Word of Mouth Dynamics in Online Social Networks: Investigating Social Influence Cascades on YouTube
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Introduction and Research Question
With its user-friendly interface and the growth in popularity of online video, YouTube has catapulted to a dominant position on the Internet. While this model is extremely attractive for marketers and content creators, recent work has recognized the relatively ephemeral nature of popularity of videos on YouTube, where only a tiny fraction of videos managed to attract most views. This makes it very important for researchers as well as practitioners to develop a deeper understanding of user behavior and the role of interpersonal influence on YouTube.

One of the characteristics of YouTube is the ease of formation of social ties such as friendship and subscription networks. YouTube also offers several avenues for user interaction through commenting on and favoriting videos. Thus, another characteristic of YouTube is the publicly observable nature of interpersonal communications (through actions such as commenting) in addition to the social structure of interactions (through observable ties such as friendship and subscriptions). This paper explores how user interactions through commenting actions early in the life of a video generate cascades of word-of-mouth (WOM) communications that influence subsequent popularity of videos. Cascades are defined as topological patterns in information propagation graphs (Leskovec et al. 2006). In the YouTube context, word of mouth arises endogenously from patterns of interaction structured through a network that individuals are embedded in. Depending on the network topology, WOM from the local network travels beyond the immediate local network neighborhood, contributing to large-scale popularity of a video, similar to models of cascades in social networks (e.g., Watts 2002). We draw upon a stream of research in physics (e.g., Watts 2002) and computer science (e.g., Leskovec et al. 2006) to conceptualize the micro foundations of WOM generated by patterns of interactions in a cohesive group. The two questions we explore are:

• How does network structure and network position impact the formation of WOM communication early in the life of a video?
• How does WOM communication early in the life of a video impact subsequent popularity?

Theory and Hypotheses
A stream of research in information systems (IS) and marketing has examined the impact of pre-release word of mouth and early promotional activities on the popularity of entertainment products. This line of research has developed forecasting models to predict future popularity of entertainment products, such as movies, by examining early indicators and prerelease market evaluation (e.g., Eliashberg et al. 2003). Another stream of work has examined the role of social network structures in the adoption and diffusion of new products, ideas and trends (e.g., Iyengar et al. 2009). This paper identifies a novel approach to understanding future popularity of content by examining the social graph of WOM interactions early in the life of a video that dictate the trajectory of aggregate popularity growth. We measure interpersonal influence and patterns of interaction by collecting data on commenting activity for videos posted on YouTube.

The growth of YouTube promises to fundamentally alter the production and consumption of entertainment products, by offering a platform for socially engaged individuals to share their
preferences with others. The networked patterns of interaction in YouTube also differ from other phenomenon of user-generated content such as online reviews where firms maintain reputation mechanisms and identify authoritative reviewers. The democratic nature of content creation and unstructured patterns of user interaction on YouTube, by contrast, provide a greater role for social influence from network neighbors rather than impersonal online reviewers.

The focus in this paper is to identify the process of sequential information transmission and network neighborhood effects that dictate formation of cascades of word of mouth communication that influence subsequent popularity of videos. We distinguish between a local network neighborhood, created by the direct social ties (e.g., Burt 1997) incident upon the channel posting a video, and the aggregate YouTube network. A friend relationship is built upon mutual agreement between users and un-directional, while a subscription relationship does not rely upon mutual agreement and therefore asymmetric.

In the parlance of the SIR (susceptible-infected-recovered) framework underlying models of diffusion (e.g., Newman 2002), once a channel posts a video, the nodes with friend and subscription ties (i.e., the local neighborhood) are susceptible to the video since they are aware about the new video through notifications and updates. A video acquires visibility and buzz through discussions and comments as well as the opinions, actions as well as tastes of an adjacent node. Since we consider the impact of comments 15 days within posting of a video, the impact of recent commenting activity enhances awareness of other nodes, compared to older commenting activity that has lower visibility. A node that posts a comment on a video becomes infected, and since comments are usually displayed on that node’s channel, stays infected forever. Commenting on a video is a relatively public signal since the commenting action is visible to other nodes with social ties to the commenting node. When two nodes are linked through a network tie, each can observe the other’s activities, including commenting. Thus, a node commenting on a video transmits information to its other social ties, acting as an infector increasing susceptibility of the other ties. For users that are in friend and subscriber relationships with the focal channel, commenting is akin to multiple exposure of an infection. That is, when an individual observes other nodes with social ties are commenting on a video posted by a node that is a direct tie to the individual, the activity by other nodes might induce the individual to comment on the video as well. Thus, the sequence of conversations creates a “friendship ripple” (Krackhardt 1996), i.e., the process whereby each node exerts local influence in inducing neighboring nodes to comment on a video.

From a network perspective, a cohesive group is one characterized by intense socialization between members of the group (Burt 1987). Members of a cohesive subgroup are characterized by strong connectivity and reachability, resulting in localized conformity that enhances contagion by increasing the susceptibility of a node when exposed to commenting activity by a proximate node. Members of a cohesive network are then more likely to engage in communication through commenting, leading to a greater amount of conversations centered on the video in the local network. Thus:

Hypothesis 1a: The cohesiveness of the local network structure of the commenting friend network has a significant positive impact on the number of early comments on a video.

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While social network structures act as conduits for information transmission, the spread of information on a social network occurs as a result of discrete communication events (Kossinets et al. 2009). Bikhchandani et al. (1992) suggest that cascades occur in simple binary choice decisions where imperfectly informed agents, acting sequentially, choose the same action as their predecessors ignoring their private information. In the context of YouTube, viewers face relatively simple choices
of whether to watch a video or not, and whether to comment or not. This results in a cascading
effect whereby subsequent viewers are likely to watch a video depending upon whether prior viewers
have watched it. The sequence of WOM conversation early in the life of a video can trigger a
cascade. Such cascades can be propagated beyond the local network and impact the aggregate
network depending on (i) the existence of a vulnerable cluster of nodes adjacent to the focal node
(channel) and (ii) the global connectivity of the node in the overall network (Watts 2002). Thus, we
examine a two-step process by which cascades are created. First, commenting activity enhances the
likelihood that other views will watch the video. A video attracts visibility through a large volume of
commenting activity, increasing the chances of discovery by other users. A video that attracts more
commenting activity also enhances the experience of viewing the video given
the role of interpersonal influence in cultural products. Second, a node that has an advantageous position in a
social network has more influence over proximate actors’ formation of an opinion as well as greater
power of disseminating information.

Cascades are propagated when small initial shocks impact highly connected nodes in a social
network (Watts 2002). The commenting activity in the local network neighborhood acquires larger
visibility due to the global connectivity of a node within the aggregate YouTube network. In other
words, the greater the amount of enthusiasm and intensity of discussion in the local neighborhood,
the more the video acquires visibility, which coupled with the global connectivity of the channel
contributes to a durable popularity surge in the aggregate network. Our method of measuring
patterns of user interaction (through commenting activity) parallels methods of cascade enumeration
in recommendation networks (e.g., Leskovec et al. 2006). Thus:

**Hypothesis 2:** Early comments have a greater impact on subsequent video popularity (total number of views after 60
days) depending on the global connectivity of the channel.

**Data and Methods**

Videos’ comments were collected via YouTube developer API, called Data API, which allows
accessing to YouTube content information and user information in the form of Google Data API
feeds\(^1\). Each comment record includes the text of the comment, the user ID of the YouTube user
who left the comment, and the date and time the comment was created\(^2\). From the time stamp of
the comment, and from the time stamp of a video when it was uploaded, we can determine how
many days have elapsed from the time the video was uploaded until the time when the comment
was created. In our sample, there are 1,190 videos with at least one comment posted in the first
fifteen days of a video. We examine all direct ties between a channel and other channels, such as
friend/subscriber relationships. We then examine the network created when channels with pre-
existing ties comment on a video in the first 15 days of a video. Thus, the network boundary is
demarcated by each video, comprising the channel uploading the video, and the nodes being users
with pre-existing ties to the channel that post comments.

Since the network relationships in YouTube are either friends or subscribers, for each video,
we first identify the friends and the subscriber relationships for each channel. We then construct
networks of (i) friends commenting on a video, and (ii) subscribers commenting on a video for each
video in the first 15 days. We then calculate the clustering coefficients and the average degree of
friends and subscribers in the commentators’ network for each video. A network’s cohesiveness can
be measured by the mean clustering coefficient of all the nodes in the network. Clustering is the
property whereby two nodes that are neighbors to a third node have a higher probability of being
neighbors (Girvan and Newman 2002). Since individuals in a dense local neighborhood are

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\(^1\) [http://code.google.com/apis/youtube/overview.html](http://code.google.com/apis/youtube/overview.html)

\(^2\) YouTube.com allows only registered and logged-in users to leave comments.
characterized by density of ties between members, the average degree of all vertices can also be used to measure the cohesion of a network (de Nooy et al. 2009). Since this measure is normalized for each network, it can be used to compare networks of different sizes.

**Empirical Approach**

One challenge in estimation is that users’ actions such as commenting and favoriting may be influenced by the networked structure of interactions rather than the result of independent actions – resulting in the well known “reflection problem” in analyzing social interactions. However, the social networks that we consider exist prior to the commenting activity. That is, we consider the impact of cascades triggered by comments from nodes that have social ties prior to the date a particular video has been posted. By restricting the social structure of interaction to that of durable network ties, we can isolate the social influence from other factors that trigger cascades. The commenting activity follows a power distribution, similar to other types of activity in online settings.

The analysis proceeds in two parts. We examine a two-step process by which (i) word of mouth conversations are generated in a cohesive local network, and (ii) such word of mouth conversations cascade through the aggregate network. In the first stage, we estimate early comments of a video posted by a channel, defined as comments in the first 15 days of a video as a function of the channel’s position within its neighborhood and the subgraph properties of the structure of interactions due to commenting activity. By examining measures of cohesion and identification of the vulnerable cluster, we can identify conditions that can trigger WOM conversations. One problem here is that of endogeneity, since commenting activity is also likely to be greater for videos that have greater number of views. Indeed, we observe that commenting follows a power law distribution on Youtube, similar to content popularity. Given the participatory nature of interaction on YouTube, a channel that is a content creator can engage in interaction with its friend and subscriber nodes by commenting on videos (which serve also as replies to comments posted by the friends and subscribers). We include as an explanatory variable the commenting activity by the channel posting a video, \( num\text{cmnt\_bych}_j \). We also include video characteristics as instruments since some genres of videos may be more likely to invite intense conversation and discussion. We conducted exogeneity tests to establish that the video characteristics are correlated with the independent variable (network structure of interaction), but not correlated with the dependent variable (later popularity), the aggregate number of views after 60 days. To account for the over-dispersion in the distribution of the comment count data, the first stage model is estimated using a generalized linear model (GLM) model with negative binomial distribution. Using \( r\text{Cat}_y \) to denote the video category, the model specification is as follows:

\[
num\text{cmnt\_e15d}_j = \beta_0 + \beta_1 \cdot \text{ntw\_size}_j + \beta_2 \cdot num\text{cmnt\_bych}_j + Y_j \cdot \beta_3 + v\text{Cat}_y \beta_4 + \epsilon_j
\]

The log transformed fitted value of the first fifteen days number of comments, \( \hat{x}_y \), is estimated from the first stage, \( \hat{x}_y = \log(\text{num\text{cmnt\_e15d}}_j) \) where \( \text{num\text{cmnt\_e15d}}_j \) is estimated from the first stage model. To adjust for the fact that some videos do not have any comments at all, we add a scaling factor of 1 to the estimated number of comments (\( \text{num\text{cmnt\_e15d}}_j \)) before the log-transformation. In the second stage, we examine how cascades of comments early in the life of a video impact aggregate popularity in the later stage of a video. The channel’s connectedness observed in the early comment network provides a proxy for group level heterogeneity that results from endogenous group formation (Hartman 2010). We conduct a nested multilevel model since a classical linear regression model is a complete-pooling model that in effect ignores variation among groups to estimate the multilevel model. As we are interested in identifying
the varying effects of cascades depending on group level characteristics of the videos, using a complete-pooling model is not appropriate. Since the threshold of contagion might vary across individuals, we use a hierarchical Bayesian approach. To capture the variance among different groups, we use partial-pooling estimates from a nested multilevel model (Gelman and Hill 2007) with unit-level predictors. Using \( n_i \) to represent the log-number of views for video \( i \), \( Y_j \) is the set of video characteristics; \( \log V\text{Age}_j \) is the log transformed video age of video \( i \) posted by channel \( j \), \( v\text{Run}T_j \) is the video runtime, and \( \text{honored}_j \) is a dummy variable indicating whether the video was reached an honored status on YouTube, partial pooling can be expressed as below with variation in the \( \alpha_k \)'s and the \( \gamma_k \)'s and also a between-group correlation parameter \( \rho \),

\[
\begin{align*}
    \alpha_k & 
    \sim N(\mu_{\alpha}, \sigma_{\alpha}^2),
    \gamma_k & 
    \sim N(\mu_{\gamma}, \sigma_{\gamma}^2),
    \text{for } j=1, \ldots, n
\end{align*}
\]

\[
\begin{align*}
    \beta_k & 
    \sim N\left(\mu_{\beta}, \begin{pmatrix} \sigma_{\beta}^2 & \rho \sigma_{\beta} \sigma_{\gamma} \\ \rho \sigma_{\beta} \sigma_{\gamma} & \sigma_{\gamma}^2 \end{pmatrix}\right),
    \text{for } k=1, \ldots, J
\end{align*}
\]

\[
Y_j = \begin{bmatrix} \log V\text{Age}_j \ v\text{Run}T_j \ \text{honored}_j \end{bmatrix}
\]

As the regression model in the second stage is a partial-pooling model, the results of the estimation are depicted with the estimated average coefficients (fixed effects), and the estimated group-level errors (random effects) for the three levels of hierarchy, i.e., degree of commenting activity on a video, the group level effects for the local network neighborhood in the friend network and the group level effects for the local network neighborhood of the channel in the subscriber network are all presented below. The magnitude of the coefficients is fairly small since we take logs. We find a significant positive impact of the subgraph cohesion on the number of comments within fifteen days, as well as a significant positive impact of the volume of early commenting activity on subsequent content popularity, as well as a significant impact of the global connectedness of channels and significant group level effects underlying popularity.

Results and Contributions

This paper does not attempt to identify critical nodes in triggering cascades, but attempts to quantify the impact of network structure and connectedness of nodes on cascade propagation. We examine the structural properties in a network of commentators that have pre-existing social ties to a focal channel. The magnitude of popularity as well as the growth of popularity is impacted by the initial buzz, which is in turn triggered by the social network structure. Aggregate diffusion and popularity patterns differ substantially depending on the early commenting patterns and the global connectivity of the channel. We find that a node’s position within its neighborhood is strongly associated with a greater number of early comments, suggesting that localized conformity in a cohesive group create the initial shock that ripples through the network neighborhood, and the impact of the bursts of commenting activity cascades through the network when the channel (uploading the video) that belongs to a vulnerable cluster is globally connected. Therefore the nature of networked interactions lends itself to an analysis of models of cascades that posit that individuals may ignore their private information and imitate other nodes. In other words, whether or not a video can morph into a runaway hit that results in a cascade depends on social influence structured through a network of connections.

Most of the prior work on diffusion and cascades identifies opinion leaders or influentials. However, as Watts and Dodds (2007) posit, large cascades of influence are not driven by influentials but by a critical mass of easily influenced individuals. Iyengar et al (2009) examine easily susceptible groups that are crucial to social interactions. Our research adds to this literature by identifying structural characteristics that trigger WOM (the vulnerable cluster of nodes incident to the channel...
posting the video). We quantify the impact of network structure and global connectedness of user activity in the form of commenting that leads to propagation of WOM cascades, even when the exact sequence of comments generating a cascade is not directly observable. Since we distinguish between nodes that merely have friend/subscriber ties and those nodes with social ties that engage in commenting, our empirical approach can distinguish between the network structure that contributes to social multiplier effects and other types of social influence. By analyzing the cascade created by the interactions between networked actors through exploring comments on videos, we can understand how informational cues inherent in WOM lead to views, which is especially critical early in the life of a video.

While researchers have traditionally highlighted the importance of opinion leaders and influencers, our study suggests that initial word of mouth effects lead to path dependent popularity patterns, with differing impacts on aggregate popularity. Given the rich structure of networked interactions in online settings, an understanding of network topology and patterns of social interactions may prove valuable in developing recommendation and collaborative filtering systems. In future work we attempt to incorporate the prominence of an actor posting comments about a video combined with the type of informational cues provided in the comments to identify the threshold conditions that lead to cascades. Given the importance of social interactions underlying the discovery and consumption of entertainment products, we hope future work could yield insights into the role of social influence underlying popularity of entertainment products.

References: