Keras -- MLPs on MNIST

In [0]:
```
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflo
w" use this command
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal  #or xaiver/Hae normilization

# Importing libraries
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import time
```

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()'''

# this function is used draw Categorical Crossentropy Loss VS No. of epochs pl
ot
def plt_dynamic(x, vy, ty):
  plt.figure(figsize=(10,5))
  plt.plot(x, vy, 'b', label="Validation Loss")
  plt.plot(x, ty, 'r', label="Train Loss")
  plt.xlabel('Epochs')
  plt.ylabel('Categorical Crossentropy Loss')
  plt.title('\nCategorical Crossentropy Loss VS Epochs')
  plt.legend()
  plt.grid()
  plt.show()
```

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]:
```python
# An example data point
#pixel value near to 255 is black and near to 0 is white. in middel is gray
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
   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 th
e 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.         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.         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.         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) #one hot incoding
Y_test = np_utils.to_categorical(y_test, 10)#one hot incoding

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.]
```

Simple Softmax classifier with optimizer='sgd'

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 th
e 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, ac
tivity_regularizer=None,
# kernel_constraint=None, bias_constraint=None)

# Dense implements the operation: output = activation(dot(input, kernel) + bia
s) 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 T
rue).

# 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 a
ctivation argument supported 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]

batch_size = 128
nb_epoch = 20
```

In [0]:
```
# start building a model
model = Sequential()#output of one model goe to input to second model

# 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 inferen
ce)
# 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'))
```

In [0]:
```
# Before training a model, you need to configure the learning process, which i
s done via the compile 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=['accuracy'].  https://keras.io/metrics/


# Note: when using the categorical_crossentropy loss, your targets should be i
n categorical format
# (e.g. if you have 10 classes, the target for each sample should be a 10-dime
nsional 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=['accu
racy'])

# 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=No
ne, validation_split=0.0,
# validation_data=None, shuffle=True, class_weight=None, sample_weight=None, i
nitial_epoch=0, steps_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 tr
aining loss values and
# metrics values at successive epochs, as well as validation loss values and v
alidation metrics values (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))
```

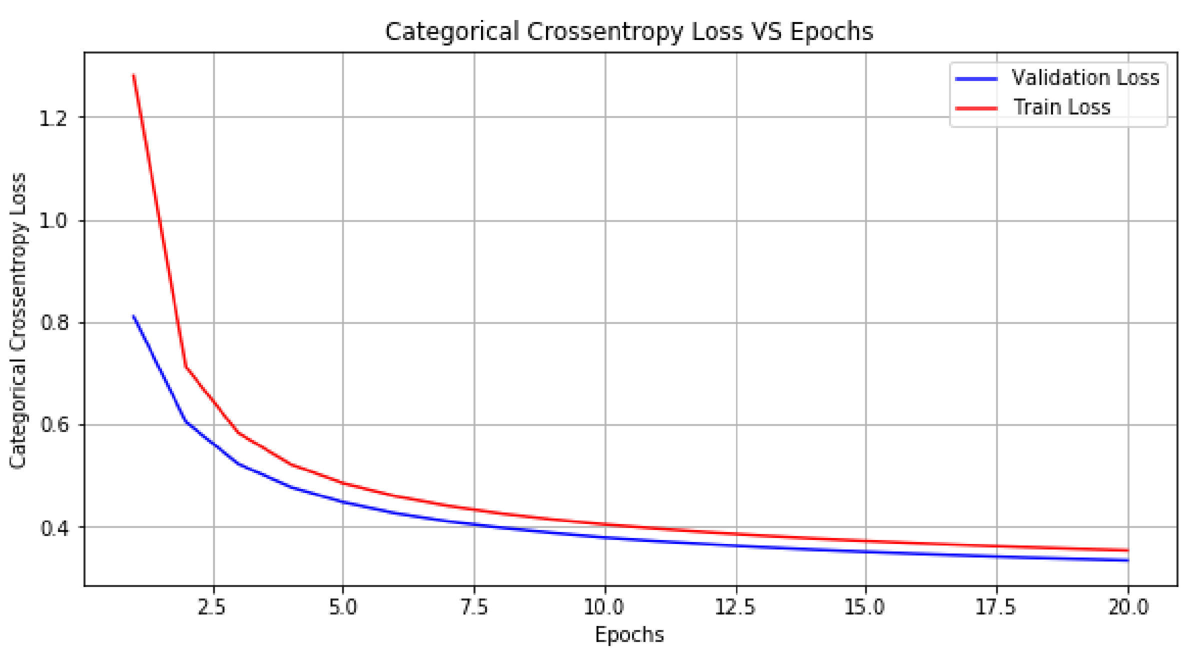
```
W0623 18:21:52.679665 140469971335040 deprecation_wrapper.py:119] From /usr/l
ocal/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.O
ptimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0623 18:21:52.716533 140469971335040 deprecation_wrapper.py:119] From /usr/l
ocal/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3295: Th
e name tf.log is deprecated. Please use tf.math.log instead.

W0623 18:21:52.828167 140469971335040 deprecation.py:323] From /usr/local/li
b/python3.6/dist-packages/tensorflow/python/ops/math_grad.py:1250: add_dispat
ch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is depreca
ted 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
W0623 18:21:52.872838 140469971335040 deprecation_wrapper.py:119] From /usr/l
ocal/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 [==============================] - 5s 82us/step - loss: 1.2807 -
acc: 0.7030 - val_loss: 0.8106 - val_acc: 0.8351
Epoch 2/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.7120 -
acc: 0.8460 - val_loss: 0.6045 - val_acc: 0.8635
Epoch 3/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.5833 -
acc: 0.8628 - val_loss: 0.5229 - val_acc: 0.8749
Epoch 4/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.5223 -
acc: 0.8710 - val_loss: 0.4777 - val_acc: 0.8816
Epoch 5/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.4852 -
acc: 0.8765 - val_loss: 0.4482 - val_acc: 0.8867
Epoch 6/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.4599 -
acc: 0.8813 - val_loss: 0.4267 - val_acc: 0.8901
Epoch 7/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.4410 -
acc: 0.8845 - val_loss: 0.4108 - val_acc: 0.8916
Epoch 8/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.4264 -
acc: 0.8873 - val_loss: 0.3983 - val_acc: 0.8955
Epoch 9/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.4145 -
acc: 0.8895 - val_loss: 0.3883 - val_acc: 0.8973
Epoch 10/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.4046 -
acc: 0.8911 - val_loss: 0.3792 - val_acc: 0.8997
Epoch 11/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3964 -
acc: 0.8930 - val_loss: 0.3721 - val_acc: 0.9011
Epoch 12/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.3892 -
acc: 0.8950 - val_loss: 0.3659 - val_acc: 0.9026
Epoch 13/20
60000/60000 [==============================] - 1s 24us/step - loss: 0.3829 -
acc: 0.8959 - val_loss: 0.3600 - val_acc: 0.9039
Epoch 14/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3773 -
acc: 0.8973 - val_loss: 0.3551 - val_acc: 0.9053
Epoch 15/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3724 -
acc: 0.8985 - val_loss: 0.3509 - val_acc: 0.9064
Epoch 16/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3679 -
acc: 0.8993 - val_loss: 0.3471 - val_acc: 0.9072
Epoch 17/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3639 -
acc: 0.9005 - val_loss: 0.3435 - val_acc: 0.9083
Epoch 18/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3602 -
acc: 0.9014 - val_loss: 0.3400 - val_acc: 0.9087
Epoch 19/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3568 -
```

```
acc: 0.9022 - val_loss: 0.3373 - val_acc: 0.9095
Epoch 20/20
60000/60000 [==============================] - 1s 23us/step - loss: 0.3536 -
acc: 0.9029 - val_loss: 0.3345 - val_acc: 0.9097
```

In [0]:
```
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))

# Test and train accuracy of the model
model_test_score = score[0]
model_test_acc = score[1]
model_train = history.history['acc']

# 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 num
ber of epochs

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

```
Test score: 0.3344697316288948
Test accuracy: 0.9097
```



MLP + ReLu activation + Adam Optimizer + 2-Layer(experiment)

In [0]:

```
# Multilayer perceptron

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

#paramter
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20

model_sigmoid = Sequential()
# Adding first hidden layer
model_sigmoid.add(Dense(364, activation='relu', input_shape=(input_dim,), kern
el_initializer=he_normal(seed=None)))

# Adding second hidden layer
model_sigmoid.add(Dense(52, activation='relu', kernel_initializer=he_normal(se
ed=None)))

# Adding output layer
model_sigmoid.add(Dense(output_dim, activation='softmax'))

model_sigmoid.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_8 (Dense)              (None, 364)               285740    
_________________________________________________________________
dense_9 (Dense)              (None, 52)                18980     
_________________________________________________________________
dense_10 (Dense)             (None, 10)                530       
=================================================================
Total params: 305,250
Trainable params: 305,250
Non-trainable params: 0
_________________________________________________________________
```

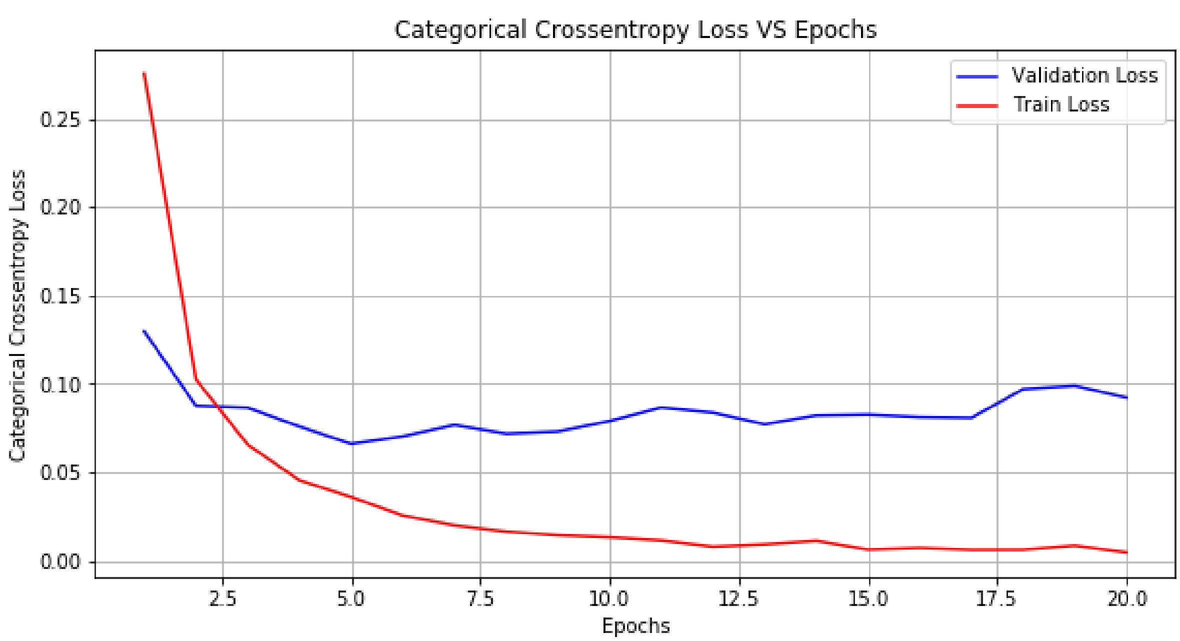
In [0]:
```
model_sigmoid.compile(optimizer='adam', loss='categorical_crossentropy', metri
cs=['accuracy'])

