Genre-based Analysis of Social Media Data on Music Listening Behavior

Are Fans of Classical Music Really Averse to Social Media?

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ABSTRACT

It is frequently presumed that lovers of Classical music are not present in social media. In this paper, we investigate whether this statement can be empirically verified. To this end, we compare two social media platforms — Last.fm and Twitter — and perform a study on musical preference of their respective users. We investigate two research hypotheses: (i) Classical music fan are more reluctant to use social media to indicate their listing habits than listeners of other genres and (ii) there are correlations between the use of Last.fm and Twitter to indicate music listening behavior. Both hypotheses are verified and substantial differences could be made out for Twitter users. The results of these investigations will help improve music recommendation systems for listeners with non-mainstream music taste.

Categories and Subject Descriptors

H.5.1 [**Information Interfaces and Presentation**]: Multimedia Information Systems

Keywords

Social Media Analysis, Music Information Retrieval

1. MOTIVATION

It has frequently been argued that listeners of Classical music are reluctant to use social media.[1] However, to the best of our knowledge, no scientific analysis has been carried out yet to verify this claim.

Age structure may play an important role here as a correlation between age and degree of inclination to Classical music is evident and easy to verify empirically. On the other hand, since the average age of users of many social media platforms has been increasing during the past few years, it is natural to presume a likewise increase of the presence of Classical music fans on social media. In fact, the average user of Last.fm is 38.2 years old, which is above the average of other social media platforms, according to a report from 2012 carried out on 24 popular social media platforms.[2] Twitter's average user is aged 37.3.

Aiming to shed light on the activity of Classical music listeners on social media, in this paper we look into two research questions: (i) are lovers of Classical music more reluctant to use social media for talking about their listing habits than lovers of other music genres and (ii) are there correlations between usage of Last.fm and Twitter as data sources to indicate music listening behavior. These questions will be answered by comparative quantitative experiments.

2. RELATED WORK

Studies analyzing personal traits or behavior of listeners of a particular music genre are rare. The existing work can be categorized into qualitative and quantitative investigations.

A qualitative study on the influence of music of a particular genre on human life can be found in [1], where an online Black Metal community is investigated. In addition to identifying the main subject matters in a Black Metal discussion forum, Ardet also found that about 70% of the community members were aged between 14 and 17. Woelfer and Lee analyze the importance of music for the life of homeless young people [10]. Surveying 100 Canadians, they found that homeless youngsters prefer Hip Hop, Rock, R&B, Techno, and Metal over other genres.

Quantitative analyses of listening events posted on social media are carried out by Schedl and Hauger in [8]. They look into geolocated musical tweets and aggregate them according to country and city. The authors then investigate particularities of music genre taste in different locations. In a subsequent work, Schedl categorizes music listening events posted on Twitter by mood tags, computes the global distribution of these mood tags, and investigates deviations from this global distribution on the country level [7].

Mining and analyzing musical preference and other personal characteristics is becoming more and more important to elaborate user-centric music retrieval systems [5]. Musical information gathered from social media, in particular from microblogs and online music platforms, can be used

[1]This statement has been made countless times in personal conversations between the author and other researchers, music lovers, musicians, and users of social media.

[2]`http://royal.pingdom.com/2012/08/21/report-social-network-demographics-in-2012`

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to build or enrich music recommender systems, as demonstrated in [11] and [2], among others. Zangerle at al. build a music recommender based on co-occurrences of music tracks in tweets [11]. Cheng and Shen mine streams of microblogs from Twitter to investigate the dynamics of popularity trends in music [2]. They combine this information with audio content and listening histories to create a unified music recommendation model.

However, as noted by Tkalčič et al. [9], personalized Classical music retrieval and recommendation is a challenge because of the apparent sparsity of data. In fact, in the paper at hand we examine the extent of this lack of information, which may impact the ability to design and implement personalized Classical music retrieval systems as opposed to the large amount of data for other, more mainstream genres.

3. DATASETS

The experiments were carried out on two datasets of listening events posted on two different social media platforms: Last.fm and Twitter.

3.1 Last.fm Dataset

As large volume data source of music listening events we exploit Last.fm. Data acquisition has been carried out by first selecting the 15 most general genres from Allmusic.com's major genres. We then obtain the 1,000 most popular artists for each of the genre tags via the Last.fm API[3], which is the maximum number the Last.fm API provides. For each of the resulting 15,000 artists, we gather the play count and listener count figures. Play count of an artist refers to the total number of listening events over all Last.fm users, whereas listener count refers to the number of users who listened to the artist at least once. Please note that the used `Tag.getTopArtists` method of the Last.fm API does not distinguish between performers, composers, and songwriters; all of these are treated as artists. The Last.fm data has been gathered on 2014-04-13.

