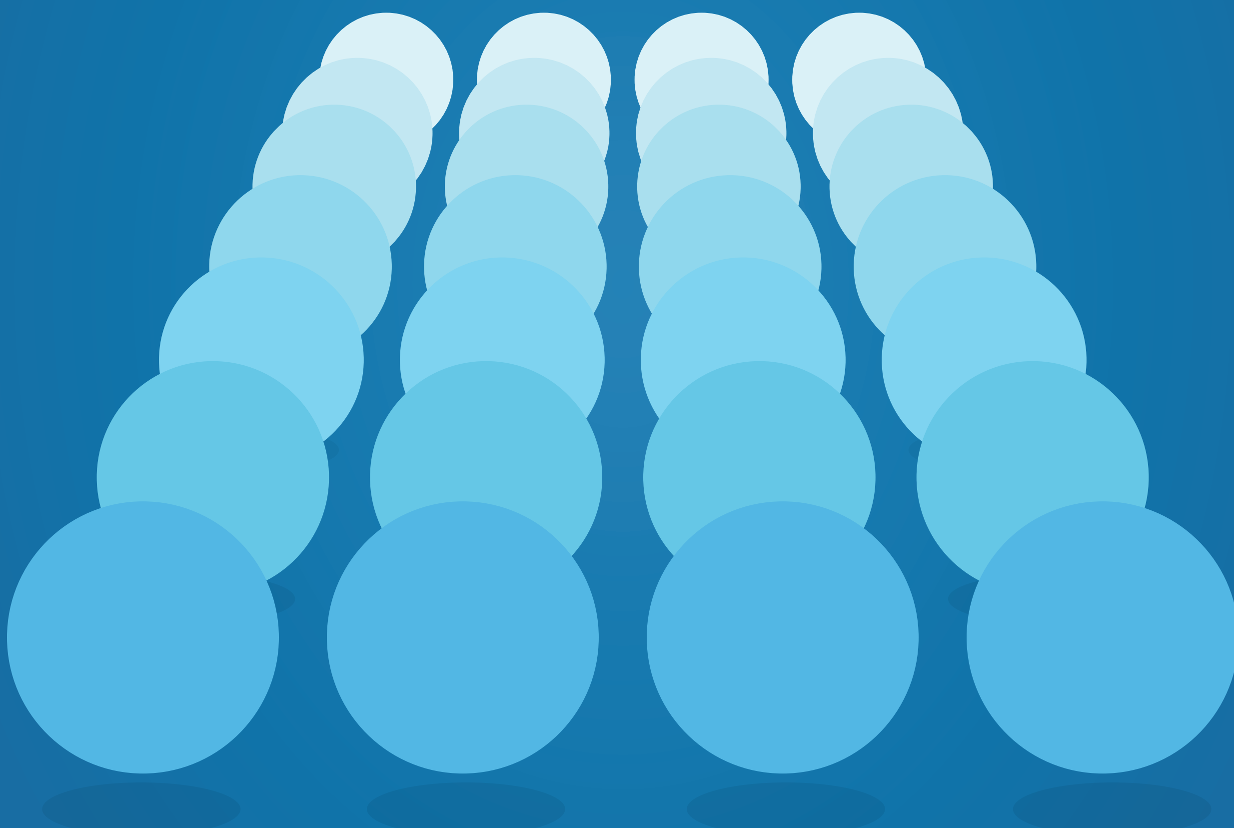
Everything You Need To Know About

Scalability



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VividCortex

Meet the Author

Baron Schwartz

Baron is a database expert who is well-known for his contributions to the MySQL, PostgreSQL, and Oracle communities. An engineer by training, Baron has spent his career studying how teams build reliable, high performance systems, and has helped build and optimize database systems for some of the largest Internet properties. Baron has applied his systems thinking skills to both computer systems and teams of people, and has written several books, including O'Reilly's best-selling High Performance MySQL. Prior to founding VividCortex, Baron was an early employee at Percona, where he managed teams including consulting, support, training, and software engineering. Baron has a degree in Computer Science from the University of Virginia.

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Introduction

What is Scalability?

