Keras -- MLPs on MNIST

In [0]:

```
# Checking if GPU is available
from tensorflow.python.client import device_lib
print(device_lib.list_local_devices())
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 12961759298813835808
, name: "/device:XLA_CPU:0"
device_type: "XLA_CPU"
memory_limit: 17179869184
locality {
}
incarnation: 7259935812420886672
physical_device_desc: "device: XLA_CPU device"
, name: "/device:XLA_GPU:0"
device_type: "XLA_GPU"
memory_limit: 17179869184
locality {
}
incarnation: 10587928147365517172
physical_device_desc: "device: XLA_GPU device"
, name: "/device:GPU:0"
device_type: "GPU"
memory_limit: 13036516148
locality {
  bus_id: 1
  links {
  }
}
incarnation: 5943975532915389494
physical_device_desc: "device: 0, name: Tesla T4, pci bus id: 0000:00:04.0, compute capability: 7.
5"
]
```

In [0]:

```
# Mouting Google drive to save our trained models
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/gdrive
```

In [0]:

```
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this command
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal  # weight initializer
```

```
Using TensorFlow backend.
```

In [0]:

```
%matplotlib notebook
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()
```

In [0]:

```
# the data, shuffled and split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

In [0]:

```
print("Number of training examples :", X_train.shape[0], "and each image is of shape (%d, %d)"%(X_
train.shape[1], X_train.shape[2]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d,
%d)"%(X_test.shape[1], X_test.shape[2]))
```

```
Number of training examples : 60000 and each image is of shape (28, 28)
Number of training examples : 10000 and each image is of shape (28, 28)
```

In [0]:

```
# if you observe the input shape its 2 dimensional vector
# for each image we have a (28*28) vector
# we will convert the (28*28) vector into single dimensional vector of 1 * 784

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])
```

In [0]:

```
# after converting the input images from 3d to 2d vectors

print("Number of training examples :", X_train.shape[0], "and each image is of shape
(%d)"%(X_train.shape[1]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d)"%(X_test.
shape[1]))
```

```
Number of training examples : 60000 and each image is of shape (784)
Number of training examples : 10000 and each image is of shape (784)
```

In [0]:

```
# An example data point
print(X_train[0])
```

```
[   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   3  18  18  18 126 136 175  26 166 255
  247 127   0   0   0   0   0   0   0   0   0   0   0   0  30  36  94 154
  170 253 253 253 253 253 225 172 253 242 195  64   0   0   0   0   0   0
    0   0   0   0   0  49 238 253 253 253 253 253 253 253 253 251  93  82
   82  56  39   0   0   0   0   0   0   0   0   0   0   0   0  18 219 253
  253 253 253 253 198 182 247 241   0   0   0   0   0   0   0   0   0   0
```

```
 253 253 253 253 198 182 247 241   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0  80 156 107 253 253 205  11   0  43 154
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0  14   1 154 253  90   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0 139 253 190   2   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0  11 190 253  70   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  35 241
 225 160 108   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0  81 240 253 253 119  25   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0  45 186 253 253 150  27   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0  16  93 252 253 187
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0 249 253 249  64   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  46 130 183 253
 253 207   2   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0  39 148 229 253 253 253 250 182   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0  24 114 221 253 253 253
 253 201  78   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0  23  66 213 253 253 253 253 198  81   2   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0  18 171 219 253 253 253 253 195
  80   9   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  55 172 226 253 253 253 253 244 133  11   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0 136 253 253 253 212 135 132  16
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]
```

In [0]:

```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets try to normalize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255

X_train = X_train/255
X_test = X_test/255
```

In [0]:

```
# example data point after normlizing
print(X_train[0])
```

```
[0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.01176471 0.07058824 0.07058824 0.07058824
 0.49411765 0.53333333 0.68627451 0.10196078 0.65098039 1.
 0.96862745 0.49803922 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
```

```
 0.         0.         0.11764706 0.14117647 0.36862745 0.60392157
 0.66666667 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
 0.88235294 0.6745098  0.99215686 0.94901961 0.76470588 0.25098039
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.19215686
 0.93333333 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
 0.99215686 0.99215686 0.99215686 0.98431373 0.36470588 0.32156863
 0.32156863 0.21960784 0.15294118 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.07058824 0.85882353 0.99215686
 0.99215686 0.99215686 0.99215686 0.99215686 0.77647059 0.71372549
 0.96862745 0.94509804 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.31372549 0.61176471 0.41960784 0.99215686
 0.99215686 0.80392157 0.04313725 0.         0.16862745 0.60392157
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.05490196 0.00392157 0.60392157 0.99215686 0.35294118
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.54509804 0.99215686 0.74509804 0.00784314 0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.04313725
 0.74509804 0.99215686 0.2745098  0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.1372549  0.94509804
 0.88235294 0.62745098 0.42352941 0.00392157 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.31764706 0.94117647 0.99215686
 0.99215686 0.46666667 0.09803922 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.17647059 0.72941176 0.99215686 0.99215686
 0.58823529 0.10588235 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.0627451  0.36470588 0.98823529 0.99215686 0.73333333
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.97647059 0.99215686 0.97647059 0.25098039 0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.18039216 0.50980392 0.71764706 0.99215686
 0.99215686 0.81176471 0.00784314 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.15294118 0.58039216
 0.89803922 0.99215686 0.99215686 0.99215686 0.98039216 0.71372549
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.09411765 0.44705882 0.86666667 0.99215686 0.99215686 0.99215686
 0.99215686 0.78823529 0.30588235 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.09019608 0.25882353 0.83529412 0.99215686
 0.99215686 0.99215686 0.99215686 0.77647059 0.31764706 0.00784314
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.07058824 0.67058824
 0.85882353 0.99215686 0.99215686 0.99215686 0.99215686 0.76470588
 0.31372549 0.03529412 0.         0.         0.         0.
```

```
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.21568627 0.6745098  0.88627451 0.99215686 0.99215686 0.99215686
 0.99215686 0.95686275 0.52156863 0.04313725 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.53333333 0.99215686
 0.99215686 0.99215686 0.83137255 0.52941176 0.51764706 0.0627451
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.        ]
```

In [0]:

```
# here we are having a class number for each image
print("Class label of first image :", y_train[0])

# lets convert this into a 10 dimensional vector
# ex: consider an image is 5 convert it into 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion needed for MLPs

Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)

print("After converting the output into a vector : ",Y_train[0])
```

```
Class label of first image : 5
After converting the output into a vector :  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

Softmax classifier

In [0]:

```
# https://keras.io/getting-started/sequential-model-guide/

# The Sequential model is a linear stack of layers.
# you can create a Sequential model by passing a list of layer instances to the constructor:

# model = Sequential([
#     Dense(32, input_shape=(784,)),
#     Activation('relu'),
#     Dense(10),
#     Activation('softmax'),
# ])

# You can also simply add layers via the .add() method:

# model = Sequential()
# model.add(Dense(32, input_dim=784))
# model.add(Activation('relu'))

###

# https://keras.io/layers/core/

# keras.layers.Dense(units, activation=None, use_bias=True, kernel_initializer='glorot_uniform',
# bias_initializer='zeros', kernel_regularizer=None, bias_regularizer=None,
activity_regularizer=None,
# kernel_constraint=None, bias_constraint=None)
```

```
# kernel_constraint=None, bias_constraint=None)

# Dense implements the operation: output = activation(dot(input, kernel) + bias) where
# activation is the element-wise activation function passed as the activation argument,
# kernel is a weights matrix created by the layer, and
# bias is a bias vector created by the layer (only applicable if use_bias is True).

# output = activation(dot(input, kernel) + bias)  => y = activation(WT. X + b)

####

# https://keras.io/activations/

# Activations can either be used through an Activation layer, or through the activation argument s
upported by all forward layers:

# from keras.layers import Activation, Dense

# model.add(Dense(64))
# model.add(Activation('tanh'))

# This is equivalent to:
# model.add(Dense(64, activation='tanh'))

# there are many activation functions ar available ex: tanh, relu, softmax


from keras.models import Sequential
from keras.layers import Dense, Activation
```

In [0]:

```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]   # passed to the first hidden layer specifying the number of inputs
it should expect

batch_size = 128
nb_epoch = 20
```

Input -> Softmax:

In [0]:

```
# start building a model
model = Sequential()

# The model needs to know what input shape it should expect.
# For this reason, the first layer in a Sequential model
# (and only the first, because following layers can do automatic shape inference)
# needs to receive information about its input shape.
# you can use input_shape and input_dim to pass the shape of input

# output_dim represent the number of nodes need in that layer
# here we have 10 nodes

model.add(Dense(output_dim, input_dim=input_dim, activation='softmax'))
```

```
WARNING: Logging before flag parsing goes to stderr.
W0804 16:31:32.464691 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:74: The name
tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

W0804 16:31:32.470091 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:517: The name
tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0804 16:31:32.474256 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4138: The name
tf.random_uniform is deprecated. Please use tf.random.uniform instead.
```

In [0]:

```
# Before training a model, you need to configure the learning process, which is done via the compi
le method

# It receives three arguments:
# An optimizer. This could be the string identifier of an existing optimizer ,
https://keras.io/optimizers/
# A loss function. This is the objective that the model will try to minimize.,
https://keras.io/losses/
# A list of metrics. For any classification problem you will want to set this to metrics=['accurac
y'].  https://keras.io/metrics/


# Note: when using the categorical_crossentropy loss, your targets should be in categorical format

# (e.g. if you have 10 classes, the target for each sample should be a 10-dimensional vector that
is all-zeros except
# for a 1 at the index corresponding to the class of the sample).

# that is why we converted out labels into vectors

model.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accuracy'])

# Keras models are trained on Numpy arrays of input data and labels.
# For training a model, you will typically use the  fit function

# fit(self, x=None, y=None, batch_size=None, epochs=1, verbose=1, callbacks=None,
validation_split=0.0,
# validation_data=None, shuffle=True, class_weight=None, sample_weight=None, initial_epoch=0, step
s_per_epoch=None,
# validation_steps=None)

# fit() function Trains the model for a fixed number of epochs (iterations on a dataset).

# it returns A History object. Its History.history attribute is a record of training loss values a
nd
# metrics values at successive epochs, as well as validation loss values and validation metrics va
lues (if applicable).

# https://github.com/openai/baselines/issues/20

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation
_data=(X_test, Y_test))
```

```
W0804 16:31:32.505516 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is dep
recated. Please use tf.compat.v1.train.Optimizer instead.

W0804 16:31:32.528835 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3295: The name tf.log i
s deprecated. Please use tf.math.log instead.

W0804 16:31:32.617900 139651759564672 deprecation.py:323] From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0804 16:31:32.658567 139651759564672 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:986: The name
tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 37us/step - loss: 1.2731 - acc: 0.7043 -
val_loss: 0.8063 - val_acc: 0.8367
Epoch 2/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.7110 - acc: 0.8448 -
val_loss: 0.6050 - val_acc: 0.8658
Epoch 3/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.5838 - acc: 0.8609 -
val_loss: 0.5247 - val_acc: 0.8742
Epoch 4/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.5231 - acc: 0.8698 -
val_loss: 0.4796 - val_acc: 0.8805
```

```
Epoch 5/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.4860 - acc: 0.8757 -
val_loss: 0.4499 - val_acc: 0.8858
Epoch 6/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.4606 - acc: 0.8803 -
val_loss: 0.4292 - val_acc: 0.8894
Epoch 7/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.4418 - acc: 0.8844 -
val_loss: 0.4128 - val_acc: 0.8925
Epoch 8/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.4270 - acc: 0.8866 -
val_loss: 0.3999 - val_acc: 0.8942
Epoch 9/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.4151 - acc: 0.8889 -
val_loss: 0.3898 - val_acc: 0.8954
Epoch 10/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.4053 - acc: 0.8910 -
val_loss: 0.3813 - val_acc: 0.8979
Epoch 11/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3969 - acc: 0.8930 -
val_loss: 0.3741 - val_acc: 0.8991
Epoch 12/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3897 - acc: 0.8940 -
val_loss: 0.3677 - val_acc: 0.9013
Epoch 13/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3834 - acc: 0.8957 -
val_loss: 0.3618 - val_acc: 0.9026
Epoch 14/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3778 - acc: 0.8968 -
val_loss: 0.3573 - val_acc: 0.9033
Epoch 15/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3728 - acc: 0.8980 -
val_loss: 0.3526 - val_acc: 0.9045
Epoch 16/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.3683 - acc: 0.8986 -
val_loss: 0.3487 - val_acc: 0.9052
Epoch 17/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3643 - acc: 0.9000 -
val_loss: 0.3451 - val_acc: 0.9061
Epoch 18/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3606 - acc: 0.9007 -
val_loss: 0.3419 - val_acc: 0.9075
Epoch 19/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.3572 - acc: 0.9016 -
val_loss: 0.3387 - val_acc: 0.9079
Epoch 20/20
60000/60000 [==============================] - 1s 22us/step - loss: 0.3540 - acc: 0.9023 -
val_loss: 0.3362 - val_acc: 0.9087
```

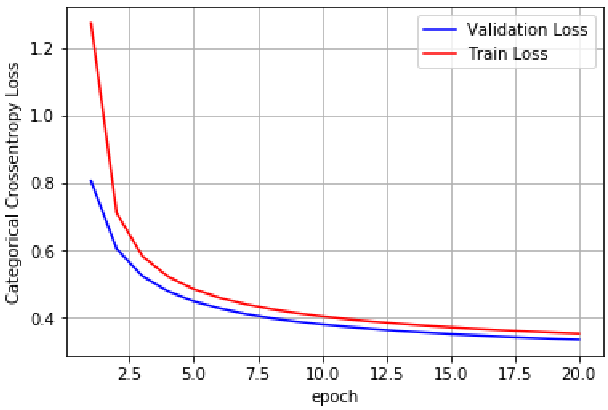
Note: The keras.evaluate() function will give you the loss value for every batch. The keras.predict() function will give you the actual predictions for all samples in a batch, for all batches. So even if you use the same data, the differences will be there because the value of a loss function will be almost always different than the predicted values. These are two different things.

In [0]:

```
%matplotlib inline
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))

# 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, va
lidation_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(x, vy, ty, ax)
```

```
Test score: 0.3362268351316452
Test accuracy: 0.9087
```



MLP + Sigmoid activation + SGDOptimizer

In [0]:

```
# Multilayer perceptron

model_sigmoid = Sequential()
model_sigmoid.add(Dense(512, activation='sigmoid', input_shape=(input_dim,)))
model_sigmoid.add(Dense(128, activation='sigmoid'))
model_sigmoid.add(Dense(output_dim, activation='softmax'))

model_sigmoid.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_2 (Dense)              (None, 512)               401920    
_________________________________________________________________
dense_3 (Dense)              (None, 128)               65664     
_________________________________________________________________
dense_4 (Dense)              (None, 10)                1290      
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
model_sigmoid.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_sigmoid.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 30us/step - loss: 2.2726 - acc: 0.2015 -
val_loss: 2.2266 - val_acc: 0.3424
Epoch 2/20
60000/60000 [==============================] - 2s 26us/step - loss: 2.1825 - acc: 0.4357 -
val_loss: 2.1259 - val_acc: 0.4958
Epoch 3/20
60000/60000 [==============================] - 2s 26us/step - loss: 2.0662 - acc: 0.5613 -
```

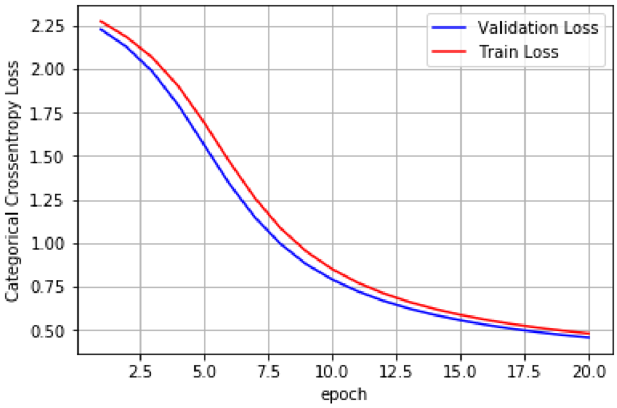
```
val_loss: 1.9858 - val_acc: 0.6221
Epoch 4/20
60000/60000 [==============================] - 2s 26us/step - loss: 1.9039 - acc: 0.6235 -
val_loss: 1.7950 - val_acc: 0.6902
Epoch 5/20
60000/60000 [==============================] - 2s 26us/step - loss: 1.6967 - acc: 0.6728 -
val_loss: 1.5688 - val_acc: 0.7118
Epoch 6/20
60000/60000 [==============================] - 2s 26us/step - loss: 1.4701 - acc: 0.7121 -
val_loss: 1.3422 - val_acc: 0.7296
Epoch 7/20
60000/60000 [==============================] - 2s 26us/step - loss: 1.2590 - acc: 0.7438 -
val_loss: 1.1481 - val_acc: 0.7611
Epoch 8/20
60000/60000 [==============================] - 2s 26us/step - loss: 1.0857 - acc: 0.7720 -
val_loss: 0.9954 - val_acc: 0.7788
Epoch 9/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.9530 - acc: 0.7917 -
val_loss: 0.8798 - val_acc: 0.8072
Epoch 10/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.8522 - acc: 0.8081 -
val_loss: 0.7928 - val_acc: 0.8204
Epoch 11/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.7743 - acc: 0.8209 -
val_loss: 0.7243 - val_acc: 0.8320
Epoch 12/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.7129 - acc: 0.8311 -
val_loss: 0.6695 - val_acc: 0.8420
Epoch 13/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.6633 - acc: 0.8391 -
val_loss: 0.6249 - val_acc: 0.8488
Epoch 14/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.6227 - acc: 0.8463 -
val_loss: 0.5885 - val_acc: 0.8545
Epoch 15/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.5889 - acc: 0.8528 -
val_loss: 0.5580 - val_acc: 0.8589
Epoch 16/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.5605 - acc: 0.8577 -
val_loss: 0.5314 - val_acc: 0.8648
Epoch 17/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.5363 - acc: 0.8617 -
val_loss: 0.5092 - val_acc: 0.8691
Epoch 18/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.5156 - acc: 0.8661 -
val_loss: 0.4897 - val_acc: 0.8727
Epoch 19/20
60000/60000 [==============================] - 2s 26us/step - loss: 0.4975 - acc: 0.8702 -
val_loss: 0.4727 - val_acc: 0.8758
Epoch 20/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.4816 - acc: 0.8731 -
val_loss: 0.4583 - val_acc: 0.8792
```

In [0]:

```
score = model_sigmoid.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))

# 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, va
lidation_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
```

