

Vorabfassung des Artikels

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TRANSLATING EDITORIAL WORK INTO ALGORITHMS FOR PERSONALIZED RADIO STREAMS

Abstract

Public radio is an important service of the public sector, as it helps to establish an informed and educated society and supports the values of democracy. Despite high-quality content, public radio broadcasters fear not to be able to reach younger audiences anymore and a generation tear-off when they fail to design their digital transformation appropriately. Yet, elaborating a novel, nonlinear, and personalized listening experience remains a tough task: working with heterogenous formats such as interviews, features, jingles, etc. contains the risk of losing the inherent flow of radio programs. Personalization works well within homogeneous media formats such as music or movies, but for highly heterogeneous formats like radio, editorial value-add seems necessary. Therefore, public radio broadcasters have to understand how to automate editorial decisions and how to integrate them into personalized playouts. We conducted a qualitative data analysis on radio content provided by a German nationwide public radio station to identify sequences using pattern mining techniques. Based on the found patterns of radio shows, we propose an approach how editorial decisions can be automated to leverage the potential of a value co-creation between broadcaster (in form of editorial value) and listener (in form of personalized content) in digital, interactive radio.

Keywords: Value co-creation, digital transformation, service-dominant logic, public radio.

1 Introduction

Public radio is one of the most important services of the public sector, as it helps to establish an informed and educated society and supports the values of democracy. Public radio broadcasters enjoy public funding and produce high quality content. As a matter of technical limitations during past decades, content items have been broadcasted only once or twice within linear playout structures, so that listeners had a hard time to meet the content they were interested in. In times of digital transformation, on-demand media has relaxed the tight time reference of linear playout, and availability of content online enabled listeners to consume content at a later point in time (Pöchhacker, Burkhardt, Geipel and Passoth, 2017). This, however, has not solved the problem of allocating produced content to matching audiences effectively for radio broadcasters. Broadcasters learned that a mere offering of content items in media libraries does not lead to an enjoyable experience that keeps listeners engaged in their programs for hours (Heidmeier, 2015). Rather, listeners consume single content items through social media links and continue their journey on social media sites, instead of consuming more items from the broadcaster's media library.

As digital radio is often still a mere digitized version of the traditional radio, it is lacking a reinvention of the service as a whole. Mobile devices represent an increasingly important distribution channel suitable for personalized and tailored audio and radio content, but several radio services are still not technologically fully developed as an alternative to the existing services (Jauert et al., 2017).

At the same time, music streaming services like Spotify or Apple Music selectively develop products for specific target groups and enable a highly individualized and customer-oriented approach. Since online music streaming services are gaining popularity, the innovation pressure is increasing rapidly on public radio broadcasters: Customer's time and attention towards audio media is limited (Crane, Talbott and Hume, 1961) and business competition for this attention takes place in a highly competitive market including radio, music streaming services, podcasts, and other media (Jauert et al., 2017). Even though traditional linear live services may still form the core of radio content in the near future, public radio offerings must transform radically and provide diverse offerings to avoid being disrupted in the long run (Shanahan, 2000; Fernández-Quijada, 2017). Especially public radio broadcasters may fail to fulfil their public-service remit, not by failing to produce high-quality content, but by failing to bring produced content to the audience.

One of the pathways to reinvent public radio is to increase the engagement of listeners with the service. Related studies suggest that nonlinear media consumption improves comprehensiveness and engagement (Mesbah, 2006). In addition, digitalization enables new interaction channels with consumers and therefore further improves consumer engagement (Nyre and Ala-Fossi, 2008). Engagement is important, as it is the basis for a participation of the listener in the value creation process. Especially in personalized media offers, a value co-creation of broadcaster and listener takes place as the listener participates in the program management.

A co-creation of *radio* streams is however much more difficult than it is for music streaming. In music, songs are of quite homogeneous nature and can be compiled into playlists or streams easily, automated for different genres or moods. In contrast, traditional linear radio follows a heterogeneous approach with a diverse mixture of content and formats compiled into an appealing sequence. Creating random sequences of radio content would not match the idea of radio, as the editorial part would be missing. To split existing content of broadcasters into unrelated content chunks and compile heterogeneous formats into a stream runs the risk of losing the cross-content flow that characterizes broadcasting media. Personalization alone works within homogeneous media formats such as music or movies, but for highly heterogeneous formats like radio, additional editorial work (and value) seems indispensable. Hence, to keep up with competition and enable a personalized, nonlinear radio, broadcasters need to rethink how to maintain the value propositions of their offerings while enabling personalized playouts. In other words, it is not enough to offer personalized collections of contents, but public broadcasters need to offer individually edited radio *programs*. The challenge is to

find an approach that automates the process of compiling a personalized collection of contents from diverse formats—like news stories, moderation parts, jingles, and features—into coherent and enjoyable radio programs.

The question what makes editorial decisions valuable and how to automate them may be as old as the underlying medium itself. The basic question is: "What are those small differences in style and format that lead to success or failure, popularity or unpopularity of a given disc jockey program?" (Borgers and Koenig, 1960). Some radio stations use so-called broadcasting clocks, some sort of template for a specific radio show. But generally, there is no easy answer to the question what typical patterns of radio shows are and how to automate editorial decisions. If a personalized radio should preserve—at least to some extent—the editorial characteristics of traditional radio, it is necessary (1) to understand editorial choices regarding the composition of radio programs and (2) to develop an approach that automates the editorial choices that eventually compose a radio program. Hence, we try to answer two research questions:

Q1: What are frequent patterns within radio shows of linear radio?

Q2: How can patterns from linear radio be used to automate the editorial composition of radio programs, in order to enable enjoyable personalized radio programs?

We aim to further understand the interior structure of radio shows and provide a framework as a foundation for personalized radio offerings. We seek to identify typical patterns in classic radio and formulate novel design recommendations that may help to increase the listening satisfaction and thus, provide us the opportunity to improve nonlinear radio streams. For example, if it is a frequent pattern in radio programs to insert music between two reports or if programs exhibit particular shares of music, reports, and moderation, an automated editorial process could emulate these patterns.

The remainder of this article is organized as follows: We start by providing a conceptual background of value co-creation and efforts to understand editorial decisions (Section 2). Afterwards, we present our data and methodology in three parts, (i) qualitative data analysis, (ii) sequence pattern analysis, and (iii) automation of editorial work (Section 3). In Section 4, we present our results and conclude—in Section 5—with a discussion, limitations, and further research.

2 Conceptual Background

Radio is a term with different meanings, as radio traditionally denotes the device, the technology, and the aesthetic. Also, users would associate different things to radio depending on their cultural background. Various forms of radio emerged with different missions, different content, and different target groups. The understanding of radio in this paper can be described as journalistic radio with a mixture of spoken-word content and music, whereas the journalistic spoken-word content accounts for the majority of content elements. A multitude of radio services exist, but due to the heterogeneous landscape of radio programs not necessarily all would fit the characteristics covered in this paper.

2.1 Value Co-Creation

Service Dominant Logic (SDL), as proposed by Vargo and Lusch (2004), argues that service rather than goods is the basis of economic exchange. Service is defined as "the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself" (Vargo and Lusch, 2004, p. 22). SDL argues that value is not created by a manufacturer or provider, embedded into products upon production, and exchanged in economic transactions (value-in-exchange). Rather, it argues that value is co-created when providers and customers interact, that is, when customers integrate their competencies with the providers' service offerings (value-in-use or value-in-context), making the customer rather a co-producer (Vargo and Lusch, 2004). If this interaction involves goods, they are merely distribution mechanisms

for services, because service has been used to produce these goods or because they are necessary to convey the providers' services (Vargo and Lusch, 2004, 2008). Goods "are appliances for service provision; they are conveyors of competences" (Vargo, Lusch, Archpru Akaka and He, 2010, p. 6). SDL is an interdisciplinary approach concerning both the fields of marketing and information systems (IS). In IS research, SDL has been applied, for example, to understand differences in the value-in-context between digitally activated self-service and personal service channels (Scherer, Wunderlich and von Wangenheim, 2015). SDL is particularly well suited for the investigation of digital innovations in IS, because IS research has recognized the importance of value creation in (service-)usage and because digital technologies can enable the innovation of many existing types of services by eliminating the need to transfer people or goods (Lusch and Nambisan, 2015).

Traditional radio focusses on producing and storing a tangible output (the radio program) that has embedded value which is exchanged during broadcasting. From a radio station's perspective, the goal is to create a product that is appealing for a target audience. Even though one might refer to traditional radio as a 'service', it offers little possibilities for customers to co-create value. Hence, we argue that radio has traditionally been managed according to a goods-centered logic. However, the technical possibilities to personalize radio contents and programs suggest that the perspective of SDL and value co-creation is more appropriate. In a nonlinear, personalized radio program, the listening offer would correspond more to an individual service offer than to a mass offer.

Wang et al. (2017) have investigated the impact of value co-creation and service experience on customer satisfaction in music streaming. They find that social presence, a variety of functions, and user-friendliness have a positive influence the service experience and value co-creation. These in turn have a direct positive impact on customer satisfaction, which motivates customers to continue using the music streaming service. We therefore regard the upcoming challenges of the radio industry as digital service innovation under a SDL perspective (Barrett, Davidson, Prabhu and Vargo, 2015). With that said, value co-creation is necessary when aiming to create personalized radio offerings. The listener may actively contribute to editorial decisions affecting their own listening experience and value creation, as well as that of other customers.

2.2 Approaches to Understand and Formalize Editorial Work

Already in the 1970s, radio scholars have been discussing how a good radio program is structured and how to support the decision-making process of editing. For instance, Lewis (1969) attempted to identify the factors used by program directors and other program makers when making their decisions and determined a multi-dimensional construct to describe these (Borgers and Koenig, 1960; Crane et al., 1961). Eastman and Ferguson (2012) note that the shift through digitalization, internet access, and media competition has a direct impact on the work of an editor: Although recipients tend to choose channels themselves, they expect someone else to have filled those channels in a knowledgeable way (Eastman and Ferguson, 2012).

Sommers (2016) investigated on understanding editorial decisions by interviewing BBC editors how they make their decisions. She finds that decisions are made in completely different ways: some are made according to guidelines, others according to a list of known potential customers, but most are made because editors have the expertise to recognize good content when they encounter it. Attempting to automate editorial decisions they identify 32 criteria, including categories, sound, mood, mobile usability, and the ability to know people, places, and themes (Sommers, 2016).

In practice, some radio stations work with the radio hour clock—a visualization that reflects the basic structure of a radio show. It exactly defines how the program is structured from various components such as word, news, and music (Heinrich, 1994).

