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Learning Utility-changes for Rule-based Adaptation of Dynamic Architectures

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Additional Key Words and Phrases: self-healing, adaptation rules, architecture-based adaptation, utility

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1 INTRODUCTION

This report details the technical steps taken to train different machine learning models and compares decisions made with these models. We report on the intermediary results for building, validating, and evaluating these models.

Summary of the final results. Here we report on the final results of model training and validation 1

2 PREREQUISITES

Fig. 1 depicts an example of an instantiation of the mrubis runtime model in form of an object diagram. In case of *rule-based adaptation* a rule r is triggered when the pre-condition of the rule (i.e the left hand side) is matched. A match m for rule r is a fragment of the runtime model that satisfies the pre-condition of the rule. Fig. 2 depicts the left hand side of a rule and the gray part of Fig. 1 presents an example for a match of this left hand side of the rules. The change of the state of a component to REMOVED is considered a failure. Such a situation is therefore considered as a match (i.e. trigger) for the repair rules.

3 METHODOLOGY

Figure. 3 represents the proposed methodology together with the activities required to evaluate it.

Evaluation setup. we exported the Prediction Model to an XML exchange format, The prediction model is developed in R and exported to an XML format, pmml (prediction modeling markup language). Each prediction model has a pmml file that can later be instantiated and called from a Java code. This architecture is presented in Figure. 3.

[1] This report provides additional supporting material (code and results), for the corresponding paper submitted to ICAC2018.
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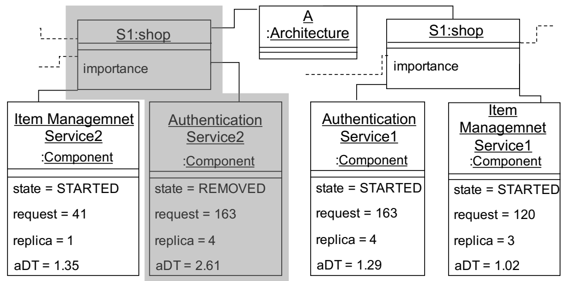

Fig. 1. Instance

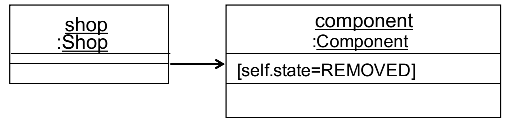

Fig. 2. Rule

4 APPLICATION

4.0.1 Training. The data used for training is publicly available [1]

[1]. https://github.com/christianadriano/ML_SelfHealingUtility/tree/master/data/

Table 1. Final Prediction Models

Method	Number of Trees	Specific hyper-parameters
XGB	500	objective="reg:linear" base_score=0.5 early_stopping_rounds=500 metrics="rmse"
GBM	15000	distribution="gaussian" interaction.depth=10 n.minobsinnode=5 shrinkage=1 bag.fraction=1
RF	100	node.size=5 metrics="rmse"

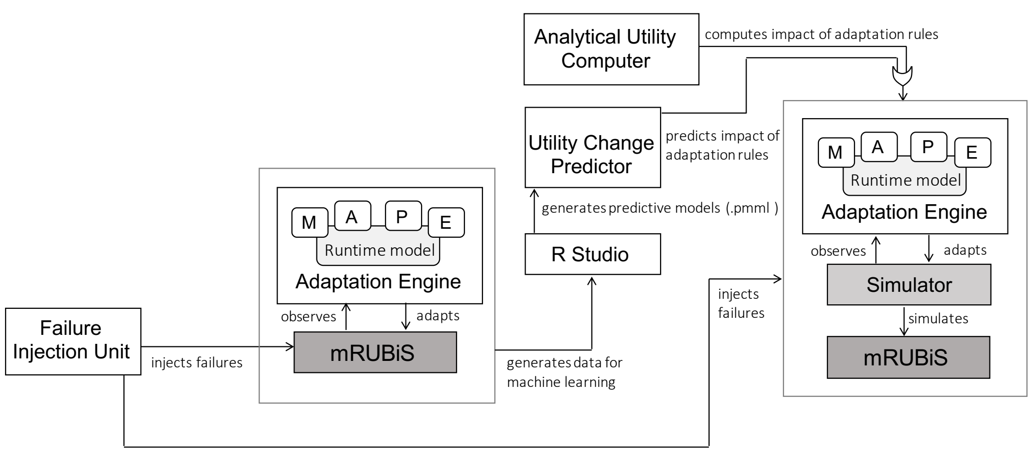

Fig. 3. Methodology and its evaluation activities

Complexity	Dataset_size	Split	Train_RMSE_MEAN	Train_RMSE_STD	Test_RMSE_MEAN	Test_RMSE_STD	RMSE	R_Squared	MAPD_%
Discontinuous	1k	90_10	0.003	0.000	26.774	16.521	3.350	1.000	0.643
Discontinuous	1k	80_20	0.002	0.000	26.879	11.300	22.850	0.990	1.968
Discontinuous	1k	70_30	0.002	0.000	26.091	14.796	32.464	0.980	2.657
Discontinuous	3k	90_10	0.003	0.000	18.549	6.138	6.823	0.999	0.197
Discontinuous	3k	80_20	0.003	0.000	18.275	5.494	11.043	0.998	0.479
Discontinuous	3k	70_30	0.018	0.003	16.528	7.459	13.210	0.997	1.256
Discontinuous	9k	90_10	0.008	0.001	21.963	9.060	4.923	1.000	0.127
Discontinuous	9k	80_20	0.005	0.000	21.739	11.884	5.393	1.000	0.185
Discontinuous	9k	70_30	0.069	0.007	20.633	9.277	21.539	0.994	0.912
Linear	1k	90_10	0.001	0.000	0.237	0.220	0.048	1.000	0.022
Linear	1k	80_20	0.001	0.000	0.294	0.294	0.106	1.000	0.048
Linear	1k	70_30	0.002	0.000	0.277	0.254	0.068	1.000	0.062
Linear	3k	90_10	0.002	0.000	0.584	0.556	0.066	1.000	0.013
Linear	3k	80_20	0.003	0.001	0.553	0.572	0.237	1.000	0.044
Linear	3k	70_30	0.002	0.000	0.726	0.606	0.342	1.000	0.066
Linear	9k	90_10	0.002	0.000	0.200	0.190	0.202	1.000	0.013
Linear	9k	80_20	0.002	0.000	0.137	0.099	0.300	1.000	0.022
Linear	9k	70_30	0.002	0.000	0.206	0.200	0.326	1.000	0.018
Saturating	1k	90_10	0.003	0.001	9.902	4.861	1.800	1.000	0.180
Saturating	1k	80_20	0.019	0.002	11.844	6.543	3.023	0.999	0.479
Saturating	1k	70_30	0.002	0.000	13.409	6.000	4.439	0.999	0.788
Saturating	3k	90_10	0.004	0.000	8.169	3.216	3.174	1.000	0.152
Saturating	3k	80_20	0.141	0.011	7.500	2.315	3.880	0.999	0.419
Saturating	3k	70_30	0.003	0.000	8.263	1.962	5.353	0.999	0.627
Saturating	9k	90_10	0.008	0.001	9.501	3.616	3.299	1.000	0.113
Saturating	9k	80_20	0.035	0.003	9.124	1.958	4.690	0.999	0.248
Saturating	9k	70_30	0.006	0.000	10.182	2.974	6.286	0.999	0.473

Fig. 4. Extreme Boost Trees trained with 500 trees over different datasets and data splits

Utility Type	Model	Dataset Size	RMSE	R_Squared	MADP%	Elapsed Time	Number of Trees
Linear10K	XGB	10K	0.57	1.00	**0.12**	19.61	**448**
Discontinuous10K	XGB	10K	24.84	0.99	**3.09**	22.98	**448**
Saturating10K	XGB	10K	9.28	1.00	**1.32**	24.80	**448**
Combined10K	XGB	10K	161.24	1.00	**1.95**	25.51	**448**

Fig. 5. Extreme Boost Trees trained with 500 trees over different datasets and data splits

XGB model: We first investigated how XGB performed with different dataset sizes under different splits of data between training and validation 4. Since the results of 70/30 split was better, we adopted this split for the other two method types (GBM and Random Forest). The source code that generated the XGB results is available.[2] We also trained XGB with other dataset sizes, 10K and 100k. However, the values for MADP saturated after 10K dataset size (Figure.5). Source code is available[3].

Random Forest - RF:. We investigate if the performance of the model would improve with a higher number of trees and sizes of datasets (Figure.6).

Random Forest - RF-Heavy. We trained a forest with 200 trees to investigate if we could improve MADP without impacting much the execution time. We were not successful with that (Figure.7).

[2] $https : //github.com/christianadriano/ML_Self HealingUtility/blob/master/models/mainControl_XGB.R$
[3] $https : //github.com/christianadriano/ML_Self HealingUtility/blob/master/models/mainControl_XGB.R$

Utility Type	Model	Dataset Size	RMSE	R_Squared	MADP%	Elapsed Time	Number of Trees
Linear	Random Forest	1k	0.28	1.00	**0.25**	13.08	**100**
Linear	Random Forest	3K	0.62	1.00	**0.26**	61.35	**100**
Linear	Random Forest	9K	0.76	1.00	**0.05**	224.22	**100**
Discontinuous	Random Forest	1K	24.80	0.98	**6.43**	49.61	**100**
Discontinuous	Random Forest	3K	27.11	0.99	**4.20**	268.01	**100**
Discontinuous	Random Forest	9K	25.06	0.99	**1.55**	1485.87	**100**
Saturating	Random Forest	1K	8.17	1.00	**2.13**	17.92	**100**
Saturating	Random Forest	3K	10.11	0.99	**1.80**	145.30	**100**
Saturating	Random Forest	9K	11.83	1.00	**1.54**	857.70	**100**
Combined	Random Forest	1K	375.88	0.97	**8.52**	45.43	**100**
Combined	Random Forest	3K	416.38	0.98	**7.24**	181.80	**100**
Combined	Random Forest	9K	429.05	0.98	**4.11**	968.25	**100**

Fig. 6. Random Forests trained with 100 trees across different dataset sizes

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Utility Type	Model	Dataset Size	RMSE	R_Squared	MADP%	Elapsed Time	Number of Trees
Linear	Random Forest	9K	0.74	1.00	**0.05**	335.53	**200**
Discontinuous	Random Forest	9K	25.55	0.99	**1.54**	1427.55	**200**
Saturating	Random Forest	9K	11.71	1.00	**1.53**	1384.28	**200**
Combined	Random Forest	9K	441.13	0.98	**4.09**	1704.05	**200**

Fig. 7. Random Forests trained with 200 trees for 9K dataset size

Utility Type	Model	Dataset Size	RMSE	R_Squared	MADP%	Elapsed Time	Number of Trees
Linear	GBM	1K	0.27	1.00	**0.37**	43.33	**9920**
Linear	GBM	3K	1.03	1.00	**1.37**	114.37	**726**
Linear	GBM	9K	0.83	1.00	**0.58**	331.79	**1342**
Discontinuous	GBM	1K	13.38	0.99	**13.19**	42.31	**9999**
Discontinuous	GBM	3K	14.04	1.00	**4.71**	107.81	**10000**
Discontinuous	GBM	9K	13.32	1.00	**2.94**	309.84	**6158**
Saturating	GBM	1K	4.41	1.00	**1.52**	42.08	**9773**
Saturating	GBM	3K	8.02	1.00	**1.49**	107.42	**10000**
Saturating	GBM	9K	7.15	1.00	**1.15**	311.08	**9999**
Combined	GBM	1K	262.94	0.99	**5.63**	51.75	**9996**
Combined	GBM	3K	288.42	0.99	**4.87**	112.5	**9979**
Combined	GBM	9K	257.20	0.99	**3.73**	316.17	**10000**

Fig. 8. GBM across different dataset sizes

Tuning GBM model: GBM require the largest number of trees compare to the other models. For this reason it also took the longer to be trained as the elapsed time column shows. We trained with 10K trees (Figure.8) and 15K trees (Figure.9). Source code is available[4].

[4] $https://github.com/christianadriano/ML_Self HealingUtility/blob/master/models/mainControl_GBM.R$

Utility_Type	Model	Dataset_Size	RMSE	R_Squared	MAPD%	Elapsed_Time	Number_of_Trees
Linear	GBM	1K	0.47	1.00	**0.82**	69.31	**171**
Linear	GBM	3K	0.87	1.00	**0.91**	179.7	**317**
Linear	GBM	9K	0.64	1.00	**0.23**	526.21	**714**
Discontinuous	GBM	1K	32.31	0.98	**42.69**	83.97	**128**
Discontinuous	GBM	3K	19.33	0.99	**12.61**	221.71	**578**
Discontinuous	GBM	9K	18.52	1.00	**7.78**	752.14	**480**
Saturating	GBM	1K	2.93	1.00	**0.78**	84.45	**14973**
Saturating	GBM	3K	5.41	1.00	**0.74**	234.61	**3445**
Saturating	GBM	9K	5.04	1.00	**0.37**	676.8	**14832**
Combined	GBM	1K	211.20	0.99	**2.72**	94.17	**14812**
Combined	GBM	3K	247.39	0.99	**3.27**	203.19	**1060**
Combined	GBM	9K	198.15	1.00	**1.24**	524.32	**14954**

Fig. 9. GBM across different dataset sizes

Complexity	Dataset_size	Split	Train_RMSE_MEAN	Train_RMSE_STD	Test_RMSE_MEAN	Test_RMSE_STD	RMSE	R_Squared	MAPD_%
Discontinuous	1k	90_10	0.003	0.000	26.774	16.521	3.350	1.000	0.643
Discontinuous	1k	80_20	0.002	0.000	26.879	11.300	22.850	0.990	1.968
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Discontinuous	3k	90_10	0.003	0.000	18.549	6.138	6.823	0.999	0.197
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Discontinuous	3k	70_30	0.018	0.003	16.528	7.459	13.210	0.997	1.256
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Linear	1k	90_10	0.001	0.000	0.237	0.220	0.048	1.000	0.022
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Linear	3k	80_20	0.003	0.001	0.553	0.572	0.237	1.000	0.044
Linear	3k	70_30	0.002	0.000	0.726	0.606	0.342	1.000	0.066
Linear	9k	90_10	0.002	0.000	0.200	0.190	0.202	1.000	0.013
Linear	9k	80_20	0.002	0.000	0.137	0.099	0.300	1.000	0.022
Linear	9k	70_30	0.002	0.000	0.206	0.200	0.326	1.000	0.018
Saturating	1k	90_10	0.003	0.001	9.902	4.861	1.800	1.000	0.180
Saturating	1k	80_20	0.019	0.002	11.844	6.543	3.023	0.999	0.479
Saturating	1k	70_30	0.002	0.000	13.409	6.000	4.439	0.999	0.788
Saturating	3k	90_10	0.004	0.000	8.169	3.216	3.174	1.000	0.152
Saturating	3k	80_20	0.141	0.011	7.500	2.315	3.880	0.999	0.419
Saturating	3k	70_30	0.003	0.000	8.263	1.962	5.353	0.999	0.627
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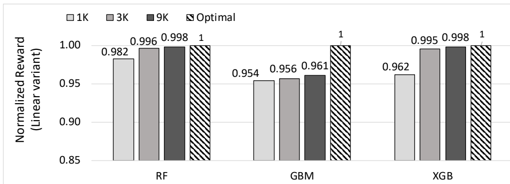
Saturating	9k	80_20	0.035	0.003	9.124	1.958	4.690	0.999	0.248
Saturating	9k	70_30	0.006	0.000	10.182	2.974	6.286	0.999	0.473

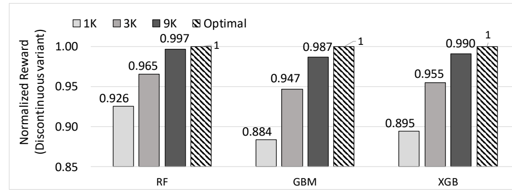
Fig. 10. XGB across different dataset sizes

5 EVALUATION

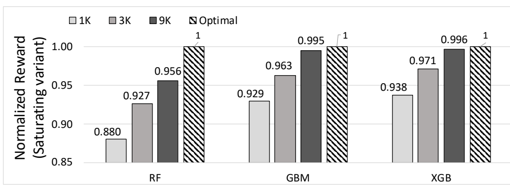
We evaluted the prediction models under for different dataset sizes. Results can be compared in Figure. 11



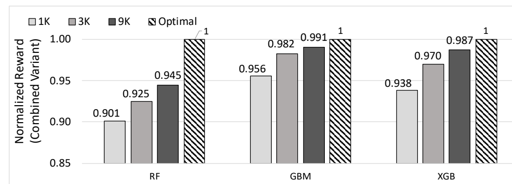
(a) Linear variant



(b) Discontinuous variant



(c) Saturating variant



(d) Combined variant

Fig. 11. Normalized reward of variants across learning methods and dataset sizes