Scalability is ambiguous for many people—a vague term often tossed about in conference presentations, for example. It's often used in ways confusingly similar to performance, efficiency, capacity, availability, and many other terms related to making things big and fast.

Wikipedia's definition of scalability, borrowed from a 2000 paper by André B. Bondi, is "Scalability is the capability of a system, network, or process to handle a growing amount of work, or its potential to be enlarged in order to accommodate that growth." This isn't wrong, but it's still a bit informal, and this ebook needs a more formal definition.

Dr. Neil J. Gunther provides one such definition: scalability is a *function*. I read Dr. Gunther's books and heard him speak for quite a while before that sunk in for me. Scalability can be defined as a mathematical function, the relationship between independent and dependent variables (input and output).

- Most important is getting the x-variable right

Bondi's definition provides a good clue: *work* is the driving factor of scalability. Useful ways to think about work include, to mention a few,

- units of work (requests)
- the rate of requests over time (arrival rate)
- the number of units of work in progress at a time (concurrency)
- the number of customers or users sending requests

Each of these can be sensible independent variables for the scalability function in different circumstances. For example, in benchmarks it's quite common to configure the number of threads the benchmark uses to send requests to a database. The benchmark usually sends requests as fast as possible, assuming zero think time, so the arrival rate is related to, but not strictly controlled by, the benchmark configuration (since it is determined by how quickly the database finishes each request).

One might say that load or concurrency is the input to the benchmark's scalability function, and the completion rate is the output.

In another scenario, you might vary the number of CPUs for the system under test (SUT) while holding constant the load per CPU, or if it's a clustered database, vary the cluster size and hold constant the load per node. In this case, the independent variable is the system resources.

In most cases I've analyzed, either concurrency or resources are usually sensible independent variables for a scalability function.[1] So for the purposes of this book, we'll consider scalability to be *a function of concurrency or capacity*. The dependent variable is usually the rate at which the system can process work, or *throughput*.

XXX chart with axes

For those who are like me and need extra emphasis, I'll repeat that this is a mathematical function, with concurrency or capacity on the X axis, and throughput on the Y axis.

Linear Scalability: The Holy Grail

In my experience, never was a marketechture slide deck created that mentions scalability without also including the word "linear." But like many

1 I have seen other scenarios, such as scaling by number of shards, but we don't need to dig into that in this book.

other things in scalability, that word is *horribly* abused.

XXX PRINCESS BRIDE MEME

Hand-waving claims of linear scaling usually coincide with vague definitions of scalability, and people who know a lot about scalability rarely say the word "linear." Here are a few of the misdefinitions of linear scalability I've heard:

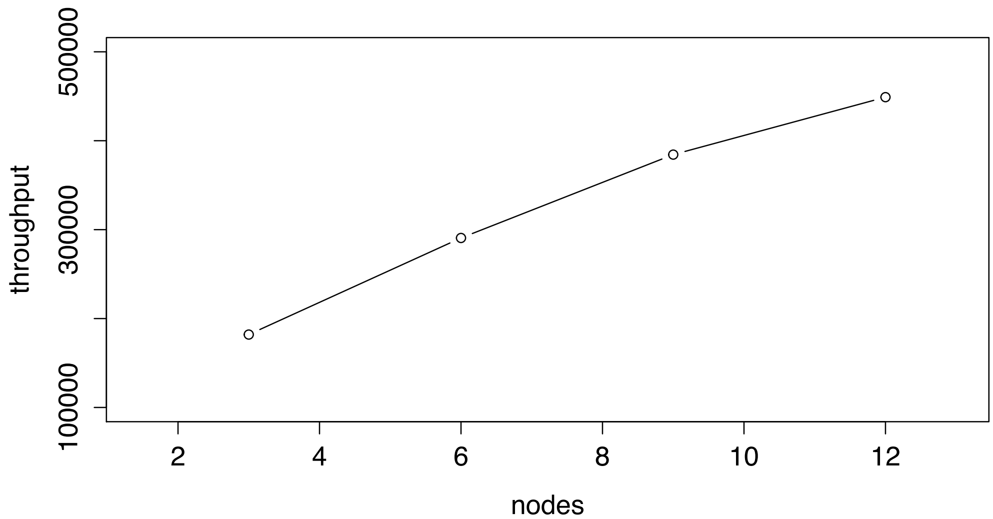
- A web architect at a conference said, "I designed our system to be shared-nothing so it would be linearly scalable." He meant there was no single resource or system imposing a hard upper limit on how many servers could be added to the system. But he didn't really know whether his system actually scaled linearly.
- A technical evangelist giving a presentation about a clustered database said, "adding a node to the cluster adds a predictable amount of capacity." Predictable isn't the same as linear.
- A sales presentation for another clustered database said the database "scales linearly, with a linearity factor of 97%," meaning that each additional node increases the system's capacity by 0.97 times the amount the previous node added. That's a curve, not a line. (Later you'll learn how to instantly determine the asymptotic upper bound on such a system's total capacity.)

