# Supplemental material for the article: "Learning-to-Rank vs Ranking-to-Learn: Strategies for Regression Testing in Continuous Integration"

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### A ONLINE SUPPLEMENTAL MATERIAL

This appendix is available online for reviewers' use at the following anonymized GitHub repository:

https://github.com/icse20/RT-CI.

Material for verifiability and replicability of the experiments is at the same repository.

The appendix contains: the settings of the prioritization algorithms; results for RQ1, RQ2 and RQ3 not presented in the main article for the sake of space.

## A.1 Algorithm parameters

Table 1 reports the parameters setting of the experimented algorithms. In all the cases except two, the default parameters are adopted: for RankNet and LambdaMART, due to overfitting causing NaN occurrences in the ranking, we needed to lower the number of epochs and trees, respectively, until obtaining a valid result.

## A.2 RQ1

Figures 1a-1f and 2a-2f report the *RPA* and *ranking time* boxplots for each subject.

Figures 3a-3f report the total training times (ms) per subject, in logarithmic scale.

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Table 1: Algorithms parameters settings

Algorithm	Parameters						
KNN	k=4						
RF	Tree=100	SplitCriterion =					
		Information Gain Ratio					
RF	Tree=100						
L-MART	Tree=30	Leaf=10					
MART	Tree=1000	Leaf=10					
RankBoost	round = 300						
RankNet	Epoch=50	Layer=2					
CA	randomRestarts=5	iterations=25					
RL	Layer=1	Neurons=12					
RL-MLP	Layer=4	Neurons=12					
RL-RF	Tree=100	SplitCriterion =					
		Information Gain Ratio					
RL-RF	Tree=100						

## A.3 RQ2

Figures 4a-4f reports the  $T^2$  Hotelling's statistic used to summarize the trend of the code metrics, computed on a set of principal components able to explain at least the 95% of the original metrics variance.

# A.4 RQ3

Table 2f reports, for each subject, the difference between the tests execution times taken from the 25%, 50% or 75% of the list of tests sorted according to the *optimal* ranking and those taken from the 25%, 50% or 75% of the list of tests sorted according to the *predicted* ranking. Similarly, the difference between the total number of failing tests considering the 25%, 50% or 75% of optimal and predicted ranking.

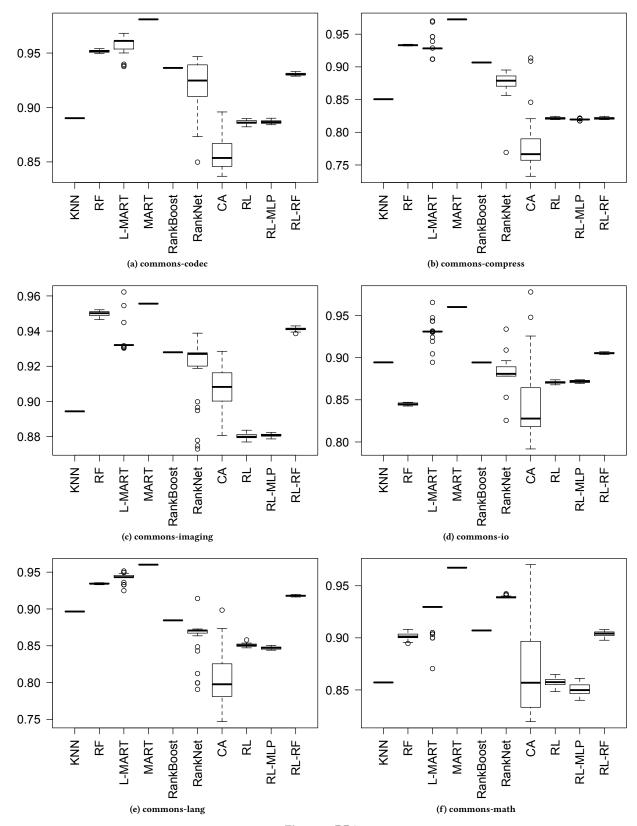


Figure 1: RPA

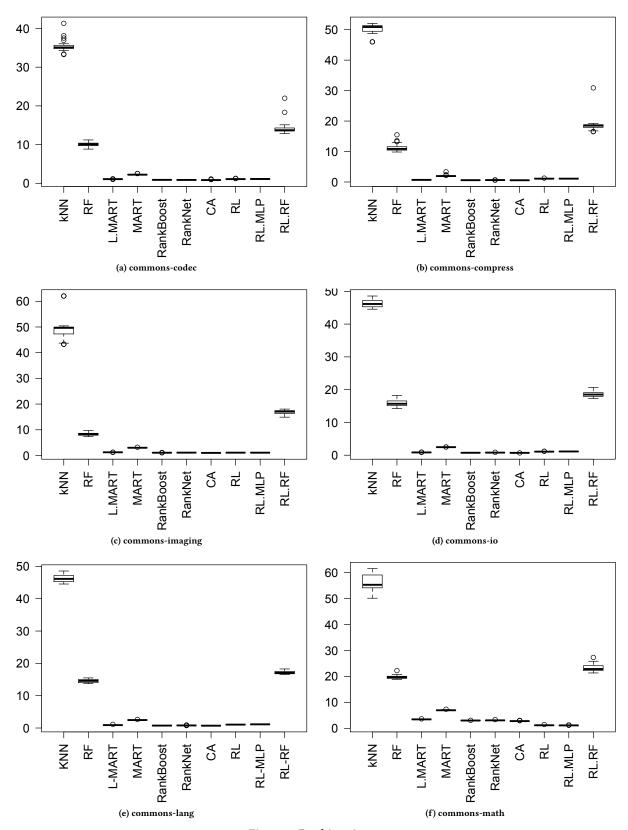


Figure 2: Ranking time

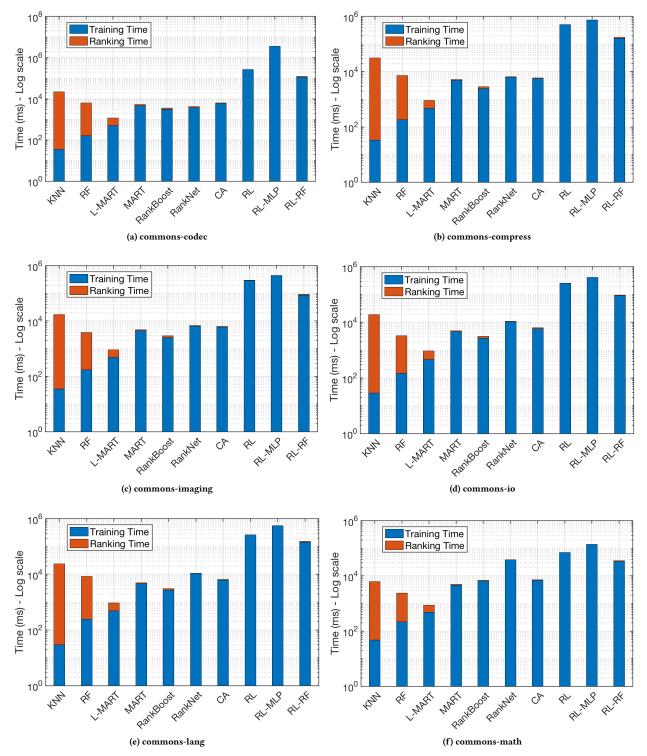


Figure 3: Training time

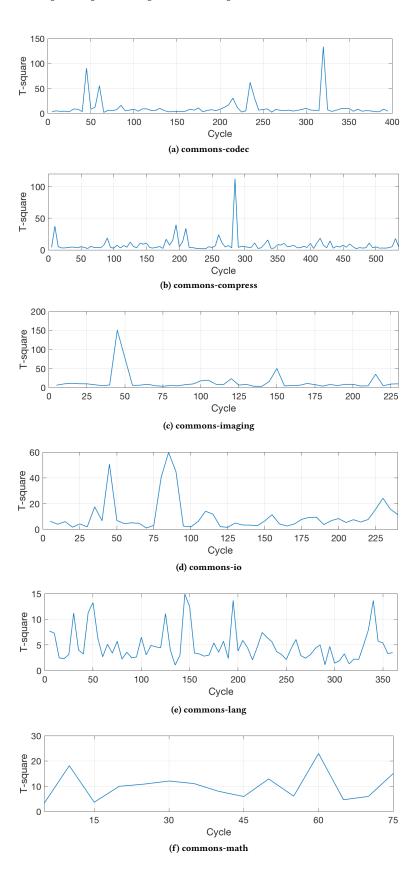


Table 2: Optimal-predicted difference of tests execution times (ms), averaged over all the commits and subjects, and of total number of failing tests, averaged over subjects

(a) commons-codec						(b) commons-compress							
Algorithms		Time-constrained scenarios					Algorithms		Time	-constra	ined sce	narios	
		25%		50%		75%			25%		50%	7	75%
	Time	Failures	Time	Failures	Time	Failures		Time	Failures	Time	Failures	Time	Failures
KNN	0.2846	0.0000	0.5775	0.0000	0.9354	0.0000	KNN	0.2951	0.0000	0.7672	0.0000	1.7559	0.0000
RF	0.0196	0.0000	0.1166	0.0000	0.3651	0.0000	RF	0.0386	-5.2000	0.4788	-1.2000	1.3699	0.0000
L-MART	0.0298	0.0000	0.3240	0.0000	0.6993	0.0000	L-MART	0.0366	-6.8000	0.2798	-4.8000	0.7783	-0.8000
MART	0.0103	0.0000	0.0680	0.0000	0.0205	0.0000	MART	0.0120	0.0000	0.0136	0.0000	0.0819	0.0000
RankBoost		0.0000	0.5288	0.0000	0.5511	0.0000	RankBoost	0.2848	0.0000	0.9204	0.0000	1.1516	0.0000
RankNet	0.2633	0.0000	0.4158	0.0000	0.5592	0.0000	RankNet	0.3164	-4.0000	0.8582	-1.6000	1.2750	-0.4000
CA	0.6300	-5.4000	0.8352	0.0000	0.8903	0.0000	CA	0.8784	0.0000	1.4143	-4.2000	1.7709	-3.0000
RL	0.2967	-1.0000	0.5357	0.0000	0.6005	0.0000	RL	0.6250	-15.5000	1.1784	-12.2000	1.6203	-8.4000
RL-MLP	0.2707	-1.0000	0.5257	0.0000	0.5641	0.0000	RL-MLP	0.6521	-17.4000	1.2036	-13.3000	1.6207	-6.2000
RL-RF	0.0510	-1.0000	0.2363	-1.0000	0.5359	-1.0000	RL-RF	0.0311	-22.0000	0.6720	-10.8000	1.8496	-5.8000
(c) commons-imaging						(d) commons-io							
Algorithms		Time-constrained scenarios			Algorithms		Time-constraine			scenarios			
-		5%		0%		5% F. :1	-		5%		50%		75%
		Failures		Failures		Failures			Failures		Failures		Failure
KNN		0.0000			4.0614	0.0000	KNN	1.5958	-2.0000	4.9703			
	0.0814	0.0000			3.8510	0.0000	RF	5.3489	-1.0000	12.7569	-0.8000		
L-MART		0.0000		0.0000		0.0000	L-MART	0.6970	-2.0000	2.4218		8.9455	
MART		-2.0000			0.1173	0.0000	MART	0.0170	-4.0000	0.2378		0.1483	
RankBoost		0.0000			2.1156	0.0000	RankBoost	8.0699	-2.0000	9.7164			
RankNet		0.0000			3.3407	0.0000	RankNet	4.2097	-0.4000	8.0319		9.1499	
	1.0650	-1.2000			3.6653	0.0000		10.3991	-2.2000	13.5966			
	1.7687	-1.4000			4.6458	-0.1000	RL	5.4701	-3.0000	9.6149			
RL-MLP		-1.5000			4.7758	-0.7000	RL-MLP	5.0147	-3.2000	9.6170			
RL-RF	0.0529	-1.2000	1.7756	0.0000	5.0547	0.0000	RL-RF	3.1774	-6.0000	9.3008	-6.0000	16.6132	2 -3.000
(e) commons-lang						(f) commons-math							
Algorithms	3	Time-constrained sce				Algorithms					ained scenarios		
	———	25% Failures		50% Failures		75% Failures	-		25% Failures		50% Failures		5% Failures
KNN		4 -4.0000					KNN		-6.0000				-6.0000
	0.0309		0.2227		1.4451			0.1043			-6.0000		-6.0000
L-MART			1.1242		1.7714		L-MART				-6.0000		-6.0000
	0.0115		0.0244		0.0605			0.0150	0.0000	0.0177	-6.0000		-6.0000
RankBoost			1.6340		2.0571		RankBoost		-6.0000		-6.0000		-6.0000
RankNet			0.8609		0.9708		RankNet				-6.0000		-6.0000
	0.1823				1.6984				-0.0000				-6.0000
	0.5868		1.5273					1.0478	-7.4000	1.4488	-6.0000 4.5000		
			1.1955		1.6581			2.5887			-4.5000		-2.8000
RL-MLF			1.1720		1.6530		RL-MLP				-4.6000		-3.4000
RL-RF	0.0281	-4.0000	0.3530	-4.0000	1.8433	0.0000	RL-RF	0.1372	-9.0000	1.4215	-5.4000	4.8902	-4.3000