How Video Production Affects Student Engagement: An Empirical Study of MOOC Videos

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Inputs

Course	Subject	University	Lecture Setting	Videos	Students	Watching sessions
6.00x	Intro. CS & Programming	MIT	Office Desk	141	59,126	2,218,821
PH207x	Statistics for Public Health	Harvard	TV Studio	301	30,742	2,846,960
CS188.1x	Artificial Intelligence	Berkeley	Classroom	149	22,690	1,030,215
3.091x	Solid State Chemistry	MIT	Classroom	271	15,281	806,362
Total				862	127,839	6,902,358

Table 2. Overview of the Fall 2012 edX courses in our data set. "Lecture Setting" is the location where lecture videos were filmed. "Students" is the number of students who watched at least one video.

- username, video ID, start and end times, video play speed, # of the play and pause triggered, and attempt to answer assessment
- Each session end when user triggers unrelated event, logout or video finishes
- filtered out all sessions < five seconds

Engagement Measurement

- Watching session
  - Limitation is that it cannot capture whether a watcher is actively paying attention to the video
- Problem attempt
  - Attempt follow-up problem within 30 minutes after watching a video?

Correlation Measurement

- Quantitative Inputs
  - Length, Speaking rate, Video type, Production style (Slides, Code, Khan-style, Classroom, Studio, Office Desk)
- Qualitative Inputs
  - Interviews with 4 edX video producers
  - Interviews with 2 program managers

Findings and Recommendation (1)

F: Shorter videos are more engaging

R: duration < 6 minutes

Note:

- Engagement Time > 1.0 if re-play
- Problems Attempts 56%, 48%, 43%, 41%, and 31%, respectively

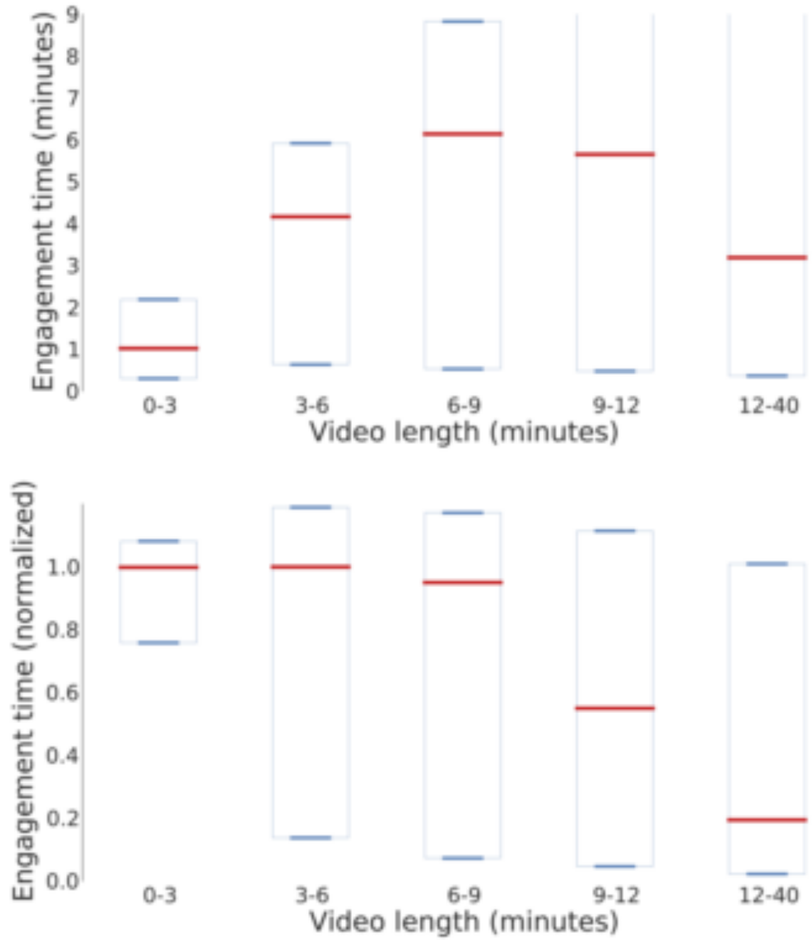


Figure 2. Boxplots of engagement times in minutes (top) and normalized to each video's length (bottom). In each box, the middle red bar is the median; the top and bottom blue bars are 25th and 75th percentiles, respectively. The median engagement time is at most 6 minutes.

Findings and Recommendation (2)

F: Talking Head Is More Engaging

R: Record the instructor's head and insert at opportune times

Note:

- No significant differences on number of play/pause events

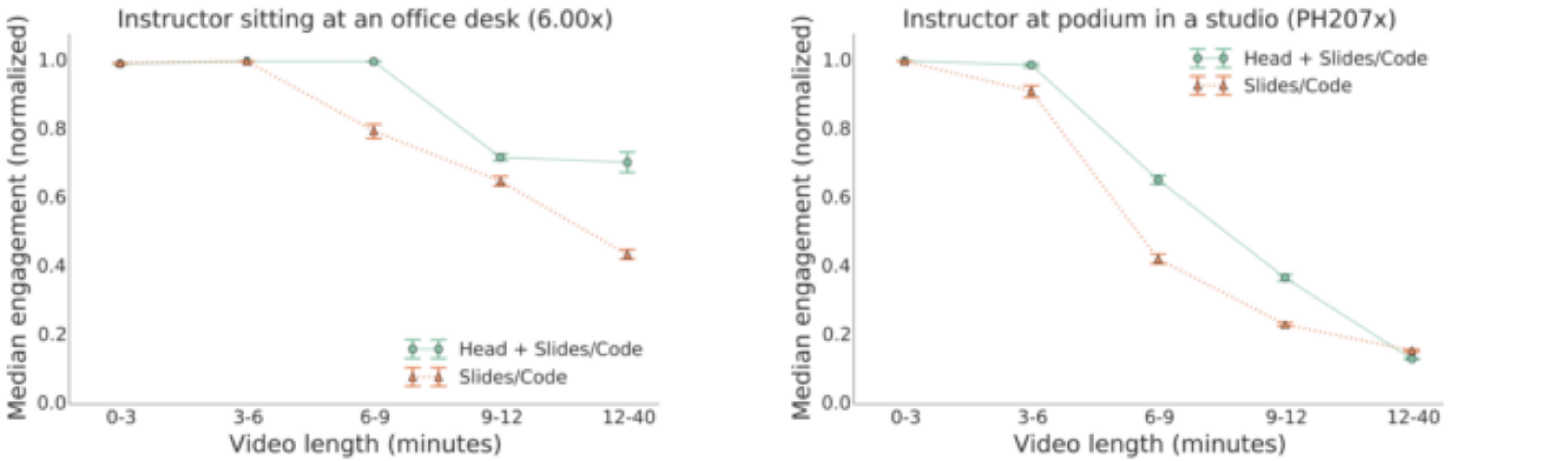


Figure 3. Median engagement times versus length for videos from 6.00x (left) and PH207x (right). In both courses, students engaged more with videos that alternated between the instructor's talking head and slides/code. Also, students engaged more with 6.00x videos, filmed with the instructor sitting at a desk, than with PH207x videos, filmed in a professional TV studio (the left graph has higher values than the right one, especially for videos longer than 6 minutes). Error bars are approximate 95% confidence intervals for the true median, computed using a standard non-parametric technique [14].

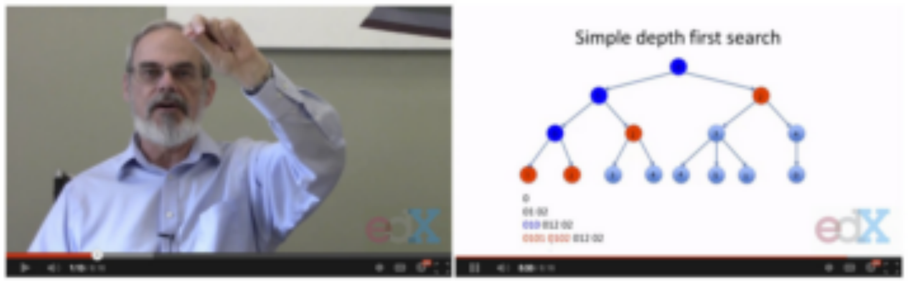
Findings and Recommendation (3)

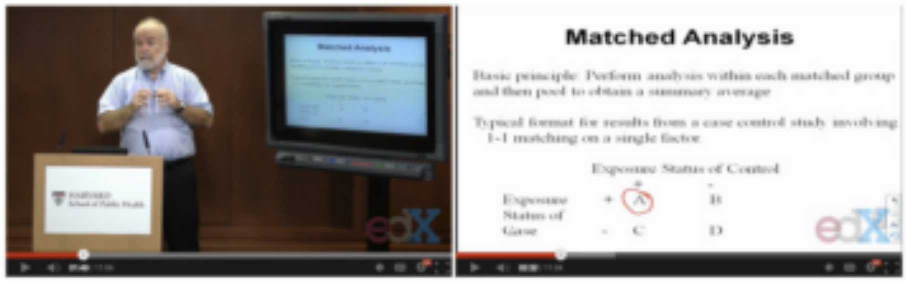
F: High Production Value Might Not Matter

R: Setting where the instructor can make good eye contact

Note:

- Previous figure show that students engaged for twice the time on 6.00x videos in 6 - 12 minutes, and for 3x the time on 6.00x videos > 12 minutes





Findings and Recommendation (4)

F: Khan-Style Tutorials Are More Engaging

R: Record Khan-style tutorials when possible

Note:

- Problem attempt is 40% with Khan-style and 31% for others

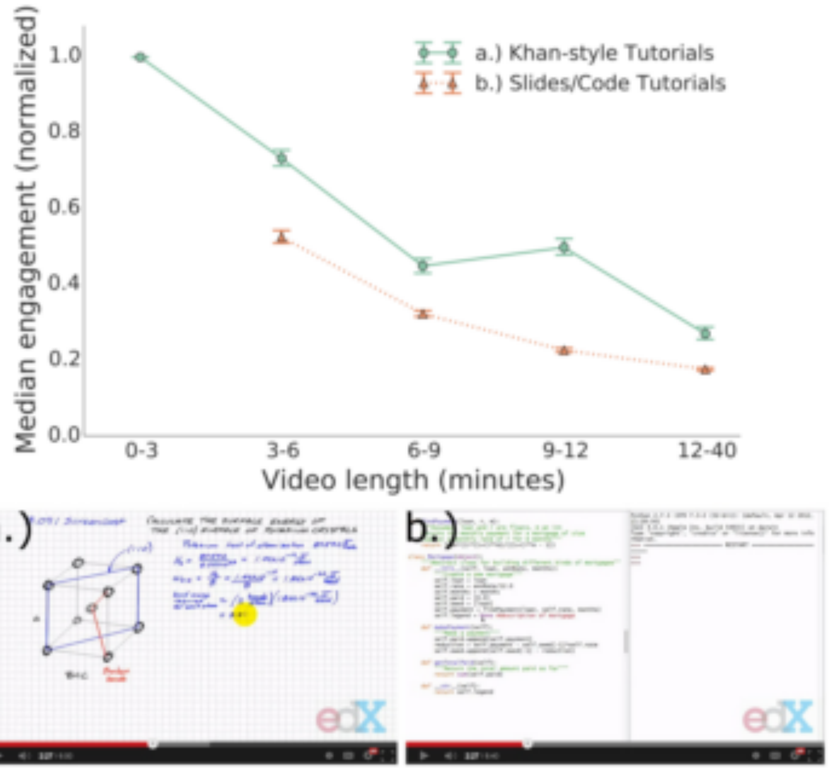


Figure 4. Median normalized engagement times vs. length for tutorial videos. Students engaged more with Khan-style tablet drawing tutorials (a.) than with PowerPoint slide and code screencast tutorials (b.). Error bars are approximate 95% confidence intervals for the true median [14].

Findings and Recommendation (5)

F: Pre-Production Improves Engagement

R: Invest in pre-production effort

Note:

- 3.091x splice up old set of lectures
- Problem attempt is 55% with CS188.1x and 41% for 3.091x

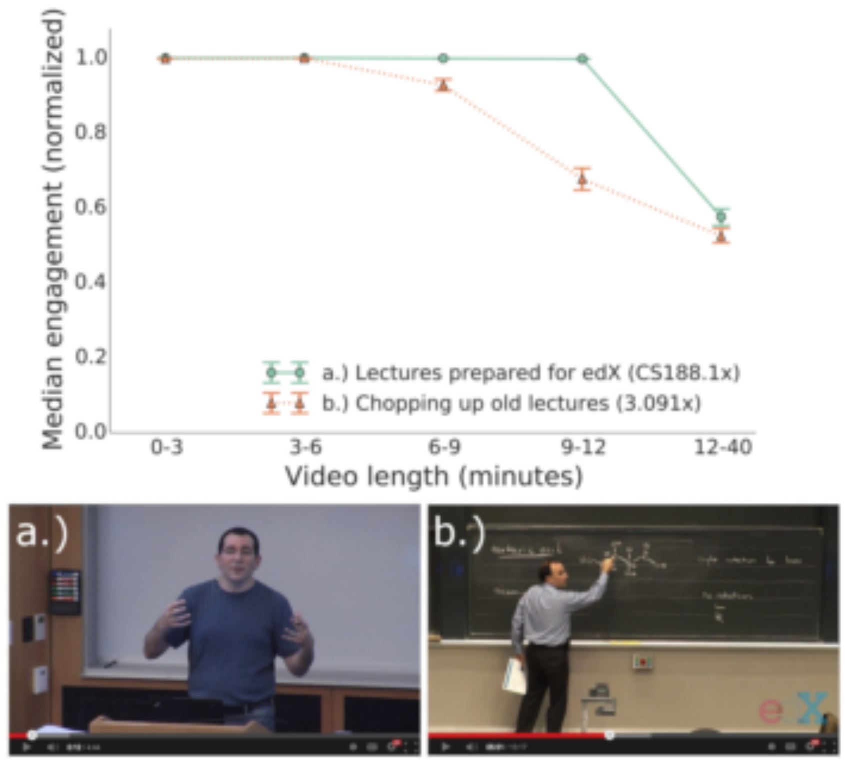


Figure 5. Median engagement times for lecture videos recorded in front of live classroom audiences. Students engaged more with lectures in CS188.1x (a.), which were prepared with edX usage in mind, than with lectures in 3.091x (b.), which were adapted from old lecture videos. Error bars are approximate 95% confidence intervals for true median [14].

Findings and Recommendation (6)

F: Speaking Rate Affects Engagement

R: Bring out natural enthusiasm and speaking fast is okay

Note:

- no significant differences on number of play/pause events
- 145 –165 wpm least energetic
- 48-130 wpm because of writing simultaneously
- Problem attempts also follow a similar trend

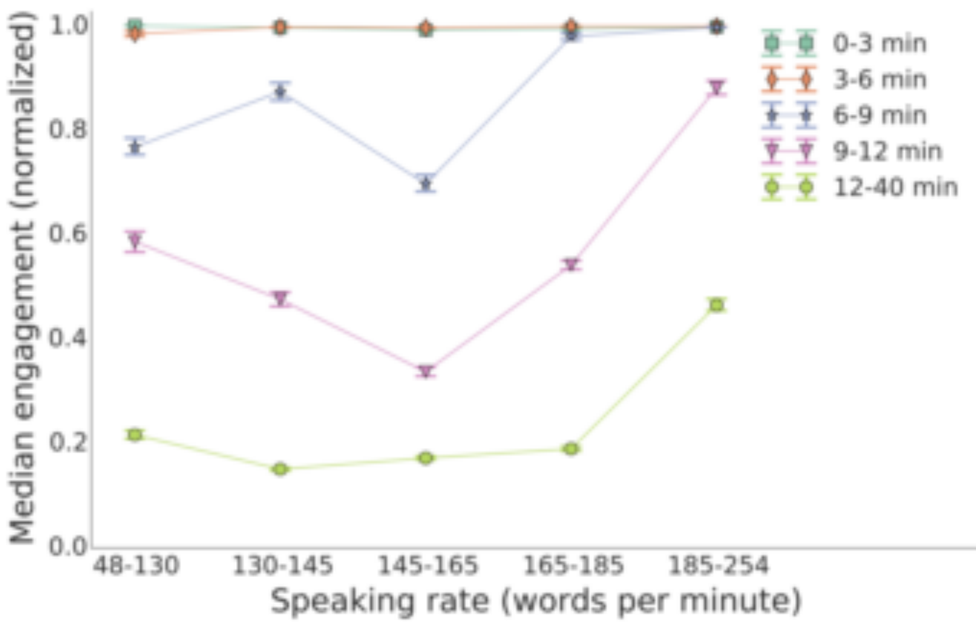


Figure 6. Median engagement times versus speaking rate and video length. Students engaged the most with fast-speaking instructors. Error bars are approximate 95% confidence intervals for the true median [14].

