Artist Popularity: Do Web and Social Music Services Agree?

Alejandro Bellogín[1,2], **Arjen P. de Vries**[1], **Jiyin He**[1]
[1]Centrum Wiskunde & Informatica, Science Park 123, 1098 XG Amsterdam
[2]Universidad Autónoma de Madrid, Departamento de Ingeniería Informática, 28049 Madrid
{A.Bellogin, Arjen.de.Vries, J.He}@cwi.nl

Abstract

Recommendations based on the most popular products in a catalogue is a common technique when information about users is scarce or absent. In this paper we explore different ways to measure popularity in the music domain; more specifically, we define four indices based on three social music services and on web clicks. Our study shows, first, that for most of the indices the popularity is a rather stable signal, since it barely changes over time; and second, that the ranking of popular artists is heavily dependent on the actual index used to measure the artist's popularity.

Introduction

Music popularity has been studied both from the psychology (Berns et al. 2010) and from the complex network theory (Zanin et al. 2009) points of view, among others. In fact, due to its high marketing potential some companies have started to analyse the presence of music artists in social media – such as ReverbNation[1] and Next Big Sound[2] – to benchmark the success of each artist.

In this heterogeneous context, there could be different definitions of what is popular in the music domain, which could lead to inconsistencies in any application where popularity is exploited. In this paper we compare four methods to define a music artist's popularity using social media. To the best of our knowledge, we are not aware of such a work in the music domain, although similar studies have been made in more general contexts, such as news articles (Ung 2011; Bandari, Asur, and Huberman 2012).

Moreover, popularity rankings are useful in the Recommender Systems domain, since they provide suggestions that tend to satisfy the majority of the people, while the cost of producing such recommendations is generally low.

We identify two types of popularity indices: *service-dependent popularity* and *web-based popularity*. The former refers to explicit popularity scores available in the most used social media music sites EchoNest[3], Last.fm[4], and Spotify[5], whereas the latter extracts click information from the Web to derive an implicit popularity score. In this work we focus our analysis on the similarity between the different popularity indices and the comparison of their temporal behaviour. More specifically, our contributions are the following:

- We obtain a dataset where information for 1,312 artists about four popularity indices using different social media sites has been recorded on a regular basis over a period of 2 months.
- We study the relation between these popularity indices and their corresponding rankings. We identify that web-based popularity is more sensitive to the temporal dimension than service-dependent popularity. We have also found that not all the popularity definitions are completely redundant, although some similarities between the indices do exist.

Our Analysis on Music Popularity

Data Description

We have collected several popularity indices from the following social media systems through their corresponding APIs: EchoNest, Last.fm, and Spotify.

To obtain a set of artists relatively diverse and famous, we consider the Last.fm's API and collect the most popular artists in their database, which we combine with the most hyped (recently promoted) artists, so our data is not too biased towards already popular musicians in Last.fm. To the best of our knowledge, the other considered social media systems have no similar method to collect a list of artists, which is why we have relied on Last.fm data to bootstrap our method.

After this step, we collected 1,398 artists that went down to 1,312 artists which were present in all three sites. Then, we periodically (every 3 hours) request the current popularity from each artist to each social music service.

At the same time, we query Bit.ly's API[6] with the name of each artist, to gather the number of clicks each retrieved

[1]http://www.reverbnation.com, accessed 11 Feb 2013
[2]https://www.nextbigsound.com, accessed 11 Feb 2013
[3]http://echonest.com
[4]http://www.last.fm
[5]http://www.spotify.com
[6]http://bitly.com

ρ	pop_E	pop_L	pop_S	τ	pop_E	pop_L	pop_S
pop_E	1.00			pop_E	1.00		
pop_L	0.88	1.00		pop_L	0.72	1.00	
pop_S	0.75	0.66	1.00	pop_S	0.56	0.47	1.00

Table 1: Spearman's ρ and Kendall's τ correlation coefficients between the service-dependent popularity indices.

link has received. A clean-up of the Bit.ly data is required due to two major issues: (1) irrelevant documents that match only one part of the artist's name (e.g., 'a-ha' or 'The xx'), and (2) ambiguous artists for whom matched documents are not actually related with the artist (e.g., 'Kiss').

