THE DYNAMICS OF THE UNIVERSITY IMPACT ON YOUTUBE: A COMPARATIVE ANALYSIS

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ABSTRACT

The impact of universities on social networks has been widely studied, especially on Facebook and Twitter. However, there is a clear lack of research on YouTube, despite an overwhelming presence of universities on this online video platform. The objective of this work is to analyse similarities in the dynamics of views and likes between the YouTube channel of a university, Polytechnic University of Valencia (UPV), and an educational channel, the saurabhschool [**25**]. This is the first work that analyzes the dynamics of online video impact of a university on YouTube, which are subsequently compared to those of an educational channel to find common patterns. The times series of views and likes are obtained for both channels, their seasonal components are calculated and compared. Observation is subsequently supported by an analysis of correlations and the Euclidean distance. Results suggest that the video impact dynamics of a university channel behave similarly to those of an educational channel. These results can help universities anticipate the behavior pattern of their videos in order to maximize the impact of their content through YouTube.

Keywords:
Impact; University; Time series; Seasonality; YouTube

1. INTRODUCTION

Online video allows universities and other higher education entities to disseminate their audiovisual contents to their students and to society in general. YouTube's success as a leading global platform for video sharing offers educational institutions a new sphere of activity. With more than 2 billion users, consuming more than 1 billion hours of video daily [38], YouTube has become the second most visited website in the world after Google [2], the second most popular social network after Facebook [27] and the world's leading video-sharing platform. For this reason, it offers users outstanding possibilities of promotion and content diffusion.

Audiovisual content on YouTube is easily accessible to all kinds of users around the world, which can therefore go viral [10; 31]. This allows universities to promote themselves globally in a context of increasing competition. As a result, university managers have identified the opportunities that YouTube offers as a free access broadcast channel with global impact and, thus, the number of university institutional accounts created on YouTube and the number of videos available on them has grown exponentially in recent years. Universities use YouTube to disseminate promotional and marketing content [23], to consolidate their image and activate communication with their academic community [11], as well as to disseminate knowledge, increase the visibility and generation of a brand image [16] and, hence, expand the outreach of their academic offer [20]. Thus, 433 out of the 500 most prestigious universities according to the ARWU ranking (2018) [1, 18] and 368 out of the first 400 universities in the QS rank [33] have YouTube accounts. It is furthermore to be highlighted that some of these accounts were created only a few weeks after the platform was launched in the early 2005, as is the case of Case Western Reserve University or Harvard University.

The success of universities on YouTube has been evaluated through different measures such as likes, comments, shares, uploads [14, 30], the proportion of likes and dislikes [29] or the H_{1000} index [12, 18]. However, the most common and accepted measures of impact are the number of views [6, 36] and the number of likes [17]. These two measures are considered relevant components of online audience engagement [9, 14, 30], a main driver of content producer´s interest on social media [5] which can be regarded as the interactivity among users and media [8, 14, 15].

Despite the existing literature on the success of educational videos on YouTube [13, 26, 28, 34], as well as scientific videos [21, 32, 35], the impact of universities on YouTube is in the early stages of research. In line with this, the evolution of the number of views over time is a topic of growing interest [4], and some works [3, 25] address the analysis of the dynamics of the impact of online video on an educational YouTube channel. However, despite the increasing importance and resources that universities devote to YouTube, there is no scientific evidence that has analysed the dynamics of the impact variables of online video from universities; which can affect the understanding of the behaviour patterns of the online impact of university video and decision making.

We believe that it is necessary to unveil the dynamics of university online video impact and, therefore, our work aims to fill this gap in the literature by characterizing the evolution of the channel of a Spanish university with a strong presence on YouTube and comparing it with the behavior pattern of a successful educational channel. Thus, we ask ourselves the following research question:

RQ1: Are the dynamics of university online video impact similar to that of an educational channel?

