The HARMONIC MEMORY

a Knowledge Graph of harmonic patterns as a trustworthy framework for computational creativity

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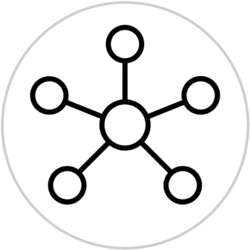
Polifonia

https://polifonia-project.eu/

Harmory in a nutshell

What is this paper about?



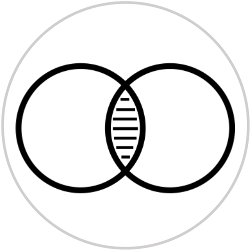
Harmory is a resource

Harmory is Knowledge Graph (KG)

Harmory contains harmonic data

Harmory contains:

1. Segmented harmonic patterns
2. Similarity information



Harmory can be used for AI creativity

Harmory can be used a trustworthy framework for computational creativity

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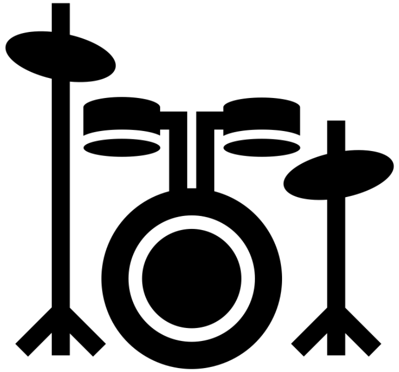
01

INTRODUCTION

- What is music creativity?
- AI creativity & music
- Our contribution

01 INTRODUCTION

A musical composition is composed by three main elements:



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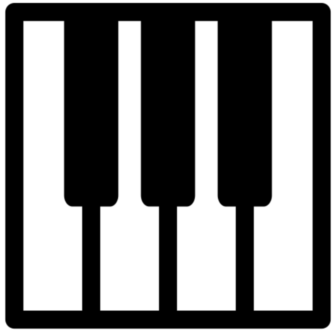

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Rhythm

Harmony

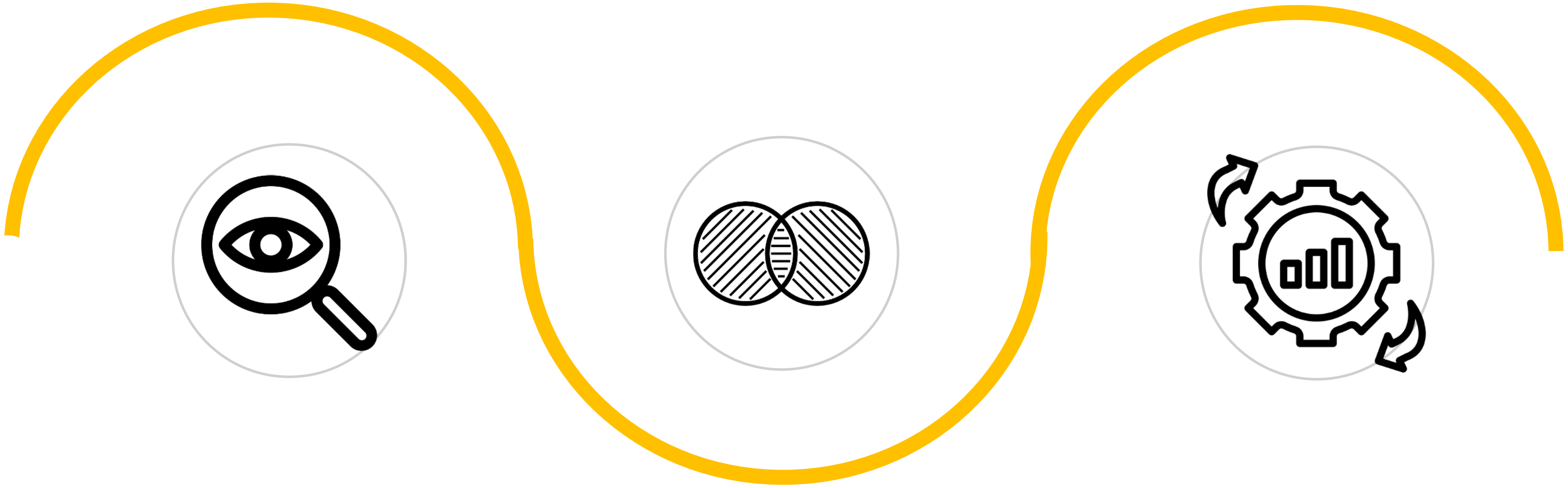
Melody

Jean-Benjamin de La Borde
Composition consists in two things only.
The first is [...] what the Ancients called melody.
The second is [...] what we call **harmony** and **it alone merits the name of composition.**

*1780**

What is creativity?

Creativity is the ability to come up with new, surprising, and valuable artefacts



Exploratory Creativity

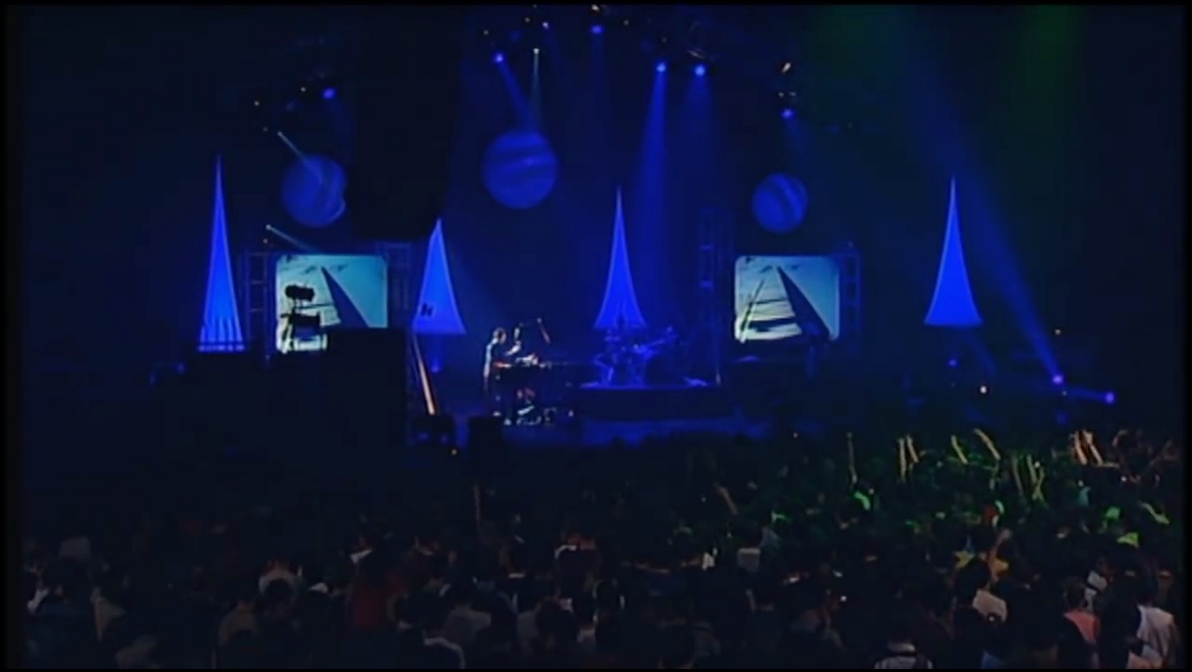
Combinatorial Creativity

Transformational Creativity

[Margaret A. Boden, 2004, *The Creative Mind: Myths and Mechanisms*]

Muse - Space Dementia

An example of **combinatorial** and **transformational creativity** in music



Muse – *Space Dementia* (2001)

?

Rachmaninoff – *Piano Concerto no. 2* (1901)

AI Creativity in the music domain

- Generative AI systems have a tendency to **replace artists**
- Generative systems typically propose an **explorative creative approach**
- Available systems lack of *accountability*, *explainability*, and *musical plausibility*

→

The Harmonic Memory

Harmory: a KG of harmonic patterns

A novel method for **Harmonic Structure Analysis**

An algorithm for **Harmonic Similarity**

Examples of possible application for trustworthy machine creativity

02

RELATED WORKS

- Related works

Related works

Exploratory Creativity

- Autoregressive models
- Starting from a prompt, they generate an output
- Based on recurrent, convolutional, or self-attention architectures

[Santosh et al., Cheng-Zhi et al.]

Combinatorial Creativity

- Variational autoencoders
- Create new ideas by interpolating between two musical passages in a latent space

[Roberts et al.]

Transformational Creativity

- Hybrid models
- Provide additional artistic stimulation
- Implemented by “hacking” the former methods

[Todd et al.]

Most of these works lack trustworthy features to support and protect creative professionals.

Related works(2)

- **Explainable Computational Creativity (XCC)** systems have been proposed, to promote a bidirectional interaction between system and user

[Llano et al.]

- This interaction is communicative, enabling the exchange of decisions and ideas in a format that can be understood by both humans and machines

- **Semantic Web technologies** have also been used to make creative systems more explainable

[Pini et al.]

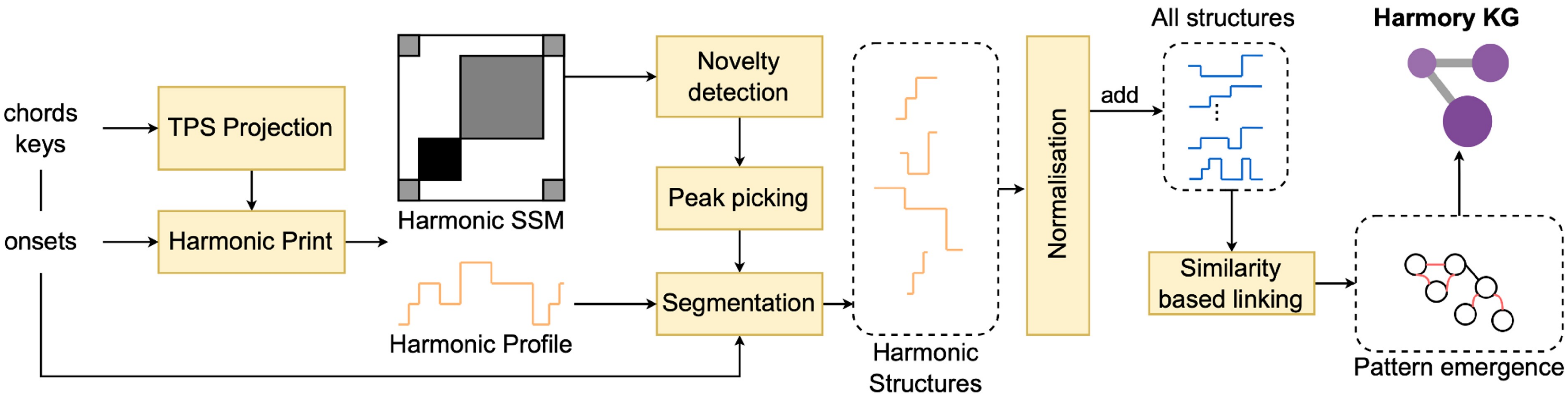
- To the best of our knowledge, no such systems have been proposed in the musical domain

03

HARMORY: the Harmonic Memory

- Encoding chords in the Tonal Pitch Space
- Novelty-based harmonic segmentation
- Linking harmonic segments via similarity
- Knowledge Graph creation

Harmory Methodology



Harmory Methodology

The creation of the Harmonic Memory can be summarised in four main steps

Encoding chords in the **Tonal Pitch Space**

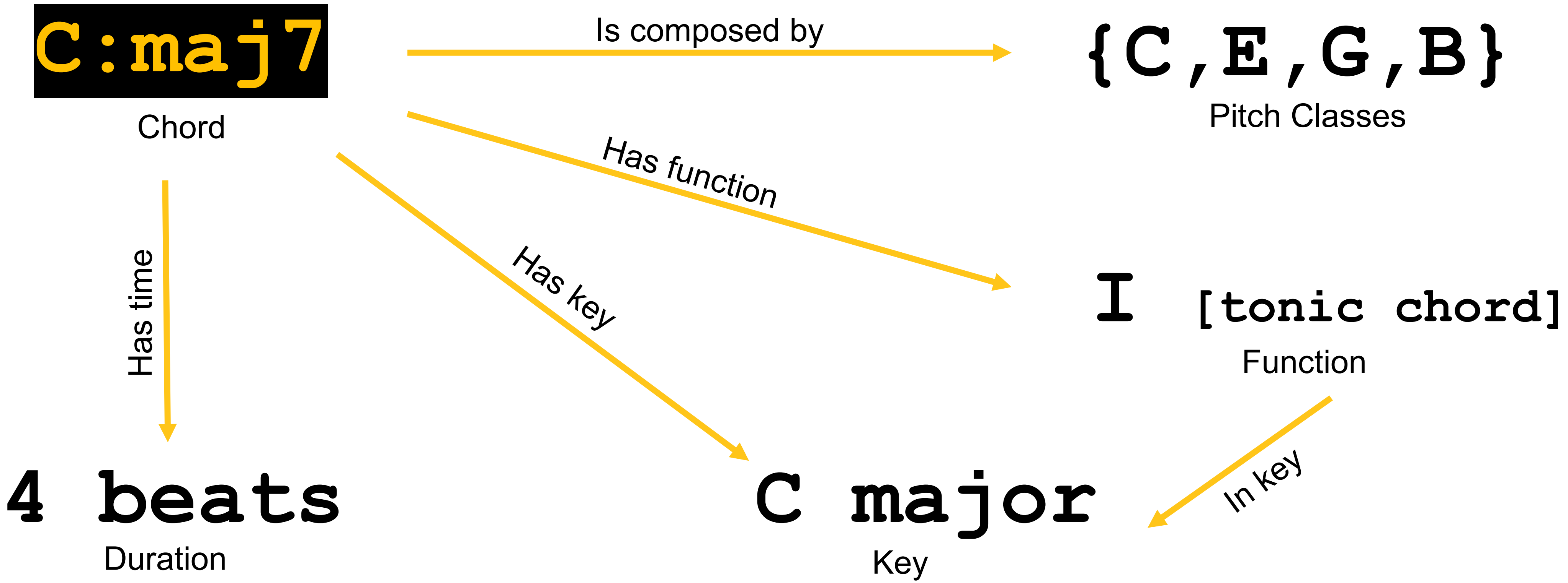
Novelty-based **harmonic segmentation**

Linking harmonic segments via **similarity**

Knowledge Graph creation

1. Need for a numerical encoding

Music chords are notoriously challenging to represent



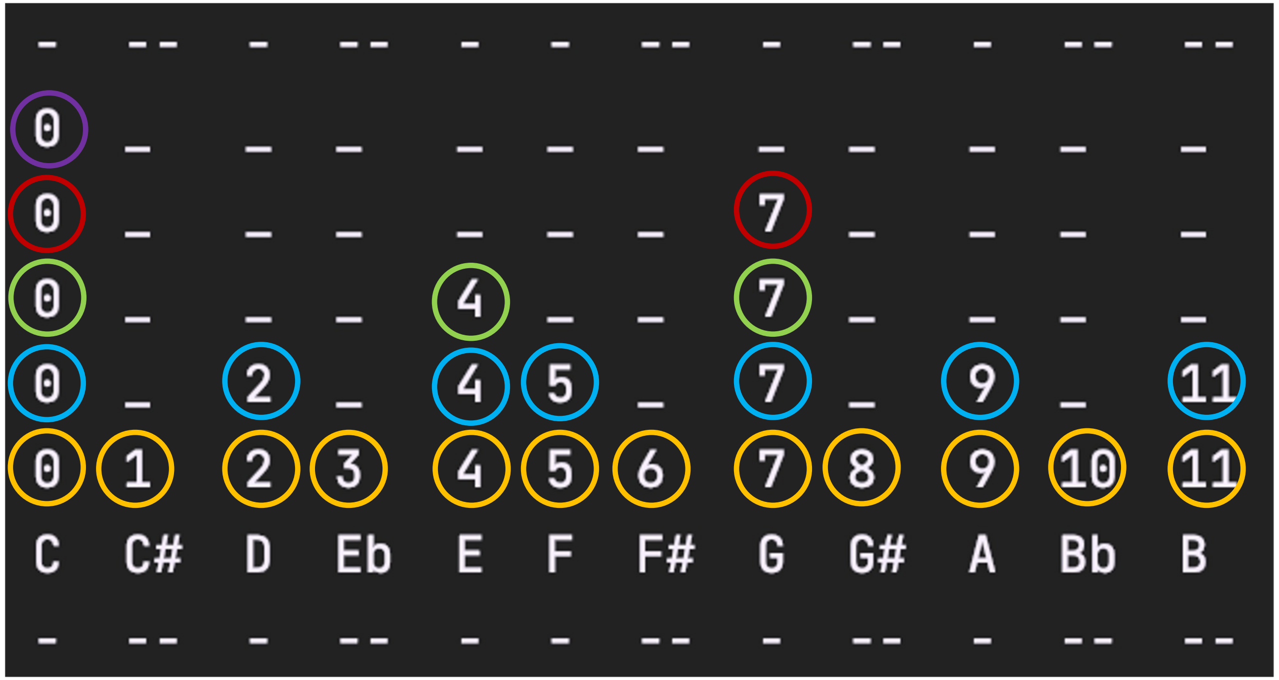
1. Encoding chords in the Tonal Pitch Space (TPS)

The TPS provides a **scoring mechanism** that predicts the **proximity between two musical chords**.

It is based on the *Generative Theory of Tonal Music* and it is musicologically grounded.

It is composed by **five levels**:

1. Root level
2. Fifths level
3. Triadic level
4. Diatonic level
5. Chromatic level



Example of a C major chord levels of the TPS

1. Encoding chords in the Tonal Pitch Space (TPS) (2)

The TPS distance between two chords (A and B) is calculated considering:

-	--	-	--	-	-	--	-	--	-	--	--
0	_	_	_	4	_	_	_	_	_	_	_
0	_	_	_	4	_	_	7	_	_	_	11
0	1	2	3	4	5	6	7	8	9	10	11
0	1	2	3	4	5	6	7	8	9	10	11
0	1	2	3	4	5	6	7	8	9	10	11
C	C#	D	Eb	E	F	F#	G	G#	A	Bb	B
-	--	-	--	-	-	--	-	--	-	--	--

Difference between a C major and a E major chords according to the TPS

1. Number of **non-common pitch classes** divided by 2 in the levels (i-iv)

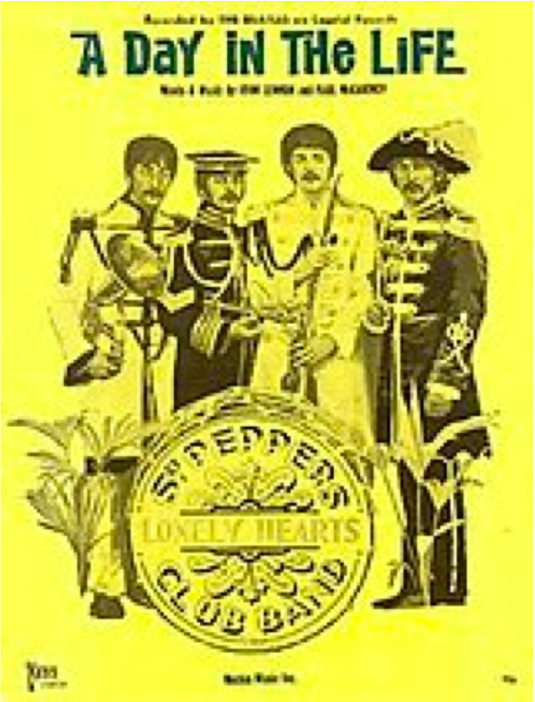
+

2. Minimum number of **Circle-of-Fifths rule** applications to shift between chord A and B

1. Encoding chords in the Tonal Pitch Space (TPS) (3)

For a chord sequence, each chord is encoded as its distance to its local key.

For each comparison between two chords, the TPS returns a value in [0, 13].



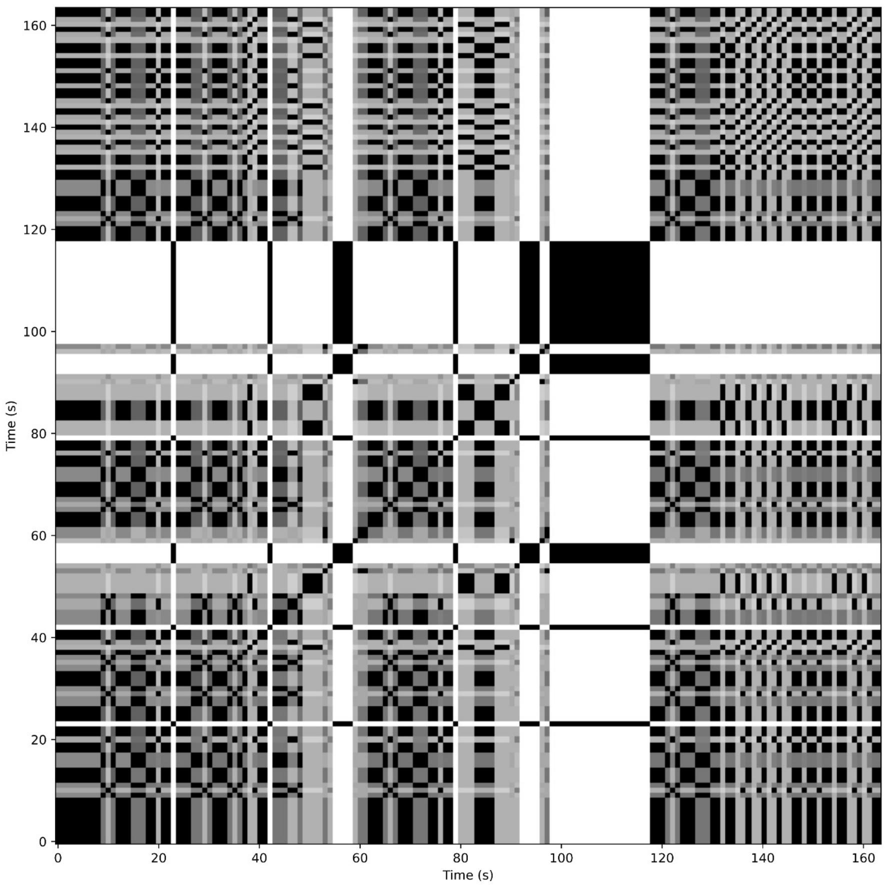
Chord sequence (*c*): [G, B:min, E:min7, . . .]
Tonal keys of c (*k*): [(G, major), (G, major), (G, major), . . .]
Onsets (*t*): [1, 3, 5, . . .]

TPS sequence: [2.0, 3.5, 0.0, 8.9, …]

2. Novelty-based harmonic segmentation

- A **Self Similarity Matrix (SSM)** is encoded starting from the TPS sequences

- Self-similarity matrices have been extensively used for **structure analysis on the audio signal**, due to their ability to reveal nested structural elements

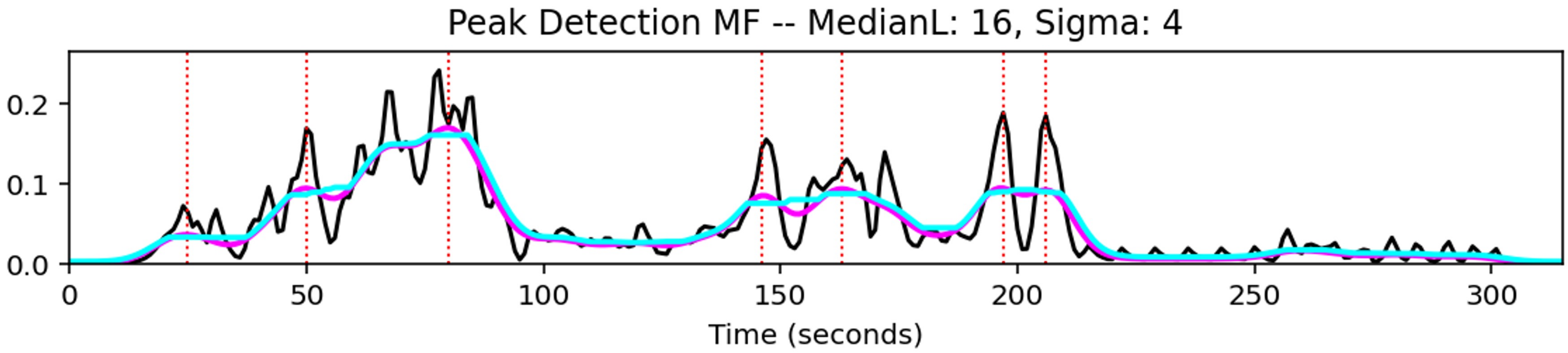


SSM of the track *"Crazy Little Thing called Love"*

2. Novelty-based harmonic segmentation (2)

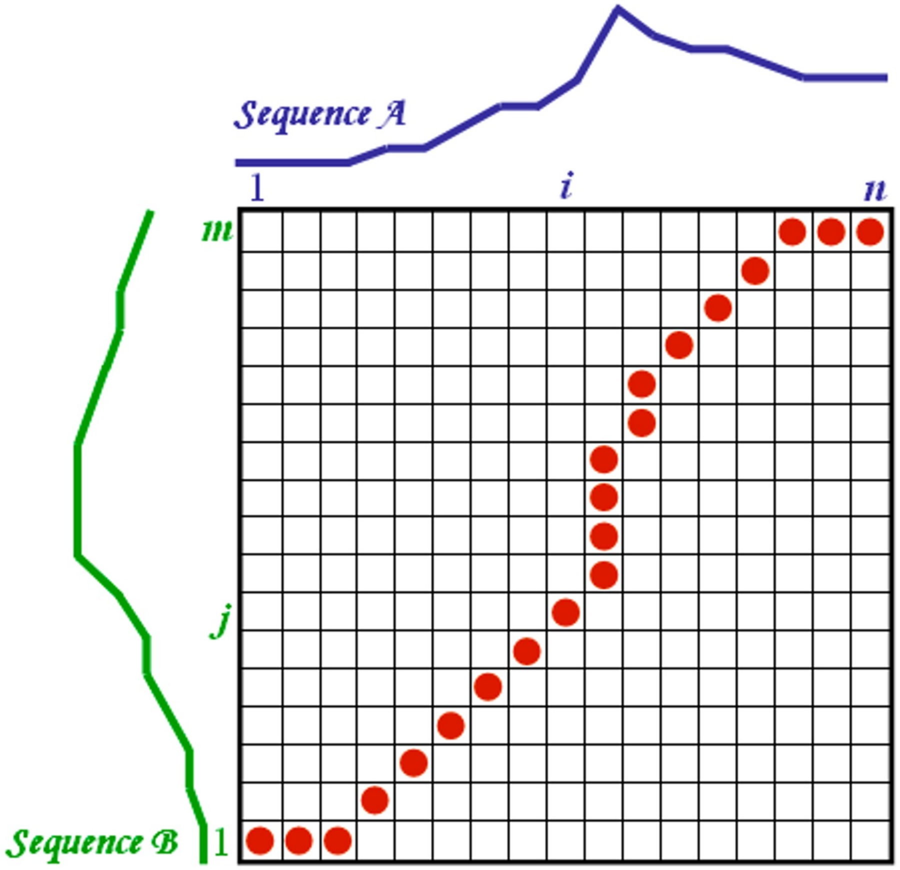
- To identify boundaries a **checkboard kernel (K)** is slided along the SSM main diagonal: this creates a **Novelty Curve:**
  - When K is located in a uniform region, **novelty** will be **low**
  - When K is at the crux of a checkerboard-like structure, **novelty** will be **high**

- Local maxima of the novelty curve are then used to **detect the boundaries** of neighbouring segments



3. Linking harmonic segments via similarity

- The TPS encoded sequences are compared using a **Dynamic Time Warping (DTW) algorithm**
- DTW is used for comparing and aligning time sequences (usually in the audio domain)
- DTW allows for non-linear alignment between the time series by considering the local warping path

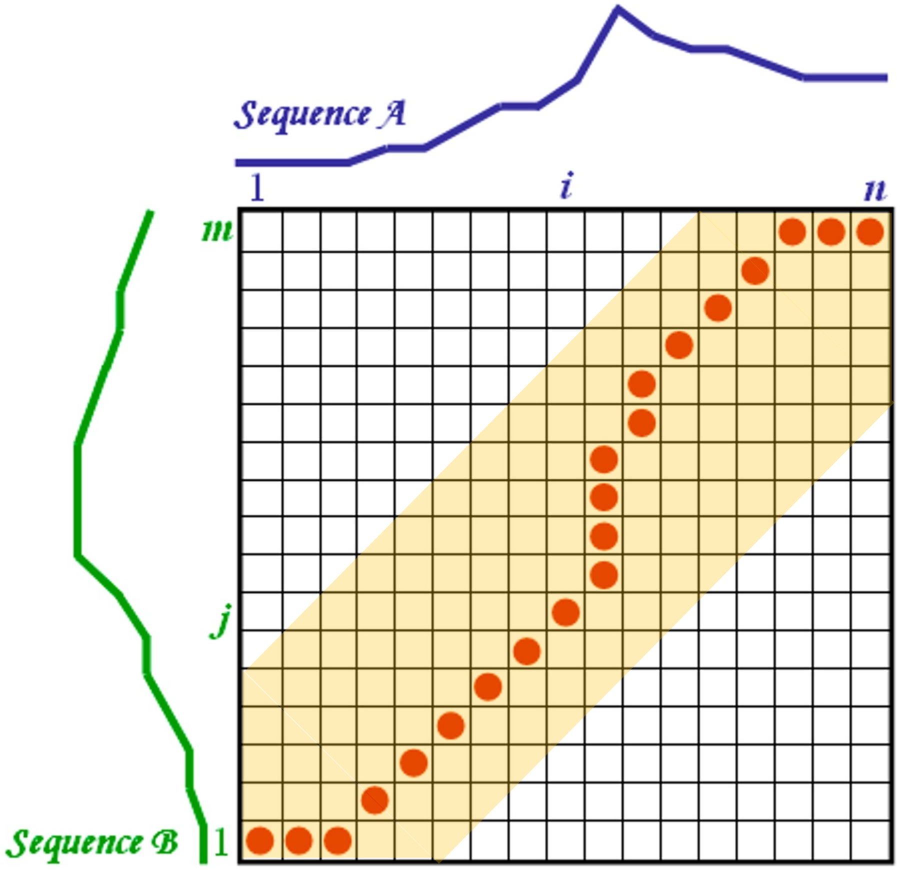


3. Linking harmonic segments via similarity (2)

- We used a variant of the vanilla DTW algorithm: **Sakoe-Chiba**

- Sakoe-Chiba allows to **constraint the search space** of the algorithm within a band ***(w)***

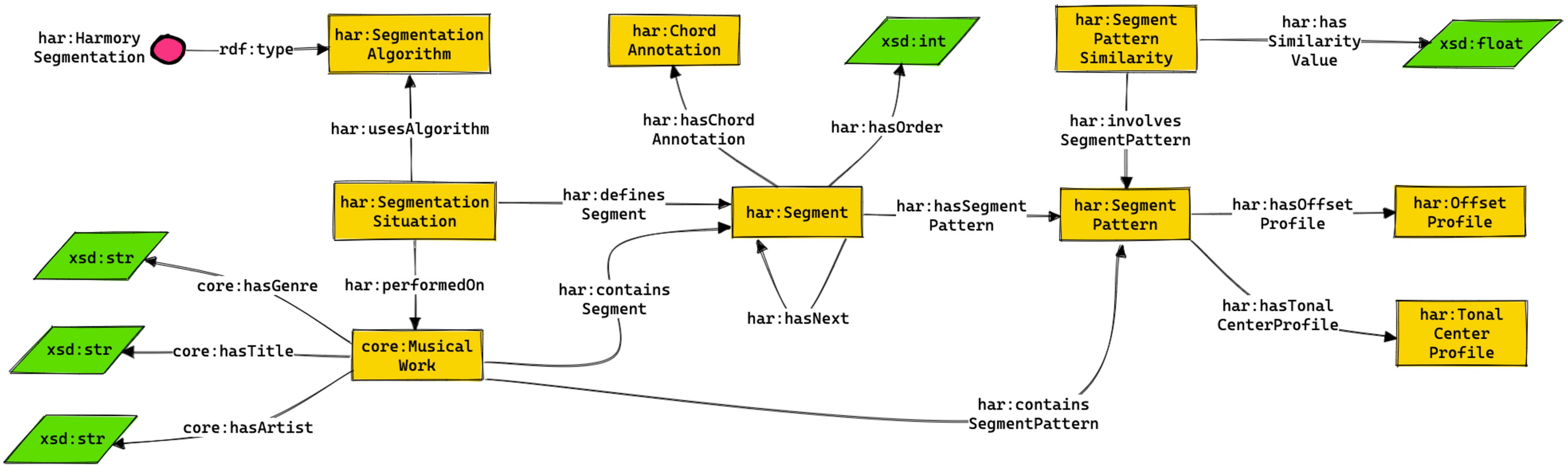
- This leads to a drop in computational time complexity:
  - Vanilla DTW: $O(N^2)$
  - Sakoe-Chiba DTW: $O(N * w)$



4. Knowledge Graph Creation

- An **ontology** for describing Harmory data has been created
- The ontology is part of the **Polifonia Ontology Network** (PON)
- Data has been transformed using **RDFLib**
- The generated Knowledge Graph contains **1429070 triples**

4. Knowledge Graph Creation (2)



Prefixes

har: http://w3id.org/polifonia/ontology/harmory/
owl: http://www.w3.org/2002/07/owl#
rdfs: http://www.w3.org/2000/01/rdf-schema#
core: https://w3id.org/polifonia/ontology/core/

04

EXPERIMENTS

- Evaluation of harmonic similarity
- Structural coverage of known patterns

Dataset

FROM | 18 datasets | 14 formats | 9 notations

TO | 1 dataset | 2 outputs | 2 notations

- ChoCo is the largest existing collection of harmonic annotations
- Allows to deal with diversity
- We used a subset of ChoCo for running our experiments

ChoCo

https://github.com/smashub/choco

[Jacopo de Berardinis et al., 2023, *ChoCo: a Chord Corpus and a Data Transformation Workflow for Musical Harmony Knowledge Graphs*]

Evaluation of Harmonic Similarity

Dataset
Subset of ChoCo:
- **Schubert Winterreise**
- **CASD**

Task
Cover song detection

Metrics
- **First-tier**
- **Second-tier**

Compared Algorithms

We compared our algorithm to:

- **Longest Common Subsequence (LCSS)**
- **Soft Dynamic Time Warping (Soft DTW)**
- **Tonal Pitch Step Distance**

Evaluation of Harmonic Similarity (2)

					Schubert		*CASD*		*Schubert+CASD*	
Algorithm	**TPS Mode**	**Stretch**	**Constraint**	**Normalise**	**First Tier**	**Second Tier**	**First Tier**	**Second Tier**	**First Tier**	**Second Tier**
TPSD	offset	-	-	-	0.49	0.63	0.62	0.68	0.58	0.67
TPSD	profile	-	-	-	0.53	0.74	0.76	0.83	0.69	0.8
DTW	offset	stretch	-	-	0.94	0.98	0.53	0.67	0.66	0.76
DTW	profile	stretch	-	-	0.97	0.99	0.6	0.69	0.71	0.78
DTW	offset	stretch	sakoe_chiba	-	0.96	0.99	0.62	0.7	0.72	0.79
DTW	profile	stretch	sakoe_chiba	-	0.97	0.99	0.69	0.77	0.77	**0.84**
DTW	offset	stretch	itakura	-	0.96	0.99	0.55	0.65	0.68	0.75
DTW	profile	stretch	sakoe_chiba	yes	0.97	0.99	0.7	0.76	**0.79**	0.83
LCSS	offset	-	sakoe_chiba	-	0.38	0.61	0.03	0.07	0.14	0.24
LCSS	offset	-	itakura	-	0.7	0.8	0.14	0.23	0.31	0.41
SoftDTW	offset	stretch	-	-	0.93	0.97	0.55	0.69	0.67	0.77
SoftDTW	profile	stretch	sakoe_chiba	-	0.98	0.99	0.62	0.73	0.73	0.81

Structural coverage of known patterns

Dataset
- Subset of ChoCo
- Known harmonic patterns from **Impro-Visor**

Task
Time series segmentation

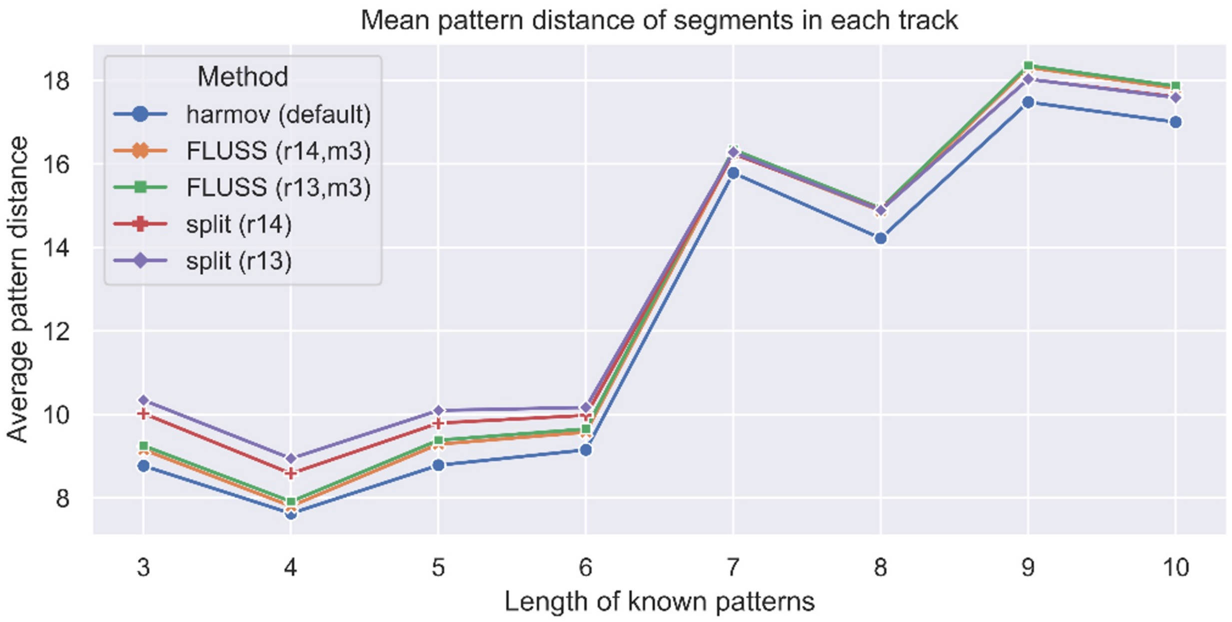
Metrics
- Mean pattern distance of segments in each track
- Mean pattern distance of the most similar segment per track

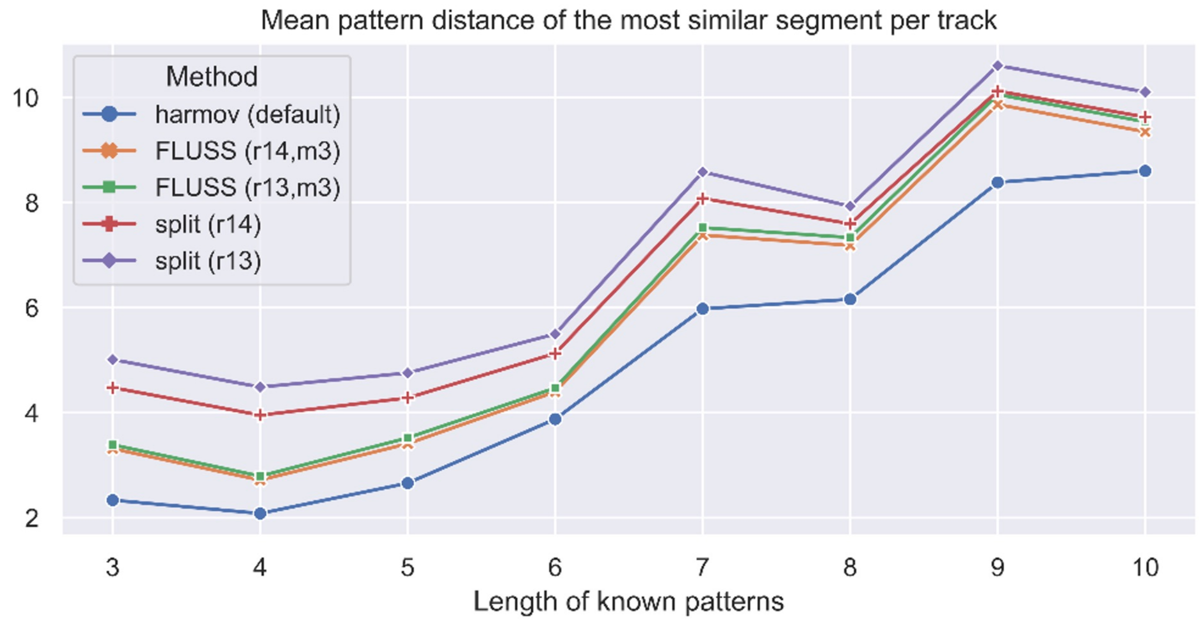
Compared Algorithms

We compared our algorithm to:

- **Fast low-cost unipotent semantic segmentation (FLUSS)**
- **Fixed sequence split**

Structural coverage of known patterns (2)





05

AVENUES FOR MACHINE CREATIVITY

- Pattern discovery
- Human-machine chord generation
- Harmonic similarity

1- Pattern Discovery

The traversal of the Harmonic Memory makes it possible to obtain granular information of the harmonic structure of songs

Prompt 1: *For a given pattern, which are the tracks (titles, artists and genres) in which the pattern can be found?*

Prompt 2: *Which harmonic patterns are used in “Michelle” by The Beatles, but also in a classical composition?*

Prompt 3: *Which tracks include a dominant cycle in seven steps?*

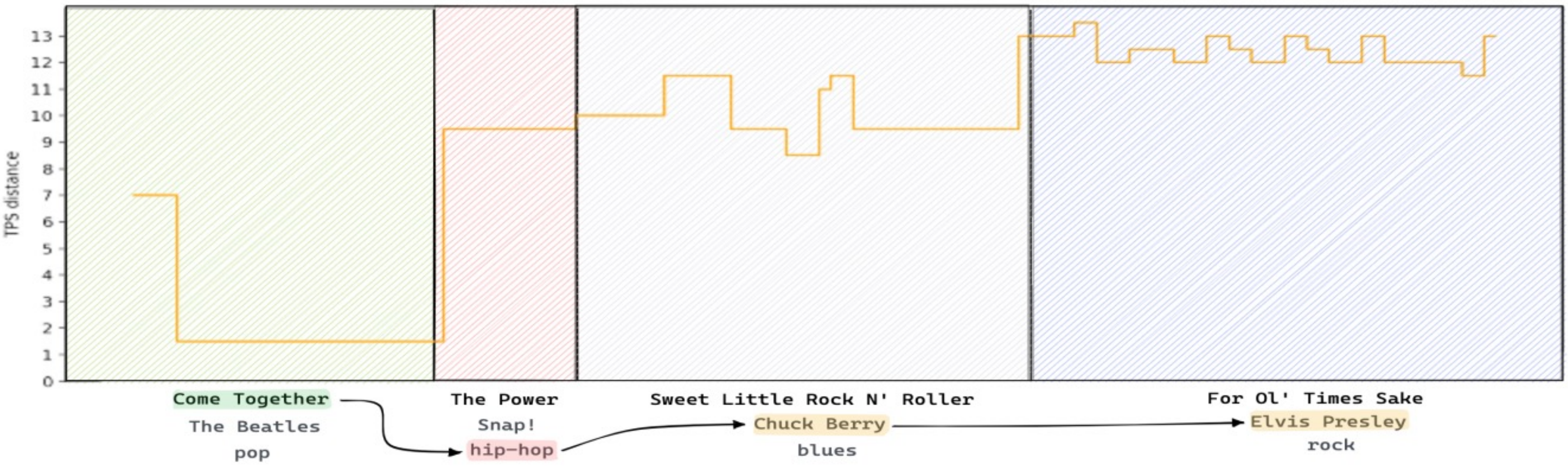
2 - Human-machine chord generation

Harmory also enables combinational creativity use cases:

Prompt 4: *Given a chord sequence, which are its variations, and which tracks these variations belong to?*

Prompt 5: *Create a progression starting with “Come Together” by The Beatles, continuing with a segment found in a Rap song, and then continuing with another by Chuck Berry and Elvis Presley*

3 - Human-machine chord generation (2)



3 – Harmonic Similarity

From a musicological perspective, the KG can also be used to analyse similarity relations between tracks:

Prompt 6: *Given a track, which tracks contain patterns with a distance of less than 0.2?*

06

FUTURE WORK

- Next steps

Future Work

We introduced the **Harmonic Memory (Harmory)** – a Knowledge Graph of interconnected chordal patterns which is perceptually and musicologically grounded

Future work include:

Linking new web resources to Harmory to enhance KG capabilities

Inclusion of **heterogeneous data** (e.g. melodic data, perceptual data, etc.)

Creation of an **interface** for browsing data and support artists’ creation

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Thanks!

*Any **question?***

https://github.com/smashub/harmory

Polifonia