Since the 1960s, the broadcasting landscape has been forced to become a more specialized and local medium serving the needs of a local audience due to the inception of television (Chambers, 2003). With specialization, also editorial choices changed. The process of specialization was further accelerated due to regulatory changes and new distribution channels for audio media through digitaliza-

tion (Shanahan, 2000; Ren and Chan-Olmsted, 2004; Fernández-Quijada, 2017). Scholars agree that radio is again going through major changes and will face market challenges induced by digitalization and changing consumption patterns in the next ten years (Jauert et al., 2017).

3 Data and Methodology

Following an inductive approach, we chose to analyse radio transmission protocols to examine editorial decisions. We obtained radio transmission protocols from a public radio stations for specific dates. In the landscape of hundreds of radio stations, we had to carefully select the radio stations to be included in our analysis, as the underlying data is key in qualitative research. Our intention was to analyse a set of different radio stations, in order to explore differences and similarities in patterns between them. Finally, we chose to analyse the programs of a public German broadcaster. The three programs are heterogeneous in nature: Program A is mainly a news-oriented program that plays hardly any music. Program B is a culture-oriented program, and Program C targets younger audiences. While there was a multitude of broadcasters to choose from, we did not want to compare stations across radio broadcasters, as similarities and dissimilarities between radio programs are subjective. Staying within a single broadcaster’s programs increases the chance that we in fact have different radio programs, and that the data we analyse is of similar size and shape (e.g., granularity), so we are less prone to biases resulting from structural differences of the underlying data set.

Our research approach consisted of three steps. First, in order to prepare radio transmission protocols for pattern analysis, we conducted a qualitative data analysis (QDA) as suggested by Mayring (2010) to assign codes of show types to program parts. Second, the resulting sequences of coded program parts were analysed by sequence pattern mining algorithms to identify frequent patterns. Lastly, we developed and evaluated an automated approach to generate radio programs that resemble the program structure of traditional radio programs, yet with personalized contents.

3.1 Qualitative Data Coding of Radio Programs

First, we created a coding frame to ensure a comprehensible and substantiated coding during the QDA. To do so, we conducted an initial literature research to collect principles and taxonomies that break down radio shows into smaller pieces. Several dimensions to structure radio programs were proposed by radio broadcasters as well as other institutions (Eastman and Ferguson, 2012; von La Roche and Buchholz, 2017). We adapted a subset of these as *show types* and, on a deeper granularity, *show segments* within a show type. Basing on these results, we derived a preliminary coding frame, which was further refined in collaboration with experts from the broadcaster. In this expert session, we decided upon the following show types to differentiate radio structures for various formats: *Polythematic Magazines*, *Monothematic Magazines*, *Monothematic Shows*, *News*, and *Talk-in Shows*. As show segments, we agreed upon *Moderation - Opening*, *Moderation - Bridging*, *Moderation - Closing*, *Jingle - Opening*, *Jingle - Bridging*, *Jingle - Closing*, *Report*, *Interview*, *Conversation*, *Music*, *Trailer*, and *Short Clip* as content elements. Finally, we contrived the following coding frame:

Show Type	Show Segment	
Polythematic Magazines	Moderation - Opening	Content - Report
Monothematic Magazine	Moderation - Bridging	Content - Interview
Monothematic Show	Moderation - Closing	Content - Conversation
News	Jingle - Opening	Content - Music
Talk-in Shows	Jingle - Bridging	Content - Trailer
	Jingle - Closing	Content - Short Clip

Table 1. Coding Frame

Not only the selection of the radio programs, but also the selection of days to analyse determines our data set. For our purposes, representativeness is the most important requirement for data selection. We discussed the representativeness of radio transmission protocols with radio experts and, as a result, agreed that the broadcasting scheme of one single day can be assumed to be representative. As schemes typically repeat on a daily basis, we assume coding multiple days would not give a significant surplus on insights. Hence, for each of the three programs distributed, we analysed one day of radio program. The broadcaster provided audio files including the corresponding metadata in the form of transmission records including the name, duration, whether it is a self-production, and the source location of each content piece. The records date back to May 18th, 2018. To ensure a reliable coding, all three coders started off coding the first hour of each program in parallel. Afterwards, results were compared in a discussion to ensure accurate and intersubjective consistent coding. Also, we obtained a general understanding for our raw data. The actual coding was conducted by three individuals by splitting up the record of each program into parts of similar size and volume. Afterwards, the coded parts were assembled into one coding.

3.2 Sequence Pattern Analysis

Subsequent to coding, we aimed to identify typical patterns in radio broadcasts. Several mining algorithms have been proposed to discover patterns in large databases to predict behaviour and enhance decision making, the most often used being Spade, PrefixSpan, CM-Spam (Fournier-Viger et al., 2017). Those algorithms present different approaches to the same problem, allowing different parameters to be set. If run with the same set of parameters on the same set of data, all of these sequential pattern mining algorithms yield the same sequential patterns (Fournier-Viger et al., 2017).

In order to carry out the sequential pattern analysis, we decided to use SPMF, an open-source data mining library specialized in pattern mining and offering implementations of more than 120 data mining algorithms (Fournier-Viger et al., 2016). After evaluating different algorithms, the implementation of CM-Spam seemed the most appropriate for our purpose because it allows efficient identification of sequential patterns with minimum and maximum length and allows to exclude gaps in patterns (Fournier-Viger, Wu, Gomariz and Tseng, 2014). While gaps in patterns are an important feature for many applications of pattern mining, such as DNA sequencing (Ferreira and Azevedo, 2005; Fournier-Viger et al., 2017), for our purposes gaps need to be explicitly excluded. Finding radio patterns allowing gaps would not make much sense as we may obtain sequences that do not represent the reality, e.g. a moderation following a moderation.

3.3 Towards Automation of Editorial Work

In terms of value creation, broadcasters and listeners co-create the resulting playlist. The broadcaster as the provider gives rich opportunities to access his media repository by browsing, searching, and recommendations. The specific and individual value for the user however emerges in a co-creation, a) content-wise - when recommender algorithms make use of user interactions and preferences to find the right content, and b) sequence-wise, when patterns are generated that frame the personalized content and make the listening enjoyable. Figure 1 depicts the co-creation as intended in this research. In the following, we depict approaches how to automate editorial work.

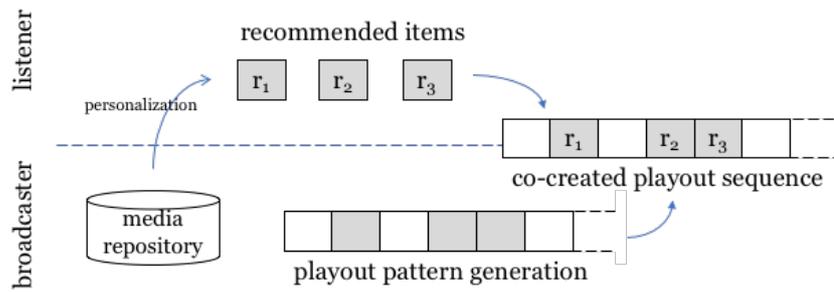


Figure 1. Value Co-Creation in Personalized Radio Streams

To progress to more sophisticated ways to automate editorial work, algorithms are needed that generate new radio programs based on identified sequence patterns and rules identified earlier. A simple approach would be to use the identified show patterns as static templates. An algorithm may randomly choose any observed show pattern and fill these with individualized content. Alternatively, instead of randomly chosen patterns, they may also be chosen depending on context influences, e.g. time of day.

However, this template-based approach has, apart from its simplicity, several drawbacks. First, the sequences are fixed in length, and no flexibility is given to obtain shorter or longer playouts than determined by the patterns. Use cases like “I have 20 minutes on my way to work, play me a nice radio show” could only partly be supported by this approach. Second, several show segment combinations that are not reflected in the identified sequences will never occur in playouts and the chosen patterns will become repetitive in the end. A higher degree of flexibility is preferable.

The template-based approach therefore resembles a petrification of traditional radio show patterns, which does not truly reflect the idea of digital transformation. Using simple templates would somehow downgrade the idea to a mere digitalization. Therefore, we aim to deeper elicit the value of editorial work and integrate it into radio streams in a more flexible way. One approach proposed here is to generate sequences dynamically upon playout, based on conditional probabilities between show segments that have been calculated from previous radio programs. More specifically, the approach would identify all sequence patterns of length 4, for example, and calculate the conditional probabilities for each subsequent show segment depending on the current. As this approach considers the actual state of the user in a (not yet fully determined) playout sequence, it is a stateful approach.

Two steps must be taken to obtain a sequence of length n with a stateful approach: 1.) The identification of a suitable seeding point and 2.) the selection of a downstream element based on the respective conditional probabilities. Considering 1.) the question emerges how a good seeding point can be identified, intuitively Jingle - Opening. Start elements could, however, be selected by the user in the radio app, as well as selection and deselection of certain show types, which could be flexibly handled in this approach. Considering 2.) to calculate conditional probabilities, for every sequence, e.g., $abcd$, we regarded d as the current state of the user, $abcd$ as the user’s history and collected all possible next transitions, e.g. $abcde$, $abcdf$, and $abcdg$. For these transitions, we assigned their support as the conditional probabilities $p(e|abcd)$, $p(f|abcd)$, and $p(g|abcd)$, respectively.

To obtain good results, certainly larger window sizes better reflect the value-add of editors, i.e. a history window size of 1 would only reflect editorial work to a limited extent. Therefore, our approach favors a large history window size. As, however, not all user histories would match identified patterns, we decrease the windows size by one when pattern matching gets stuck. For instance, if from a user history $adcdef$ (history window size of 5), there is no successor, we try to find successors of $bcdef$ (history windows size of 4).

The proposed algorithm (Figure 2) formalizes the approach stated in the previous chapter. The idea is to create a sequence of radio elements adhering to a stated set of rules derived from the previous pattern analysis. It requires to define a history window, the number of antecedent items, that will

determine the consequent element. To prevent dead ends in creating sequences the successor will be determined with a history windows reduced by one item.

4 Results

Our study first provides insights into occurring sequences in linear broadcasts. These results are based on the qualitative data analysis of the radio programs provided by the broadcaster. In a further step, we show how typical sequence patterns can be identified. Finally, we evaluate the accuracy of the prediction and develop an approach for the generation of sequences from the results.

