Keras_Assignment_MNIST

June 5, 2019

[83]:
```
import keras
from keras.datasets import mnist
from keras.utils import np_utils
import seaborn as sns
from keras.initializers import RandomNormal
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, BatchNormalization
```

[84]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

[85]:
```
# https://github.com/keras-team/keras/blob/master/examples/mnist_mlp.py

# Importing train and test data from keras
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

[86]:
```
# Reshaping the train and test data from 2D vector to 1D vector
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
```

[87]:
```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
# Min max normalization of train and test data
X_train = X_train/255
X_test = X_test/255
```

[88]:
```
# Converting 10D vector to one-hot encoded features
Y_train = np_utils.to_categorical(y_train, 10)
```

```
Y_test = np_utils.to_categorical(y_test, 10)
```

[89]:
```
# Layer parameters
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

[90]:
```
# Defining a model with 2 layers and a dropout layer
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(input_dim,)))
model.add(Dropout(0.4))
model.add(Dense(128, activation='relu'))
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_140 (Dense)            (None, 512)               401920
_________________________________________________________________
dropout_80 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_141 (Dense)            (None, 128)               65664
_________________________________________________________________
dense_142 (Dense)            (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
```

[91]:
```
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch,␣
 ↪verbose=1, validation_data=(X_test, Y_test))
```

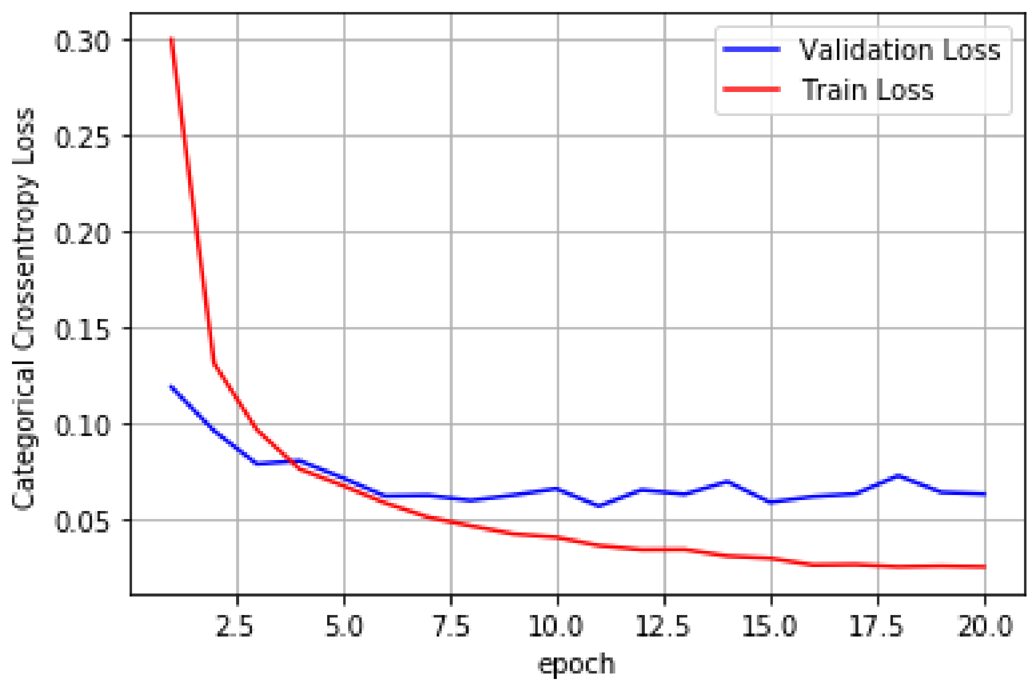
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 25s 421us/step - loss: 0.2993 -
acc: 0.9092 - val_loss: 0.1187 - val_acc: 0.9635
Epoch 2/20
60000/60000 [==============================] - 18s 292us/step - loss: 0.1310 -
acc: 0.9606 - val_loss: 0.0960 - val_acc: 0.9705
Epoch 3/20
60000/60000 [==============================] - 18s 302us/step - loss: 0.0965 -
```

```
acc: 0.9701 - val_loss: 0.0787 - val_acc: 0.9756
Epoch 4/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.0761 -
acc: 0.9764 - val_loss: 0.0804 - val_acc: 0.9737
Epoch 5/20
60000/60000 [==============================] - 19s 314us/step - loss: 0.0676 -
acc: 0.9793 - val_loss: 0.0716 - val_acc: 0.9773
Epoch 6/20
60000/60000 [==============================] - 19s 325us/step - loss: 0.0584 -
acc: 0.9805 - val_loss: 0.0621 - val_acc: 0.9812
Epoch 7/20
60000/60000 [==============================] - 22s 367us/step - loss: 0.0511 -
acc: 0.9830 - val_loss: 0.0624 - val_acc: 0.9821
Epoch 8/20
60000/60000 [==============================] - 20s 331us/step - loss: 0.0467 -
acc: 0.9845 - val_loss: 0.0598 - val_acc: 0.9826
Epoch 9/20
60000/60000 [==============================] - 20s 337us/step - loss: 0.0425 -
acc: 0.9858 - val_loss: 0.0625 - val_acc: 0.9822
Epoch 10/20
60000/60000 [==============================] - 21s 354us/step - loss: 0.0407 -
acc: 0.9863 - val_loss: 0.0659 - val_acc: 0.9802
Epoch 11/20
60000/60000 [==============================] - 21s 346us/step - loss: 0.0364 -
acc: 0.9880 - val_loss: 0.0568 - val_acc: 0.9843
Epoch 12/20
60000/60000 [==============================] - 21s 349us/step - loss: 0.0343 -
acc: 0.9883 - val_loss: 0.0653 - val_acc: 0.9820
Epoch 13/20
60000/60000 [==============================] - 23s 378us/step - loss: 0.0344 -
acc: 0.9887 - val_loss: 0.0630 - val_acc: 0.9826
Epoch 14/20
60000/60000 [==============================] - 22s 360us/step - loss: 0.0309 -
acc: 0.9897 - val_loss: 0.0696 - val_acc: 0.9817
Epoch 15/20
60000/60000 [==============================] - 23s 377us/step - loss: 0.0298 -
acc: 0.9901 - val_loss: 0.0588 - val_acc: 0.9842
Epoch 16/20
60000/60000 [==============================] - 23s 387us/step - loss: 0.0263 -
acc: 0.9907 - val_loss: 0.0618 - val_acc: 0.9849
Epoch 17/20
60000/60000 [==============================] - 23s 382us/step - loss: 0.0265 -
acc: 0.9907 - val_loss: 0.0632 - val_acc: 0.9842
Epoch 18/20
60000/60000 [==============================] - 23s 383us/step - loss: 0.0254 -
acc: 0.9915 - val_loss: 0.0726 - val_acc: 0.9826
Epoch 19/20
60000/60000 [==============================] - 23s 384us/step - loss: 0.0258 -
```

