KiSTi 한국과학기술정보연구원
Korea Institute of Science and Technology Information

2022

스마트교통 빅데이터 분석

CNN을 이용한 교통 데이터 분석

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학습 목표

❖ 목표

- ✓딥러닝 기반 이미지 분류하기 위해 지도학습과 이미지(특성) 및 레이블에 대하여 이해한다.
- ✓커널, 콘볼루션, 풀링을 이해하며 CNN 아키텍처에 대하여 이해한다.

❖ 배경

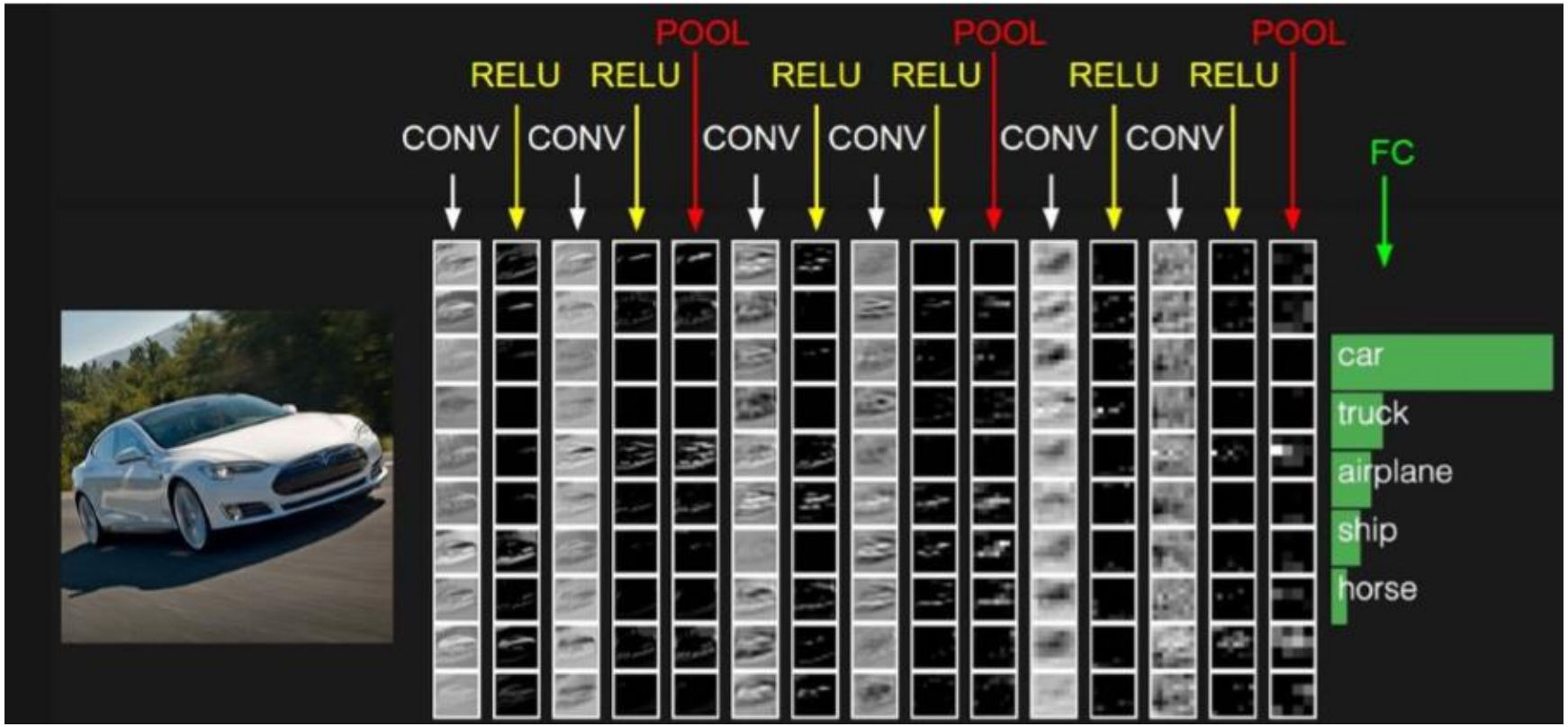
- ✓스마트 교통 데이터는 시계열 데이터와 CCTV 등 영상데이터가 대부분이다.
- ✓교통 이미지 데이터를 수집하고 분류하기 위해서 정확도가 높은 CNN 구현이 필요하다.
- ✓CNN 정확도를 이해하고 의미있는 연구결과를 얻기 위해서 필요한 연구 전략에 대하여 알아본다.

❖ 생각해볼 문제

- ✓CNN 정확도 95%가 주는 의미는 무엇이며, 실제 스마트 교통에 필요한 CNN 데이터와 분석 정확도는 얼마가 적당한가?
- ✓시계열 교통 데이터를 CNN을 처리 할 수 있을까?

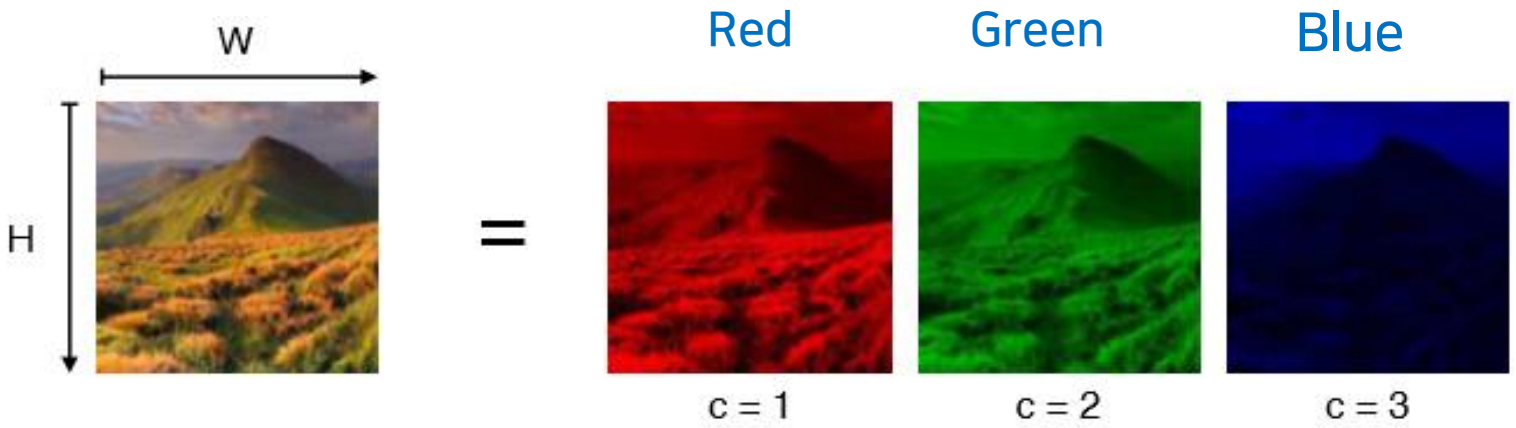
CNN의 특성 학습

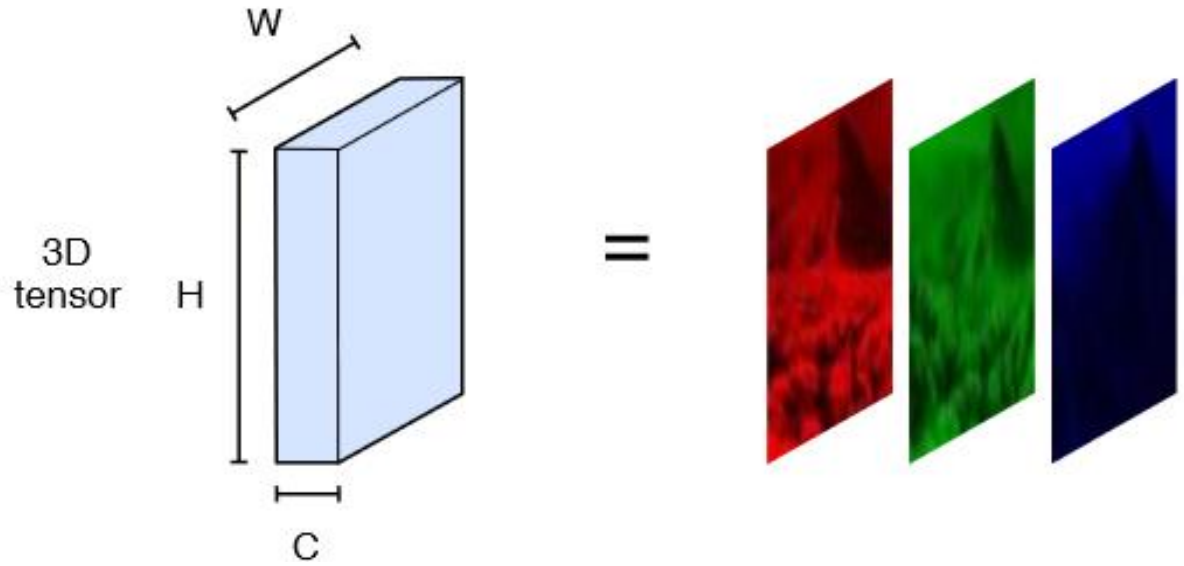
Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output



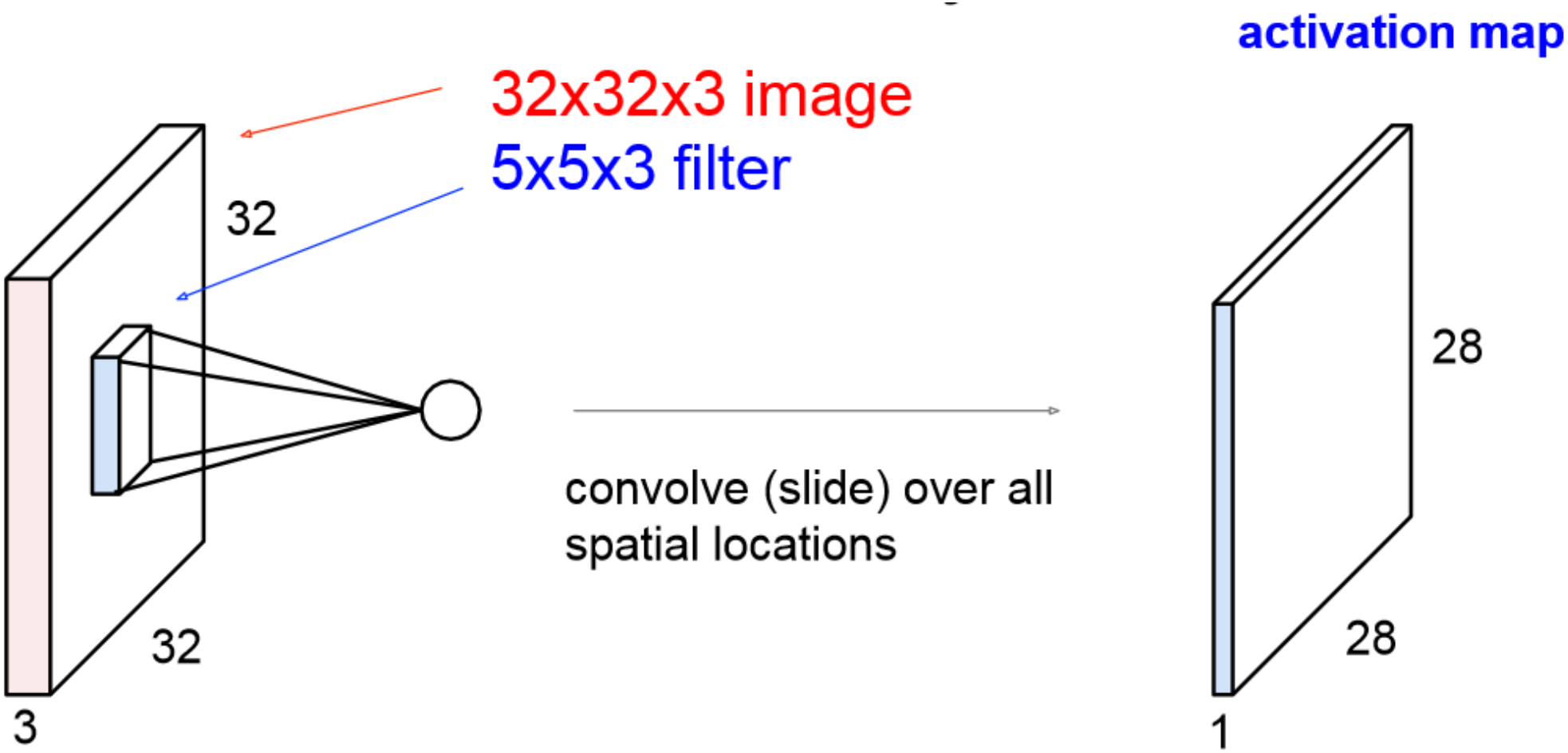
레이블링

칼러 이미지 데이터는 3차원으로 표현





Convolution Layer와 filter

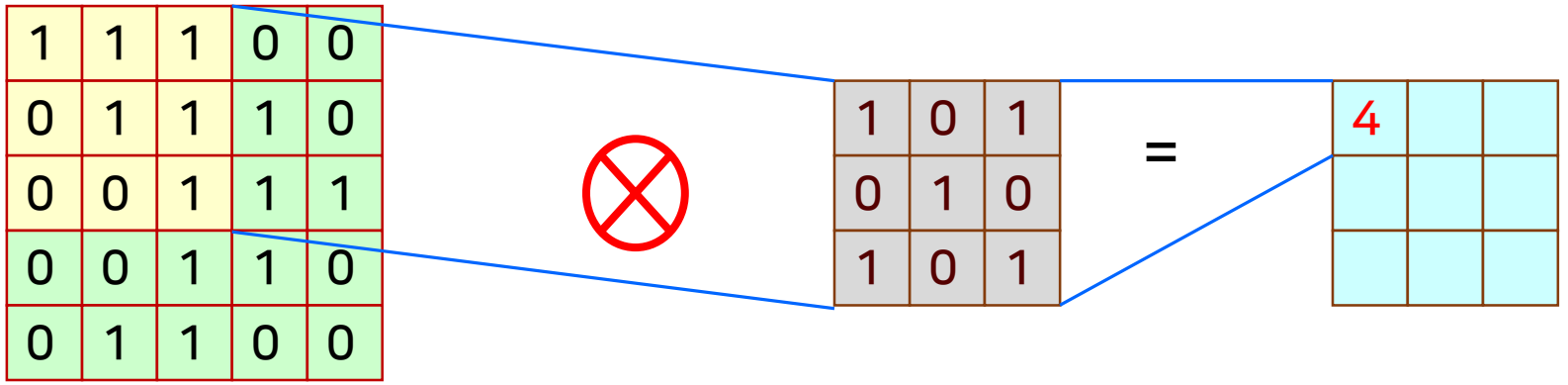


1. 콘볼루션(Convolution) 연산의 이해

Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output

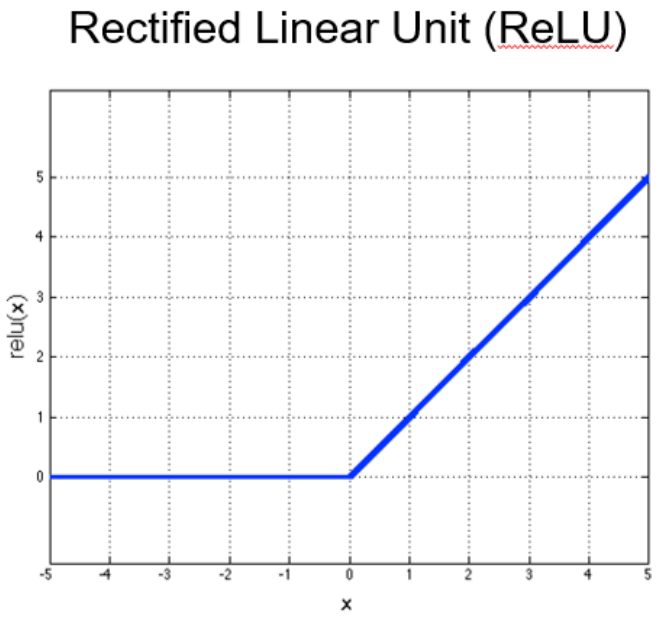
Convolution : 같은 배열끼리 곱하고 합하기

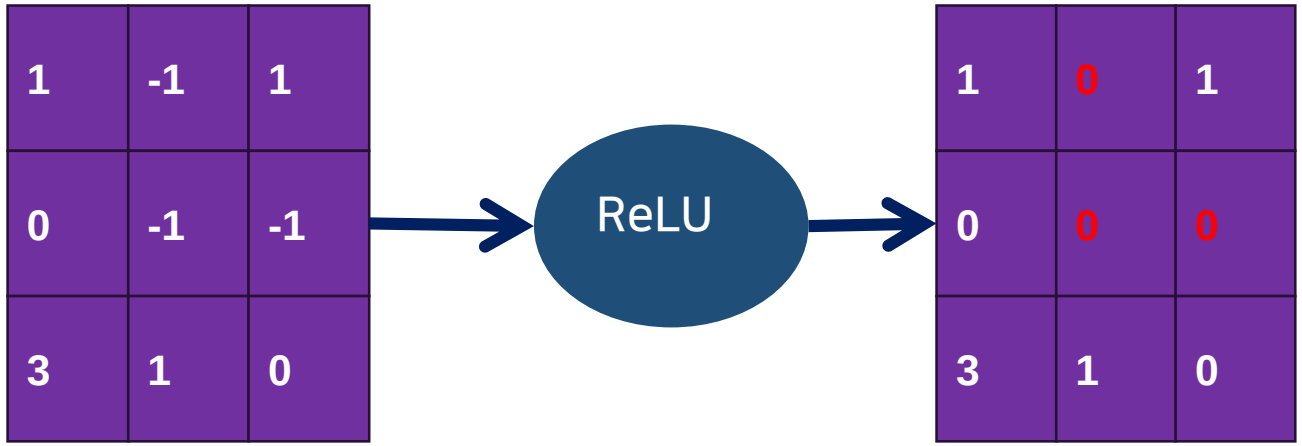
1x1 + 1x0 + 1x1 + 0x0 + 1x1 + 1x0 + 0x1 + 0x0 + 1x1 = 4



2. ReLU 활성함수 Linear chains

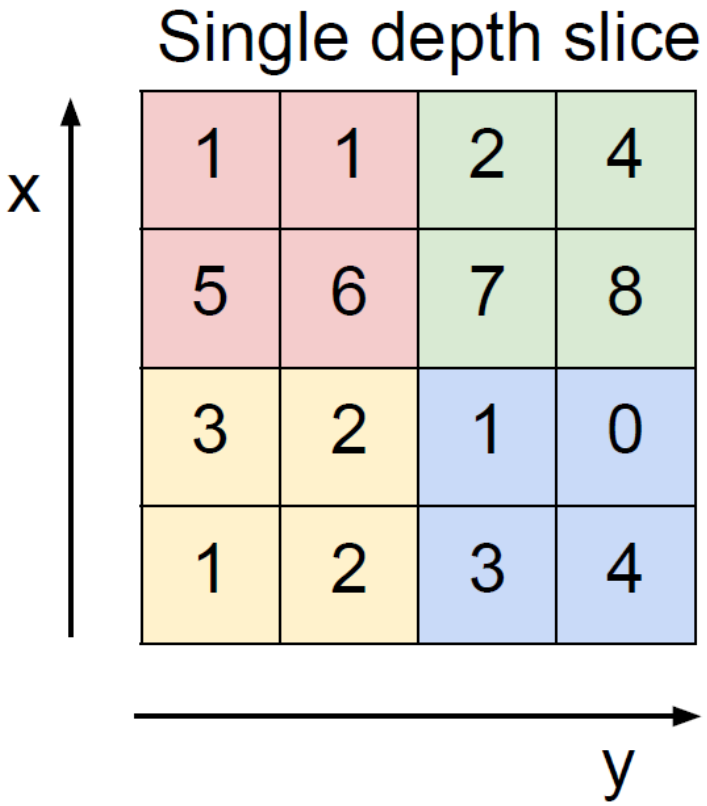
Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output



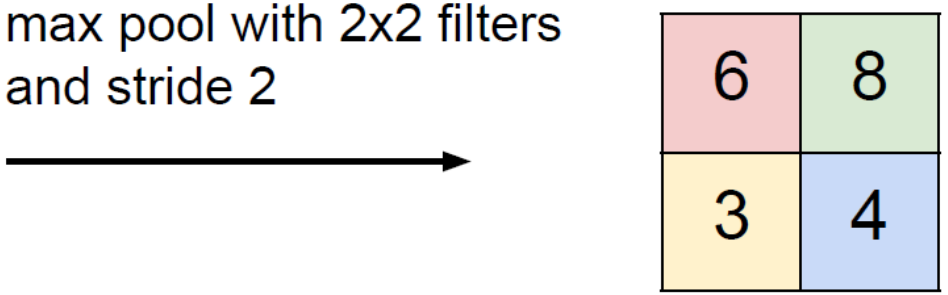


3. Pooling Layer와 ReLU 활성함수

Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output

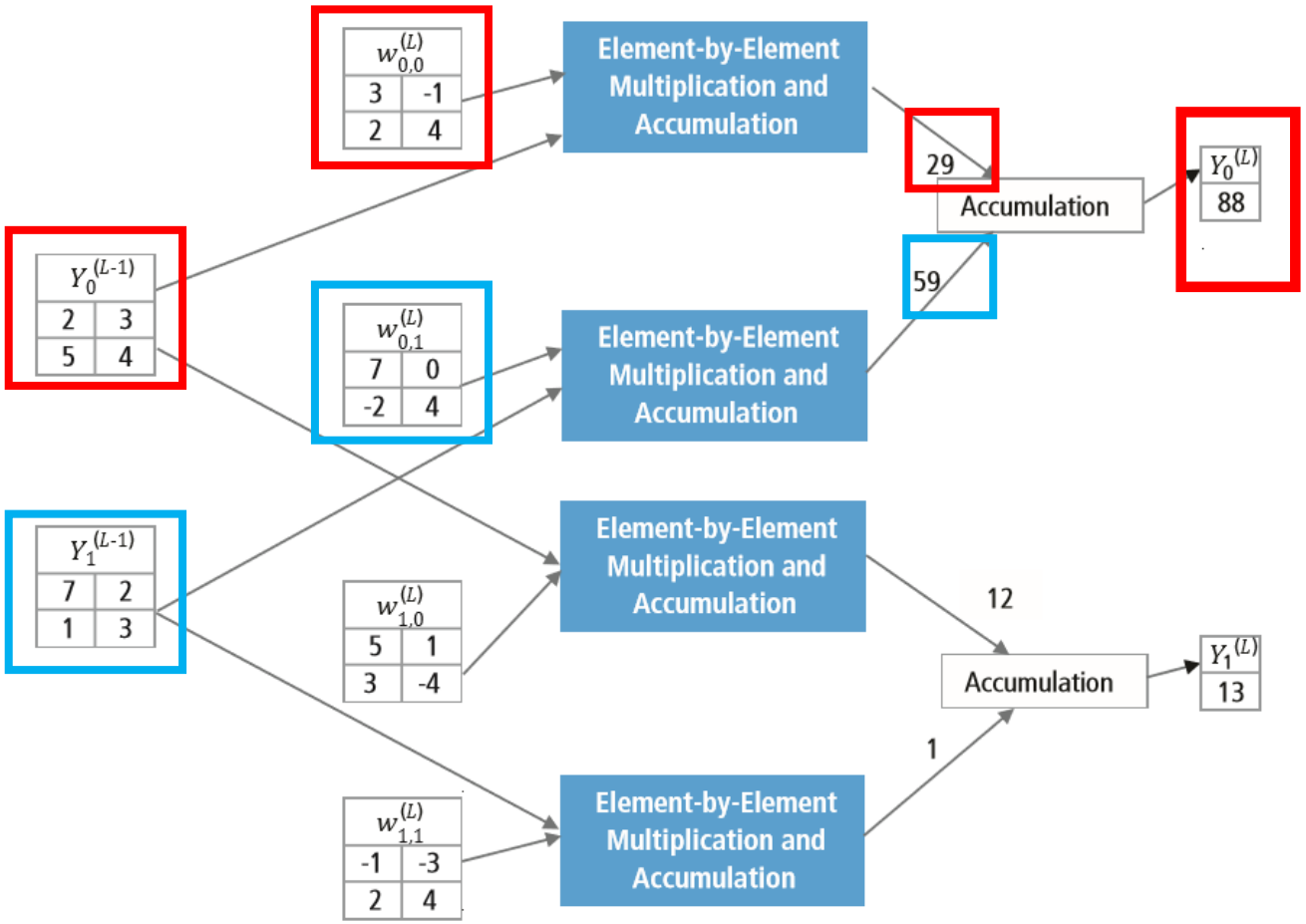


Pooling Layer : Max Pooling



4. Fully Connected Layer (예제)

Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output



1) 같은 행끼리 곱하고
2x3=6
3*(-1)=-3
5*2=10
4*4=16

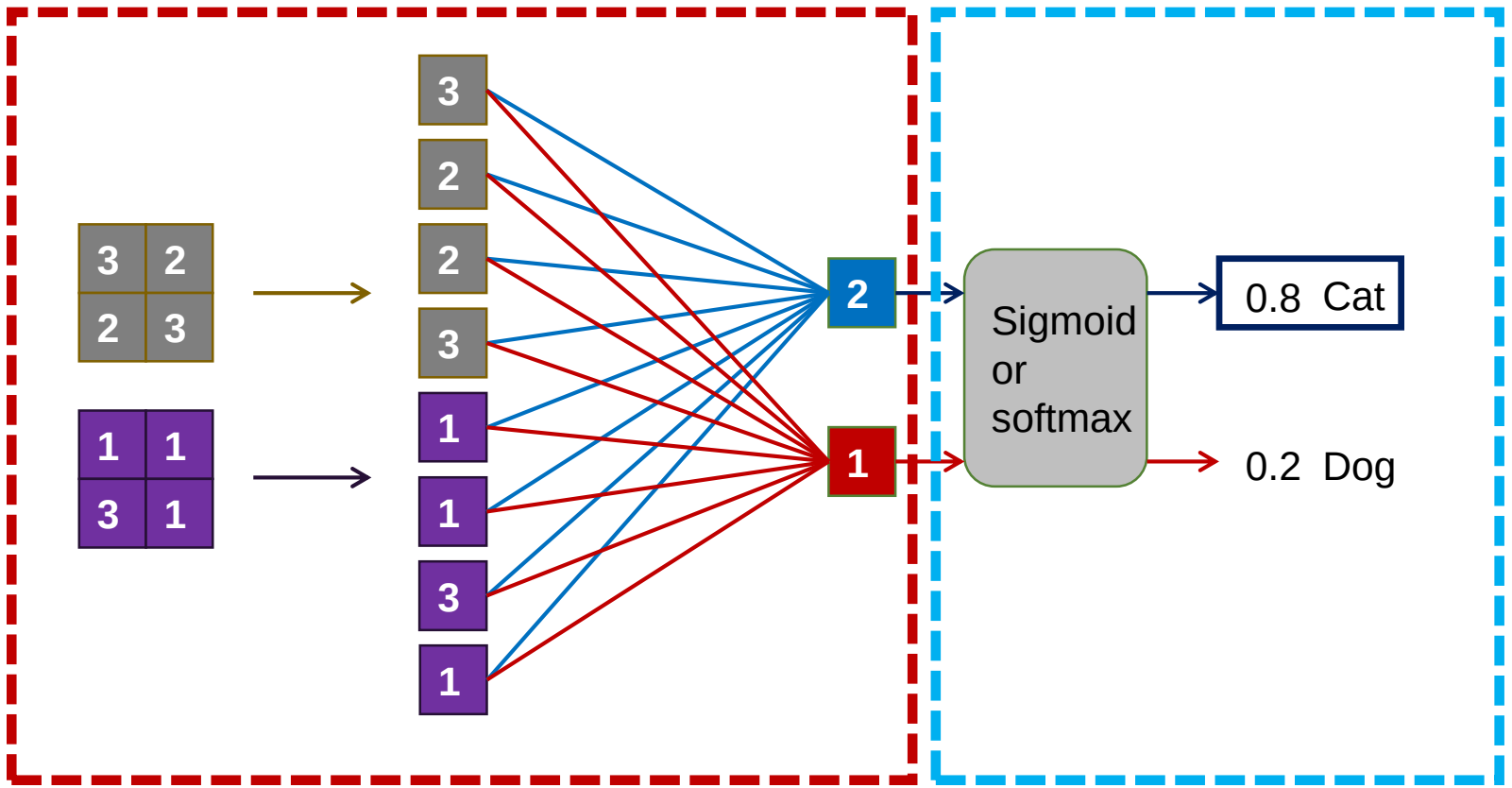
2) 모든 요소를 더하며
6-3+10+16=29

3) 7*7=49
2*0=0
1*(-2)=-2
3*4=12

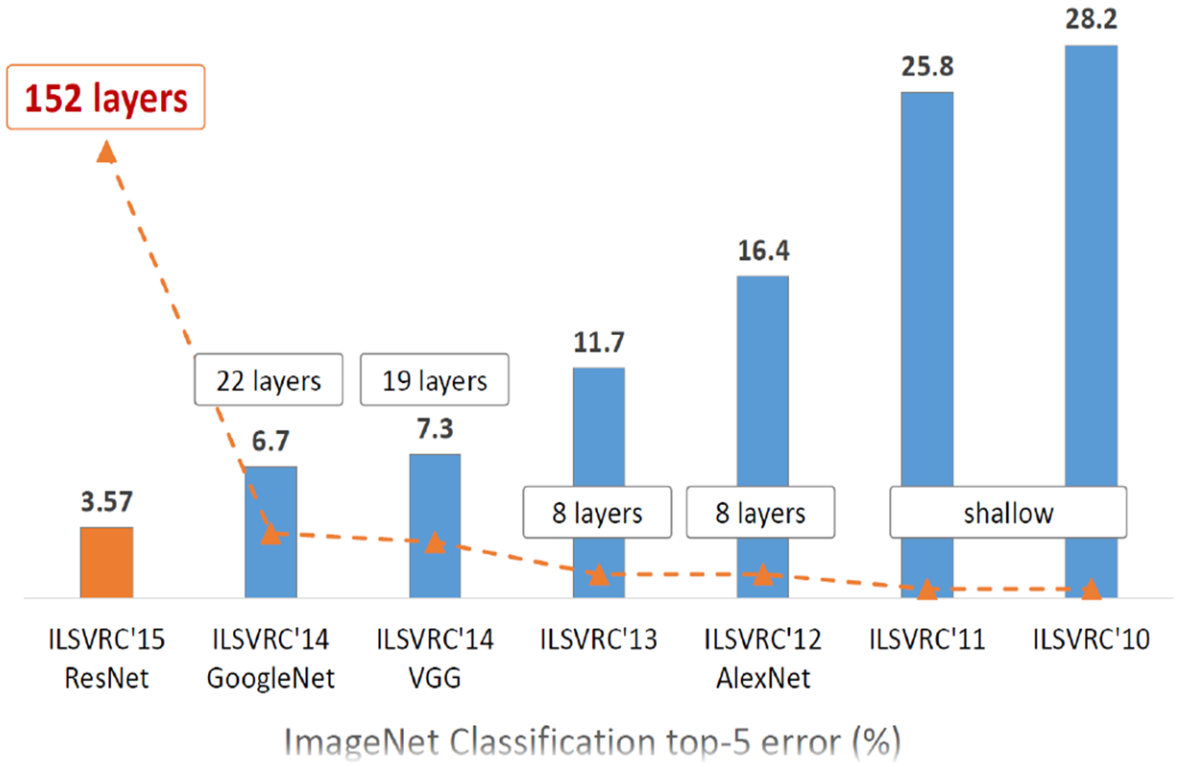
4) 49+0-2+12=59
5) 29+59=88

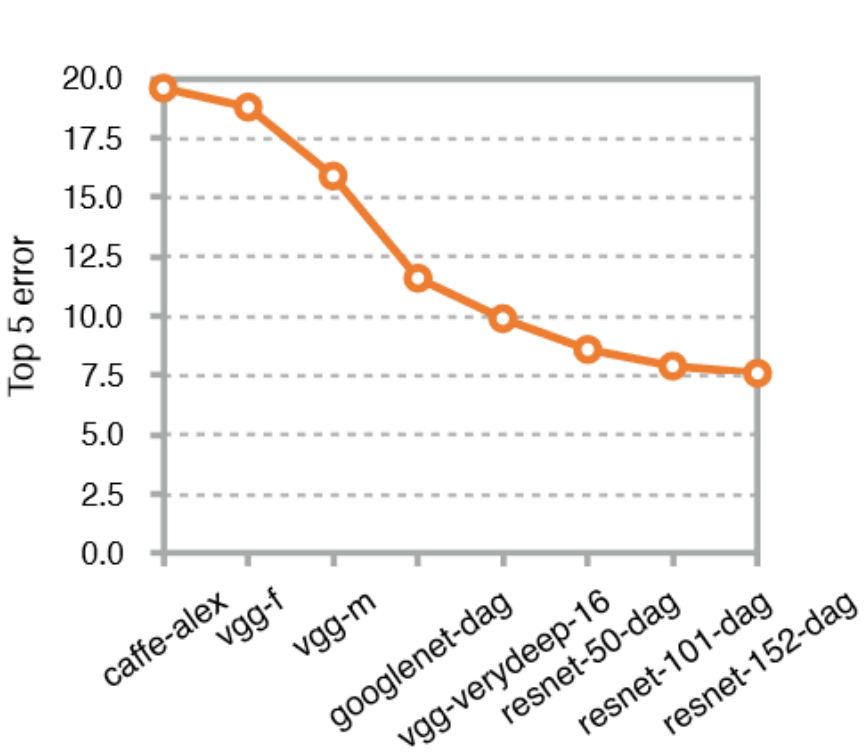
5. Fully-Connected Layer와 Output

Input → Conv → ReLU → Pooling → ReLU → Conv → ReLU → Pooling → Fully Connected → Output

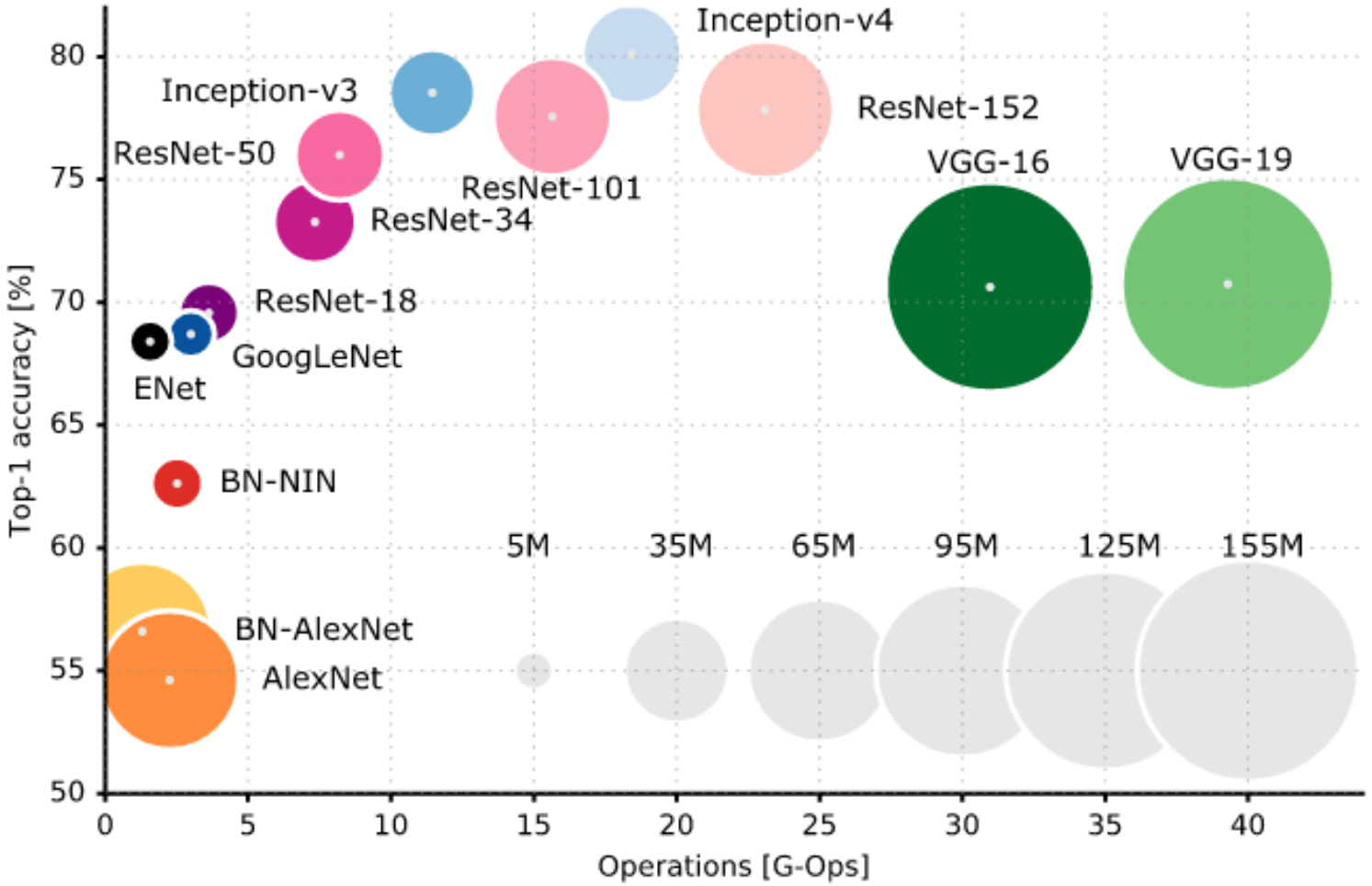


ImageNet 분류의 정확성 및 은닉층 개수 (Deep)





CNN Accuracy vs. efficiency

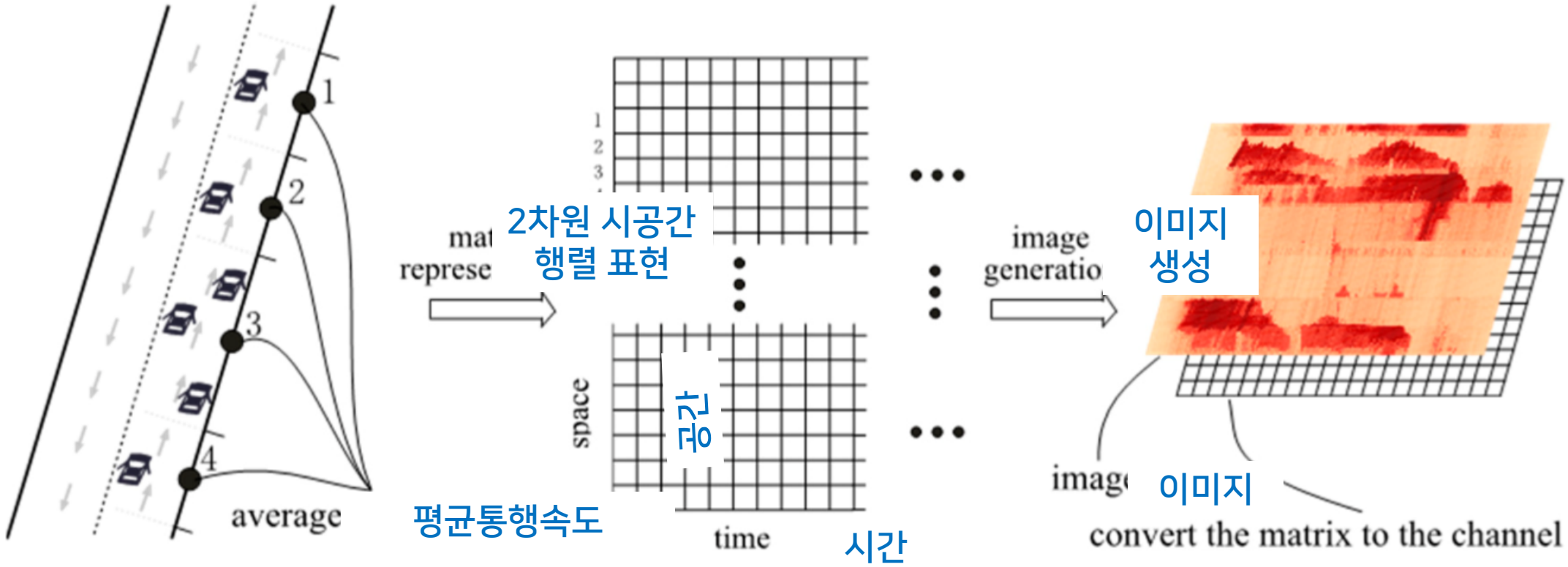


https://culurciello.github.io/tech/2016/06/04/nets.html

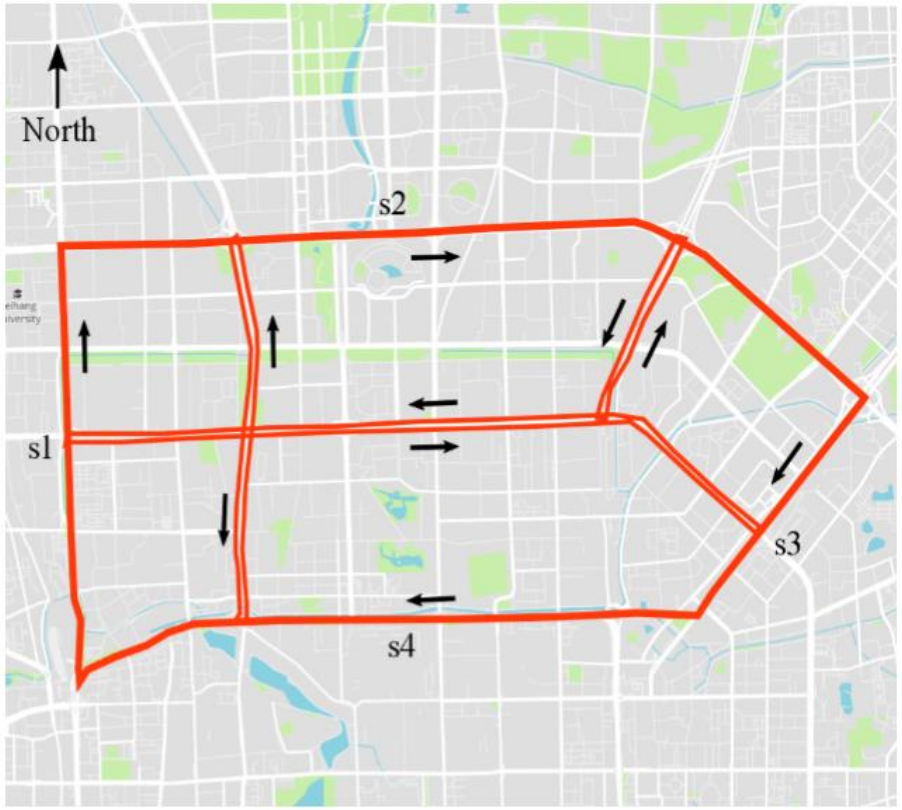
CNN 모델을 위한 교통 데이터 종류

Traffic-to-image conversion on a network

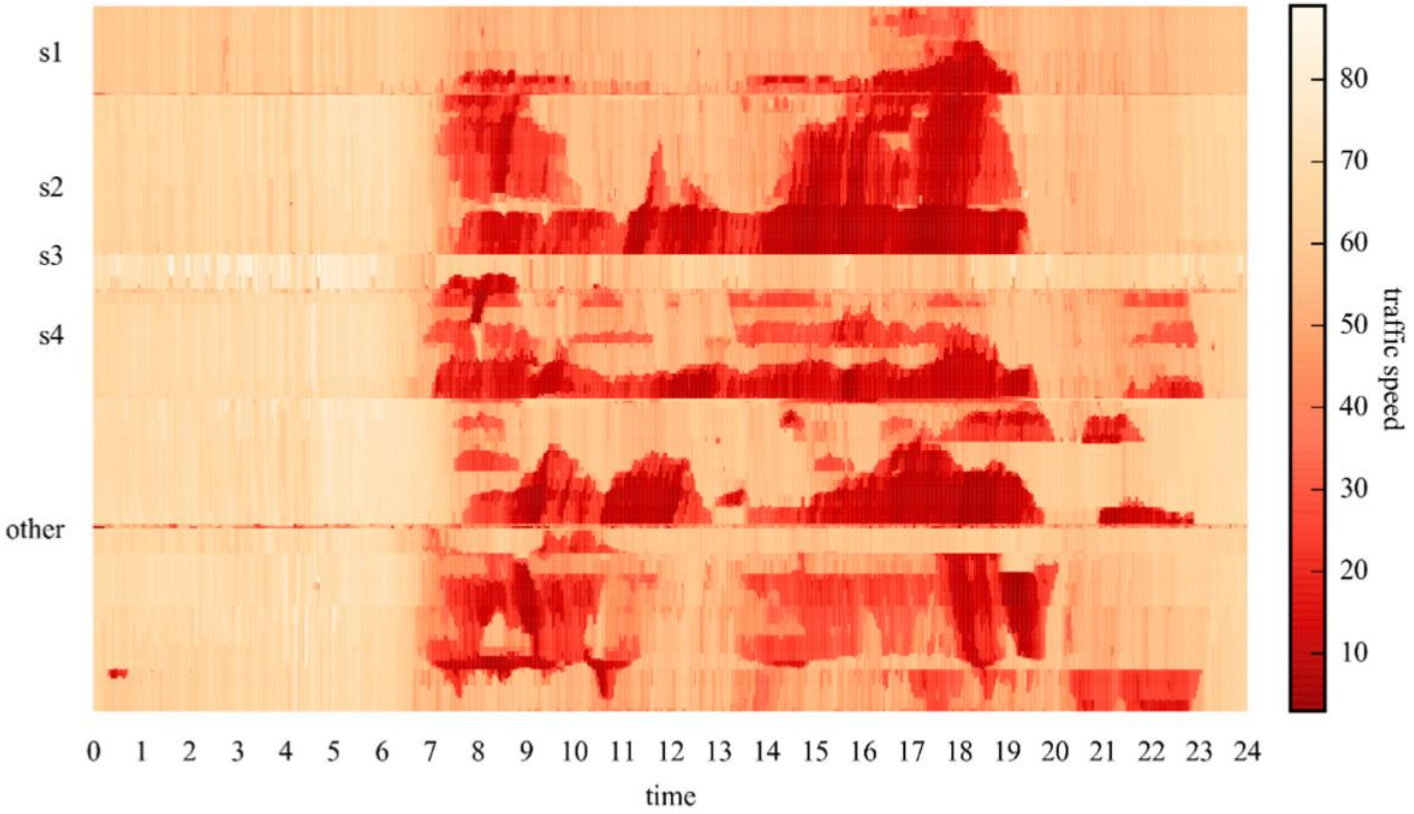
A Deep Convolutional Neural Network for Large-Scale Transportation Network Speed Prediction



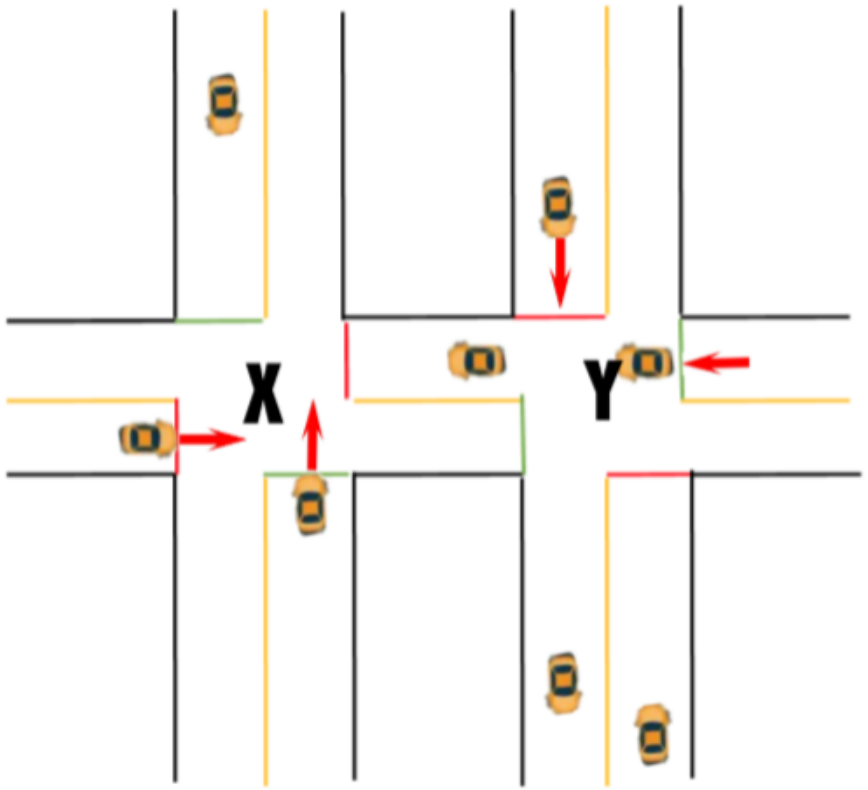
CNN 분석을 위한 교통 데이터 처리 (도심 교통 흐름)



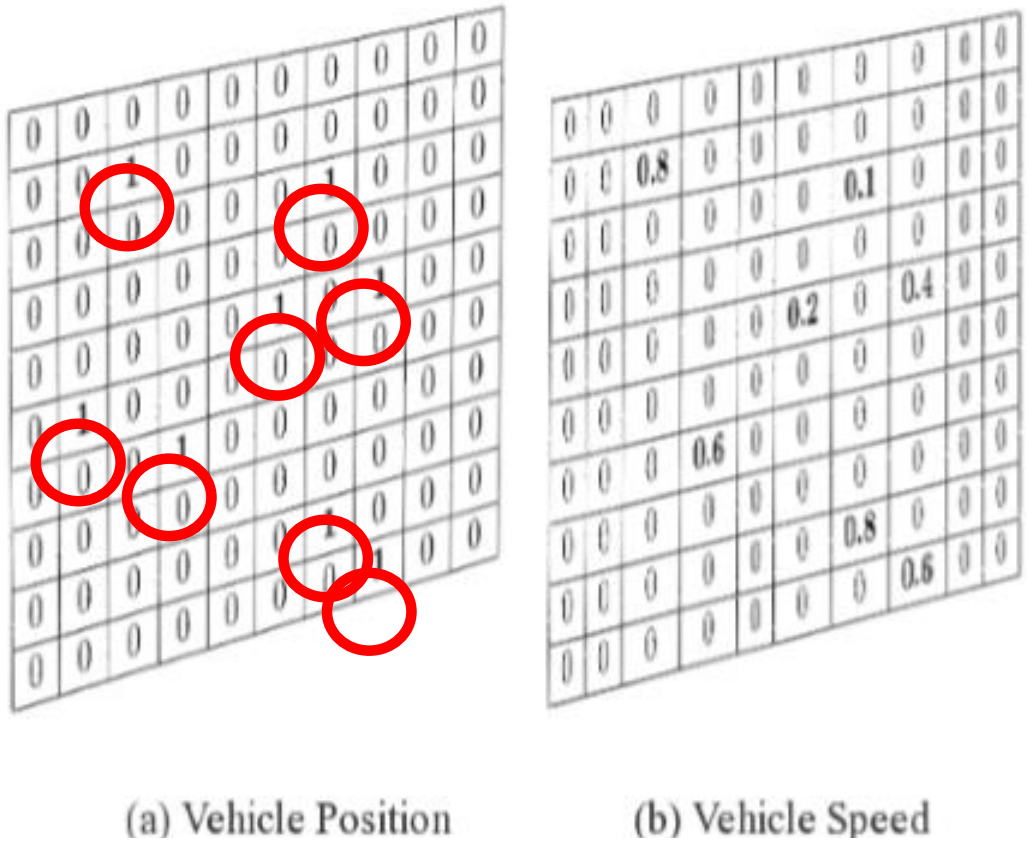
레이블링은 무엇인가?



CNN 분석을 위한 교통 데이터 처리 (교통 신호처리)



레이블링은 무엇인가?



(a) Vehicle Position

(b) Vehicle Speed

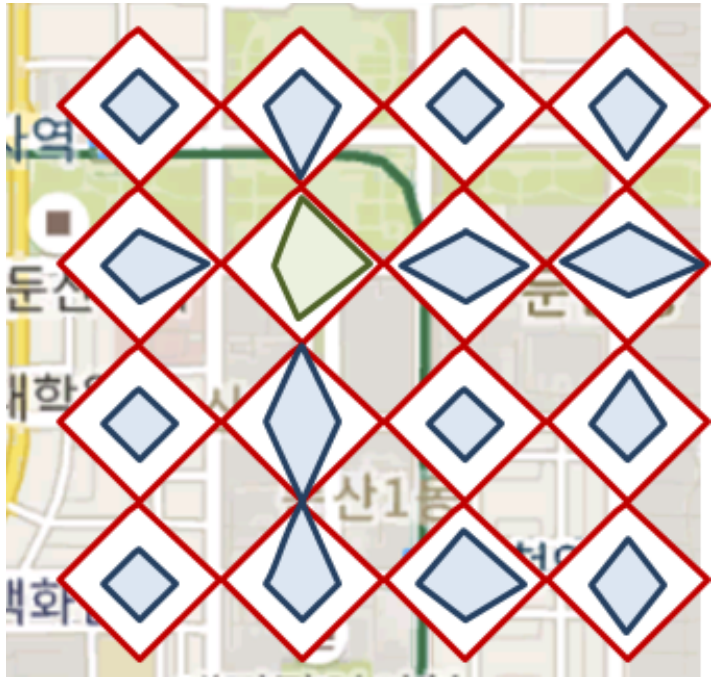
차량들 위치

차량들 속도

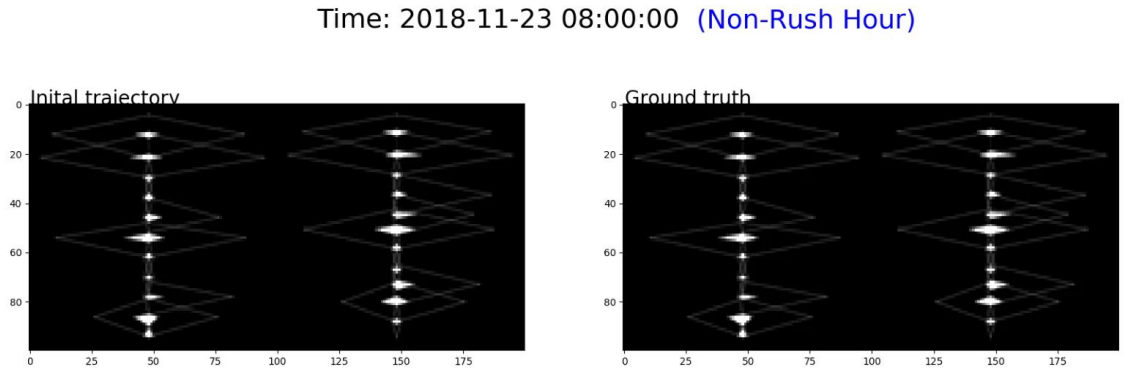
CNN 분석을 위한 교통 데이터 처리 (RSE 데이터)

❖ 인공지능 : CNN의 Top 1 Accuracy

- 13개 교차로를 1개의 이미지(교통량)로 변환
- 딥러닝 CCN을 적용하여 교통 패턴 분류한 기술



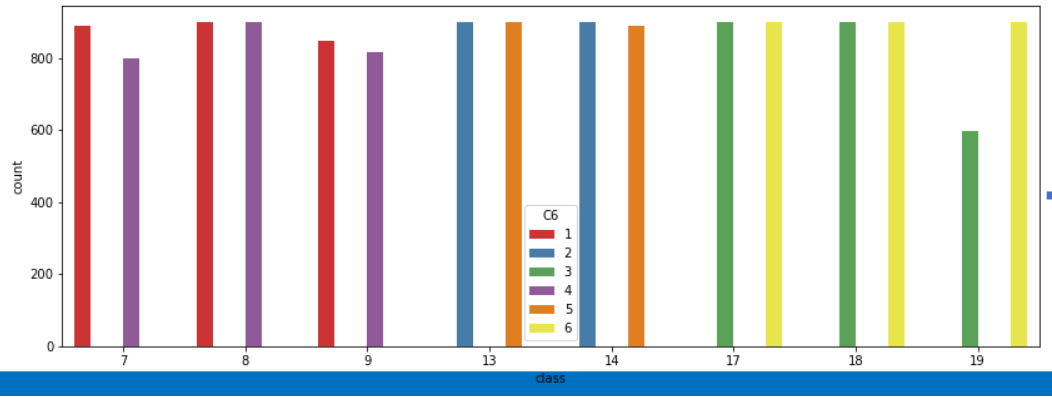
[redacted]



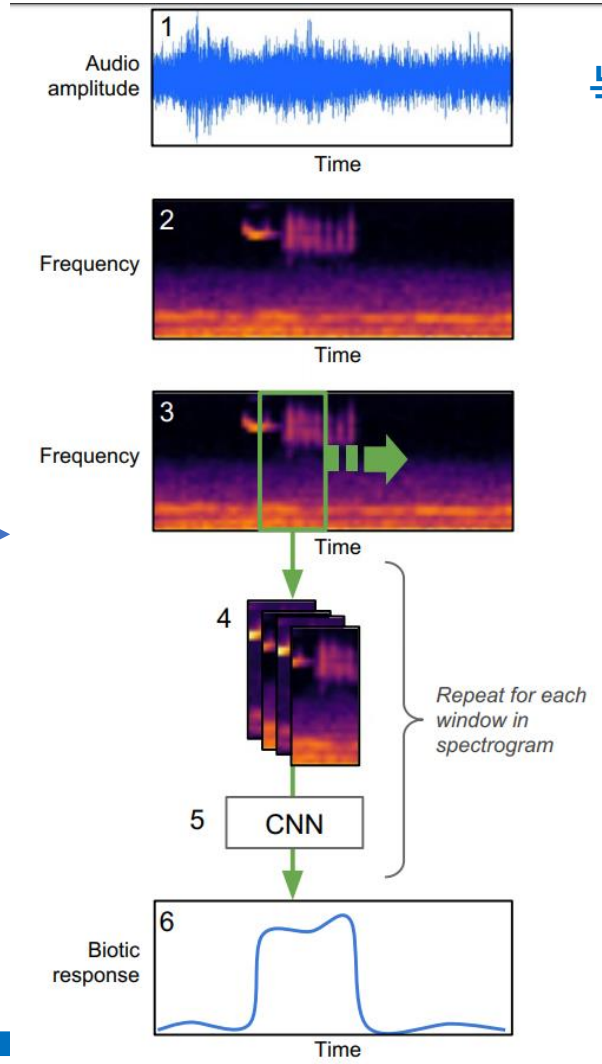
[redacted]

