

시각 지능 실무 과정

Day 3

복습 & 오늘 내용

전체 스케줄

- | | |
|-------|---|
| Day 1 | <ul style="list-style-type: none">• Computer Vision과 딥 러닝• Image Processing• TensorFlow 2.x• Basic CNN Review |
| Day 2 | <ul style="list-style-type: none">• Basic CNN Architectures• Advanced CNN Architectures• Detection CNN Architectures• 문제 해결을 위한 전략 세우기 |
| Day 3 | <ul style="list-style-type: none">• Transfer Learning• 유용한 유틸리티• 최종 미션• 다양한 시각지능 task 소개 |
| Day 4 | <ul style="list-style-type: none">• DAP Vision 개요• 서비스 구성• 서비스 실습 및 활용• Wrap Up |

DAY 3

Transfer Learning

Transfer Learning 개요

Transfer Learning 적용 전략

유용한 유틸리티

JupyterLab 소개

TensorBoard 실습

Final Mission

모델 설계 및 학습

최신 시각지능 동향

다양한 CNN Task들

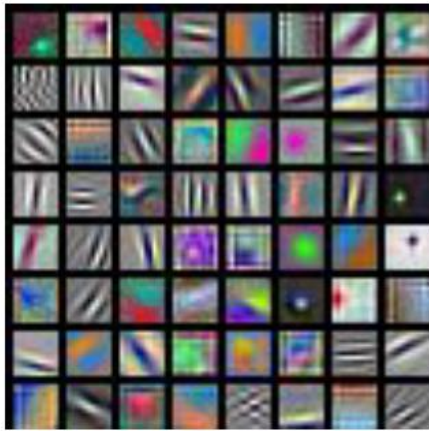
최신 시각지능 동향

Transfer Learning

Transfer Learning

학습된 Layer들은 어떤 의미를 가질까?

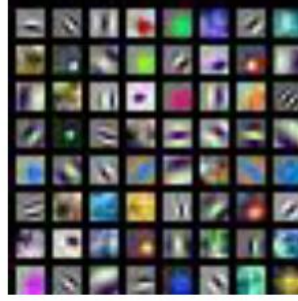
첫 번째 Layer



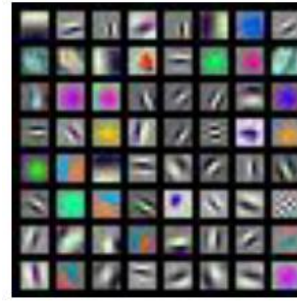
AlexNet:
 $64 \times 3 \times 11 \times 11$



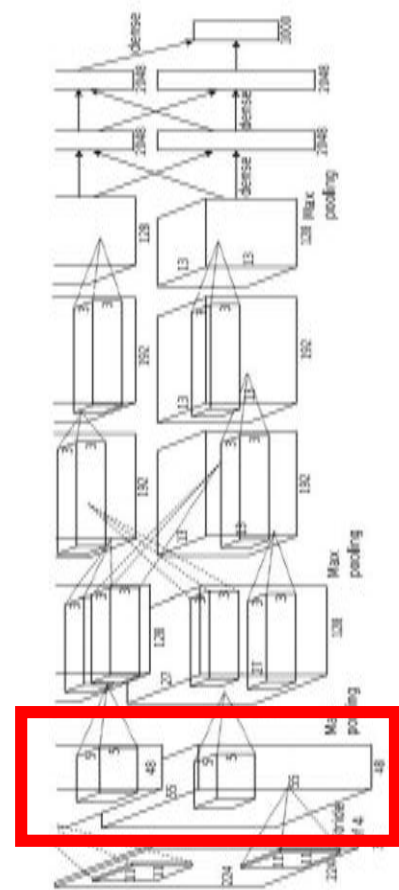
ResNet-18:
 $64 \times 3 \times 7 \times 7$



ResNet-101:
 $64 \times 3 \times 7 \times 7$



DenseNet-121:
 $64 \times 3 \times 7 \times 7$



Transfer Learning

학습된 Layer들은 어떤 의미를 가질까?

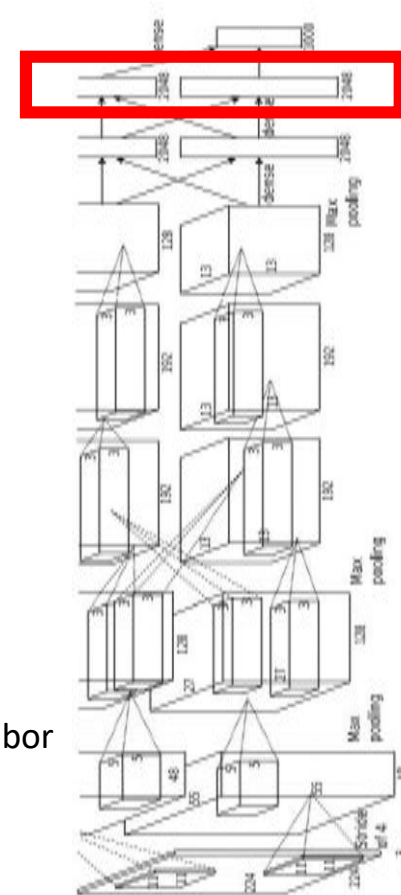
마지막 Layer



Pixel 공간에서의 Nearest Neighbor



Feature공간에서의 Nearest Neighbor



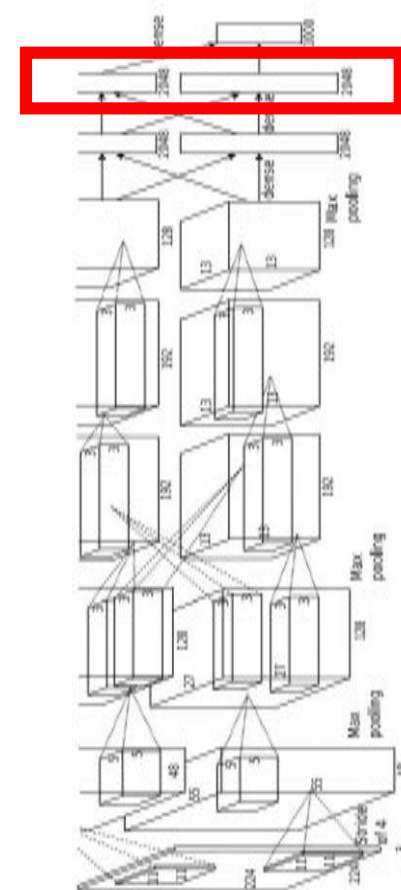
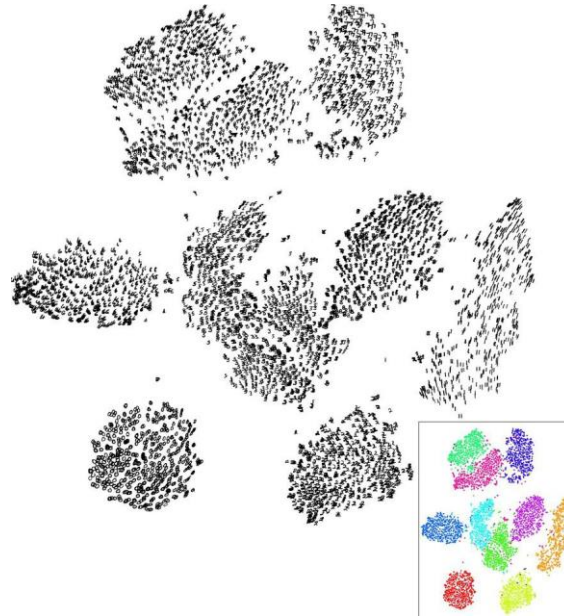
Transfer Learning

학습된 Layer들은 어떤 의미를 가질까?

마지막 Layer

주성분 분석을 통해 FC7 layer의 차원을 4096에서 2차원으로 줄인 뒤 시각화.

t-SNE 기법

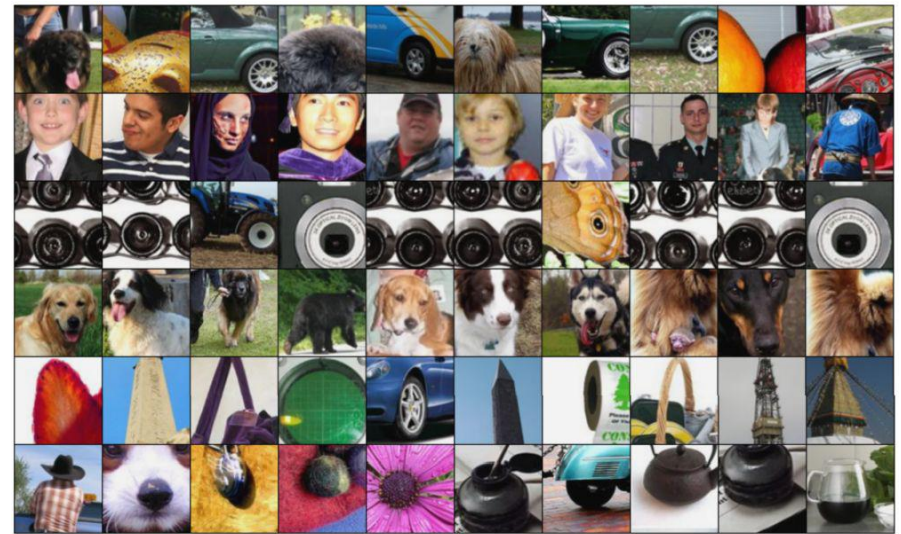
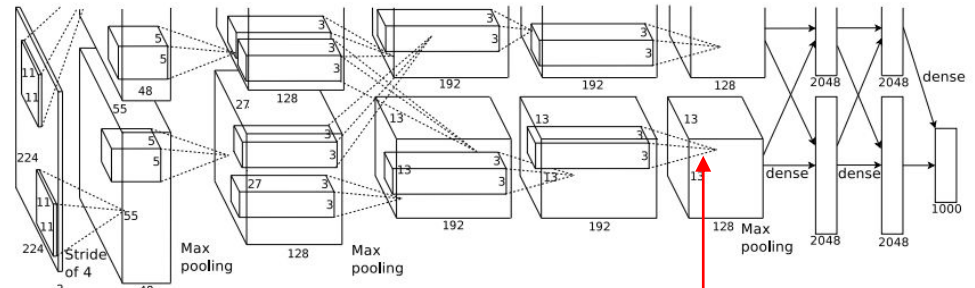


Transfer Learning

학습된 Layer들은 어떤 의미를 가질까?

