UNIVERSITY OF PRIMORSKA, KOPER
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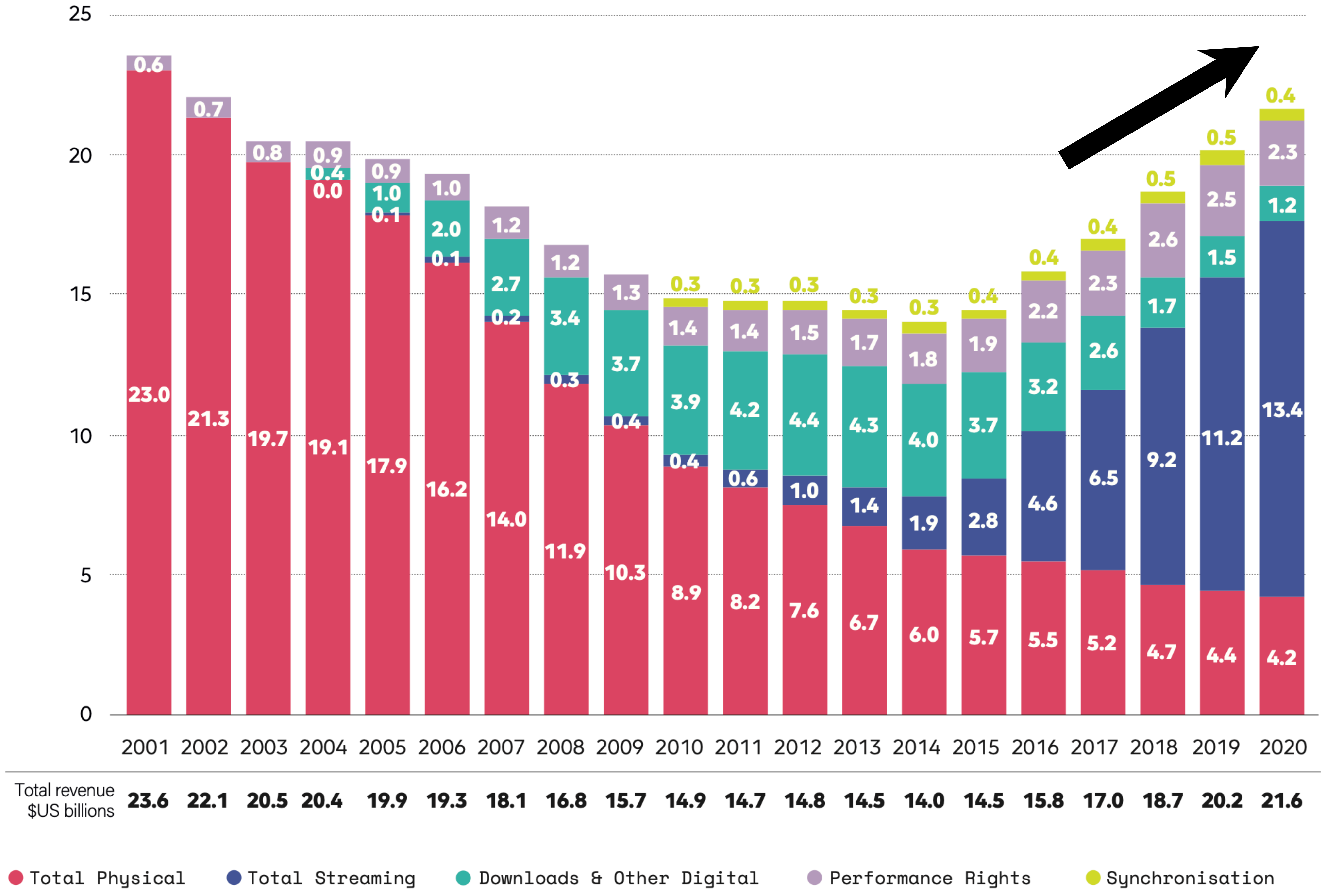
MUSIC RECOMMENDER SYSTEMS

unesco Chair

MUSIC CONSUMPTION

GLOBAL RECORDED MUSIC INDUSTRY REVENUES 2001-2020 (US$ BILLIONS)



GLOBAL RECORDED MUSIC REVENUES BY SEGMENT 2020

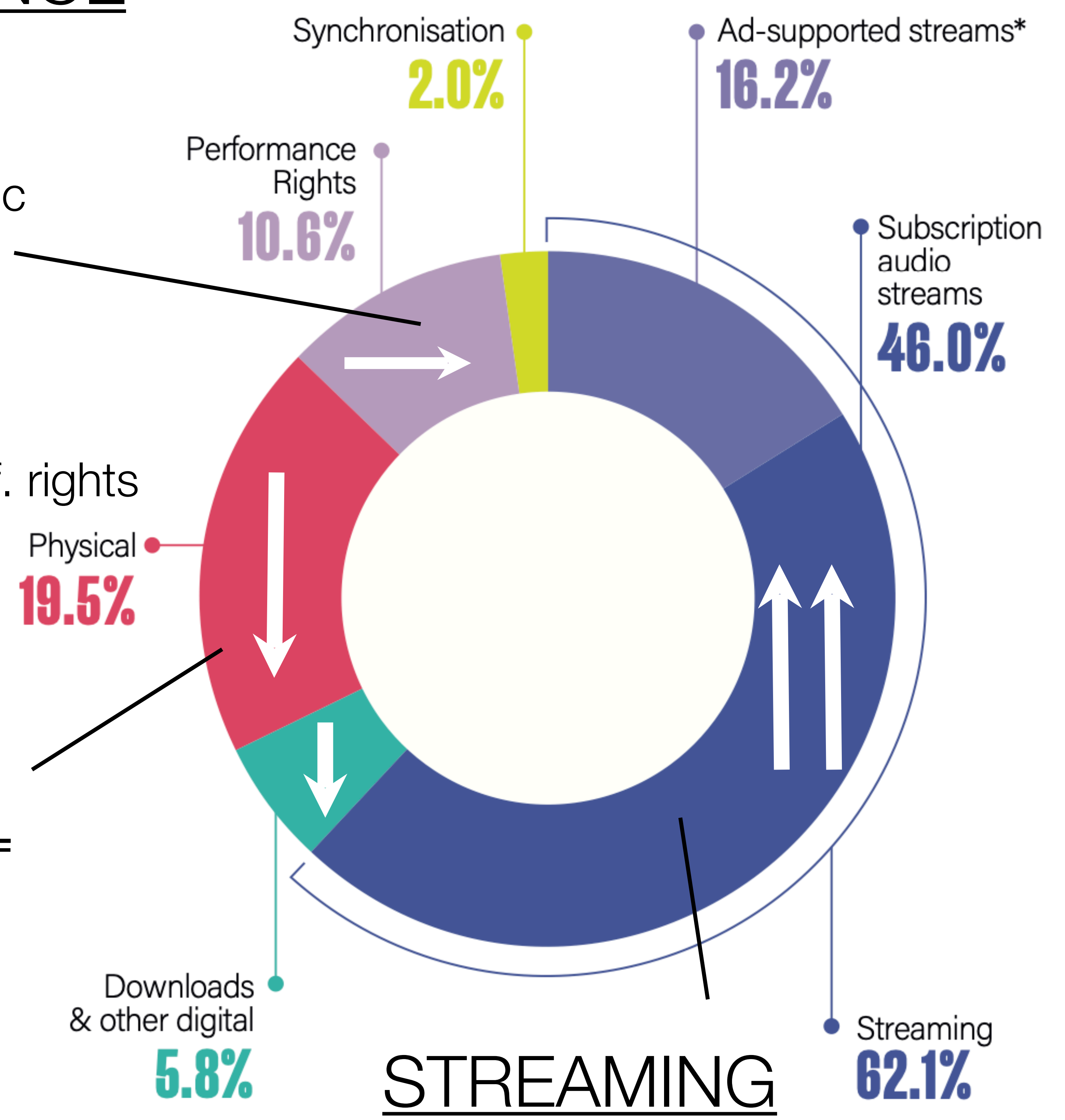
PERFORMANCE RIGHTS

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

(NB: Excluding perf. rights from Streaming)

PHYSICAL

e.g. CDs



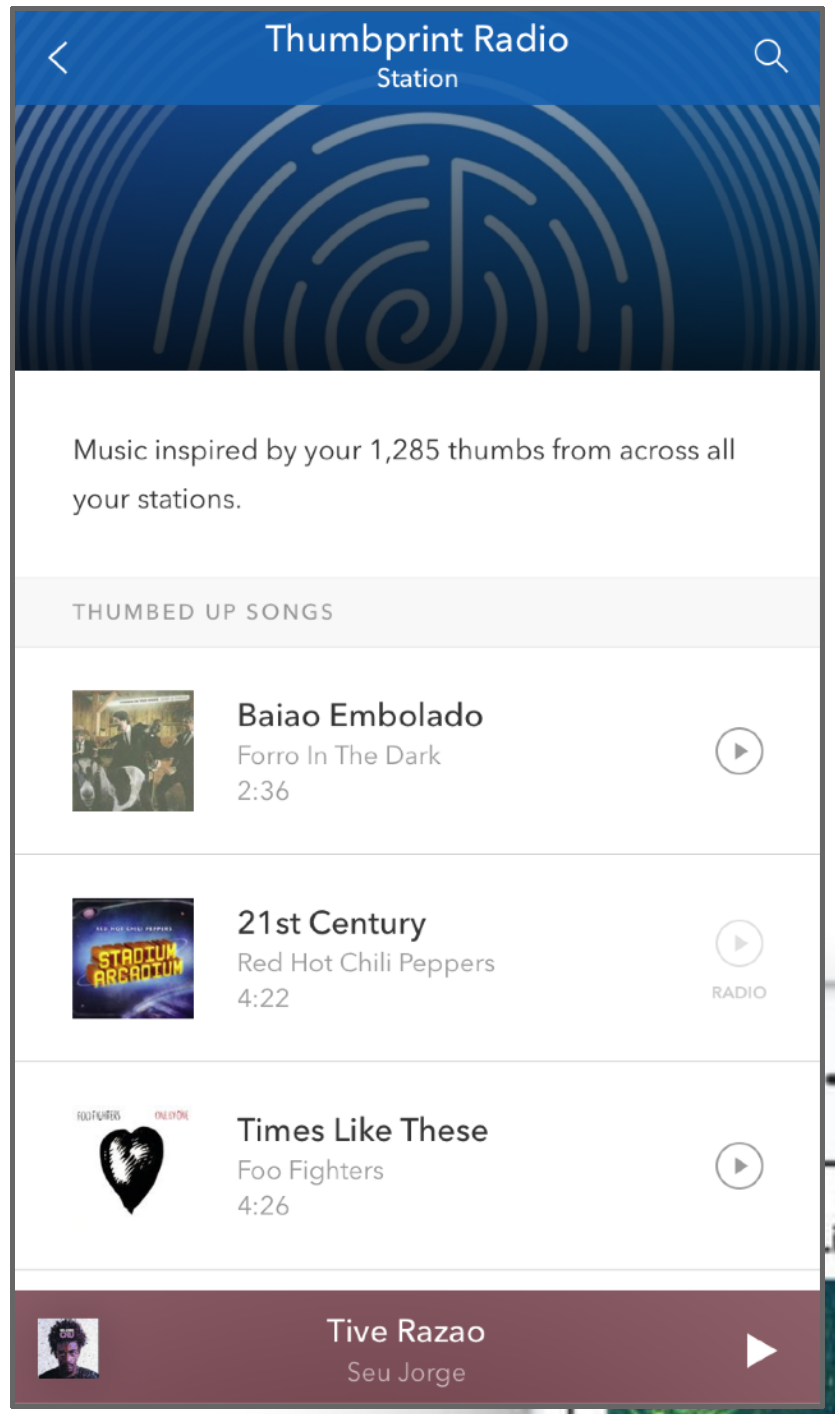
STREAMING

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

*INCLUDES AD-SUPPORTED STREAMS AND VIDEO STREAM REVENUES.

MUSIC DISCOVERY

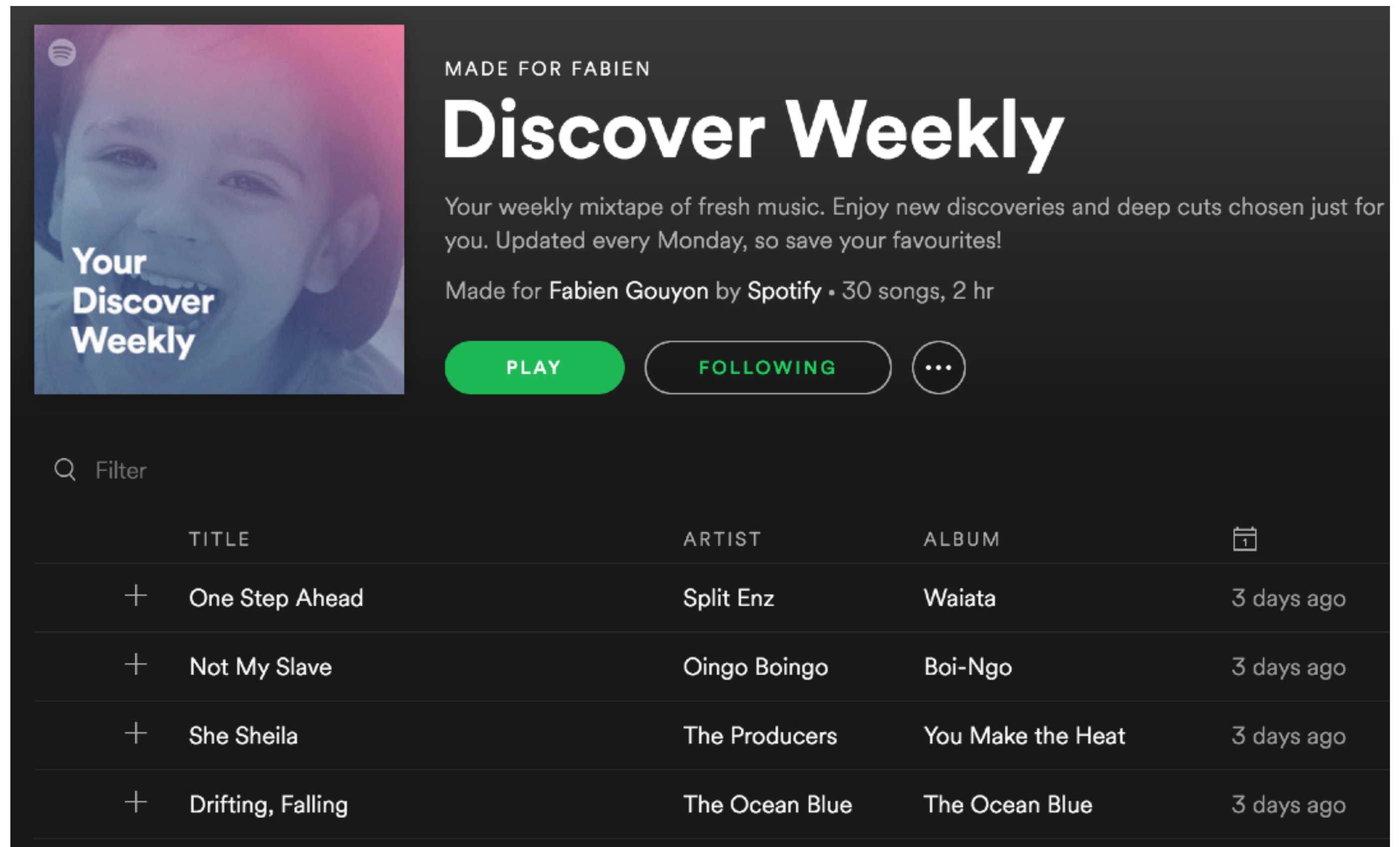
- Streaming "taking over" physical & downloads
- But competing with terrestrial radio, too

