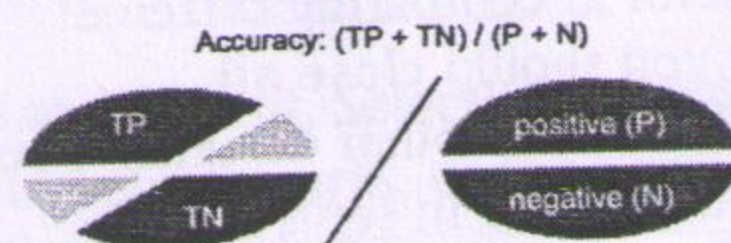


## Q.1

A) Confusion matrix- 1 mark, Accuracy- 1 mark, what is accuracy- 1 mark.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN



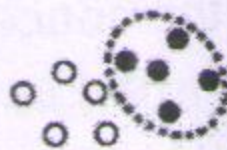
Accuracy is calculated as the total number of two correct predictions (TP + TN) divided by the total number of a dataset (P + N).

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N}$$

B) Difference- 2 marks, Exmaples- 2 marks

## Generative vs. Discriminative

- Generative:
  - probabilistic "model" of each class
  - decision boundary:
    - where one model becomes more likely
  - natural use of unlabeled data
- Discriminative:
  - focus on the decision boundary
  - more powerful with lots of examples
  - not designed to use unlabeled data
  - only supervised tasks



C) Steps: Initialize-1 mark, Positive- 1.5 mark, Negative- 1.5 mark, where to stop- 1 mark

- Initialize G, the set of maximally general hypotheses, to contain one element: the null description (all features are variables).
- Initialize S, the set of maximally specific hypotheses, to contain one element: the first positive example.
- Accept a new training example.
- If the example is positive:
  - Generalize all the specific models to match the positive example, but ensure the following:
    - The new specific models involve minimal changes.
    - Each new specific model is a specialization of some general model.
    - No new specific model is a generalization of some other specific model.
    - Prune away all the general models that fail to match the positive example.
- If the example is negative:
  - Specialize all general models to prevent match with the negative example, but ensure the following:
    - The new general models involve minimal changes.



Figure 35 is an example of a simulation using the steps provided in this tutorial.

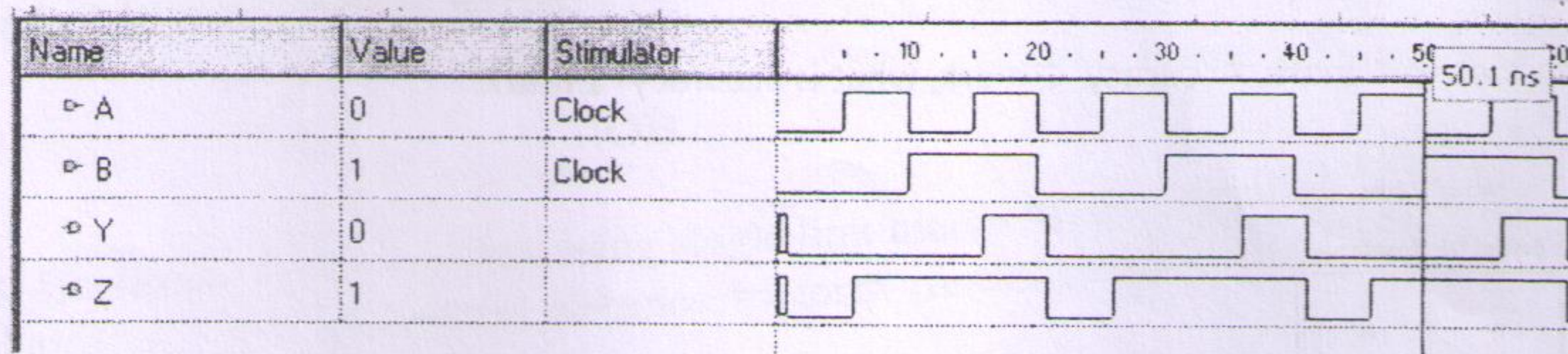


Figure 35

Now that you have ran a simulation and created a waveform, you should save that waveform. With the waveform tab active, press Ctrl-s to save, or right-click the tab and select save. Remember to use descriptive names. A good naming convention is <design name>\_wv. You may have several waveforms for the same design. This is very useful in comparing different signal values and methods of driving the input signals. However, you should **close all waveforms** when you are done to avoid confusing signals when simulating other designs. You should experiment with the different methods available and save the results in separate waveforms for comparison; however, this is optional.

