WiSSAP 2023

Exploring the human musical experience in the age of Big Data and Technology

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MUSIC COGNITION GROUP

IIIT Hyderabad

Research Focus: The Music Cognition Group is an interdisciplinary group focused on researching music and its multifaceted forms and representations. This includes the related fields of music cognition, music information retrieval, neuroscience, natural language processing, music generation, among others.

Movement

- identify universal grammar in music-induced movement
- predicting interaction from dancing dyads
- predicting individual traits from music-induced movement

Social Media

- analysing online discourse on musical experiences and associations
- online music sharing vs private streaming
- music sharing during social movements

Lyrics

- emotion prediction and topic modelling from lyrics using NLP
- lyrical structural analyses
- associating lyrical preferences with individual differences

Soundtrack Generation for Books

- automatic retrieval of soundtracks for books with movie adaptations
- automatic generation of soundtracks for books

Health and Well-being

- predicting risk for depression via music listening habits via digital traces in online music listening platforms
- autism and music preferences

Perception

- cross-cultural studies on music perception and related emotions
- role of music as a social surrogate
- musical aptitude: testing different demographics

Neuroscience

- analysing individual differences that modulate brain responses to music
- decoding brain states using functional MRI
- multimodal fusion of structural and functional MRI

Representation

- analysing music representations generated via deep learning
- analysing multimodal representations of music & lyrics

Publications

Peer-reviewed Journal Articles and Conference Proceedings	21
Conference presentations	26
Books & Book chapters	3
Awards (+Nominations), Travel Grants, Scholarships	4 (+3)

Personnel

Position	Present (+Past)
Post-Doc	1
PhD	1 (+1)
Dual Degree + MS by Research	21 (+6)

Collaborations

International (6) National (4)

Funding

Total (~1cr 9lacs)

- My Music and I: Mining Mental States and Traits Via Music Listening
- Music & Social Media: Characterizing Well-being of Indian Citizens during the Pandemic
- Music, Brain, and Culture: Modelling Implicit Musical Knowledge with Deep Neural Networks

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Department of Science & Technology, Government of India

My Music and I: Mining Mental States and Traits Via Music Listening

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Music & Social Media: Characterizing Well-being of Indian Citizens during the Pandemic

SERB INDIA

Music, Brain, and Culture: Modelling Implicit Musical Knowledge with Deep Neural Networks

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SERB INDIA

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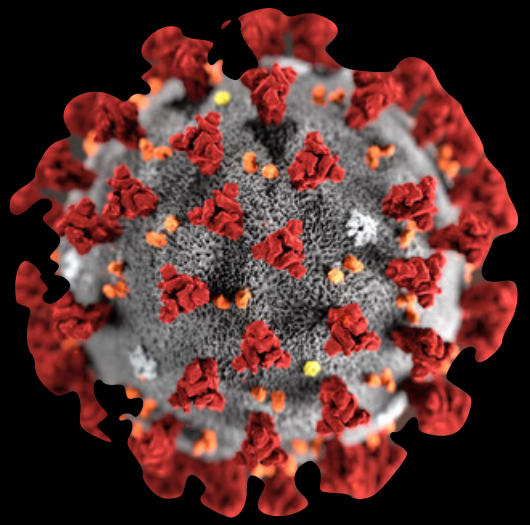
Department of Science & Technology, Government of India

Musical experience & Technology



Big (Music) Data

Big Data

- massive amounts (terabytes or petabytes), generated from various sources (social media, sensors, online music listening platforms, and more)

Big Data

VOLUME | VARIETY | VELOCITY

- massive amounts (terabytes or petabytes), generated from various sources (social media, sensors, online music listening platforms, and more)
- diverse data via several platforms

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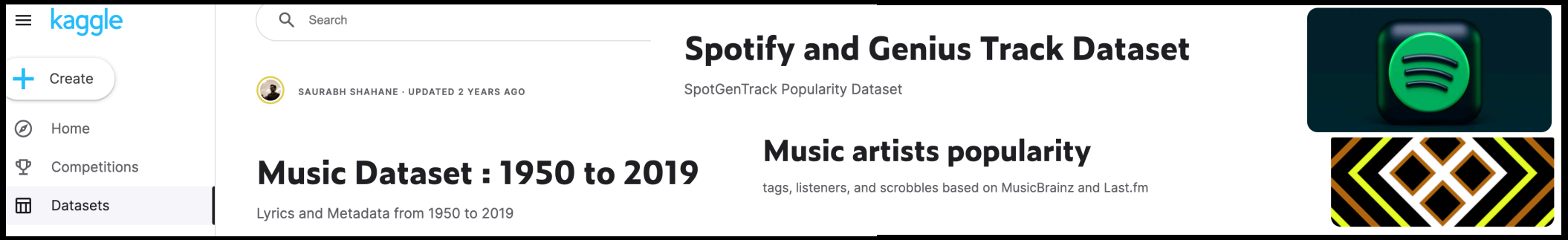
- diverse data via several platforms
  - structured data (e.g., traditional databases)



Big Data

VOLUME | VARIETY | VELOCITY

- massive amounts (terabytes or petabytes), generated from various sources (social media, sensors, online music listening platforms, and more)
- diverse data via several platforms
  - structured data (e.g., traditional databases)
  - semi-structured data (e.g., XML, JSON)


```
{
  ▸ external_urls: {…},
  ▸ followers: {…},
  ▾ genres: [
        "british blues",
        "classic rock"
    ],
    id: "22bE4uQ6baNwSHPVcDxLCe",
  ▸ images: […],
    name: "The Rolling Stones",
    popularity: 77,
    type: "artist",
    uri: "spotify:artist:22bE4uQ6baNwSHPVcDxLCe"
}
```

Big Data

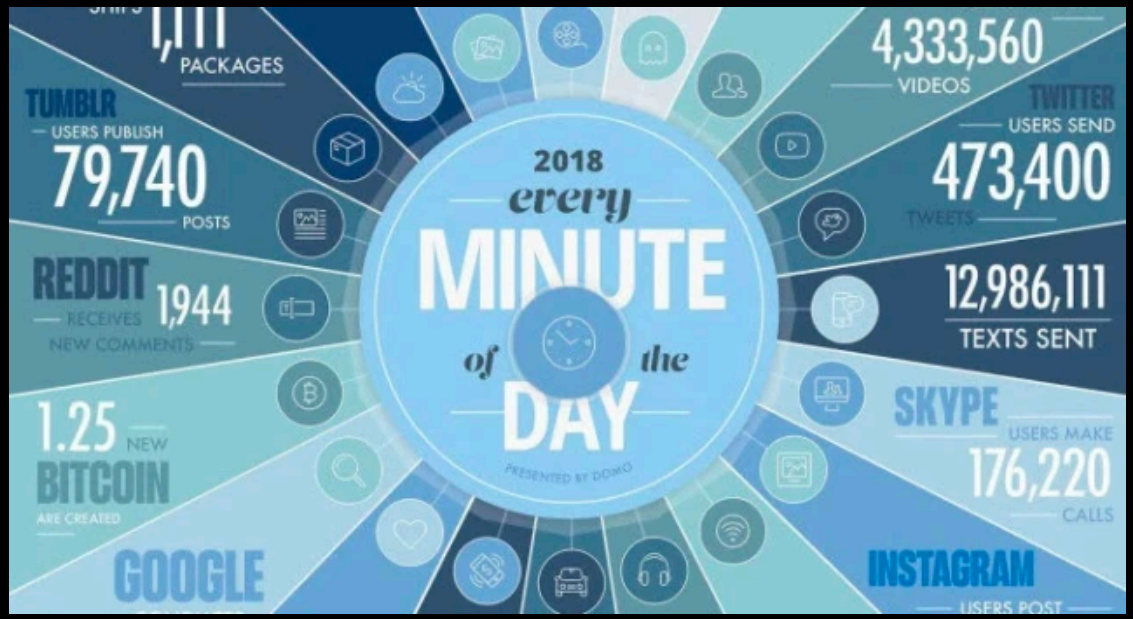
VOLUME | VARIETY | VELOCITY

- massive amounts (terabytes or petabytes), gener
  various sources (social media, sensors, online mu
  listening platforms,
- diverse dat
  - structurec
  - semi-struc
  - unstructured data (e.g., social media posts: text, images, videos)

Big Data

VOLUME VARIETY VELOCITY

- rapid content generation



Big Data

VOLUME VARIETY VELOCITY

- require advanced tools, technologies, and algorithms to extract, store, process, visualize, and analyze the data

- uncover patterns, trends, correlations, and insights that were previously difficult to obtain (at large-scale)

Big Data: What questions can you ask?

social/public

online discourse

personal/private

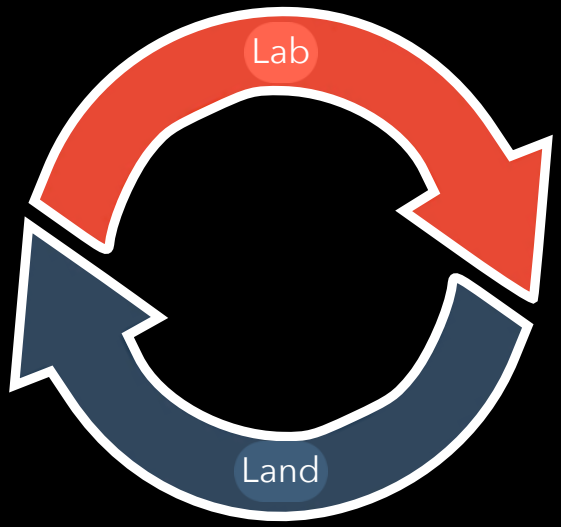
online streaming

–> each platform can address different questions

–> rephrase questions according to the platform

Example: One (question) to many platforms

unhealthy music listening strategies associated with depression risk



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Saarikallio S, Gold C, Mcferran K. 2015. Development and validation of the Healthy-Unhealthy Music Scale. Child Adolesc Ment Health. 20:210–217.

unhealthy music listening strategies associated with depression risk

Healthy-Unhealthy Music Scale

"an instrument to detect a risk for depression and potentially other mental health problems in a nonintrusive way"

Saarikallio S, Gold C, Mcferran K. 2015. Development and validation of the Healthy-Unhealthy Music Scale. Child Adolesc Ment Health. 20:210–217.

Healthy-Unhealthy Music Scale

		Never	Rarely	Some-times	Often	Always
1.	When I listen to music I get stuck in bad memories	☐	☐	☐	☐	☐
2.	I hide in my music because nobody understands me, and it blocks people out	☐	☐	☐	☐	☐
3.	Music helps me to relax	☐	☐	☐	☐	☐
4.	When I try to use music to feel better I actually end up feeling worse	☐	☐	☐	☐	☐
5.	I feel happier after playing or listening to music	☐	☐	☐	☐	☐
6.	Music gives me the energy to get going	☐	☐	☐	☐	☐
7.	I like to listen to songs over and over even though it makes me feel worse	☐	☐	☐	☐	☐
8.	Music makes me feel bad about who I am	☐	☐	☐	☐	☐
9.	Music helps me to connect with other people who are like me	☐	☐	☐	☐	☐
10.	Music gives me an excuse not to face up to the real world	☐	☐	☐	☐	☐
11.	It can be hard to stop listening to music that connects me to bad memories	☐	☐	☐	☐	☐
12.	Music leads me to do things I shouldn't do	☐	☐	☐	☐	☐
13.	When I'm feeling tense or tired in my body music helps me to relax	☐	☐	☐	☐	☐

Scoring instruction: HUMS Healthy: 3, 5, 6, 9, 13; HUMS Unhealthy: 1, 2, 4, 7, 8, 10, 11, 12. Answers are scored on a scale from 1 (never) to 5 (always).

Healthy Score

Unhealthy Score

Saarikallio S, Gold C, Mcferran K. 2015. Development and validation of the Healthy-Unhealthy Music Scale. Child Adolesc Ment Health. 20:210–217.

Healthy-Unhealthy Music Scale

"Music helps me relax"

"I feel happier after playing or listening to music"

"Music helps me connect with other people who are like me"

Saarikallio S, Gold C, Mcferran K. 2015. Development and validation of the Healthy-Unhealthy Music Scale. Child Adolesc Ment Health. 20:210–217.

Healthy-Unhealthy Music Scale

"I hide in my music because nobody understands me, and it blocks people out"

avoidance

rumination

"I like to listen to songs over and over even though it makes me feel worse"

"It can be hard to stop listening to music that connects me to bad memories"

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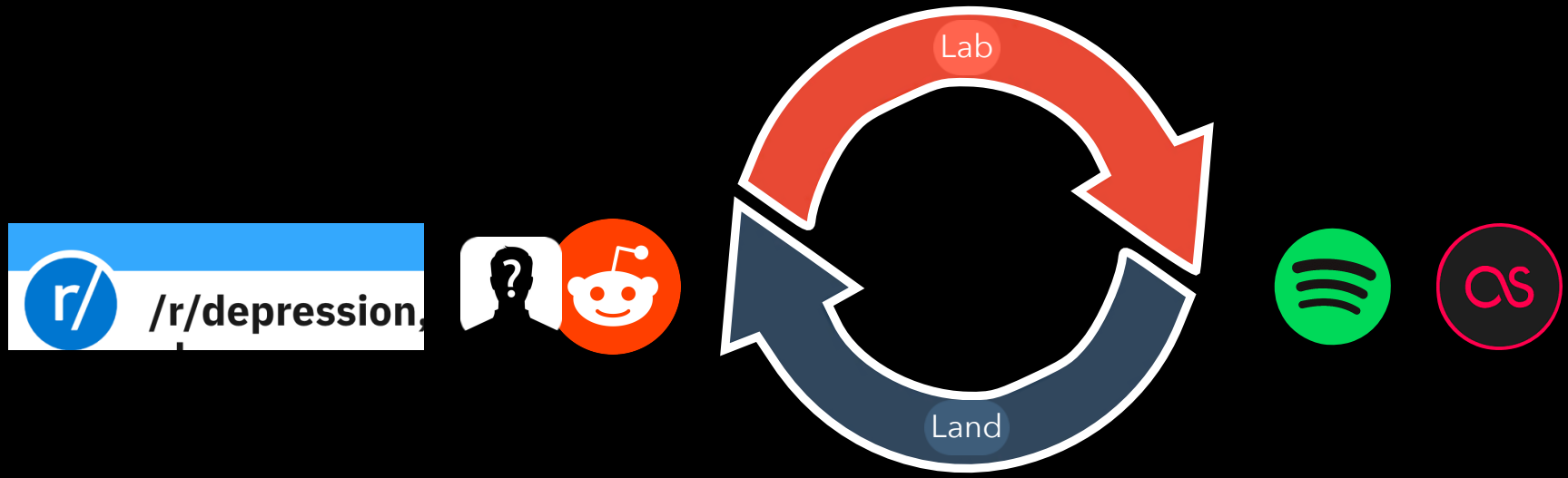
Example: One (question) to many platforms

unhealthy music listening strategies associated with depression risk

validity in naturalistic settings?

Example: One (question) to many platforms

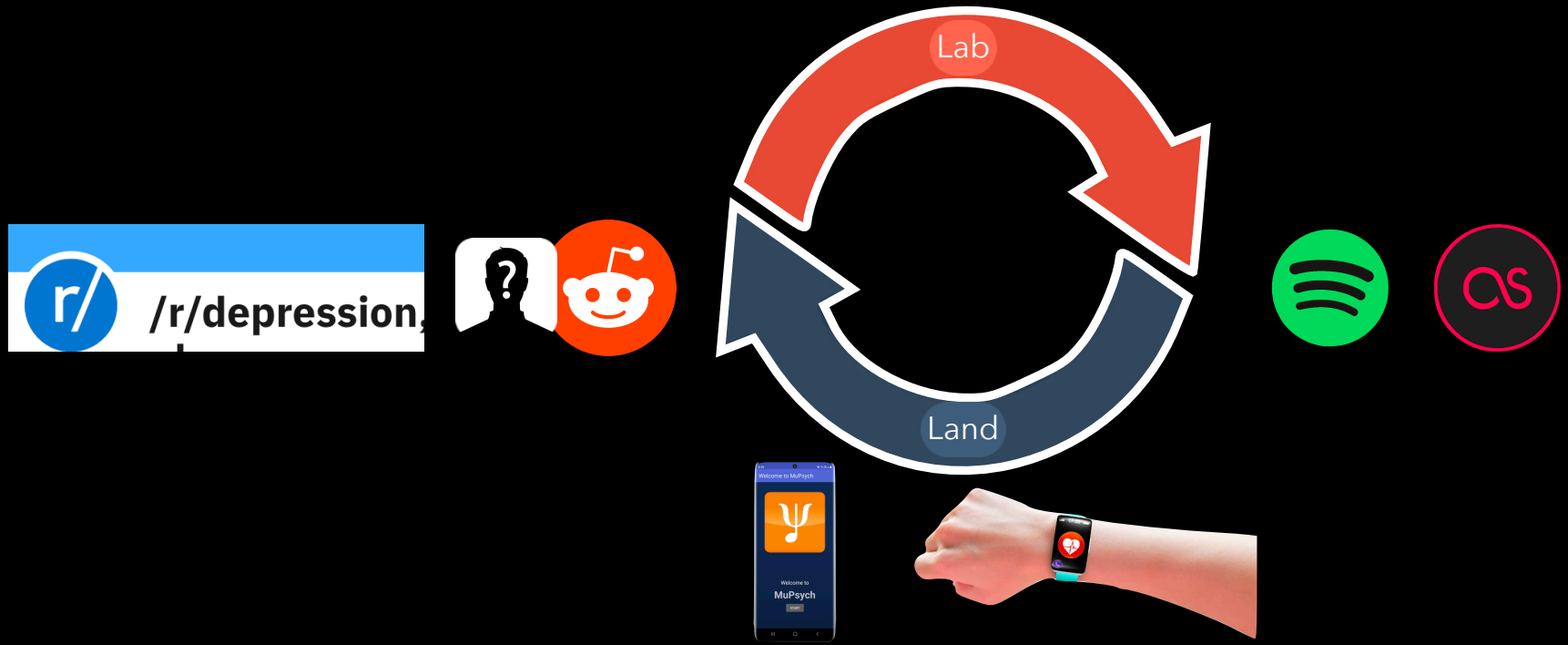
unhealthy music listening strategies associated with depression risk



what kind of music? how?

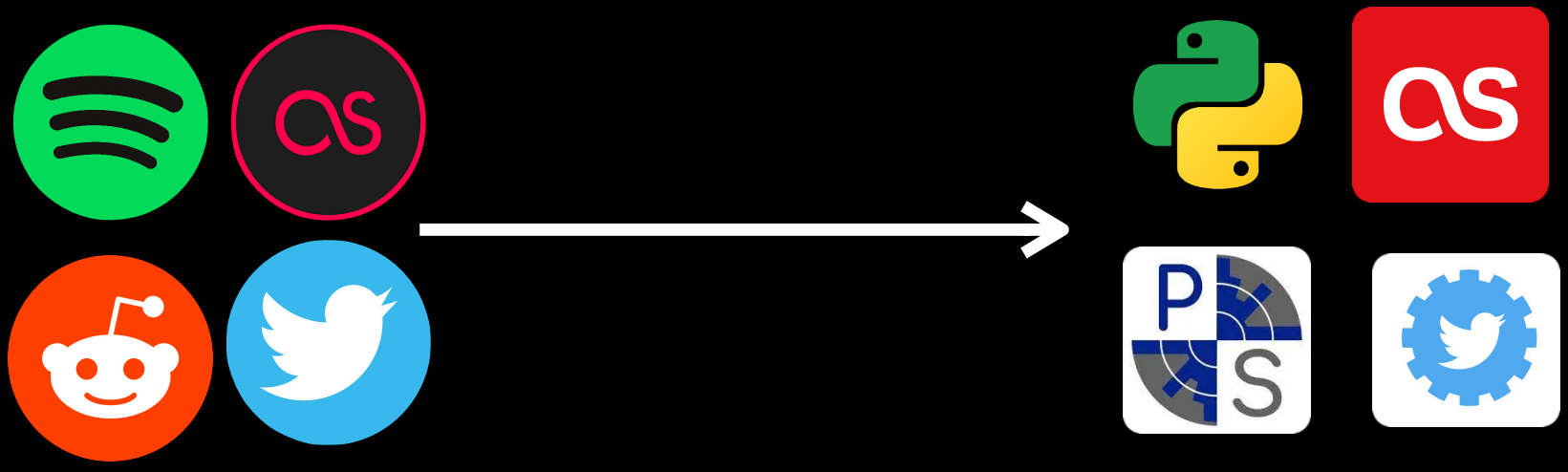
Example: One (question) to many platforms

unhealthy music listening strategies associated with depression risk



how does one feel while listening to music maladaptively?

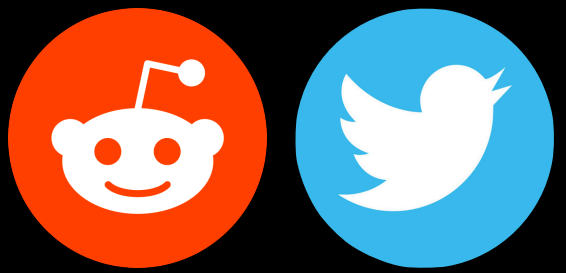
Big Data Extraction



Application Program Interfaces
(API)

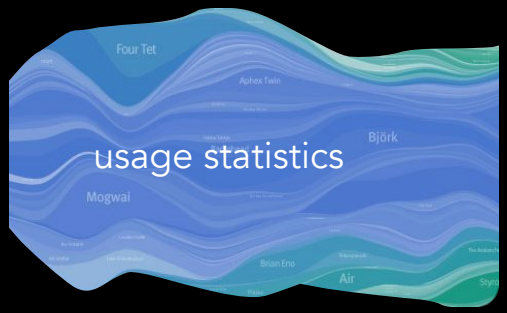
Characterising Big Music Data

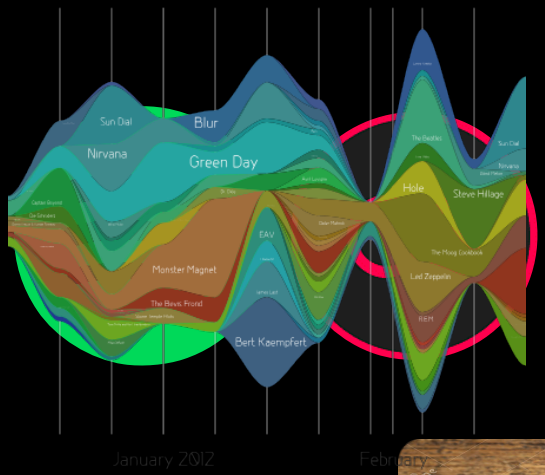
Streaming Platforms

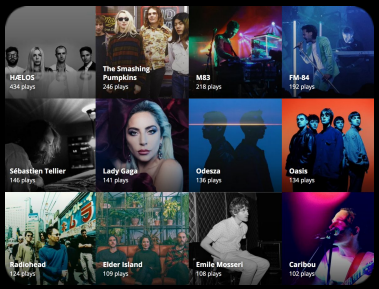


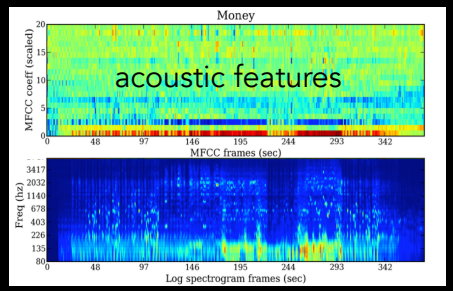
Social Media

Characterising Big Music Data: **Streaming Platforms**

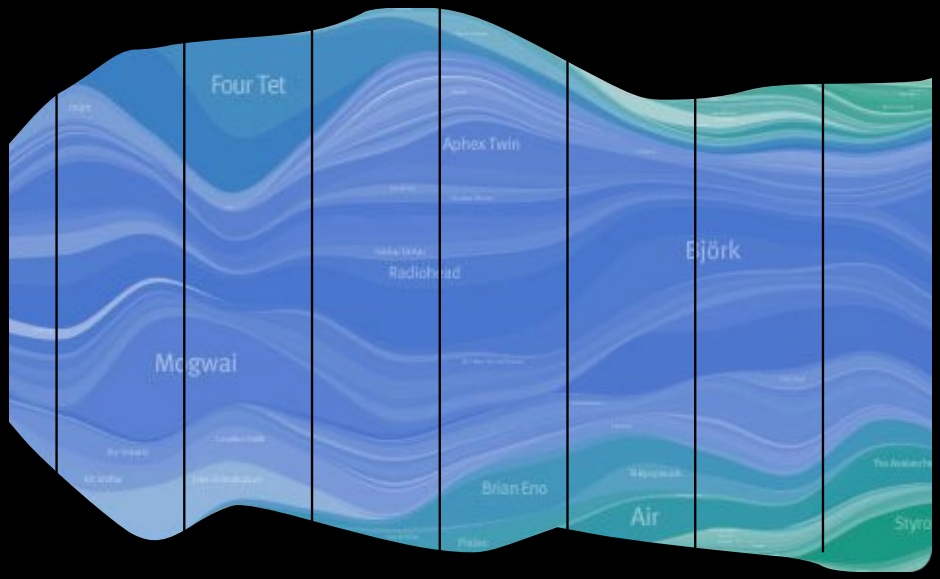








Characterising Big Music Data: **Usage Statistics**

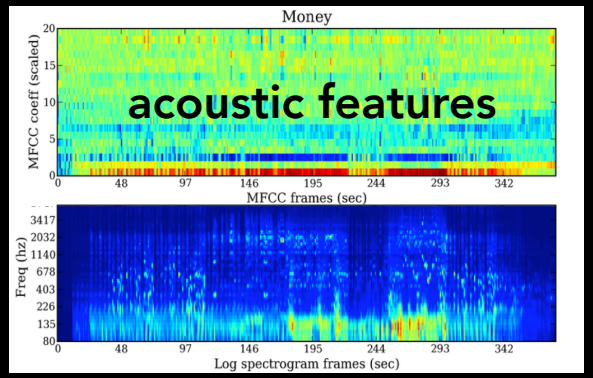


static vs dynamic

total playcount
repetitiveness index
exploration scores (artist diversity)

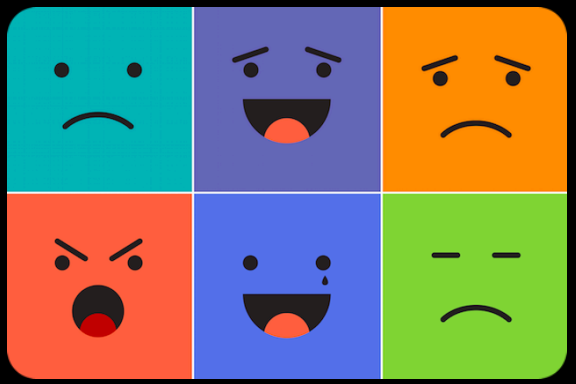
inertia & variability of
features session-wise

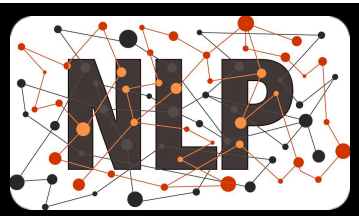
Characterising Big Music Data: **Acoustic Features**



#OVERUSED

name	Description
acousticness	The track is acoustic. From 0 to 1
danceability	The track encourages (or is adequate for) dancing. From 0 to 1
duration_ms	Duration in milliseconds
energy	The track is perceived as energetic. From 0 to 1
instrumentalness	The track is instrumental. From 0 to 1
key	Key categories encoded as integers. From C (0) to 11
liveness	The audience is audible. From 0 to 1
loudness	In decibels. From -60 to 0
mode	Major (1) or minor (0)
speechiness	Does the track contain speeches? From 0 to 1
tempo	In beats per minute (BPM)
valence	How happy is the track (BPM).

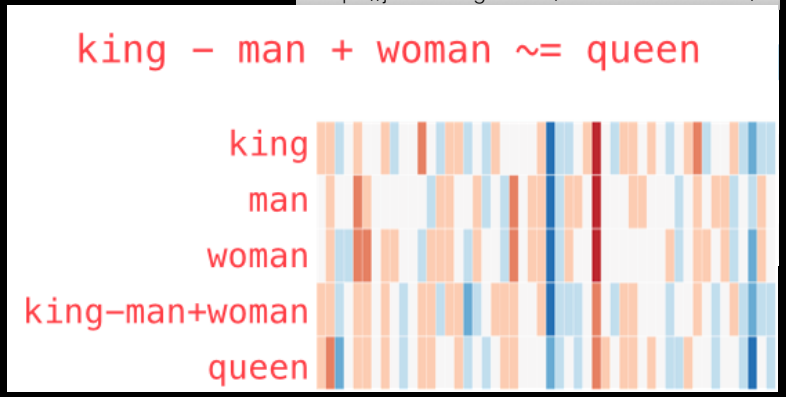


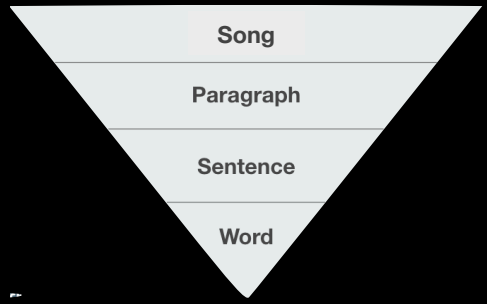


Characterising Big Music Data: **Lyrics+Tags**

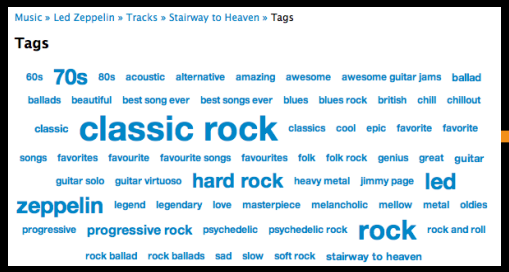
- **embeddings**:
  - a numerical representation of words or sentences in an n-dimensional continuous vector space
  - goal of word embeddings is to capture the semantic and syntactic relationships between words
  - similar words are closer together in the vector space

https://jalammar.github.io/illustrated-word2vec/





Characterising Big Music Data: **Tags**



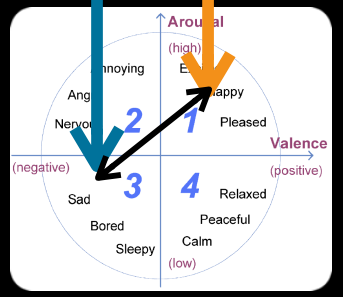
Parts-**O**f-**S**peech

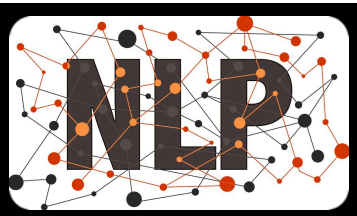
adjectives, adverbs embeddings

Word Emotion Induction Model

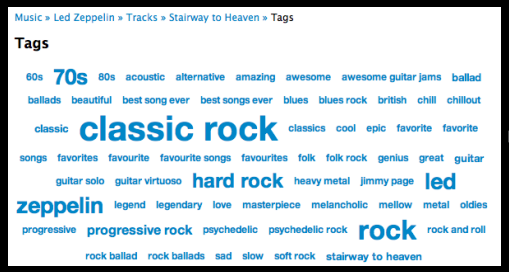
Word	Valence	Arousal	Dominance
sunshine	8.1	5.3	5.4
terrorism	1.6	7.4	2.7
orgasm	8.0	7.2	5.8

Table 2: Three sample entries from Warriner et al. (2013). They use 9-point scales ranging from 1 (most negative/calm/submissive) to 9 (most positive/excited/dominant).



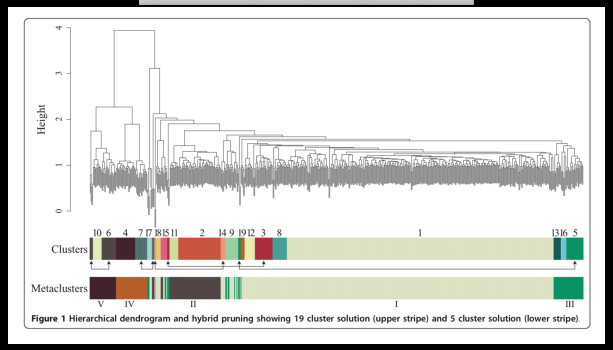


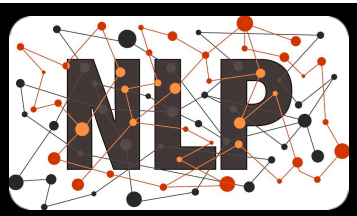
Characterising Big Music Data: **Tags**



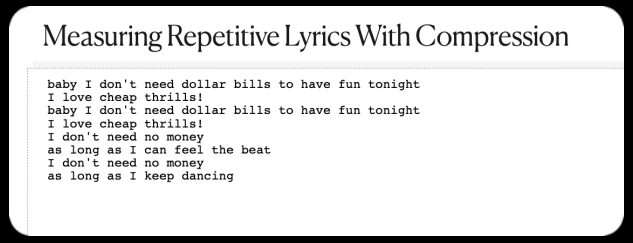
genres to

super genres

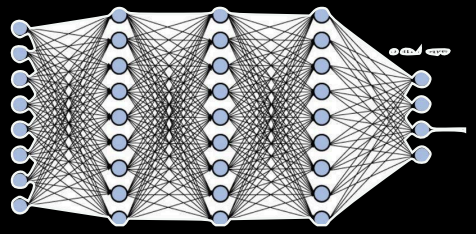




Characterising Big Music Data: **Lyrics**



repetition, information content, SMOG

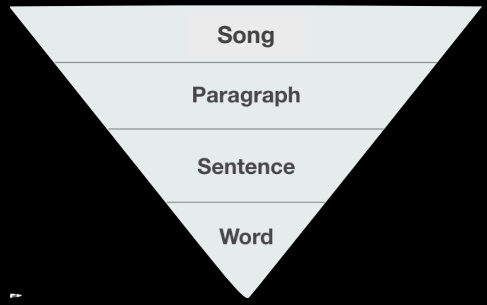


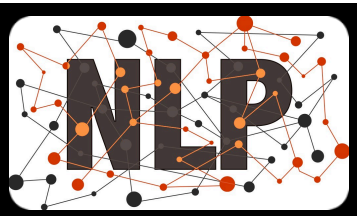
emotion (models), sentiment, themes

topic modelling

DICTION

limited (~40)





Characterising Big Music Data: **Lyrics**

God is up to something.
God is up to something.

God is up to something.
God is up to something,
So get ready,
Get ready for your miracle.

God is up to something.
God is up to something.

