Dashboard Design: Interactive and Visual Exploration of Spotify Songs

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Abstract: In this paper we describe an approach to create interactive visualization tools for simple datasets that exist in various application domains which many people are familiar with and interested in, like sports, entertainment, traffic, or health care. Such data problems require a simple but elegant visual solution to support the non-experts in information visualization at their tasks at hand, supported by easy-to-understand interaction techniques. We start our approach with the design phase in which a hand-drawn mockup is created and based on this, an interactive dashboard in Dash, Plotly, and Python is built. The design of the tool is guided by user feedback of 23 participants in qualitative interviews taking into account eight relevant criteria before starting the design of a visualization tool. We illustrate the usefulness of the tool by applying it to a dataset focusing on songs from the music streaming platform Spotify while we integrate several diagrams in a multiple and coordinated views manner to visually explore a given dataset based on several visual perspectives. With the combination of the many diagrams we can find insights in the mood categories of the songs and several other attributes, hence allowing visual analyses and explorations. Finally, we discuss limitations and scalability issues of the approach.

1 INTRODUCTION

Designing dashboards for a given dataset scenario is a challenging task, in particular if the dashboard has to include various user interface components such as sliders, menus, buttons, and so on, as well as visual components that are based on a mixture of visual variables to build interactive diagrams with which users can explore their datasets (Ware, 2004; Ware, 2008). The design phase is typically guided by hypotheses about unknown data and involved tasks that have to be answered by means of interactive visualizations (Burch, 2022) in a multiple and coordinated views manner (Roberts, 2003).

In this paper we focus on the creation of such an interactive tool in form of a dashboard implemented in Dash, Plotly, and Python, demonstrating how easy it is to come up with an appropriate solution based on a hand-drawn mockup (see Figure 1). We start by understanding the data structure and format, which insights it might contain, and a possible design solution based on the information pieces we have in the beginning. Since there are various parameters in the beginning to adapt we start by designing a dashboard on high-level design decisions and are still able to adapt the design after further iterations.

To get a better understanding for the most relevant points before starting the design and implementation phase we conducted user interviews to collect qualitative feedback about the relevance of the points to be included. This evaluation is important since we cannot include all of the points equally in the design since they stand in some kind of trade-off behavior. Hence, some kind of priority list would be beneficial based on the feedback of several users. However, independent from the users, we have to walk through a series of ideas, concepts, and technologies in the design process, always keeping in mind that the created and implemented tool has to be used by non-expert users in general which was also the major point on the participants' priority list.

We illustrate the usefulness of the designed and implemented tool by applying it to data from the music streaming platform Spotify and the stored meta data. Our goal was to allow users to easily explore the data for correlations and dependencies (Heinrich et al., 2011) in the data attributes, possibly letting them find their desired songs, based on a variety of attributes. Moreover, we discuss scalability issues and limitations of the visualization approach.

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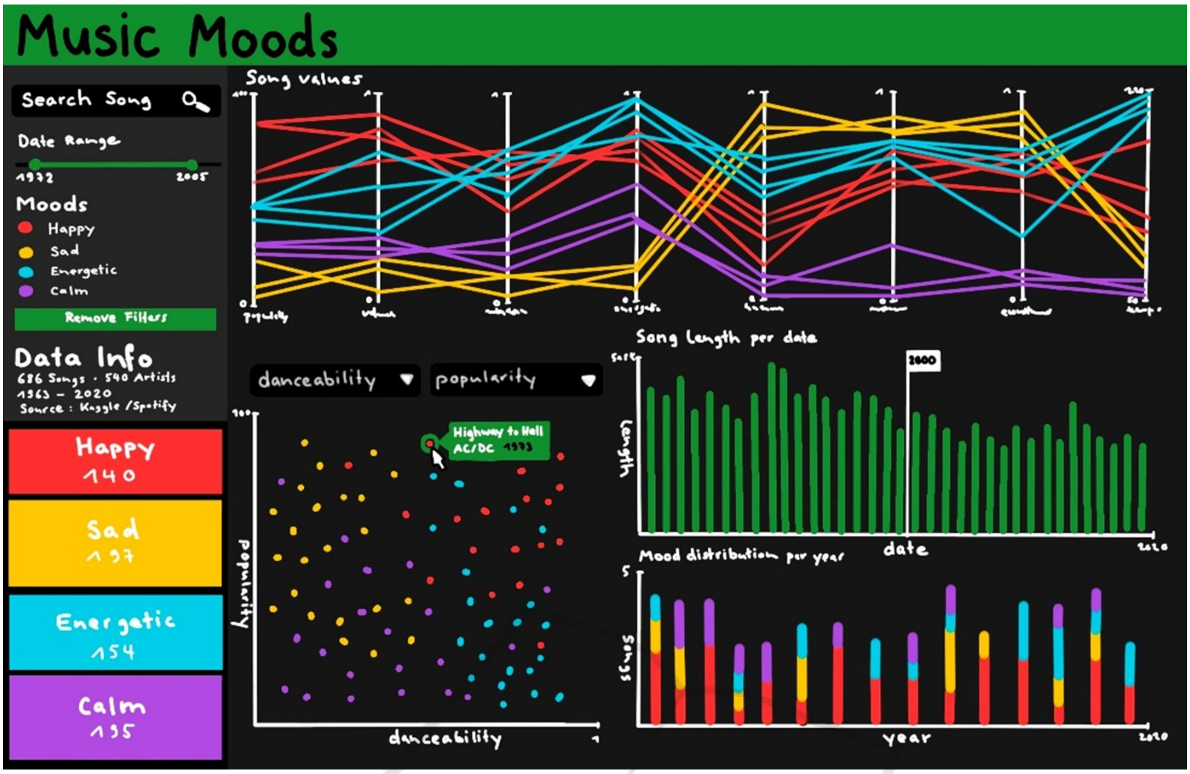


Figure 1: A hand-drawn mockup of the dashboard: The left part of the user interface contains the parameter panel while the rest of the user interface is used for the multiple and coordinated views on the data (here Spotify data). The currently visible diagrams are a parallel coordinates plot (PCP), a scatterplot, and two bar charts (the upper one only using the visual variable length and the bottom one using a stacked variant of the standard bar chart).

2 RELATED WORK

Dashboards (Bach et al., 2023) get more and more in focus in the field of information visualization (Burch and Schmid, 2024) since they provide easy-to-create and easy-to-implement solutions to data problems at hand. However, the most important aspect in dashboard design is the phase before starting the implementation in the form of producing source code. We need some knowledge about the data format and structure, the hypotheses and research questions as well as the users of the final tool with their tasks-at-hand (van Wijk, 2005) to create a successful solution for data analysis and exploration.

Designing a dashboard combines at least two major design problems which come in the form of the user interface design as well as the design of the diagrams (Rosenholtz et al., 2005; Tufte, 1992) with all of the included visual variables that build a mixture of parameters with options for changes and adaptations. But also the interaction techniques (Yi et al., 2007) and the algorithmic concepts that we typically do not see in the user interface are of importance to get the best out of it. To guarantee a suitable outcome for data analysis and exploration tasks we have to follow design rules, also focusing on aesthetic criteria (Bar and Neta, 2006).

We can find lots of dashboard examples, in particular for applications in information visualization, however, not many of the designs try to integrate design rules following interface, visualization, interaction, and algorithmic concepts at the same time. For example, FitYou (Zacheo et al., 2023) focuses on health data but it is unclear which of the four aforementioned components the tool focuses on the most. Another one (Shan, 2023) focuses on health security attacks without explicitly discussing the data in use and which algorithms are linked to which interaction techniques. Soccer athlete data is visually represented in a dashboard (Boeker and Midoglu, 2023) but the design and linking of the visualizations and the interactions is not described in much detail.

Apart from dashboards we can find a really long list of visualization tools, most of them equipped with complex visualization techniques only understandable by expert users, for example in the domain of eye tracking (Kurzhals et al., 2017), software visualization (Burch et al., 2017b), or graph and network visualization (Burch et al., 2017a). There are various examples in recent years with more and more following in the future, but still the design phase is underrepresented, in particular if the focus is on easy-to-understand visualizations.

3 QUALITATIVE USER FEEDBACK

We recruited participants working in the field of visualization to provide qualitative feedback based on a list of criteria that we took into account when designing a dashboard for data visualization. Since each user might have a different opinion on the criteria we averaged the results to get a general impression about the most relevant criteria before starting a dashboard design for a visualization tool.

3.1 Hypotheses and Research Questions

The research question in this work focuses on a list of aspects when developing a visualization tool in form of a dashboard and asks whether there is a clear order among eight important criteria for such a visualization tool: Easy to understand, application independency, interaction techniques, easy to install, comfortable data upload, several data perspectives, low costs, and easy to extend.

Before inviting people to give qualitative feedback we discussed about hypotheses that describe the outcome of the summarized qualitative feedback. Based on that we developed a list of three hypotheses:

- **Hypothesis H1.** The feedback of the recruited participants will clearly state that the major point when developing a visualization tool for their data is the easy-to-understand character.
- **Hypothesis H2.** The costs of the developed data visualization tool will only play a minor role during the development and when the tool is finally used.
- **Hypothesis H3.** There is a clear order among the points in the criteria list, that is, not all of the criteria are more or less equally ranked.

3.2 Participants

23 participants took part in the qualitative feedback experiment. We recruited them by sending emails containing clear instructions and asking for an order of the aforementioned criteria. The participants sent back their impressions as textual feedback that we had to summarize in numbers and facts. All of the participants were aged between 23 and 46 years at an average of 31.3 years while 9 were female and 14 male.

3.3 Questionnaire, Tasks, and Feedback

We asked the participants to state their age, gender, and experience in their favorite research field.

The task for them was to return the criteria in decreasing order starting with the most relevant one for a visualization tool focusing an data aspects. Moreover, they were asked to mention additional criteria that they also identify as relevant and that were not in the list.

3.4 Results

When evaluating the feedback we mostly focus on the hypotheses and the research question. We compute a priority list from the returned order given by the participants. To reach this goal we compute the average place on which a criterion is set in the priority list. This means the lower the average place of a criterion is the more it was suggested as being important, that means it was rated with a higher priority (see Table 1).

Table 1: From the qualitative feedback we created a priority list for all the eight criteria. The priorities were based on the average ratings of the participants, hence no individual opinions are taken into account in this summary.

Criterion	Average rating
Easy to understand	2.1
Application independency	3.9
Interaction techniques	4.6
Easy to install	4.9
Comfortable data upload	4.9
Several data perspectives	5.0
Low costs	5.2
Easy to extend	5.3

We see a clear tendency to the criterion that the tool should be easy to understand which is inline with hypothesis H1. Also hypothesis H2 can be confirmed stating that the low costs of the tool are not playing the biggest role. However, hypothesis H3 must be rejected. There is no clear order among the criteria. Only the easy to understand criterion stands out followed by the application independency.

The participants also mention that it might be important in which context the tool is used. For example, in an industry context, money does not matter for the user because the tool's costs are covered by the company, however, in a student's context it might be important to get cheap tools since the university is typically not offering any desired tool for free.

4 DATA AND TRANSFORMATIONS

The data under investigation in our application example contains a list of songs from the platform kaggle.com (Musicblogger, 2020) which is freely accessible. The data consists of a mixture of data attributes in various scale levels with nominal attributes, e.g. song titles, artists, ids, and mood categories which can be *happy, sad, energetic*, and *calm*.

The major part of the attributes is based on metrically scalable attributes like *popularity, length, danceability, acousticness, energy, instrumentalness, liveness, valence, loudness, speechiness, and tempo*. Those describe the measurable musicalic properties of the songs. Two more ordinal attributes can be found like *key* and *time signature*, as well as the *release date*.

In total, the dataset contains 686 lines, i.e. different songs. This number is only a small portion of the actually existing songs on Spotify since we used it only for testing purposes. The songs stem from 540 different artists and have been produced in the time period from 1963 to 2020.

To get the data in the required format for the interactive tool we applied some simple algorithmic transformations to it like sorting, data splitting, and categorization, just to mention a few from a long list worth integrating. Since the focus is on easy to understand concepts integrated in a dashboard we also take into account algorithms that are powerful but still useful by the non-expert users.

5 USER-CENTERED DESIGN

As already described earlier we focus the implementation on the result of a design phase that ends up in a hand-drawn mockup of the user interface including interactive diagrams. Moreover, tasks and hypotheses play a crucial role when developing the interactive visualization tool.

5.1 Tasks

We integrate some functionality for at least four major tasks.

- Mood correlations: We search for a list of songs with high values for the attributes *danceability* and *popularity*.
- Song lengths: We search for implications that the average song length decreases during the streaming age (Kopf, 2019).
- Attributes: We search for songs that follow a certain attribute correlation pattern (*tempo, energy* etc.) as well as the different mood categories they belong to.
- Mood distribution: We are interested in the number of songs per mood category and what a comparison between them will tell us.

5.2 Data Hypotheses

For the analysis of the data we come up with several hypotheses. Firstly, those are used to guide the dashboard design. Secondly, they are used to test whether the tool can be applied to the Spotify data in order to confirm or reject hypotheses (Keim, 2012).

- Hypothesis 1: Songs in the mood category *calm* have been mostly created in the second half of the time period.
- Hypothesis 2: The analyzed songs get shorter and shorter in length during the explored time period.
- Hypothesis 3: Songs in the mood category *calm* have a large value for the attribute *instrumentalness* compared to songs in the mood category *energetic*.

6 DASHBOARD CREATION

To test the earlier mentioned hypotheses, an interactive dashboard was designed (see Figure 1). This contains different diagrams as visualization elements.

The created visualization elements (see Figure 2) are summarized in a dashboard equipped with several filter functions. At the top left, moods that can be selected will be displayed. There is also a button that can be used to cancel this selection. Directly below is a date picker with which the displayed songs can be narrowed down by release date. Below that, basic information about the data set can be found, such as the number of songs and artists.

At the bottom of the left hand side is a simple treemap (Shneiderman, 1996) visualization that performs two tasks in one. On the one hand, the total number of songs per mood is displayed through four colored fields. The size of the field indicates the distribution of songs per mood. The exact number of songs corresponding to this category is displayed by hovering the mouse over a category. On the other hand,

Figure 2: The implemented dashboard based on the design in form of a hand-drawn mockup: We can see that the standard bar chart as designed in the mockup phase in Figure 1 has been removed and only the stacked bar chart variant is displayed.

the visualization also serves as a legend so that the mood categories can be identified in the other visualizations. This is because the color assignment of the moods runs through the entire dashboard. The colors of the moods were selected based on color theory (Lundberg, 2022). Accordingly, the color assignment is as follows: **happy:** yellow, **sad:** purple, **energetic:** red, and **calm:** green. Shaded colors were used rather than primary colors for a visually appealing look.

The core of the dashboard consists of the following charts:

- **Attribute Overview Songs.** This shows which songs have which attributes and which strengths. The attributes are lined up one after the other on several y-axes as parallel coordinates. The advantage of this is that attributes with different value ranges can be mapped simultaneously. Each song gets its own polyline. In order to be able to recognize commonalities of the songs based on their mood, the songs are color coded, as mentioned above (Hypothesis 3).
- **Correlation of Attributes.** At the bottom left, songs can be displayed and compared in a scatter plot by selecting two categories. On the one hand, correlations between the two selected attributes can be identified. On the other hand, the tough color assignment also makes any clusters of the moods visible.
- **Song Distribution.** The stacked bar chart shows how many songs per year of a mood are in the dataset. This indicates how the moods are distributed over the individual years. Moreover, it becomes easy to see if certain moods were more prevalent than others at a particular time point (Hypothesis 1).
- **Song Length.** The bar chart shows the average song length (y-axis) by release year (x-axis). This allows us to illustrate the evolution of song lengths per mood or across all moods over the years (Hypothesis 2).

Switching between the song length diagram and the song distribution diagram is possible using a button. This ensured that all visualizations were large enough and remained legible. The dashboard is based on Spotify's corporate design and was therefore designed in the so-called dark mode. However, switching between dark mode and scientific mode in the header at the top right is possible if this is appropriate and user-desired. The latter contains the same functions and color schemes as the dark mode but on a white background (see Figure 3).

7 INTERACTION TECHNIQUES

The planned functions mentioned above could be implemented in an operational dashboard. In addition to the functionality of the visualizations, emphasis was also given to interaction. The color coding of the moods mentioned above ensures that they can be assigned to each other throughout the entire dashboard and that a uniform image is created.

