Collaboration in N-th Order Derivative Creation

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Abstract

In derivative creation activity, where new content is created based on existing content, it has become popular for multiple creators to collaborate to create new derivative content. In this paper, we analyze the collaboration of music-related derivative videos on a video sharing service. Specifically, by using 83,496 collaborative videos created by 22,841 creators, we analyze the collaboration from the following two viewpoints: video popularity and creator activity. Our analysis results showed that collaborative videos tend to become more popular than non-collaborative ones, the collaboration is not a one-off activity but a continuous one, and creators who have collaboration experience are active for a longer time than inexperienced creators, etc.

1 Introduction

On video sharing services such as YouTube[1], not only professional creators but also amateur creators create and post various kinds of videos. For amateur creators in particular, since it is not always easy to create new content from scratch, it is popular to base new derivative content on existing content (Hamasaki, Takeda, and Nishimura 2008). For example, on YouTube, we can see a lot of derivative videos in which creators dance to an existing song or perform a cover of it (Liikkanen and Salovaara 2015). Such creation activity where new derivative works are created from an existing work one after another is called *N-th order derivative creation* (Goto 2012). As we will show in Section 3.2, collaborations between creators to create content in N-th order derivative creation are also common. In such content, for example, multiple creators sing a song together or one creator plays the piano and the other one dances to the piano.

The collaboration activity is not limited to video creation; it is also common in various situations in human society (e.g., a development project in a company, co-authorship of a research paper, and music activity of a band). Through such collaborations, people have created content such as products, articles, and songs. Since understanding the collaboration is important from the social scientific viewpoint, several studies have analyzed the collaboration activities to create content (Hu, Chen, and Luan 2014; Luther et al. 2010). There are some studies about N-th order derivative creation such as analyzing the citation relationships between content (Hamasaki, Takeda, and Nishimura 2008) and detecting characteristics of content that is more likely to be used as source content to create new content (Hill and Monroy-Hernández 2012; Calefato, Iaffaldano, and Lanubile 2018). However, to the best of our knowledge, no study has analyzed the collaboration in N-th order derivative creation in terms of content popularity and creator activity.

In light of the above, in this paper, we analyze the collaborations between creators by using derivative creation data of music content posted to Niconico[2], which is one of the most popular video sharing services in Japan. Our dataset consists of 83,496 collaborative videos created by 22,841 creators. We analyze the data based on the following two viewpoints.

- Video popularity: for a creator, the popularity of his/her videos is important because he/she will be motivated to create new videos if his/her videos have become popular on a video sharing service. Hence, we analyze the collaboration in terms of video popularity. (Section 4)
- Creator activity: for video sharing services, it is important that creators act (i.e., create content) for a long time because this leads to the continuous growth of the service. Therefore, we analyze the collaboration in terms of creators' activity. (Section 5)

We believe our work provides valuable insights for both creators and video sharing services. For creators, our analysis results show that collaborative videos tend to become more popular than non-collaborative ones; while for video sharing services, we reveal that creators who have collaboration experience act for a longer time than inexperienced creators.

2 Related Work

Studies dealing with collaboration in human society have been conducted in various fields such as company projects (Inoue and Liu 2015; Muller et al. 2013) and research paper writing (Hu, Chen, and Luan 2014). For example, Hu, Chen, and Luan (Hu, Chen, and Luan 2014) reported a positive correlation between the number of authors who have collaborated with another author and the number of his/her

[1]https://www.youtube.com/

[2]http://www.nicovideo.jp

publications. With the increasing popularity of online creative collaborations on web services, researchers started to analyze the collaboration activity by using large-scale data obtained from the services. These studies mainly focused on collaboration success where success is defined as completing a collaboration and releasing a finished work (Luther and Bruckman 2008). They have revealed the principles that lead to the success of collaborations (Luther et al. 2010; Settles and Dow 2013). Our study is different from theirs in that we analyze successfully created content as a result of the collaboration.

As the progressiveness and importance of N-th order derivative creation has become recognized (Goto 2012), researchers have worked in this research area from various aspects. Hamasaki, Takeda, and Nishimura (Hamasaki, Takeda, and Nishimura 2008) analyzed the relationships between an original work and its derivative works on Niconico. They reported several statistics such as the number of derivative works created from an original work. Based on the analysis, a web service called Songrium[3] was developed to help a user browse original songs and their derivative works by visualizing the relations between them (Hamasaki and Goto 2013). Tsukuda, Hamasaki, and Goto (Tsukuda, Hamasaki, and Goto 2016) proposed a probabilistic model for inferring factors that triggered derivative content creation. Several studies tried to reveal the characteristics of content that is more likely to be used as source content to create new content (Hill and Monroy-Hernández 2012; Calefato, Iaffaldano, and Lanubile 2018). For example, Hill and Monroy-Hernández (Hill and Monroy-Hernández 2012) reported that content with low similarity to other content tends to be used more often to create derivative content. Our study sheds new light on this research field by analyzing the collaboration in N-th order derivative creation in terms of content popularity and creator activity.

3 Dataset

3.1 Development

To analyze the collaboration in N-th order derivative creation, we use music-related derivative videos created by the collaboration of two or more creators on Niconico. On Niconico, derivative creation activity is very active. As of January 2018, more than 630,000 derivative videos had been uploaded to Niconico. In derivative videos, creators give a wide variety of performances such as covering a song, dancing to music, and playing a song on a musical instrument. Since Niconico does not provide collaboration data (e.g., the set of creators who collaborated to create a video), we collect the data as follows. Niconico users can make a video list to list their favorite videos, and a user can see the video lists of other users. Creators often make video lists that consist of videos created by the creator. We call such a video list a *work list*. To judge whether each list is a work list, we use several rules. For example, given a creator's video list, we check if the creator's name appears in the title, tags, or description of each video; if 90% or more videos in the list satisfy this condition, we treat the list as the work list. If a video is included in two or more creators' work lists, we regard the video as a collaborative video. By following this process, we collect collaborative videos from all creators' work lists.

[3]http://songrium.jp

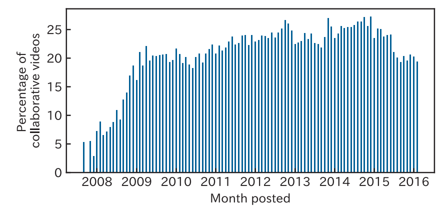

Figure 1: Percentage of collaborative videos per month.

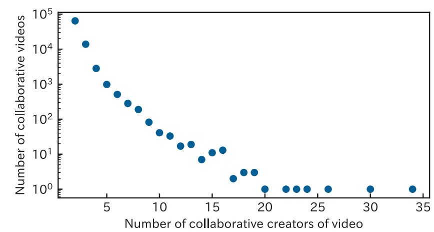

Figure 2: Distribution of the number of participating creators of each collaborative video.

We used the data of derivative videos, creators, and their video lists provided by Hamasaki and Goto (Hamasaki and Goto 2013). The derivative videos were uploaded to Niconico between September 2007 and February 2016. The aforementioned work list detecting process gave us 270,814 work lists from 515,297 video lists. The work lists had 363,338 unique derivative videos; among them, 83,496 videos were detected as collaborative videos[4].

3.2 Basic Statistics

In the work lists, the number of derivative videos that were created by one creator (i.e., the number of non-collaborative videos) is 279,842. That is, the percentage of collaborative videos is 23.0%. Figure 1 shows the percentage of collaborative videos for each month. The percentage increases when the N-th order derivative creation activity became popular around 2008. Since the percentage stays at around 20% after 2009, we can say that collaboration has occurred at a certain level in recent years. In terms of creators' collaboration experience, 22,841 creators among the 46,511 creators in the dataset (i.e., 49.1%) have created at least one collaborative video. Finally, Figure 2 shows the distribution of the number of participating creators of each collaborative video. It can be observed that collaboration between two or three creators is quite common: 77.3% (16.7%) of the collaborative videos were created by collaborations between two (three) creators.

[4]Since some of the collected collaborative videos were created by an unusually large number of creators, we manually checked 15 videos in which 20 or more creators collaborated and removed 9 videos that were wrongly judged as collaborative ones.

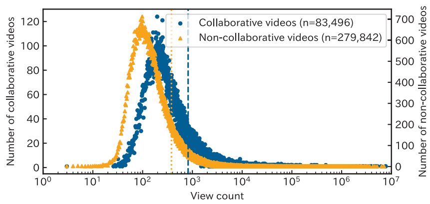

Figure 3: Distributions of view count for collaborative videos and non-collaborative ones.

The collaborative video with the largest number of participants was created by the collaboration of 34 creators. In the video, a creator sings a song with the other 33 creators in celebration of the second anniversary of the creator creating content on the video sharing service.

4 Video Popularity

For creators, the popularity of their videos on the video sharing service is an important factor because a creator will be motivated to create new videos if his/her videos have become popular. In this section, we regard the video's view count as a measure of its popularity and analyze the effect of collaboration on the popularity.

4.1 Video-based Analysis

First, to answer the research question "is there a difference in popularity between collaborative videos and non-collaborative ones?", we compare their view counts. The results are shown in Figure 3 where each blue (orange) dot represents the number of collaborative (non-collaborative) videos whose view count is x. The peak of collaborative videos is further to the right than that of non-collaborative ones. In addition, the median of each group, which is represented by vertical dotted lines, shows the same result. These results indicate that there is a difference in popularity, and collaborative videos tend to become more popular than non-collaborative ones. We presume that when multiple creators collaborate and create a video, the fans of each creator watch the video; this results in an increase of the view count compared to that of non-collaborative videos.

4.2 Creator-based Analysis

Our next research question is "is there a difference in popularity between creators with collaboration experience and ones without it?" To answer the question, we compare the view count of non-collaborative videos between experienced creators and inexperienced ones. To be more specific, for each creator, given all of his/her non-collaborative videos, we compute the median of their view counts[5]. Figure 4 shows a histogram where each bar represents the number of creators whose median view count is x. Since both the peaks and the median values of creators with collaboration experience are further to the right than those of inexperienced ones, we can

[5]In this analysis, creators who have created only collaborative videos are eliminated.

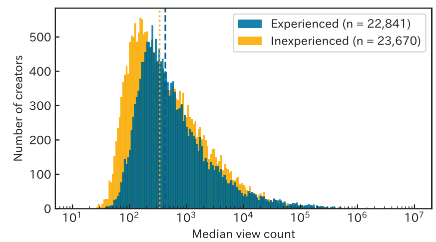

Figure 4: Distributions of median view count for creators with collaboration experience and inexperienced ones.

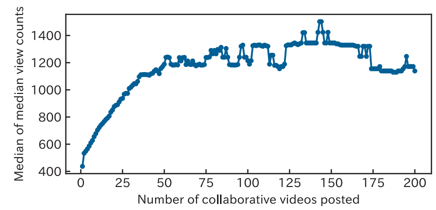

Figure 5: Relationship between the number of collaborative videos for each creator and their view counts.

say that videos created by experienced creators tend to be more popular. However, it is not clear if the videos created by experienced creators are popular regardless of their experience or the videos became popular as a result of their experience. To answer this question, periodically collecting videos' view counts and evaluating the transition of their view counts are required; we leave this as future work.

4.3 Collaboration-frequency-based Analysis

Finally, we answer the research question "is there a difference in popularity between creators who have a lot of collaboration experience and those who have a little experience?" by analyzing the relationship between the number of a creator's collaborative videos and his/her view counts. Given creators who have created x or more collaborative videos, we compute the median value of each creator's median view count. Figure 5 shows the results where x ranges from 1 to 200. It can be observed that creators who have created more collaborative videos tend to have a higher view count. If we regard a creator's median view count as his/her popularity, we can say that the more collaborative videos he/she creates, the higher his/her popularity becomes.

5 Creator Activity

For video sharing services, it is desirable that creators act (i.e., create content) for a long time because it leads to the continuous growth of the service. In this section, we analyze creators' activity in terms of the continuity of collaboration and the active period.

5.1 Collaboration Continuity

Our first research question is "once a creator collaborates with another creator, do they continuously collaborate and

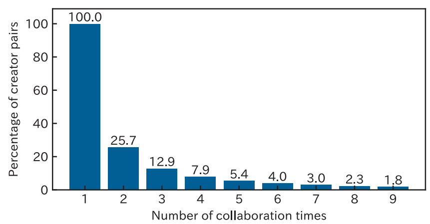

Figure 6: Percentage of creator pairs according to collaboration times.

keep creating videos?" To answer this question, we analyze how often each creator collaborates with the same creator. Given a creator, we collect all creators who have collaborated with him/her; we then compute the percentage of creators who have collaborated with him/her x or more times. Figure 6 shows the results for all creators. The number of pairs of creators who collaborated at least one time was 192,374. Among them, 25.7% pairs collaborated two or more times, and 5.4% pairs collaborated as many as five or more times. These results indicate that collaboration is not a one-off activity; rather, it is continuous at a certain level.

5.2 Active Period

Our next research question is "is there a difference in the active period between creators with collaboration experience and inexperienced ones?" To answer this question, we compare the active period for both creator groups. We define the active period of a creator as the period between the posted date of his/her first video and that of his/her latest one. Since a creator who posted his/her first video earlier tends to have a longer active period, we group creators according to the year of their first posted date and compute the active period for each group. Figure 7 shows the results of creators who posted their first video in 2012. In terms of the percentage of creators whose active period is x or fewer days, the percentage of creators with collaboration experience is always lower than that of inexperienced creators. This result means that creators with collaboration experience tend to have a longer active period than inexperienced ones. Similar results were observed in other years. Thus, we can conclude that collaboration experience has a relation with creators' active periods. At the moment, we cannot determine whether a creator's active period becomes long as a result of his/her collaboration experience. However, if we can show a causal correlation in our future work, supporting creators so that they can collaborate with others more easily would be useful to realize their continuous activity.

6 Conclusion

In this paper, we focused on the N-th order derivative creation and analyzed the collaboration of music-related derivative videos in terms of video popularity and creator activity. Our analysis results showed the positive correlation of collaboration with both of them. For future work, we plan to conduct more elaborate studies on the collaboration by considering each creator's characteristics and the content of each collaborative video. This would enable us to get a deeper understanding of collaboration such as the reasons why creators collaborate.

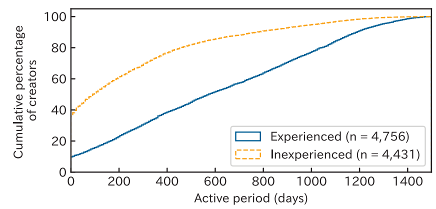

Figure 7: Distributions of active periods for creators with collaboration experience and inexperienced ones in 2012.

Acknowledgments

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