Incentive Based on Video Quality Impacts on Revenue, Video Quantity and Average Video Quality

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Abstract. Online video websites attract more and more users to make and upload their video and earn revenue through huge traffic. This digital economy requires platform making strategy to encourage user generated content. In this paper, we build a theoretical model to optimize the revenue of video sharing platform when platform offers incentive to video-maker according to the quality of their video. Through numerical analysis, we identify that proper incentive could encourage more users to generate video and increase overall video quantity which promotes platform revenue. On the other hand, incentive for video quality, no matter how much it is, could decline average video quality itself. Nevertheless, as the quantity of video increases, video-watchers could still get satisfied and platform could gain more revenue. The findings could guide online video sharing platform to set a proper incentive schemes to promote video uploaders for a better revenue.

Keywords: platform incentive; user generated video; revenue optimization; content quality

1 Introduction

Video website of user generated content (UGC) is more and more popular (i.e., YouTube, Bilibili) in recent years. Users of such platform can be divided into two types: video-maker and video-watcher. There are two essential factors to the revenue of video sharing platform: video quantity and video quality. Video quantity could provide adequate video for watching anytime, while video quality could improve user stickiness. For the video sharing website, the mode of using the membership charges and usage charges to gain revenue cannot enhance the user's stickiness, especially the video uploaders. Plus, the quantity and quality of the uploaded video have an important influence on the traffic of the video website [1]. Therefore, the video website of user generated content began to consider encouraging users to upload higher quality videos through incentives.

In this paper, we focus on how incentive for video quality could promote platform revenue, video quantity and average video quality. We build a theoretical model to analysis the following three research questions:

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RQ1. Could platform incentive promote platform revenue? If it could, how could platform give an optimal incentive rate to maximize revenue?

RQ2. With platform incentive, will video quantity and average video quality get increased?

RQ3. What factor is relevant to the optimal incentive ratio?

Through optimizing incentive rate to maximize platform revenue, we find that if platform offers proper incentive for video-makers according to their video quality, more users tend to produce video which could increase video quantity. However, the average quality of video will decrease. Nevertheless, the trade-off of video quantity and quality will increase not only platform utility, but video-watcher' s utility as well. By further analysis, we find that if user of the platform have higher ability to make video, there will be more revenue by giving incentive to video-makers. The result could help platform revise their incentive strategy for video-makers to promote revenue.

2 Literature Review

Online videos have become the fastest growing area for Internet [2]. The essence of the UGC video website is a two-sided market where users are the two sides of the market as video-watchers and video-makers (uploaders). Video websites provide video uploading and watching platforms for users, and earn money through fees and advertisements. The platform revenue we want to consider are related to the platform pricing strategies of previous studies.

Researchers have proposed different incentives modes. For example, Ghosh [3] used game theory to analyze and compare users in published literature. The mechanism provides a way to encourage content creators generate high quality content by eliminating or hiding low quality content. This is a mechanism similar to "punishing" low-quality producers. Ren [4] studies user-generated content platforms and proposes a payment scheme in which content producers can be taxed or subsidized to maximize their revenue. The taxation measures can be classified into a market pricing model, which is applicable to a model in which multiple merchants compete, while subsidies are incentives. Chakraborty et.al. [5] build a model to reveal how non-skippable and skippable ads affact video sharing platform revenue. The model shows that non-skippable ads help to bring about more niche or low content and as the amount of content increases, the proportion of skippable ads increase as well. This could help platform determining the incentive. Liu and Feng [6] identified two crowding out effects of the mechanisms that incentives may either increase or decrease UGC contribution. The first one is motivation crowding out which means that incentive reduces uploaders who upload content without expecting any money payment. The second effect is competition crowding out which means that intensified competition could prevent low-effectiveness uploaders to contribute.

Based on the above research, this paper establishes a model to study whether it is possible to maximize revenue when rewarding video-maker according to video quality. We aim to investigate the theoretical connection between incentive and video quality.

3 Model

In this section, we will present the parameters involved in our model, the user utility functions, and the revenue function of the platform. It should be noted that we divide the users into two categories in our model: video-maker and video-watcher. We assume that there is no necessary connection between the two groups (typically, a person who is both video-maker and video-watcher could be regarded as two separate people in our model). All parameters and decision variables involved in model are showed in Table 1 and Table 2.

Table 1. Parameters in our model

Parameter	Description
s	The quality of video uploaded by video-maker. Empirically, it could be measured by the video traffic or the number of likes of video or other proper measurement, according to the actual situation of the platform.
c_m	Cost of making video.
t	Fixed time cost of watching video.
θ	Sensitivity of video-watcher to the time cost *t*.
$\bar{s}$	Average quality of video for all video on the platform.

Table 2. Decision variables in our model

Variable	Description
λ	The level of incentives the platform provides to video-makers.
a	Starting point of the distribution of video-makers' capability to make high quality video.
b	Starting point of the cost distribution of video-makers making videos.

Suppose a video-maker can create videos with a fixed quality of s. s could be measured by a qualitative indicator (e.g., video traffic, the amount of likes, the total time cost on watching the video, etc.). If the video is uploaded to the platform, the video-maker can get utility U_m from the likes and plays from other people without any incentive. We assume that this utility is closely related to the quality of the video, so we set this sort of utility coefficient to 1, which means that basic utility the video-maker can get from the video is s. On the other hand, video-makers need to spend certain amount of time to create a video. The total cost is set to c_m, which has a negative impact on video-makers. We let s be evenly distributed over $[a, a+1]$, and c_m is evenly distributed over $[b, b+1]$. Video-makers who have a larger s and smaller c_m could produce more video with high quality. For video-watchers, it is assumed that the average quality of the platform $\bar{s}$ and the richness of the video on the platform q_m(In fact, q_m is the platform video richness characterized by the amount of video-makers, see Equation (3) in the following part) can bring them positive effects. While watching the video has a fixed time cost t, the sensitivity of the video-watchers to the time cost θ is evenly distributed over [0, 1]. The amount of video-watchers of the platform q_w can be represented by these variables (Equation(4) in the following part). d, the platform's revenue π depends on the amount of video-watchers q_w and the expenditure c_p which is used to motivate more video-makers to upload videos. Even if platform doesn't rent the ad slots, there will be more people buying the products that are attached to the content on the platform (e.g., Bilibili). This is in line with the general platform revenue model, which indicates that the more video-watchers there are, the higher revenue the platform could gain. In order to attract more video-makers, the platform requires an investment scheme to encourage video-makers to upload more videos with high quality. We suppose the platform gives a certain percentage of incentives based on the video quality and set this incentive rate to λ. We have already explained that the playback volume and quality of the video are positively correlated, which is equivalent to the actual incentive for each video is λs.

Therefore, we get the utility U_m of the video-maker and the utility U_w of the video-watcher as follows:

$$U_m = (1 + \lambda)s - c_m \quad (1)$$

$$U_w = (\bar{s} - a) + q_m - \theta t. \quad (2)$$

Subtracting a in Equation (2) is for standardizing the utility function of video-watchers.

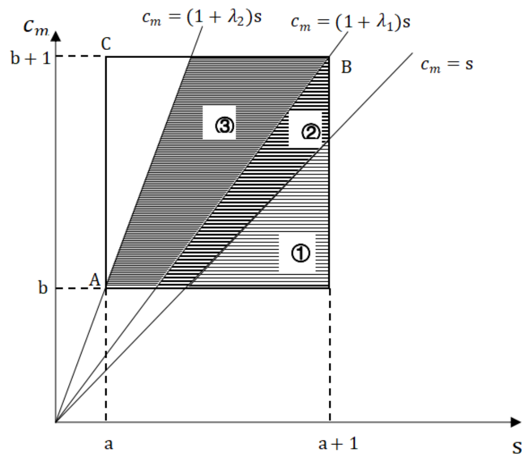


Fig. 1. Video-maker distribution

In Fig. 1 we built a cartesian coordinate system by taking the ability to video-makers and production costs as dimensions. Among them, the horizontal axis represents the video production capability, and the vertical axis represents the video production cost. Therefore, the square in the figure is the distribution range of the potential video-makers. Even if there are no incentive, a small number of video-makers are willing to upload videos, so we assume $a < b < a + 1$. If $U_m \geq 0$, that is $c_m \leq (1 + \lambda)s$ is satisfied, the video-makers will choose to make a video. Thus, when the platform does not provide an inventive ($\lambda = 0$), the users who will upload videos are distributed in the shadow area ①. If the platform provides the incentive of level λ_1, the video-makers are distributed in the shadow areas ① and ② will participate; Similarly, if the platform provides an incentive of level λ_2, video-makers are distributed in shadow areas ①, ②, and③ will make videos. The reason why the two inventive levels λ_1 and λ_2 should be specifically stated is that the inventive of level λ_1 just makes the video-maker at point B upload videos and the inventive of level λ_2 just makes the video-maker at point A upload videos. On this basis, if λ continues increasing, obviously the trend of the amount of participants will change, so we need to use these two levels of incentives as a dividing line to discuss our model.

According to the coordinates and functions in Figure 1, we have results: $\lambda_1 = \frac{b-a}{a+1}$, $\lambda_2 = \frac{b-a}{a}$.

In addition, after the video-maker at point C participated, the amount of video-makers will not increase any more. So we derive the incentive level of this point: $\lambda_3 = \frac{b+1-a}{a}$.

The amount of video-makers is also the area of the shadow:

$$q_m = \iint dc_m ds \qquad (3)$$

For video-watchers, they can choose to watch videos or not watch videos, depending on their utility. If $U_w \geq 0$, or $\theta \leq \frac{\bar{s}+q_m}{t}$ is satisfied, the video-watchers choose to watch the video. Therefore, the amount of video-watchers is:

$$q_w = \theta = \frac{(\bar{s}-a)+q_m}{t} \qquad (4)$$

$$\bar{s} = \frac{\iint s dc_m ds}{q_m} \qquad (5)$$

Now, we can get the platform's revenue function:

$$\pi = q_w - c_p \qquad (6)$$

$$c_p = \lambda \iint s dc_m ds \qquad (7)$$

Changes in platform incentive level λ cause changes in platform revenue. Next, we can use this model to discuss the three questions that have been raised.

4 Analysis

4.1 When a, b, t are fixed

Proposition 1: Platform incentive can increase platform revenue, but when the incentive rate is greater than the threshold, the increasing incentives will reduce platform revenue.

Let $a = 1$, $b = 1.5$, $t = 0.8$:

$$\max_{\lambda} \pi = q_w - c_p$$

Solution,

$$\pi = 1.24339$$

$$\lambda = 0.24335$$

When the platform incentive rate is about 0.24335, the platform revenue maximize, which is about 1.24339.

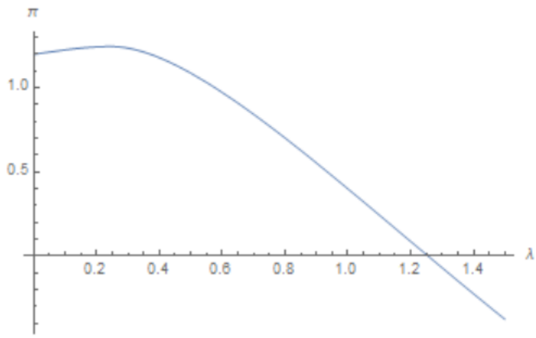
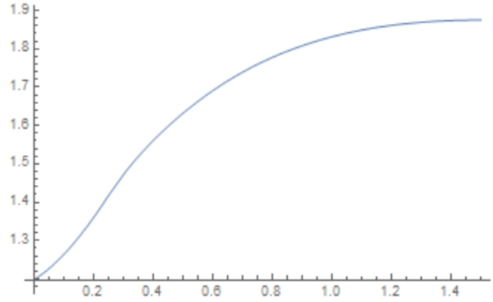
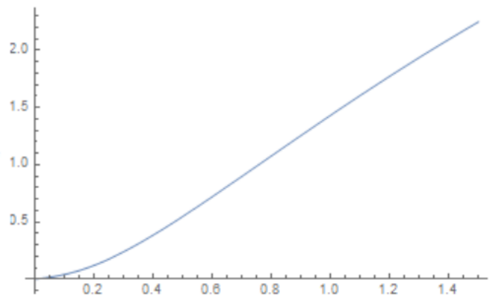


Fig. 2. revenue function (a=1, b=1.5, t=0.8)

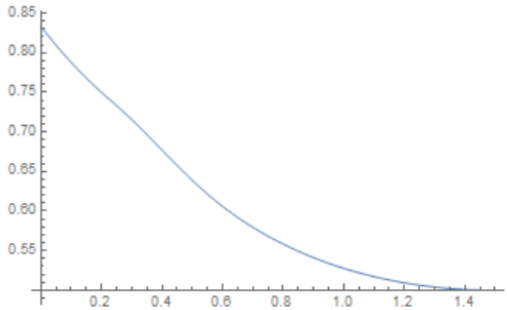
π increases with λ when λ is less than 0.24335, which is the incentive impact on increasing revenue of the platform (as revenue function π in Fig. 2 shows). π decreases with λ when λ is greater than 0.24335. With the increase of λ, the amount of video-watcher increases slower and slower (as q_w function in Fig. 3 shows) but incentive cost of platform increases at a rate close to constant (as c_p function in Fig. 4 shows). This situation could be caused by the decline of $\bar{s}$. The decline of $\bar{s}$ in Fig. 5 shows that average quality of platform videos becomes lower. With the increase of incentives, the platform attracts users with insufficient capacity to make videos while their production capacity is weaker than the existing video-makers who are willing to produce video without incentive. When incentives are lower, their $U_m = (1 + \lambda)s - c_m < 0$, so they do not produce videos. Higher incentives attract these users and increase video quantity, while the quality of videos they produce is lower. The revenue they bring to the platform are limited, and the expenditure exceeds the benefits of incentives. That explains why platform revenue declines when incentive rate is too high.



$\boldsymbol{Fig}. 3. q_w$ function (y-axis q_w, x-axis λ; a=1, b=1.5, t=0.8)



$\boldsymbol{Fig}. 4. c_p$ function (y-axis c_p, x-axis λ; a=1, b=1.5, t=0.8)



$\boldsymbol{Fig}. 5. \bar{s}$ function (y-axis $\bar{s}$, x-axis λ ; a=1, b=1.5, t=0.8)

As a result, when $\lambda = 0.24335$, the platform acquires the optimal revenue. Platform should offer a proper incentive rate to make more revenue while this could increase video quantity and reduce average video quality. The platform encourages more users to participate in the production of video which enriches the overall video richness. Although the average quality of videos decreases with the increase quantity of videos, the increasing quantity of videos contributes more on revenue, as long as the average quality maintains above a certain level, according to the user utility function $U_w = \bar{s} + q - \theta t$. Under this circumstance, the user utility will also increase. Therefore, the platform can achieve a win-win strategy for both platform and users by offering appropriate incentives according to video quality.

4.2 When we change a, b

Proposition 2: If the users of platform have lower ability to produce videos, the incentive can bring limited benefits to the platform, and the incentive effect is worse.

If we reduce the value of a, the average quality of videos produced by video-makers is lower, and there are fewer video-makers producing video without incentives.

Let $a = 0.7$, $b = 1.5$, $t = 0.8$,

$$\max_{\lambda} \pi = q_w - c_p$$

Solution,

$$\pi = 1.17709$$

$$\lambda = 0.253114$$

When the platform incentive rate is about 0.253114, the platform revenue maximize, which is about 1.17709.

Compared with the situation when $a = 1$, $b = 1.5$, $t = 0.8$, the platform obtains lower optimal revenue and requires higher platform incentive rate to achieve the optimal revenue (Fig. 6). As users have lower ability to produce videos, only higher incentives can make $U_m > 0$. The incentive will reach the threshold of that in Proposition 1 faster, which indicates that the incentive can bring limited benefits to the platform, and the incentive effect is worse.

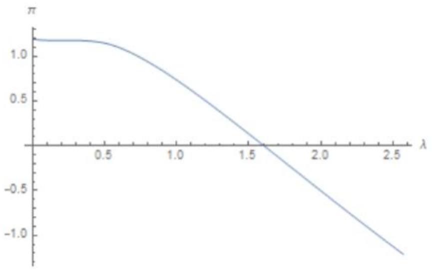


Fig. 6. revenue function (a=0.7, b=1.5, t=0.8)

4.3 When we fix a=0.2, and change the distance between a and b

Proposition 3: While the cost of making video is higher, the revenue of the platform is lower, and platform should offer more incentives to achieve the best revenue. When the cost of making video is too high, the revenue of the platform decreases monotonously.

Let $a = 0.2, b = a + 0.1, t = 0.4$,

$$\max_{\lambda} \pi = q_w - c_p$$

Solution,

$$\pi = 1.42186$$

$$\lambda = 0.189357$$

Let $a = 0.2, b = a + 0.6, t = 0.4$,

$$\max_{\lambda} \pi = q_w - c_p$$

Solution,

$$\pi = 1.22609$$

$$\lambda = 0.477762$$

Let $a = 0.2, b = a + 0.9, t = 0.4$,

$$\max_{\lambda} \pi = q_w - c_p$$

Solution,

$$\lambda = 0$$

The revenue functions of the cases of $b = a + 0.1$, $b = a + 0.6$, $b = a + 0.9$ are shown in Fig. 7.

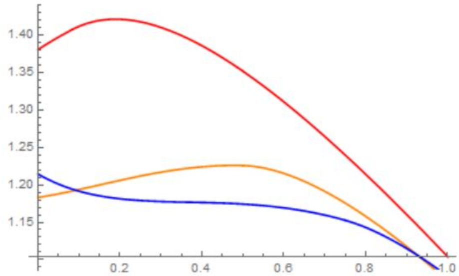


Fig. 7. revenue function π (y-axis π, x-axis λ, Red: b=a+0.1, Orange: b=a+0.6, Blue: b=a+0.9)

It is found that under the same incentive rate, the revenue represented by red line, orange line and blue line are getting lower and lower (except that the left end of the blue line is higher than the orange line). It indicates that higher cost of making video causes lower revenue of the platform. When the cost of making video is too high (the blue line), the revenue of the platform decreases monotonously. We suppose that due to the high cost of video production, the negative impact of incentives on the decreasing average quality of video overrides the positive impact on the increasing video quantity.

5 Conclusion

As user generated content becomes more and more significant for video sharing platform websites, it is meaningful to find methods to encourage more users to upload videos and promote them to generate high quality content. In this paper, we aim to investigate how platform incentive according to video quality could impact on platform revenue, video quantity and average video quality. Through building a theoretical model and optimizing platform revenue function, we conclude that proper incentive rate based on video quality (e.g., video traffic, the amount of likes, etc.) could promote platform revenue and video quantity, but could always decline average video quality. With the increase of overall users' video-making capacity to produce high quality video, platforms could gain more revenue the incentive from incentive.

This research has two remaining issues to deal with in future studies. Firstly, we hypothesis that each user has a fixed ability to make videos with a fixed quality. What if the quality of video produced by one video-maker could change with incentive? The distribution of real video-makers' capacity requires further empirical research. Secondly, how could platform attract skillful video-maker to contribute to the content? (i.e., how to increase the value of a?) The overall ability of video-makers could probably relate to some property or strategy of the platform. There should be some empirical study to examine this hypothesis.

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