Automated Reasoning and Detection of Specious Configuration in Large Systems with Symbolic Execution

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Abstract

Misconfiguration is a major cause of system failures. Prior solutions focus on detecting *invalid* settings that are introduced by user mistakes. But another type of misconfiguration that continues to haunt production services is *specious configuration*—settings that are valid but lead to unexpectedly poor performance in production. Such misconfigurations are subtle, so even careful administrators may fail to foresee them.

We propose a tool called Violet to detect specious configuration. We realize the crux of specious configuration is that it causes some slow code path to be executed, but the bad performance effect cannot always be triggered. Violet thus takes a novel approach that uses selective symbolic execution to systematically *reason about* the performance effect of configuration parameters, their combination effect, and the relationship with input. Violet outputs a performance impact model for the automatic detection of poor configuration settings. We applied Violet on four large systems. To evaluate the effectiveness of Violet, we collect 17 *real-world* specious configuration cases. Violet detects 15 of them. Violet also identifies 11 unknown specious configurations.

1 Introduction

Software is increasingly customizable. A mature program typically exposes hundreds of parameters for users to control scheduling, caching, *etc*. With such high customizability, it is difficult to properly configure a system today, even for trained administrators. Indeed, numerous studies and real-world failures have repeatedly shown that misconfiguration is a major cause of production system failures [32, 43, 45, 60].

The severity of the misconfiguration problem has motivated solutions to detect [35, 61, 63], test [37, 57], diagnose [19, 21, 50, 52, 54] and fix [39, 48, 53] misconfiguration. While these efforts help reduce misconfiguration, the problem remains vexing [1–3, 5–10, 17, 18, 31]. They focus on catching *invalid* settings introduced due to user mistakes. But another type of misconfiguration that haunts production systems, yet not well addressed, is valid but poor configuration. For simplicity, we call them **specious configuration**.

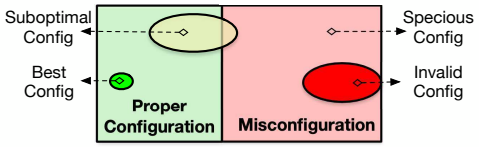


Figure 1: Value space of a configuration

Specious configuration has a broad scope. In this paper, we focus on—and use the term to refer to—valid settings that lead to extremely poor *performance*, which is a common manifestation in production incidents. This scope of focus is different from suboptimal configuration (Figure 1). The latter happens when a setting does not yield the best performance, but the performance is still acceptable. This scope is also complementary to efforts on automated configuration performance tuning [33, 51, 62, 64] to search for the best setting.

Take a real-world specious configuration that caused a service outage as an example. An engineer changed the request tracing code from a hard-coded policy (always tracing) to be configurable with a tracing `rate` parameter. This `rate` parameter was initially set to 0.0. To retain the same tracing behavior as before, she decided to change the parameter to 1.0. Based on her understanding, this change will turn on the tracing for all *message* requests that come from *internal* users. But unfortunately, there was a subtle caveat in the code that caused the actual effect to be turning on tracing for *all* requests from *all users*, which quickly overloaded all web servers as well as the backend databases, leading to a catastrophic service outage. Interestingly, before rolling out this specious configuration to production, the change in fact went through a canary phase on a small-scale testing cluster, which unfortunately did not manifest dramatic failure symptoms.

Empirical evidence suggests that specious configuration like the above is prevalent. Yin et al. [60] shows that misconfiguration in the form of legal parameters has similar or higher percentage than illegal parameters. Facebook reports [49] that more than half of the misconfiguration in their high-impact incidents during a three-month period are subtle, "valid" config-

urations. A recent study [51] on performance configurations in distributed systems reports a similar finding.

To reduce specious-configuration-induced incidents, we need to proactively detect it before production. However, what makes specious configuration subtle to detect is that its value is not a unconditionally poor choice. Rather, the setting is only problematic under certain combination with some other parameters, input, and/or environment. Currently, administrators either informally estimate the impact based on their experience, or experimentally measure it by black-box testing the program with configuration. However, neither of the approaches is sufficient to reliably capture the pitfalls.

Through analyzing real-world cases (Section 2), we realize that the crux of specious configuration lies in the fact that some slow code path in the program or library gets executed; but this effect can be only triggered with certain input, other configurations, and environment. Therefore, we argue that analytical approaches are needed to *reason about* the configuration settings' performance implications under a variety of conditions. We propose a novel analytical tool called VIOLET that uses symbolic execution [24, 38] to analyze the performance effect of configuration at the code level.

The basic idea of Violet is to systematically explore the system code paths with symbolic configuration and input, identify the constraints that decide whether a path gets executed or not, and analytically compare different execution paths that are explored. Violet derives a configuration performance impact model as its analysis output. A Violet checker leverages this model to contiguously catch specious configuration in the field. Making this basic idea work for large system software faces several challenges, including the intricate dependency among different parameters, the efficiency of symbolic execution for performance analysis, complex input structure, and path explosion problems. Violet leverages program analysis and selective symbolic execution [26] to address these challenges.

We implement a prototype of the Violet toolchain, with its core tracer built as plugins on the S^2E platform [26], the static analyzer built on LLVM [40], and the trace analyzer and checker built as standalone tools. We successfully apply Violet on four large systems, MySQL, PostgreSQL, Apache and Squid. Violet derives performance impact models for 471 parameters. To evaluate the effectiveness of Violet, we collect 17 real-world specious configuration cases. Violet detects 15 cases. In addition, Violet exposes 11 unknown specious configuration, 8 of which are confirmed by developers.

In summary, this paper makes the following contributions:

- An analytical approach to detect specious configuration using symbolic execution and program analysis.
- Design and implementation of an end-to-end toolchain Violet, and scaling it to work on large system software.
- Evaluation of Violet on real-world specious configuration.

The source code of Violet is publicly available at:

https://github.com/OrderLab/violet

2 Background and Motivation

In this Section, we show a few cases of real-world specious configuration from MySQL to motivate the problem and make the discussion concrete. We analyze how specious configuration affects system performance at the *source code* level. We choose MySQL because it is representative as a large system with numerous (more than 300) parameters, many of which can be misconfigured by users and lead to bad performance.

2.1 Definition

A program expects its configuration parameters to obey certain rules, *e.g.*, the path exists, the min heap size does not exceed the max size. Invalid configurations violate those rules and usually trigger assertions or errors.

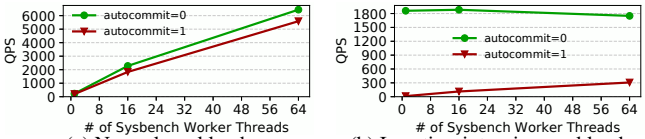
We define specious configuration to be settings that are valid but cause the software to experience bad performance when deployed to production. Admittedly, bad performance is a qualitative criterion. Like prior work, we focus on those issues that cause severe degradation and hurt usability. Ultimately, only users can judge whether the performance slowdown is sub-optimal but tolerable or it is intolerable.

Specious configuration has two classes. One is purely about performance, *e.g.*, buffer size, number of threads. Another class is settings that change the software functionality but the changes also have performance impact. Both classes are important and occur in real-world systems. For the latter class, users might want the enabled functionality and are willing to pay for the performance cost. Thus, whether the setting is specious or not depends on users' preferences. Our solution addresses both forms. Its focus is to analyze and explain the quantitative performance impact of different settings, so that users can make better functionality-performance trade-offs.

2.2 Case Studies

`autocommit` parameter controls the transaction commit behavior in MySQL. If `autocommit` is enabled, each SQL statement forms a single transaction, so MySQL will automatically perform a commit. If `autocommit` is disabled, transactions need to be explicitly committed with `COMMIT` statements. While `autocommit` offers convenience (no explicit commit required) and durability benefits, it also has a performance penalty since every single query will be run in a transaction. For some users, this performance implication may not be immediately apparent (especially since it is enabled by default). Even if users are aware of the performance trade-off, they might not know the degree of performance loss, only to realize the degradation is too much after deploying it to production. Indeed, there have been user-reported issues due to this setting [13, 15, 60], and the recommended fix is to disable `autocommit`, and manually batch and commit multiple queries in one transaction.

To quantify the performance impact, we use sysbench [16] to measure MySQL throughput with `autocommit` configura-



(a) Normal workload. (b) Insertion-intensive workload.

