

得分：

1. (a) math and scientific computing, Graph, word processing

(b) learn, analyze, organize

2. (a) brain, spinal cord, periphery -1

(b) organize, learn, computing

(c) analyze, learn, feedback

3. unipolar, bipolar, multipolar No address their function -1.5.

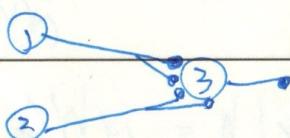
4. ① encode ^{training} = ^{production} ③ training = recall the value -1.



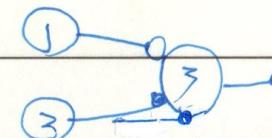
5. convergence, divergence, feedback

6. disjunction

conjoined negation



$$N_3(t) = N_1(t-1) \vee N_2(t-1)$$



$$N_3(t) = \neg N_1(t-1) \vee N_2(t-1)$$

7. $N_3(t) = N_1(t-1) \vee \alpha(t-1) = N_1(t-1) \vee (\neg N_2(t-2) \vee b(t-2)) = N_1(t-1) \vee [\neg N_2(t-2) \vee N_2(t-3)]$

$$N_4(t) - N_2(t-1) \wedge b(t-1) = N_2(t-1) \wedge N_2(t-2)$$

9. 當 A 能激發 B 且能持續發射時，代謝系統能激發 1 個或 > 個，這樣 A 的效率會提升 -5.

10. the system evolve over time

11. adaline: adaptive linear neuron

madaline: multiple adaptive linear neuron

12. ① Initialize the value $w(t_0)$

② Determine the steepest descent direction $-\nabla \xi(w(t)) = \frac{d\xi(w(t))}{dw} = 2(p^T w - R)$

③ find the weight

④ repeat 2~3

13. ∵ XOR 是比 x_1, x_2 ，當 x_1 False, x_2 True，代表不同，因此可以執行，然而 perceptron 的最後 circuit 有 not，
因此無法完整用 XOR 表示

缺圖示

-3.

也沒有 not, im

$$14. \xi(w) = \langle \varepsilon_k^2 \rangle - w^T \langle x_k x_k^T \rangle w + \langle d_k x_k \rangle w = \xi - w^T R w + p^T w - u$$

$$\frac{d\xi(w)}{dw} = 2Rw - 2p - (2)$$

$$2Rw - 2p = 0 \Rightarrow 2Rw = 2p \quad w = R^{-1}p - (3)$$

-3.

$$(3) (p_k)^2 - p^T w.$$

得分：

科目：

系級：

學號：

姓名：

15. 要知道 R, P 的值，必須事先知道曲面

③ steepest descent learning 是一個 batch method

16. advantage 較 steepest 來的容易

$$f(w) = \frac{1}{2}w^T b w + c$$

disadvantage 只有 2 維， \therefore 只有極大 or 極小

-2.5.

17. minimum disturbance principle：最小干擾定律，當 training 時不能一起全部跑完 -4.

18. 因為每一層的輸出為下層的輸入，而 BP 是由最末層把值往第一層做更新

19. 一層一層的跑，不會有人失跑出結果 -3.

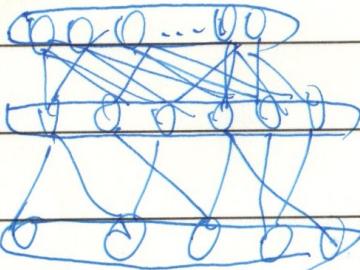
$$20. E = \frac{1}{2} \sum_k (y_k - \theta_k)^2$$

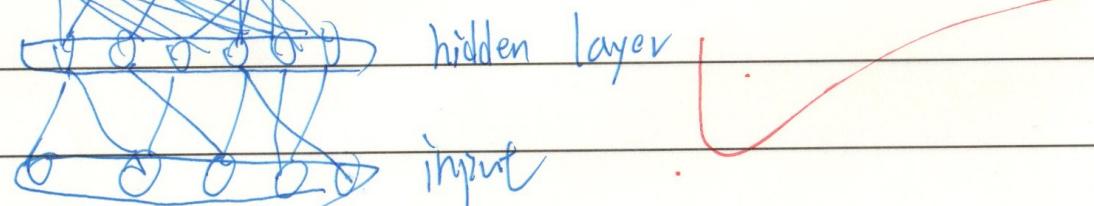
$$\left\{ \begin{array}{l} \frac{\partial E}{\partial w_{kj}} = \lambda (y_k - \theta_k) \theta_k (1 - \theta_k) (x_j - v_{kj})^2 \end{array} \right.$$

$$\left. \begin{array}{l} \frac{\partial E}{\partial v_{kj}} = \lambda (y_k - \theta_k) \theta_k (1 - \theta_k) [2w_{kj} (x_j - v_{kj})] \end{array} \right]$$

$$\left\{ \begin{array}{l} \Delta w_{kj} = \eta (y_k - \theta_k) \theta_k (1 - \theta_k) (x_j - v_{kj})^2 \\ \Delta v_{kj} = \eta (y_k - \theta_k) \theta_k (1 - \theta_k) [-2w_{kj} (x_j - v_{kj})], \quad \eta = n \lambda \end{array} \right.$$

~~21.~~ ⁻¹⁵ hidden layer 較多層計算量大，node 是代表他們的 feature 或著他們之間的 relationship

~~22.~~  output



~~23.~~ (a) Mexican-hat function can be realized using Difference of Gaussians or
8 Laplacian of Gaussian 圖?

~~(b)~~ DOG (Difference of Gaussian) 算式?
LOT (Laplacian of Gaussian)

~~24.~~ (i) LAM $\phi(b\lambda) = b\lambda$

definition & matrix memory representation?

~~(ii)~~ CAM $\phi(b\alpha) = \alpha$

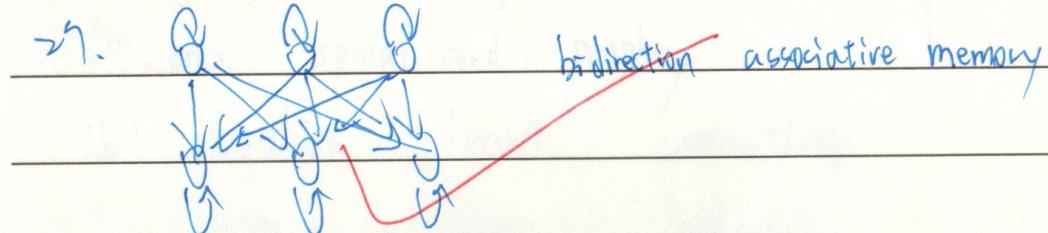
~~(iii)~~ AM $\phi(b\lambda) = b\lambda + \epsilon$

~~25.~~ (a) $[b^1, b^2, b^3 \dots b^M] \begin{bmatrix} \frac{1}{1} & \frac{1}{2} & \dots & \frac{1}{M} \\ \frac{2}{1} & \frac{2}{2} & \dots & \frac{2}{M} \\ \vdots & \vdots & \ddots & \vdots \\ M & M & \dots & M \end{bmatrix} = [a^1, a^2, a^3, \dots a^M]$

~~(b)~~ $[b^1, b^2, b^3 \dots b^M] \begin{bmatrix} 0 & -1 & \dots & -M \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ M & 0 & \dots & 0 \end{bmatrix} = [a^1, a^2, a^3, \dots a^M]$

26. $\sum (2^i - 1)^2 = \sum (-(-2^i - 1))^2$

12. 代表 $2^i - 1$ 是 $-(-2^i - 1)$ 的 complement ... 所以...?



28. crosswall phenomenon with a memory, 從 A 到 B - 2.

29. 是一種 dynamic system. *initial value* - 5.

30. $E = -\vec{y}^T W \vec{x} = -\nabla V(\vec{x}) = -\sum_{i=1}^m \sum_{j=1}^n |w_{ij}|$ 解釋?

13.