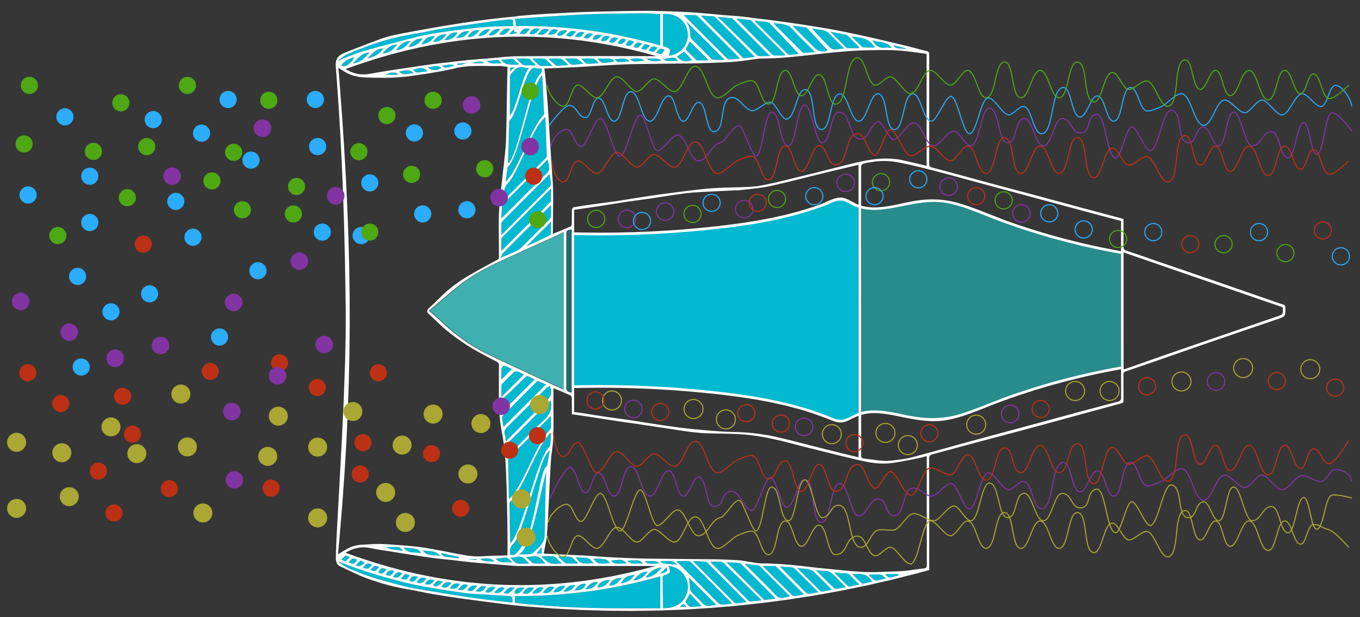
Sampling a Stream of Events

With a Probabilistic Sketch



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VividCortex

Meet the Author

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Baron is a performance and scalability expert who participates in various database, opensource, and distributed systems communities. He has helped build and scale many large, high-traffic services for Fortune 1000 clients. He has written several books, including O'Reilly's best-selling High Performance MySQL. Baron has a CS degree from the University of Virginia.

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Introduction

Stream processing is a hot topic today. As modern Big Data processing systems have evolved, stream processing has become recognized as a first-class citizen in the toolbox. That's because when you take away the *how* of Big Data and look at the underlying goals and end results, deriving real-time insights from huge, high-velocity, high-variety streams of data is a fundamental, core use case. This explains the explosive popularity of systems such as Apache Kafka, Apache Spark, Apache Samza, Apache Storm, and Apache Apex—to name just a few!

One of the "articles of faith" for Big Data is that deriving insights from small samples of the data is obsolete. Many Big Data practitioners feel that it's sacrilegious to discard any of the data. However, the reality in many systems is that you *must* discard much of the data. Such is the case with the data processing we do at VividCortex, where we derive insights from giant streams of data that are economically and physically infeasible to capture, transmit, store, and analyze in their entirety.

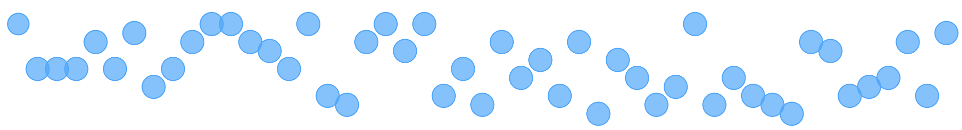
In order to provide the results VividCortex's customers need at a cost they can afford, we have had to invent or discover many novel techniques, some of which are patent-pending. In this book we discuss a sophisticated technique we've developed to select representative samples of query traffic on database servers. It uses a probabilistic data structure known as a "sketch," among other things.

Extracting a good sample of data from a stream is much harder than it seems. There are many tradeoffs and conflicting requirements to satisfy. We are sharing our work in this book because the requirements, the approach, and the solution may be applicable to a broad variety of use cases. We would love it if we could buy a log analysis solution that used these techniques, for example. Current log analysis products are performance intensive and cost prohibitive.

Describing Event Streams

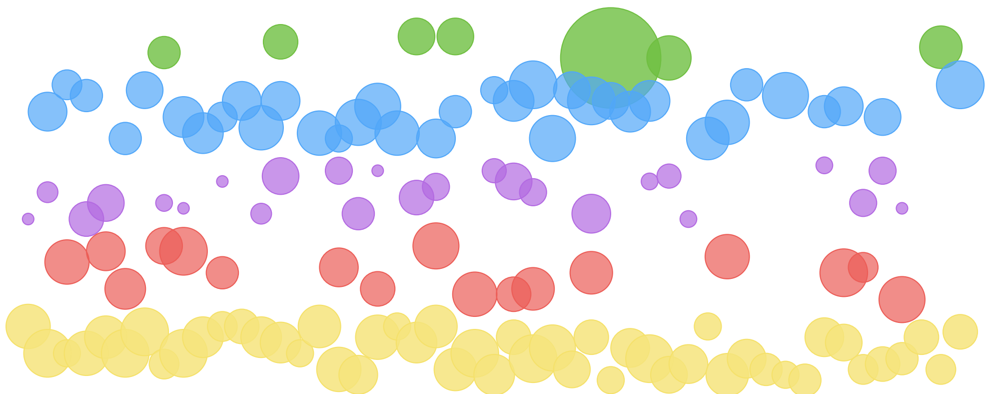
One of the fundamental problems VividCortex exists to solve is recording a very large number of high-velocity event streams in a highly descriptive level of detail. In VividCortex, events are queries (or requests, or statements) at a variety of types of databases. At the time of writing we support MySQL, PostgreSQL, Redis, and MongoDB. Database servers are just one use case, however. The same principles could be applied to any stream of events, where an *event* is a timestamped occurrence with potentially many properties or attributes. Messages in an application or system log, for example, are also events.

An event stream might look like the following, where events are circles and time flows from left to right.

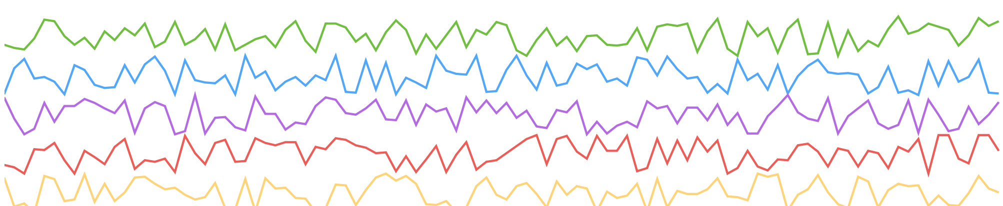


If your system observes events that are feasible to capture in their entirety, the rest of this book might not be interesting to you. But at VividCortex, we're observing tens of thousands of events per second per monitored server, across large numbers of servers. These are transmitted to our platform "in the cloud." Network bandwidth alone makes it physically impossible to transmit all of this data. The storage and compute resources that would be necessary to analyze them once transmitted is another reason not to do so. As a result, our monitoring agent software uses a variety of algorithms to *describe* the event streams.

In order to describe the streams at a useful granularity, we generate *metrics* about them. To do this, we first group events into categories by *digesting* the events. This typically results in hundreds to thousands of distinct categories of events per server; sometimes much more. The category identifier becomes another attribute of the events. The event streams are actually more complex than shown above: they have many dimensions. Some are larger than others; some are more or less frequent, some have particular characteristics such as errors. Here is a picture that hints at the complexity of typical event streams.



Then we maintain counters about these events and their attributes. For example, we sum the latencies of the events within a category. Once per second (all of VividCortex's metrics are in one-second granularity) we measure and reset that category's accumulated latency. We do this for many other types of attributes, such as error rates by error code, event size in bytes, count of events seen, and so on. A simplistic view of this set of metrics might look like the following.



This enables very fine drill-down and inspection of any desired category of events.

The Curse of Aggregates

The result of our slice, dice, and measure process is high-dimensional metrics streams—many dimensions of metrics once per second per category—describing highly granular categories of metrics. This is *a lot* of metrics. To give some perspective, we typically capture *orders of magnitude* more metrics from a single server every second than most monitoring systems produce from an entire cage of servers.

But it still isn't enough! The problem is that these metrics are *aggregates*. Aggregates, even at one-second intervals, even over subdivided categorized streams, discard or hide a lot of necessary detail. From an aggregate you can no longer discover the distribution of an attribute's values. You can no longer identify co-occurrence of interesting things. You may see that there was a spike in a query category's latency and rows returned, but you can't be sure whether this resulted from a lot of queries with high latency, or a single outlier.

The usual answer to this is to use different types of aggregates, such as histograms or quantiles. For reasons that would take too long to explain here, these don't solve all the problems either.[1]

Sampling To The Rescue

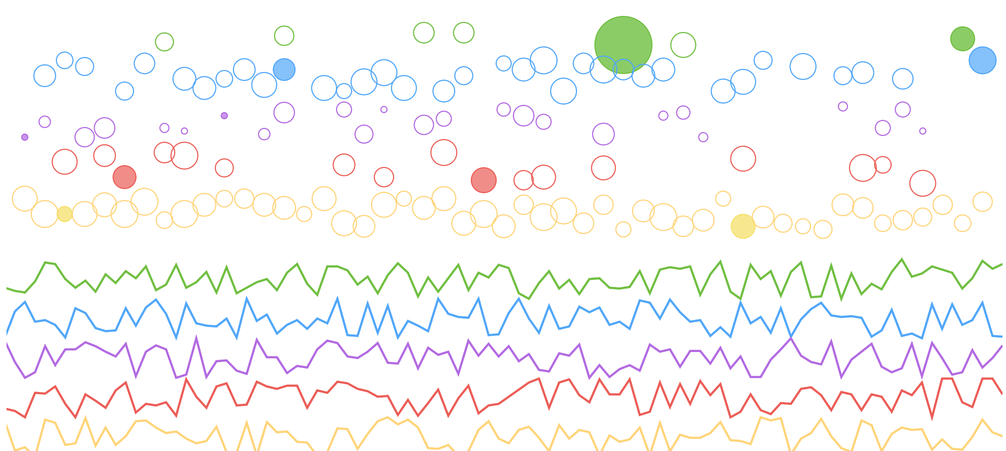
No matter how many metrics you generate and store, you can't get enough information from metrics alone. Even if you aggregate every combination of the cross-product of dimensions—the cardinality of which asymptotically approaches the cardinality of the original event stream—metrics aren't a complete solution. Sometimes you need the original event in its entirety. Using database queries as an example, here

1 See https://www.vividcortex.com/blog/why-percentiles-dont-work-the-way-you-think.

are some things you need to do in order to diagnose and solve performance problems or defects:

- Inspect the query to see if the constants or bind parameters are related to a particular type of data—perhaps a particular user ID in an application, or a particular status in a job queue. This type of analysis can reveal problems arising from skew in the data, for example.
- Inspect a query's execution plan. This is only possible to do if you have the original query text.
- See the hostname and port of the query's origin.
- Understand why a particular query causes an error or warning, when other similar ones don't.

To achieve these goals, you need a combination of data types: *metrics* and *samples*. If you combine highly granular metrics and a small selection of the actual events in the stream, and you do the selection just right, you can get a highly representative picture of the original event stream, while discarding most of it for efficiency. You essentially have a small sample of the events, plus metrics that describe the original stream in a highly compressed way.



Disambiguating Sampling

The process of selecting and keeping the smaller sample of events is what we refer to as "sampling." This is a very confusing term because it is overloaded with several meanings. We frequently receive questions or comments that reveal a misunderstanding of exactly how we sample event streams at VividCortex. Before going on, we need to clarify this so we're all thinking about the same things.

One meaning of sampling is related to digital signal processing, which describes how a continuous signal (such as an audio wave) is represented by a discrete signal, which represents the signal at points in time. In other words, sampling describes how the signal is measured at discrete moments. As we mentioned previously, our time series metrics have points once per second. If you consider the metrics about categories of events to be signals, then you'd say our sampling frequency is 1Hz. This, however, is not the type of sampling we're discussing in this book.

Another thing that comes to mind when talking about sampling is more accurately described as *polling*. Many monitoring tools take instantaneous snapshots of system state at regular intervals, sleeping in between. While sleeping they miss what is happening on the system, which can be a lot. Our monitoring agents don't work this way. They observe and measure *all* of the events in the streams, not just those that are visible at moments in time. We're not polling the event streams.

The final meaning of sampling is the way it's used in statistics, where you obtain a sample that you know to be a subset of the entire population, and analyze it. This is more more in line with the usage of sampling in this book, except that in statistics you usually don't have access to the entire population of data, and you perform your analysis only on the sample. However, our agents actually observe and analyze the entire population.

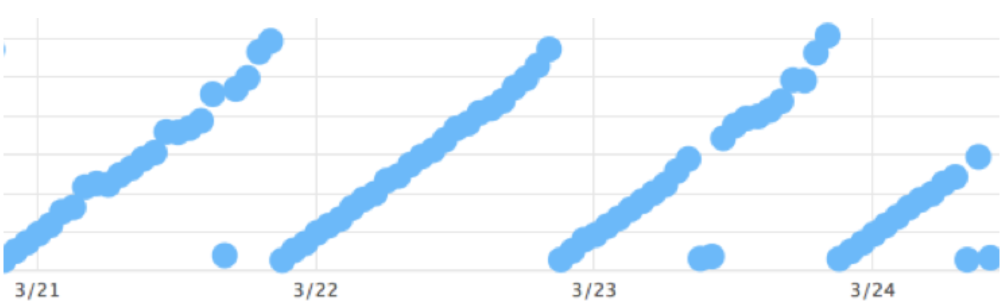
The metrics they generate are reflective of the population.

We use "sampling" in this book to describe how, after measuring the entire contents of the event streams, our agents select a sample to retain for re-analysis and inspection later. This subset of the original stream helps reveal things that metrics alone can't capture.

Requirements for the Sampling Technique

There are good and bad ways to select a sample from the stream of events. Depending on how you do it, the resulting sample might be biased or incomplete in various ways. In general, there's a desirable balance between a representative sample and a biased sample. A completely representative sample has the property that you can extrapolate from it to make inferences about the original population. A biased sample might not preserve this property, but might reflect your view of what's most important to know about the population.

Representative samples are important because without them, you lose important information about the patterns and tendencies of the original event stream. For example, the following user interface screenshot from an older version of VividCortex shows query latency over time. Without representative sampling, this pattern might be lost or skewed. This visualization made an important query problem easy to see.



Representative sampling turns out to be very hard to do well, which is what this book is about. Before we explain how we achieved representative sampling and good efficiency, let's look at our requirements overall. These requirements might not match exactly what you want, but it's what we decided VividCortex needed.

Representative Sampling With some caveats and exceptions we'll discuss next, we wanted our sample of events to be broadly representative of the original population of events in the stream.

Sampling Rate We should sample events from each category of events in the stream at a rate that allows a user to drill into smallish time intervals and find samples of interest to examine. If samples are taken too rarely, there won't be any example queries to study. If too frequently, it will cause undue strain on resources.

Bias Towards Importance Some events really are more important than others. Requests with unusually high latency, or requests that cause errors, for example, are more important to capture and retain than the general population. This enables troubleshooting of one-in-a-million events that would otherwise be missed. These unusual or unlikely events are disproportionately often the cause of serious problems, so capturing them for inspection is the difference between a dead-end diagnosis effort and a correct solution.

Flexible Customization Our customers require various special-case behaviors for query sampling. These include blacklisting, whitelisting, avoiding the capture of sensitive or private data, and guaranteeing the capture of specific types of samples for debugging or auditing purposes. These features have been the key to solving bizarre and frustrating problems, capturing bugs that no other monitoring systems were able to surface, investigating unauthorized activity, and the like.

In addition to these user-driven requirements, there were several implementation and technical requirements we needed to satisfy. Some of these are at odds with each other or with user requirements:

Balancing Sampling Rates It's hard to balance global and per-category sampling rates across very different types of event streams. For example, some categories of events are high-frequency, but others are very rarely seen. If sampling were strictly representative, we'd capture more samples of the high-frequency streams, which we don't want because it could starve low-frequency streams, meaning we wouldn't have any samples from them. And for purposes of limiting the overall rate of sampling across all streams, we need individual streams to be sampled such that we don't overload anything in the aggregate. But in edge-case scenarios where we have unusually large numbers of categories (many millions for some customers), this becomes difficult to achieve.

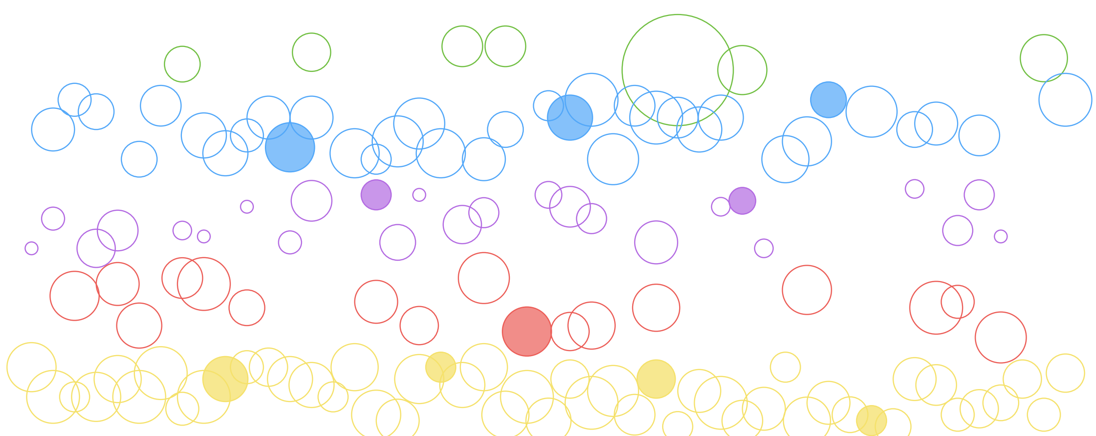
Sampling Bias Versus Rate Limits It's tricky to balance the bias towards important events with the per-category and global rate limits. If we over-bias towards important events, in some scenarios we can sample so fast that we starve events not flagged as important. The same consideration applies to customer-defined sampling criteria.

Correctness, Efficiency, and Implementation Balancing correctness and efficiency with ease of implementation and maintenance is hard. Some of the techniques we found or invented were difficult to implement, debug, or maintain. Some were computationally inefficient. This book presents the results of our third or fourth generation of sampling algorithms.

Potentially Usable Sampling Techniques

Based on the requirements—some of which were obvious from the beginning, and some discovered through hard-won experience—we considered a variety of sampling algorithms. In each case, bad behaviors can happen at edge cases, and with VividCortex's large and diverse customer base, these are not hypothetical. We'll describe them briefly here, then move on to explain the way we currently do sampling.