Findings and Recommendation (7)

F: Students Engage Differently With Lectures And Tutorials

R: Lecture videos, optimize the first-time watching experience. For tutorials, length does not matter, support re-watching and skimming.

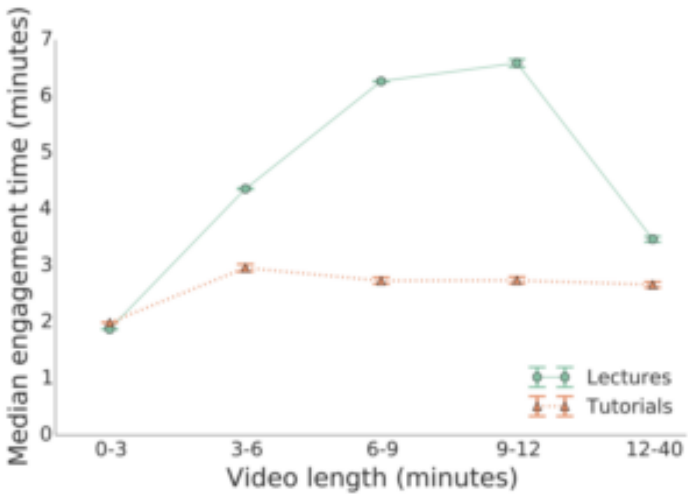


Figure 7. Median engagement times versus video length for lecture and tutorial videos. Students engaged with tutorials for only 2 to 3 minutes, regardless of video length, whereas lecture engagement rises and falls with length (similar to Figure 2). Error bars are approximate 95% confidence intervals for the true median [14].

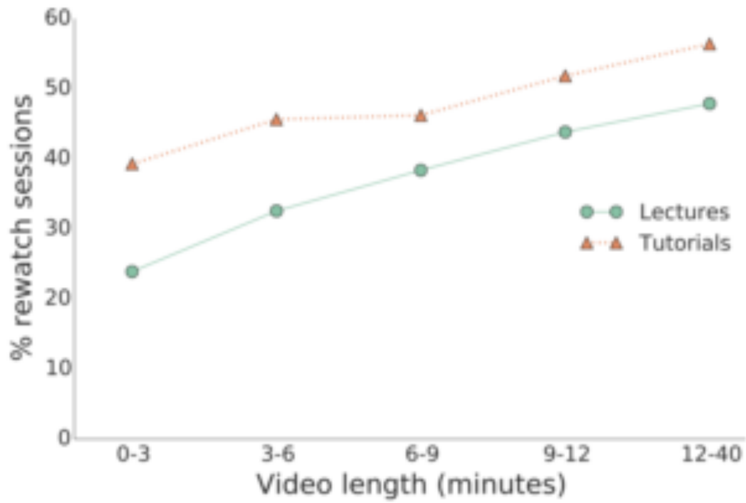


Figure 8. Percentage of re-watch sessions – i.e., not a student's first time watching a video. Tutorials were more frequently re-watched than lectures; and longer videos were more frequently re-watched. (Binomial proportion confidence intervals are so tiny that error bars are invisible.)

Limitations

- more diverse courses
- cannot measure a student’s true engagement
- cannot track viewing activities of students who watched offline

Conclusion

- To maximize student engagement, instructors must plan their lessons specifically for an online video format

Finding	Recommendation
Shorter videos are much more engaging.	Invest heavily in pre-production lesson planning to segment videos into chunks shorter than 6 minutes.
Videos that intersperse an instructor's talking head with slides are more engaging than slides alone.	Invest in post-production editing to display the instructor's head at opportune times in the video.
Videos produced with a more personal feel could be more engaging than high-fidelity studio recordings.	Try filming in an informal setting; it might not be necessary to invest in big-budget studio productions.
Khan-style tablet drawing tutorials are more engaging than PowerPoint slides or code screencasts.	Introduce motion and continuous visual flow into tutorials, along with extemporaneous speaking.
Even high quality pre-recorded classroom lectures are not as engaging when chopped up for a MOOC.	If instructors insist on recording classroom lectures, they should still plan with the MOOC format in mind.
Videos where instructors speak fairly fast and with high enthusiasm are more engaging.	Coach instructors to bring out their enthusiasm and reassure that they do not need to purposely slow down.
Students engage differently with lecture and tutorial videos	For lectures, focus more on the first-watch experience; for tutorials, add support for rewatching and skimming.

Table 1. Summary of the main findings and video production recommendations that we present in this paper.

VisMOOC: Visualizing Video Clickstream Data from Massive Open Online Courses

Conglei Shi - HKUST
Siwei Fu - HKUST
Qing Chen - HKUST
Huamin Qu - HKUST

Inputs

- Five experts, four instructors offering courses on Coursera and one educational analyst
- 2 Coursera courses (CH and GT)
  - Video clickstream data
    - userID, timestamp, in-video pos., event type (play, pause, seek, stalled, error, and rate-change)
  - Forum data
    - only about 10% learners use the forum (???)
  - Grading data
    - no particular reason

Event Type Description

Type	Meaning	% (CH)	% (GT)
play	Users clicked the play button. When the video is loaded at the first time, it will play automatically and a play event will be recorded.	21.3%	26.6%
pause	Users clicked the pause button. When a video is over, a pause event will be recorded.	16.8%	21.0%
seek	Users dragged the video from one time point to another time point.	42.3%	25.7%
stalled	The video is stalled due to buffering.	11.8%	17.1%
ratechange	Users changed the playback rate.	7.2%	8.9%
error	Errors occurred.	0.6%	0.7%

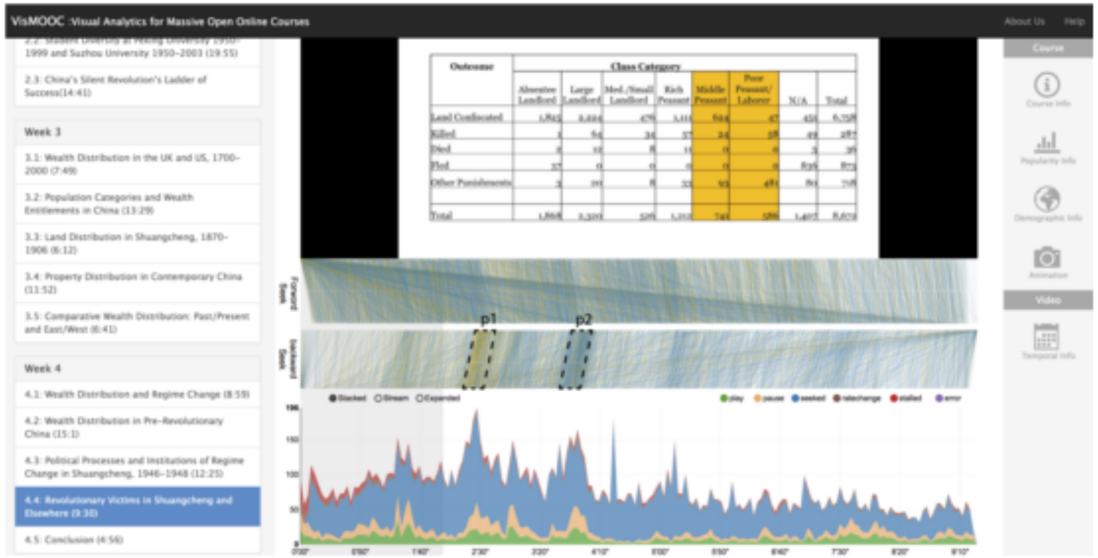
Research Questions

- What is the overall statistics of clickstream data?
  - provide guidance on filtering out irrelevant parts
- In each video, which parts are more interesting to research?
  - types of events happened at some particular position of a video
- What are the differences of viewing behaviors between different user groups?
  - compare and analyze how students from different areas react to the same course materials
- How do the learning behaviors change over time?
  - how the learning behaviors change in different time scales
- What other factors can affect the user viewing behaviors?
  - such as release time, length and content of the video, etc.

