Optimizing unit test execution in large software programs using dependency analysis

Taesoo Kim, Ramesh Chandra and Nickolai Zeldovich

MIT CSAIL

Running unit tests takes too long



It's our policy to make sure **all tests pass at all times**.



- Large software programs often require running full unit tests for each commit
- But, unit tests take about 10 min in Django
- With our work, it can be done within 2 sec!

Current approaches for shortening testing time

- Modular unit tests (e.g., testsuite)
 - Run a certain set of unit tests that might be affected
- Test bot (e.g., gtest, autotest)
 - Run unit tests remotely and get the results back

Problem: current approaches are very limited

- Manual efforts involved
 - Maintaining multiple test suites
- Overall testing still takes too long
 - Waiting for Test bot to complete full unit testing

Research: regression test selection (RTS)

- Goal: run only necessary tests instead of full tests
 - identify test cases whose results might change due to the current code modification
 - **Step 1**: analyze test cases (e.g., execution traces)
 - Step 2: syntactically analyze code changes
 - Step 3: output the affected test cases



Problem: RTS techniques are never adopted in practice

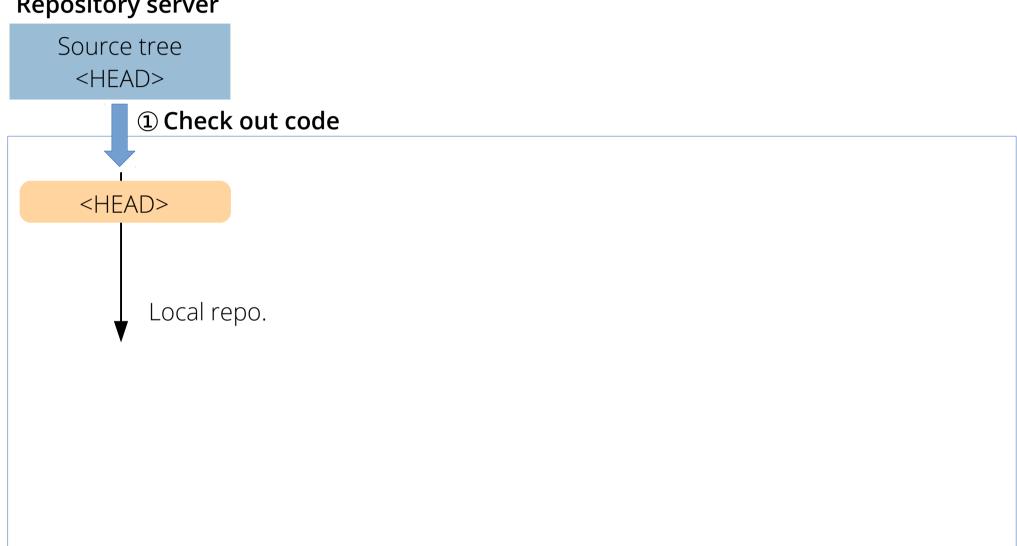
- "Soundness" of RTS techniques kills adoption
 - Soundness means **no false negatives**
 - Impose non-negligible perf. overheads (analysis/runtime)
 - Select lots of test cases (particularly in dynamic languages)
 - e.g., changes in **a global variable** → run **all** test cases

Goal: make RTS practical

- Idea 1: trade off soundness for performance
 - Keep track of function-level dependency / changes
 - Fewer tests selected, may have false negatives
- Idea 2: integrate test optimization into dev. cycle
 - Maintain dependency information in code repository

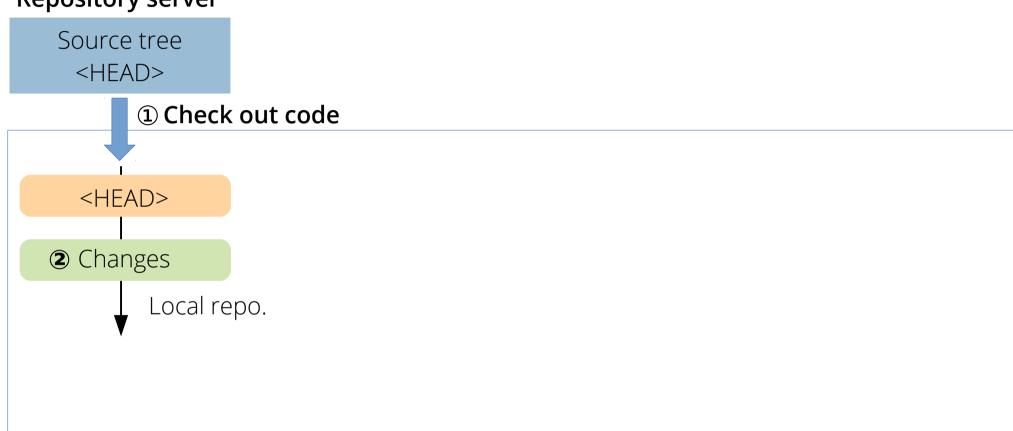
Current development cycle

Repository server



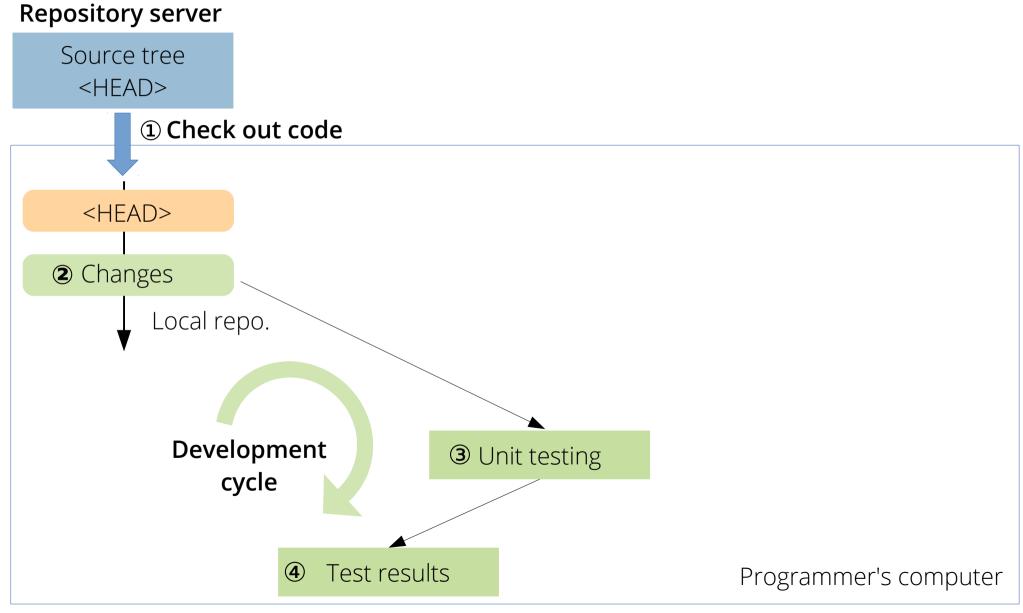
Current development cycle

Repository server

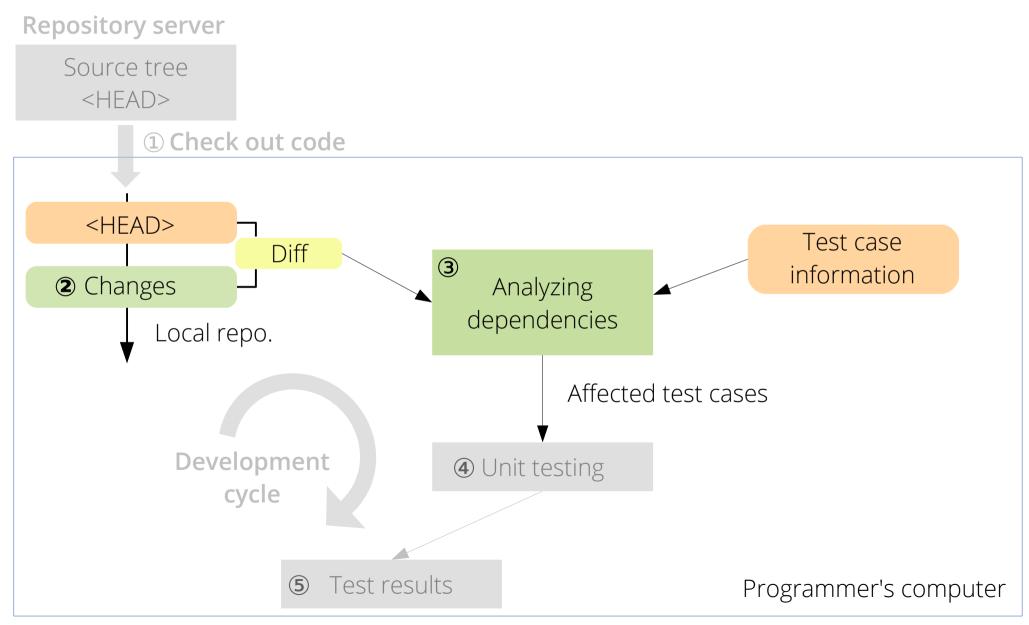


Programmer's computer

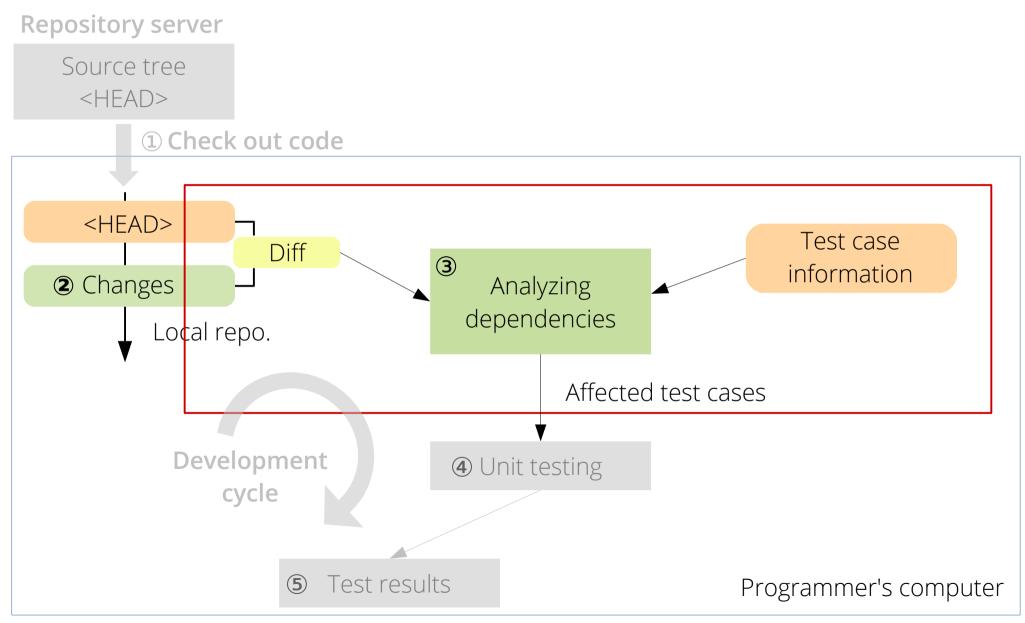
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New development cycle



