

Supplementary Figure 1

5 Pitch error corrections in two syllables that are misaligned with respect to each
other. (a) Training models of two experimental birds in imitation task 2 (left, Audio
5, playbacks 1 and 2; right, Audio 6, playbacks 3 and 4; see Supplementary Table 2).
8 Scale bars for sonograms are 100ms (x axis) and 2kHz (y axis). (b) The median pitch
9 of consecutive renditions of syllable A (top) and C (bottom) in bird 1 and 2. Both
10 pitch errors were successfully corrected. (c) Stack plots showing consecutive motif

- 11 renditions in birds 1 and 2; colors, pitch of syllables A/A^t and C/C^t (t= target pitch);
- 12 grayscale, Wiener entropy in neighboring syllables (as in Fig. 2b). Sonograms at
- 13 bottom and top show song at start and end points. Birds corrected pitch errors in
- 14 syllable A and C before changing syntax (bird 1 did not change syntax at all; bird 2
- 15 matched the target syntax). (d) Fraction of pitch error correction (left) and time (days)
- 16 to reach 50% pitch match (right) in syllables A and C across experimental birds.
- 17 Black, individual birds (lines connect the two syllables in each bird); red, mean \pm
- 18 s.e.m; n=8.
- 19



20 21 Supplementary Figure 2

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23 Pitch trajectories in birds trained with tasks 4.1 and 4.2. Median pitch in 24 consecutive renditions of the two pitch shifted syllable types in birds trained with task 25 4.1 (ABCB⁺¹ \rightarrow AB⁺²CB⁻¹) (a) and task 4.2 (AB⁺²CB⁻¹ \rightarrow ABCB⁺¹) (b), not including the two birds depicted in Fig 4c. Notation as in Fig 4c. In all birds except 26 27 one (bird 5 in (**b**)), the pitch of both syllable types shifted towards the spectrally 28 closer targets. In bird 5, the pitch of both syllable types (shown in black and green for 29 visual clarity) shifted towards the spectrally farther targets. Bird ages at the end of the 30 experimental period in task 4.2 were 121, 121, 128, 130 and 153 days post hatch. As 31 the sensitive period for song learning in zebra finches ends around day 90-100 post 32 hatch, it is unlikely that birds in this group that matched the 1-semitone targets were 33 on the way to matching the farther targets.







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37 Supplementary Figure 3

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Matching a vacant target with a vocalization initially performed outside of the song motif.

- 41 Developmental trajectories of experimental birds trained with tasks containing an
- 42 extra syllable type in the target versus the source: task 3 (ABC \rightarrow AB⁻CB⁺) (a) and

- 43 task 5 (AB \rightarrow AB⁺AB⁻) (b). Stack plots and pitch trajectories as in Fig 5 c and d
- 44 (depicting Bird 1 of task 3). All birds except one (Bird 4 in (**a**)) matched the vacant
- 45 target with a syllable type initially external to the song motif, usually a call. In bird 4
- 46 (**a**, bottom), the target B⁺ was not matched. Syllable B shifted to B^+ in the "wrong"
- 47 context (namely, after syllable A), but was also performed sparsely after syllable C;
- 48 pitch trajectories in this bird are shown separately for renditions after A and after C
- 49 (middle plots); right-most plot shows daily pitch means \pm s.e.m. for renditions after A
- 50 (black circles) and C (grey diamonds), showing a gradual divergence in pitch
- 51 (756±1.6 Hz after A versus 731±1.9 after C on last experimental day; p<0.00001,
- 52 ttest). This could potentially result from incomplete "splitting" of B^+ into two syllable
- 53 types.
- 54



d





е

Bird 4

Task 5







End point





Task 4.2



End point



Start point



Bird 1 0.8
$$B^{+1}$$
 0.99 B^{+2} 0.97 0.98 B^{+1} 1.0 B^{+1} 1.0 B^{-1} 0.95 C B 0.95 C B 0.95 C

$$\begin{array}{c} A & \stackrel{0.98}{\longrightarrow} B^{+2} \\ Bird 3 & 0.94 \\ B^{-1} & \stackrel{0.98}{\longrightarrow} C \\ \end{array} \begin{array}{c} A & \stackrel{1.0}{\longrightarrow} B^{+1} \\ 1.0 & \stackrel{0.99}{\longrightarrow} B^{-1} \\ 0.99 \\ 1.0 & \stackrel{0.99}{\longrightarrow} B^{-1} \\ 0.99 \\ 0.99 \end{array}$$