history2 = model_sigmoid.fit(X_train, Y_train, batch_size=batch_size, epochs=n
b_epoch, verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.2754 -
acc: 0.9219 - val_loss: 0.1296 - val_acc: 0.9620
Epoch 2/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.1024 -
acc: 0.9696 - val_loss: 0.0875 - val_acc: 0.9737
Epoch 3/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0656 -
acc: 0.9799 - val_loss: 0.0865 - val_acc: 0.9747
Epoch 4/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0454 -
acc: 0.9863 - val_loss: 0.0758 - val_acc: 0.9754
Epoch 5/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0360 -
acc: 0.9891 - val_loss: 0.0660 - val_acc: 0.9788
Epoch 6/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0255 -
acc: 0.9923 - val_loss: 0.0702 - val_acc: 0.9785
Epoch 7/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0199 -
acc: 0.9940 - val_loss: 0.0767 - val_acc: 0.9790
Epoch 8/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0164 -
acc: 0.9948 - val_loss: 0.0718 - val_acc: 0.9808
Epoch 9/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0144 -
acc: 0.9955 - val_loss: 0.0730 - val_acc: 0.9799
Epoch 10/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0132 -
acc: 0.9956 - val_loss: 0.0789 - val_acc: 0.9801
Epoch 11/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0114 -
acc: 0.9963 - val_loss: 0.0866 - val_acc: 0.9781
Epoch 12/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0079 -
acc: 0.9978 - val_loss: 0.0837 - val_acc: 0.9787
Epoch 13/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0092 -
acc: 0.9969 - val_loss: 0.0771 - val_acc: 0.9803
Epoch 14/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0112 -
acc: 0.9961 - val_loss: 0.0821 - val_acc: 0.9787
Epoch 15/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0062 -
acc: 0.9981 - val_loss: 0.0826 - val_acc: 0.9806
Epoch 16/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0072 -
acc: 0.9977 - val_loss: 0.0812 - val_acc: 0.9808
Epoch 17/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0061 -
acc: 0.9980 - val_loss: 0.0807 - val_acc: 0.9813
Epoch 18/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0062 -
acc: 0.9979 - val_loss: 0.0970 - val_acc: 0.9785
Epoch 19/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0085 -
```

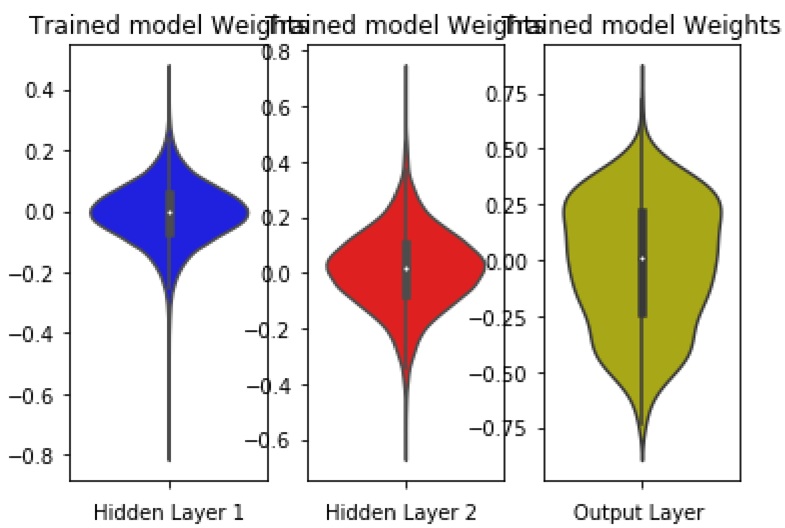
```
acc: 0.9969 - val_loss: 0.0989 - val_acc: 0.9790
Epoch 20/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0046 -
acc: 0.9986 - val_loss: 0.0922 - val_acc: 0.9814
```

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')
model_sigmoid_test_score = score[0]
model_sigmoid_test_acc = score[1]
model_sigmoid_train = history2.history['acc']

# 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 = history2.history['val_loss']
ty = history2.history['loss']
plt_dynamic(x, vy, ty)
```

```
Test score: 0.09218703215732788
Test accuracy: 0.9814
```



In [0]:
```
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()
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', metri
cs=['accuracy'])

history = model_sigmoid.fit(X_train, Y_train, batch_size=batch_size, epochs=nb
_epoch, verbose=1, validation_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 38us/step - loss: 0.5448 - 
acc: 0.8565 - val_loss: 0.2545 - val_acc: 0.9280
Epoch 2/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.2238 - 
acc: 0.9340 - val_loss: 0.1907 - val_acc: 0.9431
Epoch 3/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.1657 - 
acc: 0.9516 - val_loss: 0.1539 - val_acc: 0.9547
Epoch 4/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.1268 - 
acc: 0.9629 - val_loss: 0.1209 - val_acc: 0.9622
Epoch 5/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0989 - 
acc: 0.9709 - val_loss: 0.1023 - val_acc: 0.9682
Epoch 6/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0790 - 
acc: 0.9767 - val_loss: 0.0871 - val_acc: 0.9728
Epoch 7/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0648 - 
acc: 0.9810 - val_loss: 0.0787 - val_acc: 0.9749
Epoch 8/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0529 - 
acc: 0.9841 - val_loss: 0.0770 - val_acc: 0.9754
Epoch 9/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.0424 - 
acc: 0.9871 - val_loss: 0.0717 - val_acc: 0.9777
Epoch 10/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0347 - 
acc: 0.9903 - val_loss: 0.0695 - val_acc: 0.9784
Epoch 11/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0279 - 
acc: 0.9923 - val_loss: 0.0629 - val_acc: 0.9801
Epoch 12/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0223 - 
acc: 0.9940 - val_loss: 0.0610 - val_acc: 0.9816
Epoch 13/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0187 - 
acc: 0.9950 - val_loss: 0.0669 - val_acc: 0.9806
Epoch 14/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0146 - 
acc: 0.9963 - val_loss: 0.0608 - val_acc: 0.9820
Epoch 15/20
```

```
60000/60000 [==============================] - 2s 33us/step - loss: 0.0122 -
acc: 0.9973 - val_loss: 0.0683 - val_acc: 0.9796
Epoch 16/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0097 -
acc: 0.9977 - val_loss: 0.0676 - val_acc: 0.9792
Epoch 17/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0074 -
acc: 0.9984 - val_loss: 0.0696 - val_acc: 0.9796
Epoch 18/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0065 -
acc: 0.9987 - val_loss: 0.0734 - val_acc: 0.9778
Epoch 19/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0055 -
acc: 0.9988 - val_loss: 0.0775 - val_acc: 0.9794
Epoch 20/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0052 -
acc: 0.9986 - val_loss: 0.0684 - val_acc: 0.9815
```

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, 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 num
ber of epochs

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

```
Test score: 0.06838007308253509
Test accuracy: 0.9815
```