To handle the first situation, we require an exact match of the complete artist's name in the URL or in the document title. To handle the second situation, we manually assign some terms into a whitelist (blacklist). We then restrict the set of documents to those including (excluding) such terms. This simple method has previously shown good performance in terms of spam reduction (Boykin and Roychowdhury 2005), and is satisfactory for this study. In our dataset, an example of a whitelist term for 'Kiss' would be *rock*, whereas a blacklist term for the artist 'Rush' would be *hour*. We first considered automatic alternatives such as text classifiers, but the text available for each artist is limited and they would still require manually labelled examples. Nonetheless, we aim to include some of these techniques in the future.

The obtained dataset with timestamped information from the four social media systems described is available from our website[7], along with the code and scripts used in the process.

Service-Dependent Popularity Indices

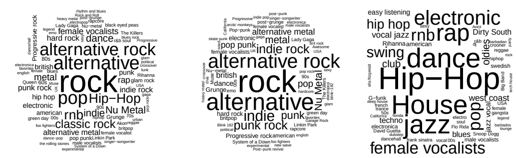
Depending on the social media system, we may define different notions of popularity, or in other terms, a service-dependent popularity index. For Last.fm, we match the number of playcounts (or *scrobblings*) of each artist to their popularity (pop_L); whereas for Spotify (pop_S) and EchoNest (pop_E) we use explicit popularity scores provided by them[8].

We analyse the similarity among the service-dependent popularity indices by computing correlation scores. As we validate later on, the temporal dimension has almost no effect on these indices, thus they can be ignored safely for the present analysis. Table 1 shows Spearman's and Kendall's correlation coefficients for the service-dependent popularity indices using the full set of 1,312 artists, allowing us to compare how related these indices are; the closer such value is to 1.0 for two popularity indices, the stronger the relation between them.

We observe that Spotify's popularity is the most divergent index in terms of correlation. We believe this could be caused by at least the following two reasons: first, the catalogue of Spotify is limited due to the contracts with several companies, and thus, its users cannot listen to some artists (such as *The Beatles*), and, second, the demography of its user base has a strong bias to Europe and the US, which may actually represent a wider diversity than Last.fm.

We may conclude from the results in the table that each index is actually capturing different nuances of an artist's popularity, since no index is perfectly correlated with any other. In fact, this effect is more clear when we compare the most frequently used tags for the top artists according to the ranking of each popularity index.

Figure 1 shows a tag cloud for each service-dependent popularity taking the Last.fm's tags from the top 20 artists according to each index. We observe that, like with the correlation values, Last.fm and EchoNest clouds are similar but not identical, whereas Spotify is the most disparate among the three social media sites discussed so far.



(a) EchoNest (b) Last.fm (c) Spotify

Figure 1: Tag clouds for the top-20 most popular artists of each media. Word size is proportional to the tag frequency.

Web-Based Popularity Index

An alternative way of measuring popularity of artists is to look at the Web at some specific moment in time and observe which artists are currently being talked about and referring to. With this goal in mind, we use Bit.ly media site as a surrogate of the Web use, and use the clicks received by each document related with an artist to define a popularity index based on Bit.ly data (pop_B).

We specifically look into the temporal dynamics of this web-based popularity, and compare it against that of service-dependent popularity indices. That is, we analyse whether popularity changes across the temporal dimension and if any difference between web-based and service-dependent popularity indices exist at this level.

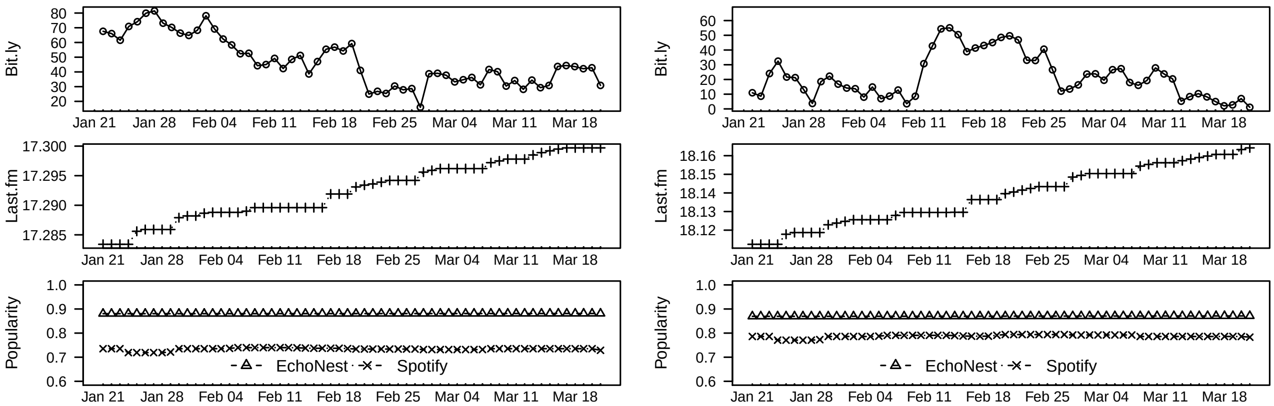
For this analysis, we show in Figure 2 the time series of the four popularity indices described previously for two artists during a period of 3 weeks. We have to note that both Last.fm and Bit.ly popularity indices have been aggregated after applying a (natural) logarithm function to the playcounts and clicks, respectively.

