**Digital Analysis on Sung Music through the Dataset of KaraFun: Do we sing what we listen to?**

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**Abstract**

With the digitalisation of entertainment, software such as KaraFun opened the potential for enjoying karaoke over the Internet. This also enabled computational analysis on comparing listened and sung songs. By using the data provided by KaraFun and Spotify, we extracted the occurrences of genres in songs and analysed the differences within and between the data of the two platforms that are meant to represent sung and listened songs respectively. Our first finding was that the factor of socialization in sung music data is likely to influence the overall preference of a genre, wherein more ‘exciting’ music gets preferred when socialization is being involved. Our second finding was that the genre of Rap is relatively more in demand in listened music data whereas Jazz is more preferred in the sung music data. Further analysis showed that the tempo of a genre may contribute to the relative lack of preference in sung music in contrast to listened music. Next, we have found that the genre labelling of KaraFun’s sung music is significantly more diverse compared with Spotify, with additional emphasis on the song’s lyrical content and singing experience. We finally propose future research possibilities on this unexplored, yet on-demand topic.

**1 The Evolutions and Limitations of Current Music Genre Analysis**

Through the advancement of technology, the scope of research on music trends and patterns has been expanded. This was possible because not only did music itself has become more digitized, but the medium that enables access to it has also seen a variety of digitization. An example of this is the upsurge of music streaming services such as *Spotify* (Spotify AB, 2022) in response to the traditional model of purchasing music. Accordingly, datasets from these services enabled an expanded computational analysis not just on music itself, but on music genre overall (Way *et al*., 2020). Such analysis on music genre is done (Pooransingh and Dhoray, 2021) due to the need for a deeper understanding of music popularity trends for artists and producers (Lee and Lee, 2018), and for the music industry overall (Naveed *et al*., 2017).

While computational research on music genre has been enabled through the digitization of music platforms, it has been limited to specifically *listened* music, ignoring the fact that music can be approached in more various ways such as visualizing and dancing (Brabazon, 2011). This may be because music can be argued to be dominantly consumed through listening, leading to more availability on data related to it. However, *sung* music has experienced ‘an explosion’ (Zhou and Tarocco, 2013, p.7) of both global demand and availability through the medium of *karaoke*, which is ‘a form of entertainment, originally from Japan and spread all over the world (Osaki, 2020), in which recordings of the music but not the words of popular songs are played, so that people can sing the words themselves’ (Cambridge, 2022). This can be also seen from karaoke’s terminology, because it is derived as a Japanese clipped compound, consisting of the words 空 (*kara*), “empty, without”, and オーケストラ(*ōkesutora*) “orchestra”, as the music is only instrumental, and the lyrics are not included.

**2 The Growth and Modernization of Karaoke**

The birth of karaoke as a business started when Daisuke Inoue, a Japanese businessman, began renting 8-track cassette tape machines to the snack bars in Japan (Kaji, 2010, p. 53). Eventually, the business of karaoke expanded throughout the world, and karaoke has become a common entertainment in the form of *karaoke box*es, which are establishments with multiple rented rooms for karaoke, or karaoke machines in bars, lounges, and pubs. However, following the upsurge of music streaming services, digitally streaming karaoke services have also been popularized. For instance, the service of *KaraFun* has achieved over 1 million android app downloads (Recisio, 2022a) and 2 million YouTube subscribers (KaraFun, n.d.). These services provide the entertainment of karaoke without the need of purchasing dedicated equipment or renting rooms. The users can pick a song of their liking by either using the search bar or searching through the pre-defined genres. Like the karaoke machines, the key, the tempo, and the level of vocal guidance can be adjusted. For the case of KaraFun, its sophistication also led to karaoke bars and other singing venues to adopt the platform in their machines (Recisio, 2022b) instead of using a dedicated Karaoke machine. Nowadays, karaoke venues include many different kinds of genres, even the songs with vocals created by voice synthesising technology (Kenmochi, 2011). As such, considering the extent of digitization and popularization karaoke has experienced, there is potential in the digital analysis of specifically sung music in terms of both ease of data retrieval and presence of demand.

