Ambient Al Bootcamp Practice 3



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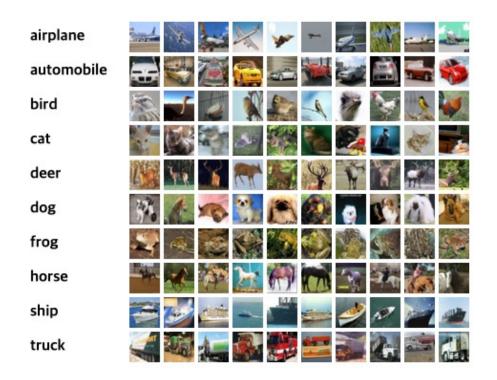
- Lightweight CNN for 2D object classification
- Transfer Learning
- HW3: MobileNet v3

3-1. Lightweight CNN for 2D classification

o. Dataset

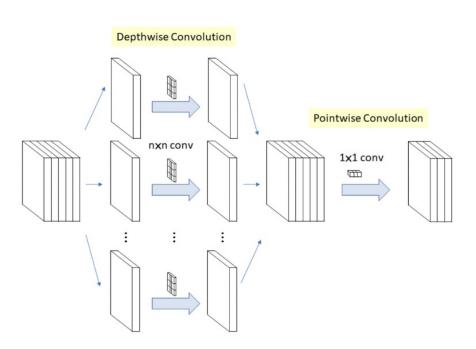
Dataset: Cifar-10

- 10개 class의 32x32 이미지
- 각 class별 6,000장씩 총 60,000장
- 50,000개의 training set과 10,000개의 test set으로 이루어져 있음



MobileNetV2: Inverted Residuals and Linear Bottlenecks, CVPR (2018)

- 임베디드 디바이스 또는 모바일 장치를 타겟으로하는 **단순한 구조의 경량화** 네트워크
- MobileNetV1을 개선함
 - Depthwise-Separable Convolution을 단순히 쌓지 않고, Inverted Residual Block을 도입함



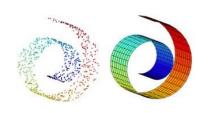
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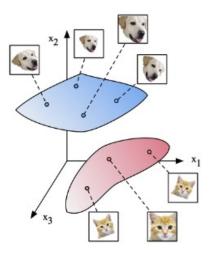
(1) Inverted Residual and Linear Bottleneck

Linear Bottlenecks

Manifold of Interest

- Manifold: high-dimensional 데이터를 low-dimension으로 옮길 때 데이터를 잘 설명하는 집합의 모형
- 데이터가 Neural Network에 입력되면, 특정 레이어의 activation은 "manifold of interest"를 구성
- "manifold of interest"는 low-dimensional subspace로 embedding
 가능. 즉, 고차원 정보는 저차원에서 표현 가능 (가정)



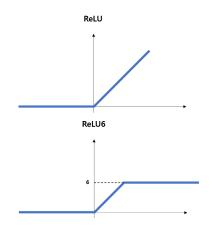


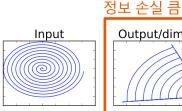
(1) Inverted Residual and Linear Bottleneck

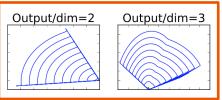
Linear Bottlenecks

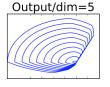
Linear Transformation

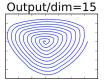
- Subspace로 embedding하는 과정에서 ReLU를 사용하면서 필연적으로 정보의 손실 발생 ("manifold of interest"가 ReLU 적용 후 non-zero volume을 가지면 linear transformation 된 것으로 정보 보존)
- 많은 채널을 사용할 경우 정보 보존이 가능하다고 주장함

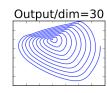












(1) Inverted Residual and Linear Bottleneck

Linear Bottlenecks

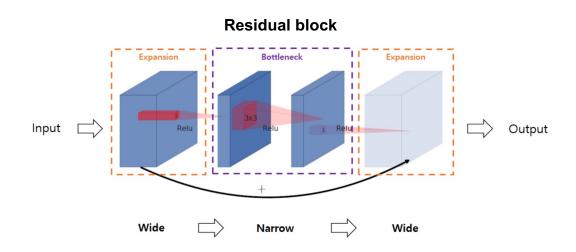
Linear Bottlenecks

- Input의 중요한 정보들인 "manifold of interest"는 layer를 거치며 low-dimensional 영역으로 전달될 수 있는데, 이때 layer가 linear transformation이면 정보가 보존된다고 가정할 수 있음
- MobileNetV2에서는 low-dimension으로 mapping하는 linear transformation을 만들 때 bottleneck 구조를 사용함
- 즉, linear transformation역할을 하는 linear bottleneck layer를 활용해서 dimension은
 줄이고 중요한 정보는 그대로 유지하는 전략을 취함

(1) Inverted Residual and Linear Bottleneck

Inverted Residuals

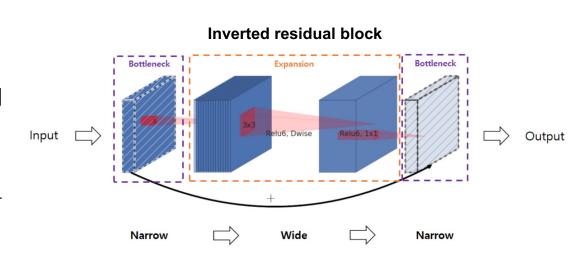
일반적인 Residual block은 Wide- Narrow - Wide형태



(1) Inverted Residual and Linear Bottleneck

Inverted Residuals

- 고차원의 정보는 저차원에 표현 가능하다고 가정했으므로 bottleneck block에 이미 "manifold of interest"가 보존되어 있다고 생각할 수 있음
- Shortcut connectio을 bottleneck
 block끼리 연결 (expansion에서는
 non-linearity 담당)