4.1 Coding of Radio Show Segments

Our results are based on 199 coded instances of radio shows with 2,118 show segments in total, all identified within the transmission records of three radio programs, depicted in Figure 1. On average, a radio show has a length of 16:41 min and consists of 10.64 individual elements within the meaning of show segments in our coding. Overall, we processed over 55 hours of radio. Figure 3 gives a comprehensive overview on the 199 instances of radio shows and their show segments based on the coding we conducted. For display purposes, we used a cut-off value of 8 for the sequence length.

```
FUNCTION generateSequence(historyWindow, seedItem)
  INIT sequence
  currentItem = seedItem
  FOR 1 to sequenceLength DO
    currentItem = getNextSequenceItem(sequence, historyWindow)
    Add currentItem to sequence
  END DO
  RETURN sequence
END FUNCTION

FUNCTION getNextSequenceItem(sequence, historyWindow)
  rules = getLongestPossibleRules<historyWindow
  nextItem = chooseRandomItemByRuleProbability(rules)
  IF nextItem is null THEN
    RETURN getNextSequenceItem(sequence, historyWindow, rules)
  ELSE
    RETURN nextItem
  END IF
END FUNCTION
```

Figure 2. *Algorithm for Sequence Generator*

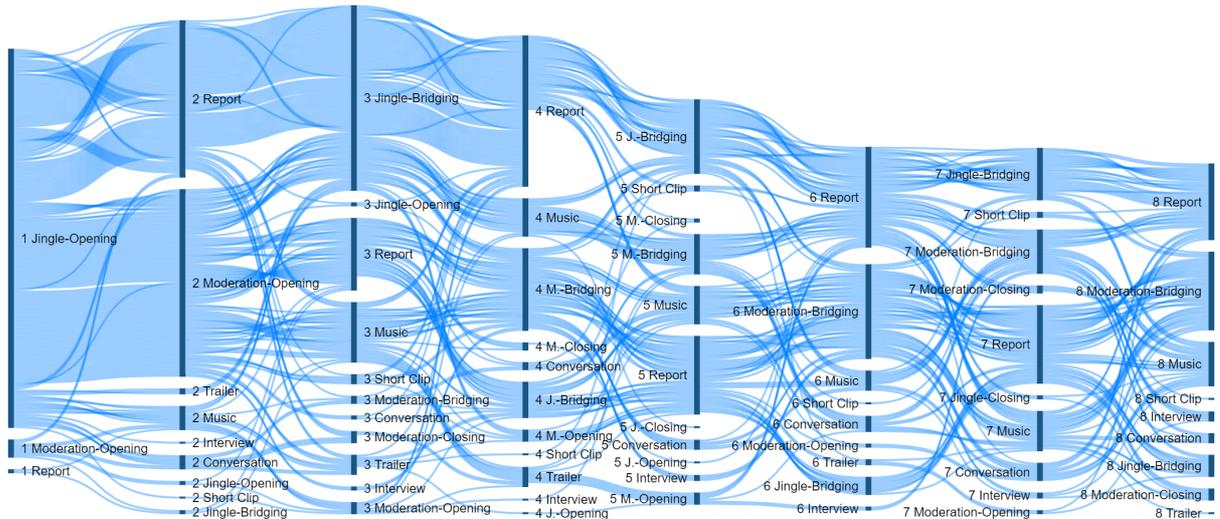


Figure 3. Visualization of coded data of all 199 radio shows

The majority (67.7%) of air time was made up of mono- and polythematic magazines followed by news (15.9%) and monothematic shows (14.2%). Talk-in shows and monothematic shows had just a few instances within our data. Even though news only counted for around one sixth of the air time overall, nearly half of the instances (96) were of this show type whereas magazines (combined monothematic and polythematic) behaved oppositely (83 instances). Moreover, news broadcast had a way shorter average length (5:30 min) compared to magazines (27:06 min).

Referring to the amount of time, most dominant show segments overall were report, moderation (in its three variants opening, bridging, and closing), and music. Within the different show types, music was underrepresented the news subset whereas report, conversations, and interviews were clearly overrepresented in monothematic shows as well as magazines. Table 2 shows descriptive statistics of our dataset, i.e. the length of show segments rounded to the next full second and the total count of instances. We specifically report on news and magazines as the most present show types.

Show Segment	All		News		Magazines	
	length in s	count	length in s	count	length in s	count
Moderation - Opening	28	124	16	30	32	85
Moderation - Bridging	38	389	22	41	40	339
Moderation - Closing	16	91	11	13	17	66
Jingle - Opening	7	194	6	97	6	80
Jingle - Bridging	4	258	4	194	4	62
Jingle - Closing	5	10	3	3	6	7
Content - Report	157	552	80	291	170	242
Content - Interview	298	28	-	0	291	27
Content - Conversation	300	82	124	5	224	71
Content - Music	182	294	193	23	181	267
Content - Trailer	45	72	35	5	45	59
Content - Short Clip	17	24	17	4	17	20

Table 2. Descriptive statistics of codes assigned to data set

4.2 Sequence Pattern Results

One of our main goals has been to identify typical sequence patterns in radio programs. We especially aimed to understand how much the identified patterns resemble across the three radio stations and between the major show types news and magazines. Due to the exploratory nature of our research, we conducted sequential pattern mining analyses on all available subsets of our data.

Comparing the patterns for the subsets however turned out to be a challenge, as no standardized way to compare patterns exists, especially when considering patterns with varying lengths. We intuitively realized that the shorter the patterns, the higher the probability that they are similar, and the lesser their discriminative explanatory power. Very long patterns in contrast are very likely not similar.

We therefore developed a dissimilarity metric that sums up the difference of the relative support of patterns of a fixed length l in two pattern sets A and B in a straightforward way. The metric is designed to compare the relative support sup of the top m patterns of A and B . The exact dissimilarity metric used is depicted in Equation (1) and its value ranges between 1 (dissimilar patterns) and 0 (exact matching patterns). The similarity is computed as 1-dissimilarity. Due to the aforementioned difficulties to perform comparisons across different pattern lengths, we compute similarity measures for each fixed pattern length and plot the similarity values depending on pattern length accordingly. As a result, we obtain several values as facets for the similarity.

Figure 4 shows the similarities between the three radio programs in pairwise comparisons (red-orange coloured lines) and similarities between several radio show types (blue coloured lines), i.e. monothematic magazines vs. polythematic magazines and news vs. magazines (combined mono- and polythematic). All similarities decrease with pattern length as expected.

Regarding radio programs, patterns do not show a high degree of similarity. Already for a very short pattern length of 3, pattern sets do not show a higher similarity than 30%. At a pattern length of 5, all computed similarities already drop below 15%.

Considering radio shows however we find a more contrasting picture. Whereas monothematic and polythematic shows point out the highest similarity of our subsets, the similarity between news and magazines (combined monothematic and polythematic) seems very weak.

Finding 1. Patterns differ across radio stations. There is no overarching pattern set valid for all radio stations independent of the radio station profile. It is therefore well worth for radio stations to identify their specific radio patterns to enhance the value co-creation in personalized radio streams.

Finding 2. Patterns from news shows strongly differ from magazine shows. Radio broadcasters should identify different patterns for their different radio show types. It may however be of minor importance to distinguish between monothematic and polythematic magazines from a structural sequence point of view, as they showed the highest similarity among all compared subsets.

$$(1) \quad Dissimilarity(A_l, B_l) = \frac{1}{m} \sum_{n=1}^m \frac{|sup_n(A_l) - sup_n(B_l)|}{sup_n(A_l) + sup_n(B_l)}$$

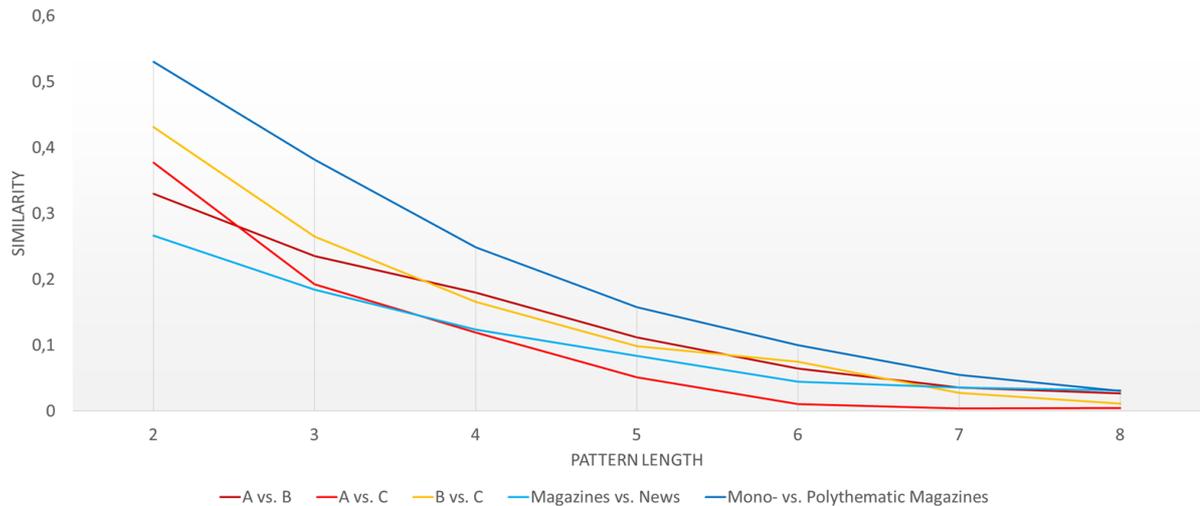


Figure 4. Comparison of similarity between radio programs and radio show types

In the following, we present the identified patterns in more detail. We refrain from presenting patterns for each of the three radio programs, as the patterns were too dissimilar. While it might be interesting to zoom into the specifics of certain radio programs, the findings would hardly be generalizable to a wider audience than for the specific radio station. For news and magazines, however, we identified that mechanisms of news and magazines seem very different, and we can draw a picture on how typical patterns look like, including all three radio programs, and therefore, obtaining a broad picture that may hold true for several radio stations. For display purposes and readability of the figures, we only display sequences of length 4.

Figure 5 shows the top 30 identified patterns for news shows. From the actual state of the user (which would be one of the three leftmost positions), the thickness of the connection to the possible next show segments visualizes the conditional probability from one state to the next. Assuming that a news show begins with a Jingle - Opening (1), it is most likely followed by a Moderation - Opening (2), a Jingle - Bridging (3) and Report (4). As an alternative way, the Moderation - Opening is sometimes directly followed by Report without a Jingle - Bridging. We found that this small difference occurs due to the different programs and their specific practices. Other patterns can be derived from Figure 5. In comparison to other show types, in news, the support of identified patterns is high across all three programs.

In contrast, Figure 6 shows the identified patterns regarding mono- and polythematic magazine shows which clearly differ from news shows. Compared to them, magazines contain a higher frequency of music. Thus, the integration of music tends to be an important part of magazines.

Finding 3. Patterns for news follow quite clear patterns like Jingle - Opening, Moderation - Opening, optional Jingle - Bridging, and Report. Patterns for magazines are more diverse, include a greater variety of show segments, and music represents a significant part of mono- and polythematic magazines.

Whereas the patterns presented give insights in the structure of typical sequences assembled by radio editors, they are of limited value to radio editors themselves. However, they serve as a first step towards the fundamental goal—to enable a value co-creation in conjunction with the listener by generating sequences that suffice an enjoyable listening experience.

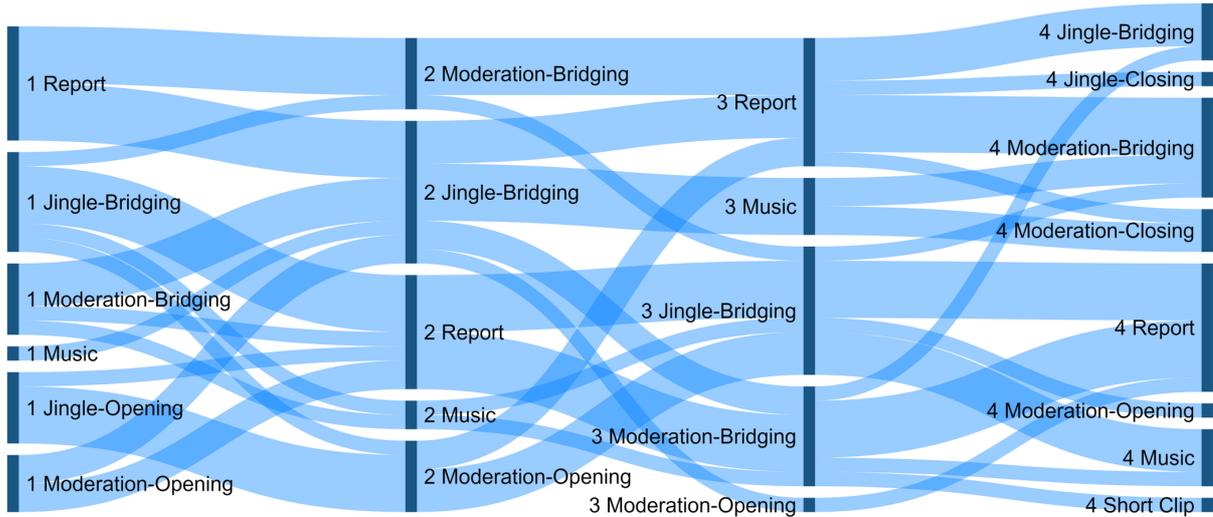


Figure 5. *Patterns for show type news (Top 30 patterns of length 4)*

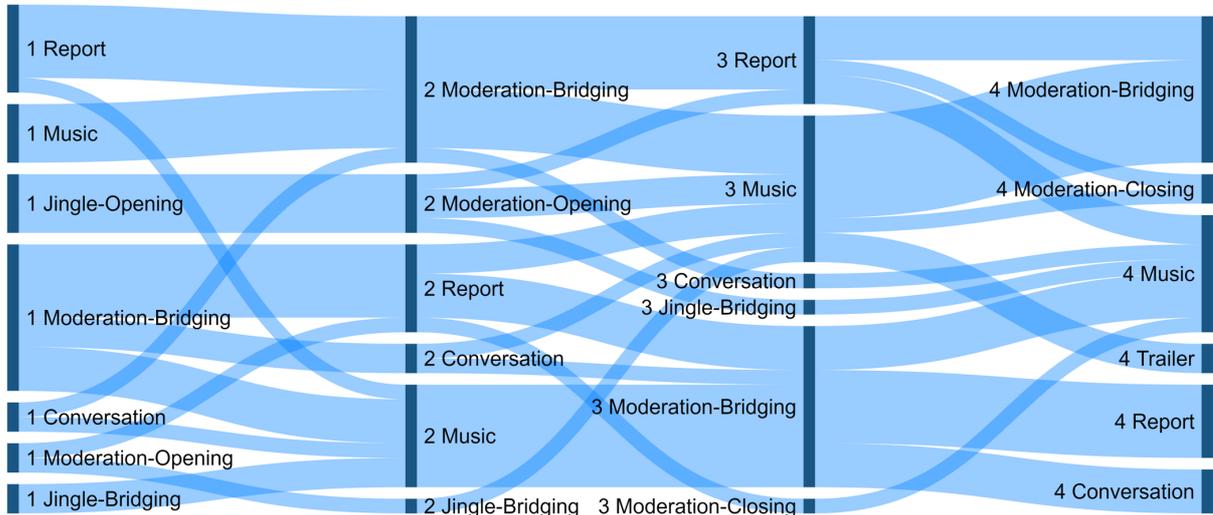


Figure 6. *Patterns for show type magazines (top 30 patterns of length 4)*

4.3 Evaluating Prediction Accuracy of the Proposed Approach

In the following, we evaluate how well the stateful approach performs, depending on the history window size taken into account for the statefulness. As our evaluation method, we chose to 1.) synthetically create 10,000 sequences with the algorithm proposed, 2.) identify the most frequent patterns using SPMF, and 3.) compared our coded pattern set with our synthetically generated pattern set.

Our data suggests a Jingle - Opening as a legitimate first element for a sequence as 94.47% of shows examined start that way. Therefore, we set Jingle - Opening as a fixed seeding point. We compared the support of each synthetically generated pattern set to its support in the original dataset, based on the similarity measure already introduced. In addition to Equation (1), we added up the deviations over the diverse pattern lengths l , starting at pattern length of 2, as a pattern of one element can hardly be called a sequence. As the maximum pattern length to compare, we chose $k = 11$ because 10.75 was the average length of radio shows we coded. The resulting measure is presented in Equation (2). We computed similarity values for several history window sizes that the algorithms used for

creation of sequences (from 8 to 0). Figure 7 shows the similarity for $m = \text{top } 10, 50, \text{ and } 100$ patterns regarding their support found in each dataset.

Evaluation results show that when generating sequences with a history window size of 0, which means not to consider conditional probabilities, but absolute probabilities of occurrence, the result is not at all comparable to what radio editors do in linear radio (the similarity is almost 0). A history windows size of 0 depicts a stateless approach and comes close to randomized sequences. With a history windows size of 1, which means to consider the last consumed show segment only, results are still poor, below 55%. Though, for a history window of 3, similarities between generated radio patterns and observed radio patterns already rise to 90% for the top 10 patterns and 50% for the top 100 patterns.

$$(2) \quad \text{Dissimilarity}(A, B) = \frac{1}{k-1} \sum_{l=2}^k \text{Dissimilarity}(A_l, B_l)$$



Figure 7. Similarity between observed and generated radio patterns depending on history window size used for sequence generation with $k = 11$

The similarity value decreases with the number of compared patterns, as the more patterns we consider, the more diversity we allow. Clearly, our results show that the larger the history window size, the more the generated radio sequences comprise the characteristics of manually compiled sequences by editors. However, a history windows of 5 already seems to suffice as the increments get marginal for history window sizes above 5.

Finding 4. To generate radio sequences with conditional probabilities of radio patterns, a history window size of 5 consumed items suffices to produce satisficing results. Larger history windows sizes do only marginally increase the quality of generated radio patterns.

5 Discussion, Limitations, and Further Research

In our analysis, we did not identify an overarching editorial pattern set which would be valid for all radio programs, but rather found that patterns should be determined on a radio program specific level. Using our approach, we were able to automate sequences that resemble those sequences created by editors to a satisficing extent. According to our similarity measure, a 70% similarity (history window = 5, top 100 patterns) can be reached. Especially in comparison to a random sequence of show segments, our approach performs well.

The question remains if a 70% similarity can be considered as high enough to be able to speak of satisficing results. Considering that a value close to 100% would indicate completely matching patterns,

which would be very unusual, it would also be an indicator that we overfitted the model. It is not our primary goal to set existing patterns into concrete, but to reuse the most important parts of it. Therefore, we argue that 70% is a high degree of similarity.

By not following fixed patterns, but by dynamically creating sequences based on conditional probabilities, the sequence generator keeps the flexibility not only to consider the user's state, but also to consider context factors, e.g. a user moving slow being stuck in a traffic jam could favour a longer sequence. The approach can therefore be extended to contextual factors, whatever is applicable in each radio program's case.

We think that our analysis could be easily extended in size and scope and deliver even better results using more data. Furthermore, this initial study and its conceptual basis could serve as a foundation for the structural analysis of other kinds of media and a slightly adjusted coding frame could enable the approach for television.

Managerial implications were already addressed in Findings 1 to 4. Next to these, broadcasters have to keep in mind, that for every show segment they identify, they also need the corresponding metadata in order to feed a productive system.

Certainly, our research is not without limitations. First, we have to address possible selection biases. We selected three radio programs with different characteristics. By doing so, we cover a certain spectrum of radio programs. It is however possible that other radio stations follow totally different schemes that cannot be covered by our methodology. Also, the selection of one representative day might, although discussed with radio experts, be subject to a selection bias.

Second, we strictly focused on structural components, whereas editorial aspects like dramaturgy were not in our scope. Also, the thematic perspective was not part of our research (sequences of politics, sports etc.). Understanding those may still be an important issue to create an appealing listening experience. However, if broadcasters want to use thematic specific patterns, they also must be aware that metadata is needed for this. Currently, metadata is rare in the broadcasting realm as technical infrastructures are optimized for linear playout, where metadata is hardly needed, if at all. Similar, sequences of mood could be an interesting research object, though it would be even harder to obtain metadata about mood, both for research and for practice.

Third, we could have validated the identified patterns with radio editors. However, as our coding was very robust, and the patterns identified are data-driven, we did not attribute much value to a validation round with editors.

Considering further research, we worked with public-law radio programs only which implied the absence of any advertisement. For a more general approach including also private broadcasters, it might be interesting to gain insights on how and when to place advertisement within a radio show. Also, we encourage scholars to consider including further context information like day of week, time of day, weather, location, speed etc.

As an alternative approach to analyse different radio programs, it might be interesting to select several very similar radio programs from several radio stations to see if the patterns resemble. This way, radio broadcasters might obtain a more robust picture of specific patterns.

As a follow-up study, we plan to integrate our algorithms into actual radio streams and perform a user study. For this, however, we need the specific metadata and all content in form of show segments. Also, we have to identify which moderation pieces can be used content-independent, as moderation is often context-specific nowadays.

On the long run, the digital transformation of radio might affect not only content playout, but also content production. Radio broadcasters might have to decouple moderation from (in the linear world) following content pieces, and radio editors in turn have to produce content in different ways to easy personalization of the program. Also, in terms of generating metadata, radio broadcasters

have to change processes, to enable value co-creation in conjunction with the listener and serve the listener in an optimal way.

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