```
acc: 0.9912 - val_loss: 0.0640 - val_acc: 0.9852
Epoch 20/20
60000/60000 [==============================] - 24s 397us/step - loss: 0.0254 -
acc: 0.9919 - val_loss: 0.0631 - val_acc: 0.9839
```

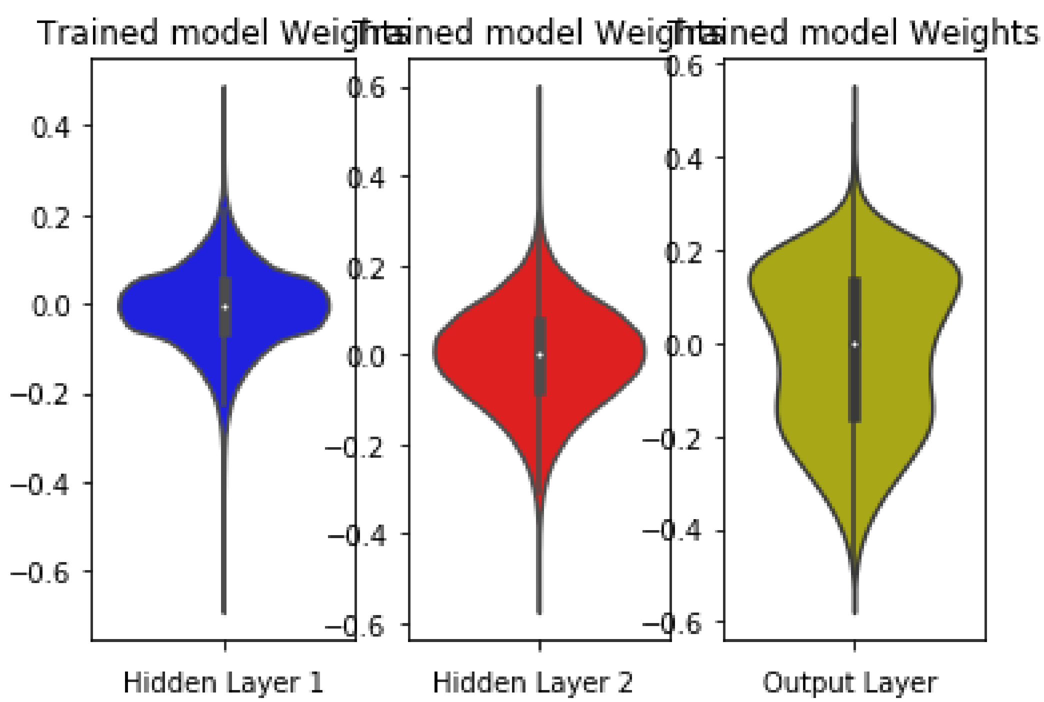
[92]:
```
score = model.evaluate(X_test, Y_test, verbose=0)

print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))


vy = history.history['val_loss']
ty = history.history['loss']

plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.06313706721574504
Test accuracy: 0.9839
```



[94]:

```
w_after = model.get_weights()

%matplotlib inline

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



[95]:
```python
# Defining a model with 3 layers and a dropout layer
model = Sequential()
model.add(Dense(500, activation='relu', input_shape=(input_dim,)))
model.add(Dropout(0.4))
model.add(Dense(300, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.4))
model.add(Dense(100, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_143 (Dense)            (None, 500)               392500
_________________________________________________________________
dropout_81 (Dropout)         (None, 500)               0
_________________________________________________________________
dense_144 (Dense)            (None, 300)               150300
_________________________________________________________________
batch_normalization_46 (Batc (None, 300)               1200
_________________________________________________________________
dropout_82 (Dropout)         (None, 300)               0
_________________________________________________________________
dense_145 (Dense)            (None, 100)               30100
_________________________________________________________________
batch_normalization_47 (Batc (None, 100)               400
_________________________________________________________________
dense_146 (Dense)            (None, 10)                1010
=================================================================
Total params: 575,510
Trainable params: 574,710
Non-trainable params: 800
_________________________________________________________________
```

[96]:
```python
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch,␣
↪verbose=1, validation_data=(X_test, Y_test))
```

