respiratory rate variability, oxygen arterial saturation, and consumption, liquid intake, sleep quality, number of steps, distance traveled, type of physical activities and many others. That could be achieved by analyses of the data obtained by various sensors such as accelerometers, gyroscopes, magnetic field, galvanic skin response and temperature sensors. Monitoring devices are presented in various forms, smartphones smartwatches and wrist fitness trackers are becoming ordinary objects for most people, some devices are attached to the body, for example, chest belts, contemporary technologies allow to design clothes with in-built textile-based sensors. Devices interconnected with nearby processing units can share the data for deeper health observations. Continuous monitoring can be performed remotely, ergonomically and in a relaxed atmosphere from one side, from the other it can help to diagnose various health problems in early stages. [23] Since, mobile phones are equipped with some sensors, mobile application of the recommendation system could also play a role in sensor-based data collection tools. In most of the cases, sensor-based data is a raw data that could be used to reason about more upper-level data such as activity, surrounding environment, emotional state, etc. Therefore, to make our system smarter and less obtrusive, we have to increase the usage of externally and automatically collected data.

4) External Supervisor driven Data: describes a used from the perspective of external supervisors, such as parents or family members, teachers, therapists, etc. To collect this data, we need an extra front-end application for survey-based data collection, or to utilize a mediator that allows data collection via existing communication channels (Social Network-based application or other external services).

5) Upper-level Data Reasoning: modules populate Personal Data Space with application-specific data taking into account all suitable data that is available in the data space and data, which is accessible via DBPedia [24] or other information services. At the same time, these modules might initiate retrieval of extra data, if a confidence level of the reasoned value is low due to lack of fresh data, or due to specific conditions that minimize the influence of available data on the final outcome of the module. For example, a module that reasons about the current emotional state of a user takes into account relevant data provided by the user via self-reporting channel, user's heartbeat rate, and emotional state description provided by external supervisor (teacher). It might happen, that in some circumstances (based on some contextual information), the algorithm applies conditions that minimize a trust level of user's self-reported data (lowering influence of this source of information). At the same time, the system might not have updated value from more reliable (in this context) external supervisor, and its old value does not make any sense. Additionally, we might also be not able to fully rely on high heartbeat measurement influence, since we might be unconfident with the current activity of a person (e.g. whether (s)he is doing some sports or not). Finally, emotion state reasoning algorithm might return us a possible value with low confidence level and it will require additional retrieval of necessary data (e.g. to submit a request to external supervisor) or/and retrieval of extra data that, for example, cannot be constantly updated in the user's Personal Data Space due to some limitations (e.g. limited amount of API based requests to the remote service). An example of such extra data could be an analysis of emotional footprints of recent messages sent by users via social communication channels (e.g. Facebook), or emotion-oriented face and voice recognition applied on top of recently captured image/video/sound.

6) Under an Upper-level Data: we might consider various contexts such as Activity, Surrounding Environment, etc. Values for these contextual parameters might be gathered from the user directly, as well as reasoned based on relevant data. For example, speed (calculated based on GPS data) might indicate that the user is traveling. Depending on the speed range and map data, the system may also reason about the type of vehicle user is traveling by. Certain speed range and temporal data (season) in combination with heartbeat measurements might indicate that the user is doing some sport activities (running, biking, rowing, skiing, etc.).

7) Music-related Features and Metadata: are retrieved by feature detection module itself or via external music/audio feature detection tools (e.g. The Echo Nest [25], etc.), and collected from music content providers (e.g. Spotify[26], Pandora, Google Play, Beats Music, SoundCloud, etc.) or other external music-related information services (e.g. MusicBrainz [27], BDTune [28], etc.). This data includes the physical features of an audio track and the meaning of corresponding lyrics. At the same time, taking into account an emotional specific of the offered system, indirectly related information, such as the meaning of an associated video track (video clip(s)) or some event(s) closely associated with the audio track, could be also considered as personalized track related data. In this case, we definitely will require a more advanced and sophisticated data-retrieving tool.

8) Personal Data Space: is constantly populated with updated values of row data as well as upper-level data provided by corresponding reasoners. These data can be updated automatically in the background, according to a defined scheduling logic, and/or could be refreshed on-demand. Therefore, direct consumption of data available in Personal Data Space may speed up and facilitate the performance of the system [29]. To be easily compatible and interoperable with other systems, Personal Data Space will follow commonly accepted W3C standards with respect to Semantic Web [30] and Linked Data [31], [32] principles. The internal data model will be built as an extension of the widely used ontologies (Music Ontology [33], Audio Features Ontology [34], Emotion Ontology [35], etc.). Being organized as a remote service and supported with the corresponding API, Personal Data Space could be utilized by other services and applications. It will facilitate the dissemination of some of the project's results, as well as, could be considered as an extra outcome of the project.

9) Interactive user feedback: Listening behavioral factors during music listening sessions play a significant role in determining preferences and emotional states. Explicit interactive feedback involves liking or disliking and music track rating. Along with that, we can get the feedback through an implicit way by analyzing actions performed during the listening session: track listening duration (was it listened fully or partly), replaying, skipping, forwarding, back warding and downloading. Music search history and strategy allows building a personal preferences picture. Such listening experience analyzes drive the system decision about user preferences and help to avoid or at least to reduce relying on obtrusive surveys and feeling of feedback forms. In such a way the system looks more natural and does not look like an imposed treatment mechanism.

B. Classifying

The primary objective of the system is selecting music tracks to change and maintain the psychophysical states of humans. Music tracks should be classified with labels that describe emotional, psychological and psychophysiological states and transitions. Therefore, we have to solve the problem of classifying for the content-based filtering (see Fig2.). Of course, to achieve more accuracy in deep neural network performance the datasets should be large enough. Other models such as k-nearest neighbors and random forest can also be considered for this task and used for the cross-validation purpose. Random forest sows more accuracy in music genre classifying based on music features in comparison with k-nearest neighbors. For more precise judgments and selection of the particular model the system should be tested with large enough real data sets.

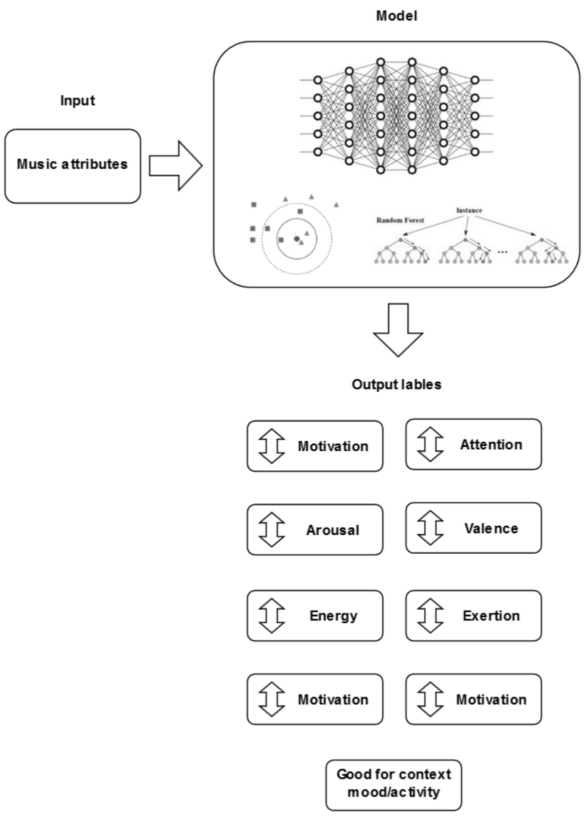

Fig. 2. Classification model overview

At the same time, having sufficient labeled training set of various sequences of musical entities (point in the space of musical types and genres), we may train Long Short-Term Memory (LSTM) [36] model to further make corresponding recommendations on the way towards desire point in emotional space. LSTM network allows training the model and labeling each song with respect to long and short-term user preferences and perceptions of particular music attributes.

C. Incremental learning

The system needs to adapt to the dynamic nature of the real-world settings and extend the knowledge without retraining of the existing model. To achieve deeper personalization, more accuracy and perform real-time recommendations Reinforcement Learning (RL) can be used as a tool to support incremental learning of the neural network model. This approach is grown in use to enrich recommendations of multimedia items in the interactive environments, as an example let’s consider the emotion aware video recommendation system [37]. RL is applicable to the dynamic music playlist generation [38], [39].

The operation principle of the RL is performing actions based on policies that have been built with respect to the environment and the operational history. Markov Decision Process is a generalized model of the RL, which includes the following components: a set of states within the environment, actions which expected to be performed by the agent against the environment, which drives the ongoing actions and the feedback or reward function which tunes the policy and directs actions. In our case the contextual listening experience with music corpus can be considered as an environment. The recommendation system takes the agent role and performs actions on the selection of music items in the model considered as states. The reward function is driven by the sensor data, surveys and the user behavioral feedback (like, dislike, skip, forward, backward, rating, listening time, etc.)

D. Real-time data processing

The recommendation system involves a lot of analyses to select useful objects with respect to appropriate context in large space of options. The system needs to be aware of listening experience events, their duration, preferences, feedback, and physical and psychophysical fluctuations. To achieve deep personalization, the system has to collect and process large amounts of individualized events in real-time. There is a need for a distributed system to support large data streams with a growing number of users. Apache Kafka is the message stream platform which can be used as a tool to bind client applications and data processing units, it has high throughput and low latency in real-time data streaming.

IV. EXPERIMENTAL PROTOTYPE

To validate the recommendation model, we elaborated the trial prototype of the system. The core of the system is a web service which receives feedback about listening sessions and music attributes, and classifies music tracks for further recommendations. The mobile application consists of the music player integrated with MuPsych tool and the Spotify platform. Users can listen to music with the player or in Spotify, it does not affect the data collection and recommendation process.

At first stages the model training process of the experimental prototype is mainly relying on the data collected by the MuPsych tool. Users can keep full anonymity, the application only offers basic information and personality surveys to bind a person to an appropriate user group to tune more accurately further recommendations. The contextual data of the music listening is based on emotional state, listening to reason and the activity. The mobile application provides questions related to the mood and the listening reasons when the user starts playing music, after 5 minutes and at the end of listening. At the same time, the MuPsych tool captures music attributes of listened music. All the data with the interactive user feedback is collected by the data processing engine. Based on the datasets already collected by the MuPsych and continuously updated data from the user side, the music recommendation system performs classification of music tracks with respect to their properties, user clusters, contextual data and listening reasons.

Fig. 3. Recommendation process.

At the second stage, the system provides generalized playlists which are created with respect to the mood and activity context for an appropriate audience group. When the system learns more about the user, it continuously classifies tracks and tunes the personalized recommendation model. Fig. 3 shows the graphic user interface of the mobile application, it involves interactive listening with the feedback, which effects on further playlist creation. Trial experiments showed that the core music attributes such as energy, valence, tempo, and loudness in generated playlists have sufficient matching with attributes of music tracks from MuPsych datasets for the particular mood and activity contexts. Therefore, we can conclude that the system selects music with similar attributes to those, which were explored during emotional state transitions during listening. There are needed further elaborations, comprehensive experiments and validations of the system to judge how recommendations effect mood and match preferences.

V. CONCLUSION AND FUTURE WORK

Paying attention to various factors, such as particular context, personal parameters, feelings and emotions, is highly important to a decision-making process of recommendations. Contemporary music recommendation systems face the gap in personalization, human feelings, contextual preferences and emotional factors while suggesting music. In this paper, we proposed emotion-driven recommendation system with respect to personalized preferences and particular life and activity contexts. The approach presented in this study is targeted to provide maximum benefits for people from the music listening experience. It is important to make the system aware of how it is doing the recommendations, to continuously improve the music selection. By feeding the data from various sources, the system is aimed to listen to each particular user and understand their purposes of listening, feelings and contextual preferences to select the best-suited music pieces for them. We observed what kind of data is needed for the recommendation system and how it can be fetched. Main data processing tools are clarified in the scope of this paper and the experimental prototype has been elaborated. However, to achieve maximum accuracy in predictions and make them more or less relevant, machine learning systems require a large amount of the data to train the models. At this moment the data collection is in active process. At the same time this kind of system requires significant clinical research and collaboration with psychologists to tune and test the model for real recommendations and reduce possible associated risks. Further work on the implementation and testing of the recommendation engine, empirical experiments and impact evaluations are considered for the next step when the appropriate amount of the data will be collected. Music creation by artificially intelligent systems with particular music attributes to move states of human emotions can be considered as the further elaboration work in this context.

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