Predicting the Popularity of *DanMu*-enabled Videos: A Multi-factor View

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Abstract. Recent years have witnessed the prosperity of a new type of real-time user-generated comment, or so-called *DanMu*, in many recent online video platforms. These *DanMu*-enabled video platforms present scrolling marquee comments overlaid directly on top of the videos by synchronizing these comments to specific playback times. In this paper, we study the prediction of video popularity in these platforms, which may benefit a lot of applications ranging from online advertising for website holders to popular video recommendation for audiences. Different from traditional online video platforms where only traditional reviews are available, these *DanMu*s make viewers easily see other viewers' opinions and communicate with each other in a much more direct way. Consequently, viewers are easily influenced by others' behaviors over time, which is considered as the herding effect in social science. However, how to address the unique characteristics (i.e., the herding effect) of *DanMu*-enabled online videos for more accurate popularity prediction is still under-explored. To that end, in this paper, we first explore and measure the herding effect of *DanMu*-enabled video popularity from multiple aspects, including the popular videos, the popular *DanMu*s and the newly updated videos. Also, we recognize that the uploaders' influence and video quality affect the video popularity as well. Along this line, we propose a model that incorporates the herding effect, uploaders' influence and video quality for predicting the video popularity. An effective estimation method is also proposed. Finally, experimental results on real-world data show that our proposed prediction model improves the prediction accuracy by 47.19 % compared to the baselines.

1 Introduction

Recent years have witnessed the rapid development of online video platforms and the prosperity of real-time user generated comment, or so-called *DanMu*, in many

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online video platforms such as Acfun[1] and Bilibili[2]. Different from traditional online reviews that are displayed in a separate space outside the video (e.g., Youtube.com[3]), *DanMu* as a new type of comment is overlaid directly on the top of videos by synchronizing the comment to specific playback times. As a matter of fact, the *DanMu*-enabled video has activated user's behaviors, such as comments, views and so on. For instance, a recent report by a leading Chinese *DanMu*-enabled platform reveals that *DanMu* has improved the online user activity by 100 times[4]. Understanding *DanMu*-enabled video's popularity growth is of great importance for a broad range of services, such as online ads. in video platforms, video recommendation for users, and other commercial opportunities.

In the literature, many efforts have been devoted to predict the popularity of online videos. For example, some works have shown that the popularity of online video is positively correlated to the historical views and the number of comments generated by users [6,7]. Intuitively, a viewer could directly see others' interactions (e.g., views and comments) with videos, which makes whether the viewer watches a particular video is easily affected by other users' previous interactions with this video. This phenomenon is known as the herding effect in social science and it is widely studied in financial markets [1,10,12]. Generally, the herding effect is defined as *everyone doing what everyone else doing, even when their private information suggests doing something quite different* [3]. For example, in the stock market, if few people begin to sell a certain type of stock, it may lead to the overall crowd panic and selling spree. Similarly, in the online video platforms, people's decision on whether to watch a particular video is also influenced by others' behaviors, thus we argue that the herding effect should play an important role for video popularity prediction.

In fact, there exists considerable works on predicting the popularity of videos based on the herding effect, which empirically show that a video will attract new views at a rate proportional to the number of views already acquired [8,16]. However, compared to traditional online videos, the *DanMu* makes the herding effect stronger and more dynamic, as the simultaneously displayed *DanMu* comments convey interesting information about the content of videos and make viewers communicate with each other in a much more direct way. Thus users are more easily affected by other users to view videos or not on *DanMu*-enabled video sites. However, few of existing approaches could be directly applied to this prediction task due to the following two challenges caused by the unique characteristics of *DanMu*-enabled videos. First, compared to traditional videos, people interact with *DanMu*-enabled videos more frequently from various aspects, e.g., the views of videos and the *DanMu*s associated with videos. In the meantime, due to the temporal variation of these videos, the herding effect is dynamic and changes from time to time. How to capture the dynamic herding effect from multiple aspects? Second, how to combine the dynamic herding effect with other

[1] http://www.acfun.tv/.
[2] http://www.bilibili.com/.
[3] http://www.youtube.com/.
[4] http://digi.163.com/14/0915/17/A66VE805001618JV.html.

features (e.g., the video quality and the uploaders' characteristics) that may influence the popularity of *DanMu*-enabled videos for the prediction?

To this end, as a pilot study, we aim at predicting the popularity growth of *DanMu*-enabled videos by leveraging the unique characteristics of *DanMu*-enabled videos. Specifically, we first propose a measurement to quantify the herding effect from multiple aspects of *DanMu*-enabled videos, including the popular videos, the popular *DanMu*s and the newly updated videos. Then we propose a prediction model to combine the herding effect with other factors that may influence the video popularity. After that an efficient estimation method is proposed to automatically learn the herding effect and other parameters. Finally, we conduct experiments with a real-world data set collected from a *DanMu*-enabled online video platform. The experimental results show that our proposed model improves the prediction accuracy by 47.19 % compared to the baselines.

2 Related Work

To the best of our knowledge, no prior work has considered the dynamic herding effect and *DanMu* information to predict the popularity of videos. However, there have been considerable prior works on predicting the popularity of videos.

Many prior works have analyzed different aspects of video's metrics such as total views, total comments, total collects and so on [6,7]. Cha et al. [7] analyzed the intrinsic statistical properties of video popularity distributions and studied the popularity lifetime of videos and the relationship between requests and video age. Mitra et al. [15] found the presence of "invariant" among video's characteristics, such as heavy-tailed total views distributions and the positive correlation between total views and total ratings.

Some researchers made preliminary studies on predicting the popularity growth of videos. For instance, Borghol et al. [5] developed a methodology that was able to assess accurately, both qualitatively and quantitatively, the impacts of various content-agnostic factors on video popularity. What's more, there exist some prediction models [8,16] based on the herding effect [4]. Such as Szabo et al. [16] leveraged the observation that the total views received soon after a video was uploaded provided a strong indication of its total future views to develop a prediction model for video views; this method is applied by some works to build predictive popularity based on applying regression to different feature spaces [2,11,14,17]. Recently, Le et al. [13] presented an adoption model that considered multiple aspects for product adoption. Our model advances their work by considering the unique characteristics of Danmu enabled videos.

Although there exist some works considering the herding effect in the popularity growth model, none of them considered the dynamic herding effect from multiple aspects over time. Especially, these works just suggested that a video would attract new views at a rate proportional to the number of views already acquired. They have not considered what the impact of the popular videos based on different aspects' herding effect to other videos over time.

To the emerging type of user-generated comment *DanMu*,some recent works focused on this new DanMu phenomenon. Among them, there are only two works that have used *DanMu* data, but neither of them use the *DanMu* information to predict the popularity growth of videos. Specifically, Wu *et al.* [19] leveraged the textual content of *DanMu*s to extract time-sync video tags automatically and Wu *et al.* [20] investigated the co-relation between the volume of one particular *DanMu* and popularity measures such as the number of replays and bookmarks of videos. Our work differs from studies as we put emphasis on predicting the popularity growth of *DanMu*-enabled videos.

In summary, in our work, we combine the unique nature of *DanMu* and the dynamic herding effect from multiple aspects to predict the popularity of videos. Besides using the *DanMu* information and the dynamic herding effect, we also make use of video quality and uploaders' influence to the proposed prediction model, which makes the prediction model more accurate and effective.

3 Data and Statistics

In this section, we first illustrate the nature of *DanMu* comments in *DanMu*-enabled websites and introduce the collected data set, and then present some unique characteristics of this data set.

3.1 *DanMu* Illustration and Data Collection

In Fig. 1, we show two snapshots of a sample video[5] that include several Chinese *DanMu*s on top of the video. We pick up four *DanMu*s by different viewers, translate them to English and show them at the bottom. The green axis at the bottom indicates the video time, where the selected four *DanMu*s are aligned based on the associated video time. The *DanMu*s "God, Norton" and "Edward Norton" written by user A and user B are about the actor of the officer in the snapshot, which are very close at the video time. Also we can observe that previous *DanMu*s have direct influence on future *DanMu*s. For instance, after users A and B mention the name of the actor in their *DanMu*s, user C mentions the movie "Fight Club" acted by the same actor, and then user D mentions another movie (i.e., "Red Dragon") acted by the same actor. From this example, we can see that *DanMu* enables much more intensive communication among users than traditional reviews.

We crawled a dataset from acfun.tv, a leading *DanMu* website in China of each day, which makes that we can capture the dynamics of the dataset. The collected dataset contains videos that are uploaded during early November to the end of May, which lasts for about half a year. For each video, we collected users' behaviors of a video that include: *Views* (the number of views), *DanMu*s (the number of *DanMu*s), *TReviews* (the number of traditional reviews), *Collects* (the number of collects), and *Coins* (the number of coins). Specifically, when a viewer thinks the video is valuable and interesting, she can give some coins to the uploader by buying it from the website. Table 1 shows a summary of

[5] Available at http://www.acfun.tv/v/ac1731008.

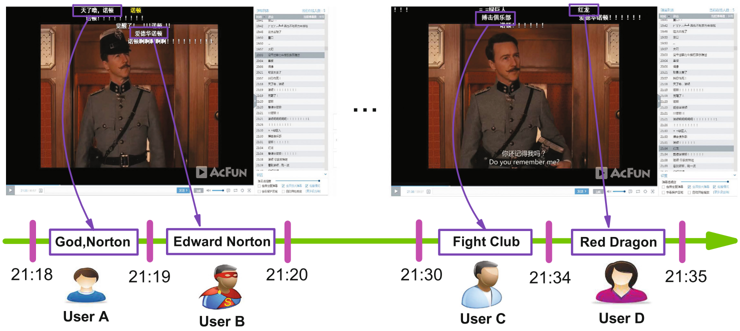


Fig. 1. Two snapshots of a *DanMu*-enabled video (Color figure online).

Table 1. Video features.

Feature	Total count	Avg count
Videos	3,623	Null
Views	73,059,811	20187.85
DanMus	883,637	243.89
TReviews	60,956	16.84
Collects	308,448	85.23
Coins	220,578	60.95

Table 2. Uploader information.

# Uploaders	745
# Videos	3,623
Avg # of Videos per uploader	4.86
# Followers	278,520
Avg # of followers per uploader	373.85

video features. As can be seen from this table, there are much more user activities on Views than other user behaviors. It is reasonable as the view behavior does not need extra action from viewers compared to other features. And the *DanMu* activities are more active than TReviews, Coins and Collects. All these comparisons reflect that the *DanMu* function has attracted much more users' contribution and that online viewers prefer to write *DanMus* rather than do other behaviors for *DanMu*-enabled videos.

Also, for each video, we collected the uploader information as shown in Table 2. We can find that some uploaders upload more than 1 video as the average number of videos per uploader is 4.86. And the average number of followers per uploader is closed to 400, which confirms that there exists strong social atmosphere in acfun.tv. It enhances that we need consider the social influence in predicting the popularity growth in our model.

As a preliminary, we first provide the formal definition of *the popularity for videos*. Intuitively, as the videos can be viewed by viewers anytime after they are uploaded, views of videos at different time compose the popularity of videos. Formally, we set v_{mt} as the views of video m until day t and v_t as the total views of all videos until day t. For simplicity, we adopt the proportion of views as the popularity of video m until day t denoted as $p_{mt} = \frac{v_{mt}}{v_t}$. Due to the herding effect towards to popular videos, then we provide the statement of *the popular videos*. Similar to the traditional definition of popular videos, we define that the popular videos are those videos which are more probably chosen by viewers. For example, if a video has the largest number of views or *DanMu*s, viewers choose this video to view with a greater probability than other videos. Also, if a video is newly uploaded, viewers prefer to choose this video to watch as well.

3.2 Volume Distributions

Video Features. Figure 2 shows the distribution of the number of views per video. As can be seen from this figure, a few videos attract much more views, which reflects that there is a strong herding effect on user's viewing behavior as most viewers toward to view few popular videos. We also draw histograms of other four video statistics (i.e., TReviews, Collects, Coins and *DanMu*s) in Fig. 3. As depicted by this figure, about 71 % videos have less than 100 *DanMu*s and 85 % videos have less than 1000 *DanMu*s. Compared to *DanMu* volume distribution, nearly 99 % videos have less than 1000 TReviews, Collects and Coins. Thus, we empirically conclude that *DanMu* behavior is more active than other three behaviors.

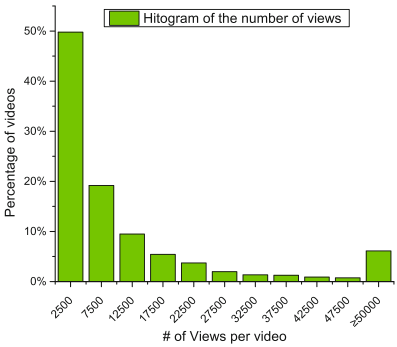


Fig. 2. Histograms of views.

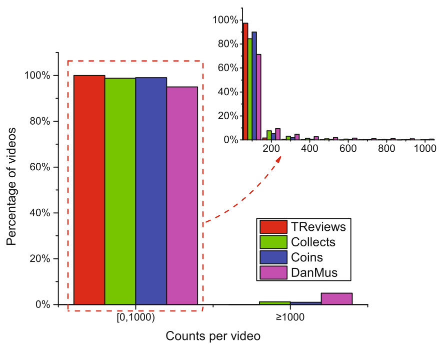


Fig. 3. Histograms of other four features.

To explore whether there are correlation between video popularity and other video features, we represent each video feature statistics in a vector $\boldsymbol{VF_f} = (VF_{f1}, \cdots, VF_{fM})$ and the popularity in a vector $\boldsymbol{VP} = (VP_1, \cdots, VP_M)$, where VF_{fm} is the value of feature f for video m, and VP_m is the value of popularity for video m. Then we compute the correlation of $\boldsymbol{VF_f}$ and $\boldsymbol{VP}$ by using Pearson correlation measure [9]. This measure is widely used to measure the liner dependency between two vectors. Detailed Pearson correlation values of video features and the video popularity is $(TReviews, Collects, Coins, DanMus) = (0.72, 0.75, 0.59, 0.70)$. We find that all Pearson values are non-negative and larger than 0.55. Based on this observation, we can conjecture that the feature statistics are positively correlated with the popularity of a video. Thus all of these four features should be leveraged when modeling the popularity of videos.

Uploader Features. Also we demonstrate a simple correlation analysis between the number of uploaded videos and followers as the correlation value will more directly reflect the uploader's activity and social influence. The Pearson correlation between the number of uploaded videos and followers is 0.47, which enhances our conjecture that the uploader who has uploaded more videos has stronger social influence.

4 The Proposed Model

As illustrated above, due to the unique characteristics of *DanMu*-enabled videos, the popularity of videos has a large dynamic herding effect from multiple aspects. In this section, we propose a model that utilizes the dynamic herding effect to predict the popularity of videos. Also, to fully leverage all the factors that influence a video's popularity, we also consider *DanMu* information, video quality and uploaders' influence. Table 3 lists the notations used in this paper.

4.1 Dynamic Herding Effect from Multiple Aspects

As we know, compared with traditional online videos, the *DanMu* makes the herding effect stronger and more dynamic, which means that users are more

Table 3. Mathematical notations.

Symbol	Description
k	The aspect of popular videos
HE_{mt}	A combination of herding effect from multi aspects of video m on day t
$o_{k,t}$	The center of aspect k's popular videos on day t
$dis_{m,o_{k,t}}$	The distance between video m and $o_{k,t}$
$\theta_{k,t}$	k-th aspect's parameter of herding effect on day t
$\boldsymbol{VQ}_m$	A vector representing video m's quality
$\boldsymbol{UI}_m$	A vector representing video m's uploader's influence
p_{mt}	The popularity of video m on day t
a_i	The coefficient of popularity between p_{mt} and $p_{m(t-i)}$
β	The coefficient of herding effect
$\boldsymbol{\gamma}$	The coefficient vector of video quality
$\boldsymbol{\delta}$	The coefficient vector of uploaders' influence
M_{t-1}	The number of videos on day $t-1$
v_{mt}	The number of views of video m until day t
v_t	The number of views of all videos until day t

inclined to view popular videos and more easily affected by other users to view videos or not on *DanMu*-enabled video sites. Specially, when viewers have no specific videos to view, they usually rank the videos by the number of views and choose top ranking videos to view. Therefore, we conjecture that the popularity of videos is affected by the dynamic herding effect of views. Besides the dynamic herding effect of views, we also find that more users tend to view newly uploaded videos and popular videos ranked by the number of *DanMu*s. Based on these observations, we propose three types of dynamic herding effect: the dynamic herding effect of views, the dynamic herding effect of *DanMu*s and the dynamic herding effect of uploaded date. Specifically, we set the aspect k as the type of popular videos: $k = 1$ stands for the popular videos measured by the number of views, $k = 2$ represents the popular videos measured by the number of *DanMu*s and $k = 3$ represents the popular videos measured by the uploaded date of videos. And we set HE_{mt} as a combination of dynamic herding effect from these three aspects of video m on day t as $HE_{m,t} = \prod_{k=1}^{K} [1 + dis_{m,o_{k,t}}]^{-\theta_{k,t}}$, where $o_{k,t}$ is the popular videos' center of aspect k on day t and $\theta_{k,t}$ stands for k-th aspect's parameter of herding effect on day t. Then we give details of $dis_{m,o_{k,t}}$, which stands for the distance between video m and $o_{k,t}$ as follows:

$$dis_{m,o_{1,t}} = \frac{|\overline{v}_{o_{1,t}} - v_{m(t)}|}{\overline{v}_{o_{1,t}}}; \quad dis_{m,o_{2,t}} = \frac{|\overline{d}_{o_{2,t}} - d_{i(t)}|}{\overline{d}_{o_{2,t}}}; \quad dis_{m,o_{3,t}} = \frac{|\overline{u}_{o_{3,t}} - u_{m(t)}|}{\overline{u}_{o_{3,t}}}.$$

where $\overline{v}_{o_{1,t}}$ is the average number of views of popular videos, $\overline{d}_{o_{2,t}}$ is the average number of *DanMu*s of popular videos and $\overline{u}_{o_{3,t}}$ is the average uploaded date of popular videos on day t.

4.2 Predicting Model on Videos

Except for the dynamic herding effect from multiple aspects, the generation of a new video's view is also driven by video quality and uploaders' influence.

Video Quality. Intuitively, if the quality of a video is high, the popularity of this video may be greater in the next time. So, we import a vector $\boldsymbol{VQ}_m$ representing video m's quality. Based on our application, we choose five features for video quality: VQ_{m1}, total views; VQ_{m2}, total TReviews; VQ_{m3}, total collects; VQ_{m4}, total coins; VQ_{m5}, total *DanMu*s.

Uploaders' Influence. We have found that many users choose videos uploaded by influential uploaders to watch. In view of this observation, we conjecture that the growth of popularity is also affected by the uploaders' influence. Intuitively, if an uploader has more followers, it means that the uploader has greater influence. Similarly, the number of uploaded videos and the average views of uploaded videos also have a positive correlation to the influence of the uploader. To this end, we set the vector $\boldsymbol{UI}_m$ as video m's uploader's influence and choose these three features representing uploaders' influence: UI_{m1}, total uploaded videos; UI_{m2}, total followers; UI_{m3}, the average views of uploaded videos.

While features' values of video quality and uploaders' influence are not in same scale, so we use the transformation $\frac{Max(f)-f}{Max(f)-Min(f)}$ to process the original values of each feature to eliminate the extreme features' influence.

Inspired by the model introduced in [18], which investigated the influence of the prevailing consensus on current analysts' recommendations' choices (strong buy, buy, hold, sell, and strong sell) in a stock, and predicted analysts' recommendations' choices based on the herding effect of the prevailing consensus in the stock by a new proposed statistical model (the prevailing consensus was defined as popular recommendations' choices), we can draw a close analogy to the context in [18]: a user chooses a video to view, which is also affected by the prevailing consensus (popular videos), and then we propose a general framework to predict the popularity p_{mt} for video m on day t as follows:

$$\tilde{p}_{mt} = \sum_{i=1}^{I} a_i \frac{p_{m(t-i)}(\beta * HE_{m,t-i} + \boldsymbol{\gamma}^T * \boldsymbol{VQ}_{m,t-i} + \boldsymbol{\delta}^T * \boldsymbol{UI}_{m,t-i})}{D_{t-i+1}}, \qquad (1)$$

where D_t ensures that all videos' popularity sum to 1, a_i is the coefficient of popularity between p_{mt} and $p_{m(t-i)}$, β stands for the coefficient of herding effect, $\boldsymbol{\gamma}$ stands for the coefficient vector of video quality, $\boldsymbol{\delta}$ stands for the coefficient vector of video uploader's influence and M_{t-1} represents the number of videos on day $t-1$. The popularity $p_{m(t-1)}$ of video m on day t is equal to $v_{m(t-1)}/v_{t-1}$ and p_{mt} is v_{mt}/v_t. While our application adds new videos over time, we adjust the $p_{mt} = \frac{v_{mt}}{v_t - v_{new,t}}$ to eliminate the effect of new adding videos, where $v_{new,t}$ is total views of new adding videos on day t.

Comparing to the original model [18]: $p_{i,j}(\sigma, \tau) = p_{i,j}(0)\left\{\frac{[1+(j-\tau)^2]^{-\sigma}}{D_i}\right\}$, where τ is the popular recommendation choice, σ is the parameter of herding effect, we have improved the original model to our model Eq. 1 on four aspects: First, the parameter of herding effect is dynamic and changes from time to time in our model, while the parameter of herding effect is constant over time in [18]. Second, we import the dynamic herding effect of multiple aspects (views, *DanMu*s and uploaded date), while the original model only adopted one aspect (the popular recommendation choice). Third, the popularity for a video correlates with several previous days in our work, while the proportion only correlates with the only day before in [18]. Fourth, we combine five features (total views, total TReviews, total collects, total coins and total *DanMu*s) of video quality and three features (total uploaded videos, total followers and the average views of uploaded videos) of uploaders' influence to predict the popularity of videos. These improvements make our prediction model more effective and more generalized.

4.3 Parameters Learning Algorithm

Optimizing Functions. The value of $\theta_{k,t}$ stands for the t-th day's herding effect of aspect k on other videos, if $\theta_{k,t} = 0$, it means that the popular videos regarding aspect k have no effect on other videos. If $\theta_{k,t} > 0$, it means that the popular videos have a positive effect on other videos. And if $\theta_{k,t} < 0$, it means that the popular videos have a negative effect on other videos. As we know p_{mt}, VQ_m, UI_m and $dis_{m,o_{k,t-1}}$, we use the Eq. 2 to learn parameters as follows:

$$J = \min_{\{\theta_{k,t-i},a_i,\beta,\gamma_j,\delta_u\}} \frac{1}{2}\left[\sum_{t=I+1}^{T}\sum_{m=1}^{M_{t-1}}(p_{mt}-\tilde{p}_{mt})^2+\sum_{i=1}^{I}a_i^2+\beta^2+\sum_{j=1}^{J}\gamma_j^2+\sum_{u=1}^{U}\delta_u^2\right] \tag{2}$$

where T is longevity of the dataset by day.

We use the gradient descent algorithm to learn all parameters, which is very effective for learning parameters. For simplicity, we define symbols $C_{m,t-i}$, $d_{mk(t-i)}$ as Eq. 3.

$$\begin{aligned} C_{m,t-i} &= p_{m(t-i)}(\beta * HE_{m,t-i} + \boldsymbol{\gamma}^T * \boldsymbol{VQ}_{m,t-i} + \boldsymbol{\delta}^T * \boldsymbol{UI}_{m,t-i}) \\ d_{mk(t-i)} &= 1 + dis(m, o_{k,t-i}) \end{aligned} \tag{3}$$

At first, we calculate the partial derivatives of all parameters. For space limitation, we omit the inferencing process of the partial derivatives and directly give the partial derivatives' equations of $a_i, \beta, \gamma_j, \delta_u$ and $\theta_{k,t-i}$ as follows:

$$J_{a_i}^{(1)} = \sum_{t=I+1}^{T}\sum_{m=1}^{M_{t-1}}(\tilde{p}_{mt}-p_{mt}) * \frac{C_{m,t-i}}{D_{t-i+1}} + a_i \tag{4}$$

$$\begin{aligned} J_{\beta}^{(2)} = \sum_{t=I+1}^{T}\sum_{m=1}^{M_{t-1}}(\tilde{p}_{mt}-p_{mt})\sum_{i=1}^{I}\Big\{ \frac{a_i}{D_{t-i+1}^2}[D_{t-i+1}p_{m,t-i}HE_{m,t-i} \\ - C_{m,t-i}\sum_{m_1=1}^{M_{t-i}}(p_{m_1,t-i}HE_{m_1,t-i})]\Big\} + \beta \end{aligned} \tag{5}$$

$$\begin{aligned} J_{\gamma_j}^{(3)} = \sum_{t=I+1}^{T}\sum_{m=1}^{M_{t-1}}(\tilde{p}_{mt}-p_{mt})\sum_{i=1}^{I}\Big\{ \frac{a_i}{D_{t-i+1}^2}[D_{t-i+1}p_{m,t-i}VQ_{mj,t-i} \\ - C_{m,t-i}\sum_{m_1=1}^{M_{t-i}}(p_{m_1,t-i}VQ_{m_1j,t-i})]\Big\} + \gamma_j \end{aligned} \tag{6}$$

$$\begin{aligned} J_{\delta_u}^{(4)} = \sum_{t=I+1}^{T}\sum_{m=1}^{M_{t-1}}(\tilde{p}_{mt}-p_{mt})\sum_{i=1}^{I}\Big\{ \frac{a_i}{D_{t-i+1}^2} * [D_{t-i+1}p_{m,t-i}UI_{mu,t-i} \\ - C_{m,t-i}\sum_{m_1=1}^{M_{t-i}}(p_{m_1,t-i}UI_{m_1u,t-i})]\Big\} + \delta_u \end{aligned} \tag{7}$$

$$J^{(5)}_{\theta_{k,t-i}} = \sum_{t=I+1}^{T} \sum_{m=1}^{M_{t-1}} (\tilde{p}_{mt} - p_{mt}) \frac{a_i}{D^2_{t-i+1}} \Bigg[C_{m,t-i} \sum_{m_1=1}^{M_{t-i}} (\beta p_{m_1,t-i} \ln d_{m_1 k(t-i)} \, {d_{m_1 k(t-i)}}^{-\theta_{k,t-i}}) - D_{t-i+1} \beta p_{m,t-i} {d_{mk(t-i)}}^{-\theta_{k,t-i}} \ln d_{mk(t-i)} \Bigg] \quad (8)$$

Updating Parameters. We have generated the partial derivatives of all parameters, then we obtain their update rules of a_i, β, γ_j, δ_u and $\theta_{k,t-i}$ as follows:

$$(a_i, \beta, \gamma_j, \delta_u, \theta_{k,t-i})^{(n+1)} = (a_i, \beta, \gamma_j, \delta_u, \theta_{k,t-i})^{(n)} - \eta(J^{(1)}_{a_i}, J^{(2)}_{\beta}, J^{(3)}_{\gamma_j}, J^{(4)}_{\delta_u}, J^{(5)}_{\theta_{k,t-i}})^{(n)} \quad (9)$$

where η is the learning rate.

Initialization. To set a proper starting point for learning, we set all features equal value at start. Under this assumption, we have the following settings:

$$\begin{cases} \beta_m = 1 & \\ \theta_{k,t-i} = 1/K, & \text{where } K \text{ is multible aspects;} \\ a_i = 1/I, & \text{where } I \text{ is linear regression days;} \\ \gamma_j = 1/J, & \text{where } J \text{ is video's featurs;} \\ \delta_u = 1/U, & \text{where } U \text{ is uploader's features;} \end{cases} \quad (10)$$

After initialization, we iterate the learning algorithms updating parameters until the objective function converges.

5 Evaluation

To evaluate the effectiveness of the proposed prediction model, we present an empirical evaluation. We use the real video data introduced in Sect. 3.1 to validate our proposed models.

5.1 Comparison Models

We compare the performance of our prediction model to five additional popularity growth models:

(a) Constant Scaling model (CSM), which has been introduced in [16]. The CSM leveraged the observation that the total views received soon after a video was uploaded provided a strong indication of its total future views to develop a prediction model for video popularity.
(b) Linear regression model about p_{mt} (pmtREG). The pmtREG is linearly correlated to previous I days' popularity as $\tilde{p}_{mt} = \sum_{i=1}^{I} a_i * p_{m(t-i)}$.

(c) Linear regression model about video quality (qualityREG). The qualityREG is linearly correlated to video quality as $\tilde{p}_{mt} = \sum_{n=1}^{N} \lambda_n * VQ_{mn,t-1}$, where λ_1 stands for the coefficient of Views, λ_2 stands for TReviews' coefficient, λ_3 stands for Collects' coefficient, λ_4 stands for Coins' coefficient and λ_5 stands for *DanMu*s' coefficient.
(d) Fixed Herding Effect model (FM). The FM only adopts fixed herding effect, which means that each day has the same herding effect about parameter θ_k, without combining video quality and uploaders' influence.
(e) Dynamic Herding Effect model (DM). The DM only uses dynamic herding effect, which means that each day has different herding effect of parameter θ_k, without combining video quality and uploaders' influence, too.

We implemented all the methods in C# and conducted experiments on a Windows 8 system with a 3.4 GHz Intel i7 CPU and 32 GB memory. For comparing the learning ability of growth models, we dynamically adjust the length of training days including 80 days, 95 days, 110 days, 125 days and 140 days and use the following days for testing.

5.2 Validating Popularity Growth Models

In this first step of experiment, we validate the effectiveness of different popularity growth models. As we predict the popularity of the video m, the most direct and efficient evaluation index is to compute the average absolute difference ratio between observation values and prediction values as $aadr_t = \frac{\sum_{m=1}^{M_t} \frac{Abs(\tilde{p}_{mt} - p_{mt})}{p_{mt}}}{M_t}$.

The experimental results of *aadr* are exhibited in Fig. 4. We find that popularity growth models (e.g. DM, HVUM) adopting dynamic herding effect have smaller *aadr* than other popularity growth models (e.g. CSM, FM) across all training days, which reflects that the dynamic herding effect contributes significantly to reducing the prediction error of popularity growth. And as training days increasing, the *aadr* of each growth models becomes decrease due to more training information conduces to learn parameters of growth models accurately.

To exhibit the improvement and difference among different growth models clearly, we add the relative improvement of *aadr* (denoted as RelativeImp), which calculates the rate of each model's improvement compared to CSM been extensively adopted in many previous popularity growth models. And Fig. 5 demonstrates the average values of *aadr* and RelativeImp. We observe that the *aadr* 13.71 % of FM is the worst one among all growth models, which shows that the fixed herding effect can not accurately capture the dynamics of popularity growth. And regarding to RelativeImp, both linear regression models (pmtREG: -30.58 %, qualityREG: -108.18 %) have no advantages on predicting popularity dynamic growth compared to CSM. It is noticed that the HVUM has the best prediction ability on popularity dynamic growth with the minimum 3.27 % of *aadr* and the maximum 47.19 % of RelativeImp. Particularly, our proposed model HVUM has improved 5 % accuracy compared to DM on RelativeImp, which demonstrates that the video quality and the uploaders' influence contribute to improving the prediction accuracy on popularity dynamic growth.

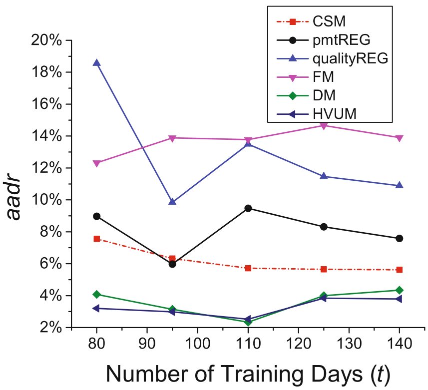
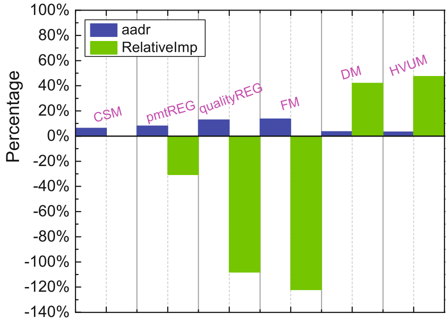


Fig. 4. *aadr* with training days.



Model	CSM	pmtREG	qualityREG	FM	DM	HVUM
aadr	6.17%	8.06%	12.85%	13.71%	3.58%	3.27%
RelativeImp	/	-30.58%	-108.18%	-122.08%	42.04%	47.19%

Fig. 5. Average *aadr* and RelativeImp.

We can thus conclude that the HVUM faithfully captures the growth dynamics of video popularity with rich and insufficient training information.

5.3 Impact of Different Video Features

Next, we take a deep analysis about the training values of video quality's coefficients $\gamma_1 = 0.0015, \gamma_2 = -0.0055, \gamma_3 = -0.0036, \gamma_4 = 0.0029, \gamma_5 = -0.0017$ to explore the impact of different features of video quality. We find that the next day's popularity is most relevant to previous day's Coins as $\gamma_4 = 0.0029$, which reflects that the only paid feedback Coins is the most relevant feature to the dynamic growth of popularity among all features. And the feature Views also plays an important role in predicting the next day's popularity as $\gamma_1 = 0.0015$. While the *DanMu*s' coefficient γ_4 equals to -0.0017, it shows that the feature of *DanMu*s plays a significantly negative effect on predicting the dynamic growth of popularity. Nevertheless, in previous works, none work adopts the *DanMu* information to improve the accuracy of popularity models.

5.4 Describing Herding Effect

In Sect. 5.2, the dynamic herding effect contributes significantly on improving the accuracy of popularity growth models. In this section, we take an in-depth analysis about fixed and dynamic herding effect respectively.

At first, we give training values of $(\theta_1, \theta_2, \theta_3) = (-0.0036, -0.0076, 0.0077)$ of FM to analyze different aspects' fixed herding effect. We find that both θ_1 and θ_2 are less than 0, which shows that the popular videos measured by the aspects of views and *DanMu*s have a negative effect on other videos. However, θ_3 is larger than 0, which shows that each day's new videos excite users to view other videos. Based on these two observations, we know that the popular videos according to the number of views and *DanMu*s inhibit users to view other videos

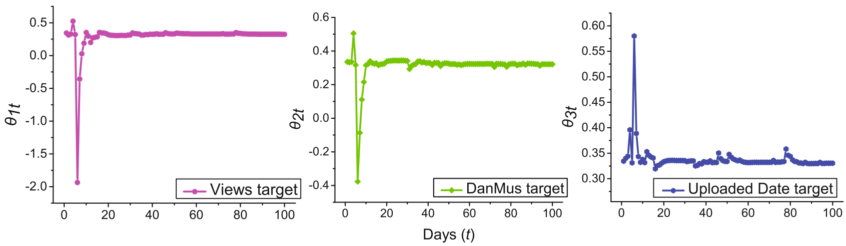


Fig. 6. Herding effect parameters' dynamic change.

and if the website holders add new videos to their owning websites everyday, the traffic of videos' services will be improved.

At the end, we demonstrate the training values of HVUM to explore the effect of the dynamic herding effect of different aspects on predicting the popularity growth in Fig. 6. Based on Fig. 6, we can draw several implications: First, the popular videos according to each aspect have different effect on other videos on different days. For example, to the dynamic herding effect of the views aspect, the popular videos have a positive effect on other videos on the day 1 as $\theta_{11} = 0.34$, while the popular videos have a negative effect on other videos on the day 6 as $\theta_{16} = -1.94$. Second, at the initial few days, the fluctuation of parameters is stronger than subsequent days. The main reason of this observation is that the videos are not enough to learn the accurate value of θ at first few days. Third, over time, we find that the values of herding effect parameters are stable as the training videos are sufficient.

6 Conclusions

In this paper, we introduced a model for predicting the popularity growth of *DanMu*-enabled videos, which combines the dynamic herding effect, *DanMu* information, video quality and uploaders' influence. We collected a large set of data from a *DanMu*-enabled online video system (i.e., acfun.tv) that includes 3,623 videos, 73,059,811 views, 883,637 *DanMu*s and 745 uploaders of each day. We first analyzed the distributions of video features and uploader features over time. Then we proposed to measure the herding effect of *DanMu*-enabled video popularity from multiple aspects, including the popular videos, the popular DanMus and the newly updated videos. We also recognized that the uploaders' influence and video quality affect the *DanMu*-enabled video popularity as well. Therefore, we combined the dynamic herding effect, uploaders' influence and video quality in a unified framework to predict the popularity of *DanMu*-enabled videos. After that, we designed an efficient estimation method to automatically learn the herding effect and other parameters. Finally, experimental results demonstrated the effectiveness of our prediction model. We believe that the successful prediction of video popularity provides valuable commercial and technical implications to improve various online video-based services.

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