Task1

March 7, 2020

In [1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

0.1 The Markov Decision Process

In [2]:
```
ACTIONS = ["SHOOT", "DODGE", "RECHARGE"]
STAMINA = [0, 50, 100]
ARROWS = [0, 1, 2, 3]
DRAGON_HEALTH = [0, 25, 50, 75, 100]

v_table = np.zeros(shape=(5, 4, 3)) # (arrows, stamina, health)
p_table = np.zeros(shape=(5, 4, 3))
q_table = np.zeros(shape=(5, 4, 3, len(ACTIONS)))
```

In [3]:
```
STATES = [(h, a, s) for h in range(v_table.shape[0])
                    for a in range(v_table.shape[1])
                    for s in range(v_table.shape[2])]
```

In [4]:
```
INFINTIY = 1e16

def get_next_utility(state: tuple, action: int) -> float:
    """
    Computes the utility of the next state
    """
    assert len(state) == 3 and state[0] < 5 and state[1] < 4 and state[2] < 3 and acti
    dragon_health, arrows, stamina = state
    if dragon_health == 0:
        return 0.0
    if ACTIONS[action] == "SHOOT":
        if arrows == 0 or stamina == 0:
            return -INFINTIY
        return 0.5 * v_table[dragon_health, arrows - 1, stamina - 1] + \
               0.5 * v_table[dragon_health - 1, arrows - 1, stamina - 1]
    elif ACTIONS[action] == "DODGE":
        if stamina == 0:
            return -INFINTIY
```

```
            elif stamina == 1:
                return 0.8 * v_table[dragon_health, min(arrows + 1, 3), 0] + \
                       0.2 * v_table[dragon_health, arrows, 0]
            elif stamina == 2:
                return 0.8 * 0.8 * v_table[dragon_health, min(arrows + 1, 3), 1] + \
                       0.2 * 0.8 * v_table[dragon_health, arrows, 1] + \
                       0.8 * 0.2 * v_table[dragon_health, min(arrows + 1, 3), 0] + \
                       0.2 * 0.2 * v_table[dragon_health, arrows, 0]
        elif ACTIONS[action] == "RECHARGE":
            return 0.8 * v_table[dragon_health, arrows, min(stamina + 1, 2)] + \
                   0.2 * v_table[dragon_health, arrows, stamina]
```

In [5]:
```
def get_action_cost(state: tuple, action: int) -> float:
    """
    Returns the reward associated with each action taken
    """
    assert len(state) == 3 and state[0] < 5 and state[1] < 4 and state[2] < 3 and actio
    if state[0] == 0:
        return 0.0
    if state[0] == 1 and action == 0:
        return -20.0 + 10.0 * 0.5
    return -20.0 # Penalty = 20 due to Team Number = 9
```

In [6]:
```
def check_convergence(old_table: np.ndarray, new_table: np.ndarray, delta: int = 0.001)
    """
    Checks if the value iteration algorithm has converged
    """
    assert old_table.shape == new_table.shape
    ans = np.max(np.abs(new_table - old_table)) < delta
    return ans
```

In [7]:
```
def random_initialize():
    """
    Randomly assigns values to the v_table and the p_table
    """
    global v_table, q_table, p_table
    v_table = np.random.random(size=v_table.shape)
    q_table = np.zeros(shape=q_table.shape)
    p_table = np.random.choice(range(len(ACTIONS)), size=p_table.shape)
```

In [8]:
```
def print_state(iteration: int, v_table: np.ndarray, p_table: np.ndarray, filename = No
    """
    Prints the entire state in the Value Iteration Algorithm
    """
    assert len(v_table.shape) == len(p_table.shape) == 3
    if filename == None:
        print("iteration=", iteration)
        for h, a, s in STATES:
            print("({0},{1},{2}):{3}=[{4:.3f}]".format(
```

```
                    h, a, s,
                    ACTIONS[p_table[h][a][s]] if h != 0 else '-1', v_table[h][a][s]))
            print("\n\n")
        else:
            with open(filename, 'a') as f:
                f.write("iteration={}\n".format(iteration))
                for h, a, s in STATES:
                    f.write("({0},{1},{2}):{3}=[{4:.3f}]\n".format(
                        h, a, s,
                        ACTIONS[p_table[h][a][s]] if h != 0 else '-1', v_table[h][a][s]))
                f.write("\n\n")
```

0.2 The Value Iteration Algorithm

```
Procedure Value_Iteration(S, A, P, R, )
    Inputs:
        S is the set of all states
        A is the set of all actions
        P is state transition function specifying P(s'|s,a)
        R is a reward function R(s,a,s')
         a threshold,  > 0$
    Output:
        [S] approximately optimal policy
        V[S] value function
    Local:
        real array Vk[S] is a sequence of value functions
        action array [S]

    assign V0[S] arbitrarily
    k  0
    repeat
       k  k+1
       for each state s do
           Vk[s] = maxa s' P(s'|s,a) (R(s,a,s')+ Vk-1[s'])
    until s |Vk[s]-Vk-1[s]| <
    for each state s do
       [s] = argmaxa s' P(s'|s,a) (R(s,a,s')+ Vk[s'])
    return ,Vk
```

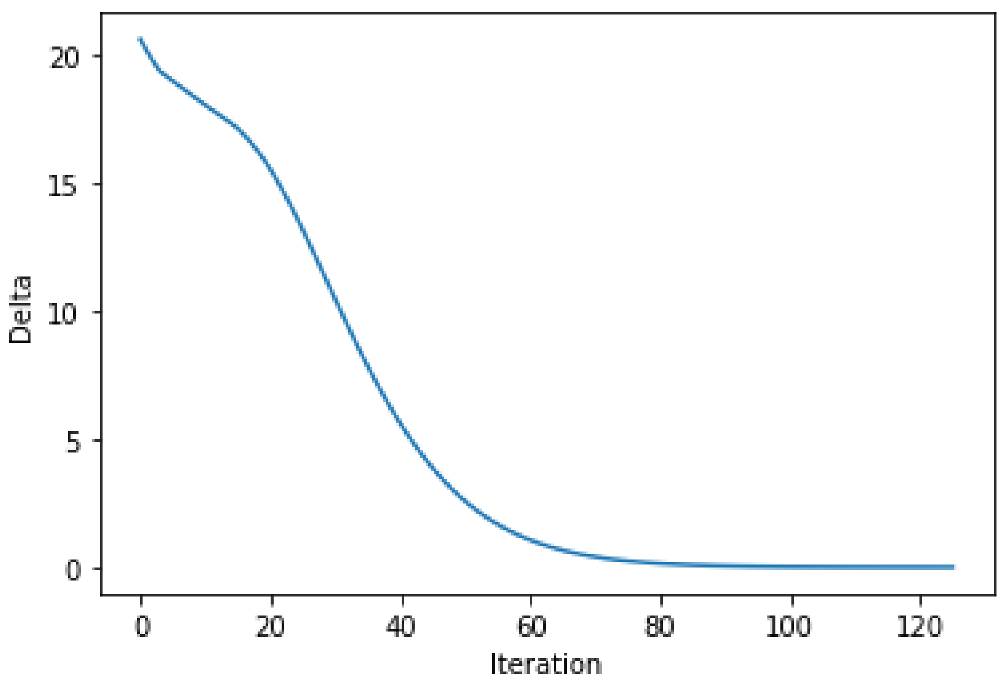
```
In [9]: history_delta = []

        def value_iteration(gamma = 0.99):
            """
            Computes the Optimal Policy and the State Values
            """
            global v_table, p_table, q_table
            random_initialize()
            converged = False
```

```
        for iteration in range(1, 1000):
            for h, a, s in STATES:
                for act in range(len(ACTIONS)):
                    q_table[h, a, s, act] = gamma * get_next_utility((h, a, s), act) \
                                            + get_action_cost((h, a, s), act)
            new_v_table = np.max(q_table, axis=3)
            p_table = np.argmax(q_table, axis=3)
            converged = check_convergence(v_table, new_v_table)
            history_delta.append(np.max(np.abs(new_v_table - v_table)))
            v_table = new_v_table
            print_state(iteration, v_table, p_table, 'outputs/task_1_trace.txt')
            if converged:
                break
```

```
In [10]: value_iteration()
```

