

# Artificial Intelligence and Machine Learning — MDP, Q-learning

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## 1 Running the program

**Requirements:** Python 3.7 or higher, gnuplot

**Installing prerequisites:** `pip install -r requirements.txt`

### 1.1 Running a program

- File `mdp_run.py` will generate all results described in section 2 of this report. All files for `gnuplot` to generate plots will be put in `results/` directory. Plots are also automatically generated in this directory.
- File `qlearning_run.py` will print all results described in section 3 of this report.
- To redraw a plot from provided output file (in `results/` directory), run: `./plotter.sh filename`. Plot will be generated under a name `filename.png`.
- Worlds are defined in `toml` format in `worlds/` directory.

## 2 Markov Decision Problem

### 2.1 World 1

First world is defined in `worlds/default.toml` file. It is a 4x3 world as defined in the task description<sup>1</sup>. Termination value of 0.0001 stopped the calculation of utilities at 15th iteration.

Listing 1: Results of MDP utility value calculation for 4x3 world. Upper left corner of each field describes the policy, upper right - type of the field (S - start, N - normal, F - forbidden, T - terminal), bottom - utility value.

1	-----				
2	>	N >	N >	N x	T
3	0.81155	0.86780	0.91780		1
4	-----				
5	^	N x	F ^	N x	T
6	0.76155	xxxxxxx	0.66027		-1
7	-----				
8	^	S <	N <	N <	N
9	0.70528	0.65526	0.61137	0.38787	
10	-----				

<sup>1</sup>[http://zpcir.ict.pwr.wroc.pl/~witold/ai/MDPRL\\_assignment.html](http://zpcir.ict.pwr.wroc.pl/~witold/ai/MDPRL_assignment.html)

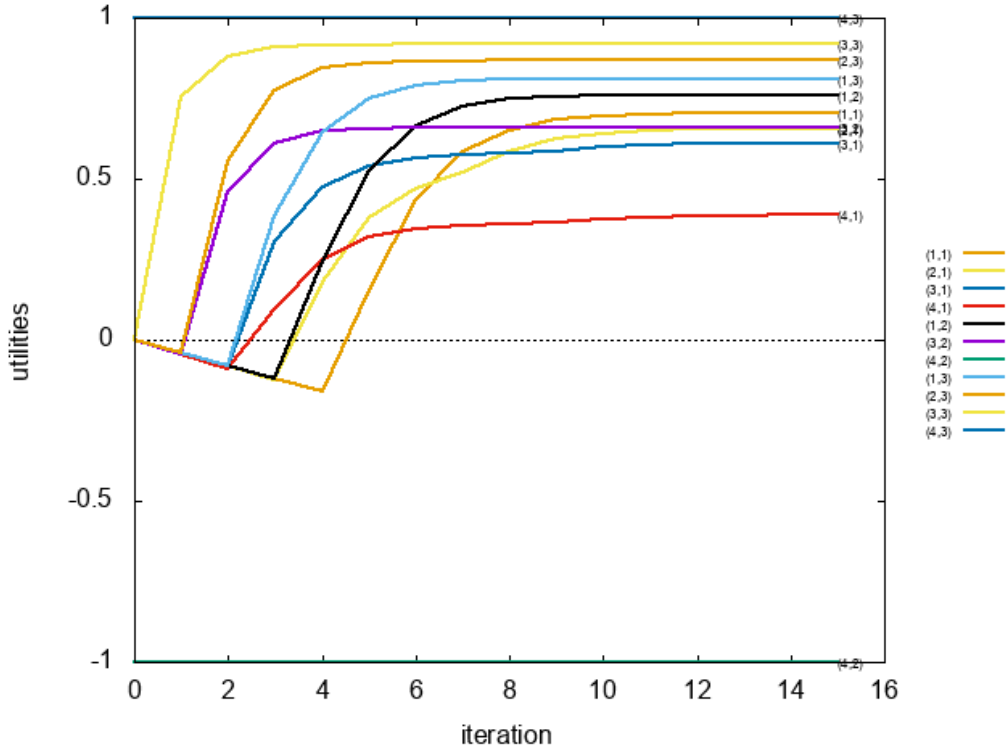


Figure 1: Convergence plot for 4x3 world

## 2.2 World 2

Second world is defined in `worlds/default2.toml` as defined in aforementioned task description. It is a 4x4 world. Termination value of 0.0001 stopped the calculation of utilities at 20th iteration.

