Online video impact of world class universities

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Abstract:

YouTube has become the standard social network for the dissemination of university multimedia content, but the impact of academic online videos has been scarcely researched. This study covers this gap and provides a new dimension to evaluate university performance. Data and statistics of 416 YouTube accounts and ca. 190000 online videos of world class universities are gathered. The H-index is adapted to quantify the online video impact, universities are ranked accordingly and the determinants of impact are analyzed. The H-based ranking of online video impact is closely related to standard rankings of world class universities, with a stronger relation than that with other online video related metrics. Research productivity and online video orientation of a university are robustly related with online video impact, whereas teaching, university size and geographical location are not.

1. Introduction

More and more people spend a sizable part of their time on YouTube. The increasing availability of broadband networks and the data sharing possibilities that Internet offers have boosted the sharing and delivery of video through networks (Simpson and Greenfield, 2009). Almost 5 billion videos and more than 100 million hours are watched daily in YouTube (Statisticbrain, 2016), which is nowadays the second most popular website in the world (after Google). Online video has become a usual mean of interaction for the whole society. Education, research and knowledge transfer are the main missions of universities. By making use of online video, universities boost their outreach disseminating knowledge beyond their own students to society.

Most of the world class universities are making major efforts to increase the impact of their research, teaching activities, portfolios of services and institutional activities through online videos. They are easily accessible to all kinds of users around the globe, who make videos viral (Kahn and Vong, 2014) motivated by their needs, personal and environmental factors (Chiang and Hsiao, 2015), so allowing universities to promote themselves globally in a context of growing competition. As a result, the number of uploaded videos and institutional accounts created by universities in YouTube has grown exponentially during the last years. Hence, universities engage in leveraging the opportunities that YouTube offers.

Among the different types of videos delivered through Internet, YouTube offers Internet video, user-generated videos broadcasted over the Internet and played on viewer request (Simpson and Greenfield, 2009). This social network has become the standard for the dissemination of university multimedia contents (Berk, 2009; Gilroy, 2010). Online teaching videos now support traditional teaching approaches and are at the core of new educational developments. They allow teachers' explanations to reach an unlimited number of students (Toven-Lindsey et al., 2015) and are becoming a natural companion of academic lives. The success of MOOC's – Massive Online Open Courses– (Pathak, 2016; Waldrop, 2013) or the recent incorporation of videos as support for research are examples (Kousha et al., 2012). Videos are used as a medium for the diffusion of the activities of an institution or researcher, or even for publishing original research (Vázquez-Cano, 2013). This is the case of video journals like JOVE, indexed in the usual scientific databases, or Audiovisual Thinking.

Despite the increasing importance of online videos for academic activities, their impact on YouTube and other video sharing platforms has not been yet quantified. This is not the case of other social media, such as Facebook or Twitter (Priem and Hemminger, 2010), in which there is a growing interest about the relation between academic research and social media impact (Priem et al., 2012). The analysis of academic activities in social media leads to an understanding of the factors that make universities more successful in this new environment (Brech et al., 2017; Lovari and Giglietto, 2012). These kinds of studies evaluate a new dimension of academic activities, which complements traditional rankings of academic prestige such as the Academic Ranking of World Universities (ARWU) or the Times Higher Education (THE). These rankings are useful tools that help stakeholders to evaluate the academic performance of the different institutions.

Although world class universities are actively taking part in academic online video, their activity has not been evaluated yet, and this is the main motivation of this study. We also seek to unveil which universities are leading this process and whether they are the most prestigious. A better understanding of the drivers of online video impact may help institutions manage these new dimensions more appropriately. Thus, we propose the following research questions:

RQ1. How should the online video impact of universities be measured?

RQ2. Which world class universities lead online video impact?

RQ3. Is the online video impact related with university prestige?

RQ4. What university and video characteristics drive online video impact?

In the next section we review the literature. In section 3 we present our research framework; in section 4 the methods; and in section 5 the results. In section 6 we discuss the implications of our research. Section 7 concludes.

2. Literature review

2.1. Academic use of social media

The use of social media by universities and academics is increasing. In the study conducted by Ann Voss and Kumar (2013), all the universities investigated used Facebook and Twitter, while 93% used YouTube. However, despite the widespread use of social media, universities only achieve low engagement levels. Lovari and Giglietto (2012) introduce an index to measure the social media performance of universities and find in their Italian sample that Facebook is the most used, mainly by small and medium universities. Brech et al. (2017) find that university reputation is related to the engagement of their fans in social media, showing a relation between university prestige and impact on Facebook. Academics use social networks for personal and professional purposes (Moran et al., 2011), motivated by the intention to share research rather than teaching (Ajjan and Hartshorne, 2008; Manca and Ranieri, 2016; Veletsianos and Kimmons, 2016). Laakso et al. (2017) show that the use of academic social networks by faculty members is mainly motivated by the dissemination of their research and increasing the number of their citations. While universities use YouTube for a broad range of objectives (Guzmán and Del Moral Pérez, 2014), other social networks like Facebook and Twitter are mainly used for marketing and branding (Bélanger et al., 2014; Koz, 2013).

Scientometrics has extended the traditional analysis of academic impact to quantify the impact of scientific production in social media (Priem et al., 2012), an approach known as altmetrics (Priem and Hemminger, 2010). Altmetrics is considered to provide a greater understanding of the academic impact of publications compared to traditional measures, as well as insights into the socio-economic impact of publications by examining online social footprints (Ravenscroft et al., 2017). As its main advantage, it complements citation analysis with broader, more diversified measures, which significantly reduce the delay of traditional approaches (Priem et al., 2012). The most common metric of the academic impact of a research paper is the citation count. Based on this, the impact factor has become the standard impact metric for journals (Garfield, 1955). Hirsch (2005) proposed the H-index which is defined as the highest number of articles (H) with at least H number of citations as the impact metric of an author. The success of this metric led to the application of this H-index to evaluate and rank journals and institutions (Braun et al., 2006; Lazaridis, 2010). The impact of academic contents in social media has been measured through the number of tweets on a given paper (Haustein et al., 2014), the number of unique Twitter users, the number of mentions in Google+ or the number of times a paper is posted in Facebook walls, among others (Costas et al., 2015; Haustein et al., 2015; Thelwall et al., 2013). Costas et al. (2015) find a weak relationship between academic impact and messages in Twitter, and no relation at all with other social media such as Facebook or Google+. Haustein et al. (2015) find different patterns when the impact of academic production is measured through citations and through social networks, suggesting that altmetrics complements traditional impact.