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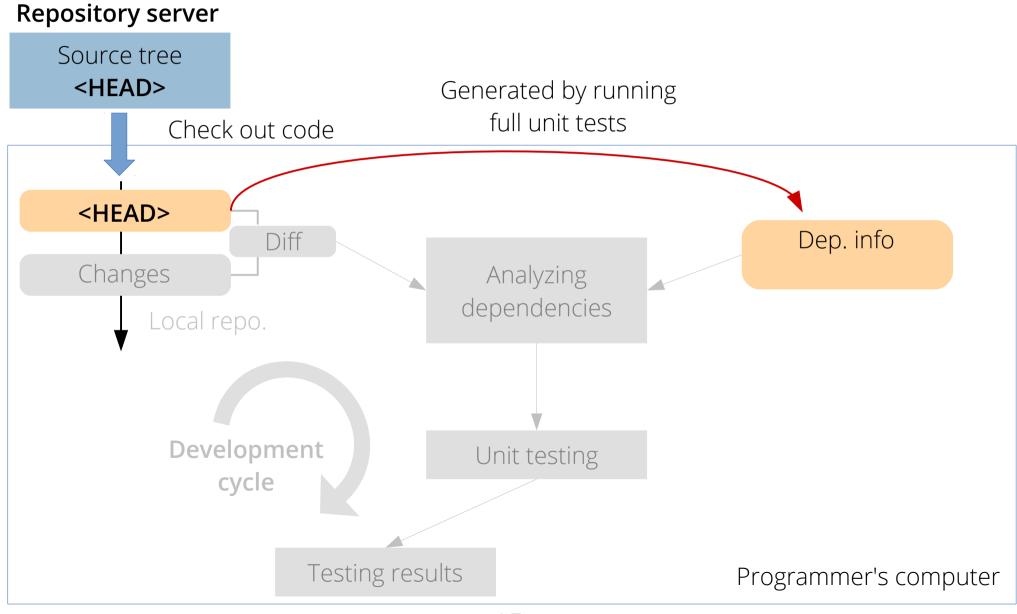
Identifying affected test cases by the code modification

- Plan: track which tests execute which functions
 - Step 1: generate function-level dependency info.
 - Map: invoked functions ↔ test case
 - Construct map by running all unit tests
 - **Step 2**: identify modified func., given code changes
 - **Step 3**: identify tests that ran the modified func.

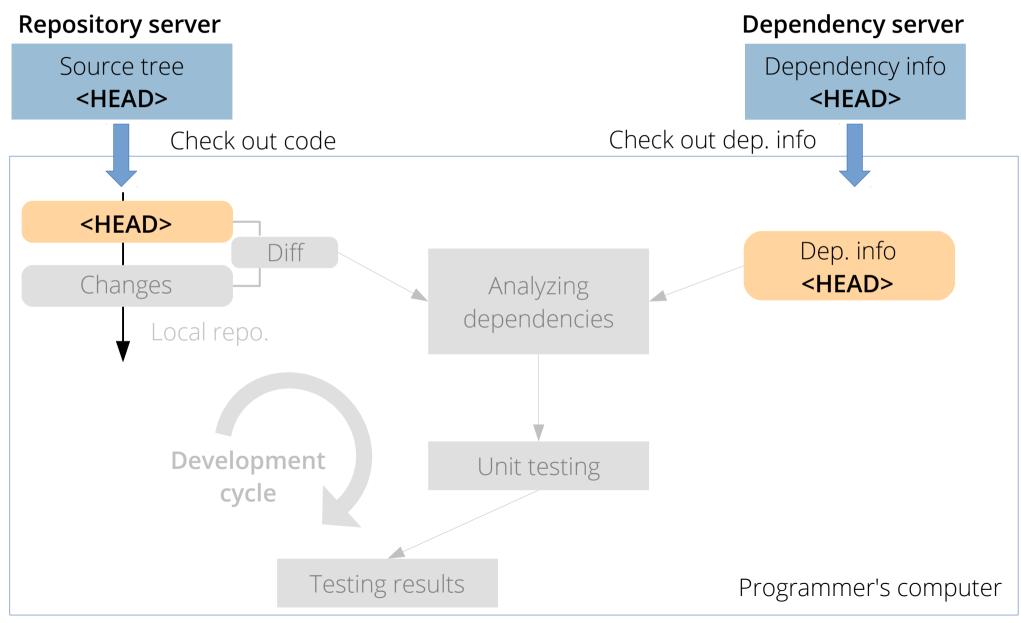
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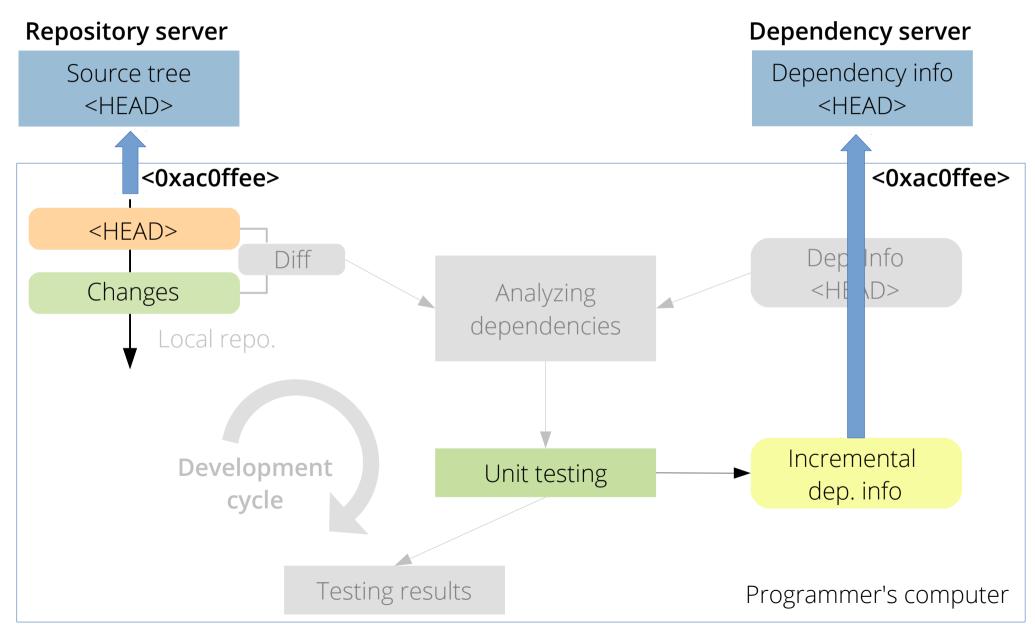
Bootstrapping dependency info.



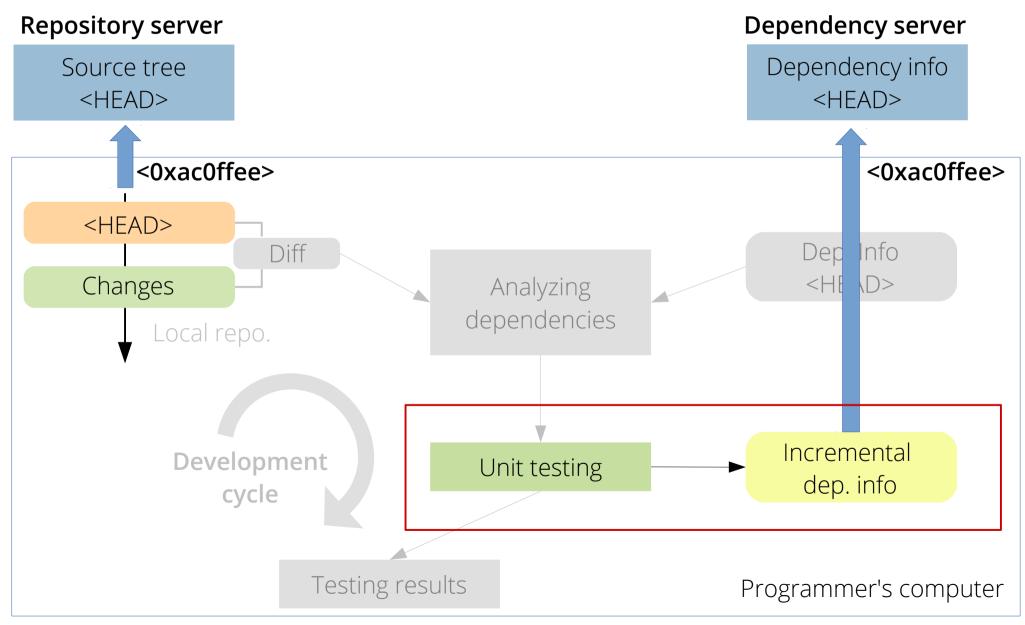
Bootstrapping dependency info.



Update dependency information



Update dependency information



Problem: false negatives

- Function-level tracking can miss some dependencies and cause false negatives
 - Failed to identify some test cases that are actually affected
- Identified **five types** of missing dependencies
 - Inter-class dependency
 - Non-determinism
 - Class variable
 - Global-scope
 - Lexical dependency

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- Function-level tracking can miss some dependencies and cause false negatives
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Example: inter-class dep. in Python

```
class A:
  def foo():
    return 1
class B(A):
  pass
def testcase():
  assertEqual(
    B().foo(), 1)
```

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Dependency info:

```
testcase() →
B.__init__()
A.foo()
```

Example: inter-class dep. in Python

```
class A:
  def foo()
    return 1
class B(A):
  pass
  def foo();
    return 2
def testcase():
  assertEqual (
    B().foo(,,
```

Dependency info:

Modified functions:

Example: missing dep. because of non-determinism in Python

```
def foo():
    return 1
    return 2

def testcase():
    if rand()%2:
        assertEqual(
        foo(), 1)
```

Dependency info:

```
testcase() \rightarrow testcase() \rightarrow rand() or foo()
```

Modified functions:

foo()

Example: missing dep. because of non-determinism in Python

```
def foo():
    return 1
    return 2

def testcase():
    if rand()%2:
        assertEqual(
        foo(), 1)
```

Dependency info:

```
testcase() →
  rand()
  foo()
testcase() →
  rand()
```

Modified functions:

```
foo()
```

Example: class-var. dep. in Python

```
class C:
    a = 1
    a = 2
    def foo():
    return C.a

def testcase():
    assertEqual(
    foo(), 1)
```

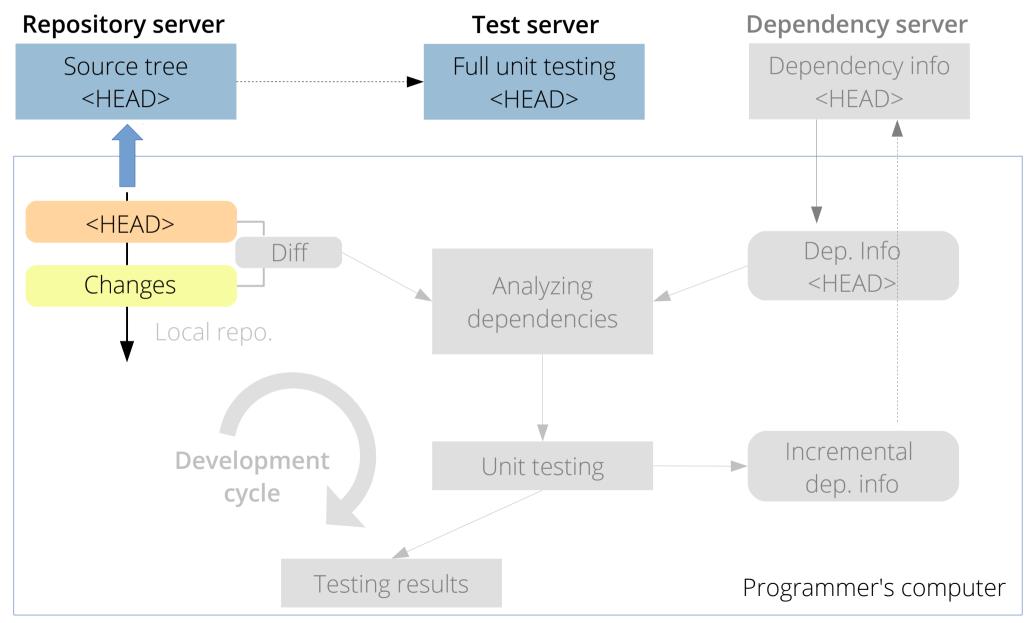
Dependency info:

```
testcase() → foo()
```

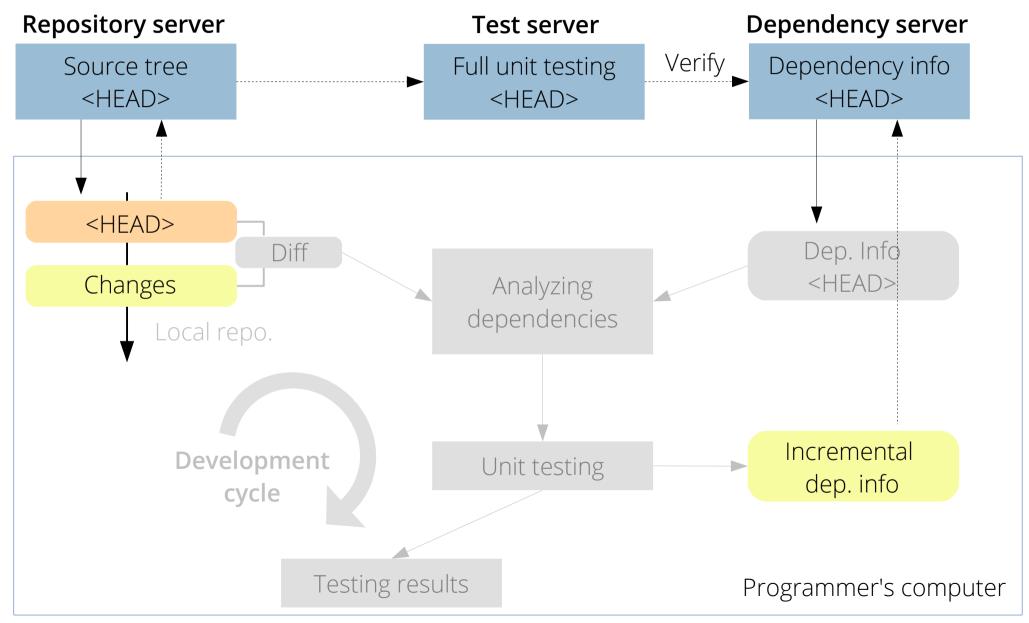
Modified functions:

N/A

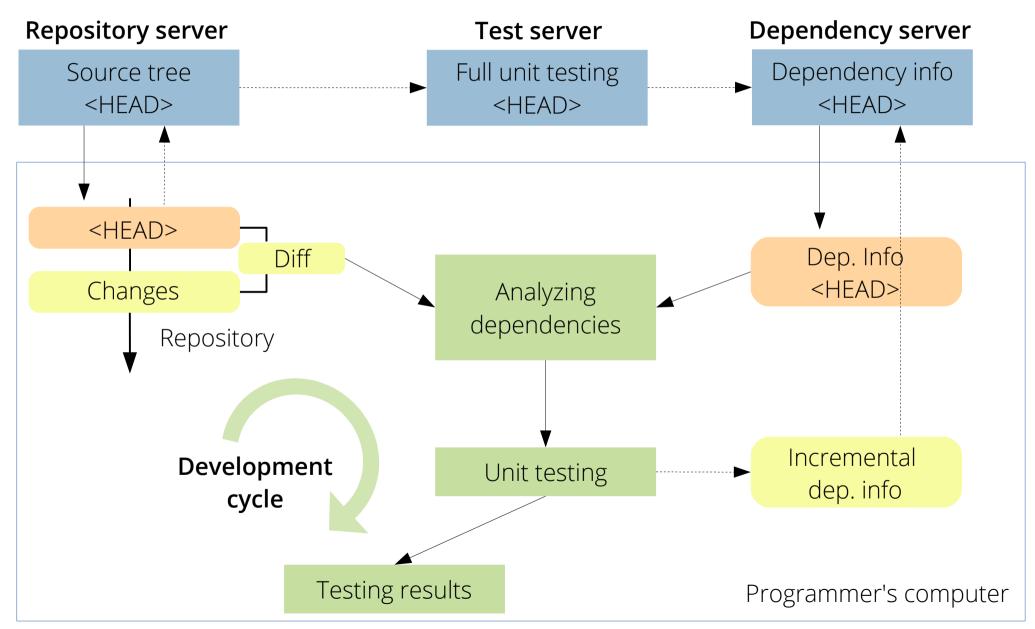
Solution: test server runs all tests async.



Test server also verifies dep. info



TAO: a prototype for PyUnit



Implementation

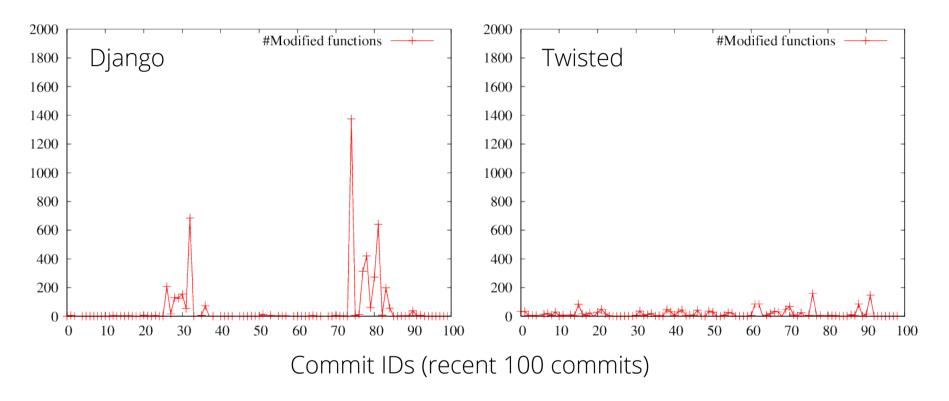
- TAO: a prototype for PyUnit
 - Extending standard python-unittest library
 - Patch analysis: using ast/diff python module
 - Dependency tracking: using settrace() interface
 - 800 Lines of code in Python

Evaluation

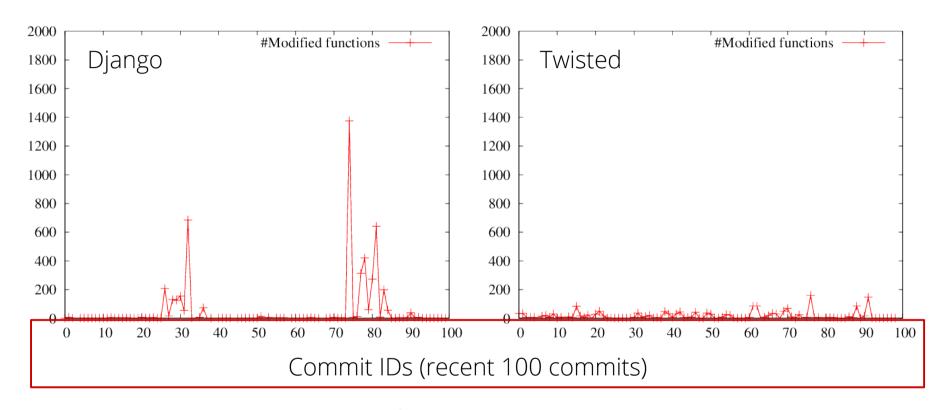
- How many functions are modified in each commit in large software programs?
- How much testing time can be saved as result?
- How many false negatives does TAO incur?
- What is the overall runtime overhead of TAO?

Experiment setup

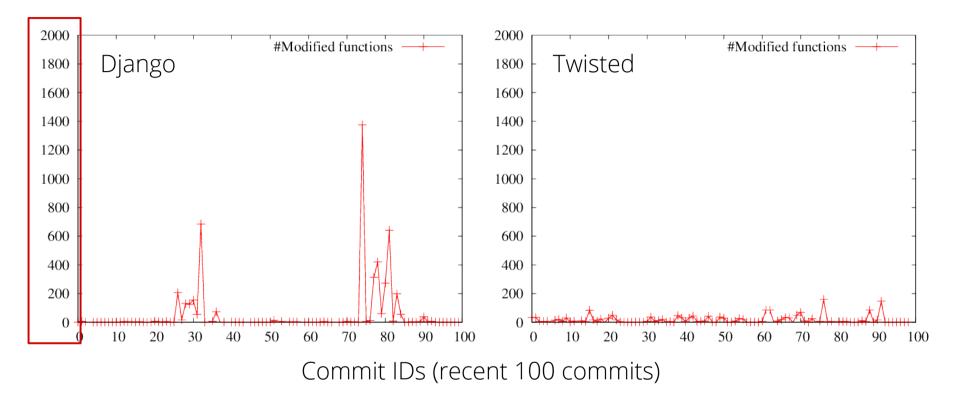
- Two popular projects: Django and Twisted
 - Django: a web application framework
 - **Twisted**: a network protocol engine
 - Use existing unit tests of both projects
 - Integrate TAO into both projects
 - Analyze the latest **100 commits** of each project



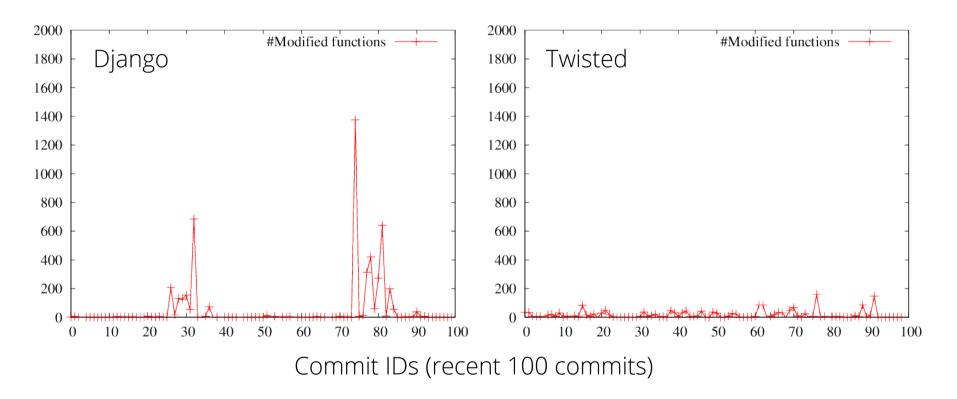
- Django: 50.8 / 13k functions (0.3%)
- Twisted: 18.2 / 23k functions (0.07%)



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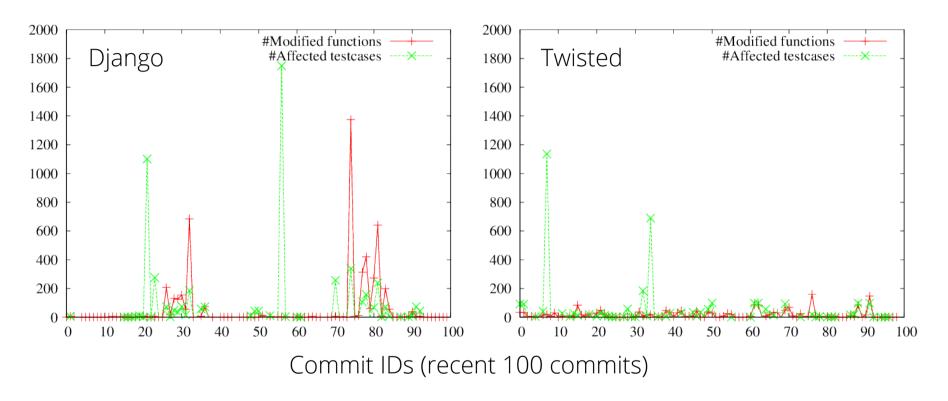


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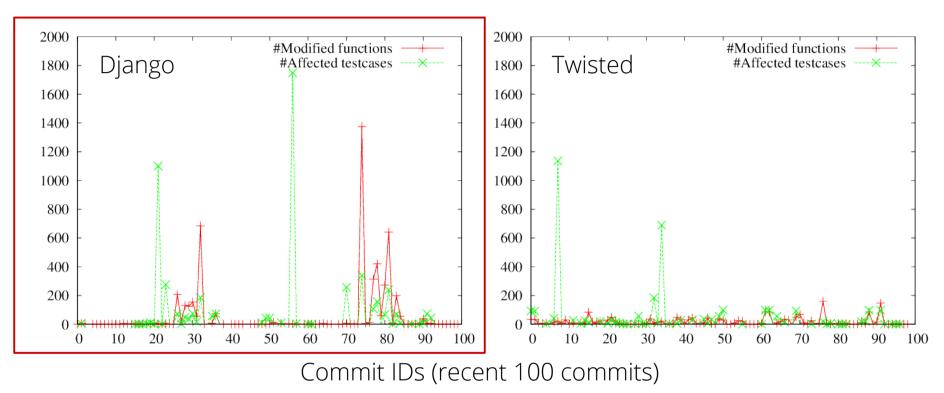
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Small number of test cases need to be rerun



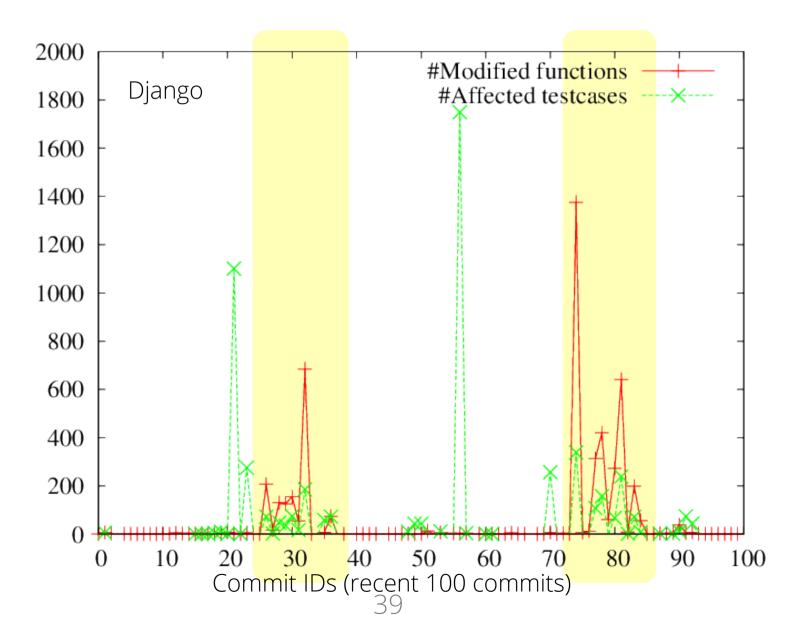
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- Twisted: 28.7 / 7k test cases (0.4%)

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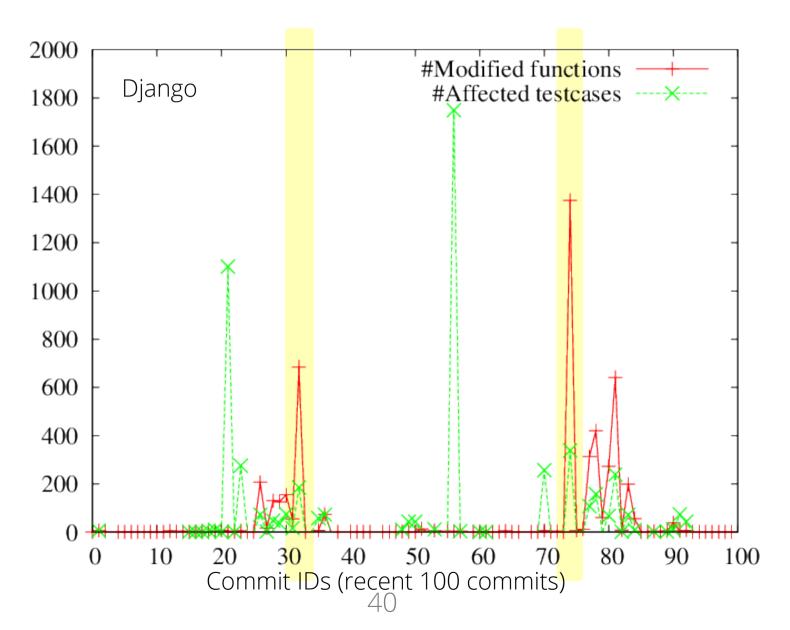


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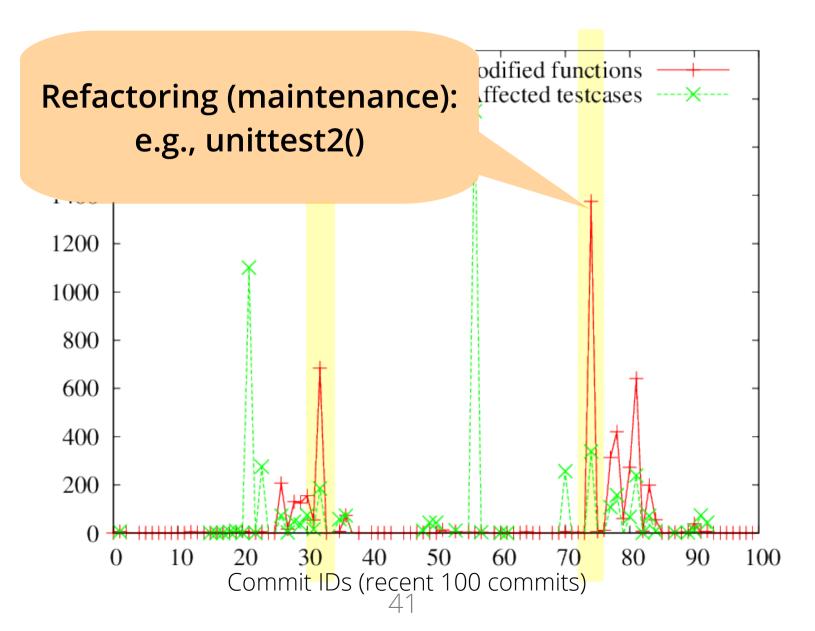
Trend 1: #affected test cases is correlated with #modified functions



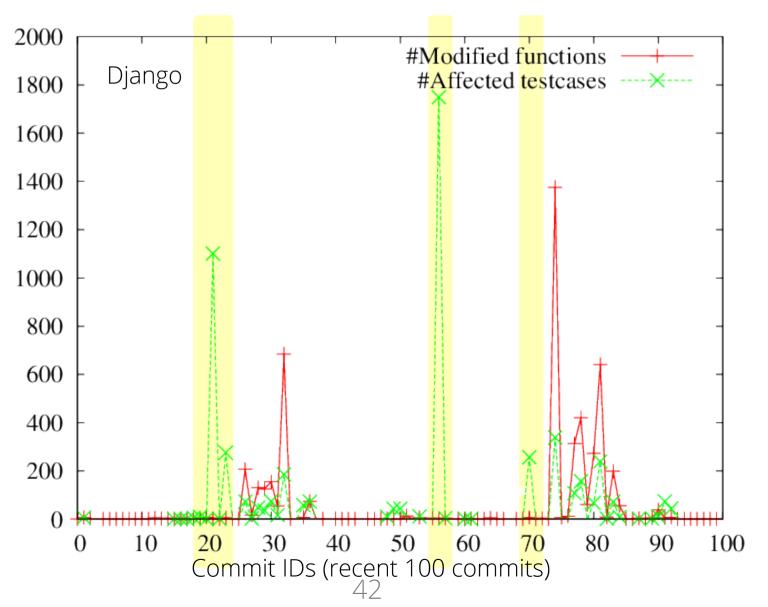
Trend 2: many modified functions, few affected test cases



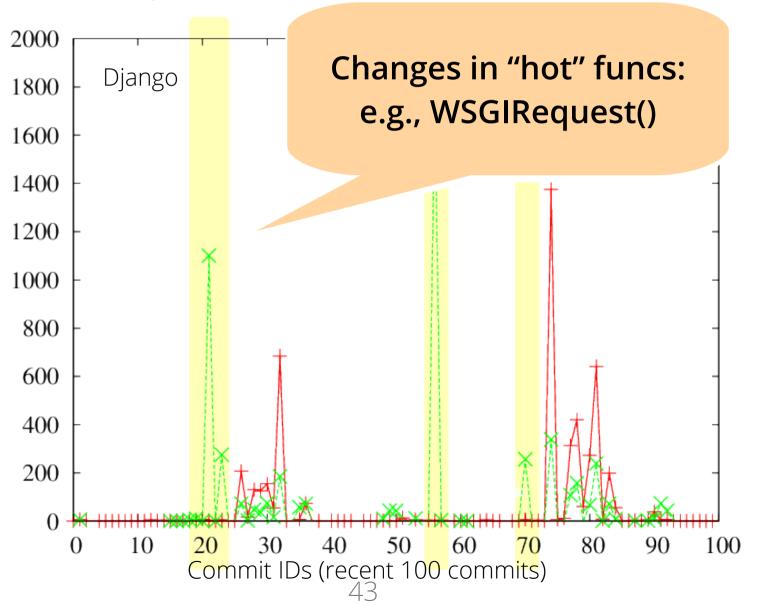
Trend 2: many modified functions, few affected test cases



Trend 3: few modified functions, many affected test cases



Trend 3: few modified functions, many affected test cases



TAO can improve the overall execution time for unit testing

Droject	#Test cases		Execution time (s)		
Project	All	TAO	All	TAO	
Django	5,166	50.8	520.3s	1.7s	
Twisted	7,150	28.7	72.1s	2.2s	

- Django: 520.3s → 1.7s (5k → 50.8 test cases)
- Twisted: 72.1s → 2.2s (7k → 29.7 test cases)

TAO has few false negatives (FN)

Project	FN/I (inter-class)	FN/N (non-det.)	FN/G (global scope)	FN/C (class var.)	FN/L (lexical dep.)
Django	0/0	0/0	2/8	1/3	1/23
Twisted	1/2	0/0	1/20	1/17	0/11

- We manually identified types of missing dependencies and false negatives on each commit
- Django: 3 false negatives (one commit is counted in both G/L)
- Twisted: 3 false negatives

TAO has few false negatives (FN)

Among class variable deps we identified, how many false negatives end up getting at?

Project	FN/I (inter-class)	FN/N (non-det.)	FN/G (global scope)	FN/C (class var.)	FN/L (lexical dep.)
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- We manually identified types of missing dependencies and false negatives on each commit
- Django: 3 false negatives (one commit is counted in both G/L)
- Twisted: 3 false negatives

Example: not all missing deps cause false negatives

```
Missing dep.: class var.
       class DecimalField(IntegerField):
            default error messages = {
                'max digits': (msg)
                'max digits': ungettext lazy(msg)
            def init (...):
                     raise ValidationError(oldmsg)
                     raise ValidationError(newmsg)

    Function-level dependency
```

Dependency tracking imposes performance overheads

Project	Runtime		Storage		
	no TAO	TAO	Full	Incremental	
Django	520.3s	1,129.1s	9.9MB	270KB	
Twisted	72.1s	115.6s	1.3MB	280KB	

- Django: 10 min (117%) to generate dep. info (9.9MB)
- Twisted: <1 min (60%) to generate dep. info (1.3MB)
- Performance can be improved if we implement function-level tracing natively, instead of using settrace() library.

Incremental dependency information is small

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	no TAO	TAO	Full	Incremental	
Django	520.3s	1,129.1s	9.9MB	270KB	
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- Django: 270KB incremental dep. info (per commit)
- Twisted: 280KB incremental dep. info (per commit)

Related work

Regression test selection:

- RTS [Biswas '11]: survey of available RTS techniques
 - → Simple function-level dependency is effective in practice
 - → TAO can be integrated into the programmer's workflow

Dependency tracking:

- Poirot [Kim '12]: intrusion recovery
- TaintDroid [Enck '12]: privacy monitoring
 - → Dependency tracking can optimize unit test execution

Summary

TAO: a system that optimizes unit test execution using dependency analysis

- Tracks function-level dependency of each unit test
- Analyzes code changes to find the affected test cases
- Runs only affected test cases (but few false negative)
- Integrated into programmer's development cycle