Haven't I just listened to this?

Exploring diversity in music recommendations

ANTONELA TOMMASEL

JUAN MANUEL RODRIGUEZ

DANIELA GODOY

CONICET

I S I S T A N

UMAP '22
BARCELONA

Filter bubbles & recommendation

- Music streaming services have become popular in the last few years, contributing to the **democratization of music access**.
- While **recommending “similar” content** might help increase click rate, sales, or conversion rates, **it does not necessarily induce users to explore new and diverse content**.
- Users with little or no exposure to diverse views can become **unintendedly trapped in filter bubbles**.
- While music access in streaming services seems fluid and diverse, platforms have been acknowledged to **recommend items in circumscribed tiers** for users and listening environments in connection with **social structures**.
- If streaming platforms foster filter bubbles, **users would not be encouraged to discover music that differs from their taste, limiting their openness and cultural awareness**.

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Harnessing recommender systems with filter bubble-aware mechanisms becomes essential to **open users perspectives**, foster **healthy consumption patterns** and **increase** the user-perceived **quality** of recommender systems.

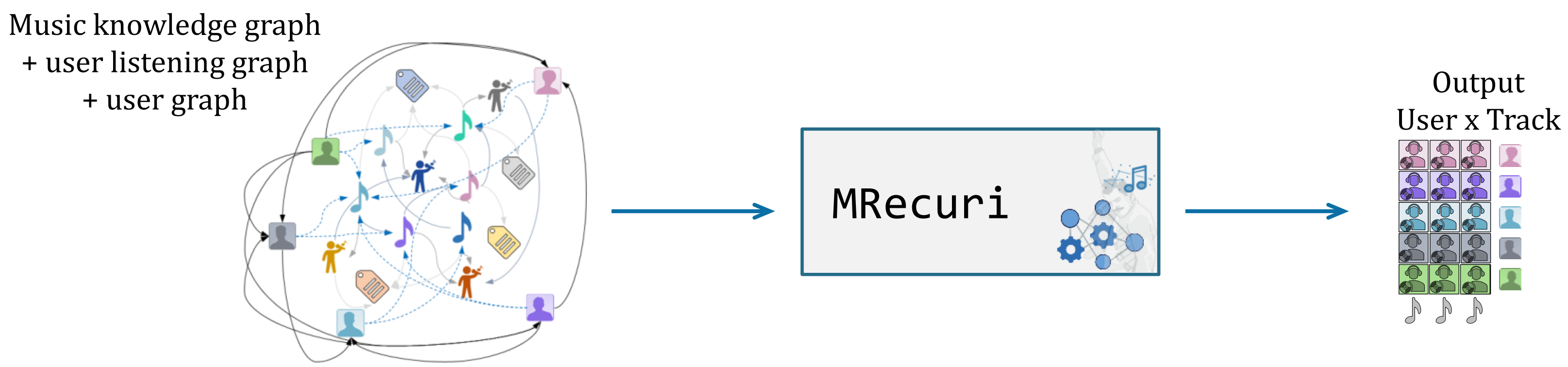
Filter bubble aware recommendations

The problem

We tackle the **music recommendation problem** by fostering **track recommendation diversification** in a **filter bubble awareness** setting.