Design Requirement

- Simple visual design
  - quickly understand the stories and make decisions
- Video-embedded design
  - Correlate user interaction with video content
- Multi-level-scale exploration
  - the time scales and the learners scales
- Multi-perspective exploration
  - encoding information from a unique perspective

VisMOOC Design (1)



- Content-based View
  - event graph
  - seek graph
- Dashboard View
  - calender visualization for daily popularity
  - bar chart for overall popularity
  - clickstream animation
- View Coordination
  - demographic chart

Results

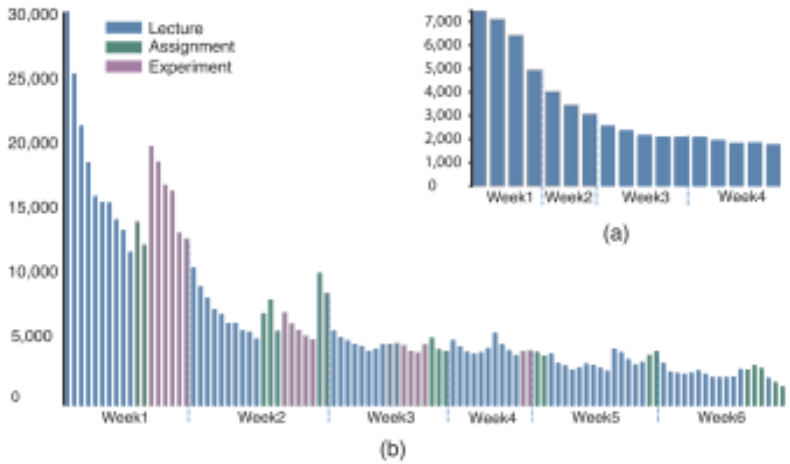


Figure 3: The histogram shows the popularity of videos. The color encodes the video type and height encodes the number of learners. We can see that the popularity becomes stable after two weeks for both courses.

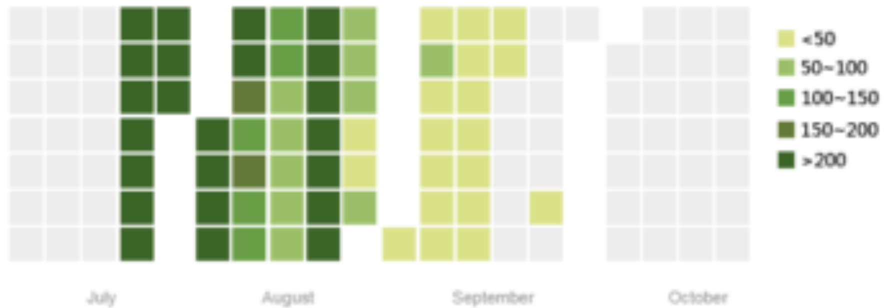


Figure 5: The calendar view shows the temporal popularity for the selected video. We can see that there are two weeks with a lot of acitons.

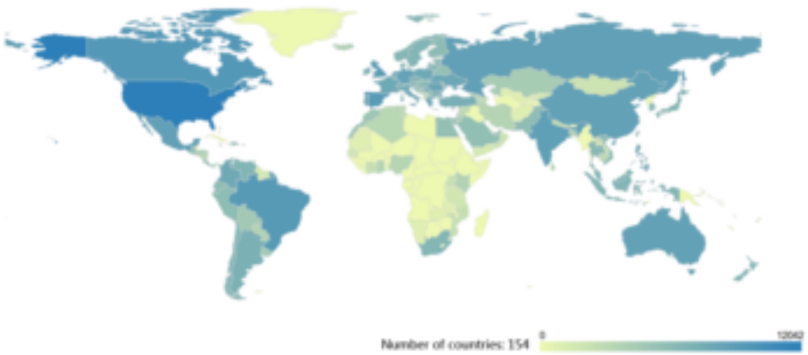


Figure 4: A world map show the distribution of learners around the world for the Course *GT*. We can see that the majority of learners are from the U.S, while all the learners are from more than 150 countries.

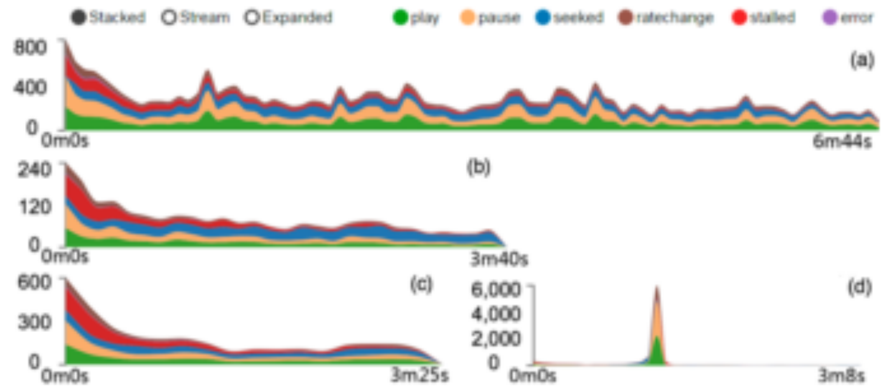


Figure 6: Event graphs show the distribution of different clickstreams in different types of videos in Course *GT*: a) the lecture video; b) the assignment video; c) the experiment video; d) the experiment video with an in-video question.

Results

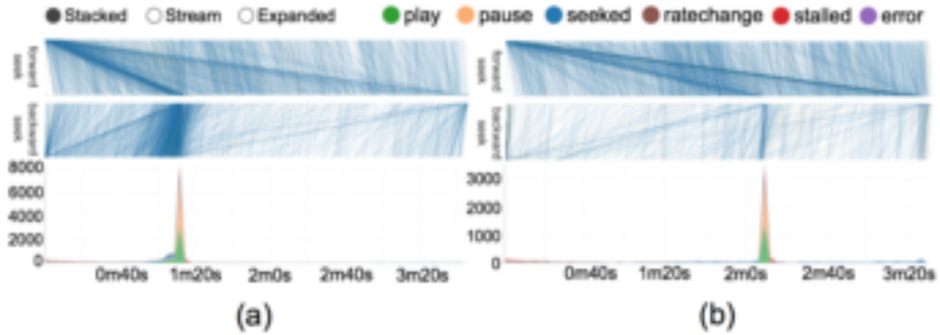


Figure 7: Comparison between the Content-based views of two videos with a in-video question.

