

ML Assignment 4 Report

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Value Iteration

Question 1

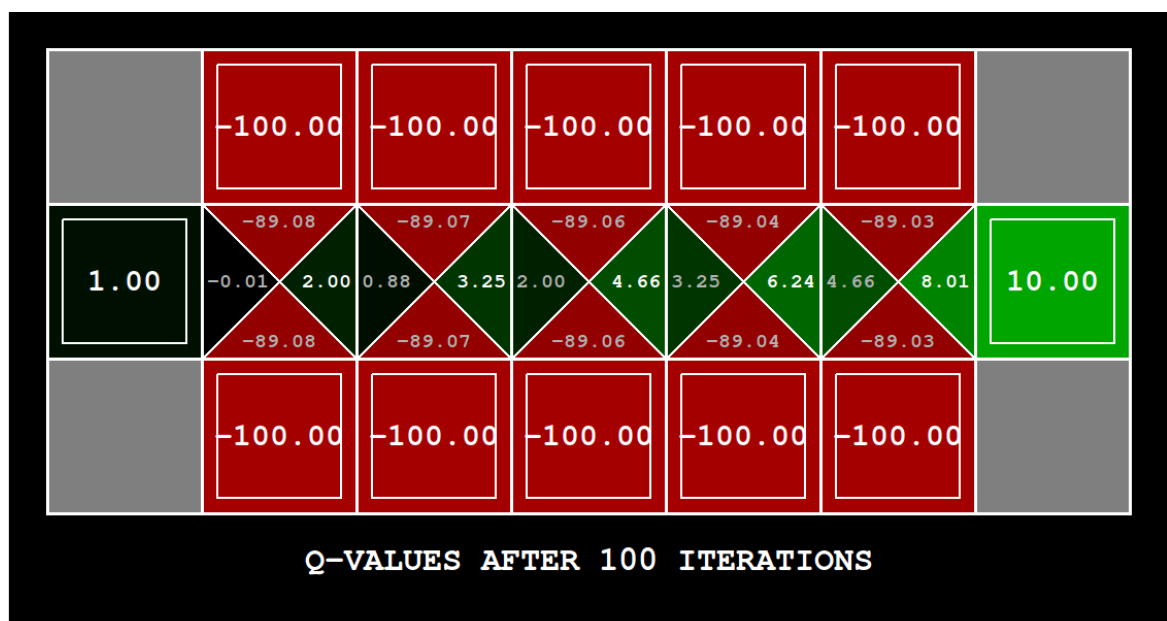
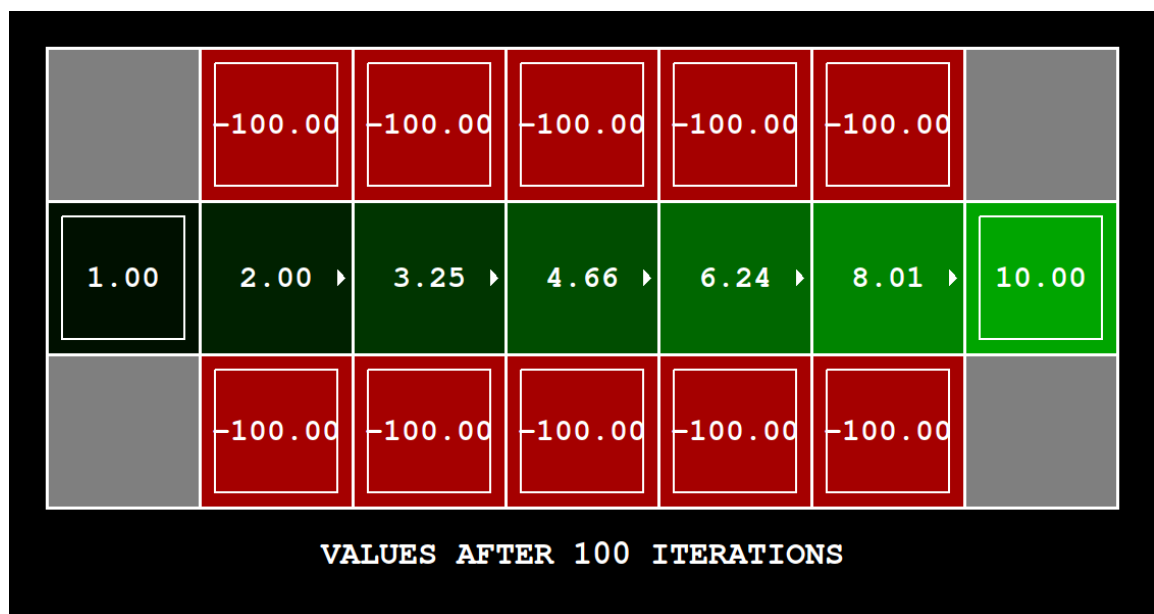
Code attached.

Question 2

Parameter changed = noise

Noise = 0.01

We decreased the noise as it decreases the probability of the agent not following the given path.



Question 3

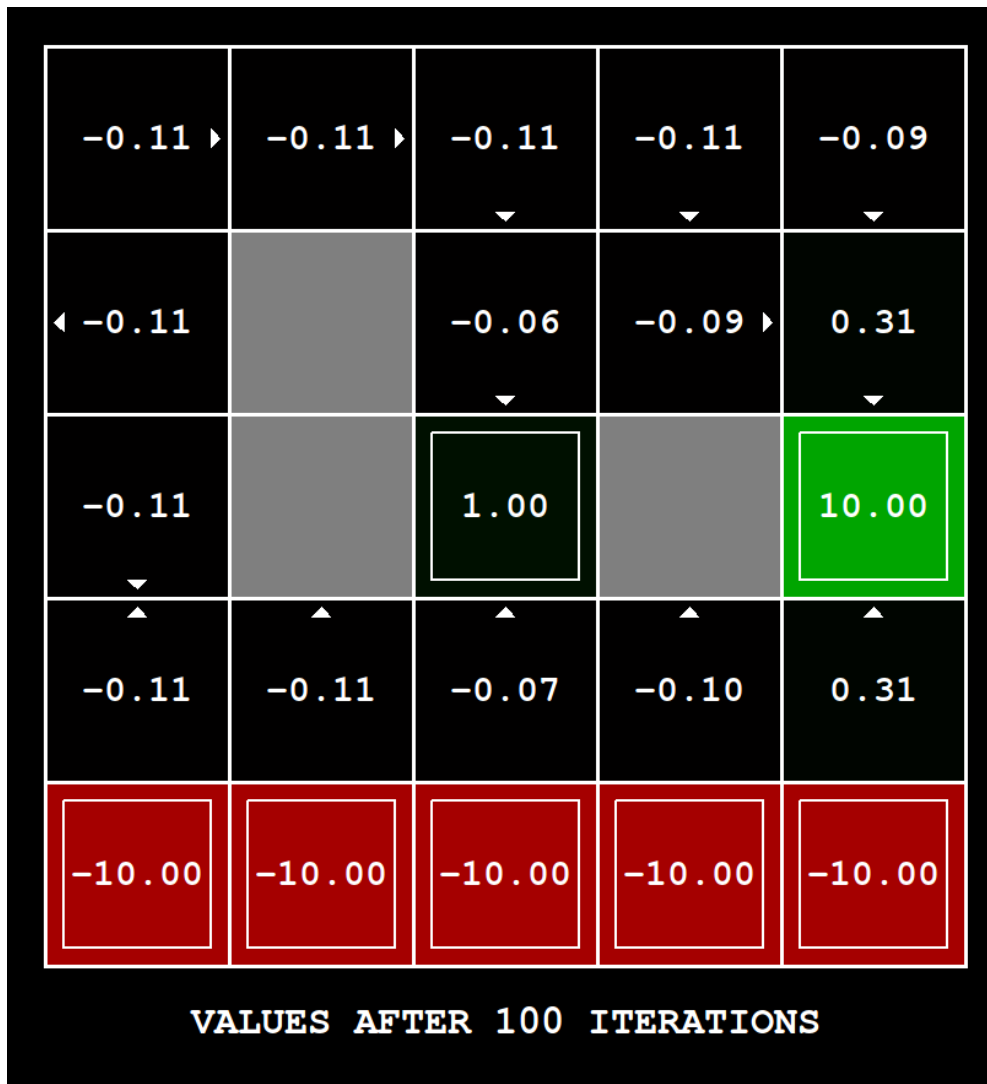
- a) Prefer the close exit(+1), risking the cliff

Chosen parameters:

Discount = 0.1

Noise = 0.6

Living Reward = -0.1



Reason:

A low discount value reduces the impact of the global max_reward in 100 iterations. Moreover, a large noise leads to a greater probability of considering the high risk path. A negative living reward further slows down the convergence.

