A Live Concert Performance Recommender System Utilizing User Ideal and Antithesis Ideal Setlist Preferences

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***Abstract* — Recommender systems look to curate personalized content and have become a ubiquitous part of our digital lives, including within the music domain. At the same time, numerous high quality live concert performances from illustrious music artists are becoming readily available, providing fans with an unwieldly abundance of choice. Whereas much work has explored music recommendation for tasks such as choosing songs for personalized playlist curation, the task of historic live music performance recommendation is less explored. Thus, in this paper we propose CPR, a Concert Performance Recommender system for historic live concert performance recordings. CPR provides an artist's fan the ability to define preferences via the notion of ideal setlist songs, denoting songs that would be part of an ideal concert, and negative ideal setlist songs, denoting songs that would represent part of the antithesis of an ideal concert for the user. The user can then define additional semantic information regarding why the ideal and negative ideal setlist songs have been chosen. This information is then utilized to recommend live concerts by the artist that are most aligned to the user's preferences. A user is provided with explanations regarding the whys behind potential recommendations, in terms of the alignment to his/her preferences. Such explainability aids a user to then interactively explore and fine tune their preferences and recommendation results.**

Keywords—Recommender Systems, Multi-criteria Decision Analysis, TOPSIS, User Modeling, Music Information Retrieval

I. INTRODUCTION

In today's digitalized world, high quality live historic music performances are becoming increasingly readily available. As a result, legendary music artists, with illustrious touring histories and a devoted fan base, are increasingly exploring the commercial opportunity of such performances. For example, the Grateful Dead have a plethora of live concert albums available on Spotify[1], whilst Bruce Springsteen is offering high quality audio recordings from every show of his 2023/24 Tour[2]. For fans of such artists, there are now so many recorded concerts available the dilemma has become one of what live concert to choose to listen to (or take the plunge and purchase). Therefore, in this work, we propose CPR, a **C**oncert **P**erformance **R**ecommender system, that provide an artist's fans with recommendations of historic live concert performance recordings aligned to their preferences.

Through knowledge of users, content, and/or interactions Recommender Systems (RS) looks to curate recommendations that are tailored to a user [1]. RS have become an integral part of our digital lives, including within the music domain where they are utilised extensively by streaming services such as Spotify [2]. In this domain, RS have been widely employed to tackle the problem of playlist curation, for example, by looking to select playlist songs based on a user's recent and long-term listening habits [3], or incorporating inferred emotion feedback from a listener to inform playlist song choices [4]. Conversely, CPR tackles the problem of recommending historic live music performance recordings, as opposed to looking to handpick individual songs to create a playlist sequence. Within historic live concert recommending, each possible live performance represents a fixed set of songs that make up a concert's setlist. Additionally, differences between some items will invariably be nuanced, for example, within shows from the same tour. Where work has explored live concert recommendations, it has been explored for recommending concerts in the future, ones that are yet to take place [5].

When appraising RS, initial focus was placed on considering RS from the perspective of accuracy metrics, however, the field has since evolved to move beyond accuracy and consider more nuanced objectives, such as serendipity and novelty [6], and user interaction congruency [7]. This has led to recent approaches looking to consider multiple objectives simultaneously when determining recommendations [1], including domain specific objectives, for example, food recommendations that seek to be of both high accuracy and 'healthiness' [8]. Such multi-objective considerations allow for scenarios where users could define preferences with respect to the multiple criteria [9]. For example, to define not just whether they liked a movie, but whether they liked it for its storyline and/or its acting. Multi-criteria-RS look to utilize such richer user information to make more informed and nuanced recommendations [10]. When RS are operating in scenarios where there is a wealth of historic user data, such as a music streaming service logging every track that every user listens to, Collaborative Filtering techniques are widely employed [11], [12]. However, we envisage the average CPR user as a music fan looking to start delving into live recordings for their favourite artist, so, the users invariably represent cold start users [13]. Collaborative methods are generally not considered applicable when users represent cold

