# 數位語音處理概論

**Introduction to Digital Speech Processing**

## 5.0 Acoustic Modeling

**References**: 1. 2.2, 3.4.1, 4.5, 9.1~ 9.4 of Huang

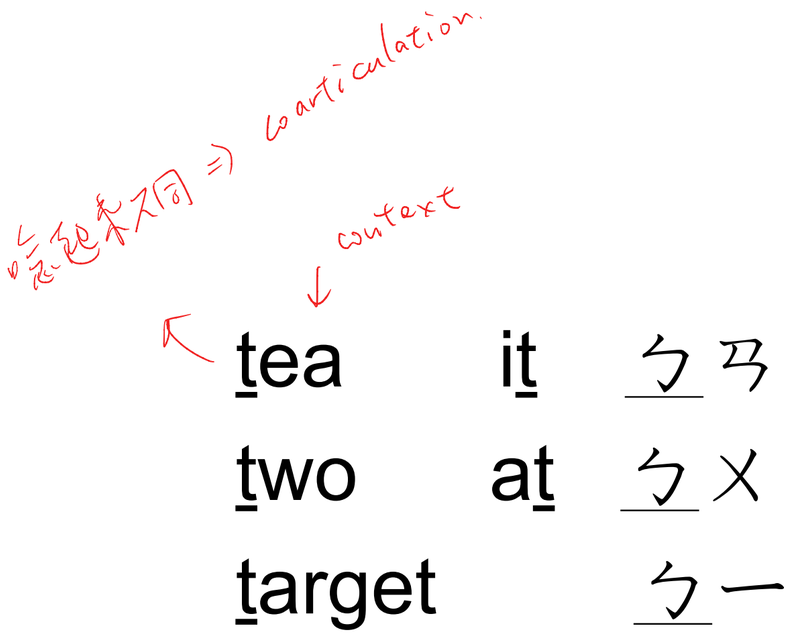
2. " Predicting Unseen Triphones with Senones",
IEEE Trans. on Speech & Audio Processing, Nov 1996

授課教師：國立臺灣大學 電機工程學系 李琳山 教授

# Unit Selection for HMMs



- **Possible Candidates**
  - phrases, words, syllables, phonemes.....
- **Phoneme**
  - the minimum units of speech sound in a language which can serve to distinguish one word from the other
    e.g. b at / p at , b a d / b e d
  - phone : a phoneme's acoustic realization
    the same phoneme may have many different realizations
    e.g. sa t / me t er
- **Coarticulation and Context Dependency**
  - context: right/left neighboring units
  - coarticulation: sound production changed because of the neighboring units
  - right-context-dependent (RCD)/left-context-dependent (LCD)/ both
  - intraword/interword context dependency
- **For Mandarin Chinese**
  - character/syllable mapping relation
  - syllable: Initial (聲母) / Final (韻母) / tone (聲調)



# Unit Selection Principles

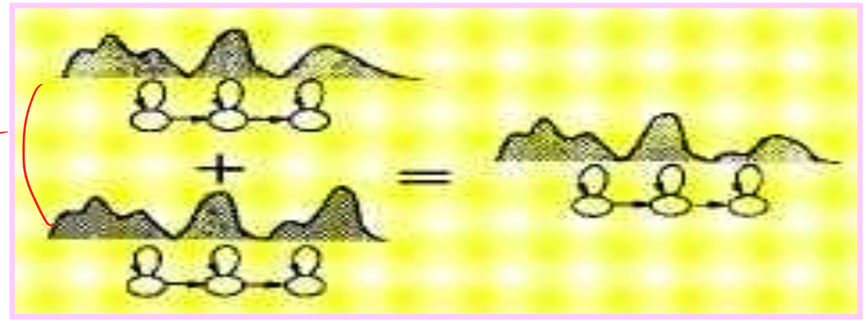
- **Primary Considerations**
  - accuracy: accurately representing the acoustic realizations
  - trainability: feasible to obtain enough data to estimate the model
  - generalizability: any new word can be derived from a predefined unit
- **Examples**
  - words: accurate if enough data available, trainable for small vocabulary,
  - phoneme : trainable, generalizable
    difficult to be accurate due to context dependency
  - syllable: 50 in Japanese, 1300 in Mandarin Chinese, over 30000 in English
- **Triphone**
  - a phoneme model taking into consideration both left and right neighboring phonemes
    $(60)^3 \rightarrow$ 216,000
  - very good generalizability, balance between accuracy/ trainability by parameter-sharing techniques

# Sharing of Parameters and Training Data for Triphones



(data sharing)

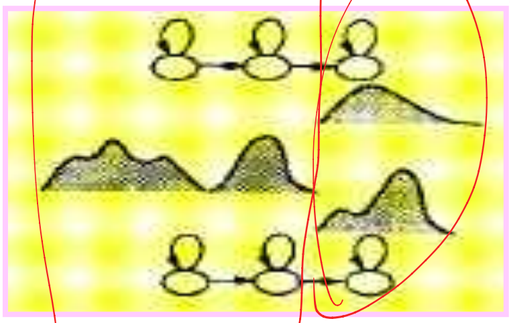
## •Sharing at Model Level




***Generalized Triphone***

–clustering similar triphones and merging them together

## •Sharing at State Level



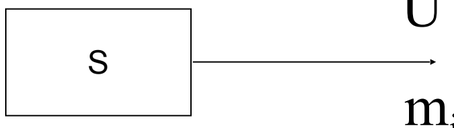
***Shared Distribution Model (SDM)***

–those states with quite different distributions do not have to be merged

# Some Fundamentals in Information Theory



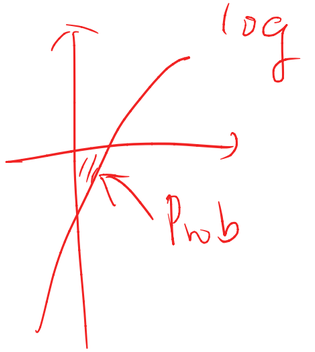
- **Quantity of Information Carried by an Event (or a Random Variable)**
  - Assume an information source: output a random variable $m_j$ at time j (很多 information)




$U = m_1 m_2 m_3 m_4 \ldots\ldots$, $m_j$: the j-th event, a random variable

$m_j \in \{x_1, x_2, \ldots x_M\}$ , M different possible kinds of outcomes

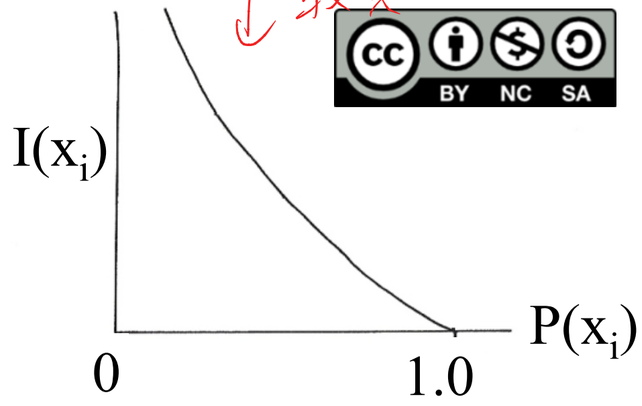
$P(x_i) = \text{Prob}[m_j = x_i]$ , $\sum_{i=1}^{M} P(x_i) = 1$ , $P(x_i) \geq 0$, i= 1,2,.....M




  - Define $I(x_i)$= quantity of information carried by the event $m_j = x_i$

Desired properties:

1. $I(x_i) \geq 0$ (1. $I(x_i) \geq 0$)
2. $\lim_{P(x_i) \to 1} I(x_i) = 0$ (2. $\lim_{P(x_i) \to 1} I(x_i) = 0$ 都看到一樣的就無 information)
3. $I(x_i) > I(x_j)$ , if $P(x_i) < P(x_j)$ (3. $P(x_i)$ 少 → 很珍貴)
4. Information quantities are additive




  - $I(x_i) = \log\left[\frac{1}{p(x_i)}\right] = -\log[P(x_i)] = -\log_2[P(x_i)]$ bits (of information)

  - H(S) = entropy of the source = average quantity of information out of the source each time

$$= \sum_{i=1}^{M} P(x_i)\, I(x_i) = -\sum_{i=1}^{M} P(x_i)\{\log[P(x_i)]\} = E[I(x_i)]$$ (平均每看到一個的 information)

= the average quantity of information carried by each random variable

# Fundamentals in Information Theory

$M = 2, \quad \{x_1, x_2\} = \{0, 1\}$

→ U = 1 1 0 1 0 0 1 0 1 0 1 1 0 0 1 … …

$P(0) = P(1) = ½$

S

U = 1 1 1 1 1 1 1 1 1 … …

$P(1) = 1, \quad P(0) = 0$

U = 1 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 … …

$P(1) \approx 1, \quad P(0) \approx 0$

$M = 4, \quad \{x_1, x_2, x_3, x_4\} = \{00, 01, 10, 11\}$

→ U = 0 1 0 0 1 0 1 1 0 1 … …

S

# Some Fundamentals in Information Theory



- **Examples**
  - $M = 2$, $\{x_1, x_2\} = \{0,1\}$, $P(0) = P(1) = \frac{1}{2}$

    $I(0) = I(1) = 1$ bit (of information), $H(S) = 1$ bit (of information)

    U = 0 1 1 0 1 1 0 1 0 0 1 0 1 0 1 1 0 … …

    ↑

    This binary digit carries exactly 1 bit of information

  - $M = 4$, $\{x_1, x_2, x_3, x_4\} = \{00, 01, 10, 11\}$, $P(x_1) = P(x_2) = P(x_3) = P(x_4) = \frac{1}{4}$

    $I(x_1) = I(x_2) = I(x_3) = I(x_4) = 2$ bits (of information),

    $H(S) = 2$ bits (of information)

    U = 0 1 0 0 0 1 1 1 1 0 1 0 1 1 … …

    ↑

    This symbol (represented by two binary digits) carries exactly 2 bits of information

  - $M = 2$, $\{x_1, x_2\} = \{0,1\}$, $P(0) = \frac{1}{4}$, $P(1) = \frac{3}{4}$

    $I(0) = 2$ bits (of information), $I(1) = 0.42$ bits (of information)

    $H(S) = 0.81$ bits (of information)

    U = 1 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 1 0 … …

    ↑ ↑

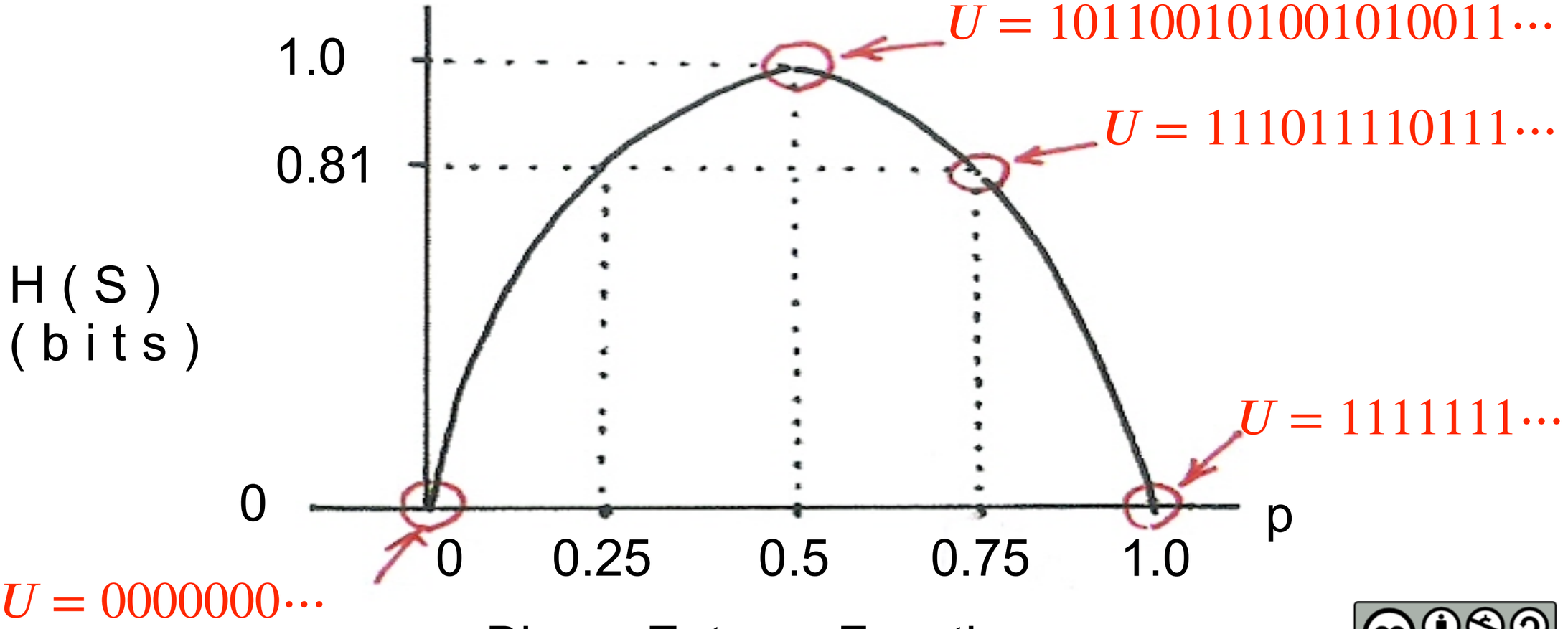
    This binary digit carries 0.42 bit of information

