Tag Relevancy for Similar Artists

Brandeis Marshall
Computer and Information Technology
Purdue University
401 North Grant Street
West Lafayette, IN 47907
brandeis@purdue.edu

***Abstract*—In music information retrieval, the rank position in similar artist lists have gained a lot of attention due to the surge in online music listening and semi-automated song recommendation approaches. Artist tags with respect to genre, style and mood are critical components in assisting these online communities. In this paper, we examine the relationship between an artist and associated similar artists by considering an artist's top tags. We are seeking to uncover patterns and correlations between pairwise rank positioning e.g., rank 1-2, rank 2-3, and so forth. The experiments show positive correlation between rank position pairs; however, the strength of the correlation is not as high as expected.**

***Keywords*-music information retrieval, knowledge dissemination, algorithms, experimentation**

I. Introduction

The music information retrieval field has grown significantly in recent years due to online music communities such as AllMusic, The Echo Nest, Idiomag, Last.fm and Pandora. In fact, the landscape for finding new music has been vastly transformed thanks to the Internet [3] as it has helped new artists such as Taylor Swift (country) and Sean Kingston (reggae) find new listeners as well. Several online music communities have user interface limitations and advantages. For instance, song 'replay' and/or previous song option is not allowed while permitting the use of 'skip' and 'pause' option with the advances of data streaming and network bandwidth capabilities.

Each online music listening website allows music listeners to create a user account in hopes of tracking music genre and artist preferences. In most cases, the user chooses a radio station with a programmed playlist. In contrast, Pandora also provides an option to construct a customized playlist with the input of a single music artist to begin the personalized user station. To assist their user in building a playlist, song recommendations are made through leveraging similar artists' ranking. Any form of music recommendation makes use of the artist profile, including primary genre, style and mood, and the user profile, including song ratings and song listening history.

Semi-automated song recommendation services are powered by the quality of similar artist rankings with the expectation that the most similar artists are ranked highly with respect to artist characteristics including audio features, genre, style, mood and music tags. As shown in Figure 1 [9], artist similarity is subjective. Daughtry (Rock), Bob Marley (Reggae) and Usher (R & B) are music artists from very distinctive genres; however, the number of similar artists vary and the proximity of their similar artists to the initial artist (center) differ widely. In this paper, we consider only music tag relevancy as related to a set of similar artists. Music tags can represent audio tones, genre, style and mood attributes unique to each artist. Hence, we expect that the music tag performance of similar artists would decrease as the rank positions increase.

Through experimentation, we record three types of performance e.g., precision, reciprocal rank and covariance, to show the relationship between an artist's music tags and corresponding similar artists' music tags. The precision performance measure records the number of tags overlapping between an artist and each of its similar artist. Reciprocal rank performance, on the other hand, computes the strength of the matching tags as higher rank positions receive greater weight. We then calculate the covariance between pairwise rank position e.g., rank 1-2, rank 2-3, and so forth, in order to investigate the quality of similar artist rankings.

The specific contributions of this paper are:

- study music tag relevancy in the context of similar artist rankings,
- perform a quantitative study showing the influence of music tags on similar artist rankings using Last.fm music data including 10 genres and nearly 500 artists
- conduct a performance analysis of tag relevancy considering precision, reciprocal rank and Spearman's ρ rank correlation coefficient.