**3 The Potential Difference of Genre Trends in Listened and Sung Music**

A notable reason why analysis on sung music can be worthwhile in contrast to the typical listened music is because listened and sung music may potentially have different characteristics. For instance, the difficulty of singing can be a prominent factor of whether a particular song is chosen to be sung or not. Even though the modern karaoke software such as *KaraFun* offer the option to adjust the key in a song, the vocal range of the song can directly affect the difficulty of singing. Moreover, the melodic and rhythmic characteristics of a song also play a role on the difficulty. A difference in genre trend may occur as although these complexities can be appealing to listeners as it displays the talent of the musician, it can function the opposite way for singers who may be pressured.

Another difference that may result to contrasting music genre trends is the extent of socialization each genre provides. Whereas most listened music can be a personal experience, sung music in the context of Karaoke may lean more to a social experience. As such, unlike the case of listened music, there could be specifically more preference for genres that can be easily sung together in the form of duets or groups. Finally, the most prominent difference that is likely to affect genre trends would be the lack or presence of vocals in specific genres. Whereas most if not all music genres may have vocals, the number of songs with vocals in each genre would heavily differ. For instance, Pop is likely to have a higher ratio of songs with vocals than Classical music. As a result, analysing specifically sang music and comparing them to listened music can reveal whether these hypothetical differences would matter, not to mention, any overlooked differences.

Therefore, in this paper, we are going to analyse, compare, and contrast the music genre popularity of both listened and sung music through their respective digital platforms. For listened music, we will retrieve data from Spotify whereas for sung music, we will rely on the Karaoke music platform, KaraFun. Specific focus would be put on how the genres of the music with a high popularity on both platforms differ. There will also be further analysis on the sung data of KaraFun, wherein we will see how long it takes for an existing song to be adapted to the KaraFun platform, thereby adding another metric of analysing demand in genres of sung music.

**4 Using Karafun for the Sung Music Database**

Among the different digital karaoke streaming services, KaraFun (Recisio, 2022a) enables digital analysis through its well-documented music database. It provides a catalogue on its website that contains information about all its available songs, including their release day, genre, day of adaptation, and even more details when needed. However, one downside of this catalogue is that it does not contain information about how famous each song was. Nevertheless, the platform contains other potential methods of quantifying each song’s fame.

First, KaraFun has a YouTube channel named ‘KaraFun Karaoke’ (KaraFun, n.d.) that has a number of its available songs uploaded in a karaoke format. As such, it is possible to use each video’s view count or the YouTube channel’s top playlists as a representation of each song’s fame. Second, when it comes to genre fame, it is possible to use KaraFun’s song addition system for another metric of each song’s popularity. This is because KaraFun (Recisio, 2022a) officially states that there are two factors that influence the choice of adding a new song to their service: first is the legal agreement from the song’s rights owners and the second is the popularity of each song based on user suggestion. This can be seen on the platform as users are asked to suggest new songs and the suggested songs are then asked to be voted within the app. After enough votes, the songs are added to the official catalogue, whereas newly suggested songs only appear in the application’s search results for voting. Considering these procedures, it is reasonable to assume that all the songs available in KaraFun’s catalogue represent a verified level of fame among its users. As such, we use KaraFun’s song catalogue provided in a CSV file and their YouTube channel extracted through Python for the sung music database.

**5 Using Spotify for the Listened Music Database**

Considering KaraFun’s characteristic of being a sort of digital streaming platform for sung music, it becomes necessary to pick a variation of digital streaming platform for its target for comparison. Among the different digital music streaming platforms, Spotify is considered to be the largest (Way *et al*., 2020). It also boasts high accessibility as its database is readily available with an in-depth API support that enables users to get the information that they want. In our use case, we received the Spotify Tracks Database (Hamidani, 2019) and modified it to enable a relatively similar comparison environment with the KaraFun catalogue and YouTube database.

**6 Preparing the Spotify and KaraFun Datasets for the Research**

It is worth noting that the Spotify and KaraFun datasets do not possess a directly comparable kind of trend index. First of all, they have vastly different numbers of songs available. The KaraFun catalogue has 47,000 songs, whereas the Spotify catalogue has 232,000. Both heavily contrast with the YouTube channel of KaraFun which only has 7,831 videos and even significantly fewer video data available due to YouTube’s API limitations. To address this, we put specific focus on the songs with the highest demand as we are looking for genre trends. For instance, we used KaraFun YouTube’s All Time Top 50 song playlist for the YouTube dataset both as a solution to YouTube’s API limitation and for the emphasis on songs with the highest demand. Then, as KaraFun YouTube did not contain genre labels, we used the respective genre labels available in the KaraFun catalogue dataset and manually assigned them to the YouTube dataset.

