# NLP on Drugs: Exploring the Language of Psychedelic Music in Public Discourse

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## Abstract

Psychedelic research is on the rise. Studies point to increased treatment efficacies of psychedelic therapy across a variety of mental health disorders, with music being seen as a main driver of treatment outcomes in such therapy. Music also plays a large role in recreational use of psychedelic drugs, with the video-hosting website YouTube often used by recreational users to compose musical playlists intended for psychedelic experiences. Leveraging tools from big data and NLP, we extracted a large dataset of comments related to music on such playlists aimed at a range of different psychedelic compounds. TF-IDF and LDA analysis revealed that public discourse on such music reflect trends in both patterns of use and the historical-cultural background of various psychedelic drugs. Finally, we discuss the possibility of using insights from public discourse about music towards informing music choice and improving treatment outcomes in psychedelic therapy.

## Introduction [LD]

The rise of social media in the last decade has brought with it new opportunities for research in the form of big data. Through the application of tools such as data mining and machine learning, vast amounts of user-generated information from social media sites like Facebook and Twitter can now be analysed to extract underlying content patterns and user behaviours (Bello-Orgaz et al., 2016). One of the most promising fields to benefit from this type of data is that of natural language processing (NLP), where large text-corpora can help answer questions about language use as well as provide clues to underlying cognitive processes (Farzindar & Inkpen, 2015).

Amongst social media sites relevant to NLP is the video-sharing platform YouTube. Unlike socially oriented platforms such as Facebook and Twitter, YouTube is primarily a content-driven site, where user attention is turned mainly towards content rather than social interactions. The ability for users to leave comments on videos thus creates a public forum for expressions of thoughts and opinions, which in turn provides considerable amounts of content-directed textual data available for analysis. Large datasets consisting of YouTube user comments have thus been used to examine everything from user sentiment (Bhuiyan et al., 2017) and emotion (Yasmina et al., 2016) to product opinions (Das et al., 2019; Severyn et al., 2016) and expressions of nostalgia in various types of music (Post-alcioglu & Aktas, 2020; Timoney et al., 2018).

One surprising area where social media data and NLP may provide new insights is the burgeoning field of psychedelic research. With a growing public interest in the medicinal and therapeutic use of psychedelic drugs (Aday et al., 2019; "Move Over, Pot," 2020), sentiments expressed about these compounds on social media could potentially help researchers to new discoveries. Despite this potential however, only a single published article tangentially relating NLP methods to psychedelic research appears to exist (Martial et al., 2019).

The current paper seeks to add to this literature. Since music not only shares a long history with psychedelic drugs, but continues to play an increasingly vital role in therapy (Kaelen et al., 2018), it presents a worthwhile first avenue of exploration. With its dual role of music video hosting and public discussion forum, YouTube similarly presents a promising source of data for such exploration.

This paper therefore aims to investigate both commonalities as well as differences in language use between comments left on user-created music playlists intended for use with various types of psychedelic drugs. As the paper is considered exploratory, no specific initial hypotheses were proposed. It was instead driven by a curiosity in how differences of culture, history, and modes of use amongst psychedelic drugs would be reflected in the language used to debate related music in public forums.

**Psychedelics & Music [LD]**

In recent years, psychedelic research has seen a revival after its temporary blossoming in the 1950s and 60s. Public health concerns and scientific reasonings for the worldwide ban of psychedelics within recreational and research settings are slowly being dismantled by a new wave of studies showcasing both the relative safety and widespread therapeutic potentials of psychedelic drugs (Belouin & Henningfield, 2018; Sessa, 2018).

Such studies have found that psychedelic drugs the likes of LSD and psilocybin (so-called 'magic mushrooms') show the least potential for harm amongst both legal and illegal recreational drugs (van Amsterdam et al., 2015). Additionally, the use of such drugs in therapeutic settings have been found to hold promise for treating a wide variety of mental health disorders including anxiety (Gasser et al., 2014), obsessive-compulsive disorder (Moreno, 2006), alcoholism (Bogenschutz et al., 2015), smoking-addiction (Johnson et al., 2017), and depression (Carhart-Harris et al., 2018; Roland R Griffiths et al., 2016; Ross et al., 2016). Curiously, a common thread throughout these therapeutic findings is the inclusion of music during therapy.

