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Using YouTube Analytics to Investigate Instructional Video Viewing Patterns

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Abstract: In recent years, there has been a growing interest in learning analytics and educational data mining in the higher education sector. Learning analytics data can be used to identify at-risk students and to help instructors identify how students are engaging with their online course materials. Despite the popularity of video-based instruction in higher education, there is limited research to-date on how instructors can use analytics data to investigate video viewing patterns, with a view to determining the efficacy of those videos. Analysing video-watching patterns provides a unique opportunity to appreciate how, and if, students learn more effectively via video. To that end, this case study explores the video viewing patterns of a cohort of 348 undergraduate business students taking a business-oriented IT module. The students had access to a series of 17 videos, spanning five practical Microsoft Excel topics, which were developed specifically for a module entitled 'Business Information Management'. Students attended two one-hour lectures per week and five one-hour computer labs over the semester. In addition to an end-of-term theory exam, there was also a one-hour end-of-term practical spreadsheet exam. This case study answers the following questions: To what extent do students use instructional videos as a tool for initial learning and revision for the end of term practical exam? Does the difficulty of the material affect video viewing patterns? How much [what proportion] of the videos are watched? Does the difficulty of the material affect how much [what proportion] of the videos are watched? To what extent do students watch a series of videos on a topic? The paper demonstrates the nature of data that can be freely obtained from YouTube analytics and how it can be further exploited to determine how instructional videos are being used (how many students access the videos, for how long, and when). The paper also highlights the importance of undertaking a deeper analysis of the data, as the initial summary data may be misleading.

Keywords: learning analytics, YouTube videos, video-based instruction, viewing patterns, videos

1. Introduction

In recent years, there has been a growing interest and awareness of learning analytics and educational data mining in the higher education sector (Siemens & Baker, 2012). Tools such as YouTube analytics enable instructors to identify the usage patterns of their instructional videos, thereby gaining insight into their effectiveness. Arnold and Pistilli (2012) suggest learning analytics data can also be of significant use to students by reporting on their individual progress. Consequently, traditional on-campus institutions are availing of technological advances to offer a richer student experience. One such advance, which has gained momentum in recent times, is video-based instruction (Greenberg & Zanetis, 2012). It is used extensively in a flipped classroom environment whereby course materials are provided to students in advance of the face-to-face (f2f) session allowing traditional home activities to be undertaken during class time, under the direction of the teacher (European Commission, 2014; Yarbrow, Arfstrom, McKnight & McKnight, 2014).

Studies carried out to date in the area of learning analytics in higher education are somewhat limited in their usage of data analytics, particularly with regards to exploiting data available from sources such as Google/YouTube. This paper attempts to bridge this gap and is novel in that it explores how teachers can use freely available data extracted from YouTube Analytics to evaluate students' video viewing patterns.

2. Background context

2.1 Use of video in higher education

In recent years, media, and video in particular, has dramatically changed the educational landscape. The effective use of video can transform the way we teach, learn, study, communicate, and work. YouTube is one of the most popular websites on the internet, with over 100 hours of video being uploaded every minute (Buzzetto-More, 2015). One billion hours of video are watched on YouTube every day and more than half of YouTube views come from mobile devices (YouTube, 2019).

Thanks to Virtual Learning Environments (VLEs), disseminating videos or URL links to videos has become much simpler. Links to YouTube videos can be embedded into course material, discussion forums, and targeted learning objects. However, according to Hansch et al. (2015), the production of quality video content still remains a significant expense. Anything that can make the production of video less expensive will enable its increased and more effective growth in higher education environments (Bakel & Groot-Kormelink, 2011; Panopto, 2014).

Buzzetto-More's (2015) research into student attitudes towards the integration of YouTube in higher education found that incorporating targeted YouTube videos significantly enhances students' perception of learning efficacy and increases engagement, so much so that its continued usage should be fostered. De Boer (2013) identified a number of patterns about how students view video material. Some students watch the complete video in one non-stop 'sitting' while others watch multiple times; some students repeatedly select specific sections (perhaps due to more challenging content), whereas others move quickly through the video jumping from one section to another. In many cases there remains a discrepancy between the way that students report how they view videos, and what the data collected from servers indicates (Gorissen, 2013; Sutherland-van den Heuvel, 2015). It must be noted, however, that it is not straightforward to track the learning process of students. Just because a video is streaming to a student's computer, it does not mean that the video is being watched, or what, if any, kind of learning is taking place.

2.2 Video and learning analytics

Several studies have explored when and how students use online instructional videos. Schiltz (2015) used Google Analytics to examine usage patterns of video tutorials created to supplement introductory physics lectures for engineering students. Interestingly, they found that although not compulsory, most students used the video tutorials and showed a high level of engagement with the materials. While students viewed video tutorials throughout the term, a significant number of students also used them as a revision aid for exams later in the term. Metz (2013) investigated the impact of (short) assigned online videos on student learning in an introductory biology programme. By tracking access, the data showed that in a 'flipped' classroom environment, video watching was consistently above 80%, suggesting that videos work well in supporting learning outside of the classroom, freeing-up precious class time. They also found that if the 'viewing burden' is heavy and students are not incentivised, videos tend not to be as well received.

Brady, Wong, and Newton (2013) measured attendance and online lecture video accesses to determine if students use online recordings of live lectures to catch-up after missing a class and also, more importantly, within what timeframe. They found students tended to use the videos variably, but when an exam is forthcoming, access patterns, particularly amongst absentees, showed a significant increase. This finding is consistent with earlier findings by Brotherton and Abowd (2004) who found a peak in access occurs around exam time.

Analysing video-watching patterns provides a unique opportunity to appreciate how, and if, students learn more effectively via video. Kim et al., (2014) carried out a large-scale analysis of in-video drop-outs and peaks in viewership and student activity using data mined from 862 videos across four different MOOCs. They found that when videos were too long, students tended to abandon them. Points of interest and/or possible points of confusion were indicated by re-watching common sections of video (peaks). Kim et al. examined these peaks further and attempted to identify explanatory student activity patterns.

2.3 Summary

Despite the growing literature on the benefits of video-based instruction, there is limited research on how instructors can use YouTube Analytics data to inform their teaching approaches. With that in mind, this study attempts to answer the following questions:

- To what extent do students use videos as a tool for (a) initial learning (b) revision?
- Does the difficulty of the material affect video viewing patterns?
- How much [what proportion] of the videos are watched?
- Does the difficulty of the material affect how much [what proportion] of the videos are watched?

- To what extent do students watch a series of videos on a topic?

3. Methodology

This section describes the characteristics of the instructional videos, the data collected, and the rationale for the data analysis method employed. Expanding on studies carried out to date and leveraging the growing body of data that can be captured via analytics, this study seeks to investigate and probe a milieu of behaviours and usage patterns—for example, exploring the significance of the difficulty of the video content.

3.1 Module description

A series of instructional videos were developed specifically for a module entitled 'Business Information Management' that covered both Information Systems theory and practical spreadsheet skills using Microsoft Excel. It was a mandatory module for first-year undergraduate students taking a Bachelor of Business Studies degree. The module assumed no prior knowledge of the material though some students had previously used spreadsheets. Students attended two one-hour lectures per week and five one-hour computer labs over the semester. In addition to an end-of-term theory exam, there was also a one-hour end-of-term practical spreadsheet exam.

Before each lab session, students were provided with the following resources:

- links to the relevant YouTube videos
- a spreadsheet containing data required for the weekly topic
- a worksheet with questions that required students to apply concepts covered by the video material, by modifying the spreadsheet data

Students attended a lecture the week before they attended the lab and the supplementary videos covered material that related to the lecture material. Additional support was provided in the five weekly computer labs during which students could work on their worksheet, ask questions of the teaching assistant, and receive individual feedback. Teaching assistants did not provide an outline of the concepts required, as students were expected to have engaged with this material prior to the lab. Students were not permitted to watch the videos during the labs. At the end of each week, an 'answer' spreadsheet was posted online. No marks for attendance were allocated and the practical component was assessed using only an end-of-term practical exam.

3.2 The video tutorials

The videos covered five topics and demonstrated how certain tasks were implemented using Microsoft Excel. The videos were recorded using 'CamStudio' and included an audio commentary. At the time of recording, the maximum length of video that could be uploaded to YouTube was 15 minutes. Therefore, longer videos had to be segmented to meet this technical constraint. In total, there were 17 videos with 7,460 views over the semester. It should be noted that a 'view' is similar to a 'hit' for a website; once a video is accessed, for whatever length of time, it is counted as a view. Comprehensive video details are provided in Table 1.

The videos were intentionally unlisted on YouTube with links provided only through the university virtual learning environment (VLE) to ensure only course participants accessed the videos. The number of hits verified that views were only logged while the courses were running.

As outlined in Table 1, each weekly topic comprised between two and four videos. These videos were intentionally not linked using a YouTube playlist to eliminate the possibility of students clicking on the first video and, without further action on their part, viewing other related videos. To view each video, students had to purposefully click on a new link.

3.3 Data collection and analysis

Data on video usage is collected automatically by YouTube and made available to YouTube channel owners. It is possible to generate specific reports in YouTube within defined time periods; given the module ran on a weekly basis, report data were summarised weekly. The data fields available for each week included:

- Number of views

- Estimated number of minutes watched
- Average view duration (in minutes)
- Average percentage viewed
- Unique views (Web only)

The weekly reports were downloaded, and the data fields were then summarised for each video based on three time periods:

- *Lab-related period:* As links to the videos were made available in the week prior to the practical laboratory classes, data was included for both weeks.
- *Exam-related period:* As we were also interested in the use of videos as a revision aid, we included the week the exams took place as well as the week preceding the exam.
- *Interval-related period:* this data summarised the period between the lab period and the exam period.

The data for each of these time periods (for each separate video) were then collated in one data file and used for the analysis presented in the next section.

4. Results and discussion

As outlined in Table 1, five weekly topics comprising 17 videos were made available to students.

Table 1: Detailed breakdown of instructional videos

| Weekly Video Topic | Series of Videos in Each Topic | Video Topic Number | Video Length (min:sec) | Sum of Unique Views * |
|---|--|--------------------|------------------------|-----------------------|
| Topic 1: Data Filtering and Totalling (Easy) | Data Filtering | 1 | 14:10 | 504 |
| | Data Sorting | 2 | 13:27 | 607 |
| | Data Outlining & Subtotalling (Part 1) | 3 | 10:14 | 511 |
| | Data Outlining & Subtotalling (Part 2) | 4 | 5:26 | 457 |
| Topic 2: Data Reporting and Visualisation (Easy) | Pivot Tables | 1 | 10:58 | 510 |
| | Conditional Formatting | 2 | 12:50 | 454 |
| Topic 3: Logical Statements (Difficult) | AND/OR | 1 | 14:49 | 459 |
| | IF | 2 | 6:15 | 522 |
| | Nested Statements (Part 1) | 3 | 8:37 | 438 |
| | Nested Statements (Part 2) | 4 | 8:35 | 388 |
| Topic 4: Cashflow Statements for Businesses (Easy) | Cashflow (Part 1) | 1 | 12:40 | 411 |
| | Cashflow (Part 2) | 2 | 15:00 | 350 |
| | Cashflow-Goalseek | 3 | 8:14 | 340 |
| | Cashflow-Scenarios | 4 | 7:53 | 317 |
| Topic 5: Linear Programming (Difficult) | Solver (Part 1) | 1 | 7:53 | 316 |
| | Solver (Part 2) | 2 | 14:27 | 397 |
| | Solver (Part 3) | 3 | 8:49 | 370 |
| Total | | 17 | | 7,460 |

* When videos were watched from a PC, unique cookies were used, which meant that if a video was watched multiple times on that PC, only one view was counted. This feature removed the risk of a small number of people

skewing the data, if they watched videos repeatedly. However, it was not possible to eliminate this risk when the views came from a mobile device.

The remainder of this section discusses the findings for each of the following research questions:

- To what extent do students use videos as a tool for (a) initial learning (b) revision?
- Does the difficulty of the material affect video viewing patterns?
- How much [what proportion] of the videos are watched?
- Does the difficulty of the material affect how much [what proportion] of the videos are watched?
- To what extent do students watch a series of videos on a topic?

Research Question 1: *To what extent do students use videos as a tool for (a) initial learning (b) revision?*

When examining views per student by time period the videos were used more as a revision aid prior to the exam. Students tended to access the videos more during the exam period than during the lab period. These access patterns during the exam period correlate with findings by Brady et al. (2013) and Brotherton and Abowd (2004), who found that access rates increased significantly around exam time.

Table 2: Number of unique views

| Unique views per student (and proportion of views) | Number |
|---|-------------|
| For the Semester | 21.44 |
| In the Lab period | 6.35 (30%) |
| In the Exam Period | 11.84 (70%) |

It should be noted that, given the available data, it was not possible to relate individual students to specific views. Therefore, it was possible that some students viewed videos during the lab period and during the exam period, while others did not view any videos. It was not possible to identify the degree to which this occurred.

Research Question 2: *Does the difficulty of the material affect video viewing patterns?*

As the number of videos per topic varied, the *average* views per student per video (Table 3) was used to provide comparable figures. Two topics, logical operators (topic 3) and linear programming (topic 5), were identified as difficult both by the researchers and teaching colleagues.

Table 3: Average views by topic (per student per video)

| | Lab Period | Exam Period |
|---|-------------|-------------|
| Topic 1: Data Filtering and Totalling (Easy) | 0.34 | 0.71 |
| Topic 2: Data Reporting and Visualisation (Easy) | 0.32 | 0.72 |
| Topic 3: Logical Statements (Difficult) | 0.47 | 0.63 |
| Topic 4: Cashflow Statements for Businesses (Easy) | 0.20 | 0.82 |
| Topic 5: Linear Programming (Difficult) | 0.55 | 0.59 |

As shown in the table above, the more difficult topics (topics 3 & 5) were viewed most during the lab period (0.47 and 0.55) while the easiest topics (topics 1, 2, and 4) were viewed least. One possible explanation could be that the lecture alerted students to the relative difficulty of material; consequently, students were more likely to watch videos on topics that they knew to be difficult, during the lab period. When it came to using the videos during the exam period, students viewed the more difficult topics (0.63 and 0.59) least.

Research Question 3: *How much [what proportion] of the videos are watched?*

The number of minutes each video was watched was also examined. This was useful as such data has not been explored in related studies in this field. Studies that rely on the number of views as a measure of engagement have limited value as an additional view is counted regardless of whether one second or the entire video was

subsequently watched. By analysing the number of minutes watched, we can also determine the *extent* of the viewing. Table 4 presents the number of minutes watched per topic.

Table 4: Minutes watched per topic

| Topic | Minutes |
|---|---------------|
| Topic 1: Data Filtering and Totaling (Easy) | 17,403 |
| Topic 2: Data Reporting and Visualisation (Easy) | 8,661 |
| Topic 3: Logical Statements (Difficult) | 12,224 |
| Topic 4: Cashflow Statements for Businesses (Easy) | 10,827 |
| Topic 5: Linear Programming (Difficult) | 8,777 |
| Total | 57,892 |

Table 5 shows the average minutes watched per student.

Table 5: Average minutes watched per student

| Topic | Average Minutes |
|---|-----------------|
| Topic 1: Data Filtering and Totalling (Easy) | 50.01 |
| Topic 2: Data Reporting and Visualisation (Easy) | 24.89 |
| Topic 3: Logical Statements (Difficult) | 35.13 |
| Topic 4: Cashflow Statements for Businesses (Easy) | 31.11 |
| Topic 5: Linear Programming (Difficult) | 25.22 |

Delving deeper, the average number of minutes watched per student per time period was also examined. Table 6 shows that the average number of minutes viewed during the exam period (column 4) was greater than during the lab period (column 2), for all 5 topics.

Table 6: Average minutes watched per student per time period

| Topic | Lab Period | Exam Period |
|---|------------|-------------|
| Topic 1: Data Filtering and Totaling (Easy) | 9.95 | 25.14 |
| Topic 2: Data Reporting and Visualisation (Easy) | 5.17 | 13.27 |
| Topic 3: Logical Statements (Difficult) | 12.49 | 16.43 |
| Topic 4: Cashflow Statements for Businesses (Easy) | 6.31 | 24.80 |
| Topic 5: Linear Programming (Difficult) | 12.41 | 12.81 |

The relatively short length of the videos is possibly a contributing factor in the viewing rates, which corresponds to findings by Kim et al. (2014) who found that students tend to abandon long videos.

Research Question 4: *Does the difficulty of the material affect how much [what proportion] of the videos are watched?*

In Table 6 it can be seen that during the lab period the more difficult topics (topics 3 and 5) were watched for longer (12.49 and 12.41 minutes on average) than the easier topics (topic 1, 2, and 4) (9.95, 5.17, and 6.31 minutes on average, respectively). One reason for this may be that the advance lecture alerted students to the relative ease or difficulty of the topic. Furthermore, despite receiving a lecture on the topic, students watched the more difficult videos for a longer period (12.49 and 12.41). For some students it seems the videos were used to reinforce the lecture content. However, during the exam period the more difficult topics (3 and 5) were watched for longer (16.43 and 12.81 minutes on average). This again suggests that the lecture alerted students to more difficult topics.

Another way of analysing the data was to look at the proportion of minutes viewed in the lab period compared to the exam period. Table 7 illustrates a number of interesting trends. The proportion of minutes watched overall indicate that the videos were used primarily as a revision aid (overall 67% of the minutes viewed were during the exam period).

Table 7: Proportion of minutes watched per time period

| Topic | Lab Period | Exam Period |
|--|------------|-------------|
| Topic 1: Data Filtering and Totalling (Easy) | 28% | 72% |
| Topic 2: Data Reporting and Visualisation (Easy) | 28% | 72% |
| Topic 3: Logical Statements (Difficult) | 43% | 57% |
| Topic 4: Cashflow Statements for Businesses (Easy) | 20% | 80% |
| Topic 5: Linear Programming (Difficult) | 49% | 51% |
| Overall | 33% | 67% |

Research Question 5: To what extent do students watch a series of videos on a topic?

Given the number of views and the number of minutes watched per video, it was possible to calculate the average minutes watched per view, both for the lab and exam time periods (Table 8). If students were going to 'give up' on a topic, it is reasonable to assume that they would likely watch the first in a series of videos for a topic and then stop watching the rest of the series; in other words, the proportion of videos watched should decrease over the series. For example, we can see that for topic 2 (easy), video 1 was watched for longer than video 2 (63% viewed on average vs. 54%), during the lab and exam periods.

Table 8: Average percentage of the video viewed

| Series of Videos in Each Topic | Lab Period | Exam Period |
|---|------------|-------------|
| Topic 1: Data Filtering and Totalling (Easy) | | |
| Data Filtering | 55% | 62% |
| Data Sorting | 51% | 60% |
| Data Outlining & Subtotalling (Part 1) | 53% | 68% |
| Data Outlining & Subtotalling (Part 2) | 47% | 71% |
| | | |
| Topic 2: Data Reporting and Visualisation (Easy) | | |
| Pivot Tables | 63% | 67% |
| Conditional Formatting | 54% | 58% |
| | | |
| Topic 3: Logical Statements (Difficult) | | |
| AND/OR | 61% | 54% |
| IF | 58% | 57% |
| Nested Statements (Part 1) | 55% | 62% |
| Nested Statements (Part 2) | 54% | 57% |
| | | |
| Topic 4: Cashflow Statements for Businesses (Easy) | | |
| Cashflow (Part 1) | 56% | 55% |
| Cashflow (Part 2) | 47% | 52% |
| Cashflow-Goalseek | 54% | 56% |
| Cashflow- Scenarios | 58% | 55% |
| | | |
| Topic 5: Linear Programming (Difficult) | | |
| Solver (Part 1) | 59% | 56% |
| Solver (Part 2) | 61% | 51% |
| Solver (Part 3) | 58% | 59% |

5. Conclusions, limitations, and recommendations for future work

5.1 Conclusions

When we examined *when* students used the videos (i.e. was it during the lab period or as a revision aid prior to the exam), we found that the videos were used more as a revision aid prior to the exam, suggesting a preference for using the videos more as a revision resource. This is an important finding, and one that would not have been apparent had we simply analysed the total or unique number of views.

We also examined the data for different video topics, to determine if the difficulty level of the topic affected viewing patterns during the lab and exam periods. We first examined views during the lab period with the more difficult topics being viewed more than the easiest topics, suggesting that the lecture was useful as it alerted students to difficult topics. When we analysed the *average* number of minutes that were watched during the lab and exam periods, we found that students spent longer watching each topic during the exam period, than during the lab period.

We also found that, during the lab period, the more difficult topics were watched for longer than the easier topics and during the exam period, difficult topics were watched for longer. When we examined the proportion of minutes watched per time period, we found that proportionately, students watched the videos for longer during the exam period than during the lab period.

Finally, when we examined which videos students tended to watch, we found that for topic 2 (easy), video 1 was watched for longer than video 2 during the lab and exam periods.

These findings have implications for how we might analyse video use moving forward. For example, rather than reviewing the data at the end of a module, it would be worthwhile to monitor video access rates at key points throughout the term, to identify levels of engagement with individual videos and topics. This deeper analysis is also useful to determine the extent of engagement (e.g. length of viewing time) with individual videos, and when students actually view the videos (e.g. during the lab period or during the exam period). It also points to the usefulness of lectures to supplement video resources.

5.2 Limitations

Because YouTube analytics did not enable us to identify individual students using multiple devices to watch the same video, the study instead focused on the number of unique views, which accounted for multiple views from the same PC (cookies were tracked). Unfortunately, it is not currently possible to calculate the number of multiple views from mobile devices (e.g. smartphones and tablet devices), so students viewing a video multiple times from a mobile device could not be accounted for.

As it was not possible to identify individual students, it is possible that some students viewed videos during the lab period and during the exam period, while others did not view any videos. It was not possible to identify the degree to which this occurred. It was also possible that a video could be accessed and allowed to play to the end, without actually reviewing the content.

5.3 Recommendations for future work

For future work, we are interested in conducting further analyses to determine:

- The number of views at each point in time in the video. For example, are there peak and trough viewing points within each video and can we identify possible reasons for those e.g. are there threshold concepts that may require further exploration in the classroom? This level of analysis would greatly facilitate further refinement of the instructional videos.
- Who watches the videos through the end - those who tended to watch the videos during the lab weeks or those who tended to watch the videos immediately prior to the exam?
- Of those who tended to watch the videos immediately prior to the exam, are they viewing the videos for the first time or as a revision aid?

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