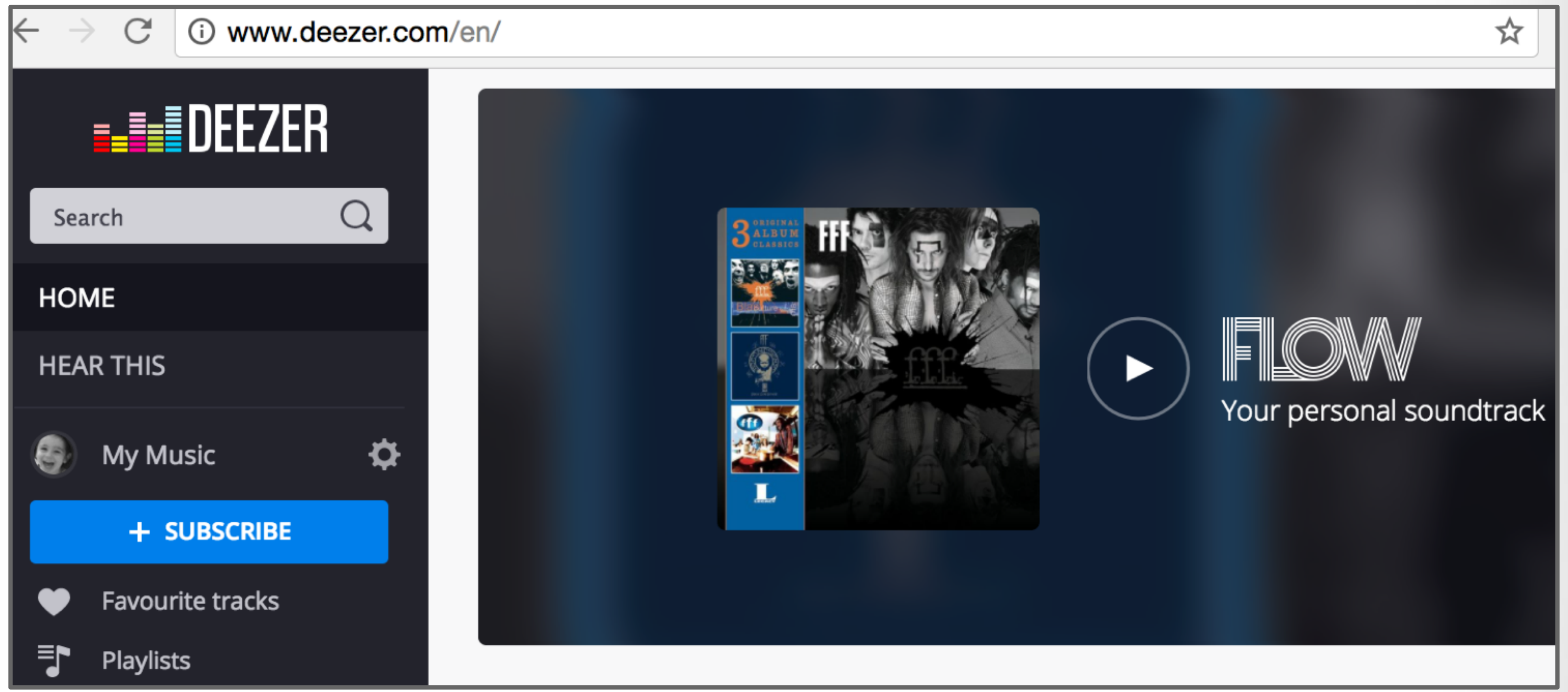


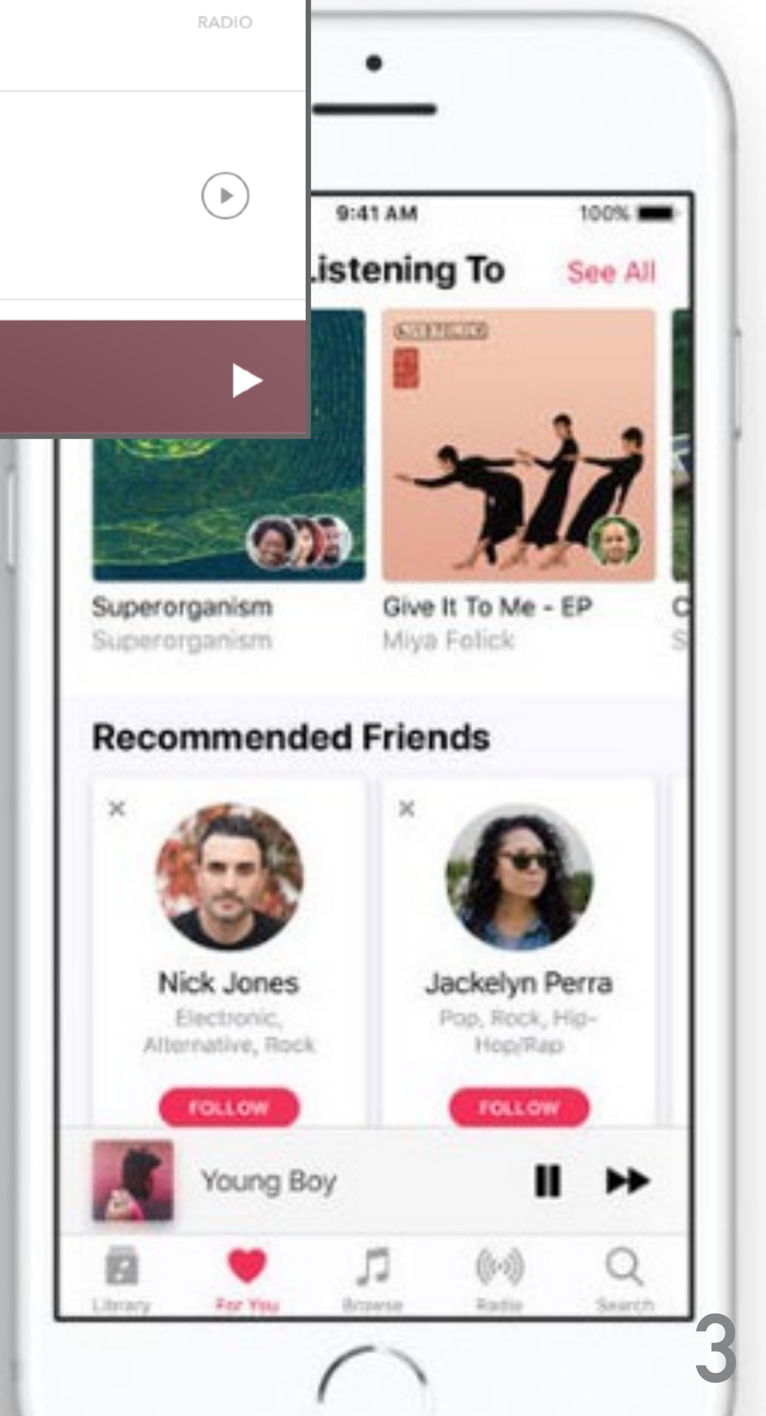
The Quest for "Discovery"

Ongoing quest for defining listening format calls for:

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







RECOMMENDER SYSTEMS

- Growing amounts of data artifacts available
(User generated + commercial)
- Providing tailored views onto massive data collections
➡ **Personalization**
- Recommender Systems are an <u>**Information Filter**</u>
- Provide right items (options, answers, …) at the right time
- Found in all areas, powers central services and platforms of digital economy

WHAT'S SPECIAL TO MUSIC RECOMMENDATION?

- Extremely relevant to the music industry due to **rise of streaming**
- Magnitude of available data items (millions) & data points (billions)
- **Various types of items** to recommend (songs, albums, artists, audio samples, concerts, venues, fans, etc.); **various tasks** (discovery, playlist building, etc.) subsumed under music recommendation
- Wide range of duration of items (2+ vs. 90+ minutes),
  Lower commitment, items more "disposable", **low item cost**
  → "bad" recommendations maybe not as severe
- Very often **consumed in sequence**
- **Re-recommendation** often appreciated (in contrast to e.g. movies)

WHAT'S SPECIAL TO MUSIC RECOMMENDATION?

- **Listener intent and context** are crucial
    - Different consumption locations/settings: static (e.g., via stereo at home) vs. variable (e.g., via headphones during exercise), alone vs. in group, etc.
    - Often consumed **passively** (while working, background music, etc.)
    - Importance of **social** component
    - Music often used for **self-expression**
    - Highly **emotionally connoted** (in contrast to products, e.g. home appliances)
- Recommendations relevant for various actors (listeners, producers, performers, etc.), **multi-stakeholder** recommendation scenarios
- **Diversity of modalities** (audio, user feedback, text, etc.)

DATA FUELS RECOMMENDERS

Interaction Data

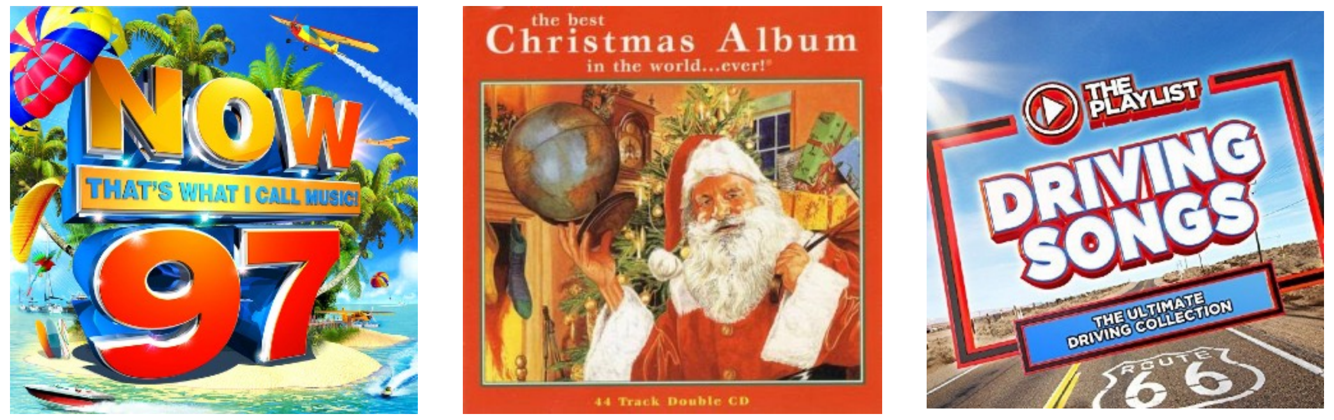
- Listening logs, listening histories
- Feedback ("thumbs"), purchases

User-generated

- Tags, reviews, stories

Curated collections

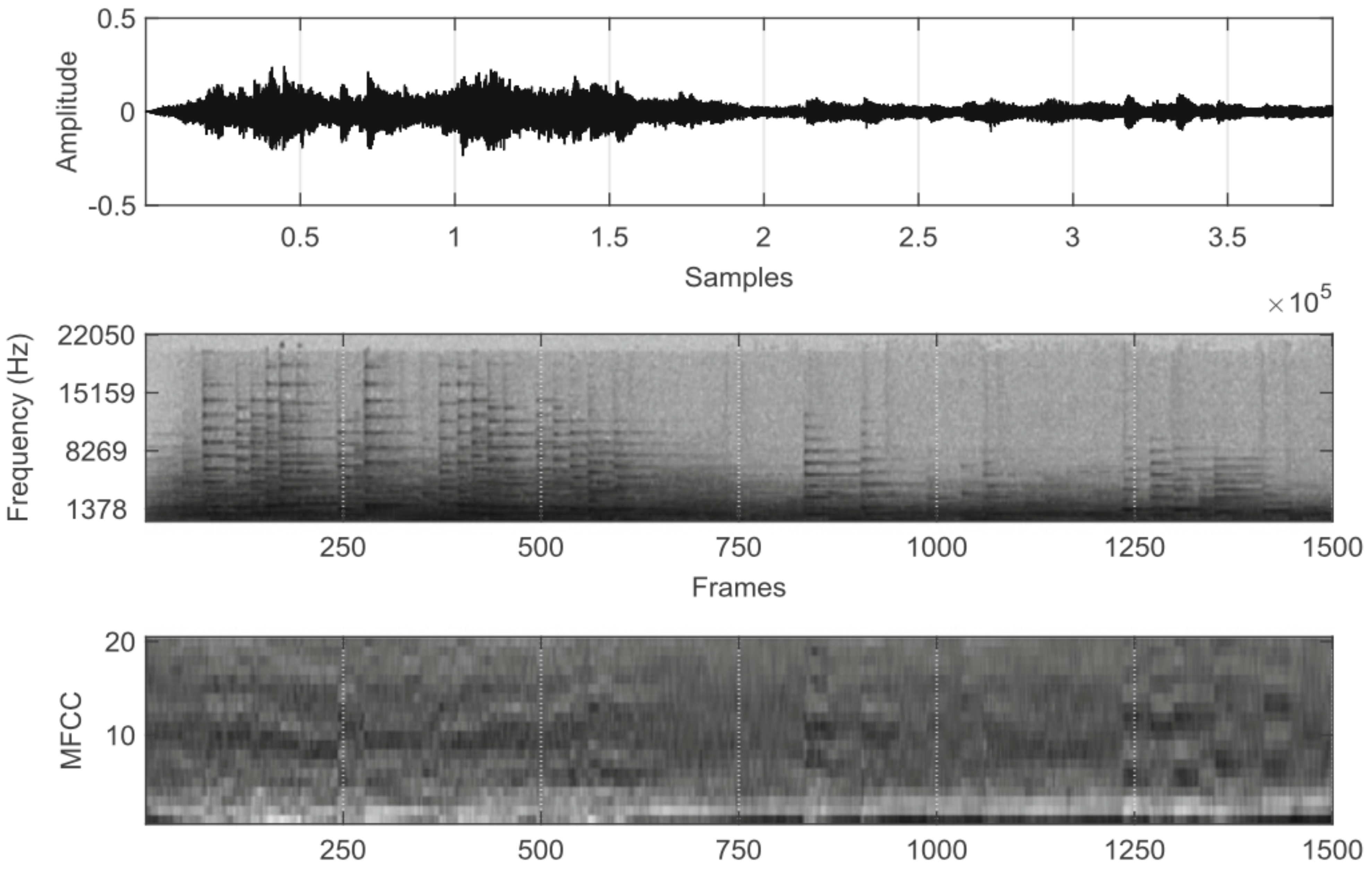
- Playlists, radio channels
- CD album compilations



DATA FUELS RECOMMENDERS

Content (audio, symbolic, lyrics)

- Machine listening/content analysis
- Human labelling



Meta-data

- Editorial
- Curatorial
- Multi-modal (album covers etc.)

AUDIO CONTENT ANALYSIS

➡️ CF. MUSIC-IR

- Finding "similar sounding" tracks
- Features can be extracted from any audio file
  → no other data or community necessary
  → no cultural biases (no popularity bias, no subjective ratings etc.)
- Manually crafted features or automatic via machine learning
- Representation learning and temporal modeling directly from signals (even as GenAI side products)

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

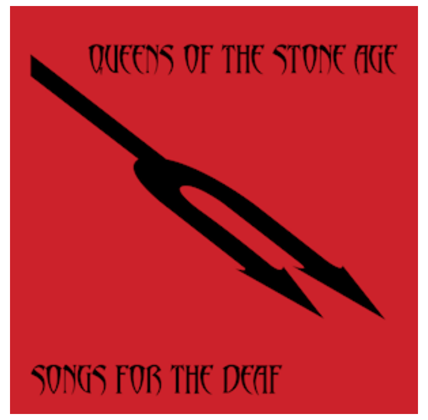
[Casey et al., 2008] *Content-based music information retrieval: Current directions and future challenges,* Proc IEEE 96 (4).

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

AUDIO CONTENT ANALYSIS: SELECTED FEATURES

Disturbed
The Sound of Silence

- Timbre (→ MFCCs)
  e.g. for genre classification,
  "more-of-this" recommendations



- Beat/downbeat → Tempo: 85 bpm

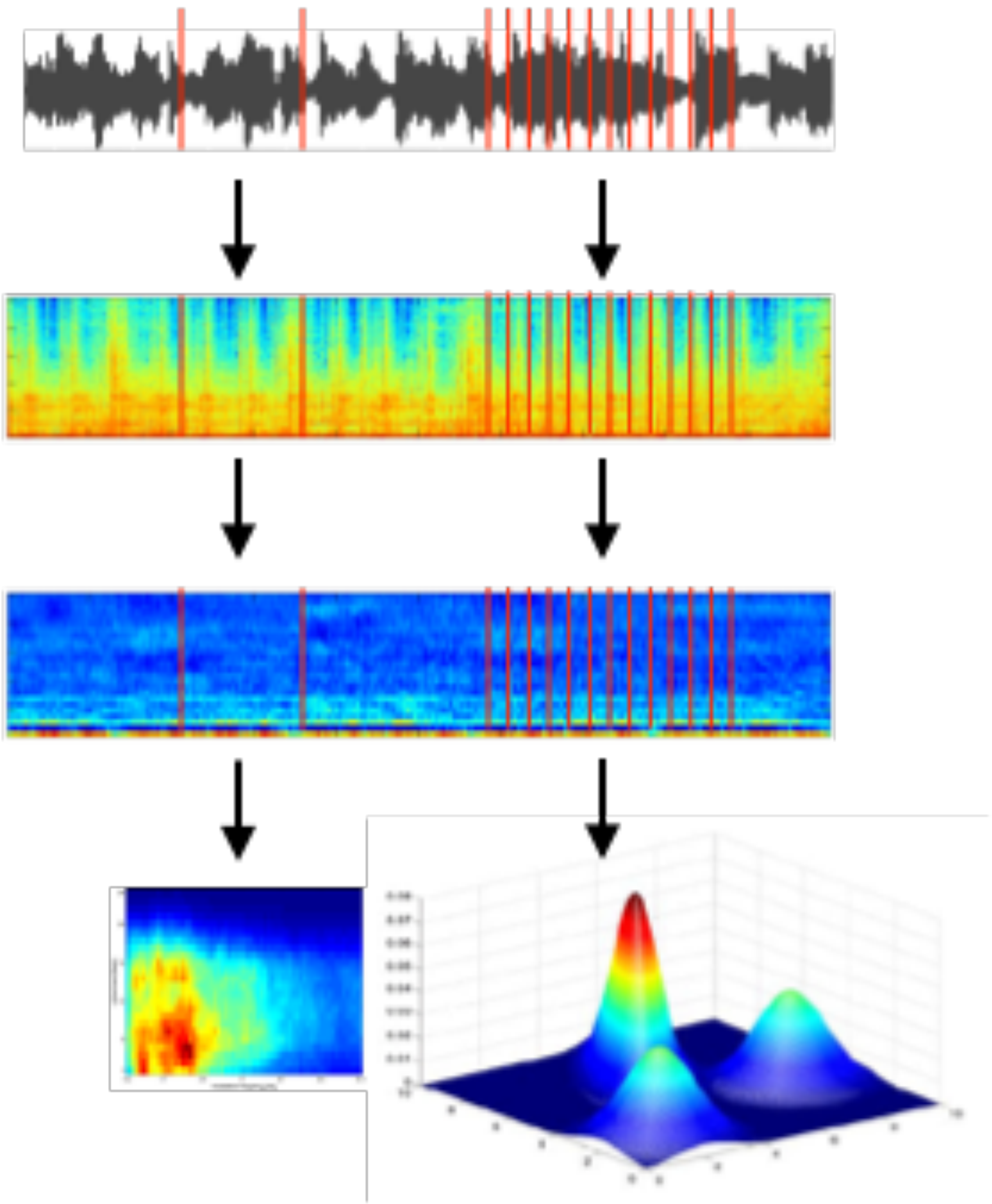
- Tonal features (→ Pitch-class profiles)
  e.g. for melody extraction,
  cover version identification

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:
  `not_danceable, gender_male, mood_not_happy`

AUDIO FEATURES: BASIC PROCESSING STEPS

- Convert signal from time domain to frequency domain, e.g., using a Fast Fourier Transform (FFT)
- Psychoacoustic transformation (Mel-scale, Bark-scale, Cent-scale, …): mimics human listening process (not linear, but logarithmic!), removes aspects not perceived by humans, emphasizes low frequencies
- Extract features, e.g.,
  - Block-level (large time windows, e.g., 6 sec)
  - Frame-level (short time windows, e.g., 25 ms) needs model distribution of frames
- Calculate similarities between feature vectors/models



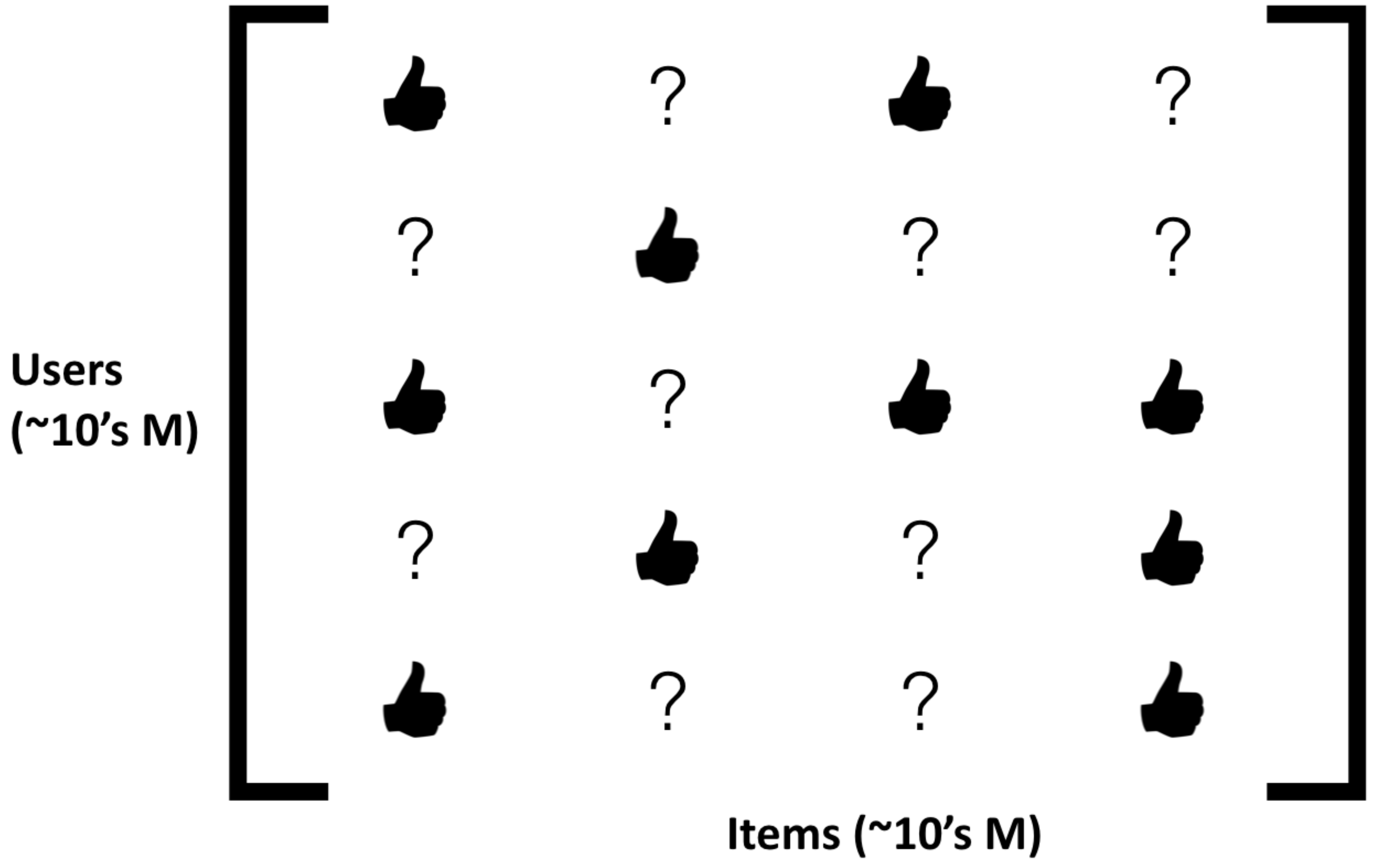
SO, GREAT … WHY IS THIS DIFFICULT THEN?

- “Objective” similarity measure of the “sound of music”
- Describes the output of the applied transformation as designed
- Works well for genre and mood classification …and that’s more or less it

- The resulting numbers represent a very narrow aspect of acoustic properties, describe no *musical* qualities (structure, development, time dependency, etc.)
- Which sound properties are important to whom and in which context?
- Lack of any personal preferences or experiences

COLLABORATIVE FILTERING (CF)

- Exploits interaction data
- *"People who listened to track A, also listened to track B"*
- Main underlying assumption: users that had similar taste in the past, will have similar taste in the future
- Stemming from "usage" of music
  → close to "what users want"
- Typical methods
  - Memory-based ("k-NN like")
  - Matrix factorization



EXAMPLE OF COLLABORATIVE FILTERING OUTPUT

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

1. Bad Wolves – Zombie

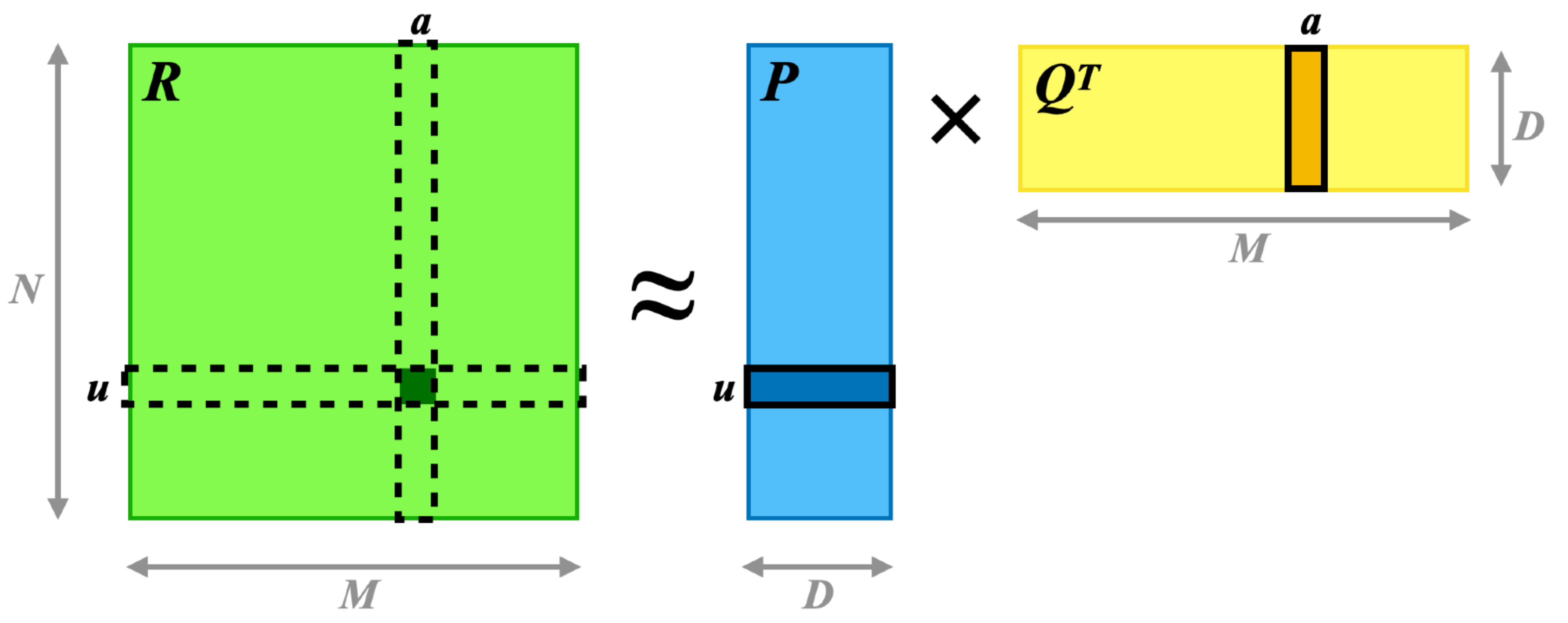
2. Five Finger Death Punch – Bad Company

3. Disturbed – The Light

4. Metallica – Nothing Else Matters

MATRIX FACTORIZATION

- Recommendation: a matrix completion problem
- Rationale: observed data are interactions of 2 factors: users and items
- Decompose interaction matrix $R \in \mathbb{N}^{N\times M}$ into user and item matrices P, Q of lower rank D: $P \in \mathbb{R}^{N\times D}$, $Q \in \mathbb{R}^{M\times D}$



- Objective: minimize reconstruction error

$$\min_{p_*,q_*} \sum_{r_{ua}\in R} (r_{ua} - p_u q_a^T)^2 + \boxed{\lambda(\|p_u\|^2 + \|q_a\|^2)}$$

regularization term

- Prediction of interaction: inner product of vectors of user u and item a

OPTIMIZATION THROUGH STOCHASTIC GRADIENT DESCENT

- Learn factors from R using stochastic gradient descent, cf. [Funk/Webb 2006]
- Gradient: calculating the direction of the steepest descent
- Need partial derivatives of the error function $\sum e_{ua}^2 = (r_{ua} - p_u q_a^T)^2$ wrt. each parameter p_{ud}, q_{ad} for all $u, a, d \quad d\ldots \textit{latent dimension}$
- Determine step length or use fixed length parameter as multiplier on the gradient ⇒ learning rate γ
- Update p_{ud} and q_{ad} using “backpropagation" (cf. neural networks)

$$p_{uD} \leftarrow p_{uD} - \gamma \frac{\partial e_{iA}^2}{\partial p_{uD}} = p_{uD} + \gamma 2(r_{uA} - r'_{uA}) q_{AD}$$

$$q_{aD} \leftarrow q_{aD} - \gamma \frac{\partial e_{iA}^2}{\partial q_{aD}} = q_{aD} + \gamma 2(r_{uA} - r'_{uA}) p_{uD}$$

- Note: factors not necessarily interpretable (just capture variance in data)

LIMITATIONS FOR MUSIC RECOMMENDATION

- Extreme sparsity in music interaction data
- Special case: Cold-start Problem
  - Recommending for new users: no prior interactions/preferences
  - Recommending new tracks: no prior usage
  - Mitigation: **incorporate additional data sources**
- Explicit feedback rare in music listening

  - Summing up listening events, often on artist level (combat sparsity)
  - **Factorization techniques for implicit data**

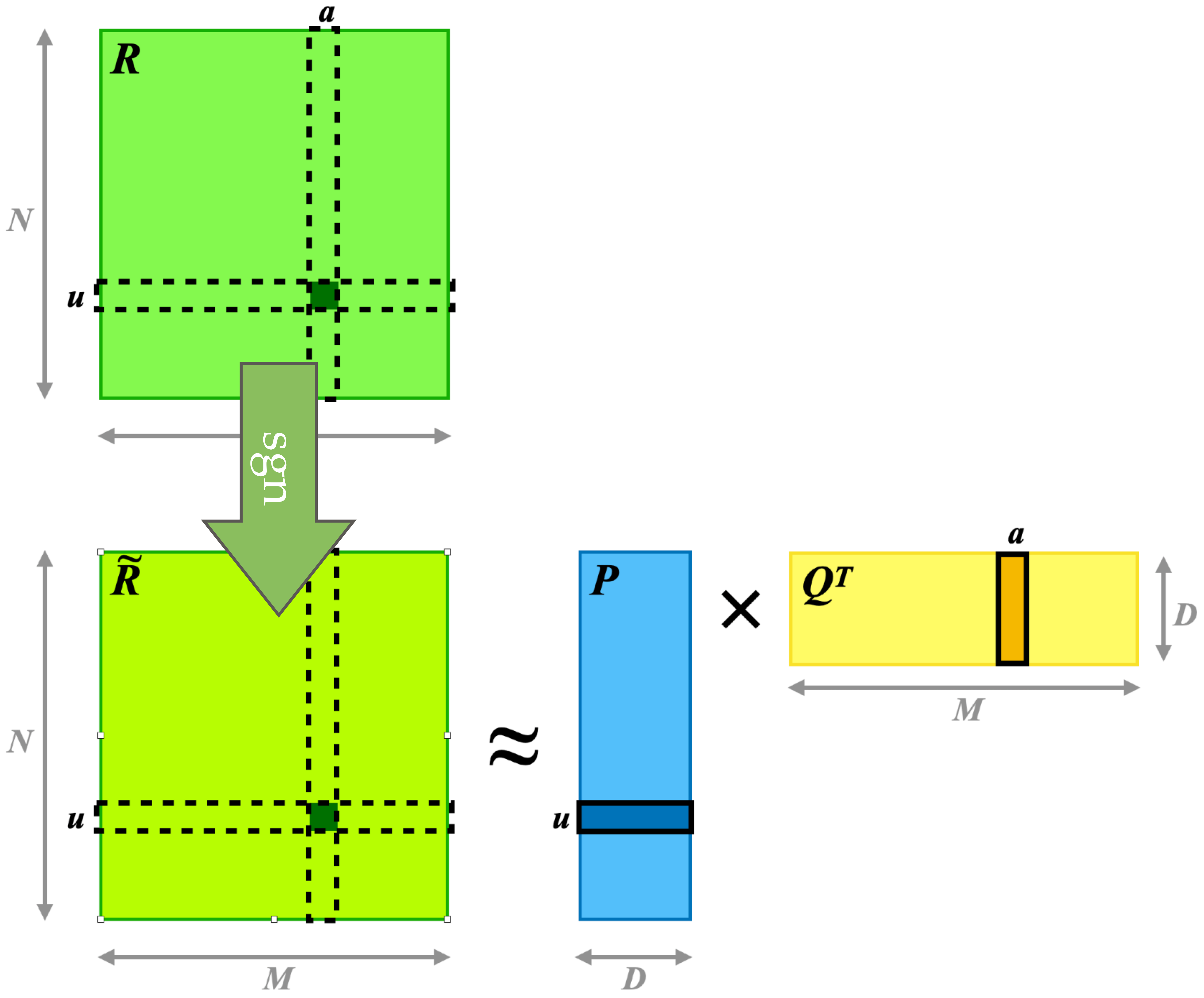
IMPLICIT FEEDBACK MATRIX FACTORIZATION (MF)

- Extension of Matrix Factorization for implicit data by Hu et al. [2008]
- R … aggregated play counts per artist
- $\tilde{R}_{ua} = \begin{cases} 1 & \text{if } R_{ua} > 0 \\ 0 & \text{if } R_{ua} = 0 \end{cases}$ $\quad w(\eta, x) = 1 + \eta \log(1 + x)$

  "preference" "confidence"
- Objective

$$\min_{P,Q} \sum_{ua \in R} w(\alpha, R_{ua})(\tilde{R}_{ua} - P_u Q_a^T)^2 + \lambda(\|P\|_F^2 + \|Q\|_F^2)$$

- λ, α determined by grid search



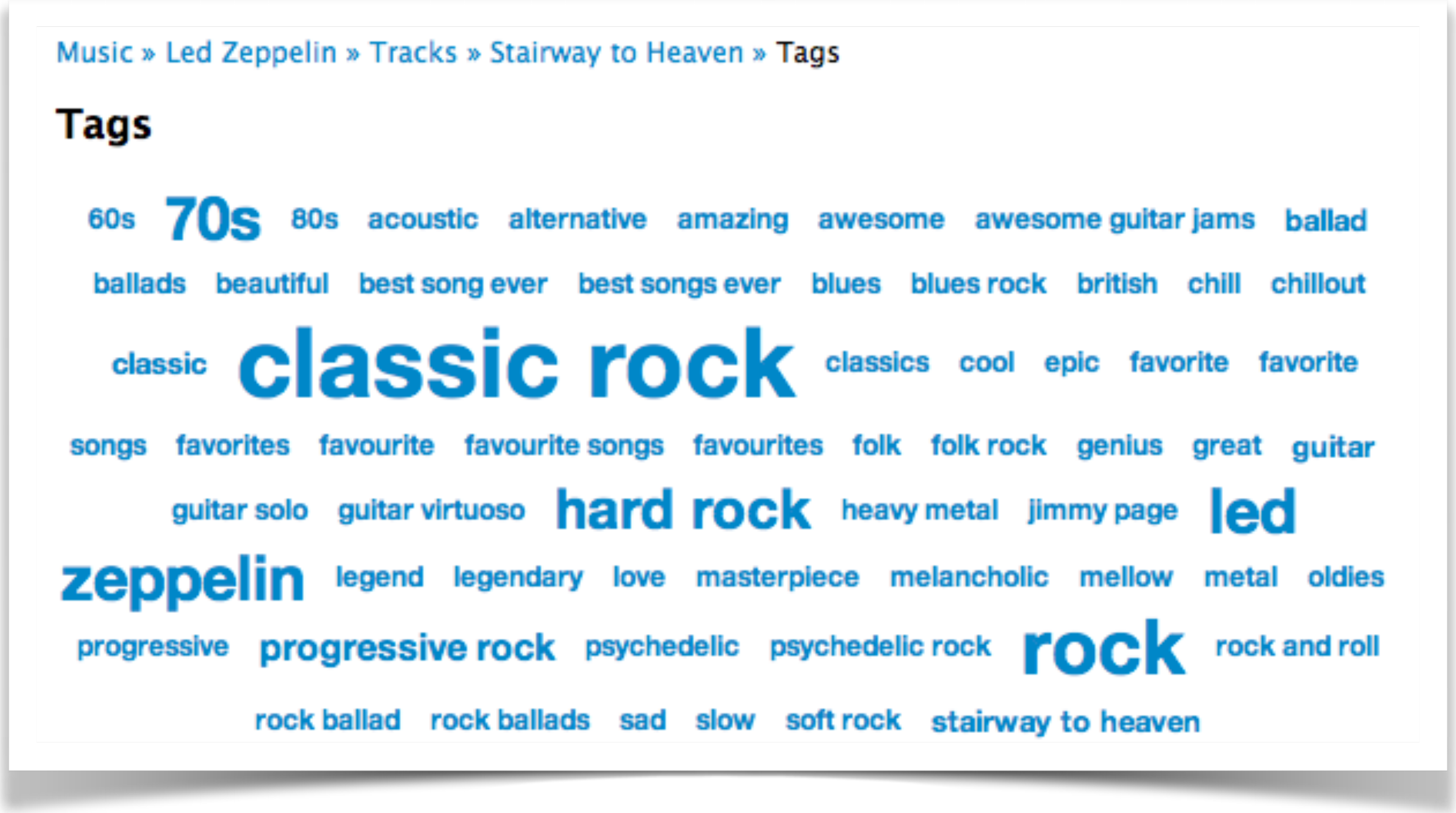
- Gradient updates

$$P_u = (Q^T W_R^{r_u} Q + \lambda I)^{-1}(Q^T W_R^{r_u} R_{r_u}^T)$$

$$Q_a = (P^T W_R^{c_a} P + \lambda I)^{-1}(P^T W_R^{c_a} R_{c_a}^T)$$

HYBRID RECOMMENDATION APPROACH

- Sparsity in interaction data
- Idea: incorporate information expressed in different types of data
- Tags: explicit semantic information assigned by users
- Combine implicit factorization with tagging data
- Extending model by Hu et al. (2008) by incorporating
  - users' tagging preferences (user-tag model)
  - how tracks have been tagged (track-tag model)



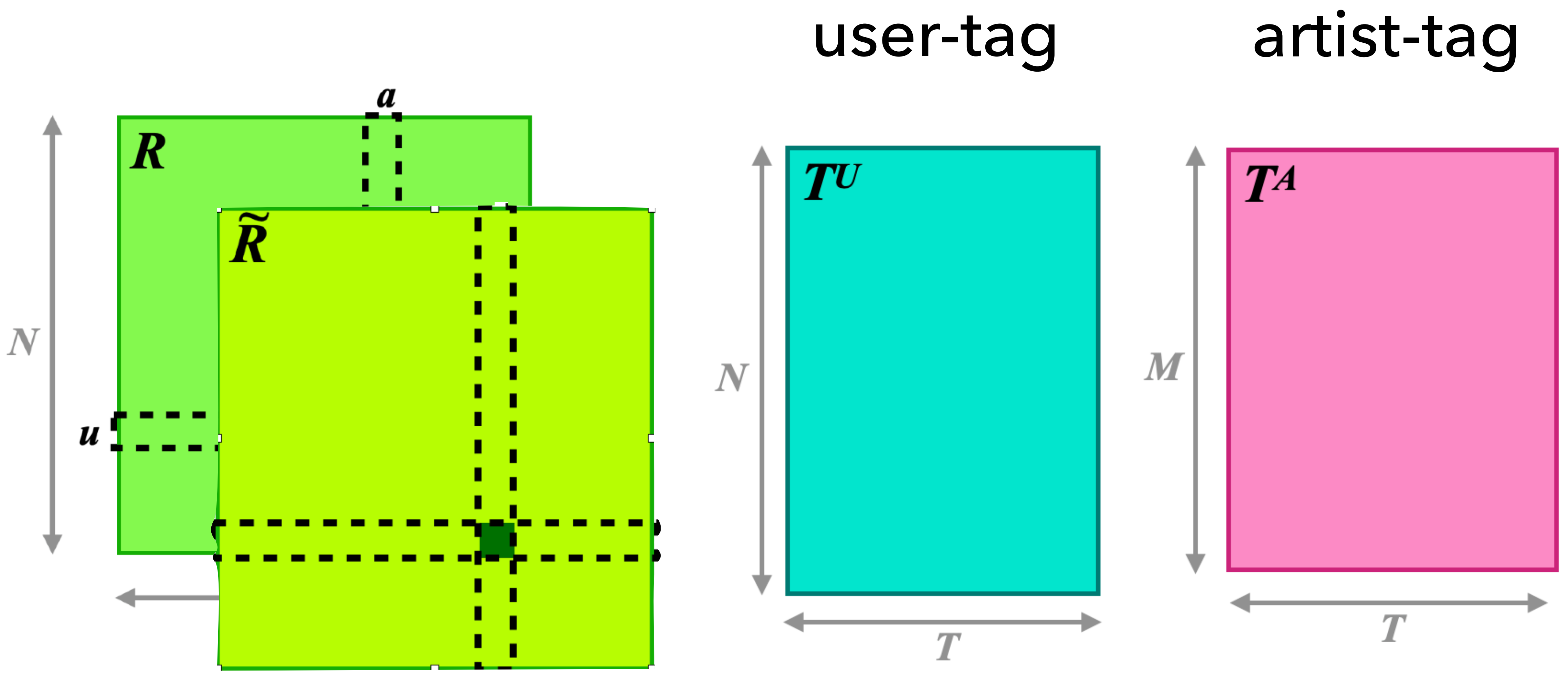
Improving Music Recommendations with a Weighted Factorization of the Tagging Activity.
A. Vall, M. Skowron, P. Knees, and M. Schedl. In: Proc 16th International Society for Music Information Retrieval Conference (ISMIR), 2015.

