The Right Chord Between Reuse and Improvisation: Melody Learning as Resource-Rational Program Induction

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machine learning new perspectives for science

Program induction under constraints

We integrate program induction with RDT to explain how humans

- ❏ **Represent** knowledge as program induction under resource constraints incl. computational costs
- ❏ Continually **adapt** the repertoire of programs (i.e., compression model) to new observations
- ❏ Show error patterns that are beyond only chunking during learning

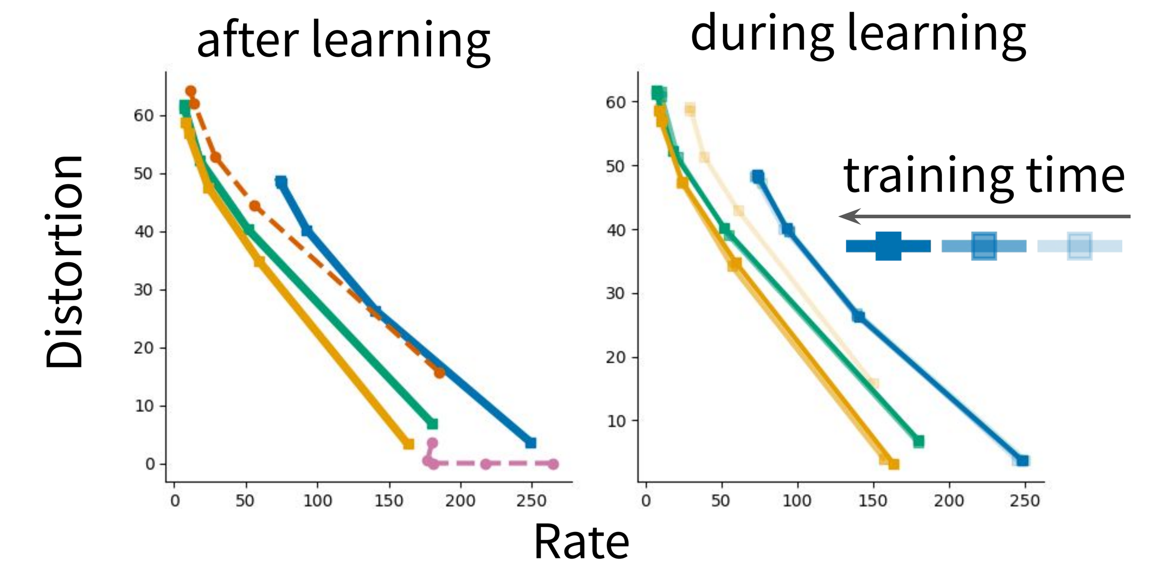
"Programs" of thought

Human concept learning can be viewed as inferring Probabilistic Programs[1,2]

Resource rationality

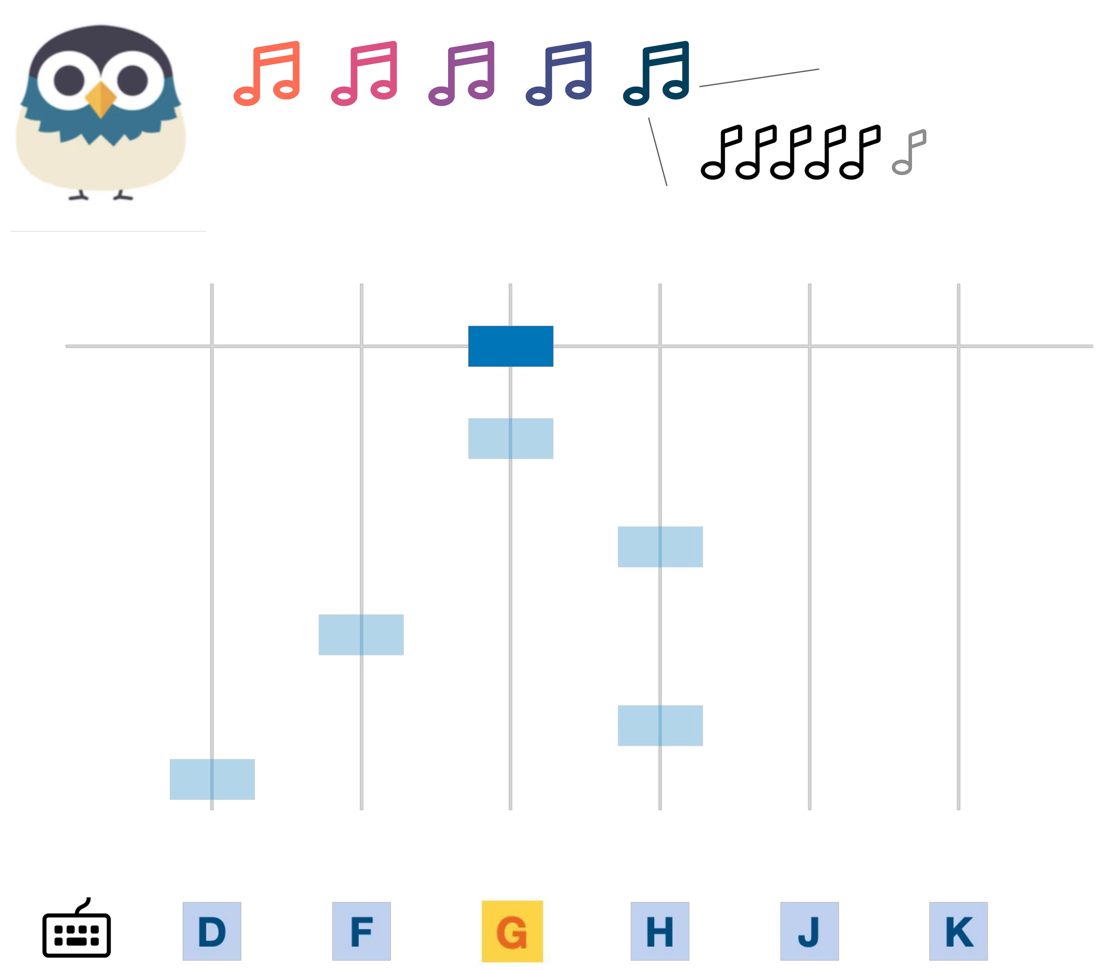
Accounting for cognitive limitations is often modeled using information theory, specifically, *Rate-Distortion Theory* (RDT)[3]

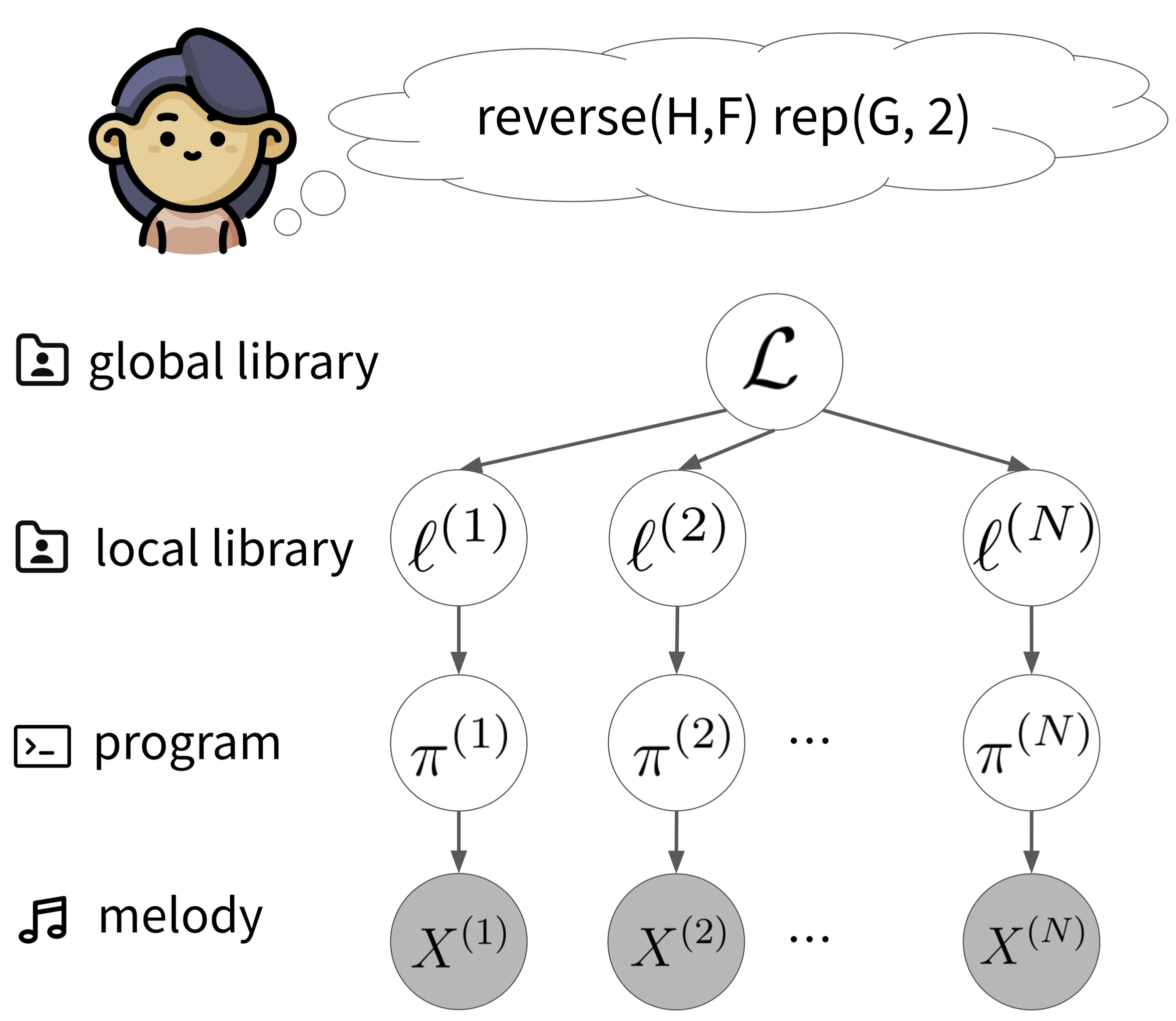
- ❏ Yet compression alone does not account for **computational costs** and how **learning changes the model**[5]

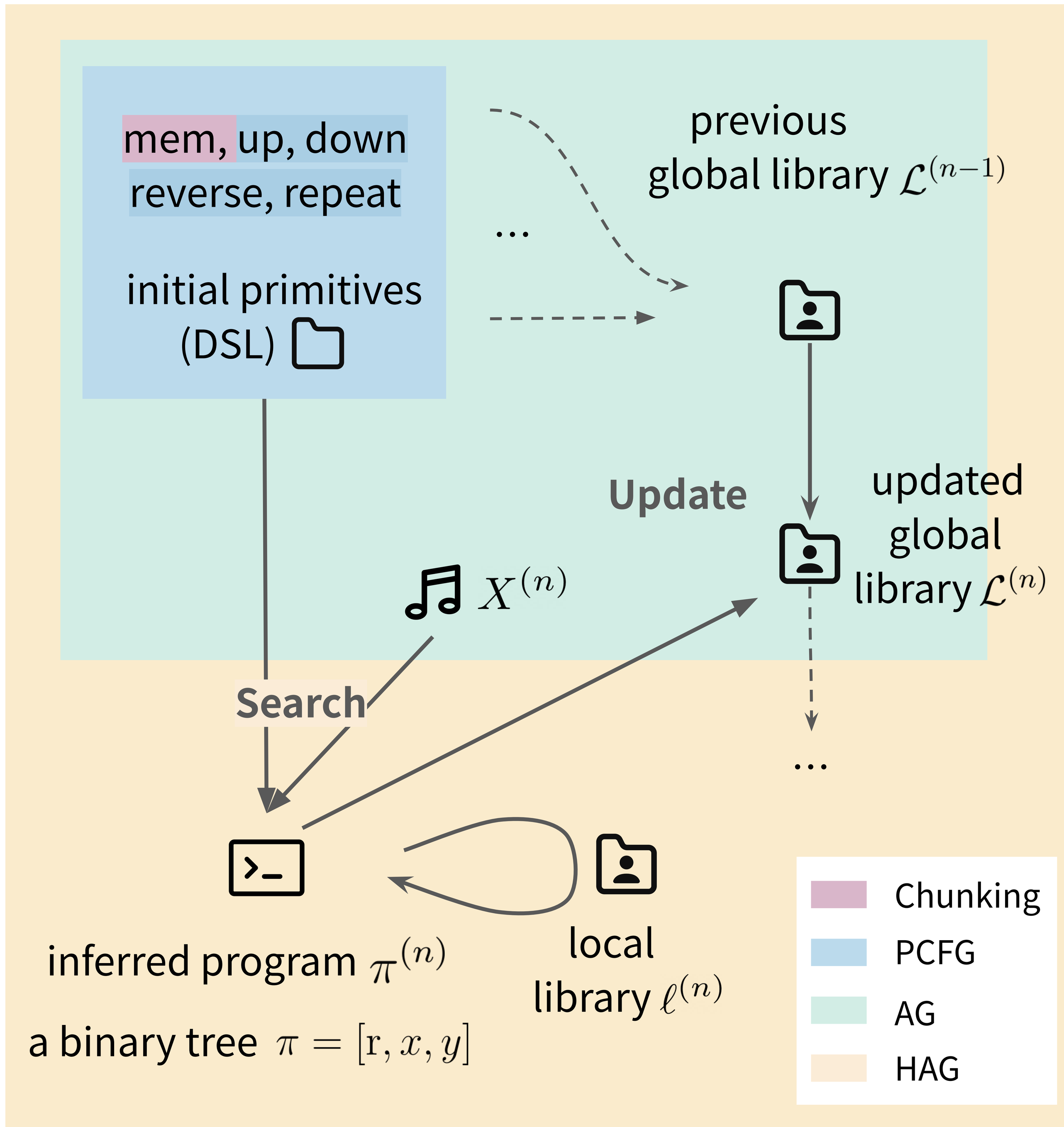


ChirpChirp: Melody learning empowered by libraries

Three phases for each ♬: Learning, Memory, Completion





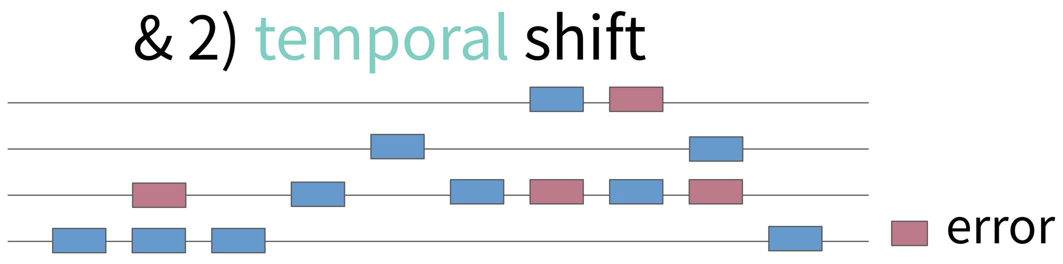


Behavioural data analysis

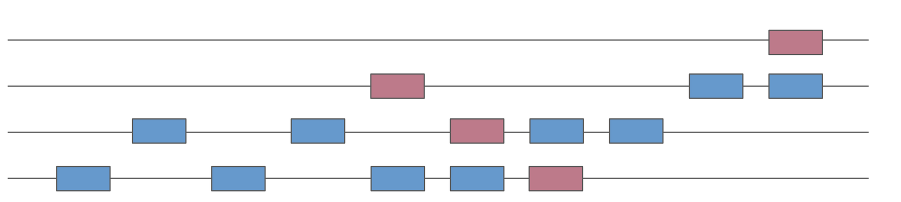
Beyond random mistakes and chunking errors

Structured patterns dominate error types

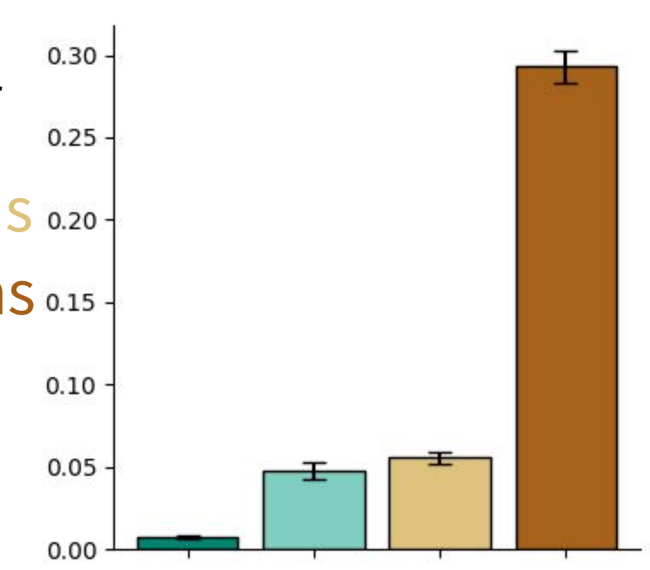
Unstructured errors: 1) vertical & 2) temporal shift



Structured errors: 3) repeating patterns & 4) explained by simpler programs



Unique error occurrence (percentage of errors not explained by other types)

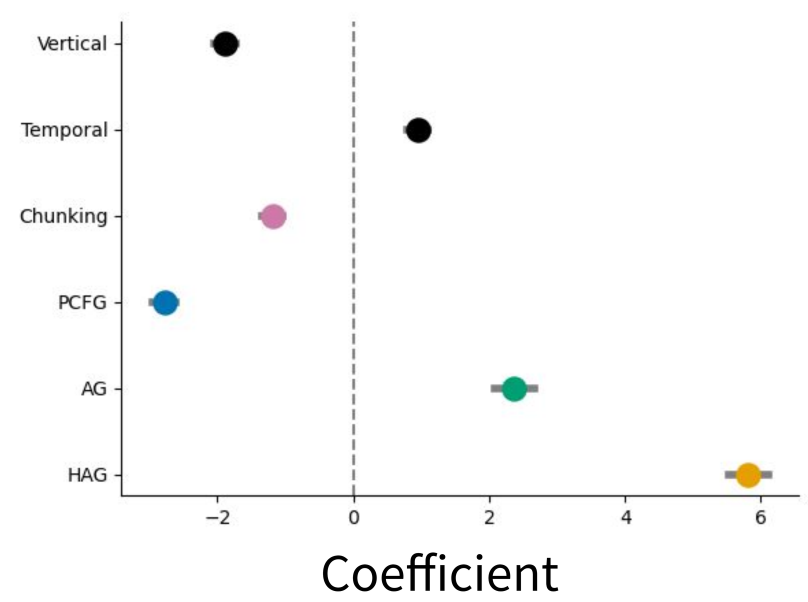


HAG is the best predictor of trial-by-trial memory

Probability of pressing a key is based on a weighted sum of model prediction:

$$\mathrm{Choice}(x) \propto \exp(F \cdot \mathbf{w})$$

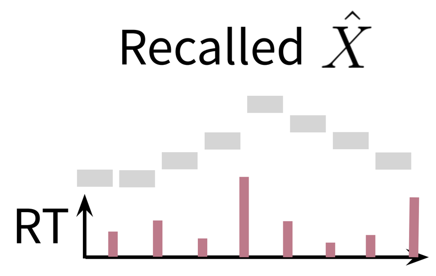
- F feature matrix (what the model predicts)
- $\mathbf{w}$ weights (learned from data)

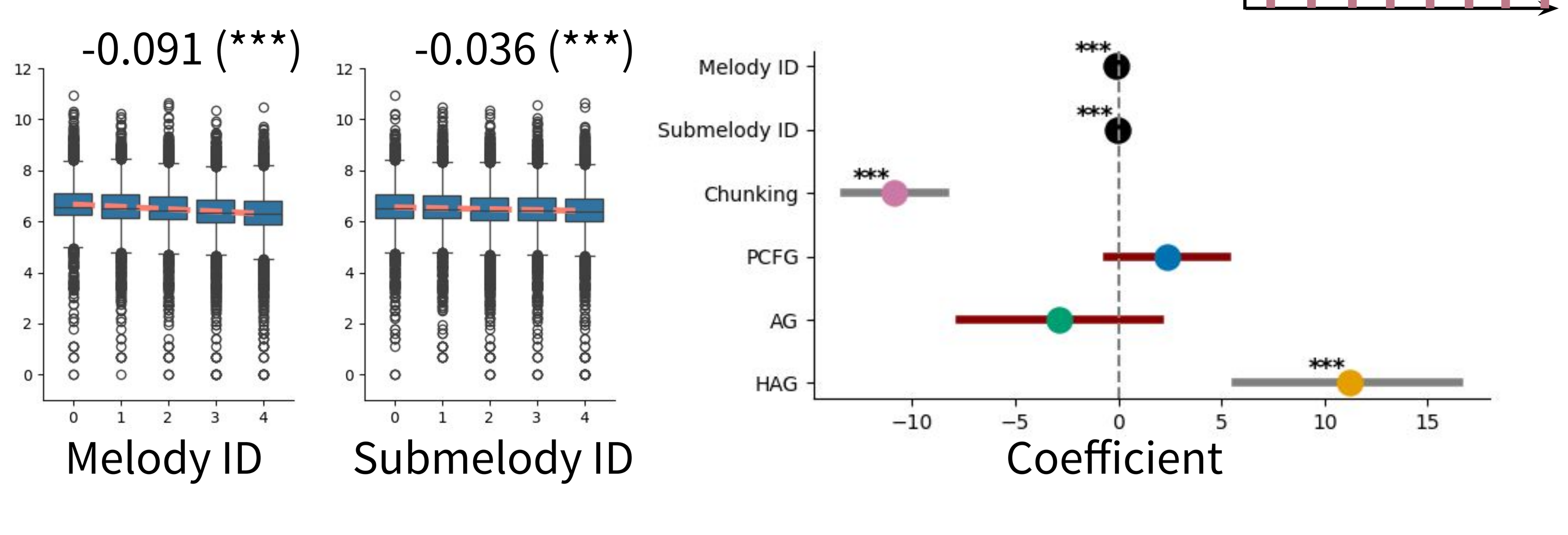


Programs explain learning effects

Program boundaries predict reaction time

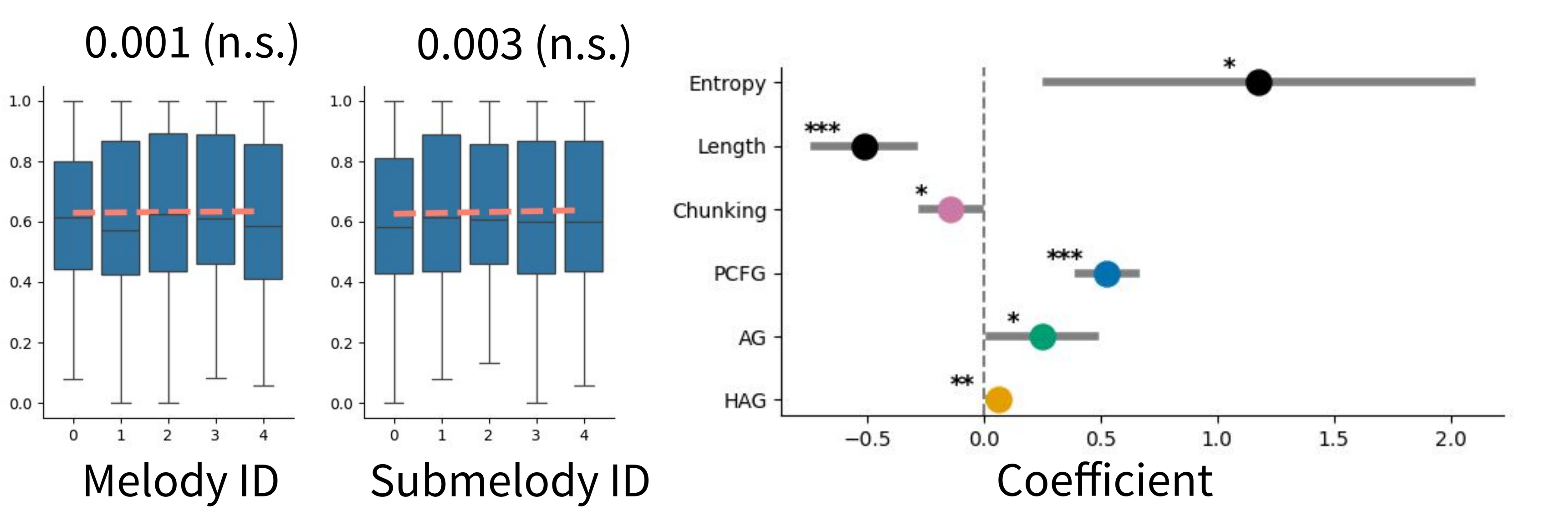
Model-predicted program endings vs. human note-wise reaction time





Program complexity predicts error rate

Model-predicted complexity vs. human melody-wise accuracy



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