

Effects of In-Video Quizzes on Lecture Viewing on Coursera

Anonymized for Submission

Abstract

Online courses on sites such as Coursera use quizzes embedded inside lecture videos (in-video quizzes) to test learners' understanding of the video. This paper analyzes how users interact with in-video quizzes, and how in-video quizzes influence users' lecture viewing behavior. We analyze the viewing logs of users who took the Machine Learning course on Coursera. We find that in-video quizzes are a common source and destination of video seeks. These seeks reflect behaviors such as searching for answers to the in-video quizzes within the video. We observe spikes in view counts in portions of the video surrounding in-video quizzes, as a result of reviewing and rewatching. Some users appear to use quiz-oriented video navigation strategies, such as seeking directly from the start of the video to in-video quizzes, or between in-video quizzes. We discuss implications that our findings have on the design of online courses and MOOC platforms.

Introduction

In-video quizzes, which are commonly featured in courses on platforms such as Coursera, are questions that users are asked to answer upon reaching a certain point in the video, as shown in Figure 1. In-video quizzes are auto-graded; the majority we observe in the Machine Learning course and other courses on Coursera are either multiple-choice or multiple-selection, though there also exist a few numeric-response quizzes.

In-video quizzes differ from standard quizzes in that users do not leave the video viewer interface when they encounter a quiz, so users can easily seek elsewhere upon encountering the quiz – seeking backward to find answers to the quiz, seeking forward to skip the quiz, etc. The presence of in-video quizzes inside videos can thus influence users' video viewing behaviors, potentially causing more seeks and other non-linear viewing behaviors.

In this paper, we analyze video-viewing logs of the Machine Learning course, iteration 4 on Coursera (ML4). We identify and discuss a set of video viewing behaviors associated with in-video quizzes that we observe in these logs, specifically:

- The region preceding in-video quizzes are a common destination for video seeks.

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Figure 1 is a screenshot of an in-video quiz interface titled "Error Metrics for Skewed Classes (12 min)". The interface includes a "Help" button in the top right corner. The main content area explains precision and recall with formulas and confusion matrices. The formulas are:
$$\text{Precision} = \frac{\text{True positives}}{\# \text{ predicted as positive}} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$
 and
$$\text{Recall} = \frac{\text{True positives}}{\# \text{ actual positives}} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$
. Two confusion matrices are shown. The first matrix is for a test set where the algorithm's performance is given to the right. The second matrix is for a test set where the algorithm's precision is to be determined. The quiz asks: "Your algorithm's performance on the test set is given to the right. What is the algorithm's precision? Enter your answer as a real number (eg. 0.11, 0.5, etc.)." Below the question is a text input field. To the right of the input field are "Submit" and "Skip" buttons. The interface also includes a video player control bar at the bottom with a progress bar, a "Discuss" button, and "Prev" and "Next" buttons.

Precision and recall are defined according to:

		Actual class	
		1	0
Predicted class	1	True Positive	False Positive
	0	False Negative	True Negative

Precision = $\frac{\text{True positives}}{\# \text{ predicted as positive}} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$

Recall = $\frac{\text{True positives}}{\# \text{ actual positives}} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$

Your algorithm's performance on the test set is given to the right. What is the algorithm's precision? Enter your answer as a real number (eg. 0.11, 0.5, etc.).

		Actual class	
		1	0
Predicted class	1	80	20
	0	80	820

Submit Skip

Figure 1: An in-video quiz, from the ML4 course on Coursera. In-video quizzes are auto-graded questions embedded into a video and shown at a certain timestamp. They can be either multiple choice, multiple selection, or numeric free-response. Their locations are indicated on the progressbar by a yellow tick.

- In-video quizzes are a common sources of video seeks.
- Users often seek backward from in-video quizzes to find the answer to the in-video quiz.
- Some users appear to be following a strategy of seeking directly to the in-video quizzes
- Some users tend to jump from one in-video quiz to the next, skipping the video segments
- Users do not tend to skip over in-video quizzes

These behaviors suggest that certain viewers attach high importance to in-video quizzes and frequently refer to them, and suggests that video-viewing interfaces should perhaps make it easier for users to refer to the in-video quiz associated with the segment they are viewing.

Related Work

Kim et al perform an analysis of reasons for peaks in viewing and seeking while viewing lectures (Kim et al. 2014b). They find that users steadily leave videos over time, a phenomenon they refer to as *video dropout*, and that visual transitions, such as slide transitions, tend to result in *interaction peaks*, such as users seeking back to the previous slide. They also present a video viewer that encourages video navigation to interaction peaks (Kim et al. 2014a). However, the courses that they perform their video log analysis on do not have in-video quizzes, hence they are unable to report on viewing peaks and seeking behaviors that result from in-video quizzes. We similarly found in our own analysis that there are many peaks in seeking behavior that can be accounted for by slide transitions, however in-video quizzes tend to also be a major factor in causing peaks in video seeking.

Guo et al discuss the effects of video properties on such as video length on viewer engagement (Guo, Kim, and Rubin 2014). They find that users become less engaged as videos grow longer, which is related to the problem of in-video dropout. However, they do not analyze the effects on in-video quizzes on viewer engagement, because the courses they analyze do not have in-video quizzes. In this paper, we argue that in-video quizzes encourage viewer engagement, as indicated by the increase in rewatching and seeking behavior in the regions of the video surrounding the in-video quiz.

Guo et al discuss factors that contribute to nonlinear navigation through MOOCs (Guo and Reinecke 2014). They discuss examples of nonlinear navigation such as jumping back to previous lectures, rewatching videos, and going back from assessments to refer to lectures. Our present work is focused on navigation within videos as opposed to within MOOCs. However, we find that in-video quizzes, being a form of assessment that is embedded into the videos, trigger similar backjumps and reviews within a video that Guo et al discuss at the course-level in their paper.

Andersson et al find that learners differ in the ways they engage with online courses: some only watch videos (“viewers”), some only do assignments (“solvers”), and some do both (“all-rounders”) (Anderson et al. 2014). These differences between learners’ engagement patterns are relevant to our work analyzing in-video quizzes, as they help explain why we find that some users’ viewing behaviors seem to be aimed towards solving in-video quizzes rather than watching videos.

In-video quizzes are not new; there are many past systems that embed quizzes into multimedia (Allen 1998), and they are believed to have positive effects on learning (Johnson-Glenberg 2010). However, to our knowledge, our paper is the first analysis of the effects on in-video quizzes on learners’ rewatching and seeking behavior in the context of MOOCs.

Dataset and Engagement Levels

The course we are analyzing in this work is the fourth iteration of the Machine Learning course on Coursera (ML4), which ran from October 2013 to January 2014. Our data

Type of event or data within the ML4 course on Coursera	Counts
Users who registered for the course	96,195
Users who visited the course page at least once	81,189
Users who started viewing at least 1 lecture	59,641
Users who finished viewing at least 1 lecture	41,643
Users who answered at least 1 in-video quiz	42,437
Users who visited the forums at least once	32,378
Users who submitted at least 1 review exercise	30,227
Number of lecture videos	113
Number of in-video quizzes	109
Number of slide transitions	339
Number of external multiple-choice assignments (“review exercises”)	18
Number of distinct lectures started viewing, across all users	1,377,238
Number of distinct lectures watched until end, across all users	976,933
Number of distinct in-video quizzes answered, across all users	1,031,061
Number of distinct review exercises answered, across all users	229,556
Seek events total	6,442,590
Seek chains total	2,103,336

Figure 2: Summary statistics for the ML4 course.

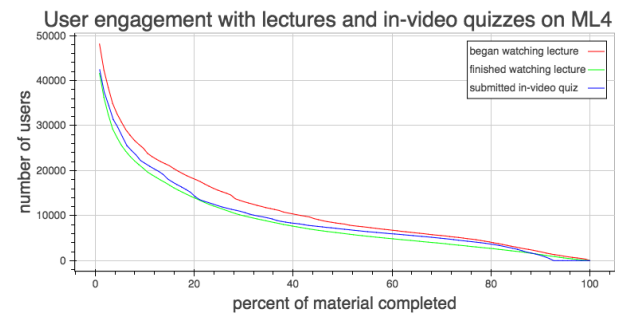


Figure 3: Response rates to the 109 in-video quizzes was similar to the watching rates of the 113 lecture videos.

dump was taken immediately after the course ended. It represents data from 96,195 users, of whom 59,641 watched at least one video. There are 113 lecture videos in the course, totaling 19.5 hours of video content, with an average length of 10 minutes per video. With 109 in-video quizzes over 19.5 hours of video, this averages out to one in-video quiz for every 11 minutes of video.

Of the 113 videos, 92 videos (81%) have 1 in-video quiz, 14 videos (12%) have no in-video quizzes, 6 videos (5%) have 2 in-video quizzes, and 1 video (1%) has 3 in-video quizzes. Videos with no in-video quizzes tend to be optional lectures covering interesting applications of machine learning, or are introductory videos that explain what will be covered next in the course.

Engagement with in-video quizzes was quite high: as shown in Figure 3, the answering rate to in-video quizzes closely mirrors the watching-completion rate for videos. This contrasts with the lower engagement rates that have typically been found for traditional assignments that are outside of the video (Kizilcec, Piech, and Schneider 2013) (Anderson et al. 2014). Other summary statistics are shown in Figure 2.

Methodology

Determining Portions of Video Seen

The Coursera logs we used for our analysis come with an action (such as play, pause, or seek) associated with a point in the video, and a timestamp. We use these logs to reconstruct the portions of the video that the user has seen, with a technique similar to the one described in (Kim et al. 2014b) – if we observe a play event associated with video position p , followed by another event at video position $p+i$, we can assume that the user watched that segment of the video.

Grouping Seek Events into Seek Chains

The seek events in the logs specify only the destination of the seek and the timestamp at which it occurred, but not the origin (the logs tell us where in the video the user sought to, but not where the user sought from). However, we were likewise able to reconstruct the seek time origins based on the previous event – for example, if the user started playing from video position p at timestamp t , and we observe a seek event at timestamp $t+i$, then we assume the seek originated from video position $p+i$ (or $p+i*2$ if the user is playing back the video at 2x speed, etc).

Additionally, we observed that many seek events tend to occur in rapid succession as the user narrows down on the actual target. For example, if the user is seeking via the keyboard, if they are at the beginning of the video and their seek target is 3 minutes into the video, they will press the right-arrow repeatedly until they reach the destination, resulting in a large number of small, noisy seek events, rather than the user’s intended seek from 0 to 3 minutes that we are interested in analyzing. Because we are primarily interested in where the user ends up seeking to, rather than the individual seek operations that got them to that point, if there are seek events that occur within 10 seconds of one each, we group them together into a single unit which we will call a *seek chain*. Using this approach, we reduced the 6,442,590 total seek events in our dataset into 2,103,336 seek chains. When we analyze seeking in this paper, as well as seek sources and destinations, we will be analyzing seek chains rather than raw seek events, to reduce noise from repeated seeks.

Limitations of Coursera’s Dataset

A limitation of this dataset is that if the user closes their browser window or their network disconnects, this event does not show up in the log, and hence there is ambiguity as to what they watched. For example, if a user starts playing a video at time t , and this play event is the last logged event, we know that the user must have closed their browser prior to the next in-video quiz or the end of the video (otherwise a pause event would have been automatically logged), however we do not know exactly when the browser was closed. We address this ambiguity by treating it as though the user had immediately stopped watching after that last play event, so we do not include the last (unknown) segment that users who quit before the end have watched in the video.

Event type	# seek chains forward	# seek chains backward	# seek chains forward, normalized by the length of the seek target (in seconds). Ratio to baseline in parentheses	# seek chains backward, normalized by the length of the seek target (in seconds). Ratio to baseline in parentheses
All seek chains	1150546	901842	16.40 (baseline)	12.86 (baseline)
Seek chains going to in-video quizzes (and their surroundings)				
Seeks to quiz (+/- 0.5 sec)	7282	4127	67.43 (4.1x)	38.21 (3.0x)
Seeks to 10 seconds preceding quiz	67140	37345	62.17 (3.8x)	34.58 (2.7x)
Seeks to 10 seconds following quiz	23646	14391	21.89 (1.3x)	13.33 (1.0x)
Seek chains going to slide transitions (and their surroundings)				
Seeks to slide transition (+/- 0.5 sec)	4612	7081	13.60 (0.8x)	20.89 (1.6x)
Seeks to 10 seconds preceding slide transition	51000	69929	15.04 (0.9x)	20.63 (1.6x)
Seeks to 10 seconds following slide transition	72602	47822	21.42 (1.3x)	14.11 (1.1x)
Seek chains coming from in-video quizzes (and their surroundings)				
Seeks from quiz (+/- 0.5 sec)	2628	23593	24.33 (1.5x)	218.45 (17.0x)
Seeks from 10 seconds preceding quiz	13283	19436	12.30 (0.8x)	18.00 (1.4x)
Seeks from 10 seconds following quiz	38828	87839	35.95 (2.2x)	81.33 (6.3x)
Seek chains coming from slide transitions (and their surroundings)				
Seeks from slide transition (+/- 0.5 sec)	6175	5498	18.22 (1.1x)	16.22 (1.3x)
Seeks from 10 seconds preceding slide transition	137912	46550	40.68 (2.5x)	13.73 (1.1x)
Seeks from 10 seconds following slide transition	56989	81714	16.81 (1.0x)	24.10 (1.9x)

Figure 4: Sources and destinations of seek chains. Users tend to seek backward from in-video quizzes (17x higher than baseline rate), forward to in-video quizzes (4x higher), and forward from after in-video quizzes (6x higher)

Analysis of Seek Chains via Seek Source and Destination Data

Sources and Destinations of Seek Chains

The sources and destinations of seek chains are shown in Figure 4. We see that in-video quizzes are a popular destination of seeks, particularly in the forward direction – users seek forward to the in-video quiz at 4x the baseline rate of all seek chain destinations. Given the high answering rate for in-video quizzes we showed in Figure 3, this suggests that these seeks are due to users who want to go answer the in-video quiz. Note that Coursera’s interface does not have any UI features for seeking to in-video quizzes apart from the progressbar, so the only way to reach the in-video quiz is to seek to a segment of video right before it. Hence, we consider seek chains to 10 seconds before the in-video quiz to also represent users intending to do the in-video quiz.

Users also seek backward from in-video quizzes at 17x the baseline rate. As we will show, these represent users re-viewing the preceding section, likely trying to find answers to the in-video quiz.

Lengths and Directions of Seek Chains

As shown in Figure 5, on average forward seek chains tend to be longer-distance, while backward seek chains tend to be shorter. A potential explanation is that forward seeks aim to go to some salient part of the video – for example, an in-video quiz – whereas back seeks aim to review a part of the video that was just missed. We also observe that users seek forward more than backward overall, including across slide boundaries; however, they tend not to seek forward over in-video quizzes. As we will see, this is because they are seeking to right before the in-video quizzes, so that they can do them.

Event type, per user, per video	Forward seek	Backward seek
Number of seek chains	0.74	0.66
Average seek chain length (in seconds)	128	51
Seconds of video sought over	100	36
Slide boundaries crossed by seek chain	0.57	0.20
In-video quizzes crossed by seek chain	0.06	0.09
Seconds of video sought over, normalized by # of seconds in the video	0.15	0.06
Slide boundaries sought over, normalized by # of slide boundaries in video	0.19	0.06
In-video quizzes sought over, normalized by # of quizzes in video	0.07	0.10

Figure 5: Locations that are sought across in the video. Users do not tend to seek forward across in-video quizzes.

Analysis of Seek Chains by analyzing seeking and viewing in an individual video

Visualization of Seeks and Watching

In order to explain why users are seeking to and from in-video quizzes, let us first visualize a representative video before moving on to videos in aggregate. This is Lecture 13 from ML4, titled “Matrices and Vectors”. We chose it because it has 2 in-video quizzes, and neither is located at the very end of the video, so results should not be overly influenced by position of the in-video quizzes.

As shown in Figure 6, in-video quizzes are a popular destination of seeks, and sources are primarily from the preceding section, confirming the stats we saw in Figure 4. We also see from the seek sources that they are primarily from the preceding section. This suggests users might have found the answer to the quiz, and are seeking forward to be able to answer the in-video quiz. However, there are also many seeks to the in-video quiz from the start of the video and the preceding in-video quiz. This suggests some users might be following a quiz-centric navigation strategy of seeking directly to the quiz to preview it before they watch the video.

Figure 7 presents the seek chain sources and destinations as a scatter plot. It shows the same phenomena of users seeking forward to in-video quizzes, going back to the preceding section to look for answers, and showing how seek chains do not tend to cross forward across in-video quizzes.

Increased rewatching near in-video quizzes

We hypothesized that if encountering in-video quizzes is causing users to try to find answers to the quiz question in the video, this should be reflected in the viewing logs. Namely, we would expect to see increased re-watching of the portion prior to the in-video quiz where the answer is located, as well as seeks that originate from the in-video quiz and go backwards to where the answer was located. We show examples of these phenomenon in this section.

We see in Figure 6 E that the portion of the video surrounding the in-video quiz tends to receive more views. We also observe in that figure a trend of less views for portions of the video that occur later, which can be explained as in-video dropout, which occurs as a consequence of users tending to watch videos linearly (Kim et al. 2014b).

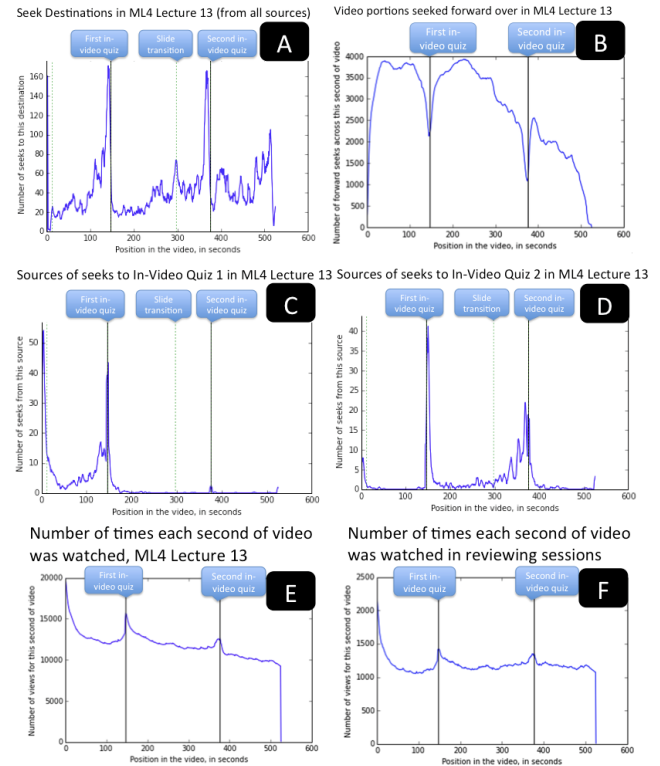


Figure 6: A) in-video quizzes are a popular destination of seeks. B) users do not tend to skip forward over in-video quizzes. C) seeks to in-video quizzes tend to be from the preceding section. D) some users are seeking directly from one in-video quiz to the next. E+F) local peaks in viewing occur around in-video quizzes.

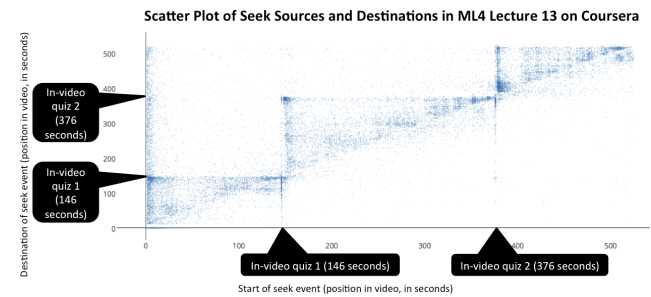


Figure 7: Seeks sources and destinations in a lecture with 2 in-video quizzes. Each point at (x,y) represents a seek from time x to y. There are many seeks to in-video quizzes from the start of the video, the previous section, and between quizzes.

We believe the increase in number of views surrounding the in-video quiz is due to the user rewatching the portion preceding the in-video quiz, perhaps hoping to find an answer to the quiz. Indeed, if we exclude each user's first-time watch, and look only at what users are rewatching in aggregate, we still observe this peak in number of rewatches around the first in-video quiz, as shown in Figure 6 F.

Because Coursera does not enforce that users take in-video quizzes, we wondered whether users are explicitly skipping across the in-video quizzes to avoid taking them. As illustrated in Figure 6 B, we found that this does not tend to be the case. On the contrary, there is actually a dip in the number of forward seeks that cross over the in-video quiz, so users are explicitly trying not to skip the in-video quizzes. This low number of forward seeks crossing over the last in-video quiz in this example might be attributed to the fact that it is at towards the end of the video, so the user may know that there is no new content to find towards the end. However, if we look at the first in-video quiz in the example, we also observe a dip in the number of forward-seeks over the in-video quiz, even though there is important content in the video after it.

Now, let us go beyond looking at individual videos and in-video quizzes, and visualize the seek chains across all 113 videos and 109 in-video quizzes in the course.

Analysis of Seek Chains by Visualizing Seeking over All Videos

Forward Seeking to In-Video Quizzes

Figure 6 shows where users are seeking forward to in all 113 videos in the course. Each horizontal line represents a video, visualizing how many times a seek chain goes to a particular segment of the video via its darkness. We denote the locations of in-video quizzes (red dots) and slide transitions (green diamonds).

In-video quizzes are a popular destination of seeks, as indicated by the black streaks immediately preceding the in-video circles (recall that Coursera doesn't let users seek directly to in-video quizzes, but requires them to seek to the segment right before the quiz if they want to take it, which is why we're seeing that the seek destinations are the preceding segment as opposed to the). As we showed in Figure 4, forward seek rates to the in-video quizzes are 4 times higher than the baseline rate.

If we look at lectures 25-30 in Figure 8, they don't visually match the pattern we see in the other lectures. This is because they're optional tutorial videos discussing interesting applications of Machine Learning, which don't have in-video quizzes or required material.

In-Video Quizzes are a Major Source of Back Seeks (Reviewing)

As we can see in Figure 9, there are many seeks in the backward direction that start from the in-video quizzes (red circles). Specifically, as shown in Figure 4, the rate of backward seek chains from in-video quizzes is 17 times higher than the baseline rate. We also see some backward seeks from right after slide boundaries (the green diamonds), which confirms

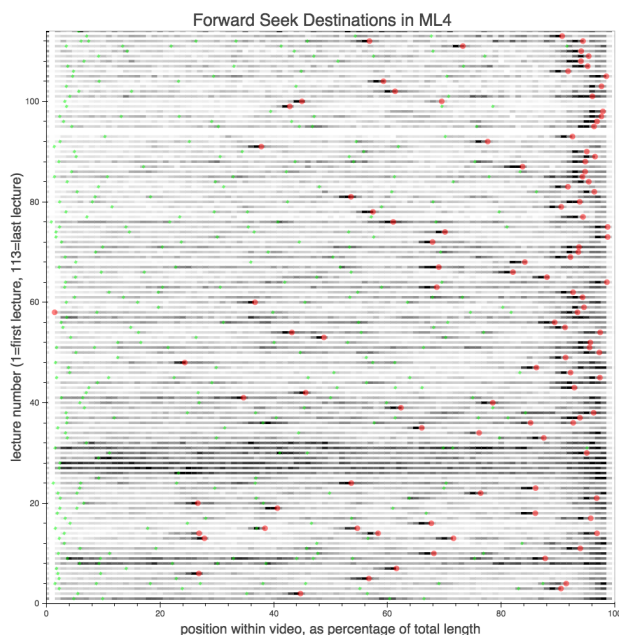


Figure 8: Destinations of forward seek chains in all videos. Each horizontal line represents a video; darkness of a segment indicates the number of seek chains going to that part of the video. Red dots indicate in-video quizzes, and green diamonds indicate slide transitions. Users tend to seek forward to in-video quizzes.

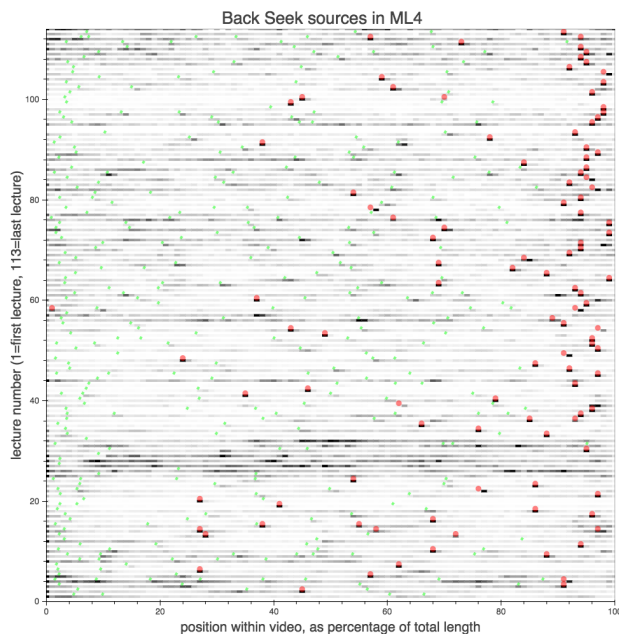


Figure 9: Sources of backward seeks. Red circles indicate in-video quizzes. In-video quizzes are a major source of backward seeks, due to users going back to the previous section to review the video.

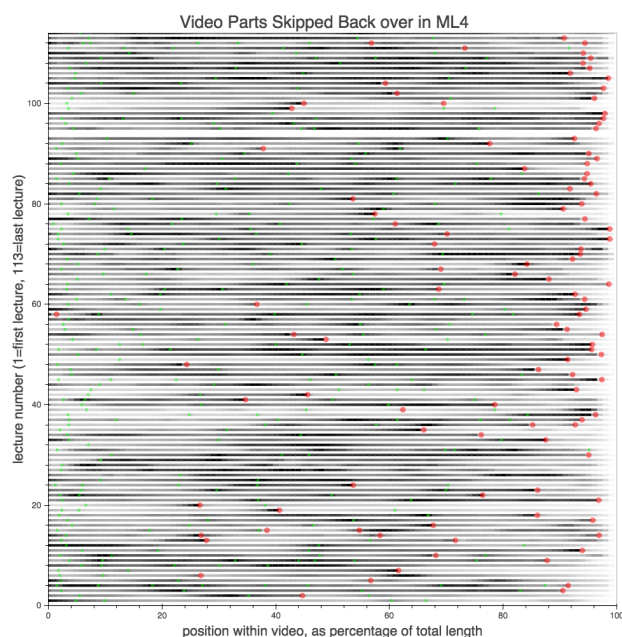


Figure 10: Parts of the video skipped back over. They tend to be the portions preceding the in-video quizzes, reflecting that users are reviewing the video in response to seeing the in-video quiz

prior findings of interaction peaks at slide boundaries in EdX videos which lack in-video quizzes (Kim et al. 2014b).

Video Parts Skipped Back Over

As we saw in Figure 10 and Figure 4, in-video quizzes are a major source of backward seek chains. As we can see in Figure 10, if we look at all portions of the video that are skipped backwards over by seek chains, it is primarily the segments preceding the in-video quizzes. This can be explained by users searching in the preceding segment for the answer the in-video quiz. We suspect that the portion of the video that is seeked backwards over may reflect where the portion of the video relevant to answering the in-video quiz can be found.

Interestingly, we observe that when the last in-video quiz occurs at the midpoint of a video, as is the case with Lecture 19 in Figure 10, there is little back-seeking which occurs after the video. This suggests that this phenomenon we observe of back-seeking occurring directly before a video is indeed a result of the in-video quiz causing users to back-wards more, as opposed to simply being a result of the fact that the in-video quizzes tend to occur towards the end of the video.

Seek Destinations from In-Video Quizzes

As we can see in Figure 11, the seek destinations from in-video quizzes are primarily backward, towards the immediately preceding portion. This is confirmed in Figure 4, which shows that there are 9x more seeks in the backward direction from in-video quizzes than in the forward direction. These

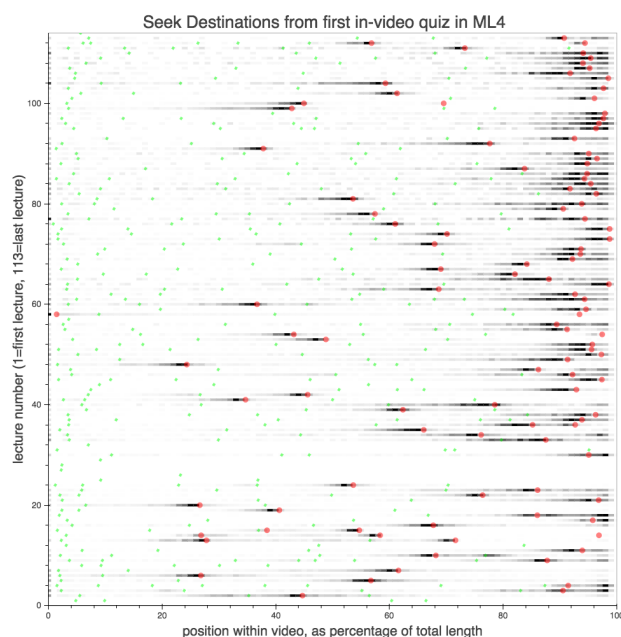


Figure 11: Seek destinations from the first in-video quiz in each lecture. The portion preceding the in-video quiz is a major seek destination.

can be explained by users who decide to go back and re-view the preceding segment in response to having seen the in-video quiz.

Seek Destinations from the Start of the video

As we can see in Figure 12, many users are seeking directly from the start of the video to in-video quizzes. This means that there are some users for whom the first action they take after opening the video is to go seek to the in-video quiz. This suggests that these users might be previewing the quizzes before they watch the video, or they are using the quizzes as a navigational tool to help them decide which parts of the video they need to see and review.