3.2 Million Musical Tweets Dataset

The Million Musical Tweets Dataset[4] (MMTD) is a publicly available dataset of music listening events inferred from microblogs [4]. It was gathered by analyzing tweets containing music-related hashtags, such as #nowplaying or #itunes, during the time period from 2011-11-09 to 2013-04-30. The MMTD contains over a million listening events to about 133,000 unique tracks by 25,000 artists, listened to by 215,000 users. Since the MMTD comes with <user, artist, track> assignments, play counts and listener counts can easily be computed, which enables comparison to the Last.fm dataset.

4. ANALYSIS

We base our investigations upon three quantitative measures related to music consumption: play count (PC), listener count (LC), and average play count per listener (APCL). While the former two were already defined above, APCL approximates the likeliness of an artist being played over and over again, as the fraction of PC and LC.

4.1 Classical music and social media?

To answer research question (i), Tables 1 and 2 depict several statistics for PC, LC, and APCL over the 15 genres under consideration, respectively, for the Last.fm dataset and the MMTD. Figures 1 and 2 show the distribution of the three quantitative measures for each genre and the two datasets Last.fm and MMTD, respectively. The plots for the Classical genre are depicted as thicker lines.

Analyzing Tables 1 and 2, please note that an artist can be assigned multiple genres in Last.fm. This is why certain statistical descriptors are the same for different genres (e.g., maximum LC in Table 1 refers to the same artist who is tagged as EasyListening, Electronic, Pop, and Rock). Also note that the sum of APCL is omitted in both tables as summing up APCL values is not informative. In both tables, the highest values in each category are printed in bold, the Classical genre is highlighted in magenta, and the last row in each category "Classical vs. Others" shows the fraction between the respective statistical measure for the Classical genre and the average of the measure for all other genres. For instance, looking at the PC values in Table 2 (column "Max"), it can be seen that the most popular Classical artist in the MMTD (with highest play count) does only have 7.9% plays of the average most popular artist of other genres. In the respective column "Sum", the two values indicate: (left) the average overall popularity of the Classical genre versus the average overall popularity of other genres and (right) the fraction of Classical music among all PC and LC events. Comparing Tables 1 and 2, we thus see that only 1.8% of all listening events on Last.fm involve Classical music and only 0.3% of all listening events in MMTD do so. Compared to the average play counts of other genres, listening events to Classical artists are almost 25 times less frequent (4.1%) in Twitter data, but only 4 times less frequent in Last.fm data (27.6%).

Looking at the APCL figures, we see that these are on average particularly low for Classical music (Tables 1 and 2, column "Mean"; mean APCL value of 12.02 for Last.fm and 0.21 for MMTD), which means that Classical listeners listen to relatively few individual pieces. Comparing these mean APCL figures for Classical music to other genres (row "Classical vs. Others"), we can calculate that Last.fm listeners of other genres play on average 47% more tracks per artist than Classical listeners. For Twitter users reflected in the MMTD, this figure even exceeds 600%.[5] An explanation for the low APCL values in Classical music may be that Classical pieces are typically longer than songs of some other genres. Indeed, mean APCL is highest for the genres Metal on Last.fm (34.35) and Pop on Twitter (5.02). Again, this means that among Last.fm users the average listener of Metal music listens to an average of 34 songs per Metal artist. The highest APCL for an artist in genre Metal is 152.61 (for Linkin Park), which means that listeners of Linkin Park listen on average to 152 (non-unique) songs by this band.

Figures 1 and 2 depict the distribution of PC, LC, and APCL values across genres for the two datasets. Please note that for easier reading the y-axis is logarithmically scaled, while the x-axis is not. Linear line fitting on the log-log-scaled PC and LC data reveals a strong similarity to a Power-law distribution, but only for the top $100-150$ artists. For lesser popular artists, PC and LC values drop faster than expected if they were Power-law-distributed. Even-

[3] `http://www.last.fm/api`

[4] `http://www.cp.jku.at/datasets/MMTD`

[5] These figures are computed as the inverse of the mean APCL values for "Classical vs. Others", i.e. 0.68^{-1} for Last.fm and 0.14^{-1} for MMTD.

tually, for about 100 artists with lowest listening counts, this decrease is extreme. Focusing on Classical music in the Last.fm dataset, the top 20 artists account for almost 50% of all Classical listening events[6], while the bottom 500 artists account for only 2% of Classical listening events[7]. The cumulative PC of the bottom 100 artists (at positions $901 - 1000$) amounts to 0.09% for the Classical genre and does not exceed 0.63% for any genre, Rock and Electronic being ones with highest values.