### Concluding Remarks

This completes the first tutorial for Active-HDL there will be three other tutorials. Remember that this tutorial has only scratched the surface of the capabilities of this program. We strongly recommend you practice using the techniques described within this tutorial while experimenting with and exploring other methods and techniques that Active-HDL offers. Don't be discouraged if you do not understand what all of the tools are used for or the concepts the tutorial covers that have not yet been covered in class. By spending time with this tool and experimenting, you will save time by being better prepared for the more complicated upcoming assignments.



- Each new general model is a generalization of some specific model.
- No new general model is a specialization of some other general model.
- Prune away all the specific models that match the negative example.

-If S and G are both singleton sets, then:

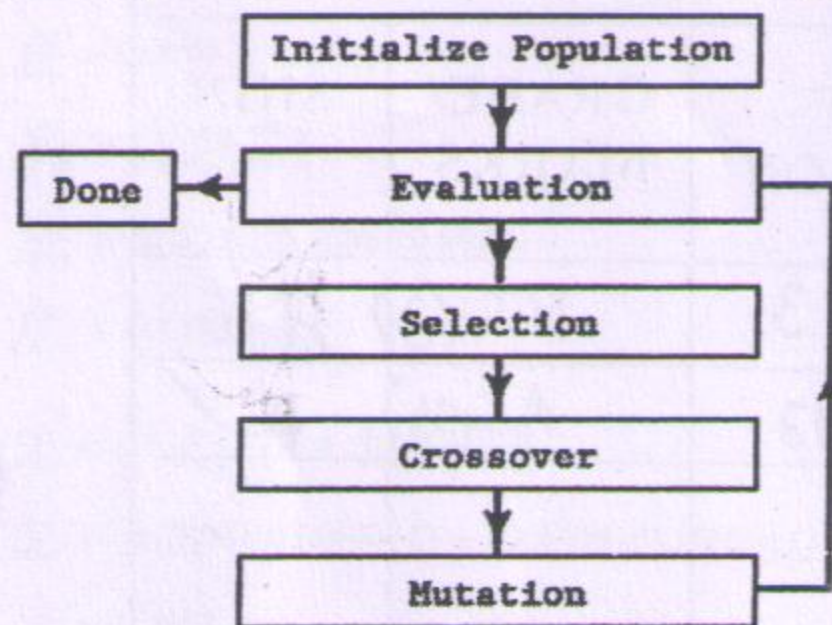
--if they are identical, output their value and halt.

--if they are different, the training cases were inconsistent. Output this result and halt.

-else continue accepting new training examples.

## Q.2

A) Steps to implement genetic algorithm:



Fitness assignment, Selection, Crossover, Mutation- 0.5 mark each.

B) Table/sets: 6 marks, correct guess of items: 4 marks

$V[i, w]$	0	1	2	3	4	5	6	7	8	9	10
$i = 0$	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	10	10	10	10	10	10
2	0	0	0	0	40	40	40	40	40	50	50
3	0	0	0	0	40	40	40	40	40	50	70
4	0	0	0	50	50	50	50	90	90	90	90

Items to be put: 2,4

## Q.3

Forward pass: 4 marks, Errors: 2 mark, Change in weights: 4 marks, new weights: 2 marks

Input to hidden layer

$$w_1x_1 + w_3x_2 + w_5x_3 + b_1 = z_{h_1}$$

$$w_2x_1 + w_4x_2 + w_6x_3 + b_1 = z_{h_2}$$

$$h_1 = \sigma(z_{h_1})$$

$$h_2 = \sigma(z_{h_2})$$

Hidden layer to output layer

$$w_7h_1 + w_9h_2 + b_2 = z_{o_1}$$

$$w_8h_1 + w_{10}h_2 + b_2 = z_{o_2}$$

$$o_1 = \sigma(z_{o_1})$$

$$o_2 = \sigma(z_{o_2})$$

$$w_1x_1 + w_3x_2 + w_5x_3 + b_1 = z_{h_1} = 0.1(1) + 0.3(4) + 0.5(5) + 0.5 = 4.3$$

$$h_1 = \sigma(z_{h_1}) = \sigma(4.3) = 0.9866$$

$$w_2x_1 + w_4x_2 + w_6x_3 + b_1 = z_{h_2} = 0.2(1) + 0.4(4) + 0.6(5) + 0.5 = 5.3$$

