

Introduction to Music Processing

Iterated Learning or 'MCMC with People'

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How does "culture" emerge?

Many important phenomena (incl. music, language, arts etc.) are <u>cultural</u>.

- They develop over a long time.
- They depend on <u>customs/habits</u>, <u>social interactions</u>, <u>knowledge</u>, <u>norms</u>, <u>beliefs</u> etc.

Thought experiment:

- What if all humans forgot (at the same time) everything they ever learned?
- How would a new "culture" emerge?
- Would it be the same or different to ours?

How do we know:

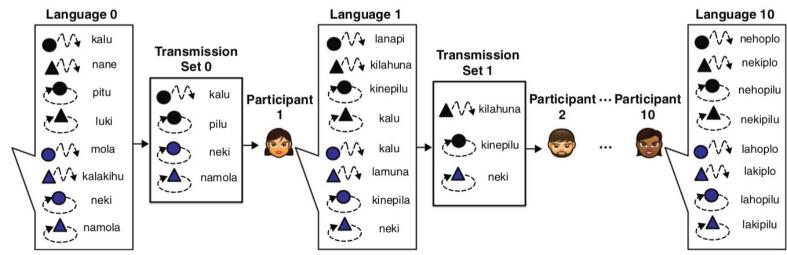
- What is <u>biologically</u>/physically determined?
- What is <u>evolutionarily</u> acquired and has become innate?
- What is <u>individually</u> learned?



Iterated Learning

Framework for studying **cultural transmission** (language, music, behaviour etc.)

- Knowledge is passed down through successive generations of learners
- Each learner's output serves as the input for the next
- Systematic/structured changes emerge over time influenced by cognitive and communicative biases/constrains





Iterated Learning for Rhythms

Self Experiment

Tap along and make a note how difficult you found it (easy / medium / hard)

- 1) 111
- 2) 223
- 3) 233
- 4) 122
- 5) 112
- 6) 123
- 7) 132
- 8) 113

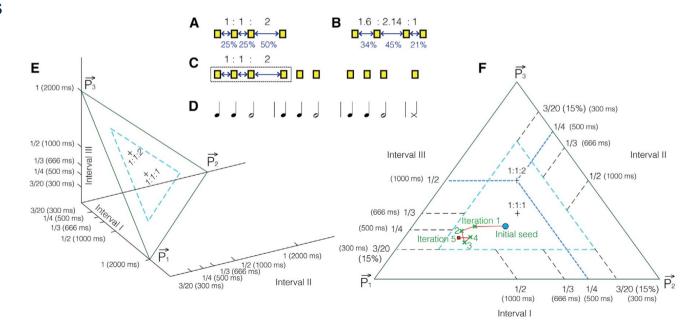




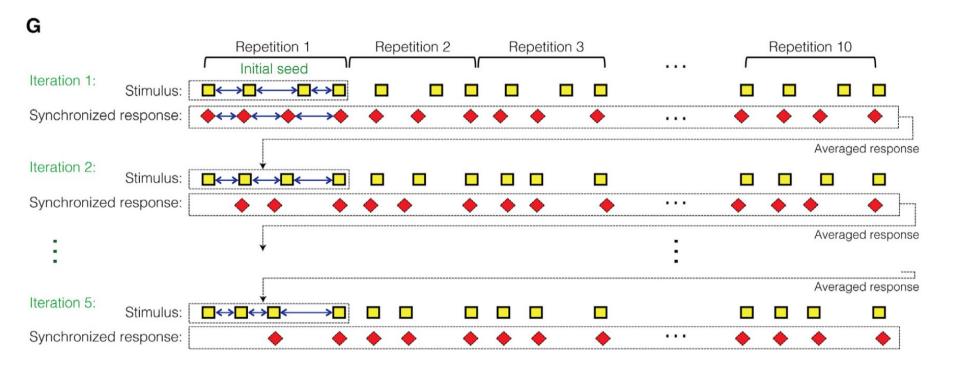
(Jacoby & McDermott, 2017)

Are "small integer ratios" in rhythms a cross-cultural universal?

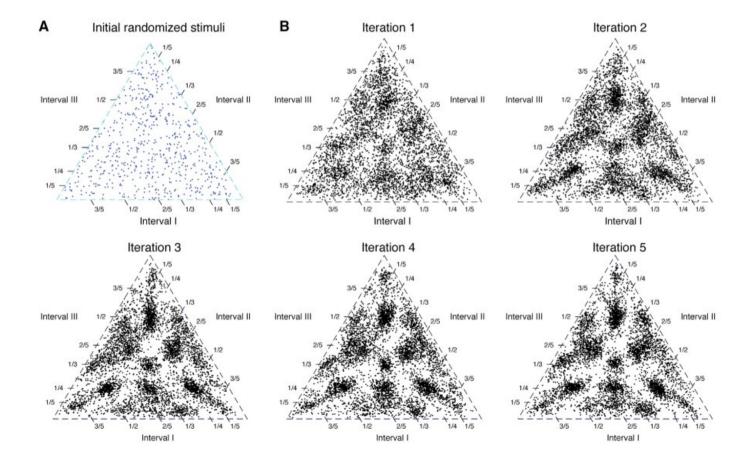
- Start with random 3-beat patterns repeated multiple times (+1 terminal beat)
- Have people reproduce (tap along, tap from memory, vocalise)
- Repeat 5 times







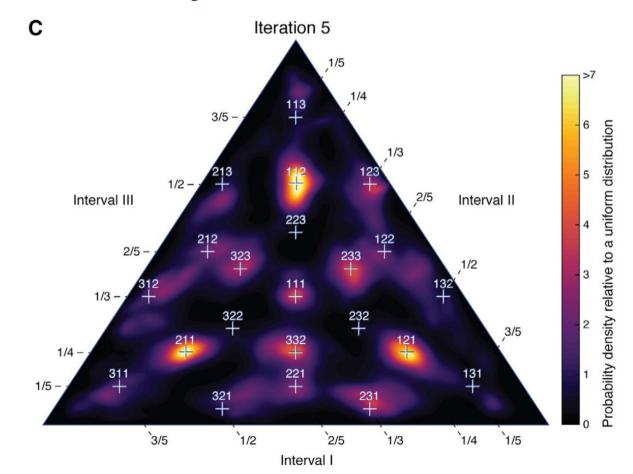






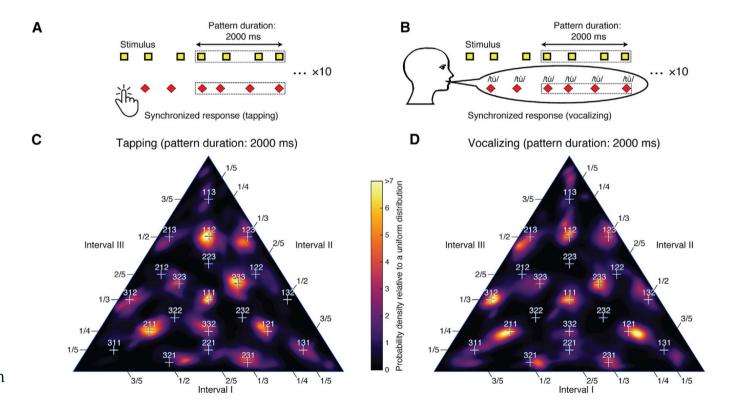


- 2) 223
- 3) 233
- 4) 122
- 5) 112
- 6) 123
- 7) 132
- 8) 113



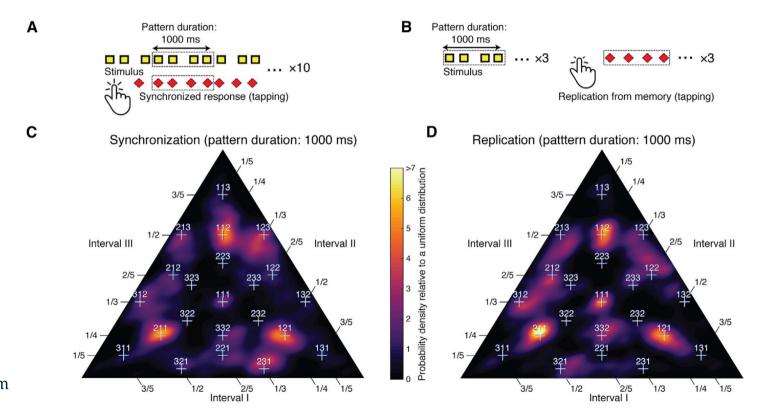


How do we control for <u>production</u> biases?





How do we control for <u>synchronisation</u> biases?



Interval I

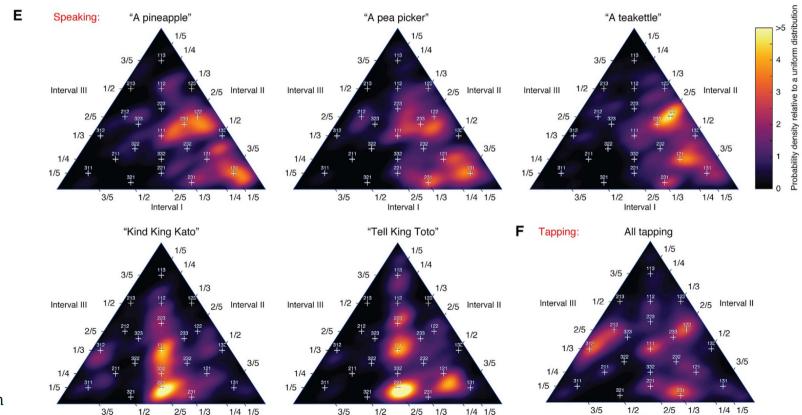


Speaking: Stimulus (spoken phrase)





Music versus Language

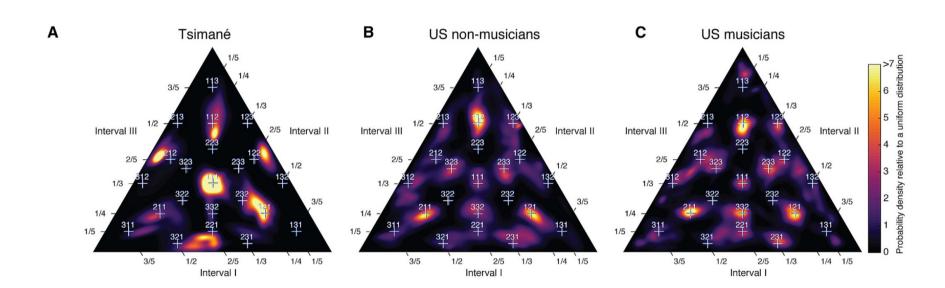


Interval I



Interval I

What role does <u>cultural background</u> play?





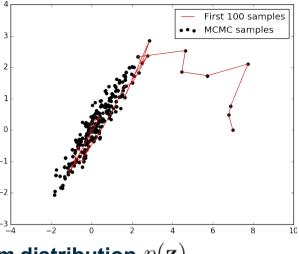
Markov Chain Monte Carlo

(with People)

Metropolis-Hastings

Sampling from an arbitrary unnormalised distribution

- full distribution is: $p(\mathbf{z}) = \widetilde{p}(\mathbf{z})/Z_p$
- but we can only compute: $\widetilde{p}(\mathbf{z})$



Strategy: Create a Markov chain of samples with equilibrium distribution $p(\mathbf{z})$

- start from z
- use proposal distribution: $q_k(\mathbf{z}^\star|\mathbf{z}^{(au)})$
- accept / reject proposal with probability: $A_k(\mathbf{z}^\star, \mathbf{z}^{(au)}) = \min\left(1, \frac{\widetilde{p}(\mathbf{z}^\star)q_k(\mathbf{z}^{(au)}|\mathbf{z}^\star)}{\widetilde{p}(\mathbf{z}^{(au)})q_k(\mathbf{z}^\star|\mathbf{z}^{(au)})}\right)$
- for symmetric proposals (Metropolis) this simplifies to: $A(\mathbf{z}^{\star}, \mathbf{z}^{(\tau)}) = \min\left(1, \frac{\widetilde{p}(\mathbf{z}^{\star})}{\widetilde{p}(\mathbf{z}^{(\tau)})}\right)$



Gibbs Sampling

(special case of Metropolis-Hastings)

Be more efficient for multiple variables

- sample proposals for one variable at a time
- choose proposals such that they are always accepted
- → sample one variable <u>conditional</u> on the other variables

$$A(\mathbf{z}^{\star}, \mathbf{z}) = \frac{p(\mathbf{z}^{\star})q_k(\mathbf{z}|\mathbf{z}^{\star})}{p(\mathbf{z})q_k(\mathbf{z}^{\star}|\mathbf{z})} = \frac{p(z_k^{\star}|\mathbf{z}_{\setminus k}^{\star})p(\mathbf{z}_{\setminus k}^{\star})p(z_k|\mathbf{z}_{\setminus k}^{\star})}{p(z_k|\mathbf{z}_{\setminus k})p(z_k^{\star}|\mathbf{z}_{\setminus k})} = 1$$



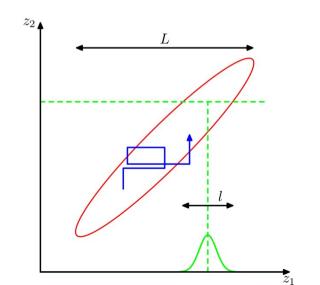
- 1. Initialize $\{z_i : i = 1, ..., M\}$
- 2. For $\tau = 1, ..., T$:
 - Sample $z_1^{(\tau+1)} \sim p(z_1|z_2^{(\tau)}, z_3^{(\tau)}, \dots, z_M^{(\tau)}).$
 - Sample $z_2^{(\tau+1)} \sim p(z_2|z_1^{(\tau+1)}, z_3^{(\tau)}, \dots, z_M^{(\tau)}).$