The comparative investigations of the Last.fm and Twitter users shows that listeners of Classical music are much less active on social media than listeners of other major musical genres. This is even more pronounced on Twitter. To assess whether listeners of Classical music are in general less active in social media, we relate the results discussed above to the 1999–2008 listening trends report of the Recording Industry Association of America[8], which shows a share of Classical music between 1.9% and 3.5% on total music purchases, the arithmetic mean being 2.6%.[9] Recalling that these figures are 1.8% and 0.3% for Last.fm and Twitter, respectively, we can conclude that listeners of Classical music in the general population are less active on Twitter and Last.fm.

A firmer statement could be made by performing a difference in proportions test[10], where we observe if the difference of proportions in two different samples (in our case the RIAA sample vs. the Twitter or Last.fm sample) is significant. If we take the RIAA mean proportion over the observed years (i.e. 2.6%), the Z-test for two population proportions yields a significant result at $\alpha = 0.05$ for the Twitter users and a non-significant result for Last.fm users. However, given the lack of absolute figures for the RIAA report, the fact that not all the requirements for the statistical test are met and other variables that are hard to control (e.g. the aforementioned cultural background and data collection time windows), we stick to the above conservative observation that the Classical music listeners are less active on social media as they are in their listening habits.

4.2 Correlation between data sources?

As for research question (ii), whether results are consistent among the Last.fm and the MMTD collections, we compute different correlations between PC, LC, and APCL scores between Last.fm and MMTD. More precisely, we investigate the correlation of the listening measure distributions between the two datasets, for the same genre (intra-genre, inter-dataset) and between all genres within each dataset (inter-genre, intra-dataset). The former experiment aims at determining whether the results of research question (i) are consistent over different data sources, while the latter addresses the question whether listening distributions are in general comparable for different genres.

Table 3 shows Pearson's correlation coefficient for the intra-genre, inter-dataset experiment. As can be seen, correlations for PC are particularly high, a bit lower for LC, and still lower, but still substantial for APCL. Please also notice that correlations between the two datasets are especially high for Classical music (0.95 for PC, 0.85 for LC), which evidences that results reported in the previous subsection, addressing research question (i), are likely to generalize well to other social media sources.

As for the inter-genre, intra-dataset experiment, a correlation within the PC and LC plots for different genres can already be seen from Figures 1 and 2. Indeed, for PC the arithmetic mean of Pearson's correlation coefficient between all pairs of distinct genres is 0.940 (for Last.fm) and 0.953 (and MMTD); for LC correlation even amounts to 0.962 (Last.fm) and 0.954 (MMTD). We can thus conclude that popularity of artists shows a highly similar distribution, irrespective of their genre. For APCL, correlation is less pronounced (0.939 for Last.fm and 0.818 for MMTD). There are thus stronger fluctuations between listeners of different genres in terms of the average number of tracks they listen to.

5. CONCLUSIONS

This paper aimed to answer whether (i) lovers of Classical music are reluctant to use social media for talking about their listening habits and (ii) correlations between usage of Last.fm and Twitter as data sources to indicate music listening behavior exist. To this end, we performed several quantitative statistical experiments on two real-world datasets, focusing on three measures related to listening behavior: play count (PC), listening count (LC), and average play count per listener (APCL).

As for question (i), we found clear evidence that listeners of Classical music do not use the social media platforms Last.fm and Twitter to post their listening behavior as frequently as listeners of other major genres. In particular, the activity of Classical music aficionados on Twitter is very limited (only 0.3% of all postings on music listening events relate to Classical music, whereas this number is 1.8% for Last.fm). In the general population, in contrast, the share of Classical music purchases ranged from 1.9% to 3.5% in the period 1999–2008.

As for question (ii), high correlations in the listening distributions (PC and LC) can be found within the two datasets, averaged over pairs of different genres (≥ 0.94 for PC and ≥ 0.95 for LC). Correlation between the Last.fm and Twitter datasets for the same genre are also substantial, though not that pronounced (≥ 0.85 for PC and ≥ 0.51 for LC). These correlations are higher for Classical music than for most other genres.

The results of this study are of particular interest for the design of personalized services for Classical music. In fact, within the PHENICX project[11], researchers are active in the development of a personalized Classical music retrieval sys-

[6] This figure is similar for Blues, Country, Jazz, Vocal, and World; but Electronic, Folk, HipHop, Metal, Pop, and Rock show smaller values for cumulative PC at top 20 artists (between 18% and 30%).

[7] These cumulative PC values on the bottom 500 artists are similar for RnB and World; smaller (around 1%) for Blues, Country, EasyListening, and Vocal; and considerably higher for Electronic, Folk, HipHop, Jazz, Metal, Pop, Rap, and Rock (between 5% and 10%).

[8] http://www.riaa.com/keystatistics.php?content_selector=consumertrends

[9] We are aware that the RIAA data only covers the USA, but given that the Last.fm community has a bias towards users from the US and that the Classical music share of Twitter users are even much lower, we are sure that the RIAA data does not underestimate the global share of Classical music in comparison to the social media data.

[10] http://www.socscistatistics.com/tests/ztest/Default2.aspx

[11] Performances as Highly Enriched aNd Interactive Concert eXperiences (PHENICX) is an EU-FP7-funded project, cf. http://phenicx.upf.edu/.

Genre	PC				LC				APCL		
	Sum ($\times 10^3$)	Max ($\times 10^3$)	Mean ($\times 10^3$)	Std ($\times 10^3$)	Sum ($\times 10^3$)	Max ($\times 10^3$)	Mean ($\times 10^3$)	Std ($\times 10^3$)	Max	Mean	Std
Classical	1991879	168703	1992	8990	95720	3337	96	241	140.67	12.02	11.87
Blues	5031033	**438219**	5031	21809	207036	3441	207	466	136.73	11.33	10.85
Country	3907296	216282	3907	16488	175459	4025	175	419	154.48	10.00	10.39
Easy Listening	6774381	**438219**	6774	23228	294616	**4787**	295	521	**647.55**	12.57	23.56
Electronic	11638651	397692	11639	28059	417558	**4787**	418	554	168.30	20.45	14.80
Folk	5747398	126142	5747	13461	228865	2559	229	356	100.48	18.59	14.11
HipHop	5840235	239943	5840	14873	320283	3982	320	514	196.89	21.06	25.05
Jazz	3085327	397692	3085	15123	167026	4252	167	309	93.53	11.29	9.61
Metal	10183140	239943	10183	21530	257709	3535	258	429	152.61	**34.35**	19.76
Pop	12894615	**438219**	12895	28176	568479	**4787**	568	653	225.51	17.14	16.67
Rap	4941372	239943	4941	14110	272730	3982	273	487	205.11	25.79	**31.20**
RnB	4692720	216282	4693	15084	289493	3982	289	517	173.28	11.54	14.67
Rock	**25071659**	**438219**	**25072**	**40781**	**800762**	**4787**	**801**	**745**	186.90	26.98	20.58
Vocal	5316390	**438219**	5316	21307	208841	3832	209	436	161.06	14.93	16.60
World	1255660	74054	1256	5377	68110	1956	68	156	83.46	9.99	8.68
Classical vs. Others	0.276/0.018	0.544	0.262	0.450	0.329/0.022	0.854	0.313	0.514	0.73	0.68	0.70

Table 1: Descriptive statistics of PC, LC, and APCL for each genre, computed on the Last.fm dataset.

Genre	PC				LC				APCL		
	Sum	Max	Mean	Std	Sum	Max	Mean	Std	Max	Mean	Std
Classical	4970	886	5	47	3292	562	3	29	9.67	0.21	0.63
Blues	47613	12640	48	452	24286	7304	24	257	54.00	0.93	2.98
Country	60055	6892	60	413	35329	4692	35	251	**561.50**	1.79	18.27
Easy Listening	128408	**18007**	128	901	65843	9159	66	496	107.25	1.60	5.22
Electronic	136577	**18007**	137	848	70283	9159	70	437	76.00	1.60	4.52
Folk	31867	2712	32	164	15165	1579	15	83	41.00	1.43	3.06
HipHop	197935	**18007**	198	1051	126057	**10537**	126	627	180.33	1.26	7.09
Jazz	22284	2369	22	144	10552	1451	11	75	294.50	1.27	9.62
Metal	64071	7323	64	360	36068	3177	36	169	7.00	0.99	0.86
Pop	**340766**	**18007**	**341**	**1265**	**179663**	**10537**	**180**	**724**	536.60	**5.02**	**31.64**
Rap	178815	**18007**	179	1039	115235	**10537**	115	619	21.00	0.76	1.19
RnB	211899	**18007**	212	1027	135066	**10537**	135	612	243.60	1.28	7.90
Rock	234747	12842	235	728	126455	7331	126	405	390.38	2.88	17.30
Vocal	33030	3262	33	190	17972	1869	18	113	54.75	0.83	2.71
World	3514	293	4	17	2192	196	2	10	30.00	0.41	1.34
Classical vs. Others	0.041/0.003	0.079	0.041	0.077	0.048/0.003	0.089	0.048	0.084	0.05	0.14	0.08

