Research Review 2017

Rapid Expansion of Classification Models to Prioritize Static Analysis Alerts for C

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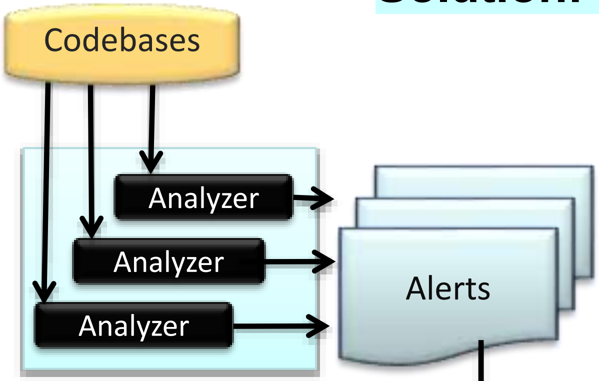
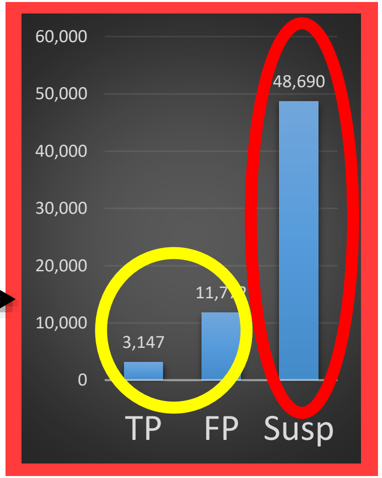
Overview

Problem: too many alerts
Solution: automate handling



Today



Project Goal

Classification algorithm development using “pre-audited” and manually-audited data, that

accurately classifies most of the diagnostics as:

Expected True Positive (e-TP) or
Expected False Positive (e-FP),
and
the rest as Indeterminate (I)

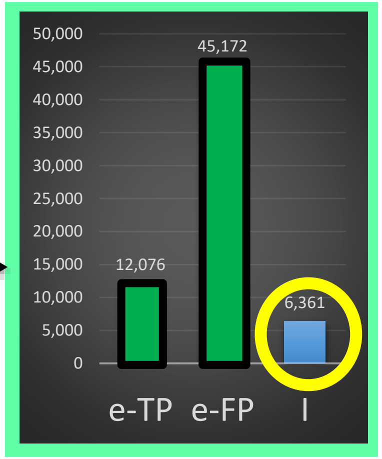


Image of woman and laptop from http://www.publicdomainpictures.net/view-image.php?image=47526&picture=woman-and-laptop “Woman And Laptop”

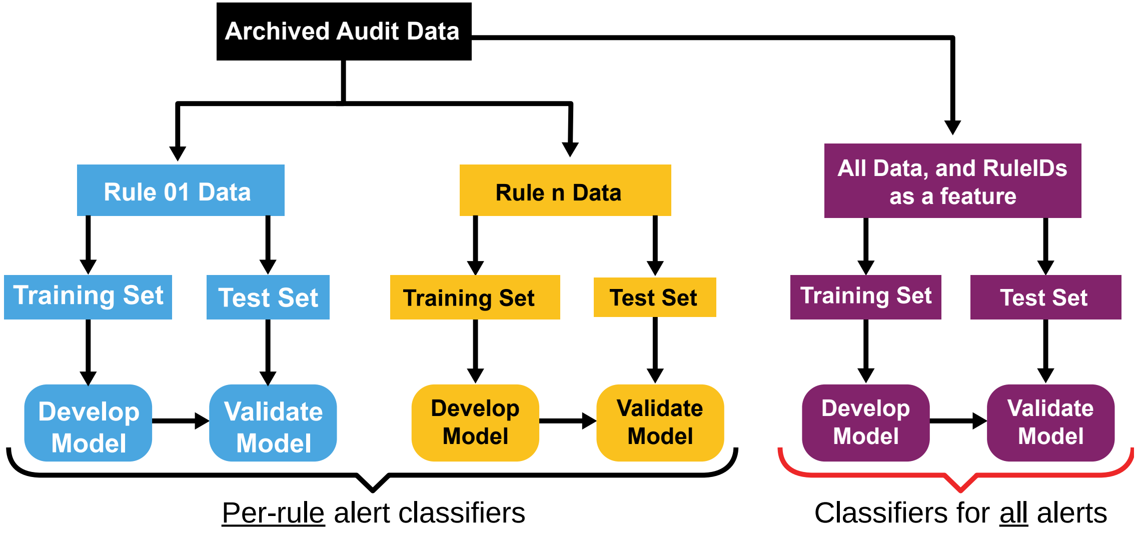
Scientific Approach

<u>Build on novel (in FY16) combined use of</u>:
1) multiple analyzers, 2) variety of features,
3) competing classification techniques!

Problem: too many alerts
Solution: automate handling

Competing Classifiers to Test
Lasso Logistic Regression
CART (Classification and Regression Trees)
Random Forest
Extreme Gradient Boosting (XGBoost)

Some of the features used (many more)
Analysis tools used
Significant LOC
Complexity
Coupling
Cohesion
SEI coding rule



Rapid Expansion of Alert Classification

Problem 1: too many alerts
Solution 1: automate handling

Problem 2

Too few manually audited alerts to make classifiers (i.e., to automate!)

Problems 1 & 2: Security-related code flaws detected by static analysis require too much manual effort to triage, plus it takes too long to audit enough alerts to develop classifiers to automate the triage.

Extension of our FY16 alert classification work to address challenges:

1. Too few audited alerts for accurate classifiers
2. Manually auditing alerts is expensive

Solution 2

Automate auditing alerts, using test suites

Solution for 1 & 2: Rapid expansion of number of classification models by using "pre-audited" code, plus collaborator audits of DoD code.

Approach

1. Automated analysis of "pre-audited" (not by SEI) tests to gather sufficient code & alert feature info for classifiers

2. Collaboration with MITRE: Systematically map CERT rules to CWE IDs in subsets of "pre-audited" test code (known true or false for CWE)

3. Modify SCALe research tool to integrate CWE (MITRE's Common Weakness Enumeration)

4. Test classifiers on alerts from real-world code: DoD data

Overview: Method, Approach, Validity

Problem 2: too few manually audited alerts to make classifiers (i.e., to automate)
Solution 2: automate auditing alerts, using test suites

Rapidly create **many** coding-rule-level classifiers for static analysis alerts, then use DoD-audited data to validate the classifiers.

Technical methods:

- Use test suites' CWE flaw metadata, to quickly and automatically generate many "audited" alerts.
  - Juliet (NSA CAS) 61,387 C/C++ tests
  - IARPA's STONESOUP: 4,582 C tests
  - Refine test sets for rules: use **mappings, metadata, static analyses**
- Metrics analyses of test suite code, to get feature data
- Use DoD-collaborator enhanced-SCALe **audits** of their own codebases, to validate classifiers. **Real codebases with more complex structure than most pre-audited code**.

Make Mappings Precise

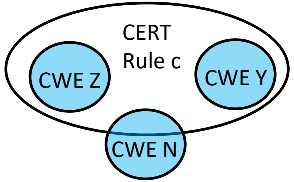
Problem 2: too few manually audited alerts to make classifiers
Solution 2: automate auditing alerts, using test suites

Problem 3: Test suites in different taxonomies (most use CWEs)
Solution 3: Precisely map between taxonomies, then partition tests using precise mappings

Precise mappings: Defines *what kind* of non-null relationship, and if overlapping, *how.*
Enhanced-precision added to "imprecise" mappings.

Imprecise mappings ("*some* relationship") → Precise mappings (set notation, often more)

2 CWEs subset of CERT rule, AND partial overlap



Mappings	
Precise	248
Imprecise TODO	364
Total	**612**

Now: all CERT C rules mappings to CWE precise

If a **condition** of a program violates a CERT rule *R* and also exhibits a CWE weakness *W*, that **condition** is in the overlap.

Test Suite Cross-Taxonomy Use

Problem 3: Test suites in different taxonomies (most use CWEs)
Solution 3: Precisely map between taxonomies, **then partition tests with precise mappings**

Partition sets of thousands of tests relatively quickly.

Examine together:

- Precise mapping
- Test suite metadata (structured filenames)
- Rarely examine small bit of code (variable type)

CWE test programs useful to test CERT rules

STONESOUP: **2,608** tests

Juliet: **80,158** tests

- Test set partitioning incomplete (32% left)

Some types of CERT rule violations not tested, in partitioned test suites ("**0**"s).

- Possible coverage in other suites

CERT rule	CWE	Count files that match
ARR38-C	CWE-119	0
ARR38-C	CWE-121	6,258
ARR38-C	CWE-122	2,624
ARR38-C	CWE-123	0
ARR38-C	CWE-125	0
ARR38-C	CWE-805	2,624
INT30-C	CWE-190	1,548
INT30-C	CWE-191	1,548
INT30-C	CWE-680	984
INT32-C	CWE-119	0
INT32-C	CWE-125	0
INT32-C	CWE-129	0
INT32-C	CWE-131	0
INT32-C	CWE-190	3,875
INT32-C	CWE-191	3,875
INT32-C	CWE-20	0
INT32-C	CWE-606	0
INT32-C	CWE-680	984

Process

Generate data for Juliet

Generate data for STONESOUP

Write classifier development and testing scripts

Build classifiers

- Directly for CWEs
- Using partitioned test suite data for CERT rules

Test classifiers

Problem 1: too many alerts

Solution 1: automate handling

Problem 2: too few manually audited alerts to make classifiers

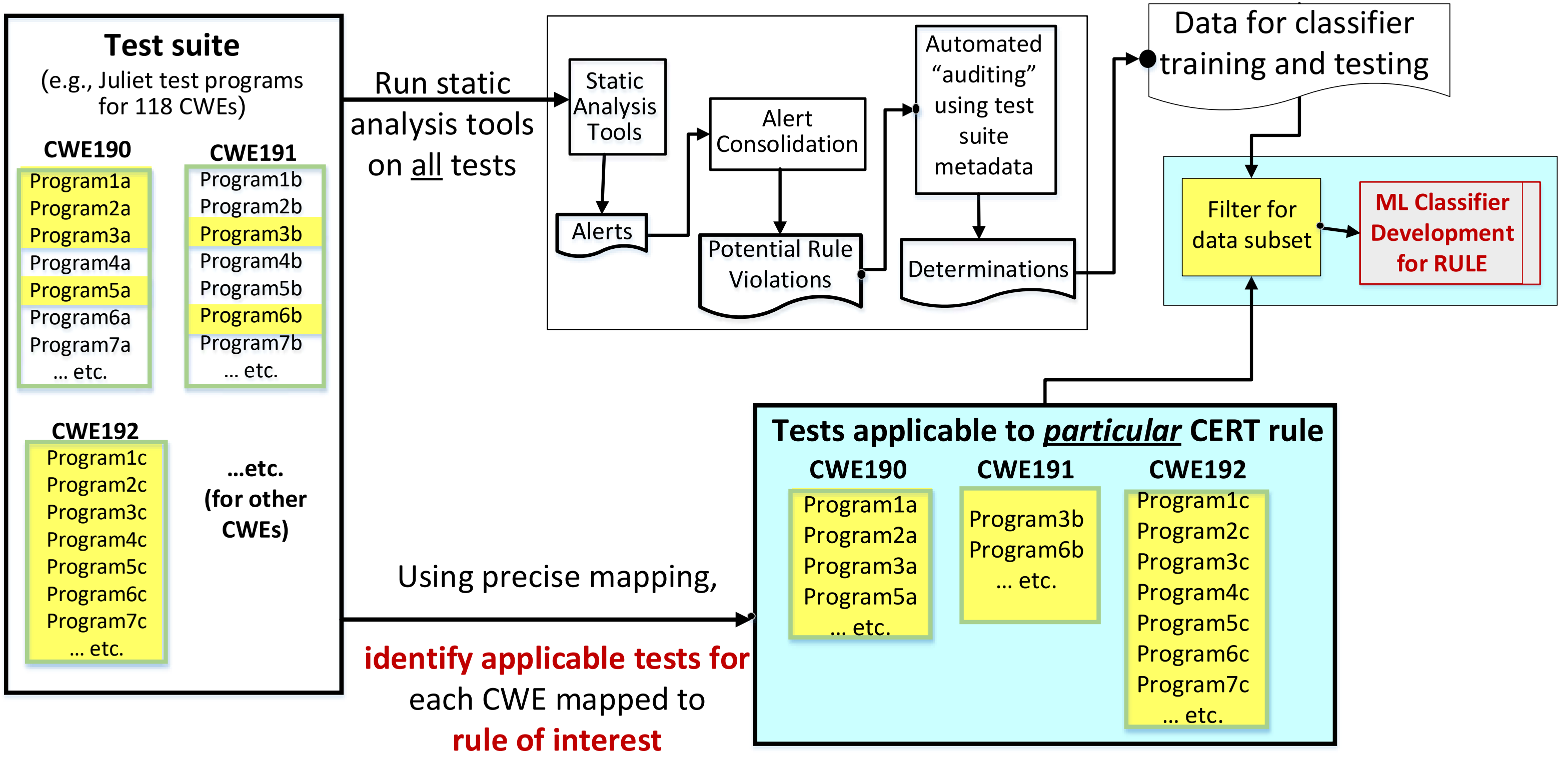
Solution 2: automate auditing alerts, using test suites

Problem 3: Test suites in different taxonomies (most use CWEs)

Solution 3: Precisely map between taxonomies, then partition tests using precise mappings

Using CWE Test Suites for Multi-Taxonomy Classifiers

One time, develop data for classifiers. Per rule or CWE classifier, filter data.



Successfully generated lots of data for classifiers

Analysis of Juliet Test Suite: Initial CWE Results

- We automated defect identification of Juliet flaws with location **2 ways**
  - A Juliet program tells about only one type of CWE
  - Bad functions definitely have that flaw
  - Good functions definitely don't have that flaw
  - Function line spans, for FPs
  - Exact line defect metadata, for TPs

Number of "**Bad**" Functions	103,376
Number of "**Good**" Functions	231,476

- Used static analysis tools on Juliet programs
- We automated alert-to-defect matching
  - Ignore unrelated alerts (other CWEs) for program
  - Alerts give line number

	Tool A	Tool B	Tool C	Tool D	Total
"Pre-audited" TRUE	1,655	162	7,225	16,958	**26,000**
"Pre-audited" FALSE	8,539	3,279	2,394	23,475	**37,687**

- We automated alert-to-alert matching (alerts fused: same line & CWE)

Lots of new data for creating classifiers!

Alert Type	Equivalence Classes: (EC counts a fused alert once)	Number of Alerts Fused (from different tools)
TRUE	**22,885**	3,115
FALSE	**29,507**	8,180

- These are initial metrics (more EC as use more tools, STONESOUP)

Juliet: Data from 4 Tools, per CWE

35 CWEs with **at least** 5 HCFPs and 45 HCTPs

More data to be added

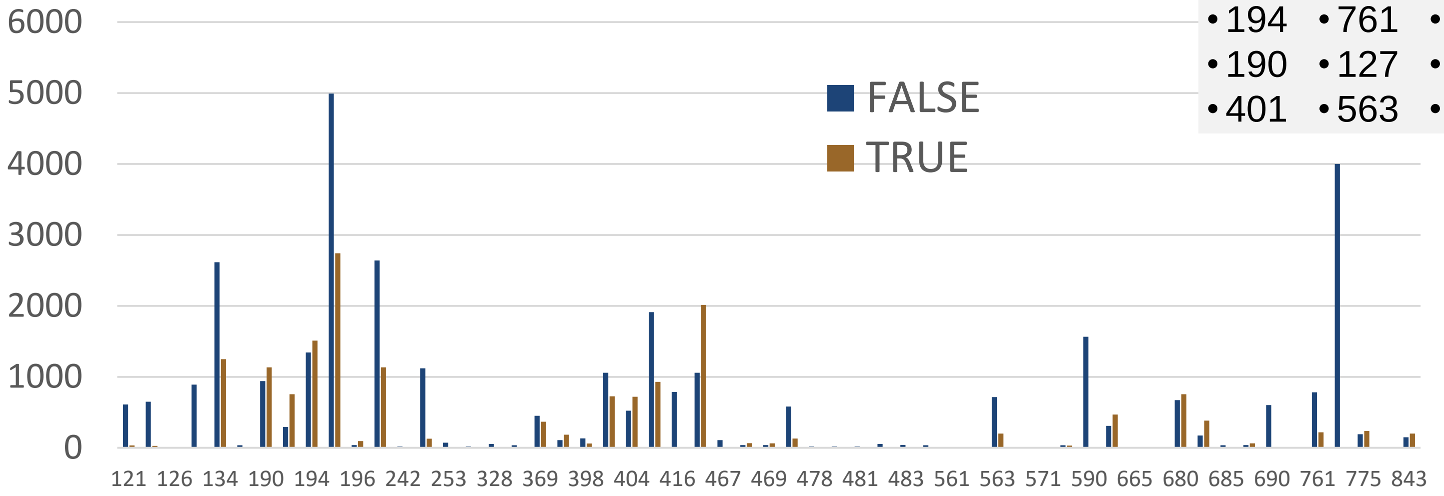
- Tools
- STONESOUP

Classifier development requires True and False

Successfully generated lots of data for classifiers

The 35 CWEs

• 457	• 680	• 252	• 843	• 483
• 195	• 404	• 369	• 377	• 126
• 197	• 415	• 606	• 398	• 835
• 134	• 665	• 122	• 196	
• 758	• 191	• 121	• 468	
• 194	• 761	• 681	• 469	
• 190	• 127	• 476	• 688	
• 401	• 563	• 775	• 587	



Classifiers: Accuracy, #Alerts, AUROC

Major improvement: **67 per-rule classifiers (and more coming!) vs. only 3 in FY16!**

Rule	Accuracy	# Alerts	AUROC
ARR30-C	96.9%	483	99.8%
ARR32-C	100.0%	947	100.0%
ARR36-C	63.3%	30	50.0%
ARR37-C	74.0%	77	83.6%
ARR38-C	94.0%	397	98.0%
ARR39-C	67.7%	31	50.0%
CON33-C	100.0%	88	100.0%
ERR33-C	91.2%	376	94.9%
ERR34-C	100.0%	947	100.0%
EXP30-C	100.0%	947	100.0%
EXP33-C	89.5%	5214	96.3%
EXP34-C	91.8%	546	95.4%
EXP39-C	70.7%	116	83.1%
EXP46-C	82.5%	143	87.8%
FIO30-C	86.5%	1065	95.1%
FIO34-C	72.5%	1132	78.5%
FIO42-C	83.9%	933	93.2%
FIO46-C	100.0%	947	100.0%

Rule	Accuracy	# Alerts	AUROC
FIO47-C	86.4%	1070	95.4%
FLP32-C	100.0%	947	100.0%
FLP34-C	70.5%	3619	78.0%
INT30-C	63.7%	1365	66.4%
INT31-C	68.7%	5139	77.5%
INT32-C	69.9%	1599	75.7%
INT33-C	79.8%	228	86.3%
INT34-C	100.0%	947	100.0%
INT35-C	64.3%	622	72.2%
INT36-C	100.0%	967	100.0%
MEM30-C	94.5%	1461	99.3%
MEM31-C	83.9%	933	93.2%
MEM35-C	66.7%	2514	76.0%
MSC37-C	100.0%	947	100.0%
POS54-C	90.0%	239	94.5%
PRE31-C	97.8%	46	99.1%
STR31-C	94.0%	397	98.0%
WIN30-C	95.6%	1465	97.8%

Model	Accuracy	AUROC
lightgbm	**83.7%**	93.8%
xgboost	**82.4%**	92.5%
rf	**78.6%**	86.3%
lasso	**82.5%**	92.5%

All-data CWE classifiers

Lasso per-CERT-rule classifiers (**36**)

Avg. accuracy	Count accuracy 95+%	Count accuracy 85-94.9%	Count accuracy 0-84.9%
85.8%	12	9	15
	99.2%	90.9%	72.1%

Similar for other classifier methods

Lasso per-CWE-ID classifiers (**31**)

Avg. accuracy	Count accuracy 95+%	Count accuracy 85-94.9%	Count accuracy 0-84.9%
81.8%	7	10	14
	98.4%	89.6%	67.9%

Similar for other classifier methods

Summary and Future

FY17 Line "Rapid Classifiers" built on the FY16 LENS "Prioritizing vulnerabilities".

- Developed widely useful general method to use test suites across taxonomies
- Developed large archive of "pre-audited" alerts
  - Overcame major challenge to classifier development
  - For CWEs and CERT rules
- Developed code infrastructure (extensible!)
- In-progress:
  - Classifier development and testing in process
  - Continue to gather data
  - Enhanced SCALe audit tool for collaborator testing: distribute to collaborators soon
- FY18-19 plan: architecture for rapid deployment of classifiers in varied systems
- Goal: optimal automation of static alert auditing (and other code analysis and repair)

<u>Publications:</u>

- New mappings (CWE/CERT rule): MITRE and CERT websites
- IEEE SecDev 2017 "Hands-on Tutorial: Alert Auditing with Lexicon & Rules"
- 2 SEI blogposts on classifier development
- Research paper in progress

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