In recreational as well as therapeutic settings, music has long held a role central to the psychedelic experience. For thousands of years, drums and shamanic chants have guided the psychedelic ceremonies of native South- and Mesoamerican tribes (de Rios, 2003). In the 1960s, these were replaced by colourful guitar riffs and basslines as the music of Jimi Hendrix and Jefferson Airplane laid backdrop to the psychedelic adventures of Western concertgoers (Partridge & Moberg, 2017, p. 295). Today, the culture of psychedelic music appears to be making an electronic return to its roots, as tribalistic beats, vocals, and soundscapes ripple through the crowds of modern psychedelic music festivals such as Boom and Ozora ("Boom Festival," 2020; "Ozora Festival," 2020).

Meanwhile, current treatment models continue to point to music as having a central therapeutic function in psychedelic therapy (Kaelen et al., 2018). But what exactly is this function? And how could it be reflected in the way patients and recreational users talk about their experiences?

**The Hidden Therapist [LD]**

Shortly after therapists made their first forays into psychedelic therapy in the 1950s, music was introduced to the therapeutic framework as a means to support and guide patient experiences (Bonny & Pahnke, 1972; Hoffer, 1965). In the latest wave of therapeutic research and treatment, it has remained a central component of the treatment model, with leading researchers in the field referring to music as a "hidden therapist" (Kaelen et al., 2018).

Several recent studies have attempted to shed light on the details of this relationship between music and psychedelics. Thus far, psychedelic drugs have been found to significantly modulate music-evoked emotion (Kaelen et al., 2017), music-evoked mental imagery (Kaelen et al., 2016), music-evoked mystical experiences and insightfulness (Kaelen et al., 2018), as well as perceived personal meaningfulness of music (Preller et al., 2017).

These studies are further supported by earlier findings from the previous wave of psychedelic research in the 1950s–1970s. A recent review of such studies found that music had been considered integral for meaningful experiences of emotion, imagery, and self-exploration during therapy (O'Callaghan et al., 2020). Additionally, it was found to elicit synesthetic and sensorial experiences, a sense of embodiment, perceptions of other worlds or dimensions, and feelings of love (ibid).

Across all such studies both past and present, a main focus has been placed on the two psychedelic drugs of LSD and psilocybin. However, several other compounds have been and continue to be widely used in both recreational as well as therapeutic settings. To get a better idea of the language that such drugs could elicit, we will therefore take a brief look at their cultures and histories.

**Cultural and Historical Differences [LD]**

Although psychedelic drugs may often be debated as though they were a single entity, their cultural and historical differences are vast. Some psychedelics have a millennia-long history of use within spiritual and religious ceremonies in tribal communities, while others are more recent discoveries that share links to modern counter-cultural movements. A similar dichotomy exists between recreational versus therapeutic use, where some drugs are used almost exclusively in recreational settings, others in therapeutic settings, and others still fall somewhere in between.

Drugs with an older history include compounds such as *mescaline*, a compound that has been part of Mexican Native American rituals for over 3,500 years (Carod-Artal & Vázquez-Cabrera, 2006), *ibogaine*, an African compound with a similarly long history of ritual use amongst the Pygmy and Bwiti tribes of African Gabon (Alper et al., 2001), and *ayahuasca*, a traditional brew of the South American Amazon that has been a part of shamanic ceremonies for at least a millennium (Miller et al., 2019). Currently, these drugs play little to no role in recreational use but have become increasingly popular amongst therapeutic retreats that focus on spiritual and mental well-being – in particularly ayahuasca, which has experienced an ever growing interest in recent years (Winkelman, 2005; Wolff et al., 2019).

Other psychedelic drugs are used primarily in recreational contexts. *Psilocybin*, the active component of magic mushrooms, shares a similar history of use within spiritual and religious traditions (Griffiths et al., 2006). However, its widespread availability (Stamets, 1996) and lack of social stigma associated with other psychedelic drugs (Shaw, 2018) has primarily made it a popular recreational drug in recent years, setting its cultural role apart from the previously mentioned compounds.

With their respective discoveries in 1943 (Ladewig & Pletscher, 1994, p. 7) and 1974 (Shulgin & Carter, 1975), the compounds of *LSD* and *2C-B* are both relatively novel and thus also mainly linked to recreational use. The cultural connotations of the two drugs are highly varied, however. While LSD is strongly linked to the psychedelic music and counter-cultural hippie movements of the 1960s

(Baumeister & Placidi, 1983), 2C-B became popular as a party-drug in the rave and nightclub scene of the 1990s (de Boer et al., 1999) – a role it likely still maintains (Papoutsis et al., 2015).

