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Testing music selection automation possibilities for video ads

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Abstract. *The importance of video ads on social media platforms can be measured by the number of views. For instance, Samsung's commercial ad for one of its new smartphones reached more than 46 million viewers at Youtube. Video ads address users both visually and aurally. Often, the visual sense is engaged by users focusing on other screens, rather than on the screen with the video ad, which is referred to as the second screen syndrome. Therefore, the importance of the audio channel seems to gain more importance. To get back the visual attention of users that are deflected from other visual impulses it appears reasonable to adapt the music to the target group. Additionally, it appears useful to adapt the music to the content of the video. Thus, the overall success of a video ad could be improved by increasing the attention of the users. Humans typically decide which music is to be used in a video ad. If there is a correlation between music, products and target groups, a digitization of the music selection process appears to be possible. Since the digitization progress in the music sector is currently mainly focused on music composing this article strives for taking a first step towards the digitization of the music selection.*

Keywords: music selection, digitization, automation, video ad, music genres.

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Introduction

The present paper is an extended version of Wiesener (2017). Video ads consist typically of a video and an audio channel whereas these channels can be seen as one unit from a consumer perspective (Bode, 2009; Hofmann, 2010). From an auditive perspective, music has in particular an effect on users, when it is combined with visual elements (Schramm, 2007). Following Schramm (2007), the aim of music in online videos is to get attention. However, social media websites typically consist of numerous visual elements. Thus, there's the danger to overexcite the visual attention of potential customers. An empirical study (n=241) at the Hochschule der Medien (University of applied sciences) revealed that 93 per cent of all participants use a second screen while watching videos (Wiesener and Christmann, 2017). In such cases, there is only an auditory recognition of the video ad. Thus, there is a separation between the video- and audio channel on the consumer side. Following the empirical study, the music of commercial video ads can bring back the attention of the user to watch a video in 83 per cent of the cases. Subsequently, choosing a target group- and product-specific music seems to be of importance in keeping the attention of potential customers (Strötgen, 2014). Some authors argue that it is even better to cancel the music in a commercial video ad instead of using unfitting music in regard to products and target groups (North, MacKenzie, Law, and Hargreaves, 2004).

The combination of automation and music seems to be of research interest in particular in the field of algorithmic composition (Nierhaus, 2009; Silhavy, Senkerik, Oplatkova, Silhavy, and Prokopova, 2016). For instance, mathematical models enable automatic music compositions on a random basis (Wang, Lei, Lau, and Zhang, 2012). Wang et al. (2012) recommend combining the automation with controllability. Thus, the creation process is not purely random but could be controlled by the user by choosing a genre, for example. The continuous advances in this area are made visible by looking at the development of composing and arranging software on the market. Based on composition algorithms, tools such as Band-in-a-Box are able to arrange songs of different genres. The software Melodyne offers features to digitize and automate vocal tracks. This way, digitized vocals can be automatically synchronized with other sound tracks. Thus, the process of composing music can be seen as automatable.

The music selection for video ads is typically the job of market and media specialists (Strötgen, 2014). Consequently, the present article opens up the question, whether and to which extent this task can be digitized and automated derived from products and target groups. Subsequently, the research question is whether the choice of the background music of a video ad can be automated based on input data such as music preferences for different product types. In a first step, literature is reviewed to categorize video ads in line with the topic of this article. Furthermore, literature in regard to the effect of different music genres will be evaluated to have a theoretical overview about possible effects that can be achieved via music. The research question will be answered by testing the significant distinctness between products based on different music genres. If that significance can be proven, the music selection for video ads can be seen as automatable based on product type.

Literature review

Classification of video ads

The mode of integration of video ads into a website enable a possible classification. As a consequence, a general differentiation can be made between in-page video ads integrated into websites and in-stream video ads that are integrated into an existing online video (Unger, Fuchs, and Michel, 2012; Mahoney, and Tang, 2016). In-page video ads are often integrated as a static banner into an existing website. By moving the mouse over the banner the video starts playing. According to Reisig and Greve (2011) in-stream video ads running in the same time dimension as the base video are often called linear video ads. Furthermore, the authors describe non-linear video ads as video ads that are uncoupled from the time of the base video. The non-linear video ads are typically overlaid and played in parallel to the original video. As an example, a non-linear video ad could be integrated within an existing video in the lower region of the screen (Reisig and Greve, 2011). This kind of overlaying technique is also used at standard TV commercial ads. Linear video ads can be sub-classified into pre-, mid- and post-roll ads (Hegner, Kusse, and Pruyn, 2015). Pre-roll ads stand for video ads that start before the base video gets started. Mid-roll ads are temporally integrated within the base video. If the video ad is integrated at the end of the base video, it is related to post-roll ads. In regard to the music context it appears obvious that non-linear videos

are mainly based on visual elements. Since the video ad is running in the background of the base video, the audio channel of the base video seems to be in the foreground.

