Is music influencing people's mood?
A comparison between people with different mental disorders

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Abstract

This study explores the intricate relationships between music preferences, mental health, and social media sentiments by analyzing data from 4,300 individuals diagnosed with mental disorders (e.g., Depression, Anxiety, PTSD). Using two datasets with around 5 million tweets and over 220,000 songs, the research investigates whether mental disorders influence musical tastes and if these preferences are reflected in social media sentiment. Methods included text preprocessing, network analysis, sentiment analysis, topic modeling, and logistic regression, utilizing Python and R. Results reveal a diverse network of music preferences, with some widely shared artists and a high presence of niche tastes. Topic modeling highlighted emotional and thematic diversity in both tweets and songs, emphasizing topics like frustration, emotions, and entertainment. Sentiment analysis revealed that users generally express more positive emotions on Twitter, despite preferring songs with negative sentiments. Logistic regression demonstrated an inverse relationship between mood and song sentiment: individuals with negative moods have a higher probability of listening to positive songs and vice versa. Interestingly, no significant variation in this relationship was observed across different mental disorders, except for PTSD, which influenced overall song preferences.

Introduction

The interconnection between music and people's mood is not a secret. There are several studies that highlight how music and mood influence each other, and if you ask someone if they agree with this connection, nine people out of ten will answer yes [1]. However, the correlation between the two can be really intricate [2]. If you add to the mix a third variable, such as mental disorders, the results are far from obvious. Nowadays everyone has access to many music libraries through applications such as Spotify, SoundCloud, and Apple Music. And moreover, anyone can share their thoughts on social networks such as Twitter/X. But how do those people arrange around their favorite artists? Do mental disorders have an influence on what people prefer? And how does all of this translate into what they write on social networks? Are people that listen to sad music also more sad on social platforms? Or, can at least other people sense this sentiment? These are all questions that will be studied in this paper.

Data

The data that has been used for this research consist of 2 main dataset sourced from kaggle [3]. The first one is a Twitter dataset, with almost 5'000'000 tweets coming from around 4'300 people that have "publicly" disclosed that they have been diagnosed with one of the following mental disorders: Depression, Anxiety, PTSD, Borderline, Bipolar, Panic. Each row of the dataset contains a unique user_id (it's an anonymized dataset), the disorder they have been diagnosed with and the text of the tweet
The second one is a music dataset, with more than 220'000 songs from Spotify, SoundCloud and/or Apple Music. It includes almost 19'000 artists connected to the same 4'300 users in the Twitter dataset. The dataset contains also lyrics gathered with the Genius API. This dataset contains, for each entry, the user_id (the same as those in the twitter one), their disorder, the name of the artist, the title of the song and the lyric. Figure 1 shows the general distribution of disorders among users in the dataset.

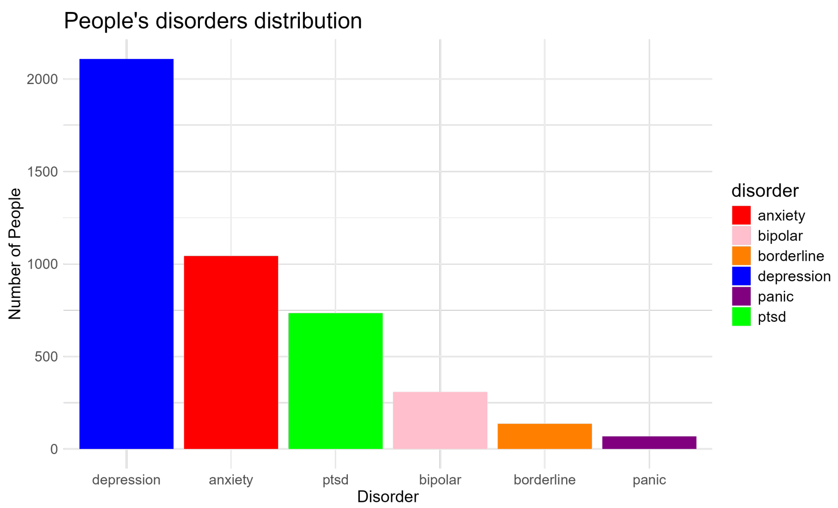

Figure 1: General distribution of disorders

Methods

The techniques used for the analysis are text pre-processing, network analysis, sentiment analysis, topic modeling and logistic regression. The analysis was done with a mixture of programming languages. In particular, text pre-processing and topic modeling was done in Python, while for all the others, R was the chosen one.