This may seem like a pointless rant, but it's actually important if you want to be able to design and improve highly scalable systems.

Spotting bogus linearity claims is fun. Here are some ways to make systems appear linear:

- Show graphs without numbers, so you can't do the math.
- Show graphs with nonlinear axes.
- Begin the axes, especially the Y axis, at a nonzero value.

Here is an example that employs some of these tricks.



Looks pretty linear, doesn't it? Yet if you do the math, it's nowhere near linear. It's an optical illusion, because the X axis begins around 1.45 instead of zero, and the Y axis starts at 100000, so you can't tell that the chart isn't going to intersect the origin if you extend it downwards.

The real test of linearity is whether the transactions per second per node remains constant as the node count increases. The chart's original source mentioned that throughput increased from "182k transactions per second for 3 nodes to 449k for 12 nodes." The math is easy: the system achieves 60700 transactions per second per node at 3 nodes, but only 37400 at 12 nodes, which represents a *39% drop in throughput* versus linear scalability. If it actually scaled linearly, it would achieve 728k transactions per second at 12 nodes.

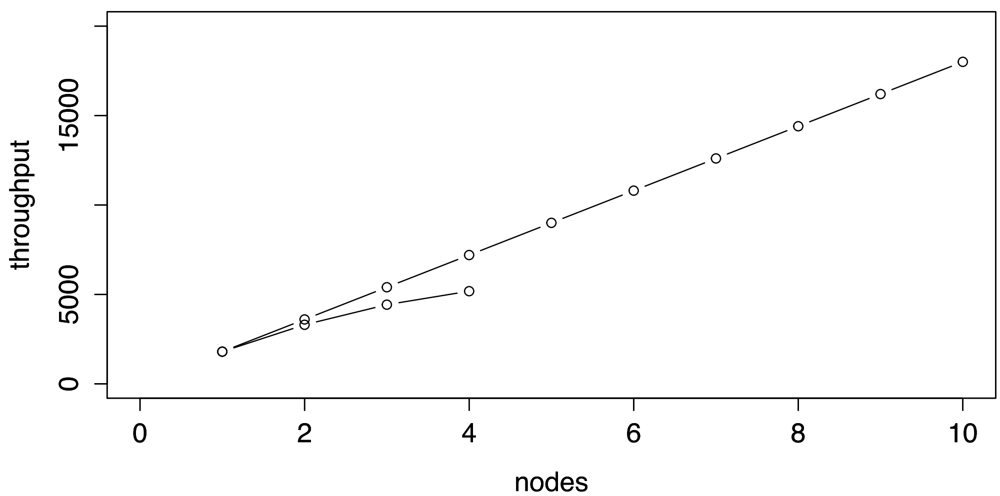
Linear means linear, folks! And seemingly small amounts of nonlinearity really matter, as you'll see later, because small sublinear effects grow very quickly at larger scale.[1]

1 In fact, they grow—wait for it—nonlinearly!

Why Systems Scale Sublinearly

Linear scalability is the ideal, yet despite the claims, systems that actually scale linearly are rare. It's very useful to understand the reasons for this, because a correct understanding of scalability, and the reasons and sources of sublinear scaling, is the key to building more scalable systems. That's why it's really important to be a linearity skeptic. It's not just being pedantic.

