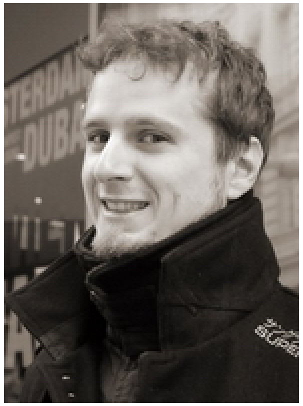
Music Information Retrieval



http://www.ifs.tuwien.ac.at/mir

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AUSTRIAN INSTITUTE OF TECHNOLOGY
TOMORROW TODAY

FACULTY OF !NFORMATICS

What is Music IR?

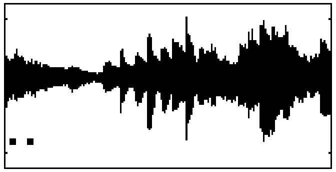
- Searching for Music
  - Searching for music on the Web
  - Query by Humming
  - Similarity Retrieval
  - Identity detection (fingerprinting)

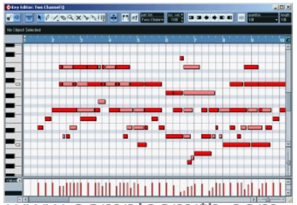
- Extraction of information from music

  → plenty of other tasks!

What is Music?

- Music
  - Audio: wav, au, mp3, ...
  - Symbolic: MIDI, mod, ...
  - Scores: Scan, MusicXML





www.samplesmith.com

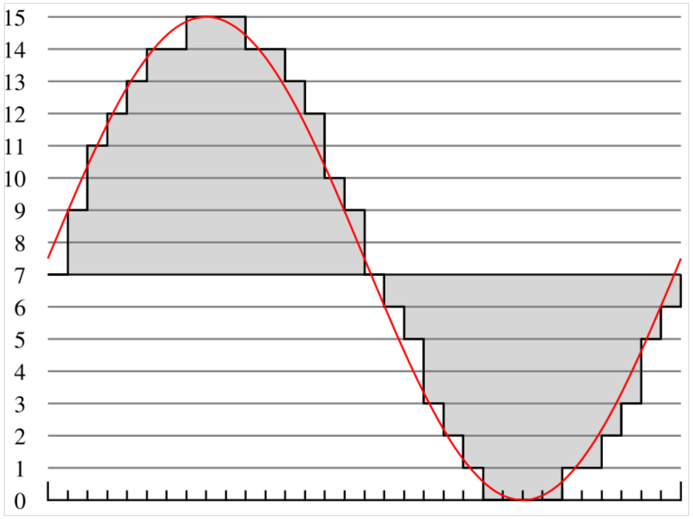
www.westminster.gov.uk

- Text
  - Song lyrics
  - Artist Biographies
  - Websites: Fanpages, Blogs, Album Reviews, Genre descriptions
- Community data
  - Market basket
  - Tags
  - Social Networks
    - Spotify
    - Last.fm
- Video/Images
  - Album covers
  - Music videos

2.
Feature Extraction from Music

Too much Audio Data

- Digital Audio
  - Sampling Rate: 44,100 Hz
  - 16-bit resolution for each channel
    - 2 channels for stereo
  - 88,200 Integers per second



Excercise: Find Documents Containing the Word „Music“

Document 1:

*“Most of these issues stem from the commercial interest in **music** by record labels, and therefore imposed rigid copyright issues, that prevent researchers from sharing their **music** collections with others. Subsequently, only a limited number of data sets has risen to a pseudo benchmark level, i.e. where most of the researchers in the field have access to the same collection.“*

Document 2:

*“The Echonest Analyzer [5] is a **music** audio analysis tool available as a free Web service accessible over the Echonest API and as a commercially distributed standalone command line tool. The Analyzer implements an onset detector which is used for segmentation.”*

Document 3:

*“The Million Song Dataset (MSD), a collection of one million **music** pieces, enables a new era of research of **Music** Information Retrieval methods for large-scale applications. It comes as a collection of meta-data such as the song names, artists and albums, together with a set of features extracted with the The Echo Nest services, such as loudness, tempo, and MFCC-like features.”*

Excercise: Find Songs with Strings

Song 1:

83, 58, 11, 11, 9, 60, 96, 25, 39, 42, 87, 90, 12, 26, 99, 69, 10, 56, 64, 41, 47, 61, 6, 40, 94, 23, 43, 52, 31, 77, 32, 57, 40, 89, 91, 28, 38, 96, 3, 90, 43, 18, 25, 16, 79, 97, 83, 64, 46, 70, 63, 34, 38, 39, 7, 66, 89, 95, 9, 47, 11, 59, 9, 17, 46, 92, 27, 58, 87, 46, 39, 100, 10, 2, 5, 53, 73, 56, 43, 46, 47, 67, 2, 60, 9, 23, 43, 21, 98, 34, 29, 62, 26, 72, 38, 98

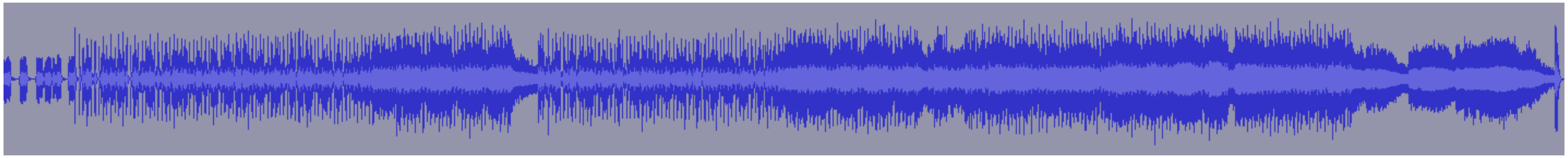
Song 2:

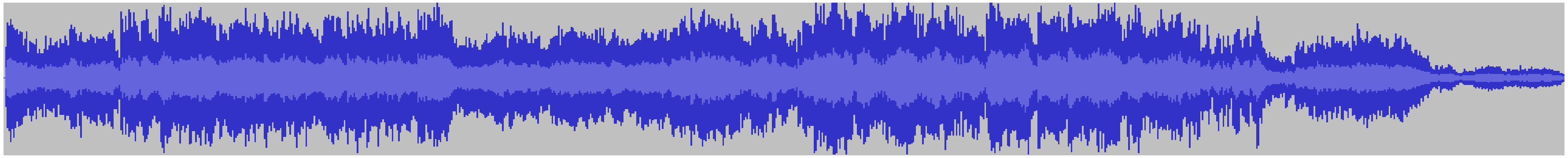
55, 96, 11, 49, 83, 58, 11, 11, 9, 60, 96, 25, 39, 42, 87, 90, 12, 26, 99, 69, 10, 56, 64, 41, 47, 61, 6, 40, 94, 23, 43, 52, 31, 77, 32, 57, 40, 89, 91, 28, 38, 96, 3, 90, 43, 18, 25, 16, 79, 97, 83, 64, 46, 70, 63, 34, 38, 39, 7, 66, 89, 95, 9, 47, 11, 59, 9, 17, 46, 92, 27, 58, 87, 46, 39, 100, 10, 2, 5, 53, 73, 56, 43, 46, 47, 67, 2, 60, 9, 23, 43, 21, 98, 34, 29, 62, 26, 72, 38, 98, 55, 96, 11, 49, 83, 58, 11, 11, 9, 60, 96, 25, 39, 42, 87, 90, 12, 26, 99, 69, 10, 56, 64, 41, 47, 61, 6, 40, 94, 23, 43, 52, 31, 77, 32, 57, 40, 89, 91, 28, 38, 96, 3, 90, 43, 18, 25, 16, 79, 97, 83, 64, 46, 70, 63, 34, 38, 39, 7

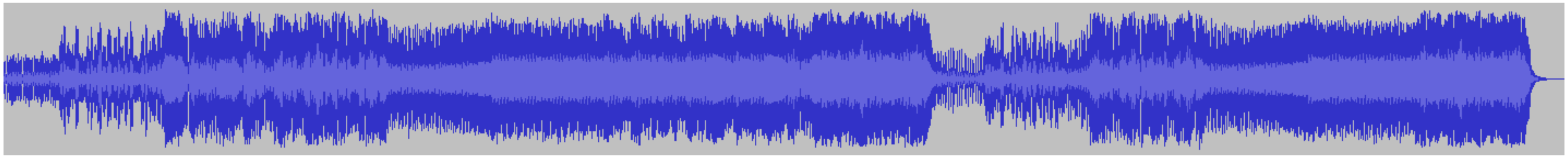
Song 3:

66, 89, 95, 9, 47, 11, 59, 9, 17, 46, 92, 27, 58, 87, 46, 39, 100, 10, 2, 5, 53, 73, 56, 43, 46, 47, 67, 2, 60, 9, 23, 43, 21, 98, 34, 29, 62, 26, 72, 38, 98, 55, 96, 11, 49, 83, 58, 11, 11, 9, 60, 96, 25, 39, 42, 87, 90, 12, 26, 99, 69, 10, 56, 64, 41, 47, 61, 6, 40, 94, 23, 43, 52, 31, 77, 32, 57, 40, 89, 91, 28, 38, 96, 3, 90, 43, 18, 25, 16, 79, 97, 83, 64, 46, 70, 63, 34, 38, 39, 7, 66, 89, 95, 9, 47, 11, 59, 9, 17, 46, 92, 27, 58, 87, 46, 39, 100, 10, 2, 5, 53, 73, 56, 43, 46, 47, 67, 2

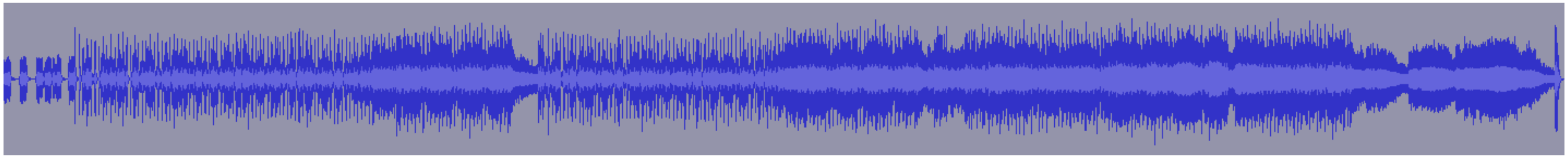
Excercise: Same Genre?



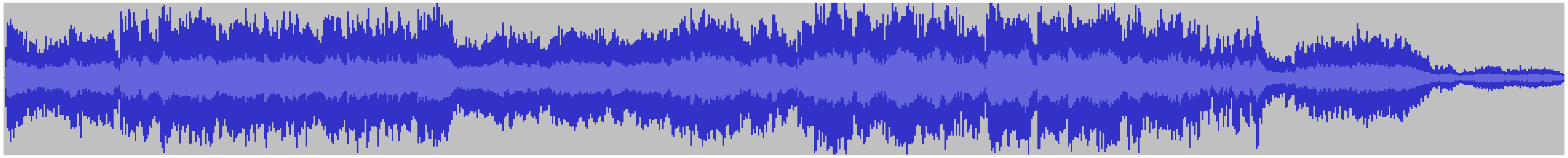




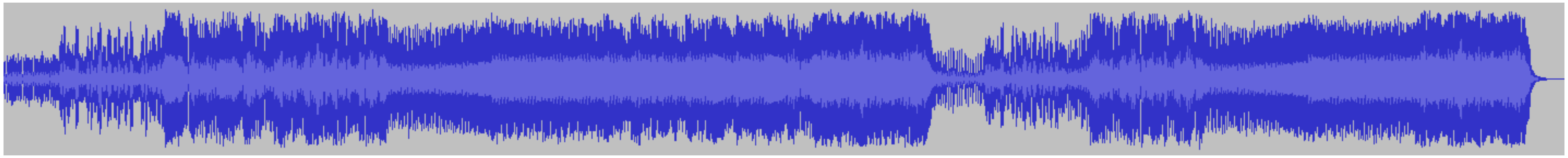
Excercise: Identify Songs



AC-DC – Highway to Hell



John Williams – Star Wars Main Theme

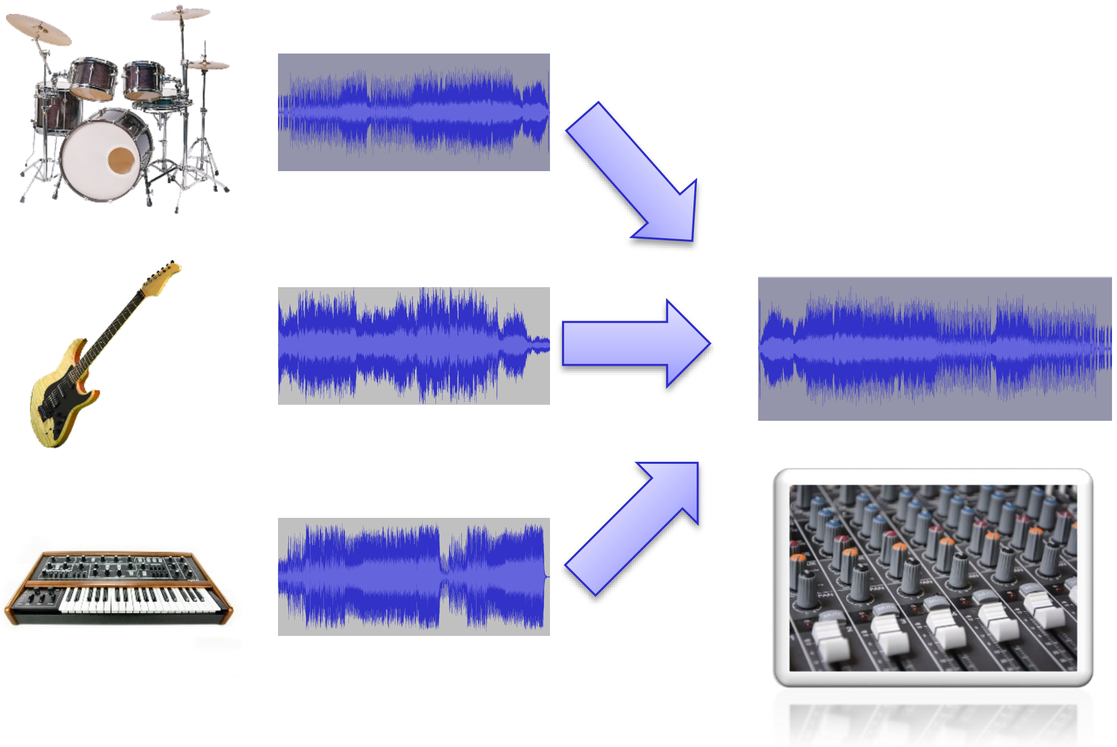


Rihanna feat. Calvin Harris – We Found Love

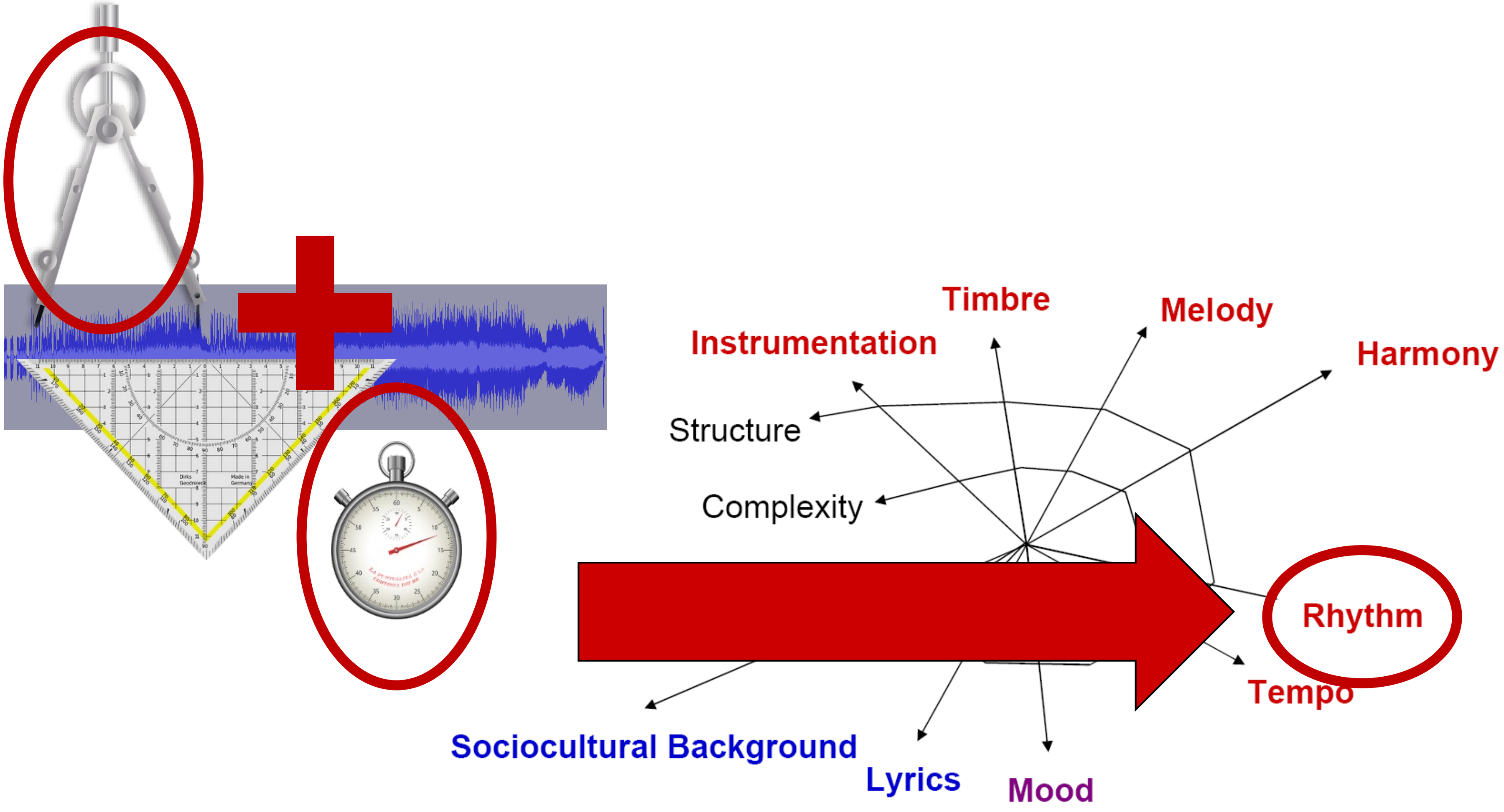
Audio Feature Extraction

- Reduce audio data by extracting information about:
  - Pitch
  - Timbre
  - Rhythm
  - etc.
- → extract „audio descriptors“

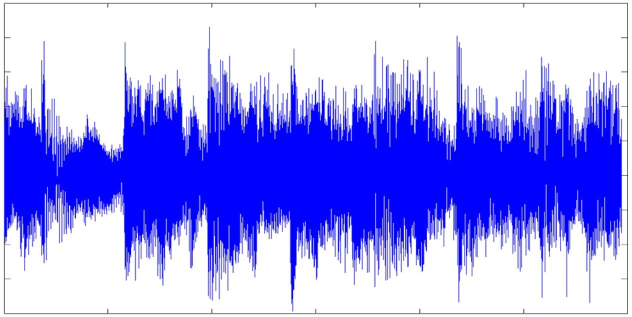
Problem: Source Separation



Audio Feature Extraction

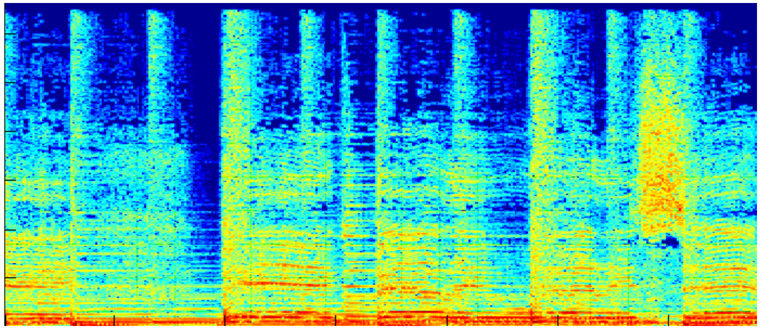


Signal Processing



Time Domain

(„Wave Form“)



Frequency Domain

(„Spectrum“)

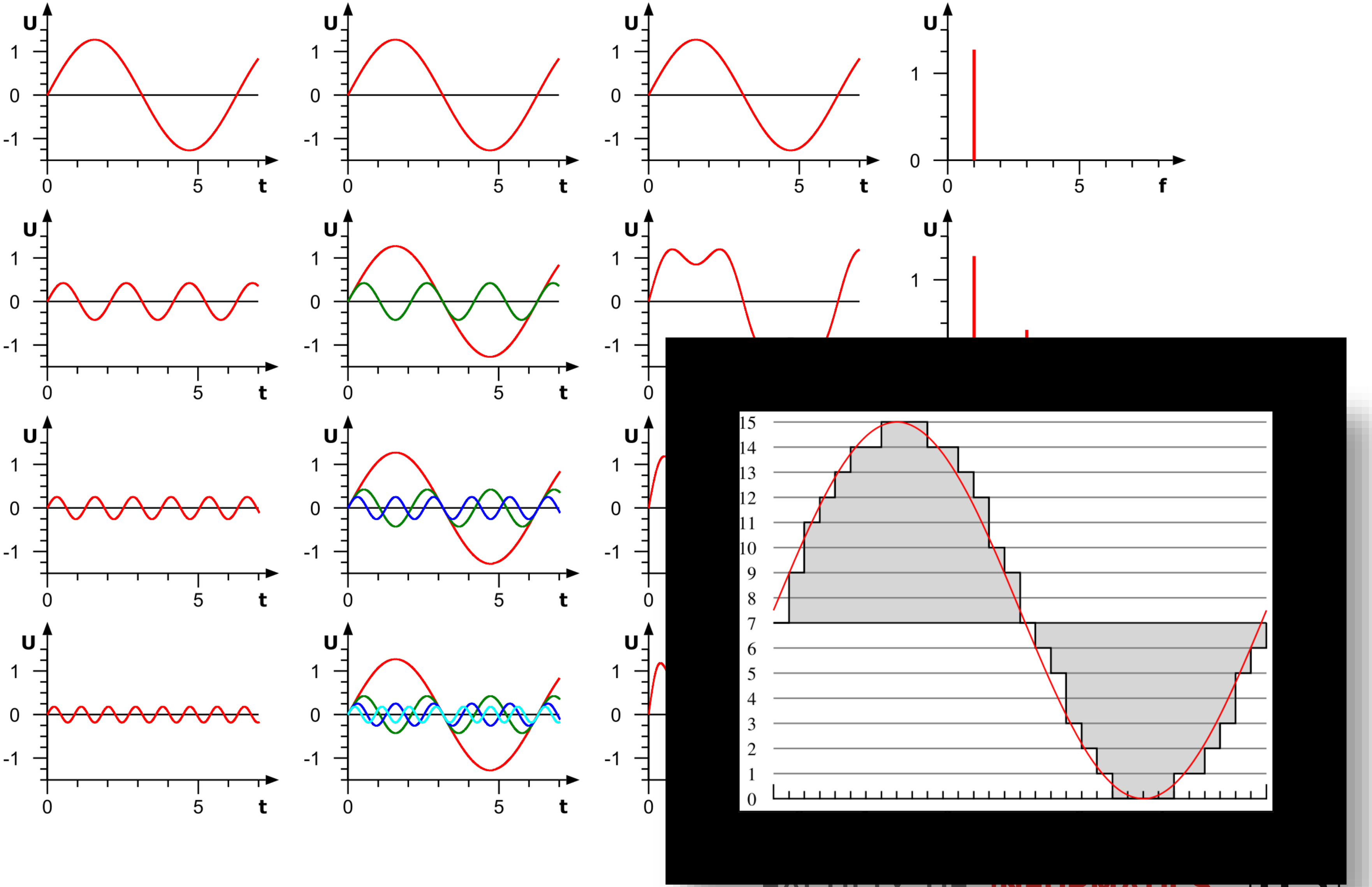
Time-Frequency Transformation

Fourier Transform (FFT)

Discrete Cosine Transform (DCT)

Wavelet Transform

Fourier Transform



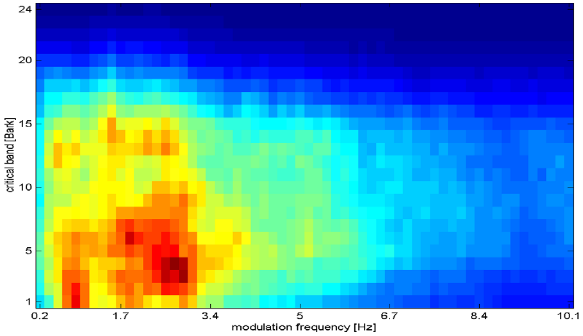
Audio/Music Feature Extraction

by example…

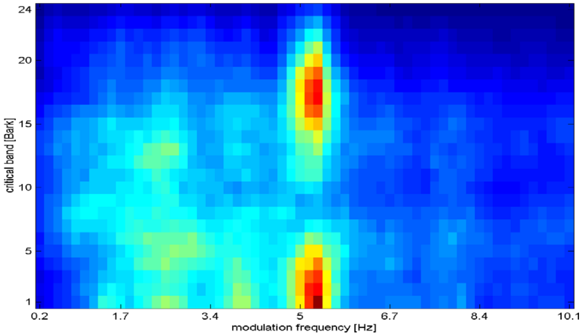
Rhythm Pattern (RP)

- fluctuations on critical frequency bands
  (a.k.a. Fluctuation Pattern)

- covers rhythm in the broad sense

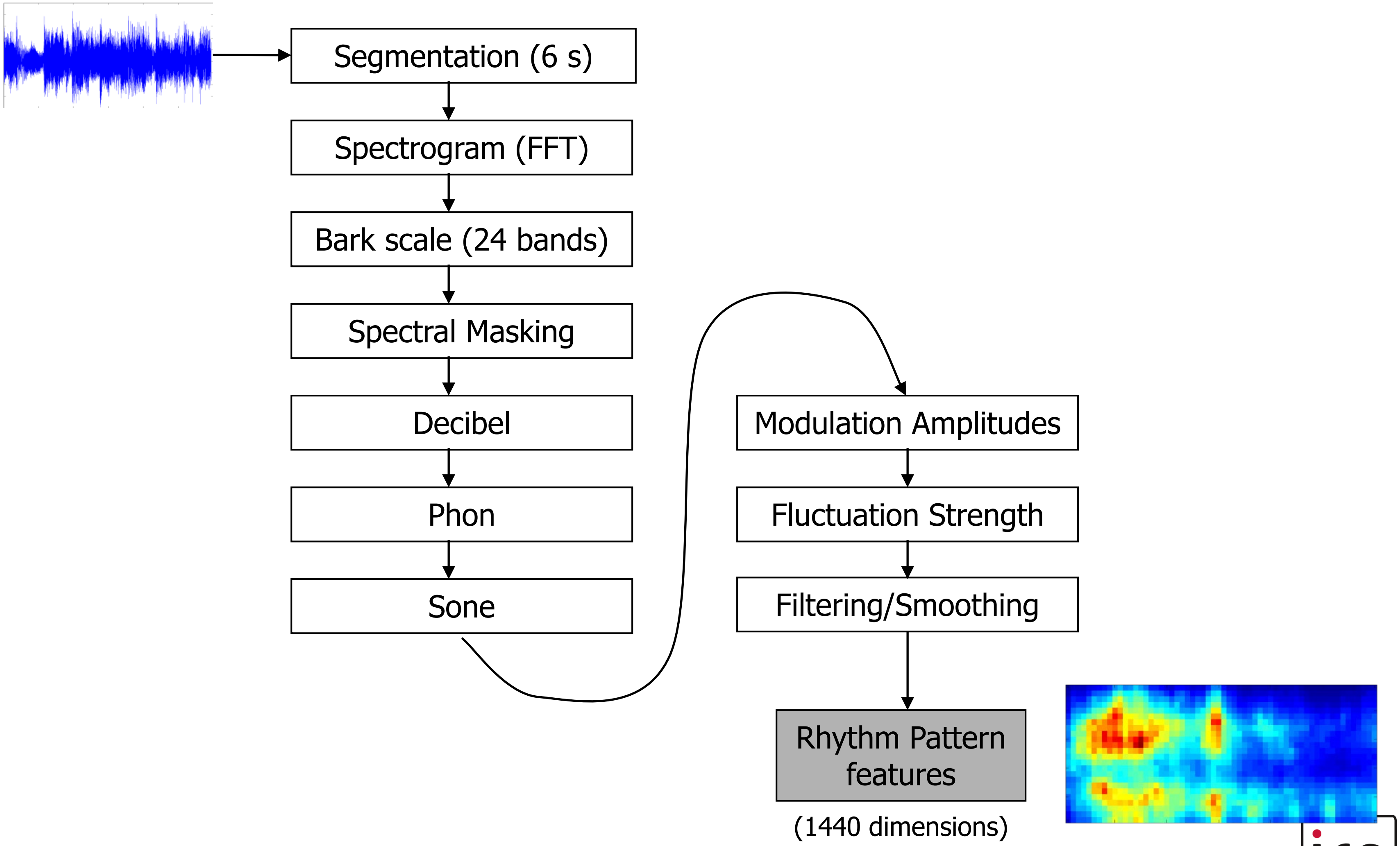


Classical



Rock

Rhythm Pattern (RP)



Segmentation (6 s)

Spectrogram (FFT)

Bark scale (24 bands)

Spectral Masking

Decibel

Phon

Sone

Modulation Amplitudes

Fluctuation Strength

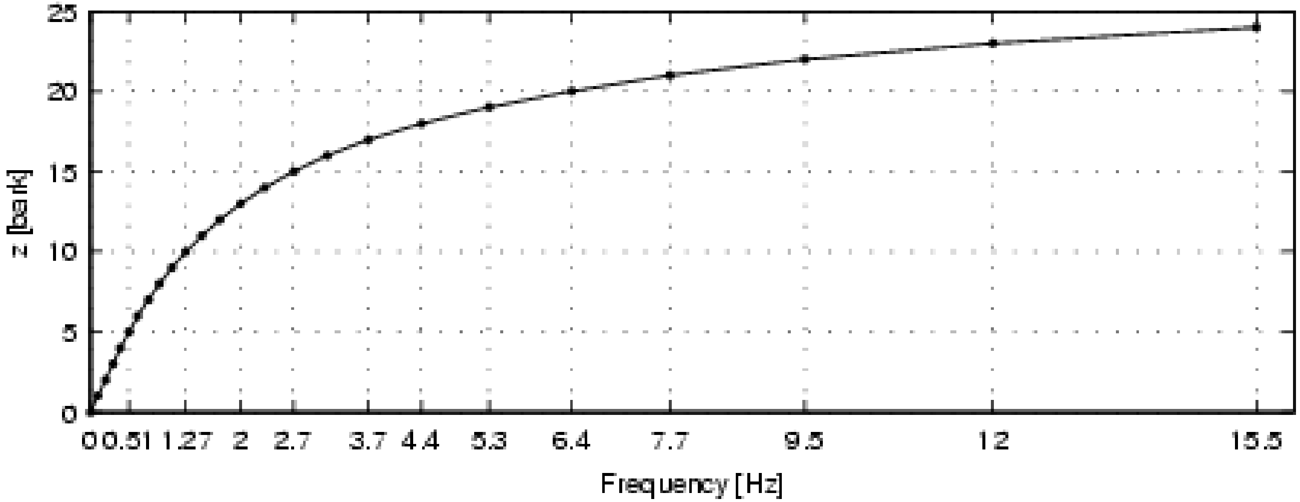
Filtering/Smoothing

Rhythm Pattern features

(1440 dimensions)

Bark Scale

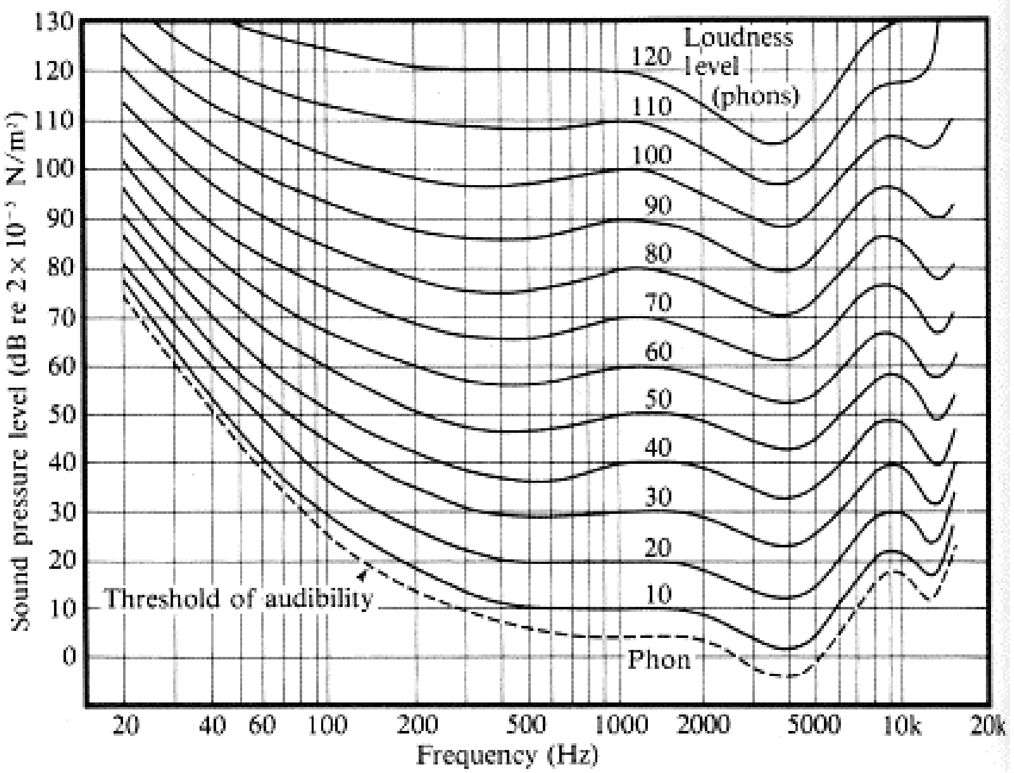
- psychoacoustical scale (related to Mel scale)
- 24 „critical bands“ of hearing (non-linear)
- proposed by Eberhard Zwicker in 1961



http://en.wikipedia.org/wiki/Bark_scale

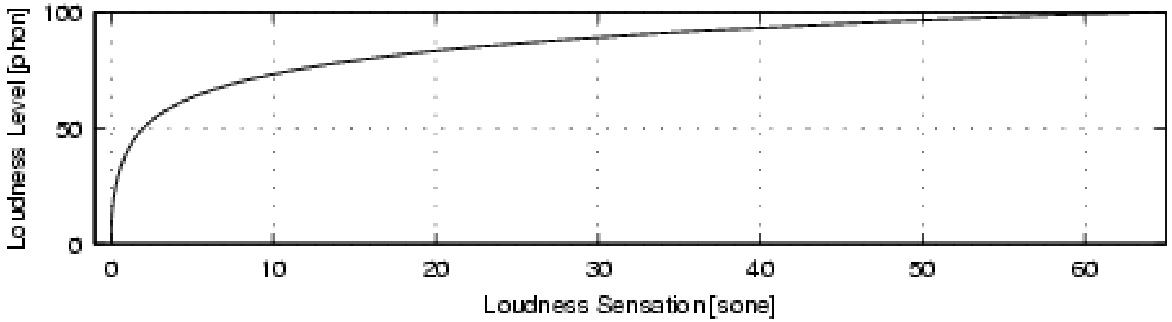
Equal loudness curves (Phon)

- Relationship between sound pressure level in decibel and hearing sensation is not linear
- Perceived loudness depends on frequency of the tone
- equal loudness contours for 3, 20, 40, 60, 80, 100 phon



on-line test: http://www.phys.unsw.edu.au/jw/hearing.html

Sone Transformation



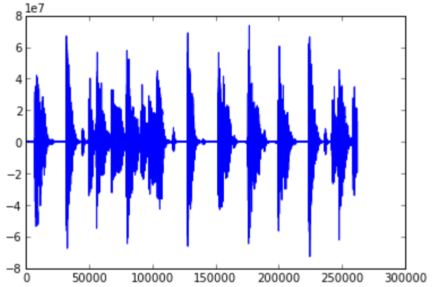
Sone	1	2	4	8	16	32	64
Phon	40	50	60	70	80	90	100

- Perceived loudness measured in Phon does not increase linearly
- Transformation into Sone
- Up to 40 phon slow increase in perceived loudness, then drastic increase
- Higher sensibility for certain loudness differences

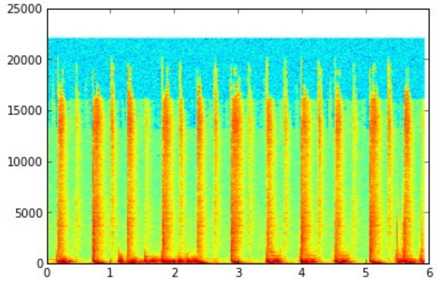
Rhythm Pattern (RP): 2 examples

Queen – Another One Bites The Dust (first 6 seconds)

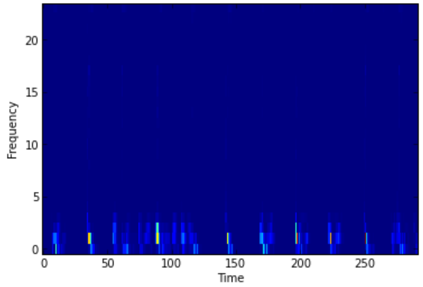
PCM Audio Signal



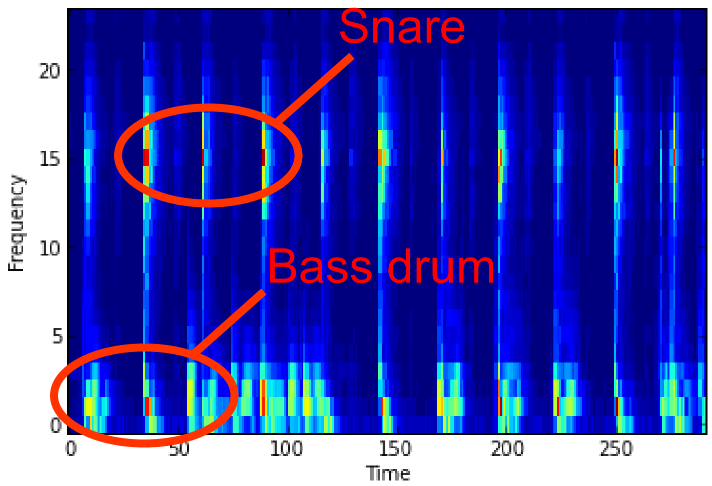
Power Spectrum



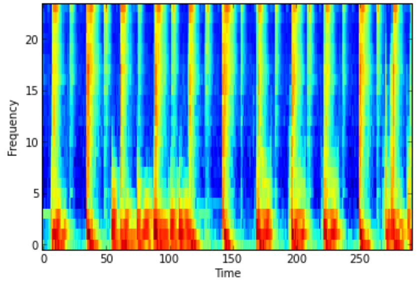
Bark Scale



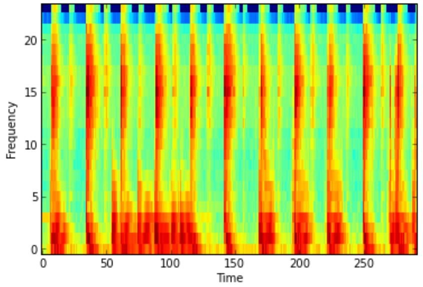
Sone



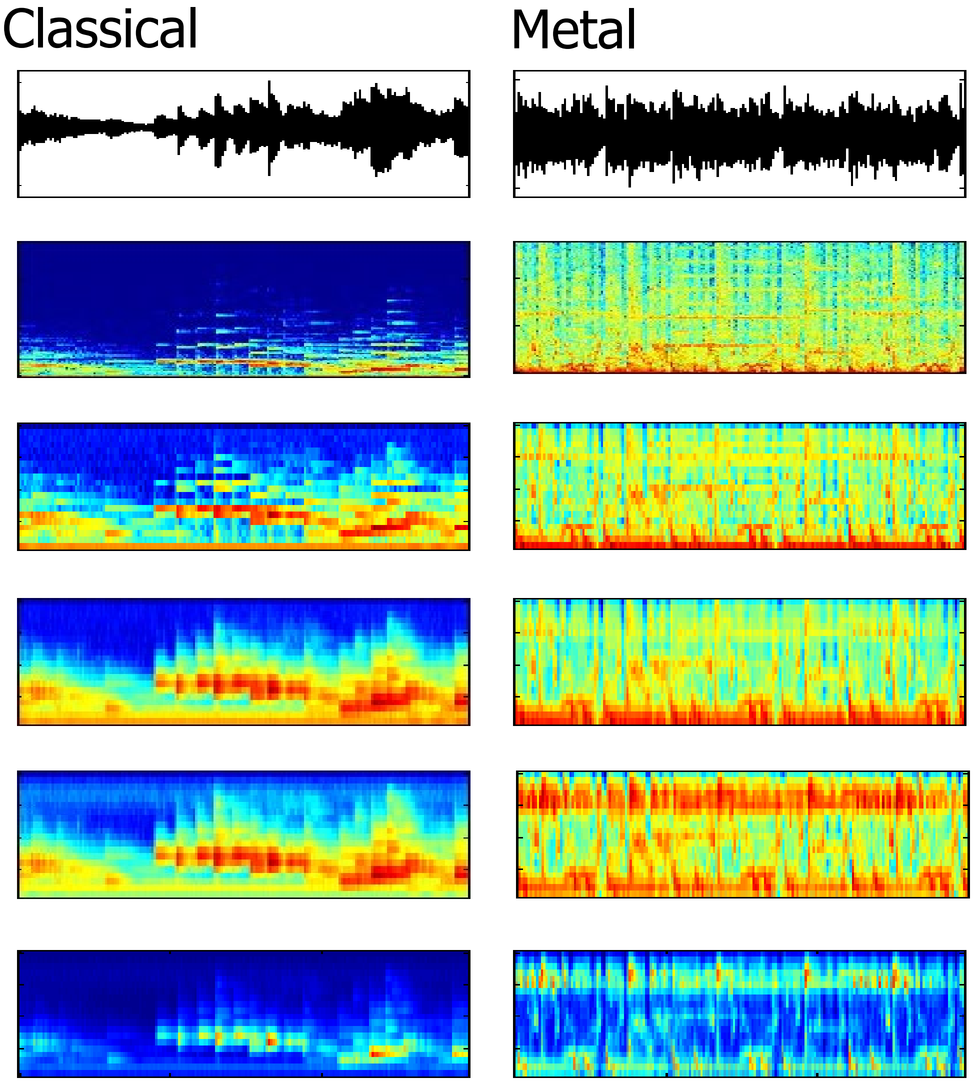
Decibel



Phon



Rhythm Pattern (RP): 2 examples



PCM Audio Signal

Power Spectrum

Frequency Bands

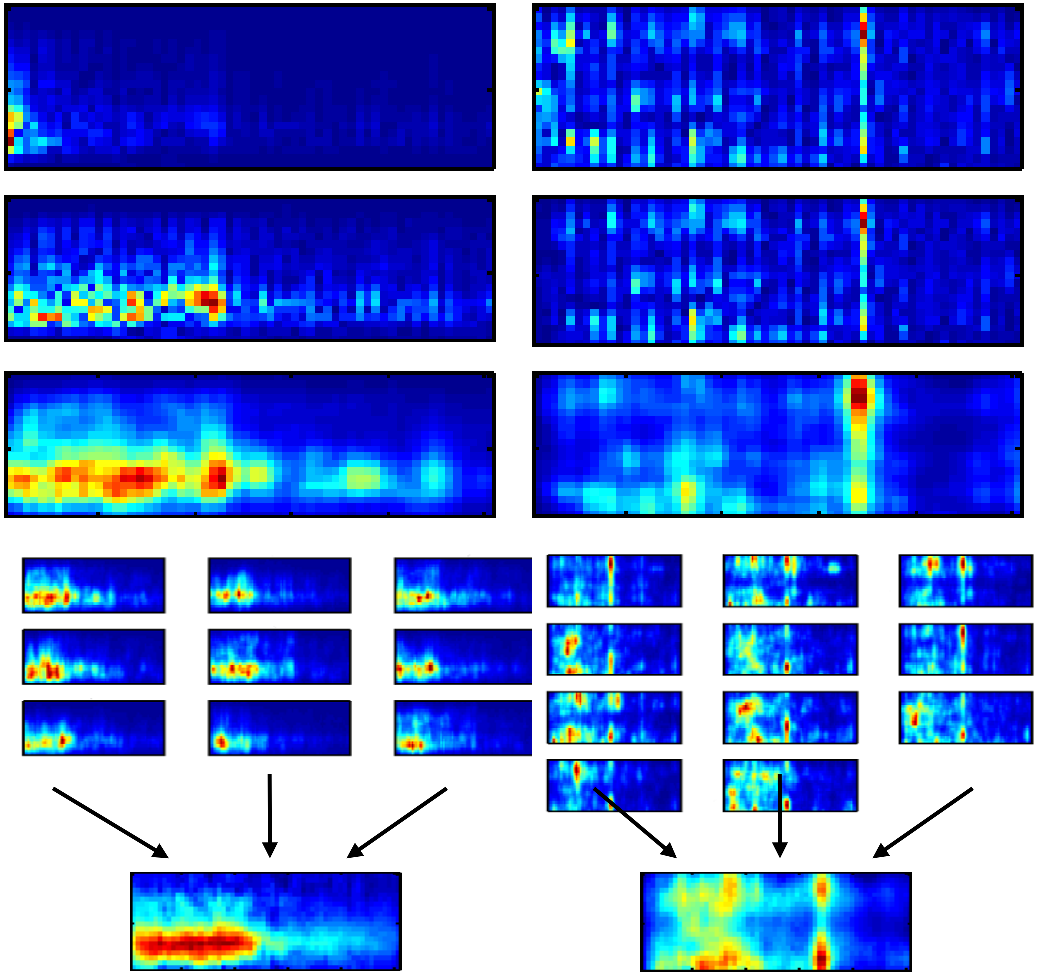
Masking Effects

Phon

Sone

Rhythm Pattern (RP): 2 examples

Classical Metal



modulation amplitude spectrum (“cepstrum”)

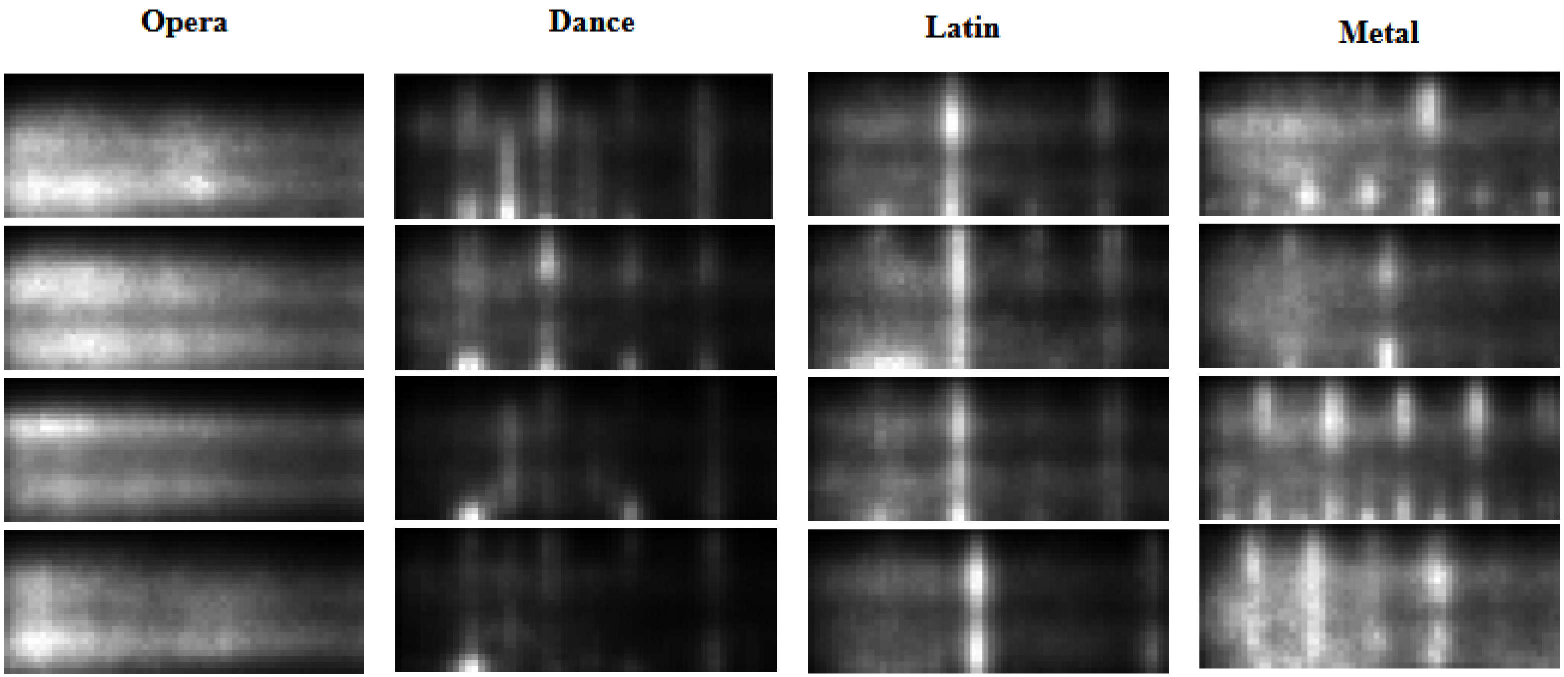
Fluctuation Strength

Filter (Gradient, Gauss)

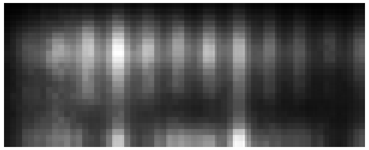
Median

24*60=
1.440-dim feature vec.

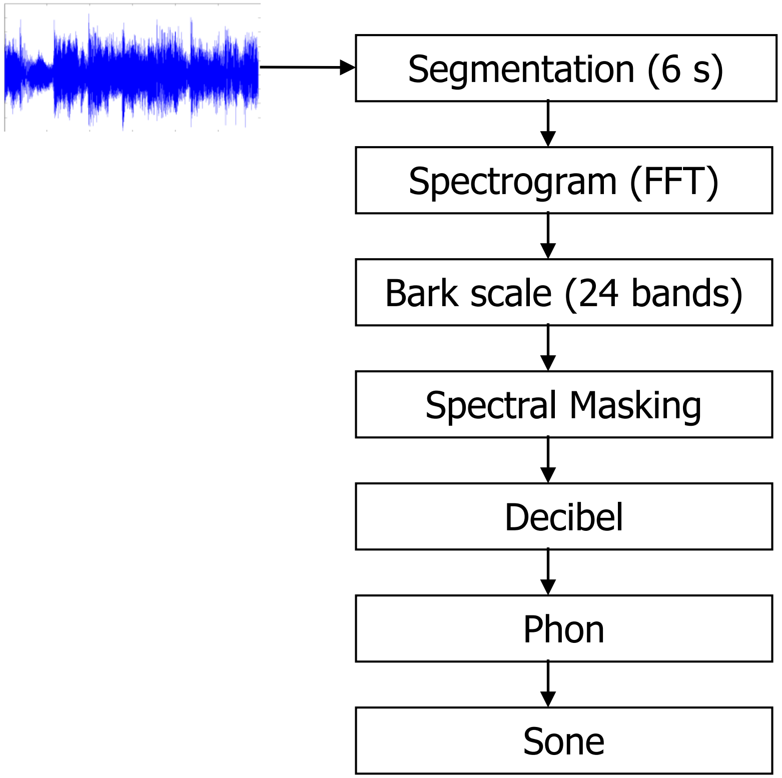
RP per Genre



Modulated Synthesizer



Statistical Spectrum Descriptors



Segmentation (6 s)

Spectrogram (FFT)

Bark scale (24 bands)

Spectral Masking

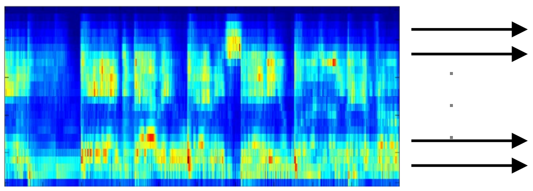
Decibel

Phon

Sone

- description of each of the 24 critical bands of the Sonogram by 7 statistical measures
- 168 feature attributes (24x7)

24
critical
Bands
(Bark scale)



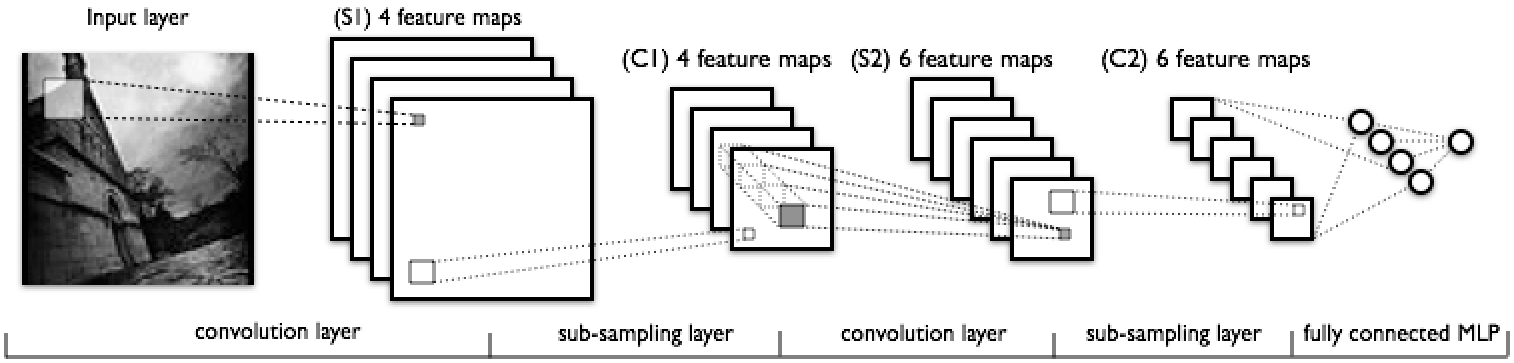
mean
median
variance
skewness
kurtosis
min
max

Bark-scale Sonogram (after Sone Step of RP)

Lidy and Rauber, ISMIR 2005

Deep Learning
for
Music Information Retrieval

Convolutional Neural Network (CNN)



http://deeplearning.net/tutorial/lenet.html

Combines three types of layers:

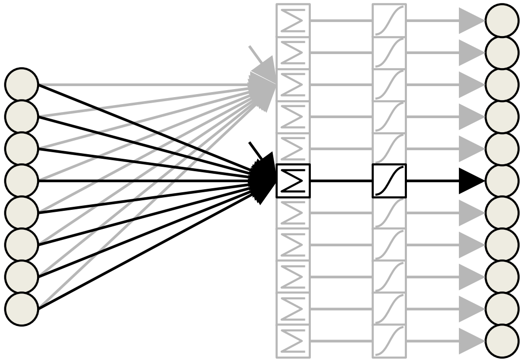
- **Convolutional layer:** performs 2D convolution of 2D input with multiple learned 2D kernels
- **Subsampling layer:** replaces 2D patches by their maximum (“max-pooling”) or average
- **Fully-connected layer:** computes weighted sums of its input with multiple sets of learned coefficients

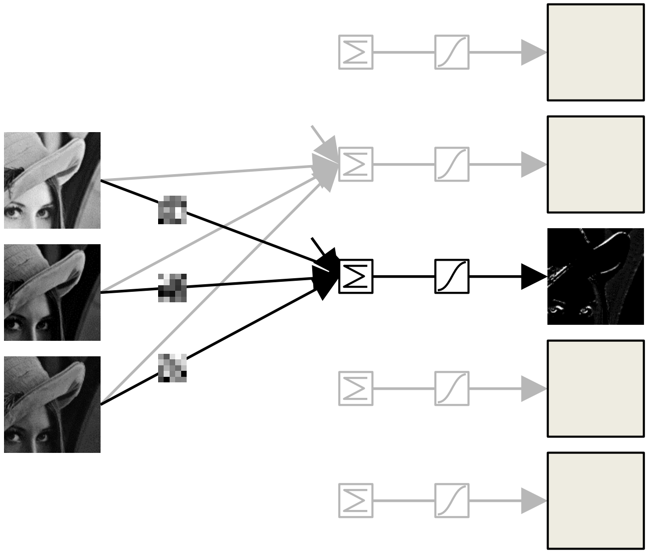
Applies a nonlinear function after each linear operation (without, a deep network would be linear despite its depth).

Full vs. Convolutional Layer / Network

Fully-connected layer:
Each **input** is a **scalar** value, each **weight** is a **scalar** value, each output is the sum of inputs **multiplied** by weights.

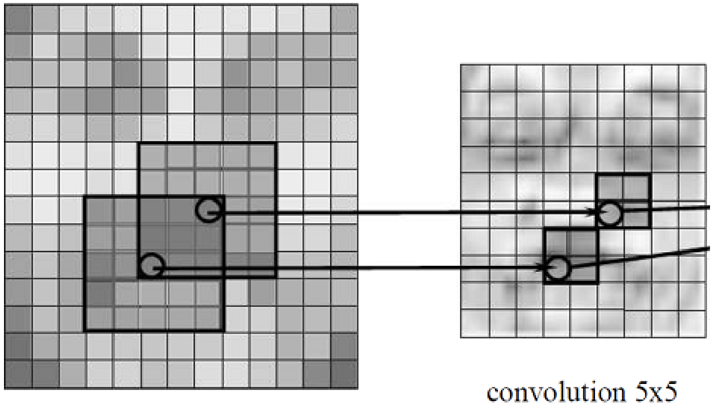
Convolutional layer:
Each **input** is a **tensor** (e.g., 2D), each **weight** is a **tensor**, each output is the sum of inputs **convolved** by weights.

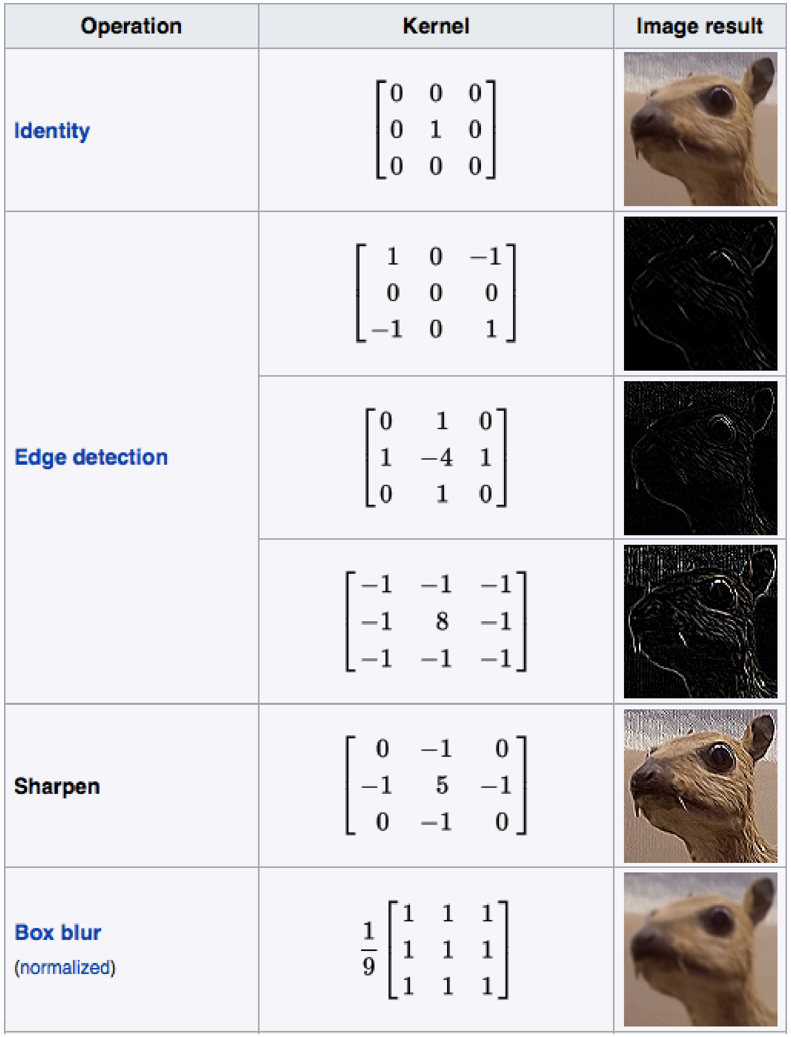




Motivation for Convolutions

- Apply local filter kernels
- These kernels are the neurons that are learned



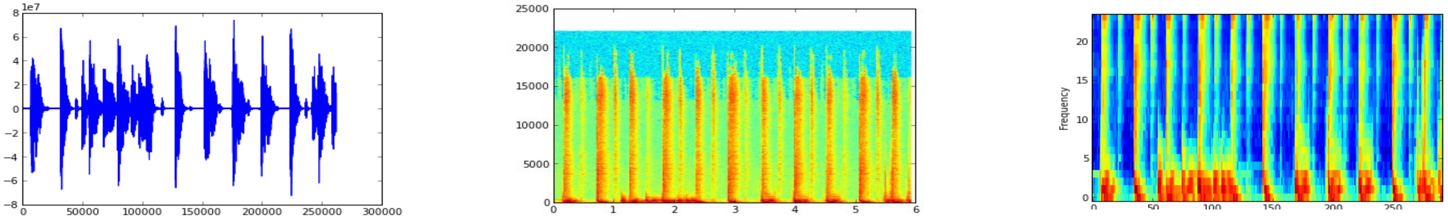


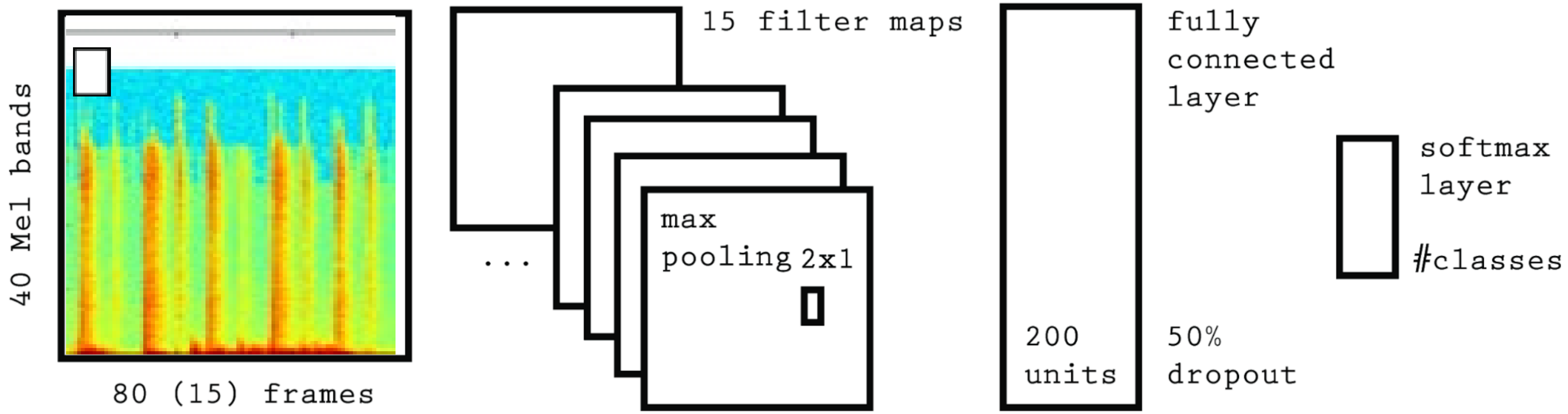
Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

Images: http://sanghyukchun.github.io/75/
https://en.wikipedia.org/wiki/Kernel_(image_processing)

Deep Learning for Music IR

Pre-Processing: Waveform → Spectrogram → 40 Mel bands → Log scale




40 Mel bands

80 (15) frames

15 filter maps

...

max pooling 2x1

fully connected layer

200 units

50% dropout

softmax layer

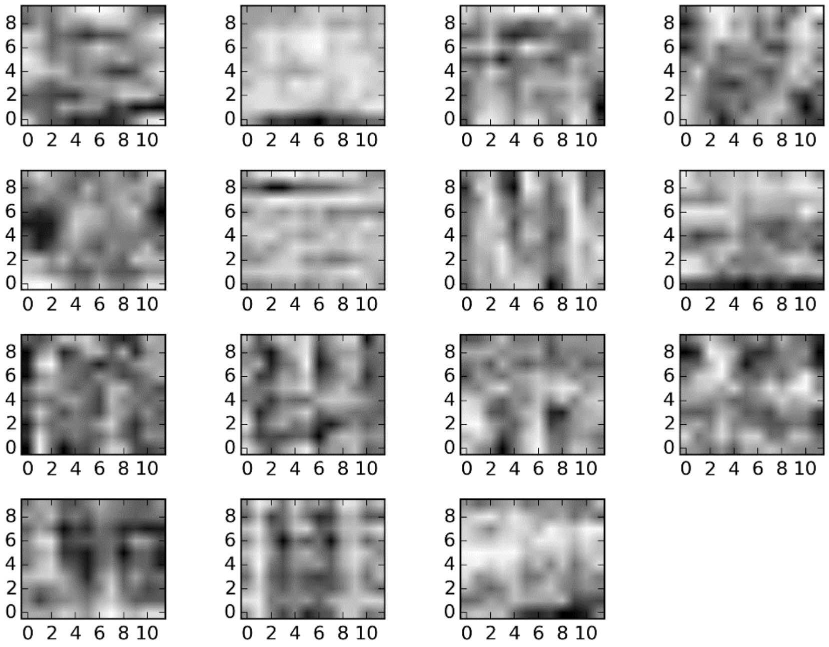
#classes

Winning algorithm MIREX 2015 music/speech classification task (99.73%) by Thomas Lidy

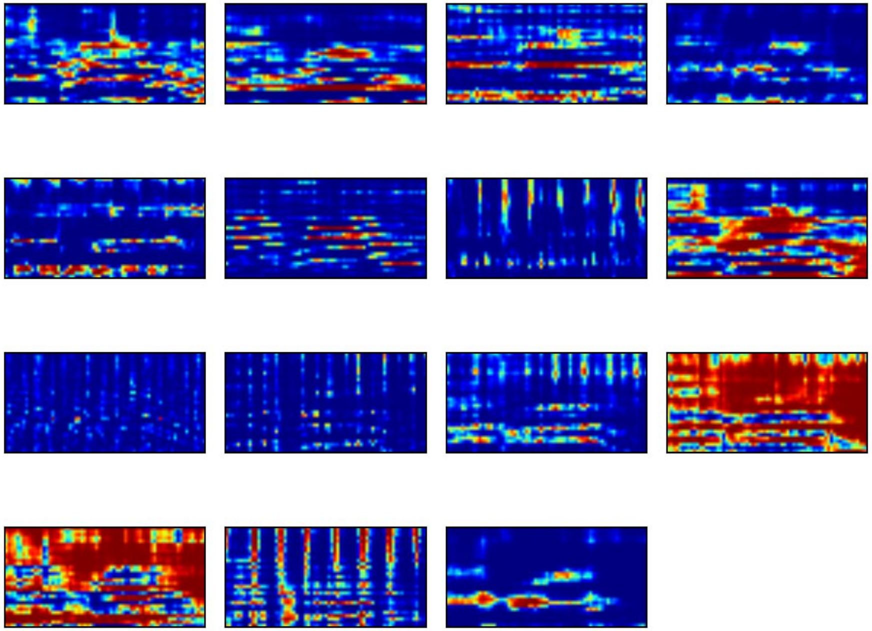
Visualizing CNN Filters

learned for Music/Speech Classification

Learned Filter Weights



Convolved Spectrograms



Audio and Music related Research at IFS

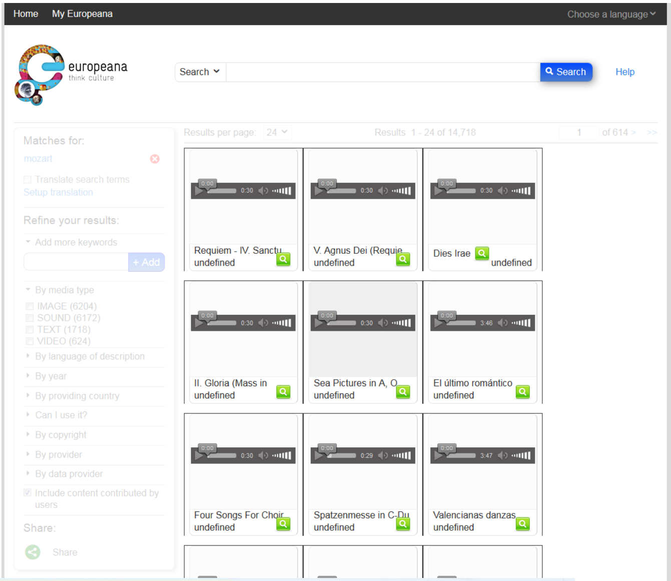
Similarity Search

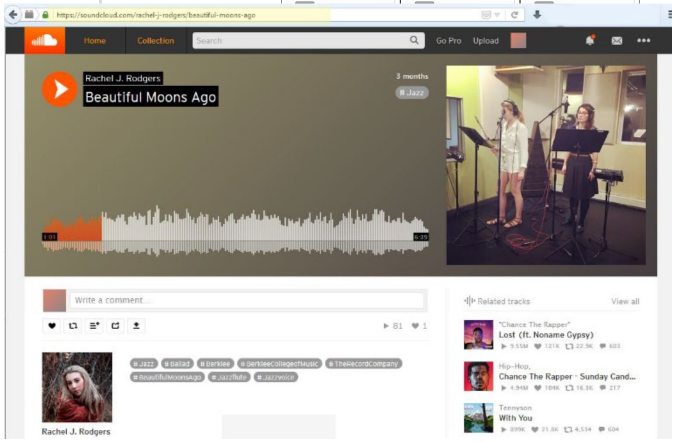
Search for similar sounding Audio Content in Europeana

- Select a favoured track
- System analyzes audio content
- Provides a list of tracks with calculated similar accustic properties

Search for similar sounding Soundcloud tracks in Europeana

- Supply a Soundcloud URL
- System downloads and analyzes track
- Provides a list of similar sounding Europeana tracks





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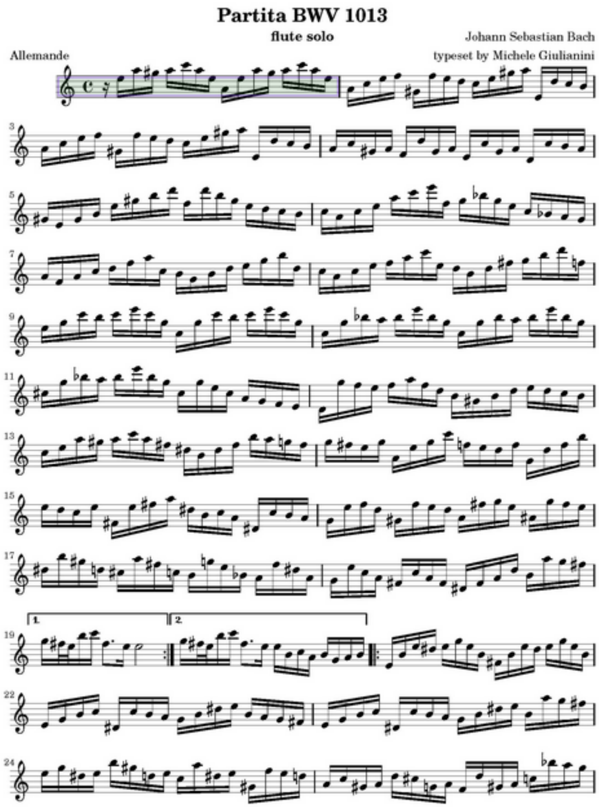
Score Following

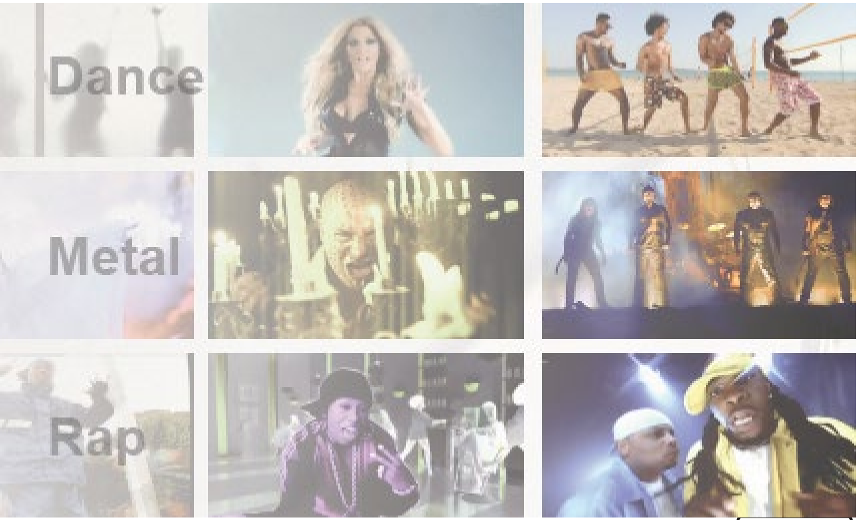


http://www.ifs.tuwien.ac.at/~schindler/files/eusounds/scorefollowing/SFP_Bach_BWV_1013.html

MVIR Objectives

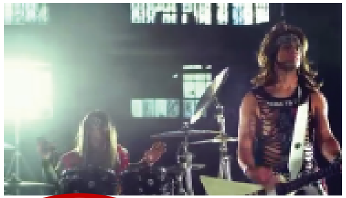
- Multimodal Approach to MIR Problems
  - Classification / Tagging
  - Mood estimation
  - Music Similarity Retrieval

- Hypothesis:
  - visual layer of music videos conta
    related information

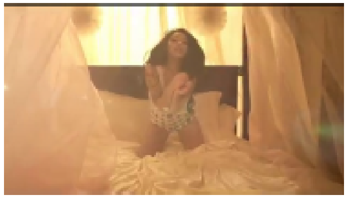


- Research Aims
  - Can this information be used?
    - Improve MIR solutions
    - Use images as queries

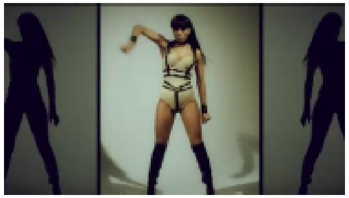
Top concepts of music video frames examples



stage	0.3162
electric guitar	0.1169
bassoon	0.0649
accordion	0.0611
drumstick	0.0386
microphone	0.0313
marimba	0.0276



mosquito net	0.0932
wardrobe	0.0857
brassiere	0.0815
shower curtain	0.0471
candle	0.0400
plastic bag	0.0204
hoopskirt	0.0187



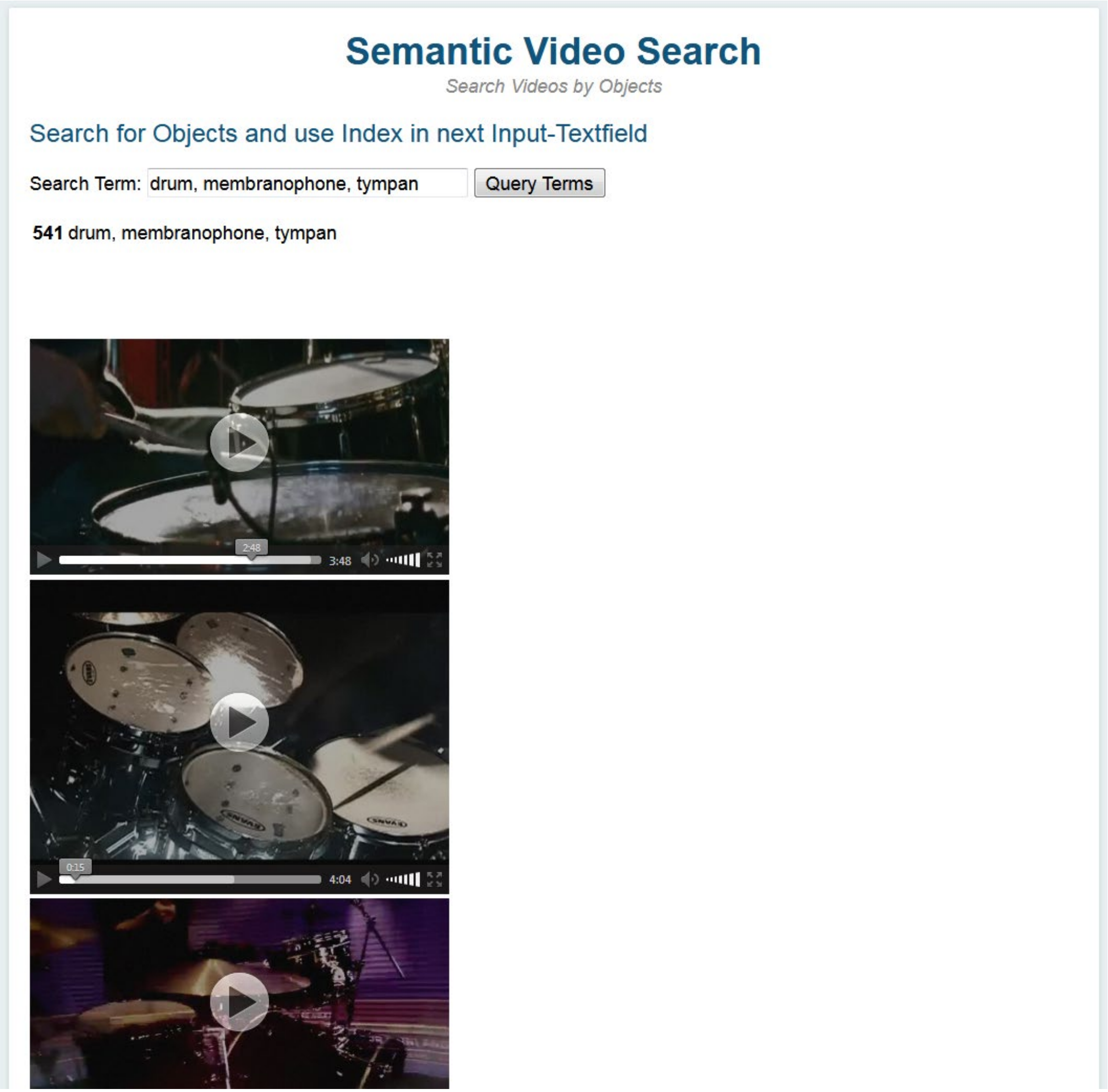
maillot	0.2745
bolo tie	0.0732
Windsor tie	0.0550
letter opener	0.0486
brassiere	0.0390
bikini	0.0384
bassoon	0.0364

lumbermill	0.1925
tow truck	0.1215
harvester	0.1152
thresher	0.0513
jeep	0.0484
half track	0.0473
pickup truck	0.0460

wig	0.4399
neck brace	0.0577
chimpanzee	0.0418
hair spray	0.0375
orangutan	0.0366
cloak	0.0267
Windsor tie	0.0236

Classification results (visual concepts only)

(c) High-level Visual Concepts											
$v_{in}1$	MEAN	1000	66.86	42.09	53.69	51.26	31.23	37.05	46.87	23.90	**33.07**
$v_{in}2$	STD	1000	69.78	46.76	50.08	51.95	29.99	32.88	48.29	26.83	29.63
$v_{in}3$	MAX	1000	73.15	44.26	46.41	54.60	33.05	31.94	50.07	26.93	27.49
$v_{in}4$	$v_{in}3+v_{in}2$	2000	73.61	46.53	**51.21**	55.04	31.48	34.00	51.30	27.03	31.04
$v_{in}5$	$v_{in}3+v_{in}1$	2000	**74.36**	47.70	53.65	55.99	**33.70**	**37.83**	**51.58**	**28.88**	33.83



Semantic Video Search

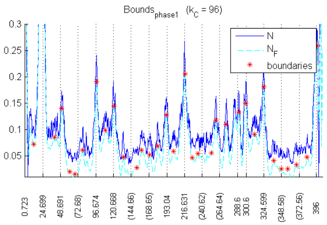
Search Videos by Objects

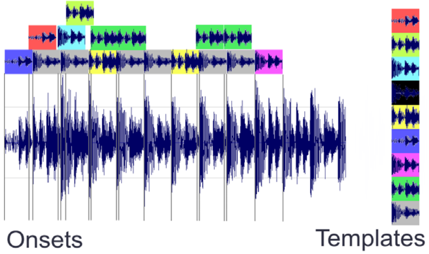
Search for Objects and use Index in next Input-Textfield

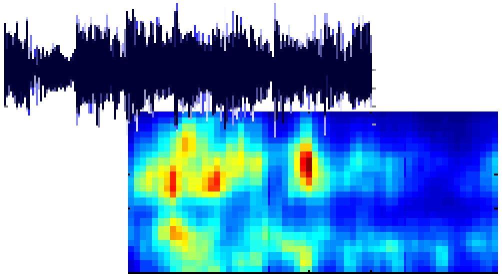
Search Term: drum, membranophone, tympan

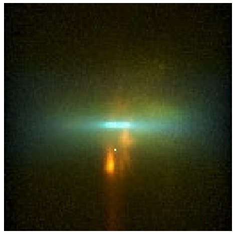
541 drum, membranophone, tympan

http://172.20.36.10:5000/

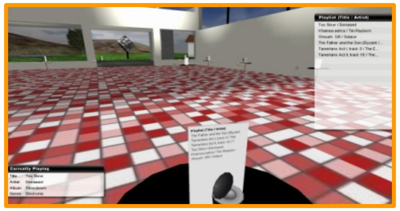








Thank You !



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