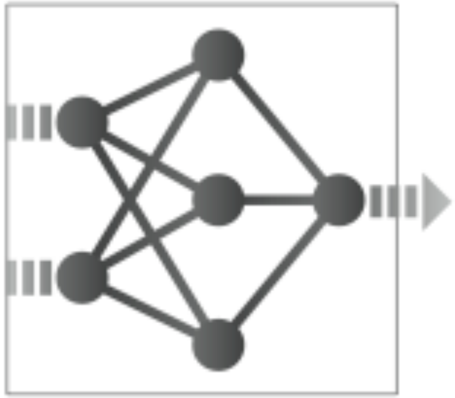
Deep & Convolutional Neural Networks
Reinforcement Learning



What you will learn in this class

- Supervised learning (continued from last week)
  - Deep learning with autoencoders
  - Deep Convolutional Neural Networks
- The Reinforcement Learning Framework
- Reward and Total Return
- The state-action value function (Q function)
- Value Learning
  - Deep Q Learning
- Policy Learning
  - Policy Gradient Learning

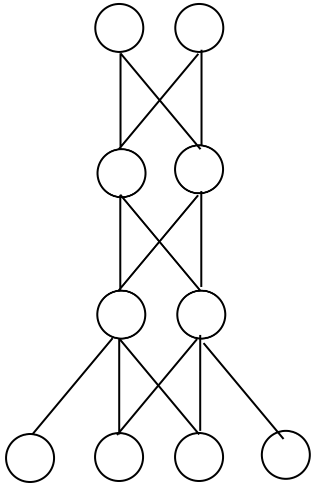
Deep vs. shallow neural networks

<u>Compact distributed encoding (smallest number of computing elements) = better generalization</u>

Compared to compact network of *k layers*, a network of *k-1 layers* requires exponentially larger number of computing elements to achieve same learning error
Given the larger number of weights, the k-1 layered network is likely to have worse generalisation

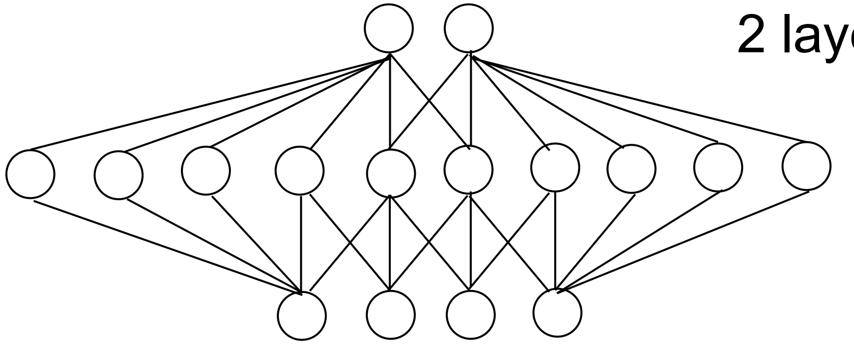
“deep”

3 layers of connections



“shallow”

2 layers of connections

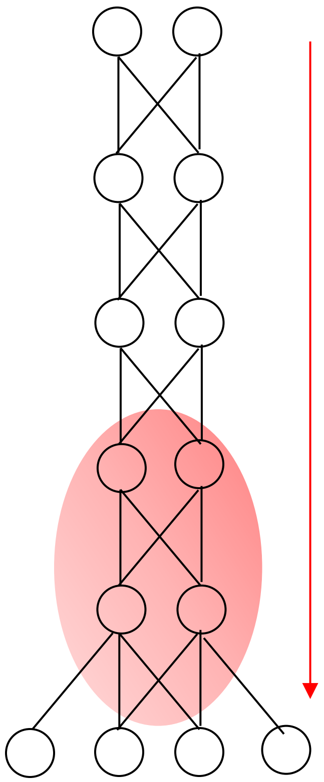


Not all connections are shown

Backpropagation in deep networks

However, Backpropagation yields poor results when applied to networks of many layers (k>3)

The problem lies in poor gradient estimation in the lower layers of the neural network, leading to smaller gradients and thus small weight modifications

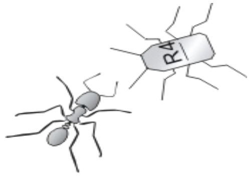


$$\delta_j = \dot{\Phi}(A_j)\sum_i w_{ij}\delta_i$$

Not all connections are shown

Features represent large data sets in a compact format

What do these images have in common?

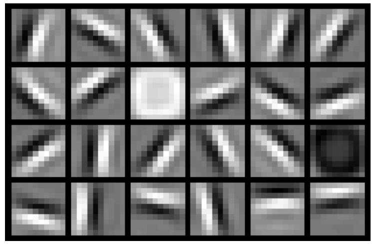


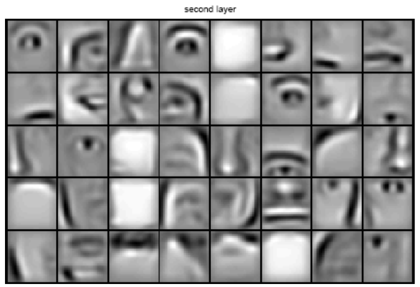
“Deep learning”, one layer at a time

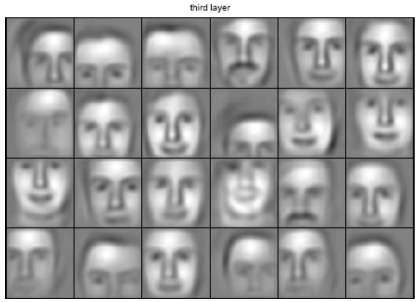
Unsupervised training of low layers to develop increasingly complex <u>feature detectors</u>

Supervised training of top layer

pixels | edges | object parts | object models | recognition







Specific person

input → output

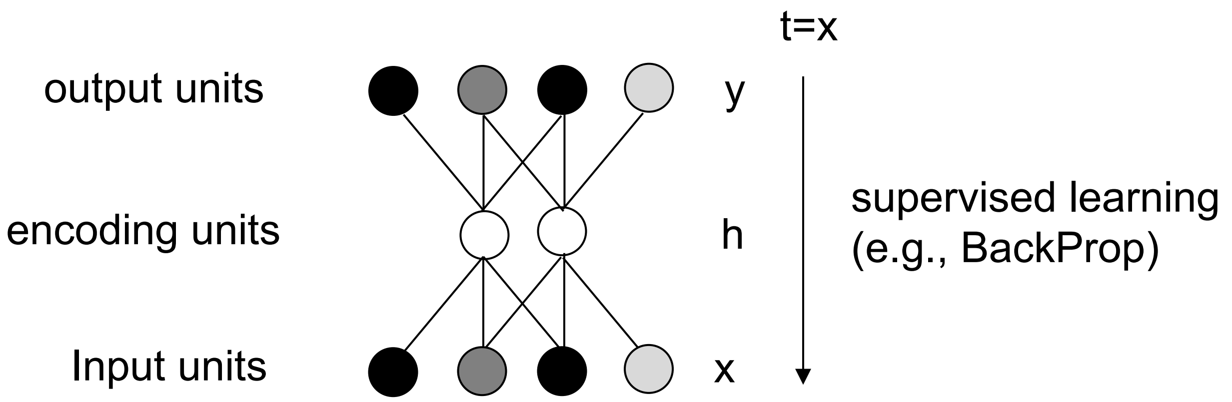
unsupervised | supervised

Hinton, Osindero, Teh, 2006
Bengio, Lamblin, Popovici, Larochelle, 2007
Ranzato, Poultney, Chopra, LeCun, 2007
See online also *Learning Deep Architectures for AI* by Yoshua Bengio, 2008

Unsupervised learning with Autoencoders

PCA (e.g., Oja's or Sanger's networks) are not suitable for deep networks because they are linear transformation of the input.

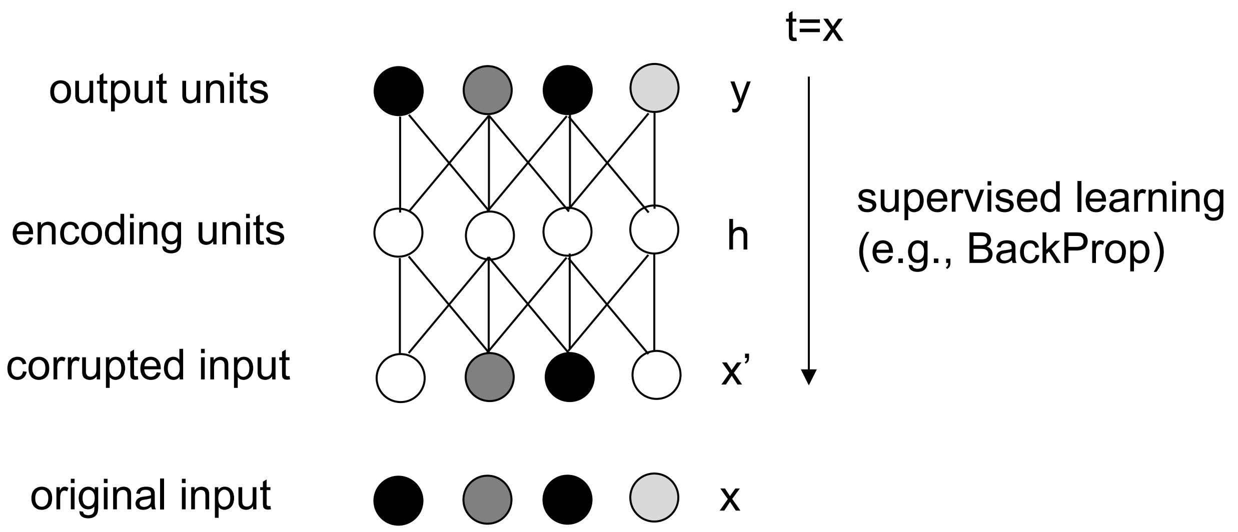
Autoencoders are non-linear supervised networks (e.g., Back-prop) that learn to reproduce the input pattern on the output layer. Usually, they have smaller set of hidden units (*encoding units*) to generate a compressed representation, which spans the same space of PCA representation, but use non-linear units.



Not all connections are shown

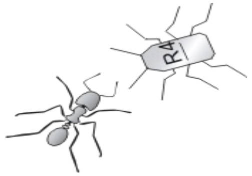
Denoising Autoencoders (dropout)

Identity coding problem arises when encoding units are equal or larger than input units



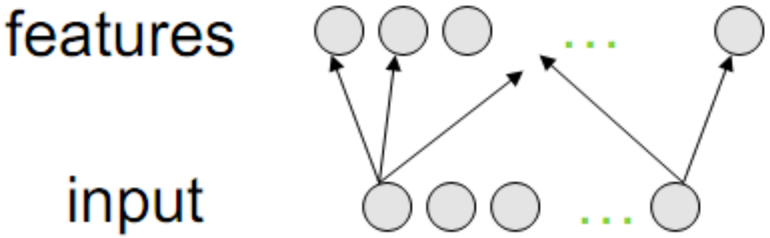
To prevent identity encoding, use *denoising autoencoders* (Vincent et al. 2008): corrupt input by randomly switching off 50% of units while keeping teaching output equal to uncorrupted input

Not all connections are shown

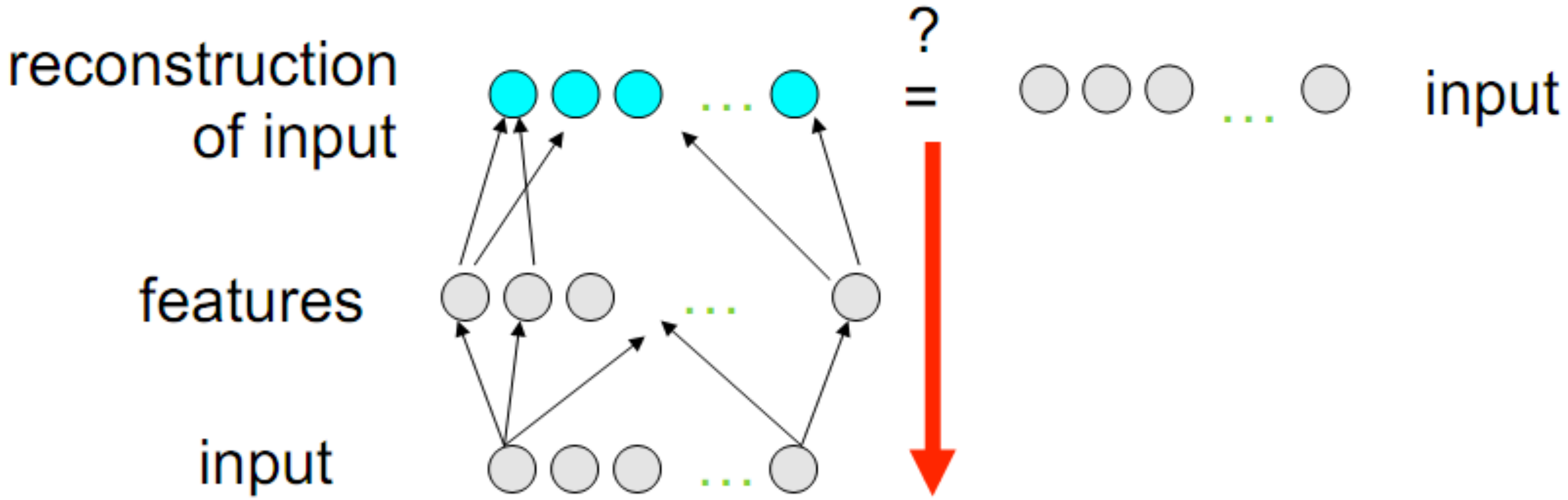


Deep training

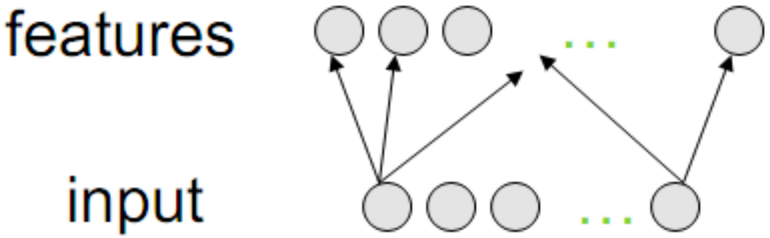
Layer-Wise Unsupervised Pre-training



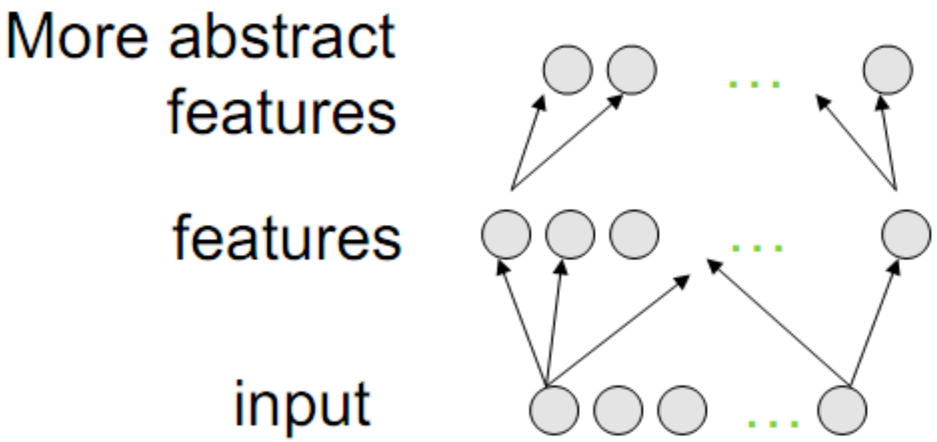
Layer-Wise Unsupervised Pre-training



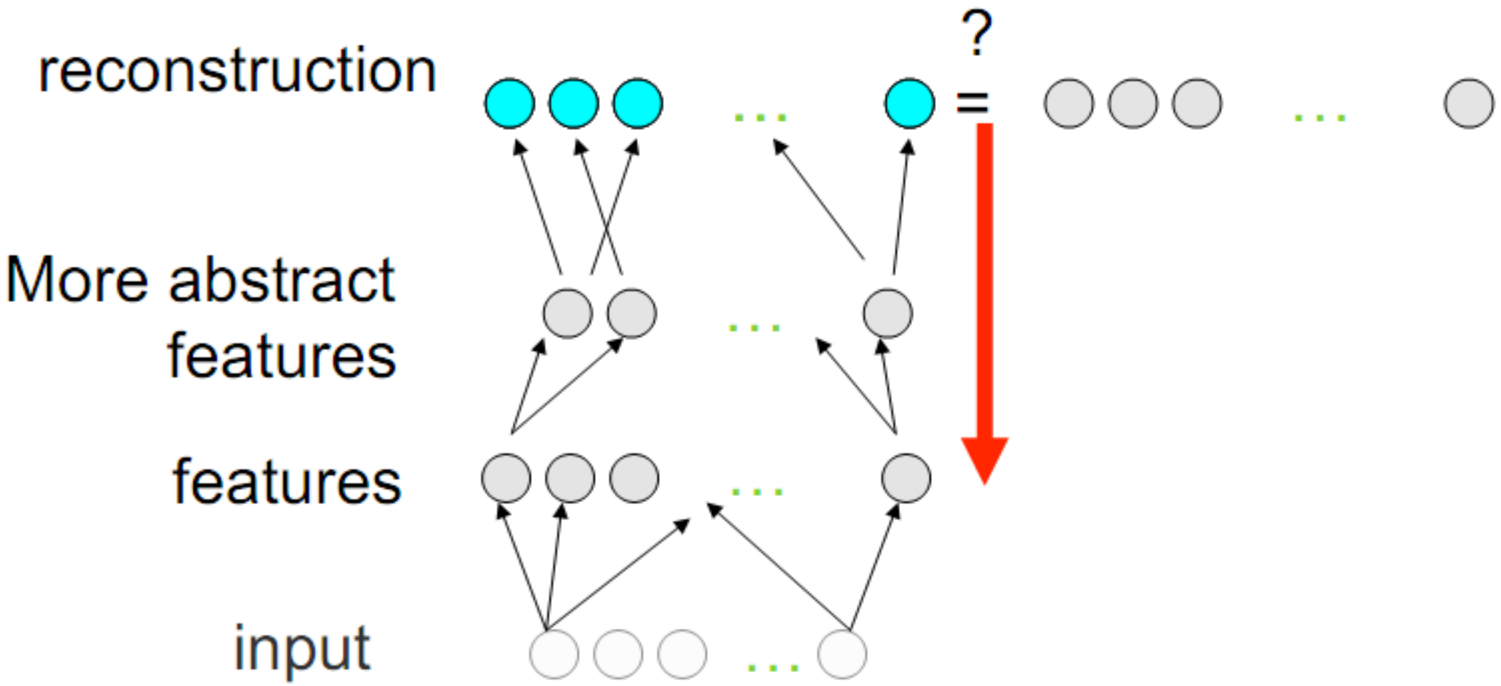
Layer-Wise Unsupervised Pre-training



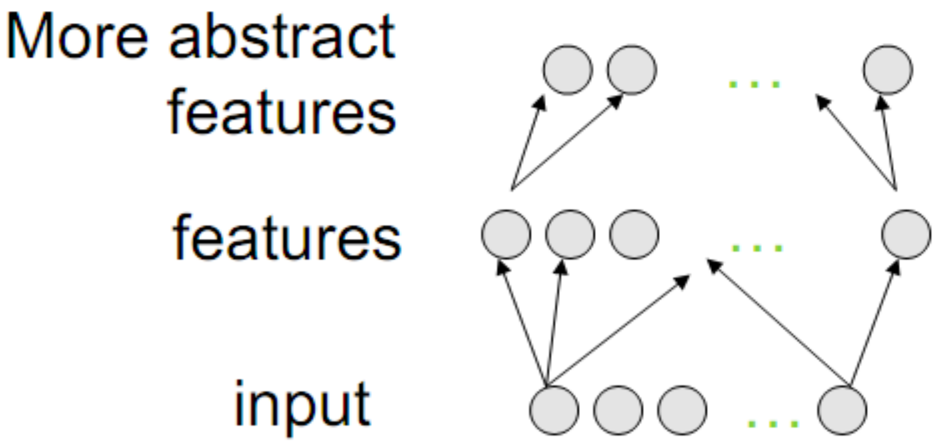
Layer-Wise Unsupervised Pre-training



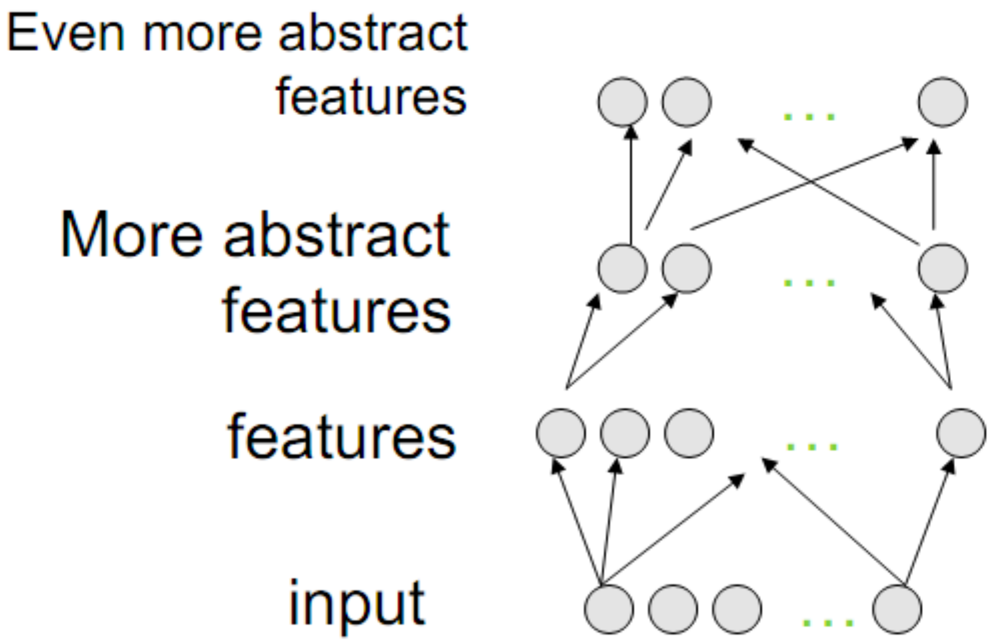
Layer-Wise Unsupervised Pre-training



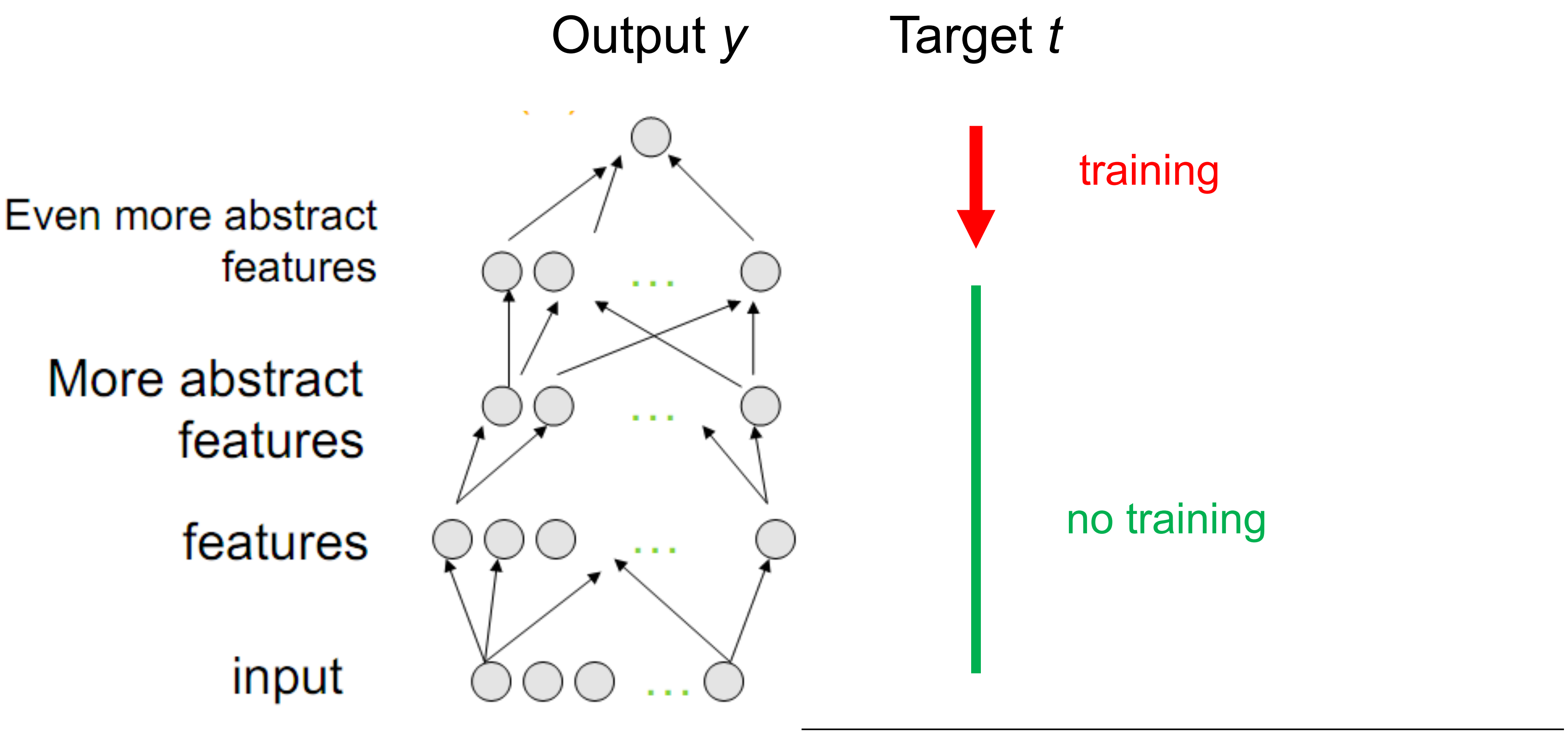
Layer-Wise Unsupervised Pre-training



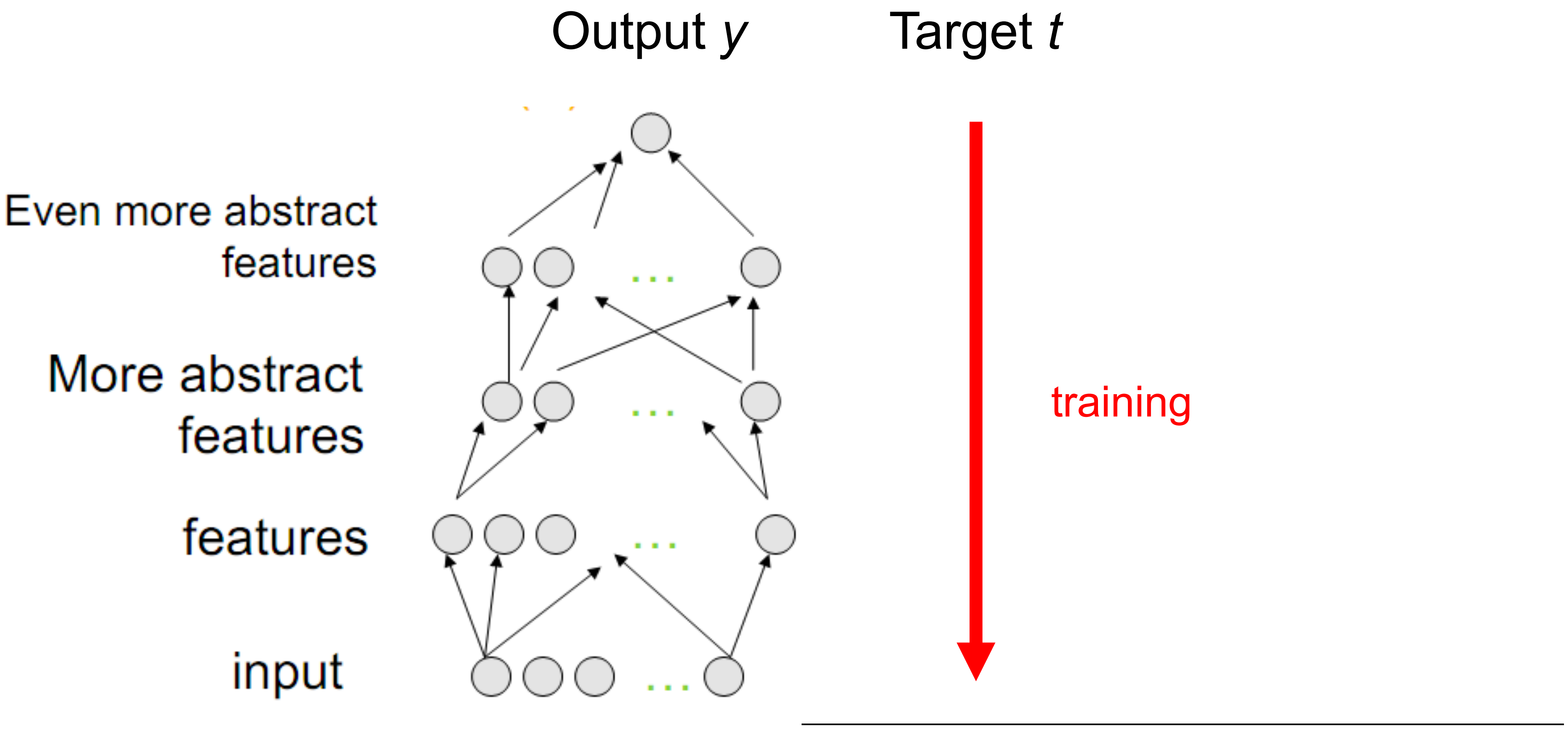
Layer-Wise Unsupervised Pre-training



Supervised training of top layer

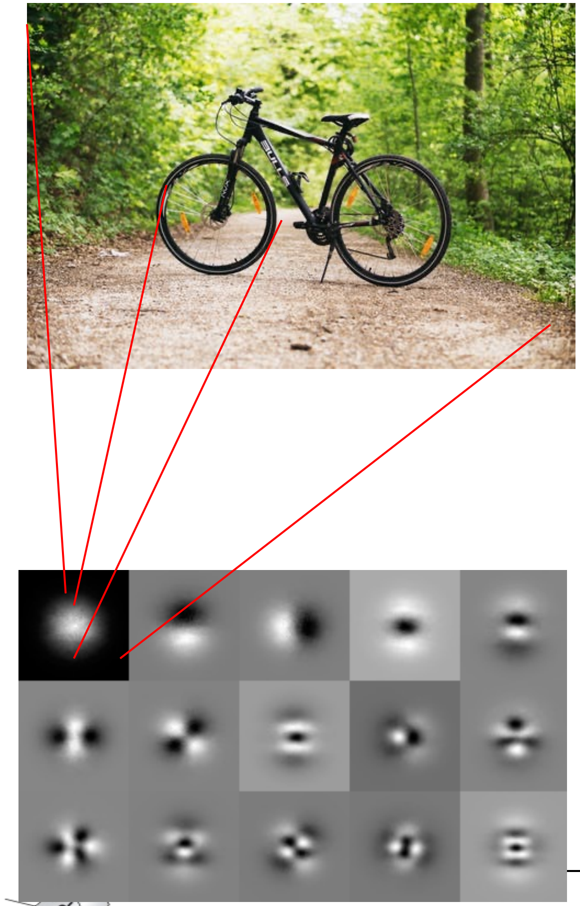


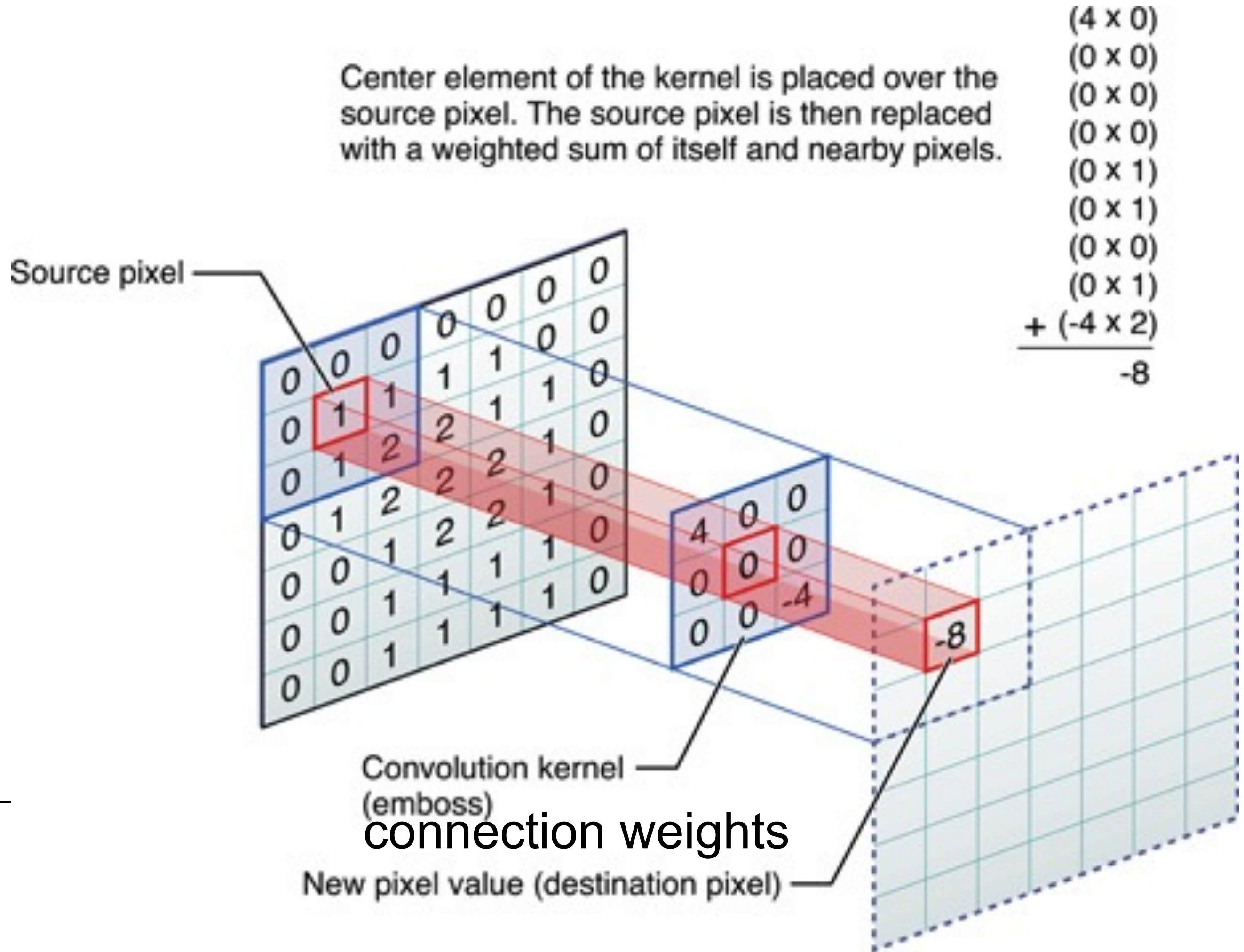
Supervised fine tuning of entire network



Convolutional Neural Networks

Instead of training weights from all input units to each detector (filter), as autoencoders do, train only weights from few neighboring input units to each detector and convolve image to generate activations of the next layer





Filter convolution for 2D images

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

⋮ ⋮

Each filter is a feature detector

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Dot product → 3 -1

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

3 -3

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

-1	1	-1
-1	1	-1
-1	1	-1

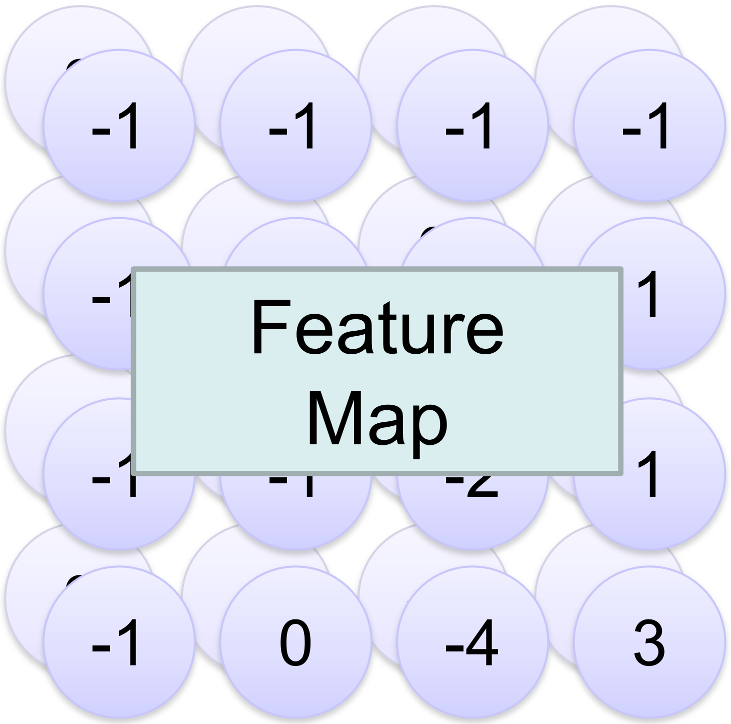
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Repeat this for each filter



x = image coordinate
y = image coordinate
d = convolutions (different filters)

Add non-linearity to each value in the block, e.g. ReLU function (Rectified Linear Unit)

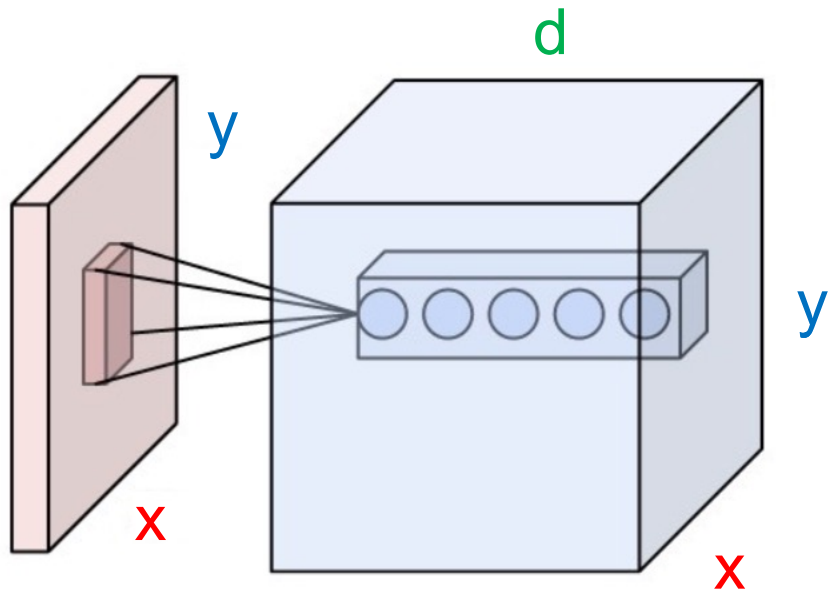
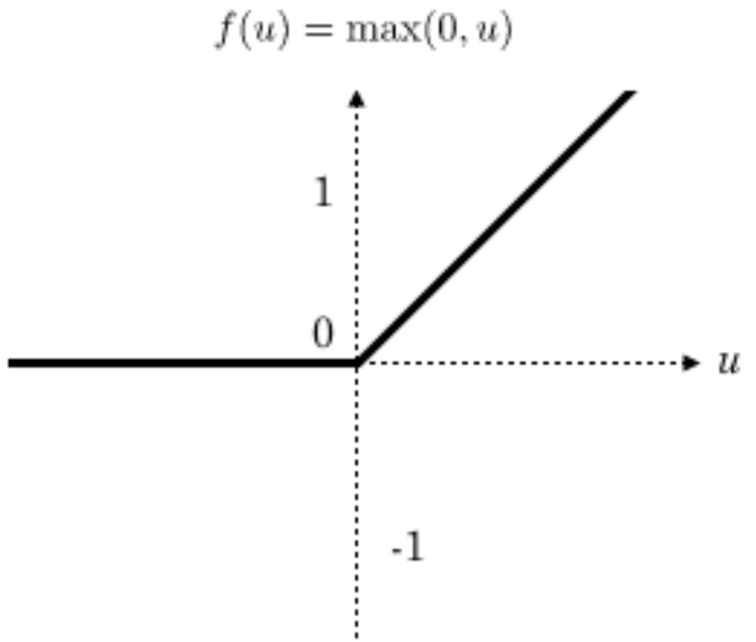


Image Convolution block



Reduce layer size by Subsampling

Layer is subdivided into pools (e.g., 3x3 neurons) and the content of each pool matrix is replaced by a single value, e.g. maximum or mean value of the pool

5	5	0	0	0	1
0	3	0	7	1	8
0	1	1	2	5	0
1	0	5	0	1	0
0	4	9	0	5	0
3	0	1	0	1	0

Max pool
3x3, stride 3

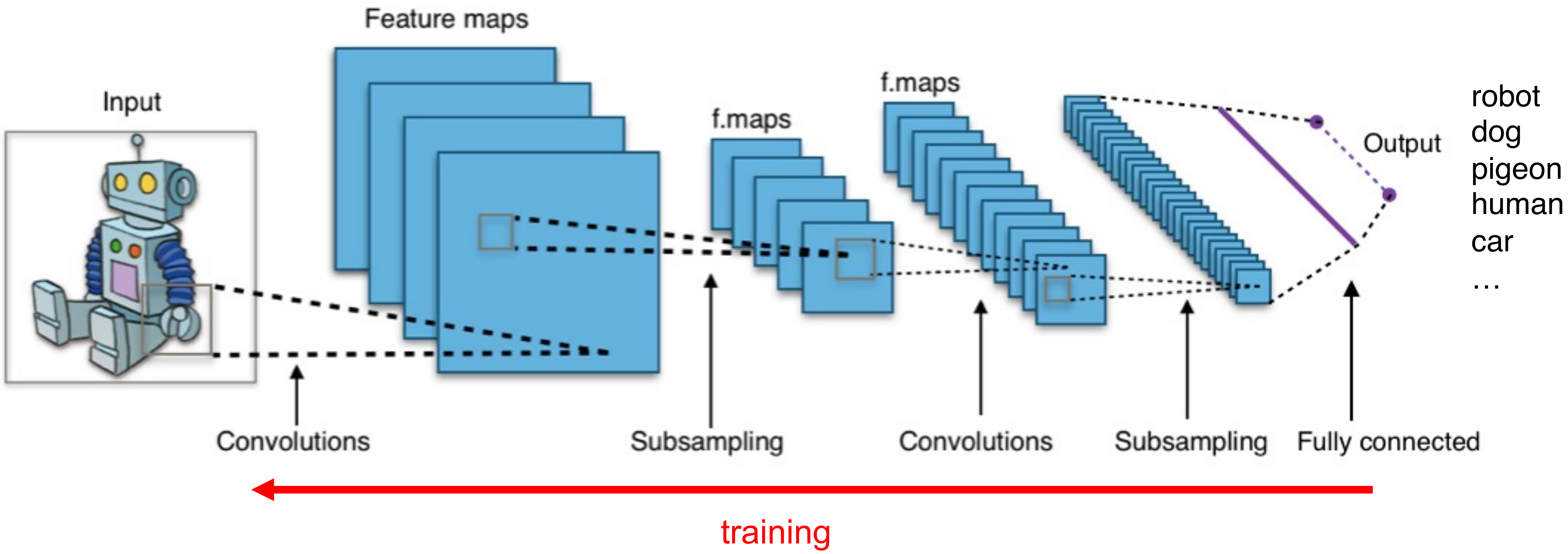
5	7
9	5

Mean pool
3x3, stride 3

1.6	2.7
2.5	0.7

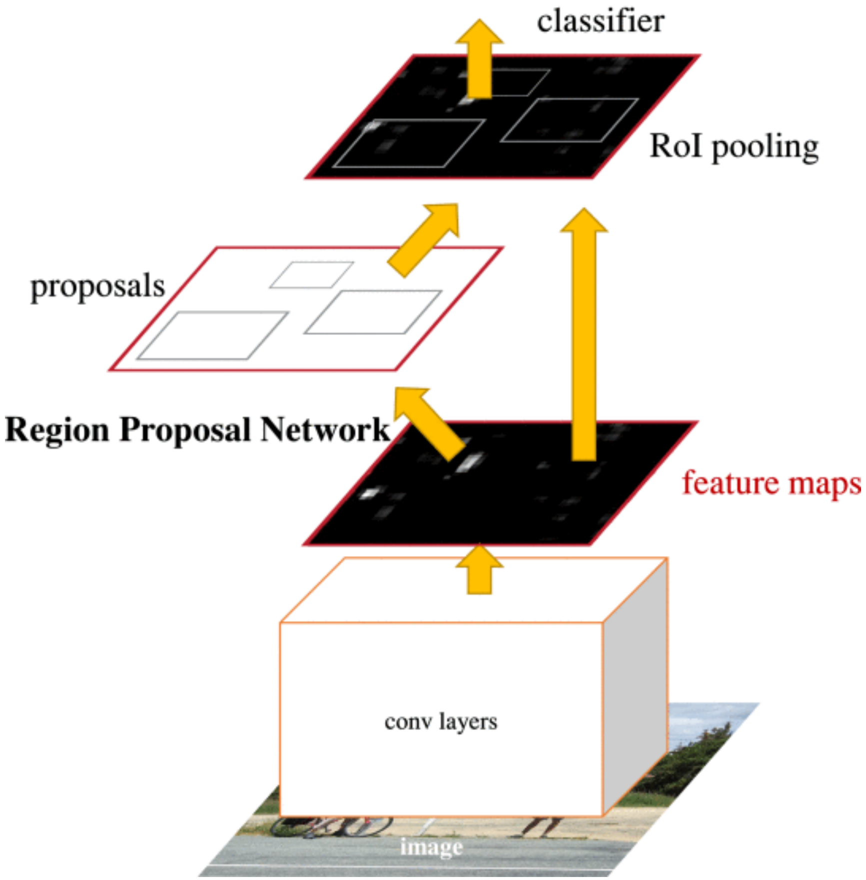
Typical Convolutional Neural Network

Only weights of one filter per layer are learned to minimize the error (loss) function



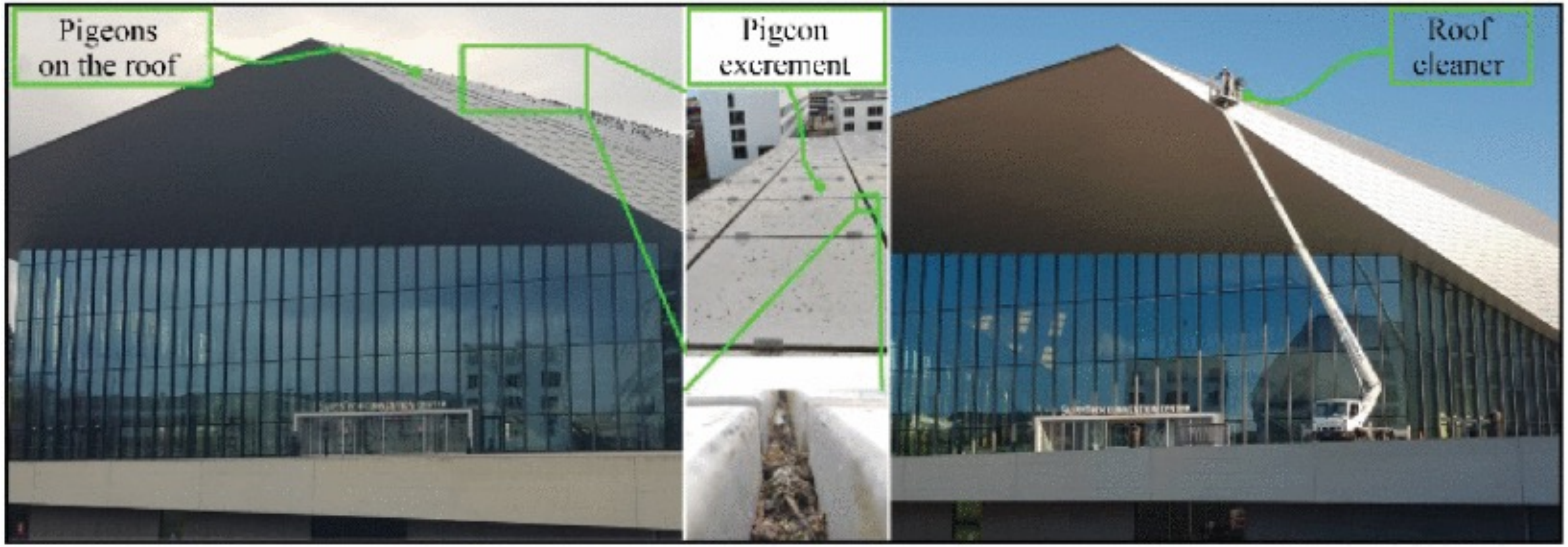
https://en.wikipedia.org/wiki/Convolutional_neural_network

Learning object classification and positions



S. Ren, K. He, R. Girshick and J. Sun (2017), *IEEE Transactions on Pattern Analysis and Machine Intelligence*, doi: 10.1109/TPAMI.2016.2577031.

Bird detection and deterrence on buildings



SwissTech building, EPF Lausanne

- City pigeon excrements damage buildings and facades
- Cleaning and repair cost up to 1.1 billion USD per year in USA (Pimentel et al, 2000)
- Pigeon droppings are reservoirs of dangerous zoonotic pathogens (Haag-Wackernagel, 2004)

Current solutions

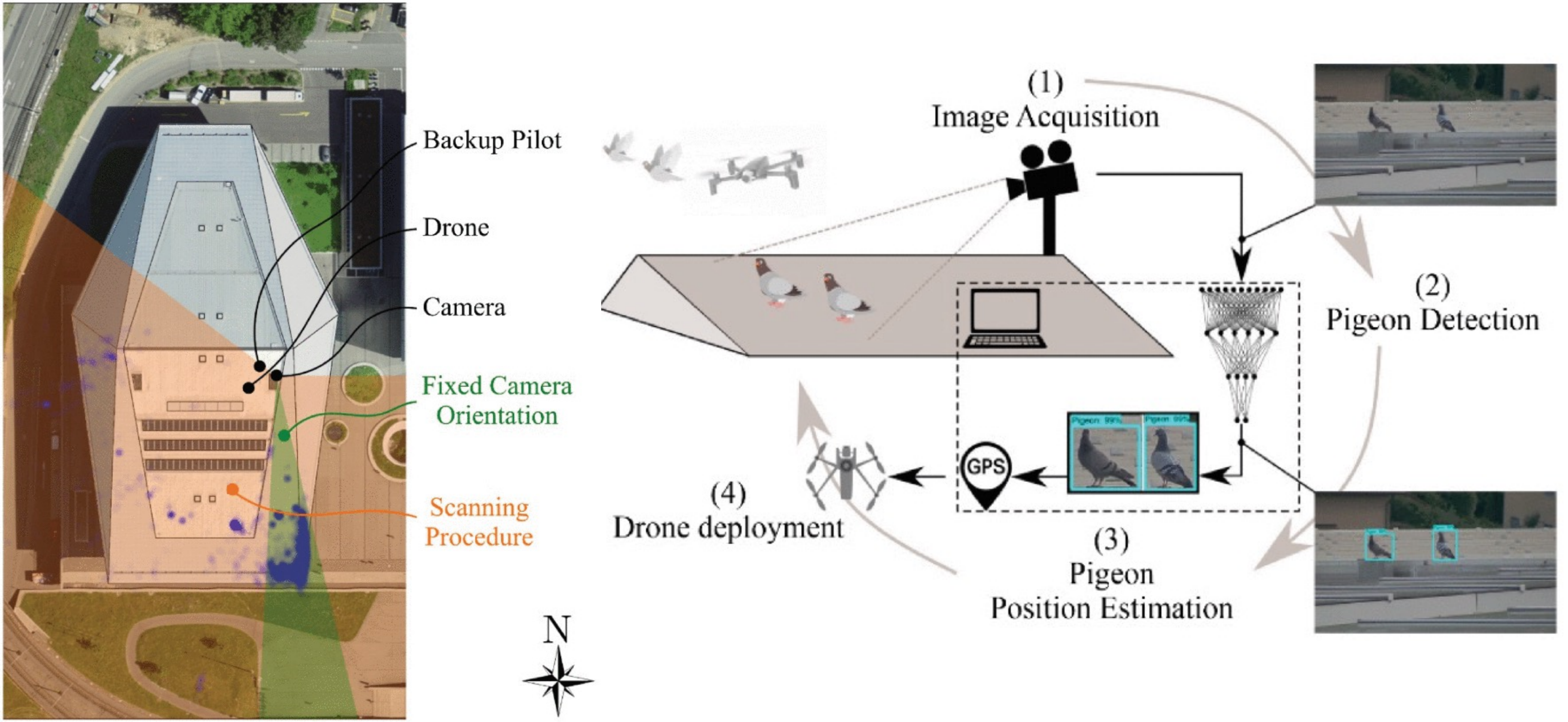
Wang Z. and Wong K.C., 2018

Bird-X.com

Credit: Warren Kovach / Alamy Stock Photo

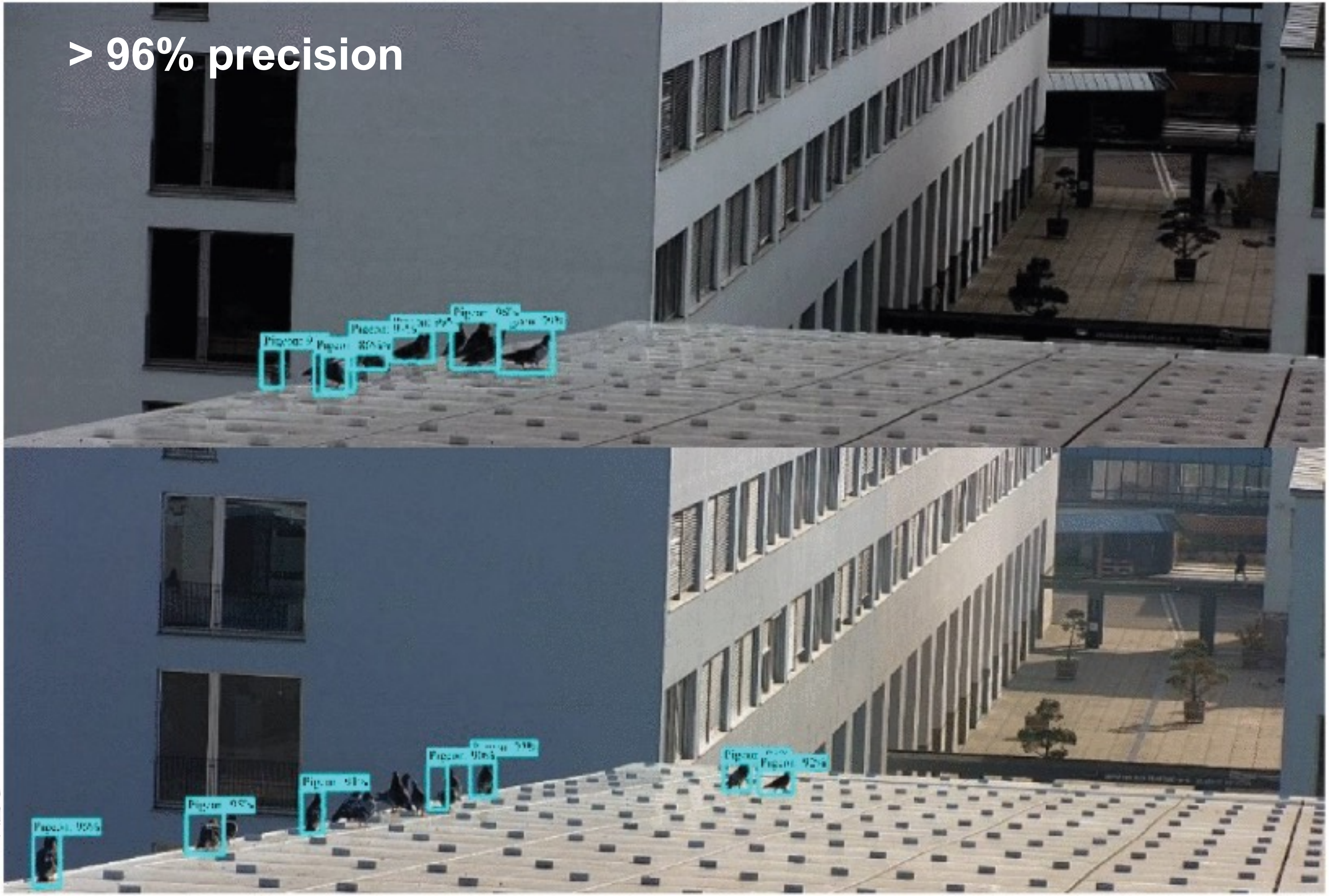
- Require human operator, or
- Are too loud for operation in urban environment, or
- Are dangerous for animals, or
- Are ineffective


Parrot Anafi



F. Schiano, D. Natter, D. Zambrano and D. Floreano (2022) Autonomous Detection and Deterrence of Pigeons on Buildings by Drones, *IEEE Access*, 10, 1745-1755, doi: 10.1109/ACCESS.2021.3137031.

> 96% precision



The system in action

Ground camera view

Drone onboard camera view

Without drone system, pigeon flock stay on roof up to 3 hours
With drone system, pigeon flock stays up to 4 minutes

Reinforcement learning

Input: *state* (sensory information, position, energy, e.g.), *action* (forward, rotate, turn, e.g.)

Reward: *r* (collected dirt, e.g.)

Goal: learn *behavior* (<u>policy</u>) that maximizes the total future rewards

Reinforcement learning framework

State s_{t+1}

AGENT

Reward r_t
can be positive, negative, or absent

ENVIRONMENT

Action a_t

The agent wants to find a mapping from states to actions (the *policy*) that maximizes the total future reward (the *Total Return*) $R_t = \sum_{i=t}^{\infty} r_i$

Reward discount and rollouts

Should all rewards, present and future, have the same weight?
The *discount* factor γ is used to give more importance to present rewards than to remote future rewards

$$R_t = \sum_{i=t}^{\infty} \gamma^i r_i \qquad\qquad 0 < \gamma < 1$$

Rollout: the finite number of steps *n* during which the agent interacts with the environment until a terminal event or time limit is reached

$$R_t = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \gamma^{t+2} r_{t+2} \cdots + \gamma^{t+n} r_{t+n}$$

The Q Function

$$R_t = \gamma^t r_t + \gamma^{t+1} r_{t+1} + \gamma^{t+2} r_{t+2} \cdots + \gamma^{t+n} r_{t+n}$$

The total return R_t is the discounted sum of all future rewards

$$Q(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t]$$

The Q function describes the *expected* total return that an agent in state s can receive by performing a certain action a. It can also be seen as a look-up table that the agent gradually builds through several rollouts, for example (*fictitious numbers!*):

Rewards	Action A	Action B
State A	3	-3
State B	1	0
State C	2	0

Q values	Action A	Action B
State A	0	0
State B	-2	4
State C	-6	0

Finding the optimal policy

s_a, a?
s_b, a?
s_c, a?
s_d, a?
…

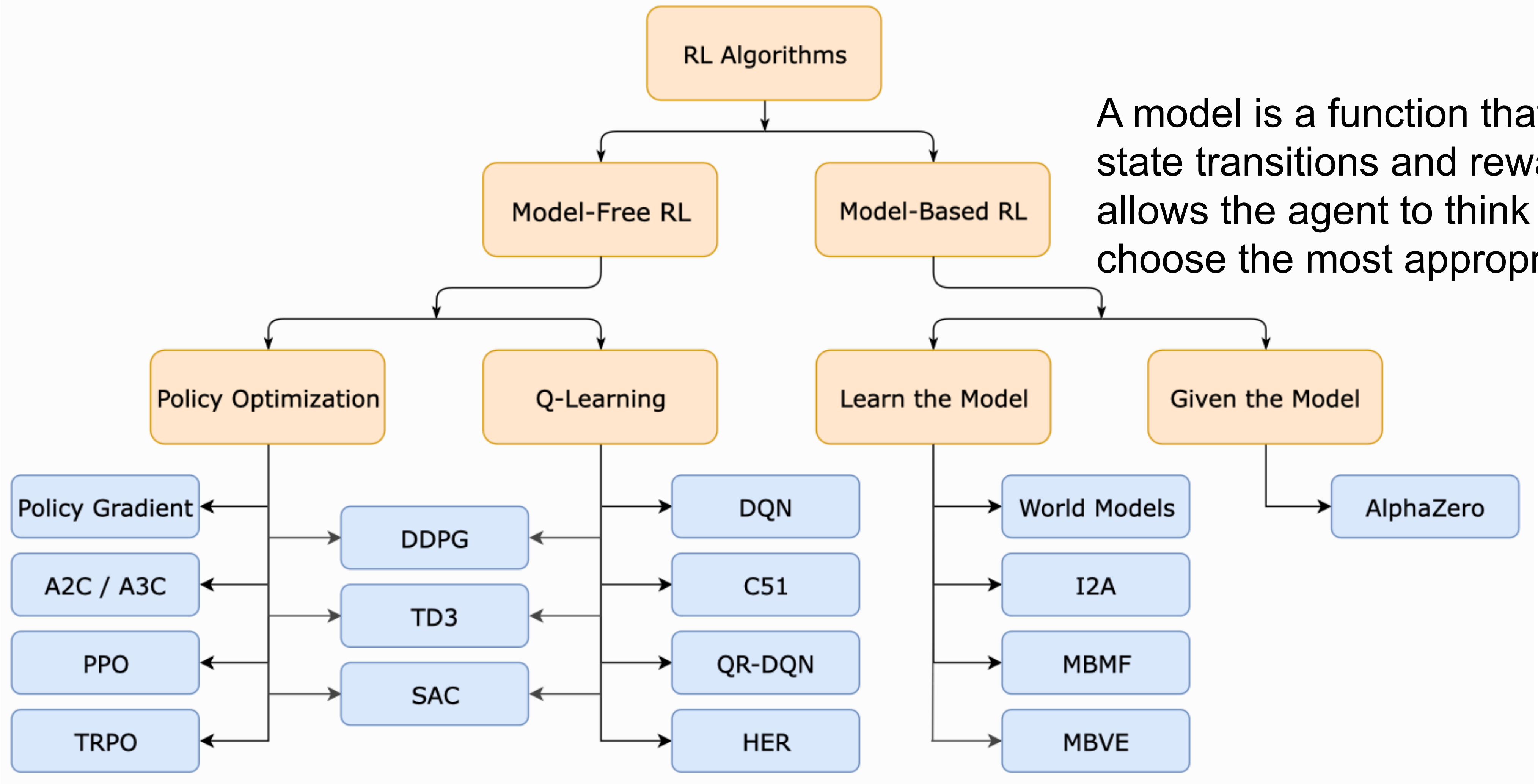
A policy $\pi(s)$ is a strategy to select an action a for a state s

The optimal policy $\pi^*(s)$ is a policy that maximizes the expected total return, which is captured by the Q function

If the agent knows the Q function, the optimal policy consists in finding for each state s the best action a over all possible actions that maximize the Q function

$$\pi^*(s) = \underset{a}{\operatorname{argmax}} Q(s, a)$$

A taxonomy of modern RL algorithms (2018)



A model is a function that predicts state transitions and rewards: it allows the agent to think ahead and choose the most appropriate action

Source: https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html

Model-free RL Methods

Q-VALUE LEARNING

Find

$$Q(s, a)$$

and pick best action

$$a = \underset{a}{\operatorname{argmax}} Q(s, a)$$

POLICY LEARNING

Directly find

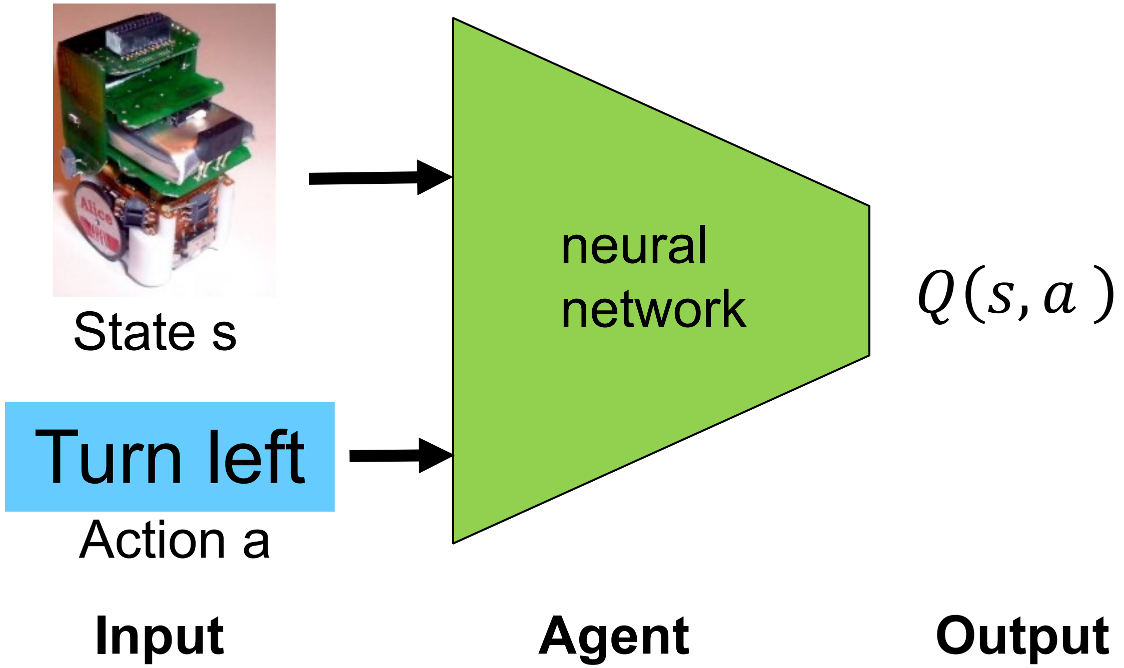
$$\pi(s)$$

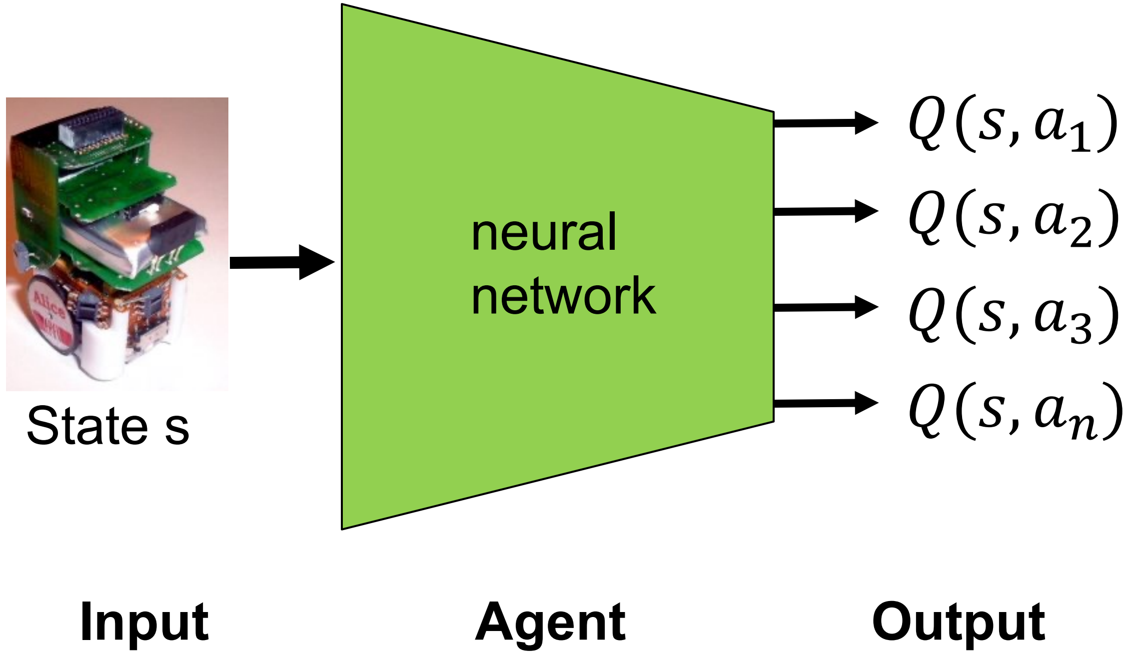
and sample (try) action

$$a \sim \pi(s)$$

Deep Q-Networks (DQN)

DQN assumes a discrete action space



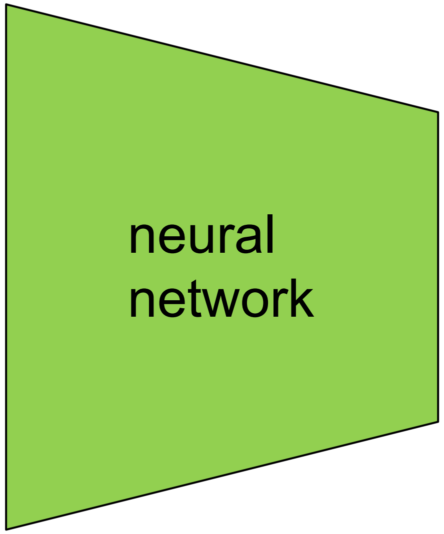


Problem: Q value must be recomputed for all possible actions at input state s

Solution: ask network to compute Q values for all possible actions of input state s

DQN learning

State s



$Q(s, a_1)$ 30

$Q(s, a_2)$ 2

$Q(s, a_3)$ 4

$Q(s, a_4)$ 0

- Initialize random weights
- Select random action with small probability ε, otherwise select action with highest prediction value
- After termination event, compute Q loss and perform gradient descent on weights

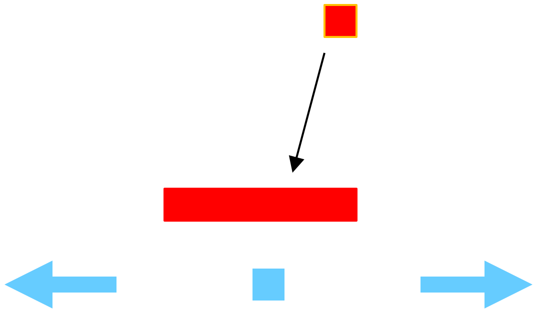
$$\text{Q-loss} = \mathbb{E}\left[\left\| \overbrace{\left(r + \gamma \max_{a'} Q(s', a')\right)}^{\text{Observation}} - \overbrace{Q(s, a)}^{\text{Prediction}} \right\|^2\right]$$

