

In [0]:

```
# if your 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
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization
```

In [0]:

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

In [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 [=====] - 0s 0us/step

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 test 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 test examples : 10000 and each image is of shape (28, 28)

In [0]:

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

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
```

In [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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
247	127	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	36	94	154
170	253	253	253	253	253	225	172	253	242	195	64	0	0	0	0	0	0	0	0
	0	0	0	0	0	49	238	253	253	253	253	253	253	253	253	251	93	82	
82	56	39	0	0	0	0	0	0	0	0	0	0	0	0	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	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
	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	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	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	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	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	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	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	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	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	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	0	24	114	221	253	253	253	253

In [0]:

```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets try to normalize the data
#  $X \Rightarrow (X - X_{min}) / (X_{max} - X_{min}) = X / 255$ 

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

In [9]:

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

[illegible]

[illegible]

1. Architecture 1: Two Hidden Layers (784-256-64-10)

With Batch Normalization and Dropout

In [19]:

```
model_relu_1 = Sequential()

model_relu_1.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot_normal'))
model_relu_1.add(BatchNormalization())
model_relu_1.add(Dropout(0.5))

model_relu_1.add(Dense(64, activation='relu', kernel_initializer='glorot_normal'))
model_relu_1.add(BatchNormalization())
model_relu_1.add(Dropout(0.5))

model_relu_1.add(Dense(output_dim, activation='softmax'))
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4479: The name tf.truncated_normal is deprecated. Please use tf.random.truncated_normal instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:148: The name tf.placeholder_with_default is deprecated. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3733: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Please use tf.random.uniform instead.

In [22]:

```
model_relu_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_1.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_core/python/ops/math_grad.py:1424: where (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3005: The name tf.Session is deprecated. Please use tf.compat.v1.Session instead.

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:190: The name tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:197: The name tf.ConfigProto is deprecated. Please use tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:207: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:216: The name tf.is_variable_initialized is deprecated. Please use tf.compat.v1.is_variable_initialized instead.
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:223: The name tf.variables_initializer is deprecated. Please use tf.compat.v1.variables_initializer instead.
```

```
60000/60000 [=====] - 6s 98us/step - loss: 0.5515 - acc: 0.8337 - val_loss: 0.1715 - val_acc: 0.9484
Epoch 2/20
60000/60000 [=====] - 5s 79us/step - loss: 0.2734 - acc: 0.9208 - val_loss: 0.1290 - val_acc: 0.9592
Epoch 3/20
60000/60000 [=====] - 5s 79us/step - loss: 0.2108 - acc: 0.9386 - val_loss: 0.1136 - val_acc: 0.9663
Epoch 4/20
60000/60000 [=====] - 5s 79us/step - loss: 0.1841 - acc: 0.9476 - val_loss: 0.0983 - val_acc: 0.9706
Epoch 5/20
60000/60000 [=====] - 5s 82us/step - loss: 0.1646 - acc: 0.9522 - val_loss: 0.0894 - val_acc: 0.9735
Epoch 6/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1500 - acc: 0.9566 - val_loss: 0.0833 - val_acc: 0.9745
Epoch 7/20
60000/60000 [=====] - 5s 81us/step - loss: 0.1365 - acc: 0.9597 - val_loss: 0.0853 - val_acc: 0.9733
Epoch 8/20
60000/60000 [=====] - 5s 80us/step - loss: 0.1310 - acc: 0.9615 - val_loss: 0.0787 - val_acc: 0.9755
Epoch 9/20
60000/60000 [=====] - 5s 79us/step - loss: 0.1206 - acc: 0.9644 - val_loss: 0.0733 - val_acc: 0.9775
Epoch 10/20
60000/60000 [=====] - 5s 79us/step - loss: 0.1151 - acc: 0.9657 - val_loss: 0.0728 - val_acc: 0.9782
Epoch 11/20
60000/60000 [=====] - 5s 78us/step - loss: 0.1057 - acc: 0.9685 - val_loss: 0.0730 - val_acc: 0.9782
Epoch 12/20
60000/60000 [=====] - 5s 79us/step - loss: 0.1054 - acc: 0.9691 - val_loss: 0.0710 - val_acc: 0.9785
Epoch 13/20
60000/60000 [=====] - 5s 78us/step - loss: 0.0999 - acc: 0.9701 - val_loss: 0.0700 - val_acc: 0.9784
Epoch 14/20
60000/60000 [=====] - 5s 80us/step - loss: 0.0984 - acc: 0.9704 - val_loss: 0.0674 - val_acc: 0.9798
Epoch 15/20
60000/60000 [=====] - 5s 78us/step - loss: 0.0978 - acc: 0.9708 - val_loss: 0.0718 - val_acc: 0.9795
Epoch 16/20
60000/60000 [=====] - 5s 79us/step - loss: 0.0938 - acc: 0.9722 - val_loss: 0.0662 - val_acc: 0.9806
Epoch 17/20
60000/60000 [=====] - 5s 78us/step - loss: 0.0888 - acc: 0.9725 - val_loss: 0.0710 - val_acc: 0.9800
Epoch 18/20
60000/60000 [=====] - 5s 79us/step - loss: 0.0885 - acc: 0.9729 - val_loss: 0.0702 - val_acc: 0.9791
Epoch 19/20
60000/60000 [=====] - 5s 78us/step - loss: 0.0797 - acc: 0.9758 - val_loss: 0.0679 - val_acc: 0.9801
Epoch 20/20
60000/60000 [=====] - 5s 78us/step - loss: 0.0836 - acc: 0.9746 - val_loss: 0.0681 - val_acc: 0.9798
```

In [23]:

```
score = model_relu_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')

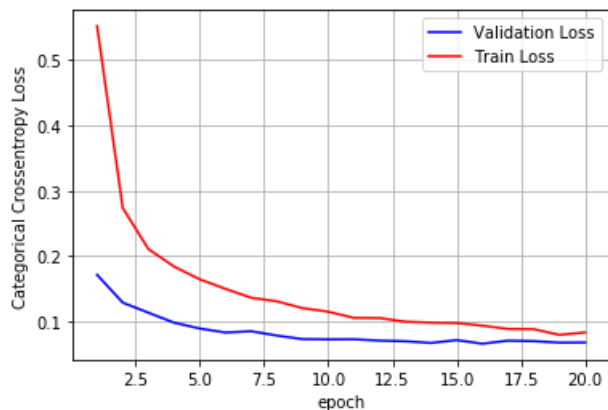
# list of epoch numbers
x = list(range(1,nb_epoch+1))

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

```

Test Score: 0.06807973722481983

Test Accuracy: 0.9798



Without Batch Normalization and Dropout

In [0]:

```

model_relu_1 = Sequential()

model_relu_1.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot_normal'))

model_relu_1.add(Dense(64, activation='relu', kernel_initializer='glorot_normal'))

model_relu_1.add(Dense(output_dim, activation='softmax'))

```

In [25]:

```

model_relu_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_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 [=====] - 4s 71us/step - loss: 0.2834 - acc: 0.9189 -
val_loss: 0.1421 - val_acc: 0.9574
Epoch 2/20
60000/60000 [=====] - 4s 64us/step - loss: 0.1117 - acc: 0.9670 -
val_loss: 0.0968 - val_acc: 0.9692
Epoch 3/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0751 - acc: 0.9775 -
val_loss: 0.0871 - val_acc: 0.9743
Epoch 4/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0550 - acc: 0.9836 -
val_loss: 0.0799 - val_acc: 0.9766
Epoch 5/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0443 - acc: 0.9860 -
val_loss: 0.0753 - val_acc: 0.9766
Epoch 6/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0320 - acc: 0.9903 -
val_loss: 0.0792 - val_acc: 0.9773
Epoch 7/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0251 - acc: 0.9924 -

```

```

val_loss: 0.0825 - val_acc: 0.9762
Epoch 8/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0193 - acc: 0.9940 -
val_loss: 0.0726 - val_acc: 0.9788
Epoch 9/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0183 - acc: 0.9942 -
val_loss: 0.0753 - val_acc: 0.9801
Epoch 10/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0135 - acc: 0.9959 -
val_loss: 0.0744 - val_acc: 0.9806
Epoch 11/20
60000/60000 [=====] - 4s 63us/step - loss: 0.0129 - acc: 0.9960 -
val_loss: 0.0805 - val_acc: 0.9779
Epoch 12/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0106 - acc: 0.9966 -
val_loss: 0.0826 - val_acc: 0.9794
Epoch 13/20
60000/60000 [=====] - 4s 63us/step - loss: 0.0093 - acc: 0.9970 -
val_loss: 0.0856 - val_acc: 0.9799
Epoch 14/20
60000/60000 [=====] - 4s 63us/step - loss: 0.0112 - acc: 0.9964 -
val_loss: 0.0881 - val_acc: 0.9789
Epoch 15/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0077 - acc: 0.9974 -
val_loss: 0.0816 - val_acc: 0.9824
Epoch 16/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0081 - acc: 0.9972 -
val_loss: 0.0920 - val_acc: 0.9789
Epoch 17/20
60000/60000 [=====] - 4s 65us/step - loss: 0.0098 - acc: 0.9968 -
val_loss: 0.0941 - val_acc: 0.9792
Epoch 18/20
60000/60000 [=====] - 4s 65us/step - loss: 0.0060 - acc: 0.9980 -
val_loss: 0.1199 - val_acc: 0.9743
Epoch 19/20
60000/60000 [=====] - 4s 65us/step - loss: 0.0072 - acc: 0.9974 -
val_loss: 0.1067 - val_acc: 0.9781
Epoch 20/20
60000/60000 [=====] - 4s 64us/step - loss: 0.0097 - acc: 0.9967 -
val_loss: 0.0991 - val_acc: 0.9794

```

In [26]:

```

score = model_relu_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')

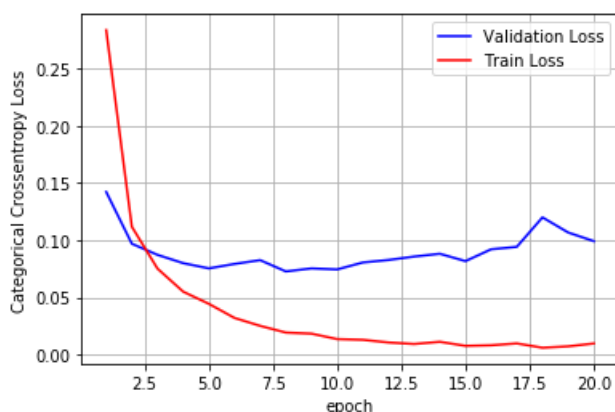
# list of epoch numbers
x = list(range(1,nb_epoch+1))

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

```

Test Score: 0.09909216562398315

Test Accuracy: 0.9794



2. Architecture: 3 Hidden Layers (784-512-256-128-10)

With Batch Normalization

In [0]:

```
model_relu_2 = Sequential()

model_relu_2.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot_normal'))
model_relu_2.add(BatchNormalization())
model_relu_2.add(Dropout(0.5))

model_relu_2.add(Dense(256, activation='relu', kernel_initializer='glorot_normal'))
model_relu_2.add(BatchNormalization())
model_relu_2.add(Dropout(0.5))

model_relu_2.add(Dense(128, activation='relu', kernel_initializer='glorot_normal'))
model_relu_2.add(BatchNormalization())
model_relu_2.add(Dropout(0.5))

model_relu_2.add(Dense(output_dim, activation='softmax'))
```

In [30]:

```
model_relu_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_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 [=====] - 11s 187us/step - loss: 0.5308 - acc: 0.8401 - val_loss: 0.1612 - val_acc: 0.9524

Epoch 2/20

60000/60000 [=====] - 10s 170us/step - loss: 0.2390 - acc: 0.9292 - val_loss: 0.1186 - val_acc: 0.9644

Epoch 3/20

60000/60000 [=====] - 10s 171us/step - loss: 0.1795 - acc: 0.9472 - val_loss: 0.1018 - val_acc: 0.9699

Epoch 4/20

60000/60000 [=====] - 10s 173us/step - loss: 0.1573 - acc: 0.9536 - val_loss: 0.0925 - val_acc: 0.9722

Epoch 5/20

60000/60000 [=====] - 10s 172us/step - loss: 0.1416 - acc: 0.9577 - val_loss: 0.0872 - val_acc: 0.9743

Epoch 6/20

60000/60000 [=====] - 10s 170us/step - loss: 0.1269 - acc: 0.9619 - val_loss: 0.0781 - val_acc: 0.9773

Epoch 7/20

60000/60000 [=====] - 10s 172us/step - loss: 0.1178 - acc: 0.9648 - val_loss: 0.0749 - val_acc: 0.9780

Epoch 8/20

60000/60000 [=====] - 10s 174us/step - loss: 0.1074 - acc: 0.9686 - val_loss: 0.0702 - val_acc: 0.9783

Epoch 9/20

60000/60000 [=====] - 10s 171us/step - loss: 0.1028 - acc: 0.9696 - val_loss: 0.0675 - val_acc: 0.9794

Epoch 10/20

60000/60000 [=====] - 10s 171us/step - loss: 0.0966 - acc: 0.9712 - val_loss: 0.0652 - val_acc: 0.9801

Epoch 11/20

60000/60000 [=====] - 10s 170us/step - loss: 0.0920 - acc: 0.9720 - val_loss: 0.0685 - val_acc: 0.9807

Epoch 12/20

60000/60000 [=====] - 10s 171us/step - loss: 0.0871 - acc: 0.9744 - val_loss: 0.0624 - val_acc: 0.9814

Epoch 13/20

60000/60000 [=====] - 10s 171us/step - loss: 0.0829 - acc: 0.9755 - val_loss: 0.0630 - val_acc: 0.9808

Epoch 14/20

```

Epoch 14/20
60000/60000 [=====] - 10s 170us/step - loss: 0.0802 - acc: 0.9761 - val_loss: 0.0647 - val_acc: 0.9809
Epoch 15/20
60000/60000 [=====] - 10s 171us/step - loss: 0.0773 - acc: 0.9759 - val_loss: 0.0609 - val_acc: 0.9828
Epoch 16/20
60000/60000 [=====] - 10s 170us/step - loss: 0.0718 - acc: 0.9779 - val_loss: 0.0619 - val_acc: 0.9819
Epoch 17/20
60000/60000 [=====] - 10s 170us/step - loss: 0.0735 - acc: 0.9773 - val_loss: 0.0595 - val_acc: 0.9828
Epoch 18/20
60000/60000 [=====] - 10s 170us/step - loss: 0.0661 - acc: 0.9802 - val_loss: 0.0554 - val_acc: 0.9830
Epoch 19/20
60000/60000 [=====] - 10s 171us/step - loss: 0.0655 - acc: 0.9793 - val_loss: 0.0633 - val_acc: 0.9820
Epoch 20/20
60000/60000 [=====] - 10s 169us/step - loss: 0.0649 - acc: 0.9806 - val_loss: 0.0612 - val_acc: 0.9818

```

In [31]:

```

score = model_relu_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))

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

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

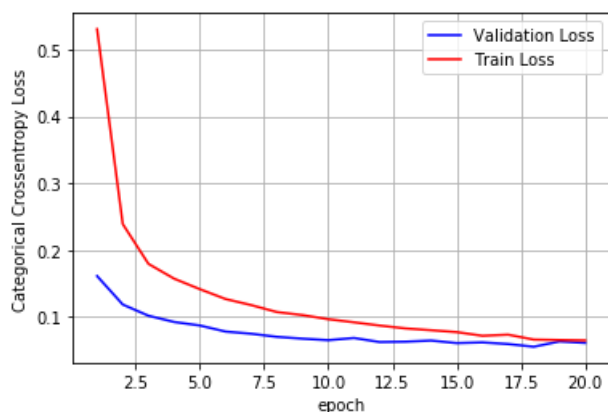
# loss : training loss
# acc : train accuracy
# for each key in history.history we will have a list of length equal to number of epochs

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

```

Test score: 0.06115838211502996

Test accuracy: 0.9818



Without Batch Normalization

In [0]:

```
model_relu_2 = Sequential()

model_relu_2.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot_normal'))

model_relu_2.add(Dense(256, activation='relu', kernel_initializer='glorot_normal'))

model_relu_2.add(Dense(128, activation='relu', kernel_initializer='glorot_normal'))

model_relu_2.add(Dense(output_dim, activation='softmax'))
```

In [33]:

```
model_relu_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_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 [=====] - 9s 148us/step - loss: 0.2272 - acc: 0.9325 - val_loss: 0.1453 - val_acc: 0.9525
Epoch 2/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0865 - acc: 0.9739 - val_loss: 0.0795 - val_acc: 0.9729
Epoch 3/20
60000/60000 [=====] - 8s 133us/step - loss: 0.0544 - acc: 0.9829 - val_loss: 0.0841 - val_acc: 0.9728
Epoch 4/20
60000/60000 [=====] - 8s 133us/step - loss: 0.0418 - acc: 0.9867 - val_loss: 0.0668 - val_acc: 0.9800
Epoch 5/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0316 - acc: 0.9898 - val_loss: 0.0729 - val_acc: 0.9795
Epoch 6/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0244 - acc: 0.9917 - val_loss: 0.0880 - val_acc: 0.9746
Epoch 7/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0233 - acc: 0.9922 - val_loss: 0.0907 - val_acc: 0.9776
Epoch 8/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0198 - acc: 0.9933 - val_loss: 0.0833 - val_acc: 0.9780
Epoch 9/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0195 - acc: 0.9936 - val_loss: 0.0676 - val_acc: 0.9821
Epoch 10/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0136 - acc: 0.9956 - val_loss: 0.0732 - val_acc: 0.9828
Epoch 11/20
60000/60000 [=====] - 8s 133us/step - loss: 0.0148 - acc: 0.9951 - val_loss: 0.0639 - val_acc: 0.9844
Epoch 12/20
60000/60000 [=====] - 8s 133us/step - loss: 0.0143 - acc: 0.9955 - val_loss: 0.0779 - val_acc: 0.9820
Epoch 13/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0098 - acc: 0.9968 - val_loss: 0.0806 - val_acc: 0.9818
Epoch 14/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0123 - acc: 0.9962 - val_loss: 0.0705 - val_acc: 0.9824
Epoch 15/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0092 - acc: 0.9969 - val_loss: 0.1200 - val_acc: 0.9725
Epoch 16/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0117 - acc: 0.9963 - val_loss: 0.0971 - val_acc: 0.9803
Epoch 17/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0073 - acc: 0.9979 - val_loss: 0.1216 - val_acc: 0.9765
Epoch 18/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0149 - acc: 0.9953 - val_loss: 0.0895 - val_acc: 0.9813
Epoch 19/20
```

```
Epoch 19/20
60000/60000 [=====] - 8s 134us/step - loss: 0.0081 - acc: 0.9975 -
val_loss: 0.0940 - val_acc: 0.9819
Epoch 20/20
60000/60000 [=====] - 8s 133us/step - loss: 0.0066 - acc: 0.9979 -
val_loss: 0.0846 - val_acc: 0.9821
```

