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Songrium Derivation Factor Analysis: A Web Service for Browsing Derivation Factors by Modeling N-th Order Derivative Creation*

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SUMMARY Creating new content based on existing original work is becoming popular especially among amateur creators. Such new content is called derivative work and can be transformed into the next new derivative work. Such derivative work creation is called "N-th order derivative creation." Although derivative creation is popular, the reason an individual derivative work was created is not observable. To infer the factors that trigger derivative work creation, we have proposed a model that incorporates three factors: (1) original work's attractiveness, (2) original work's popularity, and (3) derivative work's popularity. Based on this model, in this paper, we describe a public web service for browsing derivation factors called *Songrium Derivation Factor Analysis*. Our service is implemented by applying our model to original works and derivative works uploaded to a video sharing service. Songrium Derivation Factor Analysis provides various visualization functions: *Original Works Map*, *Derivation Tree*, *Popularity Influence Transition Graph*, *Creator Distribution Map*, and *Creator Profile*. By displaying such information when users browse and watch videos, we aim to enable them to find new content and understand the N-th order derivative creation activity at a deeper level.

key words: *user generated content, derivative creation, latent variable model, web service*

1. Introduction

The era when only professional creators were able to create and provide content on the web has passed; now amateur creators who used to be just consumers can also easily create and provide content. Such content is known as user generated content (UGC). Since not all amateur creators can create new content from scratch, it is common to use existing original (1st generation) work as the basis for new content. Such content is called *derivative work* [1] or 2nd generation work. For example, on YouTube**, there are many videos in which amateur creators dance to an existing song or perform a cover of it [2], [3]. Thingiverse*** is a web service that facilitates derivative work creation, where amateur creators can share 3D model data intended for a 3D printer. On Thingiverse, creators can download original 3D model data created by others, modify it, and upload their new version [4]. In this kind of derivative work creation activity, a creator influenced by 2nd generation content can create 3rd generation content. Similarly, N-th generation content can be transformed into N+1-th generation content. Such derivative work creation activity is called "N-th order derivative creation [5]."

We know that derivative creation is popular, but *why* are individual derivative works created? There are various factors that inspire the creation of derivative works. However, since the factors that trigger derivative creation cannot usually be observed on the web, they are difficult to detect. To get around this problem, we assume that when a creator creates a derivative work, there are three triggering factors: (1) original work's attractiveness, (2) original work's popularity, and (3) derivative work's popularity. Based on this assumption, we have proposed a model to estimate the factors that trigger derivative work creation [6]. Since the relative influence of the three factors varies among creators, our model also takes into account the latent relationships between creators and each of the three factors. Moreover, our model uses content ranking information to take into account the popularity of the original and derivative works. By referring to the examination model of a web search result [7], [8], we model popularity based on the hypothesis that higher ranked content has a larger influence because such content has probably been viewed by many creators. We quantitatively evaluated our proposed model by using music-related N-th order derivative creation datasets and showed that the proposed model considering all of the three factors outperformed the models considering one or two of them [6]. We also showed that when we considered the content popularity based on popularity ranking, the method reflecting creators' browsing behavior was the most effective to model derivative creation activity.

In this paper, we describe a public web service, called *Songrium Derivation Factor Analysis* (http://factor.songrium.jp), for browsing derivation factors estimated by using our model. To implement the web service, we applied our model to VOCALOID [9]-related original works and derivative works uploaded to Niconico****, which is one of the most popular video sharing web services in Japan. Songrium Derivation Factor Analysis mainly provides the

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**http://www.youtube.com
***http://www.thingiverse.com
****http://www.nicovideo.jp

following visualization functions:

- *Original Works Map* shows the characteristics of the original work in the N-th order derivative creation.
- *Derivation Tree* shows the N-th order derivative creation process.
- *Popularity Influence Transition Graph* shows the temporal development regarding the impact of content popularity that triggered the derivative work creation.
- *Creator Distribution Map* shows the degree to which a creator is influenced by each of the three factors.
- *Creator Profile* shows the creator's influence information.

In terms of consumers, by displaying such information when they browse and watch videos, we aim to enable them to find new content and understand the N-th order derivative creation activity at a deeper level. In terms of creators, such information would be useful to decide which content they use to create a new derivative work.

Our main contributions in this paper are as follows.

- We applied our proposed model to music-related real world datasets in three categories: (1) singing: covering an original song, (2) dancing: dancing to an original song, and (3) playing: playing an original song on a musical instrument. They include approximately 160,000, 90,000, and 100,000 derivative works, respectively.
- We implemented a web service Songrium Derivation Factor Analysis that has five main functions: Original Works Map, Derivation Tree, Popularity Influence Transition Graph, Creator Distribution Map, and Creator Profile.
- We made Songrium Derivation Factor Analysis open to the public to support both consumers and creators.

The remainder of this paper is organized as follows. Section 2 describes related work in two areas: (1) analysis of derivative creation activity and (2) modeling influences in social communities. Section 3 describes the model that adopts the aforementioned three factors. Section 4 presents the functions of Songrium Derivation Factor Analysis. Finally, Sect. 6 concludes this paper.

2. Related Work

2.1 Analysis of Derivative Creation Activity

Eto *et al.* [10] developed a 3D modeling application and a model sharing web service called Modulobe, which allows users to create 3D models from scratch or based on the work of other creators. They reported that 10.4% of the models were parents of other models and that the chains of creation reached up to four generations. Cheliotic and Yew [11] examined remixing activities in the ccMixter online music community†. They reported that derivative creation greatly boosted the output of a community as well as increasing the diversity of the output. Hamasaki *et al.* [1] analyzed derivative creation activity on Niconico. They used explicit citation information between an original work and its derivative works and discussed certain statistics (*e.g.*, the number of derivative works of an original work). Hamasaki *et al.* [12] also developed a web service called Songrium†† that helps a user browse original songs and their derivative works by visualizing their relationships.

All the studies mentioned above analyzed *how* derivative works had been created by using a network based on the relationships between the original work and derivative works. In this work, we focus on *why* derivative works were created and implement a web service for browsing derivation factors.

2.2 Modeling Influences in Social Communities

Since estimating influences among users in social activities is useful for various applications, such as influential user detection [13] and personalized recommendation [14], many methods for estimating such influences have been proposed. One major approach is to use an information diffusion model such as the independent cascade model [15]. Although discrete time is assumed with this model, Saito *et al.* [16] proposed a model based on Poisson processes, allowing for continuous time modeling. However, their model requires a network structure of users in which a node corresponds to a user and an edge between users represents the existence of influence. To overcome this limitation, Iwata *et al.* [17] proposed a model that discovers latent influences between users without a network structure. Although the cascade Poisson process [18] models a sequence of cascading events, the model proposed by Iwata *et al.*, which is called the Shared Cascade Poisson Process (SCPP), can handle multiple sequences of adoption events for multiple items by sharing parameters. Iwata *et al.* used a Bayesian approach to discourage overfitting during parameter inference. They evaluated the model by using social bookmark data, where adopting an item corresponds to bookmarking a web page. Tanaka *et al.* [19] extended SCPP to estimate the factors that trigger item purchase events. They considered the users' view histories for TV advertisements in addition to influences between users and showed that SCPP is also effective in modeling purchase events.

Our model extends SCPP and the model proposed by Tanaka *et al.* [19], differing from them in the following two respects. First, in the other models, there is no need to consider the effect of adopted items such as bookmarked web pages and purchased items. However, in derivative creation activity, adopted items (*i.e.*, derivative works) also influence other creators' creation activity. Therefore, we extended SCPP so that we can handle the effect of both original works and derivative works. Second, although the other models assume that the popularity of items is constant regardless of

†http://ccmixter.org

††http://songrium.jp

time, we assume that content popularity depends on time. Hence, our model incorporates the time-dependent popularity of both original works and derivative works by considering content ranking data and the creators' ranking browsing behavior.

3. Model

Our proposed model [6] assumes that the following three factors play an important role in modeling derivative creation activity: (1) original work's attractiveness, (2) original work's popularity, and (3) derivative work's popularity. Below, we describe notations, followed by each of the three factors.

3.1 Notations

Given a category (*e.g.*, "3D models of chairs" or "music videos covering songs") and observation time period T, let $\mathcal{I}$ be a set of original works posted to a web service (*e.g.*, Thingiverse or YouTube) between time 0 and time T. Let (t^p_{ij}, u^p_{ij}) denote the jth derivative work posting event of original work i. More specifically, creator $u^p_{ij} \in \mathcal{U}$ posts i's derivative work at time t^p_{ij}. Here, $\mathcal{U}$ is the set of creators. Without loss of generality, we assume that derivative work posting events are sorted in ascending order of their timestamps: $t^p_{ij} \leq t^p_{ij'}$ for $j < j'$. When J_i represents the total number of i's derivative works posted during the observation time period, the set of derivative work posting events of i is given by $\mathcal{D}_i = \{(t^p_{ij}, u^p_{ij})\}_{j=1}^{J_i}$. Hence, the set of derivative work posting events of all original works is given by $\mathcal{D} = \{\mathcal{D}_i\}_{i\in\mathcal{I}}$.

Suppose creators can see the ranking of original works on the web service, where original works are ranked based on the popularity computed using statistics such as view count. Let (t^o_{ik}, r^o_{ik}) denote the kth ranked event of $i \in \mathcal{I}$. That is, i is ranked at the r^o_{ik}th place at time t^o_{ik}. We also assume that the events are sorted in ascending order of their timestamps without loss of generality: $t^o_{ik} \leq t^o_{ik'}$ for $k < k'$. Let K^o_i be the total number of i's ranked events between time 0 and time T. Then, the set of ranked events of i is given by $O_i = \{(t^o_{ik}, r^o_{ik})\}_{k=1}^{K^o_i}$. Therefore, the set of ranked events of all original works is given by $O = \{O_i\}_{i\in\mathcal{I}}$.

Similarly, suppose creators can also see the ranking of derivative works. In the same manner as with the ranked event of the original work, let (t^c_{ik}, r^c_{ik}) denote the kth ranked event of i's derivative work. Let K^c_i be the total number of ranked events of i's derivative works between time 0 and time T; then the set of ranked events of i's derivative works is given by $C_i = \{(t^c_{ik}, r^c_{ik})\}_{k=1}^{K^c_i}$. Note that C_i includes ranked events of all i's derivative works: (t^c_{ik}, r^c_{ik}) and $(t^c_{ik'}, r^c_{ik'})$ can be ranked events of different derivative works. Finally, the set of ranked events of all derivative works of all original works is given by $C = \{C_i\}_{i\in\mathcal{I}}$.

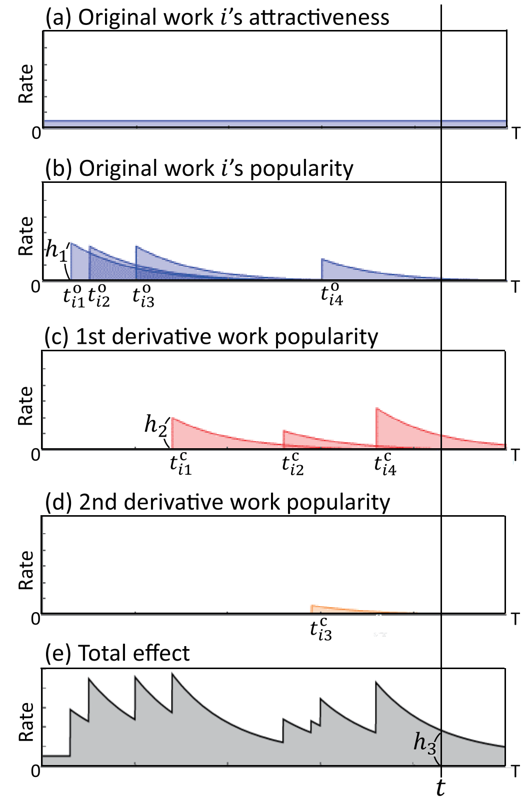

Fig. 1 Rate at which creator u posts original work i's derivative work at time t.

