Exploring Music Diversity Needs Across Countries

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ABSTRACT

Providing diversity in recommendations has shown to positively influence the user's subjective evaluations such as satisfaction. However, it is often unknown how much diversity a recommendation set needs to consist of. In this work, we explored how music users of Last.fm apply diversity in their listening behavior. We analyzed a dataset with the music listening history of 53,309 Last.fm users capturing their *total* listening events until August 2014. We complemented this dataset with The Echo Nest features and Hofstede's cultural dimensions to explore how music diversity is applied across countries. Between 47 countries, we found distinct relationships between the cultural dimensions and music diversity variables. These results suggest that different country-based diversity measurements should be considered when applied to a recommendation set in order to maximize the user's subjective evaluations. The country-based relationships also provide opportunities for recommender systems to personalize experiences when user data is limited by being able to rely on the user's demographics.

CCS Concepts

•Human-centered computing → User models; •Social and professional topics → Cultural characteristics;

Keywords

Music Recommendations; Diversity; Cultural Differences

1. INTRODUCTION

Providing recommendation diversity to users has become an important feature for recommender systems. Recommending items with high accuracy often result in a set of recommendations that are too similar to each other, and thereby not covering the full spectrum of the user's interest. Giving in on accuracy by introducing diversity can positively influence the user experience, such as user satisfaction [1].

The amount of diversity that should be provided remains a debatable topic. Prior research has identified that individual characteristics (e.g., expertise) play a role in how much diversity is desired by the user [1]. The problem that persist is that often self-report measures are used to identify these influential individual characteristics. Whereas registration and login processes are becoming easier (e.g., single sign-on buttons), asking additional questions may become a bothersome process for (new) users.

The implicit acquisition (i.e., without the use of questionnaires) of individual differences remains challenging. Especially for new users there is not enough behavioral data yet to make inferences. Country information may be a useful alternative as it already consists in a standard user profile and behavior has shown te be culturally embedded. We looked at music listening behavior of Last.fm [1] users from 47 countries and explored how they apply diversity to their playlists. We computed a diversity measure based on the unique listening events (i.e., of artists and genres) of users per country. By using The Echo Nest features we were also able to look at artist characteristics (i.e., how known, familiar, or popular the artists are that have been listened to by users). This provide insights on cultural dependent diversity patterns.

2. RELATED WORK

Recommender systems intend to create a personalized set of items that are most relevant to the user. However, highly relevant items often appear too similar to each other. A set of items showing too much similarities (e.g., highly relevant items) can cause choice overload [9]. In [1] was shown that diversity has a positive effect on the attractiveness of the recommendation set, the difficulty to make a choice, and eventually on the choice satisfaction. Additionally, individual differences were found. E.g., increased expertise has positive effects on perceived item variety and attractiveness.

Besides individual characteristics, research has shown that culture consists of useful cues as well. General behavior and preferences have shown to be rooted and embodied in culture [8]; looking at behavior on a country level may provide useful information for the desired recommendation diversity.

[1]http://www.last.fm

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Table 1: Correlation results.

	PDI	IDV	MAS	UAI	LTO	IND
Artist	.279*	-.373**	.155	-.020	-.259*	.080
Genre	.329*	-.265*	.074	-.051	-.108	-.113
Hot.	-.131	-.0.39	-.135	-.359*	-.641**	.557**
Fam.	-.100	-.229	.009	-.255	-.677**	.520**
Disc.	-.367**	-.294*	-.311*	-.366*	-.274*	.517**

Note. *p<.05, **p<.01

3. METHOD

A Last.fm dataset was used with 53,309 users of 47 countries and their *total* listening history until August 2014. [2] The dataset consists of users' listening (i.e., user ID, timestamp, artist name, and track name) and profile information (i.e., gender, age, country). A diversity measure was created by aggregating each user's listening history by artist and genre to identify the unique instances of each respectively. [3] E.g., a history of 90 events originating from two artists/genres means a diversity of two. Each diversity measure was normalized ($r \in [0,1]$) due to the unequal number of users between countries. The dataset was complemented with Hofstede's cultural dimensions (i.e., power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence [7]) and The Echo Nest features (i.e., genre, hotness, familiarity, and discovery).

4. RESULTS

Correlation analyses were used to explore the relationship between cultural dimensions and diversity, and report Pearson's correlation ($r \in [-1,1]$) to indicate the relationship.

Table 1 shows the correlation results between the cultural dimensions and listening characteristics. A negative correlation represents the degree of diversity, whereas a positive correlation indicates homogeneity. Positive correlations were found between a culture's power distance and artist (r=.279, p=.043) and genre (r=.329, p=.027) diversity. This indicates that users in countries scoring high on this dimension tend to apply less diversity by artist as well as by genre. Negative correlations were found between the individualism dimensions and artist (r=-.373, p=.012) and genre (r=-.265, p=.048) diversity, which indicates that users in individualistic countries tend to apply music diversity on an artist as well as genre level. Finally, a negative correlation was found between long-term orientation and artist diversity (r=-.259, p=.048). Users in countries scoring high on this dimension tend to listen to more diverse artists.

The Echo Nest features allowed us to gain more insights of the diversity characteristics of the artists. A negative correlation indicates that users of a country involve artists that score low on the respective feature of The Echo Nest when scoring high in the correlated cultural dimension (Table 1). **Hotness**. Hotness was found to be negatively correlated with uncertainty avoidance (r=-.359, p=.015) and long-term orientation (r=-.641, p=.000), while a positive correlation was found with indulgence (r=.557, p=.000). **Familiarity**. Familiarity was found to be negatively correlated with long-term orientation (r=-.677, p=.000), but positively correlated with indulgence (r=.520, p=.000). **Discovery**. Discovery showed a negative correlation with five out of six cultural dimensions: power distance (r=-.367, p=.013), individualism (r=-.294, p=.050), masculinity (r=-.311, p=.038), uncertainty avoidance (r=-.366, p=.013), and long-term orientation (r=-.274, p=.042). A positive correlation was found with indulgence (r=.517, p=.000).

[2]Available at http://www.cp.jku.at/datasets/LFM-1b/

[3]Genre was obtained through The Echo Nest. To maintain a manageable dataset we do not to focus on a tracks.

5. CONCLUSION & IMPLICATIONS

We show with our results that different diversity patterns exist and that they are related to cultural dimensions. When looking at the relationship between listening characteristics and cultural dimensions, distinct correlations were found.

Approaching diversity on a country level enables the creation of proxy measures for personalization when data is limited . Users' personality has gained interest to make inferences for personalization (e.g., [2, 6, 11]) on an individual level. The interconnectedness of applications and social media may be exploited to implicitly acquire personality (e.g., Facebook [4], Twitter [10], Instagram [3, 5]). However, a social media connection is still needed. Our results could be used to infer diversity needs based on country information, which is often available through the user's account.

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