The Untold Story of the Clones: Content-agnostic Factors that Impact YouTube Video Popularity

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ABSTRACT

Video dissemination through sites such as YouTube can have widespread impacts on opinions, thoughts, and cultures. Not all videos will reach the same popularity and have the same impact. Popularity differences arise not only because of differences in video content, but also because of other "content-agnostic" factors. The latter factors are of considerable interest but it has been difficult to accurately study them. For example, videos uploaded by users with large social networks may tend to be more popular because they tend to have more interesting content, not because social network size has a substantial direct impact on popularity.

In this paper, we develop and apply a methodology that is able to accurately assess, both qualitatively and quantitatively, the impacts of various content-agnostic factors on video popularity. When controlling for video content, we observe a strong linear "rich-get-richer" behavior, with the total number of previous views as the most important factor except for very young videos. The second most important factor is found to be video age. We analyze a number of phenomena that may contribute to rich-get-richer, including the first-mover advantage, and search bias towards popular videos. For young videos we find that factors other than the total number of previous views, such as uploader characteristics and number of keywords, become relatively more important. Our findings also confirm that inaccurate conclusions can be reached when not controlling for content.

Categories and Subject Descriptors

E.0 [**Data**]: General; C.4 [**Computer Systems Organization**]: Performance of Systems; H.3 [**Information Systems**]: Information Storage and Retrieval

Keywords

Popularity, Youtube, Rich-get-richer, Clones

1. INTRODUCTION

A vast amount of new video, audio, image, and text content is created each year, much of it disseminated via the Internet. What determines which items become popular and seen/heard/read by many people, and which do not? Although the content of the item (is it interesting, is it topical, is it high-quality, and so on) plays an important role, it has been widely recognized that other "content-agnostic" factors can also have a substantial impact on popularity.

For videos shared through a site such as YouTube, for example, content-agnostic factors impacting a video's current viewing rate include the video uploader's social network size, the total number of previous views to the video, the number of associated keywords, and the time that has elapsed since the video was uploaded (the video "age"). Such factors can directly impact the choices of potential viewers, as well as indirectly impact these choices through their influence on the service provider's search and featuring algorithms.

There has been considerable work on characterizing, modeling, and predicting the popularities of user-generated videos. User-generated video accesses at campus networks have been characterized [6,13]. Both static and temporal properties of view counts to a collection of user-generated videos have been studied [3,4,7,10]. Models have also been proposed for video popularity evolution [3,9,10]. Many of these models are based on the classical *rich-get-richer* phenomenon [2], which suggests that a video will attract new views at a rate proportional to the number of views already acquired.

Since both content-related and content-agnostic factors impact popularity, however, understanding how the various content-agnostic factors influence popularity has been challenging. For example, videos uploaded by users with large social networks may tend to become more popular because such users generally upload more interesting content, not because social network size has any direct impact on popularity. Prior studies have used datasets consisting of videos with widely-varying contents, and thus are unable to rigorously distinguish the impacts of content-agnostic factors on popularity, from the impacts arising from differing contents.

In this paper, we develop and apply a methodology that is able to accurately assess the impacts various content-agnostic factors have on video popularity. Our methodology is based on studying popularity differences among videos that have essentially the same content; i.e., can be considered as "clones" of each other. Popularity differences among clones can only be due to content-agnostic factors.

Using data we collected for sets of manually-identified

YouTube video clones, we apply multivariate linear regression and other statistical methods to systematically determine the content-agnostic factors that most influence a video's current popularity. In particular, by analyzing a large number of explicit measurable factors that are provided through the YouTube API, we find that the most significant content-agnostic factors are the total number of previous views and the video age. We also show that determining the relative importance of these factors without controlling for video content (i.e., ignoring clone set memberships) would result in inaccurate results; in particular, the relative importance of factors such as video age and the number of followers of the uploader would be significantly overestimated.

When controlling for video content, we find that "rich-get-richer" preferential selection based on the total number of previous views appears to provide a good model of video popularity evolution. Specifically, using regression analysis we show that current video popularity, among videos of similar "generation" (age within a multi-year window), follows a scale-free rich-get-richer model with power-law exponent of approximately one. We also show that carrying out this analysis without controlling for content would result in erroneously concluding that preferential selection is significantly weaker, not scale-free, with a power-law exponent smaller than one. We investigate a number of possible contributors to the observed rich-get-richer behavior, including the "first-mover" advantage and search bias towards popular videos.

The total number of previous views becomes less significant for very young (newly-uploaded) videos that have not yet accumulated many views. For such videos, we show that other factors such as uploader characteristics and the number of keywords become much more significant. Their significance is substantially underestimated, however, when not controlling for video content.

The remainder of this paper is organized as follows. Section 2 describes our data collection methodology and analysis approach. Section 3 presents an analysis for the relative impacts of the measured content-agnostic factors on current video popularity, while Section 4 shows the importance of controlling for video content in this analysis. Section 5 studies the applicability of rich-get-richer preferential selection models, and examines contributors to rich-get-richer behavior. Section 6 analyzes the content-agnostic factors impacting the popularity of newly-uploaded videos. Related work is discussed in Section 7. Section 8 concludes the paper.

2. METHODOLOGY

2.1 Data Collection

To analyze factors influencing video popularity, we start by identifying sets of identical or nearly identical videos on YouTube. By identical we mean the same video content and audio soundtrack. We allow subtitles, variations in encodings (quality), and small variations in video duration. In this paper, we refer to such a set of nearly identical videos as a *clone set* and videos in such a set as *clones*. Through extensive exploration, search, and viewing of YouTube videos, we manually identified 48 clone sets, each of which contain between 17 and 94 clones, with a median size of 29.5.[1] In total, we identified 1,761 videos. (Our initial dataset was somewhat larger, but we removed all videos whose duration deviated more than 15% from the median duration within their clone set.)

