1.

a)

y(t) could be either 1 or -1

When x(t) is misclassified by w(t), $w^T(t)x(t)$ will always have an opposite sign to the y(t).

$w^T(t)x(t)$ < 0 in case of y(t) = 1, hence $y(t)w^T(t)x(t)$ < 0

$w^T(t)x(t)$ > 0 in case of y(t) = -1, hence $y(t)w^T(t)x(t)$ < 0

b)

$y(t)w^T(t + 1)x(t)$

= $y(t)(w(t) + y(t)x(t))^T x(t)$ (1.3)

= $y(t)(w^T(t)x(t) + y(t)||x(t)||^2)$

= $y(t)w^T(t)x(t) + y^2(t)||x(t)||^2$

Since $y^2(t)$ > 0 and $||x(t)||^2$(square of norm of x(t)) > 0

Hence, $y^2(t)||x(t)||^2$ > 0

$y(t)w^T(t)x(t) + y^2(t)||x(t)||^2$ > $y(t)w^T(t)x(t)$

Hence, $y(t)w^T(t + 1)x(t)$ > $y(t)w^T(t)x(t)$

c)

Since $y(t)w^T(t)x(t)$ < 0, we want to fix that by directing it towards 0 and surpass it.

In problem b), we have proved that $y(t)w^T(t + 1)x(t)$ > $y(t)w^T(t)x(t)$; we also get $y(t)w^T(t + 1)x(t)$ = $y(t)w^T(t)x(t) + y^2(t)||x(t)||^2$.

This means the value of $y(t)w^T(t)x(t)$ will always have a positive increase by applying function (1.3). It will move towards 0 and finally surpass it.

Hence, the move from $w^T(t)$ to $w^T(t + 1)$ is a move in the ‘right direction’.

2.

a) Learning approach
b) Design approach
c) Learning approach
d) Design approach
e) Learning approach

3.
a) Supervised learning or reinforcement learning
For supervised learning, the training data could be the depiction of users (age, occupation, book owned, etc) (input Dx) and its corresponding correct recommandation (output Dy).
For reinforcement learning, the training data is the same as the supervised learning except it will not have the corresponding correct output. Instead, there will be some possible recommendation and its corresponding score.

b) Supervised learning or reinforcement learning
For supervised learning, the training data could be situations on the tic tac toe board from the past games (input Dx) and its corresponding correct next step (output Dy).
For reinforcement learning, the training data could be situations on the tic tac toe board from the past games (input Dx), the corresponding possible next move and a score of this move. The learning will decide what is the next best move.

c) Supervised learning or unsupervised learning
For supervised learning, the training data could be the attributes of the movies (horror, comedy, etc) (input Dx) and its corresponding category (output Dy).
For unsupervised learning, the training data could be the attributes of the movies (input Dx). Through unsupervised learning, different clusters will be formed for different categories of movies.

d) Supervised learning or reinforcement learning
For supervised learning, the training data could be the attributes of the previous music (syllable, tone, rhythm, etc) (input Dx) and its corresponding right way to play it.
For reinforcement learning, the training data could be the attributes of the previous music (Dx), possible way to play it and a corresponding score.

e) Supervised learning or reinforcement learning
For supervised learning, the training data could be a depiction of the customers (age, occupation, crime record, etc) (input Dx) and its corresponding correct allowed debt (input Dy).

For reinforcement learning, the training data could be a depiction of the customers (input Dx), some corresponding possible allowed debt and a score to that possible allowed debt.

4.

a)

One of the target functions (f8) agrees with all points; three of the target functions (f4, f6, f7) agree with two of the points; three of the target functions (f2, f3, f5) agree with one of the points; one of the target functions (f1) agrees with none of the points.

b)

One of the target functions (f1) agrees with all points; three of the target functions (f2, f3, f5) agree with two of the points; three of the target functions (f4, f6, f7) agree with one of the points; one of the target functions (f8) agrees with none of the points.

c)

One of the target functions (f2) agrees with all points; three of the target functions (f1, f4, f6) agree with two of the points; three of the target functions (f3, f5, f8) agree with one of the points; one of the target functions (f7) agrees with none of the points.

d)

One of the target functions (f7) agrees with all points; three of the target functions (f3, f5, f8) agree with two of the points; three of the target functions (f1, f4, f6) agree with one of the points; one of the target functions (f2) agrees with none of the points.

5.
Bag 1 - black, black
Bag 2 - black, white
We already know that we currently have a black ball in our hand. If it is from bag 1, definitely we will have the second black ball. If it is from bag 2, we will never make it. We get the following:
Using Bayes' theorem
P[bag 1 | black ball] = (P[black ball | bag 1] * P[bag 1]) / P[black ball]

P[black ball]: we have four situations:
Bag 1 -> black ball
Bag 1 -> black ball
Bag 2 -> black ball
Bag 2 -> white ball
Hence the probability of black ball is 3/4.

= (1 * 0.5) / (3/4)
= 2/3

6.

a)

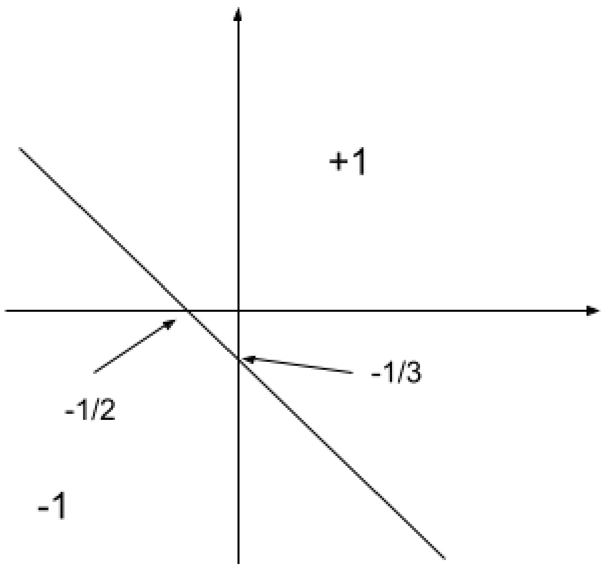
$a = -w_1/w_2$

$b = -w_0/w_2$

b)

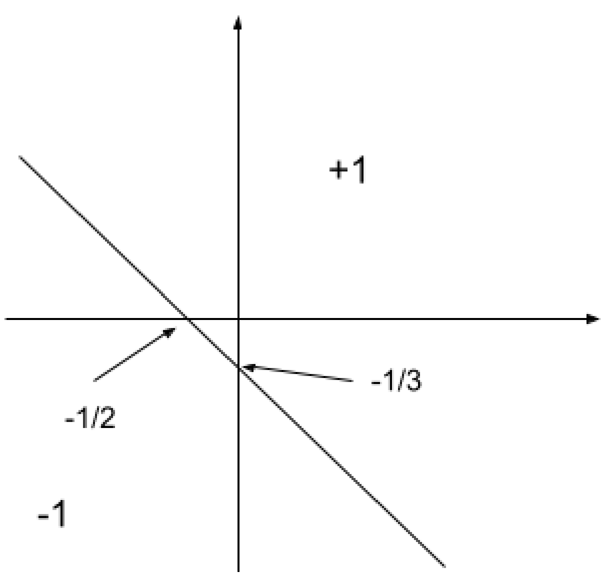
$w = [1, 2, 3]^T$:

$1 + 2x_1 + 3x_2 = 0$



$w = -[1, 2, 3]^T$

$-1 - 2x_1 - 3x_2 = 0$



7.
a) and b)
The w is being updated for 10 times
The hypothesis successfully separates the data. It is close to the target function.
c)
The w is being updated for 6 times.
Compared to b), the PLA generates a new g function on the new data set. The distance between two lines on x1=0,x2=0 is approximately the same. They are pretty much close.

d)
The w is being updated for 10 times.
Compared to b), the g function changed again based on the newly generated and larger data set. The performance is close to b) based on the observation on the distance between two lines from position x1=0,x2=0.

e)
The w is being updated for 263 times. Compared to b) and other previous tests, the updating time is largely increased on this much larger data set. The performance of the resulting g function, after observation on point x1=0,x2=0, is similar to b).