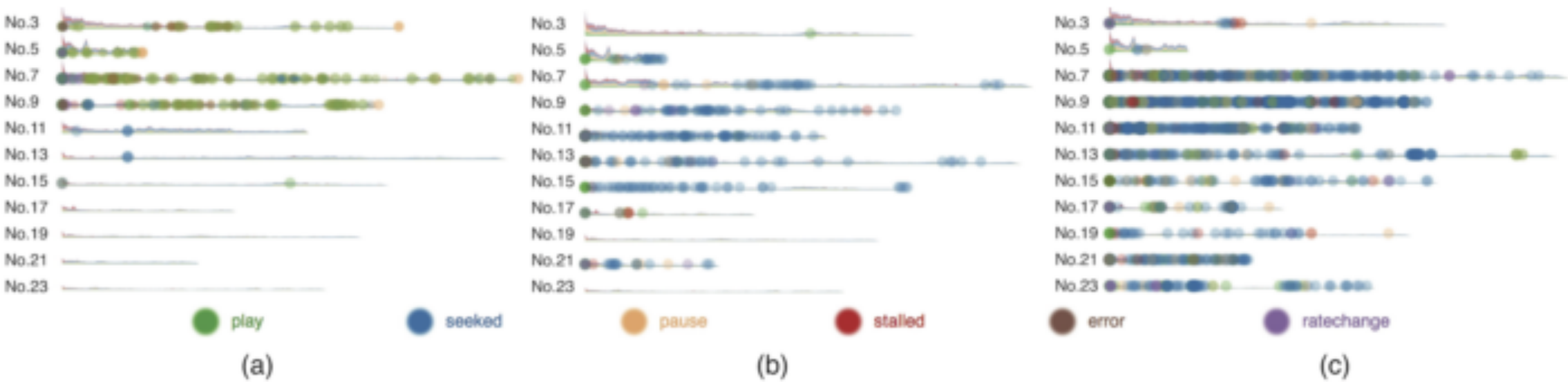


Figure 8: Animations show three patterns: a) pause events and play events are dominant when learners watch the videos for the first time; b) seek events are dominant when learners review the videos; c) there is a burst of events on the exam day.

Results

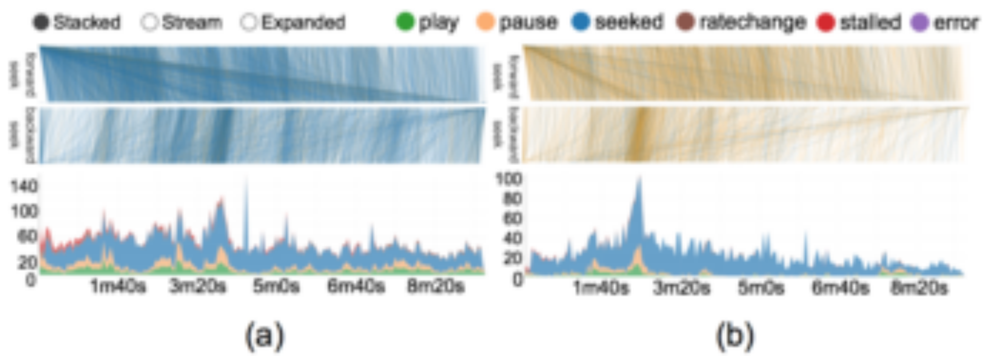


Figure 9: The Content Views for the same video shown in Figure 1 but with different time periods. a) the clickstream data from the first week when the video released; b) the clickstream data from the week when the related assignment released.

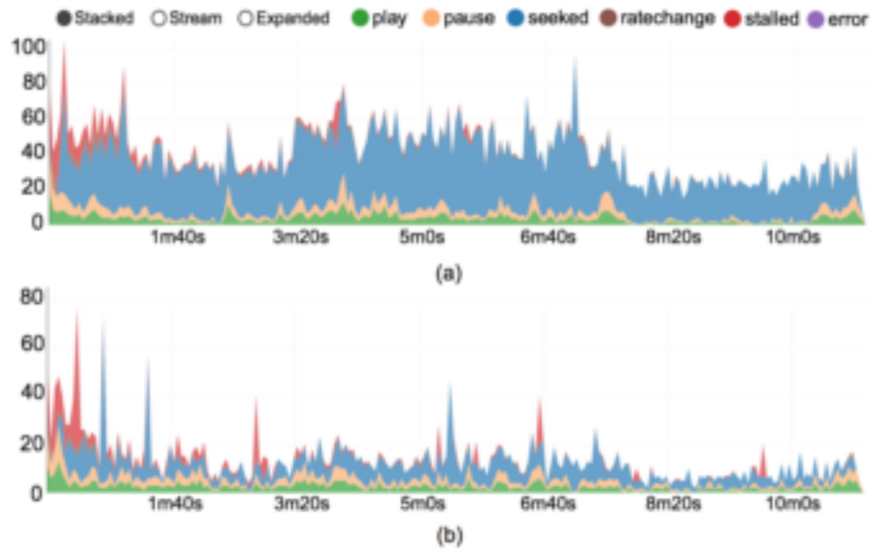


Figure 10: The Event Graphs showing the clickstream data of the same course during the same time period but for learners from different countries. a) Learners from the U.S; b) Learners from China. We can clearly see that the percentage of seek events happened in the U.S is much larger than the one in China.

Conclusions & Future work

- The first visual analytical system to specifically help the experts
- Can be extended and applied to the general analysis of other video watching behaviors

- Integrating the analysis modules for forum data and grading information
- Learning pattern w.r.t grades

MOOC Video Interaction Patterns: What Do They Tell Us?

Nan Li - EPFL
Lukasz Kidzinski - EPFL
Patrick Jermann - EPFL
Pierre Dillenbourg - EPFL

Hypothesis & Goal

- Students adapt their video interactions to the video difficulties, their personal capability and learning strategies

- Associations between video interaction patterns with (1) perceived video difficulty, (2) video revisiting behaviours and (3) students' performance

Inputs

- 2 undergrad courses in Coursera (RP and DSP)

Subject	Week	Videos	Length	Quiz	Active	Passed	Sessions	Events
RP	7	36	18:50	6	22,794	5,276	470,994	4,001,992
DSP	10	58	16:20	16	9,086	263	117,959	1,138,558

Table 1. Overview of the two MOOCs in our dataset.

- Note:
  - Weekly quizzes (RP: unlimited submission, DSP: 5 submissions)
  - Higher pass rate in RP(23.15%) than DSP(2.89%)

Data Wrangling Pipeline

1. Arranged user-based watching histories in chronological order
2. Revisited and first-time video sessions are separated
3. Aggregate the events in each watching segments into video features
4. Processed video events like pauses, seeks and speed changes
5. Removed the pause events that have a duration of more than 10 minutes
6. Seek events that are within 1 second interval are grouped as a single seeking event

Video Interaction Clustering

1. number of pauses (NP)	5. number of backward seeks (NB)
2. median duration of pauses (MP)	6. replayed video length (RL)
3. number of forward seeks (NF)	7. average video speed (AS)
4. proportion of skipped video content (SR)	8. effective video speed change (SC)

Table 2. Video Features Used for Clustering

- SC: the average amount of speed change during the video session (StartS – AvgS)

- Note:
  - all the video sessions that did not reach the last 10% categorized into the ”in-video dropout”
  - clustering will be performed only on the remaining ”complete”

Clustering and Video Interaction Pattern

- PCA, 6 new uni-variance variables
- Neural Gas
- SSI, for optimal number of clusters (9 clusters)

- Each clusters labeled with dominating features

Pattern	Proportion	NP	MP	NF	NB	SR	RL	AS	SC
Replay (RP)	3%	4.73	62.58	5.86	12.84	0.05	**531.44**	1.10	-0.00
HighSpeed (HS)	10%	1.17	23.19	1.18	0.95	0.10	27.14	**1.66**	-0.01
SpeedUp (SU)	3%	1.38	27.16	1.66	1.04	0.09	25.13	1.53	**0.39**
SkimSkip (SS)	4%	1.00	30.73	**21.70**	4.94	**0.75**	17.46	1.14	0.00
Inactive (IA)	38%	1.93	39.05	0.71	1.28	0.03	36.65	1.05	-0.00
FrequentPause (FP)	4%	**13.39**	40.58	2.87	5.13	0.05	109.37	1.08	-0.00
JumpSkip (JS)	13%	0.45	11.62	**5.38**	1.10	**0.71**	9.40	1.06	0.00
LongPause (LP)	6$	1.71	**284.96**	1.34	1.26	0.08	44.62	1.07	0.00
SpeedDown (SD)	1%	2.13	42.93	1.61	1.73	0.08	44.42	1.24	**-0.58**

