Summer hot, Winter not! – Seasonal influences on context-based music recommendations

Patrick Helmholz
Chair of Information Management
University of Braunschweig
Braunschweig, Germany
Email: p.helmholz@tu-bs.de

Dominik Siemon
Chair of Information Management
University of Braunschweig
Braunschweig, Germany
Email: d.siemon@tu-bs.de

Susanne Robra-Bissantz
Chair of Information Management
University of Braunschweig
Braunschweig, Germany
Email: s.robra-bissantz@tu-bs.de

Abstract

Nowadays music is ubiquitous in contemporary life. People listen to it wherever they are. However, there is the problem that listeners would like to have the right music for their current situation without much effort and interaction. Information systems can support this need by making use of ubiquitous and context-aware music recommendation systems. This paper will focus on the user's context in form of long-term seasonal factors combined with the music features. Therefore, a music dataset with 3644 songs and 10932 data points of audio features were used and compared with seasonal aspects. The analysis shows seasonal influences on the music consumption. A positive correlation between the music parameters valence as well as energy and the monthly temperature has been detected. In contrast to winter season more active, energetic and happy songs are preferred during summer. The findings can serve to integrate seasonal adjustments to context-aware, ubiquitous music recommender systems.

Keywords Music Data Analysis, Context-Aware Recommender System, Seasonal Music Recommendation, Music Information Retrieval, Ubiquitous Computing.

1 Introduction

Music can be listened to in almost every situation in everyday life, which makes it the most abundant accompanying activity of our society (DeNora 2011). "Whether at parties or weddings, on the car ride to work, at the gym, or alone in our homes, music is part of our social and physical environment." (Pettijohn et al. 2010, p. 329). People spend nearly 17 percent of their waking lives listening to music (Rentfrow 2012).

This means they listen to an average of 2-3 hours of music every day, which makes music the second most consumed media after television (Tan et al. 2013). 84 percent of Germans enjoy listening to music during their leisure time. Since our smartphones are capable of playing music, 80 percent of smartphone owners use their device to listen to music (Bundesverband Musikindustrie e.V 2014). Just because our possibilities of listening to music expanded and we are spending a lot of time listening to music, it is often not our main task (DeNora 2011). Nevertheless, mobile and ubiquitous solutions to listen to music and the instant access to it becomes ever more important.

This usage behaviour directs to new market players, leading to music-streaming services increasing in popularity. The customers have the possibility to choose between 40 million songs from over 7 million artists from all kinds of genres (IFPI 2016). Considering that people only listen to 35 percent of the songs they own (Lamere 2012), streaming services have the advantage that they do not occupy as much of the restricted storage space. 68 percent of the U.S. smartphone owners listen to streaming music daily (Parks Associates 2016), but providing the customer with access to a large amount of music also leads to the problem of choosing the right music to listen to in a special situation. As music is ubiquitous in contemporary life and emotional as well, it is able to strengthen and change the emotions of the listener, so people like to listen to music that fits to their mood and situation (Sloboda and O'Neill 2001). The possibilities for that are very restricted at the moment. Providers like Spotify offer their customers several playlists for different situations or moods. The problem with those playlists is that the customer has to know what situation he is in at the moment. Furthermore, he has to select the playlist and change it depending on the new situation or mood. There are applications that seek to assist the listeners while selecting and changing a playlist. Spotify, for example, provides an application called "Spotify Running"[1] for smartphones, which detects the running tempo of the user and matches the music to support the runner without slowing him down.

To enable a better and more personalized user experience – especially for music – it is important to describe and define situations. The elements of a situation are defined by the context. "Context is any information that can be used to characterize the situation of an entity" (Dey and Abowd 1999, p. 306). Furthermore, it is important to figure out what characteristics of music fit in that certain situation. Although music is very personal (Wheeler 1985), some general states are to offer a basis for an application to give suggestions or even choose the music. The difficulty is to find long-term and short-term situational parameters that influence music selection and to match them with music parameters. With the rising importance of personalized and situational music recommendations, a lot of research is going on to find and evaluate these relevant parameters.