[1] https://liveforlivemusic.com/news/grateful-dead-355-hour-playlist

[2] https://brucespringsteen.net/news/2023/2023-tour-streaming-audio

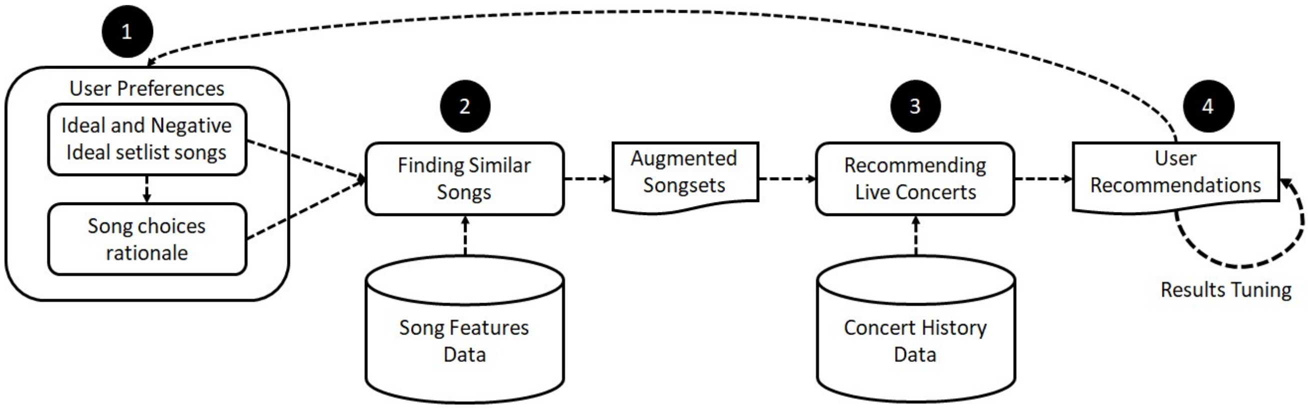

Fig 1: The stages of CPR

start users [14]. RS need to consider how to handle such a scenario, for example, by looking to elicit explicit preference data from users to utilize to aid searching for appropriate recommendations. Such elicitation could be, for example, via choice-based preference elicitation [15], or looking to optimize which specific questions to ask a user for the most information gain [14]. Such internal optimization focused approaches may however risk disenfranchising a user, as the user is asked for information most desired by the algorithm without consideration of its appeal to a user.

Conversely, CPR facilitates a user to define their preferences via semantically appealing notions of ideal setlist songs and negative ideal setlist songs, denoting songs an exemplary concert would and would not contain respectively. Moreover, for each chosen song, a user can provide additional information denoting why the song has been chosen, regarding whether it's more due to its lyrical content, or more due to its musically, or both equally. In this way, CPR provides a user to define multi-criteria preferences. The user's preferences are then utilized by CPR to determine a set of live concert performance recommendations aligned to the preferences. For this, CPR considers both the chosen user songs and similar songs, where the notion of similarity is explicitly guided by the user's preferences for why songs were chosen. This allows a user to define relatively small ideal and negative ideal setlist songs lists, and also allows a user to choose songs that the artist may never have played live before, and CPR is still able to utilize this information to seek suitable recommendations. To determine recommendations, CPR determines how close different concerts are to a user's ideal and negative ideal setlist preferences, and then uses this to determine an overall closeness score for different concerts. In this way, the approach looks to make recommendations to a user that are as close as possible to the ideal and as far as possible away from the negative ideal. This philosophy tackles the problem akin to the philosophy of decision methodologies such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [16].

Explanations (the why) of content (the what) a user is presented with is becoming essential [17], and RS need to consider the explainability of their recommendations [18]. CPR is able provide to a user the why behind the recommended concerts, in relation to their initial preferences of ideal and negative ideal setlist songs as well as calculated similar songs, including explanations behind why songs were considered similar. CPR can calculate recommendations from a user's preferences swiftly enough for a user to utilize the explanations to return to and tweak their preferences, to interactively fine tune the resulting recommendations.

II. OUR APPRAOCH

The stages of our CPR approach are shown in Fig 1, denoting how our approach utilizes a user's preferences, along with various data, to curate live concert recommendations. Next, after discussing data curation and wrangling, we outline the elements of our approach, ❶ user preference elicitation, ❷ determining similar songs and curating augmented song sets, ❸ calculating concert recommendations, and ❹ interactive user recommendations exploration and tuning. Our approach could be applied to any legendary music artists with illustrious touring histories and a wealth of possible available concerts to recommend. Within the following explanations the artist Bruce Springsteen is utilized to help illustrate the approach's data and operation.

A. Song Features Dataset

For an artist, a dataset of features relating to musicality aspects and lyrical aspects of each song is curated. The features for these two categories are:

Musicality features: A set of numerical features pertaining to the artist's songs' musicality obtained through utilizing the Spotify API[3]. From this, a set of numerical features including Danceability, Energy, Acousticness, and Tempo are obtained.

Lyrical features: For each song its textual lyrics are extracted from Official Artist sites or community Wikipedias, for example, the *BruceBase*[4] for Bruce Springsteen. From the textual lyric data, numerical features were curated through Latent Dirichlet allocation (LDA) topic analysis [19], to find separate latent underlying themes and determine to what extent

[3]https://developer.spotify.com/documentation/web-api

[4]http://brucebase.wikidot.com

every song represents different topics[5]. Also, the Sentiment of each song's lyrics was calculated - utilizing SentimentR [20], (chosen due to its strength of being able to explicitly consider nuances from the presence of negators [21], which we see as pertinent within lyrical analysis and differentiation).

B. User Preference Elictation ❶

Within CPR a user can define preferences via the notion of ideal setlist songs and negative ideal setlist songs, denoting songs that, for them, would be part of an ideal concert and songs that would be part of the opposite of an ideal concert. For both sets of songs, a user can define a full concert setlist or just a partial setlist, and CPR can cater for scenarios where a user does not know (or wish to specify) many songs. After, or during, the curation of the two sets of songs a user can define additional information for any chosen song, regarding why it was chosen to be in the ideal or negative ideal set of songs. Such additional information is with respect to lyrics or musicality. For this, the user uses a 5-point pairwise comparison scale between the criteria of Lyrics and Music. Elicitation via pairwise comparisons provides a user the ability to determine their preference, and strength of preference, between the pair of criteria [22], in an intuitively appealing way [23]. Using this a user can define that a song is chosen i) equally for its lyrics and music, ii) chosen a little due to its lyrics, iii) chosen a lot due to its lyrics, iv) chosen a little due to its music, or v) chosen a lot due to its music. This 5-point pairwise comparison scale is shown in Fig 2. This additional information provides more nuanced information regarding why a user has chosen the songs.

C. Calculating Similar Songs ❷

After defining initial user preferences CPR begins the process of finding concerts to recommend to the user. For this, CPR first looks to utilize the user preferences, of chosen songs and the rationale behind their choices, to determine additional similar songs, where similarity is measured aligned with the whys that each different song has been chosen for. For example, given a song that has been chosen by two different users, for one user due a lot to its lyrical content, and for the other user due a lot to its musicality. For these two users, songs that are considered similar songs to the chosen song, due to differing reasons of why they like the song, may be contextually very different. For each chosen song in both the ideal set of songs and the negative ideal set of songs, CPR looks to determine its 4[6] most similar songs (that have been played live). Here, distances are calculated utilizing a weighted Euclidean distance. For each chosen user song distinct similarity weights are utilized, where the weights are influenced by the semantic information regarding why the song was chosen. In this way, for a song chosen a lot due to its lyrics, the features relating to lyrics have higher weight within the similarly calculations.

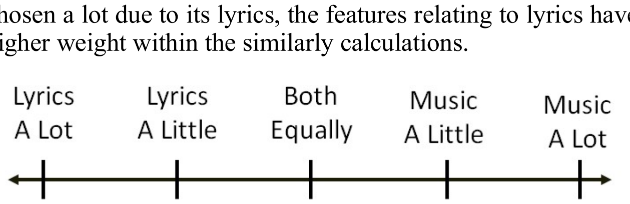

Fig 2: User preference scale for rationale of song choice

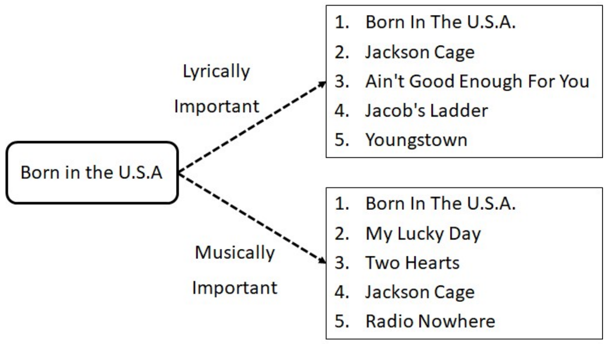

Fig 3: Differing determined similar songs to chosen song

For example, for the song *Born in the USA*, knowing that a user liked the song due to its lyrical themes, or due to its musicality, will be important, as such choices represent very different reasons for liking the song which is musically and lyrically dissonance [24]. Examples of similar songs calculated by CPR as similar to *Born in the USA*, under different user rationale, are shown in Fig 3. If lyrics are more important, then the similar songs include *Jacob's ladder* and *Youngstown*. Conversely, if musicality is important then there are differences in what songs are considered similar, for example, *Jacobs' Ladder* does not make the list and different songs such as *My Lucky Day* do. As a result, differing augmented song lists will then result in subtly different live performances being recommended, ones that are more aligned to the user preferences than just a list of songs alone. Moreover, via this augmenting of songs, CPR facilitates a user to select songs that have never been played live and still use the choice to help make recommendations. For example, given a user selects the song *The Last Carnival*, one of the Bruce Springsteen songs that he has never been played live [25], and denotes the choice is due to its lyrics. CPR looks to find similar songs can have been played live, with added weight given to lyricality when considering similarity. From which a set of similar songs can be derived by CPR that have been played before. For each user chosen song, if the user chosen song has been played live before then the song itself will be retained within the augmented list of songs, with a similarly score of 1. If the chosen song has not been played live before then only the determined list of similar songs that have been played live will be part of the augmented list of songs. The output from this stage is an augmented ideal set of songs, and an augmented negative ideal set of songs. The augmented ideal set of songs, contains the initial chosen songs that have been played live before with similarity scores of 1, and the derived similar songs, with fractional similarity scores in proportion to their calculated similarity score to an initial chosen song. The augmented negative ideal set of songs similarity contains the initial chosen songs that have been played live before along with derived similar songs.

D. Calculating Concert Recommendations ❸

Next, CPR uses the augmented ideal set of songs, and the augmented negative ideal set of songs to find live concert recommendations. For this, CPR utilizes historic data regarding an artist's set of available live concert recordings and determines

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[5]Before performing LDA analysis data cleaning pre-processed of the lyrical data was performed

[6]This value can be parametrized and thus be dynamic, either to allow it to be user controlled, or to facilitate differing sizes based on user chosen song sets sizes

how aligned each is with the user's preferences (for example, for Bruce Springsteen such live concert recording information can be obtained from http://brucebase.wikidot.com). CPR makes recommendations to a user that are as close as possible to the ideal and as far as possible away from the negative ideal, similar to the philosophy within the TOPSIS decision methodology [16]. TOPSIS is a multi-criteria decision analysis method that ranks alternatives based on their proximity to an ideal solution, and negative ideal solution. In essence, it evaluates each alternative by calculating its closeness to the most desirable solution and its distance from the least desirable solution. Within CPR we have the notion of an ideal solution (the most desirable solution) in the form of the augmented ideal set of songs, and the notion of a negative ideal solution (the least desirable solution) in the form of the augmented negative ideal set of songs.

CPR evaluates each alternative (historic concert setlist) by first calculating its closeness to the most desirable solution, and its closeness to the least desirable solution. The closeness of concert i to the augmented ideal song set, denoted as d_i^+, is calculated via first determining the augmented ideal songs that are present in concert i's setlist via:

$$\Delta = \Gamma \cap S \tag{1}$$

Where, Δ is the set of intersecting songs, Γ is the set of Augmented Ideal set songs and S is the set of songs in concert i's setlist. Then, d_i^+ is calculated via:

$$d_i^+ = 1 - \frac{\sum_1^n \delta_s}{\sum_1^m \gamma_s} \tag{2}$$

Where, δ_s is the similarity score of n^{th} song in Δ, γ_s is the similarity score of the m^{th} song in Γ, n is the size of Δ (the number of intersecting songs), and m is the size of Γ (the number of songs in the augmented ideal set).

Similarity, the closeness of concert i to the augmented negative ideal song set, denoted as d_i^-, is calculated via first determining the number of augmented negative ideal songs present in concert's i's setlist via:

$$\mathrm{E} = \mathrm{Z} \cap S \tag{3}$$

Where, E is the set of intersecting songs, Z is the set of Augmented negative ideal set songs and S is the set of songs in concert i's setlist. Then, d_i^- is calculated via:

$$d_i^- = 1 - \frac{\sum_1^n \varepsilon_s}{\sum_1^m \zeta_s} \tag{4}$$

Where, ε_s is the similarity score of n^{th} song in E, ζ_s is the similarity score of the m^{th} song in Z, n is the size of E (the number of intersecting songs), and m is the size of Z (the number of songs in the augmented negative ideal set). Through the division within (2) and (4), normalisation with respect to handling different sizes of augmented ideal and negative ideal song sets is considered, and both d_i^+ and d_i^- result in values between 0 and 1.

