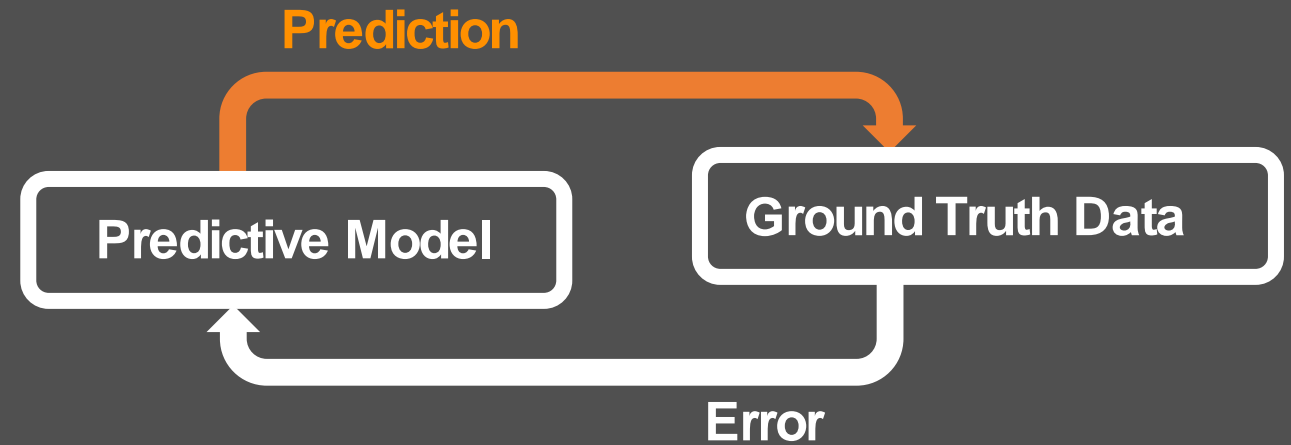
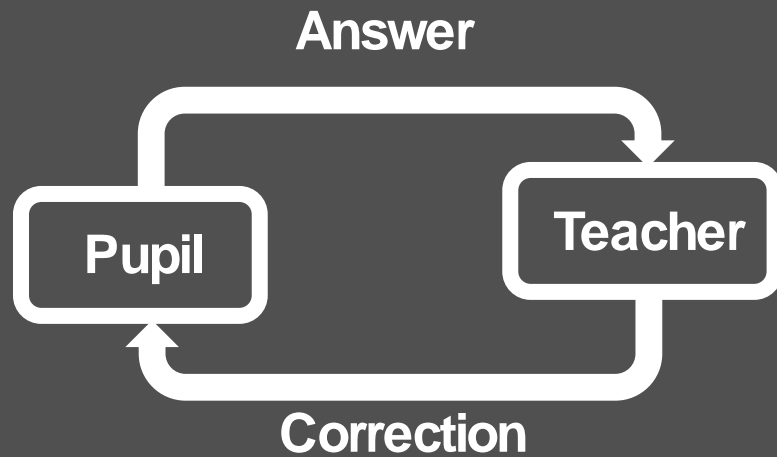


# Reinforcement Learning

## Introduction

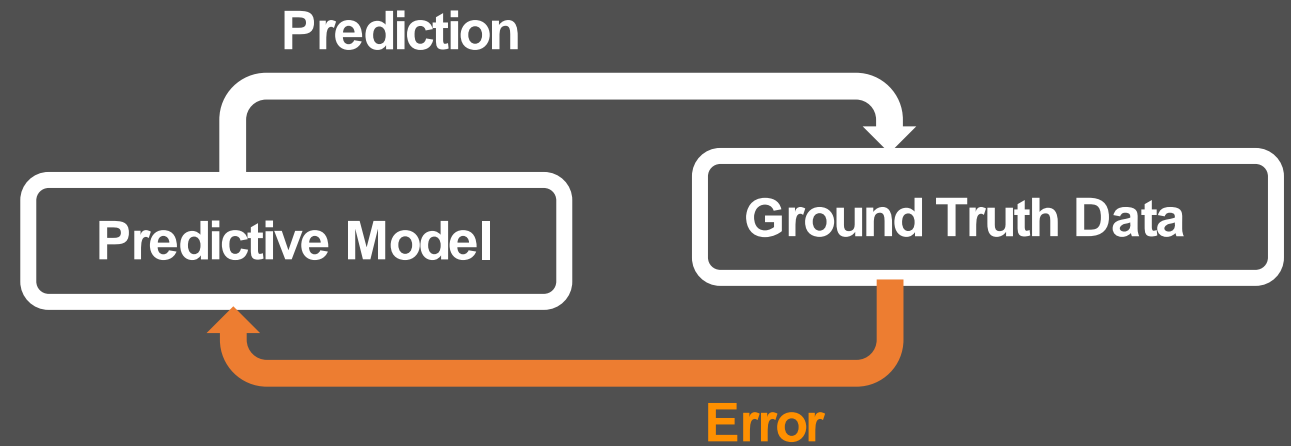
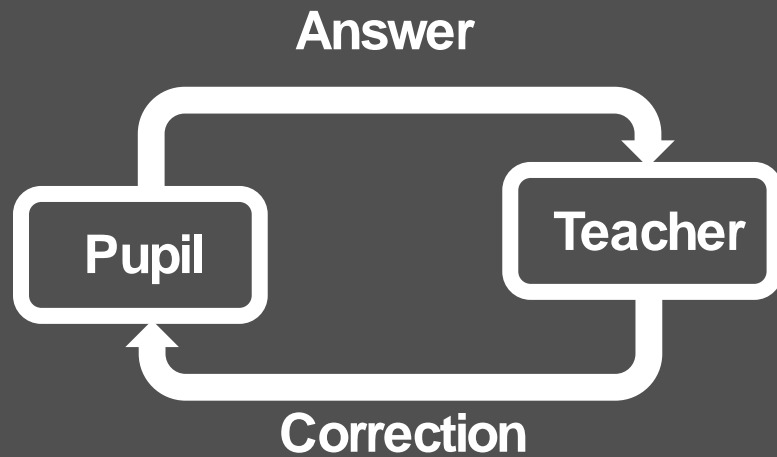
## Two Processes:

- **Forward Propagation (Prediction)**
- **Backward Propagation (Weight Tuning)**



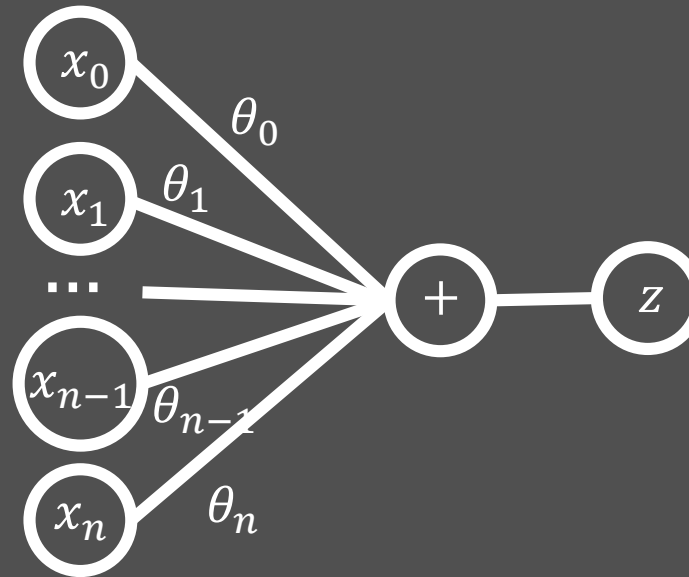
## Two Processes:

- Forward Propagation (Prediction)
- **Backward Propagation (Weight Tuning)**



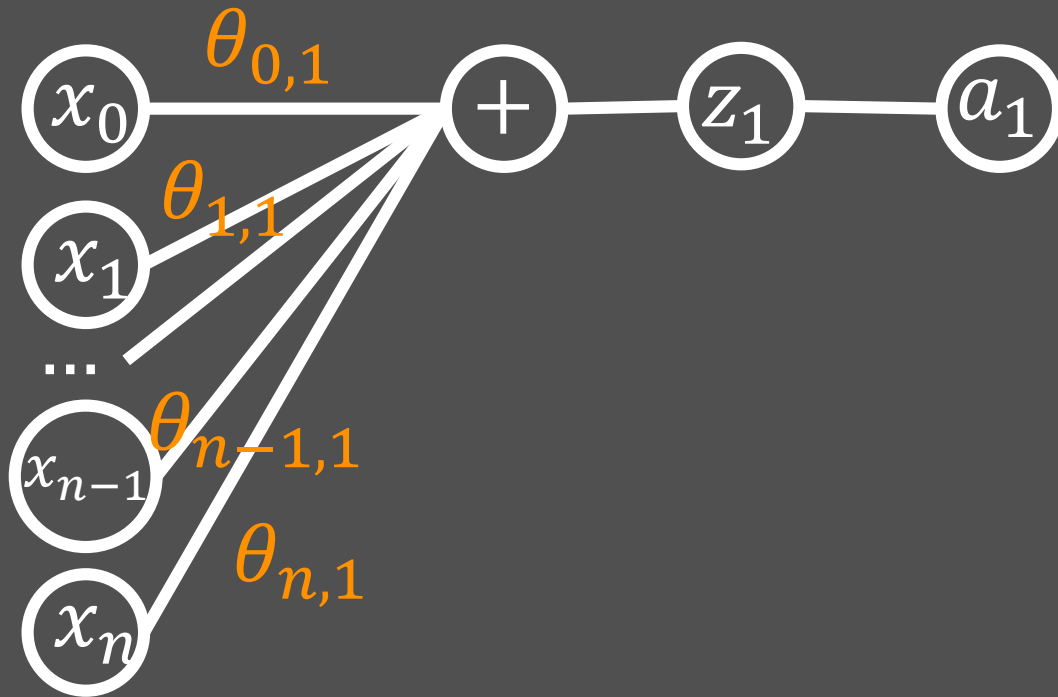
# Forward Propagation

- Compute multiple weighted sums  $z_i$
- Activate them to get  $a_i(z_i)$
- Remember from Perceptron:  $z = \theta x$