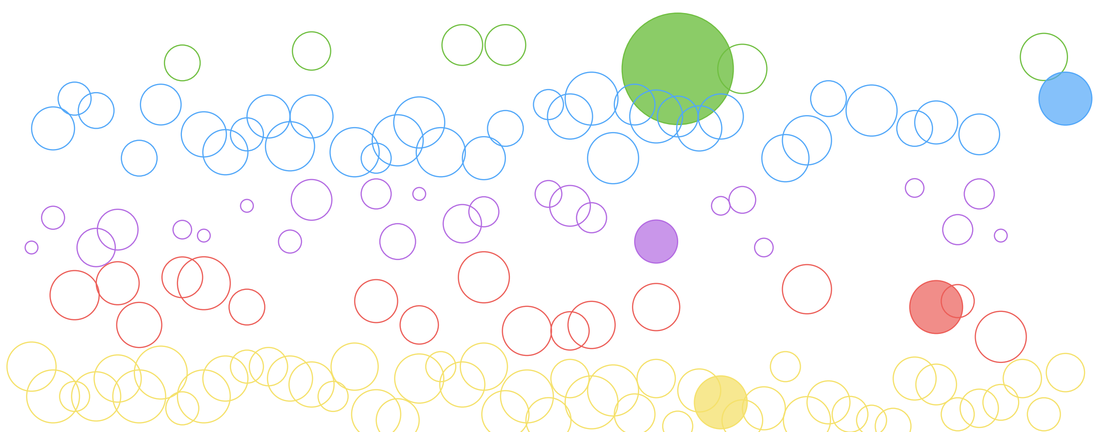
Every Nth Event Perhaps the simplest sampling technique of all is to select a fraction of events to keep. For example, you could keep every 10th event in each category of events. There are a lot of undesirable effects, though. With high-velocity event streams you'll select a lot of samples, causing performance problems. And you'll sample more from high-frequency categories of events, capturing way more than you need while not getting enough from rare categories. In the following image we have sampled every 10th event and we captured zero events from the green category.



You also need to decide how to handle a category when you see its events for the first time: do you sample immediately and then count to 10 before capturing again, or do you count to 10 before taking the first sample? If you sample immediately, you'll create a huge spike of samples upon a cold start. If you count to 10 first, you will never capture any samples at all from some categories. You also need to remember the count of events in each category.[1]

One Nth Of Events This is similar to the previous approach, except that instead of counting and selecting every Nth, you use a random number generator to decide whether to sample any given event. This algorithm doesn't need to remember anything about categories of events, but otherwise has many of the same problems.

Worst Per Interval This is a technique some readers may be familiar with, having seen it used in tools for log analysis. It's actually one of the worst you could choose. It doesn't select representative events, which is particularly bad when the event stream has characteristics such as multiple commingled populations, multimodal distributions, or outliers, which are very common in the real world. Here's an illustration of selecting extreme events, showing the skew that creates.

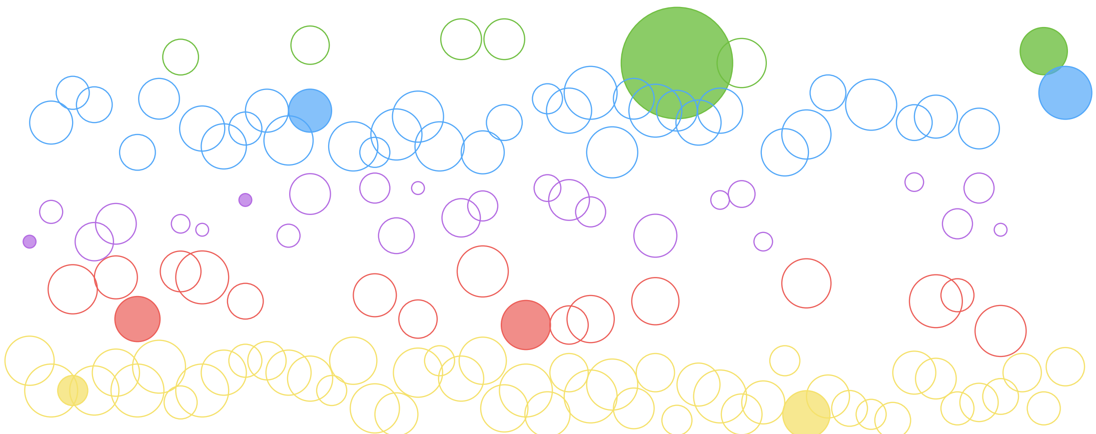


This approach requires you to keep at least one event until the time period expires, which consumes resources and causes time delays between when the event occurs and when it's selected as a sample.

1 Later we'll see why remembering *anything* about streams is difficult to do without negative consequences.

You'll also get either the first-seen or last-seen sample, depending on whether the implementation uses strictly greater-than comparisons, so your samples will also be biased in time.

Sample N Per Interval The ideal approach to create representative samples is to select N events from the stream, essentially at random, in each interval.



Ideally you'd like to sample these events as you see them, so you don't need to remember them until the end of the interval, which saves resources and avoids delay. And ideally you'd like to sample all of the categories at the same rate.

How VividCortex Selects Samples

The ideal method, selecting samples at random with a desired average rate, is not as straightforward as any of the other algorithms, but the results are superior. The only problem is how to do this efficiently.

