Do the Math

Musical creativity and improvisation under the spectrum of information science and machine learning

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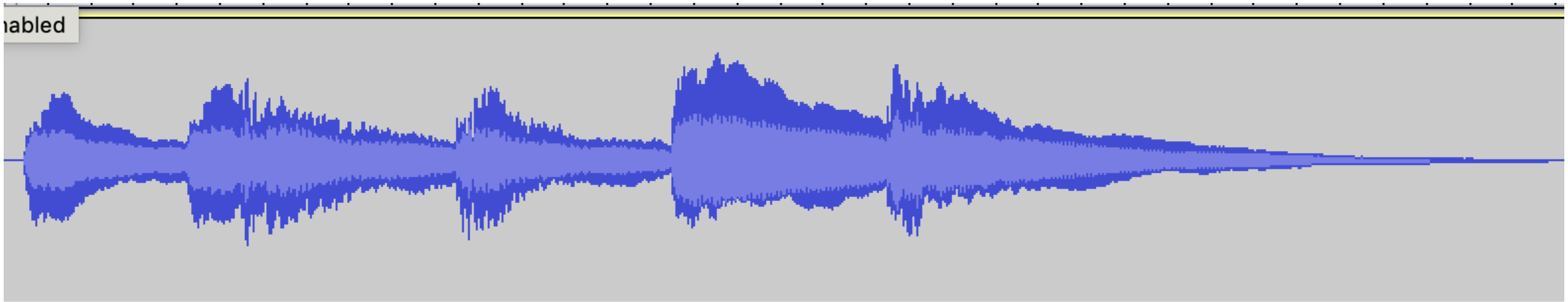
Which one is this song?



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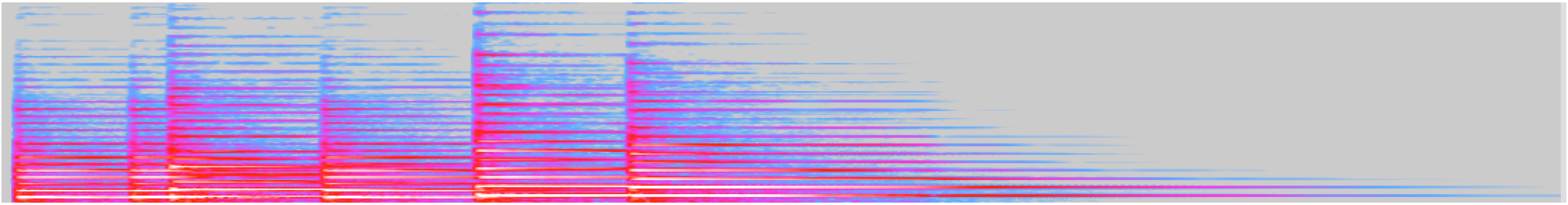

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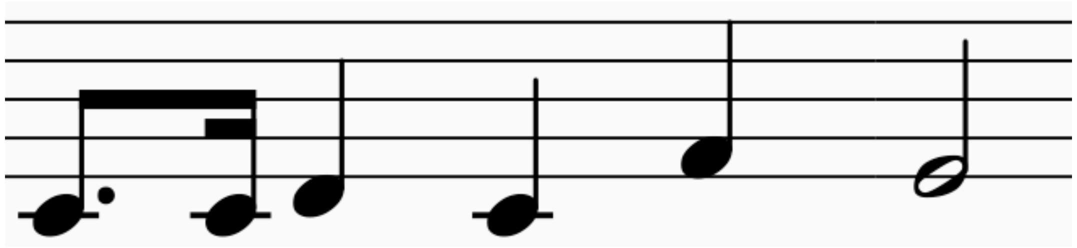
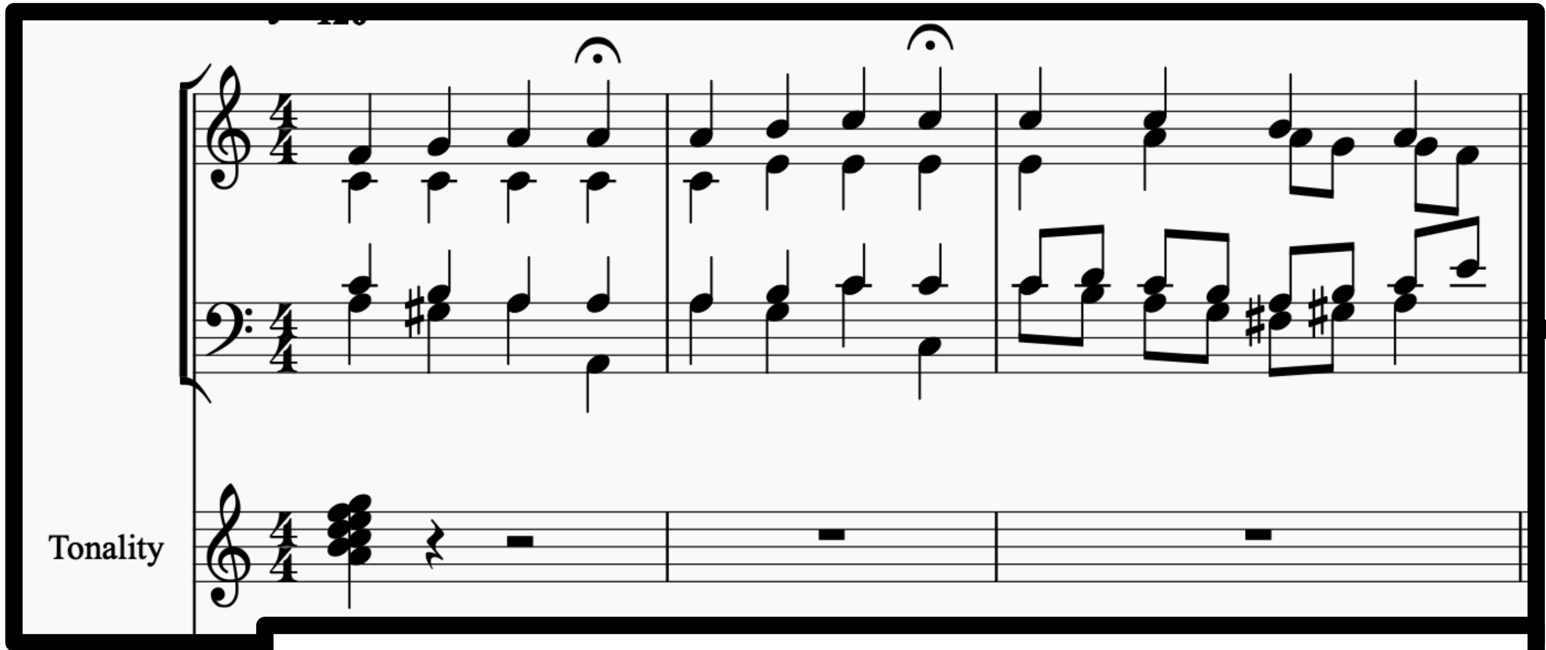
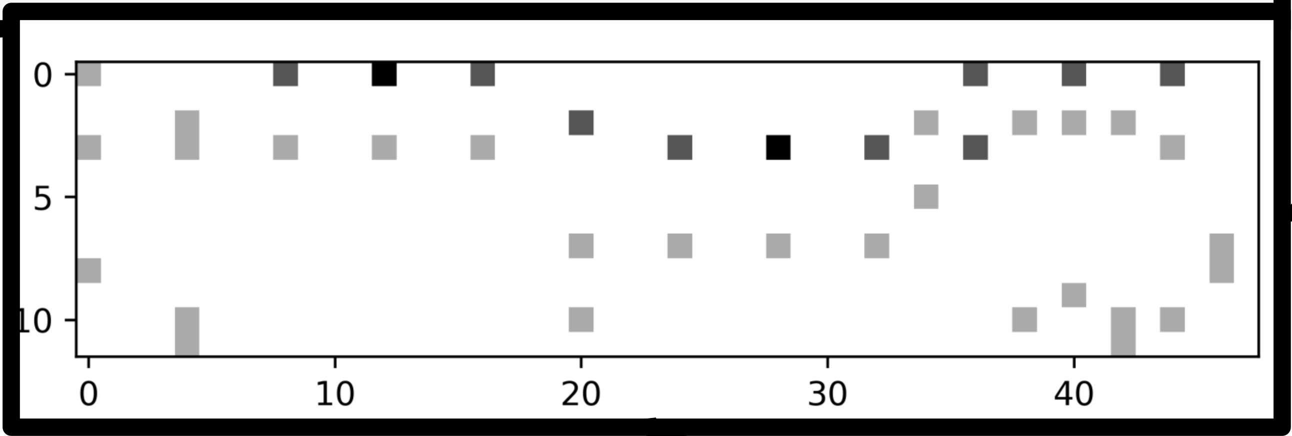


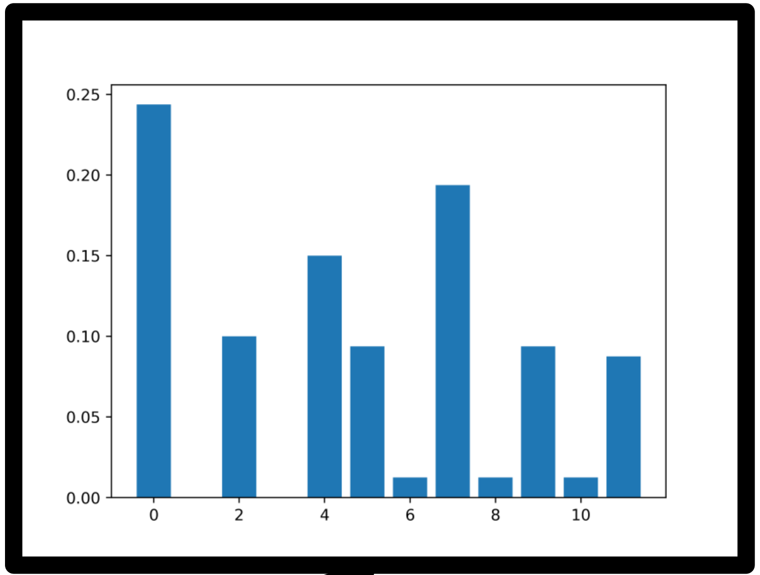
We understand objects better, at the "proper" level of abstraction

If we are only interested in pitch classes…

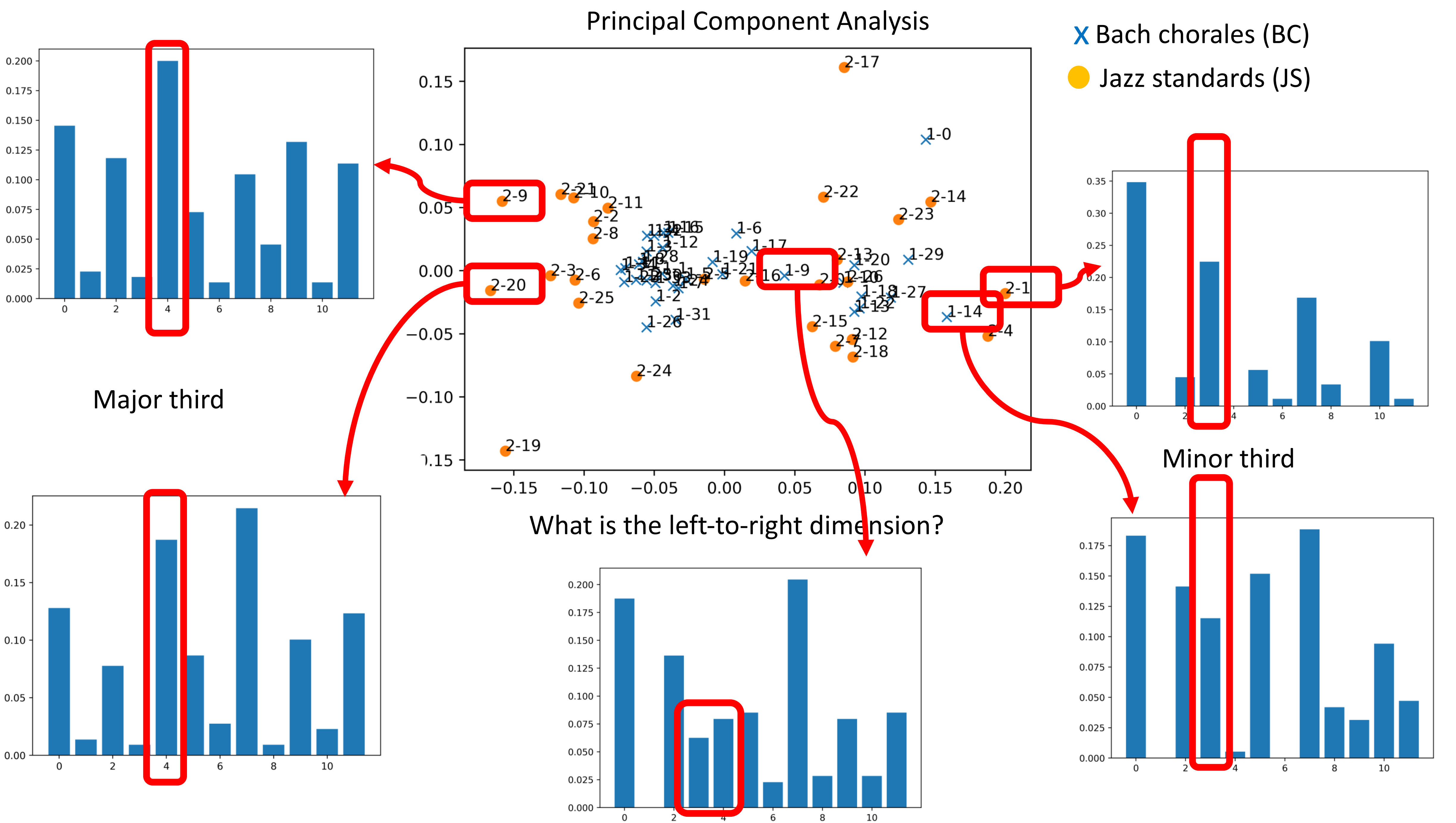




Extraction of relative pitch classes



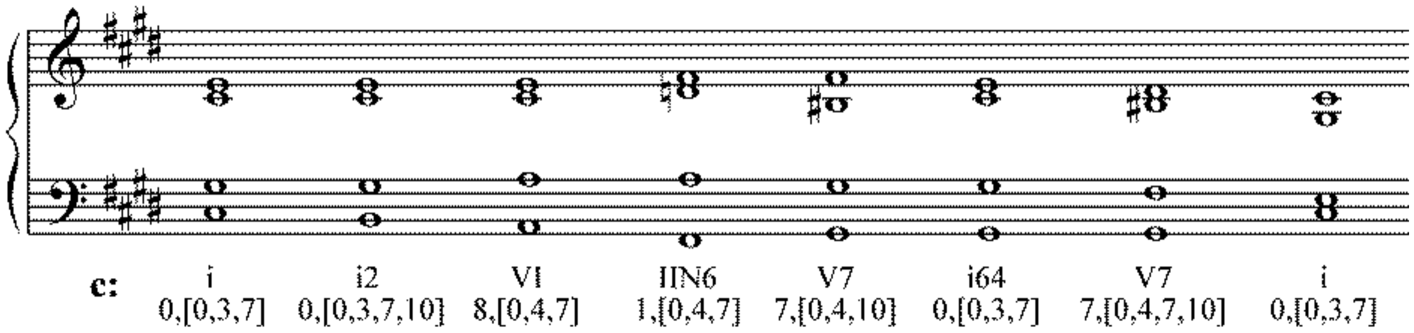
Extraction of relative pitch class profile (rPCP)



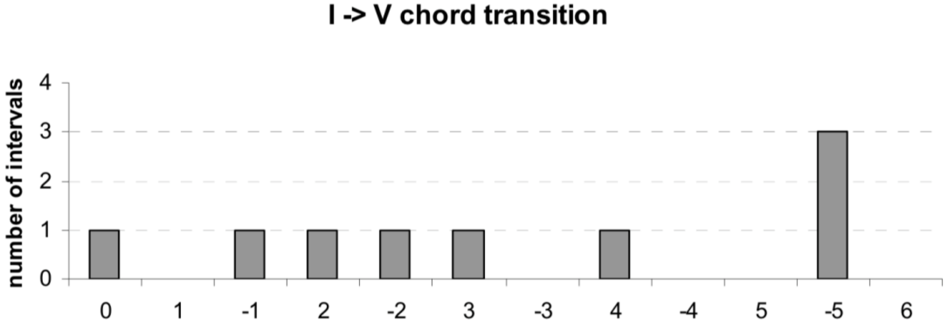
Principal Component Analysis
X Bach chorales (BC)
Jazz standards (JS)
Major third
Minor third
What is the left-to-right dimension?

Harmonic features

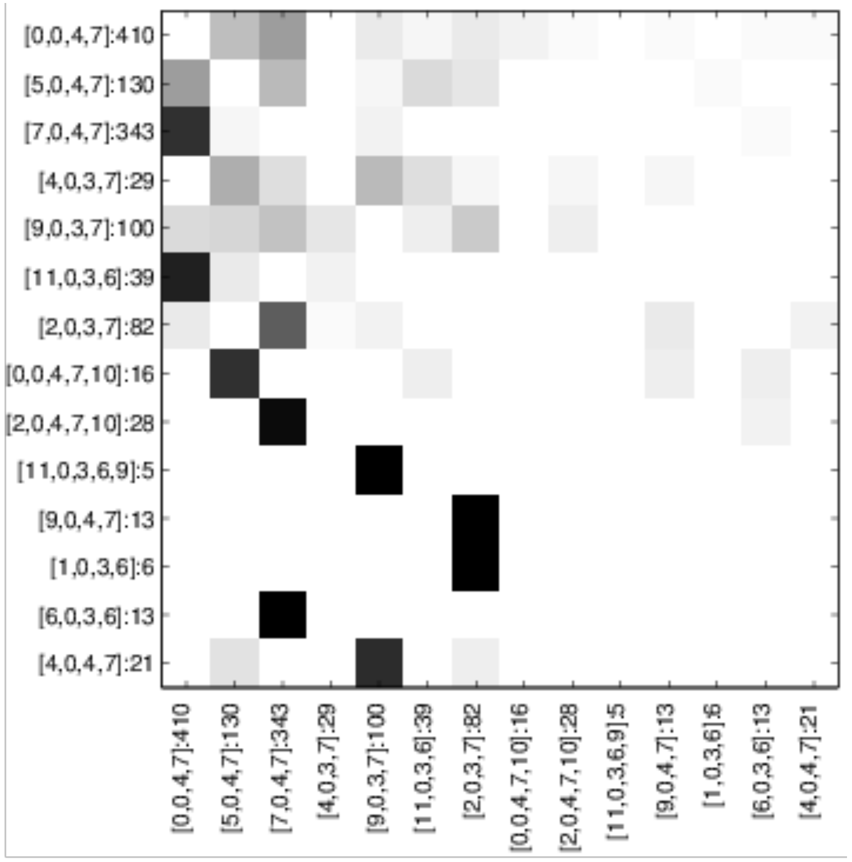
General Chord Type



Directional Interval Class



Chord Transition Spaces

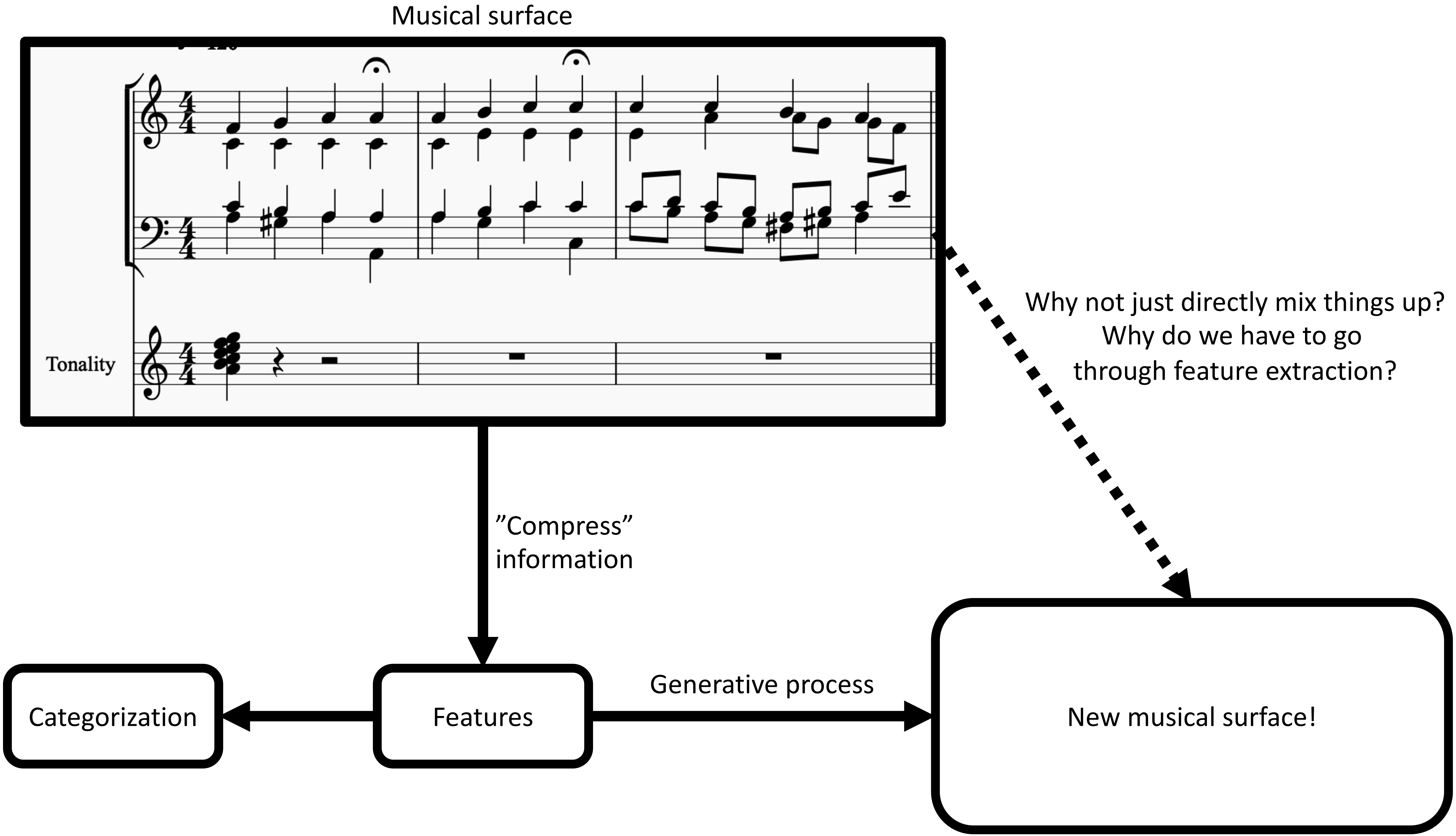


Cambouropoulos, E. (2016). The harmonic musical surface and two novel chord representation schemes. In *Computational music analysis* (pp. 31-56). Springer, Cham.

Drums features

feature indexes	feature description
1–4	density, syncopation, symmetry and weak-to-strong ratio of the strong beat
5–16	density, syncopation, symmetry and weak-to-strong ratio of each drum element (4 features times 3 elements, 12 total features)
17–19	number of simultaneous pairs of drums onsets (H–K, H–S and S–K), divided with the number of total onsets[1].
20–23	number of transitions between all combinations of K and S, divided with the number of total transitions between all combinations of K and S.
24–26	number of isolated H, S or K onsets, divided with the number of total onsets.
27–32	intensity mean value and standard deviation for each drum element.
33–40	mean value and standard deviation of intensity difference between all combinations of S and K elements. Mean values are increased by the 5, in order to have zero minimum value.

Kaliakatsos–Papakostas, M. A., Floros, A.,&Vrahatis, M. N. (2013). EvoDrummer: Deriving rhythmic patterns through interactive genetic algorithms. In *International Conference on Evolutionary and Biologically Inspired Music and Art* (pp. 25-36). Springer, Berlin, Heidelberg.


Musical surface
Tonality
Why not just directly mix things up?
Why do we have to go
through feature extraction?
”Compress”
information
Categorization
Features
Generative process
New musical surface!

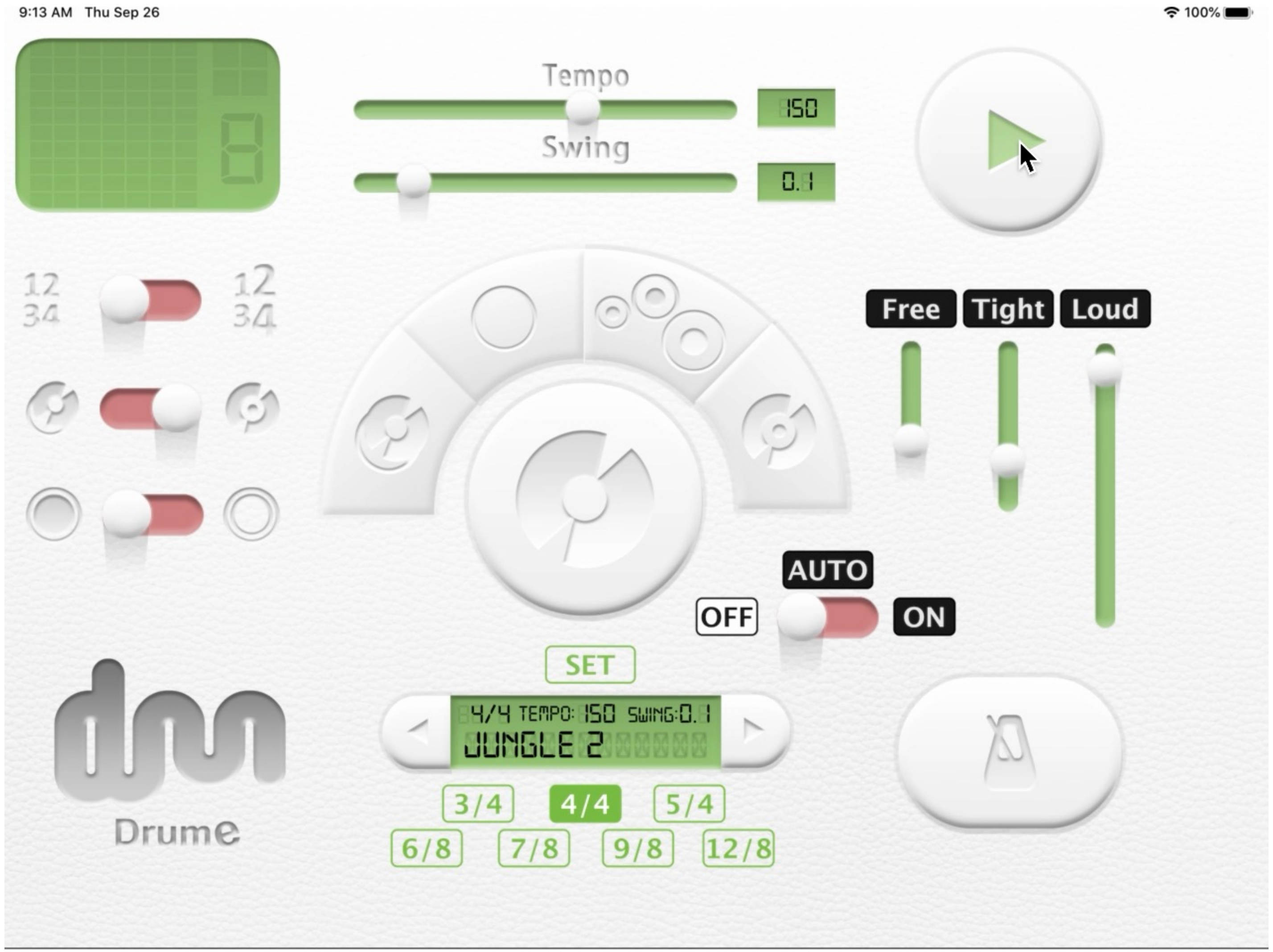
Importance of abstraction / compression / high-level features

- Simple math, as we know it, seems to work when moving to abstract representations (more on that later).
- Creating abstractions is suspected to be in the core of our cognition, consciousness and creativity (more on that later).

Simple math works well when moving to abstract representations

Example: Real-time control or “dissimilarity”

Drume – iPad app



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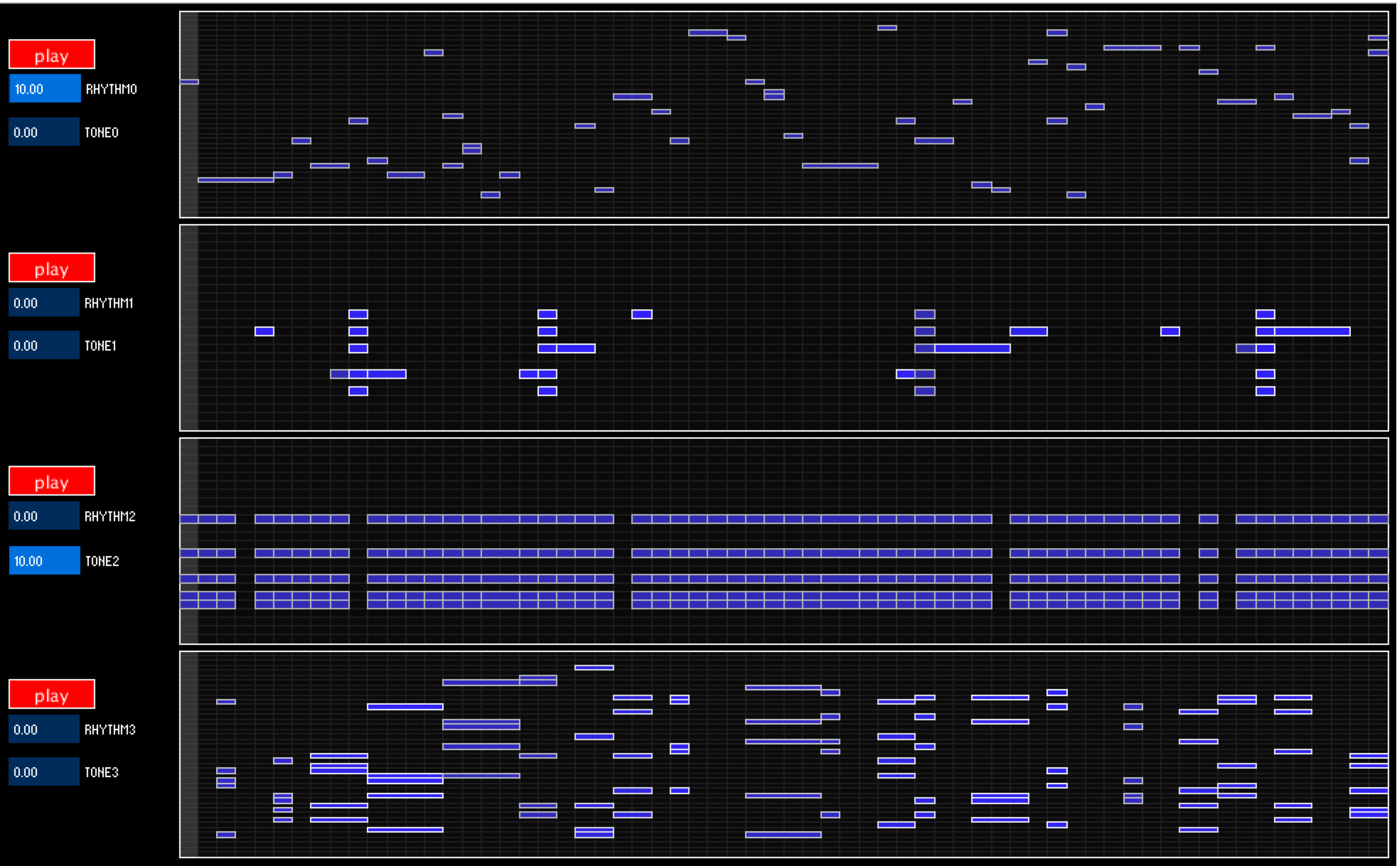
In *International Conference on Evolutionary and Biologically Inspired Music and Art* (pp. 25-36). Springer, Berlin, Heidelberg.

Example: polyphonic melodies – iteration 0

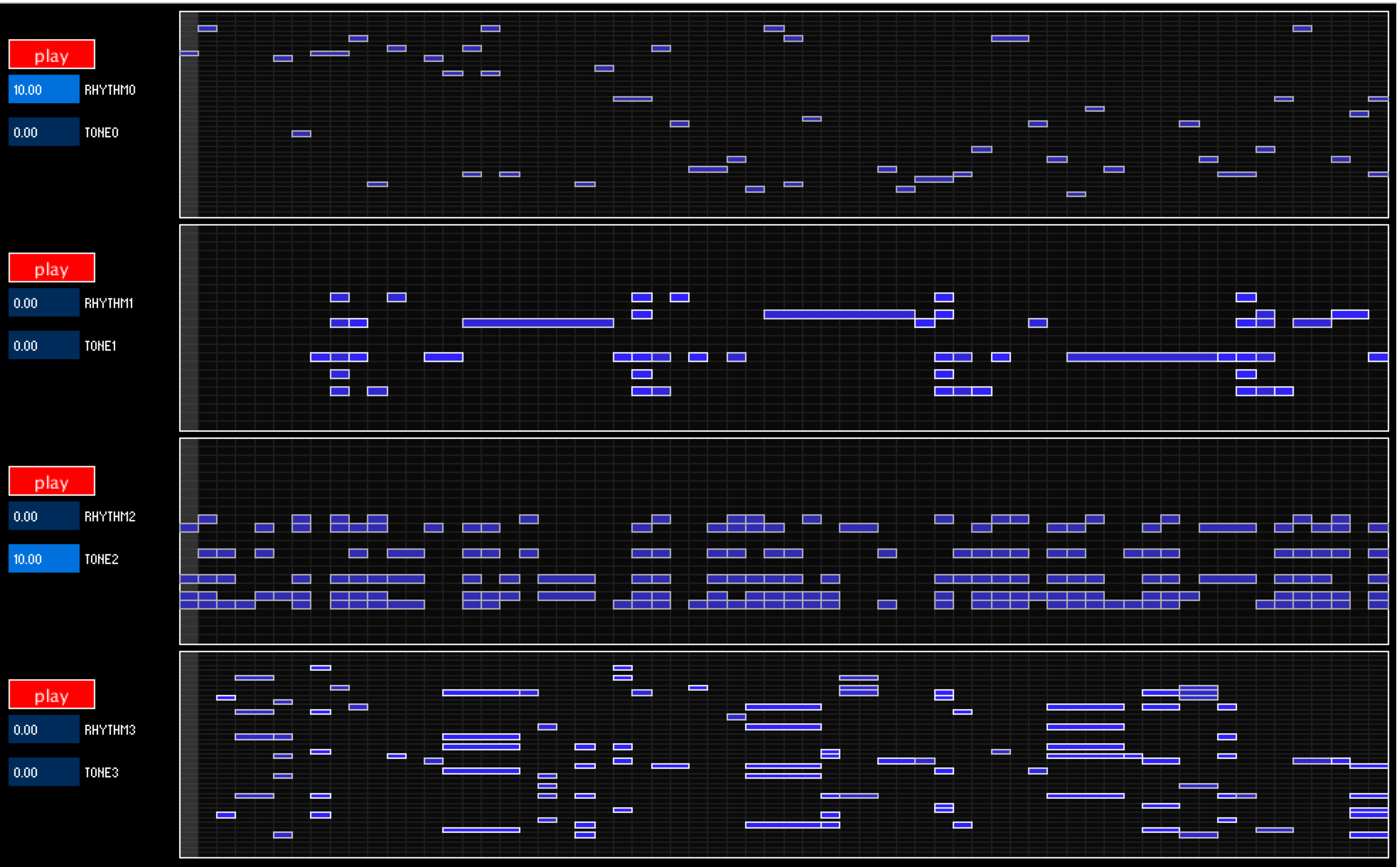


Irregular rhythm
Almost monophonic

Small range
Few notes

Kaliakatsos-Papakostas, M. A., Floros, A., & Vrahatis, M. N. (2016). Interactive music composition driven by feature evolution. *SpringerPlus*, *5*(1), 826.

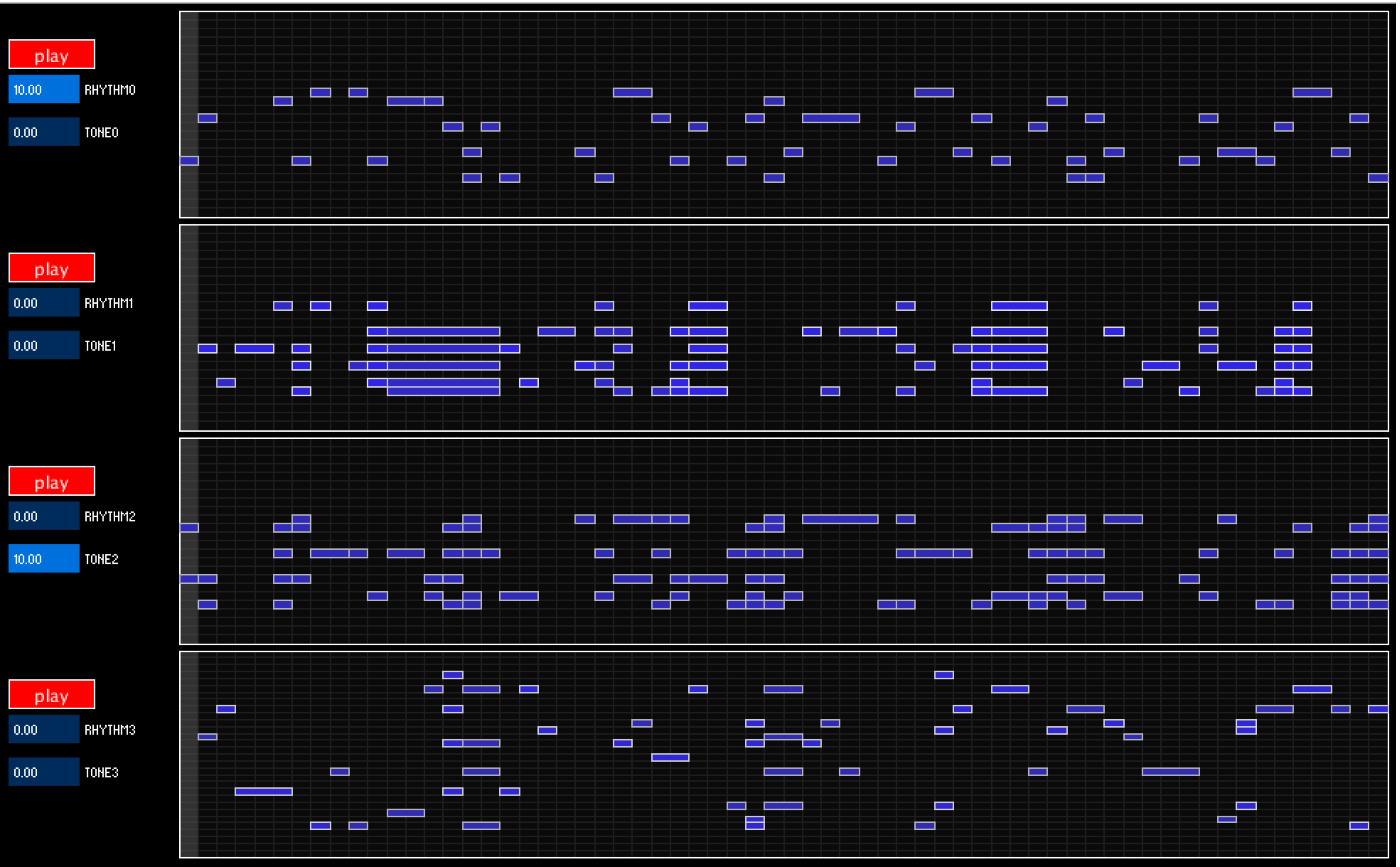
Example: polyphonic melodies – iteration 1



Irregular rhythm
Almost monophonic

Small range
Few notes

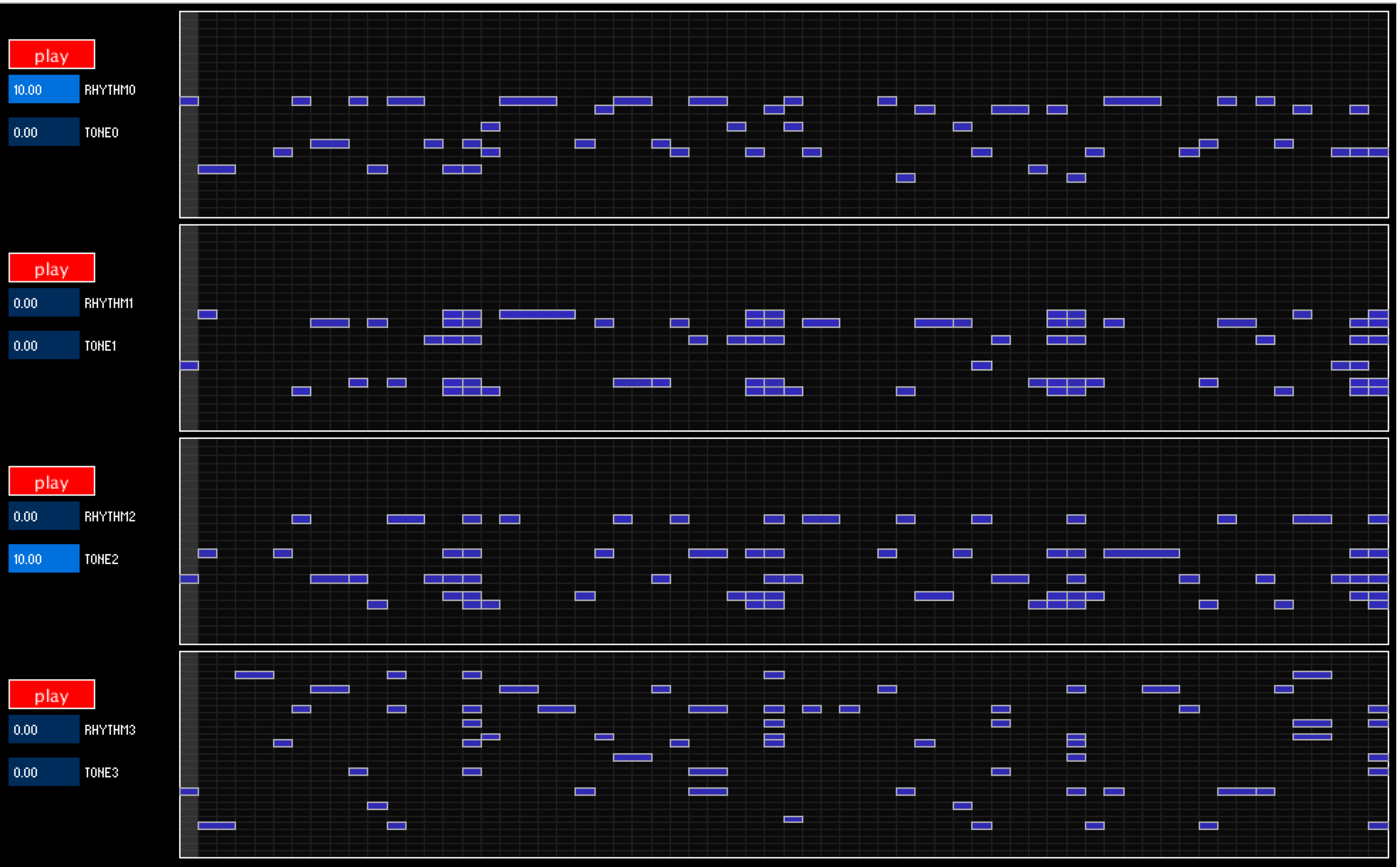
Example: polyphonic melodies – iteration 2



Irregular rhythm
Almost monophonic

Small range
Few notes

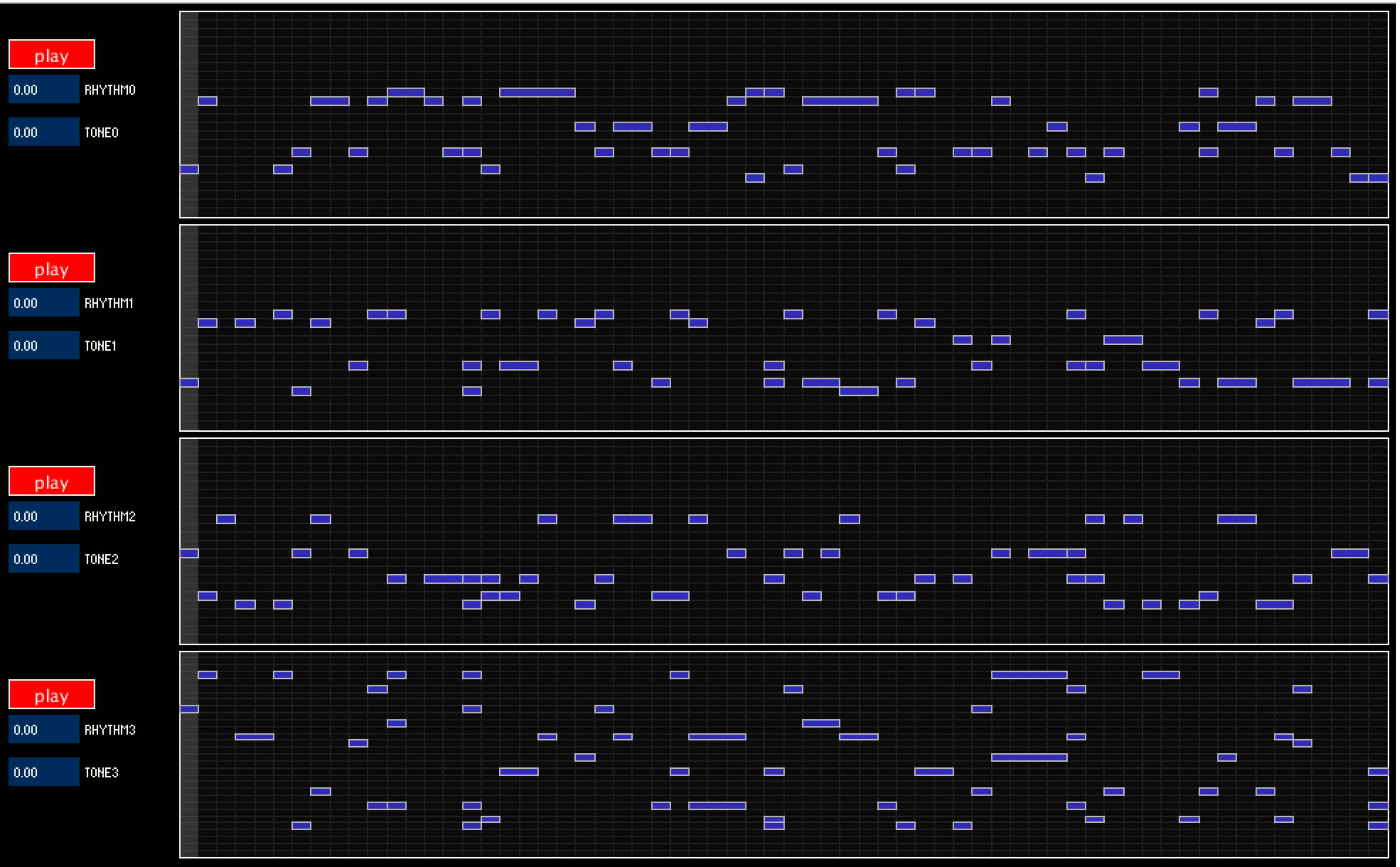
Example: polyphonic melodies – iteration 3



Irregular rhythm
Almost monophonic

Small range
Few notes

Example: polyphonic melodies – iteration 4

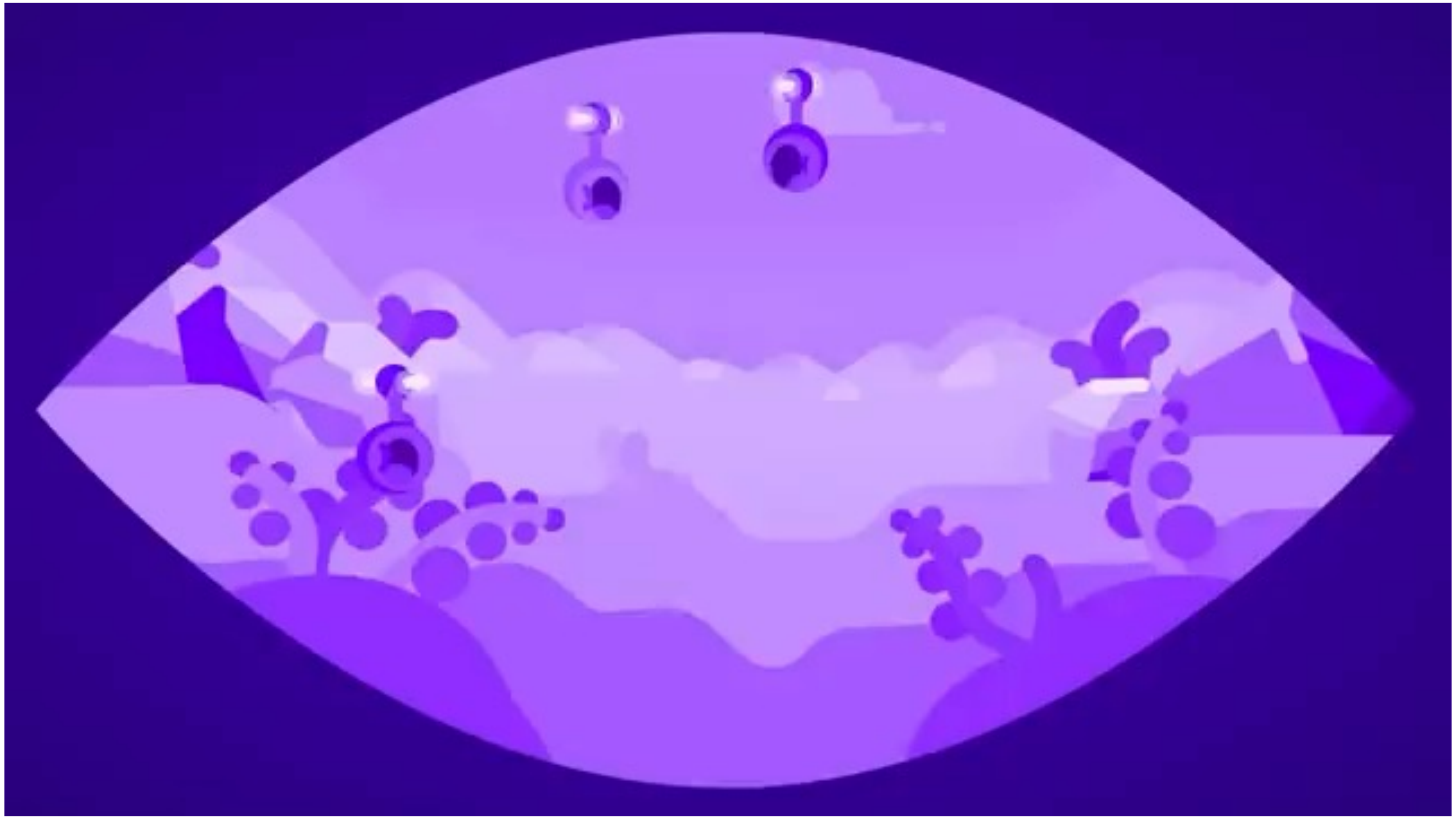


Irregular rhythm
Almost monophonic

Small range
Few notes

Creating abstractions is suspected to be in the core of our cognition, consciousness and creativity

Why is abstraction useful?



Video part from: **The Origin of Consciousness – How Unaware Things Became Aware**
https://www.youtube.com/watch?v=H6u0VBqNBQ8

Feinberg, T. E., & Mallatt, J. (2013). The evolutionary and genetic origins of consciousness in the Cambrian Period over 500 million years ago. Frontiers in psychology, 4, 667.

Conceptual Blending

Creative outcomes need to be useful in a specific context.
They reveal something new about things that we know.

(foldable) pocketknife

toothbrush

foldable toothbrush

Example from the COINVENT project (2013-2016)
http://coinvent.uni-osnabrueck.de/

Fauconnier, G., & Turner, M. (2003). *The way we think: Conceptual blending and the mind's hidden complexities*. Basic Books.

Compressing information within the most salient features

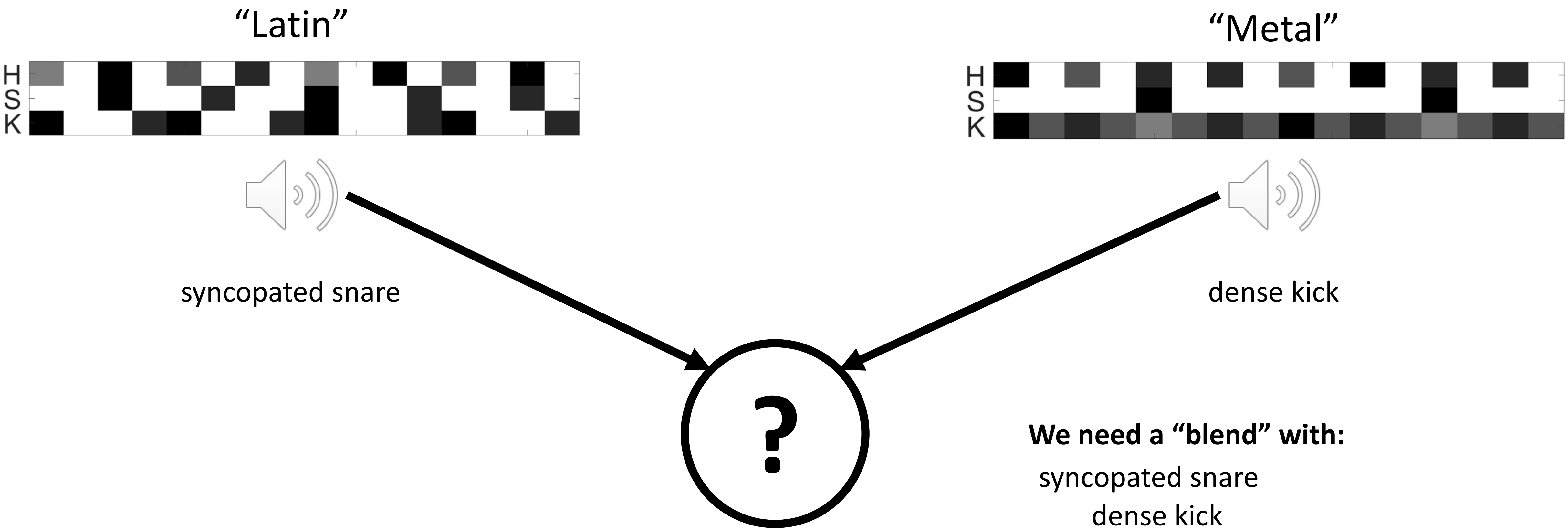
Input 1 - shark:	**Input 2 - zebra:**	**Blend:**
ftr 1 – color: `grey`	ftr 1 – color: `zebra pattern`	ftr 1 – color: `?`
ftr 2 – body shape: `fishy & fin`	ftr 2 – body shape: `horse-like`	ftr 2 – body shape: `?`

Blend A:	**Blend B:**
ftr 1 – color: `grey`	ftr 1 – color: `zebra pattern`
ftr 2 – body shape: `horse-like`	ftr 2 – body shape: `fishy & fin`

Kaliakatsos-Papakostas, M., & Cambouropoulos, E. (2019). Conceptual blending of high-level features and data-driven salience computation in melodic generation. *Cognitive Systems Research*, *58*, 55-70.

Conceptual Blending of Features

Example in drum rhythms



We need a “blend” with:

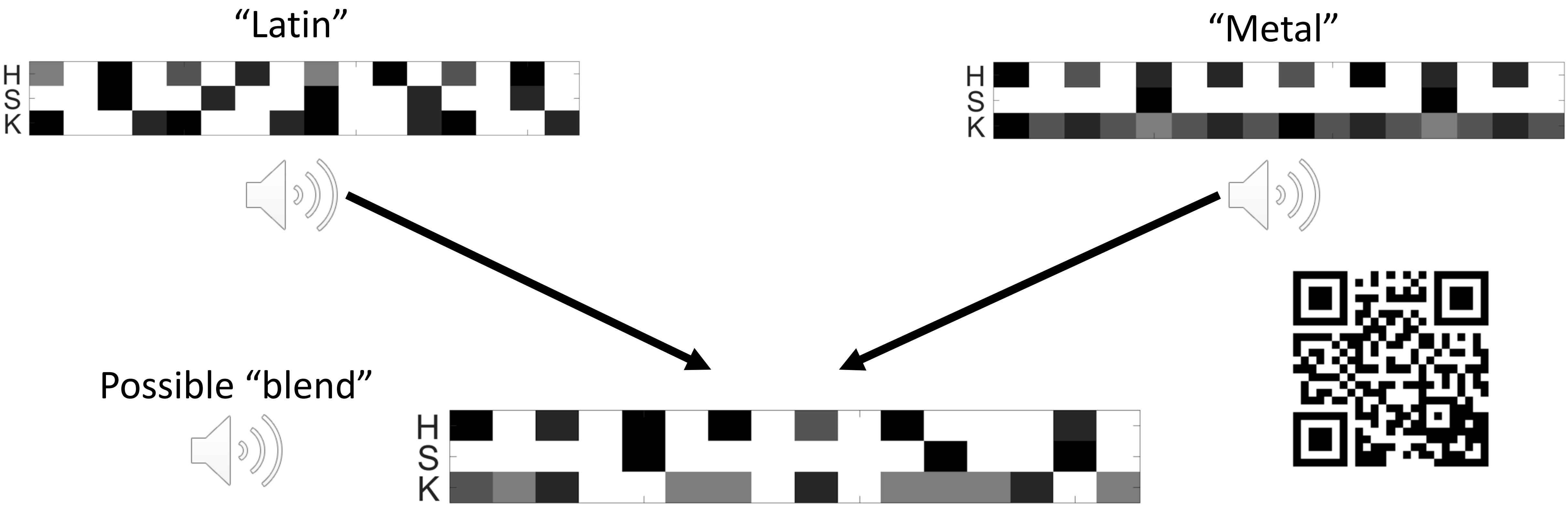
syncopated snare

dense kick

High-level **Representation**

Conceptual Blending of Features

Example in drum rhythms



Kaliakatsos-Papakostas, M. (2018). Generating drum rhythms through data-driven conceptual blending of features and genetic algorithms. In *International Conference on Computational Intelligence in Music, Sound, Art and Design* (pp. 145-160). Springer, Cham.

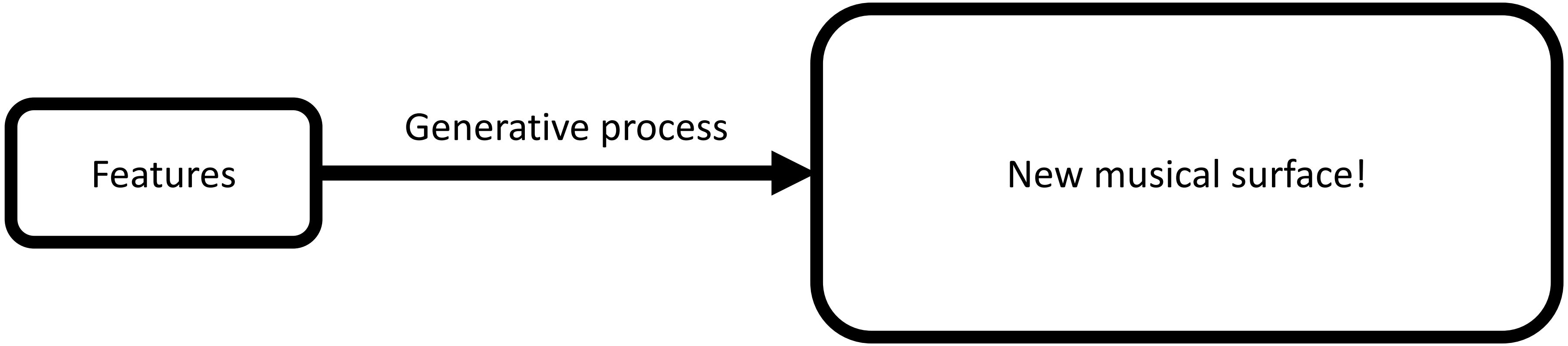
More examples at:
http://ccm.web.auth.gr/drumsblending.html

The problem with feature-driven generative systems

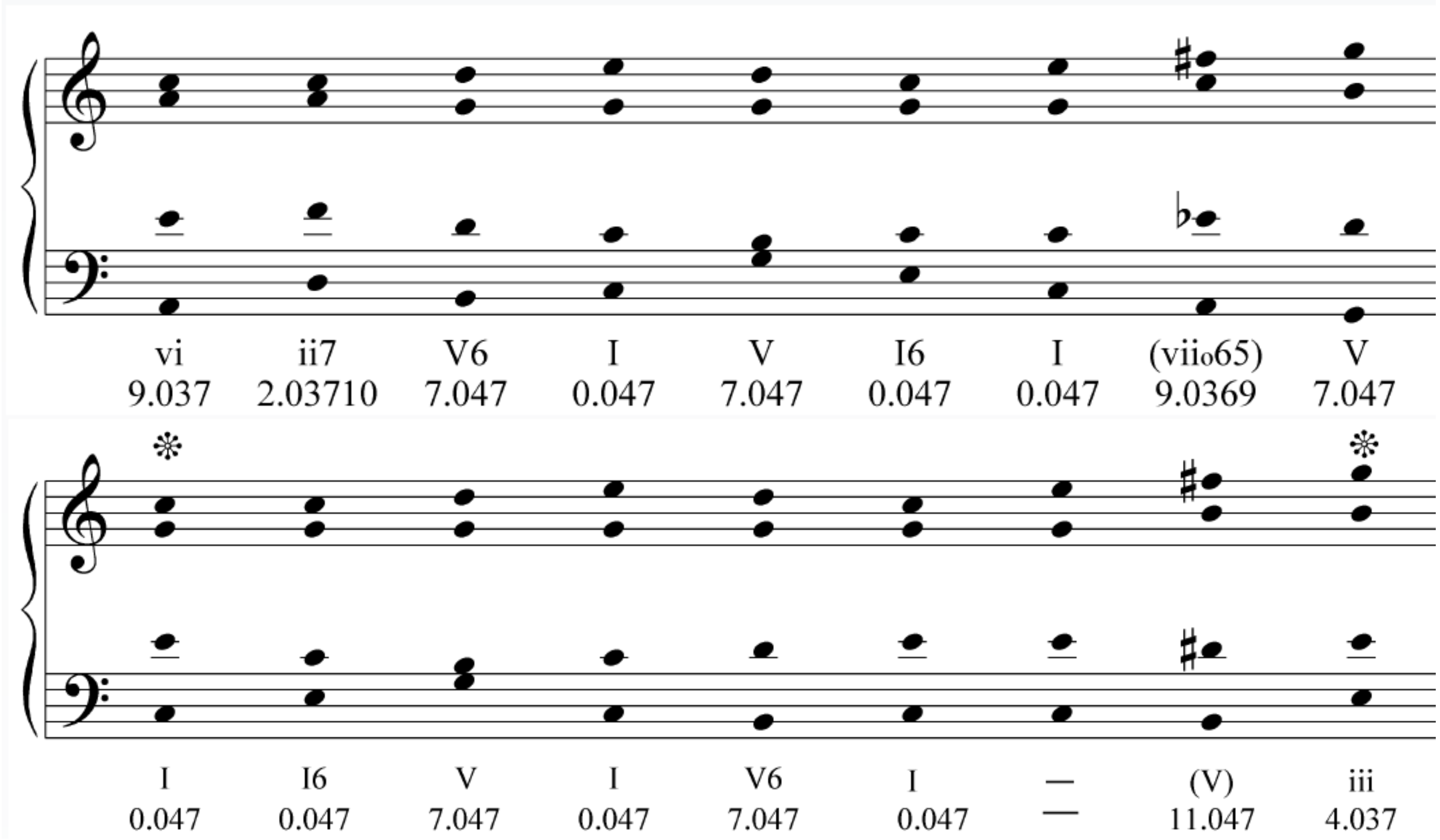
There are trillions (or more) of nonsense:

- rhythms with given syncopation and density values,
- cadences with both upward and downward step motion to the tonic,
- melodies with specific pentatonicity and syncopation values,
- improvisation accompaniments with specific characteristics…

How do we filter the bad ones out? How do we know which ones are good?

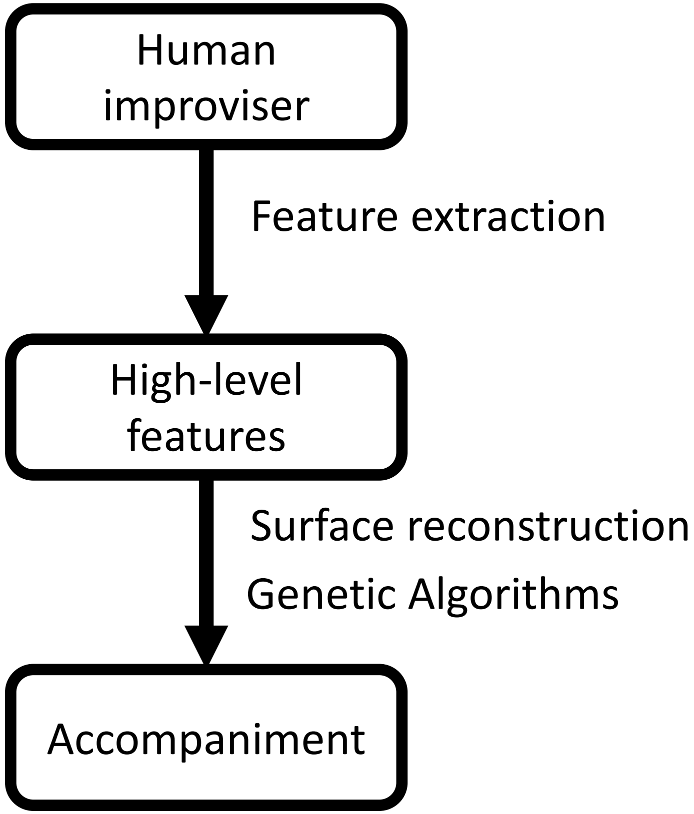


Depends on problem and researcher's intuition.
E.g. in CHAMELEON, cadences are learned independently.



Kaliakatsos-Papakostas, M., & Cambouropoulos, E. (2014). Probabilistic harmonization with fixed intermediate chord constraints. In Proceedings of The *International Computer Music C*onference (ICMC 2014).

Example: Real-time accompaniment with no constaints

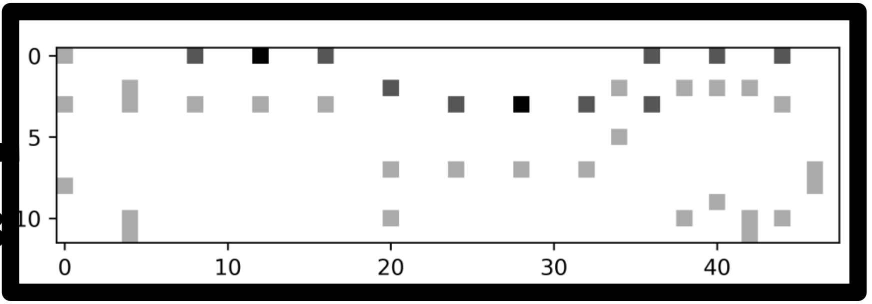


Kaliakatsos-Papakostas, M. A., Floros, A.,&Vrahatis, M. N. (2012). Intelligent real-time music accompaniment for constraint-free improvisation. In *2012 IEEE 24th International Conference on Tools with Artificial Intelligence* (Vol. 1, pp. 444-451). IEEE.

Re-inventing a solution through (many) data: when data speak for themselves

Non-negative Matrix Factorisation (NMF)

Bach chorales



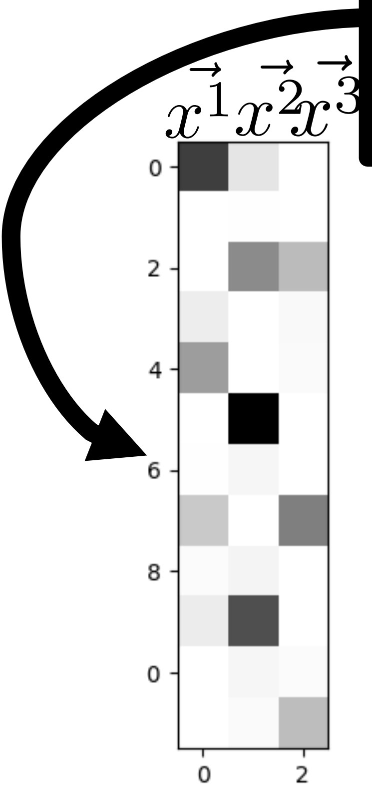
$$y_1 = x_0^1\ C + x_1^1\ C\# + x_2^1\ D + \cdots + x_{11}^1\ B$$

$$y_2 = x_0^2\ C + x_1^2\ C\# + x_2^2\ D + \cdots + x_{11}^2\ B$$

$$y_3 = x_0^3\ C + x_1^3\ C\# + x_2^3\ D + \cdots + x_{11}^3\ B$$

x_i^j Can be only non-negative…

But we lose information…



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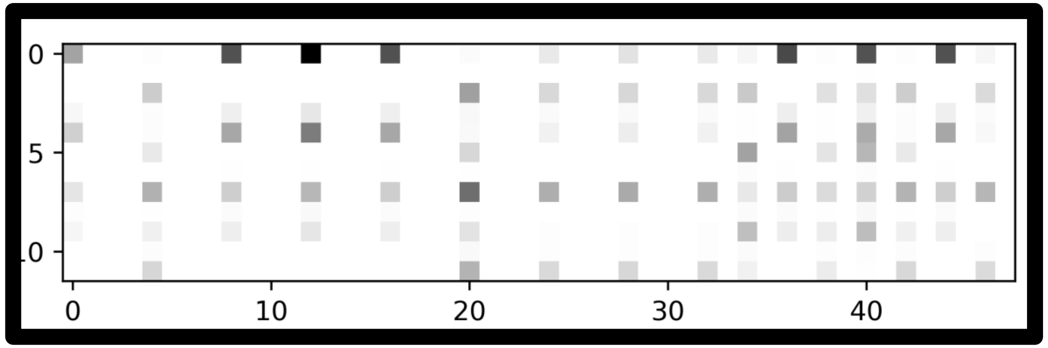
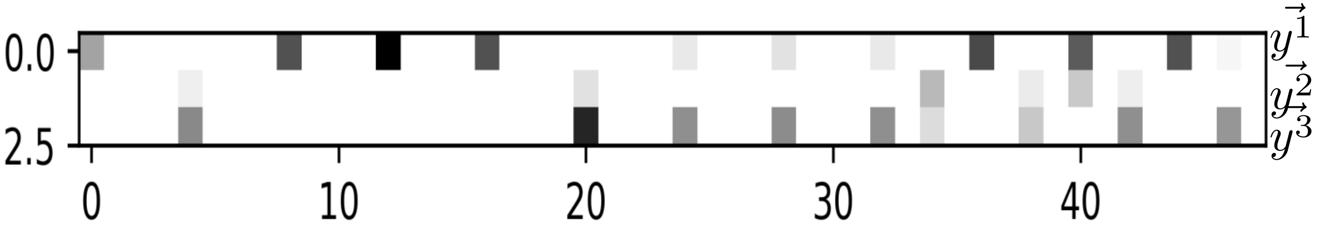
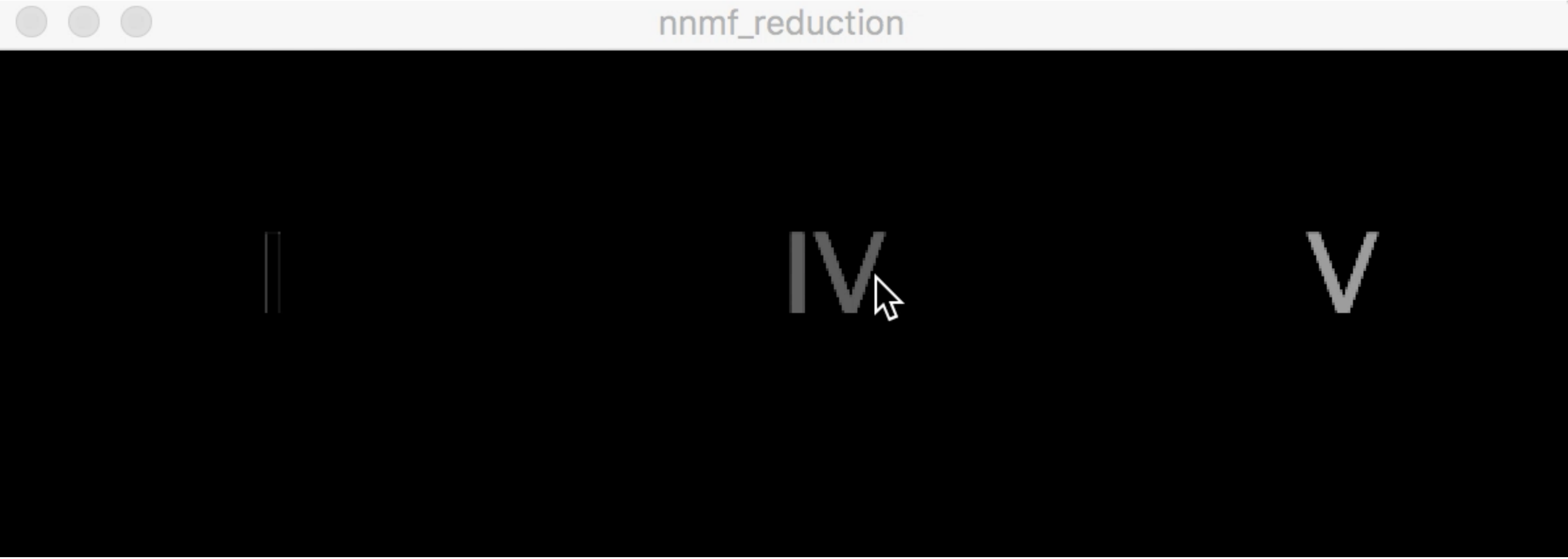


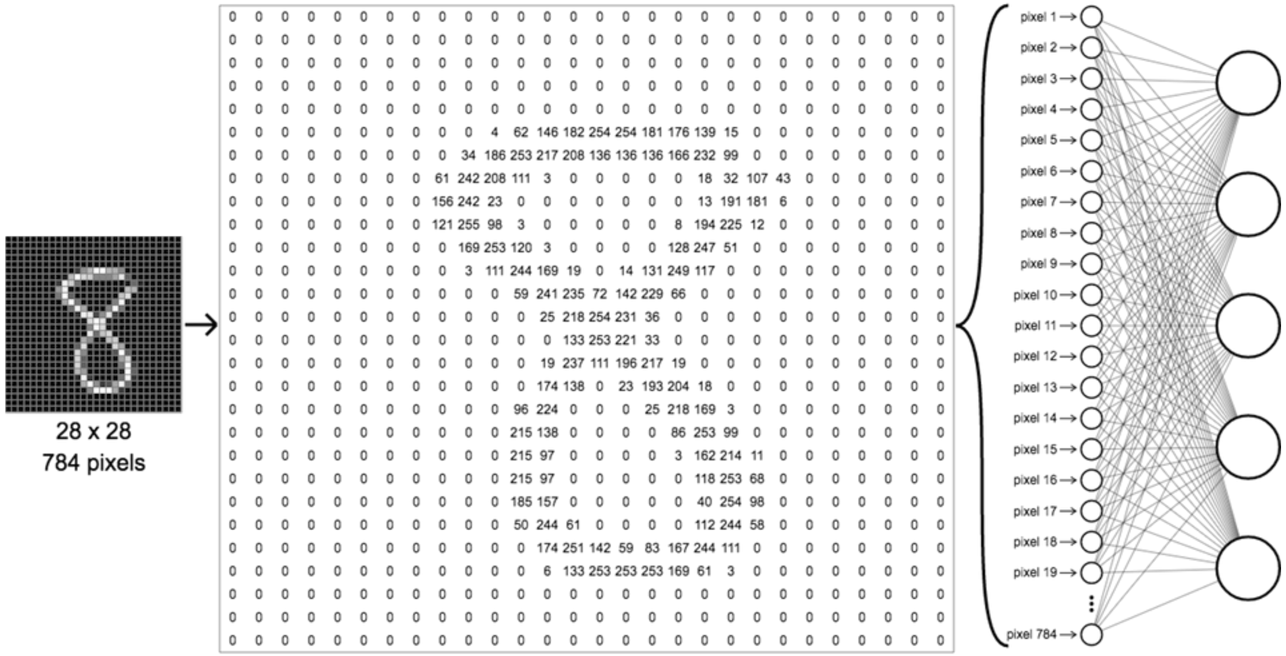
X



NMF for Bach chorales example



Compressing information with Neural networks



prediction for belonging to class 0

prediction for belonging to class 1

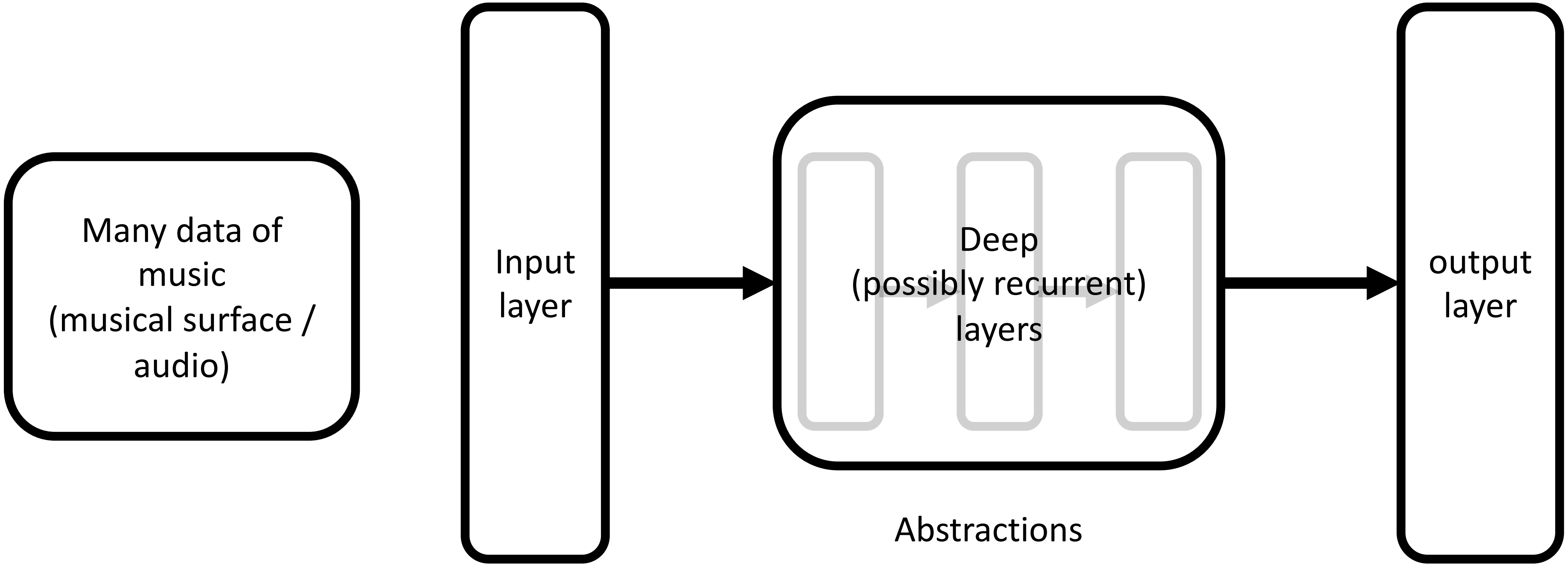
prediction for belonging to class 2

prediction for belonging to class 3

prediction for belonging to class 4

.
.
.

Neural networks on steroids



Musical surface / Audio

Abstractions

However, we don't know what those abstractions are…

Black box

Musical surface / Audio

There are ways to examine the inner workings
But we are still far away from getting symbolic
Information.

Deep neural networks

- They're **good** because
  - They are responsible for both compressing and decompressing information
  - Proper data modelling is the main concern
  - The way they learn, is inspired by how humans learn
- They're **bad** because
  - Their abstractions are merely compressions – concepts are not involved
  - Their abstractions are not transparent, so we don't know how they know
  - The way they learn, is in many cases radically different from the way humans learn

https://www.newyorker.com/tech/annals-of-technology/chatgpt-is-a-blurry-jpeg-of-the-web?fbclid=IwAR3piNz-Chwco6FVLgB9fB7Ty2Lv0BWhgP0cUvEzvYeZD87f1YAiehQ9tEw

Summary

- We understand objects better, at the “proper” level of abstraction
- Simple math works well when moving to abstract representations
- Creating abstractions is suspected to be in the core of our cognition, consciousness and creativity
- In generative systems, going back to musical surfaces from compressed / abstract spaces is hard
- Re-inventing a solution through (many) data: when data speak for themselves

Course content

- Data and visualization
- Linear and logistic regression basics
- From logistic regression to artificial neural networks
- Multilayered architectures for image recognition
- Application of ANNs in emotion recognition
- Autoencoders (Convolutional neural networks)
- Training basics
- From Autoencoders to Variational Autoencoders
- Generative Adversarial Networks – Application to audio generation
- Recurrent Neural Networks and Long Short-Term Memory
- Transformer (ChatGPT)

Course tools

- Files:
  - Github: https://github.com/maximoskp/MSc_MTA_HMU_AppliedML
  - Google drive: https://docs.google.com/document/d/1V2LzsC45swYMsUp8cpugdVGLIot7VwlTS1dHQMiIAAs/edit?usp=share_link
  - Eclass: https://eclass.hmu.gr/modules/document/?course=THM103
- Code:
  - Spyder for interactive plots
  - Google Colab as a main tool

Thank you ☺

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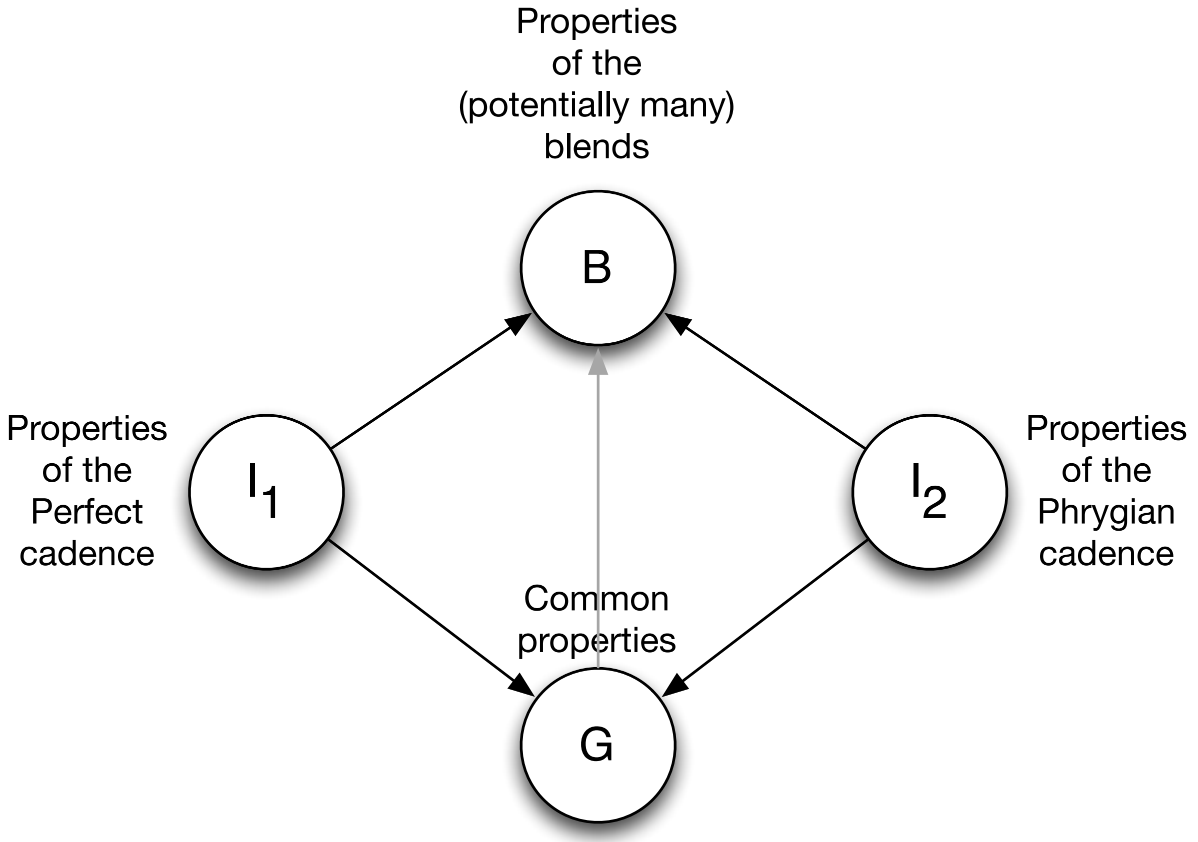
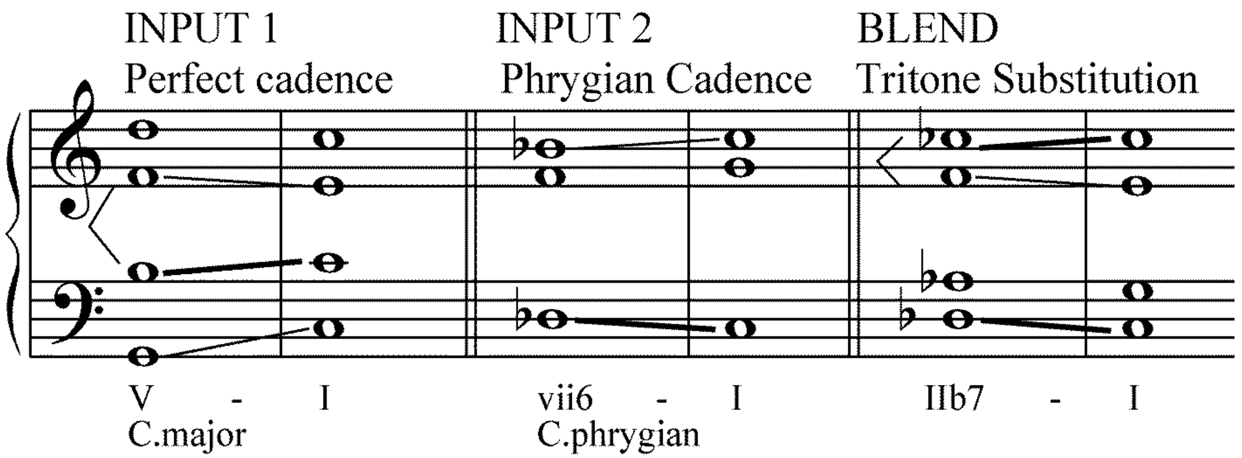
Conceptual Blending – a musical example





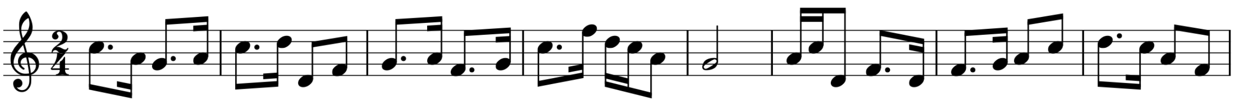
Example from the COINVENT project (2013-2016)
http://coinvent.uni-osnabrueck.de/

See also the CHAMELEON website:
http://ccm.web.auth.gr/blendedharmonisations.html

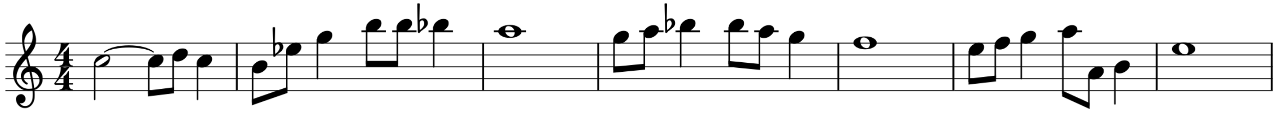
Conceptual Blending of Features

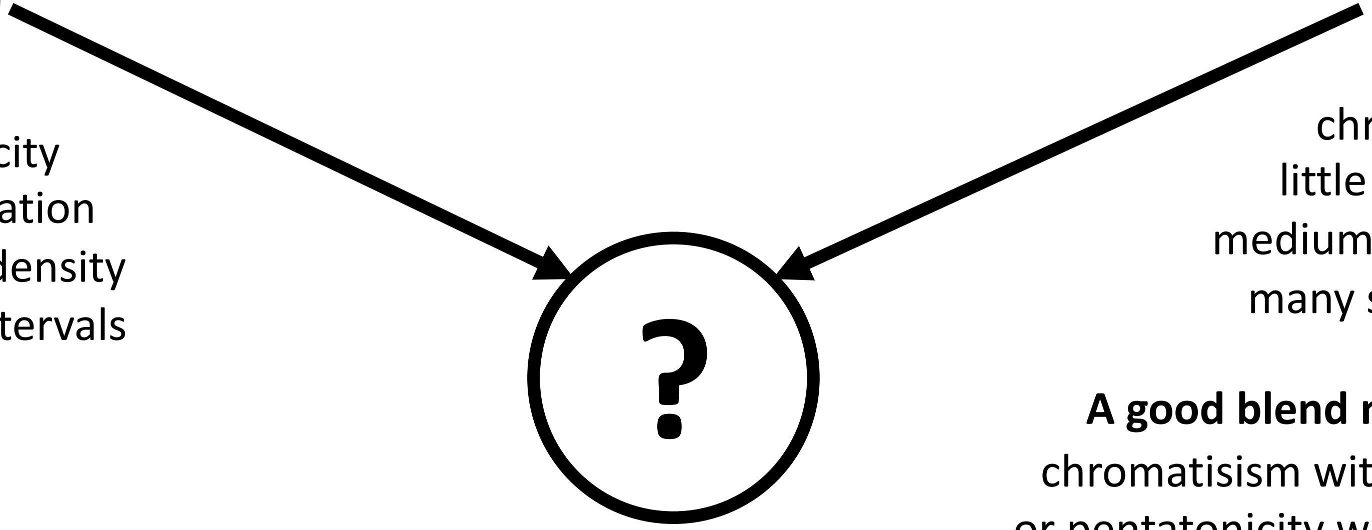
Example in melodies

"Chinese"



"Jazz"





pentatonicity
high syncopation
high rhythm density
many large intervals

chromatisism
little syncopation
medium rhythm density
many small intervals

A good blend might include:

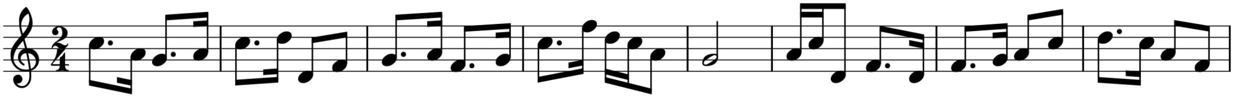
chromatisism with high syncopation
or pentatonicity with little syncopation

High-level **Representation**

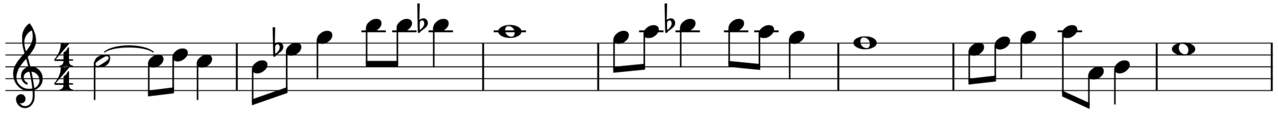
Conceptual Blending of Features

Example in melodies

“Chinese”

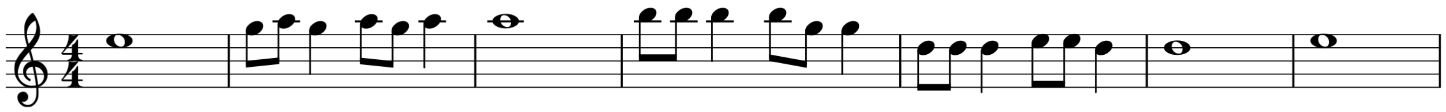


“Jazz”



rhythm density: **0.50**
syncopation: **0.63**
pentatonicity: **0.99**
small intervals: **0.43**

rhythm density: 0.26
syncopation: 0.00
pentatonicity: 0.36
small intervals: 0.76



rhythm density: 0.23
syncopation: 0.00
pentatonicity: **0.99**
small intervals: 0.75

Kaliakatsos-Papakostas, M. Examining the Generation of New Melodies through Generative Conceptual Blending of High-Level Features. IJMSTA. 2019 Sept 1; 1 (2): 35-43.