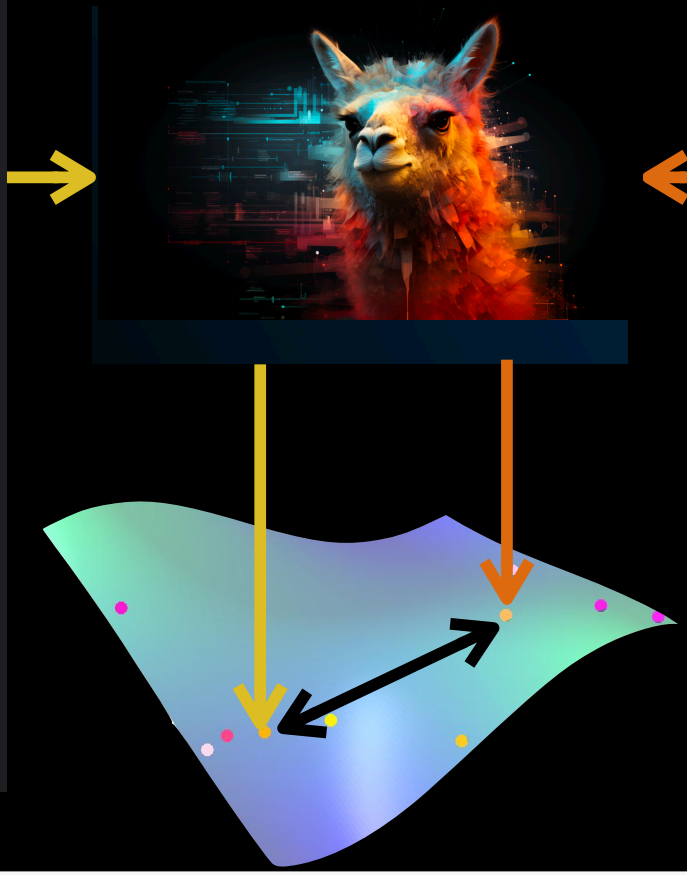
God is up to something.
God is up to something,
Get ready, get ready for your miracle.

Eyes have not seen, ears have not heard
All of the wonderful things that God has in store,
So get ready, get ready for your miracle.

It's on the way,
It's on the way,
It's on the way,
It's on the way.

It's on the way,
It's on the way,
It's on the way...

Your miracle is on the way.



ex: hopelessness

Beck Hopelessness Scale

Instructions: The Beck Hopelessness Scale is a self-report scale that was made to assess and measure the level of hopelessness that you're feeling. Please answer each question by selecting TRUE or FALSE based on how you've been feeling for the past week prior to answering this assessment, including today.

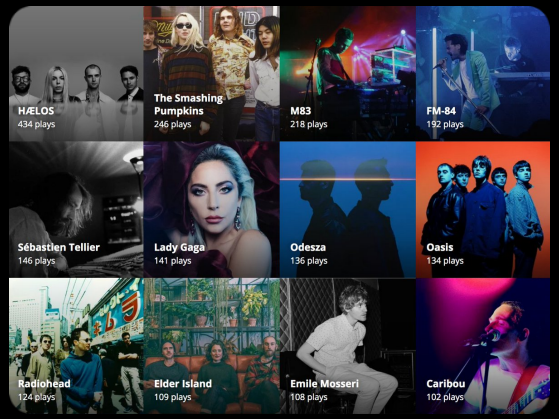
Statement	True	False
1. I look forward to the future with hope and enthusiasm	○	◉
2. I might as well give up because I can't make things better for myself	○	◉
3. When things are going badly, I am helped by knowing they can't stay that way forever	◉	○
4. I can't imagine what my life would be like in 10 years	◉	○
5. I have enough time to accomplish the things I most want to do	◉	○
6. In the future, I expect to succeed in what concerns me most	◉	○
7. My future seems dark to me	○	◉
8. I expect to get more good things in life than the average person	○	◉
9. I just don't get the breaks, and there's no reason to believe I will in the future	○	◉
10. My past experiences have prepared me well for the future	○	◉
11. All I can see ahead of me is unpleasantness rather than pleasantness	○	◉
12. I don't expect to get what I really want	◉	○
13. When I look ahead to the future, I expect I will be happier than I am now	○	◉
14. Things just won't work out the way I want them to	◉	○
15. I have great faith in the future	○	◉
16. I never get what I want so it's foolish to want anything	○	◉
17. It is very unlikely that I will get any real satisfaction in the future	○	◉
18. The future seems vague and uncertain to me	◉	○
19. I can look forward to more good times than bad times	◉	○
20. There's no use in really trying to get something I want because I probably won't get it	○	◉

*to be written by your psychologist/therapist **Hopelessness score:** 9

Beck, Aaron T. BHS, Beck Hopelessness Scale. San Antonio, Tex. : New York :Psychological Corp. ; Harcourt Brace Jovanovich, 1988.

Chaudhuri, S., Agarwala, J., Alluri, V. (2023). Organization and retrieval of songs using the CHIME framework

Characterising Big Music Data: **Artist**



Dua Lipa (/ˈduːə ˈliːpə/ (listen) *DOO-ə LEE-pə*, Albanian: [ˈdua ˈlipa]; born 22 August 1995) is an English and Albanian[3][1] singer and songwriter. Her mezzo-soprano vocal range and disco-influenced production have received critical acclaim and media coverage. She has received numerous accolades throughout her career, including six Brit Awards, three Grammy Awards, two MTV Europe Music Awards, an MTV Video Music Award, two *Billboard* Music Awards, an American Music Award, and two *Guinness World Records*. She was included on the *Time* 100 Next list in 2021.

After working as a model, Lipa signed a recording contract with Warner Bros. Records in 2014. She rose to prominence with her 2017 self-titled debut album, which peaked at number three on the UK Albums Chart and spawned the successful singles "Be the One", "IDGAF", and the UK number-one single "New Rules". Lipa was honoured with the Brit Awards for British Female Solo Artist and British Breakthrough Act. Her second chart-topping single, "One Kiss" with Calvin Harris, was the longest-running number-one single by a female artist in 2018 and won the Brit Award for Song of the Year. In 2019, Lipa won the Grammy Award for Best New Artist, as well as the Grammy Award for Best Dance/Electronic Recording for "Electricity", her collaborative single with Silk City.

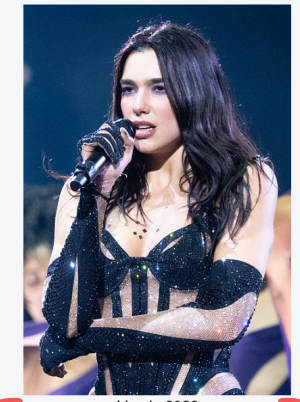
Lipa's second album, *Future Nostalgia* (2020), was met with critical acclaim and became her first UK number-one album. Its lead single, "Don't Start Now", was the year's most commercially successful song by a female artist in the US; ranking in the top-ten of the *Billboard* Hot 100 year-end chart. Its follow-up singles, "Physical", "Break My Heart", and "Levitating", were also commercially successful; with the latter song topping the Hot 100's year-end chart in 2021. *Future Nostalgia* received the Brit Award for British Album of the Year and the Grammy Award for Best Pop Vocal Album. Both of Lipa's albums are the most-streamed female albums on Spotify, with over 10 billion streams each.

Early life

Dua Lipa was born in London,[4] the eldest child of Kosovo Albanian paren and Dukagjin Lipa from Pristina, FR Yugoslavia (present-day Kosovo).[5][6] Her fa hrough her maternal grandmother, she is of Bosniak descent.[8][9][10]

Her ancestry can also be traced back to the city of Peja, Kosovo. Both of h gr historians.[11] She has a sister named Rina and a brother named Gjin.[7][12][13] Lipa was m isi ec by her father,[14][15][16] who was the lead singer and guitarist of the Kosovan rock bun [3] Her father continued to play music at home, including his own compositions and songs of s s David Bowie, Bob Dylan, Radiohead, Sting, the Police and Stereophonics.[15][16][19] Lipa star the age of five.[20]

Dua Lipa



Lipa in 2022

Born	22 August 1995 (age 27) London, England
Citizenship	United Kingdom · Albania[1]
Education	Parliament Hill School
Occupations	Singer · songwriter · model
Years active	2014–present
Works	Discography · songs recorded
Political party	Labour[2]
Awards	Full list
Musical career	
Genres	Pop · disco · house · R&B
Instrument(s)	Vocals
Labels	Warner · Urban
Website	dualipa.com

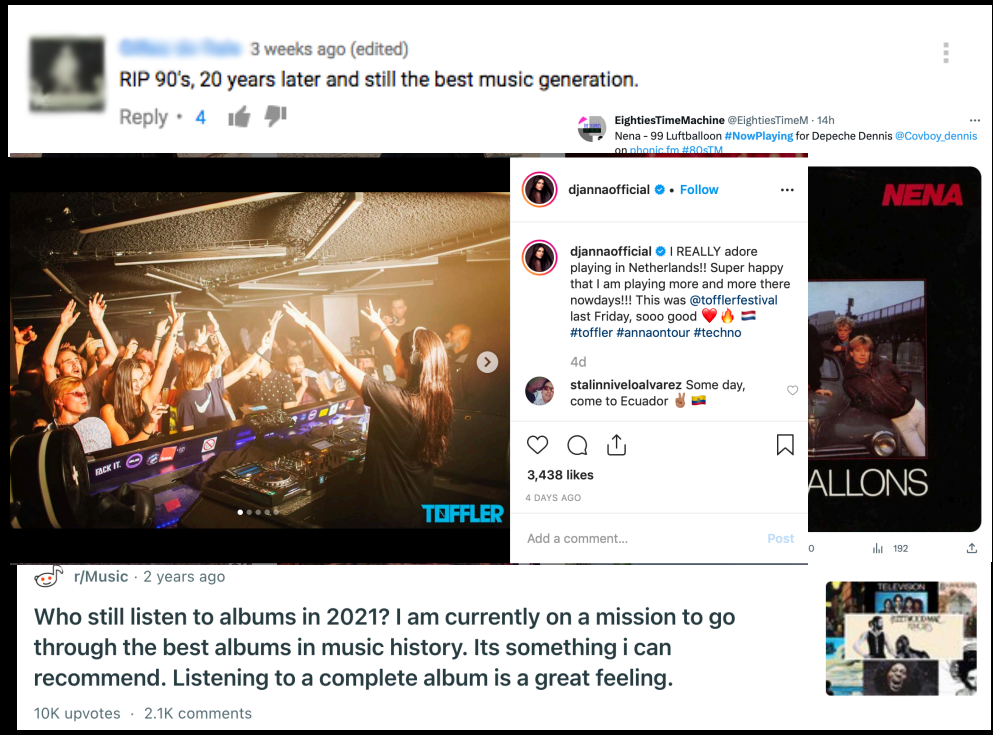
Signature

Characterising Big Music Data

Streaming Platforms

Social Media

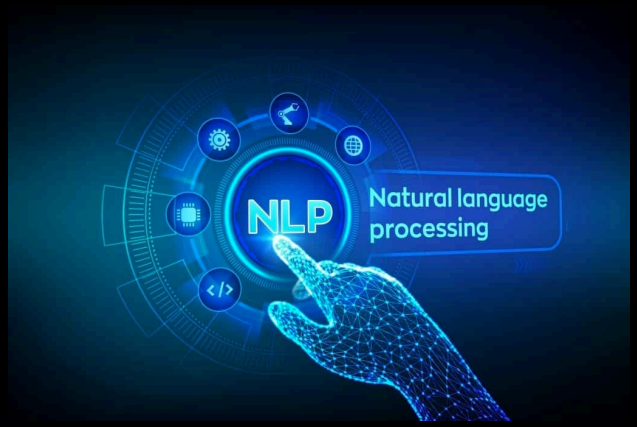
Characterising Big Music Data: **Social Media**