Summary of Results

We have found that in-video quizzes are major sources and destinations of seek chains. Based on the sources and destinations of seek chains going to/from in-video quizzes, the seeking behaviors that we observe around in-video quizzes include:

- Users seeking from one quiz to the next, presumably aiming to answer the in-video quiz questions
- Users seeking backwards to the quiz from the immediately following section, to review its contents
- Users seeking forward to the in-video quiz, presumably to respond to the question after having found the answer, or to remind themselves of what the quiz was asking them to find.

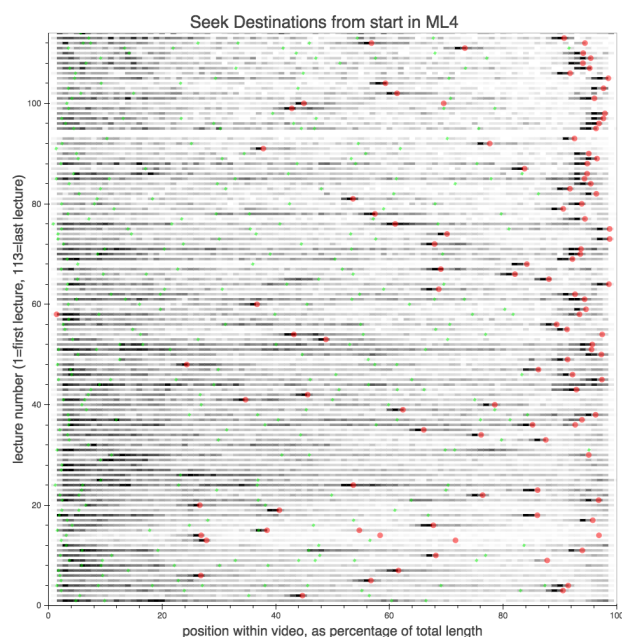


Figure 12: Seek destinations from the start of the video. Many users seek directly from the start of the video to the in-video quizzes.

Discussion

The peaks in seeking towards in-video quizzes suggest a number of possible interface improvements that could be experimented with. Coursera currently does not allow users to easily skip directly to in-video quizzes, instead requiring them to go to the preceding few seconds of videos. As indicated by how we observed that in-video quizzes were one of the most common destinations for seek chains, particularly in the forward direction, skipping to in-video quizzes should be made easier, perhaps via improved scrubbing techniques.

A limitation in this study is that it is impossible to determine exactly what point users who simply closed their browser windows stopped watching videos at. This is due to Coursera's lack of a second-by-second heartbeat showing whether the user is still connected – we can observe the last event from the user (perhaps a play event), but we do not know how much time elapsed between that event and the user closing their browser, so we do not know precisely where the final segment watched by the user ended. EdX does not currently implement a heartbeat for determining user disconnections either, so this is a limitation shared by other studies relying on EdX data. To better be able to study users' interactions with videos, and to understand exactly where users lose engagement with videos and close them, these platforms need to be able to determine when users close their browsers.

Because our study did not perform any A/B tests varying the number of in-video quizzes, we do not know whether in-video quizzes have any effect on the overall video watching completion rate, or their effects on in-video dropout rates. Due to the fact that few users attempt to skip in-video

quizzes by forward-seeking over them as shown in Figure 4, and that users tend to seek backwards to review when they encounter in-video quizzes, as shown in Figure 10, we speculate that the presence of in-video quizzes may be beneficial for keeping users engaged and encouraging them to watch and review the videos.

Conclusion

We have presented ways that in-video quizzes influence users' video watching behaviors, as indicated by seeking logs on various videos in the ML4 course on Coursera. We find that users' seeking and rewatching behaviors in videos are influenced by the presence of in-video quizzes. Specifically:

- There are peaks in rewatching behavior in the regions surrounding the in-video quiz. In particular, we see a large amount of back-seeking from in-video quizzes to the immediately preceding video section. This is likely due to users seeking answers to in-video quizzes.
- Many users skip directly to the in-video quizzes during rewatching sessions. Hence, they may be using these as a way to test themselves, to determine whether or not they need to review that video.
- Users do not tend to seek forwards over in-video quizzes to skip over them.
- In-video quizzes are a common source of seek chains within videos. Users tend to seek backward to find answers, or forward to the next in-video quiz.
- In-video quizzes are a common destination of seek chains within videos. Users tend to seek from the preceding video segment where the answer can be found, from the beginning of the video, or from the preceding in-video quiz.

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