

# CNN\_MNIST

July 5, 2019

In [2]: # Credits: [https://github.com/keras-team/keras/blob/master/examples/mnist\\_cnn.py](https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py)

```
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
from keras.layers.normalization import BatchNormalization
from keras.layers.advanced_activations import LeakyReLU

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

# the data, split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
```

```

x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

```

```

x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples

```

```

In [0]: %matplotlib notebook
        %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()
    plt.show()

```

## 1 Reference

<https://towardsdatascience.com/a-guide-to-an-efficient-way-to-build-neural-network-architectures-part-ii-hyper-parameter-42efca01e5d7>

## 2 Using 3\*3 ConvNet, Optimizer 'AdaDelta'

```

In [10]: model = Sequential()
        model.add(Conv2D(512, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
        model.add(Conv2D(256, kernel_size=(3, 3), activation='relu', padding='same'))

        model.add(Flatten())
        model.add(Dense(128, activation='relu'))
        model.add(Dense(num_classes, activation='softmax'))

        model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_13 (Conv2D)	(None, 26, 26, 512)	5120
conv2d_14 (Conv2D)	(None, 26, 26, 256)	1179904
flatten_4 (Flatten)	(None, 173056)	0
dense_7 (Dense)	(None, 128)	22151296
dense_8 (Dense)	(None, 10)	1290

Total params: 23,337,610  
 Trainable params: 23,337,610  
 Non-trainable params: 0

```
In [11]: model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adam(),
                        metrics=['accuracy'])
```

```
history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))
```

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

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

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

```
# 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

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

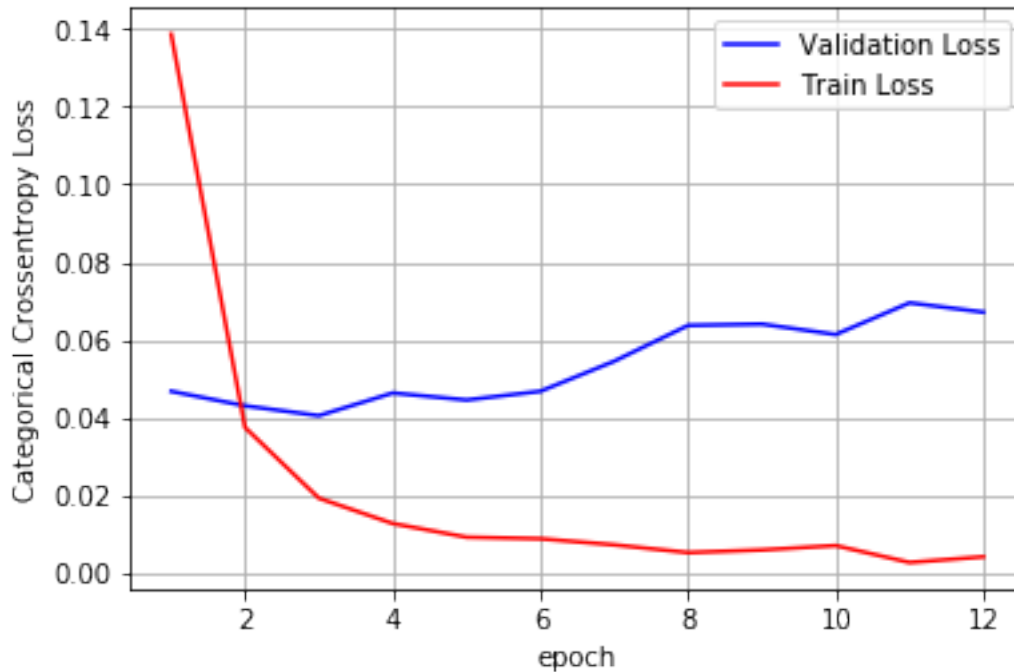
```

Train on 60000 samples, validate on 10000 samples

```

Epoch 1/12
60000/60000 [=====] - 50s 829us/step - loss: 0.1386 - acc: 0.9589 - va
Epoch 2/12
60000/60000 [=====] - 46s 765us/step - loss: 0.0376 - acc: 0.9880 - va
Epoch 3/12
60000/60000 [=====] - 46s 768us/step - loss: 0.0194 - acc: 0.9937 - va
Epoch 4/12
60000/60000 [=====] - 46s 761us/step - loss: 0.0129 - acc: 0.9960 - va
Epoch 5/12
60000/60000 [=====] - 46s 759us/step - loss: 0.0094 - acc: 0.9969 - va
Epoch 6/12
60000/60000 [=====] - 46s 758us/step - loss: 0.0090 - acc: 0.9970 - va
Epoch 7/12
60000/60000 [=====] - 45s 756us/step - loss: 0.0074 - acc: 0.9976 - va
Epoch 8/12
60000/60000 [=====] - 45s 754us/step - loss: 0.0054 - acc: 0.9982 - va
Epoch 9/12
60000/60000 [=====] - 45s 753us/step - loss: 0.0061 - acc: 0.9981 - va
Epoch 10/12
60000/60000 [=====] - 45s 753us/step - loss: 0.0072 - acc: 0.9978 - va
Epoch 11/12
60000/60000 [=====] - 45s 750us/step - loss: 0.0029 - acc: 0.9991 - va
Epoch 12/12
60000/60000 [=====] - 45s 750us/step - loss: 0.0044 - acc: 0.9986 - va
Test score: 0.06720557982521506
Test accuracy: 0.987

```



## 2.1 Evaluating Model

We can clearly see that our model is **overfitting**. If we kept filter width large at initial stage then model tends to **Overfit**,

Now we will try with less number of filter at initial stage and gradually increasing the same.

```
In [0]: model = Sequential()
        model.add(Conv2D(16, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
        model.add(Conv2D(16, kernel_size=(3, 3), activation='relu', padding='same'))

        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Conv2D(16, (3, 3), activation='relu'))

        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(BatchNormalization())
        model.add(Dropout(0.15))

        model.add(Conv2D(32, (3, 3), activation='relu'))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(BatchNormalization())
        model.add(Dropout(0.15))

        model.add(Flatten())
```

```

model.add(Dense(128, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 26, 26, 16)	160
conv2d_16 (Conv2D)	(None, 26, 26, 16)	2320
max_pooling2d_10 (MaxPooling)	(None, 13, 13, 16)	0
conv2d_17 (Conv2D)	(None, 11, 11, 16)	2320
max_pooling2d_11 (MaxPooling)	(None, 5, 5, 16)	0
batch_normalization_7 (Batch Normalization)	(None, 5, 5, 16)	64
dropout_7 (Dropout)	(None, 5, 5, 16)	0
conv2d_18 (Conv2D)	(None, 3, 3, 32)	4640
max_pooling2d_12 (MaxPooling)	(None, 1, 1, 32)	0
batch_normalization_8 (Batch Normalization)	(None, 1, 1, 32)	128
dropout_8 (Dropout)	(None, 1, 1, 32)	0
flatten_5 (Flatten)	(None, 32)	0
dense_9 (Dense)	(None, 128)	4224
dense_10 (Dense)	(None, 10)	1290
Total params: 15,146		
Trainable params: 15,050		
Non-trainable params: 96		

```

In [0]: model.compile(loss=keras.losses.categorical_crossentropy,
                      optimizer=keras.optimizers.Adam(),
                      metrics=['accuracy'])

```

```

history = model.fit(x_train, y_train,
                    batch_size=batch_size,

```

```

        epochs=epochs,
        verbose=1,
        validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epochs+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, v

# 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 e

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

```

Train on 60000 samples, validate on 10000 samples

```

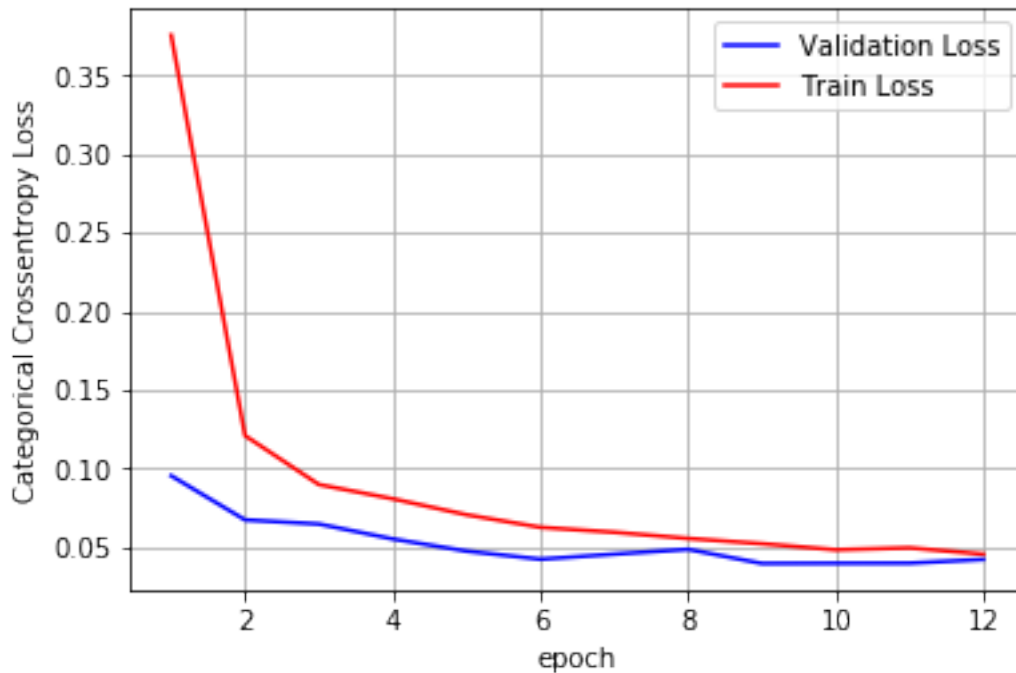
Epoch 1/12
60000/60000 [=====] - 5s 88us/step - loss: 0.3755 - acc: 0.8907 - val.
Epoch 2/12
60000/60000 [=====] - 4s 65us/step - loss: 0.1209 - acc: 0.9630 - val.
Epoch 3/12
60000/60000 [=====] - 4s 65us/step - loss: 0.0898 - acc: 0.9718 - val.
Epoch 4/12
60000/60000 [=====] - 4s 65us/step - loss: 0.0807 - acc: 0.9749 - val.
Epoch 5/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0706 - acc: 0.9776 - val.
Epoch 6/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0626 - acc: 0.9805 - val.
Epoch 7/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0594 - acc: 0.9811 - val.
Epoch 8/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0555 - acc: 0.9823 - val.
Epoch 9/12

```

```

60000/60000 [=====] - 4s 65us/step - loss: 0.0522 - acc: 0.9832 - val.
Epoch 10/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0483 - acc: 0.9844 - val.
Epoch 11/12
60000/60000 [=====] - 4s 63us/step - loss: 0.0495 - acc: 0.9841 - val.
Epoch 12/12
60000/60000 [=====] - 4s 64us/step - loss: 0.0455 - acc: 0.9857 - val.
Test score: 0.042175486064370486
Test accuracy: 0.9877

```



## 2.2 Evaluating Model

We can clearly observe that we initially we kept filter size is less and gradually increasing gives our perfect model.

Model is not overfitting.

## 3 5\*5 ConvNet, Optimizer 'ADAM'

```
In [20]: model = Sequential()
```

```

#1st laeyr
model.add(Conv2D(1, kernel_size=(5, 5),activation='relu',padding='same', input_shape=
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))

```



```

model.add(Dropout(0.10))

# 2nd layer
model.add(Conv2D(2, kernel_size=(5, 5),activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(4, activation='relu'))
model.add(Dense(8, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 28, 28, 1)	26
max_pooling2d_19 (MaxPooling)	(None, 14, 14, 1)	0
dropout_15 (Dropout)	(None, 14, 14, 1)	0
conv2d_26 (Conv2D)	(None, 10, 10, 2)	52
max_pooling2d_20 (MaxPooling)	(None, 5, 5, 2)	0
dropout_16 (Dropout)	(None, 5, 5, 2)	0
flatten_9 (Flatten)	(None, 50)	0
dense_20 (Dense)	(None, 4)	204
dense_21 (Dense)	(None, 8)	40
dense_22 (Dense)	(None, 10)	90
Total params: 412		
Trainable params: 412		
Non-trainable params: 0		

```

In [21]: model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.Adam(),

```

```

        metrics=['accuracy'])

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# 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 ...

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

```

Train on 60000 samples, validate on 10000 samples

```

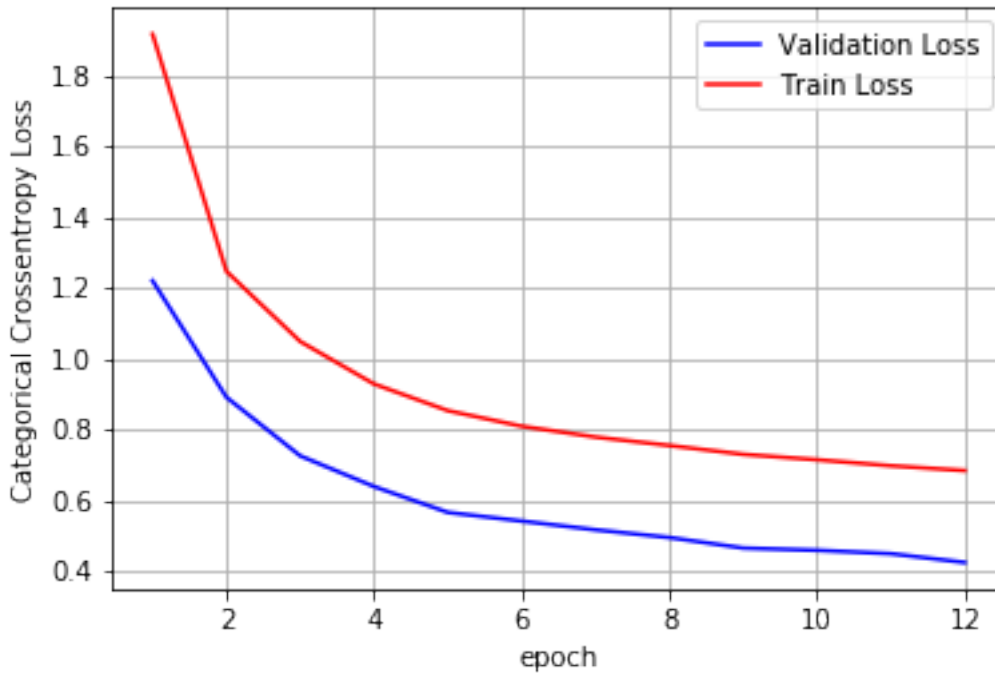
Epoch 1/12
60000/60000 [=====] - 4s 70us/step - loss: 1.9163 - acc: 0.3024 - val.
Epoch 2/12
60000/60000 [=====] - 3s 47us/step - loss: 1.2467 - acc: 0.5540 - val.
Epoch 3/12
60000/60000 [=====] - 3s 45us/step - loss: 1.0484 - acc: 0.6328 - val.
Epoch 4/12
60000/60000 [=====] - 3s 47us/step - loss: 0.9283 - acc: 0.6795 - val.
Epoch 5/12
60000/60000 [=====] - 3s 46us/step - loss: 0.8530 - acc: 0.7091 - val.
Epoch 6/12
60000/60000 [=====] - 3s 45us/step - loss: 0.8090 - acc: 0.7254 - val.
Epoch 7/12

```

```

60000/60000 [=====] - 3s 45us/step - loss: 0.7784 - acc: 0.7375 - val.
Epoch 8/12
60000/60000 [=====] - 3s 44us/step - loss: 0.7546 - acc: 0.7474 - val.
Epoch 9/12
60000/60000 [=====] - 3s 44us/step - loss: 0.7296 - acc: 0.7583 - val.
Epoch 10/12
60000/60000 [=====] - 3s 44us/step - loss: 0.7143 - acc: 0.7627 - val.
Epoch 11/12
60000/60000 [=====] - 3s 45us/step - loss: 0.6974 - acc: 0.7701 - val.
Epoch 12/12
60000/60000 [=====] - 3s 44us/step - loss: 0.6839 - acc: 0.7731 - val.
Test score: 0.424343634724617
Test accuracy: 0.8811

```



### 3.1 Evaluating Model

As we observe training error is large and validation error is small way smaller then model is **underfit**. We have used extremely small number of filters, which cause model tends to underfit.

How we will increase slightly number of filters ie increasing filter width

```

In [36]: model = Sequential()

#1st laeyr
model.add(Conv2D(8, kernel_size=(5, 5),activation='relu',padding='same', input_shape=

```

```

model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.10))

# 2nd layer
model.add(Conv2D(16, kernel_size=(5, 5),activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(200, activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

```

-----
Layer (type)                Output Shape              Param #
=====
conv2d_41 (Conv2D)          (None, 28, 28, 8)        208
-----
max_pooling2d_35 (MaxPooling (None, 14, 14, 8)        0
-----
dropout_31 (Dropout)        (None, 14, 14, 8)        0
-----
conv2d_42 (Conv2D)          (None, 10, 10, 16)       3216
-----
max_pooling2d_36 (MaxPooling (None, 5, 5, 16)        0
-----
dropout_32 (Dropout)        (None, 5, 5, 16)        0
-----
flatten_17 (Flatten)        (None, 400)              0
-----
dense_51 (Dense)            (None, 200)              80200
-----
dense_52 (Dense)            (None, 128)              25728
-----
dense_53 (Dense)            (None, 64)               8256
-----
dense_54 (Dense)            (None, 10)               650
=====
Total params: 118,258
Trainable params: 118,258
Non-trainable params: 0
-----

```

```

In [37]: model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adam(),
                        metrics=['accuracy'])

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# 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)

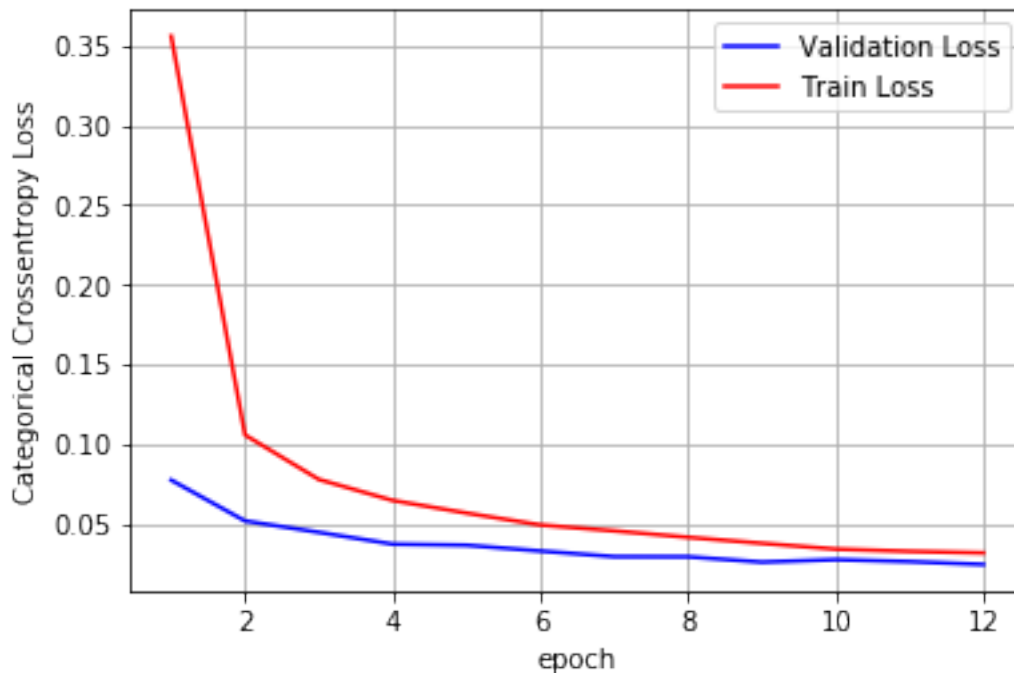
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=====] - 6s 102us/step - loss: 0.3559 - acc: 0.8856 - val_loss: 0.1058
Epoch 2/12
60000/60000 [=====] - 3s 52us/step - loss: 0.1058 - acc: 0.9670 - val_loss: 0.0779
Epoch 3/12
60000/60000 [=====] - 3s 52us/step - loss: 0.0779 - acc: 0.9755 - val_loss: 0.0647
Epoch 4/12
60000/60000 [=====] - 3s 51us/step - loss: 0.0647 - acc: 0.9801 - val_loss: 0.0512
Epoch 5/12

```

```

60000/60000 [=====] - 3s 52us/step - loss: 0.0568 - acc: 0.9820 - val.
Epoch 6/12
60000/60000 [=====] - 3s 52us/step - loss: 0.0493 - acc: 0.9844 - val.
Epoch 7/12
60000/60000 [=====] - 3s 53us/step - loss: 0.0456 - acc: 0.9851 - val.
Epoch 8/12
60000/60000 [=====] - 3s 55us/step - loss: 0.0416 - acc: 0.9866 - val.
Epoch 9/12
60000/60000 [=====] - 3s 55us/step - loss: 0.0378 - acc: 0.9876 - val.
Epoch 10/12
60000/60000 [=====] - 3s 54us/step - loss: 0.0342 - acc: 0.9892 - val.
Epoch 11/12
60000/60000 [=====] - 3s 53us/step - loss: 0.0328 - acc: 0.9894 - val.
Epoch 12/12
60000/60000 [=====] - 3s 52us/step - loss: 0.0318 - acc: 0.9896 - val.
Test score: 0.024570954338563024
Test accuracy: 0.9916

```



## 4 7\*7 ConvNet, Optimizer 'Adam'

```
In [38]: model = Sequential()
```

```
    # 1st layer
```

```

model.add(Conv2D(16, kernel_size=(7, 7),activation='relu',padding='same', input_shape=
model.add(MaxPooling2D(pool_size=(3, 3),strides=1))
model.add(BatchNormalization())
model.add(Dropout(0.15))

# 2nd layer
model.add(Conv2D(32, (7, 7), activation='relu'))
model.add(MaxPooling2D(pool_size=(3,3 ),strides=2))
model.add(BatchNormalization())
model.add(Dropout(0.20))

model.add(Flatten())
model.add(Dense(3200, activation='relu'))
model.add(Dense(800, activation='relu'))
model.add(Dense(400, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_43 (Conv2D)	(None, 28, 28, 16)	800
max_pooling2d_37 (MaxPooling)	(None, 26, 26, 16)	0
batch_normalization_21 (Batch Normalization)	(None, 26, 26, 16)	64
dropout_33 (Dropout)	(None, 26, 26, 16)	0
conv2d_44 (Conv2D)	(None, 20, 20, 32)	25120
max_pooling2d_38 (MaxPooling)	(None, 9, 9, 32)	0
batch_normalization_22 (Batch Normalization)	(None, 9, 9, 32)	128
dropout_34 (Dropout)	(None, 9, 9, 32)	0
flatten_18 (Flatten)	(None, 2592)	0
dense_55 (Dense)	(None, 3200)	8297600
dense_56 (Dense)	(None, 800)	2560800
dense_57 (Dense)	(None, 400)	320400

```

-----
dense_58 (Dense)                (None, 10)                4010
=====
Total params: 11,208,922
Trainable params: 11,208,826
Non-trainable params: 96
-----

```

```

In [39]: model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adam(),
                        metrics=['accuracy'])

```

```

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

```

```

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

```

```

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

```

```

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

```

```

# 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

```

```

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

```

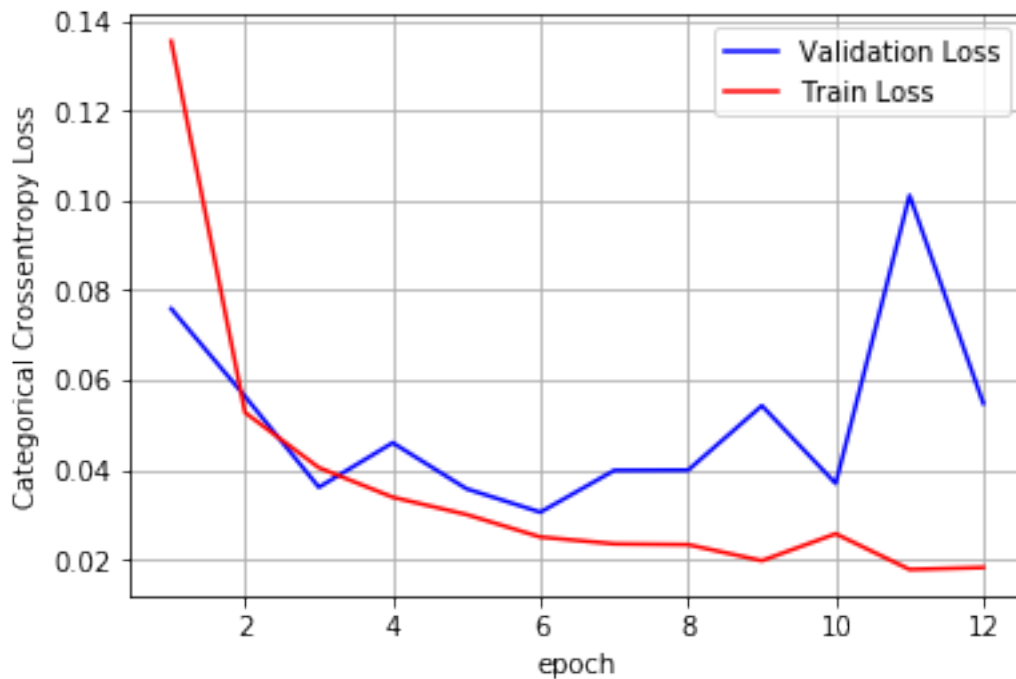
Train on 60000 samples, validate on 10000 samples

Epoch 1/12

60000/60000 [=====] - 12s 208us/step - loss: 0.1354 - acc: 0.9626 - va



Epoch 2/12  
60000/60000 [=====] - 9s 146us/step - loss: 0.0528 - acc: 0.9850 - va.  
Epoch 3/12  
60000/60000 [=====] - 9s 147us/step - loss: 0.0405 - acc: 0.9891 - va.  
Epoch 4/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0339 - acc: 0.9907 - va.  
Epoch 5/12  
60000/60000 [=====] - 9s 147us/step - loss: 0.0301 - acc: 0.9917 - va.  
Epoch 6/12  
60000/60000 [=====] - 9s 147us/step - loss: 0.0251 - acc: 0.9927 - va.  
Epoch 7/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0235 - acc: 0.9933 - va.  
Epoch 8/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0234 - acc: 0.9935 - va.  
Epoch 9/12  
60000/60000 [=====] - 9s 149us/step - loss: 0.0198 - acc: 0.9947 - va.  
Epoch 10/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0258 - acc: 0.9931 - va.  
Epoch 11/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0178 - acc: 0.9951 - va.  
Epoch 12/12  
60000/60000 [=====] - 9s 148us/step - loss: 0.0183 - acc: 0.9956 - va.  
Test score: 0.054796922633474424  
Test accuracy: 0.9884



## 4.1 Evaluating Model

It can be observe that model is overfitting because we have used Max Pooling matrices (3,3) , for ConvNet ( 7,7).

We have using 2\*2 matrices for Max Pooling.

```
In [40]: model = Sequential()
```

```
    # 1st layer
```

```
    model.add(Conv2D(16, kernel_size=(7, 7),activation='relu',padding='same', input_shape=
```

```
    model.add(MaxPooling2D(pool_size=(2, 2),strides=1))
```

```
    model.add(BatchNormalization())
```

```
    model.add(Dropout(0.15))
```

```
    # 2nd layer
```

```
    model.add(Conv2D(32, (7, 7), activation='relu'))
```

```
    model.add(MaxPooling2D(pool_size=(2,2 ),strides=2))
```

```
    model.add(BatchNormalization())
```

```
    model.add(Dropout(0.20))
```

```
    model.add(Flatten())
```

```
    model.add(Dense(3200, activation='relu'))
```

```
    model.add(Dense(800, activation='relu'))
```

```
    model.add(Dense(400, activation='relu'))
```

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

```
    model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_45 (Conv2D)	(None, 28, 28, 16)	800
max_pooling2d_39 (MaxPooling	(None, 27, 27, 16)	0
batch_normalization_23 (Batc	(None, 27, 27, 16)	64
dropout_35 (Dropout)	(None, 27, 27, 16)	0
conv2d_46 (Conv2D)	(None, 21, 21, 32)	25120
max_pooling2d_40 (MaxPooling	(None, 10, 10, 32)	0
batch_normalization_24 (Batc	(None, 10, 10, 32)	128
dropout_36 (Dropout)	(None, 10, 10, 32)	0

```

-----
flatten_19 (Flatten)          (None, 3200)          0
-----
dense_59 (Dense)              (None, 3200)         10243200
-----
dense_60 (Dense)              (None, 800)          2560800
-----
dense_61 (Dense)              (None, 400)          320400
-----
dense_62 (Dense)              (None, 10)           4010
=====
Total params: 13,154,522
Trainable params: 13,154,426
Non-trainable params: 96
-----

```

```

In [41]: model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adam(),
                        metrics=['accuracy'])

```

```

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

```

```

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

```

```

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

```

```

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

```

```

# 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

```

```

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

```

Train on 60000 samples, validate on 10000 samples

Epoch 1/12

60000/60000 [=====] - 14s 231us/step - loss: 0.1416 - acc: 0.9612 - va

Epoch 2/12

60000/60000 [=====] - 11s 177us/step - loss: 0.0563 - acc: 0.9841 - va

Epoch 3/12

60000/60000 [=====] - 10s 173us/step - loss: 0.0409 - acc: 0.9884 - va

Epoch 4/12

60000/60000 [=====] - 10s 172us/step - loss: 0.0289 - acc: 0.9917 - va

Epoch 5/12

60000/60000 [=====] - 10s 173us/step - loss: 0.0273 - acc: 0.9925 - va

Epoch 6/12

60000/60000 [=====] - 10s 174us/step - loss: 0.0279 - acc: 0.9924 - va

Epoch 7/12

60000/60000 [=====] - 10s 173us/step - loss: 0.0280 - acc: 0.9923 - va

Epoch 8/12

60000/60000 [=====] - 10s 173us/step - loss: 0.0191 - acc: 0.9948 - va

Epoch 9/12

60000/60000 [=====] - 10s 173us/step - loss: 0.0221 - acc: 0.9939 - va

Epoch 10/12

60000/60000 [=====] - 10s 174us/step - loss: 0.0196 - acc: 0.9948 - va

Epoch 11/12

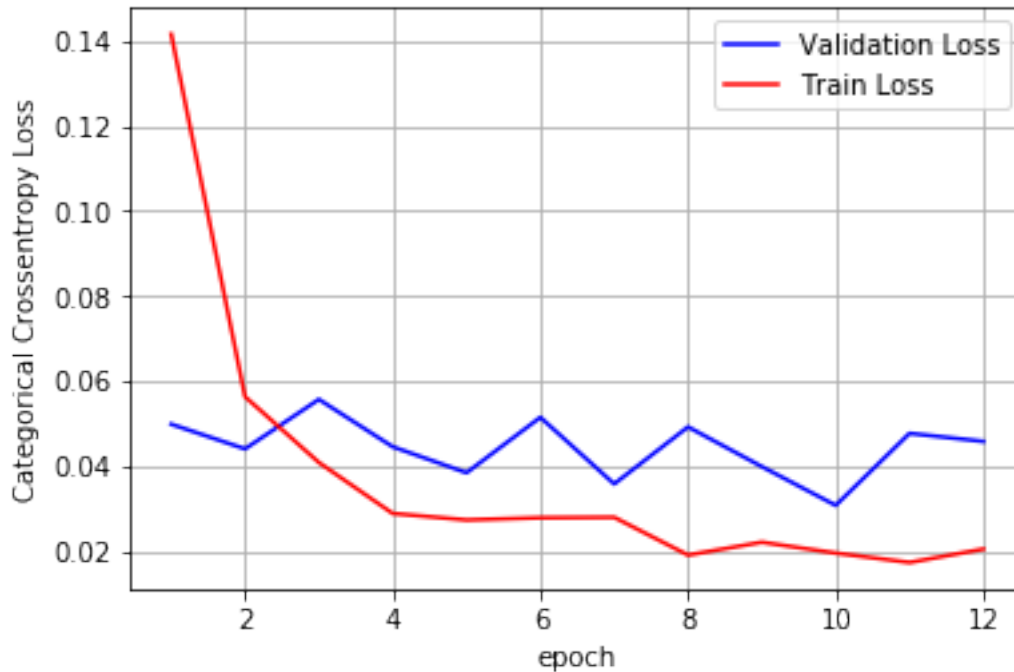
60000/60000 [=====] - 10s 174us/step - loss: 0.0173 - acc: 0.9955 - va

Epoch 12/12

60000/60000 [=====] - 10s 174us/step - loss: 0.0205 - acc: 0.9951 - va

Test score: 0.04580583838448993

Test accuracy: 0.9914



## 4.2 Evaluating model

It can be observe that, it is better than previous one, But can we experiment on dense layer?

In [42]: `model = Sequential()`

*# 1st layer*

```
model.add(Conv2D(16, kernel_size=(7, 7), activation='relu', padding='same', input_shape=(28, 28, 1)))
model.add(MaxPooling2D(pool_size=(2, 2), strides=1))
model.add(BatchNormalization())
model.add(Dropout(0.15))
```

*# 2nd layer*

```
model.add(Conv2D(32, (7, 7), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=2))
model.add(BatchNormalization())
model.add(Dropout(0.20))
```

```
model.add(Flatten())
```

```
model.add(Dense(400, activation='relu'))
```

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

```
model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_47 (Conv2D)	(None, 28, 28, 16)	800
max_pooling2d_41 (MaxPooling)	(None, 27, 27, 16)	0
batch_normalization_25 (Batch Normalization)	(None, 27, 27, 16)	64
dropout_37 (Dropout)	(None, 27, 27, 16)	0
conv2d_48 (Conv2D)	(None, 21, 21, 32)	25120
max_pooling2d_42 (MaxPooling)	(None, 10, 10, 32)	0
batch_normalization_26 (Batch Normalization)	(None, 10, 10, 32)	128
dropout_38 (Dropout)	(None, 10, 10, 32)	0
flatten_20 (Flatten)	(None, 3200)	0
dense_63 (Dense)	(None, 400)	1280400
dense_64 (Dense)	(None, 10)	4010
Total params: 1,310,522		
Trainable params: 1,310,426		
Non-trainable params: 96		

```
In [43]: model.compile(loss=keras.losses.categorical_crossentropy,  
                        optimizer=keras.optimizers.Adam(),  
                        metrics=['accuracy'])
```

```
history = model.fit(x_train, y_train,  
                    batch_size=batch_size,  
                    epochs=epochs,  
                    verbose=1,  
                    validation_data=(x_test, y_test))
```

```
score = model.evaluate(x_test, y_test, verbose=0)  
print('Test score:', score[0])  
print('Test accuracy:', score[1])
```

```

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

# list of epoch numbers
x = list(range(1,epochs+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, validation_data=(X_val, Y_val))

# 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)

```

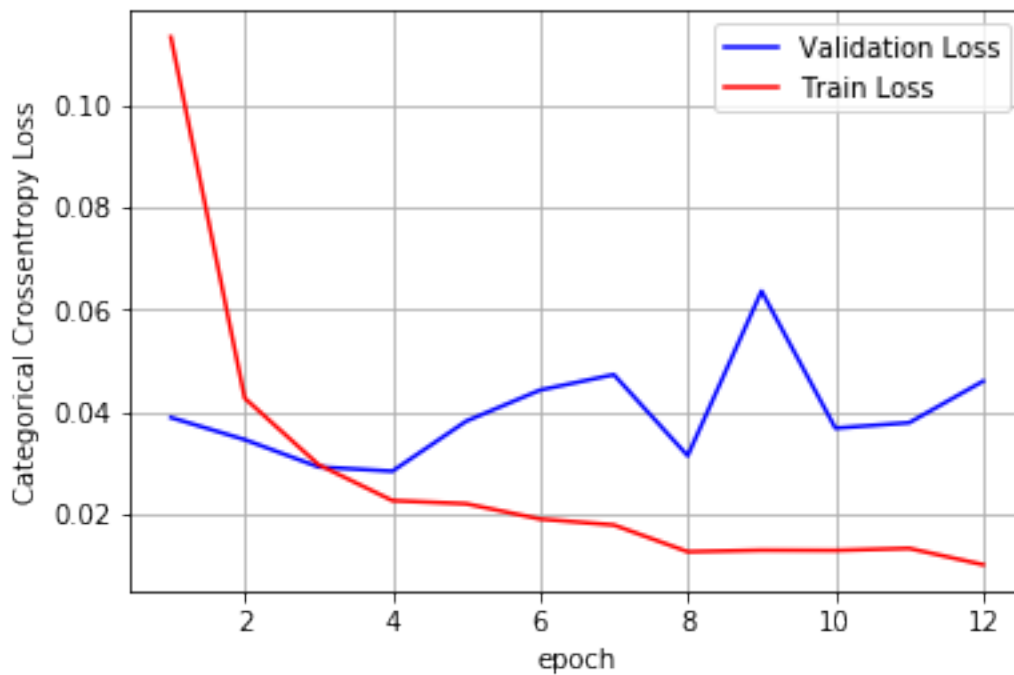
Train on 60000 samples, validate on 10000 samples

```

Epoch 1/12
60000/60000 [=====] - 9s 156us/step - loss: 0.1133 - acc: 0.9667 - val_loss: 0.0427 - val_acc: 0.9869
Epoch 2/12
60000/60000 [=====] - 6s 94us/step - loss: 0.0427 - acc: 0.9869 - val_loss: 0.0297 - val_acc: 0.9913
Epoch 3/12
60000/60000 [=====] - 6s 94us/step - loss: 0.0297 - acc: 0.9913 - val_loss: 0.0226 - val_acc: 0.9928
Epoch 4/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0226 - acc: 0.9928 - val_loss: 0.0220 - val_acc: 0.9932
Epoch 5/12
60000/60000 [=====] - 6s 94us/step - loss: 0.0220 - acc: 0.9932 - val_loss: 0.0190 - val_acc: 0.9939
Epoch 6/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0190 - acc: 0.9939 - val_loss: 0.0179 - val_acc: 0.9947
Epoch 7/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0179 - acc: 0.9947 - val_loss: 0.0126 - val_acc: 0.9960
Epoch 8/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0126 - acc: 0.9960 - val_loss: 0.0129 - val_acc: 0.9960
Epoch 9/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0129 - acc: 0.9960 - val_loss: 0.0129 - val_acc: 0.9959
Epoch 10/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0129 - acc: 0.9959 - val_loss: 0.0133 - val_acc: 0.9959
Epoch 11/12
60000/60000 [=====] - 6s 95us/step - loss: 0.0133 - acc: 0.9959 - val_loss: 0.0101 - val_acc: 0.9970
Epoch 12/12
60000/60000 [=====] - 6s 97us/step - loss: 0.0101 - acc: 0.9970 - val_loss: 0.045987277704650886
Test score: 0.045987277704650886

```

Test accuracy: 0.99



### 4.3 Evaluating Model

It can be observe that if kept single dense layer after flatten operation model start overfitting.  
Adding more Dense layer after flatten layer.

```
In [44]: model = Sequential()
```

```
# 1st layer
```

```
model.add(Conv2D(16, kernel_size=(7, 7), activation='relu', padding='same', input_shape=(28, 28, 1)))  
model.add(MaxPooling2D(pool_size=(2, 2), strides=1))  
model.add(BatchNormalization())
```

```
# 2nd layer
```

```
model.add(Conv2D(32, (7, 7), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2), strides=2))  
model.add(BatchNormalization())
```

```
model.add(Flatten())  
model.add(Dense(3200, activation='relu'))  
model.add(Dense(1600, activation='relu'))
```



```

model.add(Dense(800, activation='relu'))
model.add(Dense(400, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

```

-----
Layer (type)                 Output Shape              Param #
=====
conv2d_49 (Conv2D)           (None, 28, 28, 16)       800
-----
max_pooling2d_43 (MaxPooling (None, 27, 27, 16)       0
-----
batch_normalization_27 (Batc (None, 27, 27, 16)       64
-----
dropout_39 (Dropout)         (None, 27, 27, 16)       0
-----
conv2d_50 (Conv2D)           (None, 21, 21, 32)      25120
-----
max_pooling2d_44 (MaxPooling (None, 10, 10, 32)       0
-----
batch_normalization_28 (Batc (None, 10, 10, 32)      128
-----
dropout_40 (Dropout)         (None, 10, 10, 32)       0
-----
flatten_21 (Flatten)         (None, 3200)              0
-----
dense_65 (Dense)             (None, 3200)             10243200
-----
dense_66 (Dense)             (None, 1600)             5121600
-----
dense_67 (Dense)             (None, 800)              1280800
-----
dense_68 (Dense)             (None, 400)              320400
-----
dense_69 (Dense)             (None, 10)               4010
=====
Total params: 16,996,122
Trainable params: 16,996,026
Non-trainable params: 96
-----

```

```

In [45]: model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adam(),
                        metrics=['accuracy'])

```

```

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# 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.histrory we will have a list of length equal to number of

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

```

Train on 60000 samples, validate on 10000 samples

```

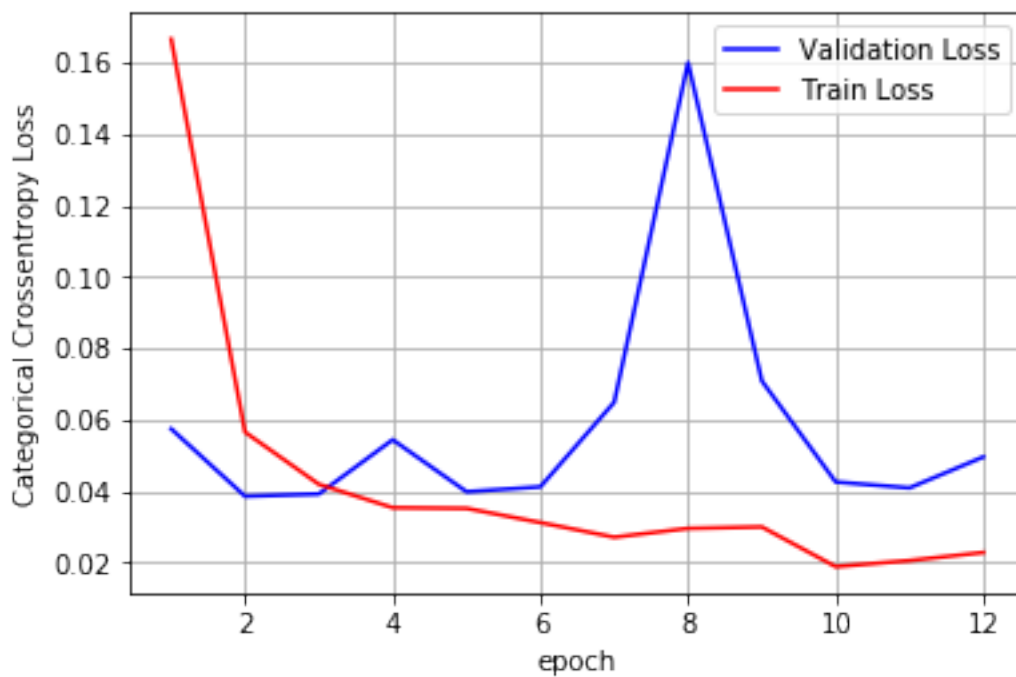
Epoch 1/12
60000/60000 [=====] - 16s 271us/step - loss: 0.1666 - acc: 0.9560 - va
Epoch 2/12
60000/60000 [=====] - 12s 202us/step - loss: 0.0565 - acc: 0.9846 - va
Epoch 3/12
60000/60000 [=====] - 12s 202us/step - loss: 0.0418 - acc: 0.9886 - va
Epoch 4/12
60000/60000 [=====] - 12s 204us/step - loss: 0.0353 - acc: 0.9909 - va
Epoch 5/12
60000/60000 [=====] - 12s 203us/step - loss: 0.0351 - acc: 0.9910 - va
Epoch 6/12
60000/60000 [=====] - 12s 202us/step - loss: 0.0311 - acc: 0.9924 - va
Epoch 7/12
60000/60000 [=====] - 12s 202us/step - loss: 0.0270 - acc: 0.9930 - va
Epoch 8/12

```

```

60000/60000 [=====] - 12s 204us/step - loss: 0.0295 - acc: 0.9929 - va
Epoch 9/12
60000/60000 [=====] - 12s 204us/step - loss: 0.0299 - acc: 0.9931 - va
Epoch 10/12
60000/60000 [=====] - 12s 203us/step - loss: 0.0188 - acc: 0.9954 - va
Epoch 11/12
60000/60000 [=====] - 12s 204us/step - loss: 0.0205 - acc: 0.9950 - va
Epoch 12/12
60000/60000 [=====] - 12s 206us/step - loss: 0.0227 - acc: 0.9949 - va
Test score: 0.04952140008617812
Test accuracy: 0.9918

```



## 4.4 Evaluating Model

Its highly Overfitting we can introduce drop out layer to reduce the overfit

```

In [66]: model = Sequential()

# 1st layer
model.add(Conv2D(16, kernel_size=(7, 7),activation='relu',padding='same', input_shape=
model.add(MaxPooling2D(pool_size=(2, 2),strides=1))
model.add(Dropout(0.50))

```

```

# 2nd layer
model.add(Conv2D(32, (7, 7), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=2))
model.add(Dropout(0.33))

model.add(Flatten())
model.add(Dense(1600, activation='relu'))
model.add(Dense(800, activation='relu'))
model.add(Dense(400, activation='relu'))

model.add(Dense(num_classes, activation='softmax'))

model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_74 (Conv2D)	(None, 28, 28, 16)	800
max_pooling2d_68 (MaxPooling)	(None, 27, 27, 16)	0
dropout_64 (Dropout)	(None, 27, 27, 16)	0
conv2d_75 (Conv2D)	(None, 21, 21, 32)	25120
max_pooling2d_69 (MaxPooling)	(None, 10, 10, 32)	0
dropout_65 (Dropout)	(None, 10, 10, 32)	0
flatten_32 (Flatten)	(None, 3200)	0
dense_104 (Dense)	(None, 1600)	5121600
dense_105 (Dense)	(None, 800)	1280800
dense_106 (Dense)	(None, 400)	320400
dense_107 (Dense)	(None, 10)	4010
Total params: 6,752,730		
Trainable params: 6,752,730		
Non-trainable params: 0		

```

In [67]: model.compile(loss=keras.losses.categorical_crossentropy,
                      optimizer=keras.optimizers.Adam(),

```

```

        metrics=['accuracy'])

history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_fit.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, ...)

