

- model architecture

layer	Input shape	Filter	Stride	Padding	Output shape
Conv1	(16, 1, 32, 32)	(3, 5, 5)	1*1	no	(16, 3, 28, 28)
ReLU	(16, 3, 28, 28)				(16, 3, 28, 28)
Maxpooling	(16, 3, 28, 28)	(3, 3)	2*2	no	(16, 3, 13, 13)
Flatten	(16, 3, 13, 13)				(16, 3*13*13)
Fully Connected 1	(16, 3*13*13)				(16, 64)
ReLU	(16, 64)				(16, 64)
Fully Connected 2	(16, 64)				(16, 3)
Softmax	(16, 3)				(16, 3)

註 1: Conv1 的 input shape=(16, 1, 32, 32)，16 為 batch size，1 為 channel(將照片灰階模式讀取並做 normalization)

註 2: Conv1 的 filter=(3, 5, 5)，3 為產生三張 feature map，5 為 kernel size

註 3: Maxpooling 的 filter=(3, 3)，意思是在 feature map 中每個 3*3 的 2D 區域內取一個最大值做降維，並且步幅為 2

- loss function

採用多類別交叉熵，公式如下：

$$L = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^M y_{ic} \log(p_{ic})$$

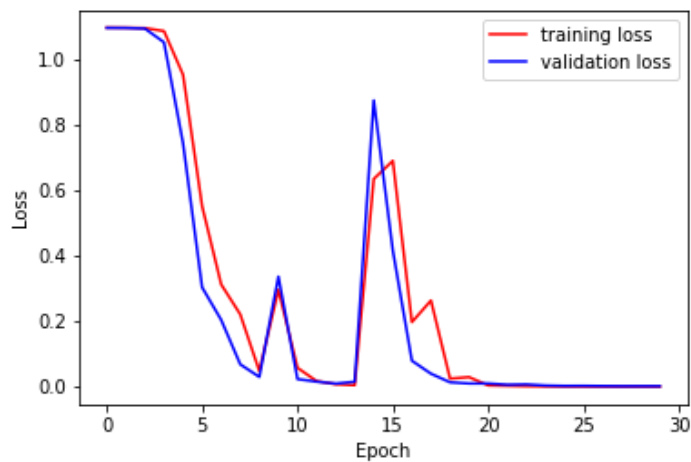
N 為樣本總數，M 為類別數， y_{ic} 為 label(one hot vector)， p_{ic} 為 model predicted probability

- screenshot of testing result

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In [1]: runfile('/homes/chen-chun-yu/DL_HW3/main.py', wdir='/homes/chen-chun-yu/DL_HW3')
Namespace(batch_size=16, epoch=30, lr=0.05)
model init...
start training...
EPOCH: 1, train_loss: 1.0995, val_loss: 1.0989, val_acc: 31.75 %
EPOCH: 2, train_loss: 1.0991, val_loss: 1.0986, val_acc: 31.75 %
EPOCH: 3, train_loss: 1.0983, val_loss: 1.0968, val_acc: 31.75 %
EPOCH: 4, train_loss: 1.0892, val_loss: 1.0548, val_acc: 53.06 %
EPOCH: 5, train_loss: 0.9556, val_loss: 0.7458, val_acc: 81.63 %
EPOCH: 6, train_loss: 0.5532, val_loss: 0.3047, val_acc: 84.35 %
EPOCH: 7, train_loss: 0.3137, val_loss: 0.205, val_acc: 95.92 %
EPOCH: 8, train_loss: 0.222, val_loss: 0.069, val_acc: 97.73 %
EPOCH: 9, train_loss: 0.0483, val_loss: 0.0305, val_acc: 99.09 %
EPOCH: 10, train_loss: 0.2974, val_loss: 0.3377, val_acc: 90.25 %
EPOCH: 11, train_loss: 0.0585, val_loss: 0.0239, val_acc: 99.09 %
EPOCH: 12, train_loss: 0.0178, val_loss: 0.0161, val_acc: 99.55 %
EPOCH: 13, train_loss: 0.0083, val_loss: 0.0101, val_acc: 99.55 %
EPOCH: 14, train_loss: 0.0053, val_loss: 0.0157, val_acc: 99.32 %
EPOCH: 15, train_loss: 0.6366, val_loss: 0.8771, val_acc: 62.59 %
EPOCH: 16, train_loss: 0.692, val_loss: 0.4174, val_acc: 82.31 %
EPOCH: 17, train_loss: 0.1984, val_loss: 0.0801, val_acc: 97.28 %
EPOCH: 18, train_loss: 0.2645, val_loss: 0.0404, val_acc: 98.41 %
EPOCH: 19, train_loss: 0.0255, val_loss: 0.0141, val_acc: 99.32 %
EPOCH: 20, train_loss: 0.03, val_loss: 0.0105, val_acc: 99.55 %
EPOCH: 21, train_loss: 0.0046, val_loss: 0.0105, val_acc: 99.32 %
EPOCH: 22, train_loss: 0.0035, val_loss: 0.0067, val_acc: 99.77 %
EPOCH: 23, train_loss: 0.0024, val_loss: 0.0077, val_acc: 99.55 %
EPOCH: 24, train_loss: 0.0018, val_loss: 0.0042, val_acc: 100.0 %
EPOCH: 25, train_loss: 0.0014, val_loss: 0.0031, val_acc: 100.0 %
EPOCH: 26, train_loss: 0.0012, val_loss: 0.0032, val_acc: 100.0 %
EPOCH: 27, train_loss: 0.0011, val_loss: 0.0026, val_acc: 100.0 %
EPOCH: 28, train_loss: 0.001, val_loss: 0.0022, val_acc: 100.0 %
EPOCH: 29, train_loss: 0.0009, val_loss: 0.0022, val_acc: 100.0 %
EPOCH: 30, train_loss: 0.0007, val_loss: 0.0022, val_acc: 100.0 %
select epoch: 28
Testing accuracy: 98.8 %

In [2]:
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- Plot training loss and validation loss



- Describe the major problem you encountered and how did you deal with it
手刻 CNN 的難度相較手刻 DNN 難上許多，不像 DNN 可以將數組攤平 (Flatten)再處理，CNN 要考慮到多維度之間的轉換，光是 input image 的 shape 就有四個維度(batch_size, channel, width, height)，若 input image 的 channel 為 3 (RGB)，那情況會更加複雜，我的作法是將其以灰階模式讀取 (一層 channel)再處理。另外就是模型參數的梯度更新，因為層數多，需要非常細心地做偏微分與連鎖率運算。