DOI:10.1145/3338112

Key lessons for designing static analyses tools deployed to find bugs in hundreds of millions of lines of code.

BY DINO DISTEFANO, MANUEL FÄHNDRICH, FRANCESCO LOGOZZO, AND PETER W. O'HEARN

Scaling Static Analyses at Facebook

STATIC ANALYSIS TOOLS are programs that examine, and attempt to draw conclusions about, the source of other programs without running them. At Facebook, we have been investing in advanced static analysis tools that employ reasoning techniques similar to those from program verification. The tools we describe in this article (Infer and Zoncolan) target issues related to crashes and to the security of our services, they perform sometimes complex reasoning spanning many procedures or files, and they are integrated into engineering workflows in a way that attempts to bring value while minimizing friction.

These tools run on code modifications, participating as bots during the code review process. Infer targets our mobile apps as well as our backend C++ code, codebases with 10s of millions of lines; it has seen over 100 thousand reported issues fixed by developers before code reaches production. Zoncolan targets the 100-million lines of Hack code, and is additionally integrated in the workflow used by security engineers. It has led to thousands of fixes of security and privacy bugs, outperforming any other detection method used at Facebook for such vulnerabilities. We will describe the human and technical challenges encountered and lessons we have learned in developing and deploying these analyses.

There has been a tremendous amount of work on static analysis, both in industry and academia, and we will not attempt to survey that material here. Rather, we present our rationale for, and results from, using techniques similar to ones that might be encountered at the edge of the research literature, not only simple techniques that are much easier to make scale. Our goal is to complement other reports on industrial static analysis and formal methods,[1,6,13,17] and we hope that such perspectives can provide input both to future research and to further industrial use of static analysis.

Next, we discuss the three dimensions that drive our work: bugs that matter, people, and actioned/missed bugs. The remainder of the article describes our experience developing and deploying the analyses, their impact, and the techniques that underpin our tools.

Context for Static Analysis at Facebook

Bugs that Matter. We use static analysis to prevent bugs that would affect our products, and we rely on our engineers' judgment as well as data from production to tell us the bugs that matter the most.

» key insights

- **Advanced static analysis techniques performing deep reasoning about source code can scale to large industrial codebases, for example, with 100-million LOC.**
- **Static analyses should strike a balance between missed bugs (false negatives) and un-actioned reports (false positives).**
- **A "diff time" deployment, where issues are given to developers promptly as part of code review, is important to catching bugs early and getting high fix rates.**

IMAGE BY ANDRIJ BORYS ASSOCIATES, USING SHUTTERSTOCK

It is important for a static analysis developer to realize that not all bugs are the same: different bugs can have different levels of importance or severity depending on the context and the nature. A memory leak on a seldom-used service might not be as important as a vulnerability that would allow attackers to gain access to unauthorized information. Additionally, the frequency of a bug type can affect the decision of how important it is to go after. If a certain kind of crash, such as a null pointer error in Java, were happening hourly, then it might be more important to target than a bug of similar severity that occurs only once a year.

We have several means to collect data on the bugs that matter. First of all, Facebook maintains statistics on crashes and other errors that happen in production. Second, we have a "bug bounty" program, where people outside the company can report vulnerabilities on Facebook, or on apps of the Facebook family; for example, Messenger, Instagram, or WhatsApp. Third, we have an internal initiative for tracking the most severe bugs (SEV) that occur.

Our understanding of Bugs that Matter at Facebook drives our focus on advanced analyses. For contrast, a recent paper states: "All of the static analyses deployed widely at Google are relatively simple, although some teams work on project-specific analysis frameworks for limited domains (such as Android apps) that do interprocedural analysis"[17] and they give their entirely logical reasons. Here, we explain why Facebook made the decision to deploy interprocedural analysis (spanning multiple procedures) widely.

People and deployments. While not all bugs are the same, neither are all users; therefore, we use different deployment models depending on the intended audience (that is, the people the analysis tool will be deployed to).

For classes of bugs intended for all or a wide variety of engineers on a given platform, we have gravitated toward a "diff time" deployment, where analyzers participate as bots in code review, making automatic comments when an engineer submits a code modification. Later, we recount a striking situation where the diff time deployment saw a 70% fix rate, where a more traditional "offline" or "batch" deployment (where bug lists are presented to engineers, outside their workflow) saw a 0% fix rate.

In case the intended audience is the much smaller collection of domain security experts in the company, we use two additional deployment models. At "diff time," security related issues are pushed to the security engineer on-call, so she can comment on an in-progress code change when necessary. Additionally, for finding all instances of a given bug in the codebase or for historical exploration, offline inspection provides a user interface for querying, filtering, and triaging all alarms.

In all cases, our deployments focus on the people our tools serve and the way they work.

Actioned reports and missed bugs. The goal of an industrial static analysis tool is to help people: at Facebook, this means the engineers, directly, and the people who use our products, indirectly. We have seen how the deployment model can influence whether a tool is successful. Two concepts we use to understand this in more detail, and to help us improve our tools, are *actioned reports* and *observable missed bugs*.