Figure 2: MySQL throughput for `autocommit` under two workloads.

```
1  int write_row() {
2   if (autocommit) {
3     ...
4     trx_commit_complete();
5   } else {
6     trx_mark_sql_stat_end();
7   }
8  }
9
10
```

```
ulint trx_commit_complete() {
  if (flush_at_trx_commit==1) {
    log_group_write_buf();
    fil_flush();  costly operation
  } else if (flush_at_trx_commit==2) {
    log_group_write_buf();
  } else {
    /* do nothing */
  }
}
```

Figure 3: Simplified code snippet from MySQL related to `autocommit`. The elements with orange-colored background represent configuration variables, and the pink ones represent slow operations.

tion set to be `ON` and `OFF`. The size of the database is 10 tables and 10K records per table. We run both a normal workload that consists of 70% read, 20% write and 10% other operations, and an insert-intensive workload. Figure 2 shows the result. We can see that in the normal workload (Figure 2a), the performance difference between `ON` and `OFF` are small. But in insertion-intensive workload (Figure 2b), enabling `autocommit` causes dramatically worse (6×) performance.

Figure 3 shows the code relevant to `autocommit`. We can see that the `autocommit` setting determines whether function `trx_commit_complete()` will be invoked. In this function, another parameter `flush_at_trx_commit`[1] further determines which path gets executed. When that parameter is set to 1, compared to 2, an additional `fil_flush` operation will be incurred, which has a complex logic but essentially will flush the table writes cached by the OS to disk through the `fsync` system call. The cost of `fsync` is the major contributor to the bad performance of `autocommit` mode; if `flush_at_trx_commit` is 2 or 0, the performance impact of `autocommit` mode will be much smaller. In addition, the function in which `autocommit` is used—`write_row()`—is called when handling `write` type queries but not `select` type queries. Therefore, the performance hit only affects insertion/update-intensive workloads.

`query_cache_wlock_invalidate` controls the validation of the query cache in MySQL. Normally, when one client acquires a `WRITE` lock on a MyISAM table, other clients are *not* blocked from issuing statements that read from the table if the query results are present in the query cache. The effect of setting this parameter to 1 is that upon acquisition of a `WRITE` lock for a table, MySQL invalidates the query cache that refers to the locked table, which has a performance implication.

As Figure 4 shows, enabling this parameter leads to the `free_query` operation (❶). Different from the `autocommit` case, this operation itself is not costly. But for other clients that attempt to access the table, they cannot use the associated

[1]Its full name in MySQL is `innodb_flush_log_at_trx_commit`. We abbreviate it and some other parameter names in this paper for readability.

```
void mysql_parse(THD *thd) {
  if (send_result_to_client(thd) <= 0) {
    mysql_execute_command(thd);  ❷
  }
}
int mysql_execute_command(THD *thd) {
  case SQLCOM_SELECT:
❸   open_and_lock_tables(thd, all_tables);
    break;
  case SQLCOM_LOCK_TABLES:
    lock_tables_open_and_lock_tables(thd);
    if (query_cache_wlock_invalidate)  ❶
      invalidate_query_block_list();
}
void invalidate_query_block_list() {
  free_query(list_root->block());
}
```

incoming queries not in query cache

free query cache

Figure 4: Code affected by `query_cache_wlock_invalidate`.

```
uint64_t log_reserve_and_open(uint len) {
  if (len >= log->buf_size / 2) {
    log_buffer_extend((len + 1) * 2);
  }
  len_upper_limit = LOG_BUF_WRITE_MARGIN + (5 * len) / 4;
  if (log->buf_free + len_upper_limit > log->buf_size) {
    mutex_exit(&(log->mutex));
    log_buffer_flush_to_disk();
    goto loop;
  }
}
```

Figure 5: Code affected by `innodb_log_buffer_size`.

query cache (❷), forcing them to open the table and wait (❸) while the write lock is held. Therefore, the effect is additional synchronization that decreases the system concurrency, which in turn can severely hurt the overall system query throughput.

Similar to `autocommit`, the performance effect depends on the parameters, execution environment and workloads. Specifically, the bad performance is only manifestable with the combination of MyISAM tables, `LOCK TABLES` statements and other clients doing `select` type queries on the locked table.

`innodb_log_buffer_size` determines the size of the buffer for uncommitted transactions. The default value (8M) is usually fine. However if MySQL has transactions with large blob/text fields, the buffer can fill up very quickly and incur performance hit. As shown in Figure 5, the parameter setting has two possible performance impacts: (1) if the length of a new log is larger than half of the `buf_size`, the system will extend the buffer first by calling `log_buffer_extend`, which in normal cases mainly involves memory allocation. But if other threads are also extending the buffer, additional synchronization overhead is incurred. If the buffer has pending writes, they will be flushed to disk first; (2) if the `buf_size` is smaller than the free size plus the length of new log, MySQL will trigger a costly synchronous buffer flush operation.

2.3 Code Patterns

Based on the above and other cases we analyze, we summarize four common patterns on how a specious configuration affects the performance of a system at the source code level:

1. The parameter causes some expensive operation like the `fsync` system call to be executed.
2. The parameter incurs additional synchronization that itself is not expensive but decreases system concurrency.

3. The parameter directs the execution flow towards a slow path, *e.g.*, not using cached result.
4. The parameter triggers frequent crossings of some threshold that leads to costly operations.

The general characteristic among them is that specious configuration controls a system's execution flows—different values cause the program or its libraries to execute different code paths. However, the performance impact is also *context-dependent*—a specious configuration is bad only when its value and other relevant factors together direct the system to execute a path that is significantly slower than others.

2.4 Approaches to Detect Specious Config

To detect specious configuration, operators rely on experience or manuals, which are neither reliable nor comprehensive. A more rigorous practice is to test the system together with configuration and quantitatively measure the end-to-end performance like throughput. However, if the testing does not have appropriate input or related parameters, the performance issue will not be discovered. Also, because the testing is carried out in a black-box fashion, the approach is *experimental*. The results are tied to the testing environment, which may not have the same hardware, dependencies or scale as the production. For example, in the incident described in Section 1, that specious configuration was tested, and the result showed a slight increase of logging traffic to a dependent database. But this increase was deemed small, so it passed the testing.

We argue that while the experimental approach is indispensable, it alone is insufficient to catch specious configuration. We advocate developing *analytical* approaches for *reasoning* about configurations' performance effect from the system code. The outcome from an analytical approach includes not only a conclusion, but also answers to questions "how the parameter affects what operations get executed?", "what kind of input will perform poorly/fine?", "does the effect depend on other parameters?", *etc.* In addition, the analysis should enable *extrapolation* to different contexts, so users can project the outcome with respect to specific workload or environment.

A potential approach is static analysis. Indeed, we can leverage the code patterns in Section 2.3 to detect potential specious configuration. However, mapping them at concrete code construct level requires substantial domain knowledge. Also, the performance effect involves many complex factors that are difficult to be deduced by pure static analysis.

The observations in Section 2.3 lead us to realize that the crux is some slow path being conditionally executed. Thus, we can transform the problem of detecting specious configuration to the problem of finding slow execution flow plus deducing the triggering conditions of the slow execution.

3 Overview of Violet

We propose an analytical approach for detecting specious configuration, and design a tool called VIOLET. Violet aims to comprehensively reason about the performance effect of system configurations: (1) explore the system without being limited by particular input; (2) analyze the performance effect without being too tied to the execution environment.

Our insight is that the subtle performance effect of a specious parameter is usually reflected in different *code paths* getting executed, depending on *conditions* involving the parameter, input and other parameters, and these paths have significant *relative* performance differences. Based on this insight, Violet uses symbolic execution with assistance of static analysis to thoroughly explore the influence of configuration parameters on program execution paths, identify the conditions leading to each execution, and compare the performance costs along different paths. After these analyses, Violet derives a configuration performance impact model that describes the relationship between the performance effect and related conditions. In this Section, we give an overview of Violet (Figure 6). We describe the design of Violet in Section 4.

