# Assignment-12: TensorFlow and Keras: Build various MLP architectures for MNIST dataset [M]

***Objective:***

- Model with three different architecture:

```
  1) 2-Hidden layer architecture (784-472-168-10 architect
ure)

  2) 3-Hidden layer architecture (784-352-164-124-10 archi
tecture)

  3) 5-Hidden layer architecture (784-216-170-136-80-38-10
 architecture)
```

- Train-Test error plot
- Activation='relu'+ Adam Optimizer+Batch_Normalization +Drop_out

In [1]:
```
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=te
nsorflow" 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 inline
import matplotlib.pyplot as plt
```

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

In [3]:
```
# the data, shuffled and split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 1s 0us/step
```

In [4]:
```
print("Number of training examples :", x_train.shape[0], "and each imag
e 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 3 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.sh
ape[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 imag
e 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   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 25
5
  247 127   0   0   0   0   0   0   0   0   0   0   0   0  30  36  94 15
4
  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   8
2
   82  56  39   0   0   0   0   0   0   0   0   0   0   0   0  18 219 25
3
  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 15
```

```
4
   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  24
1
 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  18
7
   0   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  25
3
 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  25
3
 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 19
5
  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   1
6
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   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 norma
lize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255

x_train = x_train/255
x_test = x_test/255
```

In [9]:

```
# 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 [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.]
```

## Softmax classifier

In [11]:

```
# 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 instance
s to the constructor:

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

```
#     Activation('softmax'),
# ])

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

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

###

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

# keras.layers.Dense(units, activation=None, use_bias=True, kernel_init
ializer='glorot_uniform',
# bias_initializer='zeros', kernel_regularizer=None, bias_regularizer=N
one, activity_regularizer=None,
# kernel_constraint=None, bias_constraint=None)

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

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

####

# https://keras.io/activations/

# Activations can either be used through an Activation layer, or throug
h the activation 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, soft
max


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

In [12]:
```
# some model parameters

output_dim = 10
input_dim = x_train.shape[1]

batch_size = 128
nb_epoch = 20
```

# 1) 2-Hidden layer architecture (784-472-168-10 architecture)

## 1.1 MLP + ReLU + ADAM

In [13]:
```
model_relu = Sequential()
model_relu.add(Dense(472, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_relu.add(Dense(168, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())
```

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

history11 = model_relu.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_1 (Dense)              (None, 472)               370520    
_________________________________________________________________
dense_2 (Dense)              (None, 168)               79464     
_________________________________________________________________
dense_3 (Dense)              (None, 10)                1690      
=================================================================
Total params: 451,674
Trainable params: 451,674
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.2
342 - acc: 0.9321 - val_loss: 0.1046 - val_acc: 0.9690
Epoch 2/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
859 - acc: 0.9736 - val_loss: 0.0847 - val_acc: 0.9727
Epoch 3/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
549 - acc: 0.9831 - val_loss: 0.0754 - val_acc: 0.9770
Epoch 4/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
379 - acc: 0.9877 - val_loss: 0.0749 - val_acc: 0.9757
Epoch 5/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
269 - acc: 0.9916 - val_loss: 0.0797 - val_acc: 0.9754
```

```
Epoch 6/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
213 - acc: 0.9936 - val_loss: 0.0743 - val_acc: 0.9776
Epoch 7/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
187 - acc: 0.9939 - val_loss: 0.0746 - val_acc: 0.9782
Epoch 8/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
161 - acc: 0.9946 - val_loss: 0.0806 - val_acc: 0.9780
Epoch 9/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
131 - acc: 0.9957 - val_loss: 0.0746 - val_acc: 0.9798
Epoch 10/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
143 - acc: 0.9949 - val_loss: 0.0998 - val_acc: 0.9754
Epoch 11/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
099 - acc: 0.9970 - val_loss: 0.0709 - val_acc: 0.9822
Epoch 12/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
099 - acc: 0.9967 - val_loss: 0.0737 - val_acc: 0.9814
Epoch 13/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
098 - acc: 0.9966 - val_loss: 0.0865 - val_acc: 0.9797
Epoch 14/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
111 - acc: 0.9963 - val_loss: 0.1118 - val_acc: 0.9743
Epoch 15/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
074 - acc: 0.9977 - val_loss: 0.0829 - val_acc: 0.9815
Epoch 16/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
072 - acc: 0.9978 - val_loss: 0.0882 - val_acc: 0.9812
Epoch 17/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
087 - acc: 0.9971 - val_loss: 0.0959 - val_acc: 0.9797
Epoch 18/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
067 - acc: 0.9977 - val_loss: 0.0795 - val_acc: 0.9831
```

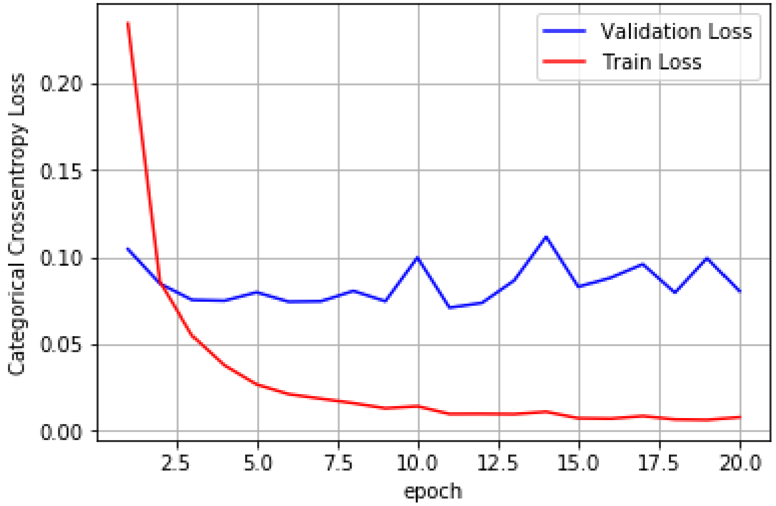
```
Epoch 19/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
064 - acc: 0.9980 - val_loss: 0.0994 - val_acc: 0.9797
Epoch 20/20
60000/60000 [==============================] - 2s 34us/step - loss: 0.0
080 - acc: 0.9974 - val_loss: 0.0804 - val_acc: 0.9824
```

In [14]:

```
score = model_relu.evaluate(x_test, y_test, verbose=0)
score1=score[0]
score2=score[1]
train_acc1=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax11 = plt.subplots(1,1)
ax11.set_xlabel('epoch') ; ax11.set_ylabel('Categorical Crossentropy Lo
ss')

# 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, epo
chs=nb_epoch, verbose=1, validation_data=(x_test, y_test))

# we will get val_loss and val_acc only when you pass the paramter vali
dation_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


vy11 = history11.history['val_loss']
```

```
ty11 = history11.history['loss']
plt_dynamic(x, vy11, ty11, ax11)
```

```
Test score: 0.0804028440125881
Test accuracy: 0.9824
```




## 1.2 MLP + Batch-Norm on hidden Layers + AdamOptimizer

In [15]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(472, activation='relu',
                      input_shape=(input_dim,),
                      kernel_initializer=he_normal(seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(168, activation='relu',
                      kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())
```

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


model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 472)               370520    
_________________________________________________________________
batch_normalization_1 (Batch (None, 472)               1888      
_________________________________________________________________
dense_5 (Dense)              (None, 168)               79464     
_________________________________________________________________
batch_normalization_2 (Batch (None, 168)               672       
_________________________________________________________________
dense_6 (Dense)              (None, 10)                1690      
=================================================================
Total params: 454,234
Trainable params: 452,954
Non-trainable params: 1,280
_________________________________________________________________
```

In [16]:
```python
model_batch.compile(optimizer='adam', loss='categorical_crossentropy',
                    metrics=['accuracy'])

history12 = model_batch.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 65us/step - loss: 0.1
869 - acc: 0.9439 - val_loss: 0.1017 - val_acc: 0.9669
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
706 - acc: 0.9788 - val_loss: 0.0791 - val_acc: 0.9757
Epoch 3/20
```

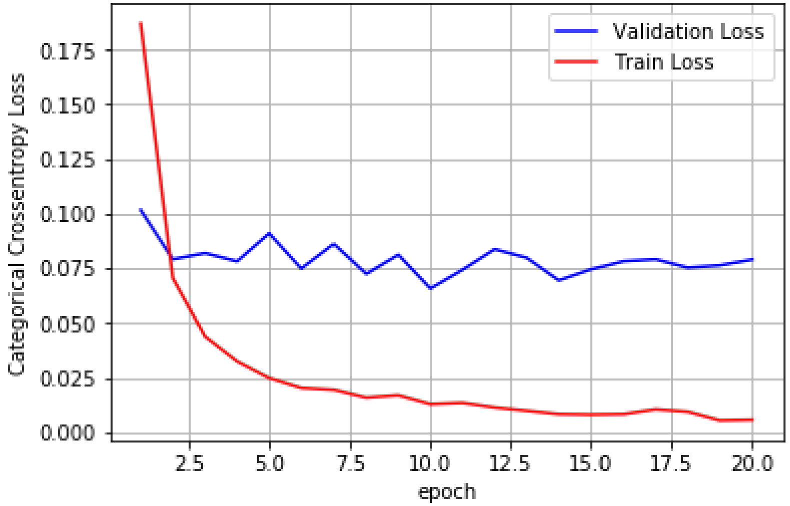
```
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
439 - acc: 0.9867 - val_loss: 0.0820 - val_acc: 0.9743
Epoch 4/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
325 - acc: 0.9893 - val_loss: 0.0782 - val_acc: 0.9767
Epoch 5/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
249 - acc: 0.9919 - val_loss: 0.0910 - val_acc: 0.9729
Epoch 6/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
203 - acc: 0.9936 - val_loss: 0.0749 - val_acc: 0.9752
Epoch 7/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
195 - acc: 0.9933 - val_loss: 0.0861 - val_acc: 0.9743
Epoch 8/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
159 - acc: 0.9945 - val_loss: 0.0724 - val_acc: 0.9794
Epoch 9/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
170 - acc: 0.9943 - val_loss: 0.0812 - val_acc: 0.9778
Epoch 10/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
129 - acc: 0.9959 - val_loss: 0.0657 - val_acc: 0.9815
Epoch 11/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
135 - acc: 0.9956 - val_loss: 0.0743 - val_acc: 0.9795
Epoch 12/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
114 - acc: 0.9964 - val_loss: 0.0838 - val_acc: 0.9762
Epoch 13/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
099 - acc: 0.9967 - val_loss: 0.0798 - val_acc: 0.9788
Epoch 14/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
083 - acc: 0.9973 - val_loss: 0.0695 - val_acc: 0.9806
Epoch 15/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
081 - acc: 0.9974 - val_loss: 0.0745 - val_acc: 0.9814
Epoch 16/20
```

```
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
083 - acc: 0.9970 - val_loss: 0.0783 - val_acc: 0.9799
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
105 - acc: 0.9965 - val_loss: 0.0791 - val_acc: 0.9803
Epoch 18/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
094 - acc: 0.9968 - val_loss: 0.0753 - val_acc: 0.9815
Epoch 19/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0
055 - acc: 0.9982 - val_loss: 0.0764 - val_acc: 0.9805
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0
057 - acc: 0.9981 - val_loss: 0.0790 - val_acc: 0.9797
```

In [17]:

```
score = model_batch.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
score3=score[0]
score4=score[1]
train_acc2=history11.history['acc']

fig,ax12 = plt.subplots(1,1)
ax12.set_xlabel('epoch') ; ax12.set_ylabel('Categorical Crossentropy Lo
ss')

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


vy12 = history12.history['val_loss']
ty12 = history12.history['loss']
plt_dynamic(x, vy12, ty12, ax12)
```

```
Test score: 0.07902511259189378
Test accuracy: 0.9797
```




## 1.3 MLP + Dropout + AdamOptimizer

In [18]:
```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batc
hnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(472, activation='relu',
                     input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(168, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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

```
model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_7 (Dense)              (None, 472)               370520    
_________________________________________________________________
batch_normalization_3 (Batch (None, 472)               1888      
_________________________________________________________________
dropout_1 (Dropout)          (None, 472)               0         
_________________________________________________________________
dense_8 (Dense)              (None, 168)               79464     
_________________________________________________________________
batch_normalization_4 (Batch (None, 168)               672       
_________________________________________________________________
dropout_2 (Dropout)          (None, 168)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1690      
=================================================================
Total params: 454,234
Trainable params: 452,954
Non-trainable params: 1,280
_________________________________________________________________
```

In [19]:

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

history13 = model_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 70us/step - loss: 0.4
343 - acc: 0.8696 - val_loss: 0.1400 - val_acc: 0.9560
```

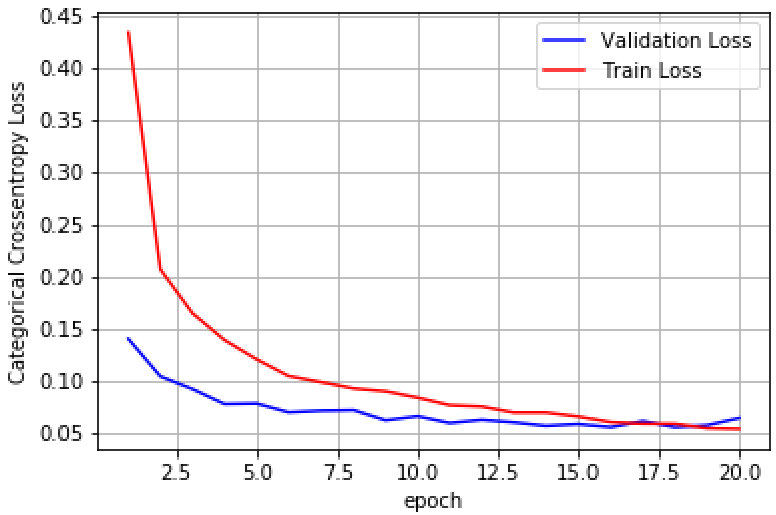
```
Epoch 2/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.2
069 - acc: 0.9376 - val_loss: 0.1039 - val_acc: 0.9668
Epoch 3/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1
648 - acc: 0.9501 - val_loss: 0.0917 - val_acc: 0.9695
Epoch 4/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1
389 - acc: 0.9583 - val_loss: 0.0773 - val_acc: 0.9762
Epoch 5/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1
204 - acc: 0.9626 - val_loss: 0.0778 - val_acc: 0.9744
Epoch 6/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1
042 - acc: 0.9674 - val_loss: 0.0693 - val_acc: 0.9764
Epoch 7/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
984 - acc: 0.9691 - val_loss: 0.0708 - val_acc: 0.9786
Epoch 8/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0
922 - acc: 0.9708 - val_loss: 0.0714 - val_acc: 0.9787
Epoch 9/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
895 - acc: 0.9716 - val_loss: 0.0615 - val_acc: 0.9817
Epoch 10/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
834 - acc: 0.9735 - val_loss: 0.0655 - val_acc: 0.9797
Epoch 11/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
762 - acc: 0.9759 - val_loss: 0.0589 - val_acc: 0.9829
Epoch 12/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0
748 - acc: 0.9766 - val_loss: 0.0620 - val_acc: 0.9814
Epoch 13/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0
691 - acc: 0.9783 - val_loss: 0.0595 - val_acc: 0.9835
Epoch 14/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
690 - acc: 0.9780 - val_loss: 0.0562 - val_acc: 0.9828
```

```
Epoch 15/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
652 - acc: 0.9790 - val_loss: 0.0579 - val_acc: 0.9820
Epoch 16/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
597 - acc: 0.9808 - val_loss: 0.0549 - val_acc: 0.9830
Epoch 17/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0
582 - acc: 0.9815 - val_loss: 0.0607 - val_acc: 0.9819
Epoch 18/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0
581 - acc: 0.9811 - val_loss: 0.0549 - val_acc: 0.9833
Epoch 19/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
540 - acc: 0.9826 - val_loss: 0.0567 - val_acc: 0.9826
Epoch 20/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0
533 - acc: 0.9832 - val_loss: 0.0636 - val_acc: 0.9820
```

In [20]:

```
score = model_drop.evaluate(x_test, y_test, verbose=0)
score5=score[0]
score6=score[1]
train_acc3=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax13 = plt.subplots(1,1)
ax13.set_xlabel('epoch') ; ax13.set_ylabel('Categorical Crossentropy Lo
ss')

vy13 = history13.history['val_loss']
ty13 = history13.history['loss']
plt_dynamic(x, vy13, ty13, ax13)
```

```
Test score: 0.06363873664251878
Test accuracy: 0.982
```




# 2) 3-Hidden layer architecture (784-352-164-124 architecture)

## 2.1 MLP + ReLU + ADAM

In [21]:
```
model_relu = Sequential()
model_relu.add(Dense(352, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_relu.add(Dense(164, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )

model_relu.add(Dense(124, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

model_relu.compile(optimizer='adam',
```

```
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])

history21 = model_relu.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_10 (Dense)             (None, 352)               276320
_________________________________________________________________
dense_11 (Dense)             (None, 164)               57892
_________________________________________________________________
dense_12 (Dense)             (None, 124)               20460
_________________________________________________________________
dense_13 (Dense)             (None, 10)                1250
=================================================================
Total params: 355,922
Trainable params: 355,922
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.2
384 - acc: 0.9297 - val_loss: 0.1191 - val_acc: 0.9635
Epoch 2/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0
917 - acc: 0.9718 - val_loss: 0.0898 - val_acc: 0.9727
Epoch 3/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
595 - acc: 0.9813 - val_loss: 0.0870 - val_acc: 0.9731
Epoch 4/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
431 - acc: 0.9861 - val_loss: 0.0912 - val_acc: 0.9733
Epoch 5/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
326 - acc: 0.9894 - val_loss: 0.0768 - val_acc: 0.9779
```

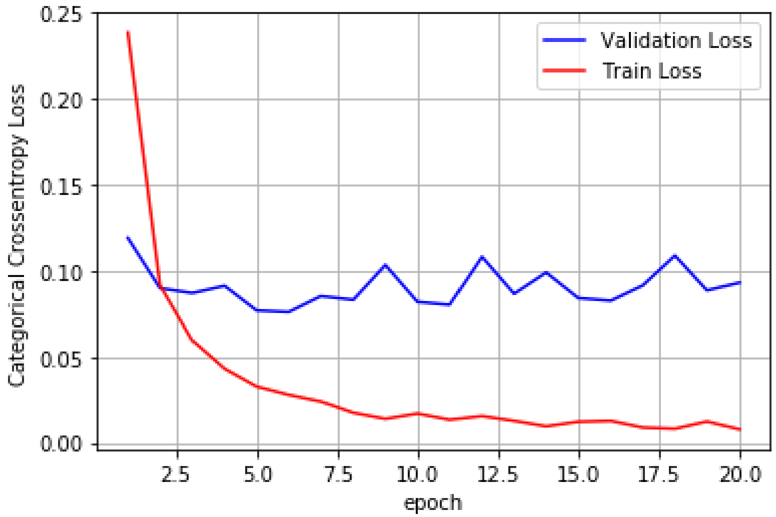
```
Epoch 6/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
278 - acc: 0.9912 - val_loss: 0.0760 - val_acc: 0.9781
Epoch 7/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
239 - acc: 0.9917 - val_loss: 0.0852 - val_acc: 0.9739
Epoch 8/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
174 - acc: 0.9942 - val_loss: 0.0831 - val_acc: 0.9772
Epoch 9/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0
139 - acc: 0.9951 - val_loss: 0.1033 - val_acc: 0.9744
Epoch 10/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
169 - acc: 0.9942 - val_loss: 0.0819 - val_acc: 0.9794
Epoch 11/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
133 - acc: 0.9955 - val_loss: 0.0802 - val_acc: 0.9820
Epoch 12/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
154 - acc: 0.9949 - val_loss: 0.1081 - val_acc: 0.9754
Epoch 13/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
126 - acc: 0.9959 - val_loss: 0.0866 - val_acc: 0.9809
Epoch 14/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
095 - acc: 0.9968 - val_loss: 0.0990 - val_acc: 0.9788
Epoch 15/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
121 - acc: 0.9963 - val_loss: 0.0841 - val_acc: 0.9803
Epoch 16/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
126 - acc: 0.9961 - val_loss: 0.0825 - val_acc: 0.9822
Epoch 17/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
088 - acc: 0.9971 - val_loss: 0.0915 - val_acc: 0.9803
Epoch 18/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
081 - acc: 0.9974 - val_loss: 0.1088 - val_acc: 0.9784
```

