CS898 PROJECT
-- Actionable Alert Detection

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OUTLINE

- Background
  - Automatic static analysis(ASA)
  - Actionable alert(AA) & Unactionable alert(UA)
- Motivation
- Related Work
- Method
- Experiment
- Summary

Automatic Static Analysis

- Static analysis is the process of evaluating a system or component based on its form, structure, content or documentation.
- ASA can identify common coding problems early in the development process via a tool that automates the inspection of source code.
- ASA tools: Findbugs, Lint, Checkstyle.

Alert

- Alerts: potential source code anomalies reported by ASA.
- Null pointer dereference
- Buffer overflows
- Style inconsistencies

Alert

- Actionable Alerts: if a developer determines the alert is an important, fixable anomaly.

- Unactionable Alerts: When an alert is not an indication of an actual code anomaly or the alert is deemed unimportant to the developer.

Alert

▪

```
static final SimpleDateFormat cDateFormat
  = new SimpleDateFormat (“yyyy-MM-dd”);
```

Alet

STCAL: Sharing a single instance across thread boundaries without proper synchronization will result in erratic behaviour of the application.

7 times in revision 1497967 of Tomcat.

Alert

```
try { socket.close (); }
catch (Exception ignore) {}
try { reader.close (); }
catch (Exception ignore) {}
```

Alert
This method might ignore an exception.

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Motivation

Alert density: 40 alerts/KLOC
35 - 91 % of alerts are UA.
Lots of UAs may lead developers and managers to reject ASA due to the overhead of alert inspection.

Suppose,
1000 alerts, 5 min/alert
need 10.4 workdays to inspect all alerts
identify UAs can save 3.6 - 9.5 days

Motivation

Actionable Alert Identification Techniques(AAIT):
use the alerts with other information to classify or prioritize alerts.

classification: divide alerts into two groups, UA and AA.
prioritization: order alerts by the likelihood an alert is AA.

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Related Work

Heckman and Williams use alert characteristics and machine learning to predict actionable FindBugs alerts. This is one of the most comprehensive actionable alert prediction studies today.

Bodden, Lam and Hendren use static analysis to deduce run-time properties of program. They use decision trees with code characteristics to decrease false positives.

Quinn et al. use alert characteristics and machine learning to find code patterns in static analysis alerts.

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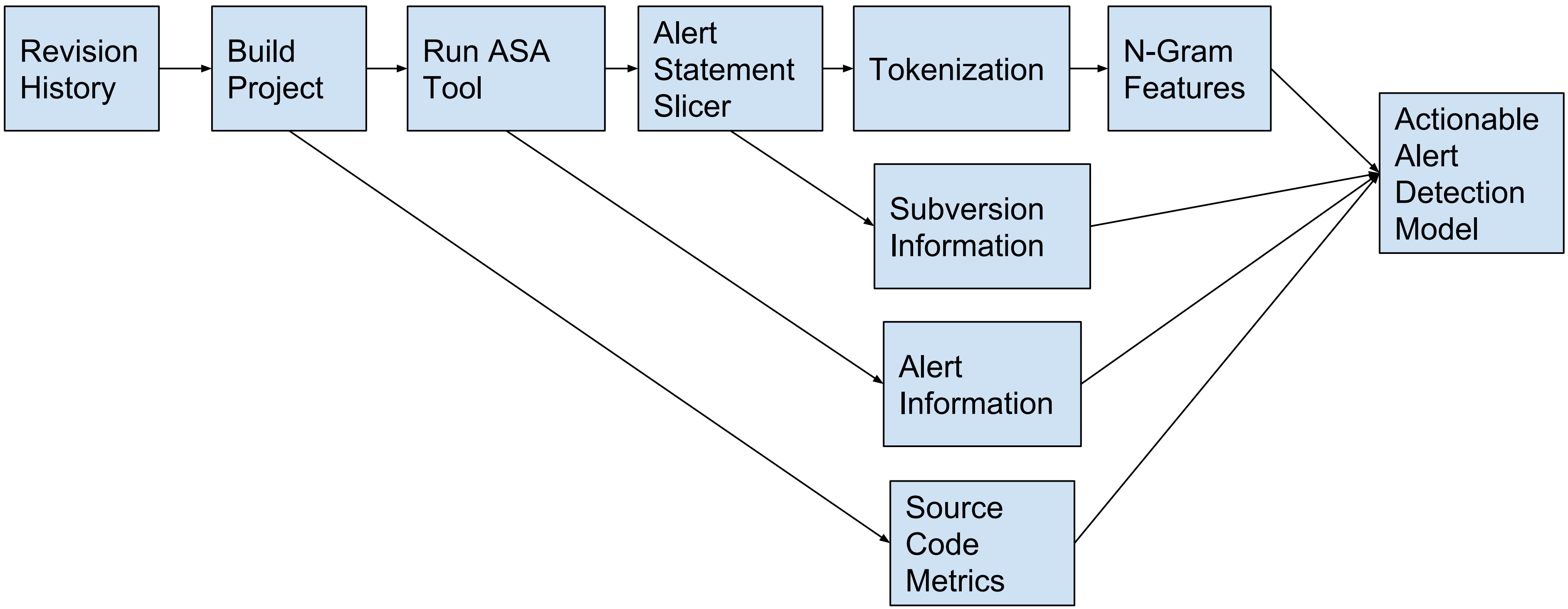
  - Revision History & Build Project
  - Run ASA Tool
  - Alert Statement Slice
  - Tokenization
  - Extract Features
  - Model

Method


Revision History
Build Project
Run ASA Tool
Alert Statement Slicer
Tokenization
N-Gram Features
Actionable Alert Detection Model
Subversion Information
Alert Information
Source Code Metrics

Revision History

Generate subject revision history from source code repository, like CVS or SVN

Build Project

Build subject project for each revision.
Delete the revisions which can not build successfully.

Run ASA Tool

Run Automatic Static Analysis Tool at each revision to get alert information.
In our method, we use FindBug.

Alert Statement Slices

program slicer included in the IBM T.J. Watson Libraries for Analysis (WALA)

- We select the SA alerts as seed statements
- The slicer use the source code and seed statements to build a call graph and pointer analysis
- Construct backwards slices for each alert

Alert Statement Slices

Original:

```
int i;
int sum=0;
int product = 1;
for(i=1; i<N; ++i){
    sum = sum +i;
    product = product *i;
}
write(sum);
write(product);
```

After slicing:

```
int i;
int sum=0;

for(i=1; i<N; ++i){
    sum = sum +i;

}
write(sum);
```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Tokenization

Control flow information is important

Granularity: High level. consider method, control flow as tokens

Tool: Eclipse JDT Core

Extract N-Gram Features

Create a dictionary of N-gram from the program slice.
Use information gain to reduce data dimensionality.
Identify 320 features with most information value.

Other Features

There are three potential features for static analysis actionable alerts:

- Alert Information
- Source code metrics
- Subversion Information

The characteristic for each alert may be different for each alert type, so we need the alert information.
Alert Information is retrieved from FindBug for each revision.

Other Features

Group	Features
Alert Information(9)	Alert Category
	Alert Type
	Project Name
	Package Name
	File Name
	Class Name
	Method Signature
	Priority
	Total Alerts for Revision

Other Features

Code complexity metrics correlate with failure-prone modeules.
Previous work have used code size metrics to predict fault counts.

Use JavaNCSS to generate metrics at the file, package, and project levels.

These tools provide information about the size of source code by lines and the complexity of the programs.

Non commenting source statements (NCSS) counts the number of all statements excluding comments, empty statements, empty blocks, closing brackets or semicolons after closing brackets.

Other Features

Group	Features
Software Metrics(7)	Classes in Package
	Functions in Package
	Functions in Class
	Cyclomatic complexity in Function
	Class NCSS
	Function NCSS
	Package NCSS

Other Features

Source code repository help determine how the set of alerts generated by static analysis and how the code base has changed over time.

We use the log files of the subversion repositories to analyze the code history.

Other Features

Subversion (15)	Alert Open Revision
	Developers
	File Creation Revision
	File Last Modified Revision
	File Age

Project Added Lines
Project Delete Lines
Project Growth
File Added Lines
File Deleted Lines
File Growth
Package Total Modified Lines
Package Percent Modified Lines
File Total Modified Lines
File Percent Modified Lines

Model

Take input from the 351 features
Add two fully-connected layer
one dropout layer
Final Layer is Sigmoid layer

Grid Search to tune hyperparameter

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  - Dataset
  - Configuration
  - Ground Truth
  - Baseline
  - Evaluation
  - Results
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Data Set

	JDOM	Log4j
Domain	Data Format	Logging Library
Size(KLOC)	9-13	12-19
Time Frame	05/2000-12/2008	08/2001-06/2007
# Built Revisions	30	11
Total Alerts	489	237
Actionable Alerts	200	97
Unactionable Alerts	254	112
Deleted Alerts	35	28

Configuration

• Gram Size - The size of an n-gram model. 3-gram model
• Minimum Token Occurrence - The minimum number of times a token must occur in the software to be included in an n-gram model. 3

Ground Truth

By definition, AA is an alert that a developer resolves by modifying the program. It will disappear from static analysis at some point.

If it is UA, the alert will never disappear. If an alert is removed because the file containing the alert is deleted, we consider the alert status as unknown and remove it from the list.

Ground Truth

FaultBench method by Heckman and Williams to accurately classify alerts as AA or UA.

- Generate revision history through the source code repository log.
- Data collection for each project. download all files associated with a revision.
- Run ASA at each revision and determine which alerts were closed during the alert history.
- Create features for each alert.

Baseline

FindBugs assigns a priority measure to each alert.
We assume high priority alerts are more actionable than low priority alerts.

Default FindBugs priority ranking:
Sort alerts according to the priority measure and randomize the order of alerts with the same priority.

Evaluation

Ten-fold cross validation to evaluate models.

randomly separate alerts into ten equal sets.
nine of the sets train the model and test the model use the last set.
repeat the process ten times.

Evaluation Metrics

Precision and Recall to evaluate how well our method performs.

Precision is the percentage of alerts classified as actionable that were actionable.

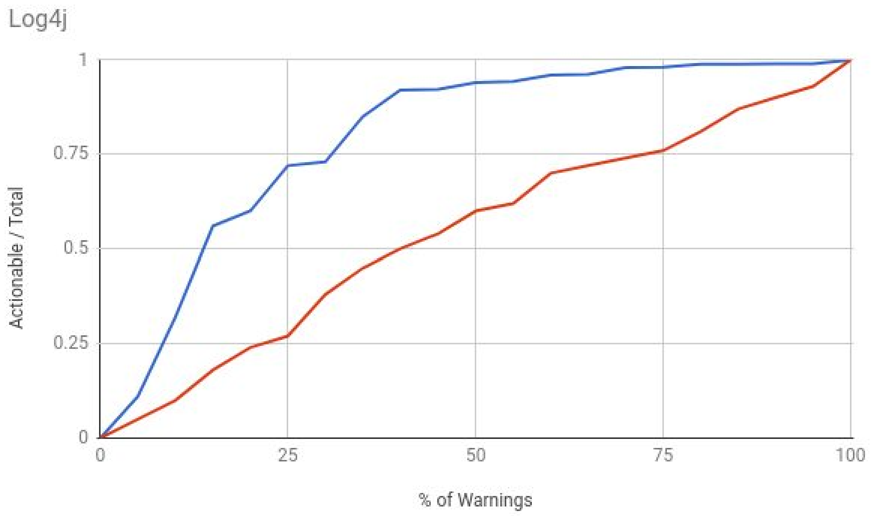
Recall is the percentage of alerts classified as actionable out of all actual actionable alerts.

Results

Project	Average Precision	Average Recall
JDOM	90.3%	86.2%
Log4j	91.4%	85.0%

Results

Example
In Log4j, when x=25, it means from the top 25% of the alerts, 74% of actionable alerts are found in our method, while 26% of actionable alerts are found using FindBugs priority ranking.



Results

Our method outperforms FindBugs priority ranking, it can help enhance alert ranking.

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Summary

After introducing different methods of actionable alert detection, this project presents the following contributions:
1) present a deep learning method to detect actionable alerts.
2) use N-Gram feature combining with other alert features.
3) apply our method to JDOM and Log4j projects.

In our experiment, our method reach precision up to 91.4% and recall up to 86.2%.
Our method outperforms FindBugs priority ranking in alert ranking.

THANKS FOR YOUR TIME!