

Question 1 : Logistics Regression On Iris Data Set

1) Load the Iris dataset, randomly split it into training set 90% and test set 10%.

- Split the data using 135 , 15 as train and test

2)

- Matrix multiplication of placeholder, with weights and bias
- multiplication with y to get the output loss over the training dataset

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

which allows us to interpret the outputs as probabilities, while [cross-entropy loss](#) is what we use to measure the error at a softmax layer, and is given by^[1]

$$L(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N H(p_n, q_n) = -\frac{1}{N} \sum_{n=1}^N \left[y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n) \right],$$

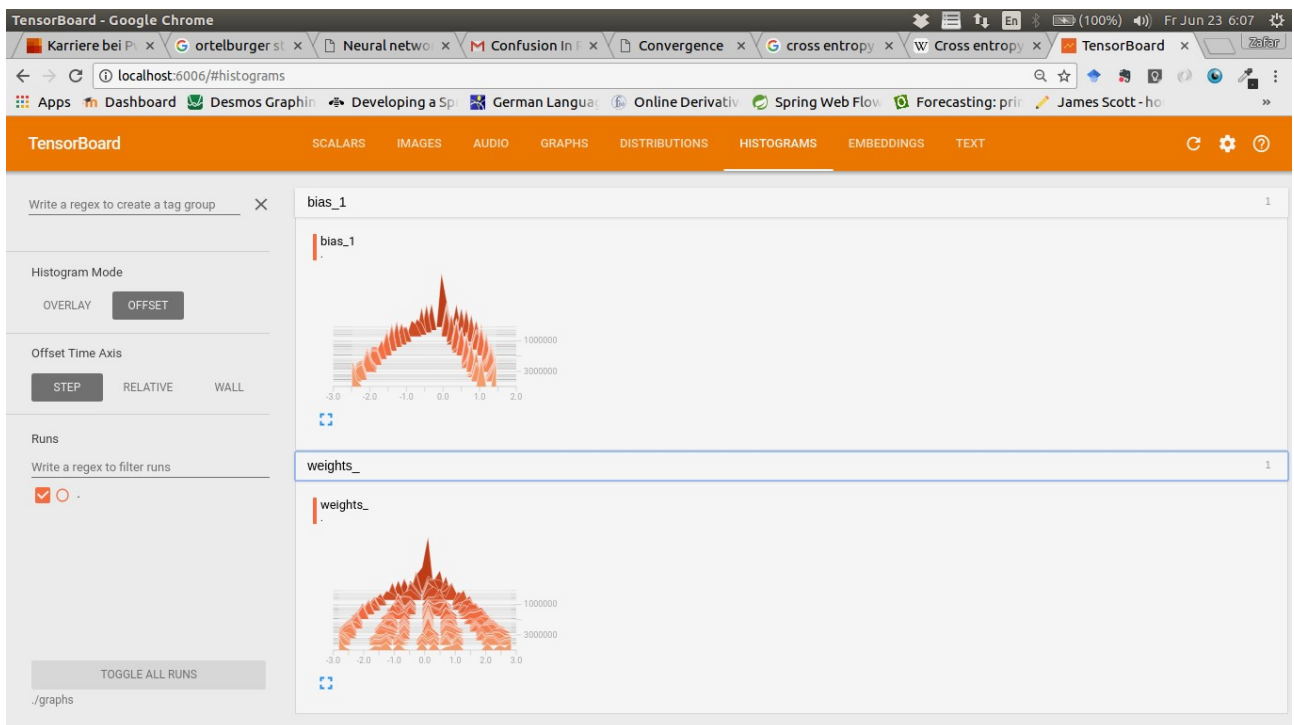
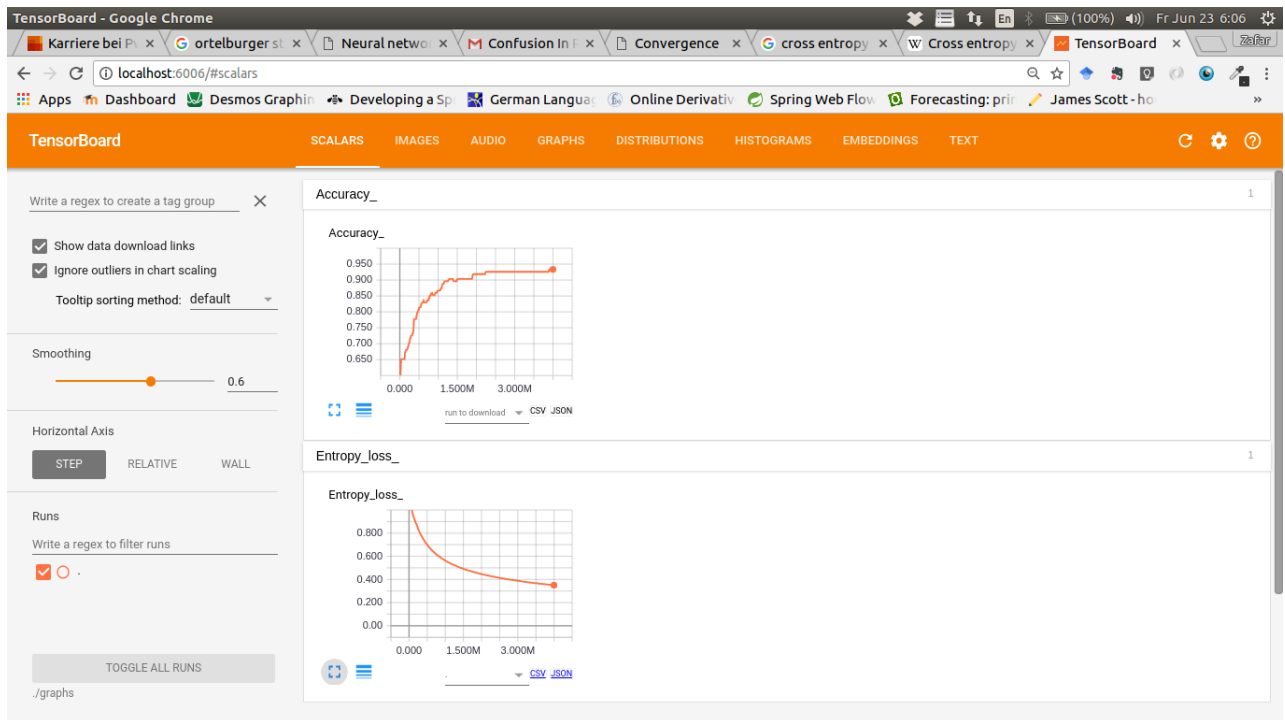
```
y = tf.nn.softmax(tf.matmul(x, W) + b)
```

```
cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_indices=[1]))
```

3) Train the model on the training set and make prediction on the test set

- training the model using two optimizer function
 - AdamOptimizer
 - GradientDescentOptimizer
- Learning rate 0.05
- The accuracy that I received
 - using the gradient decent It didn't converged although I randomly shuffled, normalized the dataset, but still the training error was not satisfactory so is the case with test set, received 93 % accuracy , if I try to increase the learning rate the it gave little better accuracy But if i run this Gradient Decent using 5000 epochs then it gives 100 % accuracy
 - using the AdamOptimizser it converged and received 100% accuracy (lower training error and 100% accuracy)

Gradient Decent Optimizer



Epochs : 5000

SCALARS

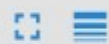
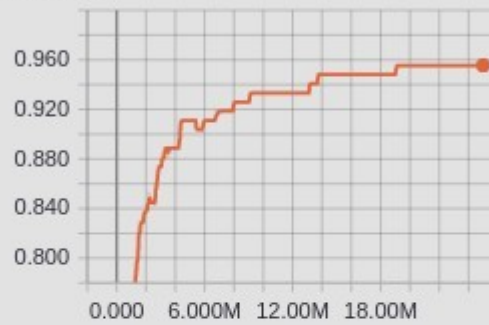
IMAGES

AUDIO

GRAPHS

Accuracy_

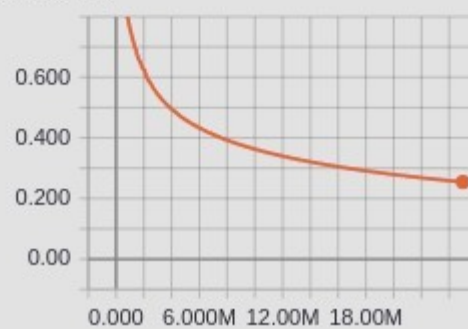
Accuracy_



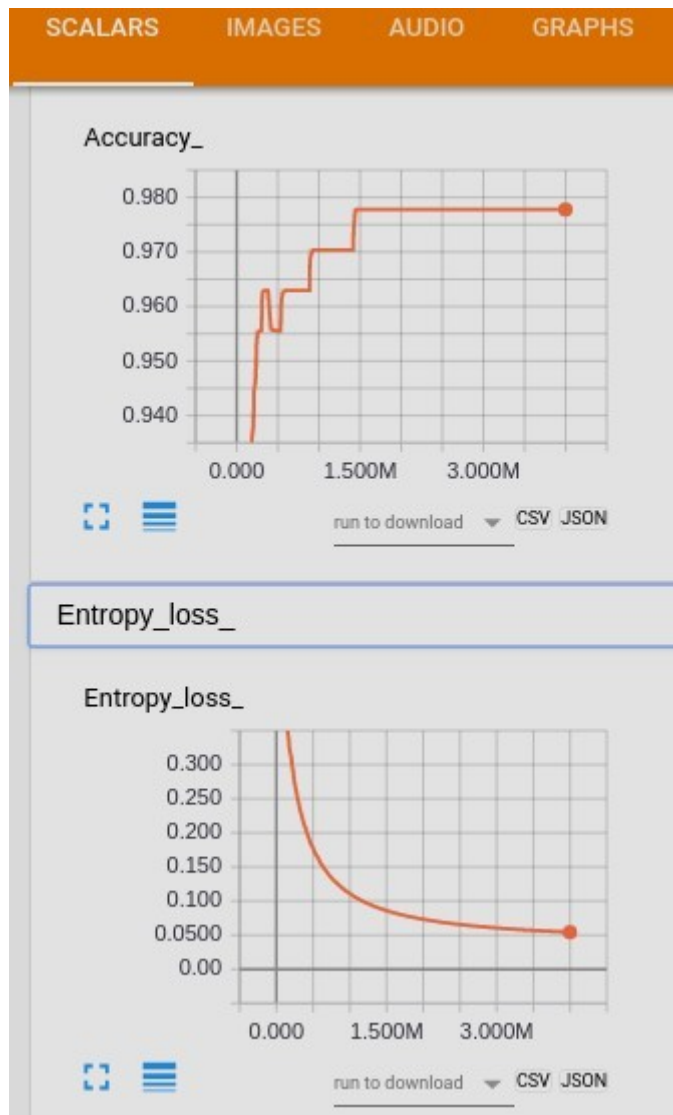
run to download ▼ CSV JSON

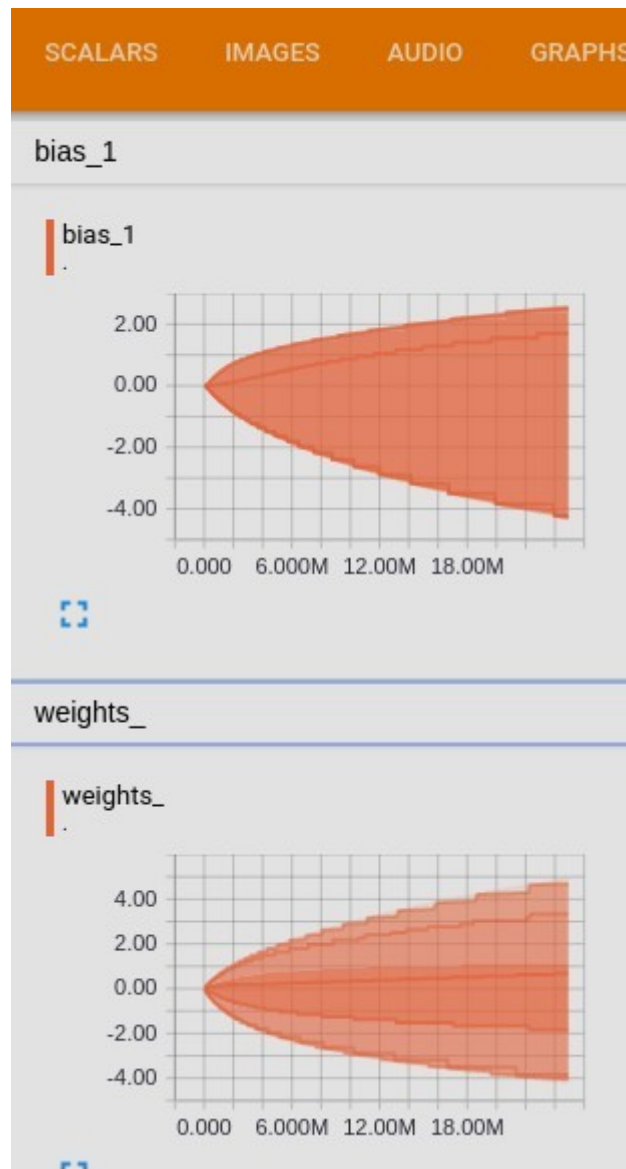
Entropy_loss_

Entropy_loss_



Adam Optimizer





TensorBoard visulization

For this visualization

created scalar variables for entropy loss and accuracy
while for histogram and distribution using bias and weights

```
tf.summary.scalar("Accuracy:", accuracy)
tf.summary.scalar("Entropy loss:", cross_entropy)
tf.summary.histogram("weights ", W)
tf.summary.histogram("bias", b)
```

Question 1 : Logistics Regression On the Olivetti faces dataset

Same execution process

pre-processed the dataset (same old but without normalizing , as that data is approximately already normalized)

```
def prepData() :  
    enc = OneHotEncoder()  
  
    olivetti = datasets.fetch_olivetti_faces()  
    X , y = olivetti.data, olivetti.target  
  
    nb_classes = 40  
    targets = np.array(y).reshape(-1)  
    y_ = one_hot_targets = np.eye(nb_classes)[targets]  
  
    X_train, X_test , Y_train, Y_test = train_test_split(X, y_, test_size=0.10, random_state=42)
```

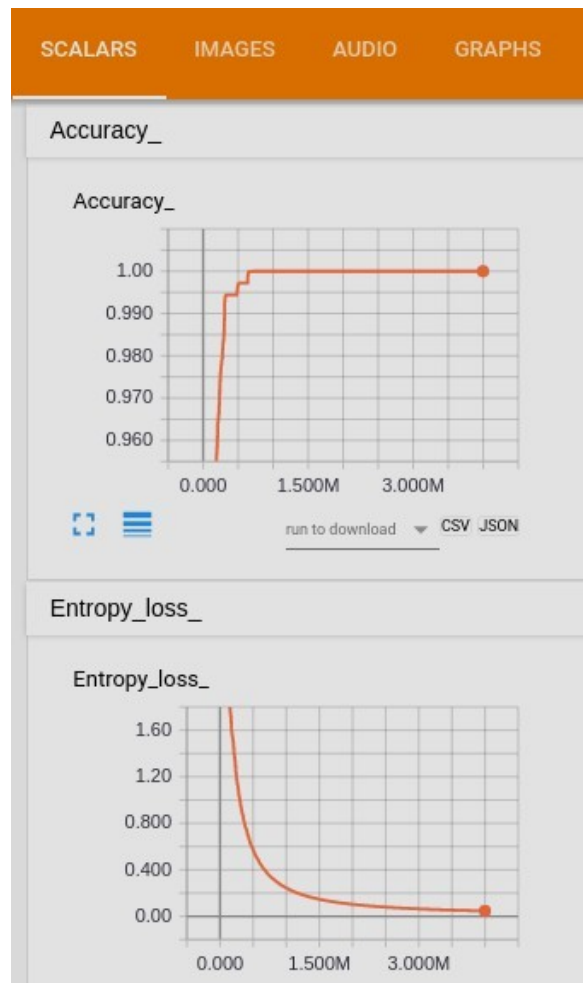
$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

which allows us to interpret the outputs as probabilities, while [cross-entropy loss](#) is what we use to measure the error at a softmax layer, and is given by^[1]

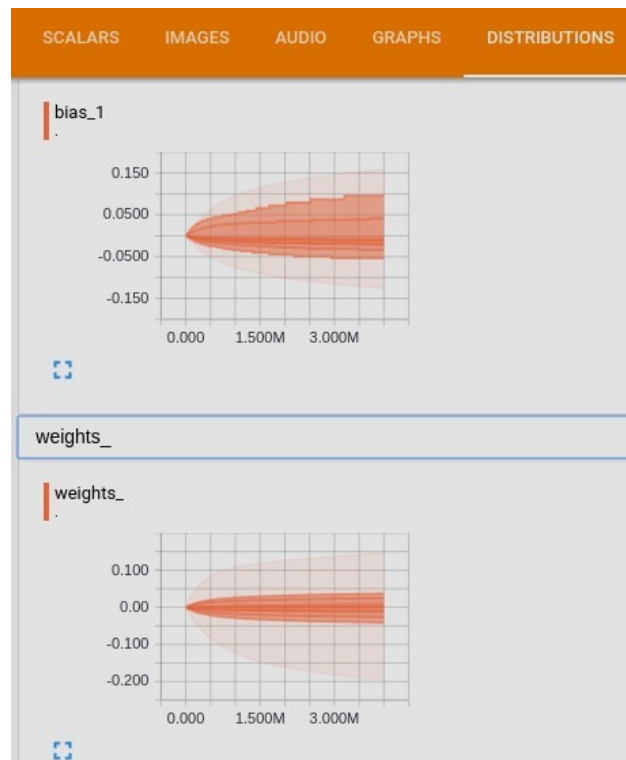
$$L(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N H(p_n, q_n) = -\frac{1}{N} \sum_{n=1}^N \left[y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n) \right],$$

Same entropy function

But the only difference is it converges on gradientDescent even with smaller learning rate



Distributions :



Histograms :

