Diversifying Music Recommendations

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Takeaways

- We compared three methods to diversify Amazon Prime Music recommendations.
- Diversifying music recommendations improves recommendation quality and user engagement.
- Incorporate recommender score into diversity measure.
- Submodular approach produces relevant and uniformly diverse mix.

Why diversify music?

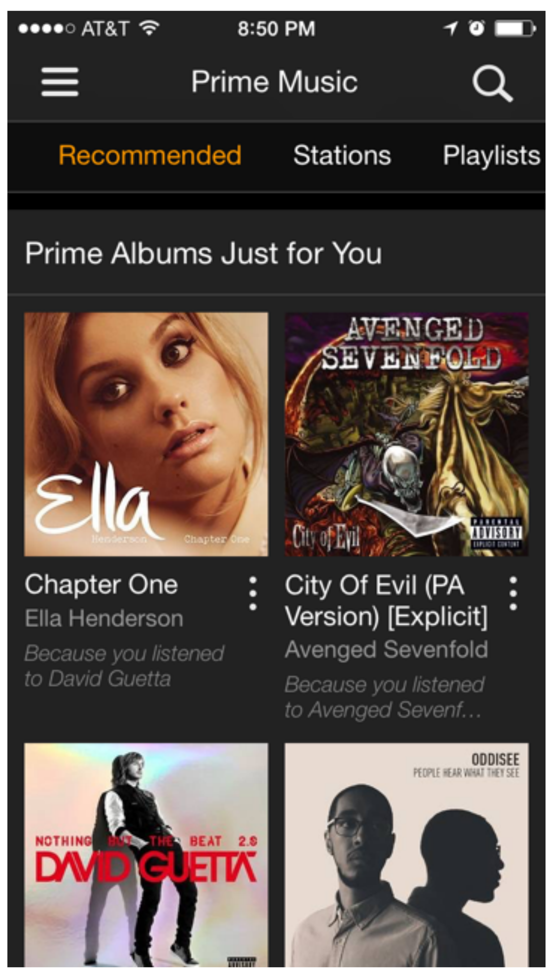
- Explicit clusters of songs, by album and artist.
- Songs within an album share album cover graphic, title and description.
- Users often play album songs back-to-back.

- Recommenders score same-album songs similarly
- Ranking by relevance results in duplications
- Problem amplified on small screens

Amazon Prime Music mobile app

- Free benefit for prime members
- Millions of songs
- Thousands of expert-programmed playlists
- Upload your own music
- Create personal playlists

- Access your music from anywhere
- List-form recommender
- Devices with limited interaction capability



Jaccard Swap diversity method

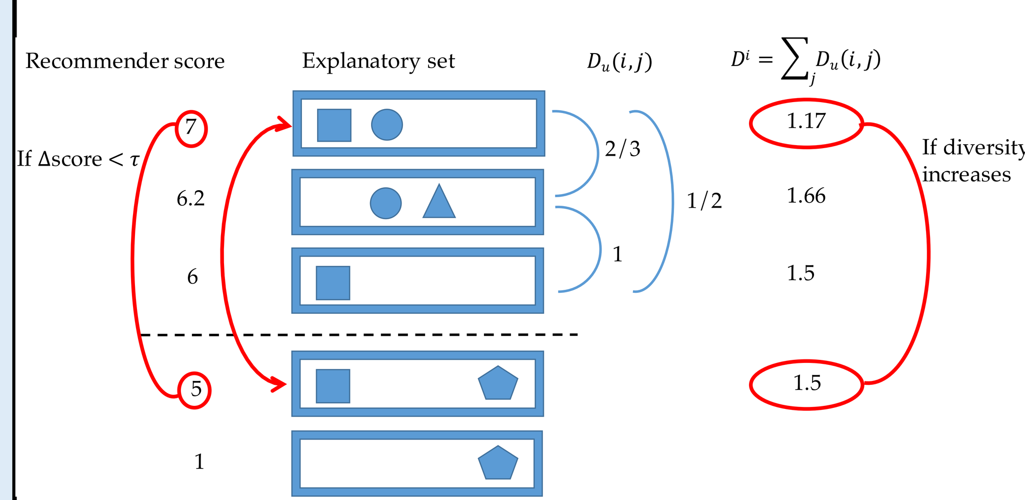
- Heuristic algorithm by Yu *et al.*

- u: user, i: item
- ItemSim(i, i'): similarity measure between two items
- Items(u): Set of items user u interacted with

- $\text{Expl}(u,i) = \{i' \mid \text{ItemSim}(i,i') > \varepsilon \;\&\; i' \in \text{Items}(u)\}$
- The explanation Expl(u,i) of recommending item i to user u is the set of items similar to item i that user u has interacted with.

- Jaccard diversity distance between items i, j for user u:

$$D_u(i,j) = 1 - \frac{|\text{Expl}(u,i) \cap \text{Expl}(u,j)|}{|\text{Expl}(u,i) \cup \text{Expl}(u,j)|}$$



Submodular diversity method

- Naturally models diminishing returns
- Incorporates recommender score into diversity utility function

- c: category, i: item, S: diversified set
- score(i): recommender score for i
- Category utility:

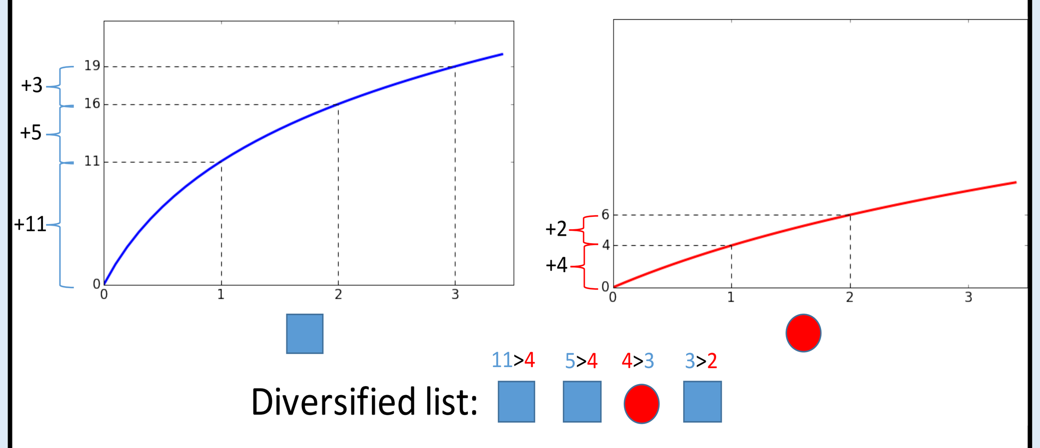
$$f_c(S) = \log\left(1 + \sum_{i \in S \cap c} \text{score}(i)\right)$$

- Maximize sum of all category utilities:

$$argmax_S\left(\rho(S) = \sum_c f_c(S)\right)$$

- Greedy near-optimal solution:

$$S_{t+1} = S_t \cup \{argmax_{i \setminus S_t} \rho(S_t \cup \{i\})\}$$



- See also Teo *et al.*

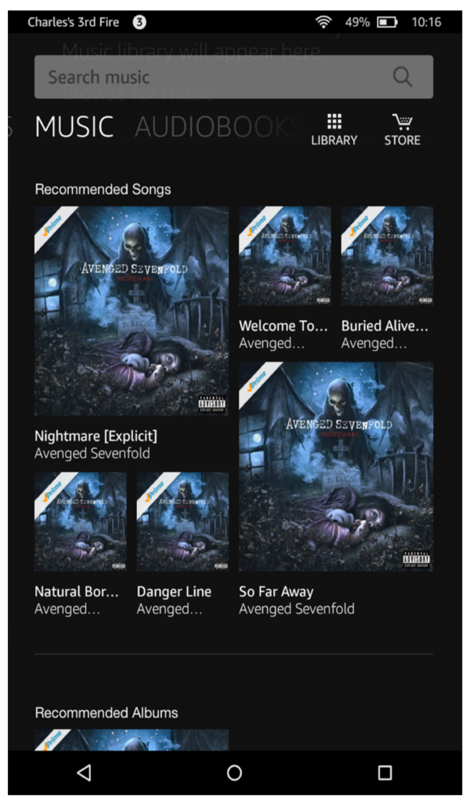
Experimental setup

- Baseline: Rank by recommender score

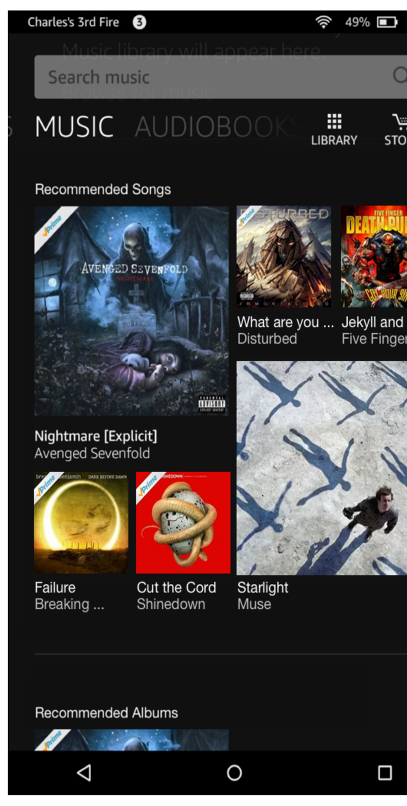
- Item-to-item collaborative filtering recommender provides item score and explanation set (by Linden *et al.*)
- Artist and album as Jaccard explanation set features and submodular categories (■●⬟)
- Randomized controlled trial with equal customer allocation

Results

Treatment comparison	Increase in minutes streamed
Submodularity vs Baseline	**0.64% (p=0.03)**
Jaccard Swap vs Baseline	0.40% (p=0.18)
Submodularity vs Jaccard Swap	0.24% (p=0.41)



Baseline



Submodular

Discussion

- Diversity affects recommendation quality
- Submodular method improvement is significant

- Smoothness:
  - Submodularity produces uniformly diverse set. All contiguous subsets are also diverse.
  - Jaccard Swap doesn't

- Relevance:
  - Submodularity ensures most relevant item is first, followed by mix of most relevant items within each category
  - Swap may not retain most relevant content

Bibliography

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