Maximally Activating Patches

네트워크 중간의 특정 채널을 골라서 해당 채널을 최대로 활성화시키는 이미지 패치들은 일관성 있는 모습들을 보인다.



Transfer Learning

Transfer Learning이란 무엇일까?

어떤 Task에서 훈련된 모델을 관련된 두 번째 Task에서 다시 사용하는 기술.



Transfer learning and domain adaptation refer to the situation where what has been learned in one setting ... is exploited to improve generalization in another setting

— Page 526, [Deep Learning](#), 2016.



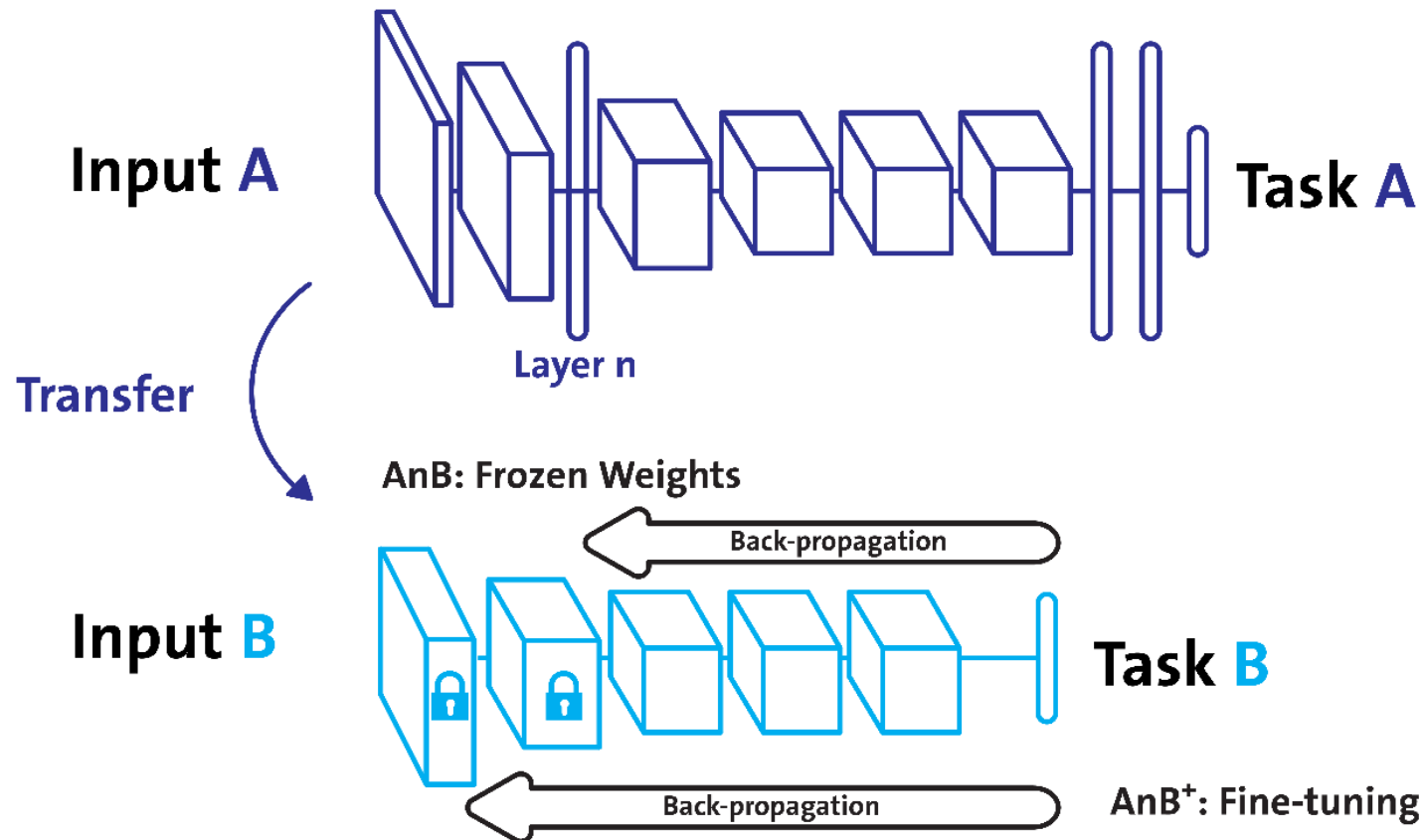
Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.

— [Chapter 11: Transfer Learning](#), [Handbook of Research on Machine Learning Applications](#), 2009.

Transfer Learning

Transfer Learning 개요

이전 모델에서 보존된 레이어의 가중치를 동결하고 다른 레이어를 학습한다.



Transfer Learning 개요

Step 1 : 소스 모델을 선택하라.

- 이미 학습된 수많은 모델들이 있을 뿐 아니라, 직접 학습시켜도 된다.

Step 2 : 모델을 재사용하라.

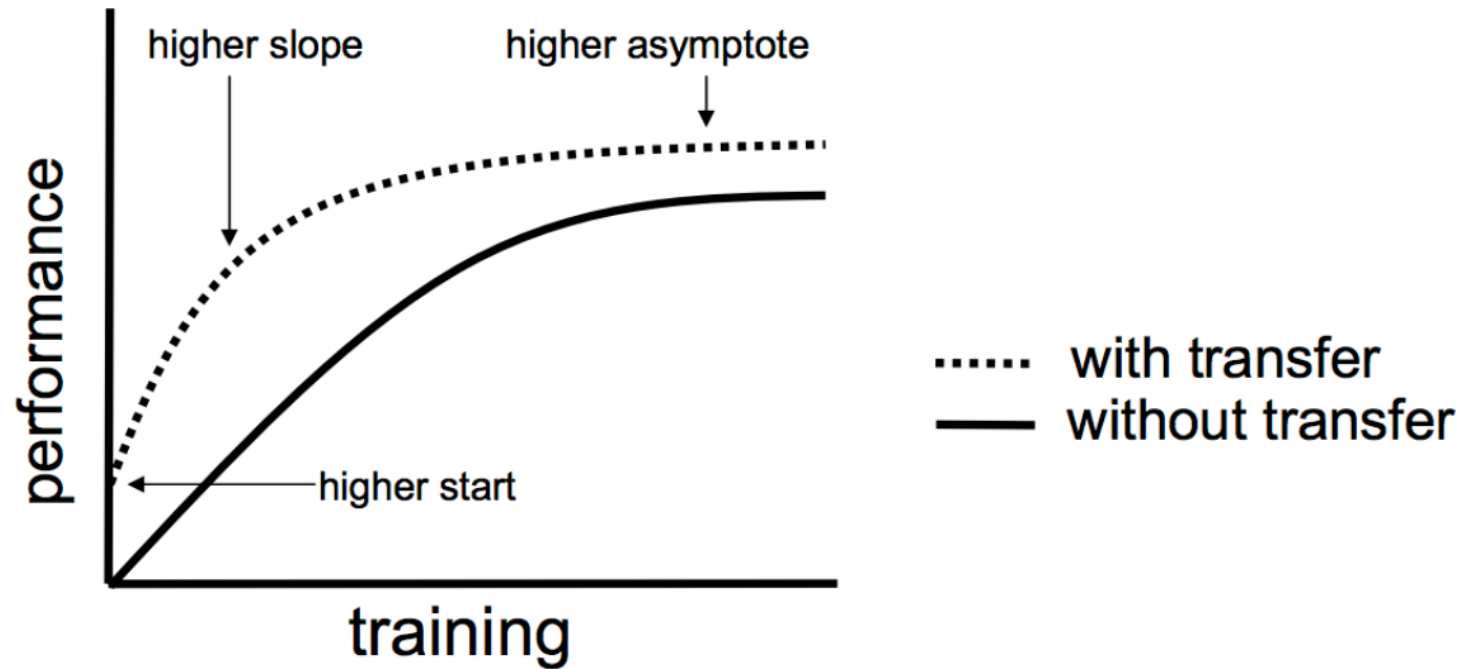
- 이미 학습된 모델을 학습의 시작점으로 삼아라. 해당 모델의 전체 또는 일부를 사용할 수 있다.

Step 3 : 모델을 튜닝하라.

- 당신의 모델을 필요한 분야에 맞게 최적화하라.

Transfer Learning

Transfer Learning을 사용한다면?

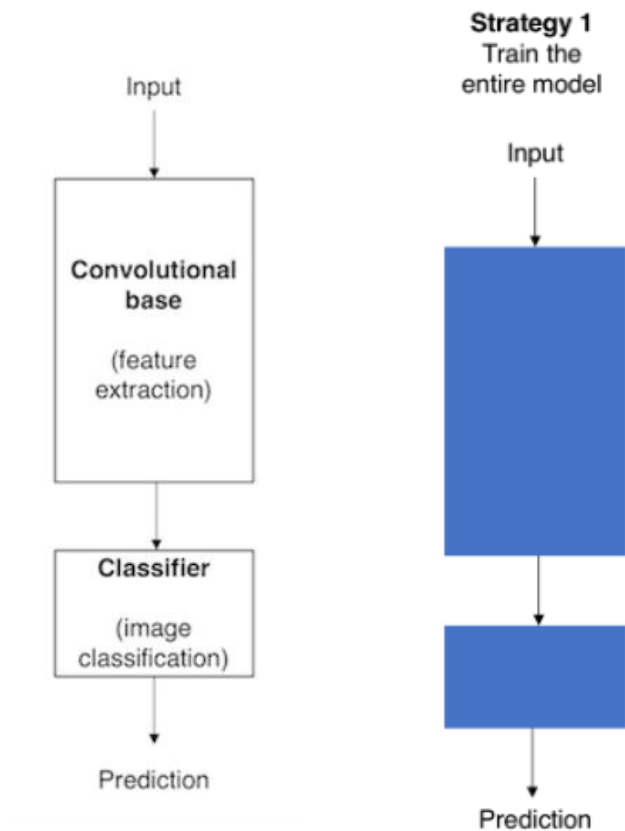


Three ways in which transfer might improve learning.
Taken from "Transfer Learning".