(1) Inverted Residual and Linear Bottleneck

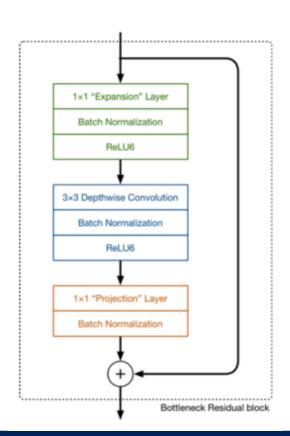
Bottleneck Residual Block

MobileNetV1 MobileNetV2 Add conv 1x1, Linear conv 1x1, Linear conv 1x1, Relu6 Dwise 3x3, stride=2. Relu6 Dwise 3x3, Relu6 Dwise 3x3, stride=s, Relu6 Conv 1x1, Relu6 Conv 1x1, Relu6 input input input Stride=1 block Stride=2 block

(1) Inverted Residual and Linear Bottleneck Bottleneck Residual Block

Input	Operator	Output
$\begin{array}{l} h \times w \times k \\ h \times w \times tk \\ \frac{h}{s} \times \frac{w}{s} \times tk \end{array}$	1x1 conv2d, ReLU6 3x3 dwise s=s, ReLU6 linear 1x1 conv2d	$h \times w \times (tk)$ $\frac{h}{s} \times \frac{w}{s} \times (tk)$ $\frac{h}{s} \times \frac{w}{s} \times k'$

Table 1: Bottleneck residual block transforming from k to k' channels, with stride s, and expansion factor t.



(2) MobileNetV2 Network

Input	Operator	$\mid t \mid$	c	$\mid n \mid$	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^{2} \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^{2} \times 96$	bottleneck	6	160	3	2
$7^2 imes 160$	bottleneck	6	320	1	1
$7^2 imes 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	_	1	-
$1\times1\times1280$	conv2d 1x1	-	k	-	

Table 2: MobileNetV2: Each line describes a sequence of 1 or more identical (modulo stride) layers, repeated n times. All layers in the same sequence have the same number c of output channels. The first layer of each sequence has a stride s and all others use stride 1. All spatial convolutions use 3×3 kernels. The expansion factor t is always applied to the input size as described in Table 1.

Input	Operator	expansion	filters	strides	개수
32x32x3	3x3 Conv2D	-	32	2	1
16x16x32	inverted_res_block	1	16	1	1
16x16x16	inverted_res_block	6	24	2	2
8x8x24	inverted_res_block	6	32	2	3
4x4x32	inverted_res_block	6	64	2	4
2x2x64	inverted_res_block	6	96	1	3
2x2x96	inverted_res_block	6	160	2	3
1x1x160	inverted_res_block	6	320	1	1
1x1x320	1x1 Conv2D	-	1280	1	1
1x1x1280	GlobalAvgPool	-	-	-	1
1280	Dense	-	-	-	1

2. Training

- 30 epoch 이상 training
- Training 예시

```
Epoch 20/50
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
Epoch 28/50
Epoch 29/50
Epoch 30/50
```

3-2. Transfer Learning

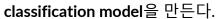
Overview

ImageNet Pre-trained MobileNetV2를 이용한 Transfer Learning

ImageNet dataset

대표적인 대규모(large-scale) 데이터셋으로 1,000개의 클래스로 구성되며, 100만개가 넘는 데이터를 포함한다. (각 클래스당 약 1,000개의 사진으로 구성)

개와 고양이도 종별로 세분화 되어있는데, Transfer Learning을 통해 **개와 고양이로 분류하는 Binary**





'German shepherd', 0.9796372), 'malinois', 0.020184083), 'Norwegian elkhound', 0.00015799515), 'African hunting dog', 5.2901587e-06), 'briard', 3.9127376e-06)]]

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standard poodle', 0.5650911), miniature poodle', 0.37279922), Irish water spaniel', 0.053150617), toy poodle', 0.0072146286), Kerry blue terrier', 0.0013652634)]]

151	Chihuahua
152	Japanese spaniel
153	Maltese dog, Maltese terrier, Maltese
154	Pekinese, Pekingese, Peke
155	Shih-Tzu
156	Blenheim spaniel
157	papillon
158	toy terrier
159	Rhodesian ridgeback
160	Afghan hound, Afghan
161	basset, basset hound
162	beagle

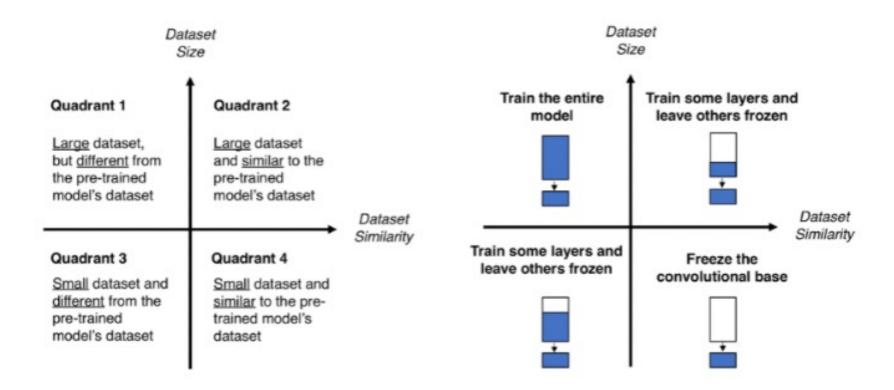
Dataset

Dog and Cat Dataset

- 개/고양이 이미지로만 구성된 데이터셋
- Train 2,000장, Validation 1,000장



Transfer Learning & Fine Tuning



Thanks!