    This binary digit carries 2 bits of information

# Fundamentals in Information Theory

$M = 2, \quad \{ x_1, x_2 \} = \{ 0, 1 \}, \quad P(1) = p, \quad P(0) = 1 - p$

$H(S) = -[p \log p + (1-p) \log (1-p)]$




Binary Entropy Function

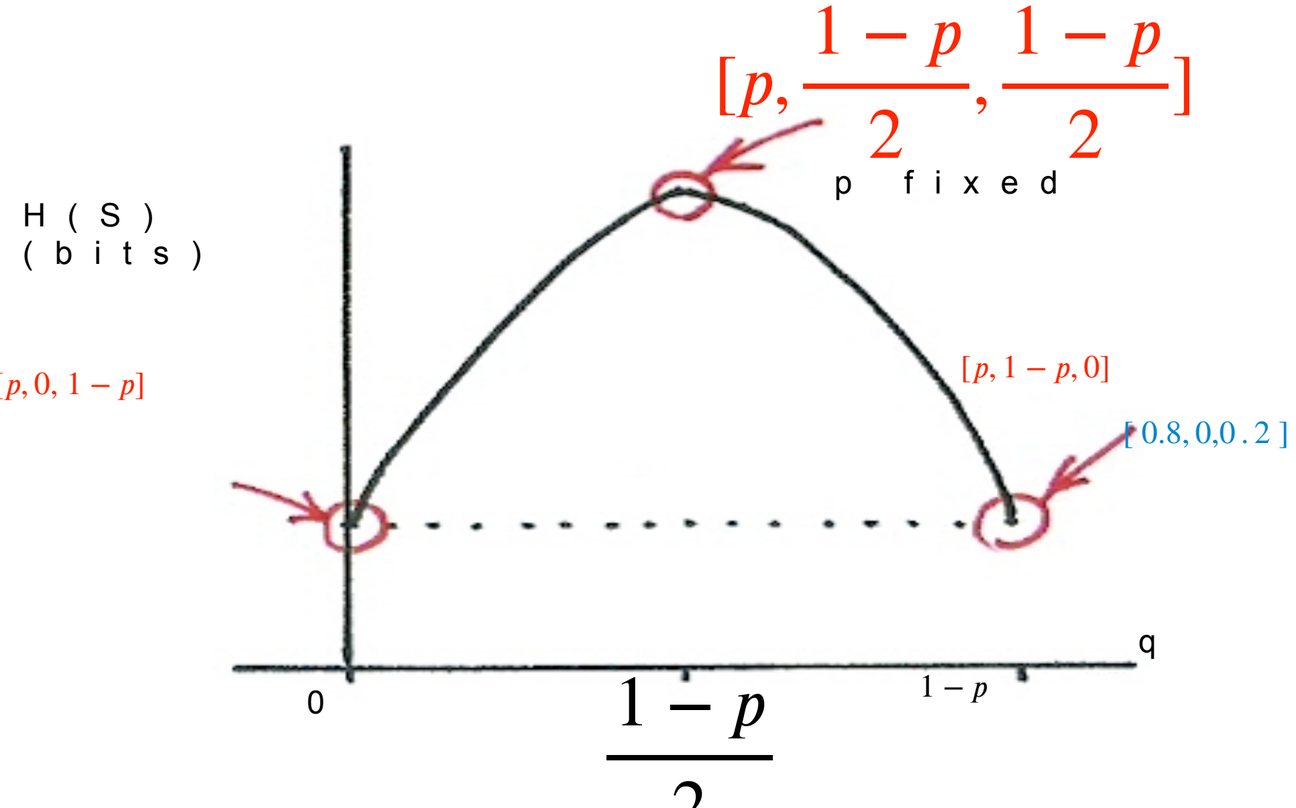
# Fundamentals in Information Theory

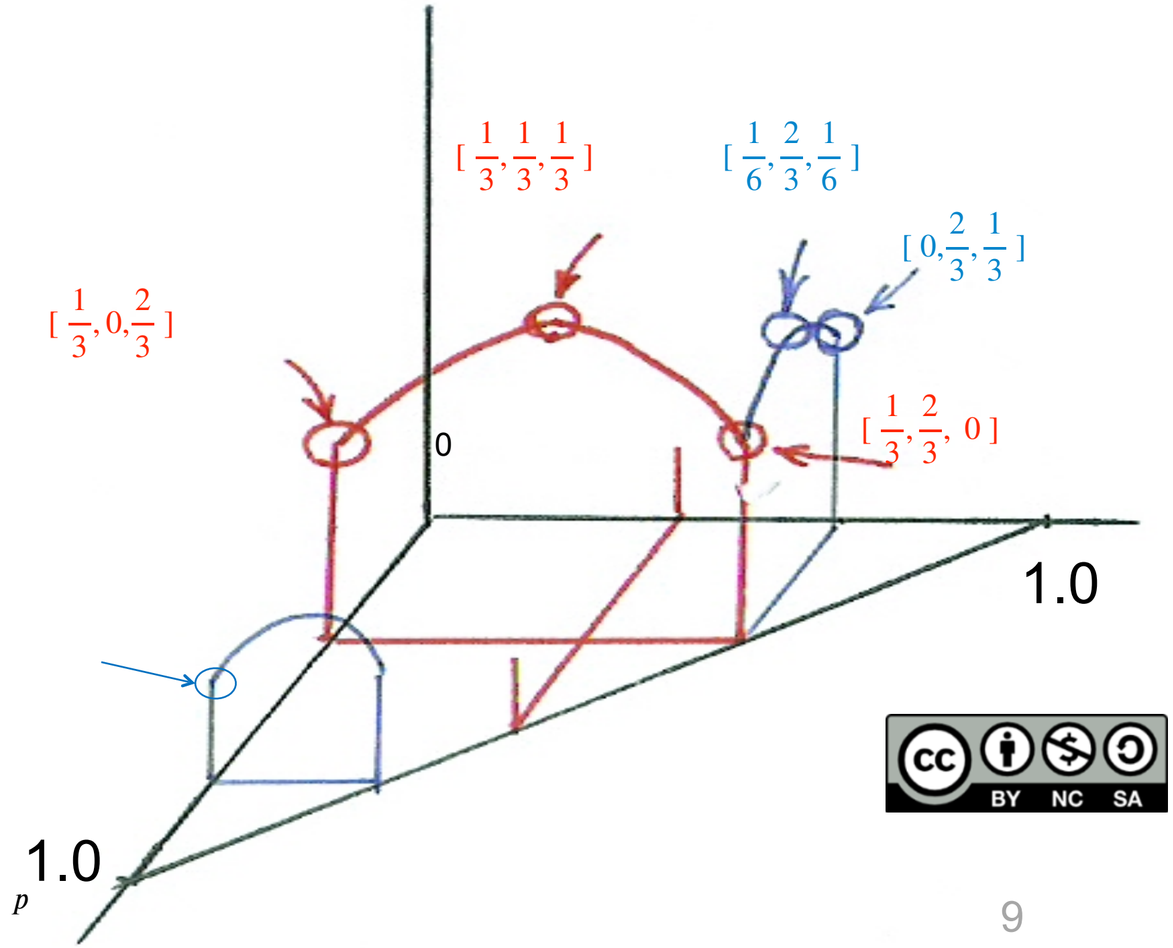
$M = 3, \{x_1, x_2, x_3\} = \{0, 1, 2\}$