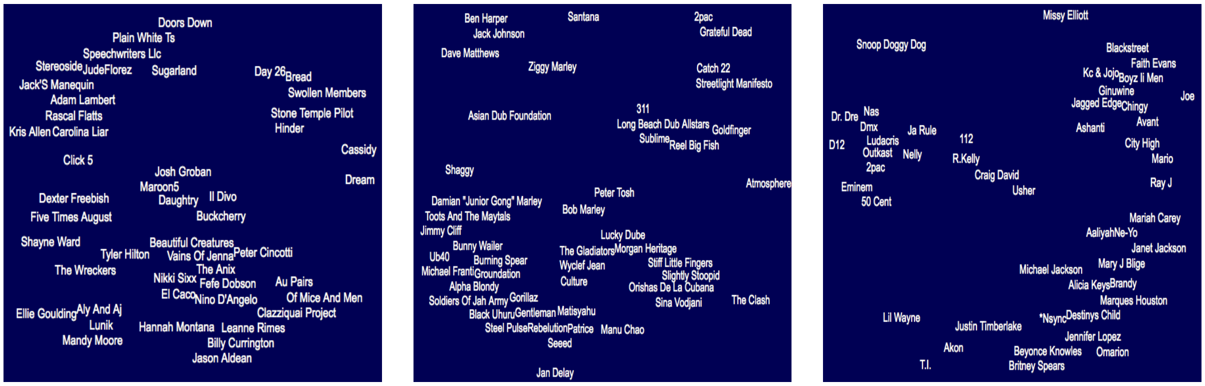
The rest of the paper is organized as follows. Section II reviews the relevant literature in music recommendation research. In Section III, we discuss the popular online music communities and describe our approach to music tag relevancy for similar artists. Section iV contains our experimental evaluation. We summarize our findings and discuss future work in Section V.

II. Related Work

Music recommendation research has three main branches: (1) content-based through audio processing, (2) pre-defined or user-generated tagging of artists, albums and/or songs and (3) mixed music content-based and tagging methods.

a) ***Content-based approaches****:* A large section of music research focuses on content-based methods by processing the audio file in order to correctly determine a song's genre. However, content-based methods are computationally expensive,

 ISBN: 978-1-61208-148-9



(a) Daughtry (b) Bob Marley (c) Usher

Fig. 1. Sample Artist Similarity Maps from Music-Map

but has led to improvements in the music genre labeling, artist style classification and identifying song moods. These improvements have been applied to construct music recommendation systems [2], [11], [18] by using collaborative filtering methods to provide user-specific results using information from many users. Other prior work [2], [18] concentrates on the users' playlist through song properties including pitch, duration and loudness. While users' playlist are customized, artist similarity can assist in generating a playlist but has a wider appeal with greater song and artist diversity. The primary disadvantages of content-based approaches are the higher computational cost of pre- and post-processing of sound recordings and the identification of relevant audio features to assist in distinguishing songs and vocalists.

*b) **Tagging approaches**:* In recommending music using text, tags associated with artists and/or songs are typically classified into either pre-defined expert opinion or community-based labeling categories. Assessing the quality of artist tagging and similarity for determining appropriate ground truth remains a challenging problem due to the current state of ill-formed music tag semantics [4].

Regardless, tagging offers the average user and experts an opportunity to catalog music in a detail unachievable with audio features. Bischoff et al. [1] emphasize that music listeners tend to label music and artist according to genre style and enjoy providing personalized opinions of the music. In Shao et al. [17], style and mood tags produced nearly identical results using a content-based approach comparing 12 artists. Magno and Sable [13] show the similarity of human recommendation with automate music recommendation services provided by *Last.fm* and *Pandora*. Nevertheless, the results also note the limitations of human recommendation as some dependencies are not captured for an individuals musical taste.

*c) **Mixed method approaches**:* Combining sound recording and tag content has become a popular method through the explosion of digital songs/albums e.g., Apple's iTunes and Google's YouTube. One goal of 21st century music research is building personal music information retrieval systems. Mixed method approaches tend to focus on either establishing customized artist similarity ([12], [19]) or song recommendation ([15], [16]). Through clustering, Li et al. [12] propose bimodal learning technique to semi-automate the process of grouping similar artists based on songs, albums and artists using the AllMusic repository as ground truth. Based on the MapReduce framework, Zhao et al. [19] consider tag semantic similarity in hopes of minimizing semantic loss and tag noise, while ensuring attribute diversity. The research reveals the scarcity of style and mood tags, but the need to give this content more importance when available. Both MusicWiz [15] and MusicBox [16] proposes specialized music management systems. MusicWiz is individual user-focused as to personalize song playlists according to an individual's feelings and memories while MusicBox is community-focused with the goal of exploiting correlation between users, tags and music content.