Listing 2: Results of MDP utility value calculation for 4x4 world. Field marked as B is a special field.

1	-----
2	>        N >        N >        N v        N
3	81.9383 84.2609 86.5860 88.8827
4	-----
5	>        N >        N >        N v        N
6	81.7354 84.2724 87.0595 91.5547
7	-----
8	^        N ^        N >        B v        N
9	79.5935 80.5997 70.4670 94.5352
10	-----
11	^        S ^        N x        F x        T
12	77.4525 78.2494 xxxxxxxx         100
13	-----

It can be noticed that special field is avoided due to its high penalty.

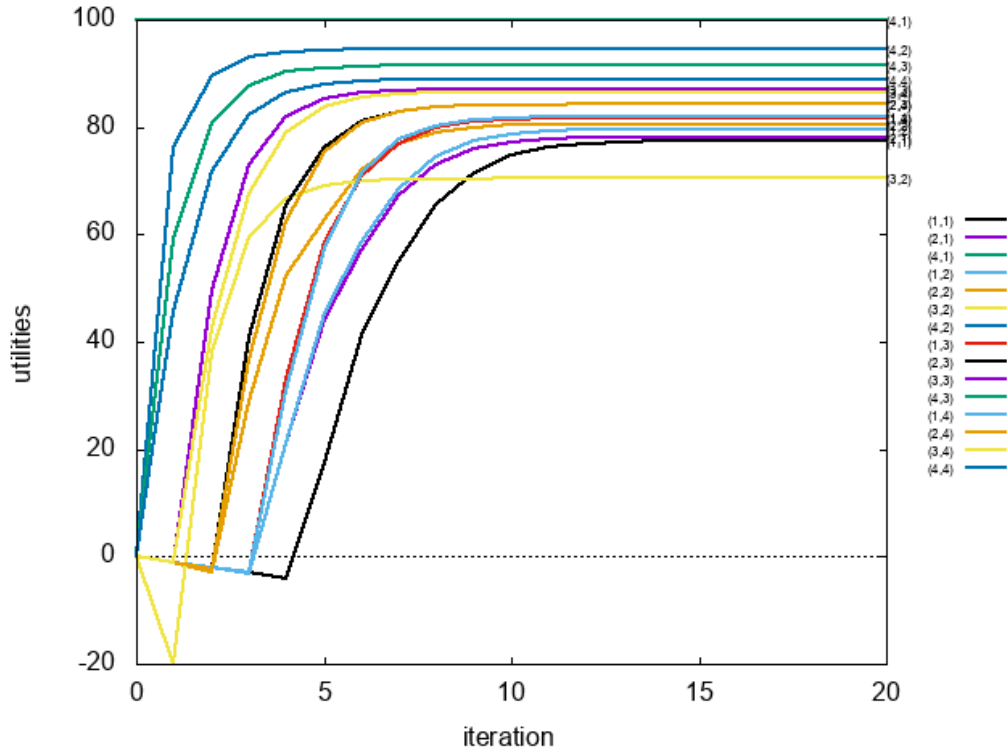


Figure 2: Convergence plot for 4x4 world

## 2.3 World 2 with modifications – reward

In this task, utility values were modified in the following way:

- default reward is  $-10$  instead of  $-1$
- special field has reward  $-1$  instead of  $-20$ .

This was defined in a file `worlds/default3.toml`.

Listing 3: Results of MDP utility value calculation for 4x4 world, modified reward

1	-----				
2	>	N >	N v	N v	N
3		29.6567	41.3267	52.9342	57.7182
4	-----				
5	>	N >	N v	N v	N
6		40.3029	53.6510	67.0818	71.6713
7	-----				
8	>	N >	N >	B v	N
9		49.2453	64.9589	81.6602	85.7762
10	-----				
11	>	S ^	N x	F x	T
12		38.4636	50.2279	xxxxxxxx	100
13	-----				

In this situation, special field starts to "attract" the policies around, because it is better to pass through this field than any other (it has less of a negative reward than all normal fields). Nevertheless, the high reward of terminal state makes policies to point towards it.

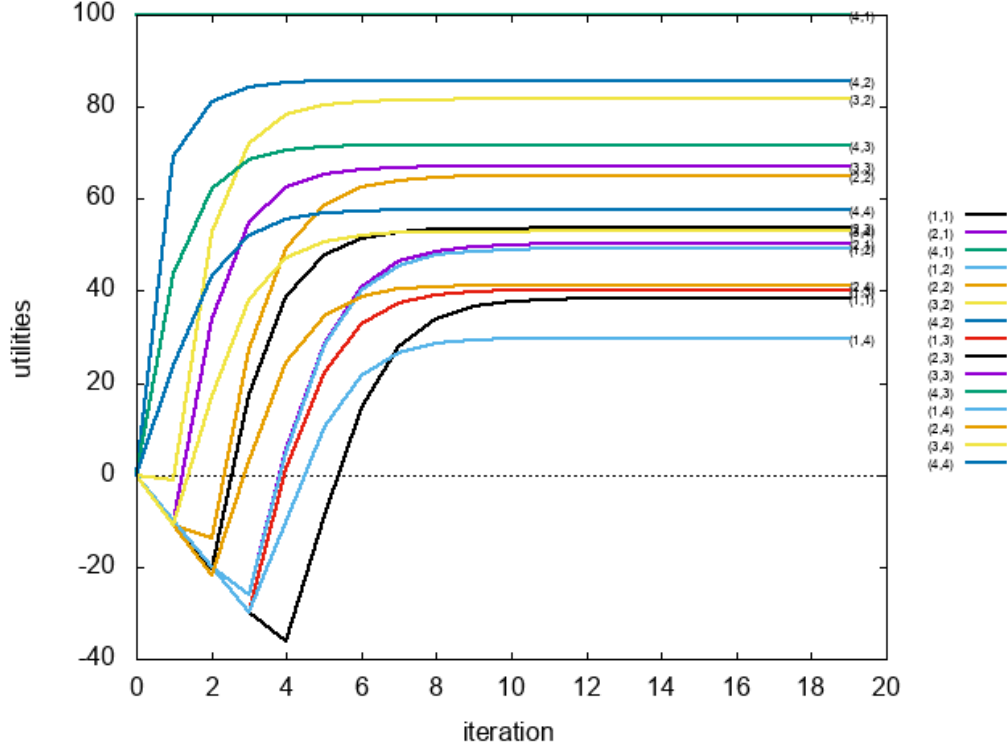


Figure 3: Convergence plot for 4x4 world, modified reward

## 2.4 World 2 with modifications – action uncertainty model

The action uncertainty model was changed to the following:

- forward action: 0.4
- left action: 0.4
- right action: 0.2
- back action: 0.0

This was defined in a file `worlds/default4.toml`

Listing 4: Results of MDP utility value calculation for 4x4 world, modified action uncertainty model

1	-----
2	>        N   >        N   >        N   v        N
3	48.2492   52.6014   57.1982   61.4599
4	-----
5	>        N   >        N   >        N   v        N
6	47.0322   51.1151   56.6142   67.6680
7	-----
8	^        N   ^        N   >        B   v        N
9	43.8584   44.7766   41.2482   77.4290
10	-----
11	>        S   >        N   x        F   x        T
12	40.7571   41.2105   xxxxxxxx          100
13	-----

Since going left than intended direction is as probable as going in the intended direction, a small policy change can be noticed at start field (left bottom corner) and the field on the left of the start field. Utility values are smaller across the whole board. A very interesting change is at position (2, 1) (while indexing from 1) – due to 40% chance of going forward and 40% chance of going left, it is better to either go up the board or stay at the same position by bouncing off the forbidden position than going back to start and take more negative reward.

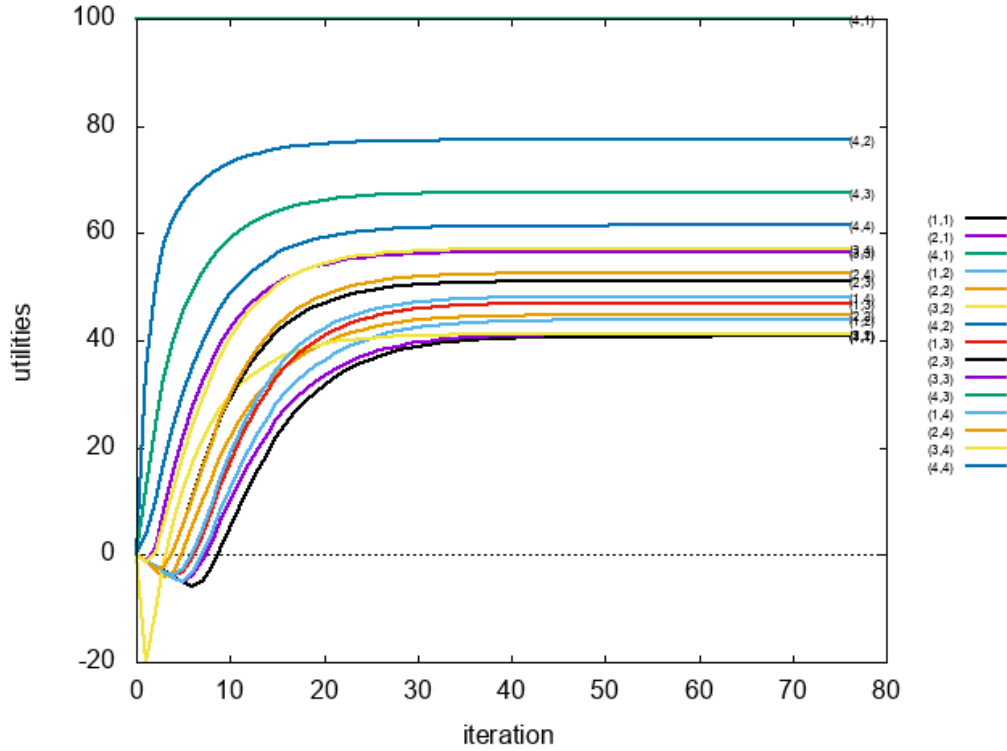


Figure 4: Convergence plot for 4x4 world, modified action uncertainty model

It takes much longer to achieve stable utility values.

## 2.5 World 2 with modifications – discounting factor

The discounting factor  $\gamma$  was changed to 0.75. The world is defined in the file `worlds/default5.toml`.

Listing 5: Results of MDP utility value calculation for 4x4 world, modified discounting factor

1	-----				
2	>	N   >	N   >	N   v	N
3	8.52018	13.3904	20.0277	28.9742	
4	-----				
5	>	N   >	N   >	N   v	N
6	11.2919	18.2602	28.5480	43.8318	
7	-----				
8	>	N   >	N   >	B   v	N
9	9.29066	15.0289	23.2913	65.6722	
10	-----				
11	^	S   ^	N   x	F   x	T
12	5.68543	9.12839	xxxxxxxx		100
13	-----				

The policy slightly changed and now allows to pass through the field with bigger penalty than regular fields have. Utility values are generally much smaller.