The best way to think about linearity is as a ratio of the system's performance at a size of 1, if possible. Neil Gunther calls this the *efficiency*. If a system produces 1800 transactions per second with 1 node, then ideally 4 nodes produce 7200 transactions per second. That would be 100% efficient. If the system loses a bit of efficiency with each node and 4 nodes produce, say, 5180 TPS, the system is only 72% efficient:

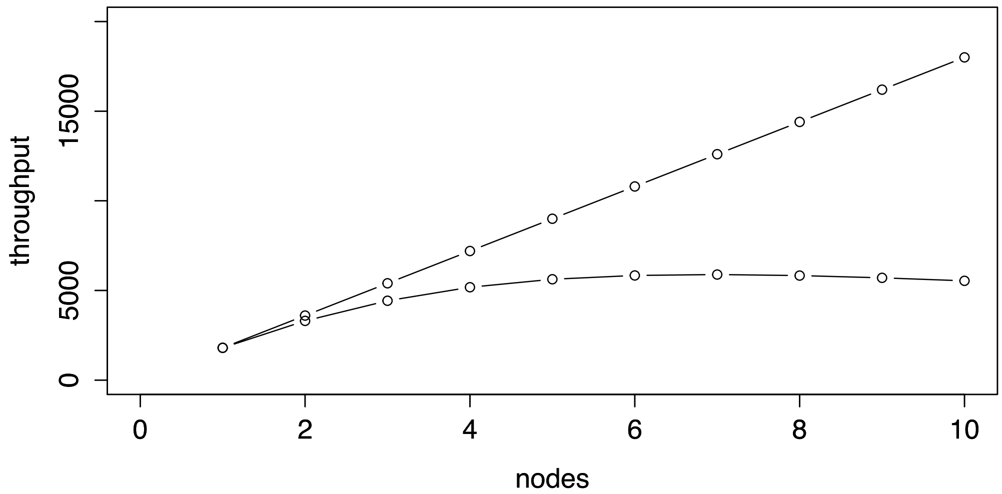


If you do this math, you'll often be surprised at how large the loss of efficiency is. Graphs can be deceptive, but the numbers are quite clear. [1]

In the real world there's almost always some loss of efficiency, and if you

[1] Drawing a linear scaling line on the graph helps, too. Without that line, the eye tends to see the graph as more linear than it really is, and the loss of efficiency becomes less obvious.

can figure out why, you may be able to fix it. In fact, you've probably noticed that real systems tend not only to fall behind linear scalability a bit, but actually exhibit *retrograde* scalability at some point:



This is quite common in the real world—you scale things up and at some point your system starts going backwards and *losing* performance, instead of just gaining more and more slowly. In the MySQL 5.0 days, for example, it was common to see people getting better performance out of 4-core servers than 8-core servers.

Why does this happen? Why don't systems scale linearly, and why do they sometimes show retrograde scalability?

According to Dr. Gunther, there are two reasons: **serialization** and **crosstalk**. Serialization degrades scalability because parts of the work can't be parallelized, so speedup is limited. Crosstalk introduces a fast-growing coherency delay as workers (threads, CPUs, etc) block on shared mutable state and communication mechanisms. We'll explore these effects in the next section.