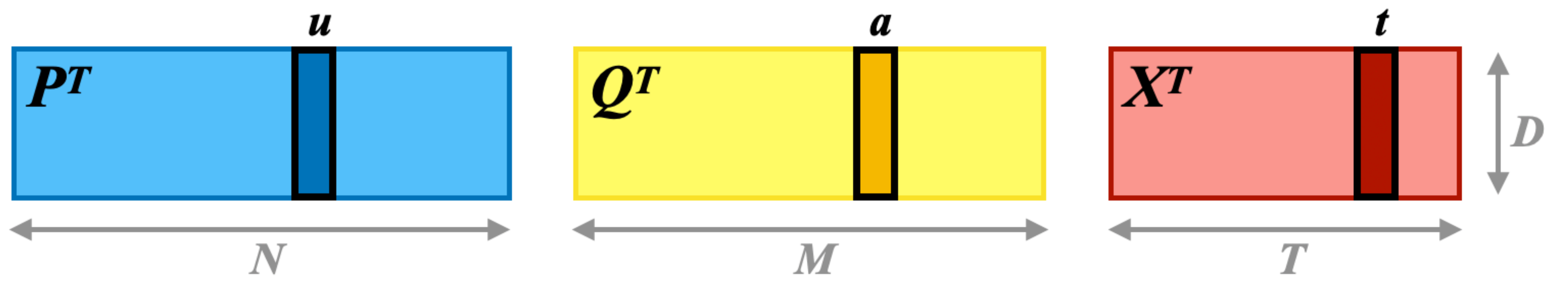
New Paths in Music Recommender Systems Research.
M. Schedl, P. Knees, and F. Gouyon. In: Proc 11th ACM Conference on Recommender Systems (RecSys), 2017.

IMPLICIT FEEDBACK MATRIX FACTORIZATION WITH TAGGING (TMF)

- Introducing T tags
- $T^U \in \mathbb{N}^{N \times T}$ … user-tag frequency matrix
- $T^A \in \mathbb{N}^{M \times T}$… artist-tag frequency matrix
- Latent factor matrix for tags $X \in \mathbb{R}^{T \times D}$
- Objective

$$
\begin{aligned}
\min_{P,Q,X} \; & \sum_{ua \in R} w(\alpha, R_{ua}) \left(\tilde{R}_{ua} - P_u Q_a^T\right)^2 \\
& + \mu_1 \sum_{ut \in T^U} \left(T^U_{ut} - P_u X_t^T\right)^2 \\
& + \mu_2 \sum_{at \in T^A} \left(T^A_{at} - Q_a X_t^T\right)^2 \\
& + \lambda \left(\|P\|_F^2 + \|Q\|_F^2 + \|X\|_F^2 \right).
\end{aligned}
$$





- Gradient updates

$$P_u = (Q^T W_R^{r_u} Q + \mu_1 X^T X + \lambda I)^{-1} (Q^T W_R^{r_u} R_{r_u}^T + \mu_1 X^T T_{r_a}^{UT})$$

$$Q_a = (P^T W_R^{c_a} P + \mu_2 X^T X + \lambda I)^{-1} (P^T W_R^{c_a} R_{c_a}^T + \mu_2 X^T T_{r_a}^{AT})$$

$$X_t = (\mu_1 P^T P + \mu_2 Q^T Q + \lambda)^{-1} (\mu_1 P^T T_{c_t}^{UT} + \mu_2 Q^T T_{c_t}^{AT})$$

IMPLICIT FEEDBACK MATRIX FACTORIZATION WITH WEIGHTED TAGGING (WTMF)

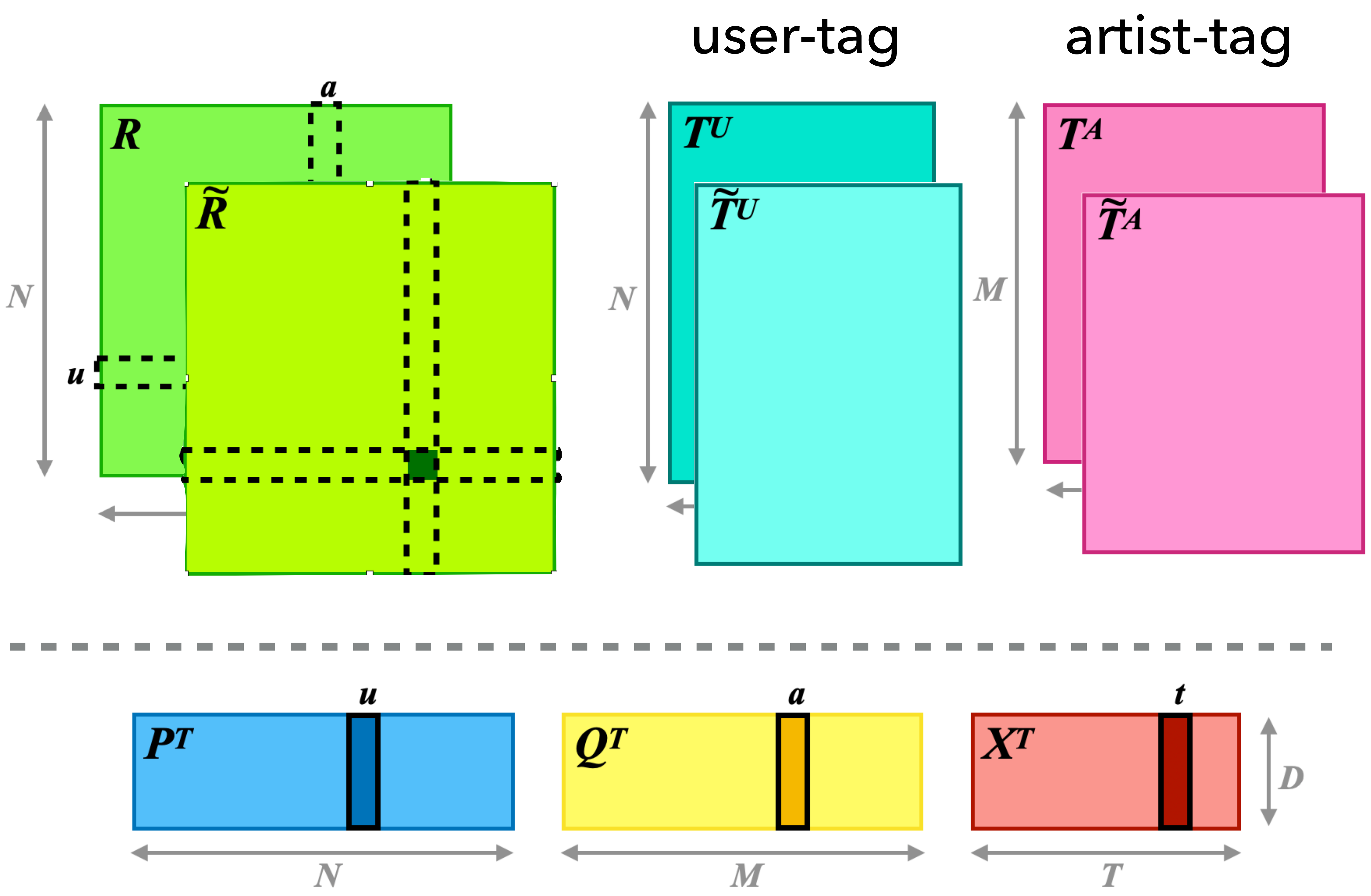
- Extending weighting to tag matrices

$$\tilde{T}^U_{ut} = \begin{cases} 1 & \text{if } T^U_{ut} > 0 \\ 0 & \text{if } T^U_{ut} = 0 \end{cases} \qquad \tilde{T}^A_{at} = \begin{cases} 1 & \text{if } T^A_{at} > 0 \\ 0 & \text{if } T^A_{at} = 0 \end{cases}$$

- Objective

$$\min_{P,Q,X} \sum_{ua \in R} w(\alpha, R_{ua}) \left(\tilde{R}_{ua} - P_u Q_a^T \right)^2 + \mu_1 \sum_{ut \in T^U} w(\beta, T^U_{ut}) \left(\tilde{T}^U_{ut} - P_u X_t^T \right)^2 + \mu_2 \sum_{at \in T^A} w(\gamma, T^A_{at}) \left(\tilde{T}^A_{at} - Q_a X_t^T \right)^2 + \lambda \left(\|P\|_F^2 + \|Q\|_F^2 + \|X\|_F^2 \right).$$

- Prediction: $Z = PQ^T$



- Gradient updates

$$P_u = (Q^T W_R^{r_u} Q + \mu_1 X^T W_{T^U}^{r_u} X + \lambda I)^{-1} (Q^T W_R^{r_u} R_{r_u}^T + \mu_1 X^T W_{T^U}^{r_u} T_{r_a}^{UT})$$

$$Q_a = (P^T W_R^{c_a} P + \mu_2 X^T W_{T^A}^{r_a} X + \lambda I)^{-1} (P^T W_R^{c_a} R_{c_a}^T + \mu_2 X^T W_{T^A}^{r_a} T_{r_a}^{AT})$$

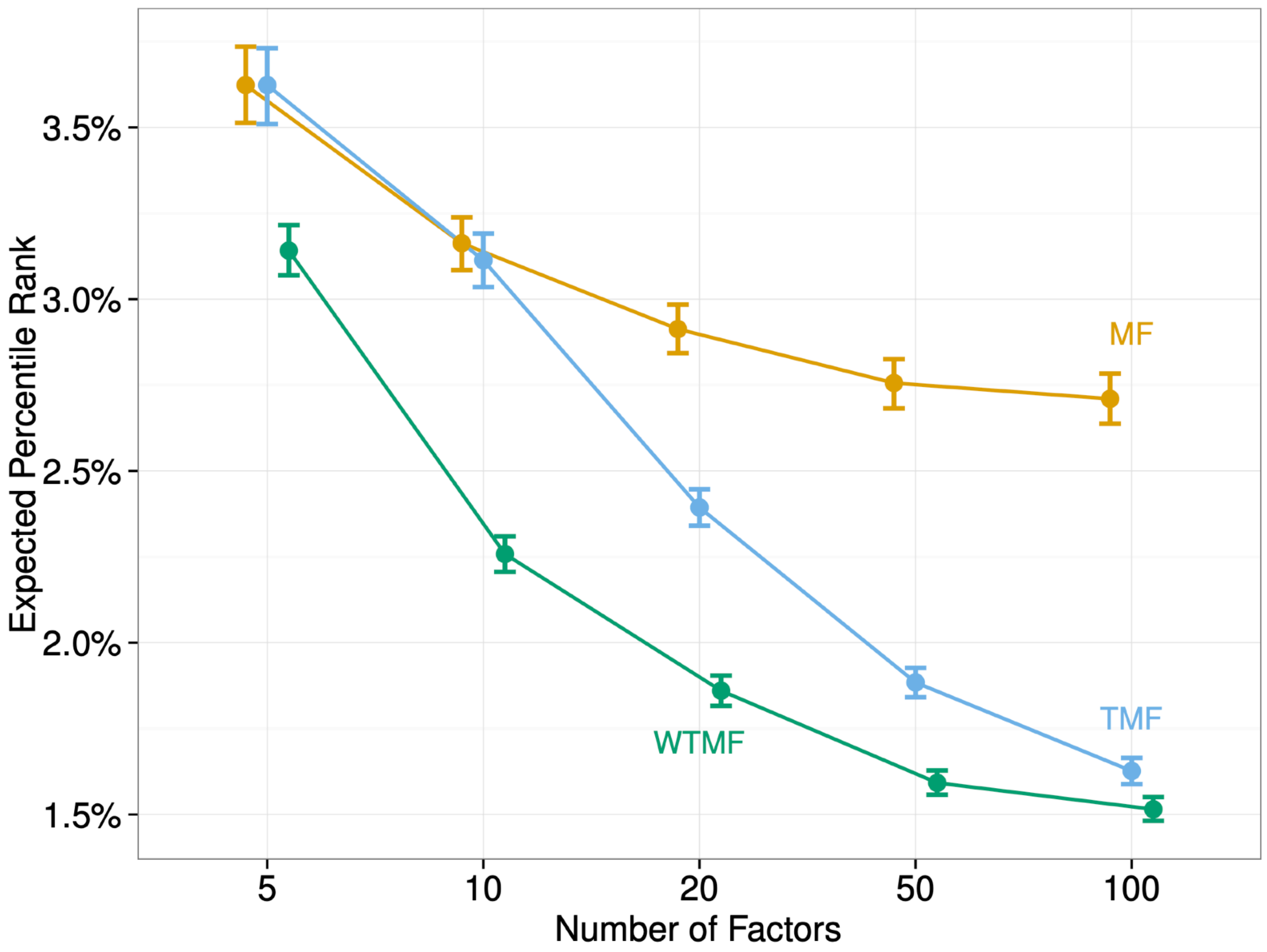
$$X_t = (\mu_1 P^T W_{T^U}^{c_t} P + \mu_2 Q^T W_{T^A}^{c_t} Q + \lambda)^{-1} (\mu_1 P^T W_{T^U}^{c_t} T_{c_t}^{UT} + \mu_2 Q^T W_{T^A}^{c_t} T_{c_t}^{AT})$$