Tried parameters:

-0.19 ▸	-0.16 ▸	-0.07 ▸	0.06 ▸	0.44 ▼
▲ -0.20		0.19 ▼	0.44 ▸	2.31 ▼
-0.20 ▼		1.00		10.00
▲ -0.19	▲ -0.14	▲ 0.13	▲ 0.33	▲ 2.29
-10.00	-10.00	-10.00	-10.00	-10.00
VALUES AFTER 100 ITERATIONS				

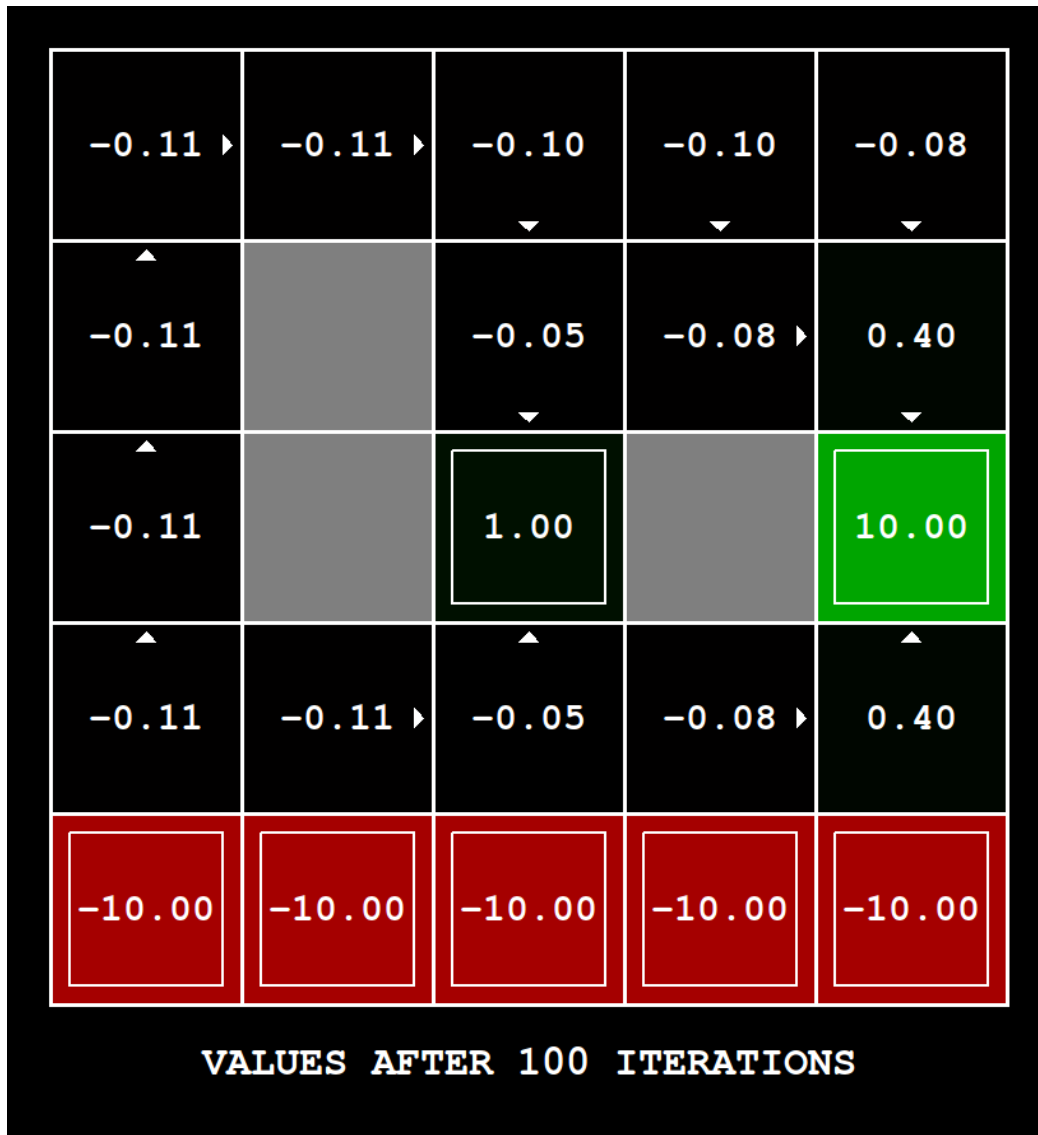
b) Prefer the close exit(+1), avoiding the high risk cliff

Chosen parameters:

Discount: 0.05

Noise: 0.01

Living Reward: -0.1



Reason:

Decreasing the noise value decreases the probability of the agent going on a path not desired by the action.

Tried Parameters:

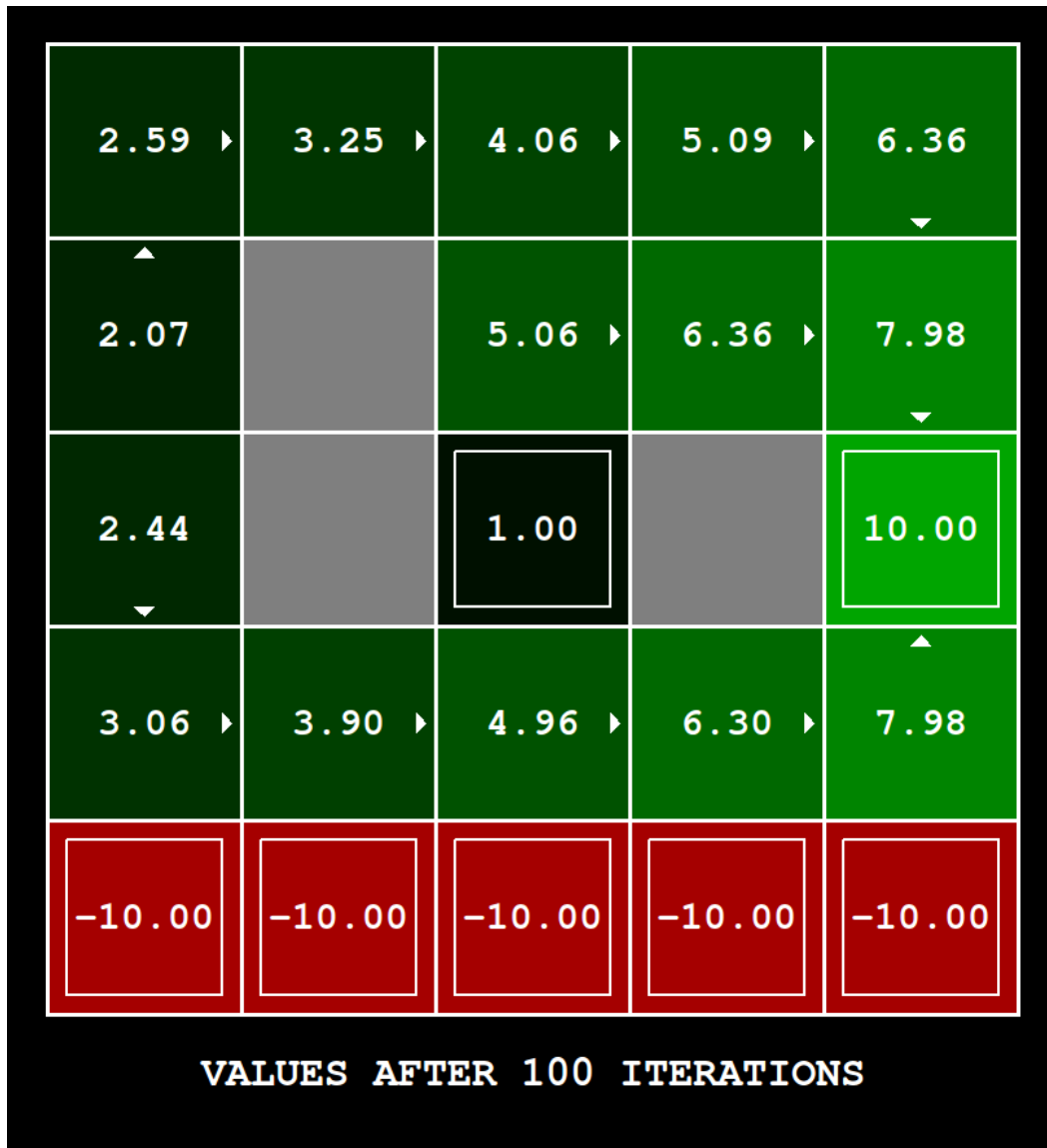
c) Prefer the distant exit(+10), risking the high risk cliff

Chosen parameters:

Discount: 0.8

Noise: 0.01

Living Reward: 0.0

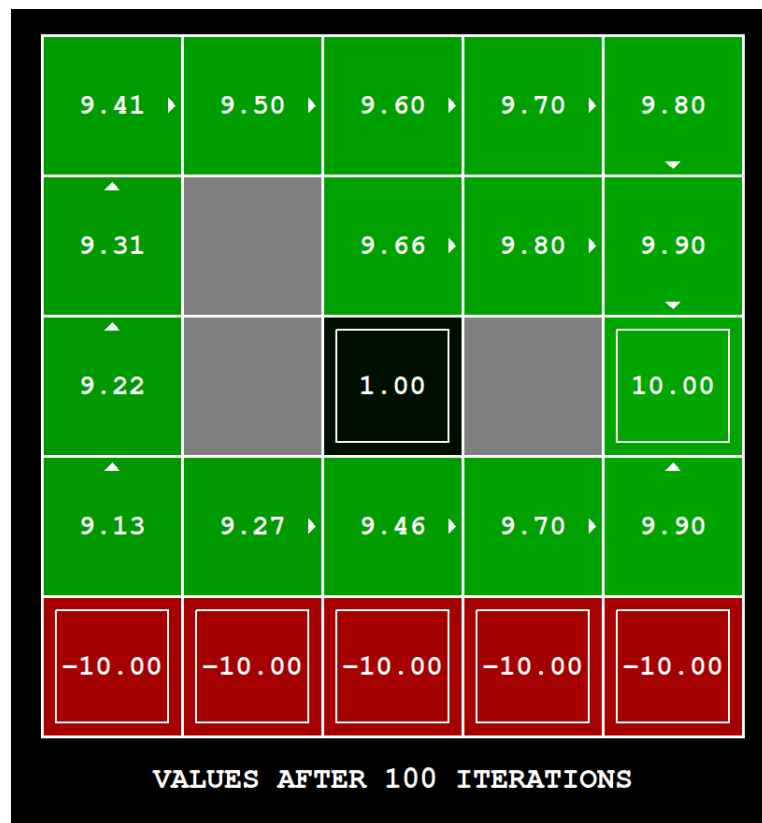


Reason:

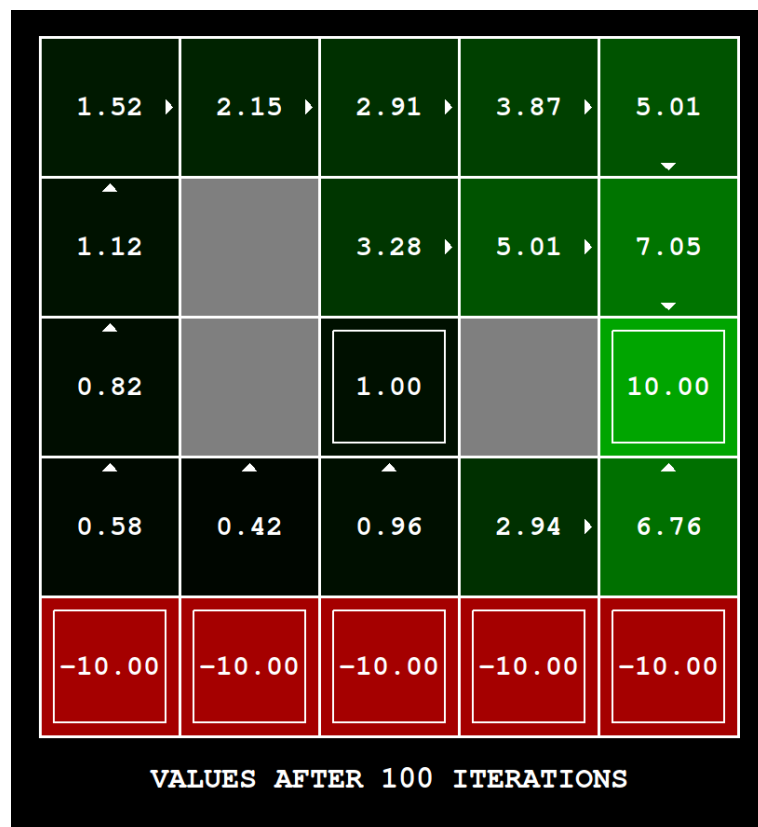
A moderately high discount leads to a big impact of the global max (+10) state in 100 iterations. Accompanied with low noise, the impact of the negative states (-100) reduces. A very high discount overcomes the impact of the negative states.

Tried Parameters:

(0.99, 0.01, 0.0)



(0.8, 0.3, 0.0)



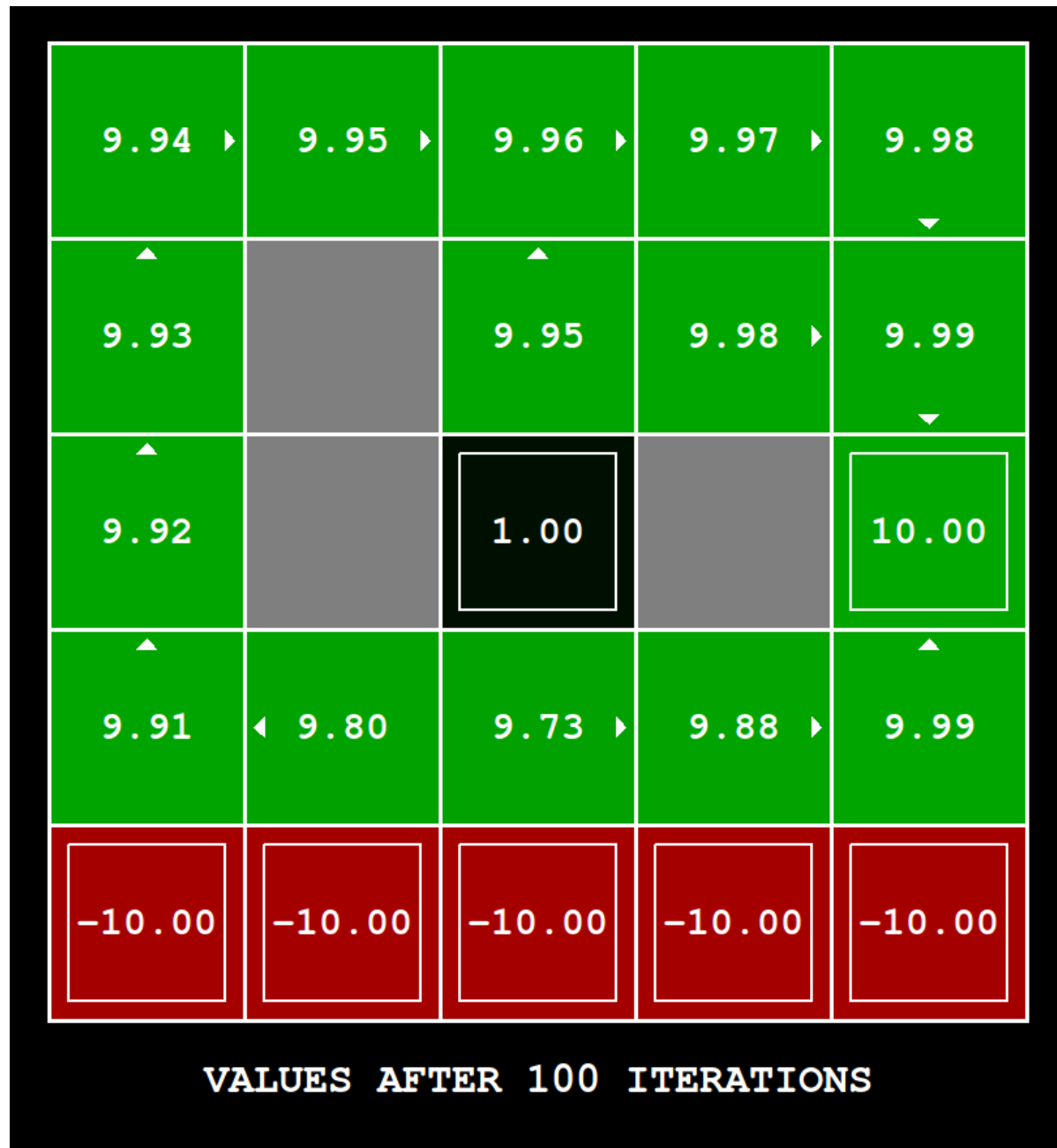
d) Prefer the distant exit(+10), avoiding the high risk cliff

Chosen parameters:

Discount: 0.999

Noise: 0.01

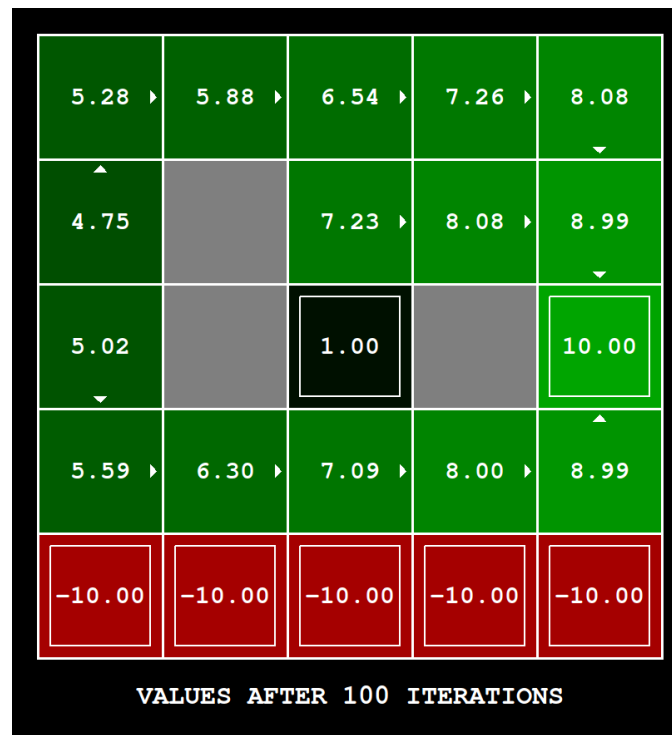
Living Reward: 0.0



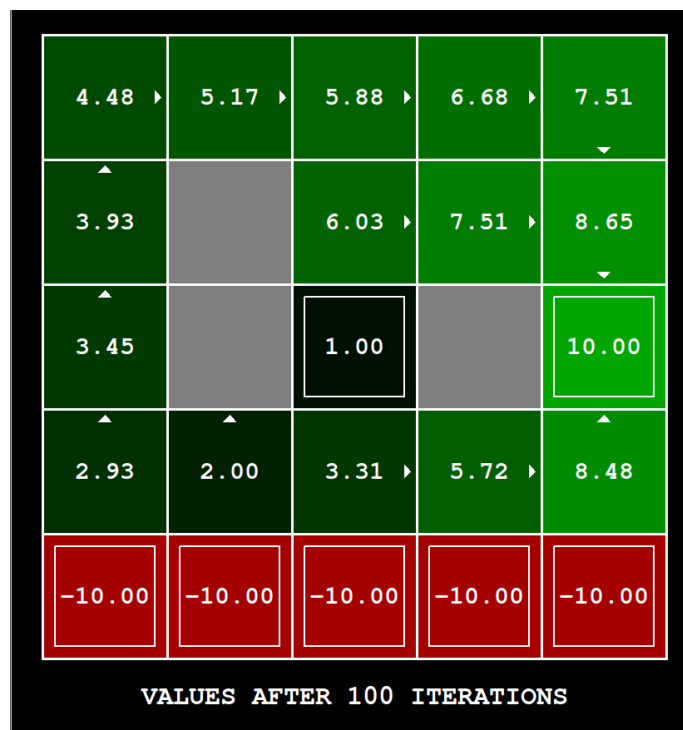
Reason:

Increasing the discount value (with a low noise), the impact of high reward state is high after 100 iterations.

