

# A Defect Dependency based Approach to Improve Software Quality in Integrated Software Products

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**Abstract:** Integrated software products are complex in design. They are prone to defects caused by integrated and non-integrated modules of the entire integrated software suite. In such software products, a small proportion of defects are fixed as soon as they are reported. Rest of the defects are targeted for fixes in future product release cycles. Among such targeted defects, most of them seem to be insignificant and innocuous in the current version but have the potential to become acute in future versions. In this paper, we propose an approach to study defect dependency of the reported defect using a dependency metric. Identifying the dependency of a defect in an integrated product suite can help the product stake-owners to prioritize them and help improve software quality.

## 1 INTRODUCTION

Integration of two or more software products forms an integrated software product. Usage of large-scale integrated products is increasing in software industry. Expanding business operations, desire for increasing top-line revenues, increasing organizational synergy, providing value-adds to the customers, etc. are some of the reasons contributing to this increased usage of integrated products. In most integrated software products, the entire product may not essentially be exposed to all the direct end users. Access may be provided to requisite business layers (sub-product or a module/sub-module) that specific users may use to execute their regular business activity.

Defects are not exceptional to integrated software products. If they are sensed, they require a good slice of time and effort of developers and testers to deal with them. Severe challenges arise for industries that are directly dependent on integrated software products when they go in for acquisitions or mergers. They tend to invest additional resources and time on merging existing softwares which are used independently. The defects are recorded when they go operational with integrated software suites. These defects are difficult to address due to higher degree of dependency between each other. For

example, let's consider an E-Commerce integrated software product consisting of the following two sub-products: Supply-Chain and Revenue Reporter. The major objective of Supply-Chain sub-product is to track product billing while the other sub-product's objective is to report revenue. One of the most common defects in the integrated product is *rounding-off of the product price*. As an end result for the integrated product, revenue reports incorrect data. If the results are taken separately, rounding-off defect can be insignificant for chain-supply but is critical for product billing. In such scenarios, product development team working on the supply chain product might decide not log it as a defect or even if it's logged, they may not choose to address the defect in the current release or not to address it at all. The same defect is considered as a severe defect for revenue reporter and hence needs to be addressed at once. In such cases, prioritization of the defect becomes important.

Product developers might not be able to judge the criticality of the defect in the integrated product until the cause of the issue is identified. Hence, this defect becomes more of a concern to the budgeting team than product development team. This gap can be filled if there exists a criterion to evaluate defect dependency in the integrated software products, such that the corresponding defects can be prioritized. The stakeholders involved may then choose to fix

the defect based on the prioritization results. Given this context, the major contributions of the paper are:

- Deduce an approach to study the dependency of defects among respective modules or sub-products in an integrated software product.
- Introduce methods to measure the defect dependency using machine-learning techniques like rule-based classification and Generalized Dependency degree  $\Gamma$  over a defect dataset.
- Evaluate the proposed approach over a real time defect dataset of an integrated software product.

The rest of the paper is organized as follows: Section 2 provides an overview of the related work and Section 3 details the background needed to understand our approach. Section 4 talks about the proposed approach. Section 5 and 6 discusses experimental details and their results. We provide some threats to our approach in section 7 and suggest possible future work in Section 8.

## 2 RELATED WORK

Clarke formulated the initial work on defect dependency by proposing a model over program dependencies (Clarke LA, 1990). Generalizations of control and data flow dependencies were studied from both semantic and syntactic perspective. The dependency implications over tester and debuggers were recorded. (Laporte, 1998) listed down the challenges and laid out processes required for developing an efficient integrated software product. The study stressed on improving quality from initial stages. (Suryan, 2004) proposed a generic life cycle model for integrated software with high stress on quality during development. (Trinitis, 2004) were the first among others to study on dependencies of models in integrated softwares. They concentrated more on quality of software in integrated mode for better implementation and integrity strategies. Their work was oriented towards reliability and maintainability. Such dependency study is now required from design and development perspective.

(Schertz, 2005) were the first to study on methods to quantify and understand integration testing. They proposed a new approach based on binary dependency framework that can determine control and data dependencies using dependency graph. (Nagappan, 2007) have studied relationship between software dependencies and churn measures to assess failure using statistically methods. (Sallak, 2014) proposed probability based methods to study

dependency and independency of modules from a reliability perspective.

Different approaches are currently followed by software practitioners for building integrated software. Moog Inc. has introduced an integration testing tool (Moog, 2014) for software used in the manufacturing industry. It studies and evaluates the behaviour of workflow in a multi-component software product. LDRA is another business leader which markets testing solutions to manufacture industries (LDRA Inc., 2014); they use integrated softwares for detecting the functional and raw-data faults. SAP Labs also provide testing solutions (SAP Labs, 2011) which studies the integration defects using priority & prediction methods with supplied pre-input test data. Oracle provides application testing tool (Oracle, 2014), which includes analysis on studying integral flow on inter-related modules with automation in test case generation. Failure mode effect analysis & Fault tree analysis (Tague, 2004) are most widely used methods in current day integration testing tools. However, they lack methods for assessing the dependencies of a defect over entire software product.

(Gartner, 2014) had released an analyst report with Magic Quadrant for Integrated Software Quality Suites. They identified market leaders who provide tools to industries to test qualitative integrated software products. From the report, the common theme seems to be the focus on automation of functional and load testing of the integrated softwares. Common deficiencies across all such quality suites include integral dependency of defects, defect life cycle, etc.

## 3 BACKGROUND

This section provides brief overview of existing methods used as part of our approach to study dependency among real-time entities.

### 3.1 Rule based Classification

Classification is a data mining technique used to understand and extract desired data patterns. *Rule based classification* or *classifier* is a type of classification based on a set of rules/conditions. While performing an experiment, it can be difficult to operate on the entire dataset. Hence certain rules can be applied to extract desired patterns from our experiment dataset to perform the experiment. Rule base classification works efficiently over larger and complex datasets. This is applied using series of

conditions for pattern extraction. It is fast and efficient in generating accurate patterns for the experiment.

Introduced by (Cohen, 1995), this classifier uses IF and THEN conditions to extract desired data pattern for evaluating our approach. For example, let us consider a dataset C from which we want to extract specific data pattern. We need to pre-process the dataset first (i.e. prune – choose only required data attributes on which we are interested to assess) and then apply IF and THEN conditions on pruned dataset C to extract the criteria. Tools like WEKA®, CART, Apache Mahout and Orange®, etc. - can be used to prune the unstructured dataset and apply respective method to fetch desired output. In this paper, we use this classifier to extract desired data pattern from defect dataset to evaluate the proposed approach.

### 3.2 Generalized Dependency Degree

Rough set theory is a mathematical approach to study sets or entities. Initial developments to rough set theory were proposed in (Pawlak, 1999). Specific studies on set dependency and dependency over equivalent classes were first proposed. (Haixuan, 2007) later proposed a generalized dependency degree  $\Gamma$  defined below, which helps to deduce the list down the dependencies of two sets over one another.

$$\Gamma(O, H) = \frac{1}{|D|} \sum \frac{|O(x) \cap H(x)|}{|H(x)|} \quad (1)$$

Here O & H are two equivalent classes that are generated over an equivalence relation framed from some disjoint sets of universal set D.

Many researchers have adopted this concept to address dependency issues. (Ivo, D, 2000) implemented this method using statistical approach to evaluate dependency. (Shamaei, 2011) have practically applied in the field of artificial intelligence to study the inter-dependency along with probability methods. In this paper we are adopting this generalized dependency degree to study the defect dependency over defect dataset.

## 4 PROPOSED APPROACH

This section contains details of proposed approach to study dependency of a defect among software modules or sub-products using a new metric called *Dependency Metric* (denoted by  $D^*$ ).