3.1 Symbolic Execution to Analyze Performance Effect of Configurations

Background. Symbolic execution [24, 38] is a popular technique that systematically explores a program. Different from testing that exercises a single path of the program with concrete input, symbolic execution explores multiple paths of the program with symbolic input and memorizes the *path constraints* during its exploration. When a path of interest (e.g., with `abort()`) is encountered, the execution engine generates an input that satisfies the constraint, which can be used as a test case. Compared to random testing, symbolic execution systematically explores possible program paths while avoiding redundancy. Consider this snippet:

```
void foo(int n) { if (n > 1000) bar(n); else bazz(n); }
```

Testing may blindly test the program many times with different `n`, e.g., 1, 10, 20, etc., but they all exercise the same path without triggering the call to `bar()`. If we use symbolic execution, we can explore the two paths of `foo` by deriving only two concrete values of `n` to satisfy the path constraints.

Basic Idea. Configuration is essentially one type of input to a program. The basic idea of Violet is simple—make the parameters symbolic, measure the cost along each execution path explored, and comparatively analyze the costs. The path constraints that the symbolic execution engine memorizes characterize the conditions about whether and when a parameter setting is potentially poor. Take Figure 3 as an example. Violet makes variable `autocommit` symbolic. Function `write_row` will fork at line 2. The first path goes into the `if` branch, with a constraint `autocommit == 1`. When `trx_commit_complete` is called in the first path, it encounters another parameter `flush_at_trx_commit`, which is also made symbolic. Two additional paths are forked within that function. While exploring these paths, Violet records a set of performance cost metrics.

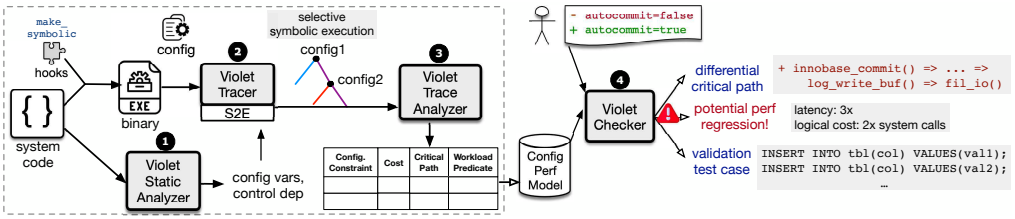


Figure 6: Overview of Violet.

Since the subtle performance effect of specious configuration is often only triggered under specific input, besides configuration parameters, Violet can also make the input symbolic. For the example in Figure 3, the input will determine whether the `write_row` function will be called or not. Only `insert` type queries will invoke `write_row`. This input constraint will be recorded so the analysis later can identify what *class* of input can trigger the specious configuration.

3.2 Violet Workflow

Figure 6 shows the workflow of Violet. The input to Violet is system code and target configuration. We require source code to identify the program variables corresponding to parameters. In addition, as we discuss later (Section 4.3), Violet uses static analysis to assist the discovery of dependent parameters. To symbolically execute the target system, we leverage a state-of-the-art symbolic execution platform S^2E [26] and insert hooks into the system code to make parameters and input symbolic. We design the Violet execution tracer as S^2E plugins to record the performance results to a trace during state exploration. The Violet trace analyzer conducts comparative cost analysis, differential critical path analysis, *etc.* The output is a configuration performance impact model that describes the relationship among configuration constraints, cost, critical path, and input predicate.

Violet further provides a checker to deploy with the software at user sites. The checker consumes the constructed configuration impact model to continuously detect whether a user-site configuration file or update can potentially lead to poor performance. Upon the detection of potential specious configuration, the Violet checker reports not only the absolute performance result, but also the logical cost and critical path to explain the danger. The checker also outputs a validation test case based on the input predict that provides hints to users about what input can expose the potential performance issue.

4 The Design of Violet

In this Section, we describe the Violet design (Figure 6). We need to address several design challenges. First, configurations have intricate dependencies among themselves and with the input, but making all of them symbolic easily leads to state space explosion. Second, conducting performance analysis in symbolic execution is demanding due to lack of explicit assertion point, mixed costs, overhead, etc. Third, deriving performance model from code requires balance between being generalizable (not too tailored to specific input or environment) and being realistic (reflects costs in real executions).

4.1 Make Config Variable Symbolic

The starting point for Violet is to make parameters symbolic. A naïve way is to make the entire configuration file a symbolic blob. While this approach is transparent to the target program, it easily leads to path explosion even at the program initialization stage. An improvement could be only making the configuration value string symbolic during parsing. e.g., `make_symbolic(value, 2); buf_size=atoi(value);` But the execution would still spend significant time in the parsing (`atoi`). Also the parameter value range will be limited by the string size, e.g., only explore `buf_size` from 0 to 99.

We should identify the program variables that store configuration parameters and directly make these variables symbolic. Prior works [56,57] observe that the mature software typically uses uniform interfaces such as an array of `struct` to store parameters. Thus they annotate these interfaces to extract variable mappings in static analysis. For Violet, we need to additionally identify the parameter type and value constraints defined by the program (e.g., 1 to 10) to restrict the symbolic value. This is because we are only interested in exploring the performance effect of *valid* values.

Since typically all the config variables are readily accessible after some point during initialization, we take a simple but accurate approach: insert a hook function directly in the source code right after the parsing function and programmatically enumerates these variables and make them symbolic using their type and other info. In this hook function, we read an external environment variable `VIO_SYM_CONFIGS` to decide which target parameter(s) to make symbolic.

Take MySQL as an example. Its configuration parameters are represented by a number of `Sys_var_*` data structures in the code, depending on the parameter's type. We add a `make_symbolic` API to these data structures, which uses the type, name, value range information to call the Violet library to make the backing store symbolic. Figure 7 shows an example of the added hook API. Then after MySQL finishes parsing its configurations, we iterate through all configuration variables (Figure 8), which are stored in a global linked list called `all_sys_vars`. If the parameter is in the target set, we invoke its new `make_symbolic` API.

```
template <typename T>
class Sys_var_unsigned: public sys_var {
public:
  Sys_var_unsigned(const char *name, T min_val, T max_val, ...) {
    option.min_value= min_val;
    option.max_value= max_val;
    ...
  }
  bool global_update(THD *thd, set_var *var) {
    global_var(T)= var->save_result.ulonglong_value;
    return false;
  }
  ...
+ bool make_symbolic() {
+   violet_make_symbolic(global_var_ptr(), sizeof(T), option.name);
+   violet_assume((unsigned)(*global_var_ptr()) <= option.max_value);
+   violet_assume((unsigned)(*global_var_ptr()) >= option.min_value);
+   return true;
+ }
}
```

Figure 7: Add API to one config. data structure in MySQL.

```
static int get_options(int *argc_ptr, char ***argv_ptr)
{
  my_init_dynamic_array(&all_options, sizeof(my_option));
  for (opt= my_long_options; opt < my_options_end; opt++) {
    insert_dynamic(&all_options, (uchar*) opt);
    ...
  }
+ violet_parse_config_targets();
+ violet_make_mysql_options_symbolic();
  return 0;
}

+ void violet_make_mysql_options_symbolic()
+ {
+  for (sys_var *var=all_sys_vars.first; var; var= var->next)
+    if (is_config_in_targets(var->name.str))
+      var->make_symbolic();
+ }
```

Figure 8: Call symbolic hooks after config. parsing in MySQL.

4.2 Make Related Config Symbolic

The performance effect of a parameter usually depends on the values of other parameters. Thus, if we only make one parameter symbolic while leaving other parameters concrete, we will only explore incomplete execution paths and potentially miss some problematic combination that leads to bad performance. A straightforward solution is to make all parameters symbolic. Since symbolic execution only forks if a symbolic value is used branch conditions, this approach seems to be feasible. However, the problem with this approach is that most combinations of configuration parameters are unrelated but will be explored during symbolic execution.

Figure 9 illustrates the problem. Suppose we are interested in the performance effect of `opty`. If we simply make all parameters (`optx`, `opty`, `optz`) symbolic in hope of exploring the combination effect, there will be at least 6 execution paths being explored. But `opty` is unrelated to `optx` and `optz`. The performance impact of `opty` is only determined by the cost of its branches. For large programs, the target parameter could be used deep in the code. Including unrelated parameters in the symbolic set can cause the symbolic execution to waste significant time or get stuck before reaching the interesting code place to explore the target parameter. The analysis result can also cause confusions. For example, it might suggest only when `optx>100 && optz==FILE && opty` is true will there be a performance issue and miss detecting specious configuration when `opty` is true but `optx <= 100` or `optz != FILE`.

