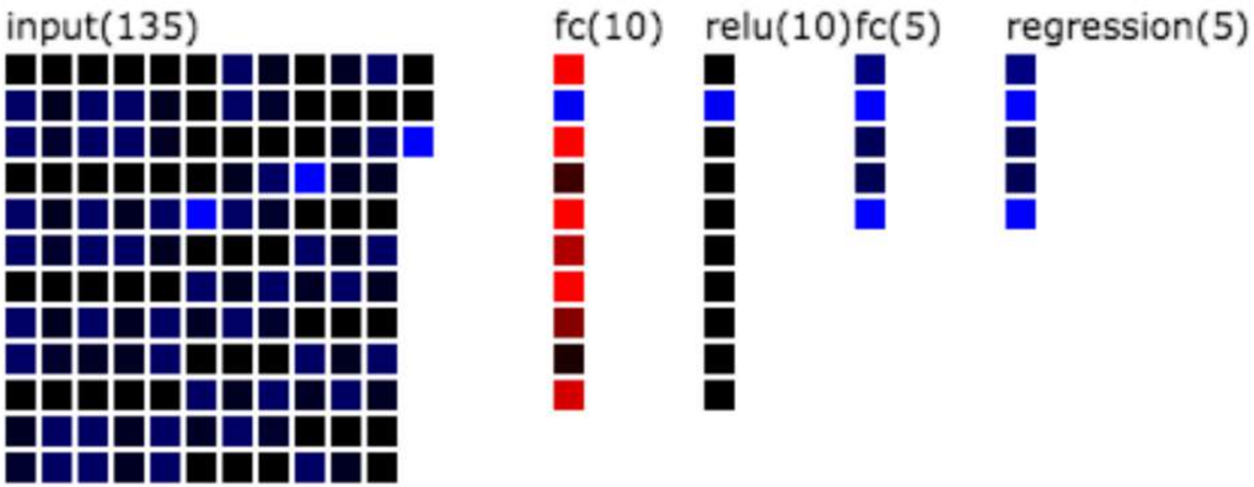
Learning to Move: Deep Reinforcement Learning for Motion Planning

cars.mit.edu



Administrative

- **Website:** cars.mit.edu
- **Contact Email:** deepcars@mit.edu
- **Required:**
  - Create an account on the website.
  - Follow the tutorial for each of the 2 projects.
- **Recommended:**
  - Ask questions
  - Win competition!

Lex Fridman
Instructor

Benedikt Jenik
TA

William Angell
TA

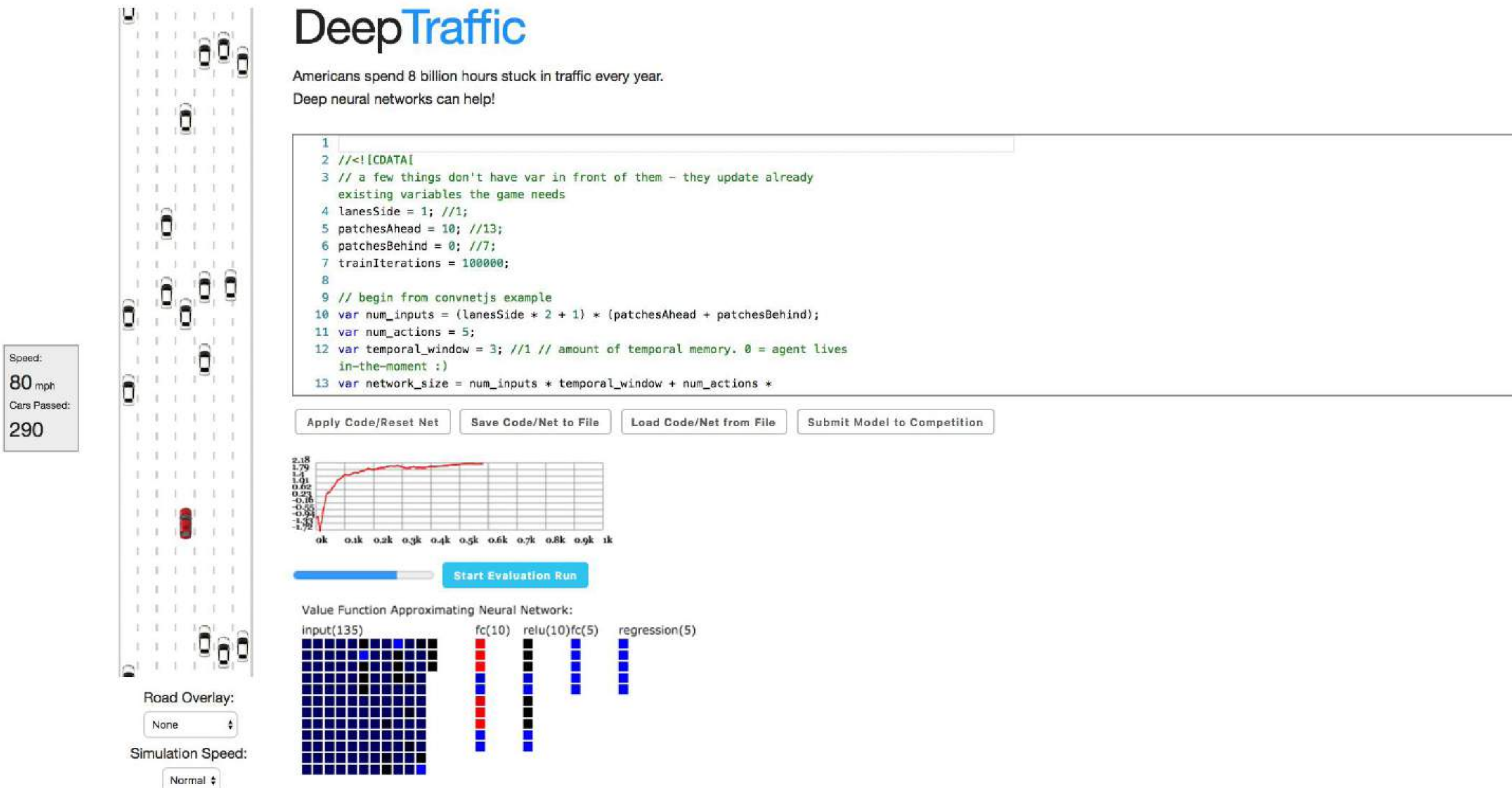
Spencer Dodd
TA

Dan Brown
TA

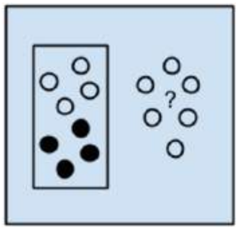
Schedule

Mon, Jan 9	Introduction to Deep Learning and Self Driving Cars
Tue, Jan 10	**Learning to Move:** Reinforcement Learning for Motion Planning
	DeepTraffic: Solving Traffic with Deep Reinforcement Learning
Wed, Jan 11	**Learning to Drive:** End-to-End Learning for the Full Driving Task
	DeepTesla: End-to-End Learning from Human and Autopilot Driving
Thu, Jan 12	**Karl Iagnemma:** From Research to Reality: Testing Self-Driving Cars on Boston Public Roads
Fri, Jan 13	**John Leonard:** Mapping, Localization, and the Challenge of Autonomous Driving
Tue, Jan 17	**Chris Gerdes:** TBD
Wed, Jan 18	**Sertac Karaman:** Past, Present, and Future of Motion Planning in a Complex World
Thu, Jan 19	**Learning to Share:** Driver State Sensing and Shared Autonomy
Fri, Jan 20	**Eric Daimler:** The Future of Artificial Intelligence Research and Development
	Learning to Think: The Road Ahead for Human-Centered Artificial Intelligence

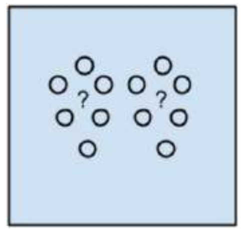
DeepTraffic: Solving Traffic with Deep Reinforcement Learning



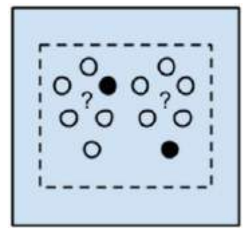
Types of machine learning:



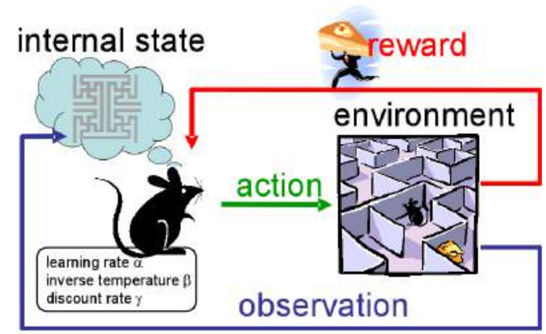
Supervised Learning



Unsupervised Learning

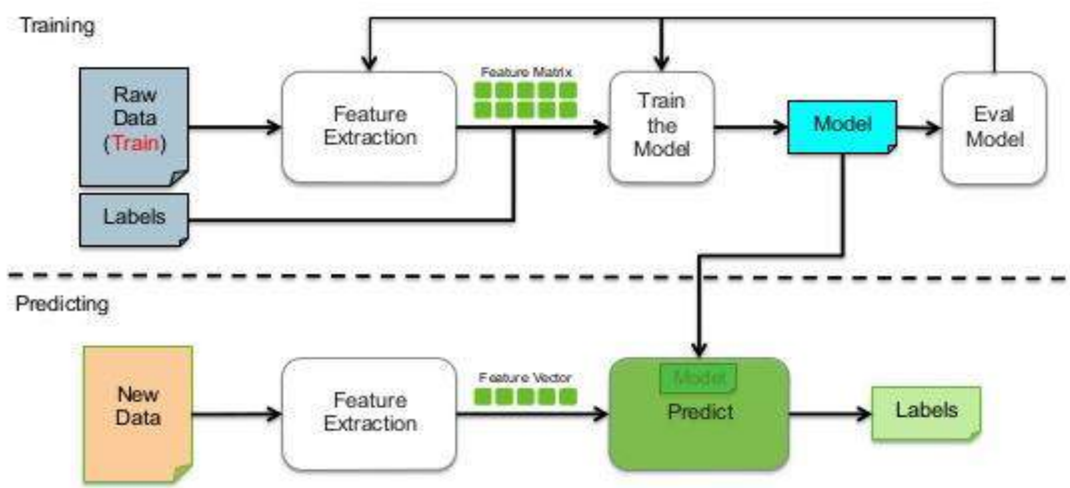


Semi-Supervised Learning



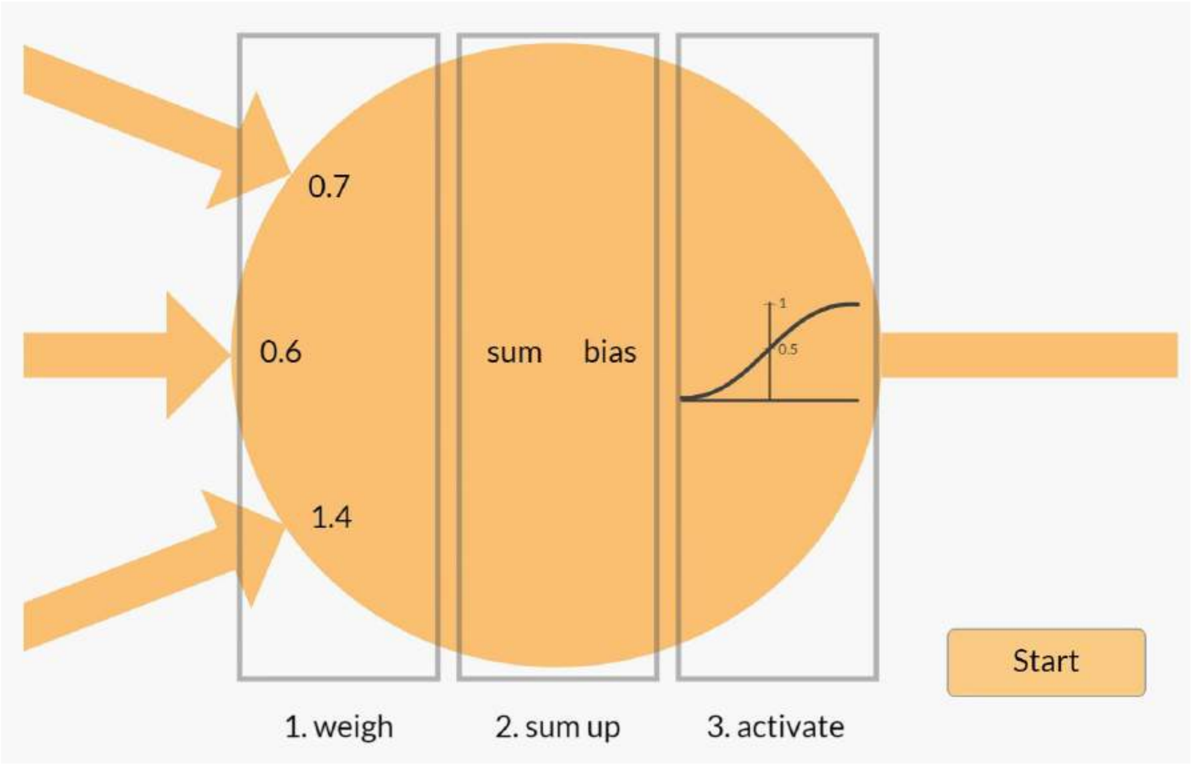
Reinforcement Learning

Standard supervised learning pipeline:



Perceptron: Weighing the Evidence

Evidence



Decisions

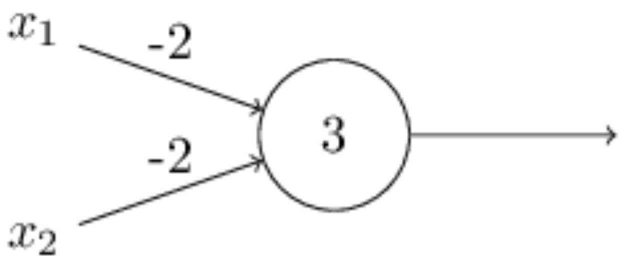
$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

Perceptron: Implement a NAND Gate

Q = NOT(**A** AND **B**)

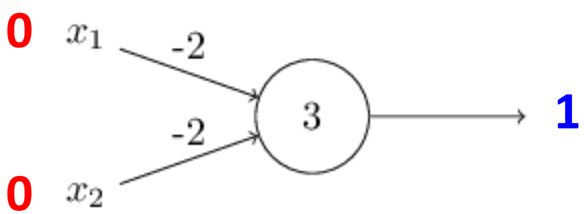
Truth Table

Input A	Input B		Output Q
0	0		1
0	1		1
1	0		1
1	1		0

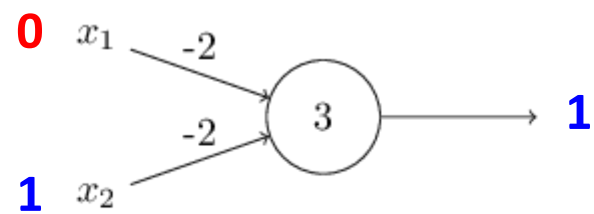


- **Universality:** NAND gates are *functionally complete*, meaning we can build any logical function out of them.

Perceptron: Implement a NAND Gate



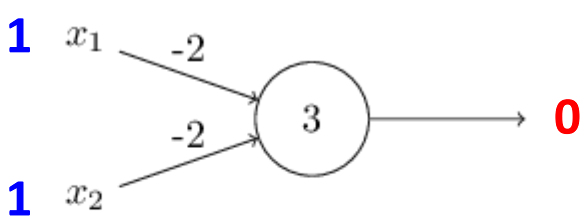
(-2)*0 + (-2)*0+3=3



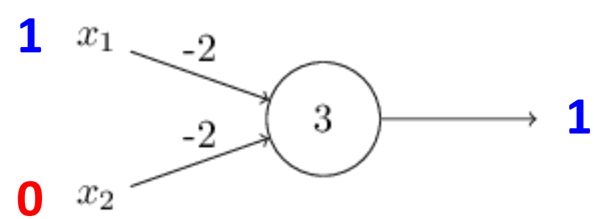
(-2)*0 + (-2)*1+3=1

Truth Table

Input A	Input B		Output Q
0	0		1
0	1		1
1	0		1
1	1		0



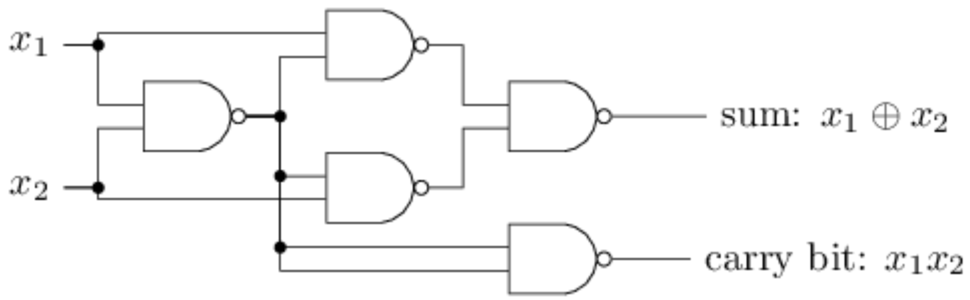
(-2)*1 + (-2)*1+3=-1



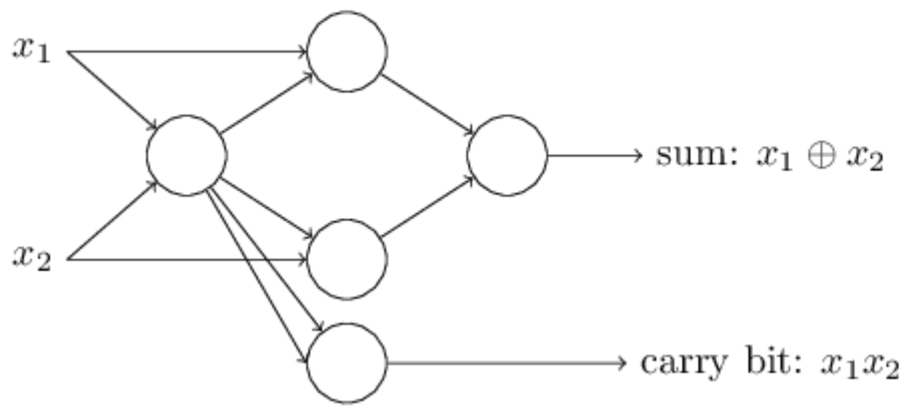
(-2)*1 + (-2)*0+3=1

Perceptron > NAND Gate

Both circuits can represent arbitrary logical functions:

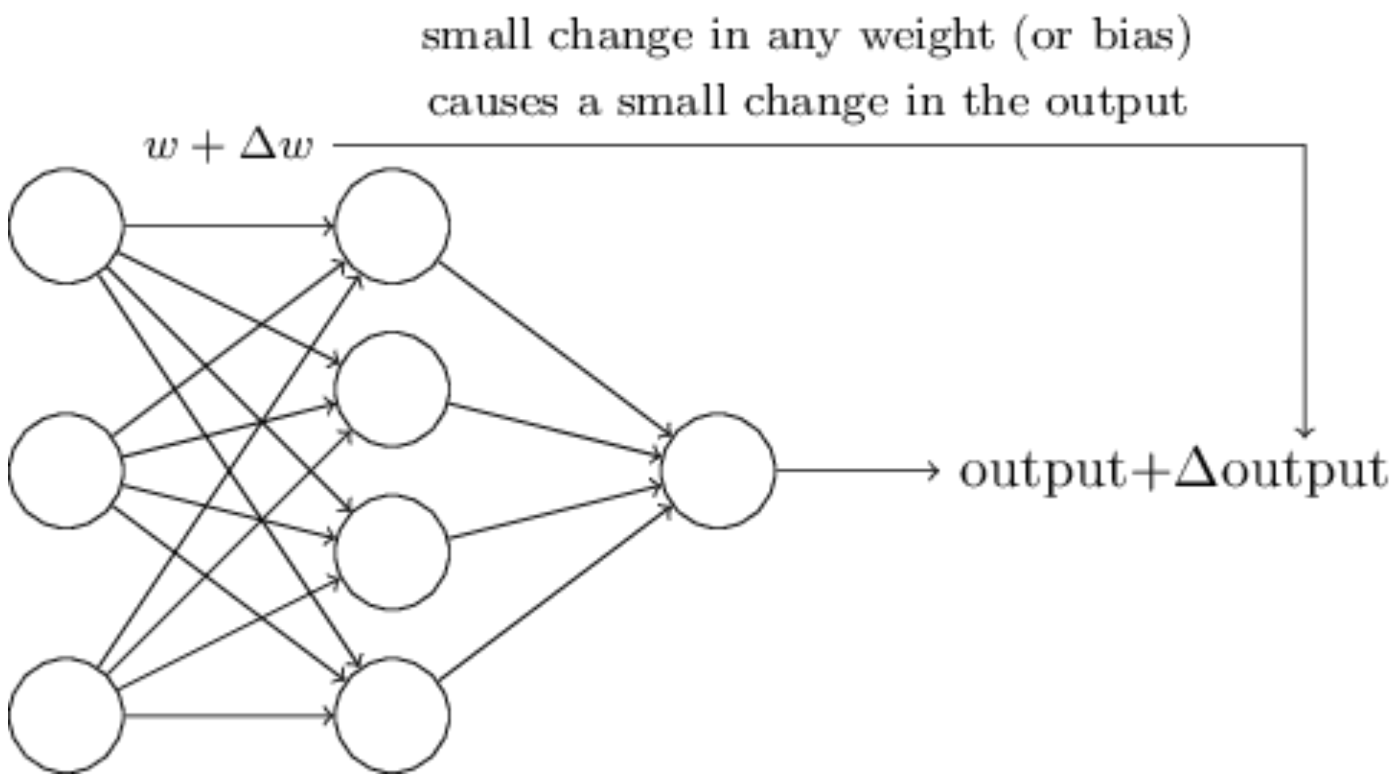


But “perceptron circuits” can learn…



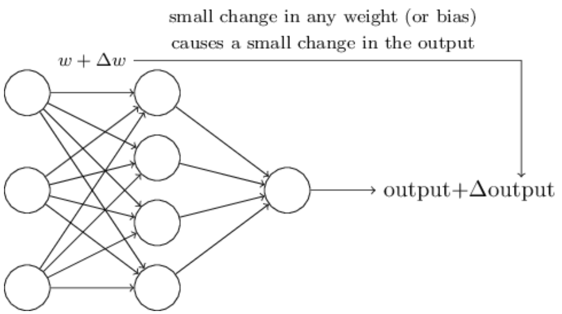
The Process of Learning:

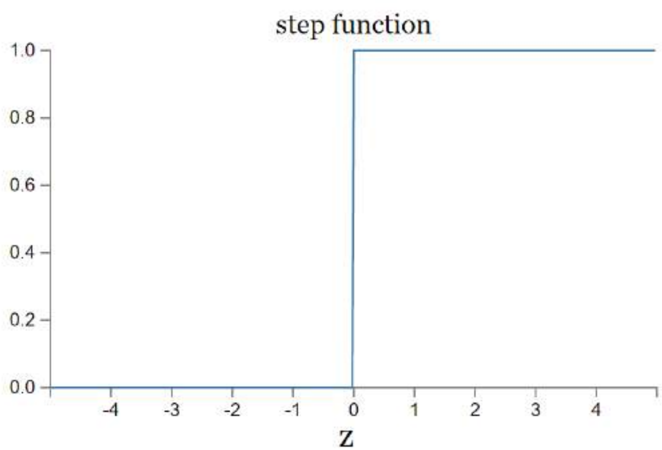
Small Change in Weights → Small Change in Output



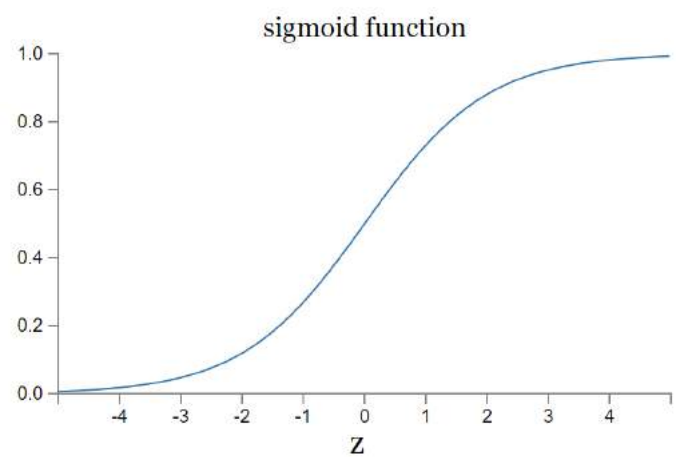
The Process of Learning:
Small Change in Weights → Small Change in Output

This requires a “smoothness” →





Perceptron

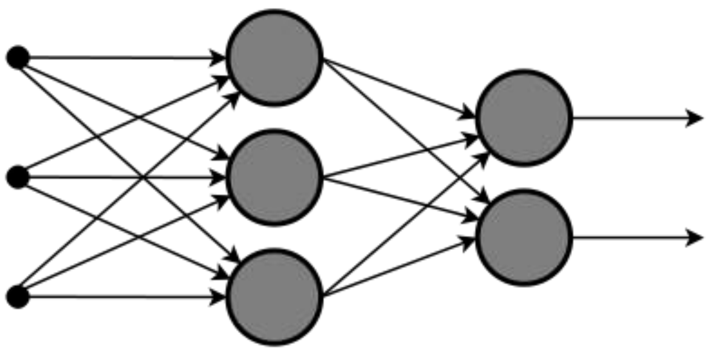


Neuron

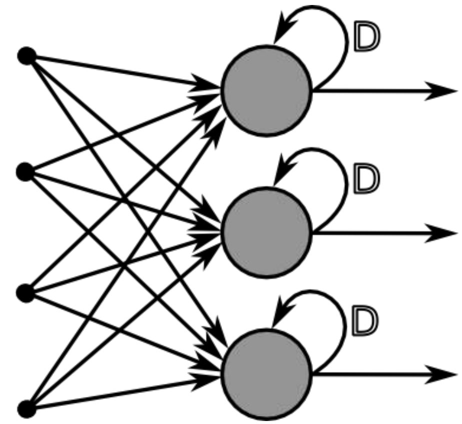
Smoothness of activation function means: **the Δoutput is a linear function of the Δweights and Δbias**

Learning is the process of gradually adjusting the weights to achieve any gradual change in the output.

Combining Neurons into Layers



Feed Forward Neural Network

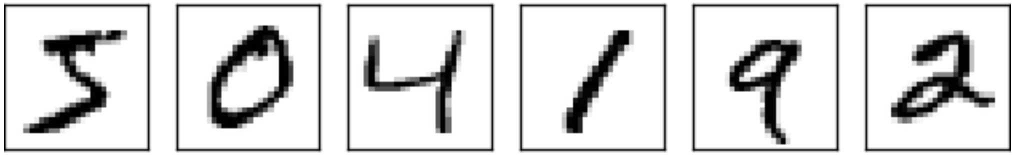


Recurrent Neural Network

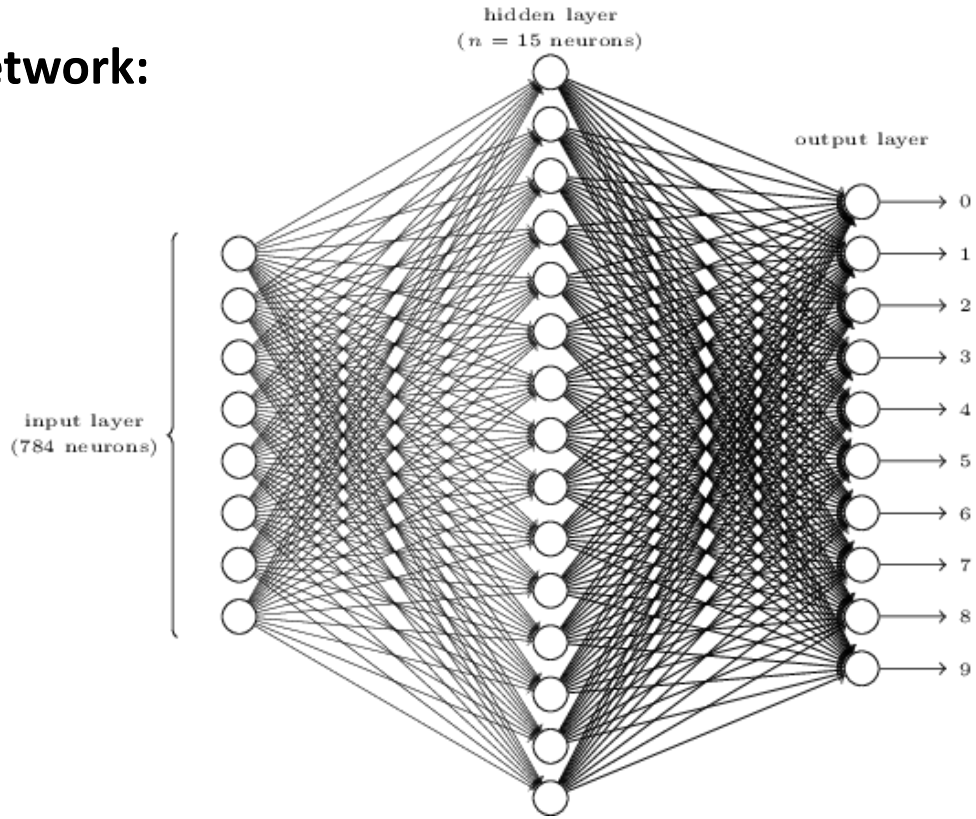
- Have state memory
- Are hard to train

Task: Classify and Image of a Number

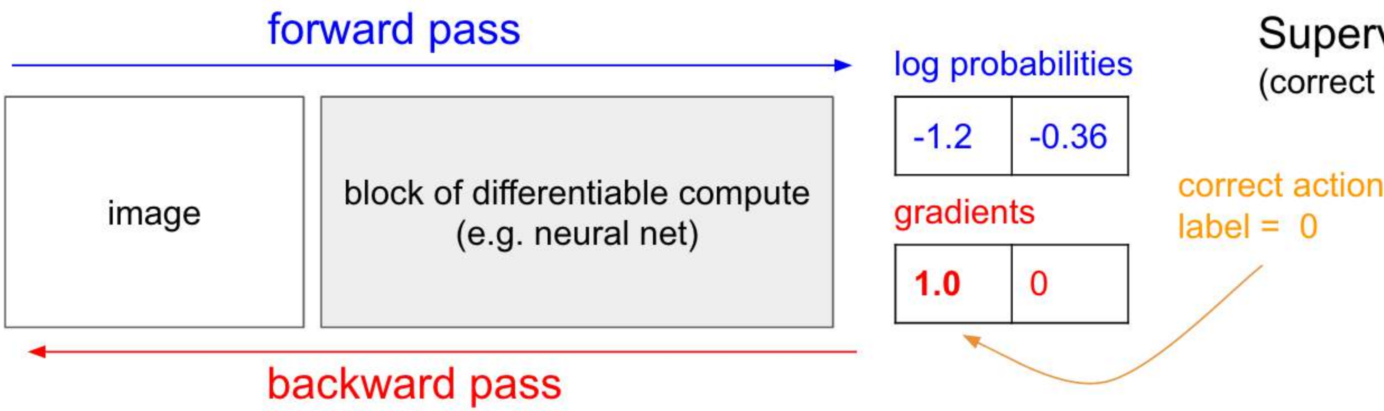
Input:
(28x28)



Network:



Task: Classify and Image of a Number



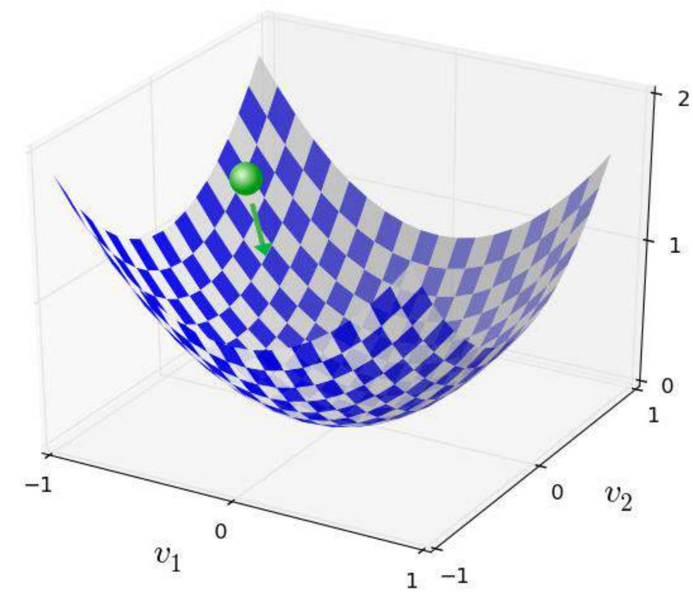
Supervised Learning
(correct label is provided)

Ground truth for "6":

$$y(x) = (0, 0, 0, 0, 0, 0, 1, 0, 0, 0)^T$$

"Loss" function:

$$C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$



Philosophical Motivation for Reinforcement Learning

Takeaway from Supervised Learning:

Neural networks are great at memorization and not (yet) great at reasoning.

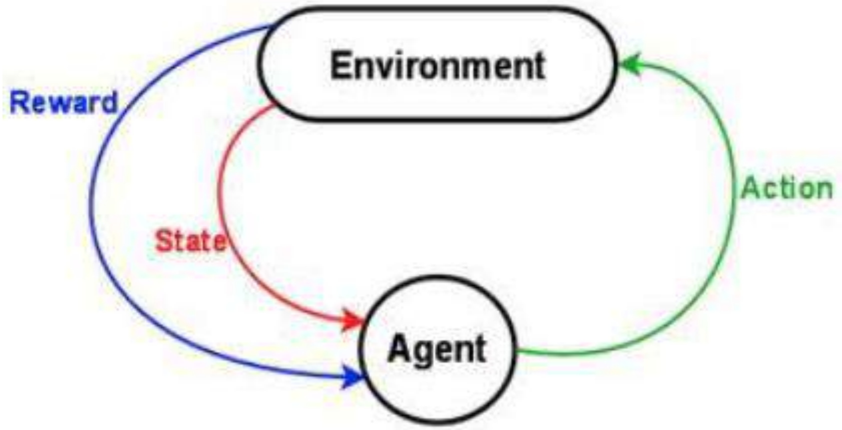
Hope for Reinforcement Learning:

Brute-force propagation of outcomes to knowledge about states and actions. This is a kind of brute-force "reasoning".

Agent and Environment

- At each step the agent:
  - Executes action
  - Receives observation (new state)
  - Receives reward

- The environment:
  - Receives action
  - Emits observation (new state)
  - Emits reward

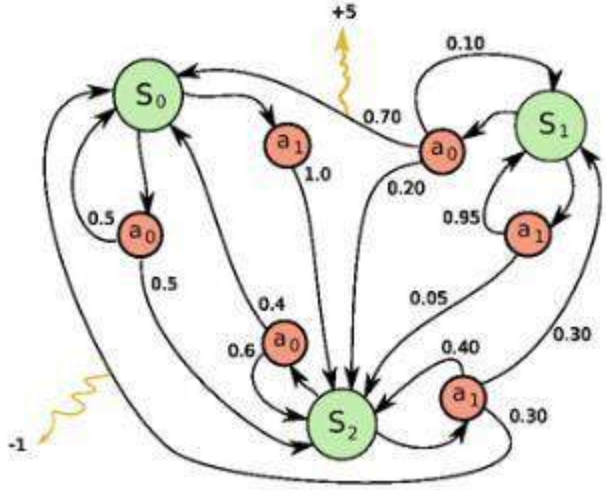


Reinforcement Learning

Reinforcement learning is a general-purpose framework for decision-making:

- An agent operates in an environment: **Atari Breakout**
- An agent has the capacity to **act**
- Each action influences the agent's **future state**
- Success is measured by a **reward** signal
- **Goal** is to select actions to maximize future reward

Markov Decision Process



$$s_0, a_0, r_1, s_1, a_1, r_2, \ldots, s_{n-1}, a_{n-1}, r_n, s_n$$

state

action

reward

Terminal state

Major Components of an RL Agent

An RL agent may include one or more of these components:

- **Policy:** agent's behavior function
- **Value function:** how good is each state and/or action
- **Model:** agent's representation of the environment

$$s_0, a_0, r_1, s_1, a_1, r_2, \ldots, s_{n-1}, a_{n-1}, r_n, s_n$$

state

action

reward

Terminal state

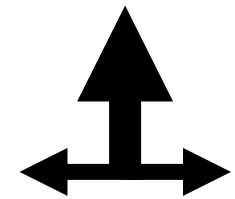
Robot in a Room

			+1
			-1
START			

actions: UP, DOWN, LEFT, RIGHT

UP

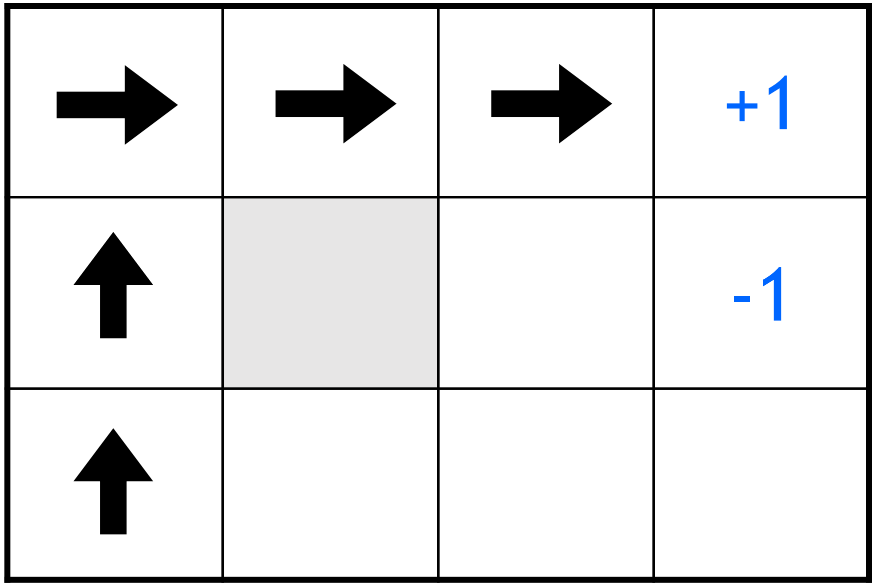
80%	move UP
10%	move LEFT
10%	move RIGHT



- reward +1 at [4,3], -1 at [4,2]
- reward -0.04 for each step

- what's the strategy to achieve max reward?
- what if the actions were deterministic?

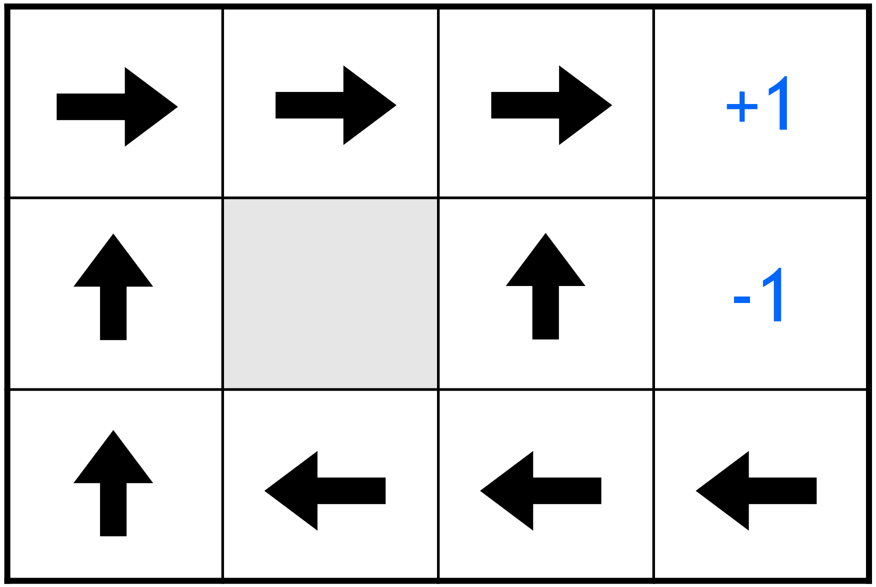
Is this a solution?



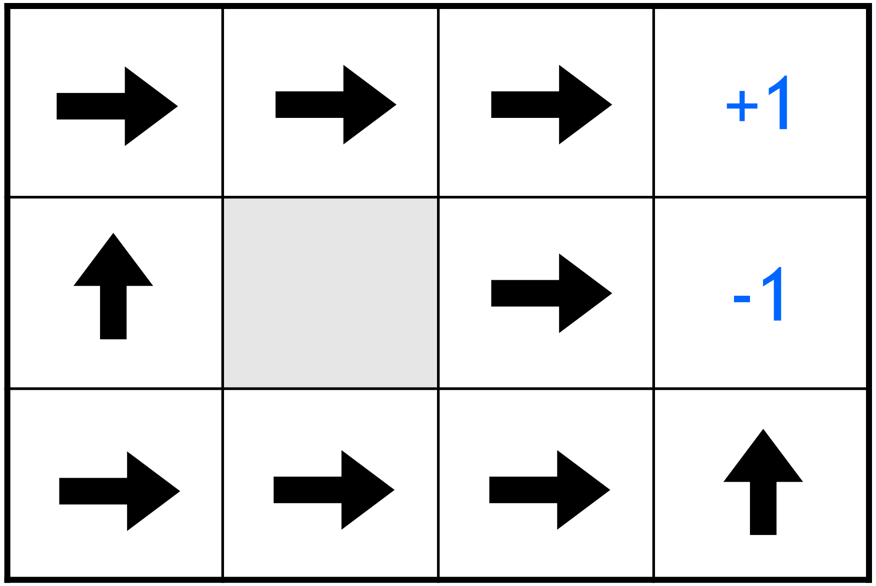
- only if actions deterministic
  - not in this case (actions are stochastic)

- solution/policy
  - mapping from each state to an action

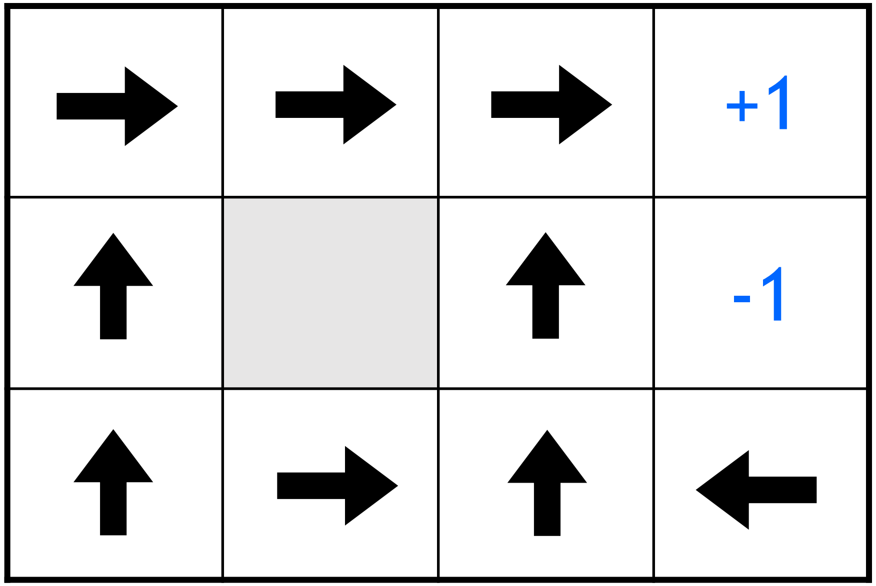
Optimal policy



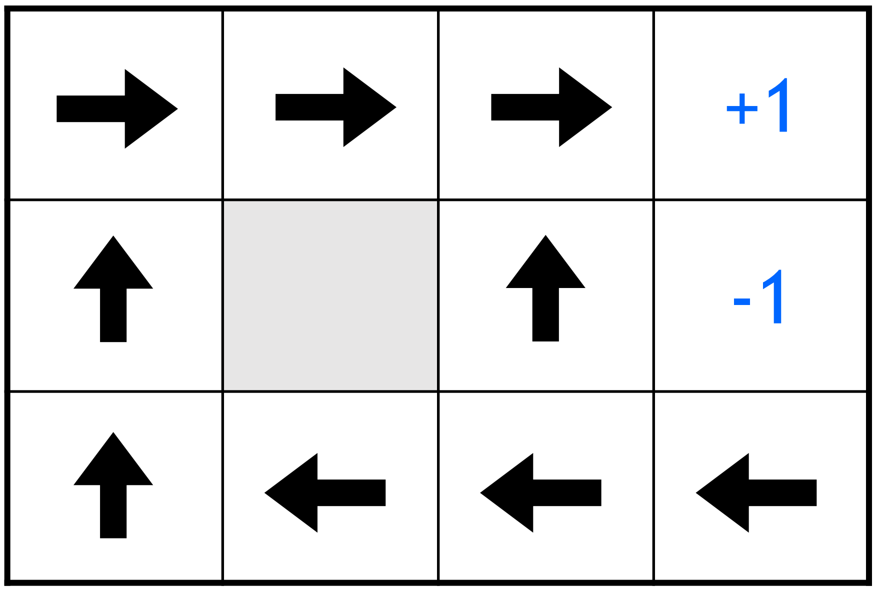
Reward for each step -2



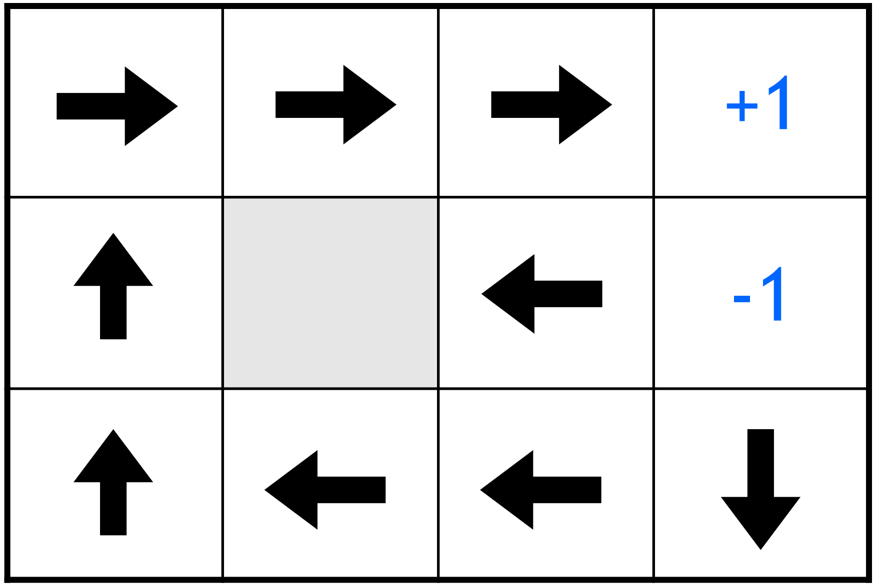
Reward for each step: -0.1



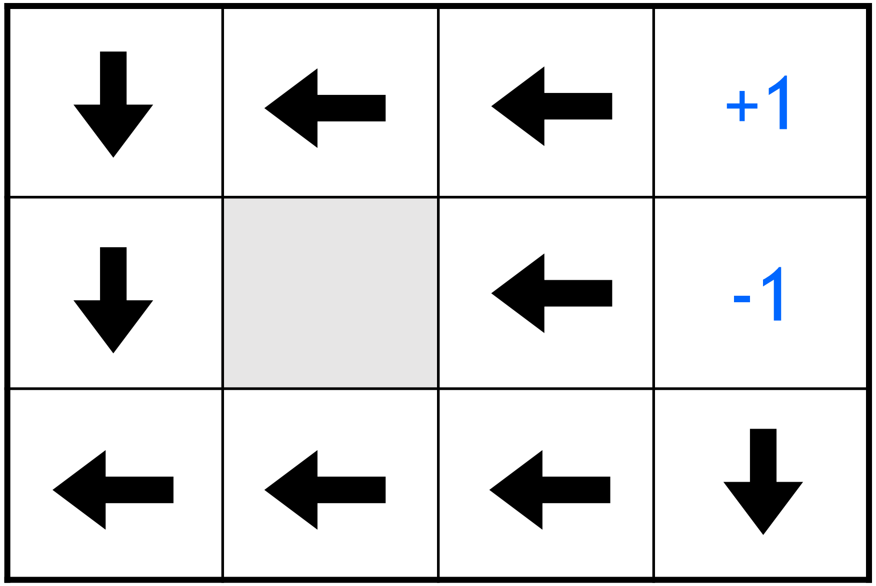
Reward for each step: -0.04



Reward for each step: -0.01



Reward for each step: +0.01



Value Function

- Future reward $R = r_1 + r_2 + r_3 + \cdots + r_n$

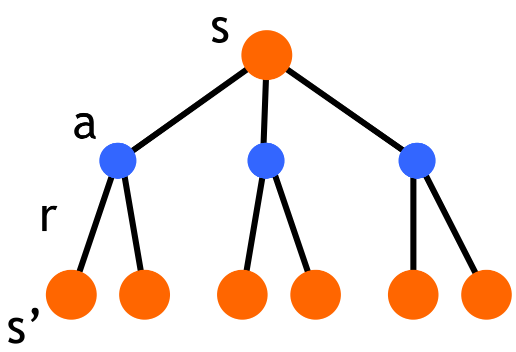
$$R_t = r_t + r_{t+1} + r_{t+2} + \cdots + r_n$$

- Discounted future reward (environment is stochastic)

$$\begin{aligned} R_t &= r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots + \gamma^{n-t} r_n \\ &= r_t + \gamma(r_{t+1} + \gamma(r_{t+2} + \cdots)) \\ &= r_t + \gamma R_{t+1} \end{aligned}$$

- A good strategy for an agent would be to always choose an action that maximizes the (discounted) future reward

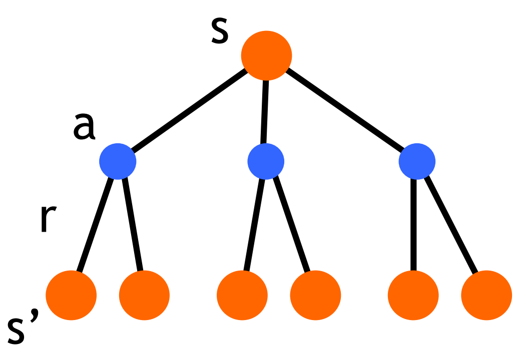
Q-Learning



- State value function: $V^\pi(s)$
  - Expected return when starting in *s* and following π
- State-action value function: $Q^\pi(s,a)$
  - Expected return when starting in *s*, performing *a,* and following π
- Useful for finding the optimal policy
  - Can estimate from experience (Monte Carlo)
  - Pick the best action using $Q^\pi(s,a)$
- Q-learning: off-policy
  - Use any policy to estimate Q that maximizes future reward: $Q(s_t, a_t) = max\ R_{t+1}$
  - Q directly approximates Q* (Bellman optimality equation)
  - Independent of the policy being followed
  - Only requirement: keep updating each (s,a) pair

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha \left(R_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t) \right)$$

Q-Learning



Learning Rate

Discount Factor

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha \left(R_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t) \right)$$

New State

Old State

Reward

Exploration vs Exploitation

- Key ingredient of Reinforcement Learning
- Deterministic/greedy policy won't explore all actions
  - Don't know anything about the environment at the beginning
  - Need to try all actions to find the optimal one
- Maintain exploration
  - Use *soft* policies instead: $\pi(s,a)>0$ (for all s,a)
- ε-greedy policy
  - With probability 1-ε perform the optimal/greedy action
  - With probability ε perform a random action

  - Will keep exploring the environment
  - Slowly move it towards greedy policy: ε -> 0

Q-Learning: Value Iteration

Learning Rate

Discount Factor

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha \left(R_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t) \right)$$

New State

Old State

Reward

```
initialize Q[num_states,num_actions] arbitrarily
observe initial state s
repeat
      select and carry out an action a
      observe reward r and new state s'
      Q[s,a] = Q[s,a] + α(r + γ max_a' Q[s',a'] - Q[s,a])
      s = s'
until terminated
```

Q-Learning: Representation Matters

- In practice, Value Iteration is impractical
  - Very limited states/actions
  - Cannot generalize to unobserved states

- Think about the **Breakout** game
  - State: screen pixels
    - Image size: $\mathbf{84 \times 84}$ (resized)
    - Consecutive **4** images
    - Grayscale with **256** gray levels

$\mathbf{256^{84\times84\times4}}$ rows in the Q-table!

References: [83, 84]

Philosophical Motivation for **Deep** Reinforcement Learning

Takeaway from Supervised Learning:

Neural networks are great at memorization and not (yet) great at reasoning.

Hope for Reinforcement Learning:

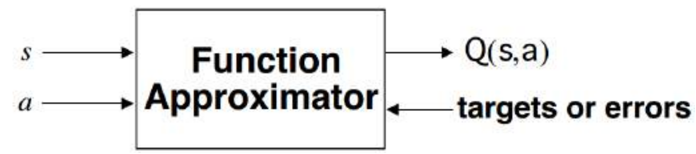
Brute-force propagation of outcomes to knowledge about states and actions. This is a kind of brute-force “reasoning”.

Hope for Deep Learning + Reinforcement Learning:

General purpose artificial intelligence through efficient generalizable learning of the optimal thing to do given a formalized set of actions and states (possibly huge).

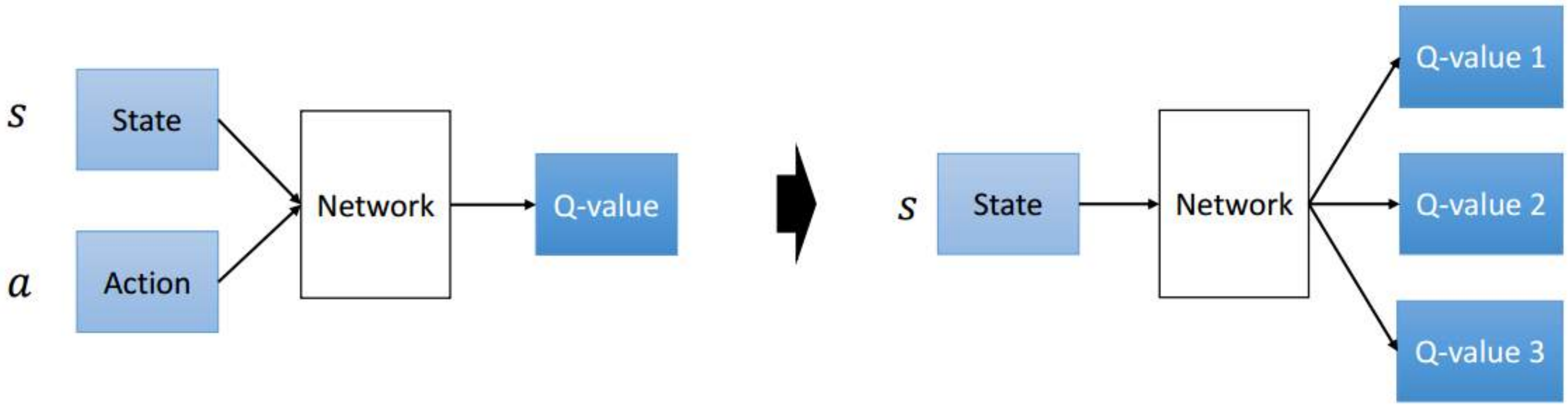
Deep Q-Learning

Use a function (with parameters) to approximate the Q-function

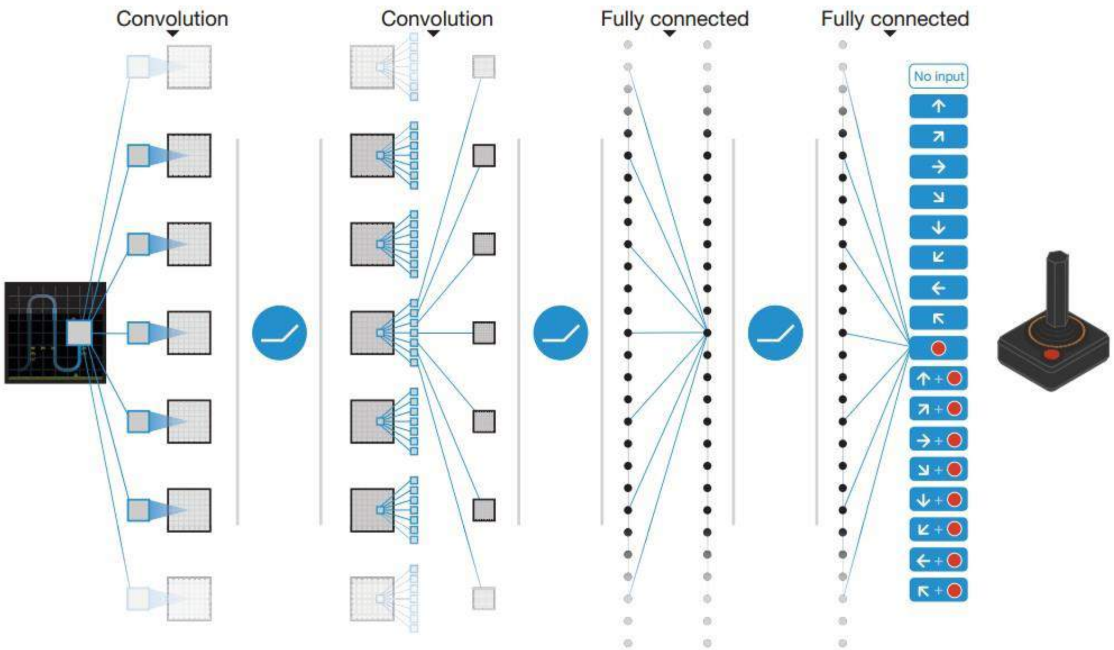


- Linear
- Non-linear: **Q-Network**

$$Q(s, a; \boldsymbol{\theta}) \approx Q^*(s, a)$$



Deep Q-Network: Atari



Layer	Input	Filter size	Stride	Num filters	Activation	Output
conv1	84x84x4	8x8	4	32	ReLU	20x20x32
conv2	20x20x32	4x4	2	64	ReLU	9x9x64
conv3	9x9x64	3x3	1	64	ReLU	7x7x64
fc4	7x7x64			512	ReLU	512
fc5	512			18	Linear	18

Mnih et al. "Playing atari with deep reinforcement learning." 2013.

Deep Q-Network Training

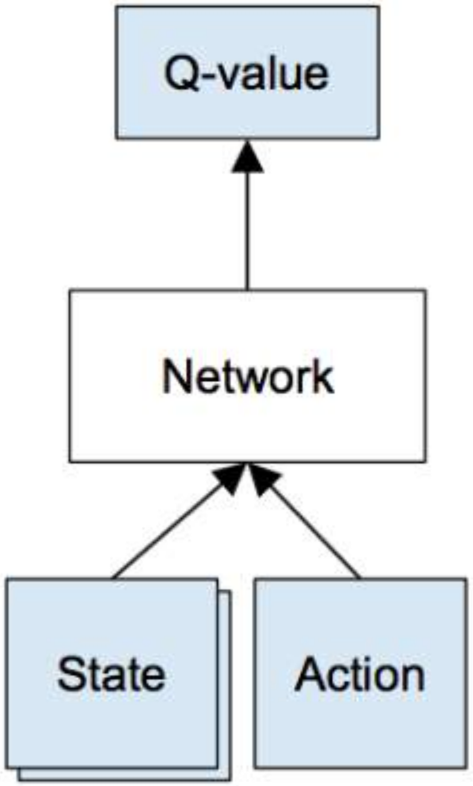
- Bellman Equation:

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

- Loss function (squared error):

$$L = \mathbb{E}[(\underbrace{r + \gamma max_{a'} Q(s', a')}_{\textbf{target}} - Q(s,a))^2]$$

Deep Q-Network Training



Given a transition < *s, a, r, s'* >, the Q-table update rule in the previous algorithm must be replaced with the following:

- Do a feedforward pass for the current state *s* to get **predicted Q-values for all actions**
- Do a feedforward pass for the next state *s'* and calculate maximum overall network outputs ***max*** $\boldsymbol{_{a'}}$ ***Q(s', a')***
- Set Q-value target for action to ***r + γmax*** $\boldsymbol{_{a'}}$ ***Q(s', a')*** (use the max calculated in step 2).
  - For all other actions, set the Q-value target to the same as originally returned from step 1, making the error 0 for those outputs.
- Update the weights using backpropagation.

Exploration vs Exploitation

- Key ingredient of Reinforcement Learning

- Deterministic/greedy policy won't explore all actions
  - Don't know anything about the environment at the beginning
  - Need to try all actions to find the optimal one

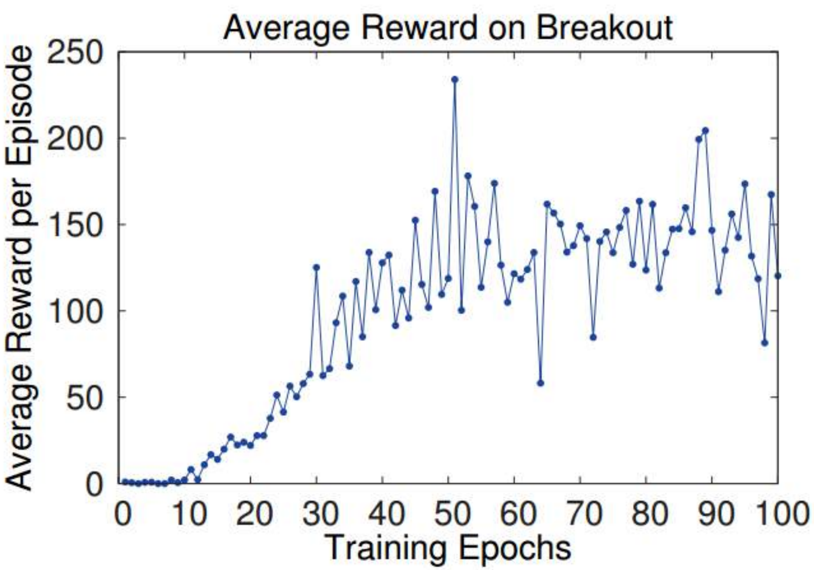
- Maintain exploration
  - Use *soft* policies instead: $\pi(s,a)>0$ (for all s,a)

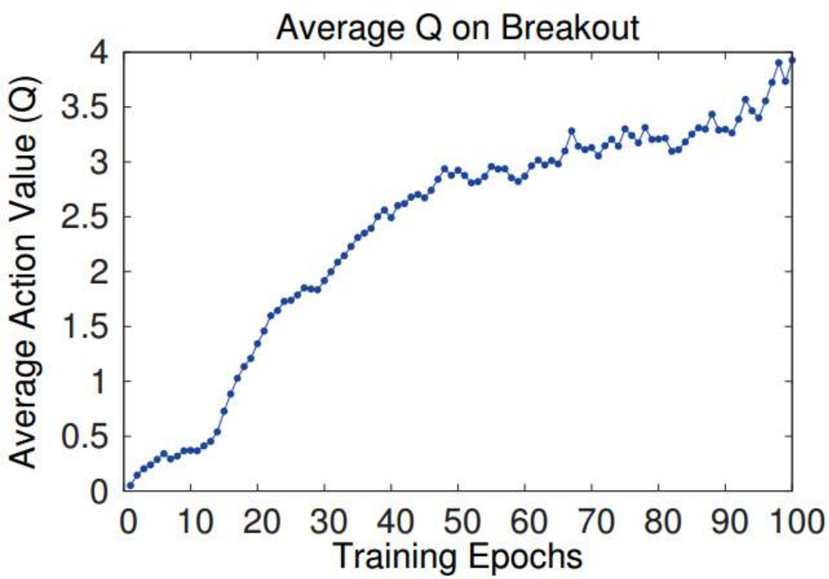
- ε-greedy policy
  - With probability 1-ε perform the optimal/greedy action
  - With probability ε perform a random action

  - Will keep exploring the environment
  - Slowly move it towards greedy policy: ε -> 0

Atari Breakout

- A few tricks needed, most importantly: experience replay

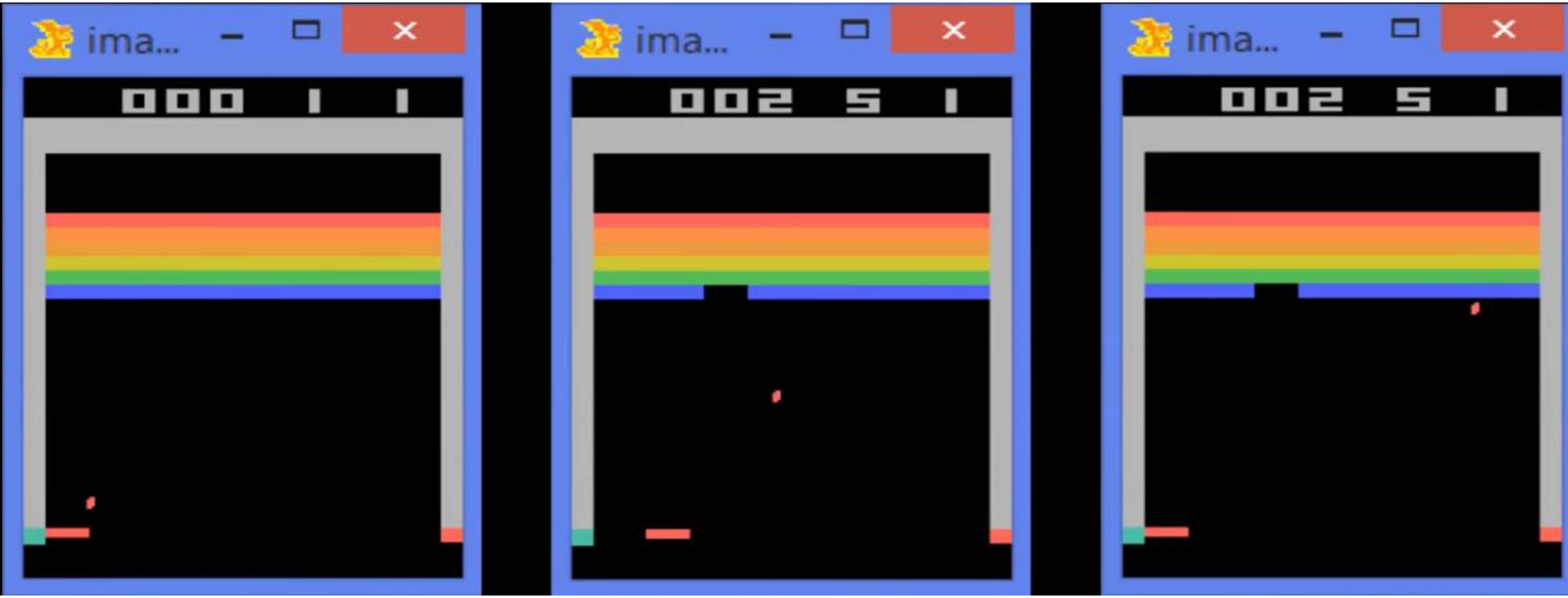




Deep Q-Learning Algorithm

```
initialize replay memory D
initialize action-value function Q with random weights
observe initial state s
repeat
      select an action a
            with probability ε select a random action
            otherwise select a = argmax_a′ Q(s,a′)
      carry out action a
      observe reward r and new state s′
      store experience <s, a, r, s′> in replay memory D

      sample random transitions <ss, aa, rr, ss′> from replay memory D
      calculate target for each minibatch transition
            if ss′ is terminal state then tt = rr
            otherwise tt = rr + γmax_a′ Q(ss′, aa′)
      train the Q network using (tt - Q(ss, aa))^2 as loss

      s = s'
until terminated
```

Atari Breakout

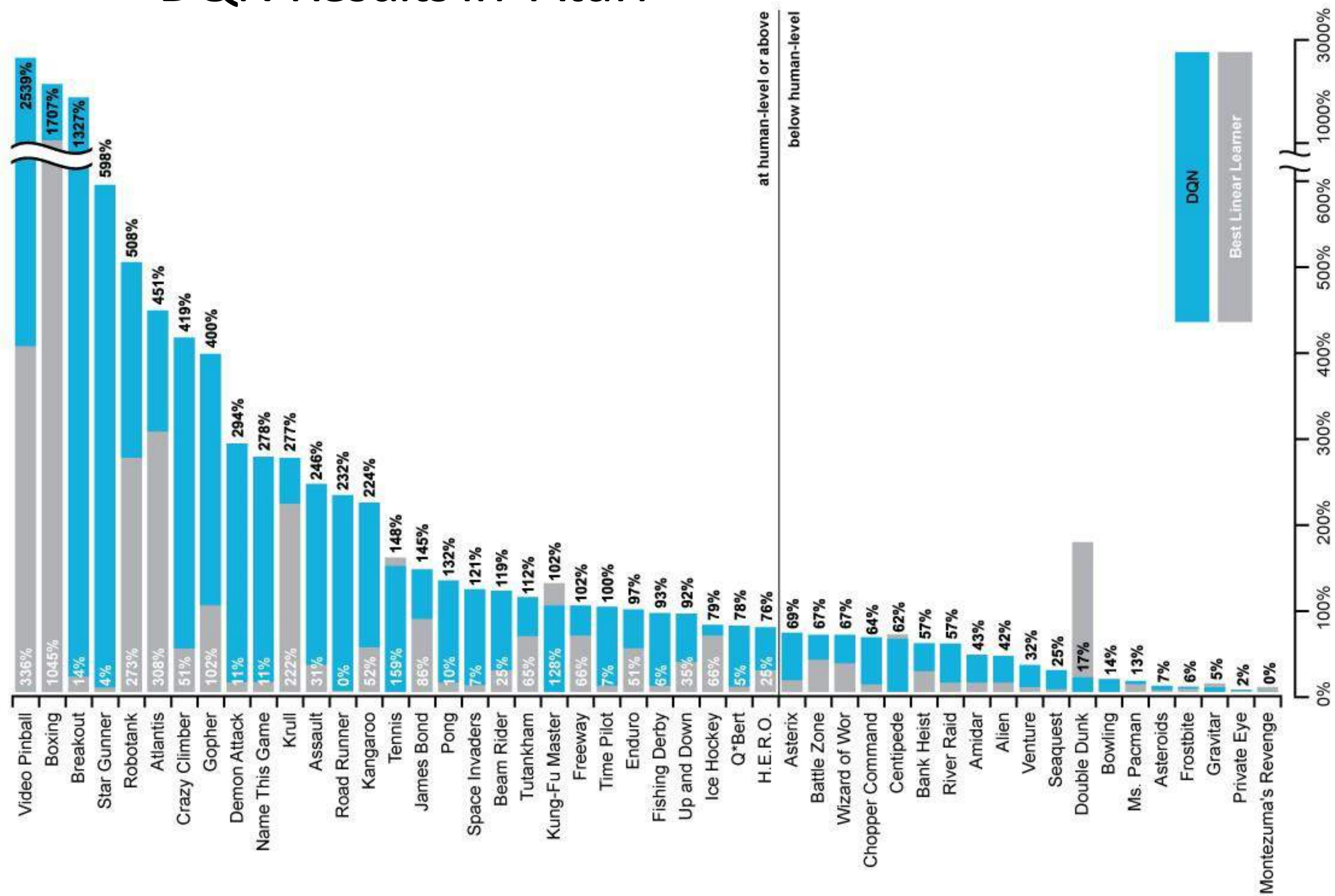


After **10 Minutes** of Training

After **120 Minutes** of Training

After **240 Minutes** of Training

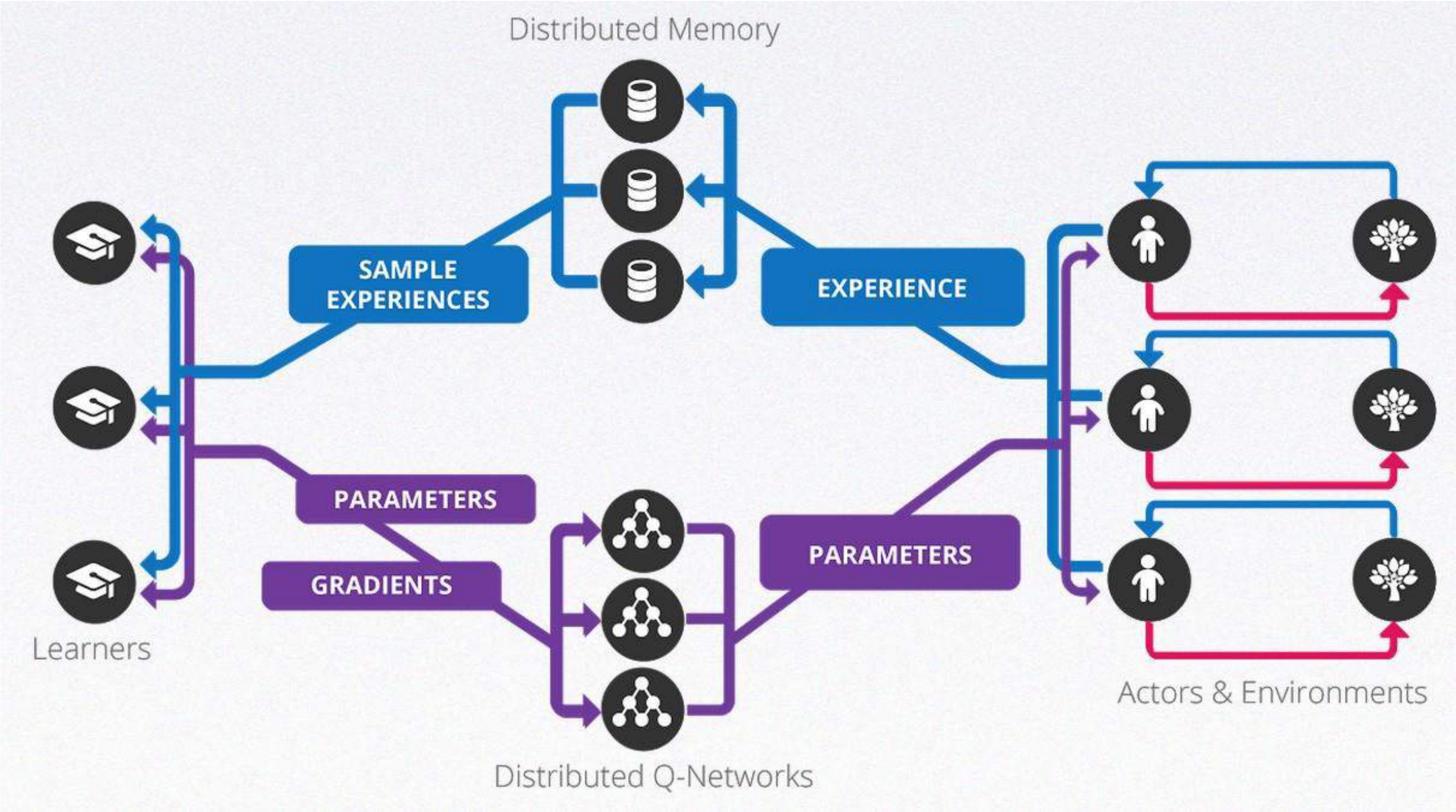
DQN Results in Atari



References: [83]

Gorila

(General Reinforcement Learning Architecture)



- 10x faster than Nature DQN on 38 out of 49 Atari games
- Applied to recommender systems within Google

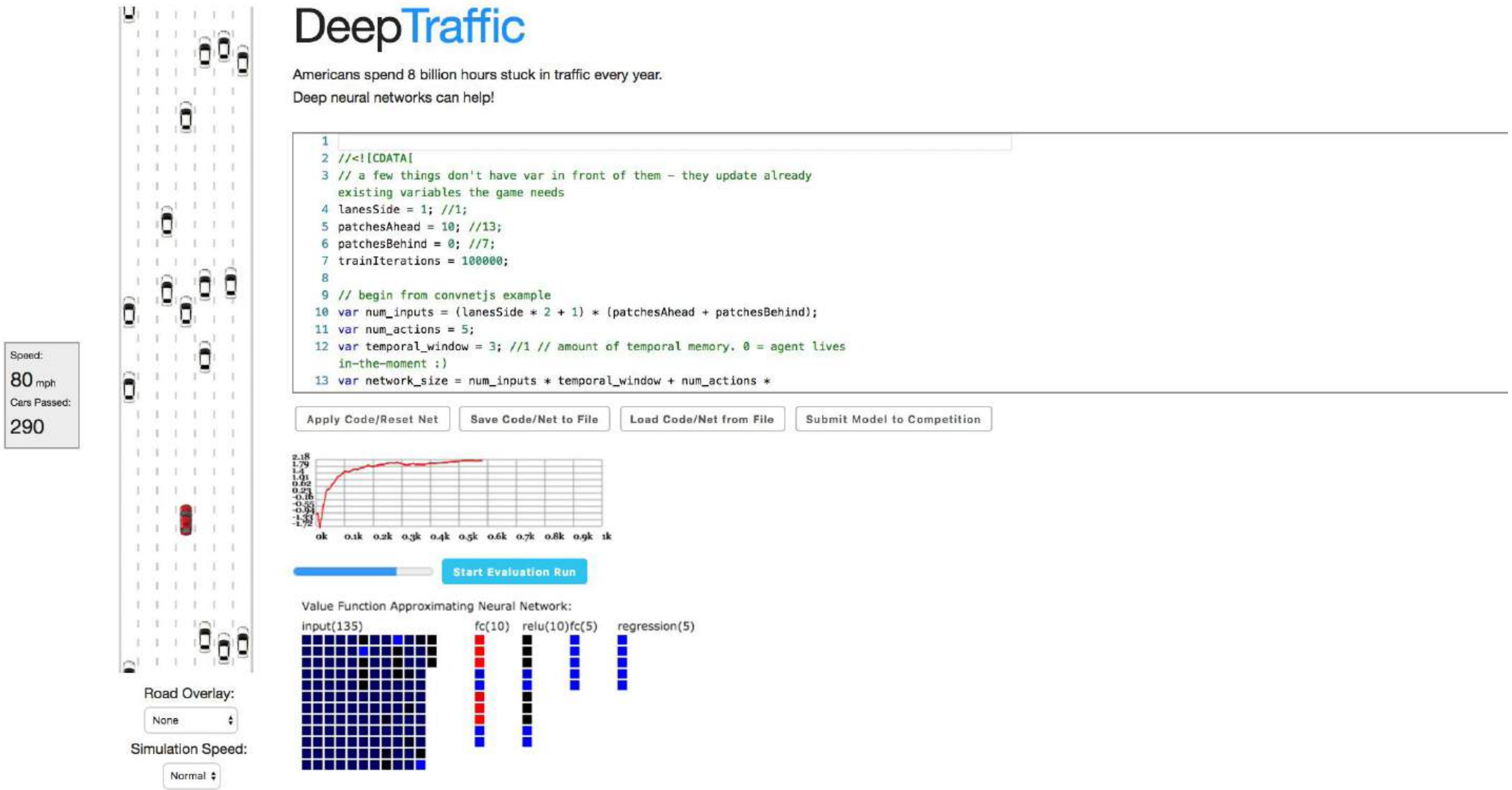
Nair et al. "Massively parallel methods for deep reinforcement learning." (2015).

The Game of Traffic

Open Question (Again):

Is driving closer to **chess** or to **everyday conversation**?

DeepTraffic: Solving Traffic with Deep Reinforcement Learning



- **Goal:** Achieve the highest average speed over a long period of time.
- **Requirement for Students:** Follow tutorial to achieve a speed of 65mph

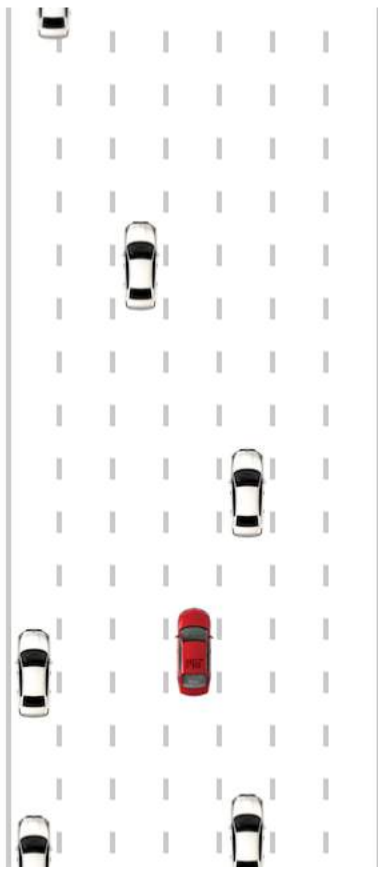
The Road, The Car, The Speed

Speed:

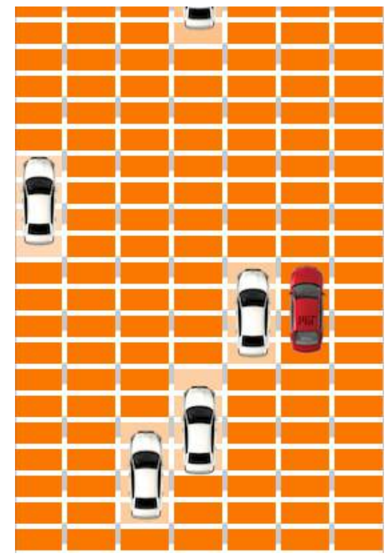
47 mph

Cars Passed:

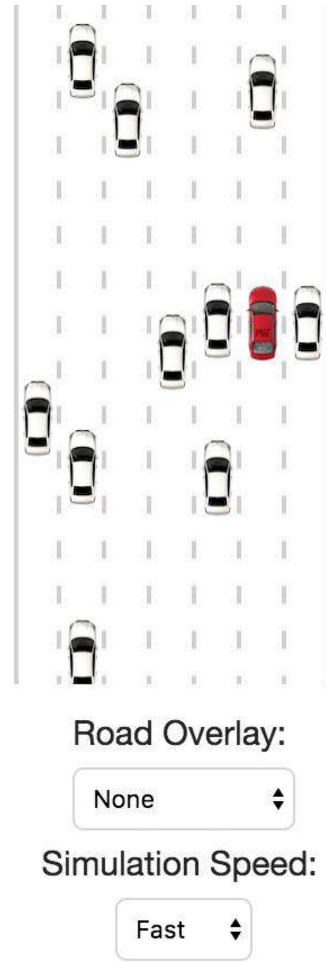
5



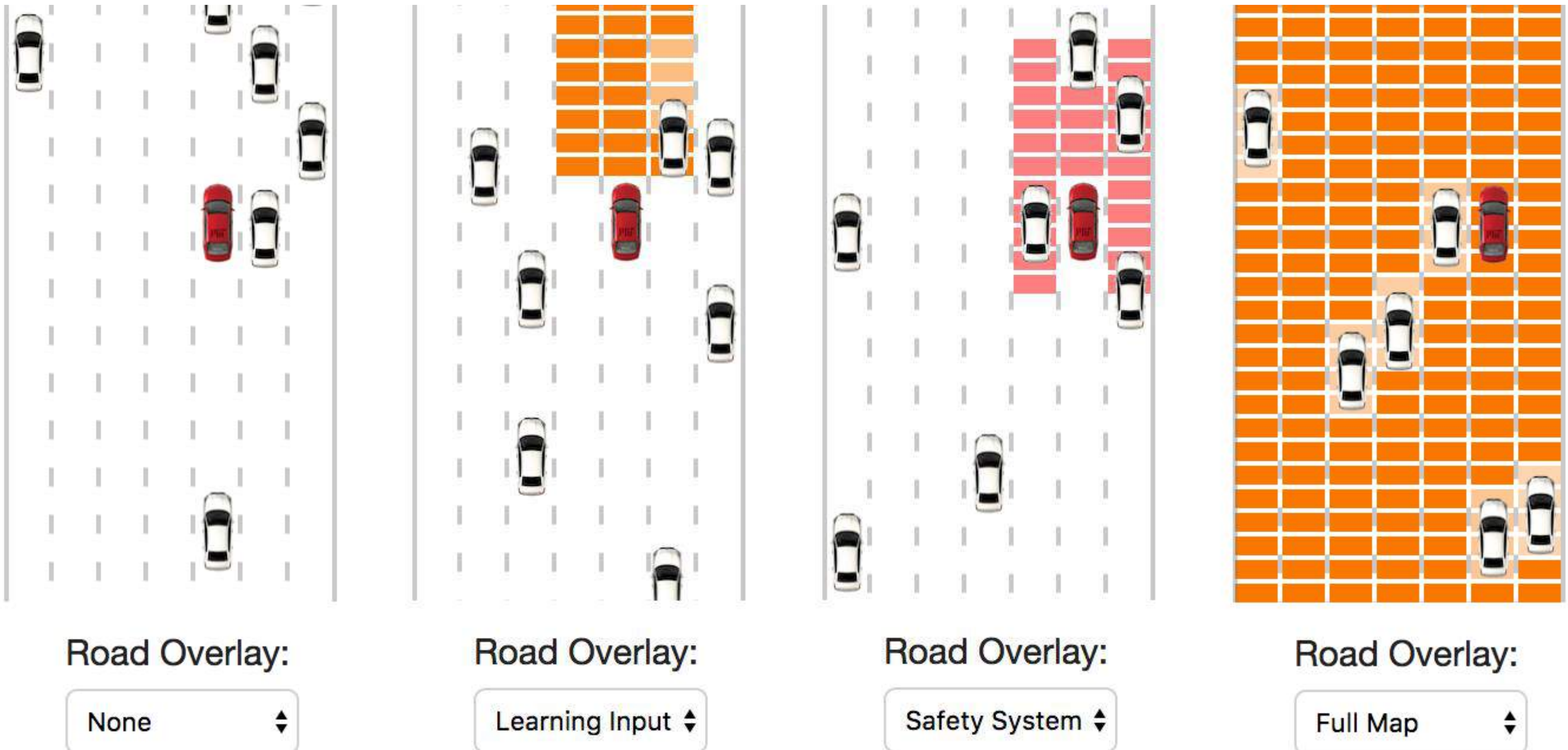
State Representation:



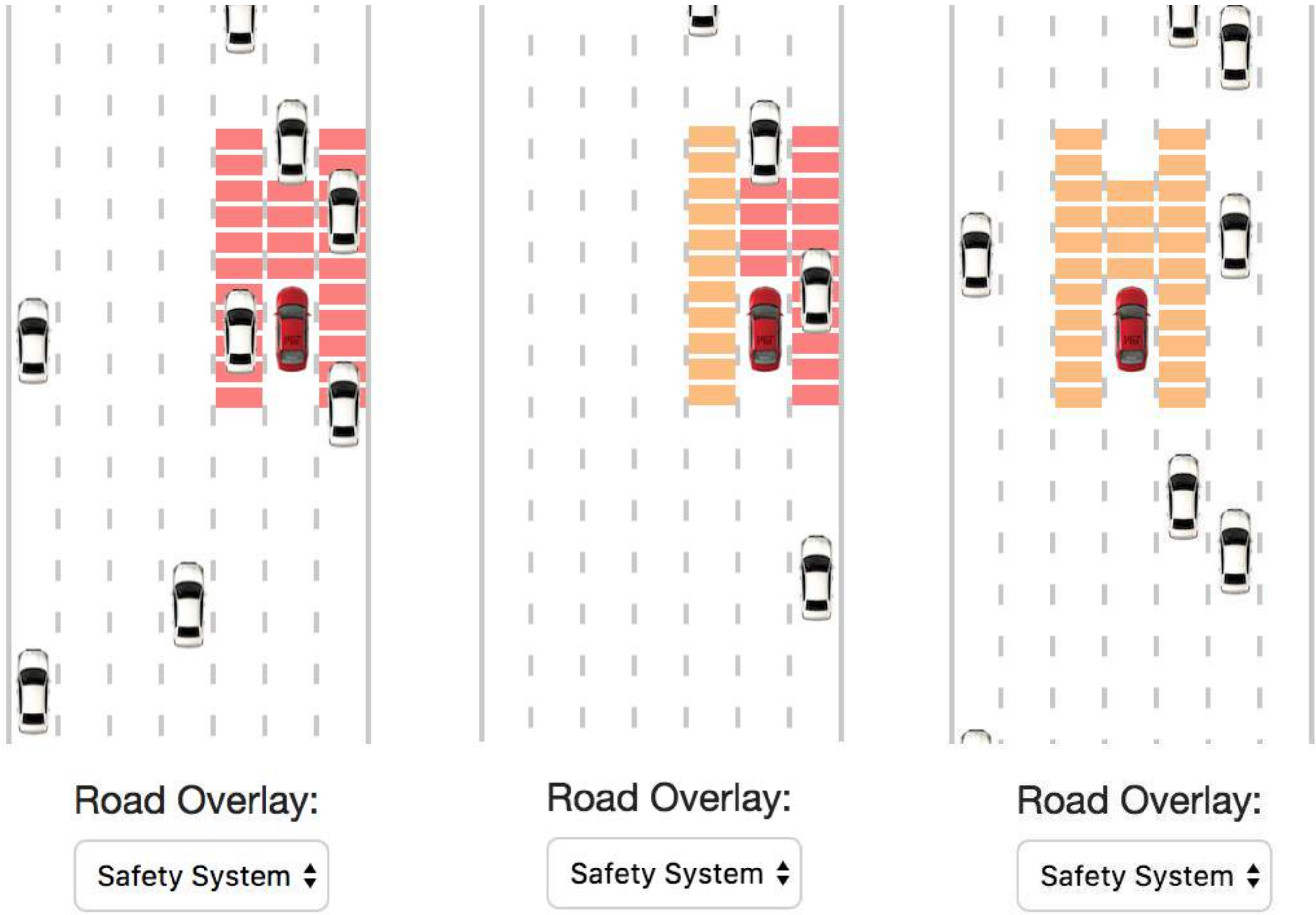
Simulation Speed



Display Options



Safety System



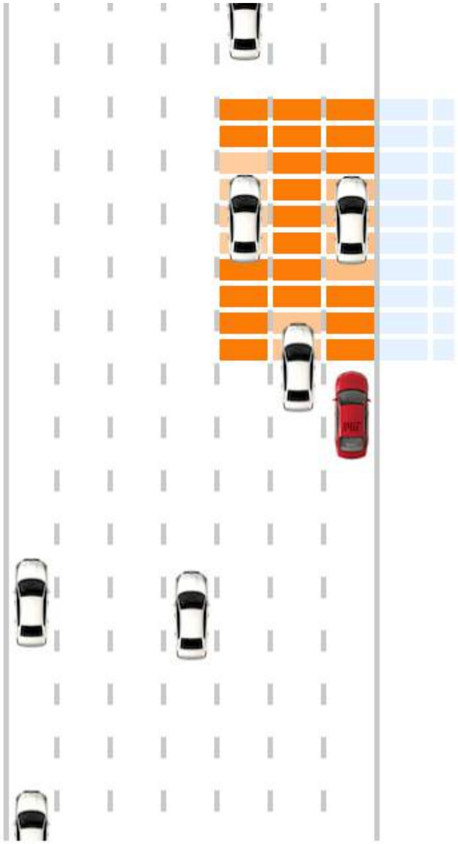
Driving / Learning


```
learn = function (state, lastReward) {
    brain.backward(lastReward);
    var action = brain.forward(state);
    return action;
}

var noAction = 0;
var accelerateAction = 1;
var decelerateAction = 2;
var goLeftAction = 3;
var goRightAction = 4;
```

Learning Input

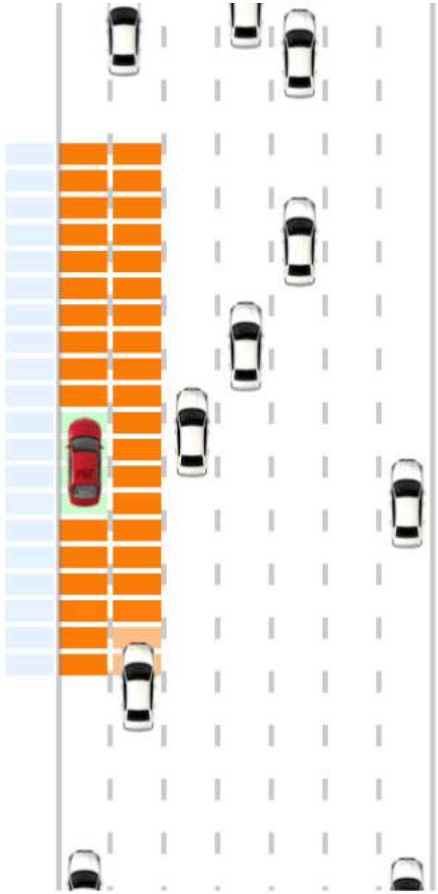

```
lanesSide = 1;
patchesAhead = 10;
patchesBehind = 0;
```

Learning Input



```
lanesSide = 2;
patchesAhead = 10;
patchesBehind = 0;
```

Learning Input



```
lanesSide = 1;
patchesAhead = 10;
patchesBehind = 10;
```

Evaluation

- Scoring: Average Speed
- Method:
  - Collect average speed
  - Ten runs, about 30 (simulated) minutes of game each
  - Result: median speed of the 10 runs
- Done server side after you submit
  - (no cheating possible! (we also look at the code …))
- You can try it locally to get an estimate
  - Uses exactly the same evaluation procedure/code
  - But: some influence of randomness
  - Our number is what counts in the end!

Evaluation (Locally)

Start Evaluation Run

...

...

Average speed: 51 mph

Coding/Changing the Net Layout

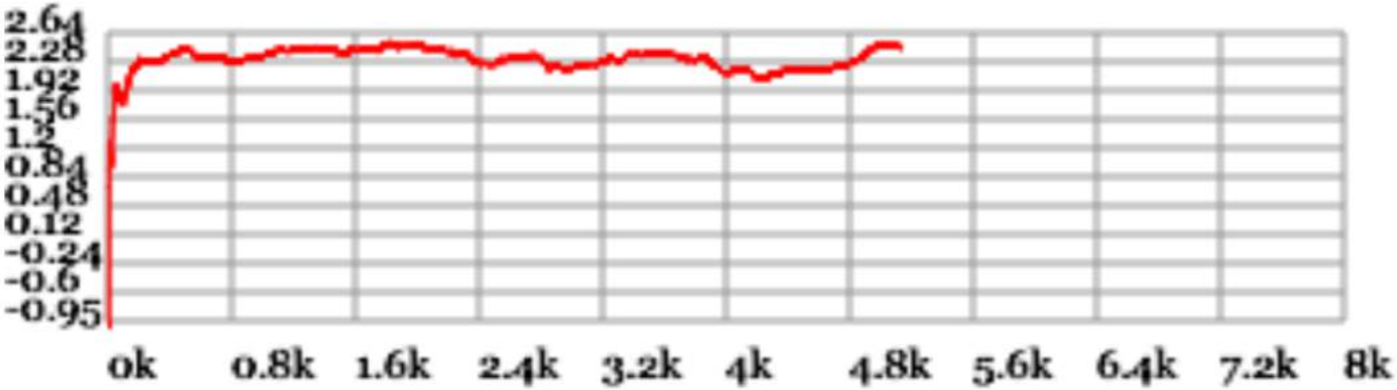
```

//<![CDATA[
// a few things don't have var in front of them - they update already existing variables the game needs
lanesSide = 1;
patchesAhead = 10;
patchesBehind = 10;
trainIterations = 100000;

// begin from convnetjs example
var num_inputs = (lanesSide * 2 + 1) * (patchesAhead + patchesBehind);
var num_actions = 5;
var temporal_window = 3; //1 // amount of temporal memory. 0 = agent lives in-the-moment :)
var network_size = num_inputs * temporal_window + num_actions *
```

Apply Code/Reset Net

Watch out: kills trained state!

Training

- Done on separate thread (Web Workers, yay!)
  - Separate simulation, resets, state, etc.
  - A lot faster (1000 fps +)
- Net state gets shipped to the main simulation from time to time
  - You get to see the improvements/learning live



Training

```
trainIterations = 100000;
```

Run Training

...

Loading/Saving

Save Code/Net to File

- Danger: Overwrites all of your code and the trained net

Load Code/Net from File

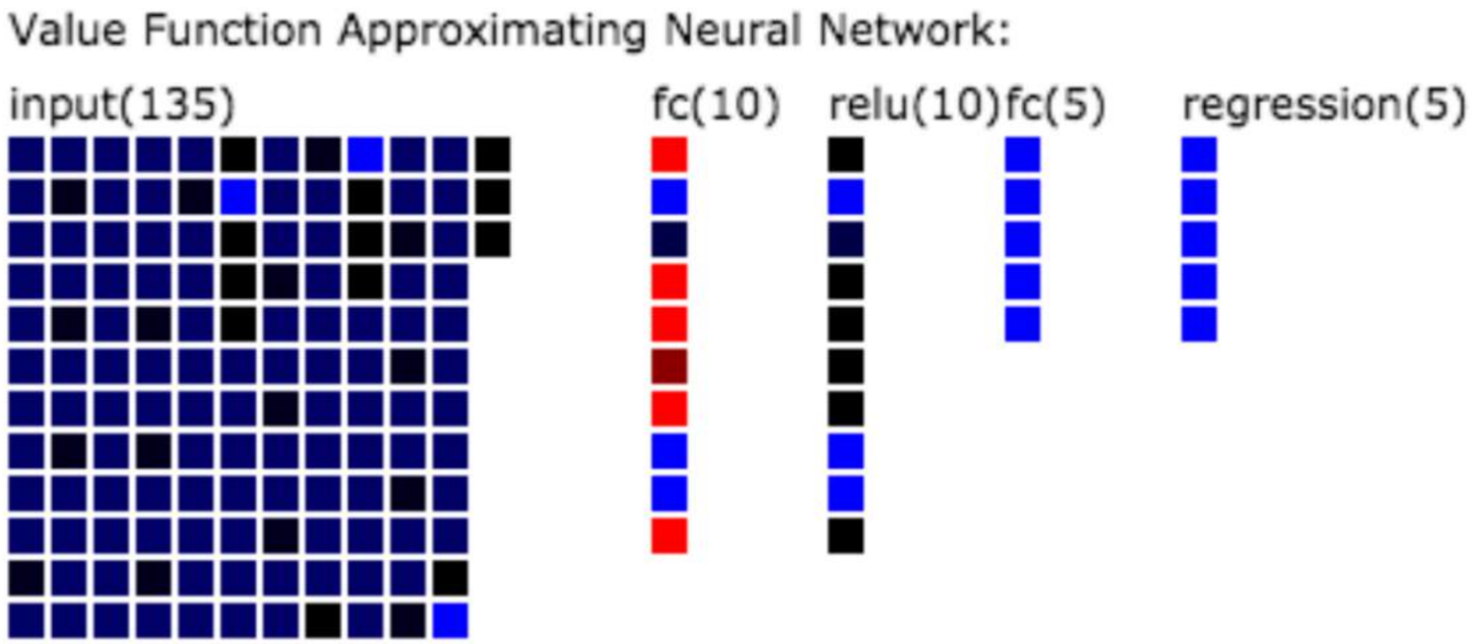
Submitting

Submit Model to Competition

- Submits your code and the trained net state
  - **Make sure you ran training!**

- Adds your code to the end of a queue
  - Gets evaluated some time (no promises here)
- You can resubmit as often as you like
  - If your code wasn't evaluated yet it we still remove it from the queue (and move you to the end)
  - The highest/most recent???? score counts.

ConvNetJS / The Actual Deep Learning Part

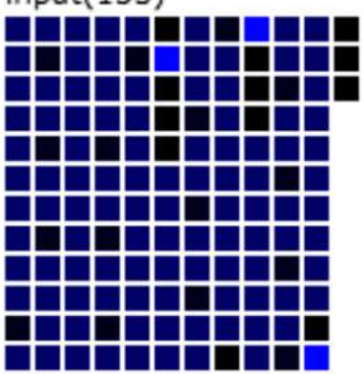


ConvNetJS: Settings

```
var num_inputs = (lanesSide * 2 + 1) * (patchesAhead + patchesBehind);
var num_actions = 5;
var temporal_window = 3;
var network_size = num_inputs * temporal_window + num_actions *
temporal_window + num_inputs;
```

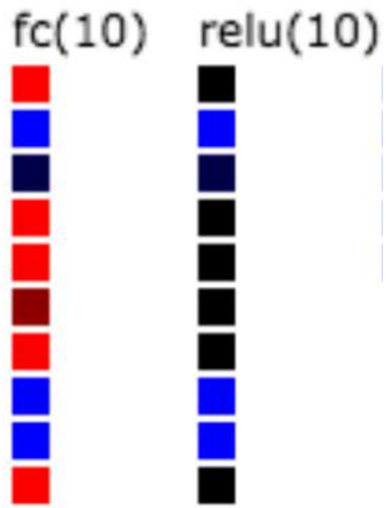
ConvNetJS: Input

```
var layer_defs = [];
layer_defs.push({
    type: 'input',
    out_sx: 1,
    out_sy: 1,
    out_depth: network_size
});
```



ConvNetJS: Hidden / Fully Connected Layers

```
layer_defs.push({
    type: 'fc',
    num_neurons: 10,
    activation: 'relu'
});
```



ConvNetJS: Output Layer

```
layer_defs.push({
    type: 'regression',
    num_neurons: num_actions
});
```

ConvNetJS: Options

```
var opt = {};
opt.temporal_window = temporal_window;
opt.experience_size = 3000;
opt.start_learn_threshold = 500;
opt.gamma = 0.7;
opt.learning_steps_total = 10000;
opt.learning_steps_burnin = 1000;
opt.epsilon_min = 0.0;
opt.epsilon_test_time = 0.0;
opt.layer_defs = layer_defs;
opt.tdtrainer_options = {
    learning_rate: 0.001, momentum: 0.0, batch_size: 64, l2_decay: 0.01
};

brain = new deepqlearn.Brain(num_inputs, num_actions, opt);
```

ConvNetJS: Learning

```
learn = function (state, lastReward) {
    brain.backward(lastReward);
    var action = brain.forward(state);

    draw_net();
    draw_stats();

    return action;
}
```

Technical Details (How We Built The Game)

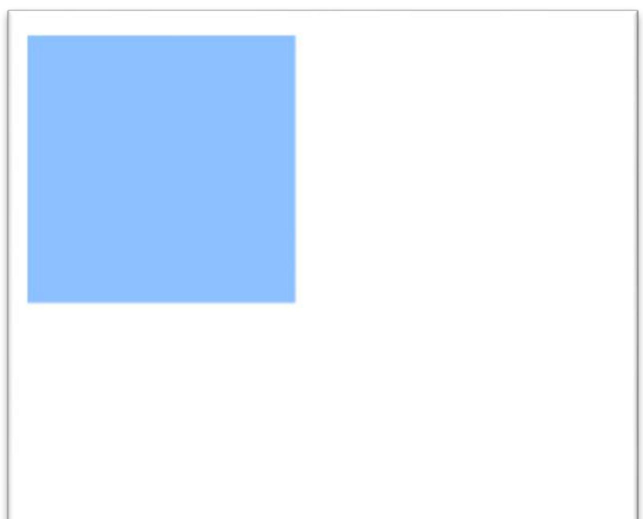
- Monaco Editor
- HTML5 Canvas
- Web Workers

Monaco Editor

```
<script src="monaco-editor/min/vs/loader.js"></script>
<script>
    require.config({
        paths: {
            'vs': 'monaco-editor/min/vs'
        }
    });
    require(['vs/editor/editor.main'], function () {
        editor = monaco.editor.create(document.getElementById('container'), {
            value: "some code ...",
            language: 'javascript',
            wrappingColumn: 75,
        });
    });
</script>
```

HTML5 Canvas

```
<canvas id="canvas" width="400" height="700"></canvas>
<script>
    var ctx = document.getElementById('canvas').getContext('2d');
    ctx.fillStyle = 'rgba(0,120,250,0.5)';
    ctx.fillRect(0, 0, 100, 100);
</script>
```



Web Workers

```
//main.js
if (window.Worker) {
    var myWorker = new Worker("worker.js");
    myWorker.onmessage = function (e) {
        console.log(e.data);
    };
}

//worker.js
postMessage("Hello world!");
```

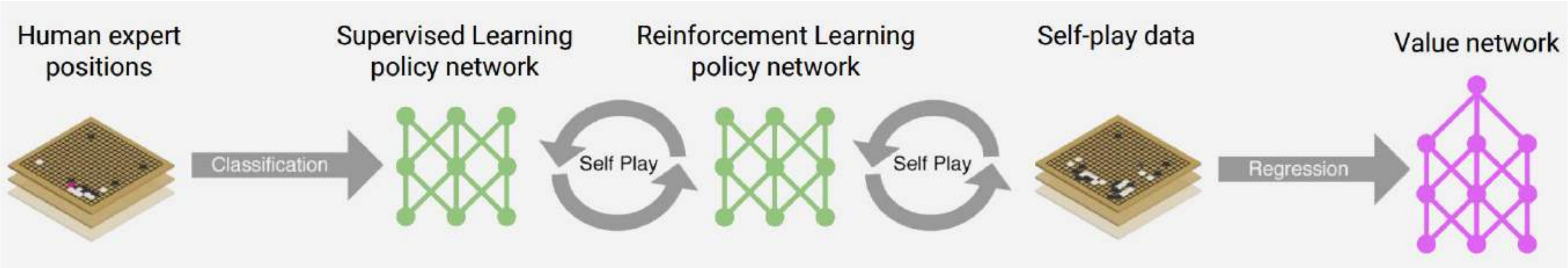
Tutorial:

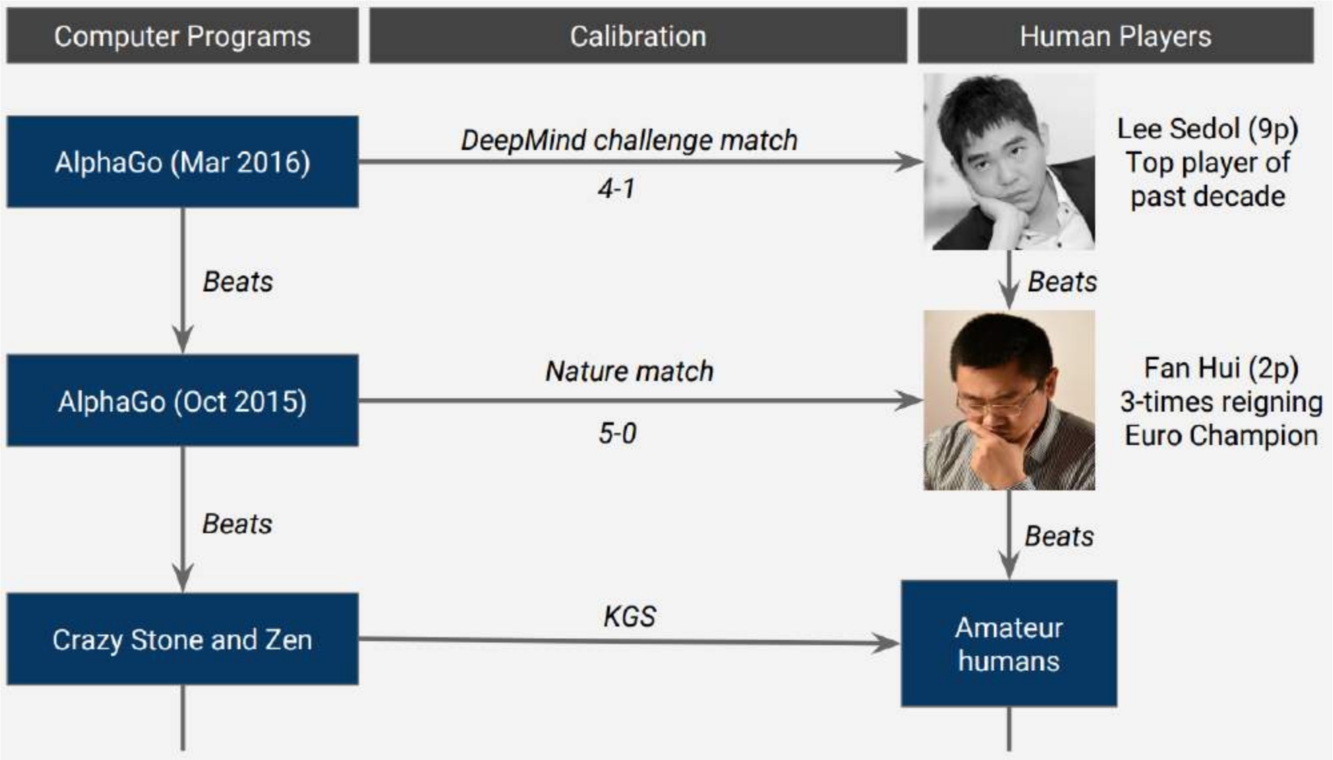
http://cars.mit.edu/deeptraffic

Simulation:

http://cars.mit.edu/deeptrafficjs

Human-in-the-Loop Reinforcement Learning: Driving Ready?





References: [83]

Reminder: Unexpected Local Pockets of High Reward

References

All references cited in this presentation are listed in the following Google Sheets file:

https://goo.gl/9Xhp2t