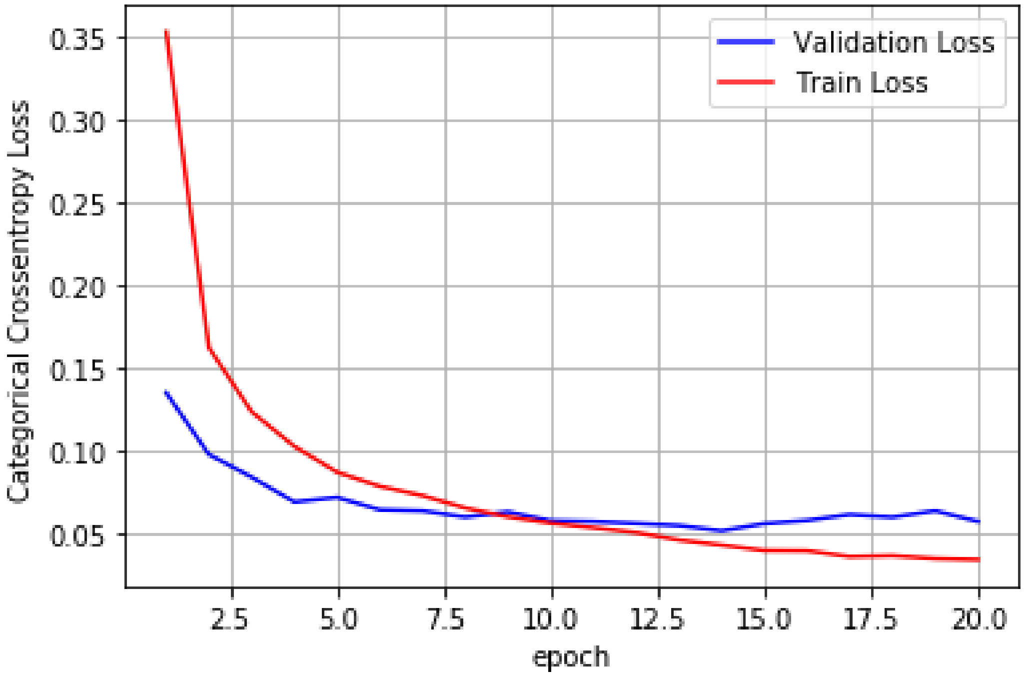
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 42s 700us/step - loss: 0.3523 -
```

```
acc: 0.8906 - val_loss: 0.1348 - val_acc: 0.9577
Epoch 2/20
60000/60000 [==============================] - 25s 411us/step - loss: 0.1620 -
acc: 0.9496 - val_loss: 0.0975 - val_acc: 0.9694
Epoch 3/20
60000/60000 [==============================] - 25s 423us/step - loss: 0.1233 -
acc: 0.9616 - val_loss: 0.0839 - val_acc: 0.9720
Epoch 4/20
60000/60000 [==============================] - 25s 415us/step - loss: 0.1024 -
acc: 0.9679 - val_loss: 0.0690 - val_acc: 0.9769
Epoch 5/20
60000/60000 [==============================] - 27s 443us/step - loss: 0.0869 -
acc: 0.9725 - val_loss: 0.0717 - val_acc: 0.9777
Epoch 6/20
  512/60000 [...] - ETA: 2:09 - loss: 0.0770 - acc:

/home/mani/anaconda3/lib/python3.7/site-packages/keras/callbacks.py:122:
UserWarning: Method on_batch_end() is slow compared to the batch update
(0.431754). Check your callbacks.
  % delta_t_median)
/home/mani/anaconda3/lib/python3.7/site-packages/keras/callbacks.py:122:
UserWarning: Method on_batch_end() is slow compared to the batch update
(0.216622). Check your callbacks.
  % delta_t_median)

60000/60000 [==============================] - 21s 358us/step - loss: 0.0784 -
acc: 0.9750 - val_loss: 0.0642 - val_acc: 0.9806
Epoch 7/20
60000/60000 [==============================] - 117s 2ms/step - loss: 0.0727 -
acc: 0.9769 - val_loss: 0.0636 - val_acc: 0.9808
Epoch 8/20
60000/60000 [==============================] - 14s 230us/step - loss: 0.0653 -
acc: 0.9789 - val_loss: 0.0598 - val_acc: 0.9828
Epoch 9/20
60000/60000 [==============================] - 14s 238us/step - loss: 0.0600 -
acc: 0.9805 - val_loss: 0.0630 - val_acc: 0.9820
Epoch 10/20
 1024/60000 [...] - ETA: 1:34 - loss: 0.0568 - acc:

/home/mani/anaconda3/lib/python3.7/site-packages/keras/callbacks.py:122:
UserWarning: Method on_batch_end() is slow compared to the batch update
(0.238180). Check your callbacks.
  % delta_t_median)
/home/mani/anaconda3/lib/python3.7/site-packages/keras/callbacks.py:122:
UserWarning: Method on_batch_end() is slow compared to the batch update
(0.119515). Check your callbacks.
  % delta_t_median)

60000/60000 [==============================] - 14s 232us/step - loss: 0.0562 -
acc: 0.9822 - val_loss: 0.0577 - val_acc: 0.9829
```

```
Epoch 11/20
60000/60000 [==============================] - 12s 201us/step - loss: 0.0534 -
acc: 0.9826 - val_loss: 0.0572 - val_acc: 0.9823
Epoch 12/20
60000/60000 [==============================] - 23s 388us/step - loss: 0.0505 -
acc: 0.9834 - val_loss: 0.0560 - val_acc: 0.9827
Epoch 13/20
60000/60000 [==============================] - 24s 395us/step - loss: 0.0460 -
acc: 0.9846 - val_loss: 0.0547 - val_acc: 0.9833
Epoch 14/20
60000/60000 [==============================] - 24s 406us/step - loss: 0.0429 -
acc: 0.9858 - val_loss: 0.0516 - val_acc: 0.9845
Epoch 15/20
60000/60000 [==============================] - 25s 423us/step - loss: 0.0397 -
acc: 0.9874 - val_loss: 0.0559 - val_acc: 0.9841
Epoch 16/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0395 -
acc: 0.9873 - val_loss: 0.0578 - val_acc: 0.9847
Epoch 17/20
60000/60000 [==============================] - 24s 403us/step - loss: 0.0360 -
acc: 0.9885 - val_loss: 0.0614 - val_acc: 0.9832
Epoch 18/20
60000/60000 [==============================] - 27s 454us/step - loss: 0.0365 -
acc: 0.9880 - val_loss: 0.0598 - val_acc: 0.9822
Epoch 19/20
60000/60000 [==============================] - 29s 487us/step - loss: 0.0348 -
acc: 0.9887 - val_loss: 0.0636 - val_acc: 0.9827
Epoch 20/20
60000/60000 [==============================] - 25s 416us/step - loss: 0.0341 -
acc: 0.9889 - val_loss: 0.0572 - val_acc: 0.9843
```

[97]:
```python
score = model.evaluate(X_test, Y_test, verbose=0)

print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))


vy = history.history['val_loss']
ty = history.history['loss']