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63 **Supplementary Figure 4**

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65 Syntax adjustments towards target across experimental groups. a-e, Syntax

66 diagrams of all experimental birds (tasks 1-5) at the start point of the experiment (the

day of switching to target training, left) and at its endpoint (last experimental day, 67

68 right). Arrows represent the fractions of performing the syllable transitions of the

69 source song (gray) and the target song (red). The thickness of arrows corresponds to

70 the fraction values, which are also indicated next to the arrows. Birds' names are the

71 same as in Supplementary Figs. 2 and 3; birds in each group are vertically arranged 72

according to the amount of syntax adjustments (maximum adjustment on top). c-d, 73 dotted gray arrows represent incorrect transitions resulting from shifting syllable pitch

74 to misaligned target syllables (note that bird 5 in (d) shifted pitch to the aligned

targets, and therefore no syntax adjustments were necessary). Newly generated

75 76 syllables in tasks 3 and 5 (c and e) are shown in red. In two cases (Bird 2 in c and Bird

- 77 1 in e) the new syllable was placed in an incorrect context in the song motif, indicated
- 78 by a dotted gray arrow.



83 84 A bird singing two-syllable-song with syllable A (black dots) and B (grey dots) 85 matching two targets (red lines). The unassigned call (green dots) converges to the 86 occupied target B in case of the standard EM algorithm (without Step N3), but (b) 87 in case of the musical-chairs enhanced EM algorithm (including Step N3) in which 88 posterior probabilities can be large for at most one syllable, the call is not attracted towards an occupied target. (c) Simulation of the $ABC \rightarrow AB^-CB^+$ task. After 89 90 switching to the new targets (discontinuity in red lines) syllable *B* 's pitch (grey dots) 91 moves almost instantly to B^- and the pitch of the (initially) unassigned call (green) 92 moves gradually to B^+ (top red line). Syllable A (black dots) and syllable C (blue dots) stay on their targets. (d) Simulation of the $ABCB^{+1} \rightarrow AB^{+2}CB^{-1}$ task. After 93 switching to the new targets the pitches of syllables B and B^+ shift greedily to the 94 closest targets, i.e. $B \rightarrow B^{-1}$ (lighter grey) and $B^{+1} \rightarrow B^{+2}$ (darker grey). Colored dots 95 represent individual syllable renditions. The simulation parameters 96 $(\alpha = 0.02, \alpha_2 = 0.5, \sigma = 25, \sigma_b = 75)$ are identical in all simulations. 97

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99 Supplementary Table 1. Training models used in imitation task 1.

n	Source model (baseline pitch of syllable C	Target model (superscripts, pitch shift from	Sound file
	Hz)	baseline, semitones)	Inc
1	A B C(680)	A C ⁺² B	Audio 1 (playbacks 1 and 2)
2	A B C(680)	A C ⁺¹ B	Audio 1 (playbacks 3 and 4)

- 101 Each model playback contained two repetitions of the motif shown (Audio 1; same
- 102 for Supplementary Tables 2-5).