```
Epoch 19/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
123 - acc: 0.9960 - val_loss: 0.0885 - val_acc: 0.9816
Epoch 20/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0
077 - acc: 0.9976 - val_loss: 0.0931 - val_acc: 0.9801
```

In [22]:

```
score = model_relu.evaluate(x_test, y_test, verbose=0)
score7=score[0]
score8=score[1]
train_acc4=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax21 = plt.subplots(1,1)
ax21.set_xlabel('epoch') ; ax21.set_ylabel('Categorical Crossentropy Lo
ss')

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


vy21 = history21.history['val_loss']
ty21 = history21.history['loss']
plt_dynamic(x, vy21, ty21, ax21)
```

```
Test score: 0.0930518318862476
Test accuracy: 0.9801
```




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

In [24]:
```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_relu.add(Dense(352, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_batch.add(BatchNormalization())
model_relu.add(Dense(164, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())

model_relu.add(Dense(124, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())

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

In [25]:
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy',
                    metrics=['accuracy'])

history22 = model_batch.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 67us/step - loss: 0.4
890 - acc: 0.8559 - val_loss: 0.8223 - val_acc: 0.7690
Epoch 2/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.3
046 - acc: 0.9136 - val_loss: 0.6800 - val_acc: 0.8069
Epoch 3/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
873 - acc: 0.9194 - val_loss: 1.3266 - val_acc: 0.6626
Epoch 4/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
784 - acc: 0.9214 - val_loss: 1.2652 - val_acc: 0.6949
Epoch 5/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
724 - acc: 0.9234 - val_loss: 0.7312 - val_acc: 0.8170
Epoch 6/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
677 - acc: 0.9246 - val_loss: 2.0437 - val_acc: 0.5762
Epoch 7/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
664 - acc: 0.9250 - val_loss: 1.6328 - val_acc: 0.6136
Epoch 8/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
636 - acc: 0.9261 - val_loss: 8.1621 - val_acc: 0.3043
Epoch 9/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
629 - acc: 0.9260 - val_loss: 1.4145 - val_acc: 0.6829
Epoch 10/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
606 - acc: 0.9267 - val_loss: 3.2574 - val_acc: 0.5500
```

```
Epoch 11/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
575 - acc: 0.9282 - val_loss: 1.2263 - val_acc: 0.7405
Epoch 12/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
570 - acc: 0.9291 - val_loss: 0.6801 - val_acc: 0.8525
Epoch 13/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
564 - acc: 0.9275 - val_loss: 1.3066 - val_acc: 0.6563
Epoch 14/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
559 - acc: 0.9280 - val_loss: 1.2406 - val_acc: 0.6985
Epoch 15/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
552 - acc: 0.9277 - val_loss: 0.6215 - val_acc: 0.8638
Epoch 16/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2
541 - acc: 0.9282 - val_loss: 2.2431 - val_acc: 0.5557
Epoch 17/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
526 - acc: 0.9285 - val_loss: 4.0150 - val_acc: 0.5063
Epoch 18/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.2
539 - acc: 0.9302 - val_loss: 1.2628 - val_acc: 0.6957
Epoch 19/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2
513 - acc: 0.9294 - val_loss: 7.2882 - val_acc: 0.2021
Epoch 20/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.2
532 - acc: 0.9285 - val_loss: 0.6960 - val_acc: 0.8508
```

In [26]:
```
model_batch.summary()
```

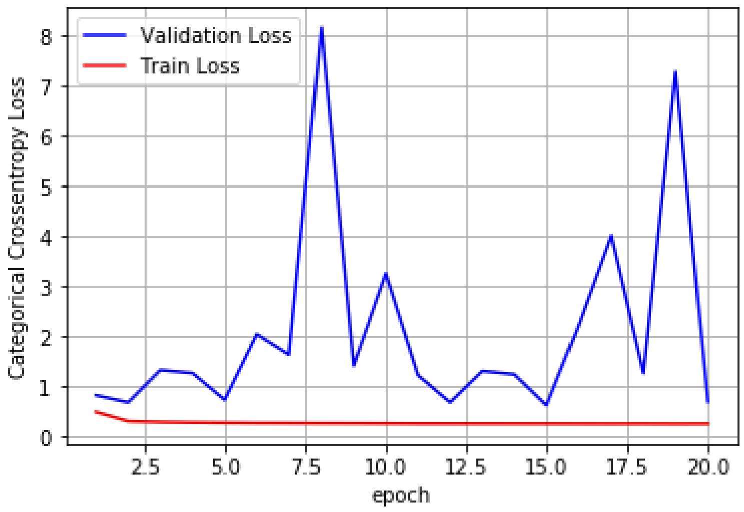
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_8 (Batch (None, 784)               3136
_________________________________________________________________
batch_normalization_9 (Batch (None, 784)               3136
_________________________________________________________________
```

```
batch_normalization_10 (Batc (None, 784)              3136
_________________________________________________________________
dense_21 (Dense)             (None, 10)               7850
=================================================================
Total params: 17,258
Trainable params: 12,554
Non-trainable params: 4,704
_________________________________________________________________
```