$$h_2 = \sigma(z_{h_2}) = \sigma(5.3) = 0.9950$$

$$w_7h_1 + w_9h_2 + b_2 = z_{o_1} = 0.7(0.9866) + 0.9(0.9950) + 0.5 = 2.0862$$

$$o_1 = \sigma(z_{o_1}) = \sigma(2.0862) = 0.8896$$

$$w_8h_1 + w_{10}h_2 + b_2 = z_{o_2} = 0.8(0.9866) + 0.1(0.9950) + 0.5 = 1.3888$$

$$o_2 = \sigma(z_{o_2}) = \sigma(1.3888) = 0.8004$$





$$\frac{dE}{dw_7} = \frac{dE}{do_1} \frac{do_1}{dz_{o1}} \frac{dz_{o1}}{dw_7}$$

$$\frac{dE}{dw_7} = (o_1 - t_1)(o_1(1 - o_1))h_1$$

$$\frac{dE}{dw_7} = (0.8896 - 0.1)(0.8896(1 - 0.8896))(0.9866)$$

$$\frac{dE}{dw_7} = 0.0765$$

$$\frac{dE}{dw_8} = \frac{dE}{do_2} \frac{do_2}{dz_{o2}} \frac{dz_{o2}}{dw_8}$$

$$\frac{dE}{dw_8} = (0.7504)(0.1598)(0.9866)$$

$$\frac{dE}{dw_8} = 0.1183$$

$$\frac{dE}{dw_9} = \frac{dE}{do_1} \frac{do_1}{dz_{o1}} \frac{dz_{o1}}{dw_9}$$

$$\frac{dE}{dw_9} = (0.7896)(0.0983)(0.9950)$$

$$\frac{dE}{dw_9} = 0.0772$$

$$\frac{dE}{dw_{10}} = \frac{dE}{do_2} \frac{do_2}{dz_{o2}} \frac{dz_{o2}}{dw_{10}}$$

$$\frac{dE}{dw_{10}} = (0.7504)(0.1598)(0.9950)$$

$$\frac{dE}{dw_{10}} = 0.1193$$

$$\frac{dE}{db_2} = \frac{dE}{do_1} \frac{do_1}{dz_{o1}} \frac{dz_{o1}}{db_2} + \frac{dE}{do_2} \frac{do_2}{dz_{o2}} \frac{dz_{o2}}{db_2}$$

$$\frac{dE}{db_2} = (0.7896)(0.0983)(1) + (0.7504)(0.1598)(1)$$

$$\frac{dE}{db_2} = 0.1975$$

$$\frac{dE}{dh_1} = (0.7896)(0.0983)(0.7) + (0.7504)(0.1598)(0.8) = 0.1502$$

Plugging the above into the formula for  $\frac{dE}{dw_1}$ , we get

$$\frac{dE}{dw_1} = (0.1502)(0.0132)(1) = 0.0020$$

The calculations for  $\frac{dE}{dw_3}$  and  $\frac{dE}{dw_5}$  are below

$$\frac{dE}{dw_3} = \frac{dE}{dh_1} \frac{dh_1}{dz_{h1}} \frac{dz_{h1}}{dw_3}$$

$$\frac{dE}{dw_3} = (0.1502)(0.0132)(4) = 0.0079$$

$$\frac{dE}{dw_5} = \frac{dE}{dh_1} \frac{dh_1}{dz_{h1}} \frac{dz_{h1}}{dw_5}$$

$$\frac{dE}{dw_5} = (0.1502)(0.0132)(5) = 0.0099$$

$$\frac{dE}{dh_2} = (0.7896)(0.0983)(0.9) + (0.7504)(0.1598)(0.1) = 0.0818$$

Plugging the above into the formula for  $\frac{dE}{dw_2}$ , we get

$$\frac{dE}{dw_2} = (0.0818)(0.0049)(1) = 0.0004$$

The calculations for  $\frac{dE}{dw_4}$  and  $\frac{dE}{dw_6}$  are below

$$\frac{dE}{dw_4} = \frac{dE}{dh_2} \frac{dh_2}{dz_{h2}} \frac{dz_{h2}}{dw_4}$$

$$\frac{dE}{dw_4} = (0.0818)(0.0049)(4) = 0.0016$$

$$\frac{dE}{dw_6} = \frac{dE}{dh_2} \frac{dh_2}{dz_{h2}} \frac{dz_{h2}}{dw_6}$$

$$\frac{dE}{dw_6} = (0.0818)(0.0049)(5) = 0.0020$$

$$\frac{dE}{db_1} = (0.7896)(0.0983)(0.7)(0.0132)(1) + (0.7504)(0.1598)(0.1)(0.0049)(1) = 0.0008$$



