# 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

# 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. bat / pat , bad / bed
  - phone : a phoneme's acoustic realization

    the same phoneme may have many different realizations

    e.g. sat / meter
- **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)

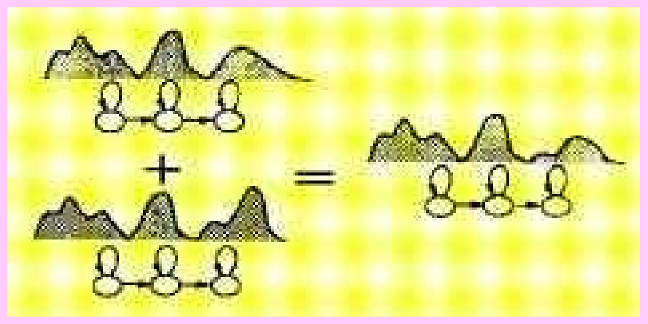
# Unit Selection Principles

- **Primary Considerations**
  - accuracy: accurately representing the acoustic realizations
  - trainability: feasible to obtain enough data to estimate the model parameters
  - generalizability: any new word can be derived from a predefined unit inventory
- **Examples**
  - words: accurate if enough data available, trainable for small vocabulary, NOT generalizable
  - phone : trainable, generalizable
    difficult to be accurate due to context dependency
  - syllable: 50 in Japanese, 1300 in Mandarin Chinese, over 30000 in English
- **Triphone**
  - a phone model taking into consideration both left and right neighboring phones

    $(60)^3 \rightarrow 216,000$
  - very good generalizability, balance between accuracy/ trainability by parameter-sharing techniques

# Sharing of Parameters and Training Data for Triphones

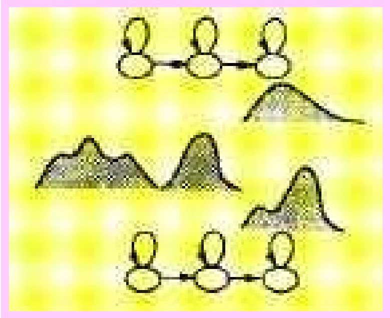
- **Sharing at Model Level**



***Generalized Triphone***

- clustering similar triplones and merging them together

- **Sharing at State Level**

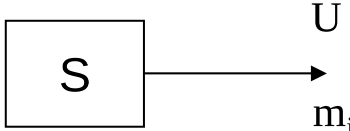


***Shared Distribution Model (SDM)***

- 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




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

$m_j \; \varepsilon \; \{ x_1, x_2, \ldots x_M \}$ , M different possible kinds of events

$P(x_i)$= 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. $I(x_i) \geq 0$
    2. $\lim_{P(x_i) \to 1} I(x_i) = 0$
    3. $I(x_i) > I(x_j)$ , if $P(x_i) < P(x_j)$
    4. Information quantities are additive
  - $I(x_i) = \log \left[ \dfrac{1}{p(x_i)} \right] = -\log \left[ P(x_i) \right] = -\log_2 \left[ P(x_i) \right]$ bits (of information)
  - H(S) = entropy of the source = average quantity of information out of the source each time

$$= \sum_{i=1}^{M} P(x_i)\, I(x_i) = -\sum_{i=1}^{M} P(x_i) \left\{ \log \left[ P(x_i) \right] \right\} = E \; \left[ I(x_i) \right]$$

= the quantity of information carried by a random variable

# 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)
  - $M = 4$, $\{x_1, x_2, x_3, x_4\}$, $P(x_1) = P(x_2) = P(x_3) = P(x_4) = \frac{1}{4}$
    $I(x_1) = I(x_2) = I(x_3) = I(x_4) = 2$ bits (of information),
    $H(S) = 2$ bit (of information)
  - $M = 2$, $\{x_1, x_2\} = \{0,1\}$, $P(0) = \frac{1}{4}$, $P(1) = \frac{3}{4}$
    $I(0) = 2$ bit (of information), $I(1) = 0.42$ bit (of information)
    $H(S) = 0.81$ bit (of information)
- **It can be shown**

$$0 \le H(S) \le \log M$$, M: number of different symbols

equality when $P(x_j) = 1$, some j, $P(x_k) = 0$, $k \neq j$

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

- degree of uncertainty
- quantity of information
- entropy
- for a random variable with a probability distribution