III. Music Tagging

Mainstream music listening is no longer primarily on the radio and playing CDs, but has become to mainly digital activity. On the Web, online music communities have been designed as a digital repository of artists, albums, songs, artist similarity and music influences & followers. In III-A, we discuss benefits and limitations of five popular music communities. Then in III-B, we describe specific challenges of music and artist tagging. We also discuss an approach to evaluate relevancy of tags for Last.fm.

A. Online Music Communities

1) **AllMusic. [6]** Originally All Music Guide or AMG, *AllGuide* offers consumers access to artist/group information containing biography, discography, songs, credits and charts & awards. The AllMusic database also includes descriptive content (genres, styles, tones, moods, themes and nationalities) and relational content (similar artists, influences and followers). The genres, styles and moods content are assigned to each artist from a pre-defined expert- approved list.
2) **The Echo Nest. [5]** Due to intellectual property rights, *Echo Nest* has not unveiled their process of relating artists. Nevertheless, the company has revealed that artist information is generated in a number of ways such as the analyzation of the raw music, blogs, song lyrics

 ISBN: 978-1-61208-148-9

and message board postings. While the exact method in rating artist similarity is unknown, test queries have shown that their artist database is multi-faceted with many musicians and genres.

3) **Idiomag. [7]** *Idiomag* uniquely labels, or tags, a given artist by weighted genre names from a preset list of 144 acceptable genre names maintained by the company's staff. Then a manual weight is applied to each of the tags by Idiomag's expert musicians/music lovers. Lastly, the artists are ordered according to their labels' values.
4) **Last.fm. [8]** *Last.fm* is highly user-centric by allowing any user to create self-defined tags. In contrast to *Idiomag*, *Last.fm* supports user-tagging which has led to a number of issues, including *duplicate tags* due to grammatical errors and *maliciously false tags* applied to artists. *Last.fm* combats this challenge by counting multiple occurrences of a single tag for a single artist as a vote for that artists tag. A tag's votes are reflected in how each tag is weighted. To determine musical similarity for an artist, *Last.fm* compares the tags of all artists in their database to the target artist.
5) **Pandora Radio. [10]** Originally the Music Genome Project (2000-2008), *Pandora Radio* is an automated customizable music recommendation service available only in the United States. The music recommendations are made based on nearly 400 attributes to describe songs using a U.S.-patented mathematical algorithm. At the core, the 5 music genomes are Pop/Rock, Hip-Hop/Electronica, Jazz, World Music and Classical. Artist and song labels are embedded within *Pandora Radio* and only partially accessible through the "Why this song?" choice in the Menu tab.

The Echo Nest, Idiomag and Last.fm offer well-developed Web APIs which allows anyone to develop specialized programs using their music data. Marshall [14] aggregates the artist tags from these three Web APIs in order to extract better and more consistent similar artists. However, Echo Nest, Idiomag and Last.fm return relatively diverse similar artists lists with a majority of agreement occurring within the top-3 similar artist list. Hence, artist similarity aggregation broadens the identification of similar artists; however, these online music communities do not have a consensus on artist similarity given a particular artist. We now examine the quality of these artist similarity rankings.

B. Tag Relevancy of Similar Artists

Much of the previous work [1], [4], [13], [16], [17], [19] used Last.fm music data since Last.fm remains an open-source environment since its creation. As a result, we use Last.fm music data as our experimental research platform.

Based on the artists presented in Figure 1, we display the top-10 tags and score values in Table I. We notice that all tags in rank position 1 have a score value of 100 indicating a universally recognizable tag associated with the artist. In addition, the tags at rank position 1 represent the primary artist genre. From rank position 2 downward, the score values decrease significantly with ties allowed where the tags are mainly genre subcategories and includes the artist's name.

