Investigating the Use of Bayesian Networks in the Hora Approach for Component-based Online Failure Prediction

Teerat Pitakrat, André van Hoorn

University of Stuttgart
Institute of Software Technology (ISTE)
Reliable Software Systems (RSS) Group
Stuttgart, Germany

Nov 27, 2014 @ SOSP 2014, Stuttgart

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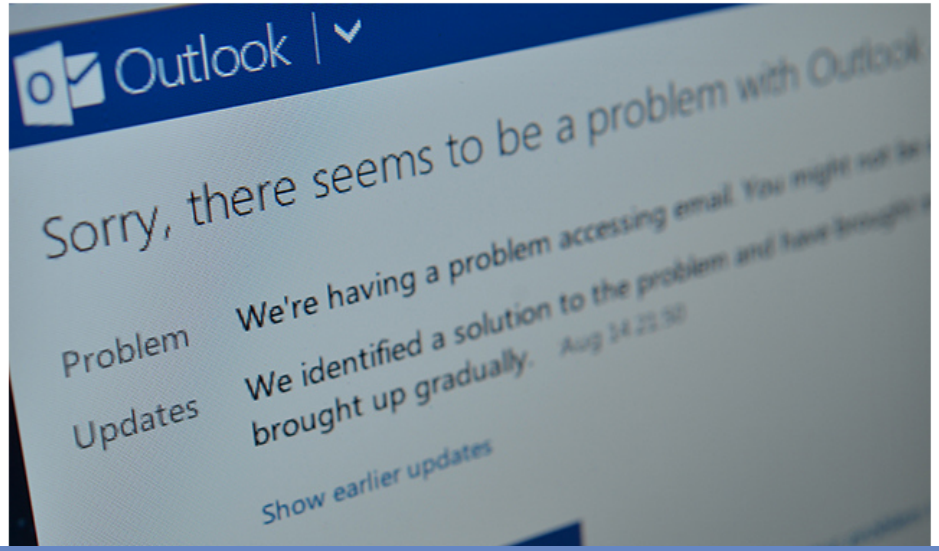

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Service Failure

Motivation: Failure Management

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AWS Server Issues Take Down Instagram, Vine, Airbnb And IFTTT

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Those of you looking to spend the rest of today watching people do other things on Instagram or Vine probably just had a rough time trying to do it. Both services went offline for over an hour, most likely because of issues with **Amazon Web Services**.

Instagram was the first of the two to **publicly acknowledge** its issues on Twitter, and Vine followed suit **half an hour later**.

The deluge of tweets that accompanied the services' initial hiccups first started at around 4 p.m. Eastern time, and only increased in intensity as users found they couldn't share pictures of their food or their meticulously crafted video

THE LATEST HEADLINES

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NETWORKS

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Systemwide outage knocks every service offline

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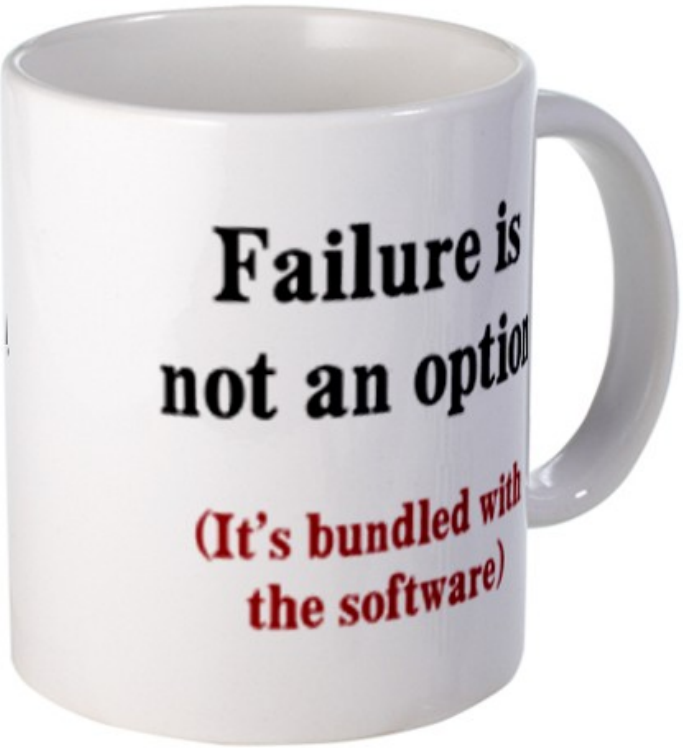
You can all relax now. The near-unprecedented outage that seemingly affected all of Google's services for a brief time on Friday is over.

The event began at approximately 4:37pm Pacific Time and lasted between one and five minutes, according to the Google Apps Dashboard. All of the Google Apps services reported being back online by 4:48pm.

The incident apparently blacked out every service Mountain View has to offer simultaneously, from Google Search to Gmail, YouTube, Google Drive, and beyond.

Big deal, right? Everyone has technical difficulties every once in a while. It goes with the territory.

Service Failure

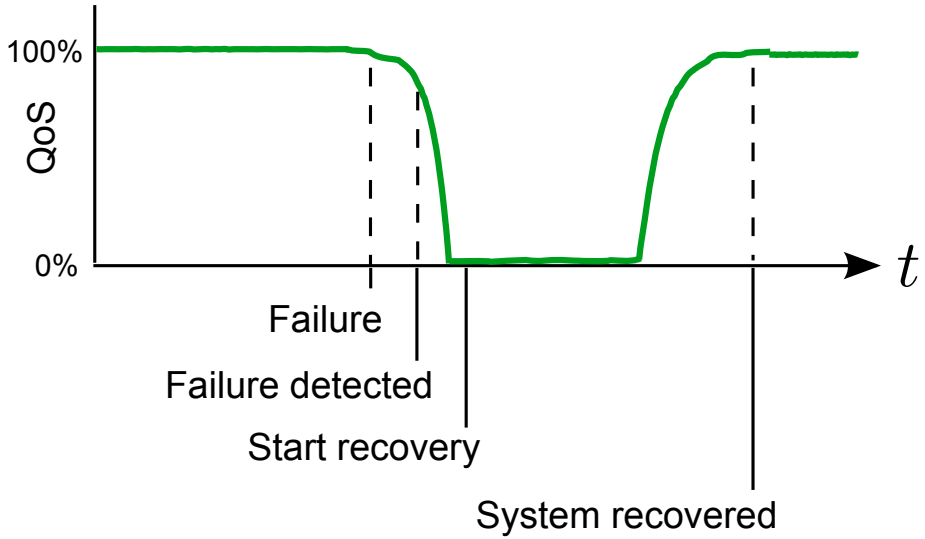


"A **service failure**, often abbreviated here to **failure**, is an event that occurs when the delivered service deviates from correct service."

— Avizienis et al. [2004]

Reactive vs. Proactive Failure Mgmt.

Reactive



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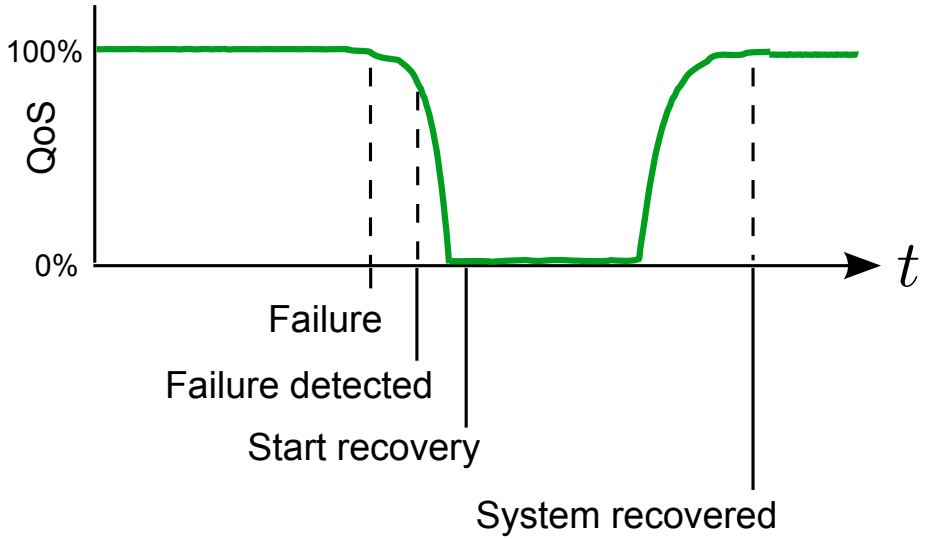
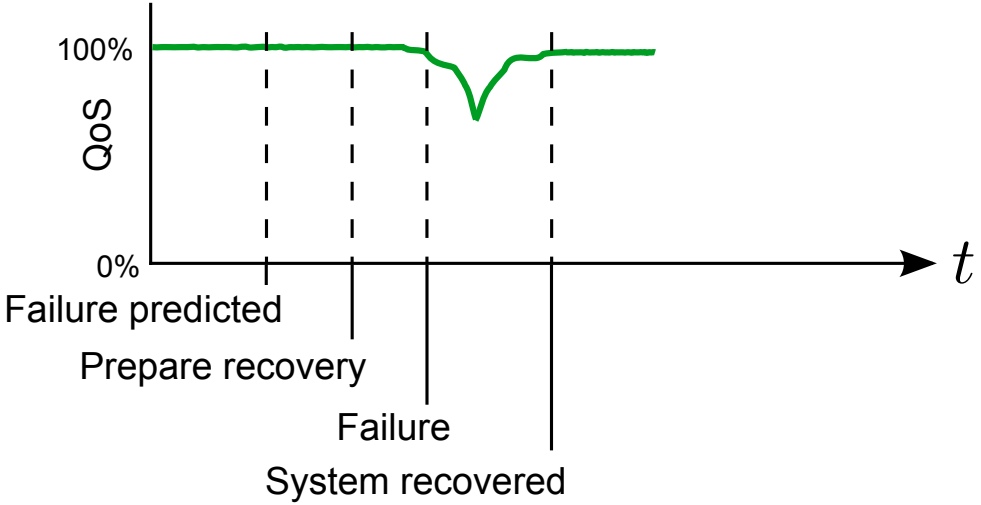
Reactive



Proactive

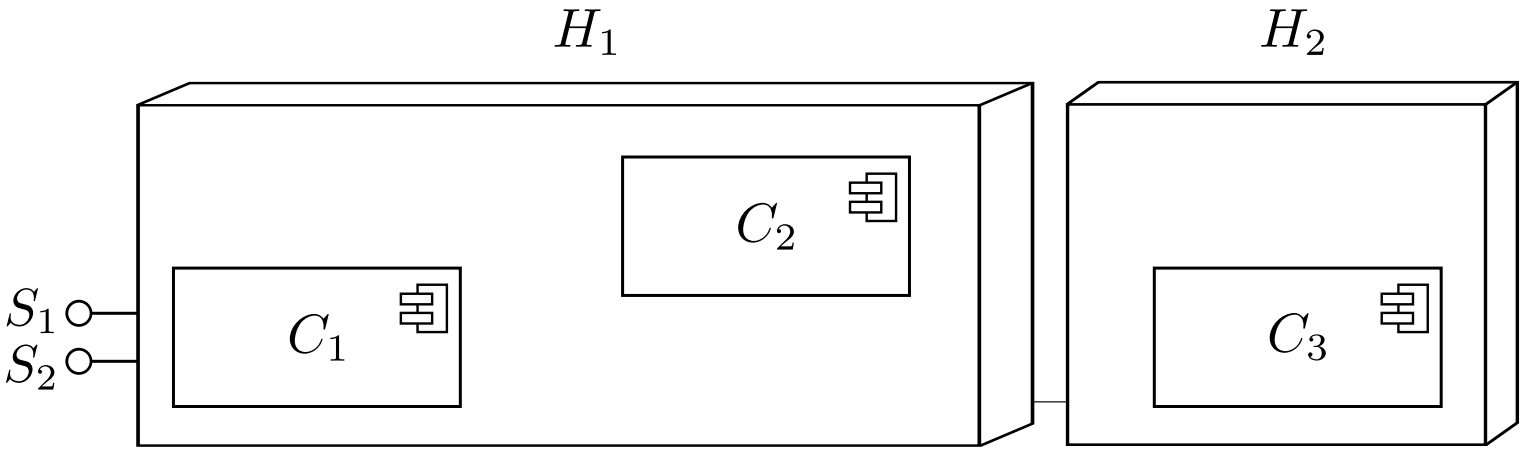


Agenda

Related Approaches vs. Hora Approach

Amin et al. [2012], Liang et al. [2007]

Related Approaches vs. Hora Approach



Bielefeld [2012]

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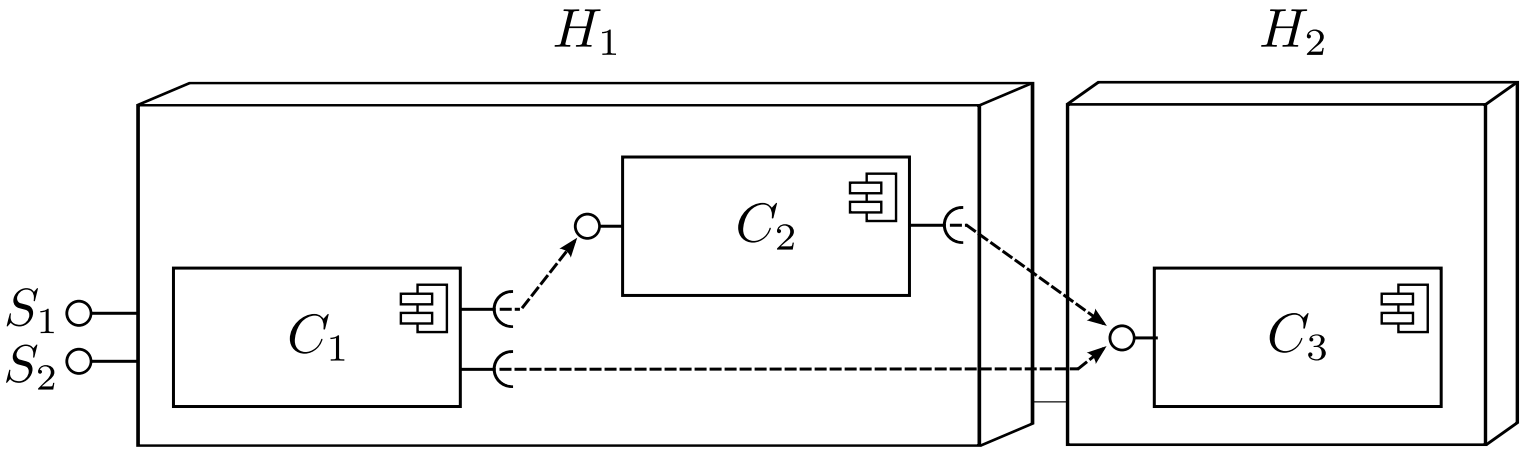

Pitakrat [2013], Pitakrat et al. [2014b]

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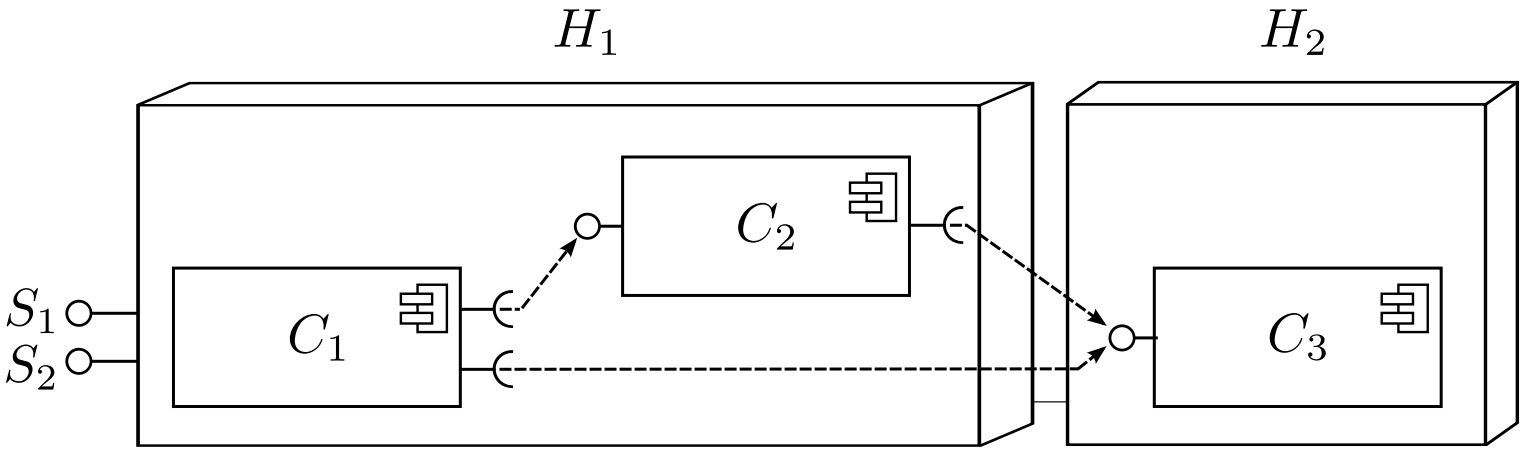

