CNN Architectures on MNIST

December 9, 2018

1 CNN Architectures on MNIST: Custom, LeNet & VGGNet-inspired

1.1 Purpose

The purpose of this study is **to try 3 drastically different Convnet Architectures on MNIST image database.**. The implementation is done in Keras.

1.2 Steps at a Glance:

1. Take the famous MNIST dataset as input. http://yann.lecun.com/exdb/mnist/
2. Feed it into **3-layered Convnet Architecture design inspired by LeNet, 1998 paper by Le Cunn.**
3. Find the **accuracy and draw the Loss vs Epoch Plot.**
4. Introduce Batch Normalization and Dropouts.
5. Evaluate the model again by estimating accuracy and drawing loss diagram.
6. Feed same input to **5 layered Convnet Architecture design inspired by VGGNet, 2014 paper by Andrew Zisserman.**
7. Introduce Pooling, Dropouts & evaluate the model again.
8. Feed same input to **7 layered Convnet Architecture self-designed with different-sized filters & dense layers.**
9. Introduce Batch Normalization and Dropouts & evaluate the model again.
10. Analyze the output from the above 3 architectures and draw conclusions.

1.3 Custom-Defined Functions

```
In [6]: %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(fig, 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()
```

In [7]:
```python
# To train the model using Adam
# This function is common to all models.
def trainModel(model):
    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))

    return history
```

In [8]:
```python
# To plot the Train & Test loss graph.
# This function is common to all models.
def plotGraph(history):

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

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

    # print(history.history.keys())
    # dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
    # history = model_drop.fit(X_train, Y_train, batch_size=batch_size,
            #epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))

    # we will get val_loss and val_acc only
    # when you pass the paramter validation_data
    # val_loss : validation loss
    # val_acc : validation accuracy

    # loss : training loss
    # acc : train accuracy
    # for each key in histrory.histrory we will have
    # a list of length equal to number of epochs

    vy = history.history['val_loss']
    ty = history.history['loss']
    plt_dynamic(fig, x, vy, ty, ax)
```

In [9]:
```python
def plotWeightM1(model):
    w_after = model.get_weights()

    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 Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

1.4 Data Loading & Pre-Processing

In [23]:
```
# Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py

from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

from keras.layers.normalization import BatchNormalization
import seaborn as sns

batch_size = 128
num_classes = 10
epochs = 20

# input image dimensions
img_rows, img_cols = 28, 28

# the data, split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
```

```
        x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
        x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
        input_shape = (img_rows, img_cols, 1)

    x_train = x_train.astype('float32')
    x_test = x_test.astype('float32')
    x_train /= 255
    x_test /= 255
    print('x_train shape:', x_train.shape)
    print(x_train.shape[0], 'train samples')
    print(x_test.shape[0], 'test samples')

    # convert class vectors to binary class matrices
    y_train = keras.utils.to_categorical(y_train, num_classes)
    y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
```

```
In [41]: #Performance Tuning: GPU Memory Allocation Growth enabled for performance gain

