TUTORIAL

ISMIR'18

23-09-2018

Overview and New Challenges of Music Recommendation Research in 2018

Markus Schedl
JKU Linz

Peter Knees
TU Wien

Fabien Gouyon
Pandora

The Band

kus Schedl (@m_schedl)
ociate Professor
annes Kepler University (JKU) Linz, Austria

Peter Knees (@peter_knees)
Assistant Professor
TU Wien, Austria

Fabien Gouyon (@fgouyon)
Principal Scientist & Head of Research, Europe
Pandora

Overview

- Bird’s-eye View on the Music Industry - Discovery & Consumption
- Data and Algorithms
- Continuation of Music Listening Experience
- Recommendation in the Creative Process of Music Making
- What’s Next?

Context

Latest version of slides available at:
https://www.slideshare.net/FabienGouyon/music-recommendation-2018

Last ISMIR tutorial on the topic: ISMIR 2007
Then RecSys tutorial in 2011 by Celma & Lamere

Then our 2017 RecSys tutorial
→ This tutorial is an adaption and extension of last year's at RecSys

What’s special to music recommendation?

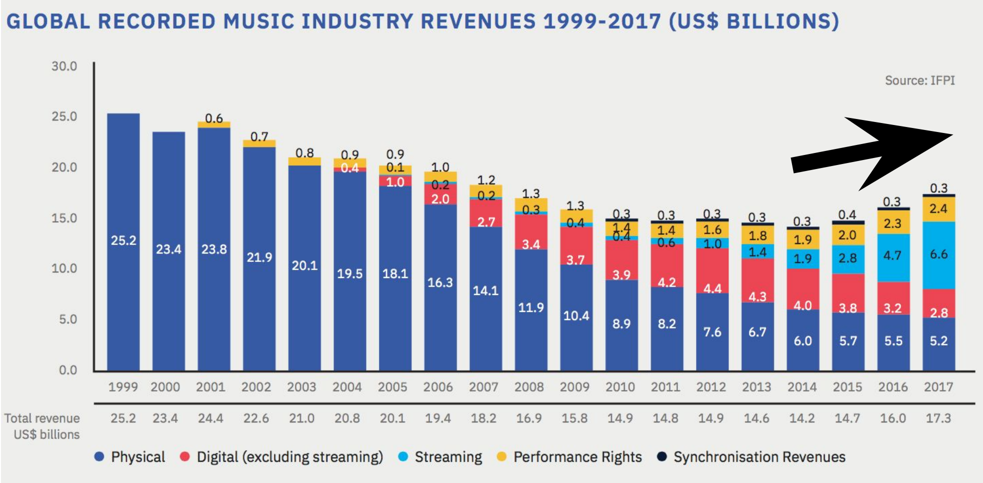
- More and more relevant to the Music Industry with rise of streaming
- Wide range of duration of items (2+ vs. 90+ minutes),
  Lower commitment, items more “disposable”, low item cost
  → “bad” recommendations maybe not as severe
- Magnitude of available data items (Millions) & data points (Billions)
- Diversity of modalities (audio, user feedback, text, etc.)
- Various types of items to recommend (songs, albums, artists, audio samples, concerts, venues, fans, etc.)
- Recommendations relevant for various actors (listeners, producers, performers, etc.)

What’s special to music recommendation?

- Very often consumed in sequence
- Re-recommendation often appreciated (in contrast to e.g. movies)
- Often consumed passively (while working, background music, etc.)
- Yet, highly emotionally connoted (in contrast to products, e.g. home appliances)
- Different consumption locations/settings: static (e.g., via stereo at home) vs. variable (e.g., via headphones during exercise), alone vs. in group, etc.
- Listener intent and context are crucial
- Importance of social component
- Music often used for self-expression

Bird's-eye View on the Music Industry - Discovery & Consumption

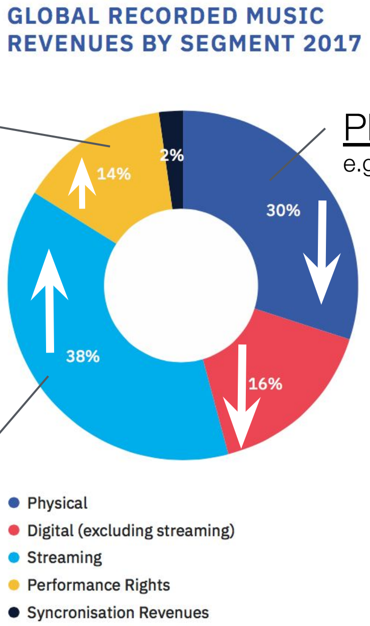
Music Consumption



PERFORMANCE RIGHTS

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

(NB: Excluding perf. rights from Streaming)

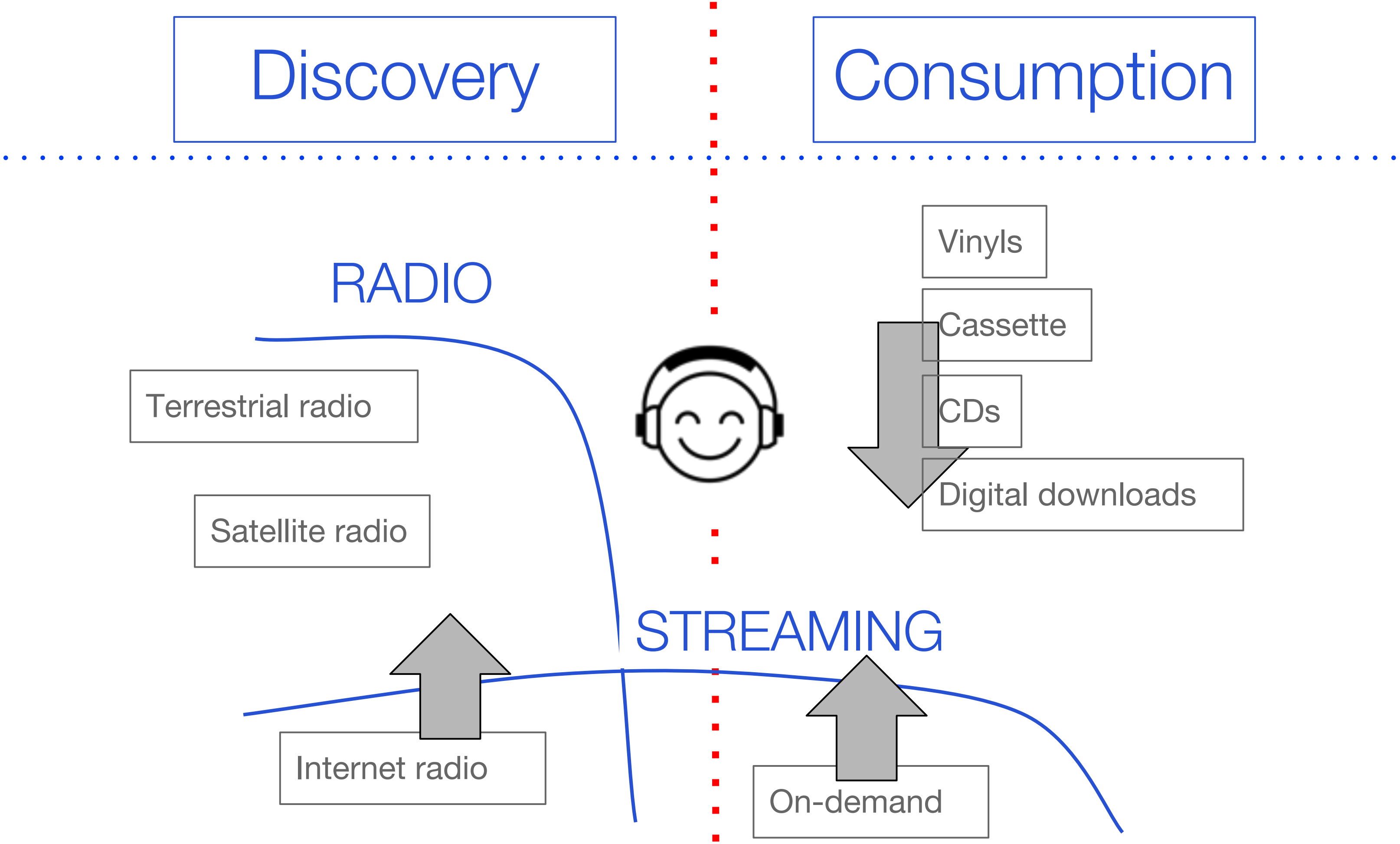


PHYSICAL

e.g. CDs

STREAMING

- Internet radio & on-demand
- Ad-supported & subscriptions

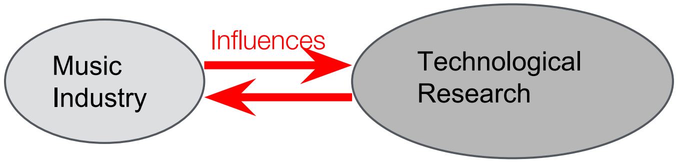

Discovery
Consumption
RADIO
Terrestrial radio
Satellite radio
Internet radio
Vinyls
Cassette
CDs
Digital downloads
STREAMING
On-demand

Music Industry Changing Landscape

- Growing industry
- Accelerating transition: Physical → Streaming

Not just a format transition, but a fundamental revolution.
Moving **away from “Discover + Own”** model, **towards “Access”** model

→ <u>Change of paradigm</u>: Recommending an **experience**, not just a product/item. Distributor now must guide listener in (never-ending) consumption, not just sell.



Influence of Tech. Research

- **"Access"** can have different meanings
- New listening format still **not well-defined**… The field is wide open
- Lots of recent developments

Lean-**in** vs. Lean-**back**

e.g. on-demand

e.g. Internet radio

Format	Interactive	Non-interactive
$€¥	Ad-supported / "free"	Subscription

(NB: These are only examples, not an exhaustive mapping)

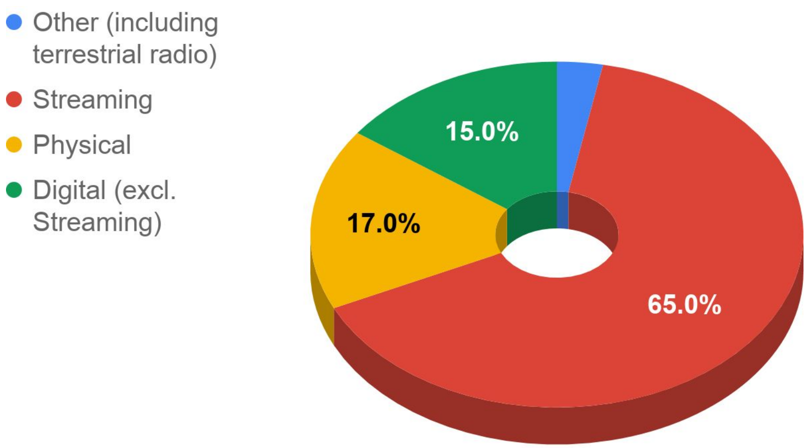
→ High impact potential from Tech. Research (i.e. YOU)

Music Discovery

Looking at where $€¥ comes from is not the full picture…
… <u>time spent listening</u>, by media, tells a different story:

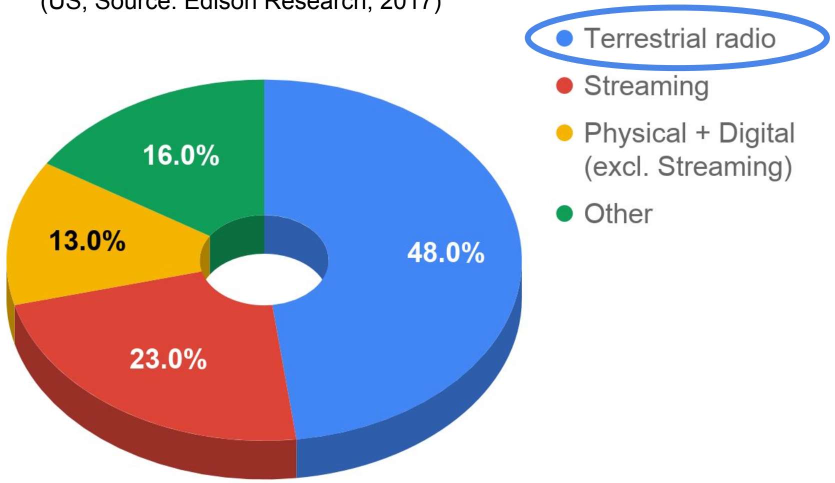
Revenue

(US, Source: RIAA, 2017)

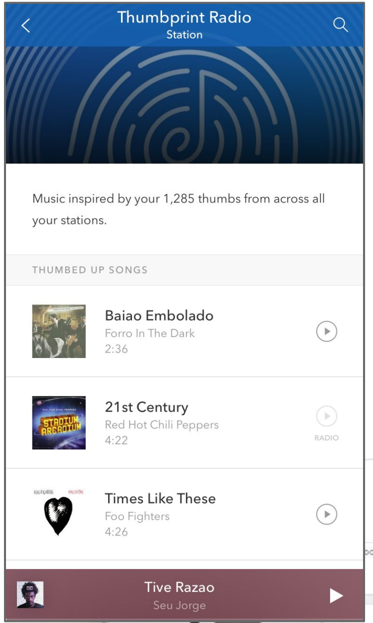


Time spent listening

(US, Source: Edison Research, 2017)



Music Discovery

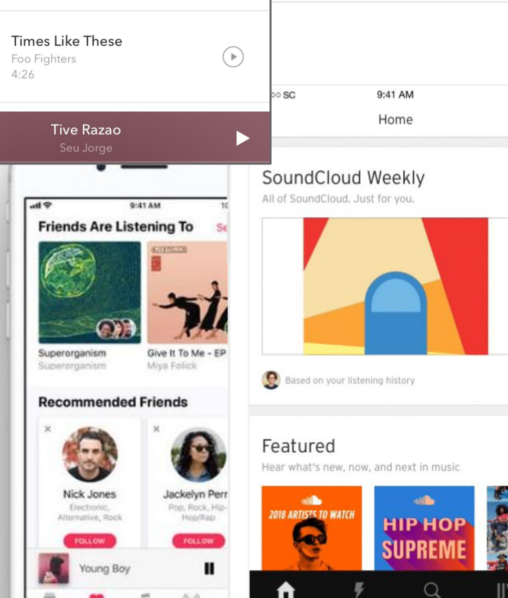


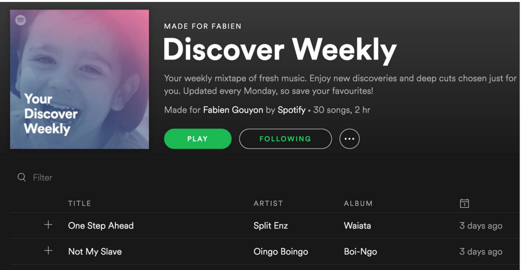
- Streaming “taking over” physical & downloads
- But competing with terrestrial radio, too

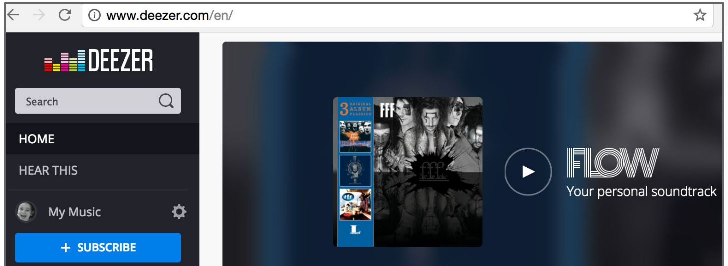
The Quest for “Discovery”

Ongoing quest for defining listening format calls for:

- Innovative Discovery features
- <u>Right balance between lean-in & lean-back experiences</u>