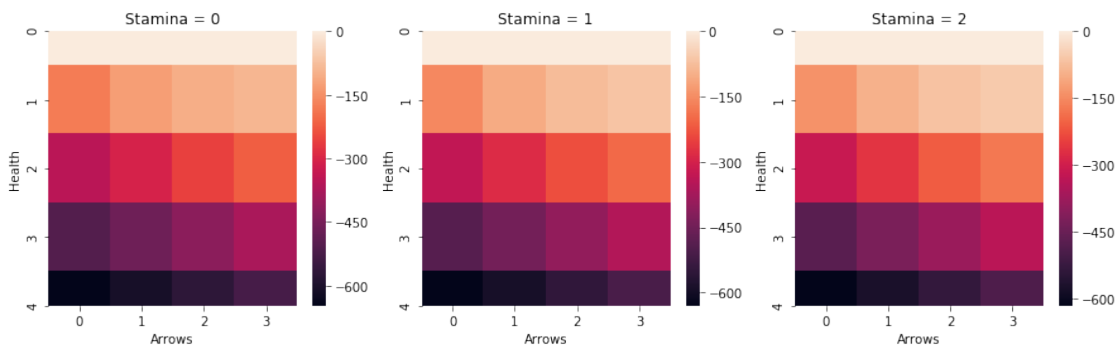
0.3 Checking our Answers

```
In [11]: plt.plot(history_delta)
         plt.xlabel('Iteration')
         plt.ylabel('Delta')
         plt.show()
```

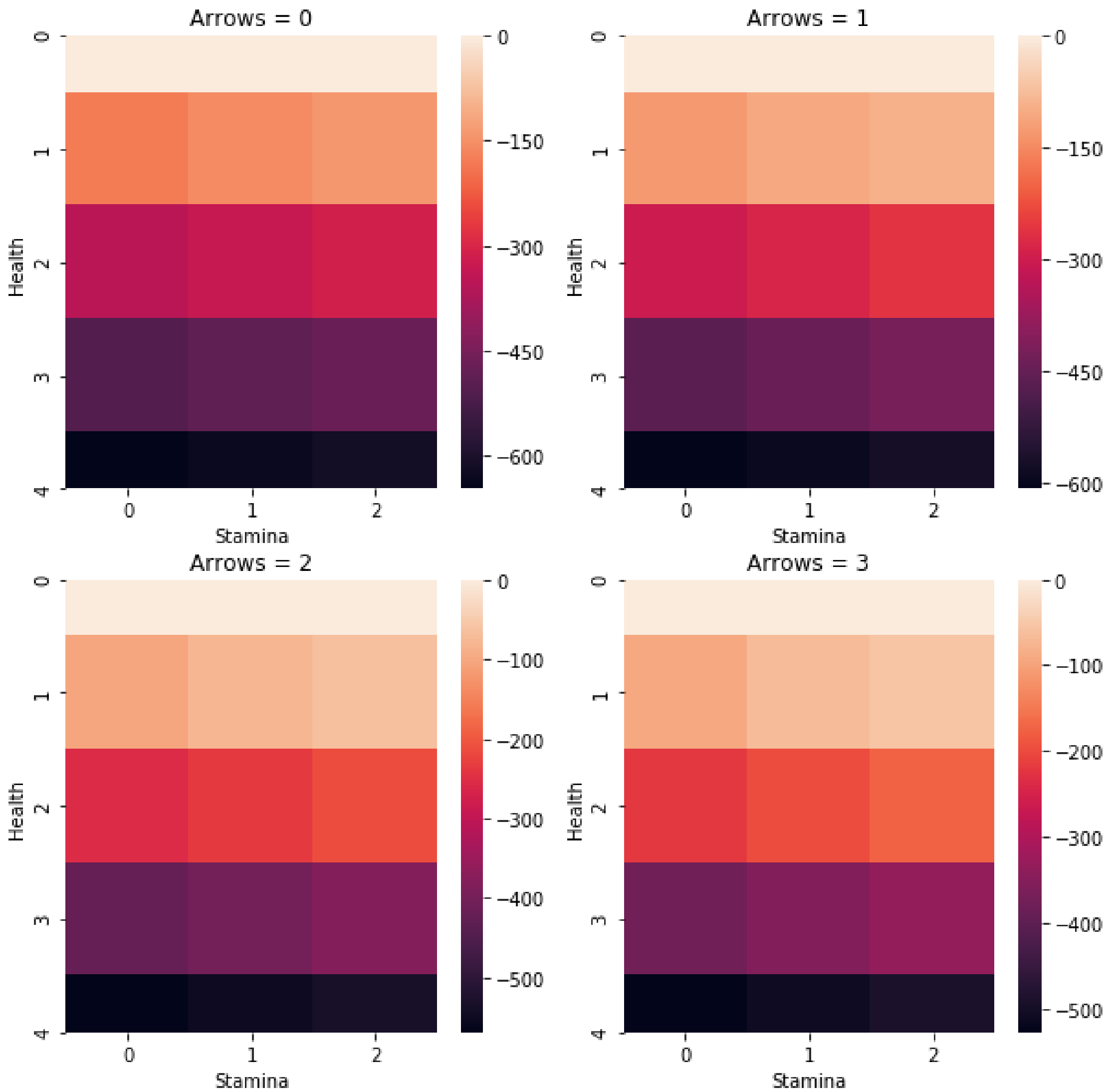



```
In [12]: fig, ax = plt.subplots(1, 3, figsize=(15, 4))
         sns.heatmap(v_table[:, :, 0], ax=ax[0])
```

```
ax[0].set_title('Stamina = 0')
ax[0].set_xlabel('Arrows')
ax[0].set_ylabel('Health')
sns.heatmap(v_table[:, :, 1], ax=ax[1])
ax[1].set_title('Stamina = 1')
ax[1].set_xlabel('Arrows')
ax[1].set_ylabel('Health')
sns.heatmap(v_table[:, :, 2], ax=ax[2])
ax[2].set_title('Stamina = 2')
ax[2].set_xlabel('Arrows')
ax[2].set_ylabel('Health')
plt.show()
```




```
In [13]: fig, ax = plt.subplots(2, 2, figsize=(10, 10))
         sns.heatmap(v_table[:, 0, :], ax=ax[0][0])
         ax[0][0].set_title('Arrows = 0')
         ax[0][0].set_xlabel('Stamina')
         ax[0][0].set_ylabel('Health')
         sns.heatmap(v_table[:, 1, :], ax=ax[0][1])
         ax[0][1].set_title('Arrows = 1')
         ax[0][1].set_xlabel('Stamina')
         ax[0][1].set_ylabel('Health')
         sns.heatmap(v_table[:, 2, :], ax=ax[1][0])
         ax[1][0].set_title('Arrows = 2')
         ax[1][0].set_xlabel('Stamina')
         ax[1][0].set_ylabel('Health')
         sns.heatmap(v_table[:, 3, :], ax=ax[1][1])
         ax[1][1].set_title('Arrows = 3')
         ax[1][1].set_xlabel('Stamina')
         ax[1][1].set_ylabel('Health')

         plt.show()
```



0.4 Final Observations

The graphs and the policy are reasonably obvious, it's better to have more stamina and arrows, and that the Dragon has less health. The actions (shown below) are quite close to the obvious greedy policy (e.g. things like - shoot if you have arrows and dragon is close to dying, dodge if you need arrows or if you have lesser stamina and the dragon is still not close to dying and recharge definitely when you have 0 stamina) since the value function of the game is very smooth.

