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The Memory Effect and Its Implications on Web QoE Modeling

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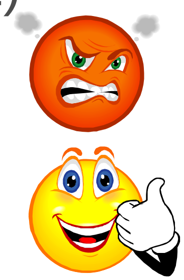
Trend towards Quality of Experience

- Increasing competition among Telco‘s and ISPs, among application and service providers, among cloud providers
- Keep customers happy, attract new customers

➔ **Quality** as key differentiator, but only as **experienced by end user**

- Shift from Quality of service (QoS) to Quality of Experience (QoE)
  - QoS: packet loss, delay, jitter, …
  - QoE: subjective experience/satisfaction of users of a service

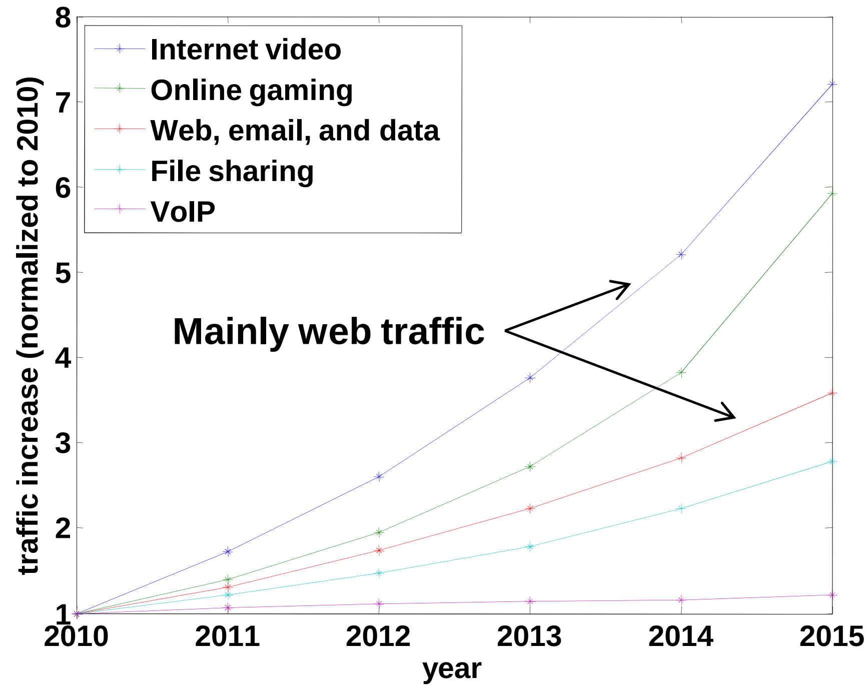


- *Example:* VoIP user interested in speech quality
  web user interested in short page load times

- What are relevant **QoE influence factors**?
- How to integrate key influence factors in appropriate **QoE models**?

QoE Model for Web Browsing

- Importance of web traffic is increasing
- Related work on QoE mainly covers multimedia applications
- Scenario: User downloads several web pages within a session
- But: Random test sequences according to standardization
- ➔ Lack of web QoE models including quality changes over time



Source: Cisco Visual Networking Index: Forecast and Methodology, 2010-2015

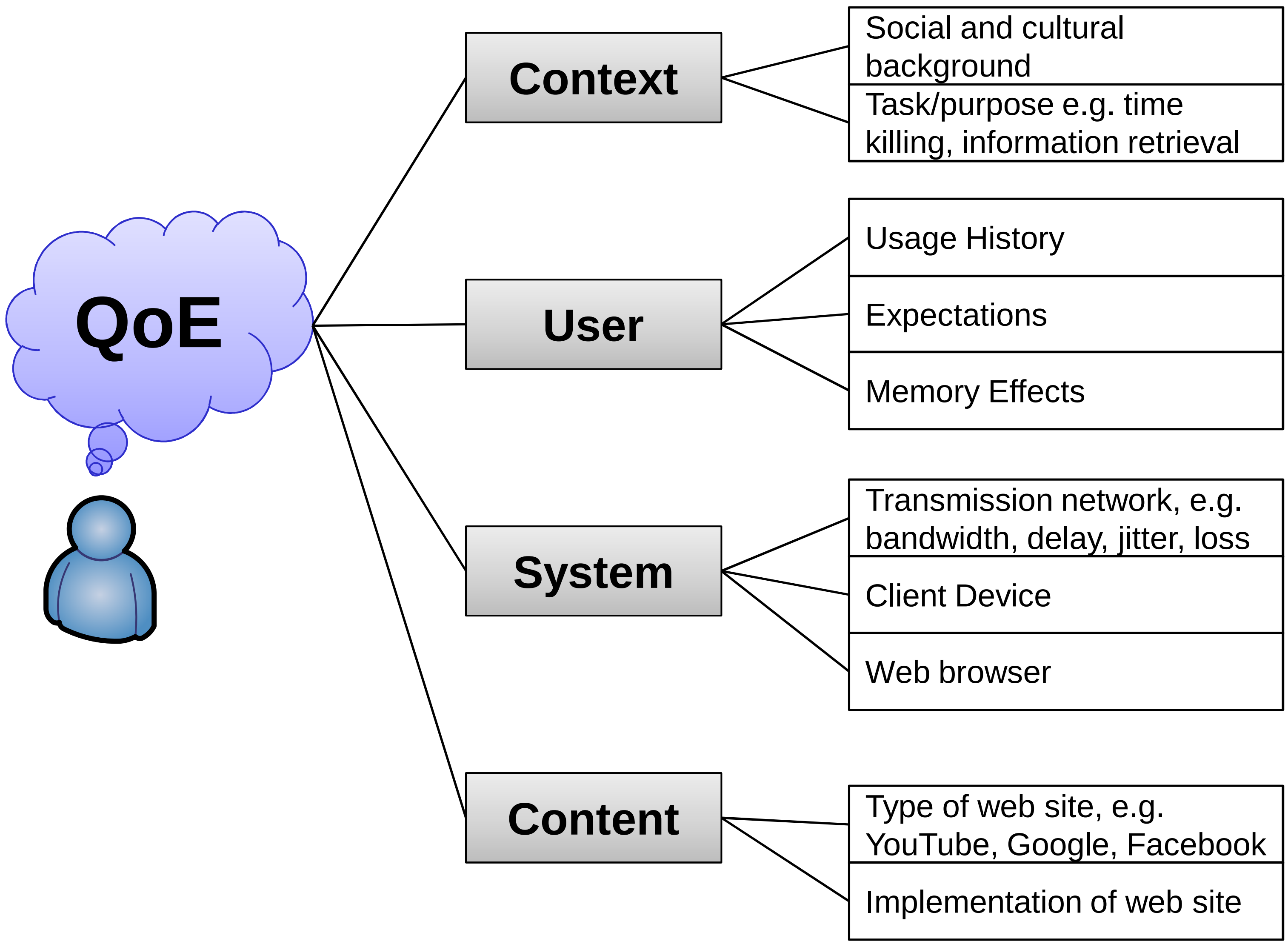
Contribution:

- **Subjective user study** on web browsing with quality changes
- Identification of **memory effect** as relevant QoE influence factors
- Integration of key influence factors in appropriate **QoE models**

Agenda

- Conducted Subjective User Study
  - QoE Influence Factors, Design of Study
  - Implementation and Measurement Setup
- Statistical Analysis of User Ratings
  - Page Load Times, Memory Effect
  - Key QoE Influence Factor via Support Vector Machines
- Implications on QoE Models
  - Iterative Regression Model
  - Hidden Memory Markov Model
- Conclusions and Outlook

QoE Influence Factors for Web Browsing



➔ Online and crowd-sourcing tests

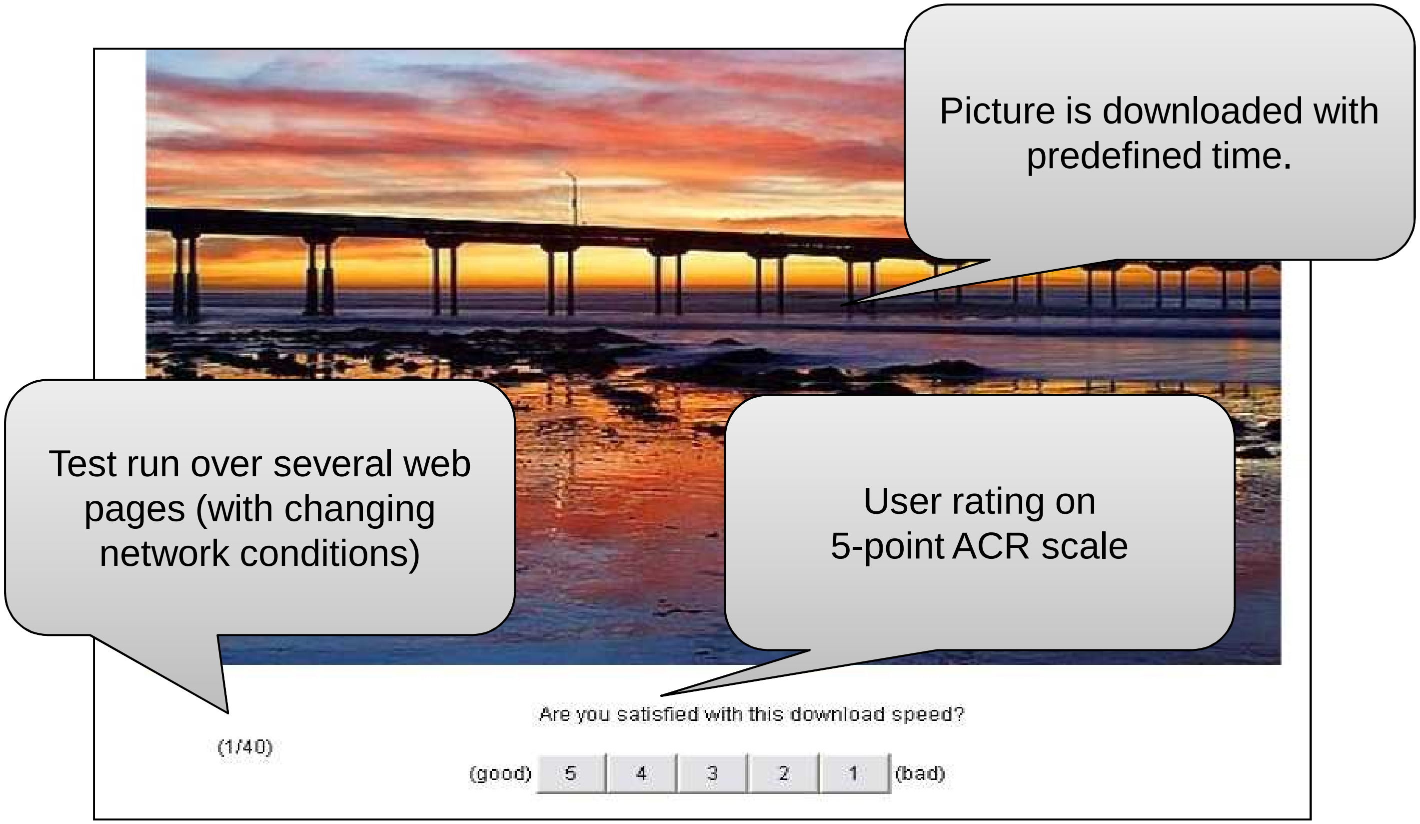
➔ Quality change per page

➔ Emulate page load time

➔ Simple Photo Page

Methodology: Subjective User Studies

- Subjective user rests required due to lack of existing studies

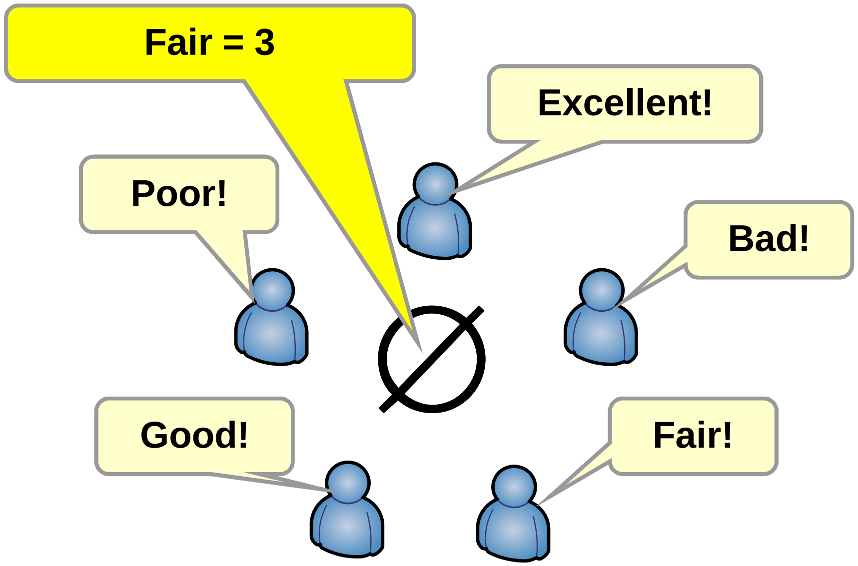


- Laboratory tests to get first insights, delay via traffic shaper
- Online tests to reach more users, local applet with def. page load times

Quantifying Quality of an Experience

Mean Opinion Score (MOS): numerical indication of the perceived quality of received media after compression and/or transmission

MOS	Quality	Impairment
5	Excellent	Imperceptible
4	Good	Perceptible
3	Fair	Slightly annoying
2	Poor	Annoying
1	Bad	Very annoying



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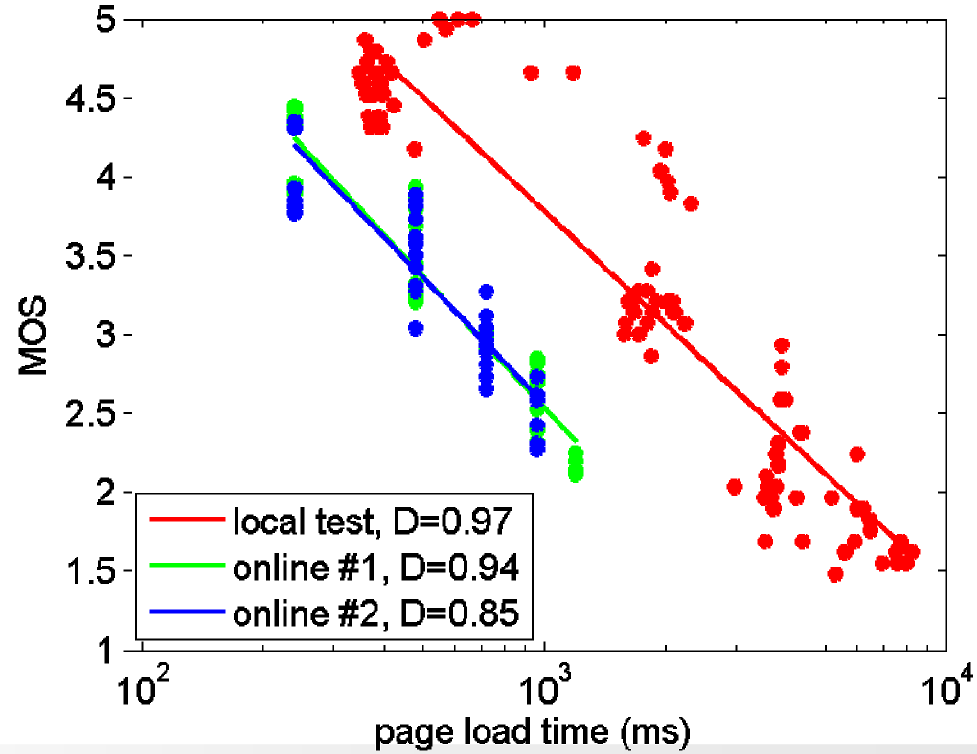
Impact of Page Load Times on QoE

- Models from literature for mapping current QoS to QoE
  - **IQX hypothesis** when using network parameters like bandwidth
    [Hoßfeld, Fiedler, Tran-Gia, ITC 2007]
    $QoE(x) = a \exp(-b\, x) + c$
  - **Weber-Fechner law** from psychophysics when using page load time as QoS parameter
    [Reichl et al., ICC 2010]
    $QoE(x) = a \ln(b\, x)$

