Exercise 1

(a) Using Theorem 3.6: With $|\mathcal{H}| = 3^3 = 27$

$$\Pr_{T \mathcal{D}^m} (\forall h \in \mathcal{H} : |err_T(h) - err_D(h)| \le \epsilon) > 1 - \delta$$

$$\Pr_{T \mathcal{D}^m} (\forall h \in \mathcal{H} : |err_T(h) - err_D(h)| \le \epsilon) > 0.9$$

$$\Rightarrow \delta = 0.1$$

$$\begin{split} m &\geq \frac{1}{2\epsilon^{2}} \log \left(\frac{2|\mathcal{H}|}{\delta} \right) \\ 143 &\geq \frac{1}{2\epsilon^{2}} \log \left(\frac{2 \cdot 3^{3}}{0.1} \right) \\ 143 &\geq \frac{1}{2\epsilon^{2}} (\log(54) - \log(0.1)) \\ 143 &\geq \frac{1}{2\epsilon^{2}} (\log(54) - \log(0.1)) \\ \epsilon^{2} &\geq \frac{(\log(54) - \log(0.1))}{1432} \\ |\epsilon| &\geq \sqrt{\frac{(\log(54) - \log(0.1))}{286}} \\ \Rightarrow &\epsilon &\geq \sqrt{\frac{(\log(54) - \log(0.1))}{286}} \\ \Pr_{T \mathcal{D}^{m}} \left(\forall h \in \mathcal{H} : |err_{T}(h) - err_{D}(h)| \leq \epsilon \right) > 0.9 \\ \Pr_{T \mathcal{D}^{m}} \left(\forall h \in \mathcal{H} : |0.03 - err_{D}(h)| \leq \sqrt{\frac{(\log(54) - \log(0.1))}{286}} \right) > 0.9 \\ \Rightarrow &err_{D}(h) \leq 0.03 + \sqrt{\frac{(\log(54) - \log(0.1))}{286}} \simeq 0.208149 \simeq 0.21 \end{split}$$

(b) Using Theorem 3.4:

 $\Pr_{T \mathcal{D}^m} (\forall h \in \mathcal{H} : \text{if } h \text{ is consistent with } T, \text{ then } err_D(h) \leq \epsilon) 1 - \delta$ $\Pr_{T \mathcal{D}^m} (\forall h \in \mathcal{H} : \text{if } h \text{ is consistent with } T, \text{ then } err_D(h) \leq 0.01) 0.9$ $\Rightarrow \epsilon = 0.01, \delta = 0.1$

$$m \ge \frac{1}{\epsilon} \ln \left(\frac{|\mathcal{H}|}{\delta} \right)$$

$$m \ge \frac{1}{0.01} \ln \left(\frac{3^3}{0.1} \right)$$

$$m \ge 100(\ln(27) - \ln(0.1)) \simeq 559.84$$

$$\Rightarrow m \ge 560$$

Exercise 2

Exercise 3

Exercise 4

(a) See Referencesappendix for code.

```
Final probabilities: [0.4 0.4 0.2]
3 Tracked weight vectors:
5 Round: 1 Weights:
                      [1. 1. 1.]
6 Round: 2 Weights:
                      [0.5 0.5 1.]
7 Round: 3 Weights:
                      [0.5 0.25 0.5]
8 Round: 4 Weights:
                      [0.25 0.25 0.25]
9 Round: 5 Weights:
                      [0.25 0.125 0.125]
         6 Weights:
                      [0.125
                             0.125 0.0625]
10 Round:
11 Round: 7 Weights:
                      [0.125
                                  0.0625
                                              0.04419417]
```

(b) No, the weights are always the same. This is because the loss matrix does not change throughout the algorithm, so the loss is always the same. If all the events still happen in the sequence, only in a different order, this won't have an effect as the loss will still be included in the updated weight.

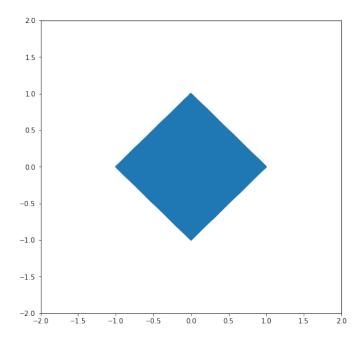
Exercise 5

(a) See Referencesappendix for code.

```
Probabilities:
Round: 1 Probabilities:
                            [0.33 0.33 0.33]
4 Round: 2 Probabilities:
                            [0.46 0.27 0.27]
                            [0.28 0.51 0.21]
5 Round: 3 Probabilities:
6 Round: 4 Probabilities:
                            [0.25 0.42 0.33]
8 Weight vectors:
10 Round: 1 Weights:
                      [1. 1. 1.]
                      [2.83 1.
11 Round: 2 Weights:
                                1.
12 Round: 3 Weights:
                      [2.83 8.48 1.
Round: 4 Weights:
                      [2.83 8.48 5.32]
```

(b) $w_1^{(4)}$ and $w_3^{(4)}$ are different because with $\gamma=0.5$ we put a certain weight on exploration. Therefore, even with the same reward, different actions can have different weights as γ is part of the weight updating calculation.

Exercise 6



- (a) (i)
 - (ii) The shape of $B_1^3 \subset \mathbb{R}^3$ would look like a octahedron with the same edge length $(\sqrt{2})$.
- (b) $|diag(B_1^2)| = 2 \xrightarrow{\text{Pythagoras}} \text{ edge length of } B_1^2 = \sqrt{2} \Rightarrow vol(B_1^2) = \sqrt{2}^2 = 2$ $vol(B_1^3) = \frac{1}{3}\sqrt{2}a^3$ with a being the edge length of the octahedron $\Rightarrow vol(B_1^3) = \frac{1}{3}\sqrt{2}^4 = \frac{1}{3}4 = \frac{4}{3} \simeq 1.33$ A more general formula for the volume $vol(B_1^l)$ is $vol(B_1^l) = \frac{2^l}{l!}$ (cmp. this paper). Using l = 1, 2 yields the same results.

(c)

$$\lim_{l \to \inf} \operatorname{vol}(B_1^l) = \frac{2^l}{l!}$$

$$\Rightarrow \lim_{l \to \inf} \operatorname{vol}(B_1^l) = \frac{2}{1} \cdot \frac{2}{2} \cdot \frac{2}{3} \cdot \dots \cdot \frac{2}{l-1} \cdot \frac{2}{l}$$

$$\leq 2 \cdot \frac{2}{l} = \frac{4}{l}$$

$$\Rightarrow \lim_{n \to \inf} \frac{4}{l} = 0$$

Appendix

Code for Exercise 4

```
import numpy as np

def mwu_algorithm(loss_matrix, events, rounds, alpha):
    # initial weight vector of 1s
    weights = np.ones((loss_matrix.shape[0]))
    weights_tracking = {}
```

```
weights_tracking[0] = weights
      # more convenient to loop through rounds and events
9
      rounds_arr = [i for i in range(rounds)]
10
      for round, event in zip(rounds_arr, events):
11
          # getting the current probabilities, not really needed here
          p = probabilities(weights)
13
          # need to use event-1 as events start at 1 but indexing at 0
          weights = np.power((1 - alpha), loss_matrix[:, event-1]) * weights
          # loss isn't really needed
16
          loss = calculate_loss(loss_matrix, p, event-1)
17
          weights_tracking[round+1] = weights
19
      return p, weights_tracking
20
21
 def probabilities(weights):
23
      return weights / np.sum(weights)
24
  def calculate_loss(loss_matrix, probabilities, event):
      return np.sum(probabilities * loss_matrix[:, event])
28
29 loss_matrix = np.array([[0,1,1,0],
                           [1,0,1,1],
                           [1,1,0,0.5]])
31
  observed_events = [3,1,2,1,2,4]
35 p_6, weights_tracking = mwu_algorithm(loss_matrix, observed_events, 6, alpha
37 print(f'Final probabilities: {p_6}\n')
38 print(f'Tracked weight vectors: \n')
39 for key, val in weights_tracking.items():
  print(f'Round:\t{key + 1}\tWeights:\t{val}')
```

Code for Exercise 5

```
1 import numpy as np
2 from copy import deepcopy
 def exp3(gamma, rounds, actions, rewards):
      weights = np.ones((len(actions)))
      rounds_arr = [i for i in range(rounds)]
      n = len(actions)
      # for tracking weights and probabilities
      weights_tracking = {}
9
      probabilities_tracking = {}
      weights_tracking[0] = np.ones(len(actions))
11
      probabilities_tracking[0] = probability_dist(weights, gamma)
      for round, action in zip(rounds_arr, actions):
13
          probabilities = probability_dist(weights, gamma)
14
          probabilities_tracking[round] = probabilities
          reward = rewards[action]
16
          weights = update_weights(weights, reward, probabilities, action,
17
     gamma)
          weights_tracking[round + 1] = deepcopy(weights)
18
19
      probabilities_tracking[rounds] = probability_dist(weights, gamma)
20
      return weights_tracking, probabilities_tracking
23 def probability_dist(weights, gamma):
```

```
return (1 - gamma) * (weights / np.sum(weights)) + gamma / len(weights)
25
def update_weights(weights, reward, probabilities, action, gamma):
      n = len(weights)
      # only update chosen action
28
     weights[action] = weights[action] * np.exp((gamma * reward) / (n *
     probabilities[action]))
     return weights
31
33 action_seq = np.array([ 1, 2, 3 ])
_{34} rewards = np.array([ 3, 5, 3 ]) * np.log(2)
weights, probs = exp3(gamma=0.5, rounds=3, actions=action_seq - 1, rewards=
     rewards)
38 print(f'Probabilities: \n')
39 for key, val in probs.items():
      print(f'Round:\t{key + 1}\tProbabilities:\t{val.round(2)}')
42 print(f'\nWeight vectors: \n')
for key, val in weights.items():
print(f'Round:\t{key + 1}\tWeights:\t{val.round(2)}')
```