FernUniversität in Hagen

Analytics on video-based learning

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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.
- can apply 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

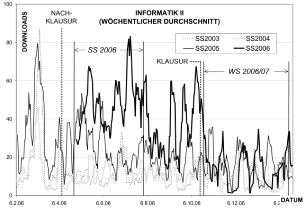
- *Video-On-Demand* traffic increase of 29 % between 2013 and 2018 [8]
- 75 % of the university students in Germany using videos for learning (n=27,473) [35]
- formats: *flipped classroom* (e.g. [13, 39, 26]), MOOCs (e.g. [16])
- many different video learning environments, `http://designingvideointerfaces.nise81.com/portals`

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

Specifics of time [23]



(cf. [22])

Granularity of time:

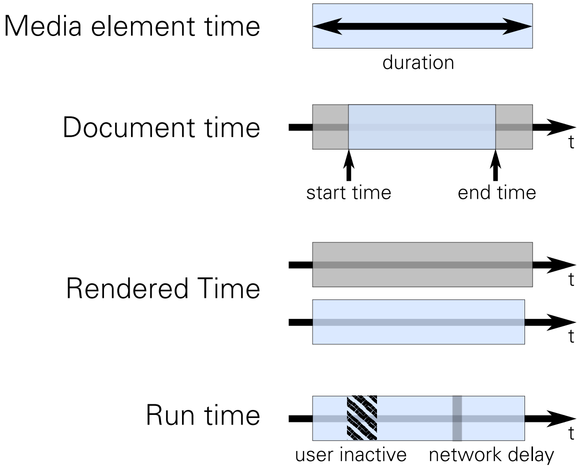
- hierarchical system of granularities:
  ..., ms, sec, minutes, hours, days, ...
- cycles and re-occurrences

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



(cf. [21])

2 Data Gathering

Gathering data from online video players

HTML

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

Javascript

```javascript
var video = document.getElementById( "myvideo" );

video.addEventListener('timeupdate', function(e){
  console.log( video.currentTime );
});

setInterval(print, 2000);

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

Resulting Logs

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

Approximating Playback Duration

Method	Source	Inadequacy
Timeupdate		No active watching; too detailed;
Segments	[28, 32, 25, 43, 24]	Segment size; rounding errors; no active watching;
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;

Challenges:

- determine active watching / learning phases
- considering varying playback rates

Determining playback duration from clickstreams [41]

Input:
Log: Clickstream log
ε Tolerance

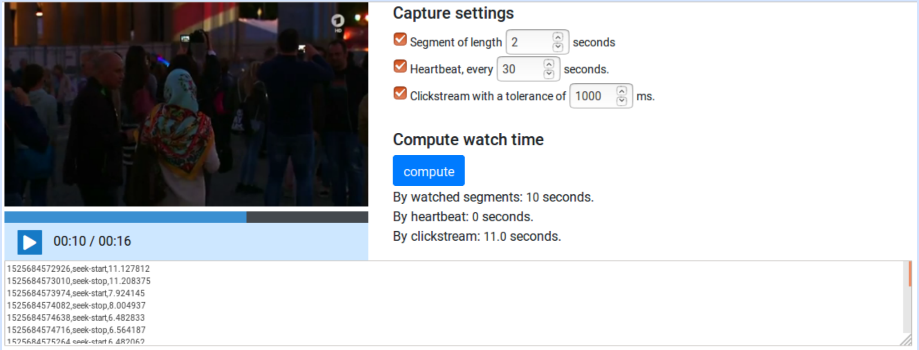
```
Function getUserPlaybackTime(userSessionLog)
  tmp ← userSessionLog[0]
  for i = 1; i < length(userSessionLog); i ← i + 1 do
    timeDistance ← userSessionLog[i].utc − tmp.utc
    playbackDistance ←
     userSessionLog[i].playbacktime − tmp.playbacktime
    if playbackDistance > 0 then
      if (timeDistance − playbackDistance) ≤ ε then
        playbackTime ← playbackTime + playbackDistance
      end
    end
    tmp ← Log[i]
  end
  return playbackTime
End
```

$aUserLog \leftarrow extractUserData(Log, userA)$
$aUserSession \leftarrow getSession(aUserLog, 2)$
$playbackTime \leftarrow getUserPlaybackTime(aUserSession)$

Hands-on: Optimal approximation of playback duration

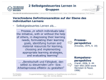
Assignment:
Use the *Video-Logger* and play around withe the log settings. Configure a perfect logger to determine the playback duration considering the precision, effort, and data economy.

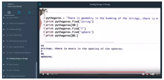
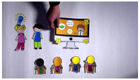
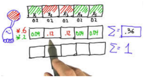
Vi-Logger: `https://nise.github.io/vi-logger/public/`



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

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

1. Extract audio from the the video

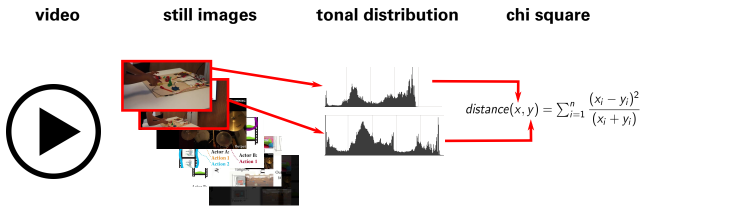
```
$ ffmpeg -i video.mp4 -ab 160k -ac 2 -ar 44100 -vn audio.wav
```

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

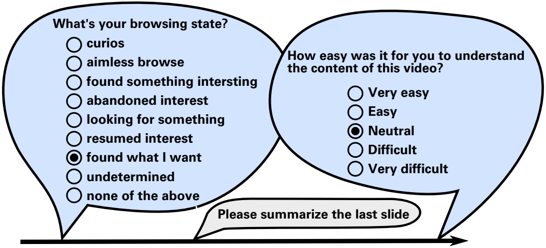
User Properties and Intentions

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



Sources of uncertainty

Error: outlier or deviation from a true value,

Imprecision: resolution of a value compared to the needed resolution (e.g., values are highly accurately given for countries but are needed for states),

Accuracy: size of smallest interval for which data values exist,

Lineage: source of the data (e.g., raw satellite images or processed images), - subjectivity – degree of subjective influence in the data,

Non-specificity: Lack of distinctions for objects (e.g., an area is known to be used for growing crops, but not its specific kind),

Noise: undesired background influence

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 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]

Example: Sequence mining of micro interactions

1. Prepare input

user1: play,playback,playback,playback,pause,addComment,play,. . .
user2: play,playback,playback,playback,playback,playback,playback,. . .
user3: play,playback,playback,pause,play,addComment,addComment,. . .

2. Sequence Mining with the SPADE algorithm[1]

```
sequence   support
1                      <{addComment}> 0.6666667
2                           <{pause}> 0.6666667
3                            <{play}> 1.0000000
4                        <{playback}> 1.0000000
5             <{addComment,playback}> 0.6666667
6                  <{pause,playback}> 0.6666667
7                   <{play,playback}> 1.0000000
8             <{pause,play,playback}> 0.6666667
9        <{addComment,play,playback}> 0.6666667
10 <{addComment,pause,play,playback}> 0.6666667
```

3. Compare frequent sequences among different groups of learners

[1] See also GSP, Prefix Span, Suffix Tree

Learner Modelling

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

Approaches [23]

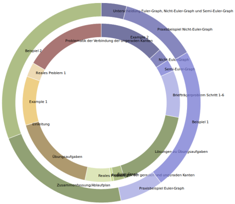
- visualize time-related data
- visualize time per se, e.g. Gant Chart

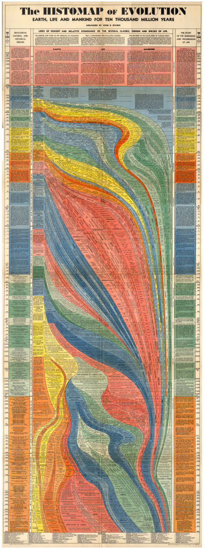
Representing time [23]

- 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])



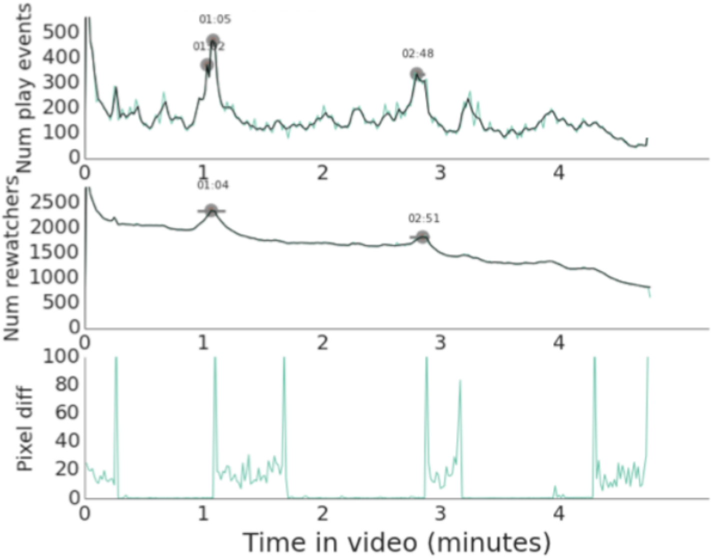


Histomap of Evolution
by John B. Sparks

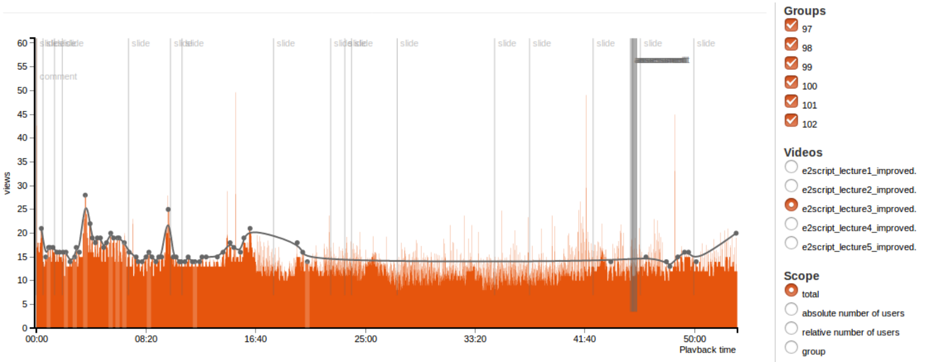
Purpose

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

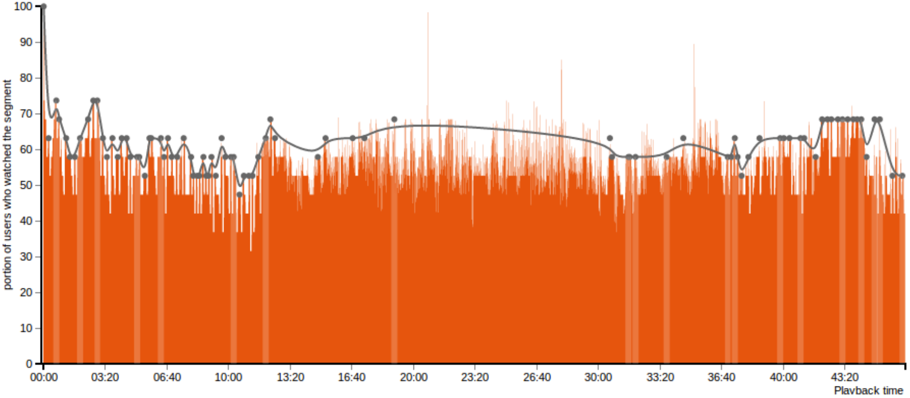
Video usage: Interaction peaks [26]



Video usage: Playback peaks II

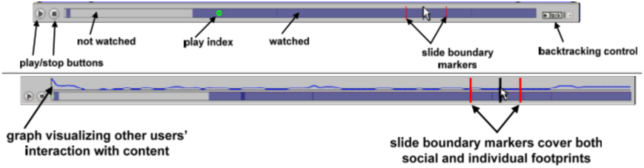


Video usage: Retention rate

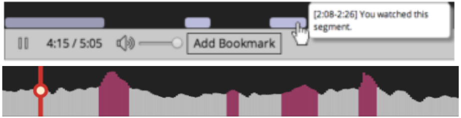


Video usage: Social Navigation

Mertens et al. (2010) [32]

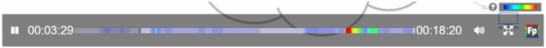


Kim et al. (2014) [25]

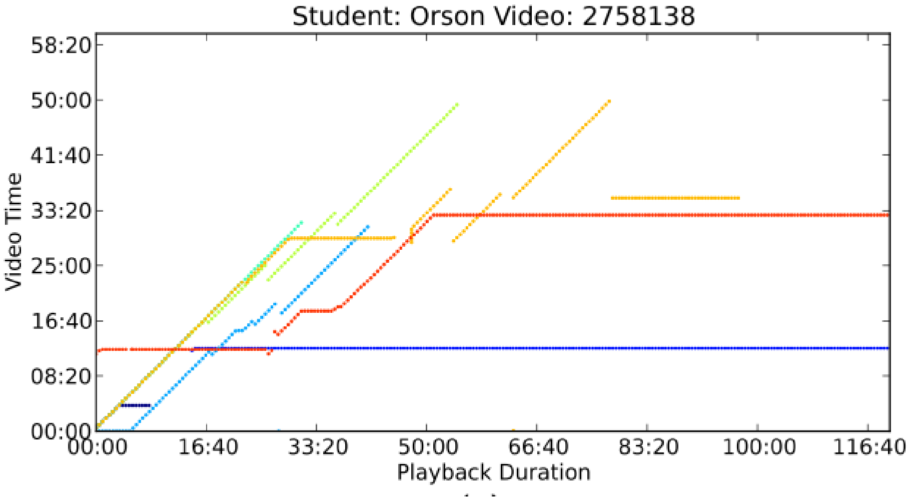


Wald et al. (2015) [45]

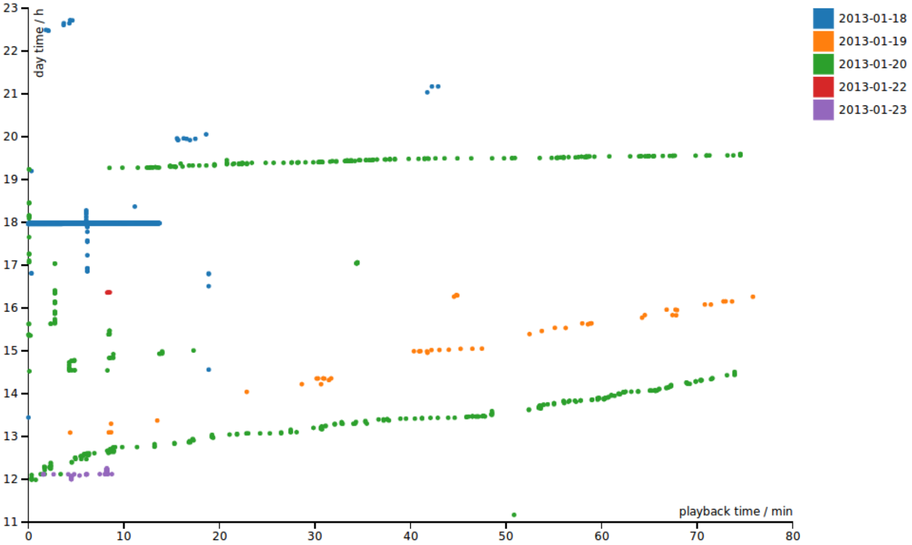
Chatti et al. (2016) [6]



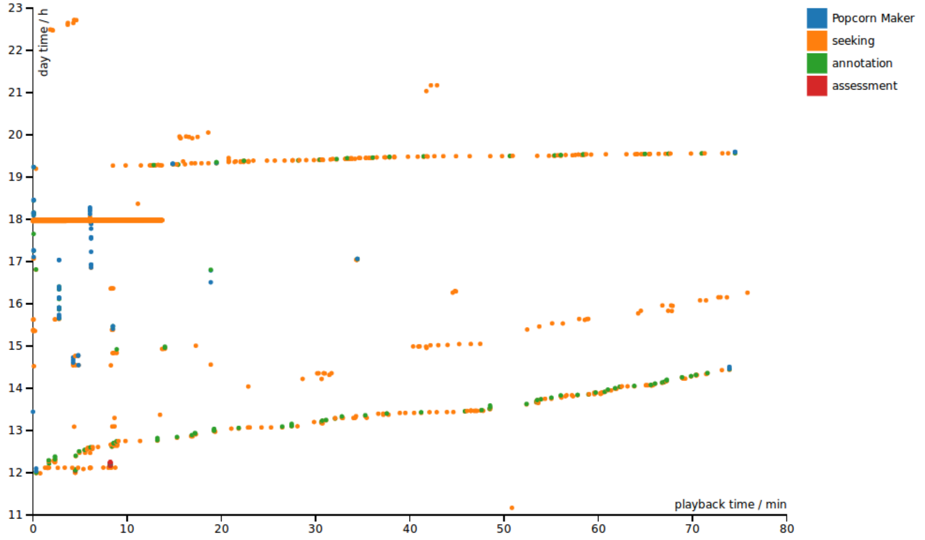
Individual activities: Rewatching graphs [5]



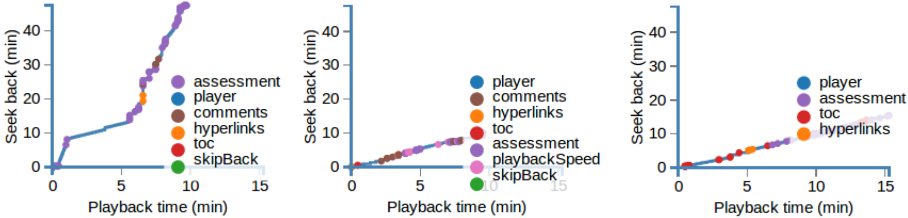
Individual activities: Rewatching graphs II (by day) [41]



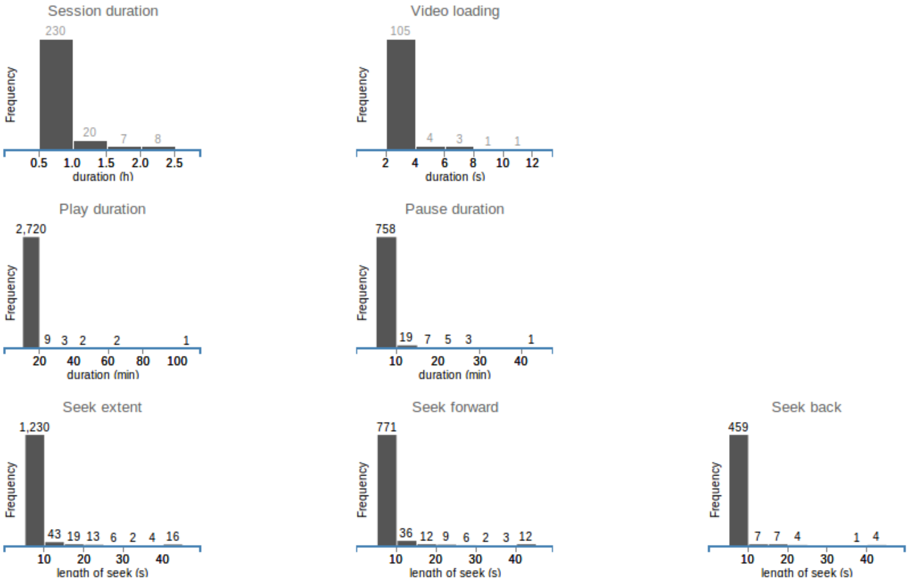
Individual activities: Rewatching graph II (by tools) [41]



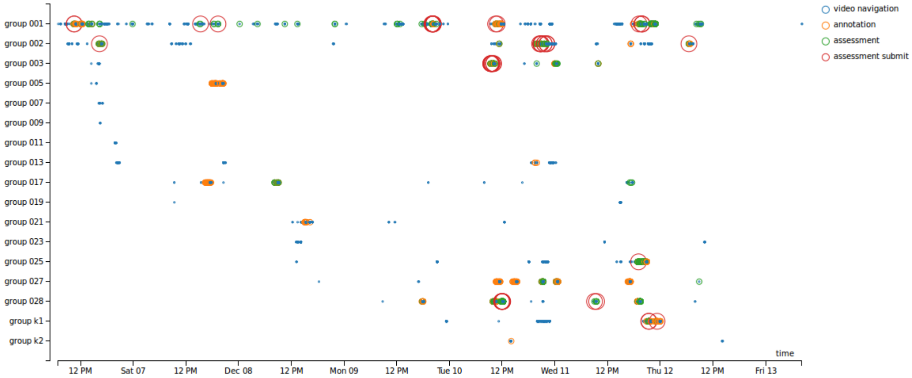
Individual activities: Forward-backward diagrams [41]



Group or cohort activities: Histograms [3]



Group or cohort activities: CORDTRA diagram (cf. [36])



Conclusion & future research direction

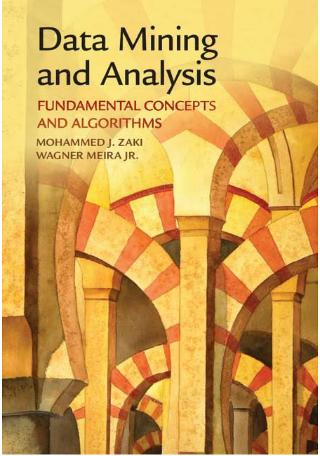
Conclusion

- 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

Furture research directions

- Generic learner models and viewing profiles
- Parameterization of data charts (e.g. forward-backward-diagram)
- Tooling: Log $\rightarrow$ report
- Learning Dashboards

Further reading



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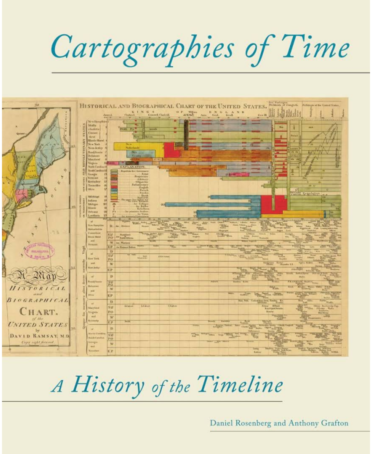

Daniel Rosenberg & Anthony Grafton

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