THE QUEST FOR GROUND TRUTH IN MUSICAL ARTIST TAGGING IN THE SOCIAL WEB ERA

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ABSTRACT

Research in Web music information retrieval traditionally focuses on the classification, clustering or categorizing of music into genres or other subdivisions. However, current community-based web sites provide richer descriptors (i.e. tags) for all kinds of products. Although tags have no well-defined semantics, they have proven to be an effective mechanism to label and retrieve items. Moreover, these tags are community-based and hence give a description of a product through the eyes of a community rather than an expert opinion. In this work we focus on Last.fm, which is currently the largest music community web service. We investigate whether the tagging of artists is consistent with the artist similarities found with collaborative filtering techniques. As the Last.fm data shows to be both consistent and descriptive, we propose a method to use this community-based data to create a ground truth for artist tagging and artist similarity.

1 INTRODUCTION

Researchers in music information retrieval widely consider musical genre to be an ill-defined concept [2, 14, 9]. Several studies also showed that there is no consensus on genre taxonomies [1, 10]. However, automatic genre classification is a popular topic of research in music information retrieval (e.g. [3, 17, 8, 11, 16, 6]).

In their 2006 paper [9], McKay and Fujinaga conclude that musical genre classification is worth pursuing. One of their suggestions is to abandon the idea that only one genre is applicable to a recording. Hence, multiple genres can be applicable to one recording and a ranked list of genres should be computed per recording.

Today, the content of web sites such as `del.icio.us`, `flickr.com` and `youtube.com` is generated by their users. Such sites use community-based *tags* to describe the available items (photos, films, music, (scientific) literature, etc.). Although tags has proven to be suitable descriptors for items, no clear semantics are defined. Users can label an item with any term. The more an item is labeled with a tag, the more the tag is assumed to be relevant to the item.

Last.fm is a popular internet radio station where users are invited to tag the music and artists they listen to. Moreover, for each artist, a list of similar artists is given based on the listening behavior of the users. In [4], Ellis et al. propose a community-based approach to create a ground truth in musical artist similarity. The research question was whether artist similarities as perceived by a large community can be predicted using data from All Music Guide and from shared folders for peer-to-peer networks. Now, with the Last.fm data available for downloading, such community-based data is freely available for non-commercial use.

In Last.fm, tags are terms provided by users to describe music. They "are simply opinion and can be whatever you want them to be" [1]. For example, Madonna's music is perceived as *pop*, *glamrock* and *dance* as well as *80s* and *camp*. When we are interested in describing music in order to serve a community (e.g. in a recommender system), community-created descriptors can be valuable features.

In this work we investigate whether the Last.fm data can be used to generate a ground truth to describing musical artists. Although we abandon the idea of characterizing music with labels with defined semantics (i.e. genres), we follow the suggestion in [9] to characterize music with a ranked list of labels. We focus on the way listeners perceive artists and their music, and propose to create a ground truth using community data rather than to define one by experts. In line with the ideas of Ellis et al. [4], we use artist similarities as identified by a community to create a ground truth in artist similarity. As tastes and opinions change over time, a ground truth for music characterization should be dynamic. We therefore present an algorithm to create a ground truth from the dynamically changing Last.fm data instead of defining it once and for all.

This paper is organized as follows. In the next section we investigate whether the data from Last.fm can indeed be used as a ground truth for describing artists and artist similarities. As the experiments in Section 2 give rise to further research, we present a method to create a ground

[1] `http://www.Last.fm/help/faq/?category=Tags`

truth for a set of artists in Section 3. Using this ground truth, we propose an approach to evaluate the performance of arbitrary methods for finding artist similarities and tags. Finally, we draw conclusions and indicate directions for future work in Section 4.

2 ANALYZING THE LAST.FM META-DATA

Last.fm users are invited to tag artists, albums, and individual tracks. The 100 top-ranked tags (with respect to the frequency a tag is assigned) for these three categories are easily accessible via the Audioscrobbler web services API [2]. By analyzing the listening behavior of its users, Last.fm also provides artist similarities via Audioscrobbler [3]. Per artist, a list of the 100 most similar artists is presented.