A first thing we notice in Figure 2 is that the web-based popularity index presents large deviations with peaks at specific events related with each artist. For instance, *Lupe Fiasco* had to be removed from the stage on January 20 during his performance in celebration of Obama's reelection, which received a lot of attention until January 28. Interestingly, we also notice a steep increase in pop_L (Last.fm scrobblings figure) when this index is updated (January 30), more prominent than the increment in *The Black Keys*'s figure, whose web-based popularity was much lower at that moment.

On the other hand, the service-dependent popularity indices do not change as frequently as web-based. This is a problem for the service-dependent popularity indices, since the update times of such indices could be different for each

[7] http://www.cwi.nl/~media/papers/ICWSM13

[8] Specifically, for EchoNest we consider the *familiarity* property equivalent to popularity, stated as their *numerical estimation of how familiar an artist currently is to the world*; the situation for Spotify is not so clear, although it is likely that an artist's popularity score depends on how many people listen to their songs.



(a) Lupe Fiasco (b) The Black Keys

Figure 2: Temporal dynamics of the web-based and service-dependent popularity indices analysed.

artist; more specifically, these updates are usually not done at real time, and not even in a daily basis, which does not allow a granularity as fine as we would desire.

We also observe in the figure that Last.fm has larger changes in its popularity index, since it is measuring the raw number of playcounts; whereas the other popularity indices (EchoNest and Spotify) have less variation. More specifically, EchoNest seems pretty stable, however we have to note that there are tiny changes (i.e., in the fifth decimal number) on the returned value; similarly, no large leaps are obtained in each update of the Spotify's index, which is updated every 5 days on average.

Therefore, we conclude that temporal dynamics are stronger in the web-based popularity and could be used to monitor the presence of an artist in the Web. Nonetheless, some correspondence has been found between such index and the Last.fm's popularity index, although finer measurements of this value would certainly be more useful. In the future we aim to validate this by predicting artist popularity based on clicks, as it was done with search logs in (Goel et al. 2010).

Comparison of Popularity Indices Based on Artist Rankings

Popularity indices are used typically in real applications to generate artist rankings according to their popularity, thus, we now analyse the similarity and temporal dynamics of the web-based and service-dependent popularity indices in terms of the rankings generated by such indices.

Figure 3 shows how the similarity changes when an increasing number of artists is considered from each index. Metrics such as correlation coefficients would not be applicable now, since the intersection could be, eventually, empty. Instead, we use Jaccard coefficient as the similarity metric, which is computed as the size of the intersection divided by the size of the union of two sets; in our context, each set corresponds to the artists at top-N of two popularity rankings.

Consistent with the correlations and tag clouds presented before, Last.fm and EchoNest are the two indices sharing a larger number of artists for any cutoff value. Web-based popularity (Bit.ly) provides a more diversified ranking in comparison with the service-dependent popularity, since the corresponding Jaccard similarities are the lowest.

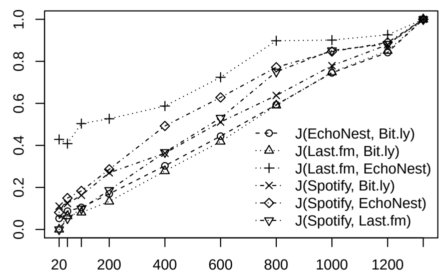


Figure 3: Jaccard similarity index when different cutoffs for the length of the top artist lists are considered.

Bit.ly	EchoNest	Last.fm	Spotify
One Direction	Coldplay	The Beatles	Johnny Cash
Kelly Clarkson	Rihanna	Radiohead	Frank Sinatra
Anne Hathaway	Radiohead	Coldplay	Elvis Presley
Taylor Swift	RHCP	Muse	Kanye West
Justin Bieber	Eminem	RHCP	Snoop Dogg

Table 2: Top most popular 5 artists for each popularity index (RHCP stands for *Red Hot Chili Peppers*).

Table 2 shows an example of these rankings when the top 5 most popular artists are considered throughout the timespan of our dataset. Again, web-based popularity presents a list of artists very different in comparison with that of the service-dependent popular rankings. Among these, Spotify's ranking has almost no intersection with the rest, confirming the behaviour shown in Figure 3.

We now analyse the stability of the different popularity indices described in the paper. Figure 4 shows the average difference in ranking position, that is, for each index p, we compute $1/|A| \sum_{a \in A} \text{rank}_t(a,p) - \text{rank}_{t-1}(a,p)$, where A is the set of all artists. This value summarises the behaviour of the artist-level time series for each popularity index p.

Thus, we observe from the figure that the ranking obtained from the web-based popularity is more sensitive to fluctuations of people's interests than the other popularity indices, reproducing the observed changes almost at real time.

Figure 4 also shows that service-dependent popularity remains quite stable through time, as we already observed in

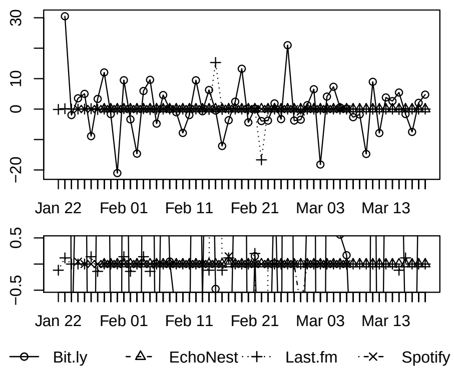


Figure 4: Average difference in the ranking position. Lower image shows a zoom of the same image to better appreciate the changes in the service-dependent indices.

the previous section with Figure 2. A plausible reason for this effect may be due to the fact that EchoNest and Spotify indices come from a ranking normalisation step. As we can observe from Last.fm data, raw popularity rankings are also pretty stable throughout time, although slight changes may arise (see the lower part of the image).

Discussion

Practical Implications

We have found that the web-based popularity index is different from the service-dependent popularity indices, and in general, no two indices are completely redundant or equivalent. This could be exploited in a recommendation environment to provide diversity into non-personalised recommendations, by combining the suggestions coming from different popularity approaches.

Regarding the stability of the service-dependent popularity, a plausible reason for this effect may come from the long tail preferences of the consumers of these services, which helps to stabilise the time series of ranking popularity for such indices. This is a key difference between the web-based and service-dependent popularity indices: whereas the latter is static and shows smaller variations, the former is dynamic, reacts to the change of mind and interests of the user in the short term, and seems to be unaffected by the preferential attachment of preferences (Zanin et al. 2009).

Limitations

Our analysis has some limitations that call for further investigation in the future. First, this study is fairly generic, with no constraint on region or country; however, even in our globalised culture, each country has its own set of circumstances that may restrict the relevance of a news item related with a particular artist. For instance, concerts are local events, important to a specific community. Thus, we should conduct a similar analysis but focused on a local area.

Second, regarding the web-based popularity index, we should take into account the sentiment of the context when an artist has been mentioned. This way, it would be possible to define a positive and negative popularity, which would provide, in turn, much richer information about how an artist is perceived throughout time. Also, it is important to develop accurate disambiguation techniques to discriminate when a document really deals about an artist; for this, entity disambiguation techniques would be very helpful.

Open questions

Once we have analysed different sources of popularity, two important questions remain open. Are users more interested in the artists that are popular *now* or do they prefer those that are *always* popular? Furthermore, should all the reasons why an artist could be popular considered equally? Perhaps users are more likely to listen to an artist when they release a new album than when they are getting married or having a baby, even though the fact of appearing in the news may increase an artist's success in general (see *Lupe Fiasco*'s case).

Conclusions

In this paper we analysed three different social music services to measure popularity in the music domain. We have found that the service-dependent popularity indices show almost no temporal patterns, probably because they are not updated in a daily basis; besides, these indices are similar but not equivalent, neither in terms of ranking nor in the genres or tags associated with their most popular artists. We also proposed a novel method to capture popularity directly from the Web, this index shows more temporal changes than the service-dependent counterparts in terms of ranking, and it arises as an alternative more biased towards the near rather than the distant past, in contrast to the more traditional service-dependent popularity indices. In the future, we aim to analyse these indices with larger amounts of data and using more sophisticated techniques, both for the process of the time series and the document filtering step required by the web-based approach.

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