The kind of action taken as a result of a reported bug depends on the deployment model as well as the type of bug. At diff time an action is an update to the diff that removes a static analysis report. In Zoncolan's offline deployment a report can trigger the security expert to create a task for the product engineer if the issue is important enough to follow up with the product team. Zoncolan catches more SEVs than either manual security reviews or bug bounty reports. We measured that 43.3% of the severe security bugs are detected via Zoncolan. At press time, Zoncolan's "action rate" is above 80% and we observed about 11 "missed bugs."

A missed bug is one that has been observed in some way, but that was not reported by an analysis. The means of observation can depend on the kind of bug. For security vulnerabilities we have bug bounty reports, security reviews, or SEV reviews. For our mobile apps we log crashes and app not-responding events that occur on mobile devices.

The actioned reports and missed bugs are related to the classic concepts of true positives and false negatives from the academic static analysis literature. A true positive is a report of a potential bug that can happen in a run of the program in question (whether or not it will happen in practice); a false positive is one that cannot happen. Common wisdom in static analysis is that it is important to keep control of the false positives because they can negatively impact engineers who use the tools, as they tend to lead to apathy toward reported alarms. This has been emphasized, for instance, in previous *Communications*' articles on industrial static analysis.[1,17] False negatives, on the other hand, are potentially harmful bugs that may remain undetected for a long time. An undetected bug affecting security or privacy can lead to undetected exploits. In practice, fewer false positives often (though not always) implies more false negatives, and vice versa, fewer false negatives implies more false positives. For instance, one way to reign in false positives is to fail to report when you are less than sure a bug will be real; but silencing an analysis in this way (say, by ignoring paths or by heuristic filtering) has the effect of missing bugs. And, if you want to discover and report more bugs you might also add more spurious behaviors.

The reason we are interested in advanced static analyses at Facebook might be understood in classic terms as saying: false negatives matter to us. However, it is important to note the number of false negatives is notoriously difficult to quantify (how many unknown bugs are there?). Equally, though less recognized, the false positive rate is challenging to measure for a large, rapidly changing codebase: it would be extremely time consuming for humans to judge all reports as false or true as the code is changing.

Although true positives and false negatives are valuable concepts, we don't make claims about their rates and pay more attention to the action rate and the (observed) missed bugs.

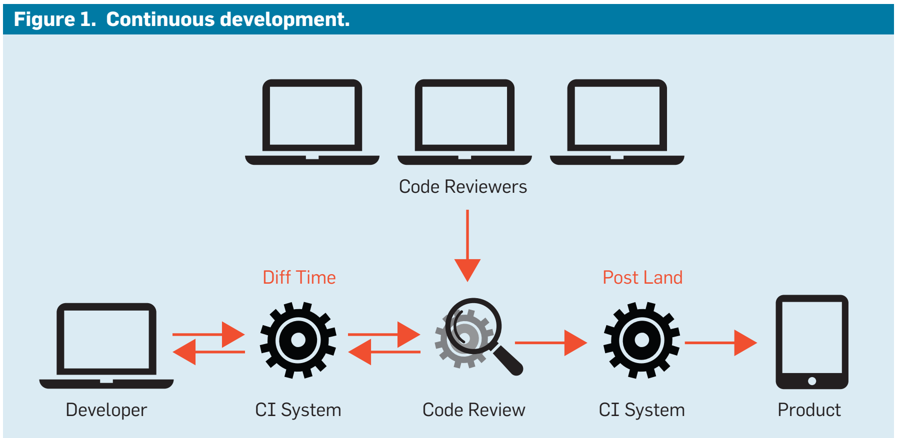
Challenges: Speed, scale, and accuracy. A first challenge is presented by the sheer scale of Facebook's codebases, and the rate of change they see. For the server-side, we have over 100-million lines of Hack code, which Zoncolan can process in less than 30 minutes. Additionally, we have 10s of millions of both mobile (Android and Objective C) code and backend C++ code. Infer processes the code modifications quickly (within 15 minutes on average) in its diff time deployment. All codebases see thousands of code modifications each day and our tools run on each code change. For Zoncolan, this can amount to analyzing one trillion lines of code (LOC) per day.

It is relatively straightforward to scale program analyses that do simple checks on a procedure-local basis only. The simplest form is linters, which give syntactic style advice (for example, "the method you called is to be deprecated, please consider rewriting"). Such simple checks provide value and are in wide deployment in major companies including Facebook; we will not comment on them further in this article. But for more reasoning going beyond local checks, such as one would find in the academic literature on static analysis, scaling to 10s or 100s of millions of LOC is a challenge, as is the incremental scalability needed to support diff time reporting.

Infer and Zoncolan both use techniques similar to some of what one might find at the edge of the research literature. Infer, as we will discuss, uses one analysis based on the theory of Separation Logic,[16] with a novel theorem prover that implements an inference technique that guesses assumptions.[5] Another Infer analysis involves recently published research results on concurrency analysis.[2,10] Zoncolan implements a new modular parallel taint analysis algorithm.