Use back-propagation of error to adapt network weights

DQN learning to play Atari Breakout game

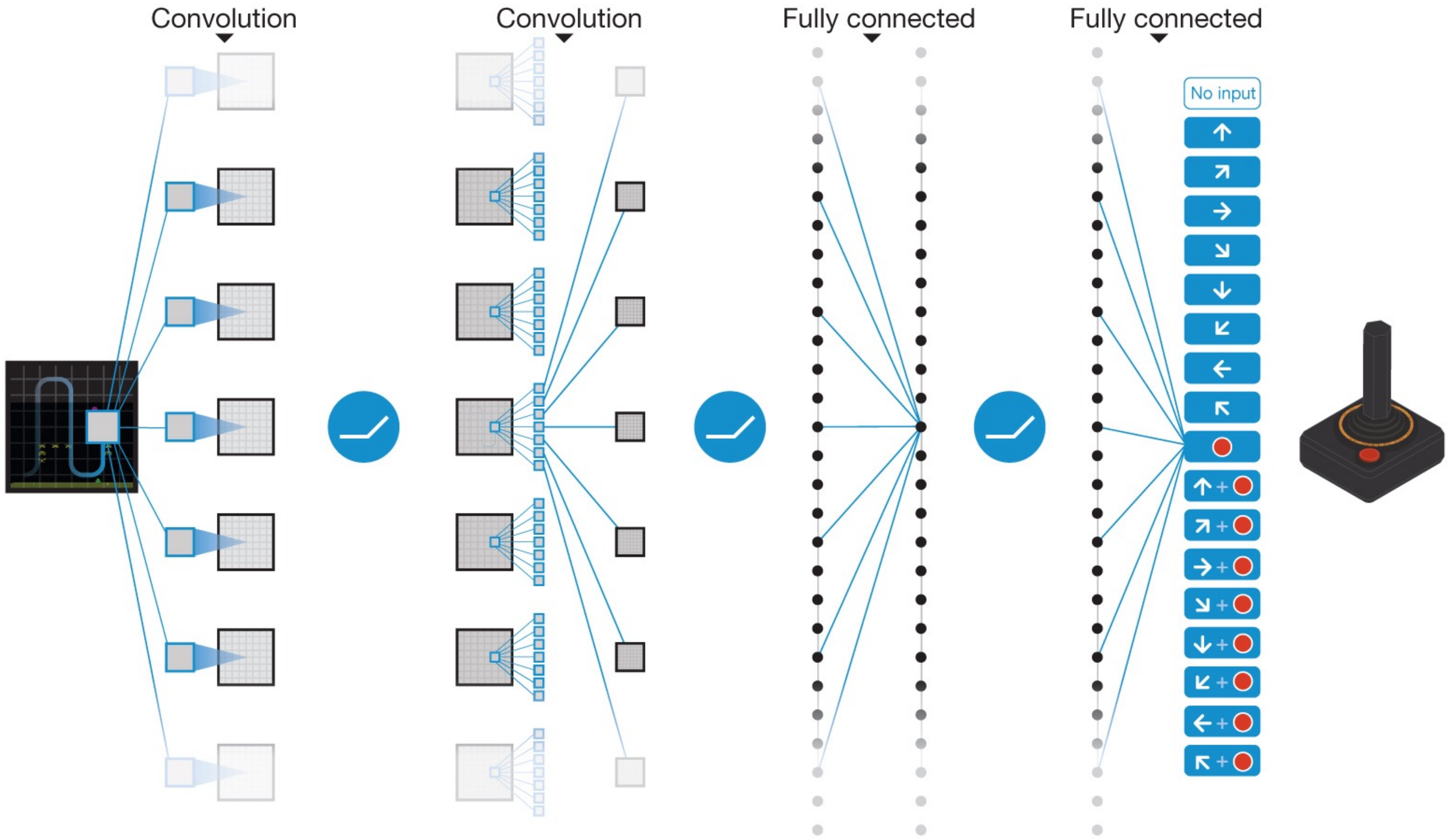
State = screen image

Paddle actions = left, stay, right

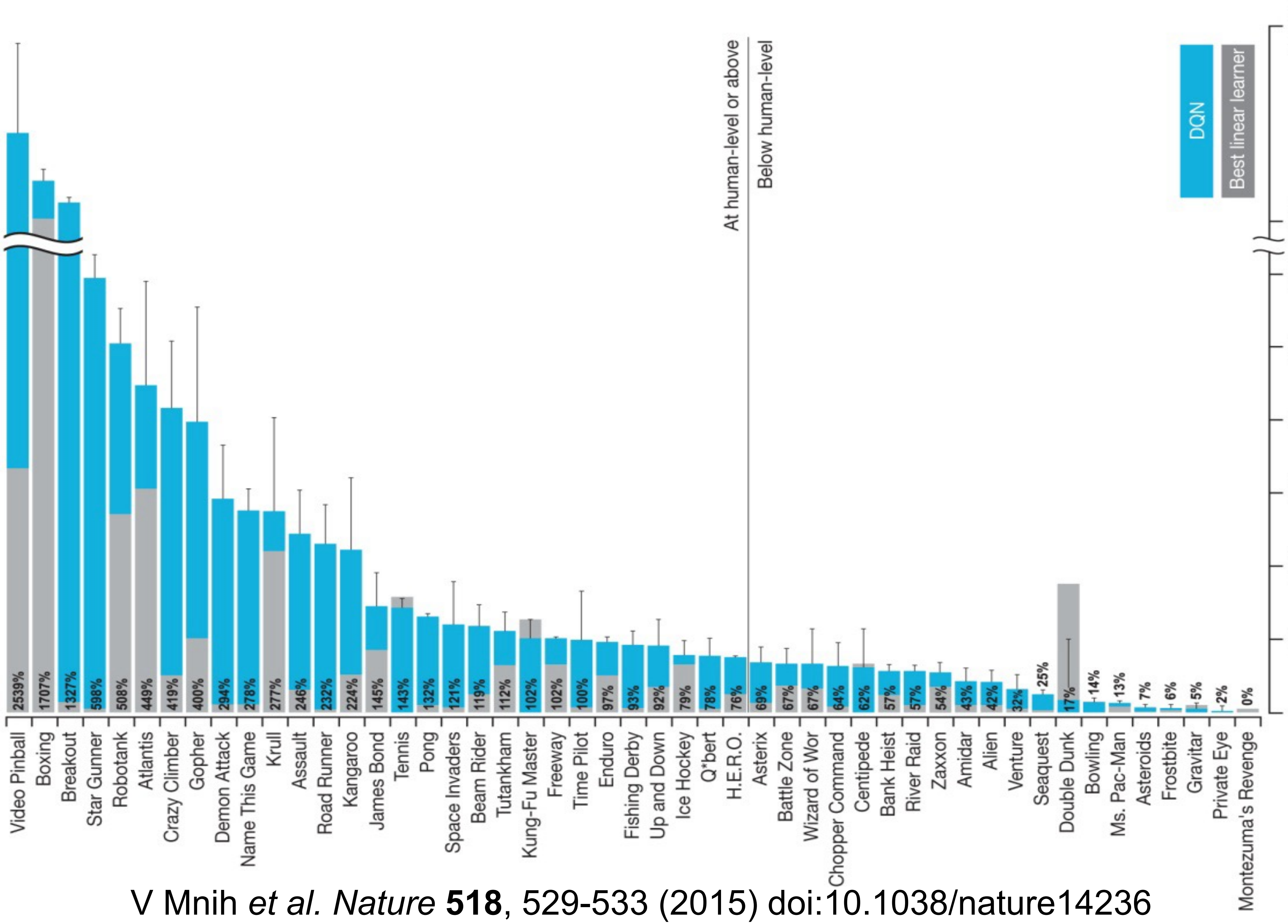


https://www.youtube.com/watch?v=V1eYniJ0Rnk

DQN playing Atari games



V Mnih *et al.* *Nature* **518**, 529-533 (2015) doi:10.1038/nature14236



V Mnih *et al. Nature* **518**, 529-533 (2015) doi:10.1038/nature14236

Q learning: strengths and limitations

It guarantees the possibility of identifying the optimal policy if the Q function is learned

BUT

It requires a discrete action space (turn left, go forward, stay, etc.)

It only works for deterministic situations (it cannot learn stochastic policies)

Policy learning

Directly learn the policy $\pi(s)$: <u>discrete action space</u>

probabilities

Probability Distribution Function must sum to 1

State s

neural network

$P(a_1|s)$ 0.4

$P(a_2|s)$ 0.3

$P(a_3|s)$ 0.3

$P(a_4|s)$ 0.0

$\pi(s) \sim P(a|s)$

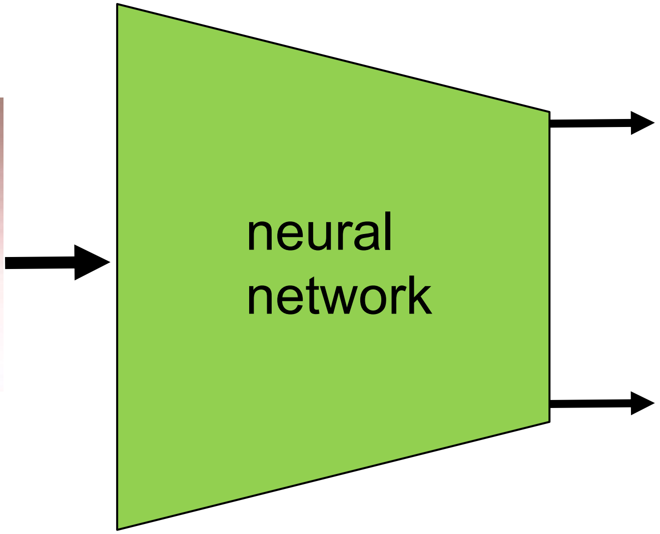
Sample the probability distribution to select action: for example, a_1

Input **Agent** **Output**

Policy learning

Directly learn the policy $\pi(s)$: <u>continuous action space</u>

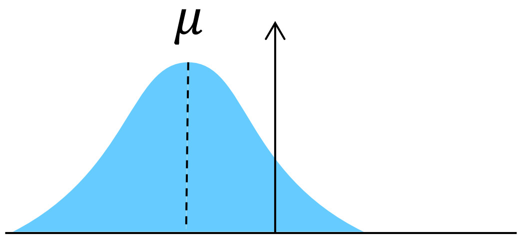
State s



$\mu = -0.8$

$\sigma^2 = 0.5$

$$P(a|s) = \mathcal{N}(\mu, \sigma^2)$$

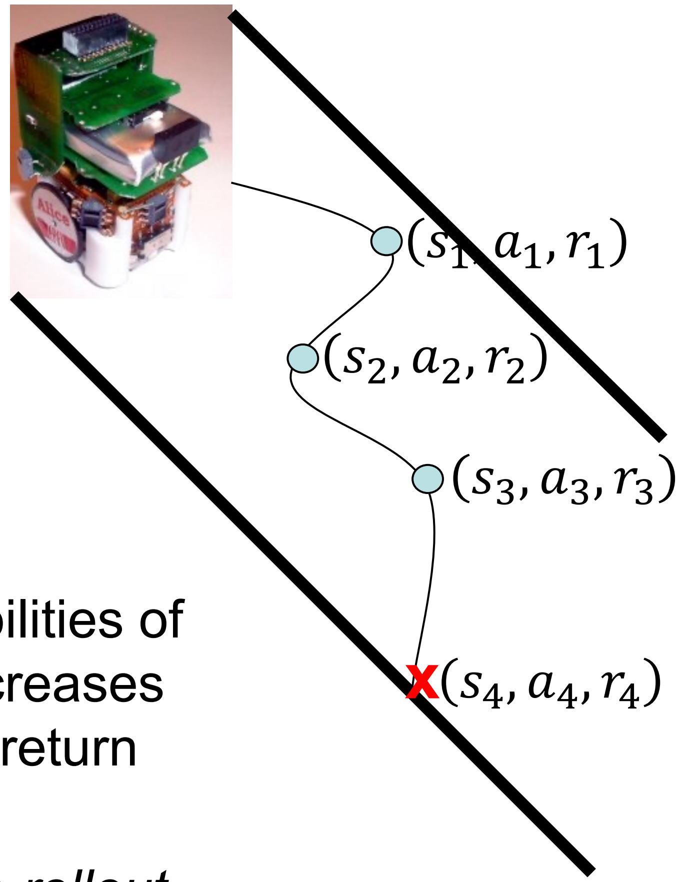


steering angle

Input **Agent** **Output**

Policy Gradient Learning

1. Initialize weights of the agent
2. Run the agent (*policy*) until termination (*rollout*)
3. At each time step of the rollout, record the triplet (s_t, a_t, r_t)
4. Increase probability of actions that led to high reward
5. Decrease probability of actions that led to low reward



$$\boxed{loss = -\log P(a_t|s_t)\, R_t}$$

The loss function increases the probabilities of actions with higher total return and decreases probabilities of actions with lower total return

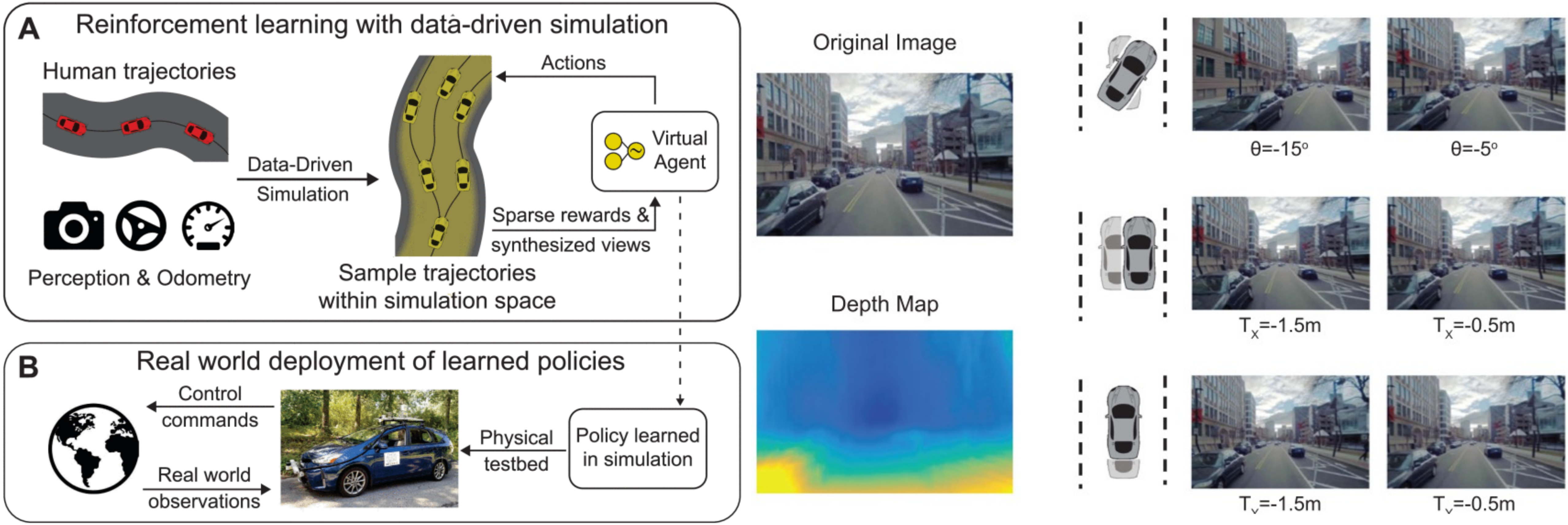
$$\Delta w = -\nabla loss$$
$$\Delta w = \nabla \log P(a_t|s_t)\, R_t$$

Weight change is performed after each *rollout*

For full derivation; https://spinningup.openai.com/en/latest/spinningup/rl_intro3.html

An alternative method that does not use gradient ascent is evolutionary computation

Autonomous driving by Policy Gradient Learning



A. Amini *et al.*, Learning Robust Control Policies for End-to-End Autonomous Driving From Data-Driven Simulation, (2020) *IEEE Robotics and Automation Letters*, 5(2), 1143-1150

Contributions

Our paper makes the following contributions