

Keras -- MLPs on MNIST

In [1]:

```
# 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
```

Using TensorFlow backend.

In [2]:

```
%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 [3]:

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

In [4]:

```
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 [5]:

```
# 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 [6]:

```
# 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 [7]:

```
# 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  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
170 253 253 253 253 225 172 253 242 195  64  0  0  0  0  0  0
  0  0  0  0  0  49 238 253 253 253 253 253 253 253 251  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  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  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  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  0  0  0  0  0  0  0  0]
```

In [8]:

```
# 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 [10]:

```
# 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.]

1st Model 784->310->150->10

In [35]:

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-function-in-keras
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout

model_1 = Sequential()

model_1.add(Dense(310, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_1.add(BatchNormalization())
model_1.add(Dropout(0.5))

model_1.add(Dense(150, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)))
model_1.add(BatchNormalization())
model_1.add(Dropout(0.5))

model_1.add(Dense(output_dim, activation='softmax'))

model_1.summary()
```

Layer (type)	Output Shape	Param #
dense_21 (Dense)	(None, 310)	243350
batch_normalization_14 (Batch Normalization)	(None, 310)	1240
dropout_14 (Dropout)	(None, 310)	0
dense_22 (Dense)	(None, 150)	46650
batch_normalization_15 (Batch Normalization)	(None, 150)	600
dropout_15 (Dropout)	(None, 150)	0
dense_23 (Dense)	(None, 10)	1510
Total params: 293,350		
Trainable params: 292,430		
Non-trainable params: 920		

In [36]:

```
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_1.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 [=====] - 9s 157us/step - loss: 0.5351 - acc: 0.8369 - val_loss: 0.1795 - val_acc: 0.9431
Epoch 2/20
60000/60000 [=====] - 7s 120us/step - loss: 0.2773 - acc: 0.9176 - val_loss: 0.1344 - val_acc: 0.9582
Epoch 3/20
60000/60000 [=====] - 7s 119us/step - loss: 0.2184 - acc: 0.9344 - val_loss: 0.1180 - val_acc: 0.9626
Epoch 4/20
60000/60000 [=====] - 7s 117us/step - loss: 0.1942 - acc: 0.9419 - val_loss: 0.1052 - val_acc: 0.9669
Epoch 5/20
60000/60000 [=====] - 7s 116us/step - loss: 0.1769 - acc: 0.9471 - val_loss: 0.0999 - val_acc: 0.9699
```

```

val_loss: 0.0982 - val_acc: 0.9693
Epoch 6/20
60000/60000 [=====] - 7s 118us/step - loss: 0.1612 - acc: 0.9515 -
val_loss: 0.0936 - val_acc: 0.9703
Epoch 7/20
60000/60000 [=====] - 7s 118us/step - loss: 0.1470 - acc: 0.9550 -
val_loss: 0.0876 - val_acc: 0.9732
Epoch 8/20
60000/60000 [=====] - 7s 117us/step - loss: 0.1419 - acc: 0.9570 -
val_loss: 0.0832 - val_acc: 0.9745
Epoch 9/20
60000/60000 [=====] - 7s 119us/step - loss: 0.1313 - acc: 0.9599 -
val_loss: 0.0809 - val_acc: 0.9748
Epoch 10/20
60000/60000 [=====] - 7s 119us/step - loss: 0.1250 - acc: 0.9620 -
val_loss: 0.0816 - val_acc: 0.9752
Epoch 11/20
60000/60000 [=====] - 7s 117us/step - loss: 0.1200 - acc: 0.9631 -
val_loss: 0.0791 - val_acc: 0.9759
Epoch 12/20
60000/60000 [=====] - 7s 116us/step - loss: 0.1119 - acc: 0.9661 -
val_loss: 0.0771 - val_acc: 0.9761
Epoch 13/20
60000/60000 [=====] - 7s 119us/step - loss: 0.1084 - acc: 0.9667 -
val_loss: 0.0806 - val_acc: 0.9753
Epoch 14/20
60000/60000 [=====] - 7s 116us/step - loss: 0.1053 - acc: 0.9679 -
val_loss: 0.0748 - val_acc: 0.9774
Epoch 15/20
60000/60000 [=====] - 7s 121us/step - loss: 0.1010 - acc: 0.9681 -
val_loss: 0.0739 - val_acc: 0.9786
Epoch 16/20
60000/60000 [=====] - 7s 120us/step - loss: 0.0983 - acc: 0.9697 -
val_loss: 0.0716 - val_acc: 0.9778
Epoch 17/20
60000/60000 [=====] - 7s 124us/step - loss: 0.0928 - acc: 0.9714 -
val_loss: 0.0725 - val_acc: 0.9792
Epoch 18/20
60000/60000 [=====] - 8s 126us/step - loss: 0.0892 - acc: 0.9724 -
val_loss: 0.0696 - val_acc: 0.9794
Epoch 19/20
60000/60000 [=====] - 7s 124us/step - loss: 0.0863 - acc: 0.9733 -
val_loss: 0.0680 - val_acc: 0.9794
Epoch 20/20
60000/60000 [=====] - 7s 117us/step - loss: 0.0861 - acc: 0.9729 -
val_loss: 0.0684 - val_acc: 0.9790

```

In [37]:

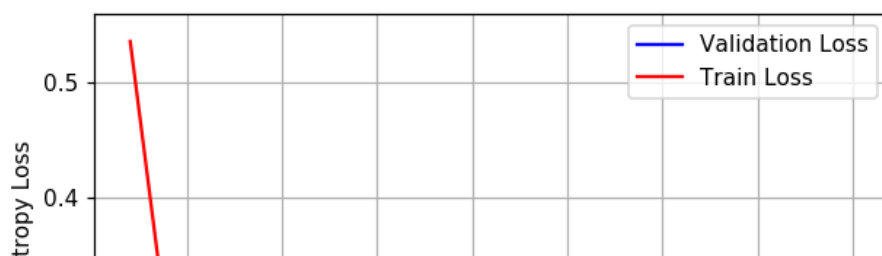
```

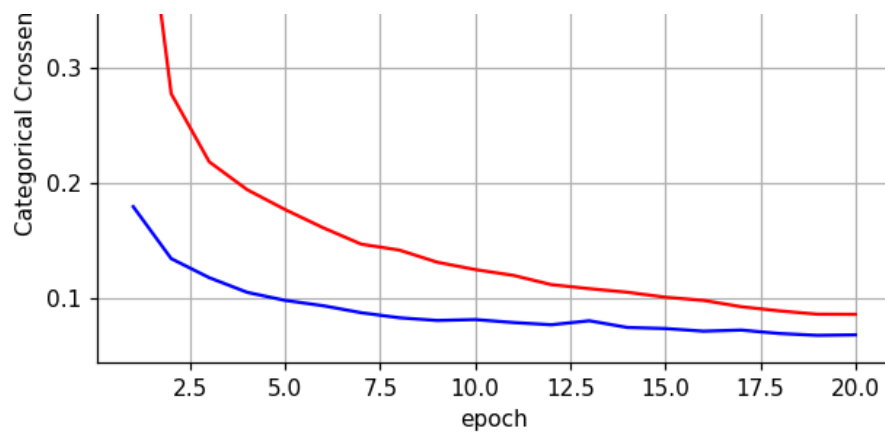
score = model_1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
x = list(range(1,nb_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Test score: 0.06840268510318129

Test accuracy: 0.979





2nd Model 784->500->300->200->10

In [32]:

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

model_2= Sequential()

model_2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(
    (mean=0.0, stddev=0.039, seed=None)))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(output_dim, activation='softmax'))

model_2.summary()
```

Layer (type)	Output Shape	Param #
dense_17 (Dense)	(None, 500)	392500
batch_normalization_11 (Batch Normalization)	(None, 500)	2000
dropout_11 (Dropout)	(None, 500)	0
dense_18 (Dense)	(None, 300)	150300
batch_normalization_12 (Batch Normalization)	(None, 300)	1200
dropout_12 (Dropout)	(None, 300)	0
dense_19 (Dense)	(None, 200)	60200
batch_normalization_13 (Batch Normalization)	(None, 200)	800
dropout_13 (Dropout)	(None, 200)	0
dense_20 (Dense)	(None, 10)	2010
Total params: 609,010		
Trainable params: 607,010		
Non-trainable params: 2,000		

In [33]:

```
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_2.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 [=====] - 13s 211us/step - loss: 0.7186 - acc: 0.7772 - val_loss: 0.2066 - val_acc: 0.9375
Epoch 2/20
60000/60000 [=====] - 11s 176us/step - loss: 0.3307 - acc: 0.9004 - val_loss: 0.1579 - val_acc: 0.9505
Epoch 3/20
60000/60000 [=====] - 11s 177us/step - loss: 0.2569 - acc: 0.9229 - val_loss: 0.1313 - val_acc: 0.9586
Epoch 4/20
60000/60000 [=====] - 11s 181us/step - loss: 0.2187 - acc: 0.9359 - val_loss: 0.1115 - val_acc: 0.9658
Epoch 5/20
60000/60000 [=====] - 11s 179us/step - loss: 0.1887 - acc: 0.9450 - val_loss: 0.1035 - val_acc: 0.9680
Epoch 6/20
60000/60000 [=====] - 11s 179us/step - loss: 0.1712 - acc: 0.9493 - val_loss: 0.0910 - val_acc: 0.9715
Epoch 7/20
60000/60000 [=====] - 11s 177us/step - loss: 0.1583 - acc: 0.9534 - val_loss: 0.0989 - val_acc: 0.9702
Epoch 8/20
60000/60000 [=====] - 11s 176us/step - loss: 0.1444 - acc: 0.9563 - val_loss: 0.0871 - val_acc: 0.9733
Epoch 9/20
60000/60000 [=====] - 11s 176us/step - loss: 0.1380 - acc: 0.9592 - val_loss: 0.0879 - val_acc: 0.9748
Epoch 10/20
60000/60000 [=====] - 10s 175us/step - loss: 0.1272 - acc: 0.9616 - val_loss: 0.0883 - val_acc: 0.9734
Epoch 11/20
60000/60000 [=====] - 11s 176us/step - loss: 0.1241 - acc: 0.9630 - val_loss: 0.0793 - val_acc: 0.9759
Epoch 12/20
60000/60000 [=====] - 10s 175us/step - loss: 0.1172 - acc: 0.9646 - val_loss: 0.0782 - val_acc: 0.9771
Epoch 13/20
60000/60000 [=====] - 11s 178us/step - loss: 0.1086 - acc: 0.9666 - val_loss: 0.0773 - val_acc: 0.9768
Epoch 14/20
60000/60000 [=====] - 11s 188us/step - loss: 0.1007 - acc: 0.9692 - val_loss: 0.0748 - val_acc: 0.9785
Epoch 15/20
60000/60000 [=====] - 11s 181us/step - loss: 0.0992 - acc: 0.9701 - val_loss: 0.0728 - val_acc: 0.9793
Epoch 16/20
60000/60000 [=====] - 11s 176us/step - loss: 0.0955 - acc: 0.9705 - val_loss: 0.0737 - val_acc: 0.9799
Epoch 17/20
60000/60000 [=====] - 11s 180us/step - loss: 0.0900 - acc: 0.9727 - val_loss: 0.0705 - val_acc: 0.9792
Epoch 18/20
60000/60000 [=====] - 11s 184us/step - loss: 0.0905 - acc: 0.9723 - val_loss: 0.0699 - val_acc: 0.9796
Epoch 19/20
60000/60000 [=====] - 12s 199us/step - loss: 0.0835 - acc: 0.9743 - val_loss: 0.0705 - val_acc: 0.9801
Epoch 20/20
60000/60000 [=====] - 12s 206us/step - loss: 0.0832 - acc: 0.9749 - val_loss: 0.0679 - val_acc: 0.9810
```

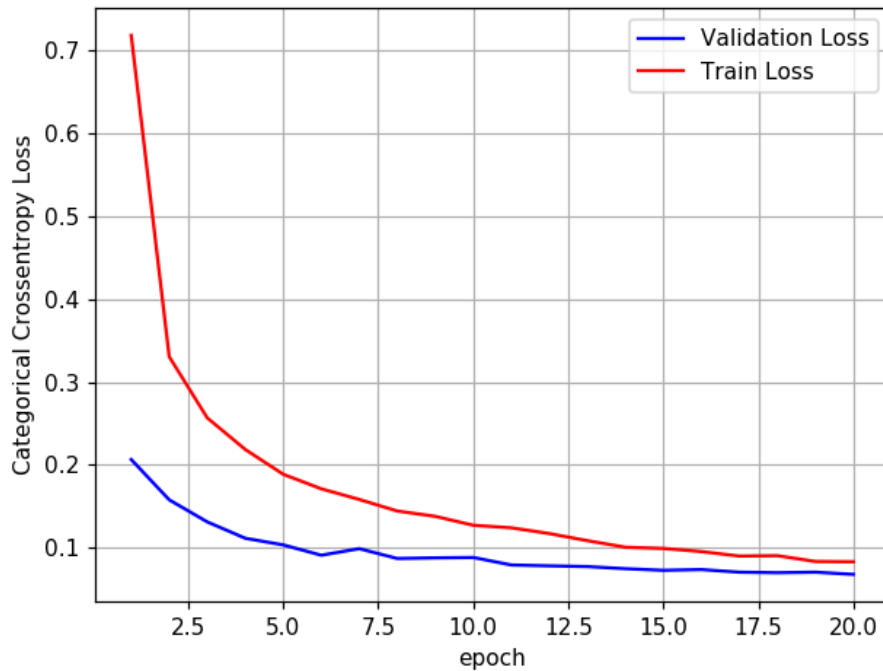
In [34]:

```
score = model_2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

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

# list of epoch numbers
x = list(range(1,nb_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

Test score: 0.06794361313983682
Test accuracy: 0.981



3rd Model 784->500->400->200->300->120->10

In [38]:

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

model_3= Sequential()

model_3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(
    (mean=0.0, stddev=0.039, seed=None))))
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

model_3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

model_3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

model_3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

model_3.add(Dense(120, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, se
ed=None)) )
```

```

cu=None, /
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

model_3.add(Dense(output_dim, activation='softmax'))

model_3.summary()

```

Layer (type)	Output Shape	Param #
dense_24 (Dense)	(None, 500)	392500
batch_normalization_16 (Batch Normalization)	(None, 500)	2000
dropout_16 (Dropout)	(None, 500)	0
dense_25 (Dense)	(None, 400)	200400
batch_normalization_17 (Batch Normalization)	(None, 400)	1600
dropout_17 (Dropout)	(None, 400)	0
dense_26 (Dense)	(None, 200)	80200
batch_normalization_18 (Batch Normalization)	(None, 200)	800
dropout_18 (Dropout)	(None, 200)	0
dense_27 (Dense)	(None, 300)	60300
batch_normalization_19 (Batch Normalization)	(None, 300)	1200
dropout_19 (Dropout)	(None, 300)	0
dense_28 (Dense)	(None, 120)	36120
batch_normalization_20 (Batch Normalization)	(None, 120)	480
dropout_20 (Dropout)	(None, 120)	0
dense_29 (Dense)	(None, 10)	1210
Total params: 776,810		
Trainable params: 773,770		
Non-trainable params: 3,040		

In [39]:

```

model_3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_3.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 [=====] - 18s 299us/step - loss: 1.7109 - acc: 0.4512 - val_loss: 0.4496 - val_acc: 0.8801
Epoch 2/20
60000/60000 [=====] - 15s 248us/step - loss: 0.6688 - acc: 0.7876 - val_loss: 0.2676 - val_acc: 0.9238
Epoch 3/20
60000/60000 [=====] - 15s 247us/step - loss: 0.4662 - acc: 0.8597 - val_loss: 0.2059 - val_acc: 0.9383
Epoch 4/20
60000/60000 [=====] - 15s 256us/step - loss: 0.3681 - acc: 0.8932 - val_loss: 0.1774 - val_acc: 0.9477
Epoch 5/20
60000/60000 [=====] - 15s 250us/step - loss: 0.3090 - acc: 0.9124 - val_loss: 0.1504 - val_acc: 0.9571
Epoch 6/20
60000/60000 [=====] - 15s 251us/step - loss: 0.2631 - acc: 0.9256 - val_loss: 0.1384 - val_acc: 0.9621

```



```

Epoch 7/20
60000/60000 [=====] - 15s 255us/step - loss: 0.2423 - acc: 0.9315 - val_loss: 0.1276 - val_acc: 0.9650
Epoch 8/20
60000/60000 [=====] - 15s 250us/step - loss: 0.2239 - acc: 0.9375 - val_loss: 0.1202 - val_acc: 0.9672
Epoch 9/20
60000/60000 [=====] - 15s 251us/step - loss: 0.2081 - acc: 0.9425 - val_loss: 0.1107 - val_acc: 0.9717
Epoch 10/20
60000/60000 [=====] - 15s 249us/step - loss: 0.1897 - acc: 0.9475 - val_loss: 0.1130 - val_acc: 0.9700
Epoch 11/20
60000/60000 [=====] - 15s 250us/step - loss: 0.1742 - acc: 0.9512 - val_loss: 0.1014 - val_acc: 0.9726
Epoch 12/20
60000/60000 [=====] - 15s 251us/step - loss: 0.1662 - acc: 0.9540 - val_loss: 0.1019 - val_acc: 0.9732
Epoch 13/20
60000/60000 [=====] - 15s 250us/step - loss: 0.1553 - acc: 0.9572 - val_loss: 0.1001 - val_acc: 0.9750
Epoch 14/20
60000/60000 [=====] - 15s 249us/step - loss: 0.1534 - acc: 0.9578 - val_loss: 0.0952 - val_acc: 0.9759
Epoch 15/20
60000/60000 [=====] - 15s 252us/step - loss: 0.1482 - acc: 0.9588 - val_loss: 0.0932 - val_acc: 0.9754
Epoch 16/20
60000/60000 [=====] - 15s 249us/step - loss: 0.1378 - acc: 0.9615 - val_loss: 0.0880 - val_acc: 0.9780
Epoch 17/20
60000/60000 [=====] - 15s 250us/step - loss: 0.1323 - acc: 0.9634 - val_loss: 0.0925 - val_acc: 0.9768
Epoch 18/20
60000/60000 [=====] - 15s 253us/step - loss: 0.1278 - acc: 0.9650 - val_loss: 0.0832 - val_acc: 0.9787
Epoch 19/20
60000/60000 [=====] - 15s 250us/step - loss: 0.1208 - acc: 0.9665 - val_loss: 0.0956 - val_acc: 0.9762
Epoch 20/20
60000/60000 [=====] - 15s 252us/step - loss: 0.1176 - acc: 0.9672 - val_loss: 0.0880 - val_acc: 0.9769

```

In [40]:

```

score = model_3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

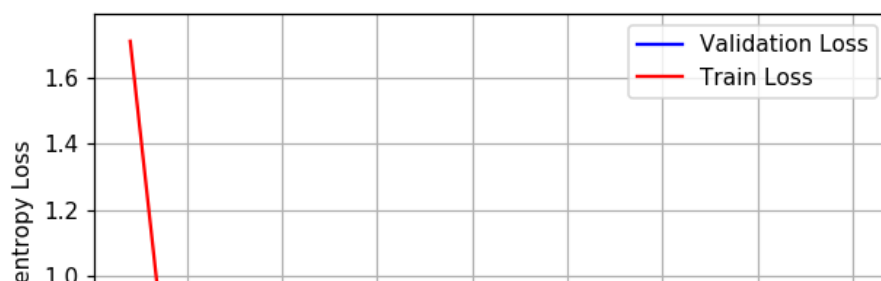
fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

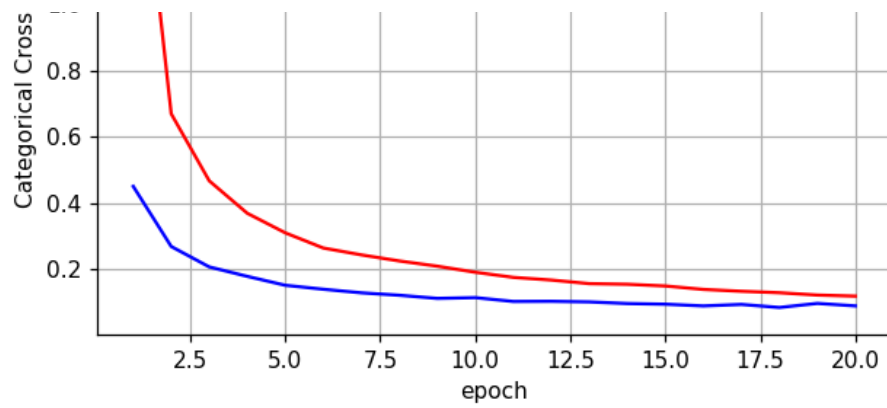
# list of epoch numbers
x = list(range(1, nb_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)

```

Test score: 0.08802014297826681

Test accuracy: 0.9769





In [42]:

```
from prettytable import PrettyTable
table = PrettyTable()

table.field_names = ["Model", "Layer info", "Accuracy"]

table.add_row(["Model 1st", "784->310->150->10", "0.979" ])
table.add_row(["Model 2nd", "784->500->300->200->10", "0.981"])
table.add_row(["Model 3rd", "784->500->400->200->300->120->10", "0.976" ])
print(table)
```

Model	Layer info	Accuracy
Model 1st	784->310->150->10	0.979
Model 2nd	784->500->300->200->10	0.981
Model 3rd	784->500->400->200->300->120->10	0.976

In []: