

# fortiss

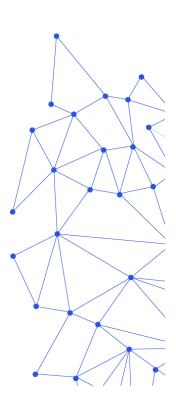
05.09.2014

# Automatic Extraction of Probabilistic Workload Specifications for Load Testing Session-Based Software Systems

Christian Vögele, André van Hoorn, Eike Schulz

SPEC RG DevOps Performance WG

fortiss GmbH An-Institut Technische Universität München



# Challenge: Specifying Representative Workoads

#### Situation

 Workload generation is essential to systematically evaluate performance properties of (session-based) software systems

#### Complication

- Manual creation of representative workload specifications is difficult, time consuming and error-prone
- Extraction and specification of workloads strongly depends on the used workload generation tool

#### Resolution

 Approach for systematically extracting probabilistic workload specification for sessionbased software systems from production usage profiles

# Agenda

- Motivation
- Background
- Approach
  - 1. Overview of M4J-DSL
  - 2. Behavior Model Extraction
  - 3. Clustering of Customer Groups
  - 4. M4J-DSL Model Generation
  - 5. Apache JMeter Test Plan Generation
- Evaluation

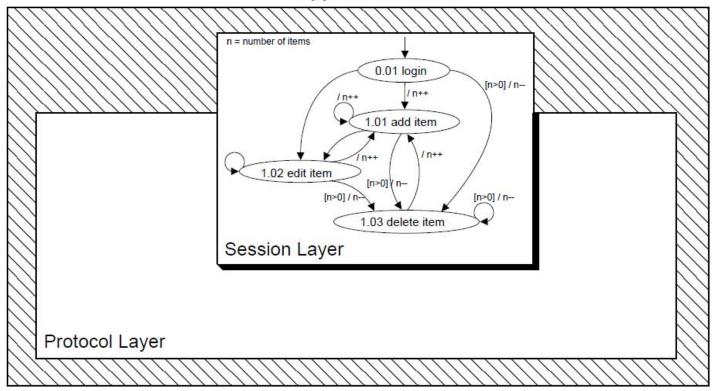
3

Future Work

# Background – Markov4JMeter [1]

#### Example of an Application Model

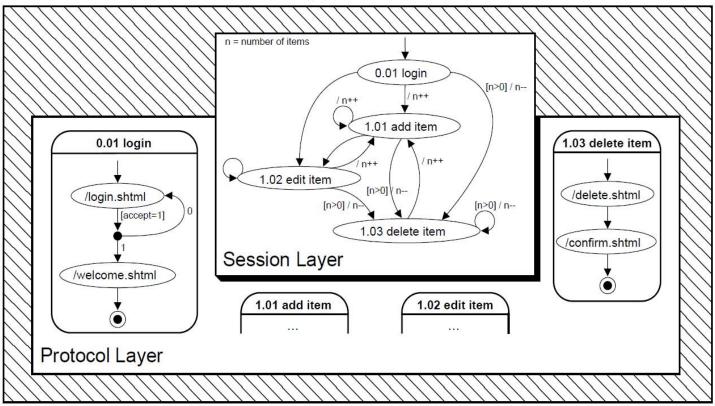
#### **Application Model**



# Background – Markov4JMeter [1]

# Example of an Application Model

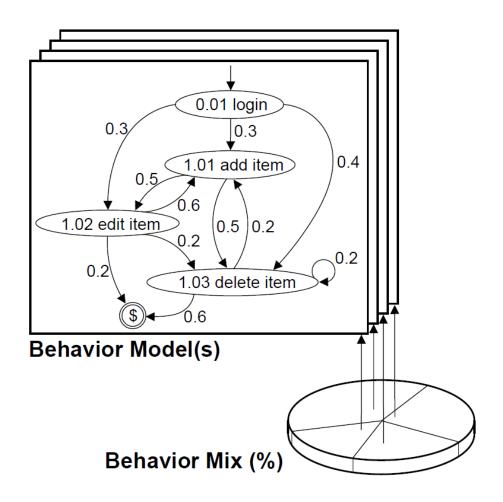
