

# Anticipated Shocks in Online Activity

## Response Functions of Attention and Word-Of-Mouth Processes

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### ABSTRACT

We test the existence of anticipated shocks in online activity, a class of collective dynamics that does not fit in the state of the art theory on social response functions. We use data on shares and views to Youtube videos, measuring their time series to classify them according to their dynamical class. We find evidence of the existence of anticipated shocks, and that they are more likely to appear in word-of-mouth interaction than in attention dynamics. Our results show that not all exogenous events in online activity are unexpected, calling for new models that differentiate social interaction and attention dynamics.

### CCS Concepts

•Human-centered computing → Social content sharing; Empirical studies in collaborative and social computing;

### Keywords

social systems; collective response; attention; word-of-mouth

## 1. INTRODUCTION

Human societies are highly adaptive systems that tend to respond to external stimuli. The collective responses to traumatic events, such as terrorist attacks, have been characterized in the Social Sciences through the time evolution of thinking and talking about the event [5]. The digital traces left by millions of users of online media offer a new opportunity to study collective responses from a more general perspective, not only covering traumatic events but also the reactions to popular and cultural content. A wide variety of online phenomena can be conceptualized as collective

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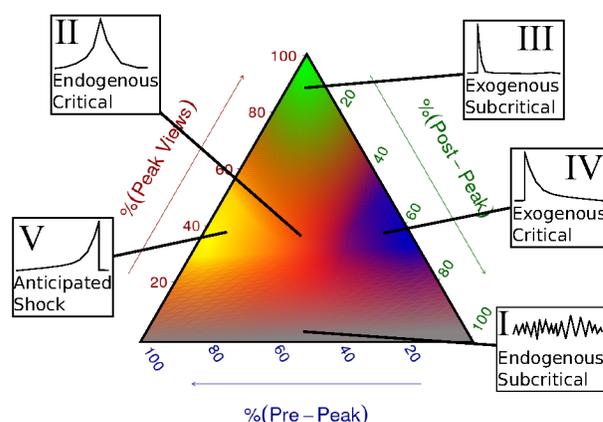
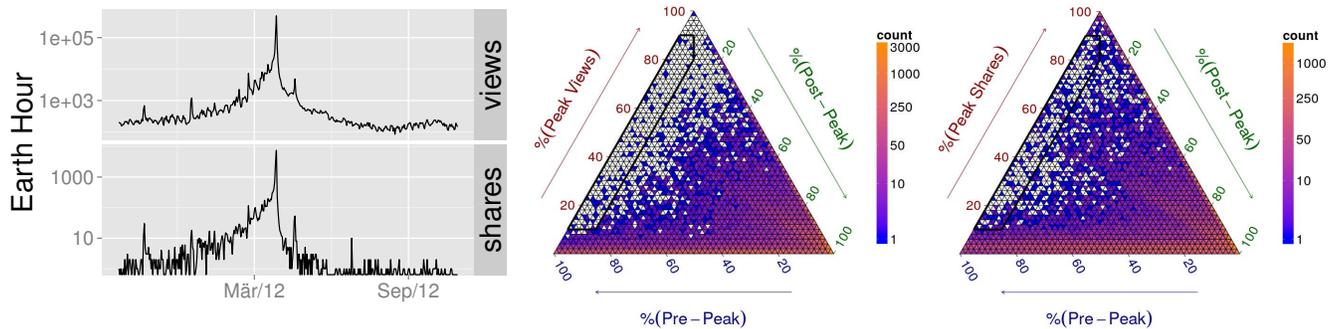


Figure 1: Classification scheme for response functions of social systems suggested by [2] (I-IV), and the new class of *anticipated shocks* (V)

responses to external stimuli, from online political mobilization to viral marketing campaigns, including collective reactions to natural disasters.

Previous work on the analysis of collective online responses focused on the univariate time series analysis of online media popularity, deriving insights from the dynamics of collective response functions [2, 3, 4], to identify dynamic classes or clusters. The current theory on the classification of online collective responses was defined by Crane and Sornette [2], identifying four response classes to YouTube videos along two dimensions: Endogenous versus exogenous triggers and critical versus sub-critical responses. These four classes can be identified over the ratio of activity before, after, and at its peak, as illustrated in the classes I-IV of Figure 1.

