Depression Risk Indicators Via Active Music Listening For Before and During COVID-19 Pandemic

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[Surana, A., Goyal, Y., Alluri, V. (2020) Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk. Proc. SMM20, Workshop on Speech, Music and Mind 2020, 1-5, DOI: 10.21437/SMM.2020-1]

Research Objective

We aim to unravel static and dynamic patterns existing in active listening behavior of individuals which may act as indicators of risk for depression pre and during COVID-19 pandemic, based on the paper “Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk”.

Hypothesis

- Several research have demonstrated that during periods of depression, there is a strong reliance on listening to music impacting moods, emotions and altering affect states of an individual.
- It is evident that using music for rumination, avoidance and mood worsening is an indicator of risk for depression. Although, due to the ongoing COVID-19 pandemic, these indicators may become more prominent.
- Standard questionnaires having self-reported musical consumption data and measures, may suffer from demand characteristics and/or social desirability bias.
- Hence, by using big data we aim to analyse these indicators being affected by COVID-19 .

Methodology

The methodology is divided into three parts : Dataset, Feature Extraction, Statistical Testing.

Dataset - Active music listening of users pre and during COVID-19 pandemic [from last.fm user data]. Users' well-being is measured using standard diagnostic questionnaire, the Kessler's Psychological Distress Scale (K10).

Feature Extraction - It majorly comprises of 3 parts Static, Session based and Dynamic feature extraction

Process for Static Feature Extraction

- Using Spotify public API for extracting 10 acoustic features from a track.
- 8 Audio features - danceability, loudness, speechiness, acousticness, instrumentalness, liveness, tempo, and mode.
- 2 Emotion features - valence and energy/arousal, forming Valence-Arousal space representing four emotional states - happiness, anger, sadness, and tenderness.
- Calculate a Quadrant Prevalence Score (QPS) which represents the proportion of tracks in the respective quadrants in each user's listening history.

Methodology

Process for Session-based Feature Extraction:

- A session is defined as a period of continuous listening activity, helps in obtaining time-varying values for audio and QPS features, for each user over his/her listening period.
- Individuals at-risk for depression may engage in repetitive music listening behaviors, to quantify this, we determine a Repetitiveness Index per user.

Process for Dynamic Feature Extraction :

- Dynamic behavior helps us to better understand users' mood shifts characterized by variability and inertia.
- Higher inertia and extreme variability are representative of ill-being and depressive moods.

Methodology

Statistical Testing :

- First, divide users using K-10 scores, K-10 < 20 fall under the No-Risk group while K10 > 29 will form At-Risk group.
- Perform Wilcoxon signed-rank test on the static features for At Risk users for before and during COVID-19
- Then test a Type 1 error (false positive), to ensure that the observed differences are not due to chance.
- Next we will perform Spearman correlations between K10 and all users' number of sessions, total play count, and RI.
- Similarly, we will find correlation between K10 and static and dynamic measures of audio and emotion features.

The observations should reveal that individuals with greater depression risk often possess higher dependency on sad music with greater repetitiveness in their listening habits. Furthermore, we compare the results for pre and during COVID-19.

Methodology Overview

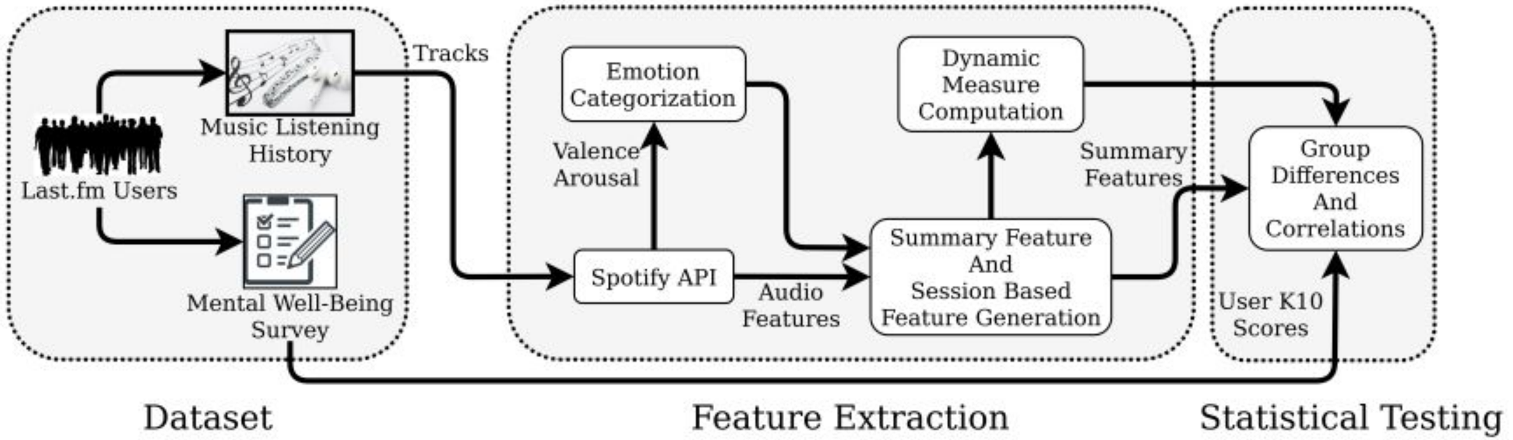


Figure 1: *Methodology*

Ref: Static and Dynamic Measures of Active Music Listening as Indicators of Depression Risk

Steps and Intermediate Results

- Number of No-Risk(K10<20) users are 180 and At-Risk users are 120 (K10>29) from 485 users.
- Acoustic features for 9,00,000+ songs extracted from Spotify API. For example: ('Oscillate Wildly - 2011 Remaster', 'The Smiths') [0.657, 0.791, 9, -5.996, 0, 0.0278, 0.0205, 0.298, 0.101, 0.783, 116.329]
- Then summarized the features based on sessions including QPS score for each quadrant for both before and After COVID-19 data. For example shown in image below.

sessionID	start	end	danceability	loudness	mode	speechiness	acousticness	instrumentalness	liveness	tempo
1	2018-12-27 2:19:	2018-12-27 3:06:	0.38099	-21.9019	0.9	0.03819	0.441810479	0.7365	0.09861	103.7552

QPS_Q1	QPS_Q2	QPS_Q3	QPS_Q4	total_tracks
0	0.2	0.7	0.1	10

- After this also summarized features and calculated repetitiveness index for each user.

user_id	K10	total_session	total_tracks	repetitiveness_index	danceability	loudness	mode	speechiness
009327643adf158a3	12	461	6225	0.09687179667	0.3612642892	-4.061922731	0.6804819277	0.1451833574

Steps and Intermediate Results

- Then we extracted Dynamic Features i.e. variability and inertia for all static features.

danceability	loudness	mode	speechiness	acousticness	instrumentalness	liveness	tempo	QPS_Q1	QPS_Q2
0.06586808857	1.003262872	0.2699236779	0.03676539978	0.02218880195	0.2014463491	0.1056489383	12.93377305	0.07232787172	0.08970458676

- After extracting these features we performed Wilcoxon signed-rank test for comparing At Risk users for Before and During COVID-19. Also performed bootstrapping to take in account for Type I error.

danceability	**loudness**	**mode**	**speechiness**	**acousticness**	**instrumentalness**	**liveness**	**tempo**	**QPS_Q1**	**QPS_Q2**	**QPS_Q3**	**QPS_Q4**
0.2621	0.7085	0.8756	0.8411	0.9309	0.9268	0.9145	0.9969	0.2966	0.1676	0.9309	0.8899

Results

- Then we have performed spearman correlation with K-10 for dynamic features.
- We have observed positive correlations for K10 and number of sessions ($r = 0.189$, $p = 0.0002$), total playcount ($r = 0.134$, $p = 0.002$) and RI ($r = 0.124$, $p = 0.005$) for before COVID-19.
- We have observed positive correlations for K10 and number of sessions ($r = 0.185$, $p = 0.0003$), total playcount ($r = 0.104$, $p = 0.024$) and RI ($r = 0.140$, $p = 0.001$) for during COVID-19.
- Also, K10 had a negative correlation with variability in instrumentalness ($r = -0.12$, $p = 0.005$). Also, K10 correlated positively with inertia in speechiness($r = 0.09$, $p = 0.03$).

	r_var	p_var	r_iner	p_iner
danceability	-0.040656	0.370649	0.023557	0.604047
loudness	-0.003603	0.936785	0.032622	0.472606
mode	-0.060360	0.183576	0.056262	0.215200
speechiness	0.044214	0.330208	0.094625	0.036842
acousticness	0.021615	0.634202	0.023119	0.610793
instrumentalness	-0.125880	0.005405	-0.002406	0.957770
liveness	-0.070061	0.122577	0.040818	0.368740
tempo	-0.056713	0.211539	0.035255	0.437597
QPS_Q1	-0.065802	0.147067	0.020689	0.648795
QPS_Q2	-0.064535	0.155033	-0.040055	0.377761
QPS_Q3	0.023978	0.597600	0.096823	0.032661
QPS_Q4	0.031152	0.492800	0.043527	0.337786

Further Analysis

Wilcoxon signed-rank test(All) - We observed the following after our experiments:-

- Inertia of QPS_Q1 → p_value = 0.040
- Static QPS_Q4 → p_value = 0.023
- Variability QPS_Q4 → p_value = 0.005

Wilcoxon signed-rank test(At Risk) - We observed the following after our experiments:-

- Inertia of QPS_Q3 → p_value = 0.010
- Inertia of QPS_Q4 → p_value = 0.010

Wilcoxon signed-rank test(No Risk) - We did not observe any significant inference after our experiments.

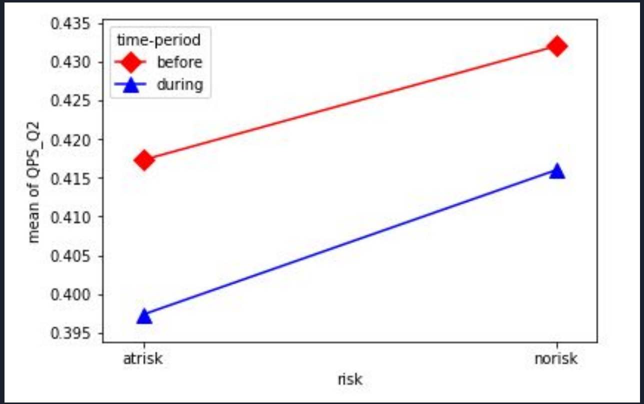
Further Analysis

Two way Anova

- Time-period (before-covid / during-covid) and risk (At-risk/No-risk) as the 2 independent variables and consider each feature as a dependent variable one at a time.

- Static QPS_Q1, corresponding to source as time-period → p-value = 0.05. As p-value is on borderline, we are not considering it for any inference.

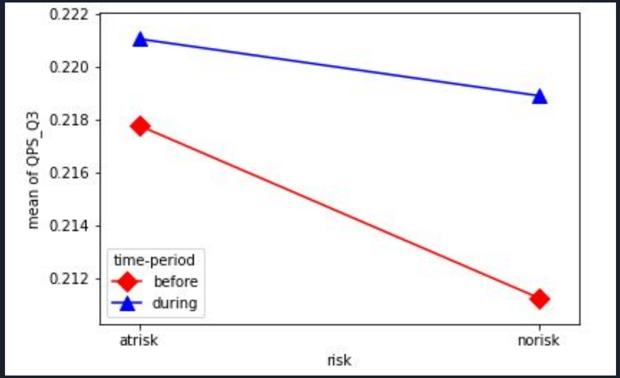
- Static QPS_Q2, corresponding to source as time-period → p-value = 0.000015. Anger quality of music for both the groups, has decreased during COVID-19..



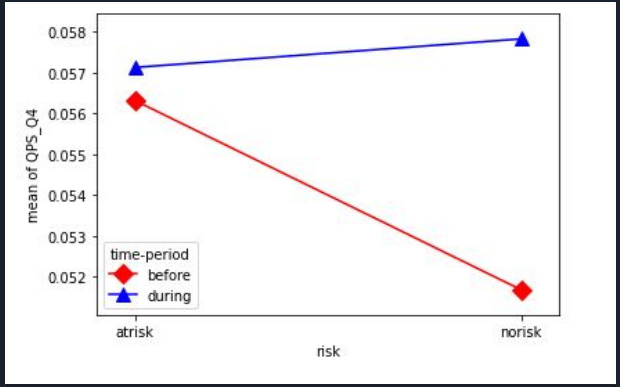
Further Analysis

Two way Anova

- Static QPS_Q3, we didn't find any significant difference. But on plotting Interaction Plot, we found increase in sad songs for both the groups during COVID-19 pandemic.



- Static QPS_Q4, corresponding to source as time-period → p-value = 0.023. It is observed, there is a significant increase in tenderness quality of music during COVID-19 for 'No Risk' group.



Further Analysis

Two way Anova

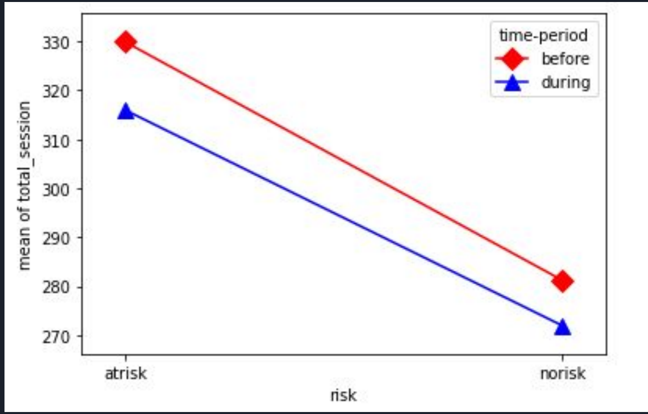
- For Repetitiveness Index and Total Tracks, , we didn’t find any significant difference.
- Total Session, corresponding to source as risk → p-value = 0.00018.

Pre COVID-19

  - Average Number of sessions per user : 302
    Average Number of total tracks per user : 6928

During COVID-19

  - Average Number of sessions per user : 290
    Average Number of total tracks per user : 7130



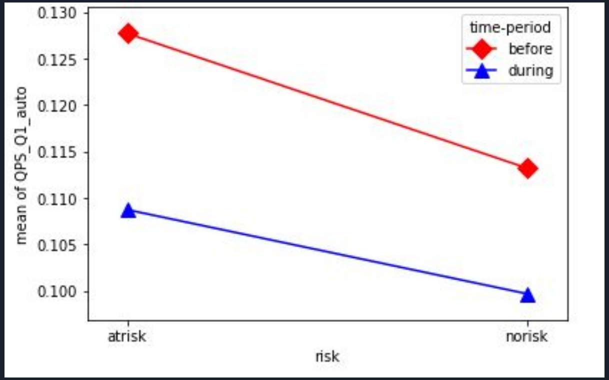
Further Analysis

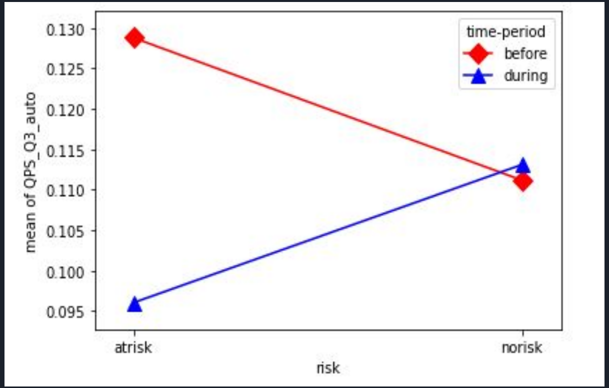
Two way Anova

- Inertia of QPS_Q1, corresponding to source as time-period → p-value = 0.035. Across sessions there is decrease in QPS_Q1 for both groups.

- Inertia of QPS_Q3, corresponding to source as interaction → p-value 0.032. There is a significant drop in inertia of QPS_Q3 for at risk users.

- Inertia of QPS_Q2, QPS_Q4 , no significant change observed.





Thank You