

Analytics on video-based learning

(Analyse und Visualisierung videobasierter Lernaktivitäten)

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1. Introduction
2. Data gathering
3. Measurements for modeling
4. Visualize video-based learning

Learning objectives

At the end of this workshop you . . .

- ▶ will know what data may be useful for video analytics.
- ▶ will understand different methods to compute the watching time.
- ▶ understand basic information retrieval techniques to analyze video footage.
- ▶ have made first experiences with tools like *Vi-Logger*, *ffmpeg*, and *Praat*.
- ▶ can explain how to make use of visual analytics in order to better understand video usage as well as learning activities of groups and individuals.

1 Introduction

Introduction

Video-based Learning

- ▶ *Video-On-Demand* traffic increase of 29 % between 2013 and 2018 [8]
- ▶ 75 % of the university students in Germany using videos for learning (n=27,473) [35]
- ▶ formats: *flipped classroom* (e.g. [13, 39, 26]), MOOCs (e.g. [16])
- ▶ many different video learning environments,
<http://designingvideointerfaces.nise81.com/portals>

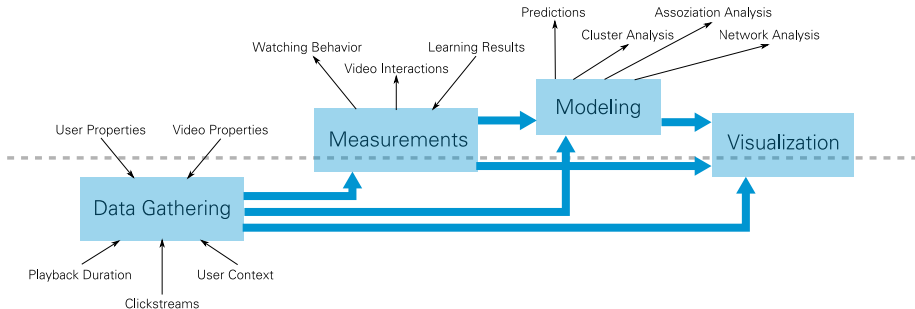
Video Analytics

Learning Analytics methods applied on video-based learning.

- ▶ inform instructors about (ongoing) learning activities
- ▶ help students to self-regulate their learning
- ▶ improve learning resources
- ▶ foster group awareness

Procedure

asynchronous

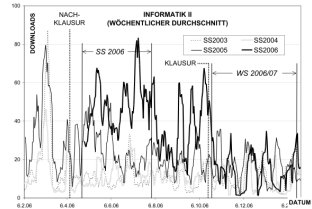


synchronous

Specifics of time [23]

Granularity of time:

- ▶ hierarchical system of granularities:
..., ms, sec, minutes, hours, days, ...
- ▶ cycles and re-occurrences



(cf. [22])

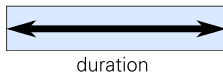
Temporal primitives: time points and intervals

Structures of time:

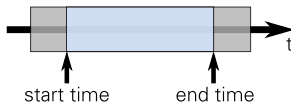
- ▶ ordered time: hierarchy and cycles
- ▶ branching time: describe or prepare planings or predictions
- ▶ multiple perspectives: subjective views on the same event

Presentation time

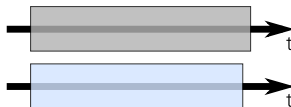
Media element time



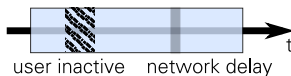
Document time



Rendered Time



Run time



(cf. [21])

2 Data gathering

Gathering data from online video players

HTML

```
<video id="myvideo" width="320" height="240" controls>
  <source src="video.mp4" type="video/mp4">
</video>
```

Javascript

```
var video = document.getElementById( "myvideo" );
video.addEventListener( 'timeupdate', function(e){
  console.log( video.currentTime );
});

function print(){
  console.log( video.currentTime );
}
setInterval(print, 2000);
```

Typical result in a log file

utc	phase	group	user	video	action	playback-time
1477209428123	6	d	34	45	playback	5.012
1477209423121	6	d	12	45	pause	9.432
1477209418125	6	a	23	46	addComment	9.432