On the other hand, despite the lack of research on the behavior of the impact of online video from universities, there exists a few seminal efforts to describe the behavioural pattern of the online video of educational channels [3, 25]. Results show that the evolution of the impact of online video is strongly characterized by a seasonal component. We consider it relevant, in turn, to delve into the seasonal aspect of the impact of online video on university channels and, therefore, the following research question is proposed:

RQ2: Are there similarities in the seasonal pattern of the evolution of the impact of online video from a university and that of an educational channel?

2. METODOLOGY

Regarding the measures utilised in the study, the variables views and likes are chosen to analyse the impact of online video as they are the most widely accepted in the literature [**6**, **36**].

Once the variables have been selected, data on the evolution of the number of views and likes of the institutional channel of the Polytechnic University of Valencia (UPV) on YouTube have been obtained. With more than 50 million views, this is the leading university in Spain by number of views in this platform. For our analysis, we obtained the data on the evolution of the variables from April 03, 2012 to October 13, 2017. This time span coincides the data provided for the educational channel saurabhschool [**24**]. As a result, data for a period of more than 5 years –namely 2020 days– are collected.

In order to answer the first research question, the evolution of both variables are graphically represented for both channels. This enables the visual verification of the possible similarities in the timely evolution of these two variables in the two channels. Subsequently, in order to statistically corroborate the possible similarities between the series, the Pearson's correlation coefficient between the series generated by both channels is calculated firstly for the variable views and, subsequently, for the variable likes. Finally, the Euclidean distance between the series of both channels is calculated for each variable in order to compare the degree of similarities in the evolution of the two variables. The Euclidean distance is calculated as the square root of the sum of the squares of the distances between the values that the variable takes for each of the channels at a specific moment.

In relation to the second research question, we draw on the STL –Seasonal Trend decomposition using LOESS– Method [**7**] to decompose and extract the trend and seasonal components of both variables´ time series, both for the UPV and the educational channels. In order to analyse whether the temporal evolution of the variables follows a similar seasonal pattern for both channels, we repeat the previous steps with the values of the seasonal component of the two variables: firstly, the graphic depiction of the seasonal component evolution of the two channels for each variable; secondly, calculation of the Pearson correlation coefficient between the series that generate the seasonal component of both channels for each variable; Finally, a comparison of the Euclidean distance between the series generated by the seasonal component of each channel for the two variables.

3. RESULTS

3.1. Comparison of the observed time series

In this section we firstly describe the observed time series of views and likes for both channels. Regarding the evolution of the number of views, as observed in Figure 1, both time series follow an increasing trend, starting with a reduced number of views that has progressively increased over time. Thus, the views of the UPV have increased from 4359 daily views at the beginning of the series to 24601 corresponding to the last observation. Similarly, saurabhschool´s views have grown from 7 to 5404 in the same period.

[INSERT FIGURE 1 HERE]

The depicted time series also show peaks and valleys following similar patterns among them, which suggest similarities in their seasonality. In particular, regarding the number views, two yearly periods can be observed in both series in which the variable experience steep decreases.

In relation to the evolution of the number of likes, as shown in Figure 2, an increasing trend is also depicted which is probably related to the increase in the number of views over time. In the same way as with the number of views, peaks and valleys can be observed in the number of likes at specific times, although greater variability is observed in the data.

[INSERT FIGURE 2 HERE]

On the other hand, the correlation coefficients of views and likes are both positive and very similar, with values of 0.554 and 0.494, respectively; both with a significance level of 99%. These results allow us to statistically corroborate the similarity in the evolution of both channels.