$$\begin{aligned}
w_1 &:= w_1 - \alpha \frac{dE}{dw_1} = 0.1 - (0.01)(0.0020) = 0.1000 \\
w_2 &:= w_2 - \alpha \frac{dE}{dw_2} = 0.2 - (0.01)(0.0004) = 0.2000 \\
w_3 &:= w_3 - \alpha \frac{dE}{dw_3} = 0.3 - (0.01)(0.0079) = 0.2999 \\
w_4 &:= w_4 - \alpha \frac{dE}{dw_4} = 0.4 - (0.01)(0.0016) = 0.4000 \\
w_5 &:= w_5 - \alpha \frac{dE}{dw_5} = 0.5 - (0.01)(0.0099) = 0.4999 \\
w_6 &:= w_6 - \alpha \frac{dE}{dw_6} = 0.6 - (0.01)(0.0020) = 0.6000 \\
w_7 &:= w_7 - \alpha \frac{dE}{dw_7} = 0.7 - (0.01)(0.0765) = 0.6992 \\
w_8 &:= w_8 - \alpha \frac{dE}{dw_8} = 0.8 - (0.01)(0.1183) = 0.7988 \\
w_9 &:= w_9 - \alpha \frac{dE}{dw_9} = 0.9 - (0.01)(0.0772) = 0.8992 \\
w_{10} &:= w_{10} - \alpha \frac{dE}{dw_{10}} = 0.1 - (0.01)(0.1193) = 0.0988 \\
b_1 &:= b_1 - \alpha \frac{dE}{db_1} = 0.5 - (0.01)(0.0008) = 0.5000 \\
b_2 &:= b_2 - \alpha \frac{dE}{db_2} = 0.5 - (0.01)(0.1975) = 0.4980
\end{aligned}$$

#### Q.4

A)i) Sup-Find-S, CE, SVM, KNN, Unsup-Clustering, kmeans: types-1 mark, example-1 mark

ii) Identify task, performance measure, training experience- 2 marks

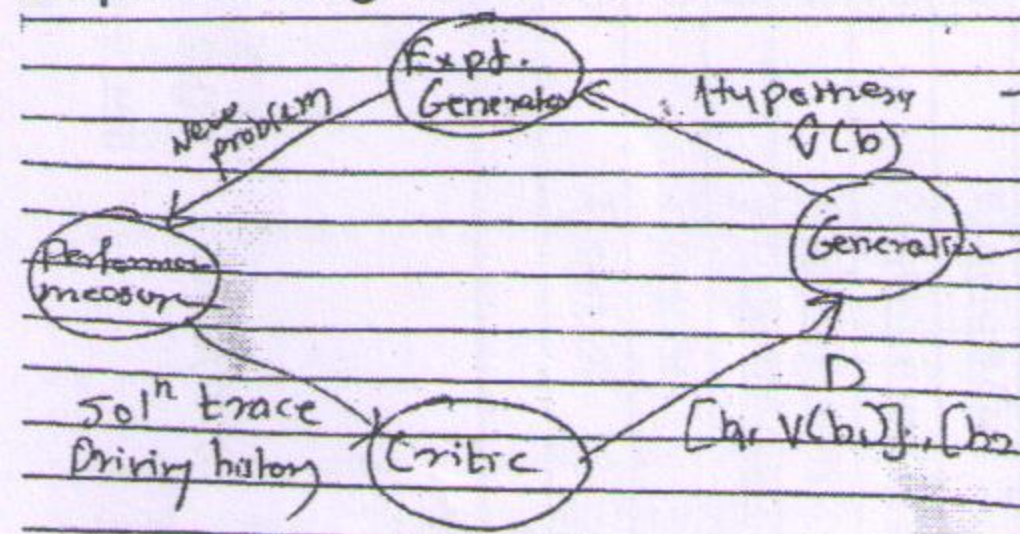
Step 1- choose E- Direct/indirect feedback, degree to which robot controls the sequence of training examples, distribution of training examples should be similar to future test examples- 2 marks