Daughtry	Bob Marley	Usher
rock (100)	reggae (100)	rnb (100)
alternative rock (80)	roots reggae (25)	Hip-Hop (52)
alternative (47)	Bob Marley (18)	soul (38)
hard rock(34)	ska (15)	pop (38)
American Idol (22)	rock (9)	rap (26)
post-grunge (13)	jamaican (4)	Usher (20)
daughtry (9)	classic rock (3)	hip hop (11)
male vocalists (7)	chill (3)	male vocalists (8)
pop rock (7)	singer-songwriter (3)	r & b (7)
american(5)	roots(2)	r and b (6)

TABLE I
LAST.FM TOP TAGS WITH FREQUENCY COUNTS

With Last.fm music data, we observe some inherent tag semantic overlap, such as rock, alternative rock, alternative, that makes assessing the quality of the similar artists' tags more difficult. For instance, depending on the matched tags between two artist, a distinctive similarity relationship may exist. In the *TRAS* function below, we follow a template in evaluating the quality of tags with respect to the similar artist list returned from the Last.fm GETTOPTAGS method. A string IA denotes the initial artist, a string array $similars$ holds n similar artists of IA and retrieving the top-k tags serve as input and returns an array of performance analysis calculations for each (IA, SA_i) pair.

function TRAS(initial:IA,similars:$\{SA_1, \ldots, SA_n\}$, count:k)
resultArray=empty //holds the result of performance measure
IAtags = LASTFM.GETTOPTAGS(initial,k)
for $i = SA_1$ to SA_n **do**
  SAtags = LASTFM.GETTOPTAGS(i, k)
  //MEASURE$(\cdot, \cdot)$ is a place holder for a performance measure e.g., precision, reciprocal rank, covariance
  result = MEASURE(IAtags, SAtags)
  resultArray.append(result)
return resultArray

IV. EXPERIMENTAL STUDY

To test the degree of similarity amongst music artists, we ran nearly 500 artist queries over 10 popular music genres. We manually selected the query artists as to guarantee the return of at least 10 similar artists from Last.FM. We present a sample of the artists queried in Table II.

For each artist query, we first gather the top 10 similar artists. Then, we extract the top 10 popular tags associated with each artist query, we denote as initial artist (IA) and its similar artists, we denote as SA. We chose the first 10 tags because the score values associated with these rank positions are consistently above 0. We examine the tag match performance between IA and each of its SA using two measures. The first error measure, precision P, is calculated by taking the two tag lists m_{IA}, m_{SA} and finding the number of common tags in relation to the number of returned elements k. We chose $k = 10$. Formally, precision is defined as follows

$$P_k(m_{IA}, m_{SA}) = \frac{m_{IA} \cap m_{SA}}{k}$$

Alternative	50	Disturbed, Korn, Muse, Nickelback, Papa Roach, The Fray
Blues/Jazz	48	B.B. King, Nina Simone, Otis Redding, Ray Charles, Stevie Wonder, Doris Day
Country	50	Garth Brooks, Faith Hill, Toby Keith, Vince Gill, Willie Nelson
Electronic	48	Air, Daft Punk, Depeche Mode, Massive Attack, Zero 7
Funk	49	Culture Club, Funkadelic, Musiq, Parliament, Sade
Hip-Hop	48	Janet Jackson, John Legend, TLC, Monica, Black Eyed Peas
Pop	50	Blackstreet Boys, Britney Spears, Coldplay, Justin Timberlake, Lady Gaga
Rap	50	Dr. Dre, Eminem, Lil' Wayne, Run DMC, Snoop Dogg, Young Jeezy
Reggae	45	Bob Marley, Black Uhuru, Matisyahu, Shaggy, Toots & The Maytals
Rock	49	Creed, Finger Eleven, Hinder, Rob Thomas, Train

TABLE II
SAMPLE ARTISTS

Precision is a commonly used measure to distinguish between relevance and non-relevance. However, precision does not indicate the degree of relevance, e.g., the rank position of relevant data. To assess relevancy based on rank position, we use the reciprocal rank measure. Formally, reciprocal rank is defined as follows

$$RR_k(m_{IA}, m_{SA}) = \sum_{l=1,\ldots,k} \frac{1}{l} \text{ if } m_{IA}(l) = m_{SA}(q)$$

where l, q ($l = q$ or $l \neq q$) refer to a position in a ranking. In the case when precision is 100% and thus, the reciprocal rank value is 2.93 (= $\sum_{l=1}^{k=10} 1/l$).