Finally, to compare the degree of similarity between views and likes of both channels, the Euclidean distance between these series is calculated. Among the possible methods to calculate distances between time series –e.g., Manhattan, Chebyshev–, we choose the Euclidean distance method as it is adequate to evaluate one-to-one mappings of pairs of sequences, providing satisfactory results when comparing the profile of the series observation by observation [19]. This allows us to compare the evolution of each pair of time series quantifying the gap between them. Additionally, the measure is easy to compute and interpret and has been applied to the analysis of social media and, in particular, of YouTube [22, 37]. In order for the Euclidean distance for both metrics and channels to be comparable in magnitude, the series are rescaled by matching the maximum of each of them with the unit. Once calculated, it is observed that the degree of similarity between views of both channels measured through the Euclidean distance (51.94) shows values very close to the degree of similarity of likes (51.98). The little difference between the Euclidean distances allows us to affirm that the degree of similarity in the dynamics of views of both channels is comparable to the degree of similarity in the evolution of likes.

3.2. Comparison of the time series seasonal component

In this section, the seasonal component of the time series of both views and likes is compared. Visual observation shows coincidences in the seasonal pattern of both time series. Thus, with regard to views (Figure 3), an increase beginning after the summer period can be observed, which is parallel to the beginning of the first semester. The increase ends in the month of December, at the end of the academic semester, when the non-school period begins. Then, a new rise is observed from January until the month of June, coinciding with the second semester.

[INSERT FIGURE 3 HERE]

As for the variable likes (Figure 4), the parallelism in the seasonal pattern of these series is not as pronounced as in the prior results. Nevertheless, as in the case of views, it can be observed that values increase as from summer, followed by declines at the end of the year. As observed in the graph, these declines take place previously in the case of the university channel (UPV) compared to the educational channel (saurabhschool).

In line with the graphic analysis, the correlation coefficient of the likes seasonal component (0.214) is somewhat lower than that of views (0.490), although both are positive and significant at 99% significance-level. As in the previous case, these results corroborate the positive relationship of the temporal evolution of the seasonal component of both channels for each variable. Finally, the Euclidean distance between the series, once rescaled setting its maximum at 1, is 192.9 for views and 295.4 for likes. This reinforces the finding of a greater similarity in the seasonal dynamics of the number of views than in that of likes.

[INSERT FIGURE 4 HERE]

4. CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

The present study introduces two research questions related to the similarity in the impact and the seasonality between the time series of a university and an educational channel on YouTube.

Regarding the first research question, the different methodologies applied allow us to corroborate the existence of similarities in the evolution of the number of views and the number of likes between a university channel and an educational channel, suggesting that both channels follow similar behavioral patterns. In fact, based on the observed time series, the differences between the channels for the two variables are minimal. Regarding the second research question, we also found similarities in seasonality between the two channels considered. Seasonality chiefly follows the evolution of the academic semesters. Additionally, the seasonal component of the views time series shows greater similarities between the channels than that of likes.

These results have implications for managers of university channels since they can anticipate in which periods the videos generate the highest impact. Because a university channel features not only teaching videos but also institutional ones, this work lays some foundations to delve into the role that institutional videos play in the impact of university channels, and the patterns of impact generation of these videos.

Finally, this work presents some limitations that deserve attention. On the one hand, the analysis is focused on the dynamics of two variables, views and likes. Hence, it would be interesting to extend the study to of other variables of success on YouTube, such as the evolution of the number of comments or subscribers. On the other hand, this research focuses on a single university and an educational channel and, thus, the generalization of results to universities in general must be done with caution. Future research should consider a broader sample of channels in order to find out whether the behaviours in the impact metrics follow similar patterns.