Step 2- choose target function, credit assignment- 2 marks

Step 3- choose representation of V, parameters- 2 marks

Step 4- function approximation- 2 marks

Sequence diagram- 2 marks



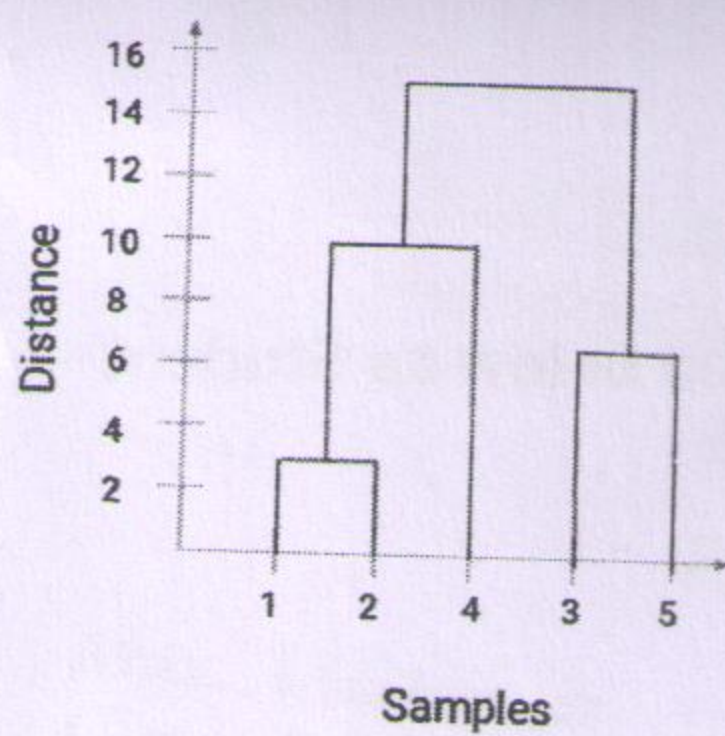
#### B)

Identify algorithm- 1 mark, correct proximity matrix at each step- 4 marks, correct clustering- 5 marks, dendrogram- 2 marks

ID	1	2	3	4	5
1	0	3	18	10	25
2	3	0	21	13	28
3	18	21	0	8	7
4	10	13	8	0	15
5	25	28	7	15	0

ID	(1,2)	3	4	5
(1,2)	0	18	10	25
3	18	0	8	7
4	10	8	0	15
5	25	7	15	0





### Q.5

Find all dependant probabilities: 5 marks

Find Flu|Y and Flu|N: 5 marks

Correct classify: 2 marks

$P(\text{flu} = Y)$	$\frac{5}{8} = 0.625$	$(P(O))$
$P(\text{chills} = Y   \text{flu} = Y)$	$\frac{3}{5} = 0.6$	$(P(E_1 O))$
$P(\text{runnynose} = N   \text{flu} = Y)$	$\frac{1}{5} = 0.2$	$(P(E_2 O))$
$P(\text{headache} = mild   \text{flu} = Y)$	$\frac{2}{5} = 0.4$	$(P(E_3 O))$
$P(\text{fever} = N   \text{flu} = Y)$	$\frac{1}{5} = 0.2$	$(P(E_4 O))$
$P(\text{chills} = Y)$	$\frac{4}{8} = 0.5$	$(P(E_1))$
$P(\text{runnynose} = N)$	$\frac{3}{8} = 0.375$	$(P(E_2))$
$P(\text{headache} = mild)$	$\frac{3}{8} = 0.375$	$(P(E_3))$
$P(\text{fever} = N)$	$\frac{3}{8} = 0.375$	$(P(E_4))$

Now calculating  $P(\text{flu} = Y | E_1, E_2, E_3, E_4)$  by plugging these probabilities in (1)

$$= \frac{0.6 * 0.2 * 0.4 * 0.2}{0.5 * 0.375 * 0.375 * 0.375} 0.625 = 0.227$$

Similarly, the various probabilities are calculated for the case of  $\text{flu} = N$ . The readers are encouraged to calculate these values and check them with the ones used below. Hence  $P(\text{flu} = N | E_1, E_2, E_3, E_4)$

$$= \frac{0.33 * 0.66 * 0.33 * 0.66}{0.5 * 0.375 * 0.375 * 0.375} 0.375 = 0.674$$

Thus  $P(\text{flu} = Y | E_1, E_2, E_3, E_4) = 0.6 * 0.4 * 0.2 * 0.2 * 0.625 = 0.006$

$P(\text{flu} = N | E_1, E_2, E_3, E_4) = 0.33 * 0.66 * 0.33 * 0.66 * 0.375 = 0.0185$

No flu.