103 Supplementary Table 2. Training models used in imitation task 2.

n	Source model (baseline pitch of syllables A and C, Hz)	Target model (superscripts, pitch shift from baseline, semitones)	Sound file
2	A(1166) B C(680)	A ⁺² C ⁺² B	Audio 5 (playbacks 1 and 2)
2	A(1166) B C(680)	A ⁺¹ C ⁺¹ B	Audio 5 (playbacks 3 and 4)
2	A(1166) B C(680)	A ⁺¹ C ⁻¹ B	Audio 6 (playbacks 1 and 2)
1	A(1235) C(640) B	A ⁻² B C ⁺²	Audio 6 (playbacks 3 and 4)
1	A(1166) B C(680)	B A ⁻² C ⁺²	Audio 7 (playbacks 1 and 2)
1	B A(1042) C(762)	B C ⁻² A ⁺²	Audio 7 (playbacks 3 and 4)

107 Supplementary Table 3. Training models used in imitation task 3.

n	Source model (baseline pitch of syllable B, Hz)	Target model (superscripts, pitch shift from baseline, semitones)	Sound file
3	A B(680) C	A B ⁻² C B ⁺²	Audio 8 (playbacks 1 and 2)
1	A B(1166) C	A B ⁻² C B ⁺²	Audio 8 (playbacks 3 and 4)

111 Supplementary Table 4. Training models used in imitation task 4.

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n	Source model			Target model			Sound		
									file
2		B	C	B ⁺¹	A Martin	B+2	C	B ⁻¹	Audio 9 (playbacks 1 and 2)
1	A Marine Marine	B ⁺²	C	B ⁻¹	A It I The	В	C	B ⁺¹	Audio 9 (playbacks 3 and 4)
4	A	B ⁺²	C	B ⁻¹	A	B	C	B ⁺¹	Audio 9 (playbacks 5 and 6)

All indicated pitch shifts are with respect to the baseline pitch of syllable B (1166Hz).

115 Supplementary Table 5. Training models used in imitation task 5.

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n	Source model (baseline pitch of syllable B, Hz)	Target model (pitch shift from baseline, semitones)	Sound file
4	A B(1042)	A B ⁺² A B ⁻²	Audio 10

- 117 To avoid a large duration difference between source and target playbacks, in this task
- 118 the source playbacks included 4 motif repetitions (Audio 10).

Supplementary Notes

122 Mathematical Supplement:

123 124 <u>Birds simplify the quadratic problem of computing performance error to a linear</u> 125 <u>assignment problem</u>

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127 <u>Performance error</u>

Associated with a song *S* we define a family of performance errors $E(S, \Delta)$ parameterized by a set of unknown parameters grouped in the matrix $\Delta = (\delta_{i,j})$. The errors are composed of an overall **phonology** (spectral) error and a **syntax** (sequence) error

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$$E(S,\Delta) = \underbrace{\sum_{i,j} e(S_j,T_i) \delta_{i,j}}_{\text{phonology}} + \underbrace{c \|\Delta\|_{\#}}_{\text{syntax}}$$
(1)

The parameter *c* represents an unknown tradeoff between phonology and syntax 133 134 errors. The overall **phonology error** between song S and target T is defined as a 135 weighted sum of the local phonological errors $e(S_i, T_i)$ between song element S_i 136 (e.g. syllable j = 1, ..., n) and target element T_i (i = 1, ..., m). The function e137 138 represents a distance metric, for example the Euclidean distance between specific sound features such as pitch (e.g. pitch deviation). The unknown assignment matrix 139 $\Delta = (\delta_{i,i})$ specifies the weight $\delta_{i,i}$ associated with the local phonology error, where 140 target assignments (which syllables are assigned to a specific target) correspond to 141 142 rows of Δ and syllable assignments (which targets are assigned to a specific syllable) 143 to columns of Δ . To illustrate this notation, a bird that does not assign a phonology error to syllable S_2 entails $\delta_{i,2} = 0$ for all *i*; and, a bird that compares S_2 with the 144 first target (syllable) T_1 entails $\delta_{1,2} = 1$. If there is local chaining of assignments then a 145 bird that compares S_1 to T_3 will also compare S_2 to T_4 ; in terms of Δ , chaining of 146 assignments means that the condition $\delta_{i,j} = 1$ implies $\delta_{i+1,j+1} = 1$ with high probability. 147 By virtue of the assignment weights $\delta_{i,i}$, the phonology errors may parameterize any 148 149 imaginable comparison between song and target. 150 The syntax error $\left\|\Delta\right\|_{\#}$ quantifies the amount of resequencing a bird must 151

- perform in order to bring its song elements into global alignment with the template. This error quantifies the new transitions to be created among existing song elements. Because of stepwise acquisition of syntax in songbirds¹, it makes sense to attribute to $\|\Delta\|_{\#}$ a cost proportional to the number of new transitions to be generated.
- 157 In the case of binary and one-to-one syllable-target assignments ($\delta_{i,j} = 0$ or 1; 158 up to one target per syllable, $\sum_i \delta_{i,j} \le 1, \forall j$, and one syllable per target,

159 $\sum_{j} \delta_{i,j} = 1, \forall i$) we can write $\|\Delta\|_{\#}$ as a sum of terms that are quadratic in the

160 assignment weights $\delta_{i,j}$:

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 $\left\|\Delta\right\|_{\#} = \sum_{i,j}^{m,n} \sum_{k \neq \lfloor j+1 \rfloor_n}^n \delta_{i,j} \delta_{\lfloor i+1 \rfloor_m,k}$ $\tag{2}$

where we use the short-hand notation $|x|_l$ to denote $1 + (x-1) \mod l$, which is 162 necessary to incorporate the circular boundary conditions arising from birds' tendency 163 to repeat motifs several times in a song bout. As can be seen, Equation (2) skips all 164 pairs of consecutive syllable assignments j and $\lfloor j+1 \rfloor_n$ that do not need 165 resequencing, namely all those that are locally diagonally chained. 166 167 168 Equations (1) and (2) model the performance error attributed to any given song. The assignment matrix is not specified therein; therefore, these equations can be thought 169 170 of as the space of all possible strategies for estimating phonology and syntax errors 171 between song and template (Fig. 1a). Our experiments were designed to resolve birds' 172 strategy in dealing with phonology and syntax errors and the on/off-diagonal structure 173 of the assignment matrix. 174 175 Next we describe the process of song learning. In terms of Equation (1), song learning is the search of a song S with vanishing performance error. 176 177 178 179 Song learning 180 181 Song learning is the process of changing the current song S towards the **final song** S^* that minimizes the performance error (ideally $S^* = T$): 182 $S^* = \arg\min_{S} E(S, \Delta)$ 183 (3) In the process of song learning, Δ is either fixed or it evolves in time, possibly 184 185 giving rise to very complex learning trajectories. If birds want to perform song 186 learning optimally, they will try to compute the initially **optimal assignments** Δ^* , 187 which are the ones that achieve minimal initial performance error, $\Delta^* = \arg\min_{\Lambda} E(S, \Delta).$ 188 (4)This optimal choice of assignment in Equation (4) is a quadratic assignment 189 problem (quadratic in the assignment weights)². In the general case, that problem is 190 191 NP-hard, meaning that there is no known algorithm for solving this problem in polynomial time. Moreover, it was proven that such problems do not even have an 192 approximation algorithm running in polynomial time³. Hence, almost certainly, birds 193 194 neither solve Equation (4) nor an approximation thereof. The question for us was how 195 birds actually assign performance errors. 196 197 Whatever birds do, we imagined they must be facing a tradeoff between 198 phonology and syntax errors, illustrated by the following example: Consider two birds

199 that need to change their songs from syllable sequence $ABC \ ABC$ to $ACB \ ACB$.

200 The first bird forms 3 new bigrams (AC, CB, and BA) among the existing

201 syllables, which would imply that its syntax error initially is $\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ \# \end{pmatrix} = 3c$ and the

- 202 phonology error is zero. However, the second bird achieves the same target song not
- 203 by permuting syllables but by making the local transformations $B \to C$ and $C \to B$,

204 implying that this latter bird produces no syntax errors $\begin{vmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix}_{+} = 0$ but a

phonology error of 2e(B,C). This example illustrates that there is a tradeoff between 205 phonology and syntax errors and that the latter are avoidable in principle. The reason 206 207 is that the second bird learns the song sequence intrinsically by globally aligning the song to the template (Δ is the identity matrix), that latter bird needs only to correct 208 209 phonology errors to also automatically learn the correct syntax. However, global alignment may not be an ideal strategy because it can entail a high phonology cost, 210 211 which is absent in the first bird. As a tradeoff we imagine that birds may chain 212 alignments locally rather than globally. Such chaining is for example suggested by the 213 sequence requirement for correct acoustic models in white-crowned sparrows⁴.