         # config = tf.ConfigProto()
         # config.gpu_options.allow_growth = True
         # sess = tf.Session(config = config)
```

1.5 Model 1: LeNet Inspired 3-Convolution Layer Architecture

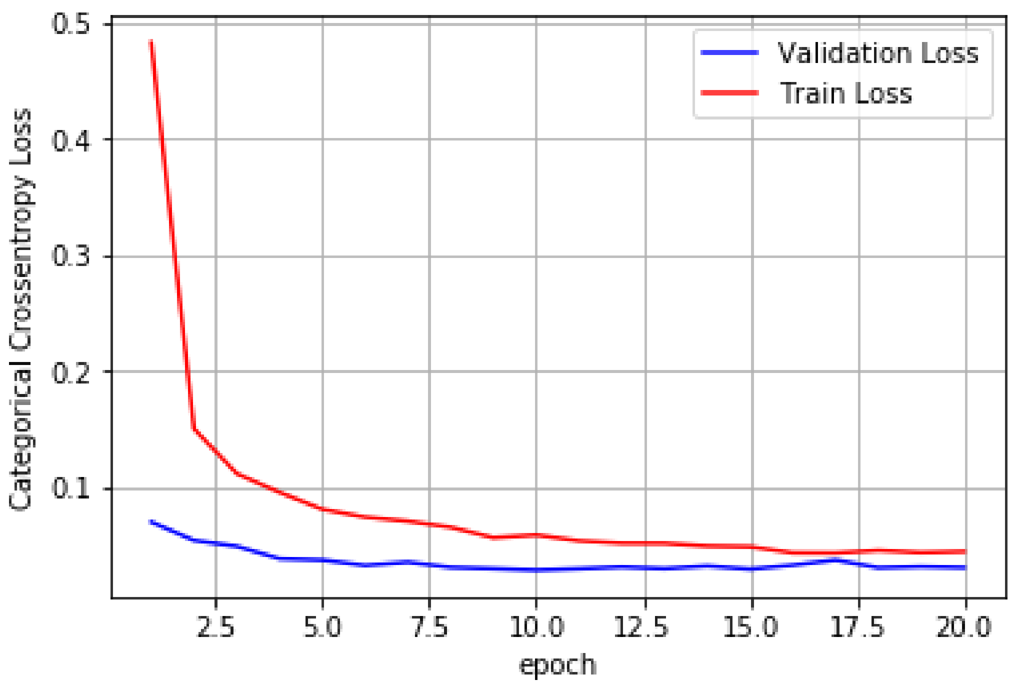
This 3-layered is different but inspired from the LeNet, 1998 paper by Le Cunn.
http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

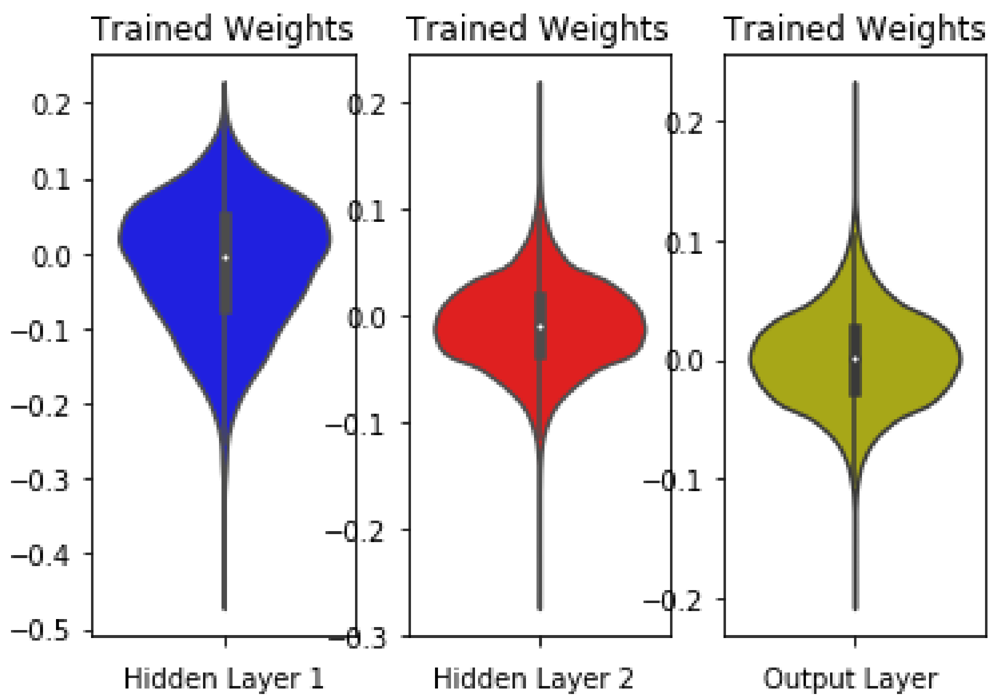
```
In [30]: # The model is inspired from the LeNet, 1998 paper by Le Cunn

         model = Sequential()
         model.add(Conv2D(256, kernel_size=(3, 3),
                          activation='relu',
                          input_shape=input_shape)) #Convolution
         model.add(MaxPooling2D(pool_size=(2, 2)))  #Subsampling
         model.add(Dropout(0.25))
         # model.add(BatchNormalization())

         model.add(Conv2D(128, (3, 3), activation='relu')) #Convolution
         model.add(MaxPooling2D(pool_size=(2, 2)))         #Subsampling
         model.add(Dropout(0.25))
         # model.add(BatchNormalization())

