

[Chap. 4 MLP 重點]

- Simplified structure of interconnected neurons
 - 2-2-1 for 16 boolean fctns
 - No jump connection; no feedback connection
-
- 不等式 轉變成 邏輯 運作在輸入空間
 - High-level abstractions (representations) of the front input patterns
 - ‘ linear algebra’s linear algebra

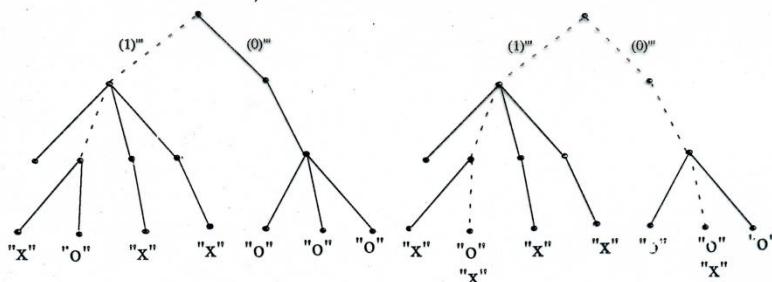
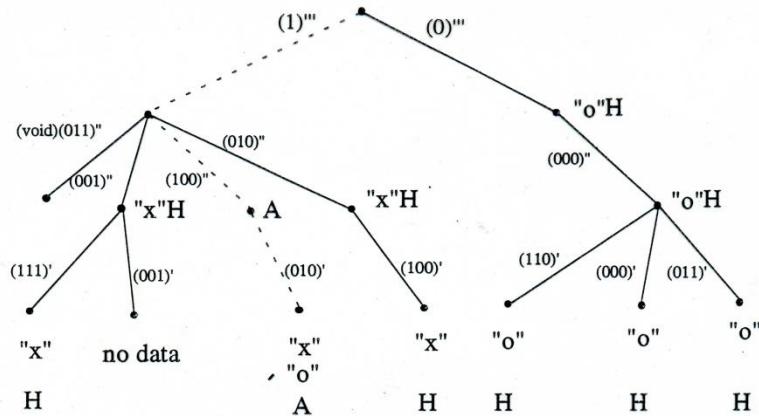
[■ It has been shown]

- that only one layer of hidden units suffices to approximate any function with finitely many discontinuities to arbitrary precision, provided the activation functions of the hidden units are non-linear (the universal approximation theorem).
- (Hornik, Stinchcombe, & White, 1989; Funahashi, 1989; Cybenko, 1989; Hartman, Keeler, & Kowalski, 1990)

[Chapter 4: Hidden tree in MLP]

- Kolmogorov theorem
- Existence theorem
- He did not show how to implement it?
- An operational solution is lack.
- Even exists such sol, it will be too much complex to operate.

• The Hamming tree



可依此圖清除整 neuron ③型

因
此
neuron
被
拆
分
後
能
得
到
homogenous
且
不
造成
ambiguous
狀況
而
清除

模糊區

MLP complex¹⁰ → MLP. 不易實現
T-PYTHON Boole 代數容易..

消除
冗余 neurons
的二种方法

① 适配于训练模式
反应一致

② 同 T neurons 适配于同一模式
一致

③ 换出
神经元

并不适用
+ ambiguous regions

granularity



MSB neuron
LSB

idle neuron (void neuron)
unchanged sign for all training patterns

/ Homogeneity unchanged
when suppress this neuron

4 complexity
 $M(J,n) = \sum_{k=0}^n \binom{J}{k} \frac{1}{2^n}$

$$L_1$$

$$L_2$$

$$L_3$$

$$L_4$$

$$L_5$$

$$L_6$$

$$L_7$$

$$L_8$$

$$L_9$$

$$L_{10}$$

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$$L_{99}$$

$$L_{100}$$

Figure 3 A typical training result of the first hidden layer
x is the first input unit
y is the second input unit

Hamming distance

- Neighboring regions $(010)'$ and $(011)'$ have a common boundary L_3 and have a Hamming distance of only one bit.
- All connected neighborhood regions have an exactly one bit Hamming neighborhood distance.
- Far and unconnected regions may have maximum Hamming distance of all three bits.