The Universal Scalability Law

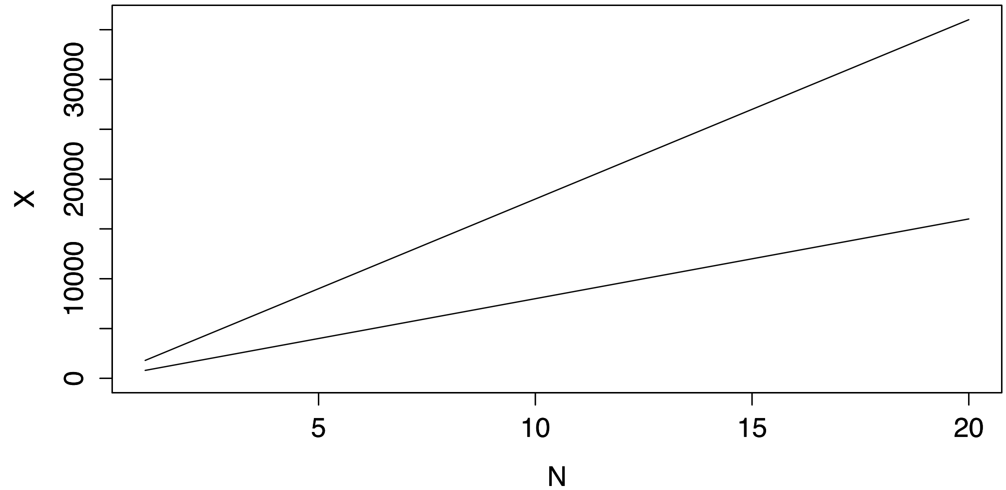
Dr. Neil J. Gunther's Universal Scalability Law (USL) provides a formal definition of scalability,[1] and a conceptual framework for understanding, evaluating, comparing, and improving scalability. It does this by quantifying the effects of linear speedup, serialization delay, and coherency delay due to crosstalk.

Let's see how this works, piece by piece. An ideal system of size 1 achieves some amount λ of throughput X, in completed requests per second. Because the system is ideal, the throughput doubles at size N=2, and so on. This is perfect linear scaling:

$$X(N) = \frac{\lambda N}{1}$$

The λ parameter defines the slope of the line. I call it the *coefficient of performance*. It's how fast the system performs in the special case when there's no serialization or crosstalk penalty. Note that every linearly scalable system is just as scalable as any other, regardless of the slope of the line. They have different performance but identical scalability characteristics: speedup is unlimited. Here are two ideal systems, with λ of 1800 and 800, respectively.

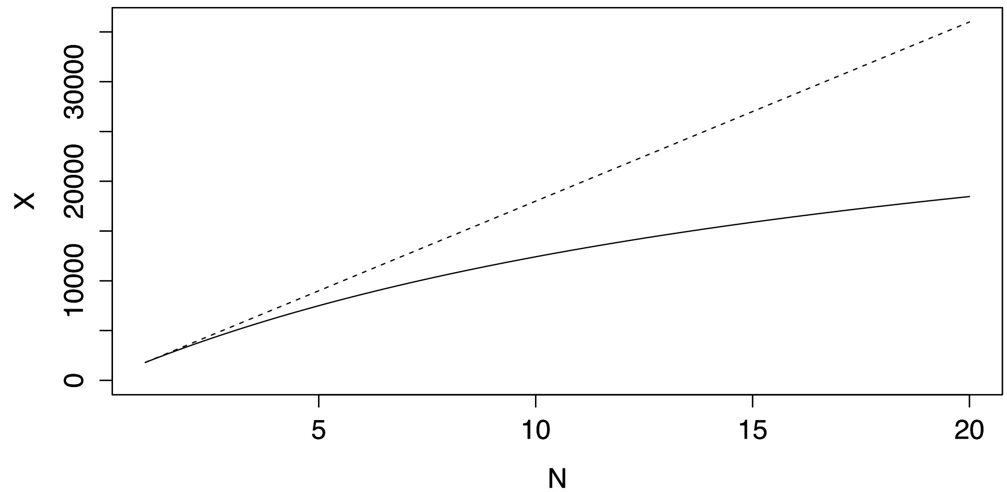
1 Gunther originally called the USL "superserial," and you may encounter this terminology, especially in older books and papers.



Serialization appears in most human and computer systems at some point, for example as a final stage of assembling the multiple outputs generated in parallel into a single final result. As parallelization increases, serialization becomes the limiting factor. This is codified in Amdahl's Law, which states that the maximum speedup possible is the reciprocal of the serial fraction. This fits neatly into the bottom of the equation. Here σ is the serial fraction of the work, the *coefficient of serialization*:

$$X(N) = \frac{\lambda N}{1 + \sigma(N-1)}$$

The resulting system will asymptotically approach a ceiling on speedup. If σ is .05, for example, the speedup approaches 20.