In [0]:
```
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()
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 condi
tion 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)

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 2s 32us/step - loss: 0.7739 -
acc: 0.7814 - val_loss: 0.3893 - val_acc: 0.8934
Epoch 2/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.3523 -
acc: 0.9004 - val_loss: 0.2989 - val_acc: 0.9156
Epoch 3/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.2888 -
acc: 0.9170 - val_loss: 0.2611 - val_acc: 0.9269
Epoch 4/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.2540 -
acc: 0.9280 - val_loss: 0.2368 - val_acc: 0.9321
Epoch 5/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.2299 -
acc: 0.9343 - val_loss: 0.2197 - val_acc: 0.9369
Epoch 6/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.2116 -
acc: 0.9396 - val_loss: 0.2043 - val_acc: 0.9401
Epoch 7/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1965 -
acc: 0.9439 - val_loss: 0.1924 - val_acc: 0.9433
Epoch 8/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1841 -
acc: 0.9470 - val_loss: 0.1826 - val_acc: 0.9459
Epoch 9/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1734 -
acc: 0.9506 - val_loss: 0.1744 - val_acc: 0.9477
Epoch 10/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1641 -
acc: 0.9531 - val_loss: 0.1678 - val_acc: 0.9489
Epoch 11/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1559 -
acc: 0.9555 - val_loss: 0.1607 - val_acc: 0.9524
Epoch 12/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1483 -
acc: 0.9581 - val_loss: 0.1550 - val_acc: 0.9528
Epoch 13/20
60000/60000 [==============================] - 2s 29us/step - loss: 0.1420 -
acc: 0.9593 - val_loss: 0.1496 - val_acc: 0.9552
Epoch 14/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1358 -
acc: 0.9612 - val_loss: 0.1445 - val_acc: 0.9576
Epoch 15/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1302 -
acc: 0.9624 - val_loss: 0.1397 - val_acc: 0.9589
Epoch 16/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1250 -
acc: 0.9643 - val_loss: 0.1372 - val_acc: 0.9594
Epoch 17/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1203 -
acc: 0.9658 - val_loss: 0.1326 - val_acc: 0.9605
Epoch 18/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1160 -
acc: 0.9669 - val_loss: 0.1304 - val_acc: 0.9618
Epoch 19/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1119 -
```

```
acc: 0.9686 - val_loss: 0.1260 - val_acc: 0.9623
Epoch 20/20
60000/60000 [==============================] - 2s 28us/step - loss: 0.1082 -
acc: 0.9693 - val_loss: 0.1236 - val_acc: 0.9636
```

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, 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 num
ber of epochs

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

```
Test score: 0.1236097104612738
Test accuracy: 0.9636
```

In [0]:
```
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()
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=RandomNormal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(m
ean=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_ep
och, verbose=1, validation_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 39us/step - loss: 0.2362 - acc: 0.9292 - val_loss: 0.1135 - val_acc: 0.9645
Epoch 2/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0872 - acc: 0.9743 - val_loss: 0.0889 - val_acc: 0.9730
Epoch 3/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0525 - acc: 0.9837 - val_loss: 0.0720 - val_acc: 0.9768
Epoch 4/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0363 - acc: 0.9892 - val_loss: 0.0656 - val_acc: 0.9783
Epoch 5/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0276 - acc: 0.9917 - val_loss: 0.0638 - val_acc: 0.9805
Epoch 6/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0184 - acc: 0.9942 - val_loss: 0.0703 - val_acc: 0.9802
Epoch 7/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0172 - acc: 0.9948 - val_loss: 0.0765 - val_acc: 0.9782
Epoch 8/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0155 - acc: 0.9953 - val_loss: 0.0747 - val_acc: 0.9785
Epoch 9/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0118 - acc: 0.9962 - val_loss: 0.0852 - val_acc: 0.9765
Epoch 10/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0131 - acc: 0.9958 - val_loss: 0.0767 - val_acc: 0.9811
Epoch 11/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0107 - acc: 0.9964 - val_loss: 0.0913 - val_acc: 0.9771
Epoch 12/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0096 - acc: 0.9967 - val_loss: 0.1016 - val_acc: 0.9763
Epoch 13/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0125 - acc: 0.9958 - val_loss: 0.0791 - val_acc: 0.9797
Epoch 14/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0055 - acc: 0.9982 - val_loss: 0.0825 - val_acc: 0.9813
```

```
Epoch 15/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0112 -
acc: 0.9962 - val_loss: 0.0926 - val_acc: 0.9783
Epoch 16/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0092 -
acc: 0.9970 - val_loss: 0.0891 - val_acc: 0.9808
Epoch 17/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0072 -
acc: 0.9975 - val_loss: 0.0898 - val_acc: 0.9806
Epoch 18/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0030 -
acc: 0.9991 - val_loss: 0.0939 - val_acc: 0.9818
Epoch 19/20
60000/60000 [==============================] - 2s 33us/step - loss: 0.0060 -
acc: 0.9982 - val_loss: 0.1058 - val_acc: 0.9789
Epoch 20/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0134 -
acc: 0.9956 - val_loss: 0.0915 - val_acc: 0.9811
```

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, 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 num
ber of epochs


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

```
Test score: 0.09147267398560358
Test accuracy: 0.9811
```

In [0]:
```
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()
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 on hidden Layers + AdamOptimizer </2>

In [0]:
```
#type of initializer ,,https://keras.io/initializers/
# Multilayer perceptron

# https://intoli.com/blog/neural-network-initialization/
# If we sample weights from a normal distribution N(0,σ) we satisfy this condi
tion 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,), ker
nel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(128, activation='sigmoid', kernel_initializer=RandomNorm
al(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]:
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics
=['accuracy'])

