CEN 5016: **Software** Engineering

Fall 2024



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*Week 5 - Class 1I:* Static & Dynamic Analysis



# Administrivia



- *• Assignment 2 Due Tomorrow*
- *• SDE Project Part 1* 
	- Due Tues, Sept 24th
	- Get started now!!
- *• Assignment 3* 
	- Will be posted tomorrow
	- Web App Deployment

# Intro to Software Architecture



# Why Document Architecture?



- Blueprint for the system
	- Artifact for early analysis
	- Primary carrier of quality attributes
	- Key to post-deployment maintenance and enhancement
- Documentation speaks for the architect, today and 20 years from today
	- As long as the system is built, maintained, and evolved according to its documented architecture
- Support traceability.

# Views & Purposes



- Every view should align with a purpose
- Views should only represent information relevant to that purpose
	- Abstract away other details
	- Annotate view to guide understanding where needed
- • Different views are suitable for different reasoning aspects (different quality goals), e.g.,
	- Performance
	- Extensibility
	- Security
	- Scalability



- Static View
	- Modules (subsystems, structures) and their relations (dependencies, ...)
- Dynamic View
	- Components (processes, runnable entities) and connectors (messages, data flow, ...)
- Physical View (Deployment)
	- Hardware structures and their connections

# Common Software Architectures







#### Pipes & Filters Example: Compilers



































# Learning Goals



- Gain an understanding of the relative strengths and weaknesses of static and dynamic analysis
- Examine several popular analysis tools and understand their use cases
- Understand how analysis tools are used in large opensource software

# Activity: Analyze the Python Program Statically



```
def n2s(n: int, b: int) -> str:
  if n \leq 0:
       return '0'
  r = "while n > 0:
      u = n \times bif u > = 10:
         u = chr(ord('A') + u - 10)n = n \mathbin{/} lr = str(u) + r return r
```
#### Answer: Yes, No, Maybe

- 1. What are the set of data types taken by variable 'u' at any point in the program?
- 2. Can the variable u be a negative number?
- 3. Will this function always return a value?
- 4. Can there ever be a division by zero?
- 5. Will the returned value ever contain a minus sign '-'?

# What Static Analysis Can & Cannot Do



- Type-checking is well established
	- Set of data types taken by variables at any point
	- Can be used to prevent type errors (e.g. Java) or warn about potential type errors (e.g. Python)
- Checking for problematic patterns in syntax is easy and fast
	- Is there a comparison of two Java strings using  $=$   $\hat{ }$ ?
	- Is there an array access `a[i]` without an enclosing bounds check for `i`?
- Reasoning about termination is impossible in general
	- Halting problem
- Reasoning about exact values is hard, but conservative analysis via abstraction is possible
	- Is the bounds check before `a[i]` guaranteeing that `I` is within bounds?
	- Can the divisor ever take on a zero value?
	- Could the result of a function call be 42?
	- Will this multi-threaded program give me a deterministic result?
	- Be prepared for "MAYBE"
- Verifying some advanced properties is possible but expensive
	- CI-based static analysis usually over-approximates conservatively



- Every static analysis is necessarily incomplete, unsound, undecidable, or a combination thereof
- *• "Any nontrivial property about the language recognized by a Turing machine is undecidable."*
- Henry Gordon Rice, 1953



- Security: Buffer overruns, improperly validated input...
- Memory safety: Null dereference, uninitialized data...
- Resource leaks: Memory, OS resources...
- API Protocols: Device drivers; real time libraries; GUI frameworks
- Exceptions: Arithmetic/library/user-defined
- Encapsulation:
	- Accessing internal data, calling private functions...
- Data races:
	- Two threads access the same data without synchronization



- Linters
	- Shallow syntax analysis for enforcing code styles and formatting
- Pattern-based bug detectors
	- Simple syntax or API-based rules for identifying common programming mistakes
- Type-annotation validators
	- Check conformance to user-defined types
	- Types can be complex (e.g., "Nullable")
- Data-flow analysis / Abstract interpretation)
	- Deep program analysis to find complex error conditions (e.g., " can array index be out of bounds?")



- Find bugs
- Refactor code
- Keep your code stylish!
- Identify code smells
- Measure quality
- Find usability and accessibility issues
- Identify bottlenecks and improve performance

# Activity: Analyze the Python Program Dynamically



```
def n2s(n: int, b: int) -> str:
  if n \leq 0:
      return '0'
  r = "while n > 0:
     u = n \% bif u > = 10:
        u = chr(ord('A') + u - 10)n = n \mathbin{/} lr = str(u) + r return r
print(n2s(12, 10))
```
Answer: Yes, No, Maybe

- 1. What are the set of data types taken by variable `u` at any point in the program?
- 2. Did the variable `u` ever contain a negative number?
- 3. For how many loop executions did the while loop execute?
- 4. Was there a division by zero?
- 5. Did the returned value ever contain a minus sign '-'?

# Dynamic Analysis Reasons about Program Executions

- Tells you properties of the program that were definitely observed
	- Code coverage
	- Performance profiling
	- Type profiling
	- Testing
- In practice, implemented by program instrumentation
	- Think "Automated logging"
	- Slows down execution speed by a small amount

# Static Analysis vs. Dynamic Analysis



- Requires only source code
- Conservatively reasons about all possible
- Reported warnings may contain false positives
- Can report all warnings of a particular class of problems
- Advanced techniques like verification can prove certain complex properties, but rarely run in CI due to cost
- Requires successful build + test inputs
- Observes individual executions
- Reported problems are real, as observed by a witness input
- Can only report problems that are seen. Highly dependent on test inputs. Subject to false negatives
- Advanced techniques like symbolic execution can prove certain complex properties, but rarely run in CI due to cost









# Static Analysis is a Key Part of CI





















Snyk, a developer-focused security startup that and identifies vulnerabilities in open source applications, announced a \$150 million Series C funding round today. This brings the company's total investment to \$250 million alongside reports that put the company's valuation at more than \$1 billion.







### What Makes a Good Static Analysis Tool?



- Static analysis should be fast
	- Don't hold up development velocity
	- This becomes more important as code scales
- Static analysis should report few false positives
	- Otherwise developers will start to ignore warnings and alerts, and quality will decline
- Static analysis should be continuous
	- Should be part of your continuous integration pipeline
	- Diff-based analysis is even better -- don't analyse the entire codebase; just the changes
- Static analysis should be informative
	- Messages that help the developer to quickly locate and address the issue
	- Ideally, it should suggest or automatically apply fixes





• Cheap, fast, and lightweight static source analysis





• Don't rely on manual inspection during code review!



## Linters Use Very "Shallow" Static Analysis



- Ensure proper indentation
- Naming convention
- Line sizes
- Class nesting
- Documenting public functions
- Parenthesis around expressions
- What else?

## Use Linters to Improve Maintainability



- Why? We spend more time reading code than writing it.
	- Various estimates of the exact %, some as high as 80%
- Code is ownership is usually shared
- The original owner of some code may move on
- Code conventions make it easier for other developers to quickly understand your code

## UseStyle Guidelines to Facilitate Communication





• Guidelines are inherently opinionated, but consistency is the important point. Agree to a set of conventions and stick to them.

Take Home Message: Style is an Easy Way to Improve Readability!



- Everyone has their own opinion (e.g., tabs vs. spaces)
- Agree to a convention and stick to it
	- Use continuous integration to enforce it
- Use automated tools to fix issues in existing code

## (2) - Pattern-based Static Analysis Tools



- Bad Practice
- Correctness
- Performance
- Internationalization
- Malicious Code
- Multithreaded Correctness
- Security
- Dodgy Code











- The analysis must produce zero false positives
	- Otherwise developers won't be able to build the code!
- The analysis needs to be really fast
	- Ideally < 100 ms
	- If it takes longer, developers will become irritated and lose productivity
- You can't just "turn on" a particular check
	- Every instance where that check fails will prevent existing code from
	- There could be thousands of violations for a single check across large codebases

# (3) -Use Type Annotations to Detect Common Errors



- Uses a conservative analysis to prove the absence of certain defects
	- Null pointer errors, uninitialized fields, certain liveness issues, information leaks, SQL injections, bad regular expressions, incorrect physical units, bad format strings, ...
	- C.f. SpotBugs which makes no safety guarantees
	- Assuming that code is annotated and those annotations are correct
- Uses annotations to enhance type system
- Example: Java Checker Framework or MyPy



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- Tracks flow of sensitive information through the program
- Tainted inputs come from arbitrary, possibly malicious sources
	- User inputs, unvalidated data
- Using tainted inputs may have dangerous consequences
	- Program crash, data corruption, leak private data, etc.
- We need to check that inputs are sanitized before reaching sensitive locations







```
void processRequest() {	
String input = getUserInput();
String query = "SELECT ... " + input;
executeQuery(query);
```
}



```
void processRequest() {	
String input = getUserInput();
String query = "SELECT ... " + input;
executeQuery(query);
}
                                      Tainted input arrives from untrusted source
                                      Tainted output flows to a sensitive sink
```


```
void processRequest() {	
String input = getUserInput();
input = sanitizeInput(input);
String query = "SELECT ... " + input;
executeQuery(query);
}
```
Taint is removed by sanitizing data

We can now safely execute query on untainted data

#### Unit Catastrophe







- Guarantees that operations are performed on the same kinds and units
- Kinds of annotations
	- @Acceleration, @Angle, @Area, @Current, @Length, @Luminance, @Mass, @Speed, @Substance, @Temperature, @Time
- SI unit annotation
	- @m, @km, @mm, @kg, @mPERs, @mPERs2, @radians, @degrees, @A, ...



- Can only analyze code that is annotated
	- Requires that dependent libraries are also annotated
	- Can be tricky, but not impossible, to retrofit annotations into existing codebases
- Only considers the signature and annotations of methods • Doesn't look at the implementation of methods that are being called
- Dynamically generated code • Spring Framework
- • Can produce false positives!
	- Byproduct of necessary approximations



- Focused on memory safety bugs • Null pointer dereferences, memory leaks, resource leaks, ...
- Compositional interprocedural reasoning
	- Based on separation logic and bi-abduction
- Scalable and fast
	- Can run incremental analysis on changed code
- Does not require annotations
- Supports multiple languages
	- Java, C, C++, Objective-C
	- Programs are compiled to an intermediate representation





 $\Box$ 

#### NULLPTR\_DEREFERENCE

Reported as "Nullptr Dereference" by pulse.

Infer reports null dereference bugs in Java, C, C++, and Objective-C when it is possible that the null pointer is dereferenced, leading to a crash.

#### **Null dereference in Java**

Many of Infer's reports of potential Null Pointer Exceptions (NPE) come from code of the form

```
p = foo(); // foo() might return null
stuff();
p.goo(); // dereferencing p, potential NPE
```


#### **Examples**

Infer's cost analysis statically estimates the execution cost of a program without running the code. For instance, assume that we had the following program:

```
void loop(ArrayList<Integer> list){
  for (int i = 0; i <= list.size(); i++){
  }
```
For this program, Infer statically infers a polynomial (e.g.  $8$  | list  $|+16$ ) for the execution cost of this program by giving each instruction in Infer's intermediate language a symbolic cost (where ||.|| refers to the length of a list). Here---overlooking the actual constants---the analysis infers that this program's asymptotic complexity is  $[0($  | list | )  $]$ , that is loop is linear in the size of its input list. Then, at diff time, if a developer modifies this code to,







#### How Many of All Bugs Do We Find? **A Study of Static Bug Detectors**

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#### **ABSTRACT**

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Static bug detectors are becoming increasingly popular and are widely used by professional software developers. While most work on bug detectors focuses on whether they find bugs at all, and on how many false positives they report in addition to legitimate warnings, the inverse question is often neglected: How many of all real-world bugs do static bug detectors find? This paper addresses this question by studying the results of applying three widely used static bug detectors to an extended version of the Defects4J dataset that consists of 15 Java projects with 594 known bugs. To decide which of these bugs the tools detect, we use a novel methodology that combines an automatic analysis of warnings and bugs with a manual validation of each candidate of a detected bug. The results of the study show that: (i) static bug detectors find a non-negligible amount of all bugs, (ii) different tools are mostly complementary to each other, and (iii) current bug detectors miss the large majority of the studied bugs. A detailed analysis of bugs missed by the static detectors shows that some bugs could have been found by variants of the existing detectors, while others are domain-specific problems that do not match any existing bug pattern. These findings help potential users of such tools to assess their utility, motivate and outline directions for future work on static bug detection, and provide a basis for future comparisons of static bug detection with other bug finding techniques, such as manual and automated testing.

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#### 1 INTRODUCTION

Finding software bugs is an important but difficult task. For average industry code, the number of bugs per 1,000 lines of code has been estimated to range between 0.5 and 25 [21]. Even after years of deployment, software still contains unnoticed bugs. For example, studies of the Linux kernel show that the average bug remains in the kernel for a surprisingly long period of 1.5 to 1.8 years [8, 24]. Unfortunately, a single bug can cause serious harm, even if it has been subsisting for a long time without doing so, as evidenced by examples of software bugs that have caused huge economic loses and even killed people [17, 28, 46].

Given the importance of finding software bugs, developers rely on several approaches to reveal programming mistakes. One approach is to identify bugs during the development process, e.g., through pair programming or code review. Another direction is testing, ranging from purely manual testing over semi-automated testing, e.g., via manually written but automatically executed unit tests, to fully automated testing, e.g., with UI-level testing tools. Once the software is deployed, runtime monitoring can reveal so far missed bugs. e.g., collect information about abnormal runtime



Figure 4: Total number of bugs found by all three static checkers and their overlap.





## Android Memory Profiler





https://developer.android.com/studio/profile/memory-profiler

### ycharm Debugger





60 https://www.jetbrains.com/help/pycharm/debugging-your-first-python-application.html#where-is-the-problem

#### Valgrind Dynamic Analysis Library





Valgrind is an instrumentation framework for building dynamic analysis tools. There are Valgrind tools that can automatically detect many memory management and threading bugs, and profile your programs in detail. You can also use Valgrind to build new tools.

The Valgrind distribution currently includes seven production-quality tools: a memory error detector, two thread error detectors, a cache and branch-prediction profiler, a call-graph generating cache and branch-prediction profiler, and two different heap profilers. It also includes an experimental SimPoint basic block vector generator. It runs on the following platforms: X86/Linux, AMD64/Linux, ARM/Linux, ARM64/Linux, PPC32/Linux, PPC64/Linux, PPC64LE/Linux, S390X/Linux, MIPS32/Linux, MIPS64/Linux, X86/Solaris, AMD64/Solaris, ARM/Android (2.3.x and later), ARM64/Android, X86/Android (4.0 and later), MIPS32/Android, X86/FreeBSD, AMD64/FreeBSD, ARM64/FreeBSD, X86/Darwin and AMD64/Darwin (Mac OS X 10.12).

Valgrind is Open Source / Free Software, and is freely available under the GNU General Public License, version 2.





- Linters are cheap, fast, but imprecise analysis tools
	- Can be used for purposes other than bug detection (e.g., style)
- Conservative analyzers can demonstrate the absence of particular defects
	- At the cost of false positives due to necessary approximations
	- Inevitable trade-off between false positives and false negatives
- The best QA strategy involves multiple analysis and testing techniques
	- The exact set of tools and techniques depends on context