In [27]:

```
score = model_batch.evaluate(x_test, y_test, verbose=0)
score9=score[0]
score10=score[1]
train_acc5=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax22 = plt.subplots(1,1)
ax22.set_xlabel('epoch') ; ax22.set_ylabel('Categorical Crossentropy Lo
ss')

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

vy22 = history22.history['val_loss']
ty22 = history22.history['loss']
plt_dynamic(x, vy22, ty22, ax22)
```

```
Test score: 0.6960192083239556
Test accuracy: 0.8508
```




## 2.3 MLP + Dropout + AdamOptimizer

In [28]:

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

from keras.layers import Dropout

model_drop = Sequential()
model_relu.add(Dense(352, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))

model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_relu.add(Dense(164, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))


model_relu.add(Dense(124, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
```

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

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

In [29]:
```
model_drop.compile(optimizer='adam',
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])

history23 = model_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: 1.3
624 - acc: 0.5675 - val_loss: 0.5117 - val_acc: 0.8760
Epoch 2/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
656 - acc: 0.7185 - val_loss: 0.4472 - val_acc: 0.8913
Epoch 3/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
441 - acc: 0.7262 - val_loss: 0.4391 - val_acc: 0.8962
Epoch 4/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
296 - acc: 0.7280 - val_loss: 0.4273 - val_acc: 0.8928
Epoch 5/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
278 - acc: 0.7296 - val_loss: 0.4224 - val_acc: 0.8943
Epoch 6/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
288 - acc: 0.7291 - val_loss: 0.4213 - val_acc: 0.8978
Epoch 7/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
293 - acc: 0.7306 - val_loss: 0.4187 - val_acc: 0.8945
Epoch 8/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.8
```

```
172 - acc: 0.7332 - val_loss: 0.4207 - val_acc: 0.8940
Epoch 9/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
207 - acc: 0.7344 - val_loss: 0.4140 - val_acc: 0.8981
Epoch 10/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
187 - acc: 0.7332 - val_loss: 0.4115 - val_acc: 0.8972
Epoch 11/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
115 - acc: 0.7365 - val_loss: 0.4126 - val_acc: 0.8920
Epoch 12/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
167 - acc: 0.7337 - val_loss: 0.4119 - val_acc: 0.8953
Epoch 13/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
166 - acc: 0.7349 - val_loss: 0.4081 - val_acc: 0.8979
Epoch 14/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
216 - acc: 0.7356 - val_loss: 0.4093 - val_acc: 0.8997
Epoch 15/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
193 - acc: 0.7368 - val_loss: 0.4048 - val_acc: 0.8976
Epoch 16/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
108 - acc: 0.7388 - val_loss: 0.4082 - val_acc: 0.8980
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.8
070 - acc: 0.7393 - val_loss: 0.4074 - val_acc: 0.8965
Epoch 18/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
123 - acc: 0.7373 - val_loss: 0.4039 - val_acc: 0.8977
Epoch 19/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
093 - acc: 0.7388 - val_loss: 0.4032 - val_acc: 0.8983
Epoch 20/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.8
050 - acc: 0.7399 - val_loss: 0.4032 - val_acc: 0.8992
```

In [30]:
```
model_drop.summary()
```

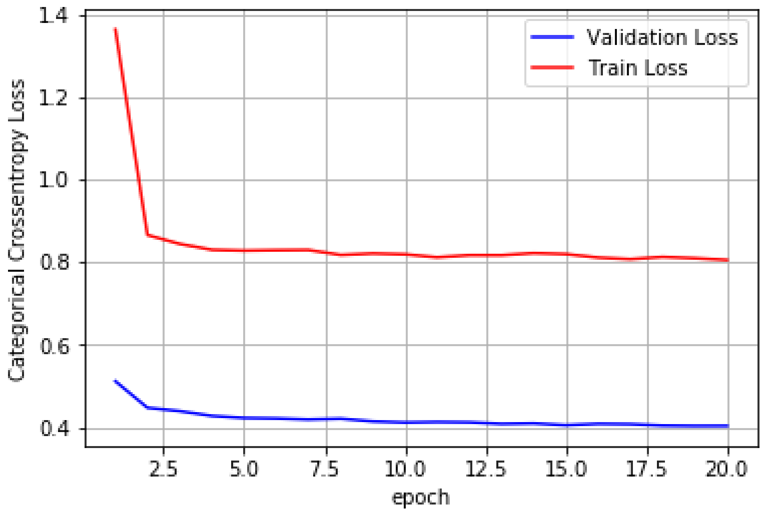
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_11 (Batc (None, 784)               3136
_________________________________________________________________
dropout_3 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_12 (Batc (None, 784)               3136
_________________________________________________________________
dropout_4 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_13 (Batc (None, 784)               3136
_________________________________________________________________
dropout_5 (Dropout)          (None, 784)               0
_________________________________________________________________
dense_25 (Dense)             (None, 10)                7850
=================================================================
Total params: 17,258
Trainable params: 12,554
Non-trainable params: 4,704
_________________________________________________________________
```

In [31]:

```
score = model_drop.evaluate(x_test, y_test, verbose=0)
score11=score[0]
score12=score[1]
train_acc6=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax23 = plt.subplots(1,1)
ax23.set_xlabel('epoch') ; ax23.set_ylabel('Categorical Crossentropy Lo
ss')

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


vy23 = history23.history['val_loss']
```

```
ty23 = history23.history['loss']
plt_dynamic(x, vy23, ty23, ax23)
```

```
Test score: 0.40321056950092315
Test accuracy: 0.8992
```




# 3) 5-Hidden layer architecture (784-216-170-136-80-38-10 architecture)

## 3.1 MLP + ReLU + ADAM

In [33]:
```
model_relu = Sequential()
model_relu.add(Dense(216, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_relu.add(Dense(170, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )

model_relu.add(Dense(136, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
```

```
model_relu.add(Dense(80, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )

model_relu.add(Dense(38, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

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

history31 = model_relu.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_32 (Dense)             (None, 216)               169560
_________________________________________________________________
dense_33 (Dense)             (None, 170)               36890
_________________________________________________________________
dense_34 (Dense)             (None, 136)               23256
_________________________________________________________________
dense_35 (Dense)             (None, 80)                10960
_________________________________________________________________
dense_36 (Dense)             (None, 38)                3078
_________________________________________________________________
dense_37 (Dense)             (None, 10)                390
=================================================================
Total params: 244,134
Trainable params: 244,134
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
```

