Using Source Code Metrics and Multivariate Adaptive Regression Splines to Predict Maintainability of Service Oriented Software

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Maintainability Prediction - Service Oriented Software

Service-Oriented Computing (SOC) paradigm is the dominant development platform for software systems

One most effective way to control the maintenance costs is to utilize software metrics during the development phase

Web Services are observed to be described using a WSDL (Web Service Description Language) document

Maintainability prediction for web service interfaces and WSDL documents is relatively unexplored

Research Aim

Aim 1: To investigate the usefulness of metrics for the source code implementing a web service for maintainability prediction

Aim 2: To examine the application of multivariate adaptive regression splines (MARS) method to build estimators based on source code metrics as predictor variables and maintainability as target variable

Aim 3: To compare the performance of MARS model with performance of the model developed using multivariate linear regression models (MLR), and support vector machine (SVM) methods

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Literature Survey and Analysis

Bingu Shim et al. [131]

Authors observed that quality attributes depends on various number of design properties, i.e., consumability, cohesion, coupling, complexity, size, different types of granularity. They derive metrics and compute the relation between design metrics and quality

Cristian Mateos et al. [100]

Authors work on the hypothesis that object-oriented source code metrics avoid the occurrence of anti-pattern. They considered twelve different types of source code metrics such as: AMC, CAM, CBO, WMC, LOC, LCOM, LCOM3, RFC, EPM, VTC, ATC, DAM to find the anti-pattern occurrence at the WSDL level

Literature Survey and Analysis

Mikhail Perepletchikov et al. [119][120]

Authors propose cohesion and coupling metrics for predicting maintainability parameters of Service-Oriented Software [119] [120]. Authors redefined the cohesion and coupling metrics for service-oriented software

Yu, Yijun [148]

OO source code metrics are being used for quality indicators of SOA system [148] [100] [39]

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Unique and Novel Contributions

[1] Development of Data Collection and Preparation Process

[2] Development of a maintainability prediction model for service oriented application using MARS and source code metrics

[3] Selection of right set of source code metrics to improve the performance of maintainability prediction model

[4] Empirical analysis to demonstrate the effectiveness of the proposed approach

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Source Code Metrics

11 Different Source Code Metrics

1. Depth of inheritance tree (DIT)
2. Weighted method per class (WMC)
3. Coupling between object (CBO)
4. Number of children (NOC)
5. Number of methods (NOM)
6. Lack of cohesion among methods (LCOM)
7. Response for class (RFC)

Source Code Metrics

11 Different Source Code Metrics

8 Data abstraction coupling (DAC)

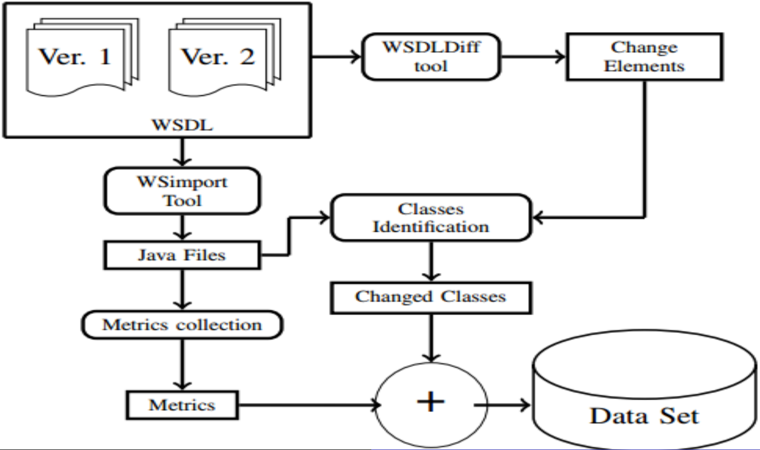
9 SIZE2

10 SIZE1

11 McCabe Cyclomatic complexity (MVG)

Source code metrics are computed using tool such as CKJM and LOC metrics. These metrics include the popular metrics suite proposed by Chidamber and Kemerer [35], and Li and Henry [92]

Data Collection and Preparation Process



Data Collection and Preparation Process

Step 1: WSDLDiff Tool

WSDLDiff tool is used for comparing subsequent versions of WSDL interfaces ([38]) and finding the name (Operation, Message etc.) and type (addition, move, removed, update etc.) of the elements affected by the changes

Step 2: WSimport Tool

Wsimport tool is used to parse WSDL document of web-service and generate Java files

Data Collection and Preparation Process

Step 3: Metrics Collection

Metrics values of source code are computed using tools such as CKJM and LOC metrics

Step 4: Class Identification

The Java classes which contain the changed elements (Operation, Message etc.) are termed as changed classes. These types of classes containing changed elements are identified

Step 5: Data Set

The change statistics from Step 4 and metrics from Step 3 are combined to generate dataset for further processing

eBay Web Service

Version	# classes	LOC	# changed classes	# non-changed classes	% changed classes
863	1507	1320264	175	1332	11.61
865	1507	1320576	102	1405	6.77
867	1524	1335460	240	1284	15.75
869	1509	1322904	128	1381	8.55
871	1509	1323080	119	1390	7.89

The number of classes for all the five versions are more than 1500. The percentage of changed classes from eBay version 863 to eBay version 865 is 11.61 and the the percentage of change classes from 865 to 867 is 6.77

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Model Variables

Analysis	Dependent Variable	Independent Variable
A1	Maintainability	DIT, WMC, NOC, RFC, CBO, NOM, LCOM, MVG, DAC, SIZE1, SIZE2
A2	Maintainability	Reduced feature attributes using feature ranking techniques
A3	Maintainability	Extracted feature attributes using feature subset selection techniques

Maintainability or change is considered as a dependent variable and set of source code metrics as a independent variables respectively

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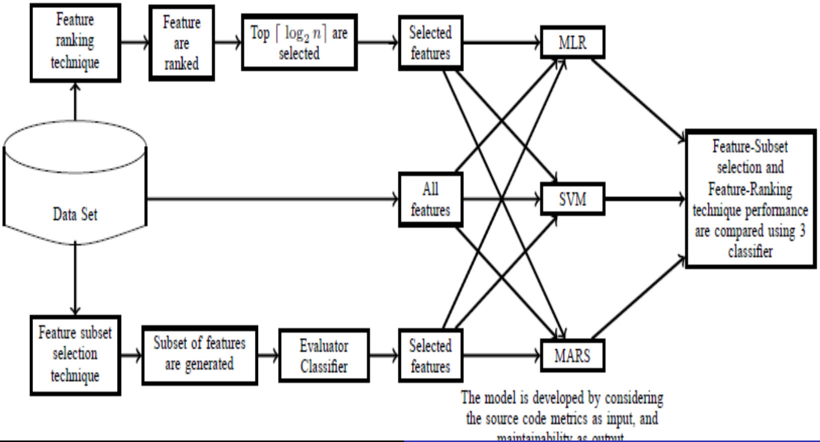
Research Methodology



Research Methodology

Four types of FR techniques and four types of FSS techniques to select optimal set of source code metrics. These all selected set of source code metrics are applied on five different versions of eBay dataset

A total of 135 ((1 considering all features+ 8 feature selection technique) * 5 datasets * 3 different classification technique) distinct classification models are considered in the study

Research Methodology

Step 1

Eleven different source code metrics from the bytecode of the compiled Java files of web service are computed

Step 2

Four different FR techniques are applied on all five versions of eBay web service. Each FR technique uses some parameter to sort the features and further top $\lceil \log_2 n \rceil$ ranked features out of n features are used as input to develop a model

Research Methodology

Step 3

Four different FSS techniques have been considered to select optimal set of features

Step 4

All elven source code metrics, selected set of source code metrics using feature selection techniques are validated using three different classification methods i.e., MLR, SVM, and MARS

Naming Conventions for different Techniques

Abbreviation	Corresponding Name
AM	All Metrics
FR1	CS test
FR2	GR Feature Evaluation
FR3	IG Feature Evaluation
FR4	OneR Feature Evaluation
FS1	Classifier Subset Evaluation
FS2	Correlation based Feature Selection
FS3	Filtered Subset Evaluation
FS4	Rough Set Analysis (RSA)

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Selected metrics after Feature ranking methods

Method	863	865	867	869	871
FR1	SIZE1, MVG, DAC, SIZE2	DAC, MVG, CBO, LCOM	SIZE1, CBO, DAC, MVG	DAC, LOCM, MVG, SIZE1	DAC, LOCM, WMC, CBO
FR2	DAC, WMC, LCOM, RFC	NOM, WMC, LOCM, DAC	NOM, DIT, MVG, SIZE2	NOM, DIT, RFC, WMC	LOCM, NOM, WMC, RFC
FR3	SIZE1, MVG, SIZE2, CBO	DAC, MVG, LCOM, WMC	SIZE1, RFC, MVG, CBO	DAC, LCOM, MVG, SIZE1	LOCM, WMC, DAC, MVG
FR4	DAC, MVG, NOC, NOM	DAC, MVG, NOC, NOM	MVG, DAC, NOM, LCOM	DAC, MVG, NOC, NOM	DAC, NOC, DIT, CBO

Observations and Results

In case of MLR, model developed by considering selected set of source code metrics using classifier subset evaluation as input produces better result as compared to others.

In case of SVM, model developed by considering selected set of source code metrics using correlation based feature selection as input produces better result as compared to others.

In case of MARS, model developed by considering selected set of source code metrics using classifier subset evaluation as input produces better result as compared to others.

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Selected metrics after Feature subset selection

Method	863	865	867	869	871
FS1	WMC, DIT, DAC, MVG	WMC, DIT, DAC	DIT, CBO, LCOM, DAC, NOM,MVG	DIT,DAC, NOM	DIT, LCOM,DAC
FS2	DIT, DAC, WMC, SIZE1, NOC	DIT, DAC, WMC, SIZE1, NOC	DIT, DAC, WMC, SIZE1, NOC	DIT, DAC, WMC, SIZE1, NOC	DIT, DAC, WMC, SIZE1, NOC
FS3	DIT, MVG, WMC, DAC	DAC, DIT, WMC	DIT, MVG, LCOM, NOM, CBO, DAC	NOM, DAC, DIT	DAC, DIT, LCOM
FS4	DIT, MVG, DAC, NOM, RFC, SIZE2, SIZE1	DIT, MVG, DAC, NOM, RFC, SIZE2, SIZE1	DIT, MVG, DAC, NOM, RFC, SIZE2, SIZE1	DIT, MVG, DAC, NOM, RFC, SIZE2, SIZE1	DIT, MVG, DAC, NOM, RFC, SIZE2, SIZE1

Observations and Results

In case of MLR, model developed by considering selected set of source code metrics using classifier subset evaluation as input produces better result as compared to others

In case of SVM, model developed by considering selected set of source code metrics using correlation based feature selection as input produces better result as compared to others

In case of MARS, model developed by considering selected set of source code metrics using classifier subset evaluation as input produces better result as compared to others

Multivariate Adaptive Regression Splines (MARS)

The hardware used to carry out our experiments are: Core i5 processor with 4GB RAM and storage capacity of 250GB hard disk

Prediction models are developed using the licensed MATLAB environment at NIT-Rourkela

Model developed for predicting web-service maintainability using MARS yields better result as compared to MLR, and SVM methods

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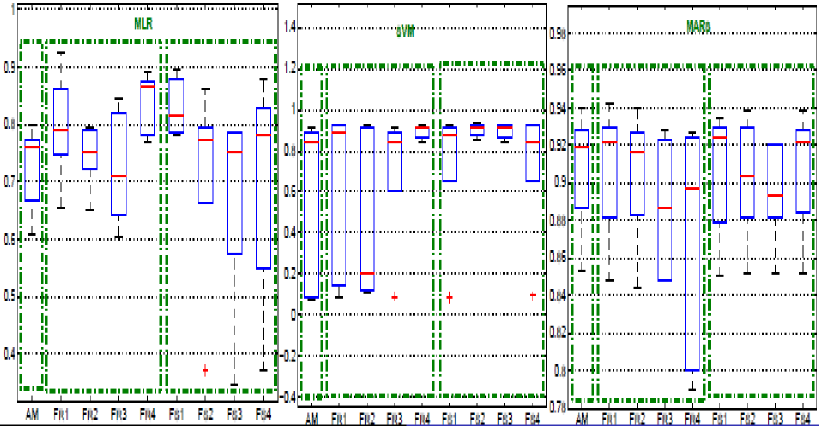
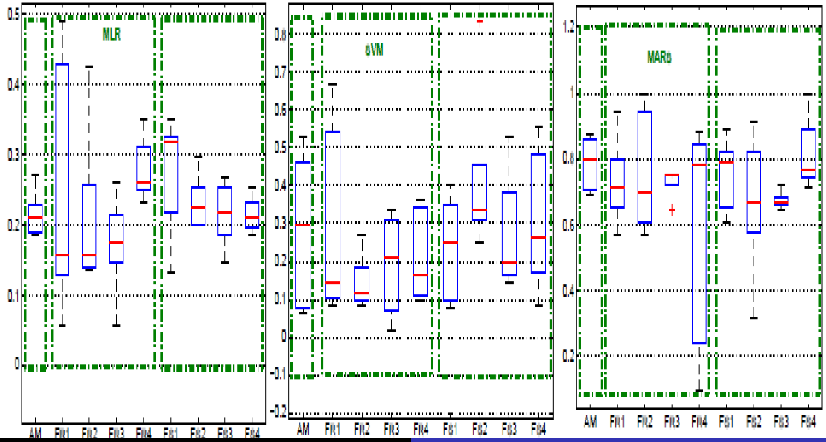
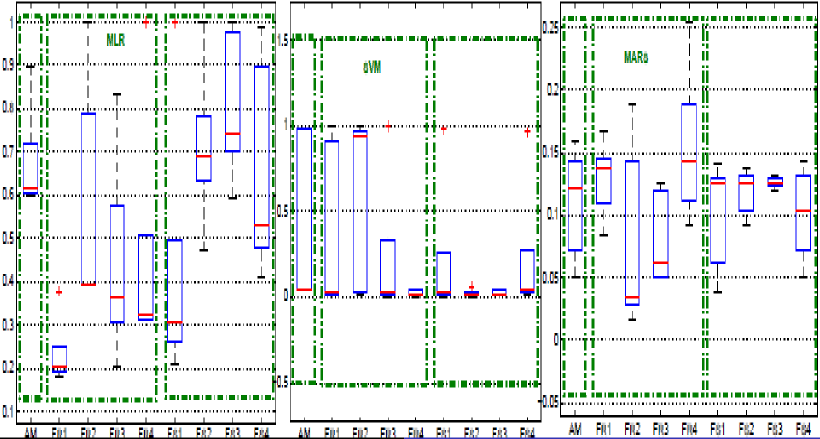
Accuracy



Precision



Recall



Overall Performance

In case of MLR method, model developed by considering selected set of source code metrics using oneR feature evaluation as input produces better result as compared to others

In case of SVM, model developed by considering selected set of source code metrics using correlation based feature selection as input produces better result as compared to others

In case of MARS, model developed by considering selected set of source code metrics using classifier subset evaluation as input produces better result as compared to others

t-test: Among Different Feature Selection Techniques

Mean Difference									
	AM	FR1	FR2	FR3	FR4	FS1	FS2	FS3	FS4
AM	0	-0.04	0.03	-0.04	-0.14	-0.09	-0.11	-0.09	-0.04
FR1	0.04	0	0.07	0	-0.1	-0.05	-0.07	-0.05	-0.01
FR2	-0.03	-0.07	0	-0.07	-0.16	-0.12	-0.13	-0.12	-0.07
FR3	0.04	0	0.07	0	-0.1	-0.05	-0.07	-0.05	0
FR4	0.14	0.1	0.16	0.1	0	0.04	0.03	0.05	0.09
FS1	0.09	0.05	0.12	0.05	-0.04	0	-0.02	0	0.05
FS2	0.11	0.07	0.13	0.07	-0.03	0.02	0	0.02	0.06
FS3	0.09	0.05	0.12	0.05	-0.05	0	-0.02	0	0.05
FS4	0.04	0.01	0.07	0	-0.09	-0.05	-0.06	-0.05	0
p-value									
	AM	FR1	FR2	FR3	FR4	FS1	FS2	FS3	FS4
AM	-	0.64	0.76	0.5	0.1	0.37	0.2	0.3	0.49
FR1	0.64	-	0.22	0.95	0.19	0.57	0.4	0.53	0.92
FR2	0.76	0.22	-	0.33	0.06	0.26	0.14	0.21	0.34
FR3	0.5	0.95	0.33	-	0.11	0.52	0.28	0.46	0.92
FR4	0.1	0.19	0.06	0.11	-	0.46	0.35	0.16	0.15
FS1	0.37	0.57	0.26	0.52	0.46	-	0.82	0.96	0.58
FS2	0.2	0.4	0.14	0.28	0.35	0.82	-	0.62	0.27
FS3	0.3	0.53	0.21	0.46	0.16	0.96	0.62	-	0.48
FS4	0.49	0.92	0.34	0.92	0.15	0.58	0.27	0.48	-

Additional t-test Results

t-test: Among different Classifier

	Mean Difference			p-value			t-value		
	MLR	SVM	MARS	MLR	SVM	MARS	MLR	SVM	MARS
MLR	0	0.03	-0.15	-	0.58	0	-	0.56	-8.13
SVM	-0.03	0	-0.18	0.58	-	0	-0.56	N-	-3.61
MARS	0.15	0.18	0	0	0	-	8.13	3.61	NaN

t-test: feature ranking Versus feature subset selection techniques (Average)

Mean Difference	p-value	t-value
-0.0362	0.36	-0.9226

t-test Analysis

We use pairwise t-test to compare the performance of feature selection techniques and classification techniques

One part of the result table shows the p-value and the other part shows the mean difference values of performance parameter

Pairwise t-test has been employed to determine whether feature ranking methods work better than feature subset selection methods or both have performed equally well

Final Conclusion and Takeaways

Experimental analysis reveals existence of a small set of source code metrics from a large number of available source code software metrics across various types which are able to accurately predict maintainability with few mis-classification errors

The web-service maintainability prediction model developed using MARS shows better results in comparison to MLR and SVM techniques

We can infer that oneR feature evaluation yields better results compared to other techniques

Final Conclusion and Takeaways

There is a significant difference between different classification techniques. According to the value of mean difference, MARS yields better result compared to other techniques.

The performance of the feature selection methods is varied with the different classification methods used

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