

Assignment No 13 : Various CNN Networks on MNIST Dataset

Resources :

- Thanks AAIC Team
- Google Search ,Kaggle,Sklearn
- KrushitReddy
- <https://www.appliedaicourse.com/lecture/11/applied-machine-learning-online-course/3428/assignment-try-various-cnn-networks-on-mnist-dataset/8/module-8-neural-networks-computer-vision-and-deep-learning>
- <https://github.com/krushithreddy>
- <https://scikit-learn.org/stable/index.html>
- <https://www.kaggle.com/>

In [1]:

```
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
```

Using TensorFlow backend.

In [2]:

```
import tensorflow as tf
from tensorflow.python.client import device_lib
print(device_lib.list_local_devices())
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 2569300072973465564
, name: "/device:XLA_CPU:0"
device_type: "XLA_CPU"
memory_limit: 17179869184
locality {
}
incarnation: 3073183043060002416
physical_device_desc: "device: XLA_CPU device"
, name: "/device:XLA_GPU:0"
device_type: "XLA_GPU"
memory_limit: 17179869184
locality {
}
incarnation: 4280592809299709593
physical_device_desc: "device: XLA_GPU device"
, name: "/device:GPU:0"
device_type: "GPU"
memory_limit: 11276946637
locality {
  bus_id: 1
  links {
  }
}
incarnation: 747777203186092895
physical_device_desc: "device: 0, name: Tesla K80, pci bus id: 0000:00:04.0, compute capability: 3.7"
]
```

In [3]:

```
# 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()
```

Downloading data from <https://s3.amazonaws.com/img-datasets/mnist.npz>
11493376/11490434 [=====] - 2s 0us/step

In [0]:

```
batch_size = 50
num_classes = 10
epochs = 30
```

In [0]:

```
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)
```

In [0]:

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

In [7]:

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

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

In [0]:

```
y_train = keras.utils.to_categorical(y_train)
y_test = keras.utils.to_categorical(y_test)
```

In [0]:

```
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()
```

MODEL-1 : 3-LAYER ARCHITECTURE

In [12]:

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
#model.add(Dropout(0.25))
```

```

model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 26, 26, 32)	320
conv2d_5 (Conv2D)	(None, 24, 24, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_6 (Conv2D)	(None, 10, 10, 128)	73856
flatten_2 (Flatten)	(None, 12800)	0
dense_3 (Dense)	(None, 256)	3277056
dropout_2 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 10)	2570
Total params: 3,372,298		
Trainable params: 3,372,298		
Non-trainable params: 0		

In [13]:

```

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))

```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.cast instead.

Train on 60000 samples, validate on 10000 samples

Epoch 1/30
60000/60000 [=====] - 23s 385us/step - loss: 0.1326 - acc: 0.9597 - val_loss: 0.0385 - val_acc: 0.9874

Epoch 2/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0491 - acc: 0.9857 - val_loss: 0.0279 - val_acc: 0.9907

Epoch 3/30
60000/60000 [=====] - 20s 328us/step - loss: 0.0337 - acc: 0.9896 - val_loss: 0.0277 - val_acc: 0.9905

Epoch 4/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0267 - acc: 0.9919 - val_loss: 0.0249 - val_acc: 0.9926

Epoch 5/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0204 - acc: 0.9937 - val_loss: 0.0199 - val_acc: 0.9942

Epoch 6/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0167 - acc: 0.9947 - val_loss: 0.0241 - val_acc: 0.9928

Epoch 7/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0167 - acc: 0.9948 - val_loss: 0.0229 - val_acc: 0.9926

Epoch 8/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0123 - acc: 0.9961 - val_loss: 0.0289 - val_acc: 0.9920

Epoch 9/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0115 - acc: 0.9961 - val_loss: 0.0295 - val_acc: 0.9930

