Rithika Harish Kumar(rihk@kth.se)

#### **AIM**

To train and test a two-layer network on a multi classification problem with stochastic mini batch gradient descent. Momentum is also applied to fasten the training while the aim is to minimize the loss function called cross entropy with a regularization term. The dataset to be used is CIFAR-10.

#### RESULTS

#### **Gradient check:**

Numerical gradients were computed by computing a base value for the cost function, making a small variation to a single weight value, recomputing the cost, estimating the derivate and resetting it. In this manner it is calculated for every weight in the network. The analytic gradients and the numerically computed gradients are compared by summing the difference between the respective values in the matrix. If the sum value is low it is better. Convinced that the implementation is correct because by choosing few hyperparameters the loss function converges to a satisfactory level.

Two-layer network with 0.0 and 0.0 regularization

```
Weight1
Difference: 2.710e-04
Mean of the values
                    Analytical: 6.622e-03
                                              Numerical: 6.622e-03
Min of values Analytical: 0.000e+00 Numerical: 0.000e+00
Max of values Analytical: 5.580e-02 Numerical: 5.580e-02
bias1
Difference: 2.997e-07
Mean of the values Analytical: 1.219e-02 Numerical: 1.219e-02
Min of values Analytical: 0.000e+00 Numerical: 0.000e+00
Max of values Analytical: 3.077e-02 Numerical: 3.077e-02
Weight2
Difference: 9.677e-07
Mean of the values Analytical: 9.121e-03 Numerical: 9.121e-03
Min of values Analytical: 0.000e+00 Numerical: 0.000e+00
Max of values Analytical: 1.234e-01 Numerical: 1.234e-01
bias2
Difference: 4.472e-07
Mean of the values Analytical: 3.648e-02 Numerical: 3.648e-02
Min of values Analytical: 4.552e-03 Numerical: 4.552e-03 Max of values Analytical: 9.601e-02 Numerical: 9.601e-02
Two-layer network with 0.1 and 0.3 regularization
Weight1
Difference: 4.775e-03
Mean of the values
                      Analytical: 1.873e-02
                                              Numerical: 1.873e-02
Min of values Analytical: 8.785e-08 Numerical: 1.421e-08
Max of values
                Analytical: 1.253e-01
                                         Numerical: 1.253e-01
```

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bias1

Difference: 2.071e-07

Mean of the values Analytical: 3.517e-02 Numerical: 3.517e-02

Min of values Analytical: 0.000e+00 Numerical: 0.000e+00 Max of values Analytical: 1.741e-01 Numerical: 1.741e-01

Weight2

Difference: 4.590e-05

Mean of the values Analytical: 1.482e-01 Numerical: 1.482e-01

Min of values Analytical: 5.435e-03 Numerical: 5.436e-03 Max of values Analytical: 4.607e-01 Numerical: 4.607e-01

bias2

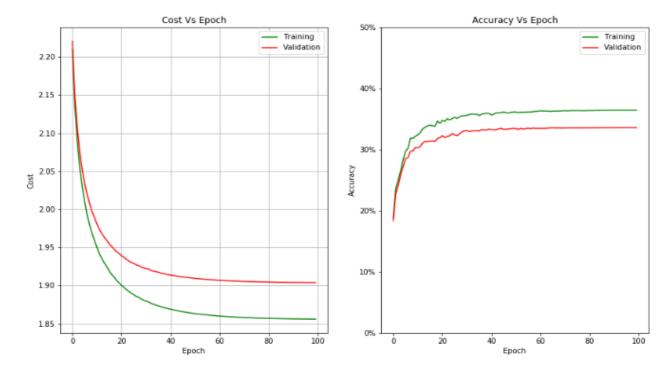
Difference: 4.441e-07

Mean of the values Analytical: 5.292e-02 Numerical: 5.292e-02

Min of values Analytical: 3.601e-03 Numerical: 3.601e-03 Max of values Analytical: 1.198e-01 Numerical: 1.198e-01

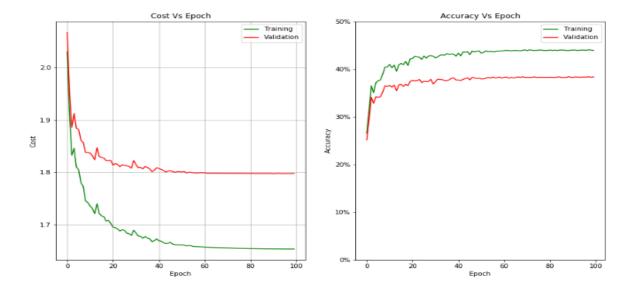
#### **Effect of momentum:**

Without momentum: eta\_initial=0.01, eta\_decay=0.95



After Adding Momentum: eta\_initial=0.01, eta\_decay=0.95, rho = 0.9

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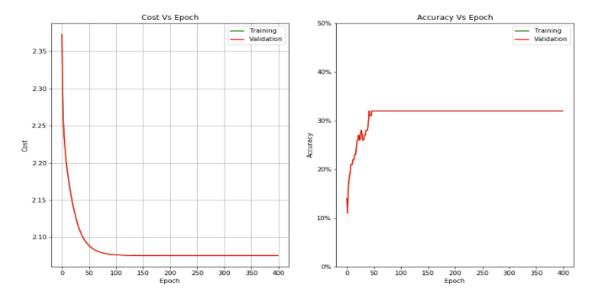


Vanilla SGD without momentum is slow compared to the momentum update. It updates the network parameters not only using current gradient but also with weighted history of the previous updates. That weight of past history is called momentum.

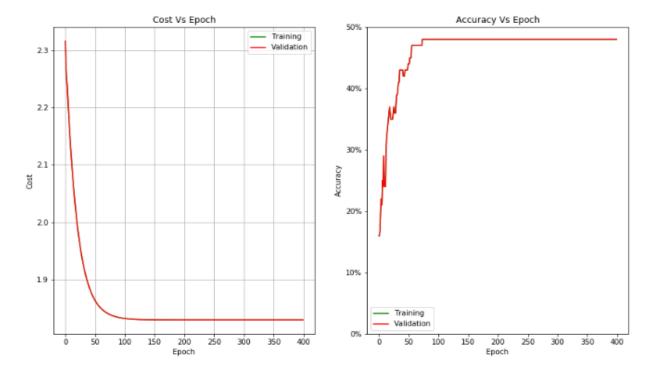
### With overfitting:

By taking a small subset of data and training for high number of epochs overfitting is done and tested for different rho values with eta\_initial=0.005, eta\_decay=0.95. Increase in momentum increases the speed of convergence. But a very high momentum leads to gradient oscillation.

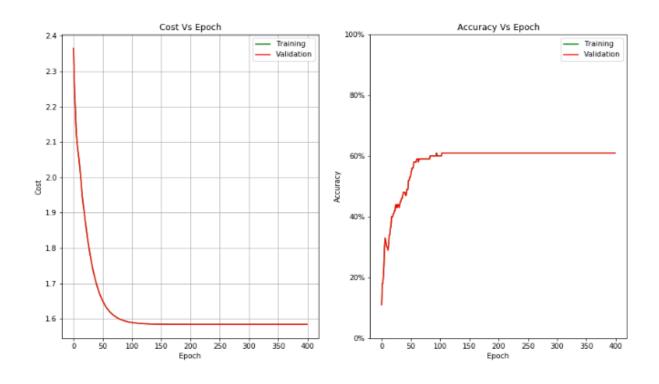
Rho = 0.5



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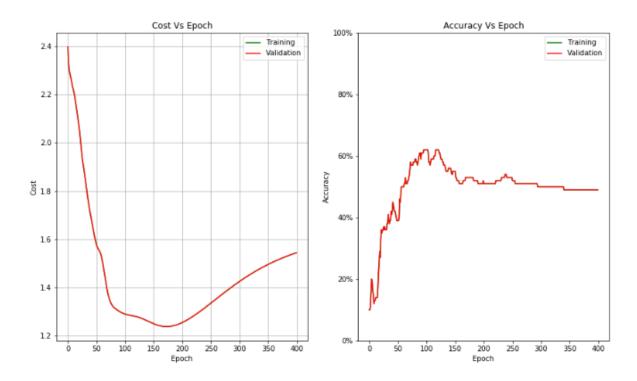


Rho = 0.9



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Rho = 0.99



### **Best parameter search:**

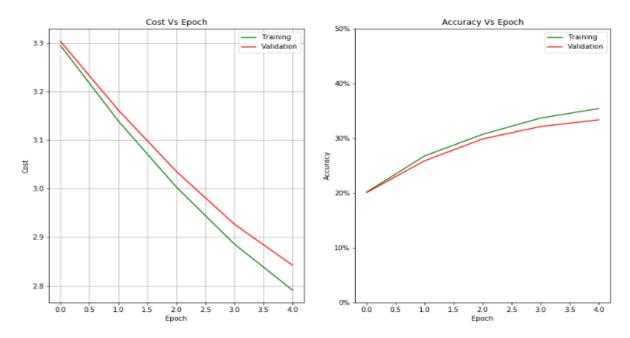
### Coarse search

The basic hyper-parameters are set as:

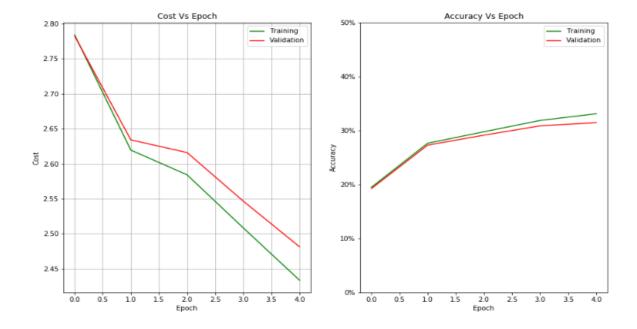
The regularization and initial learning rate have 49 combinations:

Better performing three networks are:

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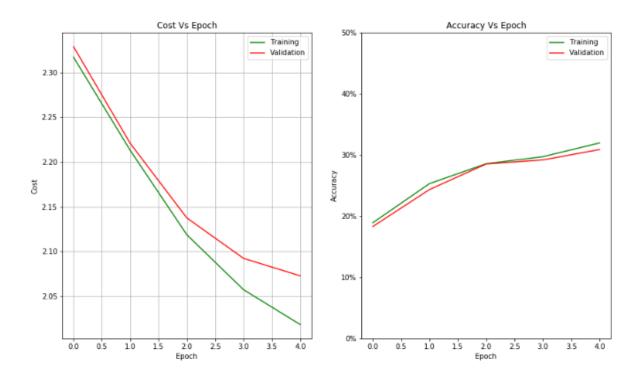


eta\_initial = 0.5
 lamda = 0.005
 Training accuracy = 33.11%
 Validation accuracy = 31.47%



eta\_initial = 0.5
 lamda = 0.001
 Training accuracy = 31.97%
 Validation accuracy = 30.89%

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### Fine search

The basic hyper-parameters are set as:

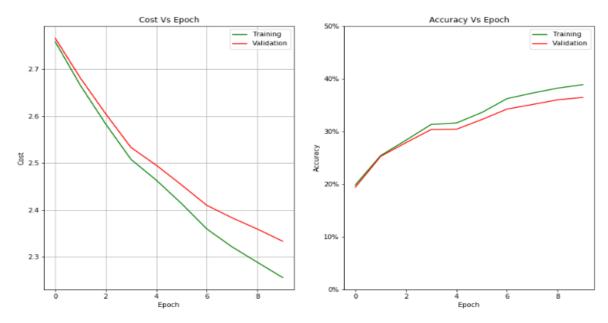
The regularization and initial learning rate have 28 combinations:

lamda= np.linspace(0.005, 0.0005, num=7) eta\_initial = np.linspace(0.35, 0.25, num=4)

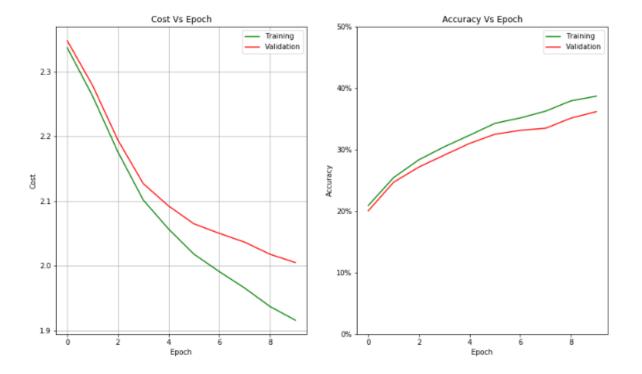
Better performing three networks are:

eta\_initial = 0.35
 lamda = 0.005
 Training accuracy = 38.89%
 Validation accuracy = 36.46%

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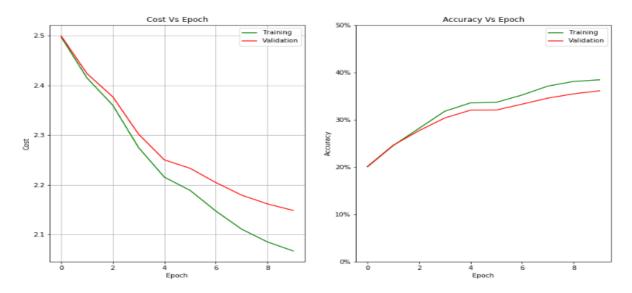
• eta\_initial = 0.35 lamda = 0.00125 Training accuracy = 38.69% Validation accuracy = 36.18%



•  $eta_initial = 0.35$ 

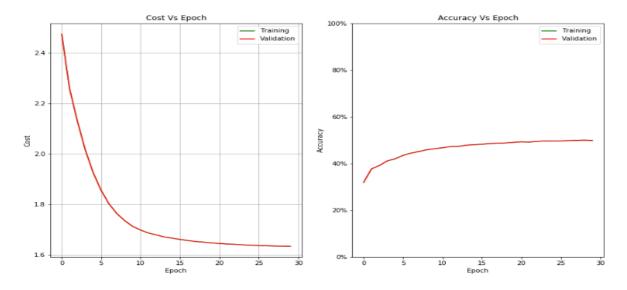
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lamda = 0.00275 Training accuracy = 38.45% Validation accuracy = 36.13%



The best network according to the highest validation accuracy obtained is trained where the whole dataset is used for training, leaving out the final 10000 images for testing.

Epochs = 30 lamda=0.005 eta\_initial=0.35 eta\_decay=0.95 and rho=.9.



Training accuracy = 49.90 % **Testing accuracy = 48.53 %**