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Parvinen, Petri

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Analyzing Commercial Collaboration Attractiveness in YouTube Based on Micro-Analytical Content Labeling and Audience Retention

Petri Parvinen
University of Helsinki
petri.parvinen@helsinki.fi

Markus Tandefelt
Media Machine Inc.
markus.tandefelt@gmail.com

Essi Pöyry
University of Helsinki
essi.poyry@helsinki.fi

Antti Lähtevänoja
Zoan
antti.lahtevanoja@zoan.fi

Osmo Mattila
University of Helsinki
osmo.mattila@helsinki.fi

Abstract

For creators of online video content, it is essential to understand how the audience reacts to different details within the content and how those reactions affect their viewing behavior, such as rewatching or skipping a moment or closing the video altogether. Understanding detailed viewing in terms of audience retention statistics is crucial for commercial collaborative content, as online video hosting such as YouTube freely allows commercial collaboration of different kinds, unlike many TV channels, for example. This paper proposes a research agenda for micro labeling commercial collaborative content to understand how to make it increase – not ruin – audience retention. We employ sport entertainment media as a case example but derive implications for not only media channel owners but also to marketers, influencer personalities and platform developers.

1. Introduction

Social media advertising, either through the voice of the advertising brand or through a paid influencer, has become the chief advertising channel for many brands. The omnipresence of branded content in social media might, however, turn consumers down, increase advertising avoidance, and decrease its effectiveness. Influencer marketing or product placement bear particular risks related to advertising avoidance; to certain extent, consumers are expected to accept the presence of paid content but when do they start avoiding it?

Understanding online video audience retention – the share of the audience that engages with an online video at a given time – can be used to assist with decision-making on how to place paid content to maximize their visibility [2]. Despite the importance of audience retention when studying audience behavior, research using such data is scarce. In addition to the studies that focus on audience retention of TV programs and commercial breaks [5,8], there are only a few studies that have focused on audience retention of online video content [see 2,4]. Online videos are interesting not only because of their increased popularity but also because of the unstructured nature compared to traditional TV programs – commercial breaks are shorter and more abrupt and there is more of “native advertising” (product placements, sponsored content, influencer advertising) [6].

YouTube is the largest online video service in the world, and, on YouTube, audience retention data reveals how large of a share of the audience stopped watching the video at a given time slot [7]. Audience retention data explains audience behavior more deeply than just by looking at the number of viewers on the videos.

In order to understand precisely what explains changes in audience retention, micro content labeling can be used to analyze the videos. In practice, micro content labeling means categorizing various moments inside a video according to predefined categories [3]. These can be, for example, an advertisement, a product demonstration, a show highlight, or a video intro. Analyzing audience retention data against these micro content labels allows the investigation of the effects of commercial contents, and other types of branded contents, on audience behavior.

2. Research context and data

The research was conducted in the context of a competitive sports fishing media channel (https://www.youtube.com/c/CanalOutdoor/videos) run by Media Machine Inc. On 25 of the videos, teams of professional sports fishing athletes compete by trying to catch and release large fish within a limited time. The competition format allows participants to select and present their sponsors’ equipment such as lures and rods as a part of the show. Equipment sales and marketing is the primary source of revenue. In

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addition to providing exciting competition content, the show provides valuable information about the best gear for the audience consisting mainly of fishing hobbyists.

2.1 Audience retention data

There are two types of traffic on YouTube videos: organic traffic and paid traffic. Organic traffic stems from direct user intentions, such as searching for the video, clicking on a suggested video and so on. Paid traffic, on the other hand, comprises views resulting from paid video advertisements on YouTube [7]. There are two types of audience retention data available in YouTube: absolute audience retention and relative audience retention. While the audience retention shows the number of views for each moment in a video as a percentage of the total number of video views, relative audience retention shows a video’s ability to keep viewers compared to all YouTube videos of similar length (note, region, genre, or creation time not accounted for) [7]. Notably, all audience retention data from YouTube is divided into 100 time slots, regardless of the video length.

2.2 Video content micro-labeling

In order to make precise analysis of audience retention, the contents of the video need to be known. Different video and content categorization methods have been used in previous research, such as category-predictive classifiers and category-specific concept classifiers [1]. as well as classification based on motion, color, and text extracted from video frames [3].

In order to understand the attractiveness or avoidance-ensuing qualities of video content moments, we suggest the labels presented in Table 1.

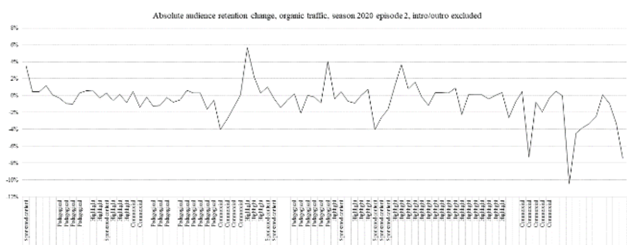
Objective labels	Subjective labels
Sponsored insert	Instructiveness
In-show promotion	Highlight
Influencer involvement	Intrusiveness
Intro/outro	Shock effect
Content duration	Content compatibility
Timing	Product-centricity
Rank order	Novelty
Sound volume	Speed of progress

Table 1. Suggested objective and subjective labels for micro-analyzing commercial video contents

Labeling and thus categorizing commercial content is proposed to follow the following research procedure. Several researchers watch the videos closely and timecode any predefined event in the video, for example “advertisement, pedagogical. Starts 11:13, ends 12:30.” After the first round of analysis, the labeling of different researchers is compared and discussed to find any different interpretations of events. Then, a new round of labeling takes place according to the new, more unified labeling instructions.

Since the YouTube data is divided into 100 time slots (regardless of the video length), the researchers also need to allocate the events to the time slots. More often than not, the events do not match the time slots as an event can start at any time, for example right at the end of a time slot. To counter this limitation in the YouTube data (more precise data would naturally be preferred), the researchers need to decide a strategy for allocation. If a time slot is 27 seconds, for example, a suitable strategy could be that any events that start in the final 10 seconds of the slot, are allocated to the next slot – given that the event lasts over 10 seconds of that slot. Second, the researchers need to decide which events are preferred if two events collide in the same slot and/or what is the minimum event length for labelling. See Figure 1 for an example of audience retention change at each time slot with labels.

Figure 11. Example of audience retention data with labels



2.3 Other data sources for variable construction and content analysis

In addition to labeling video events based on commercial content types, other data sources can be used to enrich the analysis as either dependent or independent variables. For example, live chat comments and reactions can serve as dependent variables representing audience engagement. Live chat comments suit particularly well for highly anticipated videos that the audience knows to expect at a specific time and watching the video is a common habit. YouTube has recently introduced a new more reliable automatic subtitling feature, which offers transcribed raw data for analysis. Time stamp tags, normally used only to track viewer counts of a single commercial moment, can be used all over the videos and categorize marketer and content creator moments beforehand. Content labeling could also benefit from research methods such as eye-tracking and physiological sensors as long as there are enough participants to provide data for reliable and generalizable measurement. Such methods could be used to identify distinct highlights from the videos.

3. Implications

3.1 Media channel owners and social media influencers

As stated by Eitan and Jimenez [2], companies or individuals who create online video content can use audience retention data as a feedback on videos they create and modify them based on the data insights. The modification of the videos can lead to better advertisement visibility and larger audience retention. In this paper, we suggest that different type of commercial content can have differential effect on audience retention so the analysis should go further from the traditional analysis of how a commercial break affects viewer behavior [7,8]. YouTube channels and YouTube influencers have relatively high freedom in creating different types of commercial content, which can vary from traditional advertisements that are separated from other content, sponsored content or product placement and non-paid branded content. Understanding the type of content that viewers want to see, instead of something that they are forced to see, is crucial for the long-term sustainability of the channel.

3.2 Platform developers

For platform developers, one of the most important implications of this paper is to develop opportunities to get more detailed information on audience retention. Knowing whether users quit watching a video or only skip parts of it would be extremely useful. In addition, it would be useful to have the data in a form that represents the actual timecodes of the videos, for example second by second. Currently, the time slots cause potential errors in the analysis.

Besides improved data provision, platform developers could utilize the current micro-labeling approach as a way to create a machine learning method to automatically identify the events that are of interest for the media channel owner. A service that automatically suggests labels based on the initial inputs by the channel owner and continuously improves labeling accuracy would create significant value added particularly for companies that create long and eventful videos, such as Media Machine Inc.

3.3 Marketers

Collecting information about micro-analytical content labeling should first and foremost enable marketers to design and request content that is both enjoyable and effective. The labeling taxonomy can be used for content ideation, and contents can, where applicable, be renewed on the fly for the next episode based on retention effects. The labeling process itself can be valuable for the marketers as an alpha test of sponsored content; is the content labeled by researchers the way it is intended to be perceived by the audience?

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