CNN 분석을 위한 교통 데이터 처리 (교통 소음)

- 소음 빅데이터 자체 수집 : DJ_TrafficSound14K (대덕대로)



- 딥러닝 CNN : Mel Spectrogram



녹음된 음원 추출

딥러닝 영상 분석 소개

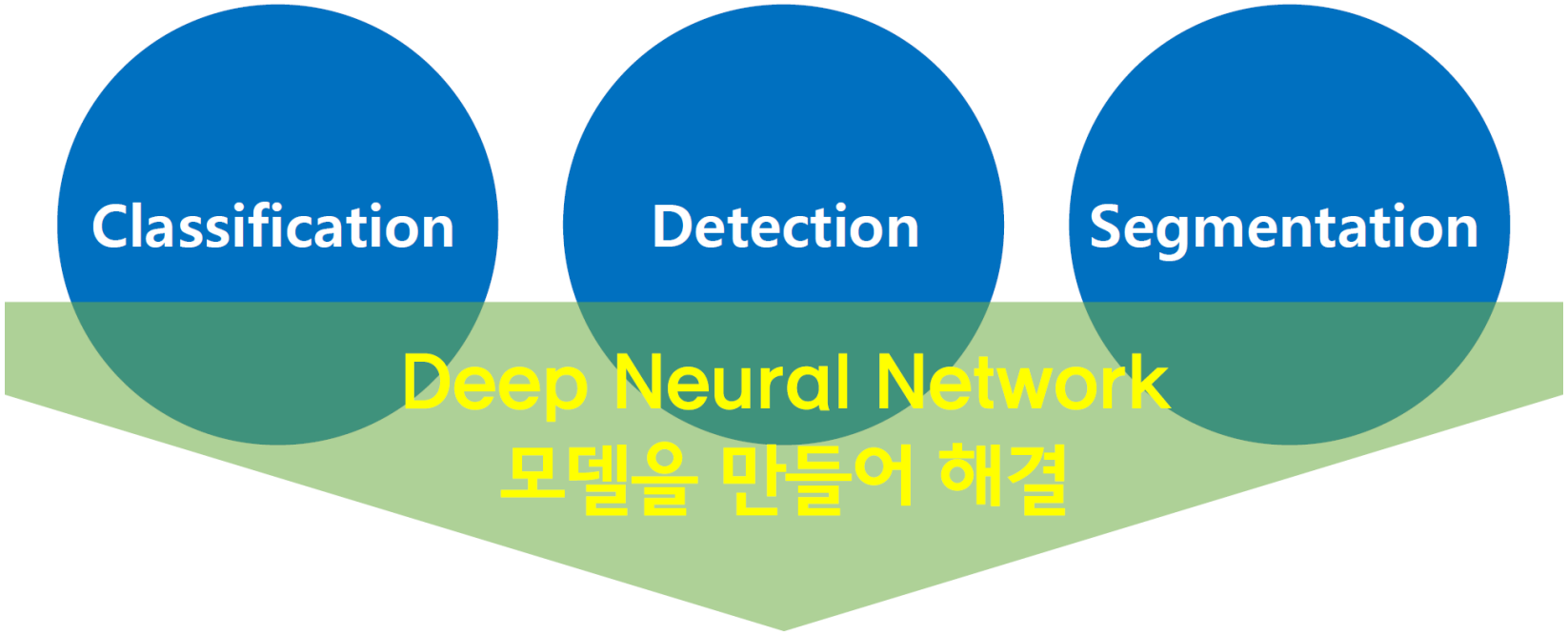
컴퓨터 비전 (Computer Vision)

❖ 컴퓨터에게 인간의 시각 능력을 갖게 하는 것

카메라를 통해서 본 사물 인식

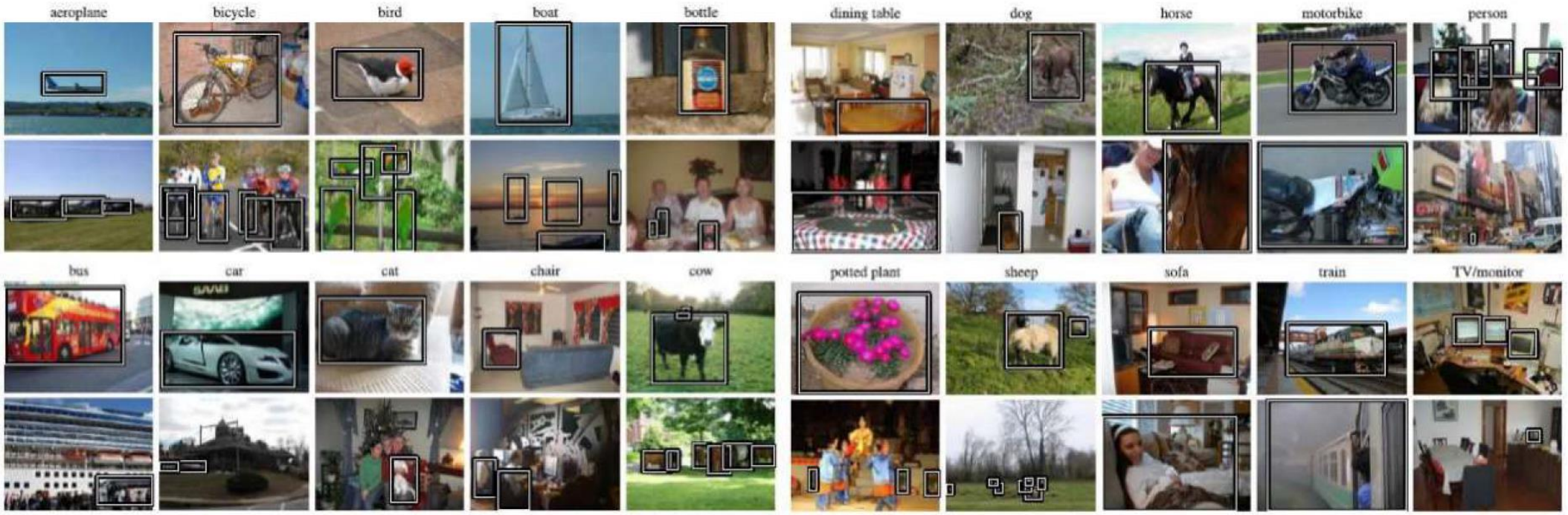
Image Recognition 문제

❖ Image Recogntition 문제



분류(Classifiction)

- 이미지 안에 어느 특정한 클래스가 포함되어 있는지 여부를 분류하는 모델을 만드는 것
  - ✓클래스(Class)란 분류대상이 되는 객체
- PASCAL VOC Challenge에서 다루는 Class는 20 가지임

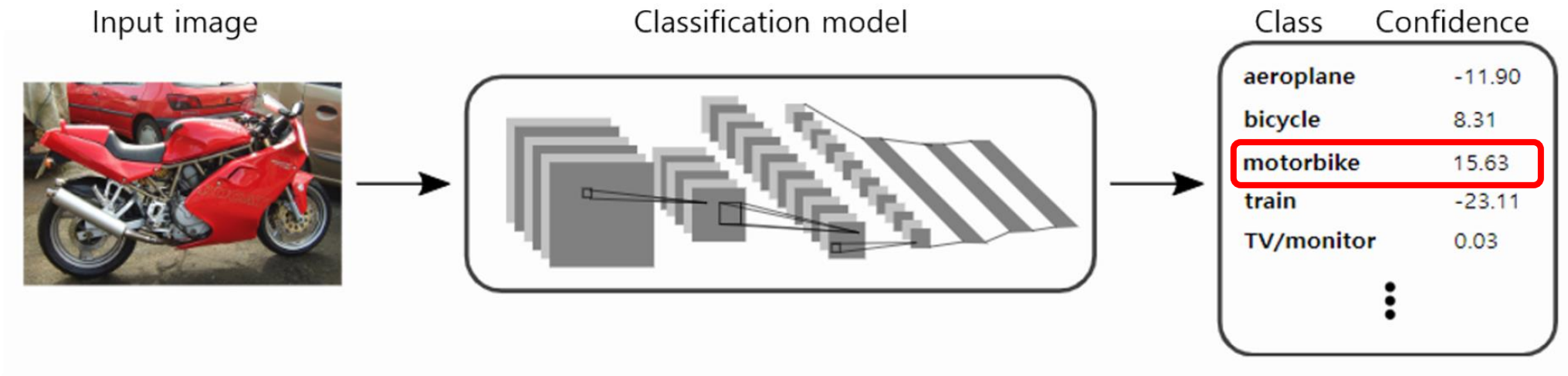


Classifiction_모델의 결과물

❖ 정의

✓존재할 가능성을 신뢰도 점수로 표현함

✓있다/없다(X)



오토바이 신뢰도

단일 사물 분류의 신뢰도 점수

- 20가지 클래스 중에서 신뢰도 점수가 가장 큰 클래스를 선정
  - ✓“주어진 이미지에서 고양이(cat)이 포함되어 있을 것이다 " 로 해석

Class	Confidence	Class	Confidence
aeroplane	-10.22	dining table	-5.98
bicycle	-1.92	dog	29.99
bird	-21.56	horse	8.89
boat	-18.77	motorbike	-20.01
bottle	0.56	person	7.67
bus	-1.09	potted plant	-1.23
car	1.11	sheep	15.23
cat	37.26	sofa	2.89
chair	5.60	train	-23.11
cow	7.27	TV/monitor	0.03

복수 사물의 신뢰도

❖ 각 클래스별 신뢰도 점수가 한계값 보다 크면 클래스를 선정함

✓각 클래스 마다 한계점(Threshold)을 미리 설정함.

✓“주어진 이미지에 cow와 person이 포함되어 있을 것이다 " 로 해석함.

Class(Threshold)	Confidence	Class(Threshold)	Confidence
aeroplane(13.72)	-1.99	dining table(7.76)	-10.11
bicycle(10.66)	2.21	dog(13.21)	-6.54
bird(17.58)	-3.14	horse(14.44)	13.21
boat(16.70)	-33.09	motorbike(8.97)	4.44
bottle(8.11)	-12.13	person(8.01)	11.33
bus(10.11)	5.72	potted plant(21.31)	-10.10
car(15.61)	9.22	sheep(17.17)	16.66
cat(15.09)	0.98	sofa(12.34)	-1.99
chair(11.22)	-8.90	train(16.06)	2.21
cow(9.98)	27.38	TV/monitor(11.99)	-29.34

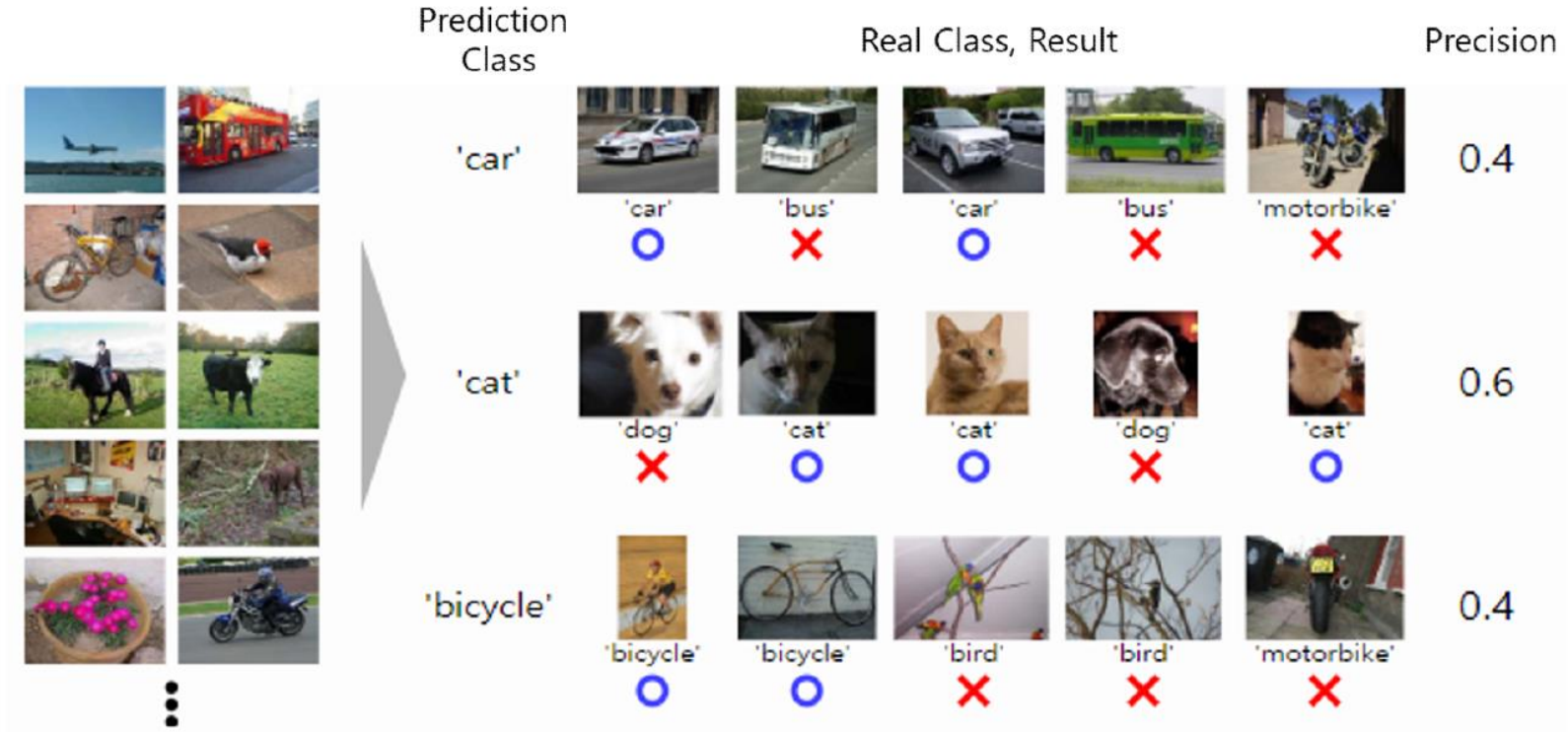
단일 사물의 성능 평가 (정확도)

$$\text{Accuracy} = \frac{\text{올바르게 분류한 이미지 수}}{\text{전체 이미지 수}} = \frac{7}{10} = 0.7(70\%)$$

	Prediction Class	Real Class	Result		Prediction Class	Real Class	Result
	'aeroplane'	'aeroplane'	○		'bus'	'bus'	○
	'car'	'bicycle'	✕		'bird'	'bird'	○
	'horse'	'horse'	○		'cow'	'cow'	○
	'train'	'TV/monitor'	✕		'dog'	'dog'	○
	'potted plant'	'potted plant'	○		'bicycle'	'motorbike'	✕

복수 사물의 성능 평가(정밀도)

$$\text{Class c의 Precision} = \frac{\text{올바르게 분류한 } Class\ C \text{ 이미지 수}}{Class\ C \text{일 것으로 예측한 이미지 수}} \qquad \text{평균 Precision} = \frac{1}{C}\sum_{c=1}^{C}(Class\ C\text{의 } precision)$$

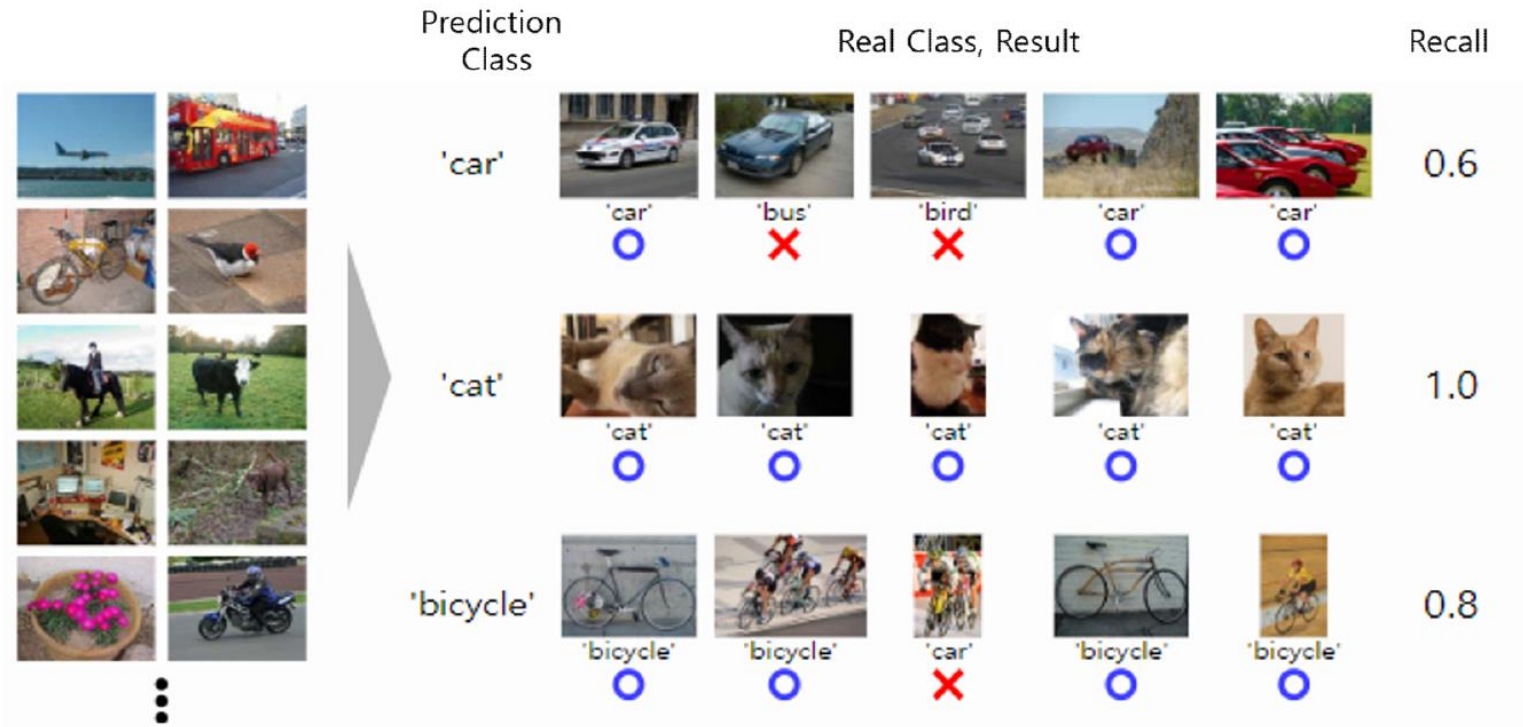


평균 정밀도: $(0.4 + 0.6 + 0.4)/3 = 0.47(47\%)$

복수 사물의 성능 평가 (재현율,Recall)

$$\text{Class c의 Recall} = \frac{\text{올바르게 분류한 } Class\ C \text{ 이미지 수}}{\text{전체 } Class\ C \text{ 이미지 수}}$$

$$\text{평균 Recall} = \frac{1}{C}\sum_{c=1}^{C}(Class\ C\text{의 } Recall)$$

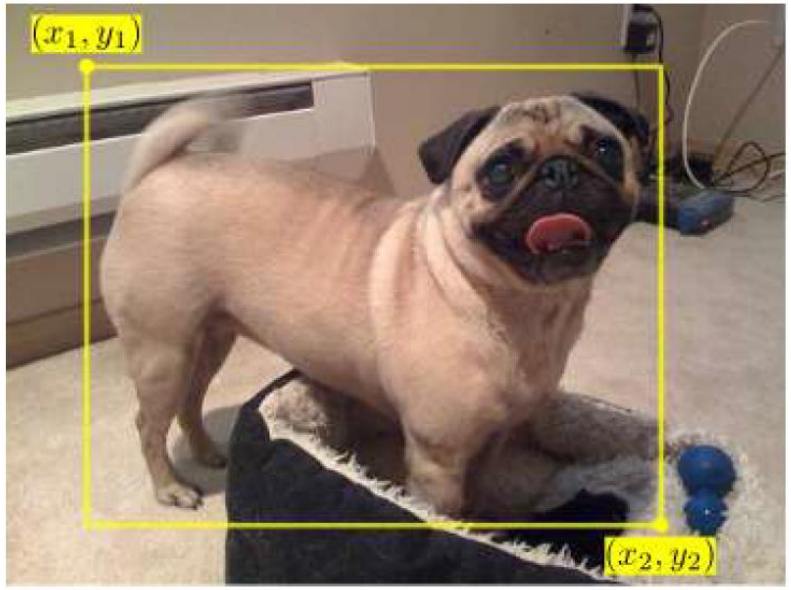


$(0.6 + 1.0 + 0.8)/3 = 0.8(80\%)$ 평균 재현율:

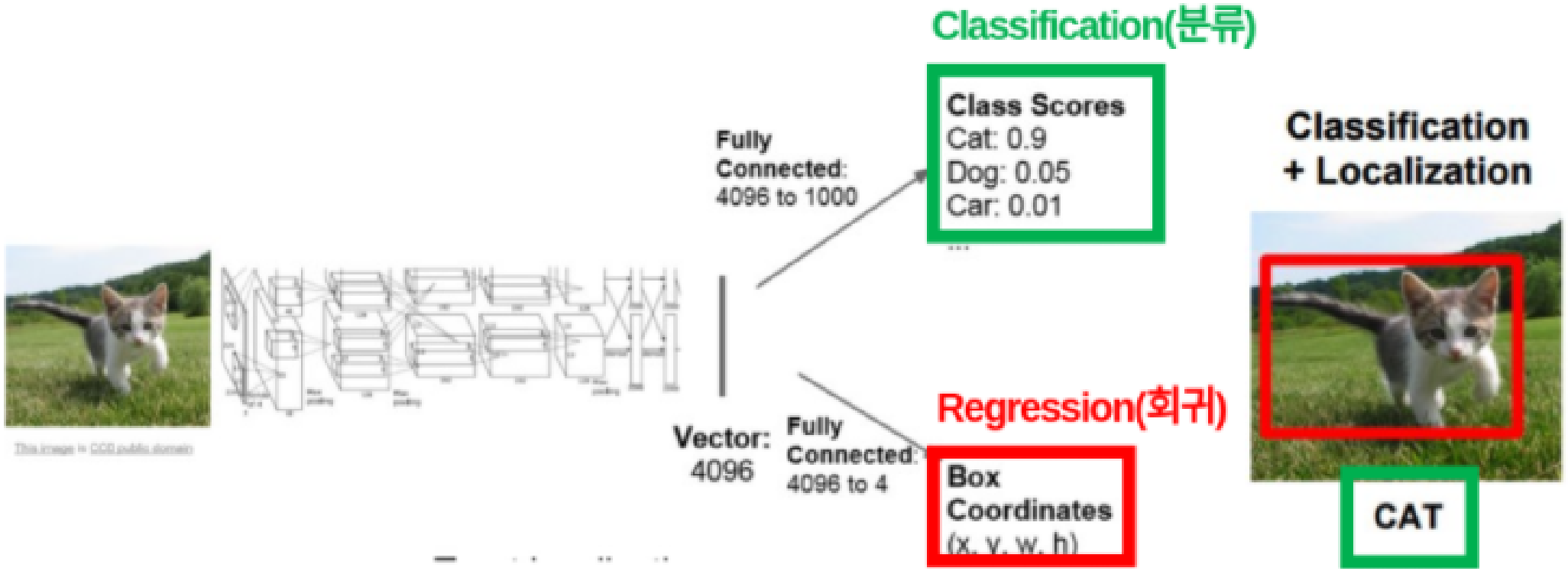
Object Detection (객체 검출)_정의

- 객체 검출은 입력 영상이 주어질 때, 영상 내에 존재하는 모든 클래스에 대하여 분류와 지역화를 수행하여 박스형태(Bounding Box)로 검출하는 모델을 만드는 것
  - ✓Localization(지역화)는 바운딩 박스를 찾는 회귀(Regression)이고
  - ✓Classification은 바운딩 박스 내 물체가 무엇인지 분류하는 문제이다.
  - ✓"주어진 이미지의 바운딩 박스 안에 dog가 포함되어 있을 가능성을 신뢰도 점수로 표현 " 한다.

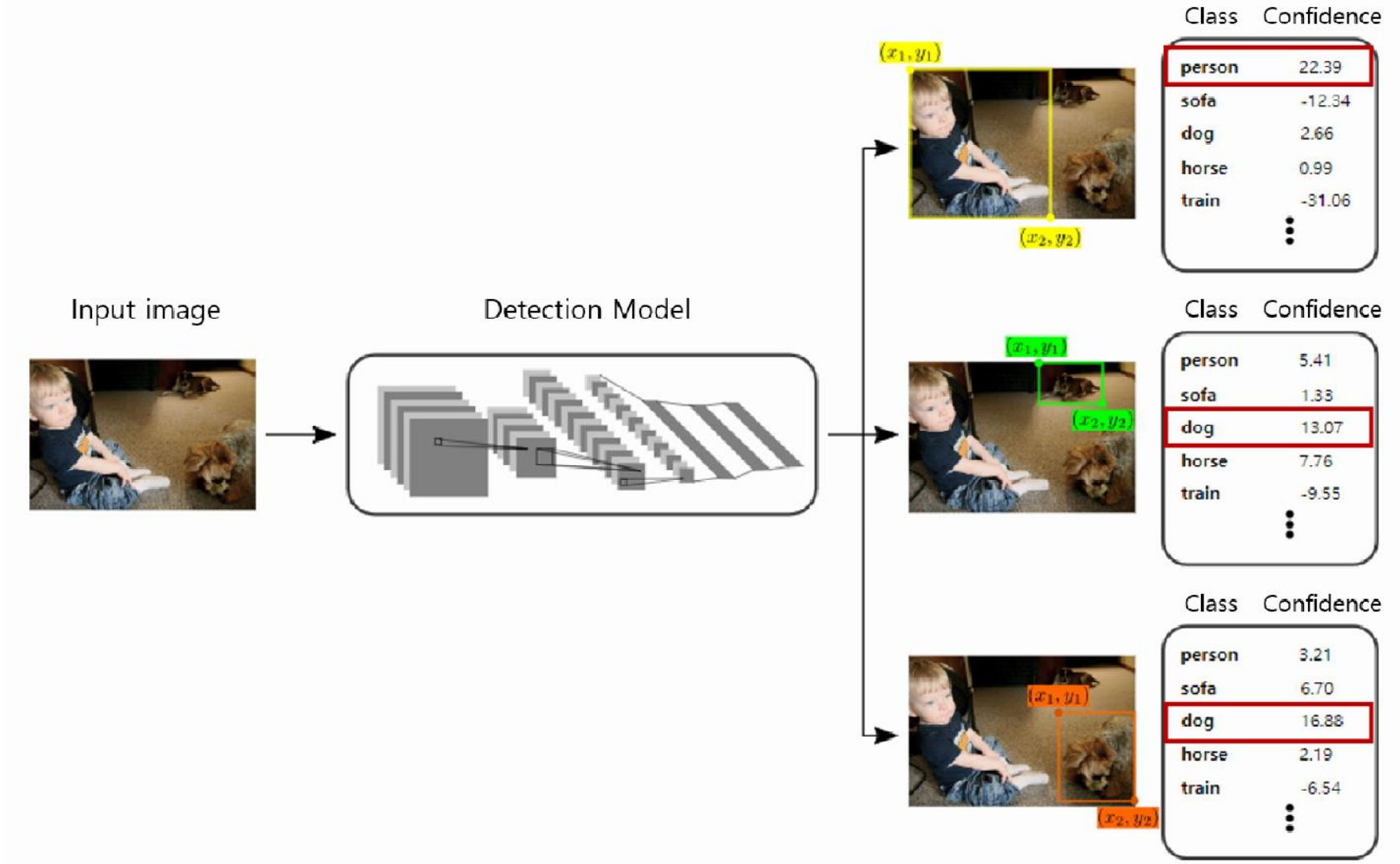
Object Detection = Classifiction + Localization



객체탐지_복수 객체 검출 모델의 결과물 예시

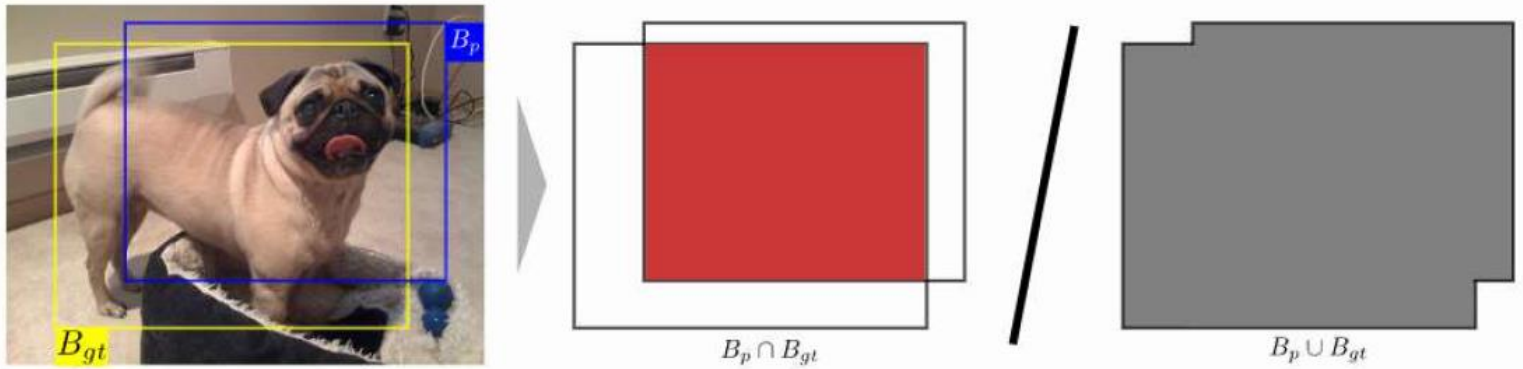


객체탐지_복수 객체 검출 모델의 결과물 예시

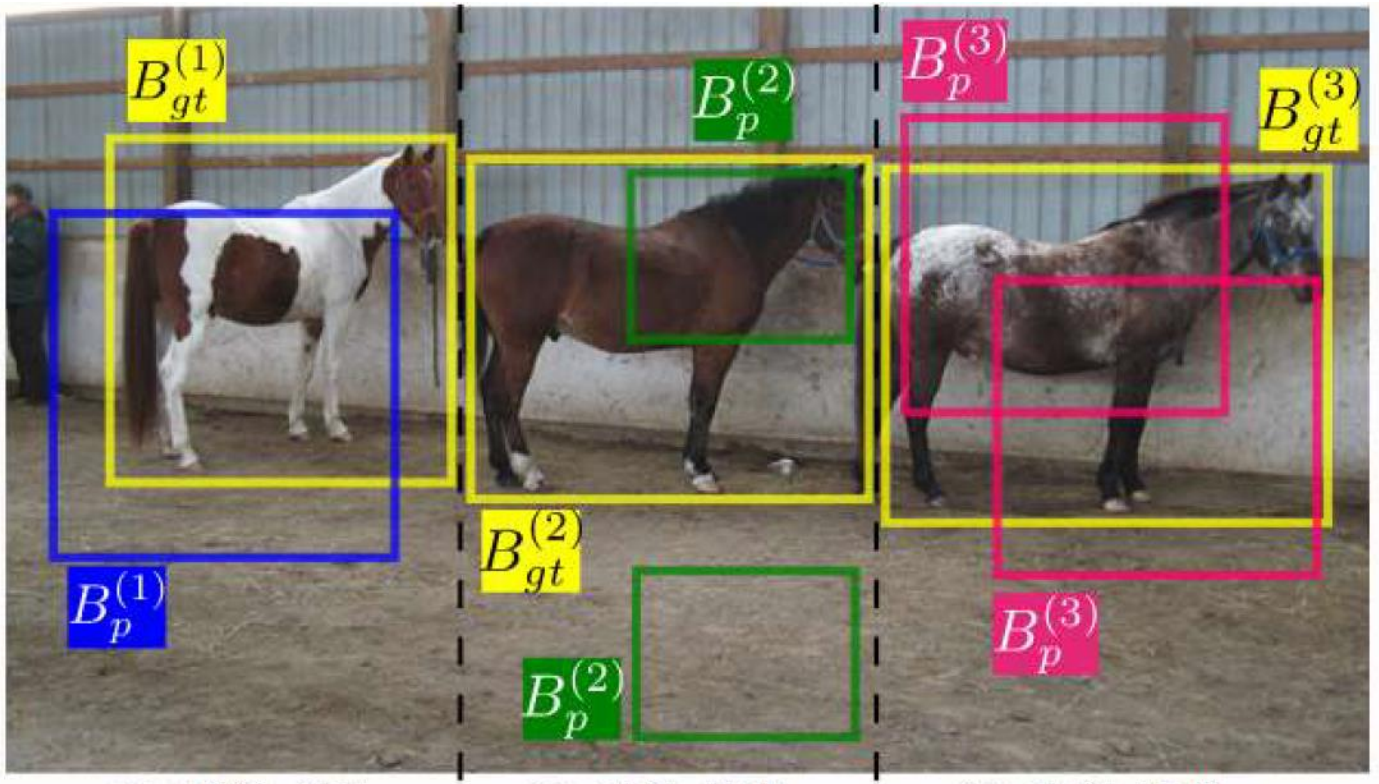


- 객체 검출에서 바운딩 박스를 얼마나 잘 예측하였는지를 IoU라는 지표를 통해서 측정함.
- IOU(Intersection over Union)
  - ✓정답인 Ground Truth와 예측된 바운딩 박스가 얼마나 겹치는가를 측정함.
  - ✓겹친 영역의 비율이 50%(한계점)를 넘겼을 때만 두 바운딩 박스를 매칭
    - 매칭된 예측 바운딩 박스가 바운딩 박스 위치로 선정

$$B_p\text{와 }B_{gt}\text{의 IOU} = \frac{B_p \cap B_{gt}\text{영역 넓이}}{B_p \cup B_{gT}\text{영역 넓이}}$$

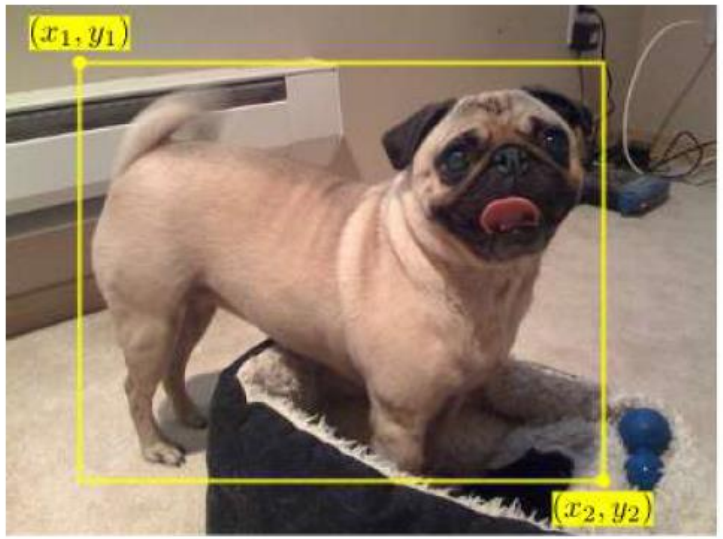


❖ Ground Truth와 예측 바운딩 박스 간의 매칭 성사 및 실패 사례



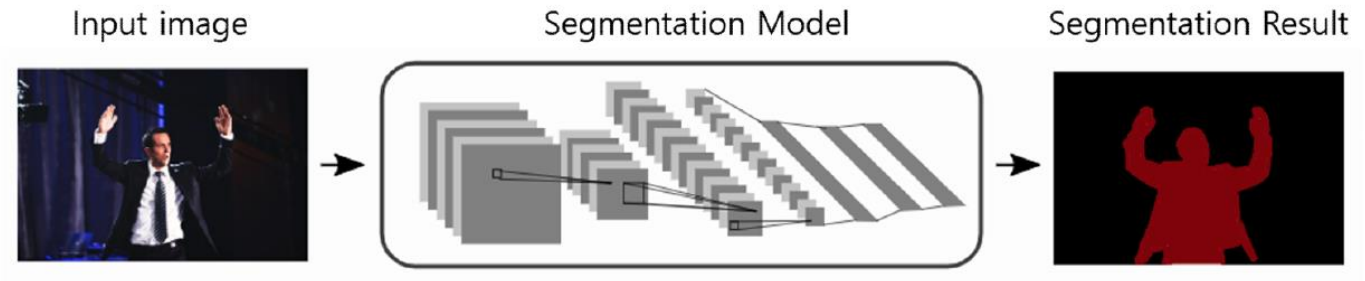
❖ 예시

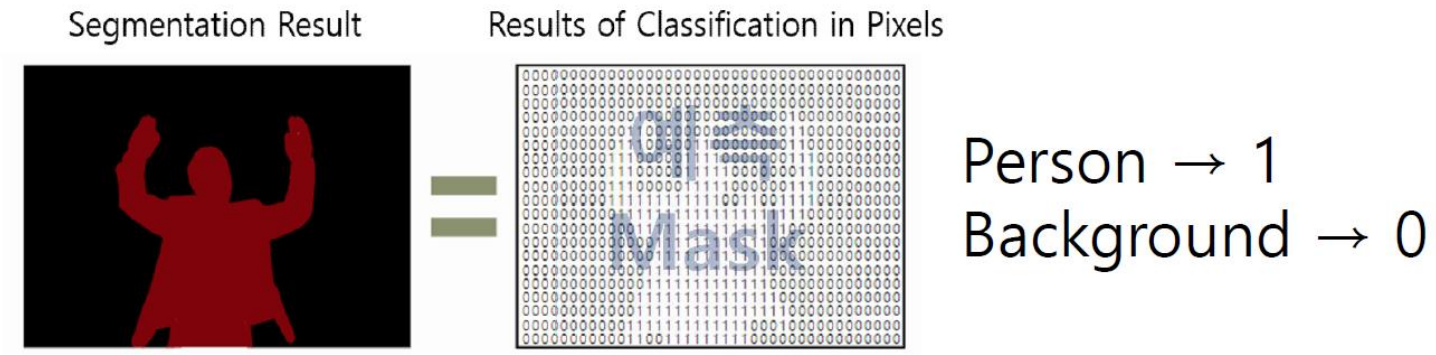
✓주어진 이미지에서 바운딩 박스 안에 dog가 포함되어 있을 가능성을 신뢰도 점수로 표현



Segmantation(분할)_정의

- 주어진 이미지 안에 어느 특정한 클래스가 포함되어 있는지?와 위치가 어디인지?를 픽셀 단위로 분할하는 모델을 만드는 것
  - ✓각 픽셀이 어떤 클래스에 해당 하는지를 곧바로 표시 : Dog->2, Cat->3 등으로 표시





Segmantation(분할)_종류

Input Image

Semantic Segmentation

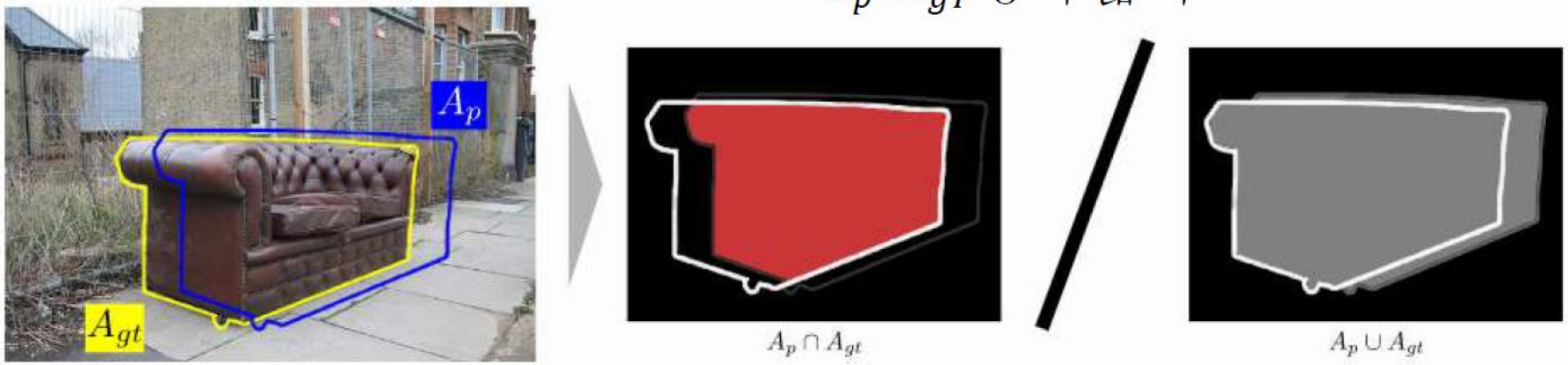
Instance Segmentation

	Semantic Segmentation	Instance Segmentation
분할 기본 단위	Class	Instance(object)
예측 Mask에 표기 방법	동일한 Class는 같은 색상으로 표기	동일한 Class라 하더라도 서로 다른 object라면 다른 색상으로 표기

Segmantation(분할)_모델의 사물 위치 표시 규정

- IOU: 예측 mask와 실제 mask가 얼마나 겹치는가?를 평가

$$A_p\text{와 } A_{gt}\text{의 IOU} = \frac{A_p \cap A_{gt}\text{ 영역 넓이}}{A_p \cup A_{gT}\text{ 영역 넓이}}$$

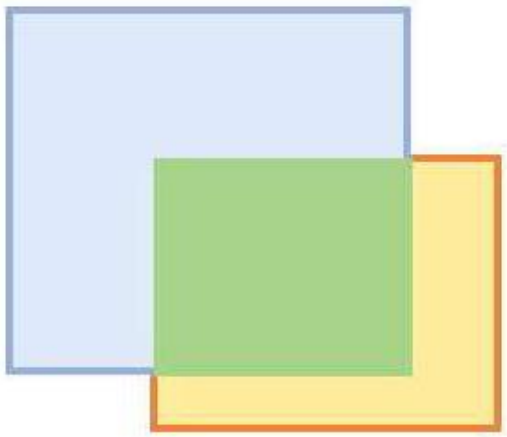


(mask상 흰색으로 표시된 픽셀들은 IOU 계산 시 고려 대상에서 제외)

Segmantation(분할)_모델의 성능 평가 척도

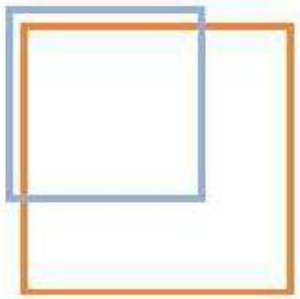
❖ 주어진 이미지에서 mask 안에 person이 포함되어 있을 가능성을 신뢰도 점수로 표현

❖ IoU란?(Intersection over Union)

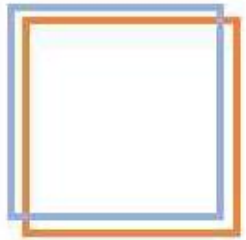


$$IoU = \frac{\text{교집합 면적}}{\text{합집합 면적}}$$

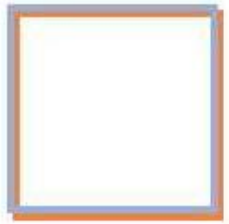
1. $0 \leq IoU \leq 1$
2. 클수록 일치도가 높음



0.4034

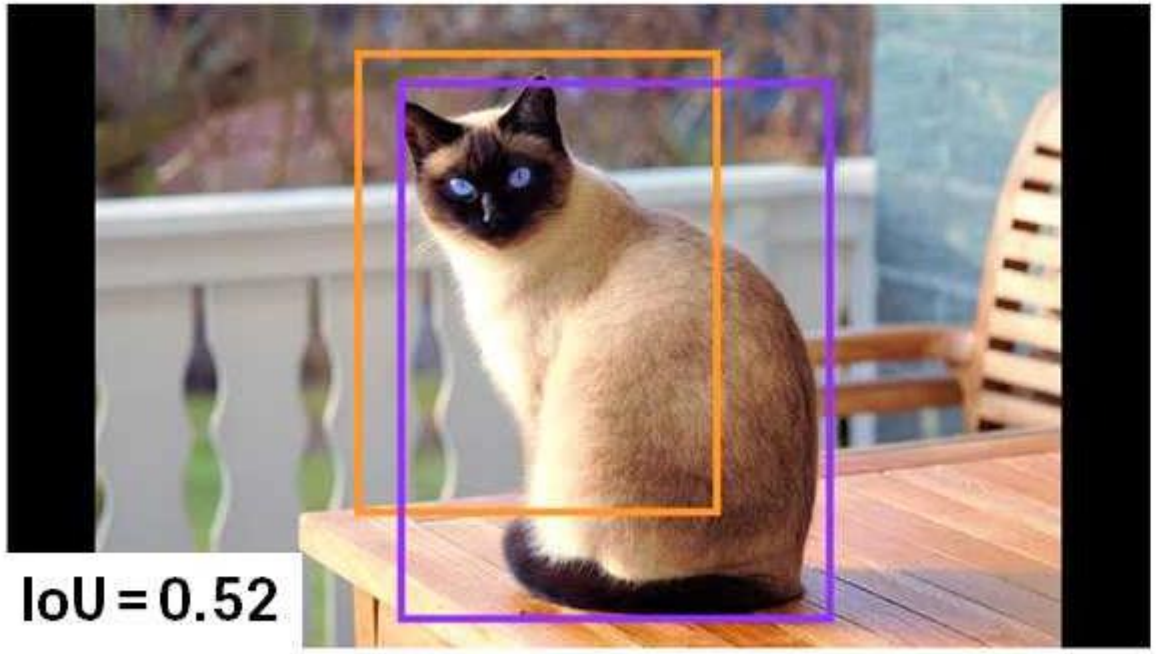


0.7330



0.9264

❖ 객체 탐지에서 IoU 기준



1 Pascal VOC

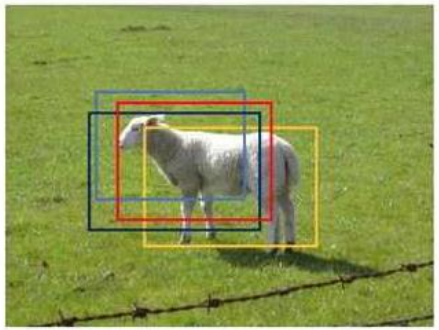
정답 IoU ≥ 0.5

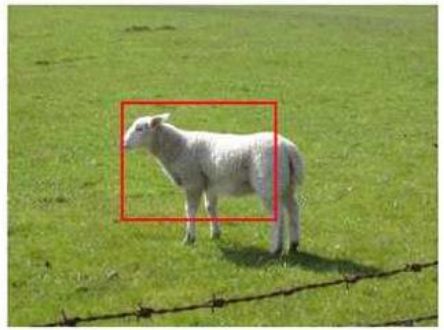
나머지는 오답

2 MS Coco

IoU 0.5부터 0.95까지
0.05 간격으로
측정하여 합산

- NMS(Non Max Suppression) : 중복된 객체의 제거에 사용
  - ✓IoU가 일정 이상 중첩된 box들 중에서 Confidence Score가 가장 높은 것만을 남김



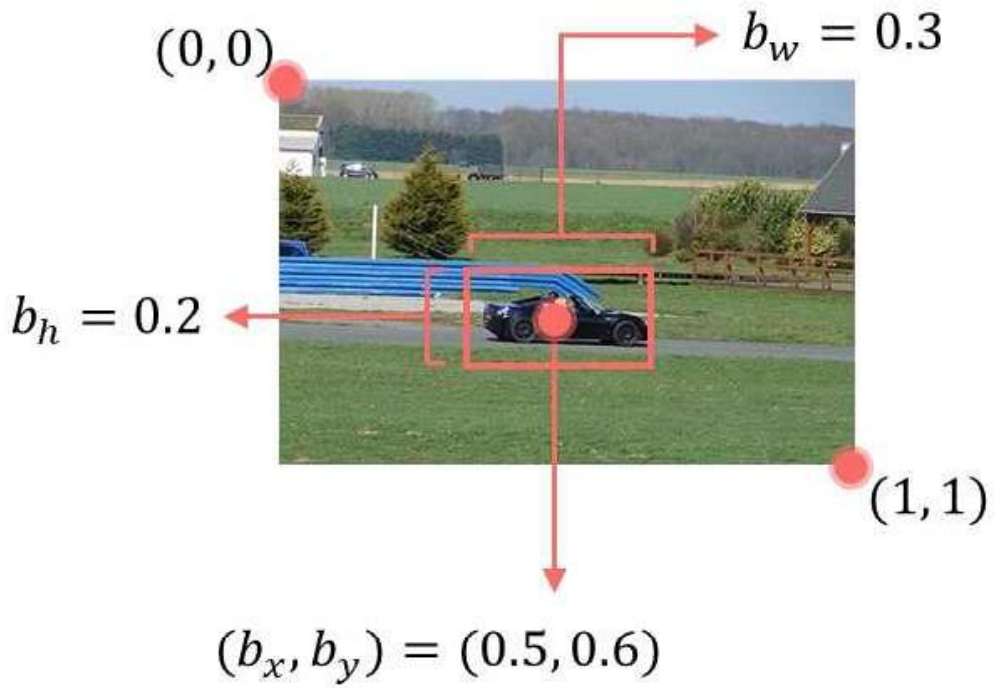


Confidence. Score: 0.5
Confidence. Score: 0.6
Confidence. Score: 0.9
Confidence. Score: 0.7

- 해당 ROI를 CNN 분류기를 통해 인식하고 Confidence Score가 threshold 이상을 결과로 출력

- 하지만, sliding window는 너무 느리므로 한번에 인식할 수 있는 다른 방안이 필요함

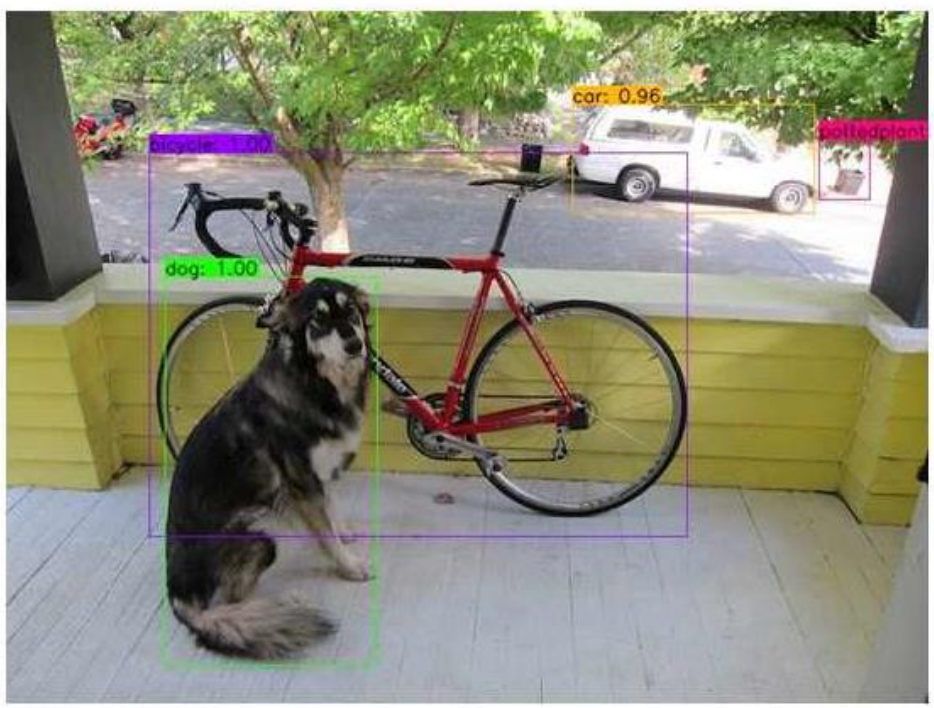
❖ Bounding box의 정의

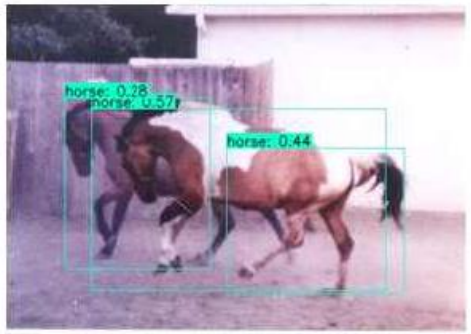


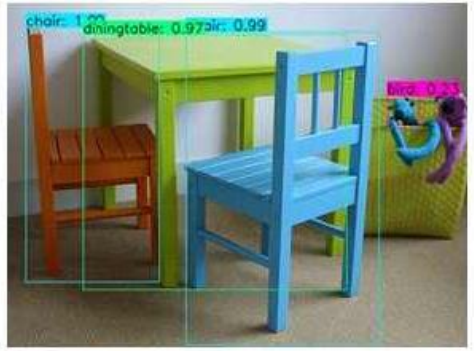
- b_x, b_y: 센터 위치
- b_w, b_h: width, height
- bounding box 출력 텐서

$$y = \begin{bmatrix} b_x \\ b_y \\ b_w \\ b_h \end{bmatrix}$$

❖ 객체탐지 실행 결과 : Pascal VOC 2012 학습 결과







❖ 객체탐지 실행 결과

1 거리 영상

Pascal VOC 2012로 학습

2 강아지 영상

COCO로 학습

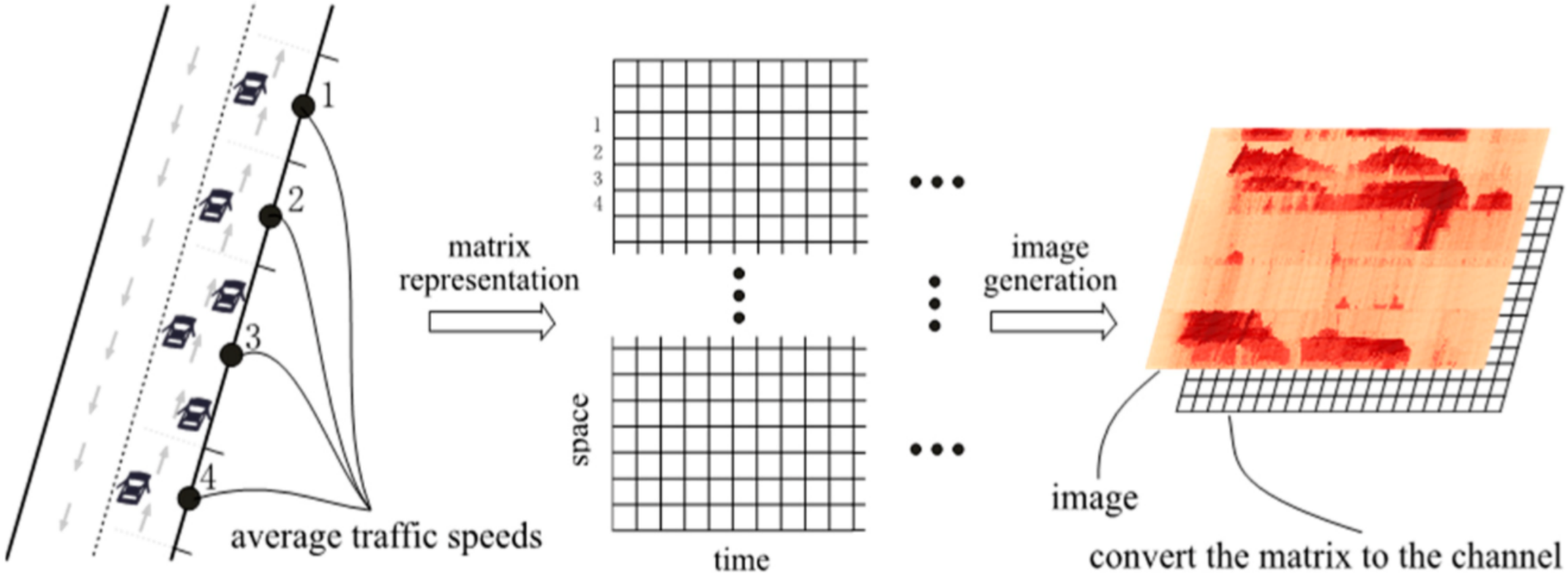
(YOLOv4의 사전 학습)

동영상 원본 출처 :
Youtube German Korb
- No copyright
Youtube CHANNEL PMI
- Create Comons Licence