         # model.add(Conv2D(256, (3, 3), activation='relu'))
         # model.add(Dropout(0.5))
```

```
model.add(Flatten())
model.add(Dense(128, activation='relu')) # Full Connection
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu')) # Full Connection
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history=model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

plotGraph(history=history)
plotWeightM1(model=model)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 174us/step - loss: 0.4831 - acc: 0.8484 - va
Epoch 2/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.1500 - acc: 0.9610 - val
Epoch 3/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.1112 - acc: 0.9718 - val
Epoch 4/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0951 - acc: 0.9770 - val
Epoch 5/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0805 - acc: 0.9799 - val
Epoch 6/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0737 - acc: 0.9819 - val
Epoch 7/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0702 - acc: 0.9829 - val
Epoch 8/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0650 - acc: 0.9846 - val
Epoch 9/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0560 - acc: 0.9863 - val
Epoch 10/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0582 - acc: 0.9866 - val
Epoch 11/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0532 - acc: 0.9871 - val
Epoch 12/20
```

```
60000/60000 [==============================] - 9s 151us/step - loss: 0.0512 - acc: 0.9877 - val
Epoch 13/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0511 - acc: 0.9882 - val
Epoch 14/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0487 - acc: 0.9884 - val
Epoch 15/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0481 - acc: 0.9888 - val
Epoch 16/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0429 - acc: 0.9892 - val
Epoch 17/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0427 - acc: 0.9899 - val
Epoch 18/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0449 - acc: 0.9899 - val
Epoch 19/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0431 - acc: 0.9896 - val
Epoch 20/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0440 - acc: 0.9899 - val
Test loss: 0.03020984925764119
Test accuracy: 0.9924
```





1.6 Model 2: VGGNet Inspired 5-Convolution Layered Architecture

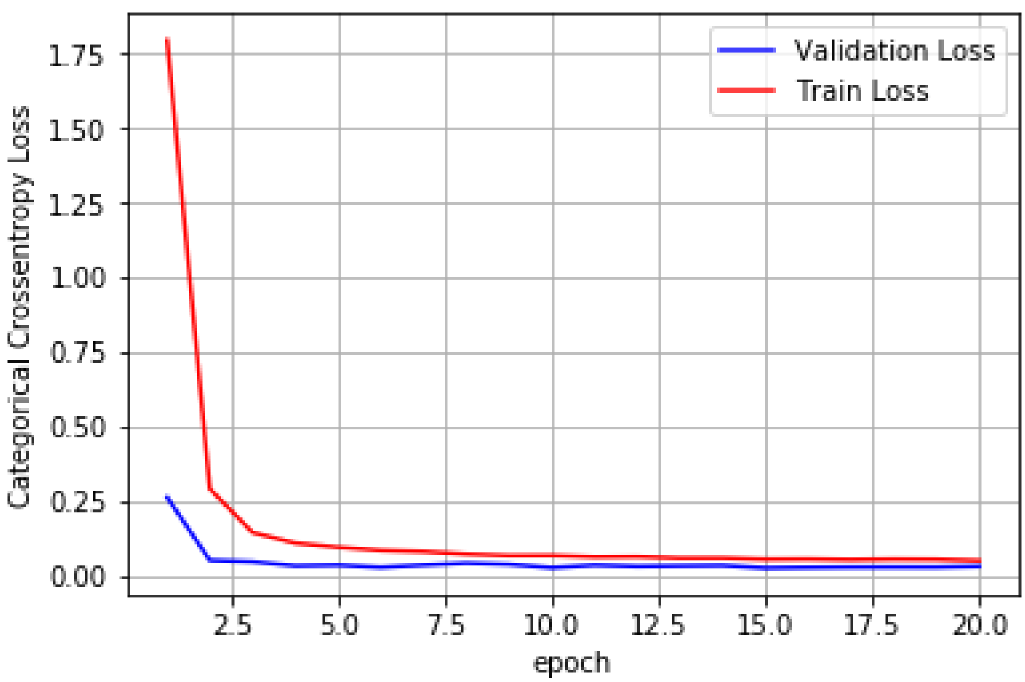
This 5-layered is different but inspired from the VGGNet, 2014 paper by Andrew Zisserman. https://arxiv.org/pdf/1409.1556.pdf

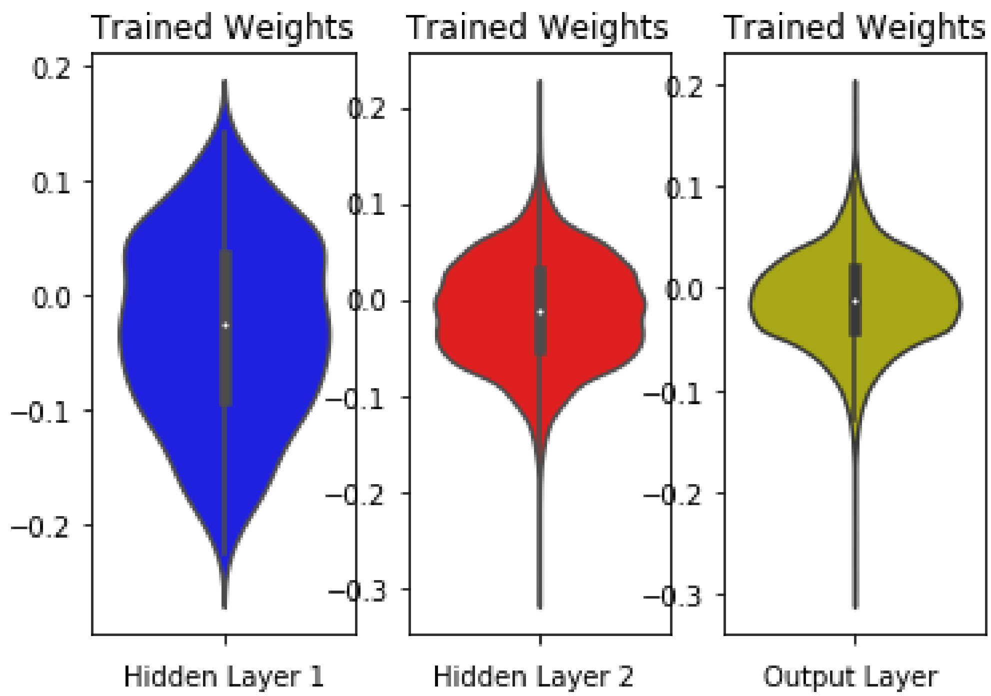
In [32]:
```
# The model is inspired from the VGGNet, 2014 paper by Andrew Zisserman.

model = Sequential()
model.add(Conv2D(64, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(256, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(256, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(512, kernel_size=(3, 3),
                 activation='relu',
```

```
                 input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history=model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

plotGraph(history=history)
plotWeightM1(model=model)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 12s 201us/step - loss: 1.7958 - acc: 0.3225 - va
Epoch 2/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.2907 - acc: 0.9210 - va
Epoch 3/20
60000/60000 [==============================] - 10s 174us/step - loss: 0.1438 - acc: 0.9672 - va
Epoch 4/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.1084 - acc: 0.9760 - va
Epoch 5/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0943 - acc: 0.9803 - va
Epoch 6/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0839 - acc: 0.9823 - va
Epoch 7/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0800 - acc: 0.9845 - va
Epoch 8/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0714 - acc: 0.9857 - va
Epoch 9/20
```

```
60000/60000 [==============================] - 10s 173us/step - loss: 0.0664 - acc: 0.9867 - va
Epoch 10/20
60000/60000 [==============================] - 11s 175us/step - loss: 0.0667 - acc: 0.9872 - va
Epoch 11/20
60000/60000 [==============================] - 11s 176us/step - loss: 0.0621 - acc: 0.9876 - va
Epoch 12/20
60000/60000 [==============================] - 11s 176us/step - loss: 0.0629 - acc: 0.9880 - va
Epoch 13/20
60000/60000 [==============================] - 10s 175us/step - loss: 0.0582 - acc: 0.9891 - va
Epoch 14/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0583 - acc: 0.9888 - va
Epoch 15/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0543 - acc: 0.9897 - va
Epoch 16/20
60000/60000 [==============================] - 10s 174us/step - loss: 0.0549 - acc: 0.9898 - va
Epoch 17/20
60000/60000 [==============================] - 10s 174us/step - loss: 0.0529 - acc: 0.9896 - va
Epoch 18/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0545 - acc: 0.9904 - va
Epoch 19/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0538 - acc: 0.9903 - va
Epoch 20/20
60000/60000 [==============================] - 11s 177us/step - loss: 0.0495 - acc: 0.9908 - va
Test loss: 0.030504648093903096
Test accuracy: 0.9949
```





1.7 Model 3: 7-Layered CNN Architecture

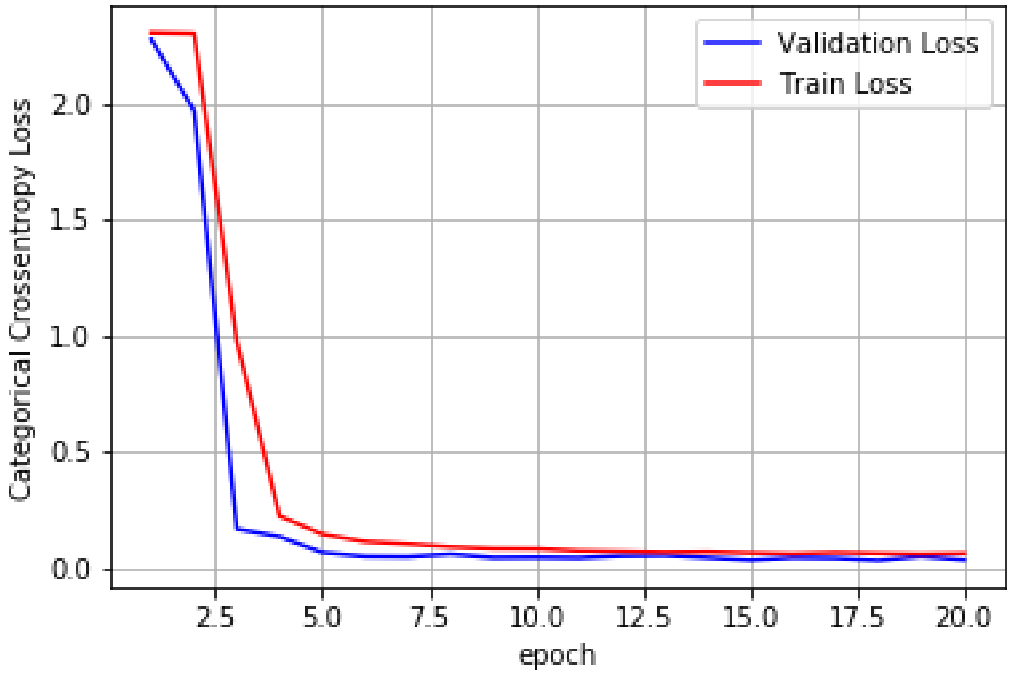
This 7-layered is Convolution Architecture is custom built with different kernel sizes and dropout/ max pool considerations.

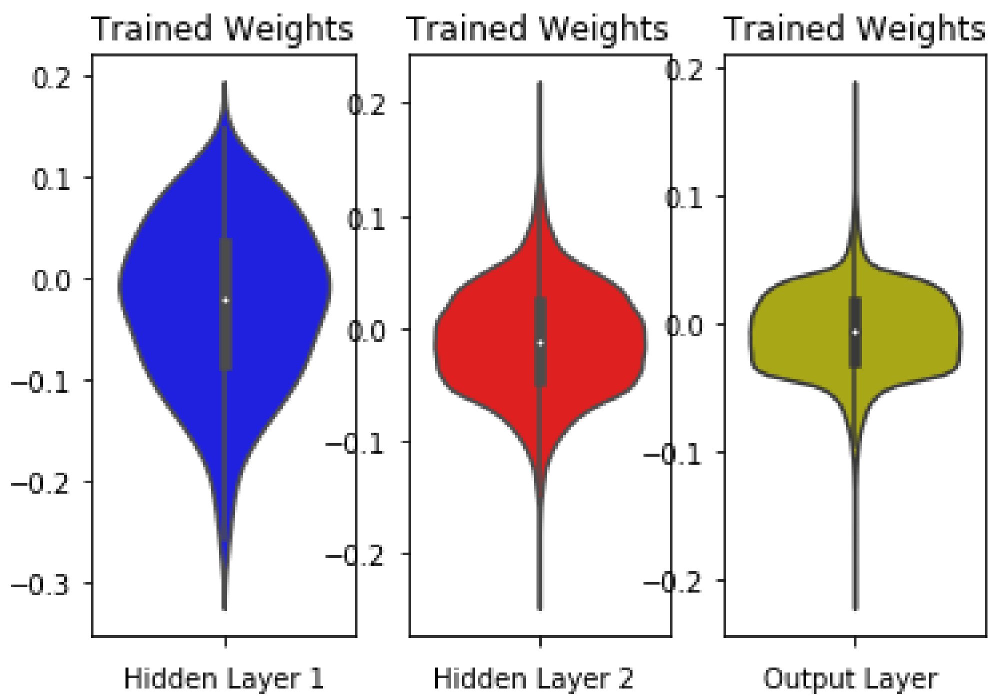
In [40]:
```
# The model is custom-built for the purpose of performance evaluation.

