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An Industrial Case Study on Improving Quality in Integrated Software Product using defect dependency

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***Abstract* – Product based organizations have diverse product offerings that meet various business needs. The products are in turn integrated to create integrated product suites. Rigorous product engineering is a must for creation of high quality integrated software products. Adequate measures must be taken to improve quality of the integrated product before every release of its module or sub-product. It is hard to imagine upgrading an integrated software product with unidentified defects prior to its release. In this paper, we share our observations on implementing a defect dependency metric to identify the dependency of a defect over a real-time industry defect dataset of an integrated software product. This defect dependency metric was captured and analyzed during release cycle(s) to avoid surprise issues post product launch.**

Keywords—integrated software products; software quality; defect; defect dependency; software metric; product development; rough-set theory; defect widespread

I. INTRODUCTION

Academic research in areas such as software architecture, automation frameworks and implementation methods has seen a tremendous growth in recent years and it has been observed that software industries apply them in real-time business to achieve better results [1][2]. Many software practitioners are currently trying to use methods and technologies proposed by academia to create products to the best of their abilities. There were many lessons learnt from industrial case studies over the past decade [3].

All new products are created with the intent of delivering better functional and quality objectives that meet or exceed end user expectations. Most software firms are now deliberately framing their mission statements with a *'grow fast or die fast'* strategy before they hit the market with a high quality product. As per Gartner's 2015 Magic Quadrant for Enterprise Integration Platform as a Service survey [4] most of the software industries that work on developing integrated software products still follow traditional approaches to develop and maintain quality standards of their existing products. As per their study, most of the new start-ups are concentrating on new trends in research for a better product(s) of similar class.

In most cases, it is easier for start-ups or new development projects to implement new trends in research on to software production. However it is a challenge for well-established and equipped products to adhere to these changes as it requires massive planning and human effort. Especially in integrated software, individual sub-products which are commonly referred as *product pillars* are bound together loosely for various functional and business reasons. Integrated software products become vulnerable if its sub-products are bounded with too many integration defects. For example, let's consider an integrated software product consisting of the following two sub-products: Supply-Chain product and Revenue Reporter product. Supply-chain sub-product generally tracks product billing while revenue reporter reports revenue. A common defect in the integrated product is *rounding-off of the product price*. As an end result, from an integrated product perspective, the revenue reports incorrect data. If the results are taken separately, rounding-off defect can be insignificant for chain-supply but critical for product billing. In such scenarios, the defect may be logged in different ways based on the product development team. The same defect may be considered as a severe defect for revenue reporter where as it may not even be logged in supply-chain [5]. Hence measuring the impact of such dependencies can be critical to the defect fix cycle and the release cycle.

Various methods have been proposed on detection of current defects and occurrence of defects, spanning the development life cycle. However, most of the methods revolve around defects in product rather than dependency of a defect over an entire product suite. Such a dependency measure can help quality teams to stabilize the product and avoid surprise defects post deployment. In this paper, we present a quantitative evaluation of the defect dependency metric introduced in our previous work. We realize the metric over a real-time industrial defect dataset of a large-scale integrated software product [5]. We discuss the consequences of the results that lead to creation of new practices and processes to improve development and testing methodologies of the integrated software product within the organization.

The primary author of this paper has been working in this domain for many years and has contributed to the integration of the integrated product suite in various roles. The primary author is also pursuing graduate studies on a part-time basis. Hence the authors could gain access to all the artifacts and the original data. Due to non-disclosure clauses, the name of the integrated product suite, its product pillars and the organization is being withheld. The product information shown in Table 1 makes use of alternate names to the existing (real) names. However the defect dataset presented in table II shows exactly the same numbers as present in the defect database for the various products and versions of the integrated software product.

The rest of the paper is organized as follows: Section II provides details of industrial examples of software quality

related to our work, section III explains the background of defect dependency with an example along with study design of our work, and section IV details the implementation setup of defect dependency metric on an industry defect dataset. Section V talks about results of our implementation and observations identified during every new release of our integrated software product. Finally in section VI we discuss the threats to validity and present some insights about future work.

II. Related Work

Software Quality Assurance (SQA) in integrated software products is a major activity during software production cycle. Advanced SQA practices were proposed by various researchers over past decade that became standard approaches in today's software production release cycle. Functional integration approaches, strategies and methodologies to integrate software by its features were initially proposed [7]. Cost based effort estimation method [8] for integrated software architecture model-COTS was proposed and deduced quality measures to choose right resource for right task. Fedrik et al. proposed quality based methods to improve software integration [9]. In [10], new methods were proposed on software product integration by analyzing build statistics with real time products as applied examples. In contrast to the existing work, a quality based dependency model [13] capable of supporting software architecture as an evolution to software production was proposed. Improvements to integration methods in requirement analysis phase using a model based object oriented approach was proposed in [11].

Researchers have presented interesting methods on implementation of integration in global software projects and veracious trends in integration [12][15][20]. Zeng et al. discuss about an interesting integration framework that includes product design concepts as a collaborative feature during development in their work [14]. Software quality based integration challenges during design and implementation phases, and its consequences were listed out through an industrial case study of enterprise software product by Rognerud et al. [16]. Quality related observations on heterogeneous architectural model for efficient integration among software modules were proposed in [17]. Optimization methods in software integration with testing efforts and test complexity were analyzed [18]. Most significant work on integration bugs specific to dependency on requirements [19] are defined during project inception were recorded. Latest work on successful integration process [21] for large scale software was proposed along with quality improvements and between development and quality teams. In parallel there was significant amount of work on software defect prediction by Chengnian et al. [22] that can help industry understand future defects with prediction methods. Overall, there is a lot work on software quality, but specific research pertinent to defect widespread and dependency of a defect over a product is limited. There aren't many practical implementations that provide examples of applying the defect dependency methods to case studies in industry. In this paper, we are trying to address this specific gap by producing our implementation results on an industry dataset.

III. Study Design

In this section we provide an overview of the defect dependency metric and the real time industry dataset.

A. Defect Dependency Metric

Large-scale software products are complex and as such are prone to defects. Software quality teams have to perform rigorous checks before releasing a fix to a defect. This includes ensuring that the fix will not cascade new defect(s) into the product. The setup can be simple in case of small products but not for complex software products or an integrated product suite. Quality teams mostly face integration issues with incorrect control flow and data flow between the sub-products or sub-modules with in entire integrated product. It is also tough to detect and track the source of a defect in a complex integrated system as this involves various other quality teams from different sub-products. Firms that integrate products due mergers and acquisitions have different set of challenges as these products may have evolved independently but not in an integrated fashion. In such a scenario, it is essential for product owners to understand the impact the defect so as to mitigate possible surprise defects from other modules of the integrated product. We introduced defect dependency metric to address this specific concern in our previous paper [5]. We proposed a Defect dependency metric (D*) to calculate defect dependency by demonstrating the application of Generalized Dependency degree (Γ) using rough set theory [6].

Defect dependency can be defined as a metric to study the widespread of a defect with unknown impact and unknown risk over a module(s) or component(s) or sub-product(s) of a software product(s). Defect dependency can be calculated for any software of any size, however heuristically it is more applicable for complex systems as it is difficult to comment on widespread of a defect without any evidence. Generalized Dependency degree (Γ) is a mathematical approach to calculate the dependency between the equivalent classes generated by equivalence relation using disjoint sets. Initial study using this approach was proposed in Rough Set theory and was later studied by Halxuan et al [23].

- Consider a rough set over an information system, it can be defined as an approximation space as a pair as S= (U, A) where U is a non-empty finite set called universal set and A is a equivalence relation defined on a U which is a nonempty finite set of attributes i.e., a: $U \rightarrow V_a$ for a ϵ A, where V_a is called the domain of a.
- Here X be a subset of U, then the lower approximation of X by A in S is defined as $\underline{R}X$= {e ϵ U | [e] $\subseteq$ A}, similarly the upper approximation of X by A in S is defined as RX= {e ϵ U | [e] $\cap$ $A \neq \emptyset$} where [e] denotes the equivalence class containing 'e'.

If we redefine above definition in terms of a defect dependency approach, consider a defect dataset (D) of a large scale complex software product (L). Then:

- If $P_1, P_2, P_3, P_4 \ldots\ldots P_N$ are sub products of L, then consider $D_{P1}, D_{P2}, D_{P3}, D_{P4} \ldots D_{PN}$ are defect subsets of respective sub-products of a universal defect dataset *D*.
- S = (*D*, D_e) is an approximation space, where *D* is a non-empty finite defect set and D_e is a equivalence relation defined over all defect subsets D_{Pi} where $\{i \in 1,2,3 \ldots . n\}$

To calculate the dependency of a defect subset attributes over another subset, we will evaluate the value for Γ (Generalized dependency degree) which is defined as

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

Here O & H are two equivalent classes generated over an equivalence relation framed from some disjoint sets of universal set D. We have utilized this method to find dependency of a defect on our industrial defect dataset. It is a simple mathematical approach to understand the dependency of a one set over another. Each data point in the dataset contains collection of attributes that are pre-processed such that it can be applied over dependency metric. If we map this method to our real time dataset, D is the total defect dataset of our enterprise software product, O and H are two equivalent classes of equivalent sets which constitutes defects of two different sub-products O and H. In case there are more than two sub-products, we need to generate equivalent sets of all the defect product sub-sets, constructs equivalence class and apply this formula. There is no definite scale to the defect dependency metric, however the value varies between 0 and 10.

B. About Industry Dataset

Our industry defect dataset contains defects of an Integrated Human Resource Integrated System (IHRIS) product with 5 primary product pillars (as shown in Table I) that are integrated as a single product suite. Each product pillar has sub-products that are implemented in an integrated mode. As stated earlier, due to non-disclosure clause, we are use the common derived names of product and their sub-products instead of the original product names.

This integrated product is deployed as Software-as-Service, Stand-alone Hosted and On-premise subscription for most of the fortune 500 companies. New service pack is released and deployed (includes feature changes or major fixes to the defects) once every 2 months in a calendar year to all the customer instances. Also a maintenance pack is released twice a month in a calendar year that includes minor fixes for the defects reported between the release timeline. All the above products once cross-sold and deployed as individual products are now deployed as an integrated suite, i.e. all users accessing the integrated suite will be able to access respective product(s) or sub-product(s) as per their role permissions defined by the global administrator of the product suite.

The defect dataset constitutes defects from all the products and sub-products of the integrated suite that are extracted from the defect database of a defect tracking tool called JIRA™. Dataset contains defects raised by QA teams every sprint cycle along with defects reported by customers post product deployment. The authors worked with quality assurance teams and customers to extract the defects from the sprint cycles and evaluated the data using product managers' inputs.

TABLE I. PRODUCT INFORMATION

S. No	Product	Sub-product
1	Learning Management System (*LMS*)	Admin Mgmt.
		Learner mode
		Manager mode
2	Human Resource System (*HRS*)	Hire Mgmt.
		Compensation Mgmt.
		Succession Mgmt.
		Performance Mgmt.
3	Business Intelligence System (*BIS*)	BI Dashboards
		Data Downloader
		Data Uploader
4	Work force Manager (*WFM*)	Attendance Mgmt.
		Payroll Mgmt.
		Reimbursement Mgmt.
5	Web Services Manager (*WSM*)	Export Mgmt.
		Integration Mgmt.
		Web Service Admin mode

C. Real Time example for Defect Dependency

To understand the need of studying defect dependency, we provide a real time industry scenario consisting of three defects reported in three different sub-products of IHRIS software:

✓ *Scenario:* A manager uses the performance management sub-product to perform an employee's year-end performance assessment. The Manager rates employee's performance (between 0-5) along with comments. As per the manager rating, a pre-defined compensation hike shall be added to the employer salary in compensation sub-product along with relevant tax calculations as per policy in payroll sub-product.

✓ *Defects*: The sensitiveness of appraisal data necessitates encryption while storage. So, decryption was necessary to view the data in other modules. Defect #191 is raised, as the decryption method is not honored by the numeric data in manager comments. Later defect #278 and #286 were recorded due to defect #191 but were practically difficult to trace within a complex product without performing a defect dependency study.

✓ *Observations*: These three defects appear to be linked, however software quality teams normally would not have proactively identified defect #278 and #286 unless customers reported them. Defect#191 caused malfunction to compensation and payroll calculation. In cases like these, defect dependency study helps in detecting such defect spread and help product managers to prioritize defects accordingly.

Defect#191	Incorrect Decryption of Manager and Employee comments in Employee Performance Cycle
Module (Product)	Performance Mgmt. (HRS)
Cause	Decryption algorithm incorrectly converts NUMERIC data causing incorrect Manager ratings and comment
Fix	Decryption logic updated to honour NUMERIC data in Manager rating and comments during Performance Cycle.

Defect#278	Invalid hike % was imported to multiple users and corrupted existing user hike information
Module (Product)	Compensation Mgmt. (HRS)
Cause	Decryption logic in Performance Mgmt. caused issue.
Fix	Exception handling is improved to handle Invalid data in Compensation process cycle.

Defect#286	Unable to deduct monthly tax for Employees due to mismatch in YTD employee payment in Payroll
Module (Product)	Payroll Mgmt. (WFM)
Cause	Lack Exception handling in Performance Mgmt. caused corruption in tax calculation.
Fix	Created exception to deduct default monthly tax in case of data corruption for Employee monthly payroll payments

D. Study Workflow

Below are the details of study workflow and teams involved.

- The study was conducted over three service packs along with five maintenance packs of the above provided integrated software suite. The study was done over a period of 9 months between September 2014 and July 2015.
- The entire defect dataset of integrated product has been chosen and equivalence classes have been generated for all the sub-products and products.
- Defect dependency metric is applied over the equivalence classes and the metric value is calculated for all the defects identified by quality assurance (QA) team during every weekly sprint cycle.
- These defects include defects recorded during sprint cycle and defects raised by customers together. The metric results are combination of two sources (QA team and customers).
- QA team will evaluate the results of the metric over post release defects and compare them with the current defects recorded during sprint cycle for regression. Primary aim of this exercise is to avoid the possible spread of defects in upcoming release version.
- The value of defect dependency metric is the indicator for improvement study. QA teams progressively compare the metric values every release and sprint cycle.
- It has to be noted that there is no specific scale for this metric as it always depends on size of the defects and attributes (products chosen to evaluate) from dataset.
- QA Team shall present the results to product management team so that defects can be prioritized and an executive decision can be taken on implementing a plan for a new feature for a stable product(s) or sub-product(s) in upcoming service packs.

E. Study Design

This section describes the steps involved on calculating the metric using the industry dataset with specific.

- Each defect in this dataset is a data point. All sub-products are considered as subset i.e., there are 16 sub-products spread across 5 product pillars (shown in Table I). For example, if Web Services Manager is a pillar product, Export Mgmt., Integration Mgmt., and Web Service Admin mode are its subsets.
- Each set contains defects of its sub-product and they are entitled to be calculated together. Let D superset which contains defects of all sub-products i.e.

  $$D = \{p_1 \cup p_2 \cup p_3 \cup \ldots\ldots\ldots\ldots \cup p_{16}\}$$

  p_i represents 16 sub-products from the enterprise product suite under union of D the superset.
- Equivalence relation is constructed using all the p_i sets considering all the entities of the individual sets
- Equivalence classes are created for each p_i set generating the classes of values that are common to all the p_i sets.
- All equivalent classes of p_i sets are now passed to calculate $\Gamma(p_1, p_2, \ldots, p_{16})$ to generate overall defect dependency metric D^*
- D^* is now the metric standard for all the input p_i set of defect for a specific release. This activity needs to be continued for every release to understand the dependency of a defect over p_i sets used to calculate D^*
- Post every release (including service pack and maintenance pack), D^* values are compared and reviewed to identify the improvement.

All the above steps are programmatically implemented using .NET 4.0 and SQL. Additional details in this regard are provided in the next section.

IV. Implementation Setup

In addition to the standard testing process, QA team and product managers executed the below implementation and evaluation plan for of the defect dependency metric. Fig. 1 shows the implementation flow of the study setup. JIRA™ is hosted against Microsoft SQL Server 2008 R2 at database level. Below 'D' is the JIRA defect database which stores defects raised by customers post product release and QA team during sprint cycle.

Using a data extract package (designed using Microsoft SQL Server Integration Services 2008 R2), we extract desired defects from available sub-products from the entire product suite. The data extract package contains SQL query logic to extract the defect dump for all the sub-products. This package pushes the defect dump to a testing database (T). We use this testing database to implement defect dependency metric. We construct another package called metric package (M) that contains the SQL query logic to construct equivalence relation and equivalence classes of sub-products chosen for metric calculation. Using .NET Code and SQL, D* is calculated and stored in testing database.

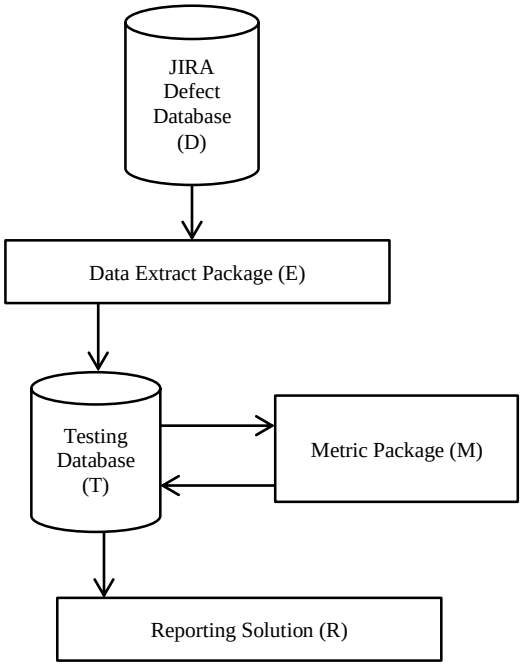

Fig. 1. Implementation flow

The implementation cycle is repeated during every release and every sprint cycle so that our QA teams can analyze and compare the metric results for taking fair decisions on improving product quality and defect prioritization. Product Managers and QA teams depend on Reporting tool (R) to visualize the trend of the metric periodically to understand and decide whether the results are conflicting or making real sense in practice.

V. Results and Observations

A. Implementation Results

We found interesting results across different version releases of our integrated software product. Table II contains the detailed trend data of metric values captured per product across entire produce suite specific to the released versions. Here {*V1, V2, V3*} being the service pack releases and {*V1.1, V1.2, V1.3, V2.1, V2.2, V3.1, V3.2, V3.3*} are the maintenance pack releases. *V1* is the considered as major service pack release and *V1.1, V1.2* and *V1.3* are its subsequent maintenance pack releases. Apart from these values, our QA team captured the metric values for every sprint release separately and for customer defects on weekly basis.

If we carefully observe, we can find the defect dependency values to be high in initial version *V1*. This was the base version of the implementation. We first calculated the metric value for *V1* version to analyze the health of the current integrated software suite and found that it had high defect dependency value of *6.78*. Human Resource System. (HRS) product was found to have high defect dependency value across overall product suite whereas Web Service Manager (WSM) was found to have low values. We started implementing the approach across different releases and found a significant changes in the quality of product and also a downtrend in the values of overall metric result for every product within a given specific version i.e. if we consider an example, in case of Learning Management System (LMS) the metric dropped down from *1.84* to *0.99* from service pack version *V1* and by end of release of maintenance pack *V1.3* which signifies improvement and stability in the product. Similar trend was identified across other product pillars in the enterprise suite. Our QA team has found significant improvement in terms of quality of product as the widespread of defects are diminishing by end of stable release as observed by the decrease in metric value for the products in below table.

Fig. 2 is the graphical representation of values from Table II highlighted in bold and italic, provides the trend analysis of the metric values across all products across version. We find a significant downtrend during the end of every version i.e. from *V1* to *V1.3*, *V2* to *V2.2* and *V3* to *V3.3*. We were able to minimize the various dependent issues across the integrated suite raising the quality levels of the entire product. This methodology helped QA teams and Product Managers to prioritize and de-prioritize defects with developers. For example, the Sustenance Engineering team responsible for providing fixes by end of upcoming release of a service pack or maintenance pack was able to select a particular defect that needed fix in a particular release cycle.

As per Fig. 2, from version *V1* to version *V3* we find a rise in dependency issues on every standard service pack release i.e. *V2* and *V3*. We studied causes of this increase and found that rise in metric is due to dependency among the new features introduced in the respective pillar products. However, as the maintenance pack(s) were released with subsequent fixes, we found downtrend in metric results within a version, i.e., *V2.1* and *V2.2*. At the end of every version, we were able to determine the impact of most of the defects. This led to prioritization of addressing high defect modules thereby easing the dependency of the defect to specific part of the product and decreasing it's widespread.

B. Observations

We present our observations partially based on the retrospective session conducted between Product Managers and QA teams for trend analysis.

- ✓ It became tough to gain confidence from Product managers in initial sprint cycles, as the defect dependency was too high which brought down initial confidence levels. Also as the approach was mathematical (based on rough set theory), the QA team didn't seem to comprehend the methodology in the beginning. As a result we had to spend some time negotiating for adoption of the approach within the Quality assurance team.

- ✓ However, as we progressed further, there has been significant improvement on stability of the product. We found exponential decrease in environment and performance related defects across releases. From the table, we can see that the "overall" numbers have decreased for every sub-product in the integrated product suite for *V1* to *V3.3*.
- ✓ By end of *V3.3* version release, as per the QA team, upon evaluation it was found that there was about *71%* decrease in overall defects reported by customers post product release. There was a *52%* decrease in internal defects raised by QA teams during sprint cycles.
- ✓ Most of the functional defects were proactively identified and resolved in timely fashion. We believe this decreased the risk of software failure during product deployments. The defect dependency metric was able to identify the spread of defects and helped to track critical surprise defects before produce release. These proactive defects constitute 12% among overall defects recorded across versions before deployment.
- ✓ In case of control flow issues among sub-products, we still have to rely on our standard approaches which are practiced by QA teams. Most of such control flow issues were free from defect dependency and were found them to be fragmented and un-connected with other modules in specific product or a sub-product.
- ✓ Business Intelligence System Reporting product and Web Services Manager product were found to be most stable products during evaluation of this metric.

C. Lessons learnt

- ✓ During this implementation, we found few architectural flaws in two of the sub-product(s) that required total makeover in terms of integration. This wouldn't have been possible if the metric was never implemented.
- ✓ It was also identified that it is expensive to re-design the sub-modules when the product is actively used by most of the customers. Hence, the faulty sub-products were removed from the integrated product suite and were to be merged as components in one of the existing product for improved quality.

TABLE II. DEFECT DEPENDENCY RESULTS BY PRODUCT AND VERSION

S. No	***Product***	***Sub-product***	***V1***	***V1.1***	***V1.2***	***V1.3***	***V2***	***V2.1***	***V2.2***	***V3***	***V3.1***	***V3.2***	***V3.3***
1	Learning Management System (LMS)	Overall	***1.84***	*1.49*	*1.24*	*0.99*	***1.26***	*1.15*	*0.53*	***0.8***	*0.41*	*0.28*	***0.14***
		Learner mode	0.19	0.18	0.14	0.17	0.14	0.11	0.07	0.09	0.03	0.03	0.03
		Manager mode	0.37	0.33	0.26	0.21	0.21	0.16	0.05	0.14	0.11	0.07	0.02
		Admin Mgmt.	1.28	0.98	0.84	0.61	0.91	0.88	0.41	0.57	0.27	0.18	0.09
2	Human Resource System (HRS)	Overall	***2.47***	*2.1*	*1.88*	*1.71*	***1.97***	*1.78*	*1.13*	***2.54***	*1.65*	*1.28*	***0.56***
		Hire Mgmt.	0.45	0.39	0.33	0.29	0.51	0.45	0.31	0.44	0.31	0.17	0.08
		Compensation Mgmt.	0.39	0.31	0.32	0.29	0.39	0.32	0.29	0.28	0.19	0.12	0.07
		Succession Mgmt.	0.22	0.21	0.16	0.15	0.18	0.13	0.12	0.14	0.11	0.05	0.02
		Performance Mgmt.	1.41	1.19	1.07	0.98	0.89	0.88	0.41	1.68	1.04	0.94	0.39
3	Business Intelligence System (BIS)	Overall	***1.02***	*0.93*	*0.81*	*0.62*	***1.08***	*0.96*	*0.72*	***0.98***	*0.72*	*0.42*	***0.19***
		BI Dashboards	0.27	0.21	0.18	0.13	0.31	0.28	0.22	0.34	0.21	0.11	0.07
		Data Downloader	0.32	0.31	0.27	0.17	0.45	0.41	0.29	0.52	0.44	0.29	0.12
		Data Uploader	0.43	0.41	0.36	0.32	0.32	0.27	0.21	0.12	0.07	0.02	0
4	Work force Manager (WFM)	Overall	***1.15***	*0.96*	*0.89*	*0.73*	***1.05***	*0.85*	*0.71*	***1.2***	*0.73*	*0.38*	***0.19***
		Attendance Mgmt.	0.31	0.25	0.19	0.12	0.44	0.37	0.31	0.58	0.31	0.21	0.09
		Payroll Mgmt.	0.24	0.21	0.2	0.11	0.21	0.17	0.14	0.24	0.15	0.06	0.02
		Reimbursement Mgmt.	0.6	0.5	0.5	0.5	0.4	0.31	0.26	0.38	0.27	0.11	0.08
5	Web Services Manager (WSM)	Overall	***0.3***	*0.26*	*0.22*	*0.22*	***0.24***	*0.1*	*0.07*	***0.17***	*0.06*	*0.04*	***0***
		Export Mgmt.	0.16	0.15	0.13	0.13	0.12	0.07	0.04	0.09	0.04	0.04	0
		Integration Mgmt.	0.05	0.05	0.05	0.05	0.09	0.03	0.03	0.07	0.02	0	0
		Web Service Admin mode	0.09	0.06	0.04	0.04	0.03	0	0	0.01	0	0	0
6	Overall Metric		***6.78***	***5.74***	***5.04***	***4.27***	***5.6***	***4.84***	***3.16***	***5.69***	***3.57***	***2.4***	***1.08***

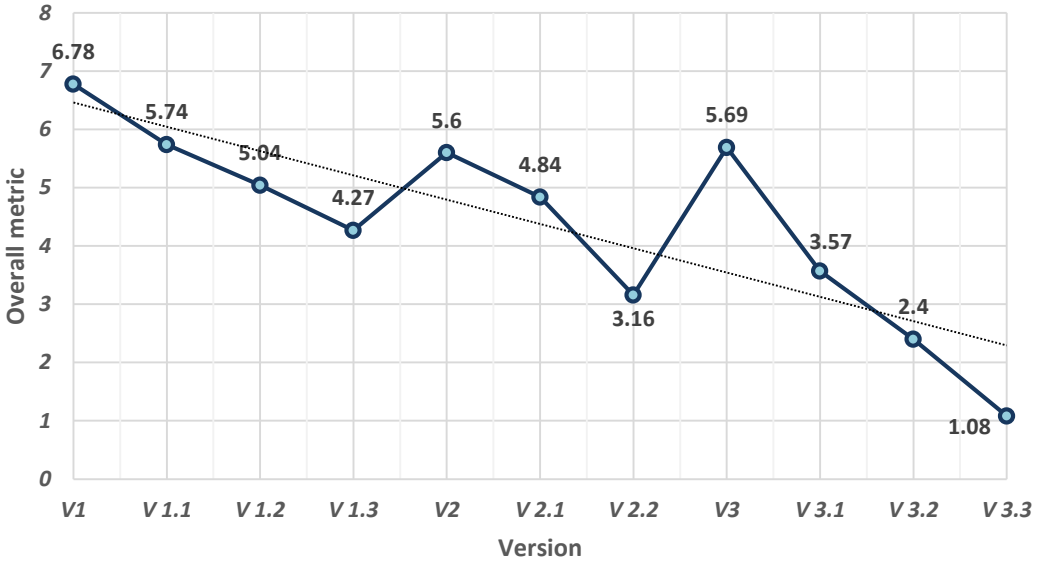

Fig. 2. Implementation flow – Trend Analysis of overall metric results across version

- ✓ QA teams have come up with improved test cases as part of future integrating testing, as traditional test cases are no longer contributing towards product quality.

In summary, defect dependency metric was one of the key contributors along with our standard processes for stabilizing our integrated software product to a greater extent. The QA team gave informal feedback that the metric was of great value and product managers stated that it has helped improve customer success across customer subscriptions.

VI. Threats to Validity

Our approach to calculate degree of Defect dependency metric is based on rough set theory. We implemented it against a real time defect dataset to improve and evaluate the quality of our large scale integrated software product during every release cycle since September 2014 to July 2015. We were successful in improving the integrated product suite. The main concern with our case study just like other case study papers is the possible extension and applicability of the work to other defect datasets. Given that we have applied it only to a single product suite, we can't convincingly state that it's applicable to other product suites too. However, it needs to be noted that our case study was based on an integrated software product that is used by most of the fortune 500 companies. It would be interesting to see if this methodology is adopted in tools used to build integrated software from mid-size software industries to large scale industries to understand its significance in reality. We believe that apart from defect dependency metric, heuristic approaches can also be used to solve our day-to-day quality issues. However we suggest fellow software practitioners to adopt our approach to improve software quality of their products. The scope of defect dependency metric is only to identify dependency of defect i.e. it's widespread; however an integrated software product can still be un-stable with no defect dependency. This can be because of poor functional and architectural design or due to control/data flow issues.

On the other hand, organizational constraints and its corresponding influence on the accuracy of metric can be questioned. However a series of evaluation by quality teams and meetings with product manager and key stake-holders of the project(s) helped us evaluate the efficiency of the metric during every release. Influence of teams with lack of process knowledge, skill set or technology used can be argued and the results may be interpreted differently at times. To limit this issue, the evaluation of this metric has to be attributed to only key decision makers within the organization.

VII. Conclusion and Future Work

In current study, we have implemented this metric only on product & sub-product defects. As an extension to this study, we will be working on alternate methods to identify dependencies and widespread of defect on various other artifacts at different levels of software production like requirement analysis, resource planning, integration strategy, maintenance and design. This will help an integrated software company to address quality issues at all levels. Lessons learnt by conducting such studies can address some of the open challenges and help take efficient decisions to produce better complex products. As a future work, we will be assessing the metric more comprehensively by getting feedback from developers and quality teams on how significant this method helps them to prioritize the defect as part of regular work. We will have to work on testing strategies while adopting this approach in real time so as to improve test cases and address proactive defects especially during maintenance phase.

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Automatic Recommendation of Software Design Patterns Using Anti-patterns in the Design Phase: A Case Study on Abstract Factory

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***Abstract*—Anti-patterns, one of the reasons for software design problems, can be solved by applying proper design patterns. If anti-patterns are discovered in the design phase, this should lead an early pattern recommendation by using relationships between anti- and design patterns. This paper presents an idea called Anti-pattern based Design Pattern Recommender (ADPR), that uses design diagrams i.e. class and sequence diagrams to detect anti-patterns and recommend corresponding design patterns. First of all, anti-patterns relating to specific design patterns are analyzed. Those anti-patterns are detected in the faulty software design to identify the required design patterns. For assessment, a case study is shown along with the experimental result analysis. Initially, ADPR is prepared for recommendation of the Abstract Factory design pattern only, and compared to an existing code-based recommender. The comparative results are promising, as ADPR was successful for all cases of Abstract Factory.**

***Keywords*—Software design, design pattern, anti-pattern, design pattern recommendation, abstract factory**

I. Introduction

Design patterns formalize reusable solutions for common recurring problems, while anti-patterns are outcome of bad solutions degrading the quality of software. Design patterns are often mentioned as double-edged sword, selecting the right pattern can produce good-quality software while selecting a wrong one (anti-pattern) makes it disastrous [1]. Thus, which patterns to use in which situation, is a wise decision to take. On the contrary, mapping software usage scenario or user description with pattern intent is a manual and hectic task. However, this task can be made easier with assistance of pattern recommendation systems.

The recommendation of a proper design pattern is yet a faulty process due to the difficulties in connecting software information with design pattern intents. The software requirements do not contain possible design problems' indication, making it infeasible to identify the required patterns. However, anti-patterns can be detected after a faulty design is created from user requirements. Now, as every design pattern has its own context of design problems that it solves and every anti-pattern causes specific design problems, a relationship should exist between anti- and design patterns that can be beneficial in pattern recommendation.

This paper presents the idea of incorporating anti-pattern detection and design pattern recommendation in the software design phase. This idea is encapsulated in a tool named as Anti-pattern based Design Pattern Recommender (ADPR). The tool recommends appropriate patterns in two phases. The analysis of anti-patterns of particular design patterns is conducted in the first phase. For capturing the full anti-pattern information i.e. class structure, interactions, and linguistic relationships, the analysis is performed in three levels - structural, behavioral and semantic analysis. In the second phase, the inputted system is matched with those anti-patterns for recommending the related design patterns. This matching is also conducted in three levels similar as the levels of analysis - structural, behavioral and semantic matching. Based on the matched anti-patterns from these levels, the corresponding 'missing [2]' design patterns are recommended. ADPR is initially designed for the recommendation of Abstract Factory as it is one of the most popular patterns, and can be extended to the other patterns.

Research has been conducted for proposing pattern recommendation systems. However, those cannot provide a good precision due to the difficulty in logically defining the manual process of mapping human requirements with design pattern intents. The human requirements i.e. usage scenario, designers' answers to questions or cases residing in the knowledge base in Case Based Reasoning (CBR), have been inadequate to accurately extract the required design patterns because of the lack of focus on the design problems. Generally, these three approaches of design pattern recommendation can be found in the literature - textual matching of software usage scenario with design pattern intents [3], [4], [5], question answer session with designers [6], [7], and CBR [8], [9]. The first approach is inefficient to identify probable design problems of software as scenario does not contain design information. The generic questions of the second approach focuses more on design pattern features than design problems of particular software. In the third approach, cases of CBR does not store possible design problems of software. Oppositely, the field of anti-pattern detection identifies bad designs in software, assuring that successful detection of anti-patterns is possible [10], [11]. However, the usage of anti-pattern in the design phase for identifying correct design patterns is yet to be discovered.

A case study has been conducted for evaluating the applicability of the proposed approach. The case study is carried on a badly designed java project requiring Abstract Factory, named as $Painter$. Based on the step-by-step analysis on the project, Abstract Factory is recommended by the tool. This case study justifies the approach that, this recommendation process leads to the correct recommendations.

The validity of this approach is further justified by experimenting ADPR on the case of Abstract Factory design pattern. For this, the prototype of ADPR was implemented for Abstract Factory using java. Moreover, implementation of a prominent

research on source based design pattern recommendation, proposed by Smith et al. [12], was also performed for the comparison. The dataset were created by gathering projects that require Abstract Factory, but intentionally has not been applied. The results are encouraging as ADPR provides better recommendation results in the design phase of software, compared to the source based one operating in the coding phase.

II. Related Work

In terms of recommending suitable patterns for software, the relationship establishment between the design pattern and anti-pattern is rare in the literature. Yet investigations have been conducted for proposing design pattern recommendation approaches from different perspectives as mentioned below. On the other hand, anti-pattern detection is a well-established research trend for successfully identifying anti-patterns to check whether the software design is bad.

A. Design Pattern Recommendation

As mentioned earlier, design pattern recommendation researches can be divided into three types – text-based search, question-answer session, and CBR. In text-based search, pattern intents are matched with the problem scenarios for identifying the design patterns that relate mostly to the software [3], [4], [5]. This intent matching is based on set of important words [3], text classification [4], or query text search using Information Retrieval (IR) techniques [5]. However, problem scenarios are ambiguous as written in human language; and are usually not written from a designer's point of view, making it impractical to identify possible design problems.

In question-answer based approach, designers are asked to answer some questions about the software and those answers lead to find the required patterns for that software [6], [7]. Here, the mapping from question-answers to design patterns is set by formulating Goal-Question-Metric (GQM) model [6], or ontology-based techniques [7]. The problem is that, the questions are often static or generic, and more related to design pattern features than software specific design problems.

In CBR, recommendations are given according to the previous experiences of pattern usage stored in a knowledge base in the form of cases [8], [9]. The retrieval of cases from the knowledge base is performed either using user provided class diagrams [8], or using inputted and reformulated problem descriptions [9]. Matching cases to identify required patterns are not feasible, as the cases do not focus on the design problems a software might have.

A few researches were conducted for recommending patterns which do not fall in any of the mentioned categories. Navarro et al. proposed a different recommendation system for suggesting additional patterns to the designer while a collection of patterns are already selected [13]. Thus, it may not be used for new software being developed. Kampffmeyer et al. presented a new ontology based formalization of the design patterns' intents making those focus on the problems rather than the solution structures [14]. However, the problem predicate and concept constraints, required by the recommendation tool, makes it's usage challenging. Both of these approaches require expertize of the designers to use those effectively.

The research question of this paper is to use anti-pattern knowledge for design pattern recommendation in the design-phase of software. The most related paper of this research is a code-level design pattern recommendation approach [12], where patterns are recommended dynamically during the code development phase. That research tried to relate anti-patterns with design patterns for recommendation. Anti-patterns were identified using structural and behavioral matching in the code, and required design patterns to mitigate those anti-patterns were recommended. However, design pattern recommendation in the coding phase is too late as the software has already been designed and needed to be changed after the recommendation.

B. Anti-pattern Detection

Anti-pattern detection is a rich area of research, that focuses on finding bad designs in software [15], [16], [17], [18]. Fourati et al. proposed an anti-pattern detection approach in design level using UML diagrams i.e. the class and sequence diagrams [10]. The detection was done based on some predefined threshold values of metrics, identified through structural, behavioral and semantic analysis. This prominent research assures that anti-pattern detection can be performed in the design phase. Another approach for anti-pattern detection was based on Support Vector Machines (SVM) [11], where the detection task was accomplished in three steps - metric specification, SVM classifier training and detection of anti-pattern occurrences. The concept of anti-pattern training has made any defined or newly defined anti-patterns detection possible, breaking the boundary of only detection of some well-established anti-patterns (e.g. Blob, Lava Flow, Poltergeists, etc.) [19].

As presented in subsection II-A, the existing approaches of design pattern recommendation in design phase use textual match with usage scenario, case match with knowledge base cases, or ask design pattern related generic questions to designers. These approaches cannot be the proper ways to recommend design patterns, as design patterns are used for mitigating design problems, and these do not focus on the system design problems. The single paper that focuses on design problems (anti-patterns), recommends design patterns in the coding phase, making its usage impractical.

III. The Proposed Approach

The novelty of this research lies in identifying design problems of software for recommending appropriate design patterns, and in the design phase of software. Without having the analysis of bad designs (i.e. anti-patterns), suggesting correct design patterns is difficult. So, an idea is formalized, where the appropriate design patterns are suggested from identifying existing design problems, that reside as anti-patterns in the initial system design.

A. Overview of ADPR

Existence of an anti-pattern in a software design discloses that the design is not appropriate; the design can be improved by application of suitable design patterns. Thus, the detection of anti-patterns can lead to the recommendation of design patterns, if the anti-patterns could properly be mapped to their related design patterns.

This idea is implemented as a system called Anti-pattern based Design Pattern Recommender (ADPR), which is initially designed for Abstract Factory design pattern. The top-level overview of ADPR is shown in Fig. 1. There are two

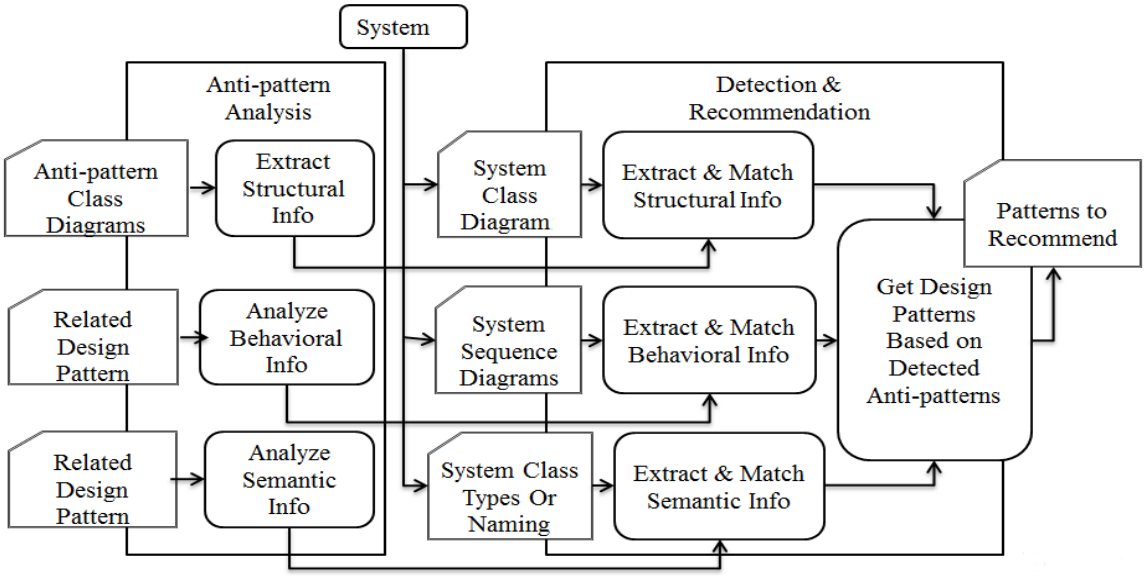
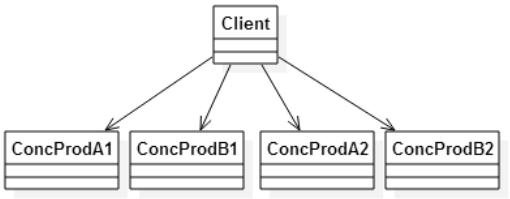
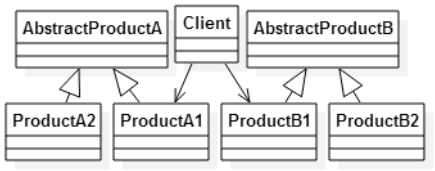


Fig. 1: Overview of ADPR

phases in the approach. At first the system analyzes the anti-patterns of particular design patterns. These anti-patterns do not necessarily be in the anti-patterns catalog like Blob, Lava Flow, etc[1]. These represent the '$missing$' design patterns [2] and their presence indicate that, a particular design pattern should have been used [20], [2], [12]. As shown in Fig. 1, in the second phase, the analyzed anti-patterns are detected in the initial system design and the corresponding design patterns to those matched anti-patterns are recommended. The detail of both these phases are described below.