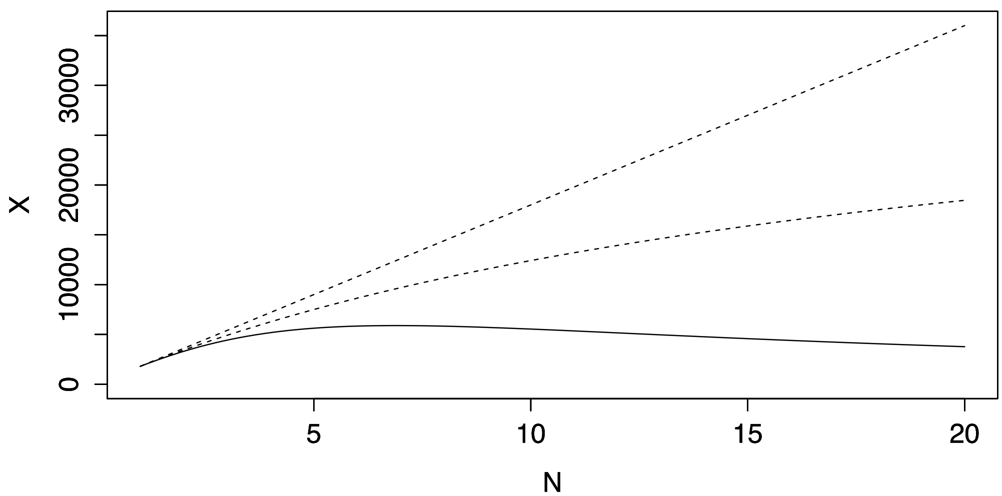


The last bit is the crosstalk penalty. Crosstalk potentially happens between each pair of workers in the system (threads, CPUs, servers, etc). We represent the amount of crosstalk with another parameter, κ.

You probably remember that the number of edges in a fully connected graph is $n(n-1)$, which is on the order of n^2 in the long run.[1] The κ coefficient quantifies the crosstalk in the denominator:

$$X(N) = \frac{\lambda N}{1 + \sigma(N-1) + \kappa N(N-1)}$$

The crosstalk penalty grows fast. Because it's quadratic, eventually it grows faster than the linear speedup of the ideal system we started with, no matter how small κ is. That's what makes retrograde scalability happen:



That's the Universal Scalability Law in all its glory. This plot has the same parameters as the ones I showed before, where a system of size 4 produced only 72% of its ideal output. That system has 5% serialization and 2% crosstalk, and now that I've plotted it out to size 20 you can see it's embarrassingly inefficient. In fact, we should have given up trying to scale this system after size 6 or so.

1 If you're not familiar with it, this blog post introduces Big-O notation.

This shows visually how much harm a "small amount" of nonlinearity can do in the long run. Even very small amounts of these damaging coefficients will create this effect sooner or later (mostly sooner). This is why it's rare to find clustered systems that scale well beyond a couple dozen nodes or so. If you'd like to experiment with this interactively, I've made a graph of it at Desmos.

If you're curious, the USL is based on queueing theory. It's equivalent to synchronous repairman queueing. You can read more about that in Neil Gunther's books. If you're not familiar with queueing theory, I wrote a highly approachable introduction called Everything You Need To Know About Queueing Theory.

Measuring Scalability

To recap, up until now we've figured out the right dimensions for a formal model of scalability that seems to behave as we know real systems behave, and examined Neil Gunther's USL, which fits that framework well and gives us an equation for scalability. (Are you excited yet?)

Now what do we do with it?

Great question! It turns out we can do a lot of extremely useful things with it. Unlike a lot of models of system behavior, this one is actually practical to apply in the real world. That's the real genius of it, in fact. Not only is the equation uncomplicated, but the variables it describes are easy to get from a lot of systems. If you've ever tried to model system behavior with queueing theory, e.g. the Erlang C formula, you're going to love how simple it is to get results with the USL. So many modeling techniques are foiled by the inability to get the measurements you need.