Therefore, instead of making all parameters symbolic, we carefully choose the set of parameters to symbolically execute

```
void main() {
  if (optx > 100)
    init_x();
  ...
  if (opty)
    task1();
  else
    task2();
}
void init_x() {
  if (optz == FILE)
    create_file();
}
```

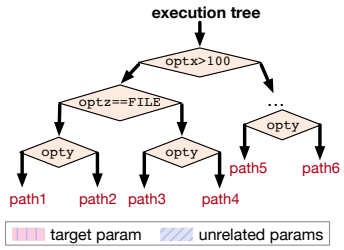


Figure 9: Making unrelated parameters symbolic results in excessive state explorations and confusing conclusions.

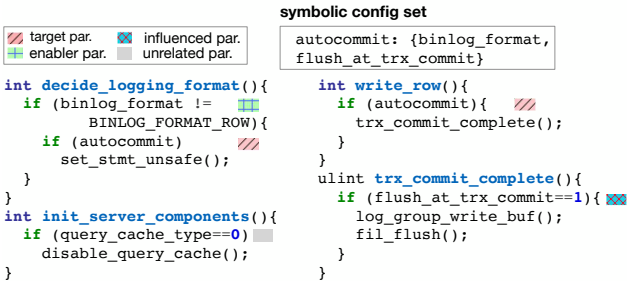


Figure 10: Symbolic config set based on control dependencies.

together. In particular, related parameters are usually control dependent on each other. We discover the parameter control dependency with methods described in the following Section.

4.3 Discover Control Dependent Configs

Violet statically analyzes the control dependency relationship of parameters to determine a reduced symbolic *parameter set*. The static analysis result can significantly help mitigate the path exploration problem during symbolic execution phase.

For a target parameter C, Violet identifies two kinds of related parameters to put in its symbolic set. The *enabler parameters* are those that C is control dependent on. The *influenced parameters* are those that are control dependent on C. Figure 10 shows an example. For target parameter `autocommit`, it is used in `decide_logging_format` and `write_row`, it has an enabler parameter `binlog_format`, which decides if `autocommit` will be activated. `autocommit` itself influences the performance effect of parameter `flush_at_trx_commit`. Thus, for `autocommit`, the set of related parameters to make symbolic together is {`binlog_format`, `flush_at_trx_commit`}.

Informally, program element Y is control dependent on element X if whether Y's executed depends on a test at X. More formally, control dependency is captured by postdominator relationship in program Control Flow Graph (CFG). Node b in the CFG postdominates node a if every path from a to the exit node contains b. Y is control dependent on X if there is a path $X \rightarrow Z_1 \rightarrow \ldots \rightarrow Z_n \rightarrow Y$ such that Y postdominates all Z_i and Y does *not* postdominate X. We use postdominator as a building block for our analysis. But our notion of control dependency is broader than the classic definition. For example, `if (X) { if (Z1) { if (Z2) { if (Y) { foo(); } } } }` , the classic definition does *not* regard `X` and `Y` as being control-dependent, because `Y` does *not* postdominate `Z1` or `Z2`;

it regards `Z2` and `Y` as being control-dependent. But for us, all the four parameters are control dependent.

Our analysis is divided into two steps. The first step computes the enabler parameters. Violet builds a call graph of the program. For target parameter p, it locates the usage points of p and extracts the call chains starting from the entry function to the function f that encloses a usage point. If any caller g in the call chain uses some other parameter q, we check if the callsite in g that eventually reaches f is control dependent on the usage point of parameter q in g. If so, q is added to the enabler parameter set of p. Violet identifies enabler parameters within f through intra-procedural control dependency. Our technical report [34] lists the algorithm.

In the second step, Violet calculates the influenced parameters from the computed enabler parameter sets of all parameters. The related config set is a union of the influenced set and enabler set. We also capture control dependency that involves simple data flow. For example,

```
void query_cache_init() {
  if (query_cache_type == 0)
    m_cache_is_disabled = TRUE;
}

bool is_disabled() {
  return m_cache_is_disabled;
}
```

any parameter that is control dependent on the regular variable `m_cache_is_disabled` or return value of `is_disabled()` is also considered to be related to parameter `query_cache_type`.

The static analysis result can be inaccurate due to imprecision in the alias analysis, call graph, infeasible path problem, *etc.* Our general principle is to be conservative and over-approximate the set of related parameters for a target parameter. During symbolic execution, having a few false control dependent parameters does not greatly affect the performance or analysis conclusion and they can manifest through the symbolic execution log if they do cause issues.

4.4 Execute Software Symbolically

After the target software is instrumented with the symbolic execution hooks, Violet symbolically executes the software with a concrete configuration file. The hook function reads the `VIO_SYM_CONFIGS` environment variable and makes symbolic the program variables corresponding to the specified parameter. In addition, the function parses the control dependency analysis (Section 4.3) result file and makes variables in the related parameter set symbolic as well. Other parameters' program variables get the concrete values from the configuration file. Besides parameters, Violet can also make program input symbolic to explore its influence on the configuration's performance impact. This is done through either symbolic arguments (`sym-args`) or identifying the input program variables and inserting `make_symbolic` calls in the code.

4.5 Profile Execution Paths

To measure the symbolic parameters' performance effect, Violet implements a tracer on top of the symbolic execution engine, specifically as a set of plugins on the S^{2}E platform.

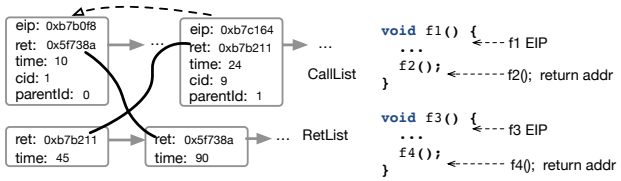


Figure 11: Match call/return records.

Measure Function Call Latency. We measure function call latency by capturing the call and return signals emitted by S^{2}E during symbolic execution. To calculate the latency, a straightforward way is to maintain a stack of call record and pops the top element upon receiving a return signal. This algorithm assumes that the call/return signals are paired and the callee's return signal comes before the caller's. But we observe this assumption does not always hold under S^{2}E. We use a safer method based on return addresses to calculate latency. In particular, the Violet tracer records the `EIP` register value, return address, and timestamp on each call and return signal. The records are stored in two lists. Later, the tracer matches call record list with return record list based on return address fields (Figure 11). The latency for a matched function call is the return record's timestamp minus the call record's timestamp. The total latency of each state (execution path) can be obtained from the latency of the root function call.

For multi-threaded programs, function calls from different threads can get mixed up. To address this issue, the Violet tracer stores the current thread id in each profile record and partitions the call and return lists by thread id.

Re-Construct Call Paths. The tracer records the function call profile to break down total latency and to enable differential critical path analysis (§4.6). To get the call chain relationship, instead of costly stack frame walk, the tracer uses a simple method with little overhead that just assigns each call record a unique incrementing `cid`. Later, the tracer reconstructs the call chain by iterating through all call records in order. If (1) call record A's `cid` is larger than call record B's `cid`, (2) the return address of A is larger than B's `EIP` (the start address of that function), and (3) the difference of the two addresses is smallest among all other pairs (i.e., B's start address is closest to the return address in A), then we assign A's `parentId` to be B's `cid` and update the current distance.

Measure Logical Costs. Besides absolute latency, we also measure a set of logical cost metrics by a similar method of capturing low-level signals from S^{2}E. In particular, for each execution path, we measure the number of instructions, the number of system calls, the number of file I/O calls, the amount of I/O traffic, the number of synchronization operations, network calls, etc. These logical costs are useful to surface performance issues other than just long latency. They are also crucial for reducing the test environment's biases and enabling extrapolation of the result to different settings. For example, if the tracer finds one execution path has a much higher number of `write` syscalls compared to other paths whereas

Configuration Constraint	Cost	Workload Predicate
`autocommit!=0 && flush_log_at_trx_commit==1`	2.6 s, {`log_write_buf→fil_flush`}, 17K syscalls, 100 I/O insts, ...	`sql_command==INSERT`
`autocommit!=0 && flush_log_at_trx_commit==2`	1.7 s, {`log_write_buf`}, 16.9K syscalls	`sql_command==INSERT`
`autocommit!=0 && flush_log_at_trx_commit!=1 && flush_log_at_trx_commit!=2`	1.2 s, {}, 16.9K syscall	`sql_command==INSERT`
`autocommit==0`	0.6 s, {`trx_mark_sql_stat_end`}, 16.8K syscalls	`sql_command==SELECT||...`

Table 1: Example raw cost table Violet generates for `autocommit` parameter from symbolic execution of MySQL code in Figure 3.

their latencies are similar. This could be an artifact of the test server having a powerful hard disk or a large buffer cache. But the software might perform poorly in a different environment. The Violet tracer maintains a separate performance profile for each execution path (state) so we can compare the performance effect of different paths. We also need to record the path constraints to identify the parameter combination and the *class* of input that leads to the execution path. The tracer records the final path constraint when an execution path terminates or it exceeds some user-specified cost threshold.