Genre	$P_{10}(min, max)$	$RR_{10}(min, max)$
Alternative	(33.20%, 73.8%)	(1.35, 2.51)
Blues/Jazz	(23.92%, 75.29%)	(1.06, 2.54)
Country	**(8.00%, 54.00%)**	**(0.41, 1.93)**
Electronic	(25.91%, 75.51%)	(1.08, 2.45)
Funk	(17.21%, 67.60%)	(0.73, 2.37)
Hip-Hop	(2.29%, 66.04%)	(0.08, 2.35)
Pop	(33.40%, 72.00%)	(1.39, 2.48)
Rap	(25.40%, 70.80%)	(1.15, 2.43)
Reggae	(20.21%, 62.82%)	(0.93, 2.26)
Rock	**(38.20%, 79.20%)**	**(1.51, 2.67)**

TABLE III
PRECISION AND RECIPROCAL RANK AVERAGE INTERVALS

In our first set of experiments, we observe the interval range of both precision and reciprocal rank for each music genre as shown in Table III. We record the minimum and maximum value observed for each IA and its 10 SA e.g., for alternative music, we record 50 minimum and 50 maximum precision values (as well as 50 minimum and 50 maximum reciprocal rank values). The observed precision values ranges from the lowest maximum of 54% for Country music to the highest maximum of 79% for Rock music. The reciprocal rank values mirrored those observed in the precision calculations. The reciprocal rank, however, assist in determining the rank positions of the matching tags. Hence, for Country music, the minimum 8% precision is seen on average 1 out of the 10 rank positions at position 2 ($RR(\cdot,\cdot) = \frac{1}{2}$) or position 3 ($RR(\cdot,\cdot) = \frac{1}{3}$) in order to compute a minimum reciprocal rank of 0.41. To achieve the maximum precision and reciprocal rank in Country music, 5 or 6 rank position has matching tags giving the average maximum precision of 54% and the matching rank position are either {1, 3, 4, 5, 6} ($RR(\cdot,\cdot) = \frac{1}{1} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5} + \frac{1}{6} = 1.95$) or {1, 4, 5, 6, 7, 8} ($RR(\cdot,\cdot) = \frac{1}{1} + \frac{1}{4} + \frac{1}{5} + \frac{1}{6} + \frac{1}{7} + \frac{1}{8} = 1.88$).

We further investigate the relationship between rank positions with respect to the precision and reciprocal rank values in our second and third experiments. We consider the change in performance values between consecutive rank positions e.g., Rank 1 to Rank 2, Rank 2 to Rank 3, and so forth. We expect that the performance between consecutive rank positions would be increasingly negative. In other words, when compared to the initial artist IA, the tag similarity of a similar artist SA at rank 1 (SA_1) is greater than the tag similarity of a similar artist at rank 2 (SA_2). In addition, we assume that as SA_w in which $w \to 10$, the difference between rank w and $w + 1$ increases. Last.fm returns a "count" value for each tag indicating the popularity of the tag with the corresponding artist. These counts are consistently and quickly decreasing in value.

Rank Position Sum Difference. For each consecutive pair of rank positions, we compute the average precision sum difference for each genre. The results are displayed in Table IV. We anticipate that the precision at rank position 1 would be higher than precision at rank position 2, precision at rank position 2 would be higher than precision at rank position 3 and so forth. However, our observations did not lead to this conclusion. Instead, we notice a *low and mainly positive* precision difference between consecutive pairs of rank positions. The highest precision value difference is -0.34 (or increase of 34% in the Hip-Hop genre from Rank 1 to Rank 2). The majority of the precision value difference is $\leq$ +/- 0.050 (or increase/drop of precision by less than 5%). In fact, no genre tested is consistently negative or positive in terms of their consecutive rank positions. This oscillating precision performance implies that the similarity ordering of artists is not primarily based on tag label.