Accordingly, the paper will start off with an overview on the theoretical fundamentals for context-based music recommendation and seasonal influences. It will proceed with the evaluation of these influences by analysing a music dataset, taken from the German single charts of the years 2006 to 2016. Thus, the data with music parameters of all songs from every month will be compared with seasonal aspects. An algorithm will fetch the predefined data for all the songs from the Spotify Web API. The predefined data will contain the energy, valence, danceability and other characteristics to classify the music. To be able to compare the months of every year, the mean value of the datasets will be computed. Afterwards the computed datasets will be analysed to find important commonalities or distinctions, which could then be used to determine a benchmark for the context-based music recommendation.

2 Related Work

2.1 Context-Aware Music Recommendation

„The idea [of Context-Aware Music Recommender Systems (CAMRS)] is to recommend music depending on the user's actual situation, emotional state, or any other contextual condition that might

[1] See www.spotify.com/running.

influence the user's emotional response and therefore the evaluation of the recommended items." (Ricci 2012, p. 865). To achieve that, the factors of musical preference have to be defined, matched and applied (Schedl and Flexer 2012).

As shown in Figure 1, left side, CAMRS should take into account firstly the music properties, secondly the context of the user and thirdly the user and his preferences. To understand the music-listening behaviour of people, it is important to consider all three types of factors (Yang and Teng 2015). Recommendation can be defined as "the process of utilizing the opinions of a community of customers to help individuals in that community more effectively identify content of interest from a potentially overwhelming set of choices" (Resnick and Varian 1997). If the recommendation is effective, it reduces the necessary effort and time a user has to invest in making decisions. Most research on recommendation have focused on applying the user's preference without considering the user's context (Lee and Lee 2007).

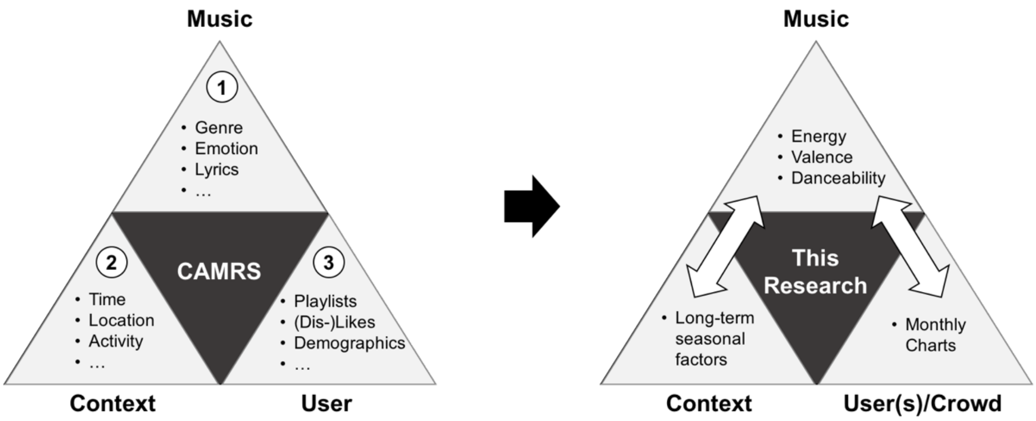


Figure 1: Factors of context-aware music recommender systems (based on (Yang and Teng 2015)) and research focus of this work

To point it out, although the user provides static data about his music liking, dynamic data about the context such as the user's mood, his activity, his social context, the time or his location are not taken into account. In the following sections, the three factors of CAMRS: music, context and user are regarded.

2.1.1 Music

It is a generally accepted fact among laymen and musicians that music has an influence on our mood (Gaston 1951). To match the musical influence on our mood with our situation, music has to be categorized first. This can happen in different ways.