The thing I've used the USL for the most is measuring system scalability, by working backwards from observed system behavior and deriving the likely coefficients. To accomplish this, you need a set of measurements of the system's size as you see fit to define it (usually concurrency or node count) and throughput. Then you *fit* the USL to this dataset, using nonlinear least squares regression. This is a statistical technique that finds the optimal coefficient values in order to calculate a best-fit line through the measurements. The result is values for λ, σ, and κ.

If you're reading about the USL in Neil Gunther's books, he takes a different approach. First, he doesn't use regression to determine λ, he assumes that is something you can measure in a controlled way at $N = 1$. (I've often found that's not true for me.) Secondly, there are a couple of different forms of the USL—one for hardware scaling and one for software scaling—which are the same equation, but with different parameters. I've found the distinction to be largely academic, although I will talk a bit more about this later.

Examples of systems I've analyzed with the USL include:

- Black-box analysis of networked software simply by observing and correlating packet arrivals and departures, looking at the IP addresses, port numbers, and timestamps. From this I computed the concurrency by averaging the amount of time the system was busy servicing requests over periods of time. The throughput was straightforward to get by counting packet departures.
- MySQL database servers. Some of its `SHOW STATUS` counters are essentially equivalent to throughput and concurrency.
- Linux block devices (disks) by looking at `/proc/diskstats`, from which you can get both instantaneous and average concurrency over time deltas, as well as throughput (number of I/Os completed).
- Lots and lots—and lots—of benchmark results.

I've built a variety of tools to help clean, resample, and analyze the data before arriving at satisfactory results. Most of them were commandline, though these days I use R more than anything else. This is an important topic, though I don't have time to go into it in detail: you will get dirty data, and that will make your results useless. You need to visualize both in scatterplot form as well as in time-series form and ensure you're working with a relatively consistent set of data. You can remove individual points or trim the time range you use, and you may need to experiment with averaging the data over time to get good results.

As for the R code, I'll give a little bit of a quickstart to show the soup-to-nuts approach. You'll save the data into a delimited file, with column headers `size` and `tput`. Then you'll load this into a variable in R and regress it against the USL.

Here's a complete sample, based on a benchmark that Vadim Tkachenko ran at Percona:

```
size tput
1 955.16
2 1878.91
3 2688.01
4 3548.68
5 4315.54
6 5130.43
7 5931.37
8 6531.08
9 7219.8
10 7867.61
11 8278.71
12 8646.7
13 9047.84
14 9426.55
15 9645.37
16 9897.24
17 10097.6
```

```
18 10240.5
19 10532.39
20 10798.52
21 11151.43
22 11518.63
23 11806
24 12089.37
25 12075.41
26 12177.29
27 12211.41
28 12158.93
29 12155.27
30 12118.04
31 12140.4
32 12074.39
```

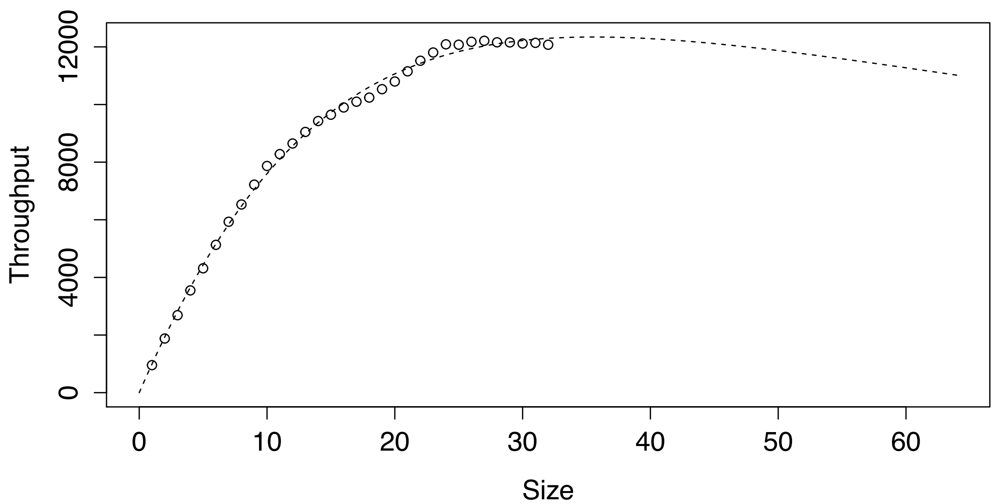
Save that data into a file, say, `benchmark.txt`. Then load it and run the following commands:

```
benchmark <- read.csv("/path/to/benchmark.txt", sep="")
usl <- nls(tput ~ lambda*size/(1 + sigma * (size-1) + kappa * size *
   (size-1)), benchmark, start=c(sigma=0.1, kappa=0.01, lambda=1000))
summary(usl)
sigma <- coef(usl)['sigma']
kappa <- coeff(usl)['kappa']
lambda <- coef(usl)['lambda']
u=function(x){y=x*lambda/(1+sigma*(x-1)+kappa*x*(x-1))}
plot(u, 0, max(benchmark$size)*2, xlab="Size", ylab="Throughput", lty="dashed")
points(benchmark$size, benchmark$tput)
```