plt_dynamic(x, vy, ty, ax)
```

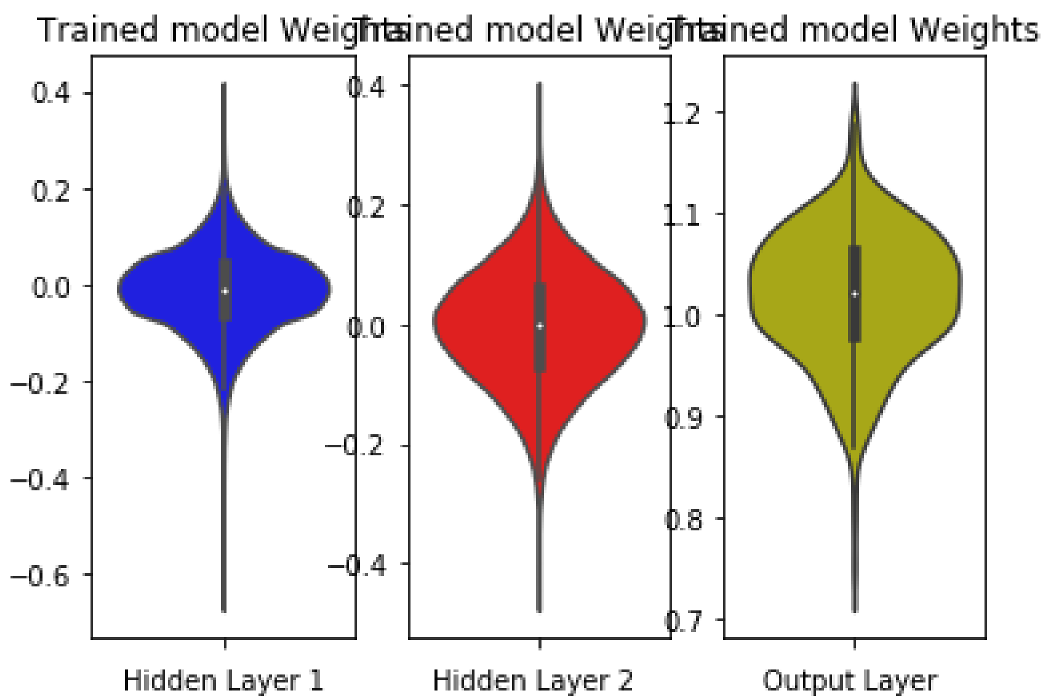
```
Test score: 0.05719636394771806
Test accuracy: 0.9843
```



[98]:

```
w_after = model.get_weights()

%matplotlib inline

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
```

```
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



[99]:
```
# Defining a model with 5 layers and a dropout layer
model = Sequential()
model.add(Dense(500, activation='relu', input_shape=(input_dim,)))
model.add(Dropout(0.3))
model.add(Dense(400, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(300, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(200, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Dense(50, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
dense_147 (Dense)            (None, 500)               392500
_________________________________________________________________
dropout_83 (Dropout)         (None, 500)               0
_________________________________________________________________
dense_148 (Dense)            (None, 400)               200400
_________________________________________________________________
dropout_84 (Dropout)         (None, 400)               0
_________________________________________________________________
dense_149 (Dense)            (None, 300)               120300
_________________________________________________________________
dropout_85 (Dropout)         (None, 300)               0
_________________________________________________________________
dense_150 (Dense)            (None, 200)               60200
_________________________________________________________________
batch_normalization_48 (Batc (None, 200)               800
_________________________________________________________________
dropout_86 (Dropout)         (None, 200)               0
_________________________________________________________________
dense_151 (Dense)            (None, 50)                10050
_________________________________________________________________
batch_normalization_49 (Batc (None, 50)                200
_________________________________________________________________
dense_152 (Dense)            (None, 10)                510
=================================================================
Total params: 784,960
Trainable params: 784,460
Non-trainable params: 500
_________________________________________________________________
```

[100]:

```
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch,␣
 ↪verbose=1, validation_data=(X_test, Y_test))
```

