Association Rule Breaking Based Diversity for Recommender Systems

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***Abstract* — Recommender systems are becoming ubiquitous within our data driven digitalized world, to help tackle issues including information overload, and provide users with personalized tailed content. When considering what makes recommendations valuable and useful, concerns of diversity, as opposed to just serving a user more of the same, is crucial. In this paper, we propose an approach to making diverse recommendations, through calculating a measure of diversity defined in terms of the level of association rule breaking or conformity. Our approach explores a novel way to consider diversity through defining the metric of *Association Rule Breaking Diversity*, a nuanced consideration of diversity that measures association relationships between parts of possible recommender content. The metric represents a different way to consider diversity than considering just the rarity of the parts that make up possible recommender content. This allows our approach to discover diverse recommendations in terms of Association Rule Breaking Diversity without suffering so much from potential trade-off issues that focusing on diversity through uniqueness and rarity may result in. We explore the application of our approach for the example domain of historic live concert recommendations. Using multiple prominent music artists, we explore association rules derived in relation to the songs that are played in concerts and demonstrate how our approach can cater for different users' preferences regarding the amount of diversity they seek.**

Keywords—Recommender Systems, Diversity, Association Rules, User Modelling, Music Information Retrieval

I. INTRODUCTION

Recommender Systems (RS) look to tackle issues such as information overload and provide personalized content aligned with user interests [1]. Through looking to utilise data about users, potential content to recommend, and/or interactions, tailored recommendations can be curated [2]. Evaluations of the quality of curated recommendations from RS initially extensively focused on the perspective of accuracy and precision metrics [3],[4]. However, the field has progressed to move beyond just accuracy, to consider more nuanced objectives for what makes recommendations valuable, such as serendipity and novelty [5], user interaction congruency [6] and diversity [7].

Through considering diversity, a RS can look to explore how users can get value from being presented diverse content, as opposed to just theoretically accurate but similar content [8]. Diversity of recommendations has been considered in terms of possible content and each's features, to endeavour to recommend diverse content through calculating the average dissimilarity between content pairs [9], or considering taxonomy information to curate personalised lists that are diverse in terms of topic diversification [10], or considering diversity in a set of ranked user recommendations, to provide a set of ranked items with diverse items closer together in the ranking [11]. However, diversity can be at odds with accuracy, and there is generally an inherent trade-off between them [12],[7]. Therefore, an excess pursuit of diversity may result in too much of a detrimental impact on accuracy and overall user satisfaction, compared to any added value diversity might provide [13].

In this paper, we propose an approach to the exploration of measuring diversity within recommendations. Through consideration of association rules between the parts that make up each possible element of recommendation content, our approach calculates a measure of the level of association rule breaking within each. Association rule mining is a data mining technique used to find interesting relationships, or associations, between variables in large datasets in the form of rules. It identifies frequent if-then patterns, identifying from analysis of, for example, many customers product purchases data that "*if a customer buys Product-X"*, they "*are likely to also buy Product-Y"* [14]. Association rules are invariably utilized to aid decision-making and prediction, for goals such as seeking to increase customer sales [15].

Association rule mining has been utilised within RS, such as for looking to find associations between content that is often consumed together by many users, to utilise when deciding what content to recommend next [16],[13]. Controversy, in our approach, we explore finding association rules within the sub parts that make up each possible piece of recommendation content, and then calculate the level of adherence or not of each possible piece of content to these rules. For this, we define a measure of the amount of *Association Rule Breaking Diversity (ARBD)* by each possible piece of recommendation content. We show that such a measure represents a nuanced way to quantify what represents diversity within recommendations, to tackle diversity without having too much reliance on just rarity. In this way, our approach utilises association rule mining for a slightly unconventional application, to use association rules to gauge the diversity of each piece of content in our dataset.

We explore the use of our approach within an example domain of historic live concert recommendations. Today, music artists with distinguished touring careers offer so many recorded concerts the quandary has become one of what live concert to choose to listen to. Much work on recommender systems within the music domain, such as by streaming services like Spotify [17], has explored problems such as playlist curation, handpicking individual songs to create playlist sequences [18],[19]. Conversely, within our problem each historic live concert represents a possible piece of content to recommend, where each one is made up of a fixed set of songs that make up its setlist. Here, differences between some concerts will invariably be nuanced, for example, within shows from the same tour, making diversity an important concern for this domain. Where work has explored live concert recommendations, it has focused more on accuracy than diversity, looking to recommend future concerts that are yet to take place [20], or through searching for recommendations aligned to a user query of likes and dislikes [21]. Conversely, our approach determines the strong association rules between songs that are played in setlists, to calculate a level of diversity, in terms of ARBD, for each concert, to utilize within making recommendations.

II. OUR APPROACH

Our approach considers recommendation diversity through first finding strong association rules between the parts that make up each piece of possible recommendation content. Then, a measure of the level of association rule breaking within each is calculated. To be presented with a set of recommendations, a user just defines how much diversity, with respect to ARBD, they seek, and how big a set of recommendations they wish to find. After being presented with an initial set of recommendations, the user can fine tune their preferences, and be promptly shown an updated set of recommendations. The stages of our approach are shown in Fig 1.

A. Calculating Association Rules

Our approach utilizes input data pertaining to each possible piece of recommendation content, and for each piece, information of the parts that make up each possible recommendation. For example, within historic live concert recommendations, each possible piece of recommendation content is a concert, and the parts that make up each possible piece of content are the songs that make up each concert. Association rules can be extracted from such a dataset, and our approach could be utilized within any other domain with similar data properties. Within Association rule mining terminology we have ***items,*** which are the elements present in a dataset, which within concert setlists are individual songs, and ***transactions,*** which are records in the dataset, each containing a set of items, which within the domain of historic live concert are setlists that each contain a set of songs.

Association ***rules*** are depicted in the form A ⇒ B, indicating a strong relationship between sets of items A and B within transactions, suggesting that when items in A are present, items in B are likely to be present too. Within live music concerts data such a rule would indicate that when songs A are played then songs B will likely also be played.

To measure the significance of association rules the measures of support, confidence, and lift, are commonly used [14]. ***Support*** measures how frequently an itemset appears in the whole dataset. It is the proportion of transactions in the dataset which contain the item set. The formula to calculate the support of an itemset A is given by:

$$Support\ (A) = \frac{Number\ of\ transactions\ containing\ A}{Total\ number\ of\ tractions} \quad (1)$$

Confidence measures the reliability of the inference made by a rule. For a rule A⇒B, it's confidence considers the proportion of transactions that contain A which also contain B. The formula for calculating the confidence of a rule A⇒B is:

$$Confidence\ (A \Rightarrow \mathrm{B}) = \frac{Support\ (A \cup B)}{Support\ (A)} \quad (2)$$

Lift is a measure that assesses the strength of a rule A⇒B by comparing the likelihood of B occurring with A, in relation to B's overall likelihood in the dataset, to indicate if A and B occur together more frequently than would be expected if they were statistically independent. A higher lift value suggests a potentially useful and strong association between them. It considers the ratio of the observed support of $A \cup B$, to the expected support if A and B were independent, essentially comparing the confidence of the rule to the overall frequency of B, and is calculated via:

$$Lift\ (A \Rightarrow \mathrm{B}) = \frac{Confidence\ (A \Rightarrow \mathrm{B})}{Support\ (B)} \quad (3)$$

Taking a dataset, such as concert data for a chosen music artist, we determine a set of association rules using the *Apriori* algorithm [22], which looks to efficiently identify frequent item sets within the data and generate association rules from those item sets. It operates on the principle that any subset of a frequent itemset must also be frequent. From *Apriori* our approach finds associations between pairs of items that make up each piece of possible recommendation content. For the historic live concert domain, this represents associations between pairs of songs that make up possible concerts to recommend. The outcome of this stage is a set of association rules along with their measures of Lift.