Table 3. Cluster centers for the RP dataset

Clustering and Video Interaction Pattern (1)

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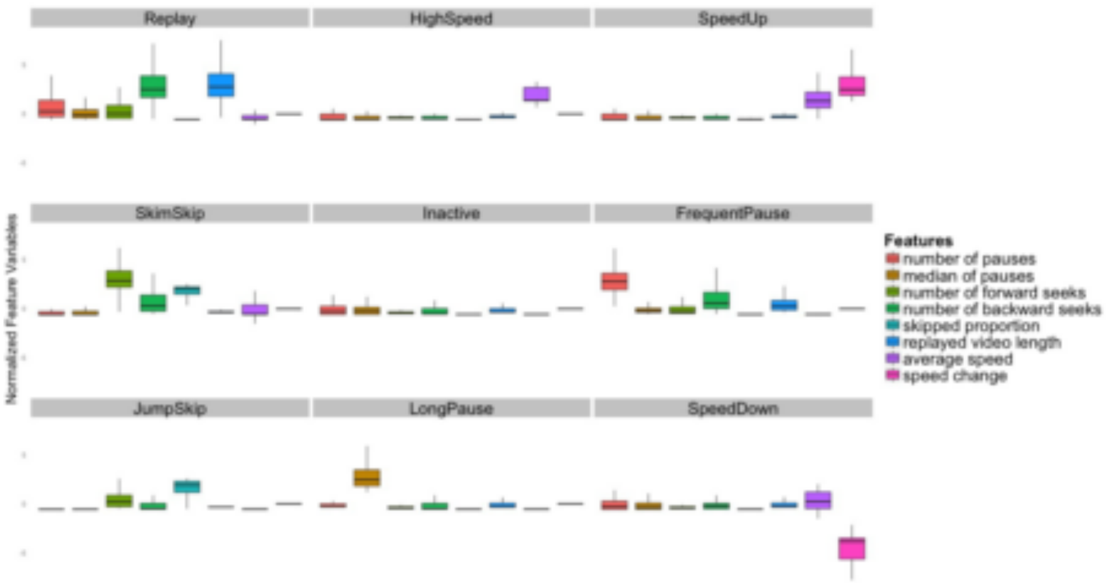

Fig. 1. Cluster Data Distributions for the RP Dataset

Perceived Video Difficulty

- **How do the different video interaction patterns reflect different levels of perceived video difficult?**

- Info:
  - How easy was it for you to understand the content of this video?
  - Focus on first watching sessions
  - RP 49.1% (diffic. 2.699), DSP 32.8% (diffic. 2.594)

Perceived Video Difficulty - Result

- RP and FP patterns reflect significantly higher difficulty

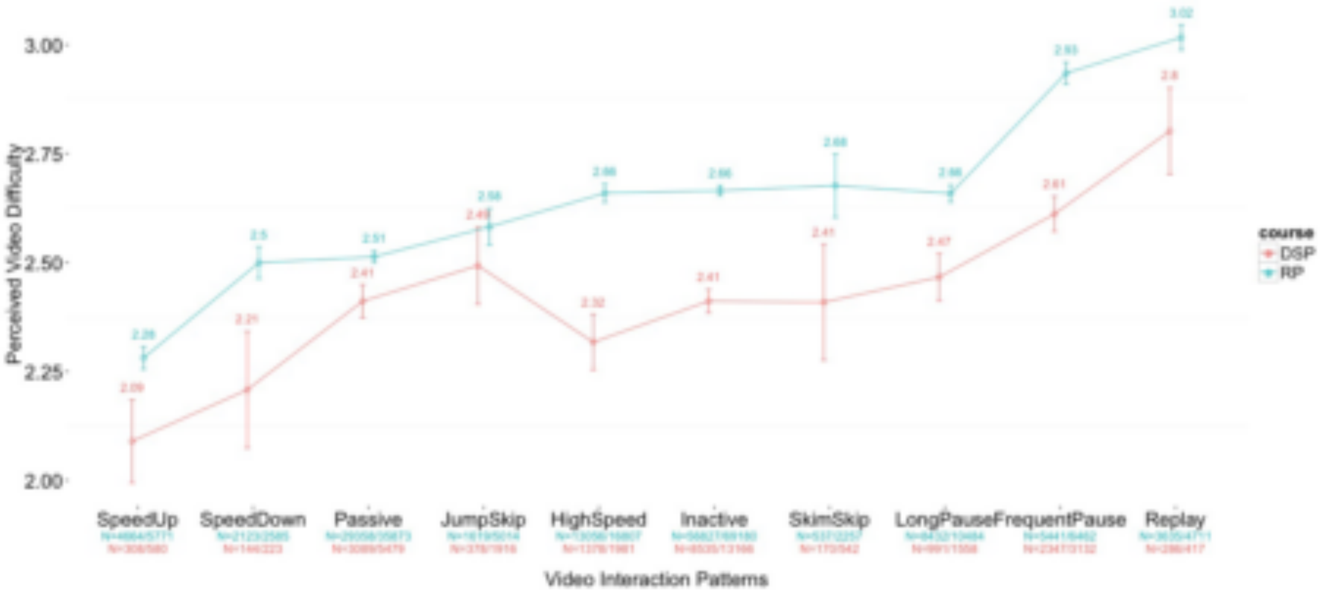

Fig. 2. Video Interactions Patterns and Perceived Video Difficulty

Video Revisiting Behaviours

- **With which first-time video interaction patterns are the videos more likely to be revisited?**

	RP		DSP	
	Completed	Dropped-out	Completed	Dropped-out
Revisiting	20.6%	73.7%	23.5%	59.3%
No Revisiting	79.4%	26.3%	76.5%	40.7%
	$\chi^2(1,220875)=55805.1$, $p < .0001$		$\chi^2(1,38825)=5114.1$, $p < .0001$	

Table 4. Proportion of Video Revisiting for Complete and In-video Dropout Sessions

		RP	**HS**	**SU**	**SS**	**IA**	**FP**	**JS**	**LP**	**SD**	**PS**
RP	Revisiting	35.7%	17.2%	15.0%	25.6%	21.6%	26.1%	21.6%	21.1%	21.3%	20.6%
		25.9	-11.3	-10.5	**5.96**	**8.93**	**11.1**	1.86	1.31	0.99	-16.8
	No Revisiting	64.3%	82.8%	85.0%	74.4%	78.4%	73.9%	78.4%	78.9%	78.7%	79.4%
		-25.9	**11.3**	**10.5**	-5.96	-8.93	-11.1	-1.86	-1.31	-0.99	**16.8**
		$\chi^2(9,156517)=1293.7$, $p < .0001$									
DSP	Revisiting	41.5%	21.8%	16.5%	22.5%	22.1%	32.0%	23.9%	23.6%	26.6%	21.6%
		7.8	-1.6	-3.57	-0.47	-4.49	**10.7**	0.32	0.1	0.95	-3.24
	No Revisiting	58.5%	78.2%	83.5%	77.5%	77.9%	68.0%	76.1%	76.4%	73.4%	78.4
		-7.8	1.6	**3.57**	0.47	**4.49**	-10.7	-0.32	-0.1	-0.95	**3.24**
		$\chi^2(9,22717)=197.7$, $p < .0001$									

Table 5. Proportion of Video Revisiting for Complete Sessions

Student Performance

- **How do Strong and Weak students differ in lecture video viewing behaviours?**

- Info:
  - subset of the data which includes students who completed all the assignments(RP: < 23%, DSP: < 3%)
  - *Strong* = obtain 80% of total points in FIRST try
  - *Weak* = otherwise
  - 86.3% of the passed students, 35.3% are *Strong*

Student Performance - Result

- *Strong* = high-freq. in HS, SU, PS and IA
- *Weak* = high-freq. in SS, JS, FP and LP

