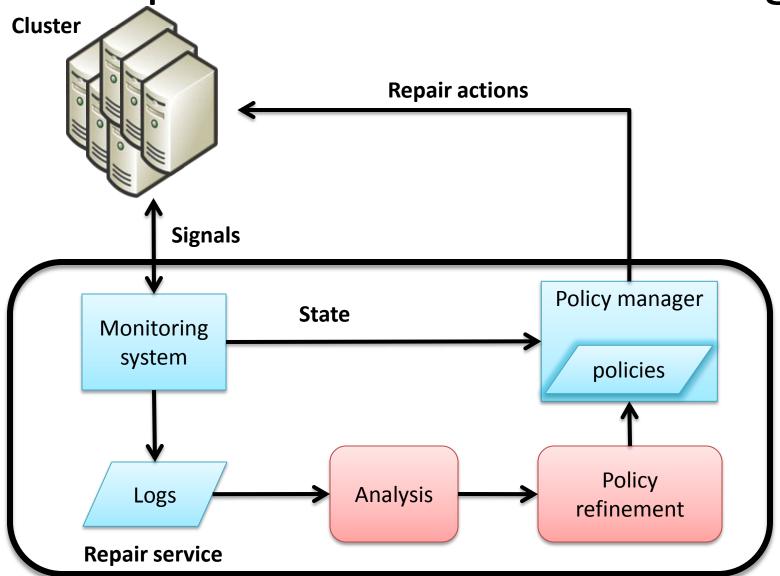
Toward Automatic Policy Refinement in Repair Services for Large Distributed Systems

M. Goldszmidt, M. Budiu, Y. Zhang, M. Pechuk Microsoft

The problem we are addressing



The repair service

Watchdogs: Asynchronously monitoring machines and sending signals E.g.: ping, execute transaction, sample cpu, etc.

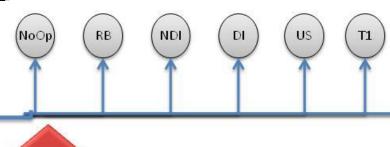


Each machine has a state associated with it



E.g.: healthy, probation, faulty, rebooted once, etc.

State transitions are regulated by an automaton.
A signal or a repair action will cause a state transition



A policy is a function from State to Repair Action

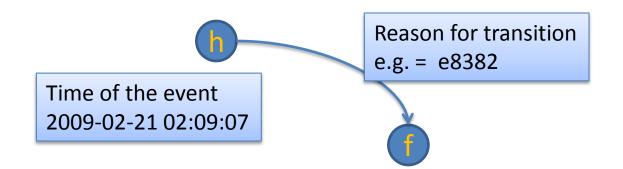
E.g.:

If probation do_nothing.
If rebooted_once reboot.
If dead call tier_1 operator

Logs

Log consists of 3 months of data collected from ~ 2k machines

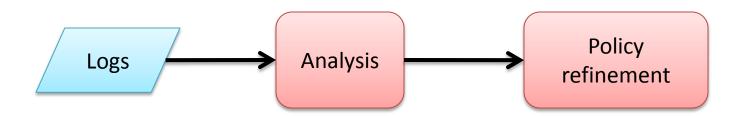
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| 10calTime | FromState | ToState | Reason | HostID | requestor | 2009-02-21 | 02:09:07.733" | H, F, 8382, 14, machine | 2009-02-21 | 02:11:03.377 | F, P, NULL | 14, machine | 2009-02-21 | 04:11:46.780" | P, H, O, 14, machine | 2009-02-21 | 04:56:31.380" | H, F, 8360, 120, machine | 2009-02-21 | 05:01:06.080" | F, P, NULL | 120, machine | 2009-02-21 | 07:07:22.430" | P, H, O, 120, machine | 2009-02-21 | 18:49:21.060" | H, F, 8360, 134, machine | 2009-02-21 | 18:51:14.690" | F, P, NULL | 134, machine | 2009-02-21 | 18:51:14.690" | F, P, NULL | 134, machine | 2009-02-22 | 05:17:26.937" | H, F, 8360, 168, machine | 2009-02-22 | 05:17:26.937" | H, F, 8360, 168, machine | 2009-02-22 | 07:21:50.440" | P, H, O, 168, machine | 2009-02-23 | 11:02:29.197" | H, F, 8360, 184, machine | 2009-02-23 | 11:06:45.733" | F, P, NULL | 184, machine | 2009-02-23 | 11:37:02.417" | P, F, 8383, 184, machine | 2009-02-23 | 11:41:46.473" | F, F, RB, NULL | 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02-23 | 11:47:22.297" | RB, P, O, 184, machine | 2009-02
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Research questions

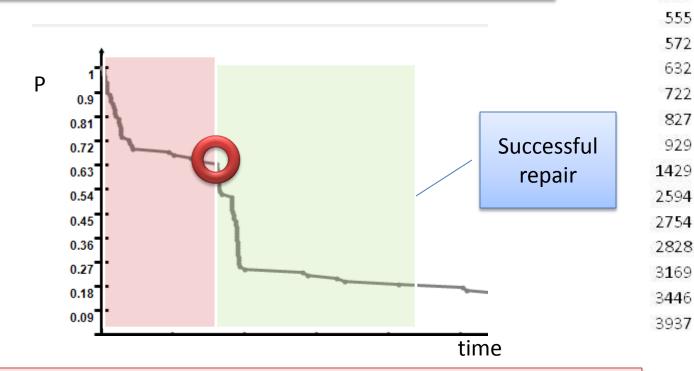
Given the data in the logs:

- 1. Estimate the 'effectiveness' of a repair action What is a "successful" repair action?
- 2. Suggest alternative (better) policies (without intervention)



Effectiveness and success

- Effectiveness \rightarrow time that a machine is 'usable'
- Estimate the survival curve of the repair action



Successful repair = threshold on P of survival and time

1

duration2

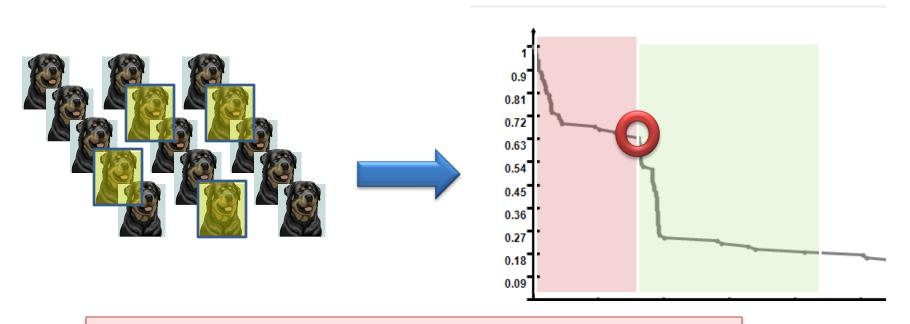
event2

19 134

827

Modeling successful repairs

Automatically find a function from watchdog-signals to success



Machine learning to the rescue: classification with feature selection.

Logistic regression with L1 regularization

Models of success

selected signals: 9

CV BA: 0.872

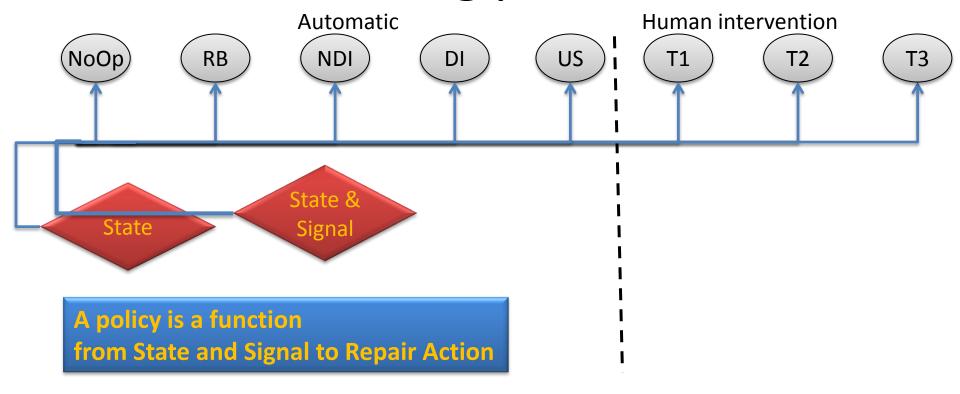
CV confusion matrix:

below above

pred below 89 14 pred above 11 71

	coeffs	ind	threshold
e50202	-0.79	0.965	0.00
e8240	-0.89	0.942	0.00
e8383	0.31	0.692	1.00
e8506	-0.84	0.861	0.00

Refining policies



QoS, Availability costs

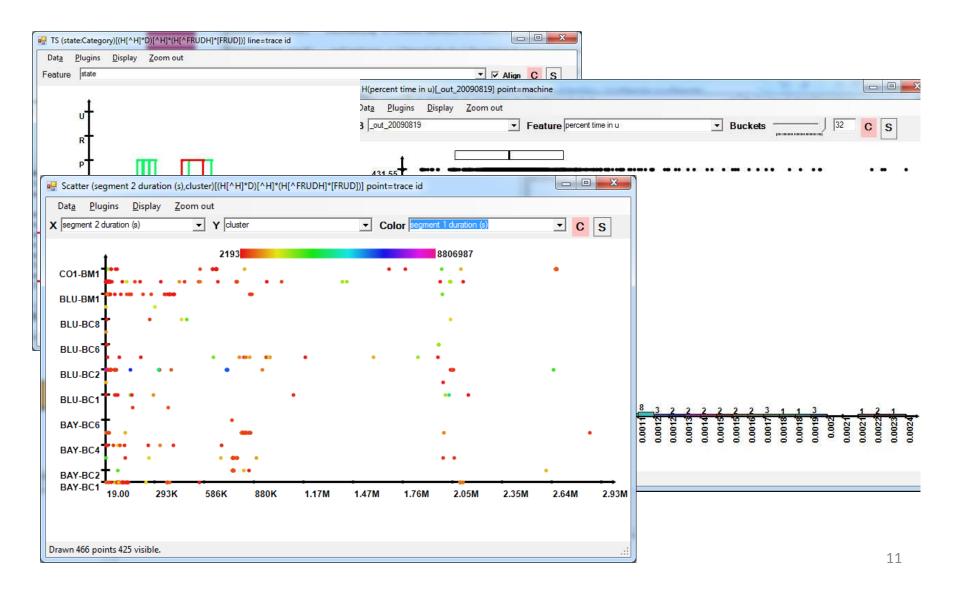
Cost increase

Money, QoS, Availability costs

Data processing (with Artemis)

- 1. Use regular expression to extract segments of data
- 2. Extract duration and censoring events
- 3. Estimate survival curves
- 4. Define success
- 5. Extract the signals before the repair action
- 6. Induce models of success/fail
- 7. Present relevant signals

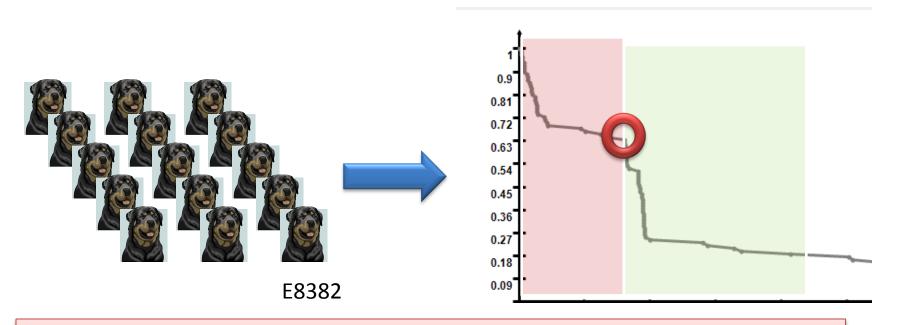
Data visualization (with Artemis)



Results

- Comparing different datacenters
 - Statistical tests on the different survivability curves
 - Visualization (correlation graphs)
- Models for different repair actions

The bad sensor case



How come 1 signal was predicting with 98% accuracy the failure to repair?

Further investigation → faulty sensor!!

New models (3 months after the fix) have a mixture of many signals and E8382 appears as evidence for success...

Faulty repair procedure

Snippet of the T1-REPAIR model

	coeffs ind	threshold
<u>S1</u>	-0.79 0.965	0.00
S2	-0.89 0.942	0.00
54	-0.84 0.861	0.00

S2 is indicative of an easy fix... Why was not effective?

Bug in the repair instructions.... Fixed!

What about S1 and S4?

Final Remarks

- Models directed the debugging of the repair service.
 - Signals that are strong indications of failed repair
 - Signals that are irrelevant
- In two weeks the results helped improve a system that was "hand-tuned" during 6 months
- Further automate the whole workflow
- Induce models of correlated watchdogs
- Correlate to performance data