Music Recommender Systems and Genre Bias

Abstract: Indexing and retrieval tools for music privilege genre-based categorization. Music recommender systems do not draw upon genre per se, but they utilize collaborative filtering algorithms that can give the appearance of doing so. This poster critiques genre’s pervasiveness, and suggests that recommender systems draw upon alternative notions of “similarity.”

Résumé: Les outils d’indexation et de repérage de la musique privilégient la catégorisation par genre. Les systèmes de recommandation de musique n’utilisent pas le genre en tant que tel, mais utilisent plutôt un algorithme de filtrage collaboratif qui en apparence fait la même chose. Cette affiche critique l’omniprésence du genre et suggère que les systèmes de recommandation devraient plutôt faire appel à la notion de « similarité ».

Although many indexing and retrieval systems draw upon genre as the primary way of categorizing music, the parameters of such boundaries remain inconsistent. Various for-profit and non-profit entities, such as record manufacturers, retailers, music publishers, and libraries, have developed their own structures and standards for constructing music genres and subgenres (Aucouturier & Pachet, 2003; Lippens et al., 2004). Among these taxonomies, the same song could be categorized within different genres, and the same genre may appear at different hierarchical levels (Aucouturier & Pachet, 2003; Pachet & Cazaly, 2000). Furthermore, individual listeners may have their own ideas about the most appropriate way to categorize a piece of music (Cunningham et al., 2003; Lippens et al., 2004).

While genre may appear to act as the basis for recommender systems on websites with music surrogates and content, this is not actually the case. On Amazon.com, its item-to-item collaborative filtering system enables registered customers to view recommendations for products that seem “similar” to others they have purchased or rated. More broadly, it bases recommendations on what other customers have tended to purchase together (Linden et al., 2003). The algorithm relies on navigational data and ratings (Symeonidis et al., 2008), which can give the appearance of making recommendations based on genre. Furthermore, it does not account for other musical and extramusical traits, which may be indicated by customer activity in different music genres (De Pessemier et al., 2009).

On some social network sites with music content, such as last.fm, users can assign tags. They may signify subjective associations, including emotional states (Bischoff et al., 2009; Kanters, 2009; Neal, et al. 2009; Hu & Downie 2010), opinions (Lamere, 2008), and individual contextual meanings (Bischoff et al., 2009). Tags seem promising as alternatives to genre for categorizing music. Nonetheless, like Amazon.com, such sites also draw upon collaborative filtering algorithms, assessing similarity based on user profiles (De Pessemier et al., 2009). In addition, more popular items receive tags than less popular ones (Law & von Ahn 2009), systems that
enable tagging reflect the biases of their respective user bases, and, as in the case of last.fm, genre remains the most common type of tag (Lamere, 2008).

With implications for recommender systems, a number of studies focus on refining automatic modes of classification that maintain the predominance of genre (Tzanetakis, et al., 2001; Grimaldi et al., 2003; Li et al., 2003; Grimaldi & Cunningham, 2004; Karydis et al., 2006; Annesi et al., 2007; Pérez-Sancho et al., 2008; Sanden, et al., 2008; McKay & Fujinaga, 2010). Many of them also acknowledge the challenges of working with the vague parameters and inconsistencies of such boundaries. Some research suggests that culture-based conceptualizations of genre, comparisons between automatic and human genre classification (Cunningham et al., 2003; Lippens et al., 2004; McKay & Fujinaga, 2006), and weighting of genre classifications (Wang, et al., 2008) could compensate for such ambiguities. Nonetheless, clearly defining the characteristics and parameters of specific genres remains problematic.

The emphasis on genre as a form of music categorization, as well as the efficiency of collaborative filtering algorithms used in many recommender systems, downplays other affinities that exist among music and musicians associated with different genres. Examples include Leonard Bernstein’s interest in an elusive “universality” of musical grammar (Burton, 1994; Bernstein, 1992); music producer Phil Spector’s usage of recording techniques to simulate “Wagnerian” effects in popular music (Long 2008); the emergence of progressive rock bands in the late 1960s, which drew upon classical and avant garde music, as well as jazz (Weinstein, 2002); the influence of classical music (in the colloquial sense) on the recording practice and concert performances of heavy metal musicians (Walser 1993); and other examples too numerous to list here. Furthermore, the lifetime experiences and knowledge of listeners can influence the ways in which they interact with music (Clarke et al., 2010), with a number of facets accounting for seemingly incongruous musical tastes. Additional research is needed to explore how multi-faceted notions of musical similarity could inform the development of more granular recommender systems, which would take into account a diverse range of musical and extramusical traits.

References:


