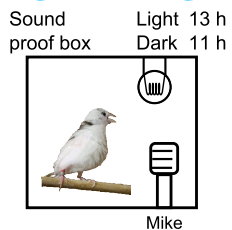


Practical classification method for birdsong with variable note sequences and its application to the whole day recordings

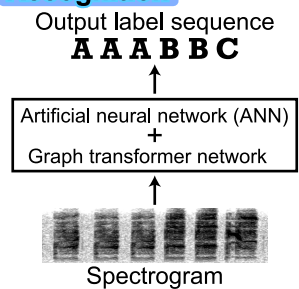
*T. KOUMURA & K. OKANOYA (The Univ. of Tokyo)

Goals Classifying notes in the songs with as little human effort as possible. Characterizing hour-scale modulation in the note sequence pattern.

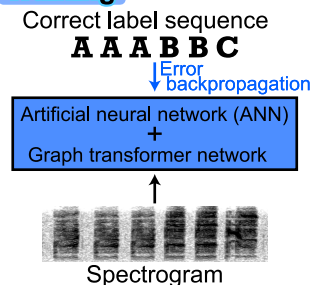
Song Recording



Recognition



Training

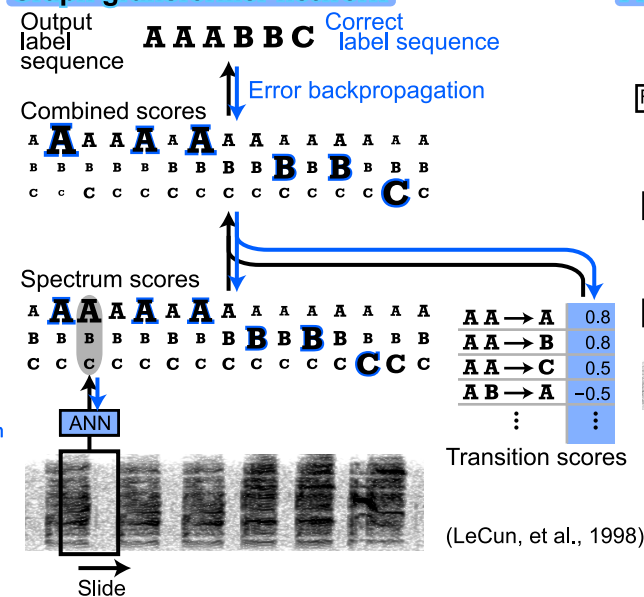


Typical result



Detected note labels & intervals

Graph transformer network



Validation score

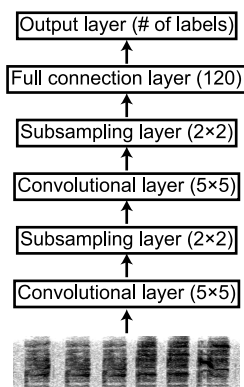
$$\text{Error ratio} = \frac{\text{Levenshtein distance between correct \& output sequences}}{\text{Length of correct sequence}}$$

Note positions	Transition scores	
	+	-
+	0.33±0.15%	0.36±0.11%
-	0.21±0.14%	0.28±0.19%

(Ave.±std over 3 birds)

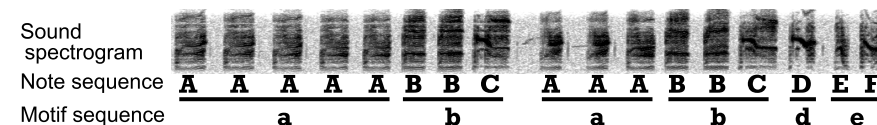
Better with transition scores note positions

ANN



Modeling of transition probabilities at branch points

Motif: frequently appearing sequence pattern



Branch points in motif sequences

$$P(x_f = \mathbf{a} | \text{Data}, w) = f_{\mathbf{b} \rightarrow \mathbf{a}}(t, \text{Data}, w)$$

$$P(x_f = \mathbf{d} | \text{Data}, w) = f_{\mathbf{b} \rightarrow \mathbf{d}}(t, \text{Data}, w)$$

Estimation of the transition probability

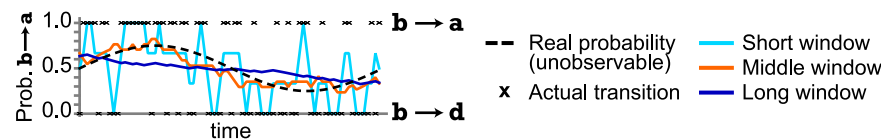
by the moving average of the motif frequencies

$$f_{\mathbf{y} \rightarrow \mathbf{x}}(t, \text{Data}, w) = \frac{n_{\mathbf{y}\mathbf{x}}[t - \frac{w}{2}, t + \frac{w}{2}]}{n_{\mathbf{y}}[t - \frac{w}{2}, t + \frac{w}{2}]}$$

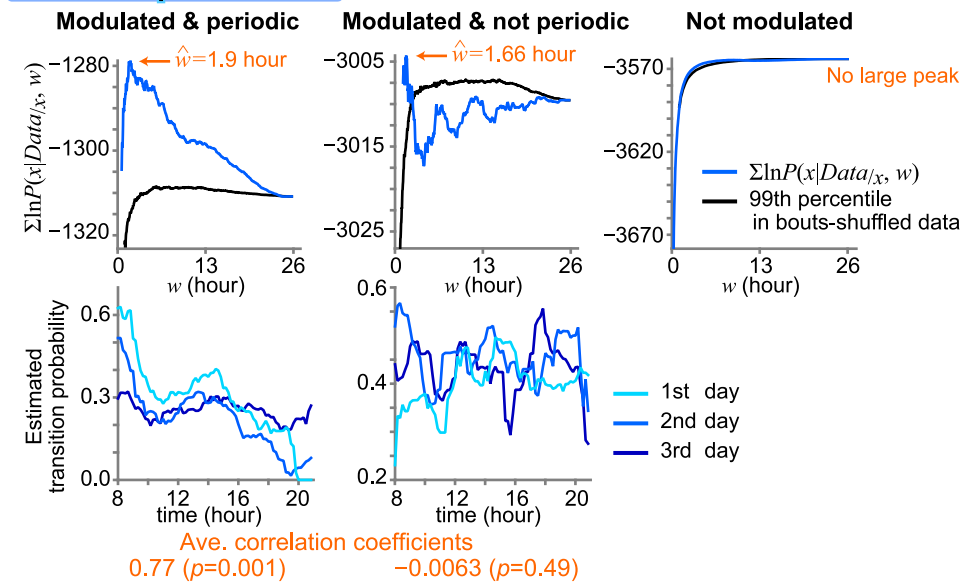
Determination of the most suitable window width

to best predict the observed data $\hat{w} = \text{argmax}_w (\sum_{x \in \text{Data}} \ln P(x | \text{Data}_{/x}, w))$

w : window width
 n : # of occurrence of a motif



Transition probabilities



Result summary

	modulated branches	periodic branches	modulated transitions	periodic transitions
Bird A	5	5	12	5
Bird B	2	2	4	0
Bird C	2	1	4	0