A Platform for Automating Chaos Experiments

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Abstract—The Netflix video streaming system is composed of many interacting services. In such a large system, failures in individual services are not uncommon. This paper describes the Chaos Automation Platform, a system for running failure injection experiments on the production system to verify that failures in non-critical services do not result in system outages.

1. Introduction

To an end-user, Netflix is a single service that allows them to stream television shows and movies over the Internet. To the engineers who work for the company, Netflix is a distributed system made up of many services that interact via remote procedure call (RPC), sometimes referred to as a microservice architecture [1].

In a large system such as Netflix, where hundreds of services run on thousands of machines and engineers are making changes every day, many things can go wrong. Fortunately, many of the internal services that make up Netflix are not critical for the user to be able to watch a video. For example, a personalized list of recommendations and bookmarks that recall where you left off when previously watching a video add value to the user, but if the services that implement these features stop working, we should still be able to provide a reasonable user experience. Hodges describes this kind of graceful degradation as partial availability [2].

Partial availability doesn’t come for free: engineers must explicitly implement fallback behavior when making RPC calls against non-critical services. If fallback behavior is not implemented correctly, a problem in a non-critical service can lead to an outage. This work addresses the following question: how can we have confidence that Netflix users will still be able to stream videos after non-critical services have failed?

At Netflix, we practice Chaos Engineering [3]. Namely, we believe there is a level of complexity in modern distributed systems that is chaotic, and that a chief architect cannot hold all of the system’s moving parts in their head. Chaos Engineering is about engineering practices that help us surface systemic effects, as embodied by the Principles of Chaos Engineering [4].

In particular, we believe that to have maximum confidence you must test in your production environment with live traffic. Chaos Monkey [5] is one example of Chaos Engineering in practice at Netflix. Another example is automated canary analysis [6], which tests new code in the production environment with live traffic. Unfortunately, canary analysis is not guaranteed to test the code paths associated with dealing with failures in non-critical services. Another tenet of Chaos Engineering is automation: we want an automated solution for ensuring the system is resilient to failures in non-critical services.

This paper describes our proposed solution: the Chaos Automation Platform, or ChAP. ChAP enables engineering teams to run Chaos Engineering experiments on live traffic in production in order to build confidence that their service will degrade gracefully when non-critical downstream services fail.

ChAP works by diverting a fraction of production traffic, injecting failures into the diverted traffic, and checking that the system behaves as expected. Section 4 describes how an engineer would use ChAP to verify that Netflix is resilient to failures in a particular service.

2. Individual service failures vs system-level failures

As Hodges notes, “distributed systems are different because they fail often” [2]. When a system runs on thousands of servers, it becomes very likely that something will go wrong somewhere.

A simple example of a failure is a bug that results in an unhandled exception, such as a null pointer exception. In Netflix’s microservice architecture, an unhandled exception results in a service returning an HTTP 500 error code [7].

There are other failure modes that are common for an individual service in a microservice architecture. One common problem is resource exhaustion. Examples of finite resources on a server include memory, disk space, CPU cycles, threads, and open TCP/IP connections. When a server runs out of one of these resources, system calls that would normally succeed may block or throw exceptions. Resource exhaustion can be caused by a resource leak, but it may also occur if the load on a server exceeds its capacity. Here the problem is that the service has been insufficiently scaled: not enough servers have been allocated to that service.

When a server runs low on one of its resources, one symptom is an increase in the average response time of the server. For example, memory pressure on a server may

1. At Netflix, most services are implemented in Java, which uses exceptions for error signaling.
lead to garbage collection pauses. Another example: for a service that allocates one thread-per-request, if the number of pending requests exceeds the number of available threads, latency will increase.

Yet another issue is the environment that these services run in. All of the Netflix services run within the Amazon Web Services Elastic Compute Cloud (EC2), an infrastructure-as-a-service cloud computing environment [8]. Because cloud providers such as EC2 compete on price, in order to reduce costs they use commodity-grade hardware instead of more reliable enterprise-grade hardware. This increases the likelihood of an individual server failing because of hardware issues. Transient networking issues such as latency spikes are also not uncommon in cloud computing environments. When deploying to a cloud computing platform, it is the responsibility of the software engineers to design systems that incorporate redundancy to compensate for occasional failures in hardware.

Individual service failures are inevitable, and Netflix engineers leverage the Hystrix [9] library to implement fallback logic to handle failures in downstream services. Our goal is to prevent system-level failures. In particular, our goal is to reduce the likelihood of an outage, when Netflix customers are not able to stream videos. The primary metric of system health at Netflix is the number of video stream starts per second, internally referred to as SPS [10].

A failure of an individual service can lead to a drop in SPS if the client calling the service does not have proper fallbacks in place. A study by Yuan et al. revealed that 92% of catastrophic system failures happened because of incorrect error-handling logic [11].

Even if fallback logic is present in a client, the failure of a non-critical service may still lead to a system-level failure due to cascading effects. Consider the following failure scenario, illustrated in Figure 1.

Typically, service $A$ calls service $B$. For some reason, $C$ starts to become overloaded, and returns errors to $B$. The fallback behavior for $B$ is not working correctly, which causes $B$ to return errors. $A$ detects a problem and calls $C$ as a fallback. Fallback behavior that should have alleviated the load on $C$ instead increased the load on $C$, accelerating the problem and resulting in an outage.

We believe that ChAP will help us identify these kinds of failure modes before they result in outages.

### 3. Example of a non-critical service: gallery

When a user logs in to Netflix, they are presented with rows of images, called galleries, that represent video content. Each gallery represents a different category. Examples of galleries include:

- Trending Now
- Recently Added
- Critically-acclaimed Comedies
- TV Dramas

The list of galleries and the contents of the gallery are personalized for each Netflix user: different users will be shown different galleries.

The Gallery microservice is responsible for generating the galleries. If this service stops working, the client that calls the Gallery service must return a sensible fallback. For example, it may return an older gallery that is present in a local cache. Or, it may return a gallery that is not personalized for the particular user. From the user’s perspective, the Netflix interface should still appear to be working properly, even if the content presented to the user is stale or not fully personalized.

Figure 2 shows the request path for requests that ultimately reach the Gallery service. The first service in the request path is Zuul [12], a reverse-proxy that serves as the front-door to Netflix. Next in the request path is a service called API [13]. API contains the Gallery client library that makes calls against the Gallery service. It is this client library that is responsible for serving fallbacks in the event that the Gallery service fails. To verify that this fallback behavior works correctly, we must inject failures on the calls from API to Gallery.

### 4. Running a ChAP experiment

Consider the following scenario: Alice, a (fictional) QA engineer on the Gallery team, wants to verify that Netflix is resilient to failures in the Gallery service. She uses ChAP's web interface to define an experiment. Because ChAP injects failures on the client side of the request, she selects the API server group as the subject of the experiment. She
specifies that all calls to the Gallery service should fail. She chooses to divert only a small amount of traffic for this experiment: 0.3%. She chooses a duration of 30 minutes for the experiment.

Finally, she selects the metrics that she is interested in observing for the experiment. She chooses a number of Hystrix commands to track for the experiment. Hystrix is a library that allows engineers to wrap RPC calls and specify what the fallback behavior should be if an RPC call fails. Each Hystrix command has a name, e.g.: “GetGallery”.

For each Hystrix command, for the control and experiment server groups, ChAP will display counts of:

- successful requests served
- successful fallbacks served
- failed fallbacks served

An example set of plots for the GetGallery Hystrix command is shown in Figure 3.

Alice expects to see a large number of successful requests served in the control group, and a large number of successful fallbacks served in the experiment group.

Once the experiment starts, the following things happen, as depicted in Figure 4.

ChAP creates two new server groups, named api-chap-control and api-chap-experiment. The servers in these two new groups are deployed with the same software as the servers in the api server group.

Of all of the requests that are destined for the API services, 99.7% are routed to the original API server group, 0.15% are routed to the api-chap-control group, and 0.15% are routed to the api-chap-experiment group. In the api-chap-experiment group, all of the RPC calls to the Gallery service fail immediately with an error.

ChAP presents Alice with a dashboard that plots the metrics specified by user for the control and experiment groups. The dashboard also shows the SPS for each group. By comparing the metrics between the two groups, Alice can determine whether the system is handling Gallery failures correctly.

6. Current status and future work

ChAP is still under heavy development, with a few teams inside of Netflix currently test-driving the system and providing feedback. Our ultimate goal is to be able to detect automatically whether a service is resilient to failure rather than relying on a human looking at dashboards and making a judgment. We also plan to integrate ChAP into the Spinnaker deployment system so that ChAP experiments can be started automatically as part of the deployment process.

There are failures that FIT (and, hence, ChAP) cannot currently model. We can only inject failures in the request path, in requests that originate from a Netflix client device. In particular, we cannot yet inject failures in calls between services that are occur during the startup of a service.

Finally, while we use SPS as our health metric, what we are ultimately concerned about is the user experience. In the future, we hope to use information from client devices to get more accurate information on the impact of a ChAP experiment on a user.

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Hystrix: GetGallery

Figure 3. ChAP plots for the GetGallery Hystrix command

Figure 4. A fraction of traffic is routed to the control and experiment server groups. Failures are only injected into the experiment server group.

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