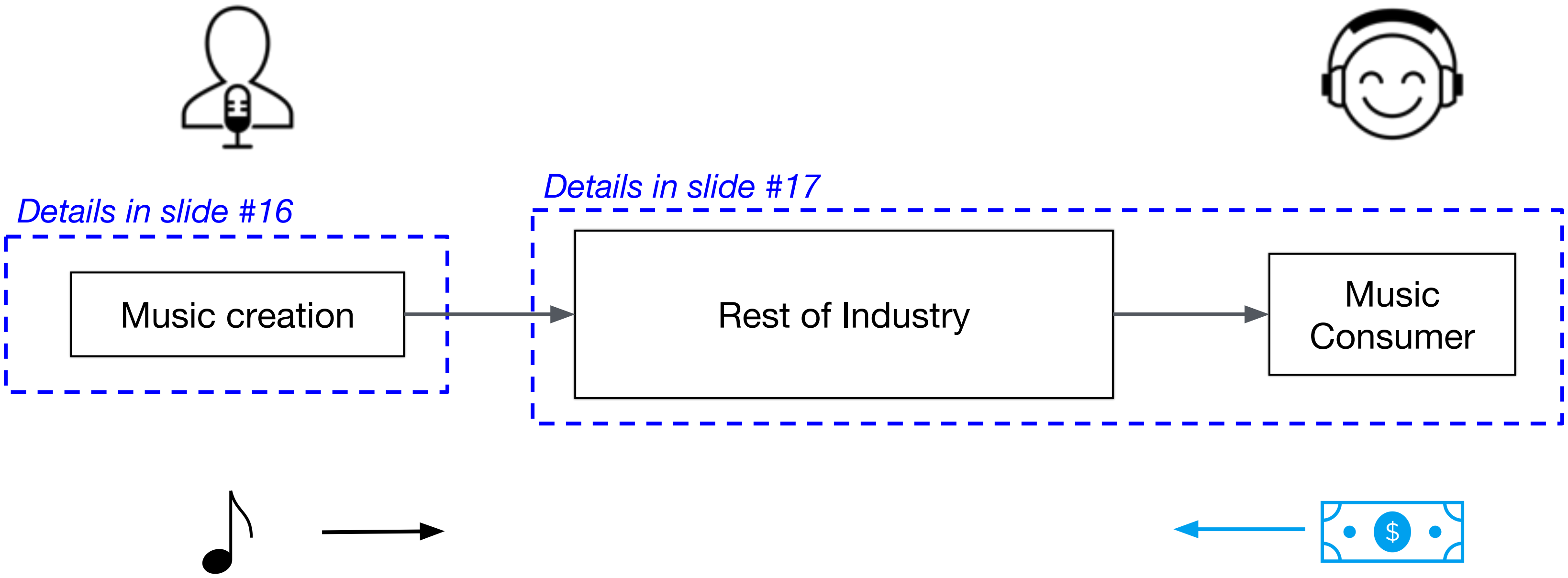




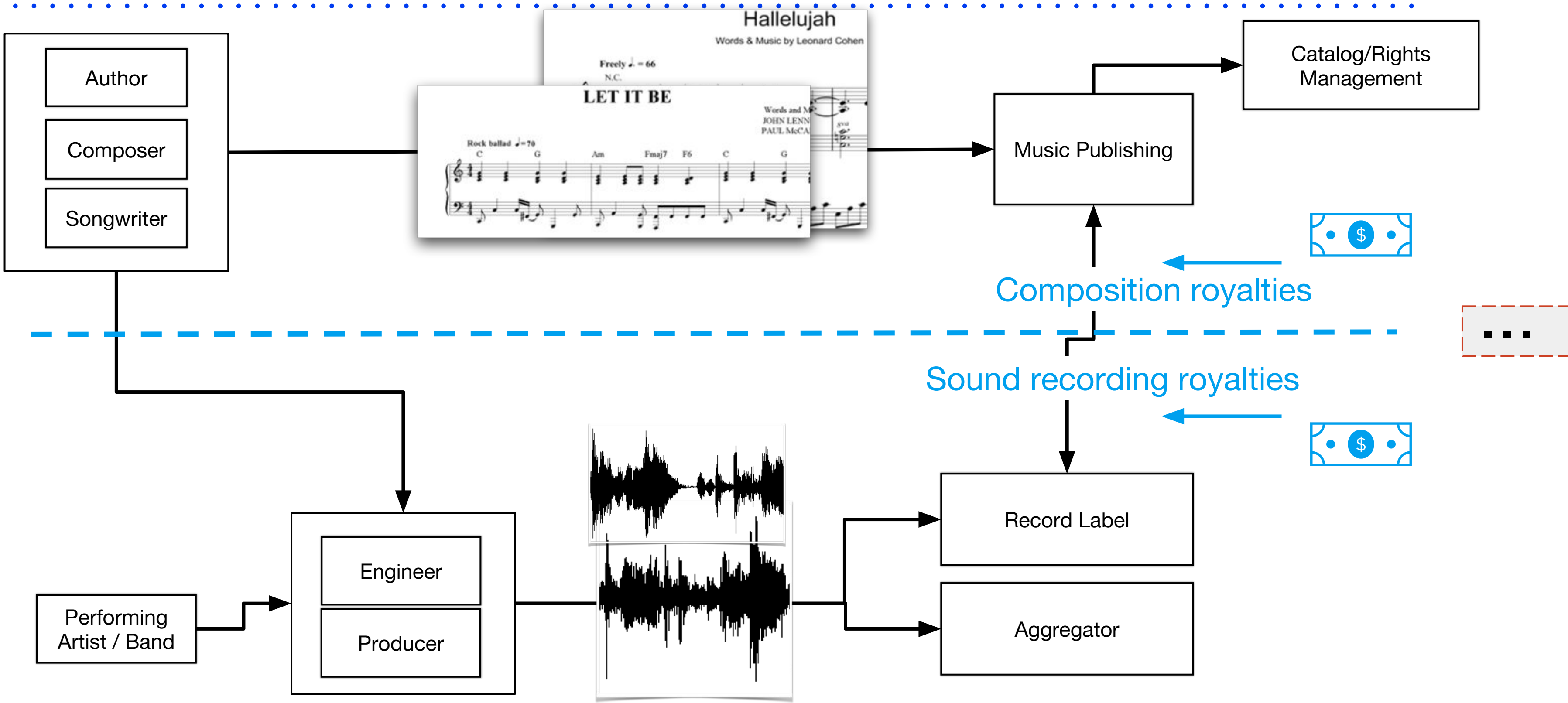
Challenge for MIR

- Produce data-driven insights that can inform new discovery products

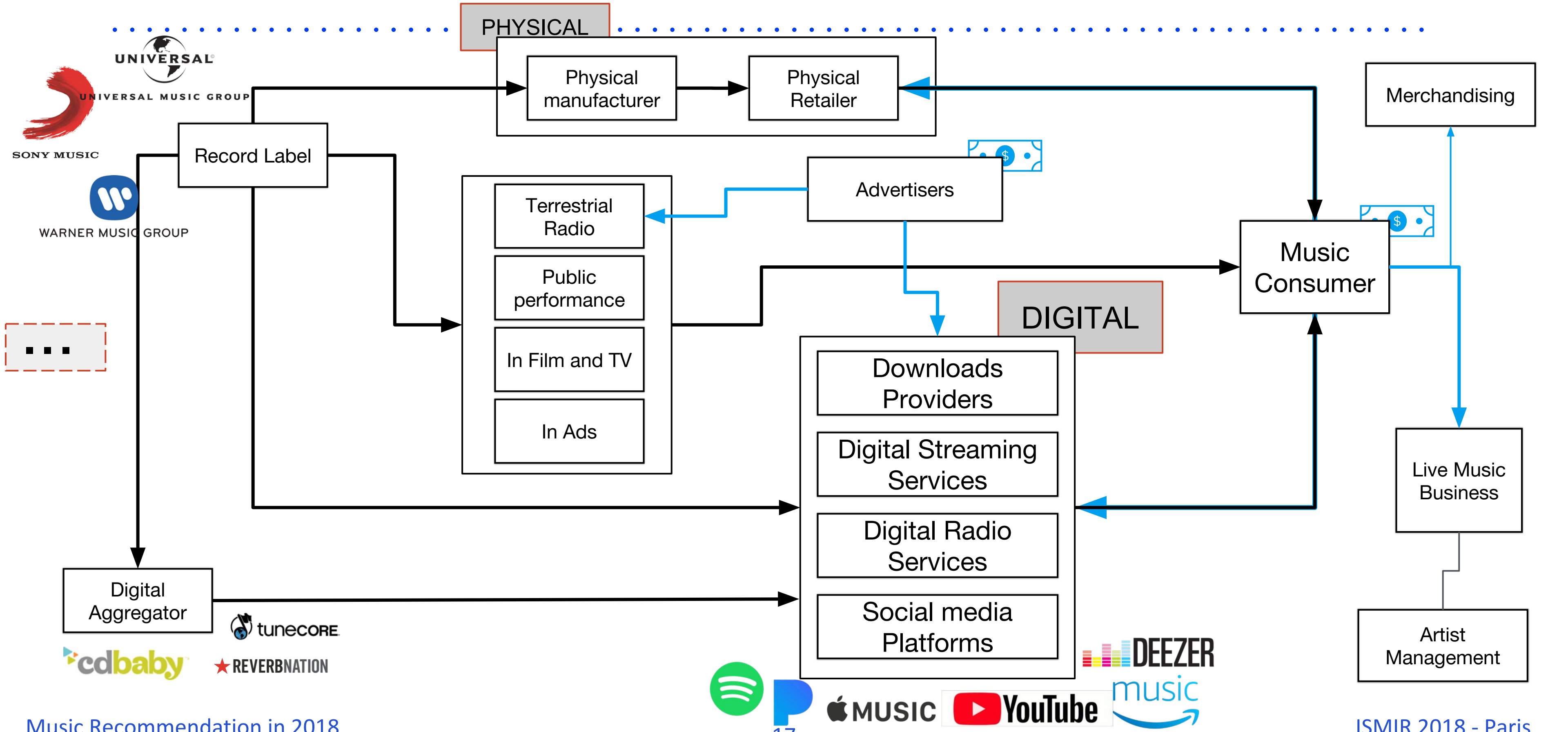
You said "Music Industry Landscape"?



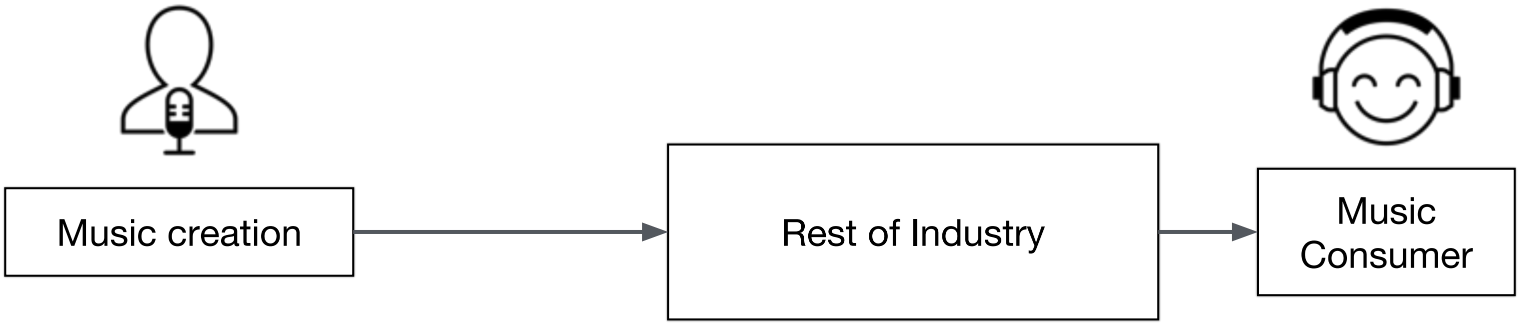
Music Industry Landscape

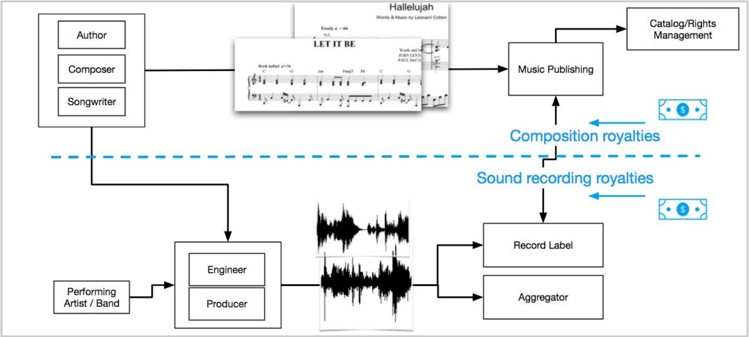


Music Industry Landscape

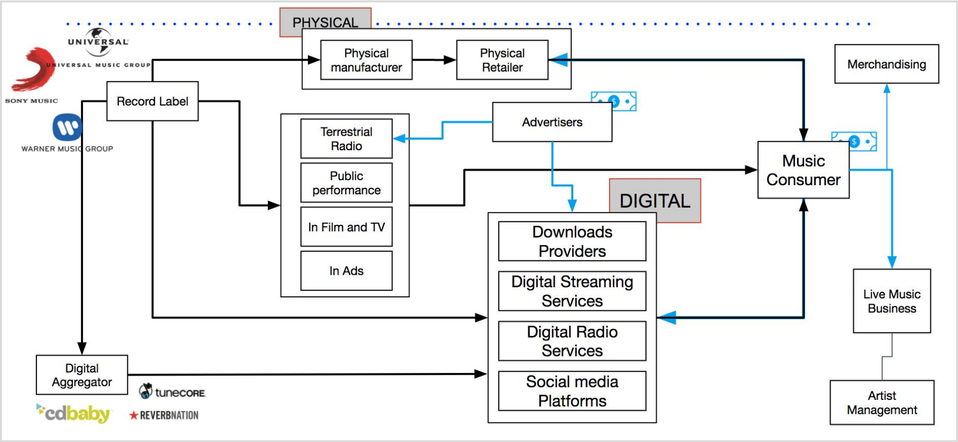


Music Industry Landscape





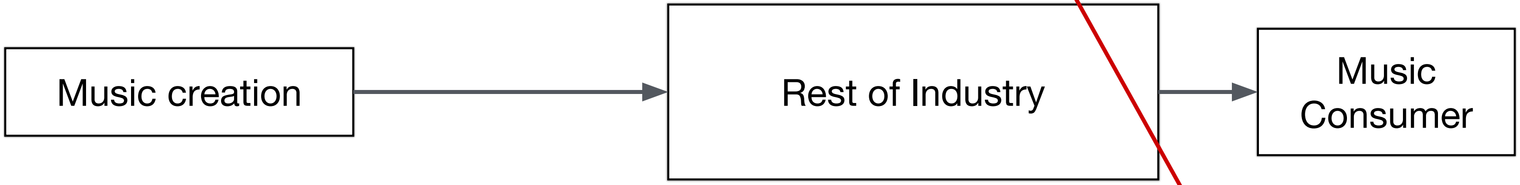
Slide #16

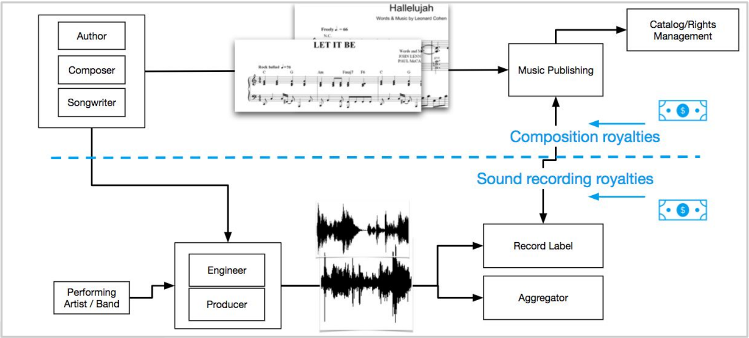


Slide #17

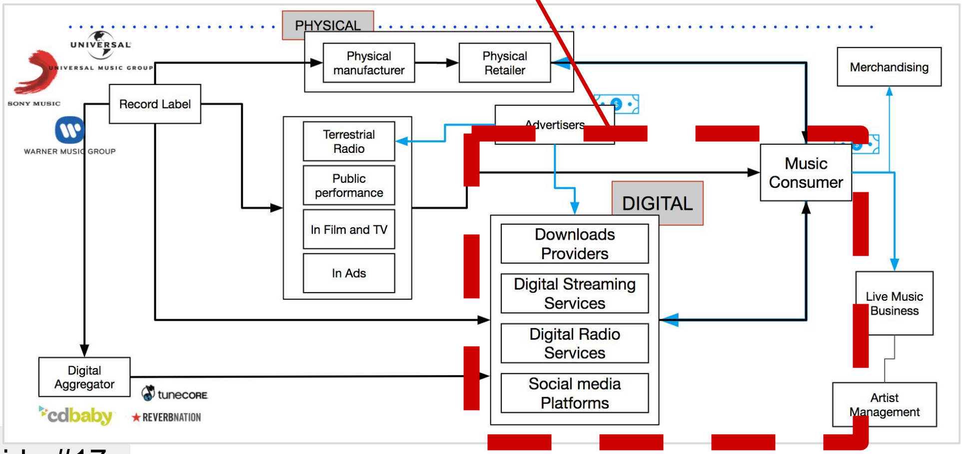
Music Industry Landscape

We'll talk about MIR applied here first...





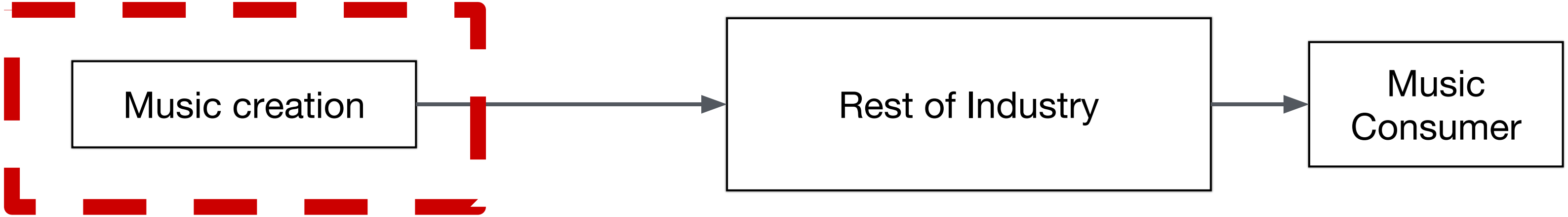
Slide #16

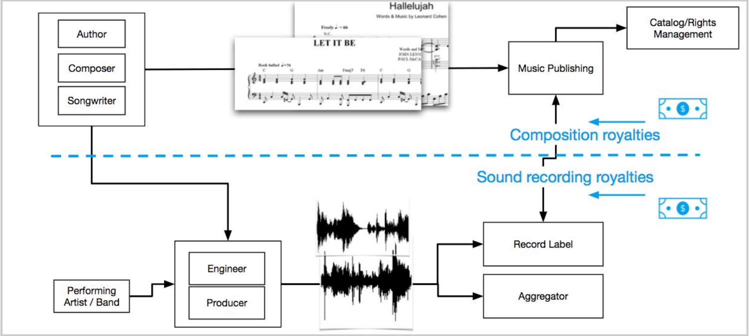


Slide #17

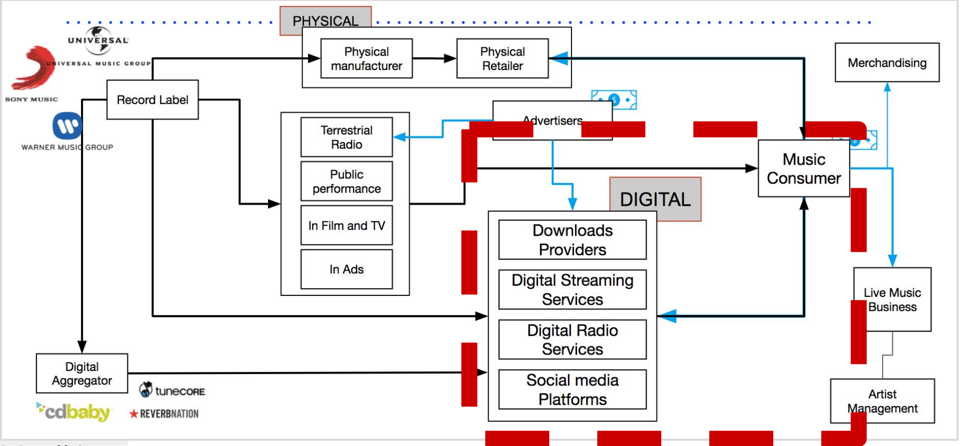
Music Industry Landscape

… and then we'll talk about MIR applied here too





Slide #16



Slide #17

Challenge for MIR

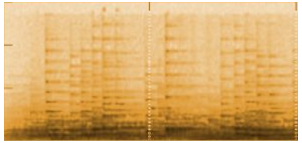
- Identify other cases where some part of the music industry --beyond music consumption-- can be disrupted by R&D in MIR

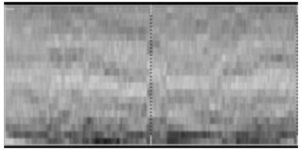
Data and Algorithms

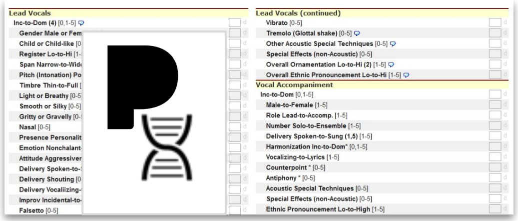
Lots of Data and Data Sources

Content (audio, symbolic, lyrics)

- Machine listening/content analysis
- Human labelling

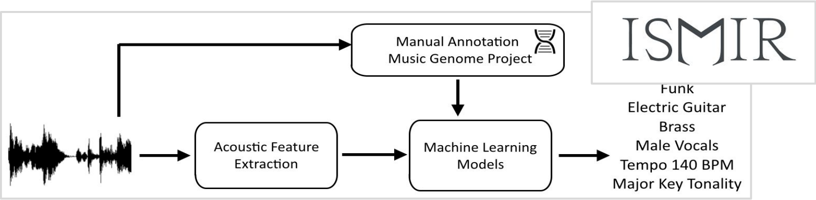






Meta-data

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



UNIVERSAL UNIVERSAL MUSIC GROUP SONY MUSIC WARNER MUSIC GROUP DDEX rovi Discogs gracenote A NIELSEN COMPANY

Lots of Data and Data Sources

User-generated

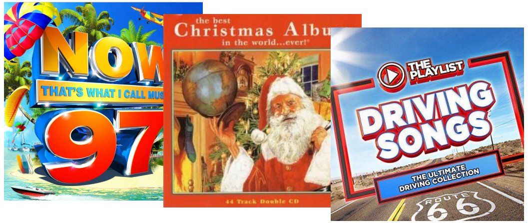
- “Community meta-data”
- e.g., tags, reviews

Interaction Data

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

Curated collections

- Playlists, radio channels
- CD album compilations



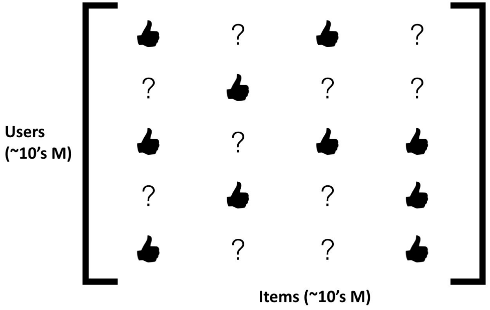
Practical: Datasets

- Million Song Dataset: https://labrosa.ee.columbia.edu/millionsong
- MuMu Dataset: https://www.upf.edu/en/web/mtg/mumu
- 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/
- Yahoo! Music: http://proceedings.mlr.press/v18/dror12a.html
- Art of the Mix (AotM-2011) playlists: https://bmcfee.github.io/data/aotm2011.html

- Spotify RecSys Challenge Datasets (Million Playlists Dataset) ?

