COSC-4117EL: Assignment 2 Report

Group Number: 2
Group Member:

NAME	STUDENT#	EMAIL	CONTRIBUTION
Haoliang Sheng	0441916	hsheng@laurentian.ca	60%
Zihao Zhou	0429993	zzhou3@laurentian.ca	20%
Jiazhou Ye	0426609	Jye1@laurentian.ca	20%

1. Abstract

In this study, the objective was to compare and contrast the performances of two reinforcement learning methods: Markov Decision Processes (MDP) and Q-Learning, in navigating a robot within a GridWorld environment. We employed known parameters for MDP, such as the transition matrix T and reward function R, while Q-Learning operated without this explicit knowledge. Through extensive experimentation, we observed that MDP generally offers faster and more consistent convergence. However, Q-Learning, with its flexibility in parameters, still manages to produce policies of consistently good quality.

2. Introduction

The task of navigating a robot within an environment, while seemingly straightforward, poses intricate challenges when we aim for efficient and optimal paths. This assignment focuses on the GridWorld environment, a simple yet effective representation that challenges algorithms to find the best paths in a grid-like structure. The significance of this problem lies in its foundational role in robotics and AI navigation systems. By optimizing pathfinding in such controlled scenarios, we can build more complex and efficient real-world systems. Our group aimed to leverage two popular reinforcement learning methods, MDP and Q-Learning, to discern their efficacy in tackling this problem. Through systematic experimentation and analysis, we aimed to unearth insights into their convergence behaviors, policy quality, and overall performance.

3. Methodology

To ensure a comprehensive analysis, our experimentation followed a structured approach:

Parameter Selection:

- **Default Parameters:**

- **Grid Constants:** The grid's size is defined by **`GRID_SIZE`** (10x10 cells) with each cell being **`CELL_SIZE`** (60 pixels) in width and height, resulting in a display size of **`SCREEN_WIDTH x SCREEN_HEIGHT`**.
- **Reward/Penalty Constants:** In our GridWorld, collecting gold offers a **`GOLD_REWARD`** of 10 points, while stepping into a trap incurs a **`TRAP_PENALTY`** of -10 points. Reaching the goal grants a **`GOAL_REWARD`** of 200 points, while every step taken costs a **`LIVING_PENALTY`** of -1, incentivizing faster goal attainment.
- **Colors:** Different entities in the GridWorld are represented with distinct colors. The robot is visualized with **`ROBOT_COLOR`** (blue), the goal with GOAL_COLOR (green), traps with **`TRAP_COLOR`** (red), and so on.
- **Actions:** The robot can perform actions defined in the **`ACTIONS`** list, allowing it to move up, down, left, or right.
- **Algorithm Constants:** The discount factor for future rewards is set to **`GAMMA`** (0.9). The **`CONVERGE_THRESHOLD`** (0.0001) determines the point of negligible change in the value function, indicating convergence.

- For both MDP and Q-Learning, multiple parameters were experimented with. This included varying the learning rate α and exploration probability ϵ for Q-Learning.

Randomized GridWorld Generation: For each parameter combination, we generated 10 distinct GridWorld environments using different random seeds. This approach allowed us to evaluate the consistency and adaptability of each method across varied environments.

Algorithm Execution: Both MDP and Q-Learning algorithms were run on each of these GridWorlds, and the results were recorded.

Results Analysis: The outcomes from the algorithms were analyzed using the mean and standard deviation across the 10 different GridWorld scenarios for each parameter combination. This provided insights into the average performance and variability of the methods.

By following this methodology, combined with the default parameters, our experiments aimed to offer a detailed understanding of the performance nuances of MDP and Q-Learning in the GridWorld environment.

4. Instructions for Using the Script

Script Execution:

- Navigate to the directory containing the script.
- Execute the command: **`python COSC_4117EL_A2_G2.py`**.

Choosing the Method:

Upon startup, choose between MDP and Q-Learning by entering 1 for MDP or 2 for Q-Learning.