Finally, the compound *DMT* is a borderline case, as it takes two distinct forms. The recreational variant of DMT is a pure, fast acting, and short-lived experience most commonly smoked amongst Western users (Winstock et al., 2014). However, DMT is also the active compound of the previously mentioned brew of ayahuasca. This potential confound is therefore worth keeping in mind, as public discourse regarding the drug may be spread across two vastly different cultures and uses.

### Potential Outcomes [LD]

Considering the previously outlined links between psychedelic drugs, music, and cultural history, one could reasonably expect such links to be reflected in the way users talk about the music involved in their experiences. This could namely come to pass on two fronts: 1) language related to music-induced changes to cognition, and 2) language related to a drug's cultural or historical background.

Regarding changes to cognition, we therefore expect to see language related to emotion, sensory perception, mental imagery, or embodiment, as well as experiences of meaningfulness, insightfulness, otherworldliness, mysticism, or love. Regarding cultural and historical background, we expect to see language reflecting either recreational or therapeutic/traditional use. In the prior case, this could be related to friendships, social arrangements, entertainment, or the party-scene; in the latter, language might reflect healing, spiritualism, or tribal culture, as well as ceremonial or shamanic connotations.

## Data

### Identifying Playlists [ER]

Data acquisition was initiated by locating music playlists relevant to the drug subcultures under investigation. Specifically, a wide search across YouTube targeted playlists containing specific keywords in either their titles or descriptions and scraped their associated URLs.

Playlists were then subjected to a qualitative assessment of whether they accurately reflected playlists dedicated to the drug-specific musical experiences of interest. After pruning, the final list amounted to 1,476 playlists containing 73,823 videos of which 51,975 were unique. *

** Note that the YouTube playlist data used for this paper is part of a larger dataset stemming from an ongoing project at Centre for Music in the Brain (MIB) at Aarhus University investigating the link between music and psychedelic drugs. The branch of data included here was collected by one of the authors of this assignment and used with permission.*

**Extracting Comments [ER]**

To obtain the comments of the individual videos, we set up a client in Google developer console capable of accessing the *YouTube Data API v3*. Because of the restrictions imposed by Google on such clients, several instantiations of our scraper were deployed with the purpose of extracting comments from all videos within a reasonable amount of time.

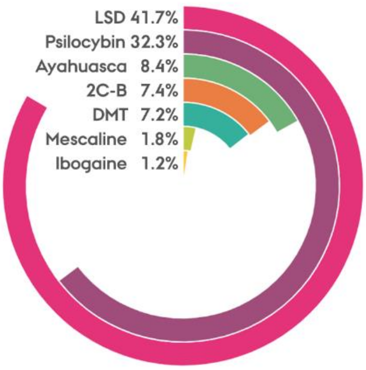


*Figure 1: Distribution of comments across drugs in the dataset.*

A python script iterated across every video of included playlists and pinged the API to extract the requested information. Specifically, video views, playlist views, the top 100 comments, and their likes were extracted. Comment replies were omitted, as they were deemed more prone towards irrelevant, niche discussions. Using this approach, 5,096,861 comments were acquired. However, as can be seen from figure 1, these were by no means equally distributed across the drugs under investigation.

Comments stemming from playlists aimed at unpopular or unspecified psychedelic drugs were removed, leaving a dataset of 4,000,854 comments. This dataset was then branched in two: for emoji analysis, only comments including emojis were included, leaving a dataset of 542,422 comments; for linguistic analysis, only English comments were included, leaving a dataset of 2,981,381 comments.

# Methods [ER]

To investigate the language usage surrounding the subcultures of psychedelic music, a somewhat branching approach was taken. A version of Term Frequency–Inverse Document Frequency (TF-IDF) was employed to assess the importance of specific words to each included drug, and what kind of information might stand out. Emojis were analysed separately, with the purpose of deciphering whether they carried any meaningful information, and the extent to which drugs differed in emoji-use. Lastly, a topic model was built, and the topic distributions used to train a classifier capable of predicting the drug associated with any given comment on such music playlists.

**Pre-processing [ER]**

Upon finishing the comment scraping, several pre-processing steps were needed before any modelling or investigation could occur (see figure 2).