From a musicological perspective, video ads can be classified in music-based and video-based ads (Bode, 2009). Music-based videos base on music and the video gets adapted to the music. Video-based ads are focused on visual elements and the music is derived from that. Furthermore, video-based ads can be categorized related to the visual content of the video. Walewski (2000) proposes a classification of video ads into storytelling, protagonist-based or product-orientated videos. That appears to influence the music selection for video ads since the music is accordingly derived from stories, products or protagonists. The current evaluation is focused on analyzing the background music of video ads in dependence of target groups and products. Consequently, in particular the product-oriented video ad seems to be of relevance. As a summary, in-stream linear video ads with video-based music derived from products are in the focus of the further analysis.

Music genres and its effects

According to Zander, the research field of music in advertisement can be categorized into the concept of involvement, the elaboration likelihood model and the concept of musical fit. The involvement concept argues that a positive stimulus based on the music can be transferred to the perception of a product. The elaboration likelihood model can be seen as a further development of the involvement concept. The concept of the music fit is focused on the fit between the audio and the video channel of a video ad (Zander 2007). Based on that, the choice of the music genre seems to be of meaning to create a desired mood (Tauchnitz, 1990). This could be explained by the high efficiency of acoustic elements in regard to cause emotions and moods (Brown 2006; Graakjær and Jantzen, 2009; Steiner, 2014). Furthermore, Strötgen (2009) recommends generating the music for a commercial ad based on a specific target group and product, for instance. However, marketers tend to select the music only when the video production is finalized. That is the reason why video and audio often doesn't fit together (Strötgen, 2009). As a result, the music channel could lead to a distraction from the product.

Often mentioned music genres are pop, rock, dance, hip hop, folk and classical (Strachan, 2006; Bronner, 2007; Hofmann, 2010). In particular rock, dance and classical appear to be very characteristic because these genres are based on guitars, synthesizers respectively strings. Following Beckermann and Gray (2014), these instruments can be classified as powerful, evolutionary and passionate. However, there doesn't seem to be the need to focus on one genre. For instance, Citroën used different genres such as rock and classical to promote a car (Strötgen, 2014). The brewery Beck GmbH & Co. KG integrated a pop song with a characteristic voice and a slow tempo into a video ad to promote beer to men as their target group (Bronner, 2007; Strötgen, 2014). Apart from a genre-based categorization, music can be categorized by rhythm, melody, harmony, dynamics, tempo and timbre (Louven, 1998; Brown, 2006; Götz, 2011). Furthermore, Bode (2009) proposes a comprehensive categorization and divides music into voice, lyrics and music genre. Since genre is defining the rhythm, tempo, harmony, dynamics and the timbre of music, a genre-based classification of music will be used in the further process. The

elements of a genre can be seen as a parameter set to generate stimuli (Bruner, 1990). For instance, a fast played music based on major chords that integrates a flowing rhythm can lead to happiness (Bruner, 1990; Vinh, 1994). Subsequently, the genre seems so be the key music segmentation criteria to differ between various moods and emotions (Esch, Roth, and Strödter, 2009). Consequently, genres could be used to achieve a desired effect on the user side. Thus, different genres seem to be suitable for different areas of use as shown in table 1. Beyond that, music can also be differed on a gender basis. For instance, Tagg (2006) found out, that women prefer slower, more dynamic music with rather acoustical instruments similar to classical music. In contrary, men seem to prefer faster music with electrical guitars that could be correlated to rock music (Tagg, 2006). Following an empirical study of Wiesener and Kryeziu (2017), particularly pop music explains a gender-specific difference at video ads.

Table 1. *Effects and areas of use of music genres*

Music genre	***Sub-genre***	***Product image***	***Areas of use***
Classical	Baroque	Precision, quality	Watches, luxury goods
	Classic	Elegance, maturity	Wine, champagne, food
	Romance	Love, Emotions	Jewelry, fragrances
Pop	Dance	Momentum, happiness	Drinks, luxury food
	Rap	Protest, differentiation	Leisure and sporting goods
	Rock	Self confidence	Beer, jeans
	New Age	Nature, Authenticity	Food
Jazz		Otherness	Cosmetics, fragrances
Folk	Traditional folk	Down-to-earthiness	Regional products
	Children's music	Light-heartedness	Toys, candies
	Military music	Force, discipline	Detergents

Source: Bertoni and Geiling 2003.

Research methodology

The current article is based on a quantitative survey, which was performed by students at the Hochschule der Medien in May 2017. This survey consists of a sample of n=362 participants within the target group of mainly 16-30 year old persons. Users had the choice to select their music preference for different products. The construct music preference has been operationalized by different music genres. Those were clustered into the six groups (i) rock, (ii) pop, (iii) dance, (iv) rap, (v) reggae and (vi) classical music. The participants judged the best fit of each genre in regard to three different product groups consisting of six products each. These were automotive, cosmetic and food products. The products were chosen by different price, hedonistic and use levels. For instance, within the car product group participants had the possibility to rate a Porsche 911. This car seems to be a premium car from a cost perspective. Additionally, that kind of sports car typically promises a high hedonistic but a rather low use level. Another product presented on a lower price level was for example Vio Water. Furthermore, this product seems to have a high use and a rather low hedonistic level. In summary, eighteen products were presented to the participants. The music genre selection was realized by a four-point-scale. In this

survey, it will be tested, whether a genre respectively a genre combination can differ between the products. If there are significant differences between the music selections for different products, it could be interpreted as a clear relation, which can be automated. Consequently, if no dependencies are found, the music selection can be seen as a randomized process. Even a randomized process could be digitized. However, digitization in the context of artificial intelligence can be seen as beyond of a random generator. This can be argued within the current topic by finding the most suitable music in regard to specific objectives and not randomly. Therefore, a possible digitization respectively automation of the music selection corresponds with the significance of certain genres explaining differences in products.

In a first step, the music genres will be tested on a univariate basis in regard to their significance towards the categorical variable. The genres correspond to the dependent variables and the products to the categorical variables. These tests will be performed for each product within a product group. Consequently, this leads to three univariate tests. Additionally, this study includes a further test in regard to all products. If at least one of the combinations between genre and product will be identified Testing music selection automation possibilities for video ads elements as described in the previous section, mutual interactions are to expect. Subsequently, a statistical analysis will be performed on a multivariate level in the second step. Backhaus et al. (2011) recommend using a discriminant analysis to analyze the contribution of different factors to differ between different categories. Furthermore, this method seems to be suitable to find multivariate relations since all factors respectively genres are integrated into the calculation. Therefore, the music selection for video ads can be seen as digitizable from a multivariate perspective, if the analysis results in a significant multivariate model. Additionally, a stepwise discriminant analysis will explain the grouping capability of each genre. Thus, the analysis integrates genres gradually depending on their contribution to the overall model. Before applying the statistical tests, the dataset will be checked in regard to outliers and in regard to correlations between the genres. Boxplots will contribute to identify outliers. Consequently, values out of the interquartile distance will be analyzed in regard to abnormalities. Since a multivariate perspective is part of the current study, mahalanobis distances will be used to identify outliers on a multivariate basis.

Results

With regard to the gender, 66 per cent of the participants of the survey are female and 34 per cent male. In regard to the age, 63 per cent are between 20 and 30 years old. 17 per cent are below 20 and 20 per cent above 30 years. Due to the high percentage of a small age range, the analysis in regard to the age will be neglected in the further process. A first difference in regard to the music choice can already be derived from the descriptive statistics. The mean preferences for each product group are shown in table 2. For instance, the genre combination between pop, dance and classical music covers approximately 70 per cent of the preferences for cosmetic and food products. For a car ad, however, a combination between rock, pop and dance music seems to be adequate. In summary, the descriptive results of the empirical study already demonstrate a clear tendency in regard to differences of the music selection between different product groups.

Table 2. *Product-group specific results of the descriptive analysis*

Product	Rock [%]	Pop [%]	Dance [%]	Rap [%]	Reggae [%]	Classic [%]
Automotive products	19,73	25,95	20,11	9,57	9,63	15,01
Cosmetic products	13,94	29,35	20,68	7,21	9,94	18,87
Food products	14,33	27,30	18,67	7,85	12,03	19,82

Source: Authors' own work.

Before applying the univariate and multivariate statistical analyses, the dataset was tested in regard to outliers and correlation. A previous study from Wiesener and Kryeziu (2017) already performed these tests. As a result, one sample can be seen as an outlier. Therefore, this sample will be excluded in the further research process. The correlation test based on a correlation matrix and resulted in a maximum value of 0.45 in the relation between the variables pop and dance. Correlation values substantial below 1 can be seen as uncritical in regard to correlation problems (Backhaus et al., 2011). As a summary, no significant correlation between the genres could be detected.

As previously described, the different products correspond to the categorical variable. Accordingly, univariate tests were performed for every genre as dependent and the products as categorical variable. Consequently, the categorical variable of the tests consists of more than two categories. Therefore, this study uses analyses of variance to test the univariate influence of each genre in regard to the product groups respectively to the products. More precisely, one analysis consists of a test of all genres in regard to all products. The result of this test corresponds to the row named "Overall" in table 3. Furthermore, table 3 includes the results of three product-group specific tests. The three values presented for each product and genre combination correspond to the mean error, the F-value and the significance level. As a result, all genres significantly separate the tested products. This pertains to the overall as well as to the product-group specific perspective. Consequently, the music selection for video ads can be seen as automatable from a univariate view.

Table 3. *Results of the univariate analysis*

Product	Rock	Pop	Dance	Rap	Reggae	Classic
Overall	3.882, 47, 0.000	5.088, 62, 0.000	0.951, 11, 0.001	3.153, 38, 0.000	13.748, 170, 0.000	2.108, 25, 0.000
Automotive products	0.876, 102, 0.000	0.293, 33, 0.000	0.067, 7, 0.006	0.260, 29, 0.000	0.355, 40, 0.000	1.048, 123, 0.000
Food products	0.857, 99, 0.000	1,179, 139, 0.000	0.674, 77, 0.000	0.579, 66, 0.000	1.254, 149, 0.000	2.586, 330, 0.000
Cosmetic products	2.601, 333, 0.000	1.844, 226, 0.000	1.486, 179, 0.000	1.351, 161, 0.000	0.990, 116, 0.000	7.493, 1351, 0.000

Source: Authors' own research.
Legend: The values in the table cells correspond to the mean error, F-value, p-value

The multivariate analysis bases on a discriminant analysis integrating all products and genres according to the method section. Table 4 shows the resulting discriminant coefficients in the second column. The columns three to five of table 4 show Wilks's lambda, the F- as well as the p-value of the discriminant model with a step-wise integration of the genres. The choice of the genre order depends on the product-separation capability of each genre in a descending order. As a result, Rock music seems to be the most influencing genre in regard to the contribution to the multivariate model. This is followed by the genres pop and dance in the second respectively third place, as shown in table 4. The integration of the further genres leads only to small changes in Wilks's lambda. Classical music seems to have the smallest effect on the product separation. However, the integration of all genres still results in a significant model. As a result, the multivariate analysis confirms the automation possibility of the music selection for video ads. According to the step-wise analysis, particularly rock, pop and dance music seem to be product-influencing genres.

Table 4. *Results of the discriminant analysis*

	all variables integrated	stepwise variable integration based on Wilks's lambda		
Genre	**Discriminant coefficients**	**Wilks's Lamda**	**F-value**	**p-value**
Rock	0.17632585	0.7793807	107.89964	0.000
Pop	0.28082112	0.5040361	155.70180	0.000
Dance	0.08784275	0.4087578	132.56192	0.000
Rap	0.01406995	0.3829977	103.57130	0.000
Reggae	0.48867329	0.3705808	83.96800	0.000
Classic	-0.95061851	0.3610769	70.81608	0.000

Source: Authors' own research.

To visualize the quality of the discriminant model Wiesener (2014) proposes a discriminant model integrating only two factors and two categories. Figure 1 shows an exemplary visualization based on a discriminant model with the products True Fruits Smoothie and Chanel No 5 as categories. These products are analyzed by the genres pop and classical. The circles in figure 1 correspond to the preference values of True Fruits Smoothies and the triangles refer to the preference values of the product Chanel No 5. The classification boundary of the discriminant model results in an error rate of 10.5 per cent. That can be interpreted as a model with high prediction capabilities. Wrongly assigned cases are triangles that are on the left side of the classification boundary. Additionally, circles on the right side of that boundary refer to incorrectly assigned cases. The filled circles show the group means of the two products.

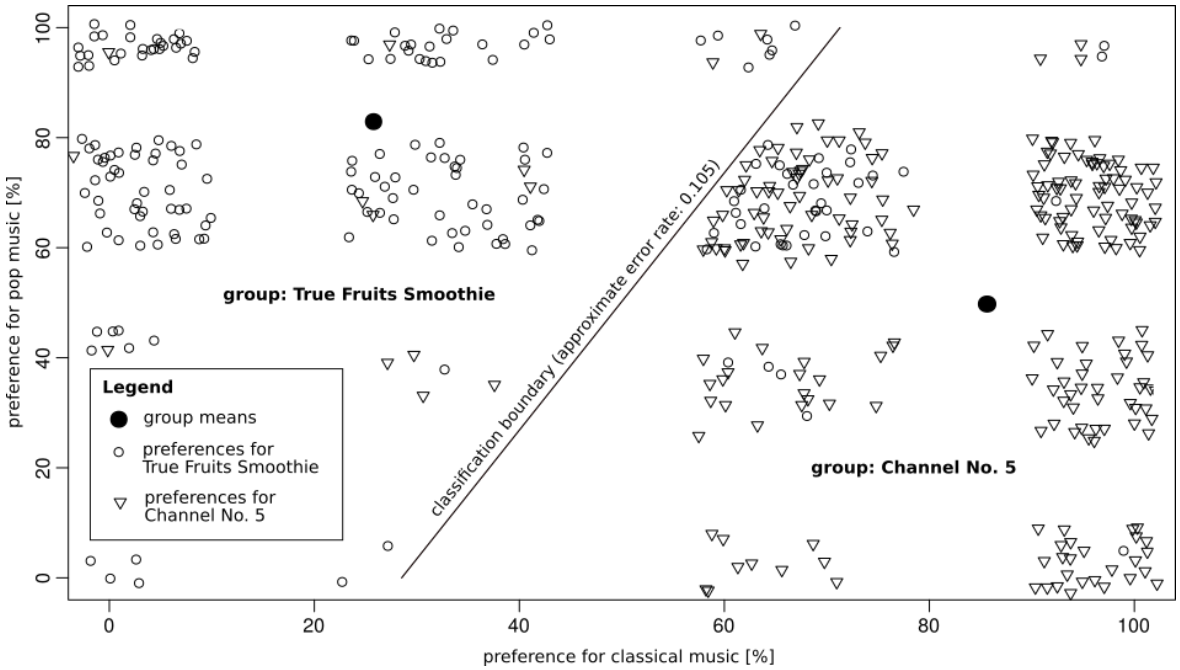

Figure 1. **Results of a discriminant model based on two product groups and two genres**
Source: Authors' own research.

As a summary, the univariate and the multivariate analyses result in highly significant models. The visualization in figure 1 shows a classification probability of about 90 per cent based on a model with only two of the six analyzed genres. Therefore, there seems to be a correlation between the genre preferences and different products. As a consequence, the music selection for video ads seems to be automatable.

Conclusion

This paper can be seen as an explorative study to test automation possibilities for product-specific music selections in the context of video ads. The base theoretical thought is grounded on the idea that machines could easily learn repeatable processes. A significant correlation between the music style and different products refers to a repeatable process. In regard to eighteen different products it was shown that all chosen genres contribute significantly to the differentiation between product

groups respectively products. Additionally, the multivariate model of this study is highly significant.

Derived from the descriptive results, different music genres meet the preferences of the users. Consequently, a genre bending can be seen as recommendable to address the target groups of different products. In particular rock, pop and dance music show a strong effect on the multivariate model. This is explainable by the specific characteristics of rock and dance music that base on guitars respectively synthesizers. Those musical elements have an expressive characteristic effect as described in the literature section. The meaning of pop music in regard to its effect on product separation can be explained by its dissemination. Subsequently, users have clear ideas about the applications of that genre. In summary, there are observable, significant differences between the preferred genres for different products. Thus, a digitization and subsequently, an automation of the music selection based on products seem to be possible.

The empirical basis of this evaluation is restricted in regard to the target group since the age of most of the participants is between 20 and 30 years. Therefore, the results of this study have only a limited explanatory value in regard to the genre preferences of persons of other ages. Subsequently, the result can be classified as a first overview in regard to automation possibilities. Additionally, this paper gives impulses towards the research in regard to the practical digitization of the music creation for video ads. If music genres are suitable for separating products, artificial intelligence could select music styles based on products and target groups. For instance, artificial neural networks could lead to generalized models. In this context, a redefinition of the product characteristics seems to be reasonable to get a metric scale describing different products. An adequate interface to tools with the capability of composing and arranging music would extend the automation process. As a consequence, the automation would cover the entire process starting from the music selection to the final music production. As a result, marketers would just enter details of their product and their target group as input for neural networks and receive final produced background music for a video ad.

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