The definition of the problem contains some clues as to a good solution. If you're familiar with analyzing events in streams—particularly in queueing systems[1]—you may be aware of some special concepts that

1 VividCortex's free ebook on queueing theory is a highly accessible introduction to the topic. See https://www.vividcortex.com/resources/queueing-theory/.

are relevant to the issue at hand. The most general way to analyze requests, which assumes and embeds the least amount of information about their behavior and about the process that generates them, is to consider them to be generated by a *Poisson process*. This type of process generates events at an average rate λ. The elapsed time between events will be exponentially distributed, which is a special "memoryless" distribution. The mean time between events will be $1/\lambda$.

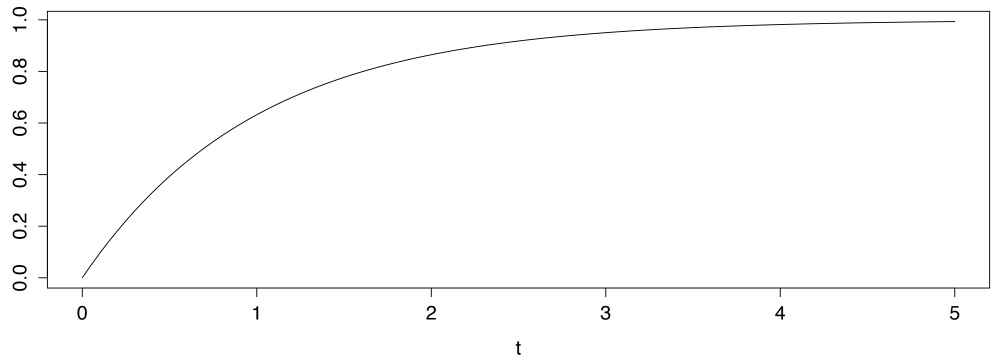
In fact, the same mathematical processes can be used to *select* events from a stream. The resulting stream of samples will have the same characteristics, because the selection process itself is Poisson. Therefore, the selected samples will have the desired average rate and the inter-sample times will be exponentially distributed.

To select samples from a stream in this manner, you'd observe the events in the stream. At each event you observe, you'd compute a probability that this event should be selected, and then compare it to a uniformly generated random number. If the probability of selection is greater than the random number, you'd select the event.

The probability that you should select any given event is given by the following equation:

$$P(t) = 1 - e^{-\lambda t}$$

Where t is the time elapsed since the previous event in the stream. This equation is a curve that begins at 0 and asymptotically approaches 1 as $t \to \infty$:



The height of that curve shows the probability that an event should be selected as a sample. (The illustration is generated with $\lambda = 1$). The only thing the algorithm needs to remember is the timestamp of the last event seen in each stream.

This theoretically ideal sampling algorithm is fine, but we actually use something a little simpler in our monitoring agents. Instead of an exponential function, we use a linear function to determine the probability that we should select an event. This is simpler and more efficient, and it's easier to implement and understand.

Importantly, it also provides a helpful guarantee. When events occur at less than the desired sampling frequency, and it has been longer than $1/\lambda$ since the previous event, the exponential function doesn't guarantee that you'll select the next event. That's because that function approaches 1, but never reaches it. A linear function with slope λ, however, not only reaches 1 but grows beyond it after the desired sampling period elapses. This guarantees that the next event in the stream is selected as a sample, making sampling reliable in rare event streams. Low-frequency streams are common, so this edge case is important.

On shorter time scales such as the time between events in a high-frequency stream, there's not much difference between the exponential and linear probabilities, and at high event rates the computational efficiency matters a lot.

Our initial implementation of this approach was wrong in a way that confused us at first. One of us saw the mistake, but the rest of us couldn't. It was like the Monty Hall problem for a while. We thought the parameter t should be computed as the time elapsed since the last time we *selected an event as a sample*, rather than the last time we *saw* one. As a result, we sampled events dramatically more often than we wanted to.

The Simple Solution Doesn't Scale

There was another problem, too. The algorithm requires "remembering" the last time we saw an event in each stream (after subdividing the main stream into categories, each of which we treat as its own stream). The trouble is that remembering things about a potentially unbounded number of streams is a bad idea, even if it's a very small amount of data. Inevitably there will be an edge case, which will cause the data structure to grow larger and larger. We have the ability to capture detailed metrics about our monitoring agent's performance, and we saw the agents consuming more and more memory over time. This was a serious problem, because our agents have to run within tight memory bounds or they'll cause problems on the systems they're watching, which is a strict no-no. When we profiled the agents that had this problem, we found that the memory was being used by the category mapping.

The reality is that you can't remember the last-seen time for every stream in situations like this. It just uses too much memory. In fact, in programs like our agents, *nothing* can be allowed to grow without bound; everything must be constrained to limit its worst-case memory usage. The obvious solution to such problems is to purge old entries from the map, using a least-recently-used (LRU) algorithm. This tried-and-true algorithm is one of the staples of computer science.

Using an LRU stabilized the agent's memory usage, but it introduced another set of problems instead! When the number of streams we remember is bounded, and is less than the number of categories of queries present in the workload the agent is observing, a phenomenon called LRU churn can occur. When this happens, entries in the LRU are "forgotten" only to be needed again shortly thereafter. And depending on how the algorithm is implemented, this will either cause oversampling or undersampling. We observed category churn in our agents, sometimes at alarmingly high speed. Some hard-to-characterize workloads[1] caused essentially 100% churn and zero reuse of any LRU entries, no matter how large the LRU.