The most roughly and commonly used way of classifying music is by genre. These music categories have arisen through a complex interplay of cultures, artists, and market forces to characterize similarities between musicians or compositions and organize music collections. However, the boundaries between genres still remain fuzzy as does their definition, making the problem of automatic classification a nontrivial task. (Scaringella et al. 2006) Yet the classification by genre is still being researched and more complex dimensions such as personality (Zweigenhaft 2008) and underlying musical parameters such as rhythm (Rho et al. 2009) are investigated. Another modern and more human-based classification is to categorize music by emotion or mood (Jamdar et al. 2015). Based on Russell's Model (see section 3.3), the main audio features are valence and arousal. In addition to this, attributes like energy and danceability are taken into account and are all provided by the music intelligence platform "The Echo Nest". Popular streaming services like Spotify also use those audio features to classify the music. (Jamdar et al. 2015) This paper also uses these music features as demonstrated in section 3.2.

2.1.2 Context

Context in computing systems is defined by one of the first works in this area as "information describing where you are, who you are with, and what resources are nearby" (Schilit et al. 1994). Dey and Abowd (1999) defined it as "any information that can be used to characterize the situation of an entity. An entity is a person, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves".

"Existing CAMRSs have explored many kinds of context information, such as location, time, emotional state, physiological state, running pace, weather, and low-level activities" (Wang et al. 2012). To gather context data, early attempts like the active badge system senses the location of a person to enable the adaption of application to the user's current location (Want et al. 1992). Current smartphones are able to gather a large extent of context data through built-in sensors like the accelerometer, GPS or the thermometer (Marcu et al. 2013).

Context can be divided into short-term and long-term parameters. Short-term temporal parameters, like weather or temperature, have to be detected in a special situation. Long-term temporal parameters, like the season, can be derived from knowledge (Dey and Abowd 1999). Long-term parameters can also be connected to short time parameters, like in this case the season with weather or temperature.

2.1.3 User

The user of a music recommendation system is very important. He is the determining factor, whether the recommendations are appropriate or not (Dey and Abowd 1999; Schedl and Knees 2013). That is why the user's preferences have to be considered. User factors can include his demographics, his personal traits, his musical background, his long-term musical preferences and liked or disliked songs or playlists (Schedl and Flexer 2012). All factors are usually static and can be expressed by the user himself.

This paper will focus on the user's context in form of long-term seasonal factors brought together with the music features. The user himself and the user's preferences will not be in the main focus of this work, they are considered indirectly by the crowd-based monthly music charts (see Figure 1, right side).

2.2 Context-aware Music Recommender Systems

There are two classical approaches for a recommendation system: content-based and collaborative recommendations (Adomavicius and Tuzhilin 2005). Collaborative recommendations are based on utilising explicit or implicit ratings from many users (Shardanand and Maes 1995). Content-based recommendations are using information from a user query or other user information to make suggestions (Mooney and Roy 2000). To enable context-aware music recommendation, the situation or context data has to be matched with the musical attributes (see Figure 1).

The literature shows various approaches how the situation can be used by CAMRS. Prototypes for example include situation data such as location (Kaminskas and Ricci 2011), time (Su et al. 2010), weather (Baltrunas et al. 2011) or activity (Wang et al. 2012).

All these approaches to involve the context in the recommendation process only investigate and integrate short-term context parameters, long-term factors such as seasonal preferences are not considered. Research about the influence of the seasons on music preferences are described as follows.

2.3 Seasonal Music Preferences

In 2010, Pettijohn et al. examined the seasonal music preferences of college students. To understand their findings, the meaning of seasons and the categorization of music dimensions have to be explained first.

In a lot of countries – especially in Europe – the four seasons spring, summer, fall and winter each mark changes in the calendar. The changes are based on ecology, weather patterns and daylight hours (Nelson 2010). Seasons elicit different emotions, physical and psychological activities and stressors, which are based on the environmental changes due to the seasons. In the USA, Germany and many other countries the summer months June, July, August (summer) are the warmest months, while November, December and January are the cold winter months (Pettijohn et al. 2010). The features of winter (colder temperatures, less sunlight and shorter days) may lead to emotional changes, including depression (American Psychiatric Association 1994).