#### **Application Model**



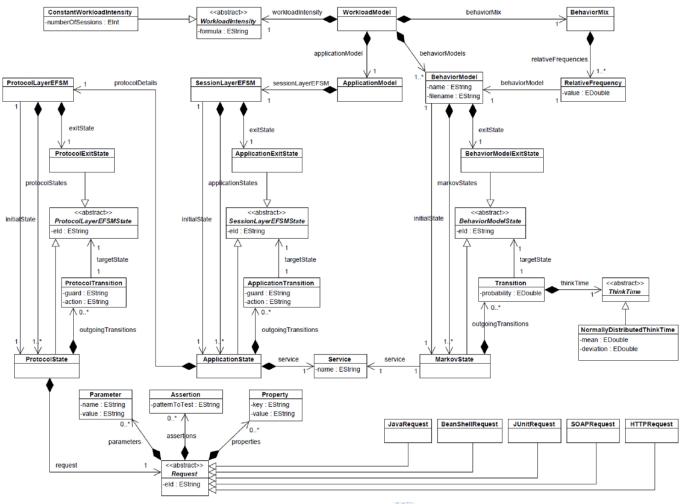


#### Behavior Model + Behavior Mix

#### Background – Markov4JMeter

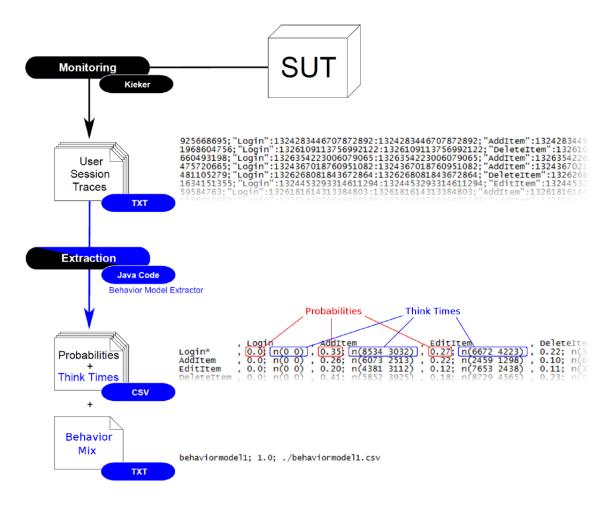


# M4J-DSL for Modeling Session-Based Workloads





#### **Behavior Model Extraction**





#### Clustering of Customer Groups

- Goal: Identification of Behavior Mix
- Advantages of extracting customer groups
  - Comprehensibility of resulting models
  - Understanding navigational pattern of customer groups
    - → Optimize navigational structure of application
  - Executing what-if analyses, e.g.,
     How is the performance if the number of heavy buyers increases by X%?
  - Optimizing paths which are navigated often by heavy buyers



#### Clustering of Customer Groups

#### Approach

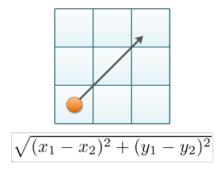
10

- Input: Transition count matrix per session
- Think time matrices are not considered for the clustering
- Usage of centroid-based clustering algorithm X-Means
- Steps of the clustering:
  - 1. For each cluster a central vector, called centroid, will be determined randomly, which represents the instances of this cluster
  - 2. Centroid comprises the mean attribute values of the instances it represents
  - 3. Iterate several times over the dataset and assigns instances to the nearest cluster centroid
  - 4. Continue until no instance is assigned to another cluster

# Clustering of Customer Groups (cont'd)

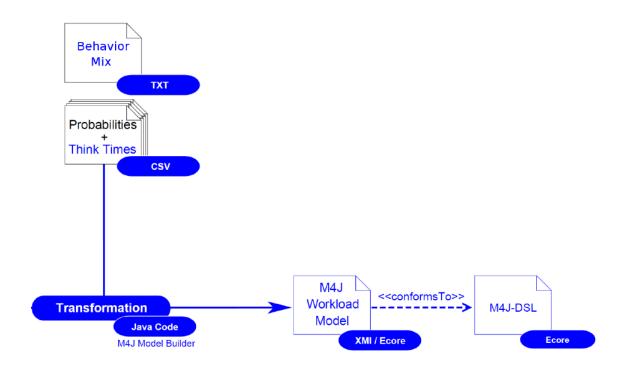
#### Approach

• Euclidean distance metric (Non-normalized and normalized)



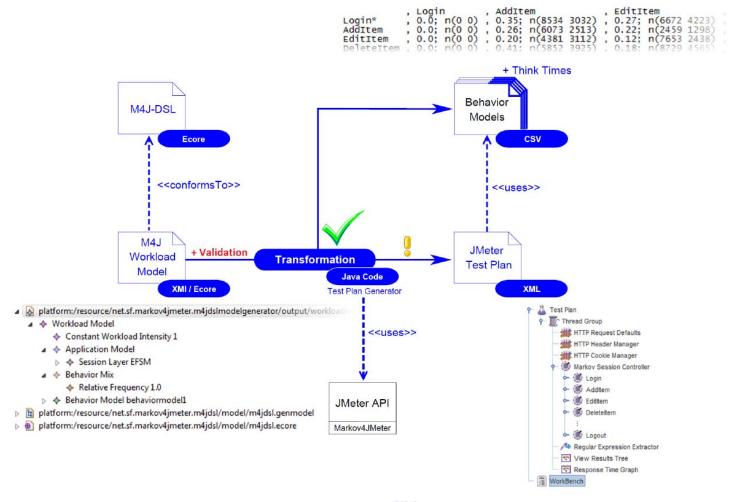
- Intregrate Weka's clustering library into our approach
- Transformation of transition count matrices into a vector (Weka cannot handle matrices as input)
- 2. Execute clustering
- 3. Transform absolut transition count matrix into relative transition matrix
- 4. Calculate think time matrices

#### M4J-DSL Model Generation



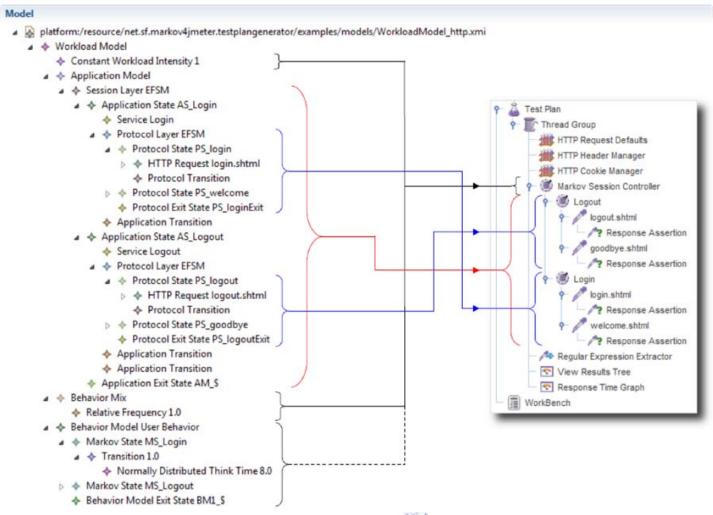


#### Apache JMeter Test Plan Generation





#### Transformation: M4J-DSL to Apache JMeter Test Plan



#### **Evaluation**

#### Methodology

- Instrumentation of SPECjEnterprise2010 with Kieker to obtain session log
- Adapt SPECj dealer driver
  - Login / logout at beginning / end of each transaction
- Extraction of behavior models and behavior mix (includes clustering)
- Transformation of M4J-instances to JMeter test plans
  - Generation of basic application model, only session layer
  - Generation of dummy HTTP requests, e.g.,
    http://localhost:8080/ActionServlet?type=Add to Cart
  - No input data
  - No guards and actions
- Create dummy web application with actionServlet
- Execute workload on dummy web application and measure workload again with Kieker

# Accuracy of Clustering

#### **Evaluation**

		X-Means (min 3 cluster, max 3 cluster)							X-Means (min 2 cluster, max 20 cluster)									
			Non-Normalized			Normalized				Non-Normalized			Normalized				N	
TM	Т	C1	C2	C3	MC	C1	C2	C3	MC	C1	C2	MC	C1	C2	C3	C4	MC	N
50	В	0	0	31,060	2.91%	0	31,060	0	0%	0	31,060	24.62%	0	0	0	31,060		61,500
25	Μ	15,298	0	0		15,298	0	0		15,298	0		632	14,666	0	0		
25	Р	1,789	13,353	0		0	0	15,142		15,142	0		0	0	15,142	0		
25	В	15,091	0	0	15.98 %	15,091	0	0	0%	0	15,091	24.96%	0	15,091	0	0	15.30%	60,089
25	Μ	0	0	15,000		0	15,000	0		15,000	0		0	0	707	14,293		
50	Р	0	20,397	9,601		0	0	29,998		29,998	0		21,513	8,485	0	0		
25	В	0	15,231	0	2.99%	15,231	0	0	0%	0	15,231	25.16%	0	0	0	15,231		61,118
50	М	30,510	0	0		0	30,510	0		30,510	0		29,375	1,135	0	0		
25	Р	1,824	0	13,553		0	0	15,377		15,377	0		0	0	15,377	0		

TM: Transaction Mix

T: Transaction

C<sub>N</sub>: Assigned Cluster

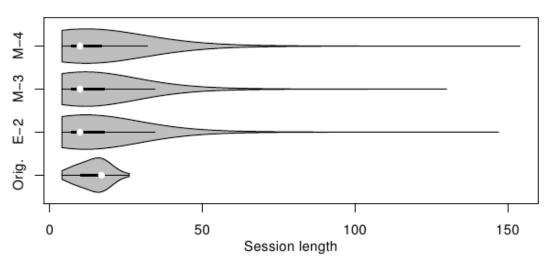
MC: Percentage of misclassified

N: Number of instances



# Accuracy of Extracted Workload Specifications

**Evaluation** 



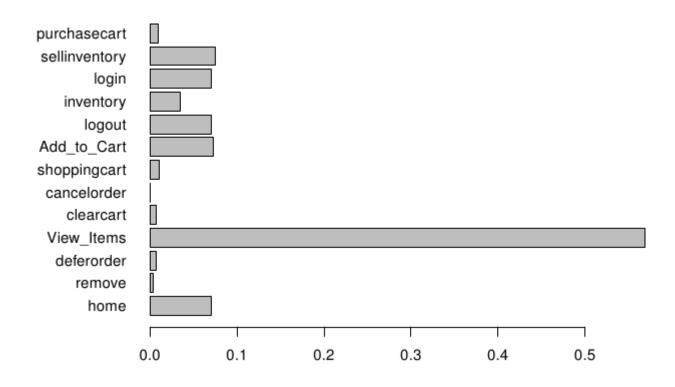
(a) Violin plot (combination of box and density plot)

	Min.	$Q_1$	Med.	Mean	$CI_{0.95}$	$Q_3$	Max.	N
Orig.	4	10	17	14.23	[14.19,14.26]	17	26	61,500
E-2	4	7	10	14.24	[14.15,14.33]	18	147	60,976
M-3	4	7	10	14.24	[14.15, 14.33]	18	130	62,054
M-4	4	7	10	14.31	[14.21,14.40]	17	154	60,084

(b) Summary statistics

Figure 7: Session length statistics for the original workload (Orig.) and the synthetic workloads (E-2, M-3, M-4)

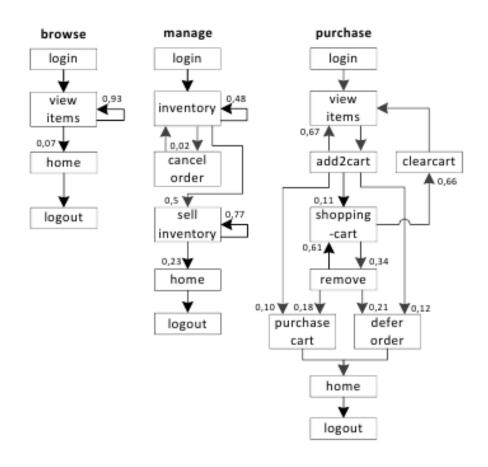
# Accuracy of Extracted Workload Specifications Evaluation





# Probabilistic Representation of SPECj Workload

#### **Evaluation**

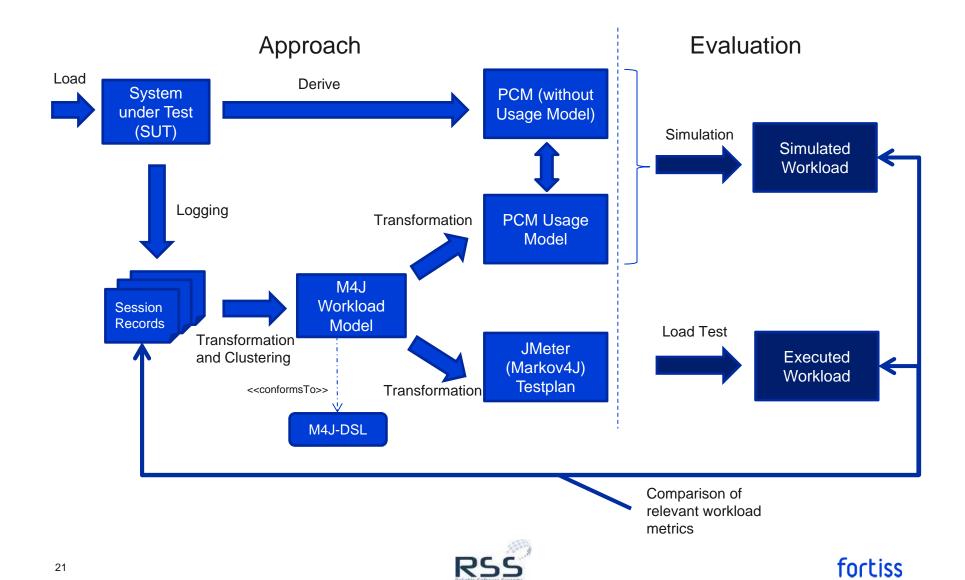




#### **Future Work**

- Automatic generation of application model → Executable load tests
  - Automatic learning of guards and actions
  - Generation of protocol layer
  - Generation of input data
- Transformation of DSL instance to PCM
- Support for workload intensity → LIMBO
- Evaluate impact of number of clusters on performance
- Evaluation of other clustering approaches
- Transformation to alternative workload generators
- Online clustering to detect evolution of behavior mix

#### **Future Work**



#### References

- 1. A. van Hoorn, M. Rohr, and W. Hasselbring. Generating probabilistic and intensity-varying workload for Web-based software systems. In Proc. SIPEW '08, pages 124–143, 2008.
- 2. E. Schulz. Integrating performance tests in a generative software development platform, June 2014. Master's Thesis, Kiel University, Germany.
- 3. C. Vögele, A. Brunnert, A. Danciu, D. Tertilt, and H. Krcmar. Using performance models to support load testing in a large SOA environment. In Proc. LT '14, 2014.

# Backup



#### **Evaluation**

#### Research Questions

RQ1: How practical is the proposed approach for realistic systems

RQ2: How accurately do cluster results match the input workload mix?

RQ3: What is the impact of the clustering results on the session-based workload characteristics?

RQ4: How accurately do the non-session-based input workload characteristics match the resulting non-session based workload characteristics?