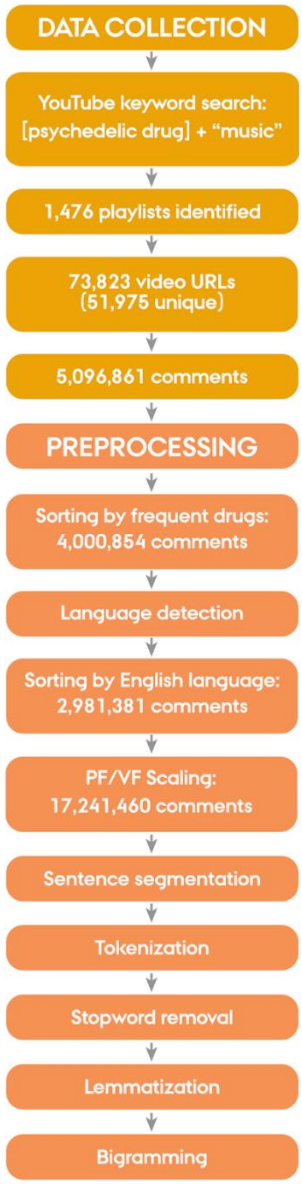

*Figure 2: Data collection and pre-processing workflow.*

As YouTube is a global entertainment service accessible to almost any nation, several languages can be present in the comment section of a video. However, it is beyond the scope of this project to assess language use surrounding psychedelic music experiences across numerous languages. As English comments were the most prevalent in the dataset, these were selected as our focus content.

To create this subset consisting exclusively of English comments, automatic language detection was employed. This was done using the *langdetect* python module (Danilak, 2020) which is a well performing, non-deterministic, Naïve Bayes language classifier that makes use of character n-grams and is trained on articles from Wikipedia.

Sentence segmentation and tokenization of comments was performed using the *utils* API from the python module *Gensim* (Řehůřek, 2009). A suitable set of English stopwords were imported from *The Natural Language Toolkit (nltk)*, but were expanded to include non-generic, YouTube-specific stopwords such as "*lyrics*", "*comments*", and "*video*" as these seemed to be ubiquitous across the comment sections of every drug under investigation and probably music videos on YouTube in general.

Subsequently, lemmatization of all tokens was performed using the *spaCy* python package (Honnibal & Montani, 2017). Importantly, we changed the default settings for allowed part-of-speech tags so as to keep tokens not recognized by the lemmatizer in the dataset unaltered rather than discarding them. This step later proved to increase the performance of the classifier. Bigram models were built by reutilizing *Gensim* and had a relatively low threshold parameter and word count for combining two words into a bigram.

**PF-VF-TF-IDF [ER]**

Traditionally, term frequency-inverse document frequency is a statistical measure that is used to assess the relevance of words to a document across a collection of documents (Aizawa, 2003). This approach was used to capture the relevance of specific keywords to the comments of drug-specific playlists. To achieve this, the tf-idf-vectorizer from Scikit-learn (Pedregosa et al., 2011) was applied to the pre-processed data.

Crucially, all comments from videos stemming from playlists dedicated to one type of drug was considered as one document. This means that the entire corpus consisted of seven documents, each containing all comments associated with a specific drug. This allowed for the inspection of the association between specific keywords and a drug relative to all other drug types.

One problem with using YouTube to acquire data aimed towards investigating drug-specific psychedelic subcultures, is that the videos in these playlists are not isolated to such subcultures. Very often, songs in these psychedelic playlists are also popular songs in other cultural contexts, such as generic pop songs listened to by millions of users with other purposes than those of psychedelic ventures. However, we cannot cleanly separate comments from these two use cases.

To solve this problem, we came up with *playlist frequency video frequency scaling*. Luckily, playlist views are recorded separately from video views. Playlists views of psychedelic videos in playlists reflect the proportion of viewers accessing the video from the communities we seek to investigate. Video views reflect all users accessing the video. This means that the comments of a video with a proportionally high amount of psychedelic playlist views relative to its general views are more likely to be interesting in our context (see figure 3).

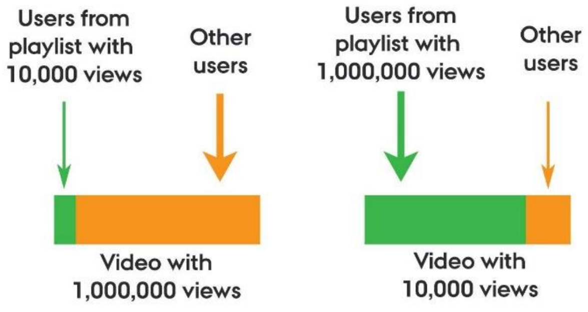


*Figure 3: An example of the proportion of playlist viewers in relation to the proportion of video viewers.*

Specifically, comments are assigned a weight $w_x$ according to the log scaled difference between playlist views and video views associated with their individual YouTube videos. This provides a scaled ratio which weighs comments based on the proportion of views that are relevant:

$$w_x = \log(playlist\ views) - \log(video\ views) = \log\left(\frac{playlist\ views}{video\ views}\right)$$

By combining tf-idf weights and pf-vf weights, the drug-specific relevance of keywords could be assessed directly and hopefully negate the noise of irrelevant comments.