history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_e
poch, verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.3067 -
acc: 0.9101 - val_loss: 0.2085 - val_acc: 0.9374
Epoch 2/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1726 -
acc: 0.9494 - val_loss: 0.1664 - val_acc: 0.9507
Epoch 3/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1375 -
acc: 0.9593 - val_loss: 0.1487 - val_acc: 0.9547
Epoch 4/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1116 -
acc: 0.9666 - val_loss: 0.1414 - val_acc: 0.9571
Epoch 5/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0939 -
acc: 0.9712 - val_loss: 0.1264 - val_acc: 0.9610
Epoch 6/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0828 -
acc: 0.9751 - val_loss: 0.1172 - val_acc: 0.9662
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0703 -
acc: 0.9780 - val_loss: 0.1144 - val_acc: 0.9666
Epoch 8/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0596 -
acc: 0.9816 - val_loss: 0.1085 - val_acc: 0.9650
Epoch 9/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0521 -
acc: 0.9834 - val_loss: 0.1033 - val_acc: 0.9671
Epoch 10/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0458 -
acc: 0.9860 - val_loss: 0.1072 - val_acc: 0.9690
Epoch 11/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0395 -
acc: 0.9876 - val_loss: 0.1001 - val_acc: 0.9703
Epoch 12/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0375 -
acc: 0.9879 - val_loss: 0.1070 - val_acc: 0.9696
Epoch 13/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0321 -
acc: 0.9898 - val_loss: 0.1056 - val_acc: 0.9702
Epoch 14/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0272 -
acc: 0.9911 - val_loss: 0.0940 - val_acc: 0.9733
Epoch 15/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0247 -
acc: 0.9918 - val_loss: 0.1031 - val_acc: 0.9723
Epoch 16/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0223 -
acc: 0.9926 - val_loss: 0.0939 - val_acc: 0.9737
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0200 -
acc: 0.9932 - val_loss: 0.1072 - val_acc: 0.9721
Epoch 18/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0205 -
acc: 0.9929 - val_loss: 0.1022 - val_acc: 0.9736
Epoch 19/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0178 -
```

```
acc: 0.9941 - val_loss: 0.0966 - val_acc: 0.9744
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0154 -
acc: 0.9949 - val_loss: 0.0993 - val_acc: 0.9745
```

In [0]:

```
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, 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 num
ber of epochs

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

```
Test score: 0.09926731985980877
Test accuracy: 0.9745
```

In [0]:
```
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()
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()
```

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, y, y_1, ax, ticks,title, colors=['b']):
    ax.plot(x, y, 'b', label="Train Loss")
    ax.plot(x, y_1, 'r', label="Test Loss")
    if len(x)==1:
        plt.legend()
        plt.title(title)
    plt.yticks(ticks)
    fig.canvas.draw()
```

MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 2-Layer

In [0]:
```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormal
ization-function-in-keras

from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

#paramter
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20


# Initialising model
model_drop = Sequential()

# Adding first hidden layer
model_drop.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_
initializer=he_normal(seed=None)))
# Adding Batch Normalization
model_drop.add(BatchNormalization())
# Adding dropout to first hidden layer
model_drop.add(Dropout(0.5))

# Adding second hidden layer
model_drop.add(Dense(52, activation='relu', kernel_initializer=he_normal(seed=
None)))
# Adding Batch Normalization
model_drop.add(BatchNormalization())
# Adding dropout to second hidden layer
model_drop.add(Dropout(0.5))

# Adding output layer
model_drop.add(Dense(output_dim, activation='softmax'))


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_27 (Dense)             (None, 364)               285740    
_________________________________________________________________
batch_normalization_13 (Batc (None, 364)               1456      
_________________________________________________________________
dropout_13 (Dropout)         (None, 364)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 52)                18980     
_________________________________________________________________
batch_normalization_14 (Batc (None, 52)                208       
_________________________________________________________________
dropout_14 (Dropout)         (None, 52)                0         
_________________________________________________________________
dense_29 (Dense)             (None, 10)                530       
=================================================================
Total params: 306,914
Trainable params: 306,082
Non-trainable params: 832
_________________________________________________________________
```

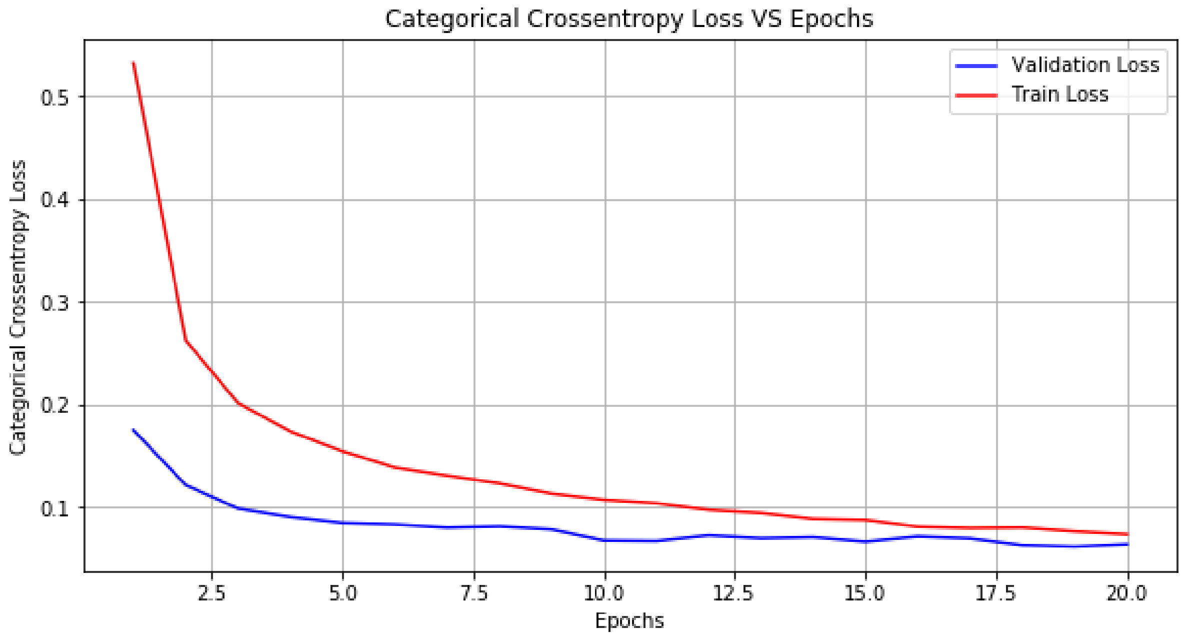
In [0]:
```
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=
['accuracy'])