Approximating playback duration

Method	Source	Inadequacy
Timeupdate	(W3C)	No active watching; too detailed;
Clickstream	[41]	Long periods without clicks are not considered;
Heartbeat	[4, 5]	No active watching; beat frequency; interactions between the beats;
Section visits	[28, 45, 32]	Partly watched section count like fully watched ones;
Segments	[28, 32, 25, 43, 24]	Segment size; rounding errors; no active watching;

Challenges:

- ▶ determine active watching / learning phases
- ▶ consider varying playback rates
- ▶ realize when a session ends

Determining playback duration from clickstreams [41]

Input:

Log: Clickstream log

ϵ : Tolerance

Function `getUserPlaybackTime(userSessionLog)`

```
tmp ← userSessionLog[0]
```

```
for  $i = 1; i < \text{length}(\text{userSessionLog}); i \leftarrow i + 1$  do
```

```
    timeDistance ← userSessionLog[i].utc – tmp.utc
```

```
    playbackDistance ←
```

```
        userSessionLog[i].playbacktime – tmp.playbacktime
```

```
    if playbackDistance > 0 then
```

```
        if (timeDistance – playbackDistance) ≤  $\epsilon$  then
```

```
            | playbackTime ← playbackTime + playbackDistance
```

```
        end
```

```
    end
```

```
    tmp ← Log[i]
```

```
end
```

```
return playbackTime
```

End

$aUserLog \leftarrow \text{extractUserData}(\text{Log}, \text{userA})$

$aUserSession \leftarrow \text{getSession}(aUserLog, 2)$


$\text{playbackTime} \leftarrow \text{getUserPlaybackTime}(aUserSession)$

Hands-on: approximation of playback duration

Assignment:

Use the *Video-Logger* and play around with the log settings. Configure a perfect logger to determine the playback duration considering the precision, effort, and data economy.

Vi-Logger: <https://nise.github.io/vi-logger/public/>



00:10 / 00:16

```
1525684572926,seek-start,11.127812
1525684573010,seek-stop,11.208375
1525684573974,seek-start,7.924145
1525684574082,seek-stop,8.004937
1525684574638,seek-start,6.482833
1525684574716,seek-stop,6.564187
1525684575268,seek-start,6.482833
```

Capture settings

- ☒ Segment of length seconds
- ☒ Heartbeat, every seconds.
- ☒ Clickstream with a tolerance of ms.

Compute watch time

[compute](#)

By watched segments: 10 seconds.
By heartbeat: 0 seconds.
By clickstream: 11.0 seconds.

Video properties

Production properties:

- ▶ length [18],
- ▶ visual transitions [26, 24],
- ▶ production style: classroom lecture, talking head, digital tablet drawing, presentation slides [18]



Content properties:

- ▶ type of video (e.g. lecture, tutorial, documentary) [18, 17],
- ▶ speaking rate [18, 24, 1],
- ▶ speech / discourse analysis [24, 14, 1],
- ▶ speech / audio volume, pitch frequency [24]

Example: speaking rate

$$speakingRate = \frac{\text{number of syllables}}{\text{video duration}} \geq \frac{\text{number of syllables}}{\text{video duration} - \text{pause time}}$$

1. Extract audio from the the video

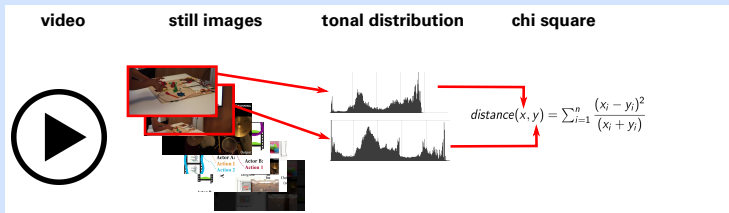
```
$ ffmpeg -i video.mp4 -ab 160k -ac 2 -ar 44100 -vn audio.wav
```

2. Install and open *Praat* from <http://www.fon.hum.uva.nl/praat/>
3. Download and open the speech rate script in *Praat*,
<https://sites.google.com/site/speechrate/Home>
4. Run the script by pressing Ctrl+R and chose a directory containing a *.wav audio file