Through precision performance, we can only assess *how many* tags consistently matched. We have no information about *which rank position* the artists appeared in the ranking. The reciprocal rank performance provides this evaluation. In Table V, we compute the average sum difference for each genre and rank position pair. Each cell value records the magnitude change between rank positions. A majority of the change is in a [-0.100,0.100] interval or within one position

 ISBN: 978-1-61208-148-9

Genre	Rank 1-2	Rank 2-3	Rank 3-4	Rank 4-5	Rank 5-6	Rank 6-7	Rank 7-8	Rank 8-9	Rank 9-10
Alternative	-0.006	0.044	-0.010	0.050	-0.056	-0.002	0.034	-0.064	0.054
Blues/Jazz	0.082	0.002	0.037	-0.012	0.006	-0.012	0.047	-0.027	0.031
Country	-0.034	0.028	-0.036	0.028	-0.064	0.076	0.012	-0.050	0.012
Electronic	0.016	0.027	-0.012	0.041	-0.006	0.031	-0.018	-0.039	0.076
Funk	0.078	-0.066	0.048	-0.030	0.028	0.016	-0.018	-0.014	0.018
Hip-Hop	**-0.340**	-0.112	-0.021	0.060	-0.019	-0.010	0.033	-0.029	-0.025
Pop	0.044	-0.036	0.032	-0.034	0.030	0.010	0.016	0.058	-0.042
Rap	-0.082	0.044	0.016	0.018	0.012	-0.036	0.006	0.032	-0.028
Reggae	0.004	0.054	-0.002	0.009	0.004	0.020	0.043	-0.061	0.011
Rock	0.020	0.004	0.002	0.022	-0.004	0.034	0.006	-0.004	-0.016

TABLE IV
PRECISION SUM DIFFERENCE: RAW VALUES (MULTIPLY BY 100 FOR PERCENTILE)

Genre	Rank 1-2	Rank 2-3	Rank 3-4	Rank 4-5	Rank 5-6	Rank 6-7	Rank 7-8	Rank 8-9	Rank 9-10
Alternative	-0.076	0.154	-0.078	0.151	-0.142	0.009	0.146	-0.210	0.116
Blues/Jazz	0.186	-0.016	0.060	0.034	-0.042	0.029	0.101	-0.100	0.103
Country	-0.130	0.053	-0.102	0.111	-0.230	0.208	0.024	-0.108	0.166
Electronic	-0.017	0.130	-0.078	0.090	-0.052	0.112	-0.004	-0.155	0.265
Funk	0.224	-0.189	0.150	-0.085	0.097	0.032	-0.107	0.099	-0.030
Hip-Hop	-1.419	-0.371	-0.037	0.165	-0.115	-0.043	0.097	-0.088	-0.077
Pop	0.053	-0.148	0.139	-0.088	0.074	0.001	0.011	0.189	-0.059
Rap	-0.317	0.101	0.048	0.100	-0.038	-0.121	-0.005	0.085	-0.007
Reggae	0.052	0.169	-0.033	0.042	-0.103	0.117	0.209	-0.265	0.036
Rock	0.071	0.023	0.003	0.041	0.028	0.074	0.030	-0.015	-0.114

TABLE V
RECIPROCAL RANK SUM DIFFERENCE: RAW VALUES (DIVIDE BY 2.93 FOR NORMALIZATION)