# 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)

```

Train on 60000 samples, validate on 10000 samples

```

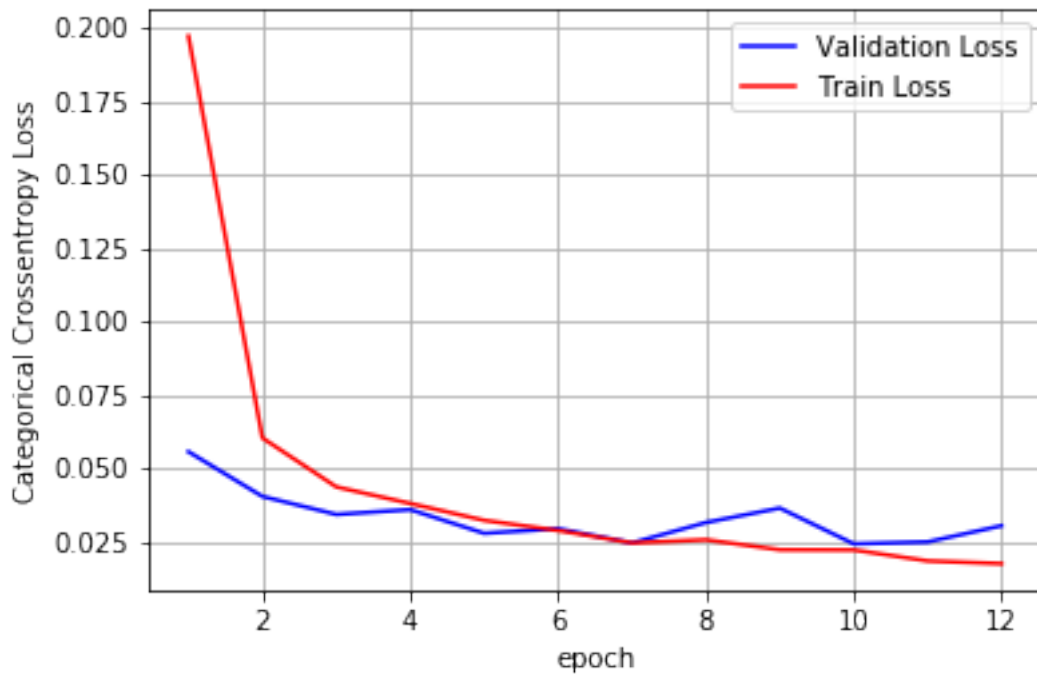
Epoch 1/12
60000/60000 [=====] - 13s 217us/step - loss: 0.1971 - acc: 0.9373 - val_loss: 0.1971 - val_acc: 0.9373
Epoch 2/12
60000/60000 [=====] - 8s 128us/step - loss: 0.0603 - acc: 0.9821 - val_loss: 0.0603 - val_acc: 0.9821
Epoch 3/12
60000/60000 [=====] - 8s 127us/step - loss: 0.0436 - acc: 0.9867 - val_loss: 0.0436 - val_acc: 0.9867
Epoch 4/12
60000/60000 [=====] - 8s 125us/step - loss: 0.0379 - acc: 0.9883 - val_loss: 0.0379 - val_acc: 0.9883
Epoch 5/12
60000/60000 [=====] - 7s 125us/step - loss: 0.0322 - acc: 0.9907 - val_loss: 0.0322 - val_acc: 0.9907
Epoch 6/12
60000/60000 [=====] - 8s 125us/step - loss: 0.0287 - acc: 0.9914 - val_loss: 0.0287 - val_acc: 0.9914
Epoch 7/12

```

```

60000/60000 [=====] - 7s 125us/step - loss: 0.0245 - acc: 0.9928 - va
Epoch 8/12
60000/60000 [=====] - 8s 125us/step - loss: 0.0256 - acc: 0.9923 - va
Epoch 9/12
60000/60000 [=====] - 8s 126us/step - loss: 0.0222 - acc: 0.9939 - va
Epoch 10/12
60000/60000 [=====] - 8s 125us/step - loss: 0.0221 - acc: 0.9940 - va
Epoch 11/12
60000/60000 [=====] - 8s 126us/step - loss: 0.0184 - acc: 0.9943 - va
Epoch 12/12
60000/60000 [=====] - 8s 125us/step - loss: 0.0174 - acc: 0.9952 - va
Test score: 0.030353180483853794
Test accuracy: 0.9919

```



## 5 Conclusion

```

In [68]: import pandas as pd
         from prettytable import PrettyTable

         bold = '\033[1m'
         end = '\033[0m'

```

```

print(bold+'\t\t\t Convolutional Neural Network '+end)

x = PrettyTable()
x.field_names = ['Metric', '3*3 ConvNet', '5*5 ConvNet', '7*7 Convnet']
x.add_row(["Optimizer ", 'AdaDelta', 'ADAM', 'ADAM'])

x.add_row(["Train Accuracy ", 0.9857, 0.9896, 0.9952])
x.add_row(["Train Loss ", 0.0455, 0.0318, 0.0174])
x.add_row(["Test Accuracy ", 0.9877, 0.9916, 0.9919])
x.add_row(["Test Loss ", 0.0422, 0.0246, 0.0304])

print('\n')
print(x)

```

### Convolutional Neural Network

Metric	3*3 ConvNet	5*5 ConvNet	7*7 Convnet
Optimizer	AdaDelta	ADAM	ADAM
Train Accuracy	0.9857	0.9896	0.9952
Train Loss	0.0455	0.0318	0.0174
Test Accuracy	0.9877	0.9916	0.9919
Test Loss	0.0422	0.0246	0.0304

## 6 Summary

1. Always start by using smaller filters is to collect as much local information as possible, and then gradually increase the filter width to reduce the generated feature space width to represent more global, high-level and representative information

2. Large filter size at beginning cause OVERFIT a model.
3. Smaller filter size cause UNDERFIT a model.
4. Adding Drop out layer can reduce overfitting of model.
5. using Sigmoid activation layer was worst output for above specific architecture.
6. Adding dense layer after flatten layer is important, It will change out dramatically
7. Larger and Complex Model take more time to train the model.