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War & Music: The impact of the Ukrainian War on the Music Listening Behaviour in Eastern Europe*

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Abstract—According to many analysts, February 2022 is dated as the exacerbation of the armed conflict between Ukraine and Russia. Of course, this shocking event has an impact on mood of people. In this context, we studied the music listening habits of people in Eastern European countries. We applied timeseries and statistical analysis of mood-relate features (danceability, valence and energy) to a Spotify dataset in order to define new paradigms of emotion-aware systems that can be applied to detect the population’s state of mind. The results show that the trend in the type of music changes notably towards songs with less genre diversity and reflecting less positivity.

Index Terms—Music-listening behaviour, Spotify, timeseries, warfare, Ukrainian War.

I. INTRODUCTION

Due to music digitization, songs can now be defined in terms of quantitative features describing certain sound- and mood-related properties such as their *danceability* or *valence*. Since these features can be analyzed from multiple points of view, it has encouraged an interesting course of action to capture people’s emotions through their music listening habits [1]. In turn, this has allowed to develop and assess novel emotion-aware systems like music recommender systems [2], [3].

Apart from that, on 24th February 2022, the conflict between Russia and Ukraine was exacerbated with a large military deployment, which has turned into a long-term warfare causing major social and economic disturbances, especially in Eastern Europe [4], [5]. Such major conflicts inevitably have a substantial impact on the mood of the population.

Considering the above, this work focuses on analyzing whether the emotional impact of the Ukrainian war is reflected in the music listening habits of the citizens of some of the most directly affected Eastern European countries (Estonia, Latvia, Lithuania, Belarus, Ukraine, Romania and Bulgaria) through Spotify. To do so, we apply different techniques from timeseries and statistical analysis to a range of mood-relate features of the most streamed songs in such countries. In utility terms, the findings of this work could be useful for defining new paradigms of emotion-aware systems capable of responding to users’ distress in severe situations.

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The remainder of the paper is structured as follows. Section 2 gives an overview about existing trends for music streaming-data analysis. Then, section 3 states the data and tools used to measure the music listening patterns from Spotify. The extracted patterns are described and evaluated in section 4. Lastly, section 5 summarizes the main findings of this work.

II. RELATED WORK

A broad line of research in the music streaming data mining field have evaluated the impact of external and disruptive events on the listening habits of the users of music streaming services. For example, some works have assessed the impact of the COVID-19 pandemic on the music consumption. As a matter of fact, authors in [6] showed a remarkable positive correlation between the levels of distress and tension of a set of volunteers and their willingness to listen to music on a regular basis during the first months of the pandemic. Besides, the study stated in [7] developed a classifier able to label the listening behaviour of Germany, Austria and Switzerland in the non-pandemic and pandemic periods to demonstrate the behavioural change that occurred during these months. Finally, the work in [8] also performed a correlation analysis between the evolution of the pandemic and the features of most popular songs in several countries showing quite different results depending on the geographical area.

Unlike the previous works, we intend to analyze the actual impact of wars on the listening behaviour of a population in terms of the mood-relate features of the most popular tracks among that population. It is true that previous works have compared the mood-related listening habits of a large population with respect to the COVID-19 pandemic, which can also be considered an extreme and longstanding event. However, we believe that a pandemic and a state of war are very different in nature and in the manner they are perceived and handled by the civil population. To the best of the authors’ knowledge, this is the first attempt to compare the evolution of war and the music listening behavior of the directly affected population.

III. EXTRACTION OF THE FEATURES TO CHARACTERIZE THE MUSIC LISTENING PATTERNS

In this section we put forward the general approach followed to model the music-listening behaviour of the target countries. To do so, we first describe the Spotify dataset used in the study. Next, we state the features extracted from such a dataset that will be analyzed later on to study the effect of the Ukrainian war.

A. Dataset description

For our analysis, we took as input the *Top 200* daily rankings released by Spotify, which contain the 200 most played songs in 69 different countries per day¹. At this point it is important to note that we have opted to center our study on Eastern Europe countries due to their geographical proximity to the Ukrainian conflict. In particular, we focused on Estonia, Latvia, Lithuania, Romania Bulgaria, Belarus and Ukraine itself as target countries. Note that there are other surrounding countries that might also be interesting for this study, such as Moldavia, but the Spotify platform did not provide access to their rank data. Besides, Russia has not been included as Spotify stopped to release its daily lists on March, 3rd 2022.

Using an ad-hoc crawler, daily rankings were extracted for each single country for a 2-year period from 2020-07-17 to 2022-10-11. As a result, we composed a raw dataset of 1,310,738 records comprising 14,816 unique songs. Each record is represented as $\langle s_{id}, l, pos, co, d \rangle$, indicating that the song with identifier s_{id} was listened to l times in country co occupying the pos position in the co ranking on date d .

B. Mood-related Timeseries

For each song in the dataset, we extracted its associated features provided by the Spotify Developer Platform (SDP) through its public API². For this study we focused on three *mood-relate features* (according to the Spotify terminology) of a song, namely

- *Danceability* (D). This feature indicates how suitable a song is for dancing. It takes values from 0 (not danceable) to 1 (highly danceable).
- *Valence* (V). It indicates how positive and upbeat a song is. Again, it ranges from 0 to 1. Hence, songs with a high valence feel cheerful and happy whereas low-valence songs feel sad and depressing.
- *Energy* (E). This attribute measures the intensity and activity of a song. A very energetic song will likely be fast, loud and noisy whereas a low-energetic song will be much more quiet and calm such a Johann Sebastian Bach's prelude score. Again, it ranges from 0 to 1.

Next, for each target country it was composed 3 different timeseries, one for each mood feature. Each series took the form $\mathcal{F}_f^c = \langle f_1^c \rightarrow f_2^c \rightarrow \dots \rightarrow f_{L-1}^c \rightarrow f_L^c \rangle$ where f_i^c indicates the mean value of feature f of the songs in the *Top-200* list of the country c at the i -th day of study (L stands

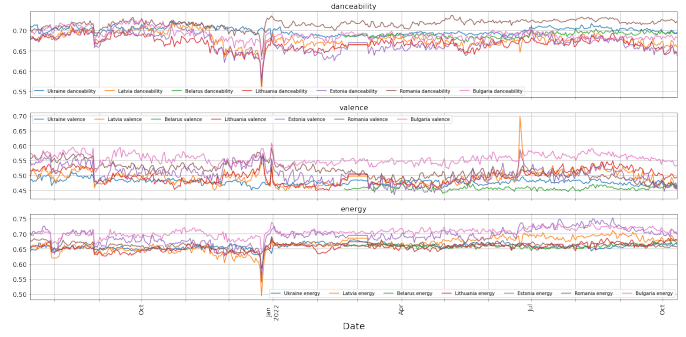


Fig. 1. Timeseries of 3 mood features (danceability, valence and energy) considering all the target countries.

for the last day of the covered period). By means of these series, it is possible to measure the evolution through time of the mood-relate features of the most popular songs in each country. The resulting timeseries are shown in Fig. 1. As we can see from this figure, the danceability of Romania was slightly higher than the other countries from the beginning of 2022. Moreover, similar patterns are observed for the valence and energy in Bulgaria.

IV. RESULTS

In this section, we evaluate how the timeseries generated in the previous section have been affected by the Ukrainian War.

A. Homogeneity Test of the Mood Timeseries

The first experiment was to perform a homogeneity test on each of the timeseries of the target countries. This test is a statistical method that checks whether two (or more) datasets originate from the same statistical distribution. In a timeseries, it allows to detect one (or more) *breakpoint* in the series. This breakpoint occurs when the data set changes its distribution.

Table I shows the breakpoints for each country and feature detected by the test for a p-value of 0.05. As can be seen, a single breakpoint was identified for each pair of countries and features. Hence, some interesting findings can be extracted.

Most notably, Ukraine's danceability and energy timeseries changed significantly during April and May 2021. It is important to note that during these months Russia initiated a major military deployment near the Ukrainian border according to some analysts. Regarding the valence feature, its breakpoint occurred in November 2020. During that time, Russia also conducted a second reinforcement along the border³. Thus, these breakpoints reflect a shift in the features of the most streamed songs in Ukraine, with a slight drop in their danceability and positivity (e.g, the mean of the danceability feature changed from 0.73 to 0.70 according to Table I) and an increment of their energy.

Comparing these results with those of other target countries, Table I shows that most of them had a slight increment in the energy of the songs a few months after the breakpoint

¹<https://charts.spotify.com/charts/overview/global>

²<https://developer.spotify.com/discover/>

³<https://taskandpurpose.com/news/russian-military-equipment-white-markings/>

TABLE I

DATES OF THE CHANGE POINTS OF THE HOMOGENEITY TEST WITH THE STANDARD NORMAL HOMOGENEITY TEST (SNHT) FOR A P-VALUE OF 0.05. THE VALUES IN BRACKETS INDICATE THE MEAN OF THE TIMESERIES BEFORE AND AFTER THE BREAKPOINT.

Country	Danceability	Valence	Energy
Ukraine	2021-04-16 (0.73, 0.70)	2020-11-30 (0.46, 0.48)	2021-05-23 (0.63, 0.66)
Latvia	2021-11-17 (0.70, 0.67)	2022-06-21 (0.49, 0.51)	2021-12-30 (0.63, 0.68)
Romania	2020-11-18 (0.73, 0.71)	2022-02-27 (0.53, 0.50)	2021-03-30 (0.63, 0.66)
Bulgaria	2021-11-15 (0.70, 0.68)	2021-06-03 (0.53, 0.56)	2021-06-17 (0.67, 0.70)
Lithuania	2020-11-21 (0.72, 0.67)	2022-07-14 (0.49, 0.52)	2021-05-11 (0.61, 0.66)
Estonia	2021-11-18 (0.70, 0.66)	2022-01-08 (0.52, 0.49)	2021-05-07 (0.65, 0.69)
Belarus	2022-06-29 (0.68, 0.69)	2022-09-21 (0.45, 0.46)	2022-08-25 (0.65, 0.66)

date of Ukraine (2021-05-23). Regarding the danceability and valence features, they changed in all countries except Belarus by the end of 2021 or the first months of 2022 as long as the likelihood of a war increased. In the case of danceability, this involved a decrease in its mean value, which is also consistent with the behaviour observed in Ukraine. For the valence feature, its behaviour was more heterogeneous: it increased in certain countries (Latvia, Bulgaria, Lithuania and Belarus) but declined in others (Romania, Bulgaria and Estonia). Moreover, most of these valence breakpoints occurred in the second half of 2021, during which the Ukrainian conflict was exacerbated.

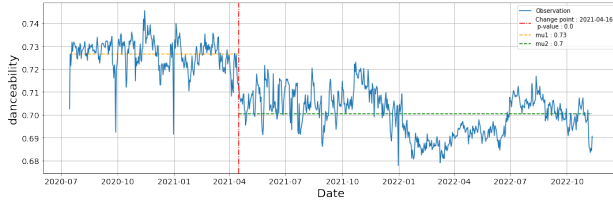
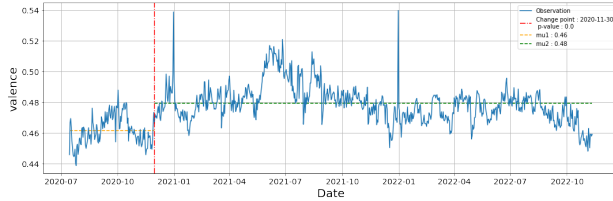
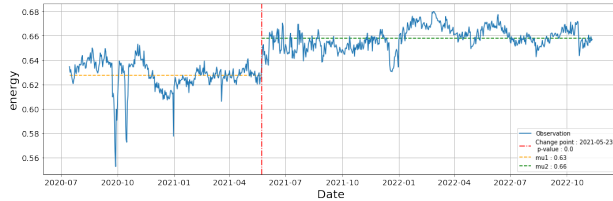
(a) Breakpoint of the \mathcal{F}_D^{UKR} timeseries.(b) Breakpoint of the \mathcal{F}_V^{UKR} timeseries.(c) Breakpoint of the \mathcal{F}_E^{UKR} timeseries.

Fig. 2. Results of the the homogeneity test made on the 3 mood-related timeseries of Ukraine. Each breakpoint is depicted as a vertical dashed red line, whereas the mean of the corresponding mood feature of each half is represented by yellow and green horizontal lines, respectively.

For the sake of completeness, Fig. 2 shows the breakpoints of each mood timeseries for Ukraine along with the mean values after and before the detected change.

B. Clustering of Countries based on the Mood Timeseries

In the previous section, the timeseries of all the target countries were analyzed in an isolated manner. In order to study the relationships among these countries, we developed a second experiment to group the target countries based on the similarity of their mood timeseries.

First, each timeseries \mathcal{F}_f^c was divided into 2 different sub-sequences, namely $\mathcal{F}_{f,prewar}^c$ that comprised the feature series before the war outrage (from 2021-07-15 to 2022-02-23) and $\mathcal{F}_{f,war}^c$ that comprised the part of the timeseries covering the war period (from 2022-02-24 to 2022-11-10). Then, we applied the Hierarchical Clustering algorithm using the Dynamic Time Wrapping (DTW) method as a distance metric [9] to each type of sub-sequence for all the target countries. DTW is a well-known distance metric for timeseries that exploits the *shape* of the input timeseries. Fig. 3 shows the resulting clusters of this procedure. Regarding the danceability feature, Figs. 3a and b show that the conflict caused a large aggregation of the target countries. In particular, a large cluster comprising Estonia, Latvia, Lithuania, Ukraine and Bulgaria was created after the conflict began. A similar pattern was observed in the case of the energy feature as Ukraine joined the cluster that already comprised Latvia, Lithuania and Romania during the state of war (Figs. 3e and f). Last, the behaviour of the valence feature was slightly different from the previous ones as, in this case, Ukraine remained in an isolated cluster before and after the war began. This is consistent with the fluctuation and previous differences observed in this feature with respect the danceability and energy patterns.

As a result, this clustering analysis reveals that, overall, the mood timeseries of the target countries has become less diverse after the war. It shows large clusters comprising almost all the target countries, at least for the energy and danceability features.

C. Variation in the Number of Daily Streams

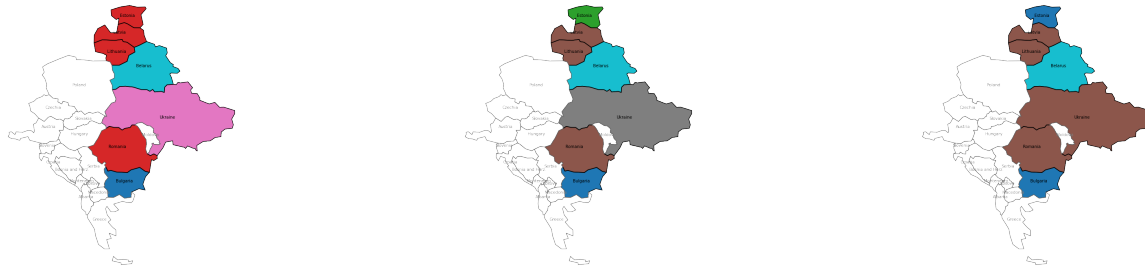
The last experiment studied the impact of the war with respect to the daily number of song stream in the Top-200 rankings of the target countries. As observed in Fig. 4, all countries suffered a sharp decline on the same date as the beginning of the war and in the following days. For example, Ukraine fell from 2,122,435 total streams in its Top-200 rank on February 23rd, 2022 to 1,442,228 (about 32% less) the day after Russia started the conflict. This may reflect the obvious impact on the daily lives of Ukrainians during that particular day. Then, the number of streams steadily increased since that date.

V. CONCLUSIONS AND FUTURE WORK

In this article we study the effect that an extreme event such as the recent war between Ukraine and Russia may have on the state of mind of the Eastern European population most affected by the conflict. To this end, we have analyzed the evolution of the music listened to by the citizens of these countries on the Spotify platform in periods before and after the start of the war. The results show that whilst the flow of songs between the



(a) Cluster of the countries before the war outrage based on the danceability feature. (b) Cluster of the countries after the war outrage based on the danceability feature. (c) Cluster of the countries before the war outrage based on the valence feature.



(d) Cluster of the countries after the war outrage based on the valence feature. (e) Cluster of the countries before the war outrage based on the energy feature. (f) Cluster of the countries after the war outrage based on the energy feature.

Fig. 3. Clustering of the target countries based on the DTW algorithm applied on their mood-related timeseries.

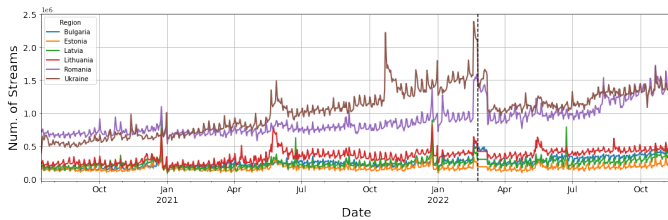


Fig. 4. Evolution in the total number of daily song stream per country. The vertical dashed line indicates the beginning of the war (February 24th, 2022).

two countries at war has not been altered, a change in the type of music listened to in Ukraine has been detected, specifically related to the danceability and energy during the first months of the conflict. In addition, we found that the type of music listened to in these countries has clearly homogenized since the beginning of the conflict. Finally, we detected that a clear drop in the number of songs played just at the beginning of the war, this number has been gradually increasing again.

CODE AVAILABILITY

The source code of the project is available at https://github.com/ferroso/war_and_music

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