Predicting code defects using interpretable static measures

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Agenda

1. Problem
2. Data
3. Methodology
4. Results

Introduction

basic measures

μ

N

G

n

McCabe and Halstead's measures

$e = 1 / D$

$V = N * \log2(\mu)$

$D = 1 / L$

$L = V / n * \mu$

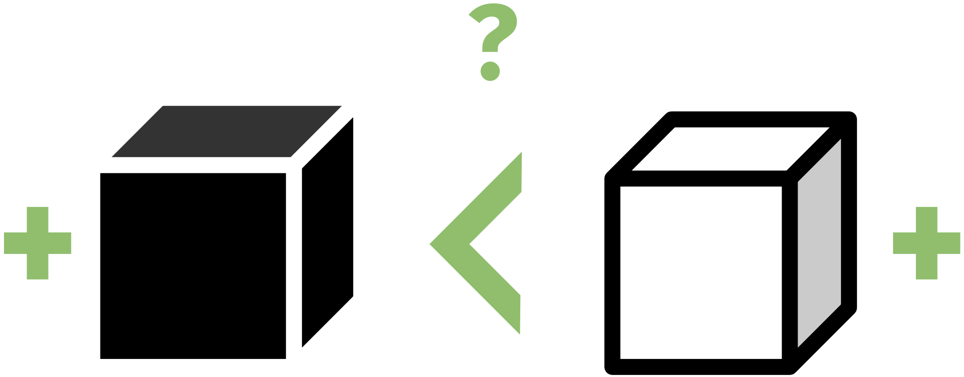
Introduction

μ

N

G

n



$e = 1 / D$

$V = N * \log2(\mu)$

$D = 1 / L$

$L = V / n * \mu$

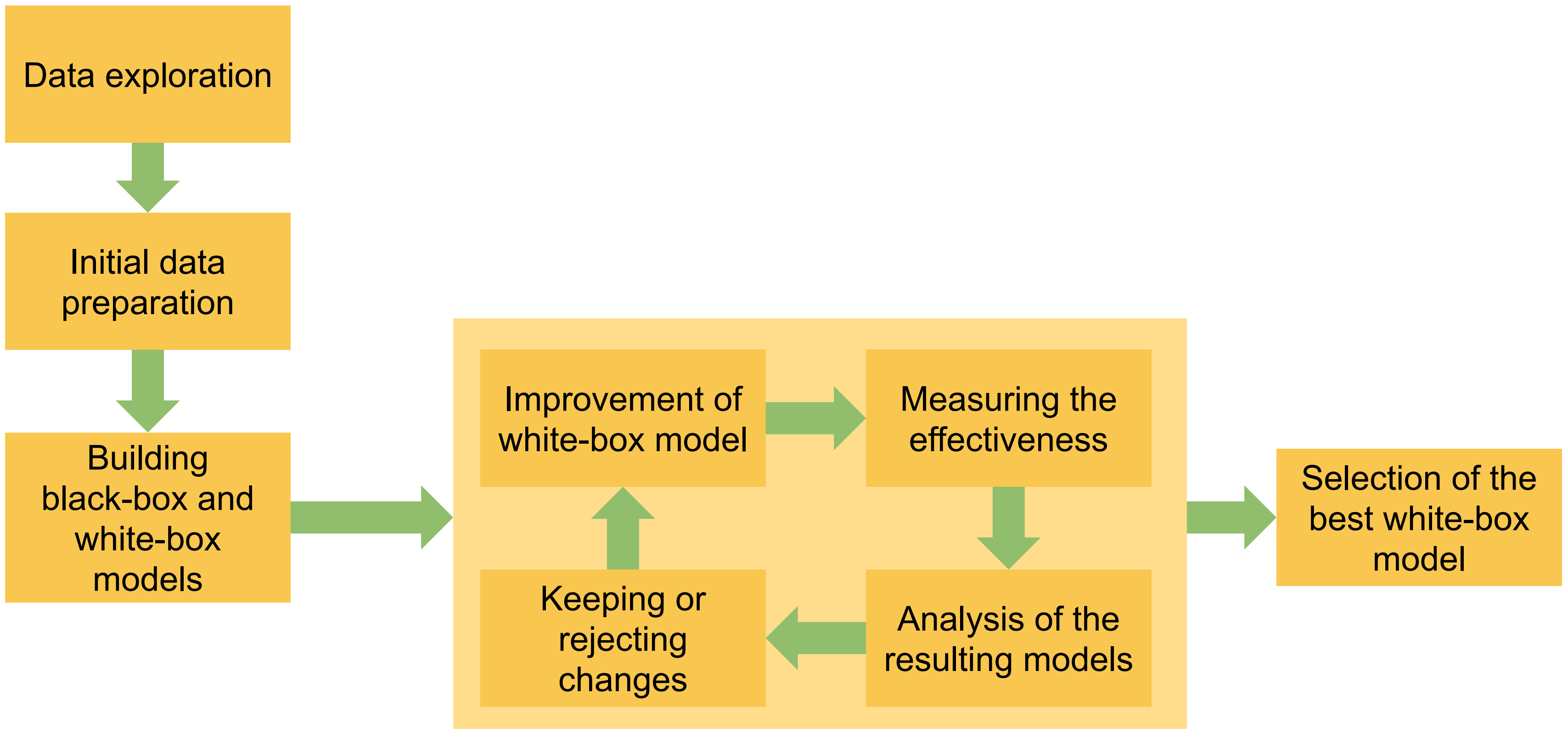
Data

23

15123

μ	N	G	D	b	...	defect
1.2	2	1.4	1.3	1.3	...	TRUE
1.0	1	1.0	1.0	1.0	...	FALSE
17.0	51	7.0	20.31	23029.10	...	FALSE
...	...	...	...	...	...	...

Methodology



Results

The main goal was to beat the ranger model AUC: 0.7916

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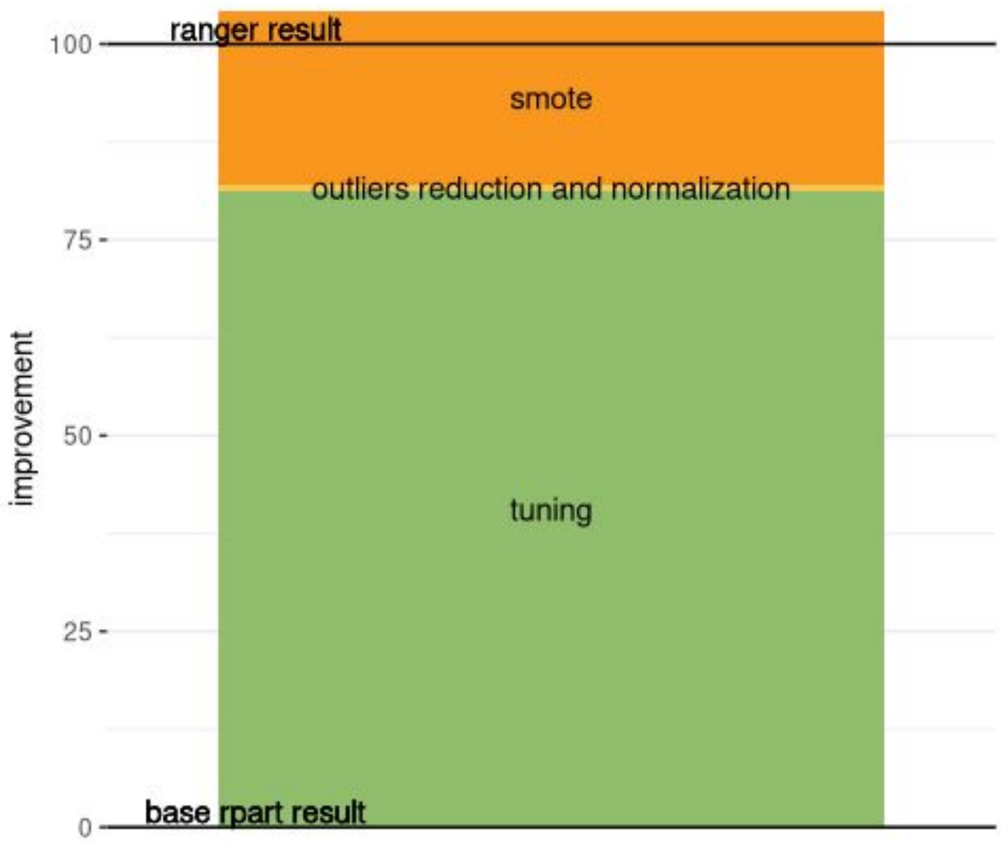
AUC results for white-box models

Operation	logreg	kknn	rpart
Base	0.7347	0.7275	0.5000
Rpart tuning	0.7347	0.7275	0.7369
Outlier reduction and normalization	0.7433	0.7320	0.7394
New features selected by ranger	0.7472	0.7288	0.7334
Smote without new features	0.745	0.736	0.804

AUC improvement relative to the base difference



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