$P(0) = p,\ P(1) = q,\ P(2) = 1-p-q$

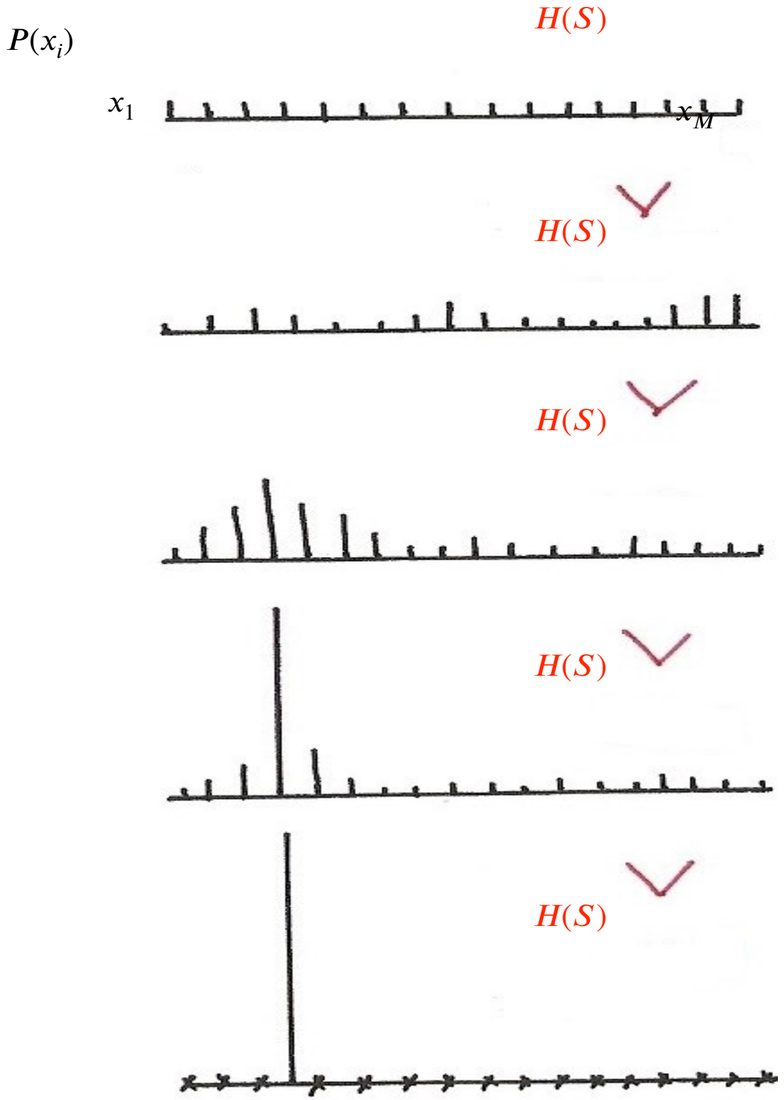
$[p,\ q,\ 1-p-q]$

$H(S) = -[p \log p + (1-p-q)\log(1-p-q) + q \log q]$



# Fundamentals in Information Theory




所帶Information 量最大

亂度最大，最random

不確定性最大

It can be shown

$$0 \le H(S) \le \log M$$

M: number of different symbols

equality when

$P(x_j)= 1$, some j

$P(x_k)=0$, $k \neq j$

一個 distribution

集中或分散的程度

equality when

$P(x_i)=\frac{1}{M}$, all i

H(S)：Entropy

確定性最大，最不random

純度最高

# Some Fundamentals in Information Theory

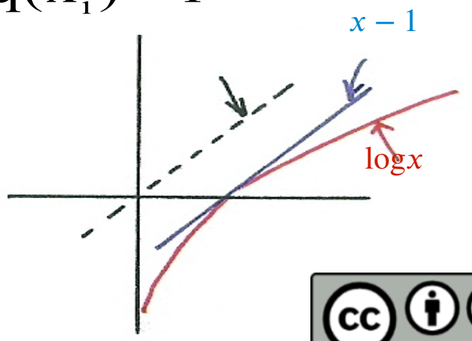


- **Jensen's Inequality**

$$-\sum_{i=1}^{M} p(x_i)\log[p(x_i)] \le -\sum_{i=1}^{M} p(x_i)\log[q(x_i)]$$

$q(x_i)$: another probability distribution, $q(x_i) \ge 0$, $\sum_{i=1}^{M} q(x_i) = 1$

equality when $p(x_i) = q(x_i)$, all i




  - proof: $\log x \le x-1$, equality when $x=1$

$$\sum_i p(x_i)\log\left[\frac{q(x_i)}{p(x_i)}\right] \le \sum_i p(x_i)\left[\frac{q(x_i)}{p(x_i)} - 1\right] = 0$$

