**Diversifying Music Recommendations**

Houssam Nassif, Kemal Oral Cansizlar, Mitchell Goodman, S.V.N. Vishwanathan

1 Amazon, Seattle, USA  
2 University of California, Santa Cruz, USA

**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-format recommender  
- Devices with limited interaction capability

**Jaccard Swap diversity method**
- Heuristic algorithm by Yu et al.  
- \( u : \) user, \( i : \) item  
- ItemSim(\( i, j \)) similarity measure between two items  
- ItemSim(\( i, j \)) > \( \varepsilon \)  
- \( \varepsilon \)  
- The explanation ItemSim of recommending item \( i \) to user \( u \) is the set of items similar to item \( i \) that user \( u \) has interacted with.

\[
D(S, i, j) = 1 - \frac{\text{ItemSim}(i, j)}{\text{ItemSim}(i, S) \cup \text{ItemSim}(j, S)}
\]

**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:  
  \[
f_c(S) = \log \left( 1 + \sum_{i \in S} \text{score}(i) \right)
\]

Maximize sum of all category utilities:

\[
\argmax_S \sum_c f_c(S)
\]

Greedy near-optimal solution:

\[
S_{k+1} = S_k \cup \{ \argmax_{i \notin S_k} \sum_c f_c(S_k \cup \{ i \}) \}
\]

- See also Teo et al.

**Experimental setup**
- Baseline: Rank by recommender score  
- Item-to-item collaborative filtering  
- Artist and album as Jaccard-explanation set (by Linden et al.)  
- Randomized controlled trial with equal customer allocation

**Results**

<table>
<thead>
<tr>
<th>Treatment comparison</th>
<th>Increase in minutes streamed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Submodularity vs Baseline</td>
<td>0.64% (p=0.03)</td>
</tr>
<tr>
<td>Jaccard Swap vs Baseline</td>
<td>0.40% (p=0.18)</td>
</tr>
<tr>
<td>Submodularity vs Jaccard Swap</td>
<td>0.24% (p=0.41)</td>
</tr>
</tbody>
</table>

**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**

**Contacts**
Houssam Nassif  
Amazon Core Machine Learning Science Team  
housanm@amazon.com, 608-443-9168  
345 Boren Ave N, Seattle, WA, 98109, USA

**Machine Learning @ Amazon**