

Does creativity have an age?

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Abstract—It is thought that creativity declines with age, but this is controversial. Studying creativity is challenging because the concept itself is elusive and it is quite expensive to perform longitudinal studies across large groups of people. Herein, we propose a design for a web application that gathers data to be used for studying creativity through people’s appreciation of music. With the addition of our intrinsic rewards scheme in the form of personality test and personalized recommendations, we ensure the quality of the data, which will be used in the development of tangible creativity measures.

I. INTRODUCTION

The impression that creativity declines with age is an ingrained stereotype in our society. Although there are some studies supporting this notion [1][2], it does remain a controversial topic [3]. On one hand, it is argued that age reduces speed of information processing leading to a decrease in willingness to risk for original solutions [1]. On the other hand, it seems that creativity is more pronounced when the attribute of originality is predominant in the sciences, as opposed to arts and humanities [2]. Furthermore, there are clear examples of disciplines and individual variation where creative peaks appear later in life [4].

The difficulty of studying creativity comes not only from the complexity of defining it, but also from the fact that there is an inherent association with productivity and achievement. However, there is also another perspective of creativity that relates to the degree of acceptance. For instance, listening to music is not necessarily a productive act, but can be seen as a proxy for understanding people’s receptiveness towards creativity. Studies in music listening tastes [5][6] seem to indicate that music preference for the different styles are comparatively similar across ages. Furthermore, a person’s preference for popular music reaches its peak at the age of 24. In the modern age of technology, people can easily access various levels of creativity in music. Therefore, it is viable to use music preferences in order to study the relation between creativity and age. In this study, we aim to investigate such relationship by the aid of web applications.

In this project, we developed a web application, called Crazy*tivity¹, to collect data regarding lay users’ music preferences and to study the variation of the creativity of the

songs. This web application provides valuable information to understand the types of music that people across various ages like. In order to prevent misconduct, the application rewards the participants by providing a set of personalized recommendations as well as personality test results according to their music preferences. The contributions of this project are threefold: (a) collection of data that can be used to study music preferences across different ages; (b) several measures to make the elusive concept of creativity tangible, and (c) personalized song recommendations to inspire users to be more creative by exposing them to other creative choices.

II. CRAZY*TIVITY WEB APPLICATION DESIGN

In this section, we present the different components of the web application along with the implementation details.

A. Web Interface

The web interface first prompts the users to fill in a survey. The survey consists of ten different songs, which are drawn from a uniformly distributed subsample from Last.fm² database as described in Section II-D. Songs are chosen randomly and the users are asked about their feelings regarding the song that is being presented on the page. The user has three options to choose from: "Like", "Dislike" and "Never heard". Upon completion of the survey, the users are asked to specify their age group and their knowledge of music. When the users submit their preferences, the feedback is sent to (1) the personality test module and (2) the recommendation system. Once the calculations are finished, the personality score is presented along with the set of recommended songs. An example of interaction is presented in a video attached³.

The user interface (UI) is a Node.js⁴ MongoDB⁵ application.

B. Intrinsic Rewards

The quality of the gathered data depends on the honesty of the participants. Monetary reward schemes can sometimes lead to inaccurate data as the users might feel they need to

¹According to Oxford Dictionary, the second definition of crazy is "extremely enthusiastic". The authors intend to use this meaning for the web application.

²Last.fm is an online music catalog with free music streaming, videos, photos, lyrics, charts, artist biographies, concerts and internet radio. (<http://www.last.fm>)

³<https://drive.google.com/open?id=0B-Gt4Qg-MpF-NE94UThhR0huXzg>

⁴<https://nodejs.org/en/>

⁵<https://www.mongodb.com>

answer in a certain way or they might get falsely reward-driven. In order to overcome this problem, we add to our web application a personality test as well as personalized recommendations based on the user's music preferences. We believe that intrinsic rewards will ensure honesty and diversity as they may encourage the participants to spread the web application among friends to compare their results.

1) *Personality Test*: The personality test is based on the well known Myers-Briggs type indicator (MBTI) [7], which comprises 16 different personalities based on four personality traits: Introversion (I) or Extraversion (E); Intuition (N) or Sensing (S); Thinking (T) or Feeling (F); Judging (J) or Perceiving (P). For constructing the link between music tastes and the personalities, we used the data from a music preferences survey⁶ of over 4000 respondents, who identified themselves with a certain personality and role (aggregation of personalities according to goals, interests and preferred activities). The genre labels used in our initial music dataset are slightly different, so we applied a pre-processing phase where we converted the tags of the musics to the ones used in the survey wherever possible. The personality of each user is, then, determined by normalizing the data of the survey with each personality and comparing this personality's music preferences with a representation of the music that the user likes. The user's *favorite music* is the average of the tags of all the songs he or she liked by genre, which gives us how much that person likes to listen to a certain genre. The personality score is then assigned according to the shortest Euclidean distance to one of the roles that are more general. While this measure is not as accurate as an introspect self-report personality survey, it offers users a match between their music preferences and their personality. Furthermore, it may inspire them to explore this personality test more, and share it on social media with their friends.

2) *Music Recommendations*: Following the results of the personality test, the web application displays a number of songs that the user might like. This functionality facilitates increasing creativity by contributing to the users' knowledge and awareness. Since the songs are retrieved and chosen according to the particular user, we use a recommender system.

Recommender systems use feelings and experiences of a base of users in order to make recommendations to other users according to their profiles. One of the most relevant systems within recommender systems are the collaborative web recommender systems. The main characteristic of these systems is that the recommendations for a user are computed based on the previous ratings of the same user. These recommender systems need to implement a collaborative filtering algorithm which might be either model/item based algorithms (i.e. item-item) or memory/user based algorithms (i.e. user-user). In our case, we use a user-user algorithm for filtering.

User-user recommender systems are based on collaborative filtering, which use the complete database in order to calculate

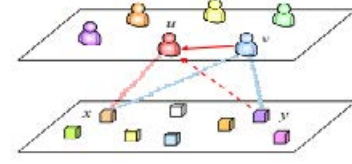


Fig. 1. User-user diagram

a prediction. The idea is to choose a user and apply different algorithms to establish the closest k neighbors (with similar preferences). The system uses these k neighbors to carry out item recommendations. Figure 1 depicts this process.

Currently this approach is the most used and extended one within commercial recommender systems. However, it presents scalability problems when the number of users grow [8]. For large scale applications, it is better to apply methods that focus on group recommendation [9].

In our web application, the recommended songs are those that have not yet been rated by the user but have been rated as *liked* by similar users (who have the same personality).

C. Defining and Measuring Creativity

Collecting data regarding the users' music preferences is not sufficient for understanding the relationship between age and creativity. We also need to define concretely what creativity means, and how creative a piece of music is. In the western society, creative musical pieces are strongly related to originality, and also to being accepted and popular. In this project, we refer to the songs that are the most original and popular as creative. This section describes the proposed metric for creativity.

Normalization is the basic method in this metric, which is based on playcount⁷ and the originality of the different tags of each song. M and N are the total number of tags and songs in our database, respectively.

Creativity in song i (C_i) is measured in terms of how popular/valuable the music is (V_i) and its originality (O_i):

$$C_i = (V_i + O_i)/2, \quad C_i \in [0, 1] \quad (1)$$

The playcount stands for the popularity. Then, the value of song i (V_i) is obtained by normalizing its playcount:

$$V_i = \text{playcount}_i / \sum_{j=1, N} (\text{playcount}_j), \quad V_i \in [0, 1] \quad (2)$$

Tags including pop, rock and so on, are description elements of the songs. By analyzing the originality of every single tag (O_{i_s}) and pairs of tags (O_{i_p}) respectively, originality of song i (O_i) can be calculated by:

$$O_i = (O_{i_s} + O_{i_p})/2, \quad O_i \in [0, 1] \quad (3)$$

⁶More information can be found at: <https://www.16personalities.com/articles/music-preferences-by-personality-type>

⁷Playcount is the number of times the song has been listened to/played on last.fm platform.

Central to measuring O_{i_s} and O_{i_p} is the calculation of the proportion ($P_{i,j}$) of musical tags j in song i . Here $C_{i,j}$ is the count that song i is marked with tag j :

$$P_{i,j} = C_{i,j} / \sum_{j=1,M} C_{i,j} \quad (4)$$

1) *Measure of originality considering single tag(O_{i_s}):*
Mainstream proportion of tag j used in one song is:

$$P_{j_mainstream} = \sum_{i=1,N} P_{i,j} / N \quad (5)$$

Distance between song i and the mainstream in terms of tag j is the originality of song i considering tag j :

$$Os_{i,j} = \sqrt{(P_{i,j} - P_{j_mainstream})^2} \quad (6)$$

Then the originality score of song i considering every single tag(O_{i_s}) is:

$$O_{i_s} = \sum_{j=1,M} Os_{i,j} / M, \quad O_{i_s} \in [0, 1] \quad (7)$$

2) *Measure of originality considering pairs of tags(O_{i_p}):*
First, we need to measure the originality score of each pair of tags. $N_{s,t}$ represents the number of songs that contain the pair of tag s and tag t . Then, the originality of this pair is:

$$Op_{s,t} = 1 - \frac{N_{s,t}}{N} \quad (8)$$

$P_{i_s(t)}$ is the proportion of one pair in all the pairs contained by song i :

$$P_{i_s(t)} = \frac{P_{i,s} \times P_{i,t}}{\sum_{x,y} (P_{i,x} \times P_{i,y})} \quad (9)$$

Then we get the originality of song i considering pairs of tags:

$$O_{i_p} = \sum (Op_{s,t} \times P_{i_s(t)}), \quad O_{i_p} \in [0, 1] \quad (10)$$

The implementation of the creativity measure is available online⁸. It is important to note that the measure is used as a proxy to estimate the creativity of the songs, which will allow us to analyze the data obtained and to understand how creative the songs liked by a user are. We foresee that such analysis will give us insights regarding how creativity relates to age.

D. Data Sources and Analysis

This section describes the data pre-processing steps as well as the data analysis. The source code is provided online⁹. The aim of the data analysis and pre-processing steps is to extract a uniformly distributed sample of songs, which are to be displayed on the web interface for experiments with lay users. Initially, we have started with a dataset of 107810 highly popular songs (i.e. the top 3% of the songs, which are sorted in descending order of their playcount on last.fm database). In order to measure song popularity, we have developed a metric as described in Section II-D2. We then used this metric to extract a uniformly distributed subsample from the

	tag_1	tag_2	$\dots$	tag_n
$song_1$	1	1	$\dots$	0
$song_2$	0	1	$\dots$	1
$\vdots$	$\vdots$	$\vdots$	$\dots$	$\vdots$
$song_m$	0	0	$\dots$	1

Fig. 2. Representation of the dataset as a matrix of songs and tags

initial dataset. The uniformly distributed subsample ensures reliable metrics and scores, which are later drawn from user interactions as described in Section II-B1 and Section II-B2.

The following subsections describe the contents of the dataset as well as the popularity metric that is used to subsample the songs.

1) *Contents of the dataset:* The initial dataset is composed of the song name, album name, artist name, tags (that are assigned by the last.fm users to describe the song), duration of the song and the playcount. The user-assigned tags also have a score attached to them. This score can be interpreted as the agreed strength of association of the tags with the corresponding song.

2) *Popularity Metric:* In our popularity metric, we made use of the tags and their scores. We have opted for considering only those tags that had more than a score of 3 (on a scale of 0-100) in our analysis. The reason why we chose a low threshold for tag elimination was to increase the collective diversity of the tags that were associated with -already- highly popular songs. It is important to note that the threshold can be determined in various ways and is introduced as a variable in our implementation. Next, we ran a normalized frequency analysis on the tags having more than the threshold score. Once we have identified the most frequently used 100 tags, we used a binary bag-of-tags vector representation for each song in the dataset. Using this representation method, we were able to represent 99.6% of the initial dataset with non-zero vectors. The representation method can be visualized in Figure 2.

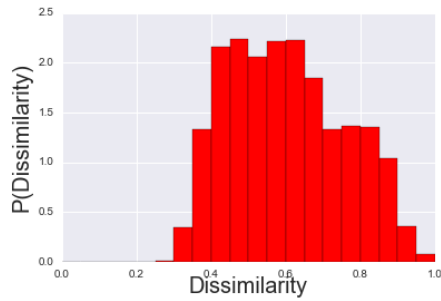
For a fairly simple and fast comparison between songs, we needed to develop a representative for the average popular song, which can be referred as the 'mainstream' song. The vector for the mainstream song is calculated by normalizing the sum of all the song vectors in the entire dataset. In order to calculate popularity, we used cosine similarity between the vector representations of each song and the mainstream song.

The similarity distribution can be visualized in Figure 3a. The x-axis shows the measure of dissimilarity (1 - similarity) and the y-axis shows the frequency. In order to extract a uniformly distributed sample, we have chosen a threshold for the minimum frequency. This frequency is also a variable and can be chosen in several ways. For the experiments reported in

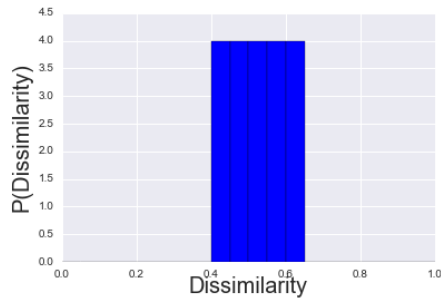
⁸<https://drive.google.com/drive/folders/0B5K1bVvNsibAd21Wc3VuS0oyWW4>

⁹<https://drive.google.com/drive/folders/0B5K1bVvNsibAd21Wc3VuS0oyWW4>

this report, the threshold is set to be such that the dissimilarity score ranges between 0.4 and 0.65 as illustrated in Figure 3b.



(a) Dissimilarity distribution of the initial dataset



(b) Dissimilarity distribution of the extracted sub-sample

Fig. 3. Visualization of the initial and sub-sampled dataset

III. CONCLUSION

In this project, we proposed a design of a web application for online collection of data to analyze the receptiveness of people towards various levels of creativity in music. We ensure the quality of the gathered data by providing intrinsic rewards to the users and by performing data science techniques to obtain a uniformly distributed sample of songs to be used in the application. Furthermore, we propose a tangible creativity measure based on playcount and originality of tags that will allow for the analysis of the collected data for acquiring insights regarding creativity. Currently, the web application serves as a proof of concept. Yet, as part of future work, we intend to make it available online, and we expect to use the obtained data to understand if creativity is indeed related with age or not.

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REFERENCES

- [1] Ruth, Jan-Erik, and James E. Birren. "Creativity in adulthood and old age: Relations to intelligence, sex and mode of testing." *International Journal of Behavioral Development* 8.1 (1985): 99-109.
- [2] Abra, Jock. "Changes in creativity with age: Data, explanations, and further predictions." *The International Journal of Aging and Human Development* 28.2 (1989): 105-126.

- [3] Lindauer, Martin S. "Does Creativity Decline with Age?." *Aging, Creativity and Art*. Springer US, 2003. 59-70.
- [4] Simonton, Dean Keith. "Creative Productivity Through the Adult Years." *Generations*. Spring (1991): 13-16.
- [5] LeBlanc, Albert, et al. "Music style preferences of different age listeners." *Journal of Research in Music Education* 44.1 (1996): 49-59.
- [6] Holbrook, Morris B., and Robert M. Schindler. "Some exploratory findings on the development of musical tastes." *Journal of Consumer Research* 16.1 (1989): 119-124.
- [7] Myers, Isabel Briggs. *The myers-briggs type indicator*. Palo Alto, CA: Consulting Psychologists Press, 1962.
- [8] Deshpande, M., & Karypis, G. (2004). Item-based top-n recommendation algorithms. *ACM Transactions on Information Systems (TOIS)*, 22(1), 143-177.
- [9] Castro, J., Quesada, F. J., Palomares, I., & Martnez, L. (2015). A ConsensusDriven Group Recommender System. *International Journal of Intelligent Systems*, 30(8), 887-906.