International Journal of e-Collaboration
Volume 19 • Issue 1

Addressing Noise and Class Imbalance Problems in Heterogeneous Cross-Project Defect Prediction:

An Empirical Study

Rohit Vashisht, Jamia Millia Islamia, New Delhi, India & KIET Group of Institutions, Delhi-NCR, Ghaziabad, India*

Syed Afzal Murtaza Rizvi, Jamia Millia Islamia, India

ABSTRACT

When a software project either lacks adequate historical data to build a defect prediction (DP) model or is in the initial phases of development, the DP model based on related source project's defect data might be used. This kind of SDP is categorized as heterogeneous cross-project defect prediction (HCPDP). According to a comprehensive literature review, no research has been done in the field of CPDP to deal with noise and class imbalance problem (CIP) at the same time. In this paper, the impact of noise and imbalanced data on the efficiency of the HCPDP and with-in project defect prediction (WPDP) model is examined empirically and conceptually using four different classification algorithms. In addition, CIP is handled using a novel technique known as chunk balancing algorithm (CBA). Ten prediction combinations from three open-source projects are used in the experimental investigation. The findings show that noise in an imbalanced dataset has a significant impact on defect prediction accuracy.

KEYWORDS

Classification, Cross-Project, Defect, Heterogeneous, Imbalance, Noise, Regression, With-In

INTRODUCTION

Software has become an essential part of everyone's daily life in today's digital era. Even a minor flaw or malfunction in this software might result in financial or even life-threatening losses. Inconsistencies, ambiguities or misinterpretation of the specifications, carelessness or negligence in writing code, insufficient testing, unsuitable or unanticipated use of the software, or other unforeseen issues can all cause software errors. Software testing should be done at the proper time in the early stages of Software Development Life Cycle (SDLC) in order to reduce overall software development cost. The SDLC software testing phase, on the other hand, accounts for 60% of the total cost of software development. As a result, it's vital to do testing on the appropriate modules at the appropriate time.

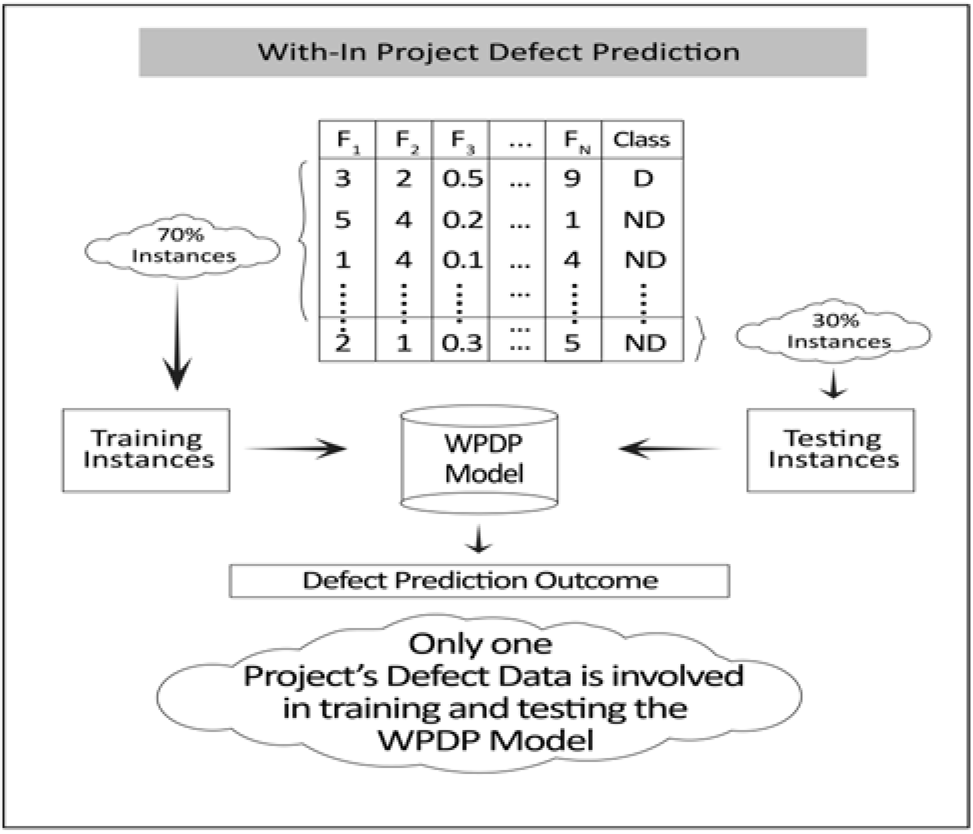
Software Defect Prediction (SDP) can be broadly split into two classes, according to the state of the art: Within Project Defect Prediction (WPDP) and Cross Project Defect Prediction (CPDP). The available defect dataset is split into two parts in WPDP in order to build the DP model in such a way that one half of the dataset (referred to as labeled observations) is used to train the DP model and the other portion is used to validate the DP model, as illustrated in Figure 1.Finding labels that

DOI: 10.4018/IJeC.315777

*Corresponding Author

are either faulty or non-faulty for unidentifiable instances in the target dataset is how the DP model is tested (Ambros et al., 2012).

Figure 1. With-In project defect prediction


With-In Project Defect Prediction
70% Instances
30% Instances
Training Instances
WPDP Model
Testing Instances
Defect Prediction Outcome
Only one Project's Defect Data is involved in training and testing the WPDP Model

F_1	F_2	F_3	...	F_N	Class
3	2	0.5	...	9	D
5	4	0.2	...	1	ND
1	4	0.1	...	4	ND
⋮	⋮	⋮	...	⋮	⋮
2	1	0.3	...	5	ND

CPDP is a type of SDP in which software projects that lack the required local defect data can develop an accurate and effective DP model using data from other projects. CPDP can also be divided into two subcategories: Homogeneous CPDP (HoCPDP) and Heterogeneous CPDP (HCPDP). HoCPDP collects common software measures/features from both the source (whose defect data is used to train the SDP model) and the target (for which the SDP model is created) applications (He et al., 2014). When using HCPDP, however, there are no uniform metrics between the prediction pair datasets. Uniform features between two applications can be determined by evaluating the coefficient of correlation between all possible software feature combinations. In the case of HCPDP, combinations of feature pairs with a similar distribution in their values are employed as common features between source and target datasets in order to forecast project-wide problems. As shown in Figure 2, correlated feature pairs for the HCPDP category include (A, Q), (B, P), and (D, S). Figure 2 provides more details on both CPDP groups.

Related Content

Cities Really Smart and Inclusive: Possibilities and Limits for Social Inclusion and Participation

Cristina Maria Pinto Albuquerque (2018). *E-Planning and Collaboration: Concepts, Methodologies, Tools, and Applications (pp. 1426-1445).*

www.irma-international.org/chapter/cities-really-smart-and-inclusive/206064

How Do Virtual Teams Work Efficiently: A Social Relationship View

Ying Chieh Liuand Janice M. Burn (2009). *International Journal of e-Collaboration (pp. 16-36).*

www.irma-international.org/article/virtual-teams-work-efficiently/37532

GSS Research for E-Collaboration

Sathasivam Mathiyalakan (2008). *Encyclopedia of E-Collaboration (pp. 337-342).*

www.irma-international.org/chapter/gss-research-collaboration/12447

Project Management Issues in IT Offshore Outsourcing

Kathy Stewart Schwaig, Stephen H. Gillamand Elke Leeds (2006). *International Journal of e-Collaboration (pp. 53-73).*

www.irma-international.org/article/project-management-issues-offshore-outsourcing/1951

An Integrated Collaboration Environment for Various Types of Collaborative Knowledge Work

Frank Fuchs-Kittowskiand Eric Siegeris (2012). *Advancing Collaborative Knowledge Environments: New Trends in E-Collaboration (pp. 102-113).*

www.irma-international.org/chapter/integrated-collaboration-environment-various-types/61187