  - replacing $p(x_i)$ by $q(x_i)$, the entropy is increased

    using an incorrectly estimated distribution giving higher degree of uncertainty

- **Kullback-Leibler(KL) distance (KL Divergence)**

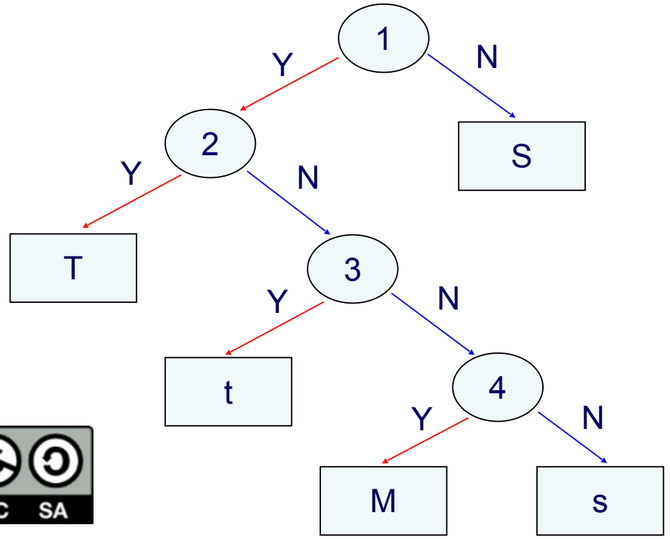
$$D[p(x)\|q(x)] = \sum_i p(x_i)\log\left[\frac{p(x_i)}{q(x_i)}\right] \ge 0$$ 其實我還是沒有 enthophy

  - difference in quantity of information (or extra degree of uncertainty) when p(x) replaced by q(x), a measure of distance between two probability distributions, asymmetric
  - Cross-Entropy (Relative Entropy)
- **Continuous Distribution Versions**

# Classification and Regression Trees (CART)



- **An Efficient Approach of Representing/Predicting the Structure of A Set of Data — trained by a set of training data**
- **A Simple Example**
  - dividing a group of people into 5 height classes without knowing the heights: Tall(T), Medium-tall(t), Medium(M), Medium-short(s),Short(S)
  - several observable data available for each person: age, gender, occupation....(but not the height)
  - based on a set of questions about the available data




1.Age > 12 ?

2.Occupation= professional basketball player ?

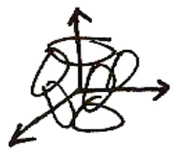
3.Milk Consumption > 5 quarts per week ?

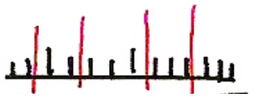
4.gender = male ?



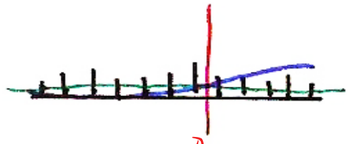
–question: how to design the tree to make it most efficient?

# Node Splitting





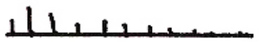

Goal



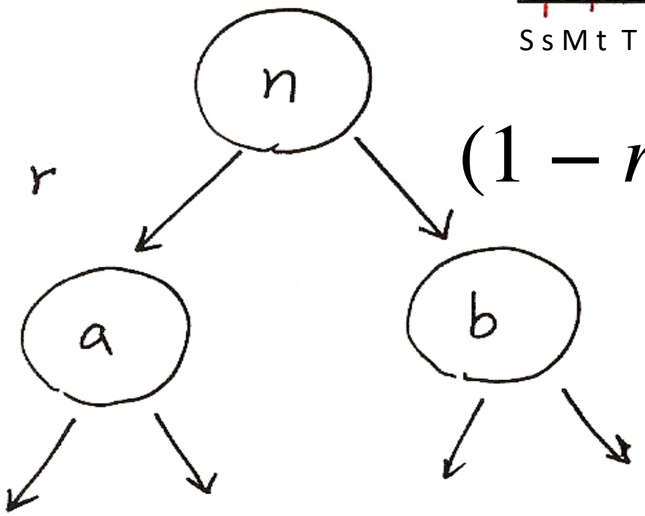
Goal

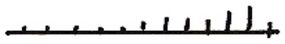
splitting question

亂七八

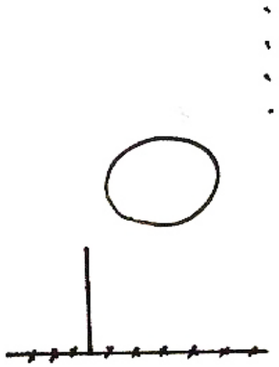


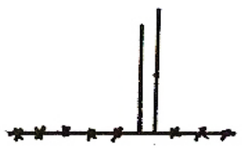
$H(a) \cdot r$



$H(b)(1-r)$





目的：min entropy

⇑

純度變高最多

# Splitting Criteria for the Decision Tree

- **Assume a Node n is to be split into nodes a and b**
  - weighted entropy

$$\overline{H}_n = \left(-\sum_i p(c_i|n)\log\left[p(c_i|n)\right]\right)p(n)$$

$p(c_i|n)$: percentage of data samples for class i at node n

p(n): prior probability of n, percentage of samples at node n out of total number of samples

  - entropy reduction for the split for a question q

$$\Delta\overline{H}_n(q) = \overline{H}_n - \left[\overline{H}_a + \overline{H}_b\right]$$