But how can Infer and Zoncolan scale? The core technical features they

Figure 1. Continuous development.



share are compositionality and carefully crafted abstractions. For most of this article we will concentrate on what one gets from applying Infer and Zoncolan, rather than on their technical properties, but we outline their foundations later and provide more technical details in an online appendix (https://dl.acm.org/citation.cfm?doid=3338112&picked=formats).

The challenge related to accuracy is intimately related to actioned reports and missed bugs. We try to strike a balance between these issues, informed by the desires based on the class of bugs and the intended audience. The more severe a potentially missed issue is, the lower the tolerance for missed bugs. Thus, for issues that indicate a potential crash or performance regression in a mobile app such as Messenger, WhatsApp, Instagram, or Facebook, our tolerance for missed bugs is lower than, for example, stylistic lint suggestions (for example, don't use deprecated method). For issues that could affect the security of our infrastructure or the privacy of the people using our products, our tolerance for false positives is higher still.

The reason we are interested in advanced static analyses at Facebook might be understood in classic terms: false negatives matter to us.

Software Development at Facebook

Facebook practices continuous software development,[9] where a main codebase (master) is altered by thousands of programmers submitting code modifications (diffs). Master and diffs are the analogues of, respectively, GitHub master branch and pull requests. The developers share access to a codebase and they land, or commit, a diff to the codebase after passing code review. A *continuous integration system* (CI system) is used to ensure code continues to build and passes certain tests. Analyses run on the code modification and participate by commenting their findings directly in the code review tool.

The Facebook website was originally written in PHP, and then ported to Hack, a gradually typed version of PHP developed at Facebook (https://hacklang.org/). The Hack codebase spans over 100 million lines. It includes the Web frontend, the internal web tools, the APIs to access the social graph from first- and third-party apps, the privacy-aware data abstractions, and the privacy control logic for viewers and apps. Mobile apps—for Facebook, Messenger, Instagram and WhatsApp—are mostly written in Objective-C and Java. C++ is the main language of choice for backend services. There are 10s of millions of lines each of mobile and backend code.

While they use the same development models, the website and mobile products are deployed differently. This affects what bugs are considered most important, and the way that bugs can be fixed. For the website, Facebook directly deploys new code to its own datacenters, and bug fixes can be shipped directly to our datacenters frequently, several times daily and immediately when necessary. For the mobile apps, Facebook relies on people to download new versions to from the Android or the Apple store; new versions are shipped weekly, but mobile bugs are less under our control because even if a fix is shipped it might not be downloaded to some people's phones.

Common runtime errors—for example, null pointer exceptions, division by zero—are more difficult to get fixed on mobile than on the server. On the other hand, server-side security and privacy bugs can severely impact both the users of the Web version of Facebook as well as our mobile users, since the privacy checks are performed on the server-side. As a consequence, Facebook invests in tools to make the mobile apps more reliable and server-side code more secure.

Moving Fast with Infer

Infer is a static analysis tool applied to Java, Objective C, and C++ code at Facebook.[4] It reports errors related to memory safety, to concurrency, to security (information flow), and many more specialized errors suggested by Facebook developers. Infer is run internally on the Android and iOS apps for Facebook, Instagram, Messenger, and WhatsApp, as well as on our backend C++ and Java code.

Infer has its roots in academic research on program analysis with separation logic,[5] research, which led to a startup company (Monoidics Ltd.) that was acquired by Facebook in 2013. Infer was open sourced in 2015 (www.fbinfer.com) and is used at Amazon, Spotify, Mozilla, and other companies.

Diff-time continuous reasoning. Infer's main deployment model is based on fast incremental analysis of code changes. When a diff is submitted to code review an instance of Infer is run in Facebook's internal CI system (Figure 1). Infer does not need to process the entire codebase in order to analyze a diff, and so is fast.

An aim has been for Infer to run in 15min–20min on a diff on average, and this includes time to check out the source repository, to build the diff, and to run on base and (possibly) parent commits. It has typically done so, but we constantly monitor performance to detect regressions that makes it take longer, in which case we work to bring the running time back down. After running on a diff, Infer then writes comments to the code review system. In the default mode used most often it reports only regressions: new issues introduced by a diff. The "new" issues are calculated using a bug equivalence notion that uses a hash involving the bug type and location-independent information about the error message, and which is sensitive to file moves and line number changes cause by refactoring, deleting, or adding code; the aim is to avoid presenting warnings that developers might regard as pre-existing. Fast reporting is important to keep in tune with the developers' workflows. In contrast, when Infer is run in whole-program mode it can take more than an hour (depending on the app)—too slow for diff-time at Facebook.

Human factors. The significance of the diff-time reasoning of Infer is best understood by contrast with a failure. The first deployment was batch rather than continuous. In this mode Infer would be run once per night on the entire Facebook Android codebase, and it would generate a list of issues. We manually looked at the issues, and assigned them to the developers we thought best able to resolve them.

The response was stunning: we were greeted by near silence. We assigned 20–30 issues to developers, and almost none of them were acted on. We had worked hard to get the false positive rate down to what we thought was less than 20%, and yet the fix rate—the proportion of reported issues that developers resolved—was near zero.

Next, we switched Infer on at diff time. The response of engineers was just as stunning: the fix rate rocketed to over 70%. The same program analysis, with same false positive rate, had much greater impact when deployed at diff time.

While this situation was surprising to the static analysis experts on the Infer team, it came as no surprise to Facebook's developers. Explanations they offered us may be summarized in the following terms:

One problem that diff-time deployment addresses is the *mental effort of context switch*. If a developer is working on one problem, and they are confronted with a report on a separate problem, then they must swap out the mental context of the first problem and swap in the second, and this can be time consuming and disruptive. By participating as a bot in code review, the context switch problem is largely solved: programmers come to the review tool to discuss their code with human reviewers, with mental context already swapped in. This also illustrates how important timeliness is: if a bot were to run for an hour or more on a diff it could be too late to participate effectively.

A second problem that diff-time deployment addresses is relevance. When an issue is discovered in the codebase, it can be nontrivial to assign it to the right person. In the extreme, somebody who has left the company might have caused the issue. Furthermore, even if you think you have found someone familiar with the codebase, the issue might not be relevant to any of their past or current work. But, if we comment on a diff that introduces an issue then there is a pretty good (but not perfect) chance that it is relevant.

Mental context switch has been the subject of psychological studies,[12] and it is, along with the importance of relevance, part of the received collective wisdom impressed upon us by Facebook's engineers. Note that others have also remarked on the benefits of reporting during code review.[17]

At Facebook, we are working actively on moving other testing technologies to diff time when possible. We are also supporting academics on researching incremental fuzzing and symbolic execution techniques for diff time reporting.

Interprocedural bugs. Many of the bugs that Infer finds involve reasoning that spans multiple procedures or files. An example from OpenSSL illustrates:

```
apps/ca.c:2780: NULL_DEREFERENCE
pointer 'revtm' last assigned on line
2778 could be null
and is dereferenced at line 2780, column 6
2778. revtm = X509_gmtime_adj(NULL, 0);
2779.
2780. i = revtm->length + 1;
```

The issue is that the procedure `X509_gmtime_adj()` can return null in some circumstances. Overall,

Figure 2. A simple example capturing a common safety pattern used in Android apps.

Threading information is used to limit the amount of synchronization required. As a comment from the original code explains: "`mCount` is written to only by the main thread with the lock held, read from the main thread with no lock held, or read from any other thread with the lock held." Bottom: unsafe additions to `RaceWithMainThread.java`.

```
@ThreadSafe
class RaceWithMainThread {
  int mCount;
  void protectedWriteOnMainThread_OK() {
    OurThreadUtils.assertMainThread();
    synchronized (this) { mCount = 1; }
  }
  int unprotectedReadOnMainThread_OK() {
    OurThreadUtils.assertMainThread();
    return mCount;
  }
  synchronized int protectedReadOffMainThread_OK() {
    return mCount;
  }
```

```
  synchronized void
  protectedWriteOffMainThread_BAD() {
    mCount = 2;
  }
  int unprotectedReadOffMainThread_BAD() {
    return mCount;
  }
```

the error trace found by Infer has 61 steps, and the source of null, the call to `X509_gmtime_adj()` goes five procedures deep and it eventually encounters a return of null at call-depth 4. This bug was one of 15 that we reported to OpenSSL which were all fixed.

Infer finds this bug by performing compositional reasoning, which allows covering interprocedural bugs while still scaling to millions of LOC. It deduces a precondition/postcondition specification approximating the behavior of `X509_gmtime_adj`, and then uses that specification when reasoning about its calls. The specification includes 0 as one of the return values, and this triggers the error.

In 2017, we looked at bug fixes in several categories and found that for some (null dereferences, data races, and security issues) over 50% of the fixes were for bugs with traces that were interprocedural.[a] The interprocedural bugs would be missed bugs if we only deployed procedure-local analyses.

Concurrency. A concurrency capability recently added to Infer, the RacerD analysis, provides an example of the benefit of feedback between program analysis researchers and product engineers.[2,15] Development of the analysis started in early 2016, motivated by Concurrent Separation Logic.[3] After 10 months of work on the project, engineers from News Feed on Android caught wind of what we were doing and reached out. They were planning to convert part of Facebook's Android app from a sequential to a multithreaded architecture. Hundreds of classes written for a single-threaded architecture had to be used now in a concurrent context: the transformation could introduce concurrency errors. They asked for interprocedural capabilities because Android UI is arranged in trees with one class per node. Races could happen via interprocedural call chains sometimes spanning several classes, and mutations almost never happened at the top level: procedural local analysis would miss most races.

We had been planning to launch the proof tool we were working on in a year's time, but the Android engineers were starting their project and needed help sooner. So we pivoted to a *minimum viable product*, which would serve the engineers—it had to be fast, with actionable reports, and not too many missed bugs on product code (but not on infrastructure code).[2,15] The tool borrowed ideas from concurrent separation logic, but we gave up on the ideal of proving absolute race freedom. Instead, we established a 'completeness' theorem saying that, under certain assumptions, a theoretical variant of the analyzer reports only true positives.[10]

> **Advanced static analyses, like those found in the research literature, can be deployed at scale and deliver value for general code.**

The analysis checks for data races in Java programs—two concurrent memory accesses, one of which is a write. The example in Figure 2 (top) illustrates: If we run the Infer on this code it doesn't find a problem. The unprotected read and the protected write do not race because they are on the same thread. But, if we include additional methods that do conflict, then Infer will report races, as in Figure 2, bottom.

Impact. Since 2014, Facebook's developers have resolved over 100,000 issues flagged by Infer. The majority of Infer's impact comes from the diff-time deployment, but it is also run batch to track issues in master, issues addressed in fixathons and other periodic initiatives.

The RacerD data race detector saw over 2,500 fixes in the year to March 2018. It supported the conversion of Facebook's Android app from a single-threaded to a multithreaded architecture by searching for potential data races, without the programmers needing to insert annotations for saying which pieces of memory are guarded by what locks. This conversion led to an improvement in scroll performance and, speaking about the role of the analyzer, Benjamin Jaeger, an Android engineer at Facebook, stated:[b] "without Infer, multithreading in News Feed would not have been tenable." As of March 2018, no Android data race bugs missed by Infer had been observed in the previous year (modulo 3 analyzer implementation errors.)[2]

The fix rate for the concurrency analysis to March 2018 was roughly 50%, lower than for the previous general diff analysis. Our de velopers have emphasized that they appreciate the reports because concurrency errors are difficult to debug. This illustrates our earlier points about balancing action rates and bug severity. See Blackshear et al.[2] for more discussion on fix rates.

a https://bit.ly/2WloBVj

b https://bit.ly/2xurbMl

Overall, Infer reports on over 30 types of issues, ranging from deep inter-procedural checks to simple procedure-local checks and lint rules. Concurrency support includes checks for deadlocks and starvation, with hundreds of “app not-responding”’ bugs being fixed in the past year. Infer has also recently implemented a security analysis (a ‘taint’ analysis), which has been applied to Java and C++ code; it gained this facility by borrowing ideas from Zoncolan.

Staying Secure with Zoncolan

One of the original reasons for the development and adoption of Hack was to enable more powerful analysis of the core Facebook codebase. Zoncolan is the static analysis tool we built to find code and data paths that may cause a security or a privacy violation in our Hack codebase.

The code in Figure 3 is an example of a vulnerability prevented by Zoncolan. If the `member_id` variable on line 21 contains the value `../../users/delete_user/`, it is possible to redirect this form into any other form on Facebook. On submission of the form, it will invoke a request to https://facebook.com/groups/add_member/../../users/delete_user/ that will delete the user’s account. The root cause of the vulnerability in Figure 3 is that the attacker controls the value of the `member_id` variable which is used in the action field of the <form> element. Zoncolan follows the interprocedural flow of untrusted data (for example, user input) to sensitive parts of the codebase. Virtual calls do make interprocedural analysis difficult since the tool generally does not know the precise type of an object. To avoid missing paths (and thus bugs), Zoncolan must consider all the possible functions a call may resolve to.

SEV-oriented static analysis development. We designed and developed Zoncolan in collaboration with the Facebook App Security team. Alarms reported by Zoncolan are inspired by security bugs uncovered by the App Security team.

The initial design of Zoncolan began with a list of SEVs that were provided to us by security engineers. For each bug we asked ourselves: “How could we have caught it with static analysis?” Most of those historical bugs were no longer relevant because the programming language or a secure framework prevented them from recurring—for instance, the widespread adoption of XHP made it possible to build XSS-free Web pages by construction. We realized the remaining bugs involved interprocedural flows of untrusted data, either directly or indirectly, into some privileged APIs. Detecting such bugs can be automated with static taint flow analysis,[18] which tracks how the data originating from some untrusted sources reaches or influences the data reaching some sensitive parts of the codebase (sinks).

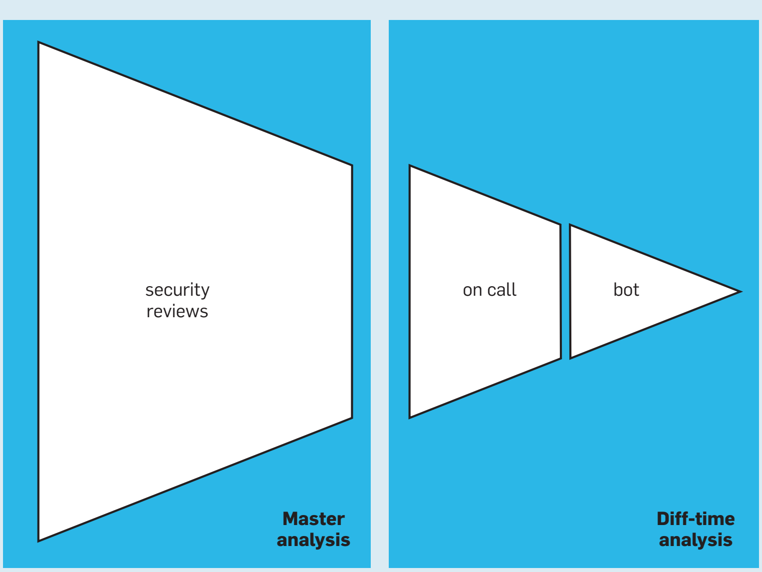
When a security engineer discovers a new vulnerability, we evaluate whether that class of vulnerability is amenable to static analysis. If it is, we prototype the new rule, iterating with the feedback of the engineer in order to refine results to strike the right balance of false positives/false negatives. When we believe the rule is good enough, it is enabled on all runs of Zoncolan in production. We adopt the standard Facebook App Security severity framework, which associates to each vulnerability an impact level, in a scale from 1 (best-practice) to 5 (SEV-worthy). A security impact level of 3 or more is considered severe.

Scaling the analysis. A main challenge was to scale Zoncolan to a codebase of more than 100 millions of LOC

Figure 3. Example of a bug that Zoncolan prevents. It may cause the attacker to delete a user account. The attacker can provide an input on line 5 that causes a redirection to any other form on Facebook at line 20.

```
1   <?hh
2   class AddMemberToGroup extends FacebookEndpoint {
3     private function getIDs (): (string, int) {
4       // User input, untrusted
5       return tuple((string) $this->getRequest('member_id'),
6                    (int) $this->getRequest('gid'));
7     }
8
9     public function render(): :xhp {
10      list($member_id, $group_id) = $this->getIDs();
11      return this->getConfirmationForm($group_id, $member_id);
12    }
13
14    public function getConfirmationForm
15     (int $group_id, string $member_id): :xhp {
16      $url = "https://facebook.com/groups/add_member/" .
17             $member_id;
18
19      return
20        <form method="post" action={$url}>
21          <input name="gid" value={$group_id}/>
22          <input name="action" value="add"/>
23        </form>;
24    }
25  }
```

Figure 4. Funneled deployment of Zoncolan



code. Thanks to a new parallel, compositional, non-uniform static analysis that we designed, Zoncolan performs the full analysis of the code base in less than 30 minutes on a 24-core server.

Zoncolan builds a dependency graph that relates methods to their potential callers. It uses this graph to schedule parallel analyses of individual methods. In the case of mutually recursive methods, the scheduler iterates the analysis of the methods until it stabilizes, that is, no more flows are discovered. Suitable operators (called widenings in the static analysis literature[7]) ensure the convergence of the iterations. It is worth mentioning that, even though the concept of taint analysis is well established in Academia, we had to develop new algorithms in order to scale to the size of our codebase.

Funneled deployment. Figure 4 provides a graphical representation of the Zoncolan deployment model. This funneled deployment model optimizes bug detection with the goal of supporting security of Facebook: The Zoncolan master analysis finds all existing instances of a newly discovered vulnerability. The Zoncolan diff analysis avoids vulnerabilities from being (re-)introduced in the codebase.

Zoncolan periodically analyzes the entire Facebook Hack codebase to update the master list. The target audience is security engineers performing security reviews. In the master analysis, we expose all alarms found. Security engineers are interested in all existing alarms for a given project or a given category. They triage alarms via a dashboard, which enables filtering by project, code location, source and/or destination of the data, length or features of the trace. When a security engineer finds a bug, he/she files a task for the product group and provides guidance on how to make the code secure. When an alarm is a false positive, he/she files a task for the developers of Zoncolan with an explanation of why the alarm is false. The Zoncolan developers then refine the tool to improve the precision of the analysis. After a category has been extensively tested, the Zoncolan team, in conjunction with the App security team, evaluates if it can be promoted for diff analysis. Often promotion involves improving the signal by filtering the output according to, for example, the length of the inter-procedutal trace, the visibility of the endpoint (external or internal?), and so on. At press time, circa 1/3 of the Zoncolan categories are enabled for diff analysis.

Zoncolan analyzes every Hack code modification and reports alarms if a diff introduces new security vulnerabilities. The target audience is: the author and the reviewers of the diff (Facebook software engineers who are not security experts), and the security engineer in the on-call rotation (who has a limited time budget). When appropriate, the on-call validates the alarm reported, blocks the diff, and provides support to write the code in a secure way. For categories with very high signal, Zoncolan acts as a security bot: it bypasses the security on-call and instead comments directly on the diff. It provides a detailed explanation on the security vulnerability, how it can be exploited, and includes references to past incidents, for example, SEVs.

Finally, note the funneled deployment model makes it possible to scale up the security fixes, without reducing the overall coverage Zoncolan achieves (that is, without missing bugs): If Zoncolan determines a new issue is not high-signal enough for autocommenting on the diff, but needs to be looked at by an expert, it pushes it to the on-call queue. If the alarm makes neither of these cuts, the issue will end up in the Zoncolan master analysis after the diff is committed.

Impact. Zoncolan has been deployed for more than two years at Facebook, first to security engineers, then to software engineers. It has prevented thousands of vulnerabilities from being introduced to Facebook's codebase. Figure 5 compares the number of SEVs, such as bugs of severity 3-to-5, prevented by Zoncolan, in a six-month period, to the traditional programs adopted by security engineers, such as manual code reviews/pentesting and bug bounty reports. The bars show that at Facebook, Zoncolan catches more SEVs than either manual security reviews or bug bounty reports. We measured that 43.3% of the severe security bugs are detected via Zoncolan.

The graph in Figure 6 shows the distribution of the actioned bugs found by Zoncolan at different stages of the deployment funnel, according to the security impact level. The largest number of categories is enabled for the master analysis, so it is not unexpected that it is the largest bucket. However, when restricting to SEVs, the diff analysis largely overtakes the master analysis—211 severe issues are prevented at diff-time, versus 122 detected on master. Overall, we measured the ratio of Zoncolan actioned bugs to be close to 80%.

We also use the traditional security programs to measure missed bugs (that is, the vulnerabilities for which there is a Zoncolan category), but the

Figure 5. Comparison of severe bugs reported by Zoncolan with respect to security reviews and bug bounty, in a six-month period (darker implies more severe).

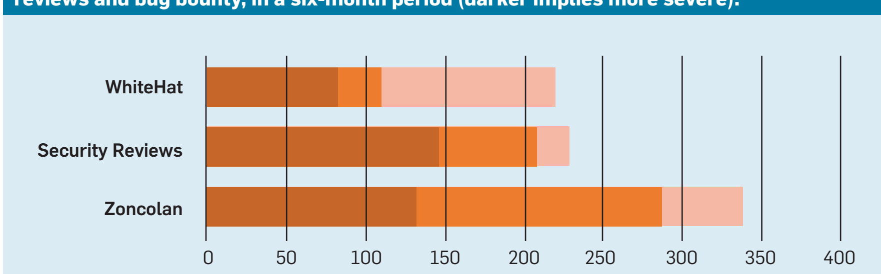
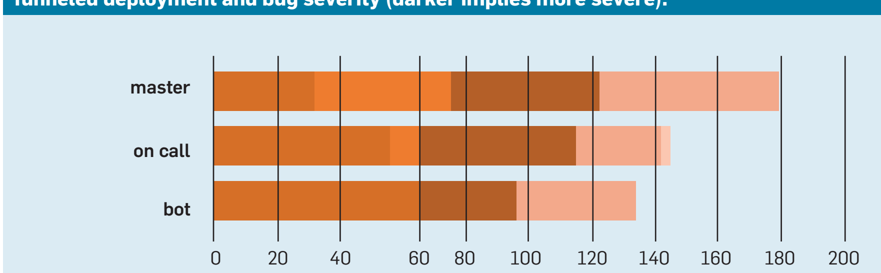


Figure 6. Distribution of all the bugs fixed, in a six-month period, based on Zoncolan's funneled deployment and bug severity (darker implies more severe).



tool failed to report them. To date, we have had about 11 missed bugs, some of them caused by a bug in the tool or incomplete modeling.

Compositionality and Abstraction

The technical features that underpin our analyses are *compositionality* and *abstraction*.

The notion of compositionality comes from language semantics: A semantics is compositional if the meaning of a compound phrase is defined in terms of the meanings of its parts and a means of combining them. The same idea can be applied to program analysis.[5,8] A program analysis is compositional if the analysis result of a composite program is defined in terms of the analysis results of its parts and a means of combining them. When applying compositionality in program analysis, there are two key questions:

a. How to represent the meaning of a procedure concisely?

b. How to combine the meanings in an effective way?

For (a) we need to approximate the meaning of a component by abstracting away the full behavior of the procedure and to focusing only on the properties relevant for the analysis. For instance, for security analysis, one may be only interested that a function returns a user-controlled value, when the input argument contains a user-controlled string, discarding the effective value of the string. More formally, the designer of the static analysis defines an appropriate mathematical structure, called the abstract domain,[7] which allows us to approximate this large function space much more succinctly. The design of a static analysis relies on abstract domains precise enough to capture the properties of interest and coarse enough to make the problem computationally tractable. The 'abstraction of a procedure meaning' is often called a procedure summary in the analysis literature.[19]

The answer to question (b) mostly depends on the specific abstract domain chosen for the representation of summaries. Further information on the abstractions supported by Infer and Zoncolan, as well as brief information on recursion, fixpoints, and analysis algorithms, may be found in the online technical appendix. It is worth discussing the intuitive reason for why compositional analysis together with crafted abstract domains can scale: each procedure only needs to be visited a few times, and many of the procedures in a codebase can be analyzed independently, thus opening opportunities for parallelism. A compositional analysis can even have a runtime that is (modulo mutual recursion) a linear combination of the times to analyze the individual procedures. For this to be effective, a suitable abstract domain, for instance limiting or avoiding disjunctions, should also contain the cost of analyzing a single procedure.

Finally, compositional analyses are naturally incremental—changing one procedure does not necessitate re-analyzing all other procedures. This is important for fast diff-time analysis.

Conclusion

This article described how we, as static analysis people working at Facebook, have developed program analyses in response to the needs that arise from production code and engineers' requests. Facebook has enough important code and problems that it is worthwhile to have embedded teams of analysis experts, and we have seen (for example, in the use of Infer to support multithreaded Android News Feed, and in the evolution of Zoncolan to detect SEV-worthy issues) how this can impact the company. Although our primary responsibility is to serve the company, we believe that our experiences and techniques can be generalize beyond the specific industrial context. For example, Infer is used at other companies such as Amazon, Mozilla, and Spotify; we have produced new scientific results,[2,10] and proposed new scientific problems.[11,14] Indeed, our impression as (former) researchers working in an engineering organization is that having science and engineering playing off one another in a tight feedback loop is possible, even advantageous, when practicing static analysis in industry.

To industry professionals we say: advanced static analyses, like those found in the research literature, can be deployed at scale and deliver value for general code. And to academics we say: from an industrial point of view the subject appears to have many unexplored avenues, and this provides research opportunities to inform future tools.

Acknowledgments

Special thanks to Ibrahim Mohamed for being a tireless advocate for Zoncolan among security engineers, to Cristiano Calcagno for leading Infer's technical development for several years, and to our many teammates and other collaborators at Facebook for their contributions to our collective work on scaling static analysis. C

Readers interested in more technical details of this work are encouraged to review the online appendix; (https://dl.acm.org/citation.cfm?doid=3338112&picked=formats).

References

1. Bessey, A. et al. A few billion lines of code later: using static analysis to find bugs in the real world. *Commun. ACM 53*, 2 (Feb. 2010), 66–75.
2. Blackshear, S., Gorogiannis, N., Sergey, I. and O'Hearn, P. Racerd: Compositional static race detection. In *Proceedings of OOPSLA*, 2018.
3. Brookes, S. and O'Hearn, P.W. Concurrent separation logic. *SIGLOG News 3*, 3 (2016), 47–65.
4. Calcagno, C. et al. Moving fast with software verification. In *Proceedings of NASA Formal Methods Symposium*, 2015, 3–11.
5. Calcagno, C., Distefano, D. O'Hearn, P.W and Yang, H. Compositional shape analysis by means of bi-abduction. *J. ACM 58*, 6 (2011), 26.
6. Cook, B. Formal reasoning about the security of Amazon Web services. *LICS* (2018), 38–47.
7. Cousot, P. and Cousot, R. Abstract interpretation: A unified lattice model for static analysis of programs by construction or approximation of fixpoints. In *Proceedings of the 4th POPL*, 1977, 238–252.
8. Cousot, P. and Cousot, R. Modular static program analysis. In *Proceedings of 2002 CC*, 159–178.
9. Feitelson, D.G., Frachtenberg, E. and Beck, K.L. Development and deployment at Facebook. *IEEE Internet Computing 17*, 4 (2013), 8–17.
10. Gorogiannis, N., Sergey, I. and O'Hearn, P. A true positives theorem for a static race detector. In *Proceedings of the 2019 POPL*.
11. Harman, M. and O'Hearn, P. From start-ups to scale-ups: Open problems and challenges in static and dynamic program analysis for testing and verification). In *Proceedings of SCAM*, 2018.
12. Iqbal, S.T and Horvitz, E. Disruption and recovery of computing tasks: Field study, analysis, and directions. In *Proceedings of 2007 CHI*, 677–686.
13. Larus, J.R. et al. Righting software. *IEEE Software 21*, 3 (2004), 92–100.
14. O'Hearn, P. Continuous reasoning: Scaling the impact of formal methods. *LICS*, 2018.
15. O'Hearn, P.W. Experience developing and deploying concurrency analysis at Facebook. SAS, 2018, 56–70.
16. O'Hearn, P.W. Separation logic. *Comm. ACM 62*, 2 (Feb 2019), 86–95.
17. Sadowski, C., Aftandilian, E., Eagle, A., Miller-Cushon, L. and Jaspan, C. Lessons from building static analysis tools at Google. *Commun. ACM 61*, 4 (Apr. 2018), 58–66.
18. Xie, Y. and Aiken, A. Static detection of security vulnerabilities in scripting languages. In *Proceedings of USENIX Security Symposium*, 2006.
19. Yorsh, G., Yahav, E. and Chandra, S. Generating precise and concise procedure summaries. In *Proceedings of 2008* POPL.

Dino Distefano is a research scientist at Facebook, London, U.K., and a professor of computer science at Queen Mary University of London, U.K.

Manuel Fähndrich is a software engineer at Facebook Research, Seattle, WA, USA.

Francesco Logozzo is a software engineer at Facebook Research, Seattle, WA, USA.

Peter W. O'Hearn is a research scientist at Facebook, London, U.K. and a professor of computer science at University College London, U.K.