Converged Policy Output

```
iteration=126
(0,0,0):-1=[0.000]
(0,0,1):-1=[0.000]
(0,0,2):-1=[0.000]
```

```
(0,1,0):-1=[0.000]
(0,1,1):-1=[0.000]
(0,1,2):-1=[0.000]
(0,2,0):-1=[0.000]
(0,2,1):-1=[0.000]
(0,2,2):-1=[0.000]
(0,3,0):-1=[0.000]
(0,3,1):-1=[0.000]
(0,3,2):-1=[0.000]
(1,0,0):RECHARGE=[-179.508]
(1,0,1):DODGE=[-156.522]
(1,0,2):DODGE=[-137.901]
(1,1,0):RECHARGE=[-127.499]
(1,1,1):SHOOT=[-103.856]
(1,1,2):SHOOT=[-92.478]
(1,2,0):RECHARGE=[-102.076]
(1,2,1):SHOOT=[-78.112]
(1,2,2):SHOOT=[-66.409]
(1,3,0):RECHARGE=[-89.648]
(1,3,1):SHOOT=[-65.527]
(1,3,2):SHOOT=[-53.665]
(2,0,0):RECHARGE=[-351.231]
(2,0,1):DODGE=[-330.413]
(2,0,2):DODGE=[-313.549]
(2,1,0):RECHARGE=[-304.128]
(2,1,1):RECHARGE=[-282.716]
(2,1,2):SHOOT=[-261.033]
(2,2,0):RECHARGE=[-255.680]
(2,2,1):SHOOT=[-233.656]
(2,2,2):SHOOT=[-211.353]
(2,3,0):RECHARGE=[-219.569]
(2,3,1):SHOOT=[-197.089]
(2,3,2):SHOOT=[-174.325]
(3,0,0):RECHARGE=[-506.755]
(3,0,1):DODGE=[-487.901]
(3,0,2):DODGE=[-472.628]
(3,1,0):RECHARGE=[-464.096]
(3,1,1):SHOOT=[-444.703]
(3,1,2):SHOOT=[-425.066]
(3,2,0):RECHARGE=[-420.218]
(3,2,1):DODGE=[-400.271]
(3,2,2):SHOOT=[-380.072]
(3,3,0):RECHARGE=[-375.086]
(3,3,1):RECHARGE=[-354.569]
(3,3,2):SHOOT=[-333.794]
(4,0,0):RECHARGE=[-647.604]
(4,0,1):DODGE=[-630.529]
(4,0,2):DODGE=[-616.697]
```

```
(4,1,0):RECHARGE=[-608.970]
(4,1,1):DODGE=[-591.407]
(4,1,2):SHOOT=[-573.623]
(4,2,0):RECHARGE=[-569.232]
(4,2,1):DODGE=[-551.167]
(4,2,2):SHOOT=[-532.874]
(4,3,0):RECHARGE=[-528.358]
(4,3,1):SHOOT=[-509.777]
(4,3,2):SHOOT=[-490.962]
```

Task2

March 7, 2020

```
In [1]: import numpy as np
        import pandas as pd
        from matplotlib import pyplot as plt
        import seaborn as sns
```

0.1 The Markov Decision Process

```
In [2]: ACTIONS = ["SHOOT", "DODGE", "RECHARGE"]
        STAMINA = [0, 50, 100]
        ARROWS = [0, 1, 2, 3]
        DRAGON_HEALTH = [0, 25, 50, 75, 100]

        v_table = np.zeros(shape=(5, 4, 3)) # (arrows, stamina, health)
        p_table = np.zeros(shape=(5, 4, 3))
        q_table = np.zeros(shape=(5, 4, 3, len(ACTIONS)))
```

```
In [3]: STATES = [(h, a, s) for h in range(v_table.shape[0])
                            for a in range(v_table.shape[1])
                            for s in range(v_table.shape[2])]
```

```
In [4]: INFINTIY = 1e16

        def get_next_utility(state: tuple, action: int) -> float:
            """
            Computes the utility of the next state
            """
            assert len(state) == 3 and state[0] < 5 and state[1] < 4 and state[2] < 3 and acti
            dragon_health, arrows, stamina = state
            if dragon_health == 0:
                return 0.0
            if ACTIONS[action] == "SHOOT":
                if arrows == 0 or stamina == 0:
                    return -INFINTIY
                return 0.5 * v_table[dragon_health, arrows - 1, stamina - 1] + \
                       0.5 * v_table[dragon_health - 1, arrows - 1, stamina - 1]
            elif ACTIONS[action] == "DODGE":
                if stamina == 0:
                    return -INFINTIY
```

```
                elif stamina == 1:
                    return 0.8 * v_table[dragon_health, min(arrows + 1, 3), 0] + \
                           0.2 * v_table[dragon_health, arrows, 0]
                elif stamina == 2:
                    return 0.8 * 0.8 * v_table[dragon_health, min(arrows + 1, 3), 1] + \
                           0.2 * 0.8 * v_table[dragon_health, arrows, 1] + \
                           0.8 * 0.2 * v_table[dragon_health, min(arrows + 1, 3), 0] + \
                           0.2 * 0.2 * v_table[dragon_health, arrows, 0]
            elif ACTIONS[action] == "RECHARGE":
                return 0.8 * v_table[dragon_health, arrows, min(stamina + 1, 2)] + \
                       0.2 * v_table[dragon_health, arrows, stamina]
```

In [5]:
```
def check_convergence(old_table: np.ndarray, new_table: np.ndarray, delta: float = 0.00
    """
    Checks if the value iteration algorithm has converged
    """
    assert old_table.shape == new_table.shape
    ans = np.max(np.abs(new_table - old_table)) < delta
    return ans
```

In [6]:
```
def random_initialize():
    """
    Randomly assigns values to the v_table and the p_table
    """
    global v_table, q_table, p_table
    v_table = np.zeros(shape=v_table.shape)
    q_table = np.zeros(shape=q_table.shape)
    p_table = np.random.choice(range(len(ACTIONS)), size=p_table.shape)
```

In [7]:
```
def print_state(iteration: int, v_table: np.ndarray, p_table: np.ndarray, filename = No
    """
    Prints the entire state in the Value Iteration Algorithm
    """
    assert len(v_table.shape) == len(p_table.shape) == 3
    if filename == None:
        print("iteration=", iteration)
        for h, a, s in STATES:
            print("({0},{1},{2}):{3}=[{4:.3f}]".format(
                h, a, s,
                ACTIONS[p_table[h][a][s]] if h != 0 else '-1', v_table[h][a][s]))
        print("\n\n")
    else:
        with open(filename, 'a') as f:
            f.write("iteration={}\n".format(iteration))
            for h, a, s in STATES:
                f.write("({0},{1},{2}):{3}=[{4:.3f}]\n".format(
                    h, a, s,
                    ACTIONS[p_table[h][a][s]] if h != 0 else '-1', v_table[h][a][s]))
            f.write("\n\n")
```

0.2 The Value Iteration Algorithm

```
Procedure Value_Iteration(S, A, P, R, )
    Inputs:
        S is the set of all states
        A is the set of all actions
        P is state transition function specifying P(s'|s,a)
        R is a reward function R(s,a,s')
         a threshold,  > 0$
    Output:
        [S] approximately optimal policy
        V[S] value function
    Local:
        real array Vk[S] is a sequence of value functions
        action array [S]

    assign V0[S] arbitrarily
    k  0
    repeat
       k  k+1
       for each state s do
           Vk[s] = maxa s' P(s'|s,a) (R(s,a,s')+ Vk-1[s'])
    until s |Vk[s]-Vk-1[s]| <
    for each state s do
       [s] = argmaxa s' P(s'|s,a) (R(s,a,s')+ Vk[s'])
    return ,Vk
```

In [8]:
```
def value_iteration(get_action_cost, gamma: float = 0.99, delta: float = 0.001, filenam
    """
    Computes the Optimal Policy and the State Values
    :return history_delta: (list<float>) The change in function over the history
    """
    history_delta = []
    global v_table, p_table, q_table
    random_initialize()
    converged = False
    for iteration in range(1, 1000):
        for h, a, s in STATES:
            for act in range(len(ACTIONS)):
                q_table[h, a, s, act] = gamma * get_next_utility((h, a, s), act) \
                                        + get_action_cost((h, a, s), act)
        new_v_table = np.max(q_table, axis=3)
        p_table = np.argmax(q_table, axis=3)
        converged = check_convergence(v_table, new_v_table, delta)
        history_delta.append(np.max(np.abs(new_v_table - v_table)))
        v_table = new_v_table
        print_state(iteration, v_table, p_table, filename)
        if converged:
```

```
                break
        return history_delta.copy()
```

```
In [9]: def get_action_cost_subtask1(state: tuple, action: int) -> float:
            """
            Returns the reward associated with each action taken
            """
            assert len(state) == 3 and state[0] < 5 and state[1] < 4 and state[2] < 3 and acti
            if state[0] == 0:
                return 0.0
            elif state[0] == 1 and action == 0:
                return (-2.5 if ACTIONS[action] != "SHOOT" else -0.25) + 10.0 * 0.5
            else:
                return -2.5 if ACTIONS[action] != "SHOOT" else -0.25

        def get_action_cost_general(state: tuple, action: int) -> float:
            """
            Returns the reward associated with each action taken
            """
            assert len(state) == 3 and state[0] < 5 and state[1] < 4 and state[2] < 3 and acti
            if state[0] == 0:
                return 0.0
            elif state[0] == 1 and action == 0:
                return -2.5 + 10.0 * 0.5
            else:
                return -2.5
```

```
In [10]: history_delta_1 = value_iteration(get_action_cost=get_action_cost_subtask1, filename=
         v_table_1 = v_table.copy()
         p_table_1 = p_table.copy()
```

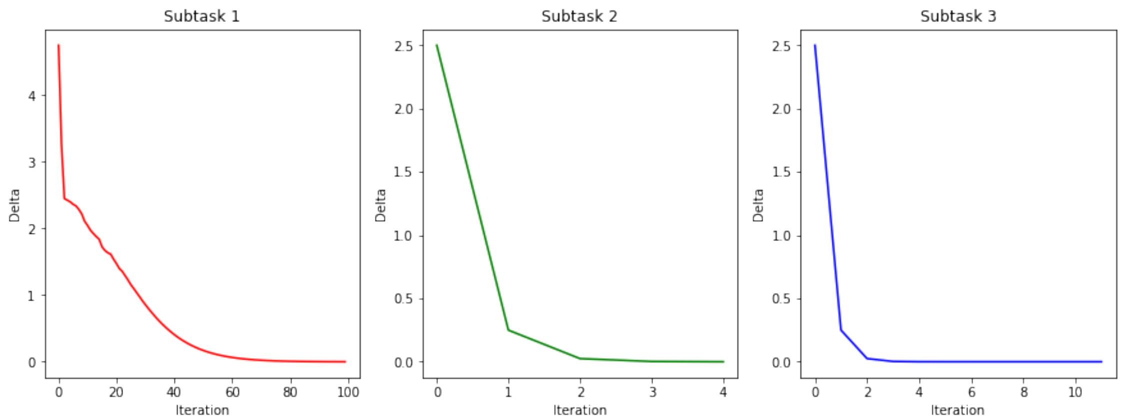
```
In [11]: history_delta_2 = value_iteration(get_action_cost=get_action_cost_general, gamma=0.1,
         v_table_2 = v_table.copy()
         p_table_2 = p_table.copy()
```

```
In [12]: history_delta_3 = value_iteration(get_action_cost=get_action_cost_general, gamma=0.1,
         v_table_3 = v_table.copy()
         p_table_3 = p_table.copy()
```

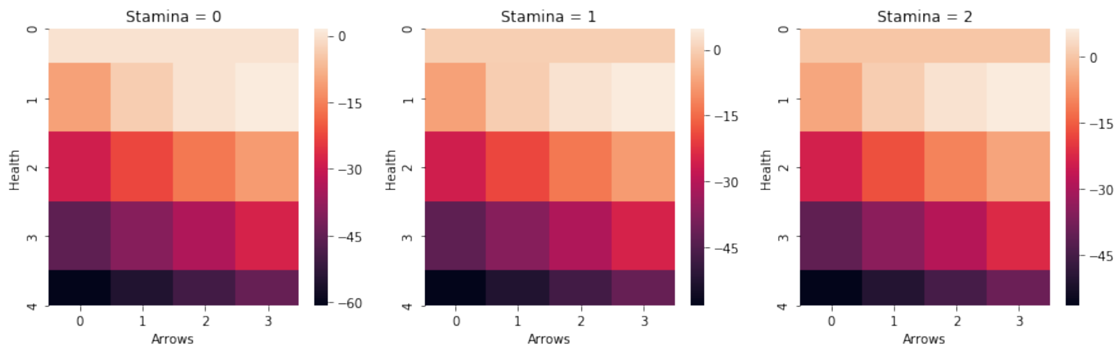
0.3 Checking our Answers

```
In [13]: fig, ax = plt.subplots(1, 3, figsize=(15, 5))
         ax[0].plot(history_delta_1, color='red')
         ax[0].set_xlabel('Iteration')
         ax[0].set_ylabel('Delta')
         ax[0].set_title('Subtask 1')
         ax[1].plot(history_delta_2, color='green')
         ax[1].set_xlabel('Iteration')
         ax[1].set_ylabel('Delta')
```

```
ax[1].set_title('Subtask 2')
ax[2].plot(history_delta_3, color='blue')
ax[2].set_xlabel('Iteration')
ax[2].set_ylabel('Delta')
ax[2].set_title('Subtask 3')
plt.show()
```

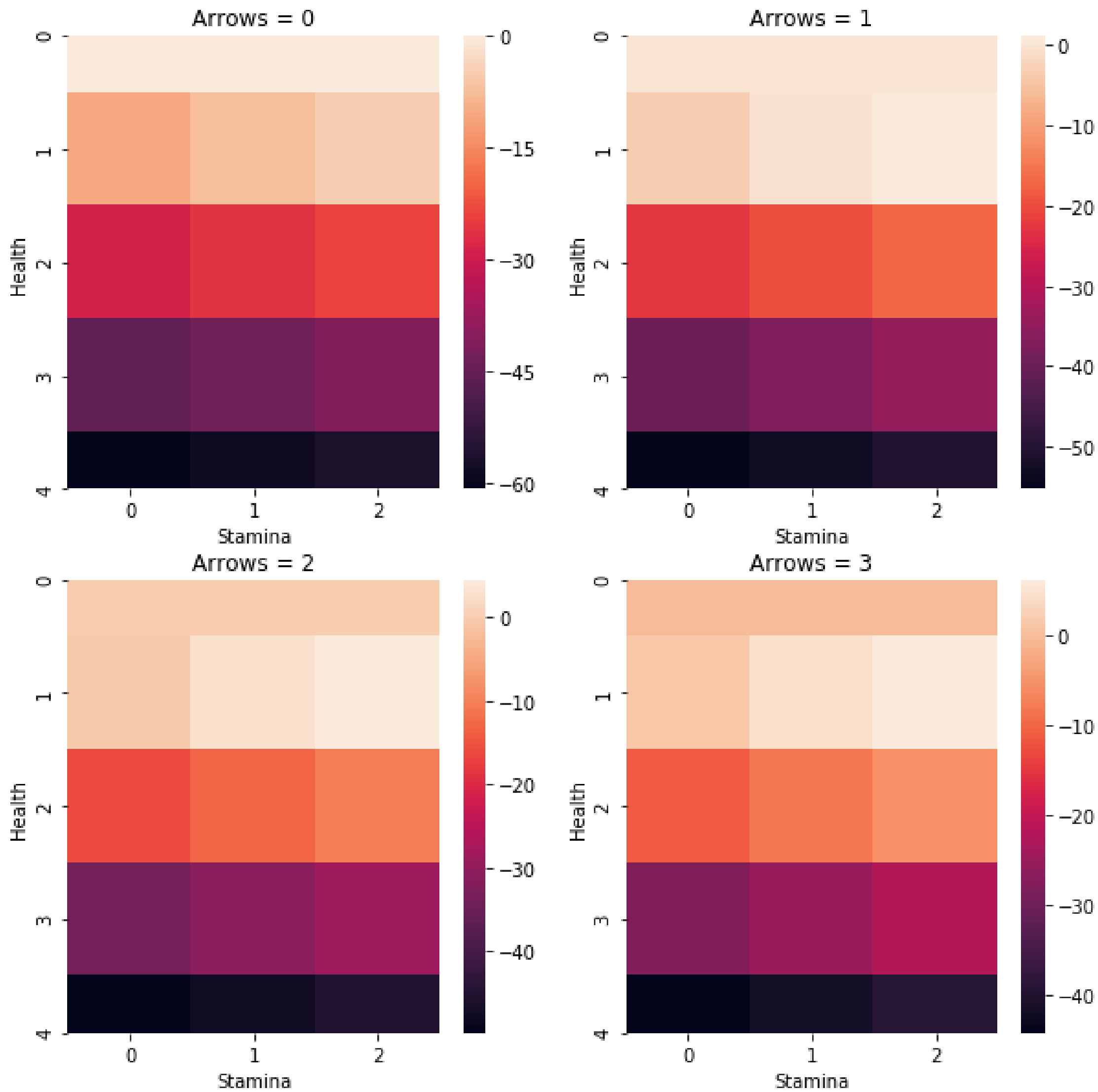


In [14]:
```
fig, ax = plt.subplots(1, 3, figsize=(15, 4))
sns.heatmap(v_table_1[:, :, 0], ax=ax[0])
ax[0].set_title('Stamina = 0')
ax[0].set_xlabel('Arrows')
ax[0].set_ylabel('Health')
sns.heatmap(v_table_1[:, :, 1], ax=ax[1])
ax[1].set_title('Stamina = 1')
ax[1].set_xlabel('Arrows')
ax[1].set_ylabel('Health')
sns.heatmap(v_table_1[:, :, 2], ax=ax[2])
ax[2].set_title('Stamina = 2')
ax[2].set_xlabel('Arrows')
ax[2].set_ylabel('Health')
plt.show()
```



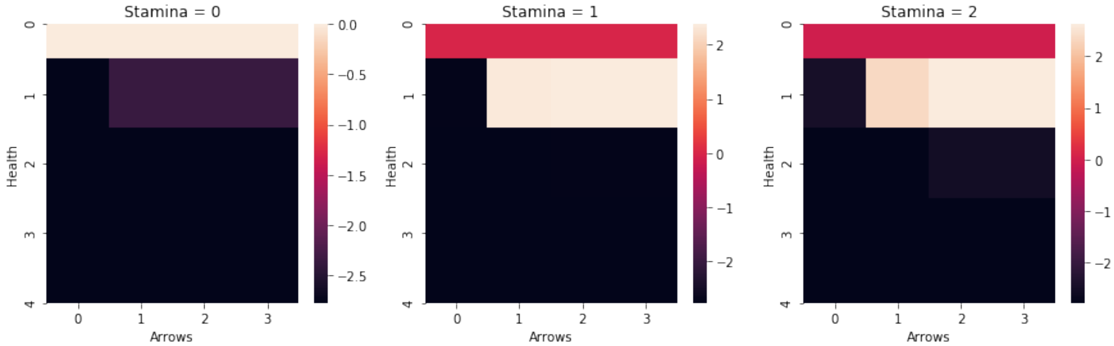
In [15]:

```
fig, ax = plt.subplots(2, 2, figsize=(10, 10))
sns.heatmap(v_table_1[:, 0, :], ax=ax[0][0])
ax[0][0].set_title('Arrows = 0')
ax[0][0].set_xlabel('Stamina')
ax[0][0].set_ylabel('Health')
sns.heatmap(v_table_1[:, 1, :], ax=ax[0][1])
ax[0][1].set_title('Arrows = 1')
ax[0][1].set_xlabel('Stamina')
ax[0][1].set_ylabel('Health')
sns.heatmap(v_table_1[:, 2, :], ax=ax[1][0])
ax[1][0].set_title('Arrows = 2')
ax[1][0].set_xlabel('Stamina')
ax[1][0].set_ylabel('Health')
sns.heatmap(v_table_1[:, 3, :], ax=ax[1][1])
ax[1][1].set_title('Arrows = 3')
ax[1][1].set_xlabel('Stamina')
ax[1][1].set_ylabel('Health')

plt.show()
```

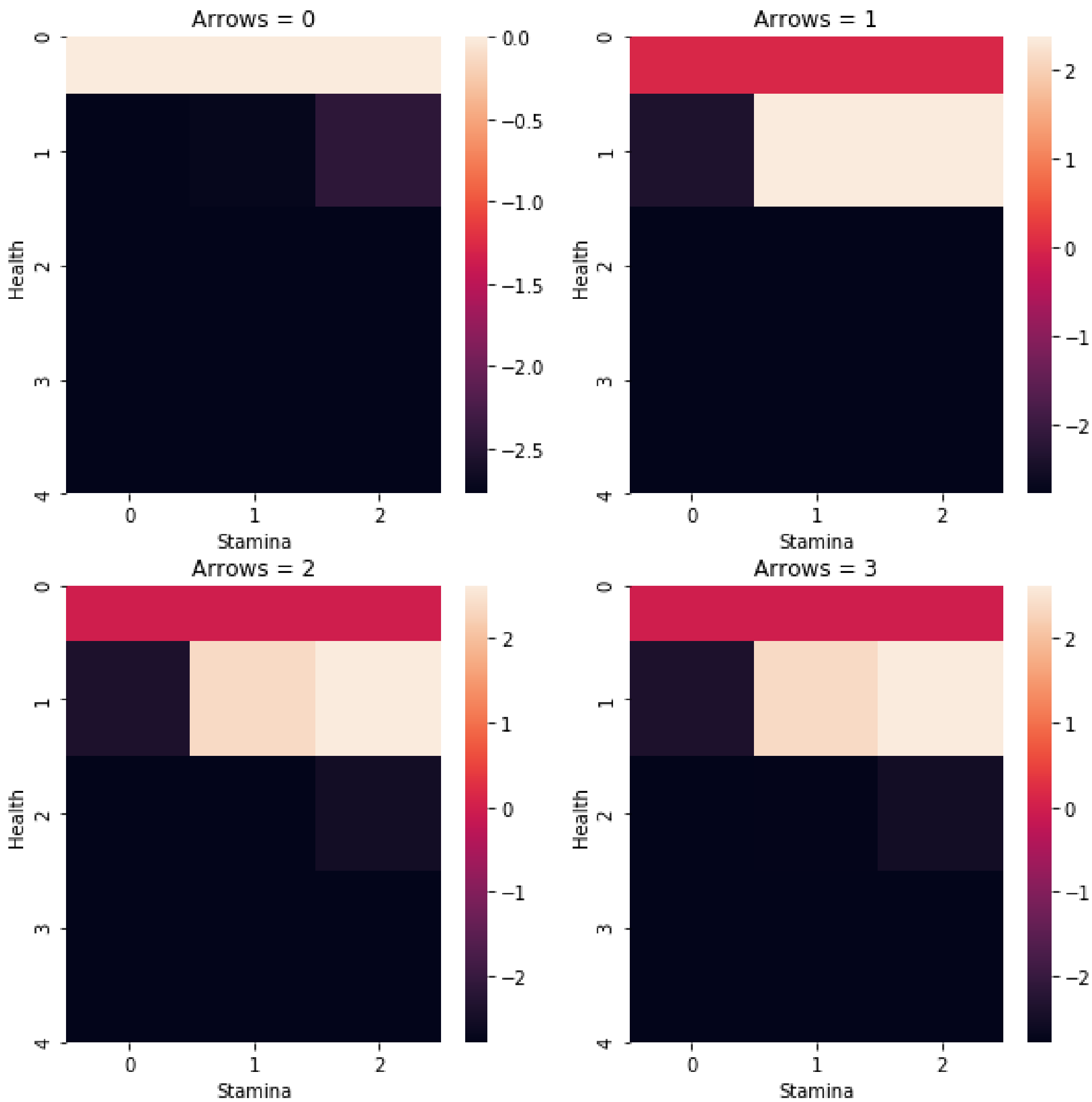


In [16]:
```
fig, ax = plt.subplots(1, 3, figsize=(15, 4))
sns.heatmap(v_table_2[:, :, 0], ax=ax[0])
ax[0].set_title('Stamina = 0')
ax[0].set_xlabel('Arrows')
ax[0].set_ylabel('Health')
sns.heatmap(v_table_2[:, :, 1], ax=ax[1])
ax[1].set_title('Stamina = 1')
ax[1].set_xlabel('Arrows')
ax[1].set_ylabel('Health')
sns.heatmap(v_table_2[:, :, 2], ax=ax[2])
ax[2].set_title('Stamina = 2')
ax[2].set_xlabel('Arrows')
ax[2].set_ylabel('Health')
```

```
plt.show()
```

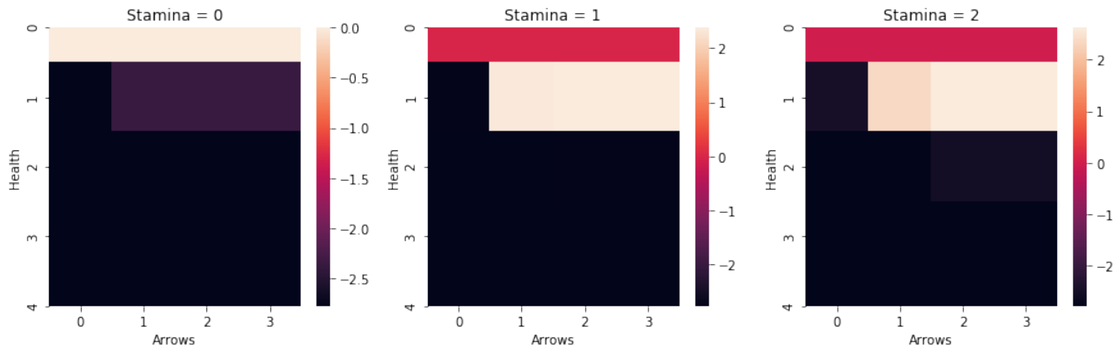



```
In [17]: fig, ax = plt.subplots(2, 2, figsize=(10, 10))
         sns.heatmap(v_table_2[:, 0, :], ax=ax[0][0])
         ax[0][0].set_title('Arrows = 0')
         ax[0][0].set_xlabel('Stamina')
         ax[0][0].set_ylabel('Health')
         sns.heatmap(v_table_2[:, 1, :], ax=ax[0][1])
         ax[0][1].set_title('Arrows = 1')
         ax[0][1].set_xlabel('Stamina')
         ax[0][1].set_ylabel('Health')
         sns.heatmap(v_table_2[:, 2, :], ax=ax[1][0])
         ax[1][0].set_title('Arrows = 2')
         ax[1][0].set_xlabel('Stamina')
         ax[1][0].set_ylabel('Health')
         sns.heatmap(v_table_2[:, 3, :], ax=ax[1][1])
         ax[1][1].set_title('Arrows = 3')
         ax[1][1].set_xlabel('Stamina')
         ax[1][1].set_ylabel('Health')

         plt.show()
```



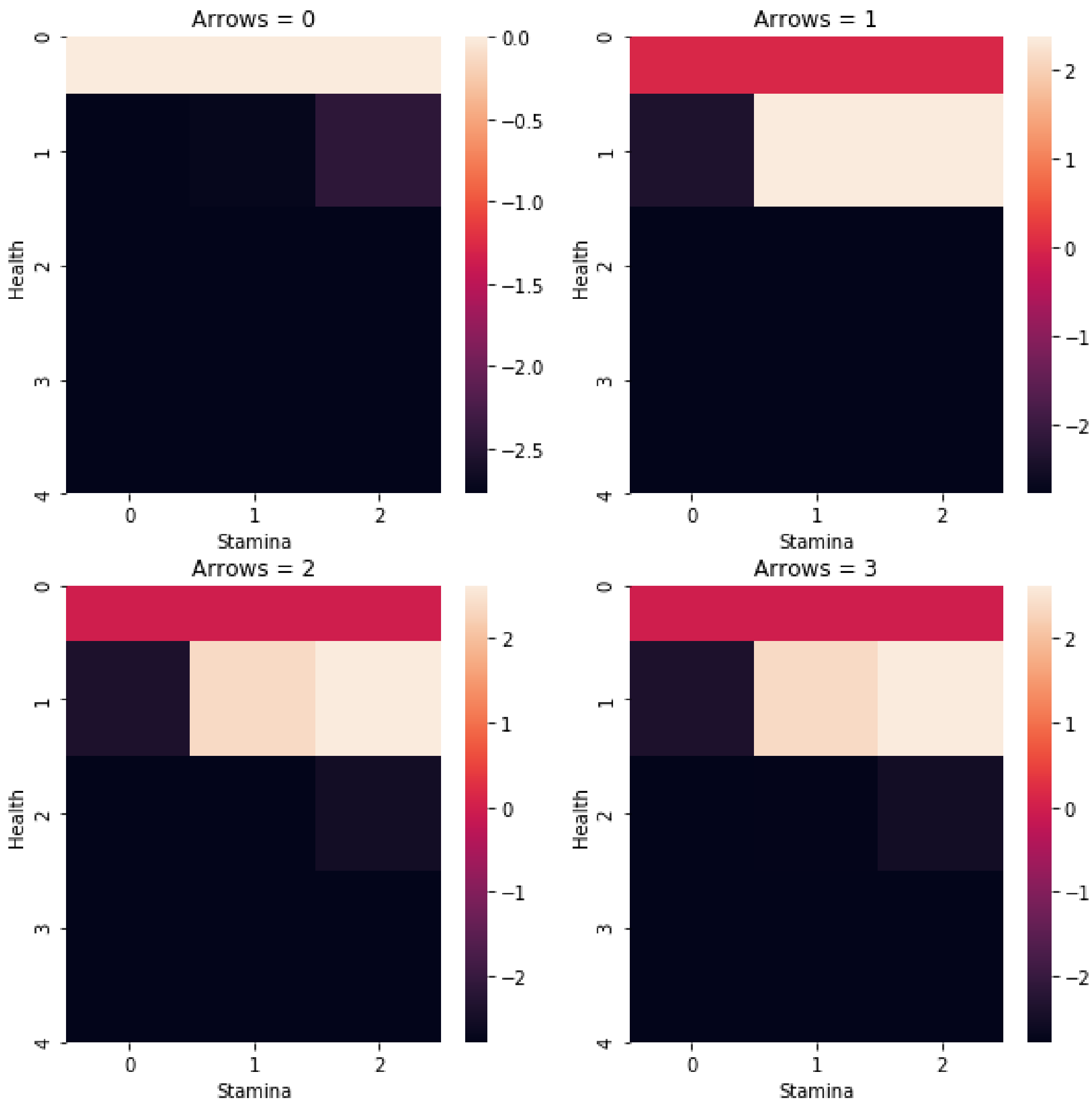
In [18]:
```
fig, ax = plt.subplots(1, 3, figsize=(15, 4))
sns.heatmap(v_table_3[:, :, 0], ax=ax[0])
ax[0].set_title('Stamina = 0')
ax[0].set_xlabel('Arrows')
ax[0].set_ylabel('Health')
sns.heatmap(v_table_3[:, :, 1], ax=ax[1])
ax[1].set_title('Stamina = 1')
ax[1].set_xlabel('Arrows')
ax[1].set_ylabel('Health')
sns.heatmap(v_table_3[:, :, 2], ax=ax[2])
ax[2].set_title('Stamina = 2')
ax[2].set_xlabel('Arrows')
```

```
ax[2].set_ylabel('Health')
plt.show()
```



In [19]:

```
fig, ax = plt.subplots(2, 2, figsize=(10, 10))
sns.heatmap(v_table_3[:, 0, :], ax=ax[0][0])
ax[0][0].set_title('Arrows = 0')
ax[0][0].set_xlabel('Stamina')
ax[0][0].set_ylabel('Health')
sns.heatmap(v_table_3[:, 1, :], ax=ax[0][1])
ax[0][1].set_title('Arrows = 1')
ax[0][1].set_xlabel('Stamina')
ax[0][1].set_ylabel('Health')
sns.heatmap(v_table_3[:, 2, :], ax=ax[1][0])
ax[1][0].set_title('Arrows = 2')
ax[1][0].set_xlabel('Stamina')
ax[1][0].set_ylabel('Health')
sns.heatmap(v_table_3[:, 3, :], ax=ax[1][1])
ax[1][1].set_title('Arrows = 3')
ax[1][1].set_xlabel('Stamina')
ax[1][1].set_ylabel('Health')

plt.show()
```



0.4 Final Observations

0.4.1 Subtask 1: New Step Rewards

The Convergence of this function is much faster than was before (in task 1), the lowered step costs and the favored shoot action allows the model to learn the kill technique much faster, which it later slowly changes to better action combinations involving dodge and recharge, improving the score further. There is more incentive to be greedy and shoot at the beginning.

0.4.2 Subtask 2: The High Future Discount

The huge discount factor **kills the incentive** to look and try to get the big reward (killing the dragon) in the future. The agent will only look 1 move deep and *only try if the dragon has health*

25 and it has both arrows and stamina, otherwise it will give up. All moves / futures look relatively equal.

0.4.3 Subtask 3: Complete Convergence

This change has no effect as compared to Subtask 2, since the agent has already almost completely discounted the future. The policy will not change as we hone down more on the utility values as the agent himself does not value anything in the future, changing convergence (δ) to 10^-3 to 10^-10 are both almost equally good. It just takes a few more iterations to get there.