Component-level Prediction Models

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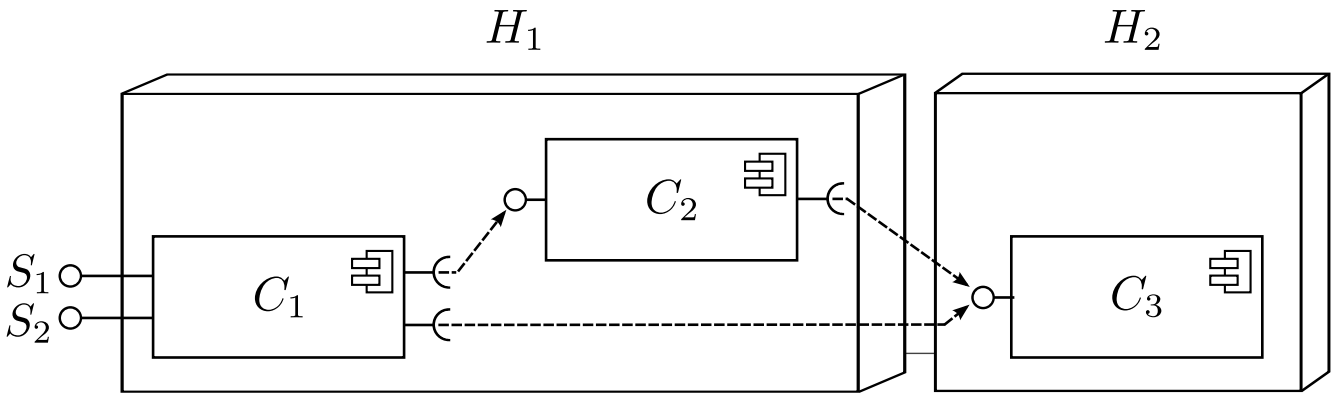
Component Dependency

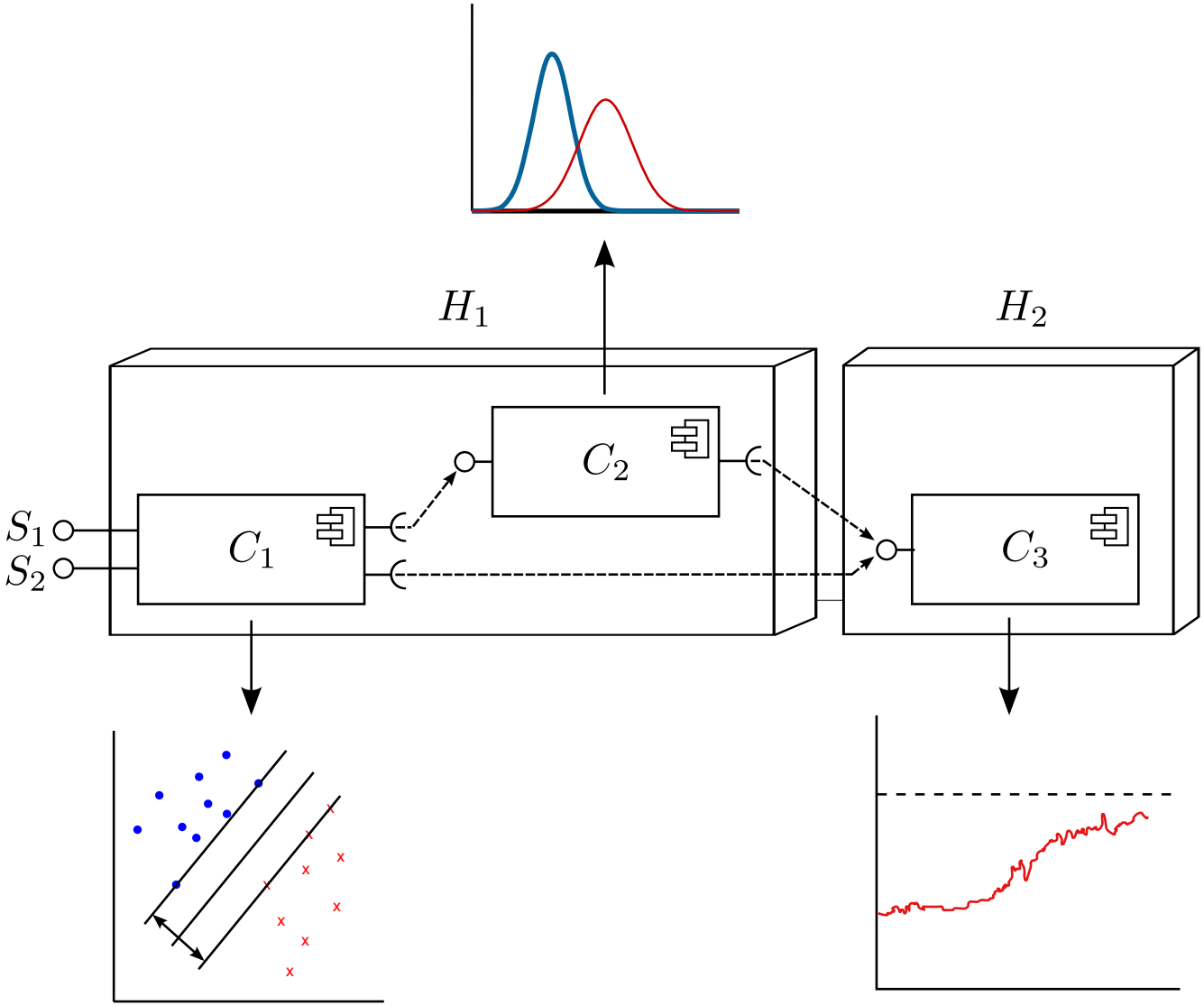
⇨ System-level Prediction Model

Pitakrat [2013], Pitakrat et al. [2014b]

Hora: Component-level Prediction Models

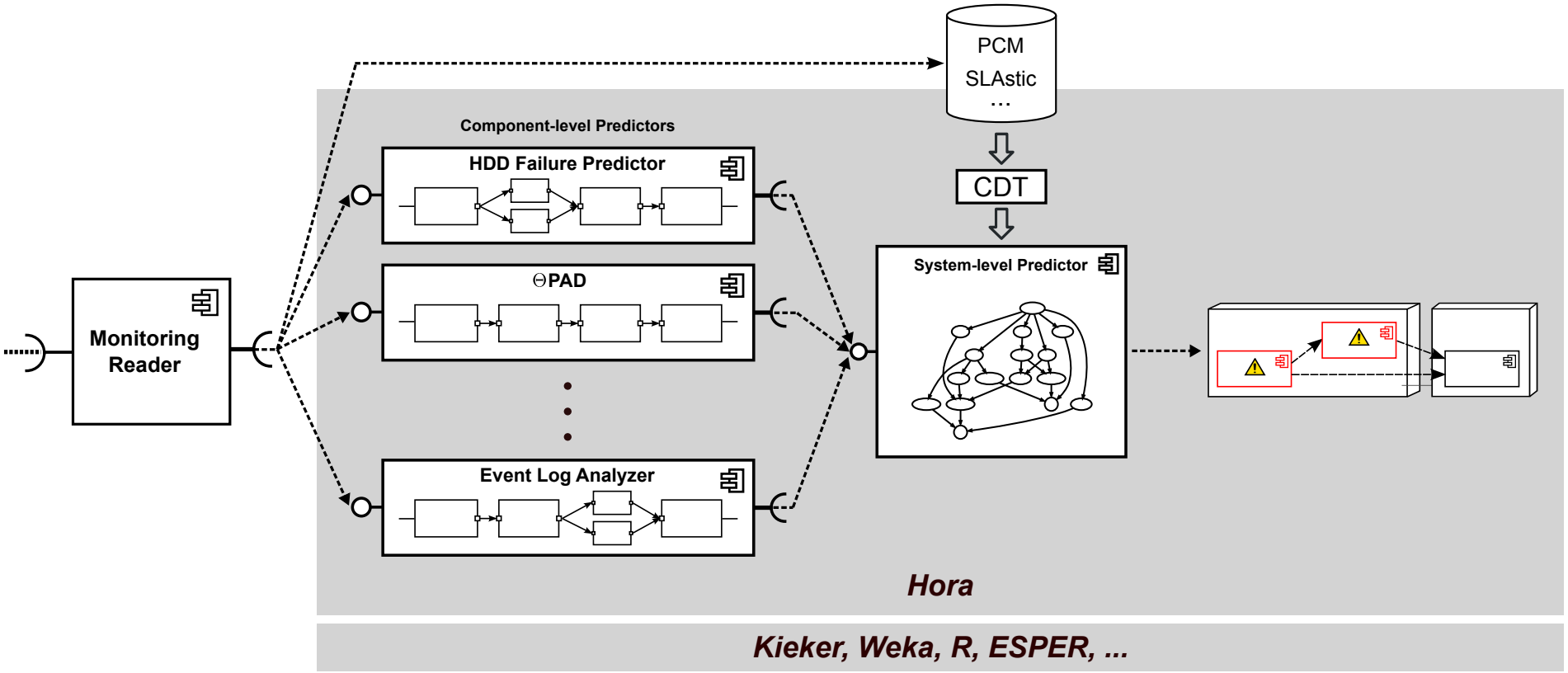


Hora: Component-level Prediction Models



Hora: Framework Architecture

[Recap] Hora: Online Failure Prediction for CB Systems



Becker et al. [2009], Bielefeld [2012], Pitakrat et al. [2013; 2014a], van Hoorn [2014]

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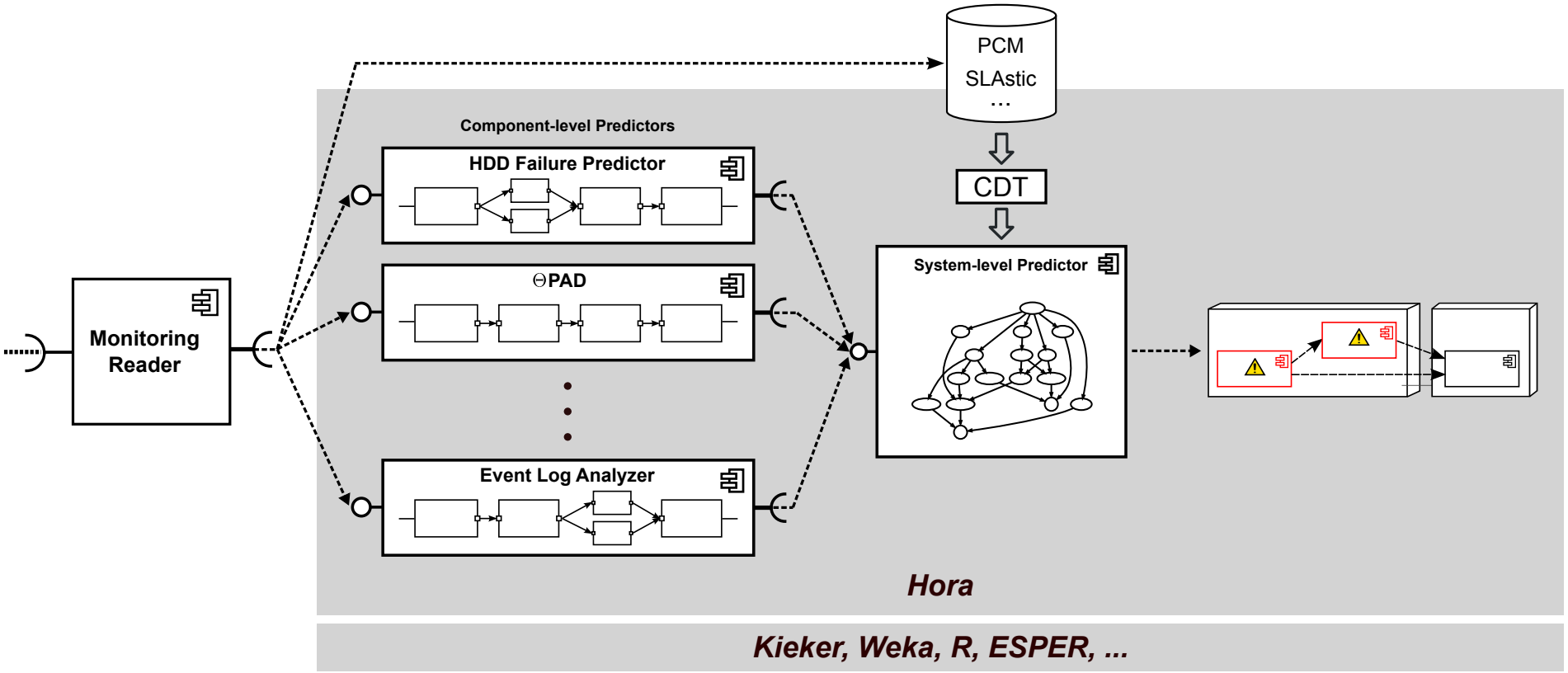


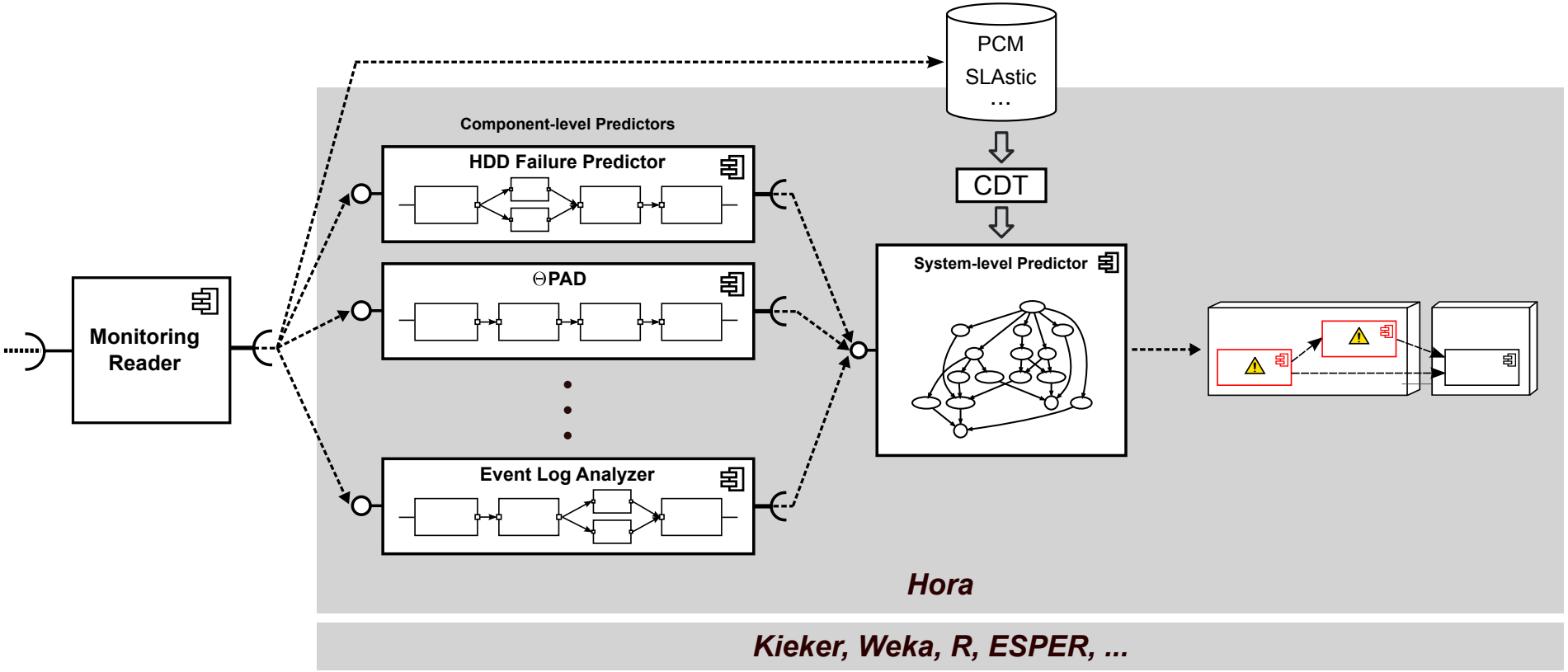
Questions:

1. What is a suitable model for System-level Prediction Model (SPM)?
2. How to transform architectural models to CDT and to SPM?
3. How does Hora improve online failure prediction?

Becker et al. [2009], Bielefeld [2012], Pitakrat et al. [2013; 2014a], van Hoorn [2014]

Agenda

Hora: Framework Architecture



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Bayesian network: probabilistic graphical model

Bayesian network library used in Hora: https://github.com/kutschkem/Jayes

System-level Prediction Model

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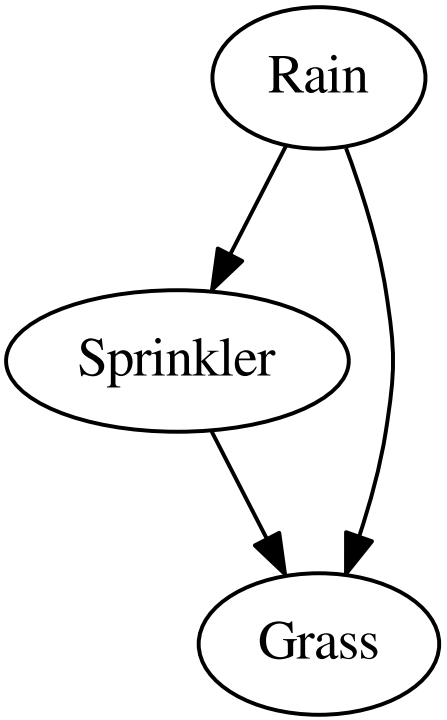
Bayesian network: probabilistic graphical model



Rain	T	F
0.2	0.8	

Rain	Sprinkler T	Sprinkler F
T	0.01	0.99
F	0.4	0.6

Sprinkler	Rain	Grass wet T	Grass wet F
T	T	0.99	0.01
T	F	0.9	0.1
F	T	0.8	0.2
F	F	0.0	1.0

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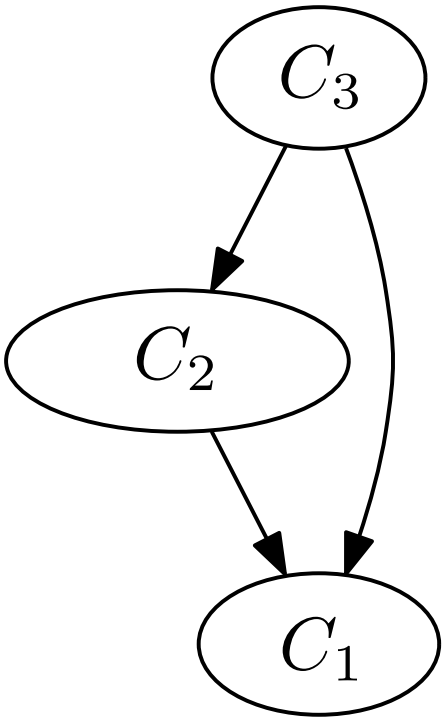
Bayesian network: probabilistic graphical model

C_3	✓	✗
0.2	0.8	

C_3	C_2 ✓	C_2 ✗
✓	0.01	0.99
✗	0.4	0.6



C_2	C_3	C_1 ✓	C_1 ✗
✓	✓	0.99	0.01
✓	✗	0.9	0.1
✗	✓	0.8	0.2
✗	✗	0.0	1.0

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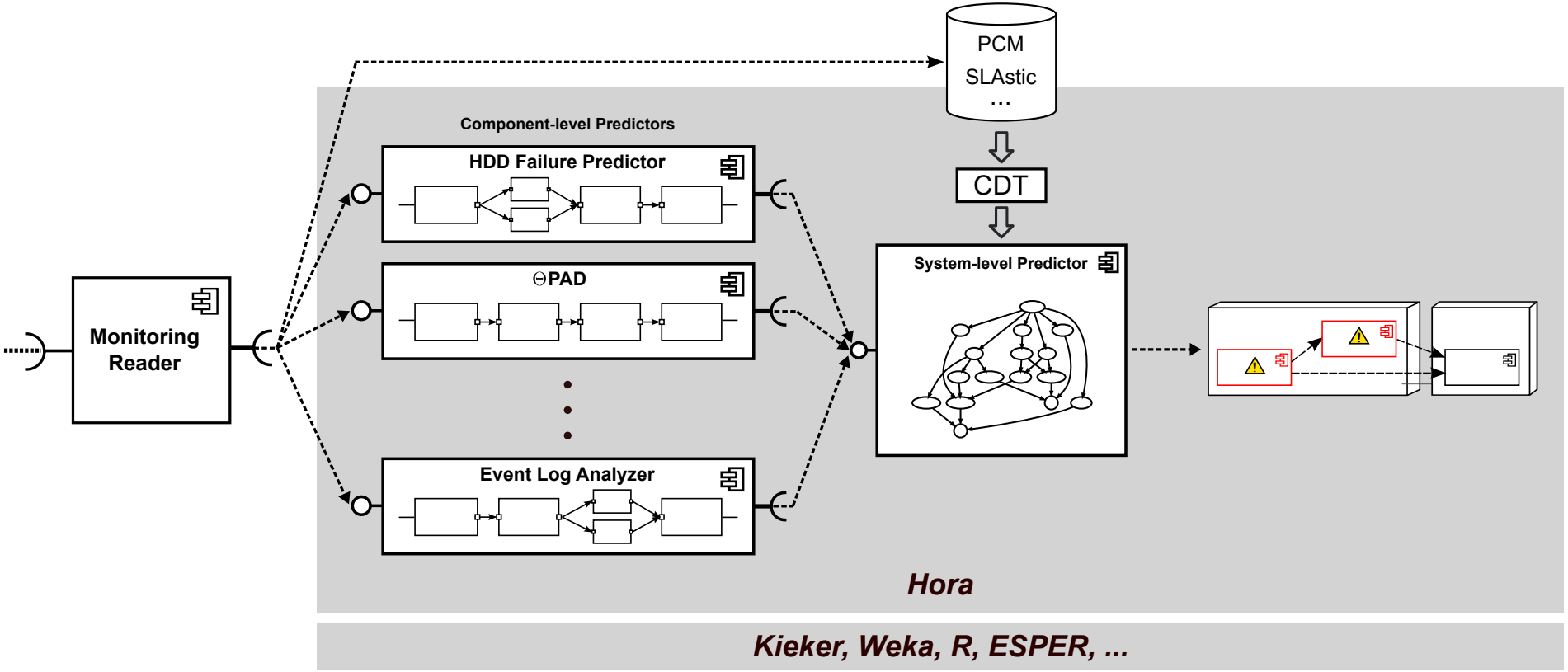
Hora: Framework Architecture



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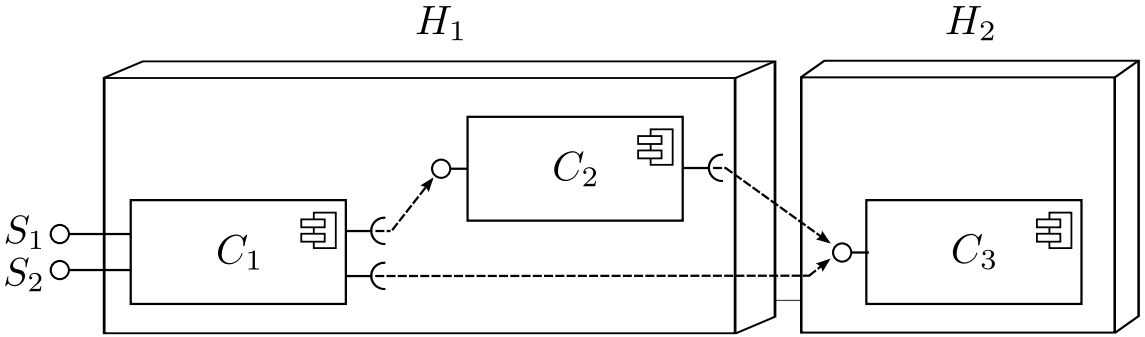
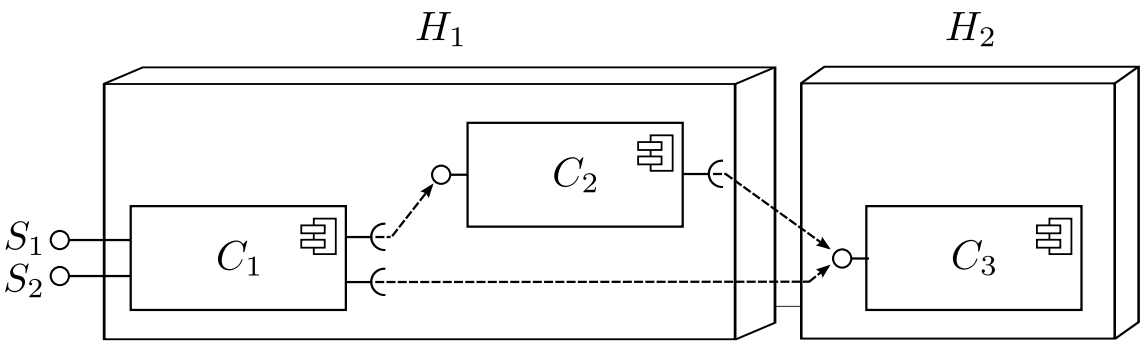
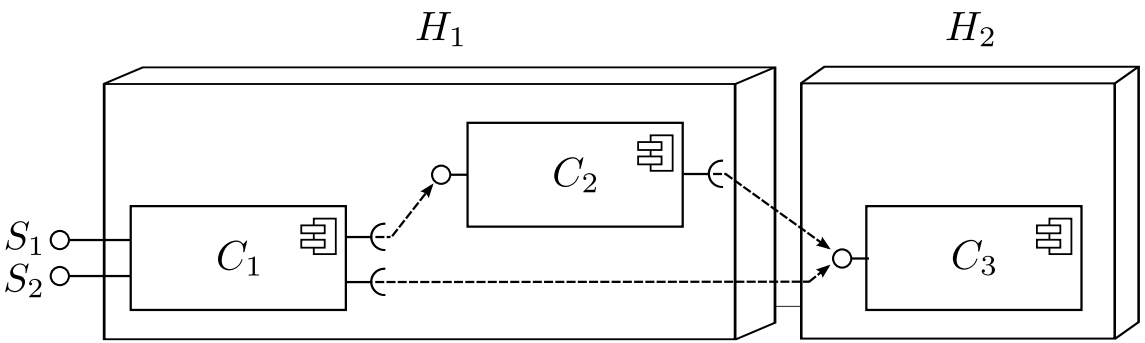

H_1
H_2
C_1
C_2
C_3
S_1
S_2

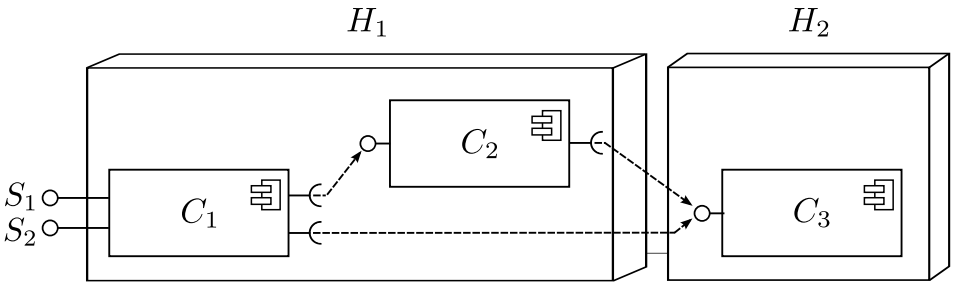


	C_1	C_2	C_3	H_1	H_2
C_1		•	•	•	
C_2			•	•	
C_3					•
H_1					
H_2					



	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

System-level Prediction Model



	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

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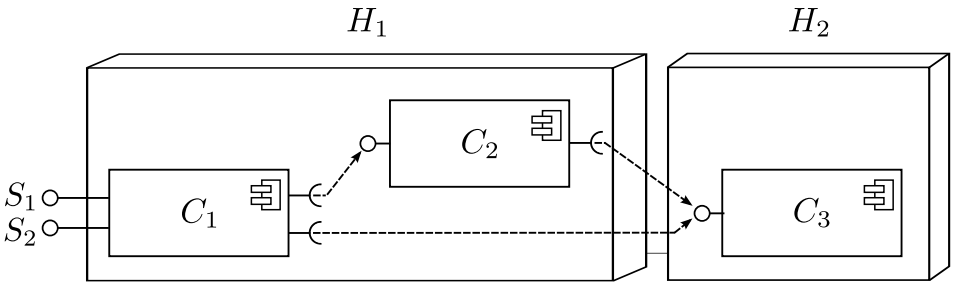

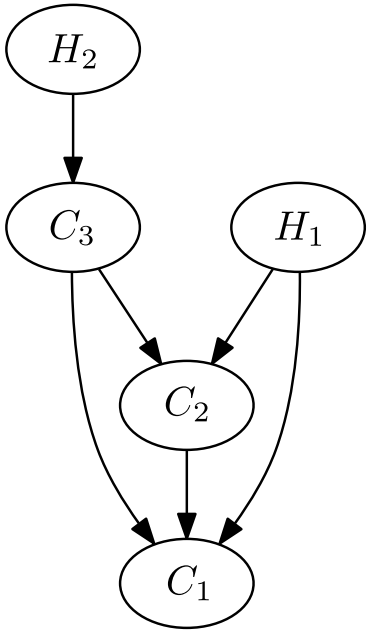

	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

System-level Prediction Model

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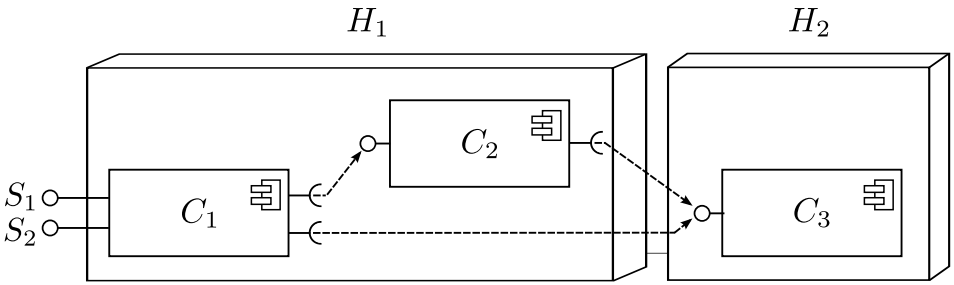
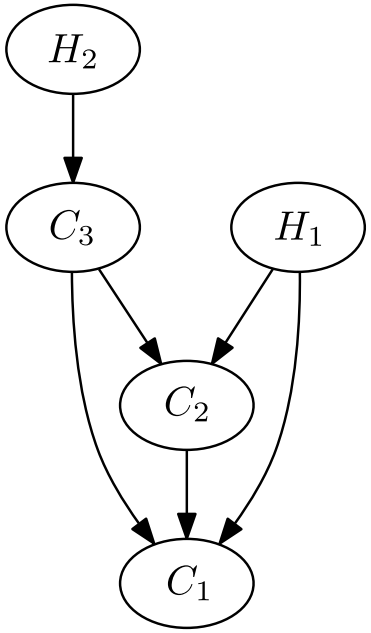
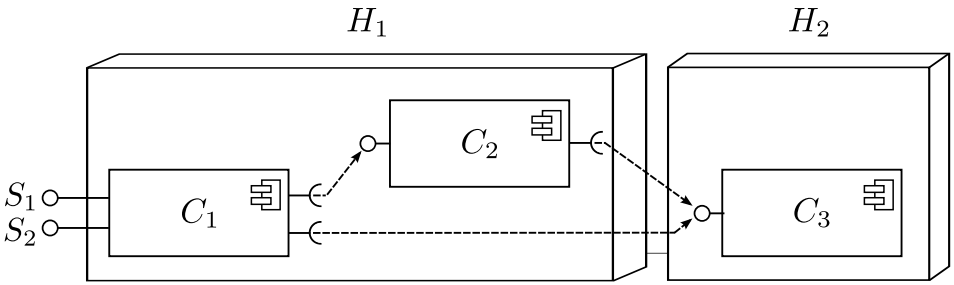


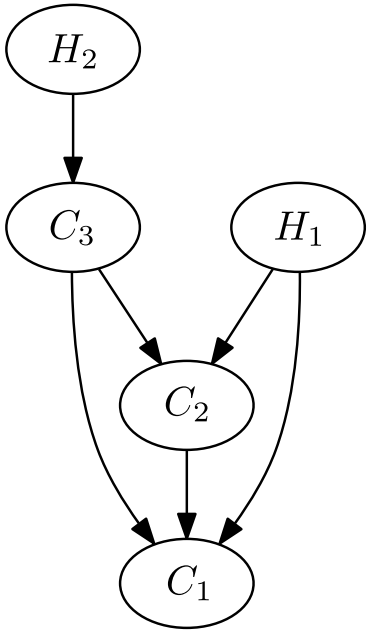


	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

H_2	
✓	✗
0.8	0.2

System-level Prediction Model





	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

	C_3	
H_2	✓	✗
✓	0.9	0.1
✗	0.0	1.0

System-level Prediction Model

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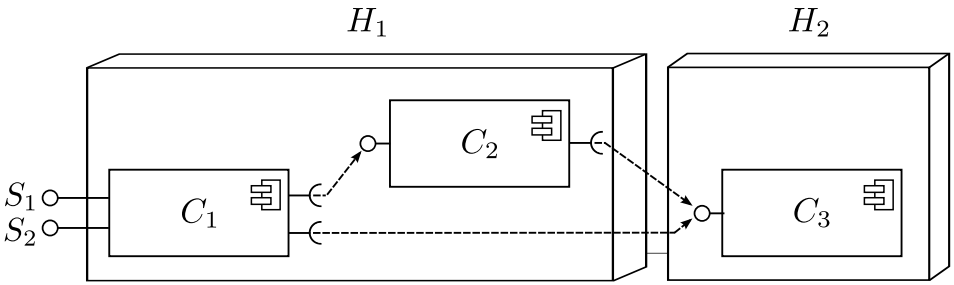
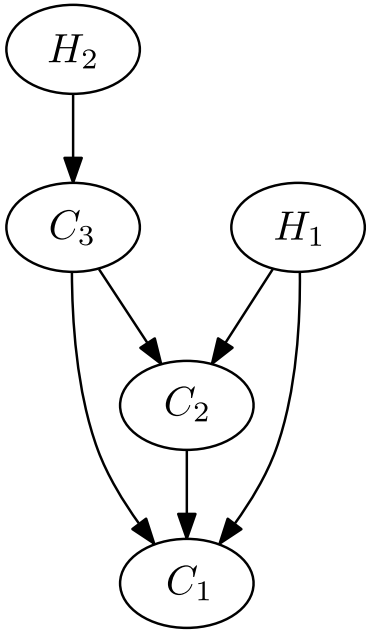
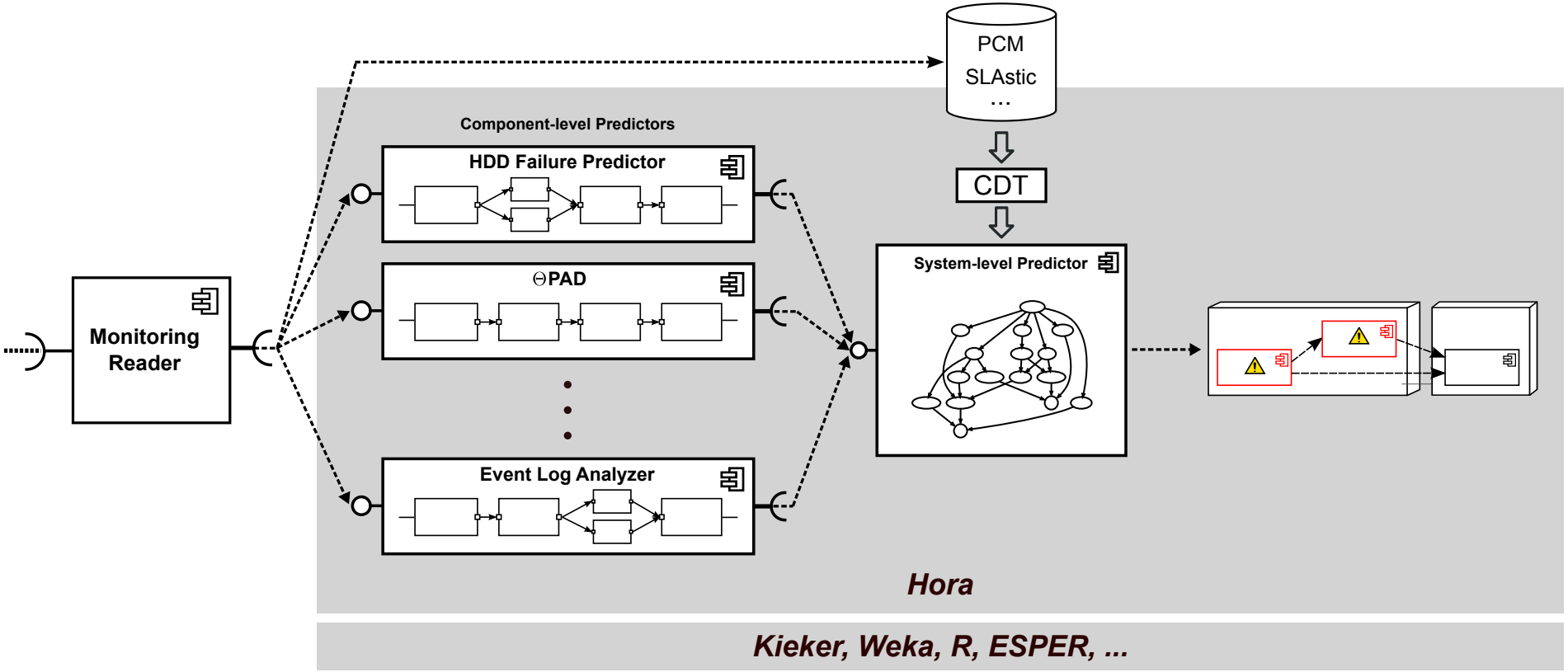




	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

		C_2	
H_1	C_3	✓	✗
✓	✓	0.9	0.1
✓	✗	0.5	0.5
✗	✓	0.0	1.0
✗	✗	0.0	1.0

Hora: Framework Architecture



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Agenda

Experiment Setup

- System under analysis

Kieker

Experiment Setup

- System under analysis

Kieker

- Fault injection

Experiment Setup

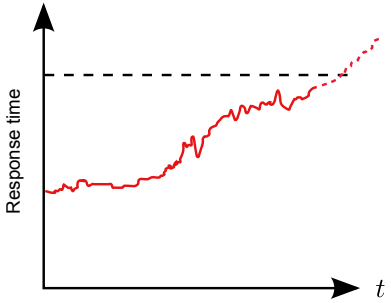
Evaluation

- System under analysis

Kieker

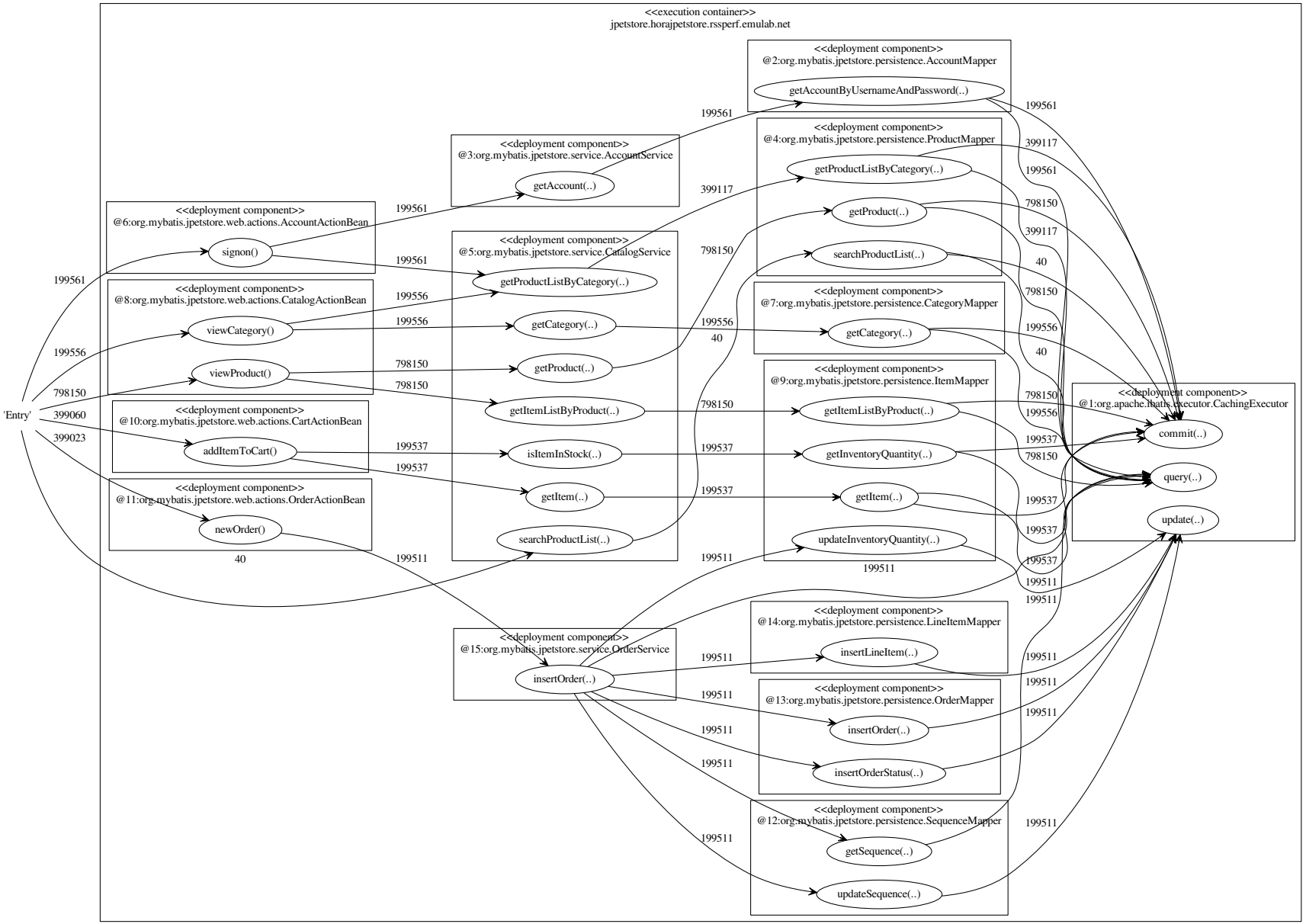
- Fault injection

- Predicting response time violation using time series forecasting



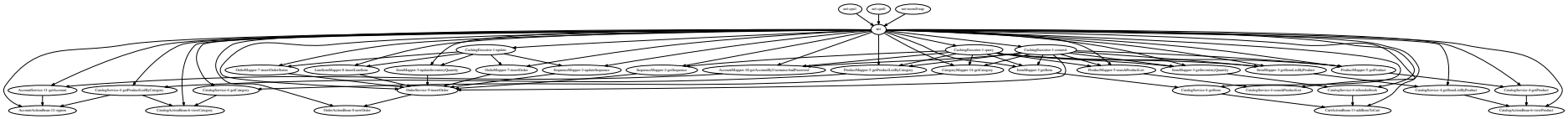
Operation Dependency Graph

Evaluation



SPM for JPetStore

Evaluation



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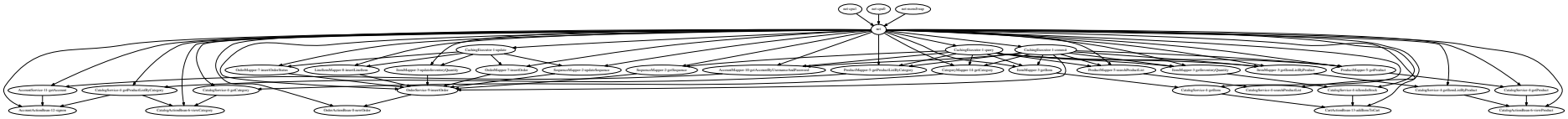
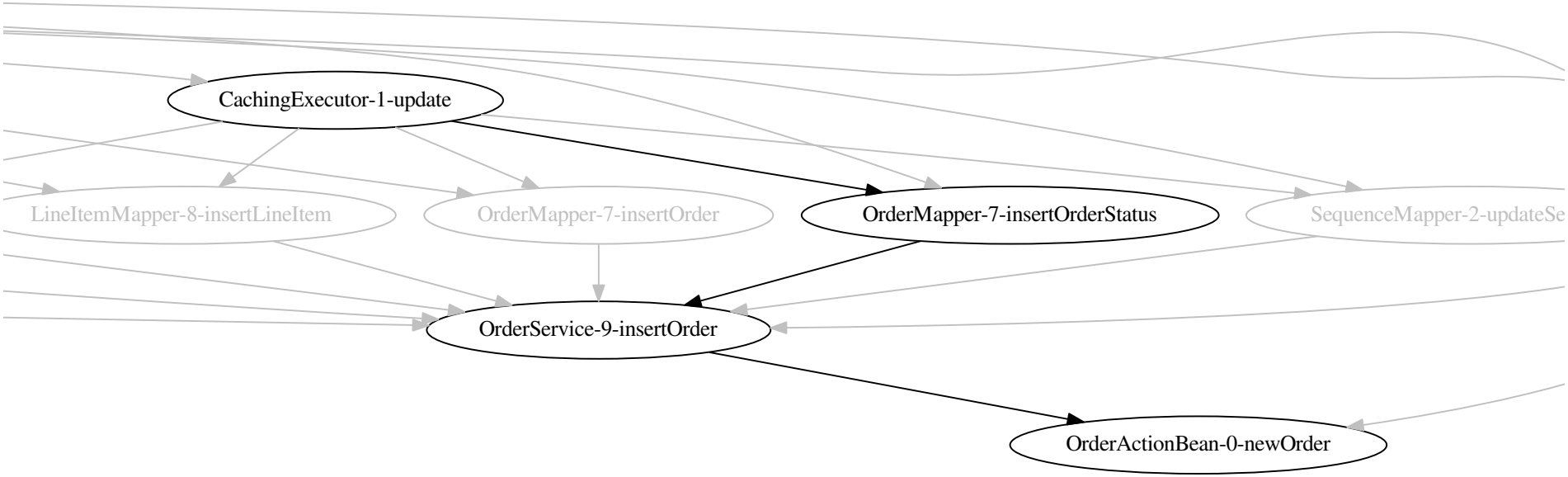
Evaluation





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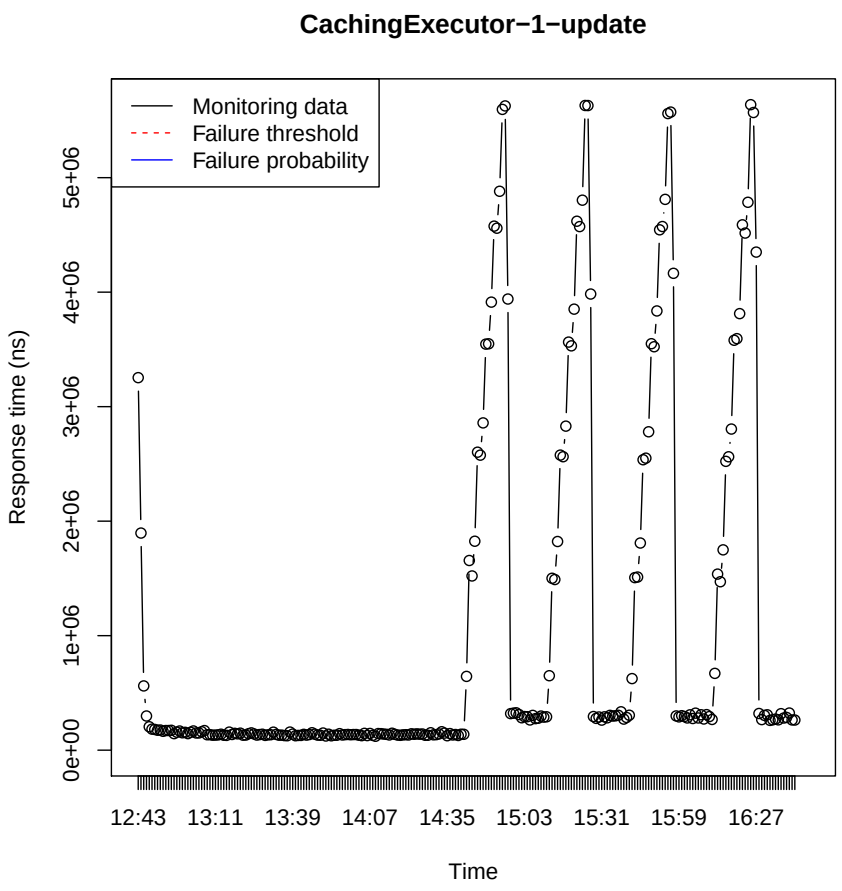
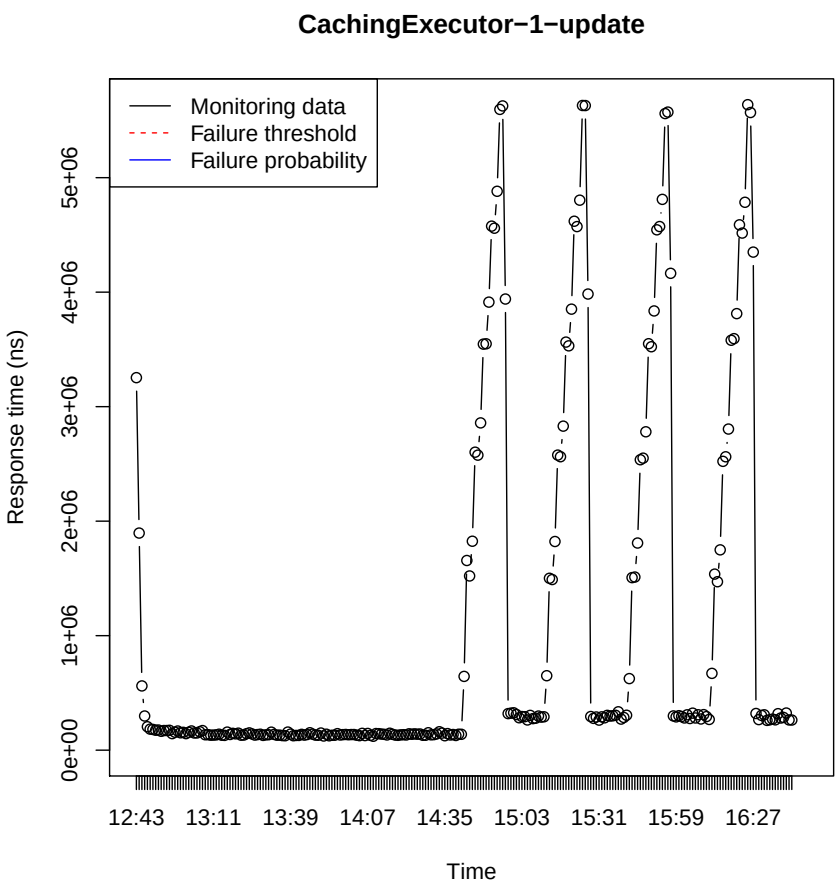
CPM



SPM



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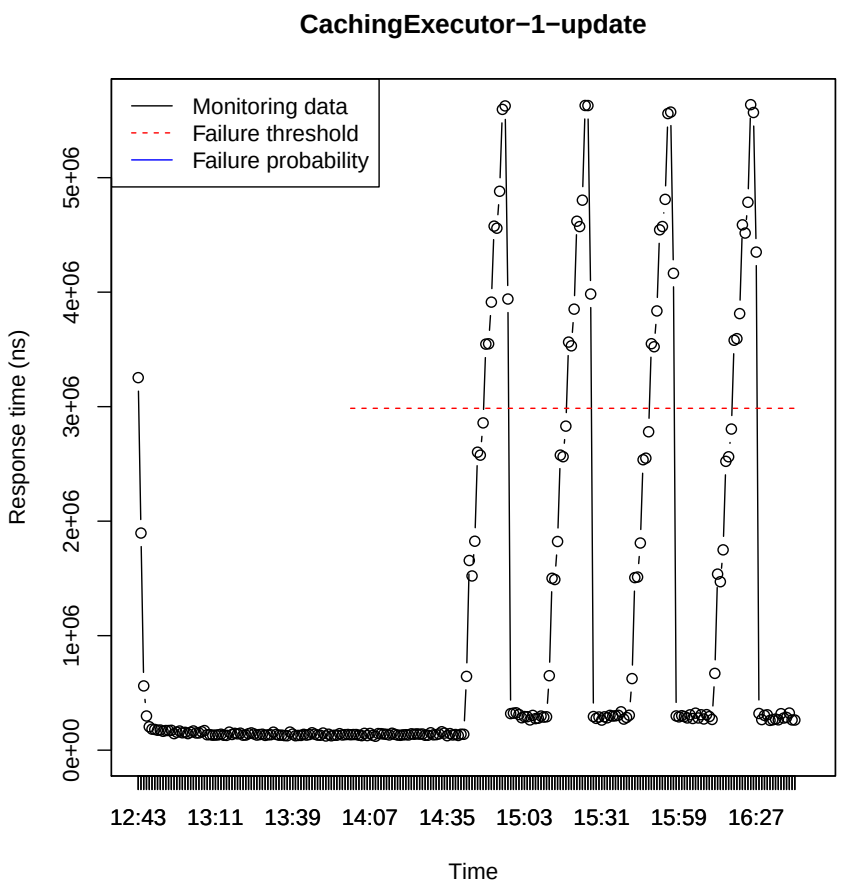
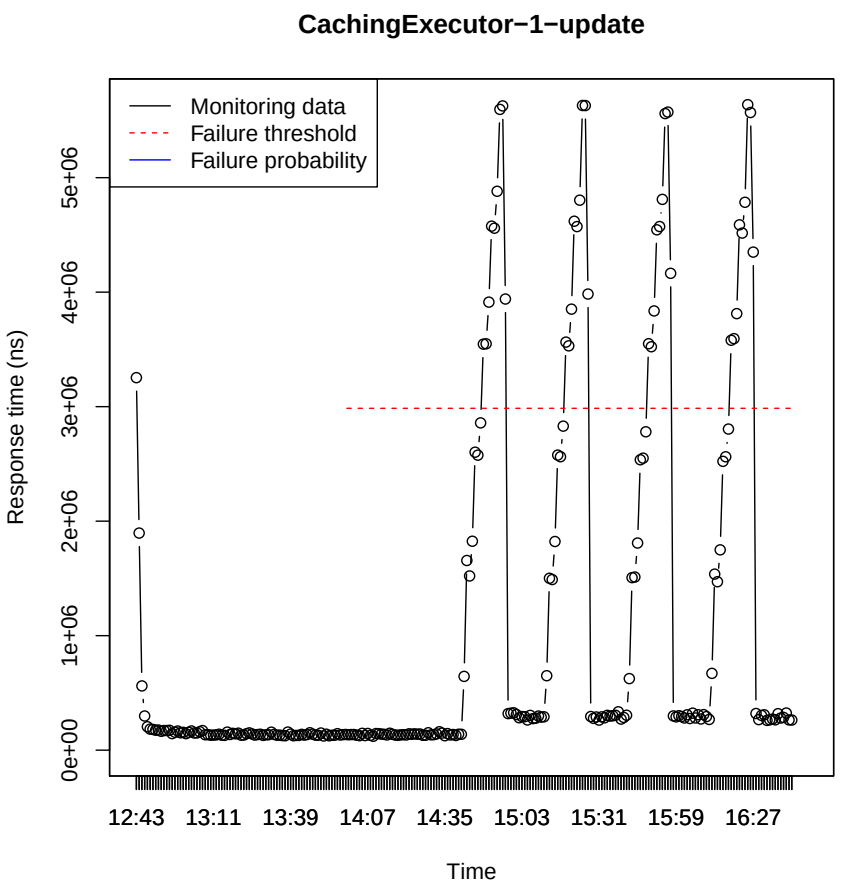
CPM

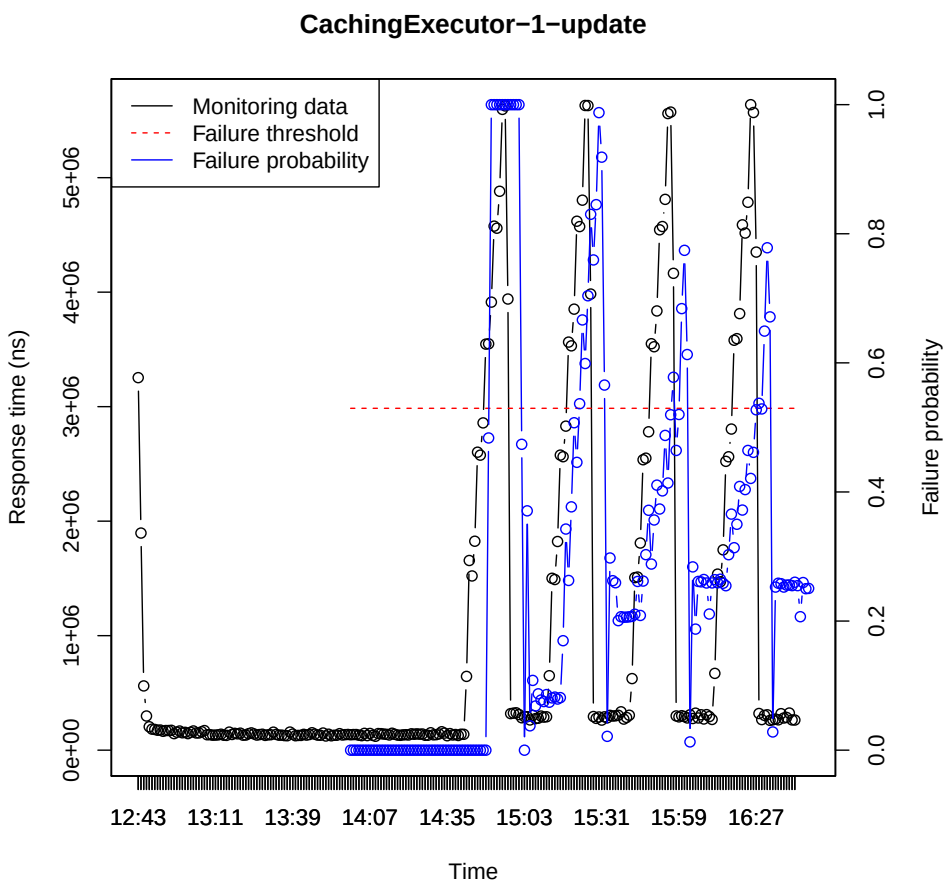


SPM



University of Stuttgart
Germany

CPM



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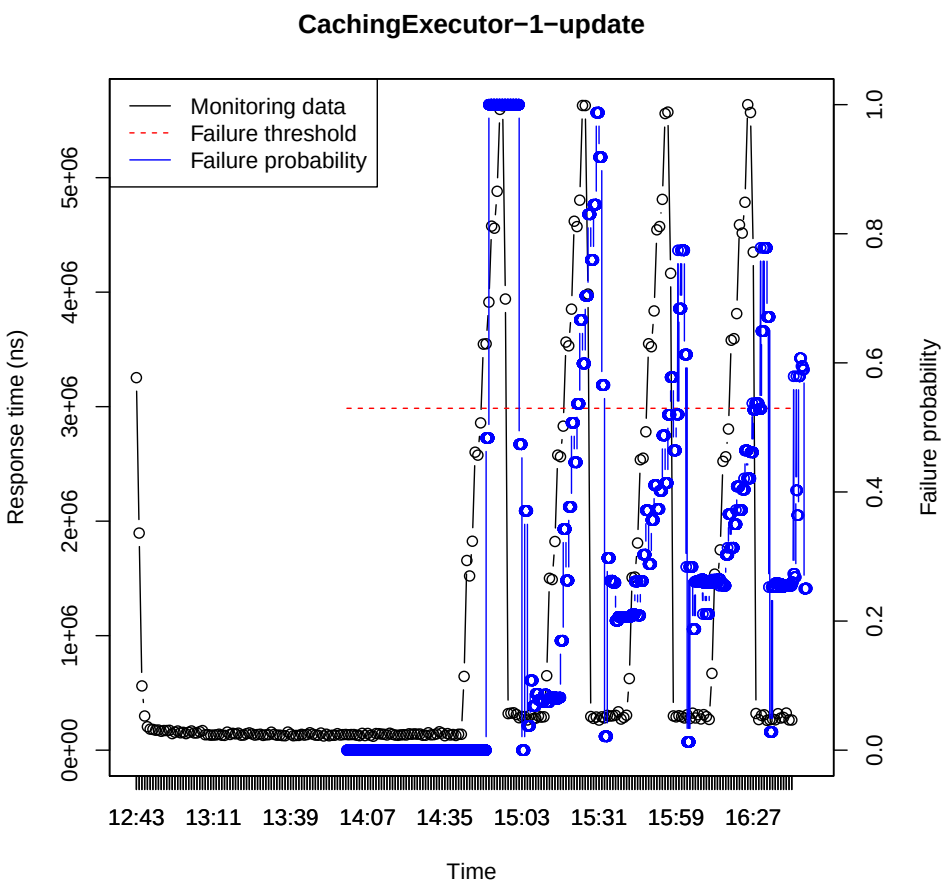
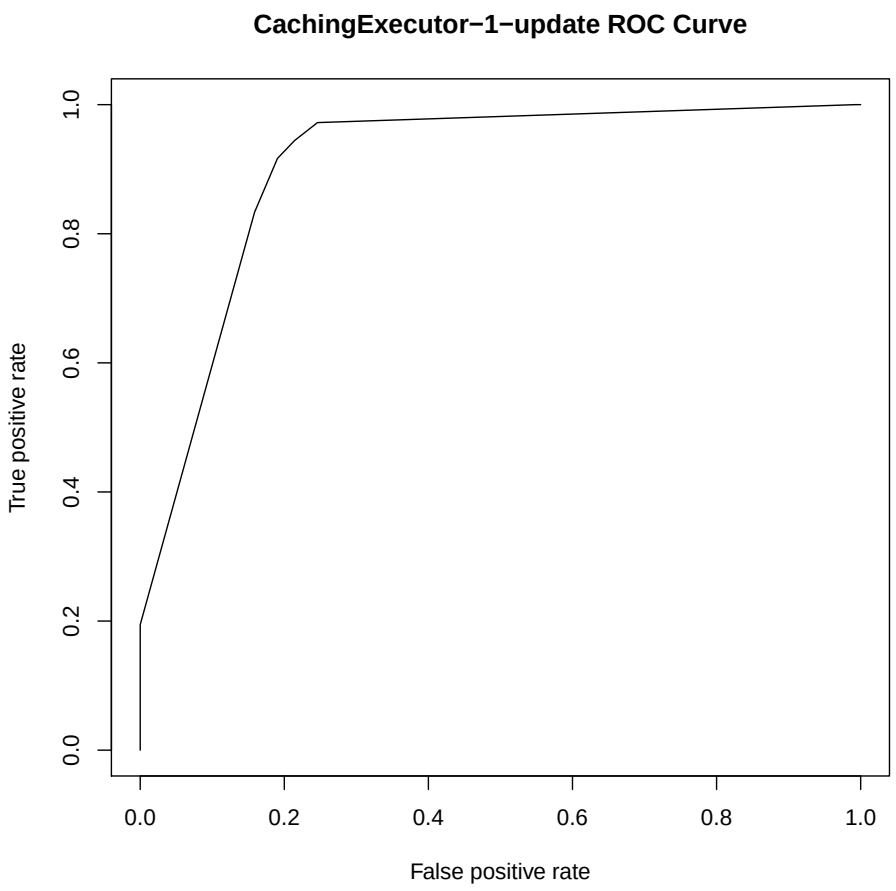
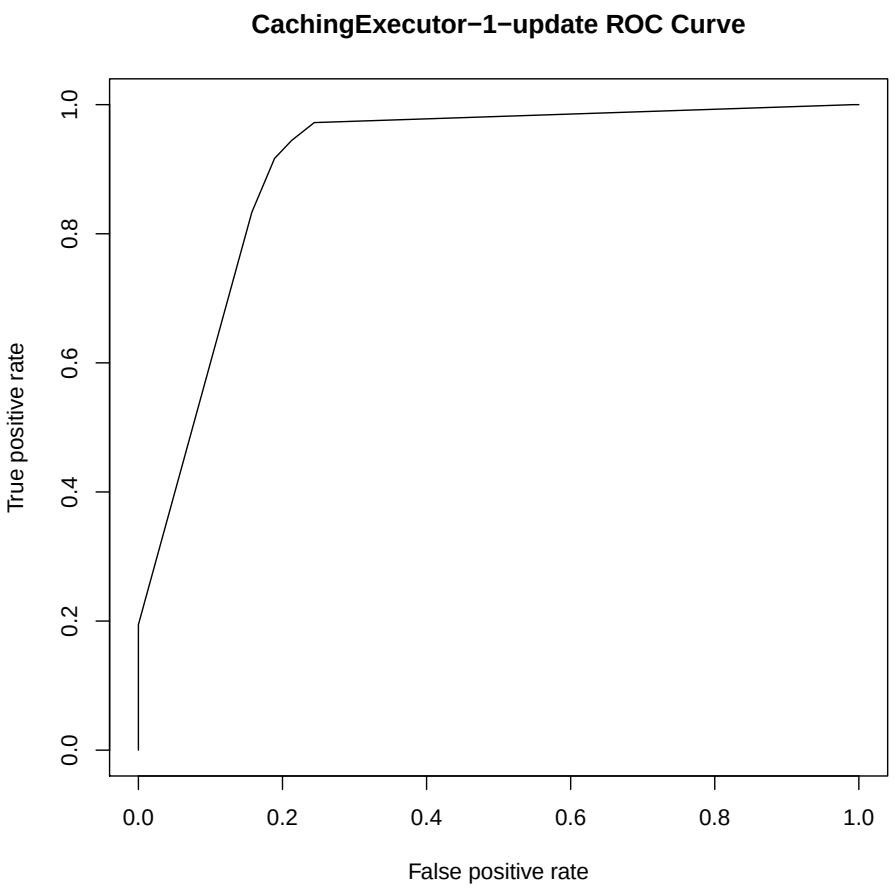


CPM

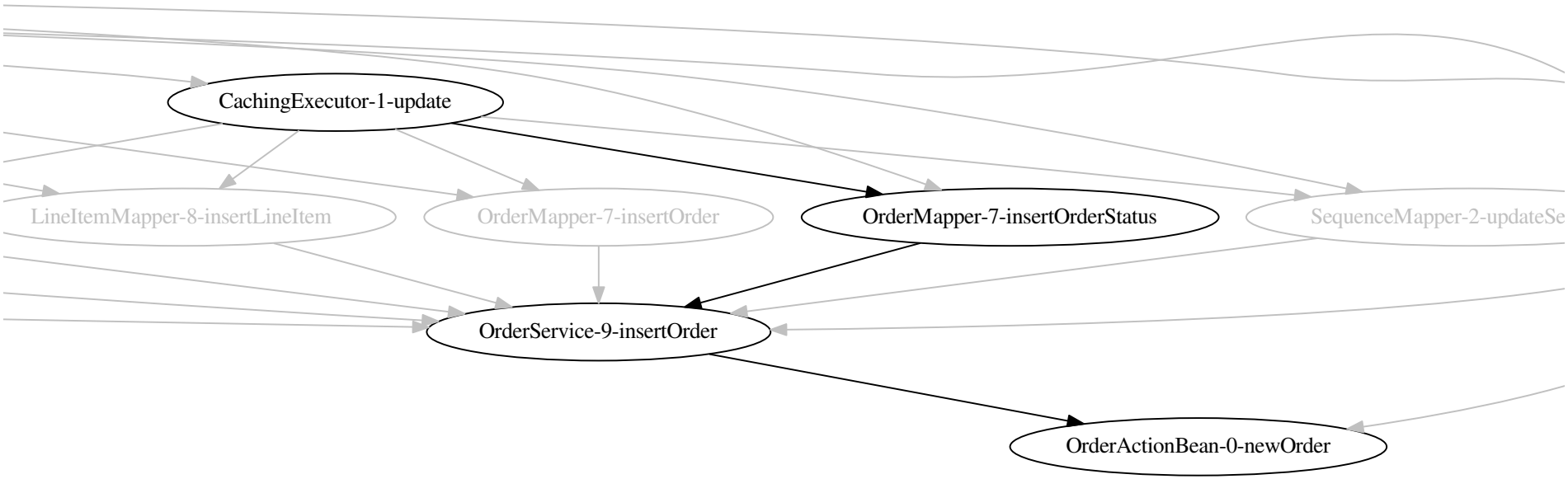

CachingExecutor−1−update ROC Curve
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

SPM

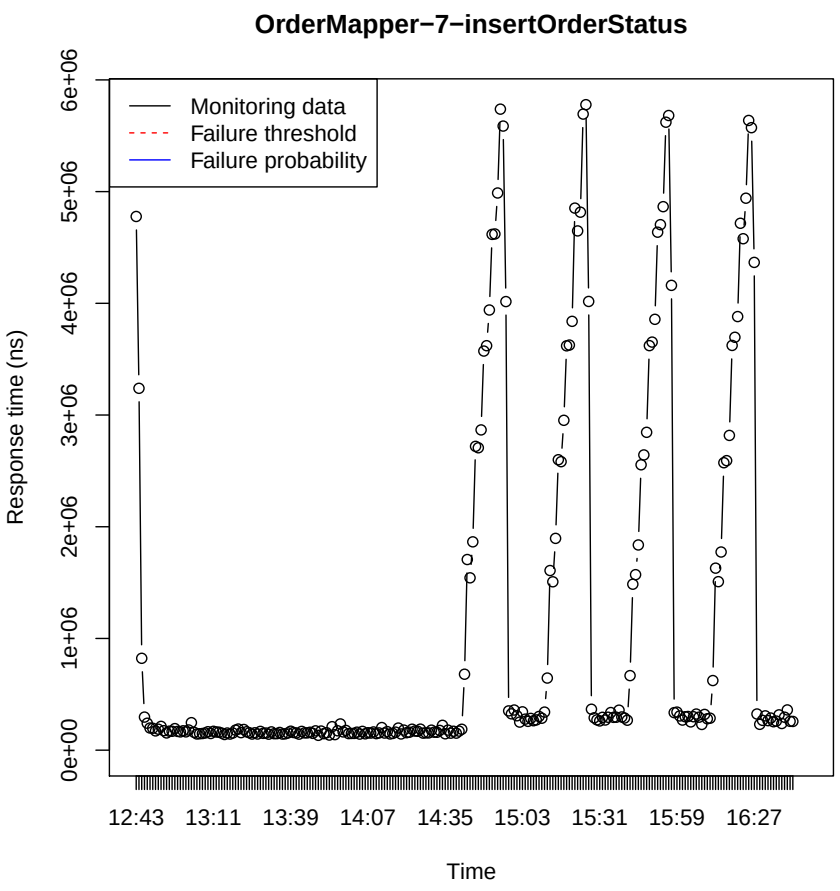

CachingExecutor−1−update ROC Curve
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

SPM for JPetStore

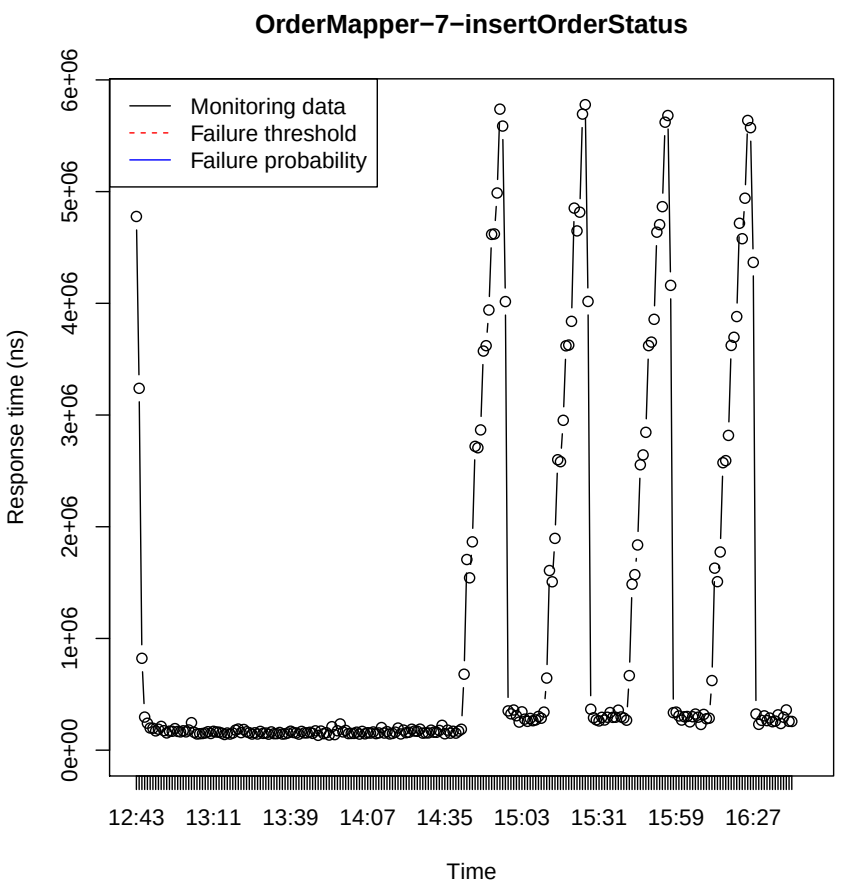
Evaluation



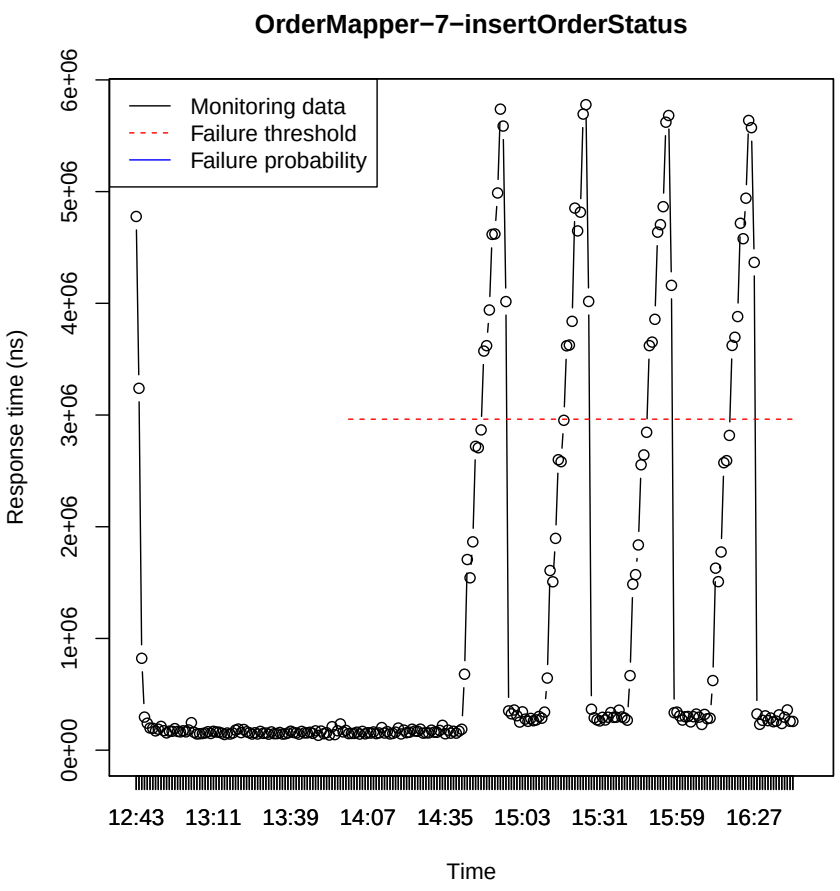
CPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

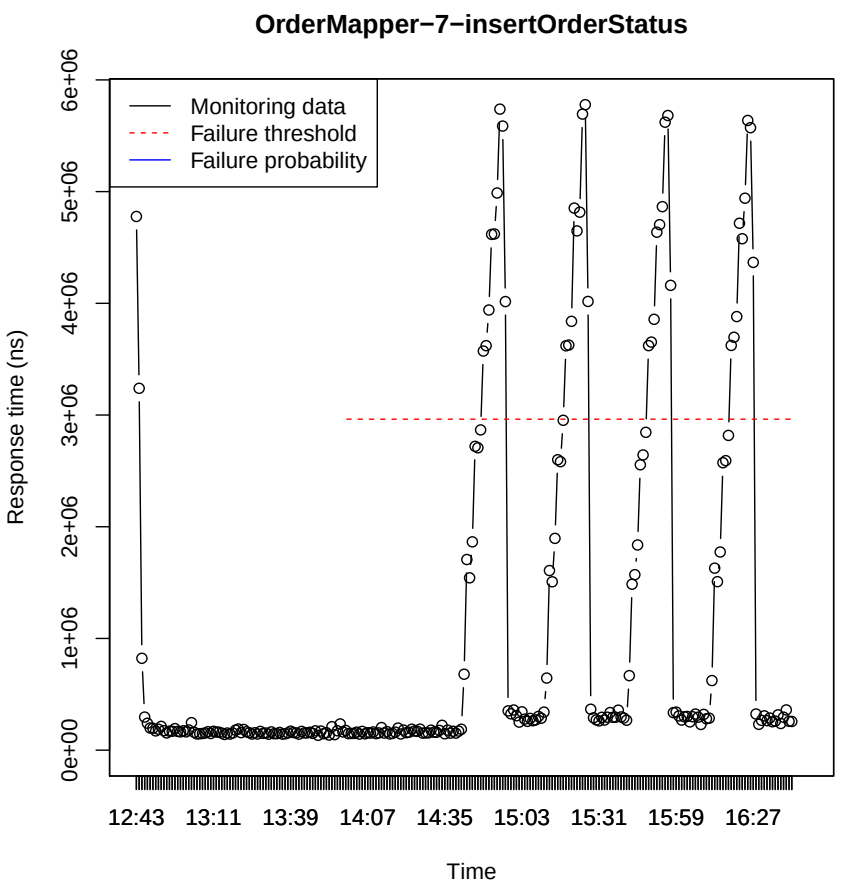
SPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

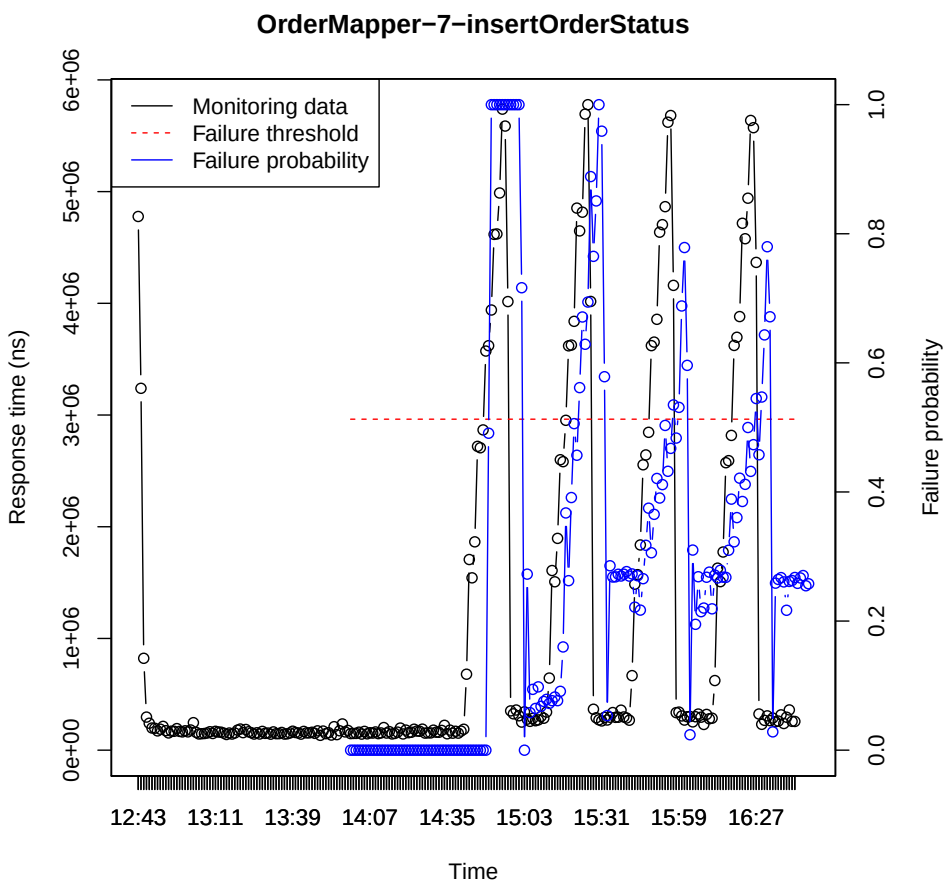
CPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

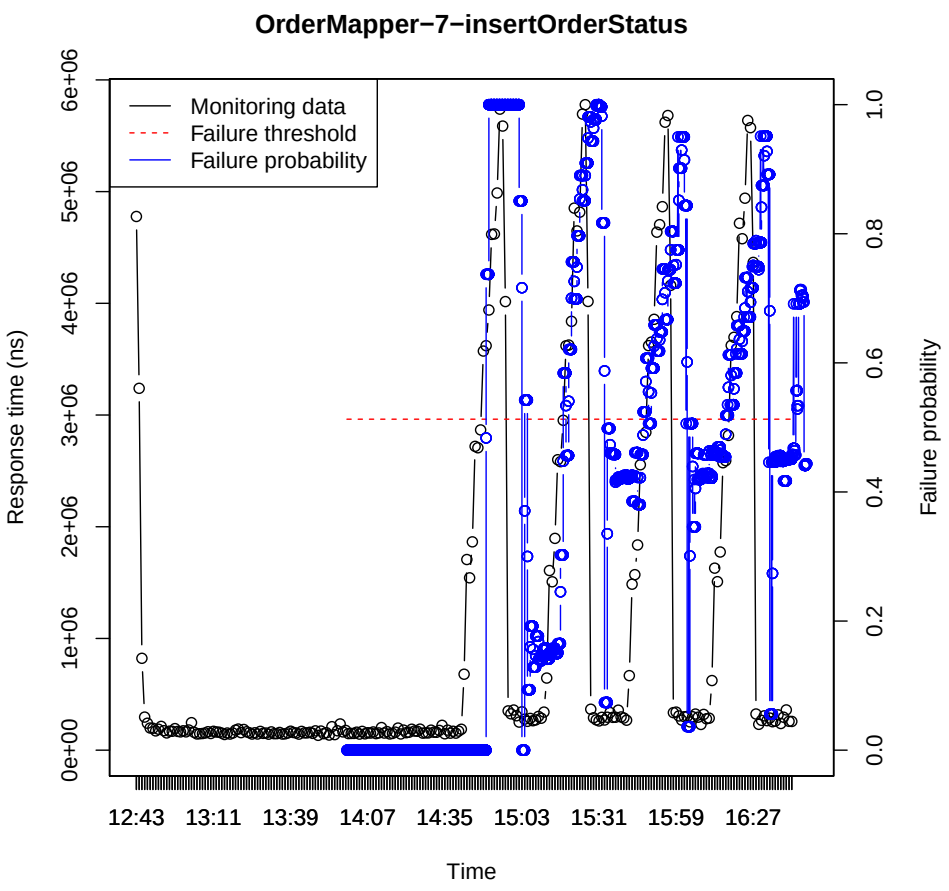
SPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

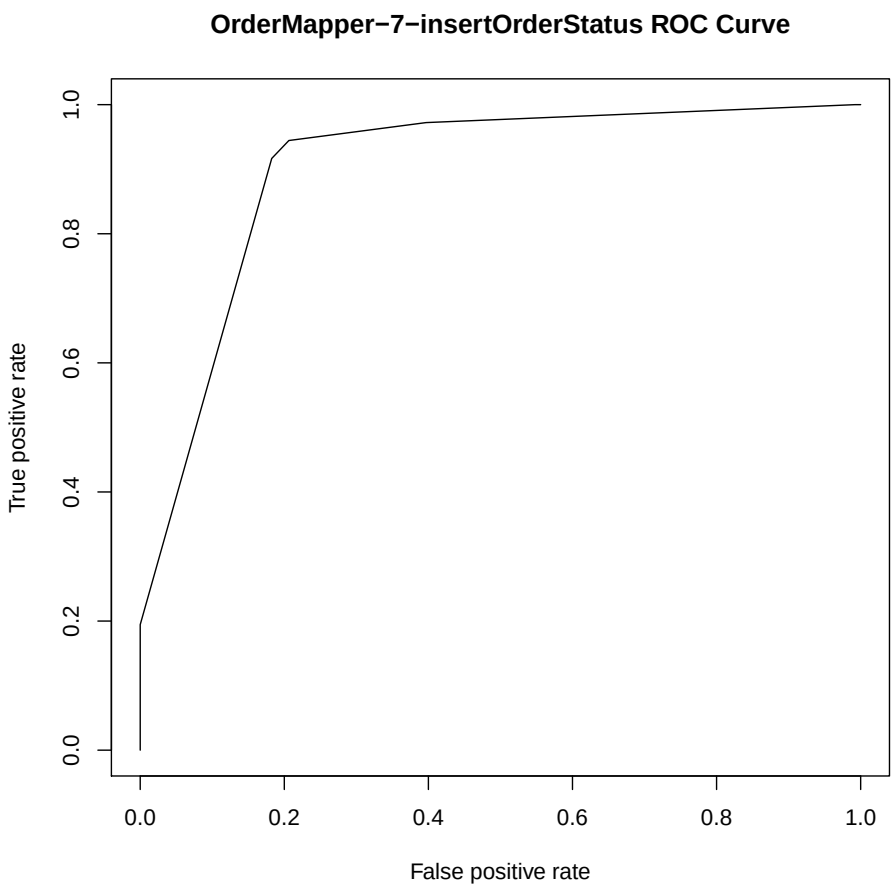
CPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Failure probability
0.0
0.2
0.4
0.6
0.8
1.0
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

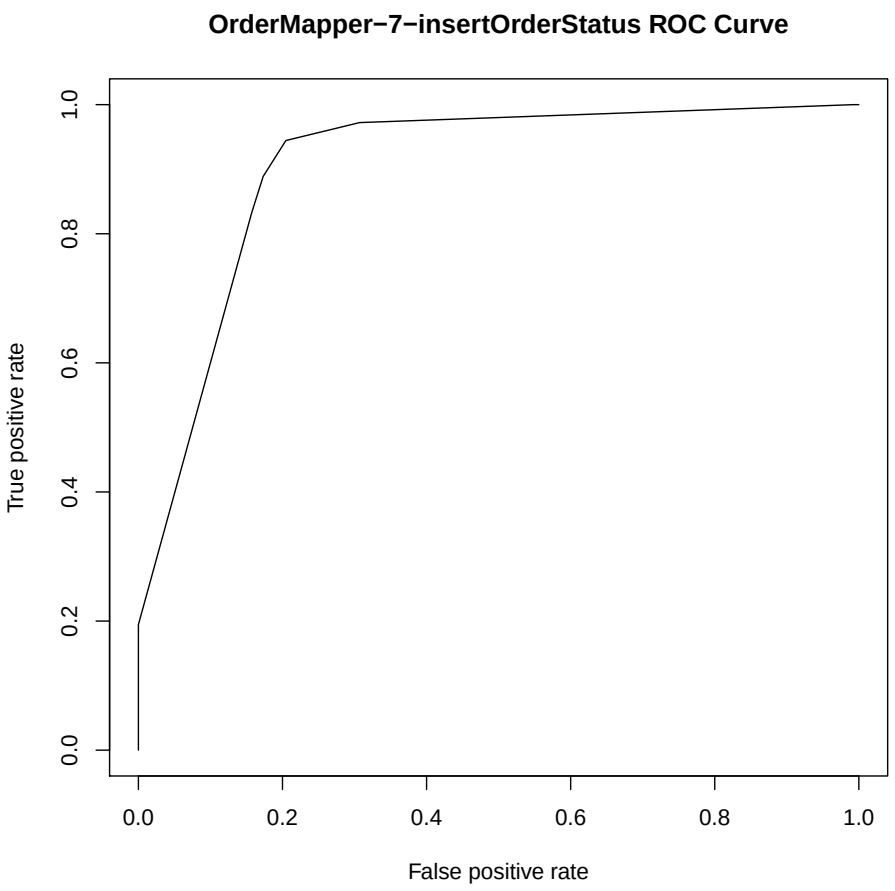
SPM


OrderMapper−7−insertOrderStatus
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Failure probability
0.0
0.2
0.4
0.6
0.8
1.0
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

CPM

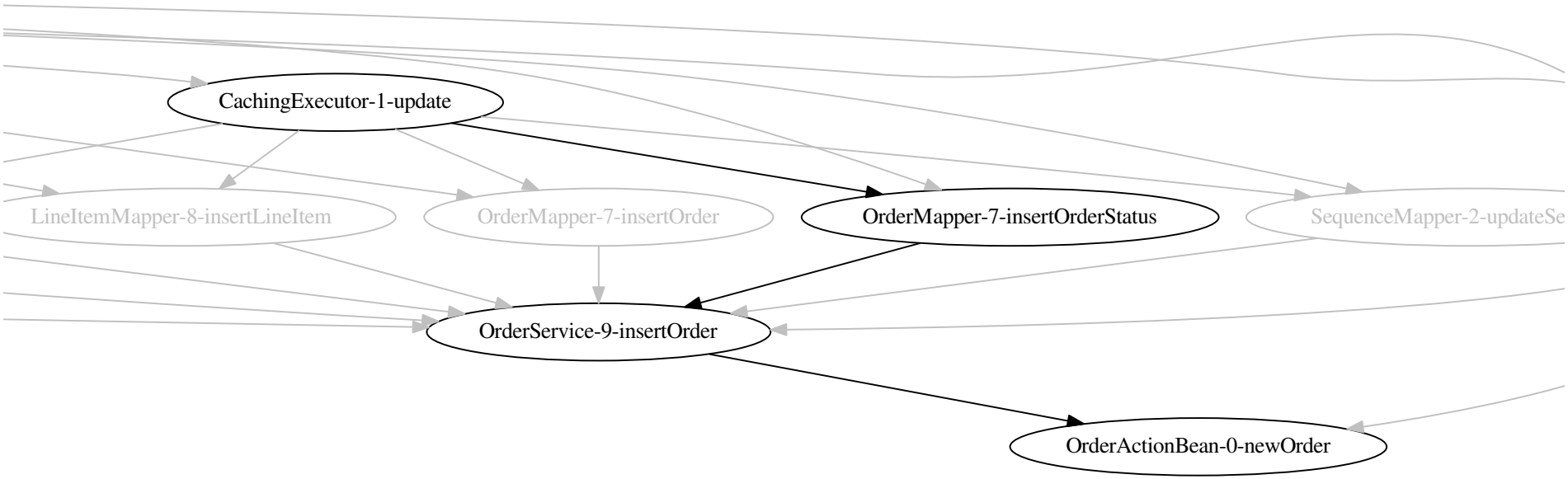

OrderMapper−7−insertOrderStatus ROC Curve
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

SPM

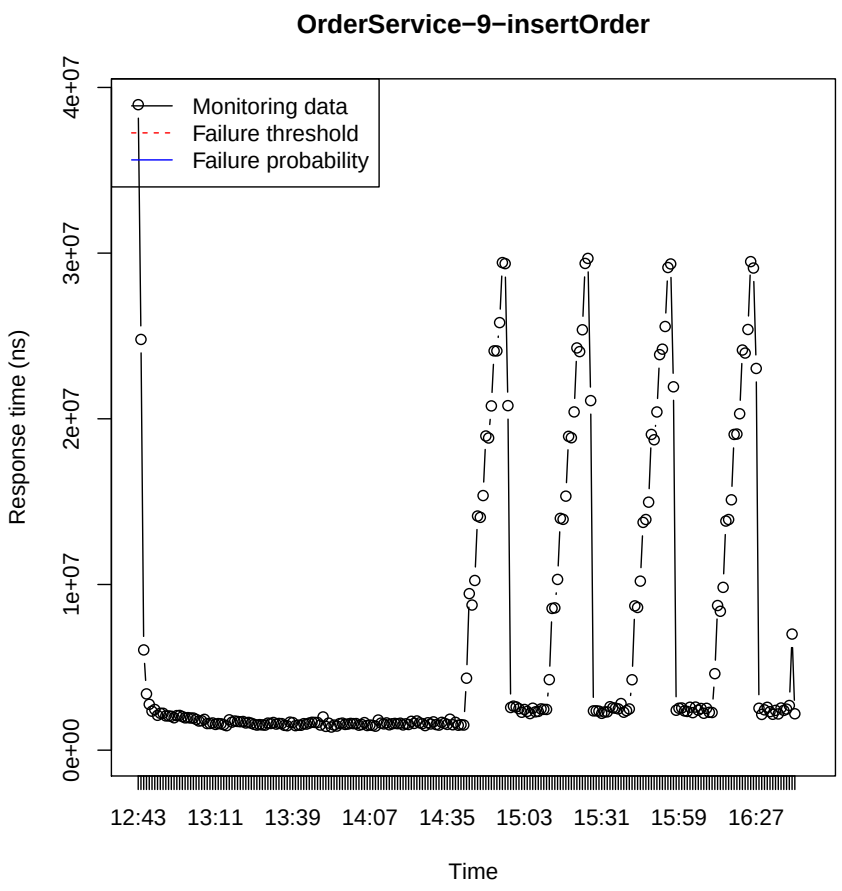

OrderMapper−7−insertOrderStatus ROC Curve
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

SPM for JPetStore

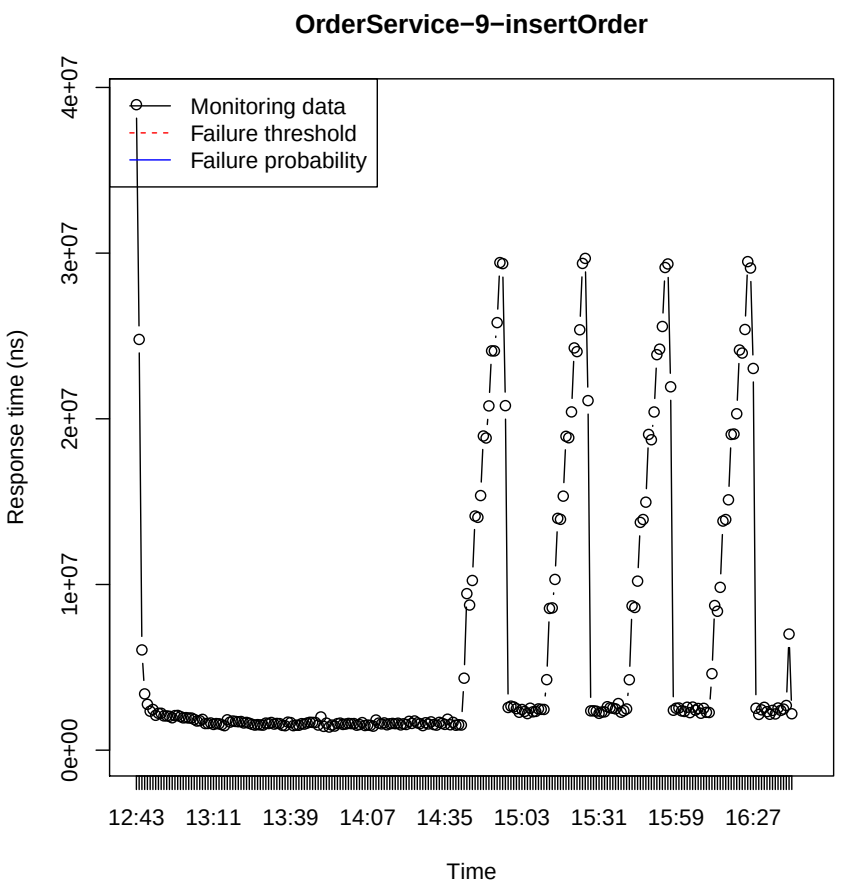
Evaluation



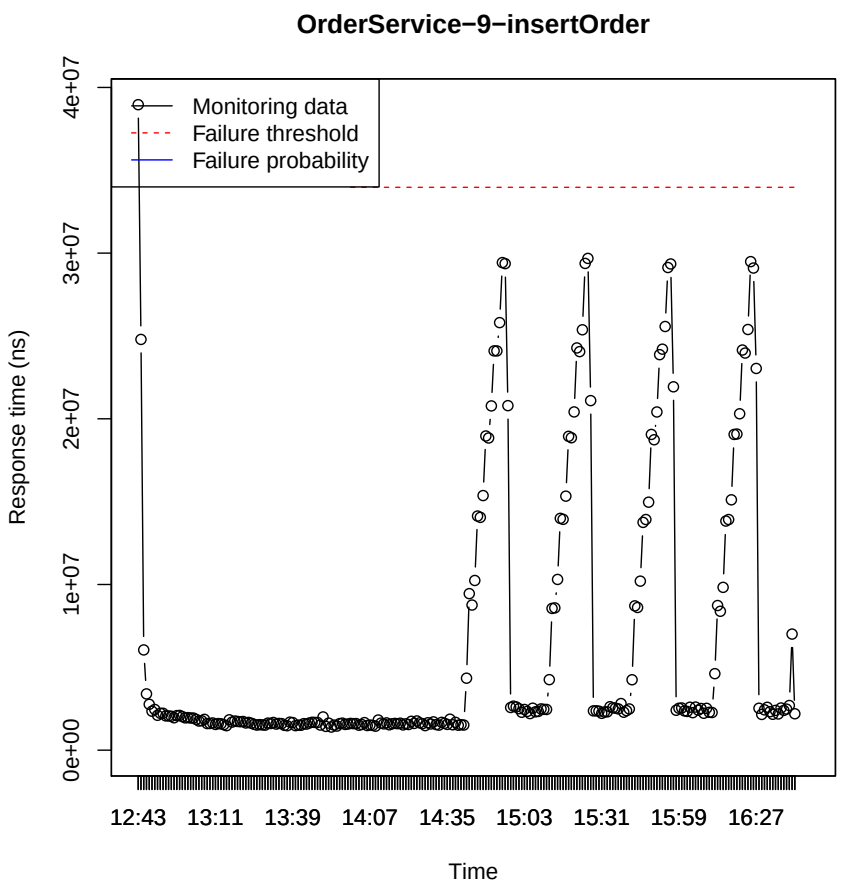
CPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

SPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

CPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
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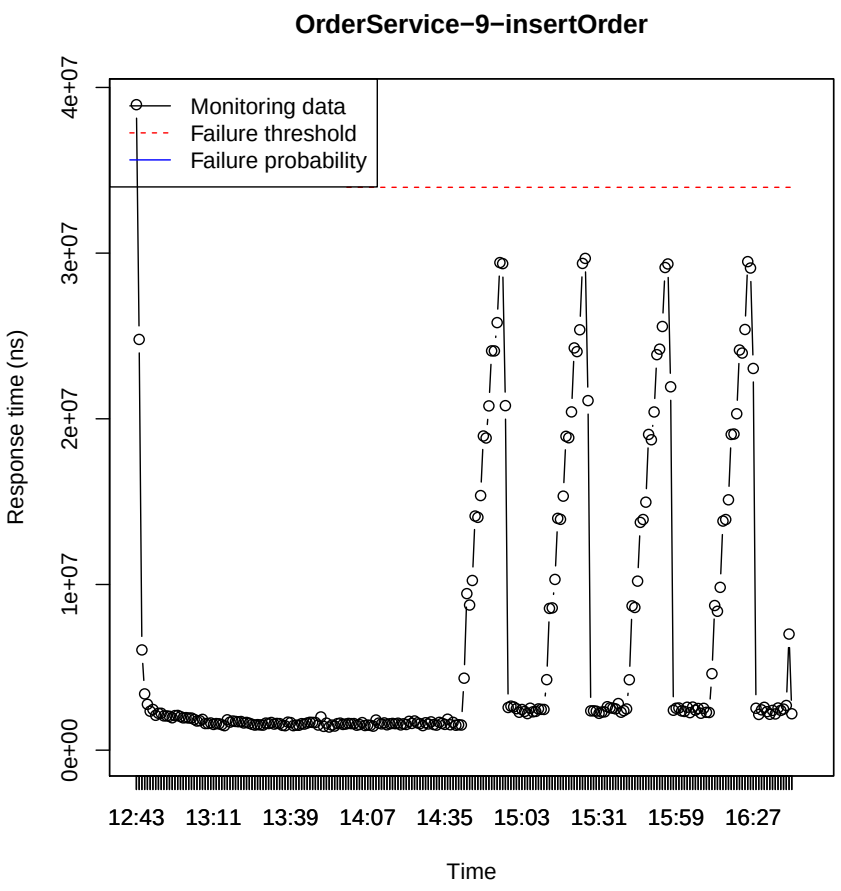
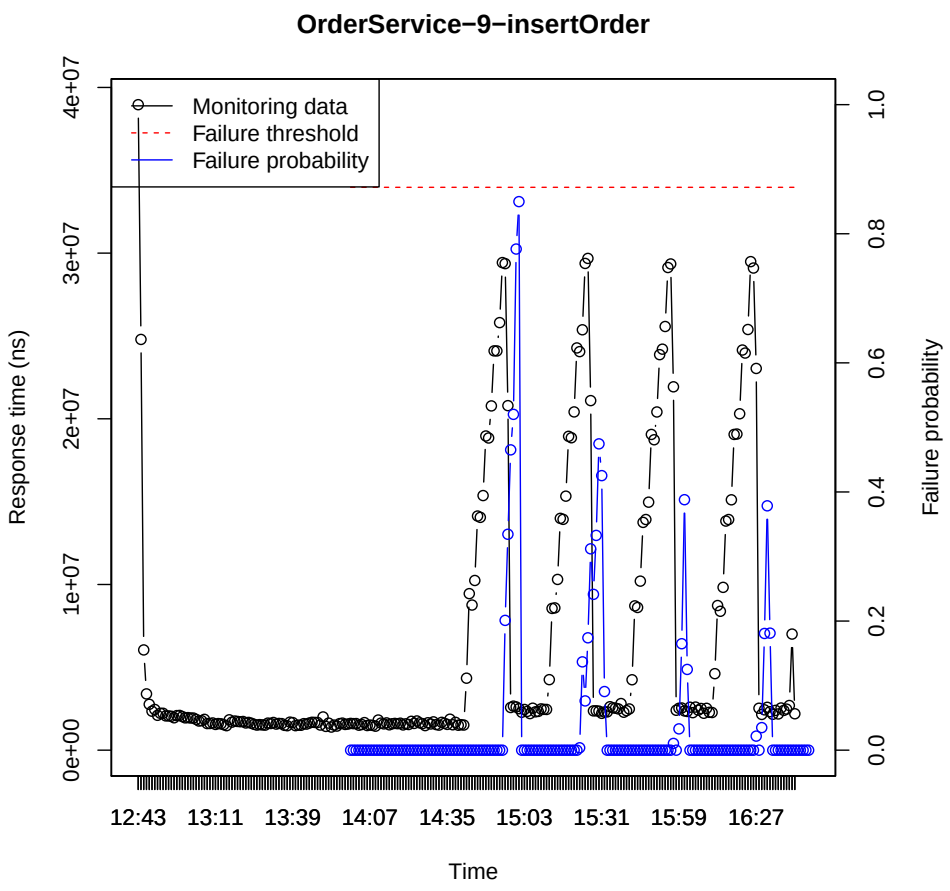
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

SPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

CPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
Failure probability
0.0
0.2
0.4
0.6
0.8
1.0
12:43
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14:07
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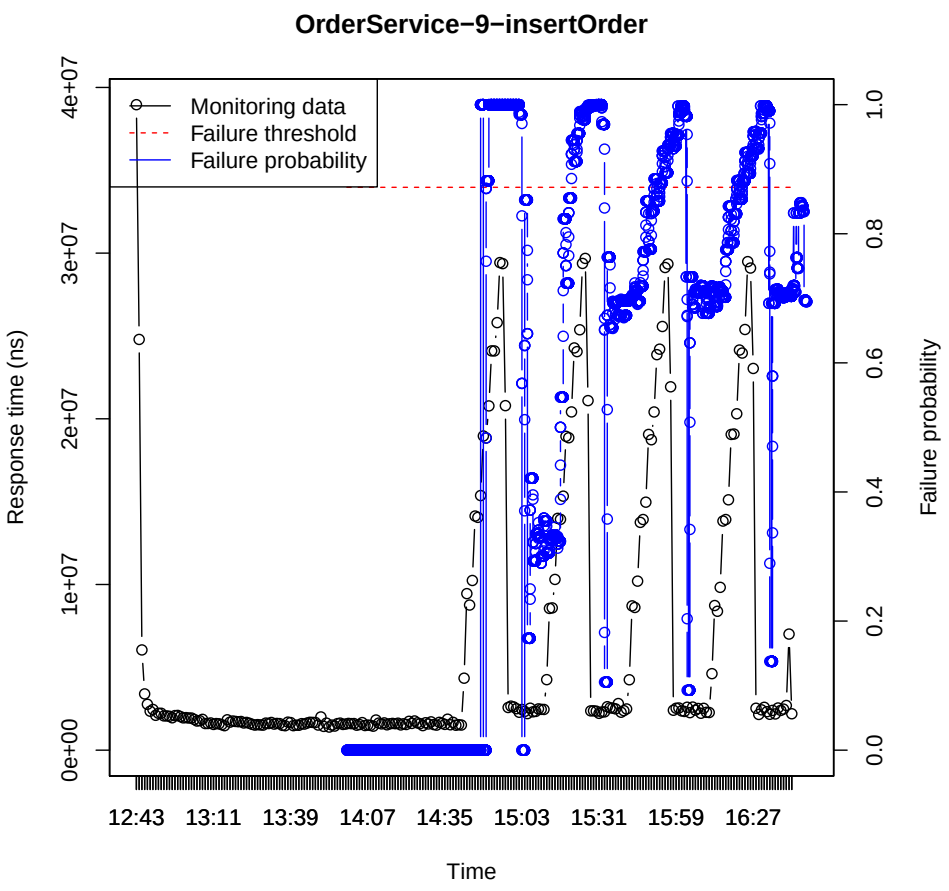
15:59
16:27
Time

SPM


OrderService−9−insertOrder
Monitoring data
Failure threshold
Failure probability
Response time (ns)
0e+00
1e+07
2e+07
3e+07
4e+07
Failure probability
0.0
0.2
0.4
0.6
0.8
1.0
12:43
13:11
13:39
14:07
14:35
15:03
15:31
15:59
16:27
Time

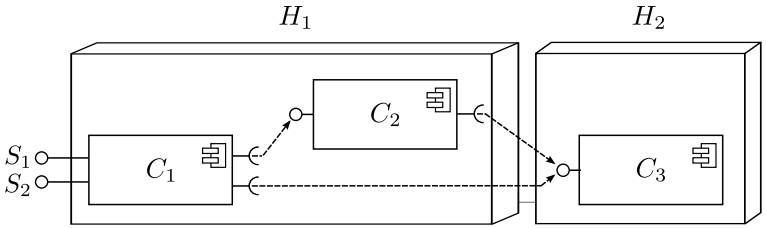
Discussion of Preliminary Results

- CPMs perform quite well but can still be improved
- SPM shows potential to predict failure propagation using component dependency
- Although the failure propagates to other components, the predictions are not very good as the failure thresholds are not set properly

Agenda

Summary

Conclusion



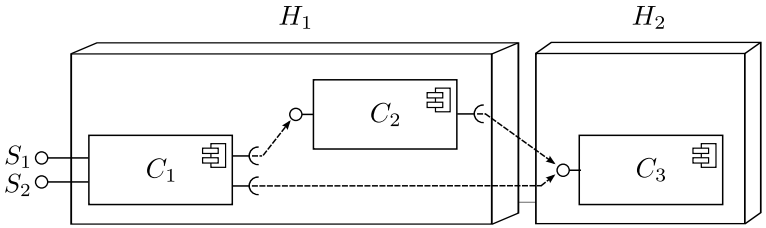
Component-level Prediction Models
+
Component Dependency

⇨

System-level
Prediction Model

Summary

Conclusion

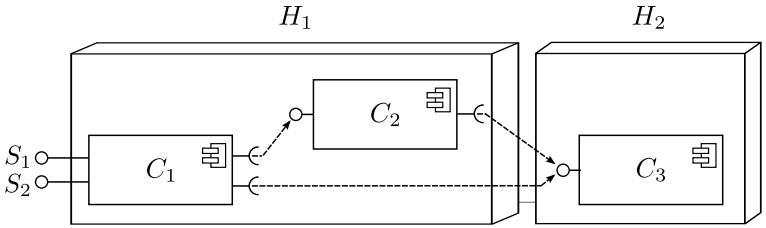


Component-level Prediction Models
+
Component Dependency
⇨
System-level
Prediction Model

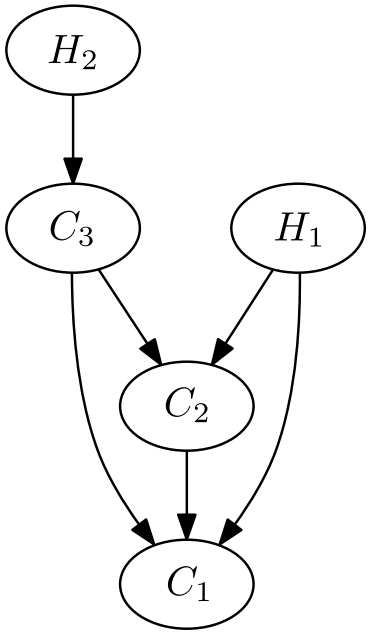
	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

Summary

Conclusion



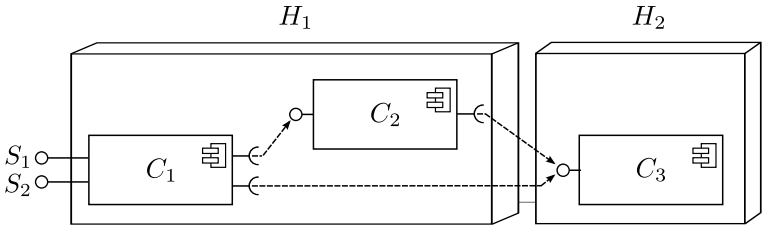
Component-level Prediction Models
+
Component Dependency
⇨
System-level
Prediction Model



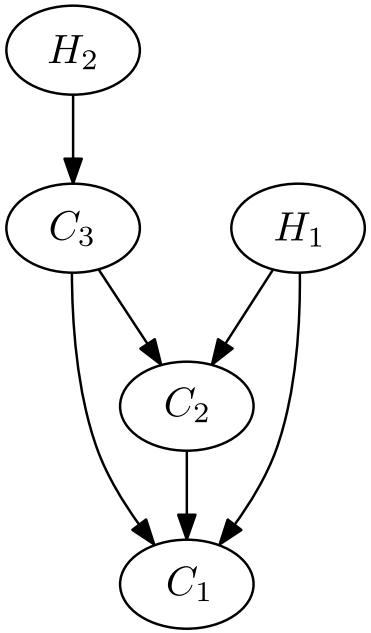
	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

Summary

Conclusion



Component-level Prediction Models
+
Component Dependency
⇨
System-level
Prediction Model



	C_1	C_2	C_3	H_1	H_2
C_1		0.5	0.5	1.0	
C_2			0.5	1.0	
C_3					1.0
H_1					
H_2					

		C_2	
H_1	C_3	✓	✗
✓	✓	0.9	0.1
✓	✗	0.5	0.5
✗	✓	0.0	1.0
✗	✗	0.0	1.0

Next Steps

- Improve prediction of CPMs
  - Apply different prediction techniques
- Calibrate the configuration parameters of Hora
  - Failure threshold
  - Lead time
  - ...
- Extend evaluation settings
  - Evaluate with distributed lab study
  - Evaluate with large-scale production systems
- Develop a failure injection framework/benchmark

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