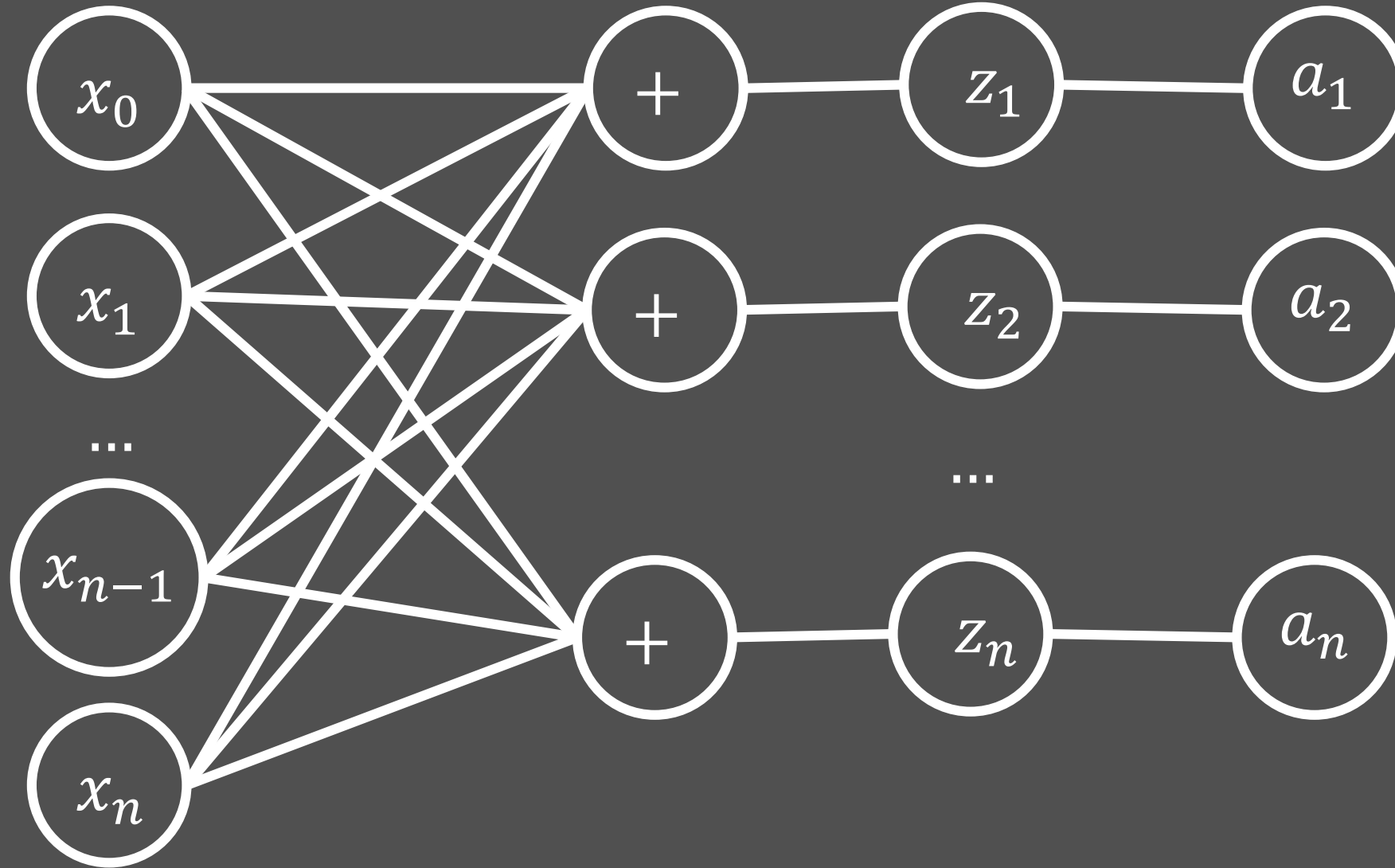


$$z_{to} = \theta_{from,to} x_{from}$$

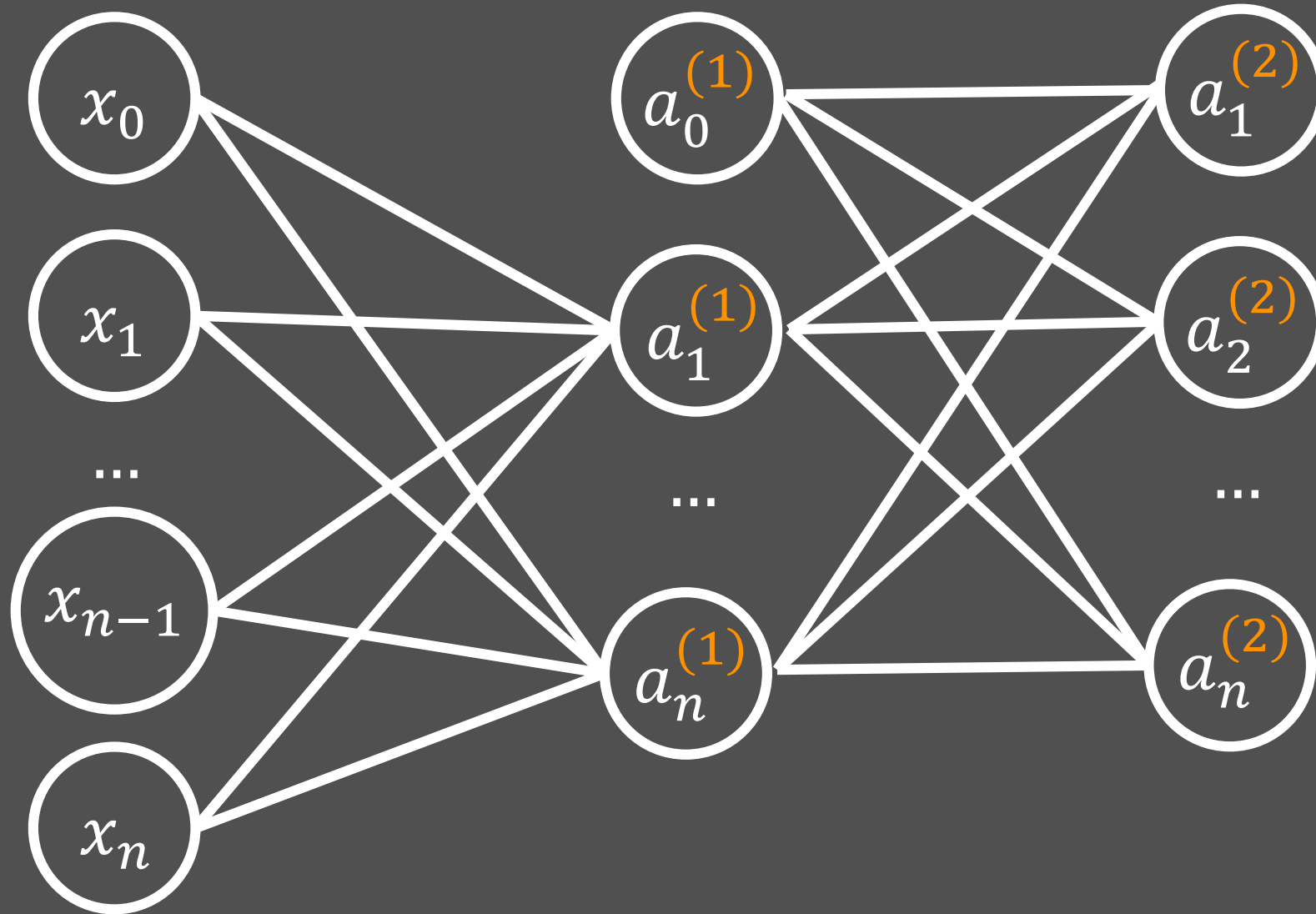
**e.g.**  $z_1 = \theta_{0,1} x_0$



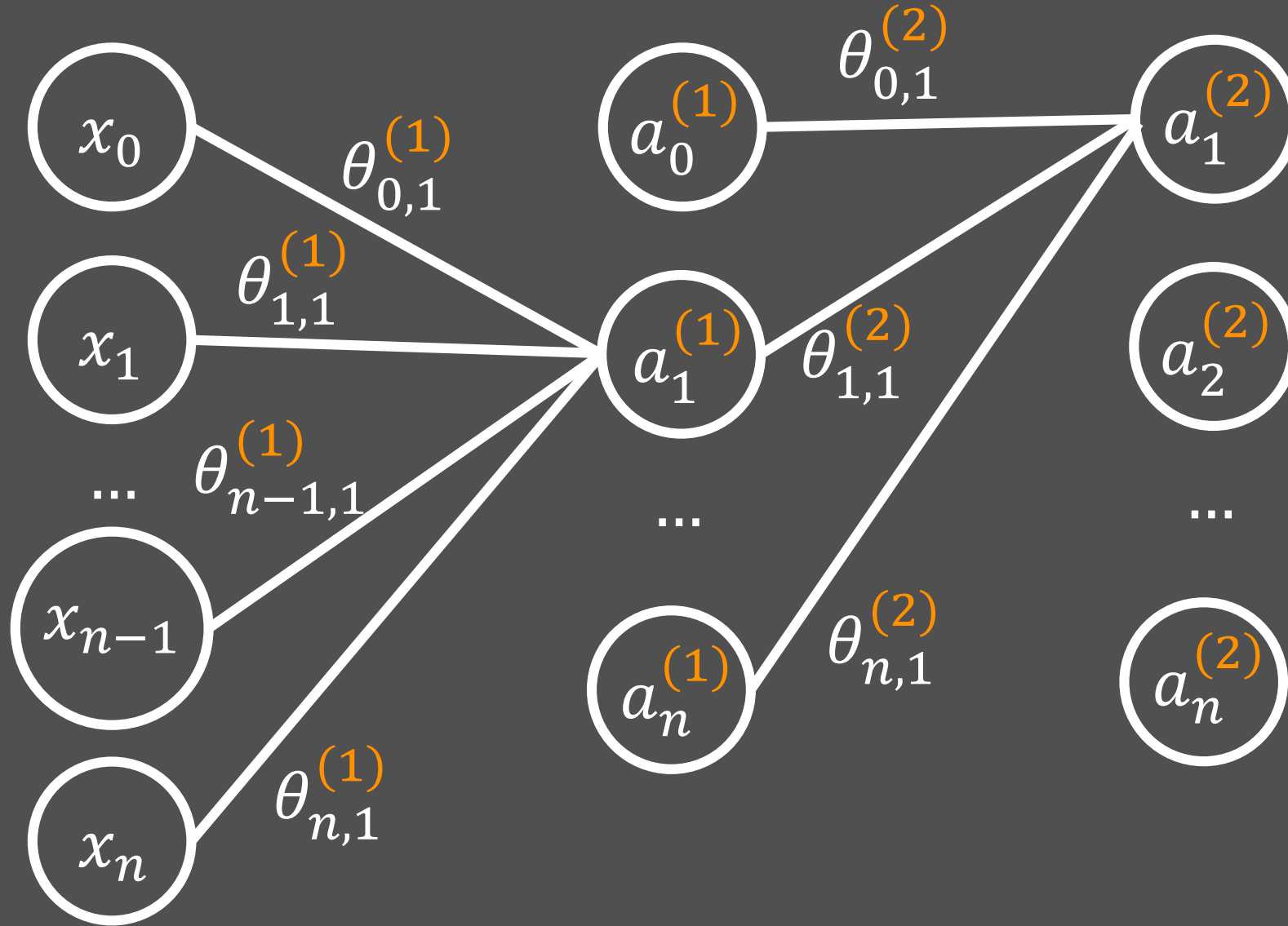
# Forward Propagation



# Forward Propagation



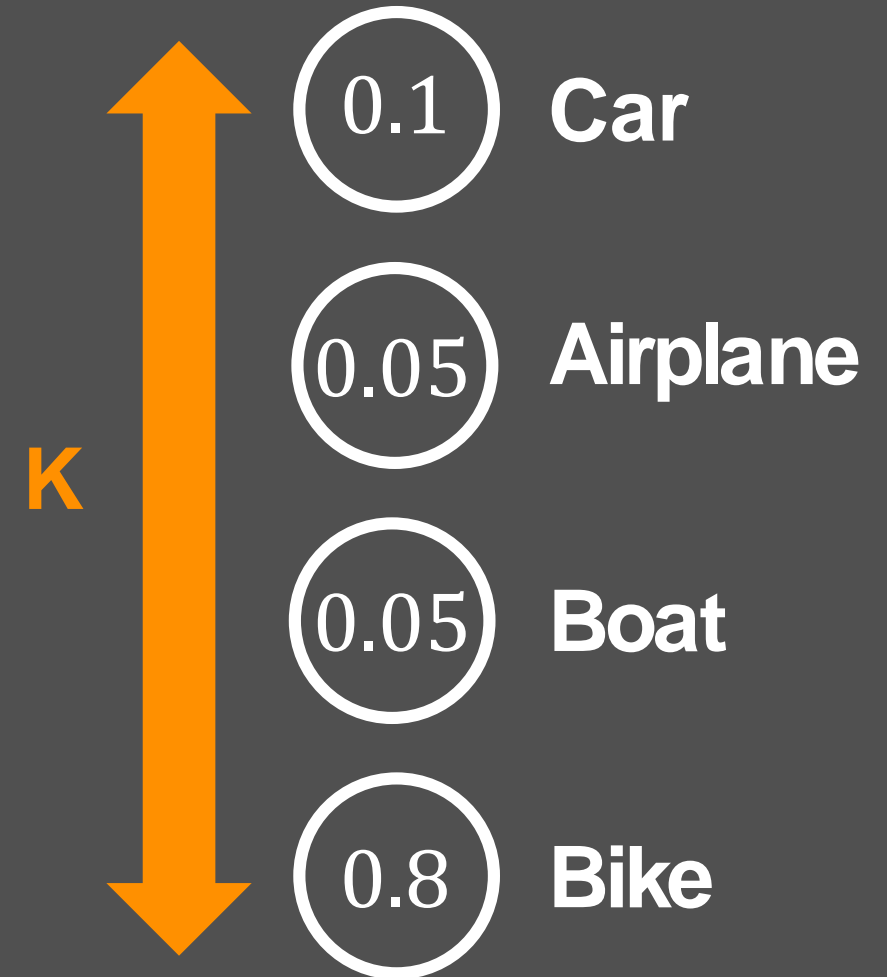
# Forward Propagation





# Forward Propagation

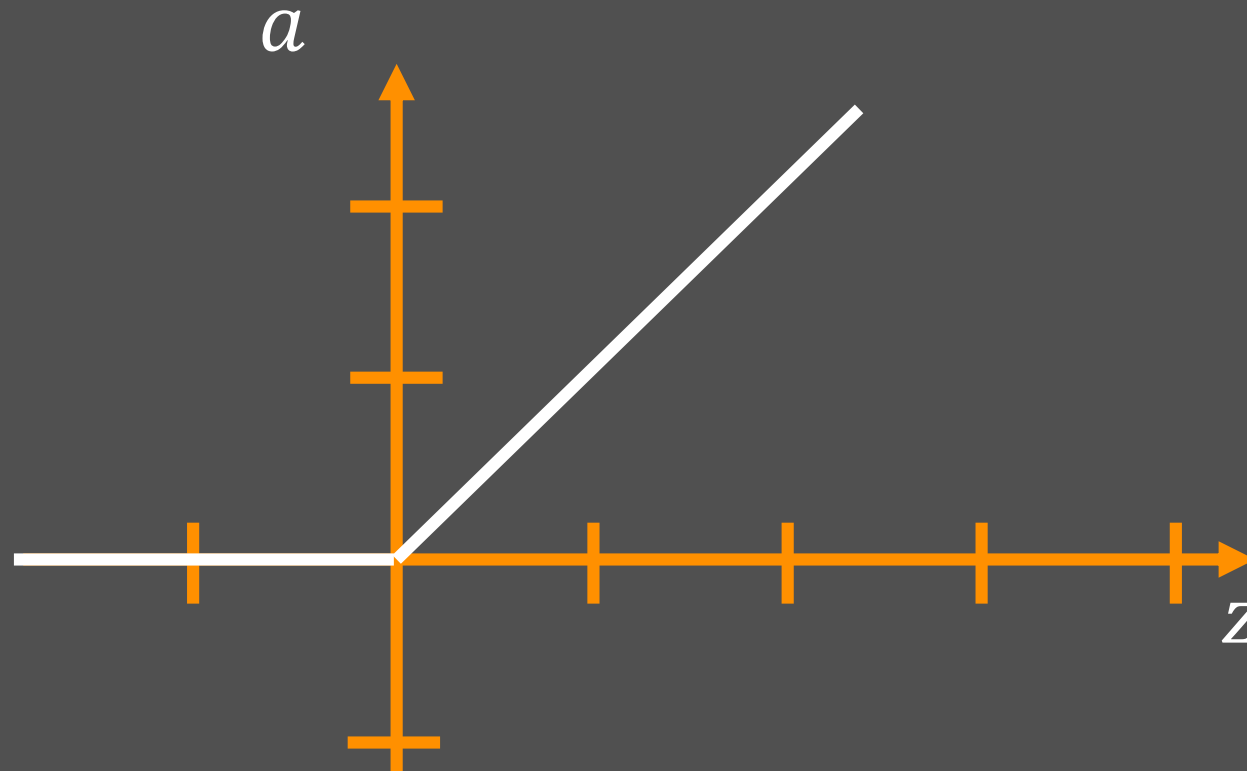
- Object Recognition
- Assume 4 classes
- L-Layer (L is the last layer)
- Softmax:  $a = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$
- Use Softmax for the last Layer



## Hidden Layer Activation Functions $a(z)$ :

- **Linear Neuron:**  $a(z) = z$
- **Binary Threshold Unit:**  $a(z) = \begin{cases} 0, & z < 0 \\ 1, & z \geq 0 \end{cases}$
- **Rectified Linear (ReLu):**  $a(z) = \begin{cases} 0, & z < 0 \\ z, & z \geq 0 \end{cases}$
- **Sigmoid:**  $a(z) = \frac{1}{1+e^{-z}}$
- **Tanh:**  $a(z) = \tanh(z)$

**Rectified Linear (ReLu):**  $a(z) = \begin{cases} 0, & z < 0 \\ z, & z \geq 0 \end{cases}$

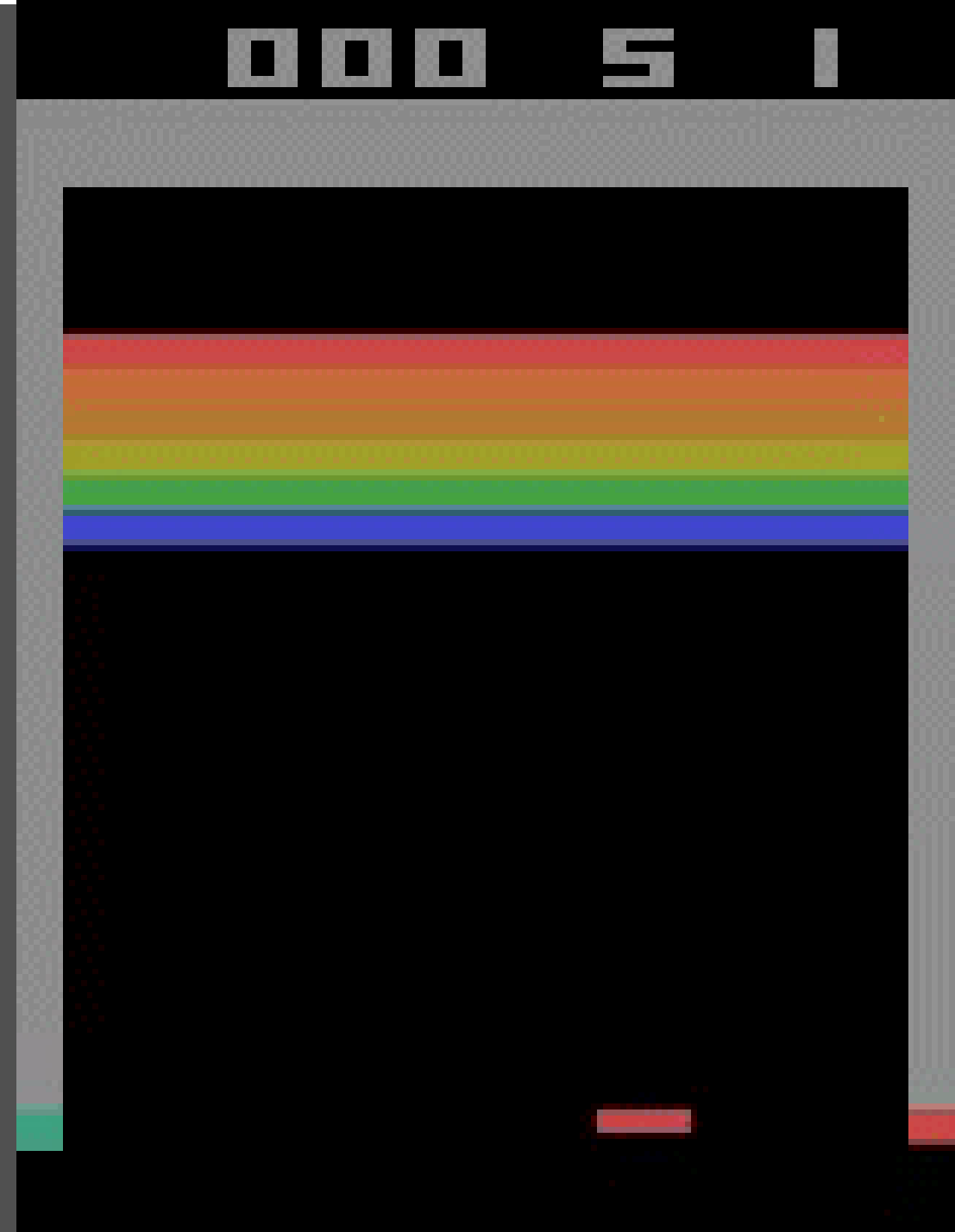


## Exercise:

- **Construct a MLP (input: 3, hidden: 4, output: 3)**
- **All activation functions are ReLu-Function**
- **The output activation is a softmax-function**
- **Initialize the weights randomly**
  - **No zero values allowed!**
- **The input vector is  $x = (1, -2, 1)^T$**
- **Compute one forward-propagation step!**

# What we will do?

- Applied AI
- Reinforcement Learning
- Train Agent to play Atari-Games



# Artificial Intelligence

## Machine Learning

Reinforcement  
Learning

Deep Learning

**Artificial Intelligence**

**Machine Learning**

**Reinforcement  
Learning**

**Deep Learning**

# Machine Learning

**Supervised  
Learning**

**Classification**

**Regression**

**Reinforcement  
Learning**

**Unsupervised  
Learning**

**Clustering**



# Reinforcement Learning

Action



Agent

Reward

Environment

State

# Reinforcement Learning

Action



Environment

Reward

Agent

State

# Reinforcement Learning

Action



Environment

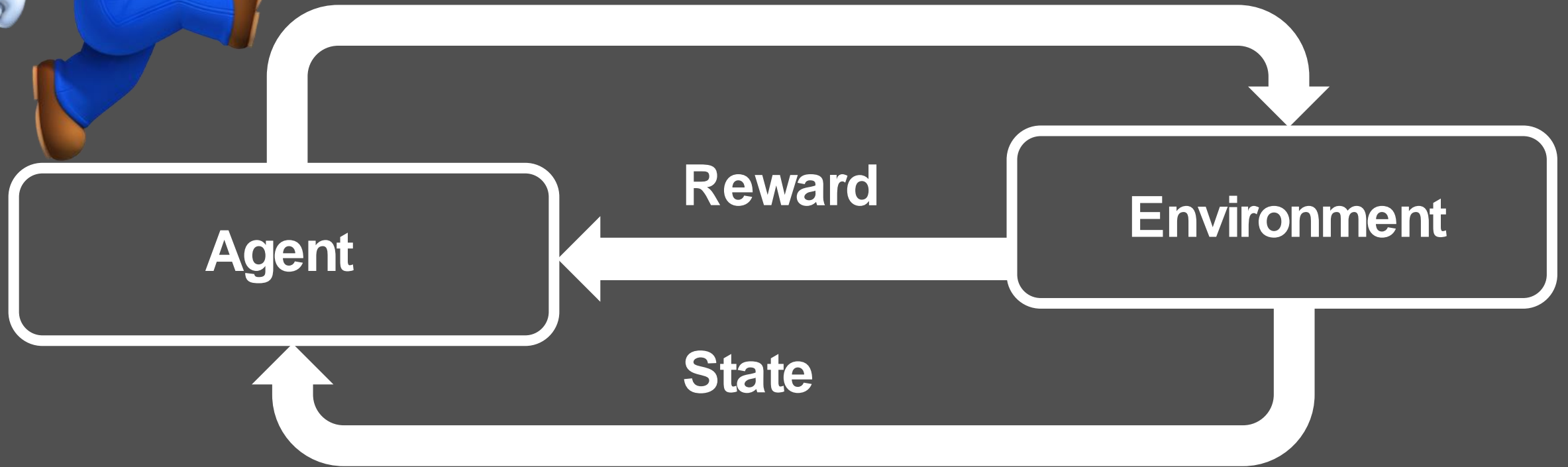
Reward

Agent

State

# Reinforcement Learning

Action



# Reinforcement Learning

Action



Agent

Reward

Environment

State



# Reinforcement Learning

Action



Reward



Environment

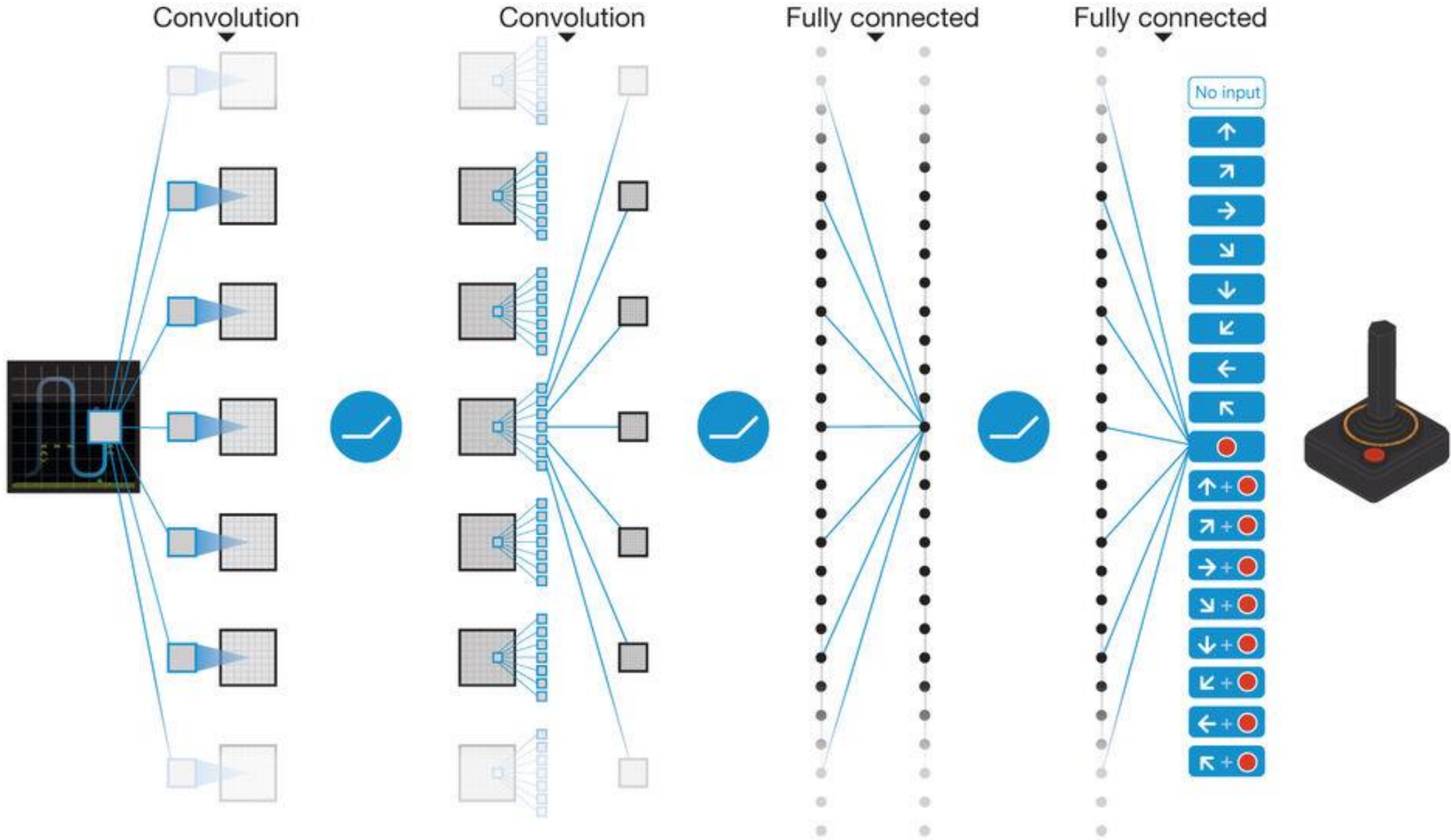
Agent

State

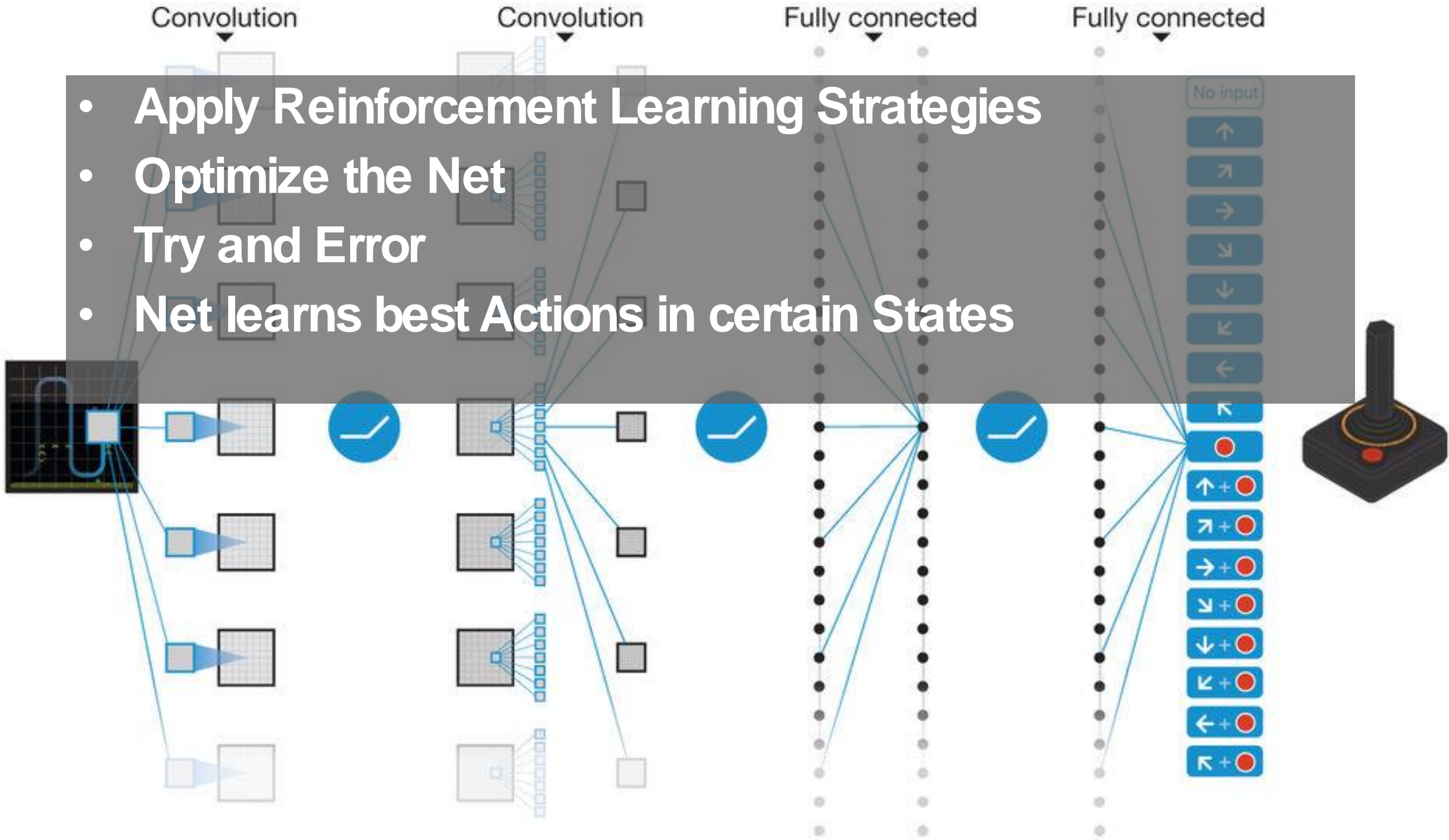
# Rewards = Goals

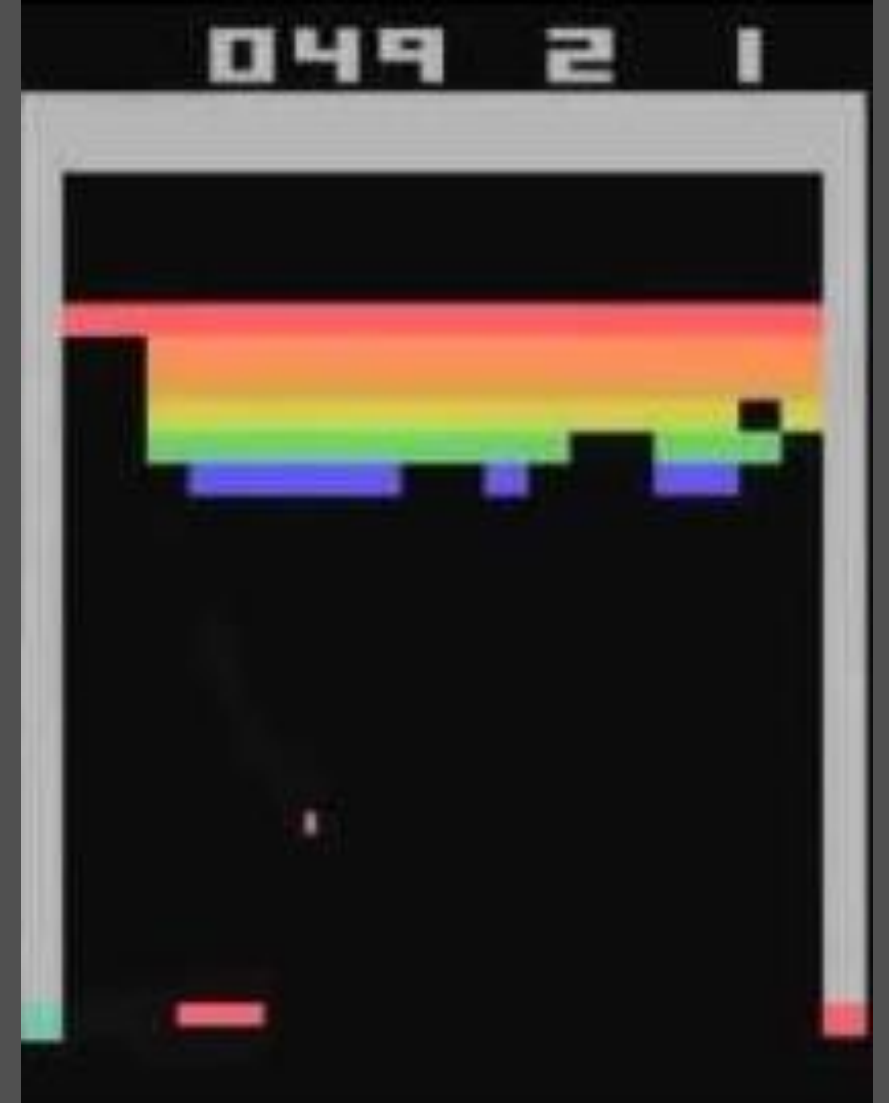
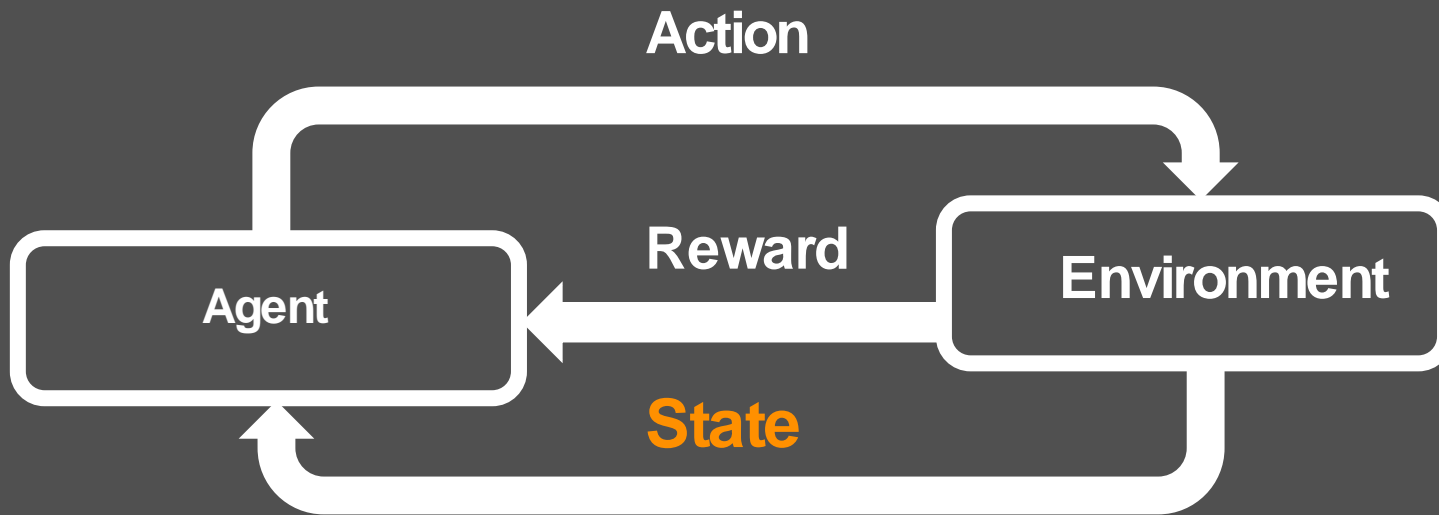




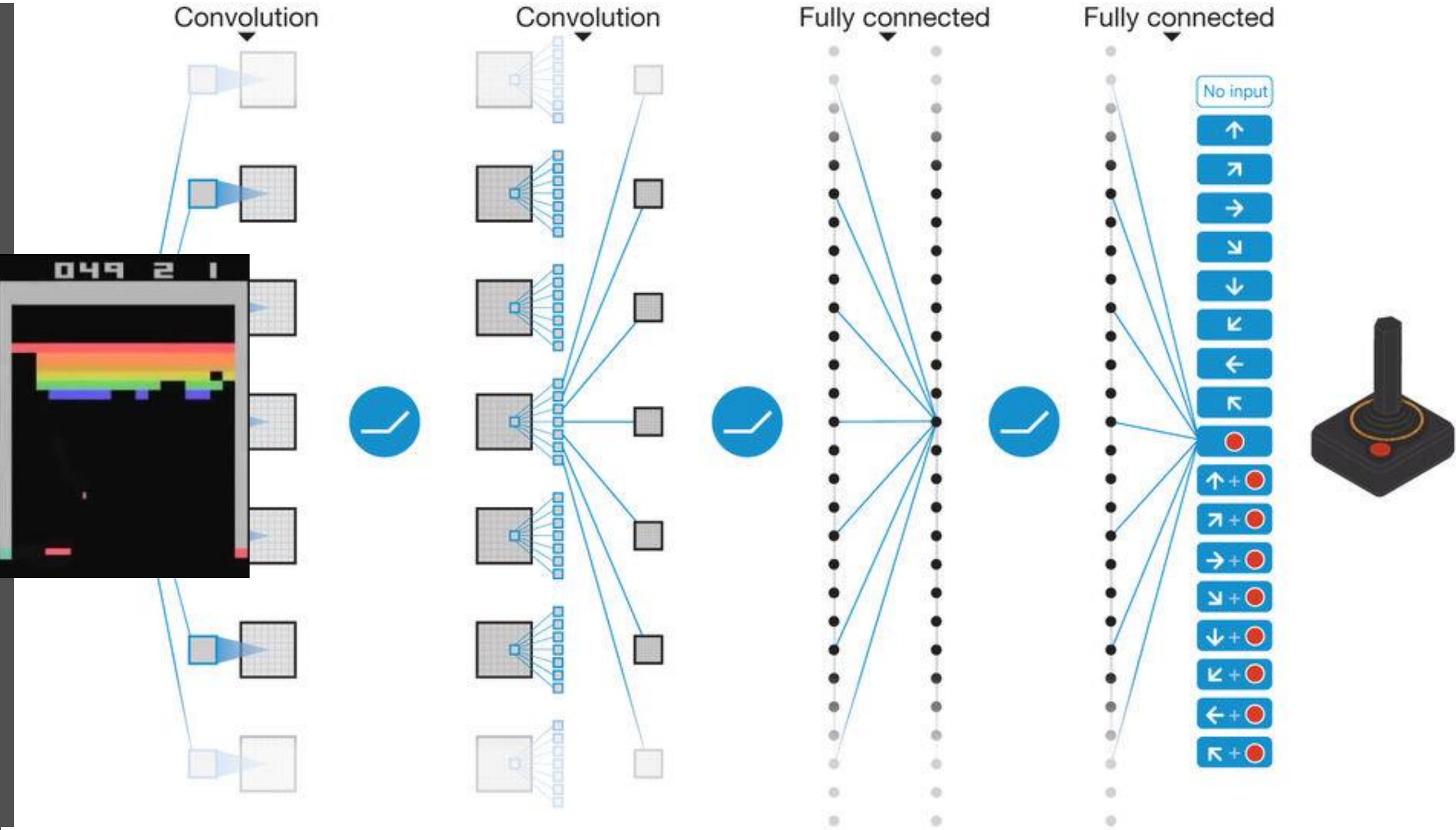


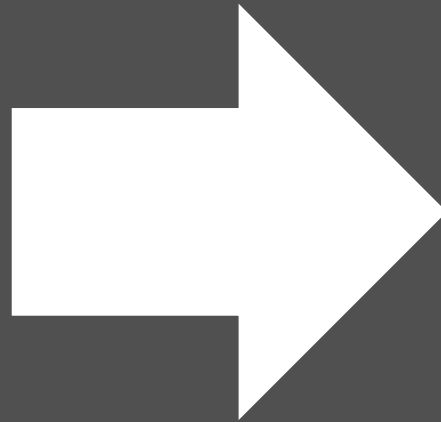
- Apply Reinforcement Learning Strategies
- Optimize the Net
- Try and Error
- Net learns best Actions in certain States



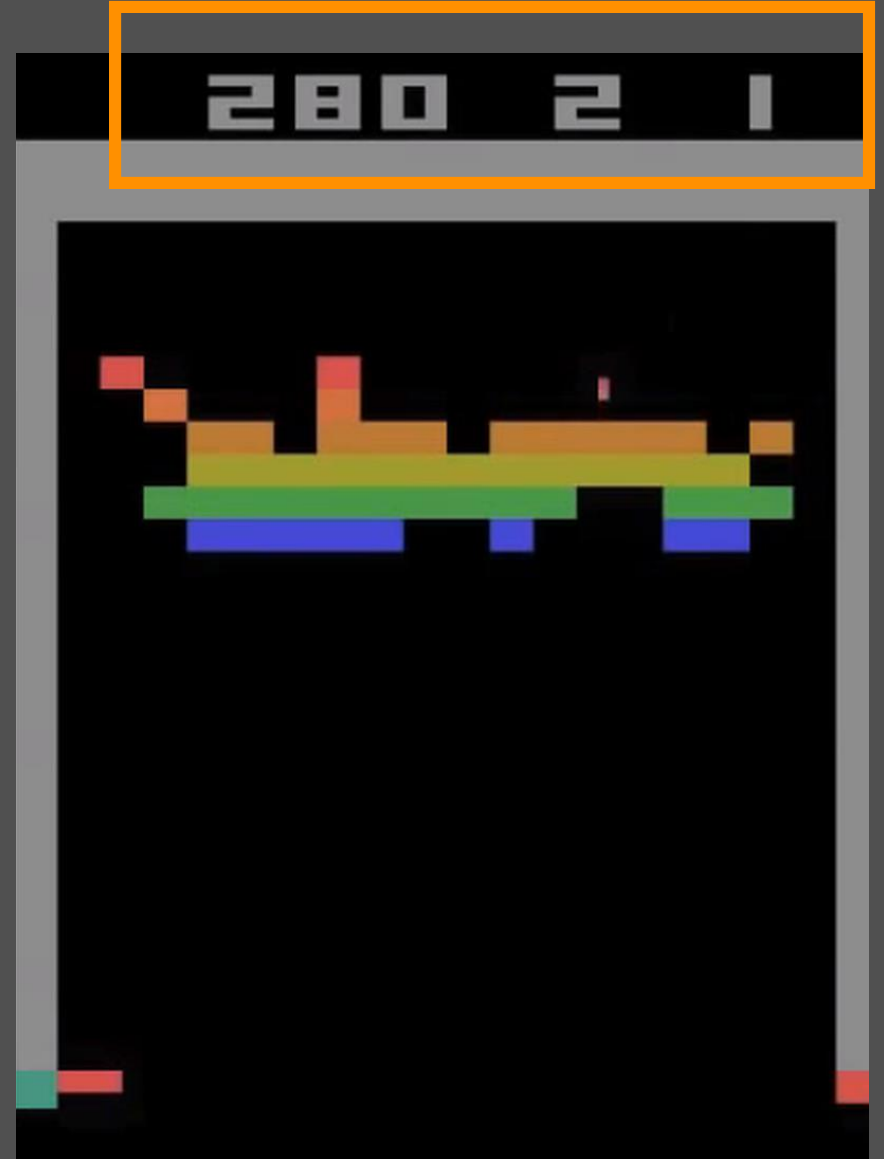
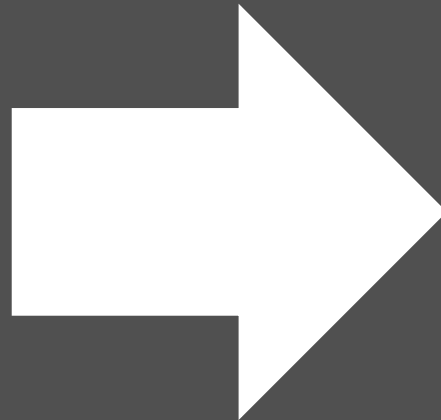