We developed a web-based collection system that allows us to easily enter clone video urls into a database. Each video entered is assigned a clone set id and a video id. Once in the database, the system then extracts video and uploader information using both the YouTube developer's API [11] and through HTML scraping. The system collects three types of information:

- **Video statistics:** These include statistics such as view count, uploader's followers count, number of comments, "likes" and "favourite" events and average rating. For each clone set, two snapshots were collected, spaced one week apart. For all videos in a clone set, the data collection was done within minutes. Table 1 describes all variables collected.
- **Historical view count:** When available, we extract historical video view counts from the YouTube HTML page. This information is referred to by YouTube as "insight data". We programmatically obtain this historical view count information by intercepting the URL request which the YouTube website uses to plot the view history graph. This URL contains 100 points with date/view count pairs.
- **Influential events:** The YouTube insight data also contains information on how users discover a video. It reveals the top 10 "most significant" sources of discovery, or where the video was linked from. Common sources of discovery include "discovered through YouTube search" and "embedded on Facebook". We also collect this list of referrers and, for each referrer, the first date of referral and the associated view count.

The dataset used in this work was collected between February 2010 and April 2011.

While the YouTube insight data provides valuable information regarding a video's popularity evolution, it has some limitations. First, this data is not available for all videos, as uploaders can choose to hide it from public view. We could retrieve the insight data for approximately 40% of the videos in our dataset. Second, the historical view count data includes only 100 points, irrespective of the video's age. To extract the view count at a specific point in time, we applied linear interpolation, which introduces an error dependent on video age. Finally, the referrer data only reveals 10 referrers, with the exact method used by YouTube to select which referrer to include in the list being unknown. This limits the number of views that can be mapped to a specific source, but also leaves some uncertainty in whether there are other more significant sources not accounted for. In our analysis we try to minimize the effect of these limitations.

2.2 Analysis Approach

In this section, we introduce our analysis approach. Since our dataset contains multiple sets of (near) identical content, we are able to apply a range of techniques, both on individual clone sets and on the overall collection of videos across all clone sets. When using the overall collection, we can then choose to take the content (clone set id) into consideration or not. This allows us to identify factors impacting video

[1] Our dataset is available at `http://www.ida.liu.se/~nikca/papers/kdd12.html`.

Variable	Description	Type	Scale	Category
Clone set ID	Unique clone set identifier	–	–	–
Capture time	Time at which this video data was captured	–	–	–
Upload time	Time at which the video was first published	–	–	–
Update time	Time at which the video was last updated	–	–	–
Categories count	Number of categories associated with this video	–	–	–
Next week views	Number of views between two weeks	Predicted	log	Video popularity
Rating average	Average rating (min and max ratings also measured)	Predictor	linear	Video popularity
Total comments	Number of comments	Predictor	log	Video popularity
Total dislikes	Number of 'dislike' events	Predictor	log	Video popularity
Total favourites	Number of time this video was 'favourited'	Predictor	log	Video popularity
Total likes	Number of 'like' events	Predictor	log	Video popularity
Total ratings	Number of ratings	Predictor	log	Video popularity
Total view count	Number of views	Predictor	log	Video popularity
Uploader age	Age of the uploader	Predictor	log	Uploader characteristics
Uploader contacts	Number of (YouTube) 'friends' of the uploader	Predictor	log	Uploader popularity
Uploader followers	Number of followers for the uploader	Predictor	log	Uploader popularity
Uploader video count	Number of videos uploaded by the uploader	Predictor	log	Uploader popularity
Uploader view count	Number of time any of the uploader's videos were viewed	Predictor	log	Uploader popularity
Video age	Age of the video	Predictor	log	Video characteristics
Video keywords	Number of keywords assigned to the video	Predictor	log	Video characteristics
Video quality	The best quality (frame size) available for this video (higher is better)	Predictor	linear	Video characteristics

Table 1: Variables collected and analyzed.

popularity, as well as evaluate the errors of other methods that do not take into account the impacts of differing video contents. Specifically, we focus on the following:

- **Individual clone set statistics**: These are calculated for each clone set. We present summaries of these as well as results for example clone sets.
- **Content-based statistics**: These are calculated across all videos using an extended model that takes into account each video's clone set identity.
- **Aggregate video statistics**: These are calculated across all videos, ignoring clone set identity. These statistics are used for comparison.

Our analysis focuses on the content-agnostic factors that most influence a video's popularity, as measured by the view count over a week. To evaluate the relative influence of different factors, we use three statistical tools. First, we characterize the relationships between variables using Principal Component Analysis (PCA). This technique allows us to identify groups of variables which are responsible for different parts of the variation. Second, we use correlation and collinearity analysis to identify interrelated variables, which can have a negative effect on regression results. For this purpose, we leverage a number of different statistical techniques, including pair-wise correlation matrices and auxiliary regression. Third, we use multi-linear regression with variable selection, to identify a subset of the variables that captures the majority of the variations, and eliminate variables that do not provide much information regarding popularity. Where appropriate, we apply standard hypothesis testing to assess the significance of our results.

Several techniques used in the following assume a linear relationship between variables and normally distributed errors. To validate these assumptions, we first performed a univariate linear regression to examine the relationship between the response variable (weekly view count) and each other variable. Second, we examine the residual plots and corresponding tests to check that the conditions for using linear regression are satisfied. Due to space limitations, we do not detail this preliminary analysis. We find that to ensure linearity with regards to the weekly view count, some variables require log transformation. In addition, some other variables clearly are weak predictors, with higher variation in their residuals. To avoid introducing subjective biases, we did not remove such variables. Instead, we allow the analysis to help us identify suitable candidates. This turned out to be important as some variables are weak predictors on their own, but complement other variables well. The resulting variables used in the remainder of this paper and any transformations used are summarized in Table 1.