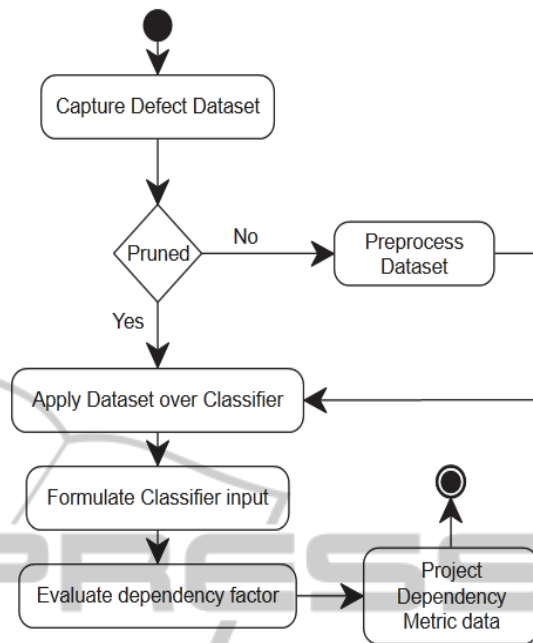


Figure 1: Approach to find dependency factor.

### 4.1 Pre-processing Defect Dataset

The first step in our approach is to identify and capture the required attributes (for example, defect reports) of the defect dataset. The input dataset may not always be accurate for performing dependency study. In practice, the defect dataset may contain lot of noise (unrelated data). Presence of noise patterns in source defect data can result in incorrect observations.

This noisy data is not relevant for dependency evaluation and hence the input defect dataset must be pre-processed to remove noise. Stake-owners should filter the bug reports and come up with required dataset. Machine learning techniques like outlier analysis or other anomaly detection methods can be performed to remove noise. Noise free dataset can be re-used to perform dependency study for any number of times.

### 4.2 Apply Rule-based Classifier on Dataset

Pre-processed dataset will be passed as an input to rule-based classifier. Rules are to be defined by the stake-owners on desired attributes. Rules follow IF and THEN conditions to formulate input data into required buckets. These rules are flexible enough to be operated at multi levels i.e. multiple IF and THEN conditions.

Let us consider an enterprise integrated software product  $L$  – consisting of  $p_1, p_2, p_3 \dots p_n$  as products. These may further contain sub-products or modules as given below:

$$\begin{aligned} p_1 &= \{m_1, m_2, m_3, m_4 \dots m_n\} \\ p_2 &= \{t_1, t_2, t_3, t_4 \dots t_n\} \\ p_3 &= \{s_1, s_2, s_3 \dots s_n\} \\ &\dots \\ p_n &= \{y_1, y_2, y_3 \dots y_n\} \end{aligned}$$

where  $m, n \dots y$  are modules in the respective product pillars. Similarly,  $m_1$  as a single module might further contain sub-modules resulting into a complex software product. For such Enterprise products, defects can be substantial, primarily due to the multiple levels of integration needed. It is difficult to perform an overall dependency study on such large dataset. Hence, specific rules are to be defined to classify the dataset into buckets and extract required defect data. Below can be an example for writing a rule  $R$  where

Rule  $R$ : IF  $P = p_2$  AND  $p_3$   
THEN  $M = t_1, t_2, t_3, s_5, s_7$

where  $p_2, p_3$  are products and  $t_1, t_2, t_3 \in p_2$  and  $s_5, s_7 \in p_3$ . These rules can also be applied on different versions of similar product to study the nature of defects  $d \in D$ , where  $D$  is Universal set of defects reported in product  $L$ .

### 4.3 Construct Attribute Value Table for Defect Dataset

Using  $d$  (obtained from rule  $R$ ), defects should be organized either in numeric form or in an attribute format for evaluation. To calculate the dependency metric, we need to convert the data points in dataset into disjoint sets. This is achieved by generating an information system that can be represented using attribute-value table. The table consists of rows and columns, where rows are labelled by objects of the  $d$  and columns by components in  $L$ .  $d$  is considered as a collection of disjoint sets of modules of product  $L$ , with attribute in rows against respective defect in columns.

Using rule set  $R$  and defect set  $d$ , below is the sample attribute-value table.

Table 1: Attribute-value table for H Defect Dataset.

	Attribute-value defect table	
	$p_2$	$p_3$
$t_1$	$\{d_1, d_2, d_3\}$	-
$t_2$	$\{d_7, d_8, d_9\}$	-

Table 1: Attribute-value table for H Defect Dataset (cont.).

	Attribute-value defect table	
	$p_2$	$p_3$
$t_3$	$\{d_{12}, d_4, d_5\}$	-
$s_5$	-	$\{d_6, d_1, d_7\}$
$s_7$	-	$\{d_5, d_0, d_3\}$

There are many ways to construct attribute value tables. We have adopted manual listing of  $d$  against components of  $L$  for sake of simplicity. It's stake-owner's choice to re-structure data by grouping them to form disjoint sets and have them recorded so that they are readable. Alternatively, the construction of attribute value table can be automated.

At times datasets may or may not be flexible enough to be described in a tabular format. In such cases defect ( $d$ ) - component ( $L$ ) attribute values can be visualized using tree based view, tile based view matrix based view, etc. The main reason for creating an attribute-value table is to describe the disjoint-ness of the defects reported across the integrated software within respective products and modules.

### 4.4 Training and Test Dataset

It is always recommended to first create a training dataset (samples) with defect counts of specific modules for sandbox validation. Say  $M$  is a module with  $o_1, o_2, o_3 \dots o_n$  where  $\forall o_n \in M$  as defects, a sample out of  $M$  can act as a Training Dataset. Upon successful validation of the training dataset, the metric can be applied over a business specific rule to generate the actual experiment's test dataset. The primary purpose of creating a training dataset is to estimate time and resource to perform the experiment.

Test dataset is a superset dataset chosen from collection of training dataset  $\in D$ . If the stake-owners would like to perform the experiment for entire suite to compare module level defect dependency, the approach can be applied on entire defect dataset.

### 4.5 Dependency Metric

Say defects reported in product  $p_i$  are defined as  $d_{p_i}$  such that

$$\{d_{p_1} \cup d_{p_2} \cup d_{p_3} \dots \cup d_{p_n} = D\} \quad (2)$$

Here  $d_{p_1}, d_{p_2}, d_{p_3} \dots d_{p_n}$  are disjoint defect sets of respective products belongs to defect dataset  $D$ . Also

$$\{\bar{d}_{p1} \cap \bar{d}_{p2} \cap \bar{d}_{p3} \dots \cap \bar{d}_{pn} = \bar{\Phi}\} \quad (3)$$

Here  $\bar{d}_{p1}, \bar{d}_{p2}, \bar{d}_{p3} \dots \bar{d}_{pn}$  are disjoint defect sets of with no common defects. In practice, such defects form disjoint sets and can be further drill downed to module or sub-modules of  $L$ . Equivalence relation ( $E$ ) can be generated over  $\bar{d}_{p1}$ . A new defect set  $D^e$  is constructed which comprises equivalent classes of  $E$  over  $D$  i.e.  $D^e$  is collection of sets of equivalent classes of  $E$ .

If  $D^e$  is considered as collection of equivalent classes defined over  $D$ , using generalized dependency degree (1) from rough set theory  $D^e$  is be applied in  $D^*$ , the dependency metric as (using (1))

$$D^* = \Gamma(O, H) \quad (4)$$

Here  $O$  &  $H$  are two equivalent classes belong to  $D^e$ . In case of more than two disjoint sets  $A_1, A_2, A_3, A_4 \dots A_n$  exists, then the function  $\Gamma$  is operated by constructing of distinct equivalent classes of all these disjoint sets. Then the metric  $D^*$  is defined as  $\Gamma(A_1, A_2, \dots, A_n)$ .

To understand the notion of disjoint sets and to study how generalized dependency degree is calculated, let's consider the example of an influenza dataset from (Haixuan, 2007). This dataset is simple and pruned so that it is feasible to calculate  $\Gamma$ . It contains 7 user samples ( $U$ ) of influenza ( $d$ ) affected people with the symptoms Headache ( $a$ ), Muscle pain ( $b$ ), Body temperature( $c$ ). The equivalence relation was represented in a tabular format.

During pruning the dataset, decision values are defined to construct the dataset in tabular format. Headache ( $a$ ) has a decision values  $Y$  for user who has headache and  $N$  for user who has no headache. Muscle pain ( $b$ ) has decision values  $Y$  for user who has muscle pain and  $N$  for user who has no muscle

Table 2: An Influenza Dataset.

U	Headache (a)	Muscle pain (b)	Body temperature (c)	Influenza (d)
e1	Y	Y	0	N
e2	Y	Y	1	Y
e3	Y	Y	2	Y
e4	N	Y	0	N
e5	N	N	1	N
e6	N	Y	2	Y
e7	Y	N	1	Y

pain. In case of body temperature( $c$ ) 0 - low, 1 - medium and 2 - high. Aggregated to form an equivalence relation, influenza ( $d$ ) takes  $Y$  for yes and  $N$  for no influenza.

Let  $A = \{a, b, c, d\}$  be the corresponding set of attributes on whose disjoint subsets the dependency degree is calculated,  $U = \{e1, e2, e3, e4, e4, e5, e6, e7\}$  are the user samples. Using Table 1, when created two disjoint subsets to operate on  $O = \{a, b, c\}$  &  $H = \{d\}$  where we will be finding dependency degree of  $H$  over  $O$ . Below are the equivalence classes defined for set  $O$  and  $H$ .

$$\begin{aligned} O(e1) &= \{e1\}, & O(e2) &= \{e2\}, & O(e3) &= \{e3\}, \\ O(e4) &= \{e4\}, & O(e5) &= \{e5\}, & O(e6) &= \{e6\}, \\ O(e7) &= \{e7\}, \\ H(e1) &= H\{e4\} = H\{e5\} = \{e1, e4, e5\}, \\ H\{e2\} &= H\{e3\} = H\{e6\} = H\{e7\} = \{e2, e3, e6, e7\} \end{aligned}$$

Then we have

$$\begin{aligned} \Gamma(O, H) &= \left( \frac{|(H(e1) \cap O(e1))|}{|O(e1)|} + \frac{|(H(e2) \cap O(e2))|}{|O(e2)|} + \frac{|(H(e3) \cap O(e3))|}{|O(e3)|} + \frac{|(H(e4) \cap O(e4))|}{|O(e4)|} + \frac{|(H(e5) \cap O(e5))|}{|O(e5)|} + \frac{|(H(e6) \cap O(e6))|}{|O(e6)|} + \frac{|(H(e7) \cap O(e7))|}{|O(e7)|} \right) / 7 \\ &= (1+1+1+1+1+1+1) / 7 = 1 \end{aligned}$$

Therefore the  $\Gamma(O, H) = 1$ , which is nothing but the generalized dependency degree of set  $H$  over set  $O$ . Similarly we can calculate the generalized dependency degree over other sets as well.

#### 4.6 Metric for Software Quality

We propose this Generalized Dependency degree  $\Gamma$  as a *Dependency metric* ( $D^*$ ) so as to calculate dependency of a defect over chosen entities. ( $D^*$ ) can be calculated by framing a equivalence relation of defect dataset, subsequently framing it's equivalent classes on disjoint defect sets over a  $D$  will generate a justifiable value to judge what and when to prioritize.  $D^e$  – the set of defect equivalence classes, should be first deduced from training dataset as a preliminary sample test. Later the approach should be applied over test dataset.

The scope of evaluating this metric study is up to the evaluation requirement of the stake-owners who are performing the action. If they would like to study the scope of dependency of a defect set over entire product, the classification step can be ignored and the entire integrated product suite becomes a test

dataset. Currently there is no generic scale defined for metric  $D^*$ , but the results mostly range between 0 and 10. Practitioners should be able to create a scale as per results obtained via training dataset. Scale might differ while calculating this metric from product to product and between one input dataset to another with in similar product. Subsequently, the scale can be mapped to test dataset.

Below is an algorithmically approach to evaluate a dependency metric over a defect dataset.

```

Algorithm DEPENDMETRIC(D, P, M, ER, EC)
begin
for i=1 to n do
  read  $P_i \in D$  //read products
for j=1 to m do
  read  $M_j \in P_i$  //read modules

get rule:R //getrule
for k=1 to z do
  read  $d_{pk}$  //read defects
for l=1 to z
   $D = ER(d_{pk}, R)$ ;
for l=1 to z
   $D^e = EC(ER(d_{pk}, R))$ ;
for l=1 to z
   $D^* = \Gamma(EC_l, D)$ ;
print  $D^*$ 
end

```

The algorithm is primarily meant to evaluate the dependency metric and doesn't focus on the time complexity of the actual computation itself. Improving the efficiency of the algorithm from a performance perspective is beyond the scope of this paper and shall be explored in future.

## 5 EXPERIMENT

A real time dataset was obtained from an Information Technology product firm to perform an experimental evaluation of our approach. Due non-disclosure clause, we are unable to list the exact name of the organization that provided the dataset. Defect dataset "H" was extracted from an enterprise bug-tracking tool called JIRA™. The "H" dataset contains defects registered for HRMS (Human Resource Management System) integrated software product which has 3 products under one master pillar (Learning Management System - LMS, Talent Management System - TM & Payroll - WFM). The 3 products consisted of 7 integrated sub-modules {(LMS – Administration, Manager and Reporting), (TM – Succession, Compensation and Talent Book), (WFM – Workforce and Pay book)}. The defect dataset "H" contains the list of defects that were considered insignificant in current version and hence

were targeted to be addressed in future versions. Below is an attribute value table for "H" with respective defect count against respective modules and products targeted for fixes in future release.

Table 3: Attribute-value table for "H" Dataset.

	Attribute-value defect table		
	$P_1$	$P_2$	$P_3$
$M_1$	24	-	-
$M_2$	56	-	-
$M_3$	4	-	-
$S_1$	-	9	-
$S_2$	-	7	-
$T_1$	-	-	43
$T_2$	-	-	24

As listed above -  $P_1$ ,  $P_2$  &  $P_3$  are 3 products that are integrated as single pillar. Product - Module relation is defined as follows  $\{M_1, M_2, M_3 \in P_1\}$ ,  $\{S_1, S_2 \in P_2\}$  and  $\{T_1, T_2 \in P_3\}$ . The figure shows the number of defects targeted for future versions under each product – module relation. For example, table 3 shows that 24 defects are targeted to be fixed for Product  $P_1$  – module  $M_1$  and 7 are targeted to be fixed for Product  $P_2$  – module  $S_2$ .

Using "H", rule based classifier was applied to perform the study of dependency of defects in a given module with another within chosen products. Below are the three rules extracted and applied to study the dependency with in each rule using the DEPENDMETRIC algorithm mentioned in the previous section:

- Rule 1: IF Product =  $P_1$  &  $P_2$   
THEN Module =  $M_1$  &  $S_1$
- Rule 2: IF Product =  $P_1$  &  $P_3$   
THEN Module =  $M_2$  &  $T_2$
- Rule 3: IF Product =  $P_2$   
THEN Module =  $S_1$  &  $S_2$

For each rule, Equivalence relation was programmatically calculated. For example, in case of rule 1, 33 defects (24 + 9) are used to frame the equivalence relation. Later, its equivalence classes are generated and applied over Dependency metric  $D^*$  to calculate how each chosen module is dependent on each other.

## 6 RESULTS

Dependency metric  $D^*$  was calculated using

equation (1). The results for respective rules (Rule 1, Rule 2, and Rule 3) are shown in table 4, 5 and 6.

Table 4: D\* for Rule 1.

D*	P <sub>1</sub>	P <sub>2</sub>
M <sub>1</sub>	0.76	0.59
S <sub>1</sub>	0.21	1.04

Table 5: D\* for Rule 2.

D*	P <sub>1</sub>	P <sub>3</sub>
M <sub>2</sub>	0.89	0.23
T <sub>2</sub>	0.14	0.97

Table 6: D\* for Rule 3.

D*	P <sub>2</sub>
S <sub>1</sub>	0.47
S <sub>2</sub>	0.31

By summarizing above results for Rule 1, dependency metric for modules M<sub>1</sub> & S<sub>1</sub> within products P<sub>1</sub> and P<sub>2</sub> can be deduced. In this case, M<sub>1</sub> module is more dependent (D\* value is 1.35) when compared with module S<sub>1</sub> (D\* value is 1.25) over products P<sub>1</sub> & P<sub>2</sub>. The stakeholders can use this value to place M<sub>1</sub> module with high priority than fixing S<sub>1</sub> module.

In case of Rule 2, module M<sub>2</sub> appears to be more dependent when compared with module T<sub>2</sub> over products P<sub>1</sub> & P<sub>3</sub>. If defects arising from P<sub>1</sub> and P<sub>3</sub> are to be fixed, module M<sub>2</sub> should be given more priority than T<sub>2</sub>. Similarly, for Rule 3, defects related to module S<sub>1</sub> should be prioritized compared to S<sub>2</sub>.

The above given metric values provide us a quantitative basis for addressing defects pertaining to specific components with in integrated software product. Based on the defect dependency metric value, we were able to list down most critical modules or sub-product that needs to be prioritized to improve the quality of integrated software product.

### 7 THREATS TO VALIDITY

The defect dependency metric provides a quantitative number for assessing the importance of fixing defects in a particular product or module or sub-module in the context of an integrated product. The technique can be used to drill down to a assess defect dependency on specific defects. However the

validity of the results are still to be assessed. Currently we have been able to monitor the results for only one release of the integrated product. The employees of the product firm followed the normal defect-fix cycle and fixed defects without taking defect dependency into consideration. We used our approach to compute the defect dependency value. However, to appropriately know the impact on our approach compared to the previous approach we need multiple releases of the integrated product and the corresponding defect datasets.

Rough set theory forms the basis for our approach. One of the fundamental concepts of rough set theory is the notion of disjoint sets. In other words, our work assumes that the defects are disjoint from each other in the defect dataset. We have not considered cases where in the defect has been double counted or the same defect has been logged in semantically different manner

Another threat to our study is the interpretation of the defect dependency value. It needs to be noted that ultimately the stake-owners have to make a decision on prioritization of defects in a specific order by taking into account factors like business strategy, competition, time to market, etc. in real world. In our work, we have not considered these factors and have just compared it based on a high-low basis.

### 8 CONCLUSION AND FUTURE WORK

In this paper, we proposed an approach to help the stake-owners prioritize defects with in modules with higher dependency degree. This in turn leads to better defect resolution cycle. If the approach is practised in every future release cycle it can lead to significant improvement in the quality of the integrated product. This also avoids surprise functional breakdown of the entire suite in future versions.

There are few shortcomings with our approach that we plan to address as part of our future work.

- Dependency metric is an initial attempt to study the dependency of a defect over a software product and is not the only solution to the reported problem. Other methods are yet to be formulated to justify and address the real time issues.
- While extracting the rules from defect dataset, we need to take care while pruning the dataset. We need to ensure that the defects are genuine

and they belong to respective modules in the integrated software product. Also it must be ensured that the defect reports have relevant relation with master product and are targeted for future release.

Below are the open challenges that require further study:

- Improve time-complexity of proposed approach and automate the calculation of the dependency metric.
- Current approach should be scaled down from module level to the level of single defect for more significant results
- Proposed dependency metric is only generalized for targeted defects. Further study is required to analyse the defect behaviour among modules that are shared among multiple product.

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