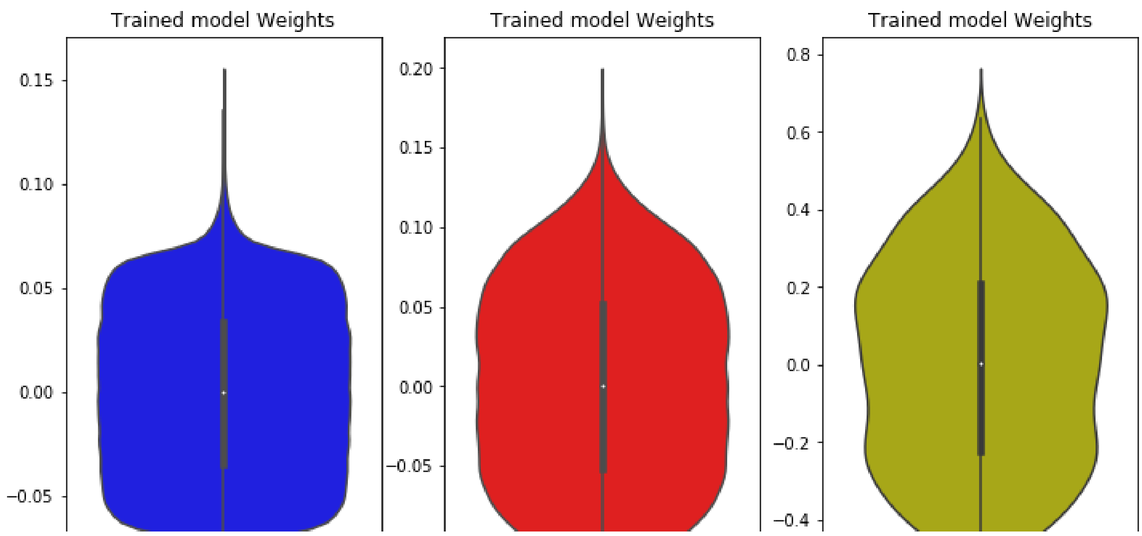
```
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

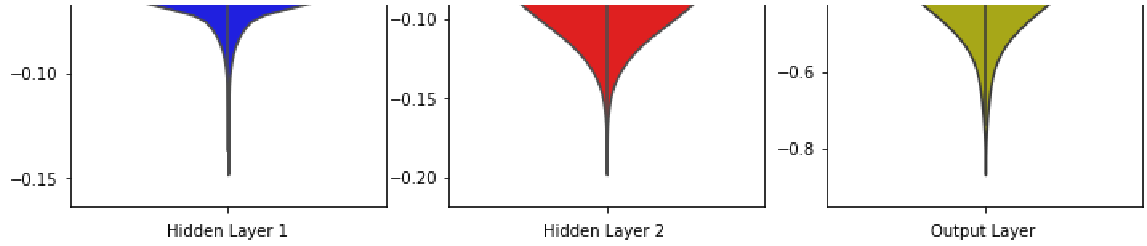
```
Test score: 0.4583240813970566
Test accuracy: 0.8792
```



In [0]:

```
%matplotlib inline
w_after = model_sigmoid.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(figsize=(12,8))
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()
```





MLP + Sigmoid activation + ADAM

In [0]:

```
model_sigmoid = Sequential()
model_sigmoid.add(Dense(512, activation='sigmoid', input_shape=(input_dim,)))
model_sigmoid.add(Dense(128, activation='sigmoid'))
model_sigmoid.add(Dense(output_dim, activation='softmax'))

model_sigmoid.summary()

model_sigmoid.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_sigmoid.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))
```

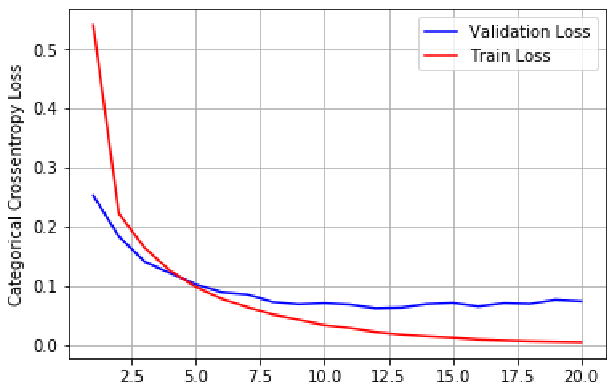
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_5 (Dense)              (None, 512)               401920    
_________________________________________________________________
dense_6 (Dense)              (None, 128)               65664     
_________________________________________________________________
dense_7 (Dense)              (None, 10)                1290      
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.5409 - acc: 0.8575 - 
val_loss: 0.2526 - val_acc: 0.9252
Epoch 2/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.2222 - acc: 0.9349 - 
val_loss: 0.1831 - val_acc: 0.9450
Epoch 3/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.1637 - acc: 0.9521 - 
val_loss: 0.1407 - val_acc: 0.9577
Epoch 4/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.1252 - acc: 0.9631 - 
val_loss: 0.1212 - val_acc: 0.9620
Epoch 5/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0978 - acc: 0.9711 - 
val_loss: 0.1023 - val_acc: 0.9696
Epoch 6/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0779 - acc: 0.9772 - 
val_loss: 0.0889 - val_acc: 0.9714
Epoch 7/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0636 - acc: 0.9814 - 
val_loss: 0.0851 - val_acc: 0.9740
Epoch 8/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0510 - acc: 0.9853 - 
val_loss: 0.0723 - val_acc: 0.9776
Epoch 9/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0422 - acc: 0.9874 - 
val_loss: 0.0684 - val_acc: 0.9790
Epoch 10/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0331 - acc: 0.9908 - 
val_loss: 0.0704 - val_acc: 0.9787
Epoch 11/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0282 - acc: 0.9919 - 
val_loss: 0.0680 - val_acc: 0.9791
Epoch 12/20
```

```
60000/60000 [==============================] - 2s 31us/step - loss: 0.0212 - acc: 0.9945 -
val_loss: 0.0616 - val_acc: 0.9809
Epoch 13/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0170 - acc: 0.9957 -
val_loss: 0.0629 - val_acc: 0.9807
Epoch 14/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0141 - acc: 0.9968 -
val_loss: 0.0689 - val_acc: 0.9791
Epoch 15/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0118 - acc: 0.9973 -
val_loss: 0.0709 - val_acc: 0.9790
Epoch 16/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0087 - acc: 0.9981 -
val_loss: 0.0648 - val_acc: 0.9805
Epoch 17/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0071 - acc: 0.9985 -
val_loss: 0.0705 - val_acc: 0.9812
Epoch 18/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0057 - acc: 0.9989 -
val_loss: 0.0691 - val_acc: 0.9800
Epoch 19/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0050 - acc: 0.9990 -
val_loss: 0.0762 - val_acc: 0.9797
Epoch 20/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0044 - acc: 0.9990 -
val_loss: 0.0737 - val_acc: 0.9801
```

In [0]:

```
%matplotlib inline
score = model_sigmoid.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

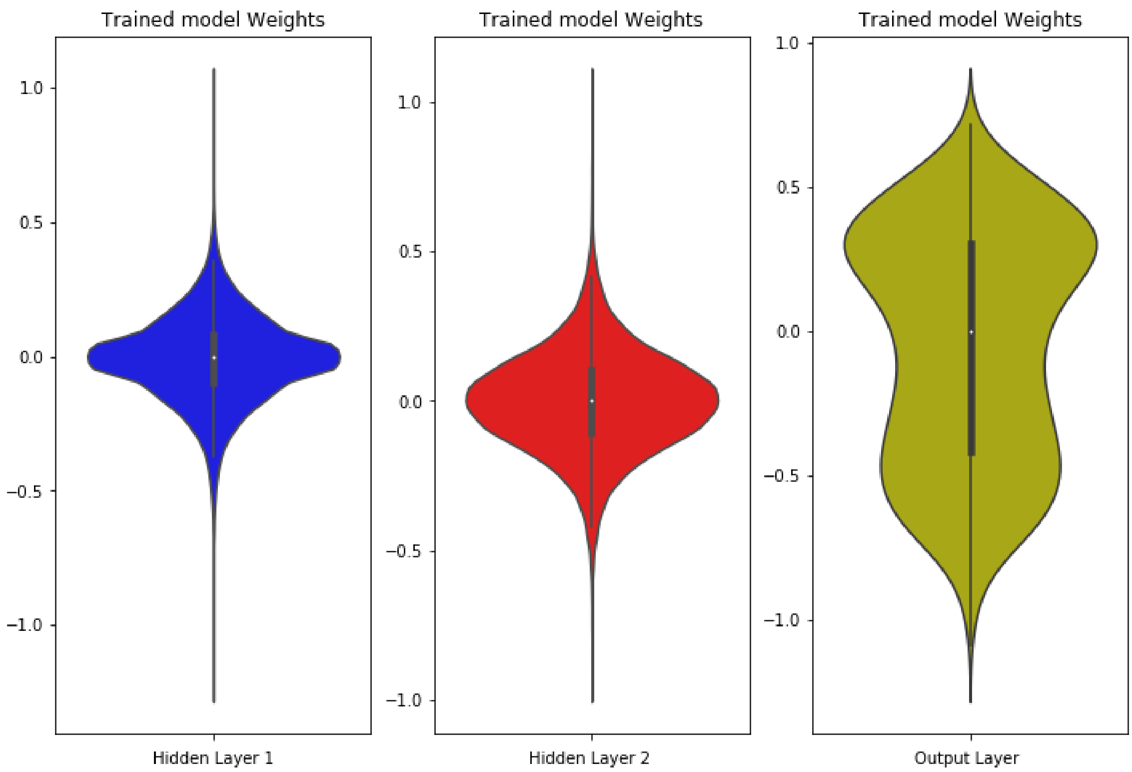
```
Test score: 0.0736692005243589
Test accuracy: 0.9801
```



epoch

In [0]:

```
%matplotlib inline
w_after = model_sigmoid.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(figsize=(12,8))
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()
```



MLP + ReLU +SGD

In [0]:

```
# Multilayer perceptron

# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.062  => N(0,σ) = N(0,0.062)
# h2 =>  σ=√(2/(fan_in) = 0.125  => N(0,σ) = N(0,0.125)
# out =>  σ=√(2/(fan_in+1) = 0.120  => N(0,σ) = N(0,0.120)
```

```python
model_relu = Sequential()
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_9 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_10 (Dense)             (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```python
model_relu.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accuracy'])

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

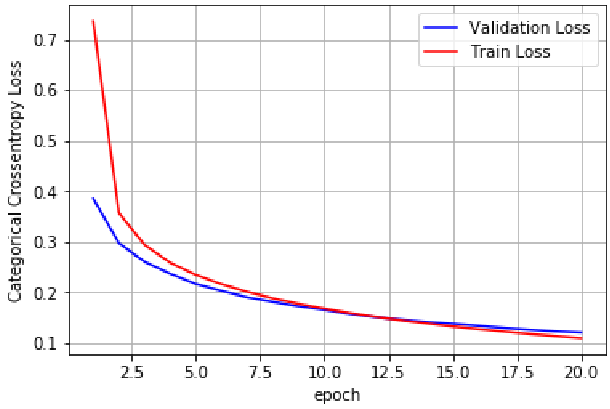
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.7357 - acc: 0.7929 - val_loss: 0.3855 - val_acc: 0.8933
Epoch 2/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.3571 - acc: 0.8995 - val_loss: 0.2975 - val_acc: 0.9147
Epoch 3/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.2938 - acc: 0.9167 - val_loss: 0.2609 - val_acc: 0.9245
Epoch 4/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.2589 - acc: 0.9259 - val_loss: 0.2372 - val_acc: 0.9326
Epoch 5/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.2349 - acc: 0.9331 - val_loss: 0.2169 - val_acc: 0.9370
Epoch 6/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.2166 - acc: 0.9385 - val_loss: 0.2035 - val_acc: 0.9416
Epoch 7/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.2015 - acc: 0.9425 - val_loss: 0.1906 - val_acc: 0.9446
Epoch 8/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1886 - acc: 0.9467 - val_loss: 0.1815 - val_acc: 0.9475
Epoch 9/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1777 - acc: 0.9500 - val_loss: 0.1729 - val_acc: 0.9492
Epoch 10/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1682 - acc: 0.9525 - val_loss: 0.1659 - val_acc: 0.9507
Epoch 11/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1595 - acc: 0.9551 - val_loss: 0.1576 - val_acc: 0.9526
Epoch 12/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1519 - acc: 0.9569 - val_loss: 0.1513 - val_acc: 0.9540
Epoch 13/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1451 - acc: 0.9596 - val_loss: 0.1464 - val_acc: 0.9556
Epoch 14/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1389 - acc: 0.9611 - val_loss: 0.1418 - val_acc: 0.9582
Epoch 15/20
```

```
60000/60000 [==============================] - 2s 27us/step - loss: 0.1330 - acc: 0.9631 -
val_loss: 0.1384 - val_acc: 0.9591
Epoch 16/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1277 - acc: 0.9646 -
val_loss: 0.1343 - val_acc: 0.9611
Epoch 17/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1228 - acc: 0.9660 -
val_loss: 0.1300 - val_acc: 0.9620
Epoch 18/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1180 - acc: 0.9671 -
val_loss: 0.1265 - val_acc: 0.9627
Epoch 19/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1140 - acc: 0.9685 -
val_loss: 0.1233 - val_acc: 0.9630
Epoch 20/20
60000/60000 [==============================] - 2s 27us/step - loss: 0.1100 - acc: 0.9699 -
val_loss: 0.1210 - val_acc: 0.9644
```

In [0]:

```
score = model_relu.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

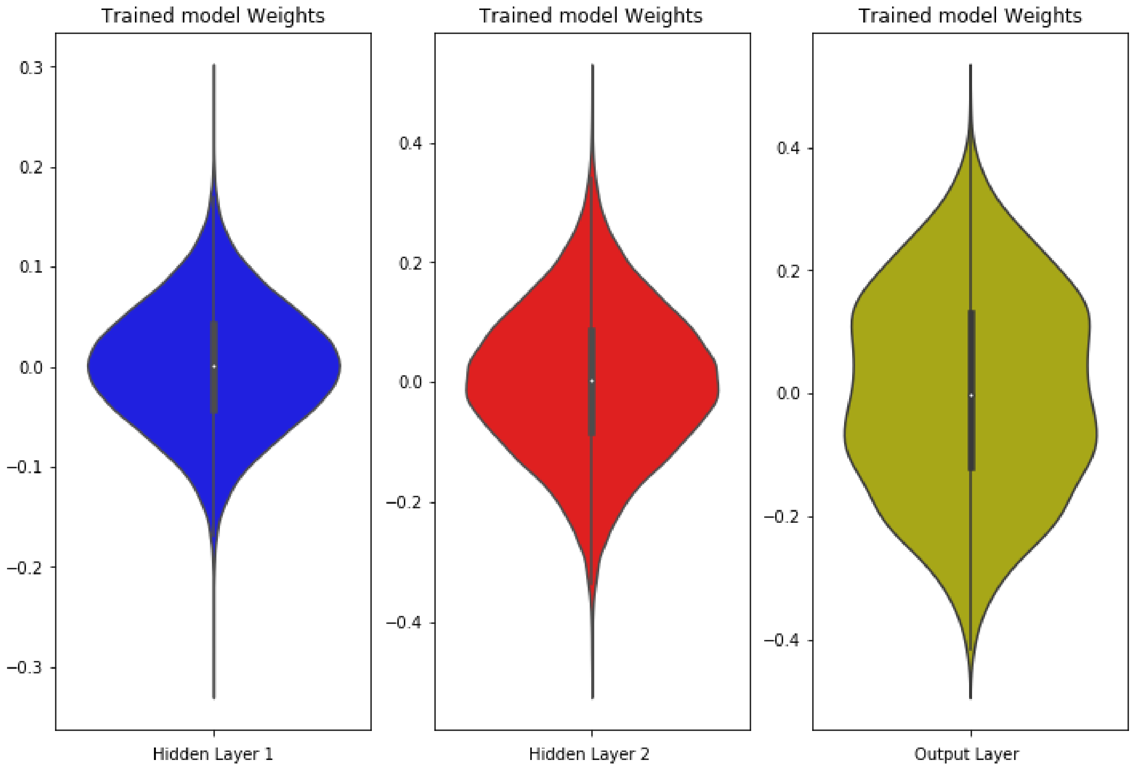
```
Test score: 0.12101748173683882
Test accuracy: 0.9644
```



In [0]:

```
%matplotlib inline
w_after = model_relu.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(figsize=(12,8))
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()
```



MLP + ReLU + ADAM

In [0]:

```
model_relu = Sequential()
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 512)               401920
```

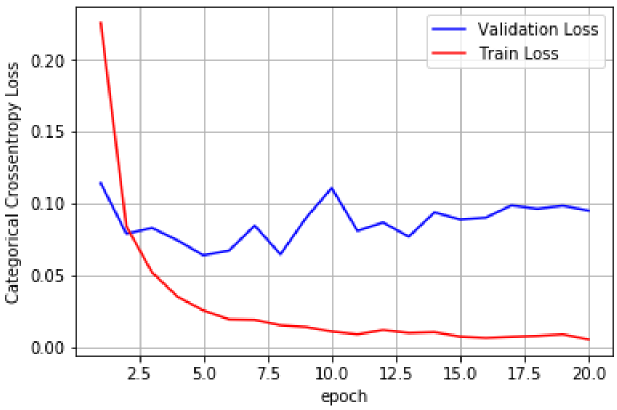
```
_________________________________________________________________
dense_12 (Dense)             (None, 128)               65664
_________________________________________________________________
dense_13 (Dense)             (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.2257 - acc: 0.9323 -
val_loss: 0.1141 - val_acc: 0.9634
Epoch 2/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0841 - acc: 0.9741 -
val_loss: 0.0790 - val_acc: 0.9759
Epoch 3/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0521 - acc: 0.9840 -
val_loss: 0.0830 - val_acc: 0.9751
Epoch 4/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0350 - acc: 0.9891 -
val_loss: 0.0743 - val_acc: 0.9775
Epoch 5/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0256 - acc: 0.9918 -
val_loss: 0.0639 - val_acc: 0.9804
Epoch 6/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0194 - acc: 0.9942 -
val_loss: 0.0672 - val_acc: 0.9800
Epoch 7/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0191 - acc: 0.9939 -
val_loss: 0.0847 - val_acc: 0.9746
Epoch 8/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0153 - acc: 0.9949 -
val_loss: 0.0646 - val_acc: 0.9810
Epoch 9/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0140 - acc: 0.9950 -
val_loss: 0.0900 - val_acc: 0.9754
Epoch 10/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0110 - acc: 0.9962 -
val_loss: 0.1109 - val_acc: 0.9720
Epoch 11/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0090 - acc: 0.9970 -
val_loss: 0.0810 - val_acc: 0.9805
Epoch 12/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0120 - acc: 0.9961 -
val_loss: 0.0868 - val_acc: 0.9787
Epoch 13/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0099 - acc: 0.9966 -
val_loss: 0.0769 - val_acc: 0.9809
Epoch 14/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0105 - acc: 0.9965 -
val_loss: 0.0938 - val_acc: 0.9789
Epoch 15/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0073 - acc: 0.9977 -
val_loss: 0.0889 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0064 - acc: 0.9978 -
val_loss: 0.0902 - val_acc: 0.9802
Epoch 17/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0072 - acc: 0.9979 -
val_loss: 0.0987 - val_acc: 0.9790
Epoch 18/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0078 - acc: 0.9975 -
val_loss: 0.0963 - val_acc: 0.9785
Epoch 19/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0089 - acc: 0.9970 -
val_loss: 0.0985 - val_acc: 0.9820
Epoch 20/20
60000/60000 [==============================] - 2s 31us/step - loss: 0.0054 - acc: 0.9983 -
val_loss: 0.0951 - val_acc: 0.9796
```

In [0]:

```
score = model_relu.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

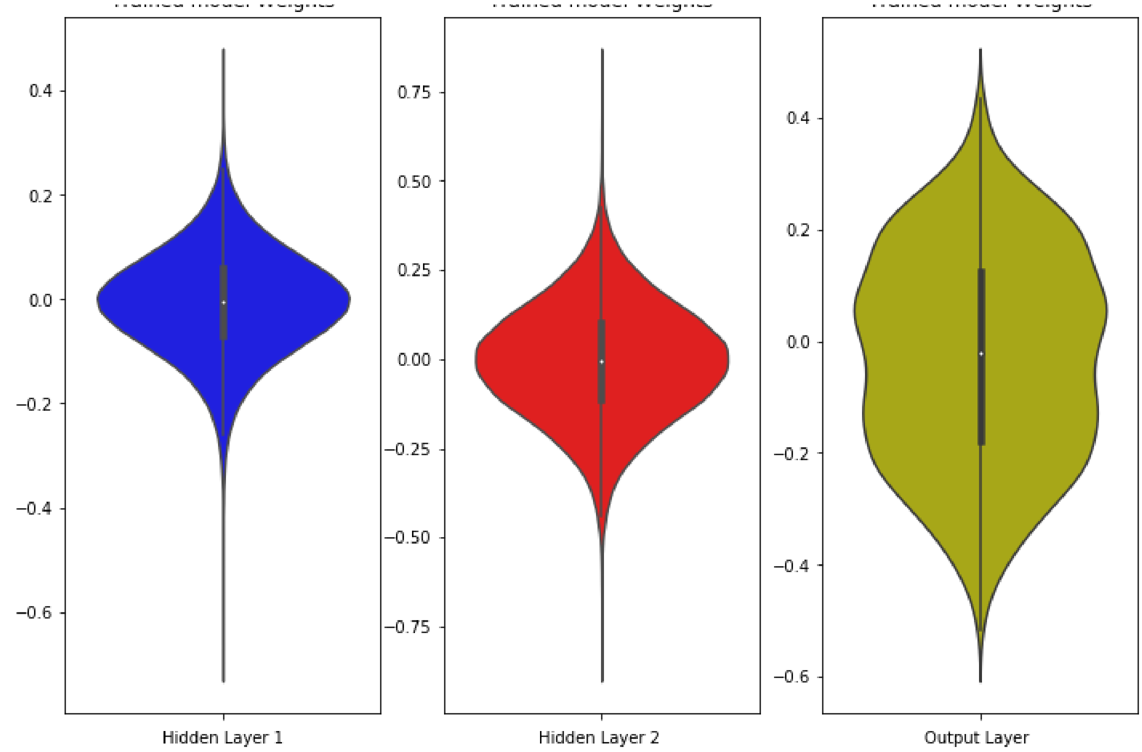
```
Test score: 0.09506532158235209
Test accuracy: 0.9796
```



In [0]:

```
%matplotlib inline
w_after = model_relu.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(figsize=(12,8))
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()
```

Trained model Weights Trained model Weights Trained model Weights



MLP + Batch-Norm on hidden Layers + AdamOptimizer </2>

In [0]:

```
# Multilayer perceptron

# https://intoli.com/blog/neural-network-initialization/
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni+ni+1).
# h1 =>  σ=√(2/(ni+ni+1) = 0.039  => N(0,σ) = N(0,0.039)
# h2 =>  σ=√(2/(ni+ni+1) = 0.055  => N(0,σ) = N(0,0.055)
# h1 =>  σ=√(2/(ni+ni+1) = 0.120  => N(0,σ) = N(0,0.120)

from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(512, activation='sigmoid', input_shape=(input_dim,), kernel_initializer=Rando
mNormal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(128, activation='sigmoid', kernel_initializer=RandomNormal(mean=0.0, stddev=0
.55, seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(output_dim, activation='softmax'))


model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_14 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048      
_________________________________________________________________
dense_15 (Dense)             (None, 128)               65664     
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512       
_________________________________________________________________
dense_16 (Dense)             (None, 10)                1290      
=================================================================
Total params: 471,434
```

```
Trainable params: 470,154
Non-trainable params: 1,280
_________________________________________________________________
```

In [0]:

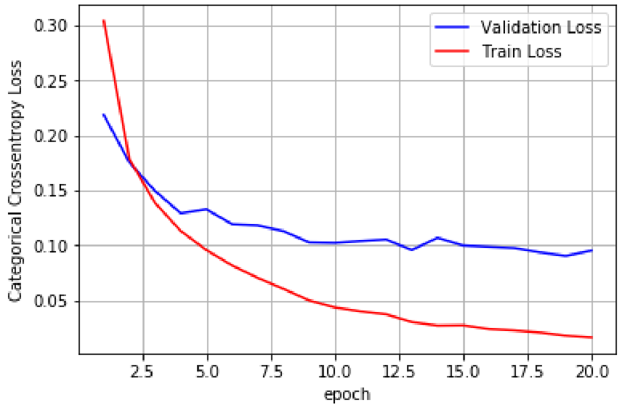
```python
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.3042 - acc: 0.9093 -
val_loss: 0.2186 - val_acc: 0.9327
Epoch 2/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.1785 - acc: 0.9474 -
val_loss: 0.1755 - val_acc: 0.9468
Epoch 3/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.1385 - acc: 0.9595 -
val_loss: 0.1494 - val_acc: 0.9534
Epoch 4/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.1130 - acc: 0.9668 -
val_loss: 0.1292 - val_acc: 0.9617
Epoch 5/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0956 - acc: 0.9711 -
val_loss: 0.1328 - val_acc: 0.9597
Epoch 6/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0817 - acc: 0.9752 -
val_loss: 0.1192 - val_acc: 0.9616
Epoch 7/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0704 - acc: 0.9784 -
val_loss: 0.1181 - val_acc: 0.9651
Epoch 8/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0604 - acc: 0.9808 -
val_loss: 0.1128 - val_acc: 0.9657
Epoch 9/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.0498 - acc: 0.9843 -
val_loss: 0.1026 - val_acc: 0.9682
Epoch 10/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0435 - acc: 0.9866 -
val_loss: 0.1022 - val_acc: 0.9701
Epoch 11/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.0399 - acc: 0.9879 -
val_loss: 0.1038 - val_acc: 0.9692
Epoch 12/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0372 - acc: 0.9878 -
val_loss: 0.1052 - val_acc: 0.9691
Epoch 13/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0301 - acc: 0.9902 -
val_loss: 0.0957 - val_acc: 0.9712
Epoch 14/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.0269 - acc: 0.9911 -
val_loss: 0.1068 - val_acc: 0.9714
Epoch 15/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0271 - acc: 0.9908 -
val_loss: 0.0998 - val_acc: 0.9738
Epoch 16/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0237 - acc: 0.9923 -
val_loss: 0.0985 - val_acc: 0.9738
Epoch 17/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0225 - acc: 0.9931 -
val_loss: 0.0975 - val_acc: 0.9731
Epoch 18/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0205 - acc: 0.9931 -
val_loss: 0.0935 - val_acc: 0.9748
Epoch 19/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0177 - acc: 0.9943 -
val_loss: 0.0903 - val_acc: 0.9754
Epoch 20/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0161 - acc: 0.9946 -
val_loss: 0.0952 - val_acc: 0.9749
```

In [0]:

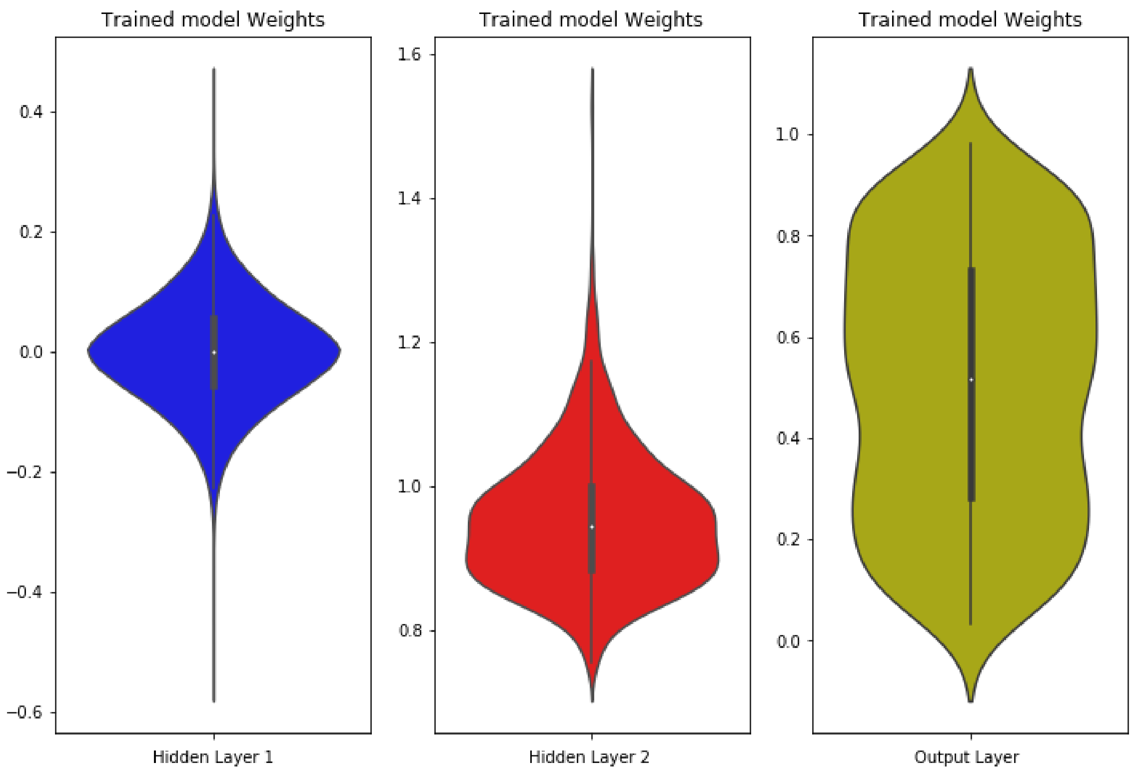
```python
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# 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, va
lidation_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(x, vy, ty, ax)
```

```
Test score: 0.09516252700814512
Test accuracy: 0.9749
```



In [0]:

```python
%matplotlib inline
w_after = model_batch.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(figsize=(12,8))
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()
```



5. MLP + Dropout + AdamOptimizer

In [0]:

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(512, activation='sigmoid', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(128, activation='sigmoid', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(output_dim, activation='softmax'))


model_drop.summary()
```

```
W0804 16:35:36.860419 139651759564672 deprecation.py:506] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

Layer (type)	Output Shape	Param #
dense_17 (Dense)	(None, 512)	401920
batch_normalization_3 (Batch	(None, 512)	2048
dropout_1 (Dropout)	(None, 512)	0
dense_18 (Dense)	(None, 128)	65664

```
batch_normalization_4 (Batch (None, 128)              512
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)              0
_________________________________________________________________
dense_19 (Dense)             (None, 10)               1290
=================================================================
Total params: 471,434
Trainable params: 470,154
Non-trainable params: 1,280
_________________________________________________________________
```

In [0]:

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

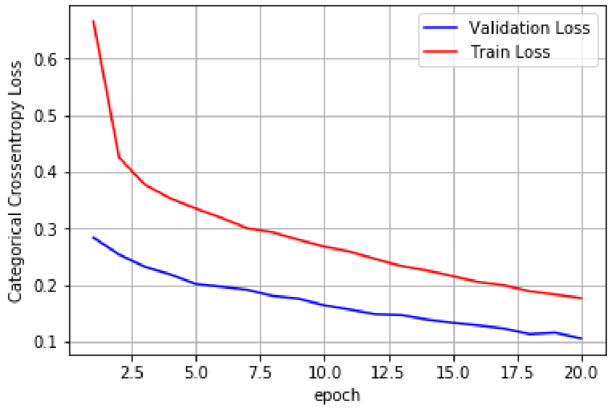
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.6652 - acc: 0.7950 -
val_loss: 0.2836 - val_acc: 0.9164
Epoch 2/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.4251 - acc: 0.8695 -
val_loss: 0.2539 - val_acc: 0.9236
Epoch 3/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3772 - acc: 0.8852 -
val_loss: 0.2323 - val_acc: 0.9309
Epoch 4/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3527 - acc: 0.8953 -
val_loss: 0.2187 - val_acc: 0.9365
Epoch 5/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3349 - acc: 0.8995 -
val_loss: 0.2018 - val_acc: 0.9415
Epoch 6/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3184 - acc: 0.9046 -
val_loss: 0.1969 - val_acc: 0.9428
Epoch 7/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3002 - acc: 0.9099 -
val_loss: 0.1915 - val_acc: 0.9432
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2929 - acc: 0.9111 -
val_loss: 0.1806 - val_acc: 0.9483
Epoch 9/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2798 - acc: 0.9172 -
val_loss: 0.1759 - val_acc: 0.9486
Epoch 10/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2677 - acc: 0.9191 -
val_loss: 0.1643 - val_acc: 0.9514
Epoch 11/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2589 - acc: 0.9218 -
val_loss: 0.1567 - val_acc: 0.9532
Epoch 12/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2459 - acc: 0.9253 -
val_loss: 0.1485 - val_acc: 0.9546
Epoch 13/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2336 - acc: 0.9302 -
val_loss: 0.1470 - val_acc: 0.9568
Epoch 14/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2257 - acc: 0.9325 -
val_loss: 0.1392 - val_acc: 0.9589
Epoch 15/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2158 - acc: 0.9349 -
val_loss: 0.1334 - val_acc: 0.9602
Epoch 16/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2055 - acc: 0.9387 -
val_loss: 0.1287 - val_acc: 0.9627
Epoch 17/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1996 - acc: 0.9395 -
val_loss: 0.1232 - val_acc: 0.9631
Epoch 18/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1891 - acc: 0.9429 -
val_loss: 0.1133 - val_acc: 0.9659
Epoch 19/20
```

```
60000/60000 [==============================] - 3s 53us/step - loss: 0.1833 - acc: 0.9449 -
val_loss: 0.1158 - val_acc: 0.9664
Epoch 20/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.1769 - acc: 0.9468 -
val_loss: 0.1058 - val_acc: 0.9683
```

In [0]:

```
score = model_drop.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

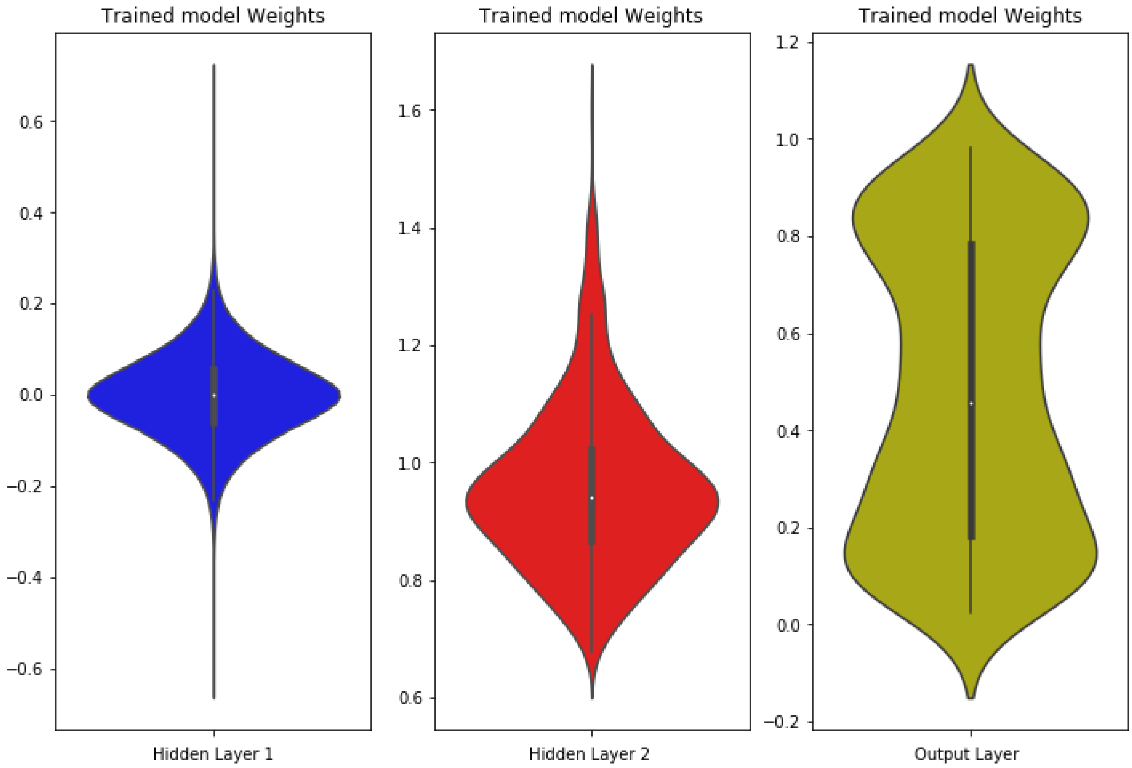
```
Test score: 0.10577300073988735
Test accuracy: 0.9683
```



In [0]:

```
%matplotlib inline
w_after = model_drop.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(figsize=(12,8))
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()
```



Hyper-parameter tuning of Keras models using Sklearn

In [0]:

```
from keras.optimizers import Adam,RMSprop,SGD
def best_hyperparameters(activ):

    model = Sequential()
    model.add(Dense(512, activation=activ, input_shape=(input_dim,), kernel_initializer=RandomNorma
l(mean=0.0, stddev=0.062, seed=None)))
    model.add(Dense(128, activation=activ, kernel_initializer=RandomNormal(mean=0.0, stddev=0.125,
seed=None)) )
    model.add(Dense(output_dim, activation='softmax'))


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

    return model
```

In [0]:

```
# https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras
/

activ = ['sigmoid','relu']

from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV

model = KerasClassifier(build_fn=best_hyperparameters, epochs=nb_epoch, batch_size=batch_size, verb
ose=0)
param_grid = dict(activ=activ)

# if you are using CPU
```

```
# grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
# if you are using GPU dont use the n_jobs parameter

grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid_result = grid.fit(X_train, Y_train)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:1978: FutureWarning: The default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
```

In [0]:

```
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.975817 using {'activ': 'relu'}
0.975017 (0.001059) with: {'activ': 'sigmoid'}
0.975817 (0.002400) with: {'activ': 'relu'}
```

With 2 Hiden layers

Architecture used: 784 (input) - 256 - 64 - 10 (ouput)

MLP + ReLu + Adam

In [0]:

```
model2_relu = Sequential()

model2_relu.add(Dense(256, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_uniform'))
model2_relu.add(Dense(64, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_uniform'))
model2_relu.add(Dense(output_dim, activation = 'softmax'))

model2_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_41 (Dense)             (None, 256)               200960    
_________________________________________________________________
dense_42 (Dense)             (None, 64)                16448     
_________________________________________________________________
dense_43 (Dense)             (None, 10)                650       
=================================================================
Total params: 218,058
Trainable params: 218,058
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
model2_relu.compile(optimizer = 'adam', metrics = ['accuracy'], loss = 'categorical_crossentropy')

history = model2_relu.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 [==============================] - 3s 54us/step - loss: 0.2851 - acc: 0.9207 - val_loss: 0.1351 - val_acc: 0.9590
Epoch 2/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.1053 - acc: 0.9687 -
```

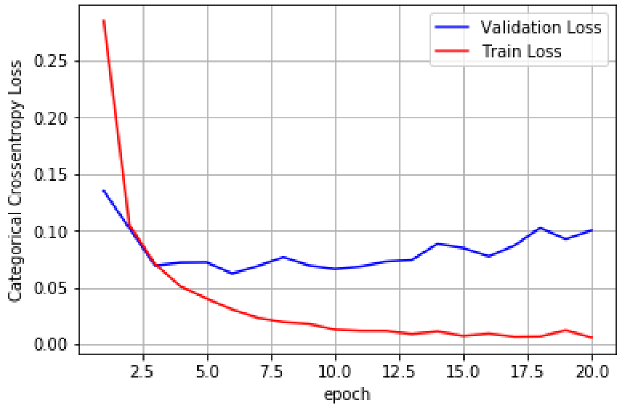
```
val_loss: 0.1022 - val_acc: 0.9695
Epoch 3/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0706 - acc: 0.9788 -
val_loss: 0.0691 - val_acc: 0.9781
Epoch 4/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0507 - acc: 0.9847 -
val_loss: 0.0719 - val_acc: 0.9769
Epoch 5/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0402 - acc: 0.9874 -
val_loss: 0.0722 - val_acc: 0.9777
Epoch 6/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0306 - acc: 0.9906 -
val_loss: 0.0621 - val_acc: 0.9820
Epoch 7/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0232 - acc: 0.9927 -
val_loss: 0.0688 - val_acc: 0.9798
Epoch 8/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0194 - acc: 0.9941 -
val_loss: 0.0767 - val_acc: 0.9781
Epoch 9/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0178 - acc: 0.9944 -
val_loss: 0.0693 - val_acc: 0.9807
Epoch 10/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0128 - acc: 0.9962 -
val_loss: 0.0662 - val_acc: 0.9807
Epoch 11/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0117 - acc: 0.9965 -
val_loss: 0.0684 - val_acc: 0.9820
Epoch 12/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0117 - acc: 0.9963 -
val_loss: 0.0728 - val_acc: 0.9801
Epoch 13/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0088 - acc: 0.9970 -
val_loss: 0.0742 - val_acc: 0.9818
Epoch 14/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0112 - acc: 0.9962 -
val_loss: 0.0885 - val_acc: 0.9780
Epoch 15/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0072 - acc: 0.9976 -
val_loss: 0.0847 - val_acc: 0.9807
Epoch 16/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0092 - acc: 0.9969 -
val_loss: 0.0773 - val_acc: 0.9828
Epoch 17/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0064 - acc: 0.9980 -
val_loss: 0.0869 - val_acc: 0.9811
Epoch 18/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0067 - acc: 0.9978 -
val_loss: 0.1025 - val_acc: 0.9769
Epoch 19/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0122 - acc: 0.9961 -
val_loss: 0.0925 - val_acc: 0.9795
Epoch 20/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0058 - acc: 0.9981 -
val_loss: 0.1004 - val_acc: 0.9788
```

In [0]:

```
score = model2_relu.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))

# 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, va
lidation_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
```

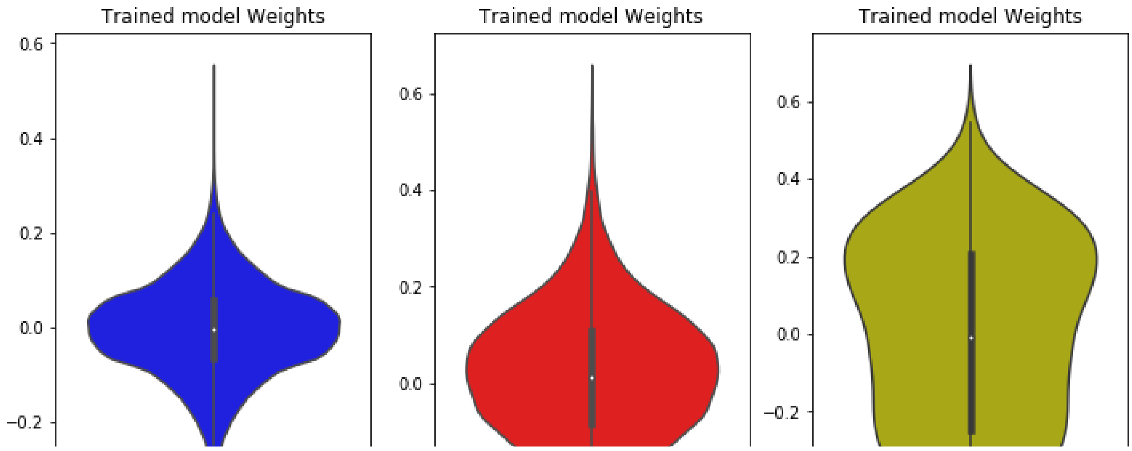
```
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


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

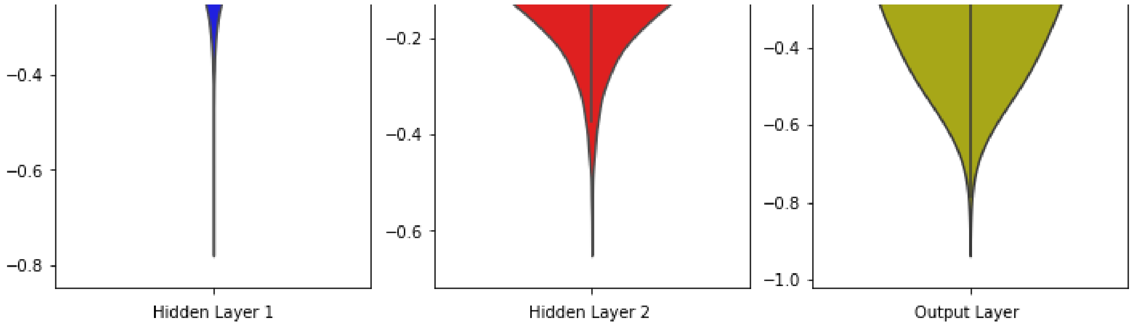
```
Test score: 0.10035725422161268
Test accuracy: 0.9788
```



In [0]:

```
%matplotlib inline
w_after = model2_relu.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(figsize=(12,8))
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()
```





MLP + BatchNorm on hidden layers + Adam

In [0]:

```
model2_relu_batchnorm = Sequential()

model2_relu_batchnorm.add(Dense(256, activation = 'relu', input_dim = input_dim,kernel_initializer=
'glorot_uniform'))
model2_relu_batchnorm.add(BatchNormalization())

model2_relu_batchnorm.add(Dense(64, activation = 'relu', input_dim = input_dim,kernel_initializer=
'glorot_uniform'))
model2_relu_batchnorm.add(BatchNormalization())

model2_relu_batchnorm.add(Dense(output_dim, activation = 'softmax'))

model2_relu_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_44 (Dense)             (None, 256)               200960    
_________________________________________________________________
batch_normalization_5 (Batch (None, 256)               1024      
_________________________________________________________________
dense_45 (Dense)             (None, 64)                16448     
_________________________________________________________________
batch_normalization_6 (Batch (None, 64)                256       
_________________________________________________________________
dense_46 (Dense)             (None, 10)                650       
=================================================================
Total params: 219,338
Trainable params: 218,698
Non-trainable params: 640
_________________________________________________________________
```

In [0]:

```
model2_relu_batchnorm.compile(optimizer='adam', metrics = ['accuracy'], loss =
'categorical_crossentropy')

history = model2_relu_batchnorm.fit(X_train, Y_train, batch_size = batch_size, epochs = nb_epoch, v
erbose = 1, validation_data = (X_test, Y_test))
```

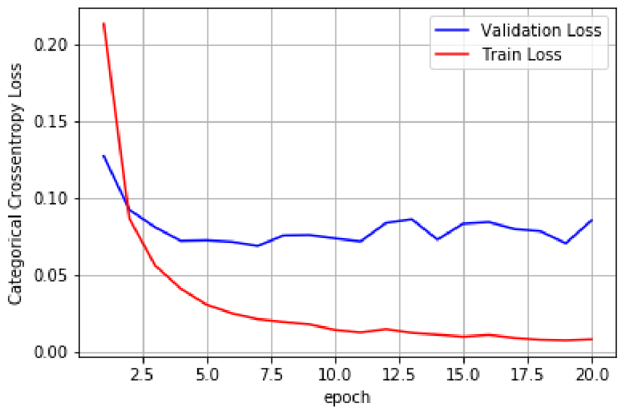
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.2128 - acc: 0.9386 -
val_loss: 0.1270 - val_acc: 0.9603
Epoch 2/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0863 - acc: 0.9741 -
val_loss: 0.0921 - val_acc: 0.9732
Epoch 3/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0560 - acc: 0.9828 -
val_loss: 0.0807 - val_acc: 0.9747
Epoch 4/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0408 - acc: 0.9875 -
val_loss: 0.0719 - val_acc: 0.9773
Epoch 5/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0305 - acc: 0.9907 -
val_loss: 0.0722 - val_acc: 0.9772
```

```
Epoch 6/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0248 - acc: 0.9919 -
val_loss: 0.0712 - val_acc: 0.9789
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0210 - acc: 0.9932 -
val_loss: 0.0685 - val_acc: 0.9812
Epoch 8/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0192 - acc: 0.9940 -
val_loss: 0.0754 - val_acc: 0.9768
Epoch 9/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0177 - acc: 0.9942 -
val_loss: 0.0757 - val_acc: 0.9792
Epoch 10/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0140 - acc: 0.9957 -
val_loss: 0.0735 - val_acc: 0.9771
Epoch 11/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0123 - acc: 0.9962 -
val_loss: 0.0715 - val_acc: 0.9789
Epoch 12/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0145 - acc: 0.9951 -
val_loss: 0.0835 - val_acc: 0.9785
Epoch 13/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0121 - acc: 0.9958 -
val_loss: 0.0859 - val_acc: 0.9779
Epoch 14/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0109 - acc: 0.9963 -
val_loss: 0.0727 - val_acc: 0.9816
Epoch 15/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0096 - acc: 0.9968 -
val_loss: 0.0830 - val_acc: 0.9791
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0108 - acc: 0.9964 -
val_loss: 0.0841 - val_acc: 0.9790
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0088 - acc: 0.9972 -
val_loss: 0.0796 - val_acc: 0.9815
Epoch 18/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0076 - acc: 0.9974 -
val_loss: 0.0782 - val_acc: 0.9807
Epoch 19/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0071 - acc: 0.9979 -
val_loss: 0.0703 - val_acc: 0.9815
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0079 - acc: 0.9972 -
val_loss: 0.0851 - val_acc: 0.9786
```

In [0]:

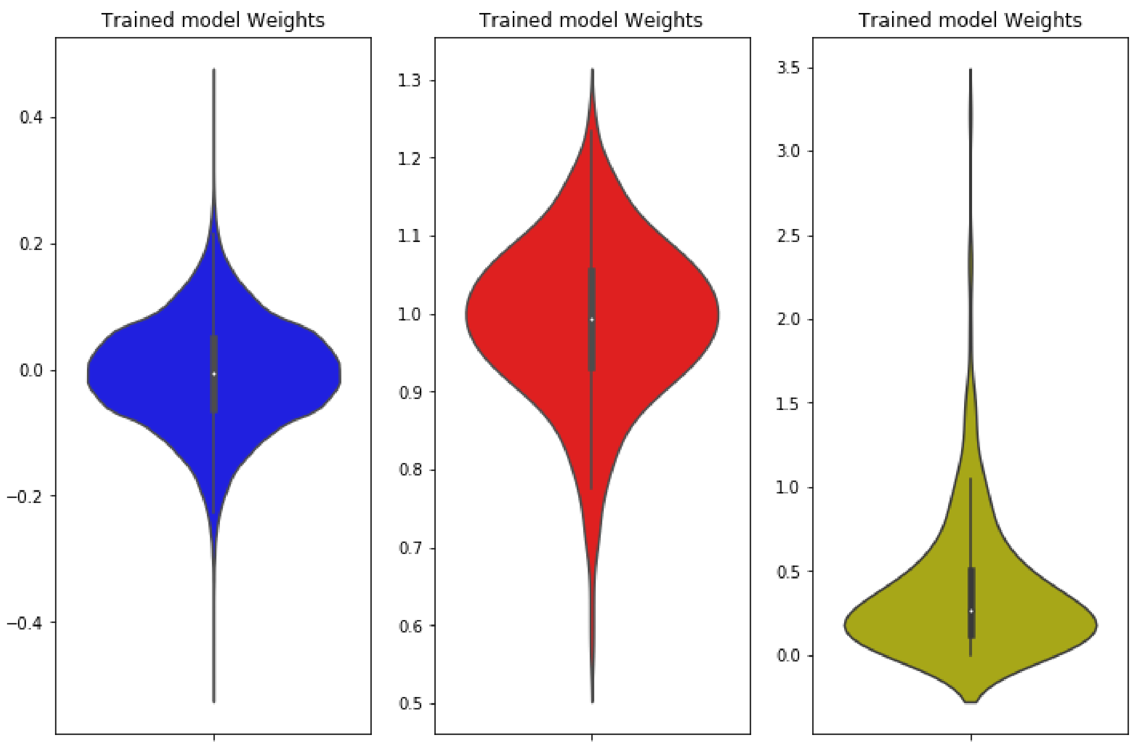
```
score = model2_relu_batchnorm.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# 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, va
lidation_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(x, vy, ty, ax)
```

```
Test score: 0.08512964024284957
Test accuracy: 0.9786
```



In [0]:

```
%matplotlib inline
w_after = model2_relu_batchnorm.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(figsize = (12,8))
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()
```



Hidden Layer 1 Hidden Layer 2 Output Layer

Observation

After applying normalization, we see that weights in the output layer are mostly between 0.0 to 0.5 and fewer between 0.5 to 1.0

Note: I am going to experiment here. First, I will place batch norm before dropout and later I will place dropout before batchnorm. After doing this, I will compare the accuracy of these models.

This is some interesting discussion:

- https://stackoverflow.com/questions/39691902/ordering-of-batch-normalization-and-dropout
- https://github.com/cvjena/cnn-models/issues/3

MLP + Batch Norm + Dropout + Adam

In [0]:

```
model2_batchnorm_drop = Sequential()

model2_batchnorm_drop.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initialize
r='random_normal'))
model2_batchnorm_drop.add(BatchNormalization())
model2_batchnorm_drop.add(Dropout(0.5))

model2_batchnorm_drop.add(Dense(64, activation='relu', kernel_initializer='random_normal'))
model2_batchnorm_drop.add(BatchNormalization())
model2_batchnorm_drop.add(Dropout(0.5))

model2_batchnorm_drop.add(Dense(output_dim, activation='softmax'))


model2_batchnorm_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_47 (Dense)             (None, 256)               200960    
_________________________________________________________________
batch_normalization_7 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_48 (Dense)             (None, 64)                16448     
_________________________________________________________________
batch_normalization_8 (Batch (None, 64)                256       
_________________________________________________________________
dropout_4 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_49 (Dense)             (None, 10)                650       
=================================================================
Total params: 219,338
Trainable params: 218,698
Non-trainable params: 640
_________________________________________________________________
```

In [0]:

```
model2_batchnorm_drop.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

history = model2_batchnorm_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbo
se=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.5546 - acc: 0.8328 -
val_loss: 0.1816 - val_acc: 0.9433
Epoch 2/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2673 - acc: 0.9218 -
val_loss: 0.1269 - val_acc: 0.9590
```

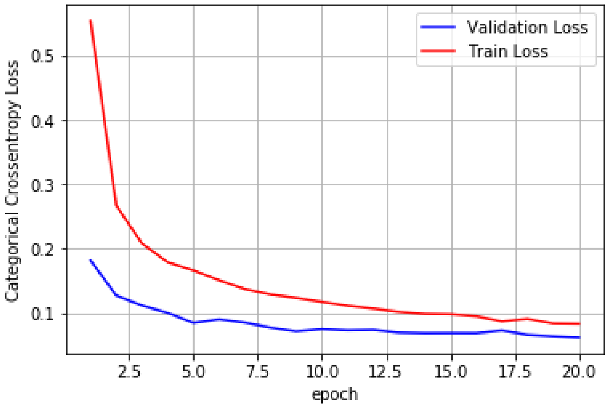
```
val_loss: 0.1209 - val_acc: 0.9590
Epoch 3/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.2081 - acc: 0.9389 -
val_loss: 0.1117 - val_acc: 0.9676
Epoch 4/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1789 - acc: 0.9477 -
val_loss: 0.1001 - val_acc: 0.9704
Epoch 5/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1661 - acc: 0.9516 -
val_loss: 0.0845 - val_acc: 0.9744
Epoch 6/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1508 - acc: 0.9558 -
val_loss: 0.0901 - val_acc: 0.9713
Epoch 7/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1371 - acc: 0.9600 -
val_loss: 0.0850 - val_acc: 0.9734
Epoch 8/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1287 - acc: 0.9622 -
val_loss: 0.0772 - val_acc: 0.9774
Epoch 9/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1233 - acc: 0.9630 -
val_loss: 0.0713 - val_acc: 0.9790
Epoch 10/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1172 - acc: 0.9642 -
val_loss: 0.0749 - val_acc: 0.9789
Epoch 11/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1113 - acc: 0.9670 -
val_loss: 0.0730 - val_acc: 0.9782
Epoch 12/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1068 - acc: 0.9678 -
val_loss: 0.0737 - val_acc: 0.9785
Epoch 13/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1017 - acc: 0.9695 -
val_loss: 0.0693 - val_acc: 0.9799
Epoch 14/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0986 - acc: 0.9704 -
val_loss: 0.0684 - val_acc: 0.9796
Epoch 15/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0980 - acc: 0.9700 -
val_loss: 0.0685 - val_acc: 0.9795
Epoch 16/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0949 - acc: 0.9715 -
val_loss: 0.0684 - val_acc: 0.9790
Epoch 17/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0869 - acc: 0.9728 -
val_loss: 0.0727 - val_acc: 0.9789
Epoch 18/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0908 - acc: 0.9719 -
val_loss: 0.0659 - val_acc: 0.9800
Epoch 19/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0835 - acc: 0.9743 -
val_loss: 0.0635 - val_acc: 0.9812
Epoch 20/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0830 - acc: 0.9753 -
val_loss: 0.0617 - val_acc: 0.9827
```

In [0]:

```
score = model2_batchnorm_drop.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))

# 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, va
lidation_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
```

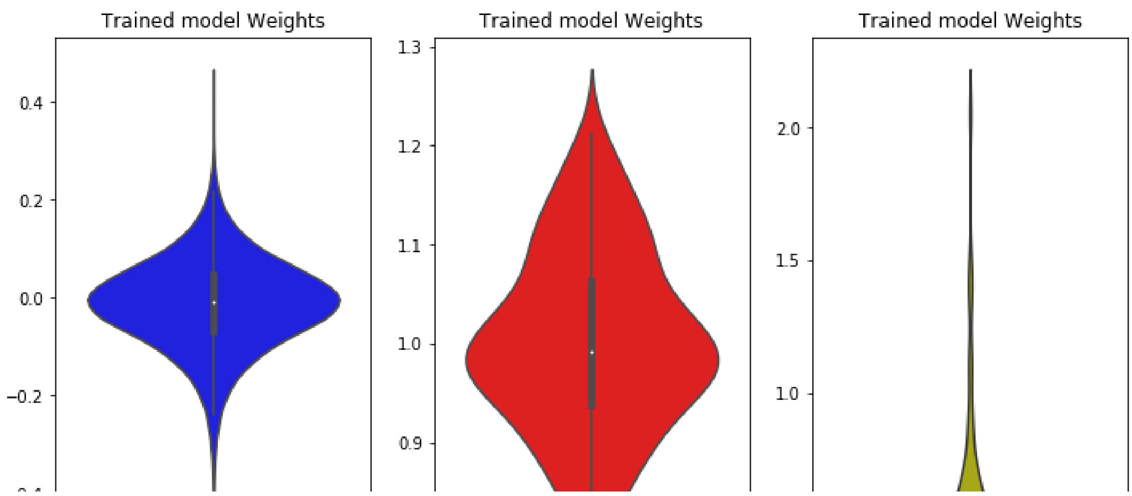
```
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