history3 = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_e
poch, verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.5326 -
acc: 0.8427 - val_loss: 0.1750 - val_acc: 0.9450
Epoch 2/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2624 -
acc: 0.9245 - val_loss: 0.1216 - val_acc: 0.9632
Epoch 3/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2014 -
acc: 0.9417 - val_loss: 0.0987 - val_acc: 0.9686
Epoch 4/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1738 -
acc: 0.9502 - val_loss: 0.0906 - val_acc: 0.9715
Epoch 5/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1544 -
acc: 0.9547 - val_loss: 0.0848 - val_acc: 0.9737
Epoch 6/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1387 -
acc: 0.9591 - val_loss: 0.0833 - val_acc: 0.9743
Epoch 7/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1307 -
acc: 0.9629 - val_loss: 0.0802 - val_acc: 0.9760
Epoch 8/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1232 -
acc: 0.9643 - val_loss: 0.0814 - val_acc: 0.9760
Epoch 9/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1133 -
acc: 0.9672 - val_loss: 0.0784 - val_acc: 0.9774
Epoch 10/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1072 -
acc: 0.9682 - val_loss: 0.0677 - val_acc: 0.9804
Epoch 11/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1039 -
acc: 0.9696 - val_loss: 0.0672 - val_acc: 0.9783
Epoch 12/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0975 -
acc: 0.9709 - val_loss: 0.0728 - val_acc: 0.9770
Epoch 13/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0944 -
acc: 0.9718 - val_loss: 0.0699 - val_acc: 0.9789
Epoch 14/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0887 -
acc: 0.9732 - val_loss: 0.0710 - val_acc: 0.9795
Epoch 15/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0876 -
acc: 0.9734 - val_loss: 0.0666 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0811 -
acc: 0.9758 - val_loss: 0.0717 - val_acc: 0.9797
Epoch 17/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0797 -
acc: 0.9761 - val_loss: 0.0697 - val_acc: 0.9793
Epoch 18/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0802 -
acc: 0.9765 - val_loss: 0.0631 - val_acc: 0.9811
Epoch 19/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0765 -
```

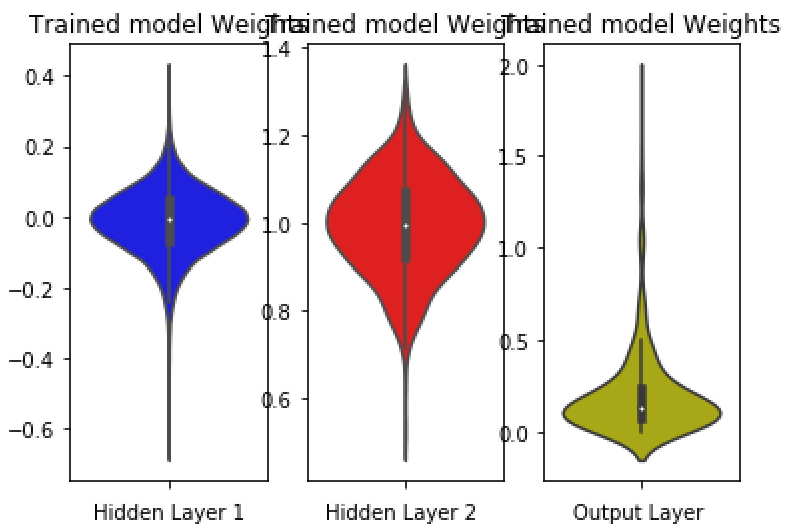
```
acc: 0.9773 - val_loss: 0.0617 - val_acc: 0.9813
Epoch 20/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0737 -
acc: 0.9780 - val_loss: 0.0639 - val_acc: 0.9810
```

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')

# Test and train accuracy of the model
model_drop_test_score = score[0]
model_drop_test_acc = score[1]
model_drop_train = history3.history['acc']


# 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 num
ber of epochs

vy = history3.history['val_loss']
ty = history3.history['loss']
plt_dynamic(x, vy, ty)
```

```
Test score: 0.06392139566795085
Test accuracy: 0.981
```



In [0]:
```
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()
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 activation + Adam Optimizer + BN+Dropout+ 3-Layer

In [0]:
```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormal
ization-function-in-keras

from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

#paramter
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20


# Initialising model
model3_drop = Sequential()

# Adding first hidden layer
model3_drop.add(Dense(554, activation='relu', input_shape=(input_dim,), kernel
_initializer=he_normal(seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

# Adding second hidden layer
model3_drop.add(Dense(225, activation='relu', kernel_initializer=he_normal(see
d=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

# Adding third hidden layer
model3_drop.add(Dense(78, activation='relu', kernel_initializer=he_normal(seed
=None)))
model3_drop.add(BatchNormalization())
model3_drop.add(Dropout(0.5))

model3_drop.add(Dense(output_dim, activation='softmax'))


model3_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_30 (Dense)             (None, 554)               434890    
_________________________________________________________________
dense_31 (Dense)             (None, 225)               124875    
_________________________________________________________________
dense_32 (Dense)             (None, 78)                17628     
_________________________________________________________________
batch_normalization_17 (Batc (None, 78)                312       
_________________________________________________________________
dropout_17 (Dropout)         (None, 78)                0         
_________________________________________________________________
dense_33 (Dense)             (None, 10)                790       
=================================================================
Total params: 578,495
Trainable params: 578,339
Non-trainable params: 156
_________________________________________________________________
```

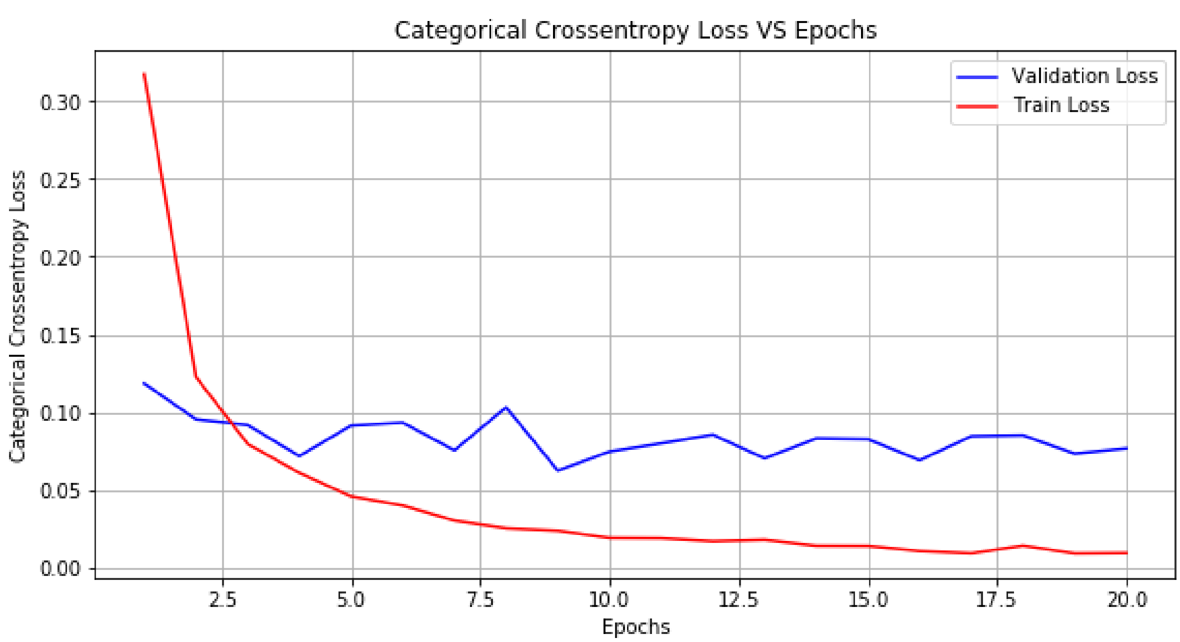
In [0]:
```
model3_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics
=['accuracy'])