(a) As Mentioned in [21]



(b) As Mentioned in [2]

Fig. 2: Anti-pattern Variants (Abstract Factory)

B. Analysis of Anti-patterns

To identify the $missing$ design patterns, the related anti-patterns are collected and analyzed first. The case of Abstract Factory is presented here as the usage example. Several anti-pattern variants of Abstract Factory may exist; initially, two of those are used (Fig. 2 [2], [21]) to show whether the proposed system works. In Fig. 2(a), there are two families of classes, $ConcreteProductA1$ ($ConcProdA1$), $ConcreteProductB1$ ($ConcProdB1$), and $ConcreteProductA2$ ($ConcProdA2$), $ConcreteProductB2$ ($ConcProdB2$). As determined by GoF, instead of being directly instantiated by the $Client$, these families should have been instantiated using abstract factories; this encourages the usage of Abstract Factory design pattern[2] in this case. Similarly in 2(b), $ProductA1$, $ProductB1$, and $ProductA2$, $ProductB2$ are two families of classes, which should not be directly instantiated by the $Client$. Thus, these two class designs represent the anti-patterns of Abstract Factory [2], [21].

These anti-patterns are analyzed and stored in the tool for further design level matching. Three levels of analysis are performed for ensuring the accurate capture of anti-pattern information - structural, behavioral and semantic (as shown in Fig. 1 'Anti-pattern Analysis' phase), similar to the design pattern analysis in [22].

The structural analysis concentrates on the structural characteristics of the anti-patterns. Similar structures of different anti-patterns can be found making this level of analysis inadequate. Thus, the behavioral analysis is provided for considering the behaviors of the anti-patterns along with the structure. One more level of validation is provided by the semantic analysis, as there can be cases where both structures and behaviors of different anti-patterns may match. Thus, these three levels of analysis ensure the proper refinement of the tool for detection of anti-patterns accurately.

Structural Analysis: The structure of an anti-pattern is defined by the relationships among the classes of it. Thus, class diagrams are used in this level [23] (as shown in Fig. 1, 'Anti-pattern Class Diagrams' are inputted to 'Extract Structural Info'), as those capture the different class-to-class relationships e.g. aggregation, generalization, association, etc. For keeping these relationship information, the structures are represented and stored in a form of $n \times n$ matrix of prime numbers as noted by Dong et al.[22] (for tracking cardinality

[1]"Anti Patterns Catalog," http://c2.com/cgi/wiki?AntiPatternsCatalog

[2]Abstract Factory intent: "Provide an interface for creating families of related or dependent objects without specifying their concrete classes." [20]

of the relationships). Hence, this level takes the UML class information of anti-patterns as input and stores those in the form of matrices. For this, the class diagrams are converted to program readable format, XML and inputted to the tool.
In case of Abstract Factory, the class XMLs of the collected anti-pattern variants are provided to the analyzer, that creates and stores the structure matrices for each of the variants as shown in Fig. 3. The first matrix of Fig. 3 is generated from Fig. 2(a). Here,

- C, $A1$, $B1$, $A2$ and $B2$ represent $Client$, $ConcProdA1$, $ConcProdB1$, $ConcProdA2$ and $ConcProdB2$ respectively.
- The four association ($\xrightarrow{A}$) relations between $Client \xrightarrow{A} ConcProdA1$, $Client \xrightarrow{A} ConcProdB1$, $Client \xrightarrow{A} ConcProdA2$, $Client \xrightarrow{A} ConcProdB2$ in 2(a) are contained in the matrix using the prime number '2'[3].

Similarly, the second matrix of Fig. 3 is generated from 2(b), where,

- $AbsA$, $A1$, $A2$, $AbsB$, $B1$, $B2$, C represent $AbstractProductA$, $ProductA1$, $ProductA2$, $AbstractProductB$, $ProductB1$, $ProductB2$, $Client$ correspondingly.
- The four generalized ($\xrightarrow{G}$) relations ($ProductA1 \xrightarrow{G} AbstractProductA$, $ProductA2 \xrightarrow{G} AbstractProductA$, $ProductB1 \xrightarrow{G} AbstractProductB$, $ProductB2 \xrightarrow{G} AbstractProductB$) and two association relations ($Client \xrightarrow{A} ProductA1$, $Client \xrightarrow{A} ProductB1$) are stored in the matrix using prime number '3' and '2' consequently[3].

	C	A1	B1	A2	B2
C	0	2	2	2	2
A1	0	0	0	0	0
B1	0	0	0	0	0
A2	0	0	0	0	0
B2	0	0	0	0	0

	AbsA	A1	A2	AbsB	B1	B2	C
AbsA	0	0	0	0	0	0	0
A1	3	0	0	0	0	0	0
A2	3	0	0	0	0	0	0
AbsB	0	0	0	0	0	0	0
B1	0	0	0	3	0	0	0
B2	0	0	0	3	0	0	0
C	0	2	0	0	2	0	0

Fig. 3: Generated Matrices of Fig. 2

Behavioral Analysis: Behaviors of a system represent the dynamic characteristics (e.g. class execution sequence in runtime) of it. Now, it is logical to assume that the behaviors of a design pattern are inherited by it's anti-patterns, as the anti-patterns provide bad software structures compared to that pattern, but preserve the software behaviors. Thus, in behavioral analysis, the behaviors of the corresponding design patterns of anti-patterns are analyzed (Fig. 1, 'Related Design Pattern' leads to 'Analyze Behavioral Info').

[3]The determined prime number value of $Association$ is 2, $Generalization$ is 3, and $Aggregation$ is 5, similar as [12].

The behavioral feature of Abstract Factory is, there are families of classes, and these families are always used together [20]. Whenever such families of classes are found, that are always instantiated in the same execution path, and the classes of different families are instantiated in different execution paths, that system is required to use Abstract Factory [20].

Semantic Analysis: Semantic features of a system capture the logical relationships between classes (e.g. same types of classes in a system, classes that are always used together, etc.). Semantics basically relate the structural and behavioral aspects of the system (information of static structure with dynamic behavior). The semantic features of anti-patterns are also assumed to be the same as corresponding design patterns, as the logical relations among classes should not be changed, no matter how the system is being designed. Thus, similar as the behavioral analysis, related design patterns of anti-patterns are analyzed for capturing semantic information as shown in Fig. 1, 'Related Design Pattern' to 'Analyze Semantic Info'.
In Abstract Factory, classes of similar types form different families [20]. Therefore, the verification of behaviorally matched families are done by checking the types of the classes (identified from static structure) in families. Super-class information are used for this purpose, as classes having the same super-classes are generally of similar types; but there can be cases like Fig. 2 (a), where the design is bad enough to not even follow that OO convention. For those cases, similarity in the names of classes can give an indication of similar types.

C. Detection and Recommendation

Once the anti-patterns are analyzed based on corresponding design patterns, those could be detected in a faulty system design for recommending the patterns. Detection of anti-patterns needs three levels of matching similar to the analysis - structural, behavioral and semantic matchings (as shown in Fig. 1 'Detection & Recommendation' phase). If a system design is matched with an anti-pattern completely (structurally, behaviorally and semantically), only then the corresponding design pattern is recommended.

Structural Matching: The system structure is represented similarly as the matrix of anti-patterns using the system class diagram. The stored anti-patterns' structures (Fig. 3) are matched to the system's structure for finding whether any of those anti-patterns is present in the system (Fig. 1, from 'System Class Diagram' to 'Extract and Match Structural Info'). For this, the system matrix is matched with anti-patterns' matrices using naive approach, as the focus is on the accuracy rather the computational complexity or time. In this approach, matrices are matched using a brute force method where every permutation of the system matrix (permutation of nodes in the system graph) are taken and matched with the anti-pattern matrices. If no match is found, the detection is stopped and the other levels of matching are postponed. Otherwise, for at least one structural match, the behavioral matching is executed.

Behavioral Matching: Sequence diagrams are used in this level as those represent the dynamic interactions of classes in execution [23] (Fig. 1, 'System Sequence Diagrams' are inputted to 'Extract and Match Behavioral Info'). The $lifelines$

of a sequence diagram are the roles or object instances[4], and represent the classes in the same execution sequence. Thus, families of classes in Abstract Factory are identified from these $lifelines$, as classes of same families are supposed to be in the same execution sequence, and so in the same sequence diagram $lifelines$. For this, the UML sequence diagrams of the system are converted to XMLs first, and inputted to the tool. Then, the XMLs are parsed to identify the $lifelines$ and the corresponding classes of those are identified. Thus, the identified classes of each sequence diagram are marked to be in the same family.

***Semantic Matching**:* Should a particular design pattern be recommended, is taken in the semantic matching step. In semantic matching for Abstract Factory, types of the classes are analyzed to validate the family information acquired from the behavioral matching as per the findings of semantic analysis (different classes of similar types form different families). A matrix containing the similar types of classes information is generated using the super-class relations. However, as mentioned earlier, sometimes the class-types could not be identified due to missing super-classes in a bad design (Fig. 2 (a)). For those cases, similarity in the names of the classes are analyzed to identify the same types (as shown in Fig. 1, 'System Class Types Or Naming' are used to 'Extract and Match Semantic Info'). The class names are split based on capital letters, and the parts are matched (For example, 'WoodenDoor' is split to 'Wooden', 'Door', and 'GlassDoor' is split to 'Glass', 'Door', and matched to each other). After the class types are determined, the mentioned type matrix is generated. Then, that matrix is used to analyze the classes in multiple families to test whether those are aligned to the assumption of Abstract Factory that, multiple families contain similar types of, but different classes.

Now, if the design is too bad to neither have super-classes nor similar names for the same types of classes, the approach will fail to generate type matrix and so, match semantics. Thus, for getting recommendation, the basic design principles should be followed by the designers. The semantic matching algorithm is shown in Algorithm 1.

For semantic matching, first of all the type matrix is generated (Algorithm 1 Line 8). As mentioned previously, it can be generated from super-class information (generalization relationship) or similar naming of classes. The type matrix is a 0,1 matrix, where the same type classes share value 1, and the others share value 0. Then, every sequences (class families) are compared to each others (Lines 9–13). The procedure CompareSeq is called for this reason. In CompareSeq, the duplicates in the sequences being compared are removed in Line 25. Then nested loops are executed for getting the positions of the classes of the sequences in the $type$ matrix using the class names list (cN) (Line 26–39). The value in those positions inside the $type$ matrix (0 or 1) is added to the seq matrix in Lines 41–42. After the calculation of the values in all the seq positions, $maxMatch$ between the sequences are identified in Lines 14–21. This $maxMatch$ is returned as the score of semantic matching. If the score value is $>= 2$, there is a valid semantic match.

[4]R. Perera, "The Basics & the Purpose of Sequence Diagrams - Part 1," http://creately.com/blog/diagrams/the-basics-the-purpose-of-sequence-diagrams-part-1/

Algorithm 1 Semantic Matching

```
1:  system: System Matrix
2:  cN: System Class Names
3:  behavioralMetric: Behaviors of Anti-pattern (Sequence
    Diagram for Abstract Factory)
4:  procedure MatchSemantic
5:      seqs ← behavioralMetric.sequenceDiagrams
6:      size ← seqs.size()
7:      seq ← [size][size]
8:      type[cN.length][cN.length] ← GenTypeMatrix()
9:      for i ← 0 to size do
10:         for j ← i + 1 to size do
11:             CompareSeq(seqs.get(i), seqs.get(j), i, j)
12:         end for
13:     end for
14:     maxMatch ← 0
15:     for i ← 0 to size do
16:         for j ← 0 to size do
17:             if maxMatch < seq[i][j] then
18:                 maxMatch ← seq[i][j]
19:             end if
20:         end for
21:     end for
22:     return maxMatch
23: end procedure
24: procedure CompareSeq(s1, s2, p1, p2)
25:     RemoveDuplicates(s1, s2)
26:     for i ← 0 to s1.size() do
27:         for j ← 0 to s2.size() do
28:             s ← −1, d ← −1
29:             for k ← 0 to cN.length do
30:                 if s1.get(i) = cN.get(k) then
31:                     s ← k
32:                 end if
33:                 if s2.get(j) = cN.get(k) then
34:                     d ← k
35:                 end if
36:                 if s! = −1 and d! = −1 then
37:                     break
38:                 end if
39:             end for
40:             if s! = −1 and d! = −1 then
41:                 seq[p1][p2] ← seq[p1][p2] + type[s][d]
42:                 seq[p2][p1] ← seq[p2][p1] + type[s][d]
43:             end if
44:         end for
45:     end for
46: end procedure
```

IV. Case Study on "Painter", a Project Requiring Abstract Factory

For an initial assessment of the competency, ADPR was used on a sample java project named $Painter$ (Shown in Table I). This step-by-step study might increase the understanding of the tool as well as justify the feasibility of the approach.

It is assumed here that, the analysis of anti-patterns have already been performed. And thus, the tool has stored

the required anti-patterns' information for the purpose of detecting those and recommending the corresponding design patterns for the inputted systems.

A. About *Painter*

The project, *Painter* is a well-known example of Abstract Factory usage[5]. For testing the recommendation tool, the project is designed without implementing Abstract Factory (badly designed). The scenario of the project is as follows: "The *Paint* can draw three types of *Shape* - *Circle*, *Triangle*, or *Square*. The *Shape*s can be filled with three *Color*s - *Red*, *Blue*, or *Green*. *Circle*s will be *Red*, *Triangle*s will be *Blue*, and *Square*s will be *Green*."

B. Structural Matching of *Painter*

As mentioned in 'Structural Matching' in subsection III-C, the system structure is to be matched with the anti-patterns' structure. For this, the initial class diagram of *Painter*, shown in Fig. 4, is inputted into the tool in XML format. This inputted XML is converted into a matrix of prime numbers for preserving the relationships between the classes (as instructed in [22]), as shown in Fig. 5. There are six association ($Paint \xrightarrow{A} Blue$, $Paint \xrightarrow{A} Green$, $Paint \xrightarrow{A} Red$, $Paint \xrightarrow{A} Square$, $Paint \xrightarrow{A} Triangle$, $Paint \xrightarrow{A} Circle$) and six generalization (($Blue \xrightarrow{G} IColor$, $Green \xrightarrow{G} IColor$, $Red \xrightarrow{G} IColor$, $Square \xrightarrow{G} IShape$, $Triangle \xrightarrow{G} IShape$, $Circle \xrightarrow{G} IShape$)) relationships in the diagram. These are fully preserved by putting value '2' in places of association and '3' in places of generalization[3].

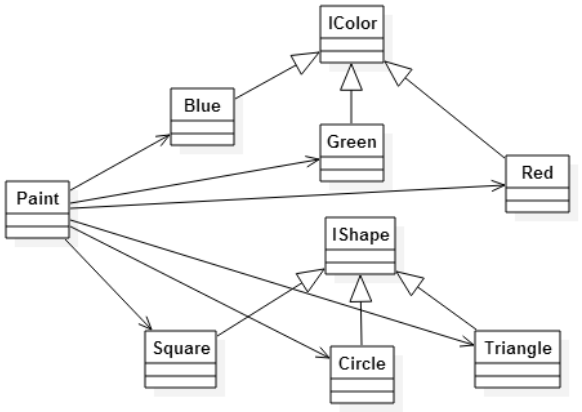


Fig. 4: Class Diagram of *Painter*

The anti-patterns' structures are assumed to be stored in the tool. Now, the structures of those stored anti-patterns are matched with the *Painter* matrix using naive matrix matching. From Fig. 4 and Fig. 2 (a), a match is encountered. Thus, the structural matching is accomplished, and the tool will proceed to the next level of matching.

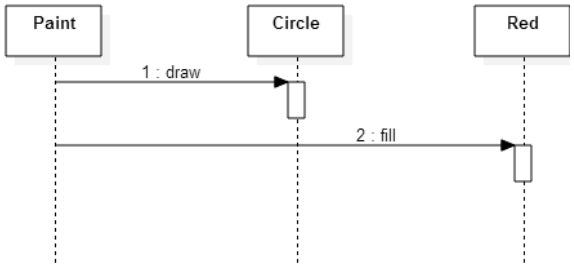
[5]"Design Pattern - Abstract Factory Pattern," http://www.tutorialspoint.com/design_pattern/abstract_factory_pattern.htm

	Blue	Green	Red	IColor	IShape	Square	Circle	Triangle	Paint
Blue	0	0	0	3	0	0	0	0	0
Green	0	0	0	3	0	0	0	0	0
Red	0	0	0	3	0	0	0	0	0
IColor	0	0	0	0	0	0	0	0	0
IShape	0	0	0	0	0	0	0	0	0
Square	0	0	0	0	3	0	0	0	0
Circle	0	0	0	0	3	0	0	0	0
Triangle	0	0	0	0	3	0	0	0	0
Paint	2	2	2	0	0	2	2	2	0

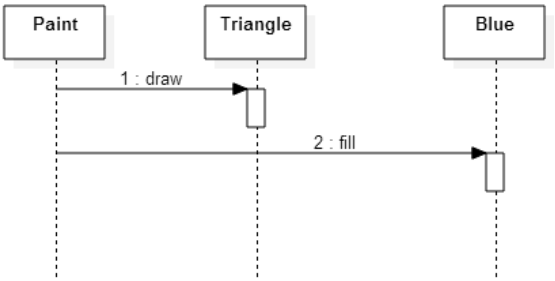
Fig. 5: Class Relation Matrix of *Painter*

C. Behavioral Matching of *Painter*

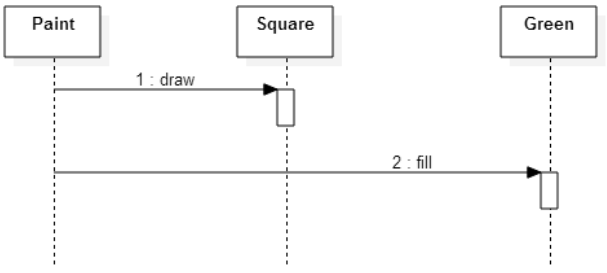
For behavioral matching, the information about the interactions between classes in execution is required. This information is extracted from the sequence diagrams. From the scenario of *Painter*, three sequence diagrams can be drawn (Fig. 6).



(a) Circle Is Red



(b) Triangle Is Blue



(c) Square Is Green

Fig. 6: Sequence Diagrams of *Painter*

The class families are identified from the *lifelines* of these sequence diagrams. As, three sequence diagrams are inputted, three families are identified from those. The first family consists of *Paint*, *Circle*, and *Red*; the second family has the classes *Paint*, *Triangle*, and *Blue*; and the third family is comprised of *Paint*, *Square*, and *Green*.

D. Semantic Matching of *Painter*

The three families identified in the behavioral matching is validated in this level. First of all, the type matrix (as mentioned in subsection III-C 'Semantic Matching') is generated using the super-class information from the class relation matrix (Fig. 5). The type matrix is shown in Fig. 7. Situations can occur that the super-class information can be missing. For example, another variation of bad-designed class diagram can be created by the designer as shown in Fig. 8. It is noticeable here that, though the super-classes are missing, type matrix will still be generated from the similarity in the names of the same types of classes. Red$Color$, Blue$Color$, Green$Color$; and Circle$Shape$, Triangle$Shape$, Square$Shape$ are identified as same types. However, if the names of same types are not similar in this case, the approach will fail to generate the type matrix. For example - if the names of the classes are similar as Fig. 4, but the super-classes $IShape$ and $IColor$ are missing, then the approach will fail.

	Blue	Green	Red	IColor	IShape	Square	Circle	Triangle	Paint
Blue	0	1	1	0	0	0	0	0	0
Green	1	0	1	0	0	0	0	0	0
Red	1	1	0	0	0	0	0	0	0
IColor	0	0	0	0	0	0	0	0	0
IShape	0	0	0	0	0	0	0	0	0
Square	0	0	0	0	0	0	1	1	0
Circle	0	0	0	0	0	1	0	1	0
Triangle	0	0	0	0	0	1	1	0	0
Paint	0	0	0	0	0	0	0	0	0

Fig. 7: Type Matrix of $Painter$

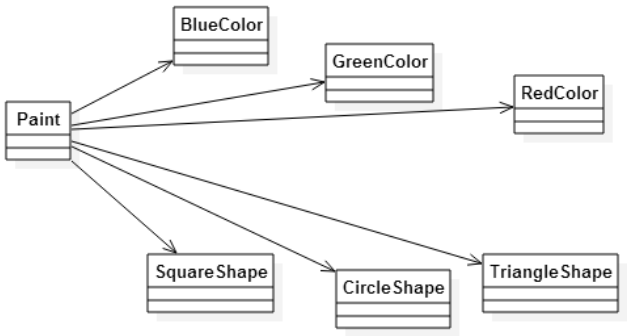


Fig. 8: Another Bad Class Diagram Example of $Painter$

After the type matrix is generated, the class families are analyzed to test whether different classes having the same types are situated in different families. Thus, the three identified families are analyzed here, and found that all three families contain classes of same types. $Circle$ (family-1), $Traiangle$ (family-2) and $Square$ (family-3) are of the same type, and similarly Red (family-1), $Blue$ (family-2) and $Green$ (family-3) are also same typed. So, the semantic matching ensures that the identified families from the behavioral matching are valid families.

All these three levels of matching indicate that the Abstract Factory design pattern is required to improve the project design. Thus, Abstract Factory is recommended for this project. This recommendation is obtained in the design phase of the project making it possible to re-design it, and provide a better design of the system.

V. Implementation and Result Analysis: for Abstract Factory

To assess the new approach, preliminary experiments have been conducted on Abstract Factory design pattern. A prototype of ADPR has been implemented in java for this purpose. The existing anti-pattern based pattern recommendation tool using source code [12] is also implemented for comparative analysis. For the justification of correct recommendations, GoF is followed [20].

A. Environmental Setup

As mentioned earlier, the ADPR prototype has been implemented in java. The equipments, used to develop the prototype are as follows:

- Eclipse Luna (4.4.1): java IDE for ADPR implementation
- StarUML Version-2.1.4: UML editor and XML converter

Four cases requiring Abstract Factory according to GoF, have been used as dataset. To test any occurrence of false positive, one project using Template pattern is used. The project source codes and UML diagrams are uploaded on GitHub [24]. The projects are shown in Table I.

TABLE I: Experimented Projects

Project Name	No. of Classes in Class Diagram	No. of Sequence Diagrams
CarDriver	8	2
GameScene	10	2
Painter	9	3
MazeGame	12	2
Trip	9	3

Before running ADPR on the sample project set, the XMLs are generated from the UMLs using StarUML to be used as input of the prototype. If the UMLs are not available, those can be produced from source code by reverse engineering in Visual Paradigm, a software design tool.

B. Comparative Analysis

For comparative analysis, the projects were run using both ADPR and the source based tool. The results of the experimentation are depicted in Table II, which shows that the code-based tool could detect two missing Abstract Factory patterns out of four. This is because, it assumed that the Abstract Factory has a behavioral aspect of having if-else or switch-case conditions for instantiating the families, which may not be always true (for example, class instantiations inside GUI onclick listener). On the other hand, ADPR was successful in all cases as the sequence diagrams do not assume the presence of any conditional operations, rather match the classes in one execution sequence. Both the tools did not produce any false-positive results.
The result identifies the fact that recommendations can be provided based on anti-patterns before the code development phase. Recommendation in the design phase gives opportunity

TABLE II: Results for Abstract Factory

Project Name	Recommend Abstract Factory		
	Code-Based	ADPR	GoF
CarDriver	Yes	Yes	Yes
GameScene	No	Yes	Yes
Painter	Yes	Yes	Yes
MazeGame	No	Yes	Yes
Trip	No	No	No

to correct the design of software which is not feasible in the coding phase. Thus, the results of ADPR are encouraging, as it could provide correct recommendations in the design phase, making the re-design of software possible.

VI. Conclusion

This paper introduces a new idea to recommend design patterns using anti-patterns. A tool is proposed named ADPR, where anti-pattern detection is utilized for recommendation of appropriate design patterns in the software design phase.
The recommendation task is executed in two phases; analysis of anti-patterns is performed in the first phase, and in the next phase, anti-patterns are detected and design patterns are recommended. For anti-pattern analysis in the first phase, anti-patterns of particular design patterns are collected and analyzed in three levels - structural, behavioral, and semantic. Then in the second phase, the identified anti-patterns are matched with system designs for recommending corresponding design patterns using the similar three levels of matching.
A case study on a sample java project evaluates the applicability of the approach. The tool was initially implemented for Abstract Factory only. A comparative analysis with an existing code based tool showed that, ADPR could correctly recommend design patterns in the design phase rather in the coding phase.
As currently the tool is developed for Abstract Factory, the future direction lies in extending it to the other design patterns incrementally, and generalizing the process.

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Correctness of Semantic Code Smell Detection Tools

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***Abstract*—Refactoring is a set of techniques used to enhance the quality of code by restructuring existing code/design without changing its behavior. Refactoring tools can be used to detect specific code smells, propose relevant refactorings, and in some cases automate the refactoring process. However, usage of refactoring tools in industry is still relatively low. One of the major reasons being the veracity of the detected code smells, especially smells that aren't purely syntactic in nature. We conduct an empirical study on some refactoring tools and evaluate the correctness of the code smells they identify. We analyze the level of confidence users have on the code smells detected by the tools and discuss some issues with such tools.**

***Index Terms*—Correctness, Detection, Maintenance, Refactoring, Semantic code smells.**

I. Introduction

Refactoring improves various qualities of code/design like maintainability (understandability and readability), extensibility, etc. by changing the structure of the code/design without changing the overall behaviour of the system. It was first introduced by Opdyke and Johnson [11] and later popularized by Martin Fowler [7]. Fowler categorized various types of refactorings in terms of their applicability and suggested various refactorings for code smells (bad indicators in code) within classes and between classes. Over the years, other researchers have added to the knowledge base on code smells [16]. Any refactoring done to address specific code smells requires one to test the refactored code with respect to preservation of the original behaviour. This is primarily done by writing test cases before the refactoring is done and testing the refactored code against the test cases. As a result, validating the correctness of a detected code smell and the automation of it's refactoring is very difficult. Explicit manual intervention may be needed.

Many code smell detection tools support (semi) automatic refactoring process [4], [8]. *iPlasma, Jdeodorant, RefactorJ, etc*. are some of the tools that can be used for detection of code smells and application of specific refactoring techniques in automated or semi-automated manner. As noted in our previous work, each of these tools can detect only certain type of code smells automatically [8]. Also, there is no standardized approach for detecting such code smells and hence tools follow their own approach [9], inevitably leading to different set of code smells being detected for the same piece of code. Most code smell detection techniques depend on static analysis and code metrics and do not consider factors like *system size, language structure* and *context*. In other words, any design-based refactorings require the tool to understand the actual semantic intent of the code itself. For example, Long method is one such code smell that requires the tool to understand the context of the method before an Extract method refactoring can be performed automatically while preserving the original semantic intent.

Despite the known benefits of refactoring tools, their usage is not widespread due to users' lack of trust on the tools' code smell detection capability, learning curve involved, and the inability of users to understand the code smell detection results [4], [6], [14]. In this paper, we study the correctness of the detected code smells of multiple open source tools like JDeodorant, InCode, etc. and the lack of trust of users on their detection capability through an empirical study of open source projects like *JHotDraw (www.jhotdraw.org)* and *GanttProject (www.ganttproject.biz)*. We believe that lack of trust is proportional to the correctness of the tools detection ability. Most code smell detection tools detect code smells that require small-scale resolutions correctly. However, correctness is an issue when design based refactorings or semantic intent is considered. Hence, we restrict our focus to tools that detect code smells that require the tool to understand the semantic intent (for example, *Feature Envy, Long Methods, Shotgun Surgery, God class, etc.*). From now on, we refer to such code smells as "`semantic code smells`". We cross validate our study results on GanttProject with the study results conducted by Fontana et al. [6] on GanttProject (v1.11.1). Additionally, we used our own dummy code with a few induced semantic code smells to check for correctness of the tools. We focus on the following in this paper:

- Correctness of the identified code smells among the chosen tools
- Deviation in confidence levels of developers in open source code smell detection tools that detect semantic code smells

The rest of the paper is structured as follows: Section II provides a brief overview of the code smells discussed in this paper and section III presents some related work. In section IV, we detail the study design. Section V and VI present the results and analysis of the results. Based on the study, we provide some guidelines for increasing the correctness of detecting some code smells in section VII. Finally, in section VIII we discuss some limitations to our work.

II. Code Smells

Complexity related metrics like coupling are commonly used in tools to detect certain semantic code smells. Threshold values are established for various metrics and the code smells are identified based on the threshold values. Code smells like Feature envy, long methods, god class, etc. are widely studied in the literature. In our study, we primarily target the following code smells:

- *Feature envy*: A method is more interested in some other class than the one in which it is defined.
- *Long methods*: Method that is too long (measured in terms of lines of code or other metrics), possibly leading to low cohesion and high coupling
- *God class*: A God class performs too much work on its own delegating only minor details to a set of trivial classes.
- *Large Class*: A class with too many instance variables or methods. It may become a God class.
- *Shotgun Surgery*: A change in one classes necessitates a change in many other classes
- *Refused Bequest*: A sub-class not using its inherited functionality

III. Related Work

Fontana et al. [6] showed the comparative analysis of code smells detected by various refactoring tools and their support of (semi) automatic refactoring. The study analyzes the differences between code smell detection tools. In our previous work [8], we analyzed various java based refactoring tools with respect to its usability and reasoned about the automation of various code smells.

Pinto et al. [14] investigated data from StackOverflow to find out the barriers for adoption of code detection tools. They listed the issues mentioned in the forum related to the adoption/usability issues users are talking about in the StackOverflow. Olbrich et al. [10] performed an empirical study for God Class and Brain Class to evaluate that detected smells are really smells. From their empirical study they have concluded that if the results are normalized with the size of the system then smell results will become opposite. In fact the detected smell classes were less likely for changes and errors.

Ferme et al. [5] conducted a study for God Class and Data Class to find out that all smells are the real smells. They have proposed filters to be used to reduce or refine the detection rules of these smells. This paper extends our previous work and complements the work done by other authors by considering semantic code smells. In [13], Palomba et al. studied developers perception of bad smells. Their study depicts gap between theory and practice, i.e., what is believed to be a problem (theory) and what is actually a problem (practice). Their study provide insights on characteristics of bad smells not yet explored sufficiently.

Ouni et al. [12] proposed search based refactoring approach to preserve domain semantics of a program when refactoring is decided/implemented automatically. They argued that refactoring might be syntactically correct, have the right behaviour, but model incorrectly the domain semantics.

IV. Study Design

The objective of our study is to analyze the correctness of tools relevant to semantic code smells by performing a study with human subjects with prior refactoring experience. Tools like *JDeodorant, PMD, InCode, iPlasma*, and *Stench Blossom*, and two large systems like *JHotDraw* and *GanttProject* that have been widely studied in refactoring research were considered. Choosing these tools and systems helped us in cross validating our work with prior work done by us [8] and other researchers using similar systems/tools.

Initially, 35 human subjects volunteered to be part of the study. The exact hypothesis of the study was not informed to the subject to avoid biasing the study results. The subjects were only informed of the specific tasks that needed to be done, i.e. to assess certain refactoring tools with respect to their ability to detect code smells based on a given criteria and fill in a template.

All the human subjects had varying levels of prior knowledge about code smells and tool based refactorings. However, they had not worked on the specific tools used for this study. The subjects had varied experience (13% subjects had 1-5 years of experience, 31% had 5-10 years of experience and rest had less than a year of experience). The detailed statistics of subjects is available at [3] . We asked them to focus on specific code smells like Feature Envy, Long Methods, Shotgun Surgery, God class, etc. and list down all these smells and record their comments/rationale for detecting these as code smells. The template [1] had a column that asked them the semantic meaning of the detected code smells. In addition, we asked them to provide reasoning for not agreeing with the refactorings detected by the tools used. The subjects were given a three-week period to perform the activity and fill in templates. After evaluation of the templates, results from 32 subjects were taken into consideration. The other three did not fill in the templates completely. To cross-check the correctness of the tools with respect to their semantic code smell detection, in addition to the two open-source systems, we instrumented one of our own projects. It was interesting to note that most of the tools were not detecting code smells that seemed obvious from our perspective.

A. Subject Systems

In our study, we chose two open source systems:

- GanttProject - a free project management app where users can create tasks, create project baseline, organize tasks in a work break down structure
- JHotDraw - a Java GUI framework for technical and structured Graphics. Its design relies heavily on some well-known design patterns.

The subject systems are available for use under open source license and are fairly well documented. In addition to being a part of Qualitas Corpus [15], these are widely studied in refactoring research and referenced in the literature. Table 1 provides details of these systems.

TABLE I: Characteristics of subject systems

	JHotDraw	Ganttproject
Version	5.4	2.7.1891
Total Lines of Code	32435	46698
Number of classes	368	1230
Number of methods	3341	5917
Weighted methods per class	6990	8540
Number of static methods	280	235

B. Code Smell Detection Tools

There are several commercial and open source code smell detection tools. Some are research prototypes meant for detection of specific code smells while others identify a wide range of code smells. In addition to detection, some tools refactor the code smells automatically, while others are semi-automated. Semi-automated refactoring tools propose refactorings that require human intervention and can be automated to a certain extent by changing rules of detection. Some of these are more or less like recommender systems that recommend certain type of refactorings but leave it to the developers to refactor or ignore the recommendations.

Some tools are integrated with the IDE itself, while others are written as plugins that can be installed on a need basis. For example, checkstyle, PMD, etc. are some eclipse based plugins that are well known. For our study, we focused on tools widely studied in the literature, their semantic code smell detection ability and usage in the industry. The list of tools and the detected code smells relevant to our study are shown in table II.

V. Experiment Results

Table III provides a cumulative summary of code smells detected and disagreements (weighted average of results from 32 results) by our human subjects. To show the disparity in results, we compare our results for the GanttProject with Fontana et al.'s results [6]. For reference, the detailed list of detected smell by our human subjects is available at [2].

Feature Envy: The number of Feature Envy methods detected by different tools varies significantly. Some tools consider any three or more calls to method of the other class as a code smell and hence give rise to large number of false positive code smells. In such cases, when it's just counting numbers, it becomes tedious to filter out the actual smells.

The degree of disagreement was found to be 9/44 for JDeodorant and 3/4 for inCode for the JHotDraw project. Disagreements by the human subjects were prevalent across all tools for detected feature envy smells. We also observed a significant difference between the results of Fontana's [6] study and our JDeodorant results. Their study reveals that over a period of time, in GanttProject version from V1.10 to 1.11.1, Feature Envy methods reduced to 2 (in v1.11.1) from 18 (in v1.10), whereas in our study of GanttProject v2.7, there were 113 Feature Envy code smells. As it can be seen from the results, the number of detected smells is significantly different from the numbers given in their work.

God Class: The number of detected God classes detected by JDeodorant for GanttProject in Fontana et al.'s [6] study was 22 (v1.11.1) where as in v2.7 it is 127. In inCode the number of god classes were significantly lesser: reduced from 13 (v1.11.1) to 4 (v2.7). Unlike JDeodrant and inCode, the results from iPlasma increased: from 13 (v1.11.1) to 42 (v2.7). This inconsistency between tools reduces the confidence level of the results.

The degree of disagreement to jDeodrant code smells for jHotDraw project was 10 out of 56. Our human subjects observed that tools were considering the data model classes (getters and setters) and parser classes as smells. Usually these classes are needed and are necessary evils. As a result, there is a need of building some sort of intelligence/metrics to detect these kinds of classes which can safely be ignored to reduce the false positives.

Large Class: This code smell is detected by the code size and is subjective to the threshold limit of LOC set by the user. Classes that contain project utility methods can grow in size with a lot of small utility methods and usually developers make these classes as singleton objects. Refactoring such smells requires one to be able understand the intent of the sentences before an *extract method* or *extract class* refactoring is applied.

Refused Bequest: Some tools considered interface methods and abstract methods that are normally overridden by the respective concrete classes as a code smell resulting in a lot of false positives.

Compared to Fontana et al.'s [6] study, inCode detected 6 (in V2.7) whereas it was 0 (in V1.11.1). The degree of disagreement to the detected code smells was 2 in inCode, 1 in iPlasma for GanttProject. For jHotDraw it was 1 (for inCode) and 2 (for iPlasma).

Shotgun Surgery: The results of our study for shotgun surgery on v2.7 were similar to the one's for the GanttProject (v1.11.1). However, from our study we can conclude that the way shotgun surgery is detected in the different code smells differs from tool to tool rather that different versions of the same tool. The degree of disagreement to the detected code smells was 2 for GanttProject using inCode and 7 using iPlasma.

Long Method: This code smell is related to number of lines of code present in the method and subject to the threshold limit set by the user for detecting the code smell. As per the disagreements documented by our subjects, methods containing large switch statements should not be counted as a long method. iPlasma had a complex detection mechanism that considers such kind of things while detecting the Long Method code smells. On the contrary jDeodrant listed fairly small methods as a long method code smell.

The degree of disagreement to the code smells detected for GanttProject was 12 in jDeodrant, 27 in Stench Blossom and 8 in PMD. For JHotDraw project, it was 10 in jDeodrant, 12 in Stench Blossom, 11 in iPlasma and 8 in PMD.

The detections from jDeodrant tool were significantly high as compared to 57 (v1.111.1) of GanttProject from Fontana et al. [6] study. Interestingly, we noticed that the long methods were reduced from 160 (in v1.10) to 57 (in v1.11.1), whereas as in our study it was still high i.e. 221.This was because as a software evolves, it is expected that long methods will grow over a period of time.

TABLE II: Code smell detection tools

Tool	Code smells	Detail
JDeodarant, (vv. 3.5 e3.6), [EP],Java	FE, GC, LM, TC	This is an Eclipse plug-in that automatically identifies four code smells in Java programs. It ranks the refactoring according to their impact on the design and automatically applies the most effective refactoring.
Stench Blossom (v. 3.3), [EP],Java	FE, LM, LC, MC	This tool provides a high-level overview of the smells in their code. It is an Eclipse plugin with three different views that progressively offer more visualized information about the smells in the code.
InCode [SA], C, C++, Java	BM, FE, GC, IC, RB, SS	This tool supports the analysis of a system at architectural and code level.It allows for detection of more than 20 design flaws and code smells.
iPlasma [SA], C++, Java	BM, FE, GC, IC, SS, RB, LM, SG	It can be used for quality assessment of object-oriented systems and supports all phases of analysis: from model extraction up to high-level metrics based analysis, or detection of code duplication.
PMD, [EP or SA],Java	LC, LM	Scans Java source code and looks for potential bugs such as dead code, empty try/catch/finally/switch statements, unused local variables, parameters and duplicate code.
Feature Envy (FE), Refuse Bequest (RB), God Class (GC), Long Method (LM), Lazy Class (LC), Intensive Coupling (IC), Shotgun Surgery (SS), Speculative Generality (SG), Dispersed Coupling (DC), Brain Method (BM). Type: Standalone Application (SA), Eclipse Plug-in (EP)		

TABLE III: Code Smell Detected & Disagreement

Code Smell	jDeodrant		inCode		iPlasma		Stench Blossom		PMD	
	$	#	$	#	$	#	$	#	$	#
JHotDraw										
FE	44	9	4	3	35	4	28	10	56	9
GC	56	10	14	15	22	2	-	-	34	10
LC	-	-	-	-	-	-	22	5	41	5
RB	-	-	4	1	2	2	-	-	-	-
SS	-	-	10	3	13	6	-	-	-	-
LM	90	10	-	-	94	11	113	12	73	8
GnattProject										
FE	113	12	11	2	42	13	53	28	38	4
GC	127	8	4	3	24	3	-	-	37	17
LC	-	-	-	-	-	-	9	-	40	9
RB	-	-	6	2	3	1	-	-	-	-
SS	-	-	7	2	42	7	-	-	-	-
LM	221	12	-	-	-	-	55	27	36	8
$ - Detected, # - Disagree										

VI. Discussion

The major challenge in assessing correctness of detected smells is the knowledge possessed by human subjects in regards to the code smells and the behavior of the code itself. Since the subjects (users) were not familiar with the tools chosen for the study, they complained about the time consumed in understanding and using the tool. At times, the focus seemed to be more on the user-interface of the tool rather than detected code smells. The authors had to revert back to the subjects to get additional clarification about the comments written in the templates regarding specific code smells.

Some tools require explicit specification of rules (for example, PMD) for detecting a specific code smell. So, selecting rules from the entire list of rules was tedious and time-consuming. Most of the users seemed to struggle with the setup and configuration issues of the tools. Few tools like jDeodorant had high memory utilization and performance issues. So re-compilation after every change and re-running the detection process was laborious.

Contrary to our belief that the same code smell must be identified in the same way by different tools, the disagreement in the correctness of the detected code smells between the various tools for the same type of smell was pretty high (as shown in table III). Additionally, the results were not complimenting the results provided in prior research [6]. In other words, the correctness of the detected smells was not accurate with respect to the semantics of the code written. To validate the results, we had to further cross-check the tools with some dummy examples. For instance, the dummy code (shown in Listing 1) was detected as a *Feature Envy* smell in some of the tools (for example, *jDeodorant*). If '`doCommit`' method is moved to any of the classes (A, B and C in this example) we must pass the other two classes as a reference parameter, that in turn increases the coupling. Moreover, semantically it makes sense to call all commit methods in '`doCommit`' method itself.

An interesting observation can be made from the tools that detected *Request Bequest* code smell instances. For example, code resembling the dummy code (shown in Listing 2) reveals that there is no behavior written in the base method and just because it was being overridden without any invocation of base methods, it was detected as a smell. In other words, intuitively the authors could conclude even such code smells are primarily being thought about as syntactic where in the tool is just looking for redundant names in the superclass and subclass. Ideally, the tool should check if there is any meaningful behavior attached to the base method and only then should it be detected as a smell.

The dummy example (shown in Listing 3) was not detected as *feature envy* except by *stench blossom* tool. The probable reason for non detection is the declaration of the phone object inside the `getMobilePhoneNumber` method. Logically may not be detected as a code smell but from a semantic perspective `getMobilePhoneNumber` should be part of "`phone`" class. This issue poses a question of correct semantic code smell detection by tools.

The dummy example (shown in Listing 4) has shotgun surgery code smell. The example shows a common mistake that users commit while creating database connection and querying tables. Users tend to create individual connections and command objects in each of the methods as shown in the example. If we have a connection timeout occurs semantically is make sense to create a utility method that takes SQL as

an argument and returns result set "DBUtility.getList" in this method we will open connection and create SQL statements. InCode and iPlasma tools did not detect this code smell.

Although, several tools detect code smells, they do not consider the semantic intent of the code and hence end up with lot of false positives. Reducing false positives is the first step towards increasing the confidence levels of users and proportionately increasing the usage of refactoring tools.

Listing 1: Feature Envy

```
public class Main {
   public void doCommit(){
      a.commit();
      b.commit();
      c.commit();}}
public class A {
   public void commit() {
       //do something
   } }
public class B {
   public void commit() {
      //do something
   } }
public class C {
   public void commit() {
      //do something
   } }
```

Listing 2: Refused Bequest

```
public class Base{
  protected void m1() { }
}
public class Inherited extends Base {
  protected void m1() { //do something }
}
```

Listing 3: Feature Envy

```
public class Phone {
 private final String unformattedNumber;
  public Phone(String unformattedNumber) {
   this.unformattedNumber = unformattedNumber;
  }
  public String getAreaCode() {
   return unformattedNumber.substring(0,3);
  }
  public String getPrefix() {
   return unformattedNumber.substring(3,6);
  }
  public String getNumber() {
   return unformattedNumber.substring(6,10);
  } }
public class Customer {
 public String getMobilePhoneNumber() {
  Phone m_Phone = new Phone("111-123-2345");
   return "(" + m_Phone.getAreaCode() + ") "
  +  m_Phone.getPrefix() + "-"
  + m_Phone.getNumber();
 } }
```

Listing 4: Shotgun Surgery

```
public List<Employee> getEmployeeList() {
 Connection conn = null;
 Statement stmt = null;
 conn = DriverManager.getConnection(DB_URL,
         USER, PASS);
 stmt = conn.createStatement();
 String sql;
 sql = "SELECT * FROM Employees";
 ResultSet rs = stmt.executeQuery(sql);
 return rs.toList<Employee>();
}
public List<Customer> getCustomerList() {
 Connection conn = null;
 Statement stmt = null;
 Class.forName("com.mysql.jdbc.Driver");
 conn = DriverManager.getConnection(DB_URL,
         USER, PASS);
 stmt1 = conn1.createStatement();
 String sql;
 sql = "SELECT * FROM Customers";
 ResultSet rs = stmt1.executeQuery(sql);
 return rs.toList<Customer>(); }
```

VII. Code Smell Detection Pre-Checks

Based on our study, we recommend some pre-checks specific to particular code smells to improve the correctness of detection:

Feature Envy:

- Are referencing methods from multiple classes. Check if moving a method increases coupling and references to the target class.
- Check if mutual work like object dispose, commit of multiple transactions is accomplished in the method. Is it semantically performing a cumulative task.
- Take domain knowledge and system size into account before detecting smell, use semantic/information retrieval techniques to identify domain concepts

Long Class/ God class:

- Ignore utility classes, parsers, compiles, interpreters exception handlers
- Ignore Java beans, Data Models, Log file classes
- Transaction manager classes
- Normalized results with system size

Long Method:

- Check if large switch blocks are written in the methods if multiple code blocks can be extracted with different functionality

Refuse Parent Bequest:

- Ignore Interface methods, they are meant to be overridden.
- Check if base method has any meaning full behaviour attached to it.

VIII. Limitations & Future Work

Our initial study has provided evidence of disagreement towards the detected code smell from tools by our human subjects. We presented sample code for incorrectly detected code smells and semantic smells that were not detected by the tools. The authors strongly felt the need of taking semantic intent of the code into consideration while detecting smells and proposing (semi) automatic refactoring.

The disagreement in detected code smells correlates to the confidence levels of users. We saw that the results from all the users were not the same for the same code smell detection tools. So, the accuracy of these results can always be questioned. The results of Fontana et al. were used for cross-validation of our work. For the degree of disagreement to the detected code smells, we took an average of the overall disagreement report by the users. But, code smell disagreement is subjective until a standardized method for detection and measurement is proposed.

As a future work we would to extend our experiment with more industry level users. We would like to share the disagreement detected by our human subjects with the actual developers of the system to validate our findings. Towards understanding the correctness of the semantic code smell we would like to compare detection logic by tools.

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A Decision Support Platform for Guiding a Bug Triager for Resolver Recommendation Using Textual and Non-Textual Features

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***Abstract*—It is largely believed among researchers that the software engineering methods and techniques based on mining of software repositories (MSR) have the potential of providing sound and empirical basis for Software Engineering tasks. But it has been observed that the main hurdles to adoption of the techniques are organizational in nature or people centric, for example lack of access to data, organizational inertia, general lack of faith in results achieved without human intervention, and a tendency of experts to feel that their inability to arrive at optimal decisions is rooted in someone else's shortcomings, in this case person who files the bug. We share our experiences in developing a use case for applying such methods to the common software engineering task of Bug Triaging within an industrial setup. We accompany the well researched technique of applying textual information content in bug reports with additional measures in order to improve the acceptance and effectiveness of the system. Specifically we present: A) use of non-textual features for factoring in the decision making process that a human would follow; B) making available effectiveness metrics that present a basis for comparing the results of the automated systems against the existing practice of relying on human decision making; and C) presenting reasoning or the justification behind the results so that the human experts can validate and accept the results. We present these non-textual features and some of the metrics and discuss on how these can address the adoption concerns for this specific use case.**

***Index Terms*—Bug Fixer Recommendation, Bug Triaging, Issue Tracking System, Machine Learning, Mining Software Repositories, Software Analytics, Software Maintenance**

I. Problem Definition and Aim

Bug Resolver Recommendation, Bug Assignment or Triaging consists of determining the fixer or resolver of an issue reported to the Issue Tracking System (ITS). Bug Assignment is an important activity both in OSS (Open Source Software) or CSS/PSS (Closed or Proprietary Source Software) domain as the assignment accuracy has an impact on the mean time to repair and project team effort incurred. Bug resolver assignment is non-trivial in a large and complex software setting, especially with globally distributed teams, wherein several bugs may get reported on a daily or weekly basis increasing the burden on the triagers. One of the primary ways, identification of resolvers for open bug reports is normally done is through a decision by Change Control Board (CCB), members of which represent various aspects of the software project such as project management, development, testing and quality control. The CCB usually works as a collective decision making body that reviews the incoming bugs and decides who to assign it to, or whether more information is required, or a bug is irrelevant, or behavior needs to be observed more. As can be imagined that the decisions made by the CCB are knowledge intensive and it requires prior knowledge about the software system, expertise of the developer, team structure and composition and developer workload. In some instances, in order to optimize the time of the entire CCB, a pre-CCB is conducted by individual members of the board on assigned subset of bugs and the individual recommendations are reviewed in complete CCB. The average time to triage a bug in such a process can be captured as following:

$$t = \frac{T_{pre-CCB} * M + T_{CCB}}{N}$$

Here, t denotes the average time it takes to triage a bug, given M committee members taking $T_{pre-CCB}$ time individually for assessing their subset of bugs and T_{CCB} time together to discuss and finalize recommendation for N bugs. From the above, its clear that any method that can assist in reducing any of M, T_{CCB} and $T_{pre-CCB}$ has potential to increase overall efficiency. Research shows that manual assignment of bug reports to resolvers without any support from an expert system results in several incorrect assignments [1][2][3][4][5]. Incorrect assignment is undesirable and inefficient as it delays the bug resolution due to reassignments. While there has been recent advancements in solutions for automatic bug assignment, the problem is still not fully solved [1][2][3][4][5]. Furthermore, majority of the studies on automatic bug assignment are conducted on OSS data and there is a lack of empirical studies on PSS/CSS data. In addition to lack of studies on Industrial or Commercial project data, application of non-textual features such as developer workload, experience and collaboration network for the task of automatic bug assignment is relatively unexplored. The work presented in this paper is motivated by the need to develop a decision support system for bug resolver recommendation based on the needs of Triagers. The specific aims of the work presented in this paper are:

1) To build a decision support system for guiding and assisting triagers for the task of automatic bug assignment, this involves application of textual (terms in bug reports) to build a classification model

2) Using of non-textual features (components, developer workload, experience, collaboration network, process map) for contextualizing the model.
3) Provide insights about the bug fixing efficiency, defect proneness and trends on time-to-repair through visual analytics and a dashboard.
4) Build the system in user centric manner by providing the justification and reasoning behind the recommended assignments.

Rest of the paper is structured as follows: in Section II we discuss and argue that user centric approach to build such recommendation systems incorporates the elements necessary to address the above goals. Next we discuss some of the contextualization measures for the model, specifically use of a practitioner survey results and process map. In Section IV, describes some of the metrics and measures that accompany the system are how can they be used. Section V presents early results from applying the system on two sets of data obtained from actual industrial projects, one active for 2 years whereas other for 9 years.

II. User centered Design and Solution Architecture

We create a User-Centered Design considering the objectives and workflow of CCB. Our main motivation is to ensure a high degree of usability and hence we give extensive attention to the needs of our users. Figure 1 shows a high-level overview of the 4 features incorporated in our bug assignment decision support system. We display the Top K recommendation (k is a parameter which can be configured by the administrator) which is the primary goal of the recommender system. In addition to Top K recommendation, we present the justification and reasoning behind the proposed recommendation.

We believe that displaying justification is important as the decision maker needs to understand the rule or logic behind the inferences made by the expert system. We display the textual similarity or term overlap and component similarity between the incoming bug report and the recommended bug report as justification to the end-user. We show developer collaboration network as one of the output of the recommendation system. The node size in the collaboration network represents the number of bugs resolved, edge distance or thickness represents the strength of collaboration (number of bugs co-resolved) and the node color represents role. As shown in Figure 1, we display the developer workload and experience to the Triager as complementary information assisting the user to make triaging decisions. Figure 1 illustrates all four factors influencing triaging decisions (Top K Recommendation, Justification and Reasoning, Collaboration Network and Developer Workload and Experience) which connects with the results of our survey and interaction with members of the CCB in our organization. Figure 2 shows the high-level architecture illustrating key components of the decision support system. We adopt a platform-based approach so that our system can be customized across various projects using project based customization and fine-tuning. The architecture consists of a multi-step processing pipeline from data extraction (from the issue tracking system) as back-end layer to display as the front-end layer. As shown in Figure 2, we implement adaptors to extract data from Issue Tracking System (ITS) used by the project teams and save into a MySQL database. We create our own schema to save the data in our database and implement functionality to refresh the data based on a pre-defined interval or triggered by the user. Bug reports consist of free-form text fields such as title and description. We apply a series of text pre-processing steps on the bug report title and description before they are used for model building. We remove non content bearing terms (called as stop terms such as articles and propositions) and apply word stemming using the Porter Stemmer (term normalization). We create a domain specific Exclude List to remove terms which are non-discriminatory (for example, common domain terms like bug, defect, reproduce, actual, expected and behavior). We create an Include List to avoid splitting of phrases into separate terms such as OpenGL Graphics Library, SQL Server and Multi Core. We first apply the Include List and extract important phrases and then apply the domain specific exclude list. Include and Exclude Lists are customizable from the User Interface by the domain expert. The terms extracted from the title and description of the bug reports represents discriminatory features for the task of automatic bug assignment (based on the hypothesis that there is a correlation between the terms and the resolver). The next step in the processing pipeline is to train a predictive model based on the Machine Learning framework. We used Weka which is a widely used Java based Machine Learning toolkit called for model building and application. We embed Weka within our system and invoke its functionality using the Java API. We train a Random Forest and Naive Bayes classification model and use a voting mechanism to compute the classification score of the ensemble rather than individual scores to make the final predictions. We also extract the component of the bug report as a categorical feature as we observe a correlation between the component and the resolver.

In terms of the implementation, we create an Attribute-Relation File Format (ARFF) that describes the list of training instances (terms and components and predictors and the resolver as the target class). As shown in the Figure 3, we extract the developer collaboration network, information on prior work experience with the project and workload from the ITS. The ITS contains the number of bugs resolved by every developer from the beginning of the project. The ITS also contains information about the open bugs and the assignees for the respective open bug. We use close and open bug status information and the assignees field to compute the prior experience of a developer and the current work load with respect to bug resolution. Similarly, the collaboration network between developers is determined by extracting information from the bugs lifecycle. The frond-end layer implementation consists of D3.JS, JavaScript, Java Servlet and Java Server Pages (JSP).

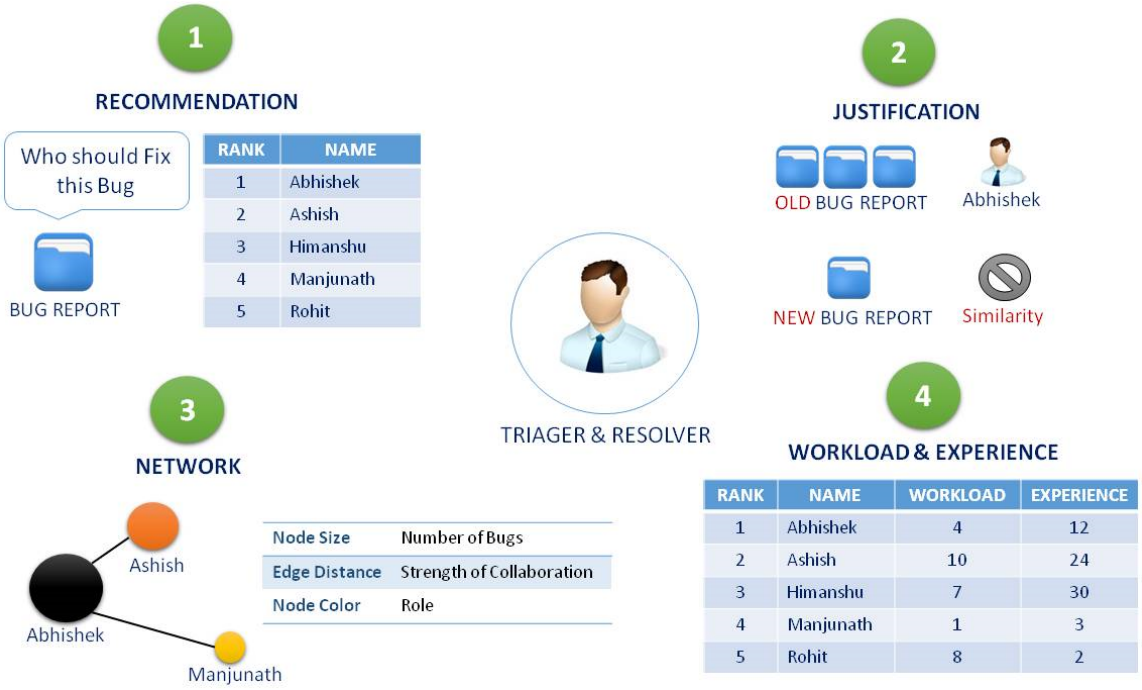

Fig. 1. A High-Level Overview of the Features: Top K Recommendation with Confidence or Score Value, Justification or Reasoning behind the Recommendation, Collaboration Network between the Developers, Workload & Prior Experience Values

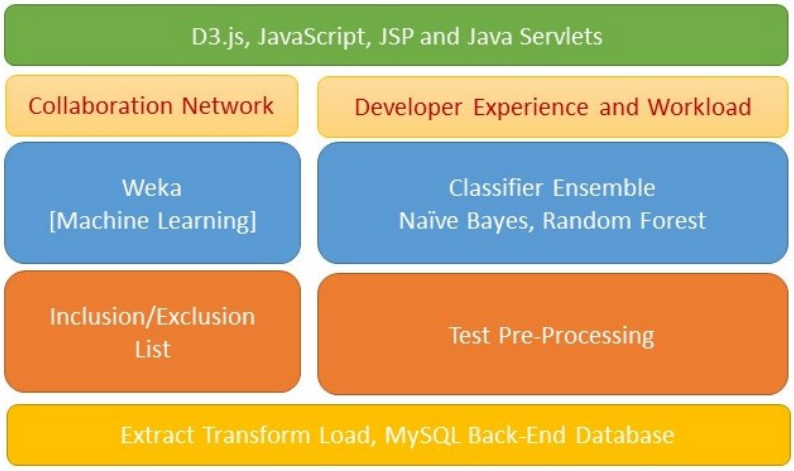

Fig. 2. High-Level Architecture Diagram displaying Key Components (Front-End, Back-End and Middle Tier) - A Platform-Based Architecture

III. Model Contextualization and Process Parameters

Since our goal is to solve problems encountered by the practitioners and model the system as closely as possible to the actual process and workflows of CCB, we conduct a survey of experienced practitioners to better understand their needs. We conduct a survey of 5 senior committee members belonging to Change Control Board (CCB) of our organizations software product lines. The average experience (in CCB) of the respondents was 7.5 years. In our organization, a CCB consists of members belonging to various roles: project manager, product manager, solution architect, quality assurance leader, developers, and testers. The survey respondents had been in various roles and active members of bug triaging process. Hence the survey responses are from representatives in-charge of various aspects such as development, quality control and management. The objective of our survey was to gain insights on factors influencing the change boards triaging decisions.

IV. Practitioner's Survey

Figure 3 shows the 5 questions in our questionnaire and the responses received. Each response is based on a 5 point scale (1 being low and 5 being high). Figure 3 reveals that

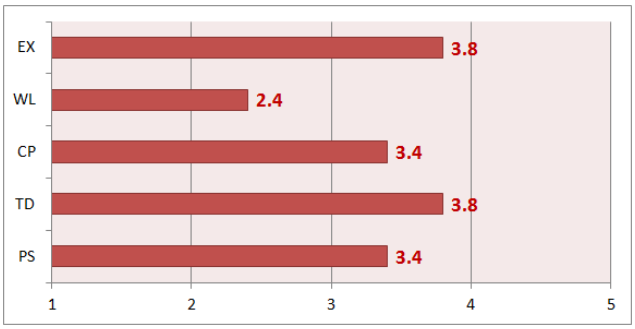

Fig. 3. Survey Results of Practitioners in Industry on Factors Influencing Bug Resolver Recommendation Decision [EX: Resolver Experience with the Project, WL: Resolver Workload, CP: Bug Report Component, TD: Bug Report Title and Description, PS: Bug Report Priority and Severity]

there are clearly multiple factors and tradeoffs involved in making a triaging and bug assignment decision. We observe that bug report title and description and the available resolvers experience with the project are the two most important factors influencing the triaging decision (both having a score of 3.8 out of 5). The priority and severity of the bug as well as component assigned to the bug are also considered quite important with a score of 3.4. The current workload of the resolvers as a criteria influencing bug triaging decision received a score of 2.4 out of 5 which is the lowest amongst all the 5 factors. The survey results support our objective of developing a bug resolver recommendation decision support system based on multiple factors (such as priority and severity of the bug report and current workload of the available resolvers) and not just based on matching the content of the bug report with the resolved bug reports of fixers.

We present our case study on a real-world project using the IBM Rational ClearQuest as Issue Tracking System. ClearQuest keeps track of entire bug lifecycle (from reporting to resolution), state changes and comments posted by project team members. We consider three roles: Triager, Developer and Tester. A comment can be posted and the state of a bug can be changed by Triager, Developer and Tester. Figure 4 shows 9 possible states of a bug report in ClearQuest and the 81 possible transitions. A comment (in the ClearQuest Notes Log) consisting of state transition from Submitted to In-Work contains the Triager and the developer role (from and to field). Similarly, In-Work to Solved state transition contains the developer and testers IDs. We parse ClearQuest Notes Log and annotate each project member ID with one of the three roles: developer, tester and triager. We then remove tester and triager and consider only the developers as bug resolvers for the purpose of predictive model building. This step of inferring developers is crucial since, triagers and testers frequently commit on the bug reports and their comments should not skew the results.

V. Decision Support System User Interface

A. Recommendation and Settings

Figure 5 shows the snapshot of the decision support system displaying the Top K recommendation, score for each recommendation, prior work experience and the current work load of the proposed resolver. Figure 5 also shows the collaboration network of the developers. Nodes in the collaboration network can be filtered using the check-boxes provided in the screen. The confidence values shown in Figure 5 are probability estimates for each of the proposed resolver. The sum of the confidence values or probability estimates across all possible resolvers (and not just the Top K) sum upto 1. We display the probability estimates and not just the rank to provide additional information on the strength of the correlation between the resolver and the incoming bug report. Figure 6 shows a snapshot of the settings page consisting of five tabs: resolvers, components, and training duration, include and exclude list and train model. We describe and provide a screenshots for one of the tabs due to limited space in the paper. We apply a platform-based approach and provide a configurable settings page so that the decision support system can be customized according to specific projects. As shown in Figure 6, a user can add, rename and modify components component names. A software system evolves over a period of time and undergoes architectural changes. New components get added, components gets merged and renamed. We provide a facility to the user to make sure that the model built on the training data is in-synch with the software system architecture. Similar to component configuration, we provide a tab to customize resolver list. For example, if a developer has left the organization then its information can be deleted through the Resolver tab and ensure that his or her name is not shown in the Top K recommendation. The training instances and the amount of historical data on which to train the predictive model can also be configured. The predictive model should be representative of the current practice and hence we provide a facility for the user to re-train the model based on recent dataset.

B. Visual Analytics on Bug Resolution Process

In addition to the Top K recommendation, justification, developer collaboration network [6], developer prior work experience and current workload, we also present interactive visualizations on the bug resolution process. Francalanci et al. [7] present an analysis of the performance characteristics (such as continuity and efficiency) of the bug fixing process. They identify performance indicators (bug opening and closing trend) reflecting the characteristics and quality of bug fixing process. We apply the concepts presented by Francalanci et al. [7] in our decision support system. They define bug opening trend as the cumulated number of opened and verified bugs over time. In their paper, closing trend is defined as the cumulated number of bugs that are resolved and closed over time [7][8].

Figure 7 displays the opening and closing trend for the Issue Tracking System dataset used in our case-study. At any instant

	Submitted	Qualified	In-Decision	Deferred	Terminated	In-Observation	In-Work	Solved	Validated
Submitted	TRG, TRG	TRG, TRG	TRG, TRG	TRG, TRG	DEV, TST	TRG, TRG	TRG, DEV	-	-
Qualified	-	DEV, DEV	TRG, TRG	TRG, TRG	TRG, TRG	TRG, TRG	TRG, DEV	-	-
In-Decision	-	-	DEV, DEV	DEV, TST	DEV, TST	DEV, TST	TRG, DEV	-	-
Deferred	-	-	TRG, TRG	TRG, TRG	TRG, TRG	TRG, TRG	TRG, TRG	-	-
Terminated	-	-	TST, TST	-	DEV, DEV	-	TST, DEV	-	-
In-Observation	-	-	TRG, TRG	TRG, TRG	DEV, TST	TST, TST	TST, DEV	-	-
In-Work	-	-	DEV, TST	DEV, TST	DEV, TST	DEV, TST	DEV, DEV	DEV, TST	-
Solved	-	-	-	-	-	-	TST, DEV	DEV, TST	TST, TST
Validated	-	-	-	-	-	-	TST, DEV	-	TST, TST

Fig. 4. List of 9 States in a Bug Lifecycle and 81 Possible Transitions. Infeasible Transitions are Represented by −. Each State Transitions is Used to Infer Roles within the Project Team. [TRG: Triager, DEV: Developer, TST, Tester]

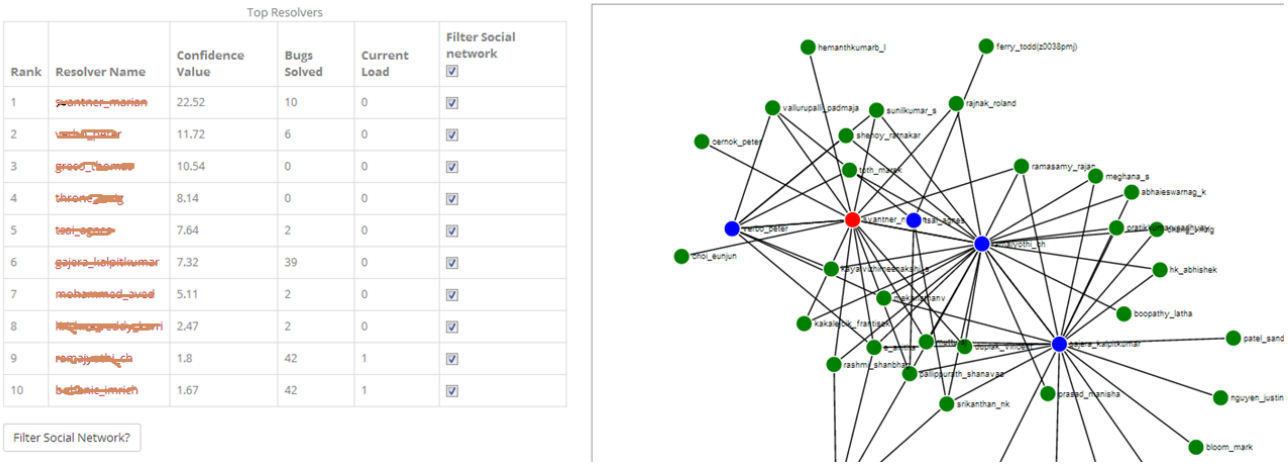

Fig. 5. A Snapshot of the Bug Resolver Recommendation Decision Support Tool displaying the Top 10 Recommendations, Confidence Value or Score, Workload and Past Experience with the Project

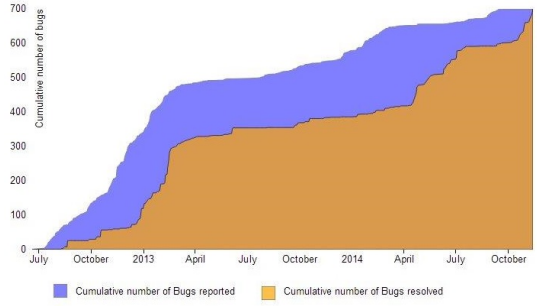

Fig. 7. Graph Depicting Bug Fix Quality as the Extent of Gap between the Bug Opening and Bug Closing Trend or Curve

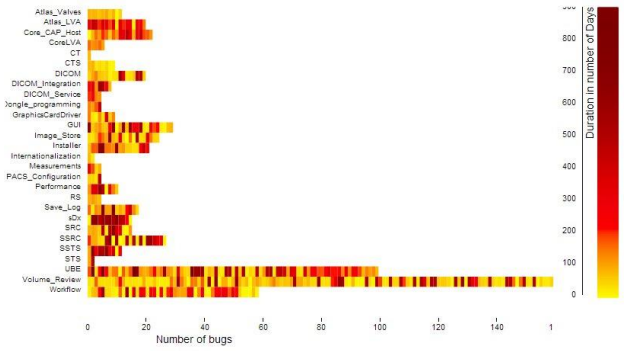

Fig. 8. A Combination of a Heat Map and a Horizontal Bar Chart displaying Three Dimensions in One Chart: Component, Number of Bugs and Duration to Resolve the Bug

of time, the difference between the two curves (interval) can be computed to identify the number of bugs which are open at that instant of time. We notice that the debugging process is of high quality as there is no uncontrolled growth of unresolved bugs (the curve for the closing trend grows nearly as fast or has the same slope as the curve for the opening trend).

Figure 7 shows a combination of Heat Map and a Horizontal Bar Chart providing insights on the defect proneness of a component (in-terms of the number of bugs reported) and the duration to resolve each reported bug. We observe that the bug fixing time for the Atlas Valves component is relatively on the lower side in comparison to the sDx component. UBE, Volume Review and Workflow are the three components on which maximum numbers of bugs have been reported. The information presented in Figure 8 is useful to the CCB as the bug resolver recommendation decision is also based on the

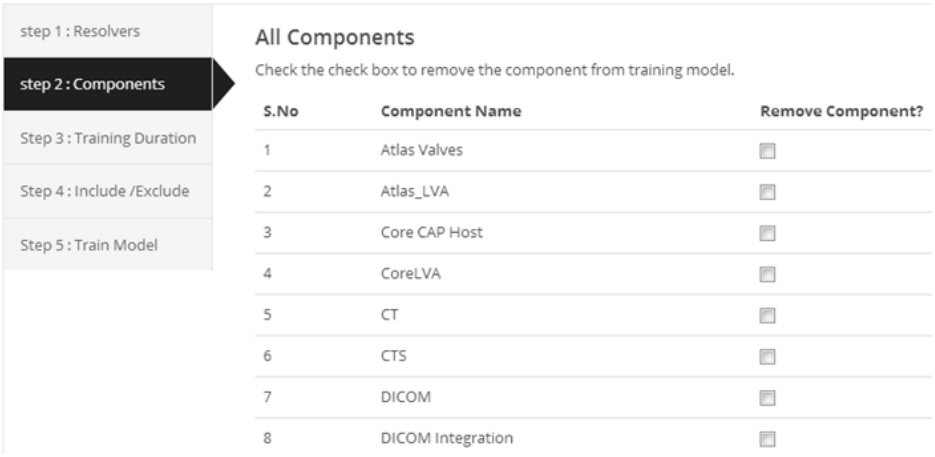

Fig. 6. A Snapshot of the Setting Page Consisting of 5 Tabs: Resolvers, Components, Training Duration, Include & Exclude List, Train Model. The Spanshot displays List of Components and the Remove Option

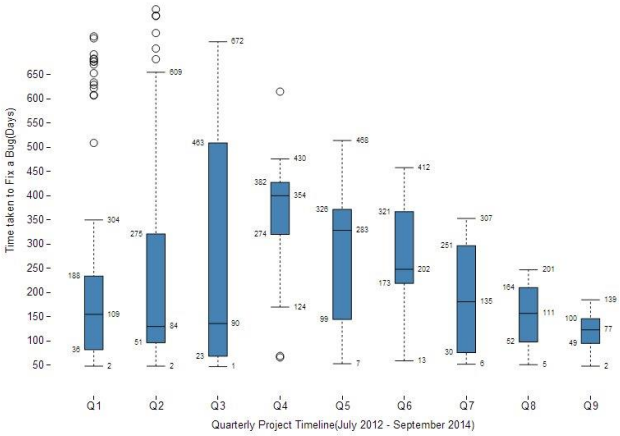

Fig. 9. A Spectrum of Boxplots Depicting Descriptive Statistics on Time Taken to Fix a Bug. Each Boxplot Corresponds to Dataset Belonging to One Quarter

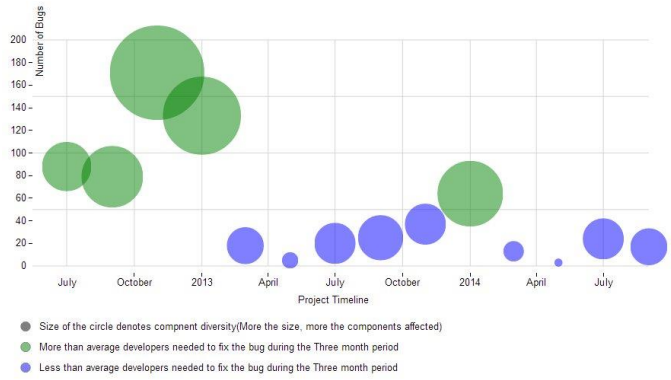

Fig. 10. A Bubble Chart displayed as a Scatter Chart in which each Data Point denotes Component Diversity (Bubble Size) and Number of Resolvers (Color) across Various Quarters

buggy component and the defect proneness of the component. Figure 9 shows a spectrum of Box plots across various years and quarters displaying descriptive statistics and five-number summary on time taken to fix a bug (bug resolution time). The spectrum of Box plots provides insights to the CCB on the changes in the distribution of resolution time over several quarters or time periods.

Figure 10 shows a bubble chart displaying component diversity and trends on the average number of developers needed to a resolve a bug across project time-line. Figure 10 reveals that the component diversity was high in July and October Quarter of the year 2013 which means that the reported bugs were spread across various components. We infer that the component diversity decreases in April and July Quarter for the year 2014 which means that majority of the bugs were reported within a small number of components. We also present insight on average number of developers needed to resolve a bug. We first compute the average number of developers needed to resolve a bug over the entire 2 years (dataset period) and then color-code the bubble for each quarter depending on its value being above or below the average value. Figure 11 displays the number of state transitions between any of the 81 state transitions. Figure 11 is a Heat Map in which every cell is color coded depending on the number transitions representing the cell. The Heap Map is useful to the CCB in gaining insights on process anti-patterns and inefficiencies. For example, Reopened bugs increase the maintenance costs, degrade overall user-perceived quality of the software and lead to un-necessary rework by busy practitioners [9]. Figure 11 reveals several cases of bug re-opening (such Solved-to-Inwork, Terminated-to-In Decision transitions).

VI. Empirical Analysis and Results

We conduct a series of experiments on real-world data from Siemens product lines to evaluate the effective of our approach. We conduct experiments on two projects to investigate the generalizability of our approach. One of the projects is a Image processing based product (Project A) deployed in Computed

TABLE I
RECALL@K , PRECISION@K AND F-MEASURE@K FOR PROJECT A

	K=1	K=2	K=3	K=4	K=5	K=6	K=7	K=8	K=9	K=10
RECALL	0.160	0.337	0.474	0.547	0.599	0.647	0.688	0.721	0.750	0.774
PRECISION	0.324	0.353	0.324	0.287	0.254	0.232	0.214	0.199	0.186	0.174
F-MEASURE	0.214	0.345	0.385	0.376	0.357	0.342	0.327	0.313	0.298	0.284

TABLE II
RECALL@K , PRECISION@K AND F-MEASURE@K FOR PROJECT B

	K=1	K=2	K=3	K=4	K=5	K=6	K=7	K=8	K=9	K=10
RECALL	0.242	0.644	0.794	0.819	0.848	0.864	0.875	0.890	0.900	0.905
PRECISION	0.437	0.599	0.493	0.408	0.342	0.292	0.255	0.228	0.206	0.188
F-MEASURE	0.312	0.620	0.609	0.545	0.488	0.436	0.395	0.363	0.335	0.311

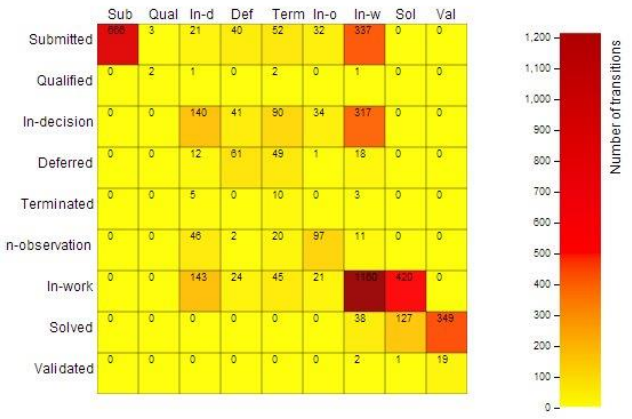

Fig. 11. A Heat Map showing the Number of Transitions (during the Bug Lifecycle of all Bug Reports in the Dataset) between the 8 Possible States

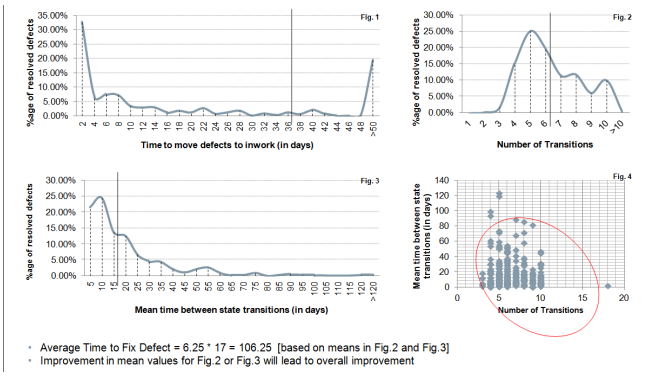

Fig. 12. Metrics to be used to track the effectiveness and usefulness of using the recommendation system.

Tomography Scan Machine. Project A started in 2012 and has 772 bugs reported till November 2014. Out of the 772 bug reports present in the Issue Tracking System, 345 have been solved and validated. We found that 236 issues have been closed due to either being duplicate bug reports or bug reports invalidated by the triager due to insufficient information to reproduce the bug. At the time of conducting the experiments, a total 78 members (project manager, product manager, testers, developers, test leads) are working on the project. The second project (Ultra-Sound Clinical Workflow Management System) is a relatively larger project (Project B) which started in 2005 and there are 17267 bugs reported till October 2014. Out of 17267 reported bugs, 12438 are resolved. A total of 253 professionals have worked on the project during the past 9 to 10 years. We consider only the resolved bugs for the purpose of conducting our experiments. N folds cross validation with N = 10 and K = [1, 10] is used for computing the precision and recall performance evaluation metrics. The formulae used for calculating precision@K and recall@K in information retrieval systems are as follows (where K is the number of developers in the ranked list):

$$Recall@K = \frac{1}{B}\sum_{i=1}^{B}\frac{|P_i \cap R_i|}{|R_i|}$$

$$Precision@K = \frac{1}{B}\sum_{i=1}^{B}\frac{|P_i \cap R_i|}{|P_i|}$$

In the formula for Precision and Recall, B denotes the number of bug reports, R represents the set of actual resolvers for a bug and P is the set of Predicted resolvers for the bug.

The calculated values have been shown in Tables I and II. We observe that the recall values increase as we increase K (which is quite intuitive). At K = 10, Project A has a recall of 0:734 with 345 solved bugs, whereas Project B has a recall of 0:905 with 1000 of the latest solved bugs. We observe that the precision values are maximum at K = 2 in both the projects. This is because in both projects the average number of resolvers per bug is very close to 2.

We conduct a manual analysis and visual inspection of a large number of bug reports and identify several instances in which a bug report is assigned to a bug fixer based on prior experience, workload, recent activity and severity and not just based on the closest match in terms of problem area expertise. We observe that in several cases the top recommended resolver (by our prediction model purely based on similar content-based recommendation) does not get the bug assigned due to factors such as workload and prior work experience of developers with the project incorporated in our decision support tool but not within the Decision Tree and

Naive Bayes based classification model. In one of the bug reports (status transition from in-work to in-work), we see a developers comments

- Due to workload issue, Alan was able to solve it partially and it needs to update the resolver.
- Since the bug is related to SRC Component, Todd has the experience in solving SRC related bugs and assigns the bug to Todd instead of Ramesh.
- The bug is high priority and assign it to Abhishek.
- Assign partial work to Rashmi and partial work to Manju
- Please assign this bug to me (I have been working in it recently).

Our manual inspection of several bug reports and the threaded discussions across two active projects in our organization demonstrates that factors in addition to content based assignment needs to be presented to the decision maker (as incorporated in our proposed decision-support system) for making better triaging decisions. In order to enable the projects to track the effectiveness and benefits of using the recommendation system, we proposed simple process metrics as shown in figure 12. The metrics are calculated for Project A, considering the data from the bugs that have already been resolved.

VII. CONCLUSIONS

Our survey results demonstrate that there are multiple factors influencing triaging decision. Terms in bug report title and description as well as resolver experience with the project are the two most important indicators for making bug assignment decision. Our interaction with practitioners in our organization reveals that justification or reasoning behind a recommendation, developer collaboration network, developer work experience and workload are also important and useful information in addition to the Top K recommendation. Descriptive statistics, trends and graphs on bug fixing efficiency, big opening and closing trends, mean time to repair and defect proneness of components are also important and complementary information for the Change Control Board while making triaging decisions. We demonstrate the effectiveness of our approach by conducting experiments on real-world CSS/PSS data from our organization and report encouraging accuracy results. We conclude that an ensemble of classifiers consisting of Decision Tree and Naive Bayes learners and incorporating factors such as workload, prior work experience, recent activity and severity of bugs is an effective mechanism for the task of automatic bug assignment.

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The Way Ahead for Bug-fix time Prediction

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***Abstract*— The bug-fix time i.e. the time to fix a bug after the bug was introduced is an important factor for bug related analysis, such as measuring software quality or coordinating development effort during bug triaging. Previous work has proposed many bug-fix time prediction models that use various bug attributes (number of developers who participated in fixing the bug, bug severity, bug-opener's reputation, number of patches) for predicting the fix time of a newly reported bug. In this paper, we have investigated the associations between bug attributes and the bug-fix time. We have proposed two approaches to apply association rule mining. In the first approach, we have used Apriori algorithm to predict the fix time of a newly coming bug based on the bug's severity, priority summary terms and assignee. In second approach, we have used *k*-means clustering method to get groups of correlated variables followed by association rule mining inside each cluster. We have collected 1,695 bug reports of three products namely AddOnSDK, Thunderbird and Bugzilla of Mozilla open source project to mine association rules. Results show that for given set of bug attributes, we can predict the bug-fix time for newly coming bugs which will help in software quality improvement. A large number of association rules having high confidence and support with higher severity and priority as antecedents and short bug-fix time as consequent show that more important bugs are fixed without any delay. This information is useful in determining software quality. We also observe that our approach for bug-fix time prediction will be helpful in bug triaging by assigning a bug to the most potential and experienced assignee who will solve the bug in minimum time period. This will again help in software quality improvement. In nutshell, we can say that association rule mining based bug-fix time prediction can help managers to improve the software development process.**

Keywords—Bug-fix time; Apriori algorithm; Association rule mining; k-means Clustering

I. INTRODUCTION

Bug-fix time prediction is useful in software quality prediction [1] or in coordinating effort during bug triaging to maintain the software systems effectively [2]. In literature efforts have been made to construct many bug-fix time prediction models, based on machine learning algorithms, on both open source and commercial projects [3-5].

A bug report is characterized by many attributes like summary, priority, severity and assignee. The textual description of a bug reported by users is known as its summary. Bug priority tells about the importance and order of bug fixing in comparison of other bugs with P1 as the highest and P5 as the lowest priority. The bug severity can be defined as: (i) the impact of bugs on the functionality of the software (business point of view) (ii) the impact of bugs on developer means how much time a bug will take in fixing. In this paper, we consider the bug severity from the business point of view. It is measured according to different levels from 1(blocker) to 7(trivial). These levels are defined in repositories as 1 for highest and 7 for lowest. Assignee is a person to whom the bug is assigned to work on.

To the best of our knowledge, no approach has been proposed till now to mine association rules among different bug attributes for bug-fix time prediction. In software development this can help the managers to improve the process in terms of cost and resources. We have proposed an approach for bug fix time prediction based on other bug attributes namely summary terms, priority, severity and assignee. We have applied association rule mining by using Apriori algorithm and *k*-means clustering followed by Apriori algorithm. For experiment of the proposed approach we have used 1,695 bug reports of AddOnSDK, Thunderbird and Bugzilla products of Mozilla open source project. Association rule mining was first explored by [7] which is the base of our prediction method.

In a database, the interesting correlations, frequent patterns, associations or casual structures among the attributes can be discovered by using association rule mining. Let C is a database of transactions and each transaction T is a set of items. An association rule is an expression $A \Rightarrow D$, where A is called antecedent and D is called consequent. $A \Rightarrow D$ reveals that whenever a transaction T contains A, then T also contains D with a specified confidence and support. The confidence of a rule is defined as percentage/fraction of the number of transactions that contain $A \cup D$ to the total number of transactions that contain A. It is a measure of the rule's strength or certainty [8]. Support of a rule is defined as the percentage/fraction of transactions that contain $A \cup D$ to the total number of transactions in the database. It corresponds to statistical significance or usefulness of the rule. Minimum support count is defined as the number of transactions required for an item set to satisfy minimum support. Association rule mining generates all association rules that have a support greater than minimum support $min.Supp(A \Rightarrow D)$, in the database, i.e., the rules are frequent. The rules must also have confidence greater than minimum confidence $min.Conf(A \Rightarrow D)$, i.e., the rules are strong.

In a wide range of science and business areas association rule mining can be applied successfully. Several performance studies have resulted in better accuracy for associative classification than state-of-the-art classification methods [9-18].

Clustering is a partitioning method in which a group of data points is partitioned into a small number of clusters. In *k*-means clustering algorithm, the function *k*-means partitions data into *k* mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, *k*-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that *k*-means clustering is often more suitable than hierarchical clustering for large amount of data.

The successful use of association rule mining in various fields motivates us to apply it to the open source software bug data set [9-18].

The organization of rest of the paper is as follows. Section 2 gives the description and preprocessing of data. Section 3 describes the model building. Section 4 presents the results. Section 5 discusses about related work. Section 6 tells about the threats to validity and finally section 7 concludes the paper with future research directions.

II. DATA SETS DESCRIPTION AND DATA PREPROCESSING

We collected bug reports from Bugzilla bug tracking system with status "verified", "resolved" and "closed" and resolution "fixed" because only these types of bug reports contain the consistent information for the experiment. We have compared and validated the collected bug reports against general change data (i.e. CVS or SVN records). Number of bug reports collected in the observed period is given in table I.

TABLE I. PRODUCTWISE NUMBER OF BUG REPORTS

Product	Bug reports	Observation period
Bugzilla	964	Sept. 1994-June 2013
Thunderbird	115	Apr. 2000-Mar. 2013
Add-on SDK	616	May 2009-Aug. 2013

In order to apply association rule mining, we have quantified different bug attributes namely severity, priority, summary, assignee and fix time.

We have preprocessed the bug summary attribute to extract terms in RapidMiner tool [19] with the help of following steps:

Tokenization: the process of breaking a stream of text into words, phrases, symbols, or other meaningful elements called tokens is called '*tokenization'*. We have considered a word or a term as a token.

Stop Word Removal: words which are commonly used in the text but do not carry useful meaning like prepositions, conjunctions, articles, verbs, nouns, pronouns, adverbs, adjectives are called stop words. We have removed all the stop words from bug summary.

Stemming to base stem: the process of converting derived words to their base word (stem) is known as stemming. Standard Porter stemming algorithm can be utilized for stemming [20].

Feature Reduction: tokens of minimum 3 and maximum 40 occurrences have been considered because most of the data mining algorithm may not be able to handle large feature sets.

Weight by Information Gain or InfoGain: it is helpful in determining the importance or relevance of the term. It helps in selection of top few terms in the data set.

We have made a workflow in RapidMiner to extract a set of terms from bug summary attribute. We have taken tokenize mode as non-letters and in filter tokens parameter we have set min chars value as 3 and max chars value as 50. We used English dictionary to filter the stop words.

III. MODEL BUILDING

Our study consists of following steps:

1. **Data Extraction**
   a. From CVS repository: https://bugzilla.mozilla.org/, downloaded bug reports for 3 products of Mozilla open source project.
   b. Store the downloaded bug reports in excel file for further processing.
2. **Data Pre-processing**
   a. In RapidMiner developed a workflow to extract individual terms of bug summary.
3. **Data Preparation**
   a. For different severity and preiority levels, we have taken numeric values from 1 to 7 and from 8 to 12.
   b. Assigned a numeric value from 13 to 43 to top 30 terms based on InfoGain.
   c. For each assignee take a unique numeric value.
   d. Filtered bug-fix time for 0 to 99 days as maximum number of bugs has fix time in this range only. Define three bug-fix time ranges: 0 to19 days, 20 to 64 days and 65 to 99 days. Assign a numeric value from 1 to 3 to these three ranges.
4. **Association Rule Mining and Clustering**
   a. ARMADA (Association Rule Miner And Deduction Analysis) is a Data Mining tool of MATLAB software that extracts Association Rules from numerical data files using a variety of selectable techniques and criteria [21]. We have applied Apriori algorithm by using ARMADA tool. As a result we get association rules for bug-fix time prediction with severity, priority, summary terms and assignee as antecedents.
   b. We have applied k-means clustering algorithm in SPSS(Statistical Package for Social Sciences) software followed by Apriori algorithm for each resulting cluster by using MATLAB software

with minimum confidence 20% and minimum support 7%.

5. Testing and Validation

Assess the resulting association rules in terms of different performance measures namely support and confidence.

IV. Results and Discussion

In this paper, we have proposed two approaches to apply association mining. In first approach, we have mined the association rules for bug-fix time prediction with bug severity, priority, summary terms and assignee as antecedents by applying Apriori algorithm of ARMADA tool in MATLAB software. We have considered association rules with minimum confidence 20% and minimum support 7% for AddOnSDK and Bugzilla products. In thunderbird product we have very less number of bug reports as a result of which we get association rules with minimum confidence 20% and support 3%. All the 3 datasets have more than 100 rules. For this reason, we do not list them all, but instead we present top 5 rules based on the highest confidence. In table II we have presented top five association rules of AddOnSDK product for three defined ranges.

TABLE II. Top five Association rules for AddOnSDK

Association Rules (minimum support=7%, minimum confidence=20%)
Bug-fix time 0-19 days
1. Priority {P1} ∧ Assignee { Alexandre Poirot} ∧ Term {con} ∧ Term {test} ∧ Term {content} ∧ Term{fail} ⇒ Bug-fix time {0-19 days} @ (10%, 100%)
2. Severity {Major} ∧ Priority {P1} ∧ Term {con} ∧ Term {test} ∧ Term {content} ∧ Term {fail} ⇒ Bug-fix time {0-19 days} @ (8%, 100%)
3. Severity {Major} ∧ Priority {P1} ∧ Assignee {Alexandre Poirot} ∧ Term {con} ∧ Term{content} ∧ Term{fail} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
4. Priority{P1} ∧ Assignee { Alexandre Poirot } ∧ Term {con} ∧ Term{content} ∧ Term{fail} ⇒ Bug-fix time {0-19 days} @ (11%, 100%)
5. Severity{Major} ∧ Priority {P1} ∧ Term{con} ∧ Term {content} ∧ Term {fail} ⇒ Bug-fix time {0-19 days} @ (9%, 100%)
Bug-fix time 20-64 days
1. Severity {Major} ∧ Priority {P1} ∧ Term {win} ∧ Term {window} ∧ Term {updat} ∧ Term {privat} ⇒ Bug-fix time {20-64 days} @ (7%, 100%)
2. Severity {Major} ∧ Assignee {Will Bamberg} ∧ Term {doc} ∧ Term {document} ∧ Term {page} ⇒ Bug-fix time {20-64 days} @ (7%, 100%)
3. Severity {Major} ∧ Priority{P1} ∧ Term {mod} ∧ Term {modul} ∧ Term {privat} ⇒ Bug-fix time {20-64 days} @ (7%, 100%)
4. Severity {Major} ∧ Term {mod} ∧ Term {modul} ∧ Term {privat} ⇒ Bug-fix time {20-64 days} @ (8%, 100%)
5. Severity {Major} ∧ Term {modul} ∧ Term {privat} ⇒ Bug-fix time {20-64 days} @ (8%, 100%)
Bug-fix time 65-99 days
1. Severity {Major} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (9%, 31%)
2. Term {text} ⇒ Bug-fix time {65-99 days} @ (9%, 29%)
3. Severity {Major} ∧ Term {con} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (7%, 27%)
4. Term {con} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (7%, 25%)
5. Priority {P1} ∧ Term {tab} ⇒ Bug-fix time {65-99 days} @ (8%, 23%)

The first association rule is a six antecedent rule, which reveals that a bug with priority *P1*, assignee *Alexander Poirot* and summary containing terms *con, test, content* and *fail* can have a fix time of *0 to 19 days* with a significance of 10 percent and a certainty of 100 percent. Second association rule means that a bug with severity *Major*, priority *P1*, and summary containing terms *con, test, content* and *fail* can have a fix time of *0 to 19 days* with a significance of 8 percent and a certainty of 100 percent. Third rule shows that a bug with severity *Major*, priority *P1* and summary containing terms *con, content* and *fail* can have a fix time of *0 to 19 days* with a significance of 7 percent and a certainty of 100 percent. Rule four reveals that 11 percent of the bugs in the bug data set have priority *P1*, assignee *Alexandre Poirot*, summary containing terms *con, content, fail* and bug-fix time of *0 to 19 days.* 100 percent of the bugs in the bug data set that have *priority P1*, assignee *Alexandre Poirot*, summary containing terms *con, content, fail* also have bug-fix time of *0-19 days.* The fifth rule shows that the bug having severity *Major*, priority *P1* and summary containing terms *con, content* and *fail* can have bug-fix time of *0 to 19 days* with a significance of 9 percent and a certainty of 100 percent. Similarly we have interpreted association rules of other bug-fix time ranges.

We have shown top five association rules to predict bug-fix time for Thunderbird product in table III.

TABLE III. Top five Association rules for Thunderbird

Association Rules (minimum support=3%, minimum confidence=20%)
Bug-fix time 0-19 days
1. Severity {Major} ∧ Term {add} ∧ Term {icon} ∧ Term {address} ⇒ Bug-fix time {0-19 days} @ (3%, 100%)
2. Severity {Major} ∧ Priority {P3} ∧ Term {text} ∧ Term {box} ⇒ Bug-fix time {0-19 days} @ (3%, 100%)
3. Severity {Major} ∧ Priority {P3} ∧ Term {window} ∧ Assignee {Andreas Nilsson} ⇒ Bug-fix time {0-19 days} @ (3%, 100%)
4. Term {tool} ∧ Term {toolbar} ∧ Assignee {Blake Winton} ⇒ Bug-fix time {0-19 days} @ (3%, 100%)
5. Term {config} ∧ Term {auto} ∧ Assignee {Blake Winton} ⇒ Bug-fix time {0-19 days} @ (3%, 100%)
Bug-fix time 20-64 days
1. Severity {Major} ∧ Assignee {David} ∧ Term {move} ∧ Term {remov} ⇒ Bug-fix time {20-64 days} @ (3%, 100%)
2. Term {add} ∧ Term {pre} ⇒ Bug-fix time {20-64 days} @ (3%, 100%)
3. Term {mail} ∧ Term {move} ∧ Term {remov} ⇒ Bug-fix time {20-64 days} @ (3%, 75%)
4. Assignee {David} ∧ Term {move} ⇒ Bug-fix time {20-64 days} @ (3%, 75%)

5.	Assignee {David} ∧ Term {messag} ⇒ Bug-fix time {20-64 days} @ (3%, 75%)
	Bug-fix time 65-99 days
1.	Priority {P1} ∧ Term {mail} ⇒ Bug-fix time {65-99 days} @ (5%, 63%)
2.	Severity {Major} ∧ Term {thunderbird} ∧ Assignee {Mark Banner} ⇒ Bug-fix time {65-99 days} @ (3%, 60%)
3.	Severity {Major} ∧ Assignee {Mark Banner} ⇒ Bug-fix time {65-99 days} @ (4%, 50%)
4.	Assignee {Mark Banner} ⇒ Bug-fix time {65-99 days} @ (5%, 38%)
5.	Severity {Major} ∧ Term {mail} ⇒ Bug-fix time {65-99 days} @ (3%, 38%)

The first association rule is a four antecedent rule, which reveals that a bug with severity *Major*, and summary containing terms *add, icon* and *address* can have a fix time of *0 to 19 days* with a significance of 3 percent and a certainty of 100 percent. Second association rule means that a bug with severity *Major*, priority *P3*, and summary containing terms *text* and *box* can have a fix time of *0 to 19 days* with a significance of 3 percent and a certainty of 100 percent. Third rule shows that a bug with severity *Major*, priority *P3* and summary containing terms *window and* assignee *Andreas Nilssson* can have a fix time of *0 to 19 days* with a significance of 3 percent and a certainty of 100 percent. Rule four reveals that 3 percent of the bugs in the bug data set have summary containing terms *tool, toolbar,* assignee *Blake Winton* and bug-fix time of *0 to 19 days.* 100 percent of the bugs in the bug data set that have summary containing terms *tool, toolbar* and assignee *Blake Winton* also have bug-fix time of *0-19 days.* The fifth rule shows that the bug with summary containing terms *config, auto* and assignee *Blake Winton* can have bug-fix time of *0 to 19 days* with a significance of 3 percent and a certainty of 100 percent. Similarly we have interpreted association rules of other bug-fix time ranges.

We have shown top five association rules to predict bug-fix time for Bugzilla product in table IV.

TABLE IV. TOP FIVE ASSOCIATION RULES FOR BUGZILLA

Association Rules (minimum support=7%, minimum confidence=20%)	
	Bug-fix time 0-19 days
1.	Severity {Major} ∧ Priority {P1} ∧ Term {check} ∧ Term {set} ∧ Term { setup } ∧ Term { checksetup} ⇒ Bug-fix time {0-19 days} @ (11%, 100%)
2.	Priority {P1} ∧ Term {ing} ∧ Term {check} ∧ Term {set} ∧ Term {setup} ∧ Term {checksetup} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
3.	Assignee {Daniel Buchner} ∧ Term{bug} ∧ Term{hang} ∧ Term{chang} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
4.	Priority{P3} ∧ Term{bug} ∧ Term{ing} ∧ Term{bugzilla} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
5.	Priority{P3} ∧ Assignee {Daniel Buchner} ∧ Term{hang} ∧ Term {chang} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
	Bug-fix time 20-64 days
1.	Priority {P3} ∧ Term {cgi} ∧ Term {edit} ⇒ Bug-fix time {20-64 days} (8%, 100%)
2.	Priority {P3} ∧ Term {edit} ⇒ Bug-fix time {20-64 days} @ (10%, 67%)
3.	Severity {Major} ∧ Term {temp} ∧ Term {templat} ⇒ Bug-fix time {20-64 days} @ (8%, 62%)
4.	Priority {P3} ∧ Term {user} ⇒ Bug-fix time {20-64 days} @ (8%, 57%)
5.	Severity {Major} ∧ Term {temp} ⇒ Bug-fix time {20-64 days} @ (8%, 57%)
	Bug-fix time 65-99 days
1.	Assignee {Gervase Markham} ∧ Term{temp} ∧ Term{templat} ⇒ Bug-fix time {65-99 days} @ (7%, 39%)
2.	Assignee {Gervase Markham} ∧ Term{cgi} ⇒ Bug-fix time {65-99 days} @ (7%, 39%)
3.	Assignee {Matthew Barnson} ⇒ Bug-fix time {65-99 days} @ (10%, 38%)
4.	Assignee {Max Kanat-Alexander} ∧ Term{ing} ⇒ Bug-fix time {65-99 days} @ (9%, 31%)
5.	Assignee {Dawn Endico} ⇒ Bug-fix time {65-99 days} @ (7%, 30%)

The first association rule is a six antecedent rule, which reveals that a bug with severity *Major*, priority *P1*and summary containing terms *check, set, setup* and *checksetup* can have a fix time of *0 to 19 days* with a significance of 11 percent and a certainty of 100 percent. Second association rule means that a bug with priority *P1*, and summary containing terms *check, set, setup* and *checksetup* can have a fix time of *0 to 19 days* with a significance of 7 percent and a certainty of 100 percent. Third rule shows that a bug with assignee *Daniel Buchner* and summary containing terms *bug, hang* and *chang* can have a fix time of *0 to 19 days* with a significance of 7 percent and a certainty of 100 percent. Rule four reveals that 7 percent of the bugs in the bug data set have priority *P3*, summary containing terms *bug, ing, bugzilla* and bug-fix time of *0 to 19 days.* 100 percent of the bugs in the bug data set that have priority *P3* and summary containing terms *bug, ing and Bugzilla* also have bug-fix time of *0-19 days.* The fifth rule shows that a bug with priority *P3*, assignee *Daniel Buchner* and summary containing terms *hang* and *chang* can have bug-fix time of *0 to 19 days* with a significance of 7 percent and a certainty of 100 percent. Similarly we have interpreted association rules of other bug-fix time ranges.

In order to analyze the rule length (number of antecedents) of association rules, we draw the distribution of association rules across all the datasets (Fig. 1 to 3).

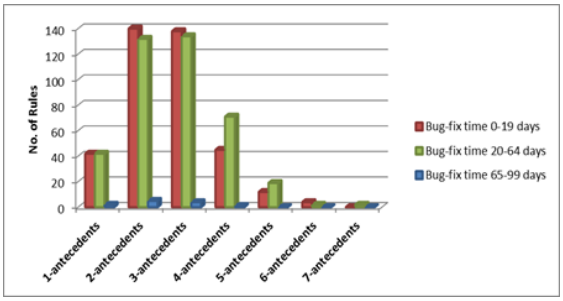

Fig. 1. AddOnSdk association rules (min.supp=7% and min.conf=20%)with different rule length

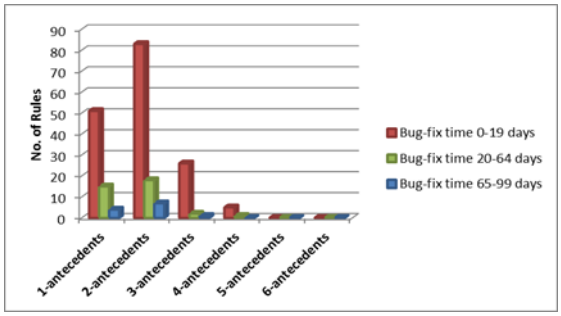

Fig. 2. Thunderbird association rules (min.supp=3% and min.conf=20%)with different rule length

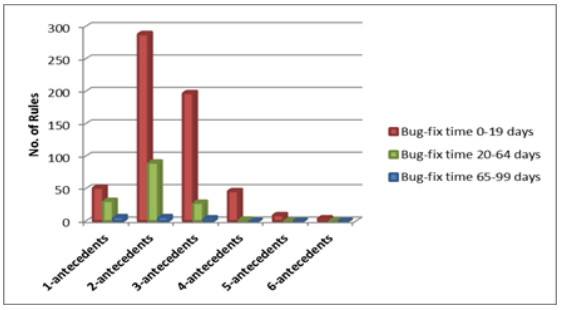

Fig. 3. Bugzilla association rules (min.supp=7% and min.conf=20%)with different rule length

Figure 1 to 3 show that we have maximum association rules with two antecedents (length 2) across all the datasets.

We observe that in all products, we have some rules with same antecedents and consequent except assignee. These rules reveal that for different assignee we have same bug-fix time for same values of other attributes. In this case we will prefer an assignee with higher confidence value to whom we can assign the bug as he is more potential and experienced in fixing such type of bugs. In this way the proposed approach will help in bug triaging which will help in software quality improvement.

We have observed following rules from AddOnSDK product.

1. Severity {Major} ∧ Term {test} ∧ Assignee {Alexandre Poirot}
   ⇒ Bug-fix time {0-19 days} @ (16%, 89%)
2. Severity {Major} ∧ Term {test} ∧ Assignee {Dave Townsend}
   ⇒ Bug-fix time {0-19 days} @ (12%, 71%)
3. Severity {Major} ∧ Term {test} ∧ Assignee {Erik Vold}
   ⇒ Bug-fix time {0-19 days} @ (8%, 50%)
4. Severity {Major} ∧ Priority {P1} ∧ Term {con} ∧ Assignee {Will Bamberg}
   ⇒ Bug-fix time {20-64 days} @ (11%, 65%)
5. Severity {Major} ∧ Priority {P1} ∧ Term {con} ∧ Assignee {Alexandre Poirot}
   ⇒ Bug-fix time {20-64 days} @ (9%, 35%)

First three rules reveals that bugs with severity *Major* and summary containing term *test* have three choices of assignee i.e. *Alexandre Poirot* or *Dave Townsend* or *Erik Vold* to get fixed in 0 to 19 days with certainty of 89, 71 and 50 percent respectively. We observe that the bug should be assigned to *Alexandre Poirot* as the rule with this assignee gives highest certainty. Similarly we can infer from last two rules that we should assign the bug to *Will Bamberg* as the rule with this assignee gives higher certainty. Similar inference we can draw for other two datasets also.

We observe that in all products we have some rules with same antecedents except assignee. These rules reveal that different assignee will fix same bugs with same attributes with different bug-fix time. In this case, we will prefer an assignee with lower fix time in fixing such type of bugs. In this way the proposed approach will help in choosing assignee which can fix the bug in shortest time.

We have observed following rules from Bugzilla product.

1. Severity {Major} ∧ Assignee {Terry Weissman}
   ⇒ Bug-fix time {0-19 days} @ (67%, 80%)
2. Severity {Major} ∧ Assignee {Bradley Baetz}
   ⇒ Bug-fix time {20-64 days} @ (7%, 44%)
3. Severity {Major} ∧ Assignee {Max Kanat-Alexander}
   ⇒ Bug-fix time {65-99 days} @ (8%, 22%)
4. Priority{P1} ∧ Assignee {Dave Miller}
   ⇒ Bug-fix time {0-19 days} @ (7%, 78%)
5. Priority{P1} ∧ Assignee {Max Kanat-Alexander}
   ⇒ Bug-fix time {20-64 days} @ (11%, 42%)

First three rules reveals that bugs with severity *Major* can be assigned to three different assignee: *Terry Weissman*, *Bradley Baetz* and *Max Kanat-Alexander*. All the three assignee will fix the same bug with severity Major with different fix time ranges. We will preferably assign the bug to an assignee who will fix it in minimum time and i.e. *Terry Weissman*. Similarly we can infer from last two rules that we should assign the bug to *Dave Miller* as he will solve the bug earliest. Similar inference we can draw for other two datasets also.

In second approach, we have presented clustering based association rule mining for bug-fix time prediction. We have partitioned the AddOnSDK dataset into 5 clusters using k-means clustering method. In cluster 1, there is only one data. Cluster 2 contains 93 data, cluster 3 contains 379 data, cluster 4 contains 115 data and cluster 5 contains 28 data. After portioning, we have applied Apriori algorithm on each cluster with minimum confidence 20% and minimum support 2%.

Table V presents top five association rules from five clusters formed by k-means clustering for AddOnSDK product.

TABLE V. TOP FIVE ASSOCIATION RULES FOR ADDONSDK

Association Rules (minimum support=2%, minimum confidence=20%)
Bug-fix time 0-19 days
Cluster 2
1. Term {con} ∧ Term {test} ∧ Term{fail} ⇒ Bug-fix time {0-19 days} @ (5%, 100%)
2. Priority {P1} ∧ Term {con} ∧ Term {test} ⇒ Bug-fix time {0-19 days} @ (5%, 100%)

3.	Assignee {Alexandre Poirot} ∧ Term {test} ∧ Term{fail} ⇒ Bug-fix time {0-19 days} @ (5%, 100%)
4.	Priority{P1} ∧ Assignee { Alexandre Poirot } ∧ Term {test} ⇒ Bug-fix time {0-19 days} @ (5%, 100%)
5.	Priority {P1} ∧ Term{con} ∧ Term {test} ∧ Term {fail} ⇒ Bug-fix time {0-19 days} @ (5%, 100%)
Cluster 3	
1.	Priority {P1} ∧ Term {fire} ∧ Term {test} ∧ Term{firefox} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
2.	Priority {P1} ∧ Assignee {Alexandre Poirot} ∧ Term {fail} ∧ Term {test} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
3.	Severity {Major} ∧ Priority{P1} ∧ Term {test} ∧ Term{firefox} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
4.	Severity {Major} ∧ Priority{P1} ∧ Term {test} ∧ Term {fire} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
5.	Severity {Major} ∧ Priority{P1} ∧ Term {test} ∧ Term {fire} ∧ Term{firefox} ⇒ Bug-fix time {0-19 days} @ (7%, 100%)
Cluster 4	
1.	Severity {Major} ∧ Priority{P2} ∧ Term {cfx} ⇒ Bug-fix time {0-19 days} @ (2%, 100%)
2.	Severity {Major} ∧ Priority{P1} ∧ Term {get} ⇒ Bug-fix time {0-19 days} @ (2%, 100%)
3.	Severity {Major} ∧ Priority{P2} ∧ Term {get} ⇒ Bug-fix time {0-19 days} @ (2%, 100%)
4.	Severity {Major} ∧ Priority{P2} ∧ Assignee {Alexandre Poirot} ∧ Term {get} ⇒ Bug-fix time {0-19 days} @ (2%, 100%)
5.	Severity {Major} ∧ Priority{P3} ∧ Term {fail} ⇒ Bug-fix time {0-19 days} @ (2%, 100%)
Cluster 5	
1.	Severity {Major} ∧ Assignee {Alexandre Poirot} ∧ Term {con} ∧ Term {content} ⇒ Bug-fix time {0-19 days} @ (5%, 83%)
2.	Severity {Major} ∧ Term {con} ∧ Term {content} ⇒ Bug-fix time {0-19 days} @ (5%, 71%)
3.	Severity {Major} ∧ Priority{P1} ∧ Term {fail} ⇒ Bug-fix time {0-19 days} @ (6%, 67%)
4.	Priority{P1} ∧ Term {fail} ∧ Term {win} ∧ Term {window} ⇒ Bug-fix time {0-19 days} @ (5%, 63%)
5.	Severity {Major} ∧ Priority{P1} ∧ Term {fail} ∧ Term {test} ⇒ Bug-fix time {0-19 days} @ (5%, 63%)
Bug-fix time 20-64 days	
Cluster 2	
1.	Severity {Major} ∧ Priority {P4} ∧ Assignee {Will Bamberg} ∧ Term {con} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
2.	Severity {Major} ∧ Priority {P3} ∧ Assignee {Will Bamberg} ∧ Term {updat} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
3.	Severity {Major} ∧ Priority {P1} ∧ Assignee {Will Bamberg} ∧ Term {document} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (6%, 100%)
4.	Severity {Major} ∧ Assignee {Will Bamberg} ∧ Term {con} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
5.	Priority {P3} ∧ Assignee {Will Bamberg} ∧ Term {con} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
Cluster 3	
1.	Severity {Major} ∧ Priority {P1} ∧ Assignee {Will Bamberg} ∧ Term {doc} ∧ Term {document} ⇒ Bug-fix time {20-64 days} @ (8%, 62%)
2.	Severity {Major} ∧ Priority{P1} ∧ Term {page} ⇒ Bug-fix time {20-64 days} @ (9%, 60%)
3.	Severity {Major} ∧ Priority{P1} ∧ Term {tab} ⇒ Bug-fix time {20-64 days} @ (10%, 59%)
4.	Severity {Major} ∧ Priority {P2} Term {mod} ⇒ Bug-fix time {20-64 days} @ (7%, 54%)
5.	Assignee {Will Bamberg} ∧ Term {document} ⇒ Bug-fix time {20-64 days} @ (16%, 53%)
Cluster 4	
1.	Severity {Major} ∧ Priority{P1} ∧ Assignee {Will Bamberg} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (2%, 100%)
2.	Severity {Major} ∧ Assignee {Will Bamberg} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (3%, 100%)
3.	Severity {Major} ∧ Priority {P1} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (3%, 100%)
4.	Priority {P1} ∧ Assignee {Will Bamberg} ∧ Term {doc} ⇒ Bug-fix time {20-64 days} @ (2%, 100%)
5.	Severity {Major} ∧ Assignee {Will Bamberg} ∧ Term {updat} ⇒ Bug-fix time {20-64 days} @ (2%, 100%)
Cluster 5	
1.	Severity {Major} ∧ Term {win} ∧ Term {window} ∧ Term {updat} ∧ Term {private} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
2.	Severity {Major} ∧ Priority{P1} ∧ Term {window} ∧ Term {updat} ∧ Term {private} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
3.	Severity {Major} ∧ Priority{P1} ∧ Term {win} ∧ Term {updat} ∧ Term {private} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
4.	Severity {Major} ∧ Priority{P1} ∧ Term {mod} ∧ Term {modul} ∧ Term {private} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
5.	Severity {Major} ∧ Priority{P1} ∧ Term {win} ∧ Term {window} ∧ Term {updat} ∧ Term {private} ⇒ Bug-fix time {20-64 days} @ (5%, 100%)
Bug-fix time 65-99 days	
Cluster 2	
1.	Severity {Major} ∧ Term {tab } ⇒ Bug-fix time {65-99 days} @ (6%, 35%)
2.	Term {tab} ⇒ Bug-fix time {65-99 days} @ (6%, 33%)
3.	Severity {Major} ∧ Term {window} ⇒ Bug-fix time {65-99 days} @ (5%, 25%)
4.	Severity {Major} ∧ Term {win} ∧ Term {window} ⇒ Bug-fix time {65-99 days} @ (5%, 25%)
5.	Term {window} ⇒ Bug-fix time {65-99 days} @ (5%, 24%)
Cluster 3	
1.	Priority{P1} ∧ Term {modul} ⇒ Bug-fix time {65-99 days} @ (7%, 25%)
2.	Severity {Major} ∧ Priority{P1} ∧ Term {modul} ⇒ Bug-fix time {65-99 days} @ (7%, 27%)
3.	Priority{P1} ∧ Term {mod} ∧ Term {modul} ⇒ Bug-fix time {65-99 days} @ (7%, 25%)
4.	Severity {Major} ∧ Priority{P1} ∧ Term {mod} ⇒ Bug-fix time {65-99 days} @ (7%, 21%)
5.	Severity {Major} ∧ Priority{P1} ∧ Term {mod} ∧ Term {modul} ⇒ Bug-fix time {65-99 days} @ (7%, 27%)
Cluster 4	
1.	Severity {Enhancement} ∧ Priority{P3} ⇒ Bug-fix time {65-99 days} @ (2%, 67%)
2.	Severity {Major} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (2%, 67%)
3.	Severity {Major} ∧ Term {sdk} ⇒ Bug-fix time {65-99 days} @ (2%, 40%)
4.	Severity {Major} ∧ Priority{P1} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (2%, 67%)
5.	Priority{P1} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (2%, 67%)
Cluster 5	
1.	Severity {Major} ∧ Priority{P1} ∧ Assignee { Dave Townsend } ∧ Term {con} ∧ Term {add} ∧ Term {text}

	⇒ Bug-fix time {65-99 days} @ (2%, 100%)
2.	Severity {Major} ∧ Priority{P1} ∧ Assignee { Dave Townsend } ∧ Term {con} ∧ Term {test} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (2%, 100%)
3.	Severity {Major} ∧ Priority{P1} ∧ Assignee { Dave Townsend } ∧ Term {con} ∧ Term {test} ∧ Term {add} ⇒ Bug-fix time {65-99 days} @ (2%, 100%)
4.	Priority{P1} ∧ Term {test} ∧ Term {add} ∧ Term {fail} ∧ Term {error} ∧ Term {addon} ⇒ Bug-fix time {65-99 days} @ (2%, 67%)
5.	Severity {Major} ∧ Priority{P1} ∧ Assignee { Dave Townsend } ∧ Term {con} ∧ Term {test} ∧ Term {add} ∧ Term {text} ⇒ Bug-fix time {65-99 days} @ (2%, 100%)

We observe that, if we apply association mining after clustering, we get different association rules. As we are partitioning the datasets into clusters, we get association rules with decreased support count i.e. 2%. Results also show that, the confidence count lies in the range of 21 to 100%.

We get the similar results for other datasets.

V. Related work

In last few years, a number of valuable studies have been conducted to address the problem of bug-fix time prediction. A study on 72,482 bug reports from nine versions of Linux software named Ubuntu has been conducted by [3]. Results show that people participating in groups of size ranging from 1 to 8 users fixed 95% bug reports. The study results in 92% linear relationship between the number of people participating in fixing a bug report and bug-fix time. The applied linear regression model resulted in R^2 up to 0.98. At attempt has been made on 512,474 bug reports of five open source projects –Eclipse, Chrome and three products of Mozilla project – Thunderbird, Firefox and Seamonkey to test the prediction performance of existing models by using multivariate and univariate regression [4]. As a result it was found that existing models have predictive power between 30% and 49% and more independent attributes can be included. No correlation was found between bug-fix likelihood, bug-opener's reputation and the time it takes to fix a bug. A model has been proposed for six projects: Eclipse JDT, Eclipse Platform, Mozilla Core, Mozilla Firefox, Gnome GStreamer and Gnome Evolution to predict that how promptly a new bug report will receive attention [5]. Results show an improvement in bug-fix time prediction accuracy if number of developers and number of comments are included. An attempt has been made to show the bug-fix time trends in Mozilla and Apache projects [22]. It was found that on average resolution time for bugs of priority levels 4 and 5 exceeds 100 days, bugs of the priority level 2 are resolved in 80 days or less and bugs of the priority level 1 or 3 are resolved in 30 days or less. An attempt has been made to focus on the delays incurred by developers during bug fixing [25]. A study has been conducted to filter out the data sets by identifying the potential outliers in the distribution of the fix-time attribute. Results showed that filtering these outliers can improve the accuracy of the prediction models [26].

An attempt has been made to present an application of association rule mining to predict software defect associations and defect correction effort with SEL defect data [23]. The results show that for the defect association prediction, the minimum accuracy is 95.38 percent, and the false negative rate is just 2.84 percent; and for the defect correction effort prediction, the accuracy is 93.80 percent for defect isolation effort prediction and 94.69 percent for defect correction effort prediction. Recently, a study discussed the application of association mining in bug triaging. Authors have used Apriori algorithm to predict the right developer to work on the bug by taking bug's severity, priority and summary terms as the antecedents [24]

To best of our knowledge, no approach has been proposed till now to mine association rules among different bug attributes to predict bug-fix time. Managers can use association rules to improve development process by doing a bug-fix time prediction for a given set of bug attributes. Several performance studies have resulted in better accuracy for associative classification than state-of-the-art classification methods [9-18]. Our work has been motivated by the successful application of association rule mining in various fields.

VI. Threats to Validity

Factors that can affect the validity of our study are as follow:

Construct Validity: We have not empirically validated the independent attributes taken in our study.

Internal Validity: Except the four attributes namely severity, priority, summary terms and assignee taken in our study, developer's reputation can also be considered as it is an important attribute which can contribute in bug-fix time prediction.

External Validity: We have considered only open source Mozilla products. The study can be extended for other open source and closed source software.

Reliability: RapidMiner, SPSS and MATLAB software have been used in this paper for model building and testing. The increasing use of these software confirms the reliability of the experiments. Errors in performance measures such as accuracy of these tools has not been considered and handled.

VII. Conclusion

The time to fix a bug after the bug was introduced is called bug-fix time. It is an important factor for bug related analysis, such as measuring software quality or coordinating development effort during bug triaging. Prior work has proposed many bug-fix time prediction models based on various bug attributes (number of developers who participated in fixing the bug, bug severity, bug-opener's reputation, number of patches) for predicting the fix time of a newly reported bug. Several studies have been conducted by using classification and regression models. We have proposed an approach for bug-fix time prediction based on other bug attributes namely summary terms, priority, severity and assignee by using Apriori algorithm and *k*-means clustering followed by Apriori algorithm. We have also used k-means clustering method to get groups of correlated variables

followed by association rules mining inside each cluster. We have validated our results on 1,695 bug reports of AddOnSDK, Thunderbird and Bugzilla products of Mozilla open source project. We have presented top five association rules for 20% minimum confidence and 3% and 7% minimum support. We observe that, if we apply association mining after clustering, we get different association rules. As we are partitioning the datasets into clusters, we get association rules with decreased support count i.e. 2%. Results show that, the confidence count lies in the range of 21 to 100%.

By using these rules we can predict the bug-fix time for a newly coming bug. We also observe that our approach for bug-fix time prediction will be helpful in bug triaging by assigning a bug to the most potential and experienced assignee that will solve the bug in minimum time period. Prediction of bug-fix time will help the managers in measuring software quality and in software development process. From results, we can observe the number of association rules having high confidence and support with higher severity and priority as antecedents and short bug-fix time as consequent. A large number for such rules show that more important bugs are fixed with out any delay. This information is useful in determining software quality during software evolution process. Further, for bugs with long predicted fix time we need to pay more attention to the related source files to make sure that the files remain stable during fixing process. This will again help in determining software quality. We will extend our work with other association mining algorithms to empirically validate the results.

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