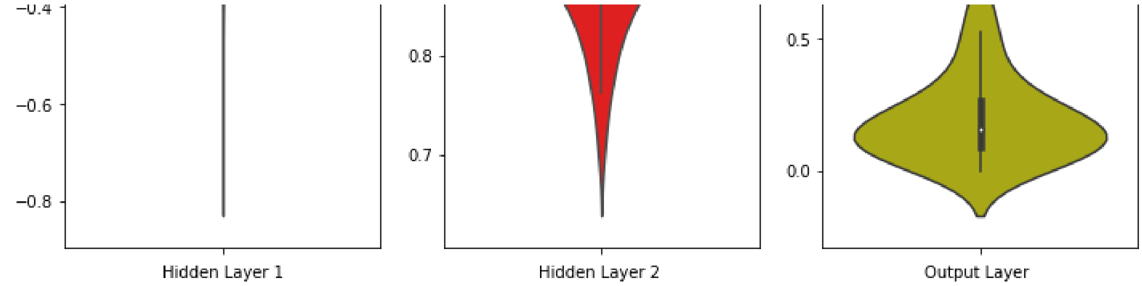
```
Test score: 0.061712297642615155
Test accuracy: 0.9827
```



In [0]:

```
%matplotlib inline
w_after = model2_batchnorm_drop.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(figsize= (12,8))
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()
```





MLP + Dropout + Batch Norm +Adam

In [0]:

```
model2_drop_batchnorm = Sequential()

model2_drop_batchnorm.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initialize
r='random_normal'))
model2_drop_batchnorm.add(BatchNormalization())
model2_drop_batchnorm.add(Dropout(0.5))

model2_drop_batchnorm.add(Dense(64, activation='relu', kernel_initializer='random_normal'))
model2_drop_batchnorm.add(BatchNormalization())
model2_drop_batchnorm.add(Dropout(0.5))

model2_drop_batchnorm.add(Dense(output_dim, activation='softmax'))


model2_drop_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_50 (Dense)             (None, 256)               200960    
_________________________________________________________________
batch_normalization_9 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_5 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_51 (Dense)             (None, 64)                16448     
_________________________________________________________________
batch_normalization_10 (Batc (None, 64)                256       
_________________________________________________________________
dropout_6 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_52 (Dense)             (None, 10)                650       
=================================================================
Total params: 219,338
Trainable params: 218,698
Non-trainable params: 640
_________________________________________________________________
```

In [0]:

```
model2_drop_batchnorm.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

history = model2_drop_batchnorm.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbo
se=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.5392 - acc: 0.8366 -
val_loss: 0.1746 - val_acc: 0.9465
Epoch 2/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2621 - acc: 0.9240 -
val_loss: 0.1209 - val_acc: 0.9629
Epoch 3/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2077 - acc: 0.9392 -
val_loss: 0.1033 - val_acc: 0.9683
Epoch 4/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1771 - acc: 0.9488 -
```

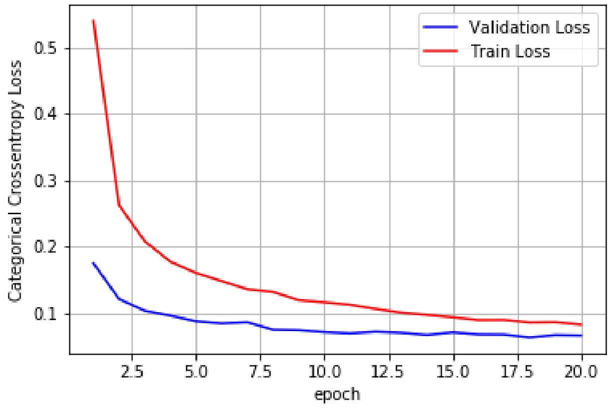
```
60000/60000 [==============================] - 3s 57us/step - loss: 0.1771 - acc: 0.9488 -
val_loss: 0.0959 - val_acc: 0.9713
Epoch 5/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1600 - acc: 0.9529 -
val_loss: 0.0874 - val_acc: 0.9735
Epoch 6/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1478 - acc: 0.9562 -
val_loss: 0.0842 - val_acc: 0.9728
Epoch 7/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1356 - acc: 0.9595 -
val_loss: 0.0859 - val_acc: 0.9740
Epoch 8/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1315 - acc: 0.9610 -
val_loss: 0.0747 - val_acc: 0.9762
Epoch 9/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.1193 - acc: 0.9645 -
val_loss: 0.0740 - val_acc: 0.9775
Epoch 10/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.1159 - acc: 0.9663 -
val_loss: 0.0711 - val_acc: 0.9789
Epoch 11/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1123 - acc: 0.9666 -
val_loss: 0.0691 - val_acc: 0.9797
Epoch 12/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1061 - acc: 0.9692 -
val_loss: 0.0717 - val_acc: 0.9798
Epoch 13/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1004 - acc: 0.9705 -
val_loss: 0.0700 - val_acc: 0.9808
Epoch 14/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0971 - acc: 0.9708 -
val_loss: 0.0668 - val_acc: 0.9797
Epoch 15/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0935 - acc: 0.9719 -
val_loss: 0.0707 - val_acc: 0.9802
Epoch 16/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0893 - acc: 0.9727 -
val_loss: 0.0676 - val_acc: 0.9805
Epoch 17/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0894 - acc: 0.9726 -
val_loss: 0.0673 - val_acc: 0.9801
Epoch 18/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0856 - acc: 0.9745 -
val_loss: 0.0630 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0860 - acc: 0.9749 -
val_loss: 0.0667 - val_acc: 0.9801
Epoch 20/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0824 - acc: 0.9750 -
val_loss: 0.0660 - val_acc: 0.9813
```

In [0]:

```python
score = model2_drop_batchnorm.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))

# 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, va
lidation_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']
```

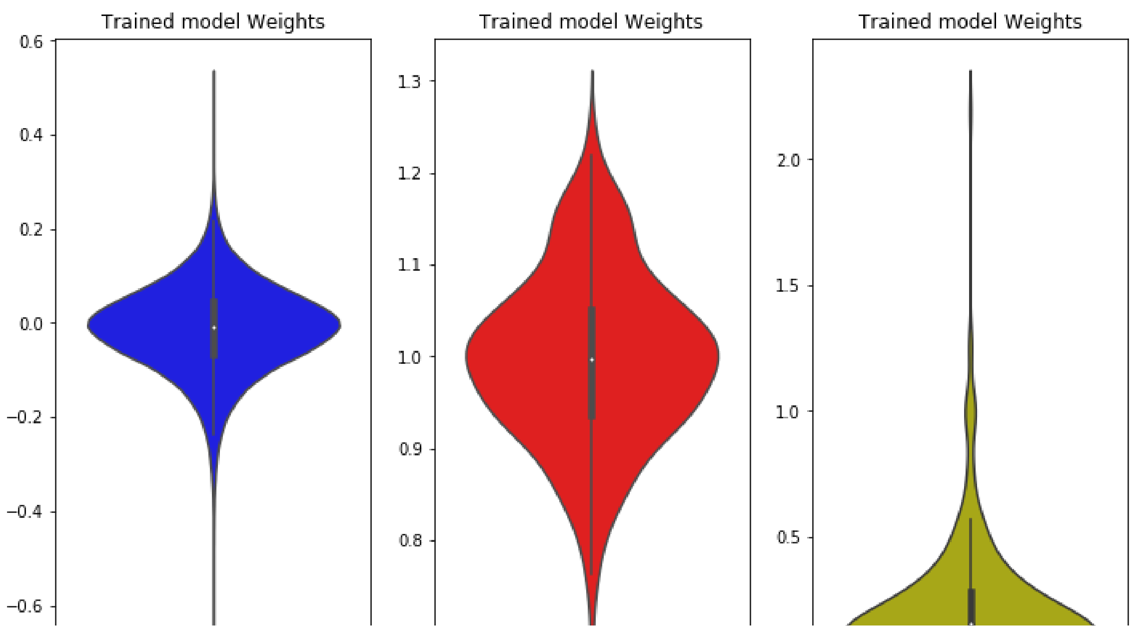
```
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

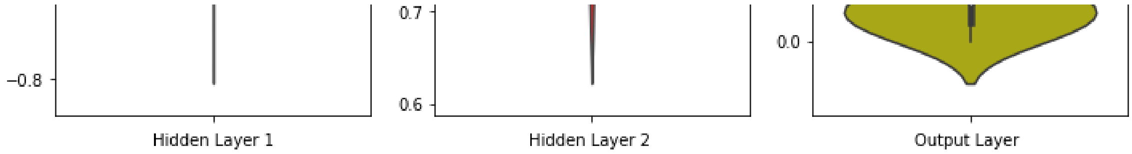
```
Test score: 0.06602386177739827
Test accuracy: 0.9813
```



In [0]:

```
%matplotlib inline
w_after = model2_drop_batchnorm.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(figsize= (12,8))
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()
```





MLP + Batch Norm + Dropout + Adam

Test score: 0.0703403844089189
Test accuracy: 0.9796

MLP + Dropout + Batch Norm +Adam

Test score: 0.06499798040131573
Test accuracy: 0.9817

In [0]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Architecture Type", "Test score", "Test accuracy"]

x.add_row(["MLP + Batch Norm + Dropout + Adam", 0.0703403844089189, 0.9796])
x.add_row(["MLP + Dropout + Batch Norm +Adam", 0.06499798040131573, 0.9817])

print(x)
```

```
+-----------------------------------+---------------------+---------------+
|         Architecture Type         |      Test score     | Test accuracy |
+-----------------------------------+---------------------+---------------+
| MLP + Batch Norm + Dropout + Adam |  0.0703403844089189 |     0.9796    |
|  MLP + Dropout + Batch Norm +Adam | 0.06499798040131573 |     0.9817    |
+-----------------------------------+---------------------+---------------+
```

Observation: There is a slight improvement in the test accuracy if we use dropout before batchnorm.

With 3 Hiden layers

Architecture used: 784 (input) - 128 - 64 - 32 - 10 (ouput)

MLP + ReLu + Adam

In [0]:

```
model3_relu = Sequential()

model3_relu.add(Dense(128, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(64, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(32, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(output_dim, activation = 'softmax'))

model3_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_53 (Dense)             (None, 128)               100480    
_________________________________________________________________
dense_54 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_55 (Dense)             (None, 32)                2080      
_________________________________________________________________
dense_56 (Dense)             (None, 10)                330       
=================================================================
```

```
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

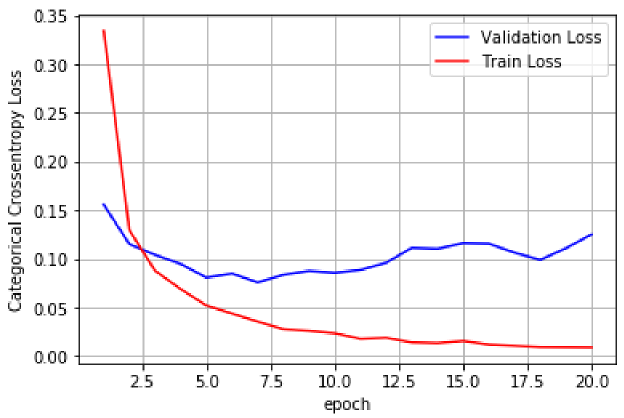
```
model3_relu.compile(optimizer = 'adam', metrics = ['accuracy'], loss = 'categorical_crossentropy')

history = model3_relu.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 [==============================] - 4s 70us/step - loss: 0.3343 - acc: 0.9039 -
val_loss: 0.1558 - val_acc: 0.9510
Epoch 2/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.1296 - acc: 0.9618 -
val_loss: 0.1152 - val_acc: 0.9641
Epoch 3/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0880 - acc: 0.9738 -
val_loss: 0.1043 - val_acc: 0.9666
Epoch 4/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0691 - acc: 0.9785 -
val_loss: 0.0949 - val_acc: 0.9707
Epoch 5/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0523 - acc: 0.9841 -
val_loss: 0.0811 - val_acc: 0.9758
Epoch 6/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0440 - acc: 0.9861 -
val_loss: 0.0851 - val_acc: 0.9750
Epoch 7/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0357 - acc: 0.9888 -
val_loss: 0.0760 - val_acc: 0.9764
Epoch 8/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0279 - acc: 0.9911 -
val_loss: 0.0839 - val_acc: 0.9762
Epoch 9/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0262 - acc: 0.9916 -
val_loss: 0.0878 - val_acc: 0.9769
Epoch 10/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0238 - acc: 0.9925 -
val_loss: 0.0859 - val_acc: 0.9781
Epoch 11/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0181 - acc: 0.9941 -
val_loss: 0.0889 - val_acc: 0.9793
Epoch 12/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0191 - acc: 0.9938 -
val_loss: 0.0961 - val_acc: 0.9778
Epoch 13/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0143 - acc: 0.9952 -
val_loss: 0.1115 - val_acc: 0.9738
Epoch 14/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0136 - acc: 0.9954 -
val_loss: 0.1105 - val_acc: 0.9755
Epoch 15/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0159 - acc: 0.9942 -
val_loss: 0.1163 - val_acc: 0.9736
Epoch 16/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0121 - acc: 0.9959 -
val_loss: 0.1157 - val_acc: 0.9753
Epoch 17/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0109 - acc: 0.9964 -
val_loss: 0.1066 - val_acc: 0.9773
Epoch 18/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0095 - acc: 0.9969 -
val_loss: 0.0991 - val_acc: 0.9792
Epoch 19/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0093 - acc: 0.9969 -
val_loss: 0.1110 - val_acc: 0.9778
Epoch 20/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0091 - acc: 0.9968 -
val_loss: 0.1252 - val_acc: 0.9748
```

In [0]:

```
score = model3_relu.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

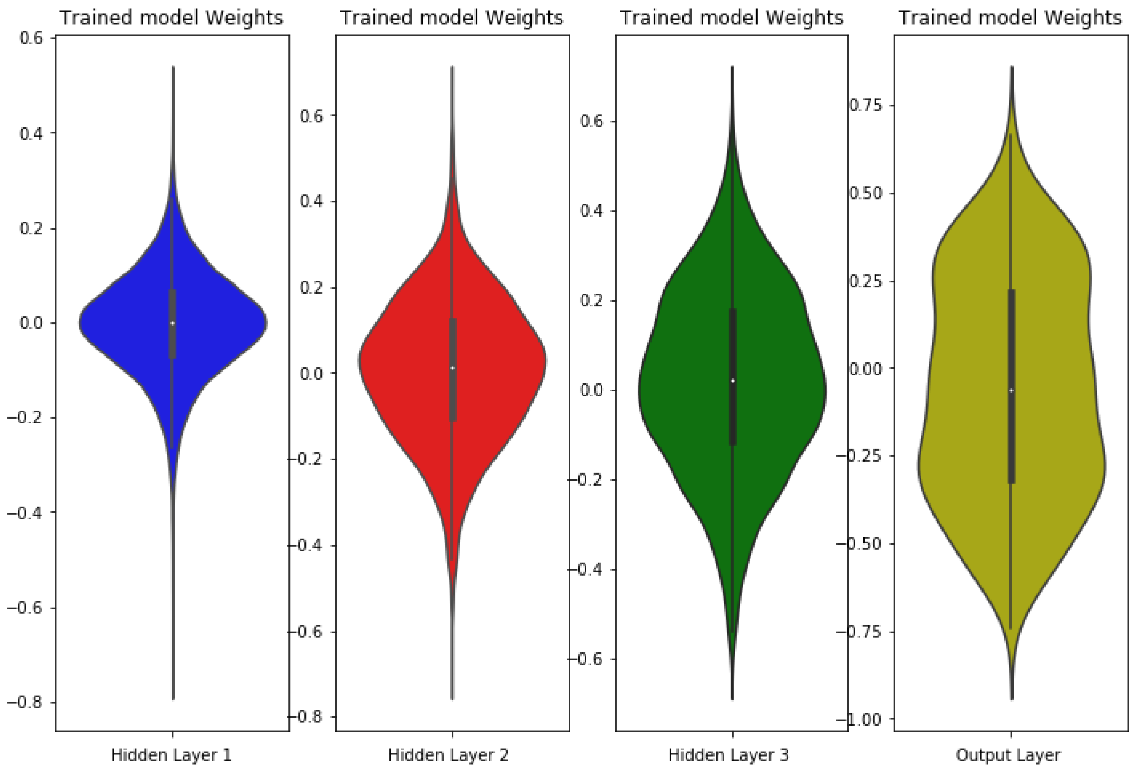
```
Test score: 0.12519279713677378
Test accuracy: 0.9748
```



In [0]:

```
%matplotlib inline
w_after = model3_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure(figsize=(12,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + BatchNorm on hidden layers + Adam

In [0]:

```
model3_relu_batchnorm = Sequential()

model3_relu_batchnorm.add(Dense(128, activation = 'relu', input_dim = input_dim,kernel_initializer=
'glorot_normal'))
model3_relu_batchnorm.add(BatchNormalization())

model3_relu_batchnorm.add(Dense(64, activation = 'relu', input_dim = input_dim,kernel_initializer=
'glorot_normal'))
model3_relu_batchnorm.add(BatchNormalization())

model3_relu_batchnorm.add(Dense(32, activation = 'relu', input_dim = input_dim,kernel_initializer=
'glorot_normal'))
model3_relu_batchnorm.add(BatchNormalization())

model3_relu_batchnorm.add(Dense(output_dim, activation = 'softmax'))

model3_relu_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_57 (Dense)             (None, 128)               100480
_________________________________________________________________
batch_normalization_11 (Batc (None, 128)               512
_________________________________________________________________
dense_58 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_12 (Batc (None, 64)                256
_________________________________________________________________
dense_59 (Dense)             (None, 32)                2080
_________________________________________________________________
batch_normalization_13 (Batc (None, 32)                128
```

```
batch_normalization_15 (Batc (None, 32)              128
_________________________________________________________________
dense_60 (Dense)             (None, 10)                330
=================================================================
Total params: 112,042
Trainable params: 111,594
Non-trainable params: 448
_________________________________________________________________
```

In [0]:

```
model3_relu_batchnorm.compile(optimizer='adam', metrics = ['accuracy'], loss =
'categorical_crossentropy')

history = model3_relu_batchnorm.fit(X_train, Y_train, batch_size = batch_size, epochs = nb_epoch, v
erbose = 1, validation_data = (X_test, Y_test))
```

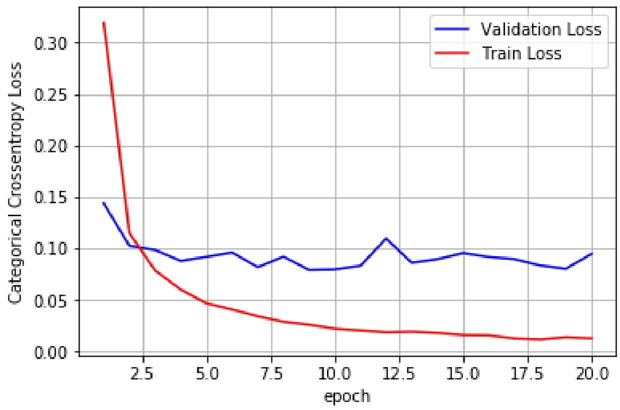
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.3190 - acc: 0.9111 -
val_loss: 0.1437 - val_acc: 0.9570
Epoch 2/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1148 - acc: 0.9657 -
val_loss: 0.1025 - val_acc: 0.9703
Epoch 3/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0787 - acc: 0.9758 -
val_loss: 0.0985 - val_acc: 0.9709
Epoch 4/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0600 - acc: 0.9815 -
val_loss: 0.0879 - val_acc: 0.9733
Epoch 5/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0467 - acc: 0.9860 -
val_loss: 0.0918 - val_acc: 0.9732
Epoch 6/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0407 - acc: 0.9868 -
val_loss: 0.0961 - val_acc: 0.9706
Epoch 7/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0342 - acc: 0.9888 -
val_loss: 0.0818 - val_acc: 0.9760
Epoch 8/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0288 - acc: 0.9907 -
val_loss: 0.0920 - val_acc: 0.9728
Epoch 9/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0260 - acc: 0.9918 -
val_loss: 0.0791 - val_acc: 0.9773
Epoch 10/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0221 - acc: 0.9929 -
val_loss: 0.0797 - val_acc: 0.9759
Epoch 11/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0203 - acc: 0.9933 -
val_loss: 0.0832 - val_acc: 0.9761
Epoch 12/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0186 - acc: 0.9941 -
val_loss: 0.1096 - val_acc: 0.9706
Epoch 13/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0192 - acc: 0.9936 -
val_loss: 0.0861 - val_acc: 0.9760
Epoch 14/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0180 - acc: 0.9939 -
val_loss: 0.0896 - val_acc: 0.9767
Epoch 15/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0159 - acc: 0.9948 -
val_loss: 0.0955 - val_acc: 0.9753
Epoch 16/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0156 - acc: 0.9946 -
val_loss: 0.0918 - val_acc: 0.9776
Epoch 17/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0126 - acc: 0.9960 -
val_loss: 0.0896 - val_acc: 0.9773
Epoch 18/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0116 - acc: 0.9960 -
val_loss: 0.0835 - val_acc: 0.9788
Epoch 19/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0138 - acc: 0.9957 -
val_loss: 0.0803 - val_acc: 0.9778
Epoch 20/20
```

```
60000/60000 [==============================] - 4s 66us/step - loss: 0.0127 - acc: 0.9955 -
val_loss: 0.0947 - val_acc: 0.9775
```

In [0]:

```
score = model3_relu_batchnorm.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

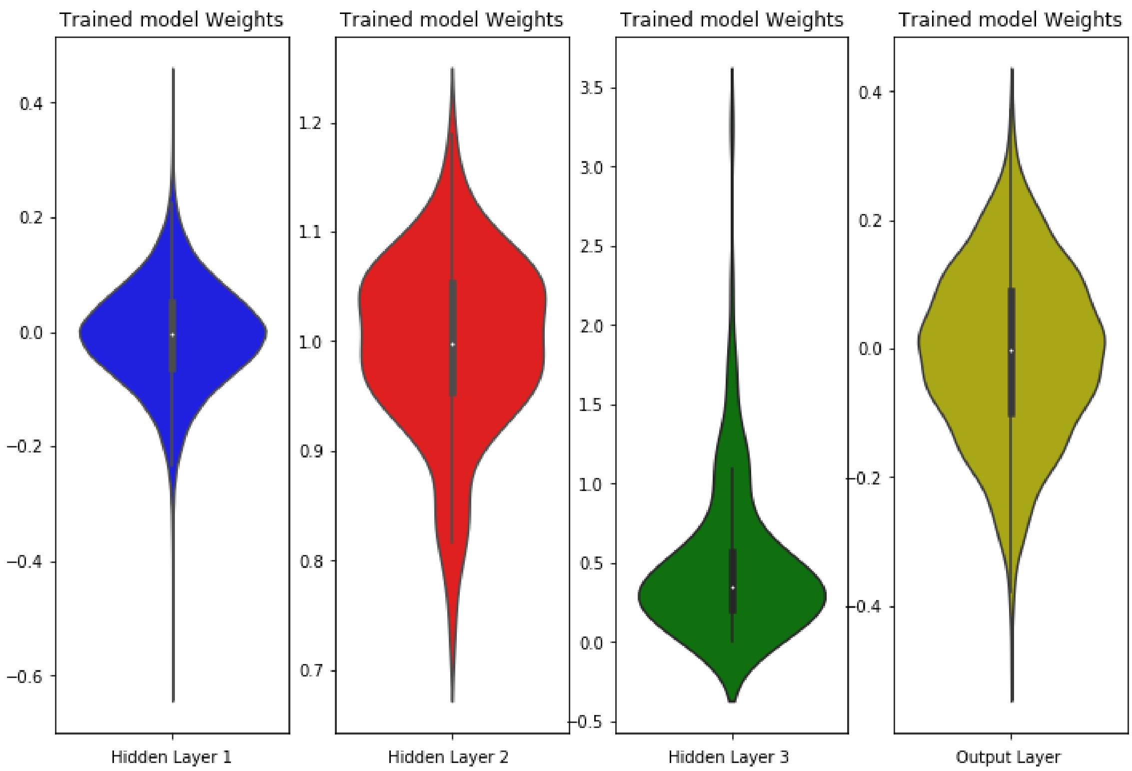
```
Test score: 0.0946673099771564
Test accuracy: 0.9775
```



In [0]:

```
%matplotlib inline
w_after = model3_relu_batchnorm.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure(figsize = (12,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
```

```
plt.subplot(1, 4, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Dropout + Batch Norm +Adam

In [0]:

```
model3_drop_batchnorm = Sequential()

model3_drop_batchnorm.add(Dense(128, activation='relu', input_shape=(input_dim,), kernel_initialize
r='random_uniform'))
model3_drop_batchnorm.add(BatchNormalization())
model3_drop_batchnorm.add(Dropout(0.5))

model3_drop_batchnorm.add(Dense(64, activation='relu', kernel_initializer='random_uniform'))
model3_drop_batchnorm.add(BatchNormalization())
model3_drop_batchnorm.add(Dropout(0.5))

model3_drop_batchnorm.add(Dense(32, activation='relu', kernel_initializer='random_uniform'))
model3_drop_batchnorm.add(BatchNormalization())
model3_drop_batchnorm.add(Dropout(0.5))

model3_drop_batchnorm.add(Dense(output_dim, activation='softmax'))


model3_drop_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_61 (Dense)             (None, 128)               100480
_________________________________________________________________
batch_normalization_14 (Batc (None, 128)               512
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
```

```
_________________________________________________________________
dense_62 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_15 (Batc (None, 64)                256       
_________________________________________________________________
dropout_8 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_63 (Dense)             (None, 32)                2080      
_________________________________________________________________
batch_normalization_16 (Batc (None, 32)                128       
_________________________________________________________________
dropout_9 (Dropout)          (None, 32)                0         
_________________________________________________________________
dense_64 (Dense)             (None, 10)                330       
=================================================================
Total params: 112,042
Trainable params: 111,594
Non-trainable params: 448
_________________________________________________________________
```

In [0]:

```
model3_drop_batchnorm.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

history = model3_drop_batchnorm.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbo
se=1, validation_data=(X_test, Y_test))
```

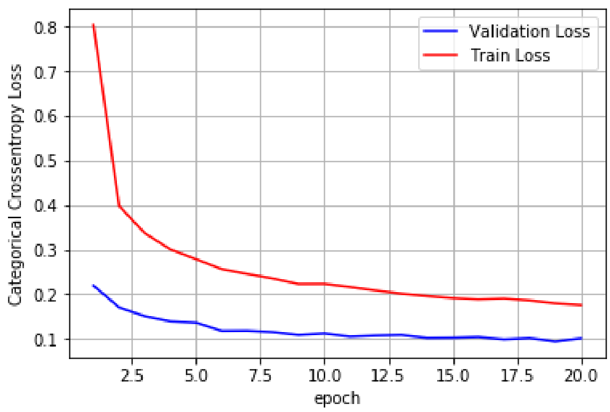
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.8041 - acc: 0.7578 -
val_loss: 0.2195 - val_acc: 0.9324
Epoch 2/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.3983 - acc: 0.8924 -
val_loss: 0.1707 - val_acc: 0.9496
Epoch 3/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.3370 - acc: 0.9115 -
val_loss: 0.1509 - val_acc: 0.9568
Epoch 4/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.3005 - acc: 0.9211 -
val_loss: 0.1393 - val_acc: 0.9594
Epoch 5/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2788 - acc: 0.9270 -
val_loss: 0.1364 - val_acc: 0.9603
Epoch 6/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2564 - acc: 0.9324 -
val_loss: 0.1178 - val_acc: 0.9664
Epoch 7/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2457 - acc: 0.9359 -
val_loss: 0.1181 - val_acc: 0.9674
Epoch 8/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2353 - acc: 0.9386 -
val_loss: 0.1151 - val_acc: 0.9688
Epoch 9/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2231 - acc: 0.9423 -
val_loss: 0.1088 - val_acc: 0.9691
Epoch 10/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2233 - acc: 0.9414 -
val_loss: 0.1122 - val_acc: 0.9682
Epoch 11/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2164 - acc: 0.9448 -
val_loss: 0.1052 - val_acc: 0.9708
Epoch 12/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2087 - acc: 0.9462 -
val_loss: 0.1076 - val_acc: 0.9706
Epoch 13/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.2013 - acc: 0.9479 -
val_loss: 0.1088 - val_acc: 0.9705
Epoch 14/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1961 - acc: 0.9497 -
val_loss: 0.1021 - val_acc: 0.9732
Epoch 15/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1914 - acc: 0.9504 -
val_loss: 0.1025 - val_acc: 0.9713
Epoch 16/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1886 - acc: 0.9512 -
```

```
val_loss: 0.1042 - val_acc: 0.9720
Epoch 17/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1904 - acc: 0.9505 -
val_loss: 0.0988 - val_acc: 0.9724
Epoch 18/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1861 - acc: 0.9517 -
val_loss: 0.1018 - val_acc: 0.9735
Epoch 19/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1797 - acc: 0.9537 -
val_loss: 0.0942 - val_acc: 0.9734
Epoch 20/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1760 - acc: 0.9551 -
val_loss: 0.1012 - val_acc: 0.9715
```

In [0]:

```
score = model3_drop_batchnorm.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

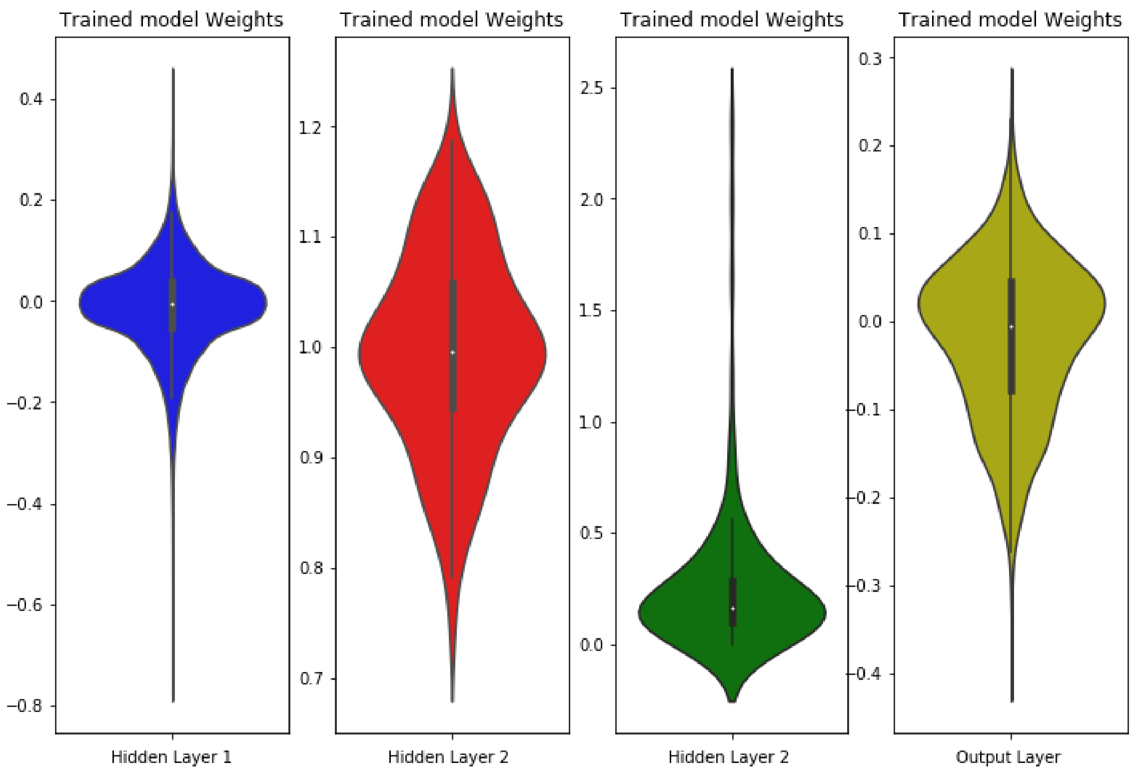
```
Test score: 0.10121105482841376
Test accuracy: 0.9715
```



In [0]:

```
%matplotlib inline
w_after = model3_drop_batchnorm.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)
```

```
fig = plt.figure(figsize= (12,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



With 5 Hidden layers

Architecture used: 784 (input) - 512 - 256 - 128 - 64 - 32 - 10 (ouput)

MLP + ReLu + Adam

In [0]:

```
model5_relu = Sequential()

model5_relu.add(Dense(512, activation = 'relu', input_dim = input_dim, kernel_initializer= 'he_norm
al'))
model5_relu.add(Dense(256, activation = 'relu', input_dim = input_dim, kernel_initializer= 'he_norm
al'))
model5_relu.add(Dense(128, activation = 'relu', input_dim = input_dim, kernel_initializer= 'he_norm
al'))
model5_relu.add(Dense(64, activation = 'relu', input_dim = input_dim, kernel_initializer= 'he_norma
l'))
model5_relu.add(Dense(32, activation = 'relu', input_dim = input_dim, kernel_initializer= 'he_norma
l'))
```

```
model5_relu.add(Dense(output_dim, activation = 'softmax'))

model5_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_65 (Dense)             (None, 512)               401920
_________________________________________________________________
dense_66 (Dense)             (None, 256)               131328
_________________________________________________________________
dense_67 (Dense)             (None, 128)               32896
_________________________________________________________________
dense_68 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_69 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_70 (Dense)             (None, 10)                330
=================================================================
Total params: 576,810
Trainable params: 576,810
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
model5_relu.compile(optimizer = 'adam', metrics = ['accuracy'], loss = 'categorical_crossentropy')

history = model5_relu.fit(X_train, Y_train, batch_size= batch_size, epochs = nb_epoch, verbose = 1,
validation_data = (X_test, Y_test))
```

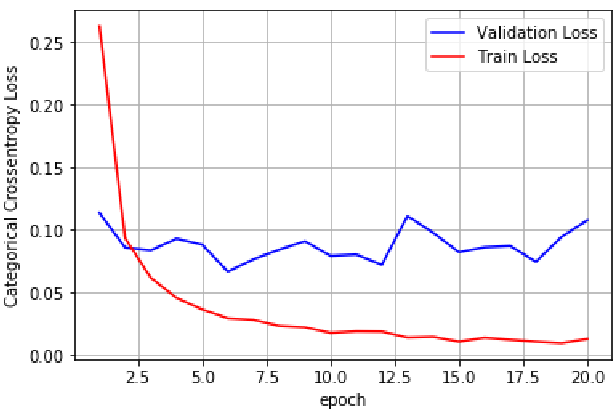
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.2628 - acc: 0.9210 -
val_loss: 0.1135 - val_acc: 0.9661
Epoch 2/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0933 - acc: 0.9716 -
val_loss: 0.0857 - val_acc: 0.9739
Epoch 3/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0617 - acc: 0.9813 -
val_loss: 0.0835 - val_acc: 0.9764
Epoch 4/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0455 - acc: 0.9856 -
val_loss: 0.0929 - val_acc: 0.9723
Epoch 5/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0364 - acc: 0.9884 -
val_loss: 0.0881 - val_acc: 0.9749
Epoch 6/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0292 - acc: 0.9904 -
val_loss: 0.0666 - val_acc: 0.9797
Epoch 7/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0279 - acc: 0.9910 -
val_loss: 0.0764 - val_acc: 0.9772
Epoch 8/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0231 - acc: 0.9926 -
val_loss: 0.0841 - val_acc: 0.9779
Epoch 9/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0220 - acc: 0.9927 -
val_loss: 0.0908 - val_acc: 0.9774
Epoch 10/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0175 - acc: 0.9941 -
val_loss: 0.0791 - val_acc: 0.9807
Epoch 11/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0188 - acc: 0.9944 -
val_loss: 0.0802 - val_acc: 0.9799
Epoch 12/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0186 - acc: 0.9941 -
val_loss: 0.0721 - val_acc: 0.9817
Epoch 13/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0137 - acc: 0.9957 -
val_loss: 0.1109 - val_acc: 0.9750
Epoch 14/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0143 - acc: 0.9956 -
val_loss: 0.0976 - val_acc: 0.9790
Epoch 15/20
```

```
60000/60000 [==============================] - 3s 45us/step - loss: 0.0105 - acc: 0.9967 -
val_loss: 0.0821 - val_acc: 0.9822
Epoch 16/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0137 - acc: 0.9955 -
val_loss: 0.0859 - val_acc: 0.9802
Epoch 17/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0120 - acc: 0.9963 -
val_loss: 0.0871 - val_acc: 0.9802
Epoch 18/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0105 - acc: 0.9966 -
val_loss: 0.0745 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0094 - acc: 0.9974 -
val_loss: 0.0943 - val_acc: 0.9819
Epoch 20/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0127 - acc: 0.9964 -
val_loss: 0.1076 - val_acc: 0.9777
```

In [0]:

```
score = model5_relu.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

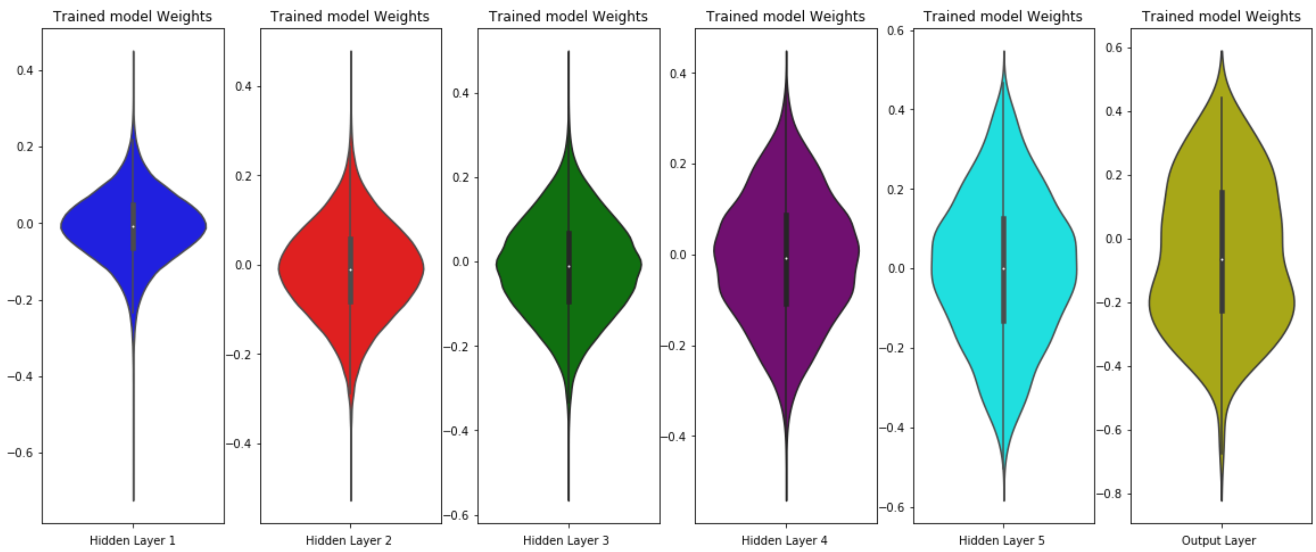
```
Test score: 0.10761469807939465
Test accuracy: 0.9777
```



In [0]:

```
%matplotlib inline
w_after = model5_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
```

```
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure(figsize=(20,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 6, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='purple')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='cyan')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(1,6, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + BatchNorm on hidden layers + Adam

In [0]:

```
model5_relu_batchnorm = Sequential()

model5_relu_batchnorm.add(Dense(512, activation = 'relu', input_dim = input_dim,kernel_initializer=
'he_uniform'))
model5_relu_batchnorm.add(BatchNormalization())


model5_relu_batchnorm.add(Dense(256, activation = 'relu', input_dim = input_dim,kernel_initializer=
'he_uniform'))
```

```
model5_relu_batchnorm.add(BatchNormalization())


model5_relu_batchnorm.add(Dense(128, activation = 'relu', input_dim = input_dim,kernel_initializer=
'he_uniform'))
model5_relu_batchnorm.add(BatchNormalization())


model5_relu_batchnorm.add(Dense(64, activation = 'relu', input_dim = input_dim,kernel_initializer=
'he_uniform'))
model5_relu_batchnorm.add(BatchNormalization())


model5_relu_batchnorm.add(Dense(32, activation = 'relu', input_dim = input_dim,kernel_initializer=
'he_uniform'))
model5_relu_batchnorm.add(BatchNormalization())


model5_relu_batchnorm.add(Dense(output_dim, activation = 'softmax'))

model5_relu_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_71 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_17 (Batc (None, 512)               2048      
_________________________________________________________________
dense_72 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_18 (Batc (None, 256)               1024      
_________________________________________________________________
dense_73 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_19 (Batc (None, 128)               512       
_________________________________________________________________
dense_74 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_20 (Batc (None, 64)                256       
_________________________________________________________________
dense_75 (Dense)             (None, 32)                2080      
_________________________________________________________________
batch_normalization_21 (Batc (None, 32)                128       
_________________________________________________________________
dense_76 (Dense)             (None, 10)                330       
=================================================================
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

In [0]:

```
model5_relu_batchnorm.compile(optimizer='adam', metrics = ['accuracy'], loss =
'categorical_crossentropy')

history = model5_relu_batchnorm.fit(X_train, Y_train, batch_size = batch_size, epochs = nb_epoch, v
erbose = 1, validation_data = (X_test, Y_test))
```

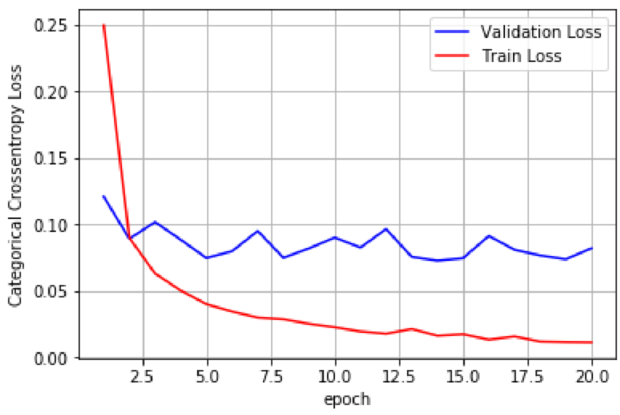
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 141us/step - loss: 0.2496 - acc: 0.9307 -
val_loss: 0.1209 - val_acc: 0.9630
Epoch 2/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0899 - acc: 0.9733 -
val_loss: 0.0893 - val_acc: 0.9713
Epoch 3/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0632 - acc: 0.9800 -
val_loss: 0.1019 - val_acc: 0.9704
Epoch 4/20
60000/60000 [==============================] - 5s 92us/step - loss: 0.0504 - acc: 0.9842 -
val_loss: 0.0886 - val_acc: 0.9735
Epoch 5/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0402 - acc: 0.9878 -
```

```
val_loss: 0.0748 - val_acc: 0.9773
Epoch 6/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0346 - acc: 0.9883 -
val_loss: 0.0799 - val_acc: 0.9766
Epoch 7/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0301 - acc: 0.9900 -
val_loss: 0.0952 - val_acc: 0.9731
Epoch 8/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0289 - acc: 0.9905 -
val_loss: 0.0750 - val_acc: 0.9791
Epoch 9/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0254 - acc: 0.9920 -
val_loss: 0.0821 - val_acc: 0.9775
Epoch 10/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0229 - acc: 0.9932 -
val_loss: 0.0902 - val_acc: 0.9749
Epoch 11/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0197 - acc: 0.9936 -
val_loss: 0.0827 - val_acc: 0.9805
Epoch 12/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0180 - acc: 0.9940 -
val_loss: 0.0966 - val_acc: 0.9747
Epoch 13/20
60000/60000 [==============================] - 5s 92us/step - loss: 0.0215 - acc: 0.9931 -
val_loss: 0.0757 - val_acc: 0.9812
Epoch 14/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.0164 - acc: 0.9944 -
val_loss: 0.0729 - val_acc: 0.9807
Epoch 15/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.0176 - acc: 0.9940 -
val_loss: 0.0747 - val_acc: 0.9817
Epoch 16/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0135 - acc: 0.9953 -
val_loss: 0.0915 - val_acc: 0.9787
Epoch 17/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0159 - acc: 0.9946 -
val_loss: 0.0810 - val_acc: 0.9803
Epoch 18/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0121 - acc: 0.9958 -
val_loss: 0.0768 - val_acc: 0.9810
Epoch 19/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0117 - acc: 0.9963 -
val_loss: 0.0740 - val_acc: 0.9815
Epoch 20/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0115 - acc: 0.9961 -
val_loss: 0.0821 - val_acc: 0.9810
```

In [0]:

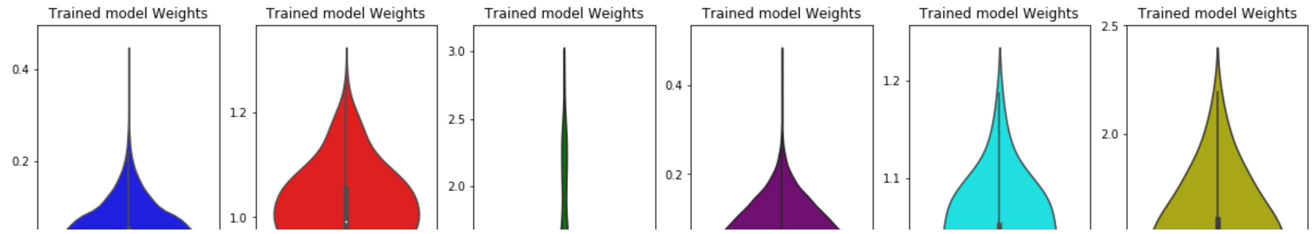
```
score = model5_relu_batchnorm.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# 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, va
lidation_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(x, vy, ty, ax)
```

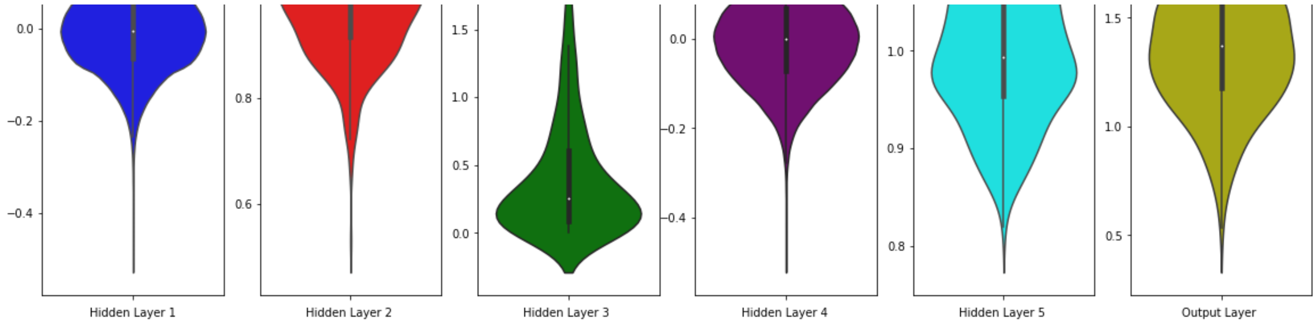
```
Test score: 0.08212392491589125
Test accuracy: 0.981
```



In [0]:

```python
%matplotlib inline
w_after = model5_relu_batchnorm.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure(figsize=(20,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 6, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='purple')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='cyan')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(1,6, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```





MLP + Dropout + Batch Norm +Adam

In [0]:

```
model5_drop_batchnorm = Sequential()

model5_drop_batchnorm.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initialize
r='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(256, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(128, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(64, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(32, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(output_dim, activation='softmax'))

model5_drop_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_77 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_22 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_10 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_78 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_23 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_11 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_79 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_24 (Batc (None, 128)               512       
_________________________________________________________________
dropout_12 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_80 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_25 (Batc (None, 64)                256       
_________________________________________________________________
dropout_13 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_81 (Dense)             (None, 32)                2080      
_________________________________________________________________
batch_normalization_26 (Batc (None, 32)                128       
```

```
_________________________________________________________________
dropout_14 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_82 (Dense)             (None, 10)                330
=================================================================
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

In [0]:

```
model5_drop_batchnorm.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

history = model5_drop_batchnorm.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbo
se=1, validation_data=(X_test, Y_test))
```

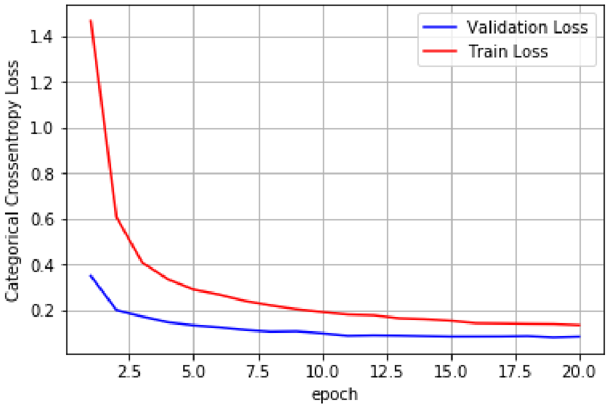
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 148us/step - loss: 1.4684 - acc: 0.5186 -
val_loss: 0.3500 - val_acc: 0.9124
Epoch 2/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.6071 - acc: 0.8267 -
val_loss: 0.1998 - val_acc: 0.9451
Epoch 3/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.4087 - acc: 0.8955 -
val_loss: 0.1712 - val_acc: 0.9553
Epoch 4/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.3354 - acc: 0.9188 -
val_loss: 0.1467 - val_acc: 0.9635
Epoch 5/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.2902 - acc: 0.9311 -
val_loss: 0.1325 - val_acc: 0.9671
Epoch 6/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.2676 - acc: 0.9374 -
val_loss: 0.1239 - val_acc: 0.9691
Epoch 7/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.2399 - acc: 0.9430 -
val_loss: 0.1128 - val_acc: 0.9720
Epoch 8/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.2205 - acc: 0.9496 -
val_loss: 0.1050 - val_acc: 0.9735
Epoch 9/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.2037 - acc: 0.9531 -
val_loss: 0.1067 - val_acc: 0.9737
Epoch 10/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1914 - acc: 0.9560 -
val_loss: 0.0976 - val_acc: 0.9774
Epoch 11/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1806 - acc: 0.9585 -
val_loss: 0.0867 - val_acc: 0.9781
Epoch 12/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1772 - acc: 0.9602 -
val_loss: 0.0888 - val_acc: 0.9781
Epoch 13/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1635 - acc: 0.9637 -
val_loss: 0.0875 - val_acc: 0.9799
Epoch 14/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1598 - acc: 0.9634 -
val_loss: 0.0852 - val_acc: 0.9789
Epoch 15/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1533 - acc: 0.9658 -
val_loss: 0.0832 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1423 - acc: 0.9678 -
val_loss: 0.0834 - val_acc: 0.9797
Epoch 17/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1411 - acc: 0.9689 -
val_loss: 0.0837 - val_acc: 0.9807
Epoch 18/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1394 - acc: 0.9690 -
val_loss: 0.0854 - val_acc: 0.9805
Epoch 19/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.1385 - acc: 0.9687 -
val_loss: 0.0796 - val_acc: 0.9806
```

```
Epoch 20/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1336 - acc: 0.9707 - val_loss: 0.0829 - val_acc: 0.9800
```

In [0]:

```python
score = model5_drop_batchnorm.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))

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

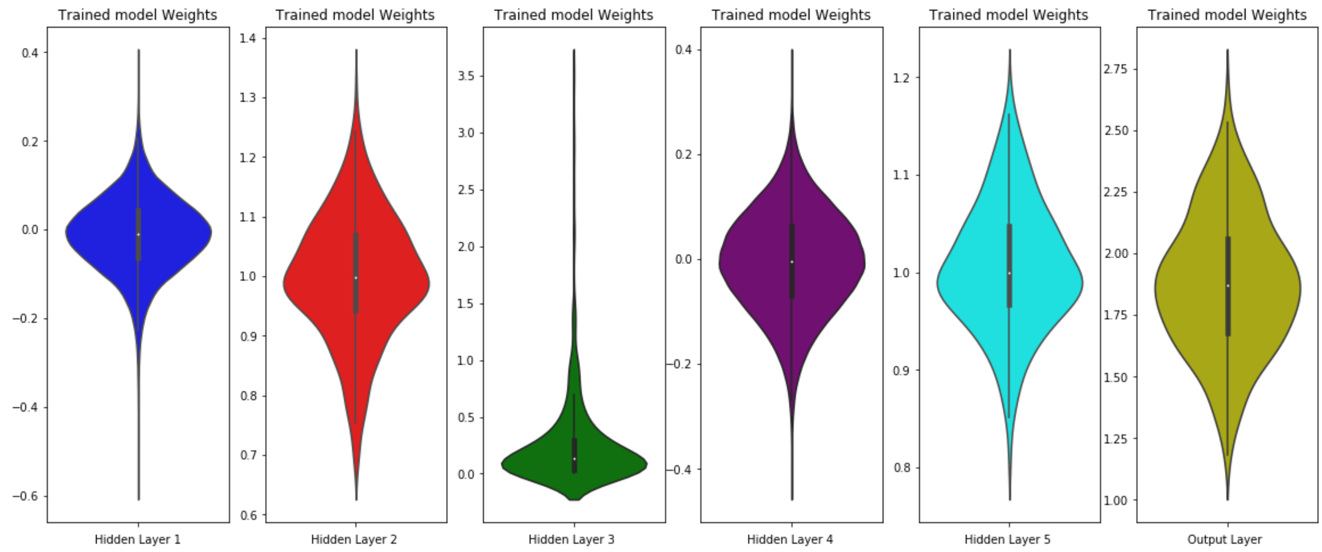
```
Test score: 0.08293465451768134
Test accuracy: 0.98
```



In [0]:

```python
%matplotlib inline
w_after = model5_drop_batchnorm.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure(figsize=(20,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 6, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 6, 2)
```

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

plt.subplot(1, 6, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='purple')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='cyan')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(1,6, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + ReLu + RMSprop

In [0]:

```
model2_relu = Sequential()

model2_relu.add(Dense(256, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_
uniform'))
model2_relu.add(Dense(64, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_u
niform'))
model2_relu.add(Dense(output_dim, activation = 'softmax'))

model2_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_83 (Dense)             (None, 256)               200960    
_________________________________________________________________
dense_84 (Dense)             (None, 64)                16448     
_________________________________________________________________
dense_85 (Dense)             (None, 10)                650       
=================================================================
Total params: 218,058
Trainable params: 218,058
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
model2_relu.compile(optimizer = 'RMSprop', metrics = ['accuracy'], loss =
'categorical_crossentropy')

history = model2_relu.fit(X_train, Y_train, batch_size= batch_size, epochs = nb_epoch, verbose = 1,
validation_data = (X_test, Y_test))
```

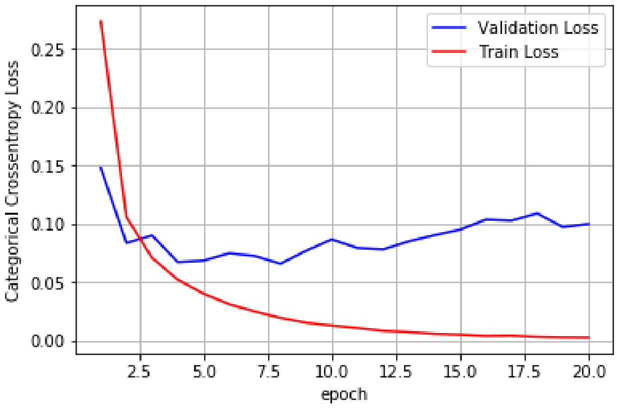
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.2732 - acc: 0.9207 -
val_loss: 0.1480 - val_acc: 0.9533
Epoch 2/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.1059 - acc: 0.9677 -
val_loss: 0.0837 - val_acc: 0.9752
Epoch 3/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0710 - acc: 0.9784 -
val_loss: 0.0902 - val_acc: 0.9718
Epoch 4/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0524 - acc: 0.9839 -
val_loss: 0.0674 - val_acc: 0.9795
Epoch 5/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0405 - acc: 0.9877 -
val_loss: 0.0686 - val_acc: 0.9796
Epoch 6/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0314 - acc: 0.9904 -
val_loss: 0.0749 - val_acc: 0.9791
Epoch 7/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0252 - acc: 0.9919 -
val_loss: 0.0726 - val_acc: 0.9797
Epoch 8/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0197 - acc: 0.9940 -
val_loss: 0.0660 - val_acc: 0.9829
Epoch 9/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0156 - acc: 0.9949 -
val_loss: 0.0771 - val_acc: 0.9818
Epoch 10/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0131 - acc: 0.9960 -
val_loss: 0.0868 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0110 - acc: 0.9966 -
val_loss: 0.0794 - val_acc: 0.9827
Epoch 12/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0087 - acc: 0.9973 -
val_loss: 0.0782 - val_acc: 0.9819
Epoch 13/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0076 - acc: 0.9977 -
val_loss: 0.0851 - val_acc: 0.9805
Epoch 14/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0060 - acc: 0.9979 -
val_loss: 0.0904 - val_acc: 0.9815
Epoch 15/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0053 - acc: 0.9983 -
val_loss: 0.0951 - val_acc: 0.9808
Epoch 16/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0042 - acc: 0.9987 -
val_loss: 0.1038 - val_acc: 0.9804
Epoch 17/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0045 - acc: 0.9984 -
val_loss: 0.1029 - val_acc: 0.9820
Epoch 18/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0034 - acc: 0.9990 -
val_loss: 0.1090 - val_acc: 0.9808
Epoch 19/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0029 - acc: 0.9991 -
val_loss: 0.0974 - val_acc: 0.9824
Epoch 20/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0028 - acc: 0.9992 -
val_loss: 0.0999 - val_acc: 0.9833
```

In [0]:

```
score = model2_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
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))

# 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, va
lidation_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(x, vy, ty, ax)
```

```
Test score: 0.0998641132327826
Test accuracy: 0.9833
```



In [0]:

```
%matplotlib inline
w_after = model2_relu.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(figsize=(12,8))
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()
```

MLP + ReLu + Adadelta

In [0]:

```
model3_relu = Sequential()

model3_relu.add(Dense(128, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(64, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(32, activation = 'relu', input_dim = input_dim, kernel_initializer= 'glorot_normal'))
model3_relu.add(Dense(output_dim, activation = 'softmax'))

model3_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_86 (Dense)             (None, 128)               100480    
_________________________________________________________________
dense_87 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_88 (Dense)             (None, 32)                2080      
_________________________________________________________________
dense_89 (Dense)             (None, 10)                330       
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
model3_relu.compile(optimizer = 'Adadelta', metrics = ['accuracy'], loss = 'categorical_crossentropy')

history = model3_relu.fit(X_train, Y_train, batch_size= batch_size, epochs = nb_epoch, verbose = 1, validation_data = (X_test, Y_test))
```

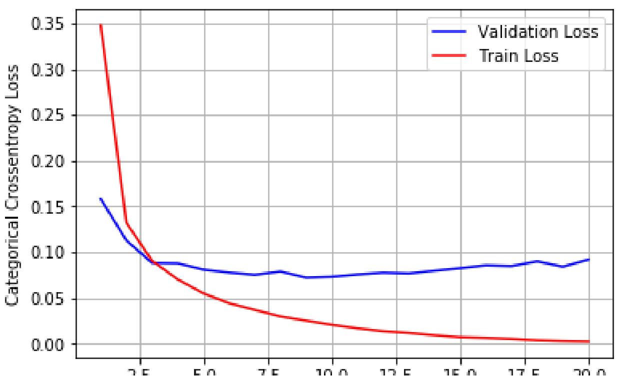
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.3476 - acc: 0.8968 - val_loss: 0.1580 - val_acc: 0.9529
Epoch 2/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.1320 - acc: 0.9609 - val_loss: 0.1127 - val_acc: 0.9636
Epoch 3/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0906 - acc: 0.9723 - val_loss: 0.0882 - val_acc: 0.9725
Epoch 4/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0702 - acc: 0.9783 - val_loss: 0.0878 - val_acc: 0.9737
Epoch 5/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0550 - acc: 0.9834 - val_loss: 0.0809 - val_acc: 0.9742
Epoch 6/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0442 - acc: 0.9864 - val_loss: 0.0777 - val_acc: 0.9772
Epoch 7/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0369 - acc: 0.9885 - val_loss: 0.0752 - val_acc: 0.9767
Epoch 8/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0297 - acc: 0.9915 - val_loss: 0.0788 - val_acc: 0.9774
Epoch 9/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0251 - acc: 0.9928 - val_loss: 0.0721 - val_acc: 0.9779
Epoch 10/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0206 - acc: 0.9937 - val_loss: 0.0731 - val_acc: 0.9775
Epoch 11/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0168 - acc: 0.9952 - val_loss: 0.0755 - val_acc: 0.9771
```

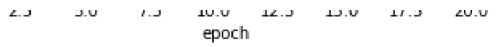
```
Epoch 12/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0136 - acc: 0.9959 -
val_loss: 0.0775 - val_acc: 0.9786
Epoch 13/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0117 - acc: 0.9966 -
val_loss: 0.0767 - val_acc: 0.9790
Epoch 14/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0092 - acc: 0.9974 -
val_loss: 0.0797 - val_acc: 0.9785
Epoch 15/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0070 - acc: 0.9983 -
val_loss: 0.0825 - val_acc: 0.9801
Epoch 16/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0062 - acc: 0.9983 -
val_loss: 0.0856 - val_acc: 0.9781
Epoch 17/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0051 - acc: 0.9987 -
val_loss: 0.0847 - val_acc: 0.9793
Epoch 18/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0036 - acc: 0.9992 -
val_loss: 0.0899 - val_acc: 0.9799
Epoch 19/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0028 - acc: 0.9994 -
val_loss: 0.0841 - val_acc: 0.9806
Epoch 20/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0023 - acc: 0.9996 -
val_loss: 0.0918 - val_acc: 0.9791
```

In [0]:

```
score = model3_relu.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

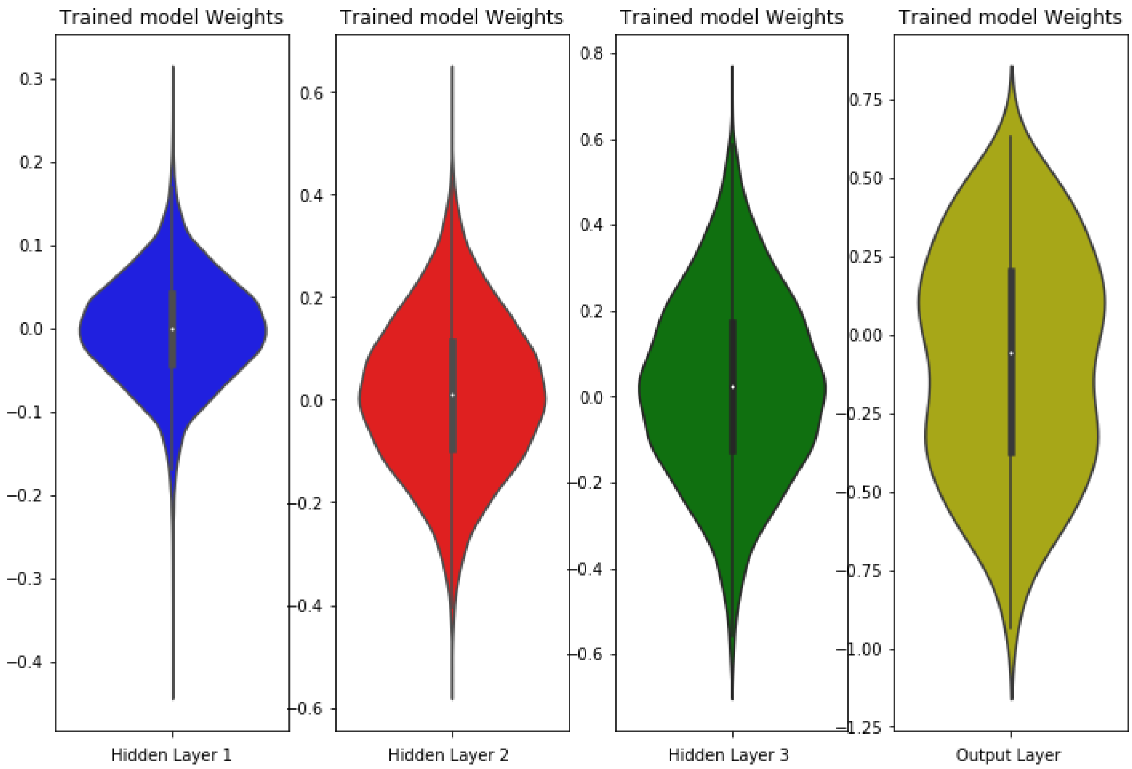
```
Test score: 0.09183809580091215
Test accuracy: 0.9791
```





In [0]:

```
%matplotlib inline
w_after = model3_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure(figsize=(12,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Dropout + Batch Norm + Nadam

In [0]:

```
model5_drop_batchnorm = Sequential()

model5_drop_batchnorm.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initialize
r='he_normal'))
```

```
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(256, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(128, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(64, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(32, activation='relu', kernel_initializer='he_normal'))
model5_drop_batchnorm.add(BatchNormalization())
model5_drop_batchnorm.add(Dropout(0.5))

model5_drop_batchnorm.add(Dense(output_dim, activation='softmax'))

model5_drop_batchnorm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_90 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_27 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_15 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_91 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_28 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_16 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_92 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_29 (Batc (None, 128)               512       
_________________________________________________________________
dropout_17 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_93 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_30 (Batc (None, 64)                256       
_________________________________________________________________
dropout_18 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_94 (Dense)             (None, 32)                2080      
_________________________________________________________________
batch_normalization_31 (Batc (None, 32)                128       
_________________________________________________________________
dropout_19 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_95 (Dense)             (None, 10)                330       
=================================================================
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

In [0]:

```
model5_drop_batchnorm.compile(optimizer='Nadam', loss='categorical_crossentropy',
metrics=['accuracy'])

history = model5_drop_batchnorm.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbo
se=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 165us/step - loss: 1.1588 - acc: 0.6263 - val_l
```

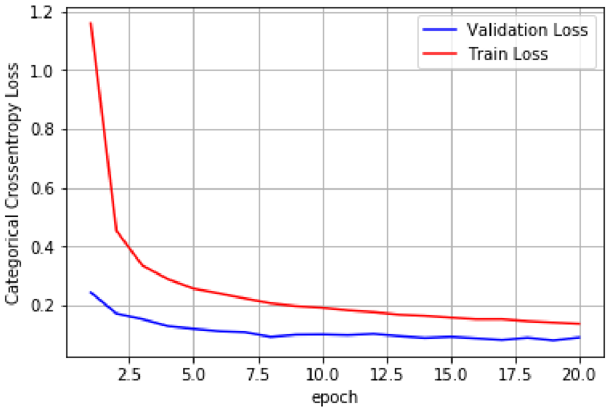
```
oss: 0.2429 - val_acc: 0.9330
Epoch 2/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.4527 - acc: 0.8792 -
val_loss: 0.1712 - val_acc: 0.9536
Epoch 3/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.3354 - acc: 0.9165 -
val_loss: 0.1522 - val_acc: 0.9614
Epoch 4/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.2882 - acc: 0.9307 -
val_loss: 0.1282 - val_acc: 0.9681
Epoch 5/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.2559 - acc: 0.9388 -
val_loss: 0.1190 - val_acc: 0.9695
Epoch 6/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2396 - acc: 0.9440 -
val_loss: 0.1110 - val_acc: 0.9722
Epoch 7/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2223 - acc: 0.9491 -
val_loss: 0.1076 - val_acc: 0.9728
Epoch 8/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2062 - acc: 0.9520 -
val_loss: 0.0915 - val_acc: 0.9773
Epoch 9/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1964 - acc: 0.9535 -
val_loss: 0.0991 - val_acc: 0.9764
Epoch 10/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.1910 - acc: 0.9563 -
val_loss: 0.0998 - val_acc: 0.9762
Epoch 11/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.1822 - acc: 0.9580 -
val_loss: 0.0976 - val_acc: 0.9763
Epoch 12/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.1761 - acc: 0.9604 -
val_loss: 0.1017 - val_acc: 0.9757
Epoch 13/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1674 - acc: 0.9618 -
val_loss: 0.0943 - val_acc: 0.9779
Epoch 14/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1635 - acc: 0.9628 -
val_loss: 0.0880 - val_acc: 0.9788
Epoch 15/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1574 - acc: 0.9642 -
val_loss: 0.0919 - val_acc: 0.9793
Epoch 16/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1518 - acc: 0.9645 -
val_loss: 0.0866 - val_acc: 0.9791
Epoch 17/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1520 - acc: 0.9664 -
val_loss: 0.0812 - val_acc: 0.9808
Epoch 18/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1449 - acc: 0.9671 -
val_loss: 0.0888 - val_acc: 0.9801
Epoch 19/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1405 - acc: 0.9681 -
val_loss: 0.0797 - val_acc: 0.9820
Epoch 20/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1364 - acc: 0.9680 -
val_loss: 0.0895 - val_acc: 0.9794
```

In [0]:

```
score = model5_drop_batchnorm.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))

# 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, va
lidation_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(x, vy, ty, ax)
```

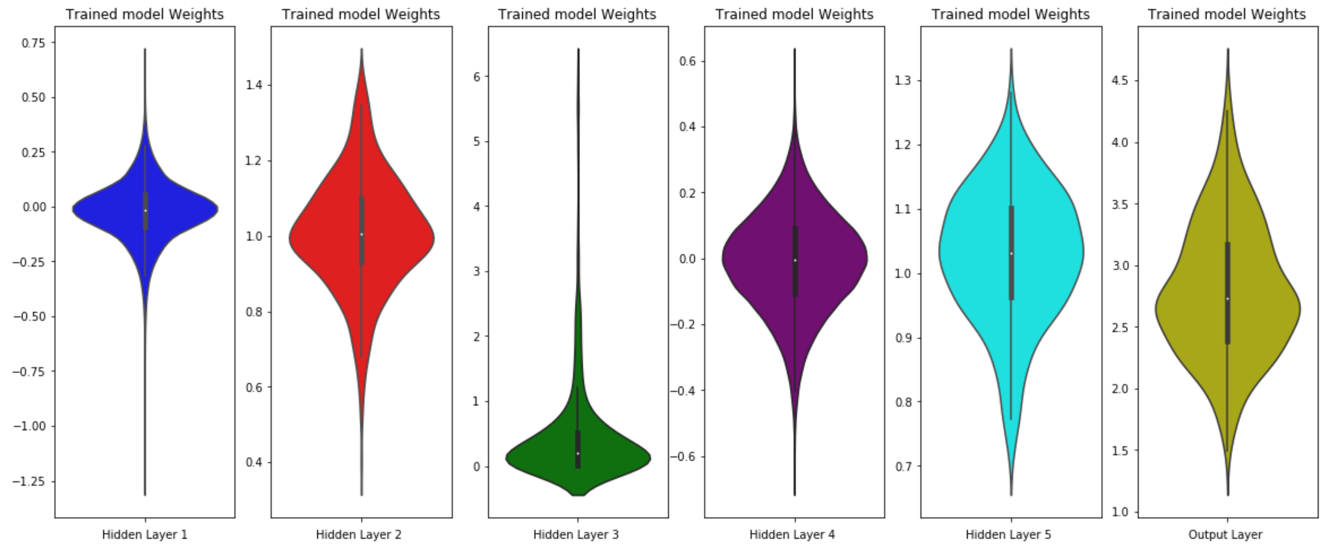
```
Test score: 0.08949376999950036
Test accuracy: 0.9794
```



In [0]:

```
%matplotlib inline
w_after = model5_drop_batchnorm.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure(figsize=(20,8))
plt.title("Weight matrices after model trained")
plt.subplot(1, 6, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='purple')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='cyan')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(1,6, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
```

```
plt.xlabel('Output Layer ')
plt.show()
```



Summary:

1. Experiemented different MLP architectures on the MNIST dataset:
   - 2 hidden layers - 784 (input) - 256 - 64 - 10 (ouput)
   - 3 hidden layers - 784 (input) - 128 - 64 - 32- 10 (output)
   - 5 hidden layers - 784 (input) - 512 - 256 - 128 - 64 - 32 - 10 (output)

1. Initialized diffferent weight vectors using:

   - glorot-normal
   - glorot-uniform
   - he-normal
   - he-uniform
   - random_normal
   - random_uniform
2. For every architecture, plotted epoch vs loss for training and validation data.
3. For sanity check, plotted violin plots of weights after training the model.
4. Also, performed batch normalization and dropout and it resulted in increase in the accuracy.
5. Conducted a comparison to see what performs better: normbatch before dropout vs dropout before normbatch. Found out dropout before normbatch performed slightly better by looking at the test accuracy.

In [4]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["No. of layers", "Architecture", "MLP type", "Optimizer", "Test Score", "Test Accu
racy"]

x.add_row([2, '784-256-64-10', "MLP + ReLu + Adam", "Adam" , 0.09701326997896285, 0.9795])
x.add_row([2, '784-256-64-10', "MLP + BatchNorm on hidden layers + Adam","Adam",
0.0820598181706071, 0.9799])
x.add_row([2, '784-256-64-10',"MLP + Batch Norm + Dropout + Adam", "Adam", 0.0703403844089189,
0.9796])
x.add_row([2, '784-256-64-10',"MLP + Dropout + Batch Norm +Adam", "Adam",0.06499798040131573,
0.9817])


x.add_row([3, '784-128-64-32-10',"MLP + ReLu + Adam", "Adam", 0.10691093345177942, 0.9765])
x.add_row([3, '784-128-64-32-10',"MLP + BatchNorm on hidden layers + Adam", "Adam",
0.11158925297728202, 0.9762])
x.add_row([3, '784-128-64-32-10',"MLP + Dropout + Batch Norm +Adam","Adam", 0.09398230195709038,
0.9758])

x.add_row([5, '784-512-256-128-64-32-10',"MLP + ReLu + Adam", "Adam" ,0.09024974172847265,0.9824])
x.add_row([5, '784-512-256-128-64-32-10',"MLP + BatchNorm on hidden layers + Adam", "Adam",
```

```
0.08782999148442759, 0.9791])
x.add_row([5, '784-512-256-128-64-32-10',"MLP + Dropout + Batch Norm +Adam", "Adam" ,
0.07287385137048549, 0.9845])


# models with different optimizers
x.add_row([2, '784-256-64-10',"MLP + ReLu + RMSprop", "RMSprop",0.0998641132327826, 0.9833])
x.add_row([3, '784-128-64-32-10',"MLP + ReLu + Adadelta", "Adadelta", 0.09183809580091215,
0.9791])
x.add_row([5, '784-512-256-128-64-32-10',"MLP + Dropout + Batch Norm + Nadam", "Nadam" ,
0.08949376999950036, 0.9794])

print(x)
```

```
+----------------+--------------------------+------------------------------------------+-----------+-
-----------------+---------------+
| No. of layers |       Architecture       |                 MLP type                 | Optimizer |
Test Score      | Test Accuracy |
+----------------+--------------------------+------------------------------------------+-----------+-
-----------------+---------------+
|       2        |      784-256-64-10       |            MLP + ReLu + Adam             |    Adam   |
.09701326997896285 |     0.9795    |
|       2        |      784-256-64-10       | MLP + BatchNorm on hidden layers + Adam |    Adam   |
0.0820598181706071 |     0.9799    |
|       2        |      784-256-64-10       |    MLP + Batch Norm + Dropout + Adam    |    Adam   |
0.0703403844089189 |     0.9796    |
|       2        |      784-256-64-10       |     MLP + Dropout + Batch Norm +Adam    |    Adam   |
.06499798040131573 |     0.9817    |
|       3        |     784-128-64-32-10     |            MLP + ReLu + Adam             |    Adam   |
.10691093345177942 |     0.9765    |
|       3        |     784-128-64-32-10     | MLP + BatchNorm on hidden layers + Adam |    Adam   |
0.11158925297728202 |     0.9762    |
|       3        |     784-128-64-32-10     |     MLP + Dropout + Batch Norm +Adam    |    Adam   |
.09398230195709038 |     0.9758    |
|       5        | 784-512-256-128-64-32-10 |            MLP + ReLu + Adam             |    Adam   |
.09024974172847265 |     0.9824    |
|       5        | 784-512-256-128-64-32-10 | MLP + BatchNorm on hidden layers + Adam |    Adam   |
0.08782999148442759 |     0.9791    |
|       5        | 784-512-256-128-64-32-10 |     MLP + Dropout + Batch Norm +Adam    |    Adam   |
0.07287385137048549 |     0.9845    |
|       2        |      784-256-64-10       |           MLP + ReLu + RMSprop           |  RMSprop  |
0.0998641132327826 |     0.9833    |
|       3        |     784-128-64-32-10     |          MLP + ReLu + Adadelta           |  Adadelta |
.09183809580091215 |     0.9791    |
|       5        | 784-512-256-128-64-32-10 |    MLP + Dropout + Batch Norm + Nadam   |   Nadam   |
0.08949376999950036 |     0.9794    |
+----------------+--------------------------+------------------------------------------+-----------+-
-----------------+---------------+
```