3.2 Factors

3.2.1 Original Work Attractiveness (Oatt)

A creator may create original work i's derivative work because he/she thinks that i is attractive. We assume that each creator has a different preference for original content attractiveness. We also assume that the post rate based on original work attractiveness is constant in the time period from 0 to T as described in Fig. 1 (a). Here, the rate at time t represents the instantaneous probability of a creator posting i's derivative work at t. Based on these assumptions, we model the rate at which creator u posts i's derivative work triggered by i's attractiveness as follows:

$$f_i(u) = \alpha_i \theta_{0u}, \tag{1}$$

where $\alpha_i \geq 0$ is the original work attractiveness, $\theta_{0u} \geq 0$ represents the probability that u is influenced by original work attractiveness when he/she creates a derivative work, and $\sum_{u\in\mathcal{U}} \theta_{0u} = 1$. In Fig. 1 (a), the height of the blue line corresponds to $\alpha_i \theta_{0u}$.

3.2.2 Original Work Popularity (Opop)

If original work i is popular among consumers, creator u may create i's derivative work because his/her derivative work might also become popular. As mentioned in Sect. 3.1, we assume creators can see the popularity ranking of original works. When two original works are ranked, we hypothesize that the higher ranked one has a larger influence than the lower ranked one based on the user's search result browsing behavior [7], [8]. In addition, we assume that each creator has a different preference for original work popularity and that the influence of original work popularity on a creator decays over time. Based on these assumptions, we model the rate at which u posts i's derivative work at time t based on the influence of i's popularity as follows:

$$h_{o(i,t',r')}(t,u) = \begin{cases} rb(r')\omega_i\theta_{-1u}\mathrm{e}^{-\gamma_o(t-t')} & \text{if} \quad t' < t \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where r' represents the rank of i at time t', and $rb(r') = \frac{1}{r'}$, which computes the rank bias. The term $\omega_i \geq 0$ represents the influence of i's popularity, $\theta_{-1u} \geq 0$ represents the probability that u is influenced by original work popularity when he/she creates a derivative work, and $\sum_{u \in \mathcal{U}} \theta_{-1u} = 1$. Finally, $\mathrm{e}^{-\gamma_o(t-t')}$ models the decay of influence over time with decay parameter $\gamma_o \geq 0$.

In Fig. 1 (b), the original work i appears four times in the popularity ranking. Let r' be the rank of the first ranked event. The influence of the event is $rb(r')\omega_i\theta_{-1u}$, which corresponds to h_1 in Fig. 1 (b) at t^o_{i1}. Then, the influence decreases as time proceeds.

3.2.3 Derivative Work Popularity (Dpop)

If original work i's derivative work is popular among consumers, creator u may also create i's derivative work because his/her derivative work might also become popular. As mentioned in Sect. 3.1, we assume creators can see the popularity ranking of derivative works. Based on similar assumptions and the hypothesis described in Sect. 3.2.2, when i's derivative work was ranked r'th at time t', we model the rate at which u posts i's derivative work at time t based on the influence of i's derivative work popularity as follows:

$$h_{d(i,t',r')}(t,u) = \begin{cases} rb(r')\sigma_i\theta_{-2u}\mathrm{e}^{-\gamma_d(t-t')} & \text{if} \quad t' < t \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where $\sigma_i \geq 0$ represents the influence of the popularity of i's derivative work, $\theta_{-2u} \geq 0$ represents the probability that u is influenced by derivative work popularity when he/she creates a derivative work, and $\sum_{u \in \mathcal{U}} \theta_{-2u} = 1$. Finally, $\mathrm{e}^{-\gamma_d(t-t')}$ models the decay of influence over time with decay parameter $\gamma_d \geq 0$.

Figures 1 (c) and (d) show the influences of i's first and second derivative work popularity, respectively. The first derivative work appears three times in the ranking, while the second one appears once. Let r' be the rank of the first ranked event in Fig. 1 (c). The influence of the first ranked event is $rb(r')\sigma_i\theta_{-2u}$, which corresponds to h_2 in Fig. 1 (c) at t^c_{i1}. Then, the influence decreases as time proceeds.

3.3 Derivative Work Post Rate

Based on the factors described in Sects. 3.2.1 to 3.2.3, the rate at which u posts i's derivative work at t is given by:

$$\lambda_i(t,u) = f_i(u) + \sum_{(t',r') \in O_{it}} h_{o(i,t',r')}(t,u) + \sum_{(t',r') \in C_{it}} h_{d(i,t',r')}(t,u), \tag{4}$$

where $O_{it} = \{(t',r')|(t',r') \in O_i \text{ and } t' < t\}$ is the set of ranked events of i before t and $C_{it} = \{(t',r')|(t',r') \in C_i \text{ and } t' < t\}$ is the set of ranked events of i's derivative works before t. Here, $\lambda_i(t,u)$ corresponds to h_3 in Fig. 1 (e).

Given $\mathcal{D}$, O, and C, the likelihood of the function of $\mathcal{D}$ is given by:

$$P(\mathcal{D}|O,C,\boldsymbol{\alpha},\boldsymbol{\omega},\boldsymbol{\sigma},\boldsymbol{\Theta},\boldsymbol{\gamma}) = \prod_{i \in \mathcal{I}} \exp\left(-\int_0^T \sum_{u \in \mathcal{U}} \lambda_i(t,u)dt\right) \prod_{j=1}^{J_i} \lambda_i(t^p_{ij}, u^p_{ij}), \tag{5}$$

where $\boldsymbol{\alpha} = \{\alpha_i\}_{i \in \mathcal{I}}$, $\boldsymbol{\omega} = \{\omega_i\}_{i \in \mathcal{I}}$, $\boldsymbol{\sigma} = \{\sigma_i\}_{i \in \mathcal{I}}$, $\boldsymbol{\Theta} = \{\boldsymbol{\theta}_{u'}\}_{u' \in \mathcal{U}_+}$, $\boldsymbol{\theta}_{u'} = \{\theta_{u'u}\}_{u \in \mathcal{U}}$, and $\boldsymbol{\gamma} = \{\gamma_o, \gamma_d\}$. Here, $\mathcal{U}_+$ denotes $\{0, -1, -2\}$, where 0, −1, and −2 represent virtual creators for Oatt, Opop, and Dpop, respectively. By using efficient Bayesian inference based on a stochastic expectation-maximization (EM) algorithm [17], we can obtain the latent triggers for derivative work posts. More details of the inference process can be found in Tsukuda *et al.*'s study [6].

4. Songrium Derivation Factor Analysis

By using our proposed model, we implemented a public web service called *Songrium Derivation Factor Analysis*, which specializes in derivative videos on Niconico. Unlike ordinary video sharing services including Niconico, our service enables users to understand more about N-th order derivative creation and find original videos, derivative videos, and creators based on the factors estimated by our model. More specifically, we aim to realize the following three goals:

- Enable consumers to explore original and derivative videos based on the estimated results.
- Enable consumers to explore creators based on the estimated results.
- Enable creators to explore original videos based on the estimated results.

To achieve the first goal, we enable consumers to find original videos according to the original videos' characteristics in the derivative creation activity (the Original Works Map function). Moreover, our service visualizes the derivative creation process so that consumers can explore derivative videos based on the influence in the derivative creation activity (the Derivation Tree function).

In terms of the second goal, given an original video,

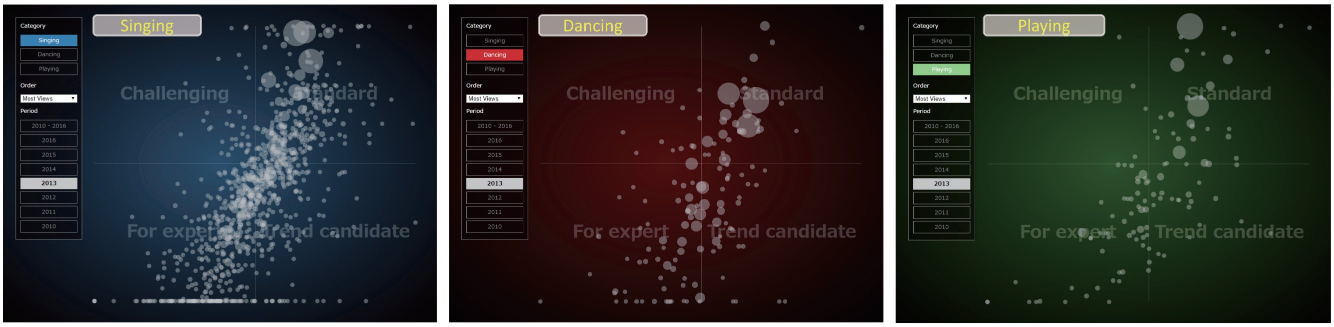

Fig. 2 Original works map.

we enable consumers to see the derivative creators' characteristics by visualizing the degree to which each creator is influenced by each of the three factors (the Creator Distribution Map function). When a consumer finds an interesting creator, our service shows the creator's profile so that the consumer can see the creator's influence (the Creator Profile function).

To achieve the third goal, displaying the original videos' characteristics mentioned in the first goal also enables creators to find an original video to create a derivative video from a new viewpoint. In addition, our service also visualizes the popularity influence in the derivative creation activity so that creators who put a high priority on content popularity can find a desirable original video (the Popularity Influence Transition Graph function).

This section describes the dataset used for Songrium Derivation Factor Analysis followed by the functions of the web service.

4.1 Dataset

For Songrium Derivation Factor Analysis, we used derivative creation activity data of music content on Niconico. On Niconico, any user can upload and view videos, and music derivative work is frequently created. As of June 2017, more than 140,000 original song videos and more than 630,000 derivative videos had been uploaded to Niconico. Most original songs are created by using singing synthesizer software called VOCALOID [9]; we restricted ourselves to original song videos of this type. With respect to derivative works, Niconico maintains three categories of derivative works:

- Singing: covering an original song. Creators typically use the original video's image and record their singing voice by using the karaoke version of the original song.
- Dancing: dancing to an original song. Most creators create dancing videos by recording their entire bodies including their faces. Since a limited number of creators can compose original choreography, most creators imitate the existing choreography.
- Playing: playing an original song on a musical instrument such as a guitar or piano. Creators often record their music instruments and their bodies excluding their faces.

Table 1 Statistics of dataset.

	$\|\mathcal{I}\|$	$\|\mathcal{O}\|$	$\|\mathcal{D}\|$	$\|\mathcal{C}\|$	$\|\mathcal{U}\|$
Singing	5,632	157,086	402,406	152,086	31,782
Dancing	784	93,828	31,677	76,457	3,095
Playing	658	95,024	9,316	52,514	1,066

In all categories, the derivative creation activity is quite popular. In the "Singing" category, for example, the most popular (in terms of the number of derivative videos) original video has more than 4,500 derivative videos as of November 2017. Among them, the most played one has a view count over 1.5 million. Similarly, in the "Dancing" ("Playing") category, the most popular original video has about 3,000 (700) derivative videos and the most played derivative video created from the original video has a view count over 2.8 million (2.8 million). We crawled original songs (*i.e.*, original works) and their derivative works posted between 11/1/2009 and 12/31/2016. In each category, we eliminated original works that had fewer than three derivative works and creators who posted fewer than four derivative works during the period.

We also collected ranking data. On Niconico, users can see the top 100 daily ranking for original songs and the top 100 daily ranking for derivatives in each of the singing, dancing, and playing categories. Ranking data on one day is created based on several statistics of the previous day (*e.g.*, view count and comment count) so that the ranking data represents the work's aggregated popularity. We crawled the top 100 ranking data in each of the original song and three derivative content categories between 11/1/2009 and 12/31/2016. Since only daily ranking data is available on Niconico, the timestamp in all our model is measured in days. Table 1 lists the statistics of the dataset used in our service.

4.2 Original Works Map

In Songrium Derivation Factor Analysis, original songs in each category are embedded in a two-dimensional space (Fig. 2). Each circle icon corresponds to an original song; the size of the icon varies in proportion to the number of its derivative works. Users can change the category by clicking on the category name on the upper left corner of the screen.

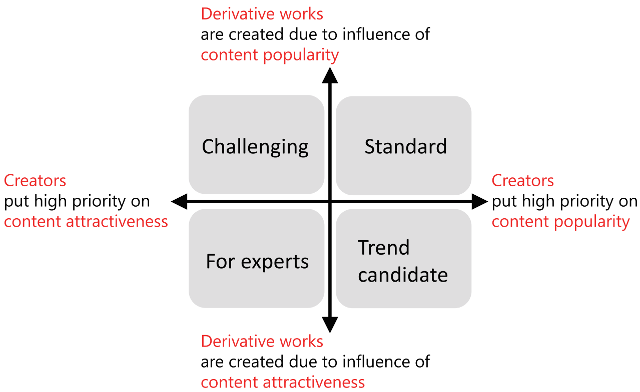

Fig. 3 Meanings of axes and quadrants.

As shown in Fig. 3, the vertical axis represents whether an original work's derivative works are created because of content attractiveness (*i.e.*, Oatt in Sect. 3.2.1) or content popularity (*i.e.*, Opop in Sect. 3.2.2 or Dpop in Sect. 3.2.3). The horizontal axis represents whether the derivative work creators put a high priority on content attractiveness or content popularity when they regularly create an original work's derivative work.

By considering these two axes, we can characterize original songs as follows. The original songs in the first quadrant are the ones used by many derivative creators who put a high priority on content popularity, so they can be regarded as "standard" original songs. When an original song appears in the original song ranking but it is not easy for most creators to create its derivative work, such an original song is mapped to the second quadrant; it is regarded as a "challenging" original song. Original songs in the third quadrant are the ones that do not frequently appear in the ranking and are used by many creators who put a high priority on content attractiveness, so such original songs are regarded as "for experts" original songs. Original songs in the fourth quadrant are the ones that do not frequently appear in the ranking; they are used by many creators who put a high priority on content popularity. Such original songs are likely to be used by many creators from that time, so they are regarded as "trend candidate" original songs. Below, we describe the way to compute the coordinates of a given original song.

4.2.1 Vertical Axis Value

Our model has latent variables $z_{ij} \in \{0, 1, \cdots, |O_{it}| + |C_{it}|\}$ to indicate the index of the latent trigger of the jth derivative work posting event of original work i (hereafter, the jth derivative work of original work i is denoted by v_{ij}). The terms $z_{ij} = 0$, $1 \leq z_{ij} \leq |O_{it}|$, $|O_{it}| + 1 \leq z_{ij} \leq |O_{it}| + |C_{it}|$ indicate that the event was triggered due to the influence of Oatt, Opop, and Dpop, respectively. By using our model, we can compute the probability at which each latent variable influences the creation of v_{ij}. Algorithm 1 shows the pseudo-code for computing the following two kinds of values. The first one, denoted by E_{att}, is the degree to which v_{ij} was created because of content attractiveness of i (*i.e.*, Oatt). The second one, denoted by E_{pop}, is the degree to which v_{ij} was created because the content popularity (*i.e.*, Opop or Dpop). By summing E_{att} of all derivative works of i, the influence degree of the content attractiveness regarding i's derivative work creation can be computed (let $SUME_{att}$ denote the sum). Similarly, by summing E_{pop}, the influence degree of the content popularity can be computed (let $SUME_{pop}$ denote the sum). We compute the vertical axis value $V(i)$ of the original song i as follows.

Algorithm 1 Calculating degree of content attractiveness (E_{att}) and content popularity (E_{pop}) for jth derivative work posting event of original work i

Require: $P(z_{ij}|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \boldsymbol{\gamma}, \beta, a, b)$
$E_{att} \Leftarrow P(z_{ij} = 0|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \boldsymbol{\gamma}, \beta, a, b)$, $E_{pop} \Leftarrow 0$
$y \Leftarrow 1$
while $y \leq |O_{it}| + |C_{it}|$ **do**
  $E_{pop} \Leftarrow E_{pop} + P(z_{ij} = y|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \boldsymbol{\gamma}, \beta, a, b)$
  $y \Leftarrow y + 1$
end while
return E_{att}, E_{pop}

$$V(i) = 2\left(\frac{SUME_{pop}}{SUME_{pop} + SUME_{att}} - 0.5\right). \tag{6}$$

$V(i)$ ranges from -1 to 1, and a larger $V(i)$ represents a higher influence of the content popularity.

4.2.2 Horizontal Axis Value

Given creator u's all derivative works, we compute CE_{att} and CE_{pop}, which are the sum of each derivative work's E_{att} and E_{pop} obtained by Algorithm 1, respectively. CE_{att} (CE_{pop}) represents the degree to which u has put a high priority on the content attractiveness (the content popularity). Given all of original song i's derivative works, we compute the sum of CE_{att} and CE_{pop} of each creator who created i's derivative work. The sum of CE_{att}, denoted by $CSUME_{att}$, is the degree to which i's derivative work creators put a high priority on the content attractiveness, while the sum of CE_{pop}, denoted by $CSUME_{pop}$, is the degree to which i's derivative work creators put a high priority on the content popularity. We compute the horizontal axis value $H(i)$ of original song i as follows.

$$H(i) = 2\left(\frac{CSUME_{pop}}{CSUME_{pop} + CSUME_{att}} - 0.5\right). \tag{7}$$

$H(i)$ ranges from -1 to 1, and a larger $H(i)$ represents a higher influence of the content popularity.

4.3 Detailed Informaion of Derivative Works

When a user clicks on an original song in the two-dimensional space in Sect. 4.2, our service shows detailed information of the original song's derivative works. Figure 4

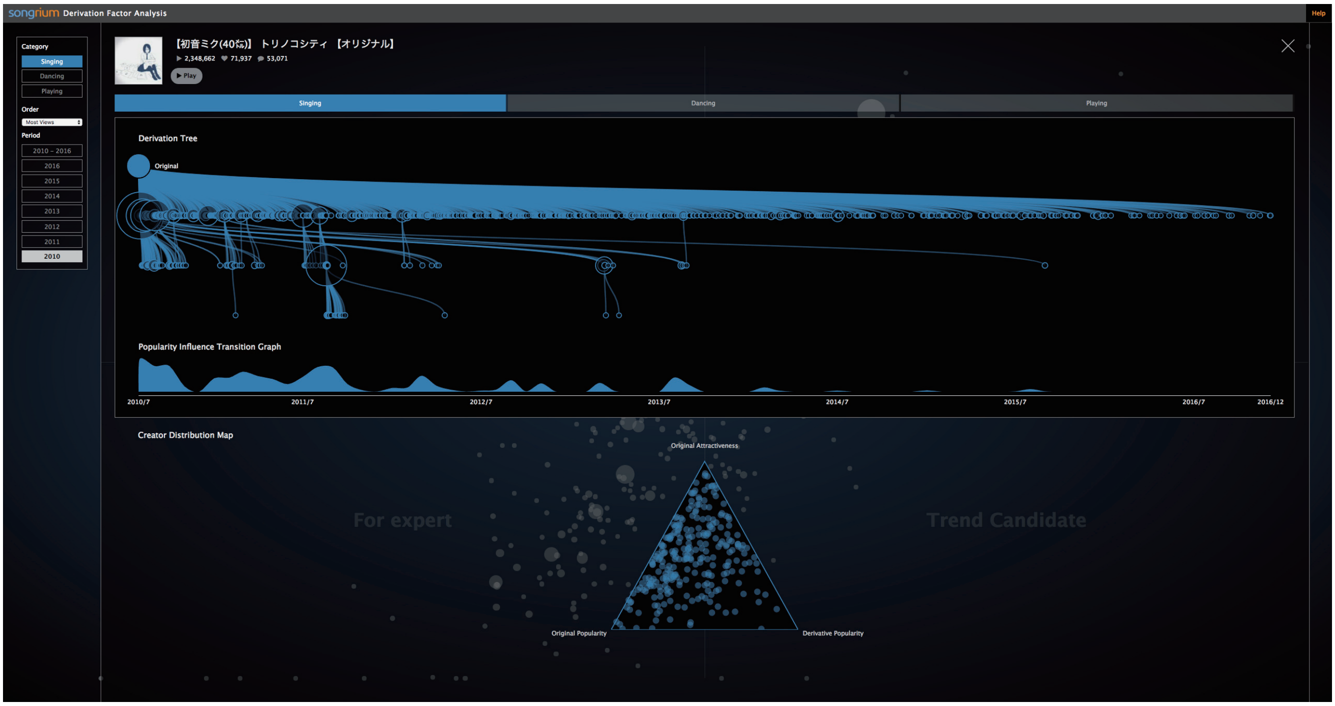

Fig. 4 Detailed information of the selected original song's derivative works.

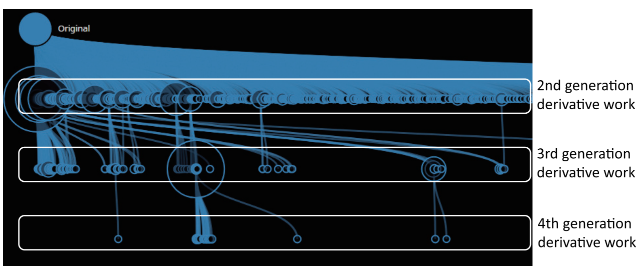

Fig. 5 Derivation tree.

shows an example result when a user clicks on an original song "Torinoko City†" in the "Singing" category. The information consists of the following three parts: (1) Derivation Tree, (2) Popularity Influence Transition Graph, and (3) Creator Distribution Map. Below, we describe each of them.

4.3.1 Derivation Tree

The Derivation Tree visualizes the derivative creation process of an original song. Figure 5 shows the enlarged Derivation Tree in Fig. 4. Each circle represents an original song or its derivative work. The horizontal axis is the time from the day when the original song was uploaded to the day when the latest derivative work was uploaded. In the Derivation Tree, the original song and its derivative works have a hierarchical structure. The original song is displayed on the first layer, and the derivative works that were created from the influence of the original song are displayed on the second layer as the second generation derivative works.

†http://www.nicovideo.jp/watch/sm11559163

Moreover, derivative works created due to the influence of the second generation ones are displayed on the third layer as third generation derivative works. The third generation derivative work v is linked to the derivative work in the second layer that has the highest influence on v. The kth ($k \geq 4$) layer is also displayed in the same manner. Although a web service that visualizes the set of derivative works of an original song has been proposed by Hamasaki *et al.* [1], by using our model, our service can visualize the relationship between derivative works.

When a user clicks on a circle icon, he/she can watch the corresponding derivative work video. In addition, as shown in Fig. 6, when the user hovers the cursor over a circle icon (*i.e.*, derivative work v), derivative works that directly or indirectly influenced v and those directly or indirectly influenced by v are highlighted. This enables the user to browse the paths related to his/her interesting derivative work in the Derivation Tree.

To create the Derivation Tree of the original song i, for each derivative work, we detect y, which is the index that gives the maximum value of $P(z_{ij})$. When $y = 0$ or $1 \leq y \leq |O_{it}|$, the derivative work v_{ij} was created by Oatt or Opop. In this case, v_{ij} is linked to the original work on the Derivation Tree. When y corresponds to a ranked event of derivative work $v_{ij'}$ ($j' < j$), v_{ij} was created from the influence of $v_{ij'}$. In this case, v_{ij} is linked to $v_{ij'}$ and displayed on the next layer below $v_{ij'}$.

4.3.2 Popularity Influence Transition Graph

This function visualizes the transition of the popularity in-

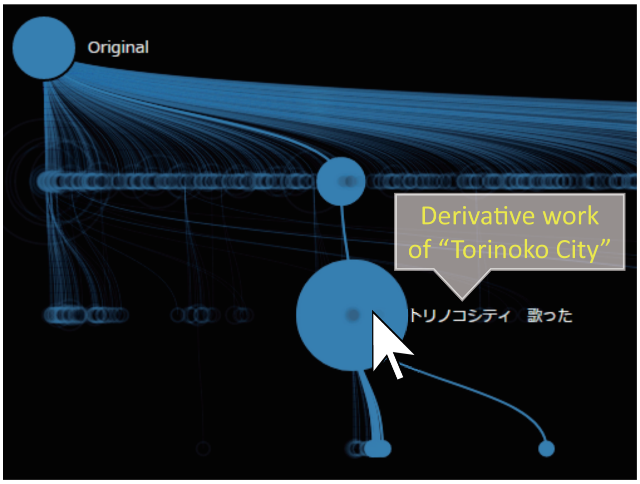

Fig. 6 Paths related to hovered derivative work is highlighted.

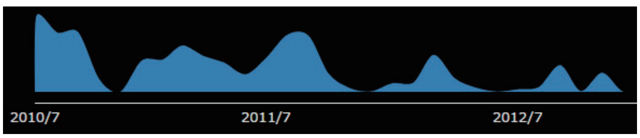

Fig. 7 Popularity influence transition graph.

fluence in N-th order derivative creation activity. Figure 7 is an enlargement of the Popularity Influence Transition Graph in Fig. 4. The horizontal axis is the time from the month when the original song was uploaded to the month when the latest derivative work was uploaded. The vertical axis represents the popularity influence in each month. A low value means that most derivative works in the month were created from the influence of content attractiveness.

When we create the graph for original song i, computing the popularity influence in each month is required. Hence, given all derivative works uploaded in a month, we compute $SUME_{att}$ and $SUME_{pop}$ as in Sect. 4.2.1. The value of the vertical axis is given by $\frac{SUME_{pop}}{SUME_{att}+SUME_{pop}}$.

4.3.3 Creator Distribution Map

The Creator Distribution Map visualizes the degree to which each creator is influenced by each of the three factors in Sect. 3.2. Figure 8 shows an enlargement of the Creator Distribution Map in Fig. 4. One circle corresponds to a creator. “Original attractiveness,” “Original popularity,” and “Derivative popularity” represent Oatt, Opop, and Dpop, respectively. In Fig. 8, it can be observed that many creators who put a high priority on Oatt and/or Opop uploaded this original work’s derivative works.

To create the map, given a creator, we need to compute the influence of each of the three factors for him/her based on all of his/her derivative works. When creator u creates the jth derivative work of original song i, the influence of each factor is computed by the pseudo-code in Algorithm 2. E_f, E_{h_o}, and E_{h_d} represent the influence of Oatt, Opop, and Dpop, respectively. Given all of u’s derivative works, let $SUME_f$, $SUME_{h_o}$, and $SUME_{h_d}$ denote the sum of E_f, E_{h_o}, and E_{h_d}, respectively. By normalizing their sum to 1, the coordinates of u on the triangle can be detected.

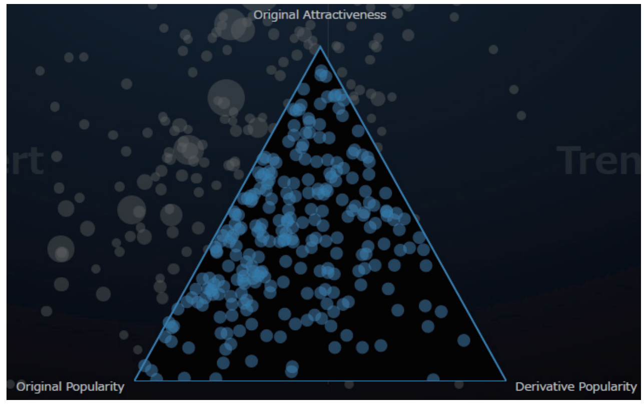

Fig. 8 Creator distribution map.

Algorithm 2 Calculating degree of three factors for jth derivative work of i

Require: $P(z_{ij}|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \gamma, \beta, a, b)$
$E_f \Leftarrow P(z_{ij} = 0|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \gamma, \beta, a, b)$, $E_{h_o} \Leftarrow 0$, $E_{h_d} \Leftarrow 0$
$y \Leftarrow 1$
while $y \leq |O_{it}| + |C_{it}|$ **do**
  if $y \leq |O_{it}|$ **then**
    $E_{h_o} \Leftarrow E_{h_o} + P(z_{ij} = y|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \gamma, \beta, a, b)$
  else
    $E_{h_d} \Leftarrow E_{h_d} + P(z_{ij} = y|\mathcal{D}, \mathcal{Z}_{\backslash ij}, O, C, \gamma, \beta, a, b)$
  end if
  $y \Leftarrow y + 1$
end while
return E_f, E_{h_o}, E_{h_d}

4.4 Creator Profile

When a user clicks on a circle icon on the Creator Distribution Map in Sect. 4.3.3, the detailed information of the creator is displayed. Figure 9 shows the example results of a creator “Yamaneko Sanae.” The user can browse the list of derivative works posted by the creator. In addition, for each derivative work v, an original work or a derivative work that influenced v (denoted by “Influenced by”) and derivative works that are influenced by v (denoted by “Influenced on”) are displayed. By clicking on “Derivation Graph,” the user can see the derivative work’s detailed information as described in Sect. 4.3.

5. Discussion

In this section, we describe how Songrium Derivation Factor Analysis is useful for both consumers and creators. In particular, we mention new findings for them by using concrete examples.

With ordinary video sharing services, consumers usually search for videos according to metrics such as the view

Fig. 9 Creator profile.

count and uploaded date; while the Original Works Map enables consumers to explore original videos based on thir characteristics in the derivative creation activity. For example, by selecting the "Dancing" category, consumers can find original videos that are standard for dancers from the "Standard" area on the map. By selecting the "Singing" category, they can also find original videos that are difficult to sing from the "Challenging" area.

This function is also useful for creators to find an original video to create a derivative video from a new viewpoint. For example, for novice creators, it would be useful to be able to search for original songs in the "Standard" area; while for skillful creators, original songs in the "Challenging" area would be fascinating. In addition, novice creators can find out that original videos having a high view count and/or many derivative works are not always appropriate to use for creating derivative videos. For example, an original video has over one million view counts and as many as 199 derivative videos in the "Dancing" category. Looking at only such statistics, this original video may seem to be appropriate for novice creators. However, this original video is mapped to the "For expert" area. By using our service, novice creators can avoid original videos that are popular but inappropriate for them. On the other hand, skillful creators can find out that original videos with low view counts and a handful of derivative videos do not always require a high level of skill because many of such videos are mapped to the "Standard" area. Our service enables skillful creators to find original videos that really require high skill from the "Challenging" area.

The Derivation Tree enables consumers to explore derivative videos from a new viewpoint: the influence of each derivative video. For example, in Fig. 6, the derivative video that the cursor is hovering over has influence because our model estimates that the video triggered eight derivative videos. Without our service, it is difficult to find such an influential derivative video. Derivative videos that have high view counts are not always influential videos, as shown

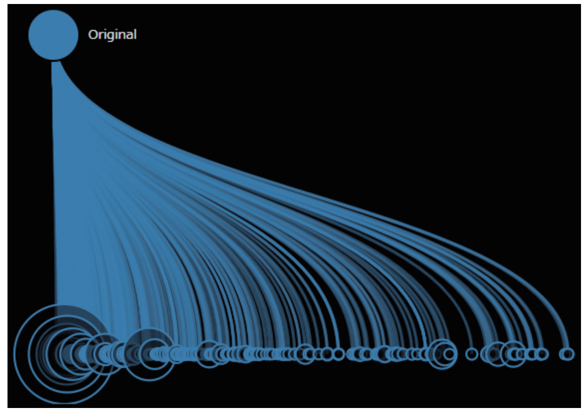

Fig. 10 Derivation tree of an original video in the "Singing" category.

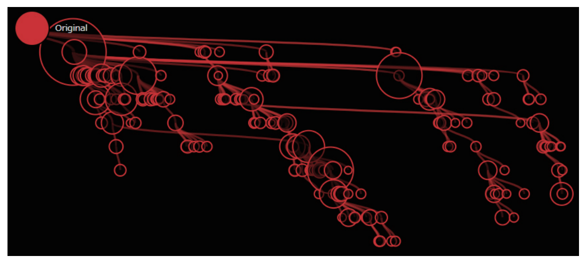

Fig. 11 Derivation tree of an original video in the "Dancing" category.

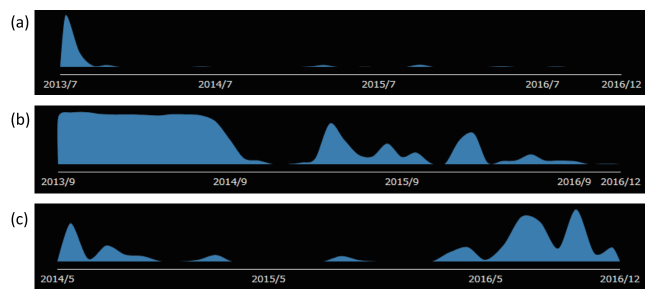

Fig. 12 Examples of popularity influence transition graph.

in Fig. 10. Hence, video exploration based on influence can only be realized by using our model. In another example, Fig. 11 shows the tree for an original video in the "Dancing" category. In the tree, one of the most influential derivative videos was the video in which the creator danced to the original song with her own choreography. Since other creators imitate the choreography, the derivative video does have a big influence. Although our model did not know which derivative video had the original choreography, our model was able to estimate that the derivative video had a big influence.

In terms of the Popularity Influence Transition Graph, as shown in Fig. 12, the popularity influence transition is very different from one original video to another. For example, Fig. 12 (a) shows that the popularity influence is high only during the earliest stage of the derivative creation activity. In Figs. 12 (b) and (c), the popularity has a big influence

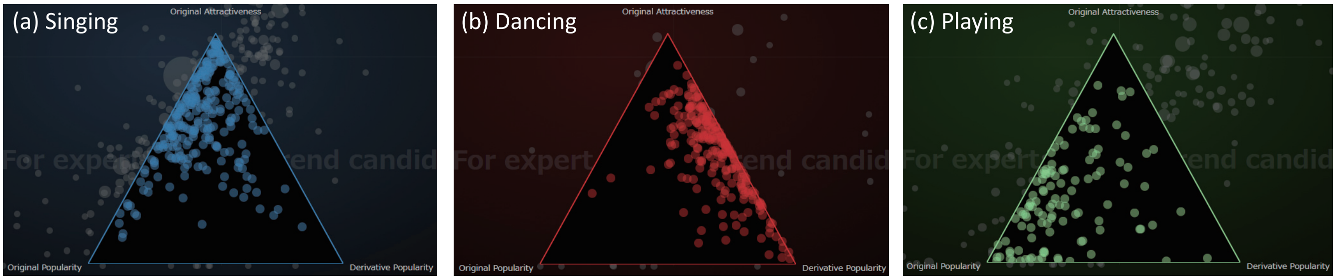

Fig. 13 Examples of creator distribution map.

during the early part and the latter part, respectively. Hence, for creators who put a high priority on popularity, the original video of (c) is more appropriate to use for creating a derivative video than those of (a) and (b) as of December 2016. By using the Popularity Influence Transition Graph, creators can find out if now is the appropriate time to create the original video's derivative video.

By viewing the Creator Distribution Map of an original video, consumers can find out which of the three factors creators tend to put a high priority on. In Fig. 13, (a), (b), and (c) represent the maps of original videos in the "Singing," "Dancing," and "Playing," respectively. The tendency is very different according to the categories and original videos. This function also enables consumers to explore creators. For example, in Fig. 13 (c), since most creators put a high priority on Opop, consumers can find a typical creator in this original video's derivative creation activity around the Opop corner of the map; while they can also find an atypical creator around the Dpop corner.

Finally, by using the Creator Profile, consumers can easily find the characteristics of a creator in terms of whether he/she tends to be influenced by an original video or other derivative videos and whether he/she tends to influence other creators' creation activity. For example, as the creator in Fig. 9 puts a high priority on Oatt, three of the four derivative videos are influenced by the original video. Moreover, since two derivative videos created by this creator triggers other derivative videos, consumers can find out that this creator has influence in the derivative creation activity.

6. Conclusion

In this paper, we described a public web service called *Songrium Derivation Factor Analysis* that was implemented by applying our proposed model, which infers latent factors and their influences in derivative creation activity, to datasets obtained from the video sharing service Niconico. Songrium Derivation Factor Analysis has several functions that could enable users to browse and watch videos from a new viewpoint and decide which content they use to create a new derivative work. We have to carry out evaluations such as a user study to clarify the sufficiency of the proposed functions; we leave this as future work. Although we applied our model to the data on Niconico, our model can be applied to any data if the conditions mentioned in Sect. 3.1 are satisfied. For future work, we plan to analyze users' click logs on our web service and discuss if our service influences users' video watching behaviors (*e.g.*, if videos that have a larger influence are watched more often). We are also interested in deeper analysis regarding how creators use our service to find an original work that they want to use for creating a new derivative work.

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