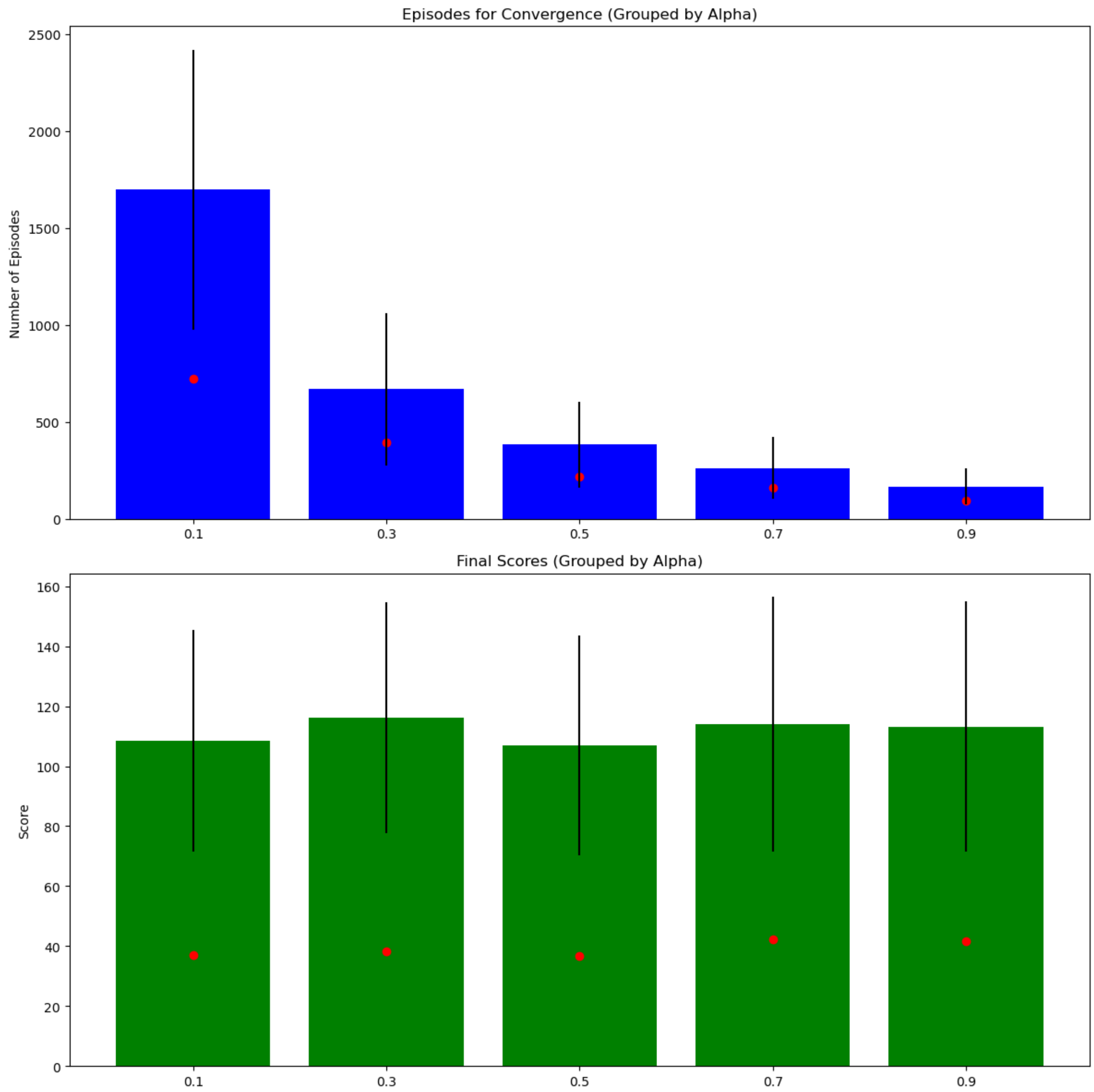
Inputting Parameters for Q-learning:
If Q-learning is selected, you'll be prompted to:

- Input the learning rate α, which defines how much new Q-value estimates overwrite previous ones.
- Specify the exploration probability ϵ, determining the chance of the agent selecting a random action over following the current policy.

Viewing the Results:
The Pygame window will showcase the GridWorld environment, visualizing the robot's journey based on the acquired policy. Interactions and the concluding goal-reaching action will be displayed, culminating with the achieved score.

Understanding Convergence with the `evaluate_policy` Function:
The script incorporates the **`evaluate_policy`** function to assess the robot's efficacy. If the robot takes more steps than the grid cells total (greater than **`size * size`** steps), it might indicate non-convergence. In such cases, a message stating "The method can't converge within time" will appear, implying that the robot may be stuck below the convergence threshold (set at 0.0001) or the chosen method/parameters might not be ideal for the GridWorld configuration.

5. Experimental Results



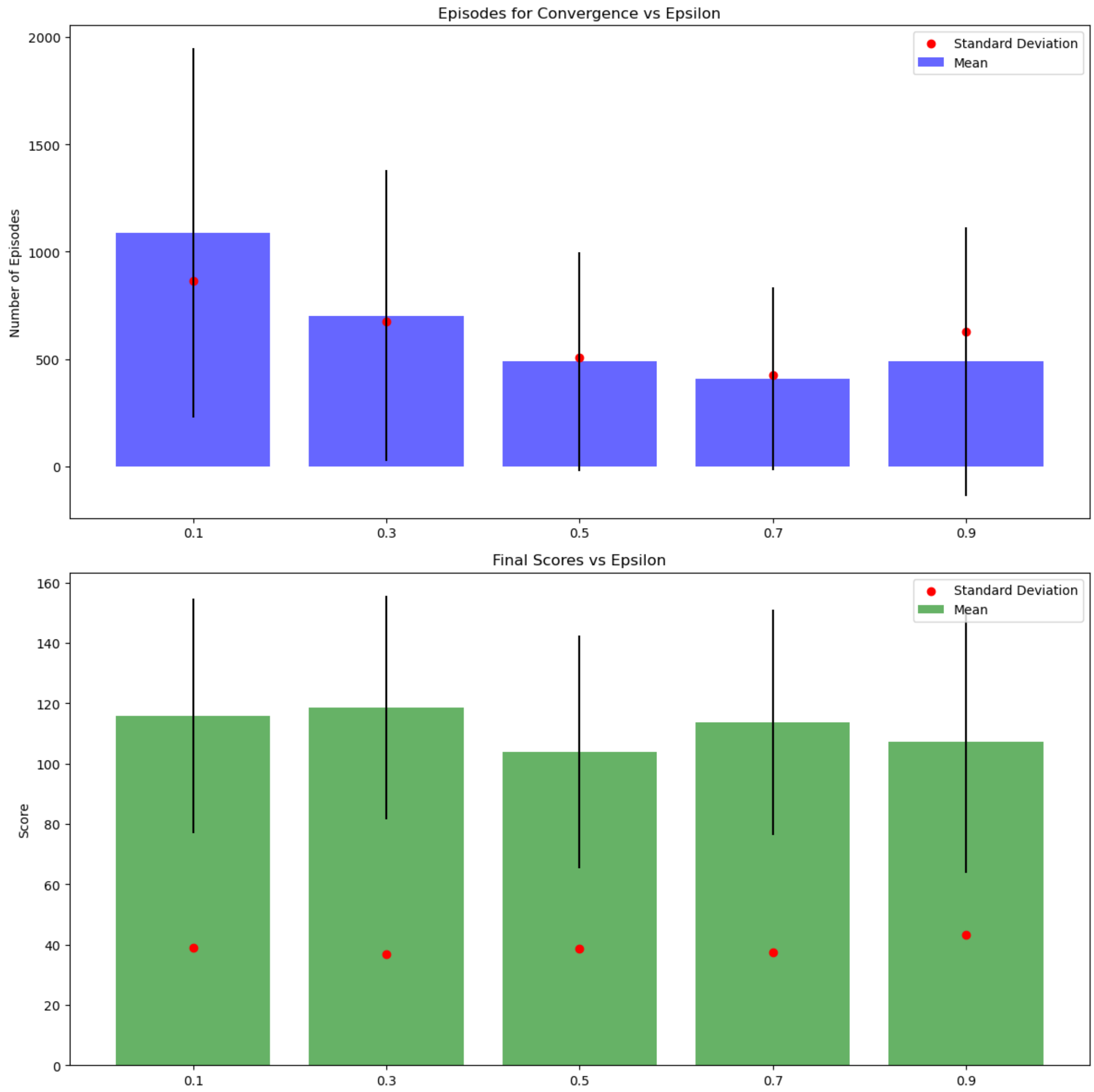
Here are the combined visualizations for both the mean and standard deviation values, as they relate to α (learning rate):

Episodes for Convergence vs. α:

- The top graph showcases the mean number of episodes required for convergence for each α value, with error bars indicating one standard deviation.
- Additionally, the red scatter points represent the standard deviation values for each α.
- We observe a decreasing trend in both the mean number of episodes and their variability (standard deviation) as α increases. This suggests that with a higher learning rate, Q-learning tends to converge faster and more consistently.

Final Scores vs. α:

- The bottom graph displays the mean final scores achieved by the robot for each α value, with error bars indicating one standard deviation.
- The red scatter points represent the standard deviation values for each α The mean final scores appear to be stable across different α values, indicating consistent policy quality. However, the variability in scores (standard deviation) remains relatively stable across different α values.