Epoch 10/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0107 - acc: 0.9968 - val_loss: 0.0107 - val_acc: 0.9968

```

oss: 0.0251 - val_acc: 0.9938
Epoch 11/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0089 - acc: 0.9973 - val_l
oss: 0.0262 - val_acc: 0.9940
Epoch 12/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0082 - acc: 0.9974 - val_l
oss: 0.0296 - val_acc: 0.9930
Epoch 13/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0081 - acc: 0.9974 - val_l
oss: 0.0402 - val_acc: 0.9913
Epoch 14/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0077 - acc: 0.9976 - val_l
oss: 0.0334 - val_acc: 0.9936
Epoch 15/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0060 - acc: 0.9981 - val_l
oss: 0.0350 - val_acc: 0.9919
Epoch 16/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0063 - acc: 0.9980 - val_l
oss: 0.0339 - val_acc: 0.9931
Epoch 17/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0057 - acc: 0.9983 - val_l
oss: 0.0367 - val_acc: 0.9935
Epoch 18/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0057 - acc: 0.9984 - val_l
oss: 0.0427 - val_acc: 0.9918
Epoch 19/30
60000/60000 [=====] - 20s 328us/step - loss: 0.0057 - acc: 0.9984 - val_l
oss: 0.0402 - val_acc: 0.9930
Epoch 20/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0058 - acc: 0.9984 - val_l
oss: 0.0342 - val_acc: 0.9933
Epoch 21/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0047 - acc: 0.9987 - val_l
oss: 0.0319 - val_acc: 0.9936
Epoch 22/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0050 - acc: 0.9987 - val_l
oss: 0.0305 - val_acc: 0.9942
Epoch 23/30
60000/60000 [=====] - 20s 330us/step - loss: 0.0041 - acc: 0.9989 - val_l
oss: 0.0399 - val_acc: 0.9931
Epoch 24/30
60000/60000 [=====] - 20s 328us/step - loss: 0.0061 - acc: 0.9984 - val_l
oss: 0.0440 - val_acc: 0.9932
Epoch 25/30
60000/60000 [=====] - 20s 327us/step - loss: 0.0047 - acc: 0.9988 - val_l
oss: 0.0347 - val_acc: 0.9933
Epoch 26/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0046 - acc: 0.9986 - val_l
oss: 0.0403 - val_acc: 0.9937
Epoch 27/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0058 - acc: 0.9984 - val_l
oss: 0.0496 - val_acc: 0.9929
Epoch 28/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0047 - acc: 0.9987 - val_l
oss: 0.0422 - val_acc: 0.9935
Epoch 29/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0050 - acc: 0.9986 - val_l
oss: 0.0357 - val_acc: 0.9941
Epoch 30/30
60000/60000 [=====] - 20s 329us/step - loss: 0.0055 - acc: 0.9985 - val_l
oss: 0.0536 - val_acc: 0.9929

```

In [17]:

```

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

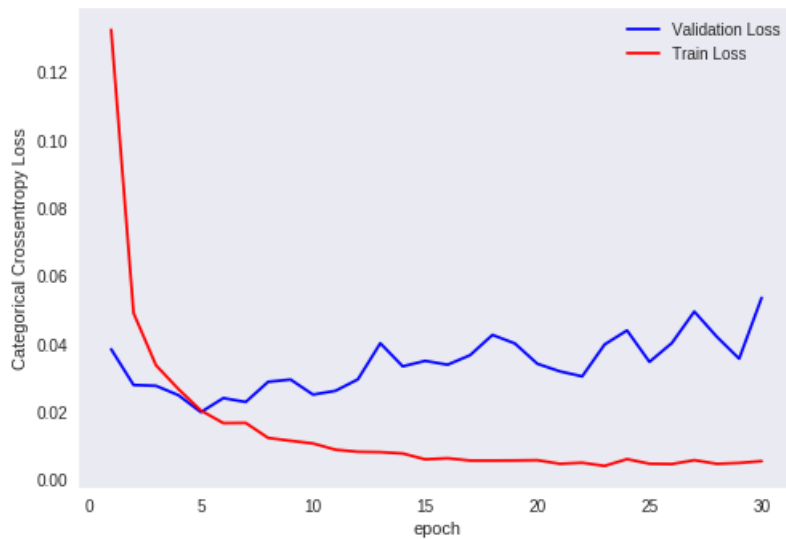
x = list(range(1, epochs+1))
fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

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