Output

nsyll	npause	duration (s)	phonation-time (s)	speechrate (nsyll/dur)	articulation rate (nsyll / phonation-time)	ASD (speaking-time/nsyll)
27999	2010	7477.91	5757.28	3.74	4.86	0.206

Example: shot detection



1. Extract still images from video

```
ffmpeg -i video.mp4 -vf fps=1/5 i%03d.jpg -hide_banner
```

(every 5 seconds)

2. Determine histogram differences using chisquare

```
sh ./histcompare.sh -p global -n 0,1 -m chisquare i001.png i002.png
```

(see <http://www.fmwconcepts.com/imagemagick/histcompare/index.php>)

3. Consider shot positions for later analysis

User properties and intentions

Questionnaires in advance

- ▶ demographic data [19, 27],
e.g. age, country of origin, prior knowledge, media usage
- ▶ personality types [37]

Surveying during video usage

- ▶ Predicting interesting segments from browsing data that was trained with in-video questions about the current usage intention [44]
- ▶ Capture perceived difficulty at the end of the video [30]
- ▶ Content summarization

The diagram illustrates in-video survey questions and a summarization prompt. It features two large blue speech bubbles and a smaller white speech bubble at the bottom. The left blue bubble contains a question about browsing state with nine radio button options. The right blue bubble contains a question about understanding difficulty with five radio button options. The white bubble at the bottom contains a text prompt. All bubbles are connected by lines to a horizontal arrow at the bottom, representing a video timeline.

What's your browsing state?

- ☐ curios
- ☐ aimless browse
- ☐ found something interesting
- ☐ abandoned interest
- ☐ looking for something
- ☐ resumed interest
- ☒ found what I want
- ☐ undetermined
- ☐ none of the above

How easy was it for you to understand the content of this video?

- ☐ Very easy
- ☐ Easy
- ☒ Neutral
- ☐ Difficult
- ☐ Very difficult

Please summarize the last slide

3 Measurements for modeling

Measurements: watching behavior

Viewing duration	Time spent on watching a video. [3, 6]
Replay segments	Counting the number of segments that were played more than once. [42]
Total watching time	Total number of seconds spent viewing all videos. [37, 12]
Watching ratio	Relative watching time per video. [12]
Watching threshold	Minimum amount of time a video has been watched. [4]
Retention rate	Number of unique users who watched a video segment [31, 24, 12] / the number of views for a particular moment of a video as a percentage of the total number of views of the video. [29]
Coverage	Fraction of the video that the student visited. [19]
Session length	Time span between start and end of a session. [3, 18, 10]
Number of sessions	Number of distinct user sessions. [3, 24]
Session views	Number of viewings per session. [3]
Session length threshold	Number of sessions longer than n . [37]

Measurements: video interactions and learning results

Micro level: In-video interactions

play, pause/breaks, volume changes, full screen on/off, captions on/off, speed changes, seek, seek forward, seek backward, seek from, seek to, slow forward, slow reverse, fast forward, fast reverse

→ access patterns [20, 4, 41]

→ viewing and interaction profiles [34, 10, 7, 9, 31, 30]

→ in-video drop-outs [30, 26, 2]

Macro level: Inter-video interactions

→ navigation strategies [19]

→ course drop-outs [20, 4]

Learning results:

- ▶ video annotations: add / edit / use (e.g. [40])
- ▶ non-video services: comments, forum posts, wiki entries, ...
- ▶ quizzes: performed quizzes, attempts, results [31, 33, 28, 15]

Learner modeling

1. Prepare data

- ▶ remove automatic pauses [31]
- ▶ remove pauses longer than 10 min [31]
- ▶ group seek events within a range of 1 s [43, 31]
- ▶ remove in-video drop outs (e.g. watched less then 10 sec)
- ▶ ignore sessions without interactions (?)

2. Compute video features

- ▶ prefer median over mean or sum for long-tail distributions

3. Clustering

- ▶ reduce dimensions: Principle Component Analysis
- ▶ select optimal number of clusters: Simple Structure Index
- ▶ clustering: e.g. unsupervised K-Means
- ▶ labeling of clusters by domination features of the centroids
- ▶ data distribution per dataset

Modeling: video features

event	frequency	duration
total events	[25, 9]	
play	[18, 34, 44, 3, 43, 17, 33, 24, 12, 9]	[3]
pause	[31, 28, 18, 34, 44, 3, 43, 17, 33, 24, 12, 42, 1, 9]	[31, 3]
volume	[28, 24]	
full screen	[24]	
show captions	[1]	
speed changes	[43, 24, 12, 1, 9]	
mean speed	[31]	
slow forward	[44]	
slow reverse	[44]	
fast forward	[34, 44, 11, 3]	[3]
fast rewind	[34, 44, 11]	[3]
seeks	[28, 44, 1, 9]	[3, 31, 1]
seek forward	[31, 28, 43, 17]	
seek back	[31, 28, 43, 17, 42]	
seek from	[12]	
seek to	[12]	

4 Visualizations

Visualizations: purpose

Scope	Target Audience		
	Learners	Instructors	Researchers
Video	self-regulate learning, reflexion	improve material, adopt instructions	*
User	self-regulate learning, reflexion, group awareness	(compare learners)	*
Groups	group awareness, co-regulation	monitor courses/groups, compare groups	*

Visualizations: foundations

Approaches [23]

- ▶ visualize time-related data
- ▶ visualize time per se, e.g. Gant Chart

Representing time [23]

- ▶ create spatial arrangements → time axis
- ▶ real world time → animation, video, etc.

Time axis:

- ▶ form: linear vs. circular
- ▶ scale: linear vs. logarithmic
- ▶ direction: left to right (cf. [38])



Histogram of Evolution
by John B. Sparks

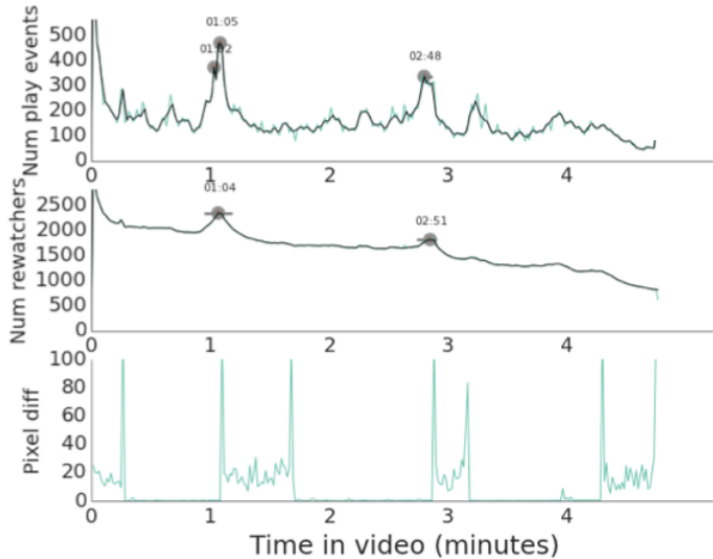
Anforderungserhebung

(1) Bitte geben Sie mögliche Funktionen oder Dashboard-Elemente an, die Sie als Anwendung in einem Learning Analytics-System haben möchten.? Please note possible features or dashboard elements you would like to have as an application in a learning analytics system.

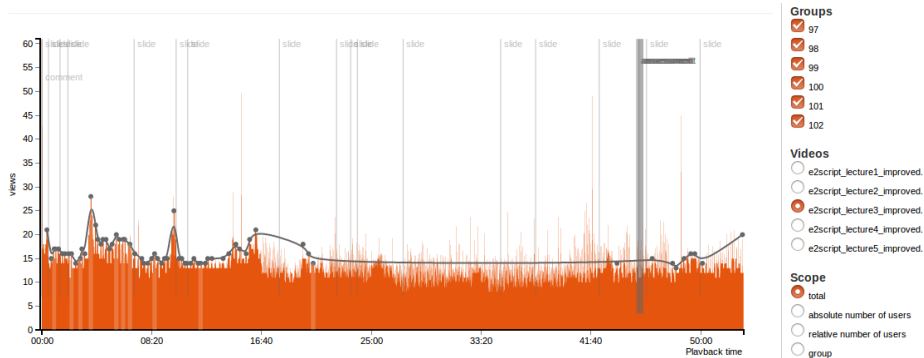
(2) Erklären Sie bitte, welche Funktionen diese Elemente haben sollten. Please explain which functions these elements should have.