Transfer Learning

Transfer Learning을 적용하기 위한 전략

전략 1: 전체 모델을 학습시킨다.

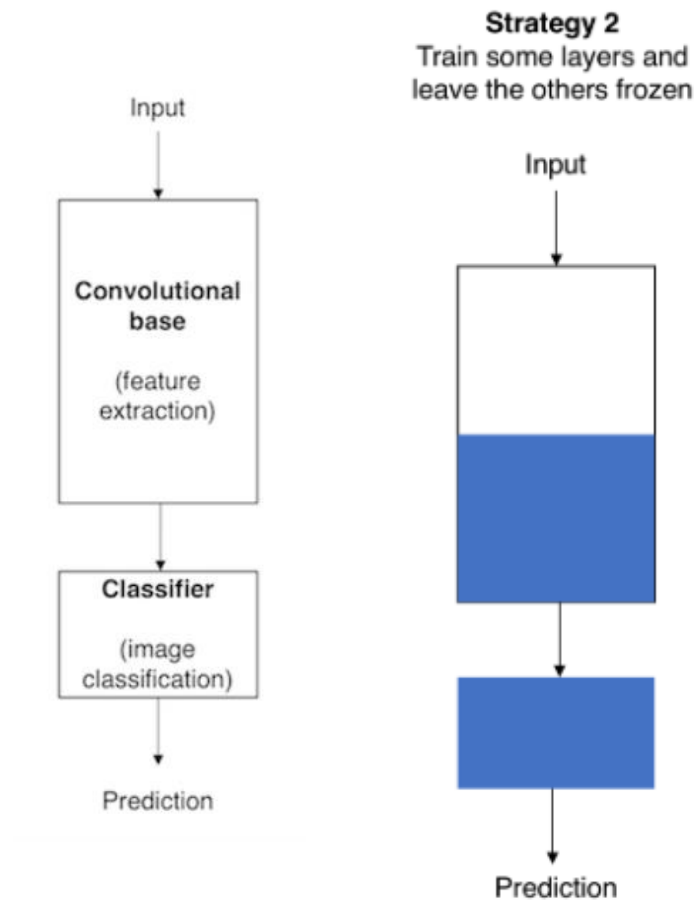


기 학습된 모델의 구조를 사용하고 해당 모델의 가중치를 초기화처럼 사용한다. 처음부터 학습하기 때문에, 큰 데이터셋과 높은 컴퓨팅 파워가 필요하다.

Transfer Learning

Transfer Learning을 적용하기 위한 전략

전략 2: 일부 레이어를 학습시키고 나머지는 동결시킨다.

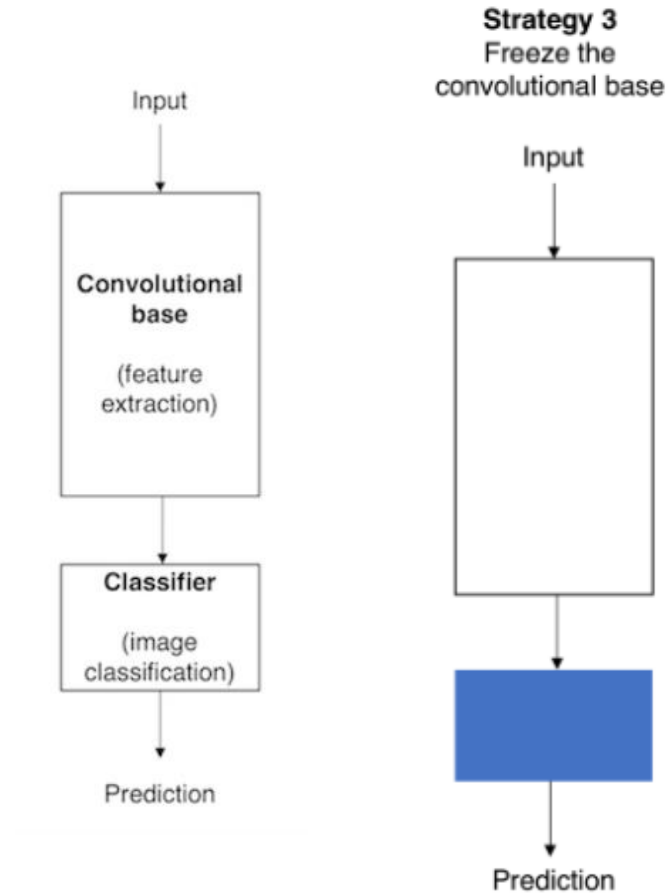


네트워크의 가중치를 얼마나 조절할 것인지 선택하라.
이는 도메인의 차이와 데이터 사이즈에 달려 있다.

Transfer Learning

Transfer Learning을 적용하기 위한 전략

전략 3: CNN 레이어들을 동결시켜라

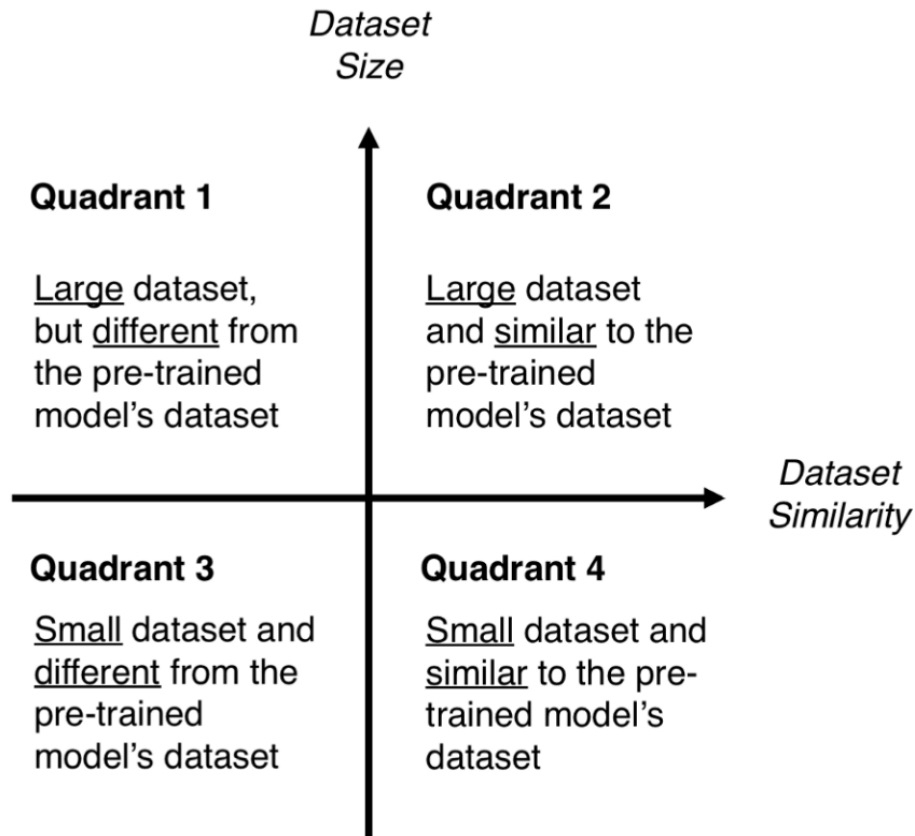


CNN 레이어들은 특징 추출기로서 동결시키고, 분류를 위한 layer만 학습시킨다.

Transfer Learning

Transfer Learning을 적용하기 위한 전략 선택

네 가지 서로 다른 학습 시나리오



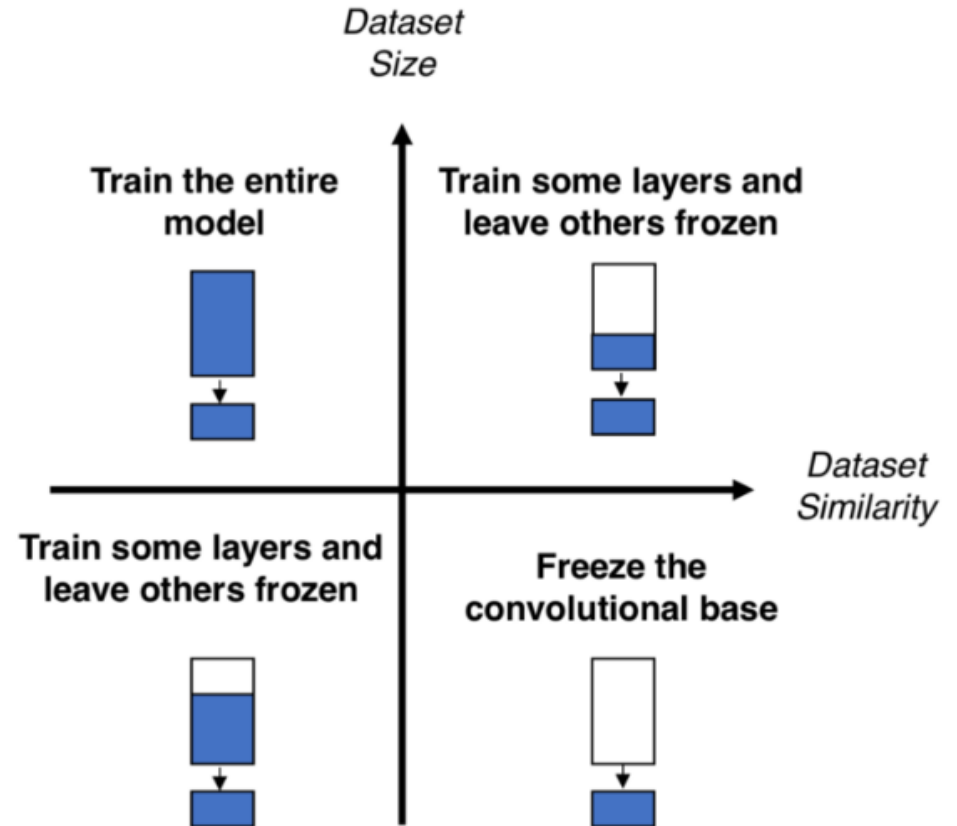
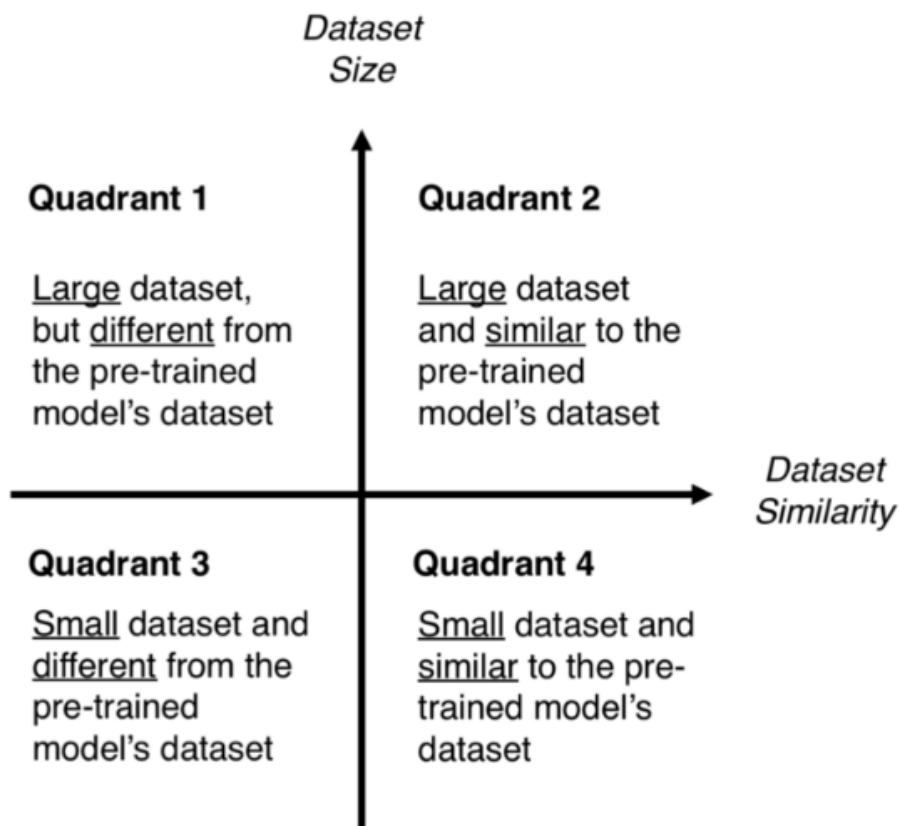
적절한 transfer learning 전략의 선택하는 방법?



