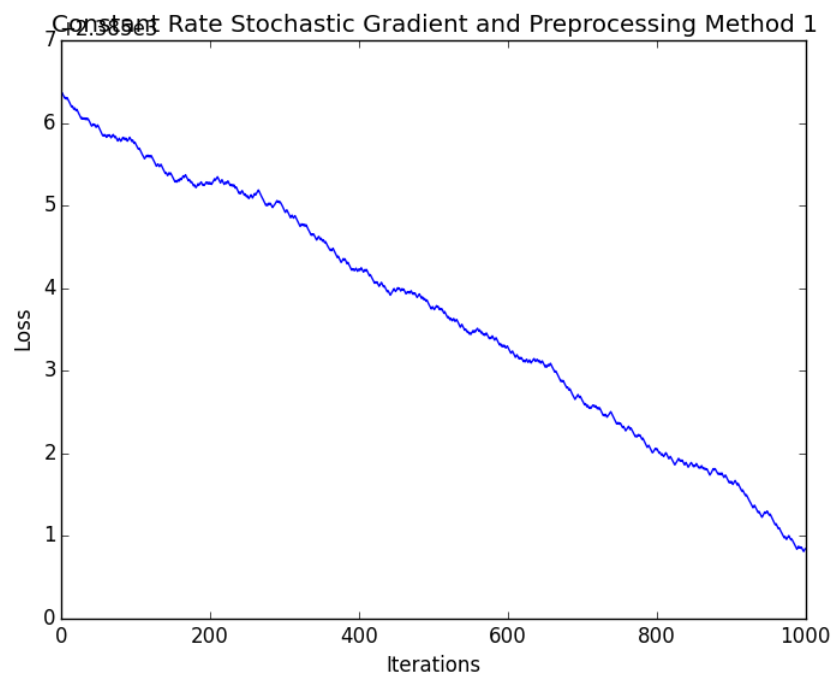
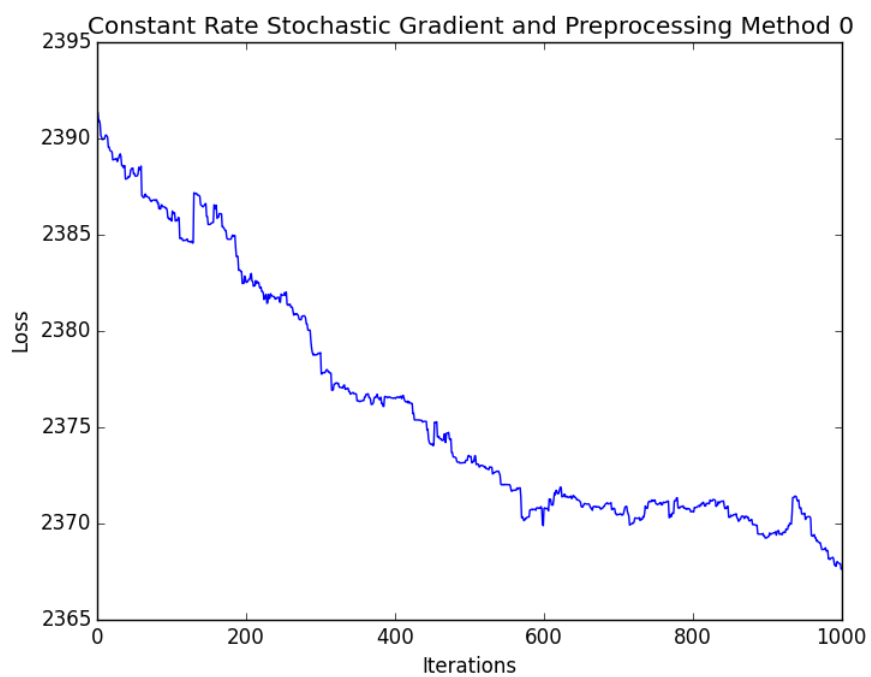


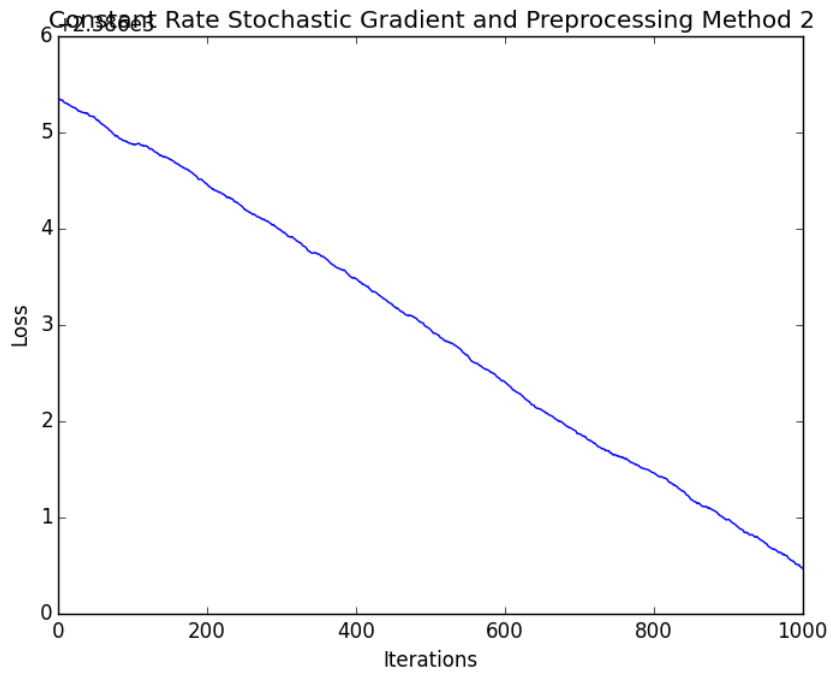


2. Stochastic Gradient with constant learning rate

$$\beta^{(t+1)} = \beta^{(t)} + \eta \left(y_{i_t} - \mu_{i_t}(\beta^{(t)}) \right) x_{i_t}$$

The graphs clearly look different from the batch gradient method above: The curve is not smooth, and does not decrease monotonically, though it does decrease over many iterations. This is because the gradient taking a single a single point may not point in the right direction, but over many samples, averages out in the right direction.





3. Stochastic Gradient with Variable Learning Rate

Using a variable learning rate seems to smoothen the graphs somewhat. I believe this to be a good idea so that once we are close to the minimum, the steps are smaller, and the code converges to this minimum.