(3) Wie glauben Sie können diese Features oder Dashboard-Elemente die Lehre unterstützen? Please indicate how you think these features or dashboard elements can support learning.

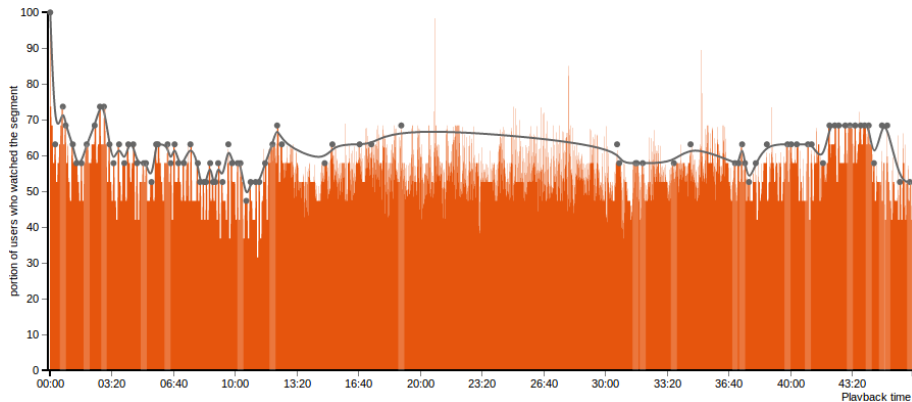
Video scope: interaction peaks [26]



Video scope: playback peaks II

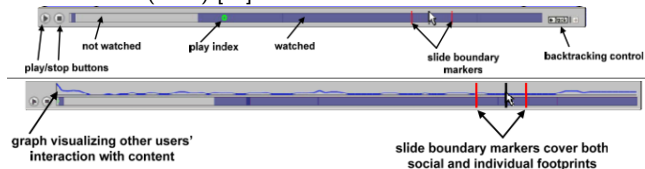


Video scope: retention rate

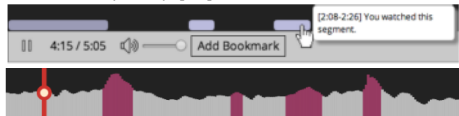


Video scope: social navigation

Mertens et al. (2010) [32]



Kim et al. (2014) [25]



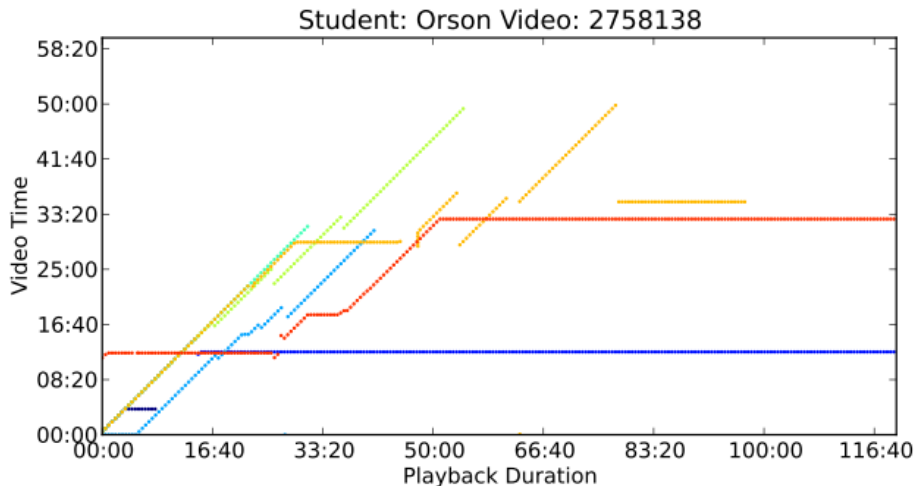
Wald et al. (2015) [45]