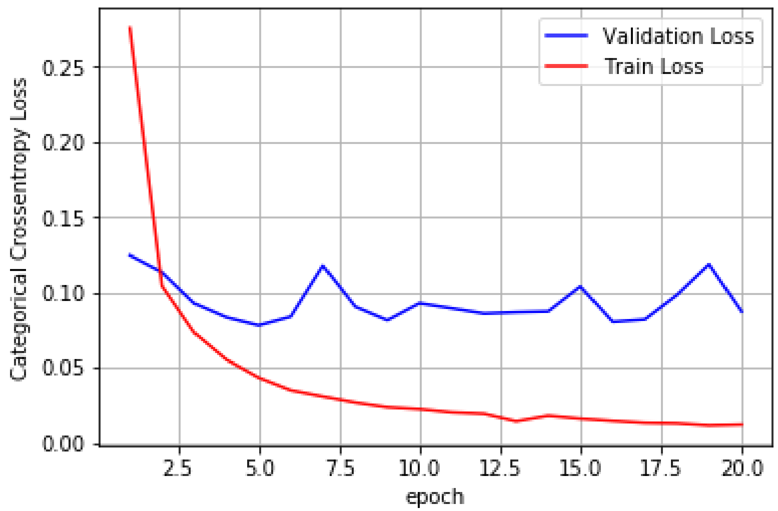
```
60000/60000 [==============================] - 3s 53us/step - loss: 0.2
755 - acc: 0.9179 - val_loss: 0.1245 - val_acc: 0.9616
Epoch 2/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.1
043 - acc: 0.9681 - val_loss: 0.1133 - val_acc: 0.9654
Epoch 3/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
731 - acc: 0.9773 - val_loss: 0.0926 - val_acc: 0.9729
Epoch 4/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
552 - acc: 0.9824 - val_loss: 0.0833 - val_acc: 0.9762
Epoch 5/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
432 - acc: 0.9857 - val_loss: 0.0780 - val_acc: 0.9764
Epoch 6/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
349 - acc: 0.9882 - val_loss: 0.0838 - val_acc: 0.9736
Epoch 7/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
308 - acc: 0.9897 - val_loss: 0.1178 - val_acc: 0.9668
Epoch 8/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
267 - acc: 0.9912 - val_loss: 0.0904 - val_acc: 0.9755
Epoch 9/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
236 - acc: 0.9924 - val_loss: 0.0814 - val_acc: 0.9793
Epoch 10/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
224 - acc: 0.9930 - val_loss: 0.0928 - val_acc: 0.9777
Epoch 11/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
202 - acc: 0.9935 - val_loss: 0.0894 - val_acc: 0.9774
Epoch 12/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
193 - acc: 0.9936 - val_loss: 0.0859 - val_acc: 0.9809
Epoch 13/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
143 - acc: 0.9954 - val_loss: 0.0868 - val_acc: 0.9795
Epoch 14/20
```

```
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
180 - acc: 0.9942 - val_loss: 0.0873 - val_acc: 0.9806
Epoch 15/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
160 - acc: 0.9952 - val_loss: 0.1039 - val_acc: 0.9770
Epoch 16/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
145 - acc: 0.9951 - val_loss: 0.0803 - val_acc: 0.9793
Epoch 17/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
132 - acc: 0.9956 - val_loss: 0.0820 - val_acc: 0.9812
Epoch 18/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
129 - acc: 0.9959 - val_loss: 0.0982 - val_acc: 0.9794
Epoch 19/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
115 - acc: 0.9962 - val_loss: 0.1187 - val_acc: 0.9754
Epoch 20/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0
120 - acc: 0.9961 - val_loss: 0.0872 - val_acc: 0.9816
```

In [34]:

```
score = model_relu.evaluate(x_test, y_test, verbose=0)
score13=score[0]
score14=score[1]
train_acc7=history11.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax31 = plt.subplots(1,1)
ax31.set_xlabel('epoch') ; ax31.set_ylabel('Categorical Crossentropy Lo
ss')

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


vy31 = history31.history['val_loss']
ty31 = history31.history['loss']
plt_dynamic(x, vy31, ty31, ax31)
```

```
Test score: 0.08723179607167986
Test accuracy: 0.9816
```




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

In [35]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_relu.add(Dense(216, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_batch.add(BatchNormalization())
model_relu.add(Dense(170, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())

model_relu.add(Dense(136, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())
```

```
model_relu.add(Dense(80, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())

model_relu.add(Dense(38, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_batch.add(BatchNormalization())

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

In [36]:
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy',
                    metrics=['accuracy'])

history32 = model_batch.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 [==============================] - 6s 96us/step - loss: 0.4
860 - acc: 0.8559 - val_loss: 14.5498 - val_acc: 0.0973
Epoch 2/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.3
060 - acc: 0.9119 - val_loss: 14.5482 - val_acc: 0.0974
Epoch 3/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
868 - acc: 0.9190 - val_loss: 14.2799 - val_acc: 0.1140
Epoch 4/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
793 - acc: 0.9210 - val_loss: 14.2871 - val_acc: 0.1136
Epoch 5/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
719 - acc: 0.9233 - val_loss: 14.5417 - val_acc: 0.0978
Epoch 6/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
689 - acc: 0.9239 - val_loss: 14.4837 - val_acc: 0.1014
Epoch 7/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
```