Results of Part 1

```
iteration=100
(0,0,0):-1=[0.000]
(0,0,1):-1=[0.000]
(0,0,2):-1=[0.000]
(0,1,0):-1=[0.000]
(0,1,1):-1=[0.000]
(0,1,2):-1=[0.000]
(0,2,0):-1=[0.000]
(0,2,1):-1=[0.000]
(0,2,2):-1=[0.000]
(0,3,0):-1=[0.000]
(0,3,1):-1=[0.000]
(0,3,2):-1=[0.000]
(1,0,0):RECHARGE=[-10.317]
(1,0,1):DODGE=[-7.291]
(1,0,2):DODGE=[-4.839]
(1,1,0):RECHARGE=[-3.470]
(1,1,1):SHOOT=[-0.357]
(1,1,2):SHOOT=[1.141]
(1,2,0):RECHARGE=[-0.123]
(1,2,1):SHOOT=[3.032]
(1,2,2):SHOOT=[4.573]
(1,3,0):RECHARGE=[1.514]
(1,3,1):SHOOT=[4.689]
(1,3,2):SHOOT=[6.251]
(2,0,0):RECHARGE=[-28.809]
(2,0,1):DODGE=[-26.016]
(2,0,2):DODGE=[-23.754]
(2,1,0):RECHARGE=[-22.490]
(2,1,1):SHOOT=[-19.617]
(2,1,2):SHOOT=[-16.737]
(2,2,0):RECHARGE=[-16.054]
(2,2,1):SHOOT=[-13.100]
(2,2,2):SHOOT=[-10.137]
(2,3,0):RECHARGE=[-11.272]
(2,3,1):SHOOT=[-8.257]
(2,3,2):SHOOT=[-5.233]
```

```
(3,0,0):RECHARGE=[-45.556]
(3,0,1):DODGE=[-42.975]
(3,0,2):DODGE=[-40.884]
(3,1,0):RECHARGE=[-39.716]
(3,1,1):SHOOT=[-37.061]
(3,1,2):SHOOT=[-34.400]
(3,2,0):RECHARGE=[-33.772]
(3,2,1):SHOOT=[-31.042]
(3,2,2):SHOOT=[-28.306]
(3,3,0):RECHARGE=[-27.720]
(3,3,1):SHOOT=[-24.914]
(3,3,2):SHOOT=[-22.100]
(4,0,0):RECHARGE=[-60.717]
(4,0,1):DODGE=[-58.328]
(4,0,2):DODGE=[-56.393]
(4,1,0):RECHARGE=[-55.312]
(4,1,1):SHOOT=[-52.855]
(4,1,2):SHOOT=[-50.395]
(4,2,0):RECHARGE=[-49.815]
(4,2,1):SHOOT=[-47.288]
(4,2,2):SHOOT=[-44.758]
(4,3,0):RECHARGE=[-44.223]
(4,3,1):SHOOT=[-41.625]
(4,3,2):SHOOT=[-39.023]
```

Result of Part 2

```
iteration=5
(0,0,0):-1=[0.000]
(0,0,1):-1=[0.000]
(0,0,2):-1=[0.000]
(0,1,0):-1=[0.000]
(0,1,1):-1=[0.000]
(0,1,2):-1=[0.000]
(0,2,0):-1=[0.000]
(0,2,1):-1=[0.000]
(0,2,2):-1=[0.000]
(0,3,0):-1=[0.000]
(0,3,1):-1=[0.000]
(0,3,2):-1=[0.000]
(1,0,0):RECHARGE=[-2.775]
(1,0,1):DODGE=[-2.744]
(1,0,2):DODGE=[-2.442]
(1,1,0):RECHARGE=[-2.358]
(1,1,1):SHOOT=[2.361]
(1,1,2):SHOOT=[2.363]
(1,2,0):RECHARGE=[-2.357]
(1,2,1):SHOOT=[2.382]
```

```
(1,2,2):SHOOT=[2.618]
(1,3,0):RECHARGE=[-2.357]
(1,3,1):SHOOT=[2.382]
(1,3,2):SHOOT=[2.619]
(2,0,0):RECHARGE=[-2.778]
(2,0,1):DODGE=[-2.778]
(2,0,2):DODGE=[-2.778]
(2,1,0):RECHARGE=[-2.778]
(2,1,1):SHOOT=[-2.778]
(2,1,2):SHOOT=[-2.776]
(2,2,0):RECHARGE=[-2.776]
(2,2,1):SHOOT=[-2.757]
(2,2,2):SHOOT=[-2.521]
(2,3,0):RECHARGE=[-2.776]
(2,3,1):SHOOT=[-2.757]
(2,3,2):SHOOT=[-2.519]
(3,0,0):RECHARGE=[-2.778]
(3,0,1):DODGE=[-2.778]
(3,0,2):DODGE=[-2.778]
(3,1,0):RECHARGE=[-2.778]
(3,1,1):SHOOT=[-2.778]
(3,1,2):SHOOT=[-2.778]
(3,2,0):RECHARGE=[-2.778]
(3,2,1):SHOOT=[-2.778]
(3,2,2):SHOOT=[-2.778]
(3,3,0):RECHARGE=[-2.778]
(3,3,1):SHOOT=[-2.778]
(3,3,2):SHOOT=[-2.777]
(4,0,0):RECHARGE=[-2.778]
(4,0,1):DODGE=[-2.778]
(4,0,2):DODGE=[-2.778]
(4,1,0):RECHARGE=[-2.778]
(4,1,1):SHOOT=[-2.778]
(4,1,2):SHOOT=[-2.778]
(4,2,0):RECHARGE=[-2.778]
(4,2,1):SHOOT=[-2.778]
(4,2,2):SHOOT=[-2.778]
(4,3,0):RECHARGE=[-2.778]
(4,3,1):SHOOT=[-2.778]
(4,3,2):SHOOT=[-2.778]
```

Result of Part 3

```
iteration=12
(0,0,0):-1=[0.000]
(0,0,1):-1=[0.000]
(0,0,2):-1=[0.000]
(0,1,0):-1=[0.000]
```

```
(0,1,1):-1=[0.000]
(0,1,2):-1=[0.000]
(0,2,0):-1=[0.000]
(0,2,1):-1=[0.000]
(0,2,2):-1=[0.000]
(0,3,0):-1=[0.000]
(0,3,1):-1=[0.000]
(0,3,2):-1=[0.000]
(1,0,0):RECHARGE=[-2.775]
(1,0,1):DODGE=[-2.744]
(1,0,2):DODGE=[-2.442]
(1,1,0):RECHARGE=[-2.358]
(1,1,1):SHOOT=[2.361]
(1,1,2):SHOOT=[2.363]
(1,2,0):RECHARGE=[-2.357]
(1,2,1):SHOOT=[2.382]
(1,2,2):SHOOT=[2.618]
(1,3,0):RECHARGE=[-2.357]
(1,3,1):SHOOT=[2.382]
(1,3,2):SHOOT=[2.619]
(2,0,0):RECHARGE=[-2.778]
(2,0,1):DODGE=[-2.778]
(2,0,2):DODGE=[-2.778]
(2,1,0):RECHARGE=[-2.778]
(2,1,1):SHOOT=[-2.778]
(2,1,2):SHOOT=[-2.776]
(2,2,0):RECHARGE=[-2.776]
(2,2,1):SHOOT=[-2.757]
(2,2,2):SHOOT=[-2.521]
(2,3,0):RECHARGE=[-2.776]
(2,3,1):SHOOT=[-2.757]
(2,3,2):SHOOT=[-2.519]
(3,0,0):RECHARGE=[-2.778]
(3,0,1):DODGE=[-2.778]
(3,0,2):DODGE=[-2.778]
(3,1,0):RECHARGE=[-2.778]
(3,1,1):SHOOT=[-2.778]
(3,1,2):SHOOT=[-2.778]
(3,2,0):RECHARGE=[-2.778]
(3,2,1):SHOOT=[-2.778]
(3,2,2):SHOOT=[-2.778]
(3,3,0):RECHARGE=[-2.778]
(3,3,1):SHOOT=[-2.778]
(3,3,2):SHOOT=[-2.777]
(4,0,0):RECHARGE=[-2.778]
(4,0,1):DODGE=[-2.778]
(4,0,2):DODGE=[-2.778]
(4,1,0):RECHARGE=[-2.778]
```

```
(4,1,1):SHOOT=[-2.778]
(4,1,2):SHOOT=[-2.778]
(4,2,0):RECHARGE=[-2.778]
(4,2,1):SHOOT=[-2.778]
(4,2,2):SHOOT=[-2.778]
(4,3,0):RECHARGE=[-2.778]
(4,3,1):SHOOT=[-2.778]
(4,3,2):SHOOT=[-2.778]
```