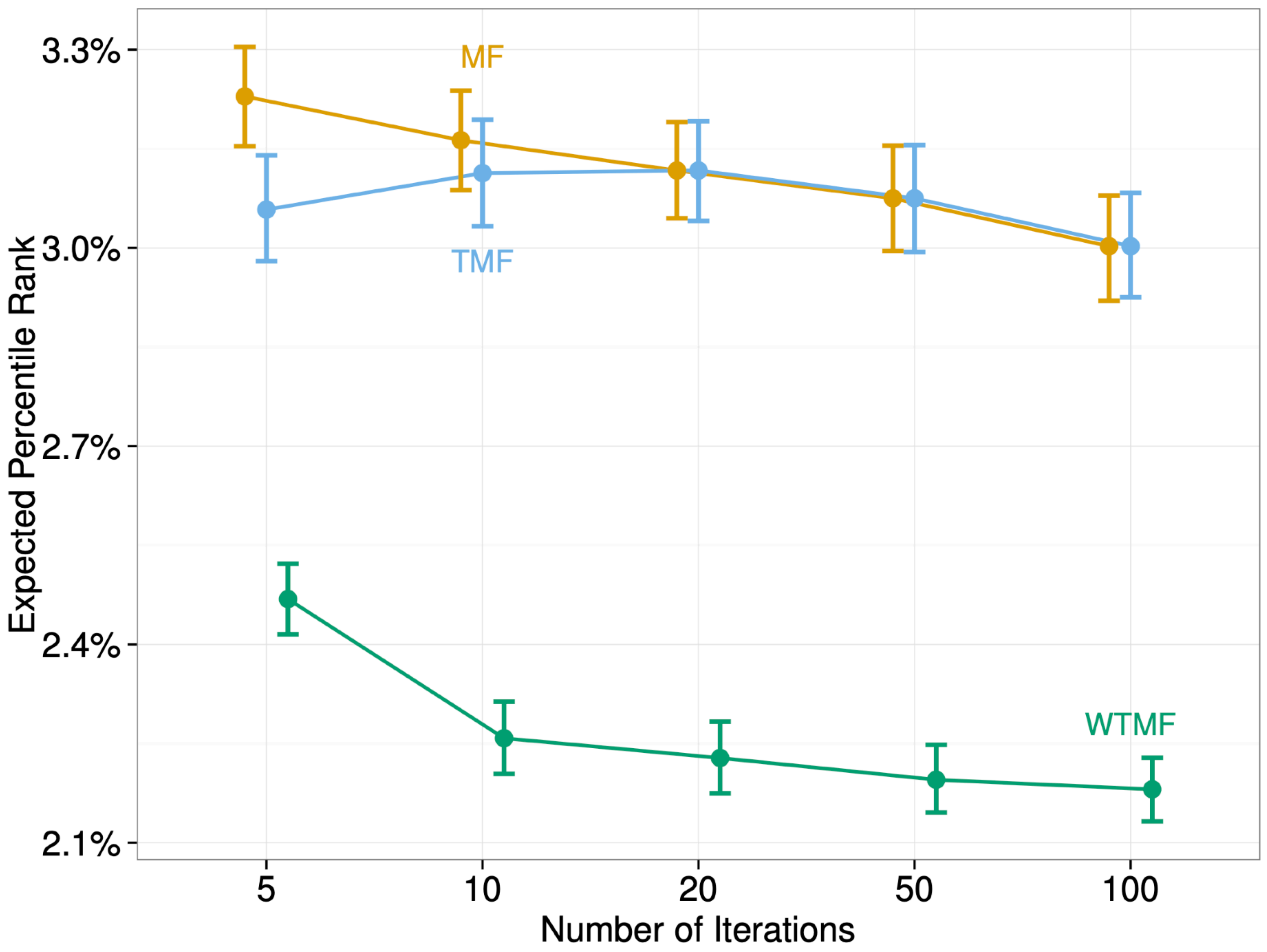
EXPERIMENTAL STUDY

- Dataset: Last.fm listening data + tagging data
  - ~22M listening events, ~3K user, ~71K artists
  - 687K matrix entries; 99.7% sparsity
  - ~500 tags; tags for nearly 100% of artists, only 20% of users
- Evaluation criteria: expected percentile rank
  - Insert artists to evaluate into ranking of randomly selected artists
  - Resulting percentile ranks averaged, weighted by frequency
  - Bootstrap confidence intervals (1K repetitions)

$$\overline{rank} = \frac{\sum_{ua \in R} R_{ua} rank_{ua}}{\sum_{ua \in R} R_{ua}}$$

EVALUATION RESULTS





TAKE AWAYS FROM THIS STUDY

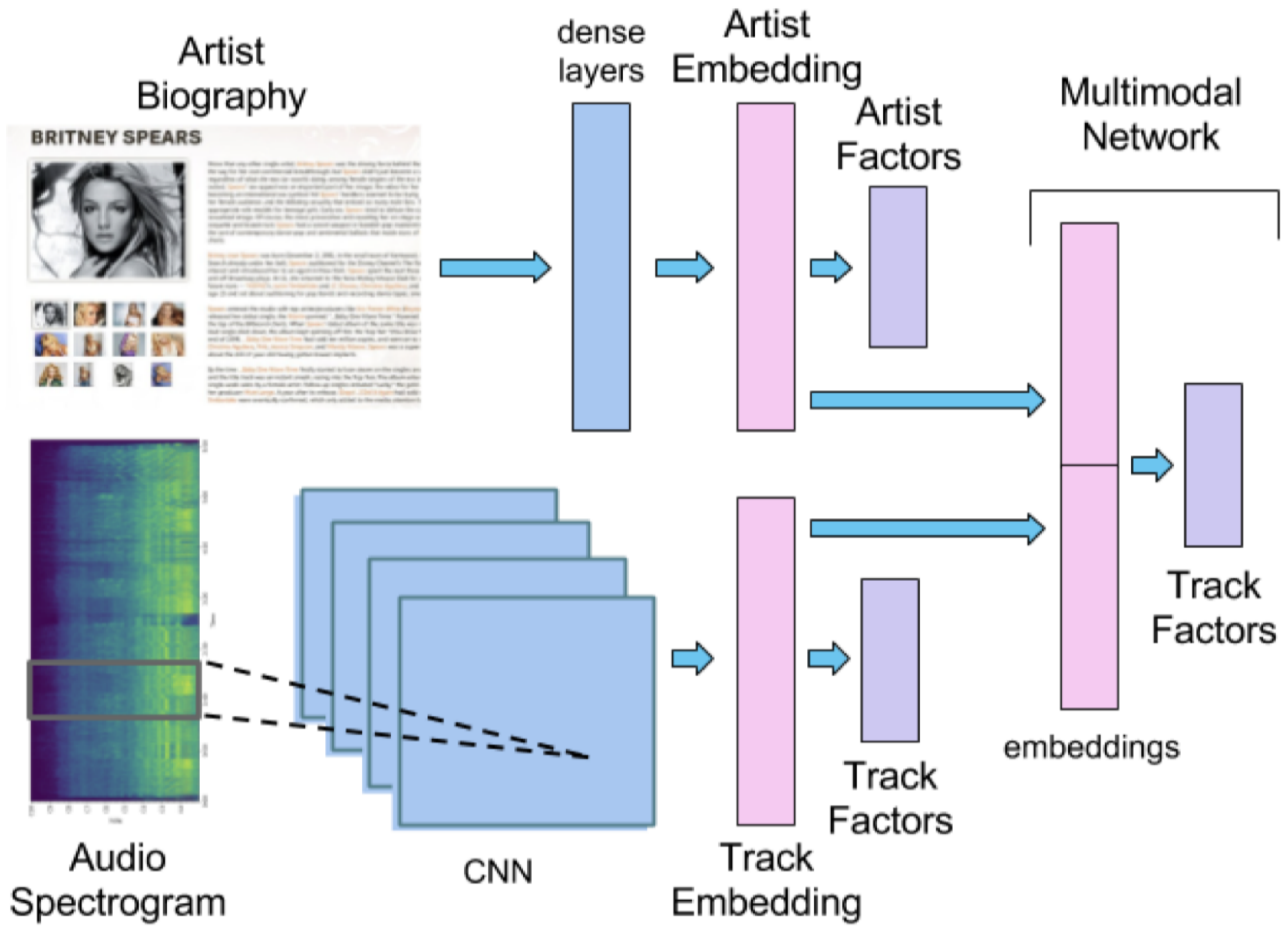
- Matrix factorization is well suited to build models for recommender systems
- Implicit matrix factorization already a strong baseline
- Cold start a central problem
- Additional information from external sources can lead to improved results, even when starting from high level
- Introduces tag cold start problem

OTHER 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.

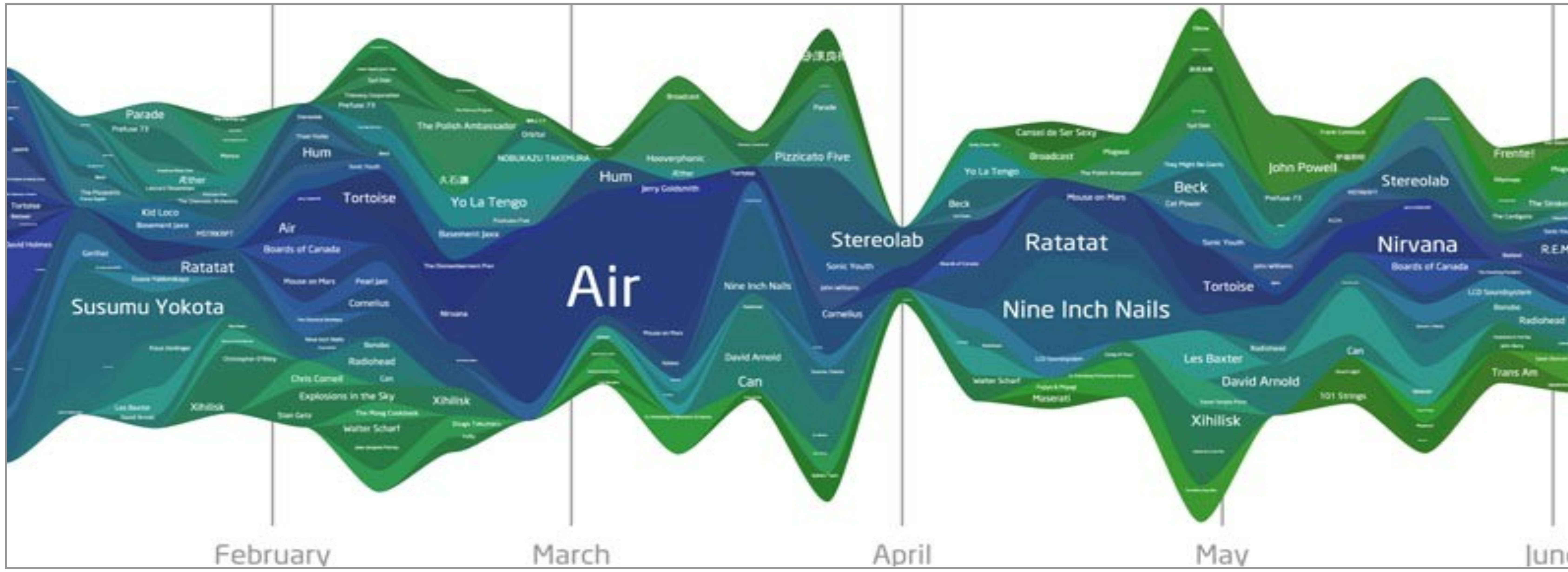


- E.g. fusing deep features from audio and image (album covers) and text

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

Sequential Listening and Playlists

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

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

It's about recommending a listening experience

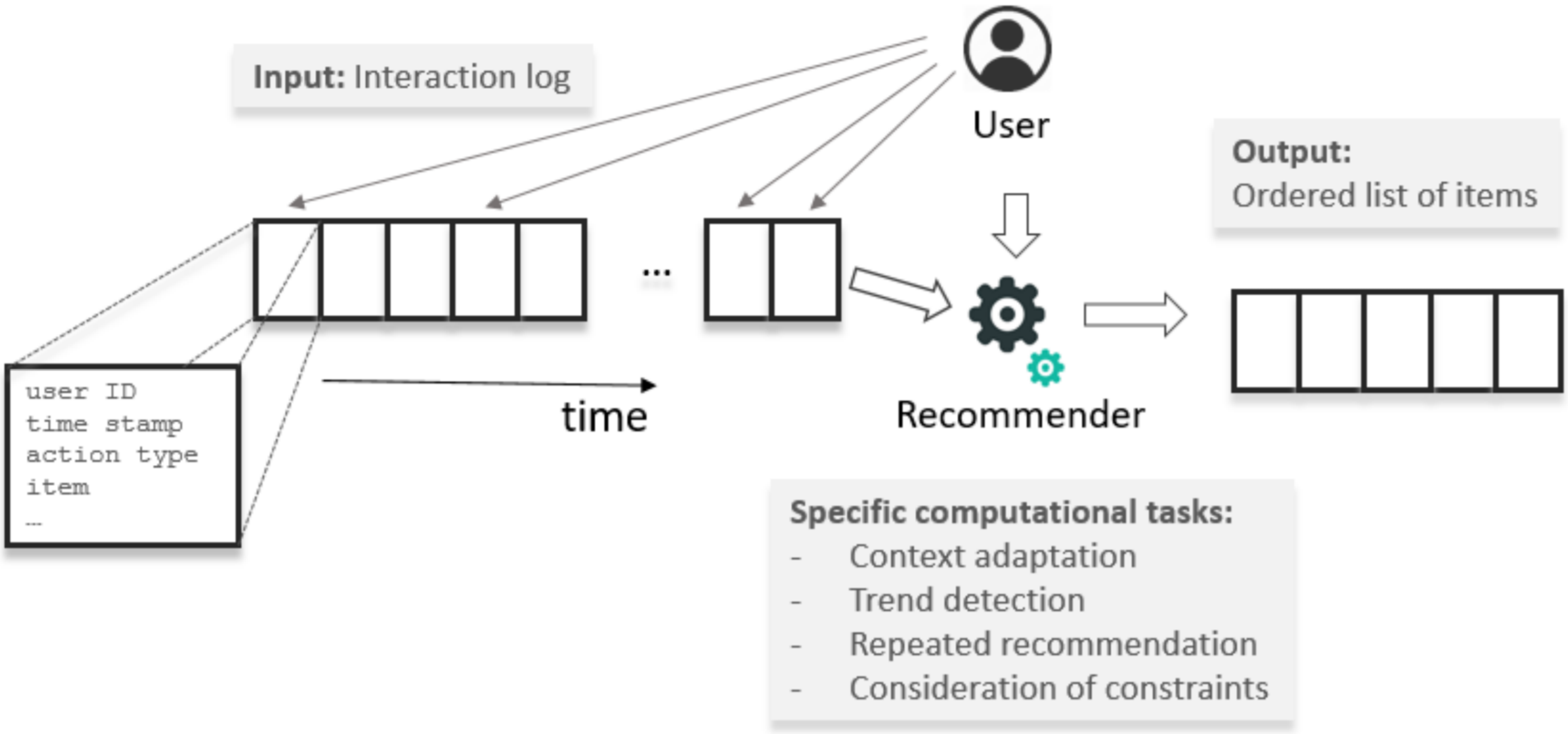
[Celma, 2010] *Music Recommendation and Discovery: The Long Tail, Long Fail, and Long Play in the Digital Music Space*, Springer