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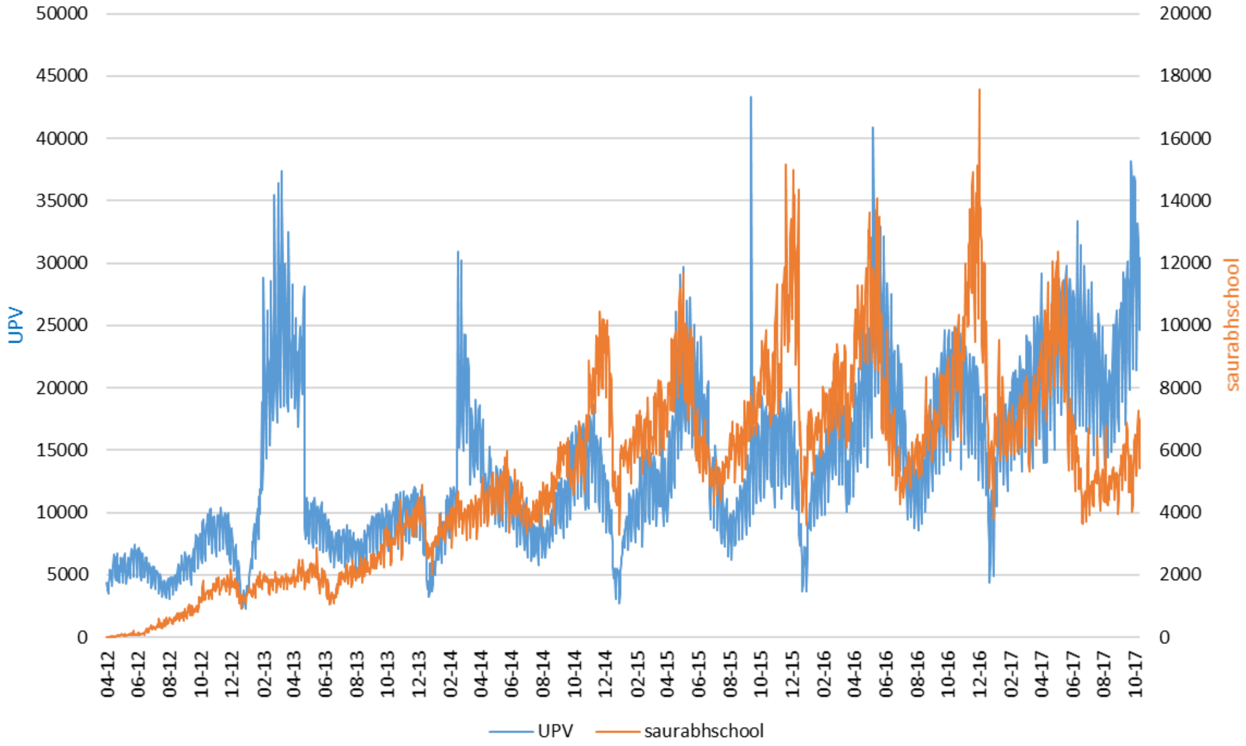
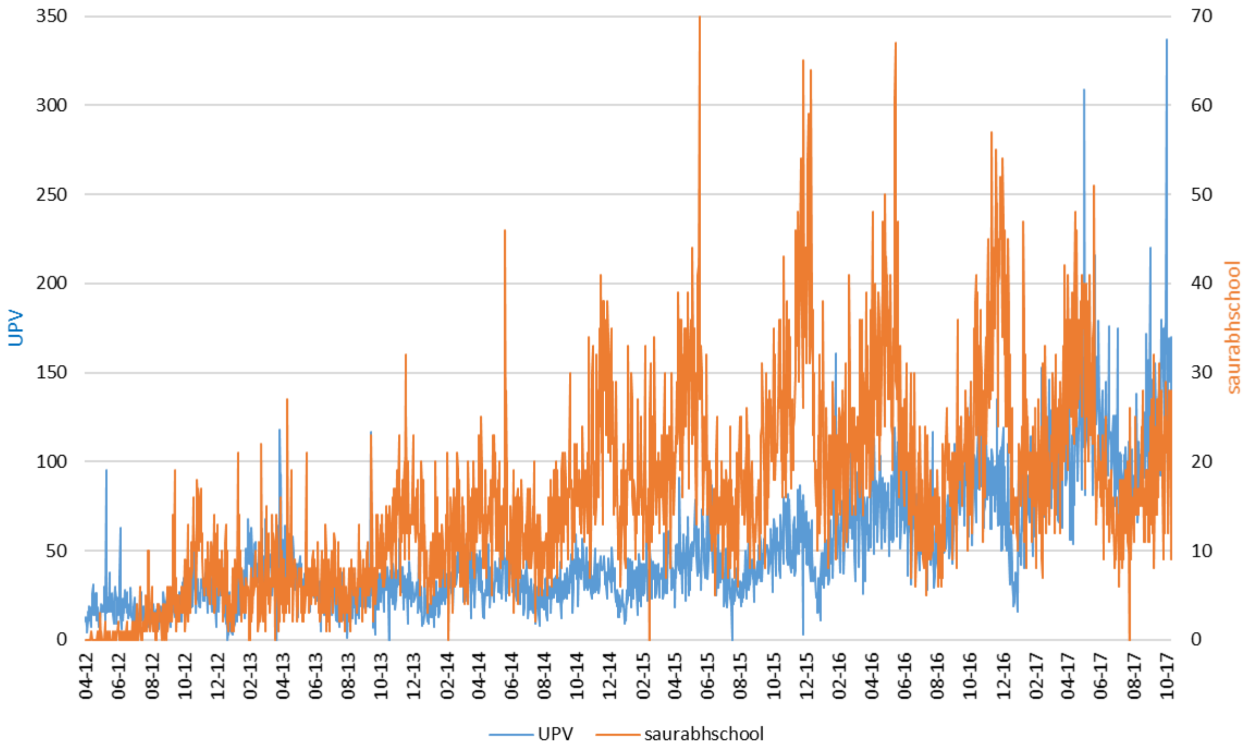
Figures