	RP	HS	SU	SS	IA	FP	JS	LP	SD	PS
Strong	38.7%	46.1%	39.7%	31.6%	35.9%	32.4%	33.8%	35.5%	38.6%	39.0%
	-1.2	**17.3**	**2.1**	-4	-9	-6.6	-3.6	-3.2	0.7	**3.8**
Weak	61.3%	53.9%	60.3%	68.4%	64.1%	67.6%	66.2%	64.5%	61.4%	61.0%
	1.2	-17.3	-2.1	**4**	**9**	**6.6**	**3.6**	**3.2**	-0.7	-3.8
	$\chi^2(9,76094)=406.3$, $p<.0001$									

Table 6. Proportion of Video Interaction Patterns based on Students Performance

Pattern	Proportion	NP	MP	NF	NB	SR	RL	AS	SC
Replay (RP)	3%	4.73	62.58	5.86	12.84	0.05	**531.44**	1.10	-0.00
HighSpeed (HS)	10%	1.17	23.19	1.18	0.95	0.10	27.14	**1.66**	-0.01
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LongPause (LP)	6$	1.71	**284.96**	1.34	1.26	0.08	44.62	1.07	0.00
SpeedDown (SD)	1%	2.13	42.93	1.61	1.73	0.08	44.42	1.24	**-0.58**

Table 3. Cluster centers for the RP dataset

Conclusion and Limitation

- Detect the change of video interaction patterns
- Provide quick access for revisiting videos
- Make use of the pauses

- Not considering the type course or the differences in video content
- Forum, quiz, students' motivations all may relate to the aspects we described

Exploring the Effect of Confusion in Discussion Forums of Massive Open Online Courses

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Inputs

- 2 Coursera courses, Algebra(2,126 users, 7,994 posts) and Microeconomics(2,155 users, 4,440 posts)
- Clickstream(Al: 8.6 millions, Mi: 2.7 million)

- Mturk(US citizens, 98% app. rate) for annotating posts(5 workers/post)
- Randomly sampled posts(Al: 522, Mi: 584)
- Annotate post from scale 1 to 4(high-confusion)
- Divide posts into 2 groups, “confused” and “unconfused”

Classifier Construction

- Click Patterns
  - Within a 3 hour window, collect N-grams behaviours
  - E.g. “quiz-quiz-forum”, “quiz-lecture-quiz-lecture”
- Linguistic Features
  - Using LIWC features(Pronouns, Sentiment, so on)
- Question Features
  - Number of question marks and heuristic rule

Classification Performance - Quantitative

- Logistic Regression with 10-cross validation

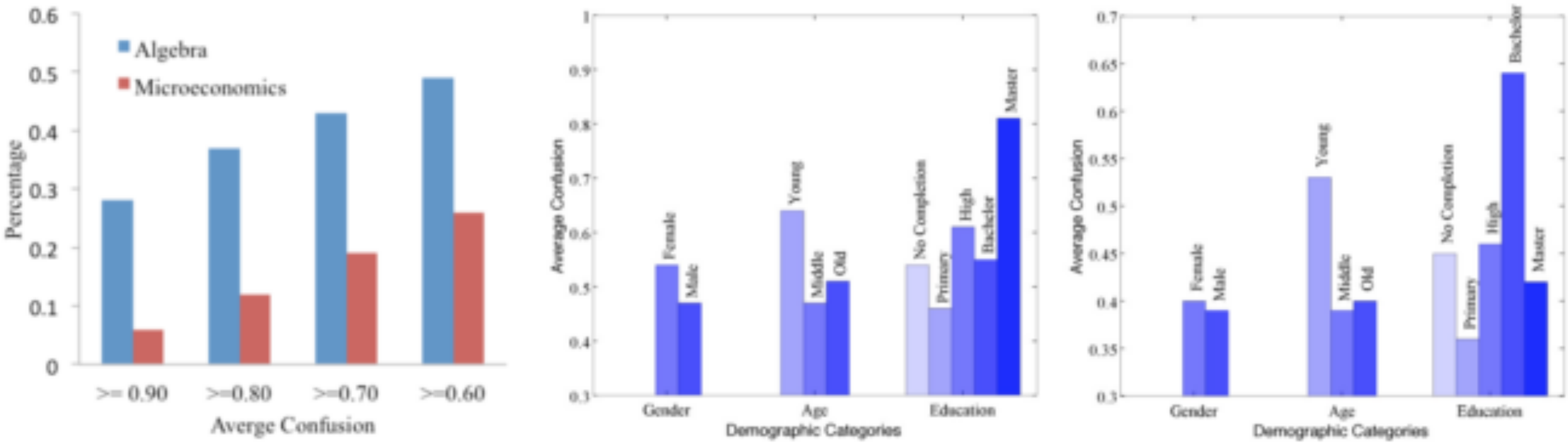
Courses	Algebra Course			Microeconomics Course		
Classifier	Accuracy	Kappa	#Features	Accuracy	Kappa	#Features
Unig	0.791	0.581	2967	0.698	0.375	4921
Click	0.587	0.176	20	0.567	0.049	20
Ling	0.647	0.293	15	0.594	0.056	15
Question	0.683	0.370	4	0.652	0.333	4
CLQ	0.723	0.448	39	0.678	0.309	39
CLQ + Unig	0.796	0.582	3006	0.706	0.388	4960
Reduced(CLQ + Unig)	0.803	0.606	632	0.712	0.403	650

Table 1. Performance of Confusion Classifiers on Two Courses

Courses	Algebra	Microeconomics
Most Important Features (Feature Weight)	question marker count(1.16) 1st pers singular (1.31) question word count(0.52) click pattern (0.38) impersonal pronouns (-0.15) certainty (-0.17) negation (-0.19) adverbs (-0.20)	question marker count(1.30) start with modal words (1.09) 1st pers singular(0.73) question word count(0.17) adverbs (-0.17) affect (-0.18) click pattern(-0.19) negation (-0.20) insight (-0.28)

Table 2. Top Ranked Features for Confusion Detection

Findings and Observations



(a) Course Difference (b) Algebra Course (c) Microeconomics Course

Figure 1. Qualitative Confusion Comparison over Courses and Demographics

Survival Analysis Design

- Using Hazard Ratio, to predict student drop-out from defined variables
- Dependent Variables
  - Dropout (1 active, 0 otherwise)
- Control Variables
  - TotalPost (# of posts/week)
  - Starter (Initiate thread)
- Independent Variables
  - Expressed Confusion (avg. confusion/week)
  - User Exposed Confusion (avg. confusion from initiate post)
  - Other Exposed Confusion (avg. confusion from other post)
  - Confusion Resolved (# of resolved initiate posts)
  - Reply (# of initiate thread with response from others)

Survival Analysis Design (1)

Courses	Algebra				Microeconomics			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
TotalPost	8.41	17.18	1	232	6.01	9.56	1	172
Starter	0.26	0.57	0	5	0.16	0.46	0	5
ExprConfusion	0.29	0.34	0	1	0.23	0.28	0	1
UserExpoConfusion	0.10	0.20	0	0.69	0.05	0.14	0	0.69
OtherExpoConfusion	0.21	0.23	0	0.69	0.15	0.17	0	0.69
Resolved	0.36	0.46	0	1	0.25	0.42	0	1
Reply	0.40	0.47	0	1	0.26	0.42	0	1

Table 3. Descriptive Statistics for the Variables in the Survival Analysis

Commitment Analysis

- Confusion on commitment

	Algebra Model 1		Algebra Model 2		Microeco Model 1		Microeco Model 2	
Variables	HZ	(Std. Err)S.E	HZ	S.E	HZ	S.E	HZ	S.E
TotalPost	0.60***	0.02	0.47***	0.02	0.71***	0.03	0.60***	0.03
Starter	1.29***	0.02	1.38***	0.05	1.19***	0.02	1.45***	0.11
ExprConfusion			1.17***	0.03			1.18***	0.05
UserExpoConfusion			1.06	0.04			1.05	0.04
OthersExpoConfusion			1.85***	0.06			1.51***	0.06

