Computation and Visualization of Subjective Artist Similarity for Music Libraries on Android Devices

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Abstract. Abstract goes here.

Keywords: subjective artist similarity, multi-dimensional scaling, audio analysis

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1 Introduction

2 Related Work

In this chapter, the reader will be introduced to the proceedings in science which are relevant or related to this thesis. They are grouped into the following topics of interest:

- **Motivation for this thesis** - Provides an explanation on why the chosen topic of this thesis is generally of interest, and why similarity measures in music are feasible (given optimal circumstances).
- **Features of digital music** - Gives an overview of existing methods of feature extraction which are purely based on computational methods.
- **Subjective artist similarity computation** - Lists literature which is related to this thesis' problem of computing the subjective similarity of artists, which is based on subjectiveness as experienced by humans.
- **Visualization of artist similarity** - Provides an overview of existing methods and models of visualization of data similarity in general, and music similarity in particular.
- **Drawing and optimization of graphs based on multidimensional scaling** - Gives an overview of literature dealing with the technical and mathematical background of multi-dimensional visualization on two-dimensional output devices.

2.1 Motivation for the Topic of This Thesis

Music is an integral part of the daily life in nearly all societies, and the list of published titles is growing every day. As huge amounts of data tend to be hard to digest, ontologies have to be created, by which music can be categorized in a hierarchical fashion. Aside from the author's motivation of choosing the topic of this thesis, a great interest in music classification can be observed in scientific literature. This is related to the problem that the categorization of arbitrary music titles is neither implicit nor trivial. Serving the demands of Electronic Music Distribution (EMD), the authors of [5] elaborate on the feasability of music similarity measures. It is found in [5] that the introduced similarity measure (timbre similarity) combined with other measures can yield interesting results. It is also mentioned that the interpretation of experimental results in the field of music similarity is challenging due to the subjective demands.

It is clear that even the best-educated music experts could hardly agree on any distinct similarity measure between two music titles, due to the implicit fuzziness of subjective measures. It can be assumed that it is rare that two humans would agree on the same similarity between music files if they vote independent of each other.

2.2 Features of Digital Music

As opposed to subjective artist similarity, there are music features or measures which can be retrieved by purely computational approaches. In the field of audio feature extraction, a wide range of classifiers (feature extractors) has been

created. These classifiers in many cases run a bitstream analysis of a digitally stored music file and extract one or more reproducible measures characterizing the file.

TODO: MORE SOURCES FOR GENERAL FEATURE EXTRACTION

Interestingly, it is confirmed in [14] that the use of psycho-acoustic enhancements before feature extraction improves the classification accuracy significantly. It can be concluded that the outcomes of audio feature extraction are influenced by many factors which are not always intuitive. As has been mentioned previously, most audio classifiers analyze the bitstream of music files - however, the bitstream is only one dimension of a piece of music, if we regard it as a multi-dimensional object. For example, it is also possible to analyse the lyrics, as has been done in [16].

2.3 Subjective Artist Similarity Computation

Subjective similarity, as the author understands it, expresses human opinions on a certain object. As previously mentioned, it is obvious that humans will hardly agree on attributes of music, and the same person might even make different statements in the course of time, depending e.g. on her mood. The following applies to both artist similarities and music file similarities, since the former may be constructed from aggregations of the latter (it has to be noted at this point that many artists tend to produce music from multiple genres, thus making an artist-to-artist-comparison difficult or even infeasible). In article [8] it is found that it is doubtable that a common ground truth for subjective artist similarity even exists, because of the inhomegeneity of measures made by the involved users. It can be deduced that a meaningful model of subjective music similarity will in most cases only resemble a compromise between different stakeholders. As inferred from [6] and [17] there are different approaches to retrieving a model of subjective similarity for a given set of music files, which include:

- Conduction of surveys with end users
- Opinions of experts
- Co-occurrence of files in end users' libraries or playlists
- Data mining of text in web sources, as performed in [22]
- Leveraging data gathered by social music services

As it is intended by this thesis to provide a concept for a fast and fully automatic approach to similarity measuring, we will concentrate on the last approach, the usage of data provided by social music services. Hybrid computation methods, such as the method described by [17] (combining acoustic features with text excerpts and tags retrieved from online services) turn out to be hardly feasible on a mobile device because of performance requirements. It is assumed by the author that for a rough estimation of music file or artist similarity, the data provided by social music services (as opposed to hybrid approaches) is sufficiently meaningful, as their daily user base is in the millions and still growing.

A combination or fusion of similarity rankings from various social music services has been performed by the author of [15]. In this article it is demonstrated

that various methods of embedding or fusing similarity rankings from online services can provide different meaningful similarity models, some of which give more weight to unknown artists. However, this approach is clearly limited to the embedding of rankings and does not compute continuous values as similarity measure.

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References

1. http://developer.echonest.com/docs/v4/
2. http://devzone.wiki.meemix.com/index.php?title=MeeMix_API
3. http://www.lastfm.de/api
4. Agarwal, S., Wills, J., Cayton, L., Lanckriet, G., Kriegman, D., Belongie, S.: Generalized non-metric multidimensional scaling. In: AISTATS. San Juan, Puerto Rico (2007)
5. Aucouturier, J.J., Pachet, F.: Music similarity measures: What's the use? In: Ircam (ed.) Proceedings of the 3rd International Symposium on Music Information Retrieval. pp. 157–163. Paris, France (October 2002)
6. Berenzweig, A., Logan, B., Ellis, D.P.W., Whitman, B.: A large-scale evaluation of acoustic and subjective music similarity measures. In: Computer Music Journal (2003)
7. Cooper, M., Foote, J., Pampalk, E., Tzanetakis, G.: Visualization in audio-based music information retrieval. Comput. Music J. 30, 42–62 (June 2006), http://portal.acm.org/citation.cfm?id=1176357.1176365
8. Ellis, D.P.W., Whitman, B.: The quest for ground truth in musical artist similarity. In: in Proc. International Symposium on Music Information Retrieval ISMIR-2002. pp. 170–177 (2002)
9. Erten, C., Kobourov, S.G., Le, V., Navabi, A.: Simultaneous graph drawing: Layout algorithms and visualization schemes. In: In 11th Symposium on Graph Drawing (GD. pp. 437–449 (2003)
10. Frank, J., Lidy, T., Peiszer, E., Genswaider, R., Rauber, A.: Creating ambient music spaces in real and virtual worlds. Multimedia Tools Appl. 44(3), 449–468 (2009)
11. Fruchterman, T.M.J., Reingold, E.M.: Graph drawing by force-directed placement. Softw., Pract. Exper. 21(11), 1129–1164 (1991)
12. Geleijnse, G., Korst, J.: Tagging artists using cooccurrences on the web. In: Proceedings Third Philips Symposium on Intelligent Algorithms (SOIA 2006), pages 171 – 182 (2006)
13. Holten, D., van Wijk, J.J.: Force-directed edge bundling for graph visualization. Comput. Graph. Forum 28(3), 983–990 (2009)
14. Lidy, T., Rauber, A.: Evaluation of feature extractors and psycho-acoustic transformations for music genre classification. In: Proceedings of the Sixth International Conference on Music Information Retrieval (ISMIR 2005). pp. 34–41. London, UK (September 11-15 2005)
15. Marshall, B.: Aggregating music recommendation web apis by artist. In: Information Reuse and Integration (IRI), 2010 IEEE International Conference on. pp. 75 –79 (2010)
16. Mayer, R., Neumayer, R., Rauber, A.: Rhyme and style features for musical genre classification by song lyrics. In: ISMIR. pp. 337–342 (2008)
17. McFee, B., Lanckriet, G.: Heterogeneous embedding for subjective artist similarity. In: Tenth International Symposium for Music Information Retrieval (ISMIR2009)) (October 2009)
18. Morrison, A., Ross, G., Chalmers, M.: Fast multidimensional scaling through sampling, springs and interpolation. Information Visualization 2, 68–77 (March 2003), http://dx.doi.org/10.1057/palgrave.ivs.9500040
19. Muelder, C., Provan, T., Ma, K.L.: Content based graph visualization of audio data for music library navigation. In: In Proceedings of The IEEE International Symposium on Multimedia (ISM2010) (December 2010)

20. Pampalk, E., Rauber, A., Merkl, D.: Content-based organization and visualization of music archives. pp. 570–579. ACM (2002)
21. Sarmento, L., Gouyon, F., Costa, B.G., Oliveira, E.C.: Visualizing networks of music artists with rama. In: WEBIST. pp. 232–237 (2009)
22. Whitman, B., Lawrence, S.: Inferring descriptions and similarity for music from community metadata. In: In Proceedings of the 2002 International Computer Music Conference. pp. 591–598 (2002)

9 Appendix A