:

- Sample $z_j^{(\tau+1)} \sim p(z_j|z_1^{(\tau+1)}, \dots, z_{j-1}^{(\tau+1)}, z_{j+1}^{(\tau)}, \dots, z_M^{(\tau)})$

:

- Sample $z_M^{(\tau+1)} \sim p(z_M | z_1^{(\tau+1)}, z_2^{(\tau+1)}, \dots, z_{M-1}^{(\tau+1)}).$

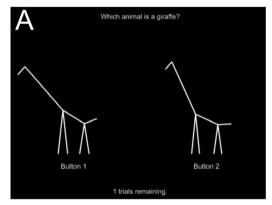


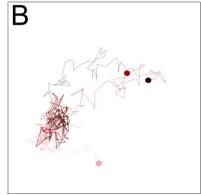
Markov Chain Monte Carlo with People (MCMCP)

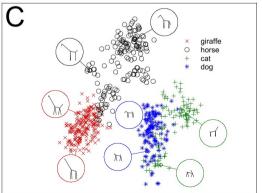
(Sanborn & Griffiths, 2007)

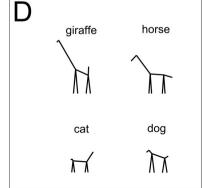
MCMC with people as acceptance "functions"

- start with a random sample
- generate a modified proposal
- present both to the participant
 → they reject / accept
- repeat







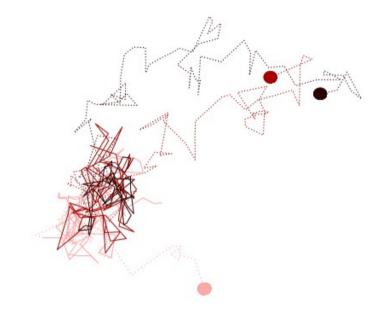




Markov Chain Monte Carlo with People

Problems with MCMCP

- binary choices generate little information
- local proposals
 - make it slow to explore entire space
 - make it hard to find narrow modes

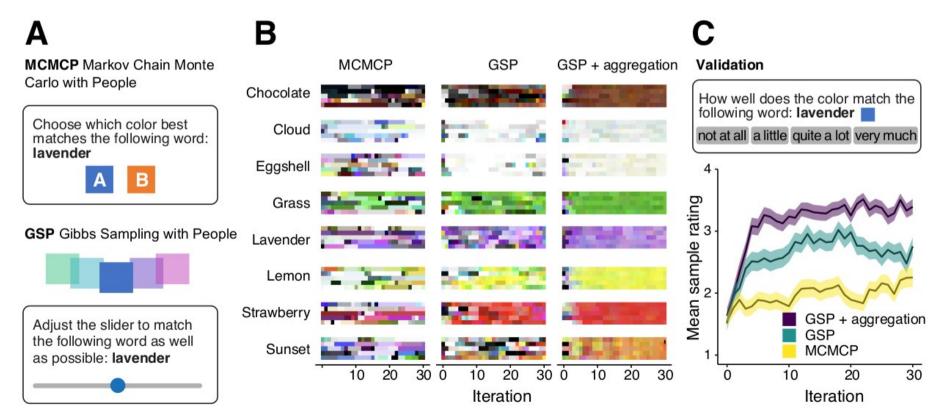




Gibbs Sampling with People

(Harrison et al, 2020)

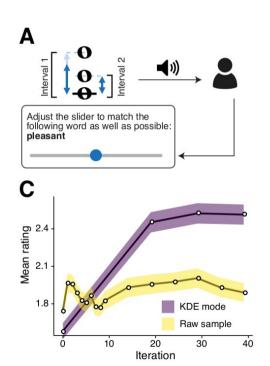
Replace binary decision with continuous slider

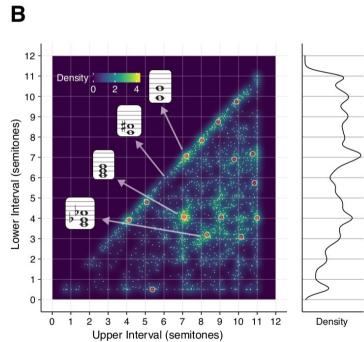


Gibbs Sampling with People

"Pleasantness" of musical chords

- maxima at semitones (esp. harmonic overtones)
- dips at minor second and tritone
- clusters at common chords (e.g. major triad)
- aggregation (clusters) gives better ratings







References

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- 7) Bishop CM (2007) Pattern Recognition and Machine Learning (Information Science and Statistics), 1st ed. 2006. Corr. 2nd printing. Springer