“Frozen Layer”를 선택하는 방법!

Transfer Learning

Transfer Learning을 적용하기 위한 전략 선택

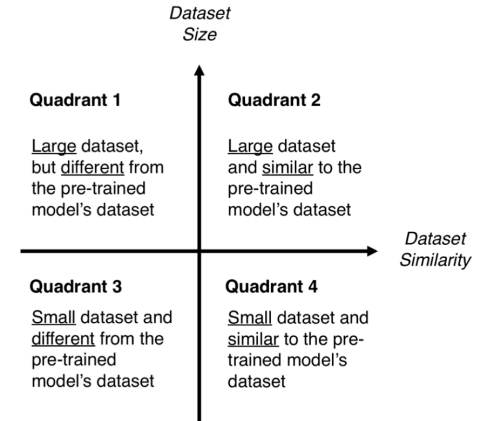


Transfer Learning

전략 선택 1 : 데이터셋 ↑ & 유사도 ↓

Q1. 많은 데이터셋을 가지고 있고, 모델을 처음부터 학습시킬 수 있고 무엇이든 할 수 있는 상황이다.

데이터셋이 유사하지 않아도 사전 훈련된 모델의 아키텍처와 가중치를 사용하여 모델 전체를 훈련시키는 것이 유용하다.



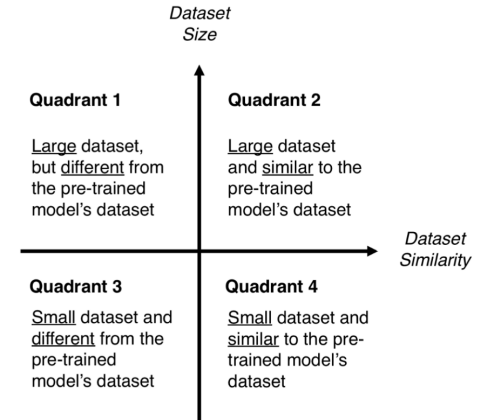
Train the entire model



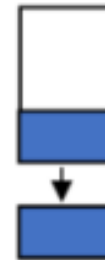
Transfer Learning

전략 선택 2 : 데이터셋 ↑ & 유사도 ↑

Q2. 많은 데이터셋을 가지고 있기에 오버피팅은 이슈가 아니며 어떠한 방식으로 얼마든지 훈련시켜도 상관없다. 다만, 데이터셋이 유사하므로 이전의 지식을 활용하여 거대한 학습 에포트를 아낄 수 있다.
그러므로 classifier와 CNN의 top layer들만 훈련시켜도 충분하다.



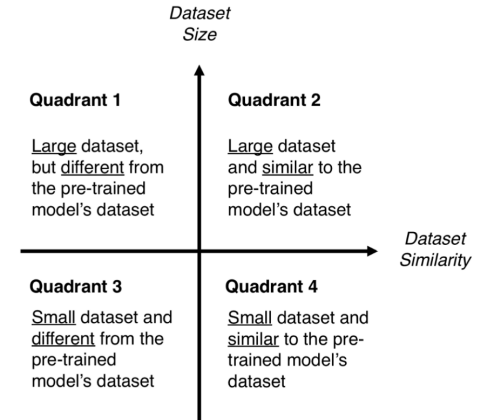
Train some layers and leave others frozen



Transfer Learning

전략 선택 3 : 데이터셋 ↓ & 유사도 ↓

Q2. 모든 상황이 좋지 않다. 학습시키고 동결시킬 레이어의 비율을 정하기가 매우 어려운 상황이다.
더 많은 레이어를 훈련시킨다면 과적합될 수 있고, 더 적은 레이어를 훈련시킨다면 제대로 학습이 이루어지지 않을 것이다.
Data Augmentation을 고려해볼 필요가 있다.



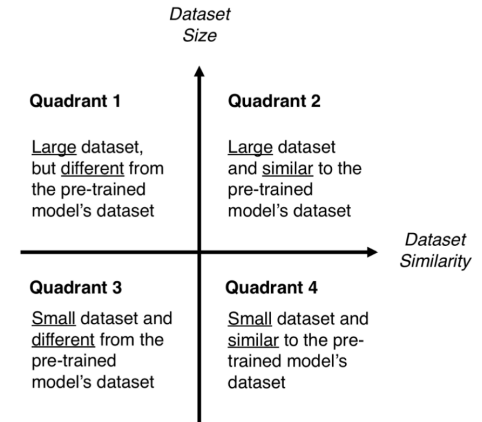
**Train some layers and
leave others frozen**



Transfer Learning

전략 선택 4 : 데이터셋 ↓ & 유사도 ↑

Q4. 사전 학습된 모델의 마지막 FC레이어들은 제외하고 남은 layer들을 고정된 특징 추출기로만 사용하여, 새로운 분류기를 학습시키는데 사용할 수 있다.



**Freeze the
convolutional base**



생각해볼 부분들

지금까지 설명한 내용은 단지 개요일뿐.

- 다양한 상황에 달려있다.
- 컴퓨팅 리소스, 목표하는 정확도, 데이터의 크기, 도메인 간 유사도 등

더 나은 전략이 있을 수 있다.

- 한 가지 예를 들자면 layer마다 서로 다른 학습 속도로 학습시킬 수 있다.

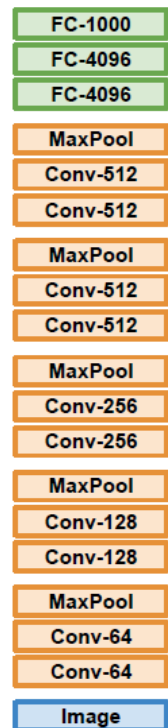
다른 task에서도 transfer learning을 활용할 수 있다.

- 특징 추출기로 사전 훈련된 CNN을 사용하여 다양한 작업이 가능하다.
- Object Detection, Segmentation, Pose Estimation etc..

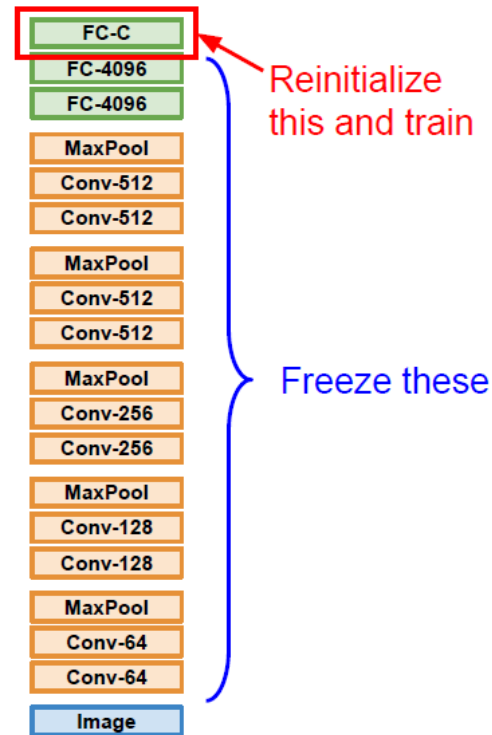
Transfer Learning

Transfer Learning 요약

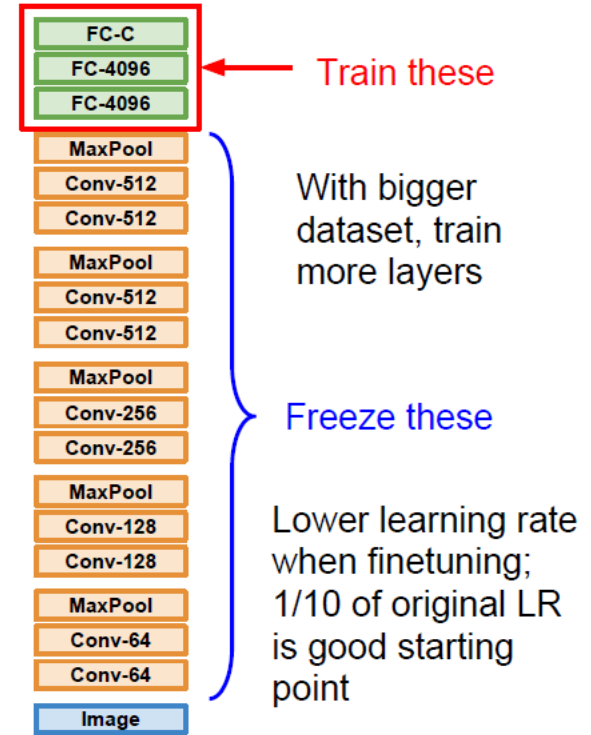
1. Train on ImageNet



2. Small Dataset(with C Classes)



3. Bigger Dataset



Quiz

	매우 비슷한 데이터셋	매우 다른 데이터셋
매우 적은 데이터		
상당히 많은 데이터		

Transfer Learning

Answer

	매우 비슷한 데이터셋	매우 다른 데이터셋
매우 적은 데이터	Top Layer의 Linear Classifier 시도	제일 어려운 상황. Data Augmentation 등 다양한 방법을 강구
상당히 많은 데이터	적은 layer들을 finetune	전체 또는 많은 layer들을 finetune

유용한 유틸리티들

JupyterLab 소개

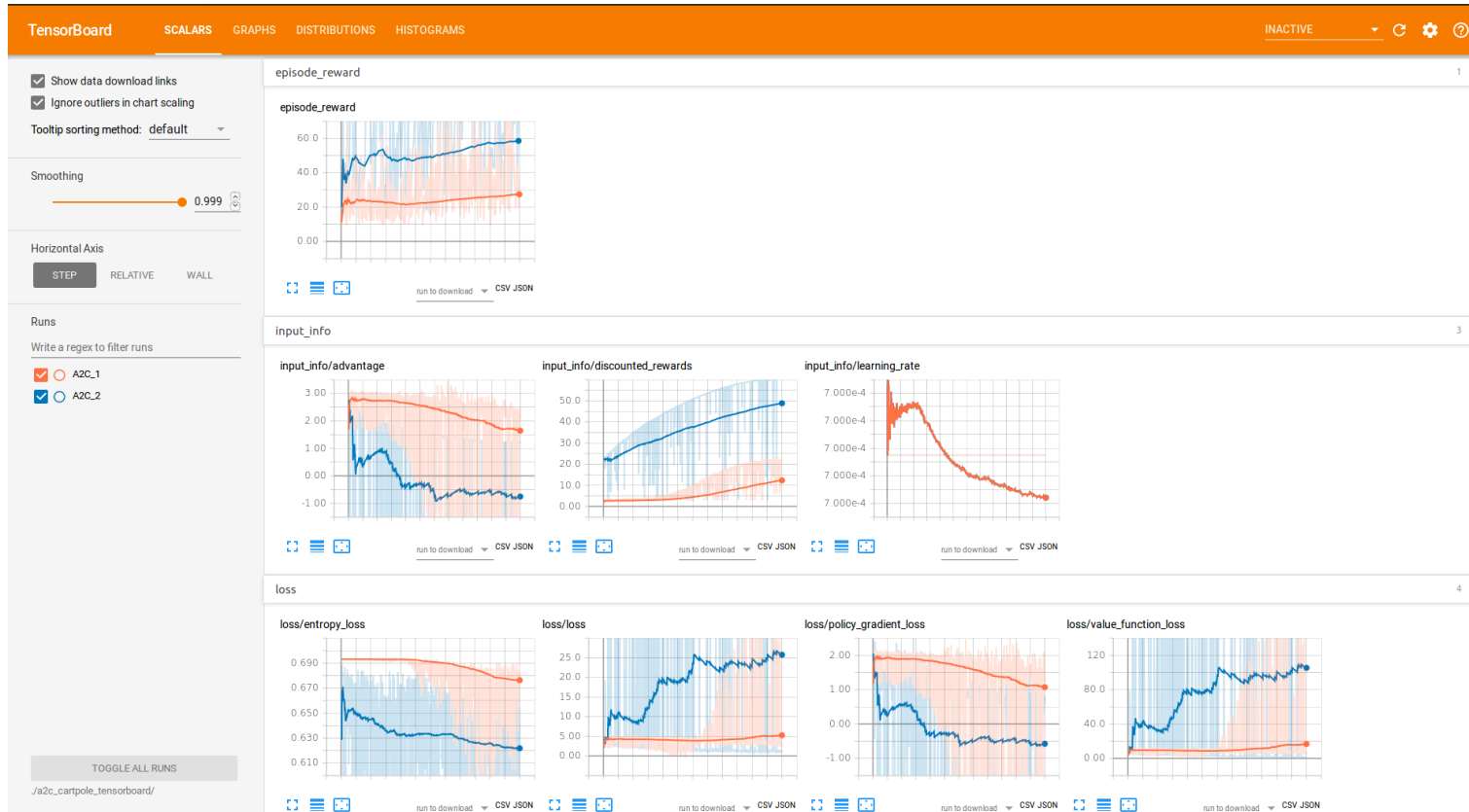


<https://jupyter.org/index.html>

<https://tec.lgcns.com/tec/display/PYTDEV/Jupyter+Lab>

유용한 유틸리티들

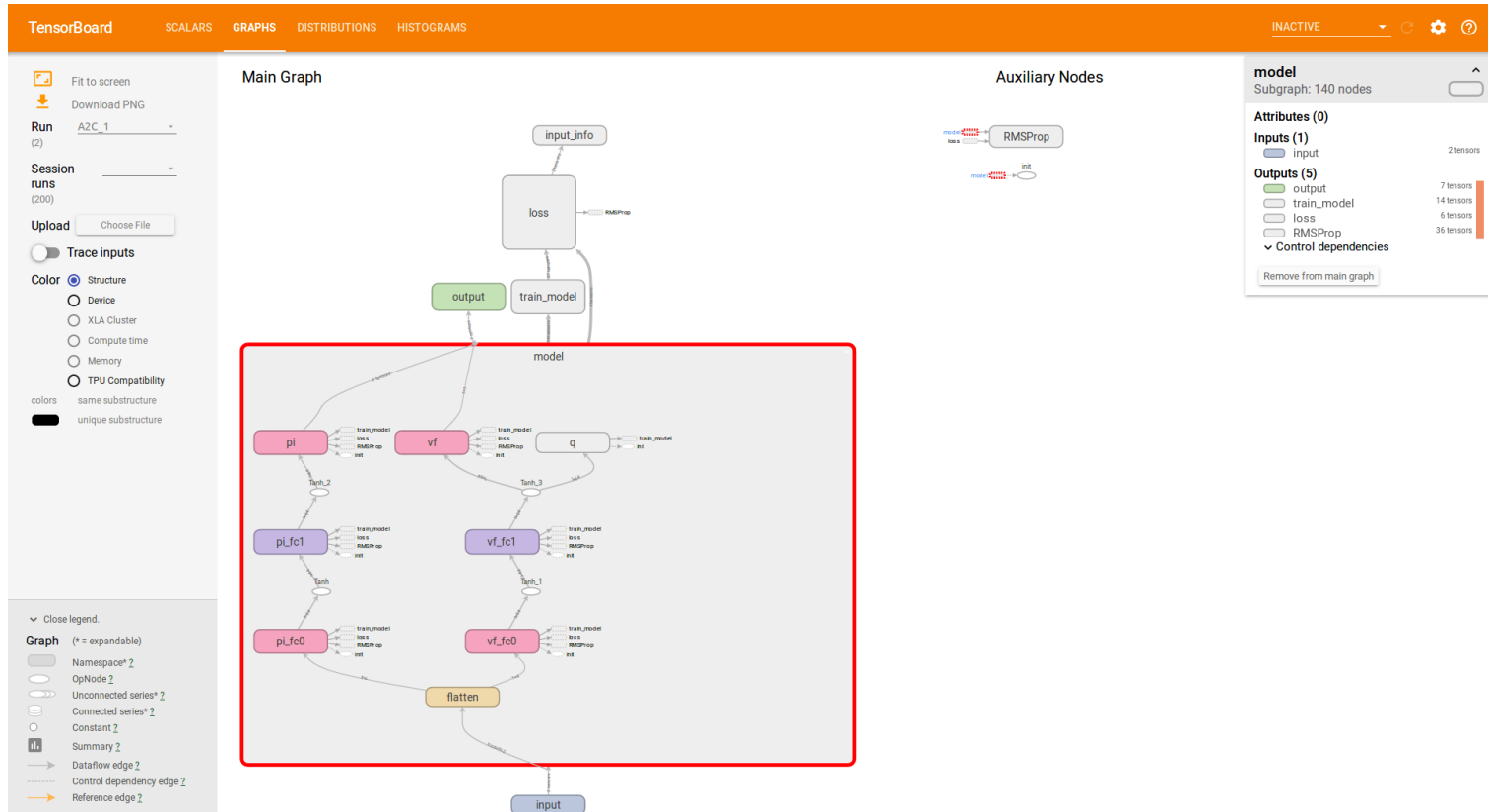
TensorBoard 사용법



https://www.tensorflow.org/tensorboard/get_started

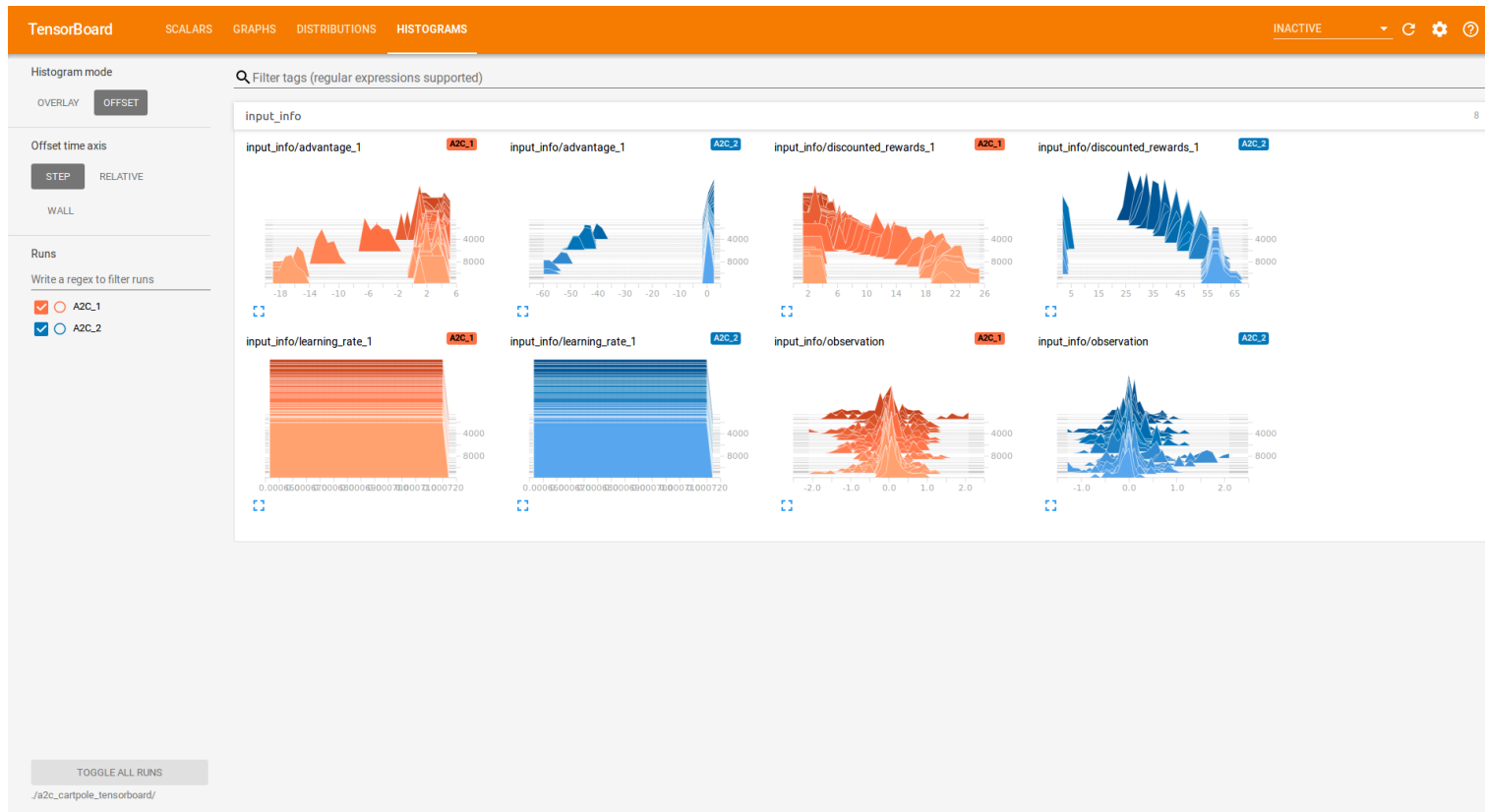
유용한 유틸리티들

TensorBoard 사용법



https://www.tensorflow.org/tensorboard/get_started

TensorBoard 사용법