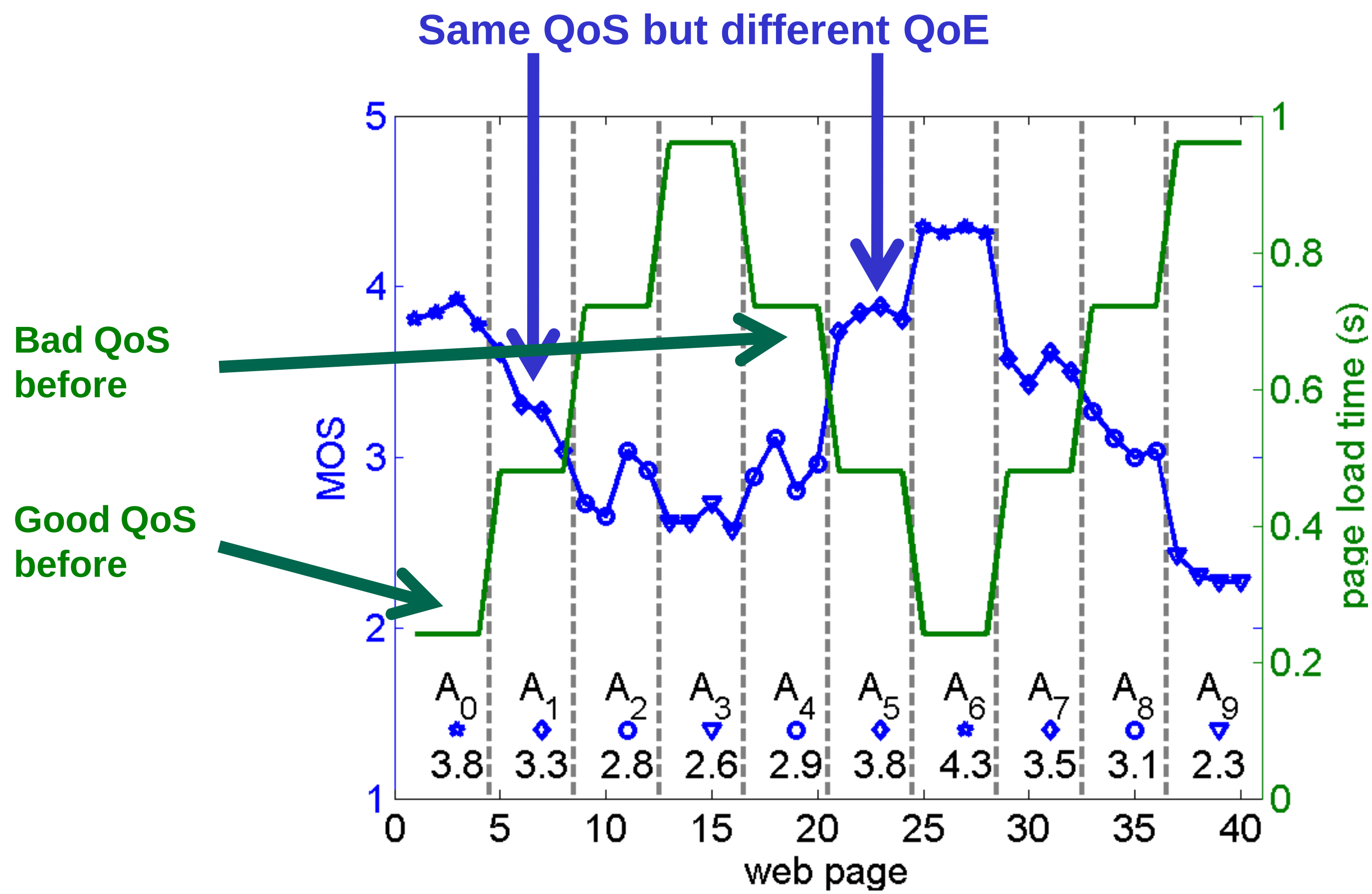


- But: strong deviations from model observable

➔ Only current QoS is considered

➔ **Temporal effects** have to be included

The Memory Effect



- Web pages with same page load time have different QoE, depending on previous QoS conditions
- Exponential decays/increase after quality changes

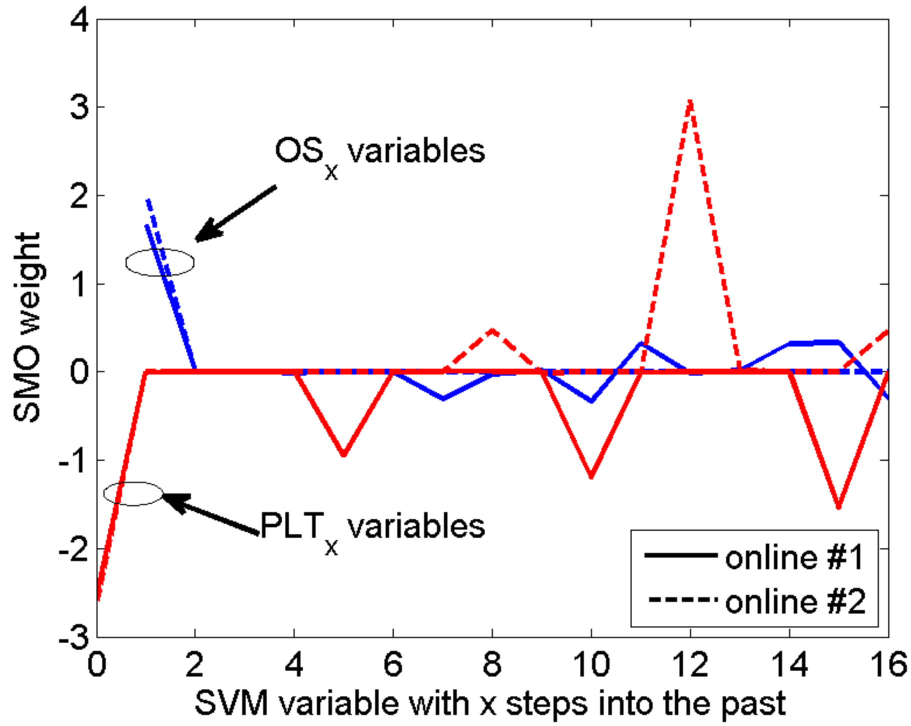
Is Memory Effect a Relevant QoE Influence Factor?

- Investigation with correlation analysis and machine learning
- Support vector machine decide two-class problems → user ratings are separated into ‘good quality’ and ‘bad quality’
- Implementation of SMO (Sequential Minimal Optimization) in WEKA machine learning software for analysis

➔ QoE from **previous web site** has relevant impact on QoE

➔ Memory effect as dominant as technical influences (PLT)

➔ Only **last QoE** has to be considered



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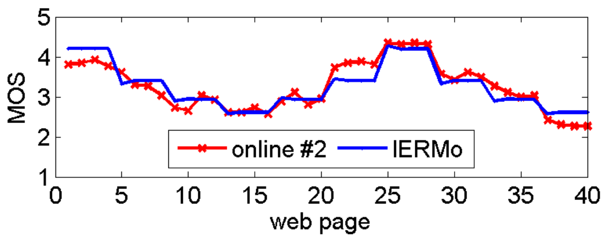
Memory has to be included in QoE Models

- Support Vector Machines
  - Consider previous experiences as own variables
  - Weighting factors indicate ‘importance’ of variables

- Exponential iterative regressions
  - Weber-Fechner law yields *f(PLT)*
  - Considering previous QoE via iteration

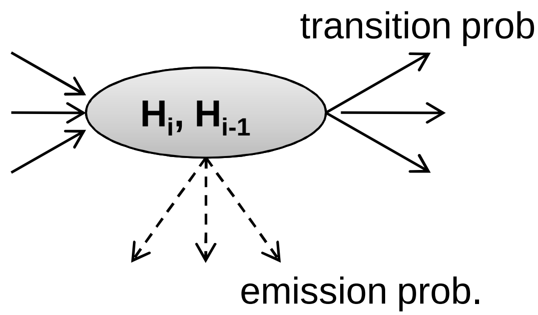


$$\mathrm{MOS}_i = f(\mathrm{PLT}_i) - \omega e^{-j} \cdot (\mathrm{MOS}_{i-1} - f(\mathrm{PLT}_i))$$

- Markov models
  - are memoryless,
  - but can include memory by appropriate state space

Hidden Memory Markov Model

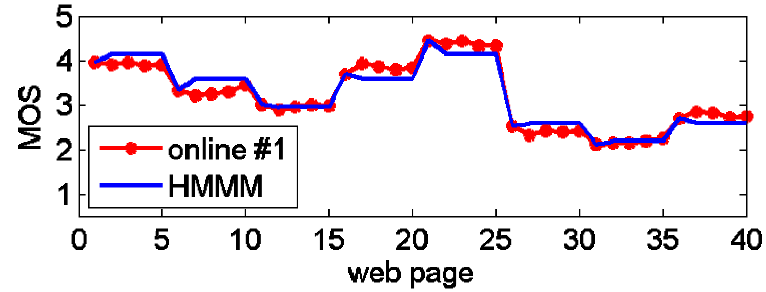
- Describe the QoE with a Hidden Markov Model (HMMM)
  - Page load time as hidden state
  - QoE i.e. user ratings as emission

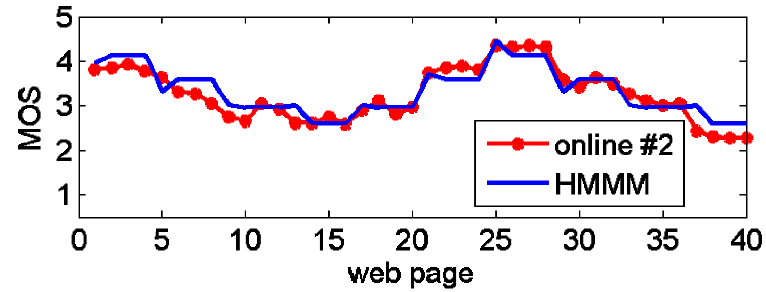


- Sequence of web pages with page load times x_i is extended to series of pairs *(x_i,x_{i-1})*
- Page load times are **discretized**

$$H_i = \begin{cases} 1 & \text{if } x_i = \min_i x_i \\ \left\lceil \frac{x_i - \min_i x_i}{\max_i x_i - \min_i x_i} \cdot M \right\rceil & \text{otherwise} \end{cases}$$

- **2D-State space** of HMMM is *(H_i,H_{i-1})*
- Transition and emission probabilities derived from user studies





Conclusions

- Time dynamics of human perception for web QoE analyzed
- Designed and conducted subjective user study on web browsing

- Identification of memory effect as relevant QoE influence factors
- Integration of key influence factors in appropriate QoE models
  - Support vector machines with additional ‘past’ variables
  - Weber-Fechner law with iterative exponential regressions
  - Hidden Markov model by increasing state space

- Consequences
  - QoE model available for performance evaluation, measurement studies, subjective user surveys
  - In case of unpredictable QoS: avoid memory effects (e.g. for QoE based traffic management, development of apps, etc.)
  - In general: Interdisciplinary research required

Questions?