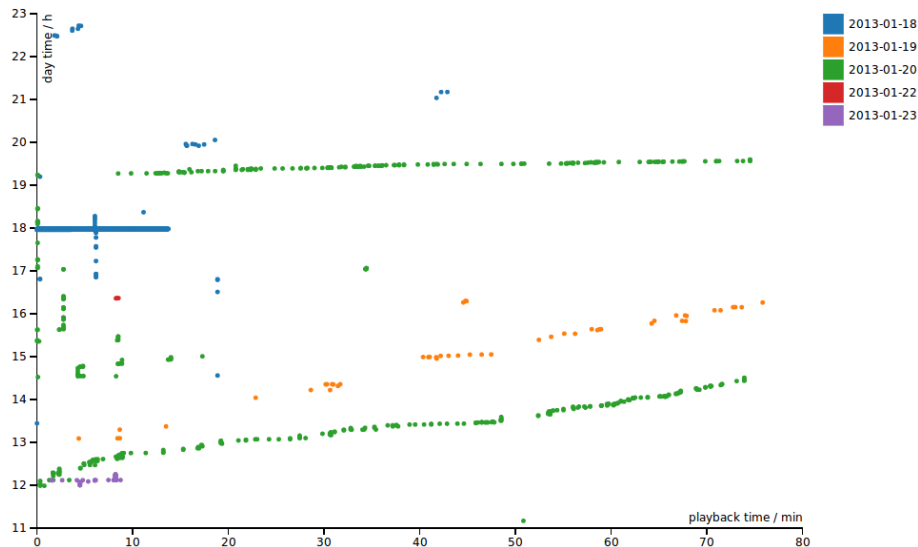
Chatti et al. (2016) [6]



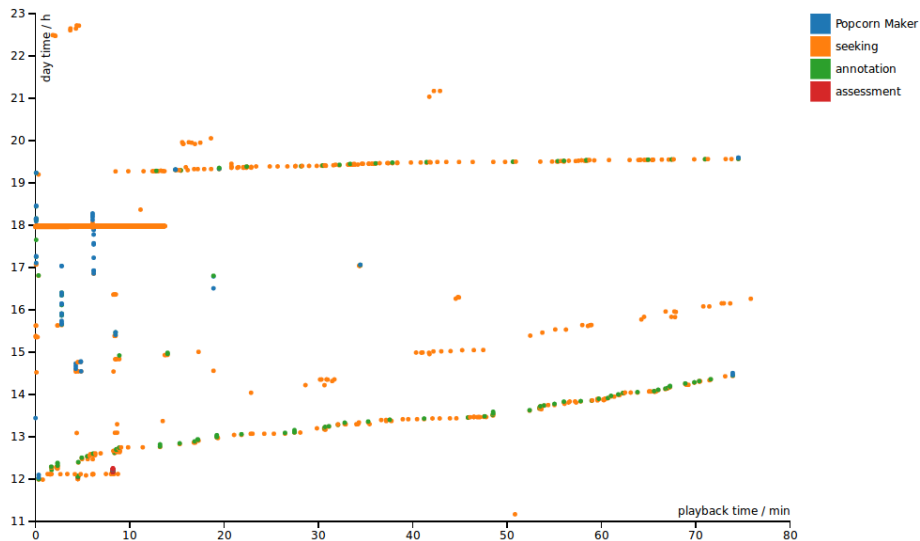
Individual scope: rewatching graphs [5]



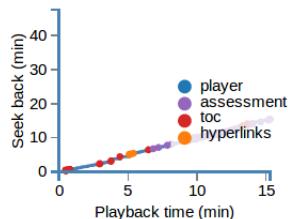
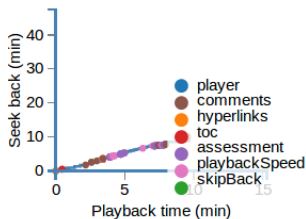
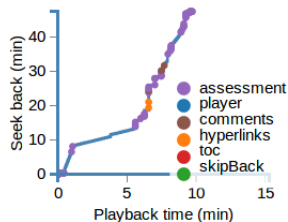
Individual scope: rewatching graphs II (by day) [41]