The first step was cleaning data and prepare the datasets for sentiment and topic analysis. For the music dataset, the following transformations was applied on the lyric field:

- Detection of english text.
- Removal of special characters, punctuations or symbols that don't contribute to the analysis.
- Lowercasing (case differences can affect tokenization and analysis)
- Removal of stopwords (e.g., "the", "is", "and") that may dominate analysis without adding value.

- Removal of musical sounds (e.g., ”lala”, ”nana”, ”bom”) that were not adding anything to the analysis.
- Removal of more common singer/artist names that were repeated during the text and where not helpful for the topic detection of the song.
- Removal of colloquialisms, slangs, offensive or sensitive terms (for paper purposes)
- Lemmatization to ensure that variants of the same word (e.g., ”running” vs. ”run”) don’t appear as different tokens.

Really similar transformation were applied to the twitter text field, with some small differences. Since musical sounds and slangs were not included in tweets, and artist and singer names were useful for the topic analysis, only english stopwords needed to be removed. Moreover, in this field there was a need to remove things like Urls and @mentions, while keeping the text of the hashtags (without the ”#” character) as they are useful for topic modeling. Also emojis were removed as the fact that people use the same emoji in different ways makes them unreliable in terms of emotion they transmit without contextualization (e.g. people who use the crying one to say that they are laughing).

For the topic modeling part, the main techniques exploited were Latent Dirichlet Allocation (LDA) and BERTopic. Latent Dirichlet Allocation (LDA) is one of the most popular algorithms in the fild of Natural language processing (NLP) [4]. In LDA, the Dirichlet distribution is used to model the distribution of topics in each document and the distribution of words in each topic [5]. The main python libraries used for this are *Scikit-learn* [6] and *Natural Language Toolkit* [7]. Regarding BERTopic, it uses a tree step approach. Firstly it converts all the tokens into an embedding representation, than reduce the dimensionality of the resulting embeddings using algorithms like UMAP, and lastly it clusters them into topics using an hierarchical clustering algorithm named HDBSCAN [8]. Regarding libraries, instead of the classical BERTopic, the one that was used it the *Top2Vec* [9], which was performing better with higher amount of data.
Speaking of high amount of data, the topic modeling of the twitter dataset was performed only on a random subset of tweets from each user (around 150’000 entries), as analyzing the entire one was impossible due to machine limitations.

Moving to the R part, the libraries exploited are the *igraph* [10] for the network analysis and the *syuzhet* [11] for the sentiment analysis. For the first one, it’ been used a bipartite network, taking users as U-nodes and artists as V-nodes. Regarding the sentiment analysis instead, to better explain how it works in this package, it takes the tokenized text that has been created (in python in this case) and returns a value for each of the following emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, trust and two more general values for positive and negative.

After analyzing all the emotions, the final two values (positive/negative) produced from the sentiment analysis of user’s tweets were used as binary indicator of the general mood of each specific person. On this indicator have been run some logistic regression to explore the relationship with variables such as the dominant emotion and topic in their songs and the mental disorder they have been diagnosed with. Dominant emotion and dominant topic are computed variables. The first one represents the emotion with the highest sum of values for each user. Dominant topic is the topic with the highest frequency between all the topics of each user’s songs.

Results

Starting from the network analysis, at first it's not really clear how people are linked to each other. Looking to the whole network in Figure 2 we can only see that it's characterized by a giant component of people with similar common artists, and an outside circle of users with no artists in common with the central part. The number of edges in this network is 93'964. However if we project the network over the users, the edge count explodes to 870'871. This gives a big insight on one of the characteristics of the network, but to better understand what's going on, the degree of the artists nodes has been computed. The average degree for artist nodes is almost 5, and only this is a factor that makes the edge count higher when the network is projected over the users. On top of that, As shown in Figure 3, the distribution of this network has a long tail, with most artists nodes having low degrees but a few nodes having very high degrees. This means that there is a majority of people that listen to more niche artists (with a degree between 1 and 4) but there are also a good amount of artists that are shared by the majority of users in the network. The second type of artist's nodes are called hubs.

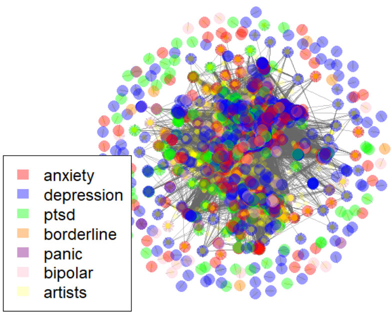

Figure 2: General Network

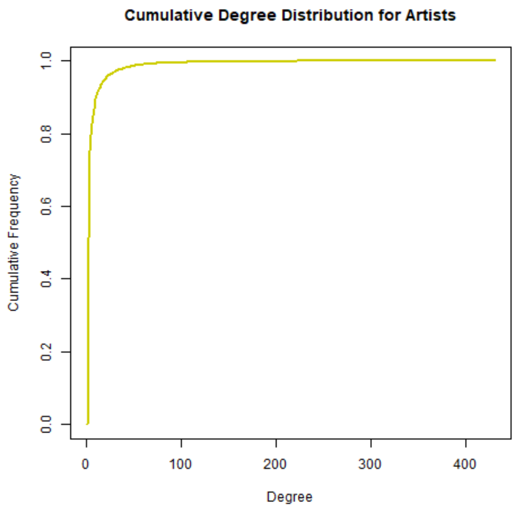

Figure 3: Cumulative distribution of artist's degrees

To better understand if people with similar disorders where distributed around similar artists, some clusters where extracted from the network. Regarding the clustering method, the louvain algorithm has been used. It is based on the modularity measure and uses a hierarchical approach. This was the algorithm that was producing faster and better results for this network. Some examples of clustered communities can be seen in Figures 4 and 5.

We can observe two main shapes for the communities, that are due to the presence or not of hubs in the cluster. The first one (Figure 4) keeps the characteristic giant component shape, with artists shared by most people, while the one without high influential points (Figure 5) is more similar to a tree. If low influential points are removed from the network, communities that where clustered around hubs remain mostly intact and maintain the shape of one giant component. On the other hand, smaller communities

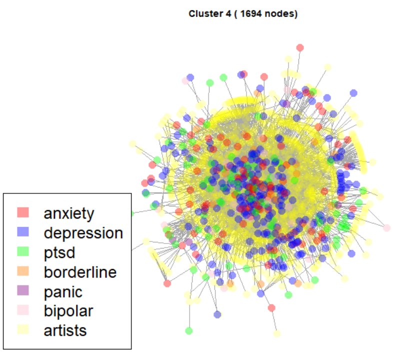

Figure 4: Cluster with hubs

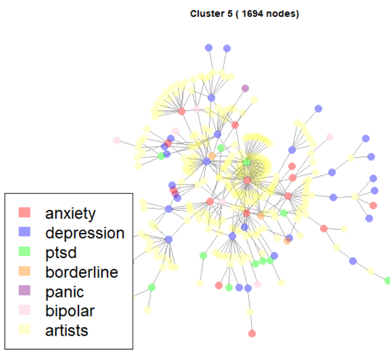

Figure 5: Cluster without hubs

without high influential points lose a good percentage of people from the main network. There are also some examples of mixed communities like in Figure 6, with a big chunk of user distributed around a small number of artists, and some other users around with small number of artists shared with the giant component.
Unfortunately, to go back on the first question, there are no clusters that are dominated by people with one particular disorder. In fact, the composition of the clusters follows more or less the distribution shown in Figure 1. But same artists can produce different types of songs, with different topics and different emotions attached to them.

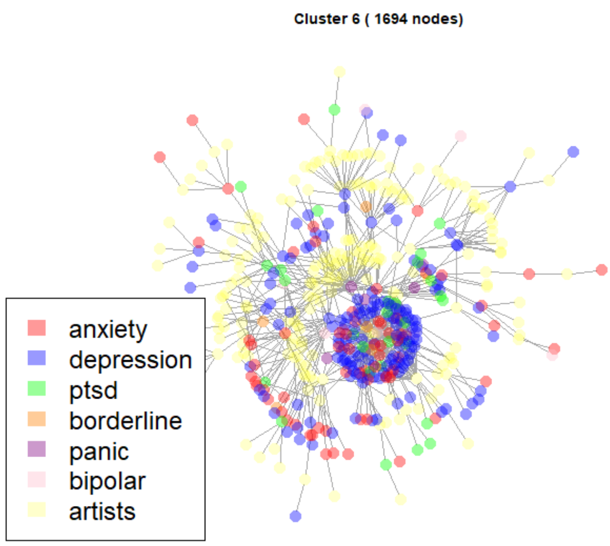

Figure 6: Custer with a mixture of high and low influential points

Regarding topic analysis, the LDA model runned on song's lyrics took a lot of time and gave terrible results, with a lot of overlapping between topics and some words being shared between all of them. On the other hand, the model trained using the Top2Vec approach gave much better results taking a fraction of the time. In songs it was able to extract 218 topics, which have been reduced to only 20 and labeled. The same thing was done for the tweets, which resulted in a stunning 996 number of topics, also then reduced to only 20 and labeled. In Figure 7 it's shown an example of a word-cloud generated whit words of a Tweet's topic that has been labeled as Mental Struggles.

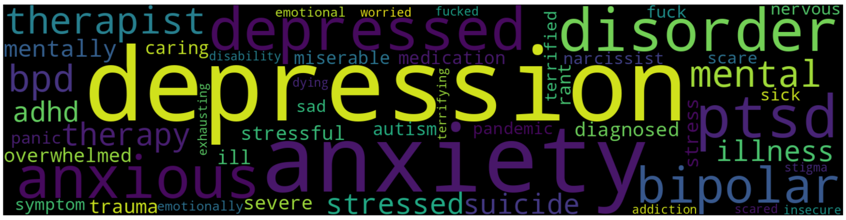

Figure 7: Example of Tweets topic

In Figures 8 and 9 it's also shown the distribution of topics. To remove the differences between groups due to the different amount of people in the group (taking as groups all people with the same mental disorder), results are adjusted for the total number of people whit that particular disorder. They are arranged in a descending order. It can be seen that a lot of frustration and insults is present among the first topics in the twitter dateset. That's not a surprise, as social media in general are quite full of this type of comments. However, looking after that, the few next topics are all about emotions, music and entertainment. This can be found also in the music dataset, which is full of topics really emotional, ranging from really happy to really sad, most of them being heart related.

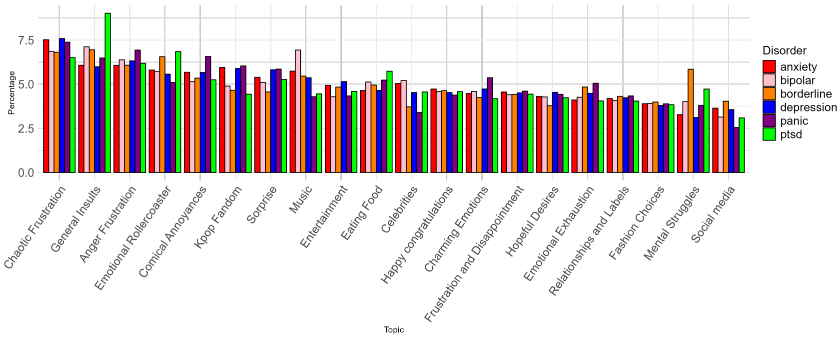

Figure 8: Tweet's topics distribution (Percentage)

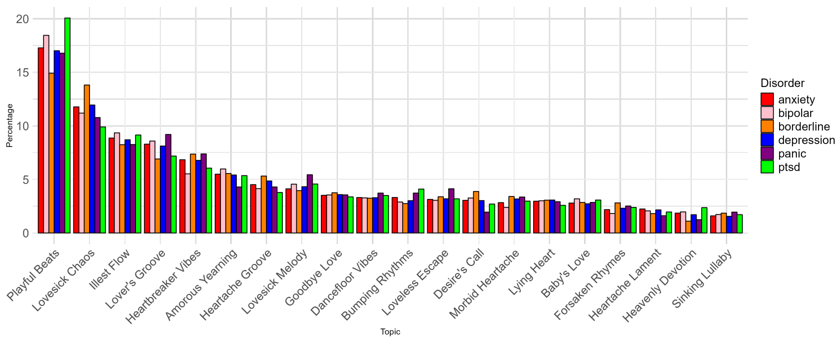

Figure 9: Song's topics distribution (Percentage)

After understanding what songs and tweets where about, the analysis went on with the sentiment part. In Figure 10 it's shown the dominant emotion of the songs listened by each group of people. The dominant emotion is the emotion with the highest value for each song. To remove the differences between groups due to the different amount of people in the group, results are shown as percentage of songs listened by the whole group. The anticipation emotion has been removed because was skewing the analysis with a really high value while not being much helpful for the analysis (as it's the more neutral emotion). The more common songs are the one with high joy scores, followed by fear, anger, sadness and trust. For each category it's also possible to see what is the group that listen more songs with that emotion, with bipolar liking songs with joy the most, while borderline have the saddest musical tastes.

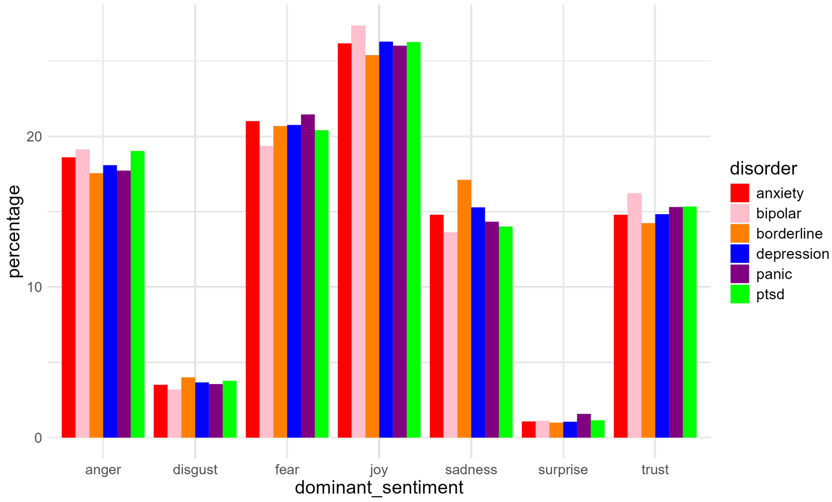

Figure 10: Dominant song sentiment across groups (Percentage)

The same type of analysis was done for tweets (Figure 11). In this case it's shown the general distribution, as the general value of the emotions people express on social is more important than seeing the number of tweets characterized by each emotion. Also in this case results are shown as a percentage of the total population. We can see that joy, fear, sadness and disgust follow a similar path of the dominant sentiments of the songs. The only exception is thrust, being particularly high in the tweets.

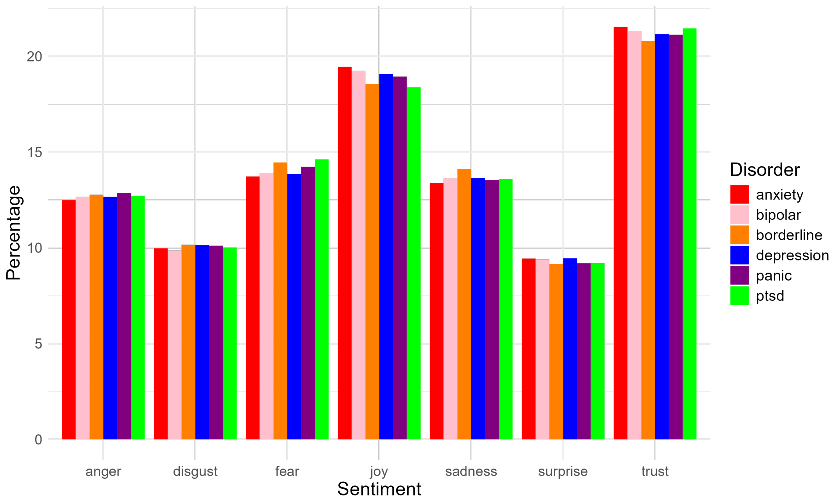

Figure 11: Tweets sentiments across groups (Percentage)

Quite particular was the comparison between the general positive/negative scores of Tweets and Songs. In Figure 12 we can see that people listen to more songs with negative emotions. On the other side, in Figure 13 is shown that people are usually more positive in their Tweets. This was a good anticipation of the final result of this research.

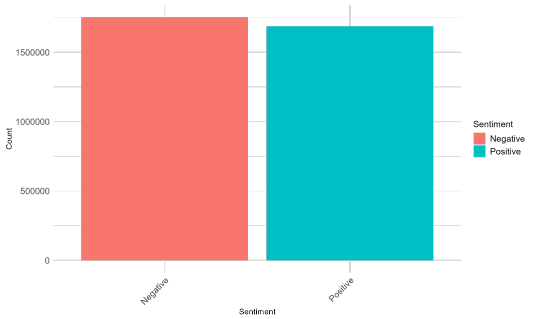

Figure 12: Positive/Negative emotion score for Songs

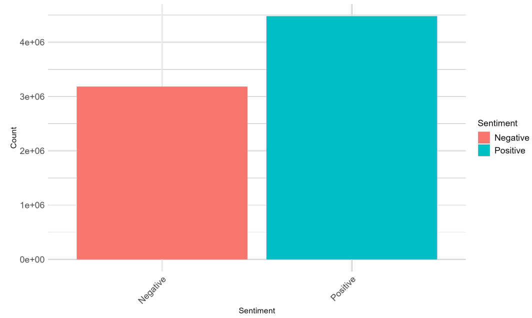

Figure 13: Positive/Negative emotion score for Tweets

Studying the dependence between the variables previously described (positive/negative tweets treated as a binary indicator of the mood of a person, dominant emotion and topic in their songs and the mental disorder they have) it came out that the songs topics are not significant for determining people mood, with the only exception being the Baby's Love topic: people listening to songs with that topic have higher probability to be sad. Neither the fact of having a particular mental disorder have an influence of the binary variable. However, the Table 1 shows instead a significance of the song sentiment on the general mood. But the correlation is quite interesting. Here the reference level for the Twitter sentiment is "positive", so a negative value value of the estimate means that people that are listening to positive songs are less likely to have positive mood. This could be interpreted as people who are in a bad mood prefer positive songs. So it seems that the correlation that was sought is the inverse of what people might have expected. If we try to reverse the regression and to re-add the disorders into the equation, the result is the one shown in the Table 2. Now the reference level is listening to negative songs. From this it can be seen that individuals with negative mood are generally more likely to listen to positive songs compared to those with positive mood. Moreover, PTSD shows a significant main effect, indicating that these individuals are also less likely to listen to negative songs overall. However, also in this case there is no significant evidence that the relationship between mood and songs sentiments varies based on specific disorders. This is shown also in Table 3, which instead of categorical variables, includes the scores given by the sentiment analysis to each song. The this regression, featuring numerical variables, is also the best one overall. From this model the inverse correlation that was observed before is still present, with a statistical significance much higher. It can be seen that Joy (being the best emotion of the group) has a negative estimate, meaning that people that listen to songs with high joy scores are less likely to have a positive mood. The inverse can be observe for sadness, leading to a higher likelihood of being positive. Also emotion like fear and anger are statistically significant, with anger having the same effect of sadness while fear is much similar to joy.

Table 1: Song's influence on Mood

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.8298	0.0545	-33.59	0.0000
dominant_song_sentimentpositive	-0.2614	0.0800	-3.27	0.0011

Table 2: Mood and Disorder influence on Song choice

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.1524	0.0574	2.66	0.0079
disorderbipolar	-0.0921	0.1194	-0.77	0.4406
disorderborderline	-0.1911	0.1706	-1.12	0.2627
disorderdepression	-0.0447	0.0703	-0.64	0.5247
disorderpanic	0.1079	0.2262	0.48	0.6333
disorderptsd	-0.2091	0.0896	-2.34	0.0195
dominant_twit_sentimentnegative	-0.3370	0.1674	-2.01	0.0442
disorderbipolar:dominant_twit_sentimentnegative	0.0430	0.3651	0.12	0.9062
disorderborderline:dominant_twit_sentimentnegative	0.6633	0.4983	1.33	0.1831
disorderdepression:dominant_twit_sentimentnegative	0.0914	0.2019	0.45	0.6509
disorderpanic:dominant_twit_sentimentnegative	-0.7706	0.7426	-1.04	0.2994
disorderptsd:dominant_twit_sentimentnegative	0.1060	0.2590	0.41	0.6823

Conclusion

From this analysis it came out that networks built around people with mental disorders are not shaped based on the type of disorders they have been diagnosed with. Even if people with same disorders have high numbers of common artists, there are also a high number of connection between people of different groups. A high number of people likes more niche artists, but there is a considerable amount of artists that are shared by the majority of the network. The shapes that the communities of this network takes are based on the presence of hubs in the network, with some of them having a giant component, others have more a tree shape, and some of them having also a mixture of the two. The topics that are more common in their tweets (after the classical insults and frustration) are built around emotions, songs and entertainment. The emotional part is present also in song's topics, with lot of them being Heart, Love and Sadness correlated, while a good chunk have also a more happy and playful vibe. This is reflected also in song's dominant sentiments, with the joy being the most common across every group, followed by fear, anger, sadness and trust. A similar distribution can be found also in sentiments coming from Tweets, whit the only exception of trust that became the more common one. Finally, from this analysis it seems that music can't influence people's mood with a direct correlation, but the music that a person listen is chosen as an inverse function of mood. However, there is no significant evidence that the relationship between mood and songs sentiments varies based on specific disorders.

Limitations

This analysis present some limitations. The first one being the music data including lots of non english songs. With the 6th topic among 20 being a K-pop based one, not taking

Table 3: Correlation between Song's emotion's scores and Mood

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.9588	0.0991	-19.76	0.0000
disorderbipolar	-0.1326	0.2085	-0.64	0.5249
disorderborderline	-0.1193	0.2918	-0.41	0.6826
disorderdepression	0.0884	0.1155	0.77	0.4440
disorderpanic	-0.0234	0.3897	-0.06	0.9522
disorderptsd	0.0210	0.1478	0.14	0.8872
anger	0.0051	0.0012	4.36	0.0000
fear	-0.0050	0.0019	-2.66	0.0077
joy	-0.0038	0.0007	-5.26	0.0000
sadness	0.0041	0.0015	2.70	0.0070

into consideration multilingual songs could have biased the research. However, due to machine limitations, it was not possible to include them without sampling, and sampling could also have biased the analysis.

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Data Reference

Here the link to access all the unprocessed and processed data:
https://drive.google.com/drive/folders/119yrk-F_Ii7C4y7BFuKB6RSut8qo6t1q?usp=sharing