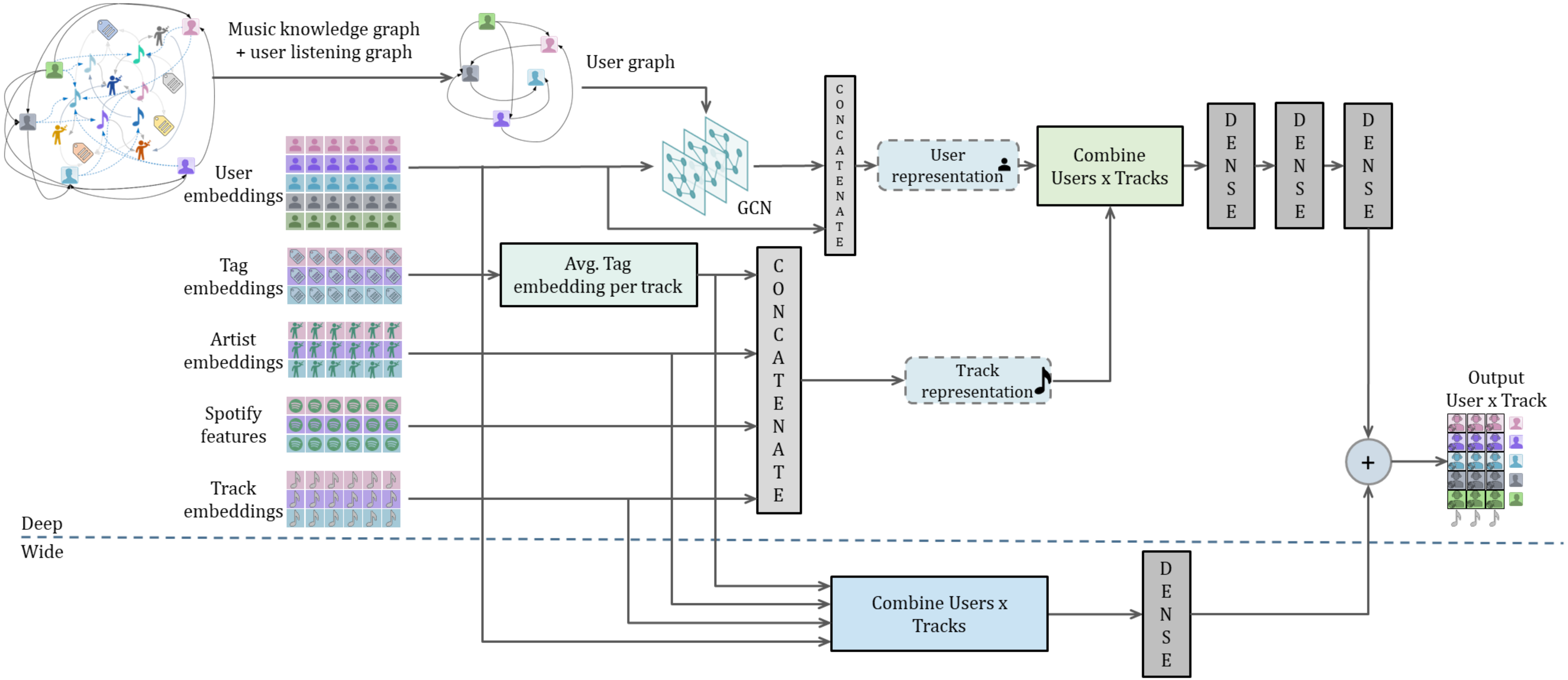
We rely on **implicitly modeling the filter bubbles** membership of users to present them with **relevant friend recommendations from outside** the influence of their community.

Music RECommender for filter bUbble diveRsIfication



MRecuri

Music REcommender for filter bUbble diveRsIfication



Experimental evaluation
Data

- Evaluation was based on data collected from **Last.fm**.
- We focused on the **track listening history** and the **users' social networks.**
- For each of the **3,307 users**, we collected their scrobble history using the Last.fm API.
- From the set of over 1 million tracks listened by the selected users, we selected approximately **252k tracks** with the highest number of listeners among the selected users, with 99% of users associated with **over 40 songs**.
- For each selected track, we collected the **total number of scrobbles and listeners**, **tags**, **artist** (and their tags) and **Spotify audio features**.

	Avg (± std)
#users	3,307
#tracks	252,014
#artists	28,540
Tracks per user	912 (± 1266)
Scrobbles per user	48 (± 73)
Interactions per user	87 (± 85)

Experimental evaluation

Baselines

Trivial, non-personalized and traditional recommenders.

- Random
- Popularity
- Content

Adapted traditional and state-of-the-art user-item recommendation techniques.