자율주행과 강화학습

Transportation network speed

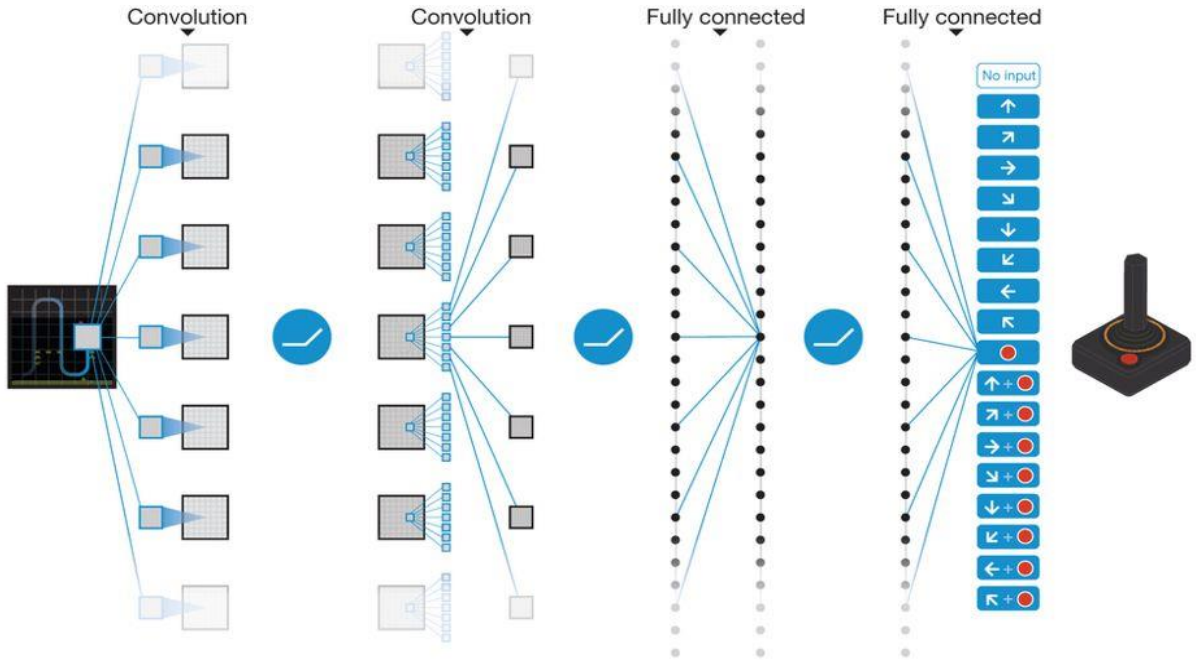
A Deep Convolutional Neural Network for Large-Scale Transportation Network Speed Prediction



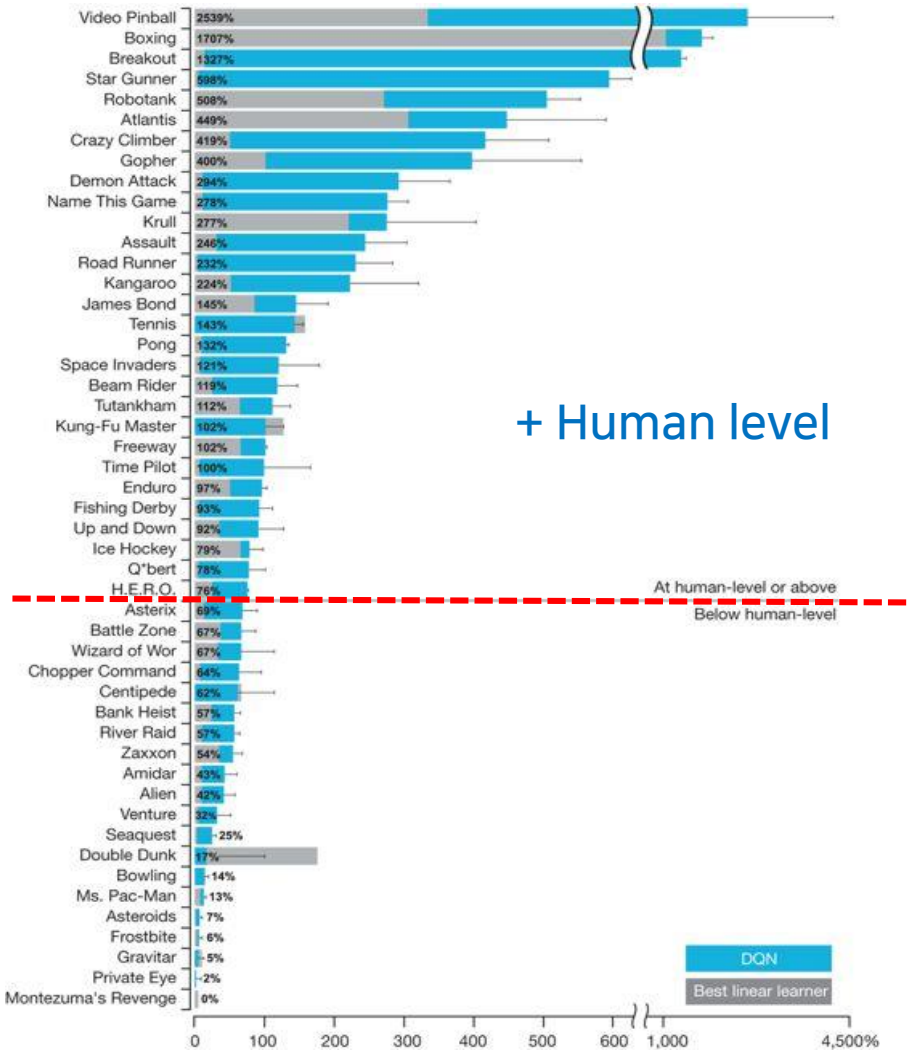
Sensors 2017, 17, x; doi:

딥러닝 강화학습은 인간 수준 넘어서야 함

Deep Reinforcement Learning



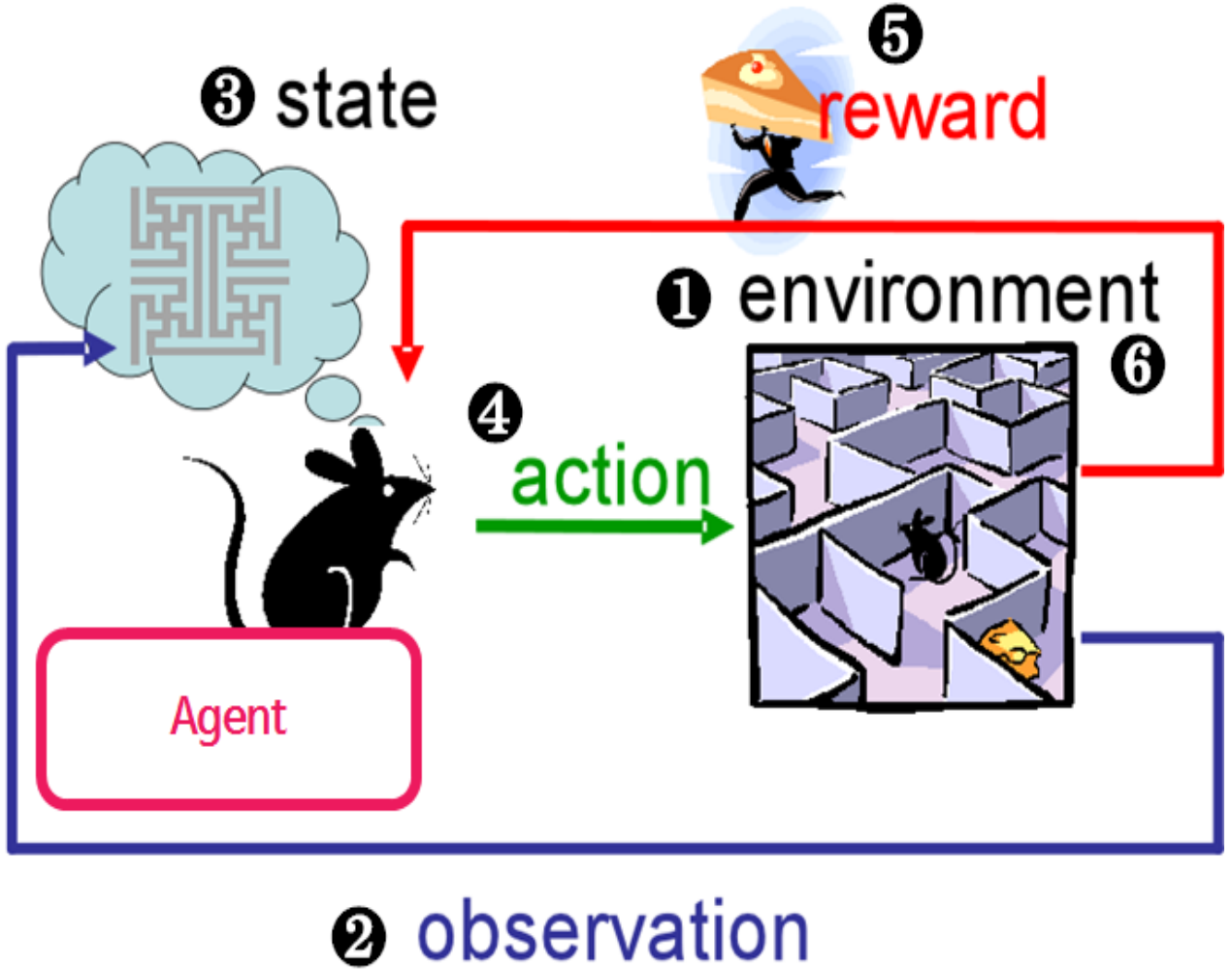
구글 딥마인드, Nature 2015



+ Human level

강화학습 이해

- 에이전트(Agent)
- 환경(Environment)
  - 상태(State)
  - 행동(Action)
  - 보상(Reward)
  - 정책(Policy)



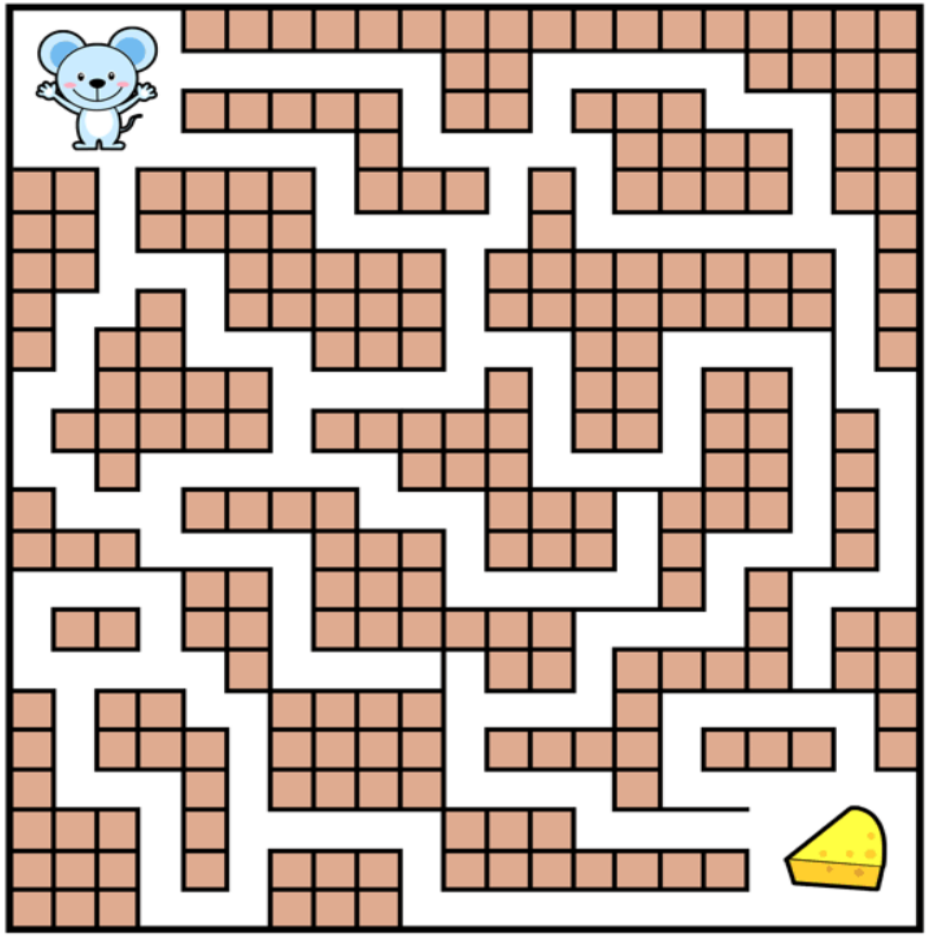
❖ 마르코프 의사 결정 과정 MDP (Markov Decision Processe)

$$\mathcal{H}_t \rightarrow S_t \rightarrow \mathcal{H}_{t+1}$$

시간(t)는 현재의 시간, 상태(S)는 현재의 상태, 메모리(H)는 현재의 기억

Markov Decision Process (MDP) $\sim \{S, A, P, R, \gamma\}$

강화학습 이해하기. (실습)



① 환경(E) : 미로 (설계자는 답을 알고 있다)
② 에이전트 : 쥐

③ 행동(A) : 위, 아래, 왼쪽, 오른쪽
④ 상태(S) : 시간(t)에서 에이전트 주위 정보
⑤ 보상(R) : 치즈 (미로 탈출 수 얻음)
⑥ MPD를 적용해보자.
⑦ 정책(P) : 보상을 최대화 할 수 있는 행동들

⑧ 매 순간 Q-에게 물어보자. Q(s,a)는 신경망으로 근사하여 계산. Deep Q-Network (DQN)

큐(Q)에게 상담을 해보자.

심화강화학습의 기본 알고리즘
DQN (Deep Q Network) : 불연속적인 (Descrete Action) 행동을 제어할 수 있는 알고리즘

큐(Q)는 미로의 구조를 알고 있다고 가정!

보상을 최대!

바로 직전 행동(t)

상태(위치, 좌표)

$$\hat{Q}(s,a) \Leftarrow r + \max_{a'} \hat{Q}(s',a')$$

새로운 행동(t+1)을 알려줌

Q Learning (Watkings89)

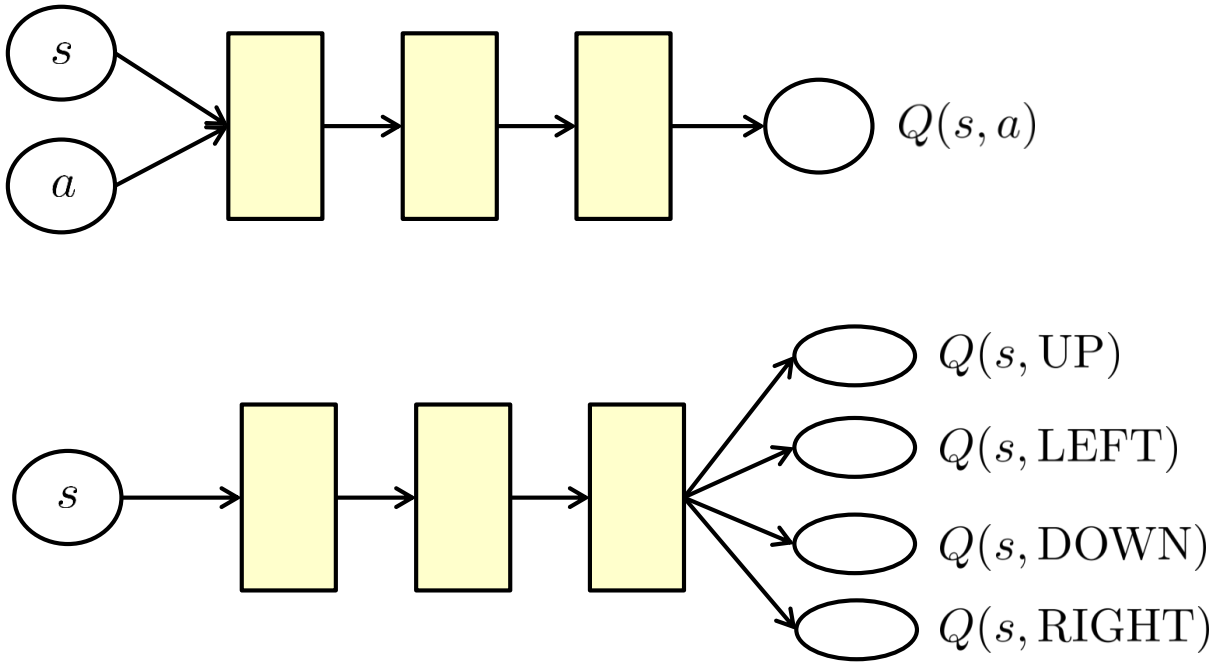
- Learn Q-function $$Q(s_t, a_t) = E[R_t]$$

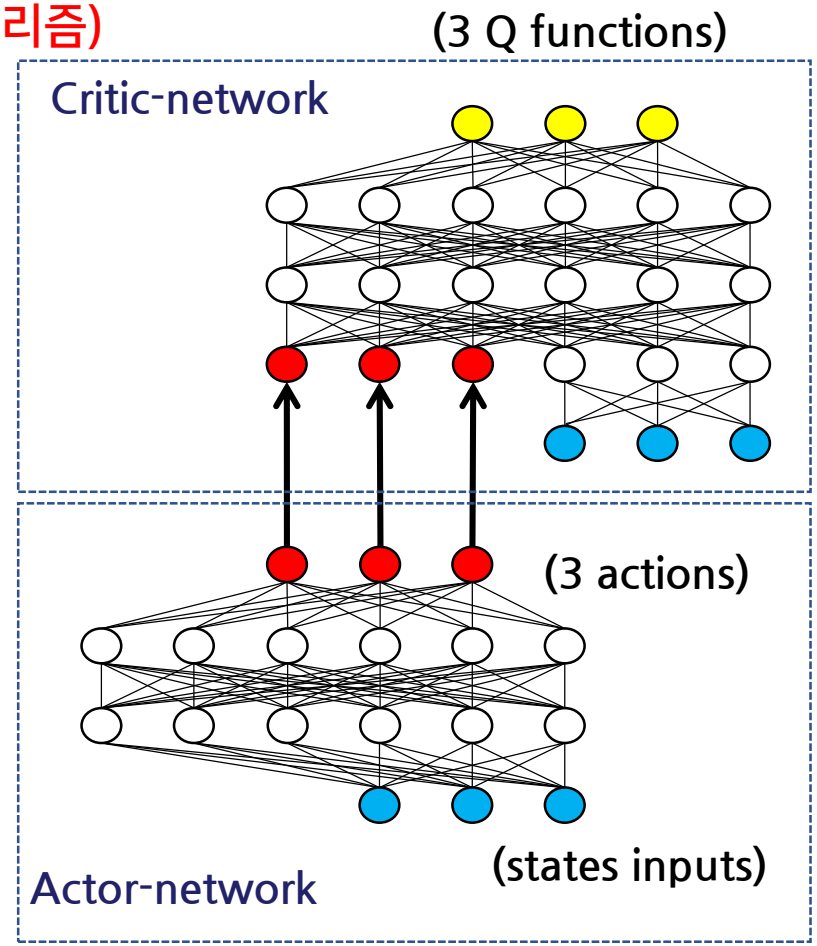
- Bellman equation $$\hat{Q}(s, a) = r + \gamma \max_{a' \in A} \hat{Q}(s', a')$$

- Estimate optimal Q using learning rate $$\hat{Q}(s, a) \leftarrow (1 - \alpha) Q(s, a) + \alpha [r + \gamma \max_{a' \in A} \hat{Q}(s', a')]$$