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215 Experimental characterization of Δ

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217 Our experiments provide the following constraints *C*1 to *C*4 on error 218 assignments in zebra finches:

219 C1) $ABC \rightarrow AC^+B$ and $ABC \rightarrow A^+C^+B$ (imitation tasks 1 and 2): Birds 220 perform the local change $C \rightarrow C^+$; therefore, off-diagonal elements of Δ can be 221 nonzero (**no global alignment**).

- 222 C2) $ABC \rightarrow AB^-CB^+$ (imitation task 3): Birds do not chain locally: as target 223 for *B*, they select either B^- (in context) or B^+ (out of context). Because birds 224 do not choose an interpolation between B^- and B^+ as target, it follows that in
- each column of Δ at most one assignment weight is nonzero, i.e., $\delta_{i,j} = \{0,1\}$
- 226 (selection); and $\sum_{i} \delta_{i,j} \leq 1, \forall j$ (winner-takes-all).
- 227 C3) $ABCB^{+1} \rightarrow AB^{+2}CB^{-1}$ (imitation task 4): Birds make the changes $B \rightarrow B^{-1}$
- 228 and $B^{+1} \rightarrow B^{+2}$ implying that assignments are **greedy**: $\delta_{i,j} = 1$ in syllable-target
- pairs for which the local phonology error $e(S_j, T_i)$ is minimal, and $\delta_{i,j} = 0$ otherwise.

231 C4) In all experiments, no two syllables or calls converge on the same target 232 (**musical chairs**); therefore, in each row of Δ exactly one assignment weight is 233 nonzero, i.e. $\sum_{i} \delta_{i,j} = 1, \forall i$.

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Linear assignment problem

241 In combination, our observations show that birds greedily choose a (binary) 242 assignment matrix Δ^* associated with minimal phonology error:

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$$\Delta^* = \arg\min_{\Delta} \sum_{i,j} \left\| S_j - T_i \right\| \delta_{i,j}$$
(5)

where $e(S_i, T_i) = ||S_i - T_i||$ is the absolute pitch difference between syllable j 244 and target i, and where Δ is a $m \times n$ permutation matrix with at most one nonzero 245 entry per column and exactly one nonzero entry per row $(\delta_{i,j} = \{0,1\}, \sum_{i} \delta_{i,j} \le 1, \forall j, j \le 1, \forall j\}$ 246 and $\sum_{i} \delta_{i,j} = 1, \forall i$). Equation (5) fully specifies the assignment matrix; what is 247 particularly interesting is that the optimization in Equation (5) does not depend on the 248 249 tradeoff constant c, implying absence of a tradeoff. The optimization in Equation (5) 250 is known as the linear assignment problem which can be conveniently solved using 251 for example the Hungarian method⁵. 252

- In the context of natural language processing, the solution to Equation (5) (the minimum in Equation (5) rather than its argument) is also known as the word mover's distance⁶ that represents the distance between two text documents. In that analogy,
- 256 $||S_j T_i||$ represents the distance between an individual word S_j in a source document
- and a word T_i in a target document. The assignments $\delta_{i,j}$ (which do not have to be binary but can take arbitrary nonnegative values), represent the flows between words.

These flows have to sum up to match the bag-of-words (vocabulary) representations

260 d_i and d'_j of the source and target documents, $\sum_i \delta_{i,j} = d_i$ and $\sum_i \delta_{i,j} = d'_j$, in

analogy to the musical chairs competition we find. The word mover's distance
 outperforms other approaches on many benchmark document categorization tasks^{6,7}.

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The fact that birds choose the assignment of minimal overall phonology error, irrespective of syntax, demonstrates a radical way of dealing with the intractability of the general assignment problem. Namely, rather than getting entangled with high complexity and large cognitive demand, birds decide to solve a much simpler tractable problem and do this remarkably well.

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270 The surprising implications are that birds do not consider the cost of 271 resequencing at all when correcting phonology errors. Phonology errors seem to be 272 associated with a high cost, perhaps reflecting the amount of effort required to change 273 syllable pitch. Counterintuitively, birds behave in this process as if there were no 274 resequencing cost at all, despite the fact that this cost is seemingly very high, given 275 that most birds try to re-sequence their syllable strings but only few succeed. Namely, 276 we found that many birds do not reach the global performance error minimum in 277 Equation (3) but get stuck somewhere on the way where some syntax errors but 278 usually no phonology errors remain.

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280 In summary, song learning is a modular, two-fold process. In a first process, 281 birds choose assignments Δ^* by solving a linear problem based on their vocal 282 repertoire but not on their song sequence. In the second process, birds reduce phonology errors defined by these correspondences and independently and moreslowly, also reduce the resulting syntax error.

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286 <u>Sub-syllabic notes</u>

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288 What is the smallest song unit to which our formalism applies? We deliberately 289 called S_j a song element and T_i a target element, implying these elements do not 290 necessarily have to represent entire song syllables but could also represent sub-291 syllabic notes. In the following we discuss this possibility.

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In our treatment of the song learning problem, we implicitly assumed that birds compute phonological error of a syllable by integrating over the errors in its constituent notes. Essentially, we assumed that birds compute the error of a syllable by globally aligning its notes with that of a template syllable. However, we have no evidence for this mini-version of global alignment. Thus, it remains to be explored whether birds can assign one of its syllable notes either to a note in a different syllable of the template or to a note in a different position within the same template syllable.

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Although it will not be possible to resolve this issue without further experimenting, we imagine that our discovered assignment strategy cannot apply to ever smaller song units. Namely, at some point, there must be an overload to shortterm memory arising from all these pairwise comparisons between song and template elements. It is therefore likely that assignment capabilities of zebra finches are limited to the syllable level and do not generalize to smaller song units below that level.

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<u>How to match syllable vocabulary using the expectation maximization (EM)</u> algorithm and Gaussian mixture models

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Song learning can be considered a density estimation problem in which the unknown parameters of the developing song syllables must be identified such that good matches with the sensory targets are achieved. In a Gaussian mixture model, the observable data points T_i (renditions of the i = 1,...,m target syllables) are modeled as a superposition of n Gaussian probability densities, where n is the number of distinct song syllables and calls in the juvenile's repertoire. In the one dimensional case of fitting the pitch parameter alone, the distribution of pitch X_i of syllable j

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$$(j=1,...,n)$$
 is given by $P(X_j) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(X_j-S_j)}{2\sigma^2}}$, where S_j is the mean pitch of

that syllable. It follows that the likelihood density that syllable
$$j$$
 will produce the
pitch T_i of template i is given by

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$$P_{i|j} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(T_i - S_j)^2}{2\sigma^2}}.$$
 (6)

Here we assume that σ^2 is the constant pitch variance of syllable j. The closer the mean pitch S_j is to the target pitch T_i , the more likely the production of syllable j will match the target i.

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The goal of the EM algorithm is to identify the set of mean syllable pitches S_j that maximize the total probability P (or its logarithm) of reproducing all the target pitches T_i . The following function L is usually maximized by the EM algorithm: $L = \sum_i \ln(P_i) = \sum_i \ln\left(\sum_j P_{i|j}p_j\right)$, where $P_i = \sum_j P_{i|j}p_j$ is the probability that target *i* is produced by any of the *n* syllables, p_j being the prior probability of singing syllable *j*. In the following, we assume that all syllables have identical prior probability,

in the following, we assume that all syllables have identical prior probability, $p_j = p$ (zebra finches sing motifs with linear syllable arrangement) and drop any further mention of p because it is an irrelevant constant. Note that the EM algorithm is an iterative algorithm aimed not at directly maximizing L, but rather its lower bound $L_L < L$:

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$$L_{L} = \sum_{i,j} P_{j|i} \ln\left(P_{i|j}\right),\tag{7}$$

where $P_{j|i}$ is referred to as the posterior probability (that syllable *j* is assigned to target *i*). To avoid confusing the posterior probability $P_{j|i}$ with the Gaussian likelihood $P_{i|j}$, it is always assumed that the index *j* refers to a syllable and index *i* refers to a target. The maximization of L_L in Equation (7) is usually done in two steps, an E step in which the posterior probabilities are updated:

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$$P_{j|i} = \frac{P_{i|j}}{\sum_{j} P_{i|j}},$$
 (8)

and an M step in which the mean pitches are updated according to

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$$S_{j} = \frac{\sum_{i} T_{i} P_{j|i}}{\sum_{i} P_{j|i}}.$$
(9)

347 Back-and-forth iteration of Equations (8) and (9) usually leads to convergence of 348 the set of mean pitches S_i towards the set of targets T_i .

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351 Birds' strategy compared with the EM algorithm

The EM algorithm operating on Gaussian mixture models just outlined exhibits several similarities with birds' strategy of minimizing performance error. Namely, if we place the Gaussian model in Equation (6) into the function L_L to be maximized in Equation (7), then we obtain the following expression:

357 $L_{L} = K - \frac{1}{2\sigma^{2}} \sum_{i,j} P_{j|i} \left(T_{i} - S_{j}\right)^{2} , \qquad (10)$

358 with $K = -m \ln(\sigma \sqrt{2\pi})$ being a constant without relevance for the

maximization (because σ is assumed to be constant). The maximization in Equation (7) is identical with the minimization in Equation (5), provided we interpret the posterior probabilities $P_{j|i}$ as assignment weights $\delta_{i,j}$.

In the EM algorithm, the posterior probabilities $P_{j|i}$ are not constrained to be binary variables that take values either zero or one. Nevertheless, the E and M steps in Equations (8) and (9) achieve to a good approximation the musical chairs competition we found.

To see this, consider the case in which for a given target there is only a single syllable with similar pitch ($P_{i|j}$ is large only for a single syllable *j*). According to

- Equation (8), $P_{j|i}$ is close to 1 for that best matching syllable j and close to 0 for the
- 369 other, non-matching syllables. This means that Equation (8) implements a soft
- 370 competition among syllables ($\sum_{j} \delta_{i,j} = 1$), which is an approximation of the musical 371 chairs interactions among syllables we found.

In a similar way, the normalization in Equation (9) implements a soft winnertakes-all mechanism. Namely, if for a given syllable *j* one of the posterior

374 probabilities (assignment weights) $P_{j|i}$ is large and the other very small, then by the 375 weighted sum in Equation (9), that syllable's pitch is drawn towards the pitch of the 376 assigned target.

To model the slow and gradual song development seen in birds, we simulated a finely discretized version of the EM algorithm in Equations (8) and (9). Because birds change pitch continuously and slowly unlike in Equations (8) and (9), we

- implemented a slow dynamical system in which we replaced the possibly large and discontinuous posterior probability and mean pitch abor gas in Equations (8) and (0)
- discontinuous posterior probability and mean pitch changes in Equations (8) and (9)
- 382 by gradual iterative processes (iterating over renditions t):
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1) We replaced the mean pitch S_j defined in Equation (9) by the iterative variables

$$S_{j}^{t+1} = S_{j}^{t} + \alpha \left(\sum_{i} T_{i} P_{j|i} - S_{j}^{t} \sum_{i} P_{j|i} \right),$$
(11)

387 where the index *t* labels the rendition number of the syllable, and α is a small 388 integration rate. At a steady state S_j^t equals S_j .

389 2) We sampled the pitch X_j^t of the rendition *t* of syllable *j* according to the 390 Gaussian model

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$$P(X_{j}^{t}) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(X_{j}^{t}-S_{j}^{t})^{2}}{2\sigma^{2}}}.$$
 (12)

392 3) We assume that birds can compute random samples and estimate their density, 393 but they cannot explicitly compute probabilities. We thus sampled the likelihoods $P_{i|j}$ 394 in Equation (6) via random variables b_{ij}^t and their running averages n_{ij}^t . First, we

395 computed the instantaneous likelihood as a binary random variable b_{ij}^{t} :

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$$P(b_{ij}^{t}=1) = \frac{1}{\sigma_{b}\sqrt{2\pi}}e^{\frac{(T_{j}-X_{j}^{t})^{2}}{2\sigma_{b}^{2}}}$$
(13)

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and $b_{ii}^{t} = 0$ otherwise with parameter σ_{b} . Second, we estimated the posterior 398 probabilities in Equation (8) according to $P_{j|i}^{t} = \frac{n_{ij}^{t}}{\varepsilon + \sum_{i} n_{ii}^{t}}$ with ε a small 399 regularization constant and n_{ij}^t a running average of b_{ij}^t : 400 $n_{ii}^{t+1} = (1 - \alpha_2) n_{ii}^t + \alpha_2 b_{ii}^t$ 401 (14)402 with integration rate α_2 . We simulated birds that produced three syllables (n = 3) and had to match three 403 targets (m = 3). Therefore, we iterated back and forth the above expressions for S_i^t 404 and $P_{i|i}^t$. 405 406 In simulations, we realized that the musical chairs competition is not well 407 captured by these equations: A call that did not match any target tended to converge 408 409 to a nearby target regardless whether the latter was occupied or not (Supplementary 410 Fig. 5a). To remedy this discrepancy, we hardened the musical chairs competition by 411 adding the constraint that at each sampled likelihood, b_{ii} could be 1 for at most one 412 vocalization, implying that matched targets could not attract any unassigned syllables or calls (Supplementary Fig. 5b). We achieved this constraint by setting b_{ij} to zero for 413 all j whenever for a given target i two or more b_{ij} 's were sampled to be one (i.e., 414

415 when
$$\sum_{j} b_{ij} > 1$$
 we set $b_{ik} = 0, \forall k$).

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- 417

- 419 In summary, we iteratively simulated the system in 5 steps (N1 to N5): 420 *N*1: sample pitch X_i^t according to Equation (12) 421 N2: sample the instantaneous likelihood b_{ii}^t according to Equation (13) 422 N3: enforce musical chairs: $\forall i$, if $\sum_{i} b_{ij}^{t} > 1$ set $b_{ik}^{t} = 0 \ \forall k$ 423 N4: update running average according to Equation (14) 424 N5: update mean pitch according to Equation (11) 425 The syllable trajectories X_{i}^{t} resulting from running this system are shown in 426 427 Supplementary Fig. 5b-d. The interesting property of these equations is that they in essence capture the 428 observations without requiring any parameter fitting other than σ_b . The latter was set 429 430 to exceed the pitch standard deviation σ . This allowed for medium size pitch shifts 431 of two semitones. The integration rates α and α_2 dictates the speed of pitch shifting,
- 432 these parameters are set to yield smooth looking transitions.
- 433

434 In summary, the competition we find in birds is harder than that in the standard EM 435 algorithm, in the sense that the EM algorithm brings all Gaussian models (syllables) to observables (targets), even if there are just 2 targets and 3 models, very unlike birds 436 437 that bring only one syllable or call to each target, in a presumed attempt to limit used 438 syllable resources. In a sense, birds are more efficient than the traditional EM 439 algorithm, similarly to ongoing machine-learning approaches for restricting the effective number of model parameters to prevent overfitting, such as sparse priors^{8,9}, 440 Bayesian learning, and Dirichlet processes^{10,11}. We believe that greedy and 441 442 competitive error assignment during vocal learning illustrates the importance of 443 minimizing used resources.

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