Table 2: Descriptive statistics of PC, LC, and APCL for each genre, computed on the MMTD.

tem. This system is supposed to address the recommendation of Classical music recordings, concerts, and supporting multimedia material. Traditional personalized recommendation techniques that rely on collaborative filtering [3] require lots of information to build user-user or piece-piece relationships upon which to build the recommendation process.

As a consequence of the results presented in this paper (i.e. little information about the consumption of Classical music through social media), alternative approaches for the acquisition of Classical music preferences through social media should be sought. The concept of cross-domain recommendations (as shown, for instance, by Loni et al. [6]) could be used; Classical and non-Classical genres can be treated as different domains and hence take advantage of the methods developed for cross-domain recommendations.

Extending the exploratory nature of the presented analysis, we plan to further dig into the reasons behind the lower usage of social media through user studies. As of writing of this paper, the data of the first study has been collected. Ultimately, our findings will help improve personalized and adaptive music recommendation algorithms, tailored to users with individual taste profiles, possibly far away from the mainstream.

Genre	PC	LC	APCL
Classical	0.949	0.849	0.917
Blues	0.892	0.506	0.911
Country	0.926	0.774	0.608
EasyListening	0.924	0.652	0.917
Electronic	0.891	0.702	0.782
Folk	0.842	0.692	0.873
HipHop	0.950	0.802	0.505
Jazz	0.881	0.791	0.496
Metal	0.851	0.799	0.947
Pop	0.955	0.758	0.780
Rap	0.951	0.810	0.815
RnB	0.953	0.789	0.540
Rock	0.932	0.744	0.542
Vocal	0.964	0.763	0.871
World	0.972	0.937	0.810
Classical/Others	1.031	1.130	1.235

Table 3: Intra-genre correlations between Last.fm and MMTD sets.