Note, when activated state vectors $<< 2^N$, N : # of neurons in that hidden layer

we can keep few neurons, $2^N = 3$, to represent the states and prune, drop, all other neurons.

We can always use 3 layers network to achieve arbitrary # of hidden layer training program.

$\begin{matrix} \text{0000} \\ \text{0001} \\ \text{0010} \\ \text{0011} \\ \text{0100} \\ \text{0101} \\ \text{0110} \\ \text{0111} \\ \text{1000} \\ \text{1001} \\ \text{1010} \\ \text{1011} \\ \text{1100} \\ \text{1101} \\ \text{1110} \\ \text{1111} \end{matrix}$ whenever a homogeneous layer is reached we augmented a new hidden layer and start the

local neurons
for local data

[Hidden tree]

- Pruning neurons
 1. two neurons both with the same or reverse responses to all patterns,
 2. delete a neuron has a same response to all patterns. Delete it.
 3. delete useless neurons 分割同類 data
 - 4 delete a neuron will not generate any mixed ambiguity cells. 簡化結構

Day 6 / 17 大進展 NetTalk 1987 wiki

- Perceptron 1943
- LMS learning = Widrow learning 1960
- Webro 1974 (Harvard)
Backpropagation
LMS 50Yr Celebration Presentation Paul Werbos part 1 (videos 2009/06/17 IJCNN)
- 1986 a “renaissance” in the field
Book by Rumelhart, Hinton and Williams

1986 多層 neurons 學習 大幅增加計算能力

[NetTalk BP分配獎懲率各取所需 還是各取所值]

- BP 分配獎懲率各取所需 還是各取所值
- BP : solve one type of credit assignment problem (舊的 homework)
- Chemistry application prediction of disulfide binding state
- http://www.uow.edu.au/~markus/teaching/SCI323/Lecture_MLP.pdf

[Day 6 / 17 NetTalk]

- From where does its mysterious power come ?
- None of the existing methods or contemporary technologies can accomplish such pronunciation task 95% corrections.
- Discovers 規則變化 (regularity 80%) 並記住不規則變化

[NetTalk]

- Discovers 規則變化 (regularity 80%) 並記住
不規則變化
- 例外使得 rule based 方法失效
- formal system 也失效
- logic 失效
- 集合論失效
- 機率失效 統計失效

[NetTalk shows MLP by LMS]

- Autonomously exploits useful hidden structures in training dataset; such as vowels and consonants.
- Discovers hidden structures (regularity 80%)
- Utilizes those implicit structure + 記住特例
- utilizes those structures to simplify the problem drastically.

[Chapter 4 showed, suggested]

- 世界是從底下自組(建築)起的 Boltzmann
-
- World not imposed from the above God,
- World merged from the low,
(33.00min in [video](#))

【Hidden tree

- Coding cell =\ 不是 binary number
 - 不是 Minsky 所說的 數
- Neuron 有 MSB and LSB 性質
- Neuron does not understand number.
- Neurons use representations to solve problem.

$$(101)' =\ 1 \times 2^2 + 0 \times 2^1 + 1 \times 2^0 = 7$$

[Chap. 4: MLP tree]

- Over simplified neural structure

No jump connections;

no feedback connections

Capable of high-level logical abstraction

May be called a kind of

‘鑑別區分 machine’ or ‘分類 machine’

or ‘a self-tuning 分類 machine’

Finest areas of the first hidden layer

- are cells, 空間被 perceptrons 切到最細碎 每一cell 只含純一類 data
- or patches 多面體形狀 polyhedral
- or building blocks of succeeding layers
- Merge → merge → merge layer by layer
- Coding → coding → coding →
- Combining 結合 → combining → combining
- Piling → piling → piling →
- Grouping → grouping → grouping →

Finest areas of the first hidden layer

- 離散化 data space 的連續空間
- 簡化後續處理
- Cell 被編上符號後 第二層與更深(上)層 hidden layers 只用前一層 cell 的符號去 training 不需用原始 data training 可簡化後續處理
- 第二層與更深(上)層 hidden layers 持續簡化 最終符號數量 會愈來愈少

[Each cell in 2-3-3-1 network]

- Each cell has a polyhedron shape and also a convex shape (first hidden layer)
- Neighborhood cells are different in one bit, in one 区分 line
- Total number # of cells for J hyperplanes in n dimensional space is
$$\#(J,n) = \sum_{k=0}^n \binom{n}{k} (J,k)$$

[Equivalent Isomorphism]

- 第一層hidden layer 異質同構 等價結構
- $\#(J,n) = \sum_{k=0}^n \binom{n}{k}$ 的等價結構
- Xun Dong
- polyhedral complex
- The bounded complex of a hyperplane arrangement
- Xun Dong 的等價結構更複雜

[Hidden tree 反映 cells 的組合結構]

- There are so many rules among cells.
有各式各樣的編織方法編織這一群 cells.
- There exist equivalent parts in the hidden tree structure.
- This tree reveals all geometrical relations of cells in hyperspace 看不到.
- One can see the relations. 搬到眼前

[Statistics and probability ways]

- 機率會使 **cells** 成為不同程度的灰色 **cell** 內的 **data** 不可能為單純一類
- MLP perceptrons 區隔不同純類 沒有灰色類
- MLP 只處理 機率=0 機率=1 兩種類
- 不處理 機率=0.3 淺灰類
- 藉 MLP tree 可以挑出 ambiguity cells 機率=0..3 的 cells
- 遇到有 機率=0..3 灰類 cells 時 針對個別 cell 另行加工

Statistics and probability ways

- 如果非要加入機率假設
 ■ 如孟德爾的雜交碗豆
- 淺灰色 $<0.5 \text{ cells}$ 與 深灰色 $>0.5 \text{ cells}$ 分別結合在不同的子樹上 可以做到 global minimum E.

[Statistics and probability ways]

- Cells 分三種情況 分別處理 (之後有時間再講)
- 1. 純黑白 cells 如 Chap.4 內容
- 2. 純黑白 cells + 灰色機率 cells
- 先區分純黑白 cells 再處理灰色機率 cells
- 3. 純灰色機率 cells 有機會再講
- 淺灰色 <0.5 cells 與 深灰色 >0.5 cells 分別結合在不同的子樹上 可以做到 global minimum E.

Minsky

- Neurons do not know 12 (數量) comes from, $12=7+5?$, see video 39.50 [37.48](#)
-
- Neurons do not know numbers.
- Neurons use representations to solve problem.
- 切割 input space 體重身高(數量)座標軸

[MLP tree & logic]

Can express any Boolean fctn by

Iterative logic fctn $F_1(F_2(F_3(X)))$

邏輯 (and, or) 也需要 nest 運作

- Tree = logic relations in spatial space. 編織架構
- Marriage 融合 logic and geometric relations
- Logic may have no spatial content,
- Conversely, space has no logic content
- 離散區割 X space into finest cells
- and coding them
- Combine coded cells into high-level codes

[MLP]

- Marriage of logic and geometric space
將空間編織上 Logic 搭 Logic 便車 利用 Logic 輔助
- MLP tree 約略可看出 data 空間結構
- Piling → piling → piling →
- Grouping → grouping → grouping →

[Hidden tree]

- Codes of areas are symbols.
- Codes are not binary numbers.
- Neurons develop symbols to solve problem.
- Neurons do not understand numbers.
- Neurons do not understand probability.
- Neurons do not use probability to solve problem $\leftarrow \rightarrow$ Bayes.

[MLP 將區割線轉變成 logic 內涵]

- Even more,
neurons do not understand logic.
- Neurons use group force
(representations) collectively to solve
區分 分類 problems.
- 搭 Logic 便車 利用 Logic 輔助

[MLP tree: constructive way]

- MSB LSB neurons
- Redundant neurons
- Retrain locally and use local data
- Divide and conquer
- Constructive way
- BP errors tend to get lost in front layers

[Tree nodes are representations]

- 1-bit neighbors, 隔一條區別線,
- Tree support 支撐 dataset 空間結構 spatial structure
- 相鄰近的兩個 data 可能隔兩條區別線 見前圖
- Hamming dist.=2
- 2-bit neighbors,
1-bit neighbors' neighbors
excluding itself and 1-bit neighbors

[Notes on BP and MLP]

- 1. 分群 grouping of output vectors of first hidden layer by PCA 取代 binary tree in NetTalk 可用目視看出分群
- 2. Mark each sample in PCA with its error (深淺色),看出錯誤率大的資料
- 3. 不同類用不同兩種顏色著色 (兩類)
- 4. 挑出相互矛盾的資料 samples 另行設法處理

Notes on BP and MLP

- 5.看出規則變化的特例 與 不規則變化共同交集激發的那一組 neurons (majority), see NetTalk
- 6.依錯誤程度訂出 MSB LSB neurons 重新訓練 LSB neurons (MSB 不更動)
- 7.調整距離輸入資料最近的幾個 hyper-planes 三點共面 四點共體

[Notes on BP and MLP]

- $| \text{weight} | \sim 0$ 區別線平行該 weight 拒絕該輸入 X
- 如果整層的 特定 $| \text{weight} | \sim 0$ 可能由於該輸入是 noise 或 無關量 如病況與石頭的顏色
- 如果整層的 所有 $| \text{weight} | \sim 0$ 代表 don't care 拒絕輸入資料 資料飽含矛盾 (BP 為降低 MSE 才造成 ~ 0 現象) 應檢查輸入資料 有時整層都 ~ 0 堵住輸入資料

[Notes on BP and MLP]

- 8. 找出 $|weight| \sim 0$ 的所有 neurons
 $|weight| \sim 0$ 代表 don't care 輸入資料資料有矛盾 (BP 為降低 MSE 才造成 ~ 0 現象)
應檢查輸入資料 有時整層都 ~ 0 堵住輸入資料
- 9. 每一sample標上 各層的 label codes
- 10. 用 hard-limit 去算每一 sample 的 error
error=0 的 sample BP不修正

[MLP 經驗法則]

- Practically, $n_1 \gg n_2 \gg n_3$
- The number of neurons in the first hidden layer is much larger than that in the second hidden layer.
- The number of neurons in the first hidden layer is estimated $n_1 = 2n+1$.
Komogorov theory 1957 Poggio(MIT)
- Nash's Embedding Theorem on $2n+1$

[Conclusions of hidden tree]

- The most important conclusion of Chapter 4 on hidden tree is:

“To get perfect performance (100% correction; global solution) on training dataset, the MLP must be accomplished in a bottom-up manner.”

Any BP algorithm will converge to a local minimum solution. BP errors will get lost in front layers.

[Chapter 4]

- LMS
 - Front layers (下樑 input)
 - Rear layers or deep layers (上樑 output)
 - 上樑 provides logical (representation) track
-
- NetTalk learns
 - 80% regular rules + 20% irregular cases

[LMS by Widrow]

Minimizing probability expectation $E(\text{error}^{**2})$
is a wrong direction. 應從原始 raw 著手
不必追求機率的完美

- Record errors for each pattern and for each neuron. One can develop various manipulations 策略 for the training sequence during training.
- Tune weights for large errors with priority.
- There is no need to introduce the assumption “stationary,” E

[舊的 Homework #1 Google cancer]

Write BP program for 2-3-3-1 network + online hidden tree.

NetTalk updating eq. for $w(t+1)$

Show how BP distributes corrections of error to each neuron. BP分配獎懲率, see NetTalk

Record the 1-bit neighbors + 2-bit neighbors

Hidden representations

+ hidden tree by Sejnowski

Generate artificial data set or use real dataset

MSB & LSB neurons + pruning

[MLP & math]

- Widrow adaptive
- Kolmogorov learning NN theory
- Kolmogorov 泛化 大陸
- MIT open course ware
- Kolmogorov space filling $2n+1$
- Kolmogorov Fr

[Komogorov theory 1957]

- *Debates*
- *Kolmogorov's Theorem Is irrelevant*
- An exact representation is hopeless
- *Kolmogorov's Theorem Is Relevant*