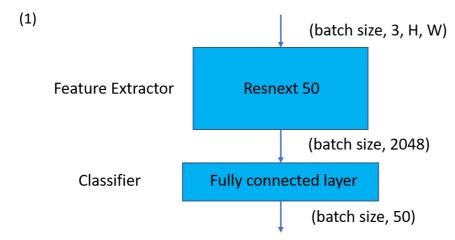
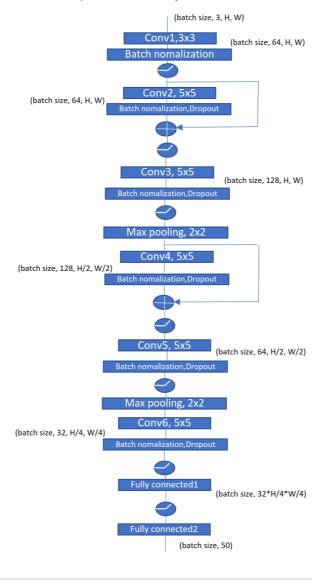
Problem 1.



- (2) Model A: 51.160%, Model B: 90.440%
- (3) Optimizer = Adam(all parameters are default in pytorch), loss function : cross entropy, epoch=120 data argumentation : horizontal flip, rotate, colorjitter, batch size = 16

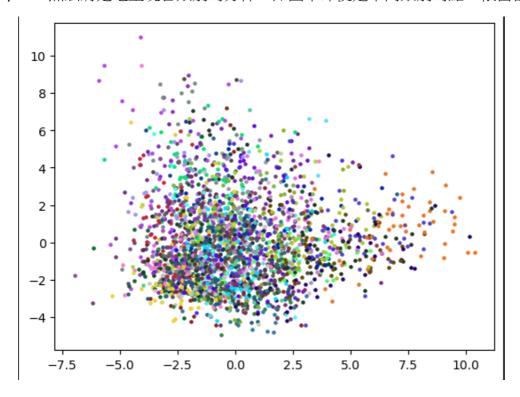


(4) Model B 使用 ResNeXt-50(32x4d),主要差異在於 residual 的部份,Model A 僅使用 2 次單一 path 的 residual,而在 ResNeXt-50(32x4d)中,conv2 共做了 3 次合併 32 條 path 的 residual,conv3,conv4,conv5 同理,因此參數量與深度均遠大於 Model A

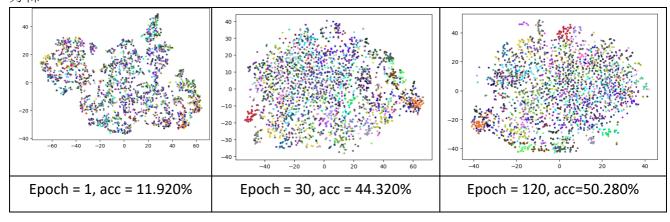
stage	output	ResNet-50		ResNeXt-50 (32×4d)	
conv1	112×112	7×7, 64, stride 2		7×7, 64, stride 2	
conv2	56×56	3×3 max pool, stride 2		3×3 max pool, stride 2	
		1×1, 64		1×1, 128	
		3×3, 64	×3	3×3, 128, <i>C</i> =32	$\times 3$
		1×1, 256		1×1, 256	
conv3	28×28	[1×1, 128]	×4	[1×1, 256	×4
		3×3, 128		3×3, 256, <i>C</i> =32	
		1×1,512		1×1,512	
conv4	14×14	1×1, 256	×6	[1×1,512	×6
		3×3, 256		3×3, 512, <i>C</i> =32	
		1×1, 1024		1×1, 1024	
conv5	7×7	1×1,512	×3	1×1, 1024	×3
		3×3, 512		3×3, 1024, C=32	
		1×1, 2048		1×1, 2048	
	1×1	global average pool		global average pool	
	1 1 1	1000-d fc, softmax		1000-d fc, softmax	
# params.		25.5×10^6		25.0 ×10 ⁶	
FLOPs		4.1 ×10 ⁹		4.2 ×10 ⁹	

XIE, Saining, et al. Aggregated residual transformations for deep neural networks. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017. p. 1492-1500.

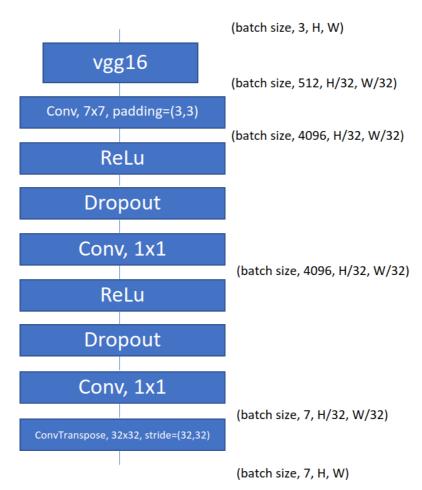
(5) PCA 無法清楚地呈現各類別的分佈,如圖中即便是不同類別的點,依舊都集中在中左下角



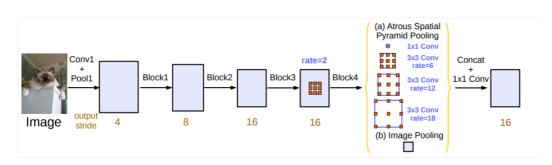
(6) t-SNE 相較於 PCA, 更能觀察到分群的趨勢, 仔細觀察隨著準確率上升, 顏色的複雜程度愈高, 這說明各群之間慢慢被區分出來, 但又不像 PCA 全部擠在一團, t-SNE 在圖上有更均勻的分佈



(1)



(2) Model B 為 Deeplabv3_resnet50,其使用 resnet50 作為骨架,並搭配 Atrous convolution + Spatial pyramid pooling(i.e. ASPP)。前者可擴大 receptive field,並由 Spatial pyramid pooling 組合不同 dilation rate 以獲得圖片不同區域大小的資訊,這與 ModelA 單純使用 FCN 有很大的差異



CHEN, Liang-Chieh, et al. Rethinking atrous convolution for semantic image segmentation. *arXiv preprint* arXiv:1706.05587, 2017.

(3) Model A: 66.920%, Model B: 73.888%