In [34]:

```
score = model_relu_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))

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

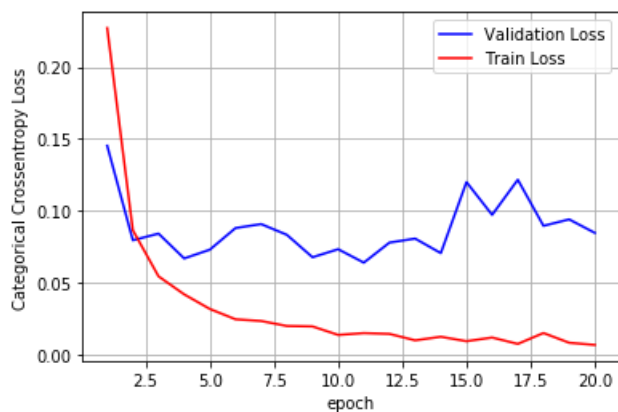
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

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

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

Test score: 0.084612847658376

Test accuracy: 0.9821



In [0]:

3. Architecture: 5 Hidden Layers (784-512-256-128-64-32-10)

With Batch Normalization

In [0]:

```
model_relu_3 = Sequential()

model_relu_3.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot
_normal'))
model_relu_3.add(BatchNormalization())
model_relu_3.add(Dropout(0.5))
```

```

model_relu_3.add(Dropout(0.5))

model_relu_3.add(Dense(256, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(BatchNormalization())
model_relu_3.add(Dropout(0.5))

model_relu_3.add(Dense(128, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(BatchNormalization())
model_relu_3.add(Dropout(0.5))

model_relu_3.add(Dense(64, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(BatchNormalization())
model_relu_3.add(Dropout(0.5))

model_relu_3.add(Dense(32, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(BatchNormalization())
model_relu_3.add(Dropout(0.5))

model_relu_3.add(Dense(output_dim, activation='softmax'))

```

In [36]:

```

model_relu_3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_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 [=====] - 13s 220us/step - loss: 1.3623 - acc: 0.5673 - val_loss: 0.2719 - val_acc: 0.9246
Epoch 2/20
60000/60000 [=====] - 11s 180us/step - loss: 0.5217 - acc: 0.8631 - val_loss: 0.1877 - val_acc: 0.9488
Epoch 3/20
60000/60000 [=====] - 11s 179us/step - loss: 0.3646 - acc: 0.9108 - val_loss: 0.1580 - val_acc: 0.9578
Epoch 4/20
60000/60000 [=====] - 11s 183us/step - loss: 0.3042 - acc: 0.9275 - val_loss: 0.1363 - val_acc: 0.9671
Epoch 5/20
60000/60000 [=====] - 11s 182us/step - loss: 0.2670 - acc: 0.9376 - val_loss: 0.1194 - val_acc: 0.9709
Epoch 6/20
60000/60000 [=====] - 11s 183us/step - loss: 0.2404 - acc: 0.9441 - val_loss: 0.1148 - val_acc: 0.9704
Epoch 7/20
60000/60000 [=====] - 11s 182us/step - loss: 0.2177 - acc: 0.9492 - val_loss: 0.1173 - val_acc: 0.9717
Epoch 8/20
60000/60000 [=====] - 11s 182us/step - loss: 0.2040 - acc: 0.9524 - val_loss: 0.1054 - val_acc: 0.9745
Epoch 9/20
60000/60000 [=====] - 11s 183us/step - loss: 0.1965 - acc: 0.9549 - val_loss: 0.0963 - val_acc: 0.9747
Epoch 10/20
60000/60000 [=====] - 11s 180us/step - loss: 0.1859 - acc: 0.9579 - val_loss: 0.0964 - val_acc: 0.9768
Epoch 11/20
60000/60000 [=====] - 11s 180us/step - loss: 0.1749 - acc: 0.9603 - val_loss: 0.0925 - val_acc: 0.9784
Epoch 12/20
60000/60000 [=====] - 11s 186us/step - loss: 0.1699 - acc: 0.9618 - val_loss: 0.0983 - val_acc: 0.9758
Epoch 13/20
60000/60000 [=====] - 11s 180us/step - loss: 0.1599 - acc: 0.9640 - val_loss: 0.0878 - val_acc: 0.9788
Epoch 14/20
60000/60000 [=====] - 11s 185us/step - loss: 0.1525 - acc: 0.9648 - val_loss: 0.0926 - val_acc: 0.9778
Epoch 15/20
60000/60000 [=====] - 11s 186us/step - loss: 0.1434 - acc: 0.9675 - val_loss: 0.0898 - val_acc: 0.9791
Epoch 16/20
60000/60000 [=====] - 11s 184us/step - loss: 0.1423 - acc: 0.9680 - val_loss: 0.0812 - val_acc: 0.9811

```

```

Epoch 17/20
60000/60000 [=====] - 11s 185us/step - loss: 0.1421 - acc: 0.9669 - val_loss: 0.0852 - val_acc: 0.9805
Epoch 18/20
60000/60000 [=====] - 11s 184us/step - loss: 0.1359 - acc: 0.9691 - val_loss: 0.0836 - val_acc: 0.9813
Epoch 19/20
60000/60000 [=====] - 11s 184us/step - loss: 0.1365 - acc: 0.9691 - val_loss: 0.0772 - val_acc: 0.9806
Epoch 20/20
60000/60000 [=====] - 11s 184us/step - loss: 0.1280 - acc: 0.9703 - val_loss: 0.0800 - val_acc: 0.9816

```

In [37]:

```

score = model_relu_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))

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

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

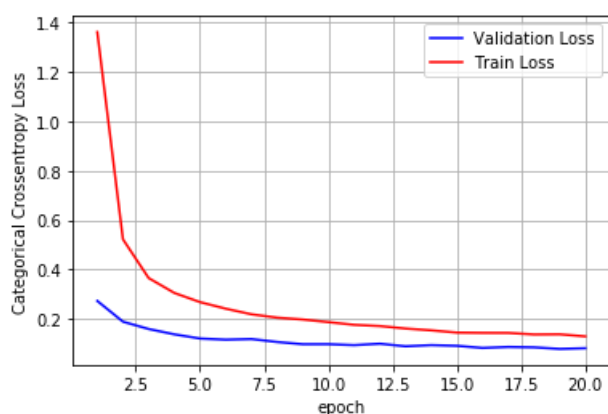
# loss : training loss
# acc : train accuracy
# for each key in history.history we will have a list of length equal to number of epochs

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

```

Test score: 0.08003878279228228

Test accuracy: 0.9816



Without Batch Normalization

In [0]:

```

model_relu_3 = Sequential()

model_relu_3.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer='glorot_normal'))

model_relu_3.add(Dense(256, activation='relu', kernel_initializer='glorot_normal'))

```

```

model_relu_3.add(Dense(128, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(Dense(64, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(Dense(32, activation='relu', kernel_initializer='glorot_normal'))
model_relu_3.add(Dense(output_dim, activation='softmax'))

```

In [39]:

```

model_relu_3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu_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 [=====] - 10s 162us/step - loss: 0.2607 - acc: 0.9216 - val_loss: 0.1193 - val_acc: 0.9627
Epoch 2/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0951 - acc: 0.9711 - val_loss: 0.0980 - val_acc: 0.9683
Epoch 3/20
60000/60000 [=====] - 8s 140us/step - loss: 0.0625 - acc: 0.9802 - val_loss: 0.0891 - val_acc: 0.9707
Epoch 4/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0480 - acc: 0.9846 - val_loss: 0.0718 - val_acc: 0.9784
Epoch 5/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0341 - acc: 0.9889 - val_loss: 0.0754 - val_acc: 0.9788
Epoch 6/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0303 - acc: 0.9903 - val_loss: 0.0998 - val_acc: 0.9712
Epoch 7/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0279 - acc: 0.9911 - val_loss: 0.0789 - val_acc: 0.9784
Epoch 8/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0213 - acc: 0.9934 - val_loss: 0.0792 - val_acc: 0.9783
Epoch 9/20
60000/60000 [=====] - 8s 137us/step - loss: 0.0226 - acc: 0.9928 - val_loss: 0.0738 - val_acc: 0.9791
Epoch 10/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0182 - acc: 0.9939 - val_loss: 0.0827 - val_acc: 0.9792
Epoch 11/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0198 - acc: 0.9938 - val_loss: 0.0762 - val_acc: 0.9808
Epoch 12/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0162 - acc: 0.9948 - val_loss: 0.0952 - val_acc: 0.9773
Epoch 13/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0162 - acc: 0.9949 - val_loss: 0.0817 - val_acc: 0.9813
Epoch 14/20
60000/60000 [=====] - 8s 140us/step - loss: 0.0135 - acc: 0.9959 - val_loss: 0.0851 - val_acc: 0.9795
Epoch 15/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0106 - acc: 0.9969 - val_loss: 0.0975 - val_acc: 0.9787
Epoch 16/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0164 - acc: 0.9951 - val_loss: 0.0840 - val_acc: 0.9819
Epoch 17/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0090 - acc: 0.9972 - val_loss: 0.1184 - val_acc: 0.9760
Epoch 18/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0121 - acc: 0.9964 - val_loss: 0.0870 - val_acc: 0.9826
Epoch 19/20
60000/60000 [=====] - 8s 138us/step - loss: 0.0099 - acc: 0.9970 - val_loss: 0.0881 - val_acc: 0.9826
Epoch 20/20
60000/60000 [=====] - 8s 139us/step - loss: 0.0079 - acc: 0.9976 -

```

```
0.0779, 0.9829]
val_loss: 0.0779 - val_acc: 0.9829
```

In [40]:

```
score = model_relu_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))

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

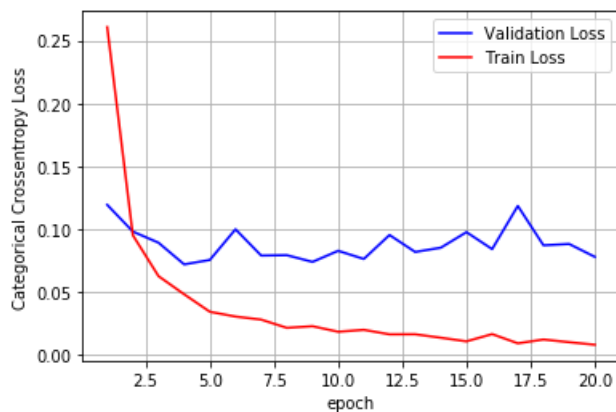
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

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

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

Test score: 0.07785627461677641

Test accuracy: 0.9829



In [2]:

```
from prettytable import PrettyTable

table = PrettyTable()

table.field_names = ['No. of Layers', 'Batch Normalisation and Dropouts', 'Test Score', 'Test Accuracy', 'Convergence']

table.add_row(['2', 'Yes', '6.81', '97.98', 'Quick'])
table.add_row(['2', 'No', '9.91', '97.94', 'Slow'])
table.add_row(['3', 'Yes', '6.12', '98.18', 'Quick'])
table.add_row(['3', 'No', '8.46', '98.21', 'Slow'])
table.add_row(['5', 'Yes', '8.00', '98.16', 'Quick'])
table.add_row(['5', 'No', '7.79', '98.29', 'Slow'])

print(table)
```

No. of Layers	Batch Normalisation and Dropouts	Test Score	Test Accuracy	Convergence
2	Yes	6.81	97.98	Quick
2	No	9.91	97.94	Slow
3	Yes	6.12	98.18	Quick
3	No	8.46	98.21	Slow
5	Yes	8.00	98.16	Quick
5	No	7.79	98.29	Slow

	2		NO		9.91		97.94		SLOW	
	3		Yes		6.12		98.18		Quick	
	3		No		8.46		98.21		Slow	
	5		Yes		8.00		98.16		Quick	
	5		No		7.79		98.29		Slow	
+-----+-----+-----+-----+										

In [0]: