

New Paths in Music Recommender Systems Research

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Overview

- Introduction to Music Recommendation
- It's All About the Use Cases
- Use Case 1: Station/Playlist Generation
- Use Case 2: Context-Aware Music Recommendation
- Use Case 3: Recommendation in the Creative Process of Music Making
- What's Next?

The Deck

Latest version of slides available at:

http://www.cp.jku.at/tutorials/mrs_recsys_2017/

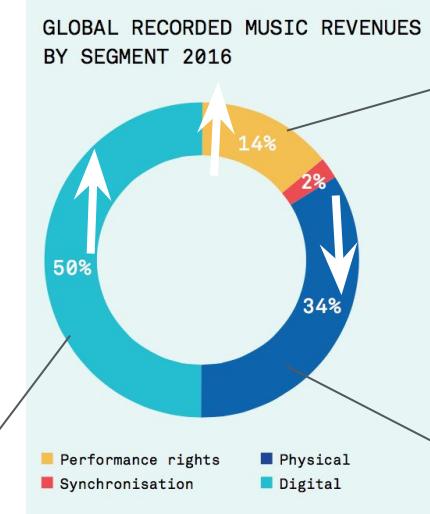
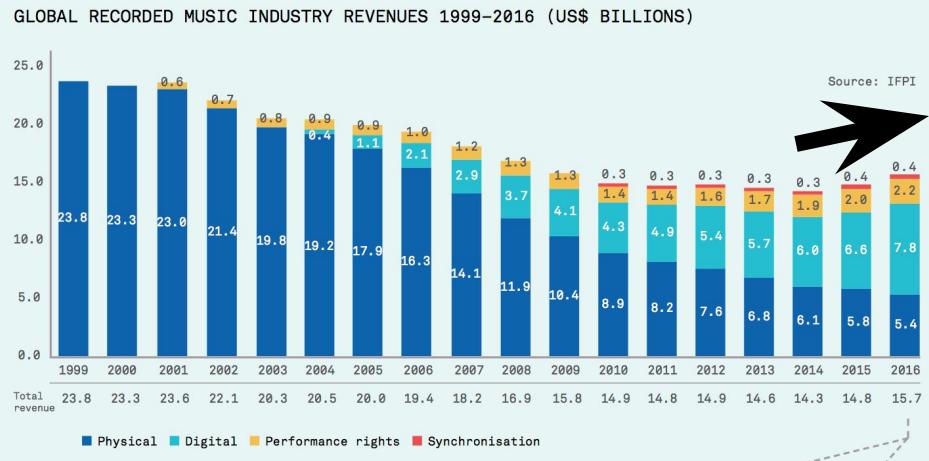
Overview paper available at:

http://www.cp.jku.at/tutorials/mrs_recsys_2017/overview_paper.pdf

Intro



Music Industry Changing Landscape



PERFORMANCE RIGHTS

Revenue from music reproduction:
- on AM/FM radio
- at public venues

(NB: Excluding perf. rights from Streaming)

PHYSICAL e.g. CDs

DIGITAL

59% of which is Streaming, i.e.:
- Internet radio & on-demand
- Ad-supported & subscriptions

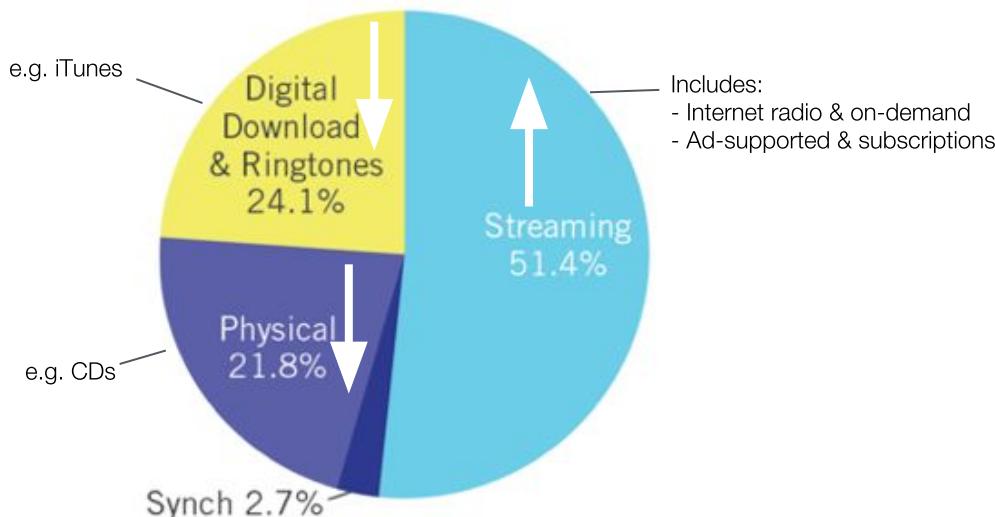
Also includes **Downloads** (e.g. iTunes) - which are **declining**



Music Industry Changing Landscape

Revenue breakdown by media, in US, 2016:
(Performance rights not shown)

Source: RIAA



Physical were 50% in 2010
Streaming was 9% in 2011

2016, in US, of those consuming music:

- 75% used streaming
- 20% bought CDs

2016: US music industry saw **biggest gains** since 1998

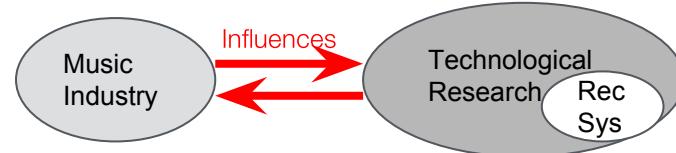
Music Industry Changing Landscape

- Growing industry
- Accelerating transition: Physical → Streaming

Not just a format transition, but a fundamental revolution.

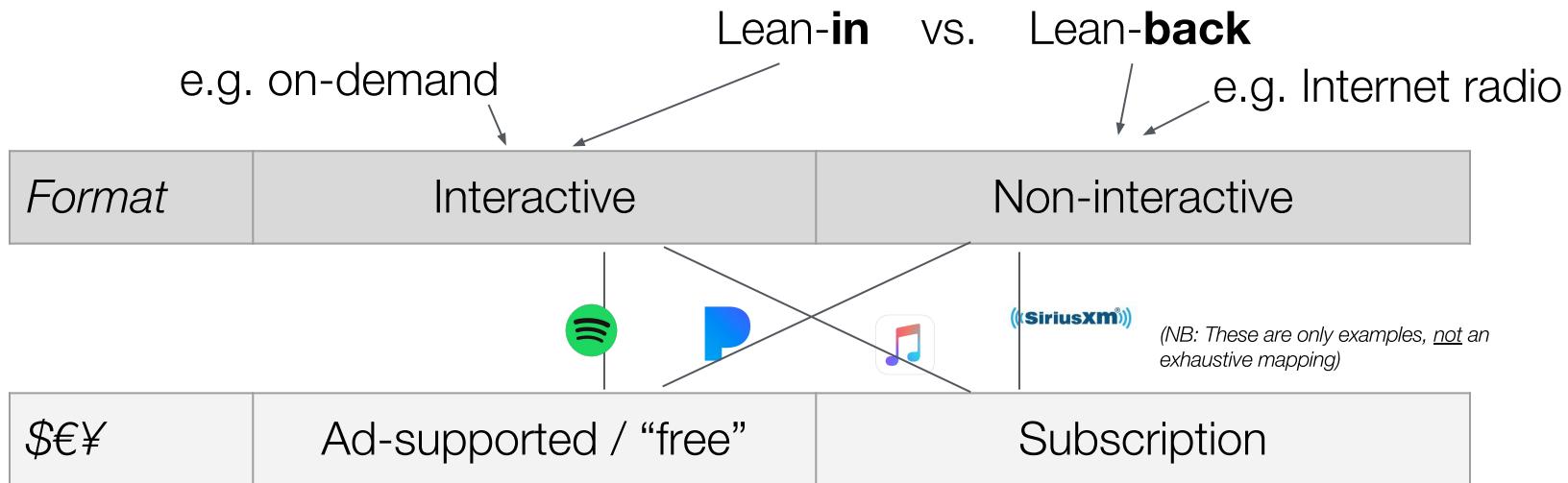
Moving **away from ownership, towards access**.

→ Change of paradigm for RecSys: Recommending an **experience**, not just a product/item



Music Industry Changing Landscape

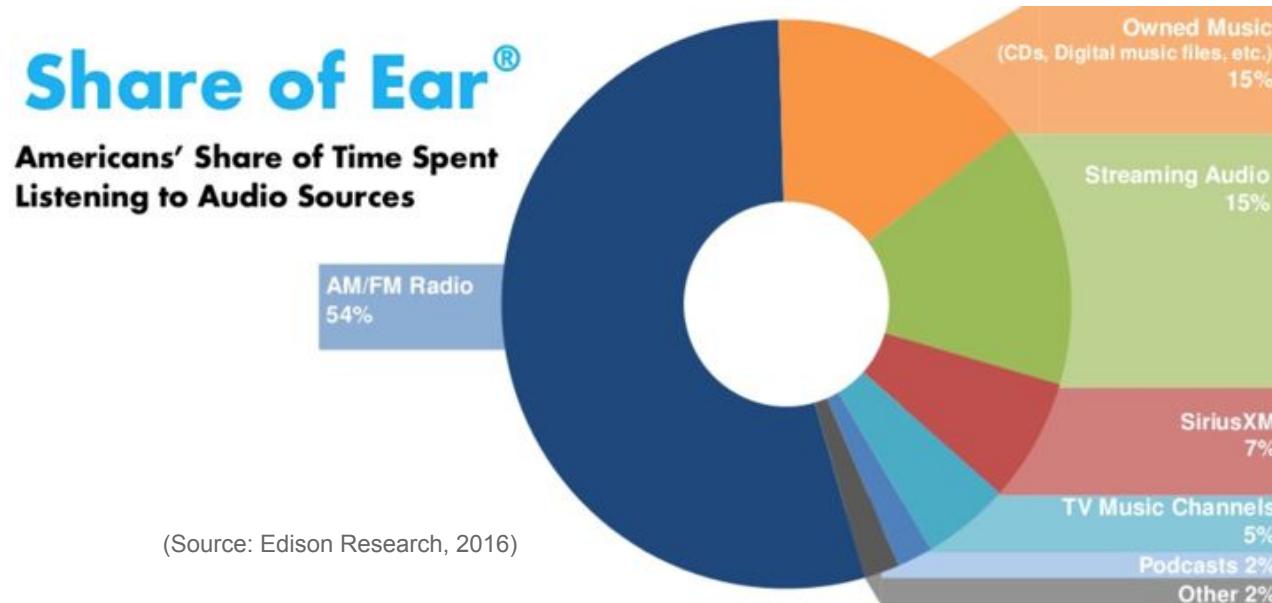
- “**Access**” can have different meanings
- New listening format still **not well-defined**... The (battle-)field is wide open.
- Lots of recent developments



→ Potential RecSys impact

Music Industry Changing Landscape

Looking at where \$€¥ comes from is not the full picture...
... time spent listening, by media, tells a different story:



Music Industry Changing Landscape

- Streaming “taking over” physical & downloads
- But competing with AM/FM radio, too

The Quest for “Discovery”

Ongoing quest for defining listening format calls for:

- Innovative Discovery features
- Right balance between lean-in & lean-back experiences

What makes music recommendation special?

- Duration of items (3+ vs. 90+ minutes in movies)
→ lower commitment necessary, items more “disposable”,
bad recommendations maybe not as severe
- Sequential consumption
- Re-recommendation may be appreciated (in contrast to movies, TV shows)
- Often consumed passively (while working, background music, etc.)
- Different consumption locations/settings: static (e.g., via stereo at home)
vs. variable (e.g., via headphones during exercise)
- Listening intent and context are crucial

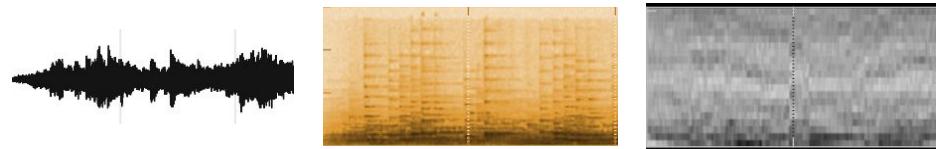
What makes music recommendation special?

- Importance of social component
- Highly emotionally connoted (in contrast to products, e.g. home appliances)
- Music often used for self-expression
- Various actors for recommendations (listeners, producers, performers, etc.)
- Various types of items (songs, albums, artists, audio samples, concerts, venues, fans, etc.)
- Magnitude of available data items/catalogs

Lots of Data and Data Sources

Content (audio, symbolic, lyrics)

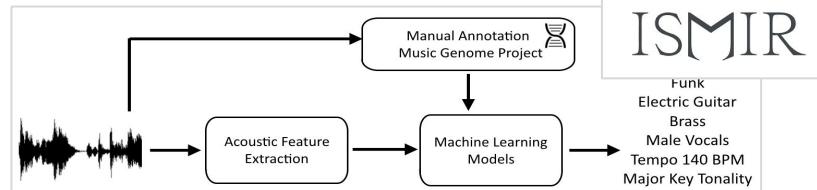
- Machine listening/content analysis
- Human labelling



Meta-data

- Editorial
- Curatorial
- Multi-modal
(e.g., album covers, booklets)

| Lead Vocal | |
|--|--------------------------|
| Be-In-Doo (H) [0-1.5] | <input type="checkbox"/> |
| Gender Male or Fem | <input type="checkbox"/> |
| Child or Child-like [0] | <input type="checkbox"/> |
| Register Lo-to-H [1-5] | <input type="checkbox"/> |
| Sig Notes [0-5] | <input type="checkbox"/> |
| Pitch (Intersection) Pe | <input type="checkbox"/> |
| Timbre Thin-to-Full [| <input type="checkbox"/> |
| Light or Breathy [0.5] | <input type="checkbox"/> |
| Smooth or Warm [0-5] | <input type="checkbox"/> |
| Gritty or Gravelly [0] | <input type="checkbox"/> |
| Nasal [0-5] | <input type="checkbox"/> |
| Presenters & Personal | <input type="checkbox"/> |
| Emotion (Inclusion) | <input type="checkbox"/> |
| Attitude Aggressive | <input type="checkbox"/> |
| Delivery Spoken-to-Delivery Speaking [0] | <input type="checkbox"/> |
| Delivery Vocalizing-Improvisation | <input type="checkbox"/> |
| Patent [0-5] | <input type="checkbox"/> |
| Lead Vocal (Continued) | |
| Variato [0-5] | <input type="checkbox"/> |
| Tremolo (Guitar Shake) [0-5] | <input type="checkbox"/> |
| Other Acoustic Special Techniques [0-5] | <input type="checkbox"/> |
| Special Effects (non-Acoustic) [0-5] | <input type="checkbox"/> |
| Overall Ethnic Pronunciation Lo-to-H [0-5] | <input type="checkbox"/> |
| Overall Ethnic Pronunciation Lo-to-H [1-5] | <input type="checkbox"/> |
| Vocal Accompaniment | |
| Inc-to-Done [0-1.5] | <input type="checkbox"/> |
| Male Solo-to-Ensem [0-5] | <input type="checkbox"/> |
| Role Lead-to-Accomp. [1-5] | <input type="checkbox"/> |
| Delivery Spoken-Sung (1,0) [1-5] | <input type="checkbox"/> |
| Harmonies Inc-to-Done [0-1.5] | <input type="checkbox"/> |
| Vocalizing-to-Lyrics [1-5] | <input type="checkbox"/> |
| Counterpoint [0-5] | <input type="checkbox"/> |
| Accompaniment | <input type="checkbox"/> |
| Acoustic Special Techniques [0-5] | <input type="checkbox"/> |
| Special Effects (non-Acoustic) [0-5] | <input type="checkbox"/> |
| Ethnic Pronunciation Lo-to-High [1-5] | <input type="checkbox"/> |



Lots of Data and Data Sources

User-generated

- “Community meta-data”
- e.g., tags, reviews



last.fm

GENIUS



amazon



Epinions.com

Interaction Data

- Listening logs/shared listening histories
- Feedback (“thumbs”)
- Purchases



pandora®



apple MUSIC

DEEZER



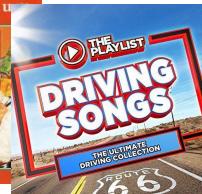
Curated collections

- Playlists, radio channels
- CD album compilations

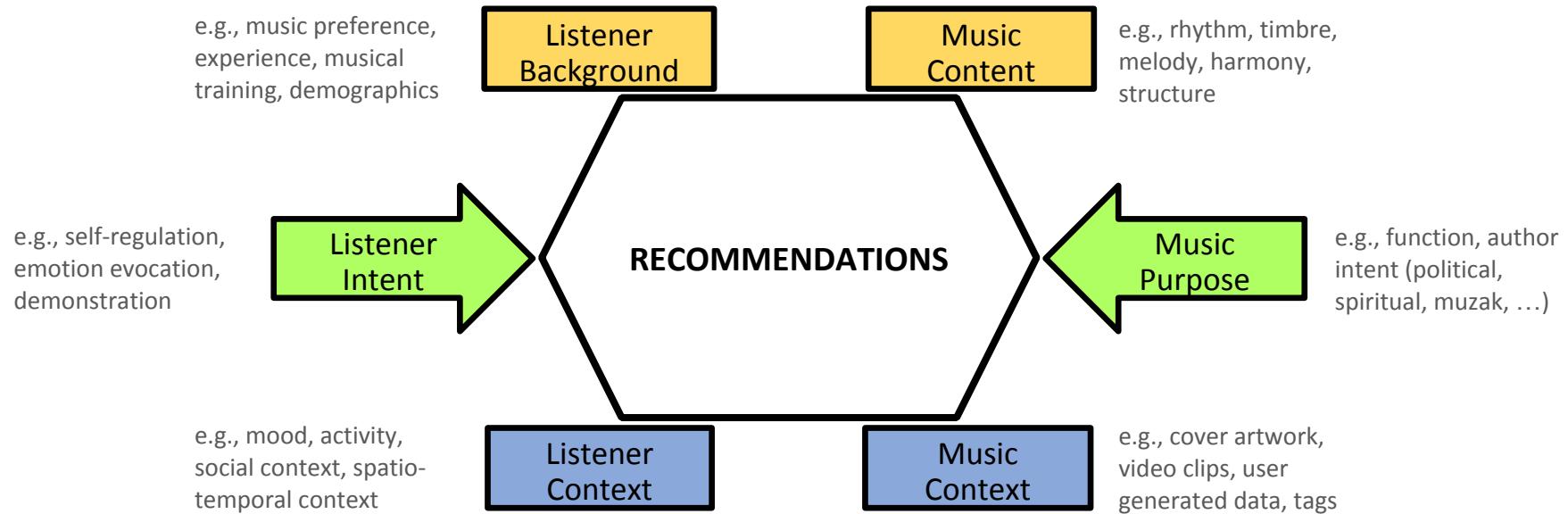


SHOUTcast

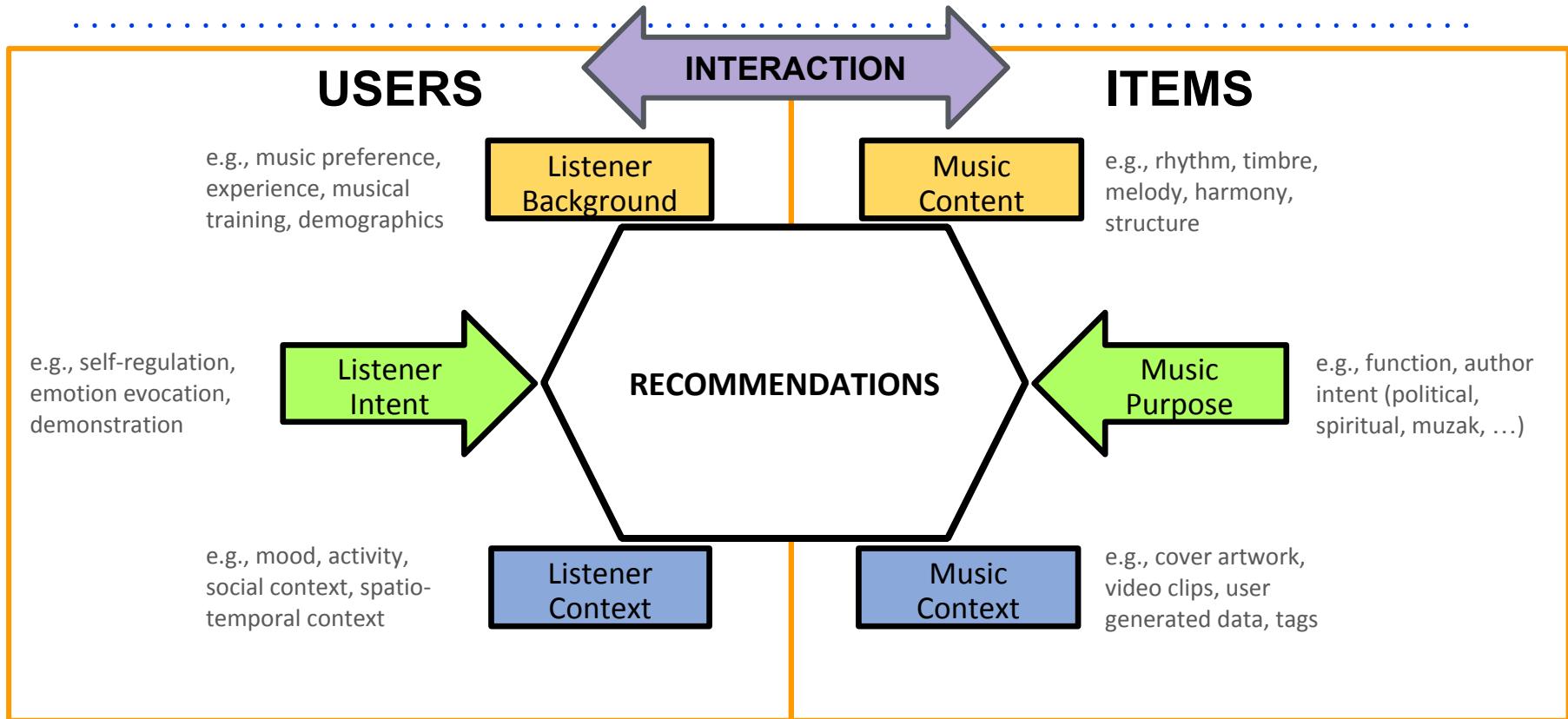
ART OF THE MIX



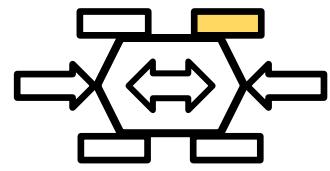
Factors Hidden in the Data



Factors Hidden in the Data



Audio Content Analysis



- In contrast to e.g., movies: **true content-based recommendation!**
- Features can be extracted from any audio file
 - no other data or community necessary
 - no cultural biases (no popularity bias, no subjective ratings etc.)
- Learning of high-level semantic descriptors from low-level features via machine learning
- Deep learning becoming more relevant
(representation learning and temporal modeling → CNNs, RNNs)

[Casey et al., 2008] *Content-based music information retrieval: Current directions and future challenges*, Proc IEEE 96 (4).

[Müller, 2015] *Fundamentals of Music Processing: Audio, Analysis, Algorithms, Applications*, Springer.

Audio Content Analysis: Selected Features



Disturbed
The Sound of Silence

Sound example

- Beat/downbeat → Tempo: 85 bpm (*madmom*)
- Timbre (→ MFCCs)
e.g. for genre classification,
“more-of-this” recommendations
- Tonal features (→ Pitch-class profiles)
e.g. for melody extraction (*Essentia*),
cover version identification

Sound example



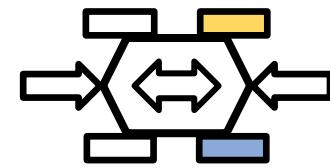
Different versions of this song:

Simon & Garfunkel - The Sound of Silence
Anni-Frid Lyngstad (ABBA) - En ton av tystnad
etc.

- Semantic categories via machine learning (*Essentia*):
not_danceable, gender_male, mood_not_happy

Toolboxes for Music Content Analysis

- **Essentia** (C++, Python): <http://essentia.upf.edu>
- **Librosa** (Python): <https://github.com/librosa>
- **Madmom** (Python): <https://github.com/CPJKU/madmom>
- **Marsyas** (C++): <http://marsyas.info>
- **MIRtoolbox** (MATLAB):
<https://www.jyu.fi/hytk/fi/laitokset/mutku/en/research/materials/mirtoolbox>
- **jMIR** (Java): <http://jmir.sourceforge.net>
- **Sonic Visualiser** (MIR through VAMP plugins): <http://sonicvisualiser.org>

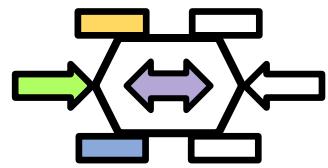


Text Analysis Methods (Basic IR)

- Text-processing of **user-generated content** and **lyrics**
 - captures aspects beyond pure audio signal
 - no audio file necessary
- Transform the content similarity task into a text similarity task (cf. “content-based” movie recommendation)
- Allows to use the full armory of text IR methods, e.g.,
 - Bag-of-words, Vector Space Model, TFIDF
 - Topic models, word2vec
- Example applications: Tag-based similarity, sentiment analysis (e.g., on reviews), mood detection in lyrics

[Knees and Schedl, 2013] *A Survey of Music Similarity and Recommendation from Music Context Data*, Transactions on Multimedia Computing, Communications, and Applications 10(1).

Collaborative Filtering



- Exploiting **interaction data**, stemming from “usage” of music
→ usually closer to “what users want”
- Implicit (e.g. plays) or explicit data (e.g. thumbs)
- Task: completion of user-item matrix
- Learning latent factors and biases
cf. [Koenigstein et al. 2011]

| Users (~10's M) | ? | ? | ? | ? |
|-----------------|---|---|---|---|
| ? | ? | ? | ? | ? |
| ? | ? | ? | ? | ? |
| ? | ? | ? | ? | ? |
| ? | ? | ? | ? | ? |

Items (~10's M)

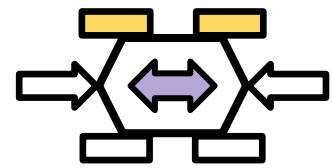
$$b_{ui} = \mu + b_{u,type(i)} + b_{u,session(i,u)} + b_i + b_{album(i)} + b_{artist(i)} + \frac{1}{|genres(i)|} \sum_{g \in genres(i)} b_g + c_i^T f(t_{ui})$$

- Special treatment of implicit data (*preference* vs. *confidence*), re-recommendation, etc.

[Hu et al., 2008] *Collaborative Filtering for Implicit Feedback Datasets*, ICDM.

[Slaney, 2011] *Web-Scale Multimedia Analysis: Does Content Matter?*, IEEE MultiMedia 18(2).

Feedback-Transformed Content



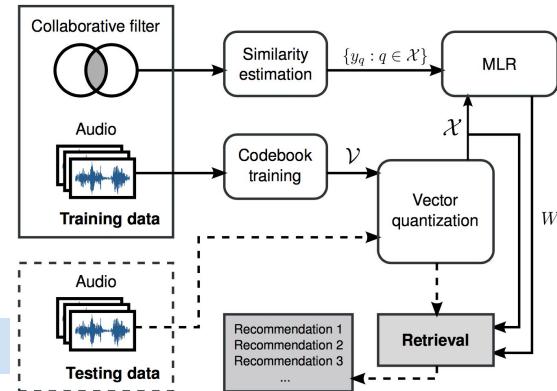
Interaction model as target for learning features from audio

- Dealing with cold-start
- Personalizing the mixture of content features

E.g.,

- Learning item-based CF similarity function from audio features using metric learning

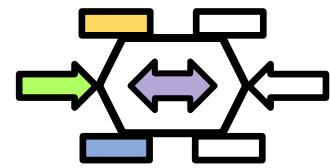
[McFee et al., 2012] *Learning Content Similarity for Music Recommendation*. IEEE TASLP 20(8).



- Learning latent item features using weighted matrix factorization
- Convolutional neural network with mel-spectrogram as input and latent item vectors as target

[van den Oord et al., 2013] *Deep Content-Based Music Recommendation*. NIPS workshop.

Sequence Mining



- Aims at modelling user preference + finer-grained session context (\approx user context+user intent)
 - User context should be reflected in selected sequence of songs
 - Model (hyper-)graph, latent factors, or topic models (e.g. LDA) on tags over **listening histories** and **playlists**
→ “session model”, “playlist dialect”, etc.

[Zheleva et al., 2010] *Statistical models of music-listening sessions in social media*. WWW.

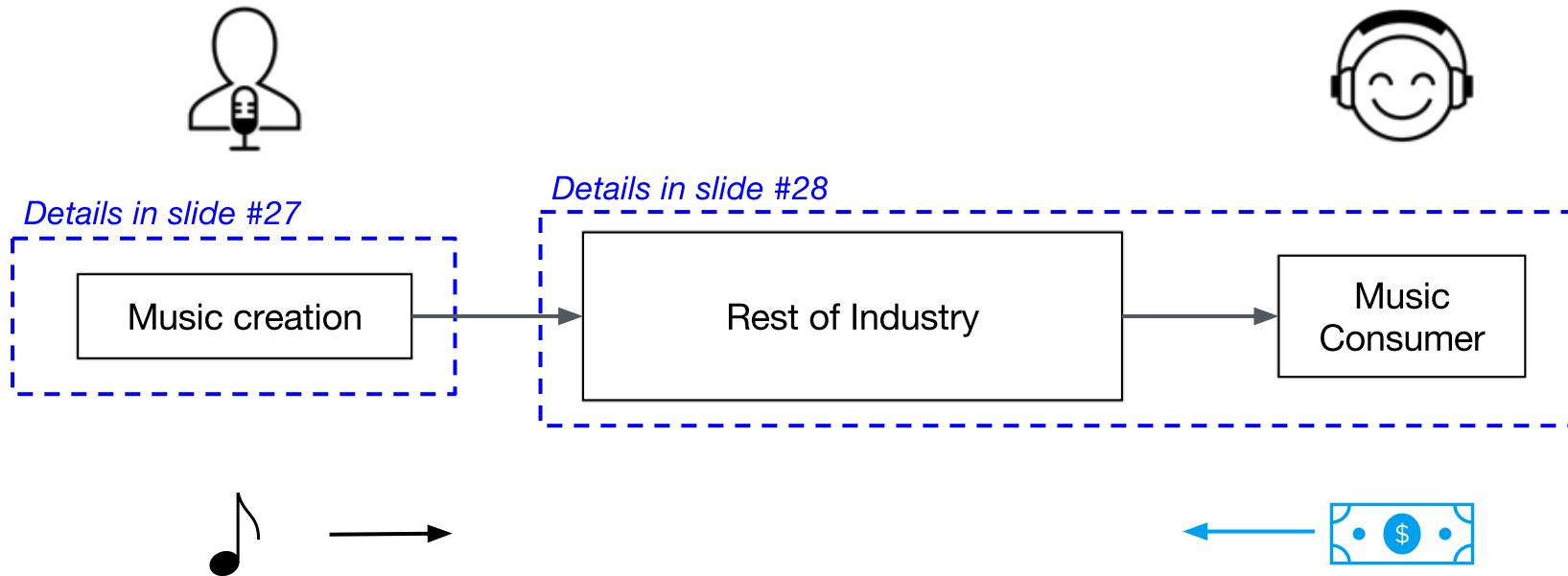
[Hariri et al., 2012] *Context-aware music recommendation based on latent topic sequential patterns*, RecSys.

[Aizenberg et al., 2012] *Build your own music recommender by modeling internet radio streams.* WWW.

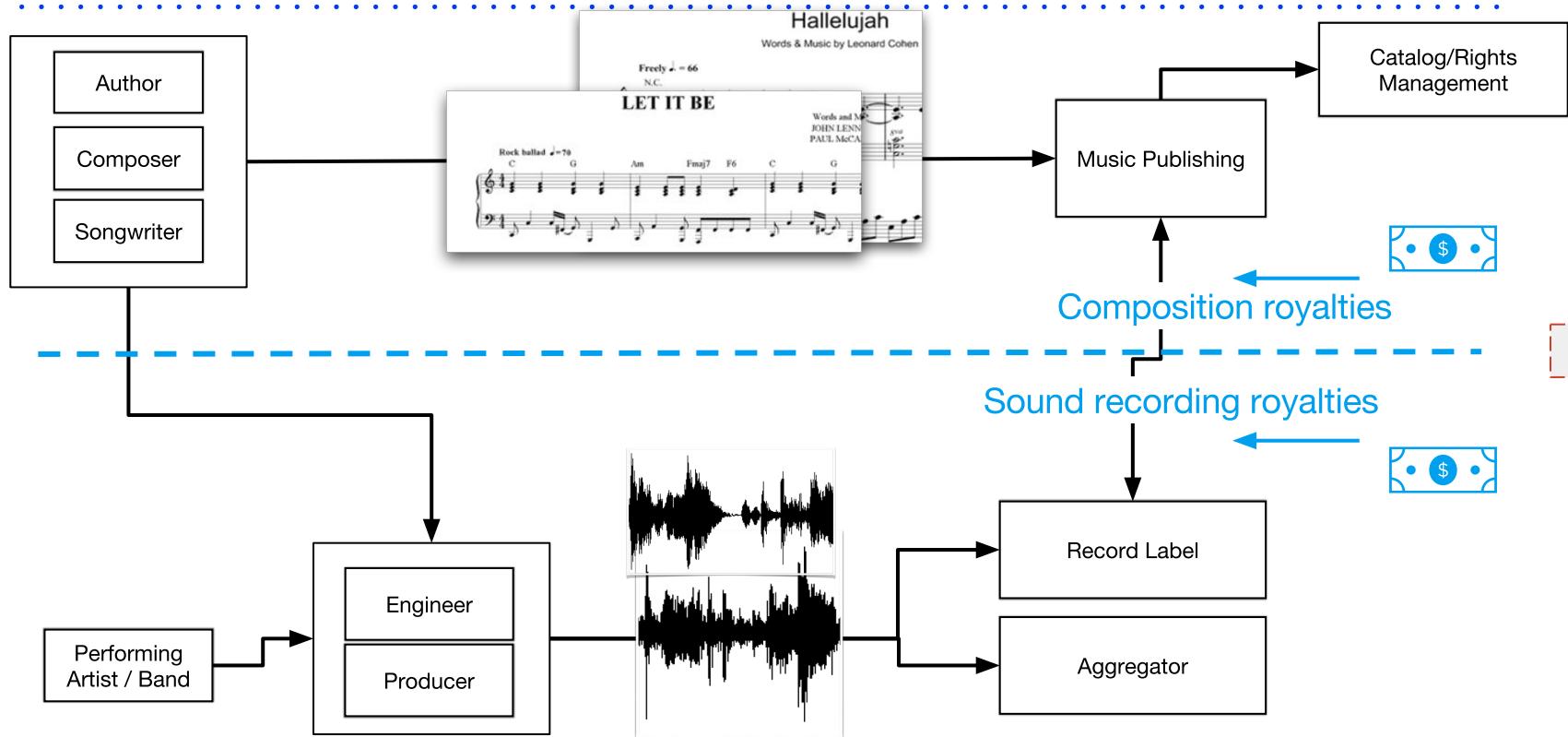
[McFee, Lanckriet, 2012] *Hypergraph Models of Playlist Dialects*, ISMIR.

It's All About the Use Case

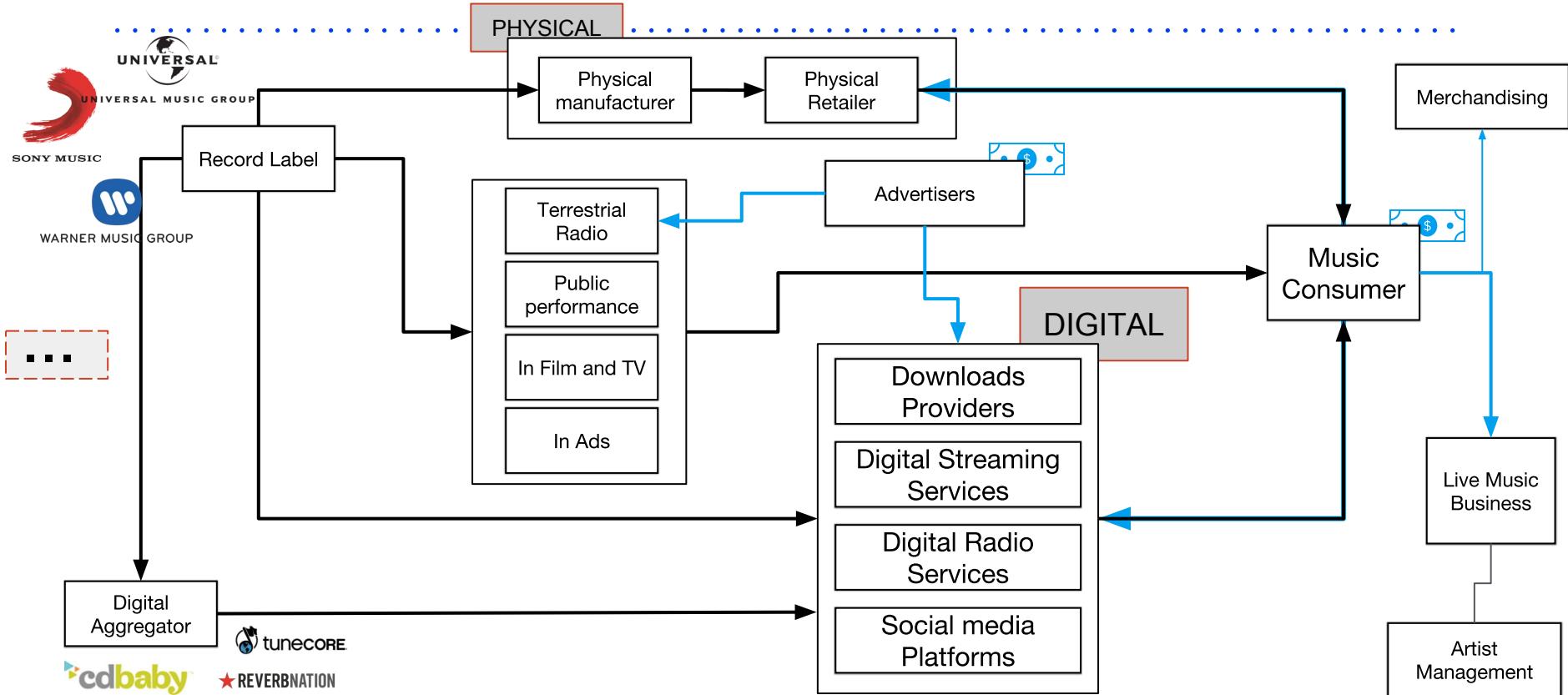
You said “Music Industry Landscape”?



Music Industry Landscape



Music Industry Landscape



Music Industry Landscape (again)

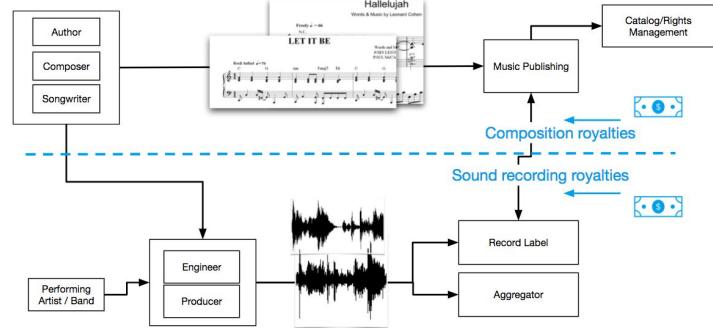


Music creation

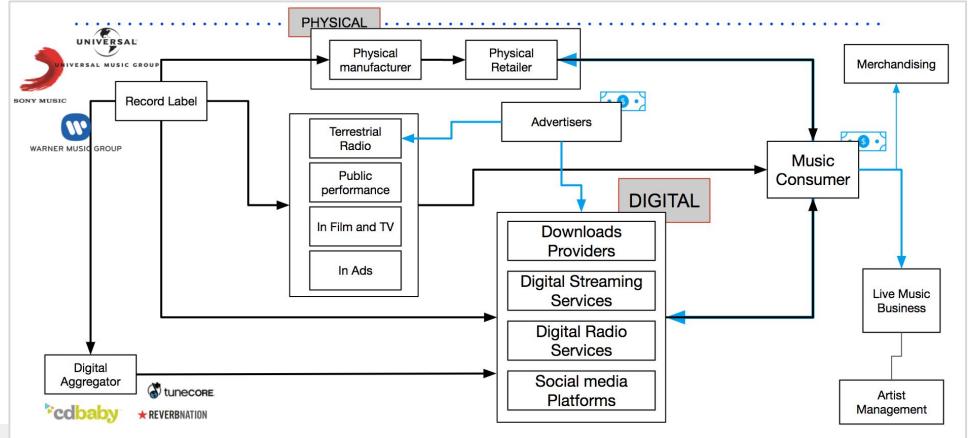
Rest of Industry



Music Consumer



Slide #27

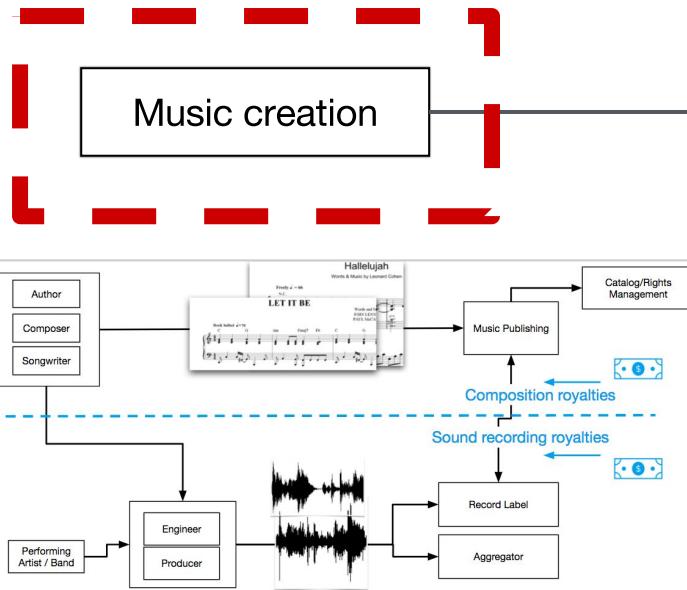


Slide #28

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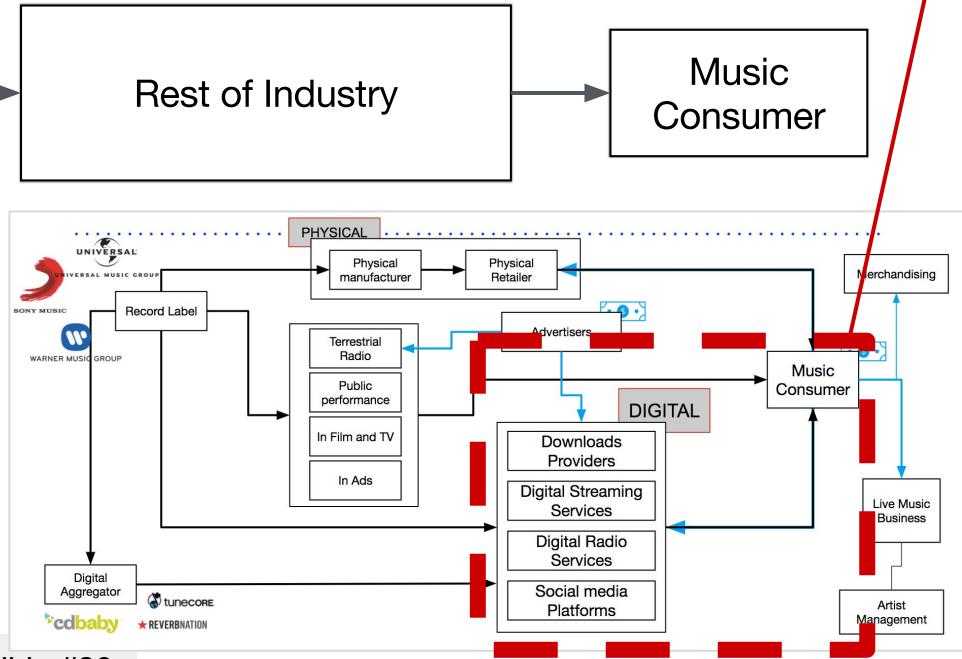
Music Industry Landscape (again)

USE CASE #3



Slide #27

USE CASES #1 & #2



Slide #28

Overview (again)

- Introduction to Music Recommendation
- It's All About the Use Cases
- **Use Case 1: Station/Playlist Generation**
- **Use Case 2: Context-Aware Music Recommendation**
- **Use Case 3: Recommendation in the Creative Process of Music Making**
- What's Next?

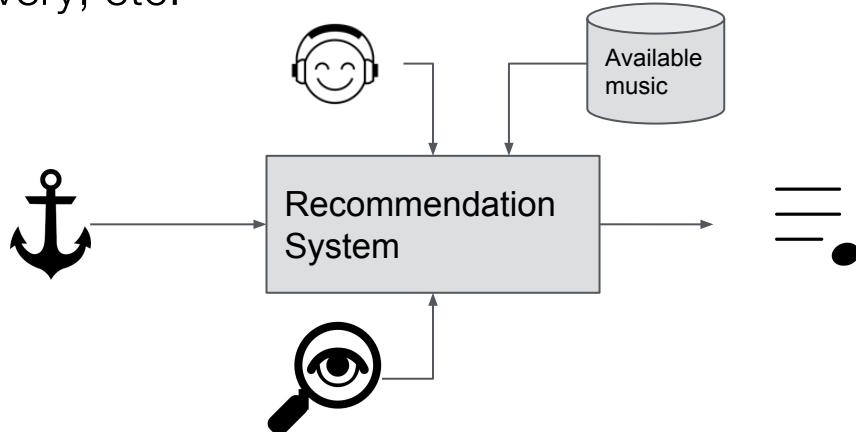
Use Case 1: Station/Playlist Generation

Station/Playlist generation problem

- A continuation problem
- Given a listener enjoying a particular musical experience, what track recommendations can we make to extend this experience as much as possible

A particular recommendation problem

- *The problem:* Given a listener, a set of available tracks to play, a musical “anchor”, and a particular focus, **recommend best next tracks**
 - **Musical anchor:** i.e. current music listening experience defined by e.g. a radio station, a set of tracks (e.g. a playlist, an album), a given artist, a genre, etc.
 - **Focus / Listener intent:** lean-in vs. lean-back, new music, (re)discovery, etc.



Station/Playlist generation - Differences

Station:

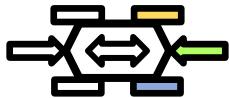
- Anchored in a track, an artist, an album, a genre, etc.
- Recommendations: Sequential, 1 track after the other. Possibly hidden.
- Learning:
 - Learning data: Feedback (lots of), user-generated data (little)
 - System is the oracle, then adapts to feedback (must be real-time)

Playlist:

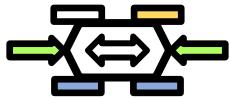
- Anchored in an arbitrary (finite) length set of tracks, either:
 - User-generated
 - Curated (e.g. by streaming service, 3rd-parties)
- Recommendations: In batch
- Learning:
 - Learning data: User-generated data, feedback

Data and Recommendation algorithms

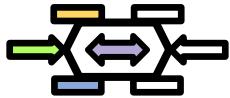
Types of algorithms / approaches:



Editorial



Curatorial



Collaborative filtering



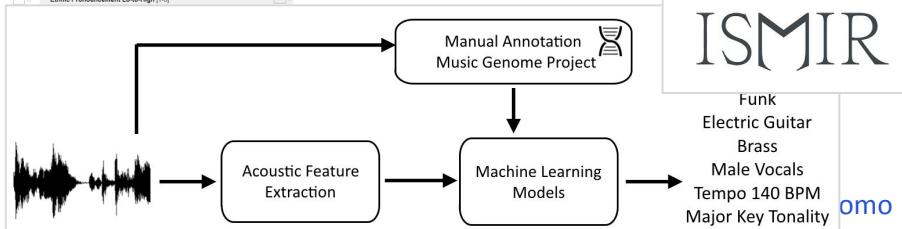
- Content-based
- Human labelling
 - Machine listening



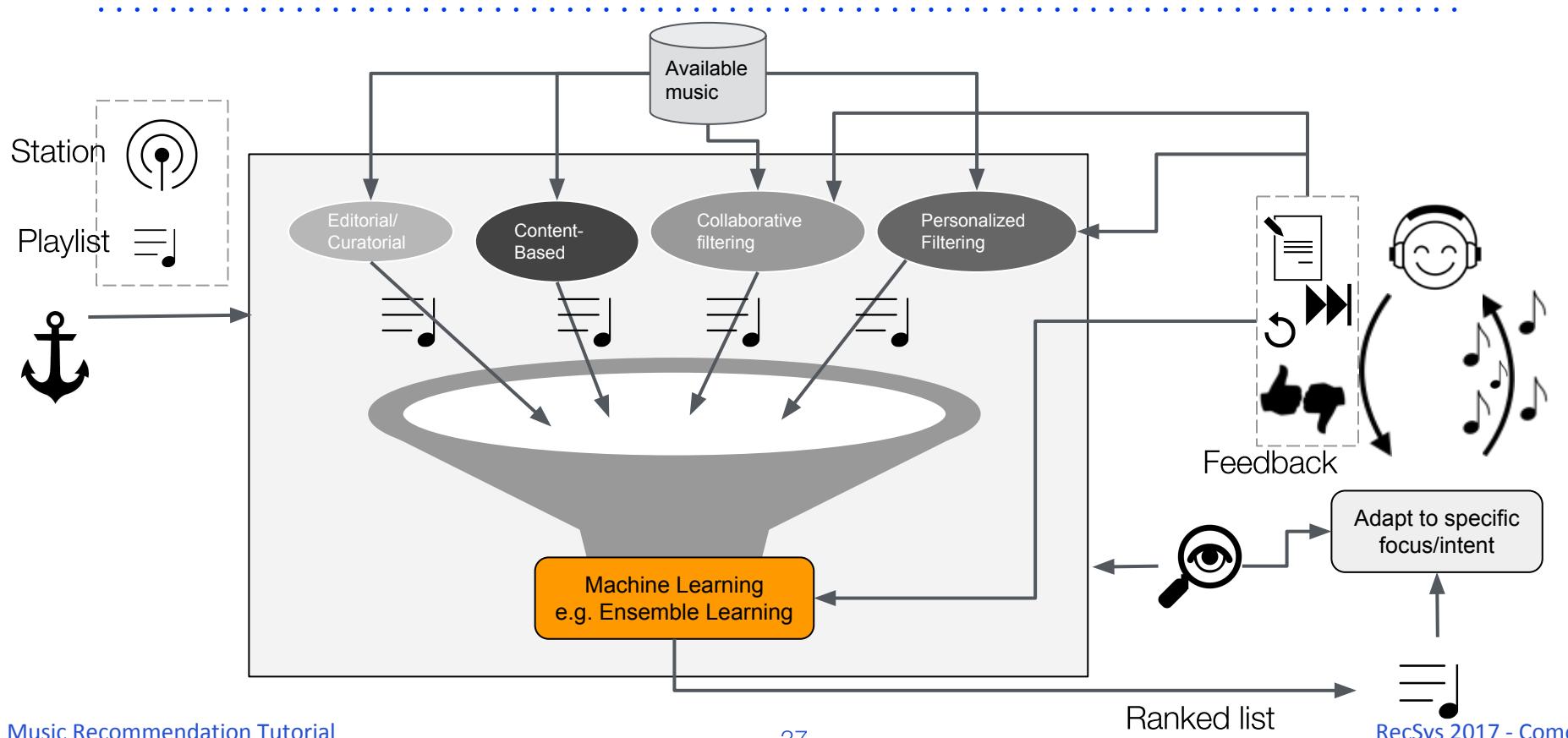
Personalized filtering



| Users (~10's M) | Items (~10's M) | | | | |
|-----------------|-----------------|---|---|---|---|
| | 1 | ? | 2 | ? | 3 |
| 1 | ? | ? | ? | ? | ? |
| 2 | ? | ? | ? | ? | ? |
| 3 | ? | ? | ? | ? | ? |
| 4 | ? | ? | ? | ? | ? |
| 5 | ? | ? | ? | ? | ? |
| 6 | ? | ? | ? | ? | ? |
| 7 | ? | ? | ? | ? | ? |
| 8 | ? | ? | ? | ? | ? |
| 9 | ? | ? | ? | ? | ? |
| 10 | ? | ? | ? | ? | ? |



Recommendation pipeline



Temporal aspect

- “*Recommending next tracks*”... Temporal ordering matters
- Notion of “music rotation” from AM/FM radio programming, e.g.:
 - Popularity categories: “Current”, “Recurrent”, “Gold”
 - Musical attributes: tempo, male vs. female vocals, danceability, major vs. minor, etc.
 - Sound attributes: synth vs. acoustic, intensity, etc.
 - Artist separation

[Price, 2015] After Zane Lowe: *Five More Things Internet Radio Should Steal from Broadcast*, [NewSlangMedia blog post](#)

- Predict best time for next user interaction with an item

[Dai, Wang, Trivedi, Song, 2016] *Recurrent Coevolutionary Latent Feature Processes for Continuous-Time User-Item Interactions*, Workshop on Deep Learning for Recommender Systems @ RecSys

- Modelling transitions in listening habits (e.g. artist transitions)

[Figueiredo, Ribeiro, Almeida, Andrade, Faloutsos, 2016] *Mining Online Music Listening Trajectories*, ISMIR

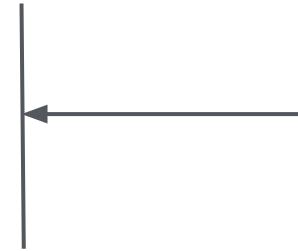
[McFee, Lanckriet, 2012] *Hypergraph Models of Playlist Dialects*, ISMIR

[Bonnin, Jannach, 2014] *Automated Generation of Music Playlists: Survey and Experiments*, ACM Computing Surveys

A “good” recommendation?

What makes a good recommendation:

- Accuracy
- Good balance of:
 - Novelty vs. familiarity / popularity
 - Diversity vs. similarity
- Transparency / Interpretability
- Listener Context



- Influential factors:
- Listener
 - Musical anchor
 - Focus / Intent

Remember: It's about recommending an experience

[Celma, 2010] *Music Recommendation and Discovery: The Long Tail, Long Fail, and Long Play in the Digital Music Space*, Springer

[Celma, Lamere, 2011] *Music Recommendation and Discovery Revisited*, ACM Conference on Recommender Systems

[Jannach, Adomavicius, 2016] *Recommendations with a Purpose*, RecSys

[Amatriain, Basilico, 2016] *Past, Present, and Future of Recommender Systems: An Industry Perspective*, RecSys

Accuracy (is not enough)

- Typically, recommendations are based on predicting the relevance of unseen items to users. Or on item ranking.
- For recommendations to be accurate, optimize recommender to best predict general relevance
 - e.g. learning from historical data from all users
- Too much focus on accuracy → biases (i.e. **popularity** and **similarity** biases)
 - Tradeoff popularity vs. personalization (is pleasing both general user base *and* each individual even possible?...)
 - Particular risk of selection bias when recsys is the oracle (e.g. station)
 - Single-metric Netflix Prize (RMSE) → only one side of the coin

Novelty

- Introducing novelty to balance against popularity (or familiarity) bias
- Both are key: Listeners want to hear what's hype (or what they already know). But they also need their dose of novelty... Once in a while.
 - How far novel? ("correct" dose?)
 - How often?
 - When?, etc...

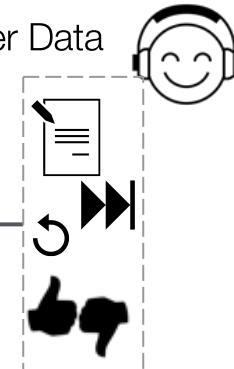
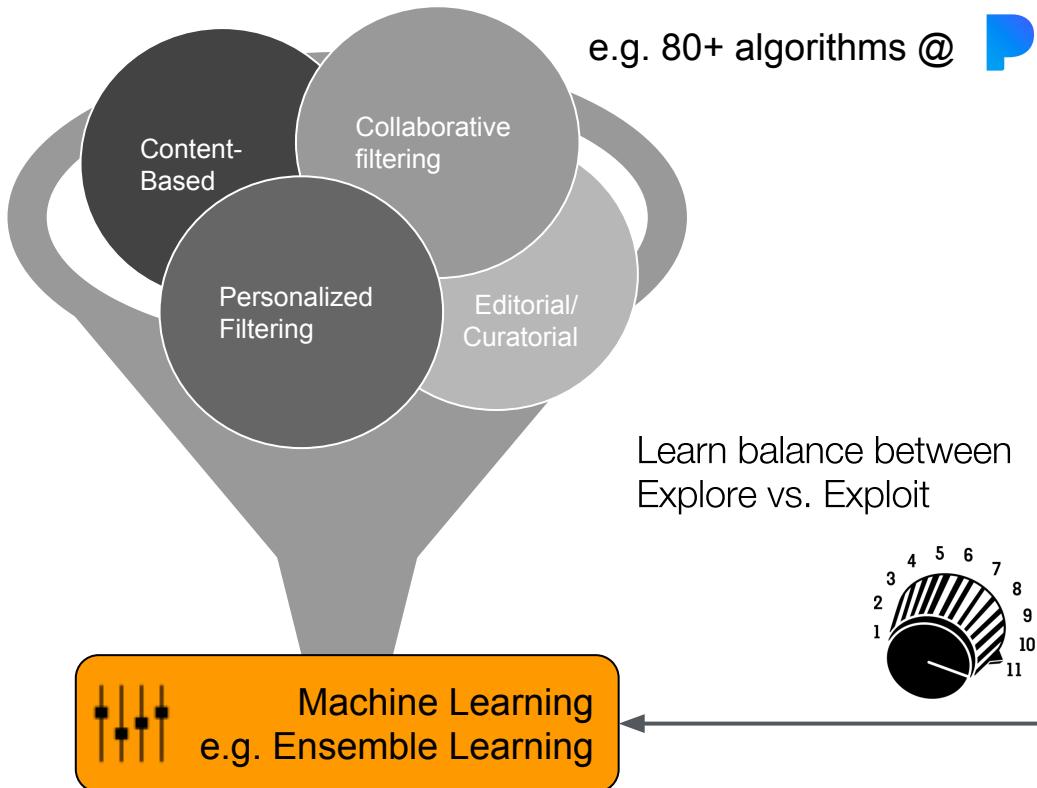
| | <i>"Yep, novelty's fine"</i> | <i>"No novelty, please!"</i> |
|----------------|--|--|
| Listener | Jazz musician | My mother |
| Musical anchor | Exploring a new friend's music library | Playlist for an official high-stake dinner |
| Focus | Discovery | Craving for my hyper-personalized stuff |

Diversity

- Introducing diversity to balance against similarity bias
- Similarity \cong accuracy
 - Trade-off accuracy vs. diversity
 - As for Novelty, adding Diversity is a useful means for personalizing and contextualizing recommendations

| | <i>"Yep, bring on diversity"</i> | <i>"No diversity, please!"</i> |
|----------------|---|--|
| Listener | A (good) DJ | Exclusive Metal-head |
| Musical anchor | Station anchored on “90’s & 00’s Hits” | Self-made playlist anchored on “Slayer” |
| Focus | Re-discovery, hyper-personalized | “Women in Post-Black Metal” |

Exploration vs. Exploitation



Exploration vs. Exploitation

- Exploit:

- **Data** tells us what works best now, let's play exactly that
- Play something **safe now**, don't worry about the future
- Lean-back experience
- "Don't play music I am not familiar with"

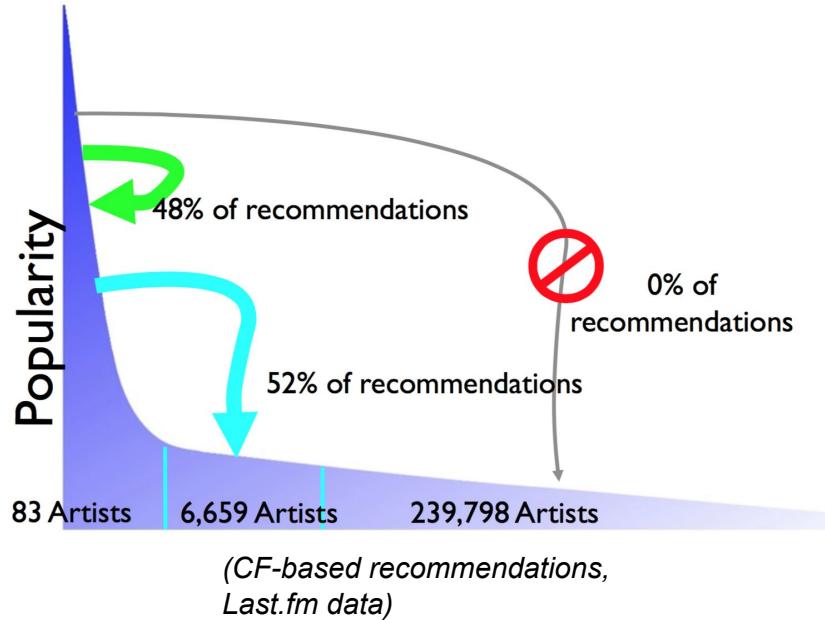
- Explore:

- Let's **learn** (i.e. gather some more data points on) what **might** work
- Play something **risky now**, preparing for tomorrow
- Lean-in experience
- "I'm ready to open up. Just don't play random stuff"



[Xing, Wang, Wang, 2014] *Enhancing Collaborative Filtering Music Recommendation by Balancing Exploration and Exploitation*, ISMIR

Exploration vs. Exploitation



Helps alleviate limited reach of some recsys:

- Coldplay, Drake, etc. vs. “Working-class” musicians (long-tail)
- Radio typically plays 10’s artists per week
- Streaming has the potential to play 100k’s artists per week
- Caveat of collaborative filtering-based algorithms

[Celma, 2010] *Music Recommendation and Discovery: The Long Tail, Long Fail, and Long Play in the Digital Music Space*, Springer

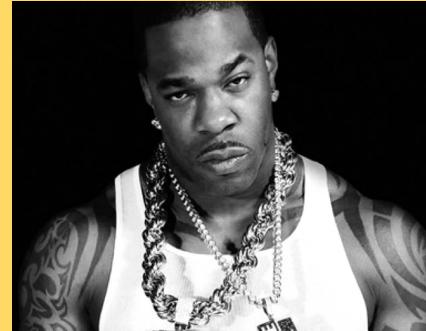
Transparency / Interpretability

- “*Why am I recommended this?*”

If you like Bernard Herrmann



You might like “Gimme some more” by Busta Rhymes



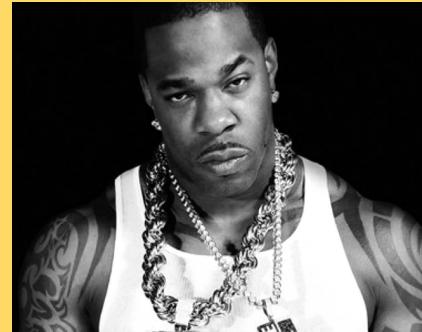
Transparency / Interpretability

- “Why am I recommended this?”

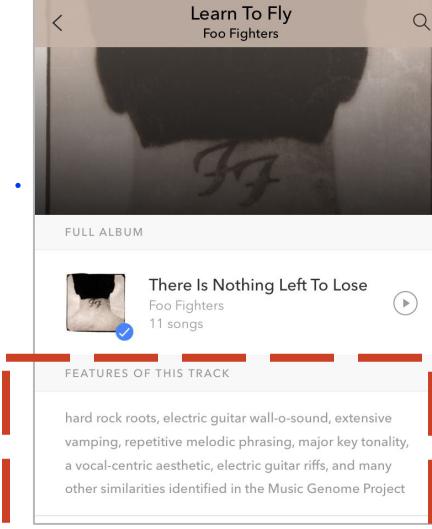
If you like Bernard Herrmann



You might like “Gimme some more” by Busta Rhymes



Because:
He sampled Herrmann’s work



- Explain how the system works: Transparency
- Increases users' confidence in the system: Trust
- Facilitates persuasion
- Fun factor → increases time spent listening
- Increases personalization (e.g. “because you *like guitar*”)
- Better experience overall
- Caveat: Users will then want to correct potentially erroneous assumptions
→ Extra level of interactivity needed

[Tintarev, Masthoff, 2015] *Explaining Recommendations: Design and Evaluation*, Recommender Systems Handbook (2nd ed.), Kantor, Ricci, Rokach, Shapira (eds), Springer

[Musto, Narducci, Lops, de Gemmis, Semeraro, 2016] *ExpLOD: A Framework for Explaining Recommendations based on the Linked Open Data Cloud*, RecSys

[Chang, Harper, Terveen, 2016] *Crowd-based Personalized Natural Language Explanations for Recommendations*, RecSys

Listener Context

- Big picture: → *Context-Aware Music Recommendation (next Use Case)*
- **Explicit focus / listener intent:**
 - Focus on newly released music (new stuff)
 - Focus on discovery (*new for me*)
 - Re-discovery (throwback songs)
 - Focus on a particular listening experience (lean-in vs. lean-back)
 - Hyper-personalized (extreme lean-back, *my best-of*)
 - etc.
- Specific focus defines:
 - Which recommendations are best
 - Which **vehicle** for recommendations is best (**how** to recommend)

Focus on: Discovering an artist

The figure consists of three side-by-side screenshots from different music platforms, all centered around the artist Bob Dylan.

Left Screenshot: A mobile application interface showing a list of Bob Dylan's top songs. The songs listed are:

- 5 Don't Think Twice, It's Alright
- 6 Don't Think Twice, It's All Right
- 7 Tangled Up In Blue
- 8 Positively 4th Street
- 9 Blowin' In The Wind
- 10 Knockin' On Heaven's Door

Below the list are playback controls (rewind, play/pause, forward) and an "AutoPlay On" toggle switch. The "AutoPlay On" section includes the text "Keep the music playing with similar songs".

Middle Screenshot: A Spotify-like interface showing a playlist titled "THIS IS: Bob Dylan". The description reads: "The career of Nobel Literature Prize winning Robert Allen Zimmerman... some of the most memorable songs to get you started." It was created by Spotify and contains 74 songs over 6 hours and 15 minutes. The playlist features a photo of Bob Dylan playing a guitar. Below the description is a "PLAY" button, a "FOLLOW" button, and a "Filter" search bar. The main content area shows a list of songs:

| TITLE | ARTIST | ALBUM |
|-------------------------------------|-----------|----------------------------|
| + Don't Think Twice, It's All Right | Bob Dylan | The Freewheelin' Bob Dylan |
| + Like a Rolling Stone | Bob Dylan | Highway 61 Revisited |
| + Hurricane | Bob Dylan | Desire |
| + Mr. Tambourine Man | Bob Dylan | Bringing It All Back Home |
| + All Along the Watchtower | Bob Dylan | John Wesley Harding |

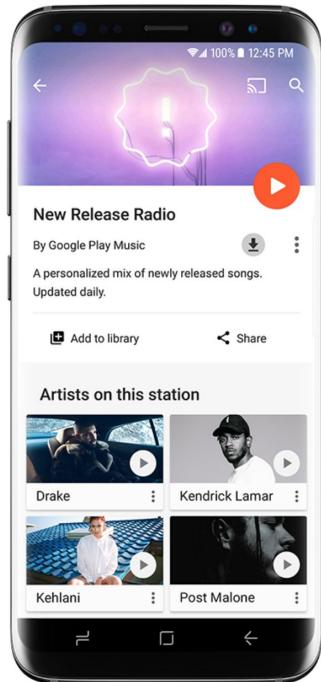
Right Screenshot: An Apple Music interface showing a playlist titled "Intro to Bob Dylan" by Apple Music. It contains 25 songs. The description highlights Bob Dylan as "the most influential singer/songwriter in popular music" and notes his career began in the early '60s. Below the description is a "Shuffle" button. The main content area shows a list of songs:

| ARTIST | SONG | DURATION | MORE |
|-----------|--------------------------|----------|------|
| Bob Dylan | Like a Rolling Stone | 6:11 | ... |
| Bob Dylan | Tangled Up In Blue | 5:40 | ... |
| Bob Dylan | Mr. Tambourine Man | 5:26 | ... |
| Bob Dylan | Don't Think Twice, It... | 3:40 | ... |

At the bottom of the screen are navigation icons for "For You", "New", "Radio", "Connect", and "My Music".

Focus on: New music

Personalized vs. non-personalized



My Music Browse

New Music View all >

Pleasure Feist Album - 11 songs

Crack-Up Fleet Foxes Album - 11 songs

Father's Song (Si... Prince Album - 1 songs

8 Incubus Album - 11 songs

Search Go back

PLAY FOLLOW ...

PLAYLIST

New Music Friday

The week's best new music featuring brand new albums from DJ Khaled and Imagine Dragons!

Created by: Spotify • 57 songs, 3 hr 27 min

PLAY FOLLOW ...

Updated Friday

| SONG | ARTIST | ALBUM |
|---------------|-------------------|----------------|
| Duele | Bomba Estéreo | Duele - Single |
| Olho do Tempo | Nômade Orquestra | EntreMundos |
| Bora Paspear | Curumin | Boca |
| Garabatos | Totó La Momposina | Oye Manita |
| 12 Meses | Profetas | Tiempo |
| No Regreso | Combo Chimbita | Abya Yala |
| Mass Trauma | Deltatron & Lao | Ego Trip |

Fabien Gouyon

Search

Release Radar

By Spotify • Never miss a new release! Catch all the latest music from artists you care about, plus new singles picked just for you. Updates every Friday.

PLAY FOLLOW ...

Focus on: Re-discovery

The songs you love and more. As you listen, the mix gets better. Refresh every Wednesday.

- Shuffle All
- Jumpman Drake & Future
- Panda Designer
- Pt. 2 Kanye West
- Odyssey

For You Browse Radio Search

Focus on stuff you know you like
Personalized, leaning towards exploit

DEEZER

Search

HOME

HEAR THIS

My Music

+ SUBSCRIBE

Favourite tracks

Playlists

FLOW Your personal soundtrack

Tive Razao Seu Jorge

3 ALBUMS

Thumbprint Radio Station

Music inspired by your 1,285 thumbs from across all your stations.

THUMBED UP SONGS

- Baiao Embolado Forró In The Dark 2:36
- 21st Century Red Hot Chili Peppers 4:22
- Times Like These Foo Fighters 4:26
- Tive Razao Seu Jorge

Focus on: Hyper-personalized Discovery

Thumbprint Radio
Station

Music inspired by your 1,285 thumbs from across all your stations.

THUMBED UP SONGS

- Baiao Embolado
Forro In The Dark
2:36
- 21st Century
Red Hot Chili Peppers
4:22
- Times Like These
Foo Fighters
4:26
- Tive Razao
Seu Jorge

www.deezer.com/en/

DEEZER

Search

HOME

HEAR THIS

My Music

+ SUBSCRIBE

Favourite tracks

Playlists

FLOW Your personal soundtrack

MADE FOR FABIEN

Discover Weekly

Your weekly mixtape of fresh music. Enjoy new discoveries and deep cuts. Updated every Monday, so save your favourites!

Made for Fabien Gouyon by Spotify • 30 songs, 2 hr

PLAY FOLLOWING

About discovering new stuff.
Intended to feel like it's curated. Just. For. Me.
Leaning towards explore

| Filter | TITLE | ARTIST | ALBUM |
|--------|-------------------|----------------|-------------------|
| + | One Step Ahead | Split Enz | Waiata |
| + | Not My Slave | Oingo Boingo | Boi-Ngo |
| + | She Sheila | The Producers | You Make the Heat |
| + | Drifting, Falling | The Ocean Blue | The Ocean Blue |
| + | New Mistake | Jellyfish | Salt Milk |

Focus on: Lean-in experience

Lean in:
Building Playlists

The screenshot shows a music application interface. At the top, there's a header with a play button and a three-dot menu. Below it is a list of songs in a playlist:

| TITLE | ARTIST | ALBUM | DATE | DURATION |
|---------------|-------------|---------------|------------|----------|
| + 24K Magic | Bruno Mars | 24K Magic | 2017-03-15 | 3:46 |
| + Fix | Blackstreet | Another Level | 2017-03-15 | 4:05 |
| + Good Lovin' | Blackstreet | Another Level | 2017-03-15 | 4:32 |

Below the playlist is a section titled "Recommended Songs" with a subtitle "Based on the songs in this playlist". It lists five songs:

| ADD | Song Title | Artist | Album | Duration |
|-------------------------------|----------------|----------------|-------------------------------|----------|
| Back & Forth | Aaliyah | Aaliyah | Age Ain't Nothing But A Nu... | 3:51 |
| Get It On Tonite | Montell Jordan | Montell Jordan | Get It On...Tonite | 4:36 |
| Wifey - Club Mix/Dirty Ver... | Next | Next | Work It Out! | 4:02 |
| Doin' It | LL Cool J | LL Cool J | Mr. Smith (Deluxe Edition) | 4:54 |
| Freek'n You | Jodeci | Jodeci | The Show, The After Party,... | 6:19 |

The screenshot shows a music player interface. At the top, there's a header with a back button, a search bar containing "Too much vocoder by fgouyon - 3 songs", and a magnifying glass icon. Below it is a "Shuffle" button.

Below the shuffle button is a list of songs:

| 24K Magic | Bruno Mars | 3:45 |
|-------------|-------------|------|
| Fix | Blackstreet | 4:05 |
| Good Lovin' | Blackstreet | 4:31 |

At the bottom, there's a red footer bar with a play button and a "Add similar songs" button.

Focus on: Mood /Activity

The interface shows a navigation bar with 'My Music' and 'Browse' tabs, and a search icon. Below is a section titled 'Moods and Activities' with six cards:

- Summer**: Popsicle icon, 27 Stations
- Workout**: Barbell icon, 23 Stations
- Party**: Balloons icon, 32 Stations
- Wind-Down**: Bathtub icon, 45 Stations
- The Pretender**: Foo Fighters album cover
- A play button icon at the bottom right.

The 'Browse' section has tabs for OVERVIEW, CHARTS, GENRES & MOODS (highlighted), NEW RELEASES, DISCOVER, and CONCERTS. It displays mood categories with corresponding images and names: Focus, Workout, Party, Gaming, Sleep, and Indie.

The 'For You' page features a 'My Chill Mix' card with 'Apple Music for Kif' and 'Updated Sunday'. It includes a download confirmation message and a red 'More' button. Below are song recommendations:

- I Am My Own Hell** by Teen Suicide
- Song for a Guilty Sadist** by Crywank
- Questions** by Donnie Trumpet & The Social Experiment
- Spooky Ghosts** by Snckpck
- Outside with the Cuties** by Frankie Cosmos

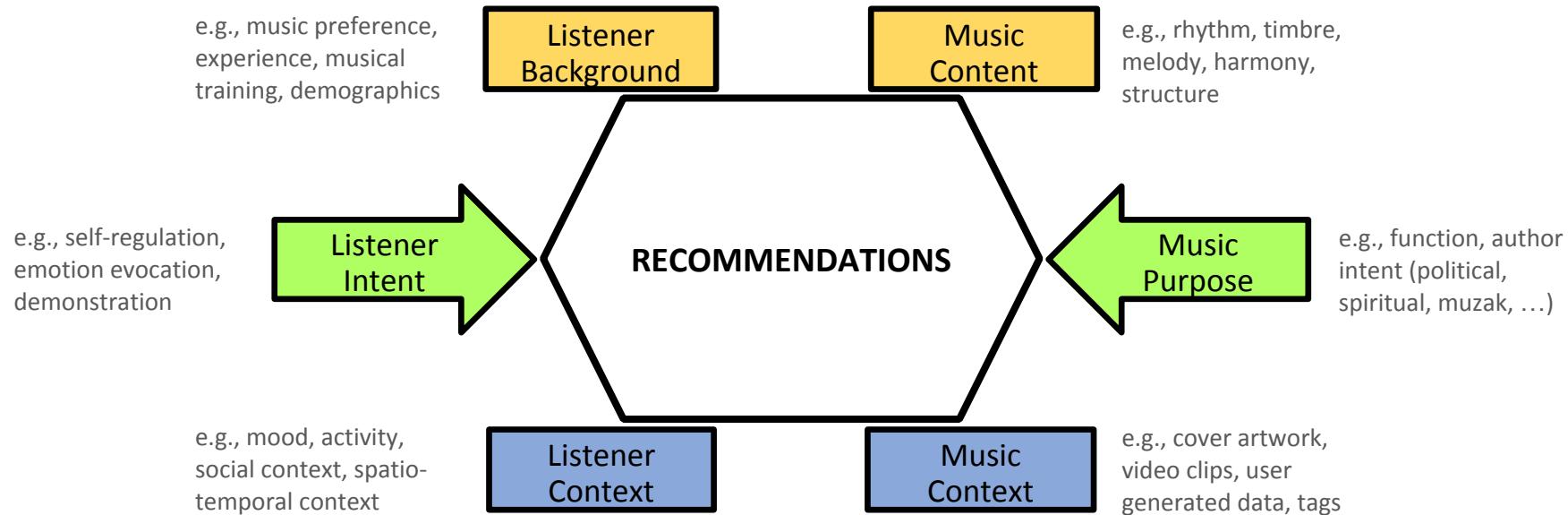
Personalized vs. non-personalized

Use Case 2: Context-Aware Music Recommendation

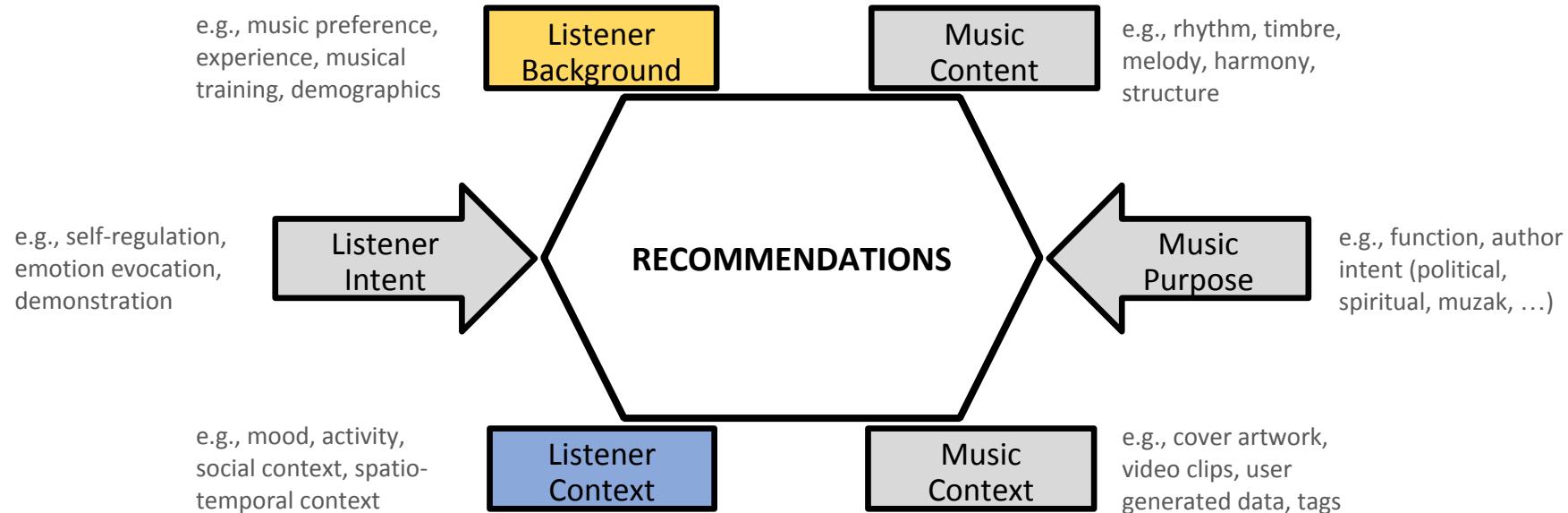
Overview

- **Context categories and acquisition:** We categorize various dimensions of the user context, e.g., time, location, activity, weather, social context, personality, etc.
- **Methods/examples:** We outline the most frequently adopted approaches in context-aware MRS.
- **Cultural/regional specificities:** We summarize findings about country-specific differences in music preferences.
- **Evaluation:** We highlight particular challenges in evaluating context-aware MRS.

Listening Hexagon



Listening Hexagon



Context categories

Environment-related context

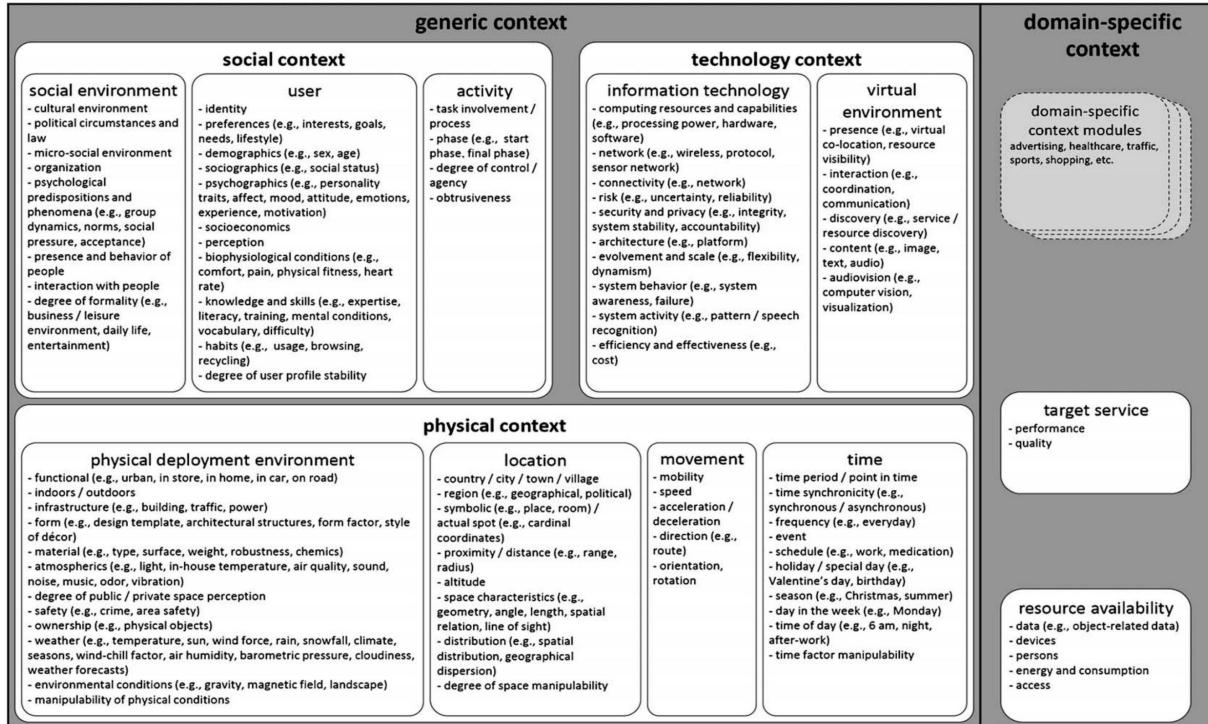
- Exists irrespective of a particular user
- Ex.: time, location, weather, traffic conditions, noise, light

User-related context/background

- Is connected to an individual user
- Ex.: activity, emotion, personality, social and cultural context

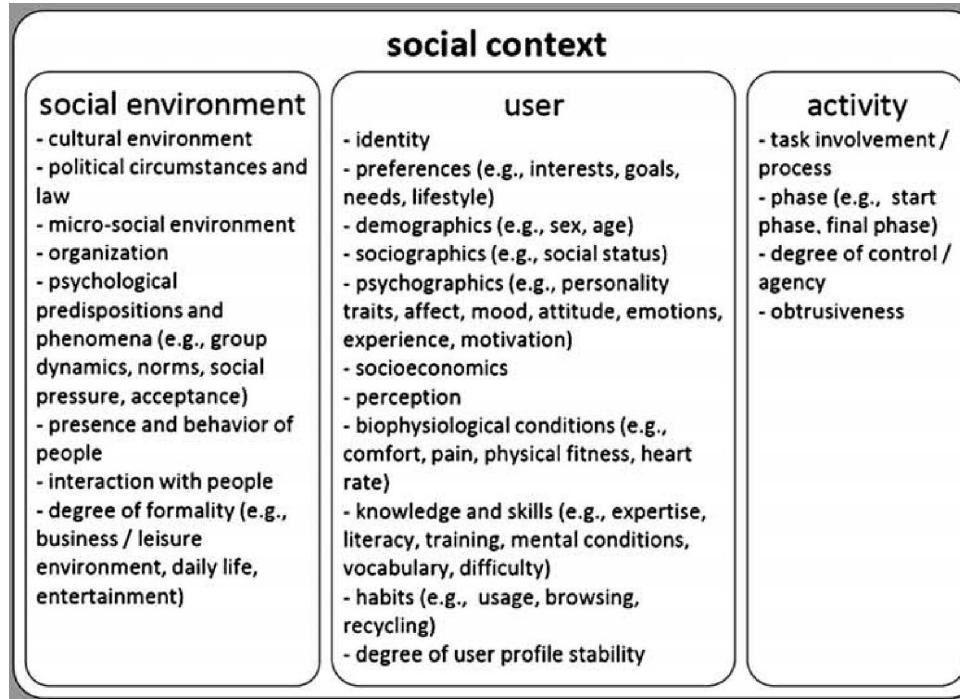
[Schedl et al., 2015] chapter *Music Recommender Systems*, Recommender Systems Handbook, Ricci et al. (eds.), 2nd ed., pp. 453-492.

Many more context categories



[Bauer & Novotny, 2017] A consolidated view of context for intelligent systems. Journal of Ambient Intelligence and Smart Environments, 9(4), 377-393. doi:10.3233/ais-170445

Many more context categories



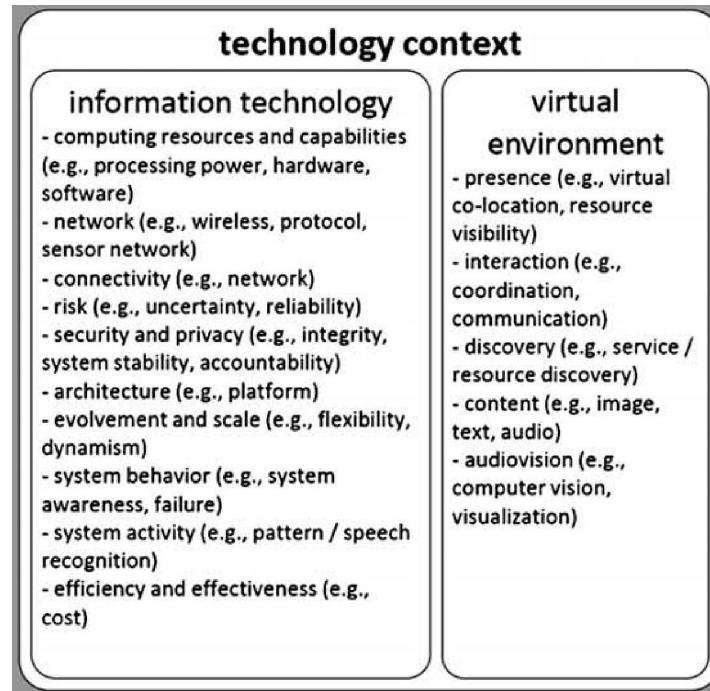
[Bauer & Novotny, 2017] *A consolidated view of context for intelligent systems*. Journal of Ambient Intelligence and Smart Environments, 9(4), 377-393. doi:10.3233/ais-170445

Many more context categories

| physical context | | | |
|---|---|--|---|
| physical deployment environment <ul style="list-style-type: none">- functional (e.g., urban, in store, in home, in car, on road)- indoors / outdoors- infrastructure (e.g., building, traffic, power)- form (e.g., design template, architectural structures, form factor, style of décor)- material (e.g., type, surface, weight, robustness, chemics)- atmospherics (e.g., light, in-house temperature, air quality, sound, noise, music, odor, vibration)- degree of public / private space perception- safety (e.g., crime, area safety)- ownership (e.g., physical objects)- weather (e.g., temperature, sun, wind force, rain, snowfall, climate, seasons, wind-chill factor, air humidity, barometric pressure, cloudiness, weather forecasts)- environmental conditions (e.g., gravity, magnetic field, landscape)- manipulability of physical conditions | location <ul style="list-style-type: none">- country / city / town / village- region (e.g., geographical, political)- symbolic (e.g., place, room) / actual spot (e.g., cardinal coordinates)- proximity / distance (e.g., range, radius)- altitude- space characteristics (e.g., geometry, angle, length, spatial relation, line of sight)- distribution (e.g., spatial distribution, geographical dispersion)- degree of space manipulability | movement <ul style="list-style-type: none">- mobility- speed- acceleration / deceleration- direction (e.g., route)- orientation, rotation | time <ul style="list-style-type: none">- time period / point in time- time synchronicity (e.g., synchronous / asynchronous)- frequency (e.g., everyday)- event- schedule (e.g., work, medication)- holiday / special day (e.g., Valentine's day, birthday)- season (e.g., Christmas, summer)- day in the week (e.g., Monday)- time of day (e.g., 6 am, night, after-work)- time factor manipulability |

[Bauer & Novotny, 2017] A consolidated view of context for intelligent systems. Journal of Ambient Intelligence and Smart Environments, 9(4), 377-393. doi:10.3233/ais-170445

Many more context categories



[Bauer & Novotny, 2017] *A consolidated view of context for intelligent systems*. Journal of Ambient Intelligence and Smart Environments, 9(4), 377-393. doi:10.3233/ais-170445

Obtaining context data

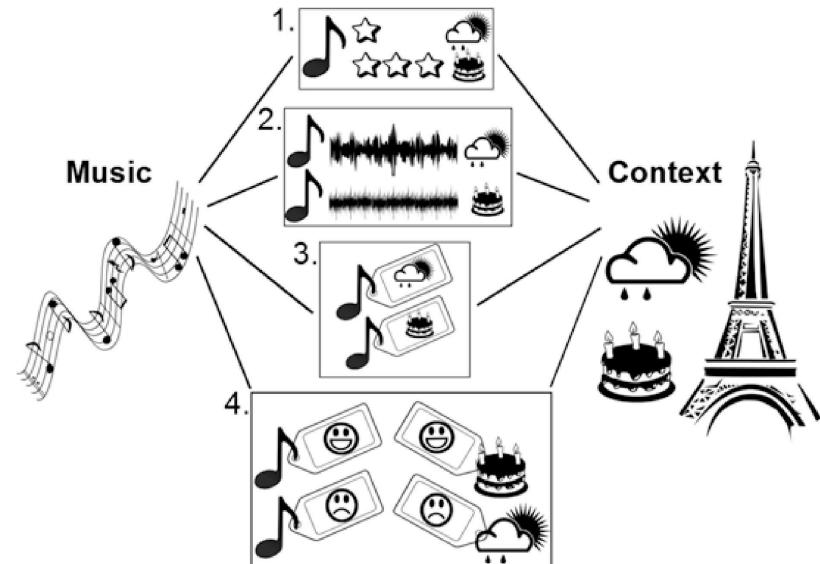
- **Explicitly:** elicited by direct user interaction (questions, ratings in context)
Ex.: asking for user's mood or music preference (Likert-style ratings)
- **Implicitly:** no user interaction necessary
Ex.: various sensor data in today's smart devices (heart rate, accelerometer, air pressure, light intensity, environmental noise level, etc.)
- **Inferring** (using rules or ML techniques):
Ex.: time, position → *weather*; device acceleration (x, y, z axes), change in position/movement speed → *activity*; skipping behavior → music preferences

[Adomavicius & Tuzhilin, 2015] chapter *Context-Aware Recommender Systems*, Recommender Systems Handbook, Ricci et al. (eds.), 2nd ed., pp. 191-226.

Obtaining context data

Methods to establish **relationship: music ↔ context**

1. Rating music in context
2. Mapping audio/content features to context attributes
3. Direct labeling of music with context attributes
4. Predicting an intermediate context



[Schedl et al., 2015] chapter *Music Recommender Systems*, Recommender Systems Handbook, Ricci et al. (eds.), 2nd ed., pp. 453-492.

Methods/examples for context-aware MRS

- Mobile Music Genius

[Schedl et al., 2014] *Mobile Music Genius: Reggae at the Beach, Metal on a Friday Night?*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

- Just-for-me

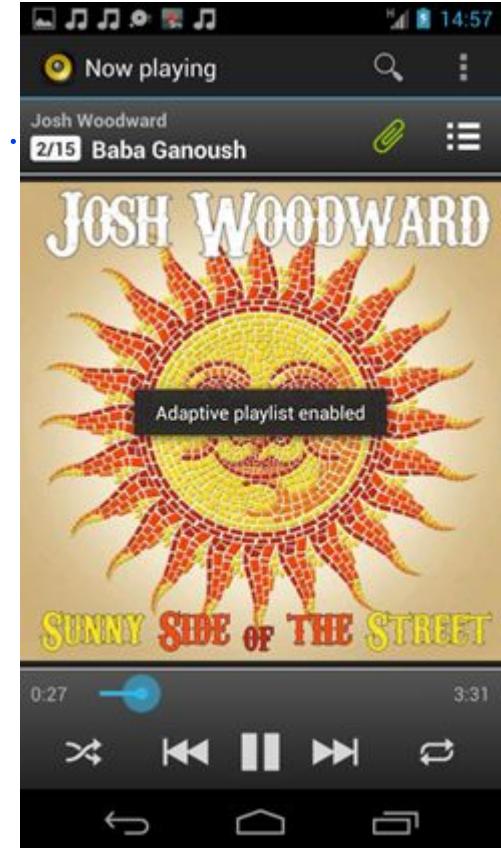
[Cheng & Shen, 2014] *Just-for-Me: An Adaptive Personalization System for Location-Aware Social Music Recommendation*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

- Music Recommendation for POIs

[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

Mobile Music Genius

- Context-aware recommendation of next track in playlist
- Variety of context/sensors used, e.g., time, location, place, weather, device, activity, ambient (light, noise, etc.)
- Decision tree classifier continuously learns relationships: genre, artist, track → context attributes from user interactions (e.g., play, skip, stop events)

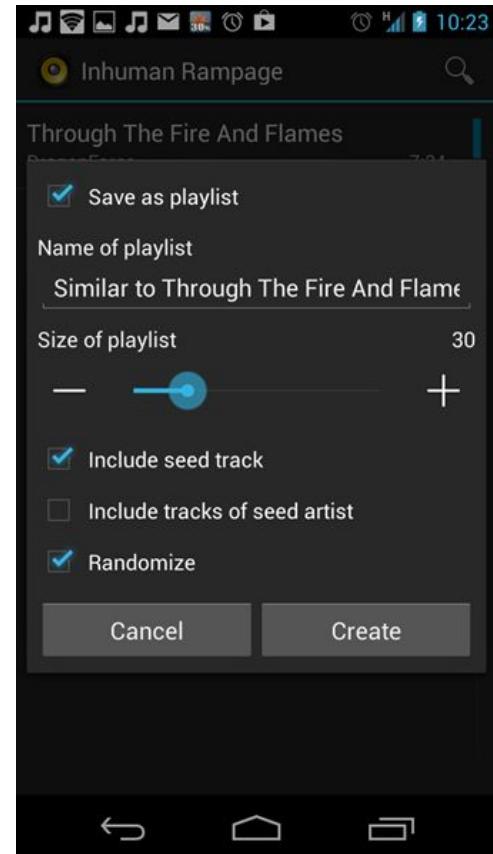


Mapping music/content features to context attributes

[Schedl et al., 2014] *Mobile Music Genius: Reggae at the Beach, Metal on a Friday Night?*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

Recommendation approach

- Playlists created by track similarity, computed from Last.fm tags (cosine similarity on weighted artist and song tags)
- During playback: if change in context attributes exceeds sensitivity parameter, classifier is used to predict new track, which is played next



Evaluation

Classification accuracy of different classifiers and prediction targets:

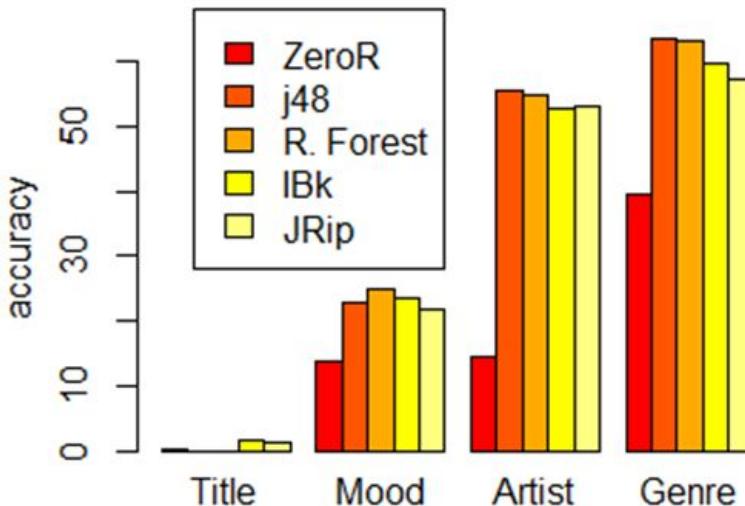
Best results

Title: 0.015

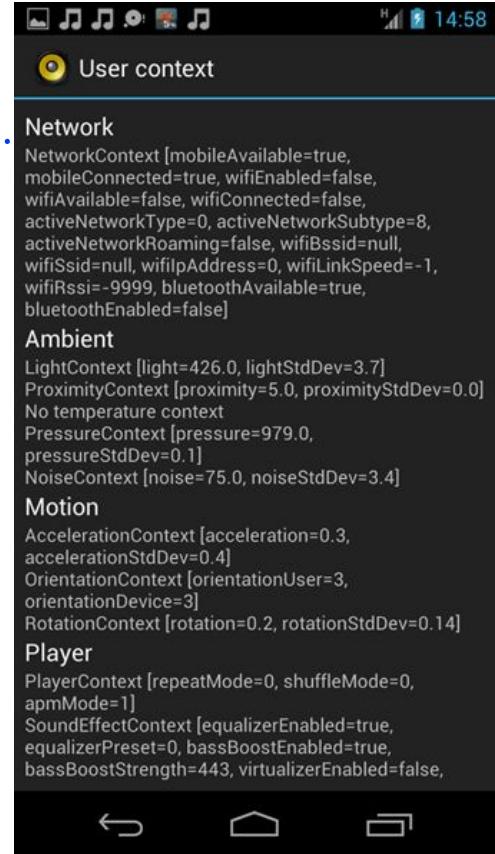
Mood: 0.230

Artist: 0.550

Genre: 0.610

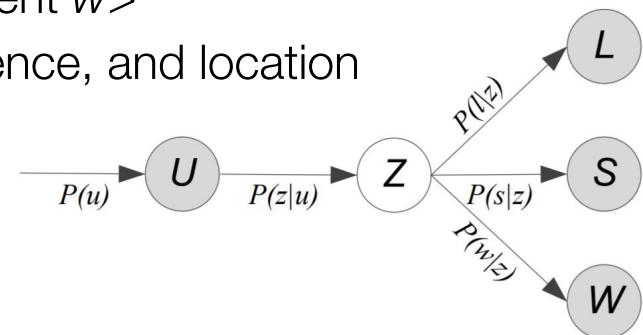


[Schedl et al., 2014] *Mobile Music Genius: Reggae at the Beach, Metal on a Friday Night?*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).



Just-for-me

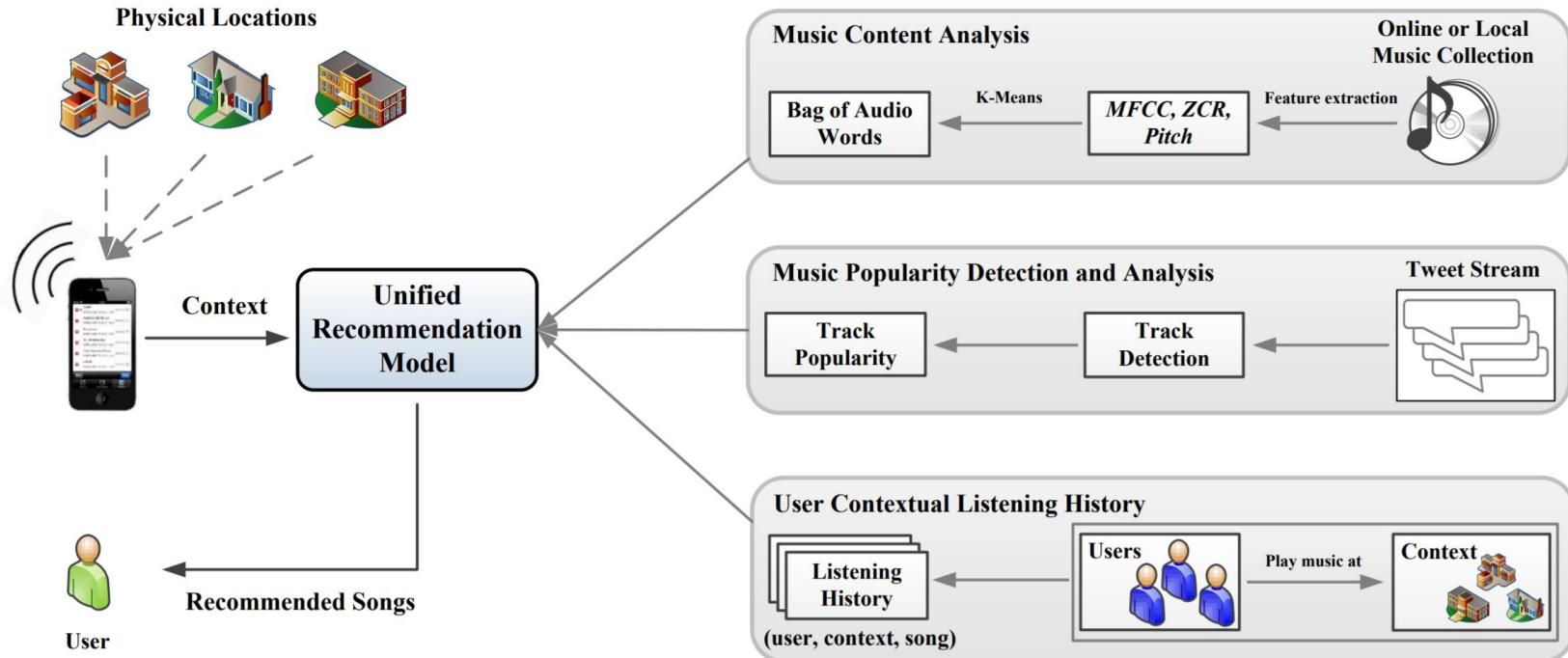
- Location-aware mobile music recommender
- Representation of play events:
 $\langle \text{user } u, \text{ location } l, \text{ track preference } s, \text{ audio content } w \rangle$
- Latent topic model used to relate content, preference, and location
- Trained via EM on existing user data
- Trained model used to predict $Pr(s|u, l)$
- Popularity estimation from tweets and integrated into track preference score (updated weekly)



Mapping music/content features to context attributes

[Cheng & Shen, 2014] *Just-for-Me: An Adaptive Personalization System for Location-Aware Social Music Recommendation*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

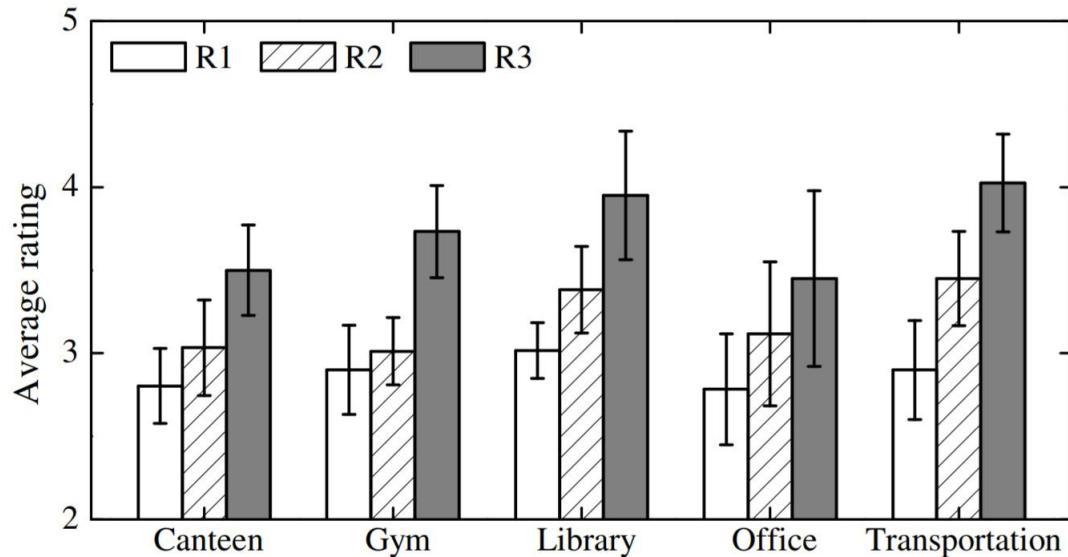
Recommendation approach



[Cheng & Shen, 2014] Just-for-Me: An Adaptive Personalization System for Location-Aware Social Music Recommendation, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

Evaluation

- 10 subjects (Asian, 6m/4f) rated up to 250 tracks in 5 contexts (canteen, gym, library, office, transportation), which are used for training
- 750 tracks used to create recommendations for user u at location l
- Subjects rated recommended tracks on Likert scale (1-5)
- Baselines
 - R1: random track selection
 - R2: location-based filtering w/o user preferences
 - R3: proposed method



Music recommendation for places of interest

- Combines: direct labeling, mapping audio/content features to context attributes, and predicting intermediate context

Direct labeling to create ground truth

La Scala, Milan, Italy
http://en.wikipedia.org/wiki/La_Scala



Session 1 out of 10: ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆

Listen to the tracks and select those that in your opinion are **suited** for the described place:

Reincidentes - Ay Dolores
<http://en.wikipedia.org/wiki/Reincidentes>

00:00 [audio player] 00:00 [MP3]

Vincenzo Pucitta - La Vestale, Opera seria 1st act
http://en.wikipedia.org/wiki/Vincenzo_Pucitta

00:00 [audio player] 00:00 [MP3]

The Shower Scene - This Is The Call Out
http://en.wikipedia.org/wiki/The_Shower_Scene

00:00 [audio player] 00:00 [MP3]

Duchess Maria Antonia of Bavaria - Pallid' ombra che d'intorno
http://en.wikipedia.org/wiki/Duchess_Maria_Antonia_of_Bavaria

00:00 [audio player] 00:00 [MP3]

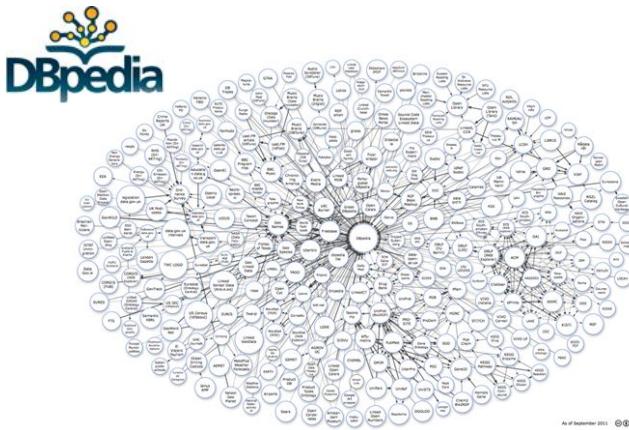
Submit

La Scala is a world renowned opera house in Milan, Italy. The theatre was inaugurated on 3 August 1778 and was originally known as the New Royal-Ducal Theatre at La Scala. The premiere performance was Antonio Salieri's 'Europa riconosciuta'. Most of Italy's greatest operatic artists, and many of the finest singers from around the world, have appeared at La Scala during the past 200 years.

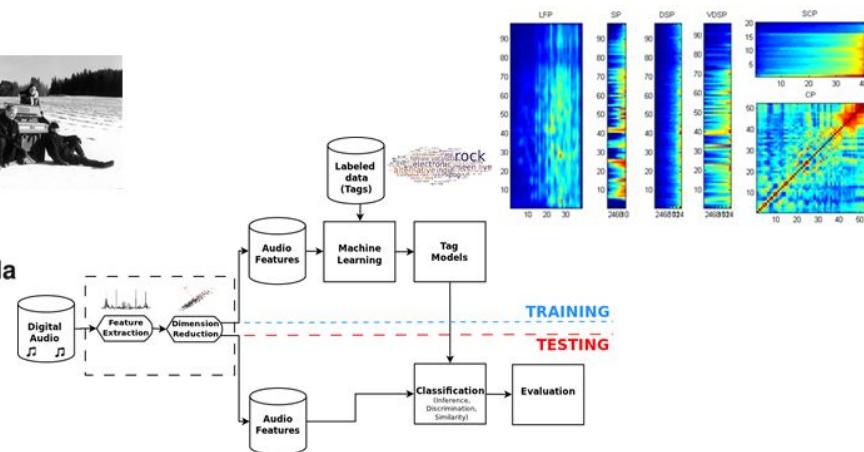
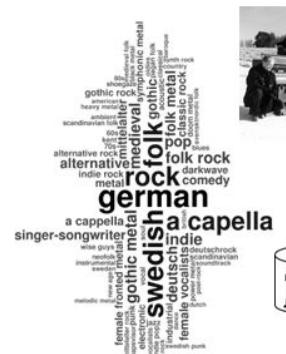
[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

Recommendation approach

- Hybrid MRS fusing **knowledge-based** recommendations and **audio content-based** recommendations obtained via auto-tagging (rank fusion)



+

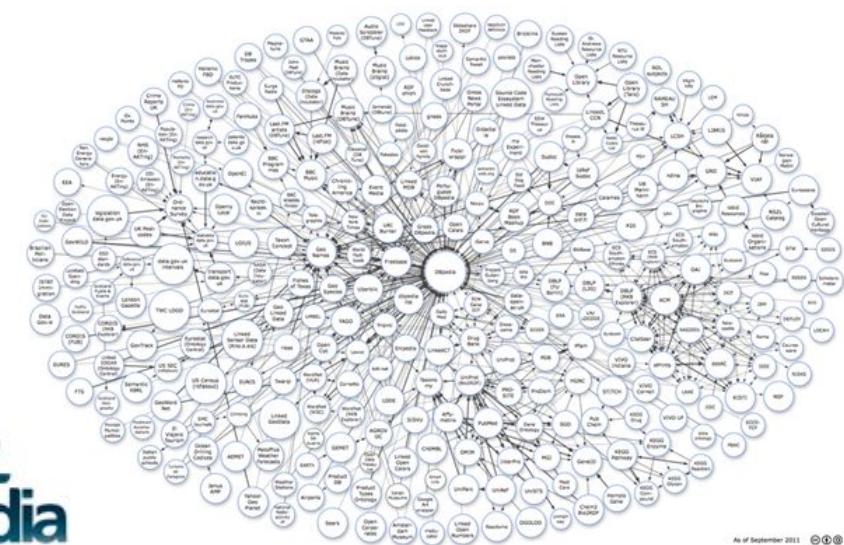


[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

Knowledge-based recommendation

- DBpedia knowledge graph
- Identify relations between musician and POIs (e.g., POI *located in* city, city *birthplace of* musician)
- Assign relevance weights to nodes and edges
- Estimate similarity/relatedness between POI and musicians via weight spreading

Predicting intermediate context



As of September 2011

[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

Audio content-based recommendation

- Establish ground truths: track \leftarrow emotions, POI \leftarrow emotions (web survey)
- Train a music auto-tagger from ground truth data (track \leftarrow emotions)
- Use auto-tagger to predict emotions for unseen tracks (track \rightarrow emotions)
- Establish similarity between POI and track via Jaccard index on “bag-of-tags” representations

Predicting intermediate context (emotions)

Mapping audio/content features to context attributes

The screenshot shows a user interface for predicting emotions from audio content. On the left, there is a list of emotion tags with checkboxes. Some checkboxes are checked (Tender, Modern, Dark, Lightweight, Open), while others are unchecked. On the right, there is a player showing a track by Fritz Kreisler titled "Liebesfreud". The player includes a progress bar at 00:08/00:31, volume control, and an FMP3 logo. Below the player is a descriptive text about Fritz Kreisler. A "Skip this item" button is located in the top right corner.

| Tag: | |
|---|--|
| <input type="checkbox"/> Melancholic | <input type="checkbox"/> Bright |
| <input type="checkbox"/> Heavy | <input type="checkbox"/> Animated |
| <input checked="" type="checkbox"/> Tender | <input type="checkbox"/> Energetic |
| <input type="checkbox"/> Cold | <input type="checkbox"/> Spiritual |
| <input checked="" type="checkbox"/> Modern | <input checked="" type="checkbox"/> Serene |
| <input type="checkbox"/> Ancient | <input type="checkbox"/> Calm |
| <input type="checkbox"/> Affectionate | <input type="checkbox"/> Sad |
| <input checked="" type="checkbox"/> Dark | <input type="checkbox"/> Strong |
| <input checked="" type="checkbox"/> Lightweight | <input type="checkbox"/> Colorful |
| <input checked="" type="checkbox"/> Open | <input type="checkbox"/> Thrilling |
| <input type="checkbox"/> Warm | <input type="checkbox"/> Agitated |
| <input type="checkbox"/> Sentimental | <input type="checkbox"/> Bouncy |

Fritz Kreisler - Liebesfreud
http://en.wikipedia.org/wiki/Fritz_Kreisler

00:08 00:31 FMP3

"Friedrich 'Fritz' Kreisler (February 2, 1875 – January 29, 1962) was an Austrian-born violinist and composer. One of the most famous violin masters of his or any other day, he was known for his sweet tone and expressive phrasing. Like many great violinists of his generation, he produced a characteristic sound which was immediately recognizable as his own. Although he derived in many respects from the Franco-Belgian school, his style is nonetheless reminiscent of the gemütlich (cozy) lifestyle of pre-war Vienna."

Skip this item

Submit

Evaluation

La Scala, Milan, Italy
http://en.wikipedia.org/wiki/La_Scala



La Scala is a world renowned opera house in Milan, Italy. The theatre was inaugurated on 3 August 1778 and was originally known as the New Royal-Ducal Theatre at La Scala. The premiere performance was Antonio Salieri's 'Europa riconosciuta'. Most of Italy's greatest operatic artists, and many of the finest singers from around the world, have appeared at La Scala during the past 200 years.

Session 1 out of 10: ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆ ◆

Listen to the tracks and select those that in your opinion are **s suited** for the described place:

Reincidentes - Ay Dolores
<http://en.wikipedia.org/wiki/Reincidentes>
0:00 0:00

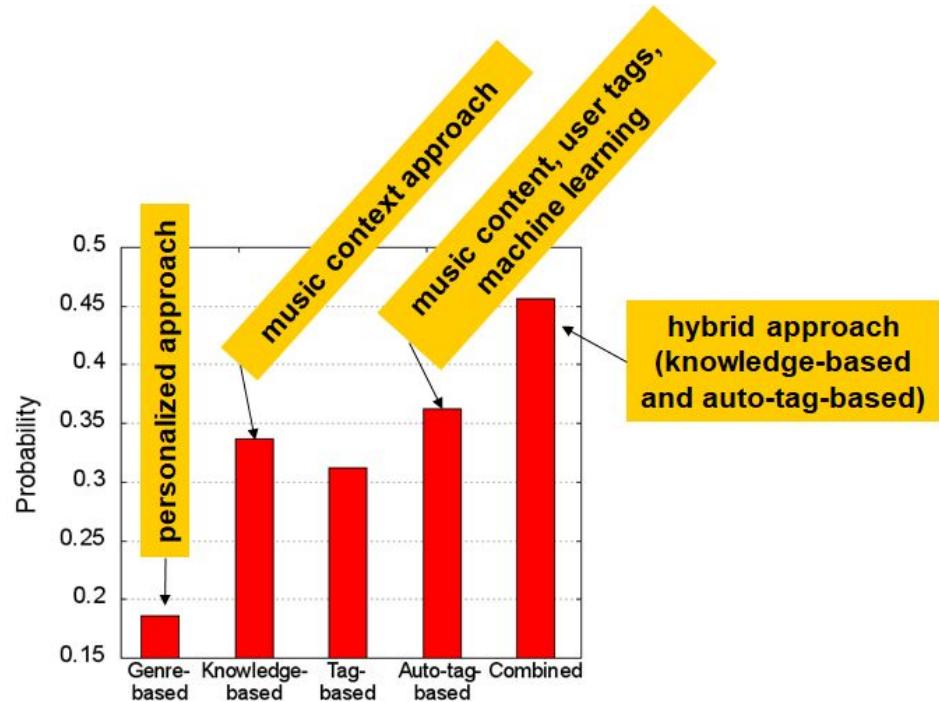
Vincenzo Pucita - La Vestale, Opera seria 1st act
http://en.wikipedia.org/wiki/Vincenzo_Pucita
0:00 0:00

The Shower Scene - This Is The Call Out
http://en.wikipedia.org/wiki/The_Shower_Scene
0:00 0:00

Duchess Maria Antonia of Bavaria - Pallid' ombra che d'intorno
http://en.wikipedia.org/wiki/Duchess_Maria_Antonia_of_Bavaria
0:00 0:00

Submit

Share of tracks marked as well-suited for POI, among all tracks recommended by given approach:



[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

More examples for context-aware MRS

- Music recommendation in **social context**,
based on social graph via friendship relationships on Last.fm and KKBOX

[Chen et al., 2015] *Exploiting Latent Social Listening Representations for Music Recommendations*, Proceedings of the 9th ACM Conference on Recommender Systems (RecSys).
- Music recommendation **in a car** (InCarMusic),
ratings in context (genre ↔ situation, e.g., driving style, sleepiness, weather)

[Baltrunas et al., 2011] *InCarMusic: Context-Aware Music Recommendations in a Car*, Proceedings of the International Conference on Electronic Commerce and Web Technologies (EC-Web).
- Music recommendation based on listener **emotion**,
content-based approach based on direct labeling and emotion classification

[Bodarwé et al., 2011] *Emotion-based music recommendation using supervised learning*, Proceedings of the 14th International Conference on Mobile and Ubiquitous Multimedia (MUM).

More examples for context-aware MRS

- Music recommendation based on **activity** and **mood**,
based on real-life user annotations of activity and mood on a smartphone,
plus sensor data, using factorization machines as RS

[Teng et al., 2013] *A large in-situ dataset for context-aware music recommendation on smartphones*, Proceedings of the IEEE International Conference on Multimedia and Expo Workshops (ICME).

- Music recommendation for **daily activities**,
based on automatic activity recognition from smartphone sensor data,
matching with audio content features via probabilistic Bayes classifier

[Chen et al., 2015] *Exploiting Latent Social Listening Representations for Music Recommendations*, Proceedings of the 9th ACM Conference on Recommender Systems (RecSys).

Cultural/regional specificities

- Example to analyze and integrate **listener background**
- Music preferences vary strongly between countries
 - recommendations should be tailored to cultural background
 - country information can be used to alleviate cold start (“single sign-on”)
- Ex.: music preferences analyzed using LFM-1b dataset (>1b listening events of 120k Last.fm users, 585k artists, user demographics)

[Schedl, 2017] *Investigating Country-specific Music Preferences and Music Recommendation Algorithms with the LFM-1b Dataset*, International Journal of Multimedia Information Retrieval 6(1):71-84.

Populations' preferences

| country | age | gender | users | rnb | rap | elect. | rock | blues | folk | jazz | punk | altern. | pop | metal | α |
|---------|-----|--------|--------|-------------|-------------|--------------|--------------|-------------|-------------|-------------|-------------|--------------|--------------|-------------|----------|
| - | - | - | 120175 | 3.34 | 3.41 | 11.18 | 18.27 | 3.28 | 5.61 | 3.97 | 6.19 | 16.75 | 13.64 | 3.98 | 0.493 |
| US | - | - | 10255 | 3.00 | 3.22 | 11.17 | 18.82 | 3.07 | 6.06 | 3.79 | 7.53 | 17.69 | 13.56 | 3.29 | 0.554 |
| RU | - | - | 5024 | 1.55 | 3.10 | 14.30 | 20.60 | 2.28 | 4.58 | 3.03 | 7.76 | 18.14 | 10.58 | 6.10 | 0.564 |
| DE | - | - | 4578 | 1.96 | 3.15 | 11.90 | 19.80 | 2.59 | 5.67 | 3.10 | 7.93 | 17.26 | 12.02 | 6.00 | 0.510 |
| UK | - | - | 4534 | 2.88 | 2.76 | 12.08 | 18.47 | 3.10 | 5.49 | 4.02 | 7.32 | 18.10 | 13.55 | 3.35 | 0.582 |
| PL | - | - | 4408 | 2.18 | 3.81 | 11.14 | 19.45 | 2.72 | 4.85 | 3.49 | 7.28 | 19.08 | 10.96 | 7.19 | 0.503 |
| BR | - | - | 3886 | 2.88 | 1.90 | 8.29 | 19.91 | 3.26 | 6.05 | 3.47 | 7.49 | 18.72 | 13.92 | 5.92 | 0.586 |
| FI | - | - | 1409 | 1.88 | 3.40 | 11.55 | 21.45 | 2.20 | 4.95 | 2.92 | 6.56 | 16.41 | 11.48 | 9.85 | 0.520 |
| NL | - | - | 1375 | 2.64 | 2.70 | 11.81 | 18.18 | 3.65 | 6.17 | 4.20 | 5.64 | 17.18 | 13.37 | 4.32 | 0.532 |
| ES | - | - | 1243 | 2.41 | 2.09 | 9.86 | 19.64 | 3.25 | 6.07 | 3.71 | 6.60 | 16.95 | 14.22 | 5.12 | 0.560 |
| SE | - | - | 1231 | 2.29 | 2.60 | 12.01 | 19.03 | 3.07 | 6.12 | 3.53 | 6.15 | 17.44 | 14.11 | 4.82 | 0.584 |
| UA | - | - | 1143 | 1.69 | 2.82 | 13.42 | 20.86 | 2.46 | 4.92 | 3.13 | 7.25 | 18.16 | 10.56 | 6.64 | 0.565 |
| CA | - | - | 1077 | 2.20 | 2.89 | 11.76 | 19.16 | 2.78 | 6.37 | 3.53 | 7.48 | 18.26 | 13.02 | 4.35 | 0.575 |
| FR | - | - | 1055 | 2.87 | 3.44 | 12.77 | 17.58 | 3.25 | 5.68 | 4.71 | 5.55 | 16.89 | 12.99 | 3.73 | 0.535 |

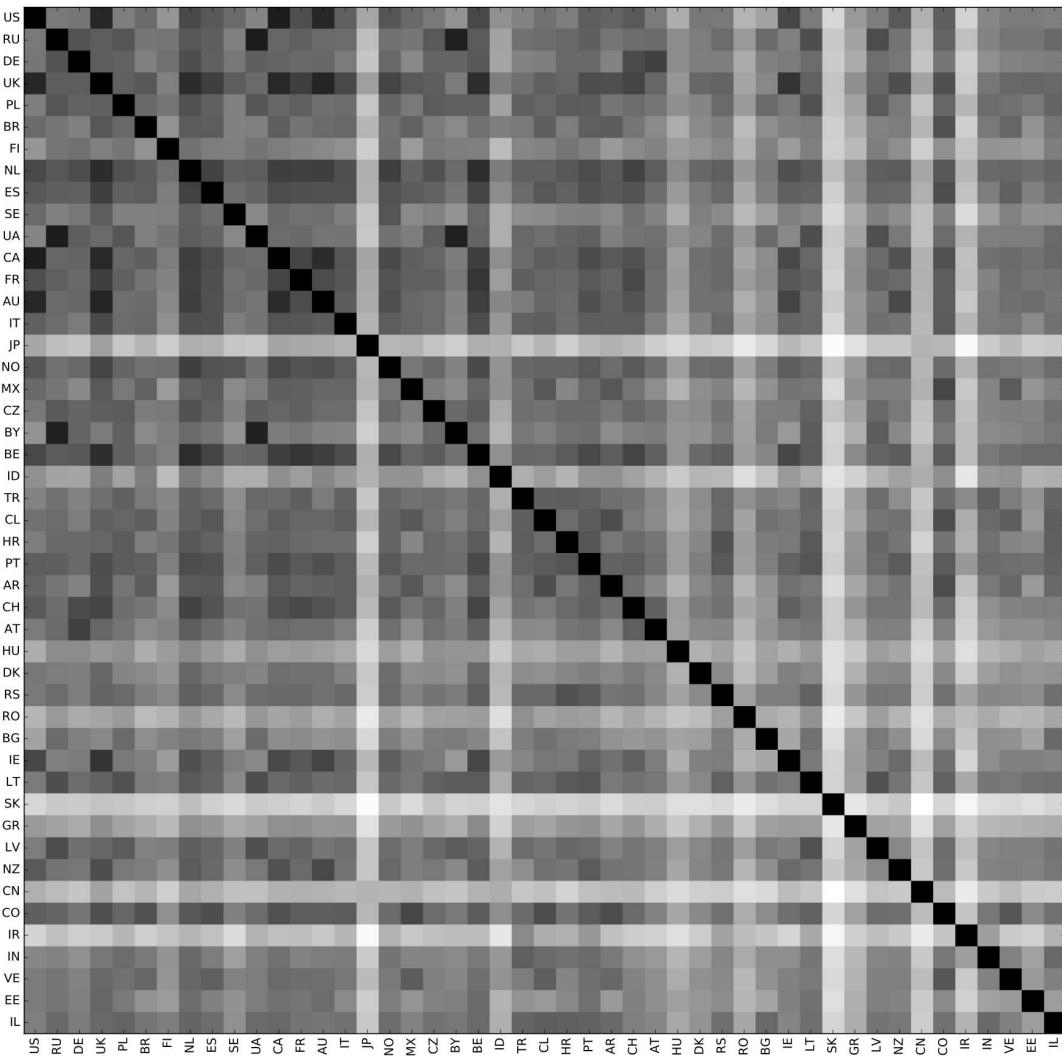
More fine-grained

| U.S.A. | | Japan | | Finland | |
|-------------------|-------|------------------|-------|-------------------|-------|
| Genre tag | PC | Genre tag | PC | Genre tag | PC |
| Rock | 12.51 | Rock | 16.01 | Rock | 11.31 |
| Alternative | 9.63 | Alternative | 8.37 | Metal | 11.15 |
| Alternative rock | 5.86 | J-pop | 5.77 | Alternative | 7.30 |
| Metal | 4.77 | Pop | 4.56 | Alternative rock | 4.56 |
| Pop | 3.62 | Metal | 4.55 | Hard rock | 4.28 |
| Indie | 3.59 | Alternative rock | 4.26 | Heavy metal | 3.44 |
| Hard rock | 3.12 | Indie | 3.63 | Death metal | 2.74 |
| Indie rock | 3.09 | Electronic | 2.29 | Classic rock | 2.61 |
| Classic rock | 2.92 | Hard rock | 2.24 | Pop | 2.21 |
| Electronic | 2.33 | Classic rock | 2.23 | Indie | 2.13 |
| Dance | 2.21 | Visual Kei | 2.03 | Electronic | 2.00 |
| Psychedelic | 1.84 | Indie rock | 2.02 | Indie rock | 1.75 |
| Blues | 1.77 | Heavy metal | 1.68 | Dance | 1.71 |
| Hip-Hop | 1.72 | Dance | 1.66 | Progressive rock | 1.67 |
| Punk | 1.61 | Punk | 1.53 | Nu metal | 1.57 |
| Heavy metal | 1.49 | Psychedelic | 1.45 | Progressive | 1.50 |
| Singer-songwriter | 1.34 | Anime | 1.43 | Power metal | 1.46 |
| Progressive | 1.25 | Electronica | 1.43 | Punk | 1.45 |
| Electronica | 1.24 | Blues | 1.18 | Alternative metal | 1.32 |
| Progressive rock | 1.16 | Japanese rock | 1.17 | Psychedelic | 1.18 |
| New Wave | 1.08 | Progressive rock | 1.06 | Hip-Hop | 1.10 |
| Punk rock | 1.03 | Pop punk | 0.91 | Electronica | 0.90 |
| Nu metal | 0.99 | Nu metal | 0.86 | Speed metal | 0.89 |
| Alternative metal | 0.85 | Progressive | 0.86 | Blues | 0.84 |

Likeminded populations

Observations:

- Clusters of countries with same language: e.g., US, UK, Ireland, Australia, New Zealand
- Clusters of countries with same historical/cultural background: e.g., Russia, Ukraine, Belarus, (Lithuania, Latvia)
- Several outliers: e.g., Japan, China, Iran



Predicting music taste from culture

- Improve MRS in cold start situations

[Skowron et al.; 2017] *Predicting Genre Preferences from Cultural and Socio-economic Factors for Music Retrieval*, Proceedings of the 39th European Conference on Information Retrieval (ECIR).

Predicting music taste from culture

- Improve MRS in cold start situations
- **Culture** model: *Hofstede*



[Skowron et al.; 2017] *Predicting Genre Preferences from Cultural and*
39th European Conference on Information Retrieval (ECIR).

the

Predicting music taste from culture

- Improve MRS in cold start situations
- **Culture** model: *Hofstede*
- **Socio-economic** model: *Quality of Government*
(e.g., GDP, life expectancy, press freedom, ethnic fractionalization)
- Predicting music preferences of country as shares of genres (Gradient Boosting and Random Forest, 16% reduction of RMSE compared to global genre shares)



[Skowron et al.; 2017] *Predicting Genre Preferences from Cultural and Socio-economic Factors for Music Retrieval*, Proceedings of the 39th European Conference on Information Retrieval (ECIR).

Evaluation summary

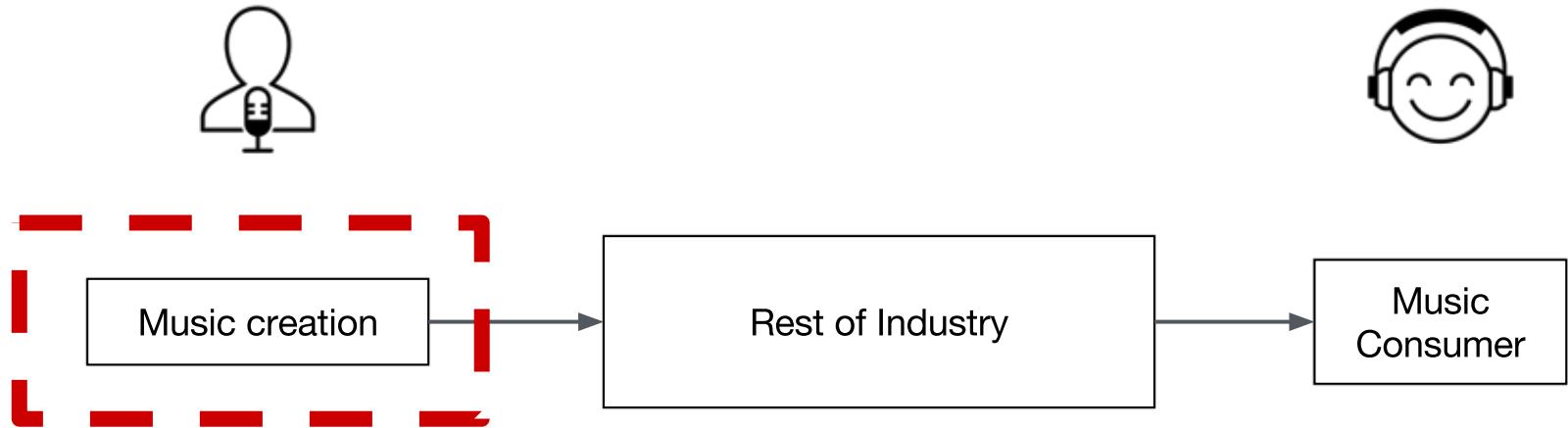
- Listener context and background are highly individual
- Need for context-sensitive evaluation strategies
- Automatic approaches typically fail:
Which preferences are due to context and which due to other factors?
- Typically via user questionnaires/web surveys
- Careful selection of participants necessary (balance w.r.t. gender, age, profession, musical knowledge and background, etc.)

Trending topics

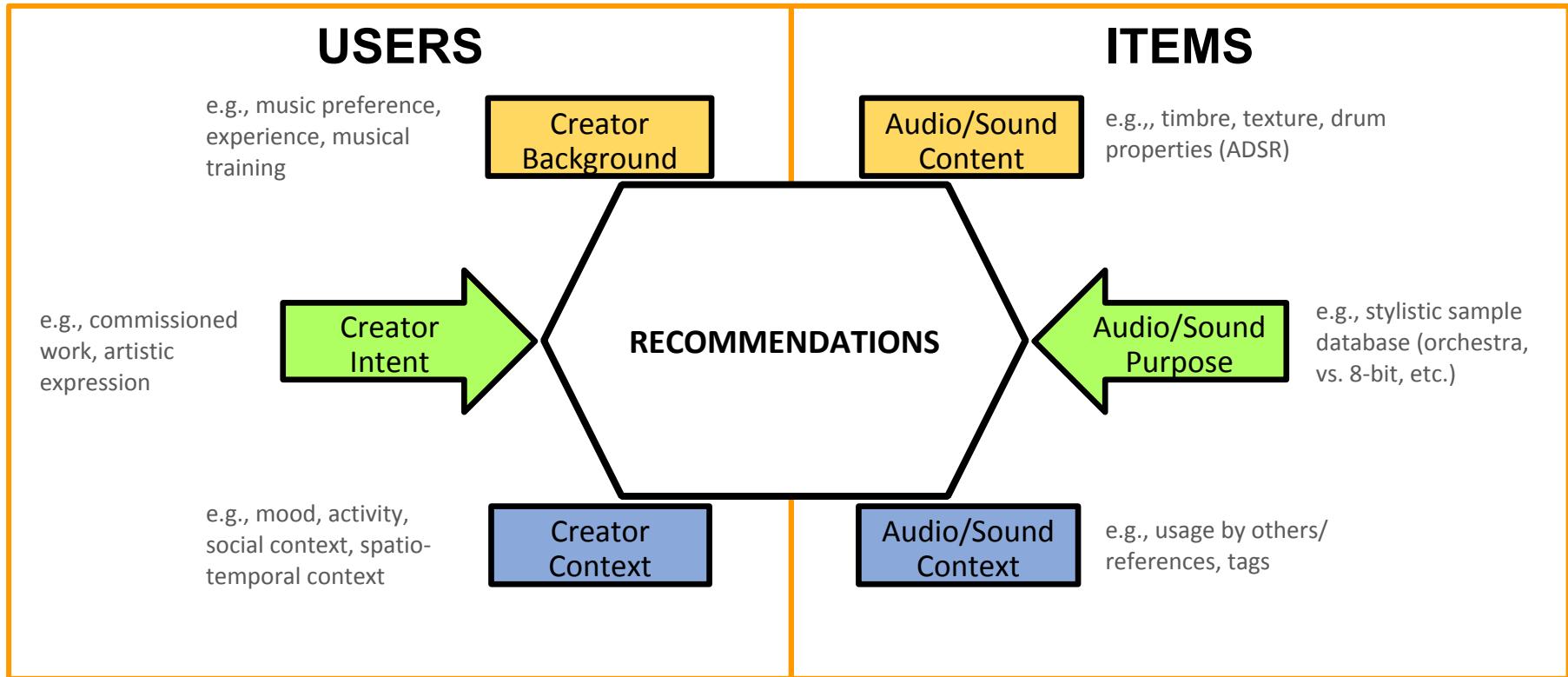
- Integrating intermediate representations (e.g., infer activity on smart phone)
- Culture-aware MRS
- Emotion-aware MRS
- Personality-aware MRS
- Exploit multimodal signals in context-aware MRS
- Automatic feature learning / deep learning

Use Case 3: Recommendation in the Creative Process

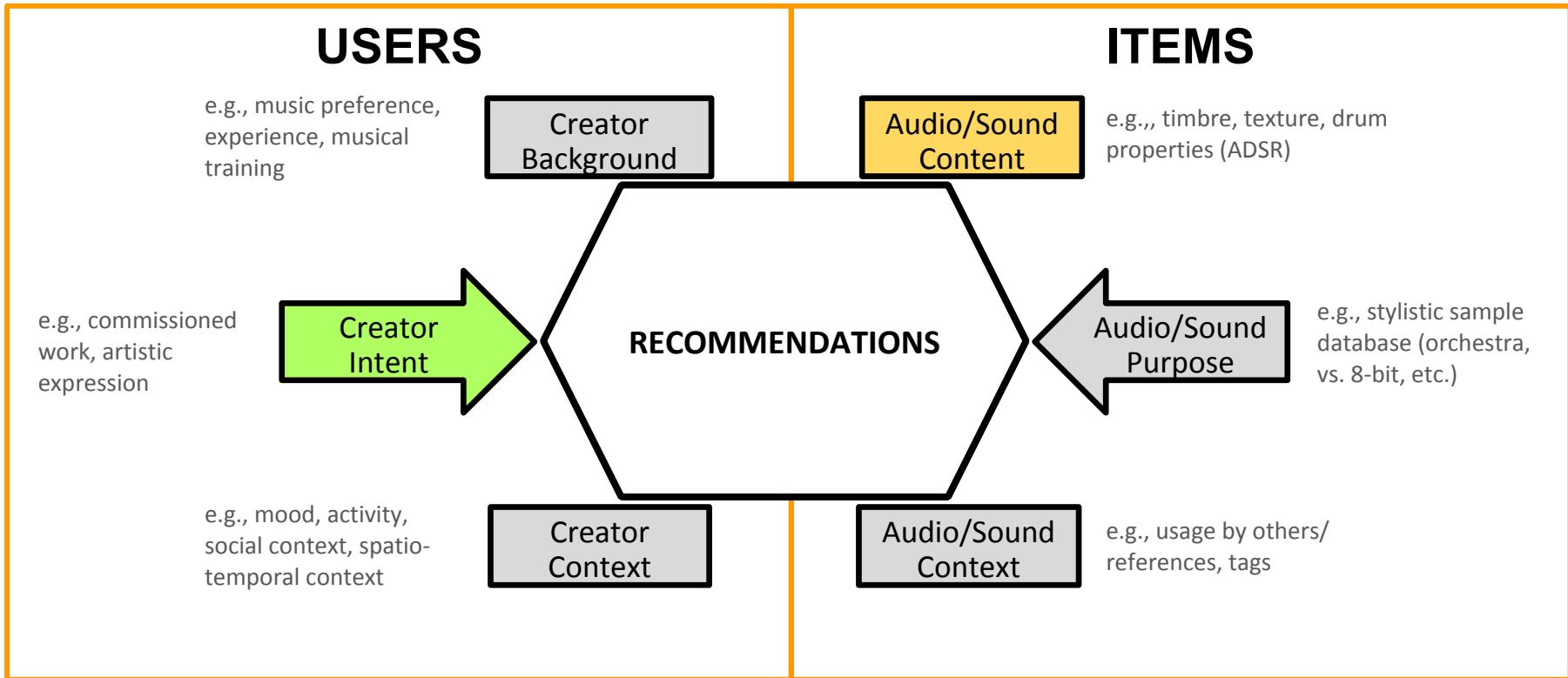
Music Industry Landscape (again)



Creator Hexagon



Creator Hexagon



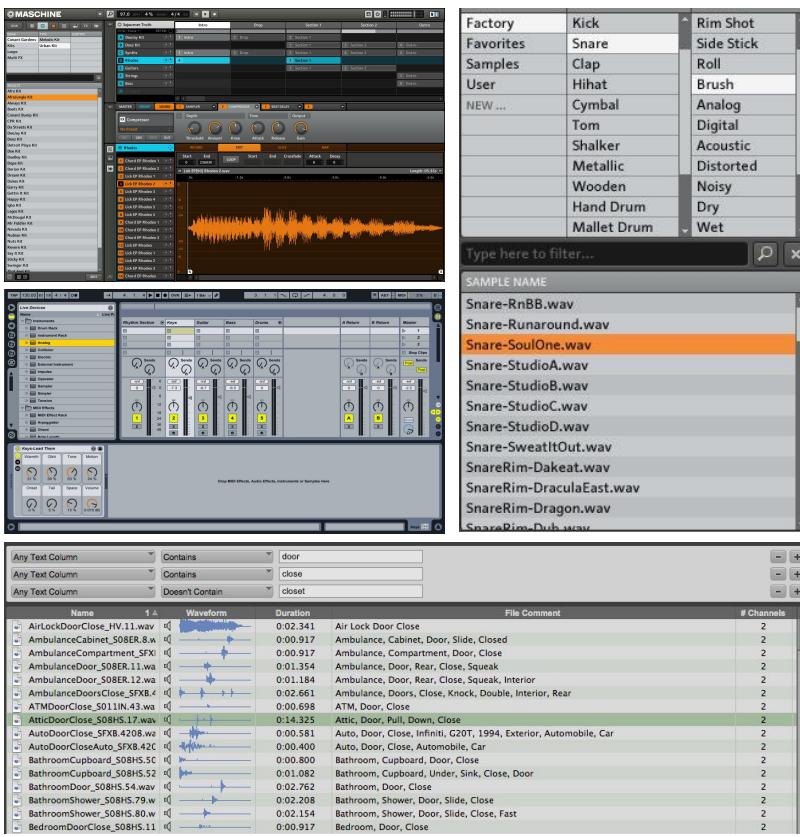
RecSys for Music Producers

- Today, basically all music and audio production becomes digital at one point
- Used tools reflect current practice of music making
 - Sound synthesis, virtual instruments, samples, pre-recorded material, loops, effects
 - Mixing, mastering, control for live performances
- Finding the right sound remains a central challenge:

“Because we usually have to browse really huge libraries [...] that most of the time are not really well organized.” (TOK003)

“Like, two hundred gigabytes of [samples]. I try to keep some kind of organization.” (TOK006)
- Actually the ideal target group for music retrieval and recommendation

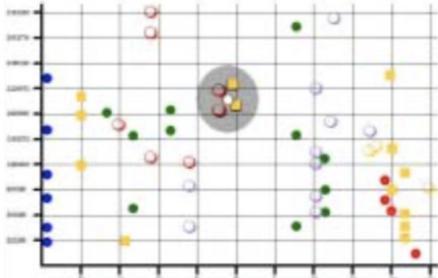
Digital Audio Workstations (DAWs)



- Commercial products come with very large databases of sounds
- Screen optimized for arrangement/mixing
- UI for finding material marginalized or external window
- Incorporated strategies:
 - Name string matching
 - Tag search/filtering
 - Browsing (=scrolling lists)
- No one tags their library!

Facilitating Sound Retrieval

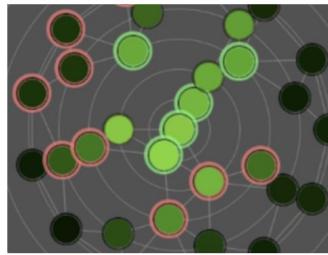
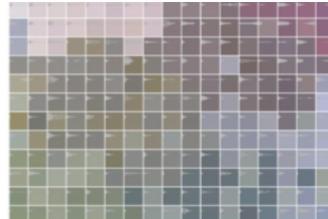
- New (academic) interfaces for sample browsing



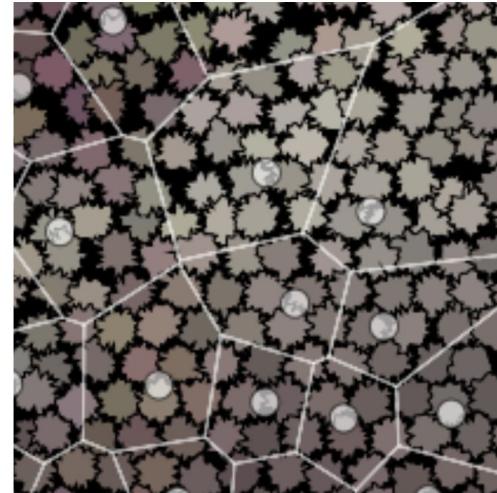
Sonic browser
(Fernström and Brazil, ICAD 2001)



Drum sample browser
(Pampalk et al., DAFX 2004)



Audio Quilt: snare, synth
(Fried et al., NIME 2014)



Texture browser
(Grill and Flexer, ICMC 2012)

- Not so much recommendation. Why?

Let's Ask the Users!

- Interviews, tests, and feedback sessions
 - Participatory workshops
 - Music Hack Days
 - Red Bull Music Academy
- Unique opportunity for research to get access to up-and-coming musicians from around the world
- Peer-conversations through semi-structured interviews
- Potentially using non-functional prototypes as conversation objects



[Andersen, Knees; 2016] *Conversations with Expert Users in Music Retrieval and Research Challenges for Creative MIR*. ISMIR.

[Ekstrand, Willemsen; 2016] *Behaviorism is Not Enough: Better Recommendations through Listening to Users*. RecSys.

The Role of Recommendation



- Recommenders are seen critical in creative work

“I am happy for it to make suggestions, especially if I can ignore them” (TOK007)

- Who is in charge?

“as long as it is not saying do this and do that.” (TOK009)

- Artistic originality in jeopardy

“as soon as I feel, this is something you would suggest to this other guy as well, and then he might come up with the same melody, that feels not good to me. But if this engine kind of looked what I did so far in this track [...] as someone sitting next to me” (NIB4)

“then it’s really like, you know, who is the composer of this?” (NIB3)



[Andersen, Grote; 2015] *GiantSteps: Semi-structured conversations with musicians.* CHI EA.

The Role of Recommendation (2)



- Users open to **personalization**, would accept cold-start

“You could imagine that your computer gets used to you, it learns what you mean by grainy, because it could be different from what that guy means by grainy” (PA008)

- Imitation is not the goal: **opposition** is the challenge

“I’d like it to do the opposite actually, because the point is to get a possibility, I mean I can already make it sound like me, it’s easy.” (TOK001)

“Make it complex in a way that I appreciate, like I would be more interested in something that made me sound like the opposite of me, but within the boundaries of what I like, because that’s useful. Cause I can’t do that on my own, it’s like having a bandmate basically.” (TOK007)

[Knees et al.; 2015] “I’d like it to do the opposite”: Music-Making Between Recommendation and Obstruction. DMRS workshop.

The Role of Recommendation (3)



Two recurring themes wrt. recommendation:

1. Virtual band mate (controlled “collaborator”)

“I like to be completely in charge myself. I don’t like other humans sitting the chair, but I would like the machine to sit in the chair, as long as I get to decide when it gets out.” (TOK014)

2. Exploring non-similarity (“the other”, “the strange”)

“So if I set it to 100% precise I want it to find exactly what I am searching for and probably I will not find anything, but maybe if I instruct him for 15% and I input a beat or a musical phrase and it searches my samples for that. That could be interesting.” (TOK003)

cf. *defamiliarization*: art technique to find inspiration by making things different

“The Other” in RecSys and Creative Work

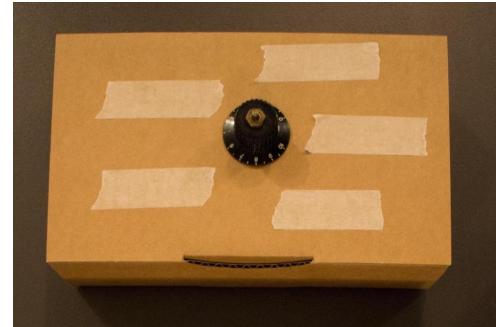
- “**Filter bubble**” effects in recommender systems:
obvious, predictable, redundant, uninspiring, disengaging results
- Responses: optimizing for diversity, novelty, serendipity, unexpectedness
- In particular in creative work
 - no interest in imitating existing ideas and “more of the same” recommendations
 - challenging and questioning expectations and past behavior
- For **collaboration with an intelligent system** for creativity, opposite goals matter:
 - **change of context** instead of *contextual preservation*
 - **defamiliarization** instead of *predictability, explainability*
 - **opposition** instead of *imitation*
 - **obstruction** instead of *automation*

[Adamopoulos, Tuzhilin; 2015] *On Unexpectedness in Recommender Systems: Or How to Better Expect the Unexpected.* ACM TIST 5(4)

[Zhao, Lee; 2016] *How Much Novelty is Relevant?: It Depends on Your Curiosity.* SIGIR.

Testing the Idea of Controlled “Strangeness”

- Instead of retrieving “more of the same” through top-N results
- As a response, we **propose the idea of the Strangeness Dial**
- Device to **control the degree of otherness**
 - turn to left: standard similarity-based recommendations,
 - turn to right: “the other”
- Built as a non-functional prototype (cardboard box) to enable conversations
- Also tested as a software prototype for strangeness in rhythm variation



[Knees, Andersen; 2017] *Building Physical Props for Imagining Future Recommender Systems*. IUI HUMANIZE.

Responses to the Strangeness Dial (Idea)

- Idea and concept are received well (via non-functional prototype)

"For search it would be amazing." (STRB006)

"In synth sounds, it's very useful [...] Then the melody can also be still the same, but you can also just change the parameters within the synthesizer. That would be very cool." (STRB003)

"That would be crazy and most importantly, it's not the same strange every time you turn it on."
(TOK016)

- ... but everybody understands it differently

"Strangeness of genre maybe, how different genre you want. [...] It depends how we chart the parameter of your strangeness, if it's timbre or rhythm or speed or loudness, whatever." (STRB001)

"No, it should be strange in that way, and then continue on in a different direction. That's the thing about strange, that there's so many variations of strange. There's the small, there's the big, there's the left, there's the right, up and down." (STRB006)

Responses to the Strangeness Dial (Prototype)

- The software prototype tried to present “otherness” in terms of rhythm
- This was perceived by some but didn’t meet expectations of the majority
 - “*I have no idea! It’s just weird for me!*” (UI03)
 - “*It can be either super good or super bad.*” (UI09)
- Concept is highly subjective, semantics differ
- Demands for personalization (i.e., “which kind of strange are you talking about?”)
 - “*Then you have a lot of possibility of strange to chose from, actually. Like for me, I would be super interested to see it in ‘your’ strange, for example.*” (STRB006)

Some Takeaways

- User intent is a major factor
- Experts need recommenders mostly for inspiration: serendipity is key
- Control over recommendation desired (...transparency could help)
- Not much collaborative interaction data in this domain
 - Strong focus on content-based recommenders
 - To find what is unexpected, new sources of (collaborative) usage data need to be tapped
- Making music is mostly a collaborative task and a useful recommender needs to be a collaborator



Trending Topics

Intelligent machines in music creation: **AI for automatic composition**



Flow Machines (ERC project; François Pachet, now at Spotify)

e.g., assisted composition, automatic continuation/accompaniment, composition in style of X (“Daddy’s Car” ... in the style of Beatles)



Magenta (Google project building on top of TensorFlow)

deep neural networks for, e.g., expressive renderings, sound generation, interactive note sequence generation



Jukedeck

automatic creation of royalty-free soundtracks, personalized music

Working with Watson

Grammy award-winning music producer Alex Da Kid paired up with Watson to see if they could create a song together. Watson's ability to turn millions of unstructured data points into emotional insights would help create a new kind of music that for the first time ever, listened to the audience.



Cognitive creation

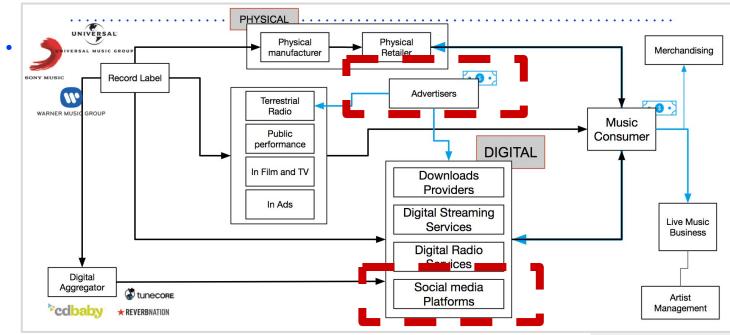
Alex Da Kid used Watson's emotional insights to develop 'heartbreak' as the concept for his first song, 'Not Easy,' and explored musical expressions of heartbreak by working with **Watson Beat**. Alex then collaborated with X Ambassadors to write the song's foundation, and lastly added genre-crossing artists Elle King and Wiz Khalifa to bring their own personal touches to the track. The result was an audience-driven song launching us all into the future of music.

RecSys just an intermediary step to personalized content creation?

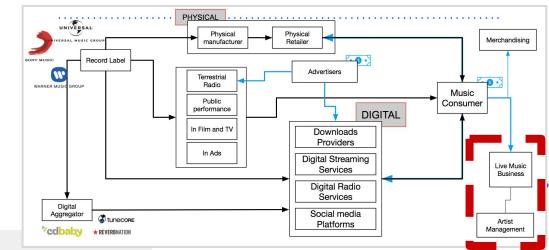


Further use cases

- Alternative audio content to music, e.g.
 - Ads (where a lot of \$\$\$ is)
 - News, Podcasts
 - Artist messages
- Central battle-place of competition with AM/FM radio
 - Streaming in a better place for ads-targetting
 - Radio in a better place for alternative content
- Open problems:
 - How to sequence different types of content? (i.e. what content when?)
 - How to personalize?
 - How to present it to the listener?
 - How to blend music and audio in social media platform experiences?



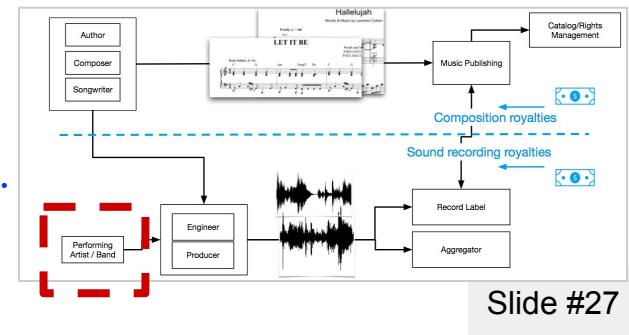
Slide #28



Slide #28

Further use cases

- Live Music Business, e.g.
 - Recommending upcoming concerts to listeners
 - Recommending artists to e.g. music festivals
- Recommendations for artist management, e.g.
 - Help agents find best opportunities for artists
- Recommendations to artists
 - Recommending artists where to play
 - Help artists grow their careers, with insights based on data
 - Help artists communication with their fanbase



Slide #27

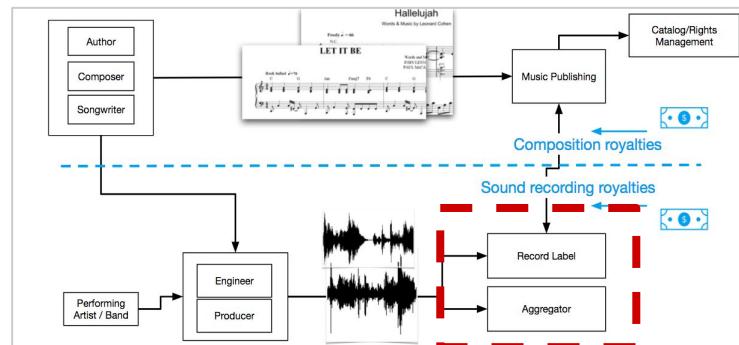
TICKETFLY



Further use cases

- RecSys (and data science) for record labels, e.g.
 - Assist A&R in finding new talents
 - An artist is launching an album, which track(s) to promote?
 - Make the best use / better monetization of back-catalogue
 - General assistance in business decisions
 - Marketing (where, to whom, how)
 - etc.
- NB: Some of these use cases addressed in upcoming H2020 project *FuturePulse*
(Multimodal Predictive Analytics and Recommendation Services for the Music Industry)

NB: Interesting explore/exploit trade-off



Slide #27

Ethics

- Business-related recommendations (e.g. promotional content) vs. what the user actually wants/needs
- Impact on popular culture (shaping what makes popular culture)
 - Responsibility to counteract algorithmic biases and business-only metrics
 - “Filter bubble”
- Impact on “how” people listen to music (e.g. influence on curiosity)
- Impact on artists, on what’s successful, on the type of music composed
- Privacy (couldn’t attend tutorial next door right now ;-)



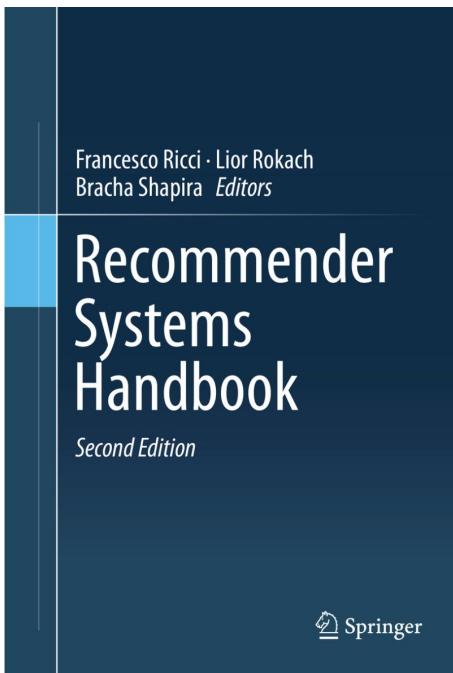
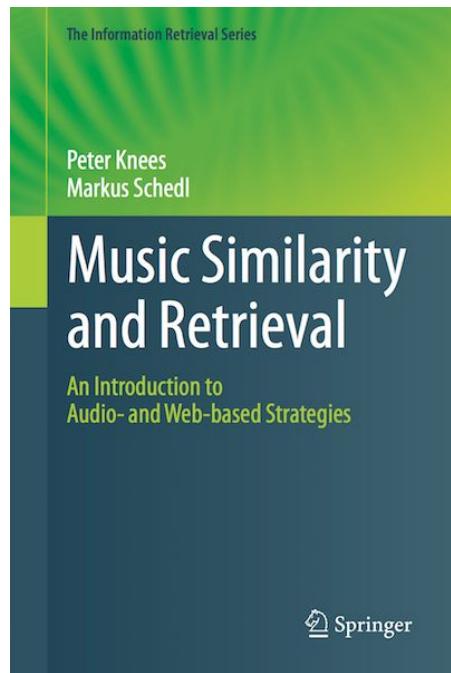
[Knijnenburg, Berkovsky, 2017] *Privacy for Recommender Systems*, Tutorial RecSys 2017

Challenges

- Recommending diverse types of content
- Understanding listening behavior in context
- Blending social interactions in music streaming
- Blending human-curated recommendations with algorithmic ones
- Transparency and trust
- Managing a listener's plurality of tastes without being disruptive
- Metrics for approximating long-term user satisfaction
- Voice-driven music interactions (in car, at home)

[Motajcsek et al. 2016] *Algorithms Aside: Recommendations as the Lens of Life*, RecSys 2016

More on This...



Music Similarity and Retrieval

by P. Knees and M. Schedl

Recommender Systems Handbook (2nd ed.)

Chapter 13: Music Recommender Systems

by M. Schedl, P. Knees, B. McFee, D. Bogdanov, and M. Kaminskas

Take-Home Messages

- Music is not “just another item”
- Dramatic changes in music consumption (growth, ownership → access) imply great challenges and impact/benefit for RecSys community
- RecSys technology has potential to be disruptive in many parts of the music industry (not just end-user consumption)
- Creating truly personalized music RecSys and evaluating user satisfaction is still challenging

Practical: Datasets

- Million Song Dataset: <https://labrosa.ee.columbia.edu/millionsong>
- Million Musical Tweets Dataset: <http://www.cp.jku.at/datasets/mmtd>
- #nowplaying Spotify playlists dataset: <http://dbis-nowplaying.uibk.ac.at>
- LFM-1b: <http://www.cp.jku.at/datasets/LFM-1b>
- Celma's Last.fm datasets:
<http://www.dtic.upf.edu/~ocelma/MusicRecommendationDataset/index.html>
- Yahoo! Music: <http://proceedings.mlr.press/v18/dror12a.html>
- Art of the Mix (AotM-2011) playlists:
<https://bmcfee.github.io/data/aotm2011.html>

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The End

Thank you

Q&A



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