```

Test score: 0.053601732978990756

Test accuracy: 0.9929



MODEL-2 : 5-LAYER ARCHITECTURE

In [18]:

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(5, 5), activation='relu', input_shape=input_shape))

model.add(Conv2D(64, (5, 5), activation='relu'))

model.add(Conv2D(128, (5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3)))
#model.add(Dropout(0.5))

model.add(Conv2D(64, (2, 2), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (2, 2), activation='relu'))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 24, 24, 32)	832
conv2d_8 (Conv2D)	(None, 20, 20, 64)	51264
conv2d_9 (Conv2D)	(None, 16, 16, 128)	204928
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 128)	0
conv2d_10 (Conv2D)	(None, 4, 4, 64)	32832
max_pooling2d_4 (MaxPooling2D)	(None, 2, 2, 64)	0
conv2d_11 (Conv2D)	(None, 1, 1, 32)	8224
flatten_3 (Flatten)	(None, 32)	0
dense_5 (Dense)	(None, 256)	8448
dropout_3 (Dropout)	(None, 256)	0
dense_6 (Dense)	(None, 10)	2570

Total params: 309,098
Trainable params: 309,098
Non-trainable params: 0

In [19]:

```
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))
```

Train on 60000 samples, validate on 10000 samples

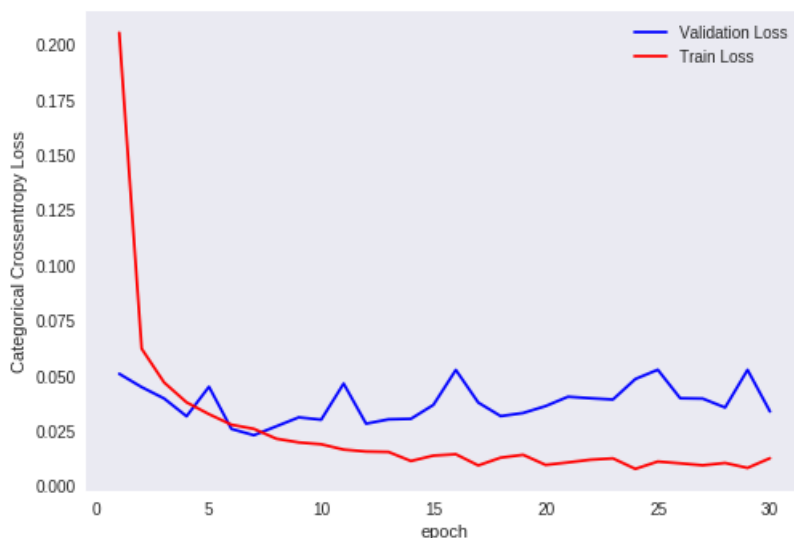
```
Epoch 1/30
60000/60000 [=====] - 23s 381us/step - loss: 0.2053 - acc: 0.9358 - val_loss: 0.0510 - val_acc: 0.9855
Epoch 2/30
60000/60000 [=====] - 22s 369us/step - loss: 0.0623 - acc: 0.9822 - val_loss: 0.0449 - val_acc: 0.9852
Epoch 3/30
60000/60000 [=====] - 22s 370us/step - loss: 0.0470 - acc: 0.9866 - val_loss: 0.0398 - val_acc: 0.9879
Epoch 4/30
60000/60000 [=====] - 22s 364us/step - loss: 0.0380 - acc: 0.9893 - val_loss: 0.0317 - val_acc: 0.9906
Epoch 5/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0327 - acc: 0.9903 - val_loss: 0.0451 - val_acc: 0.9866
Epoch 6/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0279 - acc: 0.9919 - val_loss: 0.0260 - val_acc: 0.9924
Epoch 7/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0260 - acc: 0.9927 - val_loss: 0.0231 - val_acc: 0.9924
Epoch 8/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0216 - acc: 0.9939 - val_loss: 0.0272 - val_acc: 0.9919
Epoch 9/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0199 - acc: 0.9944 - val_loss: 0.0312 - val_acc: 0.9914
Epoch 10/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0191 - acc: 0.9946 - val_loss: 0.0302 - val_acc: 0.9924
Epoch 11/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0166 - acc: 0.9949 - val_loss: 0.0465 - val_acc: 0.9905
Epoch 12/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0158 - acc: 0.9956 - val_loss: 0.0284 - val_acc: 0.9921
Epoch 13/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0156 - acc: 0.9957 - val_loss: 0.0303 - val_acc: 0.9926
Epoch 14/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0115 - acc: 0.9968 - val_loss: 0.0306 - val_acc: 0.9935
Epoch 15/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0139 - acc: 0.9964 - val_loss: 0.0369 - val_acc: 0.9918
Epoch 16/30
60000/60000 [=====] - 22s 359us/step - loss: 0.0145 - acc: 0.9961 - val_loss: 0.0527 - val_acc: 0.9890
Epoch 17/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0095 - acc: 0.9971 - val_loss: 0.0379 - val_acc: 0.9910
Epoch 18/30
60000/60000 [=====] - 22s 360us/step - loss: 0.0130 - acc: 0.9967 - val_loss: 0.0318 - val_acc: 0.9925
Epoch 19/30
60000/60000 [=====] - 22s 360us/step - loss: 0.0143 - acc: 0.9962 - val_loss: 0.0332 - val_acc: 0.9922
Epoch 20/30
60000/60000 [=====] - 22s 360us/step - loss: 0.0097 - acc: 0.9974 - val_loss: 0.0363 - val_acc: 0.9930
Epoch 21/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0108 - acc: 0.9972 - val_loss: 0.0372 - val_acc: 0.9928
```

```
60000/60000 [=====] - 22s 361us/step - loss: 0.0108 - acc: 0.9972 - val_1
oss: 0.0406 - val_acc: 0.9933
Epoch 22/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0121 - acc: 0.9972 - val_1
oss: 0.0399 - val_acc: 0.9927
Epoch 23/30
60000/60000 [=====] - 22s 360us/step - loss: 0.0127 - acc: 0.9969 - val_1
oss: 0.0393 - val_acc: 0.9931
Epoch 24/30
60000/60000 [=====] - 22s 362us/step - loss: 0.0079 - acc: 0.9980 - val_1
oss: 0.0486 - val_acc: 0.9923
Epoch 25/30
60000/60000 [=====] - 22s 363us/step - loss: 0.0112 - acc: 0.9972 - val_1
oss: 0.0528 - val_acc: 0.9914
Epoch 26/30
60000/60000 [=====] - 22s 363us/step - loss: 0.0104 - acc: 0.9973 - val_1
oss: 0.0399 - val_acc: 0.9923
Epoch 27/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0095 - acc: 0.9973 - val_1
oss: 0.0397 - val_acc: 0.9934
Epoch 28/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0106 - acc: 0.9973 - val_1
oss: 0.0357 - val_acc: 0.9940
Epoch 29/30
60000/60000 [=====] - 22s 361us/step - loss: 0.0084 - acc: 0.9980 - val_1
oss: 0.0527 - val_acc: 0.9916
Epoch 30/30
60000/60000 [=====] - 22s 360us/step - loss: 0.0127 - acc: 0.9973 - val_1
oss: 0.0339 - val_acc: 0.9930
```

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

x = list(range(1, epochs+1))
fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

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



In [29]:

```

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

model.add(Conv2D(64, (7, 7), activation='relu'))

model.add(Conv2D(128, (7, 7), activation='relu'))
model.add(MaxPooling2D(pool_size=(1, 1)))
#model.add(Dropout(0.5))

model.add(Conv2D(256, (5, 5), activation='relu'))

model.add(Conv2D(128, (3, 3), activation='relu'))

model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(1, 1)))
model.add(Dropout(0.5))

model.add(Conv2D(32, (2, 2), activation='relu'))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_46 (Conv2D)	(None, 22, 22, 32)	1600
conv2d_47 (Conv2D)	(None, 16, 16, 64)	100416
conv2d_48 (Conv2D)	(None, 10, 10, 128)	401536
max_pooling2d_13 (MaxPooling)	(None, 10, 10, 128)	0
conv2d_49 (Conv2D)	(None, 6, 6, 256)	819456
conv2d_50 (Conv2D)	(None, 4, 4, 128)	295040
conv2d_51 (Conv2D)	(None, 2, 2, 64)	73792
max_pooling2d_14 (MaxPooling)	(None, 2, 2, 64)	0
dropout_4 (Dropout)	(None, 2, 2, 64)	0
conv2d_52 (Conv2D)	(None, 1, 1, 32)	8224
flatten_4 (Flatten)	(None, 32)	0
dense_7 (Dense)	(None, 256)	8448
dropout_5 (Dropout)	(None, 256)	0
dense_8 (Dense)	(None, 10)	2570
Total params: 1,711,082		
Trainable params: 1,711,082		
Non-trainable params: 0		

In [30]:

```

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))

```

Train on 60000 samples, validate on 10000 samples

Epoch 1/30

60000/60000 [=====] - 34s 563us/step - loss: 0.5734 - acc: 0.8059 - val_loss: 0.1081 - val_acc: 0.9745

Epoch 2/30

60000/60000 [=====] - 32s 540us/step - loss: 0.1136 - acc: 0.9726 - val_loss: 0.0887 - val_acc: 0.9779


```
Epoch 3/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0862 - acc: 0.9791 - val_l
oss: 0.0664 - val_acc: 0.9826
Epoch 4/30
60000/60000 [=====] - 32s 539us/step - loss: 0.0761 - acc: 0.9818 - val_l
oss: 0.0550 - val_acc: 0.9846
Epoch 5/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0654 - acc: 0.9846 - val_l
oss: 0.0488 - val_acc: 0.9873
Epoch 6/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0631 - acc: 0.9858 - val_l
oss: 0.0584 - val_acc: 0.9872
Epoch 7/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0599 - acc: 0.9863 - val_l
oss: 0.0676 - val_acc: 0.9860
Epoch 8/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0515 - acc: 0.9882 - val_l
oss: 0.0364 - val_acc: 0.9911
Epoch 9/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0461 - acc: 0.9892 - val_l
oss: 0.0496 - val_acc: 0.9880
Epoch 10/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0446 - acc: 0.9895 - val_l
oss: 0.0661 - val_acc: 0.9862
Epoch 11/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0476 - acc: 0.9890 - val_l
oss: 0.0451 - val_acc: 0.9896
Epoch 12/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0436 - acc: 0.9905 - val_l
oss: 0.0400 - val_acc: 0.9908
Epoch 13/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0447 - acc: 0.9900 - val_l
oss: 0.0508 - val_acc: 0.9893
Epoch 14/30
60000/60000 [=====] - 32s 538us/step - loss: 0.0395 - acc: 0.9916 - val_l
oss: 0.0378 - val_acc: 0.9916
Epoch 15/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0497 - acc: 0.9896 - val_l
oss: 0.0516 - val_acc: 0.9879
Epoch 16/30
60000/60000 [=====] - 32s 541us/step - loss: 0.0321 - acc: 0.9930 - val_l
oss: 0.0382 - val_acc: 0.9917
Epoch 17/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0377 - acc: 0.9918 - val_l
oss: 0.0416 - val_acc: 0.9905
Epoch 18/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0380 - acc: 0.9915 - val_l
oss: 0.0437 - val_acc: 0.9910
Epoch 19/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0382 - acc: 0.9920 - val_l
oss: 0.0368 - val_acc: 0.9908
Epoch 20/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0443 - acc: 0.9915 - val_l
oss: 0.0661 - val_acc: 0.9859
Epoch 21/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0408 - acc: 0.9919 - val_l
oss: 0.0614 - val_acc: 0.9904
Epoch 22/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0395 - acc: 0.9921 - val_l
oss: 0.0650 - val_acc: 0.9881
Epoch 23/30
60000/60000 [=====] - 32s 537us/step - loss: 0.0352 - acc: 0.9929 - val_l
oss: 0.0508 - val_acc: 0.9902
Epoch 24/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0338 - acc: 0.9930 - val_l
oss: 0.0599 - val_acc: 0.9902
Epoch 25/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0373 - acc: 0.9927 - val_l
oss: 0.0522 - val_acc: 0.9908
Epoch 26/30
60000/60000 [=====] - 32s 539us/step - loss: 0.0454 - acc: 0.9913 - val_l
oss: 0.0593 - val_acc: 0.9905
Epoch 27/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0382 - acc: 0.9926 - val_l
oss: 0.0686 - val_acc: 0.9887
Epoch 28/30
60000/60000 [=====] - 32s 540us/step - loss: 0.0441 - acc: 0.9920 - val_l
```

```

oss: 0.0576 - val_acc: 0.9905
Epoch 29/30
60000/60000 [=====] - 32s 539us/step - loss: 0.0425 - acc: 0.9916 - val_l
oss: 0.0504 - val_acc: 0.9909
Epoch 30/30
60000/60000 [=====] - 32s 539us/step - loss: 0.0397 - acc: 0.9933 - val_l
oss: 0.0659 - val_acc: 0.9885

```

In [31]:

```

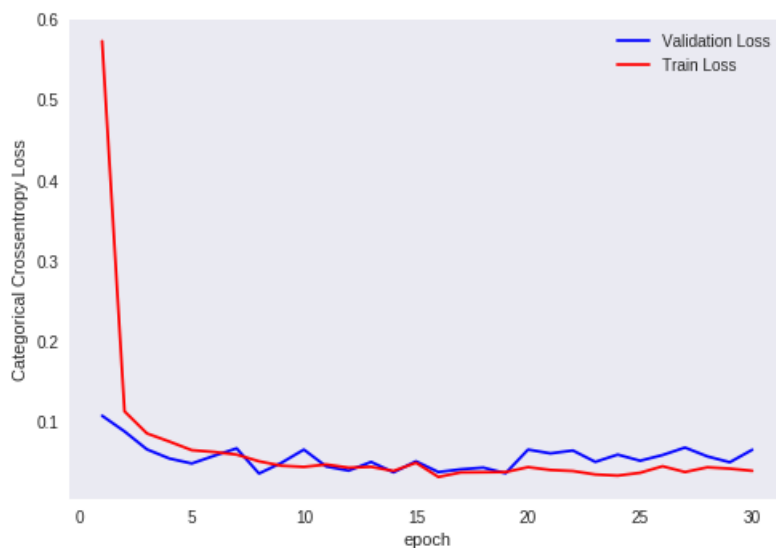
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

x = list(range(1, epochs+1))
fig, ax = plt.subplots(1, 1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

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

```

Test score: 0.06585598365341304
Test accuracy: 0.9885



Conclution :

In [2]:

```

from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Test-score", "Test-accuracy", "Epochs"]

x.add_row(["1", "0.053", "0.992", "5"])
x.add_row(["2", "0.033", "0.993", "7"])
x.add_row(["3", "0.065", "0.988", "11"])

print(x)

```

Model	Test-score	Test-accuracy	Epochs
1	0.053	0.992	5
2	0.033	0.993	7
3	0.065	0.988	11

1. As we can see in the error plots Model 1 and Model 2 are overfitting.
2. Model 3 seems to be working well even model 3 has less test-accuracy compared to model 1&2 but model 3 is not overfitting.