

# Ranking source code static analysis warnings for continuous monitoring of FLOSS repositories

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# Who am I?

- Former guest researcher at the US National Institute of Standards and Technology
- Masters degree student at University of São Paulo
- Fedora Project contributor

# What is Static Analysis?

- Extract facts from the **source code** to
- find **flaws**
- by reporting **warnings**.
- Warnings are aggregated in **reports**
- Reports are generated by **static analyzers**

# Why use Static Analysis?

- Find (and act on) **flaws**
- by exploring abstractions of **many** program behaviors
  - **Hard** to do with automated testing
- to increase software **quality**

# Motivation

## Undecidability

- Fundamental static analysis problems are **undecidable**
- Heuristics → **false positives** and **false negatives**
  
- **Reports** contain too much (misleading) information
- More misleading information → Less valuable tool
- Too much misleading information → **Worthless** tool

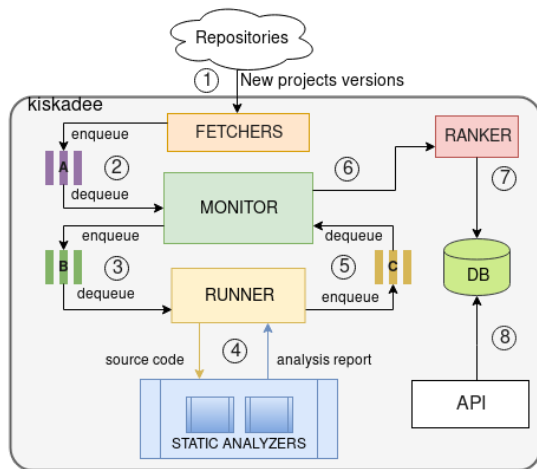
## Possible solution...

- Use **multiple** static analyzers
  - Increase coverage → reduce false negatives
- Apply a classification approach on the output (warnings)
  - Discard (**possible**) false positives

# kiskadee: a continuous static analysis tool



# kiskadee design overview



**A** New projects versions    **B** Projects to be analyzed    **C** Analysis results



# We start with a classification problem...

- True Positive / False Positive
- No information on the analyzed project
- Weak classifiers
  - AdaBoost
    - Boost decision trees
    - Can use both categorical and non-categorical features
    - DT are easy to train
- Supervised learning
  - We need a set of known flaws to train our model

# Juliet: Static analysis test suite

- NIST/SAMATE → **Juliet**
- Test suite with **61,387 test cases**
- **118** different **CWEs**
- C programming language
- Specific flaws in **known locations**

# Preparing a dataset from Juliet

	Before Pruning	After Pruning
C	36,078	22,459
C++	25,309	16,641
Total	61,387	<b>39,100</b>

**Table:** Number of Juliet test cases

# Running static analyzers on our Juliet subset

Tool	Warnings
Clang Static Analyzer	37,229
Cppcheck	124,025
Frama-C	120,573
Total	<b>281,827</b>

**Table:** Total number of warnings generated per tool



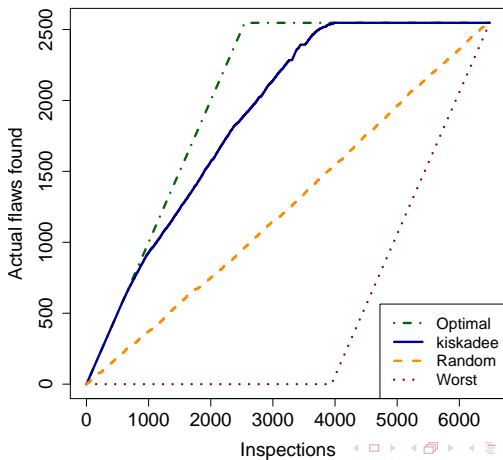
# Features and final dataset

- Dataset with features to train AdaBoost classifier extracted from labeled warnings
- Features
  - Tool name
  - Programming language
  - Severity
  - Redundancy (with tool names)
  - Number of neighbors
  - Category
  - Number of warnings in the same file
  - **True/False** positive

# Ranking warnings

- Use AdaBoost classifier probabilities
- Warnings with higher probabilities of being True Positives to the top
- Warnings with lower probabilities of being True Positives to the bottom

# Inspections vs flaws found





# Conclusions

- FLOSS static analyzers show poor FP rates
- Ranking model does not use features based on the analyzed project
- We trade accuracy for generalization

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- University of Brasília
  - All *Software Maintenance and Evolution* course students who worked on kiskadee
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- Google Summer of Code
- Fedora Project

Questions?  
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