[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

SEQUENCE-AWARE RECOMMENDATION - OVERVIEW



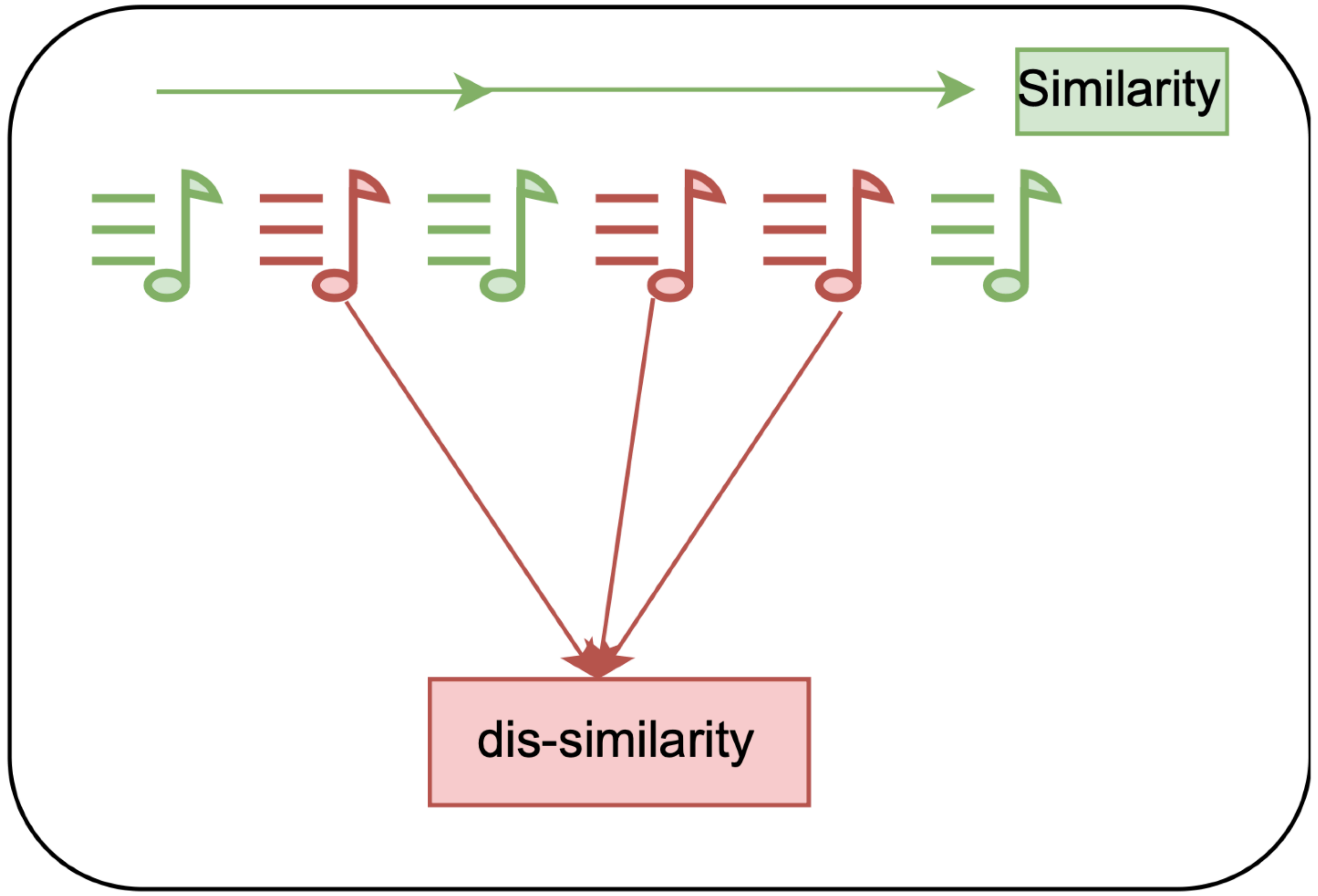
[Quadrana et al., 2018]: *Sequence-Aware Recommender Systems*, https://arxiv.org/abs/1802.08452

SEQUENTIAL MODELS

- In session-based recommendation:
  - user cold-start, (almost) no personalization
  - e.g., news recommendation, shopping basket completion, playlist continuation
- Exemplary Models:
  - **CASER**, **NextItRec**: Convolutional Neural Network-based
  - **GRU4Rec**: Recurrent Neural Network-based
  - **BERT4Rec**: Bi-directional attention mechanism
  - **SASRec**: Uni-directional attention mechanism, longer context

[Seshadri et al., 2024]: *Enhancing Sequential Music Recommendation with Negative Feedback-informed Contrastive Learning*, Proc. RecSys.

CASE STUDY



- Including also negative feedback
  - Skipped tracks, short listens
  - Should not only learn what goes together but what doesn't fit
- Contrastive Learning
  - Maximize similarity of latent factors of similar (positive) examples, while minimizing similarity of dissimilar (negative) examples
  - Changing the learning objective via loss function

[Seshadri et al., 2024]: *Enhancing Sequential Music Recommendation with Negative Feedback-informed Contrastive Learning*, Proc. RecSys.

RESULTS

Data	Metric	SASRec		BERT4Rec		GRU4Rec		CASER		WRMF			BPR		
		orig.	*ours*	*orig.*	*ours*	*orig.*	*ours*	*orig.*	*ours*	*orig.*	*-BL*	*-NR*	*orig.*	*-BL*	*-NR*
MSSD	HR@1	.377	**.410 (9%)**	.204	.355 **(74%)**	.210	.235 **(12%)**	.223	.251 **(13%)**	.203	.207	.211	.208	.213	.216
	HR@5	.615	**.628 (2%)**	.450	.608 **(35%)**	.398	.431 **(8%)**	.412	.455 **(10%)**	.400	.406	.411	.406	.413	.421
	HR@10	.696	**.706 (1%)**	.553	.693 **(25%)**	.491	.534 **(9%)**	.518	.530 **(2%)**	.488	.498	.505	.502	.510	.517
	HR@20	.767	**.774 (1%)**	.648	.767 **(18%)**	.600	.627 **(5%)**	.616	.649 **(5%)**	.597	.603	.608	.605	.609	.612
	MAP@10	.397	**.417 (5%)**	.185	.369 **(99%)**	.176	.193 **(10%)**	.195	.221 **(13%)**	.149	.156	.164	.160	.168	.173
LFM-2B	HR@1	.190	**.221 (16%)**	.101	.117 **(16%)**	.096	.102 **(6%)**	.102	.112 **(10%)**	.097	.098	.102	.098	.105	.107
	HR@5	.371	**.400 (8%)**	.227	.248 **(9%)**	.203	.221 **(9%)**	.197	.208 **(6%)**	.138	.142	.147	.143	.152	.169
	HR@10	.452	**.477 (6%)**	.292	.320 **(10%)**	.273	.291 **(7%)**	.281	.302 **(7%)**	.269	.273	.279	.276	.286	.294
	HR@20	.532	**.553 (4%)**	.366	.394 **(8%)**	.311	.342 **(10%)**	.326	.354 **(9%)**	.305	.311	.316	.314	.324	.348
	MAP@10	.188	**.219 (16%)**	.098	.110 **(12%)**	.078	.085 **(9%)**	.081	.088 **(9%)**	.062	.065	.067	.066	.072	.078
LFM-1K	HR@1	.152	**.181 (19%)**	.069	.086 **(25%)**	.048	.059 **(23%)**	.052	.071 **(37%)**	.042	.044	.047	.043	.050	.052
	HR@5	.301	**.330 (10%)**	.207	.230 **(11%)**	.182	.200 **(10%)**	.188	.198 **(5%)**	.139	.146	.177	.150	.153	.159
	HR@10	.392	**.421 (7%)**	.299	.320 **(7%)**	.261	.289 **(11%)**	.269	.293 **(9%)**	.270	.285	.294	.292	.298	.301
	HR@20	.478	**.491 (3%)**	.413	.433 **(5%)**	.388	.397 **(2%)**	.390	.404 **(4%)**	.346	.368	.375	.369	.374	.376
	MAP@10	.092	**.107 (16%)**	.049	.064 **(31%)**	.034	.042 **(24%)**	.037	.040 **(8%)**	.028	.031	.034	.032	.036	.038

Table 1: *Hit Ratio @ [1, 5, 10, 20]* and *Mean Average Precision @ 10* for the sequential models (SASRec, BERT4Rec, GRU4Rec, CASER) and the non-sequential baselines (WRMF, BPR) on the three datasets. Non *"orig."* models incorporate negative feedback. They are compared to their *"orig."* baselines which do not model negative feedback. Numbers in parentheses show the relative increase in the percentage of the approach over the respective baseline; bold entries mark the better performing approach between the baseline and negative feedback-informed approach. The overall best performance is also highlighted in bold (i.e., SASRec-ours).

MORE RESULTS

- Looking at the skipped tracks in SASRec and BERT4Rec
- Correspondingly, they should be ranked lower…
- Generally, they are

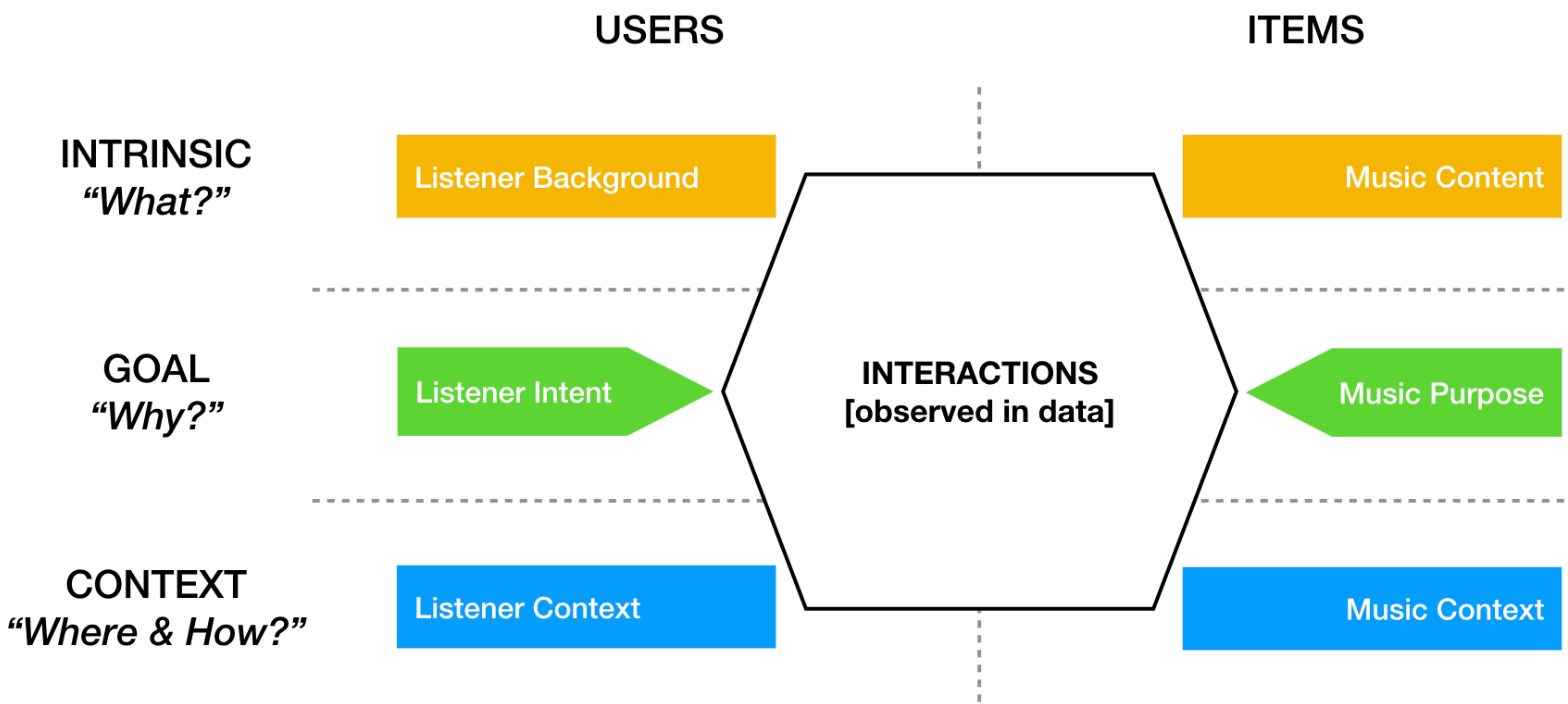
		SASRec		BERT4Rec	
Metric		*orig.*	*ours*	*orig.*	*ours*
MRR@10	**MSSD**	.960	.950 **(-1%)**	.840	.950 **(13%)**
MRR@10	**LFM-2B**	.969	.911 **(-6%)**	.953	.950 **(-0.3%)**
MRR@10	**LFM-1K**	.731	.731 **(0%)**	.540	.460 **(-15%)**

Table 2: *Mean Reciprocal Rank @ 10* on skip targets for the best sequential models (SASRec, BERT4Rec) on the three datasets. Lower values are better.