Figure 1. Observed time series (views)



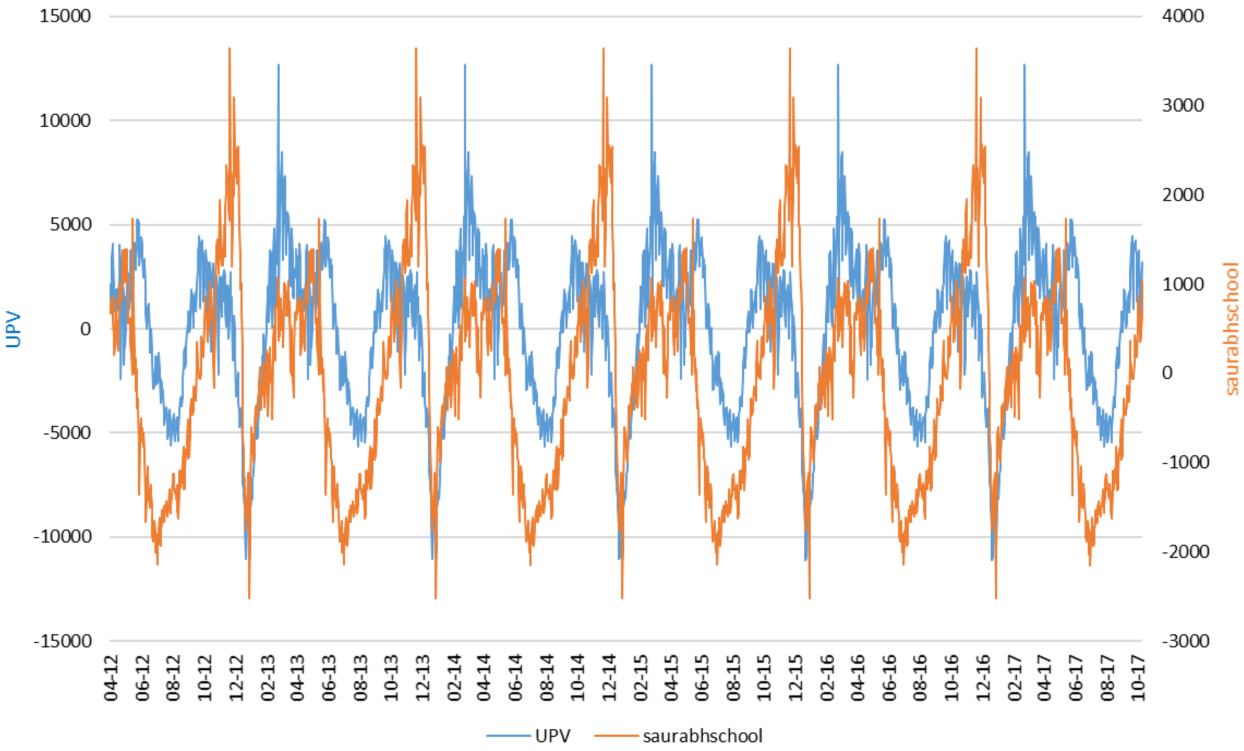
Source: own ellaboration.

Figure 2. Observed time series (likes)



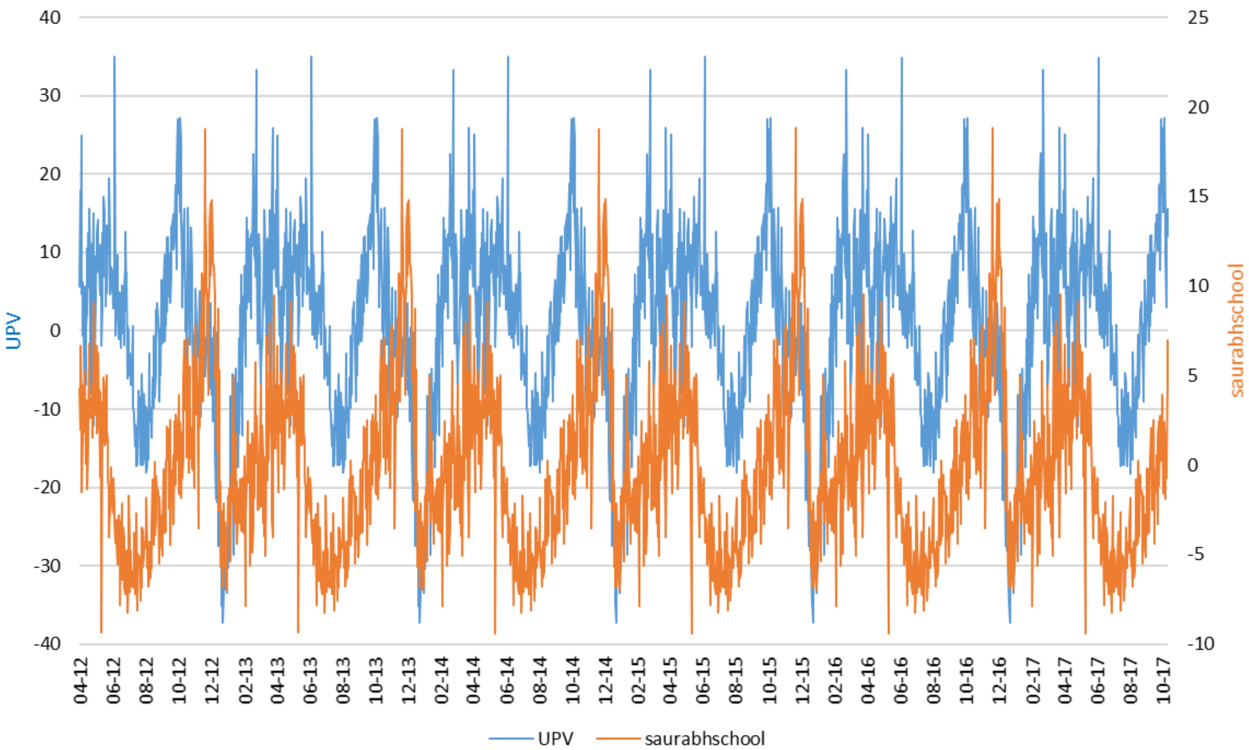
Source: own ellaboration.

Figure 3. Stational component of the time series (views)



Source: own ellaboration.

Figure 4. Stational component of the time series (likes)



Source: own ellaboration.