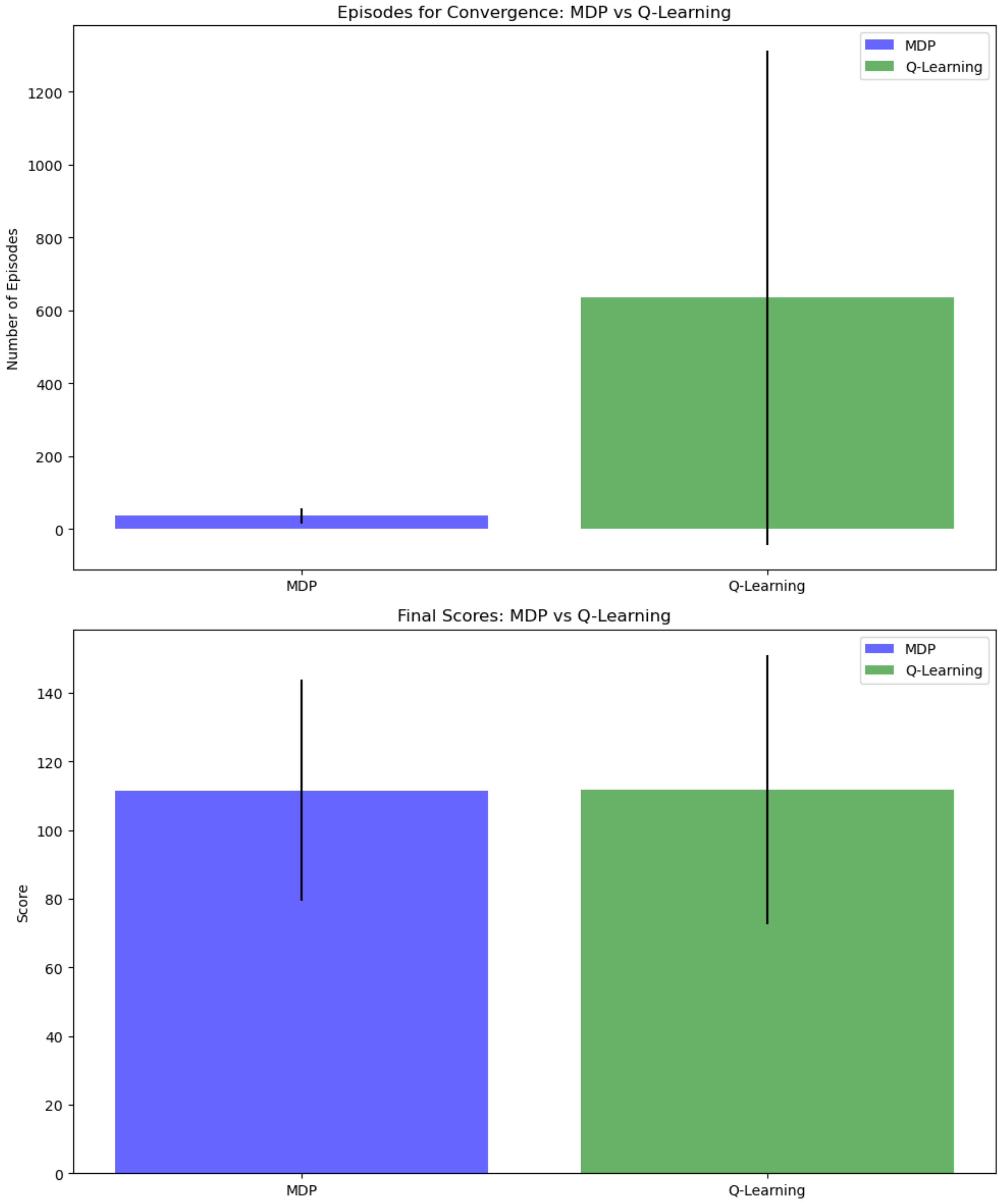
The combined visualizations for both the mean and standard deviation values, as they relate to ϵ (exploration probability), are as follows:

Episodes for Convergence vs. ϵ:

- The top graph showcases the mean number of episodes required for convergence for each ϵ value, with error bars indicating one standard deviation.
- Additionally, the red scatter points represent the standard deviation values for each ϵ.
- We observe that as ϵ increases, the mean number of episodes for convergence tends to decrease, suggesting faster learning with more exploration. Additionally, the variability in the number of episodes (standard deviation) reduces as ϵ increases, leading to more consistent convergence rates.

Final Scores vs. ϵ:

- The bottom graph displays the mean final scores achieved by the robot for each ϵ value, with error bars indicating one standard deviation.
- The red scatter points represent the standard deviation values for each ϵ.
- The mean final scores remain relatively consistent across different ϵ values. However, there are slight variations in scores across different ϵ values, suggesting that certain exploration-exploitation balances might be marginally more effective than others. The variability in scores (standard deviation) remains relatively stable across different ϵ values.



Here's the visual comparison between MDP (Value Iteration) and Q-Learning:

Episodes for Convergence: MDP vs. Q-Learning:

- The top graph compares the mean number of episodes required for convergence for both MDP and Q-Learning, with error bars indicating one standard deviation.

- We observe that MDP generally requires fewer episodes to converge compared to Q-Learning. Additionally, the variability (standard deviation) in the number of episodes is lower for MDP compared to Q-Learning.

Final Scores: MDP vs. Q-Learning:

- The bottom graph compares the mean final scores achieved by the robot using both MDP and Q-Learning, with error bars indicating one standard deviation.
- The mean final scores are comparable between MDP and Q-Learning, suggesting that both methods result in similarly effective policies. However, Q-Learning has a slightly wider spread (higher standard deviation), implying that the scores can vary more across different runs or parameter combinations.

4. Discussion

The visual and statistical analyses provide a comprehensive view of the performance of MDP and Q-learning in the GridWorld environment:

Inherent Knowledge in MDP: MDP has a distinct advantage in that its parameters, like the transition matrix T and the reward function R, are pre-defined and known. In contrast, Q-Learning operates without explicit knowledge of the transition matrix and reward function. This inherent knowledge in MDP typically allows it to converge faster and with greater stability.

Convergence Speed: Given the known parameters in MDP, it tends to converge faster and more consistently than Q-Learning. The exploration probability (ϵ) in Q-Learning influences its convergence speed, with higher ϵ values leading to quicker learning. Similarly, an increased learning rate (α) in Q-Learning accelerates its convergence.

Policy Quality: Both MDP and Q-Learning yield policies of comparable quality. However, despite the uncertainties in Q-Learning due to the unknown transition matrix and reward function, it still manages to produce policies of consistently good quality. Q-Learning displays more variability in its outcomes, potentially due to the randomness introduced by exploration and different parameter combinations.

Exploration vs. Exploitation in Q-Learning: The trade-off between exploration and exploitation in Q-Learning is evident. More exploration (higher ϵ) leads to faster learning but might introduce variability in the outcomes. On the other hand, a higher learning rate (α) facilitates faster and consistent learning without affecting the quality of the policy significantly.

In conclusion, while MDP offers rapid and consistent learning in the GridWorld environment due to its known parameters, Q-Learning provides flexibility with its parameters, allowing for potential optimizations based on the specific needs and characteristics of the environment, even without explicit knowledge of the system dynamics.

Appendix

Mdp stats

	Episodes for Convergence	Final Scores
mean	36.1	111.5098
std	20.73885	32.20729
min	21	51.77186
max	89	169

Ql_stats

		Episodes for Convergence				Final Scores			
		mean	std	min	max	mean	std	min	max
Alpha	Epsilon								
0.1	0.1	2560.2	608.7103	1398	3393	100.5932	34.30032	55.08058	141.8
	0.3	1962.2	295.6743	1789	2782	114.6383	37.17608	60.8595	168
	0.5	1346.6	495.6229	1147	2753	118.7865	42.07496	62.51866	199
	0.7	1131.1	360.1489	949	2148	114.9278	33.26522	77.09344	199
	0.9	1488.5	741.1431	999	2962	93.78336	38.20082	53.53369	178
0.3	0.1	1255.5	301.8588	743	1642	119.5798	42.03906	70.36938	178
	0.3	693.5	124.982	616	1041	130.0333	27.3679	94.269	178
	0.5	490.8	199.3979	394	1054	95.62424	32.36526	47.9047	150.8
	0.7	430.5	241.8784	337	1118	117.5964	44.14026	64.43102	199
	0.9	469.9	329.0209	328	1403	117.8354	42.5566	56.87707	178
0.5	0.1	764.6	153.9417	474	1028	103.464	39.79913	45.26394	178
	0.3	416.2	81.39315	357	640	113.3562	44.66993	54.88032	199
	0.5	266.7	13.22498	249	293	102.1582	27.11553	67.4841	136.22
	0.7	235.7	63.81057	193	414	96.65255	26.98266	69.55938	150.8
	0.9	228.2	18.65952	205	268	118.8121	44.13239	51.75566	199
0.7	0.1	534.6	56.0004	428	615	135.3211	37.30526	77.09344	178
	0.3	264.7	14.51474	244	297	109.6846	33.39012	48.26888	159
	0.5	220.7	144.182	151	625	102.8343	49.34829	0	178
	0.7	139.3	10.16585	126	152	114.2631	37.51044	55.08058	169
	0.9	150.4	11.6352	129	166	108.1024	52.2707	0	178
0.9	0.1	322.1	85.25315	223	494	119.6237	37.6906	61.93842	188
	0.3	169.1	18.1503	150	213	125.0848	43.19273	70.73753	199
	0.5	118.1	11.00959	105	138	99.36188	42.21158	50.3812	151.8
	0.7	114.1	58.12907	88	278	124.7671	43.84187	63.16679	188
	0.9	111.7	36.42969	86	208	97.10165	40.65917	40.07119	159.9

Raw_results

Method	Alpha	Epsilon	Episodes for Convergence	Final Scores

MDP	-	-	21	118.659
MDP	-	-	51	126.22
MDP	-	-	27	51.77186
MDP	-	-	41	141.8
MDP	-	-	89	94.94938
MDP	-	-	27	99.2882
MDP	-	-	24	169
MDP	-	-	24	122.098
MDP	-	-	25	106.5782
MDP	-	-	32	84.73297
Q-Learning	0.1	0.1	2841	97.06885
Q-Learning	0.1	0.1	2433	141.8
Q-Learning	0.1	0.1	2570	65.74947
Q-Learning	0.1	0.1	1398	141.8
Q-Learning	0.1	0.1	2748	108.2882
Q-Learning	0.1	0.1	3361	141.8
Q-Learning	0.1	0.1	3393	113.9492
Q-Learning	0.1	0.1	2709	77.65938
Q-Learning	0.1	0.1	2186	62.73632
Q-Learning	0.1	0.1	1963	55.08058
Q-Learning	0.1	0.3	1897	168
Q-Learning	0.1	0.3	1789	107.22
Q-Learning	0.1	0.3	1825	118.12
Q-Learning	0.1	0.3	1838	117.5592
Q-Learning	0.1	0.3	1983	67.4841
Q-Learning	0.1	0.3	1825	141.8
Q-Learning	0.1	0.3	1826	60.8595
Q-Learning	0.1	0.3	1873	141.8
Q-Learning	0.1	0.3	1984	149.9
Q-Learning	0.1	0.3	2782	73.64059
Q-Learning	0.1	0.5	1260	99.2882
Q-Learning	0.1	0.5	1147	168
Q-Learning	0.1	0.5	1153	120.198
Q-Learning	0.1	0.5	2753	101.5104
Q-Learning	0.1	0.5	1207	135.22
Q-Learning	0.1	0.5	1155	62.51866
Q-Learning	0.1	0.5	1219	132.8
Q-Learning	0.1	0.5	1172	99.41047
Q-Learning	0.1	0.5	1232	199
Q-Learning	0.1	0.5	1168	69.91964
Q-Learning	0.1	0.7	1016	99.53479
Q-Learning	0.1	0.7	1055	120.198
Q-Learning	0.1	0.7	991	199
Q-Learning	0.1	0.7	992	77.09344
Q-Learning	0.1	0.7	949	111.0738

Q-Learning	0.1	0.7	1038	122.1392
Q-Learning	0.1	0.7	1091	95.75938
Q-Learning	0.1	0.7	965	123.51
Q-Learning	0.1	0.7	1066	112.098
Q-Learning	0.1	0.7	2148	88.87147
Q-Learning	0.1	0.9	999	105.1931
Q-Learning	0.1	0.9	1079	100.0983
Q-Learning	0.1	0.9	1219	79.95
Q-Learning	0.1	0.9	1016	128.659
Q-Learning	0.1	0.9	1220	101.9738
Q-Learning	0.1	0.9	1185	62.54985
Q-Learning	0.1	0.9	1252	67.05212
Q-Learning	0.1	0.9	1148	53.53369
Q-Learning	0.1	0.9	2962	178
Q-Learning	0.1	0.9	2805	60.82369
Q-Learning	0.3	0.1	1642	93.38344
Q-Learning	0.3	0.1	743	159
Q-Learning	0.3	0.1	934	149.9
Q-Learning	0.3	0.1	1479	70.36938
Q-Learning	0.3	0.1	1604	178
Q-Learning	0.3	0.1	1402	78.53329
Q-Learning	0.3	0.1	1418	178
Q-Learning	0.3	0.1	988	106.5782
Q-Learning	0.3	0.1	1167	88.46938
Q-Learning	0.3	0.1	1178	93.56428
Q-Learning	0.3	0.3	655	94.269
Q-Learning	0.3	0.3	624	150.8
Q-Learning	0.3	0.3	689	96.65938
Q-Learning	0.3	0.3	616	141.8
Q-Learning	0.3	0.3	682	159
Q-Learning	0.3	0.3	670	120.198
Q-Learning	0.3	0.3	654	107.4374
Q-Learning	0.3	0.3	622	125.949
Q-Learning	0.3	0.3	1041	178
Q-Learning	0.3	0.3	682	126.22
Q-Learning	0.3	0.5	420	96.8492
Q-Learning	0.3	0.5	438	47.9047
Q-Learning	0.3	0.5	431	112.9492
Q-Learning	0.3	0.5	483	76.96239
Q-Learning	0.3	0.5	1054	150.8
Q-Learning	0.3	0.5	394	121.827
Q-Learning	0.3	0.5	429	122.098
Q-Learning	0.3	0.5	411	99.2882
Q-Learning	0.3	0.5	405	67.4841
Q-Learning	0.3	0.5	443	60.07966