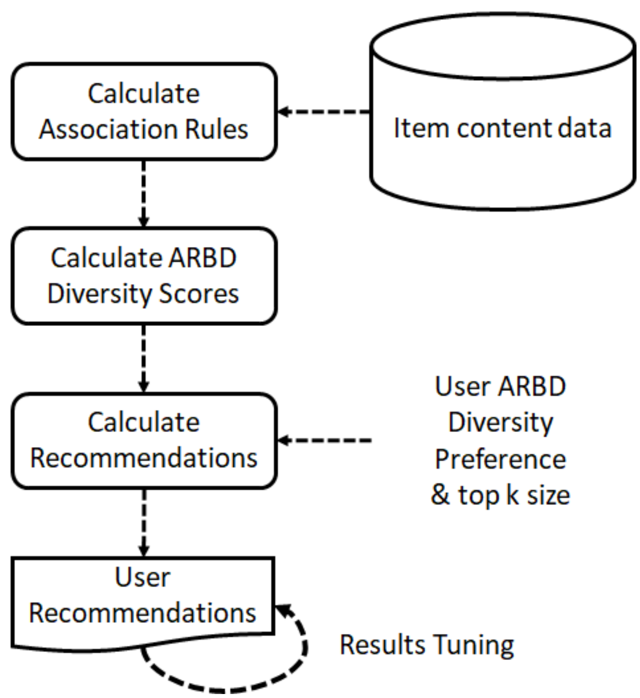

Fig 1: The stages of our approach

B. Calculating ARBD Diversity Scores

Next, our approach calculates an ARBD value for each transaction. ARBD considers the level of rule conformity and rule breaking of transactions, in relation to the set of calculated association rules. In this way, our approach utilizes association rules to measure diversity within transactions, as opposed to the more conventional use of association rules, which typically aim to find patterns of item co-occurrence rather than transaction diversity. Given a rule *{A,B}⇒{C}*, and three example transactions of i) *{A,B,D}*, ii) *{A,C,D}*, and iii) *{A,B,C}*. We can compare each of the three transactions in terms of rule conformity or rule breaking of our rule. For transaction iii) both the left-hand side and right-hand side of the rule are present and so the rule *holds* for this transaction. For transaction i) the left-hand side of the rule is present, but the right-hand side of the rule is not, and so this transaction *breaks* the rule. Finally, for transaction ii) the left-hand side of the rule is not present so the rule neither holds nor is broken. For a transaction, such a calculation is applied to each association rule and an ARBD value of transaction *t* is calculated via:

$$ARBD_t = \frac{1}{m}\left(\sum_1^m x\right) \tag{4}$$

Where m is the number of association rules found and x is calculated via:

$$x = Rule_m(A \Rightarrow B, T)\begin{cases} +L_m \; if \; A \subseteq T \; and \; B \subseteq T \\ -L_m \; if \; A \subseteq T \; and \; B \not\subset T \\ 0 \; otherwise \end{cases} \tag{5}$$

Where *A* is the left-hand side of Rule *m*, *B* is the right-hand side of Rule *m*, *T* is the set of items in transaction *t*, and L_m is the Lift value of $Rule_m$. When both the left-hand side and the right-hand side of the rule are present in the items of transaction *t*, then the rule holds. If the left-hand side of the rule is present in the items of transaction *t*, but the right-hand side is not, then the transaction breaks this rule. When the left-hand side of the rule is not present in the items of transaction *t*, then the rule neither holds nor is broken. When a rule holds its lift value is added, and when a rule is broken its lift value is subtracted. In this way, the strength of each rule is considered within the ARBD calculation. An ARBD value is calculated for each transaction in a dataset, then, the set of values are normalized, via Min-Max Scaling, to all be between 0 – 1. From this, the transaction with the highest ARBD value is assigned 1 and the transaction with the lowest ARBD value is assigned 0, via:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Where x' is the scaled value, x is the original value, and x_{min} and x_{max} are the minimum and maximum ARBD values. This normalization facilitates our approach to show ratio values to an end user, who can then more easily comprehend the values – in terms of ratio distances between different results – than if they were just shown the absolute numbers which they cannot semantically relate to [23]. Through its calculation, ARBD considers diversity through analyzing the level of rule conformity or breaking within transactions. This is contrasting to just considering diversity in terms of the occurrence of rare and unusual items within transactions. Such a Frequency Score (*FS*) measure, of the occurrence of infrequent items in transactions, can be calculated through considering the overall average relative frequency of each item that makes up a transaction via:

$$FS_t = \frac{1}{n}\sum_1^n f_i \tag{7}$$

Where, f_i is the frequency ratio score of the n^{th} item from transaction *t*, and *n* is the number of items in transaction *t*. Such a calculation differentiates transactions in terms of containing or not items that are less common. However, just looking for diversity in terms of infrequent items may result in an excess pursuit of diversity, resulting in a detrimental impact on user satisfaction [12]. Comparison between ARBD and FS values for a set of transactions highlights the differences between the semantics of them. To assist such comparison, FS values can be *inversely* normalized, via Max-Min Scaling, to be between 1 – 0 via:

$$x' = 1 - \frac{x - x_{min}}{x_{max} - x_{min}} \tag{8}$$

Where x' is the scaled value, x is the original value, x_{min} and x_{max} are the minimum and maximum values of FS. Thus, the transaction with the lowest original FS value is assigned 1 and the transaction with the highest original FS is assigned 0. Comparison between the normalized ARBD and FS values can then be explored, where the higher values for each represent its notion of more diversity. Fig 2 shows the comparison between the measures for the music artist Bob Dylan's setlist history transactions, and Fig 3 shows the comparison for the music artist Bruce Springsteen setlist history transactions. From Fig 2 and Fig 3, we observe that although there is a positive relationship between ARBD and FS, there is divergence in the transactions that each considers the most diverse. The plots highlight how having the highest normalized FS value does not mean that ARBD will also be the highest. ARBD represents a different, more subtle, measure of diversity, and its high diverse transactions might still contain some popular items. Therefore, for a user searching for intriguingly diverse recommendations, ARBD facilitates finding recommendations which still may contain some of the more popular items, as opposed to looking just for transactions with unique, infrequent, items.

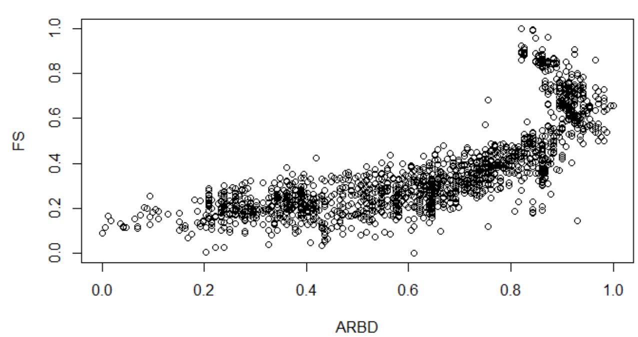

Fig 2: Bob Dylan ARBD and FS comparison

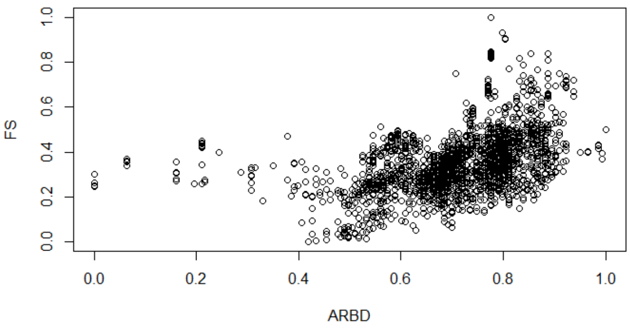

Fig 3: Bruce Springsteen ARBD and FS comparison

The outcome of this stage is a ranked list of the transactions, ranked from high to low with respect to their ARBD values.

C. *Calculating Recommendations*

Our approach utilizes the set of calculated ARBD values, along with a user's diversity inclinations, to find a set of aligned recommendations. Our approach can cater for different users' inclinations in terms of whether they seek recommendations that are more typical or ones that are more diverse, in terms of association rules breaking. For this, the user only needs to provide an indication of how diverse the recommendations should be, in terms of a percentage, along with how big a set of recommendations they want (k).

Using the set of transactions, ordered with respect to their calculated ARBD values, as illustrated in Fig 4:Left, a set of recommendations are calculated for the user through, first, selecting a candidate pool of transactions with ARBD aligned to the user's diversity preference, where the pool is larger than the value of k. For example, if the user has defined that they are interested in the most diverse recommendations and wish to be shown a set of 3 recommendations, then the top transactions of a set greater than 3 is selected, as shown in Fig 4:Centre. A candidate pool of transactions larger than the desired number to show the user is selected to ensure identical transactions are not recommended to the user, which just selecting the k most diverse items might result in, which would not be valuable. If the user, conversely, is interested in the most typical items, then a candidate pool of transactions from the bottom of the ARBD ranked list would be selected. If the user is interested in a level of diversity between these 2 extremes, then a candidate pool of transactions is selected from the list where the candidate pool's middle is aligned to the ARBD diversity percentage chosen.

Next, a set of k-recommendations are selected from the candidate pool of transactions. This selection is performed by clustering the candidate pool of transactions into k clusters, and selecting the single transaction from each cluster whose ARBD value is most aligned with the user's diversity preference. The clustering is performed in terms of similarity of the items within the transactions, so transactions that are identical or highly similar, in terms of their items, will be clustered together, ensuring that the recommendations presented to the user do not contain identical items. To perform the clustering, first, dissimilarity, in terms of Jaccard distance, between each pair of transactions in the candidate pool of transactions is calculated via:

$$Dissimilarity_{(x,y)} = 1 - \frac{|x \cap y|}{|x \cup y|} \tag{9}$$

Where x and y are a pair of transactions, $|x \cap y|$ is the number of items common to both transactions x and y, and $|x \cup y|$ is the total number of unique items in both transactions x and y combined. These distances are used within the clustering process, via Hierarchical clustering, and resulting cluster membership of each transaction when the number of clusters is k is obtained. The chosen k items are then show to the user. Fig 4:Right, illustrates an example set of 3 selected recommendations, highlighted in bold, from the candidate pool[1].

Our approach presents the set of selected k recommendations to the user, along with each recommendation's diversity information with respect to ARBD. The user can inspect the initial recommendations and fine tune their preferences, in terms of the amount of diverse sought, and/or how many recommendations they wish to receive. Given updated preferences our approach facilities updated recommendations to be swiftly calculated and presented to the user.

III. Experiment Utilization of Our Appraoch

Next, we present an application of our approach. For this, we explore the historic live music concerts domain as an example domain. First, we discuss data acquisition for this domain, followed by exploration of the use of our approach for multiple prominent music artists.

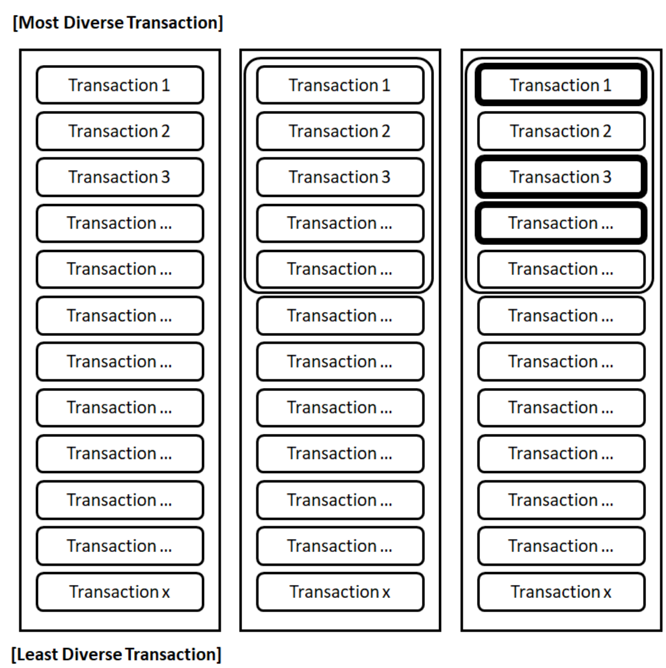

Fig 4: Example of recommendation set chosen for user – here from user preferences for 3 of the most diverse recommendations

[1] After selection of transactions from the candidate pool, an additional check of dissimilarity, like how is performed before the clustering, can be performed, to ensure no pair of recommendations to be presented have a dissimilarity distance of zero. In such cases, the size of the candidate pool of transactions can be enlarged and a modified set of recommendations swifty calculated.

A. Historic Live Concert Data Aqusistion

For the domain of historical live music concerts, transactions, in the form of setlists of the songs played at every concert for an artist, can be obtained from online repository sites such as setlist.fm. Using the setlist.fm API[2], any prominent artist's entire concert data can be obtained. We obtained such data for various prominent and distinguished artists of today including Bob Dylan, Taylor Swift, and Bruce Springsteen. Any other prominent artist's data could be obtained and utilized by our approach.

B. Application Exmaple – Bruce Springsteen

After acquiring setlist data for the entire setlist history of Bruce Springsteen, our approach's stages of finding association rules, calculating an ARBS value for each concert, and creating a ranked list of all concerts can be performed offline. For this, minimum confidence of 0.6 and minimum support of 0.2 was utilized, resulting in a set of 182 rules being found. A user starts by defining i) to what extent they are interested in being recommended more typical rule conforming concerts, or more diverse rule breaking, concerts, and ii) how many recommendations they wish to be presented with (k). Initial user preferences for Bruce Springsteen are shown in our approach's interface mock-up, in Fig 5:Left. Here, the user has defined that they wish to have 5 of the most diverse recommendations.

Our approach then utilises these preferences to find a set of recommendations. Here, a candidate pool of transactions size of $k*10$ is used, however, this is parametrized and could be more tailored for different artists, and/or configurable based on different chosen diversity preferences. The initial set of 5 recommendations found by our approach is shown in TABLE 1. Here, we observe high ARBD values within the set of recommendations, aligned with the user's preference for high ARBD diversity.

After inspecting the initial results, a user could, if desired, tune their preferences. Updated user preferences are shown in Fig 5:Right, where, now the user is seeking a set of 10 recommendations which are quite typical, but not the most typical. The updated results are shown in TABLE 2, where we observe ARBD values around the desired diversity specified.

TABLE 1: Bruce Springsteen Initial User Recommendations

	Concert Date	Name of Gig's Tour	ARBD
R1	23 Jan 2010	Other	1
R2	12 May 1997	Ghost of Tom Joad Tour	0.9884
R3	13 Jun 2005	Devils and Dust Tour	0.9826
R4	19 Dec 2004	Other	0.9826
R5	6 May 1988	Tunnel of Love Tour	0.9593

TABLE 2: Bruce Springsteen Updated User Recommendations

	Concert Date	Name of Gig's Tour	ARBD
R1	17 May 2016	The Ties That Bind Tour	0.1919
R2	8 Dec 1980	The River Tour	0.2093
R3	25 Aug 2016	The Ties That Bind Tour	0.2093
R4	26 Oct 1984	Born in the USA Tour	0.2151
R5	21 May 2016	The Ties That Bind Tour	0.2151
R6	2 Oct 1985	Born in the USA Tour	0.1802
R7	25 Feb 2017	The Ties That Bind Tour	0.1686
R8	17 May 2012	Wrecking Ball World Tour	0.2326
R9	13 Sep 1981	The River Tour	0.2326
R10	30 Jul 1984	Born in the USA Tour	0.0930

C. Application Exmaple - Taylor Swift

Next, we explore using our approach for a different artist, Taylor Swift. After acquiring the entire historical setlist data for Taylor Swift, our approach's stages of finding association rules, calculating ARBS values for each concert, and creating a sorted list of all concerts are performed offline. Here, minimum confidence was 0.6, and minimum support was 0.2, resulting in a set of 263 rules being found. To find Taylor Swift recommendations, the user just defines initial preferences such as, for example, those shown in Fig 6:Left. Here, the user has defined, they wish to be recommended only 2 of the most typical concerts.

Our approach then utilises these preferences to find a set of recommendations, and the initial set of 2 recommendations are shown in TABLE 3. Here, we observe both recommendations have an ARBD value of 0, highlighting to the user they are most typical in terms of concerts that are the most rule affirming. After inspecting the initial results, a user could, if desired, tune their preferences.

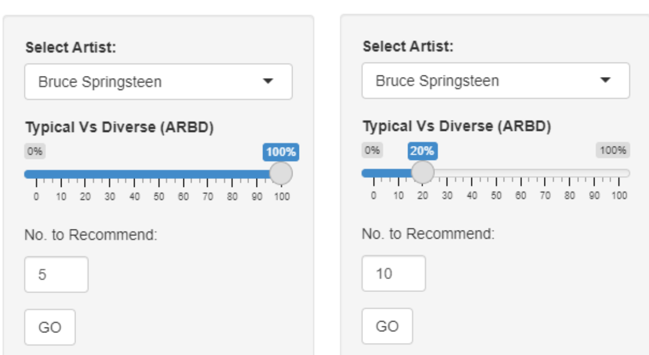

Fig 5: Bruce Springsteen user preferences, Left: Seeking 5 very diverse recommendations, Right: Seeking 10 quite typical recommendations

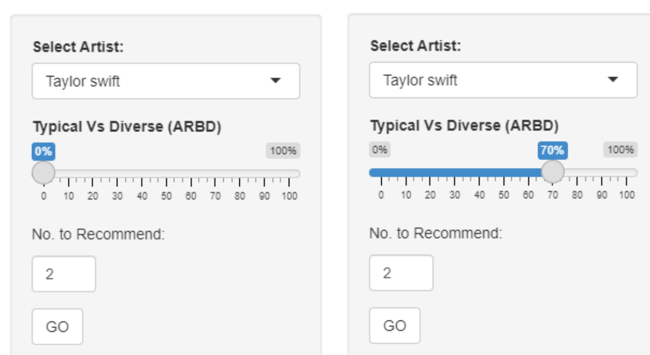

Fig 6: Taylor Swift user preferences, Left: Seeking 2 of the most typical recommendations, Right: Seeking 2 quite diverse recommendations

[2] https://api.setlist.fm/

TABLE 3: Taylor Swift Initial User Recommendations

	Concert Date	Name of Gig's Tour	ARBD
R1	26 Mar 2010	Fearless Tour	0
R2	17 Jul 2009	Fearless Tour	0

TABLE 4: Taylor Swift Updated User Recommendations

	Concert Date	Name of Gig's Tour	ARBD
R1	12 Nov 2011	Speak Now World Tour	0.7039
R2	30 Jun 2015	The 1989 World Tour	0.6872

Updated user preferences are shown in Fig 6:Right, where the user has defined that they still seek only 2 recommendations, but now they seek ones that are about 70% diverse. The updated results are shown in TABLE 4. Here, we observe our approach has returned updated recommendations with ARBD values around the user's desired diversity preference.

IV. CONCLUSIONS

In this paper, we proposed an approach to explore diversity within RS. Through calculating a measure of diversity using our proposed metric ARBD, defining Association Rule Breaking Diversity, our approach explores a novel way to consider diversity within RS in terms of the level of association rule breaking or conformity. We showed how ARBD presents a nuanced consideration of diversity through measuring association relationships between parts of possible recommender content. This represents a different way to consider diversity, compared to considering just the rarity of the parts that make up possible recommender content. Thus, our approach can find interestingly diverse recommendations, in terms of ARBD, that are not so directed related to diversity that just focuses on item uniqueness and rarity. We explored the application of our approach for the example domain of historic live concert recommendations, for multiple prominent music artists. Here, association rules are found between songs that are played in live concerts. The experiment utilization highlighted how our approach can cater for different user preferences regarding the amount of ARBD diversity they seek. Our approach could be utilized within any other domain with similar data properties, and future work will look to explore applying our approach within other domains. Moreover, future work will also explore carrying out user evaluation studies within the vibrant online communities of prominent music artists, to deepen our understanding and refine our approach.

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