Support Vector Machines for Regression and Applications to Software Quality Prediction

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Abstract. Software metrics are the key tool in software quality management. In this paper, we propose to use support vector machines for regression applied to software metrics to predict software quality. In experiments we compare this method with other regression techniques such as Multivariate Linear Regression, Conjunctive Rule and Locally Weighted Regression. Results on benchmark dataset MIS, using mean absolute error, and correlation coefficient as regression performance measures, indicate that support vector machines regression is a promising technique for software quality prediction. In addition, our investigation of PCA based metrics extraction shows that using the first few Principal Components (PC) we can still get relatively good performance.

1 Introduction

Software quality management, which is an important aspect of software project development, is an ongoing comparison of the actual quality of a product with its expected quality [16]. Software metrics are the key tool in software quality management. Many researchers have sought to analyze the connection between software metrics and code quality [8][13][14][15][17][23]. The methods they used fall into four mainly categories: association analysis (association rules), clustering analysis (k-means, fuzzy c-means), classification analysis (decision trees, layered neural networks, Holographic networks, logistic regression, genetic granular classification [12]) and prediction analysis (linear regression).

In this paper we propose to use support vector machines for regression to predict software quality. Support vector machine technique has attracted many researchers in optimization and machine learning areas [19,22]. In the case of regression, the objective is to choose a hyperplane with small norm while simultaneously minimizing the sum of the distances from the data points to the hyperplane.

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The remainder of this paper is organized as follows. In Section 2, we describe the software metrics and benchmark dataset we used. Section 3 presents the support vector regression method. Section 4 describes three comparison algorithms. Section 5 introduces PCA. Section 6 presents the performance measures and the experiment results. Conclusions are covered in Section 7.

2 Software Metrics

We investigated the twelve software metrics, as shown in Table 1, which are used in the famous benchmark dataset MIS [15,12]. Simple counting metrics such as the number of lines of source code or Halstead’s number of operators and operands describe how many “things” there are in a program. More complex metrics such as McCabe’s cyclomatic complexity or Bandwidth attempt to describe the “complexity” of a program, by measuring the number of decisions in a module or the average level of nesting in the module, respectively.

Table 1. Description of the MIS dataset with a detailed characterization of the software metrics [18]

<i>Metrics</i>	<i>Detailed Description</i>
LOC	Number of lines of code including comments, declarations and the main body of the code
CL	Number of lines of code, excluding comments
TChar	Number of characters
TComm	Number of comments
MChar	Number of comment characters
DChar	Number of code characters
N	Halstead’s Program Length $N = N1+N2$, $N1$ is the total number of operators, $N2$ is the total number of operands
N’	Halstead’s Estimate of Program Length $N’= n_1\log_1n_1 + n_2\log_2n_2$, n_1 is the number of unique operators, n_2 is the number of unique operands
NF	Jensen’s Estimate of Program Length Metric $\log_1n_1! + \log_2n_2!$
V(G)	M McCabe’s Cyclomatic Complexity Metric, where $V(G) = e-n+2$, and e represents the number of edges in a control graph of n nodes
BW	Belady’s Bandwidth measure $BW = (\sum_i iL_i)/n$, L_i represents the number of nodes at level “ i ” in a nested control flow graph of n nodes. This measure indicates the average level of nesting or width of the control flow graph representation of the program
Changes	Number of changes

In this study, MIS is represented by a subset of the whole MIS data with 390 modules written in Pascal and FORTRAN. These modules consist of approximately 40,000 lines of code. Our goal is to develop a prediction model of software quality in which the number of modifications (changes) is projected on a basis of the values of the 11 software metrics that is used to characterize a software module. We cast the problem in the setting of regression, the explanatory variables are the first eleven soft-

ware metrics and the dependent variable is the number of changes. Software modules, which have no changes, could be deemed to be fault-free, while software modules with the number of changes being too big, for example, over 10, can be sought as potentially highly faulty modules.

3 Support Vector Machine Regression (SVR)

Specifically, the ε -insensitive support vector regression will be used for predicting software quality. In the ε -insensitive support vector regression, our goal is to find a function $f(x)$ that has an ε -deviation from the actually obtained target y_i for all training data and at the same time is as flat as possible [10]. Suppose $f(x)$ takes the following form:

$$f(x) = wx + b \quad w \in X, b \in \mathfrak{R}. \quad (1)$$

Then, we have to solve the following problem:

$$\begin{aligned} & \min \frac{1}{2} \|w\|^2 \\ \text{Subject to} \quad & y_i - wx_i - b \leq \varepsilon \\ & wx_i + b - y_i \leq \varepsilon \end{aligned} \quad (2)$$

In the case where the constraints are infeasible, we introduce slack variables. This case is called soft margin formulation, and is described by the following problem.

$$\begin{aligned} & \min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ \text{Subject to} \quad & y_i - wx_i - b \leq \varepsilon + \xi_i \quad \xi_i, \xi_i^* \geq 0 \\ & wx_i + b - y_i \leq \varepsilon + \xi_i^* \quad C \succ 0 \end{aligned} \quad (3)$$

where C determines the trade-off between the flatness of the $f(x)$ and the amount up to which deviations larger than ε are tolerated. This is called ε -insensitive loss function:

$$|\xi|_\varepsilon = \begin{cases} 0 & \text{if } |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & \text{if } |\xi| > \varepsilon \end{cases} \quad (4)$$

By constructing the Lagrangian function, we formulate the dual problem as

$$\text{Max} \quad -\frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l (\lambda_i - \lambda_i^*) (\lambda_j - \lambda_j^*) x_i x_j - \varepsilon \sum_{i=1}^l (\lambda_i + \lambda_i^*) + \sum_{i=1}^l y_i (\lambda_i - \lambda_i^*) \quad (5)$$

$$\text{Subject to} \quad \sum (\lambda_i - \lambda_i^*) = 0 \quad \lambda_i, \lambda_i^* \in (0, C)$$

At the optimal solution, we obtain

$$w^* = \sum_{i=1}^l (\lambda_i - \lambda_i^*) x_i \quad (6)$$

$$f(x) = \sum_{i=1}^l (\lambda_i - \lambda_i^*) x_i x + b^* \quad (7)$$

We compute the optimal value of b from the complementary slackness conditions:

$$\begin{aligned} b^* &= y_i - w^* x_i - \varepsilon \quad \lambda_i \in (0, C) \\ \text{and } b^* &= y_i - w^* x_i + \varepsilon \quad \lambda_i^* \in (0, C) \end{aligned} \quad (8)$$

In some case, we need to map input space into feature space and try to find a hyperplane in the feature space by using the trick of kernel functions:

$$\text{Max} \quad -\frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l (\lambda_i - \lambda_i^*) (\lambda_j - \lambda_j^*) K(x_i, x_j) - \varepsilon \sum_{i=1}^l (\lambda_i + \lambda_i^*) + \sum_{i=1}^l y_i (\lambda_i - \lambda_i^*) \quad (9)$$

At the optimal solution, we obtain

$$w^* = \sum_{i=1}^l (\lambda_i - \lambda_i^*) K(x_i), \quad (10)$$

$$f(x) = \sum_{i=1}^l (\lambda_i - \lambda_i^*) K(x_i, x) + b \quad (11)$$

where $K(.,.)$ is a kernel function. Any symmetric positive semi-definite function, which satisfies Mercer's conditions, can be used as a kernel function in the SVMs context [10, 20]. In this paper, we use the linear kernel [11].

4 Regressors for Comparison

4.1 Multivariate Linear Regression

Multivariate Linear Regression (MLR) finds a set of basis vectors $w x_i$ and corresponding regressors β_i in order to minimize the mean square error of the vector y . The basis vectors are described by the matrix $C x x^T C x y$. A low-rank approximation to this problem can be defined by minimizing

$$\mathcal{E}^2 = E \left[\left\| y - \sum_{i=1}^M \beta_i w_{x_i}^T x w_{y_i} \right\|^2 \right] \quad (12)$$

where $M = \dim(y)$, $N < M$ and the orthogonal basis $w y_i$ span the subspace of y which gives the smallest mean square error given the rank N .

4.2 Conjunctive Rule

Conjunctive Rule (CR) consists of antecedents "AND"ed together and the consequent (prediction value) for the regression. This learner selects an antecedent by computing the Information Gain of each antecedent and prunes the generated rule using Reduced Error Pruning (REP) or simple pre-pruning based on the number of antecedents [1]. The Information is the weighted average of the mean-squared errors of both the data covered and not covered by the rule. In pruning, the weighted average of the mean-squared errors on the pruning data is used.

4.3 Locally Weighted Regression

Locally Weighted Regression (LWR) is a memory-based method that performs a regression around a point of interest using only training data that are local to that

point [3,4]. We consider here a form of locally weighted regression that is a variant of the LOESS model [5]. The LOESS model performs a linear regression on points in the data set, weighted by a kernel centered at x . The kernel shape is a design parameter for which we use the Linear.

5 Principal Component Analysis

Principal Component Analysis (PCA) is a famous multivariate data analysis method that is useful in linear feature extraction [6,7]. The PCA finds a linear transformation $y=Wx$ such that the retained variance is maximized. Each row vector of W corresponds to the normalized orthogonal eigenvector of the data covariance matrix.

One simple approach to PCA is to use singular value decomposition (SVD). Let us denote the data covariance matrix by $R_x(0) = E\{x(t)x^T(t)\}$. Then the SVD of $R_x(0)$ gives $R_x(0) = UDU^T$, where $U = [U_s, U_n]$ is the eigenvector matrix (i.e. modal matrix) and D is the diagonal matrix whose diagonal elements correspond to the eigenvalues of $R_x(0)$ (in descending order). Then the PCA transformation from m -dimensional data to n -dimensional subspace is given by choosing the first n column vectors, i.e., n principal component vector y is given by $y=U_s^T x$.

6 Experiment Results

10-fold cross-validation on the benchmark MIS dataset, available on [9], is used for estimating prediction performance.

6.1 Performance Measures

We use the following performance measures:

Mean Absolute Error (MAE): MAE provides a measure of how close a prediction model is to the actual data.

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - p_i| \quad (13)$$

where a_i and p_i is the actual and predicted value for the i th test case. MAE ranges from 0 to infinity, with 0 corresponding to the ideal. the smaller the MAE the better.

Correlation Coefficient (CC): CC is a measure of how well trends in the predicted values follow trends in past actual values [21]. It measures how well the predicted values from a forecast model "fit" with the real-life data. A perfect fit gives a CC of 1.0.

$$CC = \frac{\sum_{i=1}^n (p_i - \bar{p})(a_i - \bar{a})}{\sum_{i=1}^n (p_i - \bar{p})^2 \sum_{i=1}^n (a_i - \bar{a})^2} \quad (14)$$

The higher the CC the better.

6.2 Results

Fig.1 shows MAE of different regressors on the original MIS metrics and the PCA extracted data. On the original metrics, SVR with the linear kernel (SVR_L) get the

best performance by achieving a minimum of 3.98 MAE. As shown in Fig.1, using the first few Principal Components (PC) we can still get relatively good performance. For CRule, using PCs is even better than using the original metrics.

Fig. 1. MAE of different regressors on the original MIS metrics and the PCA extracted data. MLR= Multivariate Linear Regression, SVR_L=Support Vector Regression with Linear kernel, CRule=Conjunctive Rule, LWR_L=Locally Weighted Regression with Linear kernel. MIS_PCA1 means using the first Principal Component, MIS_PCA2 means using the first two Principal Components, etc.

Fig.2 shows CC of different regressors on the original MIS metrics and the PCA extracted data. SVR with Linear kernel get the best performance by achieving a maximum of 0.77 CC. For CRule, using PCs is better than using the original metrics.

Fig. 2. CC of different regressors on the original MIS metrics and PCA extracted data. MLR= Multivariate Linear Regression, SVR_L=Support Vector Regression with Linear kernel, CRule=Conjunctive Rule, LWR_L=Locally Weighted Regression with Linear kernel. MIS_PCA1 means using the first Principal Component, MIS_PCA2 means using the first two Principal Components, etc.

7 Conclusions

In this paper we propose to use support vector machines for regression applied to software metrics to predict software quality. Comparison is done with three other

techniques: Multivariate Linear Regression, Conjunctive Rule and Locally Weighted Regression. Results on benchmark dataset MIS, using MAE and CC as performance measures, indicate that support vector machines regression is a promising technique for software quality prediction. The investigation of PCA based metrics extraction show that using the first few Principal Components we can still get relatively good performance.

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