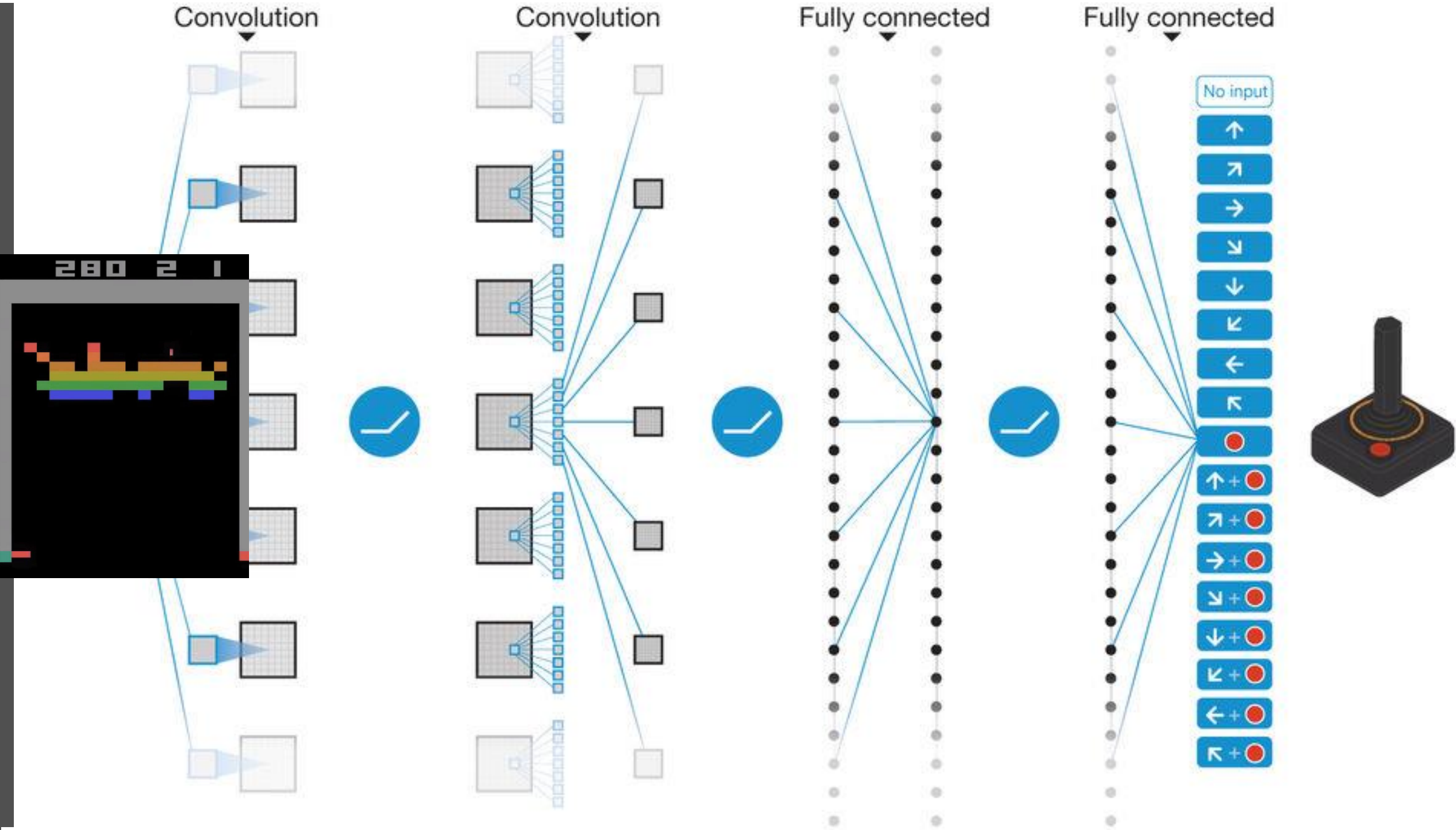


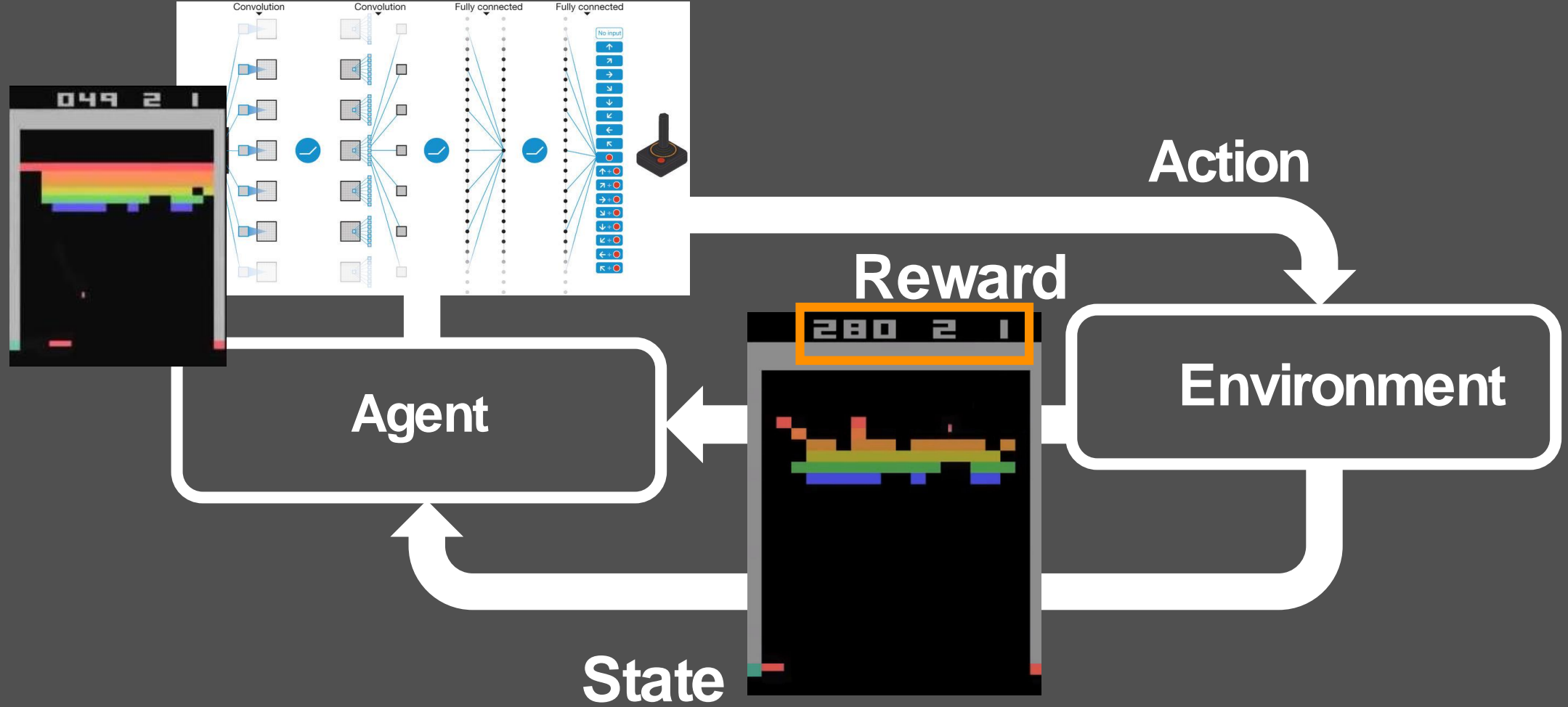




Reward

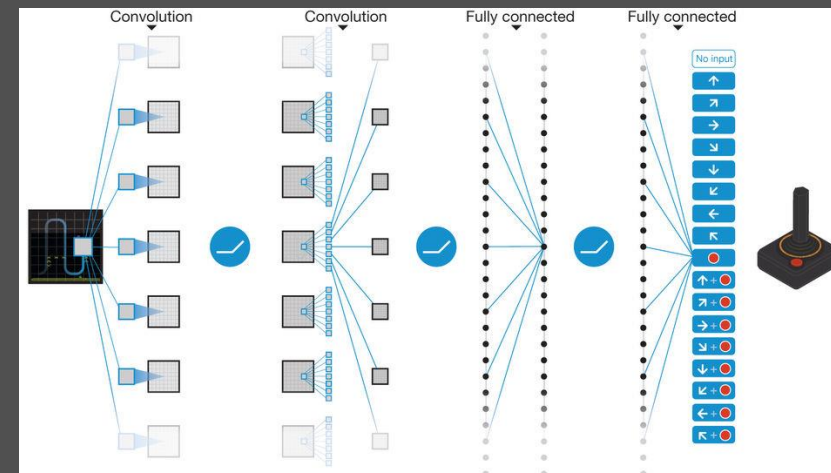






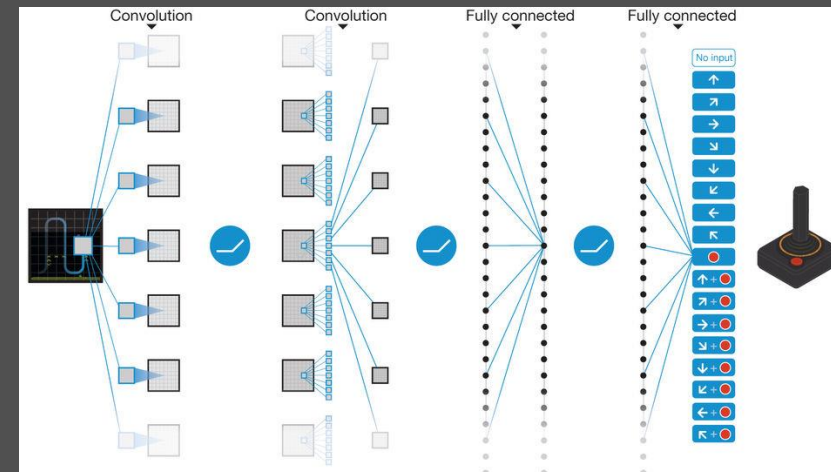


# Deep Q(uality) Network



$$Q = \begin{matrix} & \text{Actions} & & \\ & \begin{matrix} 0 & 1 & 2 \end{matrix} & & \\ \begin{pmatrix} -1 & 1 & 0 \\ -1 & 0 & -1 \\ 10 & 0 & -1 \end{pmatrix} & & \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \text{States} \end{matrix}$$

# Deep Q(uality) Network



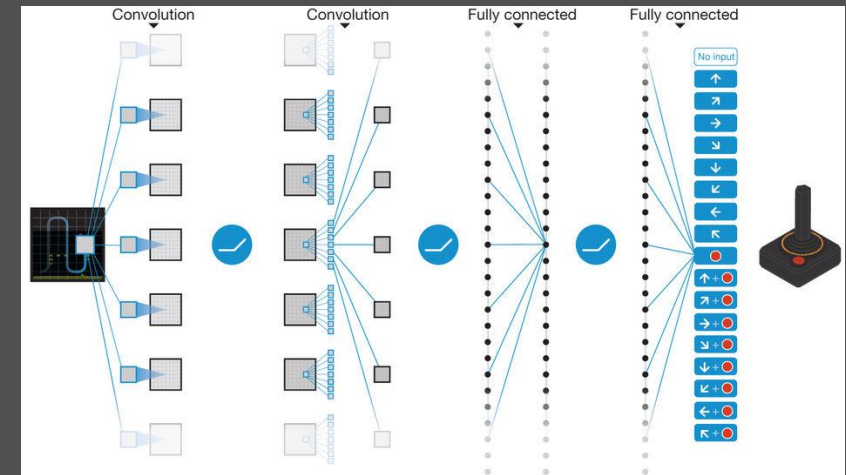
Value of take  
action 0 in  
state 0

$$Q = \begin{matrix} & \begin{matrix} \text{Actions} \\ 0 & 1 & 2 \end{matrix} \\ \begin{pmatrix} -1 & 1 & 0 \\ -1 & 0 & -1 \\ 1 & 0 & -1 \end{pmatrix} & \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} \end{matrix} \begin{matrix} \text{States} \end{matrix}$$

# Deep Q(uality) Network

How good is  
it to take  
action 0 in  
state 0?

