Bartosz Galantowicz

1700994

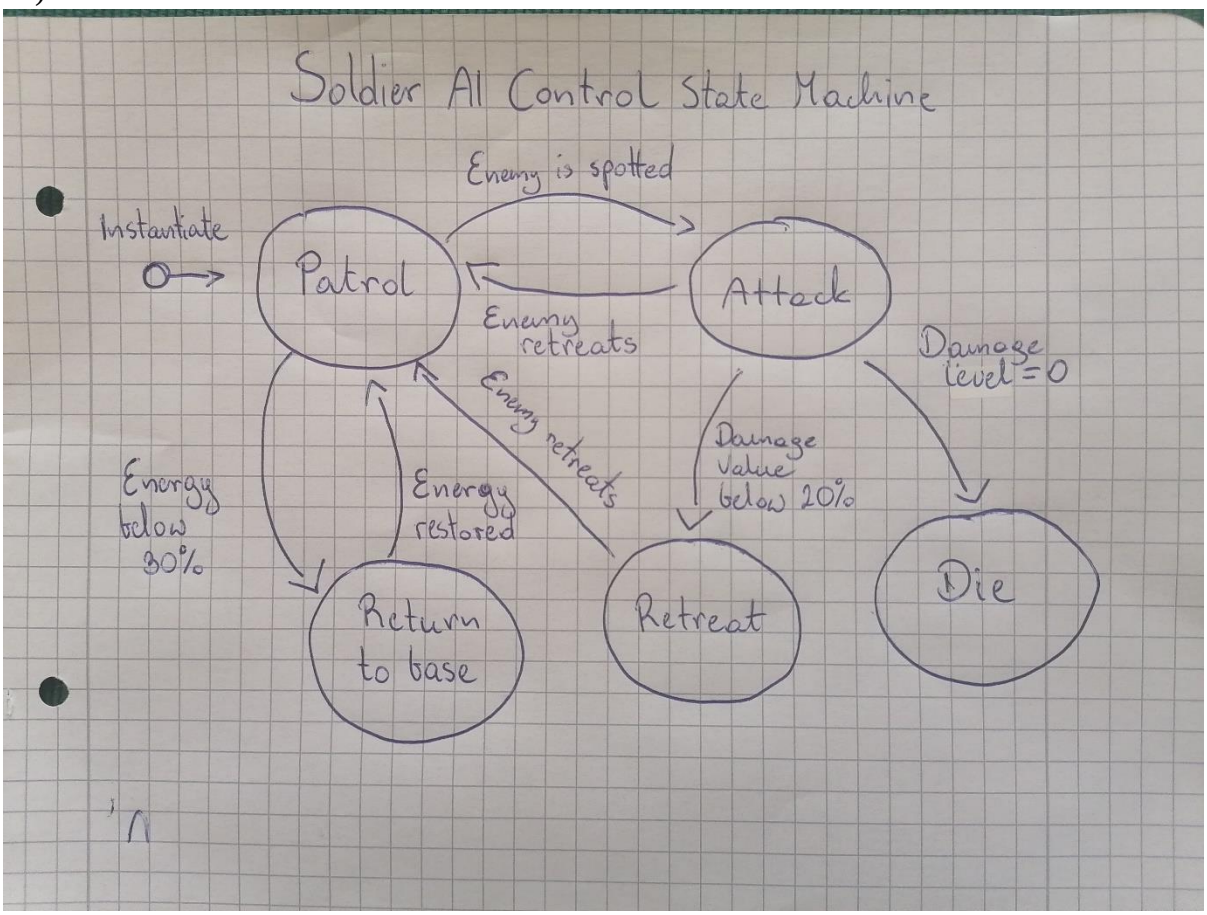
L6 - Artificial Intelligence & Machine Learning (ACCA6011)

Exam

Question 1

1a)

i)



ii)

```
Attack:: Enter (Soldier, Enemy)
{
    Soldier. Attack(Enemy);

}

Attack:: Execution (Soldier, Enemy)
{
    if (Soldier. damageValue < 20% ) then
    {   ChangeState (Soldier, Retreat);
    }

    if ( Soldier. damageValue <= 0 ) then
    {
        ChangeState (Soldier, Die);
    }

    if (Enemy. retreat == true)
    {
        ChangeState (Soldier, Patrol)
    }
}

Attack :: Exit (Soldier, Enemy)
{
    Soldier. StopAttack (Enemy)

}
```

1b)

There are three methods to implement state machines.

First and most common is Nested Switch implementation. It has simple rules for code structure. It requires enumerating states and events which will act as a trigger for the code. It also has a small memory footprint. However, it is hard to reuse the code, which means that the code is not as efficient.

Another method is a state table implementation. This method has similar requirements as Nested Switch – Enumeration and Events- but also States. However, unlike Nested Switch, the code can be reused. But it is difficult to maintain due to complex initialisation.

The third method is State Design Patter. It provides efficient state transition because the pointer can be easily re-assigned. Moreover, it is memory-efficient because it is sharing of state child objects when no new data is introduced to the child stated. There is also no enumeration of states and events unlike in previous methods. It also has O(1) performance which might be degraded if a client uses a switch to select event handler.

Question 2

2a)

A fuzzy expert system uses fuzzy logic instead of Boolean logic. Namely, it is a collection of membership functions and rules that are used to reason about data. Also, fuzzy expert system is oriented toward numerical processing.

Inferencing - applying the rules to specific values of the input variables to compute the values of the output variables. This process is combination of four processes:

Fuzzification - the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.

Inference - the truth value for the premise of each rule is computed, and applied to the conclusion part of each rule.

Composition - all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable.

Defuzzification – converting a fuzzy value to a single number called a crisp value.

2b)

The Mean of Maximum (MOM) – this defuzzification method calculates the average of those output values which have the highest degrees of membership. The problem with this method is that it does not take into account subsets with lower maximum values.

The Centre of Gravity (CoG) – this yields more accurate results that better reflects the part played by all fuzzy subsets in the system. The outputted crisp value is determined by finding the centre of gravity of the combined fuzzy manifold and taking its x value. The more points taken the more accurate the result.

I would choose the Centre of Gravity method as its more accurate and flexible because we can arrange the accuracy by regulating the number of samples. The Mean of Maximum can lead to a skewed or biased results.

2c)

Inference - Computing truth value for each rule

Rule 1.

$$\mu^{HIGH}_{POWER} \text{ OR } \mu^{LOW}_{DAMAGE} = \max\left[\mu^{HIGH}_{POWER}, \mu^{LOW}_{DAMAGE}\right]$$

$$= \mu^{LOW}_{CONFIDENCE}$$

$$\mu^{HIGH}_{POWER}(11) = 0 \quad , x < 25$$

$$\mu^{LOW}_{DAMAGE}(6) = \frac{7.5 - 6}{2.5} = \frac{1.5}{2.5} = 0.6 \quad , 5 \leq x < 7.5$$

$$\mu^{LOW}_{CONFIDENCE} = \max\left[0, 0.6\right] = 0.6$$

Rule 2.

$$\mu^{MEDIUM}_{POWER} \text{ AND } \mu^{HIGH}_{DAMAGE} = \min\left[\mu^{MEDIUM}_{POWER}, \mu^{HIGH}_{DAMAGE}\right]$$

$$= \mu^{MEDIUM}_{CONFIDENCE}$$

$$\mu^{MEDIUM}_{POWER}(11) = \frac{11 - 10}{5} = \frac{1}{5} = 0.2 \quad , 10 \leq x < 15$$

$$\mu^{HIGH}_{DAMAGE}(6) = \frac{6 - 5}{5} = \frac{1}{5} = 0.2 \quad , 5 \leq x < 10$$

$$\mu^{MEDIUM}_{CONFIDENCE} = 0.2$$

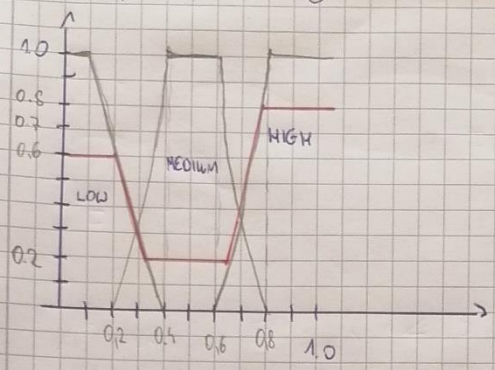
Rule 3.

$$\mu^{LOW}_{POWER} = \mu^{HIGH}_{CONFIDENCE}$$

$$\mu^{LOW}_{POWER}(11) = \frac{15 - 11}{5} = \frac{4}{5} = 0.8$$

$$\mu^{HIGH}_{CONFIDENCE} = 0.8$$

Confidence Diagram



X	Values
0.0	0.6
0.1	0.6
0.2	0.6
0.3	0.6
0.4	0.2
0.5	0.2
0.6	0.2
0.7	0.8
0.8	0.8
0.9	0.8
1.0	0.8

$$\text{Crisp Value} = \frac{\sum_{s=\text{Domain Min}}^{s=\text{Domain Max}} s \times DOM(s)}{\sum_{s=\text{Domain Min}}^{s=\text{Domain Max}} DOM(s)}$$

$$\frac{(0.1+0.2+0.3)\times 0.6 + (0.4+0.5+0.6)\times 0.2 + (0.7+0.8+0.9+1.0)\times 0.8}{3\times 0.6 + 3\times(0.2) + 4\times(0.8)}$$

$$= \frac{(0.6\times 0.6) + (1.5)\times 0.2 + (3.4\times 0.8)}{1.8 + 0.6 + 3.2} =$$

$$= \frac{0.36 + 0.3 + 2.72}{5.6} = \frac{3.38}{5.60} \approx 0.6036$$

Crisp output value for confidence is = 0.6036

Question 4

4a) The synaptic weights purpose is to represent the strength of the connection between nodes. If the weight from node 1 to node 2 has greater magnitude, it means that neuron 1 has greater influence over neuron 2. A weight brings down the importance of the input value.

4b)

i)

$x1 = 0.9$ $\quad$ $w_{k1} = 0.4$

$x2 = 0.8$ $\quad$ $w_{k2} = -0.2$

$x3 = -0.12$ $\quad$ $w_{k3} = 0.12$

Bias $w_{k0} = 0.3$

$$u_k = \sum_{j=1}^{m} w_{kj} \times x_j + w_{k0}$$

$$u_k = (0.9 \times 0.4 + 0.8 \times (-0.2) + (-0.12) \times (0.12)) + 0.3$$

$$u_k = (0.36 + (-0.16) + (-0.0144)) + 0.3$$

$$u_k = 0.1856 + 0.3 = 0.4856$$

4c)

The ReLU activation function suffers from a problem known as the “dying ReLUs” as gradient is zero when x is < 0. As there is no gradient it cannot learn using gradient descent.

The first attempt at curbing the problem of vanishing gradients in a general deep network setting. The gradient of ReLU is 1 for x>0x>0 and 0 for x<0x<0. It has multiple benefits. The product of gradients of ReLU function does not end up converging to 0 as the value is either 0 or 1. If the value is 1, the gradient is back propagated as it is. If it is 0, then no gradient is back from that point backwards.