Q-Learning	0.3	0.7	367	67.03543
Q-Learning	0.3	0.7	358	98.2882
Q-Learning	0.3	0.7	337	112.098
Q-Learning	0.3	0.7	340	159
Q-Learning	0.3	0.7	1118	64.43102
Q-Learning	0.3	0.7	351	134.41
Q-Learning	0.3	0.7	338	95.46089
Q-Learning	0.3	0.7	364	87.24
Q-Learning	0.3	0.7	361	199
Q-Learning	0.3	0.7	371	159
Q-Learning	0.3	0.9	328	136.22
Q-Learning	0.3	0.9	375	56.87707
Q-Learning	0.3	0.9	338	178
Q-Learning	0.3	0.9	341	99.50785
Q-Learning	0.3	0.9	393	120.198
Q-Learning	0.3	0.9	1403	178
Q-Learning	0.3	0.9	374	151.8
Q-Learning	0.3	0.9	374	83.65444
Q-Learning	0.3	0.9	420	72.09838
Q-Learning	0.3	0.9	353	101.9982
Q-Learning	0.5	0.1	655	149.9
Q-Learning	0.5	0.1	750	109.2882
Q-Learning	0.5	0.1	790	64.08623
Q-Learning	0.5	0.1	908	178
Q-Learning	0.5	0.1	744	100.1253
Q-Learning	0.5	0.1	474	76.71356
Q-Learning	0.5	0.1	752	97.31275
Q-Learning	0.5	0.1	660	45.26394
Q-Learning	0.5	0.1	1028	87.19082
Q-Learning	0.5	0.1	885	126.759
Q-Learning	0.5	0.3	360	85.70243
Q-Learning	0.5	0.3	428	199
Q-Learning	0.5	0.3	403	99.2882
Q-Learning	0.5	0.3	399	63.74059
Q-Learning	0.5	0.3	381	54.88032
Q-Learning	0.5	0.3	398	102.5643
Q-Learning	0.5	0.3	357	149.9
Q-Learning	0.5	0.3	402	120.198
Q-Learning	0.5	0.3	394	159
Q-Learning	0.5	0.3	640	99.2882
Q-Learning	0.5	0.5	283	119.388
Q-Learning	0.5	0.5	255	118.659
Q-Learning	0.5	0.5	260	124.8492
Q-Learning	0.5	0.5	266	82.31047
Q-Learning	0.5	0.5	261	70.9231

Q-Learning	0.5	0.5	274	67.4841
Q-Learning	0.5	0.5	249	90.2882
Q-Learning	0.5	0.5	261	77.1402
Q-Learning	0.5	0.5	265	134.32
Q-Learning	0.5	0.5	293	136.22
Q-Learning	0.5	0.7	222	91.48344
Q-Learning	0.5	0.7	232	69.55938
Q-Learning	0.5	0.7	215	150.8
Q-Learning	0.5	0.7	224	91.9982
Q-Learning	0.5	0.7	228	72.99834
Q-Learning	0.5	0.7	193	72.26707
Q-Learning	0.5	0.7	414	119.8541
Q-Learning	0.5	0.7	220	113.2931
Q-Learning	0.5	0.7	202	112.4831
Q-Learning	0.5	0.7	207	71.78877
Q-Learning	0.5	0.9	225	99.2882
Q-Learning	0.5	0.9	232	99.63251
Q-Learning	0.5	0.9	205	178
Q-Learning	0.5	0.9	237	130.198
Q-Learning	0.5	0.9	268	77.69367
Q-Learning	0.5	0.9	213	136.22
Q-Learning	0.5	0.9	240	108.0443
Q-Learning	0.5	0.9	205	199
Q-Learning	0.5	0.9	229	108.2882
Q-Learning	0.5	0.9	228	51.75566
Q-Learning	0.7	0.1	615	151.61
Q-Learning	0.7	0.1	614	159
Q-Learning	0.7	0.1	544	178
Q-Learning	0.7	0.1	544	133.51
Q-Learning	0.7	0.1	505	77.09344
Q-Learning	0.7	0.1	562	96.0031
Q-Learning	0.7	0.1	508	136.22
Q-Learning	0.7	0.1	428	84.7741
Q-Learning	0.7	0.1	531	178
Q-Learning	0.7	0.1	495	159
Q-Learning	0.7	0.3	297	75.15212
Q-Learning	0.7	0.3	263	126.22
Q-Learning	0.7	0.3	272	121.098
Q-Learning	0.7	0.3	259	159
Q-Learning	0.7	0.3	254	108.2882
Q-Learning	0.7	0.3	258	79.28854
Q-Learning	0.7	0.3	263	126.22
Q-Learning	0.7	0.3	260	141.8
Q-Learning	0.7	0.3	244	111.5104
Q-Learning	0.7	0.3	277	48.26888