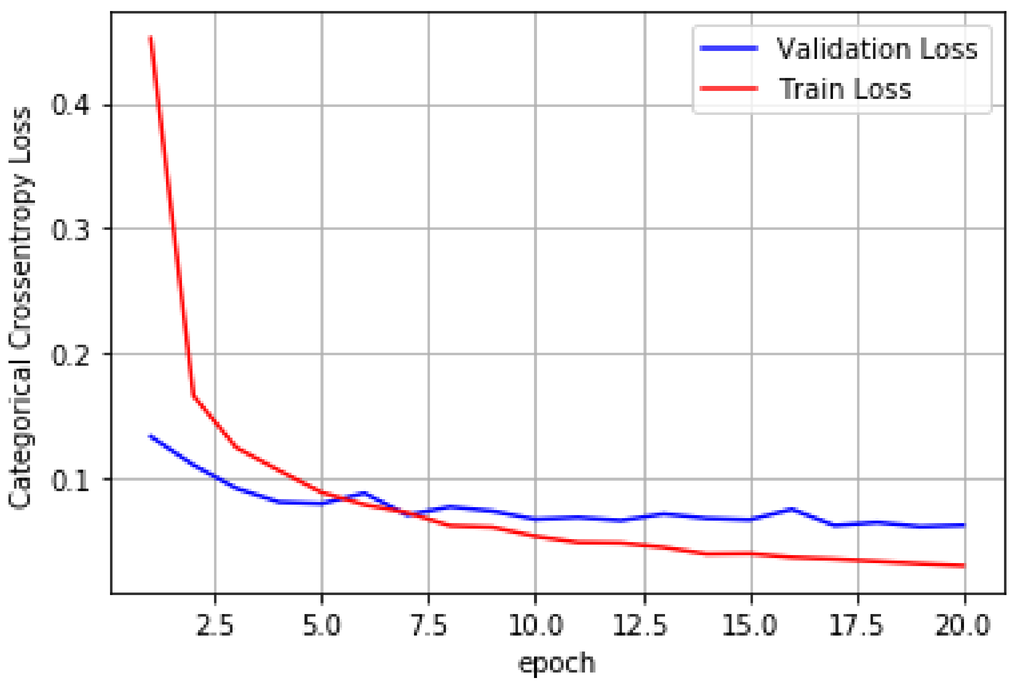
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 43s 725us/step - loss: 0.4519 -
acc: 0.8622 - val_loss: 0.1332 - val_acc: 0.9621
Epoch 2/20
60000/60000 [==============================] - 33s 542us/step - loss: 0.1658 -
acc: 0.9516 - val_loss: 0.1103 - val_acc: 0.9692
Epoch 3/20
60000/60000 [==============================] - 33s 558us/step - loss: 0.1244 -
acc: 0.9624 - val_loss: 0.0918 - val_acc: 0.9739
Epoch 4/20
60000/60000 [==============================] - 34s 569us/step - loss: 0.1060 -
```

```
acc: 0.9686 - val_loss: 0.0808 - val_acc: 0.9774
Epoch 5/20
60000/60000 [==============================] - 36s 599us/step - loss: 0.0885 -
acc: 0.9735 - val_loss: 0.0795 - val_acc: 0.9769
Epoch 6/20
60000/60000 [==============================] - 33s 557us/step - loss: 0.0787 -
acc: 0.9768 - val_loss: 0.0880 - val_acc: 0.9751
Epoch 7/20
60000/60000 [==============================] - 36s 608us/step - loss: 0.0722 -
acc: 0.9785 - val_loss: 0.0704 - val_acc: 0.9822
Epoch 8/20
60000/60000 [==============================] - 37s 621us/step - loss: 0.0618 -
acc: 0.9822 - val_loss: 0.0769 - val_acc: 0.9794
Epoch 9/20
60000/60000 [==============================] - 39s 646us/step - loss: 0.0606 -
acc: 0.9820 - val_loss: 0.0735 - val_acc: 0.9808
Epoch 10/20
60000/60000 [==============================] - 39s 647us/step - loss: 0.0533 -
acc: 0.9833 - val_loss: 0.0670 - val_acc: 0.9815
Epoch 11/20
60000/60000 [==============================] - 39s 656us/step - loss: 0.0484 -
acc: 0.9850 - val_loss: 0.0685 - val_acc: 0.9806
Epoch 12/20
60000/60000 [==============================] - 38s 640us/step - loss: 0.0480 -
acc: 0.9857 - val_loss: 0.0659 - val_acc: 0.9816
Epoch 13/20
60000/60000 [==============================] - 34s 559us/step - loss: 0.0444 -
acc: 0.9863 - val_loss: 0.0713 - val_acc: 0.9821
Epoch 14/20
60000/60000 [==============================] - 40s 661us/step - loss: 0.0391 -
acc: 0.9879 - val_loss: 0.0677 - val_acc: 0.9812
Epoch 15/20
60000/60000 [==============================] - 39s 654us/step - loss: 0.0395 -
acc: 0.9882 - val_loss: 0.0665 - val_acc: 0.9828
Epoch 16/20
60000/60000 [==============================] - 39s 656us/step - loss: 0.0365 -
acc: 0.9891 - val_loss: 0.0750 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 40s 663us/step - loss: 0.0351 -
acc: 0.9887 - val_loss: 0.0620 - val_acc: 0.9847
Epoch 18/20
60000/60000 [==============================] - 40s 666us/step - loss: 0.0332 -
acc: 0.9899 - val_loss: 0.0645 - val_acc: 0.9839
Epoch 19/20
60000/60000 [==============================] - 40s 670us/step - loss: 0.0314 -
acc: 0.9903 - val_loss: 0.0610 - val_acc: 0.9846
Epoch 20/20
60000/60000 [==============================] - 41s 689us/step - loss: 0.0298 -
```

