

# Whale Song Unit Classification

## Some Preliminary Exploration Using Linear Prediction Vector Quantization and Hidden Markov Modeling

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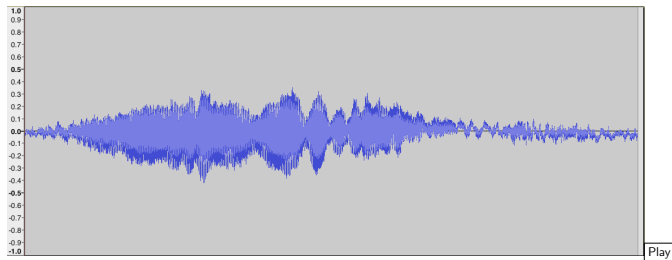
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# The Problem

Following Mitchell (1997), we state the problem as follows:

- **Task:**  
Classify whale song unit instances  
according to a given vocabulary of whale song unit types
- **Performance measure:**  
Percent of instances correctly classified
- **Training experience:**  
A database of labelled whale song unit instances

# Whale Song Units



A “modulated cry” instance, from HBS<sub>e</sub>\_20151207T070326.wav, 124.5sec-126.5sec

- Acoustic signal:

$$\mathbf{x} = \langle x_1, x_2, \dots, x_N \rangle \quad (N = 66,283)$$

# Linear Predictive Coding

- Acoustic signal:

$$\mathbf{x} = \langle x_1, x_2, \dots, x_N \rangle$$

- Transformed into a sequence of **predictor** vectors:

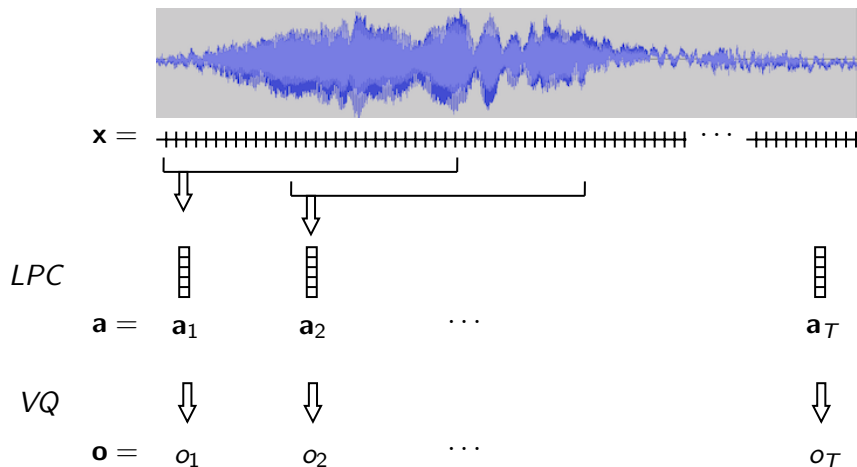
$$\mathbf{a} = \langle \mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_T \rangle$$

- Transformed into a **sequence of symbols**:

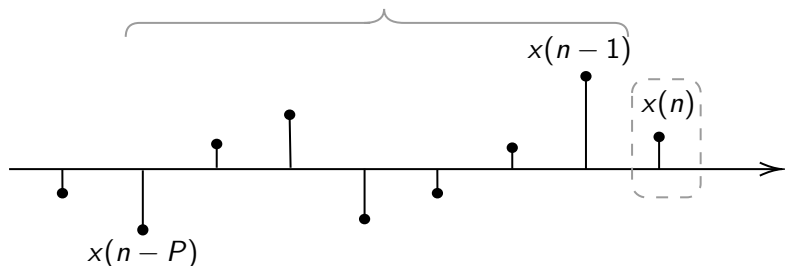
$$\mathbf{o} = \langle o_1, o_2, \dots, o_T \rangle$$

where  $o_t \in \{1, 2, \dots, M\}$

# Linear Predictive Coding



# Linear Prediction



- Estimate  $x(n)$  as a linear combination of  $P$  previous samples:

$$\hat{x}(n) = - \sum_{i=1}^P a(i) x(n-i)$$

# Linear Prediction

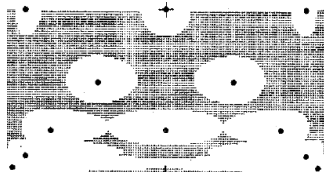
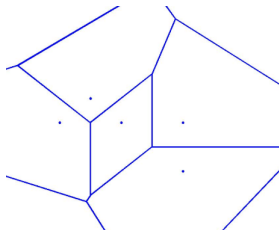
- Error:

$$\begin{aligned}e(n) &= x(n) - \hat{x}(n) \\ &= \sum_{i=0}^P a(i)x(n-i)\end{aligned}$$