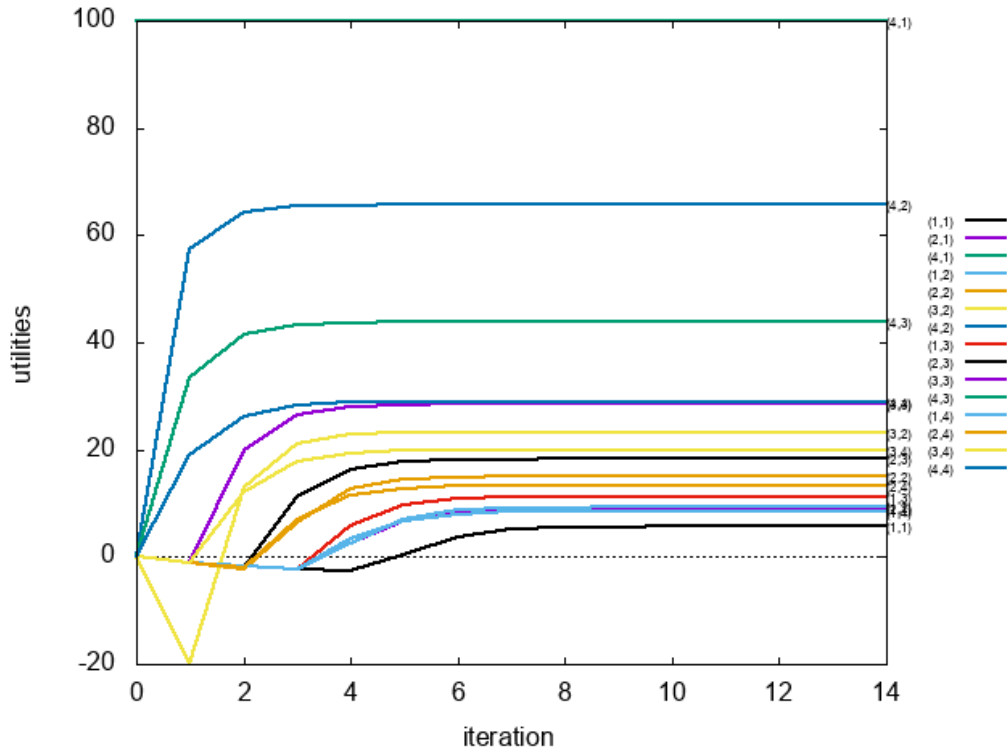


Figure 5: Convergence plot for 4x4 world, modified discounting factor

Utilities converge to stable values quicker than with higher  $\gamma$  (14 iterations). Smaller utility values suggest that the "agent" would not seek to gain a reward in the terminal state as much.

Also, allowing to pass through the special state with higher penalty for the move suggests that agent "cares" less about the final reward sum when  $\gamma$  is smaller.

### 3 Q-learning algorithm

In this task the following calculations were performed:

- Q-learning for  $\epsilon = 0.2$  (file: `worlds/default2q02.toml`):
  - 10 000 trails
  - 100 000 trails
  - 1 000 000 trails
- Q-learning for  $\epsilon = 0.05$  (file: `worlds/default2q005.toml`):
  - 10 000 trails
  - 100 000 trails
  - 1 000 000 trails

The results are listed in listings below. Q-values and policy for each field are listed in the following order: Q-value up, Q-value left, Q-value right, Q-value down, policy.

Observations:

- results are closest to those from MDP where 1 000 000 iterations were performed and  $\epsilon = 0.2$ ,
- policies from MDP and Q-learning with 1 000 000 iterations are the same,
- policies from Q-learning with 100 000 iterations are different for some fields, but Q-values of MDP solver selected action and Q-learning selected action differ slightly,
- At the same number of iterations, results are better (differ less from MDP-solved solution) with  $\epsilon = 0.2$ .