**Word Clouds [LD]**

While deceivingly simple, graphical word clouds can provide a quick and intuitive overview of textual data. Using the *wordcloud* python package (Mueller, 2020), word clouds were therefore made for each of the seven drugs included in analysis. This was done on the pre-processed dataset after PF-VF scaling, resulting in a word cloud dataset of 17,241,460 comments. Using the *sklearn* python package (Pedregosa et al., 2011), TF-IDF analysis was used to find the most relevant words within each drug. Resulting scores for each word were then plotted as a word cloud, with word sizes reflecting their TF-IDF scores.

On initial inspection of the resulting word clouds, many similar words appeared relevant across several of the psychedelic drugs. To further illustrate individual differences, a secondary set of word clouds was created after subtracting the mean TF-IDF scores from all words, as this would cause words with high mean scores (and thus high importance across all drugs) to cancel each other out.

**Emojis [LD]**

In order to analyse the use of emojis across various drugs, comments containing emojis were extracted from the full dataset using the *emoji* python package (Kim & Wurster, 2020). Notably, this took place before language detection, as written language of the comment was deemed irrelevant in the context of emoji analysis. This resulted in a subset of data consisting of 2,625 unique emojis across 542,422 comments (3,197,258 comments after PF-VF scaling). To avoid the skewing of data from comments consisting of large amounts of repeating emojis, only unique emojis within a comment were considered.

Emojis were subsequently converted into Unicode characters, as this would allow us to analyse them as though they were words in a text corpus. Once again using the *sklearn* python package, TF-IDF analysis was then conducted to compare the importance of each emoji across drugs. Finally, emoji analysis data was transferred into the programming software R and plotted using the *circlize* package (Gu et al., 2014).

### Topic Modelling using Latent Dirichlet Allocation [ER]

The next step became building a topic model from the entire corpus of comments. To clarify: Not separate topic models for the comments of each drug under investigation, but rather one model covering all comments from all drugs.

Conceptually, all the comments from one video are considered as one document. For this purpose, Gensim's implementation of latent Dirichlet allocation was used. Such models are capable of extracting hidden topics from large volumes of text but depend on a fixed number of topics. However, there is no clear consensus on how the number of topics is best determined.

While it is easy to get swayed by a topic distribution that looks sensible, it rarely happens that eyeballing provides the best results. Others have successfully implemented coherence scores to inform their decisions around the optimal number of topics (Mimno et al., 2011). Considering this, a grid search was performed across models using topic numbers from 2-40 to optimize coherence. This analysis indicated that 8 would be an optimal number of topics. But optimal how?

The coherence score is an intrinsic measure of the topic model itself and does not equate efficiency or relate the model to its purpose in the real world. Because of this, it has been pointed out that the coherence score does not provide any guarantees regarding the ideal parameters for a model (Kelechava, 2019). It is a decent guideline if you have no prior knowledge to draw on, but it offers no guarantees.

With this in mind, we started tuning model parameters with reference to the classifier at the end of the pipeline. Every modelling decision regarding the topic model would be guided by whether it resulted in a higher accuracy of the classifier relying on that topic model. The topic model was trained on roughly 3 million comments with 8 topics, a chunk size of 100 over 10 passes. *Alpha* was set to auto and no minimum topic probability was applied. The results were visualized using a t-distributed stochastic neighbour embedding dimension reduction.

### Using Topic Distributions for Classification [ER]

The topic model allows us to generate a topic distribution associated with every comment. Comment *x* might be 25% topic 1, 25% topic 2, and 50% topic 8. This means that every comment can be represented as a vector, for which each input represents a topic and the extent to which that topic is represented in the comment relative to the other topics (Kelechava, 2019).

A classification algorithm can then be trained using these vectors. In this case, we are using the unsupervised learning of the topic model with the purpose of recovering latent semantic information to solve the supervised classification of specific drugs from individual comments. This process can be seen in figure 4.