Q-Learning	0.7	0.5	237	90.94444
Q-Learning	0.7	0.5	151	82.1451
Q-Learning	0.7	0.5	156	0
Q-Learning	0.7	0.5	183	72.79851
Q-Learning	0.7	0.5	178	141.8
Q-Learning	0.7	0.5	159	112.098
Q-Learning	0.7	0.5	188	178
Q-Learning	0.7	0.5	166	112.098
Q-Learning	0.7	0.5	625	150.8
Q-Learning	0.7	0.5	164	87.65938
Q-Learning	0.7	0.7	152	91.99834
Q-Learning	0.7	0.7	129	169
Q-Learning	0.7	0.7	126	78.70341
Q-Learning	0.7	0.7	151	105.537
Q-Learning	0.7	0.7	134	169
Q-Learning	0.7	0.7	143	125.949
Q-Learning	0.7	0.7	127	112.098
Q-Learning	0.7	0.7	137	93.46444
Q-Learning	0.7	0.7	151	141.8
Q-Learning	0.7	0.7	143	55.08058
Q-Learning	0.7	0.9	129	100.1253
Q-Learning	0.7	0.9	154	159
Q-Learning	0.7	0.9	141	116.22
Q-Learning	0.7	0.9	158	0
Q-Learning	0.7	0.9	158	97.65938
Q-Learning	0.7	0.9	160	96.53741
Q-Learning	0.7	0.9	166	169
Q-Learning	0.7	0.9	136	84.38344
Q-Learning	0.7	0.9	151	80.09838
Q-Learning	0.7	0.9	151	178
Q-Learning	0.9	0.1	494	141.8
Q-Learning	0.9	0.1	291	188
Q-Learning	0.9	0.1	223	108.2882
Q-Learning	0.9	0.1	257	112.098
Q-Learning	0.9	0.1	314	108.2882
Q-Learning	0.9	0.1	429	61.93842
Q-Learning	0.9	0.1	256	66.83569
Q-Learning	0.9	0.1	358	150.8
Q-Learning	0.9	0.1	263	133.51
Q-Learning	0.9	0.1	336	124.6782
Q-Learning	0.9	0.3	163	106.5782
Q-Learning	0.9	0.3	167	159
Q-Learning	0.9	0.3	173	87.65938
Q-Learning	0.9	0.3	150	96.65938
Q-Learning	0.9	0.3	170	199

Q-Learning	0.9	0.3	213	126.22
Q-Learning	0.9	0.3	150	141.8
Q-Learning	0.9	0.3	160	70.73753
Q-Learning	0.9	0.3	181	178
Q-Learning	0.9	0.3	164	85.19344
Q-Learning	0.9	0.5	138	80.2882
Q-Learning	0.9	0.5	114	50.3812
Q-Learning	0.9	0.5	115	52.87759
Q-Learning	0.9	0.5	105	87.65938
Q-Learning	0.9	0.5	131	81.87641
Q-Learning	0.9	0.5	113	56.66702
Q-Learning	0.9	0.5	116	143.51
Q-Learning	0.9	0.5	105	151.8
Q-Learning	0.9	0.5	129	151.8
Q-Learning	0.9	0.5	115	136.759
Q-Learning	0.9	0.7	104	77.35477
Q-Learning	0.9	0.7	91	72.8337
Q-Learning	0.9	0.7	278	178
Q-Learning	0.9	0.7	113	112.098
Q-Learning	0.9	0.7	100	134.32
Q-Learning	0.9	0.7	91	141.8
Q-Learning	0.9	0.7	88	188
Q-Learning	0.9	0.7	88	121.098
Q-Learning	0.9	0.7	92	159
Q-Learning	0.9	0.7	96	63.16679
Q-Learning	0.9	0.9	133	50.71252
Q-Learning	0.9	0.9	98	159
Q-Learning	0.9	0.9	86	159.9
Q-Learning	0.9	0.9	95	85.2143
Q-Learning	0.9	0.9	86	80.89851
Q-Learning	0.9	0.9	108	80.61866
Q-Learning	0.9	0.9	107	40.07119
Q-Learning	0.9	0.9	95	85.2833
Q-Learning	0.9	0.9	101	126.22
Q-Learning	0.9	0.9	208	103.098