Table 4. Results of Confusion on Students' Survival (*: $p < 0.05$, **: $p < 0.01$, *** $p < 0.001$)

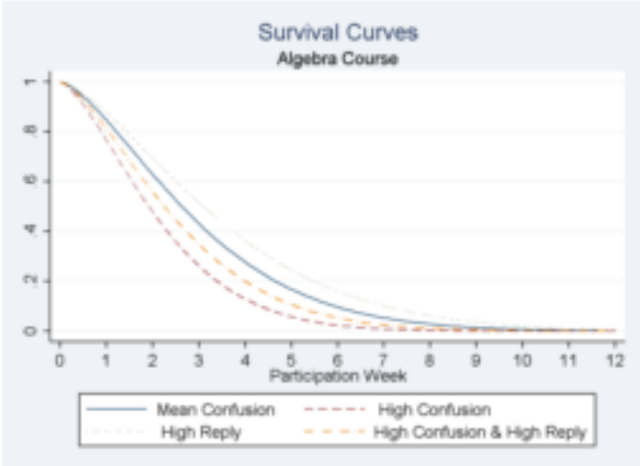
Commitment Analysis

- Resolving Threads and Receiving Replies

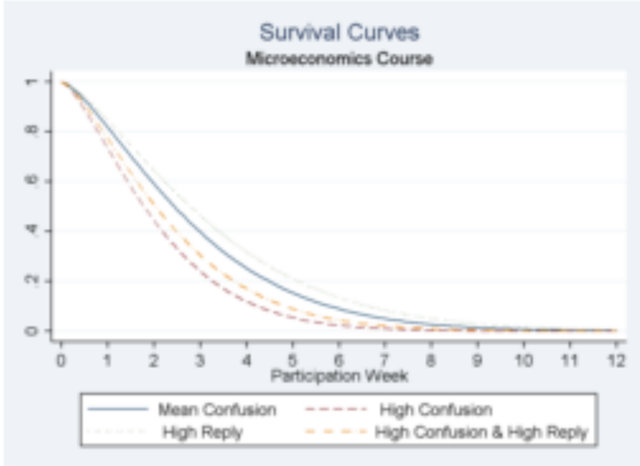
	Algebra						Microeco					
	Model 0		Model 1		Model 2		Model 0		Model 1		Model 2	
Variables	HZ	S.E	HZ	S.E	HZ	S.E	HZ	S.E	HZ	S.E	HZ	S.E
TotalPost	0.58***	0.02	0.59***	0.02	0.60***	0.02	0.66***	0.03	0.67***	0.03	0.68***	0.03
Starter	1.11***	0.02	1.22***	0.03	1.30***	0.04	1.08***	0.03	1.18**	0.04	1.21***	0.04
ExprConfusion	1.64***	0.04	1.69***	0.05	1.59***	0.04	1.54***	0.04	1.54***	0.04	1.54***	0.04
Resolved			0.83***	0.03					0.87**	0.04		
ExprConfusion ×Resolved			0.87*	0.04					0.93**	0.03		
Reply					0.79***	0.03					0.83***	0.04
ExprConfusion ×Reply					0.91***	0.02					0.93**	0.02

Table 5. Results of Survival Analysis for Interaction Effects(*: $p < 0.05$, **: $p < 0.01$, *** $p < 0.001$)

Commitment Analysis

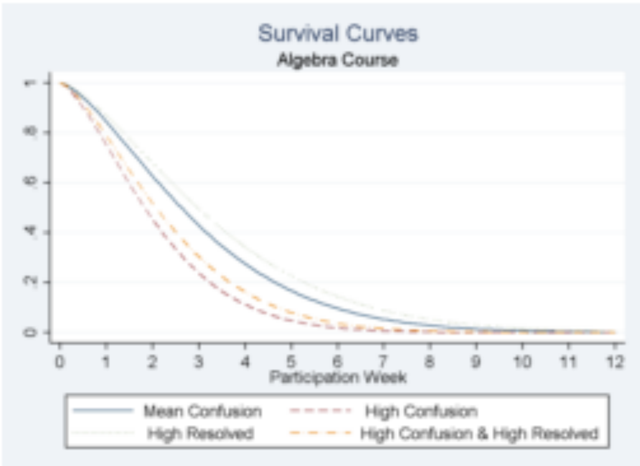


(a) Algebra Course

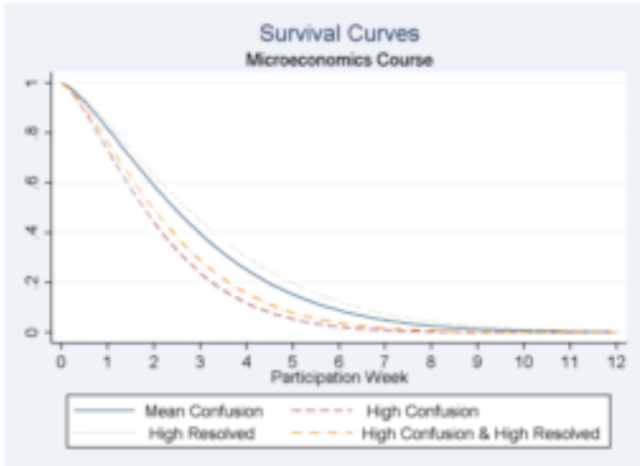


(b) Microeconomics Course

Figure 2. Survival Curves for Students Exposed to Different Levels of Confusion Being Replied



(a) Algebra Course



(b) Microeconomics Course

Figure 3. Survival Curves for Students Exposed to Different Levels of Confusion Being Resolved

Confusion Content Identification

- More likely to express confusion about recently browsed course material
- Target post: Course, Lecture and Quiz

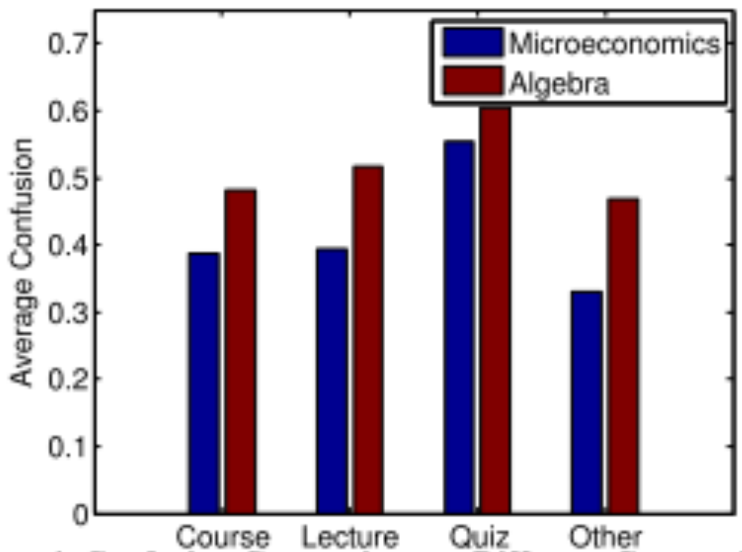


Figure 4. Confusion Comparison on Different Content Types

	Algebra		Microeco	
Variables	HZ	S.E	HZ	S.E
TotalPost	0.51***	0.02	0.63***	0.03
Starter	1.06*	0.02	1.08**	0.03
Course Confusion	1.39***	0.03	1.40***	0.04
Quiz Confusion	1.51***	0.03	1.00	0.03
Lecture Confusion	1.15***	0.02	1.26***	0.03
Other Confusion	1.01	0.03	1.03	0.03

Table 6. Confusion towards Different Course Aspects on Survival

Conclusion and Limitation

- How to identify student confusion during the learning process
- Tracking and monitoring student confusion helps instructors give appropriate feedback to students
- Accurate estimation of students' confusion expressed in the discussion forums

- All judged by Turkers who have no experience in MOOC course forums

IDEA:
Exploring the relation between user interaction with intervention