Collaborative Filtering (CF)

- Exploiting **interaction data**
- Stemming from “usage” of music
  → close to “what users want”
- Data: Implicit (e.g. plays) or explicit (e.g. thumbs)



- Task: completion of user-item matrix (matrix very sparse)
- Main underlying assumption: users that had similar taste in the past, will have similar taste in the future
- Simple methods: memory-based CF
  - User-based CF: weighted rating of nearest users (sim. of matrix rows)
  - Item-based CF: weighted rating of user’s most similar items (sim. of matrix columns)

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

Factors Hidden in the Data

Original assumption of first matrix factorization-based recommender systems:

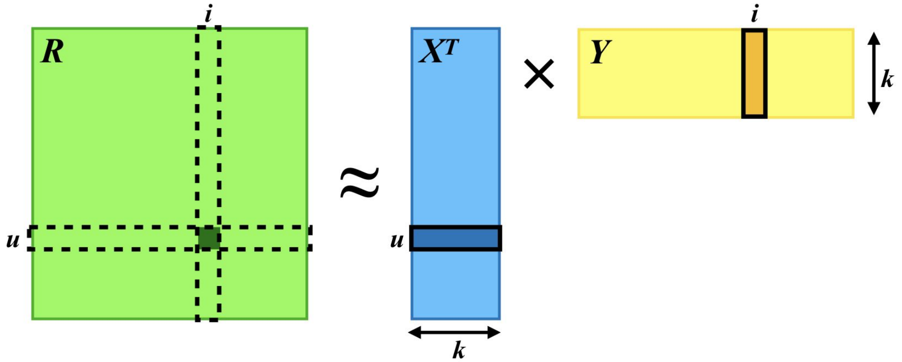
- Observed ratings/data are interactions of 2 factors: users and items
- Latent factors are representation of users and items

Matrix Factorization (cf. SVD)

- Decompose rating matrix into user and item matrices of lower dimension k
- Learning factors from given ratings using stochastic gradient descent

$$\min_{x_\star, y_\star} \sum_{r_{u,i} \text{ is known}} (r_{ui} - x_u^T y_i)^2 + \lambda(\|x_u\|^2 + \|y_i\|^2)$$

- Prediction of rating: inner product of vectors of user u and item i



- Factors not necessarily interpretable (just capture variance in data)

[Funk/Webb, 2006] *Netflix Update: Try this at home*, http://sifter.org/~simon/journal/20061211.html
[Koren et al., 2009] *Matrix Factorization Techniques for Recommender Systems*, Proceedings of the IEEE.

Matrix Factorization for Music Rec.

- For music, variants deal with specifics in data, e.g.,
- Learning factors and biases using hierarchies and relations in data
  cf. [Koenigstein et al. 2011]

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

[Koenigstein et al., 2011] *Yahoo! music recommendations: modeling music ratings with temporal dynamics and item taxonomy*, RecSys.

- Special treatment of implicit data (*preference* vs. *confidence*)

$$\min_{x_\star, y_\star} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right)$$

preference: $p_{ui} = \begin{cases} 1 & r_{ui} > 0 \\ 0 & r_{ui} = 0 \end{cases}$

confidence: $c_{ui} = 1 + \alpha r_{ui}$

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

Example of Collaborative Filtering Output

People who liked **Disturbed — The Sound of Silence**, also liked…

1. Bad Wolves — Zombie

2. Five Finger Death Punch — Bad Company

3. Disturbed — The Light

4. Metallica — Nothing Else Matters

Toolboxes for RecSys (CF)

- **MyMediaLite** (C#): http://www.mymedialite.net
- **scikit-surprise** (Python): http://surpriselib.com
- **Apache Mahout Recommenders** (with Spark): http://mahout.apache.org
- **Spotlight** (Python): https://maciejkula.github.io/spotlight/index.html
- **Rival** (Evaluation, Reproducibility; Java): http://rival.recommenders.net
- + any machine learning/linear algebra package

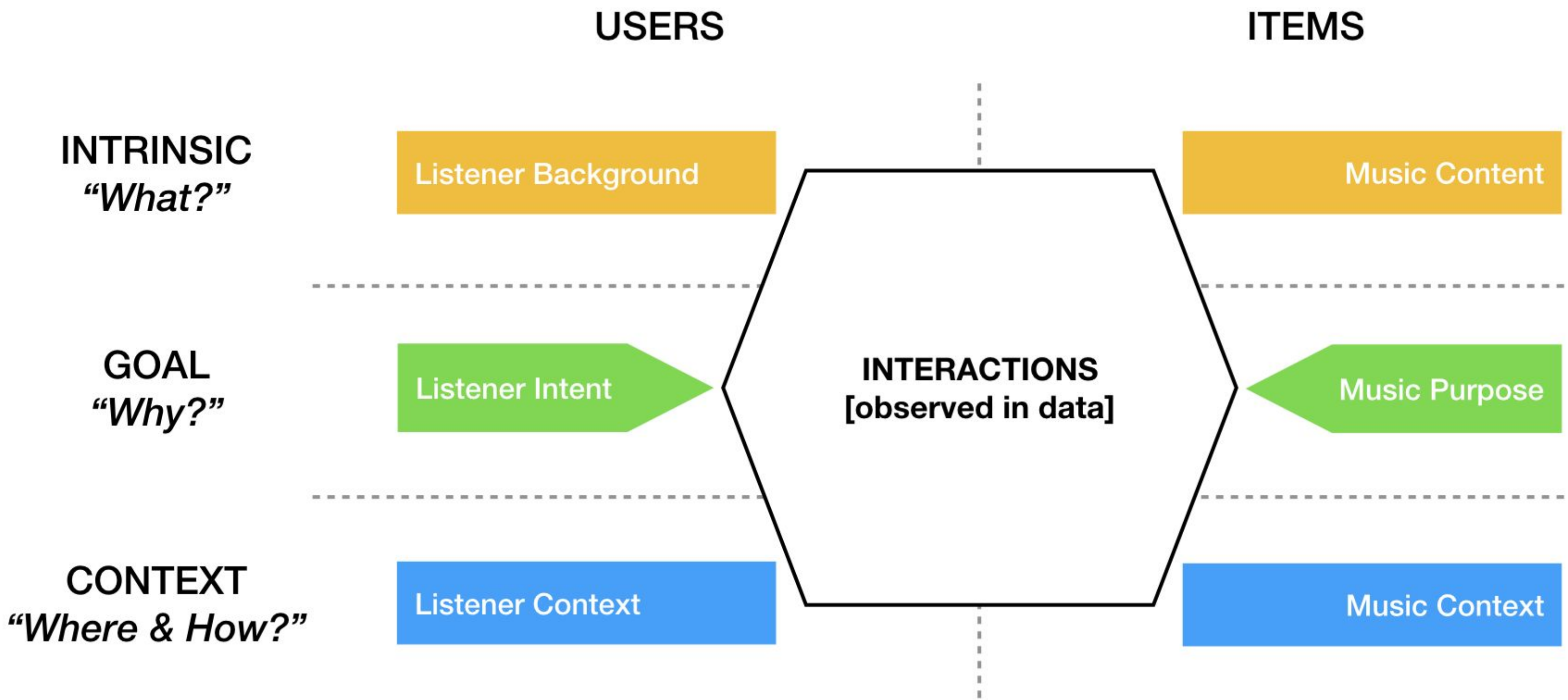
Factors Hidden in the Data

Original assumption of first matrix factorization-based recommender systems:

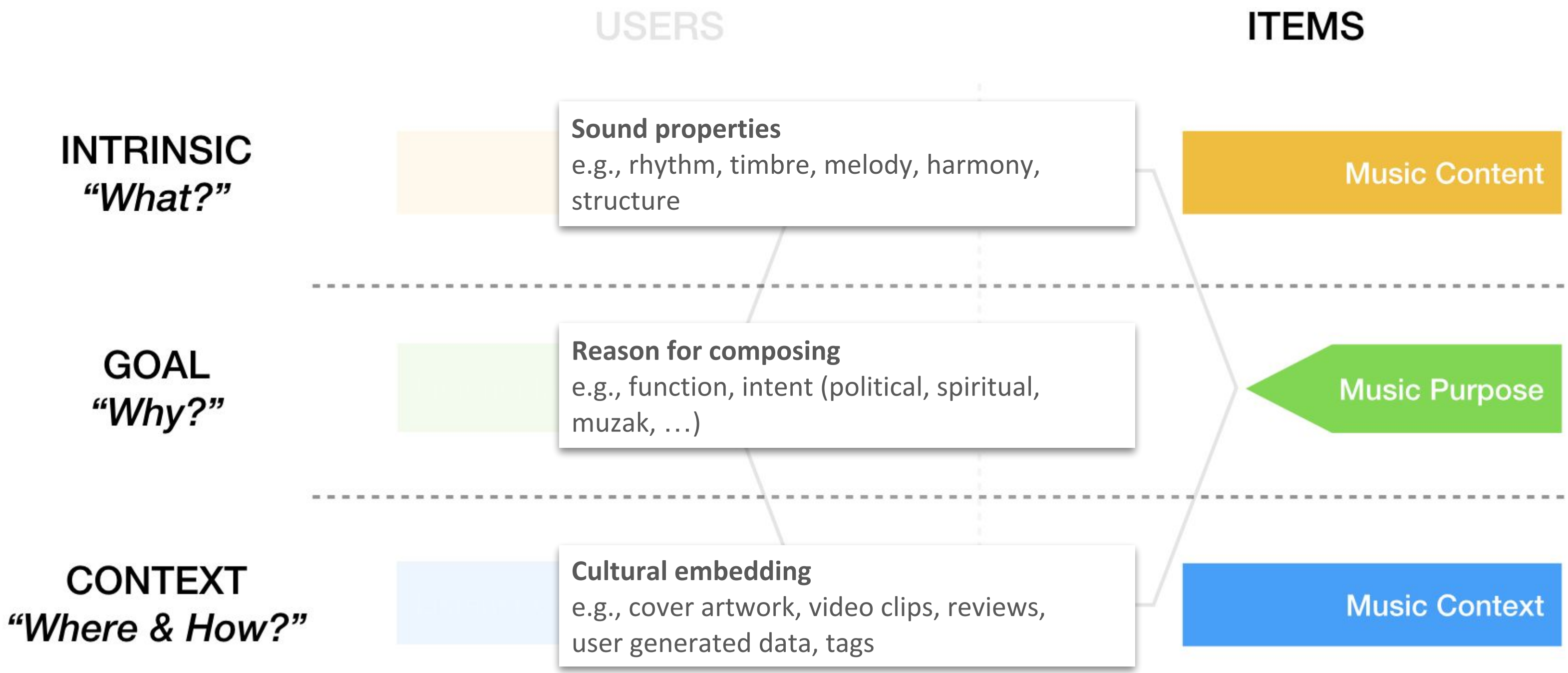
- Observed ratings/data are interactions of 2 factors: users and items
- Latent factors are representation of users and items

- But it’s a bit more complex...

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 now the thing
  (representation learning and temporal modeling → CNNs, RNNs)

>> Next door!

[Choi et al., 2017] *A Tutorial on Deep Learning for Music Information Retrieval*, arXiv:1709.04396.

[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

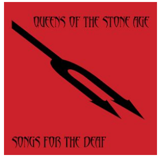
Disturbed
The Sound of Silence

Sound example

- Beat/downbeat → Tempo: 85 bpm (*madmom*)

Sound example

- 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 (cf. *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/MiningSuite** (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).

Toolboxes for Text Analysis

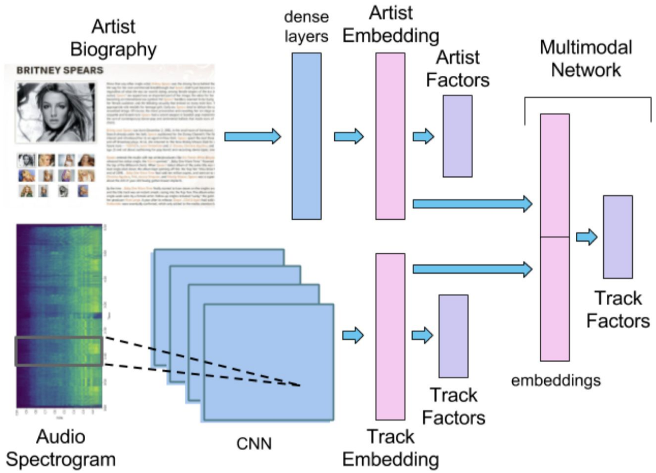
- **Natural Language Toolkit nltk** (Python): https://www.nltk.org
- **Gensim** (Python): https://radimrehurek.com/gensim/
- **GATE** (Java): https://gate.ac.uk
- **MeTA** (C++): https://meta-toolkit.org
- **Apache OpenNLP** (Java): http://opennlp.apache.org
- **jMIR** (Java): http://jmir.sourceforge.net

Multimodal Approaches

- Incorporation of different sources / complementary information
- Content to handle cold-start problem in CF

- E.g. combining artist biography text embeddings with CNN-trained track audio embeddings

[Oramas et al., 2017] *A Deep Multimodal Approach for Cold-start Music Recommendation.* RecSys DLRS workshop.



- E.g. fusing deep features from audio and image (album covers) and text

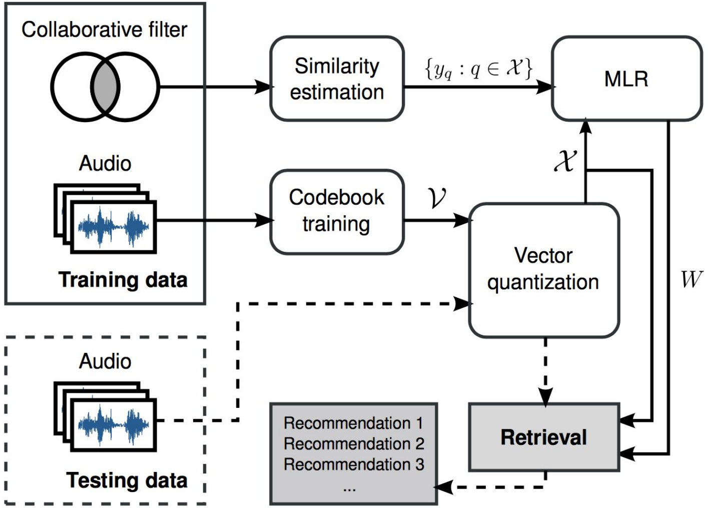
[Oramas et al., 2018] *Multimodal Deep Learning for Music Genre Classification.* TISMIR 1(1).

Feedback-Transformed Content

- CF model as target for learning features from audio
- Dealing with cold-start: predict CF data from audio
- Potentially: personalizing the mixture of content features

- E.g., learning item-based CF similarity function from audio features using metric learning

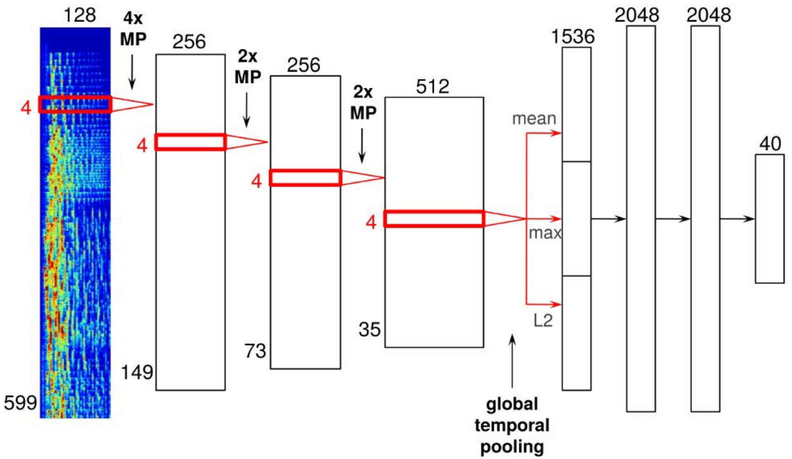
[McFee et al., 2012] *Learning Content Similarity for Music Recommendation.* IEEE TASLP 20(8).



Feedback-Transformed Content

- E.g. learning latent item features using weighted matrix factorization
  - CNN input: mel-spectrogram
  - CNN targets: latent item vectors
  - Visualization of clustering of learned song representations (t-SNE) on next slide

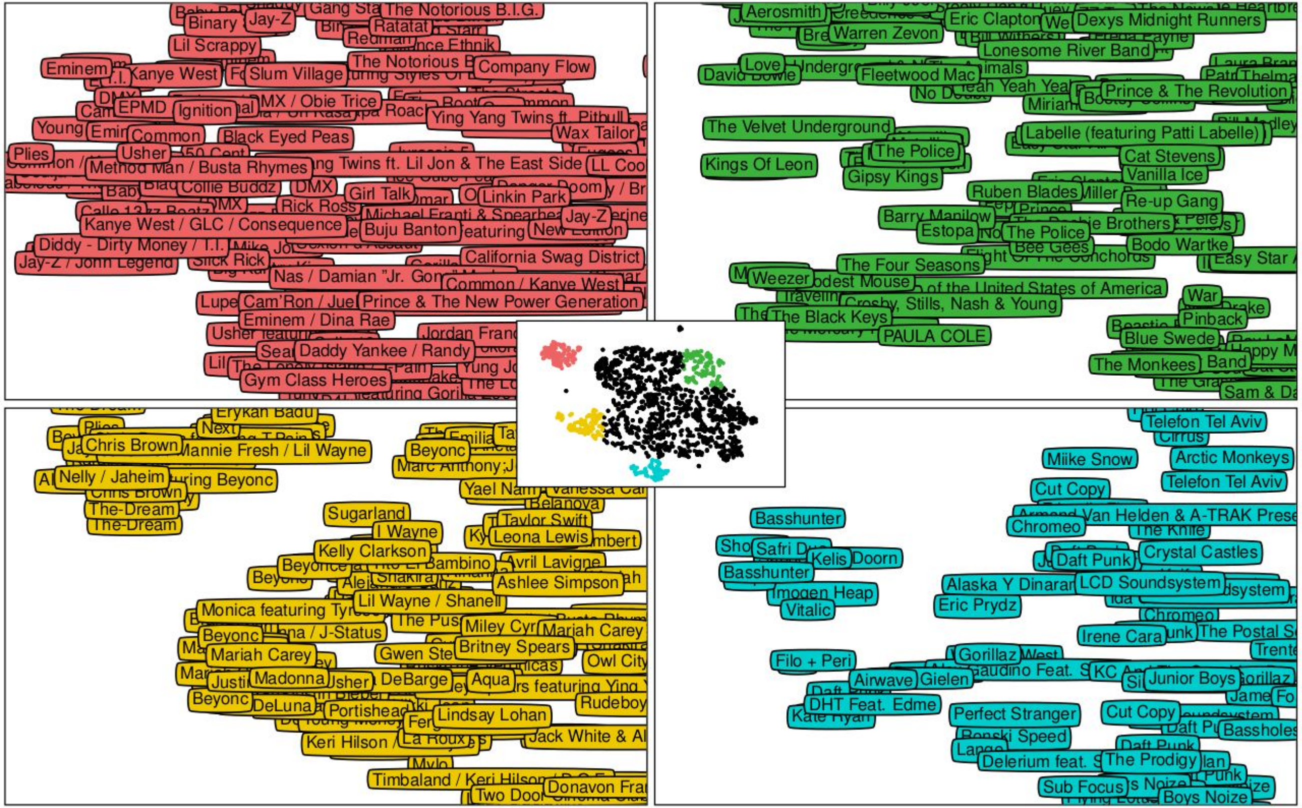
[van den Oord et al., 2013] *Deep Content-Based Music Recommendation*. NIPS workshop.



- E.g. combining matrix factorization with tag-trained neural network to emphasize content in cold-start

[Liang et al., 2015] *Content-Aware Collaborative Music Recommendation Using Pre-Trained Neural Networks*. ISMIR.

Feedback-Transformed Content



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

So much for the items

- Various ways to describe the items
- Recommendation hence completely detached from individual user/listener
- Not personalized: uses all of user data in one overall model
- **Next: the user**

Factors Hidden in the Data

USERS

ITEMS

INTRINSIC
"What?"

Listener Background

Personal characteristics
e.g., music preference, experience, musical training, demographics

GOAL
"Why?"

Listener Intent

Reason to select music/listen
e.g., self-regulation, emotion evocation, demonstration

CONTEXT
"Where & How?"

Listener Context

Situation of listener
e.g., mood, activity, social context, spatio-temporal context

Listener Background

- Psychology- and sociology research driven area
- Goals: more predictive user models; dealing with user cold start
- Gathering information on **user personality, music preference, demographics, cultural context**, etc. (e.g., via questionnaires or predicted via other source)

Some findings: • age (taste becomes more stable);

- when sad: *open* & *agreeable persons* want happy, *introverts* sad music;
- *individualist cultures* show higher music diversity; etc.

[Rentfrow, 2012] *The role of music in everyday life: Current directions in the social psychology of music*. Social and personality psychology compass, 6(5).

[Laplante, 2015] *Improving Music Recommender Systems: What Can We Learn From Research On Music Tastes?*, ISMIR.

[Ferwerda et al., 2015] *Personality & Emotional States: Understanding Users' Music Listening Needs*. Ext. Proc UMAP.

[Ferwerda et al., 2016] *Exploring music diversity needs across countries*. UMAP.

Listener Context

- **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.

Context categories

Environment-related context

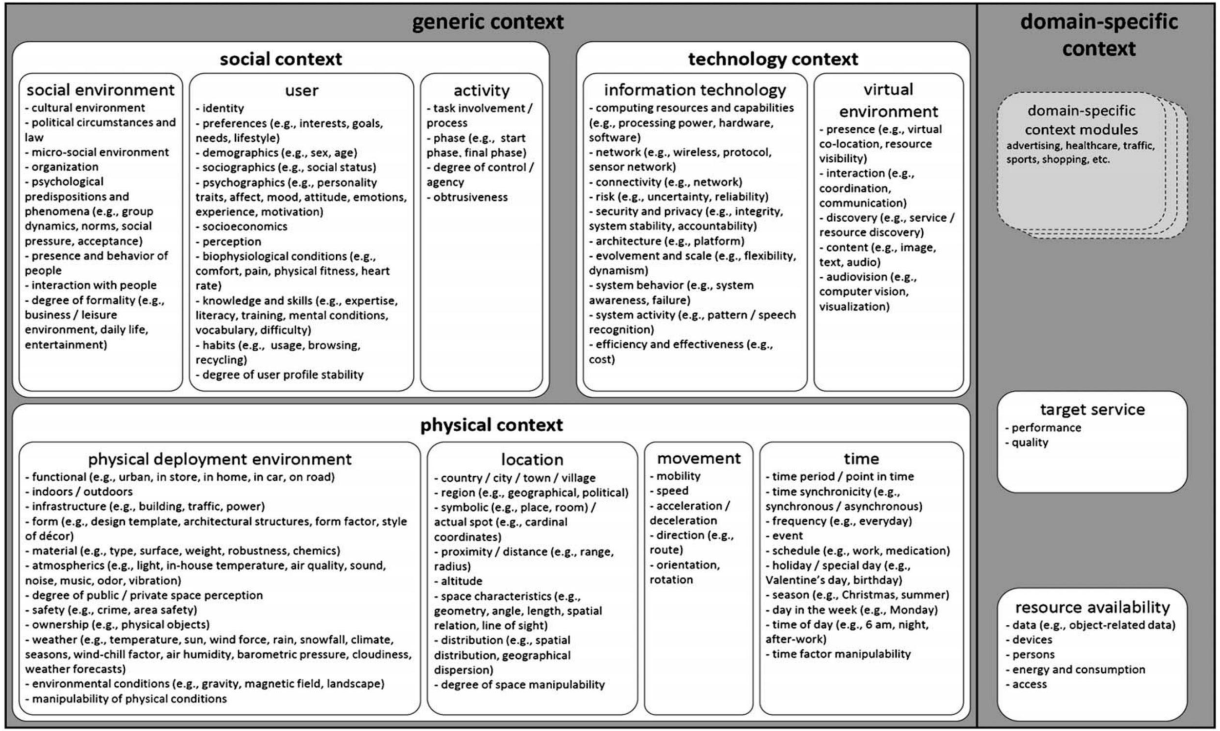
- Exists irrespective of a particular user
- Ex.: time, location, weather, traffic conditions, noise, light

User-related context/background

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

[Schedl et al., 2015] ch. *Music Recommender Systems*, Recommender Systems Handbook, Ricci et al. (eds.), 2nd ed.

Many more context categories



[Bauer & Novotny, 2017] *A consolidated view of context for intelligent systems*. Journal of Ambient Intelligence and Smart Environments 9(4).

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.)

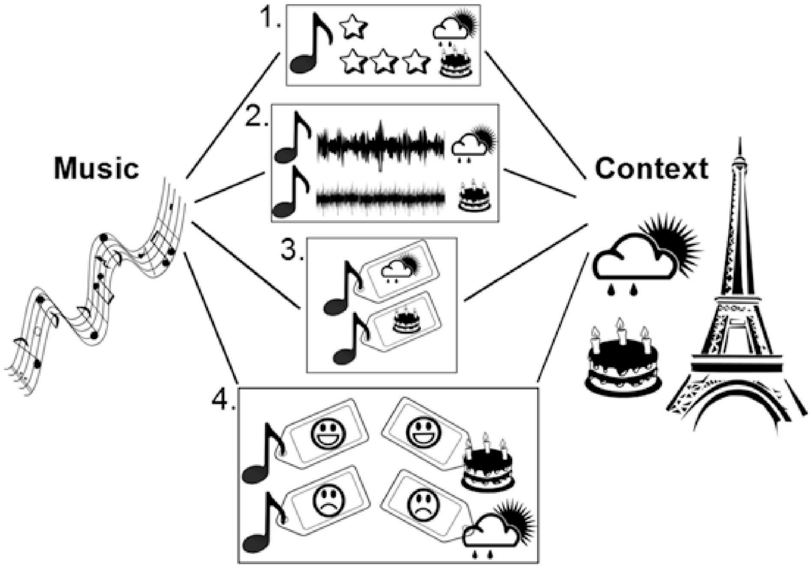
- **Inferring** (using rules or ML techniques):
  Ex.: time, position → *weather*; device acceleration (x, y, z axes), change in position/movement speed → *activity*; skipping behavior → music preferences

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

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] ch. *Music Recommender Systems*, Recommender Systems Handbook, Ricci et al. (eds.), 2nd ed.

Examples of Context-aware Music RecSys

- 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

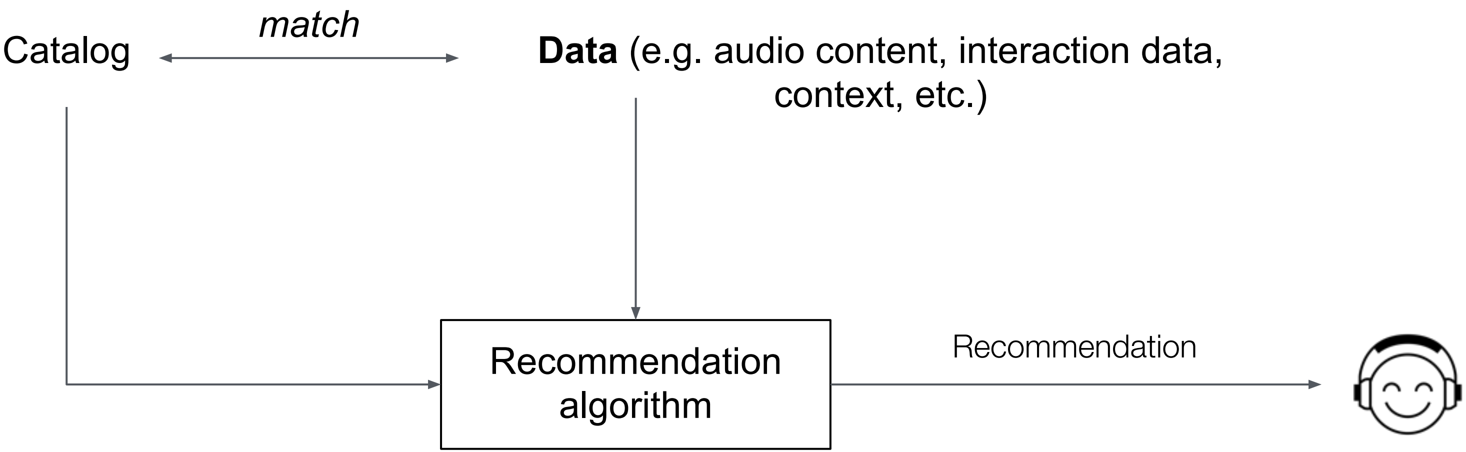
[Cheng & Shen, 2014] *Just-for-Me: An Adaptive Personalization System for Location-Aware Social Music Recommendation*, Proceedings of the 2014 ACM International Conference on Multimedia Retrieval (ICMR).

- Music Recommendation for POIs

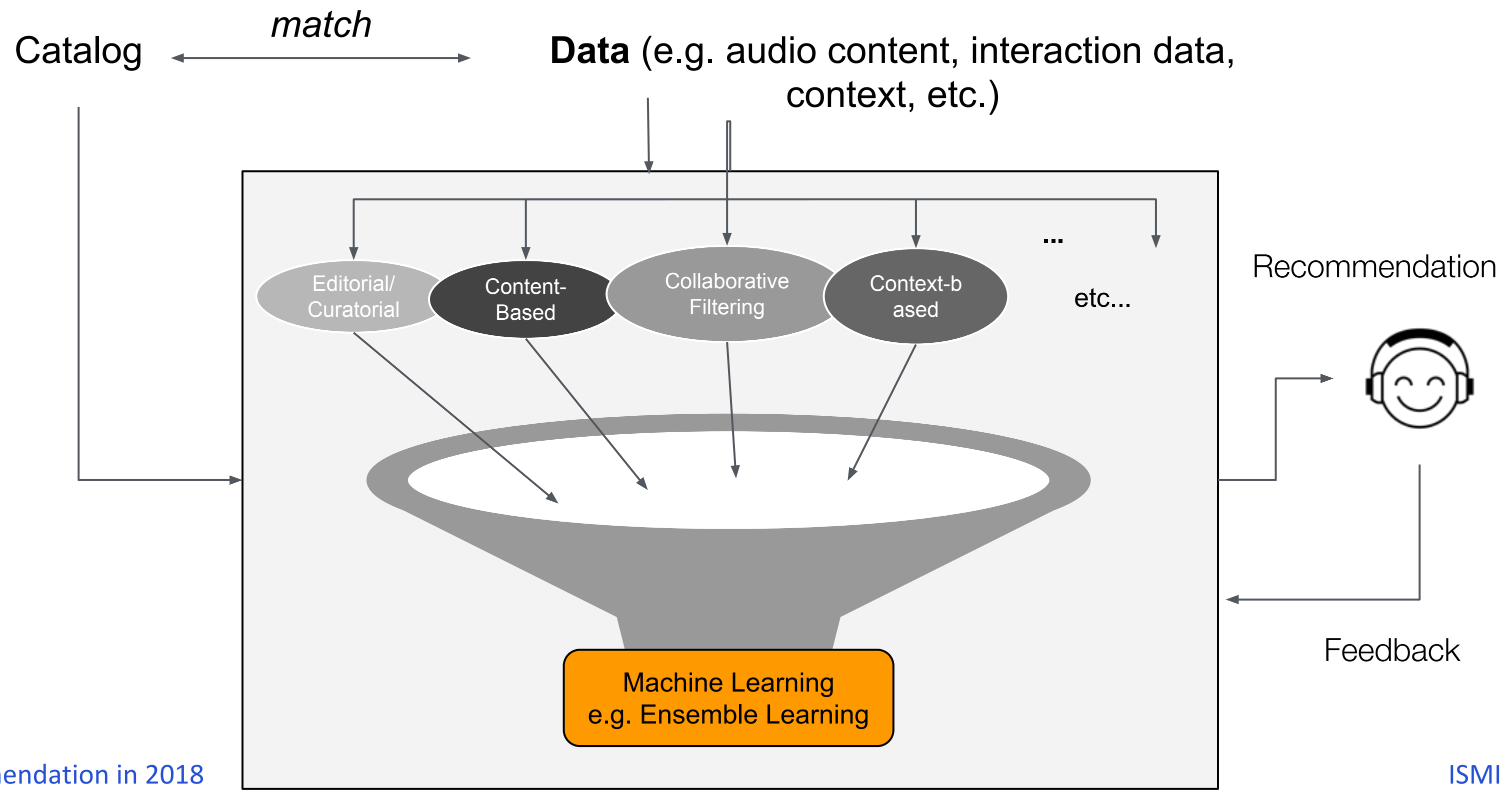
[Kaminskas et al., 2013] *Location-aware Music Recommendation Using Auto-Tagging and Hybrid Matching*, Proceedings of the 7th ACM Conference on Recommender Systems (RecSys).

(For more on this, see our 2017 RecSys tutorial)

Putting it together



Putting it together



Challenges for MIR

- Work on the missing parts!

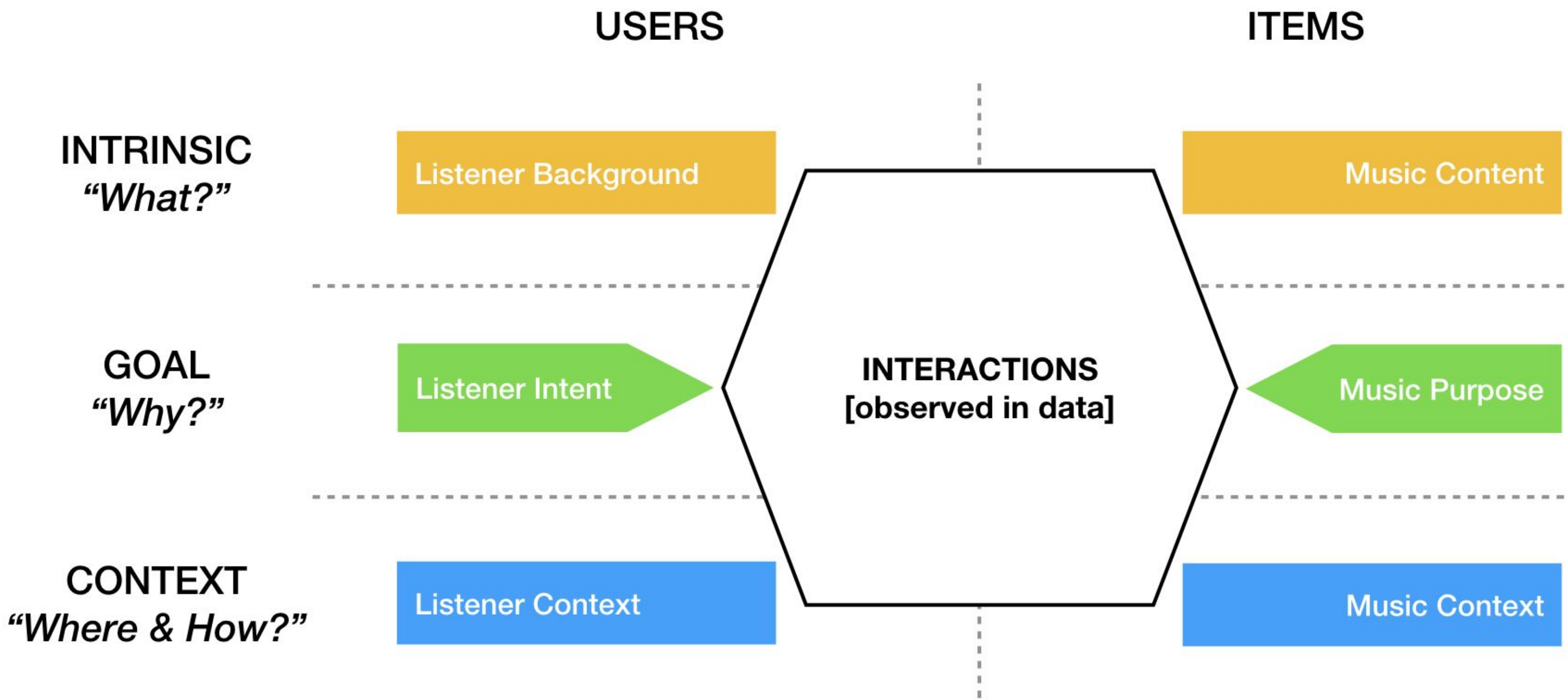
- **Listener Intent**: Lots of insights from social psychology, cf. Laplante [2015], but less impact on actual music recommenders
- **Music Purpose**: somewhat less relevant, but still missing in the picture

- **Listener Background**: Gain deeper understanding of influence of emotion, culture, and personality on music preferences (also general vs. individual patterns)

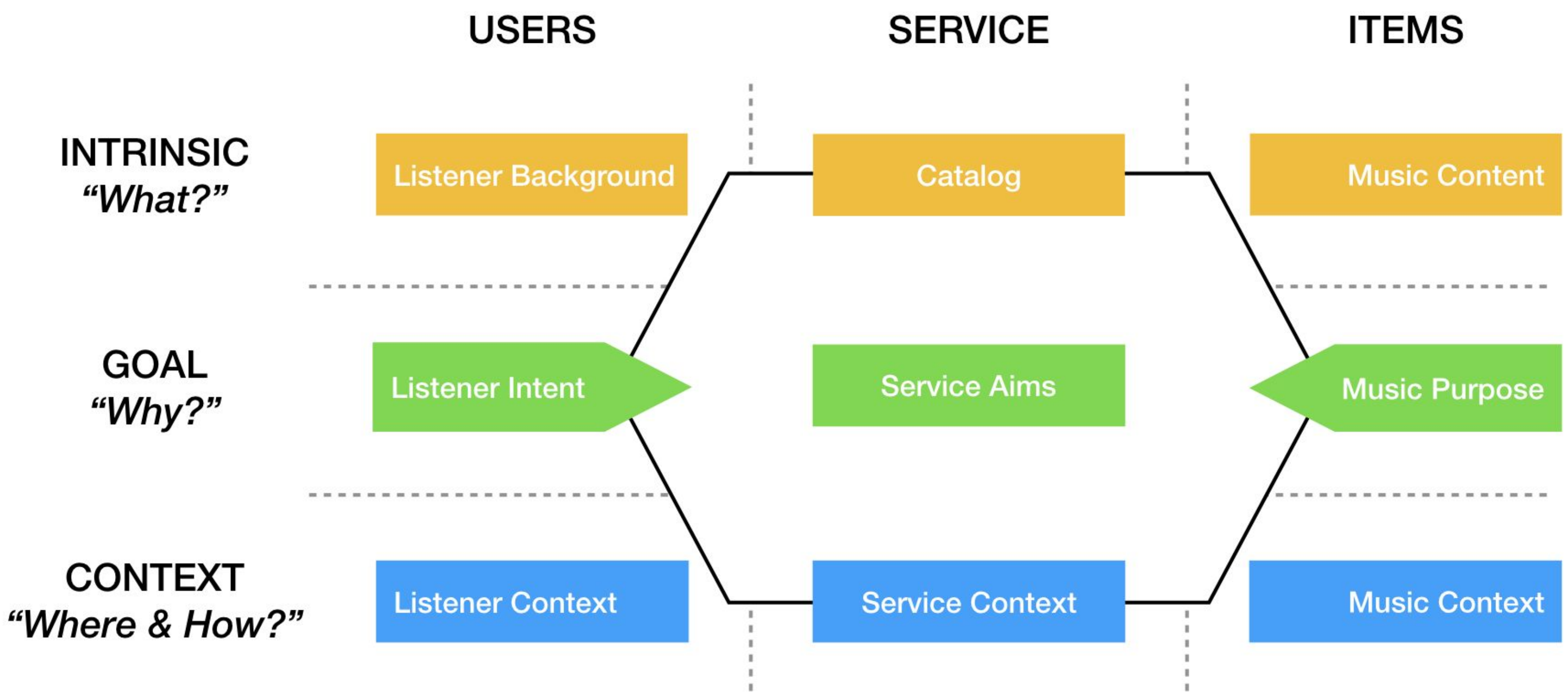
[Laplante, 2015] *Improving Music Recommender Systems: What Can We Learn From Research On Music Tastes?*,l ISMIR.

[Knees, Schedl, Ferwerda, and Laplante, 2019 (expected)] *Listener Awareness in Music Recommender Systems*. Personalized Human-Computer Interaction, Augstein et al. (Eds.)

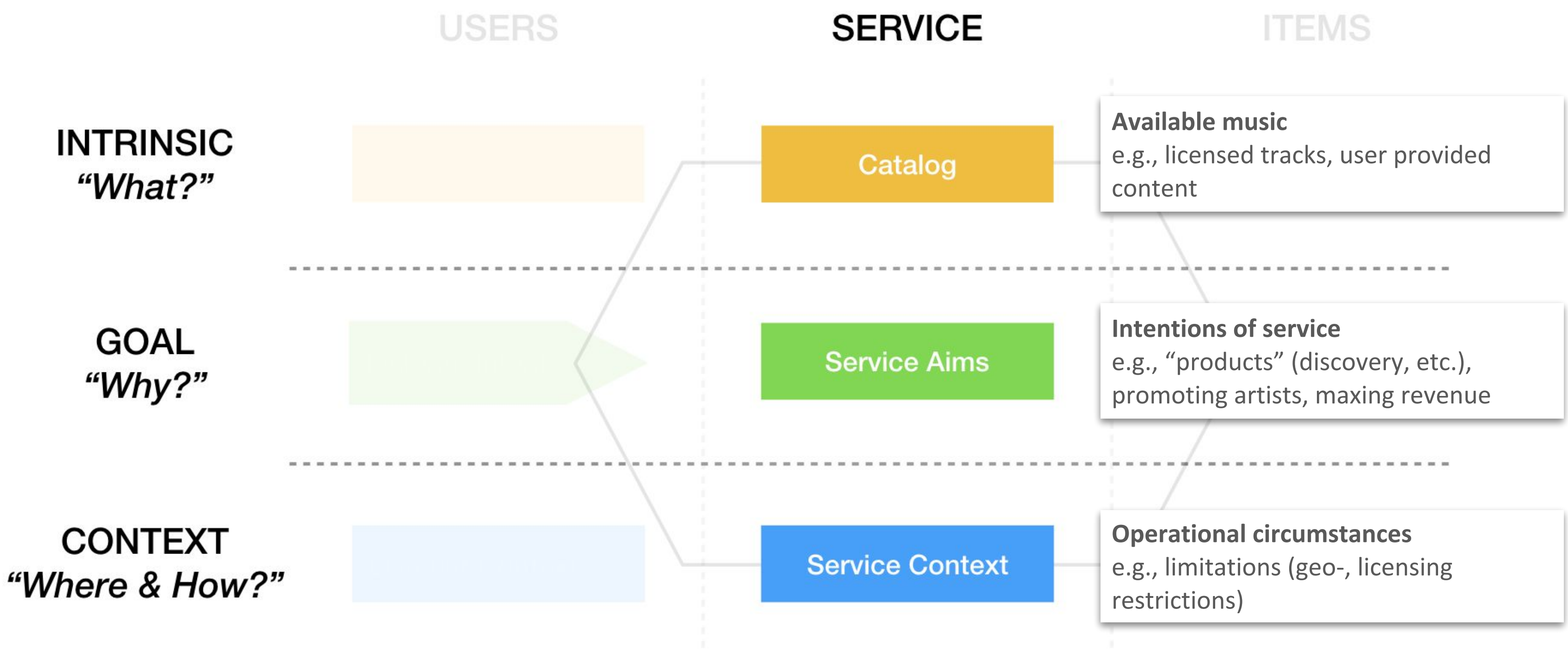
One more thing...



Factoring the Service into the Picture



Factors Hidden in the Data



Looking into Service in More Detail

Recommendations (+collected data!) depend on **factors other than users or items**

Catalog

- Which content is provided/recommended?
- e.g. Soundcloud recommends different content than Spotify

Service Aims

- Why is this service in place? What is the purpose/identified market niche?
- What are the identified use cases? (Discovery? Radio? Exclusives? Quality?)
- Do they push their own content (cf. Netflix)?

Service Context

- How do catalog and service aims depend on context?
- Are there licensing issues/restrictions in particular countries?
- Is the service context-aware? (e.g. app vs desktop/browser)

Maybe we need to talk about service biases

- Data from one service not generalizable to others
  SOUNDCLOUD ≠ bandcamp ≠ Spotify ≠ DEEZER ≠ pandora ≠ ...
- Particularly for niche market segments
  ≠ IDAGIO ≠ pono ≠ qobuz ≠ ...
- And different listening patterns (+content) in different parts of the world
  ≠ KKbox ≠ SUPERPLAYER ≠ simfy africa ≠ ...
- → campaigns focusing on underrepresented demographics to address all (and even data out)
- Service influences listening behavior; it's different to listening "in the wild"

Challenge for MIR

- Explore, evaluate, and compare different recommender services (currently, a lot of work is only focused on UX)
- Investigate “black boxes”: how do services react to controlled behavior?
- Are there biases?
  Even towards specific labels/catalogs?
  Can we uncover recommendation strategies?

- cf. “Smarter than Genius?” by Barrington et al. @ ISMIR 2009

BREAK!

Q&A #1?

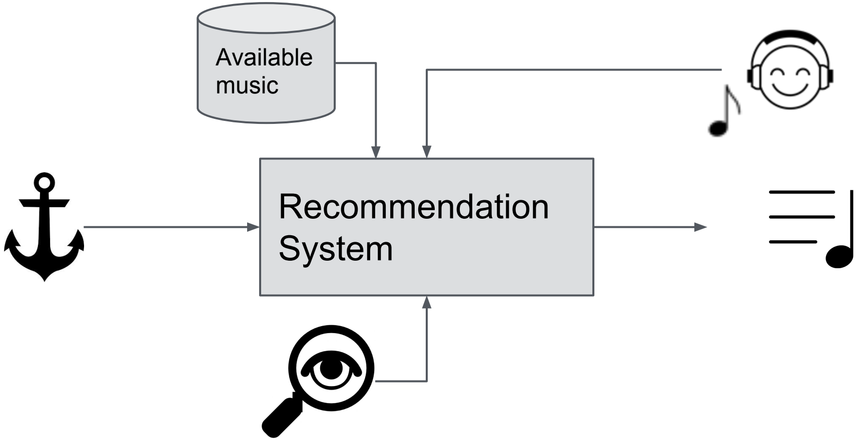
Continuation of Music Listening Experience

Continuation of listening experience

Given a listener enjoying a particular musical experience (defined by the music itself, but also contextual factors and the listener's intent), what recommendations can we make to **extend this experience in the best possible way** for the listener?

Continuation of listening experience

- **Musical anchor**: i.e. current music listening experience defined by e.g. a track, a set of tracks (e.g. a playlist, an album), a given artist, a genre, a mood, etc.
- **Focus / Listener intent**: lean-in vs. lean-back, recent music, discovery, re-discovery, favorites, etc.



Continuation of listening experience

Currently, 2 main directions for "continuation", 2 types of listening experiences:

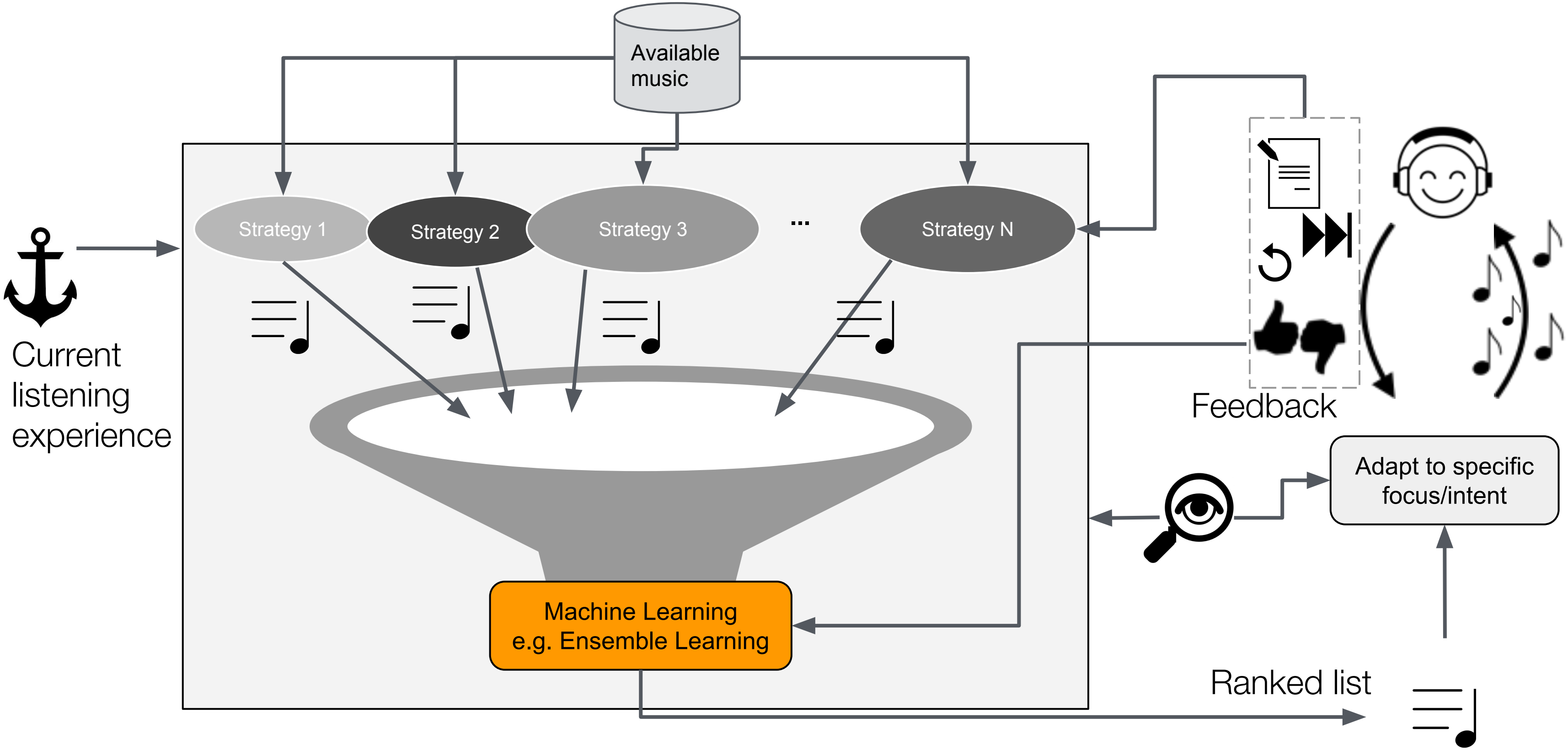
- Append next item
  - **Station** continuation (≈ Next track to play on radio)

- Make readily available a batch of content for consumption
  - **Playlist** generation (≈ Next album/mixtape to buy/get a taste of)

Station vs. Playlist - Differences

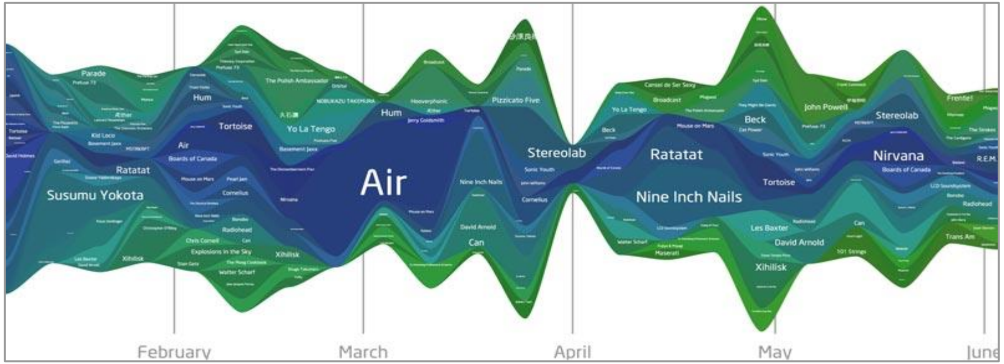
Station	Playlist
Anchored in a music item, e.g., a track, an artist, an album, a genre, etc.	**Anchored in a sequential list of tracks** of arbitrary (finite) length, either: user-generated or curated (e.g., by streaming service, 3rd parties)
Recommendations **sequential**, i.e., one track after the other, possibly hiding future tracks ("next-track recommendation") → **dynamic** approach, to be consumed **now** (experience does not end), real-time constraint	Recommendations **in a batch**, i.e., a complete (continuation of a) playlist → **static** approach (output is finite-length sequence of tracks), to be consumed **in the future**, no real-time constraint
Learning data: (lots of) **explicit feedback**, (little) user-generated data	Learning data: (lots of) **user-generated data/playlists**, (typically less) relevance/preference feedback

Recommendation pipeline



Wait, what about time?

- Well… it's important!



- "Music rotation rules" 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

Several ways to consider time

- 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

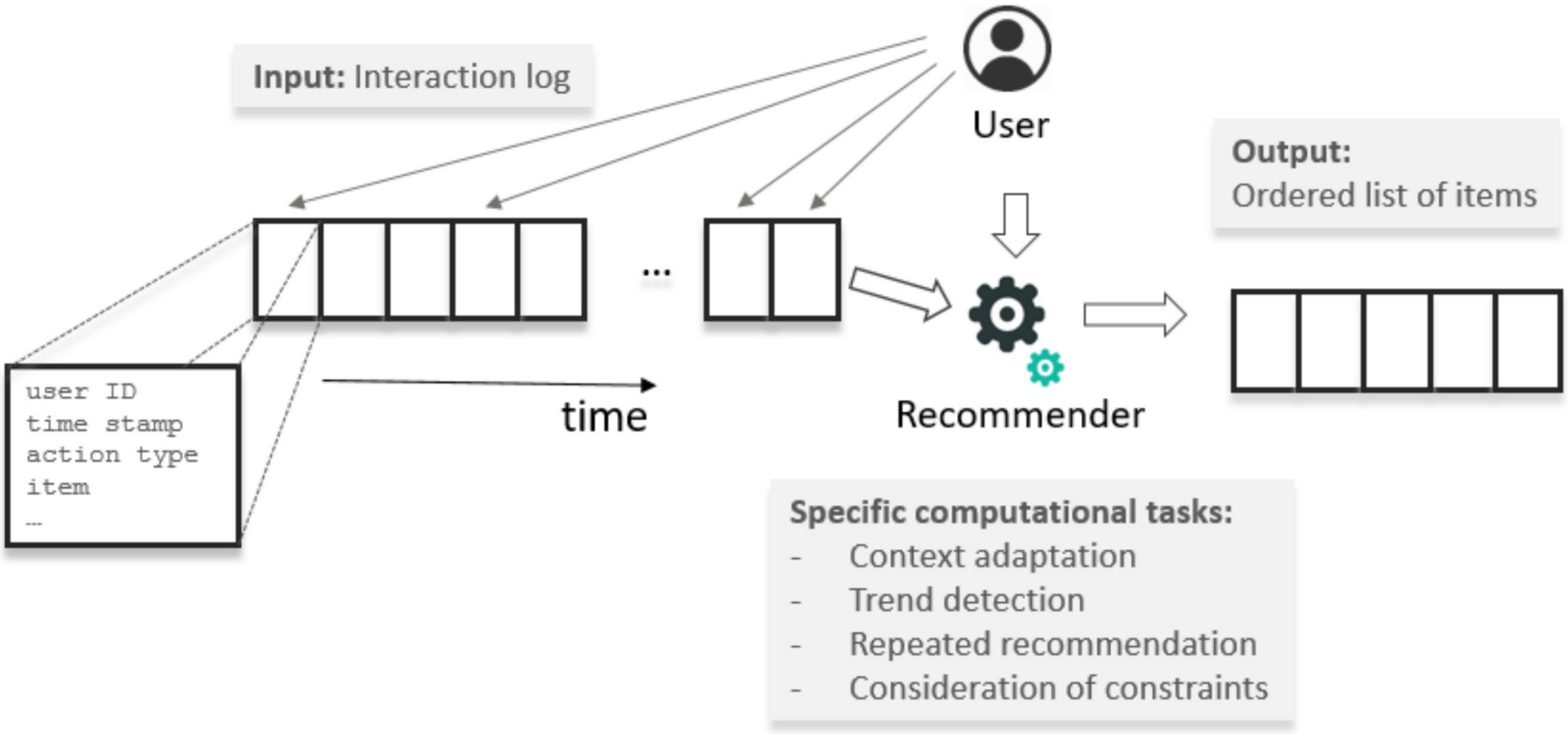
- **Sequence-aware recommendation**

[Quadrana et al., 2018]: *Sequence-Aware Recommender Systems*, https://arxiv.org/abs/1802.08452

[Quadrana et al., 2018]: *Sequence-Aware Recommendation,* RecSys tutorial

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

Sequence-aware recommendation - Overview



 [Quadrana et al., 2018]: *Sequence-Aware Recommender Systems*, https://arxiv.org/abs/1802.08452

Computational Tasks

- Context adaptation
  - Inferring context from user actions ($\neq$ observing a variable)
  - Session-based vs. session-aware
  - e.g. recognizing acoustic stuff would make more sense right now
- Trend detection
  - Identify community vs. individual trends
  - e.g. X-mas, “I’ve been reggaetonized”
- Repeated recommendations
  - Identify repetition patterns in user behavior, then reinforce (or not)
  - e.g. 8:30 AM is time for “Darth Vador theme”
- **Consideration of ordering constraints**

Consideration of Ordering Constraints

Identify ordering/sequentiality constraints and recognize when to apply them.

Two types of information:

- External domain knowledge, e.g.:
    - Music rotation rules for station continuation
- Information mined from user behavior, i.e. learn e.g.:
    - For user FabFab: “Piano for studying” during working hours weekdays followed by “Reggaeton” on Friday nights

Sequence-aware recommendation - Approaches

- Sequence learning
  - Frequent (sequential) pattern mining
  - Markov models
  - Reinforcement learning
  - Recurrent neural networks (RNN)
- Sequence-aware matrix factorization
- Other methods
  - Graph-based methods
  - Discrete optimization

[Quadrana et al., 2018]: *Sequence-Aware Recommender Systems*, https://arxiv.org/abs/1802.08452

Frequent (sequential) pattern mining

- Learning from co-occurring items in playlists or listening sessions
- Sequential patterns: $i_k, i_{k+1} \rightarrow i_m$
- Contiguous sequential patterns: $i_k, \ldots, i_{k+n} \rightarrow i_m$

- Example: Learning from <u>sequential co-occurrence of music tracks</u> in hand-crafted playlists; downweight co-occurring tracks that are not adjacent

[Baccigalupo et al., 2008]: *Uncovering Affinity of Artists to Multiple Genres from Social Behaviour Data*, ISMIR.

Markov models

- Model transitions between items in sequence as a stochastic process
- Probability of playlist: product of transition probabilities between consecutive items
- Learned from dataset of hand-crafted playlists
- Predicted next item for a given playlist: item that maximizes likelihood
- Example: Modeling coherent music playlists as paths through latent space; learn (via EM) positions of songs so that Euclidean distances between songs represent transition probabilities, using latent Markov embedding (LME); meaningful transition probabilities can be obtained also for transitions not seen during training

[Chen et al., 2012]: *Playlist prediction via metric embedding*. ACM SIGKDD.

Recurrent neural networks

- NN with hidden states that can capture dynamic temporal behavior of a sequence
- In each step, nodes are updated by new input from sequence and hidden state from last iteration
- Examples:
    - Click streams in e-commerce that may yield purchasing events, YouTube video streams of clips watched for a certain time period

      [Hidasi et al, 2016]: *Session-based recommendations with recurrent neural networks*, ICLR.

    - Sequence-aware music playlist continuation

      [Vall et al., 2017]: *The Importance of Song Context in Music Playlists*, ACM RecSys.

Sequence-aware recommendation - Limitations

- Accurately infer the intended purpose of a user-created playlist is a highly complex task
- Importance of the exact order of items in playlist may or may not be important, depending on use case and application domain
- In music recommendation, studies on importance of sequence are partly contradicting:
    - *exact order* seems not to matter a lot
    - *coherence* and direct *item-to-item transitions* seem to (e.g., death metal after piano sonata often not the best transition...)

[Kamehkhosh et al., 2018]: *How automated recommendations affect the playlist creation behaviour of users*, ACM IUI Workshop: Intelligent Music Interfaces for Listening and Creation (MILC).

[Tintarev et al., 2017]: *Sequences of diverse song recommendations: an exploratory study in a commercial system*, UMAP.

[Vall et al., 2017]: *The importance of song context in music playlists*, ACM RecSys.

Sequence-aware recommendation - Limitations

- Importance of the exact order of items in playlist may or may not be important, depending on use case and application domain

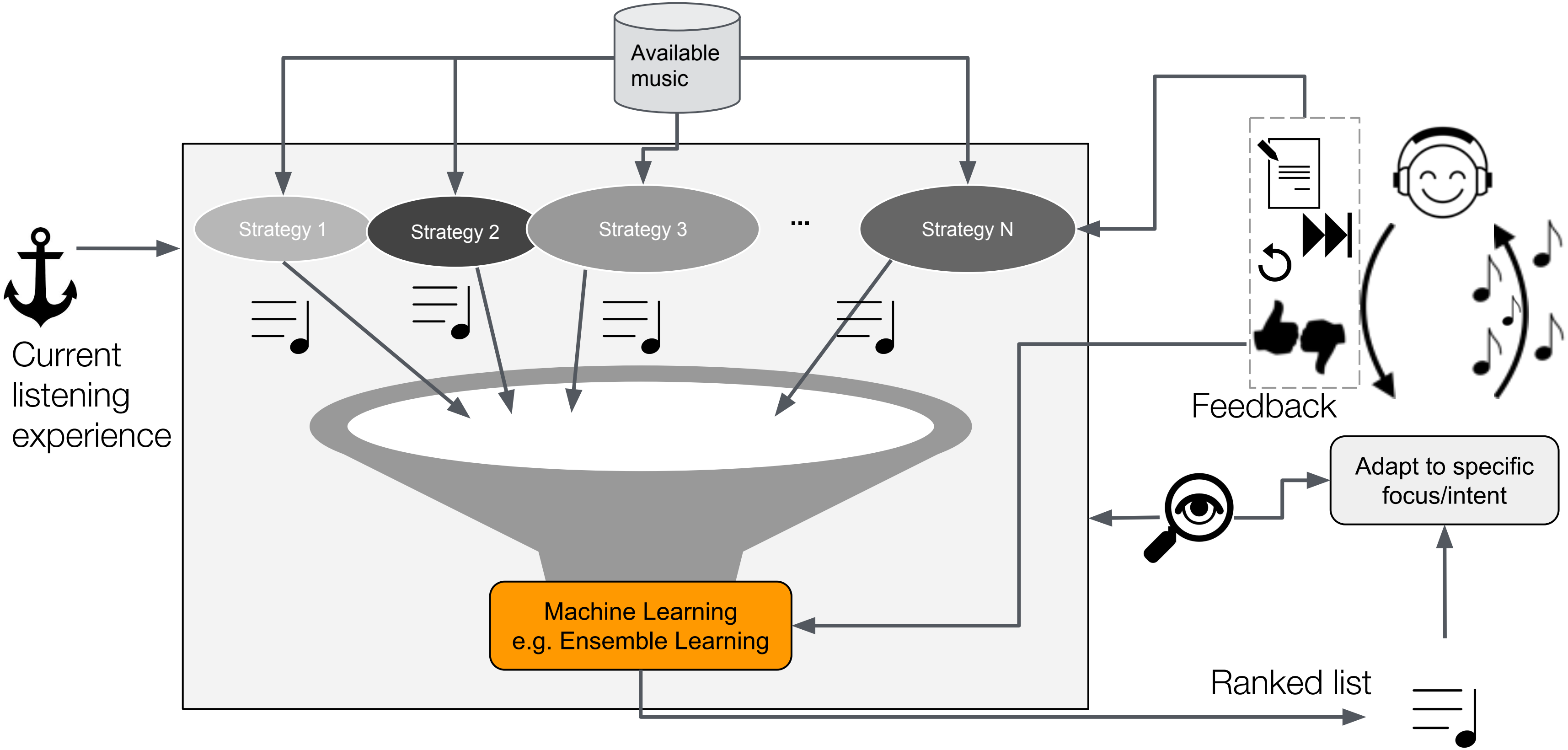
- In music recommendation, studies on importance of sequence are partly contradicting:
    - *exact order* seems not to matter a lot
    - *coherence* and direct *item-to-item transitions* seem to (e.g., death metal after piano sonata often not the best transition...)

[Kamehkhosh et al., 2018]: *How automated recommendations affect the playlist creation behaviour of users*, ACM IUI Workshop: Intelligent Music Interfaces for Listening and Creation (MILC).

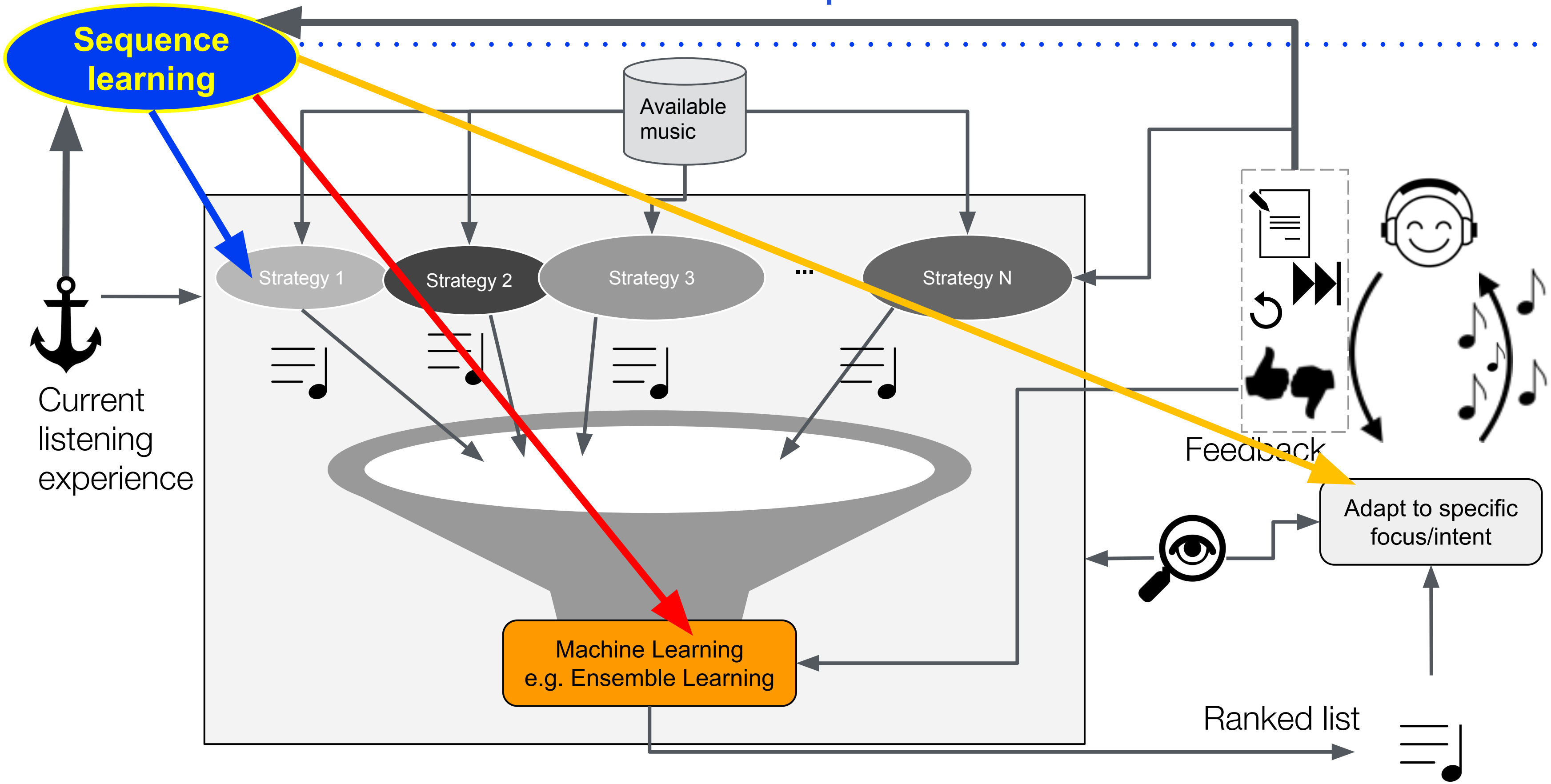
[Tintarev et al., 2017]: *Sequences of diverse song recommendations: an exploratory study in a commercial system*, UMAP.

[Vall et al., 2017]: *The importance of song context in music playlists*, ACM RecSys.

Where does sequence-awareness fit?



Where does sequence-awareness fit?



"... extend experience in the best possible way" ?

A “good” recommendation?

What makes a good recommendation:

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

It’s about recommending a listening experience

Influential factors:

- Listener
- Musical anchor
- Focus / Intent

[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 to best predict general relevance
  - e.g. optimizing on 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

[Jannach, Kamehkhosh, Bonnin, 2016] *Biases in Automated Music Playlist Generation: A Comparison of Next-Track Recommending Techniques*, UMAP

Novelty

- Introducing novelty to balance <u>against popularity (or familiarity) bias</u>
- <u>Both</u> 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…

	"Yep, novelty's fine"	*"No novelty, please!"*
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

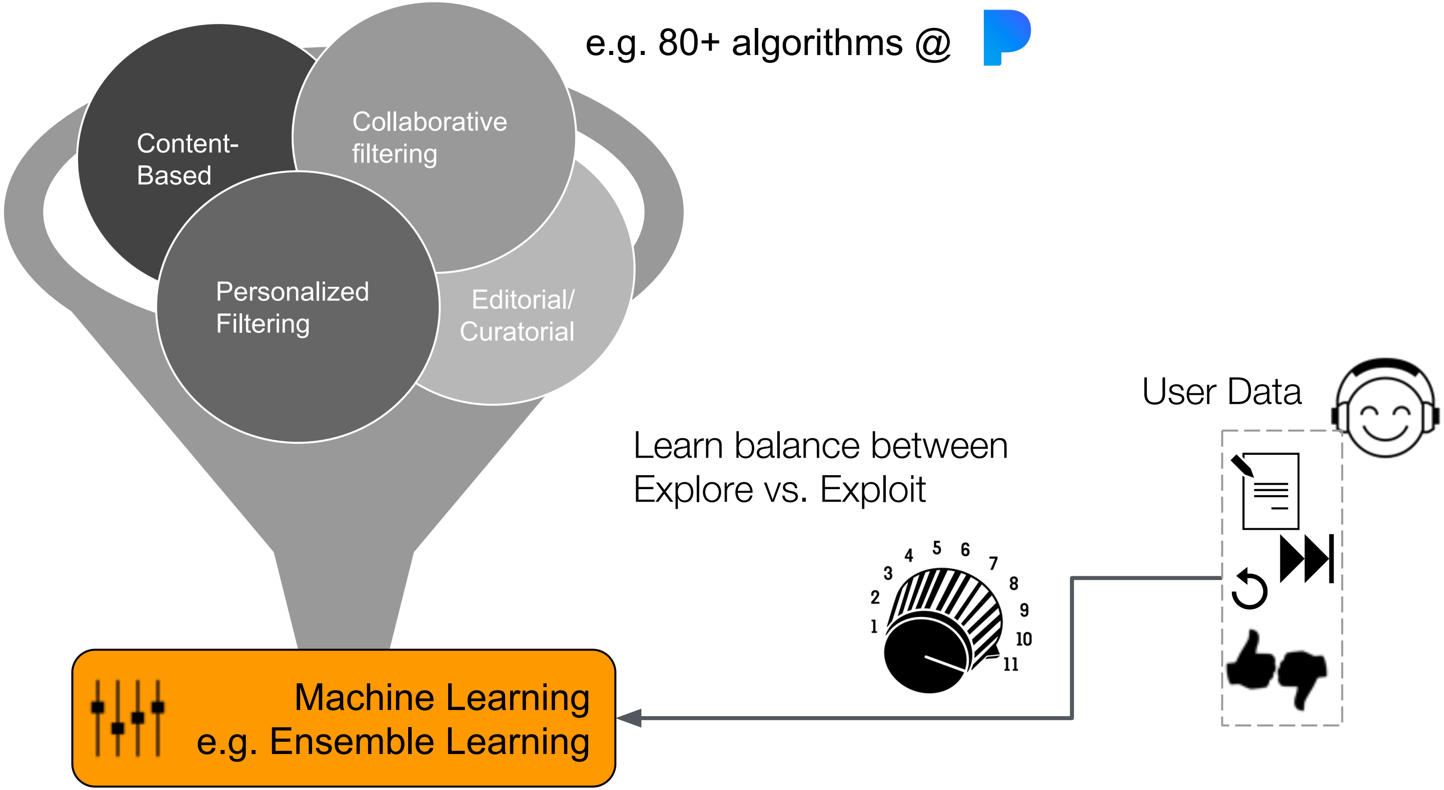
Diversity

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

	"Yep, bring on diversity"	*"No diversity, please!"*
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"

[Parambath, Usunier, Grandvalet, 2016] *A Coverage-Based Approach to Recommendation Diversity on Similarity Graph*, RecSys

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"

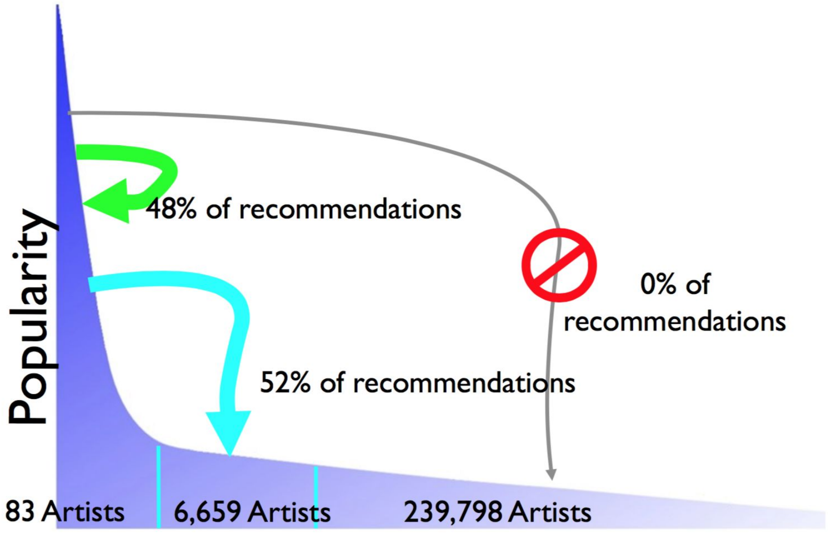
Short-term reward

Long-term reward

- 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



(CF-based recommendations, Last.fm data)

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

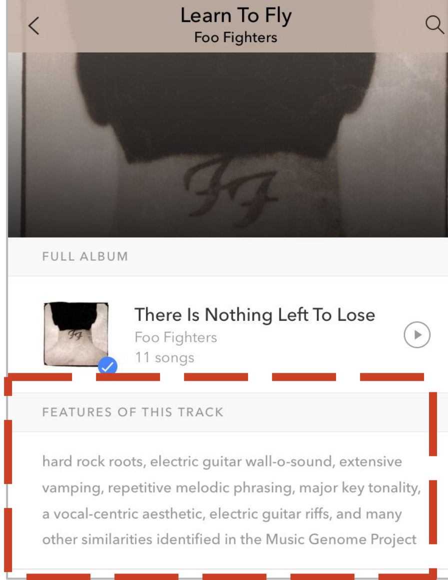
- *"Why am I recommended this?"*

If you like Bernard Herrmann

You might like "Gimme some more" by Busta Rhymes

Because:
He sampled Herrmann's work

Transparency / Interpretability



- 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

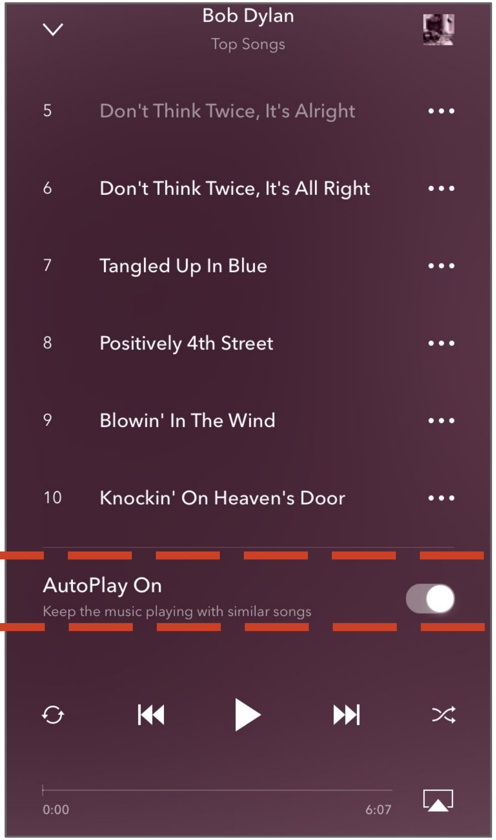
- (See 2017 RecSys tutorial for big picture of contextual recommendation)

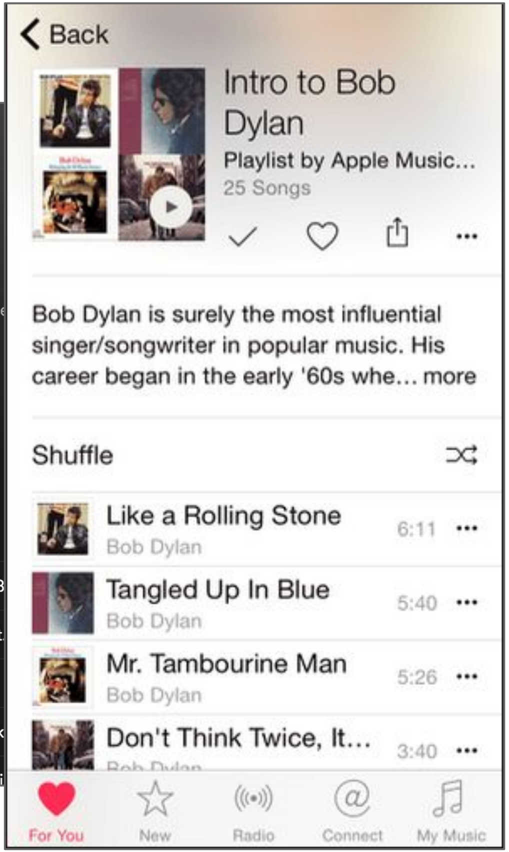
- Special case of **explicit listener focus/intent**, e.g.:
  - Focus on newly released music (new stuff)
  - Focus on activity (e.g. workout)
  - Focus on discovery (new *for me*)
  - On re-discovery (throwback songs)
  - Hyper-personalized (extreme lean-back, *my* best-of)
  - etc.

→ Each specific focus defines:

  - Which recommendations are best
  - Which **vehicle** for recommendations is best (**HOW** to recommend)

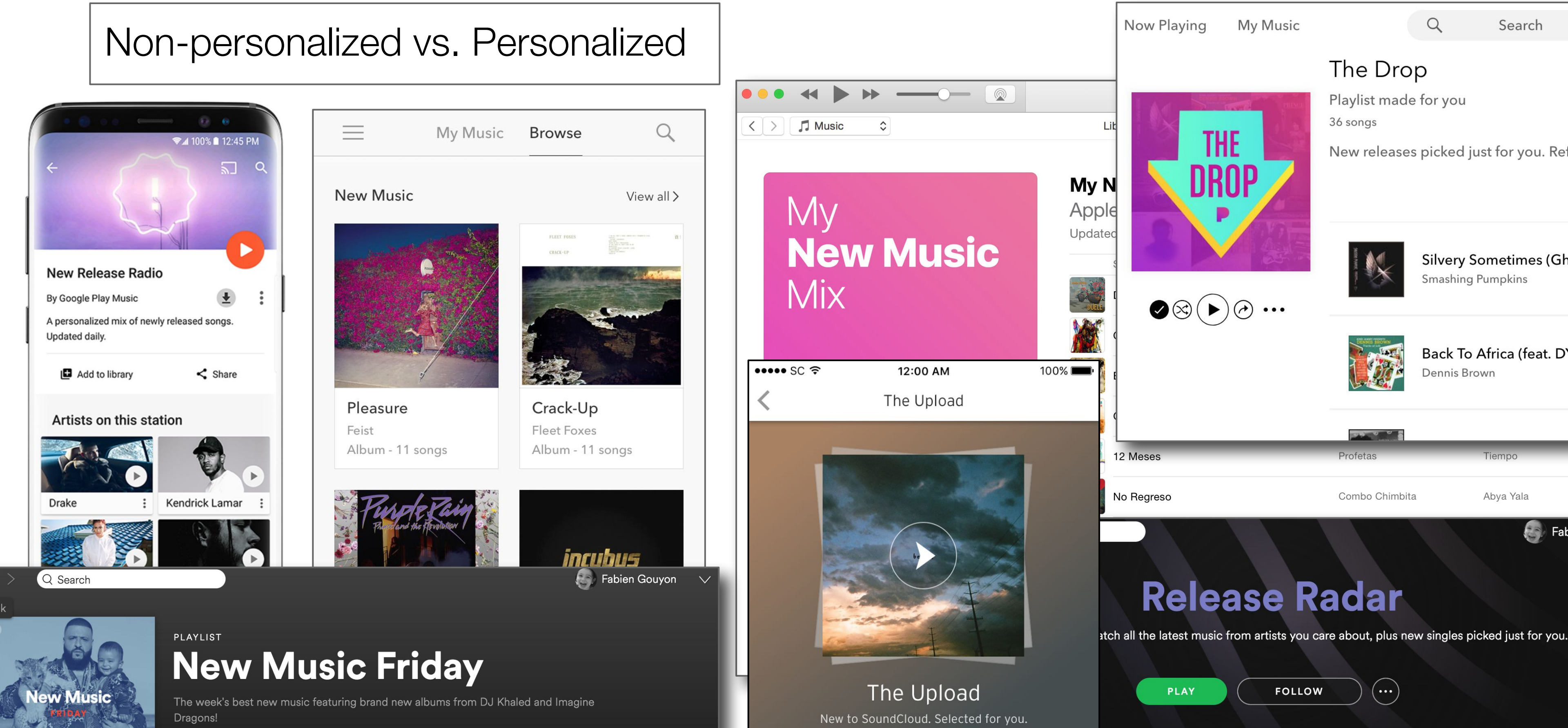
Focus on: Discovering an artist



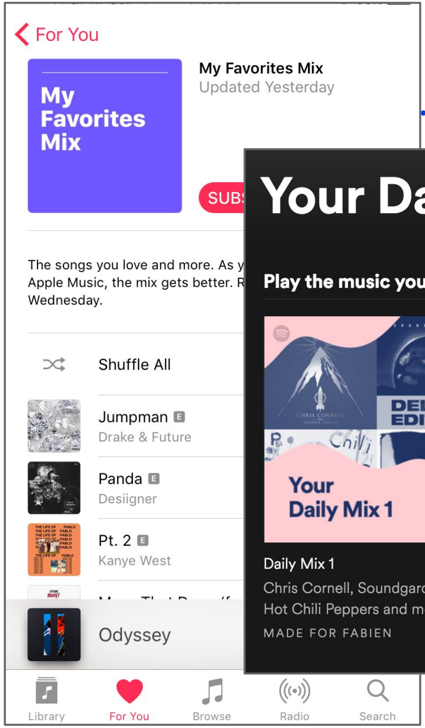


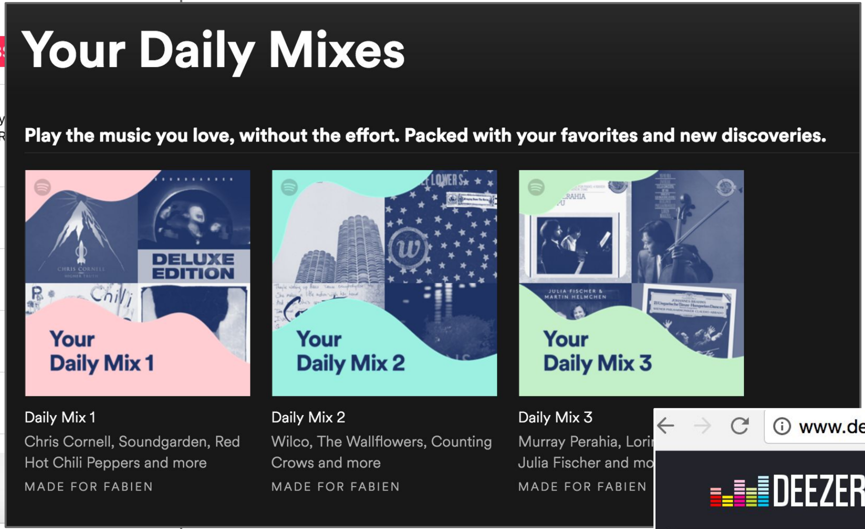
Focus on: New music

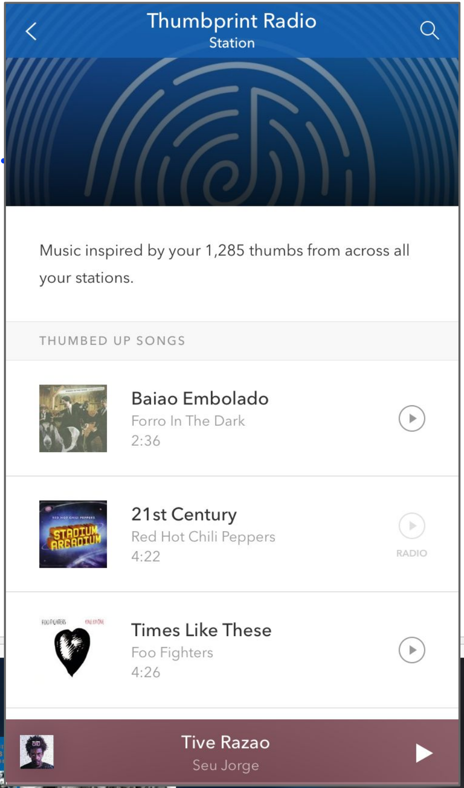
Non-personalized vs. Personalized

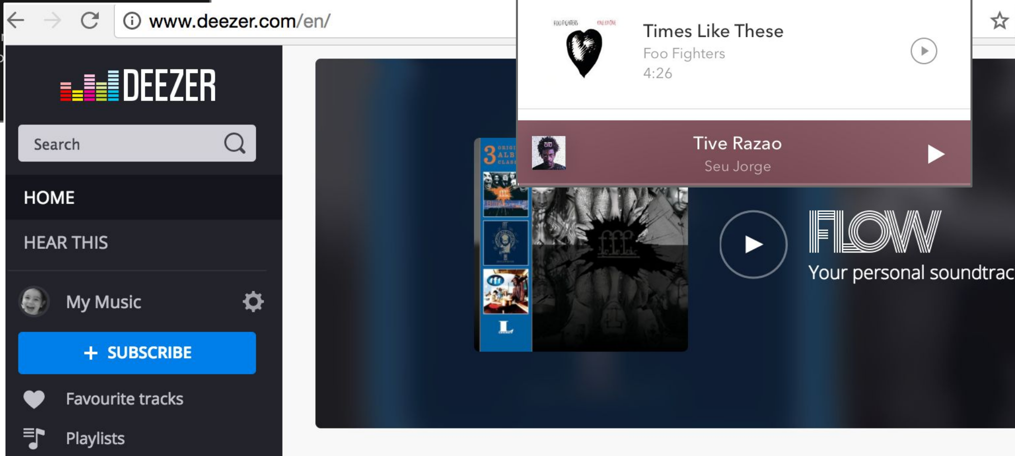


Focus on: Re-discovery



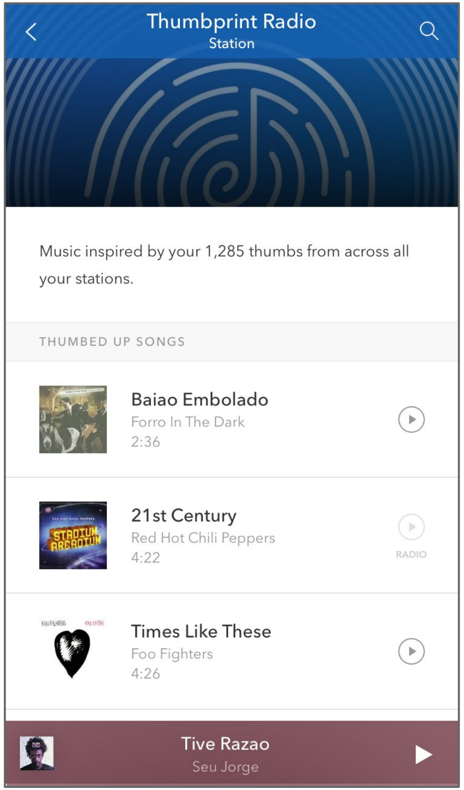


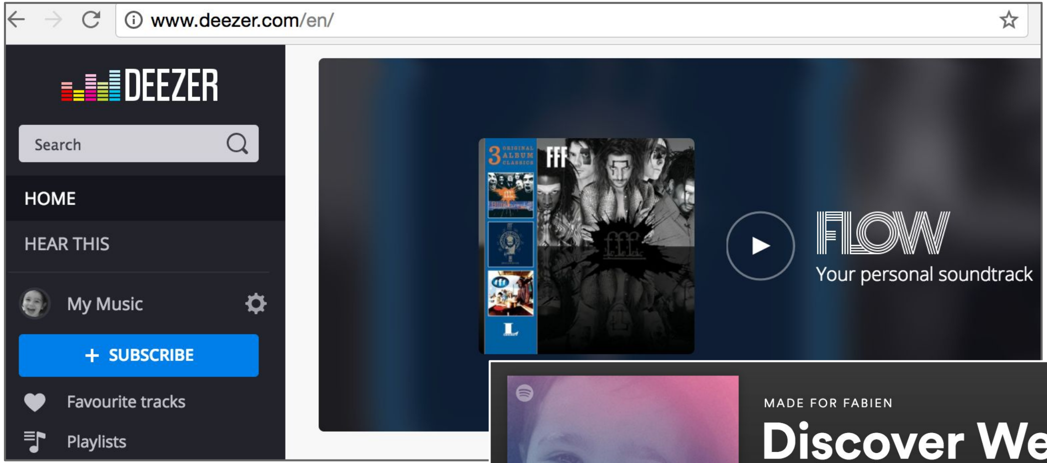


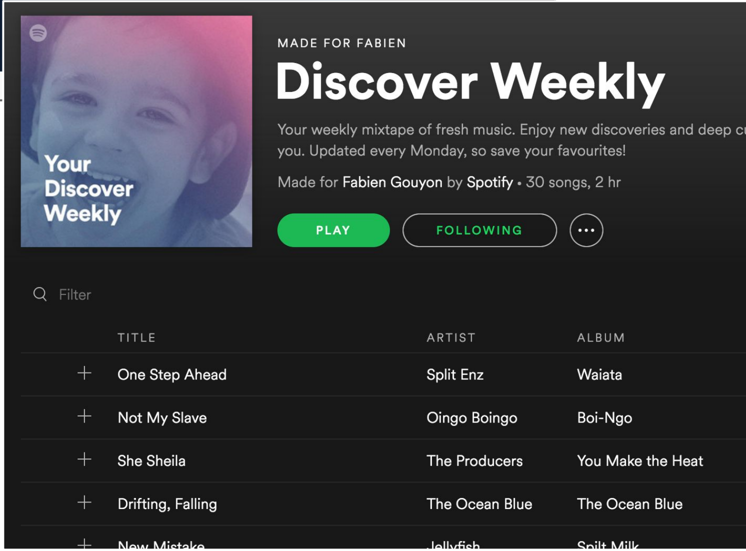


Focus on stuff you know you like
Personalized, leaning towards exploit

Focus on: Hyper-personalized Discovery





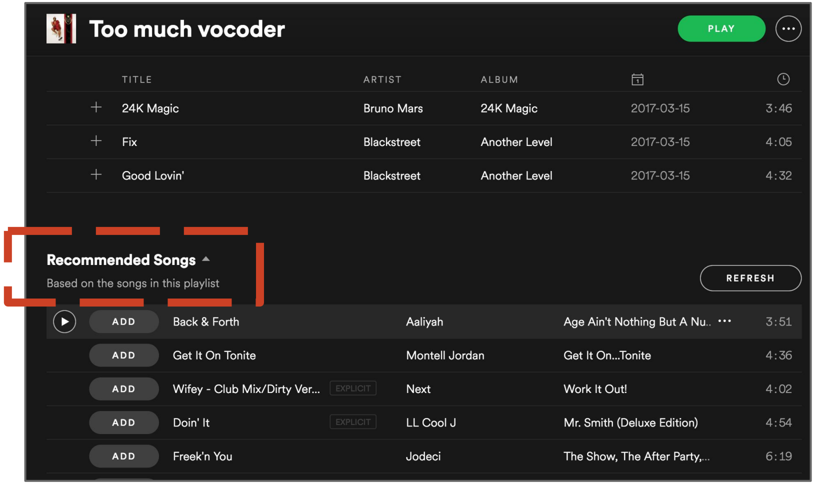


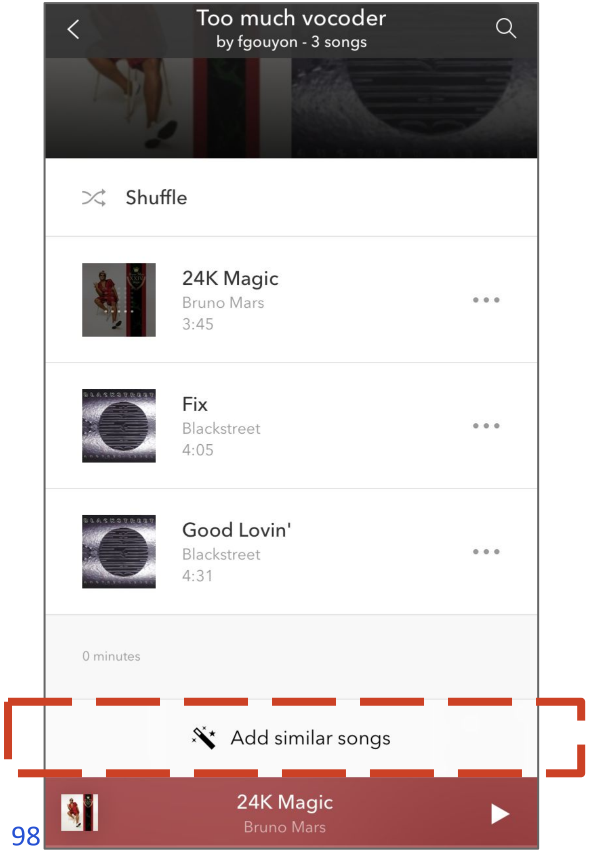
About discovering new stuff.
Intended to feel like it's curated. Just. For. Me.

Leaning towards explore

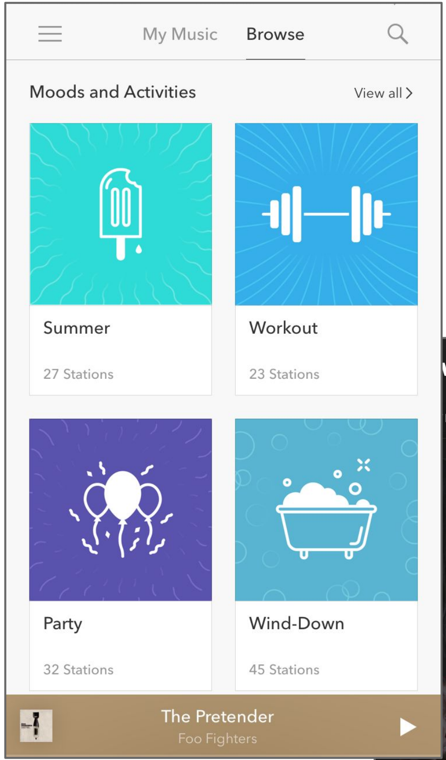
Focus on: Lean-in experience

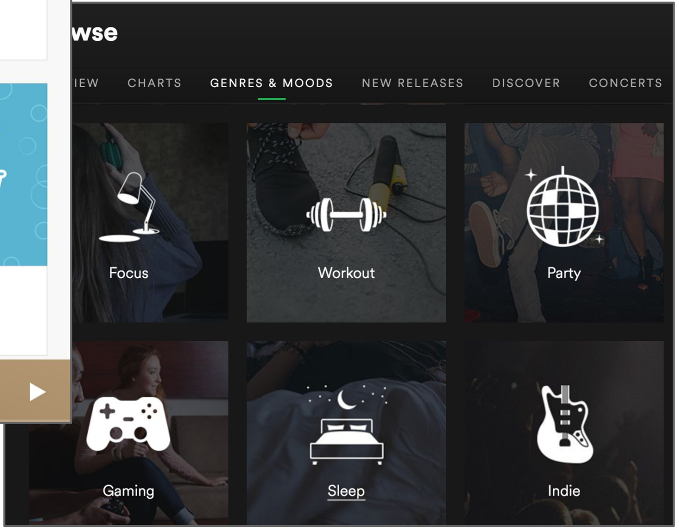
Lean in:
Building Playlists

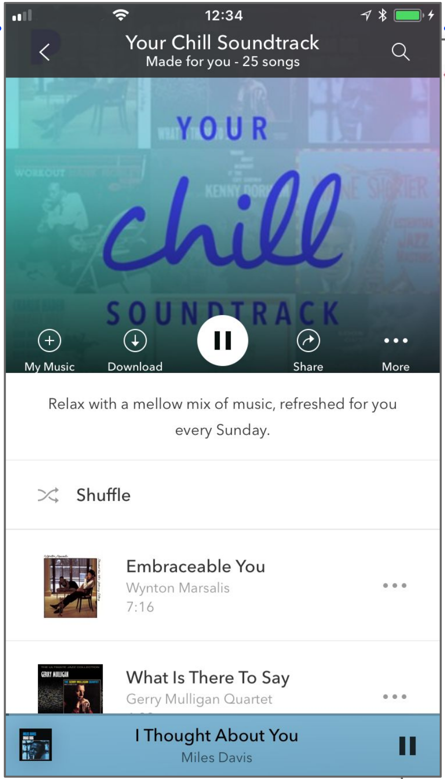


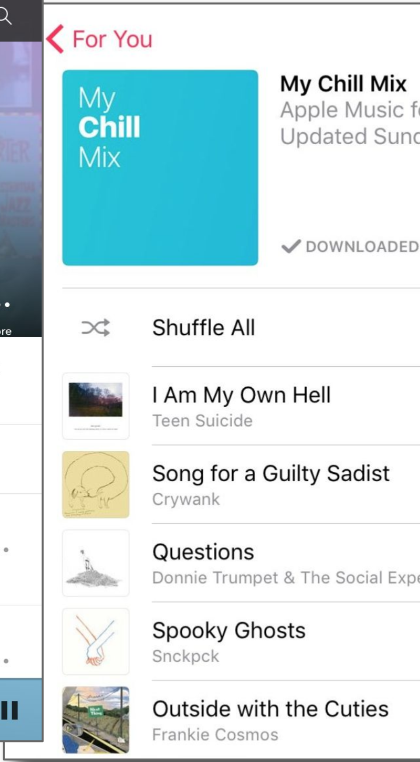


Focus on: Mood /Activity









Non-personalized vs. Personalized

Challenges for MIR

- Infer best vehicle for recommendation based on context
    - In opposition to asking user for explicit choice
- Discovery: The right balance between explore vs. exploit
- Balance lean-back vs. lean-in
- Personalization… but not too much (can be creepy)… not always (music is social)

Talking about Challenges...

Spotify RecSys Challenge 2018

RecSys Challenge 2018

ACM RecSys Challenge

- ACM RecSys Challenge (http://www.recsyschallenge.com/2018)
- Tasks involved:
  - *Automatic playlist generation* (APG): generate a new playlist from title
  - *Automatic playlist continuation* (APC): continue or complete a given playlist
- Tracks:
  - *Main track*: prediction only based on data given in Million Playlist Dataset
  - *Creative track*: all publicly available data sources can be used
- Common approach: sequential prediction models learned from given playlists
- Additionally, exploiting previous listening sessions/playlists or long-term listening preferences → "personalized APC"

RecSys Challenge 2018 - Main approaches

- Many **neighborhood-based approaches** (e.g., item-based and playlist-/session-based CF; i.e. sims between indiv. tracks vs. entire playlists)
- Often **simple filtering** w.r.t. playlist titles (e.g. TFIDF+cosine)
- Integration of **text and audio** information in CBF
- Combining **CF and CBF** (e.g., enhancing CF with playlist tile information)
- **Two-stage models**: usually, 1st stage for quick candidate track selection (often via model-based CF), 2nd to reweigh candidates (e.g., gradient boosting including additional playlist features)

RecSys Challenge 2018 - Main approaches

- **Deep learning**: RNNs, adapted CNNs, AAE, etc.
- **Graph-based** models: e.g., model playlists and tracks as graph, playlist-title-based graph filtering, random walk for playlist generation
- Measuring **aspects of seed playlist** (e.g., coherence, diversity, etc.) and adding **track sequences matching the aspect level** in seed playlist
- Most approaches did **not** consider the order of tracks

RecSys Challenge 2018 - Lessons learned

- **Winner used quite complex approach:**

  2-stage pipeline, comprising

  1. linear combination of WRMF, adapted CNN, item-item and user-user k-NN,

  2. five feature sets (weights + scores from 1st stage, playlist and song features and similarities, artist/album overlap, differences in duration and length, etc.);
     tree-based gradient boosting for optimization/reranking

RecSys Challenge 2018 - Lessons learned

- But: quite **simple 2-staged approaches** (NN, filtering + boosting) often **performed very well** (e.g., based on track frequencies and co-occurrences, recreating the level of diversity or coherence, etc.)
- Approaches in ***creative track*** which exploited public external data (e.g., audio features) **did not outperform** those in ***main track*** that did not use external data (results of winners almost identical w.r.t. R-prec., NDCG, click rate)

Challenge for MIR

- Understanding to which extent and in which contexts the **sequential order** of input (listening sessions, user-generated playlists) and output (stations or playlists) **matters**

- Generally, sequential recommendation is trending in RecSys
- ISMIR has done a lot of prior work on playlist generation and sequential ordering, using different data sources and signals

Bigger Challenge for MIR

- Need for **context- and sequence-sensitive evaluation strategies**, e.g., using ratings in context, considering playlist coherence and diversity
    - Accuracy/relevance measures barely suited: which preferences are due to context/sequence and which due to other factors?
    - How to evaluate a “listening experience”? (subjectivity, repeatability!)
    - When using questionnaires/web surveys, careful selection of participants necessary (gender, age, profession, knowledge, background, etc.)

Recommendation in the Creative Process of Music Making

Recommenders for Music Creators

- 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)

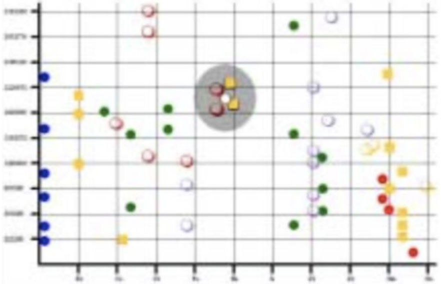
- Actually the ideal target group for music retrieval and recommendation

Digital Audio Workstations (DAWs)

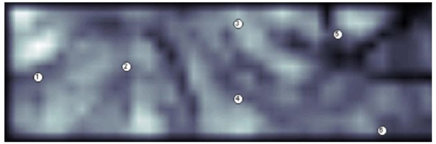
- Commercial products come with very large databases of sounds
- Screen optimized for arrangement/mixing
- UI for finding material marginalized or external window
- Incorporated strategies:
  - Name string matching
  - Tag search/filtering
  - Browsing (=scrolling lists)
- No one tags their library!

Facilitating Sound Retrieval

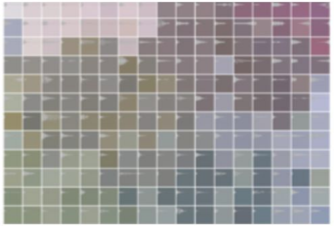
- New (academic) interfaces for sample browsing

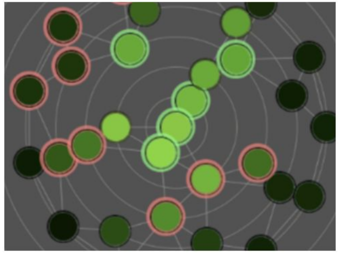


Sonic browser
(Fernström and Brazil, ICAD 2001)

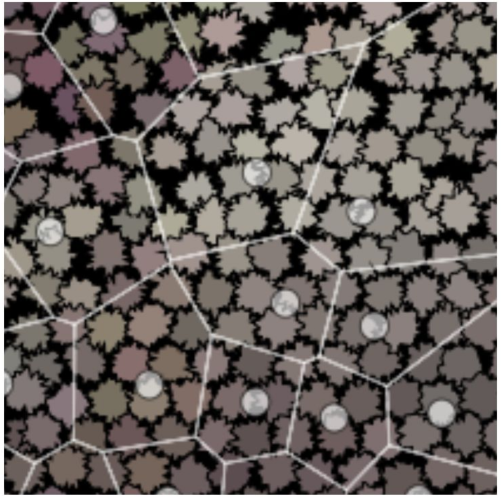


Drum sample browser
(Pampalk et al., DAFx 2004)





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

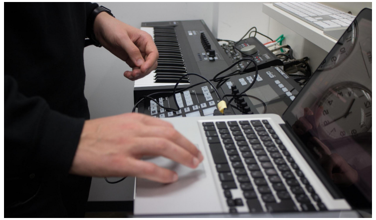
- Peer-conversations through semi-structured interviews

- 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)

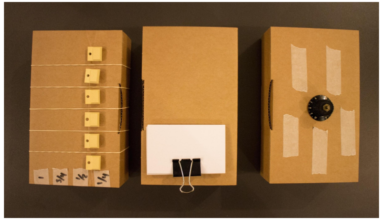
- Imitation is not the goal: **opposition** is the challenge

"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 Creative Work

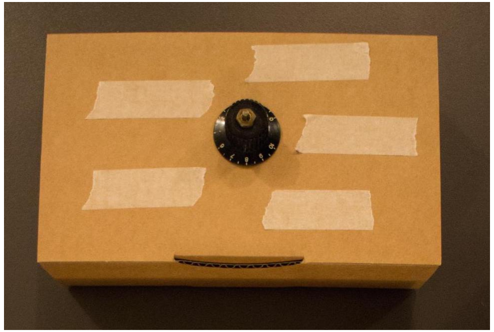
- **"Filter bubble" effects** in recommender systems:
  obvious, predictable, redundant, uninspiring, disengaging results
- Responses: optimizing for diversity, novelty, serendipity, unexpectedness
- In particular in creative work
  - no interest in imitating existing ideas and "more of the same" recommendations
  - 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 <u>rhythm</u>
- 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 choose from, actually. Like for me, I would be super interested to see it in 'your' strange, for example." (STRB006)

Some Takeaways

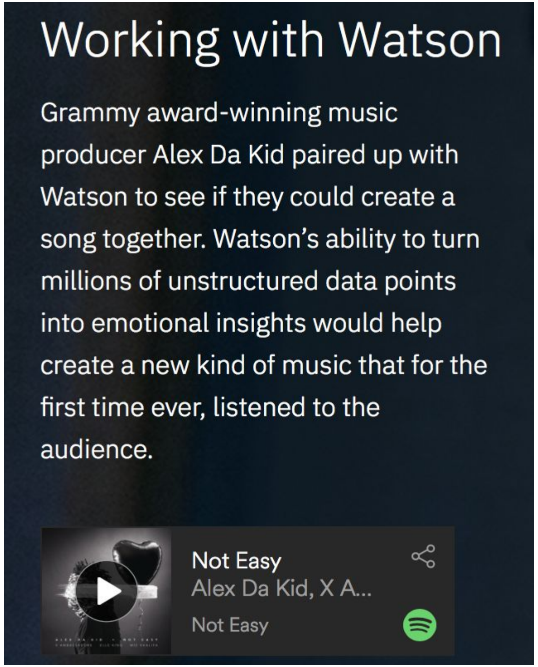
- **User intent** is a major factor also in this area
- Experts need recommenders mostly for **inspiration**: serendipity is key
- Control over recommendation desired (...transparency could help)
- Not much collaborative interaction data in this domain

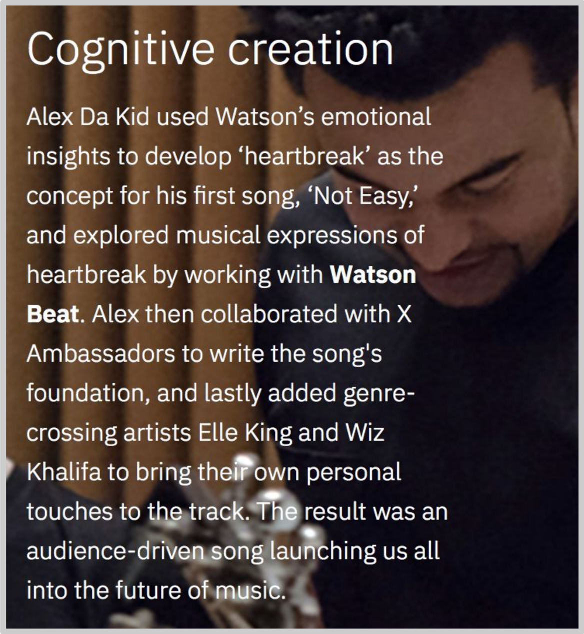
  → Strong focus on content-based recommenders

  → 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**

“Virtual Collaborator”

IBM Watson Music





Recommendation just an intermediary step to personalized content creation?

Trending Topics

- Intelligent machines to support music creation
- Many **supportive system prototypes and tools** in products, e.g.,
  - melody/composition: Lumanote, JamSketch
  - rhythm: Vogl [2017], Reactable STEPS/SNAP
  - “semantic” control, automatic remixes, …
- **AI for automatic composition**
  - Generative models
  - Producing royalty-free music (?)

[Granger et al.,, 2018] *Lumanote: A Real-Time Interactive Music Composition Assistant*. MILC@IUI.
[Kitahara et al., 2017] *JamSketch: A Drawing-based Real-time Evolutionary Improvisation Support System*. NIME.
[Vogl, Knees, 2017] *An Intelligent Drum Machine for Electronic Dance Music Production and Performance*. NIME.
[Cartwright, Pardo, 2013] *Social-Eq: Crowdsourcing An Equalization Descriptor Map*. ISMIR.
[Davies et al. 2014] *AutoMashUpper: automatic creation of multi-song music mashups*. TASLP.

AI-based Music Generation

Google Magenta

- deep neural networks for, e.g., expressive renderings, interpolations

Flow Machines/Spotify

- automatic continuation/accompaniment, composition in style of X

Jukedeck, melodrive, et al.

- Automatic, royalty-free soundtracks, video game music, "personalized music"

Other big tech companies somewhat active as well: IBM Watson (Beat), Baidu

melodrive
adaptive music generation

Further sources on generative music:

- How Generative Music Works: A Perspective (https://teropa.info/loop/)
- Neural Nets for Generating Music (Medium)

Where could this be going?

- Parameters of music + usage patterns, context, etc.
  → train generative model to generate “the right music” for free?
- Does music need to be good to be a success, i.e., listened to?
- (in AI terms: will the Turing test be passed?)
- In any case: music production will get increasingly automatized

Challenges for MIR

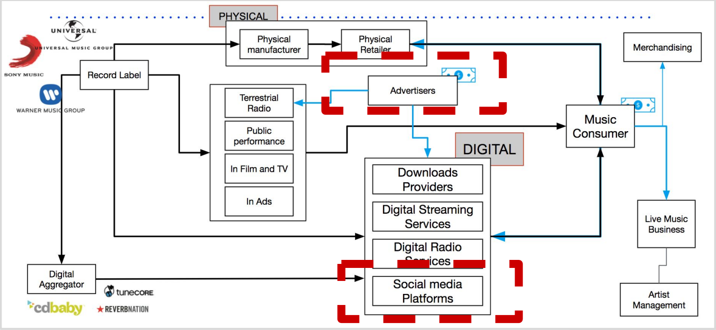
Two posed challenges in ISMIR 2016 paper:

- **Challenge 1: exploring dissimilarity in search**
  - Exploring opposition
  - Context-dependent, personalized user models for “dissimilarity”
  - Final goal: artificial collaborator capable of inspiring
- **Challenge 2: retrieval methods for visual queries**
  - “Semantics” of sound often visual (synaesthetic)
  - Goal: search for sound based on visual sketches

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

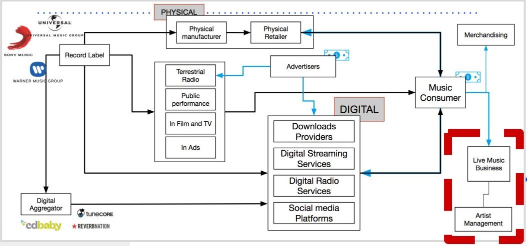
What's Next?

Further opportunities



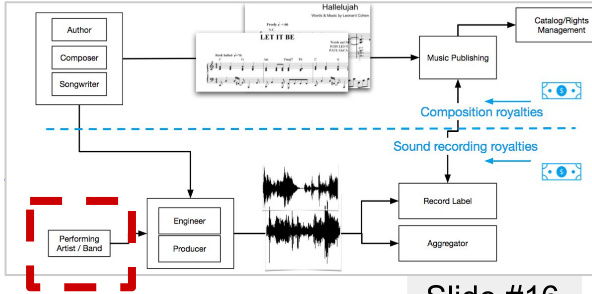
Slide #17

- 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 than radio for ads-targeting
  - 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 #17

Further opportunities



Slide #16

- Live Music Business, e.g.
  - Recommending upcoming concerts to listeners
  - Recommending artists to e.g. music festivals

TICKETFLY

- Recommendations for artist management, e.g.
  - Help agents find best opportunities for artists

Musicverb

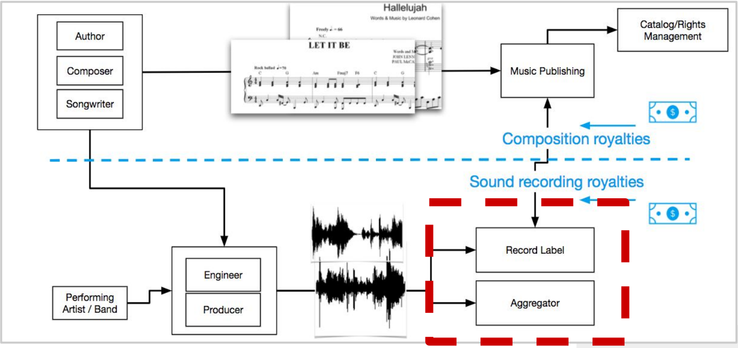
- Recommendations to artists
  - Recommending artists where to play
  - Help artists grow their careers, with insights based on data
  - Help artists communication with their fanbase

NEXT BIG SOUND

Further opportunities

- Data Science (and MIR) 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.

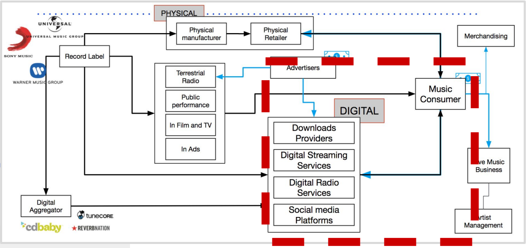
NB: Interesting explore/exploit trade-off



Slide #16

- NB: Some of these use cases addressed in H2020 project FuturePulse

Further opportunities



Slide #17

- Voice-driven interaction with music
  - Dedicated hardware (for home or car) vs. usual interfaces (e.g. phone)
  - Smart speaker growth
  - Today: “command-and-fetch”, e.g. “Play God’s Plan by Drake”
  - Tomorrow: More casual interactions, ambiguous queries, conversations
  - Calls for: Metadata, Personalization
  - Competes with terrestrial radio (more passive listening)

[Dredge; 2018] *Everybody’s talkin’: Smart speakers and their impact on music consumption*, Music Ally Report fo BPI and ERA.

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 accessibility
  - e.g. Are we all equal in the eyes of ASR technology?
- 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

algodiv
Information Diversity and Algorithmic Recommendation

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

Challenges

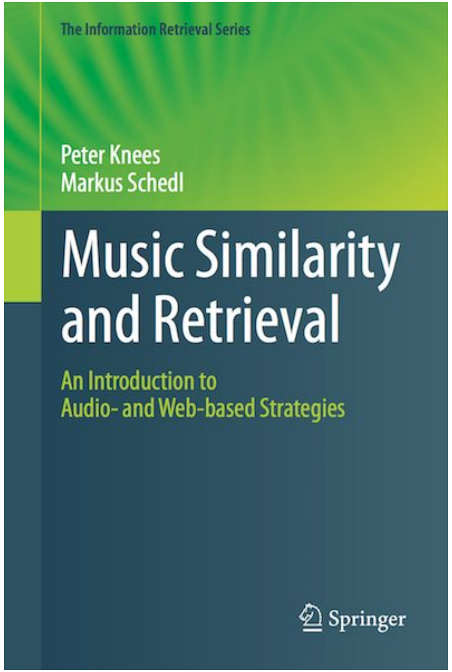
- Leveraging human-curated recs into algorithmic ones
- Inferring context/focus from listening behavior (and historical data)
- Exploring a listener's plurality of tastes without being disruptive
- Blending diverse types of content in listening experience (music, spoken words, etc.)
- Blending social interactions in music streaming
- Transparency and trust
- Metrics for approximating long-term user satisfaction
- Improving ASR, NLP, NLG & Dialog Systems for voice-driven music interactions

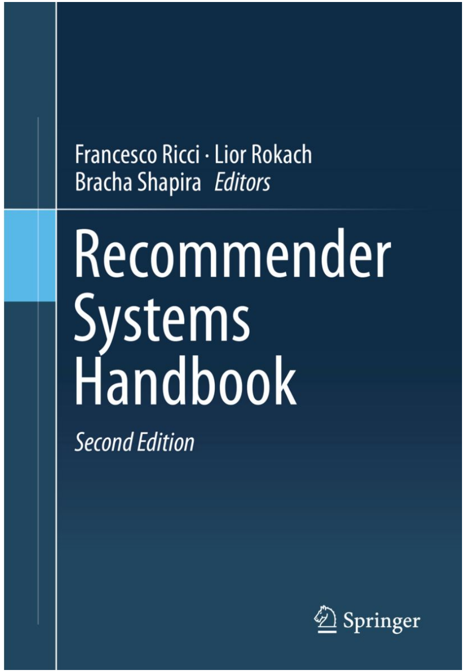
[Motajcsek et al. 2016] *Algorithms Aside: Recommendations as the Lens of Life*, RecSys 2016

Want to address these challenges?

- Shameless self-promotion for open reqs and collaboration opportunities:
  - @ Pandora → https://pandora.com/careers/product-technology
  - @ TU Vienna → https://www.ifs.tuwien.ac.at/~knees/
  - @ JKU Linz → http://www.cp.jku.at/people/schedl/
- Shameless self-promotion for related workshop (announced soon):
  - 2nd Workshop on Intelligent Music Interfaces for Listening and Creation (MILC) in conjunction with IUI 2019, Los Angeles, CA, USA, March 17-20, 2019

Want to read 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

Just waking up? → Take-Home Messages

- Dramatic changes in music consumption (Industry growth; Transition from "ownership" to "access") imply great challenges
  - Potential impact/benefit for ISMIR community
  - Opens up many research directions

- MIR has potential to be disruptive in many parts of the music industry (not just end-user consumption)

- Creating truly personalized and contextual music listening experiences, and evaluating listener satisfaction, are still very challenging research topics

Acknowledgments

- The SmarterJam project (FFG)
- Faculty of Informatics, TU Wien
- The GiantSteps project
- Oscar Celma
- Andreas Ehmann
- Gordon Rios
- Tao Ye
- Sid Patil
- Cristina Sá
- Massimo Quadrana
- Kristina Andersen
- Ching-Wei Chen
- Paul Lamere

The End

Thank you

Q&A #2

http://www.cp.jku.at/people/schedl/
https://www.ifs.tuwien.ac.at/~knees/
https://www.linkedin.com/in/fgouyon/

@m_schedl
@peter_knees
@fgouyon