

# Reinforcement Learning using the example of Mancala

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# Structure

- ▶ Mancala rules
- ▶ Q-learning
- ▶ Backpropagation
- ▶ Network
- ▶ Training
- ▶ Troubleshooting
- ▶ Results / Improvement

# Mancala

- ▶ ancient two player game



- ▶ **as vector:**  $[6, 6, 6, 6, 6, 6, 6, | 6, 6, 6, 6, 6, 6, | 0, 0]$
- ▶ **Goal:** catch more than half of the beans (37)

# Mancala Rules

- ▶ choose non empty hole
- ▶ collect all beans of a hole and drop one in each clockwise following hole
- ▶ catch all beans of the last hole, if it contains 6, 4 or 2 beans
- ▶ going backwards: collect beans from all following holes with 6, 4 or 2 beans, if there are no other holes in between
- ▶ game ends if either one player has no more beans or one player catches at least 37 beans
- ▶ total sum of beans: caught beans + beans on own side

# MDP

- ▶ Mancala can be represented as a Markov Decision Process (MDP)
- ▶ set of states  $S$ , set of actions per state  $A$ , action  $a \in A$
- ▶ finite but very large number of states
- ▶ How does the Mancala agent learn to choose the best action?

# Reinforcement Learning

- ▶ **Idea:** reward or punish some action
- ▶ **Goal of agent:** maximize total reward
- ▶ **possible rewards for Mancala:** Small reward for catching beans, bigger reward for winning the game, punish illegal actions and loosing
- ▶ use Q-Learning

# Q-learning

- ▶ small state space: Q-table
- ▶ replace Q-table by Q-function

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (1)$$

- ▶ agents often need to learn actions that do not lead immediately to a reward
- ▶ allow a small amount of random actions (exploration rate)

- ▶ **activation function:** Sigmoidfunction
- ▶ learningrate for the update-weights-function



# play

- ▶ choose action by feeding the current board to the net and take the argmax of the output
- ▶ get board and reward after action
- ▶ append board and reward to trainingslists
- ▶ change player (turn board)

# Rewards and Discount

- ▶ choosing the right rewards is key for the Q-function to work properly
  - ▶ too high rewards lead to large q-value estimations (maybe higher than the activation function would allow)  
⇒ the network is going to increase q-values with every iteration
  - ▶ too low rewards lead to q-values close to zero
  - ▶ get 0.05 as reward for every caught bean and 10.0 for a winning action
- ▶ selecting the right discount and learning rate is difficult and depends on the reward strategy

# Training

- ▶ let the agent play against itself and save pairs of actions and rewards
- ▶ update for each board state and action the underlying Q-function
- ▶ save each board state and dedicated Q-values as training data
- ▶ feedforward a boardstate to the net
- ▶  $\text{loss} = \text{output} - \text{Q-values}$

# Backpropagation

**1. Step** Generate training data: for a given input set an expected output (e.g. with Q-function)

**2. Step** Calculate for the input  $a^{x,1}$ :

- ▶ activation  $a^{x,l}$  of layer  $l = 2, 3, \dots, L$  by

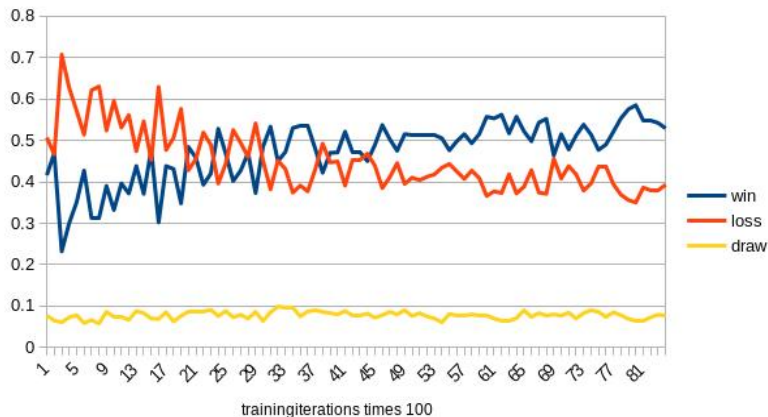
$$a^{x,l} = \sigma(z^{x,l}), \quad z^{x,l} = w^l a^{x,l-1} + b^l$$

- ▶ Output error  $\delta^{x,L} = \nabla_a C_x \odot \sigma'(z^{x,L})$
- ▶ Backpropagate error to each layer:

$$\delta^{x,l} = ((w^{l+1})^T \delta^{x,l+1}) \odot \sigma'(z^{x,l})$$

**3. Step** Use error of each layer to update weights and biases

## Results for a straightforward adaptation



- ▶ simple q-learning tends to stagnate very early, gets worse after some time
- ▶ a 'large' learning rate doesn't always improve the rate

# Origins of problems

- ▶ couldn't identify any coherence
- ▶ to see how the network learns Mancala, we need to simplify the game

## simple game

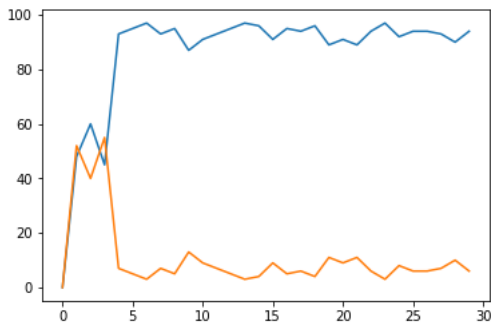
- ▶  $[1, 1, 5, 1, 1, 1 | 1, 1, 5, 1, 1, 1 | 0, 0]$
- ▶ play against random
- ▶ network ist startplayer
- ▶ obvious way of playing at least tied
- ▶ after some training iterations the second player does not win at all
- ▶ → network is ok

## simple board

- ▶ reduce the board size:  $[2, 2|2, 2|0, 0]$
- ▶ obvious way of loosing the game: choose first hole
- ▶ compare guessed Q-Values with choice of hole
- ▶ Q-function decides for wrong side  $\rightarrow$  solve this error
- ▶ net performs good, if it starts in the right direction
- ▶ use flexible exploration rate

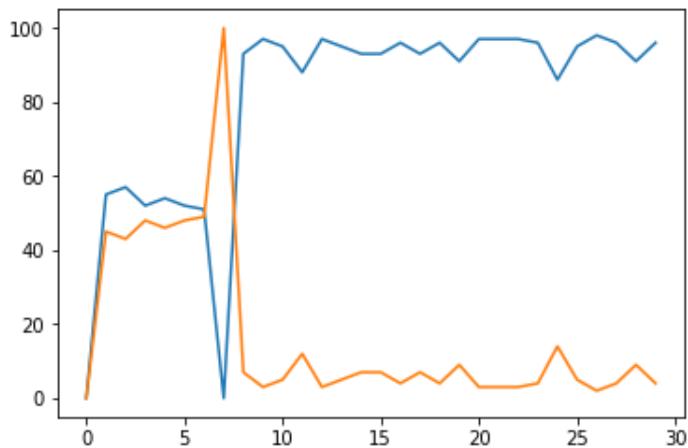


## simple board results



- ▶ 1 hidden layer with 10 neurons
- ▶ 1 Unit = 100 Trainingiterations

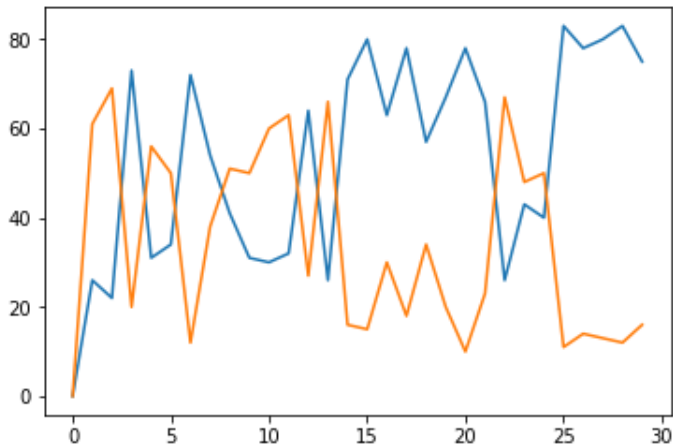
## simple board results: jump



# Mancala with 4 beans per hole

- ▶  $[4, 4, 4, 4, 4, 4 | 4, 4, 4, 4, 4, 4 | 0, 0]$
- ▶ transfer findings to this game (flexible exploration rate, ...)
- ▶ learns something but oscillates
- ▶ learns better if starts in the right direction

## Mancala with 4 beans per hole



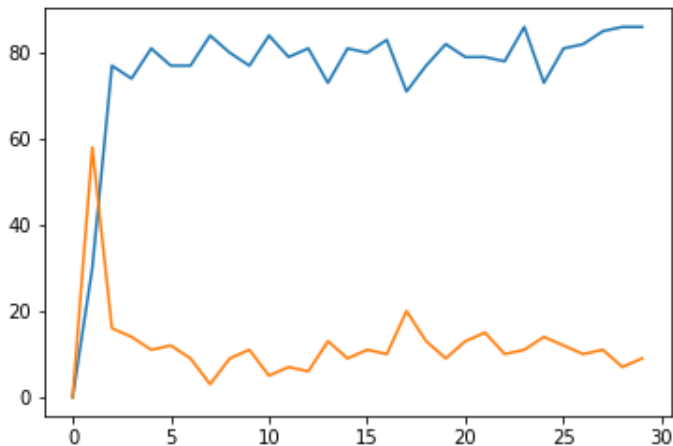
## improved Mancala with 4 beans per hole

- ▶ Idea: reduce learning rate if net performs good otherwise increase learning rate
- ▶ reward only winning not catching beans

## flexible parameters

```
if Spieler1gewonnen > 80:  
    l=0.01  
    ma.a = ma.a/10  
    ma.exploration_rate = 0  
elif Spieler1gewonnen >70:  
    l=0.01  
    ma.a = ma.a/10  
    ma.exploration_rate = 0.1  
else:  
    l=1  
    ma.a = ma.a+0.1  
    ma.exploration_rate = 0.3
```

## improved Mancala with 4 beans per hole



- keep in mind: Mancala ist still more complex and will possible take more time to converge

# Adapting learning of Mancala

- ▶ generating a random network of size  $[14, 10, 6]$  Picture



# Possible improvements

- ▶ use multiple network to guess optimal parameters of q-function and network, e.g:
  - ▶ exploration rate, rewards
  - ▶ discount, learning rate
- ▶ use tree search algorithm to guess rewards over multiple future actions

# Approved agents of other Mancala like games

- ▶ MinMax
- ▶ Monte Carlo Tree Search
- ▶ Asynchronous Advantage Actor-Critic
  - ▶ runs parallel agents
  - ▶ 3 networks work in concert: input, action and critic