2.2. Impact of online videos

Individuals in today’s society are relying increasingly on online videos for purchasing and behavioral decisions (Oh et al., 2017; Tseng and Huang, 2016); therefore, understanding the success of online videos is of utmost importance. Watching online video, according to the Uses and Gratification Theory (Blumler and Katz, 1974), is associated with psychological and interpersonal satisfaction. Participation in YouTube yields engagement and social collaboration (Balakrishnan and Griffiths, 2017), being information sharing, self-status seeking, and relaxing entertainment predictors of watching videos online (Khan, 2017). Regarding user motivations to seek for science videos on YouTube, the main motives are enjoyment of science, informational use of YouTube and seeking-related subjective norm –i.e. engage in behaviors compliant with subjective social norms– (Rosenthal, 2017).

The most commonly utilized metric of online video impact is, by far, video view count (e.g., Borghol et al., 2011; Szabo and Huberman, 2010; Xiao et al., 2015), although other variables like comments, proportion of likes to dislikes (Sugimoto et al., 2013) or number of likes (Meseguer-Martinez et al., 2017) are also used. Video views follow a fat-tailed distribution (Cha et al., 2007; Cheng et al., 2013); which means that a significant part of the videos receive a huge number of views. This is due to rich-get-richer effects on video views, led by YouTube´s recommendation system (Borghol et al., 2012), and viral processes (Khan and Vong, 2014). Online video success is related to video characteristics and social dynamics (Crane and Sornette, 2008). It has also been argued that cultural differences drive geographical dependencies on online video impact (Brodersen et al., 2012). Dynamics of popularity have been modeled through different approaches (Borghol et al., 2011; Figuereido, 2013; Ratkiewitcz et al., 2010; Trzcinski and Rokita, 2017), with virality being a case of particular interest (Figuereido et al., 2011; Jiang et al., 2014). Khan and Vong (2014) study characteristics of successful videos and conclude that networks dynamics play a key role in virality.

User-generated scientific videos yield higher impacts than those professionally generated (Welbourne and Grant, 2016). Impact depends to a great extent on the target audience, e.g. scientific demonstrations address smaller audiences than public dissemination lectures (Thelwall et al., 2012). In their study on TED talks, Sugimoto et al. (2013) show that the status of the presenters´ universities is significantly correlated with the number of video views. Pan et al. (2016) also find in their content-analysis that the interest raised by topics varies significantly across countries. Thelwall et al. (2012), Welbourne and Grant (2016) and Meseguer-Martinez et al. (2017) also identify technical quality as an important factor in explaining video success. When describing good teaching videos practices; short-length videos are recommended (Liao, 2012; Meseguer-Martinez et al., 2017). This contrasts with the non-significant relation of video length with views in some studies (Cha et al. 2007, 2009). Concerning video oldness, Cha et al. (2007) find a positive relation with views for recent videos but no clear relation as time passes, whereas Khan and Vong (2014) even find a negative relation across the 100 most viewed videos.

2.3. University rankings

Since their introduction in the 1980´s in the US, university rankings have gained prevalence worldwide. They measure institutional performance as a proxy for academic excellence (Moed, 2017) or academic quality (Olcay and Bulu, 2016; Szentirmai and Radács, 2013). Unlike national rankings, global university rankings rely on a limited number of indicators and avoid soft data (Çakır et al., 2015; Saisana et al., 2011). They measure university performance through research, citations, teaching and quality of education, and quality of faculty (Olcay and Bulu, 2016). The most influential global university rankings are the Academic Ranking of World Universities (ARWU) and the Times Higher Education Ranking (THE). ARWU considers four criteria to measure prestige (Quality of education, Quality of Faculty, Research Output and Per Capita Performance). All the indicators within each criterion are research-related, based on citations, publications and prizes awarded to students or faculty. THE goes beyond research to assess university prestige, as education indicators count for 30% of the total score (technology transfer and internationalization are also given marginal consideration). It is worth noting that this ranking emphasizes reputation surveys to measure teaching and research. The measurement of teaching is not as straightforward as for research, whose measures are mainly based on objective indicators such as indexed publications or citations (Çakır et al., 2015; Olcay and Bulu, 2016).

Global university rankings significantly differ in their institutional and geographical coverages; and they also apply different sets of indicators and measurement methods (Moed, 2017). In spite of this, global university rankings are considered mono-dimensional, as they are based mainly on research output measured through bibliometric indicators (ARWU, 2015; Liu and Cheng, 2005; Szentirmai and Radács, 2013; THE, 2015). The different rankings of university prestige yield relatively similar results despite applying different methodologies (Aguillo et al., 2010), even when they rank universities using web indicators (Aguillo et al., 2008). This shows that rankings measure some intrinsic property of universities (Safón, 2013). It has been suggested that the older and the bigger the university, the greater its prestige (Piro et al., 2014). Holmberg (2015) finds that bigger Finnish universities attract higher attention in social media. The relation between university prestige and social media impact has been scarcely studied because academic rankings based on social media are at an incipient stage. To date, they have been applied to journals (Thoma et al., 2015; Fernandez-Cano and Fernandez-Guerrero, 2017) and universities (Holmberg, 2015), but there currently exists no ranking based on the impact of online videos.