- ImplicitMF
- GraphRec
- MultVAE

Techniques focused on enhancing the structural diversity of recommendations to mitigate filter bubbles.

- Rank Aggregation
- MMR
- VC

Experimental evaluation

Evaluation

Relevance

- Precision@k
- DCG@k

Diversity

- Variations of intra-list dissimilarities were used to assess:
  - **Diversity** (i.e., differences within the recommended list)
  - **Novelty** (i.e., differences between the known users and the recommended ones).
- Euclidean distance over structural and content-based representations.

- All evaluations were performed over the **same data partitions** and evaluated using the same set of metrics.
- We selected the top-10 recommended users (96% of users have 10 or more interactions).
- Recommendations were considered correct if they appeared in the test set.

- Training set: the first 70% listened tracks of each user.
- Test set: remaining interactions.

Experimental evaluation

Results - Highlights

	Traditional	State-of-the-art	Original structure
Avg. relevance Improvements	60%	29%	-
Avg. diversity/novelty improvements	25%	20%	6%

- `MRecuri` was among the **best performing techniques for most metrics**, including precision and nDCG.
- `MRecuri` was able to **improve the diversity/novelty** of the **original graph**.
- In general, **novelty was higher than diversity**, meaning that even when recommending similar tracks, they differed from those in the listening history.
- `MRecuri` achieved the **highest structural novelty results**, implying that recommendations were **outside the influence** of the co-listened community of the already listened tracks, which can effectively broaden users' music perspectives.

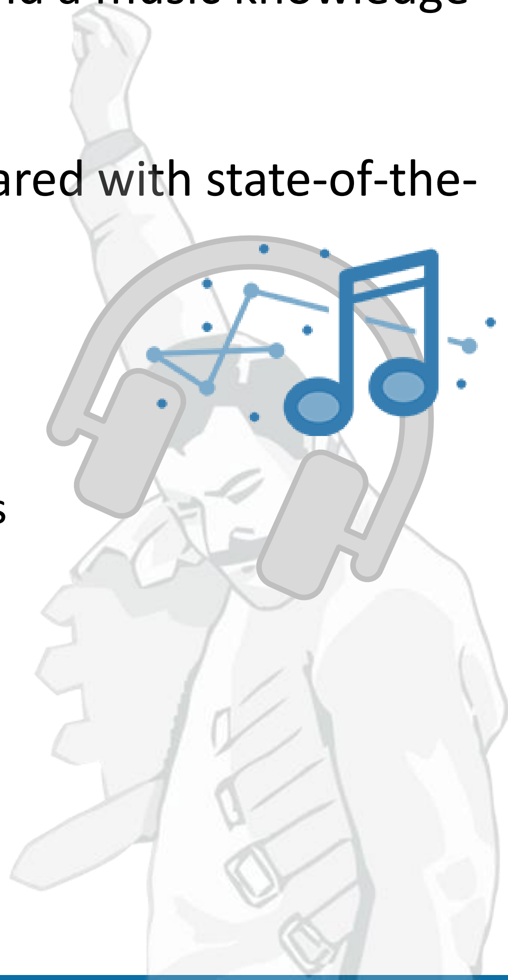
Summary & conclusions

- We developed `MRecuri` inspired by a **graph convolutional network** and a **Deep & Wide** architecture, focused on implicitly characterizing filter bubbles based on user listening history, social interactions, and a music knowledge graph to balance the <u>relevance</u>, <u>diversity</u> and <u>novelty</u> of recommendations.

- `MRecuri` showed the potential for **expanding users' listening diversity and novelty** compared with state-of-the-art techniques while maintaining competitive precision and nDCG results.

- [Data and code](#) are publicly available.

- Perform a more extensive evaluation in large-scale scenarios to fully assess the technique's usefulness, generalizability, and scalability.
- Perform an ablation study to assess the contribution (or effects) of the different components.
- Include information of the listening history as an ordered sequence.
- Explanations to better guide users in broadening their interactions.



Thanks!

Questions?

antonela.tommasel@isistan.unicen.edu.ar

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