- Find prediction coefficients by minimizing the sum of the squared error over the signal interval:

$$\begin{aligned}E &= \sum_n e^2(n) \\ &= \sum_n \left( \sum_{i=0}^P a(i)x(n-i) \right)^2\end{aligned}$$

# Vector Quantization



- Partition the  $P$ -dimensional space into  $M$  regions that "best" represent the predictor vectors arising from song units instances
- "Best" in terms of minimizing some overall distortion measure
- Let  $\mathbf{C} \equiv \langle C_1, C_2, \dots, C_M \rangle$  be the set of centroids that best represent the space



# Vector Quantization

- **Quantization:**

With  $\mathbf{C}$ , we can map each  $\mathbf{a}^{(t)}$  to a symbol  $o_t$ :

$$o_t \leftarrow \operatorname{argmin}_{k=1}^M d(\mathbf{a}^{(t)}, C_k)$$

# Hidden Markov Model

- $\pi$ , initial state probability distribution:

$$\pi = (\pi_1, \pi_2, \dots, \pi_N)$$

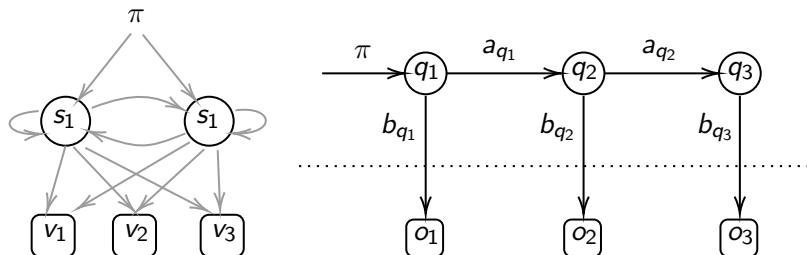
- $A$ , state transition distributions:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1N} \\ a_{21} & a_{22} & \dots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \dots & a_{NN} \end{bmatrix}$$

- $B$ , observation symbol probabilities:

$$B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1M} \\ b_{21} & b_{22} & \dots & b_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ b_{N1} & b_{N2} & \dots & b_{NM} \end{bmatrix}$$

# Hidden Markov Modeling



- $\mathbf{q} = \langle q_1, q_2, \dots, q_T \rangle$ : hidden state sequence
- $\mathbf{o} = \langle o_1, o_2, \dots, o_T \rangle$ : our acoustic signal

# HMM Operations

With  $\lambda = (\pi, A, B)$  denoting an HMM

- For given  $\mathbf{o}$  and  $\lambda$ , compute  $P[\mathbf{o}|\lambda]$
- For given  $\mathbf{o}$  and  $\lambda$ , estimate a most likely state sequence  $\mathbf{q}^*$
- Learn a model  $\lambda^* \equiv (\pi^*, A^*, B^*)$   
such that  $P[\mathbf{o}|\lambda^*]$  is maximized for a given observation sequence  $\mathbf{o}$

# Statistical Pattern Classification

- Vocabulary of  $R$  song unit types:

$$U = \{u_1, u_2, \dots, u_R\}$$

- Assume we have a **model**  $h_r$  for each unit type  $u_r$ .  
We are interested in computing:

$$P[h_r|\mathbf{x}] \equiv \text{Probability of } h_r \text{ given } \mathbf{x}$$

- Classification of an observation sequence  $\mathbf{x}$   
is based on a **maximum likelihood** model selection:

$$h^* \equiv \operatorname{argmax}_{h \in H} P[h|\mathbf{x}]$$

where  $H = \{h_1, \dots, h_R\}$ .

# Maximum Likelihood model selection

$$h^* \equiv \operatorname{argmax}_{h \in H} P[h|\mathbf{x}]$$

$$= \operatorname{argmax}_{h \in H} \frac{P[\mathbf{x}|h]P[h]}{P[\mathbf{x}]} \quad (\text{Bayes' theorem})$$

$$= \operatorname{argmax}_{h \in H} P[\mathbf{x}|h]P[h] \quad (P[\mathbf{x}] \text{ is constant wrt } h)$$

$$= \operatorname{argmax}_{h \in H} P[\mathbf{x}|h] \quad (\text{Assuming models are equiprobable})$$