## Part1

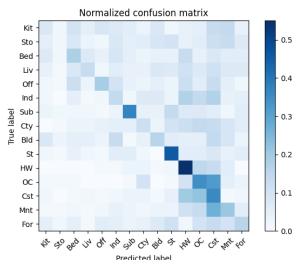
## 1. Accuracy of two setting

Tiny image (K = 1): 0.232

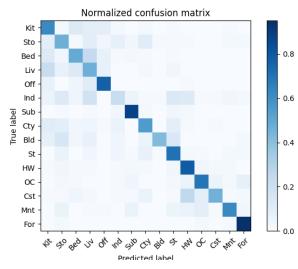
Bag of sift (K = 10, vocab size = 100, sift step in build\_vocabulary = 16, sift step in get bag of sifts = 3): 0.608

## 2. Confusion matrix

### Tiny image



# Bag of sift



## 3. Compare

### Different K of KNN

K\setting	Tiny image	Bag of sift	K\setting	Tiny image	Bag of sift
1	0.232	0.5333	8	0.22	0.584
2	0.2007	0.5206	10	0.226	0.608
4	0.216	0.558	12	0.2287	0.5987
6	0.2147	0.5687	14	0.2273	0.5913

對於 tiny image 來說 K 為 1 時結果最好,因為只是把圖片縮小而已,如果 K 過多反而會

讓一些與目標不相關的特徵但相似的點被算進來;而 bag of sift 則是在 K 為 10 結果最好,認為是因為 sift 可以抽取到局部的特徵,bag of sift 則是去看這張有多少訓練資料的局部特徵,因此在 K 增加可以給予更多的資訊,但如果 K 太大結果會下降,可能是因為與Different distance function in KNN

Distance function\setting	Tiny image	Bag of sift
Euclidean	0.2327	0.5346
Cosine	0.2327	0.5453
standardized Euclidean	0.232	0.608

對於 tiny image 來說,距離函式影響沒那麼大;而對 bag of sift 來說, standardized euclidean 結果最好,因為是使用 histogram 所以每個 feature 數量是不平均的,直接用 euclidean,會對於比較大的那一個 feature 的權重比較重,因此對每一個 feature 做標準化才比較能代表真正的距離。

#### Part2

#### 1. The network architectures & number of parameters

#### conv

```
ConvNet(
  (cnn): Sequential(
    (0): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
    (classifier): Sequential(
    (0): Linear(in_features=256, out_features=120, bias=True)
    (1): ReLU()
    (2): Linear(in_features=120, out_features=84, bias=True)
    (3): ReLU()
    (4): Linear(in_features=84, out_features=10, bias=True)
)
)
```

Layer (type)	Output Shape	Param #
Conv2d-1 ReLU-2 MaxPool2d-3 Conv2d-4 ReLU-5 MaxPool2d-6 Linear-7 ReLU-8 Linear-9 ReLU-10 Linear-11	[-1, 6, 24, 24] [-1, 6, 24, 24] [-1, 6, 12, 12] [-1, 16, 8, 8] [-1, 16, 8, 8] [-1, 16, 4, 4] [-1, 120] [-1, 120] [-1, 84] [-1, 84] [-1, 10]	156 0 0 2,416 0 30,840 10,164 0 850

Total params: 44,426 Trainable params: 44,426 Non-trainable params: 0

Input size (MB): 0.00 Forward/backward pass

Forward/backward pass size (MB): 0.08

Params size (MB): 0.17

Estimated Total Size (MB): 0.25

#### Mynet

```
MyNet(
  (cnn): Sequential(
    (0): Conv2d(1, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): Dropout(p=0.1, inplace=False)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (7): ReLU()
    (8): Dropout(p=0.1, inplace=False)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(10): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(11): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (12): ReLU()
(13): Dropout(p=0.1, inplace=False)
    (14): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (16): ReLU()
    (17): Dropout(p=0.1, inplace=False)
    (18): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (classifier): Sequential(
    (0): Linear(in_features=576, out_features=120, bias=True)
    (1): ReLU()
    (2): Linear(in_features=120, out_features=84, bias=True)
    (3): ReLU()
    (4): Linear(in_features=84, out_features=10, bias=True)
```

Layer (type) Output Shape Param #  Conv2d-1 [-1, 16, 28, 28] 160  BatchNorm2d-2 [-1, 16, 28, 28] 32  ReLU-3 [-1, 16, 28, 28] 0  Dropout-4 [-1, 16, 28, 28] 0  MaxPool2d-5 [-1, 16, 14, 14] 0  Conv2d-6 [-1, 32, 14, 14] 4,640  BatchNorm2d-7 [-1, 32, 14, 14] 64  ReLU-8 [-1, 32, 14, 14] 0
BatchNorm2d-2 [-1, 16, 28, 28] 32 ReLU-3 [-1, 16, 28, 28] 0 Dropout-4 [-1, 16, 28, 28] 0 MaxPool2d-5 [-1, 16, 14, 14] 0 Conv2d-6 [-1, 32, 14, 14] 4,640 BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
ReLU-3 [-1, 16, 28, 28] 0 Dropout-4 [-1, 16, 28, 28] 0 MaxPool2d-5 [-1, 16, 14, 14] 0 Conv2d-6 [-1, 32, 14, 14] 4,640 BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
Dropout-4 [-1, 16, 28, 28] 0 MaxPool2d-5 [-1, 16, 14, 14] 0 Conv2d-6 [-1, 32, 14, 14] 4,640 BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
MaxPool2d-5 [-1, 16, 14, 14] 0 Conv2d-6 [-1, 32, 14, 14] 4,640 BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
Conv2d-6 [-1, 32, 14, 14] 4,640 BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
BatchNorm2d-7 [-1, 32, 14, 14] 64 ReLU-8 [-1, 32, 14, 14] 0
ReLU-8 [-1, 32, 14, 14] 0
- , , , -
Dropout-9 [-1, 32, 14, 14] 0
MaxPool2d-10 [-1, 32, 7, 7] 0
Conv2d-11 [-1, 64, 7, 7] 18,496
BatchNorm2d-12 [-1, 64, 7, 7] 128
ReLU-13 [-1, 64, 7, 7] 0
Dropout-14 [-1, 64, 7, 7] 0
Conv2d-15 [-1, 64, 7, 7] 36,928
BatchNorm2d-16 [-1, 64, 7, 7] 128
ReLU-17 [-1, 64, 7, 7] 0
Dropout-18 [-1, 64, 7, 7] 0
MaxPool2d-19 [-1, 64, 3, 3] 0
Linear-20 [-1, 120] 69,240
ReLU-21 [-1, 120] 0
Linear-22 [-1, 84] 10,164
ReLU-23 [-1, 84] 0
Linear-24 [-1, 10] 850

Total params: 140,830 Trainable params: 140,830 Non-trainable params: 0

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Input size (MB): 0.00

Forward/backward pass size (MB): 0.81

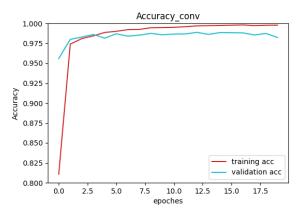
Params size (MB): 0.54

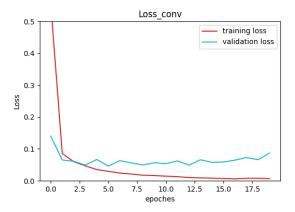
Estimated Total Size (MB): 1.35

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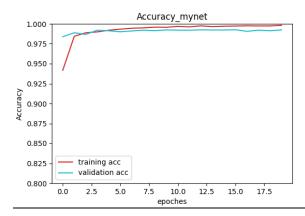
### 2. The learning curve

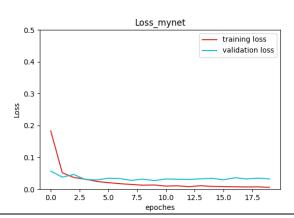
#### conv





#### mynet





### 3. Compare

從 learning curve 來看,可以看到 mynet 比較快收斂,認為是因為加了 batchnorn 使得 error surface 變得更平滑,較容易訓練。

另外 convolution layer 也增加,讓 model 可以看到更遠的資訊。

由於參數變多,所以使用 dropout 減緩 overfitting 的發生。

最後結果如下,在 validation set 上 mynet 比起 conv accuracy 高了 0.004。

Best validation accuracy

conv: 0.989 mynet: 0.993