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Music Information Retrieval 2.0

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Why 2.0?

Music Information Retrieval (MIR) from a very traditional IR perspective is to have a short piece of music (symbolic, audio) and to find relevant pieces in a repository (e.g., that exact piece, “similar sounding” pieces, cover versions)

MIR spans more than that:

- MIR is not only query-by-example retrieval
- MIR is about music retrieval in general, i.e., also (textual) meta-data and not just musical representations alone
- Moreover, “MIR 2.0” deals with vast amounts of data + utilizes the power-of-the-crowds, e.g., for “semantic” song annotations

Who are we ?



Markus Schedl

Assistant Professor at the

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M.Sc. in Computer Science from Vienna University of Technology

Ph.D. in Computational Perception from Johannes Kepler University Linz

M.Sc. in Int'l Business Administration from Vienna University of Economics and Business Administration

Research interests: social media mining, music and multimedia information retrieval, recommender systems, information visualization, and intelligent/personalized user interfaces



Peter Knees

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M.Sc. in Computer Science from Vienna University of Technology

Ph.D. in Computer Science from Johannes Kepler University Linz

Research interests: music and web information retrieval, multimedia, user interfaces, recommender systems, digital media arts

Introduction to MIR

1. **Definitions**
2. **Applications**
3. **Typical Tasks and Challenges**
4. **Types of Computational Features**

Introduction to MIR: Definitions

“MIR is a **multidisciplinary** research endeavor that strives to develop innovative **content-based searching schemes**, novel **interfaces**, and evolving **networked delivery** mechanisms in an effort to make the world’s vast store of music accessible to all.”

[Downie, 2004]

“...actions, methods and procedures for **recovering stored data** to provide information on music.”

[Fingerhut, 2004]

“MIR is concerned with the **extraction, analysis, and usage** of information about **any kind of music entity** (for example, a song or a music artist) on **any representation level** (for example, audio signal, symbolic MIDI representation of a piece of music, or name of a music artist).

[Schedl, 2008]

Applications

Automatic Playlist Generation

Pandora.com

- continuously plays similar music
- based on the *Music Genome Project*
- manually annotated tracks
- songs can be rated



Applications

Browsing Music Collections

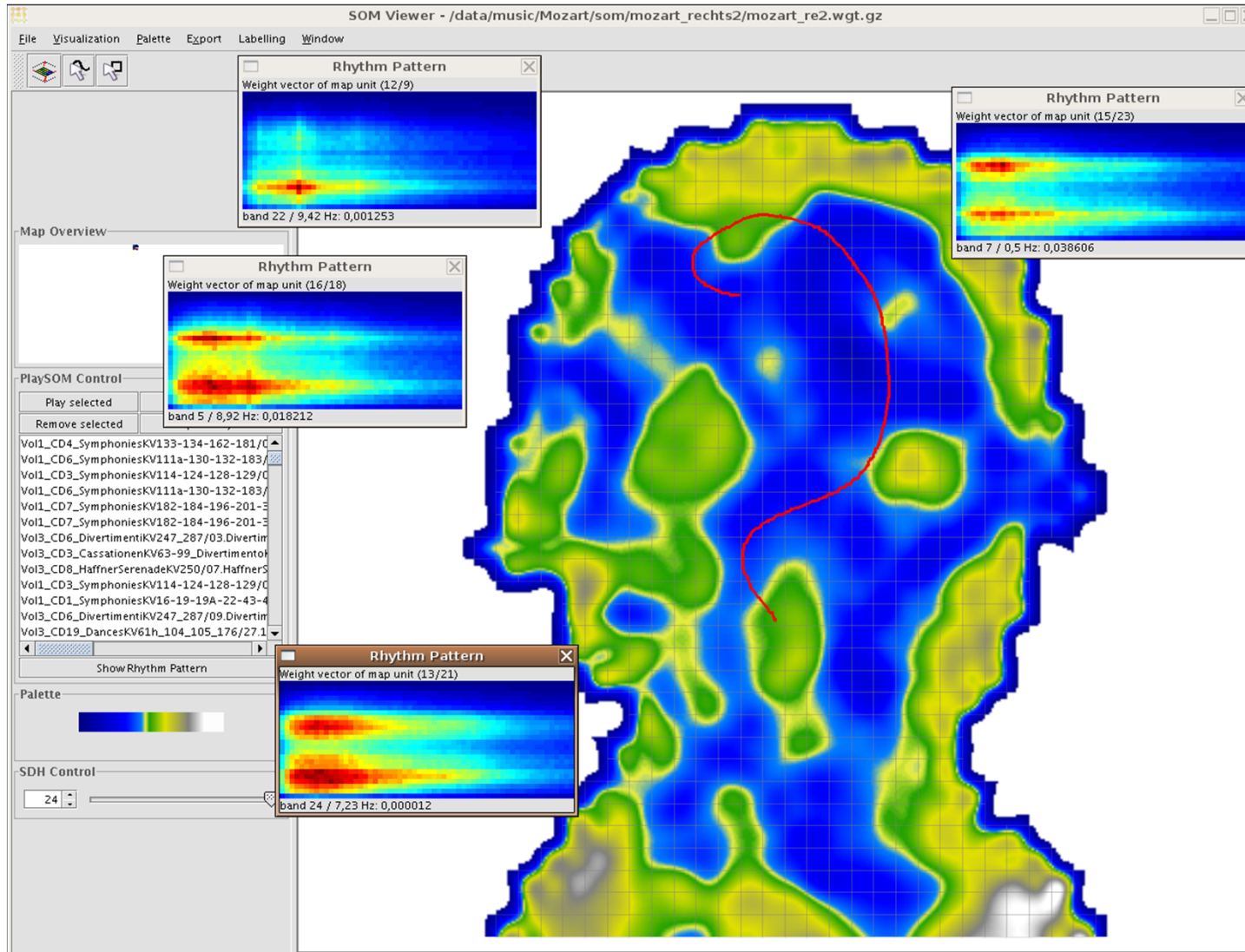
- music collections become larger and larger (on PCs as well as on mobile players)
- most UIs of music players still only allow organization and searching by textual properties according to scheme (*genre-artist-album-track*)

→ novel and innovative strategies to access music are sought in MIR



„intelligent iPod“ by CP@JKU
[Schnitzer et al., MUM 2007]

Music Information Retrieval 2.0

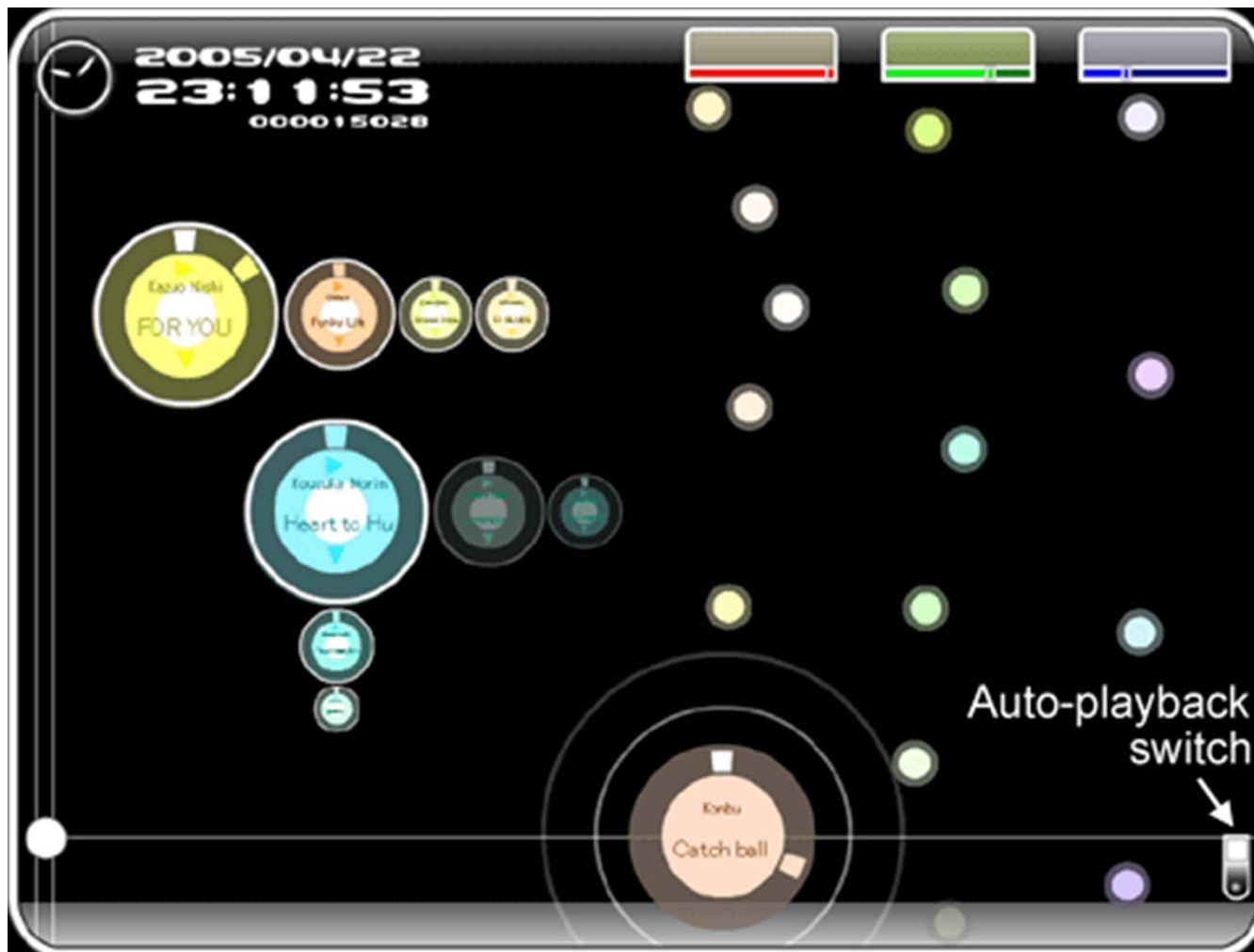


Browsing Music Collections

IFS @
TU Wien, 2006

[Mayer et al.,
ISMIR 2006]

Applications



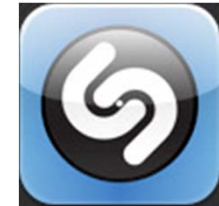
„Musiccream“,
[Goto and Goto, ISMIR 2005]

Applications

Audio Fingerprinting

Query-by-example:

excerpt of a song (potentially recorded in low quality) used to identify the piece



Query-by-humming:

input is not excerpt of a song, but melody hum by the user



www.shazam.com

www.musicline.de/de/melodiesuche

www.soundhound.com



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Applications

„Yanno“ – Chord Detection in Youtube videos, C4DM@QMUL, 2012

Dragonforce - Through The Fire And Flames (Video) centre for digital music

[\[on YouTube\]](#) [\[Print version\]](#)



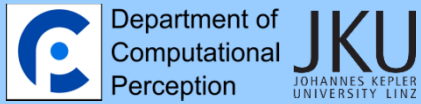
[loop end](#)

[toggle detailed chords](#)

Dragonforce - Through The Fire And Flames (Video)
by dragonforceofficial



Music Information Retrieval 2.0

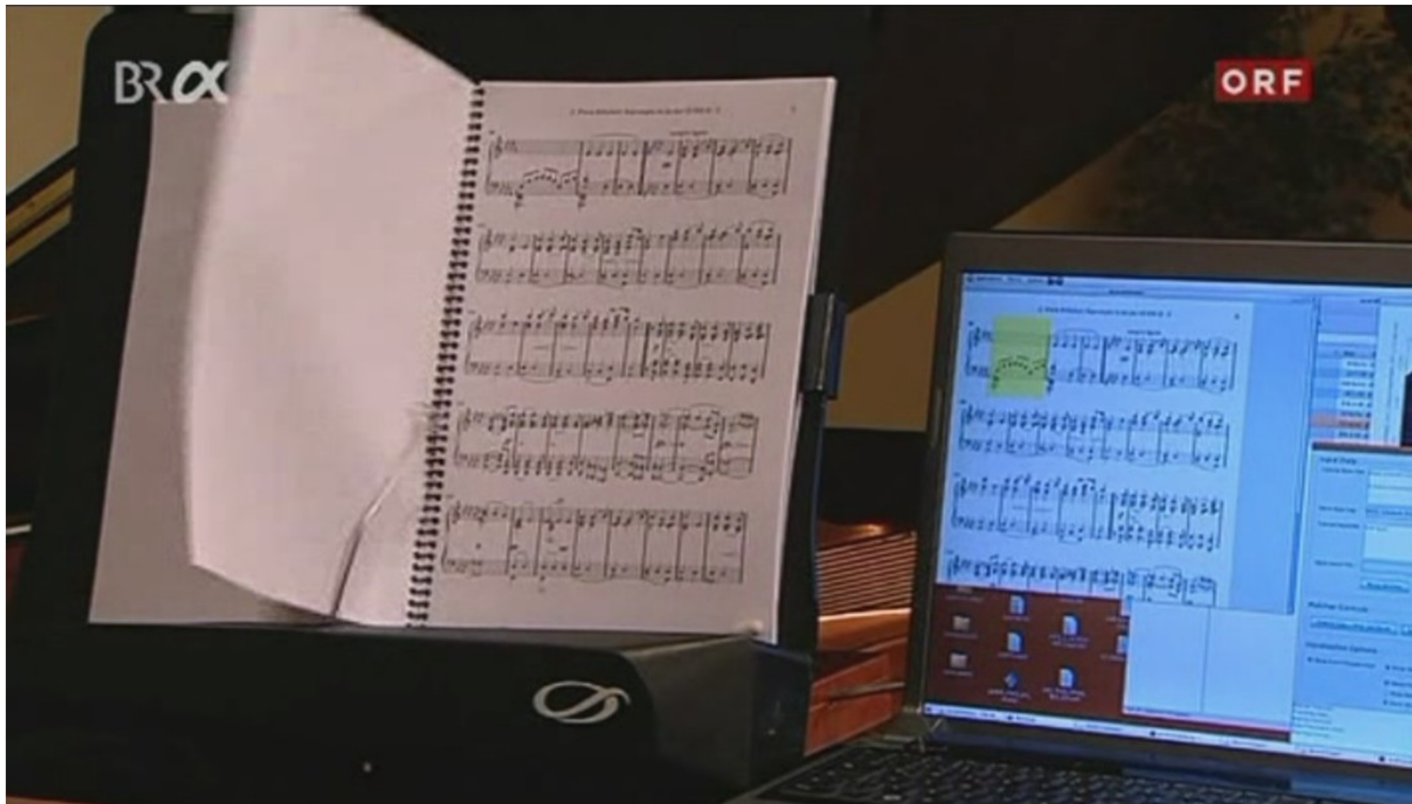


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Applications

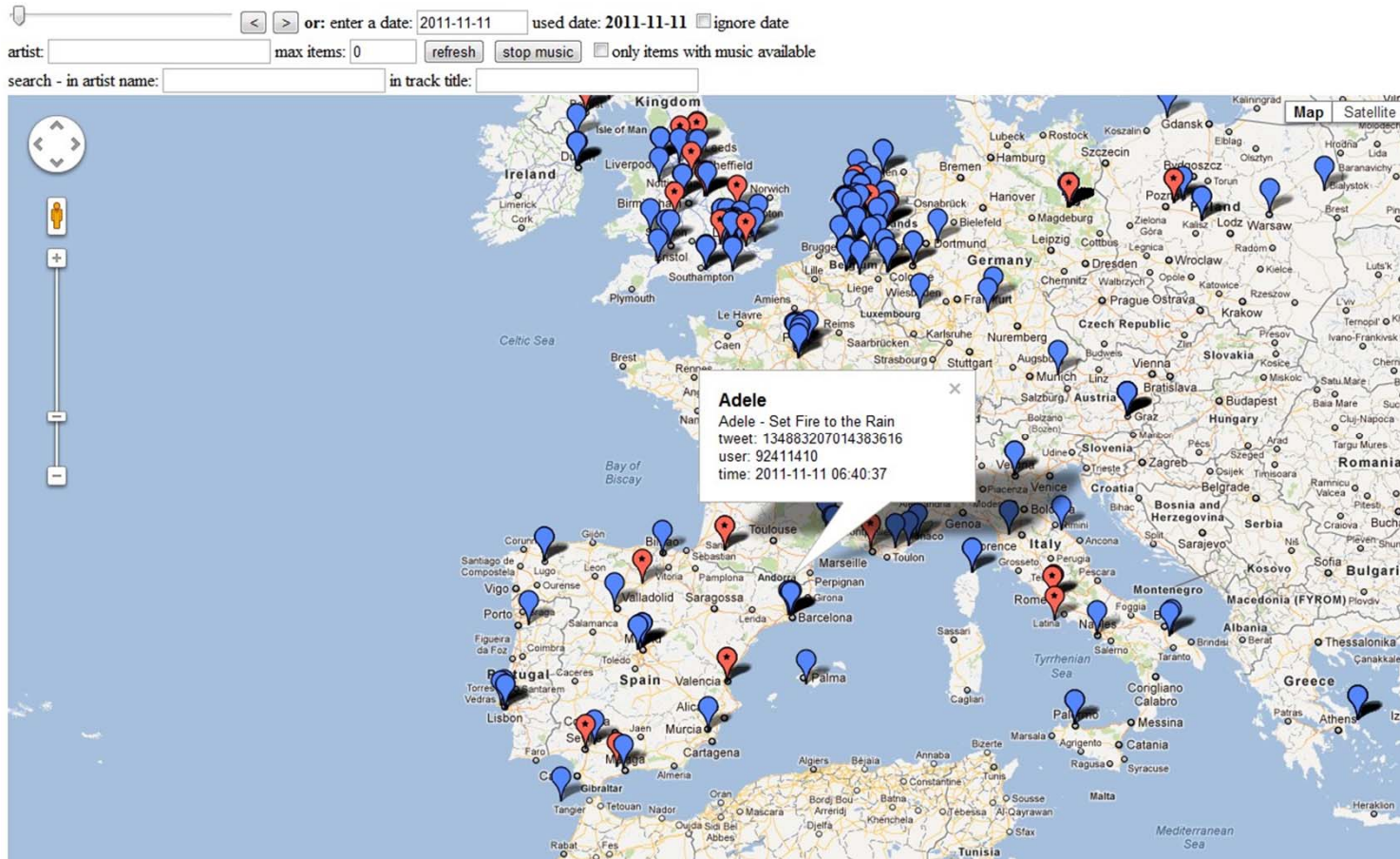
Real-time Music Following



Music Information Retrieval 2.0

Applications

Geospatial Popularity Estimation

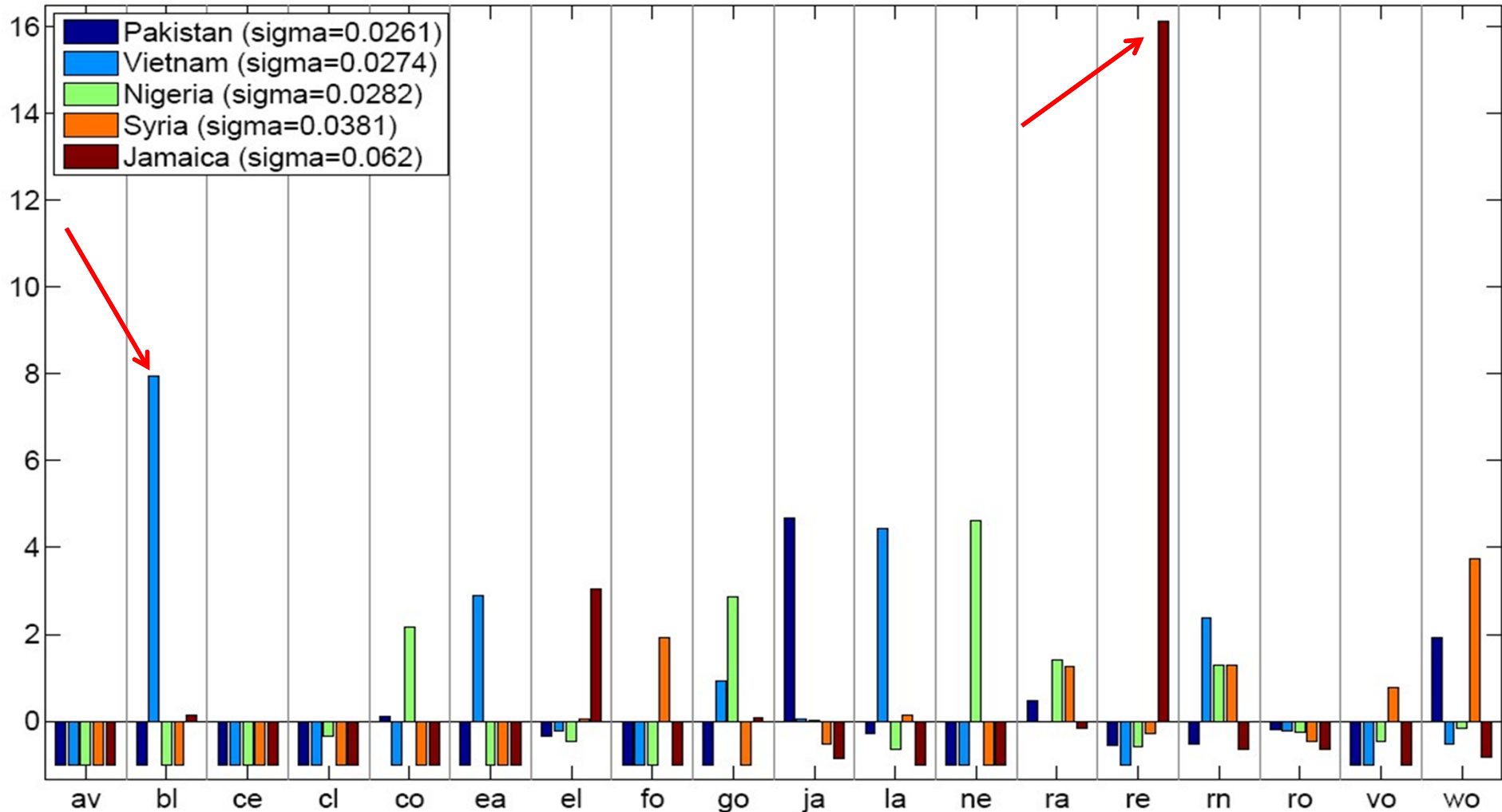


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Geospatial Listening Patterns

Applications

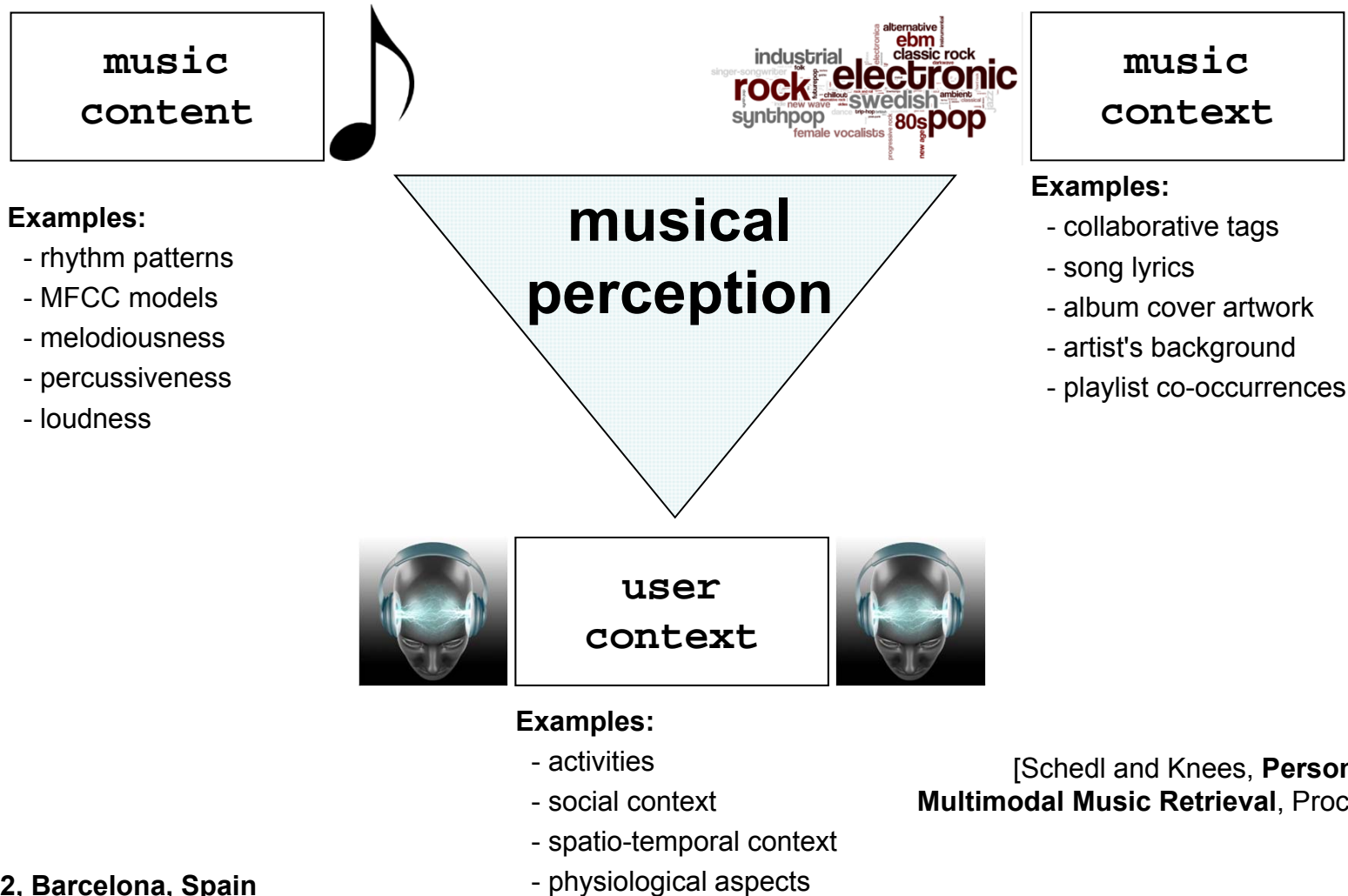
[Schedl and Hauger, AdMIRe 2012]



Typical Tasks and Challenges

- feature extraction (audio-based vs. context-based approaches)
- similarity measurement, recommendation, automated playlist generation (last.fm, Pandora, Echo Nest, ...)
- user interfaces, visualization, and interaction
- audio fingerprinting (copyright infringement detection, music identification services like shazam.com or musicbrainz.org)
- voice and instrument recognition, speech/music discrimination
- structural analysis, alignment, and transcription (segmentation, self-similarities, music summarization, audio synthesis, audio and lyrics alignment, audio to score alignment aka score following, and audio to score transcription)
- optical music recognition (OMR)
- classification and evaluation (ground truth definitions, quality measurement, e.g. for feature extraction algorithms, genre classification)

The Feature Extraction Triangle



[Schedl and Knees, **Personalization in Multimodal Music Retrieval**, Proc. AMR 2011]

Music Content vs. Music Context

Challenges for Context-based Feature Extractors

- Dependence on availability of sources (Web pages, tags, playlists, ...)
- Popularity of artists may distort results
- Cold start problem of community-based systems
(newly added entities do not have any information associated, e.g. user tags, users' playing behavior)
- Hacking and vandalism (cf. last.fm tag "brutal death metal")
- Bias towards specific user/listener groups
(e.g., young, Internet-prone, metal listeners in last.fm)
- (Reliable) data often only available on artist level
- Artist names that equal common speech terms

Challenge for both Content and Context Analysis

- Extraction of relevant features from *noisy signal*

Content-based Feature Extraction



- 1. Categorization of Content-based Features**
- 2. Scheme of a Content-based Feature Extractor**
- 3. Different Feature Extractors (low-level, mid-level, high-level)**

Categorization of Content-based Features



Level of abstraction:

low-level

closest to audio signal (e.g., energy, zero-crossing-rate);
app: audio identification

mid-level

aggregate low-level, apply psycho-acoustic models (e.g., MFCC, FP);
app: similarity estimation, query-by-humming

high-level

directly meaningful to end user (e.g., semantic tags learned from audio features);
app: autotagging, genre classification

Categorization of Content-based Features



Temporal scope:

instantaneous

feature is valid for a “point in time”, time resolution of ear is several msec!

segment

feature is valid for a segment, e.g., phrase, chorus (on a high level), or a chunk of X consecutive seconds in the audio signal

global

feature is valid for whole audio excerpt or piece of music

Categorization of Content-based Features



Acoustic property to describe:

timbre

rhythm

pitch and melody

chords and harmony

Categorization of Content-based Features



Domain:

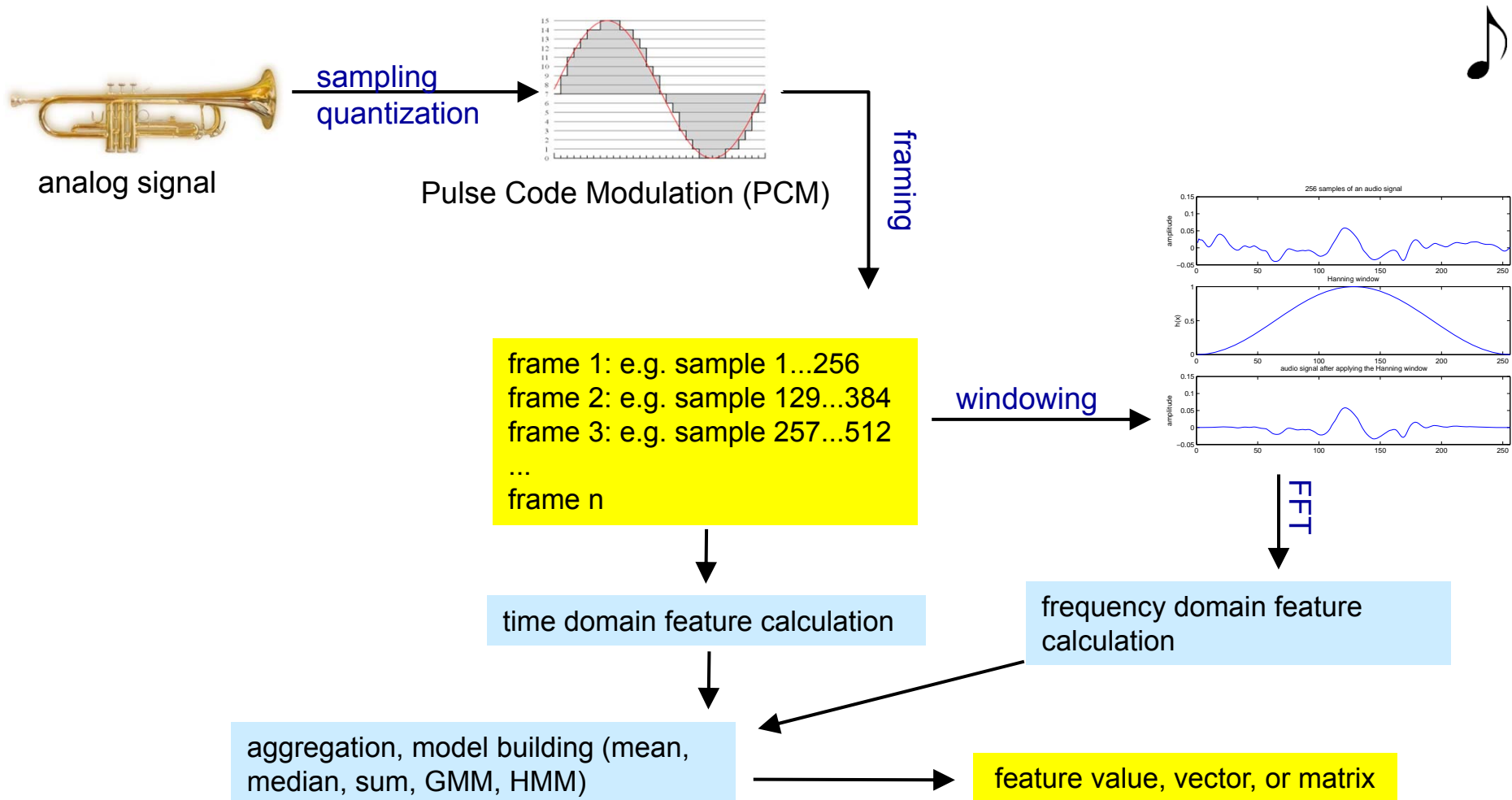
time domain

consider signal in *time/amplitude* representation

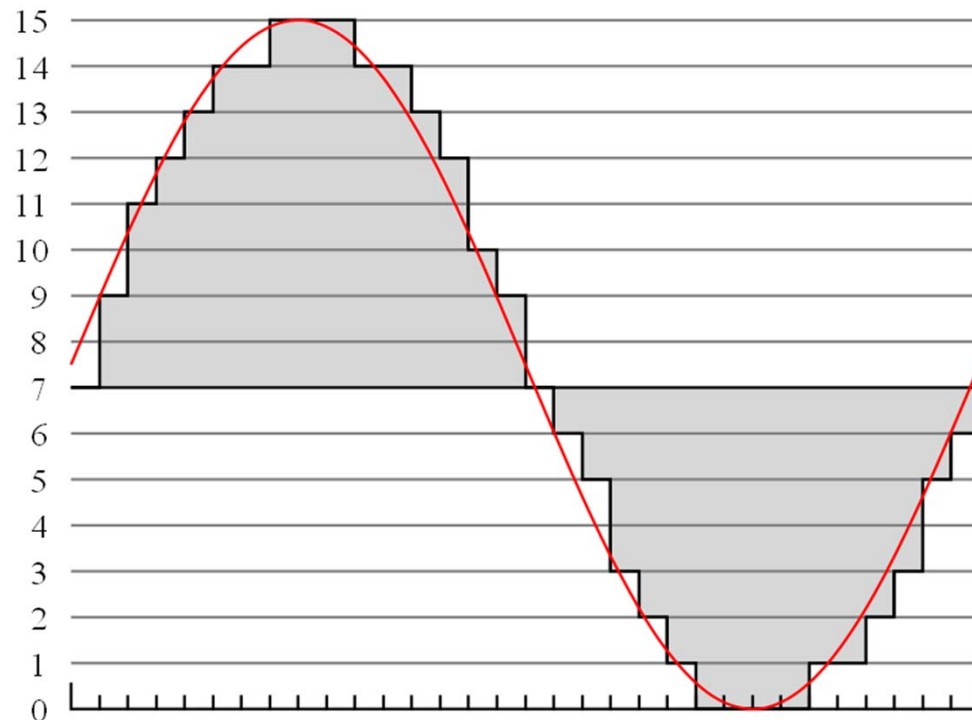
frequency domain

consider signal in *frequency/magnitude* representation, Fast Fourier Transform

Scheme of a Content-based Feature Extractor



Analog-Digital-Conversion (ADC)



PCM: analog signal is sampled at equidistant intervals and quantized in order to store it in digital form (here with 4 bits)

Problems that may occur in ADC:

quantization error: difference between the actual analog value and quantized digital value



solution: finer resolution (use more bits for encoding), common choice in music encoding: 16 bits per channel

due to **Nyquist–Shannon Sampling Theorem**, frequencies above $\frac{1}{2}$ of sampling frequency (Nyquist frequency) are discarded or heavily distorted

solution: choose a sampling frequency that is high enough (e.g. 44,100 Hz for Audio CDs)

Frame

In short-time signal processing, pieces of music are cut into segments of fixed length, called frames, which are processed one at a time; typically, a frame comprises 256 - 4096 samples.

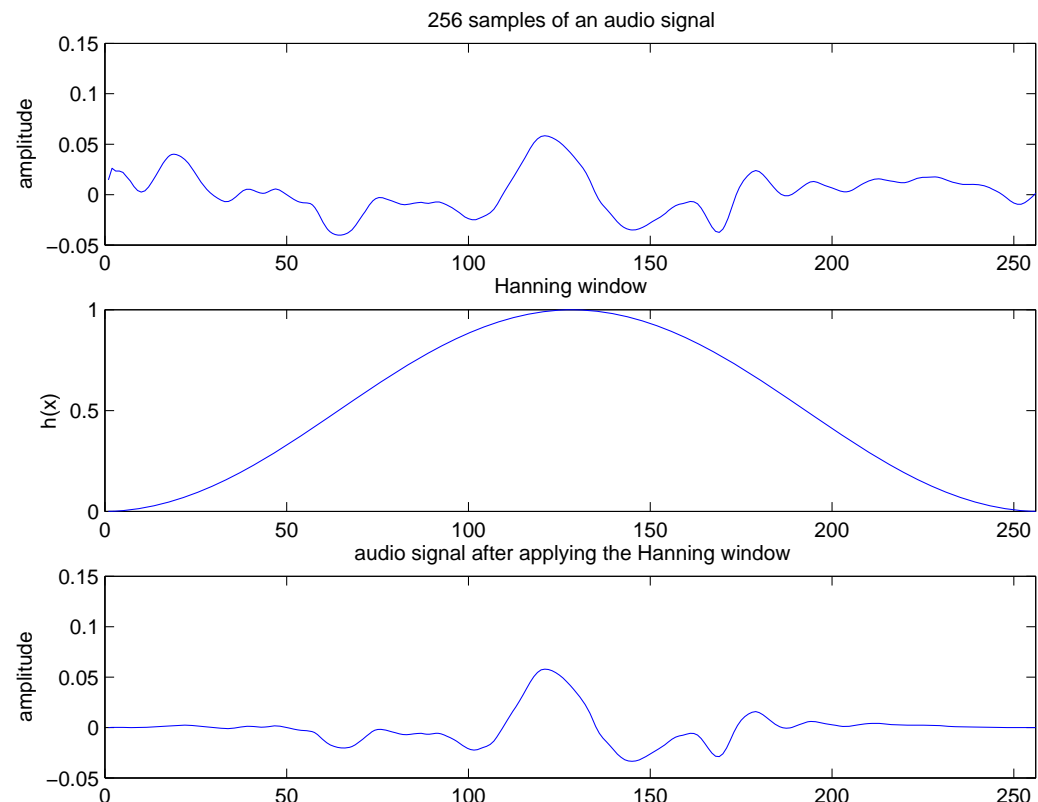
Windowing

To calculate the FFT, we need a periodic signal; thus, the PCM magnitude values of each frame are multiplied point-by-point with a suited function

e.g. Hanning window (Julius von Hann, Austrian meteorologist)

$$h(x) = \frac{1}{2} \cdot \left[1 + \cos\left(\frac{\pi + x}{n}\right) \right]$$

n ...number of samples in frame

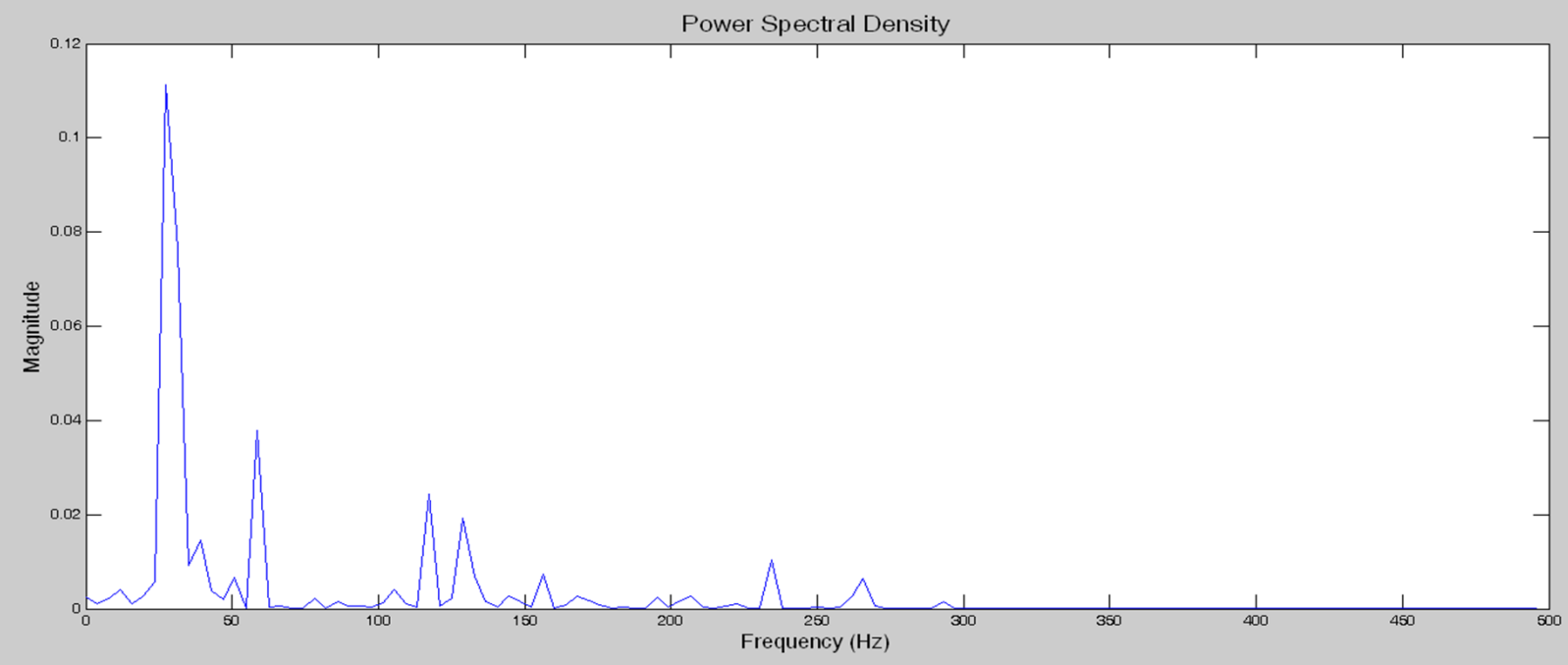
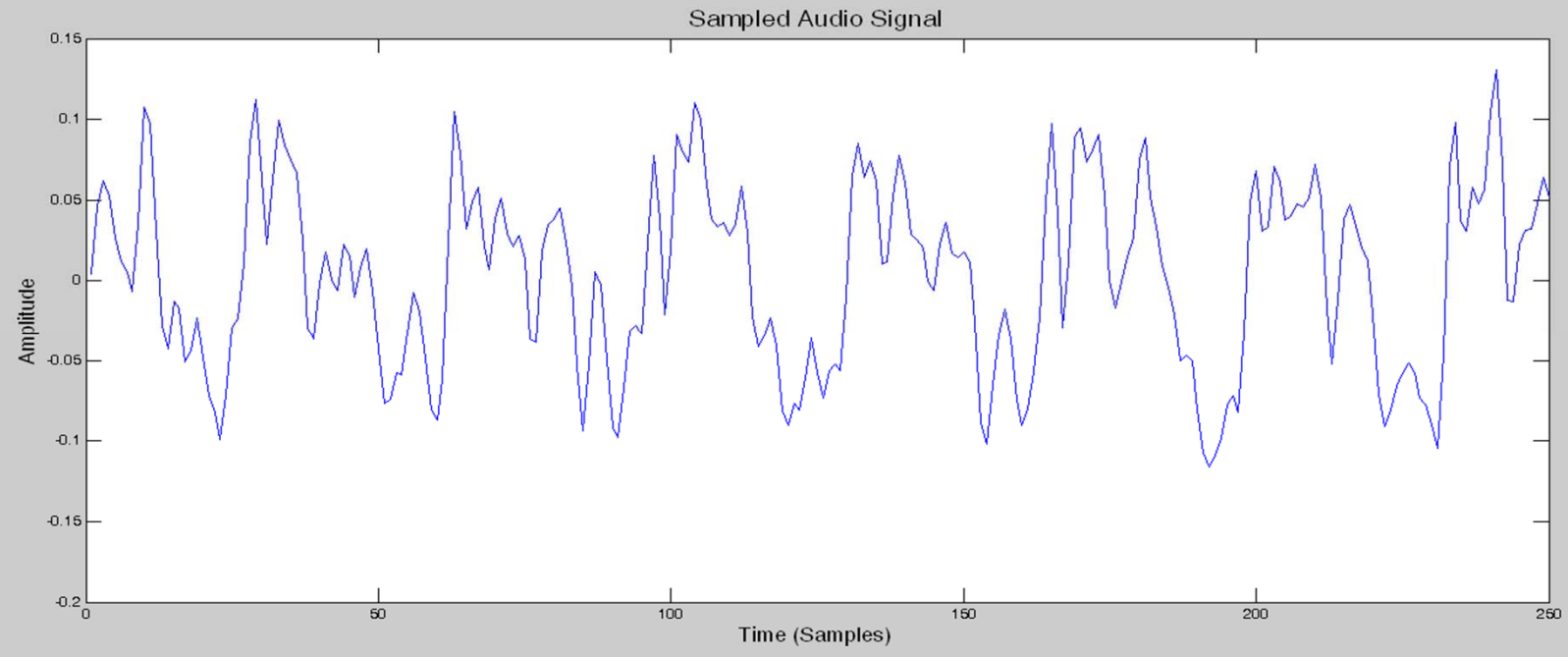


Fourier Transform

(after “Jean Baptiste Joseph Fourier”)

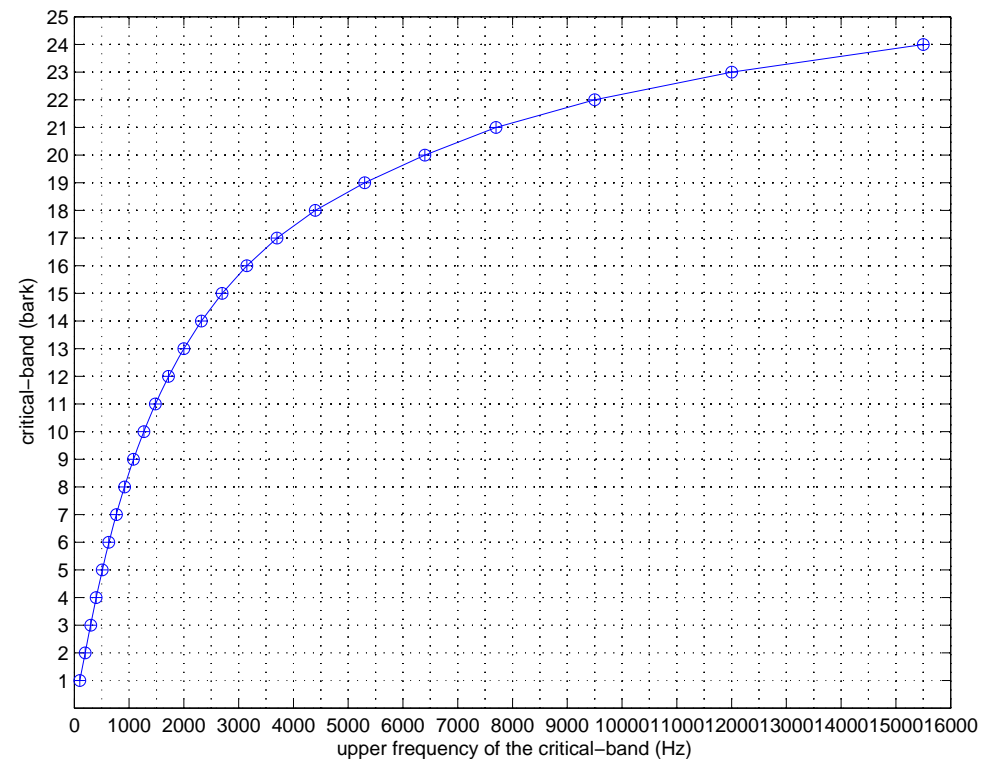


- transformation of the signal from **time domain** (time vs. amplitude) to **frequency domain** (frequency vs. magnitude)
- theorem: **any continuous periodic function with a period of 2π can be represented as the sum of sine and/or cosine waves**
- implication: any (analog) audio signal can be decomposed into an infinite number of overlapping waves (of different frequencies) given that it is periodic (windowing!)
- if the domain of the input function (audio signal) is discrete as in our case:
→ **Discrete Fourier Transform (DFT)**
- in practice: DFT is efficiently calculated via **Fast Fourier Transform (FFT)** by [Cooley and Tukey, 1965]



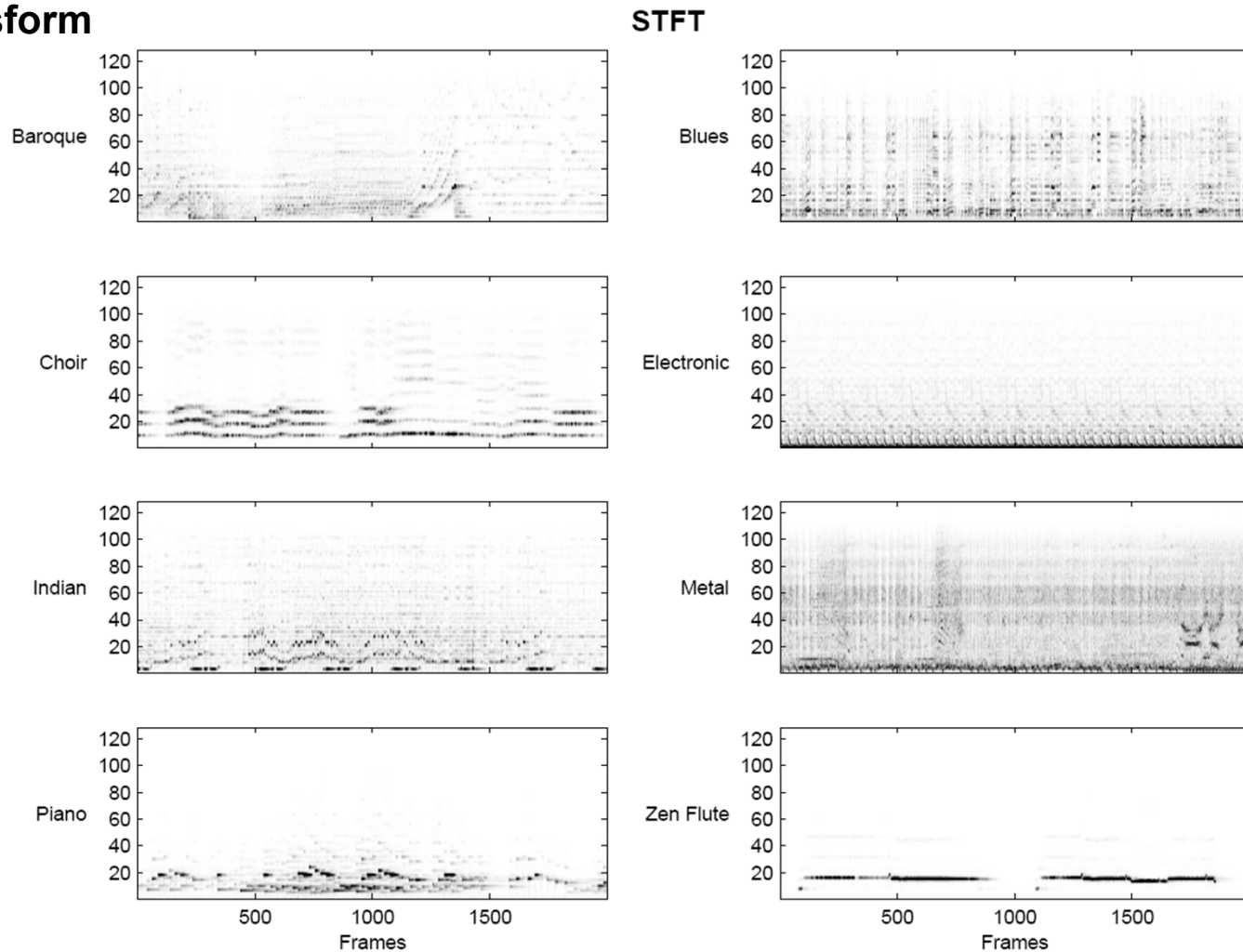
Critical Bands (Bark Scale)

- perceptually uniform measure of frequency
- reflects characteristics of human auditory system (our auditory perception is logarithmic!)
- measured according to **bark scale**
- used for psychoacoustic postprocessing



Music Information Retrieval 2.0

Representation as Short-time Fourier Transform



Low-Level Feature: Root-Mean-Square (RMS) Energy

(aka RMS power, RMS level, RMS amplitude)

scope: time domain

calculation:
$$RMS_t = \sqrt{\frac{1}{K} \cdot \sum_{k=t \cdot K}^{(t+1) \cdot K - 1} s(k)^2}$$

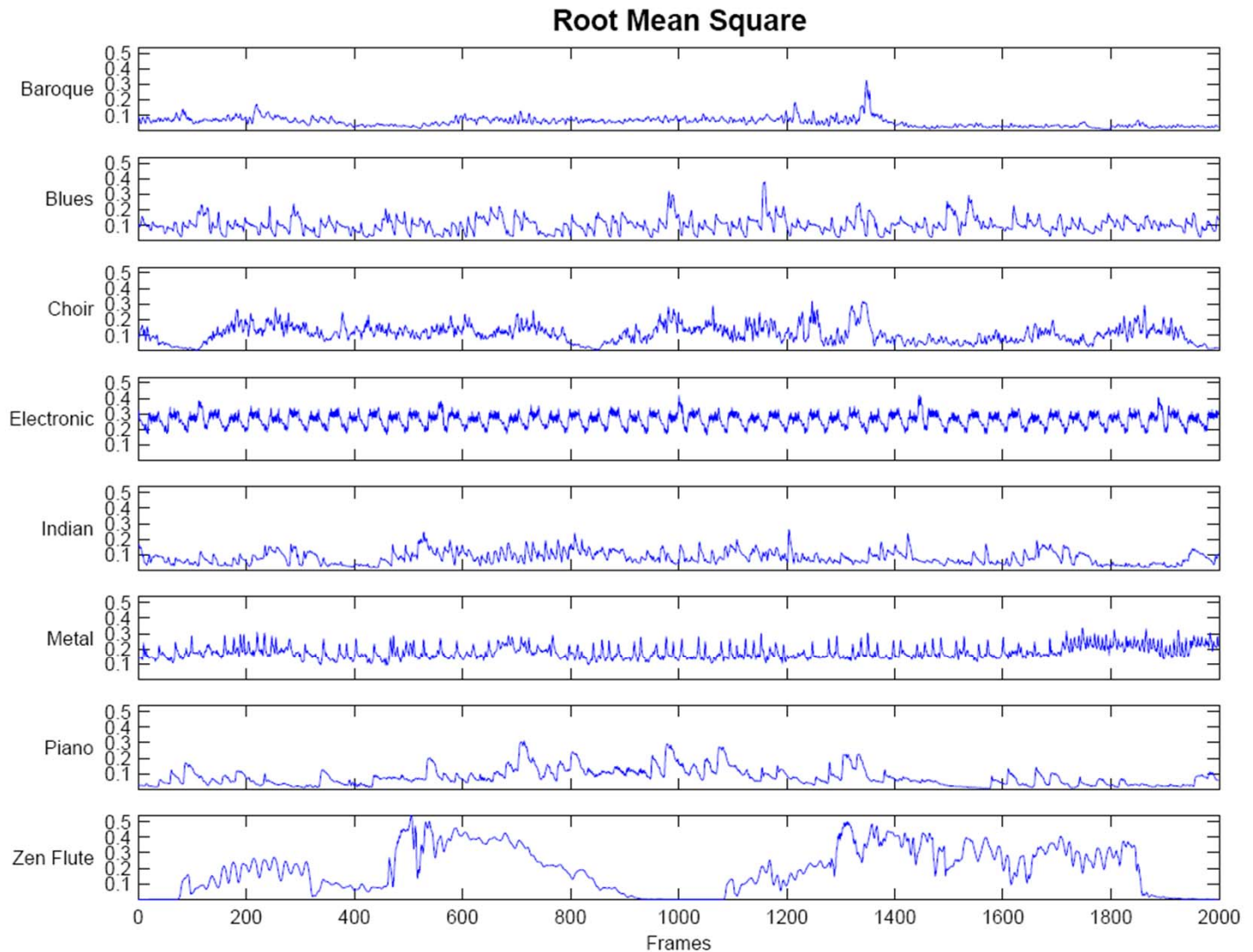
remarks:

- + beat-related feature, can be used for beat detection
- + related to perceived intensity
- + good loudness estimation
- discriminative power not clear

$M_t(n)$...magnitude in frequency domain at frame t and frequency bin n
 $s(k)$...amplitude of k^{th} sample in time domain
 K ...frame size (number of samples in each frame)
 N ...number of highest frequency band

Music Information Retrieval 2.0

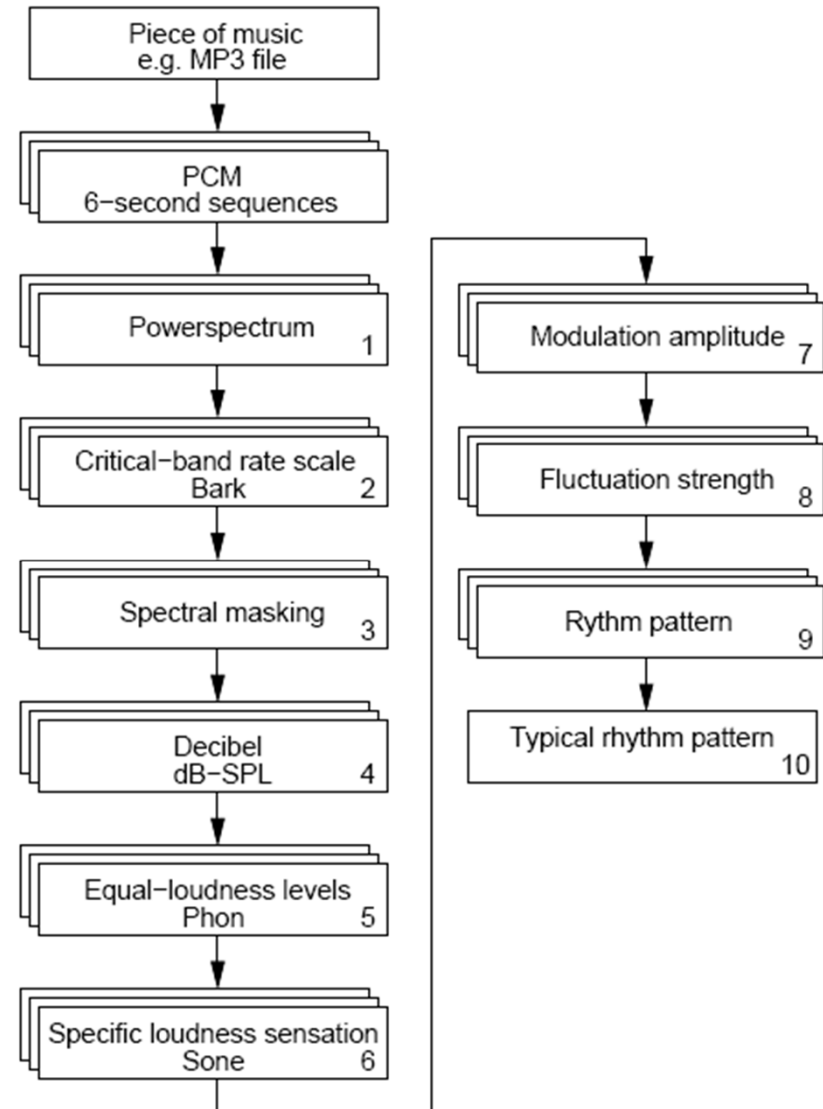
RMS Energy: Illustration



Mid-Level Feature Extractor: Fluctuation Patterns

Idea:
measure how strong and fast beats are
played within certain perceptually adjusted
frequency bands

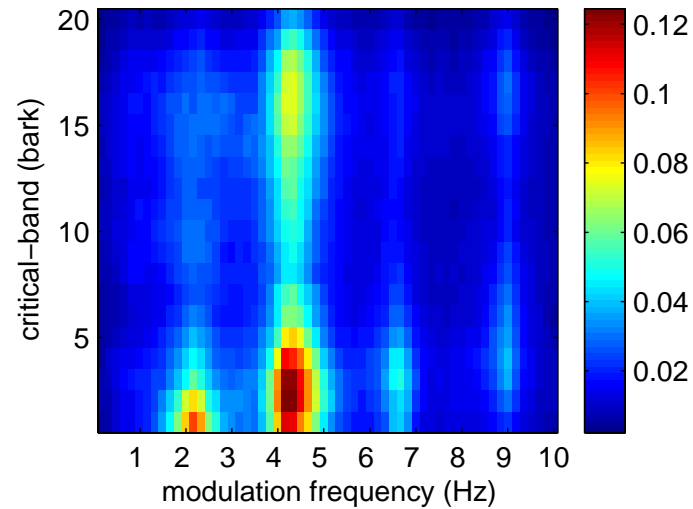
[Pampalk et al., ACM Multimedia 2002]



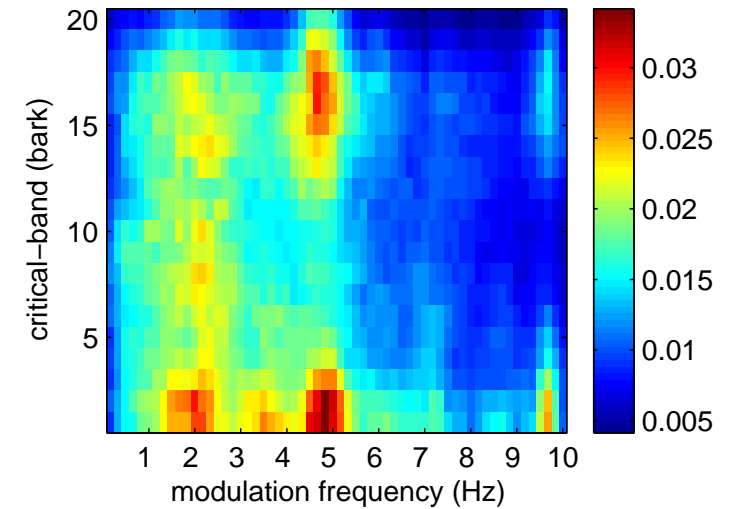
Music Information Retrieval 2.0

Fluctuation Patterns: Illustration

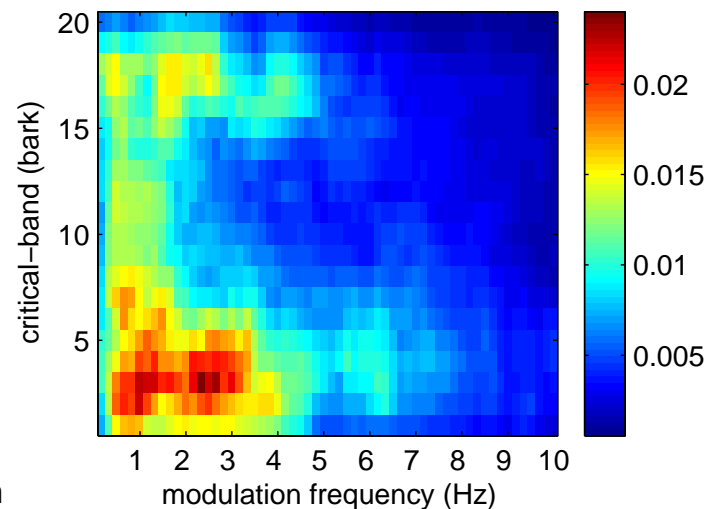
Floorfilla, Anthem #5



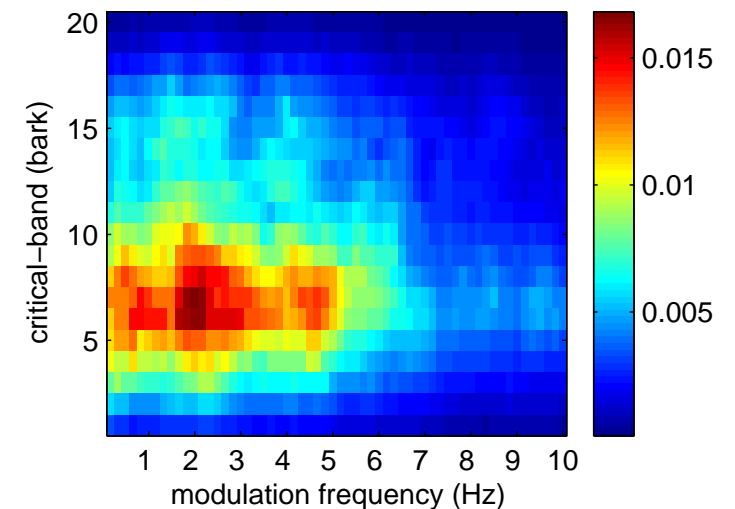
Nightwish, Come Cover Me



Clannad, Caislean Oir



Mozart, Piano Sonata in C Major, K.330



High-Level Feature Extractor: Block-Level Framework (BLF)

[Seyerlehner et al., DAFx 2010]

Most low-level and mid-level feature extractors apply the **Bag-of-Frames** (BoF) model, i.e., features calculated for each frame are treated in an unordered fashion when aggregating.

→ **Loss of Temporal Information**

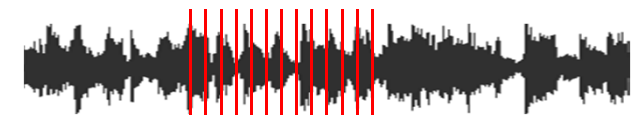
However, for most non-trivial music relations, temporal information is vital.

Idea of BLF:

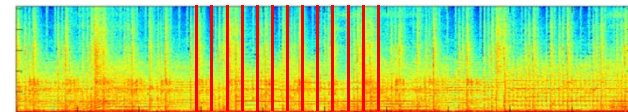
Process **blocks of frames** instead of single frames.

A Typical **Frame-Level** Similarity Algorithm

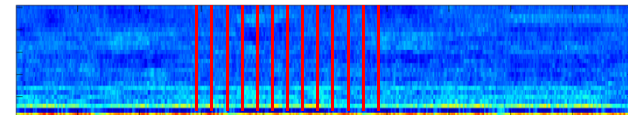
- 1) digitized audio signal (PCM)
- 2) transform to frequency domain (FFT)
- 3) extract frame-level features
- 4) model each song as distribution of its feature vectors → **Bag of Frames (BoF)**



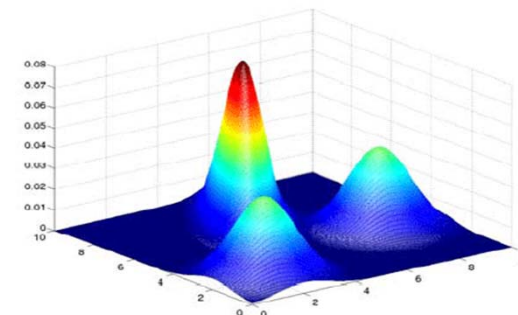
↓ Preprocessing,
Transform to frequency domain,



↓ Model human perception,
Extract local features

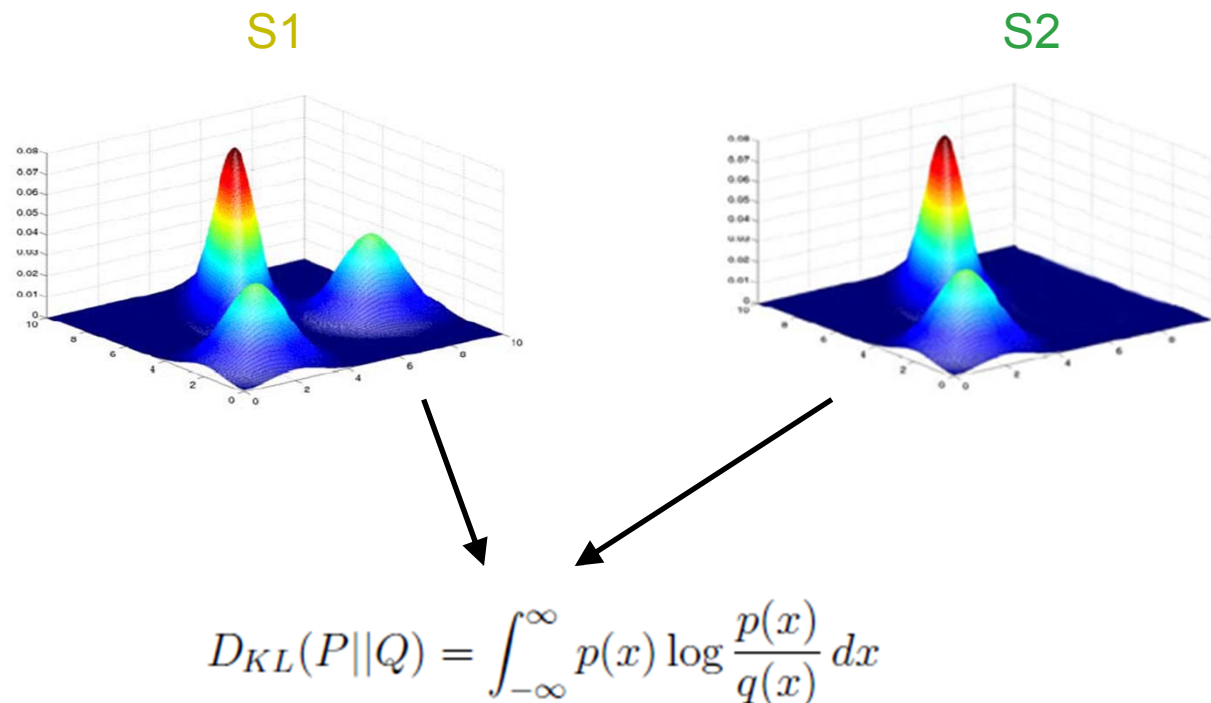


↓ Model distribution of frames



A Typical **Frame-Level** Similarity Algorithm: *How to measure similarity?*

As distance function the **KL-Divergence** (Kullback–Leibler), a measure of the relative entropy of two probability distributions, is frequently used.



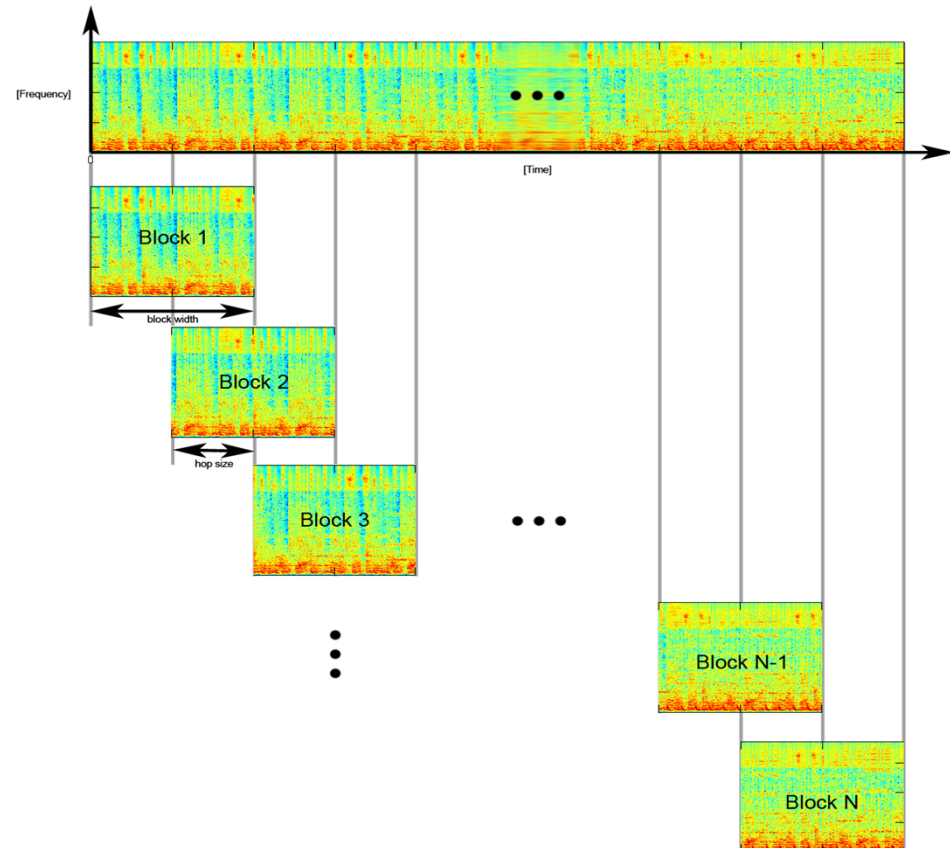
High-Level Feature Extractor: **Block-Level** Framework (BLF)

Idea:

process audio signal in blocks
instead of single frames

- better capability to capture temporal information
- entire feature extraction process is defined on block-level

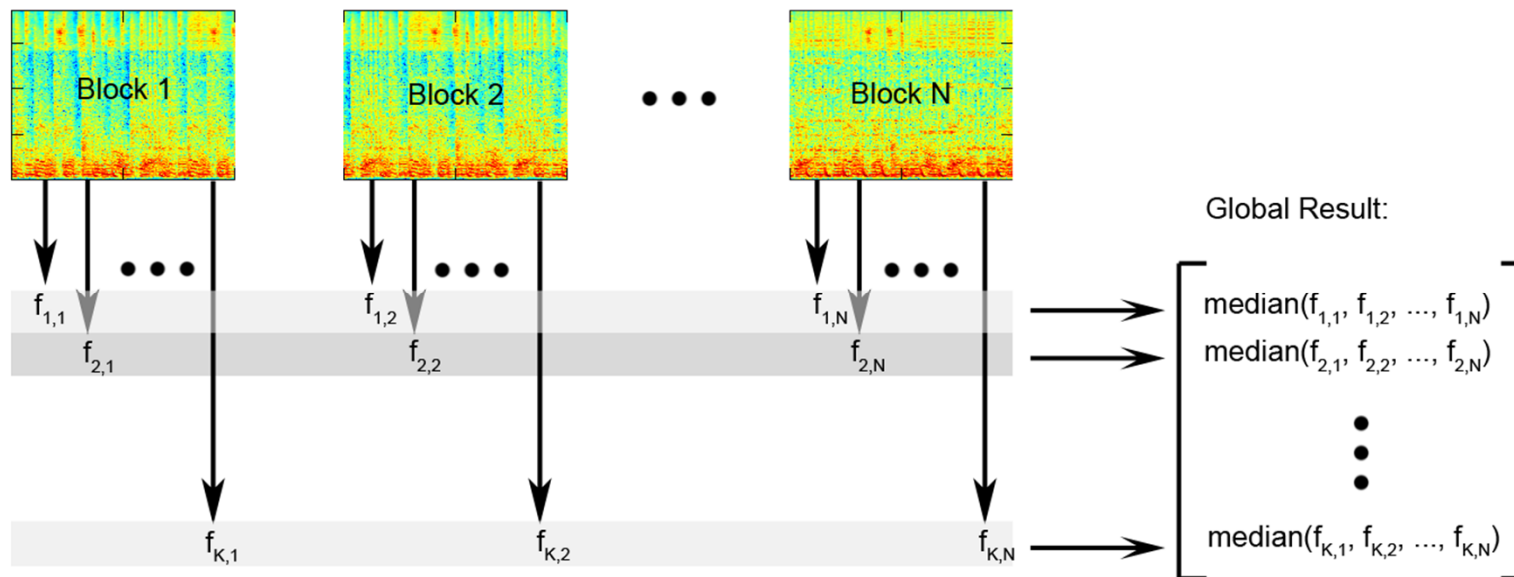
The Block-Processing Framework



High-Level Feature Extractor: Block-Level Framework (BLF)

Aggregating Block-Level to Song-Level Features

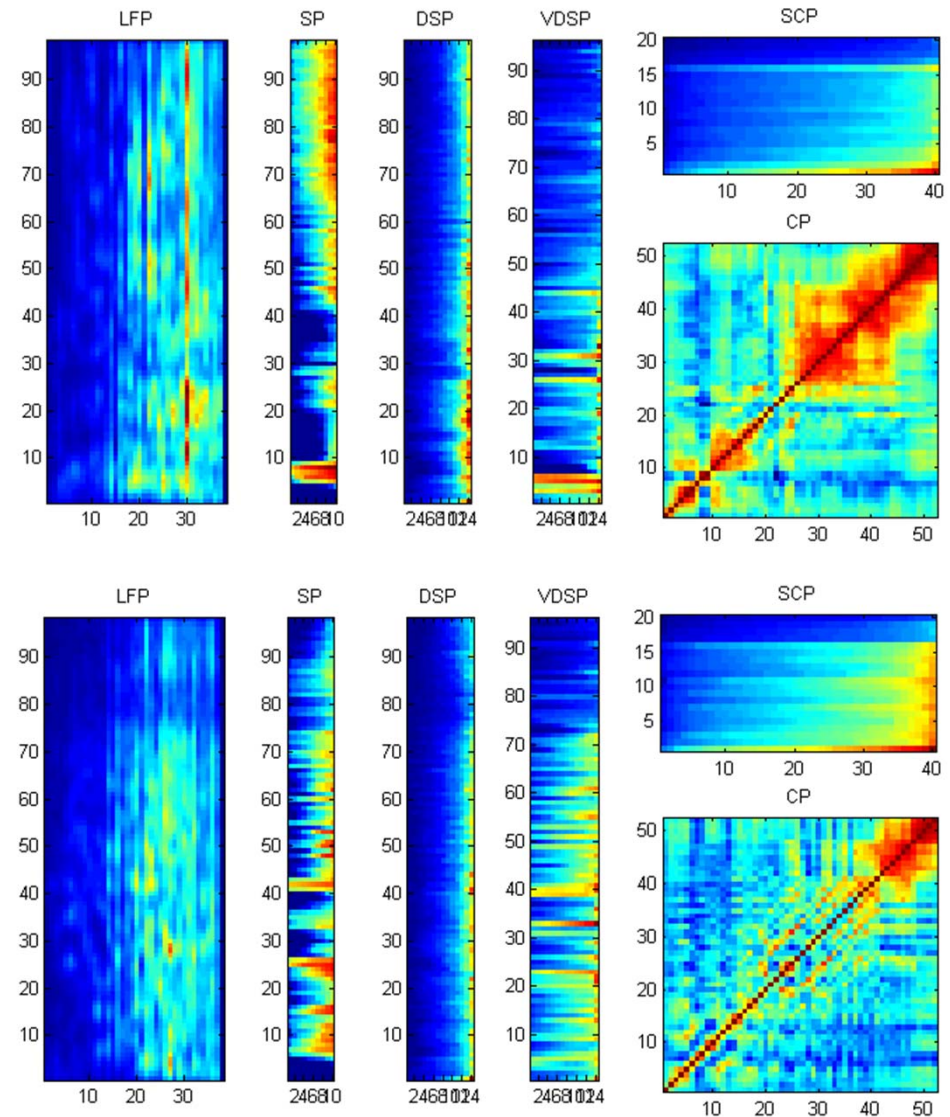
To obtain one feature vector for the entire song, a generalization step is performed, which is realized by an *aggregation function*.



High-Level Feature Extractor: Block-Level Framework (BLF)

BLF differ significantly from other features.

- **Advantages:**
 - + Vector Space Model: The whole mathematical toolbox of vector spaces is available.
 - + easy to use in classification
 - + song models can be visualized
- **Disadvantages:**
 - high dimensional feature space



High-Level Feature Extractor: Block-Level Framework (BLF)

Aggregating Block-Level to Song-Level Features

Several Block-Level Features have been defined in the Block-Processing Framework:

1. **Spectral Pattern (SP)**
2. **Delta-Spectral Pattern (DSP)**
3. **Variance Delta-Spectral Pattern (VDSP)**
4. **Logarithmic Fluctuation Pattern (LFP)**
5. **Correlation Pattern (CP)**
6. **Spectral Contrast Pattern (SCP)**

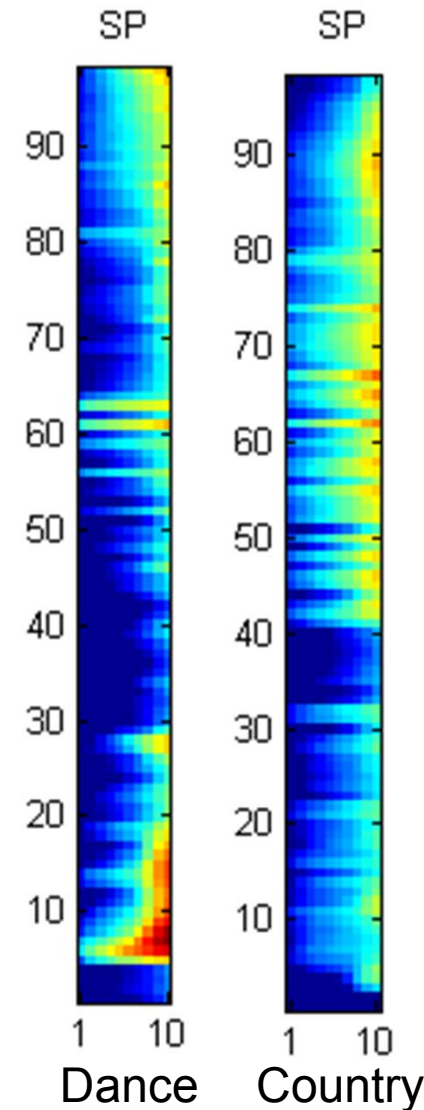
High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Pattern (SP)

- An audio descriptor that captures the frequency content of an audio file
- Each frequency band of an audio block is simply sorted along the time axis.

$$SP = \begin{bmatrix} \text{sort}(b_{H,1} & \dots & b_{H,W}) \\ \vdots & \ddots & \vdots \\ \text{sort}(b_{1,1} & \dots & b_{1,W}) \end{bmatrix}$$

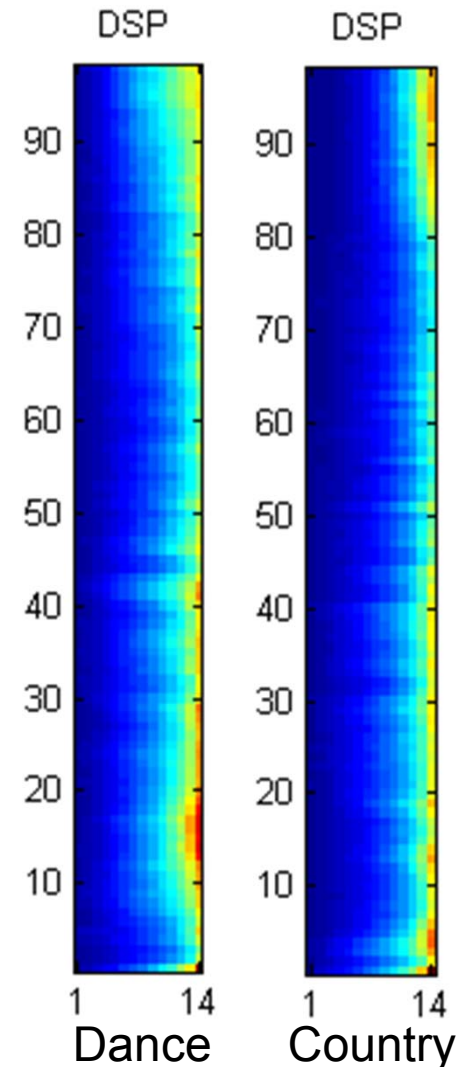
- The 0.9-percentile is used as aggregation function.



High-Level Feature Extractor: Block-Level Framework (BLF)

Delta-Spectral Pattern (DSP)

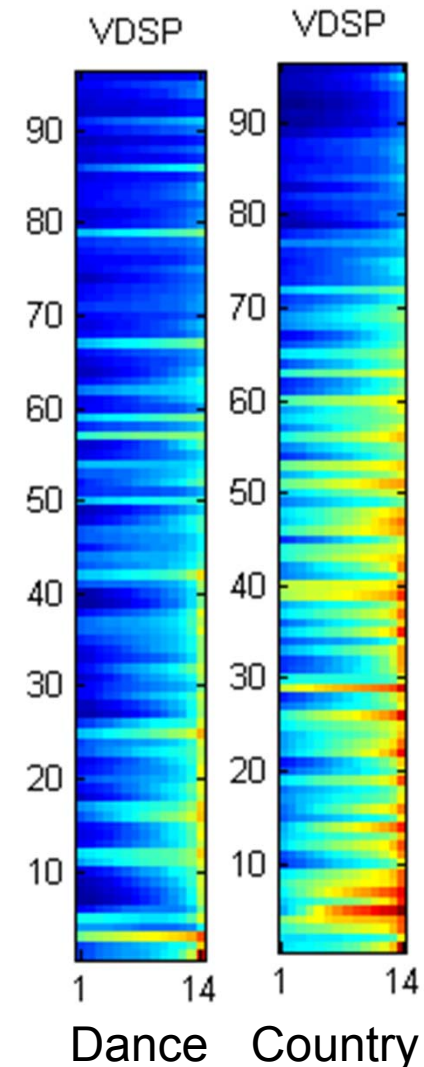
- First the delta spectrum, i.e., the difference of the original and a delayed version (by 3 frames) is computed to emphasize onsets.
- The same strategy as for the SP is followed – all frequency bands are sorted.
- The 0.9-percentile is used as aggregation function.



High-Level Feature Extractor: Block-Level Framework (BLF)

Variance Delta-Spectral Pattern (VDSP)

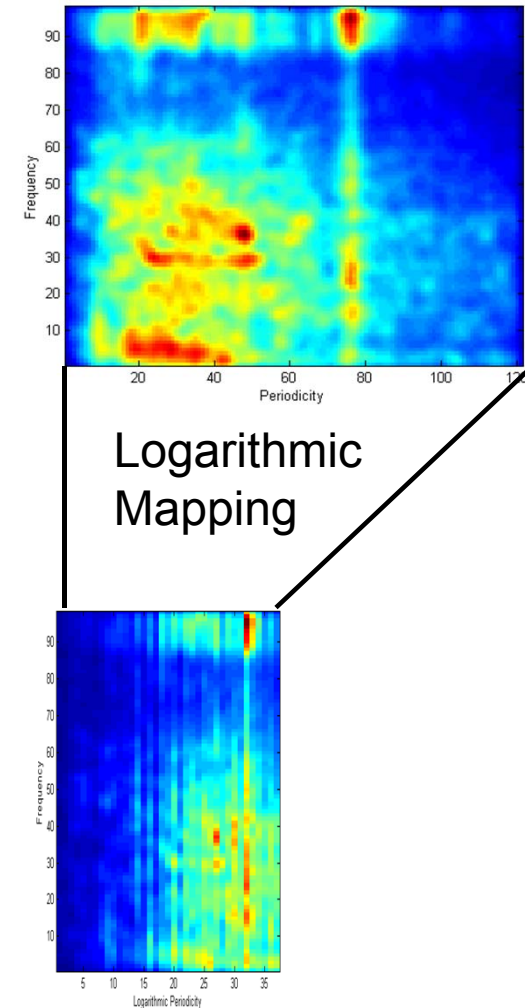
- Similar to the DSP
- The variance is used instead of the 0.9-percentile as aggregation function.
- Captures temporal variations of the onset strength



High-Level Feature Extractor: Block-Level Framework (BLF)

Logarithmic Fluctuation Pattern (LFP)

- Modified version of the Fluctuation Patterns
- The Cent scale is used instead of the Sone representation.
- The periodicity dimension of the pattern is logarithmically scaled to yield a more tempo invariant representation.



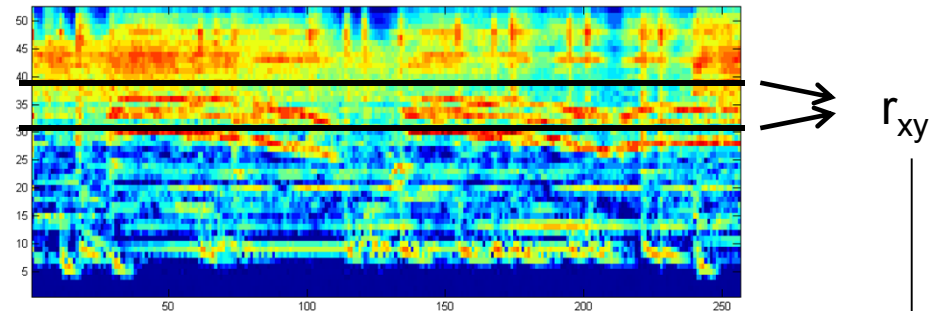
High-Level Feature Extractor: Block-Level Framework (BLF)

Correlation Pattern (CP)

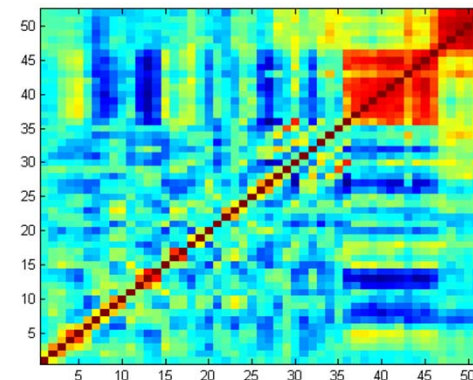
- Reduce the Cent spectrum to 52 frequency bands
- Captures the temporal relation of the frequency bands
- Compute the pairwise linear correlation between each frequency band.

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y}$$

- The 0.5-percentile is used as aggregation function.



CP

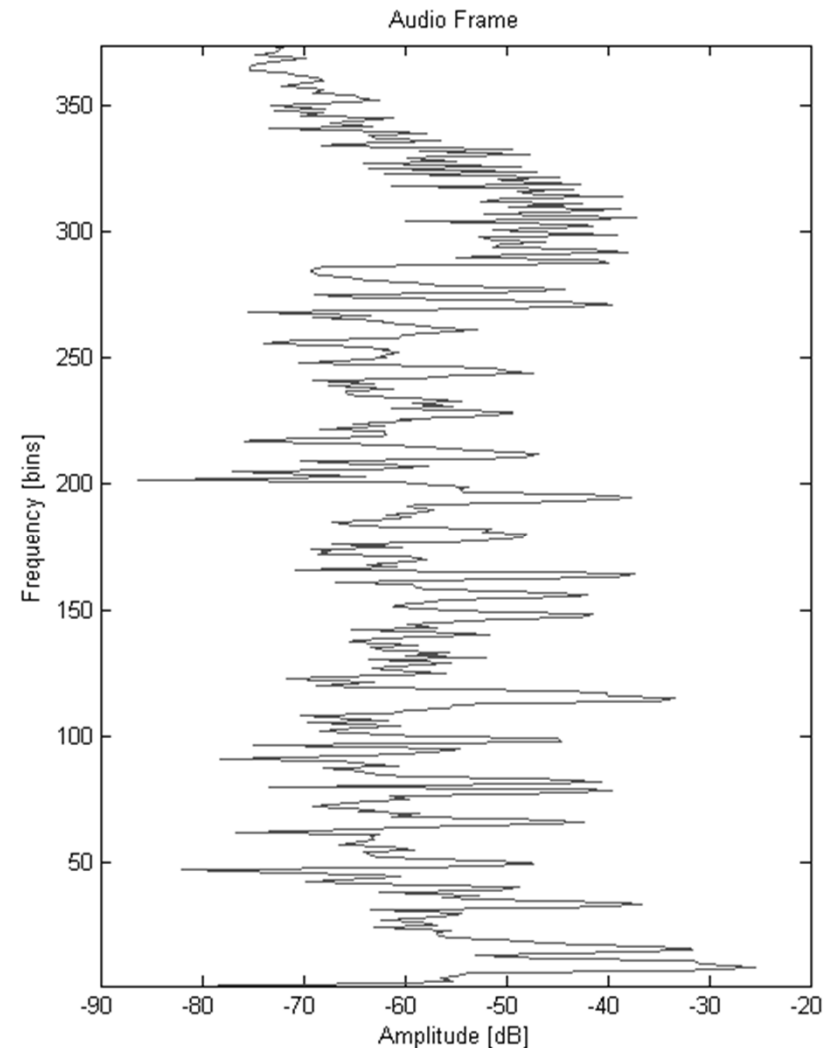


for all pairs

High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

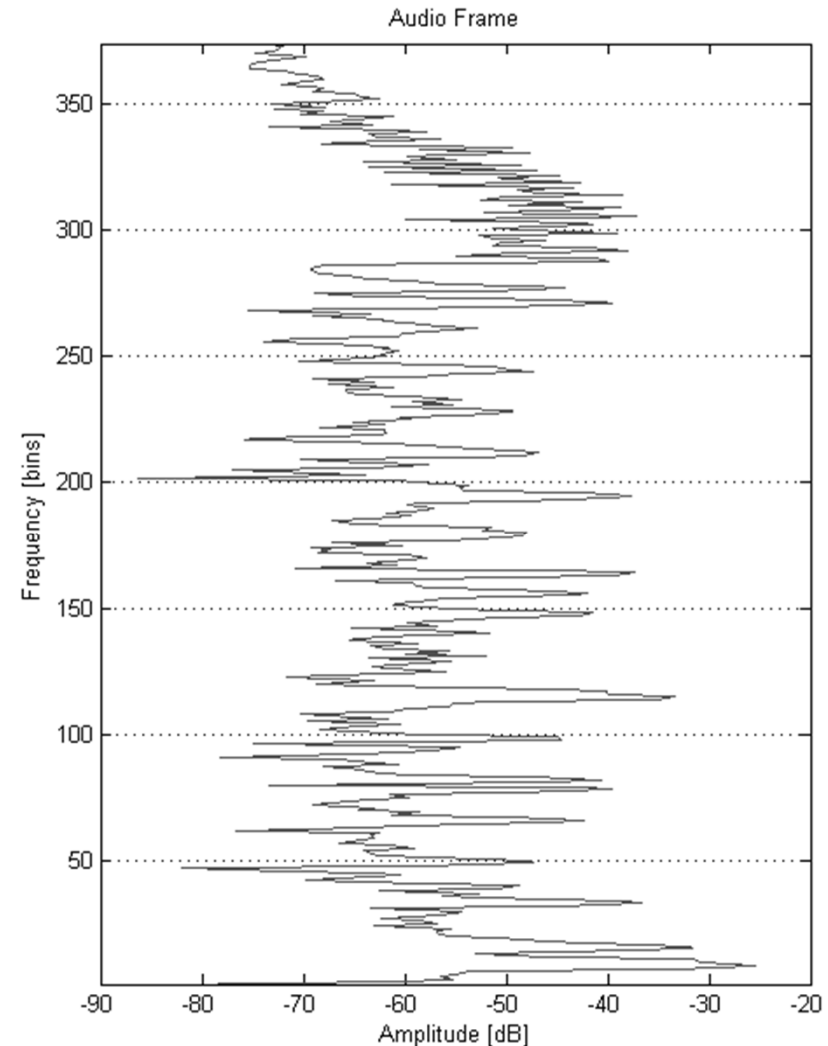
- Compute the **spectral contrast** per frame to estimate the *“tone-ness”*.
- This is performed separately for 20 frequency bands of the Cent spectrum.
- Sort the spectral contrast values of each frequency band along the whole block.
- The aggregation function is the 0.1-percentile.



High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

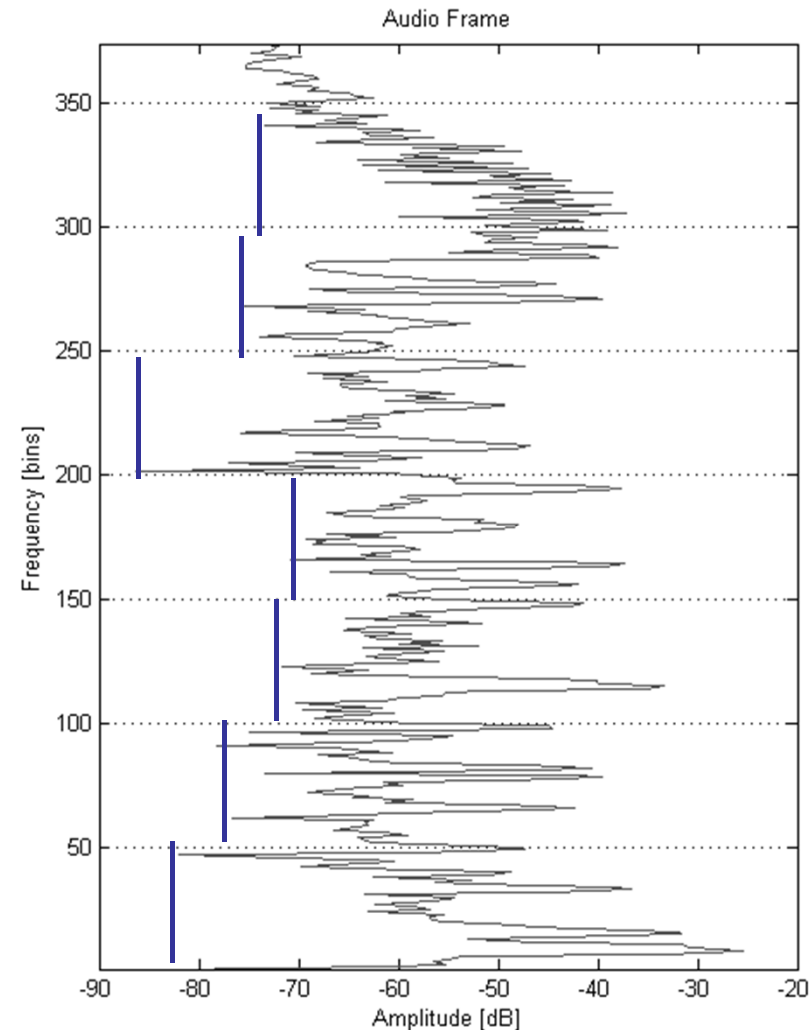
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High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

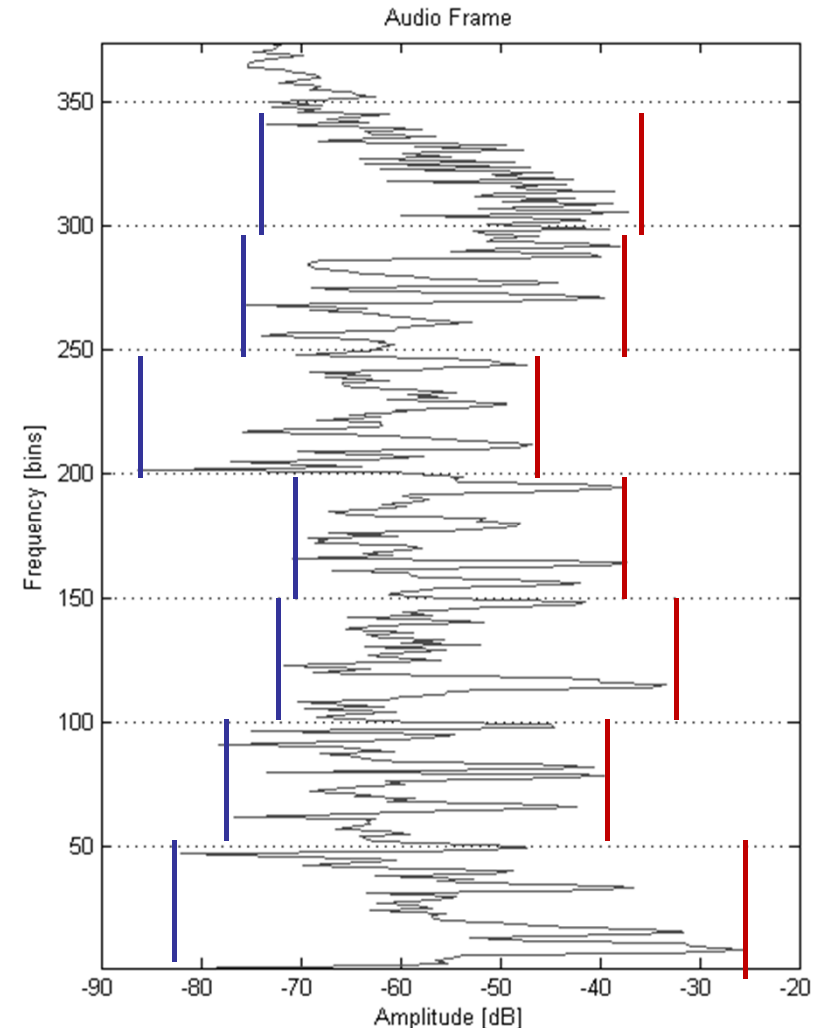
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High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

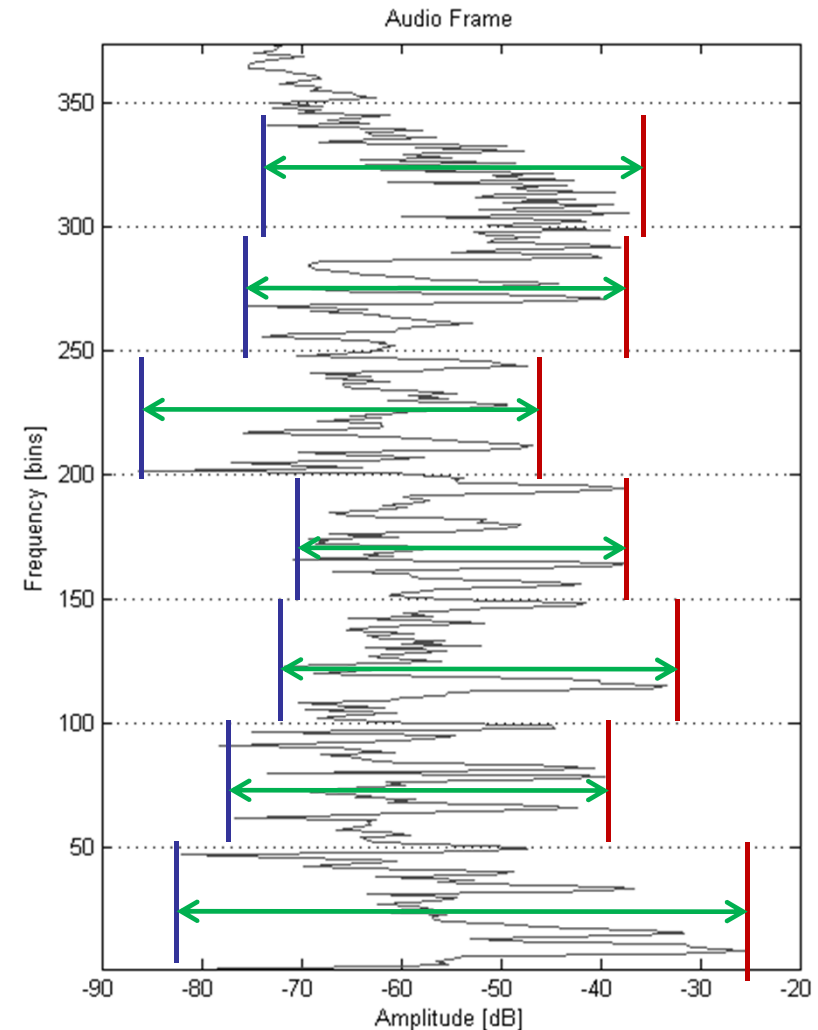
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High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

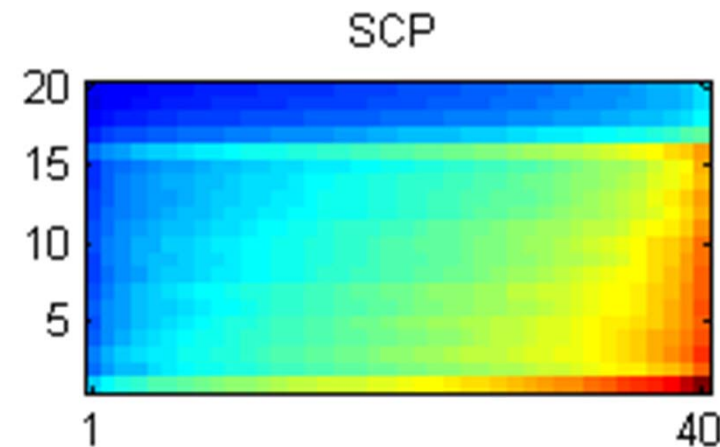
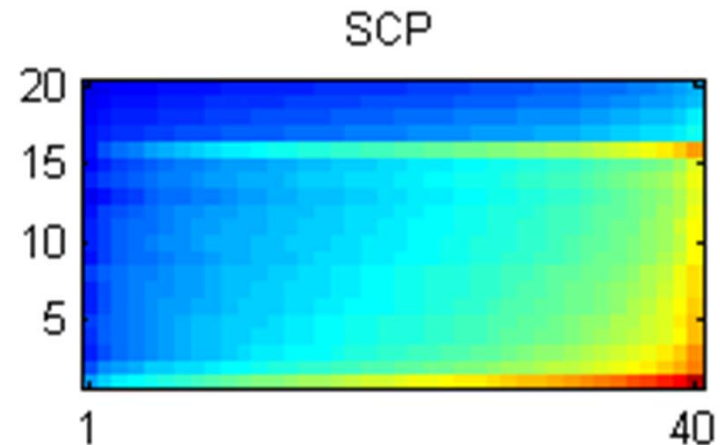
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- Sort the spectral contrast values of each frequency band along the whole block.
- The aggregation function is the 0.1-percentile.



High-Level Feature Extractor: Block-Level Framework (BLF)

Spectral Contrast Pattern (SCP)

- Compute the **spectral contrast** per frame to estimate the ``*tone-ness*``.
- This is performed separately for 20 frequency bands of the Cent spectrum.
- Sort the spectral contrast values of each frequency band along the whole block.
- The aggregation function is the 0.1-percentile.



High-Level Feature Extractor: Block-Level Framework (BLF)

Defining Similarities in the BLF

How to estimate song similarities for multiple block-level features?

$$D(S1, S2) = ?$$

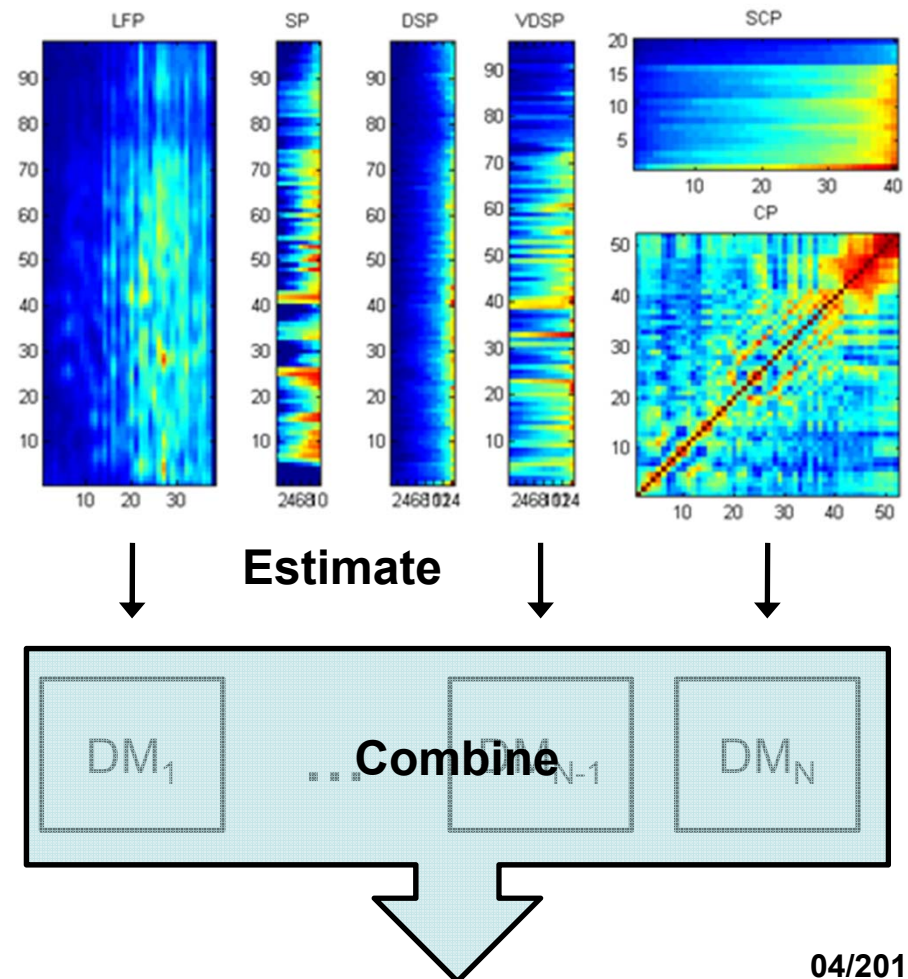
Two music similarity algorithms possible:

- The first one is based on **directly comparing and combining** the block-level features (**BLS**).
- The second similarity measure performs a **mapping over a semantic tag space** (**TAG**).

High-Level Feature Extractor: Block-Level Framework (BLF)

- **Estimate** song similarities separately for each pattern (by computing **Manhattan distance**).
- **Combine** the similarity estimates of the individual patterns into a single result.

BLS: Fusing Features



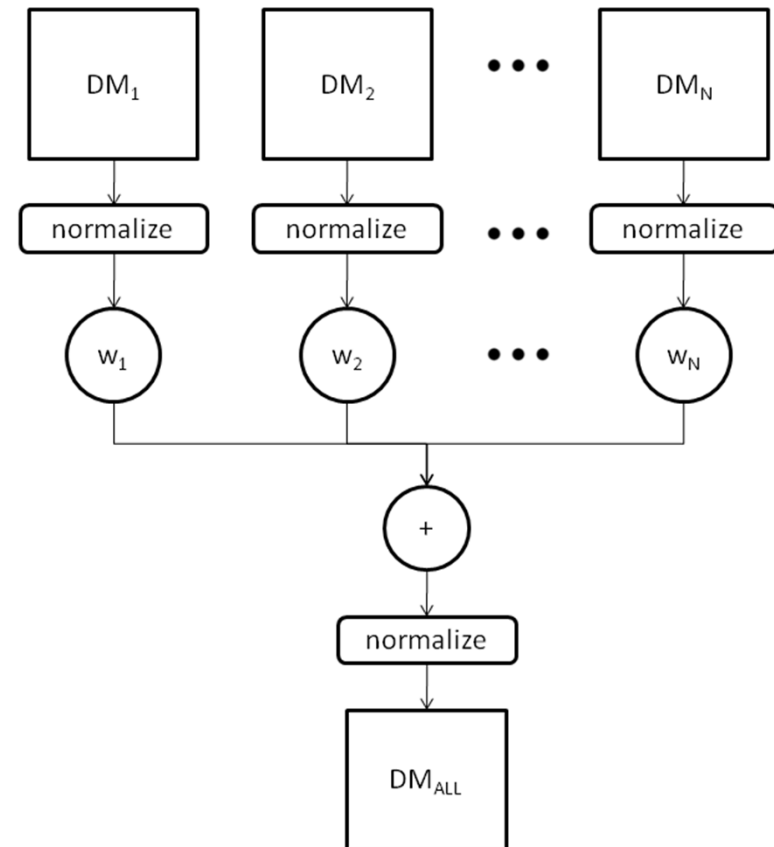
High-Level Feature Extractor: Block-Level Framework (BLF)

Naïve approach: linearly weighted
combination of BLFs

Problem: Similarity estimates of the
different patterns (block-level features)
have different scales.

→ special normalization strategy is used:
Distance Space Normalization

BLS: Combining Estimates



High-Level Feature Extractor: Block-Level Framework (BLF)

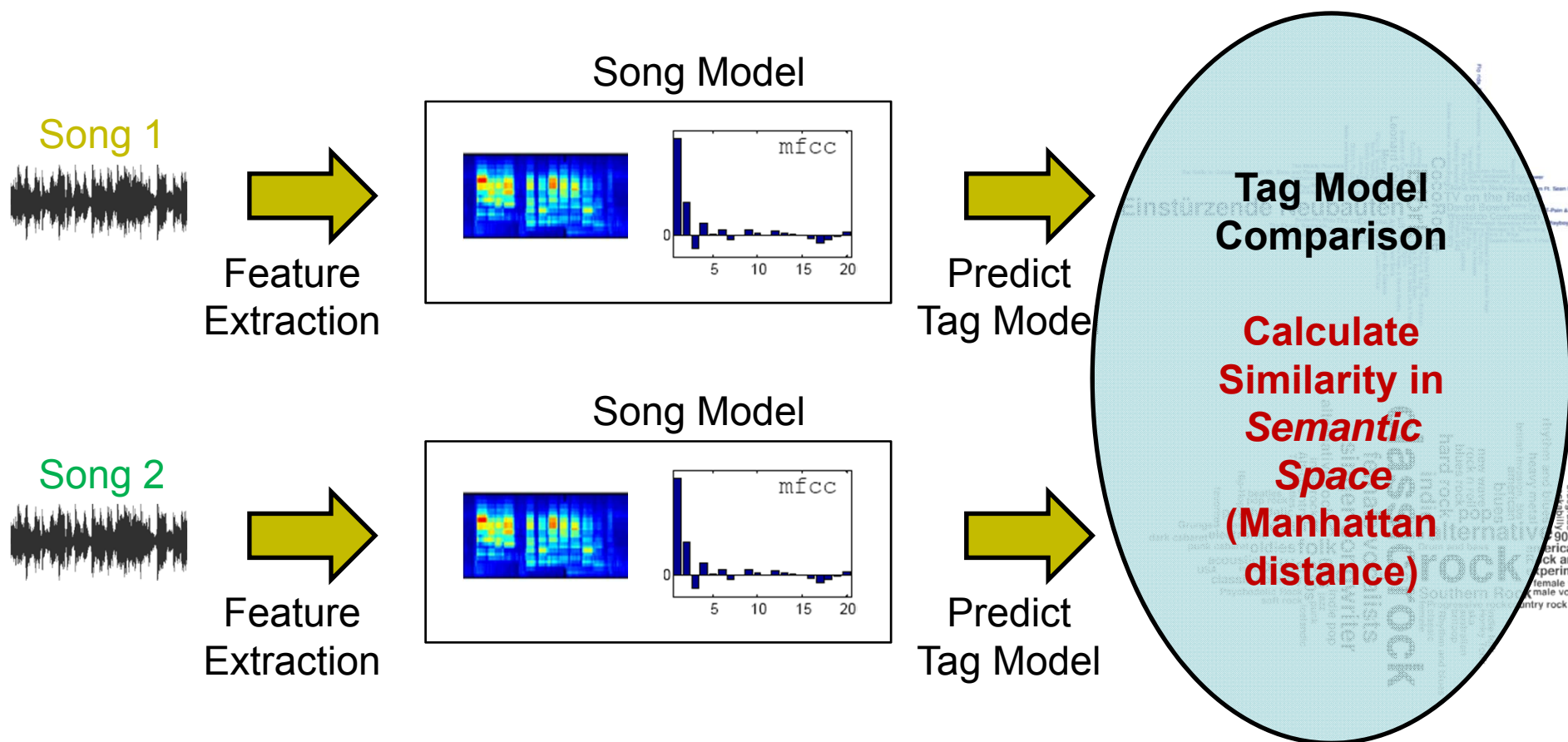
- Operates on the distance matrix
- Each distance $D_{n,m}$ is normalized using Gaussian normalization.
- Mean and standard deviation are computed over both **column** and **row** of the distance matrix.
- Each distance has its own normalization parameters.
- Observation:** The operation itself can improve the nearest neighbor classification accuracy.

BLS: Distance Space Normalization (DSN)

	S_1	S_2	S_3	...	S_m	...	S_{N-1}	S_N
S_1								
S_2								
S_3								
...								
S_n					$D_{n,m}$			
...								
S_N								

High-Level Feature Extractor: Block-Level Framework (BLF)

TAG: The Semantic Space Approach



Music Information Retrieval 2.0

nepTune

Browsing Music Collections...

...can be fun

CP@JKU, 2006



nepTune

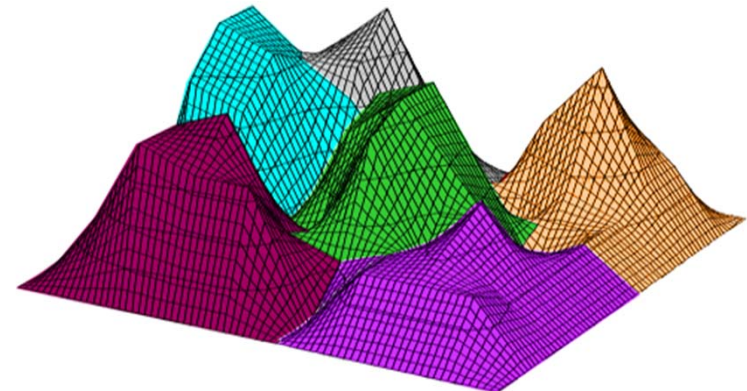
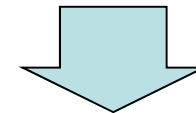
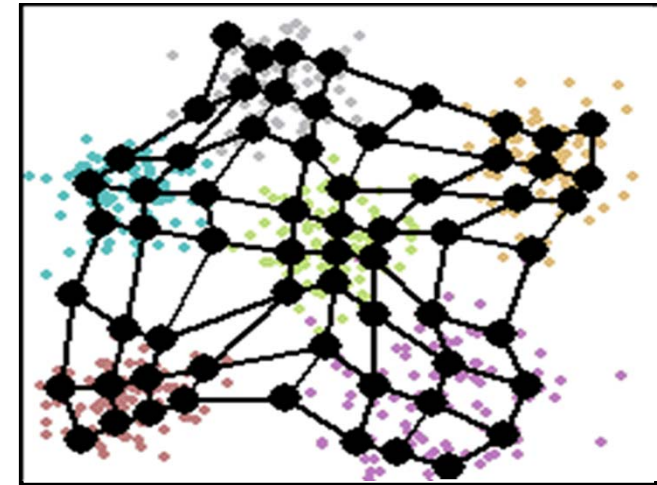
Clustering of music pieces

Each song corresponds to point in feature
(similarity) space

Self-organizing Map

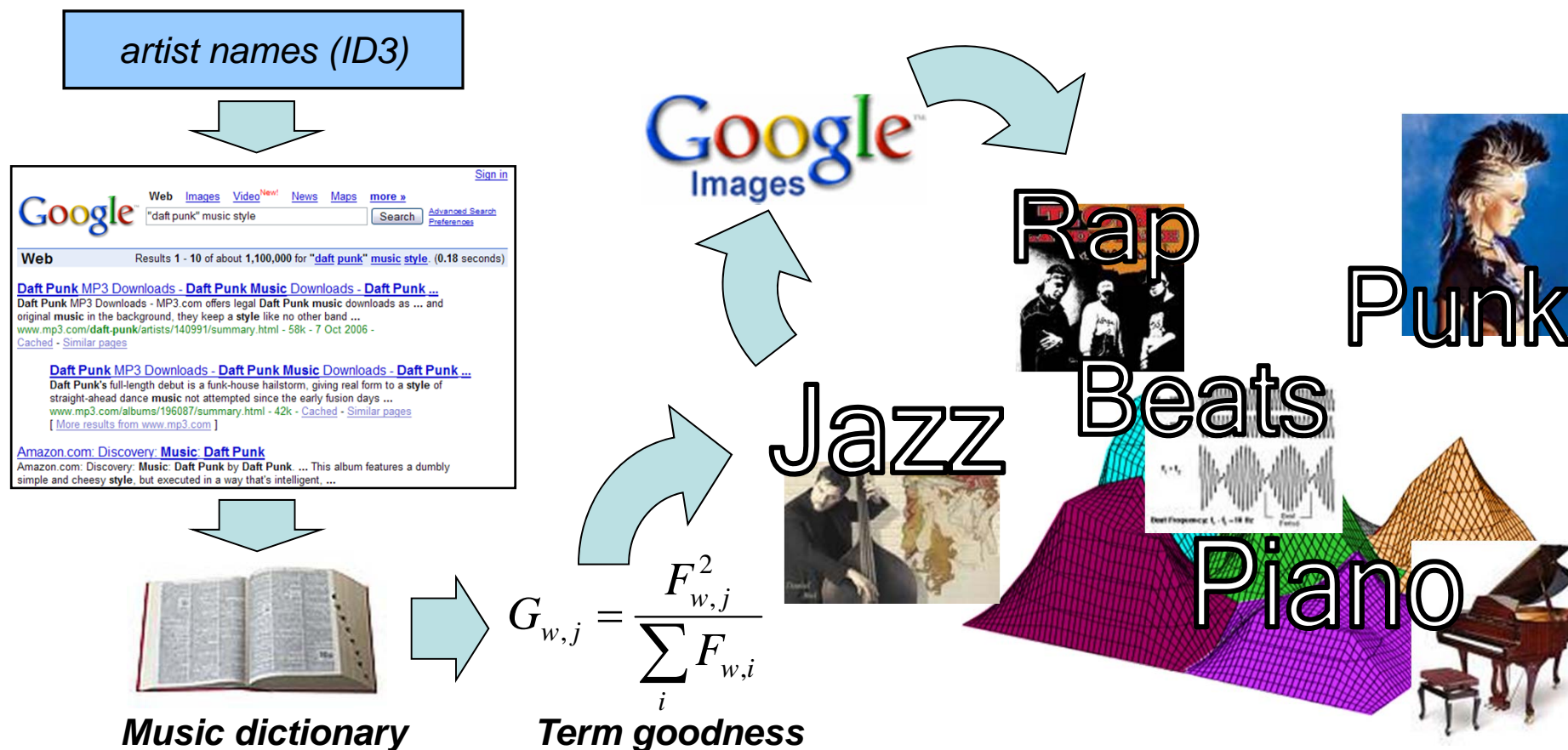
High-dimensional data (content-based features) is
projected to 2-dim. plane

Number of pieces per cluster
→ landscape height profile



nepTune

Automatic description of landscape via Web term extraction





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Music Information Retrieval 2.0

Part II – Context-based MIR

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Johannes Kepler University (JKU)
Linz, Austria



Context- and Web-based Methods

“Music is more than just the signal”

“Similarity” as perceived by humans is not exclusively determined by the audio but also by the outside world, i.e., the context

Influenced by, e.g., marketing strategies, political views of artists, language of songs, decade of activity, etc.
(also listening context, mood, peers – see later)

Analysis of audio alone can't capture these aspects

Context- and Web-based Methods

In the following, *contextual data* refers to *extended meta-data*, usually

- Generated by users
- Unstructured data-sources
- Accessible via the Web

Two main classes of approaches covered in the following

- Text processing
- Co-occurrence analysis

As for content-based methods, *similarity* is a central concept

Text-based Approaches

Data sources:

- Web pages retrieved via Web search engines



- microblogs on *twitter*



- product reviews



- semantic tags



- lyrics





Text-based Similarity and Genre Classification

Use Web data to transform the **music similarity** task into a **text similarity** task

Allows to use the full armory of IR methods, typically...

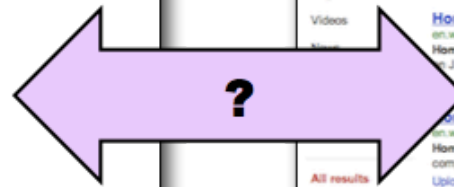
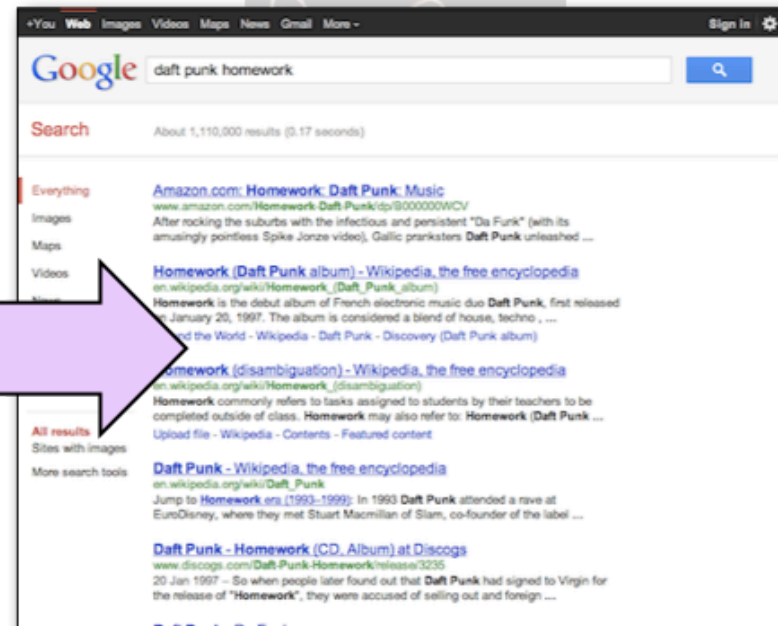
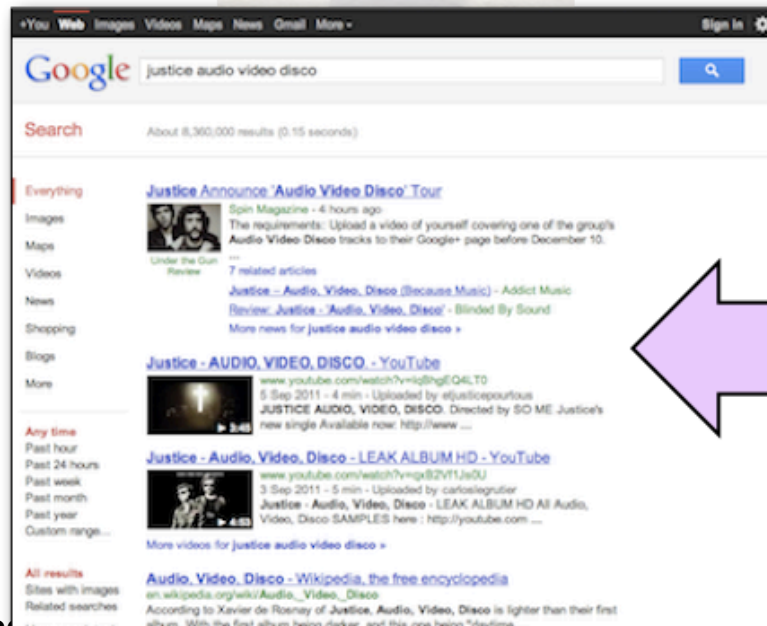
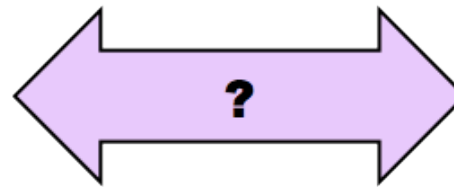
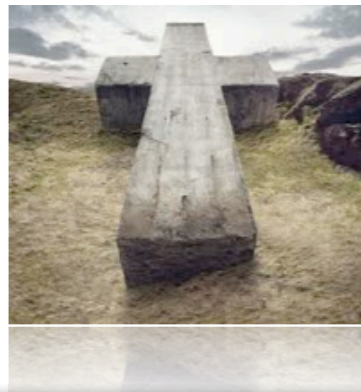
- Bag-of-words, Vector Space Model
- Stopword removal, dictionaries, term selection
- TF · IDF
- Latent Semantic Indexing
- Part-of-Speech tagging
- Named Entity Detection
- Sentiment analysis

Large range of possible similarity measures

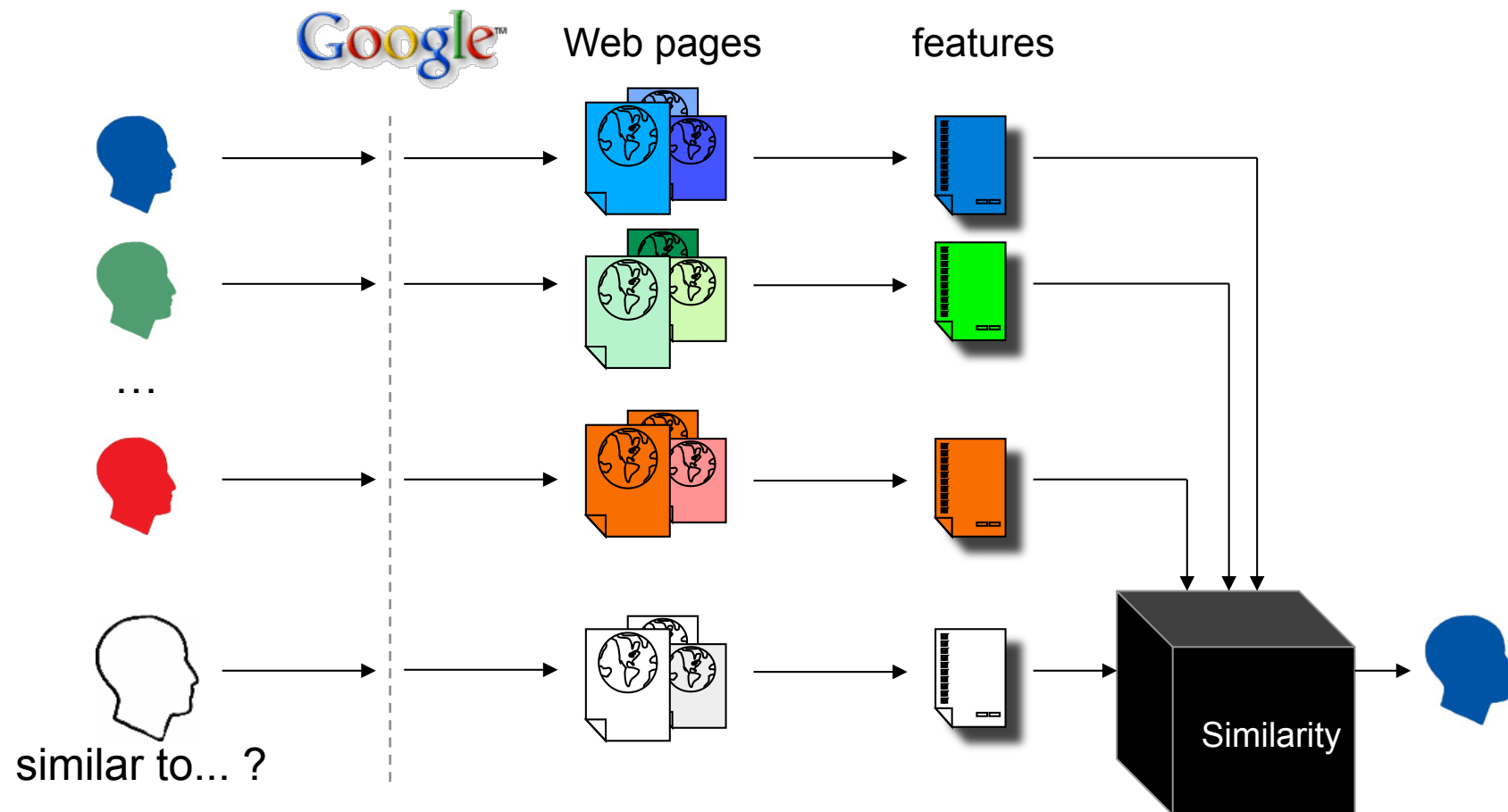
- Overlap, Manhattan, Euclidean, Cosine, etc.

Music Information Retrieval 2.0

Related Web Pages as Text Source



Related Web Pages as Text Source





Related Web Pages as Text Source

Using search engines and queries such as

“*artist*” +music

“*artist*” +music +review

[Whitman and Lawrence, ICMC 2002] [Baumann and Hummel, WEDELMUSIC 2003]

[Knees et al., ISMIR 2004]

Analyze result page directly or **download** up to **top 100 Web pages**
(combine into one “virtual document” or analyze separately)

Apply “IR magic”

Applicable for similarity estimation, classification, retrieval, annotation

(NB: Most discriminating terms between genres are artist names and album/track titles)

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- term frequency

Abbr.	Description	Formulation
TF_A	Formulation used for binary match SB = b	$r_{d,t} = \begin{cases} 1 & \text{if } t \in \mathcal{T}_d \\ 0 & \text{otherwise} \end{cases}$
TF_B	Standard formulation SB = t	$r_{d,t} = f_{d,t}$
TF_C	Logarithmic formulation	$r_{d,t} = 1 + \log_e f_{d,t}$
TF_C2	Alternative logarithmic formulation suited for $f_{d,t} < 1$	$r_{d,t} = \log_e(1 + f_{d,t})$
TF_C3	Alternative logarithmic formulation as used in <i>ltc</i> variant	$r_{d,t} = 1 + \log_2 f_{d,t}$
TF_D	Normalized formulation	$r_{d,t} = \frac{f_{d,t}}{f_d^m}$
TF_E	Alternative normalized formulation. Similar to [55] we use $K = 0.5$. SB = n	$r_{d,t} = K + (1 - K) \cdot \frac{f_{d,t}}{f_d^m}$
TF_F	Okapi formulation, according to [55, 36]. For W we use the vector space formulation, i.e., the Euclidean length.	$r_{d,t} = \frac{f_{d,t}}{f_{d,t} + W_d / \text{av}_{d \in \mathcal{D}}(W_d)}$
TF_G	Okapi BM25 formulation, according to [35].	$r_{d,t} = \frac{(k_1+1) \cdot f_{d,t}}{f_{d,t} + k_1 \cdot \left[(1-b) + b \cdot \frac{W_d}{\text{av}_{d \in \mathcal{D}}(W_d)} \right]}$ $k_1 = 1.2, b = 0.75$

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages

(9,200 experiments):

- term frequency

- inverse document frequency

Abbr.	Description	Formulation
IDF_A	Formulation used for binary match SB = x	$w_t = 1$
IDF_B	Logarithmic formulation SB = f	$w_t = \log_e \left(1 + \frac{N}{f_t} \right)$
IDF_B2	Logarithmic formulation used in <i>ltc</i> variant	$w_t = \log_e \left(\frac{N}{f_t} \right)$
IDF_C	Hyperbolic formulation	$w_t = \frac{1}{f_t}$
IDF_D	Normalized formulation	$w_t = \log_e \left(1 + \frac{f_m}{f_t} \right)$
IDF_E	Another normalized formulation SB = p	$w_t = \log_e \frac{N - f_t}{f_t}$
	The following definitions are based on the term's noise n_t and signal s_t .	$n_t = \sum_{d \in \mathcal{D}_t} \left(-\frac{f_{d,t}}{F_t} \log_2 \frac{f_{d,t}}{F_t} \right)$ $s_t = \log_2(F_t - n_t)$
IDF_F	Signal	$w_t = s_t$
IDF_G	Signal-to-Noise ratio	$w_t = \frac{s_t}{n_t}$
IDF_H		$w_t = \left(\max_{t' \in \mathcal{T}} n_{t'} \right) - n_t$
IDF_I	Entropy measure	$w_t = 1 - \frac{n_t}{\log_2 N}$
IDF_J	Okapi BM25 IDF formulation, according to [35, 31]	$w_t = \log \frac{N - f_t + 0.5}{f_t + 0.5}$

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- **term frequency**
- **inverse document frequency**
- **virtual document modeling:**

concatenate all Web pages/posts of the artist or perform *aggregation* via mean, max, etc.

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- **term frequency**
- **inverse document frequency**
- **virtual document modeling:**
concatenate all Web pages/posts of the artist or perform *aggregation* via mean, max, etc.
- **normalization with respect to document length**

Abbr.	Description	Formulation
NORM_NO	No normalization.	
NORM_SUM	Normalize sum of each virtual document's term feature vector to 1.	$\sum_{t \in T_d} r_{d,t} = 1$
NORM_MAX	Normalize maximum of each virtual document's term feature vector to 1.	$\max_{t \in T_d} r_{d,t} = 1$

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages

(9,200 experiments):

- term frequency
- inverse document frequency
- virtual document model
- concatenate all Web pages
- normalization with respect to document length
- similarity measure

Abbr.	Description	Formulation
SIM_INN	Inner Product	$S_{d_1, d_2} = \sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})$
SIM_COS	Cosine Measure	$S_{d_1, d_2} = \frac{\sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})}{W_{d_1} \cdot W_{d_2}}$
SIM_DIC	Dice Formulation	$S_{d_1, d_2} = \frac{2 \sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})}{W_{d_1}^2 + W_{d_2}^2}$
SIM_JAC	Jaccard Formulation	$S_{d_1, d_2} = \frac{\sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})}{W_{d_1}^2 + W_{d_2}^2 - \sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})}$
SIM_OVL	Overlap Formulation	$S_{d_1, d_2} = \frac{\sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} \cdot w_{d_2, t})}{\min(W_{d_1}^2, W_{d_2}^2)}$
SIM_EUC	Euclidean Similarity	$D_{d_1, d_2} = \sqrt{\sum_{t \in \mathcal{T}_{d_1, d_2}} (w_{d_1, t} - w_{d_2, t})^2}$ $S_{d_1, d_2} = \left(\max_{d'_1, d'_2} (D_{d'_1, d'_2}) \right) - D_{d_1, d_2}$
SIM_JEF	Jeffrey Divergence-based Similarity	$S_{d_1, d_2} = \left(\max_{d'_1, d'_2} (D_{d'_1, d'_2}) \right) - D_{d_1, d_2}$ $D(F, G) = \sum_i \left(f_i \log \frac{f_i}{m_i} + g_i \log \frac{g_i}{m_i} \right)$ $m_i = \frac{f_i + g_i}{2}$

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- term frequency
- inverse document frequency
- virtual document modeling:

concatenate all

- normalization w

- similarity meas

- index term set

Abbr. / Term Set	Cardinality	Description
TS_A - all_terms	C224a, QS_A: 38,133 C224a, QS_M: 19,133 C3ka, QS_A: 1,489,459 C3ka, QS_M: 437,014	All terms (stemmed) that occur in the corpus of the retrieved Twitter posts.
TS_S - scowl_dict	698,812	All terms that occur in the entire SCOWL dictionary.
TS_N - artist_names	224 / 3,000	Names of the artists for which data was retrieved.
TS_D - dictionary	1,398	Manually created dictionary of musically relevant terms.
TS_L - last.fm_toptags	250	Overall top-ranked tags returned by last.fm 's <i>Tags.getTopTags</i> function.
TS_F - freebase	3,628	Music-related terms extracted from Freebase (genres, instruments, emotions).

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- **term frequency**
- **inverse document frequency**
- **virtual document modeling:**
concatenate all Web pages/posts of the artist or perform *aggregation* via mean, max, etc.
- **normalization with respect to document length**
- **similarity measure**
- **index term set**
- **query scheme**

Abbr.	Query Scheme
QS_A	“artist name”
QS_M	“artist name”+music

Large-Scale Study

[Schedl et al., TOIS 2011]

Investigating different aspects in modeling artist term profiles from Web pages
(9,200 experiments):

- **term frequency**
- **inverse document frequency**
- **virtual document modeling:**
concatenate all Web pages/posts of the artist or perform *aggregation* via mean, max, etc.
- **normalization with respect to document length**
- **similarity measure**
- **index term set**
- **query scheme**

implemented in our **CoMIRVA** framework available from <http://www.cp.jku.at/comirva>

Interesting Findings [Schedl et al., TOIS 2011]

- modeling artists as *virtual documents* is preferable
- using query scheme “*artist*” + *music* outperforms “*artist*”
- *normalization* does not yield a statistically significant difference
- standard *cosine similarity* measure does not yield the very best results, but the most stable ones (varying other parameters)
- *consistent results* among the (top-ranked) variants for two collections
- *minor change in one parameter* can have a huge impact on performance
- overall winners in terms of term weighting functions:

TF_C3.IDF_I

TF_C3.IDF_H

TF_C2.IDF_I

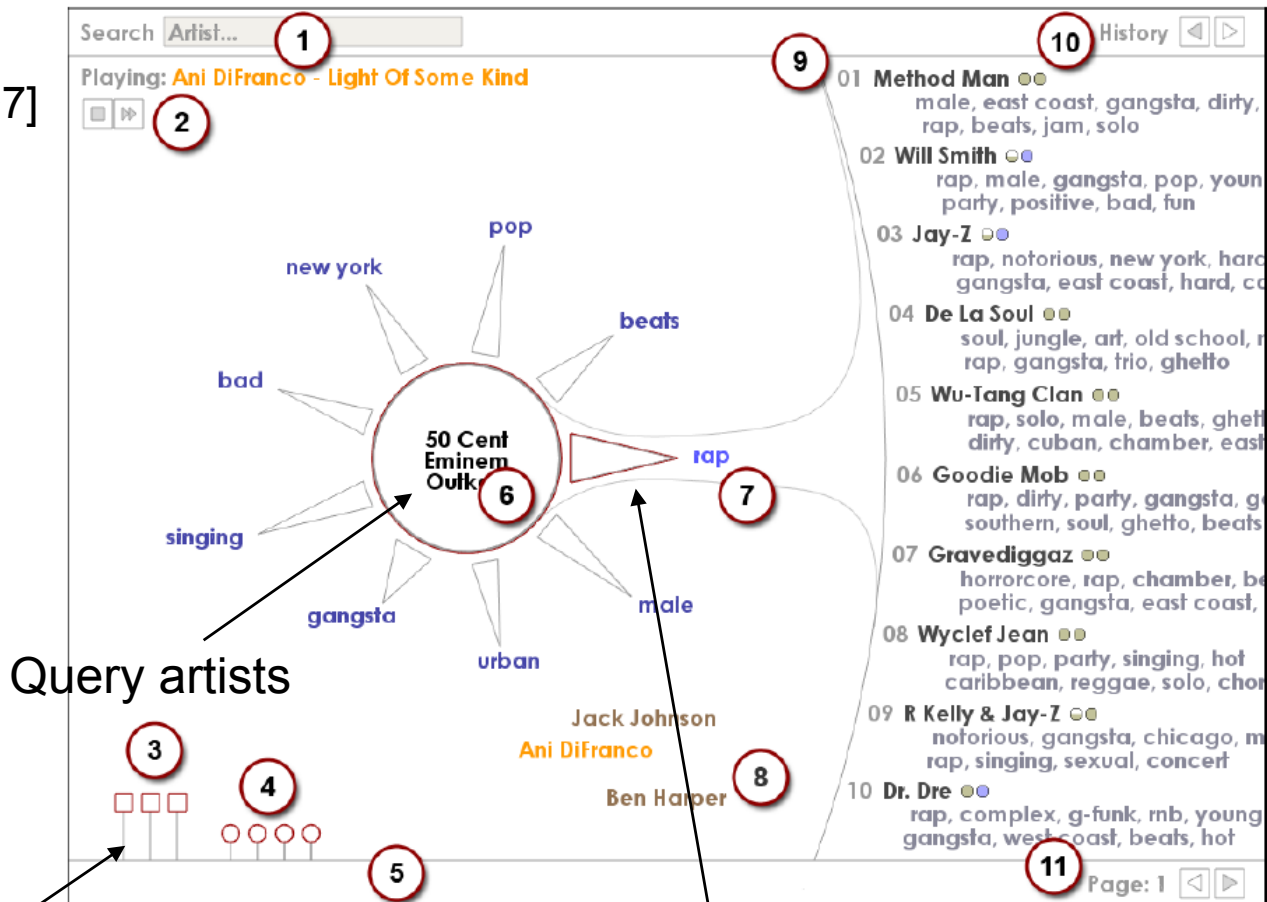
→ logarithmic formulations for TF and IDF

Web-based Descriptions for Browsing

“MusicSun”

[Pampalk and Goto, ISMIR’07]

- Interactive “Artist Recommender”
- Recommendation is influenced/directed by selecting relevant similarity dimensions
- Combines different similarity measures



3 types of similarity: audio, web-based, word
 overall similarity = weighted average of ranks

Relevant word dimension

Web-based Texts for Indexing and Retrieval

Use Web data to transform **music retrieval** into a **text retrieval** task

Find associated (or associable) texts and use them instead of music

Allows for diverse and semantic queries (e.g, “chilled music”, “great riffs”)

Search Sounds [Celma et al., ISMIR 2006]:

Crawl list of RSS feeds and use Weblog entries to index pieces

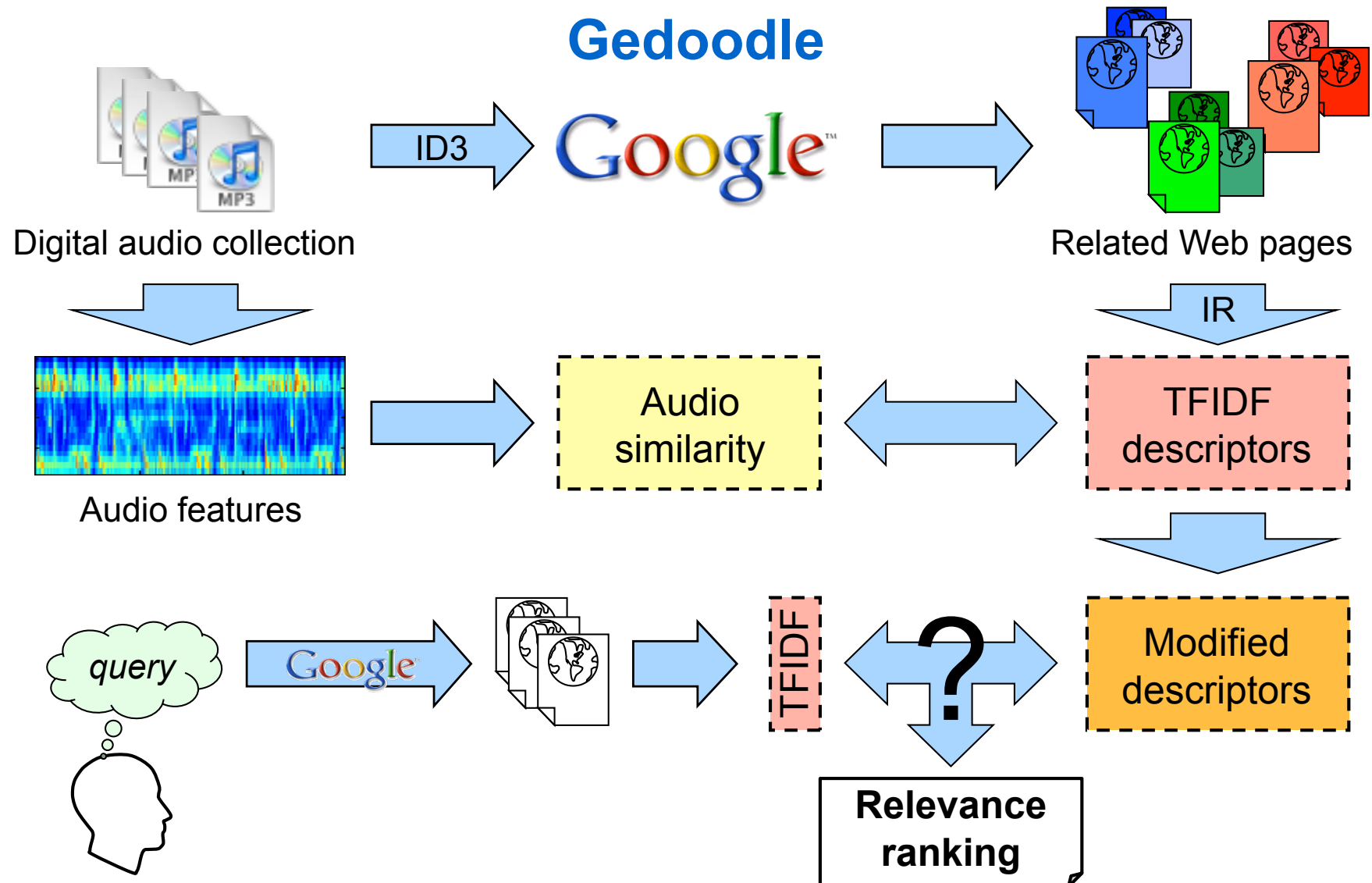
Squiggle [Celino et al, SAMT 2006]:

Combines meta-data databases (like MusicBrainz) for rich indexing

Gedoodle [Knees et al., SIGIR 2007]:

Query Google and combine Web pages to index pieces

Music Information Retrieval 2.0





Gedoodle

[Knees et al., SIGIR 2007]

For each track: join 100 Google results of

- “*artist*” music
- “*artist*” “*album*” music review
- “*artist*” “*title*” music review -lyrics

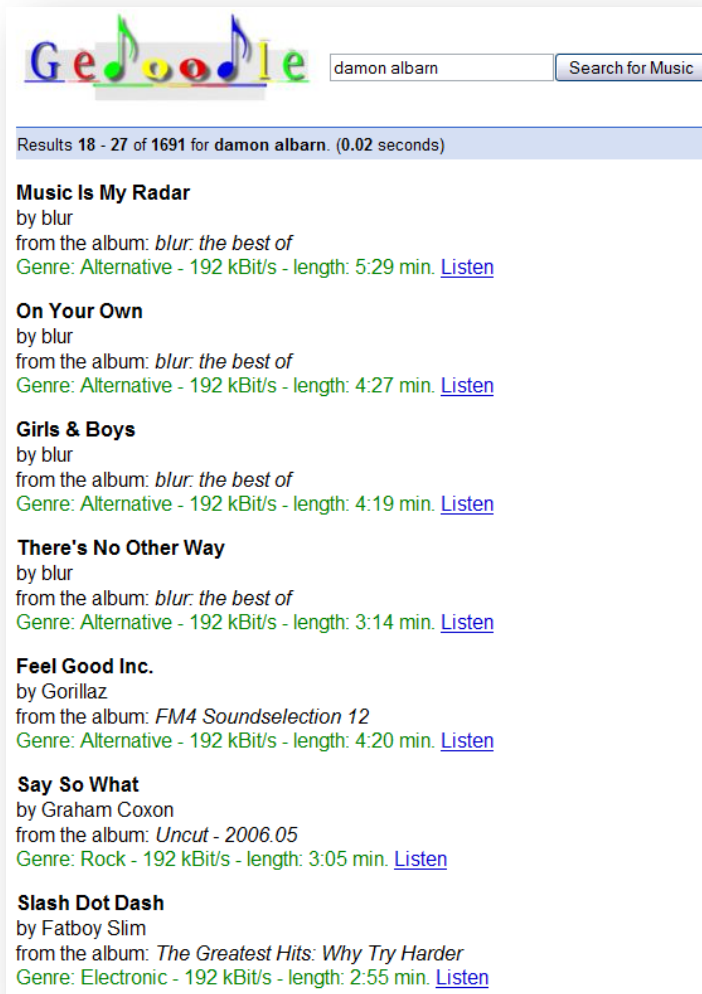
Combine all pages into one virtual document

Create normalized TFIDF vector for each track

Include audio similarity for vector modification and dimensionality reduction

Music Information Retrieval 2.0

Gedoodle (Example queries)



Google Music search results for "damon albar". The search bar contains "damon albar" and the button "Search for Music". The results show 18 - 27 of 1691 results in 0.02 seconds. The first five results are:

- Music Is My Radar** by blur, from the album: *blur: the best of*, Genre: Alternative - 192 kBit/s - length: 5:29 min. [Listen](#)
- On Your Own** by blur, from the album: *blur: the best of*, Genre: Alternative - 192 kBit/s - length: 4:27 min. [Listen](#)
- Girls & Boys** by blur, from the album: *blur: the best of*, Genre: Alternative - 192 kBit/s - length: 4:19 min. [Listen](#)
- There's No Other Way** by blur, from the album: *blur: the best of*, Genre: Alternative - 192 kBit/s - length: 3:14 min. [Listen](#)
- Feel Good Inc.** by Gorillaz, from the album: *FM4 Soundselection 12*, Genre: Alternative - 192 kBit/s - length: 4:20 min. [Listen](#)

Additional results shown include "Say So What" by Graham Coxon and "Slash Dot Dash" by Fatboy Slim.



Google Music search results for "smooth and relaxing". The search bar contains "smooth and relaxing" and the button "Search for Music". The results show 1 - 10 of 1774 results in 0.02 seconds. The first five results are:

- Joy And Pain** by Count Basic, from the album: *Moving In The Right Direction*, Genre: Acid Jazz - 168 kBit/s - length: 6:25 min. [Listen](#)
- Higher** by Count Basic, from the album: *Bigger & Brighter*, Genre: Acid Jazz - 192 kBit/s - length: 4:00 min. [Listen](#)
- Sweet Luis** by Count Basic, from the album: *Moving In The Right Direction*, Genre: Acid Jazz - 158 kBit/s - length: 5:11 min. [Listen](#)
- Got To Do** by Count Basic, from the album: *Moving In The Right Direction*, Genre: Acid Jazz - 167 kBit/s - length: 4:58 min. [Listen](#)
- John Lee Huber** by Tosca, from the album: *J.A.C.*, Genre: Electronica/Dance - 192 kBit/s - length: 4:33 min. [Listen](#)

Additional results shown include "No More Olives" by Tosca and "Naschkatze" by Tosca.

Music Information Extraction from Web Pages

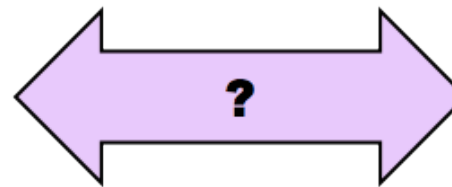
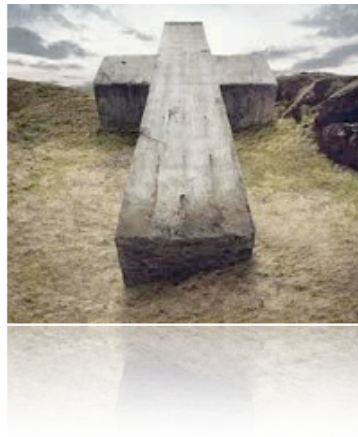
Web data is a rich source for all types of meta-data and semantic relations

Apply methods from NLP, IE, Named Entity Detection to extract data

- **Genres, Moods, Similarities** using Rule Patterns [Geleijnse and Korst, ISMIR'06]
- **Band Members and Line-Up** using Rule Patterns [Schedl and Widmer, AMR'07]
- **Band Members, Discography, Artist Detection** using rules in GATE
[Krenmair, JKU 2010]
- **Band Members, Discography** using Supervised Learning (in GATE)
[Knees and Schedl, WOMRAD 2011]
- **Album cover** detection and extraction [Schedl et al., ECIR 2006]

Music Information Retrieval 2.0

Microblogs as Text Sources

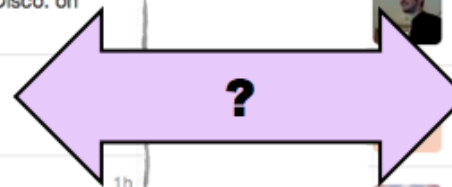


Radio Voome @up_radiovoorme 7m
Nu op @RadioVoome: Justice vs. Simian - We Are Your Friends
#radiovoorne #nowplaying

Jai Jones @jonesjai 9m
Love this track. #NowPlaying Justice – Audio, Video, Disco. on
#Spotify open.spotify.com/track/6iqBiGFv...

Sophie Stratford @sophiestratford 1h
#nowplaying Helix - Justice

radio2XS @radio2XS 1h
JUSTICE - On 'n' On is #nowplaying @radio2XS. Listen at
tiny.cc/2xs



Bawse @SneakerMike 9m
#nowplaying daft punk - something about us (remix)

Marcos Martin @marcos6m 1h
Escuchando The Grid por Daft Punk #nowplaying #tuesday
tinysong.com/Yav2

Spencer @dozycats 1h
#nowplaying Tron Legacy (End Titles) - Daft Punk

david. @dvzLun
#nowplaying LCD soundsystem - daft punk is playing



Microblogs as Text Sources

Retrieving tweets from *twitter.com*
using hashtags such as

#nowplaying

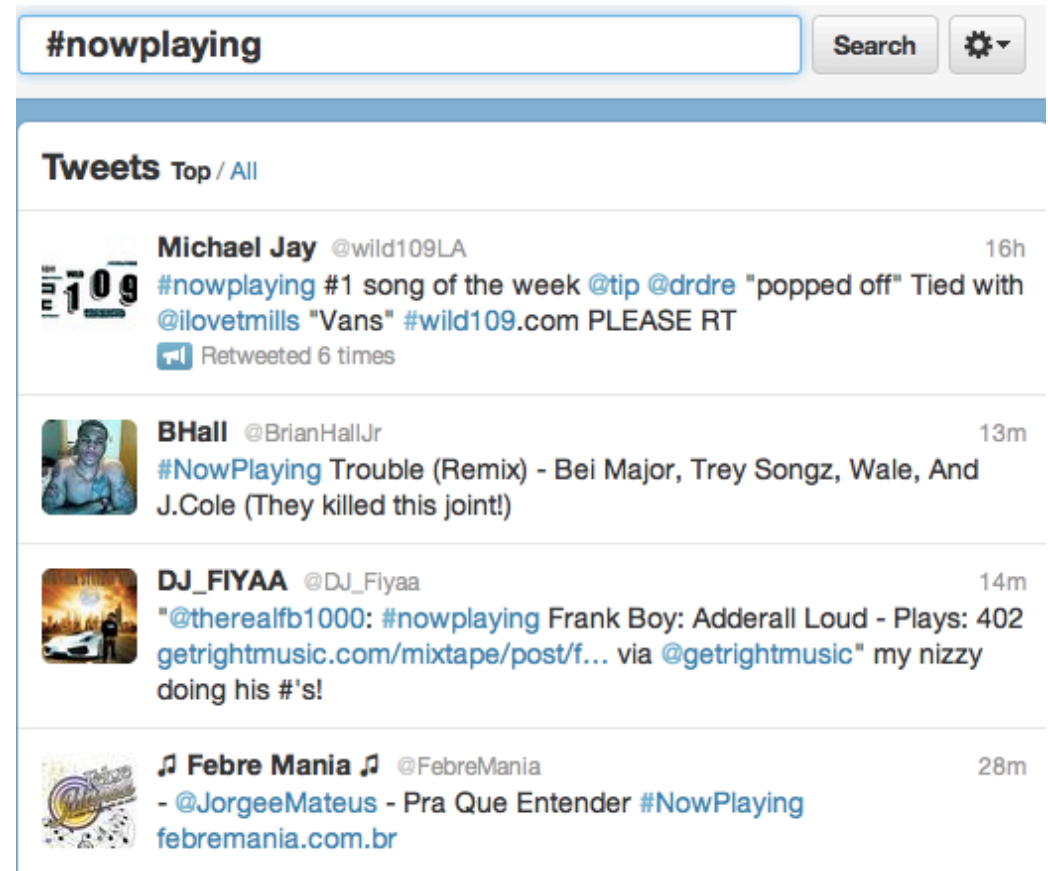
#np

#itunes [Schedl et al., ISMIR 2011]

Highly compressed, non-natural
language due to 140 character
restriction

Artist/track identification and
matching often challenging

#nowplaying also used for movies



The screenshot shows a Twitter search interface for the hashtag #nowplaying. The search bar at the top contains the text "#nowplaying" and has "Search" and "Settings" buttons to its right. Below the search bar, the results are displayed under the heading "Tweets Top / All". There are four tweets visible:

- Michael Jay** (@wild109LA) 16h: "#nowplaying #1 song of the week @tip @drdre "popped off" Tied with @ilovetmills "Vans" #wild109.com PLEASE RT" Retweeted 6 times
- BHall** (@BrianHallJr) 13m: "#NowPlaying Trouble (Remix) - Bei Major, Trey Songz, Wale, And J.Cole (They killed this joint!)"
- DJ_FIYAA** (@DJ_Fiyaa) 14m: "@therealfb1000: #nowplaying Frank Boy: Adderall Loud - Plays: 402 getrightmusic.com/mixtape/post/f... via @getrightmusic" my nizzy doing his #'s!"
- Febre Mania** (@FebreMania) 28m: "- @JorgeeMateus - Pra Que Entender #NowPlaying febremania.com.br"

Interesting Findings on Large-Scale Evaluation

[Schedl, IR 2012]

- modeling artists as *virtual documents* is preferable
- using query scheme “*artist*” outperforms “*artist*” + *music* (sparsity!)
- *normalization* does not improve results! → 140-character limit
- *term set* has an important influence: **TS_A** best, but at highest cost!
TS_N good compromise
- simple *inner product* as similarity measure performed better than cosine
→ consistent with observation for normalization
- no clear picture for TF and IDF variants (just don't use binary match!)
TF_C2 (log) and TF_E performed best, on average
IDF_B2 (log), IDF_J (Okapi), IDF_E (log) performed best, on average

Music Information Retrieval 2.0



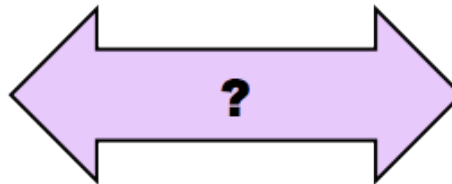
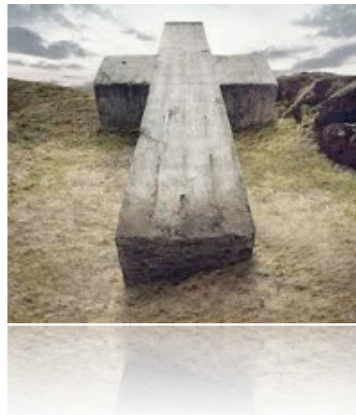
Department of
Computational
Perception

JKU
JOHANNES KEPLER
UNIVERSITY LINZ

Markus Schedl, Peter Knees

{markus.schedl, peter.knees}@jku.at | http://www.cp.jku.at

Product Reviews as Text Sources



4 of 6 people found the following review helpful:
★★★★★ **Bolder than Cross; prog-dance in the making.**, 25 Oct 2011
By **Kieren Thomson "Kieren"** (Bradford, Isle Of Wight) - See all my reviews
This review is from: *Audio, Video, Discs (Audio CD)*
Imagine if the Sex Gens decided to make a prog-rock album, or that Jeff Wayne's War Of The Worlds was conducted in a disco. That's how Justice have played out on their follow up to one of the greatest dance albums of the last 10 years, Cross. They've dropped the samples and have made an electro-instrumental album with tinges of progressive rock.
A wonder to behold, Audio Video Discs contains nods to some of the greatest rock of the 70's, but keeps the great elements of experimental dance from the 00's. Highlights include Canon - a club-stomper built for Daft Punk, and Helix - a nod to the last album but with bigger and bolder synths.
It's not Cross, but it doesn't need to be. It's a bold, guitar-laden album built on rock instead of experimental-dance. Rejoice.
Help other customers find the most helpful reviews
Was this review helpful to you? Yes No

0 of 1 people found the following review helpful:
★★★★★ **great great great.**, 12 Nov 2011
By **kj coleman (england)** - See all my reviews
This review is from: *Audio, Video, Discs (Audio CD)*
The first album in my favourite dance album ever initially a bit of a shock - the prog rock/ heavy metal direction, but after several listens its still quality! spinal tap it is not.
Help other customers find the most helpful reviews
Was this review helpful to you? Yes No

Most Recent Customer Reviews
★★★★★ **Try all of this...**
The negative reviews dragging this album down are silly. You can not compare Justice to anyone. No longer do they present as the angry high pitched mates of Daft Punk.
[Read more](#)
Published 1 month ago by A. Livingstone
★★★★★ **Brilliantly Innovative, but in the same streak**
From the very moment I heard "Civilisation" in the Adidas advert, I got excited about this album. Listening to it did not leave me disappointed at all! [Read more](#)
Published 1 month ago by Boris Taylor
★☆☆☆ **On'n'On'n'On'n'On...**
Justice has seriously tamed the "Audio, Video, Discs."
If you are looking for the most soundscapes and swashbuckling "Cross" in it's... [Read more](#)
Published 1 month ago by Diapace
★★★★★ **"New Justice"**
This album is different from their first album, but although I am a huge fan of "Cross", I do enjoy this new album a lot, too.
[Read more](#)
Published 1 month ago by Christian Schwaner
★☆☆☆ **Such a disappointment for a hardcore Justice fan**
Having seen Justice live on at least 5 occasions and being a big fan and proud owner of Cross and A Cross the Universe, I am disappointed to say that there is no such

It is that good.
When this one ends we hear "Da Funk" cleverly slide in with it's weird but very addictive warbled beat. The album after that is definitely in the realms of experimentation but if you listen carefully to this album you'll begin to notice similar sounds in later dance tracks.....
I'm very impressed.
Help other customers find the most helpful reviews
Was this review helpful to you? Yes No

11 of 13 people found the following review helpful:
★★★★★ **debut daft punk**, 22 Jan 2004
By **E. P. "spideredd"** (Suffolk, England) - See all my reviews
After discovery, so my expectations were a little high house fan and found this album right up my alley. Still sounds as fresh as it did back then! Absolute quality music!!!
Compare the two albums, but I feel that homework has the better layout and appeal.
One or two friends of mine won't listen to this album because there is little to break the album up. This is the only reason that I haven't given this the whole five stars.
All in all a good, if somewhat strange album. I'd recommend that anyone should at least listen to it.
Help other customers find the most helpful reviews
Was this review helpful to you? Yes No

1 of 1 people found the following review helpful:
★★★★★ **Terrible !!!**, 19 Oct 2011

Most Recent Customer Reviews
★★★★★ **Superior house music**
This album will never be beaten, much much imitated but never equalled. Play it loud and proud as this was released in 1996 and still "Around the world" sounds as "fresh" as it...
[Read more](#)
Published 4 months ago by H. D. Ballinger
★★★★☆ **If summer was a sound it would sound like this**
I think I got Daft Punk backwards. Beyond hearing the odd single and track in a bar I didn't really pay them a lot of mind.
[Read more](#)
Published 6 months ago by Christopher Long
★★★★☆ **Quality**
Had this album on vinyl when it first came out. Since then lost that so had to get it on cd. Still sounds as fresh as it did back then! Absolute quality music!!!
Published 13 months ago by Craig L. Gendring
★★★★★ **Such a great album!**
This CD puts a smile on my face. This is sooooo good. Look up the video from around the world and you're sold. The rest of the album is just as good.
Published 13 months ago by Ake
★★★★★ **Brilliant**
As a born-again Daft Punk fan I bought this having not long ago bought Discovery, and I love it.
Other people can express what's great about this more eloquently than... [Read more](#)
Published 21 months ago by Mark Whithead



Product Reviews as Text Sources

Exploiting sources such as *amazon.com* or *epinions.com* [Hu et al., 2005]

This review is from: [Ray of Light \(Audio CD\)](#)

This is Madonna's work of art. And this CD is the very best collection of any music she has ever produced since "Erotica." Madonna's lyrics are beautiful and strong because even after 9 years it still stands the test of time. It's completely impossible for this CD to be dated; with the electronica feel to it and fast moving dance numbers, such as the title-track this CD was way ahead of its time. Even in the double-00's "Ray of Light" is still very important as both a dance record and a record of reflection and interpersonal renewal.

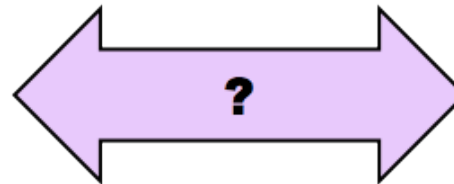
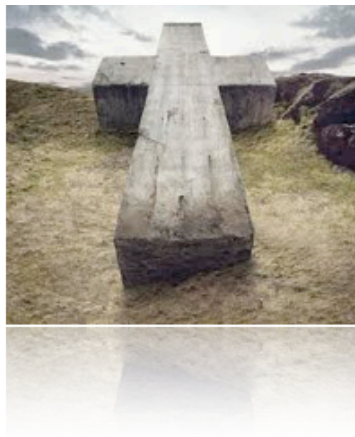
This review is from: [Never Gonna Give You Up \(MP3 Download\)](#)

This is truly Astley's greatest opus. The track is flawless. It is instantly accessible, but features many hidden layers and pleasures that cannot be discovered upon the first listen alone. With this and all of his other fantastic work, it's no wonder that Radiohead calls Astley their "greatest inspiration."

Allows for sentiment analysis and associated rating prediction

Very prone to attacks (remedy: consider "helpfulness" ratings)

Community Tags as Text Sources



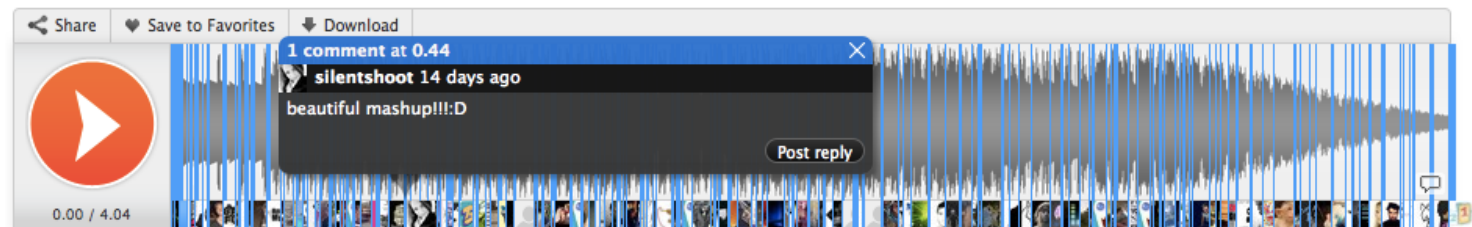
00s alternative ambient chillout club cool **dance** dance punk dance-punk death 00s 80s 90s alternative alternative rock ambient awesome big beat blues chillout classic
metal digital dirty electro disco distortion ed banger **electro** electro dance rock club daft punk **dance** disco dub **electro** electro house electroclash
electro house electroclash **electronic** **electronica** electropop **electronic** **electronica** electropop experimental favorites
elektro eletronic experimental favourite france **french** french elektro french french electro french house french touch funky funky great
french touch funk funky german glitch hardcore hardcore punk ha se french french electro french house french touch funky funky great
indietronica instrumental justice love metal new rave noise nu rave pa party pop paris pe pop progressive house psychedelic psytrance punk robots rock soul
psychedelic punk rock sexy synthpop techno thrash metal trance want to see live soundtrack synth synthpop **techno** trance trip-hop

Tag Sources

- Community
e.g., last.fm

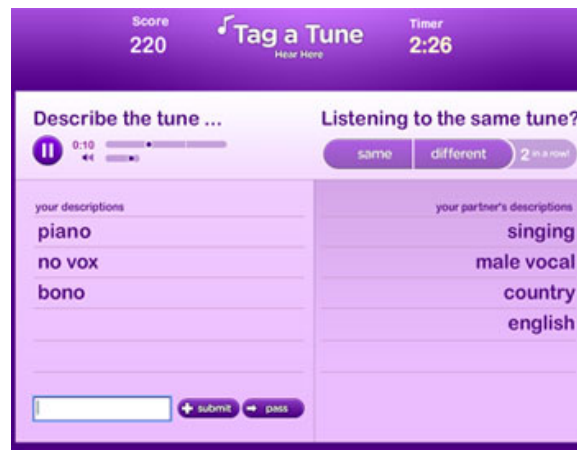
1960s 60s acoustic american bacharach baroque baroque pop
boltoneseq brill building pop burt bacharach chill classic composer disco driving
easy **easy listening** everything favorite artists favorites
film music film score fusion genius god great innovators guitar hal david inspirerande
instrumental jazz lounge male male vocalists master melancholy music to
warm the heart and hands my ancients my tag oldies outstanding pop relax
rock score sexy singer-songwriter smooth songwriter sophistopop soul
soundtrack space age pop swing symphonic pop us usa virtuoso vocal 2005

- Soundcloud (annotations along timeline)



- Games with a purpose
e.g., Tag-a-Tune
[Law and von Ahn, CHI'09]

- Autotags (see before)



Community Tags as Text Sources

Treating collections of tags (e.g., from last.fm) as documents

[Pohle et al., ISMIR 2007] [Levy and Sandler, JNMR 2008] [Hu et al., ISMIR 2009]

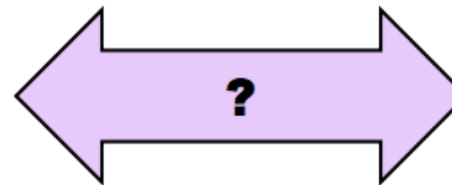
- Retrieve tags for artist or track from last.fm
- Cleaning of noisy and redundant tags
 - manually
 - automatically [Geleijnse et al., ISMIR 2007]
- List of collected terms is treated as text document and TF-IDF'd [Levy & Sandler, ISMIR 2007]
- Optionally, LSA to reduce dimensionality
- Comparison of vectors via cosine similarity (or overlap score)

- Data often available in standardized fashion, dedicated terms for music
- Lower dimensionality (13,500 tags vs. >200,000 Web terms [Levy & Sandler, ISMIR 2007])
- Depends on community, needs annotators
- Hacking and Attacks!

Lyrics as Text Source



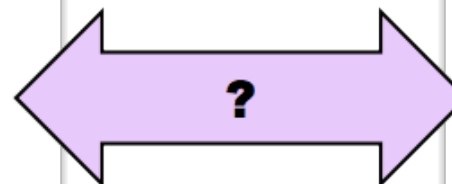
Before day break there was none
And as it broke there was one
The Moon, the sun, it goes on 'n' on
The winter battle was won
The summer children were born
And so the story goes on 'n' on
Come woman if your life beats
Those we buried with the house keys
Smoke and feather where the fields are green
From here to eternity
Come woman on your own time



Around the world, around the world
Around the world, around the world
Around the world, around the world

Around the world, around the world
Around the world, around the world
Around the world, around the world

Around the world, around the world
Around the world, around the world
Around the world, around the world



Lyrics as Text Source

Topic Features

[Logan et al., ICME 2004]

- Typical topics for lyrics are distilled from a large corpus using (P)LSA (“Hate”, “Love”, “Blue”, “Gangsta”, “Spanish”)
- Lyrics are transformed to topic-based vectors, similarity is calculated via L_1 distance
- Alternative approaches use TF·IDF with optional LSA and Stemming for

Mood Categorization

[Laurier et al., ISMIR 2008], [Hu et al., ISMIR 2009]

Rhyme Features [Mayer et al., ACM MM 2008] [Hirjee and Brown, ISMIR 2009]

- Phonetic transcription is searched for patterns of rhyming lines (AA, ABAB, AABB)
- Frequency of patterns + statistics like *words per minute*, *punctuation freq.* etc.

Other Features [Mahedero et al., ACM MM 2005] [Hirjee and Brown, ISMIR 2009]

- Language, structure



Text-based Similarity Approaches: Summary

	Web-Terms	Microblogs	Reviews	Tags	Lyrics
Source	Web pages	platform	shops, platform	Web service	portal
Community-based	depends	depends	yes	yes	no
Level	artists	artists (tracks)	albums	artists (tracks)	tracks (artists)
Feature Dimensionality	very high	high	possibly high	moderate	possibly high
Specific Bias	low	low	personal	community	none
Potential Noise	high	high	low	moderate	low

Similarity from Co-Occurrences

Idea: expect entities that occur frequently in the same context to be similar

Data sources:

- page count estimates from Web search engines



- shared folders/search queries on the *Gnutella* file sharing network



- collaborative filtering on playcounts from *last.fm*



- occurrences in playlists





Search Engine Page Count Estimates



[Schedl et al., CBMI 2005]

For all pairs of artists: query “**artist 1**” “**artist 2**” **+music +review**

For each artist: query “**artist**” **+music +review**

Use **page counts** for sim. (results in quadratic page count matrix)

$$sim_{pc_cp}(A_i, A_j) = \frac{1}{2} \cdot \left(\frac{pc(A_i, A_j)}{pc(A_i)} + \frac{pc(A_i, A_j)}{pc(A_j)} \right)$$

To avoid quadratic number of queries: download top 100 pages for each artist and parse for occurrences of other artists (linear compl.)

NB: asymmetry of pc matrix can be used to identify prototypical artists!

Shared Folders in a P2P Network



Make use of meta-data transmitted as files names or ID3 tags in P2P network OpenNap [Whitman and Lawrence, ICMC 2002] [Ellis et al., ISMIR 2002]

Information gathered from users' shared folders (no file downloads!)

Similarities via artist co-occurrences in collections (cond. prob.)

Sparse co-occurrence matrix

Experiments on Gnutella network [Shavitt and Weinsberg, AdMIRe 2009]:

- meta-data highly inconsistent
- can be used as song-based similarity measure and to estimate localized popularity/trends (matching IP addresses difficult!)

Last.fm Playcounts

Use *explicit* or *implicit* ratings of users or interpret number of plays of a song as a “rating”



Results in a user-track rating matrix

Use standard **collaborative filtering** approaches to predict similarities (or to recommend unknown music) e.g., [Resnick et al., CSCW'94]

Item-based: compare tracks by calculating similarity on vectors over all users

User-based: find similar users by comparing listening pattern vectors; use to find relevant/similar and yet unknown tracks

Playlist Co-Occurrences

Analysis of co-occurrences of artists and songs on radio station playlists (French radio station Fip) and compilation CD databases (CDDDB) [Pachet et al., WEDELMUSIC 2001]

$$\text{sim}_{pl_cooc}(A_i, A_j) = \frac{1}{2} \cdot \left[\frac{\text{cooc}(A_i, A_j)}{\text{cooc}(A_i, A_i)} + \frac{\text{cooc}(A_j, A_i)}{\text{cooc}(A_j, A_j)} \right]$$

Analysis of 29,000 playlists from “Art of the Mix” [Cano and Koppenberger, ISMIR’04]: artists similar if they co-occur in playlist (highly sparse)

Analysis of > 1 million playlists from “MusicStrands” [Baccigalupo et al., ISMIR 2008]:

- distance in playlists taken into account $\beta_0 = 1, \beta_1 = 0.8, \beta_2 = 0.64$

$$\text{dist}_{pl_d}(A_i, A_j) = \sum_{h=0}^2 \beta_h \cdot [d_h(A_i, A_j) + d_h(A_j, A_i)]$$

- playlist prediction using case-based reasoning

Co-occurrence-based Approaches: Summary

	Web Co-Ocs	Playcounts	P2P nets	Playlists
Source	search engines, Web pages	listening service	shared folders	radio, compilations, Web services
Community-based	no	yes	yes	depends on source
Level	artists	tracks	artists (tracks)	artists (tracks)
Specific Bias	"wikipedia"-bias	popularity	community	low
Potential Noise	high	low	high	low



Current and Future Challenges

Improving content- and context-based methods (scale and speed)

Most urgent challenge: Modelling **User Context**

Perception of music is highly subjective

Influenced by personal experiences, preferences, taste, etc.

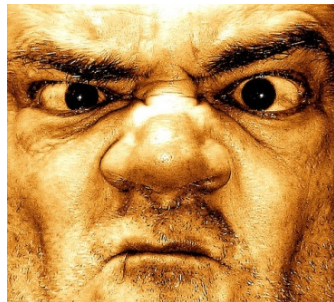
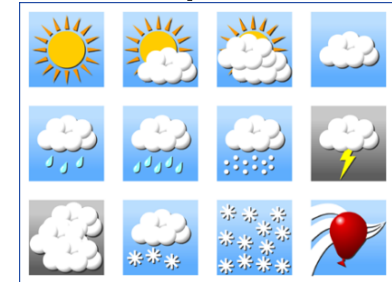
Analysis of audio and Web data alone can't capture these aspects

Essential for truly personalized recommendations
(in contrast to e.g., collaborative filtering)

Dimensions of User Context

adapted from [Göker and Myrhaug, 2002]

Environmental Context: people & things surrounding user, temperature, noise, light, humidity



Personal Context:

- *physiological context:* weight, blood pressure, pulse, ...
- *mental context:* stress level, mood, expertise, ...

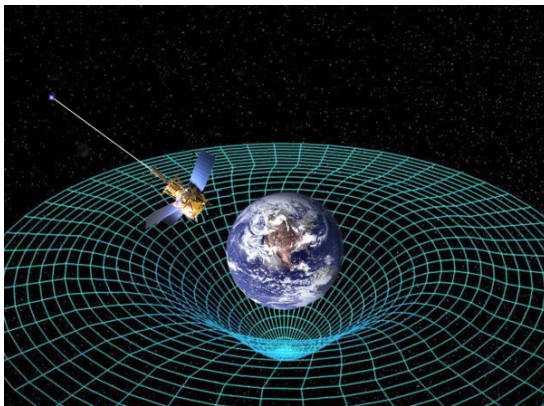
Task Context: current activities, running apps



Dimensions of User Context

adapted from [Göker and Myrhaug, 2002]

Social Context: relatives, friends, enemies, collaborators



Spatio-temporal Context: location, place, direction, speed, and time

User-Aware Music Recommendation on Android Phones

(Ongoing Master's Thesis G. Breitschopf)

“Mobile Music Genius”: music player for the Android platform

- collecting user context data while playing (next slides)
- adaptive system that learns user taste/preferences from implicit feedback (player interaction)
- two basic research questions:
 - + Can we solve a binary classification problem (like/dislike) from context features and feedback? (assuming skipping indicates <dislike>, actively selecting a song indicates <like>)
 - + Can we relate user context features to music the user wants to listen to?
- ultimate aim: dynamically and seamlessly update the user's playlist according to his/her current context

Music Information Retrieval 2.0

User-Aware Music Recommendation on Android Phones

(Ongoing Master's Thesis G. Breitschopf)

The image displays three screenshots of an Android music application interface. The left screenshot shows a main menu with buttons for 'Interpreten', 'Alben', 'Titel', 'Genres', 'Jahre', and 'Playlisten'. The middle screenshot shows the album 'Starlight' by Muse, with a play button and a progress bar. The right screenshot shows a 'Debug Informationen' screen with 'User context data' including Reason, Time, Personal, Location, and Weather information.

Debug Informationen

User context data

Reason: phone_state

Time

20110713T151957Z - 1310570397692

Timezone [id=Europe/Vienna]

Personal

User [mEmail=georg.breitschopf@gmail.com, mGender=M, mBirthdate=1981-4-13]

Location

LocationState [time=1310570292346, provider=network, latitude=48.3334302, longitude=14.6251067, accuracy=3296.0, networkProviderEnabled=true, networkProviderAvailable=true, gpsProviderEnabled=false, gpsProviderAvailable=false]

Altitude [latitude=48.3334302, longitude=14.6251067, altitude=474]

Weather [latitude=0.0, longitude=0.0, metar=null, stationICAO=null, stationName=null, stationLatitude=null, stationLongitude=null, stationElevation=null, stationCountryCode=null, timeString=null, windDirection=null, windSpeed=null, clouds=null, temperature=null, dewPoint=null, humidity=null, airPressure=null, weatherCondition=null]

Place [latitude=0.0, longitude=0.0, city=null, nearby=null]



User Context Features from Android Phones

Time: timestamp, time zone

Personal: userID/eMail, gender, birthdate

Device: deviceId (IMEI), sw version, manufacturer, model, phone state, connectivity, storage, battery, various volume settings (media, music, ringer, system, voice)

Location: longitude/latitude, accuracy, speed, altitude

Place: nearby place name (populated), most relevant city

Weather: wind direction, speed, clouds, temperature, dew point, humidity, air pressure

Ambient: light, proximity, temperature, pressure, noise, digital environment (WiFi and BT network information)

Activity: acceleration, user and device orientation, UI mode (undocked, car, desk), screen on/off, running apps

Player: artist, album, track name, track id, track length, genre, playback position, playlist name, playlist type, player state (repeat, shuffle mode) audio output (headset plugged)



Currently in Evaluation...

Which granularity/abstraction level to choose for representation/learning?

user context data:

e.g., position as GPS coordinates or nearest agglomeration
→ data transformation/aggregation

musical metadata:

artist/performer, album, track, genre, mood, other tags?



Conclusions

Music Information Retrieval is a broad and diverse field

Various approaches to extract information directly from the audio signal

Various sources and approaches to extract contextual data and similarity information from the Web

Multi-modal retrieval promising and allows for exciting applications

Next big challenges:

- modeling user context
- personalization
- situation-based retrieval

Thank you !



Latest version of the slides will be available at
http://www.cp.jku.at/tutorials/ecir2012_mir20.html