Improving and Adapting Finite State Transducer Methods for Musical Accompaniment

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introduction

given an input melody,
generate harmonic accompaniment

data-driven approaches

finite state machines are a natural fit for solving this problem, and have been used extensively in natural language processing

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outline

introduction to finite state machines

general approach to generating musical accompaniment

application of this approach

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finite state machines

used in natural language processing, bioinformatics, computer vision

directed graphs (nodes, edges)

edges labelled with symbols

edges and nodes can have weights (e.g. probabilities)

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finite state machines

make it relatively easy to break down a complex problem into simpler sub-problems

allow use of a purely data-driven approach

can also incorporate higher-level knowledge into system

require relatively little training data

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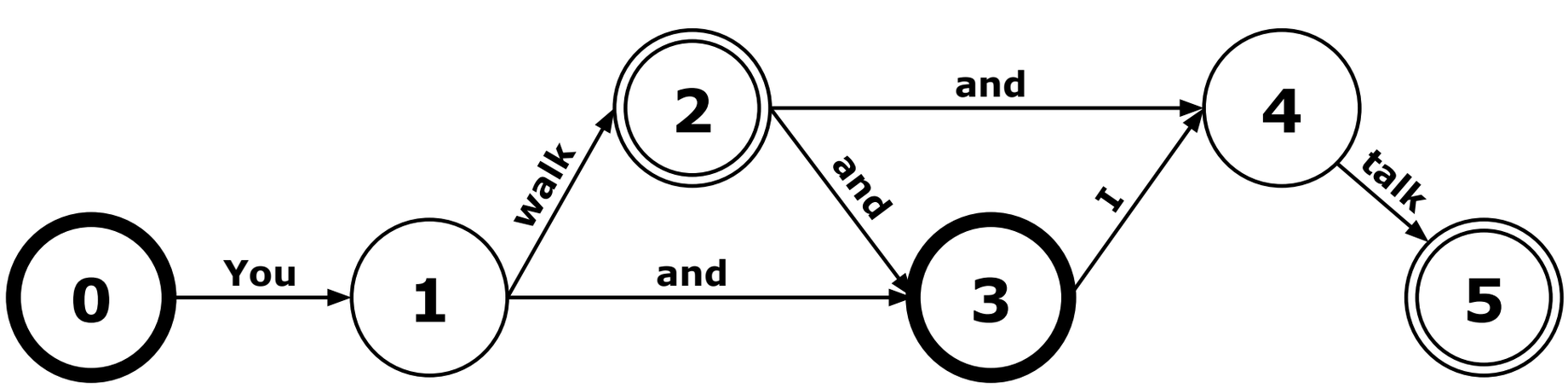
finite state automaton

FSA defined by the 5-tuple:

$$\langle \Sigma, Q, I, F, \delta \rangle$$

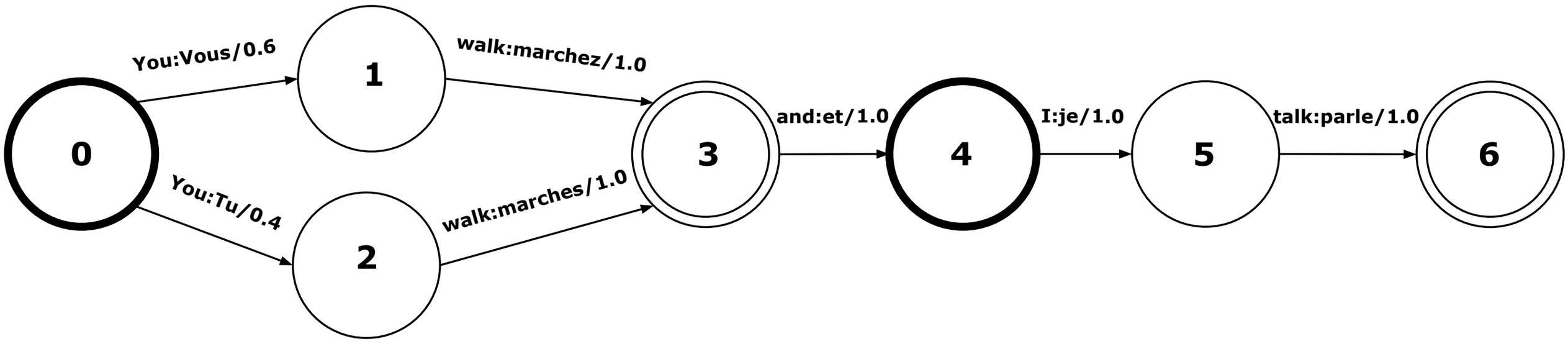


(sometimes referred to as an “acceptor”)

finite state transducer

FST defined by the 6-tuple:

$$\langle \Sigma, \Delta, Q, I, F, \delta \rangle$$



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finite state operations

composition

determinization

minimization

shortest path

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generating accompaniment

approach to accompaniment generation
borrowed from speech recognition

speech recognition problem:

find the most likely sequence of words
given a sequence of phonemes

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generating accompaniment

general framework:

$$\hat{\mathbf{c}} = \underset{\mathbf{c}\in\Sigma^*}{\arg\max} \Pr\left[\mathbf{c} \mid \mathbf{m}\right] = \underset{\mathbf{c}\in\Sigma^*}{\arg\max} \Pr\left[\mathbf{m} \mid \mathbf{c}\right] \cdot \Pr[\mathbf{c}]$$

$\mathbf{m}$: input melodic sequence

$\hat{\mathbf{c}}$: most likely sequence of accompaniment chords

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generating accompaniment

$$\hat{\mathbf{c}} = \underset{\mathbf{c} \in \Sigma^*}{\arg\max} \Pr\left[\mathbf{c} \mid \mathbf{m}\right] = \underset{\mathbf{c} \in \Sigma^*}{\arg\max} \Pr\left[\mathbf{m} \mid \mathbf{c}\right] \cdot \Pr[\mathbf{c}]$$

model components separately:

FST (*L*) to model Pr[m | c]

FSA (*G*) to model Pr[c]

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generating accompaniment

input alphabet (Σ_i): pitch classes

output alphabet (Σ_o): chord symbols or quantized chroma vectors[1]

training data: pairs of sequences of melodic symbols and sequences of harmonic symbols

[1] Forsyth, J. P., & Bello, J. P. (2013). Generating Musical Accompaniment Using Finite State Transducers. In *Proceedings of the16th International Conference on Digital Audio Effects (DAFx-13)*.

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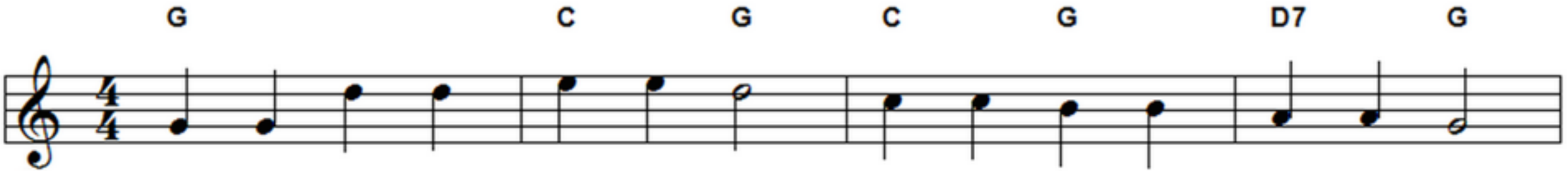
training *L* FST



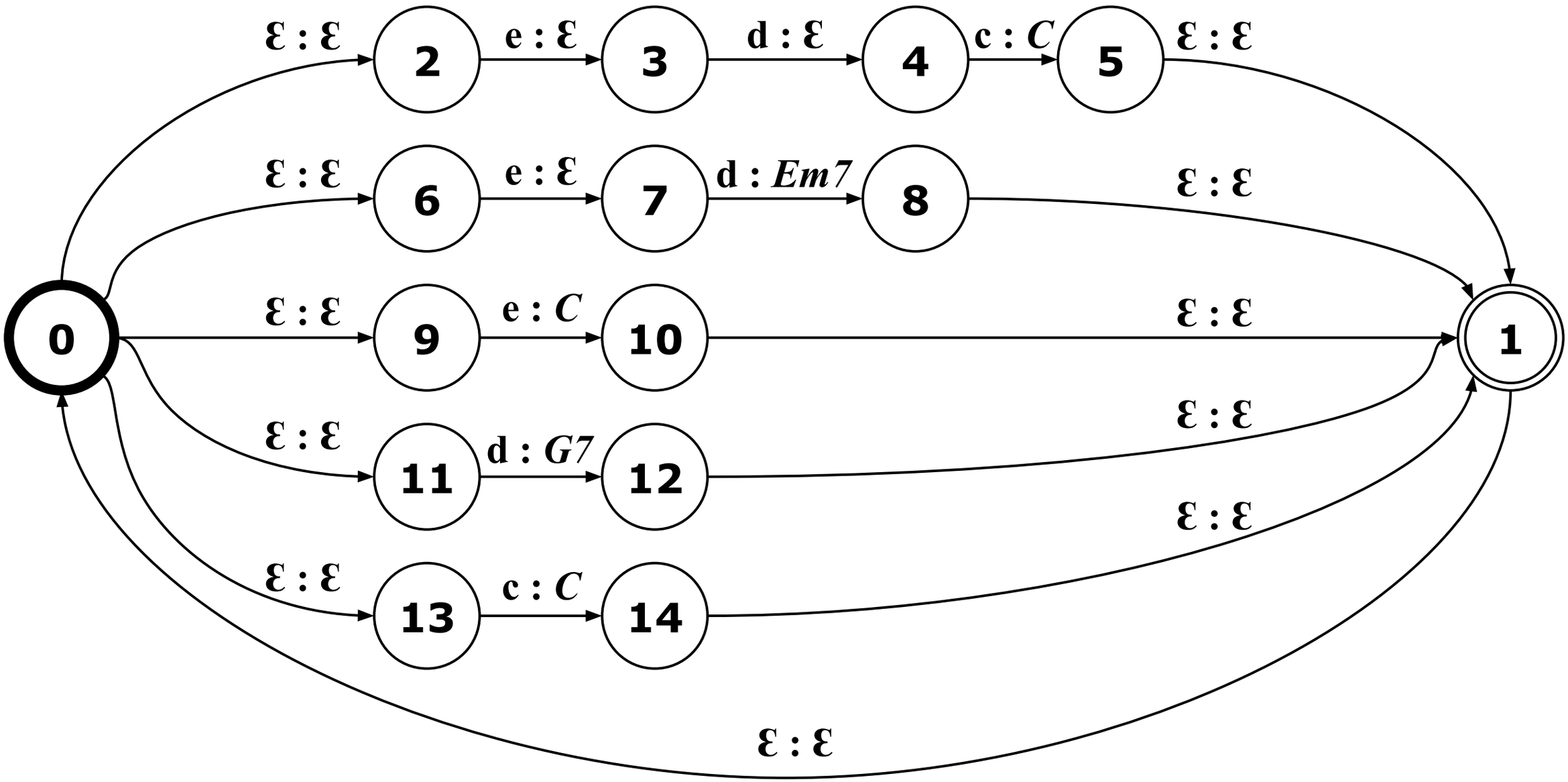
example training sequence

training *L* FST

generates the training sequences:

g,g,d,d ⟶ G
e,e ⟶ C
d ⟶ G
c,c ⟶ C
b,b ⟶ G
a,a ⟶ D7
g ⟶ G

training *L* FST



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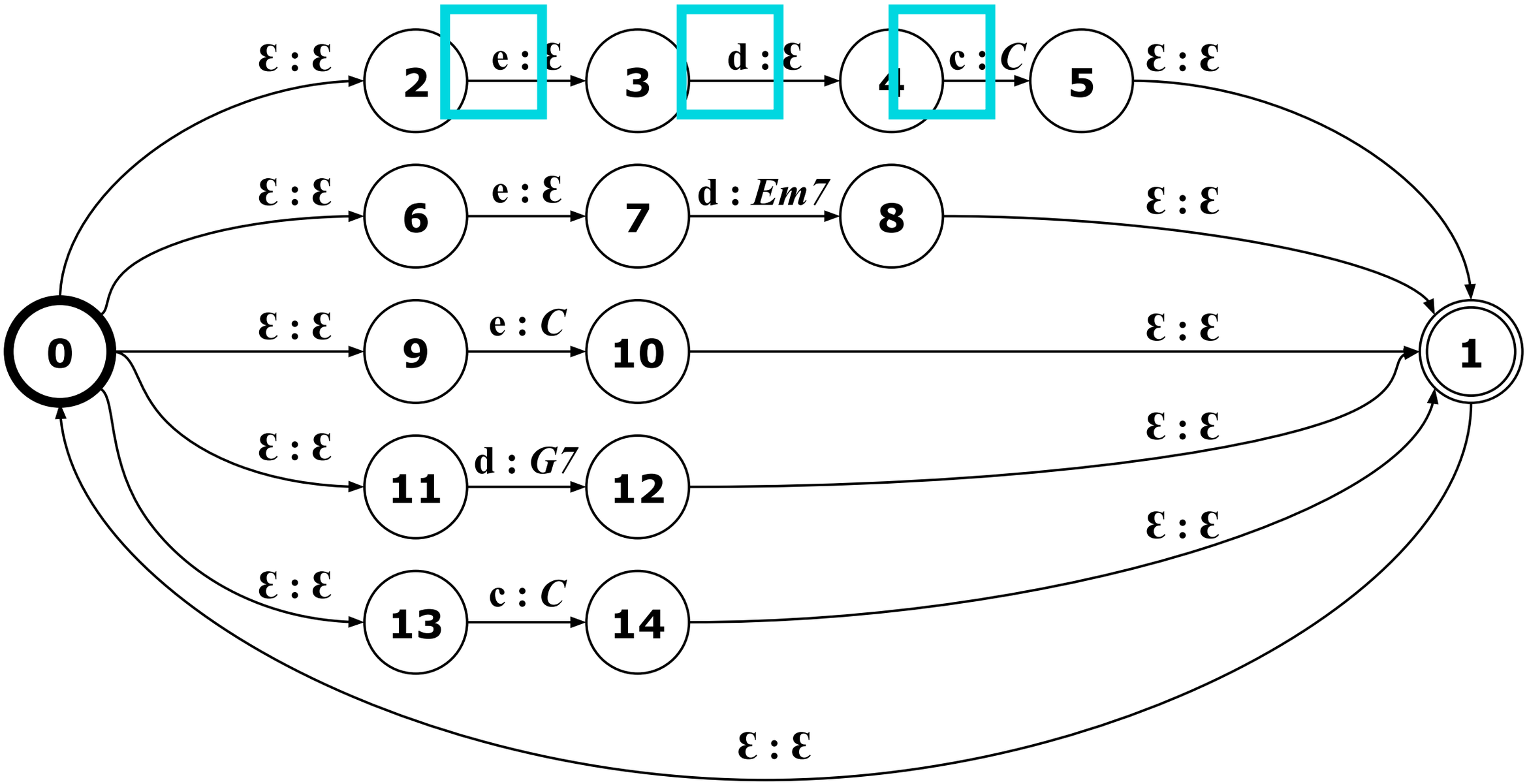

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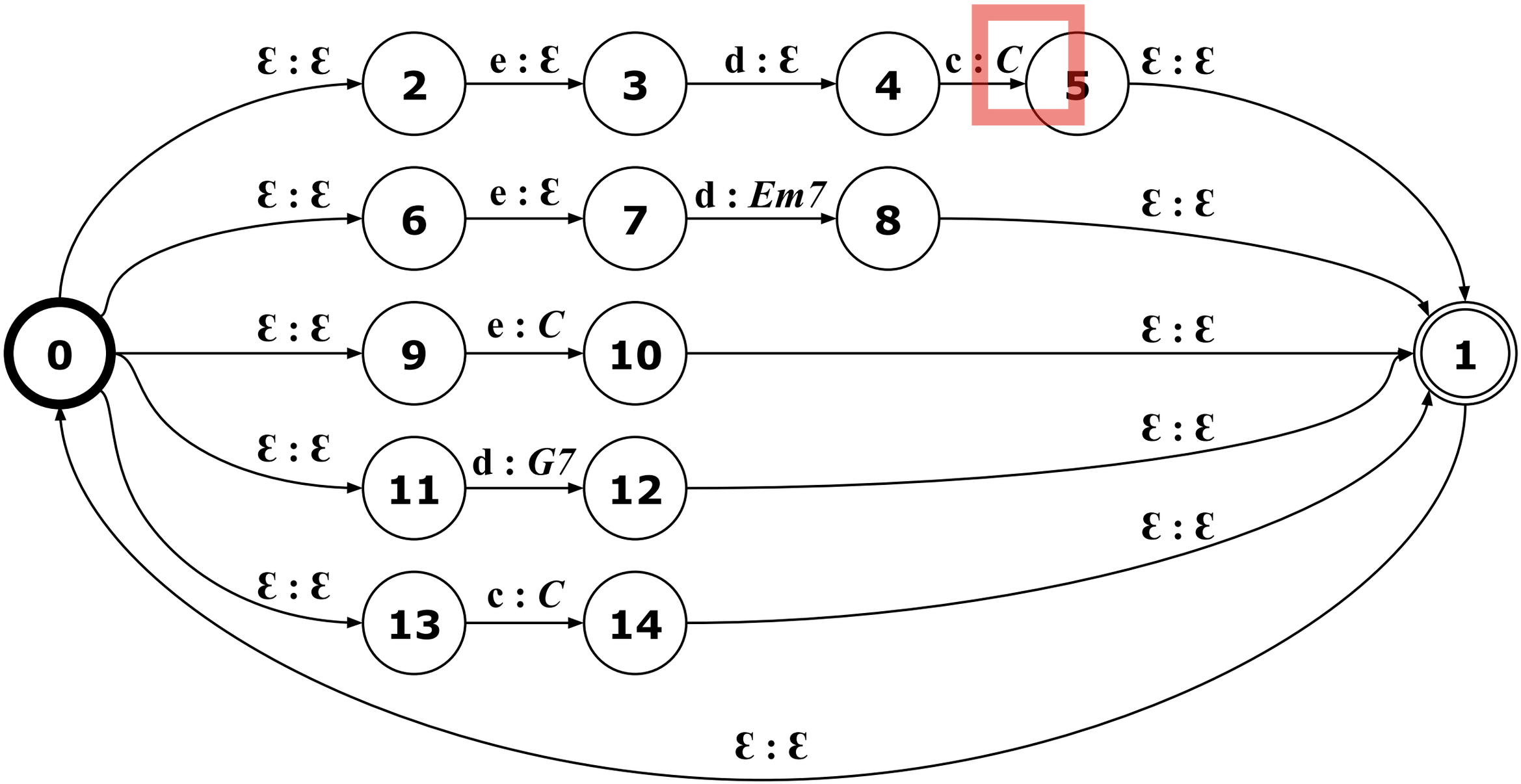
training *L* FST



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training *L* FST

same melodic sequence may map to different chords

(e.g. [*c,e,g*] may map to *C* or *Amin7*)

training *L* FST

same melodic sequence may map to different chords

(e.g. [*c,e,g*] may map to *C* or *Amin7*)

analogous problem in speech recognition:

same set of phonemes map to “red” and “read”

training *L* FST

an FST with conflicting mappings cannot be determinized, which is required for minimization

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training *L* FST

solution:

append different disambiguation symbol (typically, ‘#0’, ‘#1’, etc.) to each sequence that maps to more than one chord

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training *L* FST

e.g., our training data contains pairs
[*c,e,g* : *C*] and [*c,e,g* : *Amin7*]

add disambiguation symbols to get the pairs

[*c,e,g,#0* : *C*] and [*c,e,g,#1* : *Amin7*]

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training *L* FST

after training full model, replace disambiguation symbols with **ε**

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training *G* FSA

use an n-gram trained on all length-n chord sequences in training data

n-grams model sequential data with context of n-1 symbols

n-gram represented as an FSA (*G*)

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full model

combine the individual models:

$$\mathcal{T} = \pi_\epsilon(min(det(\tilde{\mathcal{L}} \circ \mathcal{G})))$$

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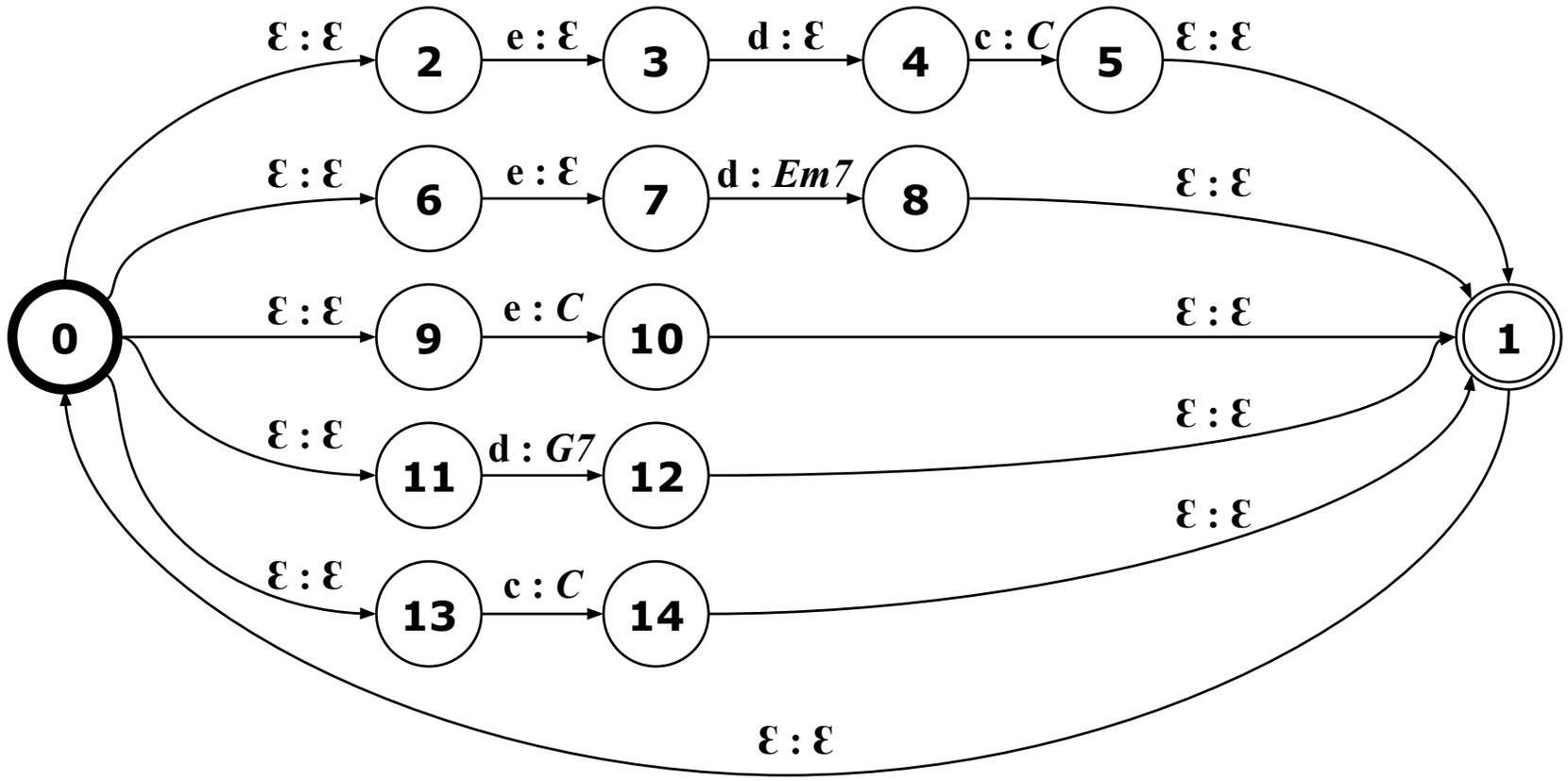
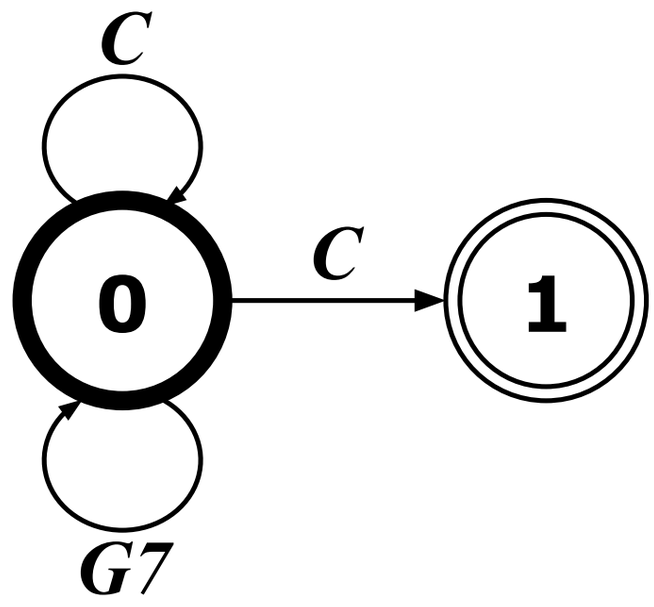
chord generation example

melody->chord FST (*L*):



chord generation example

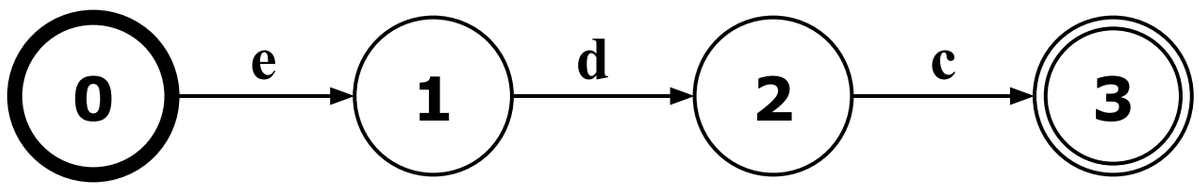
chord model FSA (*G*):



chord generation example

input melody sequence m = [*e*,*d*,*c*]

construct “linear chain” FST, *M*, from melody:



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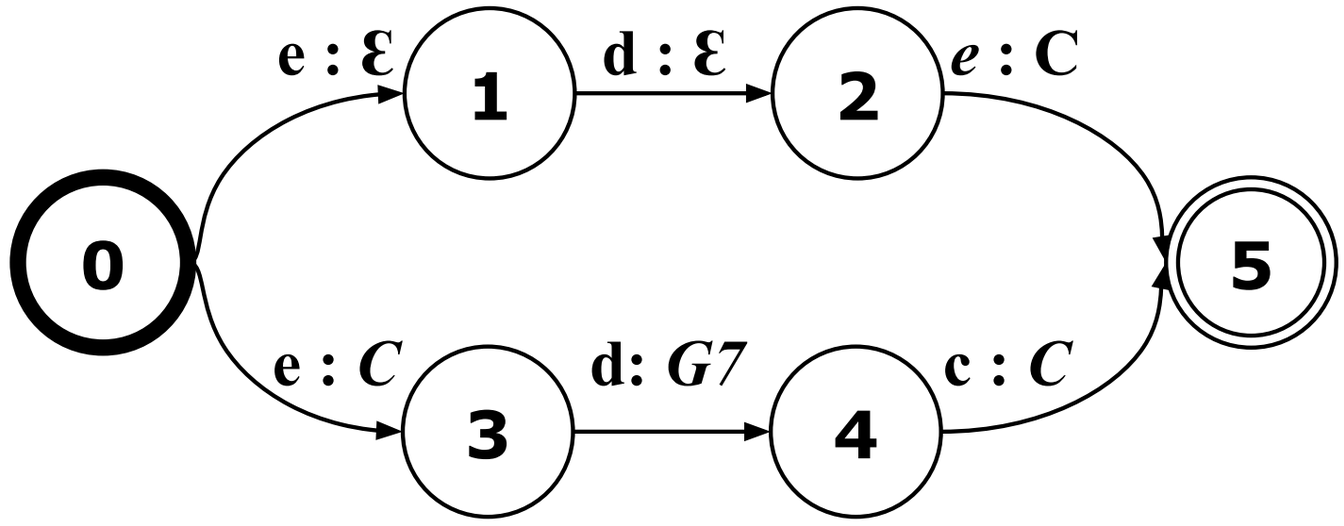
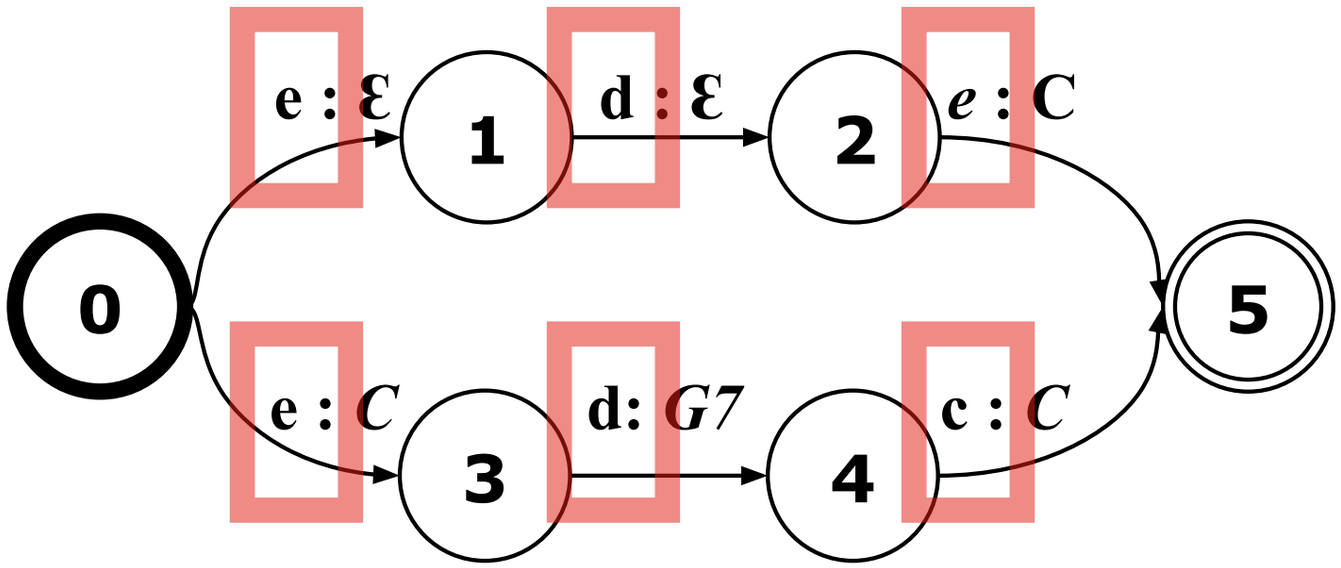
chord generation example

compute $C = M \circ T$



chord generation example

compute $C = M \circ T$



chord generation example

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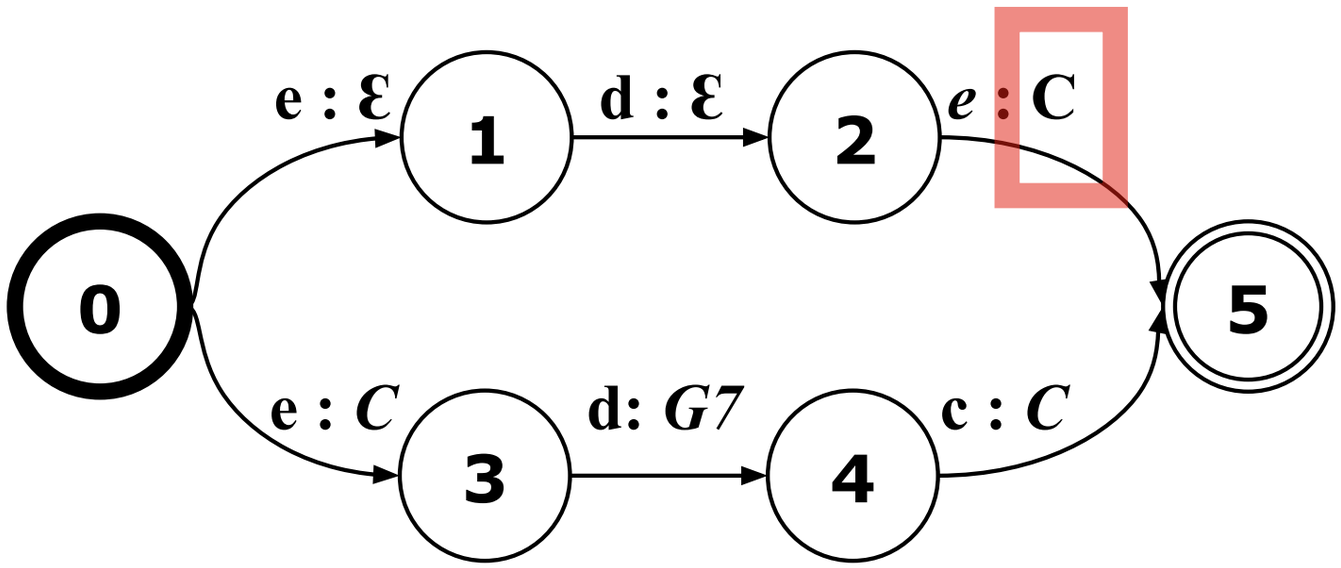

chord generation example

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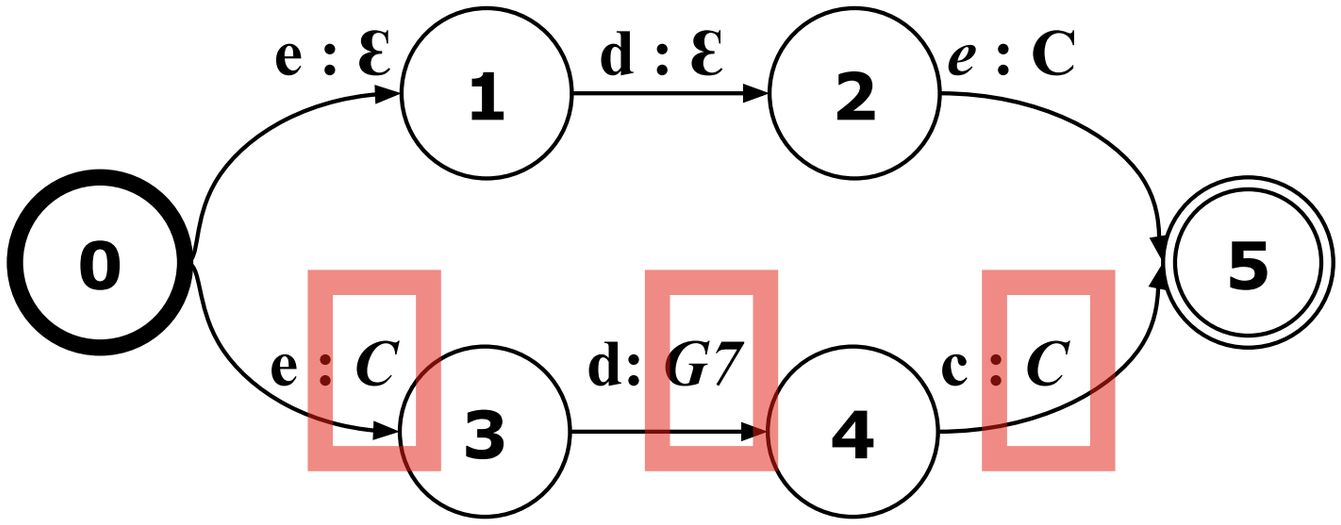

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chord generation example

finding the accompaniment sequence from *C*:

shortest path (most likely chords)

randomly generate (uniform sampling or weights as negative log probabilities)

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extension to rhythm

harmonic accompaniment model doesn't incorporate rhythm, so we add an separate rhythmic model

extension to rhythm

use the same basic approach as in the case of generating harmonic accompaniment :

$$\hat{\mathbf{r}} = \arg\max_{\mathbf{r} \in \Sigma^*} \Pr\left[\mathbf{r} \mid \mathbf{s}\right] = \arg\max_{\mathbf{r} \in \Sigma^*} \Pr\left[\mathbf{s} \mid \mathbf{r}\right] \cdot \Pr[\mathbf{r}]$$

alphabet consists of quantized inter-onset times

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The Harmonically Ecosystemic Machine

collaboration with Michael Musick

interactive installation that incorporates FST-based harmony and rhythm generation[2]

[2] Musick, M., Forsyth, J.P. , & Bittner, R. (2015) Building a Harmonically Ecosystemic Machine: Combining Sonic Ecosystems with Models of Contemporary Harmonic Language. In *Proc. of the 41th International Computer Music Conference (ICMC), Denton, TX.*

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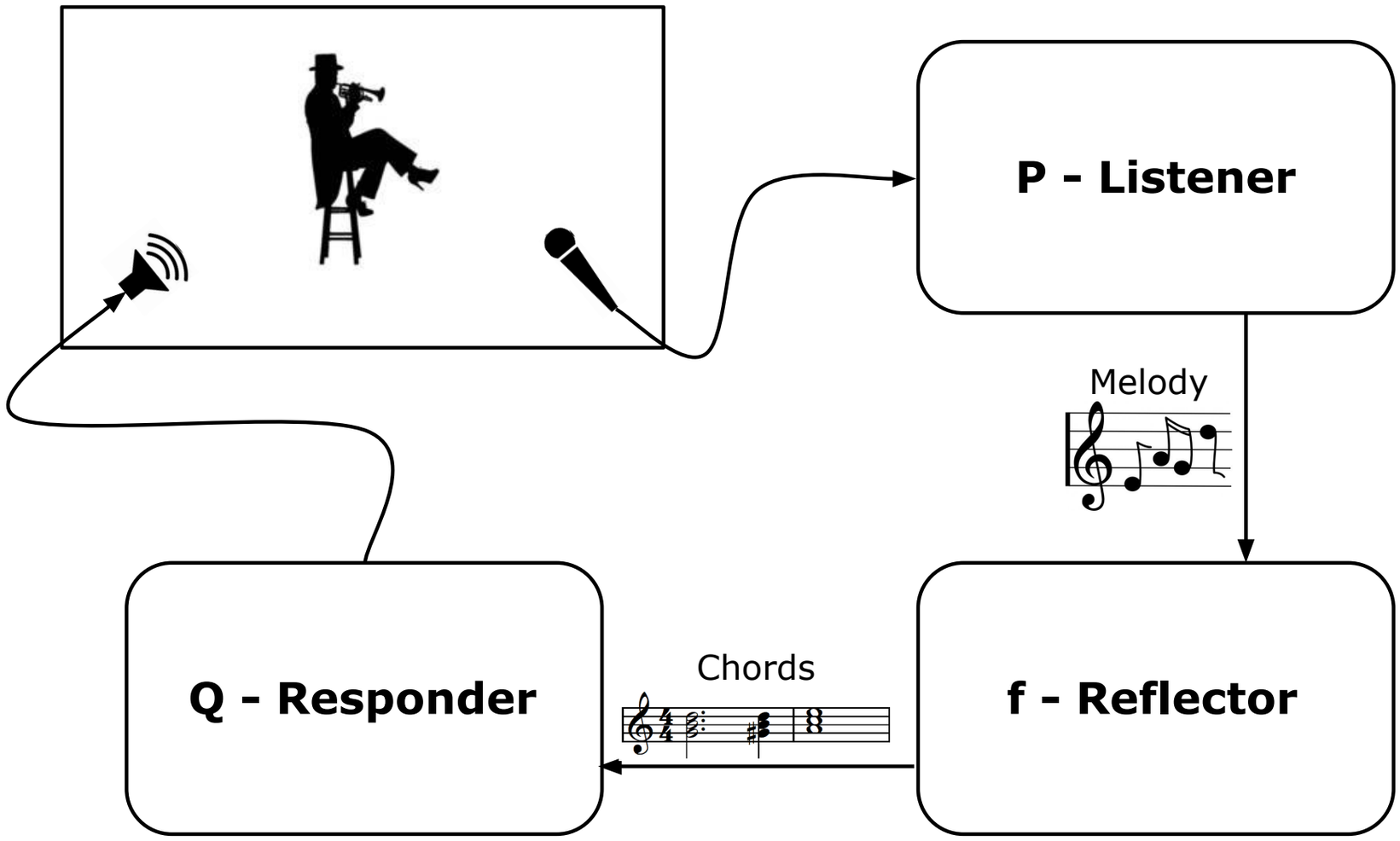
The Harmonically Ecosystemic Machine



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The Harmonically Ecosystemic Machine

Listener and *Responder* modules implemented in SuperCollider

Reflector/Decision Maker module implemented in Python

uses OpenFst and OpenGrm libraries

communication via OSC

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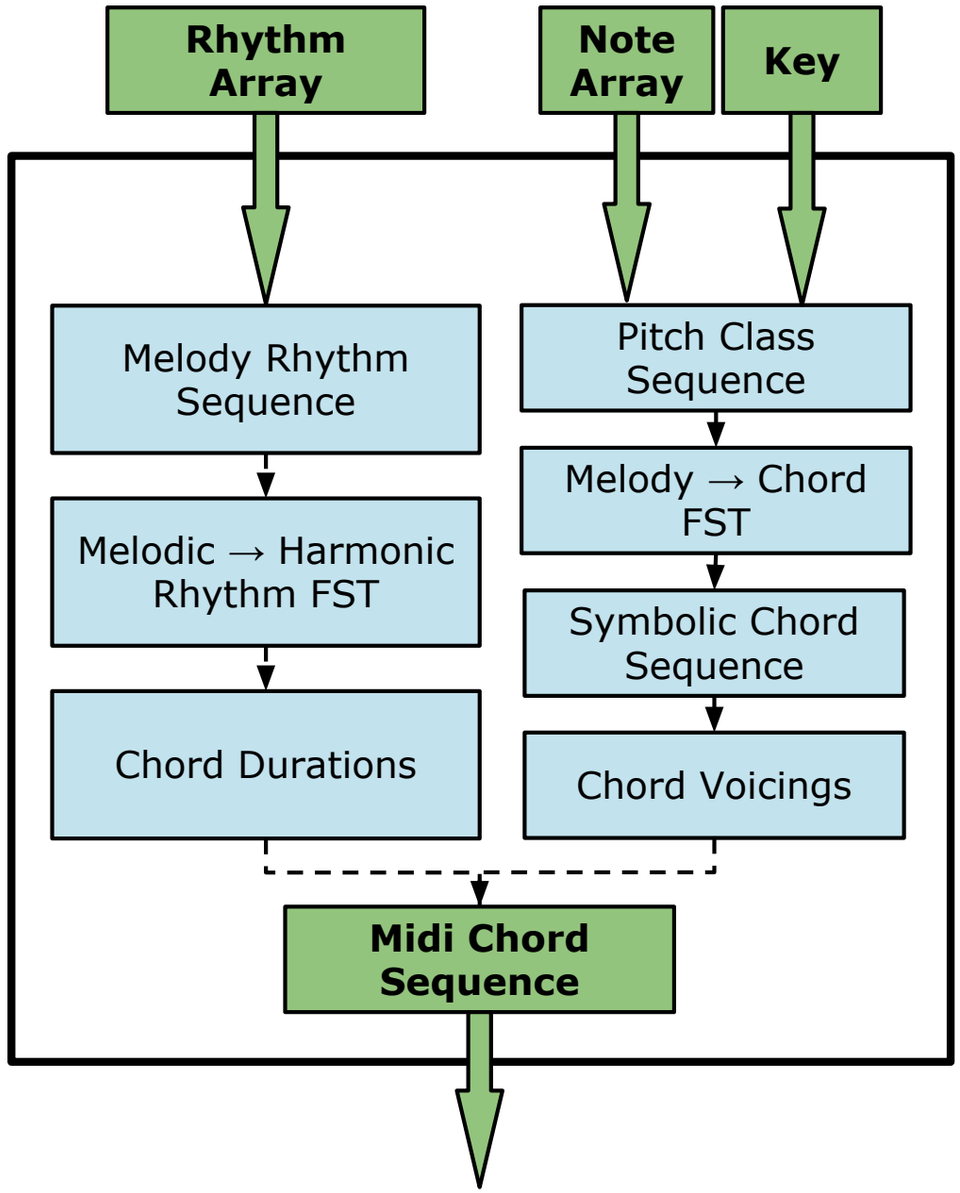
The Harmonically Ecosystemic Machine



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The Harmonically Ecosystemic Machine

training data:

harmony: Rock Corpus dataset

rhythm: works by Mozart

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The Harmonically Ecosystemic Machine

why?

aesthetics: create familiar harmony and rhythms for participants

practicality: limited number of useful datasets

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The Harmonically Ecosystemic Machine

installation is located in the UNT Music Building room 2009

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adapting to real-time

computational efficiency more important in real-time than offline system

improving efficiency involves tradeoffs

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adapting to real-time

reduce size of *L* FST to improve efficiency:

key normalize melody/harmony

... but this requires key estimation, which is error-prone

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adapting to real-time

reduce size of *G* FST to improve efficiency:

limit n-gram order

... but longer context may be preferable

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adapting to real-time

length of melodic input also impacts efficiency

- longer input melody is more computationally expensive
- ... but longer context generally provides better harmonizations
- also impacts system latency

adapting to real-time

for our implementation:

key-normalized *L* FST

key independent chord representation

n-gram order = 3

input melody length of 8 beats

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conclusions

harmonic generation system was only offline

project was an opportunity to explore system in a real-time setting

practical and aesthetic benefits

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Thanks!

Music Building room 2009

http://steinhardt.nyu.edu/marl/research/sonic_spaces

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