4.6 Analyze State Traces

Once the symbolic execution finishes, the Violet trace analyzer parses the performance traces. It then builds a cost table. Each row represents a state (path) that was explored in symbolic execution. The analyzer does a pair-wise comparison of performance in different rows. If the performance difference ratio exceeds a threshold (default 100%), the analyzer marks that state suspicious. The analyzer compares not only the absolute latency metric but also the collected logical metrics. Even if the latency difference does not exceed the threshold but some logical metric does, the analyzer still marks the state.

Not all pair comparisons are equally meaningful when the symbolic execution explored multiple symbolic variables. To elaborate, assume our target parameter is `autocommit`, which has a related parameter `flush_log`. Since both are made symbolic, one state could represent constraint `autocommit==0 && flush_log==1` and another state could represent constraint `autocommit==1 && flush_log==2`. In this case, comparing the costs of these two states is not very meaningful.

The analyzer tries to compare state pairs that are most "similar" first. Determining the similarity of two paths can be challenging. We use a simple approach: in one state's constraints formula, for each constraint involving a related parameter, if it also appears in the other state's formula, the similarity count is incremented by one. This method is imprecise as it merely checks the appearances, not constraint equivalence. For our use cases, the inaccuracies are generally acceptable. Besides, the analyzer can compare all pairs first, surface the bad state-pairs, and then we can decide the meaningfulness of the suspicious pairs.

For each pair that has a significant performance difference, the analyzer computes the *differential* critical path. It first finds the longest common subsequence of the call chain records in the two states. Then it creates a diff trace that stores the common records with performance metrics subtracted, as well as the records that only appear in the slower state. The analyzer finally locates the call record (excluding entry) with the largest differential cost and constructs the critical call path based on the `cid` and `parentId` of the call records.

When Violet makes the input symbolic, the path constraints in each state will contain constraints about the input. The analyzer separates the input related constraints as input predicate. This is useful to tell what *class* of input can expose the potential performance issue for the combination of parameter values that satisfies the configuration constraint in a state. The final output from the Violet analyzer is the configuration performance impact model that consists of the raw cost table (Table 1) with configuration constraints, cost metrics, and input predicate for each state, the state pairs that have significant performance difference, and the differential critical paths.

4.7 Continuous Specious Config Checker

Violet provides a standalone checker tool to detect specious configuration. It leverages the configuration performance impact model from the analyzer and validates a concrete user configuration file. The checker tool supports three modes:

1. Some config update introduces performance regression.
2. Some default parameter is poor for users' specific setup.
3. Code upgrade or workload change make old setting poor.

For scenario 1, the checker references the cost table and locates the state(s) that have configuration constraints satisfying the updated parameter' old value and the parameter's new value. If the state pair has significant performance difference, the checker alerts the operators and generates a test case based on the input predicate for operators to confirm the performance regression. For scenario 2, the checker validates if the state that the default value lies in appears in some poor state-pair. If so, it means this default value potentially performs significantly worse than another value. For scenario 3, if the system code changes, Violet rebuilds the cost impact table. The checker then identifies if some state in the new table performs much worse compared to the old cost table. If workload changes, the checker validates if cost table rows that previously satisfy the input predicate perform worse compared to rows that satisfy the input predicate now.

5 Scaling Violet to Large Software

In this section, we describe the challenges and our solutions for scaling Violet to large software.

5.1 Choice of Symbolic Execution Engine

We initially build Violet on the KLEE [24] symbolic execution engine because it is widely used and convenient to exper-

iment with. However, while KLEE works well on moderate-sized programs, it cannot handle large programs like MySQL. KLEE models the environment (POSIX runtime and libc) with simplified implementation. Large programs use many libc or system calls that are unimplemented or implemented partially/incorrectly, e.g., `fcntl`, `pread`, and socket. KLEE also does not support symbolic execution of multi-threaded programs. We spent several months patching KLEE to fix the environment model and add multi-threading support. When we were finally able to run MySQL with KLEE, it took 40 minutes to just pass initialization even without symbolic data.

We thus decided to switch to the S^{2}E platform [26]. S^{2}E uses real environment with complete OS and libraries. Executing large software would encounter almost no compatibility issues. In addition, S^{2}E uses QEMU and dynamic binary translation to execute a target program. For instructions that access symbolic data, they are interpreted by the embedded KLEE engine; but instructions that access concrete data are directly executed on host CPU. Overall, while the choice of using real environment in symbolic execution in general means slower analysis compared to using simplified models like KLEE, executing concrete instructions on host CPU offsets that slowness and allows S^{2}E to achieve significant speed-up. After migrating Violet to S^{2}E and with some minor adjustments, we can start MySQL server within one minute.

5.2 Handle Complex Input Structure

Since specious configuration is often only triggered by certain input, Violet makes input symbolic besides configuration. For small programs, the input type is typically simple, *e.g.*, an integer, a string, which is easy to be made symbolic. However, large programs' input can have very complex structure. If we make such complex input symbolic, the program may be stuck in the input parsing code for a long time and the majority of the input generated is invalid. For example, we make input variable `char *packet` (32 bytes) in MySQL symbolic and execute it in S^{2}E for 1 hour, which generates several hundred test cases, but none of which is a legal SQL query. Even after adding some additional constraints, the result is similar.

This challenge is not unique to our problem domain. Compiler testing [58] or fuzzing [11] also faces this challenge of how to generate valid input to programs like C compiler or DBMS. We address this problem through a similar practice by introducing workload templates. Instead of having the parser figure out a valid structure, we pre-define a set of input templates that have valid structures. Then we parameterize the templates so that they are not fixed, *e.g.*, the query type, insertion value, the number of queries, etc. In this way, we can make the workload template parameters symbolic.

5.3 Reduce Profiling Overhead

Profiling large programs can incur substantial overhead. We build Violet tracer using low-level signals emitted by S^{2}E rather than intrusive instrumentation. Nevertheless, symbolic execution is demanding for performance analysis as the program runs much slower compared to native execution. Fortunately, Violet cares about the relative performance between different paths. We can still identify specious configuration if the relative differences roughly match the native execution, which we find is true for most cases. Violet conducts differential analyses to capture performance anomalies. We describe three additional optimizations in Violet tracer.

First, the Violet tracer controls the start and end of its function profiler. This is because if we enable the function profiler at the very beginning, it can be overwhelmed by lots of irrelevant function calls. We add APIs in the tracer and will start the tracer when the target system finishes initialization and stop the tracer when the system enters the shutdown phase.

Second, the tracer avoids guest memory accesses and on-the-fly calculation. Accessing memory in an execution state goes through the emulated MMU in QEMU. Violet tracer only accesses and stores key information (most from registers) about the call/return signals. It defers the record matching, call chain and latency calculation to path termination.

Third, Violet will disable state switching during latency tracking if necessary. Since the function profiler calculates the execution time by subtracting the return signal timestamp from call signal timestamp, if S^{2}E switches to execute another state in between, the recorded latency will include the state switching cost. This in general does not cause serious problems because the costs occur in all states and roughly cancels out with our differential analysis. But in rare cases, the switching costs can distort the results. When this happens, Violet will force S^{2}E to disable state switching.

5.4 Path Explosion and Complex Constraints

A common problem with symbolic execution is path explosion, especially when the symbolic value is used in library or system calls. In addition, some library calls with symbolic data yield complex constraints that make the symbolic execution engine spend a long time in solving the constraints.

Violet leverages a core feature in S^{2}E, *selective symbolic execution* [26], to address this problem. Selective symbolic execution allows transition between concrete and symbolic execution when crossing some execution boundary, *e.g.*, a system call. Violet uses the Strictly-Consistent Unit-Level Execution consistency model, which silently concretizes the symbolic value before entering the boundary and adds the concretized constraint to the symbolic value after exiting the boundary. This consistency model sacrifices completeness but it would not invalidate the analysis result. To improve completeness, we add some relaxation rules in Violet without causing functionality errors: 1) if the library call does not add side effect, such as `strlen`/`strcmp`, we make the return value symbolic and remove the concretized constraint; 2) if the library call has side effect but does not hurt the functionality, such as `printf`, we directly remove the concretized constraint.