  - choosing the best question for the split at each node

$$q^* = \arg\max_q \left[\Delta\overline{H}_n(q)\right]$$

- **It can be shown**

$$\Delta\overline{H}_n = \overline{H}_n - (\overline{H}_a + \overline{H}_b)$$
$$= D\left[a(x)\|n(x)\right]p(a) + D\left[b(x)\|n(x)\right]p(b)$$

a(x): distribution in node a, b(x) distribution in node b

n(x): distribution in node n, $D[\cdot\|\cdot]$: cross entropy

  - weighting by number of samples also taking into considerations the reliability of the statistics
- **Entropy of the tree T**

$$\overline{H}(T) = \sum_{\text{terminal n}} \overline{H}_n$$

  - the tree-growing (splitting) process repeatedly reduces

# Training Triphone Models with Decision Trees



- **Construct a tree for each state of each base phoneme (including all possible context dependency)**
  - e.g. 50 phonemes, 5 states each HMM

    5*50=250 trees
- **Develop a set of questions from phonetic knowledge**
- **Grow the tree starting from the root node with all available training data**
- **Some stop criteria determine the final structure of the trees**
  - e.g. minimum entropy reduction, minimum number of samples in each leaf node
- **For any unseen triphone, traversal across the tree by answering the questions leading to the most appropriate state distribution**
- **The Gaussion mixture distribution for each state of a phoneme model for contexts with similar linguistic properties are "tied" together, sharing the same training data and parameters**
- **The classification is both data-driven and linguistic-knowledge-driven**
- **Further approaches such as tree pruning and composite questions**

  **(e.g. $q_i \bar{q}_j + q_k$)**

$50^3$ 很難做 ⇒ 做 50 次分的 HMM

少見的 triphone 就照 tree 去分即可

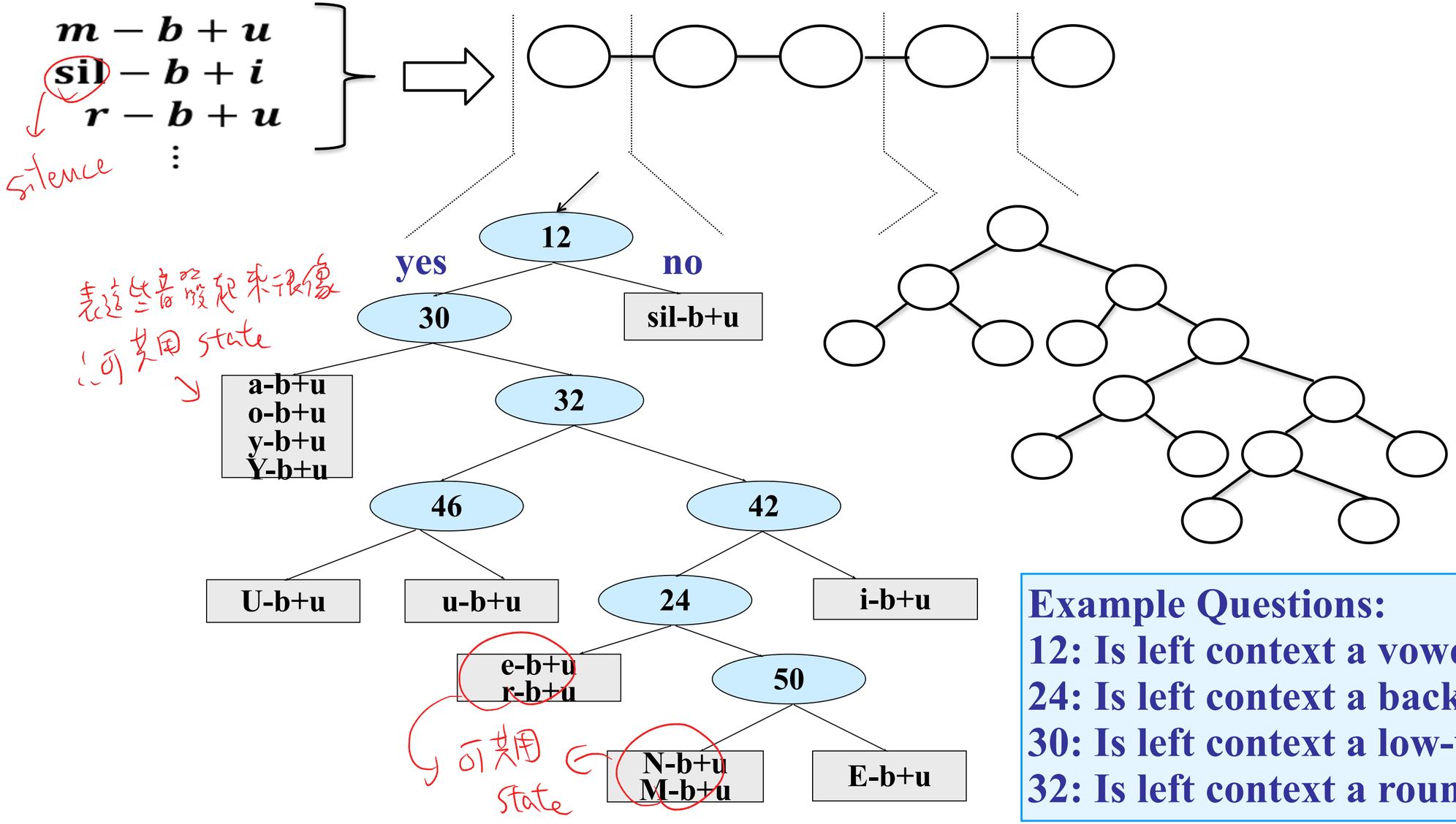
修剪 tree

question 可以 and/or/nor ---

# Training Tri-phone Models with Decision Trees



- An Example: "( _ – ) b ( +_ )"






**Example Questions:**
**12: Is left context a vowel?**
**24: Is left context a back-vowel?**
**30: Is left context a low-vowel?**
**32: Is left context a rounded-vowel?**

# Phonetic Structure of Mandarin Syllables



<table>
<tr><td colspan="4">Syllables (1,345)</td><td rowspan="5">Tones (4+1)</td></tr>
<tr><td colspan="4">Base-syllables (408)</td></tr>
<tr><td rowspan="2">INITIAL's (21)</td><td colspan="3">FINAL's (37)</td></tr>
<tr><td>Medials (3)</td><td>Nucleus (9)</td><td>Ending (2)</td></tr>
<tr><td>Consonants (21)</td><td colspan="3">Vowels plus Nasals (12)</td></tr>
<tr><td colspan="4">Phonemes (31)</td></tr>
</table>

# Phonetic Structure of Mandarin Syllables



巴 拔 把 霸 吧：**5 syllables, 1 base-syllable**

ㄅ(不計聲調) tone

Same RCD INITIAL'S

| | | |
|---|---|---|
| ㄕ ㄐ ㄇ ㄒ ㄐ ㄉ | **聲母(INITIAL's)** | (艾,宜,烏,于)<br>空聲母 |
| ㄨ ㄧ ㄚ ㄧ ㄩ ㄨ | **韻母(FINAL's)** | 空韻母 |
| ㄢ ㄝ ㄢ | | (制,尺,時,日,<br>紫,次,思) |

ㄅ ㄆ ㄇ ㄈ
ㄚ ㄢ ㄠ ㄤ
ㄚ ㄚ ㄚ
ㄣ ㄨ ㄥ

Medials

**-n** ：ㄣ ㄢ

**-ng**：ㄥ ㄤ

Nasal ending

**Tone**：聲調

**4 Lexical tones 字調**

**1 Neutral tone 輕聲**

# Subsyllabic Units Considering Mandarin Syllable Structures

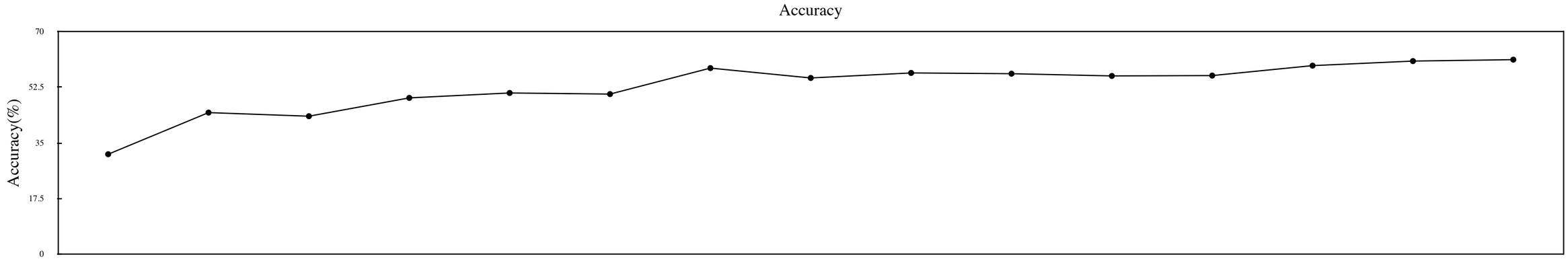


- **Considering Phonetic Structure of Mandarin Syllables**
  - INITIAL / FINAL's
  - Phone(me)-like-units / phonemes
- **Different Degrees of Context Dependency**
  - intra-syllable only
  - intra-syllable plus inter-syllable
  - right context dependent only
  - both right and left context dependent
- **Examples :**
  - 113 right-context-dependent (RCD) INITIAL's extended from 22 INITIAL's plus 37 context independent FINAL's: 150 intrasyllable RCD INITIAL/FINAL's
  - 33 phone(me)-like-units extended to 145 intra-syllable right-context-dependent phone(me)-like-units, or 481 with both intra/inter-syllable context dependency
  - At least 4,600 triphones with intra/inter-syllable context dependency

# Comparison of Acoustic Models Based on Different Sets of Units



- **Typical Example Results**






- **INITIAL/FIANL (IF) better than phone for small training set**
- **Context Dependent (CD) better than Context Independent (CI)**
- **Right CD (RCD) better than Left CD (LCD)**
- **Inter-syllable Modeling is Better**
- **Triphone is better**
- **Approaches in Training Triphone Models are Important**
- **Quinphone (2 context units on both sides considered) are even better**