

Adaptive Step sizes weekly report

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1 Week of November 19th and November 12th, 2018

1.1 Comparing performances of the algorithms

1.1.1 Least Squares Regression

When the step-sizes/ γ for the algorithms was properly tuned, the epoch-wise periodicity remains. The algorithm SGD1/2 performs equivalent to SGD with Averaging, but is worse to SGD with decaying step-size and averaging.

Also, the performance of SGD1/2 was pretty unreliable, with very different performance on two runs with same hyperparameters. This may suggest for refinement of the restart condition.

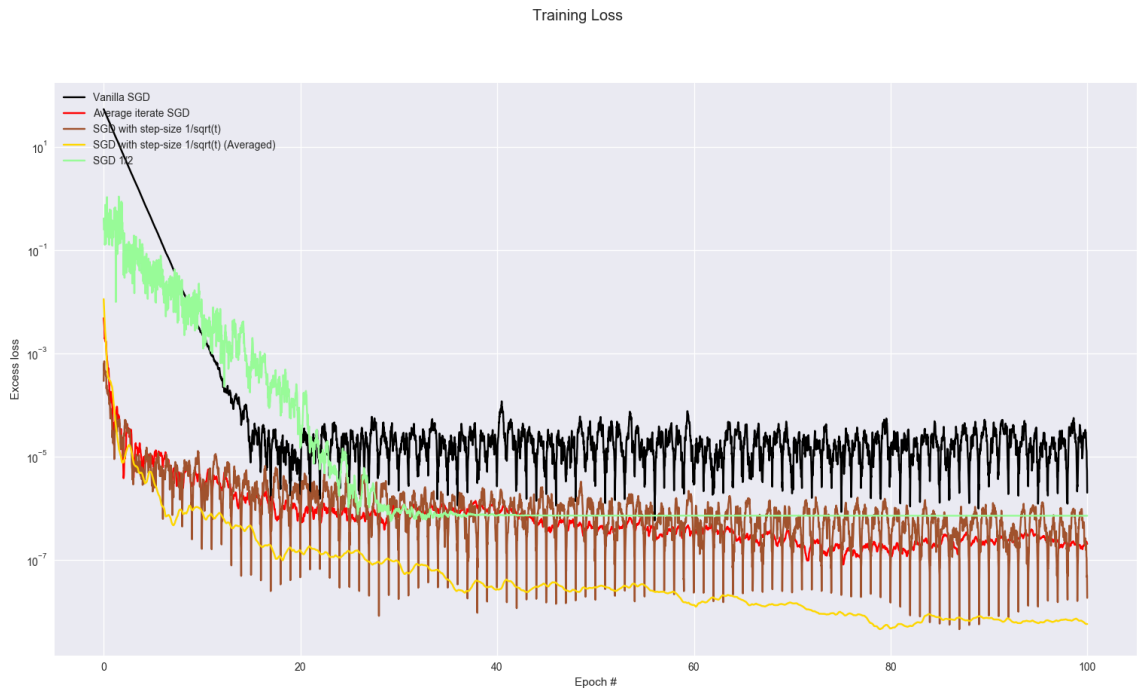


Figure 1: Performance of algorithms on Least squares (SemiLog)

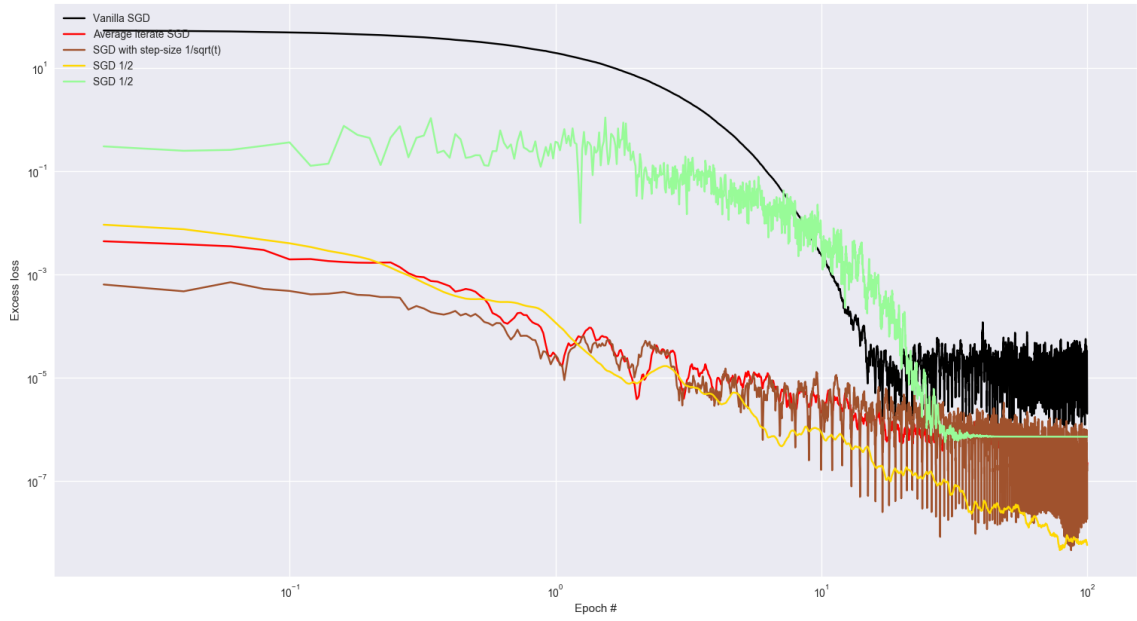


Figure 2: Performance of algorithms on Least squares (LogLog)

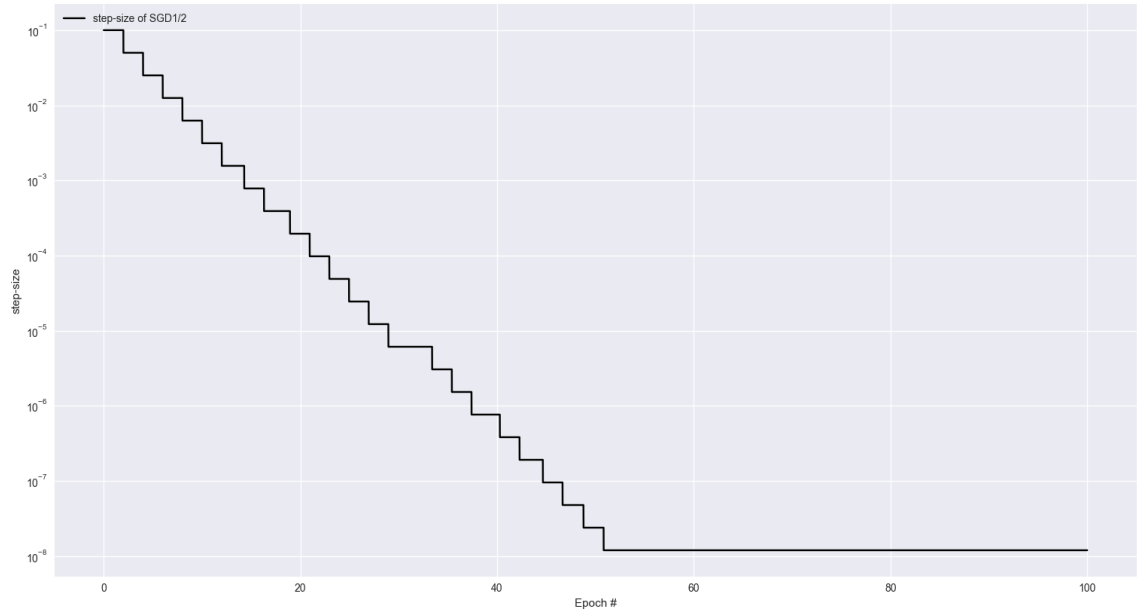


Figure 3: Step size change in SGD1/2

1.1.2 Logistic Regression

Again, the performance of SGD1/2 was too inconsistent across multiple runs. Sometimes its performance was same as that of Sgd with decaying step-size (averaged), while other times it was much worse.

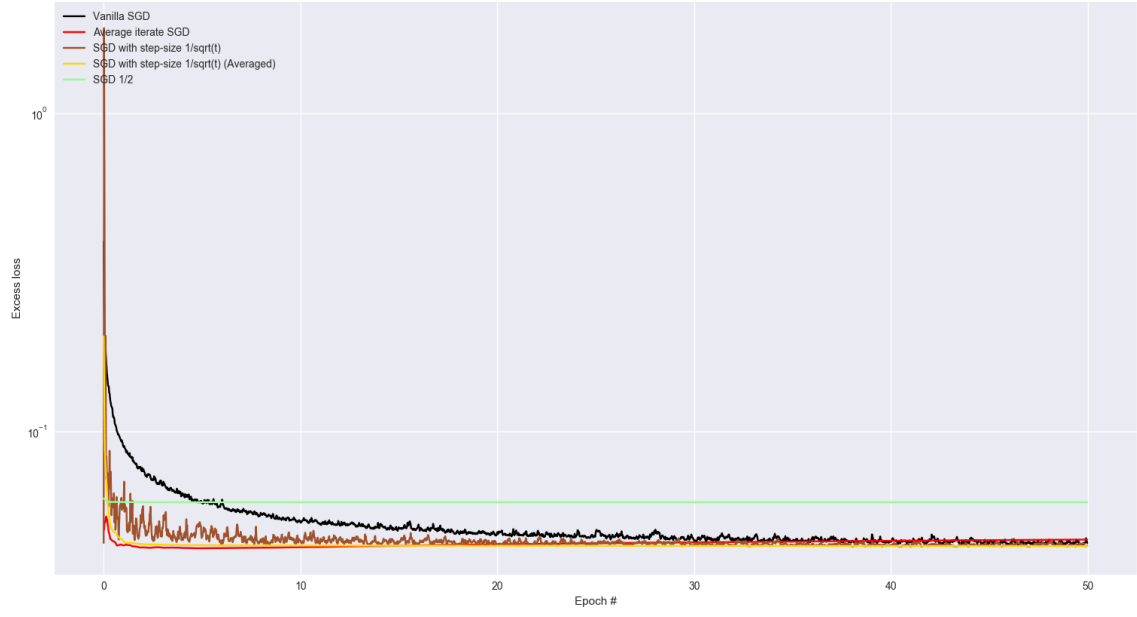


Figure 4: Performance of algorithms on Least squares (SemiLog)

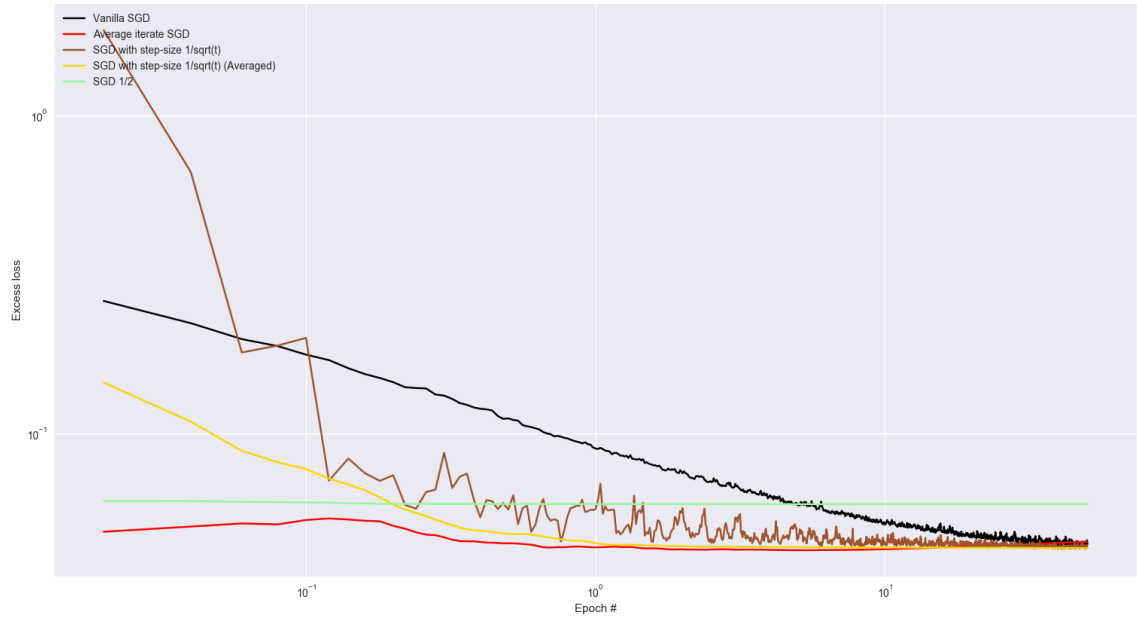


Figure 5: Performance of algorithms on Least squares (LogLog)

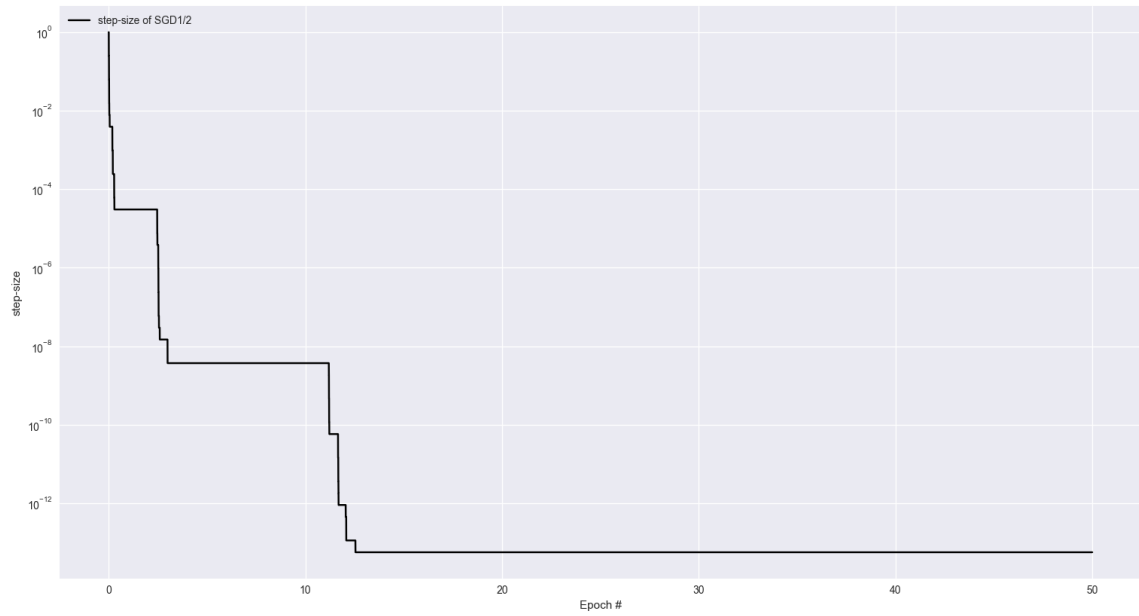


Figure 6: Step size change in SGD1/2

1.2 Improving step sizes

For all the algorithms, I tried to include the best step size for better comparison (All the codes are up at git). This is all for the synthetic dataset we generate, as described in the Convergence diagnostics paper.

1.2.1 Least Squares Regression

1. For standard SGD in LSR, step-size chosen=0.0001

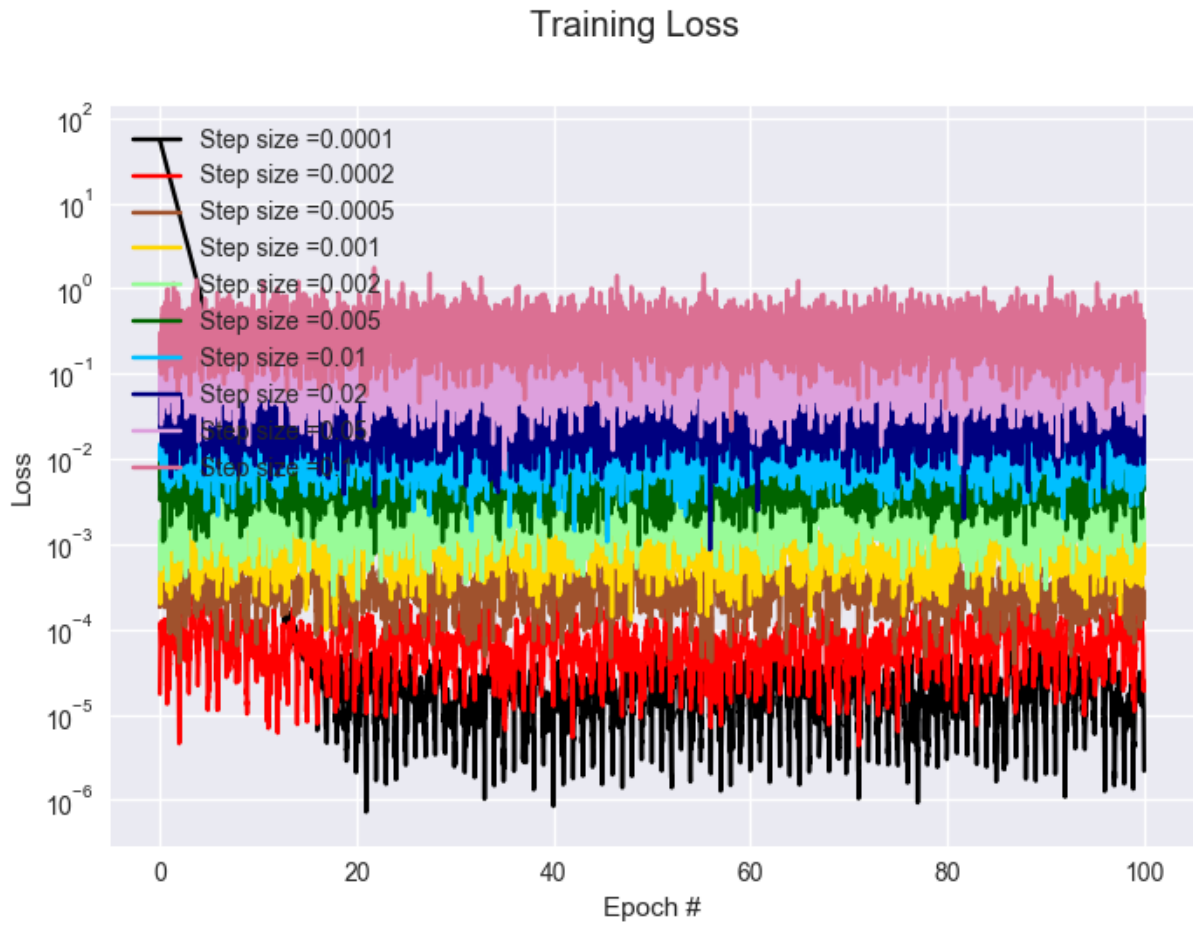


Figure 7: Vanilla SGD for Least squares

2. For average SGD in LSR, step-size chosen=0.01

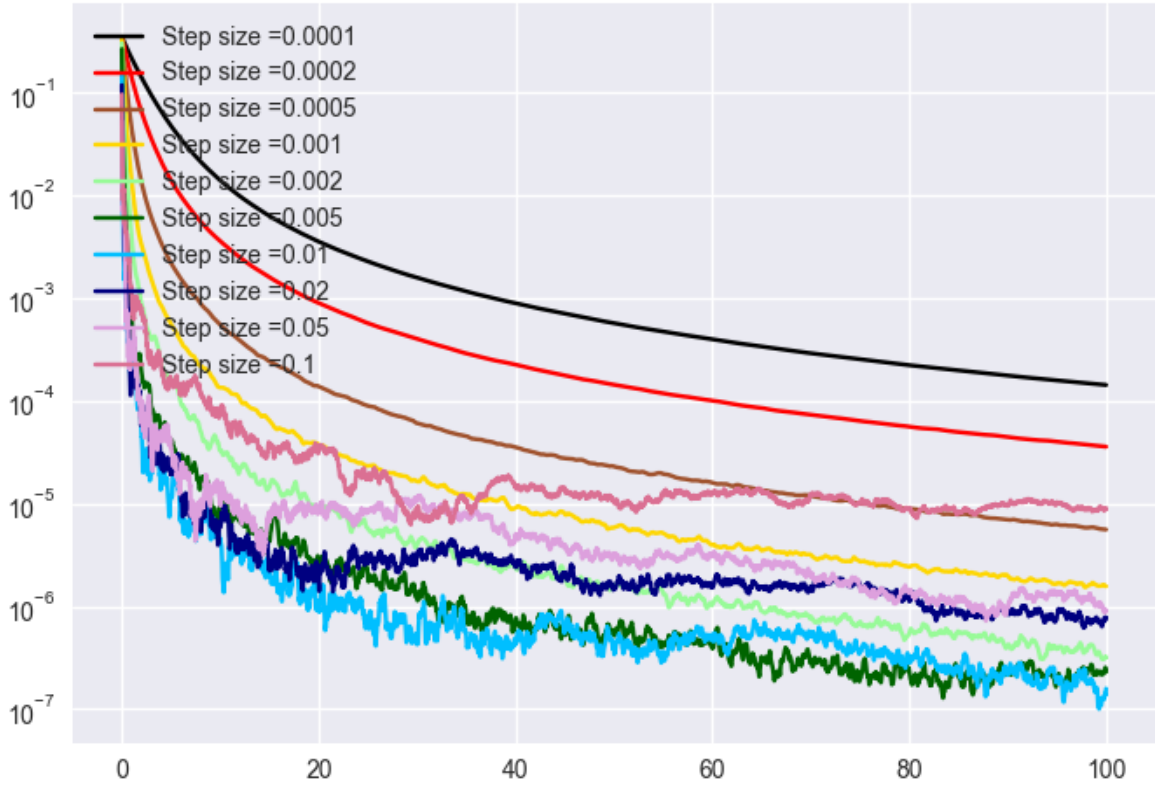


Figure 8: Average SGD for Least squares

3. For SGD with γ/\sqrt{t} decaying stepsize, in LSR, chosen $\gamma=0.01$

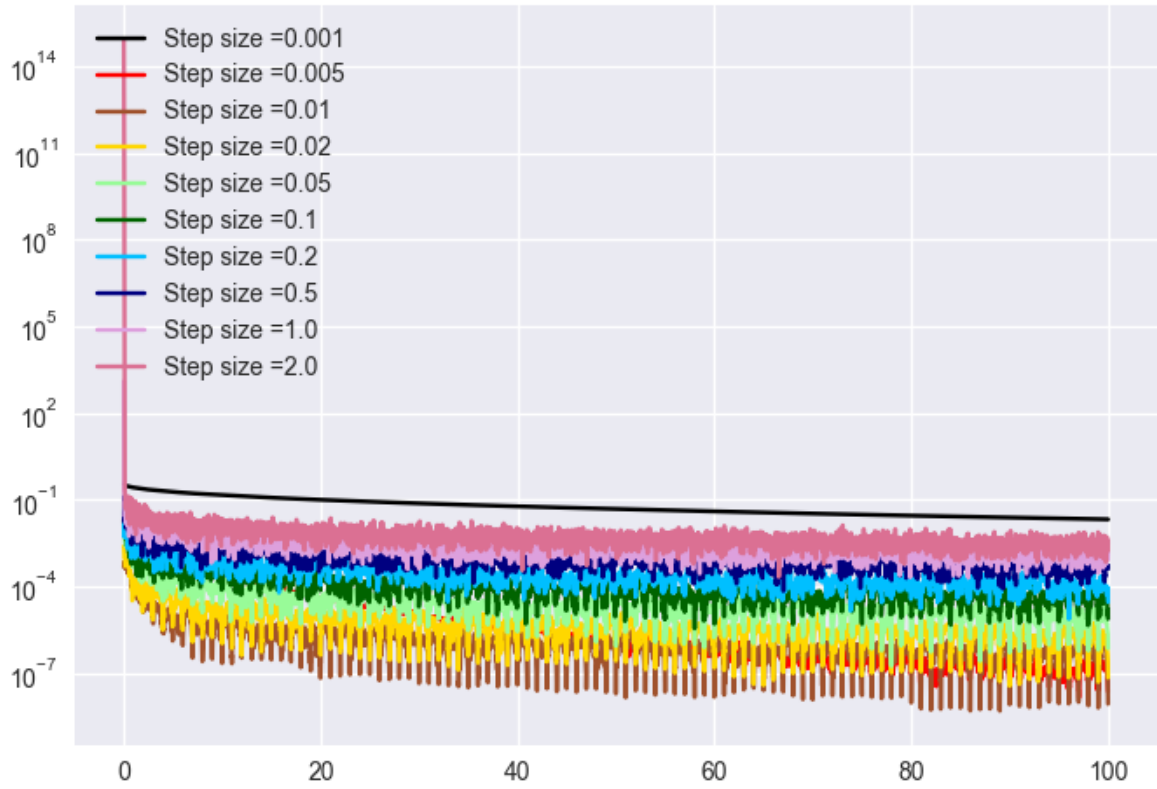


Figure 9: SGD with γ/\sqrt{t} decaying stepsize, for Least squares

4. For SGD with γ/\sqrt{t} decaying stepsize (Averaged), in LSR, chosen $\gamma=0.05$

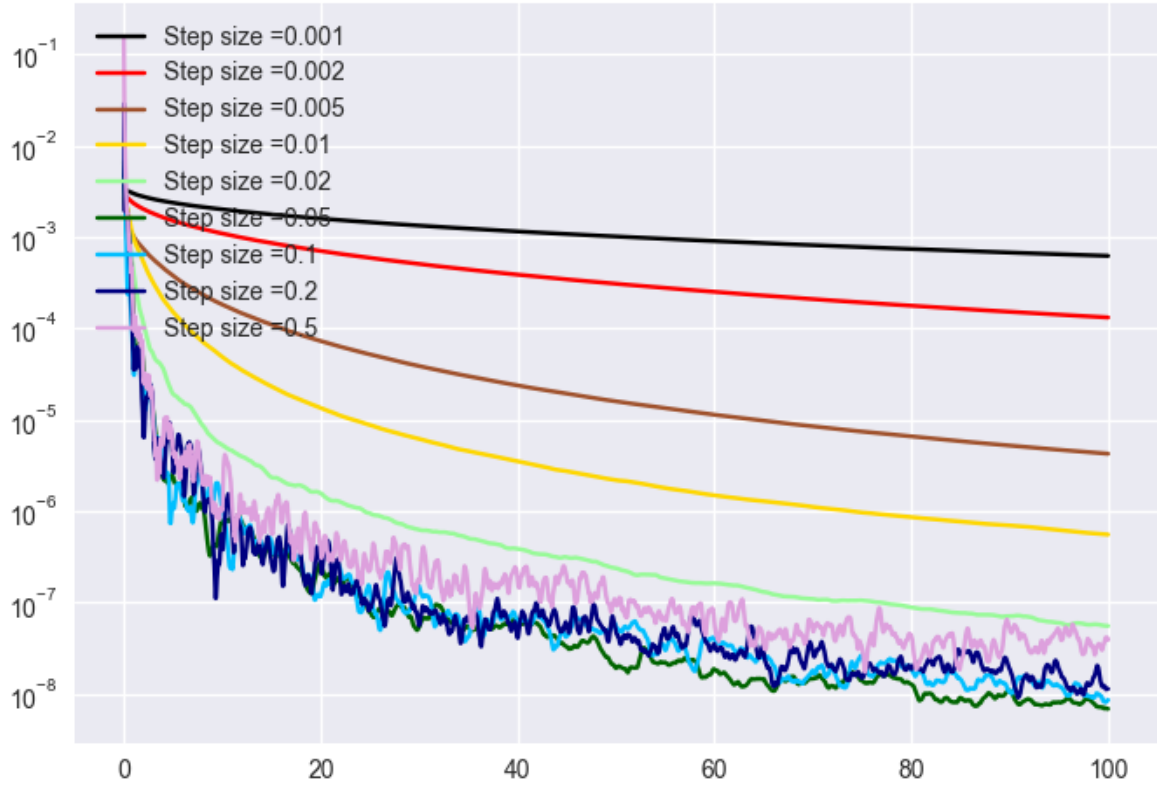


Figure 10: SGD with γ/\sqrt{t} decaying stepsize (averaged), for Least squares

5. For SGD1/2 in LSR, burnin = 10000 iter (or 2 epochs)



Figure 11: SGD1/2 for Least squares