The findings of Lehmann et al. [4] suggest that Twitter hashtags can follow a pattern in which most of the activity precedes the peak. In this article, we seek to test the existence of this kind of *anticipated shocks*, which we identified as the new class V in Figure 1. Following the conceptual difference between the collective responses of attention versus verbal interaction [5], we will test if this new class of collective responses is more likely to manifest in word-of-mouth processes than in attention processes, as respectively measured by the `shares` and `views` of YouTube videos.



**Figure 2: Right: Example of anticipated shocks as a *strongly pre-peak* response (class V). Center and left: Simplices with the density of responses in views (center) and shares (left). The enclosed area on the left of the triangle contains the responses characterized as *strongly pre-peak*.**

## 2. DATA AND METHODS

We use the time series of **views** and **shares** of a dataset of 1.1 million YouTube videos analyzed through the YouTube API[1]. After selecting only videos with at least 100 **shares** over their lifetime and at least 500 days of data, our study covers more than 50,000 time series with sufficient evidence for our longitudinal study. Note that the **shares** time series only measures those **shares** that were conducted directly via the **Share**-button on YouTube, and that further external **shares** are possible.

We classify the dynamic responses to the videos similar to the methods of [2], focusing on the characterization of the class V. For each video, we count the percentage of activity before the peak, after the peak, and at the peak day, both for the time series of **views** and for **shares**. By definition, the sum of these three values is 1, and locates the collective responses to the video in the 2D simplex shown in Figure 1. We identify strongly anticipated shocks (class V) as *strongly pre-peak* time series with less than 10% activity after the peak and at least 10% activity before the peak, a peak fraction of at least 10% to get rid of sub-critical videos with very high probability, and a peak fraction of 0.9 at most.

## 3. RESULTS

We found various examples of anticipated shocks in YouTube videos, displaying *strongly pre-peak* dynamics for both **views** and **shares**. One example is shown on the left panel of Figure 2, with increasing **views** and **shares** as the “global Earth hour” approached, to decay strongly afterwards. The center and right panels of Figure 2 show the density of **views** and **shares** responses. We find very frequent post-peak responses, in line with previous results [2]. Even in the presence of this frequent reactive behavior, there are examples of strongly pre-peak responses for both **views** and **shares**, as highlighted in the left black rectangles of Figure 2. Besides their clear existence, anticipated shocks are extreme events that happen with low frequency, counting for roughly 0.5% of the videos in our dataset.

There are striking differences between the dynamics of the word-of-mouth and attention processes, evidenced by the differences between the center and right panels of Figure 2. The time series of **shares** shows much more peaked behavior, with larger density towards the upper corner of the simplex. Furthermore, the density of strongly pre-peak responses, characteristic of anticipated shocks, is higher for the case of word-of-mouth dynamics in **shares** than for attention dynamics in **views**. Comparing the frequency of strongly pre-peak dynamics, we find that **shares** are 2.37

times more likely to be strongly pre-peak than **views** ( $\chi^2$  p-value < 0.05). The fractions for the *pre-peak*, *post-peak*, and *strongly post-peak* responses are not distinguishable between **shares** and **views**. These patterns are robust to slightly varying the ratios used to define the classes, and shows that collective responses are not equivalent when analyzing word-of-mouth and attention processes.

## 4. CONCLUSIONS

We found evidence of anticipated shocks as a new class of collective responses, which account for a small but non-negligible fraction of YouTube videos. This complements the attention dynamics based on self-excited Hawkes conditional Poisson processes suggested by [2] by the additional response class V that we explored here.

Anticipated shocks occur less often in attention (**views**) processes than in word-of-mouth (**shares**) processes. This difference calls for an extension of the current theory on the dynamics of collective responses, including the differentiation between attention and social interaction [5]. Online platforms can adapt to this difference and give more weight to predictions based on word-of-mouth signals, like **comments** and **shares**, as they are more proactive and tend to anticipate shocks more frequently than passive attention signals, like **views** or **searches**.

## 5. ACKNOWLEDGMENTS

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