*Figure 4: The process of using LDA topic probability distributions within every comment to train a drug classifier.*

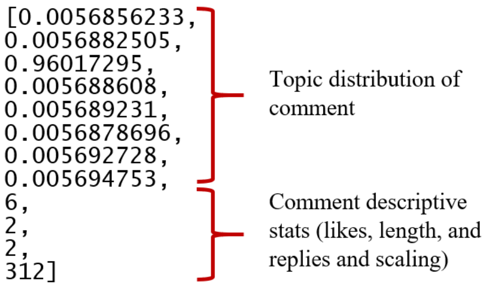


*Figure 5: Example of the vector representation of a comment. Inputs constitute both the probability distribution of topics and hand-engineered features.*

Some simple feature engineering allowed us to extend the 8th dimensional topic vector to also account for the length of the comment as well as its amount of likes and replies and its pf-vf-scale (see figure 5).

The classifier was trained using sklearn (Pedregosa et al., 2011). Influenced by similar work, we used both Logistic Regression, Stochastic Gradient Descent with Log Loss, and Stochastic Gradient Descent with Modified Huber loss (Kelechava, 2019). We also added a random forest classifier. Because of the imbalanced amounts of drug videos, undersampling was employed.

To evaluate performance, the f1-score was used averaged across a 5-fold cross validation. The classifier was also evaluated on a set of comments on which the topic model was not trained, to assess the extent to which the semantic information contained in the topic distribution generalizes. A principal component analysis of the pf-vf-tf-idf data for all drugs was used to locate problematic separation cases.

# Results

### Word Clouds [LD]

The two sets of word clouds produced show a wide range of words both common and unique across drugs (see figure 6). A visual inspection of the word clouds on the left quickly reveals multiple commonalities. The importance of words like *love, feel,* and *thank* show that emotions and feelings of gratitude are expressed across the music of all drugs. Cognition-related words like *know, think,* and *mind* similarly hint at shared feelings of insight, while *music* unsurprisingly appears to play a shared role as well. Meanwhile, only the drug ayahuasca appears to have multiple words uniquely standing out, including *ego*, *infinite*, *within*, and, perhaps unsurprisingly, *ayahuasca*.


*Figure 6: Word clouds showing the most important words for the music associated with each drug. On the left, words are based on TF-IDF scores. On the right, the mean TF-IDF scores of words across all drugs have been subtracted from each word to further highlight words uniquely popular within a given drug. Word size is directly proportional to its score.*

The mean-subtracted word clouds on the right make this picture much clearer. Ayahuasca and ibogaine appear highly similar with primarily spiritual and religious words. Mescaline stands out with a strong focus on emotional words and expressions of gratitude and beauty. LSD, while dominated by *think* and *know*, shows otherwise casual language related to people and music, a sentiment shared by psilocybin. 2C-B is uniquely focused on music, with words like *track*, *mix*, *house*, and *beat* hinting at electronic genres. Finally, DMT appears to be a mix of emotion and gratitude, while showing a range of words usually associated with new-age culture like *meditation*, *energy*, *frequency*, *dream*, and *vibration*.

## Emojis [LD]


*Figure 7: Top seven most frequent emojis within each drug. Scores are not shown, as the actual TF-IDF scores are meaningless outside comparison.*

Analysis of emoji use across drugs revealed an apparent split between drug groups (see figure 7). For ayahuasca, mescaline, and ibogaine, nearly all top emojis used were expressions of love, a feature partially shared with DMT. Across all four of these drugs, a symbol for prayer was found to be the most frequent.

Meanwhile, psilocybin, LSD, and 2C-B, while also including love-related emojis, heavily featured expressions of joy and excitement such as the fire-symbol, thumbs-up, and crying-with-laughter. Notably, the prayer-symbol found to be the most frequent in the other four drugs was not present in the top emoji use of these.

## Topic Model [ER]

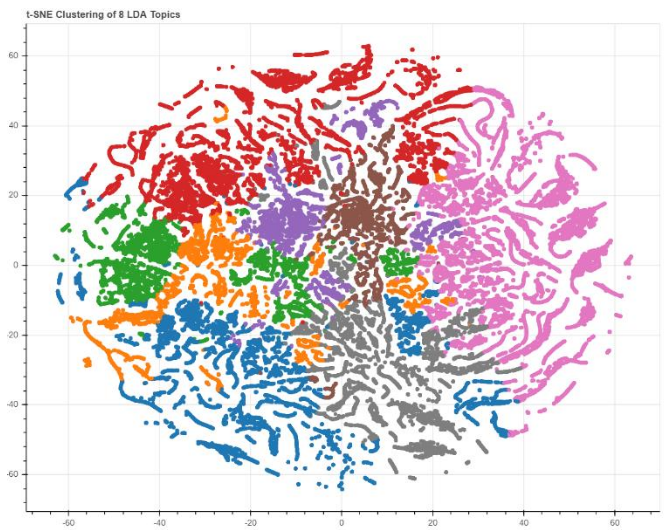


*Figure 7: t-SNE plot of the downsampled clustering of comments in 2D space, based on their dominant topic.*

The topic model had a perplexity of -8.25 and a coherence score of 0.61. The t-SNE plot in figure 7 shows the down-sampled clustering of comments in 2D space, based on their dominant topics.

Unlike principal component analysis for instance, distances and axis do not really convey meaning in the case of t-Distributed Stochastic Neighbour Embeddings. However, it illustrates that the topic model has achieved reasonable separation of its topics which are based on comparable amounts of documents. This is also reflected in the classifiers ability to accurately use topic distributions in comments to separate drugs as seen below.

**Classifier [ER]**

The results of the first iteration of using topic distributions from a topic model to classify drugs from comments can be seen in figure 8.

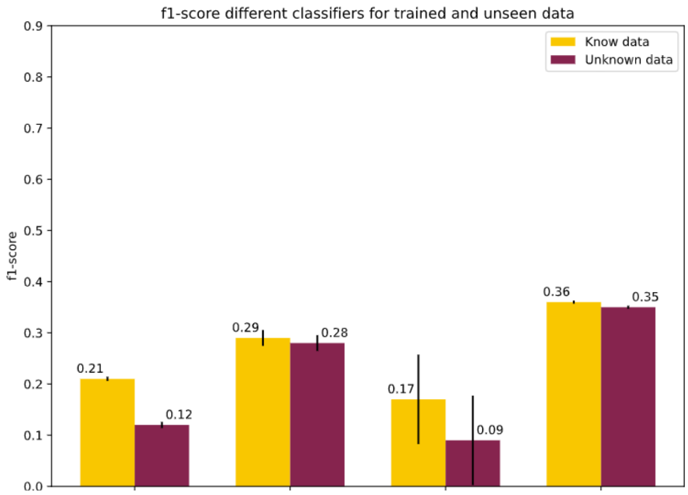


*Figure 8: Drug classification performance on known and unknown comments across Logistic Regression, Stochastic Gradient Descent with Log Loss, Stochastic Gradient Descent with Modified Huber loss, and random forest classifiers.*

As is evident, accuracy is disappointingly low which is reflected in the f1-scores. With 7 possible drug predictions, chance level is expected at 14% and only the log loss stochastic gradient descent and random forest models manage to reasonably exceed that level. These models also show to generalize reasonably well. Accuracy on unknown comments, that the topic model is not trained on, remains relatively robust. This is not the case for standard logistic regression and SGD with Huber loss.

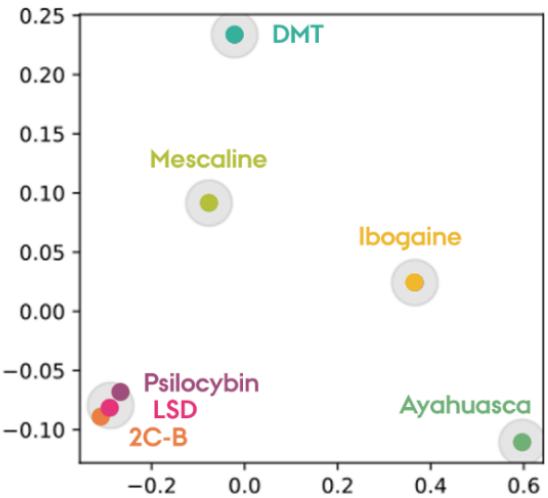


*Figure 9: PCA plot of PF-VF-TF-IDF vectors across drugs. K-means clustering shows overlapping clusters between psilocybin, LSD, and 2C-B.*

To locate the driving factors behind this poor classification accuracy, a principal component of the pf-vf-tf-idf keyword vectors was performed (see figure 9).

This dimensionality reduction revealed that the drugs *psilocybin*, *LSD*, and *2C-B* share very similar features in vector space and are hard to distinguish based on their keyword relevance compared to the other drugs. This close similarity is likely also represented in the topic distribution of the comments and cause the poor accuracy.

With this in mind, a second iteration of the classifier was run to classify drug clusters instead. The model did not have to classify those 3 problematic drugs specifically, but rather their cluster, i.e. whether a comment belonged to any of those 3 drugs.

This step improved accuracy immensely for all four classifiers (see figure 10). Moreover, the ability to generalize to unknown comments is now present in all but the standard logistic regression classifier. Admittedly, the chance level is similarly higher at 20% as the list of possible predictions is diminished. The random forest model scantily comes out on top.


*Figure 10: Drug cluster classification performance on known and unknown comments. Psilocybin, LSD, and 2C-B are considered as one shared cluster, while all other drugs are considered separately.*

# Discussion [LD]

Results from both qualitative and quantitative analysis reveal clear differences in drug use between the music associated with various psychedelic drugs. These findings appear to lean heavily into previously outlined differences between patterns of use as well as cultural differences.

Qualitative assessment of word clouds paints a picture of spiritual, religious, and introspective language use primarily associated with ayahuasca, ibogaine, and mescaline, reflecting both their historic roots in shamanism and current role as tools of healing and introspection. To some extent, DMT shows similarities with these, but is mainly coloured by words associated with new-age and meditative practices.

Meanwhile, psilocybin, LSD, and 2C-B appear to share language relating to a social and musical experience, along with expressions of joy and surprise. Here, 2C-B appears to occupy one end of the spectrum, as language primarily focused on club and dance music appears to hint at its cultural ties to recreational use in the party scene. LSD occupies the other end, with more introspective expressions related to thought and people revealing similar qualitative hints at its historical role in the counter-cultural movement. Finally, psilocybin gives the impression of a middle ground between the two, as *school*, *kid*, *young*, and *play* appear to allude to feelings of melancholy, or potentially recreational use in a younger generation.

### Room for improvement [ER]

The classification improvement achieved by clustering the three drugs *psilocybin*, *LSD*, and *2C-B* as well as the results of the PCA clearly illustrates that the language use of their communities is strikingly similar. While the best performance achieved of .76 accuracy in classifying drugs is not perfect, it does demonstrate that the topic distribution of comments *can* be used to distinguish comments stemming from different psychedelic drug playlists.

That being said, steps could be taken to improve both topic model and classifier performance. One possibility is offered by (Kelechava, 2019) who similarly tried to classify and predict sentiment of Yelp reviews using a topic model. Here classification was improved by filtering out both the most common and the rarest words. Moreover, other topic model frameworks have also proven to provide better topics. For instance, the MALLET implementation of the LDA algorithm (McCallum, 2002; Prabhakaran, 2020) has been demonstrated to achieve higher quality of topics.

Lastly, guided LDA might be implemented to further improve topic model results and therefore classification accuracy. This entails seeding specific keywords to the topic model around which topics are created (Li, Chen, Xing, Sun, & Ma, 2018). Specifically, the comments stemming from the three drugs that are hard to separate might benefit from a seeding process targeted specifically towards making that separation. Doing exactly this was demonstrated by (Singh, 2017) who managed to deploy such semi-supervised guided LDA to separate merged topics that would be entangled in the standard unsupervised LDA.

**Potential Applications in Therapy [LD]**

While the findings of this paper may appear to merely satisfy curious minds, they could potentially also help heal troubled ones. One possible direction could be the application of classification algorithms, such as the ones discussed in this paper, in selecting or verifying music suitable for various types of therapy. For although music is considered a central component of ongoing psychedelic therapy frameworks, no standardization or official guidelines for music selection in such therapy currently exists (Barrett et al., 2017).

Meanwhile, recent studies have shown that so-called mystical-type experiences are strong predictors of psychedelic treatment outcomes (Griffiths et al., 2016; Johnson et al., 2017; Ross et al., 2016), leading researchers to call for ways to enhance these experiences in patients (Roseman et al., 2018). Since music has been shown to modulate such mystical-type experiences (Kaelen et al., 2018), using our data to help identify relevant music by the language used to discuss it could therefore prove particularly relevant.

# Conclusion [LD & ER]

Analysis of YouTube commentary across music targeted at various psychedelic drug experiences revealed multiple commonalities and differences between drugs. We found that words related to gratitude, joy, and love were common across all drugs. Qualitative inspection of word clouds and emoji use revealed an apparent semantic split between groups of drugs, with ayahuasca, ibogaine, mescaline, and DMT sharing mainly expressions of spiritualism, religion, and introspection, while LSD, 2C-B, and psilocybin were generally aimed towards expression of joy, music, and people. Topic modelling and classification tools confirmed this apparent split, placing LSD, 2C-B, and psilocybin in an overlapping group, and the remaining drugs in individual groups.

Our findings largely mirror recreational versus therapeutic patterns of use as well as cultural and historical differences between drugs. In addition to shedding light on these differences, we believe that findings such as these could potentially aid current efforts within psychedelic therapy by using the language of public discourse to identify music particularly suited for improving patient outcomes during treatment.

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