Genre	Rank 1-2	Rank 2-3	Rank 3-4	Rank 4-5	Rank 5-6	Rank 6-7	Rank 7-8	Rank 8-9	Rank 9-10
Alternative	0.544	0.651	0.668	0.640	0.627	0.617	0.588	0.578	0.574
Blues/Jazz	0.333	0.376	0.404	0.448	0.452	0.475	0.459	0.465	0.438
Country	0.083	0.165	0.276	0.310	0.309	0.330	0.329	0.325	0.352
Electronic	**0.699**	**0.627**	**0.633**	**0.638**	**0.608**	**0.598**	**0.569**	**0.559**	**0.539**
Funk	0.358	0.397	0.380	0.347	0.358	0.377	0.382	0.387	0.377
Hip-Hop	**-0.010**	**0.017**	**0.127**	**0.216**	**0.181**	**0.211**	**0.235**	**0.236**	**0.257**
Pop	0.551	0.470	0.515	0.530	0.555	0.553	0.554	0.557	0.578
Rap	0.260	0.426	0.461	0.518	0.521	0.512	0.530	0.537	0.542
Reggae	0.565	0.648	0.581	0.530	0.528	0.543	0.545	0.544	0.547
Rock	0.512	0.495	0.375	0.361	0.359	0.364	0.383	0.401	0.411

TABLE VI
SPEARMAN'S ρ EVALUATION OF PRECISION VALUES

Genre	Rank 1-2	Rank 2-3	Rank 3-4	Rank 4-5	Rank 5-6	Rank 6-7	Rank 7-8	Rank 8-9	Rank 9-10
Alternative	0.592	0.669	0.688	0.638	0.611	0.602	0.594	0.579	0.577
Blues/Jazz	0.470	0.490	0.483	0.530	0.520	0.524	0.495	0.499	0.483
Country	0.254	0.371	0.436	0.470	0.486	0.493	0.500	0.488	0.484
Electronic	**0.831**	**0.714**	**0.686**	**0.666**	**0.636**	**0.623**	**0.594**	**0.593**	**0.570**
Funk	0.326	0.381	0.390	0.354	0.375	0.386	0.402	0.397	0.393
Hip-Hop	**0.016**	**0.041**	**0.145**	**0.218**	**0.210**	**0.240**	**0.259**	**0.270**	**0.290**
Pop	0.544	0.506	0.553	0.544	0.564	0.576	0.569	0.587	0.607
Rap	0.345	0.509	0.545	0.603	0.595	0.593	0.620	0.629	0.625
Reggae	0.571	0.663	0.621	0.551	0.546	0.568	0.564	0.553	0.555
Rock	0.468	0.364	0.246	0.228	0.259	0.291	0.313	0.330	0.344

TABLE VII
SPEARMAN'S ρ EVALUATION OF RECIPROCAL RANK VALUES

at rank 10. Hence, we conclude that, on average, the matched tags differ by one or two rank positions in the higher ranks e.g., rank 8, rank 9 or rank 10. The anomaly is the Hip-Hop genre at rank 1-2 with a value of -1.419, which implies rank 1 has low matching tags to a much higher matching tags at rank 2.

Spearman's ρ Evaluation. However, precision nor reciprocal rank measure the covariance of two variables or two rank positions in our case e.g., rank 1-2, rank 2-3, etc. To assess the covariance between rank positions, we use the Spearman's rank correlation coefficient (Spearman's ρ). Formally, Spearman's ρ is defined as follows

$$\begin{aligned} rho_k(rp_X, rp_Y) &= \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (1) \\ &= \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2}\sqrt{\sum(Y-\bar{Y})^2}} \end{aligned}$$

Spearman's ρ values have a [-1,1] interval in which -1 denotes that the two variables are negatively correlated, 1 denotes that the two variables are positively correlated and 0 denotes no correlation between these two variables. We calculate the covariance between rank positions for both the precision and reciprocal rank performance, which are displayed in Tables VI and VII. The Electronic genre is the most positively correlated while Hip-Hop genre is the least correlated. The Spearman's ρ evaluation of the reciprocal rank values are only slightly different from the equivalent precision values in Table VI. We conclude that there is moderate correlation between consecutive rank positions for both performance measures. The oscillating nature between rank positions for each genre observed in Tables IV and V is observed once again as the positive correlation slightly fluctuates.