Software	Desc.	Arch.	Version	SLOC	Configs	Hook
MySQL	Database	Multi-thd	5.5.59	1.2M	330	197
Postgres	Database	Multi-proc	11.0	843K	294	165
Apache	Web server	Multi-proc-thd	2.4.38	199K	172	158
Squid	Proxy server	Multi-thd	4.1	178K	327	96

Table 2: Evaluated software. Hook: SLOC of core Violet hooks.

One issue we encounter with the S^{2}E silent concretization is that its `concretize` API will only concretize the symbolic variable. The symbolic variable can taint other variables (make them symbolic) when it is assigned to these variables, but these tainted variables are not concretized during silent concretization. Having these tainted variables remain symbolic can add substantial overhead. We thus add a new API in S^{2}E, `concretizeAll`, that concretizes not only the given symbolic variable but also its tainted variables. We implement this API by recording in each write operation a mapping from the symbolic expression to the target address in the memory object. Later when `concretizeAll` is called, we will look up the memory objects to find addresses that contain the same symbolic expression and also concretize them.

6 Implementation

We implement the major Violet components in C/C++. The Violet checker is implemented in Python. The Violet tracer is written as S^{2}E plugins and leverages S^{2}E's existing plugin to capture low-level signals. The Violet static analyzer is built on top of LLVM framework [40]. The Violet trace analyzer is implemented as a standalone tool.

In function profiling, for efficiency, the tracer captures the addresses instead of names of invoked functions. This means the analyzer needs to resolve the addresses to names. The problem is that the virtual address of the target program can change in each run. We address this issue by modifying the ELF loader of the S^{2}E Linux kernel to expose the `load_bias`. Then the tracer will record the offset from the `load_bias`. The analyzer can then use the offsets to resolve the names.

7 Evaluation

We evaluate Violet to answer several key questions:

- How effective is Violet in detecting specious configuration?
- Can Violet expose unknown specious configuration?
- How useful is Violet's checker to the user?
- What is the performance of Violet?

The experiments are conducted on servers with Dual Processor of Intel Xeon E5-2630 (2.20GHz, 10 cores), 64 GB memory, 1 TB HDD running a Ubuntu 16.04. Since S^{2}E engine runs in QEMU, we create a guest image of Debian 9.2.1 x86_64 with 4 GB memory for all the Violet tests.

7.1 Target Systems

We evaluate Violet on four popular and large (up to 1.2M SLOC) open-source software (Table 2): MySQL, PostgreSQL, Apache, and Squid. Violet can successfully analyze large multi-threaded programs (MySQL and Squid) as well as multi-process (PostgreSQL, Apache) programs.

The manual effort to use Violet on a target system is small, mainly required in two steps: (1) add configuration hooks (Section 4.1); (2) supply input templates (Section 5.2). The other steps in the workflow are automated.

Table 2 shows SLOC of the core hooks we add to the four systems. The hook size varies across systems. MySQL hooks are largest in size mainly because the system defines many (22) configuration types (`Sys_var_*`) so we need to add hook (about 7 SLOC) to each type. But the overall effort for different systems is small. The changes are typically contained in a few places with other codes untouched. In addition, most software rarely modifies the configuration data structure design, so the effort can carry through versions.

For (2), users typically already have some workload profiles. The effort needed is to parameterize and organize them into our format. In our experience with the four evaluated software, this process is straightforward and can be done in a few hours.

7.2 Detecting Known Specious Config

To evaluate the effectiveness of Violet we collect 17 *real-world* specious configuration cases from the four systems. Table 3 lists the case descriptions. We collect them from ServerFault [14], dba [4], blog posts [12], and prior work [19]. A case is marked as detected when Violet explores at least one poor state in its trace *and* the poor states enclose the problematic parameter value(s).

In total, Violet detects 15 of the 17 cases. Table 4 shows the detailed result. For each case, Table 4 lists the total states Violet explored, poor states, related configs, and maximum cost metric differences. The explored states include forks from related configurations and the symbolic workload parameters. In most cases, the specious configuration requires specific related settings to expose the issue. The high success rate of Violet comes from its in-vivo multi-path profiling, dependency analysis, and differential performance analysis.

Another aspect to interpret the high success rate is that the 17 cases we collect admittedly have a selection bias—all cases cause severe performance impact. This is reflected in the max diff column. If a misconfiguration only introduces mild performance issue, Violet may miss it due to the noises in symbolic execution. However, Violet's goal is to exactly target specious configuration that has severe performance impact, rather than suboptimal configurations.

Violet misses two Apache cases, c14 and c15. Triggering them requires enabling the HTTP KeepAlive feature in the workload. In our Apache workload templates, this feature is not part of the workload parameters and is disabled by default.

We describe two representative cases. MySQL c1 is the running example in the paper. Violet identifies four related parameters for `autocommit` and explores 88 states in total, 4 of which are identified as poor. The configuration constraints

Id.	Application	Configuration Name	Data Type	Description
c1	MySQL	autocommit	Boolean	Determine whether all changes take effect immediately
c2	MySQL	query_cache_wlock_invalidate	Boolean	Disable the query cache when after WRITE lock statement
c3	MySQL	general_log	Boolean	Enable MySQL general log query
c4	MySQL	query_cache_type	Enumeration	Method used for controlling the query cache type
c5	MySQL	sync_binlog	Integer	Controls how often the MySQL server synchronizes binary log to disk
c6	MySQL	innodb_log_buffer_size	Integer	Set the size of the buffer for transactions that have not been committed yet
c7	PostgreSQL	wal_sync_method	Enumeration	Method used for forcing WAL updates out to disk
c8	PostgreSQL	archive_mode	Enumeration	Force the server to swtich to a new WAL periodically and archive old WAL segments
c9	PostgreSQL	max_wal_size	Integer	Maximum number of log file segments between automatic WAL checkpoints
c10	PostgreSQL	checkpoint_completion_target	Float	Set a fraction of total time between checkpoints interval
c11	PostgreSQL	bgwriter_lru_multiplier	Float	Set estimate of the number of buffers for the next background writing
c12	Apache	HostNamelookup	Enumeration	Enables DNS lookups to log the host names of clients sending requests
c13	Apache	Deny/Domain	Enum/String	Restrict access to the server based on hostname, IP address, or env variables
c14	Apache	MaxKeepAliveRequests	Integer	Limits the number of requests allowed per connection
c15	Apache	KeepAliveTimeOut	Integer	Seconds Apache will wait for a subsequent request before closing the connection
c16	Squid	cache	String	Requests denied by this directive will not be stored in the cache
c17	Squid	Buffered_logs	Integer	Whether to write access_log records ASAP or accumulate them in larger chunks

Table 3: Description of 17 known specious configuration cases we collect in the four evaluated software.

Id.	Detect	Explored States	Poor States	Related Configs	Cost Metrics	Analysis Time	Max Diff*
c1	✓	88	17	4	Latency	6 m25 s	14.5×
c2	✓	24	3	1	Lat.&Sync.	3 m13 s	15.7×
c3	✓	224	88	5	I/O	19 m41 s	2.0×
c4	✓	787	100	2	Latency	53 m50 s	11.7×
c5	✓	494	44	3	Latency	17 m56 s	29.9×
c6	✓	891	12	5	I/O	112 m24 s	3.0×
c7	✓	89	7	2	Lat.&I/O	4 m6 s	4.3×
c8	✓	195	8	3	Latency	13 m8 s	1.8×
c9	✓	110	2	3	Lat.&I/O	15 m20 s	3.5×
c10	✓	231	13	7	Latency	23 m30 s	2.4×
c11	✓	61	9	2	Latency	13 m17 s	8.6×
c12	✓	34	4	2	Latency	7 m15 s	3.8×
c13	✓	50	5	3	Latency	6 m10 s	8.9×
c14	✗	112	0	2	Latency	3 m42 s	0.6×
c15	✗	23	0	3	Latency	6 m12 s	0.2×
c16	✓	81	1	0	Latency	433 m32 s	4.3×
c17	✓	3	1	0	I/O	1 m32 s	2.0×

Table 4: Violet detection result. Poor states are what Violet considers as suspicious. *: relative difference, $\alpha\times$ means $B = (1+\alpha) * A$.

of the four poor states describe the combination conditions for the 5 parameters to incur significant cost.

In c6, innodb_log_buffer_size controls the size of the log buffer. Interestingly, in this case, Violet determines the latency metric difference is not significant, but the I/O logical cost metric is. Specifically, Violet explores almost 100 different queries, and finds that in states with queries involving large row changes and a relatively small buffer size, the I/O metric—pwrite operations—is much larger than other states.

7.3 Comparison with Testing

We evaluate the 17 cases with testing as well. We use popular benchmark tools sysbench and ab. For each case, we set the target parameter and related parameters with concrete values from one of the poor states discovered. We enumerate the standard workloads in the benchmark to test the software with the configurations. Since the absolute performance result are difficult to judge, we use configurations from the good states and collect performance result with them as a baseline. If the performance difference ratio exceeds 100% (the same threshold used by Violet), we consider the case detected. In total, testing detects 10 cases, with a median time of 25 minutes.

Violet is not meant to replace configuration performance testing. In theory, exhaustive testing can expose all cases, but the cost of it is not affordable in practice. Violet systematically explores program states while avoids the redundancy in exhaustive testing (Section 3.1). Even though in some cases, as shown in Table 4, the Violet analysis time is relatively long, Violet is exploring the performance effects thoroughly, including the combination effect with other parameters and input. Therefore, the performance impact models Violet derives are complete. Once the exploration is done, the outcome can be reused many times while testing needs to be done repeatedly.

Another challenge with testing is to find the baseline for good performance. Our experiment above assumes the existence of good configuration, which users may not have. Violet, in comparison, conducts in-vivo, multi-path analysis, so it naturally has baselines to compare with. The analysis enables Violet to collect deeper logical metrics, which can reveal performance issues that end-to-end metrics may not find.

7.4 Exposing Unknown Specious Config

Besides detecting know specious configuration, we evaluate whether Violet can expose unknown specious configuration. We first apply Violet to derive performance models for all parameters if possible (Section 7.6). We then analyze the results for parameters not in the known case dataset (Section 7.2). We manually check (1) if some parameter's default or suggested value is in a poor state; (2) if a poor state of a parameter contains related parameters that are undocumented. The manual inspection involves checking the Violet output, the descriptions in the official documentation and tuning guide,

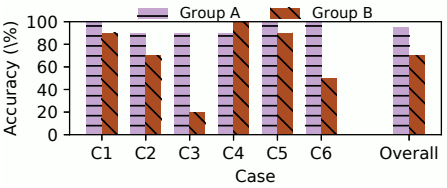


Figure 12: Overall accuracy of judgment in the user study.

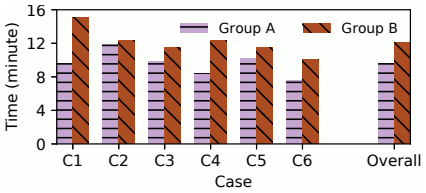


Figure 13: Average decision time in the user study.

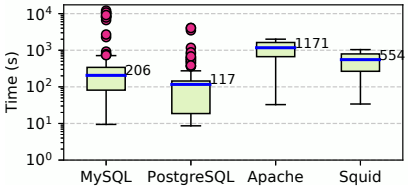


Figure 14: Violet analysis times for the configs in the four software.

Sys	Configuration	Performance Impact
Postgres	`vacuum_cost_delay`	Default value 20 ms is significantly worse than low values for write workload.
Postgres	`archive_timeout`	Small values cause performance penalties.
Postgres	`random_page_cost`	Values larger than 1.2 (default 4.0) cause bad perf on SSD for join queries.
Postgres	`log_statement`	Setting `mod` causes bad perf. for write workload when `synchronous_commit` is `off`.
Postgres	`parallel_setup_cost`	A higher value would avoid unnecessary parallelism when executing join query
Postgres	`parallel_leader_participation`	Enabling it can cause select join query to be slow if `random_page_cost` is high.
MySQL	`optimizer_search_depth`	Default value would cause bad performance for join queries
MySQL	`concurrent_insert`	Enable concurrent_insert would cause bad performance for read workload
Squid	`ipcache_size`	The default value is relatively small and may cause performance reduction
Squid	`cache_log`	Enable cache_log with higher debug_option would cause extra I/O
Squid	`store_objects_per_bucket`	Higher objects per bucket would enlarge the search time

Table 5: Unknown perf. effect of 11 parameters Violet identifies.

and running tests to confirm, which takes significant time. We only carefully inspect a subset of the results.

The four systems are very mature and maintain high-quality documentations, so it is not easy to find many errors in them. Indeed, a significant portion of the poor states we examined turns out to be already documented. Still we have identified 11 parameters that have potential bad performance effect and the documentation is incomplete or incorrect.

Table 5 lists the cases. For example, our analysis of `vacuum_cost_delay` shows that a higher value can incur large cost for write-intensive workloads, but the default value is 20 ms. Interestingly, we find PostgreSQL 12 (our experiments use v11) changes the default to 2 ms. For `log_statement`, Violet discovers multiple poor states that are not mentioned in the official document. Our analysis revels that setting it to `mod` causes performance issues for write query when `synchronous_commit` is `off`. Violet finds some unexpected parameter combination that leads to bad performance, e.g., `parallel_leader_participation` and `random_page_cost`.

We reported our findings to the developers. Eight reports are confirmed. Five lead to documentation or Wiki fixes. For some confirmed cases, developers do not fix them because they assume users should know the performance implications or such performance description should not be put in the reference manual (e.g., *"There are a lot of interactions between settings, and mentioning all of them would be impossible"*).

7.5 User Study on Violet Checker

To understand whether Violet checker helps users catch specious configuration, we conduct a controlled user study with 20 programmers (no authors are included). Fourteen are undergraduate students who have taken the database class. Six are graduate students. They all have decent experience with databases and Unix tools. We further give a tutorial of MySQL and PostgreSQL, the descriptions of the common configuration, and available benchmark tools they can use.

We use 6 target parameters from MySQL and PostgreSQL. For each parameter, we prepare two versions of configuration files. In one version (bad), the parameter is set with the poor value and the related parameters are also set appropriately that would cause bad performance impact under a workload. In another version (good), we set the target parameter to a good value, or we change the related parameter values, or we tell users the production workloads are limited to certain types (e.g., read-intensive). So in total, we have 12 cases.

Each participant is given 6 configuration files. They need to make a judgment regarding whether the configuration file would cause potential performance issue. Since a configuration file contains many parameters, we explicitly tell users the set of parameters they can focus on, which disadvantages Violet because users in practice do not have this luxury.

The participants are randomly assigned into two groups: *group A* (w/ Violet checker help) and *group B* (w/o checker help). Users in group B can run any tools to help them make the decision. We also tell group A users that they do not have to trust the checker output and are free to run other tools.

Figure 12 shows the accuracy of user study result for each group. Overall, programmers w/o Violet checker's help have 30% misjudgment rate while programmers with Violet checker's help only have 5% misjudging rate. Figure 13 shows the time for making a judgment. On average, participants took 20.7% less time (9.6 min. versus 12.1 min.) to make a judgment when they were provided with Violet checker. The reason that time saving is not very large is partly because we explicitly tell users the set of parameters, which creates a biased advantage to group B users; and some of our group A users are extra cautious and spend time running other tools.

7.6 Coverage of Analyzed Configs

We conduct a coverage test of Violet by applying Violet on the four software and try to derive performance models for as many parameters as possible. We manually filter the parame-

MySQL	PostgreSQL	Apache	Squid	Total
169 (51.2%)	210 (71.4%)	51 (29.6%)	176 (53.3%)	606 (53.9%)

Table 6: Number of configs Violet derives performance models for. The number in parentheses is the percentage of total configs.

	parA		parB		parC			parD		
	=0	=1	=0	=1	=0	=1	=2	=0	=1	=2
Violet	12.0	23.0	9.81	10.19	9.05	10.92	10.74	4.68	4.77	5.27
S^{2}E	10.8	21.0	7.67	8.94	6.24	7.77	7.92	3.57	3.91	4.59
Native	0.7	1.2	0.55	0.77	0.45	0.63	0.67	0.07	0.07	0.08

Table 7: Absolute latency (ms) for four parameters' different settings w/ Violet, vanilla S^{2}E and native execution. parA: `autcommit`, parB: `synchronous_commit`, parC: `archive_mode`, parD: `HostNameLookup`.

ters that are not related to performance based on the parameter description (*e.g.*, `listen_addresses`). Table 6 shows the result. Violet successfully derives models for a total of 606 parameters. The average ratio of analyzed parameters over the total number of parameters for software is 53.9%. The average number of states explored in these generated models is 23. Apache and Squid have a relatively small number of parameters analyzed. This is because the configuration program variables in the two systems are set via complex function pointers and spread in different modules, which make it challenging to write hooks to enumerate all of them (Section 4.1). For parameters that Violet did not generate impact models, one reason is that they are used in code for special environment. Another reason is that the data type of some parameter is too complex (*e.g.*, timezone) to make symbolic.

7.7 Accuracy of Violet Profiling

Since symbolic execution can introduce significant overhead, it seems that the latency traced by the symbolic engine will not be accurate. However, we observe that while the absolute latency under symbolic execution is indeed much larger than native execution, the comparative results between different paths are usually similar. We add a micro-benchmark experiment to test the latency measurement from Violet, vanilla S^{2}E and native mode. Table 7 shows the result from four representative parameters. Take parA as an example. The latency results from Violet and S^{2}E are much later than native result. But the ration of setting 1 to setting 0 is similar: 1.92× for Violet, 1.94× for S^{2}E, and 1.71× for native execution.

7.8 False Positives

The Violet differential performance analysis in general can absorb the performance noises in symbolic execution. But we observe some false positives in the Violet performance analysis output. For example, S^{2}E somehow has a delay in emitting the return signal of some system call functions like `gettimeofday`, which causes Violet to record inaccurate latency. These false positives are relatively easy to suppress by discounting the cost of the noisy instructions.

We manually inspect the performance models of 10 random parameters that Violet analyzes in the coverage experiment.

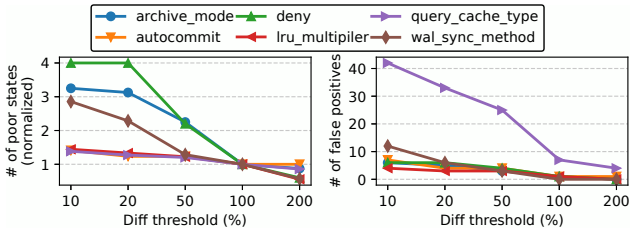


Figure 15: Sensitivity of the performance diff threshold (default 100%). For readability, the number of poor states is normalized by values under the default threshold.

We check the accuracy of the reported bad states by verifying them with `sysbench`. The false positive rate is 6.4%.

7.9 Performance

We measure the Violet analysis time for the 471 parameters in the coverage experiment (Section 7.6). Figure 14 shows the result in boxplots. The median analysis times are 206 s (MySQL), 117 s (PostgreSQL), 1171 s (Apache), and 554 s (Squid). On average, the log analyzer time is 68s. As explained in Section 7.3, even though for some parameters the analysis time is relatively long, the benefit is that Violet derives a thorough performance model for different settings of the target parameter and the combined effect with other parameters and input. The outcome can be re-used many times by the Violet checker. With the performance models, the checker time is fast. On average the checking only takes 15.7 seconds.

7.10 Sensitivity Analysis

Violet uses a differential threshold (default 100%) to detect the suspicious state from the trace log (Section 4.6). We evaluate the sensitivity of this threshold by measuring how many poor state pairs Violet reports when analyzing a parameter under threshold t. For each poor state pair Violet reports, we run benchmarks on the native machine to check whether it is false positive (performance difference is $\geq t$%).

Figure 15 shows the result for six representative parameters. We can see that if the threshold is set to a relatively lower value, the number of detected specious configuration can dramatically increase, but at cost of higher false positives.

8 Limitations

Violet has several limitations that we plan to address in future work. First, Violet explores the configuration under normal conditions. Some specious configuration may be only used in error handling. Exploring their effect requires specific faults. One solution is to combine symbolic execution with fault injection. Another potential solution is to use under-constrained symbolic execution [46]. Second, our handling of floating point type parameters is imperfect due to limited support in existing symbolic execution engines. We currently explores float parameters by choosing from a set of concrete floating-point values in the valid value range. Third, we use concrete (the host) hardware in the symbolic execution, which may not

capture specious configuration that is only visible in specific hardware. We rely on logical cost metrics to surface such issues. Lastly, Violet does not work on distributed systems.

9 Related Work

Misconfiguration detection and diagnosis. A wide body of work has been done to detect and troubleshoot misconfiguration [20–22, 27, 30, 30, 48, 50, 52, 54, 61, 63]. For example, ConfAid [21] uses dynamic taint tracking to locate configuration errors that lead to failures; Strider [52] and PeerPressure [50] take statistical approaches to identify misconfiguration; EnCore [63] enhances statistical learning with environment information to detect misconfiguration.

These solutions mainly target illegal configuration and have limited effects on specious configuration. X-ray [19] targets performance-related misconfiguration. Our work is inspired by X-ray and is complementary to it. X-ray is a diagnosis tool and uses deterministic record and replay of a specific program execution. Violet focuses on detecting specious configuration beforehand. Violet uses symbolic execution to explore the performance effect in multiple execution paths. Violet is more suitable for performance tuning/bug finding, whereas X-ray is better at diagnosing misconfiguration that has occurred.

LearnConf [41] is recently proposed to detect performance misconfiguration using static analysis. LearnConf summarizes common code patterns of performance configuration and uses simple formulas to approximate the performance effect, *e.g.*, linear relationship. It uses static analysis to identify these patterns and derive parameters to the formulas. The solution is simpler compared to Violet, but its completeness is limited because obtaining comprehensive code patterns is hard. Moreover, the performance effect is often quite complex, which cannot be accurately captured by simple formulas. Static analysis also suffers from well-known inaccuracies for large software. Violet explores a configuration's influence in the code without requiring or being limited by common patterns; it analyzes the performance effect by executing the code. Additionally, Violet explores the performance impact of input and a large set of related configurations together.

Performance tuning of configuration. There is a wealth of literature on automatic performance tuning, e.g., [33,44,51,55, 59, 62, 64]. They work basically by devising an approximate function between configuration values and the performance metrics measured through testing. While tunable parameters are common specious configuration, performance tuning and detecting specious configuration are two directions. The former searches for settings that yield the best performance, while the latter identifies settings that lead to extremely poor performance. Violet takes an analytical approach to derive configuration performance impact model from the code, instead of exhaustive testing. The result from our in-vivo, multi-path analysis is also less susceptible to noises and enables extrapolation to different contexts.

System resilience to misconfiguration. ConfErr [37] uses a human error model to inject misconfiguration. SPEX [57] uses static analysis to extract configuration constraints and generates misconfiguration by violating these constraints. The injected misconfigurations are illegal values that can trigger explicit errors like crash. Specious configuration typically does not cause explicit errors.

Configuration languages. Better configuration languages can help avoid misconfiguration. Several works make such efforts [23, 25, 28, 29, 35, 42, 47]. PRESTO [29] proposes a template language to generate device-native configuration. ConfValley [35], proposes a declarative validation language for generic software configuration. These new designs do not prevent specious configuration from being introduced.

Symbolic execution in performance analysis. Symbolic execution [24, 38] is typically used for finding functional bugs. S^2E [26] is the first to explore performance analysis in symbolic execution as one use case to demonstrate the generality of its platform. The Violet tracer leverages the advances made by S^2E, particularly its low-level signals, to build our custom profiling methods (Section 4.5). Our tracer also addresses several unique challenges to reduce the performance analysis overhead (Section 5.3). Bolt [36] extracts performance contracts of Network Function code with symbolic execution. Violet targets general-purpose software and analyzes performance effect of system configuration.

10 Conclusion

Specious configuration is a common and challenging problem for production systems. We propose an analytical approach to tackle this problem and present a toolchain called Violet. Violet uses symbolic execution and program analysis to systematically reason about the performance effect of configuration from code. The derived configuration performance impact model is used for subsequent detections of specious configuration. We successfully apply Violet on four large system software and detect 15 out of 17 real-world specious configuration cases. Violet exposes 11 unknown specious configuration, 8 of which are confirmed by developers.

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