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Enhancing User Engagement Among Younger Viewers: Implementing Diversity, Relevance, and Serendipity into the NPO Recommender System

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Introduction

The NPO is a Dutch public broadcaster that relies on the government and the Dutch population for funding and feedback. It is thus essential for the NPO to maintain strong relationships with its stakeholders, including the government, the general audience, and content creators. By serving the public interest, the NPO aims to provide high-quality, diverse, and informative content that meets the expectations and needs of a wide range of viewers (NPO, 2023).

However, the NPO is currently facing challenges in engaging younger audiences. Over three-quarters of its viewers are now over 50, while people under 35 are watching less of its content and spending more time on streaming services such as Netflix, YouTube, and Disney Plus (Libbenga, 2021). In response, the NPO must prioritize public values that resonate with younger viewers, such as diversity and serendipity, in its recommender system (RS).

Diversity, relevance, and serendipity are particularly important for younger viewers because they often have a wide range of interests and are more likely to be open to discovering new topics and perspectives (Visser & Tersteeg, 2019). By prioritizing these public values, the RS can expose younger viewers to new and interesting content that reflects the wide range of perspectives and experiences in Dutch society (Bonenberger et al., 2022).

However, individual characteristics can influence users' tolerance for diversity (Eskandanian et al., 2017). To address this challenge, this study proposes a value-sensitive design approach for developing a recommendation algorithm that has the following main objectives: Increase user engagement among younger viewers, enhance exposure to diverse content that caters to a wide range of interests and preferences, ensuring relevance as the foundation for this diversity, promote serendipitous discoveries by offering unique recommendations, while maintaining a certain degree of relevance to create a balance between unexpected discoveries and user interests.

To achieve these objectives, the RS will incorporate a hybrid approach, combining collaborative filtering and content-based filtering techniques to provide personalized and diverse recommendations. Additionally, an interactive interface will be created to allow users to control the level of diversity in their recommendations, ensuring a consistent user experience that aligns with individual preferences. The performance of the implementation of the values will be measured with the metrics described in Appendix 3. The structure of the paper consists of the following sections: 1) critical discussion, 2) methodology, 3) results, and 4) conclusion.

Critical discussion

In the digital era, companies fiercely compete to maintain user engagement and capture attention. Recommender systems (RSS) play a crucial role in this landscape, as they calculate and provide relevant content based on user information, content, and interactions (Falk, 2019). To ensure that these systems are designed with public values in mind, it is essential to adopt a value-sensitive design approach. This literature review discusses the concepts of public values, value-sensitive design, and the chosen public values of diversity, relevance, and serendipity in the context of RSS.

Public Values and Value-Sensitive Design

Value-sensitive design is an approach that integrates ethical and social considerations into the design and evaluation of technology, including RS (Friedman et al., 2006). By considering public values such as diversity, relevance, and serendipity, RSS can balance personalization with broader societal concerns, promoting an inclusive and engaging media environment.

Diversity

Diversity is a public value that emphasizes the representation of various social and identity dimensions in media content, such as gender, race, and sexual orientation, promoting inclusivity and equal representation (Kunaver & Požrl, 2017). External diversity addresses the variety of content types and genres available in the media landscape, including movies, TV shows, documentaries, and other formats, fostering a rich and engaging media environment (Kunaver & Požrl, 2017). However, promoting diversity may sometimes be at odds with personalization, which aims to tailor content to individual preferences (Vargas et al., 2011). To address this challenge, value-sensitive design can help strike a balance between diversity and personalization.

Relevance

Relevance focuses on the importance of providing content that users find meaningful and engaging. A relevant item is one that a user likes, consumes, or is interested in, depending on the specific context of the recommendation system (Kotkov et al., 2016). Personalization and accuracy are essential criteria in determining a user's perceived utility of the system (Shin & Zhong, 2020). However, high accuracy can potentially suggest low overall content diversity. Value-sensitive design can be employed to balance relevance with diversity, ensuring that recommendations are both personalized and varied.

Serendipity

Serendipity refers to suggestions that are not only relevant and novel to the target user but also significantly different from items they have interacted with, improving user satisfaction in RSS (Kotkov et al., 2016). Although there is no consensus on how to conceptualize and operationalize serendipity, Helberger (2018) notes that unexpectedness is a key element. Serendipity and diversity share theoretical and algorithmic similarities, despite not being synonymous. Designing RSS that incorporate serendipity is challenging due to the need to balance unexpectedness with relevance, but value-sensitive design principles can help guide this process.

By adopting a value-sensitive design approach, RSS can better promote public values such as diversity, relevance, and serendipity, leading to a more inclusive and engaging media environment. Relevance establishes a basis for diversity and serendipity, ensuring a certain degree of pertinence in recommendations. This literature review has critically discussed these concepts and their implications for RSS, highlighting the challenges and potential trade-offs that designers and developers must consider. By integrating value-sensitive design principles, RSS can strive to balance personalization with broader societal concerns, ultimately benefiting both users and society.

Methodology

1. Defining Personas

We conducted an online survey using Microsoft Forms to define personas and understand our key stakeholders, young people in The Netherlands. The 10-question survey (Appendix 2) covered demographics, psychographics, and opinions on diversity, serendipity, and media content (movies, series etc.). After analyzing 68 complete responses, we created 4 distinct personas based on likeability of serendipity, external diversity, and within-content diversity. We also considered their favorite content types and titles for a realistic depiction of user preferences. The personas are: Øjvind, a 21-year-old documentary lover; Yara, a 24-year-old series streamer; Nelson, a 27-year-old content devourer; and Zeynep, a 25-year-old movie buff with diverse interests. Below these personas are depicted in detail in Image 1.

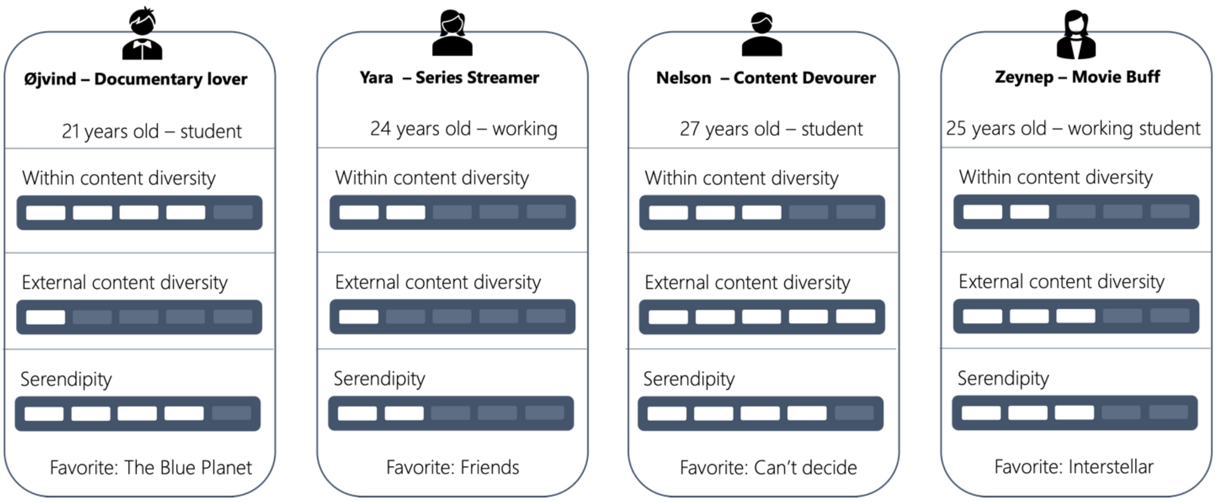

Image 1. Depiction of personas and their preferences.

2. Data Collection and Preparation Techniques

As it was not possible to find a reliable source for obtaining the data required to implement within-content diversity, it was decided to focus solely on implementing external-content diversity in the RS.

First, the NPO website was scrapped to obtain a comprehensive list of media items along with their descriptions and images. Next, each of the items were searched on MovieMeter, a Dutch movie and TV show reviews website, to retrieve their corresponding tags (such as drama, comedy, horror) and complete any missing descriptions and images. This process was implemented using Python with the help of Beautiful Soup and Selenium libraries. The final set of items consist of 930 TV shows, 308 films, 193 documentaries, and 262 series.

3. Synthetic Data Generation

A simulated environment was created to train the RS with interactions data from 1000 users, reflecting the preferences of the four identified personas through probabilistic weighting. These weights were used to define user behaviour and increase the likelihood of interacting with their favourite content. The interaction probabilities, such as rating and sharing, were also assigned based on whether the user viewed or clicked the content preview. The final dataset, which is illustrated in Appendix 1, contains 99,700 rows of interactions.

4. Implementing Value-Sensitive Recommendation Algorithms.

Hybrid Algorithm to Provide Personalised and Serendipitous Recommendations.

The hybrid algorithm (Image 2) incorporates collaborative filtering for diversity and content-based filtering for relevance. The collaborative filtering function identifies users with similar interaction histories to the target user, selecting the top K similar users based on cosine similarities. The value of K is determined by the level of diversity specified by the user; the higher the diversity, the greater the value of K. The algorithm then computes the average interaction score of the selected users to identify candidate items for the target user. Finally, the items that the user has previously viewed are removed, yielding a list of top candidate items.

The content-based filtering function identifies content with which the user has positively interacted while also considering the user's media type and categories preferences into account. The algorithm then ranks and returns candidate recommendations in sorted order based on these preferences. The user-selected level of diversity is used to order the final recommendation set. If this value is low, the list retains its original order, and only the top 15 items are returned. For medium diversity, A balanced mix of the original top item order and a random selection from the candidate list is used. For high diversity, only the top 25% of the items are retained, and the remaining items are replaced with random items from the user's candidate list.

Additionally, to introduce serendipity, this algorithm includes a feature that retrieves the last item in the final set of recommendations. The algorithm considers the user's tolerance for diversity, ensuring that the last recommended item is different but not too dissimilar to the user's previous interactions.

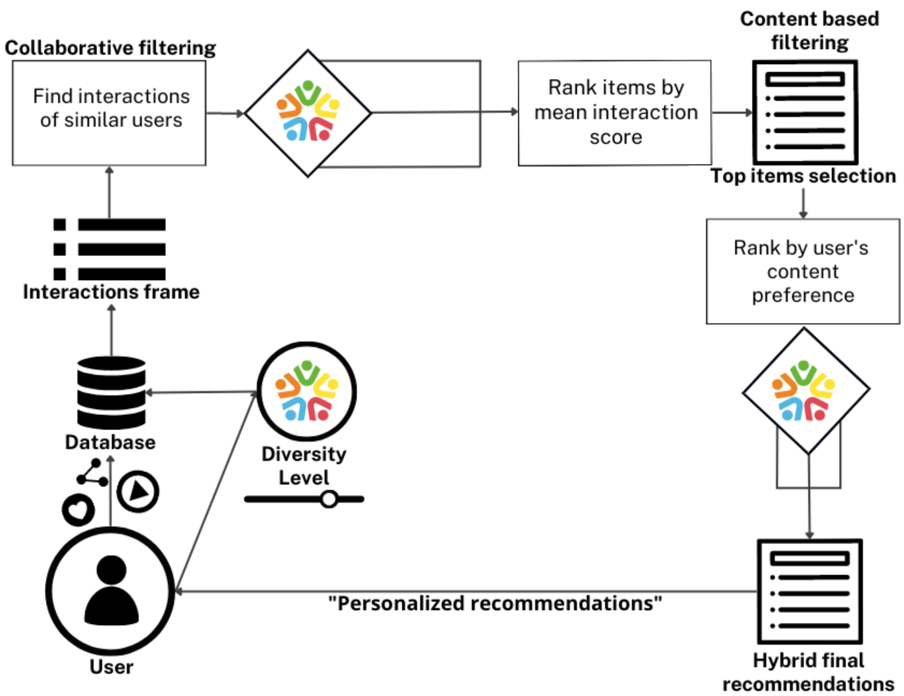

Image 2. Diagram of the Hybrid Algorithm.

Content-Based Recommendations to Find Similar Content to the Last Viewed Item.

The algorithm (Image 3) identifies a group of potential items that closely resemble the most recently watched content. To achieve this, the items are initially sorted based on the similarity of their descriptions, which is computed generating vectors using TF-IDF and calculating the cosine similarity between them. Also, their tags are considered by calculating their similarity using Jaccard similarity. The resulting list of candidate recommendations is then adjusted based on the user's preference for diversity.

For a low diversity level, the top 15 items from the sorted list are presented as recommendations. For medium diversity, the list includes a combination of the first ordered items and randomly selected items from the first 100 elements of the candidate list. Finally, for high diversity, the list contains a mix of a few first ordered items, and the remaining recommendations are randomly selected from the first 200 elements of the candidate list.

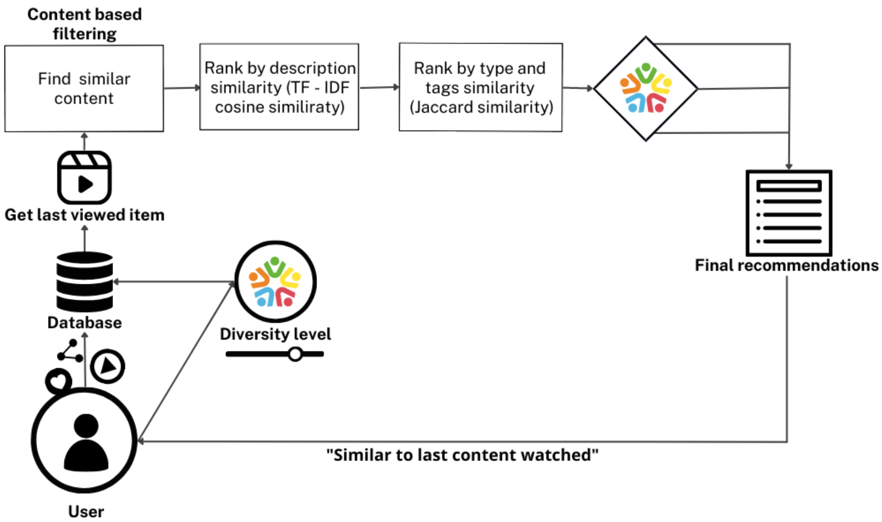

Image 3. Diagram of the Content-Based Algorithm.

Collaborative-Based Recommendations for Frequently Liked Together Items.

The RS also generates suggestions by considering the user's previous likes (Image 4). To achieve this, the algorithm searches for other users who have also liked the same item and then examines which other items those users liked. Based on the frequency of those items being liked together, the algorithm generates a list of sorted candidate recommendations The final recommendation list is generated using the same diversity-based approach as described in the content-based algorithm.

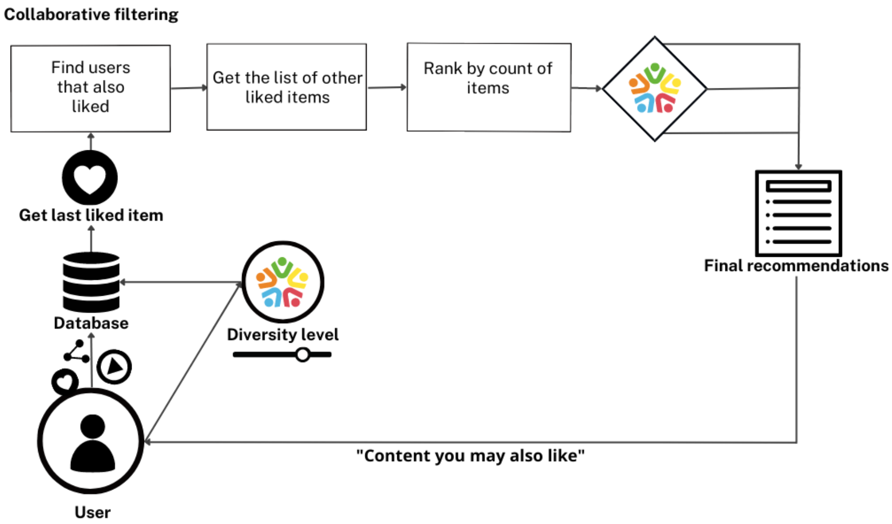

Image 4. Diagram of Collaborative filtering Algorithm.

5. Interface design.

The proposed user interface (Image 5), comprises recommendation lists with titles indicating the algorithm used to generate them. Each item in the list features two buttons, namely the “play” and “more information” button. The latter opens a pop-up window (Image 6) that displays the name of the item, type of content, categories, and description. It also includes “share” and “play” buttons, as well as “thumbs-up” and “thumbs-down” buttons to provide feedback on the item.

The interface tracks all the clicks on the previously mentioned buttons to inform the recommendation algorithm and ensure that recommendations are precisely tailored to the user’s interests and preferences. Users can visualize their interactions history to understand why specific recommendations appear on their dashboard.

The top bar of the interface includes a “settings” button that reveals a slider enabling users to adjust the level of diversity of their results between low, medium, and high. By respecting the users’ level of tolerance, the interface provides tailored recommendations, while also encouraging exploration and discovery of new items.

In the centre of the page, a banner provides access to a serendipitous button, which allows users to find something new and unexpected with a single click. The use of a button adds an element of surprise and excitement to the user experience, which can be more engaging and satisfying than merely browsing through a list of recommendations.

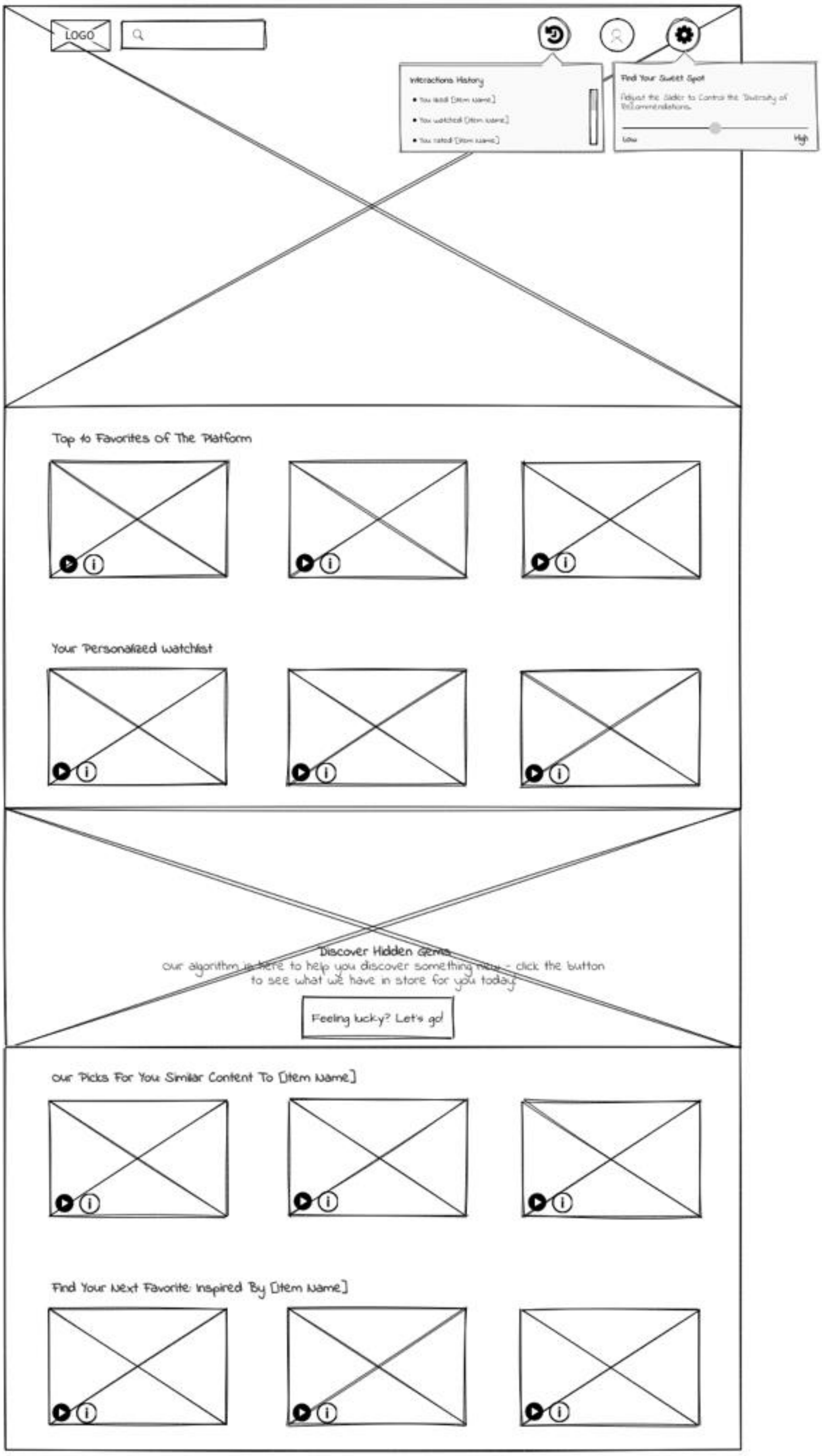

Image 5. Wireframe of the interface design.

Image 6. Popup with more information about an item.

6. Integration.

As shown in Image 7, the RS described above is a combination of several technologies that provide a robust and efficient system. Angular is a widely used Typescript framework for building modern and intuitive user interfaces. Flask is a lightweight Python web framework that enables rapid development of the server-side logic. Python, with its extensive range libraries and tools, provides all the elements needed to implement advanced recommendation algorithms, while MongoDB is a flexible and scalable database technology used to store and retrieve data.

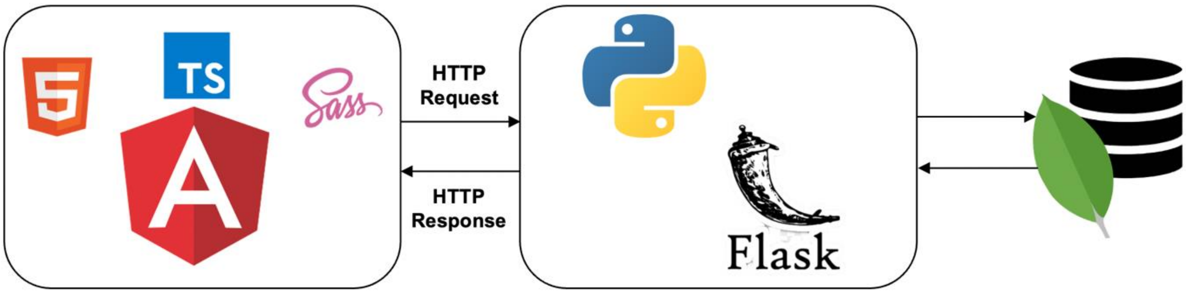

Image 7. Technologies Integration to build the NPO RS.

This integration is made possible through a series of API endpoints defined in the Flask server, which enable communication and data exchange between the front-end Angular interface and the back-end Python-based recommendation engine. When a user interacts with the interface, the Angular framework sends an HTTP request to the Flask server. Flask processes the request, communicates with the MongoDB database if necessary, and returns a response to the front-end. A live preview of the final product can be accessed through **this link.**

Results

To assess the performance of the proposed value metrics, an assessment was carried out by comparing the personalized recommendation set of the system for a subset of 100 randomly selected users at varying levels of diversity (low, medium, and high) to that of a random recommender. The evaluation was based using metrics for relevance (Equation 1), Bradley & Smyth (2001) diversity (D_B, Equation 2), Vargas & Castells (2011) diversity (D_V, Equation 3), and serendipity (Equation 4), which are described in Appendix 2.

The evaluation results (Image 8) demonstrate the algorithm's successful implementation of diversity, surpassing the performance of the random recommender in all measured metrics. As expected, increasing the level of diversity in the model resulted in a corresponding increase of D_B. The medium and high diversity levels exhibited superior performance in terms of D_B compared to the random recommender, potentially because the non-uniform distribution of item categories created an inherent imbalance for the random recommendations.

However, the relevance of the RS was indirectly affected by the diversity implementation, resulting in tradeoff between relevance and D_B, which is presented in Image 9. Diversity increases the distance of the recommended items from the user's top preferences, leading to a decrease in relevance. Nonetheless, the algorithm still outperformed the random recommender in terms of relevance, even at its high diversity level. The medium diversity level yielded the highest D_V, suggesting that it may be an optimal level for the general user experience in terms of diversity- relevance tradeoff.

Although the algorithm shows higher serendipity values than the random recommender, the behavior of the serendipity metric was not as anticipated. The implementation aimed to increase serendipity with increasing diversity level, but an opposite effect was observed. This can be explained by the fact that relevance holds significant weight in the serendipity formula, and the proposed RS does not address the unexpectedness level of the recommendations.

Image 8. Comparison of the Algorithm for Different Levels of Diversity.

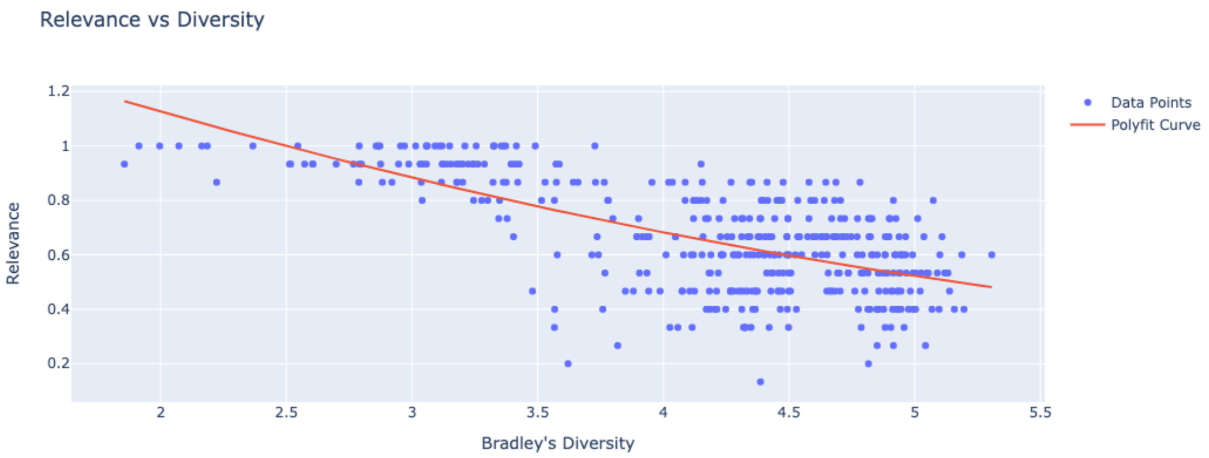

Image 9. Tradeoff between Diversity and Relevance.

Conclusion

The implemented recommender system works well for diversity and relevance globally when compared to a random recommender. Furthermore, users get control over some settings defining the quality of their recommendations, which is an aspect missing on the NPO platform. However, the study still presents some limitations. First, the trade-off between diversity and relevance results in a natural decrease in serendipity when increasing diversity. Since serendipity was implemented using the hybrid-based algorithm, one possible solution to address this limitation is to develop a new RS that can offer users more unexpected recommendations.

Secondly, despite identifying two types of diversity during the data collection, there is a lack of a within-content diversity algorithm, primarily due to data limitations and availability. Future research could address this issue by utilizing natural language processing (NLP) and advanced machine learning techniques to extract information about a show or movie's cast and their demographic data from sources like Wikipedia (Kríž, Hladká, & Knap, 2014).

The third limitation pertains to the data collection process, wherein the survey's population sample consisted majorly of international participants rather than Dutch individuals. This limitation arose from the authors' network bias. To mitigate this issue, future studies could employ alternative data collection methods such as interviews or focus groups with a strictly Dutch demographic (Richard, Sivo, & Witta, 2020).

Lastly, it is essential to consider the implications of constructing an algorithmic system, as these systems inherit biases from their creators, which can then be transmitted to users. Incorporating algorithmic affordances, such as user autonomy and transparency, can help minimize biases and ensure a more equitable system.

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Appendices

Appendix 1

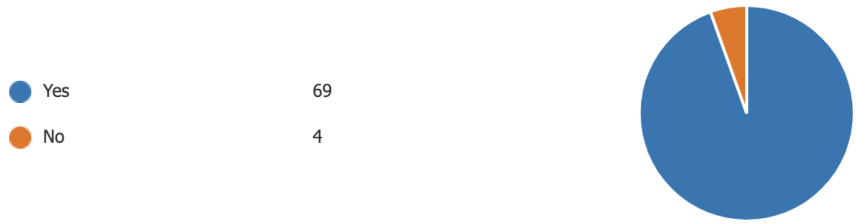
User Type	Interaction Date	View	Preview	Shared	Rating	Item ID	Type	Tags
Content devourer	Apr 08 2022 08:02	1	1	0	1	998	Tv	['Drama', 'Romantiek']
Content devourer	May 14 2022 10:20	1	0	0	0	643	Series	['Animatie', 'Familie']
Content devourer	Apr 18 2022 12:23	1	1	1	-1	1341	Tv	['Familie', 'Muziek']
Series Streamer	May 26 2022 07:19	1	1	1	0	312	Documentary	['Drama', 'Fantasy']
Series Streamer	Mar 06 2023 12:15	0	1	1	1	520	Series	['Drama', 'Misdaad']
Series Streamer	Dec 27 2022 02:50	1	1	1	-1	652	Series	['Drama']
Movie Buff	Aug 09 2022 10:46	1	1	0	-1	604	Series	['Avontuur']
Movie Buff	Jul 09 2022 11:40	1	1	1	0	148	Movie	['Drama']
Movie Buff	Apr 23 2022 09:09	1	1	1	1	77	Movie	['Actie']
Docume ntary Lover	Mar 25 2022 08:23	1	0	0	0	485	Documentary	['Documentaire', 'Biografie']
Docume ntary Lover	May 05 2022 08:39	1	1	0	-1	426	Documentary	['Documentaire', 'Historisch']
Docume ntary Lover	Aug 27 2022 08:08	1	1	1	1	383	Documentary	['Documentaire']

Appendix 2

Online survey

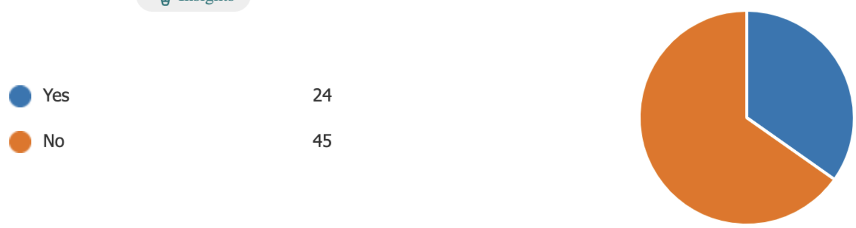
1. Is it okay that we use your answers for educational purposes? Your data is anonymized and can be deleted anytime at request by sending an email to a.c.banke@students.uu.nl

Flere detaljer



2. Is your nationality Dutch?

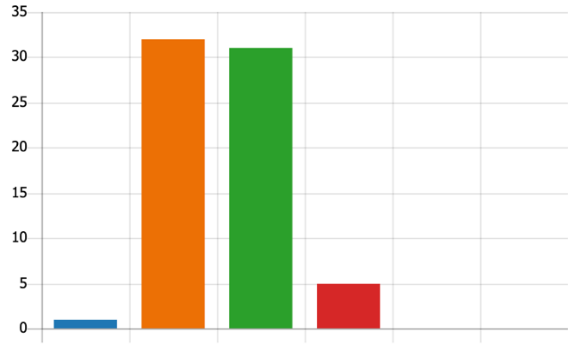
Flere detaljer Insights



3. What is your age

Flere detaljer   Insights

<18	1
18-24	32
25-31	31
31-40	5
40-50	0
50+	0



4. What's your occupation?

Flere detaljer   Insights

Student	61
Working	3
Not employed	1
Andet	3

5. Do you like to be surprised when provided recommendations in streaming services such as Netflix? (i.e. do you enjoy it when content outside of your usual genres are recommended to you?)

1. is not at all and 5. is all the time

More Details   Insights

68
Responses

3.34
Average Number

6. For diversity of content, how important is within-content diversity (such as a diverse characters in terms of gender, age, religious background, sexuality etc.)

1. is not important and 5. is very important

More Details   Insights

68
Responses

3.37
Average Number

7. For diversity of content, how important is external-content diversity (such as a diverse types of media, like tv-shows, documentaries, movies, different genres etc.)

1. is not important and 5. is very important

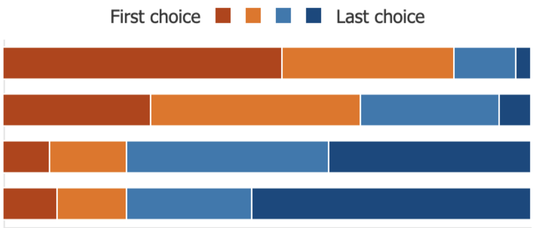
More Details   Insights

68	3.46
Responses	Average Number

8. What are your favorite categories for media content such as movies and tv-shows? Please rank these options below where 1. is most preferred

More Details

Rank	Options
1	Series
2	Movies
3	Documentaries
4	TV-shows



Appendix 3

Evaluation of Relevance

Relevance can be assessed based on various actions that a user takes with respect to an item, such as giving it a high rating or an interaction. To encompass these different factors, a relevant item is one that a user likes, consumes, or is interested in, depending on the specific context of the recommendation system (Kotkov et al., 2016). In order to account for the rank of the item within the rs, we can use a rank discount factor, as demonstrated in the work of Vargas & Castells (2011). This enables us to estimate the probability of an item being relevant based on its position in a list of all platform items ranked according to the user's most engaged content preference. As a result, the relevance of rs can be quantified by taking the average relevance of all the items within it.

$$Rel = \frac{\sum_{i=1}^{|rs|} P\left(\frac{|RL| - Pos_{RL}(i)}{|RL| - 1}\right)[0,1]}{|rs|}$$

Equation 1. Relevance equation

Where:

- *Rel*: Relevance of the recommendation set.
- $|rs|$: length of the recommendation set.
- $|RL|$: length of user's preferences ranked list.
- Pos_{RL}: Position of the item in the user's preferences ranked list.

Evaluation of Diversity

According to Bradley & Smyth (2001), diversity can be quantified by calculating the mean dissimilarity between every possible pair of items within the set of recommendations. For this study, we have defined the term "dissimilarity" as a function of three different types of pairwise similarities among all the objects in the recommendation set (rs). These similarities include the Jaccard similarity of content category tags, the similarity of content media type, and the cosine similarity of the TF-IDF matrix generated from the description text of each series. The resulting formula has been derived to measure the level of diversity within the recommendation set.

$$D_B = \frac{\sum_{i=1}^{|rs|}\sum_{j=1}^{|rs|}(3 - (Sim_{tags}(rs_i, rs_j) + Sim_{type}(rs_i, rs_j) + Sim_{description}(rs_i, rs_j)))}{\frac{|rs|}{2} * (|rs| - 1)}$$

Equation 2. Bradley & Smyth (2001) Diversity equation

Where:

- D_B: Diversity according to Bradley & Smyth (2001).
- $|r_s|$: length of recommendation set.
- Sim_{tags}: Jaccard similarity between tags lists.
- Sim_{type}: Similarity between items' type [0,1].
- $Sim_{description}$: Cosine similarity between items' description TF-IDF matrix.
- rs_i, rs_j: Items on the recommendation set to be compared.

Additionally, Vargas & Castells (2011) proposed a definition of diversity between items, which takes into account both their relevance and similarity. Specifically, they define the diversity between items as the product of their relevance and similarity scores.

$$D_V = D_B \times Rel$$

Equation 3. Vargas & Castells (2011) Diversity equation

Where:

- D_V: Diversity according to Vargas & Castells (2011).

Evaluation of serendipity

To evaluate the serendipity of recommendations, the work of Adamopoulos & Tuzhilin (2014) was used as a starting point. In order to conduct this evaluation, two sets of items are required: the set of expected items for the user (E_u) and the set of items generated by a primitive prediction model (PM). E_u represents a finite collection of items that the user typically considers as candidates for fulfilling their current needs or intentions, based on their interactions with the recommendation system. For this study, E_u was constructed using the past positive interactions of users and the three most similar items to each of them in terms of type, tags, and description.

According to Adamopoulos & Tuzhilin (2014), a primitive prediction model, on the other hand, refers to a basic or simple model that provides initial recommendations to users without using advanced or sophisticated algorithms or techniques. In this case, the top 25 selections of a PM based on the weighted-average score of the items were used.

The evaluation of serendipity is based on a formula that calculates the sum of the number of items in the recommendation set that are not included in the union of E_u and PM, multiplied by the relevance of the list, and then divided by the length of the recommendation list. According to Kotkov et al. (2016), this serendipity metric successfully captures the concepts of popularity, unexpectedness, and relevance. By including these factors, it provides a comprehensive assessment of the degree to which the recommendations are surprising and diverse, while still being relevant to the user's needs and interests.

$$Ser = \frac{Rel * \sum_{i=1}^{|rs|} rs_i \setminus E_u \cup PM \ [0,1]}{|rs|}$$

Equation 4. Serendipity equation

Where:

- *Ser*: Serendipity of the recommendation set.
- *rs*: Recommendation set.
- $|rs|$: length of the recommendation set.
- E_u: Expected user's set.
- *PM*: Primitive model's set.
- *Rel*: Relevance of the recommendation set.