We analyze tags for artists in the next subsection. As the lists of the top-ranked tags tend to contain noise, we propose a simple mechanism to filter out such noise (Section 2.2). In order to check the consistency of the tags, we inspect, in Section 2.3, whether users label similar artists with the same tags. In Section 2.4, we compare the performance of the Last.fm data with results from previous work on a traditional genre classification task. Section 2 ends with conclusions on the suitability of Last.fm data to create a ground truth in artist tagging and similarity.

2.1 Tagging of Artists

In Table 1, the 20 top-ranked tags for the artist Eminem are given, as found with the Audioscrobbler web service. The terms *rap*, *hiphop* and *detroit* can be seen as descriptive for the artist and his music. Eminem is tagged with multiple terms that reflect a genre but the tag *rap* is more significant than *metal*.

Without questioning the quality or applicability of the terms in the list in Table 1, we observe some noise in the tagging of this artist. Whether we consider Eminem to be a hip-hop artist or not, after encountering the second highest ranked tag *Hip-Hop*, the tags *hip hop*, *hiphop* do not provide any new information. Moreover, the tag *Eminem* does not provide any new information with respect to the catalogue meta-data. The tags *favorite* and *good* do not seem very discriminative.

To investigate whether the tags are indeed descriptive for a particular artist, we collected the tags applied to a set of artists. In [16] [4], a list of 1,995 artists was derived from All Music Guide. We calculated the number of artists that are labeled with each of the tags. The most frequently occurring tags over all artists are given in Table 2. Table 3 contains some of the tags that are applied only to one artist. For the 1,995 artists, we encountered 14,146 unique tags.

rap	Gangsta Rap
Hip-Hop	Aftermath
hip hop	favorites
Eminem	metal
hiphop	Favorite
pop	rnb
rock	dance
alternative	american
detroit	classic rock
seen live	r and b

Table 1. Top 20 tags for Eminem.

jazz:809	country:308
seen live:658	hard rock:294
rock:633	singer songwriter:291
60s:623	oldies:289
blues:497	female vocalists:285
soul:423	punk:282
classic rock:415	folk:281
alternative:397	heavy metal:277
funk:388	hip-hop:267
pop:381	instrumental:233
favorites:349	rnb:231
american:345	progressive rock:229
metal:334	electronica:215
electronic:310	dance:209
indie:309	alternative rock:208

Table 2. The 30 most popular tags and their frequencies for the set of 1995 artists.

If a tag is applied to many diverse artists, it cannot be considered to be discriminative. We observe that there are no tags that are applied to a majority of the artists. The high number of artists labeled with jazz can be explained by the fact that the 1,995-artist-set contains 810 jazz artists. All frequent tags seem relevant characterizations for musical artists or for the relation of the users to the artists (e.g. *seen live*).

The most debatable tag among the best scoring ones may be *favorites*. Table 4 contains a list of the top artists for this tag, as extracted from audioscrobbler. We notice that no mainstream dance or pop artists are among the list of 100 top artists for *favorites*. The 100 top artists for *seen live* are artists that toured in the 00s.

Tags that are applied to only one, or only a few artists are not informative either. Since we do not consider the semantics of the tags, uniquely occurring tags cannot be used to compute artist similarities.

We observe that the tags that are only applied once to artists in this set are more prosaic, are in a different language, or simply contain typos (cf. "electro techo" in Table 3). It is notable that in total 7,981 tags (56%) are applied to only one artist. Only 207 tags are applied to at least 50 out of the 1,995 artists.

To check whether the 7,981 tags are descriptive for a larger set of artists, we computed the top count. That is, the total number of times each tag is applied to its at most 100 top artists [5]. Table 5 contains examples of

[2] http://ws.audioscrobbler.com

[3] e.g. http://ws.audioscrobbler.com/1.0/artist/Madonna/similar.xml

[4] http://www.cp.jku.at/people/schedl/music/C1995a_artists_genres.txt

[5] e.g. http://ws.audioscrobbler.com/1.0/tag/post-hardcore/topartists.xml

crappy girl singers:1
stuff that needs further exploration:1
disco noir:1
knarz:1
lektroluv compilation:1
gdo02:1
electro techo:1
808 state:1
iiiii:1
grimy:1
mussikk:1
grimey:1
good gym music:1
techno manchester electronic acid house:1
music i tried but didnt like:1
richer bad rappers have not existed:1
american virgin festival:1

Table 3. Some of the least used tags for the 1995 artists.

Radiohead	Coldplay
The Decemberists	Pink Floyd
Death Cab for Cutie	The Postal Service
The Beatles	Bright Eyes
The Shins	Elliot Smith

Table 4. The 10 top artists for the tag 'favorites'.

tags applied once in the 1995 artist collection and their top counts. If this sum is one, only one user has tagged one artist with this tag. Hence, the larger the top count, the more people will have used the tag to describe their music. Out of these 7,981 tags, 7,238 have a top count of at most 100. For comparison, the tag 'rock' has a top count of 150,519. Hence, we can conclude that the tags that are found only once in a collection of artists are in general uncommon descriptors for an artist.

Based on these small experiments, we conclude that all frequently used tags are relevant to characterize an artist. Moreover, although users can tag an artist with any term, the list of frequently used tags is relatively small. We conclude that the number of tags that describe multiple artists is in the order of thousands. If we select the tags that apply to 5% of the artists, the number is in the order of hundreds.

2.2 Filtering the Tags

As indicated above, not all tags provide sufficient information for our task since tags occur with small spelling variations and catalogue meta-data is used as tag as well. Moreover, tags that are only applied to few artists cannot be used to discriminate between artists. Suppose that we have a collection A of artists. We present a simple method

post-hardcore:8134	fagzzz:0
twee:4036	when somebody loves you:0
futurepop:3162	ravens music:0
mathcore:2865	bands i met:0
piano rock:2558	most definitely a bamf:1

Table 5. Examples of tags occurring only once with the high and low top counts.

hip hop	alternative
Eminem	seen live
hiphop	metal
Aftermath	classic rock

Table 6. Tags removed for Eminem after normalization (l.) and track-filtering (r.).

to filter out such meaningless tags.

Normalizing Tags. As we want tags to be descriptive, we filter out tags attached to $a \in A$ as follows.

– If a tag is equal to the name of the artist, we remove it.

– We compute a normalized form for all tags by

  – turning them into lowercase,

  – computing the stem of all words in the tags using Porter's stemming algorithm [13], and

  – removing all non-letter-or-digit characters in the tags.

– If two tags have the same normalized form, we remove the second one in the list.

– We remove every tag that is applied to less than 5% of the artists in A.

As we want the tags to reflect the music of the artist, we propose a next filtering step based on the tags applied to the best scoring tracks of the artist. Audioscrobbler provides the most popular tracks per artist, based on the listening behavior of the Last.fm users. As tracks can also be tagged individually, we can compare the tags applied to the artist with the tags applied to the top tracks. In the Track Filtering step, we filter out tags applied to the artist, that are not applied to his top tracks.

Track Filtering. By removing the tags that do not reflect the music of an artist, we perform a second filtering step.

- We collect the 10 top-ranked tracks according to Last.fm for every artist in the list.

- For each of these, we retrieve the most popular tags.

- We compute a normalized form for the tags for each track.

- For the list of the normalized tags of $a \in A$, we retain only those whose normalized form is applied to at least 3 out of the 10 top-ranked tracks for the respective artist.

The tags from Table 1 for Eminem that are removed after normalization and track filtering are given in Table 6.

2.3 Checking the Consistency of the Tags

The artist similarities as provided by Last.fm are based on the listening behavior of the users, and thus computed independently of the tags applied to the artists. Since we want to use the Last.fm data as ground truth in music characterization, the tagging should be consistent, i.e. similar artists should share a large number of tags.

To ensure this criterion, we selected the set of 224 artists used in [7] [6], where the artists were originally chosen to be representatives of 16 different genres. For each of the

[6] http://www.cp.jku.at/people/knees/publications/artistlist224.html

224 artists, we collected the 100 most similar artists according to Last.fm. For the resulting set of the 224 artists and their 100 nearest neighbors, we downloaded the lists of the 100 most popular tags. Per artist in the list of 224, we first compared the list of tags of the most similar artist. We did the same for the following (less) similar artists in the list.

We computed the average number of overlapping tags for the 224 artists and their k nearest neighbors and display the results in Figure 1. As – especially after track filtering – often less than 100 tags are assigned to each artist, we also computed the *similarity score* for each of the 224 artists and their k nearest neighbors by taking the average number of tags relative to the total number of tags for the nearest neighbors. For example, if an artist shares 34 out of 40 tags with an artist in the list of 224, the relative tag similarity score for this artist is $34/40$. The average similarity scores are given in Figure 2. The scores are computed using unfiltered, normalized and track-filtered Last.fm data.

The average number and score of overlapping tags decreases only slightly for the unfiltered and normalized data with increasing k. For the track-filtered data, we even note a small increase in the relative amount of tags shared (starting from $k = 25$). This can be explained by the small number of tags that remain after track-filtering, as can be found in Table 1.

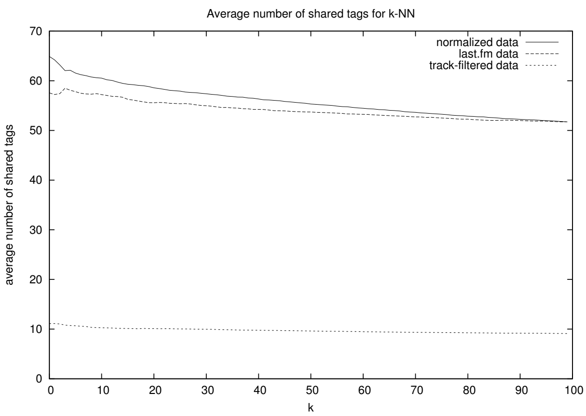

Figure 1. Average number of shared tags for the 224 artists.

Using the unfiltered Last.fm tags of all retrieved artists, we estimate the expected number of tags shared by two randomly chosen artists as 29.8 and the relative number of shared tags as 0.58. When we filter the tags by normalization and compare the normalized forms of the tags, we obtain an average of 29.8 shared tags, with a relative number of 0.62. For the track filtering, these numbers are 3.87 and 0.64 respectively. Hence, the number of tags shared by similar artists is indeed much larger than that shared by randomly chosen artists.

2.4 Using Last.fm in Genre Classification

To get further assess the usefulness of the Last.fm tags, we investigate whether this data can be used in a 'traditional' genre classification task. We evaluate whether the Last.fm data can be used to classify the earlier mentioned 224 artists into the 16 genres (with 14 artists per genre) as defined in [7]. Using data from web pages found with a search engine, earlier work reports precision values of around 88% [7, 6, 15].

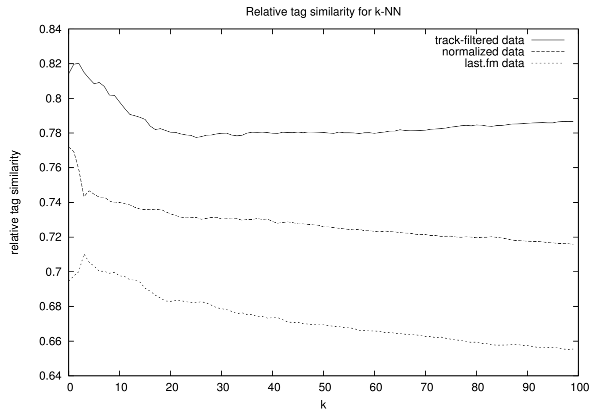

Figure 2. Relative tag similarity score for the 224 artists and their k Nearest Neighbors

We repeated the experiment as described in [6] using the data from Last.fm. For each artist, we initially selected the genre that gets the highest score. In this case, we thus select the genre that is mentioned as the highest ranked tag. If no genre is mentioned for an artist, initially no genre is assigned.

We compare the genre classification using the Last.fm data with the methods PM and DM as discussed in [6]. With PM we use *patterns* to find relevant search engine snippets. Using DM, we scan full *documents* that are obtained by querying the term *music* together with either a genre name or an artist name.

As the experiments in [6] showed, the use of similar artists can improve the classification results. For the experiment with the Last.fm data we therefore retrieved, for each artist of the 224 artist set, the list of the (at most) 100 most similar artists. On average, 14 artists from the 224-list were mentioned among the 100 most similar artists of an arbitrarily chosen artist from the 224-set.

Having obtained an initial mapping between each of the 224 artists and a genre, we use the nearest neighbors to compute a final mapping. Alike [6], we compute a majority voting among the initial genre for each artist and its k nearest neighbors using PM, DM and the Last.fm data.

We compare the results of the Last.fm-based artist classification with the best two results from [6] in Figure 3. For the method DM co-occurrences between artists and genres within full web documents are used to compute the initial mapping. To compute artist similarity using DM, we use co-occurrences of artist names within documents. The method PM uses co-occurrences within phrases that express the relations of interest.

The results for artist classification using the Last.fm data are similar to the ones gained using web-data collected with a search engine. The results for Last.fm are best when incorporating the tags of the 3 nearest neighbors of every artist. Since an average number of 14 similar artists (out of the set of 224) is identified, the performance deteriorates for larger values of k.

It is notable that for all three methods most misclassifications were made in the *Folk*, *Heavy* and *Rock 'n Roll* genres, where often the genre *Indie/Alternative* was assigned to the artist.

When we classify the artists using the Last.fm data after track filtering, the initial mapping ($k = 0$) improves slightly as *Cubby Checker* is now correctly classified. For values of k larger than 1, the performance using the track filtered data is equal to the one using either the raw or the normalized Last.fm data.

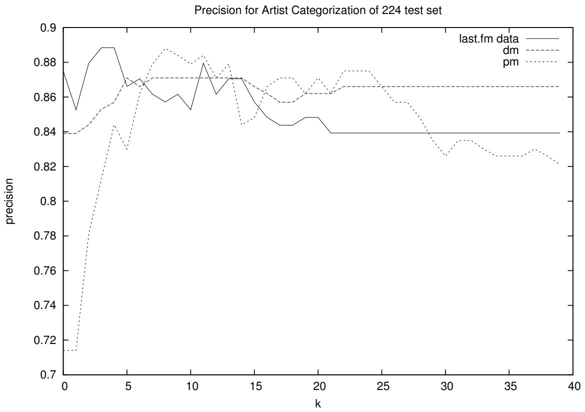

Figure 3. Precision of the 224 artist categorization for k nearest neighbors.

As the results of the genre classification using the Last.fm data are equally good as those gained with the best, high performance methods using arbitrary web-data, we conclude that the tags from Last.fm are a reliable data source for this classification task.

2.5 Conclusions

We have seen that the best scoring tags per artist are characterizations of the artist, the music, and the relation of the user to the artist. All three categories are considered informative and useful for e.g. a recommender system. The experiments with the 224 artists and their 100 nearest neighbors of each indicate that similar artists share a high amount of tags. On a genre-classification task, using Last.fm data gave similar results as methods using data retrieved with a web search engine.

Due to spelling variations, not all tags contain valuable information. Moreover, we cannot deduce information from rarely used tags, as no semantics are given for the tags. Hence, if a tag only occurs once in a collection, this tag is not descriptive and can neither be used to find similar artists or music.

We proposed a normalization method to remove meaningless tags. Tags that do not reflect the music can be filtered out by comparing the tags of the artist with the tags of the artist's top tracks.

From the experiments, we conclude that frequently used tags give faithful descriptions of the artists. Using a simple normalization method, we can filter out 'double' tags, i.e. tags with small variations in spelling. The filtering step using the tags applied to the tracks, however, seems less useful as there is little overlap between the tags for the top tracks and the ones applied to the artist.

3 EVALUATING WITH LAST.FM DATA

In earlier work (e.g. [16, 12, 5]) computed artist similarities were evaluated using the assumption that two artists are similar when they share a genre. To our best knowledge, only the tagging of artists with a single tag, usually a genre name, has been addressed in literature.

As the Last.fm data shows to be reliable, we propose to use it as a ground truth for evaluating algorithms that identify tags for artists tagging and compute artist similarity. The use of such a rich, user-based ground truth gives better insights in the performance of the algorithm and provides possibilities to study the automatic labeling of artists with multiple tags.

3.1 A Dynamic Ground Truth Extraction Algorithm

As the perception of users changes over time, we do not propose to create a constant set of artists and ranked tags, but an algorithm to extract the ground truth from Last.fm [7]. For comparison purposes, we propose the sets of 224 and 1,995 artists used in earlier experiments for evaluation of methods in automatic artist tagging.

For the evaluation of artist similarity, we use the similar artists for the artists in the set U as provided by Last.fm. For the lists of similar artists, we discard the artists that are not in U.

To create a ground truth for the ranked tags applicable to the artists in U, we download the top tags for each artist and compute the Normalized Tags as described in Section 2.2. Using all normalized tags applied to the U artists, we identify a set T of known tags.

3.2 Proposed Evaluation Measures

For a tag or an artist t_i given by the ground truth, $g_a(t_i)$ denotes the rank of t_i with respect to artist a. Hence, $g_a(t_i) - 1$ tags or artists are considered to be more applicable (or similar) to a. In contrast, with $r_a(t_i)$ we denote the rank of t_i for a as computed by the method to be evaluated.

We propose two evaluation measures. The first focuses on the traditional information retrieval measures precision and recall, the second evaluates the ranking.

Precision and Recall. We select the set S of the top n tags for artist a in the ground truth and evaluate precision and recall of the computed ordered list $\mathcal{L}_m$ of the m most

[7] The algorithm is available online via `http://gijsg.dse.nl/ismir07/`.

applicable tags according to the tagging approach to be evaluated.

Ranking. We do not only consider important the retrieval of the n top-ranked tags in the ground truth, we also want to evaluate the ranking itself, hence the correlation between the ranking in the ground truth $g_a(t_i)$ and the computed ranking $r_a(t_i)$. We evaluate the ranking for each artist using Pearson's Correlation Coefficient.

Having proposed both a test set of artist, an algorithm to dynamically create a ground truth and evaluation measures, we aim to facilitate research in automatic tagging of artist similarity.

4 CONCLUSIONS AND FUTURE WORK

We have proposed to adopt the concept of community-based tagging in music information retrieval research [4].

Contrary to expert-defined ground truth sets for genre classification, the Last.fm data is composed by a large community of users. As artists are described by ranked lists rather than single terms, the characterization is richer than a single genre [9].

Tags are valuable characterizations of artists and their music. In the social web, the user-input *tags* have proven to be a valuable method to characterize products. We believe that the characterization of music by a large user-community deserves to be addressed by the MIR community.

Our experiments indicate that the tags applied to artists in Last.fm are indeed consistent with respect to artist similarities. Tags showed to be descriptive and using the Last.fm data good results were achieved in a 'traditional' genre-classification task.

By providing a method to create a ground truth for artist tags and similarities, we want to facilitate research in a promising novel area in music information retrieval from the web.

5 REFERENCES

[1] Z. Aleksovski, W. ten Kate, and F. van Harmelen. Approximate semantic matching of music classes on the internet. In *Intelligent Algorithms in Ambient and Biomedical Computing*, Philips Research Book Series, pages 133 – 148. Springer, 2006.