history4 = model3_drop.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 73us/step - loss: 0.3175 -
acc: 0.9073 - val_loss: 0.1184 - val_acc: 0.9651
Epoch 2/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.1226 -
acc: 0.9649 - val_loss: 0.0953 - val_acc: 0.9699
Epoch 3/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0795 -
acc: 0.9769 - val_loss: 0.0917 - val_acc: 0.9740
Epoch 4/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0608 -
acc: 0.9818 - val_loss: 0.0717 - val_acc: 0.9785
Epoch 5/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0457 -
acc: 0.9858 - val_loss: 0.0913 - val_acc: 0.9734
Epoch 6/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0399 -
acc: 0.9879 - val_loss: 0.0932 - val_acc: 0.9738
Epoch 7/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0302 -
acc: 0.9910 - val_loss: 0.0754 - val_acc: 0.9791
Epoch 8/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0252 -
acc: 0.9921 - val_loss: 0.1031 - val_acc: 0.9734
Epoch 9/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0237 -
acc: 0.9926 - val_loss: 0.0623 - val_acc: 0.9834
Epoch 10/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0190 -
acc: 0.9943 - val_loss: 0.0746 - val_acc: 0.9799
Epoch 11/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0188 -
acc: 0.9943 - val_loss: 0.0799 - val_acc: 0.9803
Epoch 12/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0169 -
acc: 0.9946 - val_loss: 0.0854 - val_acc: 0.9801
Epoch 13/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0178 -
acc: 0.9942 - val_loss: 0.0702 - val_acc: 0.9829
Epoch 14/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0139 -
acc: 0.9957 - val_loss: 0.0830 - val_acc: 0.9817
Epoch 15/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0138 -
acc: 0.9956 - val_loss: 0.0826 - val_acc: 0.9810
Epoch 16/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0106 -
acc: 0.9966 - val_loss: 0.0690 - val_acc: 0.9850
Epoch 17/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0091 -
acc: 0.9971 - val_loss: 0.0845 - val_acc: 0.9812
Epoch 18/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0140 -
acc: 0.9955 - val_loss: 0.0850 - val_acc: 0.9810
Epoch 19/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0090 -
```

```
acc: 0.9972 - val_loss: 0.0732 - val_acc: 0.9849
Epoch 20/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0092 -
acc: 0.9972 - val_loss: 0.0766 - val_acc: 0.9838
```

In [0]:
```
score = model3_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')
# Test and train accuracy of the model
model3_drop_test_score = score[0]
model3_drop_test_acc = score[1]
model3_drop_train = history4.history['acc']

# 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 num
ber of epochs

vy = history4.history['val_loss']
ty = history4.history['loss']
plt_dynamic(x, vy, ty)
```

```
Test score: 0.07663734175693944
Test accuracy: 0.9838
```



MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 5-Layer

In [0]:
```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormal
ization-function-in-keras

from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

#paramter
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20

# Initialising model
model4_drop = Sequential()

# Adding first hidden layer
model4_drop.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel
_initializer=he_normal(seed=None)))
# Adding Batch Normalization
model4_drop.add(BatchNormalization())
# Adding dropout
model4_drop.add(Dropout(0.5))

# Adding second hidden layer
model4_drop.add(Dense(256, activation='relu', kernel_initializer=he_normal(see
d=None)))
# Adding Batch Normalization
model4_drop.add(BatchNormalization())
# Adding dropout
model4_drop.add(Dropout(0.5))

# Adding third hidden layer
model4_drop.add(Dense(128, activation='relu', kernel_initializer=he_normal(see
d=None)))
# Adding Batch Normalization
model4_drop.add(BatchNormalization())
# Adding dropout
model4_drop.add(Dropout(0.5))

# Adding fourth hidden layer
model4_drop.add(Dense(64, activation='relu', kernel_initializer=he_normal(seed
=None)))
# Adding Batch Normalization
model4_drop.add(BatchNormalization())
# Adding dropout
model4_drop.add(Dropout(0.5))

# Adding fifth hidden layer
model4_drop.add(Dense(32, activation='relu', kernel_initializer=he_normal(seed
=None)))
# Adding Batch Normalization
```

```
model4_drop.add(BatchNormalization())
# Adding dropout
model4_drop.add(Dropout(0.5))

# Adding output layer
model4_drop.add(Dense(output_dim, activation='softmax'))


model4_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_34 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_18 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_18 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_35 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_19 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_19 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_36 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_20 (Batc (None, 128)               512       
_________________________________________________________________
dropout_20 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_37 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_21 (Batc (None, 64)                256       
_________________________________________________________________
dropout_21 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_38 (Dense)             (None, 32)                2080      
_________________________________________________________________
batch_normalization_22 (Batc (None, 32)                128       
_________________________________________________________________
dropout_22 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_39 (Dense)             (None, 10)                330       
=================================================================
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