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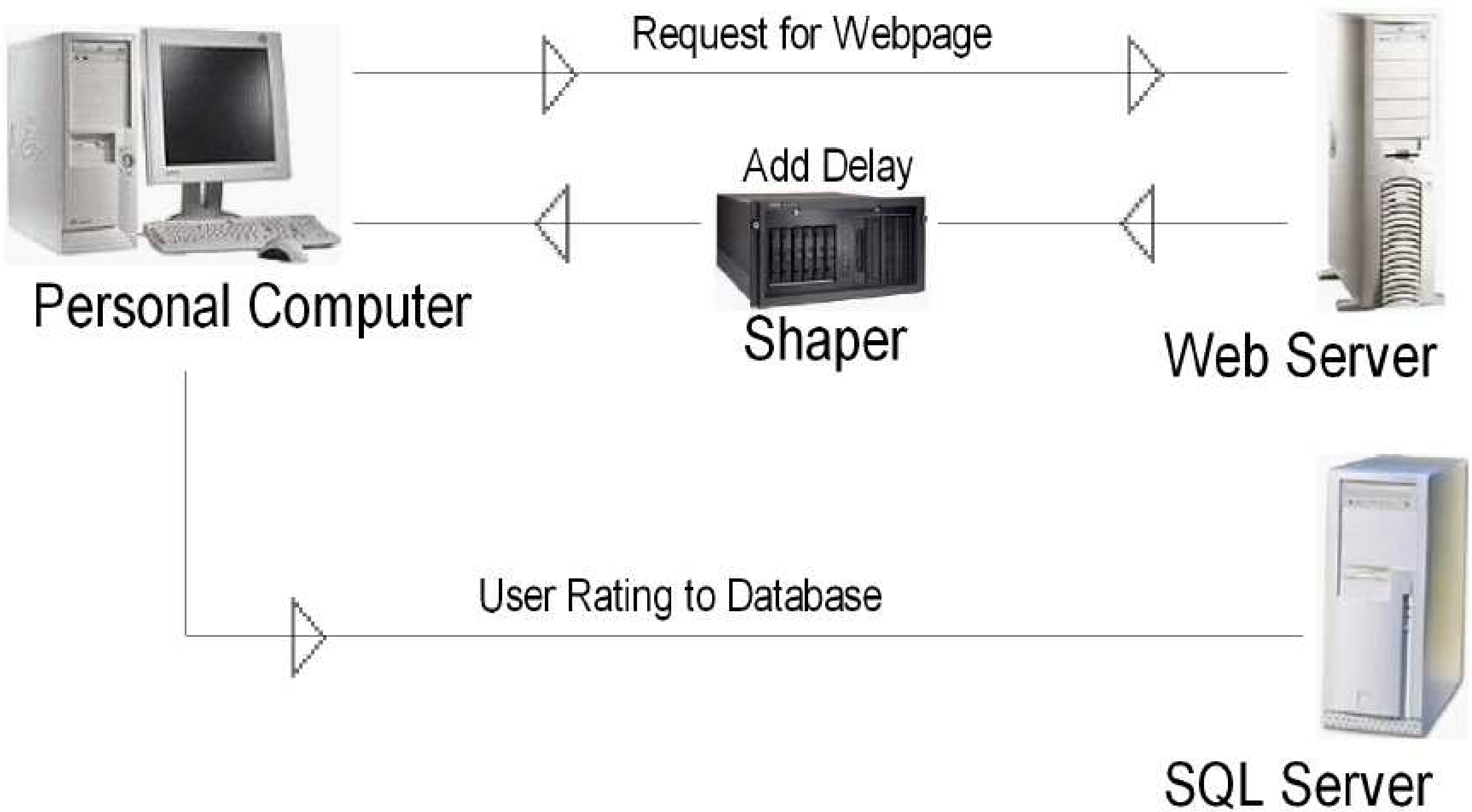
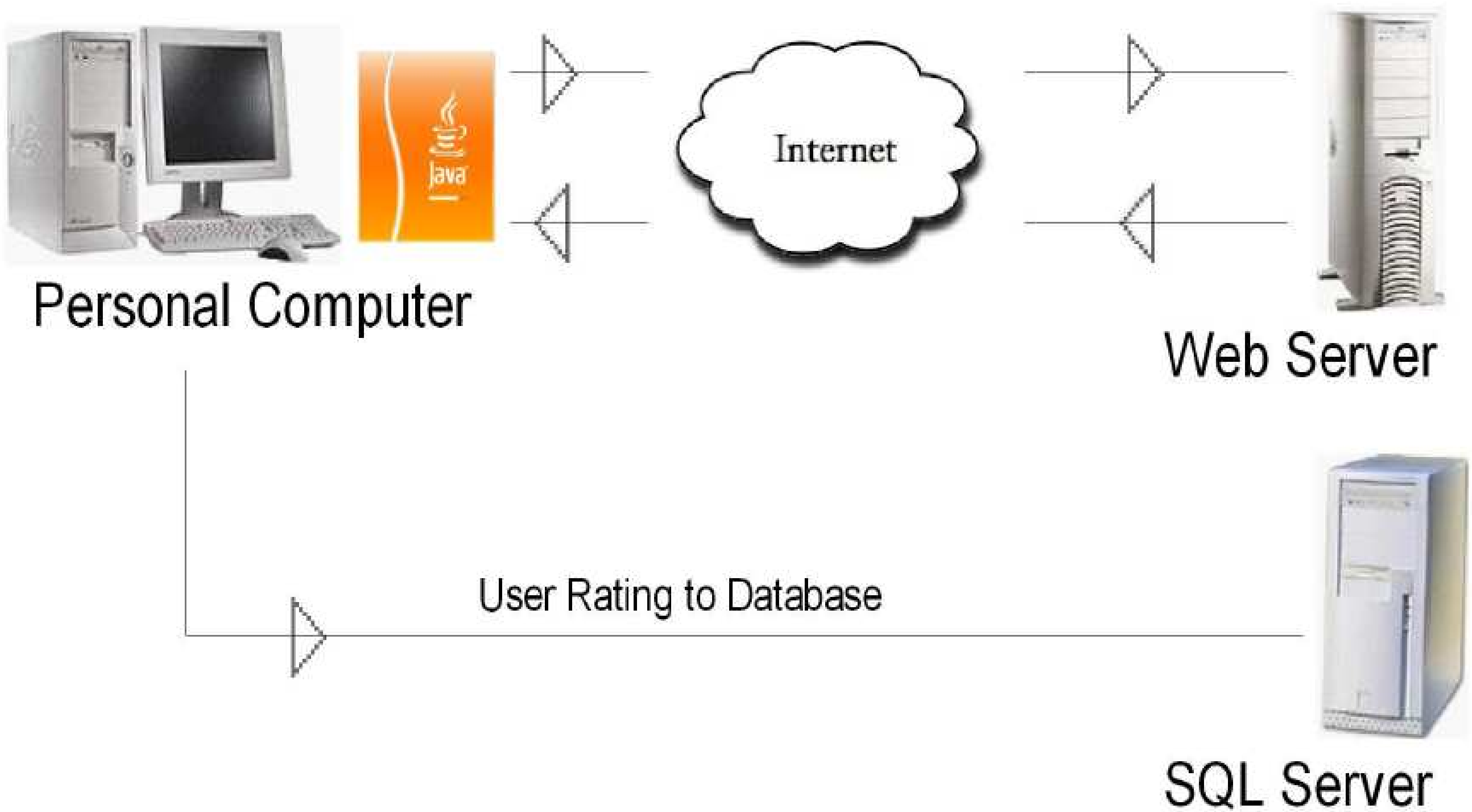
Local Tests in Laboratory Environment



Online Tests with “Net-Sim-Applet”

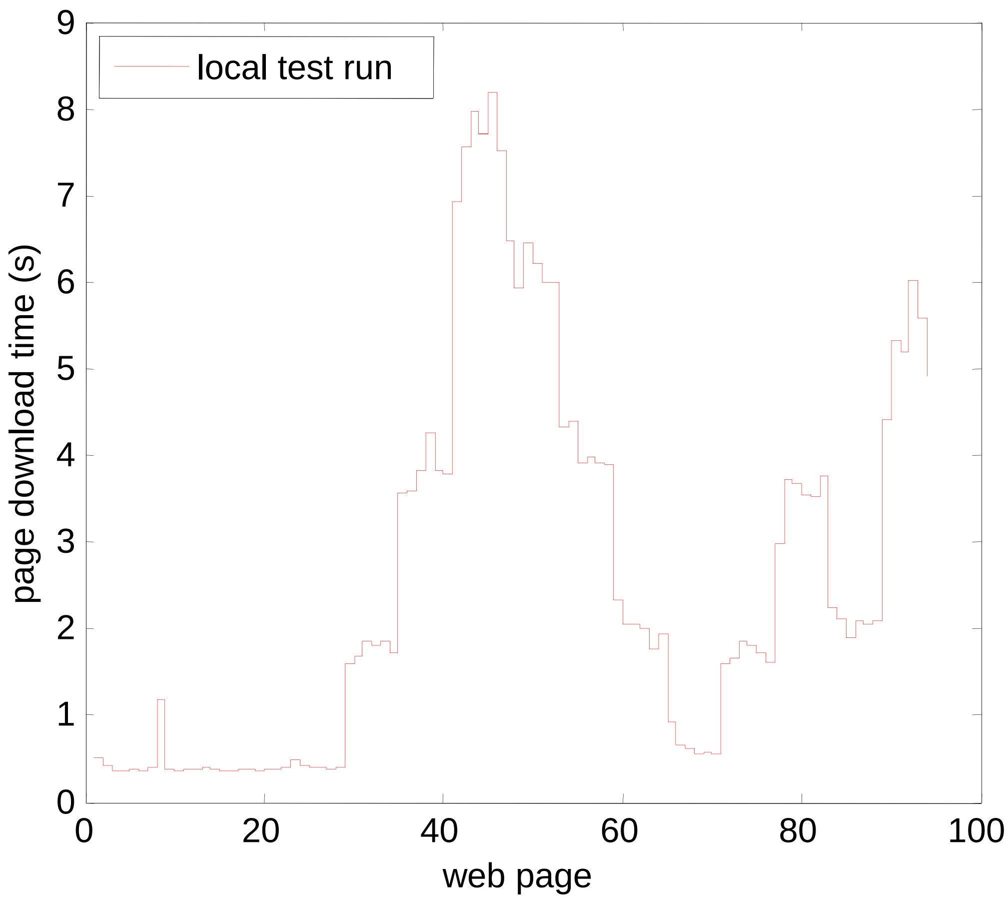


Statistics about the Conducted Experiments

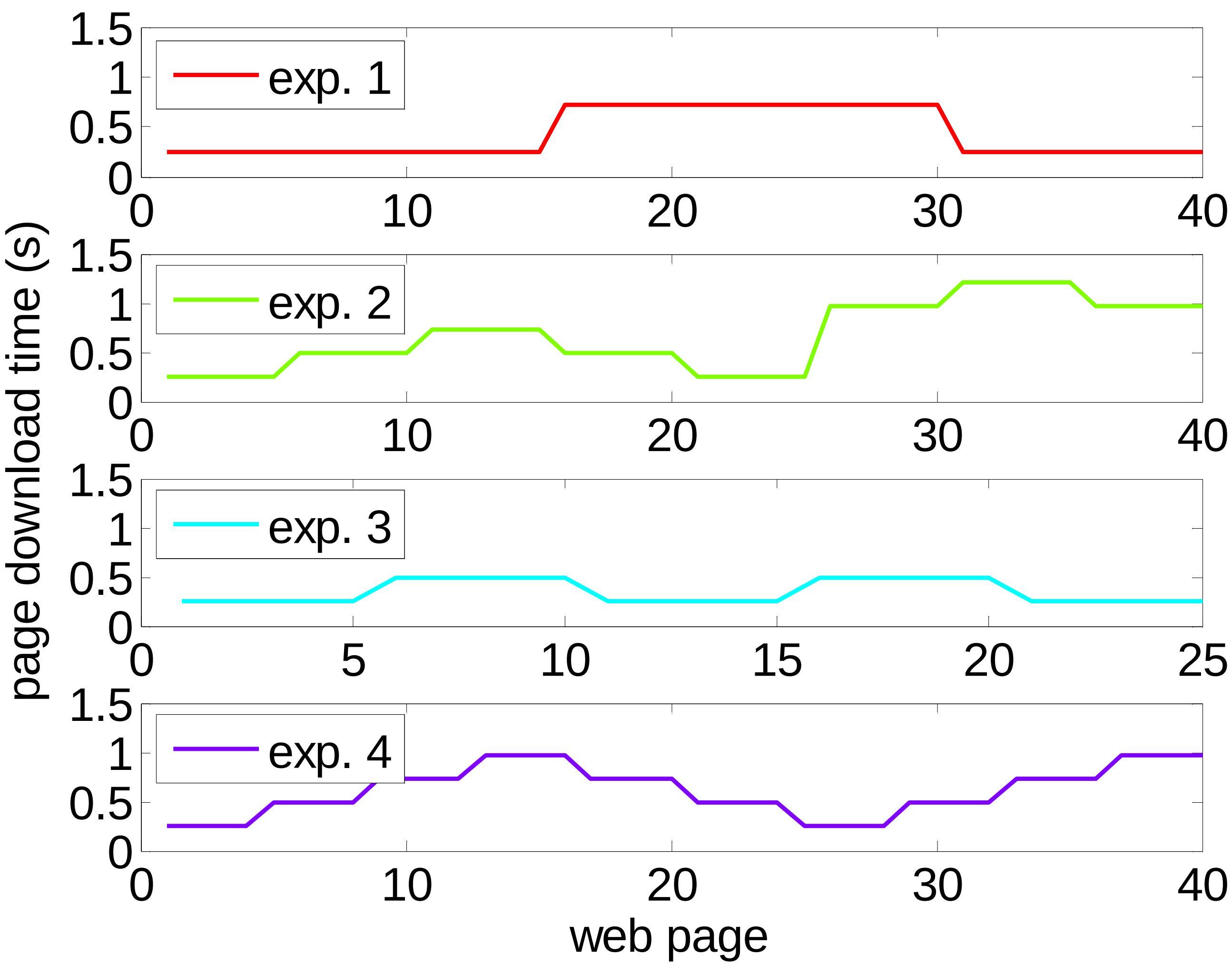
Exp. Id	#test users	X-point scale	#web pages	#changes of PLT	Min PLT (ms)	Mean PLT (ms)	Max PLT (ms)
0	29	3	93	21	348	2594	8184
1	12	3	40	2	240	420	720
2	72	5	40	7	240	660	1200
3	30	3	25	4	240	336	480
4	26	5	40	9	240	600	960
5	15	5	25	4	240	528	720

Local Test Run (Exp. 0)

- Page download times measured via TCPDump / HTTPFox



Online Test Runs



- Test memory effect
- Test several effects
- Test. exp. regressions
- Test several effects

Agenda

- Existing QoE Models for Web Traffic
- Measurement Settings
- QoE Characteristics
- Identification of User Groups
- QoE Models

Existing QoE Models for Web Traffic

- Fidel Liberal, Armando Ferro, Jose Oscar Fajardo: "PQoS based model for assessing significance of providers statistically" (2005)
  - MOS = 6 - log2(t),   t: total download time [s]

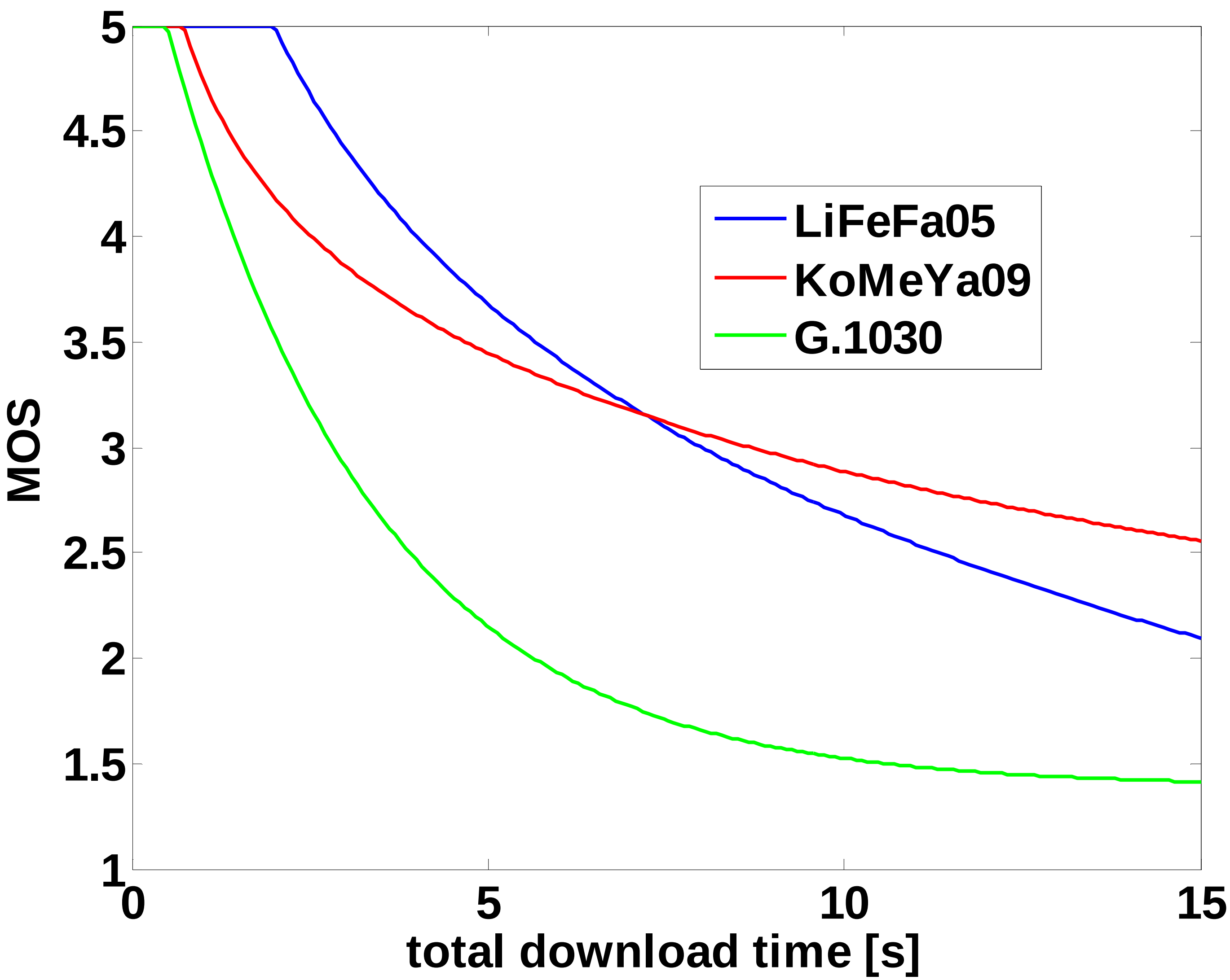
- R.E. Kooij, R.D. van der Mei, R. Yang: "TCP and web browsing performance in case of bi-directional packet loss" (2009)
  - MOS = 4.75 - 0.81log(t),   t: total download time [s]

- ITU-T Recommendation G.1030: "Estimating end-to-end performance in IP networks for data applications" (2005)
  - MOS = 4.298·exp(−0.347·t)+1.390,   t: weighted session time [s]

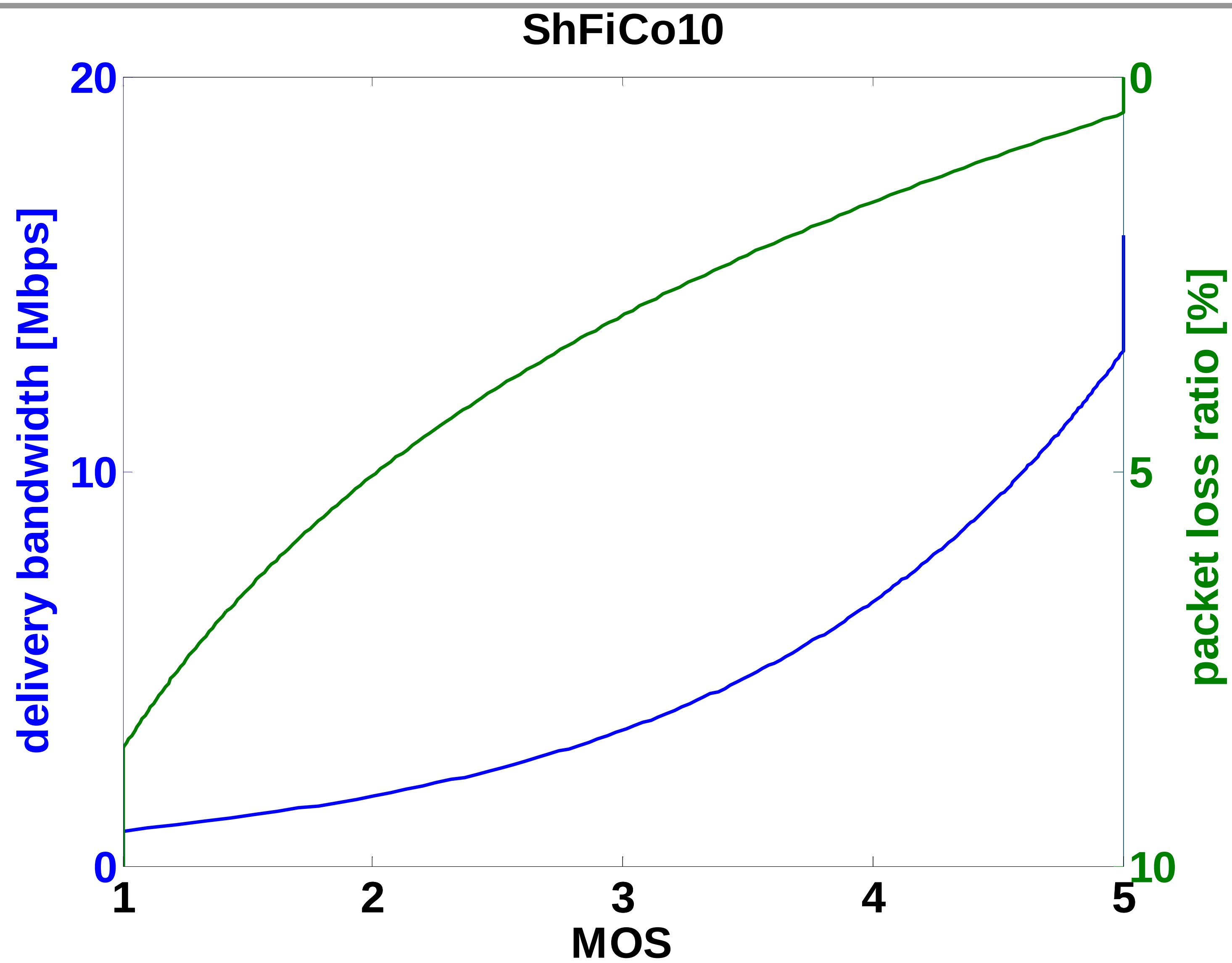
- J. Shaikh, M. Fiedler, D. Collange, "Quality of Experience from user and network perspectives" (2010)
  - MOS = 1.15 + 1.50 ln(R),   R: delivery bandwidth [Mbps]
  - MOS = 5.50 exp(−0.2L) ,   L: packet loss ratio [%]

- **What's missing? Psychological and temporal effects!**

QoE Related to Page Download Time



QoE Depending on Bandwidth and Loss

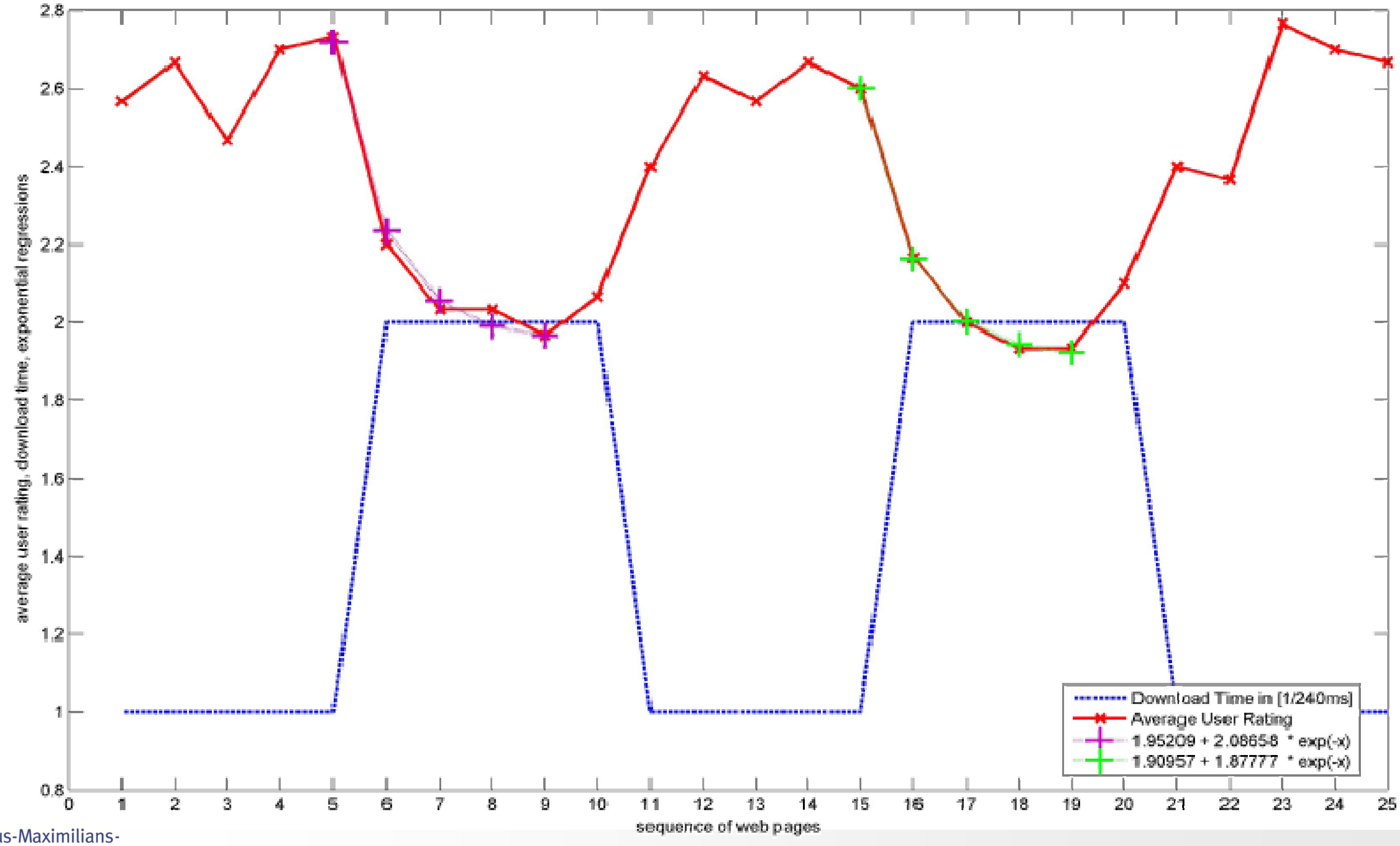


Overview on Test Runs

	Local test-run	*Online test-run*				
		01	02	03	04	05
Sensitivity	x					
Cognition of Changes	x		x			
Uncertainness	x					
'Get-bored'-effect	x					
Abort rate			x			
Memory Effect		x	x		x	
Cluster Analysis	x		x			
Exponential QoE Model	x		x	x		
Hidden Markov Model			x		x	x

Exponential Regression

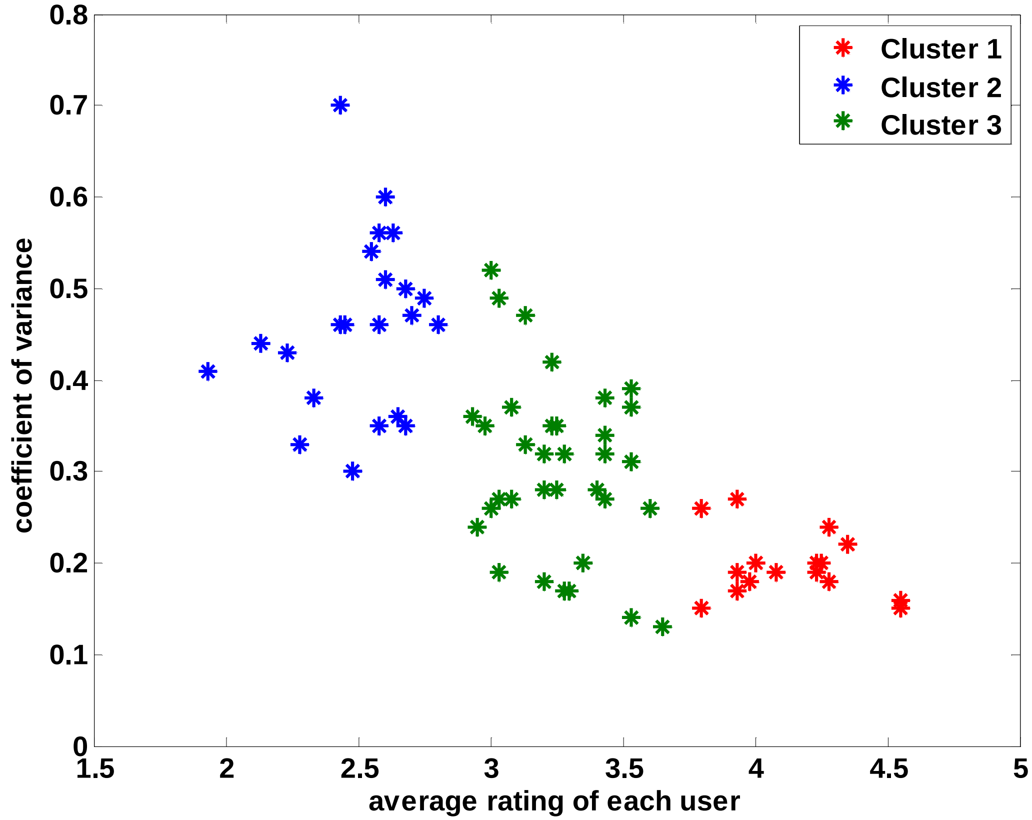
- Exponential decay / increase (similar to Raake, A. (2006a) *Short- and long-term packet loss behavior: towards speech quality prediction for arbitrary loss distributions)*



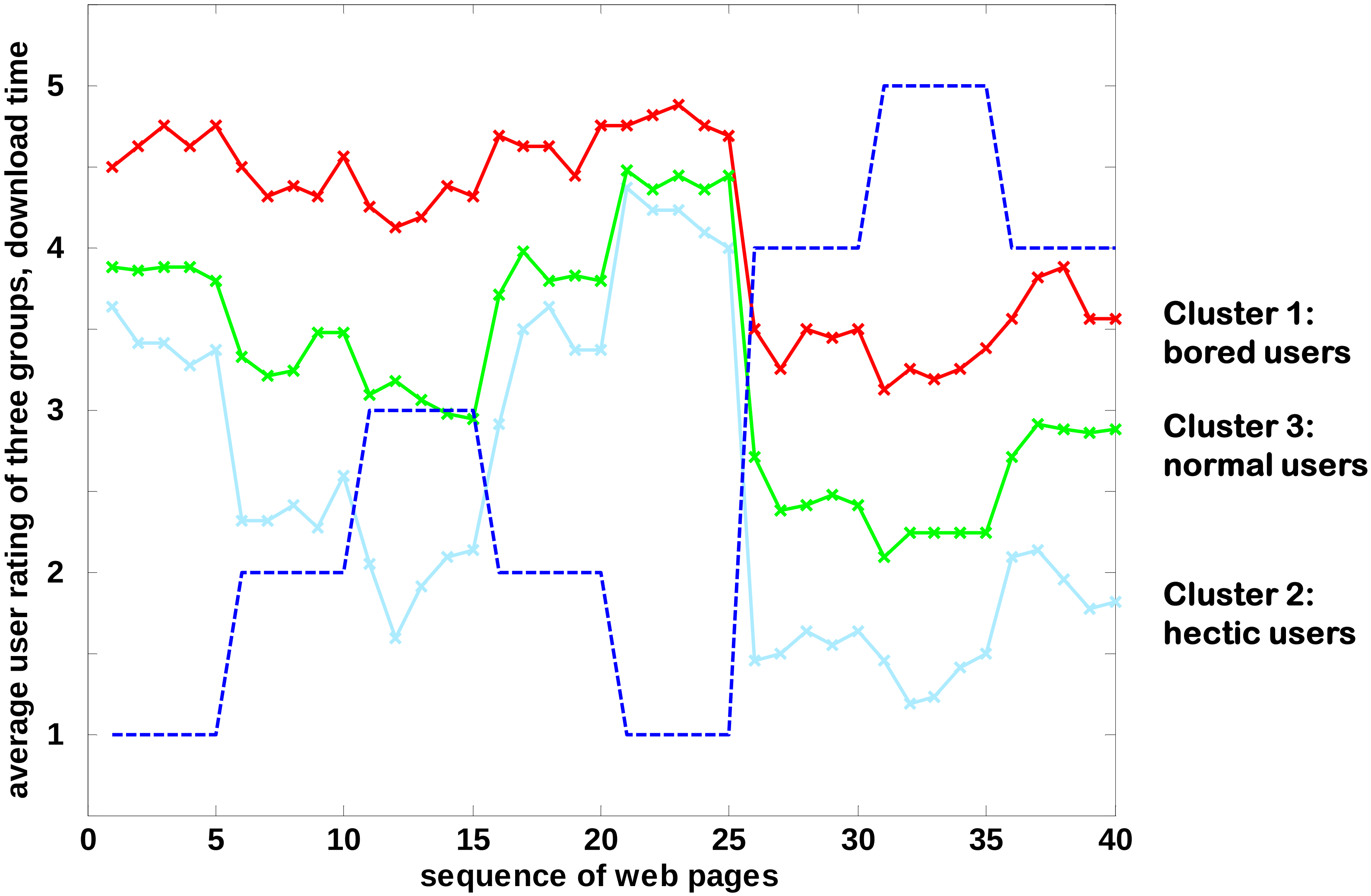
Simple Cluster Analysis

- For each user, the average rating and the coefficient of variation of the user ratings is calculated

- Cluster analysis with k-means algorithm (Matlab, RapidMiner)
- As input parameter, only these two parameters are used
- Simple approach is already sufficient to detect the different clusters

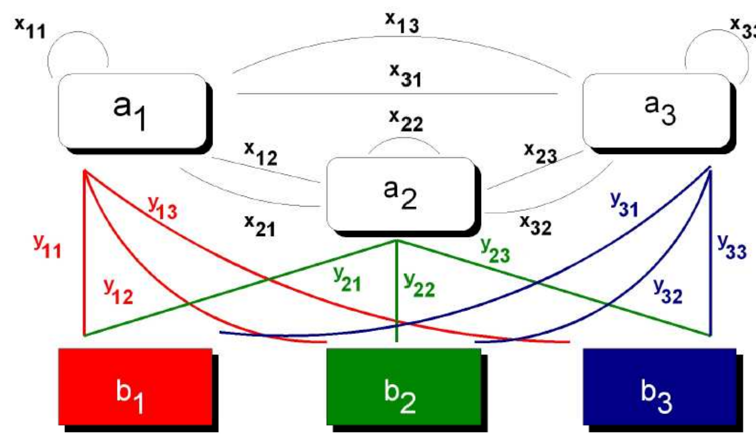


QoE Ratings for Different Clusters



Implicit QoE Model: Hidden Markov Model

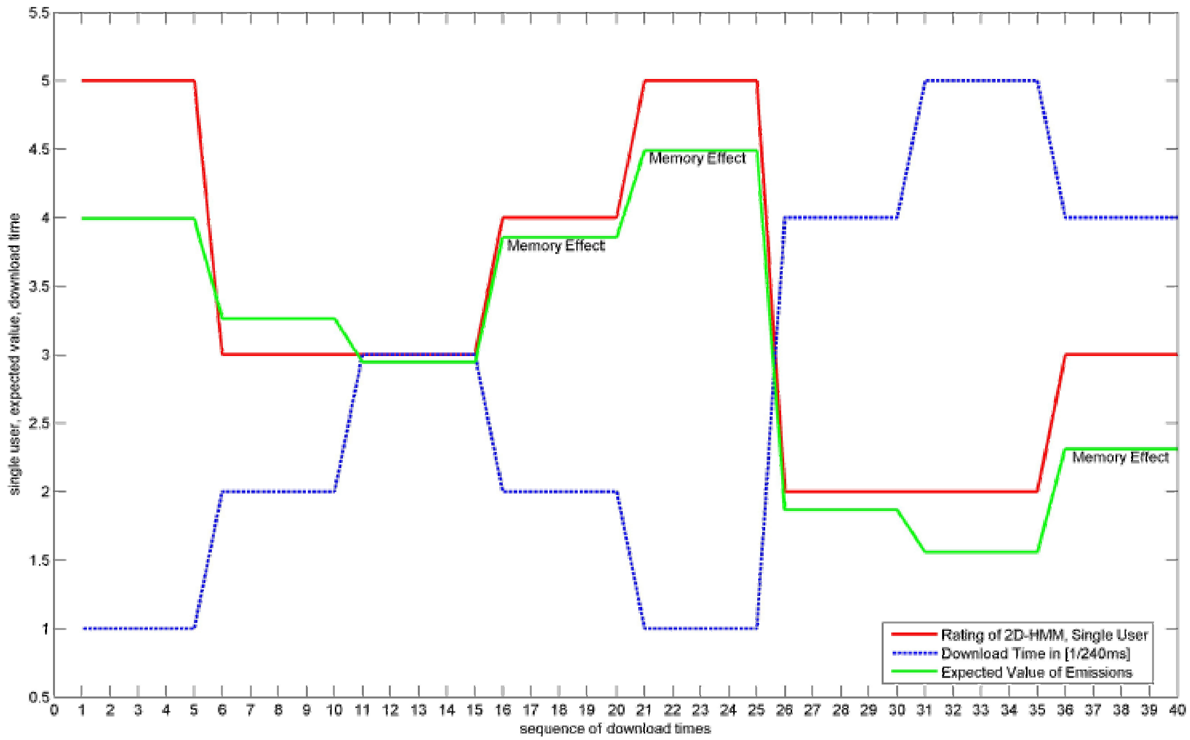
- Describe the QoE with a Hidden Markov Model (HMM)
  - Download time as hidden state
  - QoE / user ratings as emission



- State transition matrix describes system dynamics (in terms of QoS)
- Emission probabilities for perception categories (MOS 1, …, 5) according to actual state and user group
- One-dimensional HMM fails, since memory effect is not taken into account

2D Hidden Memory Markov Model

- Enhance the HMM by one dimension wrt. memory effect
  - State of the system is a tupel
    (actual download time dt_i, previous download time dt_i-1)
  - QoE / user ratings as emission



Notes about the 2D-HMMM

- Relevant outcome of subjective tests are emission probabilities (for given, i.e. tested, network tupels)

- Underlying network model (i.e. hidden states) can be changed
  - for a proper description of a system wrt. QoE, it is important to describe it as 2D MMM (due to memory effect)
  - then emissions probabilities remain the same and can be applied

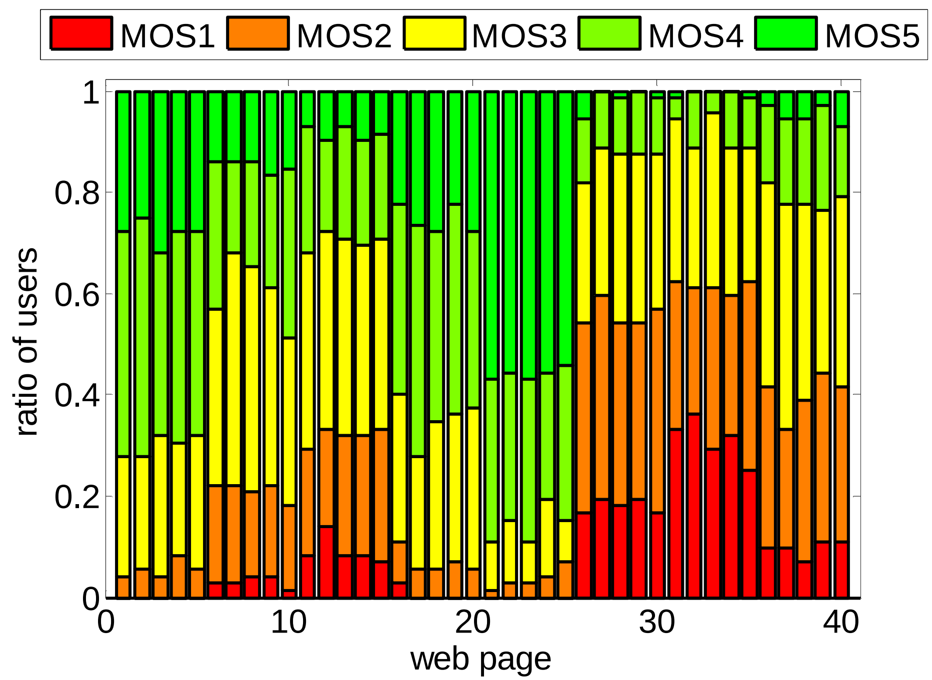
- Problem is to get measurement data for all N^2 states, when N download times are observed

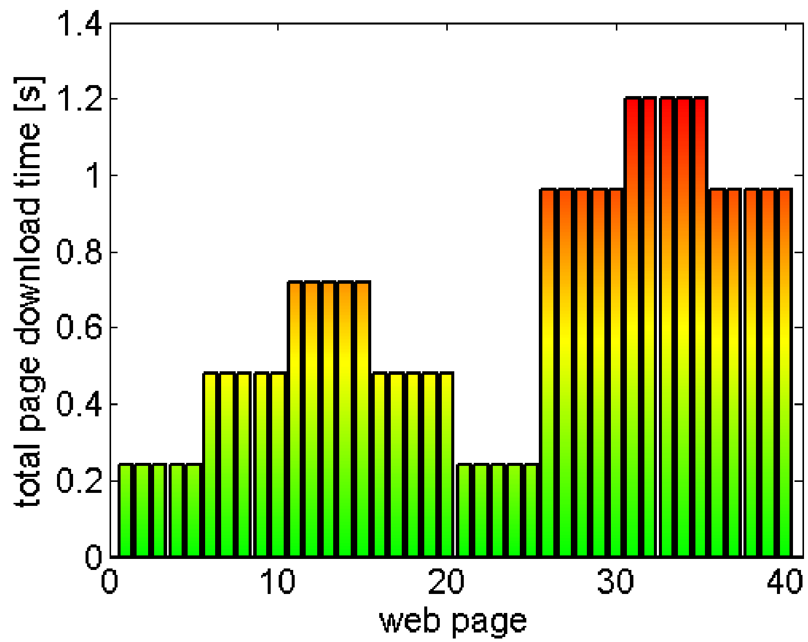
Discussion

- Discrete States of HMM
  - Weber's law from psychophysics (1840): The just-noticeable difference (ΔR) of the change in a stimulus's magnitude is proportional to the stimulus's magnitude (R), rather than being an absolute value.
  - $\Delta R / R = k$ and states of HMM are defined accordingly
- State of the system
  - previous download time vs. average download time (using exponential moving average and discretization of download times)
  - Similar to Oliver Rose: *A Memory Markov Chain for VBR traffic with strong positive correlations,* ITC 16, Jun 1999.

Test Run 2: Complete User Survey

- Simulated QoS settings in terms of page download time are colored according to MOS
- Complete CDF gives overview on actual user experience, not on average users (MOS1+MOS5 ~= MOS3+MOS3)





Weber-Fechner Law

- Web traffic experiments@UniWue