V. Conclusion

Music listening has become a mainly digital activity with online music communities such as Pandora and Last.fm. Music listening has become a science with relevant song recommendation methods at its core. Song recommendations are guided by appropriate artist similarity rankings. Using the frequently-used Last.fm music data across 10 genres, we investigate the relevancy of music tags with respect to the similar artists' ranking by looking at pairwise rank positions. We expected to discover a strong relationship between an artist and its corresponding similar artists. With precision, we explore how many tags consistently matched while with reciprocal rank, we evaluate the rank position of matching tags. In both performance analysis measures, we did not observe any logarithmic, polynomial, power or exponential trendlines. We also perform a Spearman's ρ evaluation across genre and rank positions. We found a moderately positive correlation between pairwise rank positions.

In the future, we plan to examine how to better randomize music song recommendation by mixing highly and moderately similar artists. To this end, we will consider a two-prong approach: 1) artist tag classifications and 2) artist song collaborations. We will investigate the influence of artist song collaborations on artist similarity. These song collaborations can increase the interestingness of the song by highlighting the unique sound of each artist. The tends in popular song collaborations based on determining genre, style and mood correlation of each artist.

References

[1] K. Bischoff, C. Firan, W. Nejdl, and T. Paiu. Can all tags be used for search. In *Proceedings of ACM CIKM*, pages 203–212, 2008.
[2] H.-C. Chen and A. L. P. Chen. A music recommendation system based on music data grouping and user interests. In *Proceedings of ACM CIKM*, pages 231–238, 2001.
[3] S. Cunningham, D. Bainbridge, and D. McKay. Finding new music: a diary study of everyday encounters with novel songs. In *International Conference on Music Information Retrieval (ISMIR)*, pages 83–88, 2007.
[4] G. Geleijnse, M. Schedl, and P. Knees. The quest for ground truth in musical artist tagging in the social web era. In *International Conference on Music Information Retrieval (ISMIR)*, pages 525–530, 2007.
[5] http://developer.echonest.com/. Echo nest : The musical brain, 2005.
[6] http://www.allmusic.com/. All music guide, 1991.
[7] http://www.idiomag.com/api/. Idiomag, 2006.
[8] http://www.lastfm.com/api/. Last.fm, 2002.
[9] http://www.music map.com/. Musician map, 2002.
[10] http://www.pandora.com/. Pandora radio, 2007.
[11] I. Im and A. Hars. Does a one-size recommendation system fit all? the effectiveness of collaborative filtering based recommendation systems across different domains and search modes. *ACM Transactions on Information Systems*, 26(1), 2007.
[12] T. Li, M. Ogihara, W. Peng, B. Shao, and S. Zhu. Music clustering with features from different information sources. *IEEE Transactions on Multimedia*, 11(3):477–485, 2009.
[13] T. Magno and C. Sable. A comparison of signal-based music recommendation to genre labels, collaborative filtering, musicological analysis, human recommendation, and random baseline. In *International Conference on Music Information Retrieval (ISMIR)*, pages 161–166, 2008.
[14] B. Marshall. *Recent Trends in Information Reuse and Integration*, chapter Music Artist Similarity Aggregation. Springer-Verlag, 2011.
[15] K. Meintanis and F. M. Shipman. Visual expression for organizing and accessing music collections in musicwiz. In *Proceedings of the European Conference on Research and Advanced Technology for Digital Libraries*, pages 80–91, 2010.
[16] A. Nanopoulos, D. Rafailidis, P. Symeonidis, and Y. Manolopoulos. Musicbox: Personalized music recommendation based on cubic analysis of social tags. *IEEE Transactions on Audio, Speech and Language Processing*, 18(2):407–412, 2010.
[17] B. Shao, T. Li, and M. Ogihara. Quantity music artist similarity based on style and mood. In *Proceedings of the ACM International Workshop on Web Information and Data Management*, pages 119–124, 2008.
[18] M. Slaney and W. White. Measuring playlist diversity for recommendation systems. In *Proceedings of the ACM Workshop on Audio and Music Computing Multimedia*, pages 77–82, 2006.
[19] Z. Zhao, X. Wang, Q. Xiang, A. M. Sarroff, Z. Li, and Y. Wang. Large-scale music tag recommendation with explicit multiple attributes. In *Proceedings of the International Conference on Multimedia*, pages 401–410, 2010.