Then, to determine the relative closeness value for each alternative. The relative closeness of the i-th alternative is calculated, akin to as in TOPSIS [16], via:

$$R_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{5}$$

Such calculations can swiftly be calculated (and are trivially parallelizable), and a ranking of the alternative concerts can then be determined. Finally, the vector of all alternative R values for all the concerts can be normalized into relative scores, relative to the top-ranking alternative, to provide a user with relative information regarding different ranked recommendations. Thus, the top-ranking recommendation will have a normalized value of 1, and every other rank's normalized value will be fractional values in relation to this top-ranking alternative, to provide a user with more informative values than raw relative closeness values.

E. Interactive Recommendations Exploration and Tuning ❹

From the calculated ranking of alternatives, the user can view the top x recommendations, which defaults to 10, but can be personalized by a user to be a smaller or larger number. For each recommended item in a presented top x ranking, a user can explore which augmented ideal setlist songs are present, and see which ones are specific user chosen songs and which are calculated similar songs. Likewise, similar information regarding negative ideal songs is also provided. Within an artist's set of available live concert recordings there are potentially many items that are very similar, such as the setlists of concerts from a particular tour. Therefore, CPR provides capabilities for a user to control and modify the level of diversity in the results. For this, each alternative gets assigned to an epoch, such as the specific tour it is a part of, which can easily be determined from official sites or fan communities. The user can then utilize this to define a threshold hold of items to show for each tour. In this way, if the user wishes, a more diverse assortment of items can be recommended, where the level of diversity can be tuned by the user themselves. This feature could be used to only recommend a single item from each tour, allowing a user to be recommended only the most aligned show from each separate tour of the artist.

III. Utilization and Discussions

Next, we present an application example of CPR for the artist Bruce Springsteen, followed by discussions and future work.

A. Bruce Springsteen Application Exmaple

Here, we show experimentation of the use of our approach with example user input and resulting initial recommendations and user tuned recommendations. First, a user starts to define preferences of ideal setlist songs and negative ideal setlist songs, and for each song define information regarding why it was chosen. Part of the CPR interface mockup, of a user in the process of such elicitation, is shown in Fig 4. Here, the user has so far chosen ideal setlist songs of *Born to Run*, *Out in the Street, Badlands*, and *Racing in the Street*. They have further defined rationale for the choices, for example, that for *Born to Run* the music is a little bit bit more important for it being chosen, whereas for *Racing in the Street* its Lyrics are a little bit more important for it being chosen.

Fig 4: User preference interface facilitating a user to define preferences regarding why selected songs were chosen

The complete example user input of ideal setlist songs is shown in TABLE 1, and user input of negative ideal setlist songs is shown in TABLE 2. Here, the user has curated an ideal set of songs consisting of 12 songs, and curated a set of songs that would be part of a negative ideal set totalling 8 songs. Additionally, TABLE 1 and TABLE 2 denote the user rationale regarding why a song has been chosen. Some songs have been chosen more due to lyrical considerations either a little bit or strongly, and some songs have been chosen more due to musical considerations, either a little bit or strongly.

CPR then looks to take these two sets of songs along with the choice rationale to curate a set of concert recommendations for the user. For this, it first looks to find an augmented ideal set of songs and an augmented negative ideal set of songs. The two augmented song sets are then utilised by CPR to explore and recommend concerts aligned to the users preferences and create a ranking of concerts based on their relative closeness values.

TABLE 1: Example User Ideal Set Songs

Song Title	Rationale
Born To Run	Music A Little
Out In The Street	Music A Lot
Badlands	Both Equally
Racing In The Street	Lyrics A Little
Point Blank	Lyrics A Little
Long Walk Home	Both Equally
Born In The U.S.A	Lyrics A Lot
The Rising	Music A Little
Waitin' On A Sunny Day	Music A Lot
You're Missing	Both Equally
Independence Day	Lyrics A Little
The Last Carnival	Lyrics A Lot

TABLE 2: Example User Negative Ideal Set Songs

Song Title	Rationale
Outlaw Pete	Music A Little
Kitty's Back	Lyrics A Lot
57 Channels (And Nothin' On)	Both Equally
Cadillac Ranch	Both Equally
Ramrod	Music A Lot
Let's Be Friends (Skin To Skin)	Both Equally
Crush On You	Music A Little
Mary Queen Of Arkansas	Lyrics A Little

The top x concert recommendations can then be provided to the user. From the user input provided the top 10 concerts found are shown in TABLE 3. Here we can see that the top recommended concert is the 16th of July 2016 show from *The Ties That Bind Tour*. For each recommended concert, the user can inspect the concert and get additional information regarding why it was recommended in terms of the ideal set songs it contains they explicitly choose, and the ideal songs it contains that have been deemed similar, as well as the negative ideal songs it contains that they explicitly chose along with the negative ideal songs it contains that have been deemed similar. Moreover, for each concert in the ranking the relative score denotes the amount of decrease in relative closeness for each subsequent rank in the ranking.

Once a user is presented with the initial set of concert recommendations by CPR the user could tune the recommendations. For example, the user can tune any of their preferences, such as altering the chosen songs, and/or altering the rationale for songs' inclusion, and see the impacts upon the updated recommendation results. Moreover, a user could define a threshold value, of how many items to show for each tour and thus have control over the level of variety within the recommendation results. In TABLE 3 we see that of the top 10 recommendations five of them are from the same tour (*The Rising Tour*). The user could explore tuning the recommendations, to look to increasing the diversity within the recommendations, through adding a constraint to subset the recommendations to only a certain number of recommendations from each tour. In a scenario where the user tunes the results to subset the results to only 1 recommendation from each tour, the updated top 10 recommendations are shown in TABLE 4. Here, we now have 10 recommendations from 10 different tours, providing a user with more variety in the set of recommendations than the initial set shown in TABLE 3, which has recommendations from 6 tours.

TABLE 3: Initial Top 10 Concert Recommendations

	Gig Date	Tour Name	Relative Score
1	16/07/2016	The Ties That Bind Tour	1
2	20/08/2002	The Rising Tour	0.9545
3	11/04/1999	E Street Band Reunion Tour	0.9364
4	08/05/2013	Wrecking Ball World Tour	0.9088
5	14/07/2009	Working on a Dream Tour	0.9080
6	04/12/2002	The Rising Tour	0.8940
7	08/07/2008	Magic Tour	0.8882
8	02/12/2002	The Rising Tour	0.8865
9	10/08/2002	The Rising Tour	0.8833
10	12/08/2002	The Rising Tour	0.8833

TABLE 4: Tuned Top 10 Concert Recommendations

	Gig Date	Tour Name	Relative Score
1	16/07/2016	The Ties That Bind Tour	1
2	20/08/2002	The Rising Tour	0.9545
3	11/04/1999	E Street Band Reunion Tour	0.9364
4	08/05/2013	Wrecking Ball World Tour	0.9088
5	14/07/2009	Working on a Dream Tour	0.9080
6	08/07/2008	Magic Tour	0.8882
7	07/02/2014	High Hopes Tour	0.8780
8	28/08/1984	Born in the USA Tour	0.7846
9	27/04/1996	Ghost of Tom Joad Tour	0.7751
10	04/11/1978	Darkness Tour	0.7395

B. Discussions and Future Work

CPR provides the ability for a fan of a legendry artist to provide preferences and be recommended concerts by the artist. Initially explored for separate artists, CPR could be tasked with making recommendations across artists. For example, facilitating a Bob Dylan fan to define an ideal set list of Bob Dylan songs then look to recommend setlists that might be most aligned to the chosen songs for another artist that may be less well known to the user. This could allow fans of one artist to explore across artists they are less familiar with. Furthermore, the CPR approach could be explored for applications outside of the historic live concert recordings domain, within other tasks where there are possible alternative items made up of item parts for which a user defines preferences in terms of item parts. Moreover, it is envisaged that future work will also explore performing online user evaluations of CPR directly within legendary artists' online communities, to help study and refine the system.

IV. Conclusions

In this paper we proposed CPR, a Concert Performance Recommender system for live concert performance recordings. CPR facilitates a fan to define preferences via the notion of songs that, for them, would be part of an ideal setlist and songs that would be part of a negative ideal setlist. Along with this the user can define further information regarding why songs are chosen in terms of more due to their lyrics or musicality. CPR then looks to consider the user's preferences to recommend live concerts aligned to the preferences and provides details regarding why the live concerts are recommended, in relation to their preferences.

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