Software Performance Engineering in Complex Distributed Systems

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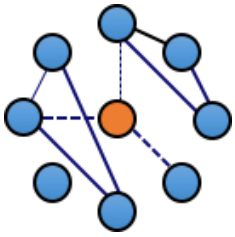

Software Performance Engineering in Complex Distributed Systems

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Abstract

Performance is a make-or-break quality for software. When making changes it is essential to ensure no *performance regression* has occurred i.e. the program performs more slowly or consumes more resources than previous versions. Tribler is the result of ten years scientific research in complex distributed systems. Over the course of years Tribler's performance has fallen below acceptable user experience levels. All past attempts to gain insight into key performance indicators have failed. By making use of *software performance engineering*, we address Tribler's dramatic performance. We resolve Tribler's blocking synchronous I/O, the main bottleneck, by introducing asynchrony and show that we improve the performance i.e. responsiveness significantly. Additionally we implement a regression testing system to prevent the deterioration of performance in the future, making Tribler ready for large scale usage and another decade of research.

Preface

preface here.

Acknowledgements here.

Laurens Freydis Dene Versluis

Delft, The Netherlands
13th August 2016

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Chapter 1

Introduction

Performance is a make-or-break quality for software. In today's society we expect manufacturers to progress in their expertise and their products to advance. We take for granted that new cars have a larger radius, are more powerful, less pollute and more safe with each iteration of design. In contrast, software does not has this image; software updates breaking functionalities, adding severe performance issues or increasing the complexity of the user interface are common. The Facebook mobile Android application is a prime example of this, having more than one billion installs and being in development for years by a complete development department still receives updates which causes performance issues for users, see Figure 1.1. Just as with their cars users expect software performance to advance or at least not become *worse* in terms of performance.

Performance can be divided in two dimensions: *responsiveness* and *scalability*. Responsiveness is the ability of a system to meet the requirements for response time or throughput. The response time can be measured by how fast a system can respond to an event, where throughput can be measured by how many events can be processed in a set amount of time. Scalability is the ability of a system to meet the required response time or throughput when faced with a growing demand of its software functions.

Performance plays an important role in both industrial and academic areas. Smith et al. have shown that the cost of a software product is determined more by how well it achieves its objectives for quality attributes such as performance than by its functionality [1]. For instance, an increase of 500 milliseconds latency in Google's search results could cause 20% traffic loss [2]. The deterioration of performance introduced by changes is often referred to as *performance regression*. Performance regression can lead to several undesired consequences such as damaged customer relationships as the software does not meet its required performance. Huang et al. provide the example of an e-commerce website that saw an increase of 2000% in their page loading times because of an update to the underlying database engine [3]. These situations can lead to lost revenue and possibly missed market windows. Other consequences of performance failures may express themselves in lost pro-

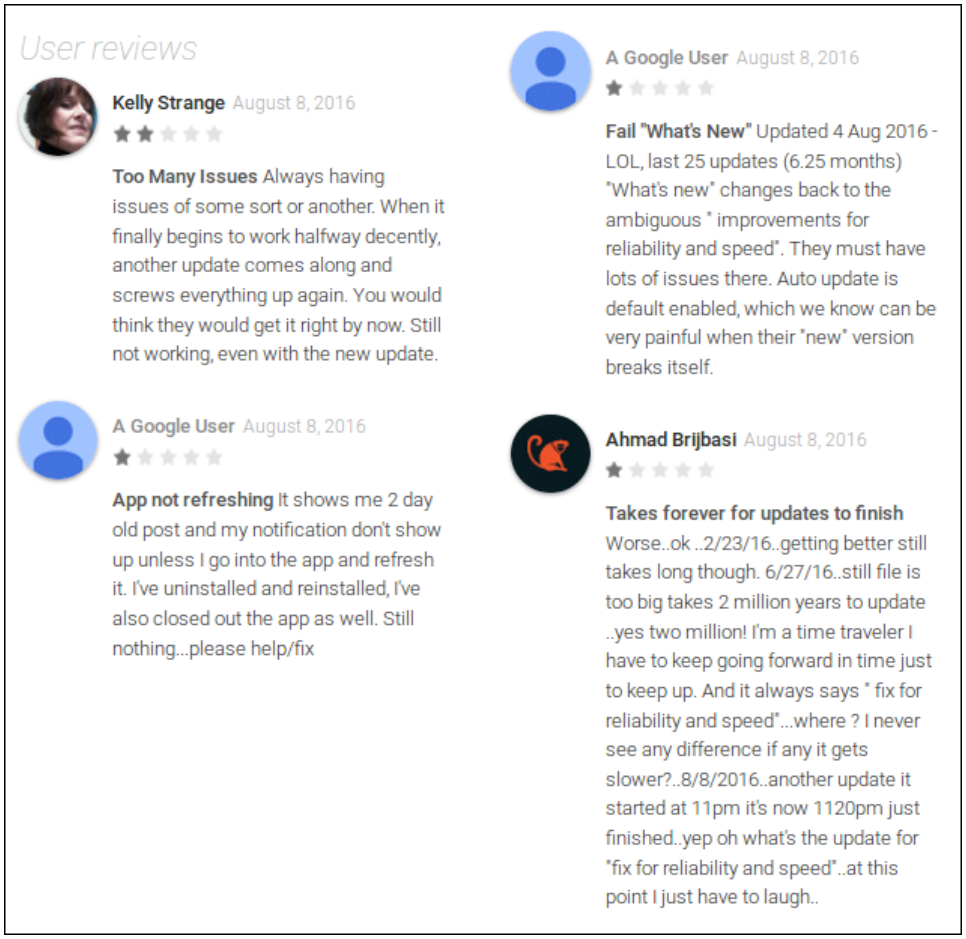

Figure 1.1: Bad reviews showing the Facebook Android application introducing issues with updates.

ductivity for users, increased costs, failures on deployment or even abandonment of projects [4, 5].

To inspect whether the performance of a system has decreased, performance regression testing can be applied. Using this method, the system is tested for performance regression under various loads [4]. Traditional software development focusses on correctness, causing regression testing to be deferred to a late stage in the development cycle, if applied at all. To illustrate the varying amounts of regression testing appliances, Huang et al. mention the performing testing interval of MySQL, Linux and Chrome. These projects apply performance tests every release, every week and every four revisions, respectively. Once performance regression is detected, developers have to spend extra efforts determining what causes said regression, especially when a lot of changes have been applied to the code base since the last measurement [3]. Performance tests should be executed as frequently as possible, ideally per change made by developers. However, as some tests take hours or even

weeks, this approach is not always feasible.
Software performance engineering (SPE) is the discipline concerned with constructing software systems that meet performance objectives [6]. It prescribes principles for creating responsive software, methods to obtain performance specifications and offers guidelines for the types of evaluations to be conducted at each development stage. SPE features two general approaches [4] where the first approach is purely measurement based. This characterizes itself by performing actions late in the development cycle such as applying regression tests, diagnosis and tuning, when the system can be run and measured in real-time. The second approach features a model-based style. Using this approach, performance models are created at the early stages of development, influencing the architecture and design of the system to meet performance requirements.

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Uitleggen dat performance in centralized architecturen makkelijker is te tunen dan een decentraal systeem + plaatje met verschil

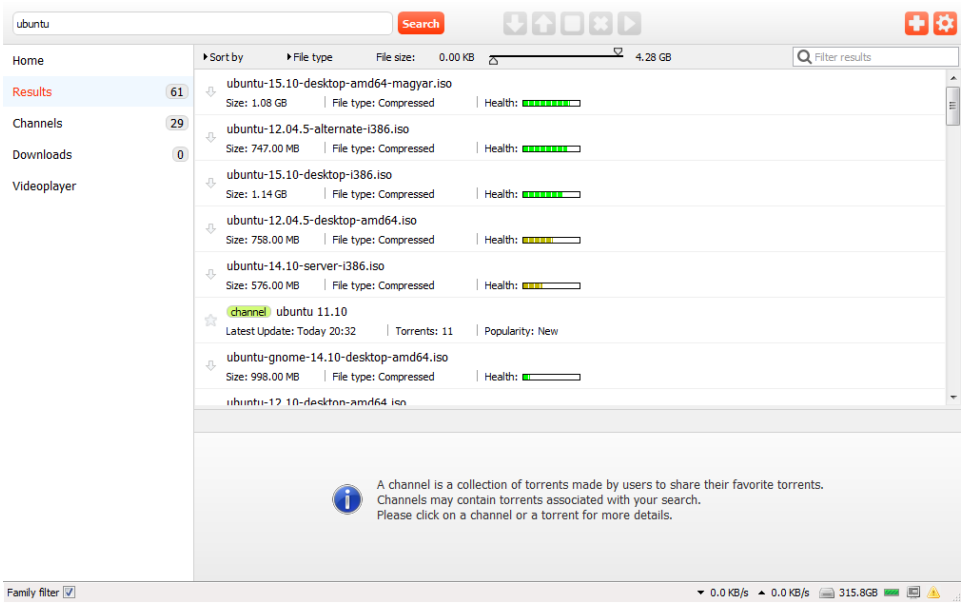


Figure 1.2: Screenshot of Tribler v6.5.2.

Tribler is the result of ten years of scientific research in the field of decentralized systems and online cooperation. Over 100 scientific publications have Tribler in their foundation. Tribler is completely open-source and can be downloaded from the Tribler website[1]. Tribler's interface is visible in Figure 1.2.
Over the course of more than a decade Tribler has gained a tremendous amount of attention in both media and academia. It has been downloaded approximately 1.8 million times [7] and has more than two thousand monthly active users. This makes Tribler one of the research projects that allow researchers to run experimental code 'in the wild' on a large scale.

[1] `https://www.tribler.org`

One of Tribler's unique features is that it allows users to discover and exchange data in a complete decentralized way. This introduces additional challenges compared to centralized solutions.
Using a centralized structure, heavy computations can be offloaded to servers which are often more powerful and more responsive than a consumer grade computer. Once the result has been computed, it can be communicated back to the user at only the cost of the communication. It has been demonstrated that for devices with a finite power supply such as smartphones, this technique can be applied to save energy or to boost performance [8, 9].
Decentralized systems such as Tribler do not have such servers present that can be offloaded to, restricting the area of computation to the device itself. It is thus essential that the software performs well on heterogeneous devices, possibly facing challenging network conditions.
To enhance privacy and anonymity, support for anonymous downloads was introduced in 2014 by R. Plak [10] and R. Tanaskoski [11]. In 2015, the support for anonymous seeding of torrents using Tor-like hidden services was added by R. Ruigrok [12]. A trade-off has to be made by Tribler between the desired performance and the level of anonymity provided, as any additional layer of privacy comes with an increased number of cryptographic operations.
Not only anonymity impacts the overall performance of Tribler: architectural flaws introduced in the past have led to a decrease in performance today. This manifests itself in users frequently reporting high system load, a non-responsive Graphical User Interface and low download speed. Furthermore, Tribler is plagued with a high number of disk operations which has been known since 2013 [13].
The focus of this thesis is to improve Tribler's performance by making use of software performance engineering techniques in the late stages of the development cycle with a particular focus on the performance of disk operations and software regression testing.
The rest of this thesis is structured as follows. Chapter 2 provides the problem description and the research questions this thesis attempts to answer. Chapter 3 explains the python threading model and why we observe performance issues with Tribler. Chapter 6 presents experimental results of this work. Finally, Chapter 7 concludes this thesis and provides future work.

Chapter 2

Problem description

Tribler's goal is to offer a YouTube-like experience with similar performance and ease of use. All Tribler's features are implemented in a completely distributed manner, not relying on any centralized component.
Numerous initiatives exist around these goals of re-decentralisation, censorship-resilience, and attack-resilient. However, none of them gathered any significant usage compared to the social media usage levels. For instance, YouTube features one billion unique monthly users [14] and there are 1.8 billion monthly active Facebook users [15].
The problem is that the performance, usability, and features offered by decentralised alternatives are inferior when compared to the experience offered by central solutions. Creating academically pure self-organising systems such as Tribler has proven to be notoriously difficult. For example, the extensive list of 194 projects which all aim to create an alternative Internet experience using decentralisations shows the amount of years spent and lines of code produced [16]. Most of these project are abandoned and few of them have actual real-world usage.

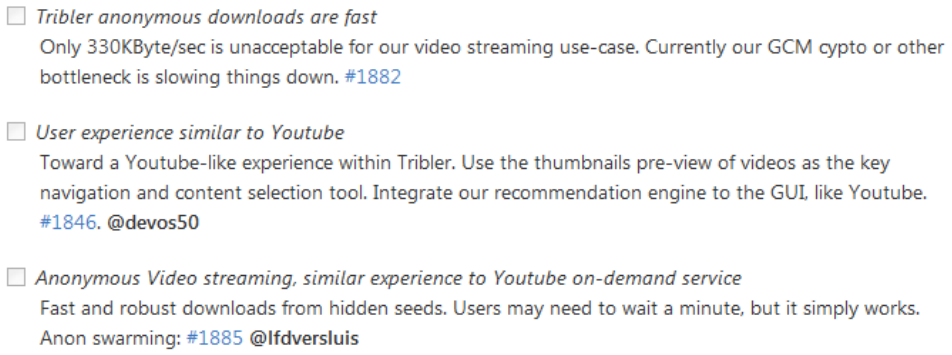


Figure 2.1: Three of the six uncompleted Tribler roadmap items.

The Tribler project created a roadmap – available on its GitHub repository – to offer the same service, features, user experience, and performance as the YouTube

video-on-demand service. However, especially the poor performance of Tribler is hampering wide-spread adaption and usage. Figure 2.1 shows three of the six main uncompleted roadmap items.

2.1 Key performance optimizations

Tribler can be seen as a large and complex distributed system. Metrics from Open-HUB show that Tribler, along with its components, features more than 169 KLOC, received contributions from 111 unique contributors and took approximately 44 years of effort [17].
In large and complex systems there are likely to be many performance issue present, often referred to as *bottlenecks*. J. M. Juran's Pareto principle admonishes that one should "Concentrate on the vital few, not the trivial many" [18]. This principle is also known as the 80/20 rule. Concretely, this means that resolving the vital bottlenecks yields the best diminishing returns, even for large systems such as Tribler. After careful scrutiny it was decided that the most vital bottleneck to address, within the context of a nine month thesis, is Tribler's database I/O.

2.2 Tribler's database dependency

The problem we address within this thesis is the underlying reason for poor performance and unacceptable user experience. Measurements dating back from 2014 indicate that Tribler's performance is I/O-bound [13]. Especially with slow hard disks, but also with fast SSD storage the main performance bottleneck seems to be around database access. With our focus on the fundamental issue we believe we can make a significant step forward in making decentralized technology able to compete with centralized solutions on large-scale usage.
All information within Tribler is stored in a database for persistence and ease of use. Information about the network i.e. peers, messages and authentication is stored in a separate database managed by the Distributed Permission System (Dispersy). Dispersy is an elastic database system written in the Python programming language and uses SQLite as its underlying database engine. It lies at the heart of Tribler, providing the means to discover peers and content in a decentralized way while offering security and anonymity.
Dispersy is fully decentralized with the exception of bootstrap servers. It can run on systems with a large number of nodes, without any sever architecture needed [20, 21]. All nodes perform the same algorithmic procedures and tasks and do not differentiate between any node i.e. all nodes are equal.
Furthermore, Dispersy provides on-to-one and one-to-many data dissemination mechanisms to forward data to nodes. Eventually, all data will reach all nodes in the network, overcoming challenging network conditions. The current overview of the database structure is presented in Figure 2.2 (Johan Pouwelse, 2013).

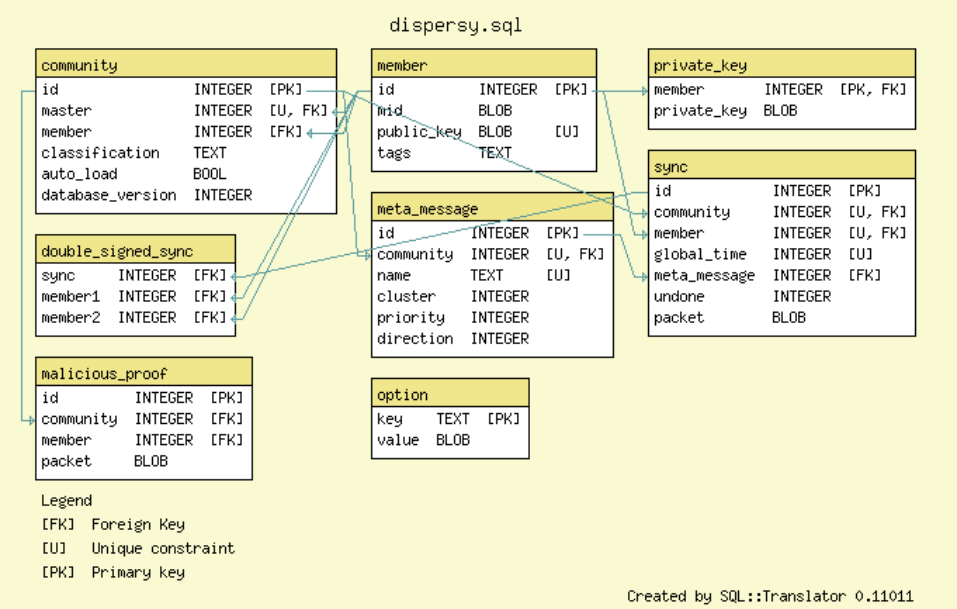


Figure 2.2: The database schema of Dispersy, (source: Johan Pouwelse, 2013) [19].

This database is becoming a key performance bottleneck [13]. Back in May 2013 measurements indicated that Tribler read and wrote 660 Megabytes per hour to and from disk. Back in April 2014 this number was somewhat reduced to 623. In May 2014 efforts were made to reduce this enormous amount of I/O and after batching database statements the number dropped to 538 Megabytes per hour.
So far this metric has only been measured sporadically by hand, running Tribler for an arbitrarily amount of time and check the amount of I/O by using htop[1]. htop produces an overview similar to Figure 2.3 (Johan Pouwelse, 2014). Measurements to observe to which extent Dispersy is responsible for these numbers were never conducted, however it is strongly suspected by the Tribler developers that Dispersy is responsible for most of it. Since 2014 no work or measurements have been done related to this issue.

2.2.1 Blocking I/O

One of the main causes of Tribler's dramatic performance can be explained by the blocking behaviour of I/O. Currently, Dispersy is deeply embedded into Tribler, running on the same (main) thread Tribler is running on. Tribler, just like Dispersy, is written in the Python programming language. In Python, a thread performing an I/O operation will block, causing all operations on the thread to suspend. This means whenever Dispersy performs I/O all functions of Tribler halt and vice versa.

[1] http://hisham.hm/htop/

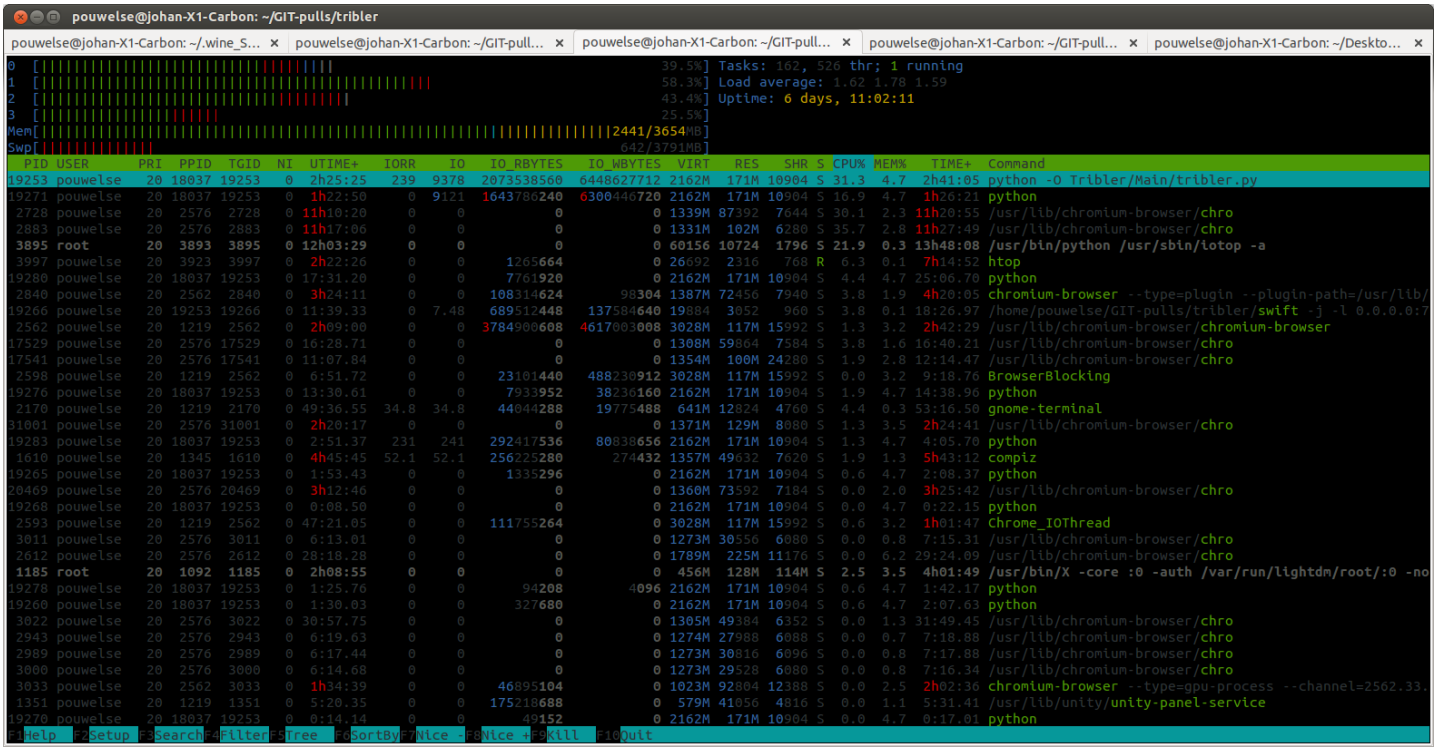


Figure 2.3: A screenshot of htop showing Tribler's I/O, (source: Johan Pouwelse, 2014 [13]).

With the enormous amount of I/O Tribler is performing, this forms a huge limiting factor on the responsiveness and hence performance of Tribler.

When a thread suspends, other threads can take over and perform operations, yet besides the main thread there are only two additional threads in Tribler: the Graphical User Interface (GUI) thread and the Dispersy endpoint thread. As the name implies, the GUI is running on the GUI thread as the framework Tribler currently uses requires this. Ironically, the Dispersy endpoint thread was introduced because of the blocking I/O behaviour. Under heavy load, Dispersy drops packets because it cannot keep up. As processing is done on the main thread and this frequently blocks because of the I/O, the buffers overflow causing packet loss. These two threads do not saturate the available processing time offered by the main thread blocking, leading to wasting valuable CPU cycles.

In the meantime, Tribler has seen several changes to its code base including the addition of the MultiChain: Tribler's own Blockchain like structure [22]. This feature heavily relies on its database to store blocks and other information about the user and other peers their chains. Moreover, the MultiChain makes use of its own database rather than Dispersy's. Norberhuis points out: 'The information is stored in two places within Tribler and this could be eliminated. It would reduce the disk footprint and the amount of read/write transactions as only one database

would have to be maintained. The I/O ineractions are a problem according to Tribler maintainers.' [22], yet numbers on how much I/O the MultiChain generates are not presented. This makes it hard to estimate Tribler's current I/O rates.
Furthermore, a feature called 'credit mining' is currently in development that will also interact with the database of Tribler. There are no metrics on the current situation of Tribler and it's hard if not impossible to estimate the impact of any addition to come. Currently, there is a lack of insight in these metrics, or a lack of *software performance engineering*, causing the exact extent of the problem to be unknown.

2.3 A lack of software performance engineering

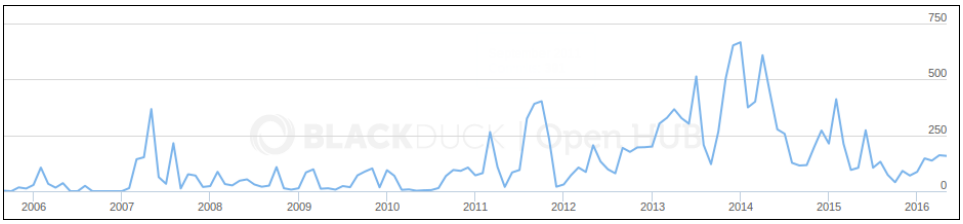


Figure 2.4: The distribution of commits on Tribler (source: OpenHUB, 2016 [17]).

Nowadays, programs are evolving at a rapid speed and Tribler is no exception. Since 2005 Tribler is under continuous development, over seventeen thousands commits have been made, spanning more than a decade [17]. The distribution of these commits can be seen in Figure 2.4. Code commits to fix bugs, refactor code, enhance or add functionality are pushed to code repositories at a frequent rate. It is important that software performance engineering is a part of this process: performance should not get compromised by changes, if any it should improve. Naturally trade-offs can be made performance wise, but it should be done with a clear understanding of the consequences.
For the past three years, attempts have been made to monitor the performance, yet all of them have failed. The first attempt was to create probes using Systemtap[2]. While some success was reported, this system is no longer being maintained nor functional. After this, code was added to the Dispersy code base to track and log if a function was running longer than a fixed amount of time. While this implementation does provide some insight, its workings are crude and only covering some of the functions present. For instance, it cannot handle asynchronous constructions. Tribler did not have any observation system integrated, leaving the development team in the dark regarding its performance.
It is apparent that there is a lack of software performance engineering in the development cycle of Tribler. Performance has never been one of the priorities in

[2] `https://sourceware.org/systemtap/`

Tribler's lifetime; only 6% of all tickets on GitHub are (indirectly) related to performance. To ensure performance will no longer degrade realistic benchmarks need to be developed which Tribler can be tested with. Changes can then be compared against the current codebase, tracking important performance statistics such as the amount of I/O, run time of functions, throughput and responsiveness. These benchmarks can then be integrated into a regression testing system which can be integrated in our Jenkins continuous integration system. Using Jenkins, performance regression tests can run on every proposed change and at predetermined moments, having a continuous updated overview of Tribler's performance.

2.4 Realistic benchmarks

Directly related to the performance problem is the benchmark problem. In order to improve user performance we require making assumptions about realistic use cases. Each user has different usage patterns, hardware and network conditions, all affecting performance. Creating one of more several benchmarks testing several scenario's is required to accurately tune the system for real world usage. At the same time, a benchmark cannot consume too much time. Benchmarking is by nature time consuming [3], however running long regression tests per commit done on a pull request will severely strain the development speed.
Therefore, it is important to create a reference benchmark which has a close resemblance to real world usage without consuming too much time.
The next step is to introduce a solution, tracking changes in vital numbers such as CPU consumption or I/O produced. Any improvement indicated by this benchmark should reflect improvement for real world users. This system should benchmark the current code base against proposed changes, capturing any differences in performance.

2.5 Objective and research questions

The objective of this thesis is to improve the performance and responsiveness of Tribler and to introduce an I/O regression test system. The verification of the performance regression test system is done by focussing on removing bottlenecks present i.e. in parallel with improving performance. These improvements will be applied by means of refactoring current code, which is largely undocumented, poorly tested and unnecessary complex.
The research presented in this thesis was carried out in cooperation with the Tribler team. The Tribler team consists of both staff members of the Technical University of Delft as well as Bachelor and Master students. Based on the objectives of Tribler, this thesis aims to answer the main research question formulated below.

Main Research Question: How can we improve Tribler's performance, responsiveness and code base?

To answer this main research question, we have defined three research questions below. Each of these research questions will be justified as why they contribute to the main research question.

Research Question 1: How can we identify bottlenecks in a complex system such as Tribler?

Software projects such as Tribler are often dependent on libraries i.e. third party code and combine several components or modules to form a program. To improve the performance of such a system, one needs to be able to identify bottlenecks. Bottlenecks are parts of the code where often performance and responsiveness can be gained. Sometimes by implementing a more efficient algorithm or by introducing parallelization these bottlenecks can be resolved. Identifying these bottlenecks is the first step to resolve them.

Research Question 2: Can a system such as Tribler benefit from asynchrony?

To improve performance and responsiveness, parts of Tribler can be rewritten to become asynchronous. By performing tasks asynchronously the performance and responsiveness of a program can improve. However, an asynchronous approach can have its drawbacks. One of these drawbacks is that it requires a different mindset for the programmers as the whole call chain and structure of a program becomes different. Identifying these drawbacks and deciding if the benefits outweigh the costs is necessary to prevent the current state from worsening.

Research Question 3: How do we incorporate benchmarking and regression testing into Tribler to gain insight into performance statistics?

To be able to conclude performance has improved, we need to benchmark current and new code using a regression testing system. The key issue here is to define metrics and workloads to benchmark with. If the metrics do not represent a realistic use-case the benchmark may be flawed, rendering the outcome unreliable and inaccurate.
Preferably, the regression testing system should not clog the throughput of the current test architecture. Running an one hour benchmark per change per pull request will severely strain the development speed.

2.6 Main contributions

The main contributions of this thesis are as follows. First, we elaborate on the subject of multitasking and parallelization in the context of the Python programming language and provide arguments where asynchronous programming is preferred

over synchronous programming, using Tribler as a case study. We then resolve the vital I/O bottleneck currently present in Tribler using asynchrony and a multi-threaded approach. Next, we introduce software performance engineering into Tribler's development process by adding a regression testing system that benchmarks different versions of the same code base to gain insight into performance metrics such as disk I/O. Finally, experimental results and measurements will be provided to confirm the main goal of this thesis i.e. improving responsiveness, performance and user experience.

Chapter 3

Python's threading model

Before we can address Tribler's blocking I/O problem, we first need to better understand Python's threading model and how the Python interpreter behaves. By looking in depth how the operating system (OS) and the python interpreter behave together, how threads run concurrently and the pros and cons of concurrency, we can look into if asynchrony can boost Tribler's performance. This allows us to answer the second research question 'Can a system such as Tribler benefit from asynchrony?' and gives us a direction of design and implementation.

3.1 Threads in Python

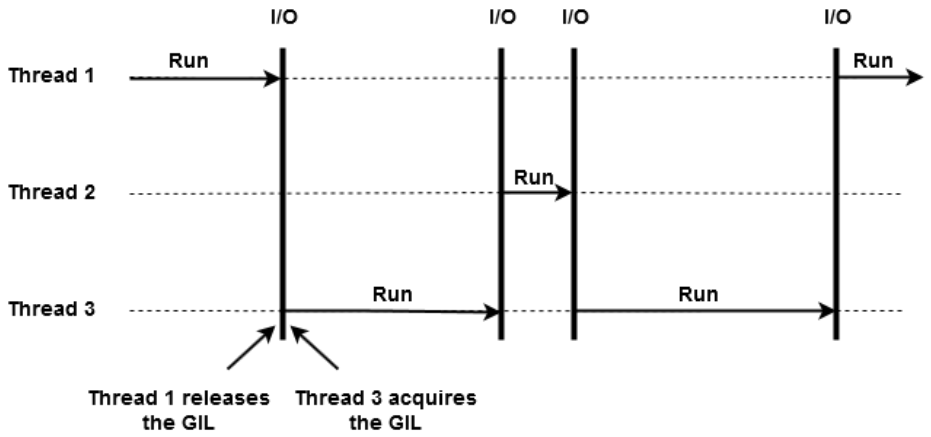


Figure 3.1: A schematic view of how threads release the GIL when performing IO in Python.

Python threads are normal OS threads, either POSIX (pthread) or Windows threads [23, 24]. Python does not feature a thread scheduler, threads are fully managed by the operating system that hosts them. To control thread execution Python features

a construct called the Global Interpreter Lock (GIL). This GIL ensures that only one thread can run in the python interpreter at once, i.e. a thread needs to hold the GIL in order to execute. This means there cannot be any parallel execution. Once a thread is done executing or needs to block it releases the GIL. This gives way for cooperative multitasking as other threads that are ready to execute can try to acquire the GIL, visualized in Figure 3.1.
To make sure Central Processing Unit (CPU) bound tasks do not hold the GIL indefinitely a simple check mechanism is built in that 'checks' every thread once per 100 ticks. Ticks are loosely mapped to interpreter instructions and do not define a time unit. Listing 3.1 contains two code samples that only take one tick each, but take require different amount of time to compute.

```
a = 5 * 5 # A fast one tick instruction

numbers = xrange(100000000)
b = -1 in numbers # A slow one tick instruction
```

Listing 3.1: Two code samples that each take one tick yet require a different amount to compute.

When a check is run the following four steps are executed:

1. The thread that holds the GIL resets its tick counter.
2. If the current thread it the main thread, it runs the signal handlers.
3. The thread releases the GIL.
4. The thread tries to reacquire the GIL.

Note that a thread may immediately reacquire the GIL after releasing it. Since every thread has this check, CPU-bound threads will engage in cooperative multitasking.

3.2 Multi threaded programming performance

Component	**Specifications**
Operating System	Ubuntu 16.04 LTS
Python version	2.7.12
CPU	Intel Core i5-2410M
HDD	Samsung 850 EVO 250GB
RAM	8 GB DDR3 1600MHz

Table 3.1: Specifications of the setup used during the rerun David Beazly's experiment.

Because threads cannot run in parallel, this changes the performance one may expect from a multi-threaded program. Dadiv Beazly presented his findings in his Python Concurrency Workshop (2009) [24]. By running a trivial CPU-bound function using two threads on a dual-core MacBook, processing time increased 24.6 to 45.5 seconds; an increase of 185%. Disabling one of his cpu cores yielded 38.0 seconds, an increase of 154% in run time.
To confirm this behaviour still exists in the latest version of Python2, we rerun Beazly's experiment. The setup used in this experiment can be found in Table 3.1. Running it sequentially gives us a run time of 8.17 seconds, whereas running it using two threads provides us with a run time of 14.49 seconds; an increase of 177% which is in range of Beazley's observations
To investigate this behaviour, Beazley studied the underlying C code to inspect why he was observing these performance results. Whenever a (Python) thread releases the GIL, it sends out a signal. The OS then propagates this signal to other threads which then can attempt to acquire the GIL. The time or *lag* between thread switching and execution may be significant depending on the OS, according Beazley. Most operating systems make use of a priority system for threads: the thread with the highest priority will be scheduled by the OS. Often, CPU-bound threads have a low priority and I/O-bound threads a high priority. If a signal is send to a low priority thread and all CPUs are currently busy processing other, high priority threads, it won't be run until one of the CPUs becomes available.
As it turns out, the GIL signalling is the source of the performance loss. Whenever the periodic 'check' runs, the following happens:

- First the Python interpreter locks a mutex.
- Next, it signals on a condition variable/semaphore where another thread is *always* awaiting execution.
- Because of this waiting thread, additional pthread processing and system calls are generated to deliver the signal.

Beazley provided rough measurements on the number of system calls generated, summarized in Table 3.2. From these numbers Beazley concludes that the amount of additional calls generated is significant and the main reason for the performance loss. He then dived deeper into these numbers to find a cause.
By recording a real-time trace of all GIL related operations i.e. acquisition, release, etc., Beazley was able to reconstruct the key problem. When running multiple CPU-bound threads on multiple cores, all of them will be scheduled *simultaneously*. The threads proceed to battle over GIL acquisition. Whenever a thread releases the GIL because of the 100 tick 'check', it immediately tries to reacquire it. Another thread will also try to acquire the GIL upon this signal, but as this signal arrives with a delay it will most likely fail. This processes is visualized by Figure 3.2 (David Beazley, 2009). Beazley argues that here two competing goals are clashing. On the one hand Python wants to only run one thread at a time where

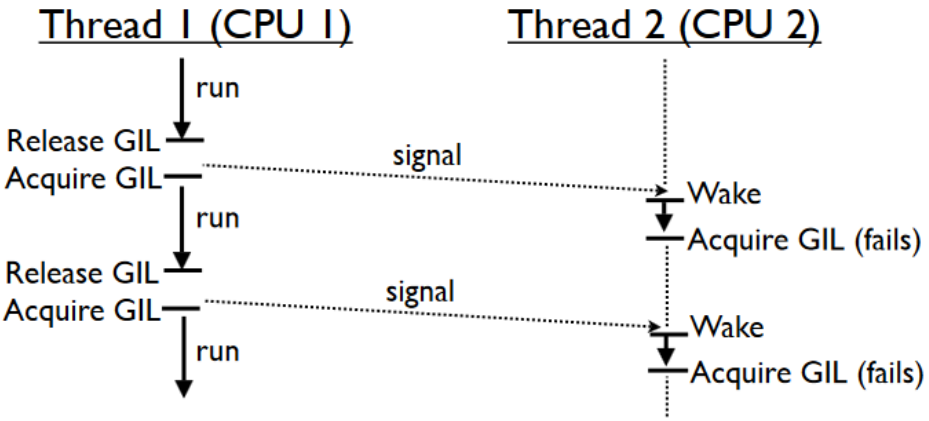


Figure 3.2: A schematic view of two threads battling for GIL acquisition (source: David Beazley, 2009).

Table 3.2: A summary of the measurements from David Beazley [24].

Threads	Cores	Unix system calls	Mach system calls
1	1	736	117
2	1	1149	3.3M
2	2	1149	9.5M

on the other hand the OS wants to schedule as many processes/threads to take advantage of its multiple core architecture. This clash raises a lot of overhead, which results in a severe performance penalty.
Even running threads on one core result in these GIL acquisition battles. I/O-bound threads which are high priority may fail to acquire the GIL when a CPU-bound thread is busy, degrading the response time of the I/O thread.

3.2.1 A new GIL

To solve the excessive amount of GIL signalling, a new GIL has been introduced in Python 3.2 [23]. Instead of having the 100 ticks 'check', there is now a global variable. A thread will continue running until this variable is set to one (1), indicating another thread requests to acquire the GIL at which the running thread must release the GIL. This means whenever only one thread is running, the variable will never be set (there is no competing thread) and no signalling takes place. Whenever another thread is present, it will be in a suspended state as it does not hold the GIL, and starts a five millisecond timeout. From here two things can happen: the running thread releases the GIL voluntarily within the timeout (e.g. an I/O operation is performed) at which the other thread can immediately acquire it, or the timeout expires. If the timeout expires, the other thread will set the global

variable to one and enters another timeout, awaiting a signal that the GIL has been released. The running thread will release the GIL, sends out a signal that it has done so and starts a wait period. When the other thread acquires the GIL it will send out an acknowledgement to the thread that just released the GIL and starts its computations. Finally, the former running thread will now enter a timeout upon receiving the acknowledgement so that it may require the GIL again.
To observe if the new GIL has any better performance, Beazley ran the same experiment using Python 3.2 and the results look promising. Running the code sequentially, using two threads and using four threads on a quad core MacBook resulted in run times of 11.53, 11.93 and 12.32 second respectively. Unfortunately, there are caveats when performing I/O operations using the new GIL. Whenever an I/O operation does not block, the thread still releases the GIL which requires the thread to initiate the timeout again to reacquire the GIL. Meanwhile CPU bound threads will also attempt to acquire the GIL since it was released, causing stalls. Beazley argues that some more work is required on the GIL to get rid of this behaviour, yet expresses that even with the GIL present threads can still deliver excellent performance and programmers still should use threads when appropriate.
Unfortunately, Tribler currently runs on Python 2.7 and a considerable amount of work is required to migrate to Python3. However, as the new GIL does look promising with respect to blocking I/O it can be noted down as an item for future work.

3.3 Attempts to parallelize Python

Parallelize Python by removing the GIL and other means to speed up Python are topics that regularly return in the Python mailing list and at PyCon [25]. Throughout the years many attempts have been made to alter Python or remove the GIL to fully benefit from multiple CPUs. To date, no one has succeeded in removing the GIL and meet the (hard) requirements for replacement [25].
On of the most well-known alternative implementations of Python is PyPy. It makes use of a tracing Just-in-Time compiler to produce optimized code [26]. By doing so, PyPy offers increased speed, reduced memory usage and support for stackless mode while providing a high compatibility with existing python code [27]. PyPy's geometric average is 7.6 times faster than CPython (normal Python) [28]. While it has many popular libraries ported to be used with PyPy, it still lacks some common used packages. Moreover, most of these libraries are not available on the official packaging repositories of Ubuntu and/or Debian, rendering PyPy unusable for the Tribler project as publishing Tribler on said repositories requires the dependencies to be available on them as well.
Two other popular implementations are JPython and IronPython. Both these projects have removed the GIL and can fully exploit multiprocessor systems [25].
JPython is a Python interpreter implemented in Java. It can be integrated in Java applications and allows python applications to be compiled into Java classes. Using

JPython, Python after compiled to java bytecode will run in the Jython virtual machine, giving full access to all Java APIs and classes [29].
IronPython does basically the same as JPython, compiling the source to in-memory bytecode and runs it on the Dynamic Language Runtime [30]. It allows developers to run Python using the .NET framework.
To illustrate the attempts to remove the GIL are still on going, Larry Hastings presented 'The Gilectomy' at PyCon 2016. He showed that removing the GIL is fairly easy, but has a huge negative impact on CPython's performance, cache misses being the main reason. Additionally, Hastings names some methods that may make The Gilectomy a viable alternative to CPython.

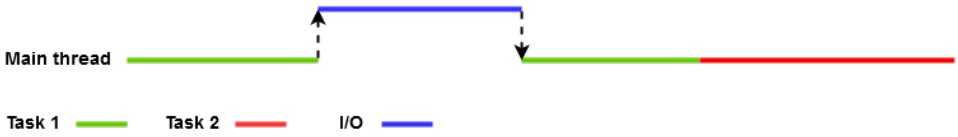
Libraries that introduce parallelism or asynchrony to gain performance are also available in large numbers. In particular, many projects exist that attempt to make I/O asynchronous [31]. Often, these leverage the multiprocessing package in the standard library of Python.
Decorated Concurrency (DECO) uses the multiprocessing package of Python to parallelize functions using a 'concurrent' decorator [32]. Different processes have their own Python interpreter which in turn has its own GIL, which allows for parallel processing. Using the 'concurrent' decorator, a function will be wrapped and executed on a new process. Similarly, the 'synchronized' inserts synchronization events to automatically refactor assignments of the results of 'concurrent' function calls to happen during synchronization events. However, because of the overhead creating a new process generates and communicating between different processes, this approach is only viable for heavy loads that generally can run on its own. The authors mention that a function should at least have an execution time of one millisecond for this method to be beneficial.

3.4 Asynchronous programming

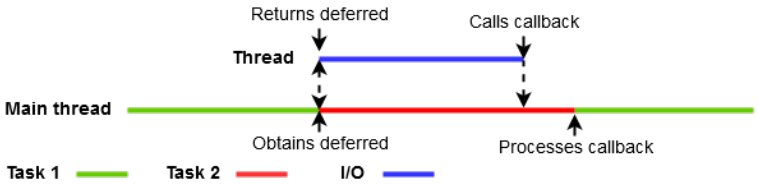
Figure 3.3: Synchronous processing of tasks

A second option it to make use of asynchronous programming to gain performance. Traditionally, synchronous programs execute tasks one by one as visualized in Figure3.3. When these functions perform an I/O operation, they are waiting for the disk or network to catch up, visualized in Figure 3.4. In turn, the thread these functions run on will block, see Figure 3.5a. This means the main thread of a program will block if the I/O call happens on that thread. A synchronous program that performs I/O operations regularly will therefore spend much of its time blocked

Figure 3.4: Tasks will be waiting when disk or network has to catch up.



(a) A schematic overview of an I/O operation done by the main thread (synchronous).



(b) A schematic overview of an I/O operation executing on a separate thread, retuning a deferred (asynchronous).

Figure 3.5: A schematic overview of a how an I/O call is handled in a synchronous versus an asynchronous manner.

waiting for disk or network to catch up.
In asynchronous programming, tasks are split into multiple chunks and executed interleaved, see Figure . The fundamental idea behind this approach is that when faced with a task that would normally block waiting for I/O, it will instead execute some other task that can still make progress. This approach can outperform a synchronous program dramatically.
Support for asynchrony in python 2.7 is poor so the use of a framework is required. Tribler makes use of Twisted, an event-driven networking engine written in Python which allows for event-driven and asynchronous programming [33].
When programming asynchronously in Twisted, the function that is being called (callee) returns a deferred. A deferred is a place holder for the actual value that the callee eventually will return once its done computing.
To ensure I/O operations does not block the main thread, the I/O can be moved to a separate thread, returning a deferred. By attaching a callback and an errback, the caller can handle the case of a success and failure respectively. These callbacks are handled by Twisted's event loop. This thread can then block while the main thread continues executing other scheduled task. Once the thread is done with its task it can invoke the callback of the deferred, notifying Twisted's event loop. The

event loop will then schedule the continuation of the previous task and proceeds executing the current task if not done yet, see Figure 3.5b.

3.4.1 Drawbacks

The main drawback of asynchronous programming is that it makes the structure and execution of a program more complex. As any task can run while another task is blocking, one must be careful that the current task does not modify information the blocking task is dependant on. Especially when working with databases one needs to make sure that the order of database queries is not different.
A second point of attention is the overhead generated when creating multiple threads. As pointed out by the previous sections, offloading work to multiple threads may actually have a negative impact on performance.

3.4.2 Initial measurements

Table 3.3: Specifications of the setup used in the initial CPU/IO/Network experiment

Component	**Specifications**
Operating System	Ubuntu 15.10
Python version	2.7.11
CPU	Intel Core i7-2630QM
HDD	Samsung 850 EVO 500GB
RAM	8 GB DDR3 1600MHz

To observe if Tribler can benefit from asynchrony, an experiment has been conducted which replicates Tribler's workload. An overview of the system this experiment is available in Table 3.3. As Tribler functions as both a client and a server, CPU,

Table 3.4: Overview of which workload is processed asynchronously per run configuration.

Configuration	**I/O Asynchronous**	**CPU Asynchronous**	**Network Asynchronous**
0	no	no	no
1	yes	no	no
2	no	no	yes
3	yes	no	yes
4	no	yes	no
5	yes	yes	no
6	no	yes	yes
7	yes	yes	yes

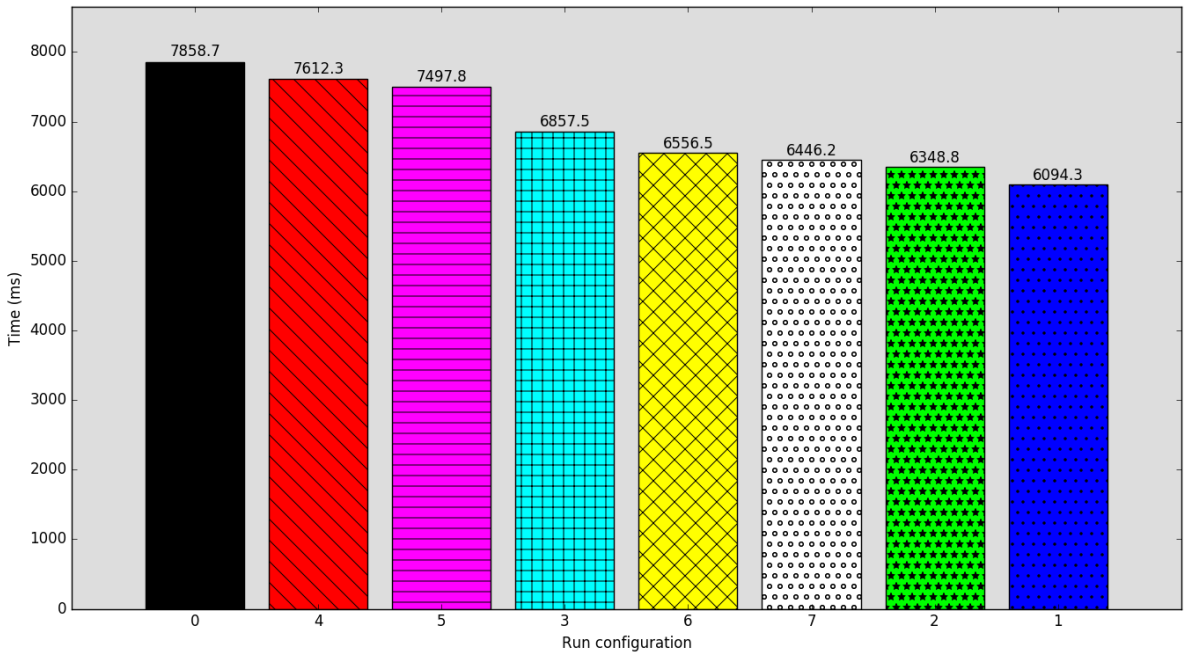


Figure 3.6: Results of the initial experiment.

I/O and network tasks are run interchangeably. To mimic these workloads, the experiment has been set up as follows.

First, as Tribler is both a client and a server, six client-server pairs are constructed where each server runs on a separate port. Each pair has its own SQLite database containing two tables: one for the server to fetch data from and one for the client to insert data into. The table for the server to read from is filled with fixed data beforehand.

Next, the client performs ten requests to the server, representing network traffic. Upon receiving the request, the server performs a database query, generating I/O. Unique queries are performed to avoid caching or other optimization techniques employed by the database engine that could bias the results. Once the results have been fetched from the database, the server will perform several calculations on the data and compress the data using zlib, creating a CPU-based load. After that, the server returns the compressed data to the client upon which it decompresses and parses said data, generating additional CPU load. Finally, the client will insert the data into the database generating additional I/O.

By measuring the time it takes for all client-serve pairs to complete the requests, we can measure the impact when processing the three different workloads (CPU, I/O and network) synchronously versus asynchronously. To perform these task asynchronously, the Twisted framework has been used at it currently embedded

into Tribler. This framework features utilities to offload work to a thread-pool, running the task on a separate thread and taking care of the communication to and from this thread-pool.
In total there are eight possible configurations, defined in Table 3.4. The results of the experiment are visible in Figure 3.6. From this figure we conclude that offloading tasks to separate threads yield a superior performance over the synchronous case. Solely offloading I/O offers the best result: the time required to perform all requests decreased by 22.5%. As a Solid State Drive (SSD) was used in this experiment, it is possible that the performance gain when using a hard disk with moving parts would be bigger as read and write operations are slower on such disks.
Offloading all components using asynchronous programming results in a decrease of 18.0% run time, 4.5% less than only offloading I/O, which can be explained by the fact that the main thread is now mostly idle as all operations are offloaded to separate threads.
From these results we conclude that Tribler can benefit from asynchronous programming especially since I/O is the primary bottleneck.

3.5 Conclusion

In this chapter we analysed the python threading model in detail. We explained why parallelism is not possible using standard Python and presented numerous initiatives that attempt to change this behaviour.
We investigated the performance behaviour of multi-threaded programs in Python and explained why multiple threads can cause performance regression. Additionally, we have shown and repeated experiments conducted by David Beazley to confirm that this performance behaviour is still present in Python 2.7.
We shortly elaborated on the the new GIL introduced in Python 3.2, which could be a point of future work to improve Tribler's performance. Next, we presented the use case of asynchrony in the context of I/O in Python and elaborated on its drawbacks. Our initial experiment shows that we can indeed gain performance when using asynchrony, answering the second research question presented in Section 2.5.

Chapter 4

Design & Implementation

After the initial results and discussion, it is evident that asynchronous I/O is beneficial to Tribler's performance. The next step is to make Dispersy's database I/O asynchronous and non-blocking. Tribler has Twisted integrated for years, yet Dispersy has not seen any integration despite the decision to do so in 2014 [34]. To ensure a good foundation to build upon without reinventing the wheel, it is key to search for a framework that supports both SQLite (Dispersy's current database system) and asynchronous I/O using Twisted. This framework will then become the basis of a new database manager.

4.1 A new database framework

With the recent addition of the MultiChain there are three distinct database files with three distinct database managers in the Tribler code base. None these database managers are fully documented or tested. A proper solution is to replace these three database managers with the new asynchronous one. This will result in less code to maintain, all logic in one place and easier to cover with proper unit tests and documentation, yielding increased stability and speed, improved maintainability and enhances the productivity of developers.
After careful scrutiny, four database frameworks that offer integration with Twisted and SQLite were selected: Axiom, Storm, Alchemia and Twistar. Next, they

Table 4.1: An overview which features each of the four frameworks support.

	Twistar	**Storm**	**Axiom**	**Alchimia**
Available in the Debian & Ubuntu repositories	✗	✓	✓	✗
Allows 'raw' queries	✓	✓	✓	✓
Allows an ORM approach	✓	✓	✓	✗
Framework is mature	✓	✓	✓	✗

were compared on the possibility to use it as an object-relational mapper (ORM), the possibility to query the database using 'raw' queries, its maturity and the availability in the official repositories of Ubuntu and Debian which is a must as Tribler is published on the official repositories as well. The results of this comparison can be found in Table 4.1.
From this table it is clear that Twister and Alchimia are not good fits; neither of them are available in the official repositories of Ubuntu and Debian. After comparing Axiom and Storm in better detail the final decision led us to choose Storm. The Storm database framework which is developed by Canonical and is featured in several other products such as Launchpad [35], showing its real world use and maturity. The Storm website features a rich tutorial and documentation section, superior to that of Axiom, where new developers joining Tribler will benefit from. Additionally, all table creation and updates must explicitly be handled by the developer which is Tribler's and Dispersy's current approach. As we favour this enforcement over automatically generated tables, Storm was chosen as the foundation of the new database manager: 'StormDBManager'.

4.2 Designing StormDBManager

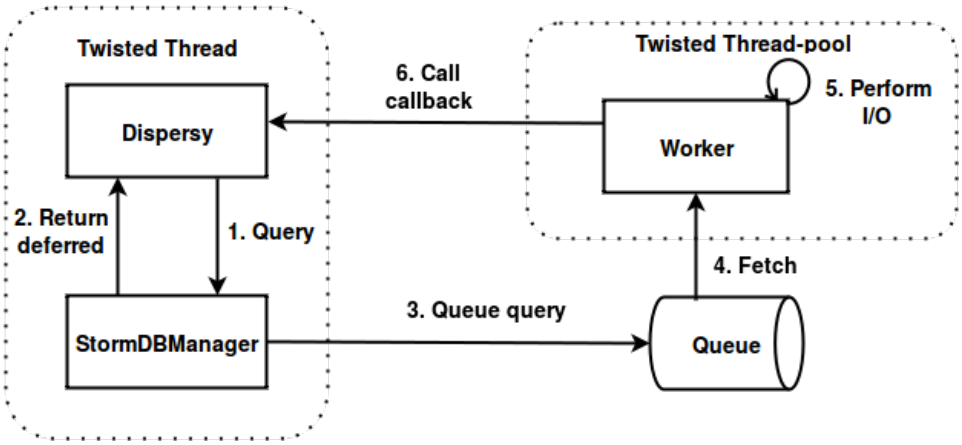


Figure 4.1: An overview of the queueing mechanism of StormDBManager.

StormDBManager features a complete asynchronous, non-blocking yet serialized interface to handle database access. Because Storm also features ORM support, this database manager can be the foundation for an ORM based approach in the future.
Since multi-threaded support is severely limited using SQLite, we decided to leverage the Twisted thread-pool to allocate a thread for a longer period of time to run a worker on. This worker will be owned by the StormDBManager. Using this approach, all database operations happen on the same thread but outside the Twisted main thread, guaranteeing I/O does not block it. Furthermore, the StormD-

BManager guarantees that queries will be executed in the same order as they are scheduled, guaranteeing no conflicts in database fields can occur because of race conditions. The system works as follows, visualized in Figure 4.1. Fist, a Dispersy function calls the StormDBManager to run a query (1). The StormDBManager generates a deferred and returns this to the caller (2). Next, the StormDBManager queues a tuple of four elements (3):

1. The function to be called, e.g. execute or fetchone.
2. The arguments to be passed to the function i.e. the query.
3. The keyword arguments to be passed to the function.
4. A deferred to handle the response in an asynchronous way.

Note that by using a thread-safe queue, all calls are scheduled in the same order as required, ensuring serialized behaviour. The worker running on the thread waits blocking for new items to come, preventing the thread from dying. Once it a tuple is available it fetches it (4). It then executes the function (5) and calls the deferred's callback with the result (6). After that, the worker proceeds to wait blocking for a new item, or executes the next tuple if present. To make sure the worker can still commit or release the thread, two predetermined values can be queued upon which the worker will commit or shut down, respectively.

4.3 Implementing StormDBManager

As the new StormDBManager will start retuning deferreds, functions of Dispersy need to be able to coop with this new paradigm. Every caller of this function will need to be transitively updated as well to handle the deferreds being returned.

```
def foo(x):
  y = x + 1
  z = bar(y)
  self.variable = z
```

Listing (4.1) Foo synchronous

```
@inlineCallbacks
def foo(x):
  y = x + 1
  z = yield bar(y)
  self.variable = z
```

Listing (4.2) Foo asynchronous

Example of the same function synchronous and asynchronous.

To keep the amount of changes to a minimum we have made extensive use of the 'inlineCallbacks'[1] decorator. The inlineCallbacks decorator allows programmers to write asynchronous code in a synchronized manner. To illustrate this in an example, consider the two code samples of the same function called 'foo' in Listings

[1] http://twistedmatrix.com/documents/current/api/twisted.internet.defer.inlineCallbacks.html

4.1 and 4.2. The left listing shows the synchronous version of foo calling a function 'bar' which for example performs a database query. After refactoring bar to make use of the 'StormDBManager' it will become asynchronous, returning a deferred. To handle this, we can need to update foo to cope with this. The right listing shows the refactored version of foo; it is decorated with the inlineCallbacks decorator and has now a 'yield' statement in front of the bar function call. Twisted automatically waits for bar's deferred to fire and then continues with the execution.
Consequentially, because of the inlineCallbacks decorator, foo is now an asynchronous function as well, returning a deferred whenever called. As a result all functions that call foo needs to be updated transitively as well.
In total there are 129 function calls to Dispersy's database (excluding tests): 26 fetchall, 29 execute, 53 fetchone, 2 insert, 9 executescript, 10 executemany. There functions were spread across X methods which all needed to be refactored transitively as with the example provided previously. After Dispersy was fully refactored, 47 files were modified with 4605 lines of additions and 2003 of deletion. To express the extent of this refactoring, approximately 90% of all Dispersy functions were updated to handle the asynchrony introduced. Naturally Tribler also required modifications; in total 106 files required modifications spanning 3572 additions and 1242 deletions to the code base. Finally, an experiment framework called Gumby (see Section 5.1) required modifications as well, resulting more than eleven thousand modified lines of code spanning more than six months of work.

Replace 90% with actual number.

Chapter 5

Introducing software performance engineering

In this chapter we look into the topic of introducing software performance engineering (SPE) into Tribler by adding a performance regression test system into the Tribler development cycle. By looking at the tools already available and prior work, we come up with a system that is both extensive and has minimal impact in Tribler's current architecture. By comparing two version of Tribler, one with the asynchronous I/O rework done in this thesis and Tribler's current code base, we show that this performance regression test system is an asset to Tribler from which many future developers can benefit in the coming years. Moreover, this performance regression test system should force developers to keep an eye on performance when making code changes, gradually improving Tribler performance over time.

5.1 Introduction to Gumby

Gumby is an experiment runner framework for Dispersy and Tribler. It is being used by Tribler developers to run experiments on local computers as well as remote servers such as the DAS5 super computer[1]. Gumby takes care of most of the steps required in order to run an experiment, including:

- Clearing the output directory at the start of an experiment.
- Syncing workspace directories with remote nodes.
- Run setup scripts concurrently to set up the experiment on all nodes.
- Spawn trackers to monitor the experiment and abort in case errors occur.
- Start both local and remote process instances in parallel at the exact same time.

[1] `http://www.cs.vu.nl/das5/`

- Fetch all the data from the output directories residing on remote servers.
- Run post-experiment scripts to generate items such as graphs and tables.

To run an experiment one can specify configurations and scenario files to be executed.
Configuration files specify which experiment to run and define all the settings needed in order to run this experiment using Gumby. These settings often include paths to data, variables such as how many nodes to create and how long the experiment has to run. Once a configuration file has been created, it can be passed to Gumby which takes care of running the experiment specified.
Scenario files allow for a carefully timed execution of functions. This is extremely useful in order to repeat the exact same procedure many times. In a scenario file, each line specifies which nodes executes which function at what time. An example of a scenario file is provided in Listing .

make listing and explain

The combination of configuration and scenario files enable a setting in which a developer can run an experiment many times with the exact same execution order and timing. This enables us to perform regression tests using Gumby which we will elaborate on next.
Whenever a push happens on a pull request on GitHub, our Jenkins continuous integration system automatically schedules this experiment to be run.
Moreover, statistics such as CPU, memory consumption and I/O are automatically tracked by Gumby. Any additional information that one wishes to track can be logged and parsed using auxiliary post experiment scripts. All graphs are being generated in the R programming language using the ggplot2 library.
To realize a regression testing system, we decided to extend Gumby with additional functionalities and scripts. First the proposed commits first have to be run inside a benchmark using a predetermined scenario and configuration file. This will produce data about the changes made to the codebase. Once this experiment is done, we can compare this data with the data generated by running the current code base using the same benchmark. To create a comparison that requires little effort to interpret, graphs and tables will be generated and presented to the developer. By creating a side-by-side plot of two graphs using the same scales, developers can immediately see any big changes, for a more in-depth view the developer can refer to the table which presents the results in a more fine grained fashion.

5.2 Performance regression using Gumby

By using configuration files and scenario files, we can create experiments which run Tribler and perform certain actions such as downloading content. These experiments can in turn be used to compare different versions of Tribler which allows us to test for performance regression. To allow for such comparisons, we decided to extend Gumby by adding experiments or *benchmarks* and additional data processing mechanisms. This procedure works as follows.

First, we run the current version of Tribler or Dispersy i.e. the current code base using a certain benchmark which may spawn several nodes running this version. Next, we run the exact same benchmark using the exact same amount of nodes on a modified version of Tribler or Dispersy. Gumby will ensure that all functions will be called at the exact same moments, ensuring the execution of both runs is identical. While the experiment is running, Gumby tracks statistics such as memory usage or response times and writes these to a specified output directory. At the end of each experiment, all (relevant) data is fetched from the nodes and combined into a dataset. Using post-experiments scripts we can then compare the data from the two obtained datasets and check if there are changes in e.g. resource usage or response times.

5.3 Representative benchmarks

One of the challenges of regression testing using benchmarks is that there should be benchmarks present which feature representative, real-world usage scenarios [36]. While it is intriguing to put a system to the limit of its capabilities and review if it performs better with made modifications, eventually real users should also profit from said modifications, improving the user experience of the software. To provide developers with adequate scenarios, we have devised three benchmarks which feature a realistic use-case of Tribler.