model = Sequential()
model.add(Conv2D(64, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
# model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
# model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))
#
model.add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
# model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))
##
model.add(Conv2D(512, kernel_size=(3, 3), activation='relu'))
```

```python
# model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(768, kernel_size=(4, 4), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(1024, kernel_size=(4, 4), activation='relu'))
# model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(2048, kernel_size=(4, 4), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))


model.add(Flatten())
model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

history=model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

plotGraph(history=history)
plotWeightM1(model=model)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 241s 4ms/step - loss: 2.3024 - acc: 0.1124 - val
Epoch 2/20
```

```
60000/60000 [==============================] - 237s 4ms/step - loss: 2.2988 - acc: 0.1217 - va
Epoch 3/20
60000/60000 [==============================] - 238s 4ms/step - loss: 0.9734 - acc: 0.6832 - va
Epoch 4/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.2232 - acc: 0.9510 - va
Epoch 5/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.1447 - acc: 0.9698 - va
Epoch 6/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.1128 - acc: 0.9772 - va
Epoch 7/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.1029 - acc: 0.9796 - va
Epoch 8/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.0903 - acc: 0.9827 - va
Epoch 9/20
60000/60000 [==============================] - 236s 4ms/step - loss: 0.0830 - acc: 0.9841 - va
Epoch 10/20
60000/60000 [==============================] - 237s 4ms/step - loss: 0.0822 - acc: 0.9842 - va
Epoch 11/20
60000/60000 [==============================] - 236s 4ms/step - loss: 0.0732 - acc: 0.9856 - va
Epoch 12/20
60000/60000 [==============================] - 236s 4ms/step - loss: 0.0706 - acc: 0.9867 - va
Epoch 13/20
60000/60000 [==============================] - 235s 4ms/step - loss: 0.0667 - acc: 0.9873 - va
Epoch 14/20
60000/60000 [==============================] - 234s 4ms/step - loss: 0.0689 - acc: 0.9877 - va
Epoch 15/20
60000/60000 [==============================] - 227s 4ms/step - loss: 0.0635 - acc: 0.9884 - va
Epoch 16/20
60000/60000 [==============================] - 227s 4ms/step - loss: 0.0600 - acc: 0.9890 - va
Epoch 17/20
60000/60000 [==============================] - 226s 4ms/step - loss: 0.0651 - acc: 0.9878 - va
Epoch 18/20
60000/60000 [==============================] - 225s 4ms/step - loss: 0.0614 - acc: 0.9889 - va
Epoch 19/20
60000/60000 [==============================] - 227s 4ms/step - loss: 0.0592 - acc: 0.9892 - va
Epoch 20/20
60000/60000 [==============================] - 228s 4ms/step - loss: 0.0617 - acc: 0.9889 - va
Test loss: 0.03418135848310676
Test accuracy: 0.9932
```


Validation Loss
Train Loss
Categorical Crossentropy Loss
epoch
0.0
0.5
1.0
1.5
2.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


Trained Weights
Trained Weights
Trained Weights
Hidden Layer 1
Hidden Layer 2
Output Layer

2 Conclusions

1. The **performance of standard-model inspired networks are found higher** than complex custom built architectures.
2. The **convergence of model M2 happened much before Model 1. Number of epochs required is less.**
3. The **99.5% accuracy of VGGNet-inspired M2 model is better than LeNet-inspired M1.**
4. The distribution of weights are found to be normally distributed.
5. The huge increase in number of filters and different sized kernels did not help much.
6. **VGGNet-inspired 5-layered model, M2 is found to be model of choice.** It even outperformed a 7-layered Convnet with huge number of parameters. The convergence speed w.r.t. epochs is also comparable between M2 and M3.