2.3 Multi-linear Regression

In this section, we describe how we use multi-linear regression to determine which factors most influence video popularity. For this purpose, we define the response variable as the weekly view count (difference in view count between our two data collections), and the measured factors (also called predictors) as all the other variables. The use of linear regression is motivated by the observed linear relationships between the measured predictors and the response variable.

We perform three types of multi-linear analysis. We first use the standard multi-linear regression model

$$Y_i = \beta_0 + \sum_{p=1}^{P} X_{i,p}\beta_p + \epsilon_i,$$

where the response variable Y_i is modelled as a linear function of the independent variables ($X_{i,p}$), and the method of least squares is used to estimate the coefficients β_p for the P predictors. *Individual clone set statistics* are obtained by applying the above model on each clone set independently; this allows us to determine which factors are the best predictors for each clone set. We then apply this model on all videos together, regardless of the clone set identity, to obtain *aggregate clone set statistics*. This allows us to evaluate the error when not using our content-aware approach as discussed below.

In order to obtain *content-based statistics*, we design an extended model that incorporates a categorical variable for the clone set identity. This model is useful in understanding the influence of individual clone sets on the regression, and whether or not the classification makes a difference. Assuming that we have K clone sets (or categories), we introduce $K-1$ additional category variables, each capturing the relative difference against a reference clone set. The extended multi-linear model is then given as:

$$Y_i = \beta_0 + \sum_{p=1}^{P} X_{i,p}\beta_p + \sum_{k=2}^{K} Z_{i,k}\gamma_k + \epsilon_i,$$

where K is the number of clone sets; P is the number of predictors; and $Z_{i,k}$ is the category regressor, encoded as $Z_{i,k} = 1$ if clone i is from clone set k, and as 0 otherwise. Note that γ_k can be interpreted as the relative distance between the regression lines of clone sets 1 and k, or in other words, a measure of their relative popularity.

3. FACTOR STRENGTH

3.1 Preliminary Analysis

Before looking at which factors best capture the future popularity, we perform a preliminary analysis to discover any correlations between the factors themselves, and if there are groups of variables that provide redundant information and/or explain the same variation. First, we investigate the strength of the linear relationships among the variables using Pearson's correlation. Figure 1 shows the correlation matrix plot for an example clone set. The variables in the matrix plot are ordered based on their correlation with the response variable, and each entry shows the pairwise correlations between the corresponding two variables. The correlation's magnitude is represented by the ellipse symbol, and its sign is represented by colors (and slope), with red (with slope to the left) used for negative values and blue (with slope to the right) for positive values. We note that many of the variables have high pairwise correlation and very similar clustering of the pairwise correlation for most clone sets. In particular, two sets can be identified: (i) the set of variables related to the past video popularity (i.e., the total view count, favourite count, comment count, ratings count, likes and dislikes), and (ii) the set of variables related to the uploader characteristics (e.g., the number of uploader followers, contacts, videos, and views).

Second, we apply Principal Component Analysis (PCA) on each of the individual clone sets. We find the two aforementioned variable groups to correspond to the two primary principal components, particularly for younger clone sets. Figure 2 shows a PCA plot of the first two principal components for one such clone set. Referring to Table 1, these roughly correspond to *video popularity* and *uploader popularity* metrics, respectively. For many other clone sets, particularly clone sets with big variation in video age, other *video characteristics* (such as video age and video quality) forms a third important component.

Understanding and detecting collinearity is important, as interrelated variables could negatively affect the regression results. To find out whether predictor X_i is a linear combination of other predictors, we run auxiliary regressions to determine the coefficient of determination R_i^2 of how well the remaining explanatory variables $X_{j \neq i}$ explain X_i.

While the full results are omitted due to lack of space, the auxiliary regressions on all individual clone sets and on all videos aggregated across clone sets show that the R_i^2 values of the following regressor factors exceed the overall R^2 value of the model including all the explanatory variables: the total view count, the number of times a video was favourited, the number of comments, the number of ratings, the number of times the video was "liked" or "disliked", as well as the total number of views to all videos uploaded by the uploader, and the count of the uploader's followers. We note that these factors fall into the two previously identified groups of correlated variables. Overall, these results provide evidence of a serious collinearity and its sources.

3.2 Variable Selection within Clone Sets

To determine which predictors have the most impact on the popularity of a clone within a clone set, we applied multivariate regression analysis on individual clone sets.

To limit the impact of collinearity and additional noise on the regression models, we eliminate redundant variables

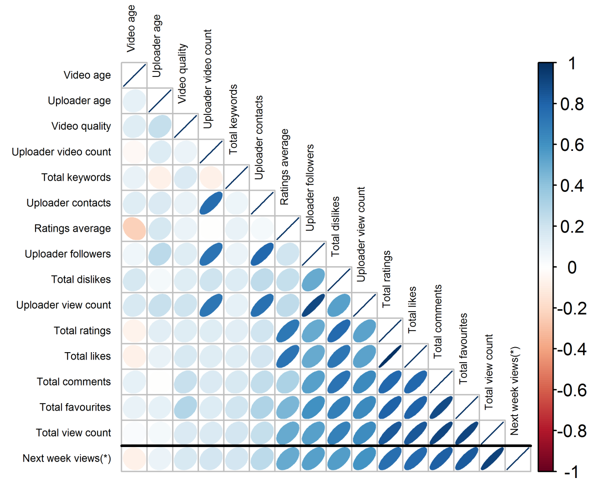


Figure 1: Correlation matrix for clone set 41.

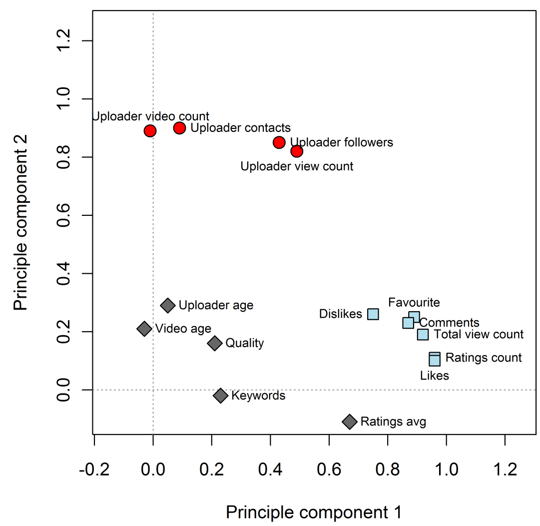


Figure 2: Principal components plot for clone set 41.

using the best subset search technique and Mallow's C_p as the selection criterion [1]. We have obtained qualitatively similar results using other commonly used regression methods and selection criteria. The results in Figure 3 show that the total view count is the most important explanatory variable. It is selected in 92% of the total set of "best models", and is determined to be highly significant. The video age is the second most important predictor, being very significant and being the second most common variable in the models. While the video age did not appear to be a good predictor on its own, as exemplified by the ordering in Figure 1 and low individual R^2 values (with a median of 0.081), its frequent inclusion indicates that it accounts for different variations than the total view count. This has also been observed in some of our PCA analyses. It is also interesting to note that other independent variables, such as variables related to the uploader characteristics, did not appear important in the original regression are now significant when selected in the final model, and are often significant for younger clone sets. One factor that seldomly is significant (even when included) is the video quality. In part, this may be a consequence

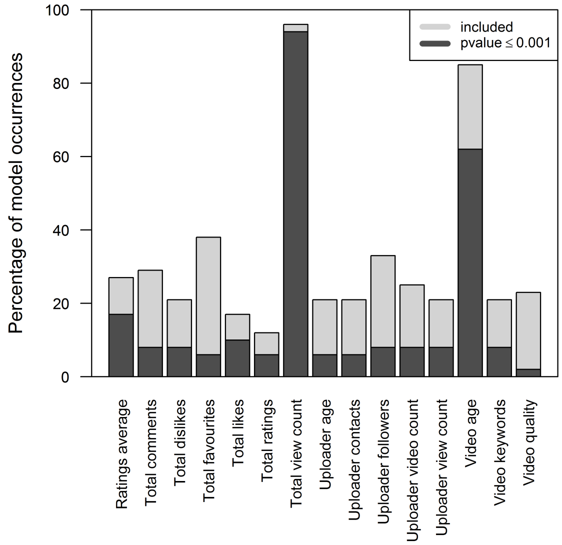


Figure 3: Percentage of occurrences in the set of "best models", using the best subset approach with Mallow's C_p. Dark color shows fraction of models in which the variable was selected while having a p-value smaller than 0.001 in the final model. In the remaining occurrences the variable was selected, but with a higher p-value.

of use of default encodings. However, although our analysis does not find a significant linear relationship, we believe that quality differences may be important in clone sets with wide variations in video age and associated wide variations in quality. The quality variations in such cases may play a role in making age our second most important predictor.

From Figure 3, we can see that the best subset approach with Mallow's C_p, on average, reduces the number of variables by about 60%. The multiple R^2 values for the chosen models are then only slightly smaller than the original R^2 value of the full model.

An interesting observation is that the most influential factors also are the only statistics available to the YouTube users, when searching for a video.

4. IMPACT OF CONTENT IDENTITY

The regression analysis presented in the preceding section was applied on individual clone sets. Using the model extension presented in Section 2.3, we perform regression analysis over the entire dataset while taking into account the content identity, and thus by extension study the impact of the video content on popularity dynamics. Evaluating the importance of the clone set categorical variable is important as it allows us to separate the impact of content-related and content-agnostic factors.

We perform the content-based regression analysis using the most important explanatory variables identified in Section 3.2. We use our default clone set ordering, where sets are numbered from 1 to 48, and choose one clone set as the baseline set.

Summary results are presented in Table 2, for the baseline clone set number 1. The coefficients of the category variables (γ_k) explain by how much the intercept of the selected clone set differs from the intercept of the baseline clone set. The significance of the categorization, i.e., the impact of video content, is then measured by the corresponding p-values. We also report range values $\min_k \gamma_k$ and $\max_k \gamma_k$, across the 47 non-baseline clone sets.

	Estimate	Std. Error	t-value	p-value
Total view count (β_i)	1.100	0.013	87.83	0.000 * * *
Video age (β_i)	-1.008	0.039	-25.80	0.000 * * *
Clone set ($\min_k \gamma_k$)	-0.727	0.348	-2.08	0.037 *
Clone set ($\max_k \gamma_k$)	2.802	0.345	8.08	0.000 * * *

Table 2: Summary of extended regression analysis using categorical variables for clone set identification. With 95% confidence, the rejection rate of the hypothesis that the category variables (γ_k) are equal to zero is 94%.

	View count (1 variable)	+ age (2 var.)	+ followers (3 var.)	all (15 var.)
Individual (mean)	0.788	0.864	0.871	0.933
Individual (median)	0.803	0.873	0.875	0.940
Individual (41)	0.861	0.870	0.874	0.895
Content-based	0.792	0.850	0.852	0.855
Aggregate	0.707	0.808	0.808	0.821

Table 3: Summary of R^2 values for example models.

We find that 44 out of 47 category variables have p-value smaller than 0.05. When averaging over all possible baseline clone sets, we found approximately 60% of the category variables to be significant. This illustrates the importance of taking clone identity into consideration.

As a second step to evaluate the importance of video content, we compare the regression analysis results of the content-aware extended model and the regular individual clone set models with the aggregate model which ignores clone identity.

For each model type, we used four different models: three partial models and one full model. The first partial model includes only the view count variable, the second model includes both the view count and the video age, and the third model further adds the uploader followers.

Table 3 shows the coefficient of determination R^2 for each model when running the regression analysis on each clone set individually ("Individual"), across all clones and clone sets as an aggregate ("Aggregate"), and when we take the clone identity into account using category variables ("Content-based"). Comparing the last two rows, we note that the "Content-based" models consistently explain a larger portion of the variation, as evidenced by higher R^2 values. This is another indication that taking into account the clone identity is important in modelling video popularity.

Table 3 also reveals that the view count by itself explains the biggest percentage of the variance, especially when taking into account the clone identity. Adding the video age variable increases the R^2 values relatively significantly. Adding the uploader followers variable can result in an occasional incremental increase in the goodness of fit, while the other variables impact is even less important.

However, perhaps more importantly, this table also shows that if one tried to analyze the relative importance of age, followers, etc., without controlling for video content, one would conclude that factors such as age and followers are relatively more important (compared to view count) than they really are. This is illustrated by comparing the difference in values from left to right, for the aggregate and the content-based models. In one case, R^2 is improved by 0.114, and in the other by only 0.063.

The next section will take a closer look at the impact clone identity may have on predictive models, such as the rich-get-richer model.

	Slope estimate	Confidence intervals	
Metric	α (σ)	90%	95%
Individual	1.027 (0.091)	0.988-1.065	0.981-1.073
Content-based	1.003 (0.014)	0.98-1.027	0.976-1.031
Aggregate	0.932 (0.016)	0.906-0.958	0.901-0.963

Table 4: Rich-get-richer slope estimates.

5. RICH-GET-RICHER

Prior works have suggested that video popularity evolves according to rich-gets-richer preferential selection [2] or a variant thereof (e.g., [3, 9]), wherein the current viewing rate of a video is proportional to the total number of views the video has already acquired. In Section 5.1, we evaluate whether or not our data is consistent with a rich-get-richer model of popularity evolution. Section 5.2 considers a more restricted form of rich-get-richer behavior, the "first mover" advantage. Finally, Section 5.3 explores other phenomena that may result in rich-get-richer behavior, including search bias towards popular videos.

5.1 Models

We consider rich-get-richer models wherein the probability $\Pi(v_i)$ that a video i with v_i views will be selected for viewing follows a power law

$$\Pi(v_i) \propto v^{\alpha},$$

where α is the power exponent.

Perhaps most interesting is when $\alpha = 1$. This case corresponds to linear preferential selection, was considered by Barabasi and Albert [2], and can be shown to result in a scale-free distribution (in our context, of total view counts).

Basic rich-get-richer models as described above consider only the number of accumulated views as a determinant of the rate of acquiring additional views. With YouTube videos, however, user interest in particular subjects changes over time, causing a deviation from rich-get-richer behavior when one considers a collection of such videos with differing contents. An important question is whether a rich-get-richer model is applicable when one removes the impact of changing user interests, as we are able to do with our clone-based methodology.

To answer this question, we first identify within each clone set videos of similar "generation" (age within a multi-year window). We restrict attention to videos of similar generation to avoid our analysis being impacted by wide variations in video quality (or other generation-related effects). Specifically, for each clone set, we first find the video clone with the highest current popularity (i.e., the video that acquired the most additional views during our one week measurement window). We then consider only the videos in the clone set that were uploaded within two years of the upload time of this video.

We now take a closer look at the impact differences in video identity can have on the rich-get-richer phenomena. We examine how the rate at which videos attain new views depends on the total view count using univariate linear regression (using log-transformed data). All three analysis approaches, namely regression analysis on individual clone sets, on the aggregate, and the aggregate considering content identity, were applied. Table 4 summarizes our results.

The first column in Table 4 shows the coefficient estimates and standard deviation resulting from the univariate regression analysis. The second and third columns show the corresponding confidence intervals. For the individual clone sets, and the extended content-based model, α is typically equal or slightly higher than one. The selection rate is linearly dependent on the current total view count, suggesting that the popularity evolution is scale free, and strongly controlled by rich-get-richer behavior. For the aggregate model, α is less than one, indicating popularity evolution that could result in a much more even popularity distribution than that suggested by the pure (linear) rich-get-richer dynamics.

	1st	2nd	3rd	4th	5th	later
Winner uploaded	27.1	12.5	8.3	6.3	6.3	39.6
Winner searched	66.7	8.3	0.0	8.3	8.3	8.3

Table 5: The percentage of times a video clone that obtained the highest total view count was the first, second, third, fourth, fifth (or later) among the videos in the clone set with respect to being uploaded or searched. (Clone sets with relevant statistics considered.)

5.2 First Mover Advantage

Rich-get-richer behavior may result in part from a "first mover" advantage. The first video to include particular content may have already achieved significant dissemination by the time that clones appear, causing it to acquire new views at a higher rate (for example, via recommendations from previous viewers, featuring, or bias in search algorithms). Using our clone-based methodology, we now evaluate the advantage of being the first to upload particular content.

To track video popularity over time, we use YouTube's insight data collected through HTML scraping. As a first step, we consider the success of the first mover in each clone-set, where a success event for a particular video is defined as when that video accumulates the largest number of total views compared to all other videos within the clone set. We first consider how often the most successful video within a clone set is the first to either be uploaded or discovered through search. Table 5 shows the number of times the video clone that obtained the highest total view count was first, second, third, fourth, or fifth, among the videos in the clone set, to be uploaded or found through search. Overall, the winner was uploaded first among the videos in the clone set in 27.1% of the observed cases, and was among the first five in 60.4% of the cases. Similarly, the winner is the first to be found through search in 66.7% of the cases for which we have (insight data) statistics, and among the first five to be found through search in 92% of the cases. Clearly, there is a significant advantage to being first mover.

While these results suggest that the first mover typically is relatively successful, it is interesting to note that there are cases where other videos have been able to surpass the first mover in popularity. What is it that allows some other video to overtake the spot as the most popular clone? Section 6 takes a closer look at some influences that can cause such overtakings.

5.3 Video Discovery and Featuring

We now examine the roles that video discovery and featuring mechanisms may play in the observed rich-get-richer preferential selection behavior. Aspects such as featuring on YouTube, ranking of a video in YouTube search, and embedding of a video on external sites, are difficult to capture over time. Nonetheless, the "video referrers" part of the YouTube

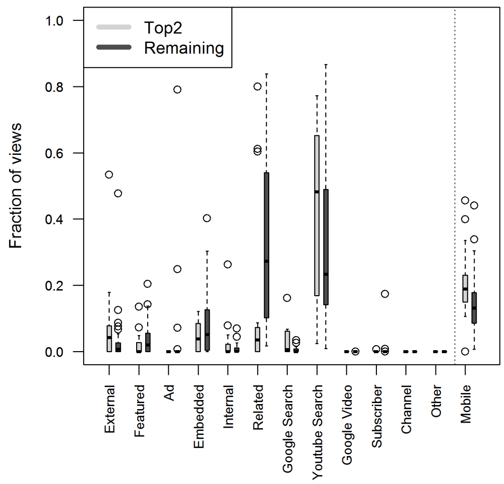


Figure 4: Boxplot of the average fraction of views (per clone-set) coming through different referrer categories.

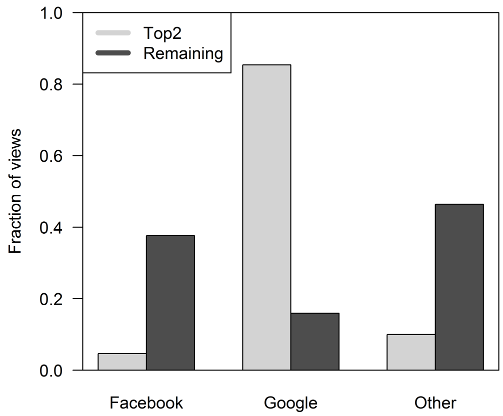


Figure 5: The fraction of views coming through external sources, for clones that are externally linked.

insight data provides (for some videos) additional information necessary for our analyses. The results presented here are based on analysis of clone sets that have multiple videos with insight data. We use YouTube's classification of registered referrers.

We first consider how the most popular videos within each clone set have obtained their views, compared to their less popular counterparts. Figure 4 compares the average fraction of views coming through different referrer types for the most popular clones, with that of the remaining clones.[2]

The results are somewhat counter-intuitive. Notice that the "Top 2" most popular videos are not necessarily the videos that are prominently featured or externally linked. Instead, the search discovery method alone accounts for most of the difference. For example, for the search referrer category, the median of the top clones is almost equal to the 90th quartile of the remaining videos. The less successful clones get most of their views through related (video) referrals.

Figure 5 shows the fraction of views coming through external referrers only (not including embeds). Note that Google is shown as an external source of traffic and it is driving most of the external views of the popular clones. Google is considered an external referrer because views may come from a number of Google non-search services such as Google News, Google Reader, and Google Group posts.

Overall, the highest fraction of clicks to a video is coming through the search referrers. As all videos can potentially be found through search, but not all videos are featured or embedded on external websites, we take a closer look at these referrers. Figures 6(a) and 6(b) show the corresponding boxplots of the fraction of views coming through different referrer types for only the clones that are featured and externally linked, respectively. The same conclusion applies to these data subsets. Search referrers are the most powerful in terms of the percentage of traffic they bring. Further, the biggest differences between successful and less successful videos can be seen in the fraction of views owing to search and mobile referrers.

Recall that we are considering multiple videos containing essentially the same content, and this allows us to remove biases introduced because of differences in content (e.g., popular content is more likely to be searched than non-popular content). Our results suggest that successful videos are much more prominently selected through searches. This could occur because of YouTube's internal search mechanism, the keywords associated with the videos, the keywords entered by the users, user biases when selecting among search results, or a combination thereof. For example, people may be more likely to pick the first search results than pick items lower down on the list, or to pick videos with higher view counts (visible to the user at the time of selection) [8].

As previously discussed, the first mover advantage can be important for the success of a video. In addition to being uploaded, it is important that the video is discovered and/or made available through different paths. Using correlation analysis, we have observed that there is often a significant positive correlation between the total view count and the order in which clones are first referred, featured, or accessed through mobile devices. While omitted, these results suggest that there also is a *first-discovery advantage*, where videos discovered earlier through internal search methods, featured earlier, or that are accessed through mobiles earlier, tend to be ranked higher.

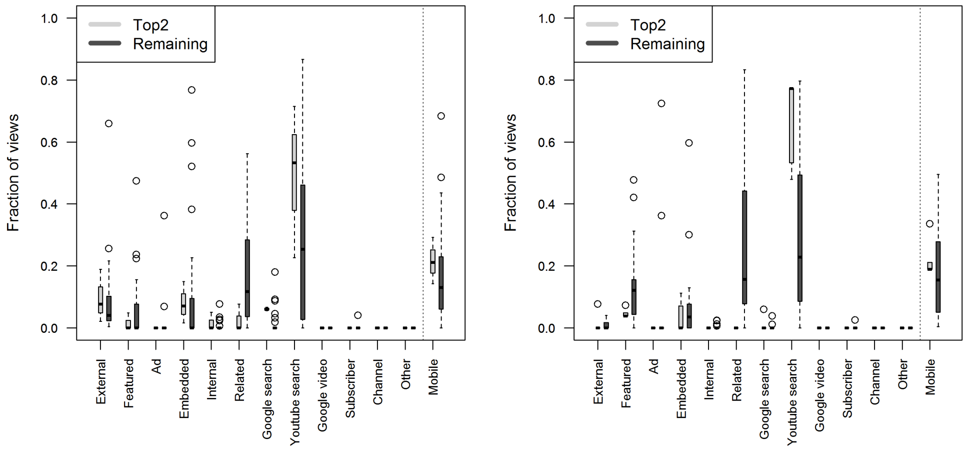
6. FACTORS IMPACTING INITIAL POPULARITY

This section considers factors impacting the view count early in a video's life, which in turns impact the overall video popularity due to the rich-get-richer behavior, as shown in the previous section.

6.1 Uploader Characteristics

We analyzed the YouTube social network size of the uploaders observed in our dataset. In general, uploaders of top-ranked videos have large social networks. Furthermore, manual examination of the top uploaders confirmed that they are often commercial entities. Usually commercial uploaders are the "first-movers". In fact, even when they were not, it appears that their videos often manage to move ahead in popularity. Figure 7 shows an example clone set where

[2]We present the mobile referrers separately as it is not a source of discovery per se, but it nevertheless impacts discoverability, as more users are accessing videos exclusively through mobile devices.



(a) Externally linked clones (b) Featured clones

Figure 6: Boxplot of the fraction of views of clones externally linked and featured, coming through different referrer categories.

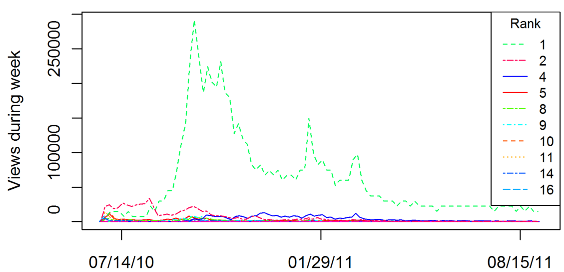


Figure 7: The weekly views for a number of example videos in clone set 14 (18 clones).

	Aggregate				Content-based			
Predictor / Age	1d	3d	7d	14d	1d	3d	7d	14d
View count	0.44	0.42	0.50	0.55	0.60	0.59	0.66	0.70
Video quality	0.08				0.35			
Number of keywords	0.04				0.36			
Uploader view count	0.41				0.64			
Uploader followers	0.40				0.58			
Uploader contacts	0.19				0.42			
Uploader video count	0.08				0.38			
Uploader age	0.02				0.35			

Table 6: Age effect on R^2 values when taking into account clone set identity (content-based) and when not (aggregate).

a commercial user (video with rank 1) catches up and surpasses a private uploader (video with rank 2) even though the former was not the first uploader. This is a typical example of the impact of uploader characteristics on the popularity.

6.2 Age-based Analysis

While the total view count can be an important factor when predicting a video's future popularity, it is less useful for young videos and not useful at all for a newly uploaded video which starts with a view count of zero. For such videos, other predictors such as the size of the uploader social network and the prior success of the uploader may be important, as seen in Section 6.1 and in our PCA analysis in Section 3. We now perform an age-based regression analysis to determine how the relative importance of the total view count changes with time, relative to these more static factors.

Table 6 shows the coefficient of determination R^2 between the predictors in the first two weeks since a video's upload and the total view count at the half-year point since upload. We calculate the total view count of videos at 1 day, 3 days, 1 week, 2 weeks, and half a year using the historical view statistics. Linear interpolation is needed to calculate the approximate total view count at specific time thresholds, as the data provides only 100 points, equally spaced through the video's lifetime. The file-related information and the uploader characteristics properties are assumed constant. The first four columns show results for the aggregate set of videos and the last four columns show results when clone set identity is accounted for.

These results show that the total view count quickly becomes the strongest predictor of the view count at the half-year point. The results also confirm that during the early stages of a video's lifetime, the uploader's social network is a more significant factor than the total view count. Indeed, already at upload, approximately 64% of the variation in views can be explained by the uploader view count alone, and it takes a week for the total view count to become a similar or better predictor than the uploader social network. The impact of the uploader characteristics are significant in the beginning, probably because an established social network is a source of initial views from subscribers.

Finally, we note that some factors have much more impact when the influence of the content is considered through the clone set identity factor. For instance, factors such as the number of keywords and the video quality, have a great impact in the early stages of a video's lifetime. The keyword metric, although appearing to be insignificant in the aggregate analysis, is an important factor when a video is first uploaded, explaining up to 36% of the variation in views. This may suggest that keywords in fact may be one of the main factors in helping find the video in the first place (when competing against videos with the same content). The more targeted keywords a video has, the greater the probability that it will be discovered after its upload.

7. RELATED WORK

To the best of our knowledge, no prior work has separated out the impacts of content-related and content-agnostic factors on video popularity. However, there has been considerable prior work concerning measurements, analyses of these measurements, and/or models, for various user-generated video properties including popularity.

Many prior works have analyzed different aspects of user-generated video metrics such as total views, total ratings, total comments, and uploader social network size (e.g., see [3, 4, 7]). For instance, Mitra et al. [7] compared four video sharing workloads and established the presence of "invariants" among their characteristics, such as heavy-tailed total view count distributions and positive correlation between total views and total ratings to a video.

Cha et al. [3] postulated that heavy-tailed view counts can be explained by combining a "rich-get-richer" model [2] with a limited fetch model. Szabo and Huberman [9] found that the total views received soon after a video is uploaded provides a strong indication of its total future view count; they leveraged this observation to develop a prediction model for video views. More recently, Borghol et al. [10] empirically demonstrated that individual video popularity is highly unstable and unpredictable, and proposed a model for how the popularity statistics of a collection of recently-uploaded videos evolve over time, instead of considering popularity evolution for individual videos.

YouTube's internal search and recommendation engines have been noted to be an important source of video views [5, 12]. For instance, Zhou et al. [12] observed strong correlation between the total view count of a video and the view count of its "related" videos. Similarly, Figueiredo et al. [5] noted that search and other internal mechanisms are the most important sources of views for Youtube videos. Our work is complementary to these as we have also sought to understand factors influencing video popularity, but unlike these prior works we are able to study the significance and impact of content-agnostic factors while controlling for differences in video content.

Cha et al. [3] noted the presence of YouTube video clones which they referred to as "aliases". They observe that aliases tends to "dilute" popularity, as the views for the same content are spread out over several videos. The authors did not use aliases to study how different factors influence content popularity, as we have done in our work.

8. CONCLUSIONS

Video sharing services provide a convenient platform for widespread dissemination of content. Every day, millions of videos are uploaded and there are billions of videos viewed for YouTube alone. Over time, some videos reach iconic status, while many others are simply forgotten.

Our first contribution is a methodology that is able to accurately assess the impact various content-agnostic factors have on popularity. We identify and collect a large dataset that consists of multiple near-identical copies (called clones) of a range of different content; we make this dataset available to the research community. We then develop a rigorous analysis framework, which allows us to control bias introduced when studying videos that do not have the same content.

Using our clone-based methodology, we provide several findings. First, we show that inaccurate conclusions may be drawn when not controlling for video content. Second, controlling for video content, we observe scale-free rich-get-richer behavior, with view count being the most important factor except for very young videos. Third, we find that while the total view count is the strongest predictor, other content-agnostic factors can help explain various other aspects of the popularity dynamics. For example, the uploader's social network can be a good predictor for newly uploaded videos. Finally, we present concrete evidence of the first-mover advantage where early uploaders have an edge over later uploaders of the same content.

While this paper considers video popularity, we note that the methodology presented and employed may be applicable to other domains and research questions. For example, a popular news story will result in many "clones" disseminated through different forums. The relative popularity of each such clone will depend on content-agnostic factors such as age, previous popularity, and publisher. Text-based content raises some interesting new methodological issues, as it may permit a more objective definition of "clone". Such studies are left for future work.

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10. REFERENCES

[1] A. Allen. *Probability, Statistics, and Queuing Theory with Computer Science Applications*. Academic Press, 1990.

[2] A. Barabási and R. Albert. Emergence of Scaling in Random Networks. *Science*, 286:509–512, October 1999.

[3] M. Cha, H. Kwak, P. Rodriguez, Y. Ahn, and S. Moon. Analyzing the Video Popularity Characteristics of Large-Scale User Generated Content Systems. *ACM/IEEE Transactions on Networking*, 17(5):1357–1370, October 2009.

[4] X. Cheng, C. Dale, and J. Lui. Statistics and Social Network of YouTube Videos. In *Proc. International Workshop on Quality of Service (IWQoS)*, pages 229 – 238, Enskede, The Netherlands, June 2008.

[5] F. Figueiredo, F. Benevenuto, and J. M. Almeida. The Tube over Time: Characterizing Popularity Growth of YouTube Videos. In *Proc. ACM International Conference on Web Search and Data Mining (WSDM)*, pages 745–754, Hong Kong, China, February 2011.

[6] P. Gill, M. Arlitt, Z. Li, and A. Mahanti. YouTube Traffic Characterization: A View from the Edge. In *Proc. ACM Internet Measurement Conference (IMC)*, pages 15–28, San Deigo, CA, October 2007.

[7] S. Mitra, M. Agrawal, A. Yadav, N. Carlsson, D. Eager, and A. Mahanti. Characterizing Web-based Video Sharing Workloads. *ACM Transactions on the Web*, (2):8:1–8:27, May 2011.

[8] M. J. Salganik and D. Watts. Leading the Herd Astray: An Experimental Study of Self-fulfilling Prophecies in an Artificial Cultural Market. *Social Psychology Quarterly*, 71:338–355, December 2008.

[9] G. Szabo and B. A. Huberman. Predicting the Popularity of Online Content. *Commun. ACM*, 53(8):80–88, August 2010.

[10] Y. Borghol and S. Mitra and S. Ardon and N. Carlsson and D. Eager and A. Mahanti. Characterizing and Modelling Popularity of User-generated Videos. *Performance Evaluation*, 68(11):1037 – 1055, November 2011.

[11] YouTube. http://code.google.com/apis/youtube/overview.html.

[12] R. Zhou, S. Khemmarat, and L. Gao. The Impact of YouTube Recommendation System on Video Views. In *Proc. ACM Internet Measurement Conference (IMC)*, pages 404–410, Melbourne, Australia, November 2010.

[13] M. Zink, K. Suh, and J. Kurose. Watch Global, Cache Local: YouTube Network Traffic at a Campus Network - Measurements and Implications. In *Proc. SPIE Multimedia Computing and Networking (MMCN) Conference*, San Jose, CA, January 2008.