Using an LRU is a poor solution to a problem like this, because there is no true guarantee how well it will work. It might work well in most cases, but that isn't good enough for software like VividCortex's agents, which have to be immune to edge cases.

A Sketch To Store Last-Seen Times

An LRU is a way to bound the memory usage of an exact solution, but misbehaves when the workload doesn't have the expected characteristics. What if there were a cheap, approximate way to remember last-seen timestamps per stream? And what if the approximation error didn't lead to bad behavior?

We were able to find such a solution, in the form of a *sketch*. A sketch is a data structure, paired with an algorithm, that replaces an exact answer with a probabilistic (approximate) answer. In exchange for introducing a small margin of error, it provides strong bounds on the cost of the structure and associated algorithms. Sketches usually have guaranteed upper bounds on memory and CPU cost. You have probably heard of some sketches, such as Bloom filters.

One of us was inspired by the Count-Min Sketch, which stores the

1 See our previous ebook, Best Practices for Architecting Highly Monitorable Applications for more on this.

frequency of items in a high-dimensional stream. Errors are created by *collisions*, when different items map to the same storage locations in the sketch. We thought it could be adapted to storing last-seen times instead of frequencies. It proved straightforward to do so, and the result was what we call the Last-Seen Sketch. Its implementation is identical, except that instead of incrementing the stored value, the algorithm updates it unless the stored value is larger than the value to be stored.[1]

When a Count-Min Sketch has a collision, the stored frequencies for an item are overwritten by other items' values, and a lookup in the sketch might return an erroneously large value. The likelihood of this happening has been analyzed in great detail by several researchers. It depends on how large you configure the sketch to be.[2] In contrast, when a Last-Seen Sketch has a collision, a lookup finds an erroneously recent timestamp, meaning the program thinks the stream has had an event more recently than it really did. When the result is fed into the sampling algorithm, the result is *undersampling*, not oversampling. In other words, the error's effect guards against a storm of sampling and the resultant abuse of resources, which is a good thing.

When it's all put together, the sampling algorithm works as follows:

1. Define λ, the desired sampling rate in samples per second.
2. Receive an event from the stream.
3. Compute the event's category.
4. Use the category and the sketch to look up the last-seen timestamp for that type of event.
5. Compute the elapsed time between then and the event's timestamp, in seconds.

1 We have open-sourced the basic implementation on GitHub at https://github.com/VividCortex/lastseen.
2 We configure our agents' sketches for less than 1% collisions.

6. Using the elapsed time and λ, compute the probability this event should be selected as a sample.

7. Generate a uniform random number. If it is less than the probability from the previous step, select the event as a sample.

8. Store the event's timestamp into the sketch under its category.

The VividCortex agent software's sampling algorithm is actually more sophisticated than that. Events are not only categorized, but they're also flagged in various ways. *Important* events are flagged for having errors or warnings, high latency, or other user-defined characteristics. *Ineligible* events are flagged for matching blacklist regular expressions or user-defined criteria. Depending on these flags, the events are either disqualified, sampled with greater preference, or flagged for guaranteed sampling.

Results

The end result gives us highly representative sampling, while also achieving the requirements we mentioned earlier in this book.

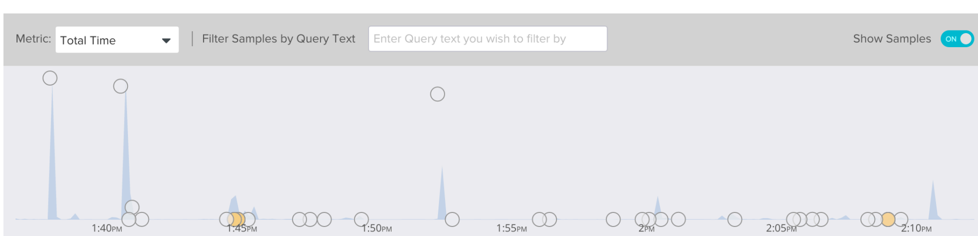
In combination with the highly detailed metrics we generate about query categories, the VividCortex user interface lets users immediately see important or unusual patterns of query behavior, then drill into the categories and examine samples in a single click.

As a result, our users are able to get insight that they'd otherwise never achieve with other monitoring solutions. Sometimes the results are achievable but only after spending a lot of time and effort.

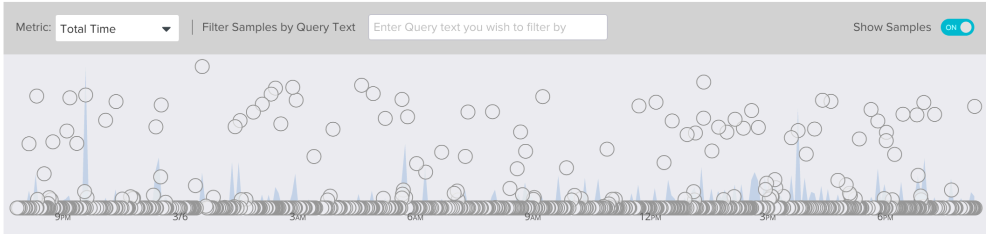
One use case we've seen many times is solving "one in a million" query problems. An example that comes to mind is a commercial off-the-shelf clustering solution for MySQL that, in rare edge cases, tried to set an unsigned variable to a negative value. Although this software has been running in production on tens of thousands of servers for many years, no one had ever noticed the bug. One of our customers found it immediately after deploying VividCortex and reported it to the vendor. This was only possible because of our sampling algorithm's bias towards capturing those individual queries that cause errors.

A second example is a query that occasionally produces warnings when trying to insert into a MySQL table:

Because not all queries produce warnings, the only way to solve this is to capture examples of those queries that do, and see what's specifically wrong with them. When we help our customers with this, we often find invalid input, such as numbers that aren't numbers or malformed dates. In all cases, it's easy to locate and inspect the offending queries, because the samples are shown in an interactive scatterplot, with time on the horizontal axis and query latency on the vertical axis. The samples are shown as small circles, which are color-coded depending on features such as warnings or errors. Selecting a sample with the mouse lets you inspect it.



The next illustration shows how the samples reveal more about the distribution of query latencies than the metrics alone do!



A final example is sporadic query errors on a large, multi-tenant SaaS application using MongoDB as the backend storage. In multi-tenant SaaS applications, it can be challenging to notice errors that affect only one customer. One of this vendor's databases hadn't gotten an important index because of a failure in the query syntax to generate the index. As a result, many queries against that tenant were returning an error. The offending queries were color-coded red in the user interface, and the error code and message were immediately obvious upon selecting the circle.

We've helped our customers find and solve many "rare" problems in this way. It isn't just limited to warnings, errors, and syntax or input problems, either. It includes queries with outlying latencies, queries that refuse to use indexes even though the vast majority of similar queries do, and so on. Again, in today's high-load Internet-facing applications, most of the problems are caused by a tiny minority of queries. Monitoring solutions that don't capture enough detail to diagnose these problems end up leading users on wild-goose chases.

Regardless of your monitoring platform, it's *really hard* to find these rare problems in high-traffic production systems. Smart algorithms are part of the solution, but not enough by itself. The combination of high-resolution metrics and intelligently sampled events is much more useful than metrics alone. Likewise, relatively compact metrics make it practical to measure and analyze server activity at a scale that isn't possible to achieve with event-logging solutions.

Future Work

Our work is never done, naturally. We know there are some areas we can still improve the way we capture our metrics and events.

One improvement we expect to implement at some point is adaptive global rate limits. Currently, in order to avoid a rush of samples when a high cardinality workload changes suddenly, we have a global quota on the overall sampling rate in all of the event streams (categories). This quota is allocated and reset on a periodic basis. We know this can cause some samples to be denied in the face of "noisy neighbors." In the future, we'll likely use a technique such as an exponentially weighted moving average to gently throttle sampling, smoothly adapting to sudden swings in conditions as workload characteristics vary over time. That said, our current solution works fine in practice, even if it theoretically has some edge cases where it could undersample.

Conclusions

Sampling from diverse, complex streams of events is hard. After several implementations proved to have undesirable behavior, we matured our algorithms until we knew exactly what was required of a good solution, and we found a good way to build it without bad edge cases.

The result is that we're able to reduce enormous amounts of query traffic into high-resolution, multidimensional metrics that are feasible to store and analyze. Along with these we capture representative samples of the original queries, which we allow users to examine interactively after drilling into a query category of interest.

The exact method of solving this problem required a great deal of time, effort, and cleverness. In the end, we found an elegant, efficient, and convenient way to do what we needed, which involved a probabilistic data structure we've called the Last-Seen Sketch.

Thanks to the talented engineering team at VividCortex for suggestions and reviews. Mistakes and shortcomings are solely mine; many of the things you might like about this book are their contributions.

Thanks to Preetam Jinka, who wrote the code for the Last-Seen Sketch and co-presented on this topic several times, and John Berryman, who helped implement the algorithm and peer reviewed the results.

Further Reading

If you're interested in further research on this topic, the following links may prove helpful.

- Why percentiles don't work the way you think.
- Best practices for architecting highly monitorable applications.
- The Count-Min Sketch.
- The Last-Seen Sketch.
- After implementing the Last-Seen Sketch, we found Kong et al had described a similar approach in Time-out Bloom Filter: A New Sampling Method for Recording More Flows.

About VividCortex

VividCortex is SaaS database performance monitoring that significantly eases the pain of database performance at scale for the entire IT department. Unlike traditional monitoring, we measure and analyze the system's work and resource consumption. This leads directly to better performance for IT as a whole, at reduced cost and effort.

Related Resources From VividCortex

Case Study: Tradesy

After deploying VividCortex, Tradesy reported "We were able to bring maximum CPU utilization spikes down from 80% to 10%. VividCortex is incredibly straightforward—it's the best MySQL tool I've ever used to monitor and analyze databases."

Best Practices for Architecting Highly Monitorable Applications

Is your application easy to monitor in production? Many applications are, but sadly, some are designed with observability as an afterthought.