Tried Parameters:
 (0.9, 0.01, 0.0)



(0.9, 0.2, 0.0) – also works



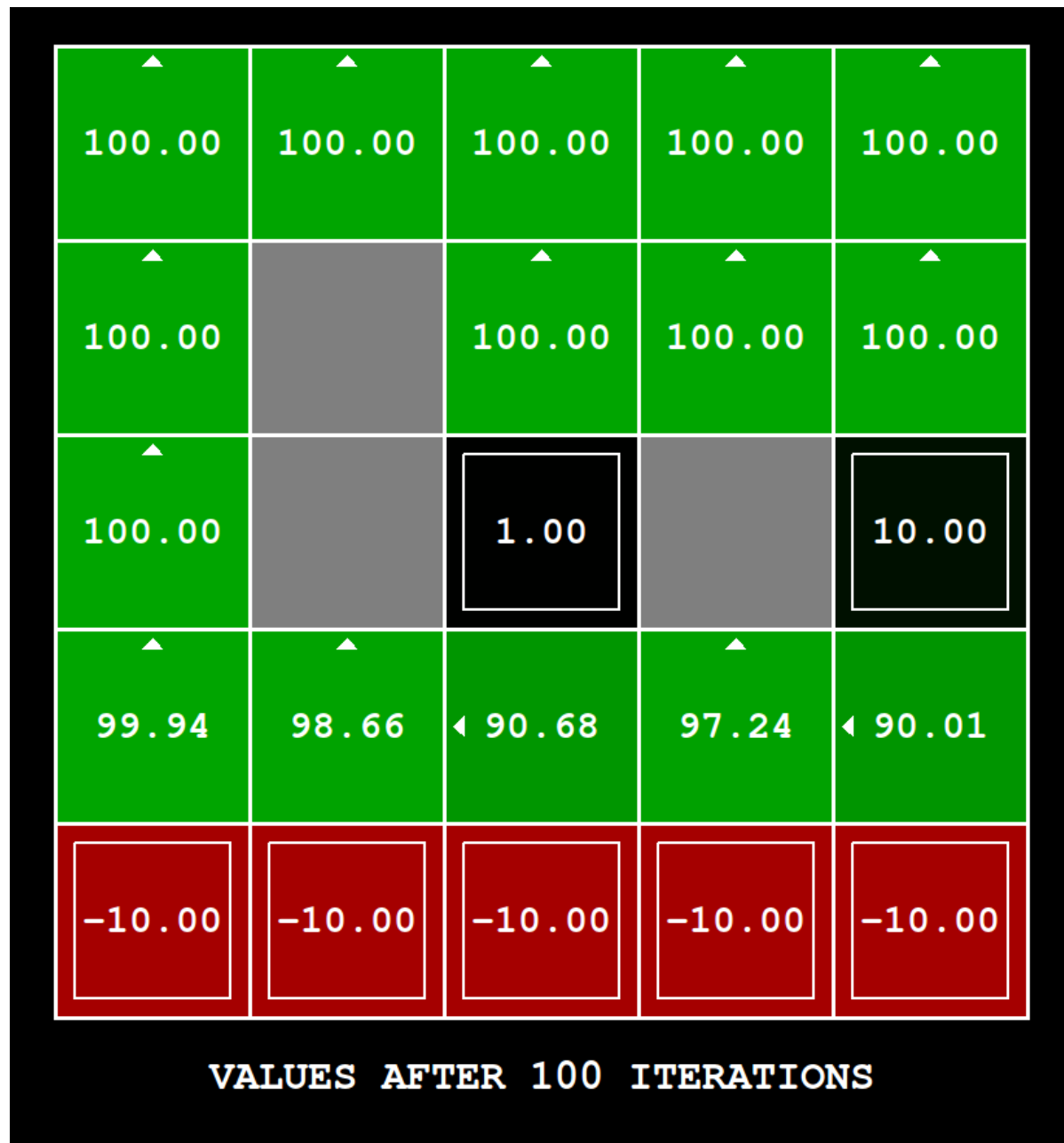
e) Avoiding both exits and the cliff

Chosen parameters:

Discount: 0.8

Noise: 0.1

Living Reward: 20.0



Reason:

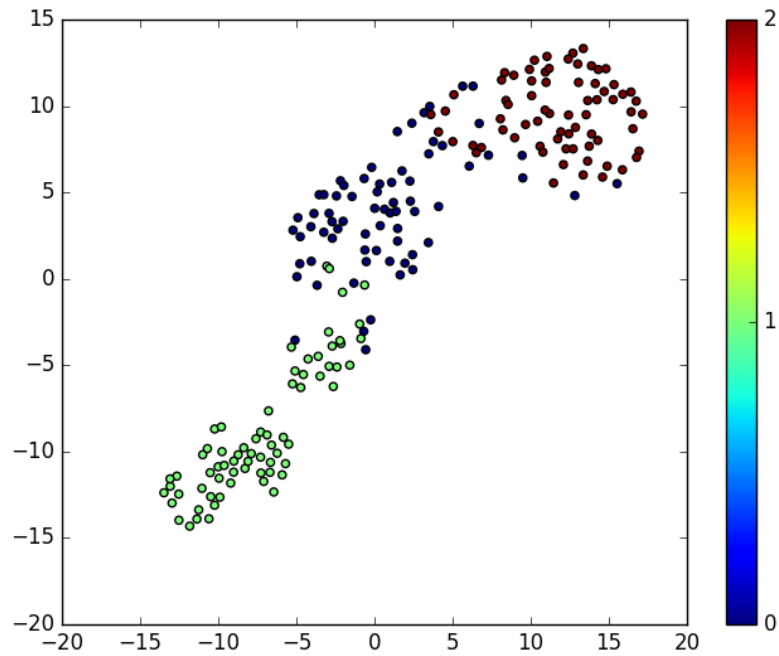
Setting an initial reward higher than the terminal states makes the terminal states less important.

K-means

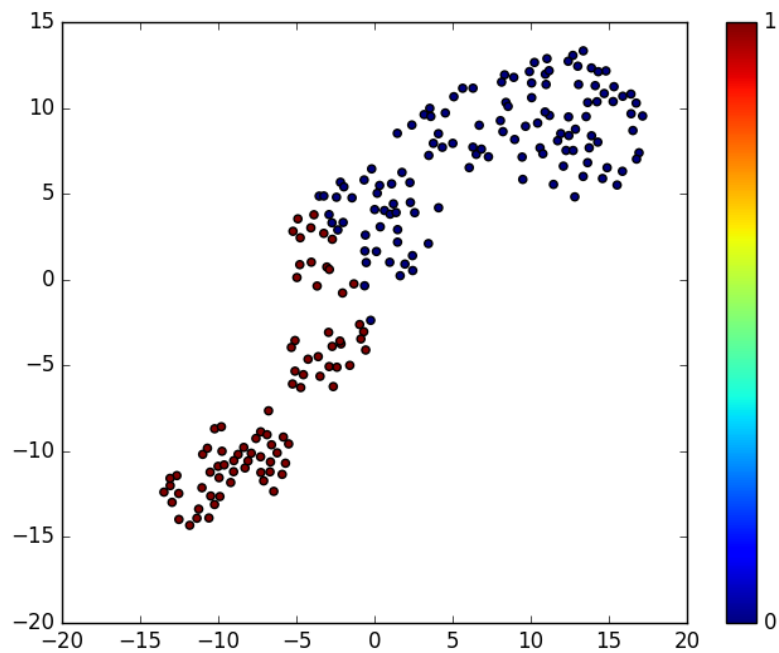
Qualitative Analysis

1. Seeds Dataset

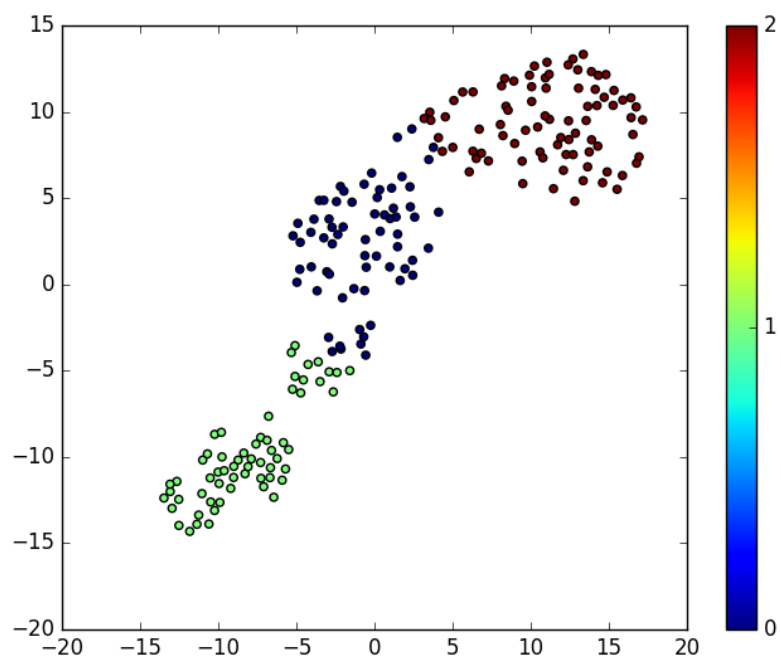
a) Plotting actual data



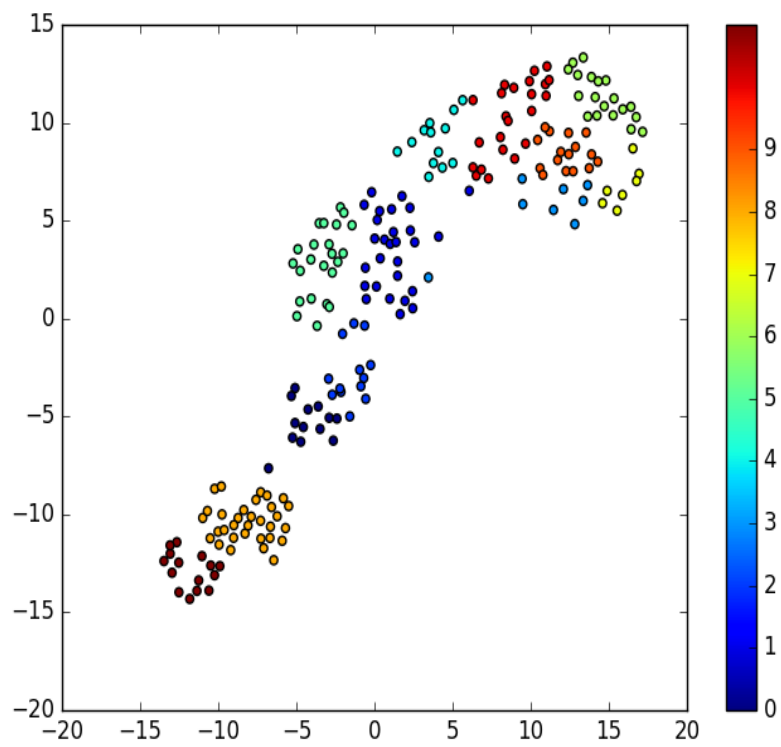
b) $K = 2$



c) $K = \text{actual}(3)$

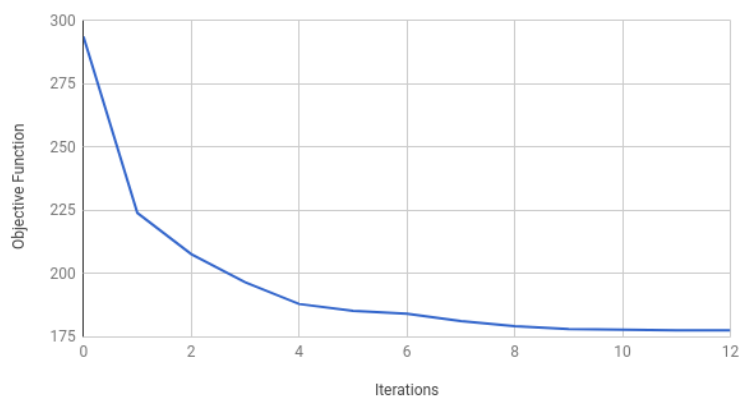


d) $K = 12$

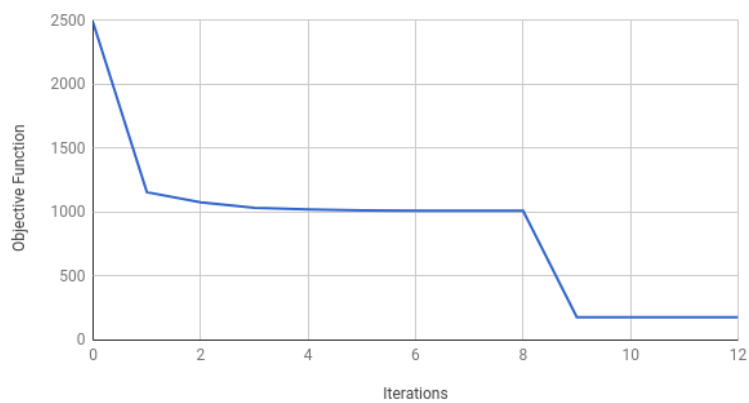


e) Objective Function vs Iteration

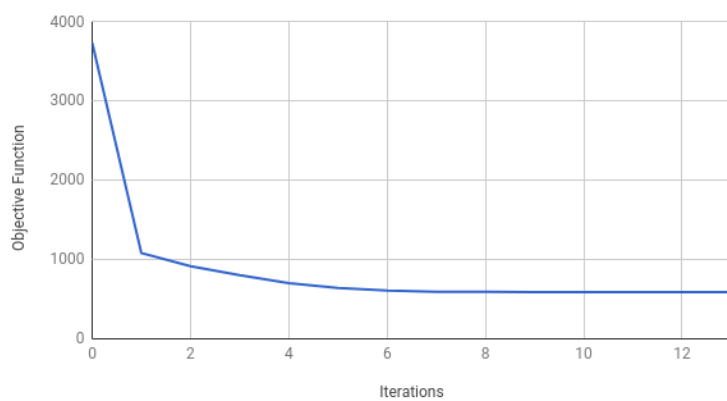
K = 12



K = 2

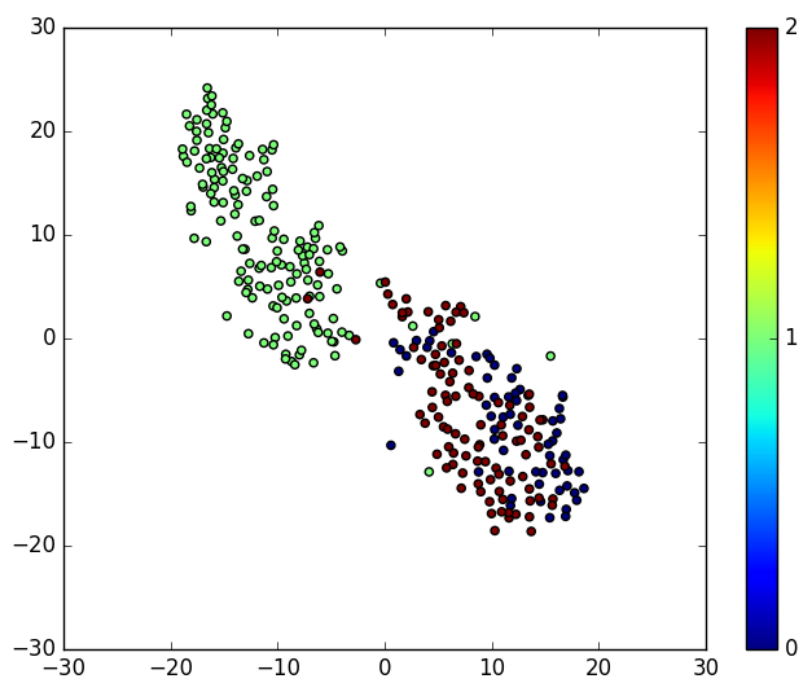


K = 3

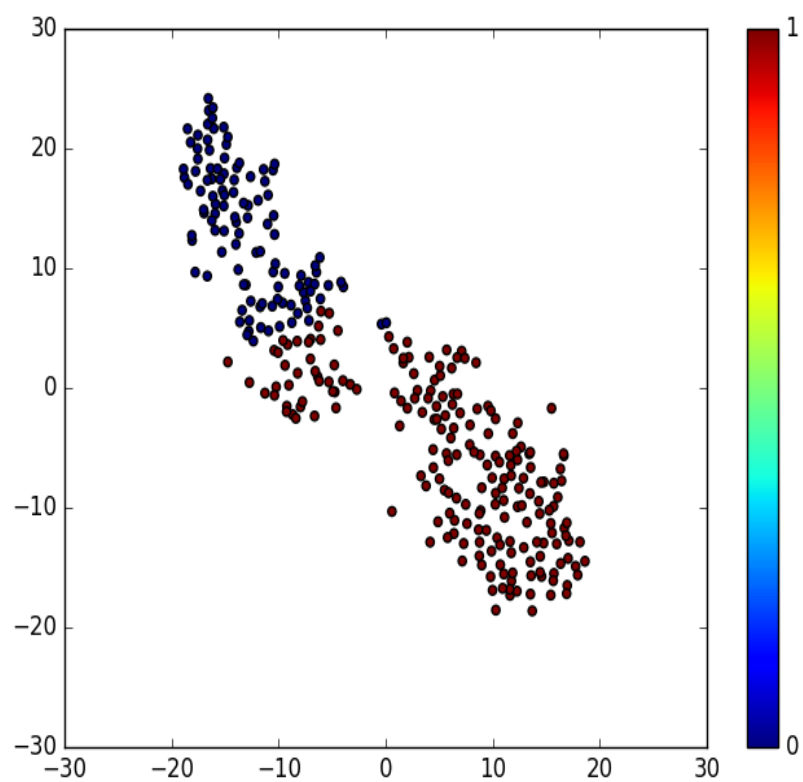


2. Vertebral Column

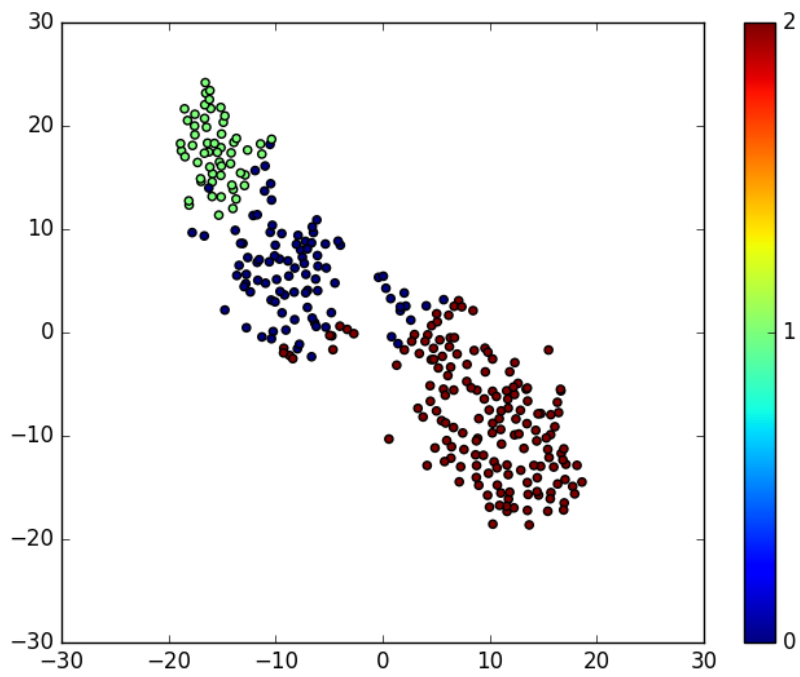
a) Plotting Actual Data



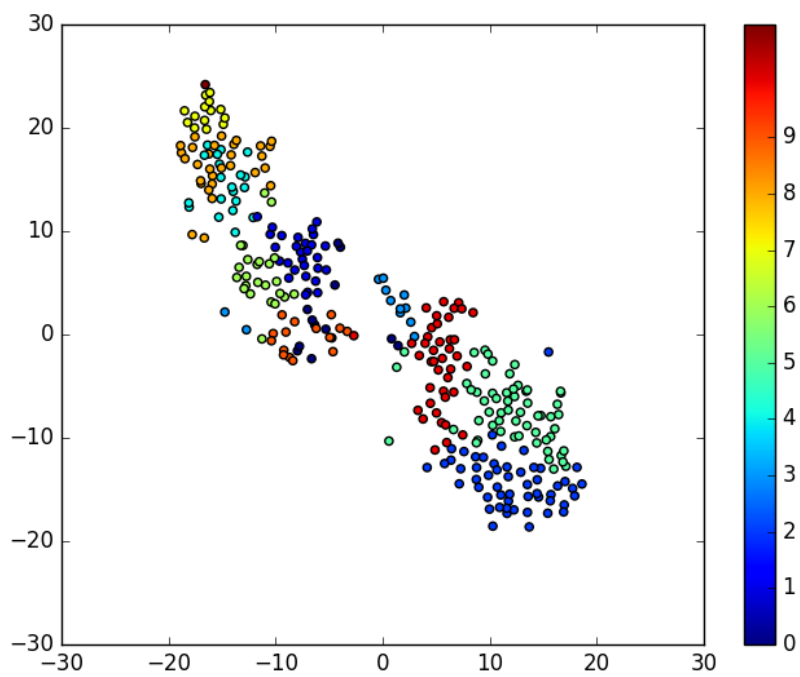
b) $K = 2$



c) $K = \text{actual}(3)$

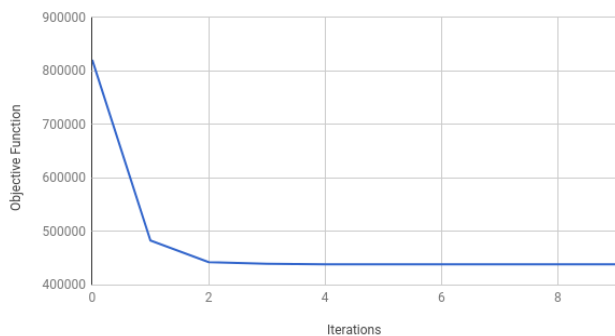


d) $K = 12$

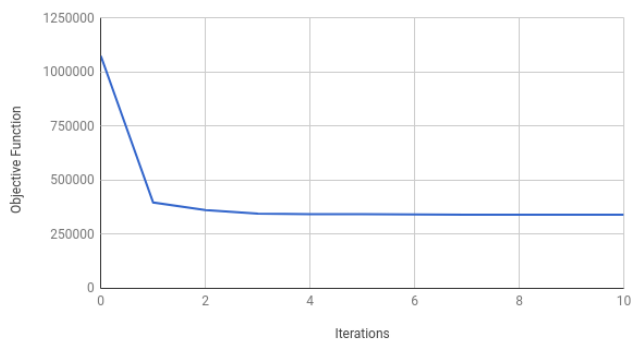


e) Objective Function vs Iteration

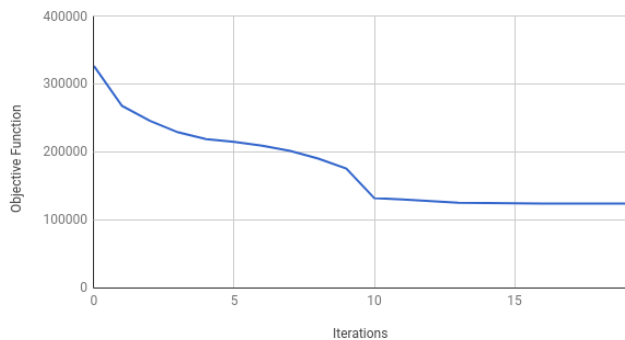
K = 2



K = 3

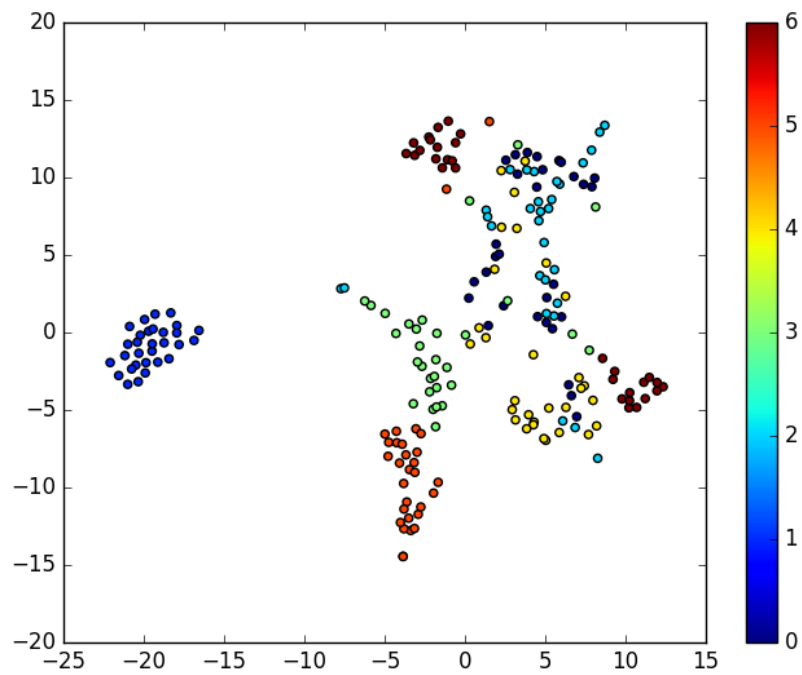


K = 12

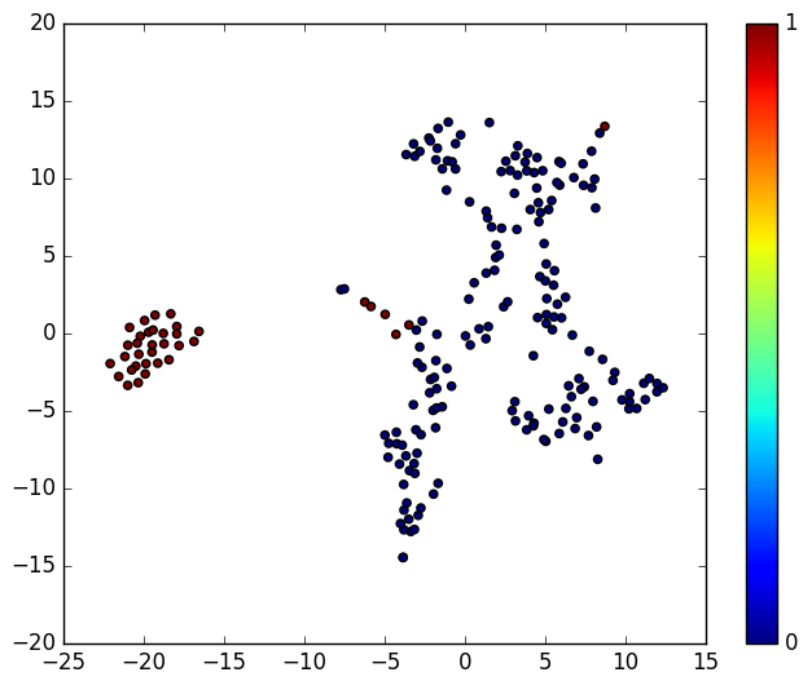


3. Image Segmentation

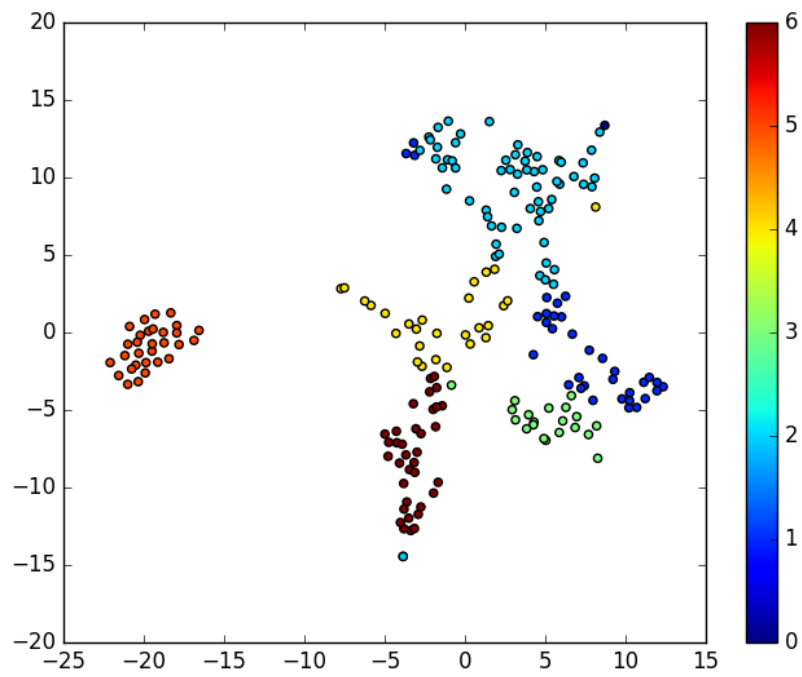
a) Plotting Actual Data



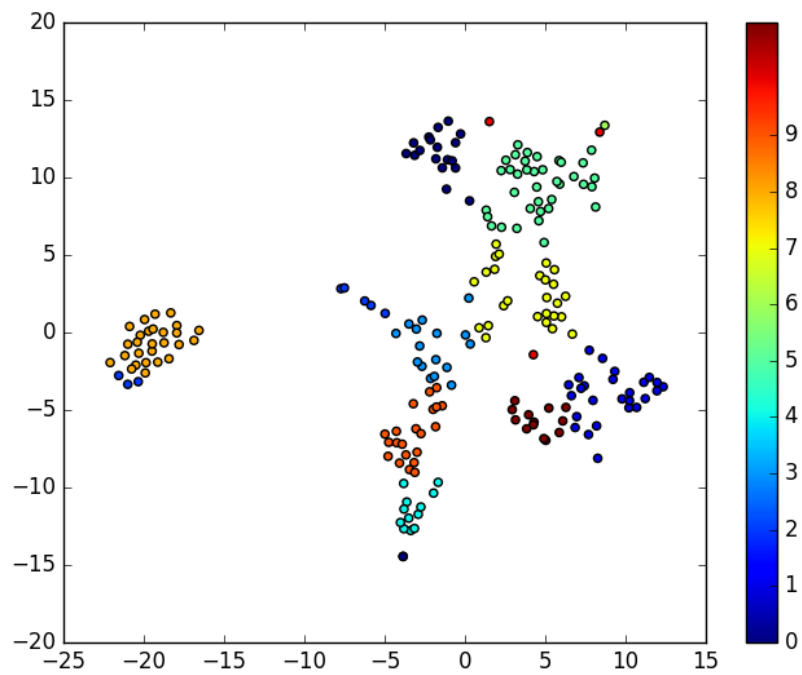
b) $K = 2$



c) $K = \text{actual}(7)$