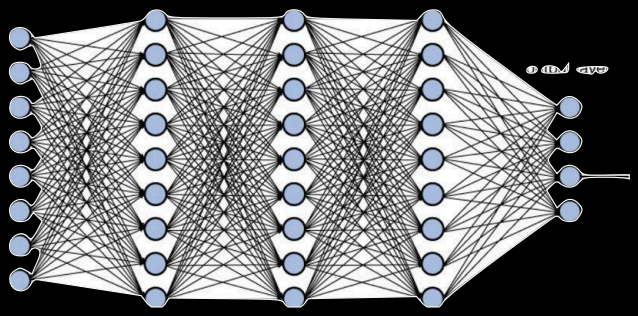
unstructured data

Big Data: Social Media

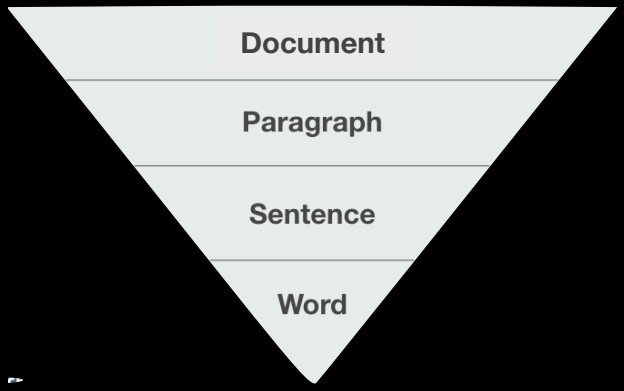
summary



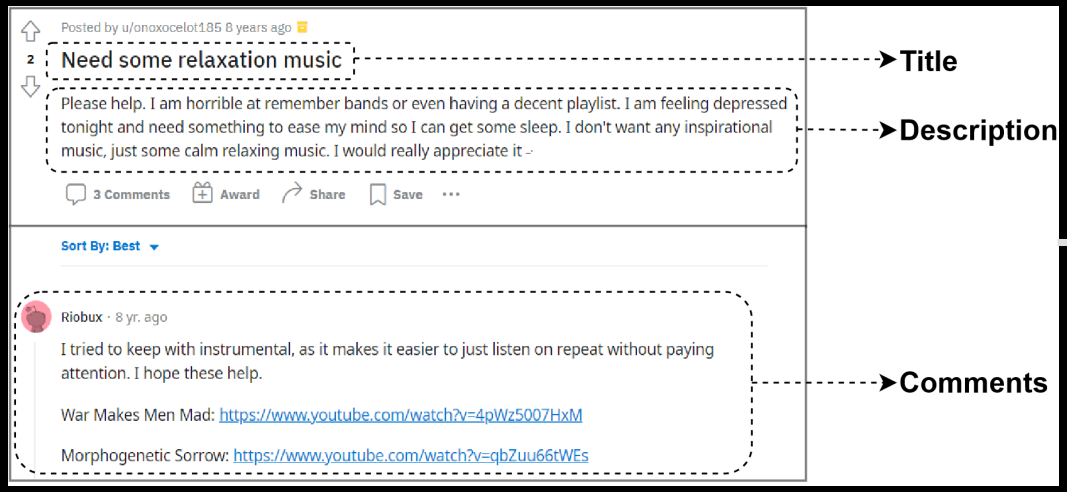
topics/keywords/
themes



sentiment/emotions



Big Data: Social Media



sentence clustering

"need some relaxation music"
"music is the only thing that can keep me calm"

topic modelling

"relaxing, relief"

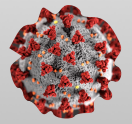
Characterising Big Music Data: **Social Media**

music tags vs social tags

lyrics vs free text

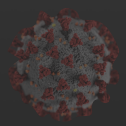
Music Consumption and Emotional Health

Music Sharing in times of distress



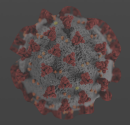
Music Consumption and Emotional Health

Music Sharing in times of distress



Music Consumption and Emotional Health

Music Sharing in times of distress



Music Choices, listening patterns & Depression

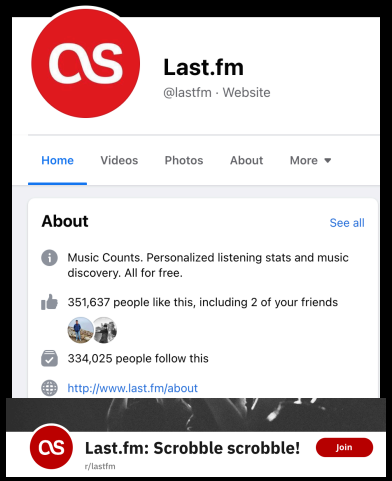
- people with a tendency for depression demonstrate a liking for sad music (Garrido & Schubert, 2015)
- higher musical engagement for emotion focused-coping especially during periods of depression (Stewart et al., 2019; Miranda et al., 2012)
- maladaptive music usage indicative of depression risk (Saarikallio & McFerran, 2016)

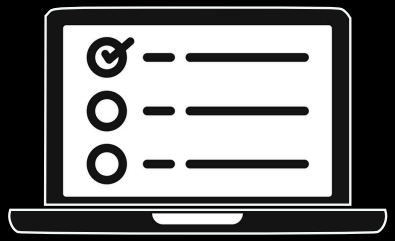
Objectives

- what are the kinds of online music consumption patterns associated with individuals at risk for depression?
- how well can risk of depression be predicted from these patterns?

Big Data Collection

~600 users

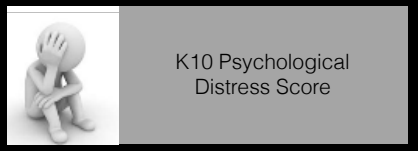




- Kessler's Psychological Distress Scale (K10)
- Healthy-Unhealthy Music Scale
- Personality
- last.fm user name

Surana, A., Goyal, Y., Srivastava, M., Saarikallio, S, and Alluri, V. (2020). TAG2RISK: Harnessing Social Music Tags for Characterizing Depression Risk. In Proceedings of the 21st International Society for Music Information Retrieval. Montreal, Canada.

Data Reliability



K10 Psychological Distress Score

Cronbach $\alpha = .91$

541 (444 males)

mean age = 25.4, sd = 7.3

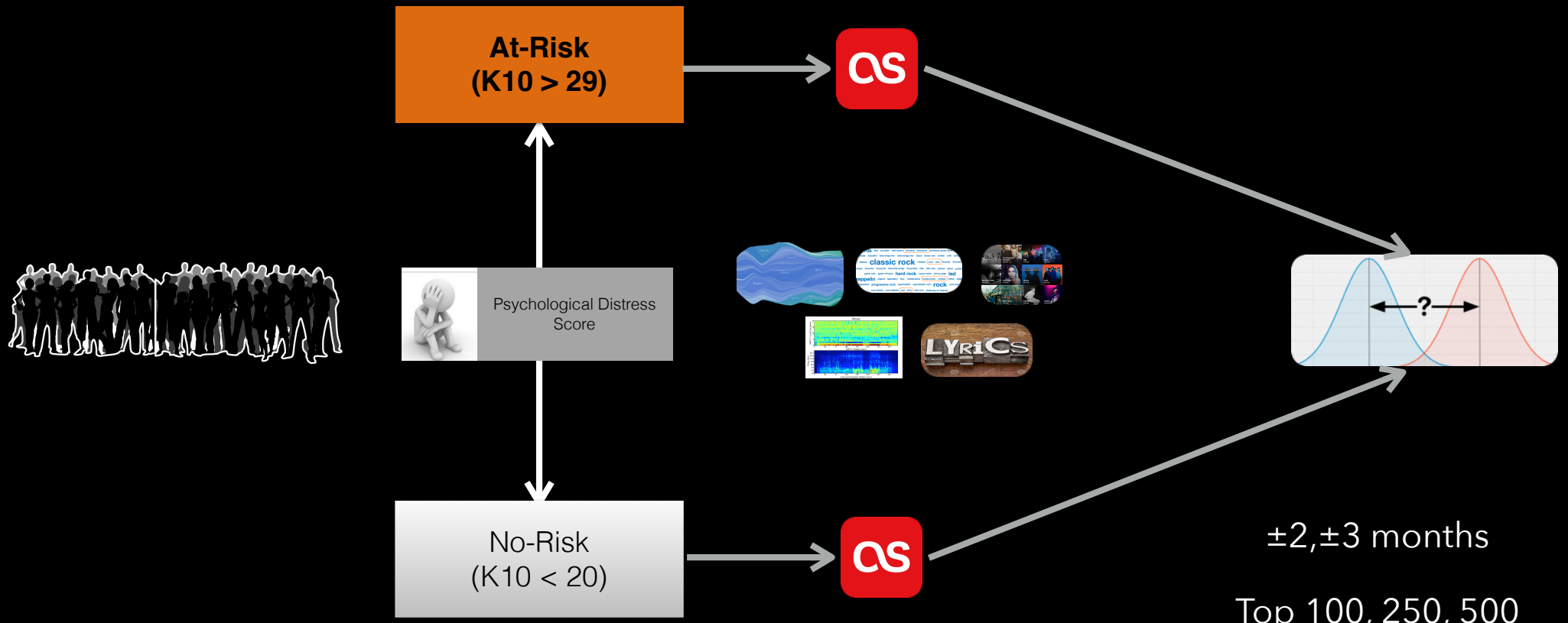
$r \geq 0.55$

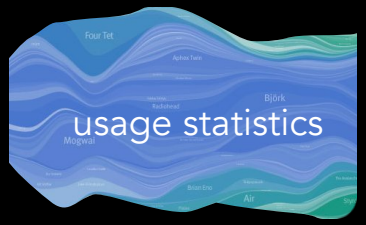
Cronbach $\alpha = .71$

HEALTHY-UNHEALTHY MUSIC SCALE

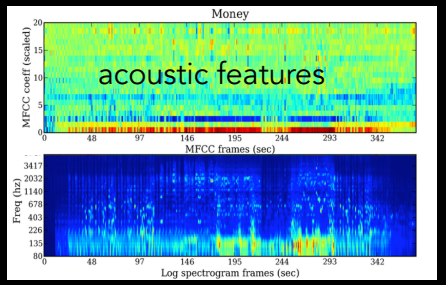
Cronbach $\alpha = .80$

User Categorization





- **At-Risk** associated with
  - **increased**
    - no. of sessions
    - total playcount
    - repetitiveness index
  - **decreased**
    - exploration scores



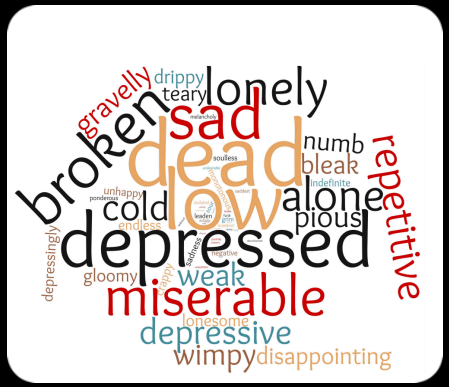
- No group differences in acoustic features
- **At-Risk** associated with higher *inertia* in the emotion quadrant representing ***Sadness***

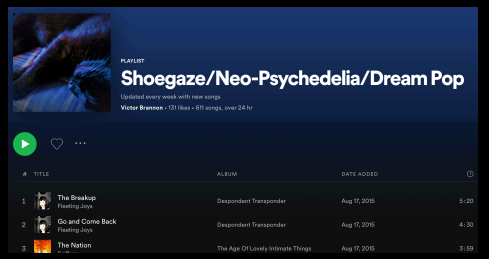
Surana, A., Goyal, Y., and Alluri, V. (2020). Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk. Mining Mental States using Music Associations. In Speech, Music, and Mind with Audio Satellite Workshop, Interspeech 2020.

Goyal, Y. and Alluri, V. (2021) Artist2Risk: Predicting Depression Risk based on Artist Preferences. In 16th International Conference on Music Perception and Cognition. Virtual Conference

Tags

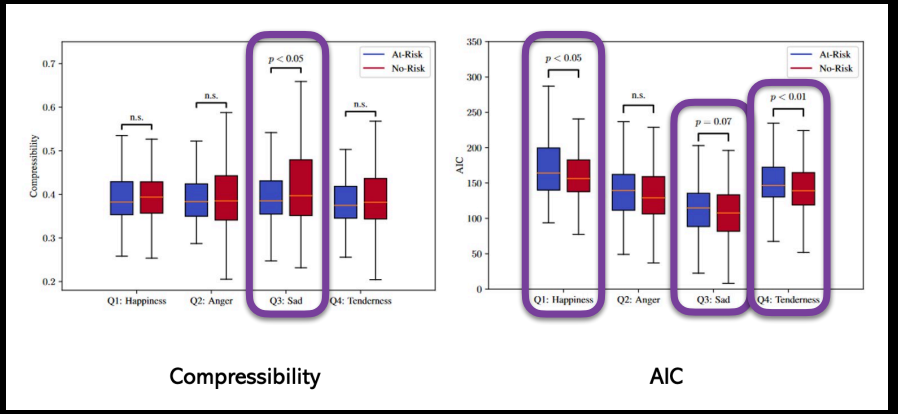
- **At-Risk**
  - associated with consuming music that is tagged with ***Sadness-related*** emotion terms
  - gravitated more towards neo-pop/ dream-pop genres and less towards black metal





Surana, A., Goyal, Y., Srivastava, M., Saarikallio, S, and Alluri, V. (2020). TAG2RISK: Harnessing Social Music Tags for Characterizing Depression Risk. In Proceedings of the 21st International Society for Music Information Retrieval. Montreal, Canada.

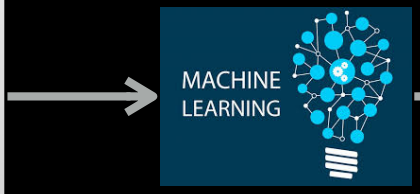
- **At-Risk** individuals prefer songs with
  - low valence and low arousal
  - *greater information content,* especially those tagged as *Sad*



Shriram et al. (2021), How Much do Lyrics Matter? Analysing Lyrical Simplicity Preferences for Individuals At Risk of Depression Cognition. In Speech, Music, and Mind with Audio Satellite Workshop, Interspeech 2021.

- **At-Risk** individuals prefer songs with
  - topics DICTION
    - high in *Denial, Self-reference, Ambivalence,* and *Tenacity*
    - low in *Liberation, Familiarity*
  - specific themes
    - high in *hopelessness*

To Do .....

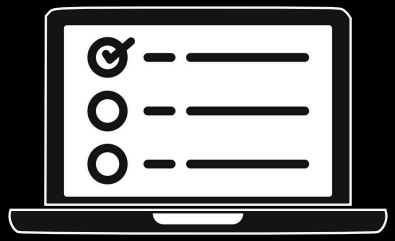


High-Risk

No-Risk

Big Data Collection

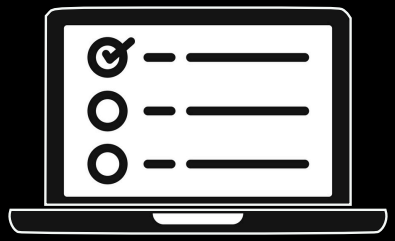
~250 users



- Kessler's Psychological Distress Scale (K10)
- Healthy-Unhealthy Music Scale
- Empathy (IRI)
- Highly Sensitive Person Scale
- Life Satisfaction
- Perceived Social Support
- Spotify 1-yr history

Big Data Collection

~250 users



- Kessler's Psychological Distress Scale (K10)
- Healthy-Unhealthy Music Scale
- **Empathy (IRI)**
- Highly Sensitive Person Scale
- Life Satisfaction
- Perceived Social Support
- Spotify 1-yr history

Some results……

- contrary to previous (western) research *personal distress* is negatively associated with psychological distress

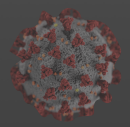
- people with high *empathic concern* and *ease of excitation* tend to use music in unhealthy ways

–> need to situate music research taking into account environmental and cultural factors

Arora, G., Kumaraguru, P., Alluri, V. (2023). Examining the Relationship between the Highly Sensitive Person Scale, Music Listening Strategies and Subjective Well-Being in India. @ICMPC 2023

Music Consumption and Emotional Health

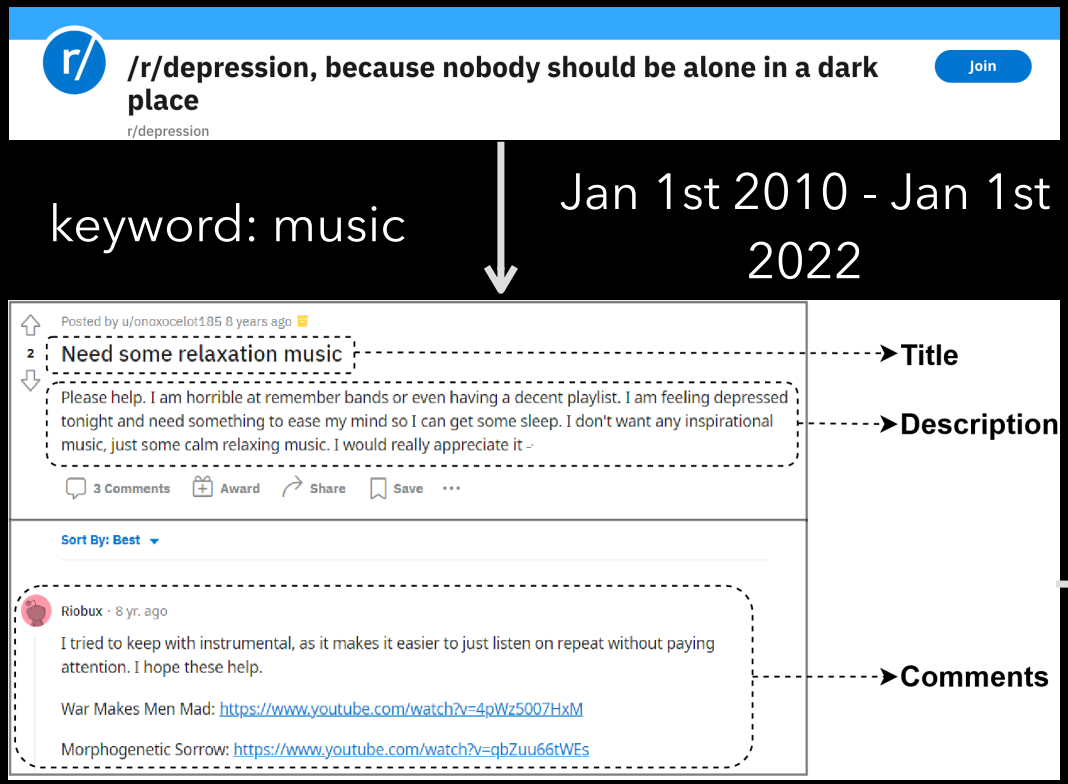
Music Sharing in times of distress



Singh B, Vaswani K, Paruchuri S, Saarikallio S, Kumaraguru P, Alluri V (2023) “Help! I need some music!”: Analysing music discourse & depression on Reddit. PLoS ONE 18(7): e0287975. https://doi.org/10.1371/journal.pone.0287975

Online Discourse

957k members+ created Jan 2009



keyword: music

Jan 1st 2010 - Jan 1st 2022

2788 posts

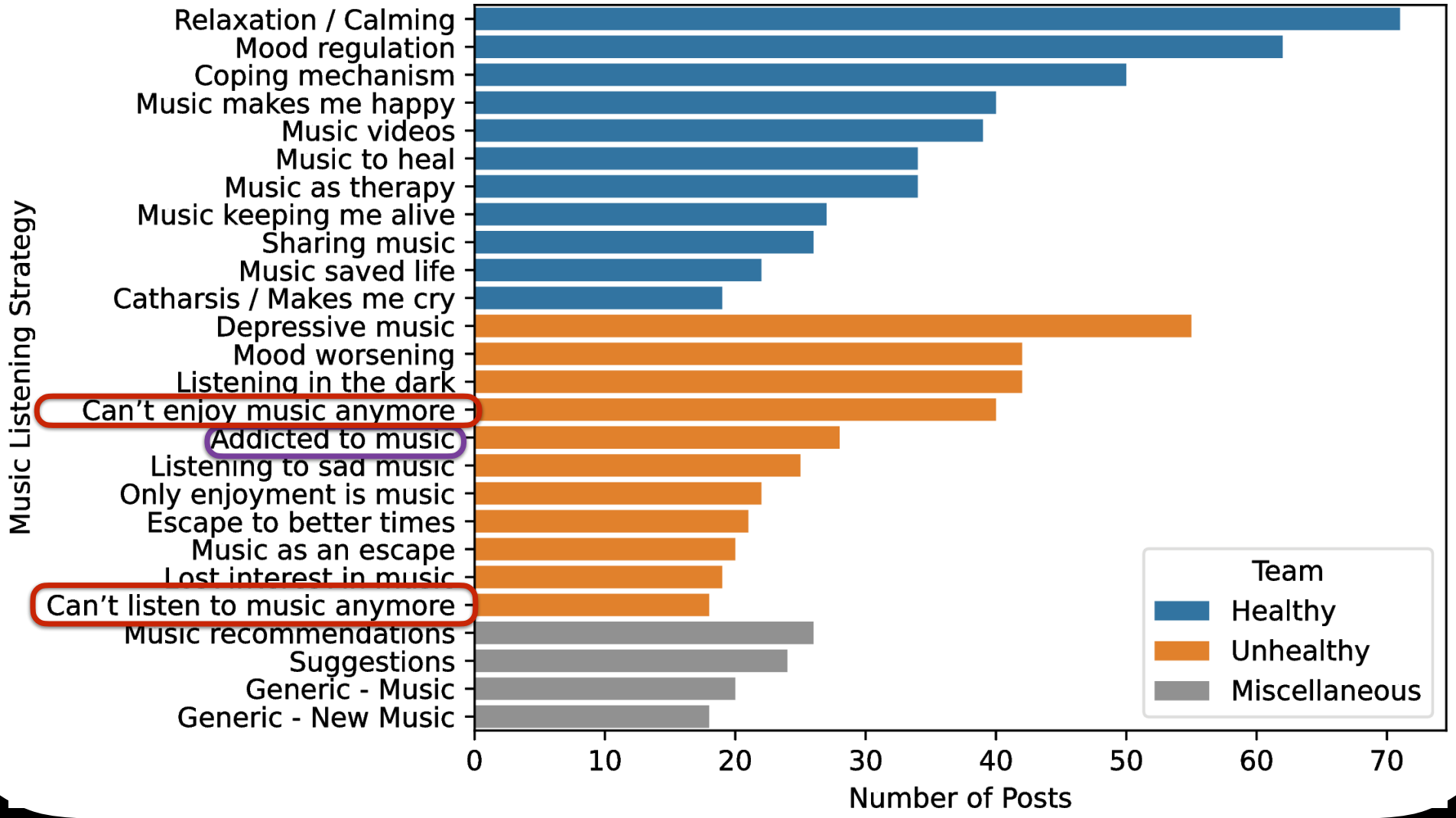
title clustering

"need some relaxation music"
"music is the only thing that can keep me calm"

topic modelling

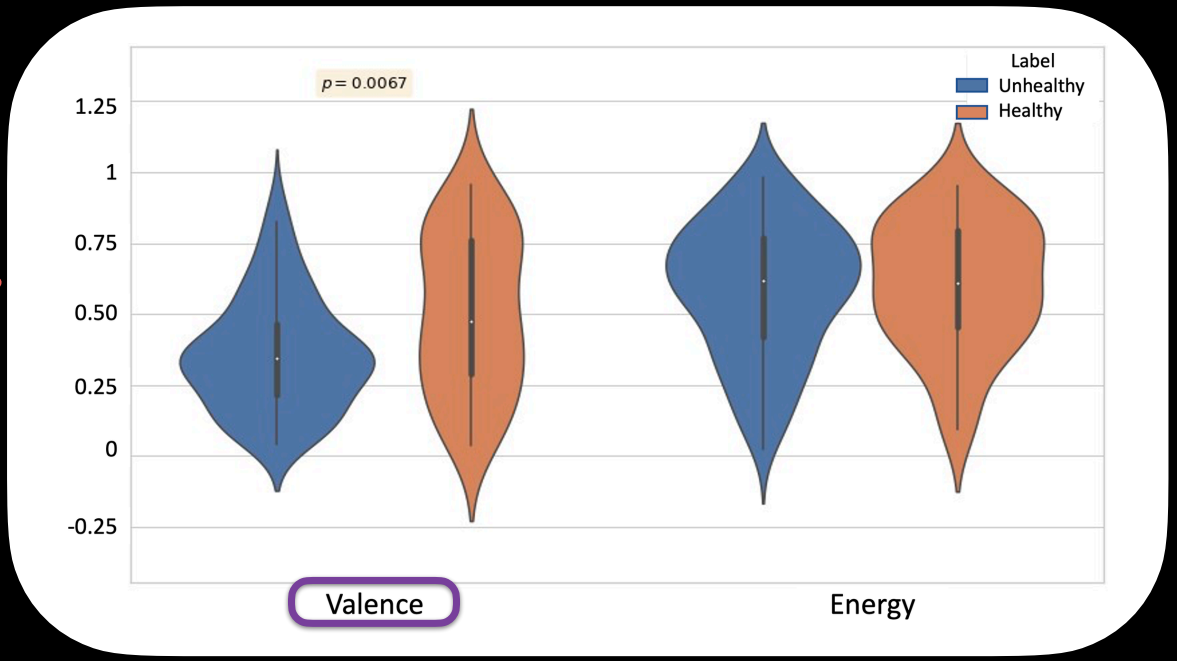
"relaxing, relief, anxiety, stress, sleep"