Parts of the dashboard are designed to be interac-

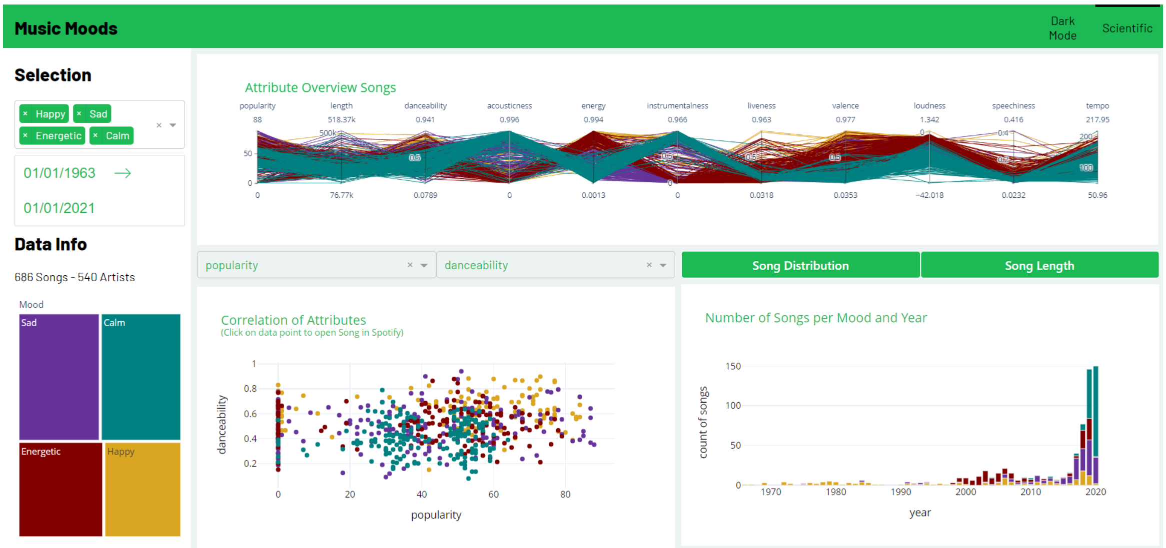


Figure 3: The dashboard in scientific mode, for example by using a different background color

tive to enable individual exploration of the data in the dataset.

- **Mood Filter.** At the top left of the diagram, as already mentioned, individual moods can be selected or deselected. The dashboard will then only show the songs of the selected moods. At least one mood must be selected.
- **Year Filter.** The period to be displayed can be specified below. This filter also applies to the entire dashboard.
- **Manual Adjustments Attributes Overview Songs.** Using the mouse, a range of values of a desired attribute can be selected. The songs which are in this range will then be highlighted. Further, the attributes can be arranged in the desired order using *drag and drop* (see Figure 4).
- **Further Information on Song Length.** Hovering over individual bars displays the year with the average song length in minutes (see Figure 5 (a)).
- **Display Correlation of Attributes.** The moods and periods displayed here can be adjusted using the filter functions on the left side of the dashboard. Above the chart, two drop-down menus can also be used to select the song attributes to be compared. If a specific value space is to be displayed, it can be selected manually by moving the horizontal or vertical lines. By mouseover over a displayed point, the values of the attributes, the song title, and the artist are indicated (see Figure 5 (b)). The user gets a helpful additional feature if the dashboard is started locally via a Python development environment. The corresponding song is opened in Spotify's web application by clicking on a point in the scatter plot. This allows the user to compare the songs visually and acoustically.

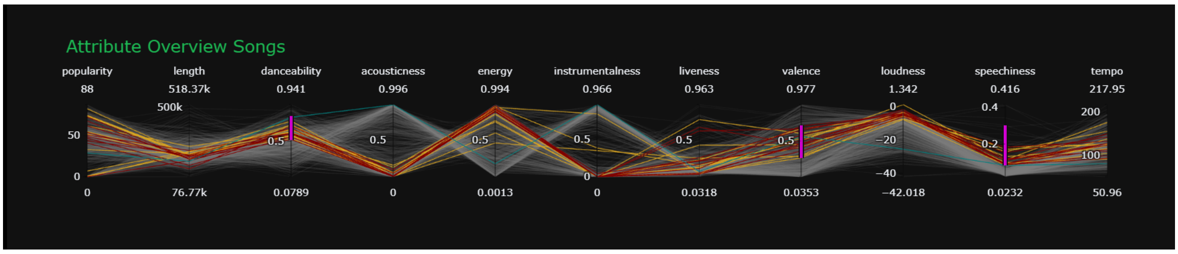
8 ANALYSIS OF PERFORMANCE

Since the data basis for the visualizations is relatively tiny and the algorithms used belong to the simpler ones, the response time of the dashboard shows an expected fast value of 271ms at a maximum. Many users abort the loading process after waiting for about two seconds (Guelle, 2022). Therefore, long loading times should be avoided at all costs, suppose too long loading times still occur when expanding the database. In that case, they can be reduced by performing the calculations already at the data set level instead of loading the visualizations, as constructed for this dashboard.

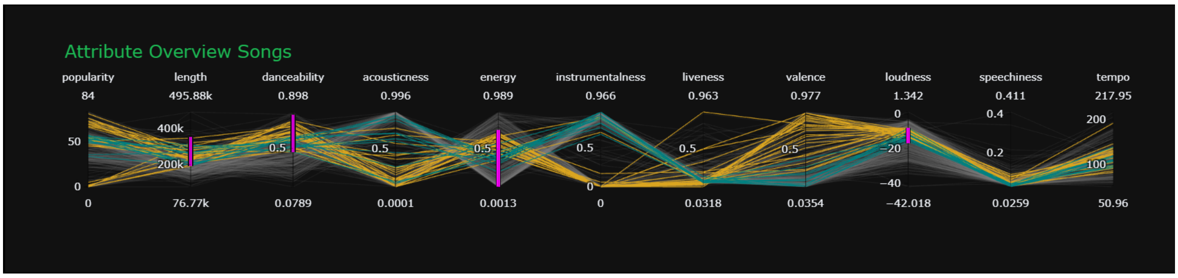
The dashboard is ideally used on a screen that measures 15 inches or more. Since there is no responsive design, not all representations are displayed as intended on smaller screens. Viewing with mobile devices such as smartphones is, therefore, only sometimes possible.

9 CONCLUSION AND FUTURE WORK

In this paper we have shown an approach to create interactive visualization tools in form of dashboards by using Dash, Plotly, and Python. We start with a design phase, taking into account tasks and hypotheses,

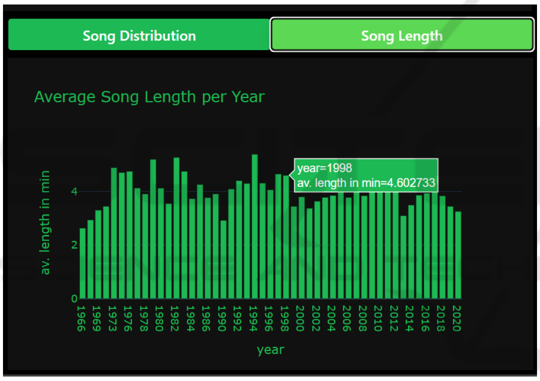


(a)

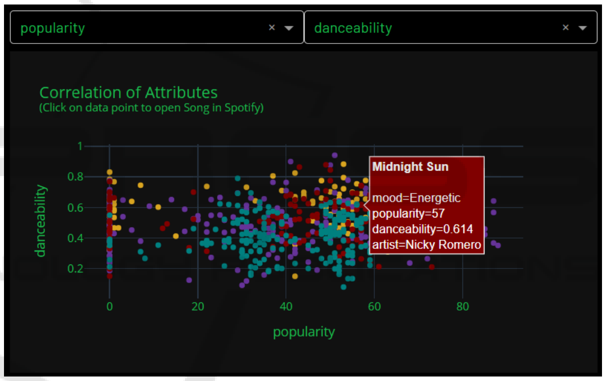


(b)

Figure 4: Manually setting filters in combination with selected moods.



(a)



(b)

Figure 5: Two visual insights into the dataset: (a) The average song length when hovering over. (b) Mouseover in a manually adjusted scatter plot.

and based on that design we start implementing an interactive visualization tool. The designed and implemented dashboard provides some opportunities to explore an existing dataset interactively, however, the visualizations are by no means complete and could be further expanded. Since the dashboard was developed for a specific dataset, care should be taken when extending it to use the same attributes for additional songs, or even more, for other datasets in the same data format.

The search for a song is not included in the dashboard by means of a search window, which is recognizable in the draft. This was omitted because the dashboard is more about the attributes and moods of the songs and not necessarily about the ability to find a specific song.

The selection at the date picker needs to be more practical due to the default functionalities of Plotly. The goal would be to set the period via the displayed windows. However, if data from 2000 to 2010 is to be displayed, all previous years and months must first be clicked through. The alternative is to edit the data directly by typing in the desired span. In this case, however, the displayed windows are again disturbing. If there is a possibility to improve this with reasonable effort in the future, this should be implemented to increase the usability of the dashboard.

As mentioned, the presented dashboard is only usable well over specific screens. Therefore, the dashboard still needs to be extended with a responsive design so that the application is possible without problems with smaller screens and mobile devices.

To further improve the user experience, implementing an additional feature to listen to songs on Spotify would be recommended. Moreover, we plan to evaluate the created dashboard in a user study, also with eye tracking (Duchowski, 2003; Holmqvist et al., 2011). Finally, the dashboard should be extended in a way to make it easy to extend to other dataset scenarios, i.e. the dashboard might be able to detect the data types in the dataset and the data format and based on this, can start with a desired user interface and visual components.

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