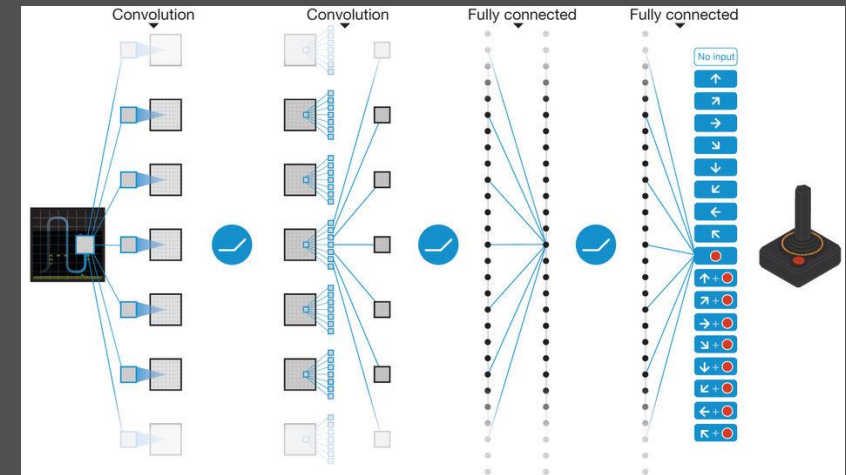
$$Q = \begin{matrix} & \begin{matrix} \text{Actions} \\ 0 & 1 & 2 \end{matrix} \\ \begin{pmatrix} -1 & 1 & 0 \\ -1 & 0 & -1 \\ 1 & 0 & -1 \end{pmatrix} & \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} \end{matrix} \begin{matrix} \leftarrow \\ \text{States} \end{matrix}$$



# Deep Q(uality) Network

Q Table will be  
optimised by  
Neural Net

$$Q = \begin{matrix} & \begin{matrix} \text{Actions} \\ 0 & 1 & 2 \end{matrix} \\ \begin{pmatrix} -1 & 1 & 0 \\ -1 & 0 & -1 \\ 10 & 0 & -1 \end{pmatrix} & \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} \end{matrix} \begin{matrix} \text{States} \end{matrix}$$



## Q-Learning Algorithm:

- **Estimate row in the Q table for the current state (Prediction)**
- **Apply action and get next state + reward**
- **Estimate row in the Q table for next state**
- **Apply Bellman Equation (Target):**
  - $Q(s, a) := r + \gamma * \max_{a'} Q(s', a') = Q(s, a) * \max_{a'} Q(s', a')$
- **Minimize Loss between Target and Prediction:**
  - $L = \frac{1}{2} (r + \gamma * \max_{a'} Q(s', a') - Q(s, a))^2$

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- Apply action and get next state + reward
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  - $Q(s, a) := r + \gamma * \max_{a'} Q(s', a') = Q(s, a) * \max_{a'} Q(s', a')$
- Minimize Loss between **Target** and Prediction:
  - $L = \frac{1}{2} (r + \gamma * \max_{a'} Q(s', a') - Q(s, a))^2$

## Q-Learning:

- Estimate row in the Q table for the current state (**Prediction**)
- Apply action and get next state + reward
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  - $L = \frac{1}{2} (r + \gamma * \max_{a'} Q(s', a') - Q(s, a))^2$

$$Q(s, a) := r + \gamma * \max_{a'} Q(s', a')$$

**Maximum future reward for this state and action is the immediate reward plus maximum future reward for the next state**



- **Minimize Loss between Target and Prediction:**
  - $$L = \frac{1}{2} (r + \gamma * \max_{a'} Q(s', a') - Q(s, a))^2$$
- $r + \gamma * \max_{a'} Q(s', a') \in R^n$
- $Q(s, a) \in R^n$
- **Q-Learning is very similar to regression**
  - Try to predict continuous variables

## Implementation Tricks:

- **Use  $\varepsilon$ –Greedy Policy**
- **Experience Replay**
  - Minibatch training samples from past experience
  - Avoid to get stuck in a local minimum
- **Discount Future Reward with  $\gamma$** 
  - $Q(s, a) := r + \gamma * \max_{a'} Q(s', a')$

- 4 Images form a training sample for the neural net

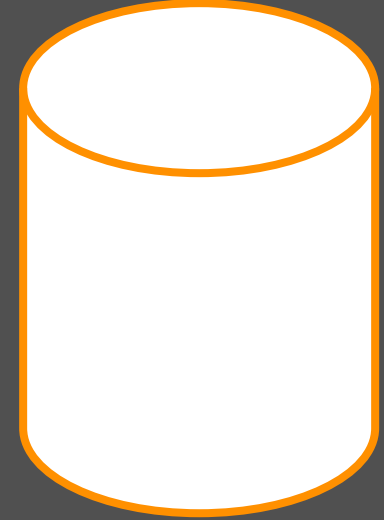


# Will the ball go up or down?



## Your Task:

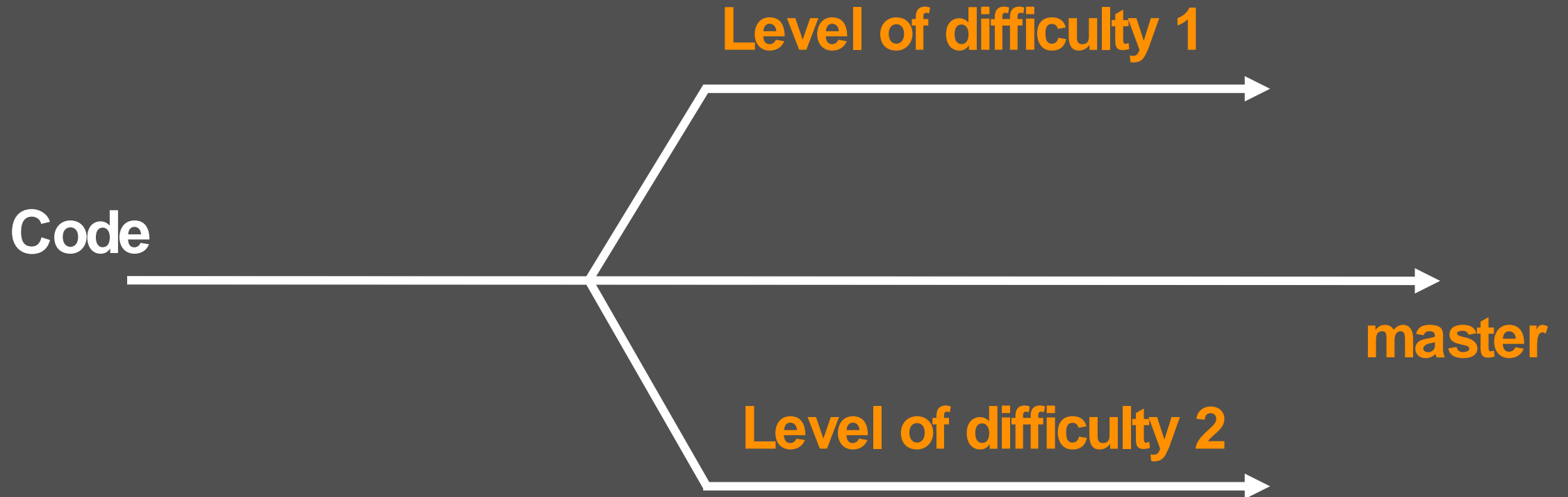
- We give you code with gaps
- You have to **fill in the gaps** with appropriate code
- The **gaps** are marked with a **comment with TODO**
- Gaps can be in all scripts
- Each script has an order of the TODOs, e.g. TODO 1, TODO 2, ...



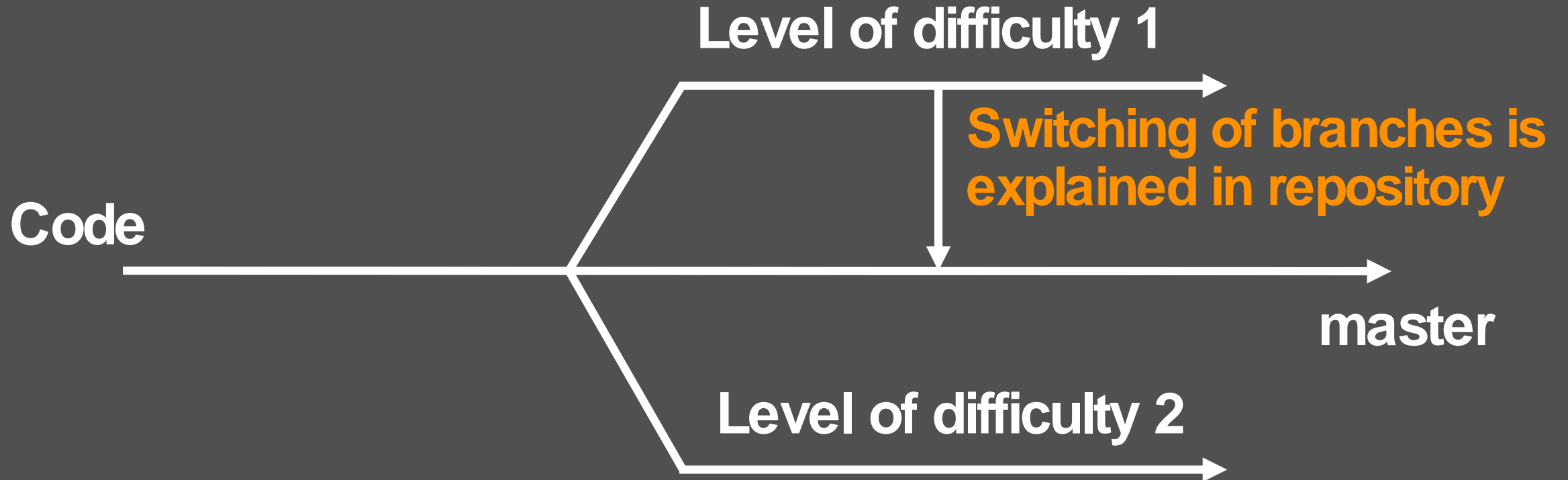
<https://github.com/mati3230/MetaMarathon>

- Code-Repository
- How to setup the working environment
- Tipps and recommendations
- **3 branches** for different levels of difficulties
  - easy, medium, hard
- Solution will be pushed (uploaded) at the end in the **master** branch ;)

## Branching:



## Branching:





## 3 Files:

- **main.py: should be executed**
- **estimator.py: neural net**
- **state\_processor.py: image preprocessing**

**main.py**: should be executed

- Mother-Script
- Management processes (training, playing)
- Execution of steps in the environment
- Optimization of Q-values

## **estimator.py**: neural net

- **Convolutional Neural Net (CNN)**
- **Prediction of Actions**
- **Training of Network**

## **state\_processor.py**: image preprocessing

- Grayscale
- Cropping of relevant area
- Scaling to 84x84

## First Steps:

- Go to the repository:  
<https://github.com/mati3230/MetaMarathon>
- Setup the environment (**use manual**)
- Clone Repository
- Choose a level of difficulty and switch branch
- Search **TODOs** and get familiar with code

<https://github.com/mati3230/MetaMarathon>