[2] J.-J. Aucouturier and F. Pachet. Representing musical genre: A state of the art. *Journal of New Music Research*, 32(1):83 – 93, 2003.

[3] R. Basili, A. Serafini, and A. Stellato. Classification of musical genre: a machine learning approach. In *Proceedings of 5th International Conference on Music Information Retrieval (ISMIR'04)*, October 2004.

[4] D. P. Ellis, B. Whitman, A. Berenzweig, and S. Lawrence. The quest for ground truth in musical artist similarity. In *Proceedings of the Third International Conference on Music Information Retrieval (ISMIR'02)*, pages 170 – 177, Paris, France, 2002.

[5] G. Geleijnse and J. Korst. Tagging artists using co-occurrences on the web. In W. Verhaegh, E. Aarts, W. ten Kate, J. Korst, and S. Pauws, editors, *Proceedings Third Philips Symposium on Intelligent Algorithms (SOIA 2006)*, pages 171 – 182, Eindhoven, the Netherlands, December 2006.

[6] G. Geleijnse and J. Korst. Web-based artist categorization. In *Proceedings of the Seventh International Conference on Music Information Retrieval (ISMIR'06)*, pages 266 – 271, Victoria, Canada, October 2006.

[7] P. Knees, E. Pampalk, and G. Widmer. Artist classification with web-based data. In *Proceedings of 5th International Conference on Music Information Retrieval (ISMIR'04)*, pages 517 – 524, Barcelona, Spain, October 2004.

[8] T. Li, M. Ogihara, and Q. Li. A comparative study on content-based music genre classification. In *SIGIR '03: Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*, pages 282 – 289, New York, NY, USA, 2003. ACM Press.

[9] C. McKay and I. Fujinaga. Musical genre classification: Is it worth pursuing and how can it be improved? In *Proceedings of the Seventh International Conference on Music Information Retrieval (ISMIR'06)*, pages 101 – 106, Victoria, Canada, October 2006.

[10] F. Pachet and D. Cazaly. A taxonomy of musical genres. In *Content-Based Multimedia Information Access Conference (RIAO)*, Paris, France, 2000.

[11] E. Pampalk, A. Flexer, and G. Widmer. Improvements of audio-based music similarity and genre classificaton. In *Proceedings of the Sixth International Conference on Music Information Retrieval (ISMIR'05)*, pages 628 – 633, London, UK, September 2005.

[12] T. Pohle, P. Knees, M. Schedl, and G. Widmer. Building an interactive next-generation artist recommender based on automatically derived higher-level concepts. In *Proceedings of the Fifth International Workshop on Content-Based Multimedia Indexing (CBMI'07)*, Bordeaux, France, 2007.

[13] M. F. Porter. An algorithm for suffix stripping. In *Readings in information retrieval*, pages 313 – 316. Morgan Kaufmann Publishers Inc., San Francisco, CA, 1997.

[14] N. Scaringella, G. Zoia, and D. Mlynek. Automatic genre classification of music content. *IEEE Signal Processing Magazine : Special Issue on Semantic Retrieval of Multimedia*, 23(2):133 – 141, 2006.

[15] M. Schedl, P. Knees, and G. Widmer. A Web-Based Approach to Assessing Artist Similarity using Co-Occurrences. In *Proceedings of the Fourth International Workshop on Content-Based Multimedia Indexing (CBMI'05)*, Riga, Latvia, June 2005.

[16] M. Schedl, T. Pohle, P. Knees, and G. Widmer. Assigning and visualizing music genres by web-based co-occurrence analysis. In *Proceedings of the Seventh International Conference on Music Information Retrieval (ISMIR'06)*, pages 260 – 265, Victoria, Canada, October 2006.

[17] G. Tzanetakis and P. Cook. Musical genre classification of audio signals. *IEEE Transactions on Speech and Audio Processing*, 10(5), 2002.