```
641 - acc: 0.9253 - val_loss: 14.5530 - val_acc: 0.0971
Epoch 8/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
616 - acc: 0.9276 - val_loss: 14.2758 - val_acc: 0.1143
Epoch 9/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
613 - acc: 0.9268 - val_loss: 14.2887 - val_acc: 0.1135
Epoch 10/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.2
600 - acc: 0.9268 - val_loss: 14.4515 - val_acc: 0.1034
Epoch 11/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
574 - acc: 0.9276 - val_loss: 14.2855 - val_acc: 0.1137
Epoch 12/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
575 - acc: 0.9277 - val_loss: 14.2822 - val_acc: 0.1139
Epoch 13/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
564 - acc: 0.9284 - val_loss: 14.2871 - val_acc: 0.1136
Epoch 14/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.2
552 - acc: 0.9279 - val_loss: 14.5514 - val_acc: 0.0972
Epoch 15/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
552 - acc: 0.9284 - val_loss: 14.5434 - val_acc: 0.0977
Epoch 16/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
551 - acc: 0.9282 - val_loss: 14.5401 - val_acc: 0.0979
Epoch 17/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.2
542 - acc: 0.9289 - val_loss: 14.5691 - val_acc: 0.0961
Epoch 18/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
521 - acc: 0.9290 - val_loss: 14.5514 - val_acc: 0.0972
Epoch 19/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
533 - acc: 0.9290 - val_loss: 14.2774 - val_acc: 0.1142
Epoch 20/20
```

```
60000/60000 [==============================] - 4s 71us/step - loss: 0.2
514 - acc: 0.9294 - val_loss: 14.5482 - val_acc: 0.0974
```

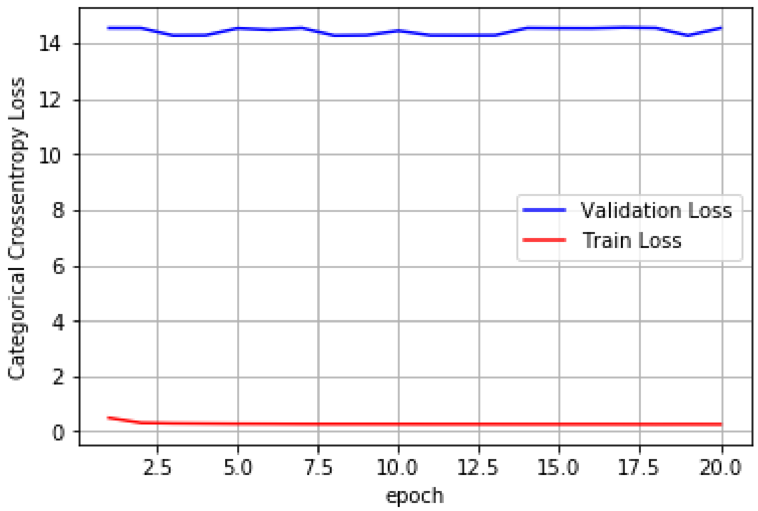
In [37]:
```
model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_14 (Batc (None, 784)               3136
_________________________________________________________________
batch_normalization_15 (Batc (None, 784)               3136
_________________________________________________________________
batch_normalization_16 (Batc (None, 784)               3136
_________________________________________________________________
batch_normalization_17 (Batc (None, 784)               3136
_________________________________________________________________
batch_normalization_18 (Batc (None, 784)               3136
_________________________________________________________________
dense_43 (Dense)             (None, 10)                7850
=================================================================
Total params: 23,530
Trainable params: 15,690
Non-trainable params: 7,840
_________________________________________________________________
```

In [39]:
```
score = model_batch.evaluate(x_test, y_test, verbose=0)
score15=score[0]
score16=score[1]
train_acc8=history32.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax32 = plt.subplots(1,1)
ax32.set_xlabel('epoch') ; ax32.set_ylabel('Categorical Crossentropy Lo
ss')

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

```
vy32 = history32.history['val_loss']
ty32 = history32.history['loss']
plt_dynamic(x, vy32, ty32, ax32)
```

```
Test score: 14.548192663574218
Test accuracy: 0.0974
```




## 3.3 MLP + Dropout + AdamOptimizer

In [40]:
```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batc
hnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()
model_relu.add(Dense(216, activation='relu', input_shape=(input_dim,),
                     kernel_initializer=he_normal(seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_relu.add(Dense(170, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
```

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

model_relu.add(Dense(136, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_relu.add(Dense(80, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_relu.add(Dense(38, activation='relu',
                     kernel_initializer=he_normal(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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

In [41]:

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

history33 = model_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 [==============================] - 6s 106us/step - loss: 2.
1378 - acc: 0.3107 - val_loss: 1.0547 - val_acc: 0.8325
Epoch 2/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.6
071 - acc: 0.4430 - val_loss: 0.9704 - val_acc: 0.8447
Epoch 3/20
60000/60000 [==============================] - 5s 77us/step - loss: 1.5
920 - acc: 0.4488 - val_loss: 0.9579 - val_acc: 0.8452
```

```
Epoch 4/20
60000/60000 [==============================] - 5s 77us/step - loss: 1.5
923 - acc: 0.4474 - val_loss: 0.9549 - val_acc: 0.8456
Epoch 5/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
842 - acc: 0.4502 - val_loss: 0.9419 - val_acc: 0.8458
Epoch 6/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
851 - acc: 0.4478 - val_loss: 0.9492 - val_acc: 0.8455
Epoch 7/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
809 - acc: 0.4495 - val_loss: 0.9455 - val_acc: 0.8507
Epoch 8/20
60000/60000 [==============================] - 5s 77us/step - loss: 1.5
809 - acc: 0.4507 - val_loss: 0.9446 - val_acc: 0.8530
Epoch 9/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
800 - acc: 0.4545 - val_loss: 0.9391 - val_acc: 0.8507
Epoch 10/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
730 - acc: 0.4524 - val_loss: 0.9367 - val_acc: 0.8446
Epoch 11/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
697 - acc: 0.4563 - val_loss: 0.9396 - val_acc: 0.8498
Epoch 12/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
773 - acc: 0.4530 - val_loss: 0.9417 - val_acc: 0.8515
Epoch 13/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
672 - acc: 0.4578 - val_loss: 0.9393 - val_acc: 0.8496
Epoch 14/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
659 - acc: 0.4565 - val_loss: 0.9358 - val_acc: 0.8436
Epoch 15/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
699 - acc: 0.4541 - val_loss: 0.9395 - val_acc: 0.8475
Epoch 16/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
641 - acc: 0.4596 - val_loss: 0.9332 - val_acc: 0.8458
```

```
Epoch 17/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
722 - acc: 0.4563 - val_loss: 0.9375 - val_acc: 0.8522
Epoch 18/20
60000/60000 [==============================] - 5s 76us/step - loss: 1.5
593 - acc: 0.4602 - val_loss: 0.9359 - val_acc: 0.8533
Epoch 19/20
60000/60000 [==============================] - 5s 77us/step - loss: 1.5
578 - acc: 0.4607 - val_loss: 0.9285 - val_acc: 0.8512
Epoch 20/20
60000/60000 [==============================] - 5s 77us/step - loss: 1.5
583 - acc: 0.4602 - val_loss: 0.9346 - val_acc: 0.8529
```

In [42]:
```
model_drop.summary()
```

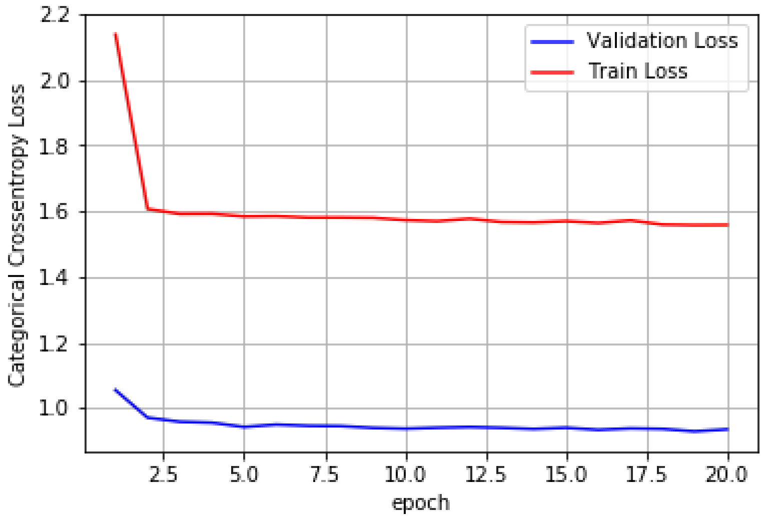
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_19 (Batc (None, 784)               3136
_________________________________________________________________
dropout_6 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_20 (Batc (None, 784)               3136
_________________________________________________________________
dropout_7 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_21 (Batc (None, 784)               3136
_________________________________________________________________
dropout_8 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_22 (Batc (None, 784)               3136
_________________________________________________________________
dropout_9 (Dropout)          (None, 784)               0
_________________________________________________________________
batch_normalization_23 (Batc (None, 784)               3136
_________________________________________________________________
dropout_10 (Dropout)         (None, 784)               0
_________________________________________________________________
dense_49 (Dense)             (None, 10)                7850
```

```
=================================================================
Total params: 23,530
Trainable params: 15,690
Non-trainable params: 7,840
_________________________________________________________________
```

In [43]:

```
score = model_drop.evaluate(x_test, y_test, verbose=0)
score17=score[0]
score18=score[1]
train_acc9=history33.history['acc']
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax33 = plt.subplots(1,1)
ax33.set_xlabel('epoch') ; ax33.set_ylabel('Categorical Crossentropy Lo
ss')

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


vy33 = history33.history['val_loss']
ty33 = history33.history['loss']
plt_dynamic(x, vy33, ty33, ax33)
```

```
Test score: 0.9346290021896362
Test accuracy: 0.8529
```




# Final observation:

In [44]:
```
from prettytable import PrettyTable
```

In [45]:
```
models=['2_hidden_layer MLP+ReLu+Adam',
        '2_hidden_layer MLP+Relu+adam+BN',
        '2_hidden_layer MLP+reLu+Adam+BN+Drop-out',
       '3_hidden_layer MLP+ReLu+Adam',
        '3_hidden_layer MLP+Relu+adam+BN',
        '3_hidden_layer MLP+reLu+Adam+BN+Drop-out',
       '5_hidden_layer MLP+ReLu+Adam',
        '5_hidden_layer MLP+Relu+adam+BN',
        '5_hidden_layer MLP+reLu+Adam+BN+Drop-out']
```

In [46]:
```
training_accuracy=[train_acc1,train_acc2,train_acc3,train_acc4,
                   train_acc5,train_acc6,train_acc7,train_acc8,
                   train_acc9

                  ]
```

In [47]:
```
test_score=[score1,score3,score5,score7,score9,score11,score13,score15,
         score17]
```

In [48]:
```
test_accuracy=[score2,score4,score6,score8,score10,score12,score14,
              score16,
              score18]
INDEX = [1,2,3,4,5,6,7,8,9]
```

In [ ]:
```
# Initializing prettytable
Model_Performance = PrettyTable()
# Adding columns
Model_Performance.add_column("INDEX.",INDEX)
Model_Performance.add_column("MODEL_NAME",models)
Model_Performance.add_column("TRAINING ACCURACY",training_accuracy)
Model_Performance.add_column("TESTING ACCURACY",test_accuracy)
Model_Performance.add_column("TEST SCORE",test_score)

# Printing the Model_Performance
print(Model_Performance)
```

+--------+------------------------------------------+------------------------------------------------------------------------
---------------------------------------------------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------------------------------------------
---------------------------------------------------------------------------+-------------------+---------------------+ | INDEX.
| MODEL_NAME | TRAINING ACCURACY | TESTING ACCURACY | TEST SCORE | +--------+---
---------------------------------------+-------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------------------------------------------
----------------------------------------------------------+-------------------+---------------------+ | 1 | 2_hidden_layer
MLP+ReLu+Adam | 0.9974 | 0.9824 | 0.0804028440125881 | | 2 | 2_hidden_layer
MLP+Relu+adam+BN | 0.9974| 0.9797 | 0.07902511259189378 | | 3 | 2_hidden_layer
MLP+reLu+Adam+BN+Drop-out | 0.9974 | 0.982 | 0.06363873664251878 | | 4 | 3_hidden_layer
MLP+ReLu+Adam | 0.9974 | 0.9801 | 0.0930518318862476 | | 5 | 3_hidden_layer
MLP+Relu+adam+BN | 0.9974| 0.8508 | 0.6960192083239556 | | 6 | 3_hidden_layer
MLP+reLu+Adam+BN+Drop-out | 0.9974 | 0.8992 | 0.40321056950092315 | | 7 | 5_hidden_layer

MLP+ReLu+Adam | 0.9974 | 0.9816 | 0.08723179607167986 | | 8 | 5_hidden_layer
MLP+Relu+adam+BN | 0.9293 | 0.974 | 14.548192663574218 | | 9 | 5_hidden_layer
MLP+reLu+Adam+BN+Drop-out | 0.9345 | 0.8529 | 0.9346290021896362 | +--------+-----------------
------------------------+---------------------------------------------------------------------------------------------------
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----------------------------------------+-----------------+--------------------+