```
acc: 0.9907 - val_loss: 0.0622 - val_acc: 0.9837
```

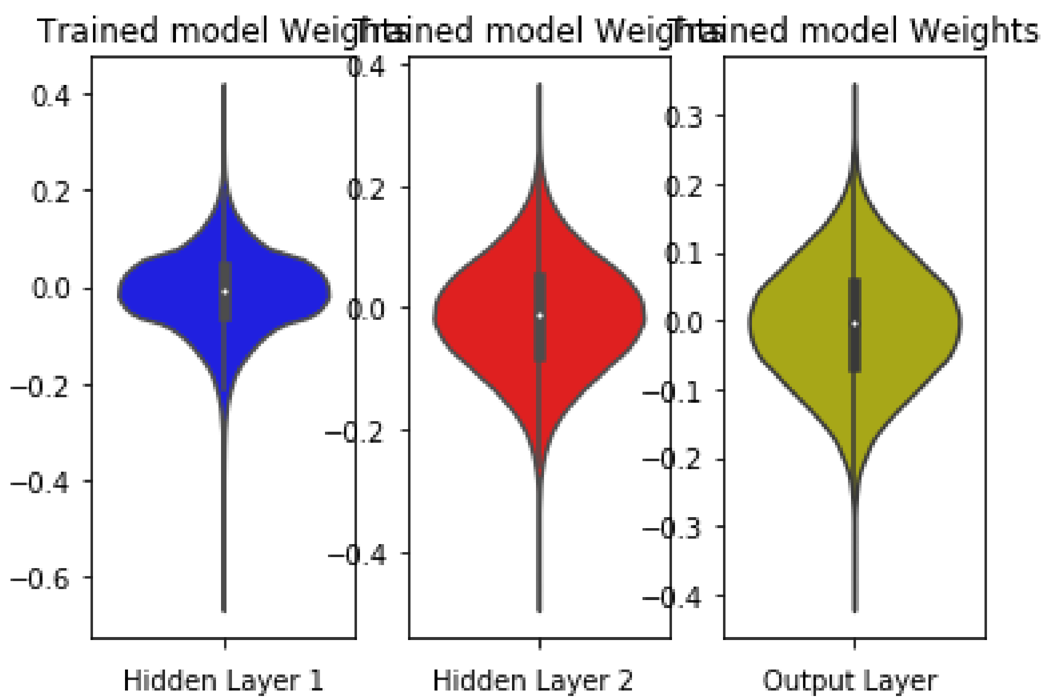
[101]:
```
score = model.evaluate(X_test, Y_test, verbose=0)

print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))


vy = history.history['val_loss']
ty = history.history['loss']

plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.062166284874500071
Test accuracy: 0.9837
```



[102]:
```
w_after = model.get_weights()

%matplotlib inline
```

```
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



0.1 Observations

1. The train and validation loss has a very steep difference when only two layers are trained with only Dropout layer.
2. When models trained with multiple Dropout layers and BatchNormalization with 3 and 5 layers the train and validation loss are very close.
3. Weight distributions are smooth guassian curves in the violin plot for 3 and 5 layered networks.