Pettijohn et al. (2010) designed two studies in different geographic regions to explore the seasonal influence on the preferred music dimension of college students. In the first study, college students from the North-eastern U.S. reported their musical preferences after reading a winter or a summer seasonal condition scenario. In the second study, college students from the South-eastern U.S. reported their musical preferences after writing a fall, winter, spring or summer personal seasonal story.

The results of their studies point out, that reflective and complex music is preferred after thinking about fall or winter seasons. Energetic and rhythmic music is preferred after thinking about spring or summer. The music classification type upbeat and conventional was independent from seasonal influence. Pop music might be preferred continuously during the year, which could explain the independence towards seasonal influence. Meaningful songs are preferred during fall and winter and dance songs are preferred during spring and summer. (Pettijohn et al. 2010)

The preferences for more serious, complex music during the more exhausting fall and winter seasons and preferences for the more vivid, energetic and rhythmic music during the calmer spring and summer seasons match the findings from other studies (Pettijohn and Sacco 2009a). Unfortunately, the studies from Pettijohn et al. (2010) are based on small surveys that do not reflect the everyday behaviour of the participants. The studies from Pettijohn and Sacco considered the actual listening behaviour by using the Billboard No.1 songs for each year from 1955 to 2003, but only investigated their data under social and economic condition terms (Pettijohn and Sacco 2009a, 2009b).

This paper combines the relevance of the actual listening behaviour by regarding the top tracks of the German single charts with the context factor time. Furthermore, the correlation of the weather data with the seasons is taken into account.

3 Data Collection

This section will summarize the data collection process and explain the relevant obtained music parameters, which are essential for the analysis of the seasonal influences on context-based music. At first the collection of tracks will be covered, followed by the extraction of the corresponding music title features energy, valence and danceability.

3.1 Data Collection Process

For the collection of the music parameters from the monthly top tracks in the German single charts, a process with three main steps was used (refer to Figure 2). Germany was chosen for the data base of this study, as there are distinctive seasonal weather effects as mentioned in section 2.3.

In the first step the weekly music charts from January 2006 until June 2016 were extracted from the official German singles charts[2]. Afterwards, these weekly charts were used to aggregate the monthly charts because the weekly charts are temporarily too detailed for an analysis of seasonal influences. Therefore, a ranking system by points was used. This works, by assigning points to the best 20 songs of each week.[3] The first place gets 25 points, the second place 20, third 18, fourth 17 and so on. Afterwards the points for each song in a month were counted and the songs were arranged in respect to overall points. Accordingly, the number of tracks within the monthly charts can vary between 20 and 30 songs, depending on the number of new tracks that enter the top 20 weekly charts within a month. The third step included the extraction of the musical parameters for each song of the determined monthly charts. For the extraction of music features, the Spotify Web API[4] was used because it is easy to access and provides the necessary song data. The Spotify Web API endpoints return metadata in JSON[5] format about artists, albums and tracks directly from the Spotify catalogue. With the request “audio-features” and the corresponding Spotify-ID of a track, a list of features related to the track is returned. For this analysis, only the parameters energy, valence and danceability are important and used.

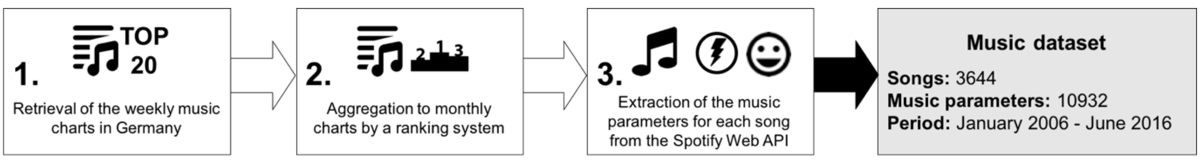


Figure 2: 3-Step-Music-Data-Collection-Process of this work and final dataset

The data collection contains 3684 songs from the top tracks in the German single charts from January 2006 till June 2016. 40 of the 3684 songs are not listed in the Spotify Web API and therefore have no ID and audio features. To analyse all songs with related attributes the ones without an ID were

[2] For the German single charts, see www.offiziellecharts.de/charts.
[3] This ranking system was used based on the system of www.springbock.de.
[4] For more information about the Spotify Web API, see https://developer.spotify.com.
[5] JSON (JavaScript Object Notation) is an open-standard format to transmit data objects consisting of attribute-value pairs.

removed from the dataset. Therefore 3644 songs with 10932 data points of audio features were used for the evaluation.

3.2 Relevant Music Parameters

Energy is measured from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy (Kim et al. 2011; Pollacci et al. 2016).

The valence describes the musical positiveness conveyed by a track as a measure from 0.0 to 1.0 as well. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry) (Kim et al. 2011; Pollacci et al. 2016).

These two music features can be separated into three sections; the section “low”, ranging from 0.0 to 0.33, “medium” from above 0.33 to 0.66 and “high” for a value over 0.66.

Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable (Pollacci et al. 2016).

To get a better understanding of the Spotify audio features, look at the comparative example of two songs in section 4, Table 1. The data shows, that the first song has a medium amount of energy and a low amount of valence. This values are describing, that this song has a lower level of power and transmits a sad atmosphere. Furthermore, this song has a medium value of danceability. The second song is a pop/rock track, which has, compared to the first song, a higher amount of energy, valence and danceability. This song sounds happier and more powerful than the first one. The higher amount of danceability makes it easier to dance to the song.

Valence and energy are strong indicators of acoustic mood and the general emotional qualities of a song (Krause and North 2014). Often, songs have a positive relationship between valence and energy, so that a song with high valence also has a higher energy value and vice versa.

3.3 Emotional model of music

These music characteristics can be assigned to the human emotional circumplex model of affect by Russell (Russell 1980). This model arranges 28 human emotions according to the two dimensions arousal and pleasure in circular order (see Figure 3, left side).

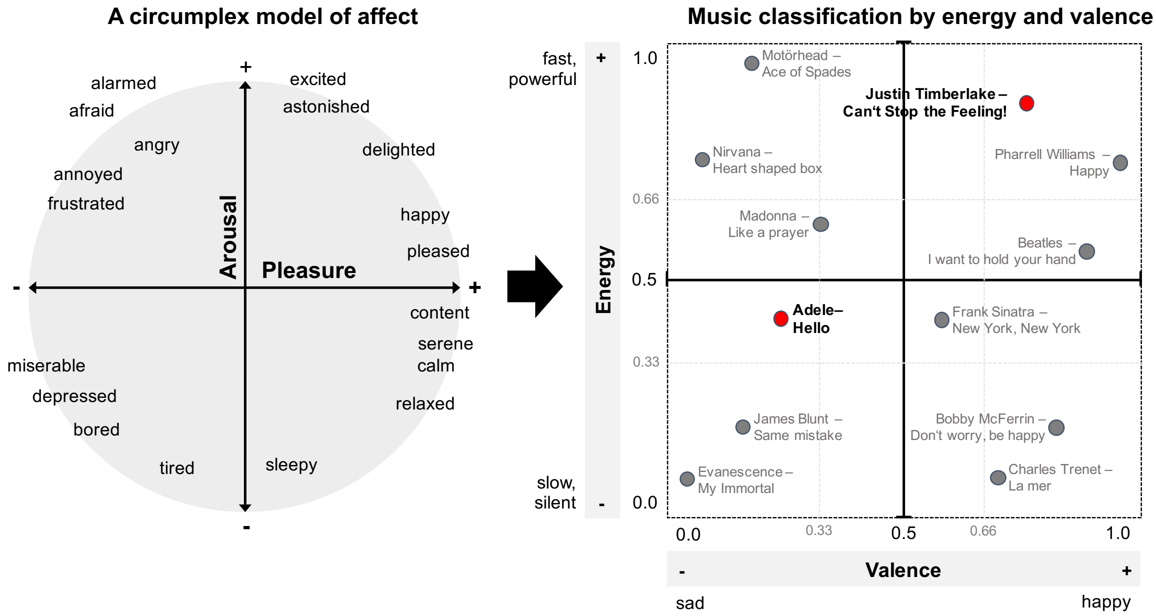


Figure 3: Classification of songs by energy and valence based on the human emotional Pleasure-Arousal-Model by (Russell 1980))

In the case of music, which is also driven by emotions, the two-dimensional scale can be used to classify music songs. In this case the energy corresponds the human activation or arousal and the valence corresponds the human pleasure (Krause and North 2014; Russell 1980). Nevertheless, these automatically determined parameters do not consider the lyrics of the song. Lyrics can differ semantically from the perceived acoustic mood. After all, songs with a special acoustic effect also have a text, which is accordingly marked (Kim et al. 2011). The visualization of valence and energy parameters on the right side of Figure 3 enables the graphical classification of some sample songs with different values compared to the tracks from Table 1. The track "Can't Stop the Feeling!" from Justin Timberlake, which feels like a fast and happy track, is located in the top right quadrant of the visualization and the slower and sadder song "Hello" from Adele is located in the bottom left corner.

4 Evaluation

The following section presents the analysis of the data collection to point out the coherence of the features energy, valence and danceability in the context of the seasonal influence. For this paper, it is important to take a look at the general climate trend in Germany. The temperature is one important factor that describes the differences between the seasons. Typically, the temperature increases from spring to summer and decreases in autumn until winter like the graphs average temperature (Ø temperature) in Figure 4 shows. This is important for the analysis of the given data collection, because the weather influences the mood of the listener (ebd. seasonal music preferences). The entire weather data was taken from the German Weather Service "Deutscher Wetterdienst"[6]. To compare each attribute with the temperature it was needful to calculate the mean value of each month from January 2006 through June 2016. Therefore, the attributes energy, valence and danceability are shown on the primary vertical axis with values between zero and one. The temperature needs an individual scale, due to different values which are, especially for Germany, between zero and 20 degrees Celsius. Furthermore, the mean value of the attributes energy, valence and danceability has to be calculated. The results of this are shown in the following Figure 4.

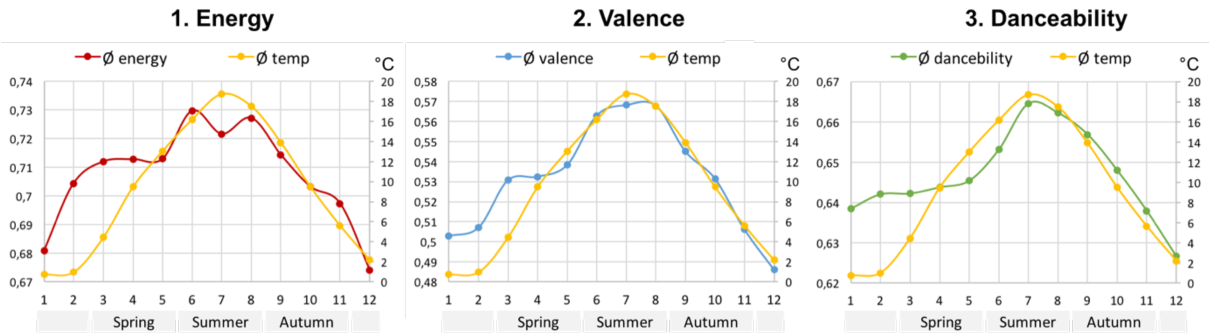


Figure 4: Energy, valence and danceability parameter analysis compared to the temperature of the validated songs over the year (2006-2016)

The first graph in Figure 4 shows that the mean value of energy depends on the progress of the mean temperature over a year. During spring the energy of the favoured songs is low and increases in summer at the same time that the temperature increases. The peak of average energy (Ø energy) is in June. Facing autumn and winter the energy level decreases slowly.

The second graph shows the coherence between the mean valence and mean temperature over the year. As shown by energy and temperature, we can see that the progress of temperature and valence has a positive correlation. The valence of the favoured songs increases from spring to summer. In July and August, the valence is reaching a peak and is decreasing slowly until winter.

Finally, the third graph shows the progress of the mean danceability of the favoured songs during the seasons. From spring to summer the value of mean danceability increases and reach its peak in July. From there, the mean danceability decreases slowly.

Taking a closer look at the illustrated progresses, there seems to be a coherence between the attributes of the songs and the temperature over a year. During warmer months, the charts are filled with happier, active and energetic songs with a higher danceability. The progress of the valence shows that

[6] Deutscher Wetterdienst (DWD) is the national meteorological service of Germany: www.dwd.de.

during November and December, the mood is more desolate and the chart contains less active songs. The songs in winter and spring are not as danceable as in summer. This relationship is shown in Table 1. Two different kinds of songs are listed, one for winter and one for summer.

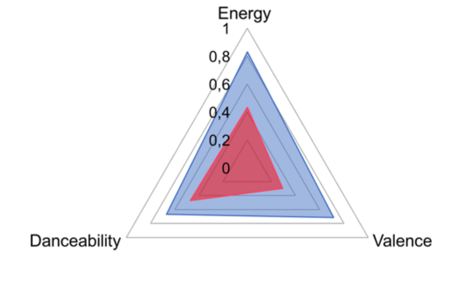
Song/ Parameter	1. Adele *Hello*	2. Justin Timberlake *Can't Stop the Feeling!*	
Released (seasons)	23. October 2015 (autumn and winter)	6. May 2016 (spring and summer)	
Energy	0.431 (0)	0.830 (+)	
Valence	0.293 (-)	0.716 (+)	
Danceability	0.470 (0)	0.667 (+)	

Table 1. Comparison of two sample songs for different seasons and their characteristic audio features

The first one is the song “Hello” from Adele. This song was released at the end of October 2015 and very popular during 2015/2016 winter. This typical winter song serves as a proof for the seasonal music preferences of music listeners. It stayed in the charts for four months and was on the first place in November (100 points) and December 2015 (125 pts) as well as in January 2016 (86 pts). In February, it went down to the 14th place (30 pts) before it was gone from the top charts. The song has a low energy intensity, sounds sad and has a low amount of danceability.

The second song is from Justin Timberlake “Can't Stop the Feeling!” and is a typical summer song. This song was released at the end of spring 2016 and ranked high in popularity in the following summer. It stayed in the charts for five months with an entrance on the 13th place in May (39 pts), followed by 2nd in June (103 pts), 5th in July (63 pts), 7th in August (50 pts) and finally the 30th place in September (1 pt) before it went out of the charts. Like a typical summer song, it has a higher amount of energy and danceability compared to a winter song. Also important is the mood of this song, which is happier than a typical winter song.

To prove this relation between music features and seasonal influences, the bivariate Pearson correlation is used. For this calculation, the whole non-averaged dataset between January 2006 through June 2016 has been used. The Pearson correlation between the attributes energy and temperature of the dataset equals $r=0.315$, $p=0.005$, therefore they are positively correlated. Pearson’s r for valence and temperature is an $r=0.426$, $p=0.005$ and shows a positive correlation, too.

Another relevant outcome is the coherence between energy and valence which was already mentioned to classify acoustic mood and the general emotional qualities of a song. The progress of the correlation between these two music features over the years from January 2006 until June 2016 is shown in Figure 5. The progress of the two graphs’ energy and valence is very similar over the years, whereby the average energy is always above the valence. The peaks and lows of them are often synchronized. This is one reason why the gap between the graphs is roughly the same. The linear relationship between both of these attributes in the dataset is $r=0.553$, $p=0.005$, which describes a positive correlation as well.

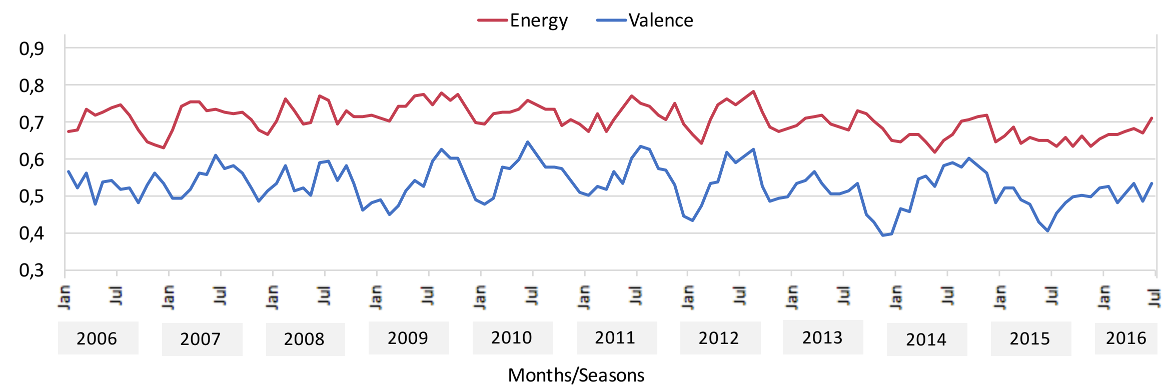


Figure 5: Correlation between energy and valence of the top German chart songs from 2006 through 2016

5 Limitations

There are some limitations in the consideration of the results. First of all, the focus was to explore the popular songs in Germany based on a weekly top 20 songs data collection aggregated to monthly charts. The dataset including 3644 songs with 10932 data points of audio features over ten years is a good indicator but too small to make final conclusions for seasonal influences.

A larger dataset with, for example, the top 100 songs and an extended investigation period could work out. In addition, the charts always appear at the end of the investigated period. A slight shift in the impact of the data is therefore to be seen in parts of the evaluation. Also, the charts are somehow stagnant, so frequently the songs only change the place. Only a few songs fall off the charts and are replaced by new once. This prevents major changes across the entire chart. An approach to take this into account would be to examine only the new entrants or to give them a higher weighting. However, much more data would be required as well. Moreover, the retrieved music parameters are all automatically determined by software from Spotify or The Echo Nest and were not questioned in this work. Other providers or systems may assign other values for music recommendation systems.

From seasonal data side, only the average monthly temperature was used. Further data such as the sun hours or weather data could be used here in addition.

6 Conclusion and Future Work

It is important in these days to develop a ubiquitous music recommendation system, which reacts to current circumstances considering short-term and long-term parameters. The research field on context-based music recommendation is a relatively new but growing. Only a few studies examine long-term factors like seasonal aspects on music (see section 2.3). In contrast to these studies which are based on surveys, this study has investigated a big dataset to identify correlations between the chosen music attributes (valence, energy and danceability) and the temperature over the year.

The analysis confirms the assumption that there is a seasonal influence on the music consumption in Germany. The analysis shows a positive correlation between valence and the monthly temperature as well as between the energy and the monthly temperature. During summer, more active, energetic and happy songs are preferred and during the colder seasons listeners choose more calm and relaxed songs. Additionally, it has been proven that there is a positive correlation between energy and mood in popular music songs, which means that positive songs are mostly more energetic than negative songs.

The findings can serve as a basis to integrate a seasonal filter into CAMRS. Of course, music is somehow personal and differs from person to person, but these filters could be applied to their own playlists. Additionally, the change of users into other areas with other seasonal effects could lead to a suitable music selection in combination with location tracking.

In addition, information systems are increasingly offering the opportunity not only to filter existing music, but to enable context-based music correction or production on the user's listening device. Here seasonal parameters can help to make this possible. Like for example music experts at Spotify have devised a formula[7] for a perfect summer track. They say that a summer hit tends to sound more artificial than the average song, but it will be slightly happier and energised, meaning it's better to dance to (Griffiths 2015). These results support the findings of this scientific work.

This work is fundamental research in the field of application. Future research should consider seasonal factors more differentiated to investigate which seasonal influences lead to a change in mood and music listening behaviour. This will allow seasonal factors to be taken into account more precisely in application systems for consumers. Due to its high dynamics and emotional engagement to the listener, particularly the music market will offer various possibilities for context-aware and ubiquitous adaptions and services in the future.

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[7] Successful Summer Hit = Tempo + (Energy x 1.48) + (Danceability x 1.17) + (Acousticness x 0.17) + (Valence x 1.14).

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