https://www.tensorflow.org/tensorboard/get_started

Final Mission

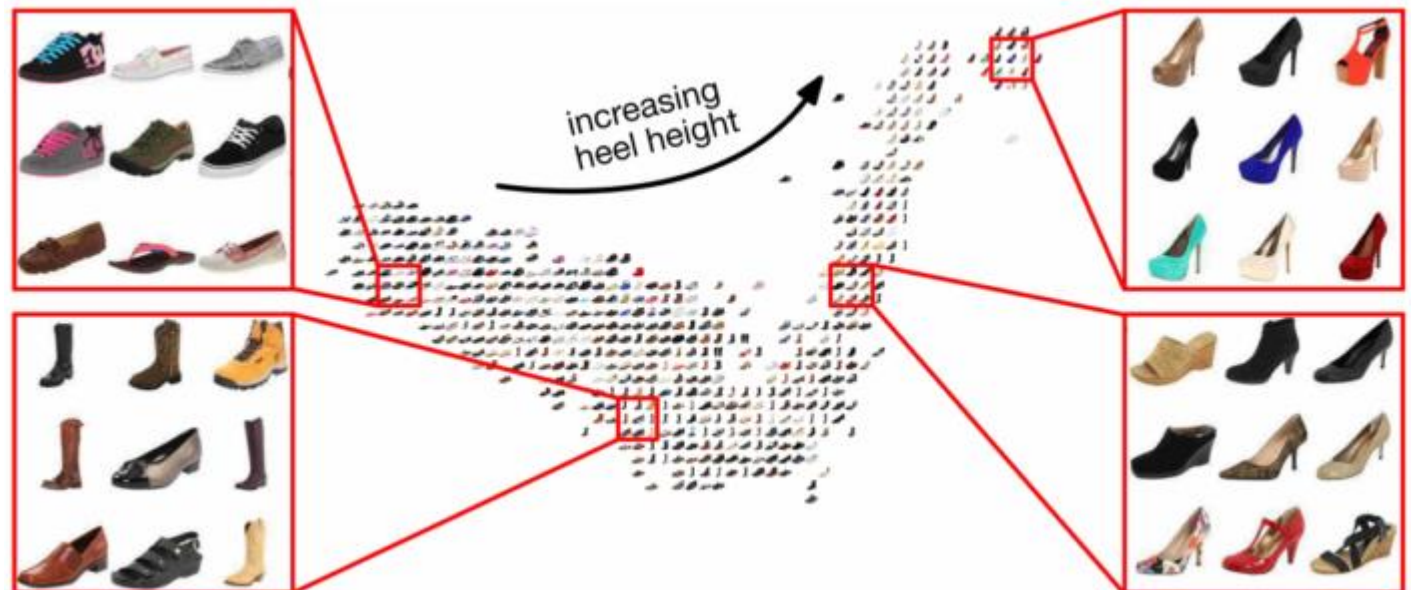
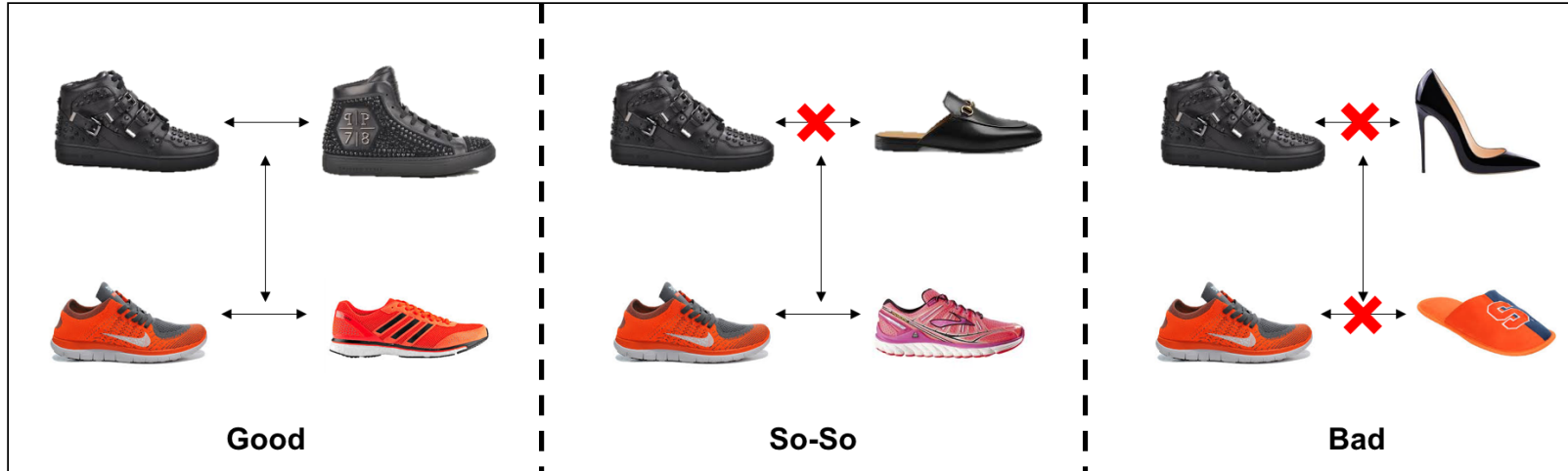
다양한 CNN Task들

Deep Learning으로 HOT한 시각지능 Task는 무엇이 있을까?



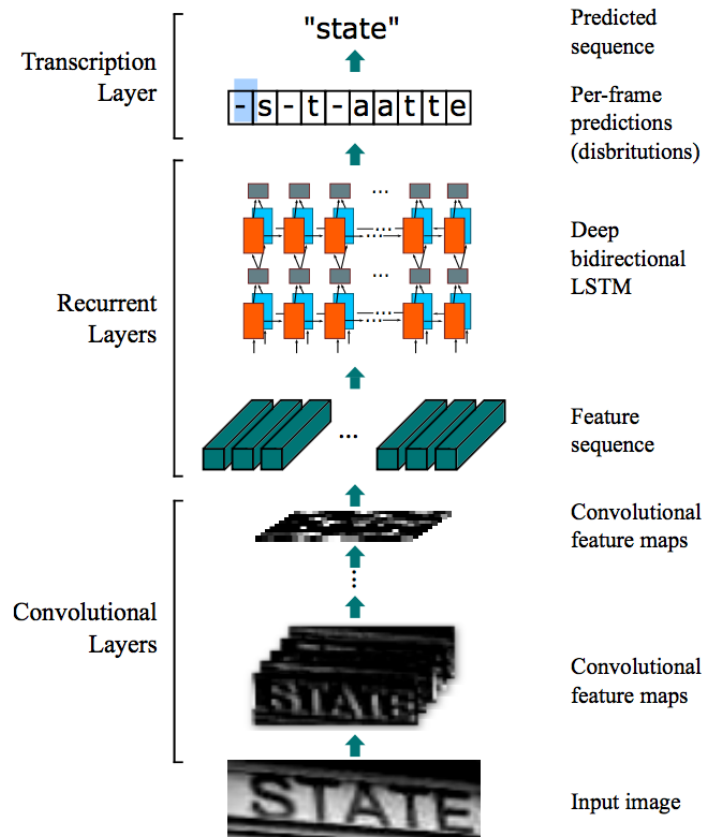
다양한 CNN Task들

Similarity Learning

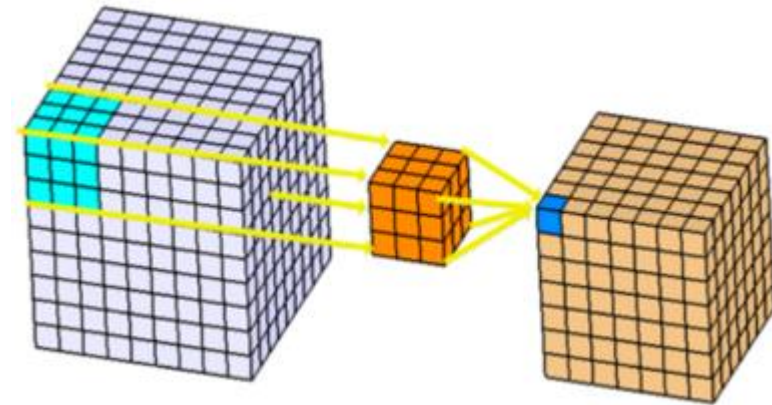


다양한 CNN Task들

Video



Convolutional RNN



3D Convolution

다양한 CNN Task들

Video

Visual Tracking



[Youtube](#)

행동 감지

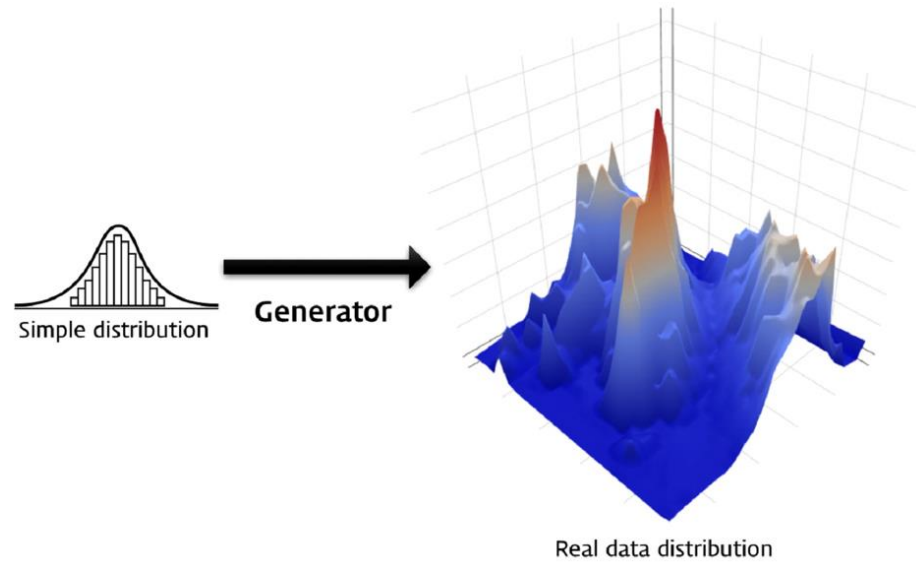
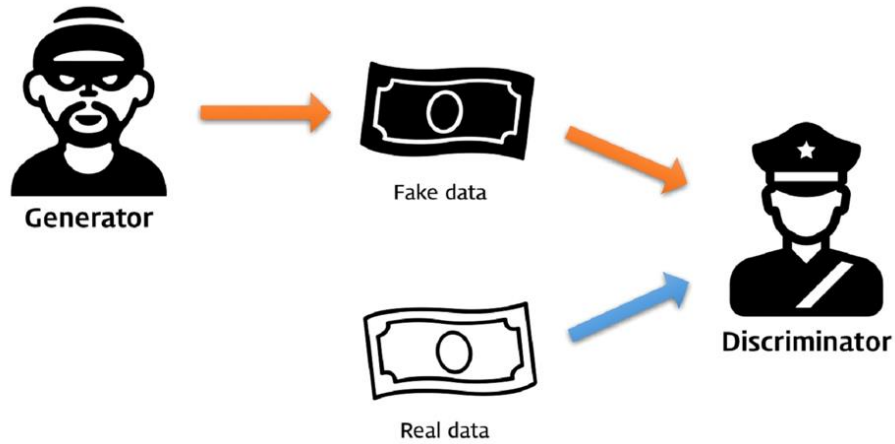


Label:1
(1) Clapping:0.99
(2) Clapping:0
(3) Waving:0
(4) Jogging:0
(5) Running:0
(6) Walking:0
(0) None:0



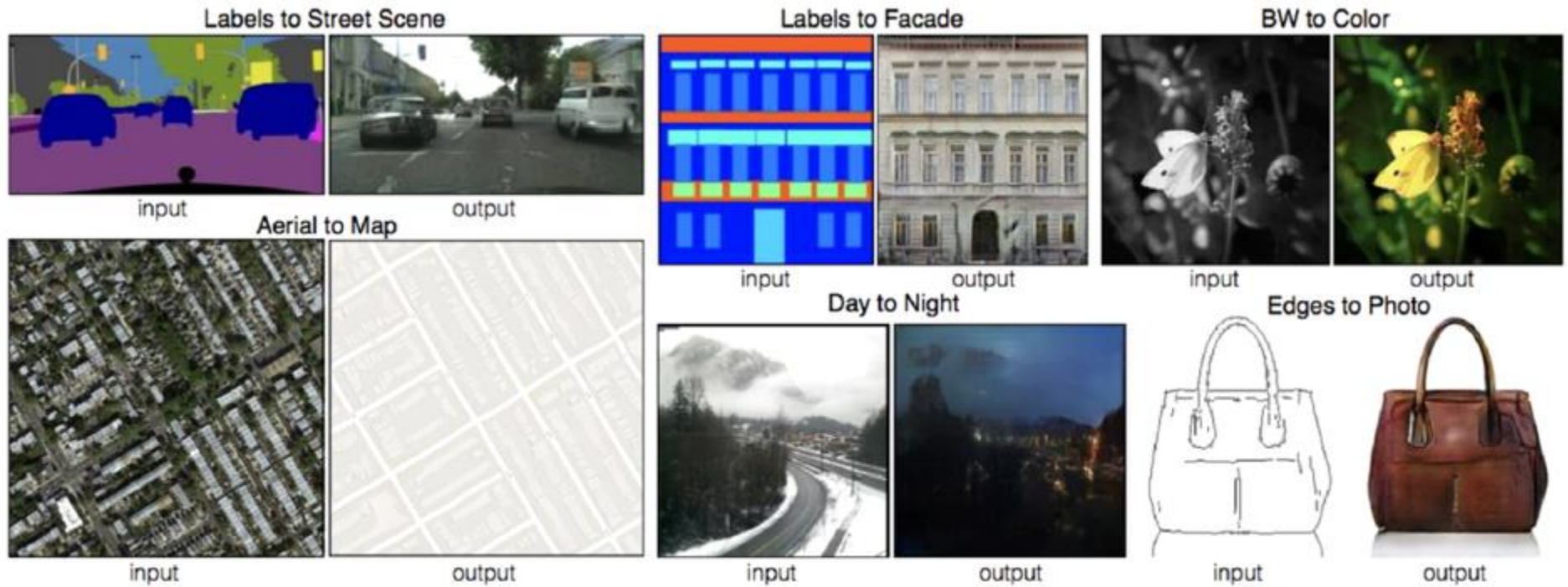
[Youtube](#)

GAN



다양한 CNN Task들

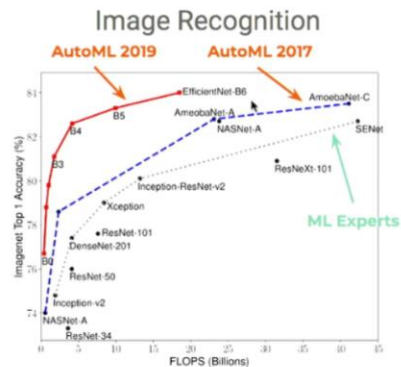
GAN



다양한 CNN Task들

AutoML

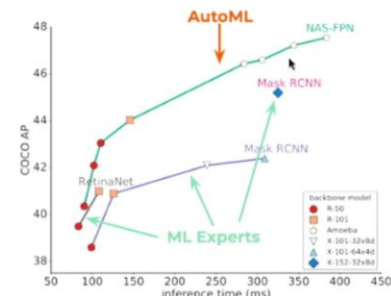
Better Models, Across Multiple Modalities/Domains



Google Tan et al. EfficientNet: Rethinking Model Scaling for Deep Convolutional Neural Networks, ICML 2019, arxiv.org/abs/1905.11964

Better Models, Across Multiple Modalities/Domains

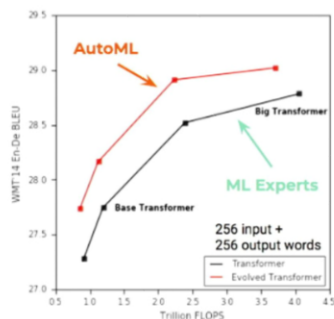
Object Detection



Google Ghiasi et al. Learning Scalable Feature Pyramid Architecture for Object Detection, 2019, arxiv.org/abs/1904.07289

Better Models, Across Multiple Modalities/Domains

Language Translation



Google So et al. The Evolved Transformer, 2019, arxiv.org/abs/1901.11117

Better Models, Across Multiple Modalities/Domains

Video Classification

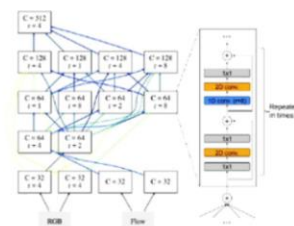


Table 1: State-of-the-art action classification performances on Charades [19].

Method	modality	mAP
2-Strm. [20] (from [18])	RGB+Flow	18.6
Asyn-TF [18]	RGB+Flow	22.4
CoViAR [28]	Compressed	21.9
MultiScale TRN [33]	RGB	25.2
I3D [3]	RGB	32.9
I3D [3] (from [25])	RGB	35.5
I3D-NL [25]	RGB	37.5
STRG [26]	RGB	39.7
LFB [27]	RGB	42.5
SlowFast [6]	RGB+RGB	45.2
Two-stream (2+1)D ResNet	RGB+Flow	46.5
AssembleNet	RGB+Flow	51.6

State-of-the-art accuracy

Google Ryoo et al., 2019. AssembleNet: Searching for Multi-Stream Neural Connectivity in Video Architectures, [http://arxiv.org/abs/1905.13209](https://arxiv.org/abs/1905.13209)

다양한 CNN Task들

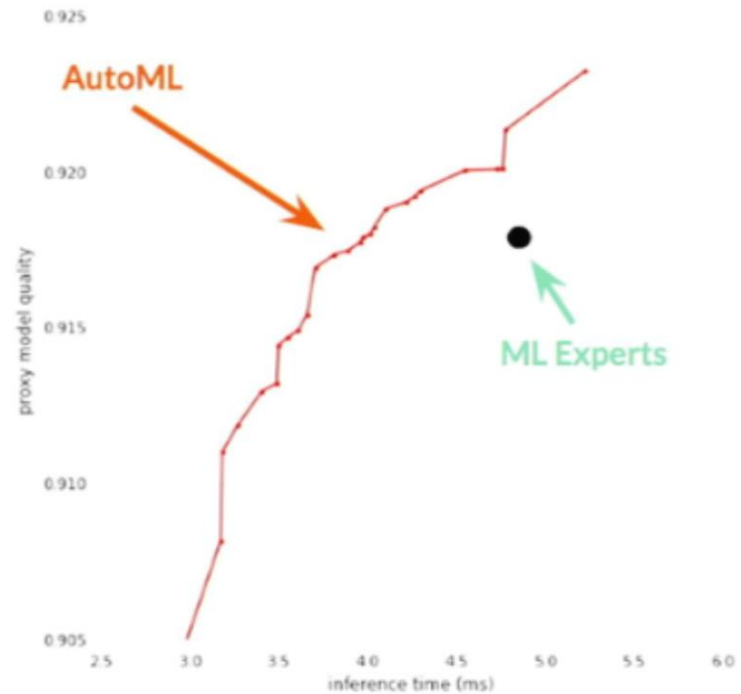
AutoML



Collaboration between Waymo and Google Research:

- 20–30% lower latency / same quality.
- 8–10% lower error rate / same latency.

'Interesting' architectures:

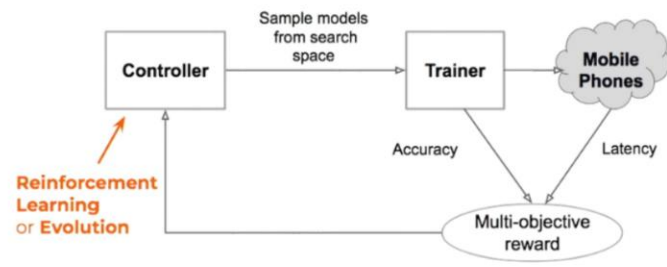


medium.com/waymo/automl-automating-the-design-of-machine-learning-models-for-autonomous-driving-141a5583ec2a

다양한 CNN Task들

AutoML

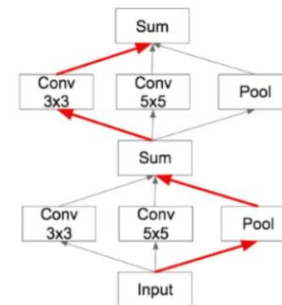
Platform-aware search



Google

Tan et al., MnasNet: Platform-Aware Neural Architecture Search for Mobile. CVPR, 2019
arxiv.org/abs/1807.11626

ENAS: Efficient Neural Architecture Search



Key idea:

1. One path inside a big model is a child model
2. Controller selects a path inside a big model and train for a few steps
3. Controller selects another path inside a big model and train for a few steps, reusing the weights produced by the previous step
4. Etc.

Results: **Can save 100->1000x compute**

Related work: DARTS, SMASH, One-shot architecture search

Google

Pham, Guan, Zoph, Le, and Dean, ICML 2018. Efficient Neural Architecture Search via Parameter Sharing. arxiv.org/abs/1802.03268

다양한 CNN Task들

AutoML

Learn the Optimization Update Rule

Figure 1. Overview of Neural Optimizer Search.

Optimizer	Final Val	Final Test	Best Val	Best Test
SGD	92.0	91.8	92.9	91.9
Momentum	92.7	92.1	93.1	92.3
ADAM	90.4	90.1	91.8	90.3
RMSProp	90.7	90.3	91.4	90.3
$\begin{aligned} &[e^{\text{clip}(g, 10^{-4})} + \text{clip}(g, 10^{-4})] * g \\ &\text{clip}(\eta, 10^{-4}) * e^{\eta} \\ &\eta * e^{\eta} \\ &g * e^{\text{clip}(g, 10^{-4})} \\ &\text{drop}(g, 0.3) * e^{\text{clip}(g, 10^{-4})} \\ &\eta * e^{\eta} \\ &\text{drop}(\eta, 0.1) / (e^{\eta} + \epsilon) \\ &\text{drop}(g, 0.1) * e^{\text{clip}(g, 10^{-4})} \\ &\text{clip}(\text{RMSProp}, 10^{-5}) + \text{drop}(\eta, 0.3) \\ &\text{ADAM} * e^{\text{clip}(g, 10^{-4})} \\ &\text{ADAM} * e^{\eta} \\ &g + \text{drop}(\eta, 0.3) \\ &\text{drop}(\eta, 0.1) * e^{\eta} \\ &g - \text{clip}(g^2, 10^{-4}) \\ &e^{\eta} - e^{\eta} \\ &\text{drop}(\eta, 0.3) * e^{\eta} \end{aligned}$	92.5	92.4	93.8	93.1
	93.5	92.5	93.8	92.7
	93.1	92.4	93.8	92.6
	93.1	92.8	93.8	92.8
	92.7	92.2	93.6	92.7
	93.1	92.5	93.6	92.4
	92.6	92.4	93.5	93.0
	92.8	92.4	93.5	92.2
	90.8	90.8	91.4	90.9
	92.6	92.0	93.4	92.0
	92.9	92.8	93.3	92.7
	93.4	92.9	93.7	92.9
	92.8	92.7	93.7	92.8
	93.4	92.8	93.7	92.8
	93.2	92.5	93.5	93.1
	93.2	93.0	93.5	93.2

Table 1. Performance of Neural Optimizer Search and standard optimizers on the Wide-ResNet architecture (Zagoruyko & Komodakis 2016) on CIFAR-10. Final Val and Final Test refer to the final validation and test accuracy after training for 300 epochs. Best V corresponds to the best validation accuracy over the 300 epochs and Best Test is the test accuracy at the epoch where the validation accuracy was the highest.

Bello *et al.*, Neural Optimizer Search with Reinforcement Learning. ICLR 2018. arxiv.org/abs/1706.02542

How about Data Augmentation?

Enlarge your Dataset

Summary:
Search over a search space of **OP1(p1, OP2 (p2, Image))**
where **OP1**, and **OP2** are two image transformation operations
p1, and **p2** are the probabilities to apply these operations

Cubuk & Zoph *et al.*, AutoAugment: Learning Augmentation Policies from Data. CVPR 2018. arxiv.org/abs/1805.09594

Learn the Activation Function

$f(x) = x \cdot \text{sigmoid}(x)$

Summary:
1. Found by search over many possible equations of the form $f(g(x), h(x))$ where f, g, h are selected from predefined functions we've tried
2. Gives consistent improvements over ReLUs on many architectures
3. Now used in MobileNetV3 and EfficientNets

Previously discovered manually by Elfwing *et al.*, and called SiL

Ramachandran *et al.*, Searching for Activation Functions. ICLR Workshop 2018. arxiv.org/abs/1710.08441

AutoAugment Results

Dataset	Error measure	Handcrafted Data augmentation	AutoAugment
		Best published results	Our results
CIFAR-10	Top-1	2.1	1.5
CIFAR-100	Top-1	12.2	10.7
SVHN	Top-1	1.3	1.0
Stanford Cars	Top-1	5.9	5.2
ImageNet	Top-5	3.9	3.5

Table 1. Error rates (%) from this paper compared to the best results so far on five datasets.

Cubuk & Zoph *et al.*, AutoAugment: Learning Augmentation Policies from Data. CVPR 2018. arxiv.org/abs/1805.09594

Automating Reinforcement Learning (AutoRL)

Evolution + RL = Better policies with less engineering

Reward Search

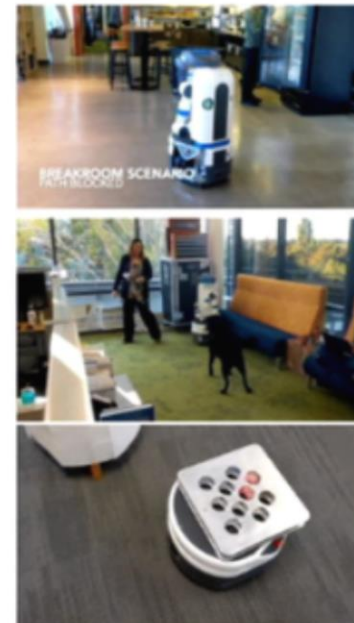
Neural Architecture Search



AutoRL:

1. Evolve the reward that completes task.
2. Evolve neural network architecture that fits the reward.

[Video 1](#)
[Video 2](#)



Learning Navigation Behaviors End to End with AutoRL, Chiang, Faust, Fiser, Francis, RA-L/ICRA 2019, arxiv.org/abs/1809.10124
Evolving Rewards to Automate Reinforcement Learning, Faust, Francis, Mehta, 6th AutoML@ICML '19, arxiv.org/abs/1905.07621

Review

1. Transfer Learning

Transfer Learning 전략을 세우기 위해 고민해야 할 두 가지!
학습 데이터의 양 / 도메인 연관성

2. Useful Utilities

JupyterLab
TensorBoard

3. Final Mission

배운 내용들을 토대로 진행해보는 최종 미션

4. 시각지능 동향

Video / GAN
경량 모델링 / 모델 경량화
AutoMLs