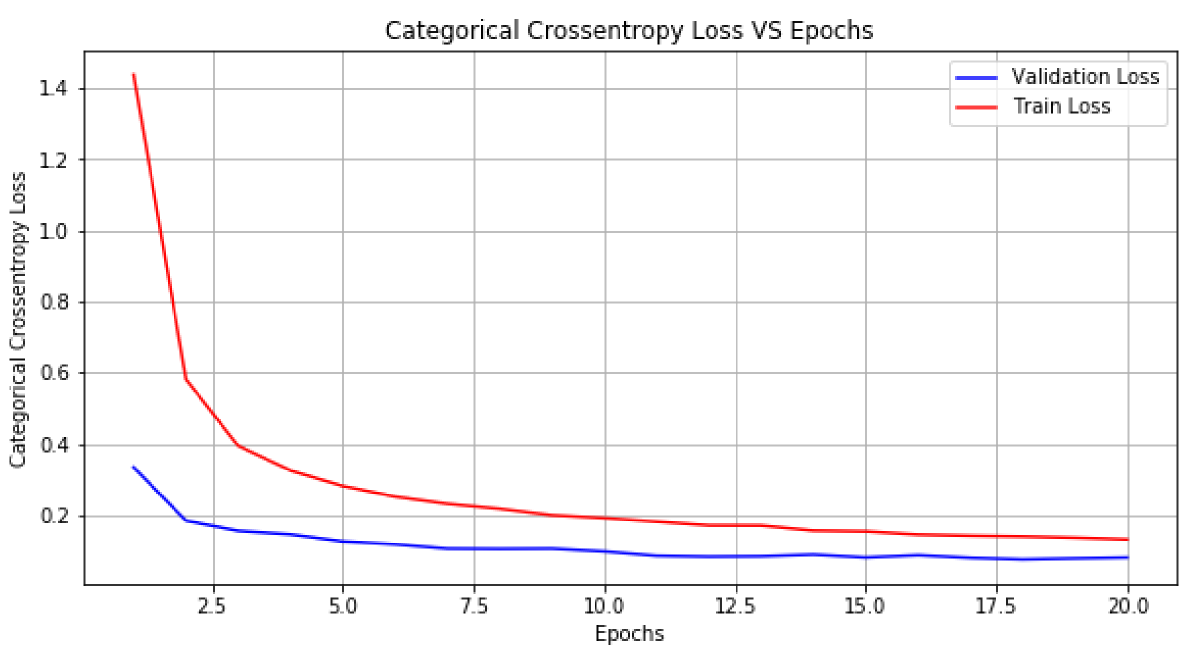
In [0]:
```
model4_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics
=['accuracy'])

history5 = model4_drop.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 [==============================] - 8s 138us/step - loss: 1.4364 -
acc: 0.5277 - val_loss: 0.3345 - val_acc: 0.9116
Epoch 2/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.5814 -
acc: 0.8349 - val_loss: 0.1847 - val_acc: 0.9483
Epoch 3/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.3939 -
acc: 0.8993 - val_loss: 0.1560 - val_acc: 0.9589
Epoch 4/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.3255 -
acc: 0.9214 - val_loss: 0.1461 - val_acc: 0.9617
Epoch 5/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.2819 -
acc: 0.9328 - val_loss: 0.1263 - val_acc: 0.9671
Epoch 6/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.2521 -
acc: 0.9405 - val_loss: 0.1182 - val_acc: 0.9713
Epoch 7/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2322 -
acc: 0.9458 - val_loss: 0.1061 - val_acc: 0.9732
Epoch 8/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.2182 -
acc: 0.9490 - val_loss: 0.1054 - val_acc: 0.9738
Epoch 9/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.2002 -
acc: 0.9541 - val_loss: 0.1061 - val_acc: 0.9751
Epoch 10/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1920 -
acc: 0.9565 - val_loss: 0.0983 - val_acc: 0.9764
Epoch 11/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1820 -
acc: 0.9591 - val_loss: 0.0862 - val_acc: 0.9783
Epoch 12/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1715 -
acc: 0.9614 - val_loss: 0.0839 - val_acc: 0.9794
Epoch 13/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1711 -
acc: 0.9610 - val_loss: 0.0848 - val_acc: 0.9797
Epoch 14/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1567 -
acc: 0.9649 - val_loss: 0.0895 - val_acc: 0.9785
Epoch 15/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1546 -
acc: 0.9650 - val_loss: 0.0815 - val_acc: 0.9814
Epoch 16/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.1456 -
acc: 0.9668 - val_loss: 0.0877 - val_acc: 0.9802
Epoch 17/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1425 -
acc: 0.9676 - val_loss: 0.0804 - val_acc: 0.9811
Epoch 18/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1403 -
acc: 0.9682 - val_loss: 0.0761 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1369 -
```

```
acc: 0.9696 - val_loss: 0.0788 - val_acc: 0.9816
Epoch 20/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.1322 -
acc: 0.9698 - val_loss: 0.0812 - val_acc: 0.9820
```

In [0]:
```
score = model4_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')
model4_drop_test_score = score[0]
model4_drop_test_acc = score[1]
model4_drop_train = history5.history['acc']

# 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 num
ber of epochs

vy = history5.history['val_loss']
ty = history5.history['loss']
plt_dynamic(x, vy, ty)
```

```
Test score: 0.08122210750945379
Test accuracy: 0.982
```



Summerize

In [0]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model","Train accuracy", "Test accuracy"]
x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 2-Layer", mod
el_drop_train[19],model_drop_test_acc])
x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 3-Layer", mod
el3_drop_train[19],model3_drop_test_acc])
x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 5-Layer", mod
el4_drop_train[19],model4_drop_test_acc])
print(x)
```

```
+--------------------------------------------------------------+-------------
-------+---------------+
|                            Model                             |   Train accu
racy   | Test accuracy |
+--------------------------------------------------------------+-------------
-------+---------------+
| MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 2-Layer | 0.9780333333
651224 |     0.981     |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 3-Layer | 0.9971833333
333333 |     0.9838    |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout+ 5-Layer | 0.9697666666
348775 |     0.982     |
+--------------------------------------------------------------+-------------
-------+---------------+
```

Observation:

for 2-Layer Model, train accuracy little lower than test accuracy

train accuracy also low for higher number of layer

Test accuracy almost same for all case