Automated Music Transcription based on Formal Language Models

Florent Jacquemard, Inria Paris

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Vertigo team & Codex Exploratory Action

Philippe Rigaux
le cnam Paris

Florent Jacquemard
Inria

Raphaël Fournier-S’niehotta
le cnam

Lydia Rodriguez-de la Nava
PhD (Codex, Inria)

Tiange Zhu
PhD (Polifonia, H2020)

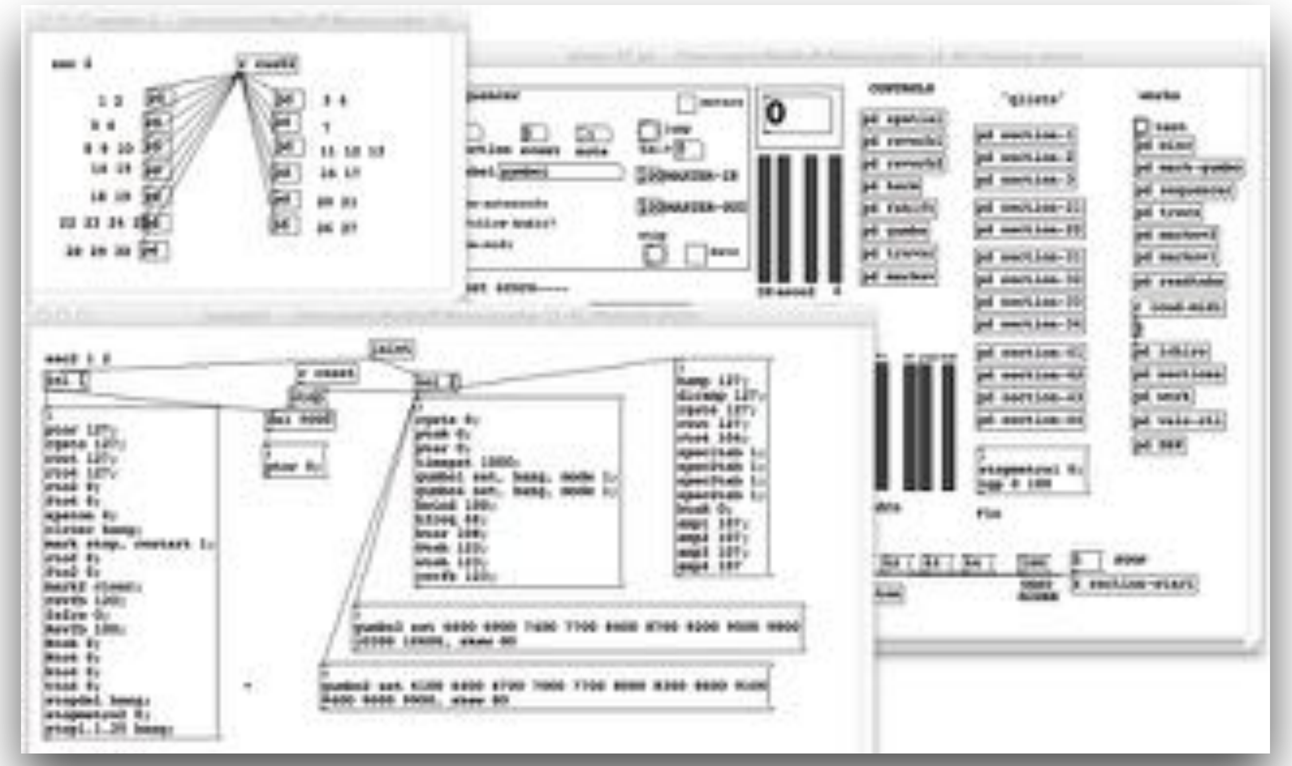
post-doc (Collabscore, ANR)

Music Notation Processing

E. Granados, Goyescas
typesetted with Lilypond

Why studying Music Notation Processing?

Western Music Notation = graphical format for music practice,
in use since ~1000 years (Guido d'Arezzo)



vs

Philippe Manoury
Tensio for string quartet and electronics

(digital) music scores, a natural language for

- performers
  performance : real-time reading or memoization
- composers
  authoring, exchange
- teachers & students
  transmission
- editors
  access digital score libraries *e.g.* nkoda.com
- librarians
  cultural heritage preservation: *e.g.* Gallica
- scholars (historians, musicologists…)
  research, analysis

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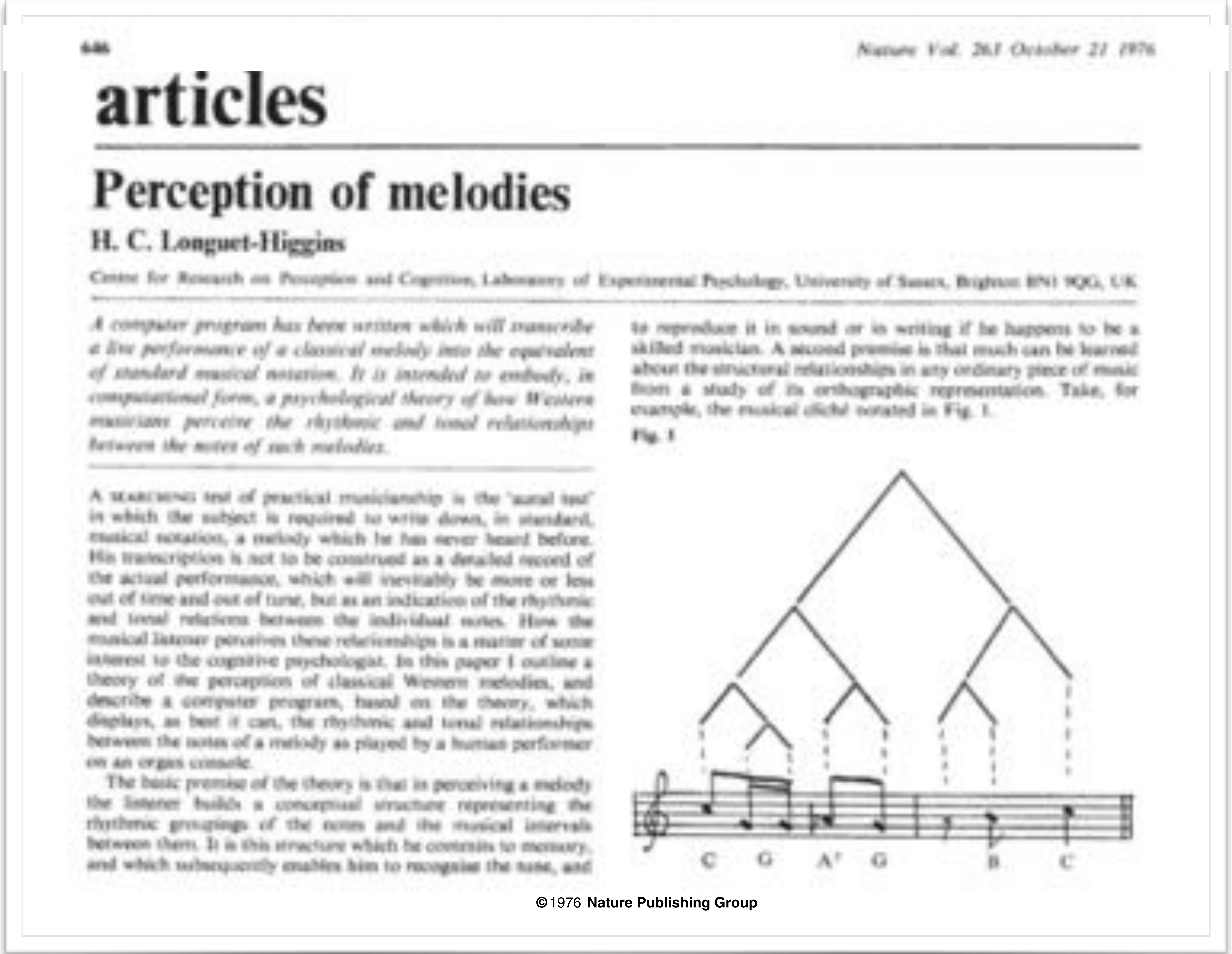
Music Notation Processing

- Structured music score models
  hierarchical representation of music scores
- Music scores languages
  finite representations of ∞ sets of scores (*style*)
- Search and retrieval
  indexing, exact or approximate search, facetted
- Similarity metrics
  string and tree edit-distances

Applications

- Databases of digital music scores
  Cultural heritage preservation H2020 Polifonia - U. Bologna, Open University, King's College, Vrije U. Amsterdam
- Computational Musicology
  neuma.huma-num.fr - IReMus (Paris), AlgoMus (Lille)
- Optical Music Recognition, Crowdsourced correction
  ANR Collabscore - IRISA (Renne), French National Library, Royaumont
- Automated Music Transcription
  JSPS 採譜, grant Yamaha Music Foundation - JAIST, Nagoya U.

Conversion of a recorded music performance into a music score ~ *speech-to-text* in NLP
a holy graal in Computer Music since 1970’s



646 Nature Vol. 263 October 21 1976

articles

Perception of melodies

H. C. Longuet-Higgins

Centre for Research on Perception and Cognition, Laboratory of Experimental Psychology, University of Sussex, Brighton BN1 9QG, UK

A computer program has been written which will transcribe a live performance of a classical melody into the equivalent of standard musical notation. It is intended to embody, in computational form, a psychological theory of how Western musicians perceive the rhythmic and tonal relationships between the notes of such melodies.

A SEARCHING test of practical musicianship is the 'aural test' in which the subject is required to write down, in standard musical notation, a melody which he has never heard before. His transcription is not to be construed as a detailed record of the actual performance, which will inevitably be more or less out of time and out of tune, but as an indication of the rhythmic and tonal relations between the individual notes. How the musical listener perceives these relationships is a matter of some interest to the cognitive psychologist. In this paper I outline a theory of the perception of classical Western melodies, and describe a computer program, based on the theory, which displays, as best it can, the rhythmic and tonal relationships between the notes of a melody as played by a human performer on an organ console.

The basic premise of the theory is that in perceiving a melody the listener builds a conceptual structure representing the rhythmic groupings of the notes and the musical intervals between them. It is this structure which he commits to memory, and which subsequently enables him to recognise the tune, and to reproduce it in sound or in writing if he happens to be a skilled musician. A second premise is that much can be learned about the structural relationships in any ordinary piece of music from a study of its orthographic representation. Take, for example, the musical cliché notated in Fig. 1.

Fig. 1

Conversion of a recorded music performance into a music score

source(s)

Audio recording

MIDI device
(score edition)

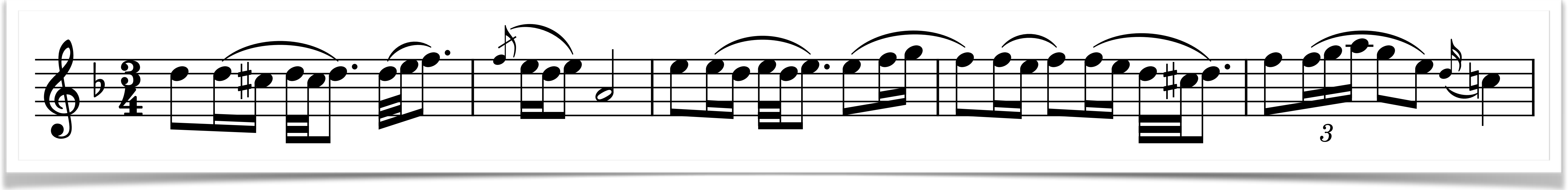
Algorithmic composition
DAW

audio Music Information Retrieval
- fundamental freq. estimation
- onset detection
- beat tracking …

intermediate representation
piano roll (MIDI file)
- unquantized onsets, durations
- quantized pitches

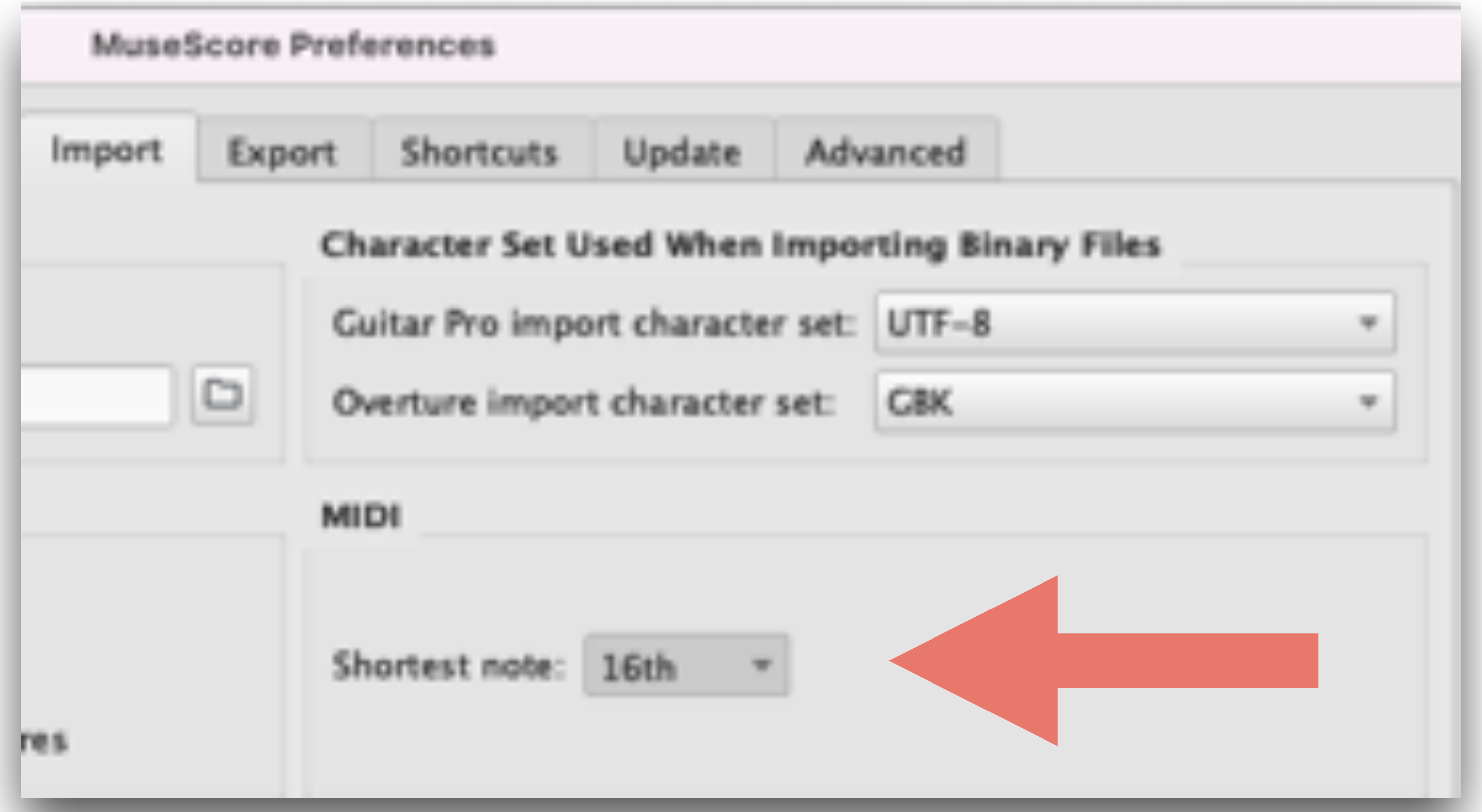
symbolic Music Information Retrieval
- rhythm quantization
- tempo tracking
- score engraving…

target
music score
(XML file)

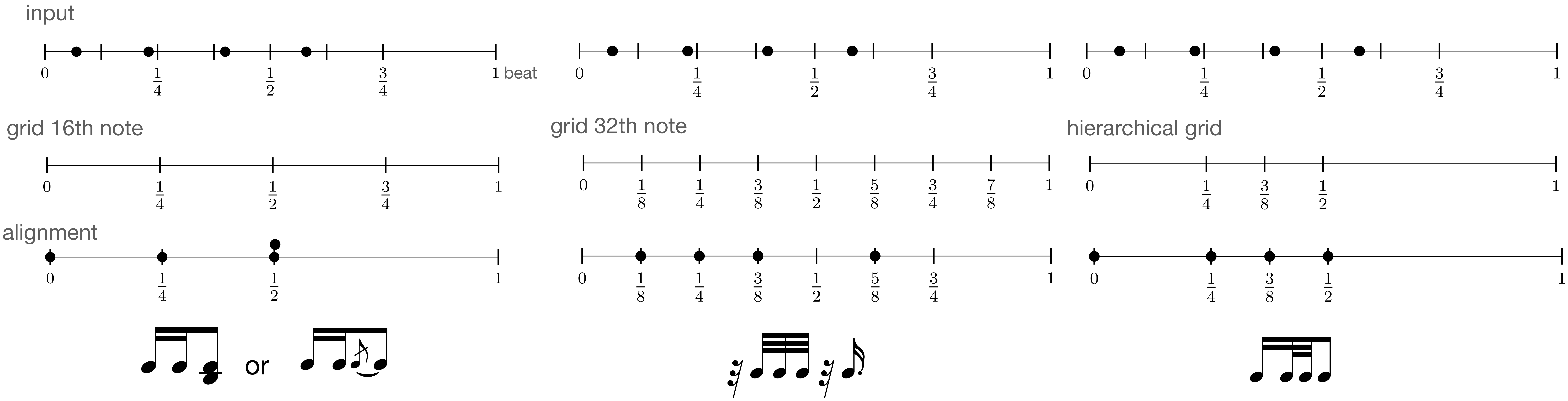


Grid based Approaches to Rhythm Quantization

Rhythm quantization with grids, *e.g.* MIDI files import
- in score editors (Finale, Sibelius, Dorico, Musescore…),
- or in DAWs (Ableton Live, Logic…)



Alignment of every input time point (onset) to the closest position in a *grid* = sequence of equidistant time position.

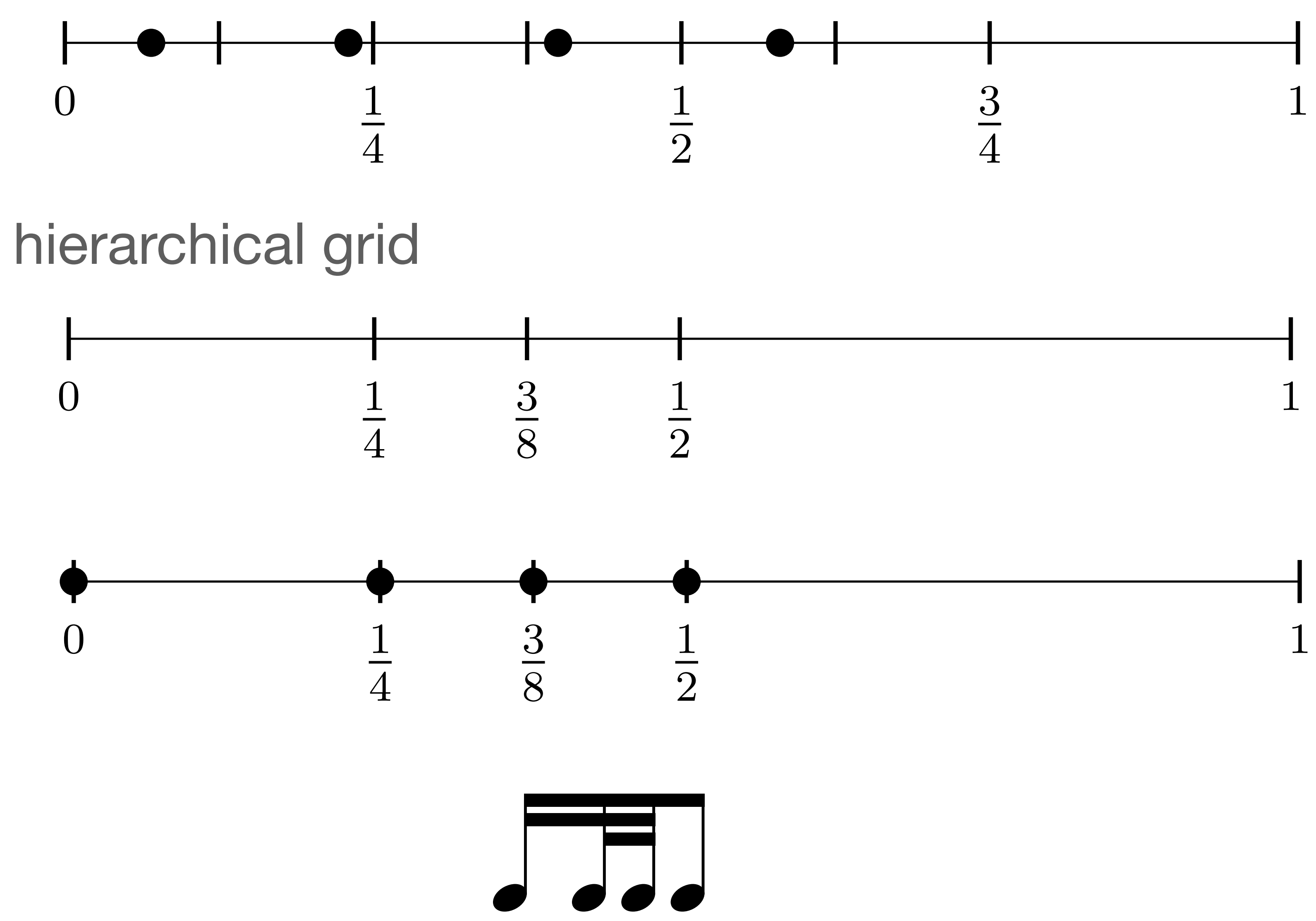


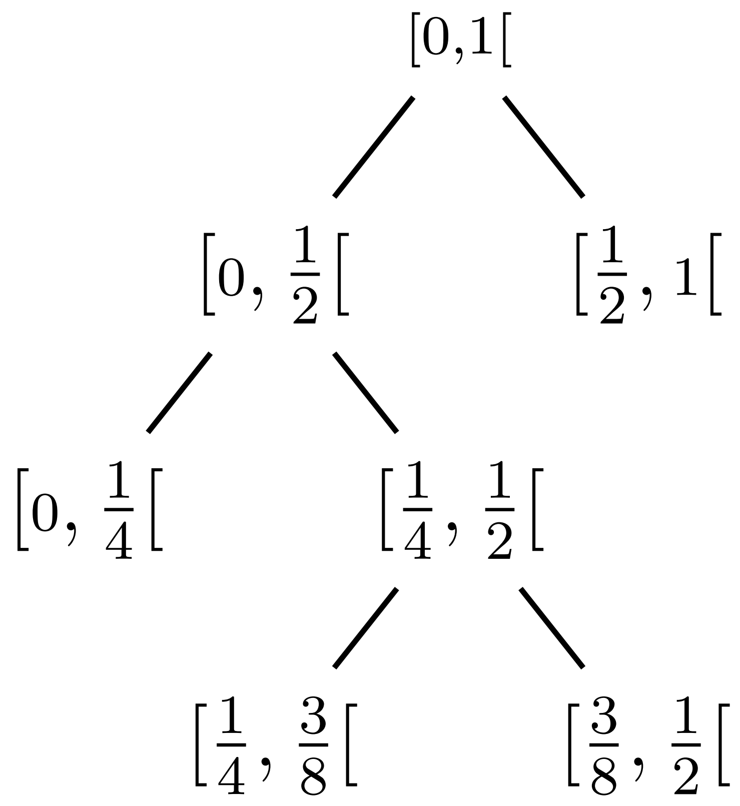
poor fit, good readability

good fit, bad readability

closer to intuition

Regular *vs* Irregular Grids



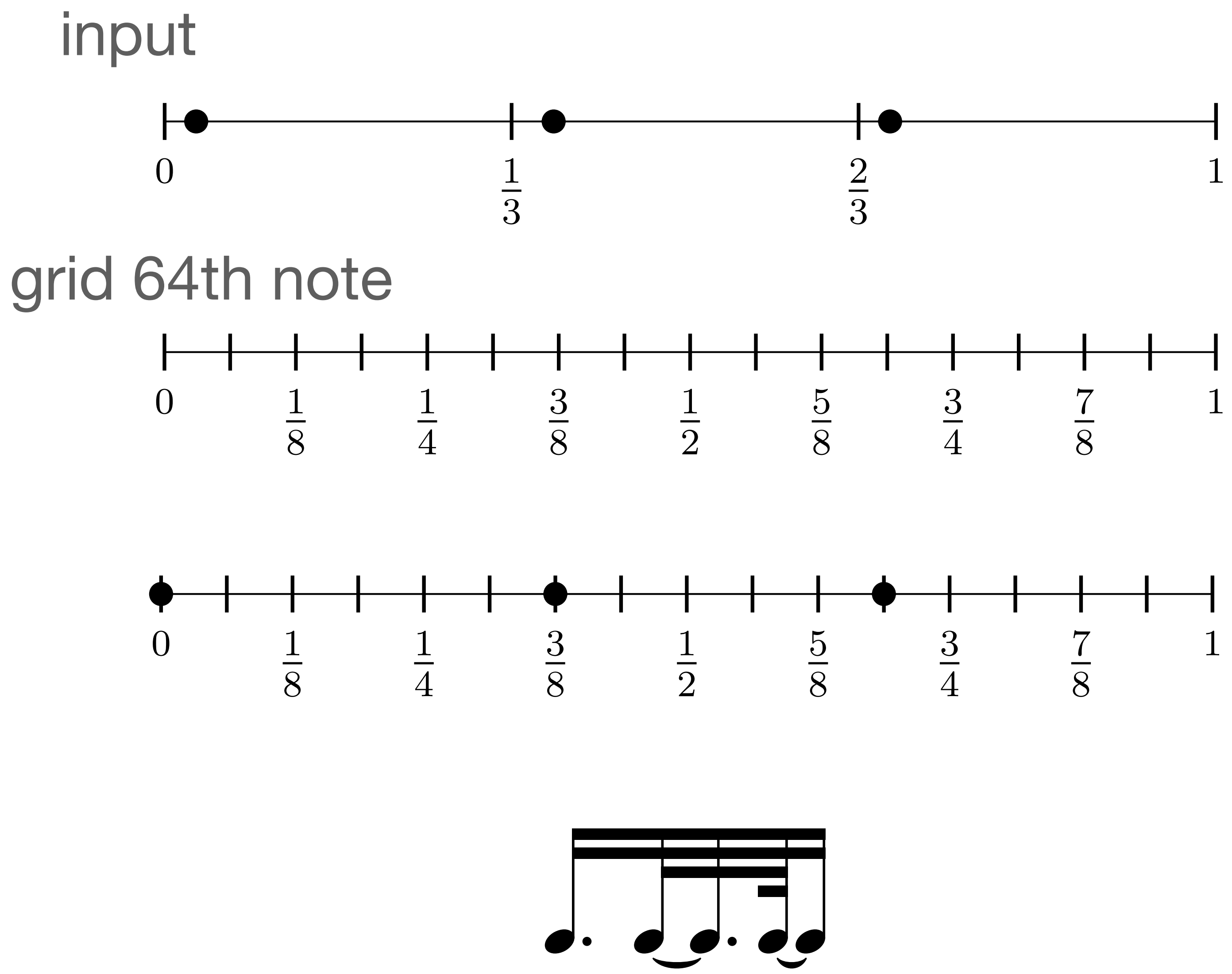


regular grids

- search of a best quantization is possible by a brute-force enumeration: 8th note grid, 16th, 32th, 64th…
- result not always optimal
- problems with tuplets (so called “*irrationals*” 3, 5, 7…*)*

hierarchical grids

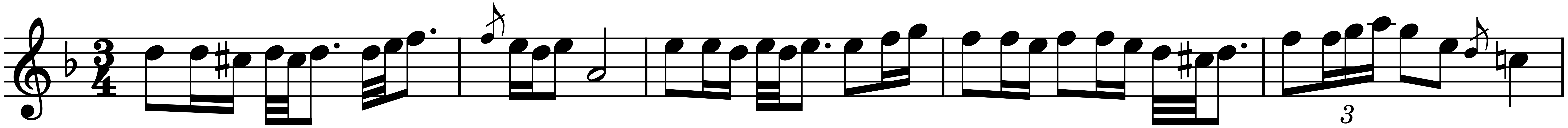
- more “natural” results
- brute force enumeration impossible
- how to specify the grids to try ?



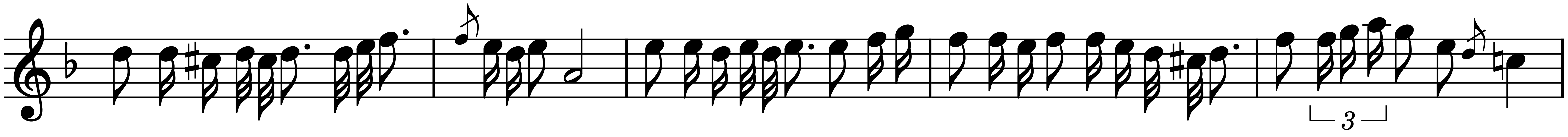
Common Western Music Notation

Polonaise in D minor from Notebook for Anna Magdalena Bach   BWV Anh II 128

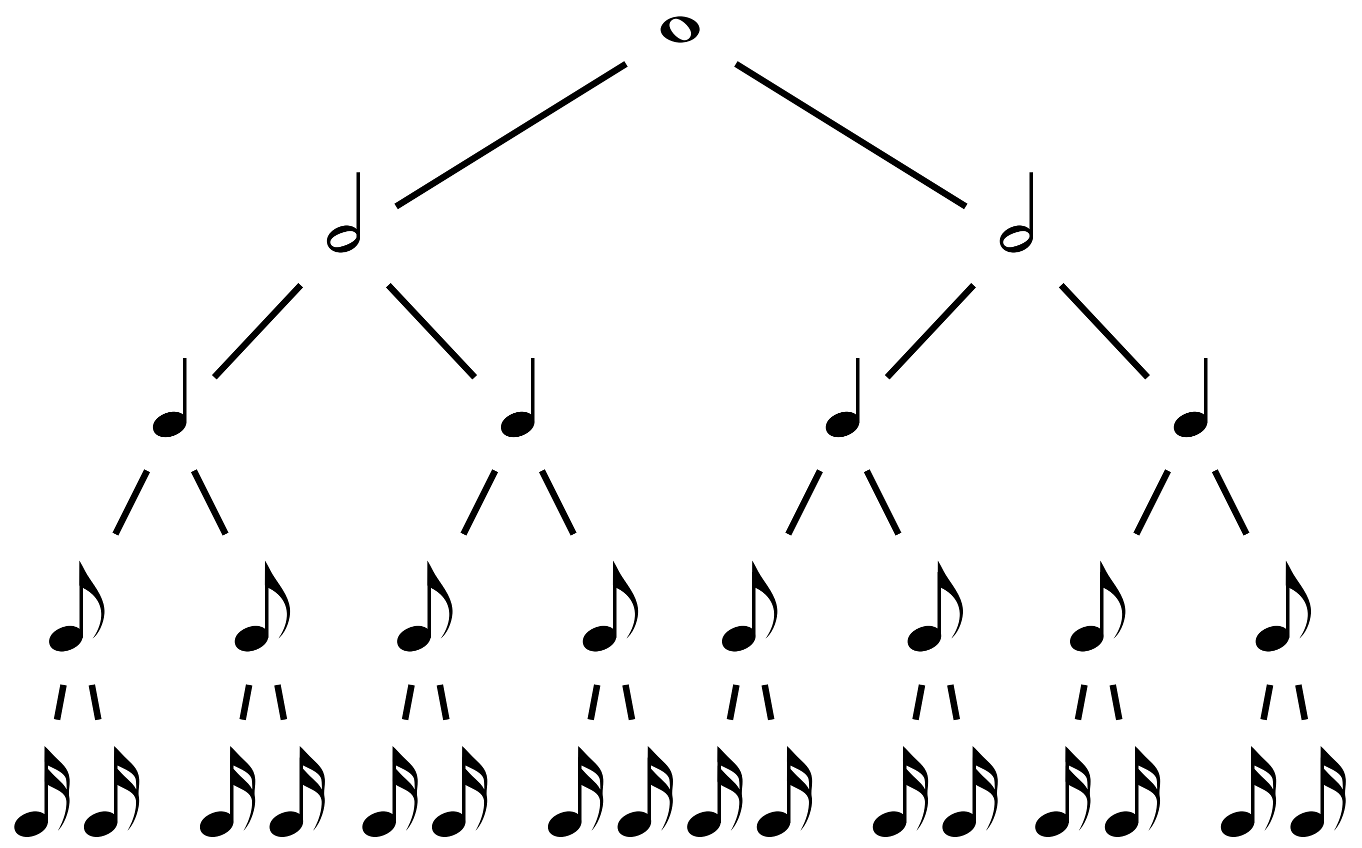
beamed



unbeamed



hierarchical
note
durations



Polonaise in D minor from Notebook for Anna Magdalena Bach BWV Anh II 128

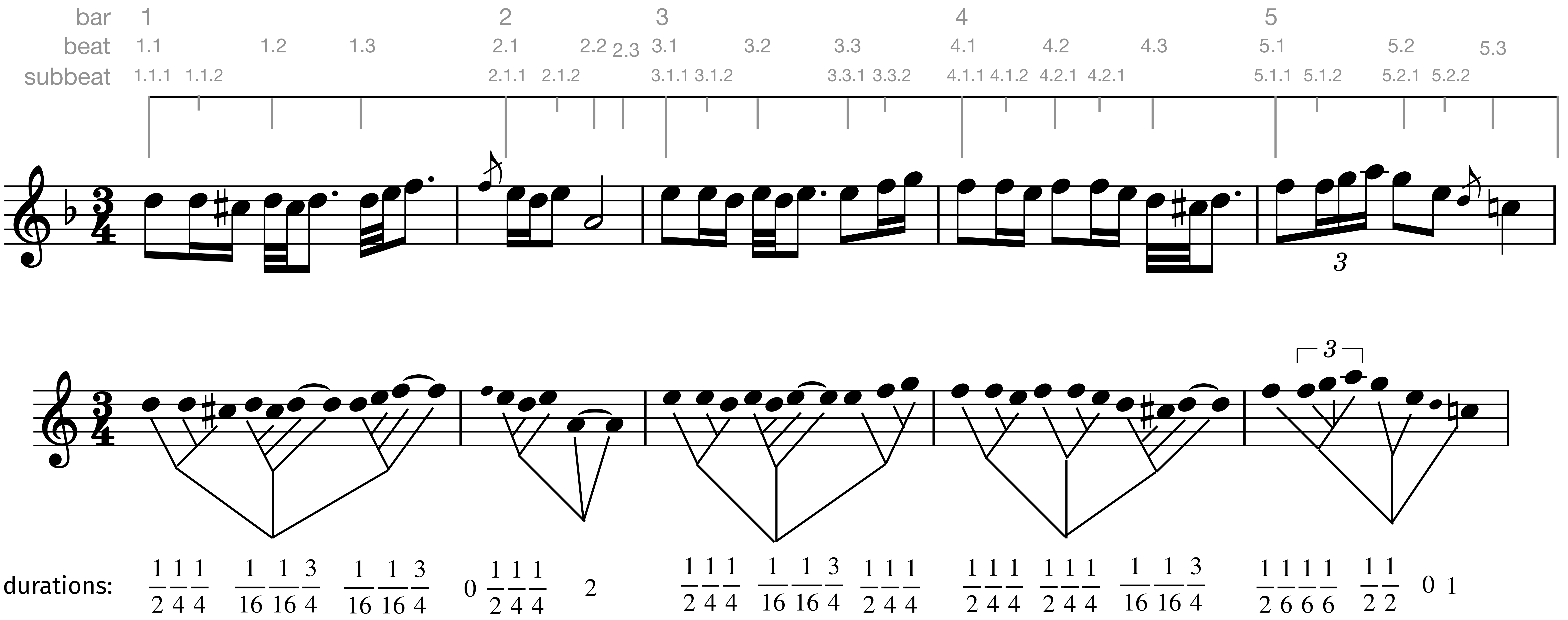
grouping notes with measure bars and beams

- eases readability (player reads in a real-time context)
- highlight the metric structure
  hierarchy of strong / weak beats

Common Western Music Notation

Polonaise in D minor from Notebook for Anna Magdalena Bach   BWV Anh II 128

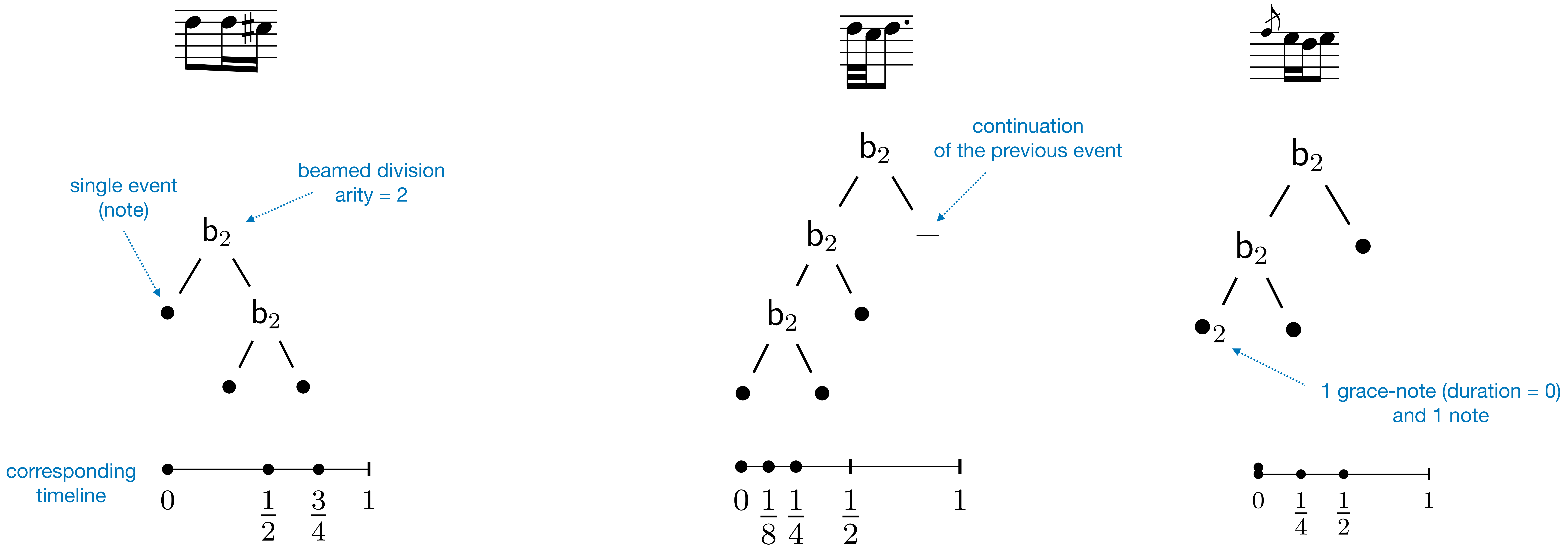
metric structure



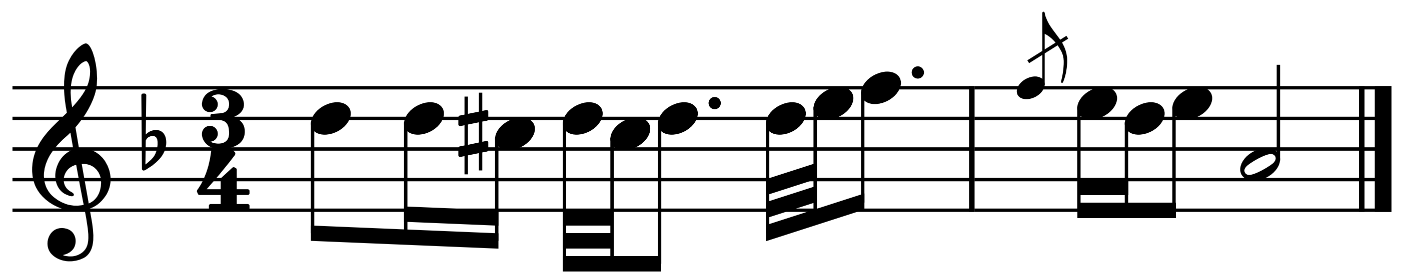
Tree-structured Representation of Music Notation

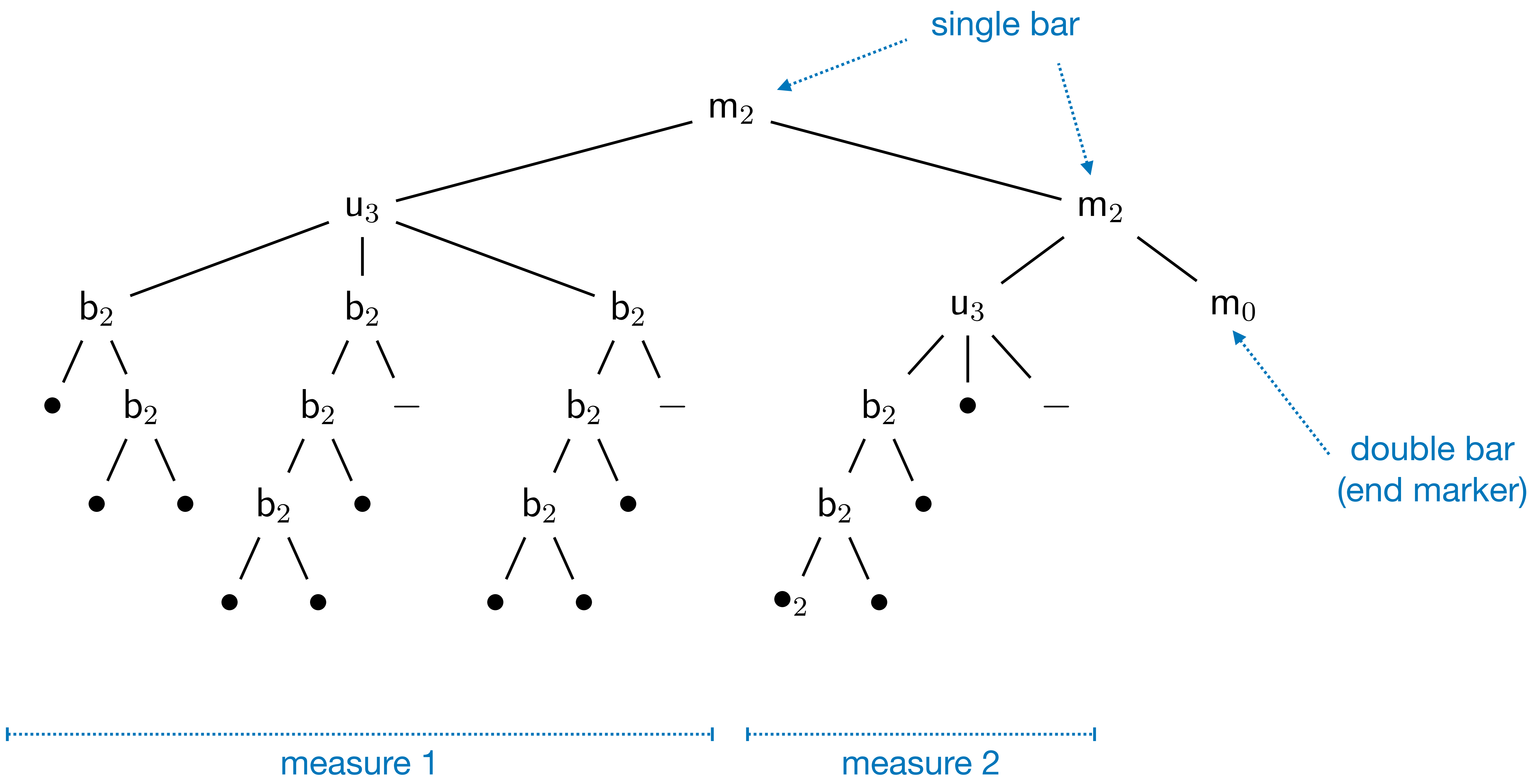
Tree representation of the proportional rhythmic notation
with hierarchical encoding of durations: “*the* (duration) *data is in the structure*”

- the tree leaves contain the events
- the branching define durations, by partitioning of time intervals



Tree-structured Representation of Music Notation





defined by a Regular Tree Grammar:

- non-terminal symbols: $q, q_0, q_1, \ldots$
- terminal symbols (constants): $\bullet$ (1 note), $\bullet_2$ (1 grace-note + 1 note), $-$ (continuation)
- production rules:

$$q \to \mathrm{m}_2(q_0, q) \mid \mathrm{m}_0$$

$$q_0 \to \mathrm{u}_3(q_1, q_1, q_1) \mid \bullet$$

$$q_1 \to \mathrm{b}_2(q_2', q_2) \mid \bullet \mid \bullet_2 \mid -$$

$$q_2' \to \mathrm{b}_2(q_3', q_3) \mid \bullet \mid \bullet_2 \mid - \qquad q_2 \to \mathrm{b}_2(q_3, q_3) \mid \bullet \mid -$$

$$q_3' \to \bullet \mid \bullet_2 \mid - \qquad q_3 \to \bullet \mid -$$

measure

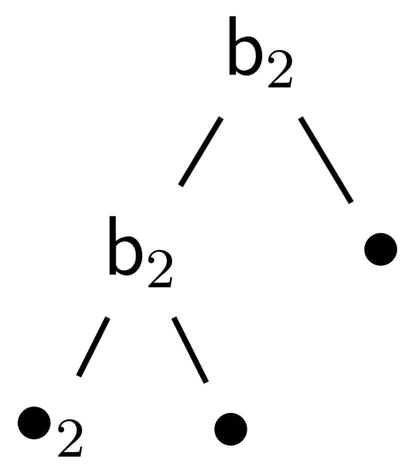
beat = ♩

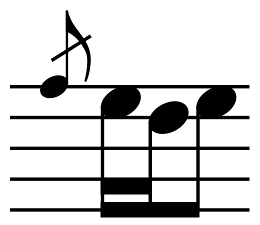
sub-beat = 8th-note = ♪

sub-sub-beat = 16nth note = 𝅘𝅥𝅯

derivations (lefmost)

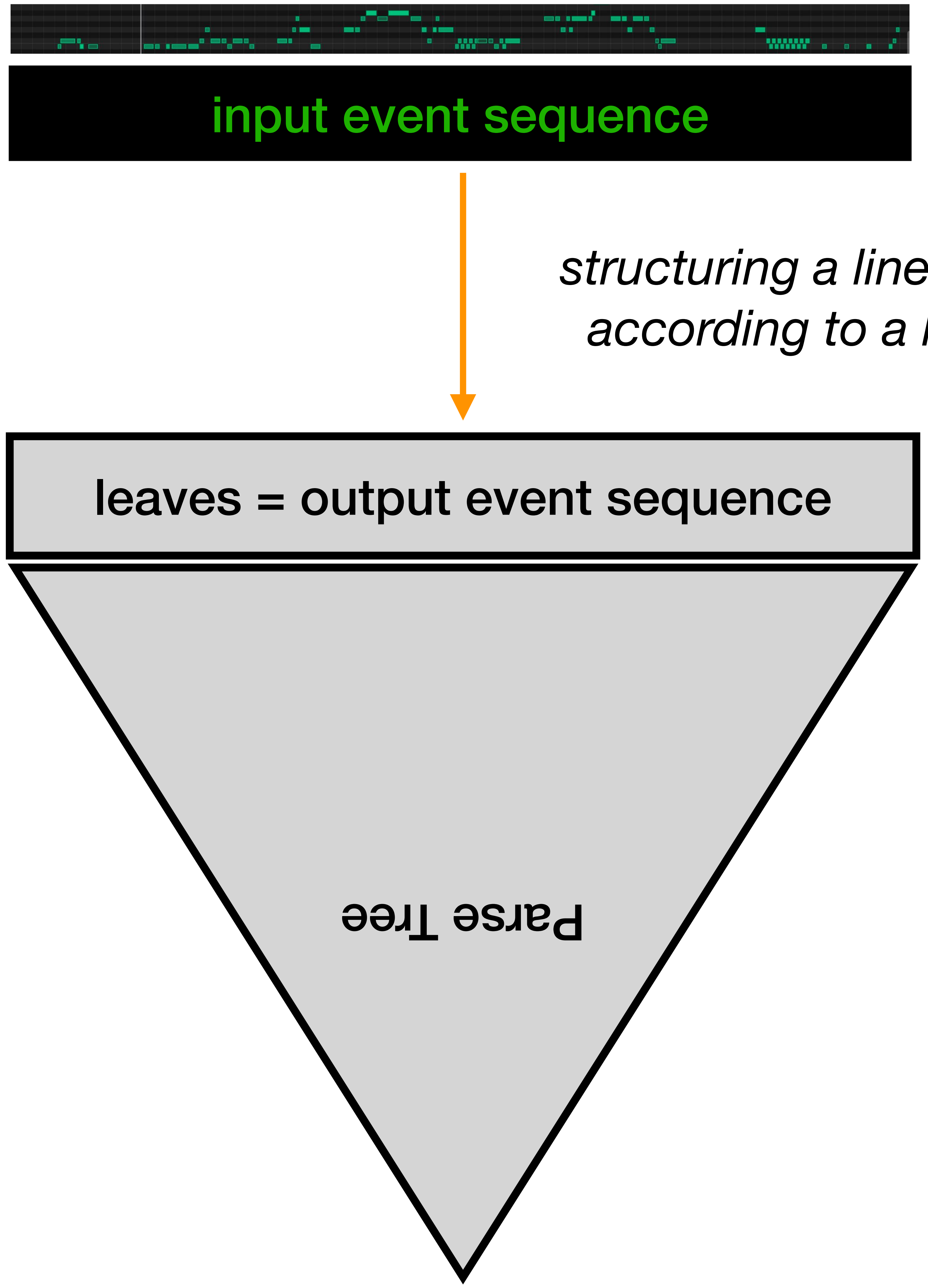
$$q_1 \to \mathrm{b}_2(q_2', q_2) \to \mathrm{b}_2(\mathrm{b}_2(q_3', q_3), q_2) \to \mathrm{b}_2(\mathrm{b}_2(\bullet_2, q_3), q_2) \to \mathrm{b}_2(\mathrm{b}_2(\bullet_2, \bullet), q_2) \to \mathrm{b}_2(\mathrm{b}_2(\bullet_2, \bullet), \bullet)$$





$$q \to \mathrm{m}_2(q_0, q) \to \mathrm{m}_2(\mathrm{u}_3(q_1, q_1, q_1), q) \to \mathrm{m}_2(\mathrm{u}_3(\mathrm{b}_2(q_2', q_2), q_1, q_1), q) \to \mathrm{m}_2(\mathrm{u}_3(\mathrm{b}_2(\bullet, q_2), q_1, q_1), q) \to \ldots$$

Transcription as Parsing



piano roll
= sequence of timestamped input events

structuring a linear representation according to a language model = **parsing**

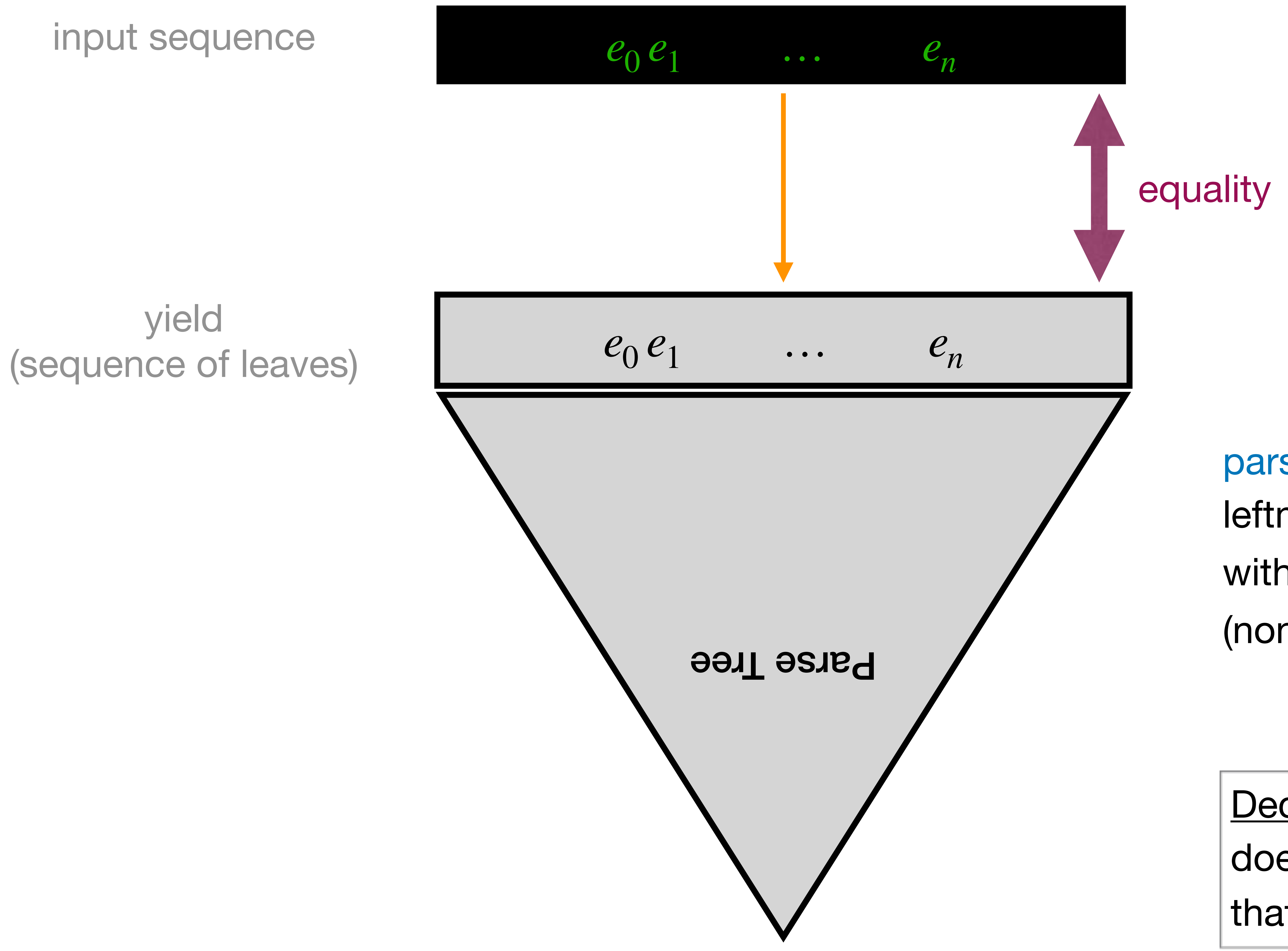
tree-structured representation of an output **music score**

conforming to a prior language (expected notation)

2 nested extensions of parsing are needed for the case music transcription:

- weighted extension
- symbolic weighted extension (*quantitative parsing*)

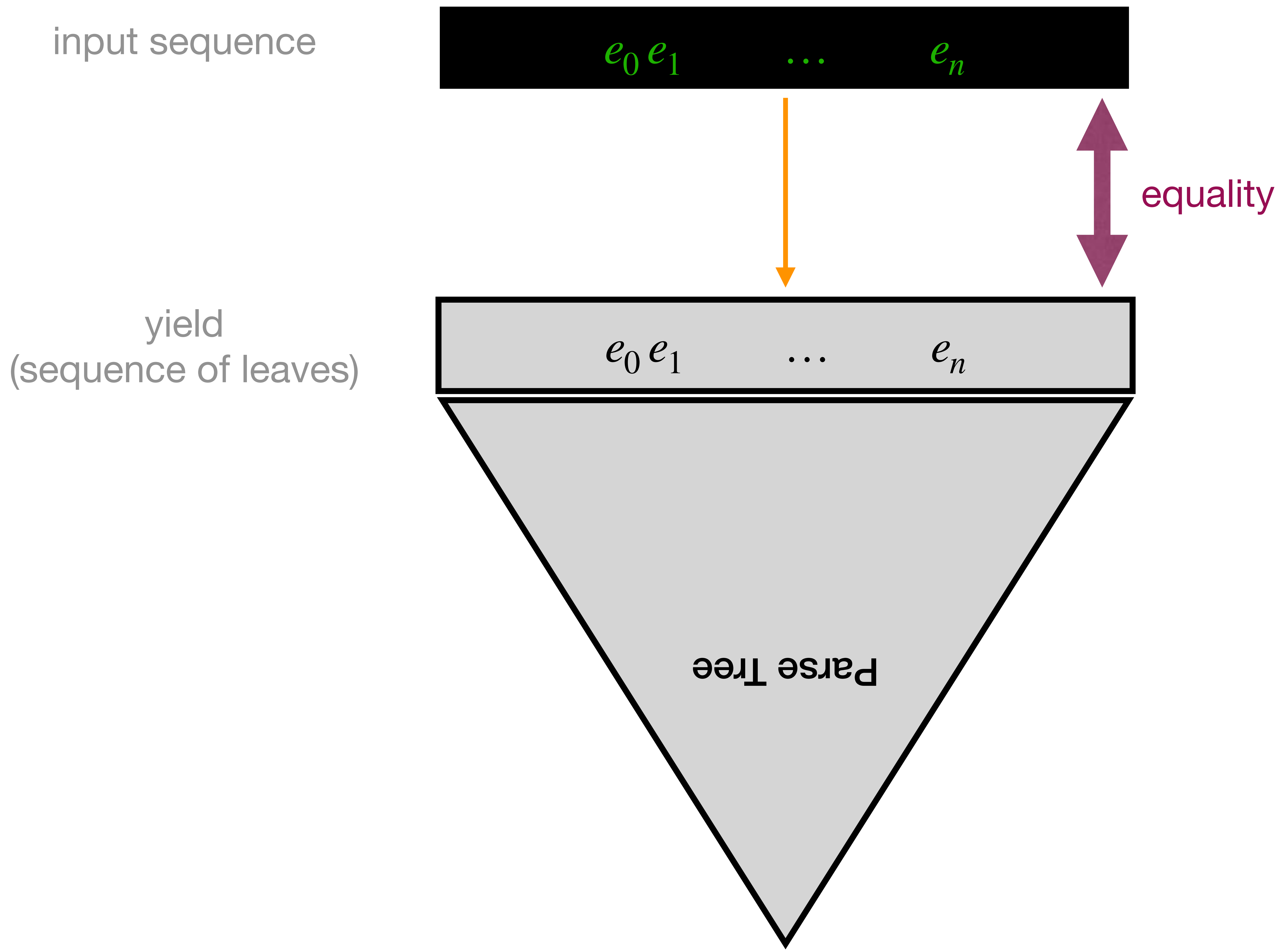
terminal symbols: $e_0, \ldots$ in a finite alphabet



parse-tree = representation of a leftmost derivation of $e_0\, e_1 \ldots e_n$ by a prior CF-grammar $\mathscr{G}$ with production rules: $q_0 \to q_1\, q_2$ or $q_0 \to e$ (non-terminal symbols: $q_0, q_1, \ldots$)

Decision problem: (membership)
does there exists a parse tree (leftmost derivation) of $\mathscr{G}$ that yields $e_0\, e_1 \ldots e_n$?

Returning a parse tree of $\mathscr{G}$ that yields $e_0\, e_1 \ldots e_n$



With an ambiguous prior CF-grammar $\mathscr{G}$ there might exists several parse trees (exponentially many).

in order to choose one (or some) parse trees, rank them according to their weight values, computed by Weighted Tree Grammar

Weighted Tree Language (*tree series*)

Weighted Regular Tree Grammar $\mathscr{G}$:

- non-terminal symbols: $q, q_0, q_1, \ldots$
- terminal symbols (constants): • (1 note), $\bullet_2$ (1 grace-note + 1 note), — (continuation)
- every production rule is assigned a weight value (*e.g.* cost to read):

$q \xrightarrow{0} \mathsf{m}_2(q_0, q)$	$q \xrightarrow{0} \mathsf{m}_0$					
$q_0 \xrightarrow{0.1} \mathsf{u}_3(q_1, q_1, q_1)$	$q_0 \xrightarrow{1} \bullet$					measure
$q_1 \xrightarrow{0.1} \mathsf{b}_2(q_2', q_2)$	$q_1 \xrightarrow{1} \bullet$	$q_1 \xrightarrow{1.9} \bullet_2$	$q_1 \xrightarrow{1} -$			beat = ♩
$q_2' \xrightarrow{0.1} \mathsf{b}_2(q_3', q_3)$	$q_2' \xrightarrow{1} \bullet$	$q_2' \xrightarrow{2.25} \bullet_2$	$q_2' \xrightarrow{1} -$			sub-beat = 8th-note = ♪
$q_2 \xrightarrow{0.1} \mathsf{b}_2(q_3, q_3)$	$q_2 \xrightarrow{1} \bullet$		$q_2 \xrightarrow{1} -$			
	$q_3' \xrightarrow{1} \bullet$	$q_3' \xrightarrow{3.25} \bullet_2$	$q_3' \xrightarrow{1} -$	$q_3 \xrightarrow{1} \bullet$	$q_3 \xrightarrow{1} -$	sub-sub-beat = 16th note = 𝅘𝅥𝅯

derivation (lefmost): $d : q_1 \xrightarrow{0.1} \mathsf{b}_2(q_2', q_2) \xrightarrow{0.1} \mathsf{b}_2(\mathsf{b}_2(q_3', q_3), q_2) \xrightarrow{3.25} \mathsf{b}_2(\mathsf{b}_2(\bullet_2, q_3), q_2) \xrightarrow{1} \mathsf{b}_2(\mathsf{b}_2(\bullet_2, \bullet), q_2) \xrightarrow{1} \mathsf{b}_2(\mathsf{b}_2(\bullet_2, \bullet), \bullet)$

cost of derivation: $\mathsf{weight}(d) = 0.1 + 0.1 + 3.25 + 1 + 1$

learning weight values from corpus statistics
Francesco Foscarin

In general, the weight values are taken in a commutative Semiring $\langle \mathbb{S}, \oplus, \mathbb{0}, \otimes, \mathbb{1} \rangle$

- $\oplus$ and $\otimes$ are associative and commutative, with neutral elements $\mathbb{0}$ and $\mathbb{1}$
- $\otimes$ distributes over $\oplus$: $x \otimes (y \oplus z) = (x \otimes y) \oplus (x \otimes z)$
- $\mathbb{0}$ is absorbing for $\otimes$: $\mathbb{0} \otimes x = \mathbb{0}$

	domain	$\oplus$	$\otimes$	$\mathbb{0}$	$\mathbb{1}$
Boolean	$\{\bot, \top\}$	$\vee$	$\wedge$	$\bot$	$\top$
Viterbi	$[0,1] \subset \mathbb{R}$	max	$\times$	0	1
Tropical min-plus	$\mathbb{R}_+ \cup \{+\infty\}$	min	$+$	$+\infty$	0

Moreover, $\oplus$ is assumed to extend to infinite sums: there is an operation $\bigoplus_{i \in I} x_i$ for all $I \subseteq \mathbb{N}$ such that:

infinite sums extend finite sums: $\forall j, k \in \mathbb{N}, j \neq k, \bigoplus_{i \in \emptyset} x_i = \mathbb{0}, \bigoplus_{i \in \{j\}} x_i = x_j, \bigoplus_{i \in \{j,k\}} x_i = x_j \oplus x_k$

associativity and *commutativity*:
for all partition $(I_j)_{j \in J}$ of I, $\bigoplus_{j \in J} \bigoplus_{i \in I_j} x_i = \bigoplus_{i \in I} x_i$

distributivity of products over infinite sums: for all $I \subseteq \mathbb{N}$, $\forall x, y \in \mathbb{S}$
$\bigoplus_{i \in I} (x \otimes y_i) = x \otimes \bigoplus_{i \in I} y_i$ and $\bigoplus_{i \in I} (x_i \otimes y) = (\bigoplus_{i \in I} x_i) \otimes y$

Weight of derivations and trees

	domain	$\oplus$	$\otimes$	$\mathbb{0}$	$\mathbb{1}$
Boolean	$\{\bot, \top\}$	$\vee$	$\wedge$	$\bot$	$\top$
Viterbi	$[0,1] \subset \mathbb{R}$	$\max$	$\times$	0	1
Tropical min-plus	$\mathbb{R}_+ \cup \{+\infty\}$	$\min$	$+$	$+\infty$	0

$\otimes$ is for composition of rule's weights in derivations and $\oplus$ is for optimal choice:

For a Weighted Regular Tree Grammar $\mathcal{G}$

$$\mathrm{weight}_{\mathcal{G}}(d : q \xrightarrow{w_1} \ldots \xrightarrow{w_n} t) = \bigotimes_{i=1}^{n} w_i \quad \text{and} \quad \mathrm{weight}_{\mathcal{G}}(q, t) = \bigoplus_{d : q \xrightarrow{+} t} \mathrm{weight}_{\mathcal{G}}(d)$$

or recursively:

$$\mathrm{weight}_{\mathcal{G}}(q, a(t_1, \ldots, t_n)) = \bigoplus_{q \xrightarrow{w} a(q_1, \ldots, q_n) \in \mathcal{G}} \left(w \otimes \bigotimes_{i=1}^{n} \mathrm{weight}_{\mathcal{G}}(q_i, t_i) \right)$$

	domain	$\oplus$	$\otimes$	$\mathbb{0}$	$\mathbb{1}$
Boolean	$\{ \bot, \top \}$	$\vee$	$\wedge$	$\bot$	$\top$
Viterbi	$[0,1] \subset \mathbb{R}$	max	$\times$	0	1
Tropical min-plus	$\mathbb{R}_+ \cup \{+\infty\}$	min	$+$	$+\infty$	0

$\mathbb{S}$ is assumed :

- idempotent $x \oplus x = x$
  that induces a partial ordering: $x \leq_\oplus y$ iff $x \oplus y = x$
- total : $\forall x, y \in \mathbb{S}$, either $x \oplus y = x$ or $x \oplus y = y$ *i.e.* $\leq_\oplus$ is total
- bounded : $\mathbb{1} \oplus x = \mathbb{1}$, or equivalently: $\forall x, y \in \mathbb{S}, x \leq_\oplus x \otimes y$
  i.e. combining elements with $\otimes$ always increases their weight,
  see the *non-negative weights* condition for Dijkstra's shortest path algorithm

k-best parsing : enumeration of the k best weighted trees *wrt* $\leq_\oplus$ for $\mathcal{G}$ and a non-terminal q, in PTIME, user the above assumptions.

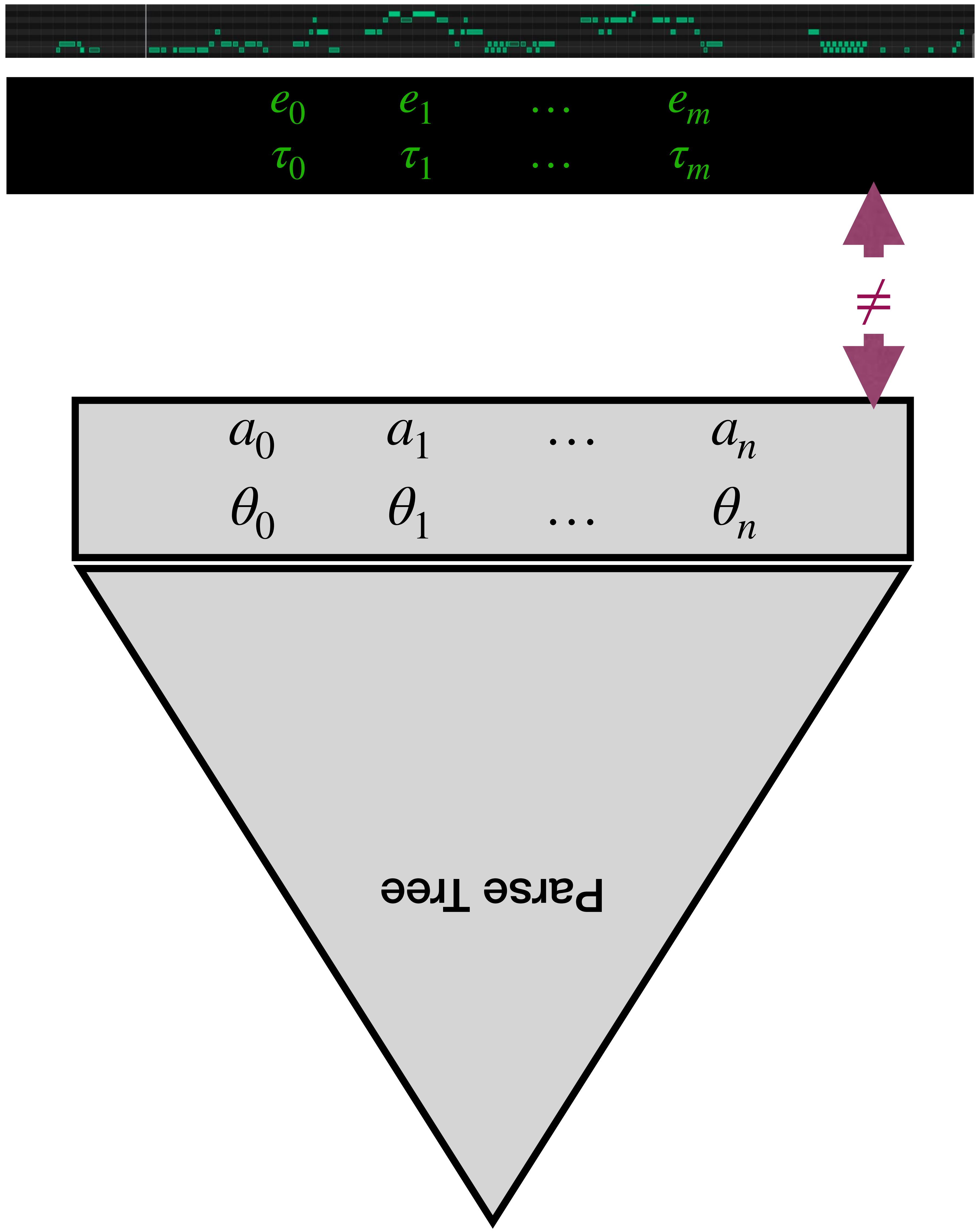
Similar to best path search in hyper-graphs (Dynamic Programming)

- Viterbi algorithm in acyclic case
- Knuth generalization of Dijkstra's algorithm in the general case

there is no 1-1 correspondance between input sequence and output leave sequence

input sequence

yield
= sequence of leaves



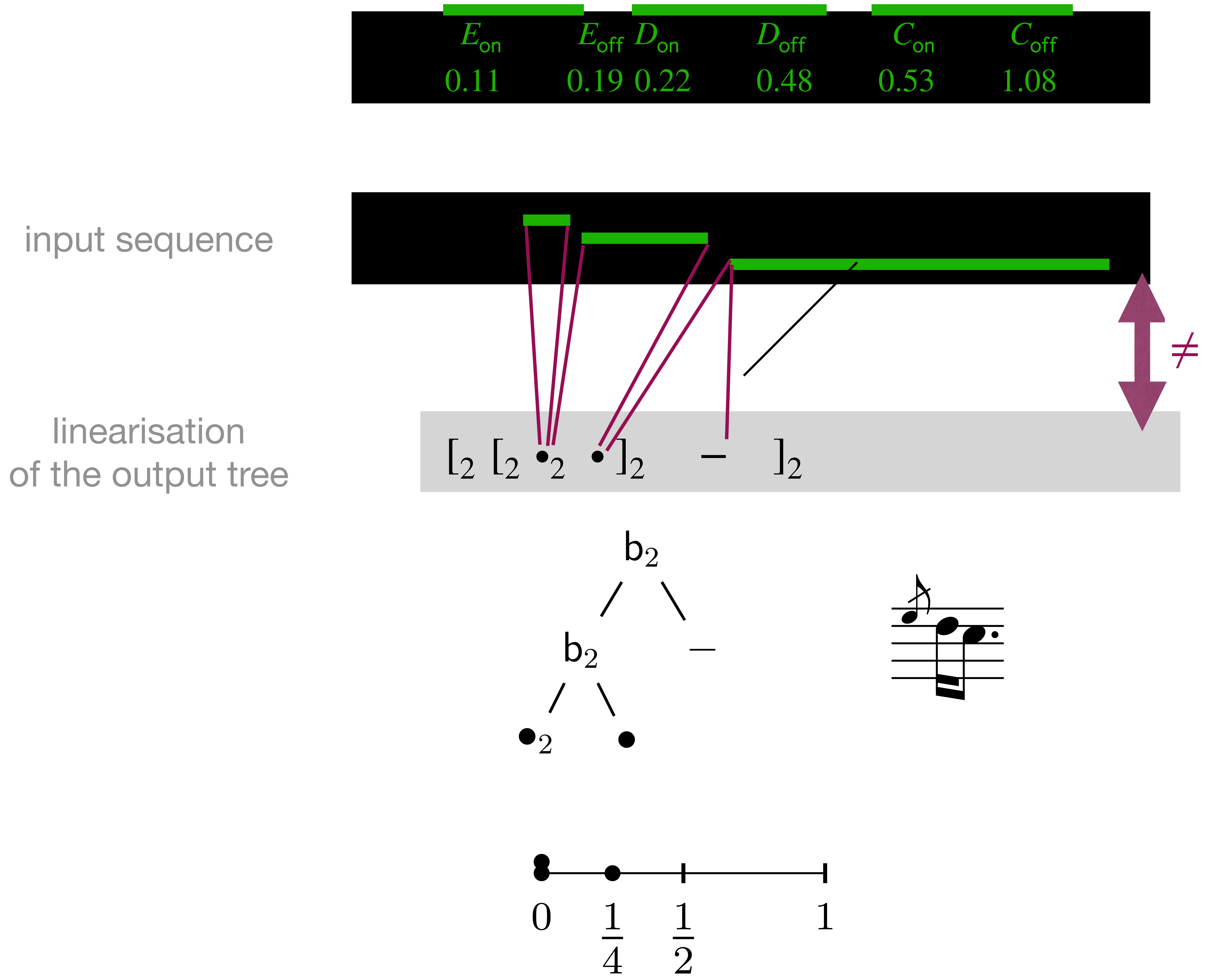
we extend weighted parsing by ranking solutions with:

a measure of input / output fitness
= cost of IO alignement

$\otimes$

measure of cost-to-read
weight value
computed by the Weighted Tree Grammar

measure of input/output fitness



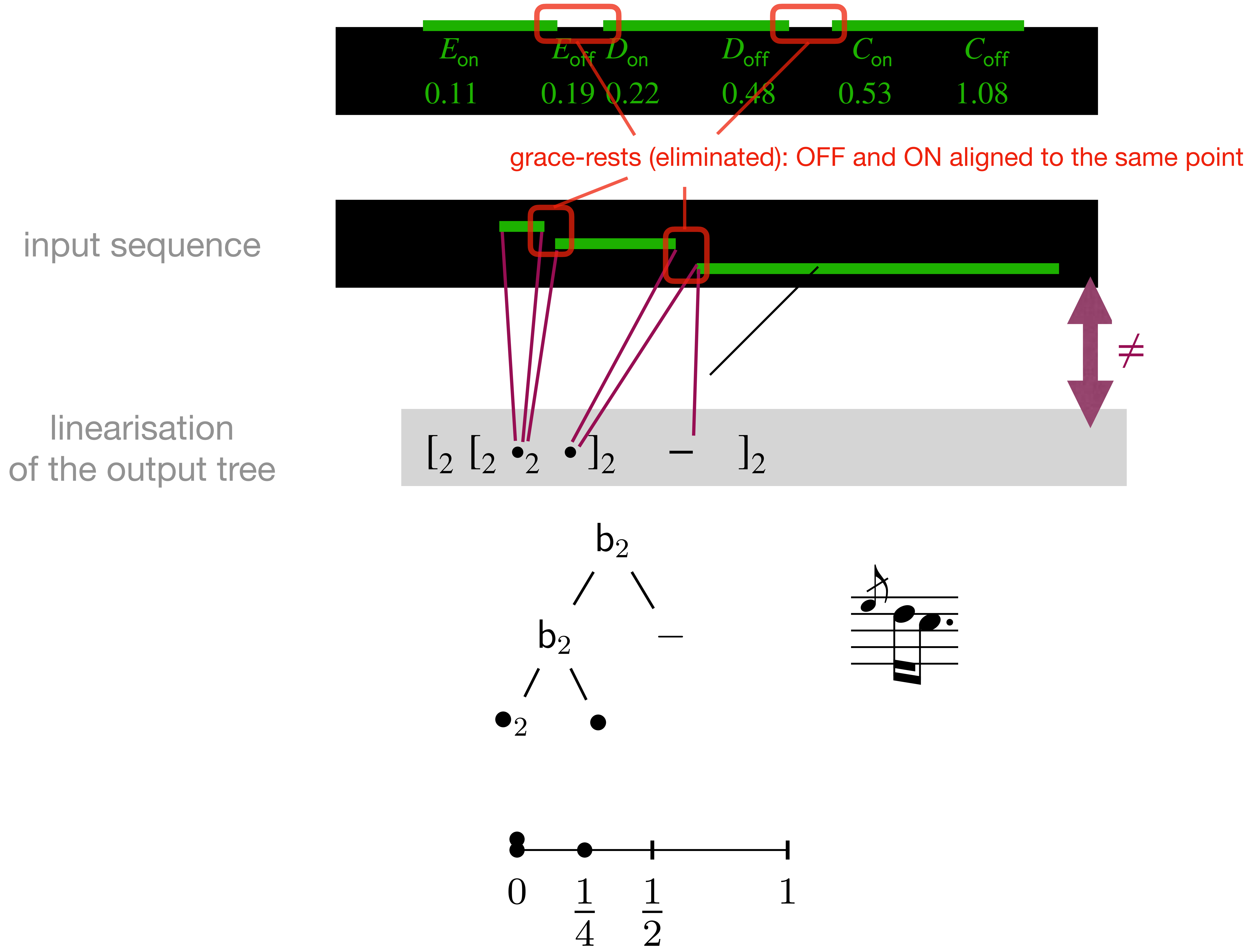
cost of IO alignement
computed by a
Weighted word-to-word Transducer
(stateful definition of an edit-distance)

input symbol — output symbol — desynchronise

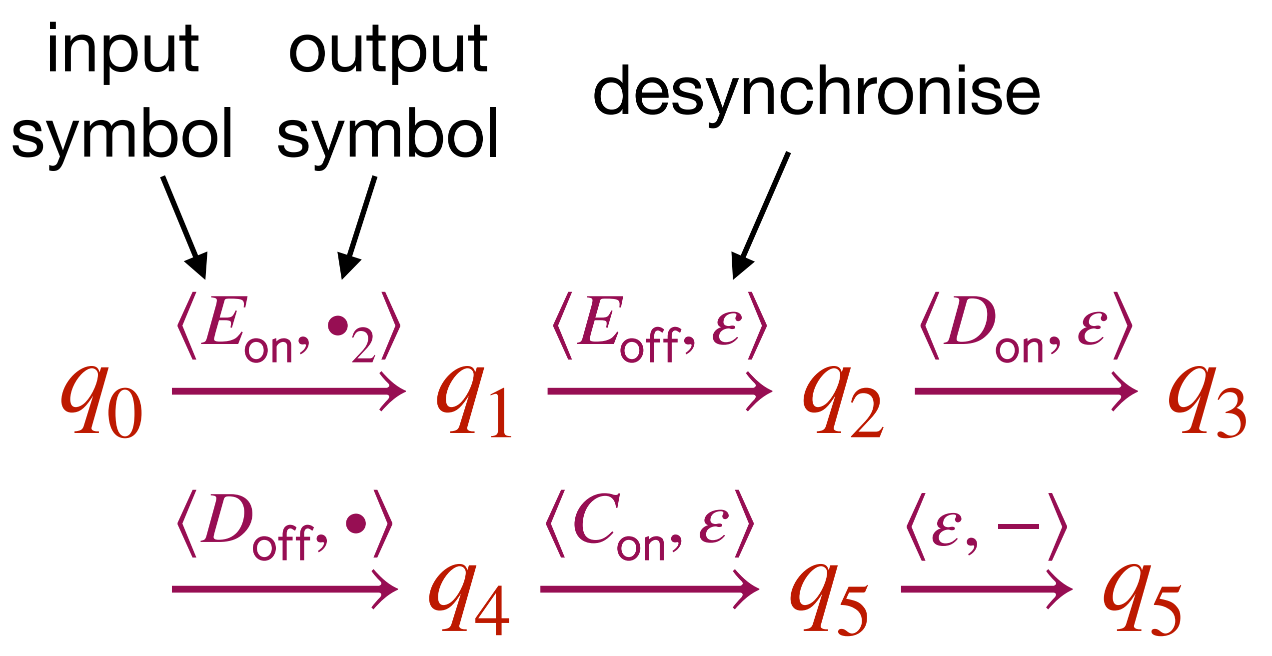
$$q_0 \xrightarrow{\langle E_{on}, \bullet_2 \rangle} q_1 \xrightarrow{\langle E_{off}, \varepsilon \rangle} q_2 \xrightarrow{\langle D_{on}, \varepsilon \rangle} q_3$$

$$\xrightarrow{\langle D_{off}, \bullet \rangle} q_4 \xrightarrow{\langle C_{on}, \varepsilon \rangle} q_5 \xrightarrow{\langle \varepsilon, - \rangle} q_5$$

measure of input/output fitness



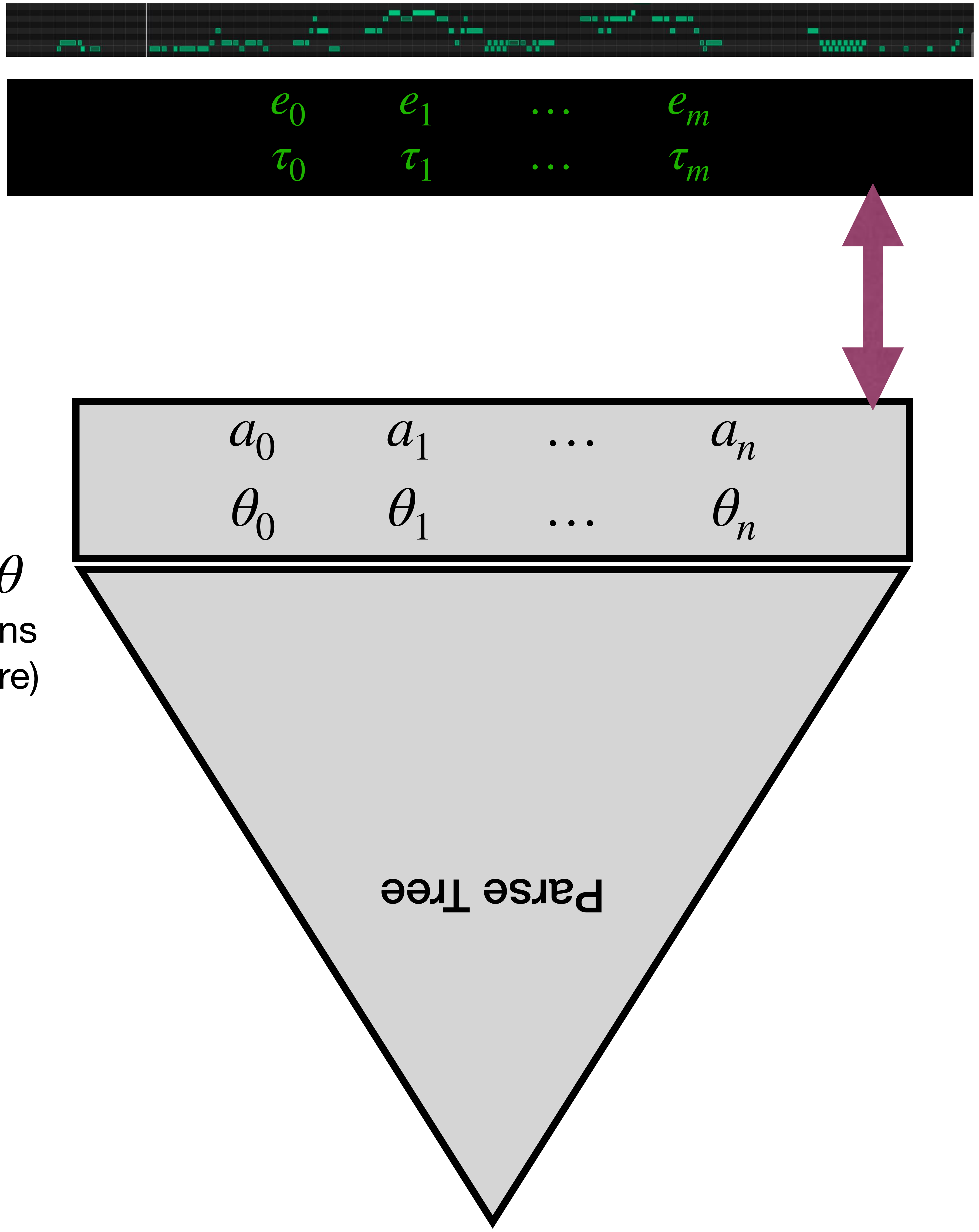
cost of IO alignement
computed by a
Weighted word-to-word Transducer
(stateful definition of an edit-distance)



Quantitative Parsing (extension 2’) : infinite alphabet

in the context of music transcription, the symbols are timestamped → infinite alphabet Σ_{inf}
the weighted formalisms below must be able to read such symbols → symbolic extension

input sequence



yield
= sequence of leaves
decorated with dates θ
(computed with the durations encoded in the tree structure)

measure of input / output fitness
= cost of IO alignement
computed by a
Weighted word-to-word Transducer

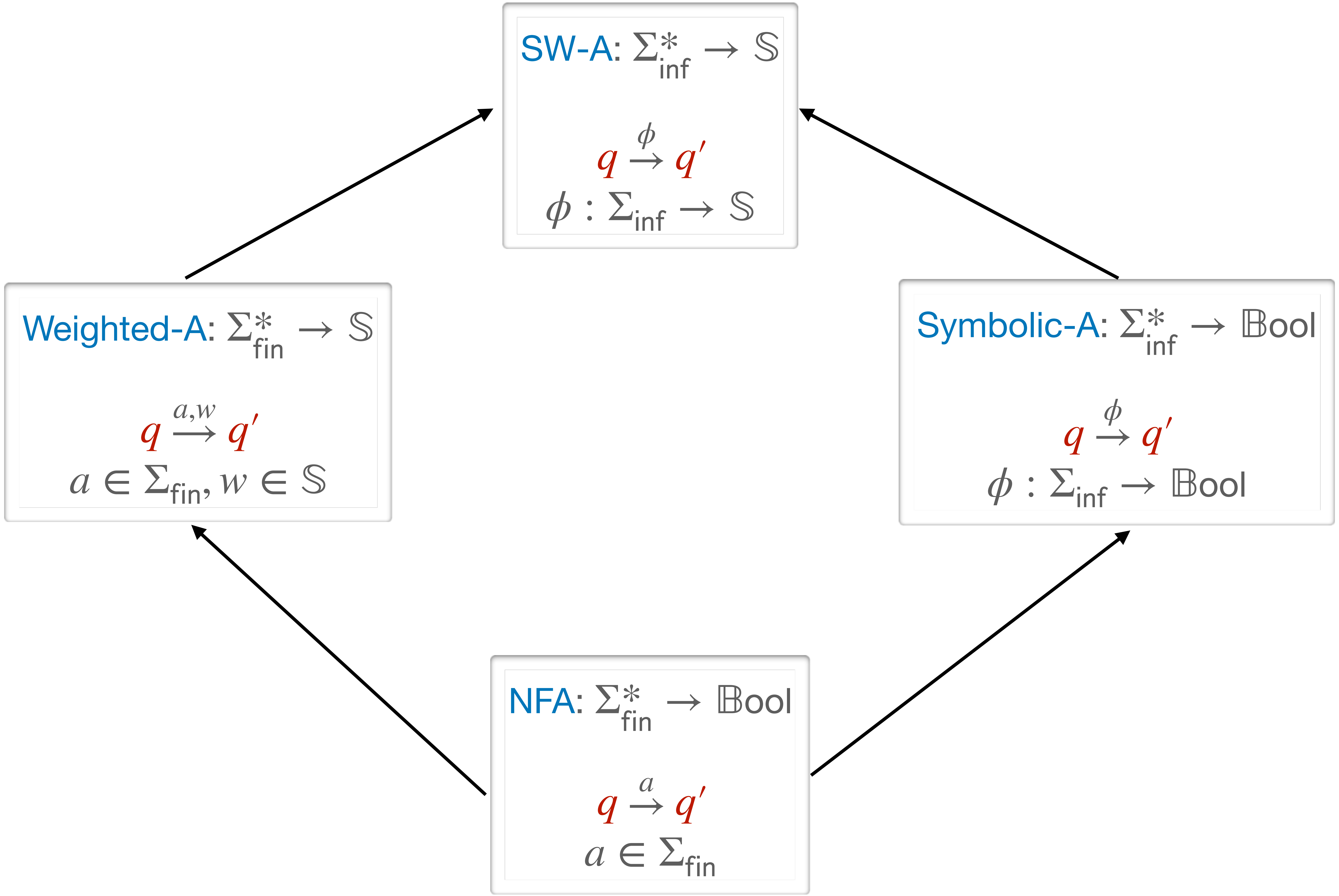
$\otimes$

measure of cost-to-read
computed by the Weighted Tree Grammar

Symbolic Weighted Language Models

Droste, M., Kuich, W., Vogler

Handbook of WA, 2009



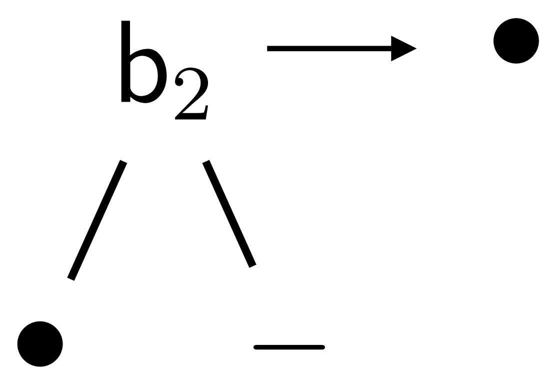
Veanes et al.

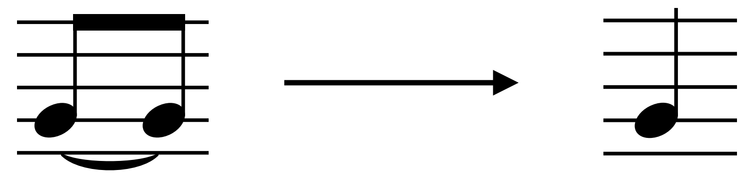
CAV 2017, CACM 2021

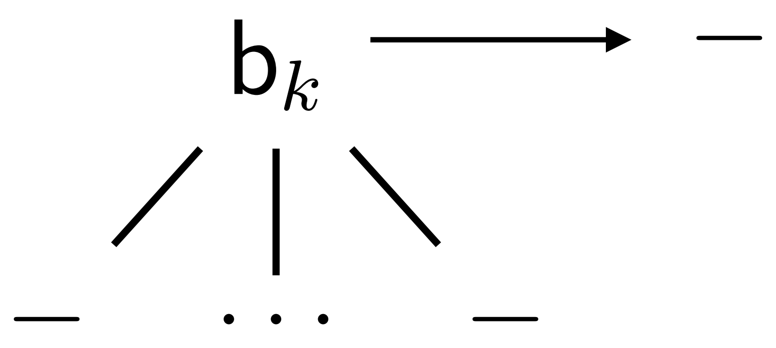

Symbolic-Weighted
word-to-word
Transducer
cost of IO alignment
Weighted
Regular Tree Grammar
cost of readability
converted into
SW Visibly Pushdown
Automata
(intermediate model)
⊗
input MIDI file (unstructured)
SW
word-to-tree
Transducer
SW
Regular Tree
Grammar
k-best
parsing
Parse
Tree
new
k-best parsing
procedure
for SW-VPA
(hence SW-RTG)
term
rewriting
Intermediate
Score
Representation
(structured)
XML/MEI
score file
Music 21
structure
ontologies…

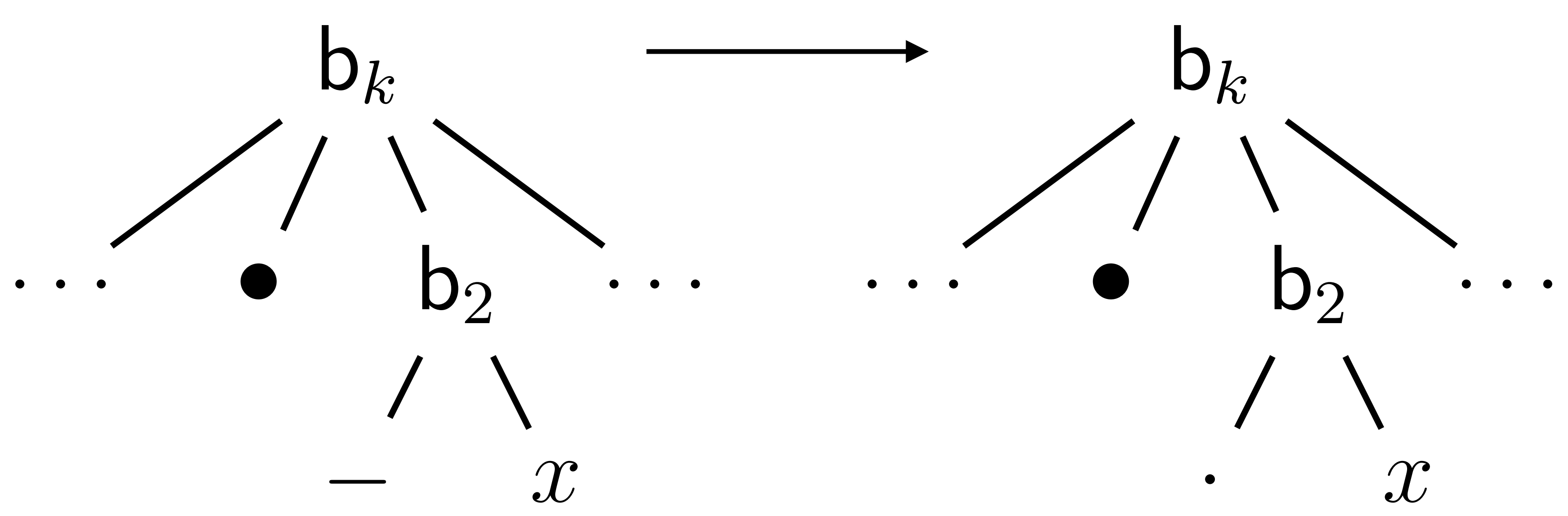
Term Rewriting Rules

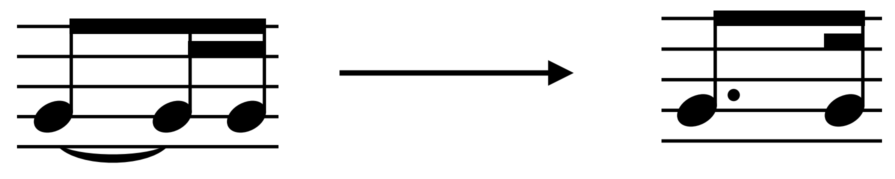
for the transformation of the intermediate score representation

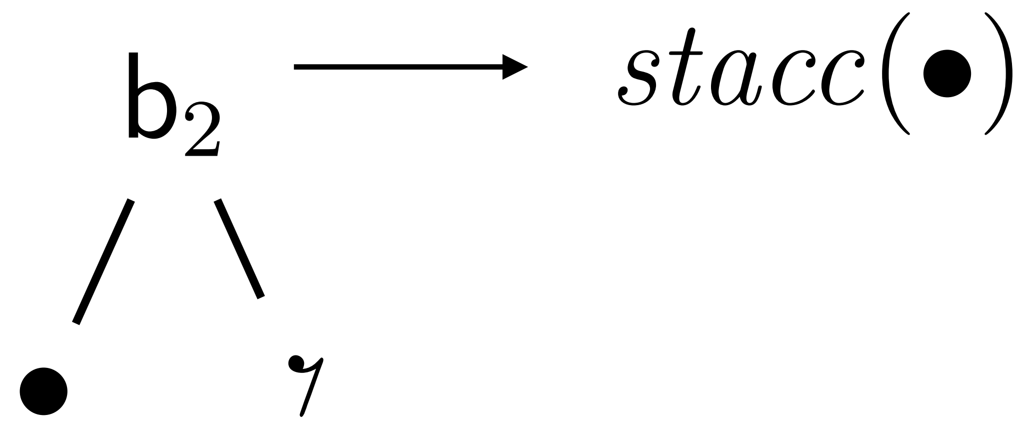


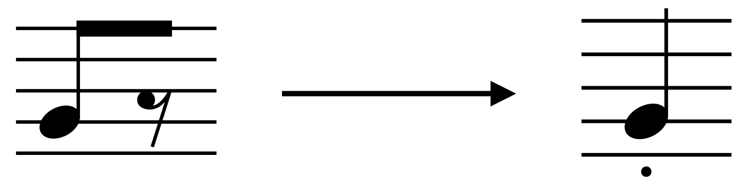












questions: rewrite strategies (*e.g.* IO or OI), conflicts…

Related work

- Piano transcription system (Kyoto U.)

Non-local musical statistics as guides for audio-to-score piano transcription
Kentaro Shibata, Eita Nakamura, Kazuyoshi Yoshii

  - deep-neural-network-based multipitch detection
    audio to unquantized MIDI
  - statistical-model-based (HMM) rhythm quantization
    unquantized MIDI to quantized MIDI
  - delegate to Muse Score + Voice separation algorithm for
    quantized MIDI to score
  - study of use of non-local statistics (pitch and rhythm)
    for the inference of global characteristics (metre, bar line positions…)

- Score Transformer (Yamaha) - piano transcription

Score Transformer: Generating Musical Score from Note-level Representation
Masahiro Suzuki

Transformer model trained with popular songs (piano arrangements), KernScores (piano Sonata)
MIDI to score (tokenization)

Implementation (FJ) of

- the above transcription by parsing framework
- the intermediate score model (w. Philippe Rigaux)
- other subtasks: pitch-spelling, key estimation, beat tracking…

https://gitlab.inria.fr/qparse/qparselib
https://qparse.gitlabpages.inria.fr

qparse: 75 Kloc C++

- command lines tools:
  `monoparse`, `drumparse`, grammar-learning, engraving (from quantified input)
- Python binding - Lydia Rodrigez-de la Nava
  scripts for automatic evaluation
- online port, real-time - Leyla Villaroel

OpenMusic RQ lib
Adrien Ycart 2016-17
IRCAM

https://forge.ircam.fr/p/omlibraries/downloads/
http://repmus.ircam.fr/cao/rq

CommonLisp/CLOS, 350 functions, 4900 lines of code

UI: Open Music object, input from chord-seq (notes, onset, dur) + segmentation marks,
output to voice (OM rhythm trees)

Score diff

by Francesco Foscarin

- identify the diff. between 2 XML music scores
- string/tree edit distance applied to a intermediate score representation

Lamarque-Goudard dataset (w. Francesco Foscarin, Teysir Baoueb)

- 283 monophonic extracts
  of classical repertoire
  inspired by a rhythm learning method
- ~ 20 measures per extract
- progressive difficulty
  cover a very large spectrum of rhythmic features
- score files (XML) and MIDI performances
  for evaluation and calibration of transcription tools

Generation of artificial performances
Madoka Goto, Masahiko Sakai (Nagoya U.), Satoshi Tojo (JAIST)

- construction of a GTTM tree
- segmetation accordingly
- performance generation by Director Musices (Anders Friberg)

Monophonic transcription

monophonic : one note at a time
Good results for complex cases (ornaments, mixed tuplets, mixed note durations, silences…)
~ 100ms for the transcription of 1 score

Polonaise in D minor from Notebook for Anna Magdalena Bach   BWV Anh II 128

original score

transcription of MIDI recording by qparse

Monophonic transcription

Polonaise in D minor from Notebook for Anna Magdalena Bach   BWV Anh II 128

original score

transcription of MIDI recording by Finale

Beethoven, Trio for violin, cello and piano, op.70 n.2 (2d mov)

original score

transcription of MIDI recording by qparse

Beethoven, Trio for violin, cello and piano, op.70 n.2 (2d mov)

original score

transcription of MIDI recording by Finale

options:
- mixed rhythms,
- tuplets
- smallest note = 32nd

The time signature and the tempo are given.

FiloBass by John-Xavier Riley (QMUL, C4DM)
project "*Dig That Lick*"

- jazz bass lines, acc. of saxophone
- 48 tracks,
  24 recorded hours of melodies and improvisations
- qparse as backend of an audio-to-MIDI transcription procedure
- prior beat (measure) tracking

Drum transcription

Groove MIDI Dataset

- by Google Magenta
- 13.6 hours, 1150 MIDI files, ~ 22000 measures recorded by professional drummers on a electronic drum kit
- audio (wav) files synthesized from (and aligned to) MIDI files for evaluation of audio-to-MIDI drum transcription
- no score files!

Scoring the GMD with qparse

Martin Digard (INALCO)

- all score files (XML) produced from the MIDI files with the same generic tree grammar (4/4 measure)
- polyphonic case-study, simpler than piano
- specific drumming constraints (hands ≤ 2, feet ≤ 2)
- processing errors from MIDI sensors

- Dataset **ASAP** - Francesco Foscarin, Andrew Mc Leod
  MIDI and audio recording from Yamaha piano competition
  + XML scores
  + alignments
  + beat tracking annotations

- **Voice separation** - Lydia Rodrigez-de la Nava, evaluation Augustin Bouquillard
  and for piano guitar transcription.
  integration in transcription:
  - before parsing, or
  - after parsing (on intermediate model), or
  - joint with parsing.

MIDI-to-Score Automated Music Transcription approach

- quantitative parsing technique
  based on Symbolic Weighted formal language formalisms
  Tree Automata and word-to-word Transducers
- with prior quantitative language of notation *style*
  and prior IO measure
- (abstract) hierarchical score model
  as intermediate representation for score generation

- can handle complex notation cases:
  ornaments, mixed tuplets, mixed note durations, silences…
- efficient

- case studies: Monophonic, Drums
- ongoing work on Polyphonic case studies: guitar, piano

MERCI!
THANK YOU!