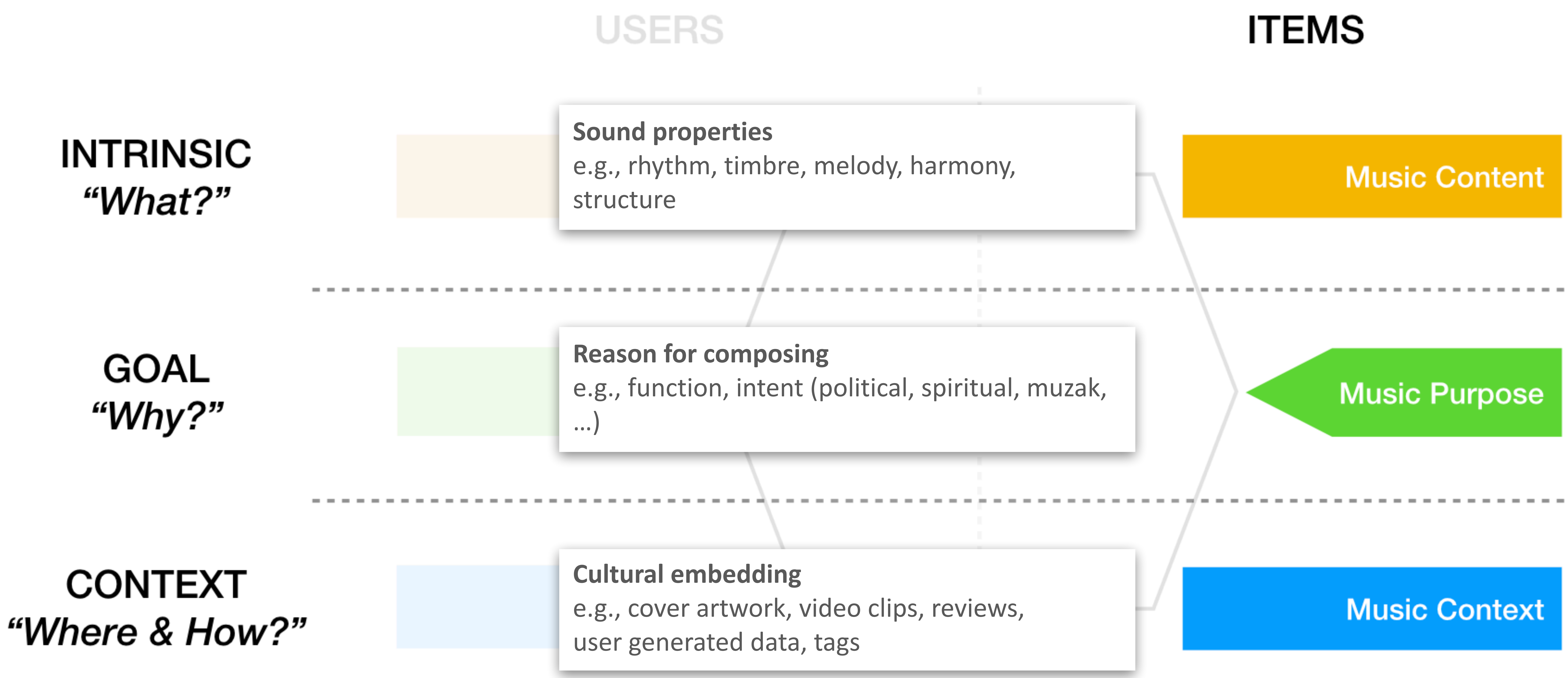
- But on MSSD, they are also ranked higher, i.e., positive and negative tracks get more likely recommended
- Hypothesis: BERT4Rec with negative feedback closer to Spotify recommendations

It’s even more complex

TWO FACTORS…


USERS
ITEMS
INTRINSIC
"What?"
Listener Background
Music Content
GOAL
"Why?"
Listener Intent
INTERACTIONS
[observed in data]
Music Purpose
CONTEXT
"Where & How?"
Listener Context
Music Context

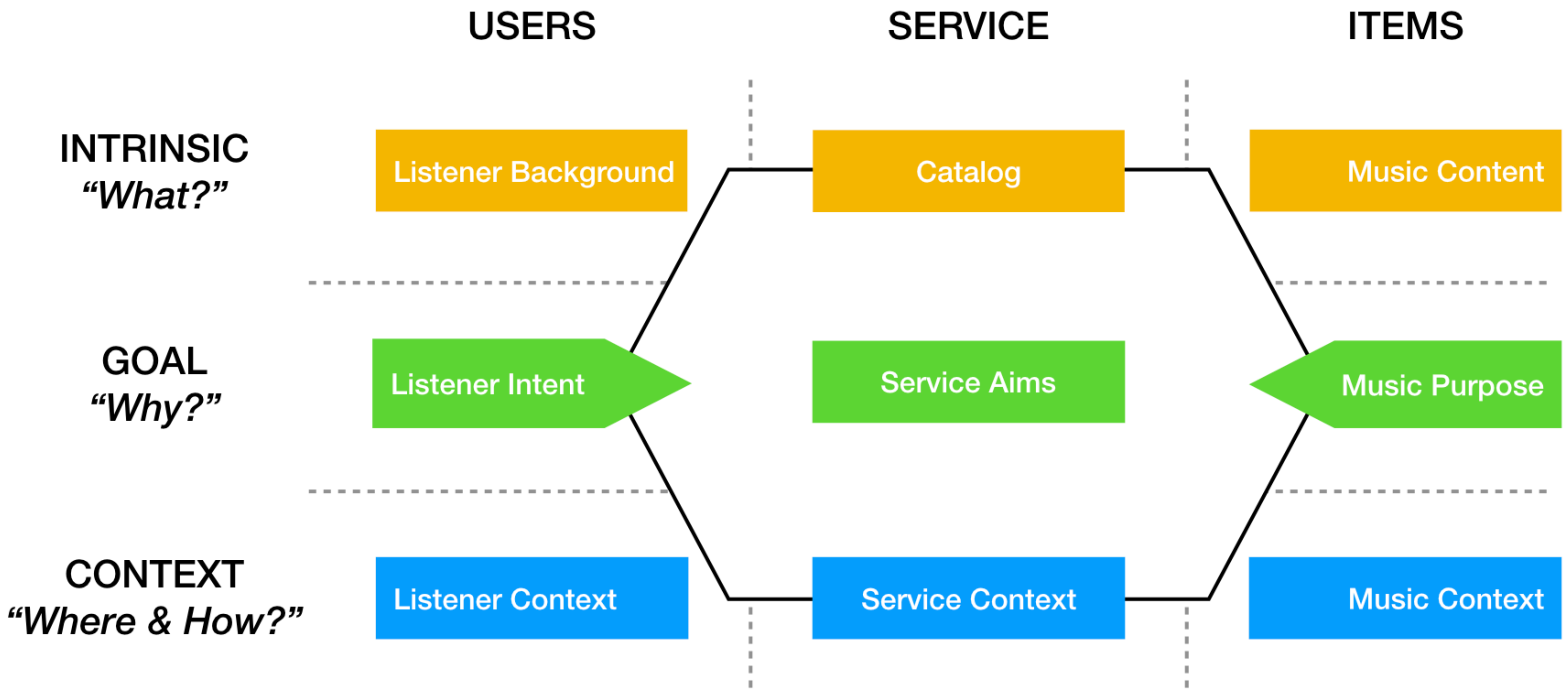
FACTORS HIDDEN IN THE DATA



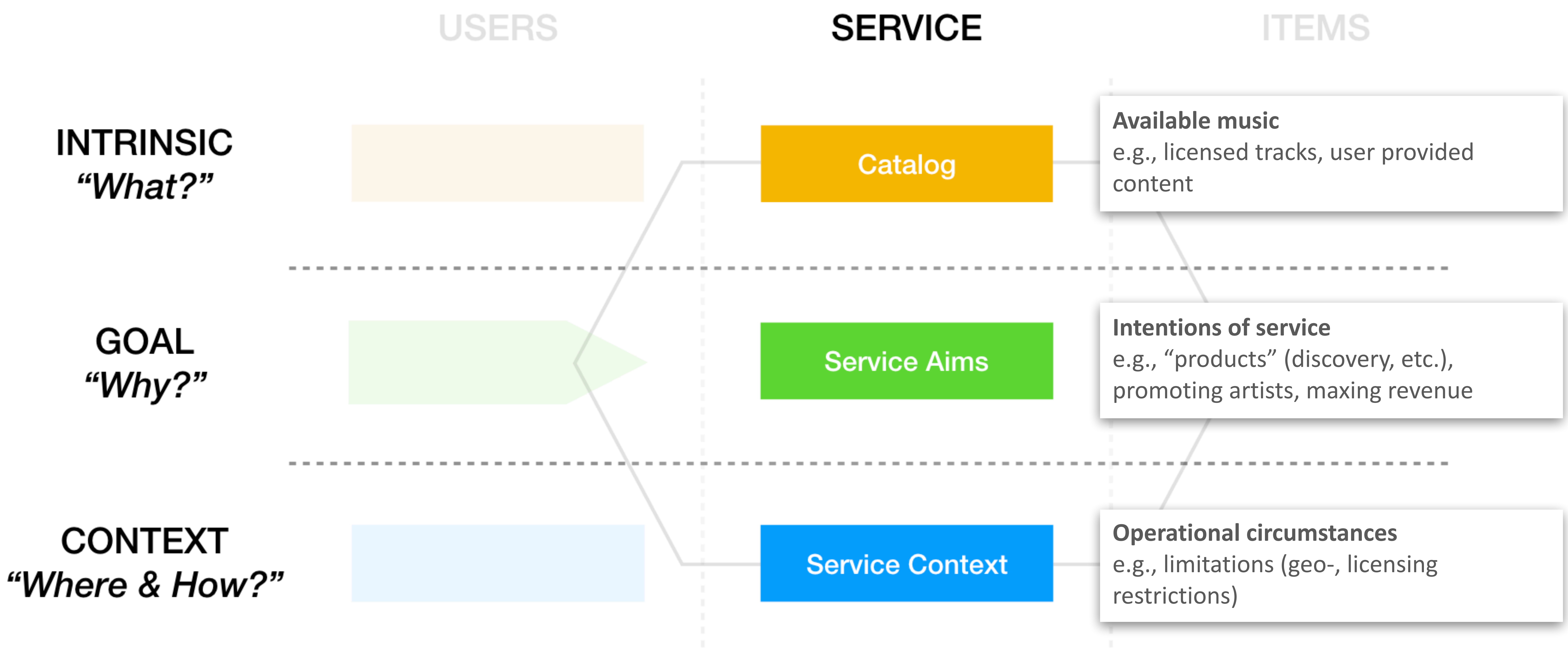
FACTORS HIDDEN IN THE DATA

	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	

FACTORING THE SERVICE INTO THE PICTURE



FACTORS HIDDEN IN THE DATA



THE SERVICE IMPACTS DATA COLLECTED

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/market niche?
- What are the identified use cases? (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)

THE SERVICE PLAYS A CENTRAL ROLE

- Data from one service not generalizable to others

SOUNDCLOUD ≠ bandcamp ≠ Spotify ≠ DEEZER ≠ pandora ≠ …

- Particularly for niche markets and different parts of the world

≠ IDAGIO ≠ qobuz ≠ KKbox ≠ SUPERPLAYER ≠ simfy africa ≠ …

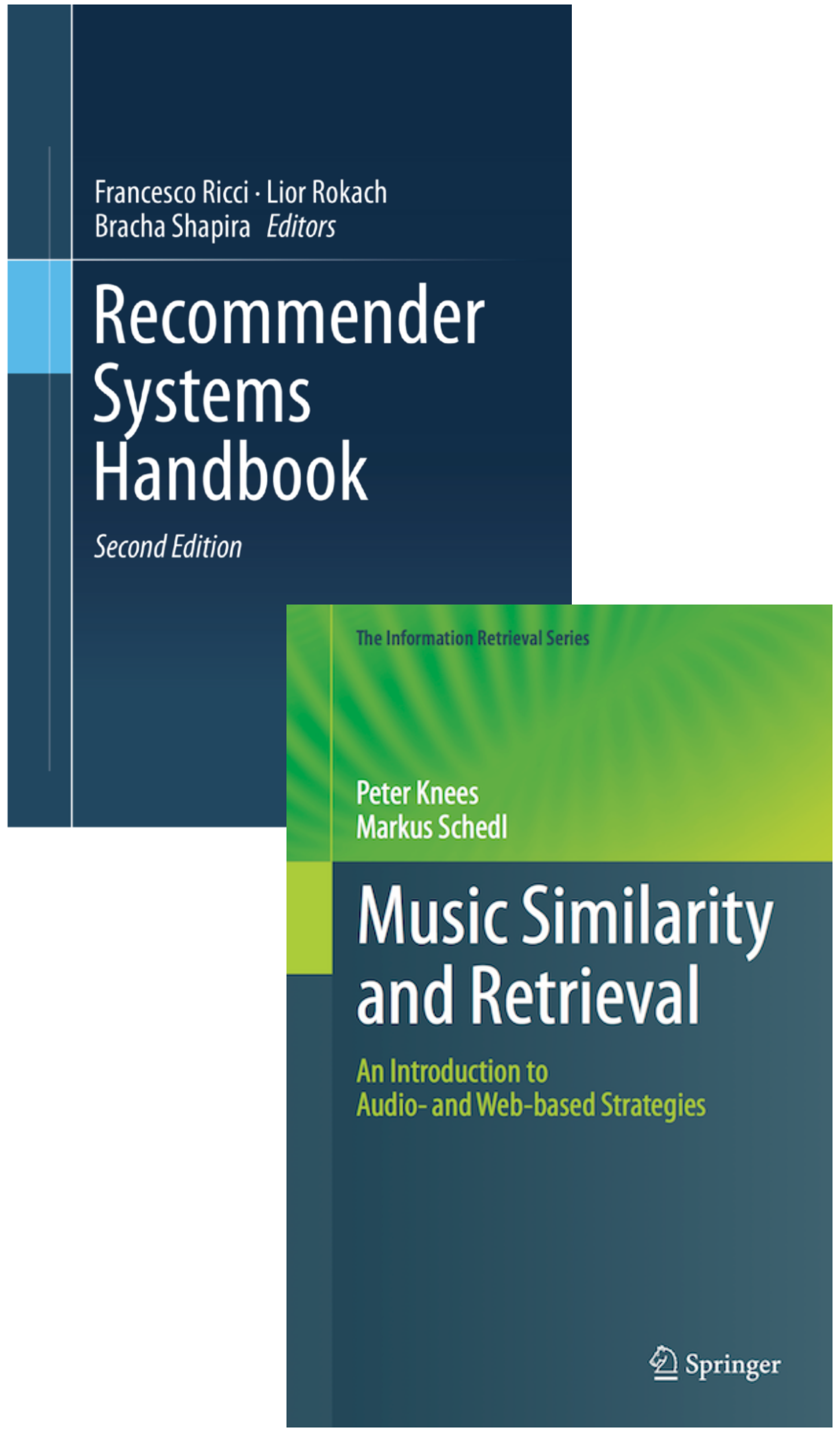
- **Service influences listening behavior**
- But there is no listening "in the wild"

cf. [Porcaro & Gomez, 2019] *20 years of Playlists: a Statistical Analysis on Popularity and Diversity",* ISMIR.

CONCLUSIONS

- Various music listening use cases, stakeholders, data
  - similarity-based retrieval methods
  - model-based recommendation techniques
  - exploitation of multi-modal data
- Real-world data not only noisy but potentially biased, exhibits interests of various stakeholders
- Academic research does not have the data of industry, but could focus on uncovering commercial biases and interests

FURTHER READING



- Recommender Systems Handbook (3rd ed.)
  Chapter: Music Recommendation Systems: Techniques, Use Cases, and Challenges
  by M. Schedl, P. Knees, B. McFee, D. Bogdanov. Springer, 2022.
- **Music Similarity and Retrieval: An Introduction to Audio and Web-based Strategies**
  by P. Knees and M. Schedl. Springer, 2016.
- **Tutorial: Overview and New Challenges of Music Recommendation Research in 2018**
  by M. Schedl, P. Knees, F. Gouyon. ISMIR'18.
  https://www.slideshare.net/FabienGouyon/music-recommendation-2018-116102609