Singh B, Vaswani K, Paruchuri S, Saarikallio S, Kumaraguru P, Alluri V (2023) "Help! I need some music!": Analysing music discourse & depression on Reddit. PLoS ONE 18(7): e0287975. https://doi.org/10.1371/journal.pone.0287975

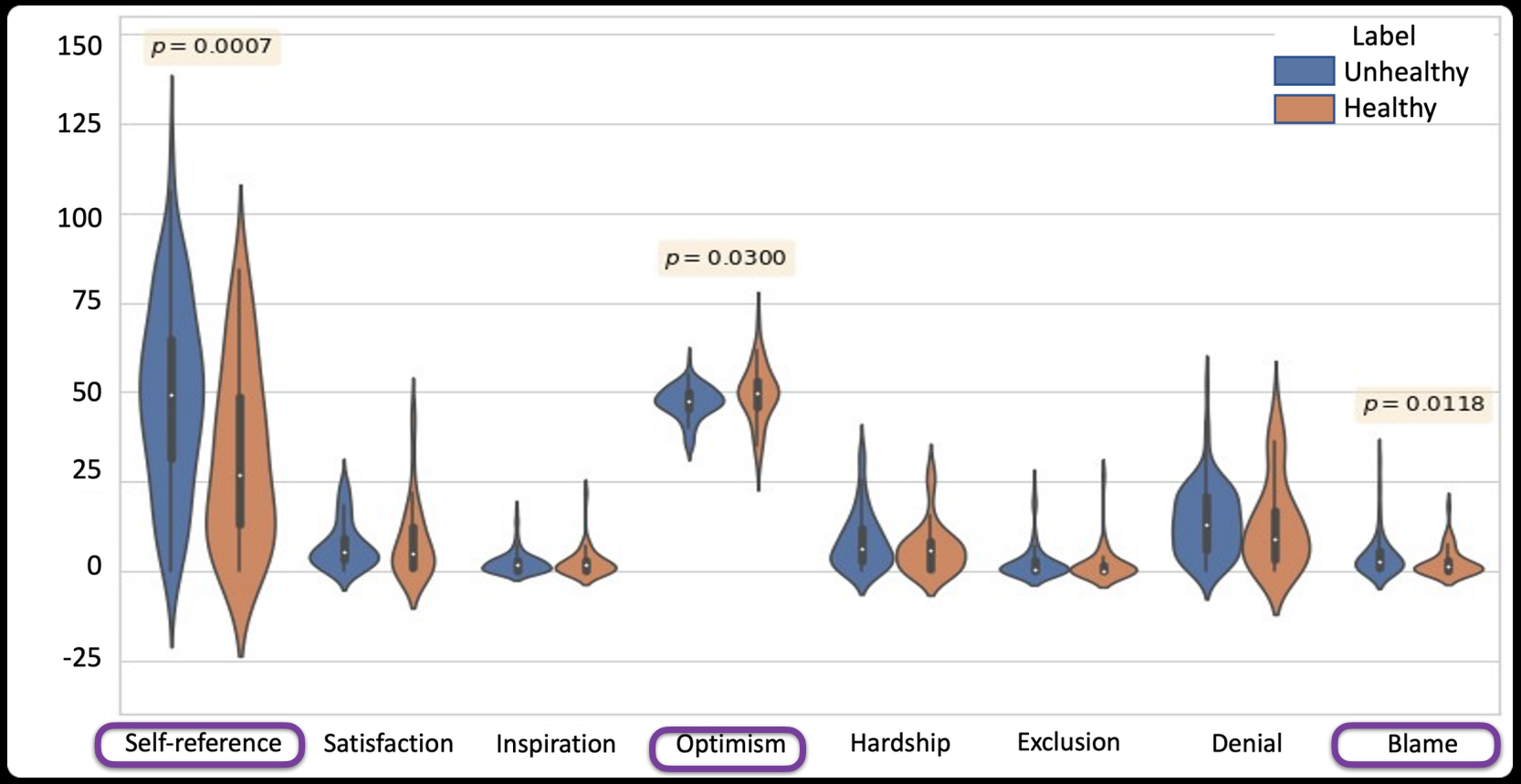

Relaxation / Calming
Mood regulation
Coping mechanism
Music makes me happy
Music videos
Music to heal
Music as therapy
Music keeping me alive
Sharing music
Music saved life
Catharsis / Makes me cry
Depressive music
Mood worsening
Listening in the dark
Can’t enjoy music anymore
Addicted to music
Listening to sad music
Only enjoyment is music
Escape to better times
Music as an escape
Lost interest in music
Can’t listen to music anymore
Music recommendations
Suggestions
Generic - Music
Generic - New Music
Music Listening Strategy
0
10
20
30
40
50
60
70
Number of Posts
Team
Healthy
Unhealthy
Miscellaneous

Results

Feature name	Description
acousticness	The track is acoustic. From 0 to 1
danceability	The track encourages (or is adequate for) dancing. From 0 to 1
duration_ms	Duration in milliseconds
energy	The track is perceived as energetic. From 0 to 1
instrumentalness	The track is instrumental. From 0 to 1
key	Key categories encoded as integers. From C (0) to 11
liveness	The audience is audible. From 0 to 1
loudness	In decibels. From -60 to 0
mode	Major (1) or minor (0)
speechiness	Does the track contain speeches? From 0 to 1
tempo	In beats per minute (BPM)
valence	How happy is the track (BPM).



Results



DICTION

Results

Topic Modelling of titles + **Qualitative Assessment**

Healthy

calming, healing, mood regulation, therapy, sharing, save life, catharsis

Unhealthy

mood worsening, listening in dark, escape, addiction, depressive music

Anhedonia

can't listen to/enjoy music anymore, lost interest in music

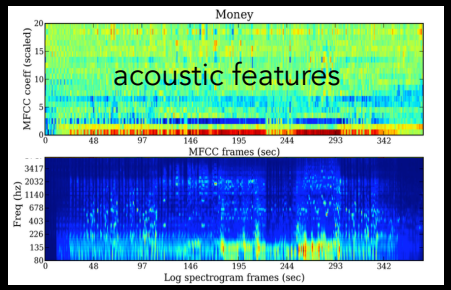
Seeking

recommendations, suggestions, new music, need music

Singh B, Vaswani K, Paruchuri S, Saarikallio S, Kumaraguru P, Alluri V (2023) "Help! I need some music!": Analysing music discourse & depression on Reddit. PLoS ONE 18(7): e0287975. https://doi.org/10.1371/journal.pone.0287975

Results

music & lyrical characteristics of **healthy** vs **unhealthy** listening strategies



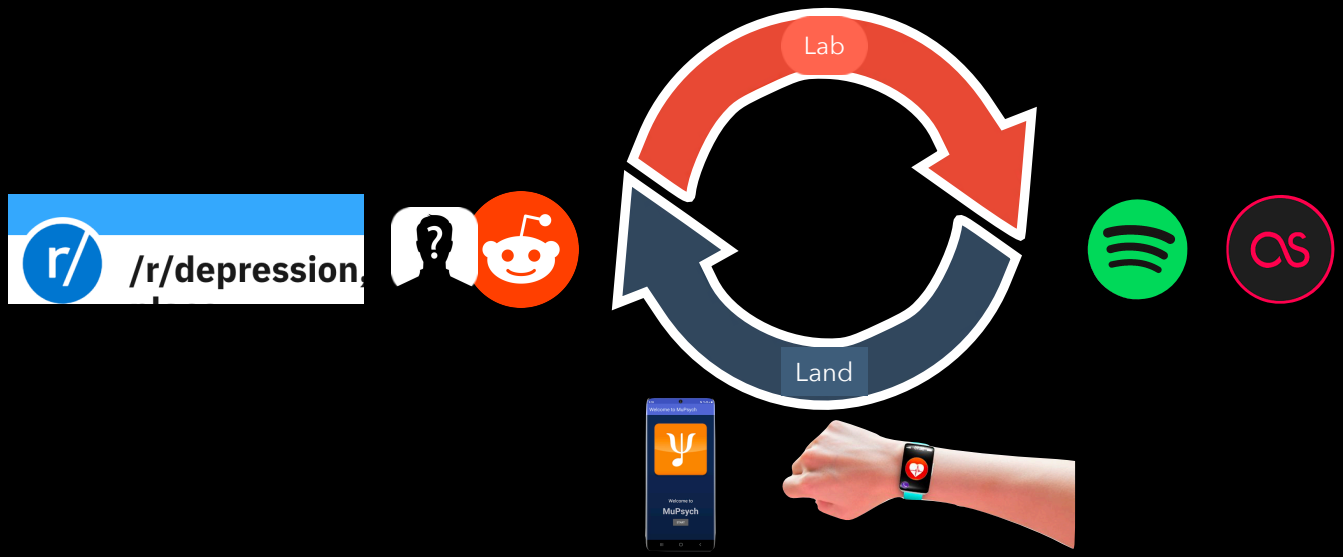
low valence

high self-reference, blame
low optimism

Singh B, Vaswani K, Paruchuri S, Saarikallio S, Kumaraguru P, Alluri V (2023) “Help! I need some music!”: Analysing music discourse & depression on Reddit. PLoS ONE 18(7): e0287975. https://doi.org/10.1371/journal.pone.0287975

What next.....?

unhealthy music listening strategies associated with depression risk



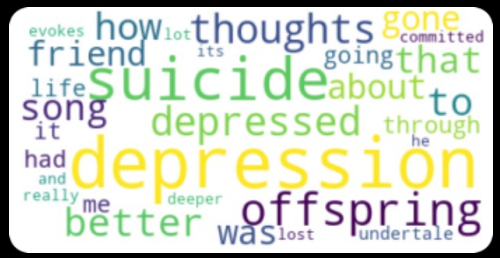
Anti-recommender system?!

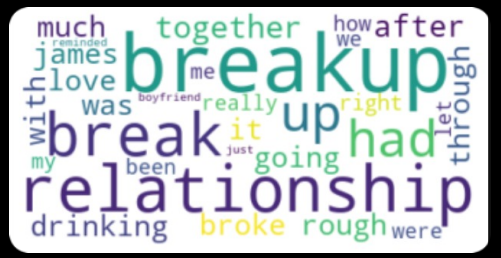
Moving Music

- characteristics (acoustic features) of moving music

low valence, energy, danceability

- personal associations with such music



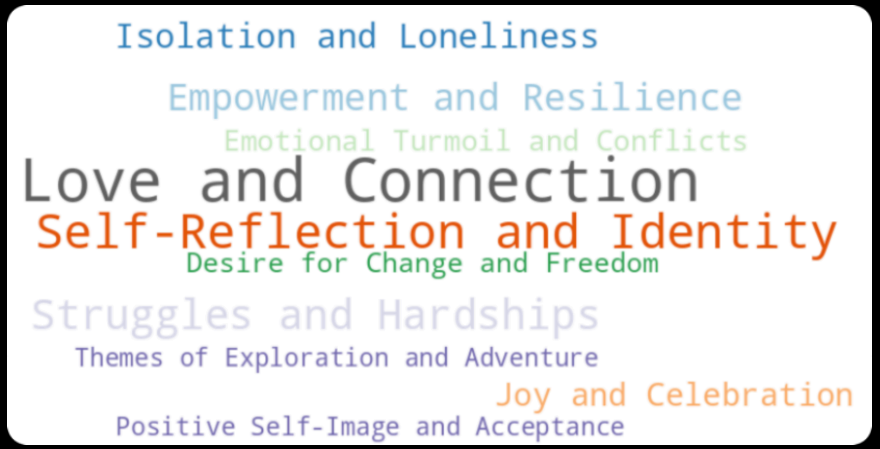


Autism & Music

- title topics

repetitive music listening, music for mood management and productivity (focus), music queries and preferences, reluctance in sharing music

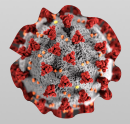
- lyrical themes



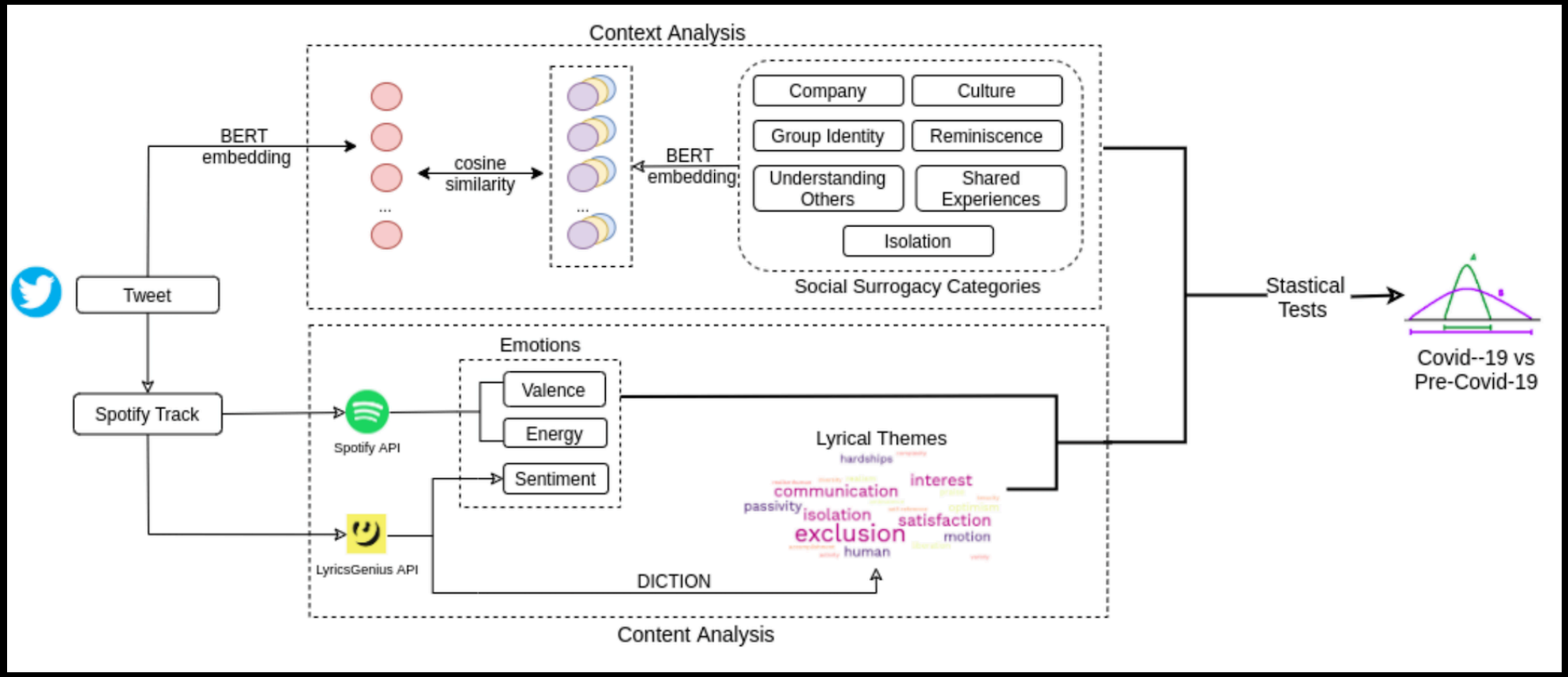
Varghese, S., Alluri, V. (in prep). Role of Music songs say so much: Analyzing moving music shared online

Music Consumption and Emotional Health

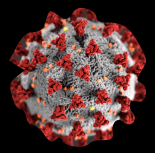
Music Sharing in times of distress



Music Sharing



Desur, P., Kamble, T., Krause, A., Kumaraguru, P., Alluri, V. (2022) “The Times They Are-a-Changin”: The Effect of the Covid-19 Pandemic on Online Music Sharing in India. In the 13th International Conference on Social Informatics. Preprint: https://lnkd.in/dBi3a_5u



Music Sharing

Data Group	Tweets with Spotify URL	Tweets with English Songs	Songs with correct English Lyrics
Wave-1 (July-November 2020)	808	416	323
Control-1 (July-November 2019)	607	271	204
Wave 2 (April-June 2021)	556	317	263
Control-2 (April-June 2019)	351	177	155

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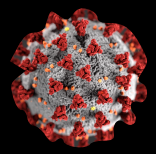

Music Sharing

- music as a social surrogate: community focused function rather than tending to a more self-serving utility
- acoustic features - music shared had lower valence and high energy in wave-1

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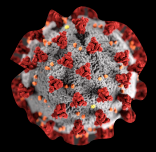

Music Sharing

- lyrical themes

Wave-1 (vs. Control-1)	Exclusion* ↑, $Satisfaction$ ↑, $Hardship$ ↑, $Motion$ ↑
Wave=2 (vs. Control-2)	Communication ↑, $Satisfaction*$ ↓
Wave-1 + Wave-2 (vs. Control-1 + Control-2)	Hardship ↑, $Exclusion$ ↑, $Motion$ ↓

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Music Sharing

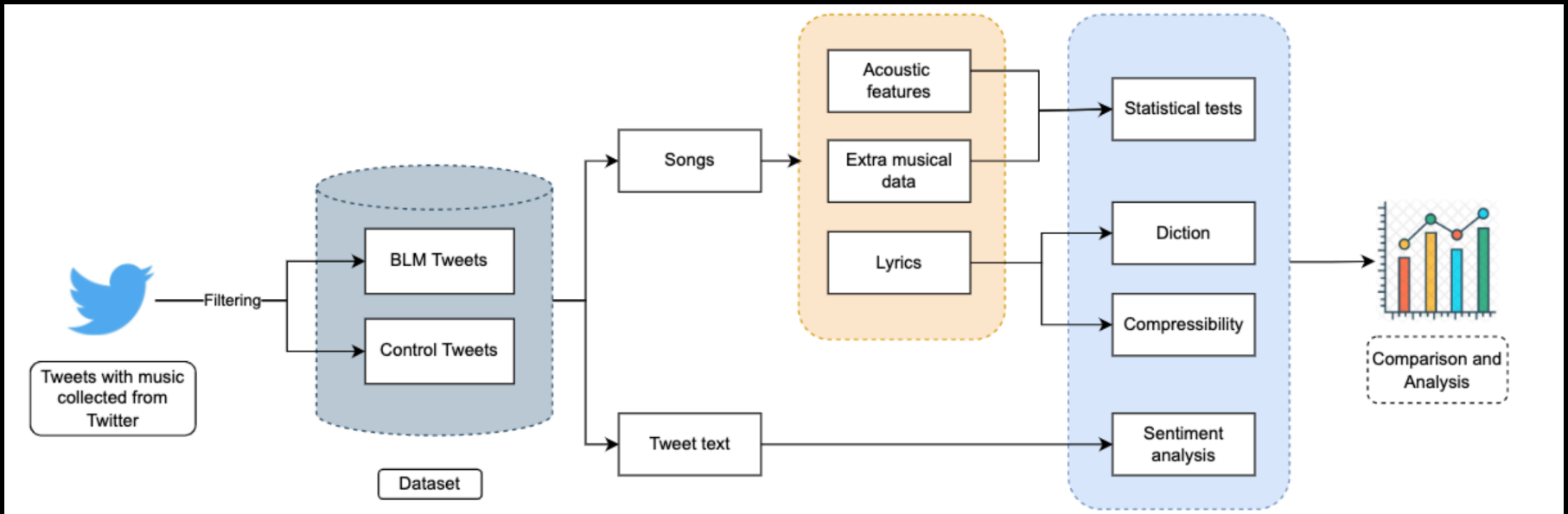


Figure 1: Flowchart describing the pipeline used for the analysis

Singh, B., Krause, A., Kumaraguru, P., Alluri, V. (in prep)

Music Sharing

Metric	Control	BLM
Number of tweets	14,672	12,661
Total songs (w playlists)	19,613	11,131
Single tracks	1,726	4502
Tracks with lyrics	1,398	3,727

Table 1: Dataset Statistics

Singh, B., Krause, A., Kumaraguru, P., Alluri, V. (in prep)

Music Sharing

- within 6 months - more than ten thousand tweets along with music had been shared
- artists of the 1960s who wrote protest music most popular
- protest music characterised by high *valence, danceability, instrumentalness, and speechiness*

Singh, B., Krause, A., Kumaraguru, P., Alluri, V. (in prep)

Music Sharing

- lyrics for the songs shared in context of BLM have *less repetition (low compressibility)*

- lyrical themes:
  - high *Aggression, Hardship, Cooperation* and *Accomplishment*
  - low *Satisfaction, Optimism, Self-reference*

Singh, B., Krause, A., Kumaraguru, P., Alluri, V. (in prep)

Big Data: The Good

- fantastic opportunities to generate knowledge and technology
- anonymity
  - "safety net" to share music and musical experiences
  - discourse on music related to specific conditions/topics (depression, autism, ADHD, earworms, music for concentration, etc…)
  - naturalistic responses

Big Data: The Good

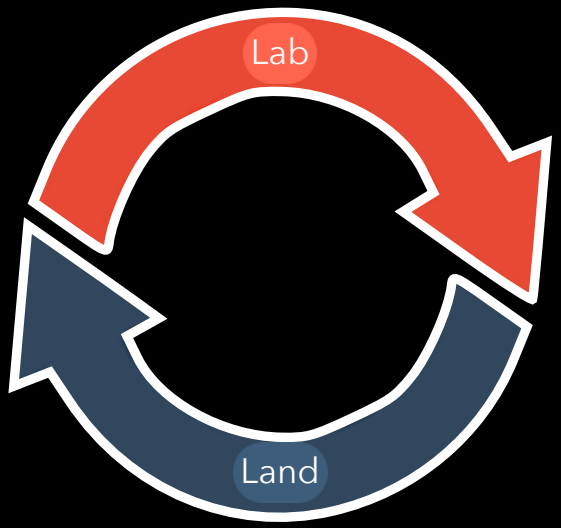
- streaming platforms
  - psychological insights
  - cultural and social influences
  - music trends
  - market research and recommendations
  - personalised music therapy

Big Data: The Bad & The Ugly

- **is Big(ger) always better?**
  - **Value** & **Veracity?**
    - noise
    - language model errors
    - solution—> mixed-methods
  - platform-specific bias (ex: social desirability, english-speaking population)
    - solution-> rephrase and situate questions accordingly
  - access?

To Conclude……..

hypothesis-generation



hypothesis-testing

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WiSSAP 2023

Exploring the human musical experience in the age of Big Data and Technology

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Assistant Professor
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