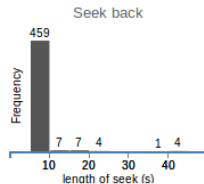
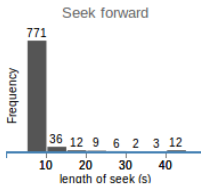
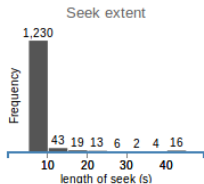
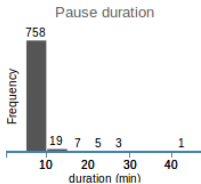
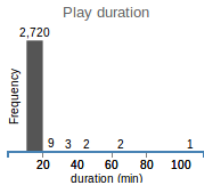
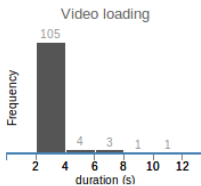
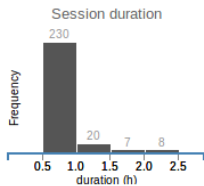
Individual scope: rewatching graph II (by tools) [41]



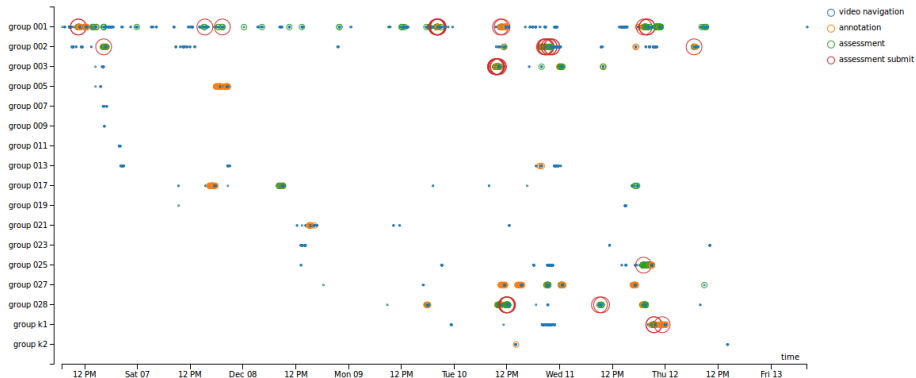
Individual scope: forward-backward diagrams [41]



Group scope: histograms [3]



Group scope: CORDTRA diagram (cf. [36])



Conclusion & future research direction

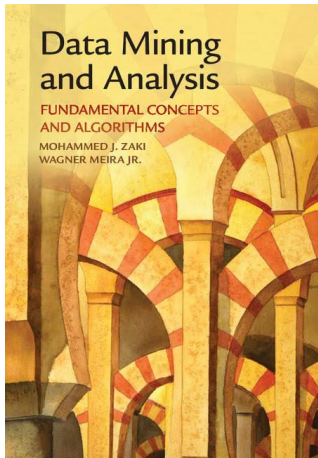
Conclusion

- ▶ Possible data sources for video analytics
- ▶ Different methods to approximate the watching time
- ▶ Analyzed video footage with information retrieval techniques
- ▶ Introduction to tools like *Vi-Logger*, *ffmpeg*, and *Praat*
- ▶ Applied visual analytics techniques in order to understand video usage and learning activities

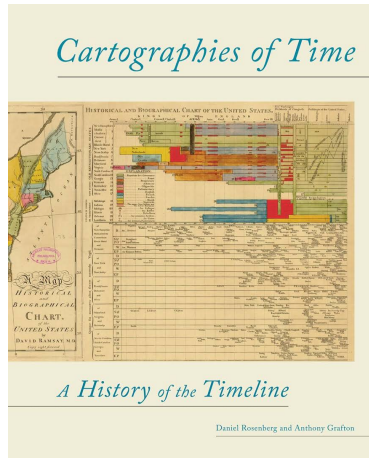
Future research directions

- ▶ Standardization and interoperability of video log data
- ▶ Generic learner models and viewing profiles
- ▶ Parameterization of data charts (e.g. forward-backward-diagram)
- ▶ Tooling: Log → report
- ▶ Learning analytics dashboards for video-based learning

Further reading



Zaki J. Mohammed & Meira Wagner Jr.



Daniel Rosenberg & Anthony Grafton

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