3. Research framework

3.1. Quantification of online video impact

RQ1 asks how the online video impact of universities should be measured. Online video impact has been traditionally addressed through the number of views that a video receives (Xiao et al., 2015; Zhou et al., 2016), which is considered the fundamental parameter of popularity in YouTube (Chatzopoulou et al., 2010). However, view count may fail to measure the broad impact and productivity of a content creator because it can be biased by a small number of highly popular videos (Hovden, 2013). To solve this problem, we draw on the H-index (Hirsch, 2005) as proposed by Hovden (2013) and introduce the H_{1000} as an appropriate measure to calculate the impact of universities through online videos. With respect to RQ2, the online video impact of universities in YouTube is computed using both metrics, Views and H_{1000}, and the first ranking of world class universities is elaborated according to their online video impact.

3.2. Online video impact and university prestige

RQ3 aims to investigate whether online video impact is related to university prestige. The reputation of the content creator plays an important role in social media as it can have a positive effect on user engagement (Dijkmans et al., 2015; Hsu et al., 2013), also in the case of universities (Brech et al., 2017). University rankings, such as ARWU and THE, are considered relevant tools to measure university prestige and reputation (Moed, 2017; THE, 2015). Rankings yield relatively similar results despite their broad range of methodologies (Aguillo et al., 2010). This applies to rankings using web indicators too, as web presence reflects the overall academic activity (Aguillo et al., 2008). In light of this, we ask ourselves whether a link between online video impact of universities and prestige exists. Hence, we present the following hypothesis:

H1: University prestige is positively related to online video impact at university level.

3.3. University and video characteristics driving online video impact

RQ4 aims to explore which university and video characteristics drive online video impact. Thus, in order to disentangle this question, we propose two models. First, we introduce the determinants of the online video impact at university level. Subsequently, we explore the determinants of the online video impact at video level. Hypotheses are proposed accordingly.

Determinants of the online video impact at university level

First we explore the determinants of the online video impact at university level, analyzing how their online video orientation, research orientation and university characteristics are related with their impact.

Online video orientation of the university. Online video orientation is the commitment of universities with the production and dissemination of online video. It is reflected by the level of activity of the university on YouTube as well as by how long the university has been present. The extent to which universities are active in producing and releasing online videos is expected to increase the impact of their YouTube accounts. Hence, the earlier the accounts have been created and the more videos released, the higher the likelihood of yielding higher impacts (Susarla et al., 2012; Welbourne and Grant, 2016). Thus, we propose the following hypothesis:

H2: Online video orientation of the university is positively related to online video impact at university level.

Research orientation of the university. Research orientation is the commitment of the university with research activities, which is reflected by the production of new knowledge. Despite studying different dimensions, research is the only common and overwhelmingly utilized measure by university rankings (Çakır et al., 2015; Olcay and Bulu, 2016), which are devoted to quantify university prestige. Prestige is measured based solely on research in ARWU whereas it accounts for 60% of the total value in THE. We ask ourselves whether the research orientation of the university drives online video impact since there is evidence of the link between university prestige and social media impact (Brech et al., 2017). Based on this, we expect high research performance to yield a high online video impact. This leads to the following hypothesis:

H3: Research orientation of the university is positively related to online video impact at university level.

Additionally, in order to check the robustness of the model we use a set of relevant university characteristics. Along with research, teaching is the other great mission of universities. Teaching is not a commonly agreed on determinant of university prestige (Çakır et al., 2015; Moed, 2017) despite being used in some global rankings (e.g. THE). University size has been found to be positively related to impact in social media (Brech et al., 2017). Given that university videos are partially directed towards their university communities, the bigger the university the more potential viewers. Finally, cultural differences in the use of online video result in regional differences in the use of YouTube (Brodersen et al., 2012). Hence, we consider it relevant to control for the potential effects of teaching orientation, size and geographical location of the university. Thus, we propose the following hypothesis:

H4: Teaching orientation, size and location of the university are related to online video impact at university level.

Determinants of the online video impact at video level

Our video sample encompasses a great variety of university videos –e.g., research, teaching, promotional– from which we have restricted information. Thus, rather than seeking for a model to explain the impact of university videos, we aim to check whether the oldness and length of the videos are related with its views, thus controlling for university characteristics.

Video characteristics. As video characteristics, we consider two basic features, oldness and length. It has been argued that shorter teaching videos are more engaging for students (Guo et al., 2014; Liao, 2012; Meseguer-Martinez et al., 2017); hence, we believe they should yield more views. Additionally, although the relation between oldness and view count is not clear (Cha et al., 2009), we consider that the number of views should increase along time, because view count is a cumulative metric. Therefore, we propose the following hypothesis:

H5: Video characteristics are related to online video impact at video level.

University characteristics. As university characteristics related to online video impact at video level, we consider research orientation, teaching orientation, size and location. Based on the rationale stated for online video impact at university level, we study whether these university characteristics are associated with the success of university videos. Thus, we state the following hypothesis:

H6: University characteristics are related to online video impact at video level.

4. Methods

4.1. Measures

In what follows, we report and describe the variables in our study. Two different metrics are proposed as a measure of online video impact at university level. *Views* accounts for the total number of views of the videos published on a university YouTube account. The H_{1000} score of a university is defined as the highest number H of videos with at least H x 1000 views. Regarding prestige, we rely on ARWU and THE, using both rankings in our comparisons. They are usually considered the most relevant university rankings together with QS ranking (Szentirmai and Radács, 2013).

Online video orientation of the university has been addressed through *Oldness*, which shows the number of days since the YouTube account was created, and *Uploads*, which is the number of videos uploaded. Both metrics describe the activities on a YouTube account and are publicly available on the platform. We approximate research orientation of the university by the *Per Capita Academic Performance (PCP)*. *PCP* is a composite index that comprises the rest of the metrics considered in ARWU, normalized by the number of full time equivalent academic staff. Regarding teaching orientation, the THE ranking evaluates this dimension through a mixture of opinion surveys and quantitative data. Since the validity of surveys is often questioned (Bowman and Bastedo, 2011), we opt for the *Student/Staff ratio* as a proxy for teaching quality. Although THE considers different metrics, the *Student/Staff ratio* is the only teaching variable considered in other leading rankings (Olcay and Bulu, 2016). The *size* of the universities is measured through the number of students, again following the THE ranking. We group universities according to their *geographical location*. Regarding the measures of university videos, we rely on the information publicly available on YouTube. The online video impact at video level is quantified by *Vviews*, the total number of views that a video has received. The video characteristics are the video duration (*Vlength*) and the time elapsed since the video was uploaded (*Voldness*). Table I summarizes the variables in our study, their expected relations and hypotheses.