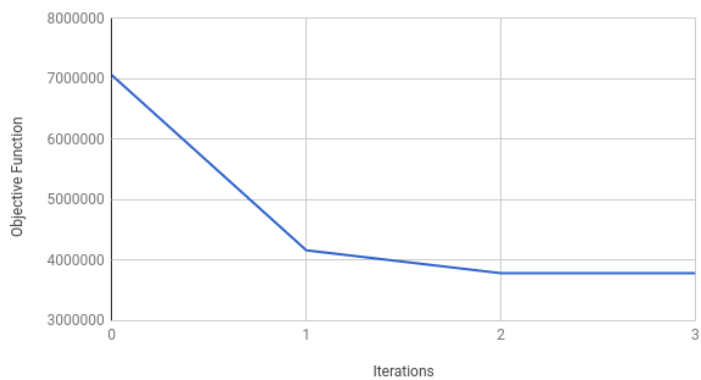


d) $K = 12$

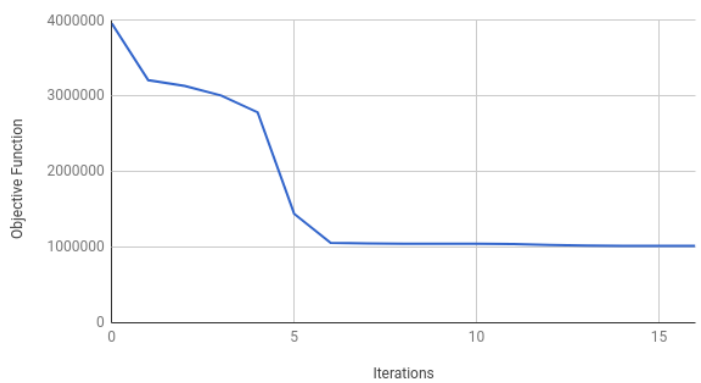


e) Objective Function vs Iteration

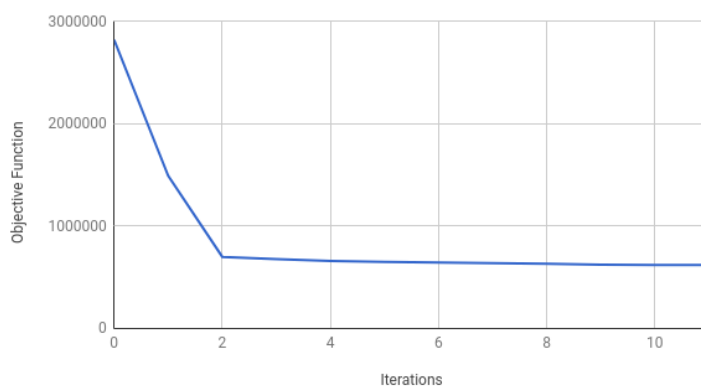
K = 2



K = 7

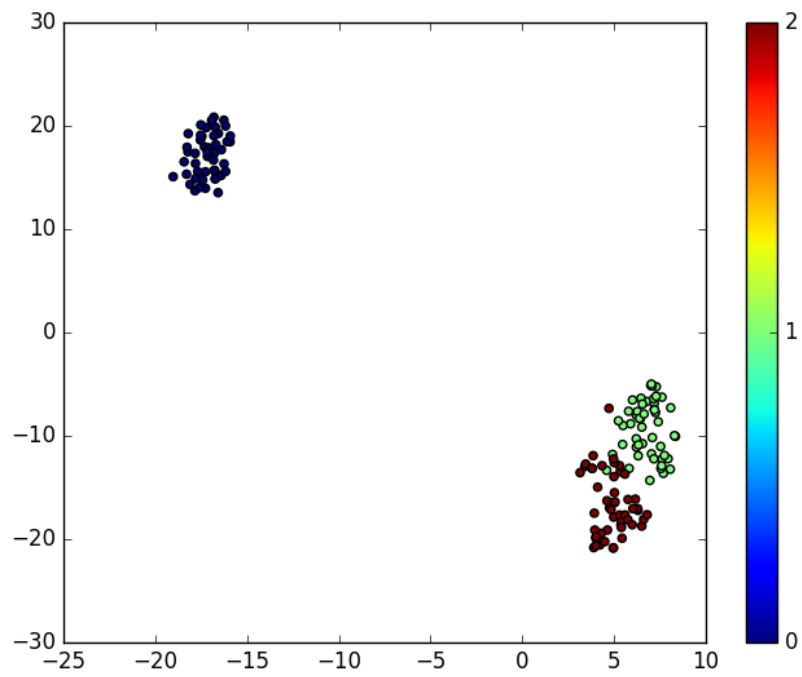


K = 12

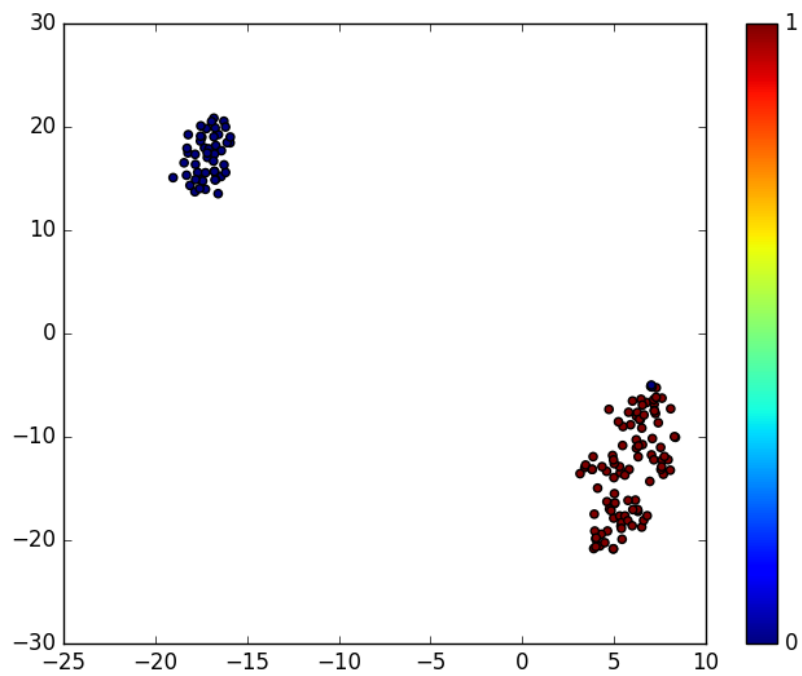


4. Iris

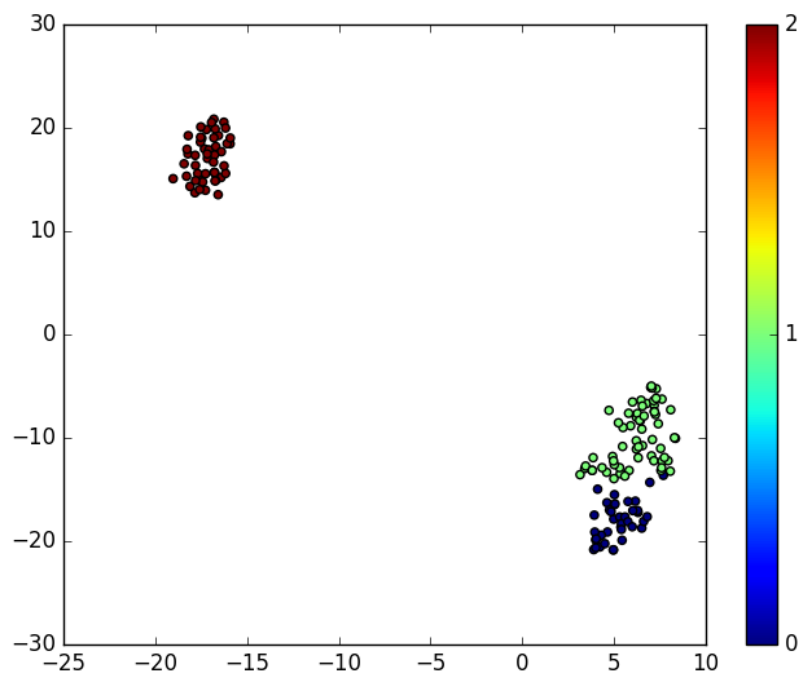
a) Plotting Actual Data



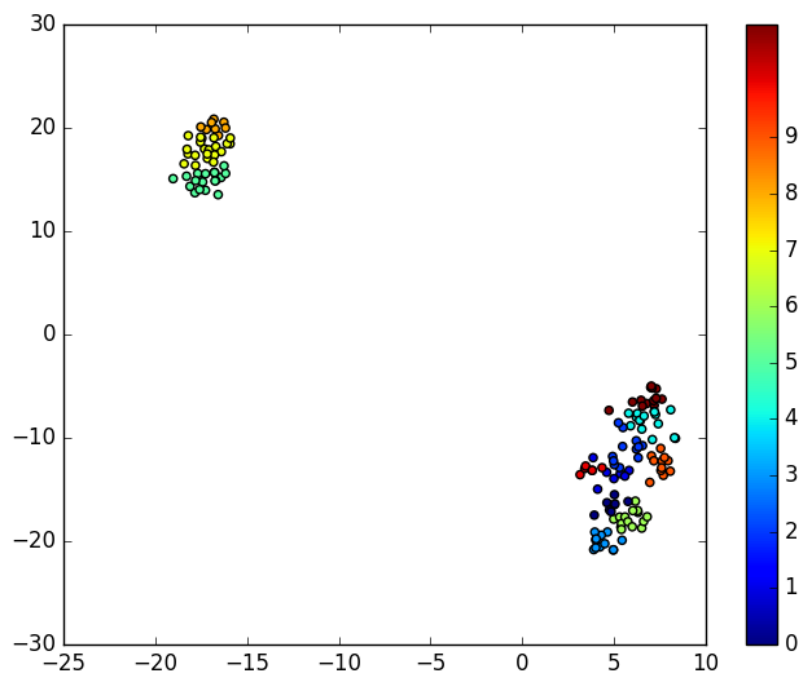
b) $K = 2$



c) $K = \text{actual}(3)$

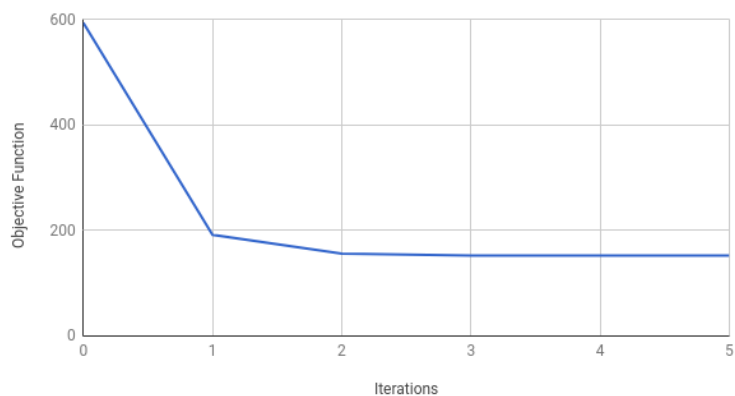


d) $K = 12$

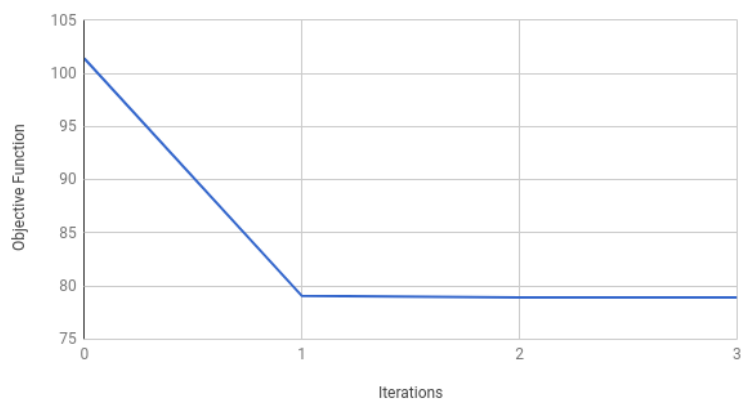


e) Objective Function vs Iteration

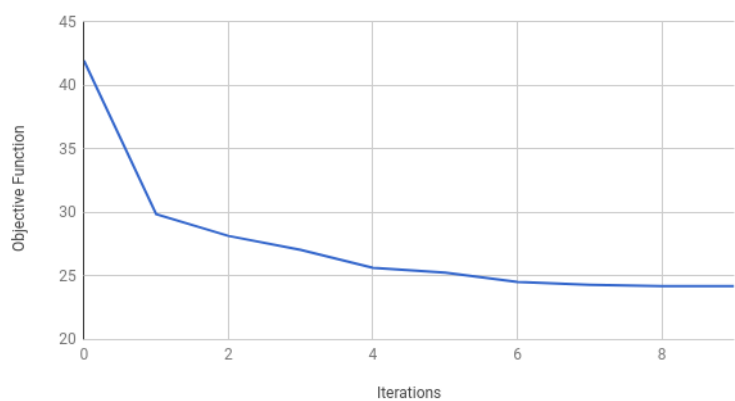
K = 2



K = 3



K = 12



Quantitative Analysis

Data	K = 2			K = ACTUAL			K = 12		
	ARI	NMI	AMI	ARI	NMI	AMI	ARI	NMI	ARI
Iris	0.539 92182	0.679 32270	0.519 36080	0.716 34211	0.741 93229	0.733 11807	0.337 07250	0.640 57094	0.416 38137
Segmen	0.099 5061	0.394 9393	0.185 36872	0.359 27835	0.509 79284	0.459 00800	0.390 29994	0.573 65020	0.491 77745
Seeds	0.468 32262	0.552 24503	0.429 73890	0.710 34170	0.710 06830	0.704 94101	0.293 84832	0.546 99271	0.355 31004
Vertebrl	0.298 84607	0.424 96680	0.334 93495	0.311 62034	0.420 96432	0.412 80224	0.164 35767	0.409 84949	0.264 55241

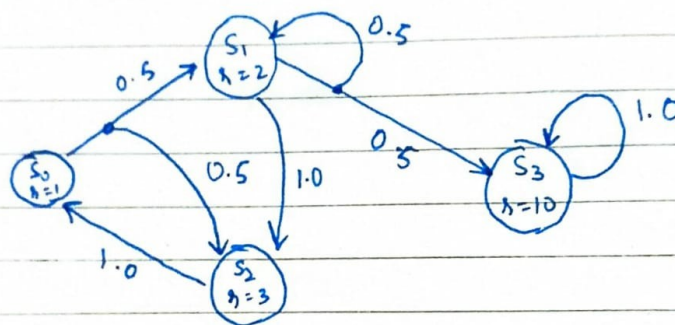
THEORY QUESTIONS

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ML ASSIGNMENT - 4 THEORY QUES.

1.



$$V_0(s_0) = V_0(s_1) = V_0(s_2) = V_0(s_3) = 0 \quad [\gamma = 0.9]$$

Iteration 1 :

$$\begin{aligned}
 V_1(s_0) &= \max_{a \in A(s_0)} \sum_{s'} P(s, a, s') [R(s') + \gamma V_0(s')] \\
 &= 0.5 * (2 + 0.9 * 0) + 0.5 * (3 + 0.9 * 0) \\
 &= 1 + 1.5 \\
 &= 2.5
 \end{aligned}$$

$$\begin{aligned}
 V_1(s_1) &= \max_{a \in A(s_1)} \left(\sum_{s'} P(s, a, s') [R(s') + \gamma V_0(s')] \right) \\
 &= \max \left([1.0 * (3 + 0.9 * 0)], [0.5 * 2 + 0.5 * 10] \right) \\
 &= \max(3, 6) \\
 &= 6
 \end{aligned}$$

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$$V_1(s_2) = \max_{a \in A(s_2)} \left(\sum_{s'} P(s_2, a, s') * (R(s') + \gamma V(s')) \right)$$

$$= 1.0 * (1 + 0.9(0))$$

$$= 1$$

$$V_1(s_3) = 1 * 10$$

$$= 10$$

Situation 2

$$V_2(s_0) = 0.5(2 + 0.9 * 6) + 0.5(3 + 0.9 * 1)$$

$$= 3.7 + 1.95$$

$$V_2(s_1) = \max(1 * (3 + 0.9 * 1), 0.5 * (2 + 0.9 * 6) + 0.5 * (10 + 0.9 * 10))$$

$$= 3.9, \max(3.9, 13.2)$$

$$= 13.2$$

$$V_2(s_2) = 0.5 * 1 + 0.9 * 2.5 = 3.25$$

$$V_2(s_3) = 1(10 + 0.9 * 10) = 19$$

Iteration 3

$$V_3(S_0) = \frac{0.5(2 + 0.9 \cdot 13.2) + 0.5(3 + 3 \cdot 25)}{2} = 9.06$$

$$V_3(S_1) = \frac{0.5(2 + 0.9 \cdot 13.2) + 0.5(10 + 0.9 \cdot 19)}{2} = 14.49$$

$$V_3(S_2) = 6.085$$

$$V_3(S_3) = 27.1$$

- (b) Optimal value at S_1 : Action that goes to S_3 with 0.5 probability since Expected value is greater than other action.

- (c) i. False: If MDP is cyclic, it will not converge in N iterations since the cycle's value will improve forever.
- ii. False: If $\gamma = 1$, an MDP does not converge since the full impact of ~~next~~^{prev} state reaches next state.

iii) True: Any next state does not depend on previous state since $x = 0$.

iv) True: Since the impact of terminal states propagates in every iteration to its neighbours. It will take at most N iterations to reach of start state since there are no cycles.

v) True:

Ans 2

K-means clusters the colours into K colours. To encode the K -colours we need $\log_2 K$ bits.

Moreover, we require a look-up table that maps original colours to K -colours.

⇒ Size of table = $24 * K$.

⇒ Compressed size = $N^2 \log_2 K + 24K$

Uncompressed size = $N^2 * 24$

⇒ Ratio = $24N^2 / (N^2 \log_2 K + 24K)$