Listing 6: Q-learning: 10 000 iterations,  $\epsilon$ : 0.2

```

1 -----
2 | ^20.63|^35.75|^51.31|^62.42|
3 | <15.99|<21.15|<39.39|<49.49|
4 | >35.29|>44.20|>68.69|>59.47|
5 | v25.95|v51.59|v47.57|v79.20|
6 |   >   |   v   |   >   |   v   |
7 -----
8 | ^21.48|^38.75|^58.30|^70.32|
9 | <32.52|<37.63|<54.83|<73.33|
10 | >48.66|>65.82|>78.64|>81.43|
11 | v37.01|v52.86|v63.17|v88.28|
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^30.22|^53.94|^51.60|^82.49|
15 | <42.88|<46.55|<40.28|<68.90|
16 | >53.45|>62.27|>68.02|>90.60|
17 | v38.47|v46.33|v47.01|v93.95|
18 |   >   |   >   |   >   |   v   |
19 -----
20 | ^45.28|^54.20|^xxxxx|^   100|
21 | <35.84|<35.97|<xxxxx|<   100|
22 | >44.46|>45.23|>xxxxx|>   100|
23 | v35.75|v42.84|vxxxxx|v   100|
24 |   ^   |   ^   |   x   |   x   |
25 -----

```



Listing 7: Q-learning: 10 000 iterations,  $\epsilon$ : 0.05

```

1 -----
2 | ^6.979|^19.77|^37.01|^51.96|
3 | <2.848|<1.949|<30.93|<41.56|
4 | >12.91|>44.22|>61.73|>51.73|
5 | v27.03|v14.41|v48.67|v74.48|
6 |   v   |   >   |   >   |   v   |
7 -----
8 | ^13.23|^30.51|^51.77|^62.31|
9 | <21.29|<28.21|<43.42|<64.13|
10 | >41.25|>60.03|>75.58|>77.62|
11 | v25.64|v38.74|v59.66|v86.90|
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^27.09|^37.34|^52.04|^80.46|
15 | <31.43|<32.53|<34.69|<57.86|
16 | >52.95|>61.18|>67.25|>89.94|
17 | v21.81|v39.57|v32.45|v93.66|
18 |   >   |   >   |   >   |   v   |
19 -----
20 | ^38.22|^49.80|^xxxxx|^   100|
21 | <22.22|<9.334|<xxxxx|<   100|
22 | >27.81|>14.51|>xxxxx|>   100|
23 | v22.32|v23.02|vxxxxx|v   100|
24 |   ^   |   ^   |   x   |   x   |
25 -----

```

Listing 8: Q-learning: 100 000 iterations,  $\epsilon$ : 0.2

```

1 -----
2 | ^35.77|^55.11|^69.24|^78.03|
3 | <39.46|<42.82|<60.29|<72.75|
4 | >53.05|>68.32|>78.36|>80.09|
5 | v47.72|v64.00|v76.31|v84.69|
6 |   >   |   >   |   >   |   v   |
7 -----
8 | ^35.58|^59.65|^71.81|^80.27|
9 | <53.45|<56.09|<68.48|<80.46|
10 | >65.11|>75.09|>83.54|>86.78|
11 | v54.48|v62.18|v68.92|v90.23|
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^57.06|^62.64|^60.24|^85.69|
15 | <52.98|<55.28|<45.64|<71.89|
16 | >60.06|>65.99|>69.31|>92.17|
17 | v47.13|v55.40|v50.02|v94.25|
18 |   >   |   >   |   >   |   v   |
19 -----
20 | ^53.01|^59.90|^xxxxx|^   100|
21 | <45.28|<47.10|<xxxxx|<   100|
22 | >52.93|>54.40|>xxxxx|>   100|
23 | v45.54|v52.79|vxxxxx|v   100|
24 |   ^   |   ^   |   x   |   x   |
25 -----