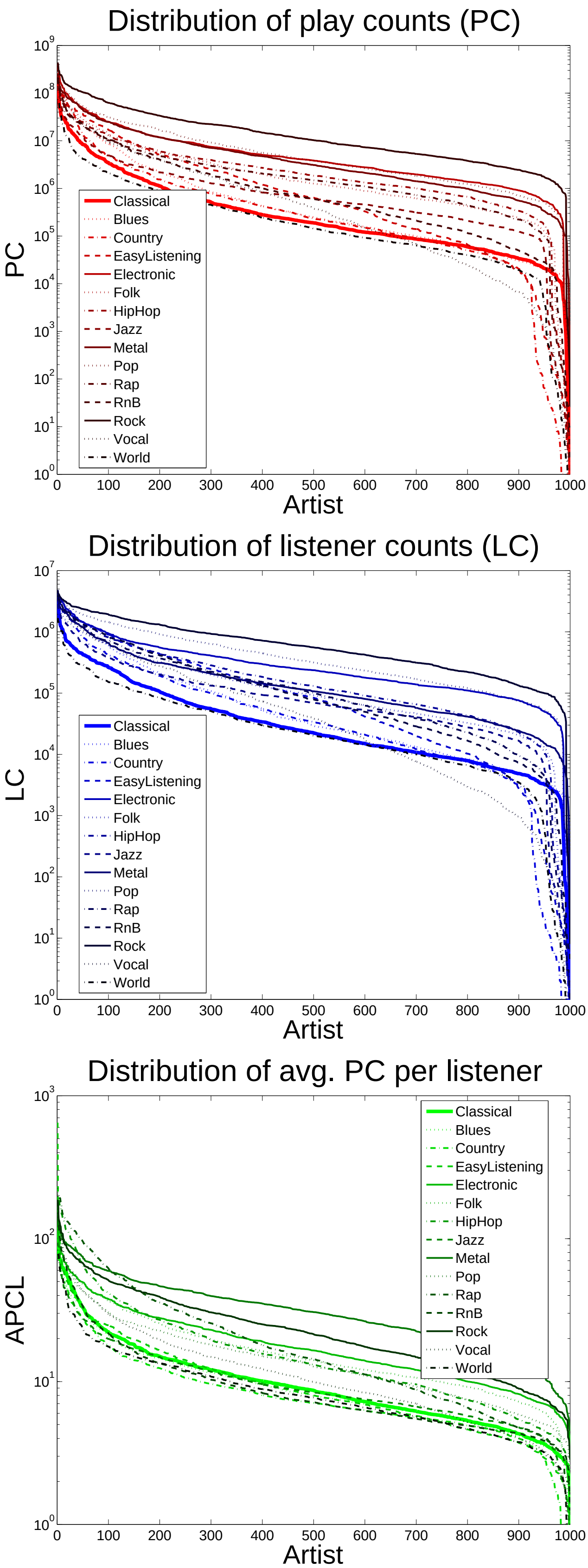

Figure 1: Distribution of PC, LC, and APCL for different genres, computed on the Last.fm dataset.

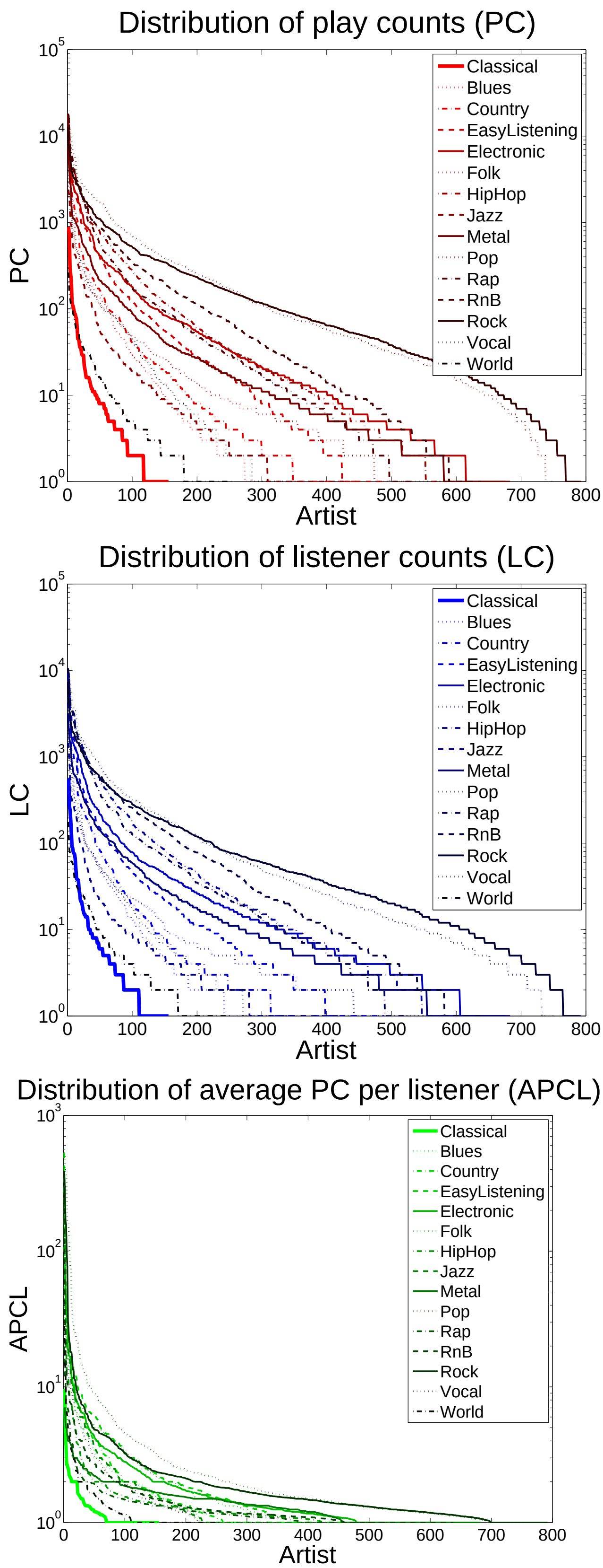

Figure 2: Distribution of PC, LC, and APCL for different genres, computed on the MMTD.

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