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Compliance of Personalized Radio with Public-Service Remits

ABSTRACT

Public radio broadcasters do not consider personalization in their compliance with their public mandate so far. However, personalization brings along the risk of filter bubbles, which contradicts with the ideas of the public mandate. We shed light on the interconnection of personalization and the public mandate of broadcasters anchored in an analysis of the interstate treaty on broadcasting and tele-media. The contribution of this paper is two-fold. First, we propose an approach how to selectively avoid filter bubbles in personalized radio consumption. Second, we develop a framework that helps to assess the compliance of personalized radio offers with public mandates.

1 INTRODUCTION

Neutral media coverage is considered as one of the pillars of democracy. In many countries, a dual broadcasting system exists in form of public and private radio broadcasters that are subject to different regulations. As personalization finds its way into media coverage in general and therefore also radio in particular, broadcasting agencies have to cope with the challenge of filter bubbles [1]. Especially for public radio broadcasting agencies, the effects of personalization should carefully be considered with respect to their public mandate.

The necessity to take care for personalized playouts puts public radio broadcasters in a new situation. So far, public radio broadcasting agencies had to take the responsibility for one single program per radio station. With personalization, not only one program, but thousands of playouts have to be taken into account and taken responsibility for.

Regularly (e.g. in Germany every two years according to the German interstate treaty for broadcasting and tele-media (ITBT) §11e (2)), broadcasters publish a report concerning their compliance to the public mandate., i.e. in which way their service offer corresponds to the democratic, social and cultural needs of the society (§ 11f (4)). Until now, personalized playouts have not been considered in these reports. One reason is that personalization is still emerging in the radio industry. Another reason is that in a traditional perspective, the linear broadcasting program is always the primary service offer, whereas tele-media is a secondary utilization of content, and personalization is just a special form of tele-media, therefore playing a minor role.

But as tele-media and non-linear consumption of radio increases, the problem of filter bubbles becomes increasingly present and gains social relevance. At the latest, when non-linear consumption will outperform linear consumption and account for more than 50% of all radio playouts, personalization in public service offers needs to be discussed.

In case broadcasters want to report on their personalized service offers, they need to do it in a different way than for the linear program. Classic radio allowed to shape the program in terms of weighting of topics and positioning to time slots. In contrast, in a personalized world of thousands of individual programs, it is impossible to refer to every individual playout. Rather, the argumentation could be supported by algorithmic designs of personalization and corresponding methods to avoid filter bubbles. Broadcasters therefore have to undergo a shift from mainly assessing their service offer in terms of available content (in one program) towards also regarding the content dissemination as an integral part of their public mandate. Within personalization, broadcasters find themselves in the ambivalent role to provide a program that suits the needs of the user and to comply with the public mandate at the same time.

Still, the question remains whether public broadcasters have to take care for filter bubbles that may emerge from their personalized playouts at all. Assuming the answer is: Yes, to the extend they can influence, we ask the question:

How can broadcasting agencies comply with the public mandate when offering personalized radio?

The remainder of this paper is structured as follows: First, we present related work on filter bubbles and mechanisms to avoid them in the next section. Then, we carve out the requirements of a public mandate written down in the ITBT which are relevant for a personalized radio playout. On this basis, we sketch an approach that reflects these requirements for individualized playouts in section 4. On top, in section 5 and 6 we construct a framework how radio broadcasters can reflect and self-assess their personalized offer with regards to compliance with their public mandate.

2 RELATED WORK

2.1 Filter Bubbles within Personalization

Personalization through algorithms is largely invisible. While this has advantages in terms of ease of use, it is problematic at the same time: users' opinions may be influenced without them being aware of it [2]. Conventional recommender systems that pro-actively suggest items of potential interest to the user make it often difficult to understand their outcome [3]. The algorithms' central position as an intermediary between information and users makes them information providers, such as search engines, which are able to influence the presented results [4]. The informational sphere that emerges when non-transparent algorithms influence the opinions and preferences of users has been labelled Filter Bubbles by Pariser [5] or Echo Chambers by Sunstein [6]. Pariser argues that the root of human intelligence consists in the ability to adapt to new information, but a system of recommendations turns a user into an immutable environment that they have shaped. The filter bubble reduces a user's creativity and learning ability and strengthens his/her beliefs [5]. The iTunes study of Hosanagar et al. confirms this assumption - they found out that users tend to consume similar content because recommender systems help to expand existing interests [7]. Iaquinta et al. see the main hazard in overspecialization, caused by a lack of serendipity [8].

Public broadcasters who want to integrate recommendation systems into their services in order to meet the changing reception habits of their listeners with a modern and attractive non-linear broadcasting service are confronted with this problem in particular [9]. But there are also voices against the fear of filter bubbles. For example, Linden, one of the authors of Amazon's recommender system, believes that personalization does not limit user selection, but rather serendipity. Recommendation systems help users discover content that they would not otherwise have searched for because they did not know about it [10].

In addition to the algorithmic influence, streaming services also have a human component that influences which content is consumed by the user. Self-selected personalization is strongly associated with selective exposure [11]. Selective exposure occurs when a person deliberately seeks messages that support his/her own point of view and thus creates a feeling of confirmation [12]. Even if algorithms propose fully balanced news, the user could be free to view only those items that match his preferences. This would lead to a lack of perceived diversity as well as the filtering out of various topics. On the other hand, there are users who use a news portal with filtering and still seek additional information or information that does not correspond to their opinions from another source in order to be well informed [11].

When considering the influence of a filter bubble on information formats, it is noticeable that the predisposition of a user is of particular importance for news: How motivated a user is to look for various information from several sources or different points of view strongly depends on how much he is interested in the topic [13]–[15].

Broadcasters are gatekeepers who control the floss of information [5]. This means that there is already a certain degree of filtering in the public media institutions. E.g., not all daily events are reported or can be reported. Also the time slot of each radio show may influence the probability of a program's audience being large or small [1]. Which topic makes it into the show is ultimately decided by the editors. Algorithms would primarily replace human gate keepers. The difference between editors and algorithms is that people follow ethics and have an eye for the public interest [5]. But, as Friedman elucidated, technology may have ethics, too: Algorithms are not neutral and the opinions and values that developer hold will manifest themselves in the product [16].

2.2 Approaches to Avoid Filter Bubbles

Several approaches exist to avoid or reduce the risk of filter bubbles. Ekstrand et al. propose a way to prevent filter bubbles by giving the user control over the algorithmic settings. This can be the selection of algorithms, or a variant for combining one algorithm with another. It is also possible to give the user control over the degree of diversity or the used information from the user profile using adjustable variables [17]. Interactive Recommender Systems have been proposed that aim to give the user more control over the recommendation process and to improve transparency (e.g. [18]), though not explicitly for public broadcasting.

Liu et al. propose a combination of personal interests with local trends. Their study shows that users often click on the articles recommended to them in this way, but then search less for articles in the topics they subscribe to [19]. Li et al. propose a system called "SCalable two-stage pErsonalized News rEcommendation system" (SCENE) to avoid filter bubbles. SCENE is a two-level algorithm whose first level divides articles into topic categories relevant to the user and whose second level recommends individual articles from these categories [20].

Iaquinta et al. present a concept of a hybrid recommender system that combines a content-based approach with serendipitous heuristics in order to avoid filter bubbles with surprising suggestions. Required for their serendipity method is a content-based recommender system, that implements their "anomalies and exceptions" approach. They follow the idea that content should not be recommended if it is too similar to items the user has already consumed [21].

Burke applies the technique of "heuristic similarity". This approach takes into account the semantics of the assessments themselves. The similarity of users is examined on a rating scale in order to highlight qualitative differences between ratings [22].

Pöchhacker et al. investigated on algorithms with regard to the challenge of public service broadcasting and propose the possibility of using an anti-recommender system to send out other content to users. Furthermore, they point out that the stakeholders in the broadcasting system need to be reconsidered. For personalized broadcasting, the committees should be expanded to include developers, data scientists, database administrators, web designers and network technicians who were not previously suspected of working as journalists [23].

Hirschmeier et al. propose an architecture that allows non-recommender content to be played out, which would also reduce the risk of emerging filter bubbles [24].

Looking into practice, the National Public Radio (NPR) in the U.S. manages to reduce the risk of filter bubbles in its personalized service NPR One by also playing out non-recommender content next to recommender content. NPR's so-called "flow" always starts with a news sequence. This is skippable by the user, but is initially offered [25].

3 REQUIREMENTS FROM THE ITBT

The ITBT is the relevant legal document that explicitly states the mandate of public radio broadcasters. In order to grasp a more detailed picture what the implications of the public mandate are, we analyzed the ITBT for requirements that are relevant for personalization.

3.1 Methodology

We carved out requirements from the German ITBT, the "Staatsvertrag für Rundfunk und Telemedien", more commonly known as "Rundfunkstaatsvertrag" (RStV), in its 19th version[1] from June 1st, 2016, by means of qualitative data analysis.

Before coding the document, we set up a coding frame. Considering the requirements for public broadcasters, we found two levels addressed by the ITBT: a) content production and b) content composition.

Content production: Content has to be produced according to requirements mentioned in the ITBT, e.g. media coverage has to be independent and objective, content checked for truth, produced according to journalistic standards etc.

Content composition: The sequence of the content items is what makes up the radio program. Therefore, the program composition might also account for the emergence of filter bubbles.

In a non-linear playout, the produced content pieces themselves cannot be changed as they are given as atomic items; the only possibility to create a multitude of personalized programs automatically is by composing content pieces in different ways. Therefore, we focus on the content composition and neglect the content production. For coding purposes, we established a simple coding framework with just two codes: a) concerns content production and b) concerns content composition. Two coders performed the coding procedure independently. After coding, assigned codes were discussed, and differences resolved.

3.2 Results

In the following, we only present the requirements that concern the content composition, i.e. the program compilation. In the end, we elicited 7 requirements.

R1. Comments must be separated and clearly distinguishable from reports (§ 10 (1)).
R2. The service offer of public broadcasters should include information, education, culture, and entertainment (§ 11 (1)).
R3. The service offer should give a comprehensive overview over international, national, and regional events in all essential areas of life (§ 11 (1)).
R4. The service offer should be balanced (§ 11 (2)).
R5. The service offer should reflect the diversity of opinions (§ 11 (2)).
R6. The service offer should support the process of forming a free and individual opinion and therefore fulfil the needs of a democratic, social and cultural society (§ 11f (4)).
R7. Broadcasters must offer counterstatements of an affected person in equivalent way. For the linear program, the counterstatement should be sent in an equivalent time slot in equivalent length. For the non-linear program in tele-media (especially internet), the counterstatement must be offered as long as the original statement in direct connection to it (§ 56 (1)).

4 A USER HISTORY BASED APPROACH

The approaches to avoid filter bubbles depicted in section 2 are user history-agnostic. With the requirements given in section 3, it is however also plausible to pursue an approach that keeps the user in a "safe corridor" (in the understanding of the public mandate) based on his/her user history. E.g., having consumed too much entertainment content, a user would get more cultural content recommended, so the balance is kept.

[1] The full treaty can be found under http://www.gesetze-rechtsprechung.sh.juris.de /jportal/?quelle=jlink&query=RdFunkStVtr+SH&psml=bsshoprod.psml&max=true

In the following we derive design proposals that fulfil the requirements presented in the section before. The design proposals are constructed in a straight-forward argumentation, lining out logic and metadata requirements.

D1. Information, education, culture, or entertainment. If broadcasters want to better control the balance of their mix (R4), every content item should be assigned to one of the four categories. For implementation of a non-linear playout, radio broadcasters might determine a lower and upper bound for the allowed percentage for each of the four categories, e.g., for education min. 20% and max. 35% of all content. On the basis of the user listening history, broadcasters are able correct their playout to keep the balance. With D1, public broadcasters can meet R2 in conjunction with R4.
D2. Report or comment (or other formats like news, interview, concert, feature, etc.). If report and comments are already clearly distinguishable in the produced content, there is no need to make the difference explicit on a composition level. If not, the distinction could be pointed out clearly in a personalized radio stream by inserting a play-in. In this case, content items should also carry the metadata information whether they represent a report or a commentary in order to meet R1.
D3. International, national, or regional matter. To meet R3 in conjunction with R4, content items should carry the information about their regional, national or international extent and again provide lower and upper bounds for their specific playout.
D4. Counterstatement. Content item metadata should include the information whether they represent counterstatements, and if yes, to which item, in order to meet R7. On the basis of the user history, it can be checked if the user consumed an item for which a counterstatement should be sent.
D5. Diversity of opinions. The probably most challenging task is to reflect the diversity of opinions in an automated personalized program in order to meet R5 and R6, as it is neither trivial which set of metadata suffices to describe opinions nor how content items could be classified. The political spectrum from right to left might help to structure the space of opinions, or sinus milieus and other proxies that allow to landscape opinions. Broadcaster would have to interpret the diversity of opinions and model it for their purposes. Classifiers would need to be trained in order to classify content items to the chosen model of opinion diversity.

The approach depicted, covering D1 to D5, can be seen as correction to keep the user in a safe corridor. In a positive view, the approach can be understood as a special form of a recommender system. However, in a more negative view the approach could also be regarded as a manipulation of the user. Following this approach, for software implementation, a "compliance component" would have to be built in conjunction with the recommender component, containing the logic of the design proposals.

The main purpose of this paper is however not just to propose an approach how to selectively avoid filter bubbles, but to construct a comprehensive framework that sets personalization in relation to the public mandate. In the following two sections, we develop a framework for the assessment of personalized programs.

5 PROGRAM MANAGEMENT WITHIN PERSONALIZATION

In personalization, the program management, which is classically the editorial task of the broadcaster, is shifted to the user, at least in parts [26]. Broadcasting organization and user both act as program managers, and they are guided by different motivations. While editors have several years of experience how to compile a good and enjoyable program for classic radio [27], in personalized radio the program is conjointly managed by an algorithm and the user.

Depending on how the program management task is shared, different responsibilities emerge for users and broadcasters with regard to filter bubbles. We analyze responsibilities for filter bubbles by distinguishing two interaction models in personalized radio consumption: a) the stream interaction model ("skip-one" model), and b) the media center interaction model ("pick-one" model).

5.1 Interaction Models in Personalization

Stream model ("skip-one" model): Just as classic radio is a low-interaction medium and allows the user to enjoy the radio program without any need for interaction, the stream model also allows the user to lean back and consume the automatically assembled personalized program without interaction. An ideal recommender would succeed in playing only content that the user does not want to skip. The stream model therefore comes close to a lean-back experience (see [28]). As a characteristic of this model, the interaction that leads to the next song is a negative choice ("skip-one").

Media center model ("pick-one" model): In contrast to the stream model, the pick-one model requires user interaction. The user needs to click on every item that he/she wants to hear and therefore make a positive choice from a set of recommended items. This model is typical for a lot of media centers on the internet. As user interaction is required, this model comes closer to a lean-forward experience (see [28]) than the stream model. As a characteristic of this model, the interaction that leads to the next song is a positive choice ("pick-one").

Hybrid forms of both models exist, e.g. when media centers have an auto-play option, so they offer also the stream experience. For this paper, however, we need to differentiate the two models in order to analyze the program management roles of the consumer and the broadcaster's algorithm in each model.

5.2 Shared Program Management

In the different radio models, broadcasters and listeners find themselves in different roles regarding a (shared) program management.

Program management in classic radio. In classic radio, the listener has very limited program management possibilities: turn on, turn off, change channels. There is no feedback to the system about his preferences. The program management is – apart from the option to switch channels – completely on the broadcaster's side (fixed program).

Program management in the stream model. In personalized playouts, the program management is shifted to the user to a certain extent. Still, the broadcaster (or better the broadcaster's algorithm) makes a choice for the radio program, but this time, the user can interact by either skipping the item that is currently played or liking it. While skipping has an immediate effect on the program, liking only affects the personalized playout on the long run. Still his interactions are always corrections to the predefined program, rather than an active choice. The user has no possibility to choose an item from a set of recommended items, his only option to influence the program directly is to skip. In the worst case, he/she might have to skip several times to get an item that he/she wants to hear.

Program management in the pick-one model. In the pick-one model, the user influences his program by positive choices (play instead of skip). Also affecting his future playouts with every interaction, he/she is capable of (and at the same time required to) driving the program into the direction that he/she likes. The navigational path in the pick-one model is a different one than in the stream (skip-one) model.

Fig. 1 depicts both models in comparison. In the media center model (Fig. 1 left), the program management "handover" (dotted line) is at the set of recommended items, from which the user picks one. In the stream model (Fig. 1 right), the handover takes place during consumption. The stream model can be interpreted to give the broadcaster a greater responsibility, but also a greater control by directly pushing content to the user. Fig. 1 depicts both the areas of influence and responsibility for both user and broadcaster.

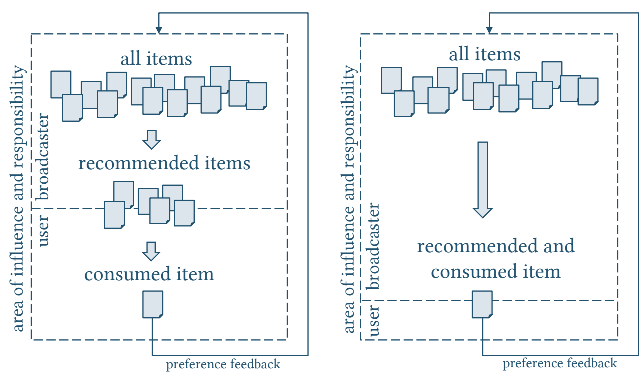

Figure 1: Responsibility for filter bubbles a) in the media center model (left) and b) in the stream model (right)

Possibly emerging filter bubbles might exhibit different characteristics for the media center model and the stream model. It is however not trivial to argue if there is a systematic difference in the filter bubbles that may emerge. Therefore, it remains unclear which interaction model is subject to create stronger filter bubbles with regard to the public mandate of radio broadcasters.

6 A FRAMEWORK FOR COMPLIANCE CONSIDERATIONS

So far, radio broadcasting agencies do not take personalization and the risk of filter bubbles into account when self-assessing their service offer. Personalization is not yet a big part of the reality of broadcasters. On the basis of the previous sections, we propose a framework that can help broadcasters to self-assess their compliance with the public mandate for their personalized playouts (Fig. 2) and also help scholars to further elaborate this field.

On the line of arguments how filter bubbles can be effectively avoided by an implementation of a personalized radio service, broadcasters might refer to the three major types of mechanisms pointed out in sections 2 and 3 (Fig. 2 left): First, we have heuristic approaches to play out non-recommender content in the hope that this might break up filter bubbles. A second group of mechanisms relies on user control, i.e. to adjust parameters or select algorithms. The third approach is the one depicted in this paper.

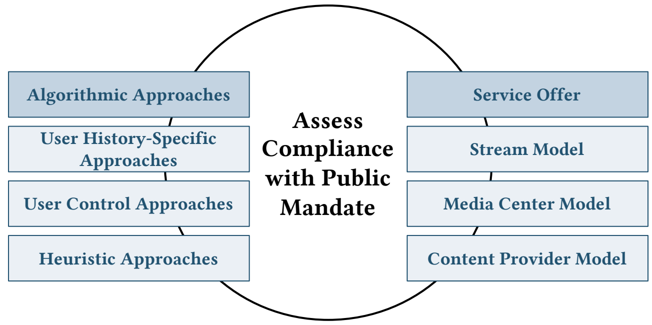

Figure 2: A basic framework for assessing the compliance of personalized radio offers with the public mandate

So far, we do not have enough knowledge which mechanism is preferable for which use cases. Pointing out the algorithmic layer seems however valuable, if not crucial, to provide transparency for e.g. a compliance report.

As pointed out in sections 4 and 5, also the type of service offer is essential for the extent of responsibility for filter bubbles (Fig. 2 right). In the media center model, the user actively picks one content item out of a set of recommended items. In contrast, the streaming model directly makes the user consume the recommended item. Both models imply a different extent of responsibility for filter bubbles. Explicitly considering the extent of responsibility in a broadcaster's playouts increases transparency in compliance considerations. As a third option referring to personalization – not discussed in this paper so far – but to date a very common option, we find that broadcasters may provide their content for inclusion in third party digital products that use personalization (such as TuneIn or Radioplayer). This way, broadcasters do not have to cope with filter bubble issues, as the content compilation is out of their hands. It however has to be discussed if this way – to avoid making the playout themselves and retreat by being content provider only – broadcasters can get out of the responsibility to take care for filter bubbles.

Both the algorithmic layer of how to avoid filter bubbles (Fig. 2 left) and the service layer how content is provided (Fig. 2 right) are essential building blocks for assessing personalized offers.

The framework might not only help broadcasters to self-assess their personalized service offer, but also – in a medium-term perspective – be a valuable instrument for the broadcasting council that regularly checks the programs of broadcasting stations as the highest supervisory board in public broadcasting.

7 DISCUSSION

This paper represents early work in the area of compliance of personalized radio playouts with public mandates and followed the idea to initially structure the field, carve out and propose different options, and propose a basic framework for compliance considerations.

The contribution of this paper was presented two-fold. First, we proposed an approach to comply with the public mandate of radio broadcasters in addition to existing approaches to avoid filter bubbles. Second, we proposed a framework for assessing the compliance with the public mandate which might be valuable for scholars, broadcasting organizations and broadcasting councils.

Stepping one step backwards, it should be discussed if efforts to keep the listener in a "safe corridor" of radio consumption can also be interpreted as a manipulation. Recommendation can also be seen as manipulation. It has to be discussed if an influence guided by balanced reporting, variety of opinions etc. can be regarded as a manipulation. Therefore, an influence on the user in the sympathy of the ITBT could be regarded as a value, but in another perspective also as a threat.

The approach and the framework presented also impose the question if there are best ways – a best way how to build algorithms to cope with filter bubbles, and a best way how to present personalized content to the user. Future research has to show if different use cases put different approaches in favor or if one approach turns out to be imperative.

Also, the question remains which interaction models imply which characteristics of filter bubbles. As of now, we can only say that every distribution way may haul a different filter bubble. Even classic radio is subject to create a filter bubble surrounding all its listeners, however not creating a personal bubble.

In the framework presented, we did not take serendipity into account. Serendipity extends the concept of novelty by helping a user find an interesting item he/she might not have discovered otherwise [29]. Serendipity might therefore help to avoid filter bubbles. Future, more elaborate frameworks on the compliance of personalized radio with public mandates should therefore also include serendipity in several facets.

The work we presented was based on the public mandate in Germany. In an international context, requirements may differ. Still, the framework could serve as a foundation for future research in an international context.

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