```

Listing 9: Q-learning: 100 000 iterations,  $\epsilon$ : 0.05

```

1 -----
2 | ^24.04 | ^45.22 | ^62.29 | ^47.00 |
3 | <25.17 | <39.99 | <54.89 | <70.90 |
4 | >55.88 | >66.23 | >59.16 | >16.88 |
5 | v34.51 | v58.80 | v75.91 | v50.20 |
6 |   >   |   >   |   v   |   <   |
7 -----
8 | ^43.22 | ^40.53 | ^70.93 | ^67.15 |
9 | <49.61 | <54.53 | <68.97 | <79.00 |
10 | >67.04 | >77.10 | >84.12 | >85.77 |
11 | v50.68 | v61.42 | v69.18 | v90.68 |
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^57.08 | ^65.04 | ^61.17 | ^86.24 |
15 | <53.72 | <55.67 | <46.11 | <72.08 |
16 | >60.76 | >66.60 | >69.61 | >92.17 |
17 | v48.18 | v56.39 | v50.25 | v94.38 |
18 |   >   |   >   |   >   |   v   |
19 -----
20 | ^54.09 | ^60.58 | ^xxxxx | ^   100 |
21 | <46.87 | <48.19 | <xxxxx | <   100 |
22 | >52.54 | >52.80 | >xxxxx | >   100 |
23 | v47.12 | v51.63 | vxxxxx | v   100 |
24 |   ^   |   ^   |   x   |   x   |
25 -----

```

Listing 10: Q-learning: 1 000 000 iterations,  $\epsilon$ : 0.2

```

1 -----
2 | ^77.91 | ^80.83 | ^83.86 | ^86.23 |
3 | <77.52 | <77.89 | <81.64 | <84.72 |
4 | >80.50 | >83.42 | >86.07 | >86.78 |
5 | v75.35 | v79.17 | v83.94 | v88.55 |
6 |   >   |   >   |   >   |   v   |
7 -----
8 | ^78.00 | ^80.62 | ^83.98 | ^86.53 |
9 | <76.98 | <76.84 | <79.81 | <85.56 |
10 | >80.01 | >83.28 | >86.71 | >89.37 |
11 | v74.71 | v76.58 | v71.70 | v91.39 |
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^77.09 | ^78.37 | ^65.24 | ^87.58 |
15 | <72.42 | <71.85 | <56.33 | <73.46 |
16 | >72.78 | >68.46 | >70.28 | >92.71 |
17 | v67.78 | v68.94 | v52.48 | v94.47 |
18 |   ^   |   ^   |   >   |   v   |
19 -----
20 | ^71.63 | ^73.74 | ^xxxxx | ^   100 |
21 | <66.75 | <67.00 | <xxxxxx | <   100 |
22 | >69.54 | >69.98 | >xxxxxx | >   100 |
23 | v66.46 | v69.09 | vxxxxxx | v   100 |
24 |   ^   |   ^   |   x   |   x   |
25 -----

```

Listing 11: Q-learning: 1 000 000 iterations,  $\epsilon$ : 0.05

```

1 -----
2 | ^72.67 | ^78.07 | ^83.00 | ^86.16 |
3 | <72.29 | <73.79 | <79.32 | <84.64 |
4 | >77.68 | >82.47 | >86.11 | >86.71 |
5 | v74.91 | v79.09 | v82.10 | v88.60 |
6 |   >   |   >   |   >   |   v   |
7 -----
8 | ^73.74 | ^78.62 | ^82.77 | ^86.37 |
9 | <74.22 | <74.97 | <78.83 | <85.37 |
10 | >78.36 | >82.83 | >86.67 | >89.40 |
11 | v72.31 | v75.26 | v71.57 | v91.42 |
12 |   >   |   >   |   >   |   v   |
13 -----
14 | ^74.71 | ^78.16 | ^64.19 | ^87.54 |
15 | <68.93 | <67.24 | <52.36 | <73.51 |
16 | >64.93 | >68.22 | >70.23 | >92.76 |
17 | v63.55 | v63.99 | v52.10 | v94.50 |
18 |   ^   |   ^   |   >   |   v   |
19 -----
20 | ^67.72 | ^69.55 | ^xxxxx | ^   100 |
21 | <62.06 | <61.54 | <xxxxx | <   100 |
22 | >64.28 | >64.13 | >xxxxx | >   100 |
23 | v61.57 | v62.90 | vxxxxx | v   100 |
24 |   ^   |   ^   |   x   |   x   |
25 -----

```