Table I

List of variables, expected relations and hypotheses.

Category	Variable	Description	Online video impact: University level	Online video impact: Video level	Hypotheses
Online video impact at university level	Views	Total number of views of the YouTube account.	*		
	H_{1000}	Highest number H of videos with at least H x 1000 views.	*		
Online video impact at video level	Vviews	Total number of views of a video.		*	
University prestige	ARWU	Academic Ranking of World Universities (ARWU).	(+)		H1
	THE	Times Higher Education (THE) World University Rankings.	(+)		H1
Online video orientation	Oldness	Elapsed days since the YouTube account was created.	(+)		H2
	Uploads	Number of videos uploaded by the university.	(+)		H2
Research orientation	PCP	Composite index of different research metrics normalized by full time equivalent academic staff (ARWU, 2015).	(+)	(+)	H3 / H6
University characteristics[1]	Student/Staff ratio	Number of undergraduates admitted per academic (THE, 2015).	(?)	(?)	H4 / H6
	Size	Total number of students of the university (THE, 2015).	(+)	(+)	H4 / H6
	Location	Region where the university is located (own elaboration).	(?)	(?)	H4 / H6
Video	Vlength	Duration of the video.		(-)	H5

characteristics	Voldness	Time elapsed since the video was uploaded.	(+)	H5

Variables elaborated based on YouTube information, except when indicated. Asterisks indicate dependent variables, (+) and (-) signs expected relations. (?): no specific sign is expected in the relation with online video impact. [1]Teaching orientation, university size and geographical location.

4.2. Procedure

We built a database with information from 416 universities and 189160 online videos. The database was built through the following process.

Drawing on the ARWU 2015, we looked up the official YouTube channel of the 500 universities listed in the ranking. Accounts were found through Google search, YouTube search, and surfing through university sites when necessary. Given that not all of the universities have YouTube accounts, we finally obtained data from 416 universities. In order to obtain information about them, we used Webometric Analyst 2.0. This software interacts with YouTube API in order to gather statistics of YouTube accounts. We compiled the total number of video views (*Views*), total number of uploaded videos (*Uploads*) and registration date of the YouTube account (*Oldness*), between 21st and 22nd January 2016.

A web crawler was programmed to access each university´s video list between February 8th and 10th 2016. Regardless of the total number of videos, the channel´s video list showed a maximum of 500 videos. The crawler was programmed to retrieve the 500 *newest* videos, then the 500 *oldest* videos, and finally the 500 *most viewed* videos. This process guaranteed that we had the full set of videos for universities with 1000 or less videos –367 universities– and that we had at least the 500 most viewed videos for the remaining universities –49–. This procedure provided data on 189160 videos from the 416 universities listed in the ARWU 2015 ranking with YouTube accounts. Of the 416 universities, only 352 were included in THE 2015 (which encompass 167161 of the 189160 videos). For each video, apart from the title, URL and University name, we gathered the number of video views (*Vviews*), number of days posted (*Voldness*), and video duration (*Vlength*). With these data, we calculated the H_{1000} index for each university. As previously mentioned, university´s H_{1000} index is the highest number H of videos with at least H x 1000 views. Since the highest H_{1000} value is 114 –below 500– we got the exact score for each university.

After explaining how the database was built, we describe the statistical techniques applied to analyze the data and test the hypotheses.

4.3 Statistical analyses

With regards to the data at university level, we first show descriptive statistics by region and, subsequently, a ranking of world class universities is presented. Then, correlations between data at university level are calculated; firstly, Spearman correlations between online video impact at university level and ranking variables and, secondly, Pearson correlation among online video impact at university level and the rest of the variables. Hypothesis H1 –relation between university prestige and online video impact at university level– is tested based on the significance level of the Spearman correlations adjusted by the Bonferroni correction (Savin, 1980). Hypotheses H2 to H4 –determinants of the online video impact at university level– are tested by means of linear regressions (OLS) and the validity of the model is checked through hierarchical regressions.

At online video level, first, descriptive statistics by region are presented. Subsequently, Pearson correlations among online video impact at video level and video characteristics are calculated, and significance levels are adjusted by the Bonferroni correction. Following the same rationale as with online video impact at university level, hypotheses H5 and H6 –determinants of the online video impact at video level– are tested with linear regressions (OLS) and the validity of the model is checked through hierarchical regressions.

5. Results and discussion

The first university included in ARWU (2015) to create a YouTube account was Case Western Reserve University. This account was created in August 2005, just 6 months after YouTube was launched. At the time of study, it had more than 2000 online videos and 3.1 million overall video views. Many other universities in our sample opened up accounts right afterwards, e.g.: Harvard University (26/09/2005), New York University (28/09/2005), Boston University (06/10/2005), MIT (11/10/2005), etc. The number of accounts created by world class universities has grown overwhelmingly ever since, and so has the number of available videos and views. The levels of activity vary among universities. However, accounts from universities such as Stanford University or the Massachusetts Institute of Technology had more than 2600 and 3400 videos, and an overall count of more than 95 million views and 78 million views respectively.

US and Canada universities were the first to join YouTube. As shown in Figure 1, universities from Latin America and Oceania opened YouTube accounts relatively early, while European, Asian and especially African universities did so later.

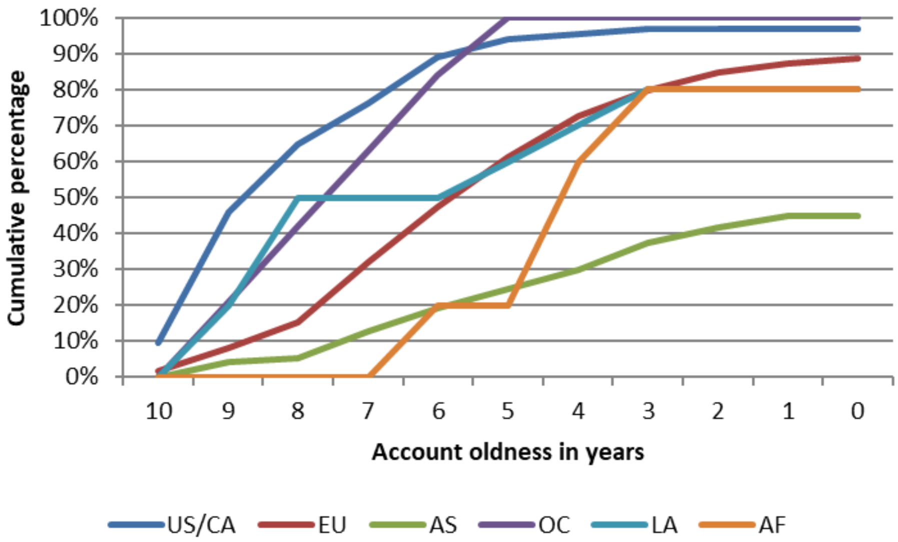

Fig. 1. Cumulative number of university official accounts in our sample, by region. US/CA – U.S. and Canada, EU – Europa, AS – Asia, OC – Oceania, LA – Latin America, AF – Africa.

In Table II we disaggregate our data by regions. Most of the universities with an official YouTube account are from Europe (42.8%) or US/Canada (39.6%). Asian universities are underrepresented. Only 10.1% of universities with a YouTube account are Asian, whereas they account for 22.6% of the Universities in ARWU 2015. On average, universities from US and Canada drive the highest figures for H_{1000}, views and uploaded videos, and their accounts are older. It is worth noting that, compared to Europe, Asian universities have newer YouTube accounts on average, but a higher number of views and uploads.

Table II

Descriptive statistics on the YouTube official accounts.

Location	Universities	H_{1000}[1]	Views[1]	Uploads[1]	Oldness[1]
World	*416 (500)*	*19*	*2128025*	*1143*	*2893*
US/Canada	165 (171)	23	3784203	1295	3212
Europe	178 (201)	14	926519	748	2496
Asia	42 (94)	17	1238465	1969	2401
Oceania	19 (19)	16	2132598	723	2818
Latin America	8 (10)	10	342047	682	2548
Africa	4 (5)	7	168273	218	1887

Data by region. Universities: universities with an official YouTube account in ARWU 2015. Views in units. Uploads in videos. Oldness in days. [1]Average per university.

At country level, the most represented ones in our sample are US (146 universities), UK (35), Germany (32), Canada (19), Australia (17), France (17), Italy (16), Netherlands (12), Japan (11), Spain (11) and Sweden (10).

Next, we provide and describe a ranking of world class universities after measuring online video impact. Subsequently, the relation between online video impact and university prestige is analyzed. Finally, we explore what university and video characteristics are related to online video impact.

5.1. A ranking of world class universities

Following our RQ1 and RQ2, we quantify online video impact of world class universities as listed in ARWU 2015 and provide the complete ranking for the top 100 Universities in the Appendix A (Table A.1). Universities have been ranked by H_{1000} following Hovden (2013). The ranking of each university according to Views is also provided.

Stanford University leads the ranking both by H_{1000} and Views, followed by Massachusetts Institute of Technology. Both universities had 114 and 113 videos viewed more than 114000 and 113000 times respectively. A long way behind, the University of California, Berkeley is the third university according to the H_{1000}, and Harvard University the fourth, with their positions reversed according to Views. The first European university by H_{1000} is Cambridge University (6th in the global ranking), the first Asian university is Technion-Israel Institute of Technology (8th), the first Oceanian one is the University of New South Wales (11th), the first South American university is the Federal University of Rio Grande do Sul (117th) and the first African is the University of Cape Town (167th). Although rankings by H_{1000} and Views are similar, their differences are well illustrated by the case of Carnegie Mellon University, which ranks 21st by H_{1000} but 5th by views. This is due to its most viewed video, which has more views than any other university ranked 7th or below according to views.

5.2. Online video impact and university prestige

RQ3 addresses the relation between online video impact at university level and university prestige. Most of the university rankings present significant correlations with each other. In this section we show that online video impact is also related with these rankings of world class universities. In Table III we report the Spearman correlation between our online video metrics and two of the most used university rankings. According to Cohen et al. (2003), correlation values in the range 0-0.19 are considered very weak, 0.20-0.39 weak, 0.40-0.59 moderate, 0.60-0.79 strong and 0.80-1 very strong. We find a positive significant correlation in all the cases, adjusting by Bonferroni multiple testing correction (Savin, 1980), meaning that the higher a university´s ranking

–in both ARWU and THE– the higher its H_{1000}, views, uploads and the older its YouTube account. The online video impact of universities is positively and significantly correlated to the rankings of university prestige, with H_{1000} being more correlated than views. Correlations with uploads and oldness are positive and weak, but significantly different from 0. We find, moreover, that both rankings have higher correlations with the H_{1000} index than with the rest of the measures of online video impact and university´s orientation to online video. Therefore, we accept our H1.

Table III

Spearman's correlations among rankings and online video metrics.

		Online video impact at university level		**Online video orientation**	
		H_{1000}	Views	Uploads	Oldness
University prestige	ARWU *(N=416)*	0.398*	0.372*	0.238*	0.188*
	THE *(N=352)*	0.435*	0.413*	0.247*	0.254*

Significance levels at 95% are shown with a star (p<0.05, adjusted by Bonferroni multiple testing correction).

5.3. University and video characteristics and online video impact

With regards to RQ4, we investigate what university and video characteristics drive online video impact. We find significant correlations of our online video impact metrics with online video orientation variables, as well as other relevant performance variables used in ARWU and THE. In Table IV we present the correlation matrix of a set of university variables and several online video metrics. In particular, H_{1000} shows a strong correlation with Uploads and a moderate correlation with Oldness, meaning that the more videos a university uploads and the older the account, the higher the online video impact. It also shows a moderate positive correlation with PCP and a weak negative one with the Student/Staff ratio. This result implies that the more students a teacher is in charge of, the lower online video impact the university reaches. Surprisingly, online video impact at university level (H_{1000} and Views) is uncorrelated with the size of the university (measured by the number of students). These results suggest the validity of our hypotheses H2 and H3 and are unclear about H4. The relations posed in the hypotheses are further tested in the next subsection.

Table IV

Correlations among university variables.

	Online video impact at university level		**Online video orientation**		**Research orientation**	**University characteristics**	
	H_{1000}	Views	Uploads	Oldness	PCP	Student/Staff	Size
H_{1000}	1						
Views	0.852*	1					

Uploads	0.671*	0.526*	1				
Oldness	0.444*	0.237*	0.311*	1			
PCP	0.475*	0.434*	0.248*	0.116	1		
Student/Staff	-0.207*	-0.130	-0.129	-0.171*	-0.210*	1	
Size	-0.044	-0.048	-0.033	-0.104	-0.073	0.227*	1

Significance levels at 95% are shown with a star ($p<0.05$, adjusted by Bonferroni multiple testing correction).

Determinants of the online video impact at university level

The previous analyses show that online video orientation and research productivity are related with online video impact.

In Table V we present the results of the regressions, Model 1 for H_{1000} and Model 2 for Views. We report three alternative regressions for both models. In regressions A, we study the model with the original data with 416 universities. In regressions B we introduce a set of control variables, including the characteristics of universities reported in THE 2015 (Student/Staff ratio and Size), as well as region controls (we consider US/Canada, Europe and the rest of the world). As explained in subsection 4.2, this reduces the number of observations from 416 (the number of universities listed in ARWU 2015 with an official YouTube account) to 352 (universities also listed in THE 2015). Finally, in regressions C we reproduce regressions A for this reduced sample.

According to regressions A, uploads, oldness and PCP are significantly and positively related with H_{1000}, while oldness is not significant to explain the number of Views. Note that the explanatory power of the model is much higher for H_{1000} (R^2=0.606) than for Views (R^2=0.379). These results persist after including the set of university controls in regressions B. Thus, we accept our H2 because of the significant effect of online video orientation and H3 because of the significant effect of research productivity per capita. Regarding the set of controls, neither Student/Staff ratio nor size has any additional explanatory power with respect to our model. This could be expected for size, since it was uncorrelated with online video impact at university level, however, in the case of the Student/Staff ratio, this implies that its correlation occurs through online video orientation and research orientation. Surprisingly, geographic region is not significant, although, as seen in Table I, US/Canada universities has on average a much higher impact. This means that the additional online video impact of those universities is due to a higher online video orientation and research productivity. Accordingly, we reject H4. In line with this, the addition of each variable in the hierarchical regression, i.e. Uploads, then Oldness, then PCP and finally the rest of controls, is significant both for H_{1000} and Views in all cases but for the control variables, as shown in Appendix B (Table B.1 and Table B.2).

Table V

Determinants of the online video impact **at university level**.

		Model 1 - H_{1000}			Model 2 - Views		
		A	B	C	A	B	C
Online video orientation	Uploads	0.007 ***<0.001***	0.006 ***<0.001***	0.006 ***<0.001***	3496.208 ***<0.001***	3338.389 ***<0.001***	3379.757 ***<0.001***
	Oldness	0.003 ***<0.001***	0.003 ***<0.001***	0.003 ***<0.001***	580.438 *0.098*	407.024 *0.383*	671.945 *0.101*
Research orientation	PCP	0.410 ***<0.001***	0.418 ***<0.001***	0.425 ***<0.001***	242936.4 ***<0.001***	258624.4 ***<0.001***	257964.5 ***<0.001***
University characteristics	Student/Staff		-0.034 *0.409*			10384.71 *0.742*	
	Size		0.000 *0.399*			-2.159 *0.892*	
	US		1.462 *0.257*			922189.4 *0.347*	
	EU		0.005 *0.996*			-94252.23 *0.917*	
	Constant	**-10.492** ***<0.001***	**-10.165** ***<0.001***	**-11.127** ***<0.001***	**-6785434** ***<0.001***	**-7162175** ***<0.001***	**-7415159** ***<0.001***
	R^2	0.606	0.596	0.592	0.380	0.368	0.365
	Adj. R^2	**0.604**	**0.588**	**0.588**	**0.376**	**0.355**	**0.359**
	F	**211.7** ***<0.001***	**72.55** ***<0.001***	**168.3** ***<0.001***	**84.14** ***<0.001***	**28.57** ***<0.001***	**66.58** ***<0.001***
	N	**416**	**352**	**352**	**416**	**352**	**352**

For each variable, regression coefficients in regular font (above), p-value in italic font (below).

Determinants of the online video impact at video level

In this section, we change the focus to the determinants of the online video impact at video level. In Figure 2 we plot the cumulative number of videos by region and years online. Videos from US/Canada universities are much older than the rest. In fact, more than 20% of the videos uploaded in YouTube by these universities are aged 5 years and above. Videos this age only account for 10% in all the other regions.

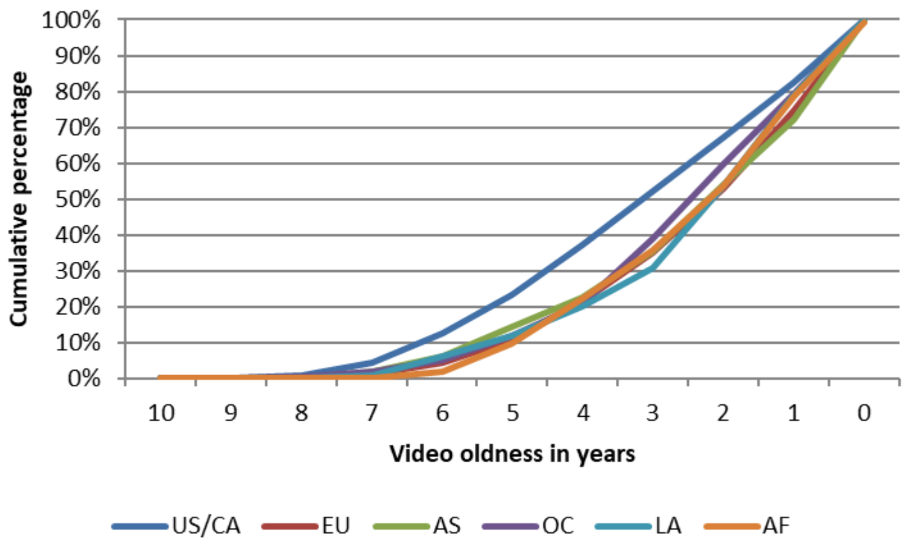

Fig. 2. Cumulative number of videos in our sample, by region.

In Table VI we present descriptive statistics of the videos in our database sorted by region. Although European universities represent 42.8% of the universities with YouTube accounts, they only accumulate 28.9% of the videos. US/Canada videos show the highest impacts, while videos from Latin America and African universities yield the lowest ones. This is congruent with the lower population with Internet access in those regions. Oceania is the second region in terms of online video impact at video level and oldness. Videos from universities have an average length of 11 minutes and 45 seconds (705 seconds), and a standard deviation of 20 min and 37 seconds (1237 seconds). The length of US/Canadian and European videos is very similar, while Asian videos almost double that length.

Table VI

Descriptive statistics on the videos.

Location	Videos	Vviews[1]	Vlength[1]	Voldness[1]
World	*189160*	*4391*	*705*	*930*
US/Canada	102482	5676	692	1054
Europe	54745	2931	662	771
Asia	16154	2615	1141	796
Oceania	11331	3605	498	831
Latin America	3606	1188	443	772
Africa	842	1319	540	773

Data by region. Videos: number of university videos. Videos and Views in units. Vlength in seconds. Voldness in days. [1]Averages per video and region.

In Table VII, we present the correlations among video characteristics, *Vviews*, *Vlength* and *Voldness*. The size of all the correlations is very weak although significant. As expected, *Vviews* and *Voldness* are positively correlated. However, the correlation between *Vlength* and the other variables may seem more surprising.

Table VII

Correlations among video variables.

	Online video impact at video level	**Video characteristics**	
	Vviews	Vlength	Voldness
Vviews	1.000		
Vlength	0.011*	1.000	
Voldness	0.037*	-0.017*	1.000

Significance levels at 95% are shown with a star ($p<0.05$, adjusted by Bonferroni multiple testing correction).

First, we find a negative and very weak (but significant) correlation between *Vlength* and *Voldness*, meaning that universities are creating longer videos. Second, the positive relation between *Vviews* and *Vlength* means that longer videos accumulate more views, which might suggest that universities should focus on longer videos, in line with the previous finding. Note that this effect is significant but very weak. This relation does not differ qualitatively among regions, since it is always positive, although only significant for US/Canada (0.017), Asia (0.034) and Latin America (0.104).

In Table VIII we present the results of the regression with and without university-related controls. In regression A, we analyze whether video characteristics are related to the number of views using the sample of 189160 videos of the 416 ARWU-ranked universities with official YouTube accounts. Regression B enriches regression A controlling by university characteristics reported in THE as well as region controls, which restricts the sample to 167131 videos from the 352 universities on the ARWU and THE rankings, and with official YouTube account. We verify that both *Vlength* and *Voldness* remain significant explanatory variables. Finally, in regression C we replicate regression A on the restricted sample. Results are robust and aligned and show that the longer and the older the videos, the higher their impact. Thus, we accept our H5. With respect to university characteristics, research orientation positively influences video views, while teaching quality, size and location do not. In the hierarchical regression starting from Vlength as independent variable, then introducing Voldness, PCP and finally the university controls, the only variables which do not increase the explanatory power of the model significantly are the university controls (Appendix B, Table B.3). Based on this, we partially accept our H6. Note, however, that the explanatory power is very low ($R^2<0.005$), meaning that these variables, although significantly related to the views of university videos, are explaining just a small part of its success.

Table VIII

Determinants of the online video impact at video level.

	Vviews

		A	B	C
Video characteristics	Vlength	0.827 ***<0.001***	0.455 *0.011*	1.016 ***<0.001***
	Voldness	4.510 ***<0.001***	4.951 ***<0.001***	4.914 ***<0.001***
Research orientation	PCP		416.479 ***<0.001***	
University characteristics	Student/Staff		24.045 *0.315*	
	Size		-0.019 *0.133*	
	US		90.367 *0.880*	
	EU		-591.280 *0.362*	
	Constant	**-387.8** ***0.250***	**-10524** ***<0.001***	**-812.3** ***0.031***
	R^2	**0.0016**	**0.0045**	**0.0017**
	Adj. R^2	**0.0016**	**0.0045**	**0.0017**
	F	**148.94** ***<0.001***	**108.23** ***<0.001***	**143.59** ***<0.001***
	N	189160	167131	167131

For each variable, regression coefficients in regular font (above), p-value in italic font (below).

6. Implications

The results of this study have some theoretical implications. Despite universities increasingly seeking online presence as an important part of their outreach activities, no prior studies analyze the online video impact of world class universities. We contribute to the research on altmetrics, focusing more on social media than other video-sharing platforms.

Impact on social media has been quantified by the number of tweets, unique Twitter users, mentions in Google+, postings on Facebook walls (Costas et al., 2015; Haustein et al., 2014; 2015; Thelwall et al., 2013). As an answer to our RQ1, we introduce the H_{1000} index as a measure that adequately assesses the online video impact of universities, contributing therefore to the measurement of academic activities in social media. As used in our study, H-indexes can be adapted to social media other than YouTube. Additionally, the first ranking of (world class) universities based on their online video impact –H_{1000} index– is drawn up (RQ2).

Besides the well-known relation among measures of university prestige, we add the connection with online video impact (RQ3). With respect to RQ4, our results underline that university research productivity is associated with online video impact both at university and video level. This contributes to the literature on the characteristics of successful academic-related videos, since this is the first time the whole set of videos produced by world class universities has been analyzed. University online video orientation is related to online video impact, while teaching quality, size and university location do not. The success of university videos shows a positive (very weak but significant) relation with their length, in contrast with recommendations for teaching videos (Guo et al., 2014; Liao, 2012). Interestingly, university characteristics other than research productivity show no relation with online video impact. It is to be emphasized that these variables only account for a very small part of the success of university videos.

This study has also practical implications for rankings and universities. Rankings aim to capture a wide range of activities in order to offer a detailed image of the university. Results show that online video impact is closely related to university prestige (RQ3). We suggest rankings to include online video impact as an additional dimension to assess. In this way, they would cover an increasingly important activity for universities.

Universities have the chance to leverage their online video impact beyond their intrinsic characteristics through online video orientation (RQ4). Therefore, higher efforts directed towards YouTube can support universities in the diffusion of their activities. Although short teaching videos are usually recommended, our findings show that universities do not necessarily need to focus on short videos in order to yield high impacts.

7. Conclusions, limitations and further research

In this paper we set out to analyze the online video impact of universities. Apart from the natural metric total number of views, we introduce an adapted index of online video impact based on Hirsch (2005) in line with RQ1. According to RQ2, we rank 416 world class universities according to the H_{1000} index and find that Stanford and MIT have, by far, the highest impact. It is also worth noting that the University of Cambridge, Technion-Israel IT, and New South Wales lead the ranking in Europe, Asia and Oceania respectively. All of these are among the 11 universities with the highest online video impact within the world ranking.

We identify regional differences in online video orientation, as well as among the broadcast videos. US/Canada universities were the first to set up YouTube accounts and have a higher impact, despite Asian universities uploading more videos on average than the others. Videos produced by US/Canada universities are the most viewed, whereas videos from Asian universities are the longest. Then, we analyze the correlation between online video impact and university rankings, as well as university characteristics. Online video impact, measured as H_{1000}, is moderately correlated with ARWU and THE (RQ3). We also find a positive moderate correlation between H_{1000} and research productivity of the university. Note that prestige and research are moderately correlated with online video impact, thus many other factors play an important role in explaining it.

Next, we model university online video impact as a function of university characteristics (RQ4). We find that video orientation and research productivity have a robust positive relation with our H_{1000} measure, while the student/staff ratio, size of the university and location do not. Finally, we explore how the number of views of a video is associated with characteristics of the video and its university. Length and oldness of the video, as well as university research productivity, are related to the number of video views in a positive and significant manner, while other characteristics do not.

As highlighted by our results, online video impact at university level is related but not completely determined by university prestige. Video orientation plays an important role as well. Among the Top 10 universities in online video impact, by H_{1000}, we find Mayo Medical School (5^{th}), Technion-Israel Institute of Technology (8^{th}) and the Polytechnic University of Valencia (9^{th}). In the ARWU ranking, these universities are in positions 150, 77 and 350 respectively; while in the THE ranking only the last one is listed (in position 700). These universities are among those with the highest number of uploads.

Some relevant limitations to this study deserve mentioning. First, video views may be a vitiated metric. While YouTube seems to have a good protection system, bots can be programmed to artificially boost video views (Chen et al., 2015; Marciel et al., 2016). Additionally, the sample includes videos that have been paid by the university to boost their views, and which cannot be identified. Second, with respect to the YouTube accounts analyzed, this study focuses on world class universities, thus leaving aside universities not listed in ARWU. Among those listed in ARWU, Asian universities are underrepresented because YouTube is not popular in some Asian countries (or has even been banned, as in China). Chinese universities do not have official accounts in Youku Tudou, the most popular Chinese online video-sharing platform. Third, our sample does not encompass all the videos for universities with more than 1000 uploads, which may lead to a bias in our analysis at video level (although it poses no problem when studying universities, as explained in the Procedure subsection). Therefore, we need to be cautious about the generalizability of our results. Finally, we could not perform a content analysis of university videos due to the sample size. We acknowledge that this would provide valuable fine-grained information, enabling deeper insights into the online video impact of universities and also the delivery of further recommendations.

Several of the results invite further research. First, adapted H-indexes can be used to elaborate academic rankings in social media other than YouTube. For instance, a ranking of university impact in Twitter can be performed with an H_x index of university tweets according to their X number of retweets. Second, the relation between university rankings and online video impact, especially measured through the H_{1000} metric, suggests the existence of a causal relation that should be explored. In the same vein, the robust relation between research productivity and online video impact call for a deeper analysis. All these results suggest that some research-related property of the universities is associated with online video impact. Third, although we consider that account oldness should be naturally related to online video impact, the mechanism that explains why oldness is related to H_{1000} but not to views is far from being clear. Fourth, previous research has shown the appropriateness of shorter teaching videos in YouTube. However, we find that longer videos yield more views. It should be checked whether the type of video –teaching, promotional, research– explains this fact. Results also show that recent videos tend to be longer. Whether the production of longer videos is motivated by their higher impact should also be investigated. Finally, other dimensions should be explored when analyzing the online video impact at video level, since our variables account for just a very limited part of its variability. On the one hand, content analyses can be performed in order to gain insights into the role on the online video impact of universities of further technical quality features –resolution, join time, clarity of image– and speaker/viewer characteristics –gender, age, background, language, speech–. On the other hand, the analysis of the comments both from a quantitative and qualitative point of view (for instance, through a sentiment analysis of the texts) could enrich the current analysis.

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