5.3.1 Benchmark 1

The first benchmark that we have devised consists of a user having just installed the Tribler client and is about to join the network. This use case is especially important for user satisfaction as first impressions add to this impression [36].
When a new client joins the network it has no knowledge of this network yet besides the location of bootstrap servers which are hard-coded in the Tribler client. To gather information about the network and to start discovering peers and content, the client connects to the bootstrap servers, requesting the locations of peers in the network to exchange data with. After the bootstrap client provides this information, the client will connect to these peers and start exchanging information about content and peers. This process is visualized in Figure 5.1. Over time, this new peer will learn of all content in the network.
By running a Tribler client with no prior knowledge idle for a fixed amount of time, measurements on Tribler's resource usage such as CPU and I/O rates can be tracked. As Dispersy facilitates Tribler's peer and content discovery, all data will be written to a SQLite database which generates I/O. Meanwhile incoming messages are processed which creates CPU load.
To create this benchmark, an old experiment that runs Tribler idle has been fixed. This experiment was introduced by a Tribler developer to run Tribler for various amounts of time, ranging from 1 hour to 1 week, at set times. Unfortunately it

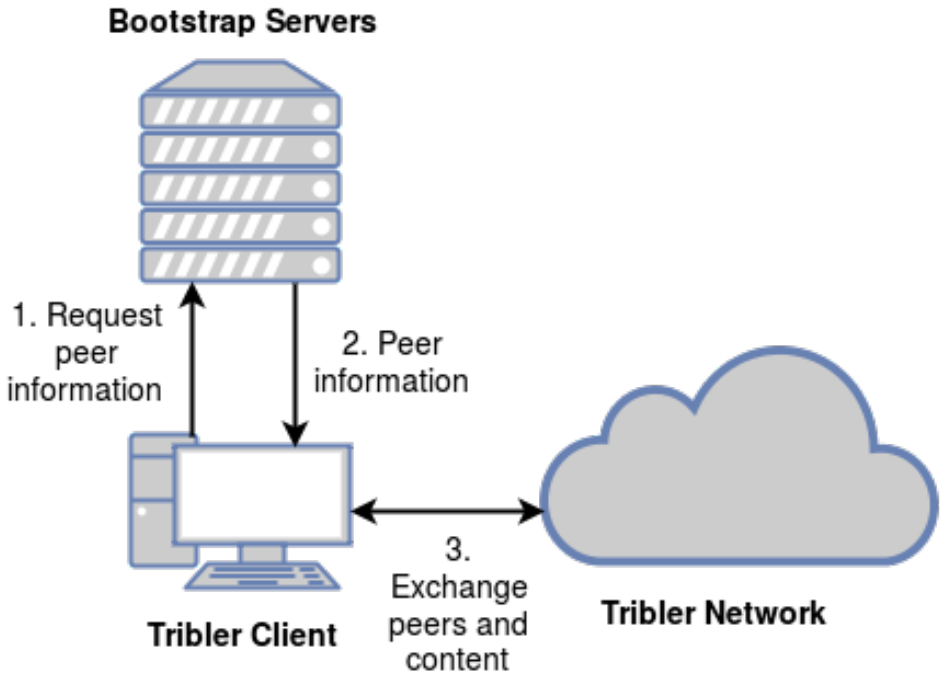


Figure 5.1: The bootstrap procedure of Tribler.

was not updated when changes were made to Tribler. By updating this experiment, it is now functional again and can be run using the latest version of Tribler and Dispersy.

5.3.2 Benchmark 2

The second benchmark represents a user downloading content by opening a magnet link or torrent file using Tribler, closing it as soon as it's finished downloading. This benchmarks represents the free-riding problem: users downloading content without uploading it back to the network i.e. seeding [37]. To mimic this behaviour, we start Tribler and immediately start downloading a file using a magnet link, as if someone opened a magnet link from a third party website. By periodically checking the download status, Tribler can be shutdown when the download is complete.

Using this benchmark, statistics such as CPU usage and download rates can be measured between different versions. This provides insight into Tribler's core functionality: decentralized access to distributed content.

To implement this, the code of the first benchmark was used as a foundation, adding the download, download progress check and shutdown procedure logic to it.

5.3.3 Benchmark 3

In this third benchmark we stress test Tribler by performing requests to the newly introduced application programming interface (API). This API is work that is being done in parallel to this thesis by other members of the Tribler development team where the graphical user interface (GUI) is decoupled from Tribler's core logic. This GUI will instead run in a separate process, communicating through a socket with Tribler's core, allowing Tribler to run headless i.e. without a GUI.
Somewhat related to the first benchmark, the response times of this API are equally important. Hassenzahl et al. show that web designers have 50 milliseconds to make a good first impression [38]. Just like most websites, Tribler's user interface will receive data from an API, rendering response times of this API an important factor. Especially when the GUI has just been opened on a fresh install, various requests will be send to API requesting channels, torrents, upload and download rates, the amount of free space on the machine, etc. Meanwhile Tribler's core will also be busy connecting to the bootstrap servers as previously discussed. To still deliver good response times, Tribler's core should be as responsive as possible to process incoming requests to this API as fast as possible.
To measure the responsiveness of this API, and indirectly that of Tribler, we have created a benchmark which can perform a varying amount of requests per second to Tribler's API. To perform these requests, we have used Apache JMeter[2]. Apache JMeter was designed to "simulate a heavy load on a server, group of servers, network or object to test its strength or to analyse overall performance under different load types." (jmeter.apache.org, 2016). JMeter tracks the average, maximal en minimal response times and calculates the standard deviation. Additionally, it tracks how many responses are received per second and what the throughput of the API is.
By running this benchmark on two different versions of Tribler, we can observe if the are changes in any of the mentioned statistics captured by JMeter. Since the responsiveness is directly related to the performance of a program, this will provide a good indication.

5.4 Continuous regression testing using Jenkins

To include software performance engineering in Tribler's development cycle, it was decided to include regression testing in our Jenkins continuous integration system. Using Jenkins, one can create jobs to run specific tasks. Examples of this is checking out the current version of Tribler using git and running the unit tests on this version. Additionally, Jenkins can automatically run jobs on defined events such as commits pushed to a pull request or a new pull request being opened on the GitHub repository.
At the start of this thesis, Jenkins would only run unit tests on a Linux server.

[2] `http://jmeter.apache.org/`

To be able to run tests on all major platforms Tribler supports, three additional servers were set up running Windows 32-bit, Windows 64-bit and OS X Yosemite, respectively. After these were deployed a code coverage and pylint checker job were added which track how much of the code has been tested and if the code adheres the PEP8[3] code style, respectively. When either the code coverage drops or the pylint check fails, the build is marked as failed, safeguarding deterioration of the code base.
To further improve Tribler's development process, we have created a performance regression job that runs the third benchmark using five requests per second. To merge this job into the development cycle, we have added it to the 'GH_Tribler_PR' MultiJob. This 'GH_Tribler_PR' MultiJob runs whenever a user pushes a commit to an open pull request, forces a rerun or opens a new pull request on GitHub. Whenever this performance regression job fails, indicating performance regression has occurred, the 'GH_Tribler_PR' is marked as failed. Upon failure, the author who proposes the changes must then investigate and adjust the code accordingly.
To be able to compare old and new code, we have created a separate job that runs the current code base of Tribler daily using the same experiment. Next, we command Jenkins to fetch the data from this job so we can create a comparison graph and table depicting changes between the outputs of each job. If a pull requests gets merged into the code base, this job will automatically run again to ensure comparisons happen against the most recent version.
To make sure the build server can process all jobs in parallel without running out of resources, each server has a specific amount of slots defined. In Jenkins, every job that is running takes up a slot on a build server. To avoid allocating too many slots at once, the 'GH_Tribler_PR' MultiJob consists of three phases:

1. The first phase is the testing phase. In this phase tests are run on the four build servers and in parallel the code style is being checked. Because the current code base is under heavy maintenance by other members of the Tribler team, the next phase is always entered to obtain coverage information.

2. The second phase is the code coverage phase. After the tests have run, all code coverage statistics are merged together to obtain the full coverage report. Next, the full report is compared against the full report of the current code base. If the code coverage dropped with this version, the build is marked as failed, otherwise the third and final phase is entered.

3. The third phase is the experimental phase. In this phase an experiment called 'Allchannel+ChannelCommunity_short' is run which checks if Dispersy can still synchronize data properly.

As our benchmark can be categorized as experiment, we decided to add our job to the third phase. Figure 5.2 visualizes the three phases of the 'GH_Tribler_PR' MultiJob.

[3] `https://www.python.org/dev/peps/pep-0008/`

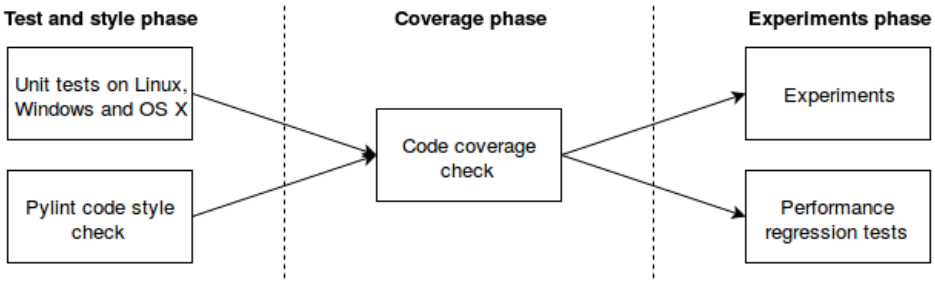


Figure 5.2: The three stages of testing

5.4.1 Multiple platforms

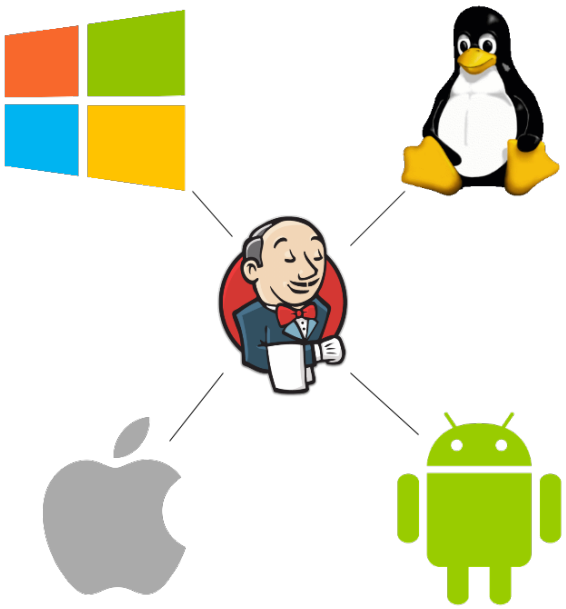


Figure 5.3: Jenkins running on four major operating systems.

As each of these operating systems could influence performance, it is evident regression testing should be performed on these operating systems. Currently, the build servers are used to package Tribler for official releases and to run unit tests on. Soon a build server running the Android operating system will be added as there is an official Android Tribler app in development.
Using Jenkins, we can schedule benchmarks automatically on all available servers, visualized in Figure 5.3. By doing so, we can observe if Tribler performs the same on all operating systems. In case a specific operation system does not match the signature of the others, developers can look into the inner workers of this operating system to better understand the situation. As this item was not feasible to implement giving the time left of this thesis, it is noted down as future work.

Chapter 6

Experimental results

Table 6.1: Specifications of the setup used during the idle iotop measurement of Tribler 6.6.0-pre-exp.

Component	Specifications
OS	Ubuntu 15.10
Python version	2.7.10
CPU	1 Core with 4 processors (2.5 GHz each)
HDD	25 GB
RAM	8 GB

To evaluate Tribler's current situation and to validate our implementations are working correctly, experiments have been conducted. In this chapter we elaborate on these experiments and discuss the results. All experiments with the exception of one have been conduction on a virtual private server whose specifications can be found in Table6.1.

6.1 Tribler's I/O over the years

As explained in Section 2.2, Tribler's I/O has been a problem for years. To observe if and how the amount of I/O has changed over time, we have performed measurements on four different versions of Tribler using iotop[1]. The versions and their release dates are depicted in Table 6.2.

change if needed

As these measurements were never performed systematically, it is vital to perform these measurement now to observe if any changes have occurred between releases and document them. This will provide valuable insight in Tribler's behaviour and the extent of the problem. Moreover it will show us if the amount of I/O is being reduced since the creating of the ticker on GitHub.

[1] http://guichaz.free.fr/iotop/

Table 6.2: The versions of Tribler and their release dates.

Tribler version	Release date
6.3.5	2014-11-06
6.4.3	2015-01-21
6.5.2	2016-05-13
6.6.0-exp1	2016-07-26

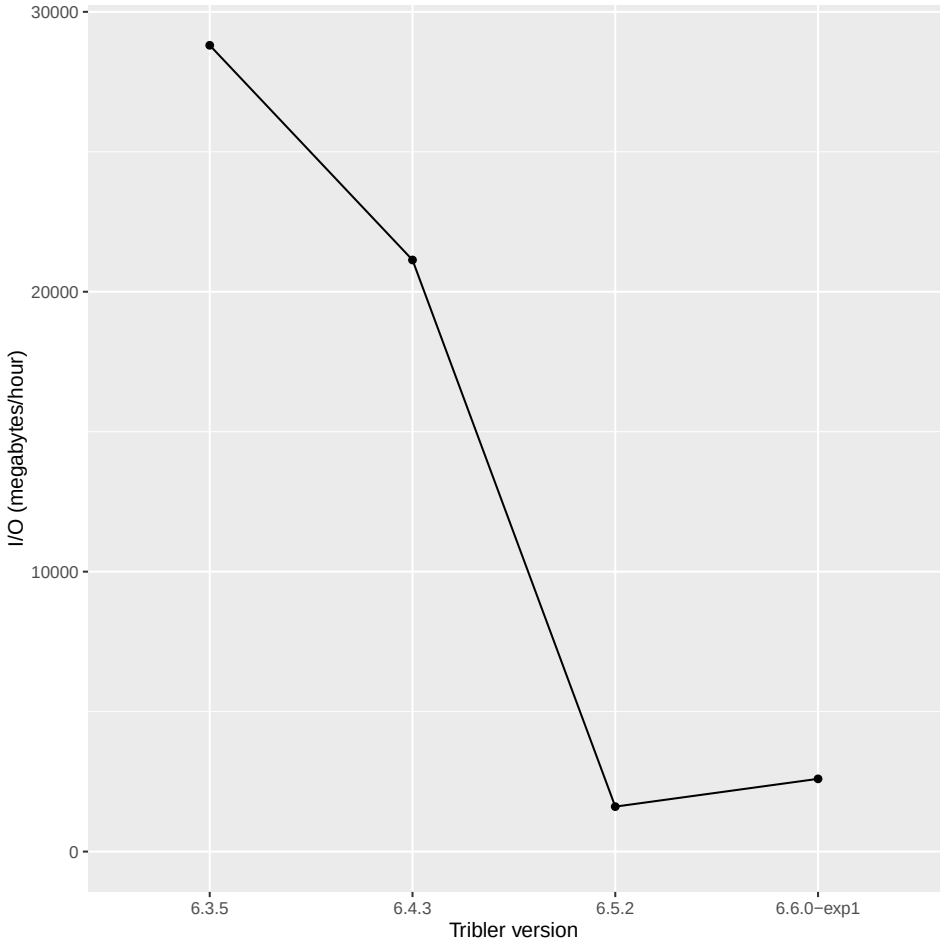


Figure 6.1: The amount of I/O per version of Tribler.

Each version of Tribler will run for one hour idle, using a clean state directory i.e. no prior knowledge of the network and its contents. During the idle run, Tribler will start discovering peers and content such as channels and torrents, storing the obtained data in the database which gets flushed to disk. Additionally, peers will start requesting data from this Tribler instance such as search and peer exchange requests, causing Tribler to read data from the database. These read and writes

Table 6.3: The packets collected for each version by Tribler when running idle for one hour using a clean state directory.

Paket type	Tribler version	Amount
Dispersy-identity	6.3.5	20,026
	6.4.3	38,268
	6.5.2	46,890
	6.6.0-exp1	41,480
Dispersy-undo-own	6.3.5	40,594
	6.4.3	45,095
	6.5.2	47,409
	6.6.0-exp1	44,279
votecast	6.3.5	44,990
	6.4.3	90,339
	6.5.2	116,557
	6.6.0-exp1	96,509

operations will be monitored by iotop and the amounts automatically accumulated. After one hour, the amount of read and write I/O is noted down and Tribler is shutdown.

The results of this experiment are visible in Figure 6.1. From this figure we observe that Tribler's I/O has been reduced significantly in version 6.5.2. This decrease was the result of batching multiple database queries and periodically flush them to disk, an effective optimization technique also applied in other work [39, 40]. Furthermore we observe the amount of I/O is increasing again in the latest 6.6.0-exp1 release due to the MultiChain feature added.

Peculiarly, the numbers observed in this experiment are significantly higher than the numbers reported in the original ticket. We believe the reason two reasons contribute to these numbers. The first one is due to the 100 mbit connection of the experiment machine, providing excellent connectability conditions. Secondly, the fact that this instance began with a clean state directory while running idle, provides ideal conditions for Tribler to spend most of its resources on discovering peers and content.

To observe the cost versus the benefits, we have tracked the amount of packets Tribler managed to synchronize while running one hour idle using a clean state directory for each version. The results are visible in Table 6.3. From this table we conclude that while version 6.3.5 and 6.4.3 perform much more I/O, the amount of packets obtained is significantly less. From these numbers we this conclude that the cost of having high I/O rates is not justified by the benefits as they perform even worse. Interestingly, the numbers of the latest 6.6.0-exp1 version are similar to that of 6.4.3, while we cannot explain this fully, we believe it may be caused by external network conditions or the MultiChain feature.

In conclusion, we believe that the I/O rate of Tribler does not show a correlation

with the amount of packets synchronized. As the I/O rate of Tribler rises again in the latest version, possibly because of the MultiChain feature requiring additional computations, it shows the urgency of the I/O to become asynchronous and non-blocking.

6.2 I/O breakdown

Table 6.4: Specifications of the setup used during the idle iotop measurement of Tribler 6.6.0-pre-exp.

Packet type	**Amount**
Operating System	Ubuntu 16.04 LTS
Python version	2.7.12
CPU	Intel Core i5-2410M
HDD	Samsung 850 EVO 250GB
RAM	8 GB DDR3 1600MHz

Run this experiment on the ubuntu 15.10 machine.

To observe the individual components separately, we have created a breakdown of the database queries performed by Dispersy.

6.3 Tribler's performance

To measure the performance gain of Tribler, we have conducted two sets of experiments where two instances of Tribler, one with a synchronous, blocking Dispersy implementation and one with the asynchronous, non-blocking version of Dispersy, are compared.
In the first experiment we have ran Tribler idle for one hour while querying the Twisted event loop every 100 milliseconds for delayed calls. By doing so we can observe if certain tasks have been delayed past their set time of execution i.e. measure the latency in the system.
In the second experiment we have stress-tested Tribler's new API. By requesting data from an endpoint at several rates per second, we can observe the throughput, response times, variance in these response times and throughput of Tribler.

Table 6.5: A breakdown of the Dispersy database function calls when running Tribler idle for one hour using a clean state directory.

Query	**Amount of calls**	**Total time (s)**	**Max**	**Average**	**Min**
execute	1,099,211	36.068	0.24959	0.00003	0.00001
commit	65	11.089	1.12432	0.17061	0.00001
executemany	4282	0.233	0.00071	0.00005	0.00001

6.3.1 Measuring the latency of Tribler

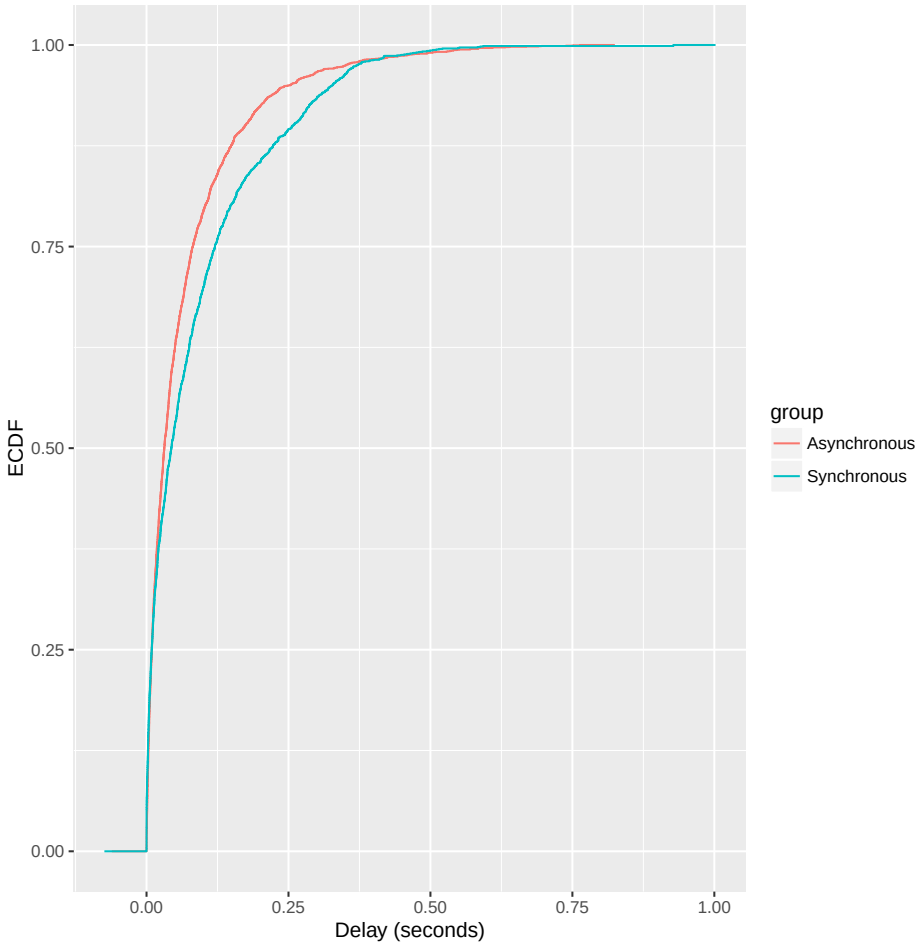


Figure 6.2: An ECDF plot of the latency when running Tribler idle.

In this experiment we have compared two versions of Tribler, one with Dispersy having blocking, synchronous I/O and one with Dispersy running StormDBManager and thus having non-blocking, asynchronous I/O. Each instance of Tribler was run one hour idle where every 100 milliseconds the event loop of Twisted was queried for delayed calls. By observing if scheduled calls are past their set time of execution, we can measure the amount of delay or *latency* in the system. Latency occurs when the twisted reactor thread is blocked or busy with a task that takes a relative long time to complete, causing other tasks to become delayed. Latency is therefore directly related to the responsiveness of a program. The lower the latency, the more responsive a system is.

In theory, making functions asynchronous slices them into smaller 'chunks' which can be executed interleaved, creating a more responsive system as e.g. user actions

will be executed in between (background) operations.
In this experiment the hypothesis is that the latency of the asynchronous version will be lower than its synchronous counterpart. Since Tribler is running idle it has more resources i.e. CPU time available to tend to Dispersy which is running in the background, which most likely will cause the difference to be smaller than when Tribler is experiencing additional load. However, we believe the average may still be significant enough to prefer the asynchronous implementation.
After running the experiment, we have created an empirical cumulative distribution function (ECDF) plot of the delayed calls, visible in Figure 6.2. From this figure we observe that the asynchronous version performs better than the synchronous version. On average, the synchronous version has a latency of 87 milliseconds, where the asynchronous version has a latency of 66 milliseconds, a difference of 24%. Furthermore, the synchronous case has more outliers, some even touching the one second mark. This observations are enough to confirm the hypothesis: both on average and in maxima the latency of the asynchronous version are lower.

6.3.2 Measuring the responsiveness of Tribler

To measure the responsiveness of Tribler while under load, we have stress tested the API of Tribler using the procedure described in Section 5.3.3.
In this experiment we use a state directory containing around 1200 channels. By querying Tribler's channel API endpoint for all discovered channels, all channels in the database will be fetched and returned. As this is Tribler's heaviest endpoint in terms of computation, it's the best way to put Tribler under load. In total the experiment will be run six times, querying the channel endpoint exactly 1000 times per run using 1, 2, 5, 10, 15 and 20 requests per second respectively. By tracking the response times, the amount of requests per seconds and the throughput the API can offer, we can measure the gain in responsiveness and thus in performance (T) of Tribler. We expect that the asynchronous version will outperform the synchronous version significantly in both response times as throughput.
The results of the experiment can be found in Table 6.6. From this table we observe that asynchronous version has a significant less amount of response time, both on average and in maximal duration. The reduction in response times (on average) ranges between 32.1% and 57.5%. As the responsiveness of a program can be directly linked to its performance (see Section 5.3.3), this looks very promising. Interesting to note here is that the average response times of the synchronous version go down when the amount of requests per second goes up. We believe this may be due to Twisted caching responses.
Another indication that the system has become more responsive is the the standard deviation. For every run the standard deviation of the asynchronous version is significantly less than its synchronous counterpart, indicating the response times are more stable than the synchronous version. This can be explained by the slicing of tasks because of asynchrony; as tasks are more interleaved, smaller tasks such as a request will be processed in between bigger tasks, yielding a higher and more

Table 6.6: The results of the six experiments runs with and without asynchronous, non-blocking I/O in Dispersy.

Req./s	Async.	Avg (ms)	Min	Max	Std. Dev.	T (KB/s)	Resp./s
1	✗	315	53	4774	615.90	564.19	0.9
	✓	134	57	2576	189.89	612.60	1.0
2	✗	237	52	4524	475.31	1049.31	1.7
	✓	113	56	1224	162.62	1197.90	1.9
5	✗	143	52	2865	259.64	2399.57	3.9
	✓	67	56	846	38.50	3058.27	5.0
10	✗	135	54	3338	259.37	3827.02	6.2
	✓	89	52	1138	92.58	5435.71	8.8
15	✗	133	51	4678	382.57	4521.46	7.3
	✓	88	52	963	82.23	6799.35	11.0
20	✗	109	51	3400	239.23	5599.75	9.1
	✓	74	52	1051	57.37	8264.01	13.4

stable responsivity.

A third promising statistic is the throughput. As the response is 613 kilobytes (KB) in size, the theoretical maximum throughput will be 613, 1226, 3065, 6130, 9195 and 12260 KB/s, respectively. If we plot the theoretical, asynchronous and the synchronous throughput we obtain Figure 6.3. As we can see the throughput of the asynchronous case lies close to the theoretical maximum until around the ten requests per second. At this point Tribler starts to show signs of being overloaded, which is also visible in the table when looking at the amount of responses received per second.

At ten requests per second both the asynchronous and the synchronous version cannot keep up. If we look at the responses per second for fifteen and twenty requests per second, we observe that the gap between requests and responses grows percentage wise. The question that arises here is why Tribler can't provide 13.4 responses per second with fifteen requests per second as in the case with twenty. Again we believe the answer lies in the Twisted framework.

As more tasks are scheduled on the event loop of Twisted, it will process each of them fairly where priority is given to the most delayed task. Since there are now more requests pending, it will spend more computation power on the requests. Even though this means that more responses per second can be provided, percentage wise the amount of replies per request drops: for fifteen requests this percentage is 73% where for twenty requests per second this percentage is 67%.

All in all, this experiment demonstrates that the asynchronous system has superior performance over the synchronous case, increasing the throughput up to 150%.

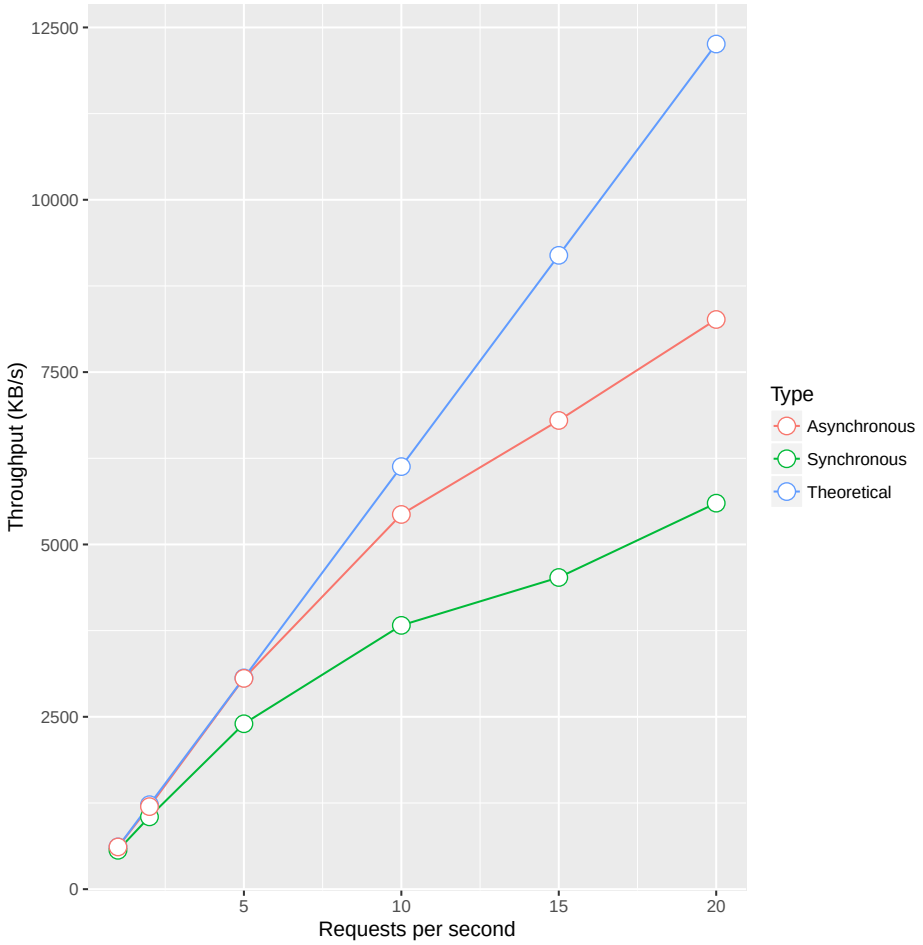


Figure 6.3: The throughput theoretically and of Tribler running Dispersy with asynchronous, non-blocking and synchronous, blocking I/O

6.3.3 Validating the performance regression test system

To validate the performance regression system, we run the experiment above with 5 requests per second. From the results, Gumby creates a side-by-side comparison graph and a table with an overview of the differences in the data obtained.

Figure 6.4 shows the comparison graph generated. From this figure, it is clear that the left hand side – showing the current code base – has higher response times than the right side. From this graph it is immediately clear that the proposed changes have a positive impact on the responsiveness of the API.

todo

To look at the data generated by the benchmark in more detail, the generated table shown in Figure provides a breakdown of the data. This breakdown highlights the average, minimum, maximum and standard deviation in response times as well as the throughput obtained.

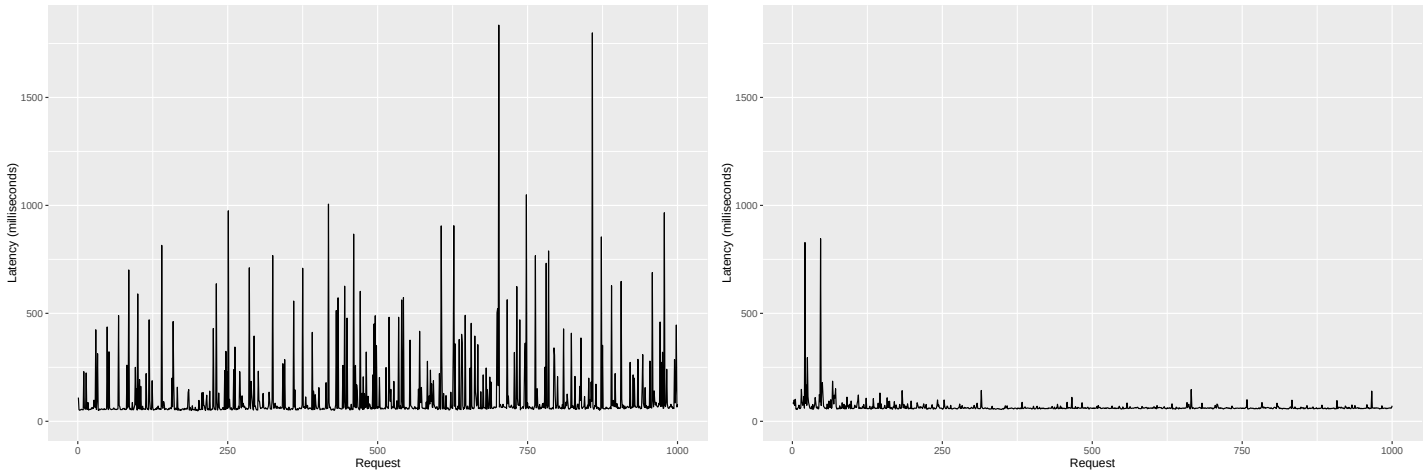


Figure 6.4: The comparison graph showing the response times of Tribler's API. Left: Tribler running Dispersy with synchronous, blocking I/O, right: Tribler running Dispersy with asynchronous, non-blocking I/O.

From these figures we conclude that the performance regression test system provides a suitable overview for developers to get a quick overview of the current state.

Chapter 7

Conclusion and future work

In this thesis we have improved Tribler's performance significantly by making use of software performance engineering. We have addressed Tribler's blocking database I/O, its main performance bottleneck, by integrating the Storm database framework into a new database manager: 'StormDBManager'. StormDBManager features a complete asynchronous, non-blocking interface for database access while still maintaining a serialized query execution strategy. Additionally we have created a regression test system and added this to our Jenkins continuous integration system to adopt software performance engineering in the development cycle, further maturing the project. We have verified both the regression test system and the resolving of the bottlenecks by providing experimental results. We believe that with this performance boost and software engineering focus, we have prepared Tribler for further years of research and strengthened Tribler's chances on becoming a decentralized alternative for YouTube-like streaming.
Future work

- Move storage to a per-community level. This will mean less flushing of data when sending items. In Tribler one only sends messages in the allchannel and to the channelcommunity (if you own a channel).
- A threadpool with sqlite3 multithreaded enabled?
- Move database stuff into classes and use Storm's ORM. That auto-caches items, doesn't commit immediately.
- Extend the regression test system with more metrics? Memory, network etc. ?
- Scan for commits that look scary [3] and tests those. Will reduce amount of regression testing needed. Or use Jenkins pipeline to only run experiment when a value is set to true or tests pass?
- Benchmarks not dependent on the internet, such as seeders for a torrent.

- As discussed in Chapter 5, add regression testing to all operating systems with Jenkins.

Bibliography

[1] C. U. Smith and L. G. Williams, "Software performance engineering," in *UML for Real*, pp. 343–365, Springer, 2003.

[2] M. Mayer, "In search of a better, faster, stronger web," in *Velocity Conference*, 2009.

[3] P. Huang, X. Ma, D. Shen, and Y. Zhou, "Performance regression testing target prioritization via performance risk analysis," in *Proceedings of the 36th International Conference on Software Engineering*, pp. 60–71, ACM, 2014.

[4] M. Woodside, G. Franks, and D. C. Petriu, "The future of software performance engineering," in *Future of Software Engineering, 2007. FOSE'07*, pp. 171–187, IEEE, 2007.

[5] L. G. Williams and C. U. Smith, "Performance evaluation of software architectures," in *Proceedings of the 1st international workshop on Software and performance*, pp. 164–177, ACM, 1998.

[6] C. U. Smith and L. G. Williams, "Best practices for software performance engineering," in *Int. CMG Conference*, pp. 83–92, 2003.

[7] GitHub, "Releases," 2016.

[8] K. Kumar and Y.-H. Lu, "Cloud computing for mobile users: Can offloading computation save energy?," *Computer*, vol. 43, no. 4, pp. 51–56, 2010.

[9] R. Kemp, N. Palmer, T. Kielmann, and H. Bal, "Cuckoo: a computation offloading framework for smartphones," in *International Conference on Mobile Computing, Applications, and Services*, pp. 59–79, Springer, 2010.

[10] R. Plak, *Anonymous Internet: Anonymizing peer-to-peer traffic using applied cryptography*. PhD thesis, TU Delft, Delft University of Technology, 2014.

[11] R. J. Tanaskoski, *Anonymous HD video streaming*. PhD thesis, TU Delft, Delft University of Technology, 2014.

[12] R. Ruigrok, *BitTorrent file sharing using Tor-like hidden services*. PhD thesis, TU Delft, Delft University of Technology, 2015.

[13] J. Pouwelse, "Reduce io activity from 623mbyte/hour," 2014.

[14] A. Mainka, S. Hartmann, W. G. Stock, and I. Peters, "Government and social media: A case study of 31 informational world cities," in *2014 47th Hawaii International Conference on System Sciences*, pp. 1715–1724, IEEE, 2014.

[15] J. Sharma, "Strategies to overcome dark side of social media for organizational sustainability," *International Journal of Virtual Communities and Social Networking (IJVCSN)*, vol. 8, no. 1, pp. 42–52, 2016.

[16] redecentralize.org, "Alternative internet," 2016.

[17] OpenHUB, "Tribler," 2016.

[18] G. Ammons, J.-D. Choi, M. Gupta, and N. Swamy, "Finding and removing performance bottlenecks in large systems," in *European Conference on Object-Oriented Programming*, pp. 172–196, Springer, 2004.

[19] J. Pouwelse, "Documentation: Tribler, dispersy and libswift developers portal," 2013.

[20] Tribler, "Dispersy," 2016.

[21] N. Zeilemaker, B. Schoon, and J. Pouwelse, "Dispersy bundle synchronization," *TU Delft, Parallel and Distributed Systems*, 2013.

[22] S. D. Norberhuis, *MultiChain: A cybercurrency for cooperation*. PhD thesis, TU Delft, Delft University of Technology, 2015.

[23] D. Beazley, "Understanding the python gil," in *PyCON Python Conference. Atlanta, Georgia*, 2010.

[24] D. Beazley, "Inside the python gil (slides)," in *Python Concurrency Workshop*, 2009.

[25] Python, "Global interpreter lock," 2015.

[26] C. F. Bolz, A. Cuni, M. Fijalkowski, and A. Rigo, "Tracing the meta-level: Pypy's tracing jit compiler," in *Proceedings of the 4th workshop on the Implementation, Compilation, Optimization of Object-Oriented Languages and Programming Systems*, pp. 18–25, ACM, 2009.

[27] PyPy, "Pypy," 2016.

[28] Pypy, "Speed center," 2016.

[29] Jython, "Why jython," 2016.

[30] Python, "Ironpython," 2014.

[31] asyncio.org, "Python async io resources," 2016.

[32] A. Sherman and P. Den Hartog, "Deco: Polishing python parallel programming," 2016.

[33] K. Kinder, "Event-driven programming with twisted and python," *Linux journal*, vol. 2005, no. 131, p. 6, 2005.

[34] J. Pouwelse, "Consider a new networking/threading framework: Twisted, gevent or keep our own," 2013.

[35] Canonical, "Storm," 2011.

[36] X. Ferré, N. Juristo, H. Windl, and L. Constantine, "Usability basics for software developers," *IEEE software*, vol. 18, no. 1, p. 22, 2001.

[37] E. Adar and B. A. Huberman, "Free riding on gnutella," *First monday*, vol. 5, no. 10, 2000.

[38] G. Lindgaard, G. Fernandes, C. Dudek, and J. Brown, "Attention web designers: You have 50 milliseconds to make a good first impression!," *Behaviour & information technology*, vol. 25, no. 2, pp. 115–126, 2006.

[39] X. Ouyang, D. Nellans, R. Wipfel, D. Flynn, and D. K. Panda, "Beyond block i/o: Rethinking traditional storage primitives," in *2011 IEEE 17th International Symposium on High Performance Computer Architecture*, pp. 301–311, IEEE, 2011.

[40] O. C. Lin, A. T. Kwee, and F. S. Tsai, "Database optimization for novelty detection," in *Information, Communications and Signal Processing, 2009. ICICS 2009. 7th International Conference on*, pp. 1–5, IEEE, 2009.