- Optimal policy $$\pi^*(s) = \operatorname{argmax}_{a \in A} Q(s, a)$$

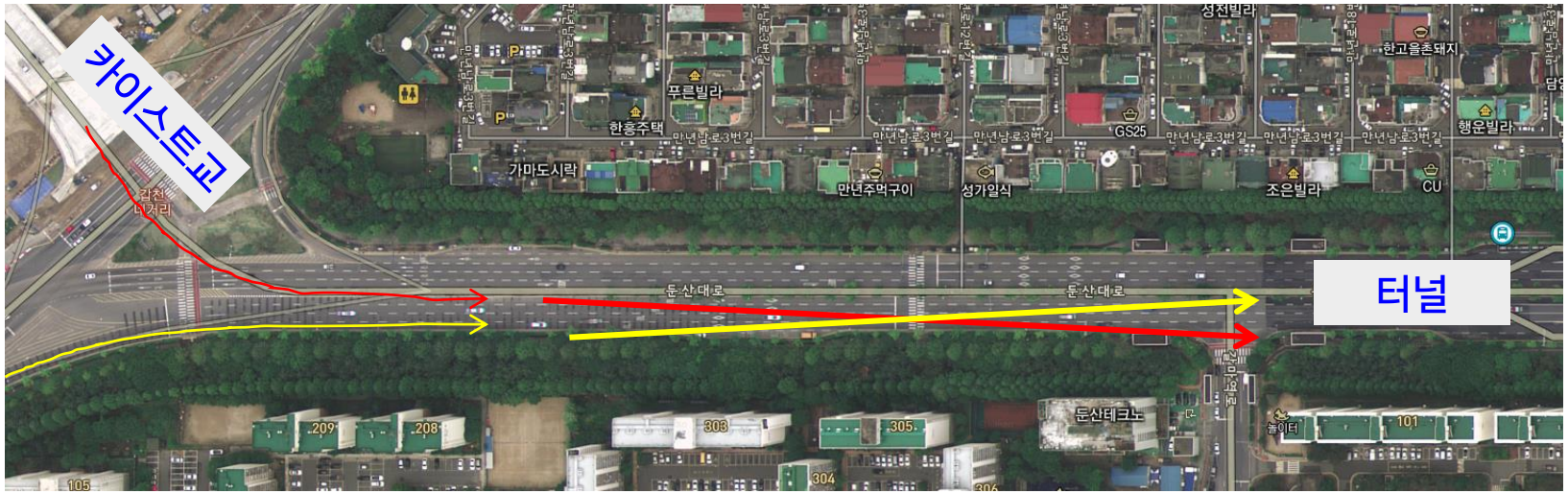
심화강화학습의 기본 알고리즘 : 연속적인 행동 제어
Actor-Critic 알고리즘 기반의 DDPG (심화 불연속적인 정책 경사 알고리즘)



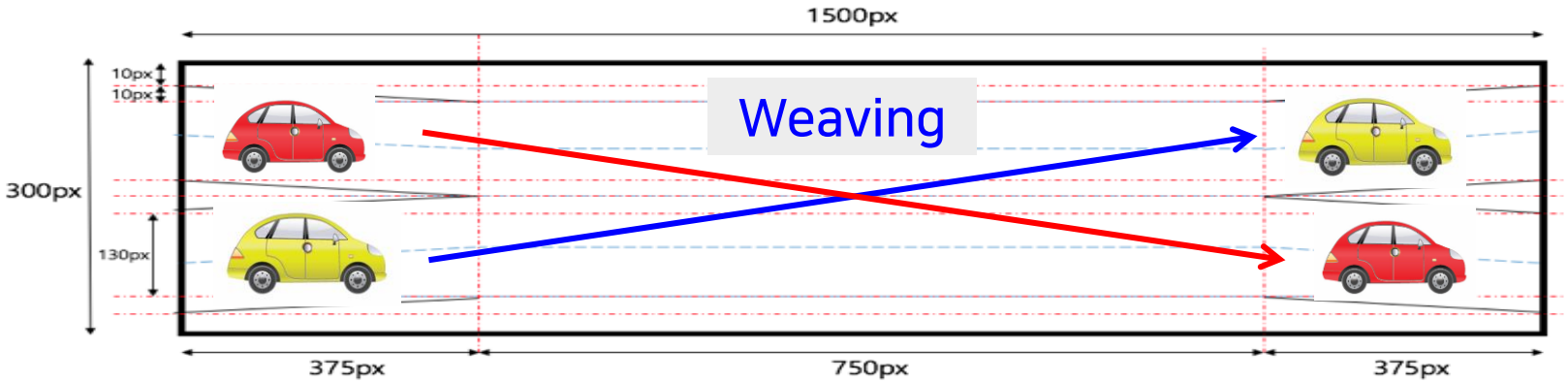


강화학습 활용 사례:
위험도로에서 자율주행

Weaving 구간 (카이스트교) : 차선 변경이 빈번히 발생하는 위험도로 구간



강화학습을 위한 환경(Environment) 설정



강화학습 멀티에이전트 : 환경, 상태, 행동

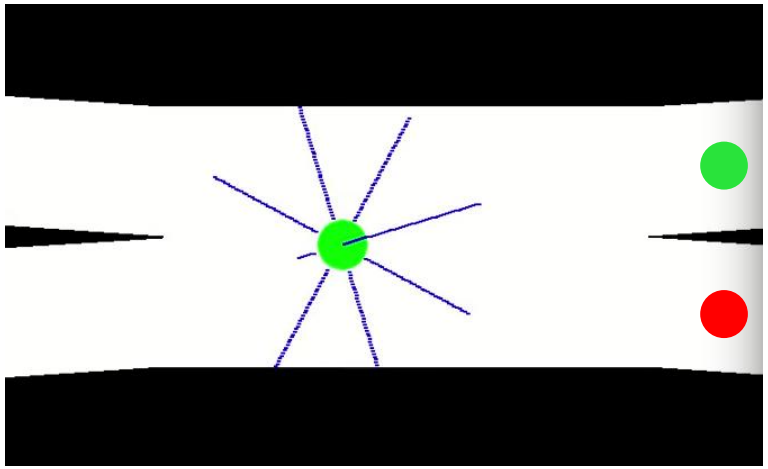
➢ 3-Actions

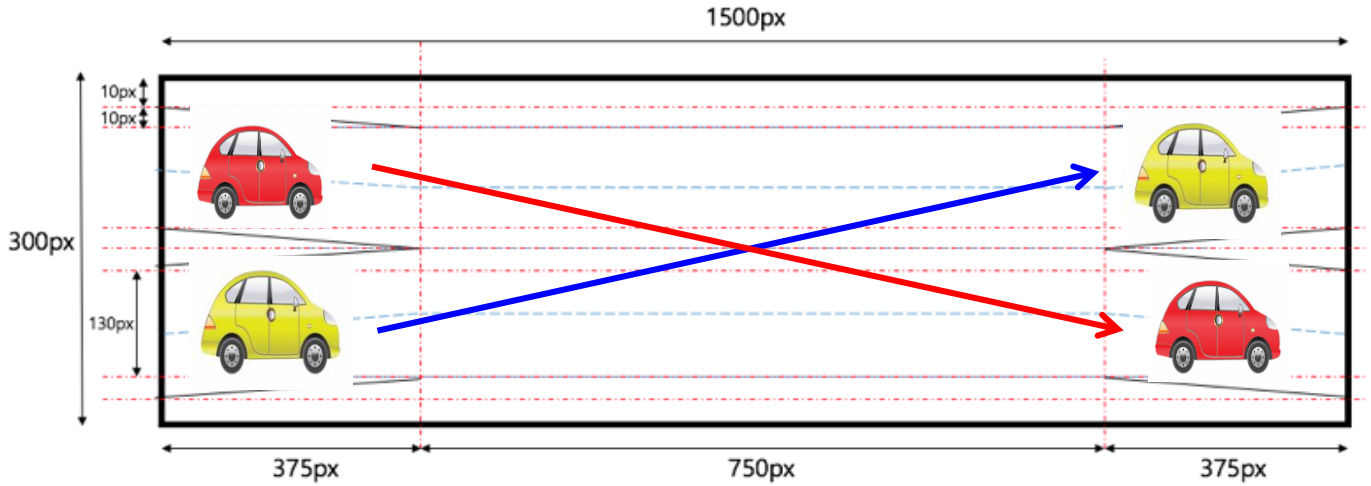
- Steering ∈ [-1, 1] (tanh)
- Acceleration ∈ [0, 1] (sigmoid)
- Brake ∈ [0, 1] (sigmoid)

➢ 12-States

- car body positions : x, y to ∈ [-1,1]
- car angle(radian) ∈ [-0.78,0.78]
- car velocity ∈ [0, 1]; car colors : 0 or 1
- 7 Sonar sensors [-90˚~+90˚] : ∈[0,1]

➢ Environment



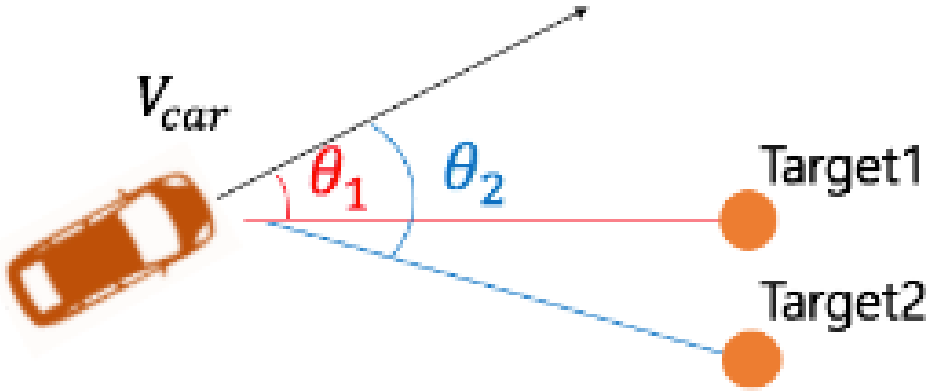


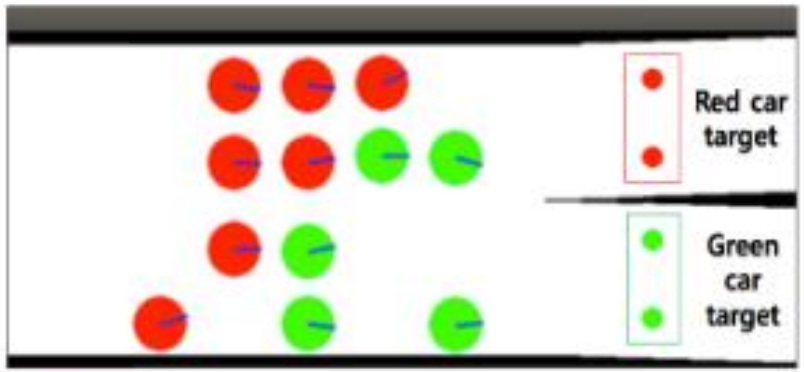
보상(Reward) 설계: 가장 주요함

- **Driving**

$$R = \max(V_{car}\cos(\theta_1), V_{car}\cos(\theta_2))$$

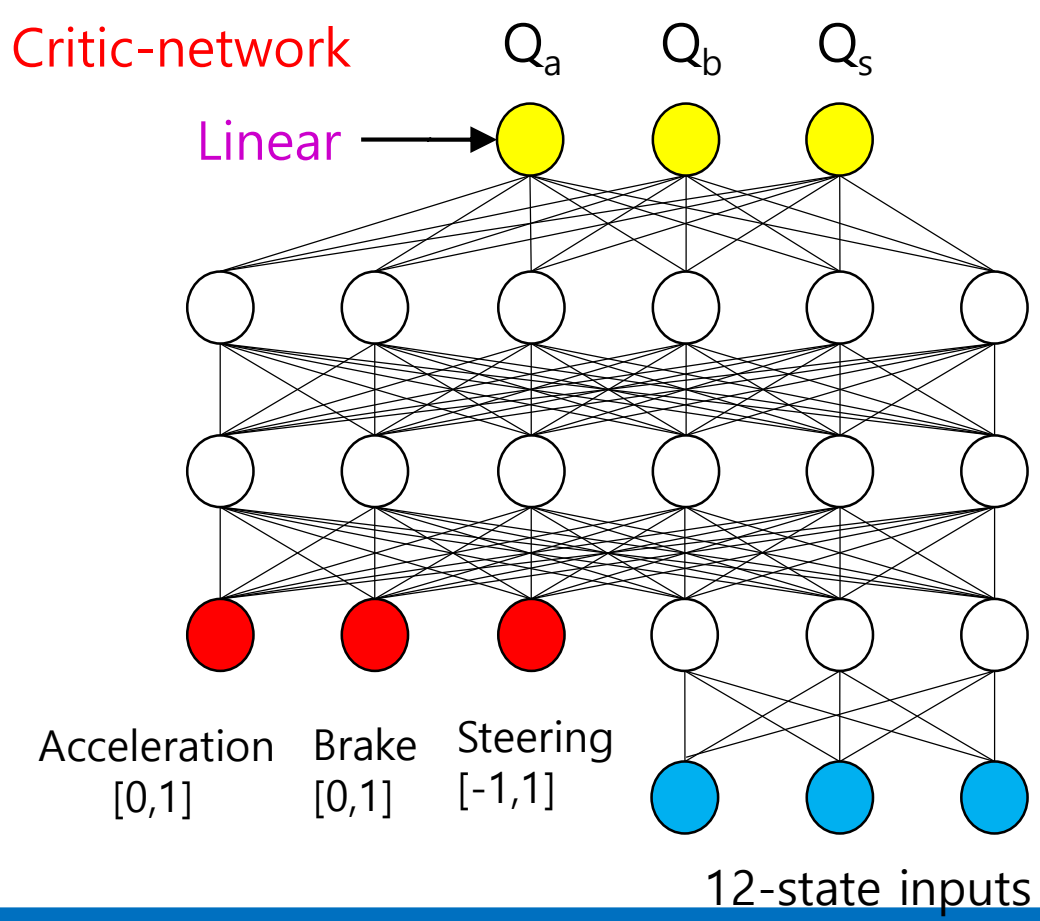
- **Got to Target**
  - ✓+500 : colors are matched
  - ✓-500 : colors are mis-matched
- **Collision**
  - ✓-600 : when a agent makes collision

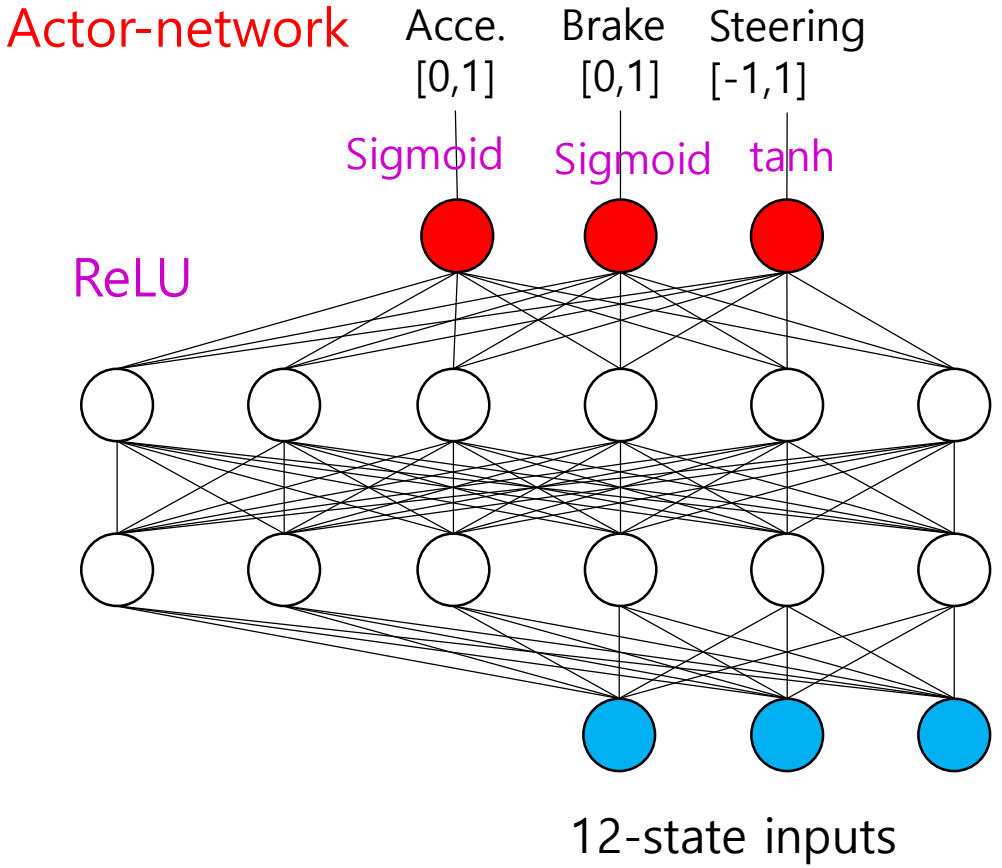




Actor-Critic Neural network Architecture

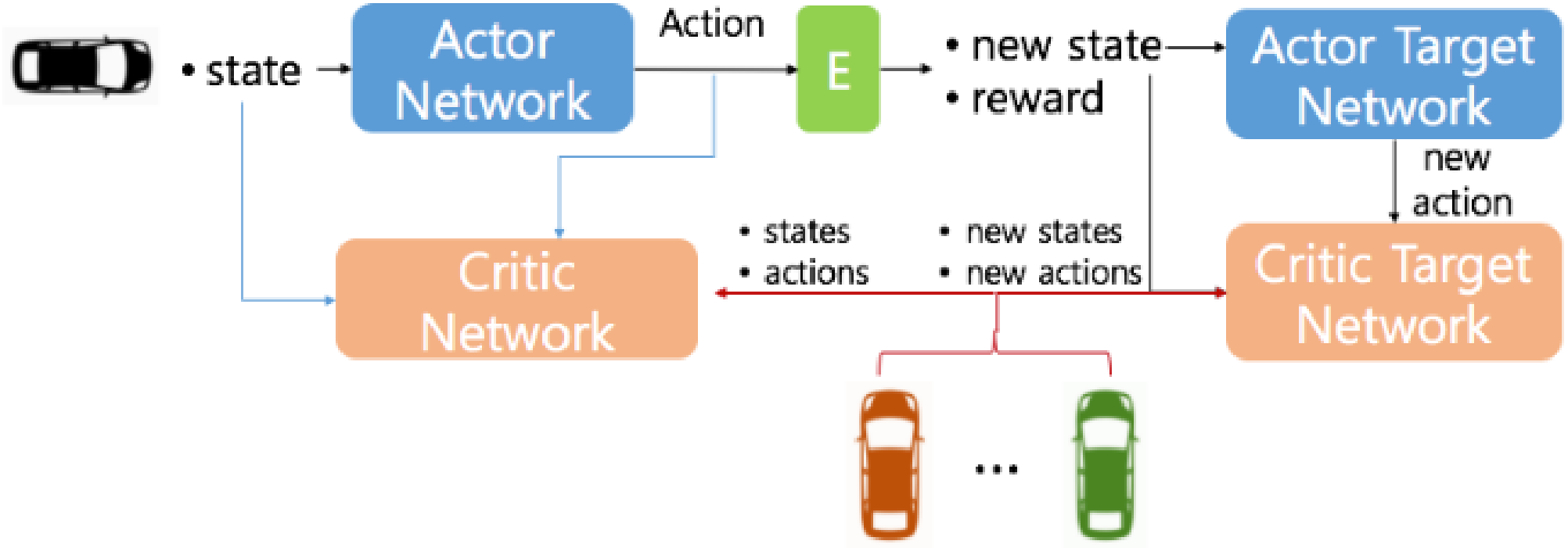
The critic model estimates Q-function values while the actor model selects the most optimal actions for each state based on those estimates.





Multi-Agent Network Architecture

- So we decide to apply this mechanism to our double merge scenario
  - ✓ All vehicles make their own reward to the maximum by sharing the same network parameters.



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