1.2.2 Logistic Regression

1. For standard SGD in Logistic Regression, step-size chosen=0.05

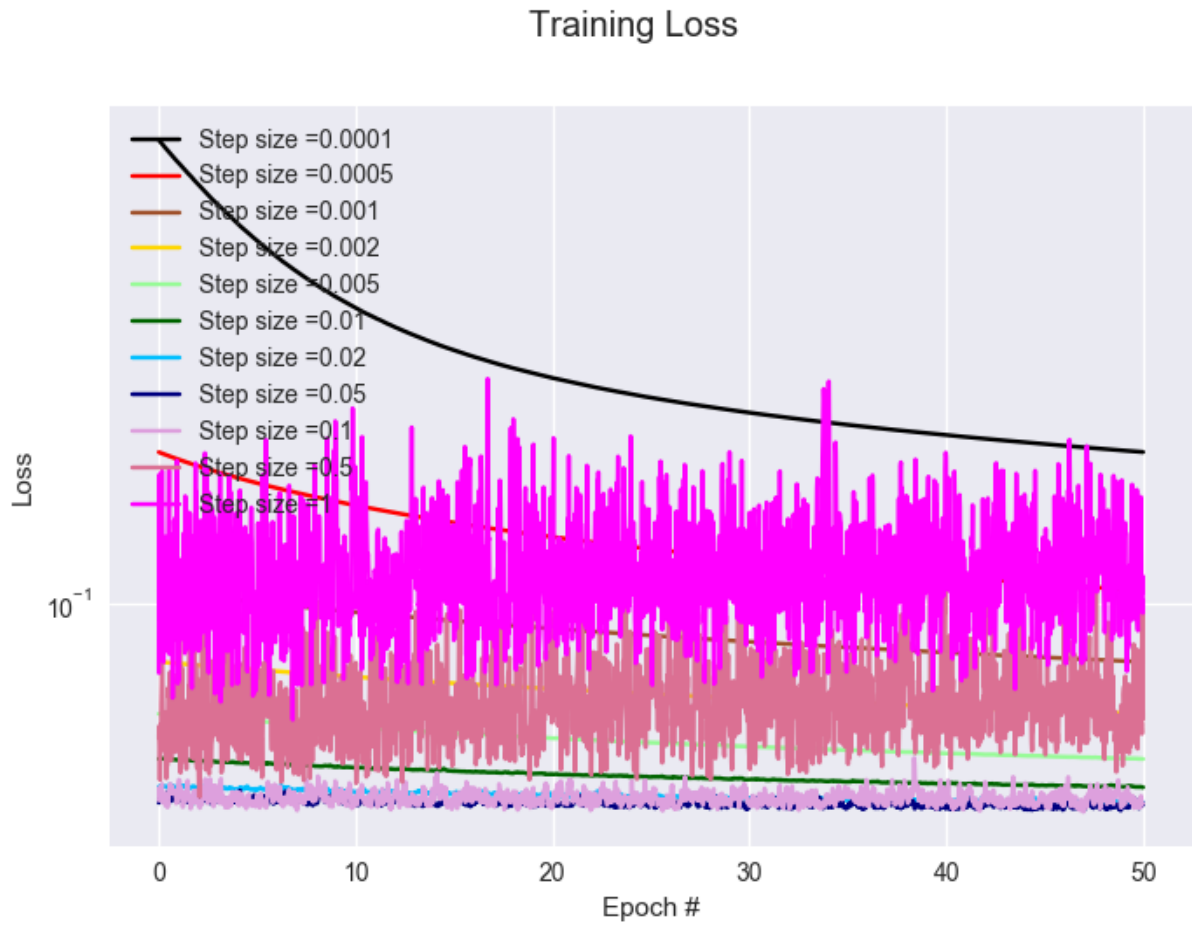


Figure 12: Vanilla SGD for Logistic Regression

2. For average SGD in Logistic Regression, step-size chosen=0.5

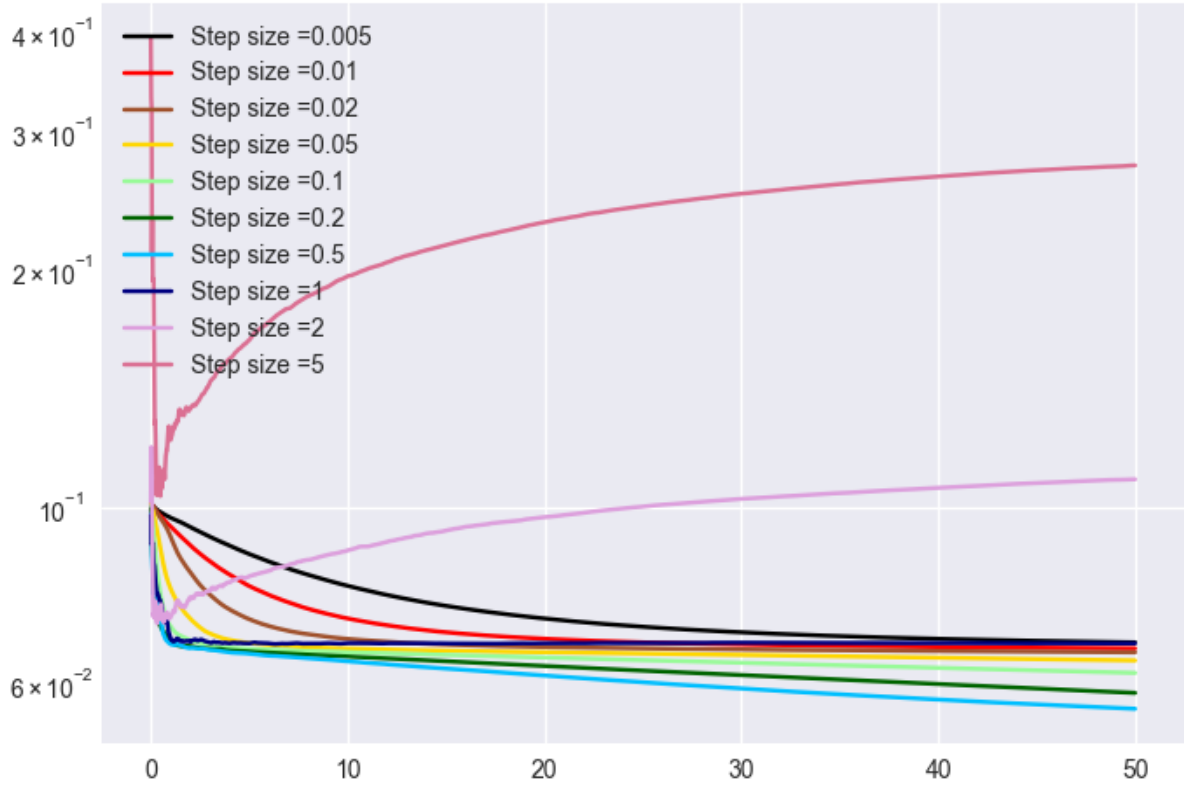


Figure 13: Average SGD for Logistic Regression

3. For SGD with γ/\sqrt{t} decaying stepsize, in Logistic Regression, chosen $\gamma=20$

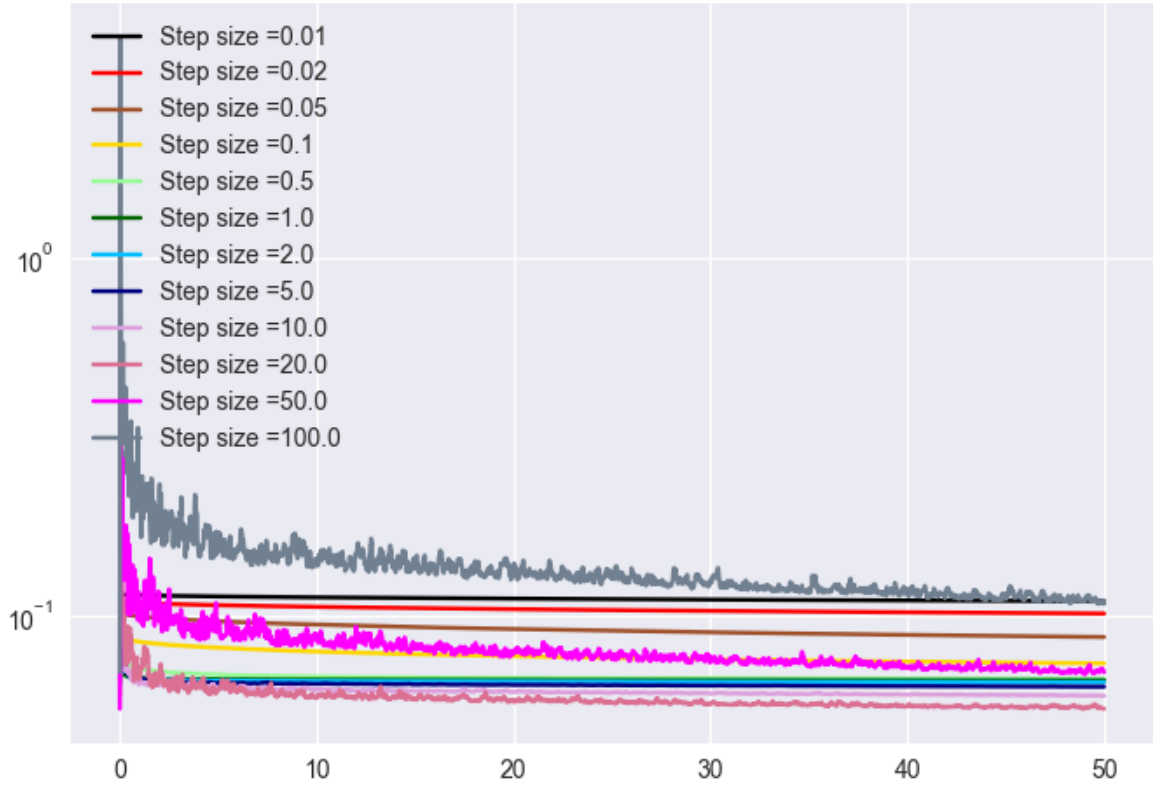


Figure 14: SGD with γ/\sqrt{t} decaying stepsize, for Logistic Regression

4. For SGD with γ/\sqrt{t} decaying stepsize (Averaged), in Logistic Regression, chosen $\gamma=10$

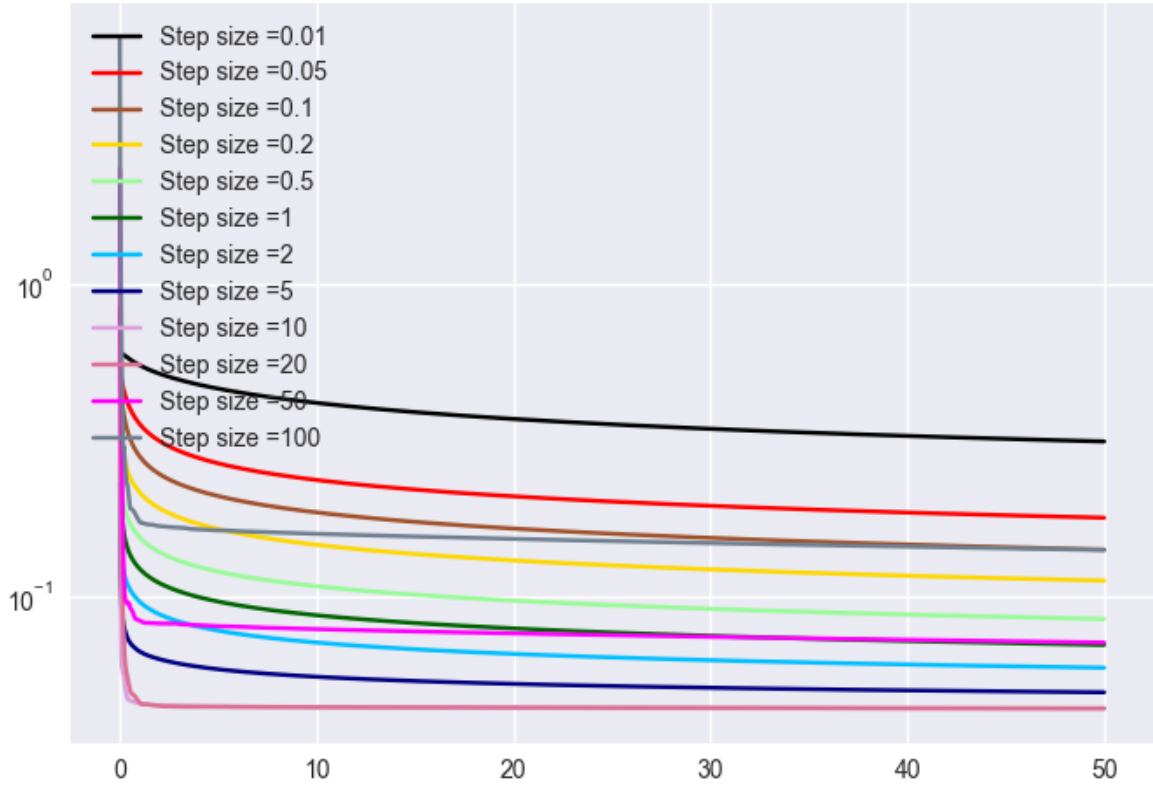


Figure 15: SGD with γ/\sqrt{t} decaying stepsize (averaged), for Logistic Regression

5. For SGD1/2 in Logistic Regression, burnin = 20 iter

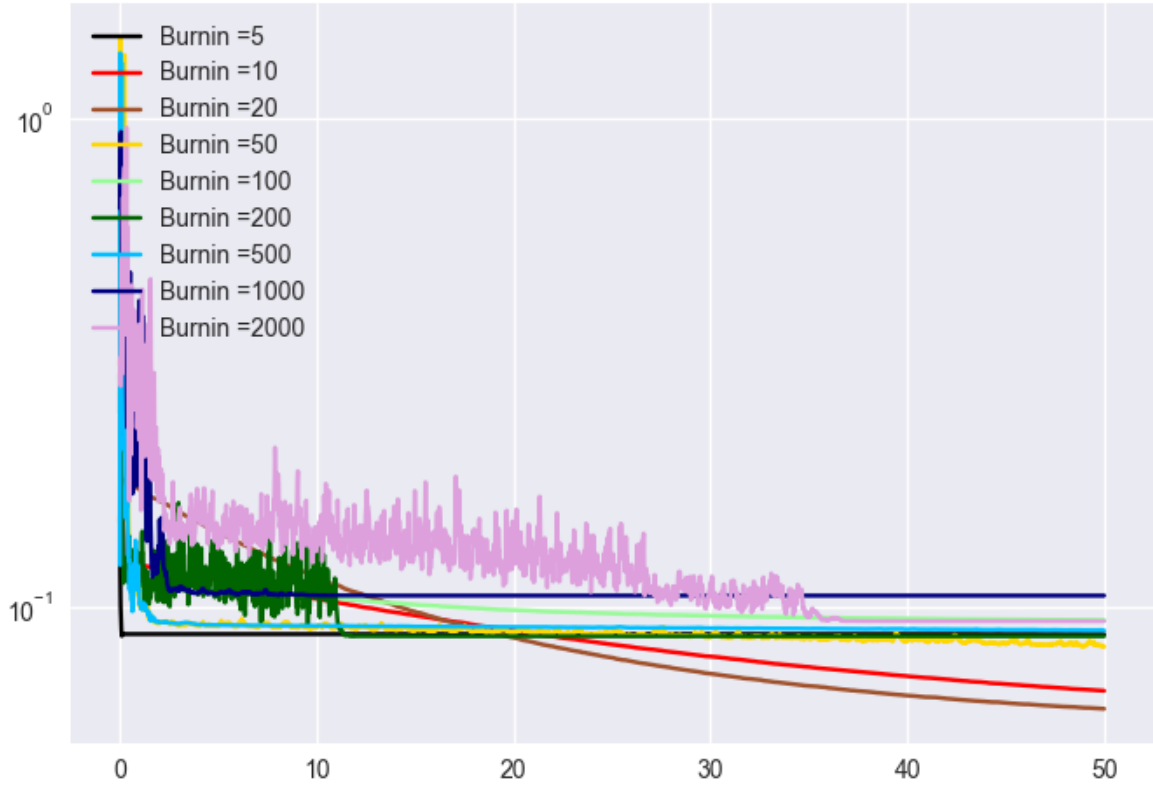


Figure 16: SGD1/2 for Logistic Regression

2 Week of October 29th, 2018

I implemented and compared the performance of different types of SGD, on artificially generated dataset with the following parameters:

- Feature dimension $p = 10$, $SNR = 2$ where $SNR = \text{var}(x) / (p \cdot \text{var}(y \text{ given } x))$.
- weight vector w is fixed as $w_j = 10 * \exp(-0.75j)$.
- number of data points $N=5000$, with each $x_i \sim N(0, I)$, $y_i \sim N(w^T x_i, \sigma^2)$

Training Loss

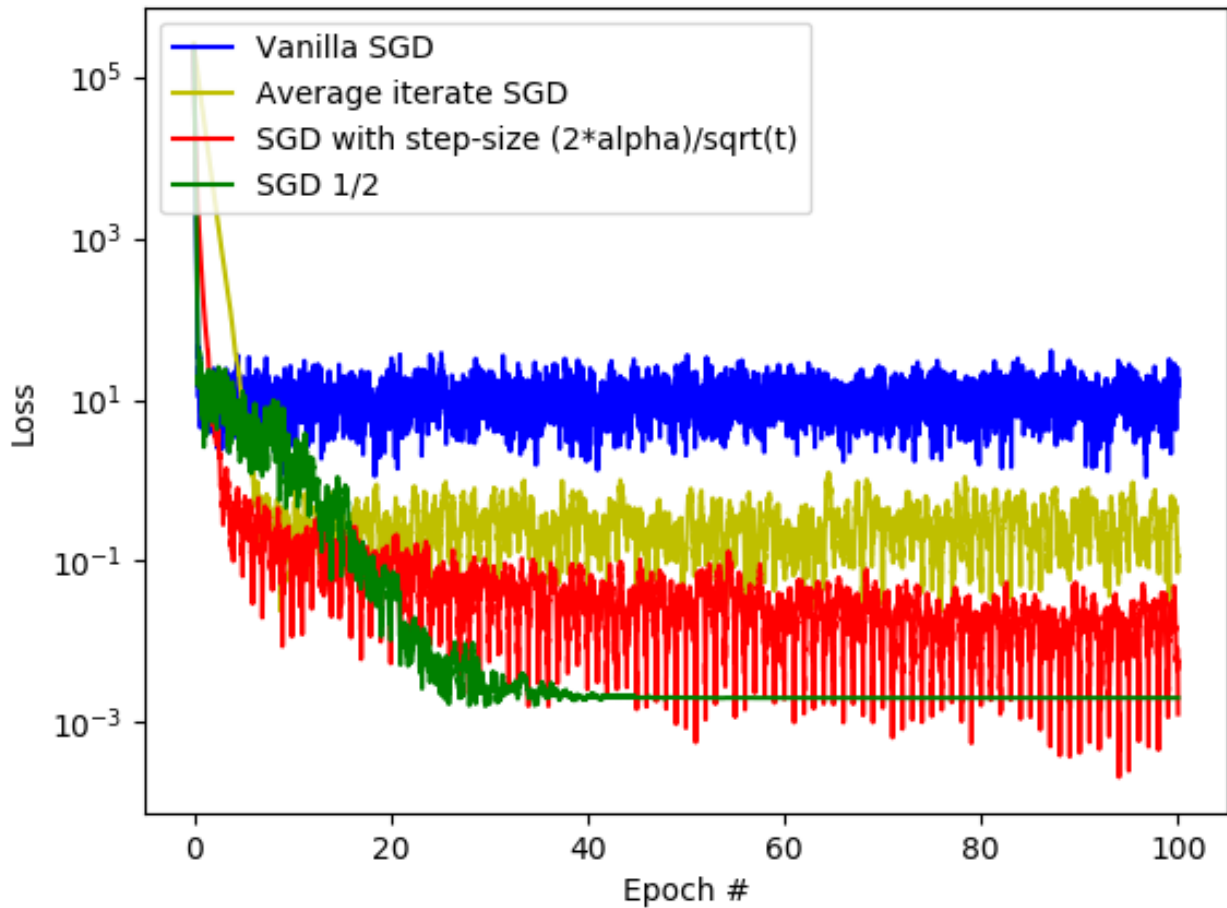


Figure 17:

As clear from the figure, performance of SGD 1/2 is comparable to SGD with $1/\sqrt{t}$ step size.

Issues:

- We know that the sum of dot product of gradients will eventually get a negative value, but in the initial epochs, the value of the dot product of the gradients is very large, and it so happens that if I start adding the dot product of gradients from the first epoch, the value becomes so large that it does not go negative for even 200 epochs. I chose to start summing from epoch 3 for this reason in the code.
- The loss values increase rapidly at the start of each epoch, then go down through the epoch. It may be a bug in the data generation, or in the training, has to be cleared up.