Considering that KaraFun’s songs all equally represent a verified extent of fame and/or demand, we limited the songs of Spotify to have a ‘popularity’ score of 65 and above through Microsoft Excel. According to Spotify’s API documentation (Spotify AB, 2022b), the popularity score ranges from 0 to 100 and is calculated by an algorithm that considers the total number each song is played along with their recency. This makes it safe to assume that all songs available in both platform’s datasets are noticeably in demand, thereby being viable as data for analysing genre popularity. Another difference between the datasets is the availability of music without lyrics. In our use case, we would like to ideally compare the trends of similar music genres but in different platforms. As such, like the popularity score, we limited the ‘speechiness’ score of the Spotify dataset to go no lower than 330 as this is meant to be an indication that the song lacks vocals according to Spotify’s algorithm (Spotify AB, 2022b). These limitations reduced the Spotify catalogue from 232,000 to 10,256. While this will be used for the genre trend comparison with the KaraFun catalogue, we also sorted Spotify’s top 50 songs with the highest popularity score for a separate comparison with the KaraFun YouTube dataset.

Another difference between the KaraFun and Spotify datasets are the latest year available. While the KaraFun dataset consists of dates up to 2022, the Spotify dataset ends in 2019. For a closer comparison, we limit the KaraFun dates to 2019 as well. Finally, the genre labels of both datasets are different. While KaraFun contains multiple genre labels per song, Spotify keeps one genre per track, and both have marginally different ways of naming their genres. For example, Rap and Hip Hop are clearly divided on Spotify whereas KaraFun does not mention Hip Hop. To address these issues, we first compared the datasets through the number of occurrences of each genre relative to the total count of songs. By doing so, we can still enable the comparison of total genre preferences between the two platforms. Next, considering that music genres are not fixed and require active engagement for their conceptualization (Lewis, 2017), we perform qualitative analysis on the genre results to address the difference in terminology between the two platforms.

As the songs chosen to be added to KaraFun are determined based on its users’ votes, it is possible to find out how long it takes for a song to be added to KaraFun’s database after the song is released. This information is extracted by calculating the time interval between the release of a song and the date that the song was added to KaraFun’s database through Python. One issue with this approach is that there are many songs that outdate KaraFun. The earliest date that a song was added to KaraFun is the 4th of May 2007. In order to calculate the time interval of being picked up for those songs which were released before that date, their days of release are all converted to the 4th of May 2007. After replacing the date of release of the earlier songs with the first day that KaraFun began adding songs to the database, the pick up time for each song is calculated by subtracting the day that the song was added to the database, from the day it was released. Thereafter, the mean value for songs to be picked up is measured per genre.

The resulting datasets from KaraFun and Spotify were prepared in the form of CSV and Microsoft Excel files. Then they were prepared for the reproduction of results through GitHub links available in the code for the paper, which can be seen in the project GitHub, “https://github.com/Alcoris0987/CLS-Project”. As can be seen in the project files, all the data were cleaned through Pandas in Python. Accordingly, null values and other invalid values such as music data with improper date information were removed. After all the data were cleaned, we created 5 different datasets: The number of occurrences per genre in the KaraFun Catalogue, KaraFun YouTube’s Top 50 Songs, Spotify, and Spotify’s Top 50 Songs, and the average days it takes for a song to be adapted in KaraFun based on its genre. Then, we plotted the results into bar graphs with Matplotlib in Python. These results are reported in the next section.

**7 Results of the Five Datasets**

Rectangle

Description automatically generatedAmong the 36.157 songs from the KaraFun dataset, we have found that the top five genres that occurred the most are respectively: Pop, Rock, French pop, and Country. Among these, Pop is by far the most common genre. On the contrary, the top five genres that occurred the least are: Oriental, Musette, Classical, Ska, Traditional, with negligible numbers compared to the rest of the dataset. These are all shown in Figure 1 below.

F*igure 1. Occurrences per Genre in KaraFun Catalogue*

A picture containing histogram

Description automatically generatedMeanwhile, Figure 2 shows that among the most popular 50 songs on the KaraFun YouTube dataset, the top five most common genres are: Pop, Rock, Soft rock, Love, and Soul. Like the case of Figure 1, Pop remains to be significantly more common than the rest. On the other hand, the top five least common genres are: Dance, Country, Christmas, Kids, Musical.

F*igure 2. Occurrences per Genre in KaraFun YouTube Dataset*

Chart, bar chart

Description automatically generatedFigure 3 represents the average pick up times in the KaraFun Catalogue dataset. Here, the top five genres that are voted and picked up fastest are: Electro, Dance, Celtic, Teen pop, Pop. On the contrary, the top five genres that take the longest time to be picked up are: Ska, Oriental, Hard/Metal, 80s, Zouk/Creole.

F*igure 3. Average Days Before Being Picked Up per Genre in KaraFun Catalogue*

Histogram

Description automatically generated with medium confidenceFigure 4 shows that among the 10,256 songs from Spotify, the top five genres that are the most popular are: Pop, Rap, Rock, Dance, Hip Hop. In contrast, the top five genres that are least popular are: Anime, Classical, Ska, Movie, Soundtrack.

F*igure 4. Popularity of Genres in Spotify Dataset*

A picture containing chart

Description automatically generatedAmong the top 50 most popular songs from the Spotify Dataset shown in Figure 5, the most popular five genres are: Pop, Dance, Hip Hop, Rap, Reggaeton. As this data includes only the top 50 most popular songs on Spotify, the total number of genres decreased substantially. Nevertheless, it is apparent that Pop remains to be the dominant top genre on both Spotify datasets.

F*igure 5. Popularity of Genres in Spotify Dataset (Top 50)*

**8 KaraFun Catalogue vs KaraFun YouTube**

The KaraFun Catalogue dataset includes 36,157 songs after processing. These are the songs that were voted by the users of KaraFun, and got chosen and added to the KaraFun database in a form that is suitable for singing as a karaoke. KaraFun YouTube dataset, on the other hand, includes the all-time top 50 songs according to KaraFun’s YouTube channel. Therefore, in contrast to the KaraFun Catalogue, they represent only the most popular songs for singing.

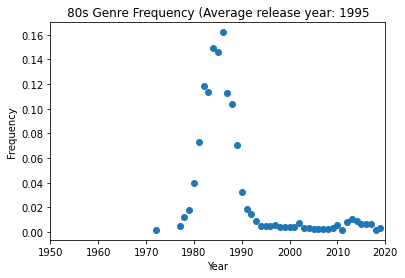
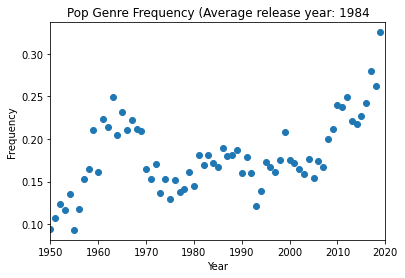
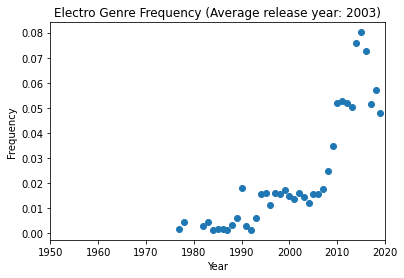
When the two datasets are compared, several dissimilarities are prevalent. One contrast is that the genre of “Dance” is ranked the last in KaraFun YouTube dataset, whereas it is a relatively popular genre in KaraFun Catalogue. One possible explanation for this contrast is that the karaoke establishments would be using the KaraFun software itself, rather than the YouTube videos. As karaoke boxes or karaoke machines in pubs or clubs are often enjoyed in groups, songs that are aimed at dancing could be requested more in those establishments. Most establishments that have karaoke as an entertainment also provide dedicated equipment for karaoke, such as disco balls, smoke machines, and other instruments that are suitable for dancing. As a result, it is plausible that viewers of the KaraFun YouTube videos do not aim toward dance songs, due to the lack of those assets at disposal.

One other difference between the two datasets is the lower prevalence of “Country” and “French pop” genres on the KaraFun YouTube dataset in comparison with the KaraFun Catalogue. It can be predicted that the general audience of these two genres have distinct choices on where they prefer singing.

**9 KaraFun Catalogue vs KaraFun Average Pick Up Times**

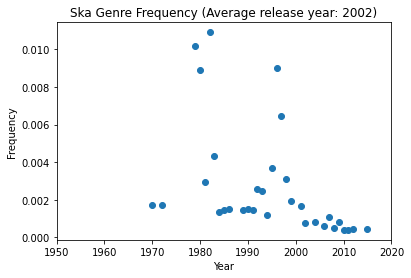
The average number of days required for a song to be picked up to be added to the KaraFun database differs based on the genre. As KaraFun adds songs based on the users’ votes, it is possible to comment on the demand of the users by looking at how long it takes for songs belonging to a genre are chosen to be made available.

One notable genre that is picked up fastest is “Electro”. The time it takes for a song in that genre to be picked up is 277 days faster on average when compared to the second fastest picked up genre, which is “Dance”. On the other hand, “Electro” is a genre that does not appear particularly often in the KaraFun Catalogue. One possible explanation for the short pick up times for “Electro” is that the genre has gained rapid interest after the mid 2000s and the average release year of the genre is 2003, as can be seen in Figure 6. In contrast, even though Pop has the highest occurrences per genre throughout the years, it is shown to not be the quickest picked up genre. This could be explained by the fact that unlike electro music, Figure 6 shows that Pop has been constantly available from the past, which could possibly mean that the average pick up times might be influenced by the older songs. This is further reinforced by the average pick up times of the 80s genre, which is among the slowest in the dataset.



F*igure 6. Occurrences of Electro, Pop, 80s Genres from KaraFun Catalogue*

Figure 7 below further demonstrates how the popularity of a genre in terms of occurrences may not significantly correlate with each genre’s average pick up time. For instance, both Ska and Celtic genres are one of the lowest ranking genres in terms of occurrences. However, being a relatively modern increasing genre (O’Flynn, 2014) with an average release year of 2010, Celtic has one of the top fastest pickup times whereas Ska is the lowest among all. As such, we have found that it is less viable to consider average pick up time as a metric for reflecting genre demand in the case of the KaraFun dataset.



F*igure 7. Occurrences of Ska and Celtic Genres from KaraFun Catalogue*

**10 Main Datasets vs Their Top 50s**

One of the noticeable differences between the popularity of genres in the Spotify Top 50 Dataset and the overall Spotify dataset is that the variety of genres decreases significantly from 23 to 8. This contrasts with KaraFun’s 41 genres being reduced to 21 in the KaraFun YouTube top 50 dataset. A possible explanation for this is the fact that, as previously stated, KaraFun assigns multiple genres per song whereas Spotify assigns one per song. Besides this, the genre trends between Spotify’s overall and top 50 songs are shown to be similar, with the only exception of Reggaeton in the top 50 songs replacing Children Music on the top 8 genres in the overall dataset. This shows that while there are a significant number of Children Music with moderate popularity, notably less could be seen amongst the highest popularity.

**11 Spotify vs KaraFun: Listened Music vs Sung Music**

Considering that Spotify’s pop label encompasses French Pop, the top genres of Spotify and KaraFun show their similarities with Pop and Rock being the top three for both platforms. However, while Rap was shown to be one of Spotify’s top three, Rap is shown to rank noticeably lower in KaraFun and instead replaces its top three spots with Country music, in which Spotify ranks significantly lower as well. If we include Spotify’s Anime, Movie, and Soundtrack genres together considering that they could all be seen as soundtracks and KaraFun’s Musette genre into World/Folk and/or French Pop after analysing KaraFun’s Musette song list, similar trends on the bottom genres can also be seen between the two datasets. That is, Classical, Ska, and World are the bottom five for both platforms. A noticeable exception, in this case, is the fact that while Spotify shows Jazz to be one of the least popular, Jazz is one of the top five genres for KaraFun.

The fact that Rap ranks significantly higher on Spotify than in KaraFun could reflect the hypothesis that the difficulty of the song can notably influence the preference of a genre depending on whether it is sung or listened to. It is worth noting that the top 5 genres of Spotify, Pop, Rock, Rap, Dance, and Hip-Hop, can be represented as usually having moderate to fast tempos. This differs with KaraFun’s top genres, Pop, Rock, Country, Soul, and Jazz, which the latter three open more options for slower tempos in comparison to Spotify’s latter three. This also becomes apparent when we analyse the KaraFun YouTube dataset, wherein the top five genres are shown to be Pop, Rock, Soft Rock, Love, and Soul. The fact that the ‘less driving and gentler sounding’ (Merriam-Webster, 2022) Soft Rock, has been added along with Love and Soul genres as the top five reflects a potential preference towards genres with slower-tempo song options.

As previously discussed, both platforms differ in the way of labelling genres. We further analysed which genres are unique to each platform. To achieve this, we used both Python and manual filtration to extract the genres of each platform. As shown in Table 1, KaraFun possesses more unique genres than Spotify, having 21 genres compared to Spotify’s 4. A notable characteristic among KaraFun’s unique genres is the fact that a number of them have a particular appeal to the song’s lyrical content such as ‘Humor’ and ‘Love’. Moreover, KaraFun has a unique genre label called ‘Duet’ which can further reflect the emphasis on the singing experience.

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| --- | --- |
| **KaraFun Unique Genres** | Traditionnal, Christmas, Duet, Gospel, Celtic, Latin Music, Musette, French pop, Musical, Humor, Schlager, Love, Rock 'n Roll, Soft rock, Zouk/Creole, Oriental, Disco, Funk, Punk/Grunge, Hard/Metal, Teen pop, 80s |
| **Spotify Unique Genres** | Anime, Hip-Hop, Indie, Reggaeton |

Table *1. Genres Unique to Each Platform*

**12 Conclusion and Limitations**

We have detected noticeable differences in KaraFun Catalogue and KaraFun YouTube datasets in regard to the general tendency of the users. One of the limitations of this paper is that we were unable to consider the demography of each digital platform for the analysis. We have already seen the potential of demography influence even between the KaraFun catalogue and KaraFun YouTube dataset but were unable to address the potential demographic influences between Spotify and KaraFun. As such, this research cannot be seen as a one-to-one comparison between sung and listened music, but rather as a literal comparison between two different digital platforms with the way of music consumption being a potential factor in their differences. Therefore, even though the difference in preferences is predicted to be caused by the demographics of the audience, in-depth analyses are required to find out the causes of the differences.

By extracting the information of how long a song belonging to a genre requires in average to be picked up by KaraFun, we demonstrated the leaning of KaraFun users on voting for the songs. We predict that the difference in how fast a song is picked up can potentially depend on the age of the genre, with more recent and trending genres being picked up. That being said, in order to have a concrete conclusion, detailed analyses on music history are necessary. Another dataset we used in the research is the Spotify dataset. We have determined several noteworthy differences between the Spotify dataset and the KaraFun dataset. The lower popularity of music with faster tempo in KaraFun compared to Spotify, potentially indicates that the difficulty of singing a song affects whether a song is chosen or not to be sung.

Finally, we found out that both platforms had a different way of labelling genres, with KaraFun dataset having recognisably more unique genres in comparison to the Spotify dataset. The difference in labelling led to the limitation of using further quantitative methods in analysing genre preference differences in detail. Nevertheless, we have found noticeable similar and different patterns in both platforms and were able to explain potential reasons for the way they are consumed. That is, considering the fact that Spotify is dominantly listened to and KaraFun is dominantly sung contributed significantly to the analysis of music genre trends.

Further research can address the aforementioned issues by designing a controlled demography setting and using state-of-the-art genre classification methods on sung and listened data rather than relying on the genre labels from differing sources. The latter is becoming a viable option as several attempts and evaluation (Li *et al*., 2003; Meng *et al*., 2007; Pelchat and Gelowitz, 2020) have been made and developed throughout time for automating music genre classifications, which opens the possibility of ensuring a more consistent music genre data for comparison.

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