# Some Fundamentals in Information Theory

- **Jensen's Inequality**

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

$q(x_i)$: 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≤ 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

- **Cross-Entropy (Relative Entropy)**

$$D\left[p(x) \| q(x)\right] = \sum_i p(x_i)\log\left[\frac{p(x_i)}{q(x_i)}\right] \ge 0$$

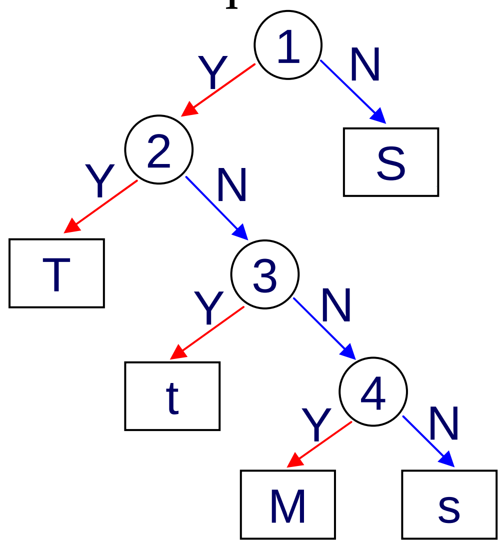
  – difference in quantity of information (or extra degree of uncertainty) when p(x) replaced by q(x), a measure of distance between two probability distributions, asymmetric
  – Kullback-Leibler(KL) distance

- **Continuous Distribution Versions**

# Classification and Regression Trees (CART)

- **An Efficient Approach of Representing/Predicting the Structure of A Set of 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?

# 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 , $D[\bullet\|\bullet]$ : 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 $\overline{H}(T)$

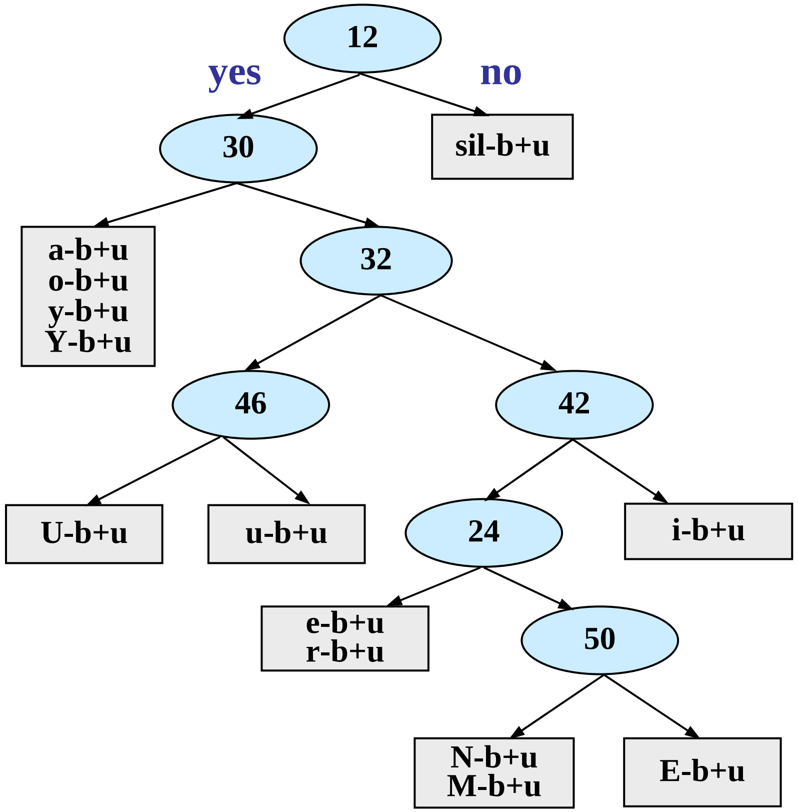
# Training Triphone Models with Decision Trees

- **Construct a tree for each state of each base phone (including all possible context dependency)**
  - e.g. 50 phones, 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 phone 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.** $q_i \overline{q}_j + q_k$ **)**

# Decision Tree Approach Extended to Different Context-dependent Units

- **An Example for the First State of the Unit "b(+u)"**




**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

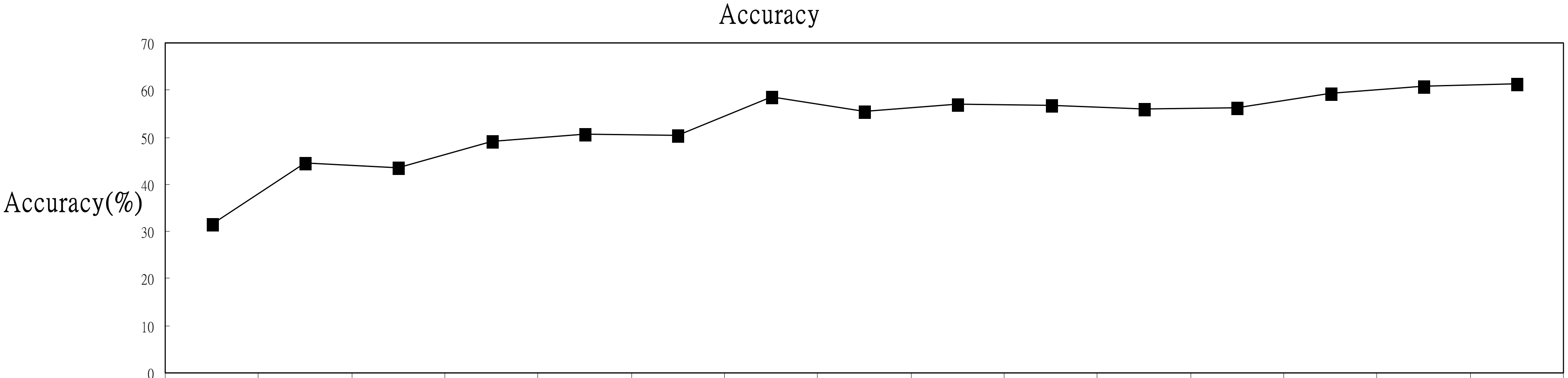
<table>
<tr><td colspan="5">Syllables (1,345)</td></tr>
<tr><td colspan="4">Base-syllables (408)</td><td rowspan="5">Tones (4+1)</td></tr>
<tr><td rowspan="2">INITIAL’s (21)</td><td colspan="3">FINAL’s (37)</td></tr>
<tr><td>Medials (3)</td><td>Nucleus (9)</td><td>Ending (2)</td></tr>
<tr><td>Consonants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

# Subsyllabic Units Considering Mandarin Syllable Structures

- **Considering Phonetic Structure of Mandarin Syllables**
  - INITIAL / FINAL’s
  - Phone-like-units / phones
- **Different Degrees of Context Dependency**
  - intra-syllable only
  - intra-syllable plus inter-syllable
  - right context dependent only
  - both right and left context dependent
- **Examples :**
  - 22 INITIAL’s extended to 113 right-context-dependent INITIAL’s
  - 33 phone-like-units extended to 145 intra-syllable right-context-dependent phone-like-units, or 481 with both intra/inter-syllable context dependency
  - FINAL’s divided into 12 groups based on ending phonemes, INITIAL’s into 7 groups based on co-articulation phenomena, so the inter-syllable context dependency categorized into 12x7 classes
  - 4606 triphones with intra/inter-syllable context dependency

# Comparison of Acoustic Models Based on Different Sets of Units

- **Typical Example Results**




| CI Phone | CI IF | LCD Phone | RCD Phone | RCD IF | Demi-Phone | Inter-RCD | Inter-RCD IF | Inter-Demi- | Triph . backoff | Triph . ml.cb | Triph . ml.rb | Triph . sl.cb | Triph . sl.rb | Triph . sl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 31.47 | 44.56 | 43.43 | 49.19 | 50.74 | 50.39 | 58.56 | 55.46 | 57.04 | 56.8 | 56.1 | 56.21 | 59.34 | 60.77 | 61.22 |

- **Inter-syllable Modeling is Better**
- **Triphone is better**
- **Approaches in Training Triphone Models are Important**