The results are as follows:

$$\begin{array}{ll} \lambda & 995.6486 \\ \sigma & 0.02671591 \\ \kappa & 0.0007690945 \end{array}$$

Note the extremely small value for κ which nonetheless degrades scalability before N becomes very large. Here's the resulting plot:



If you're an R user, that's probably all you need to get going. You really should do more diligence, such as checking the R^2 value of the fit. But instead of doing all this work manually (which you can certainly do if you want), I suggest using the USL package from CRAN. It has all the niceties built in.

One final thing: if the $kappa$ coefficient has a nonzero value, the function has a maximum. You can find the size of the system at that maximum as follows:

$$N_{max} = \left\lfloor \sqrt{\frac{1-\sigma}{\kappa}} \right\rfloor$$

Of course, to find the maximum predicted throughput, you just plug N_{max} into the USL equation itself. Doing so with the coefficients in this example predicts the system's throughput will increase until $N = 35$, which in this case means 35 threads, and the peak throughput will be 12341 queries per second. It also found $lambda$, the throughput at $N = 1$, to be 995 QPS, which is close to the actual value of 955.

It's always interesting to use the USL on a subset of the performance data, such as the first third or so, to see how well it predicts the higher N values. This can be quite educational.

Note that you should have at least half a dozen or so data points in order to get good results in most circumstances. In practice I usually try to capture at least a dozen for benchmarks, and more—often thousands—when analyzing systems that aren't in a controlled laboratory setting.

Relating Scalability and Performance

request performance is response time system performance is throughput USL already predicts and explains system performance but what about request performance, can we predict it too? little's law says yes, we can just use it to predict avg response time at a given concurrency

$$y = \frac{1 + s(x-1) + kx(x-1)}{c}$$

https://www.desmos.com/calculator/vjlnruxxdi is it valid? is r-time quadratic wrt concurrncy? if so then appd might be OK don't confuse this with r-time and utilization chart; concur -> infinity further reading: neil claims that this is not universally valid "Be careful. That's only true when Z = 0 (user/generator think time). Otherwise, you miss the "foot" of the hockey stick." * https://groups.google.com/d/topic/guerrilla-capacity-planning/hei8zL2muuE/discussion * http://perfdynamics.blogspot.com/2015/07/hockey-elbow-and-other-response-time.html however, in my tests of real world systems, it is exactly right it does not predict the dsn of resp time, only avg, however you could use queueing theory to predict that, given the offered load and thus the rho

Capacity Planning with the USL

common question - how much work can I handle with this system? - will I need more for the holidays? - how much spare runway do I have? - hard to tell, often inscrutable whether we're close to a breaking point USL's max capacity equation predicts max thruput but that's not really max capacity capacity is max work-getting-done with SLA of good perf (typically as percentile) at this point, system probably gives horrible perf by he way this is a problem with benchmarks - they push the system bad perf benchmarks are always unrealistic predicting system capacity is something queueing theory is often used for predict utilization, etc * queueing theory - hard because of service times * USL instead; much easier to measure - forecasting - lets us predict beyond what we can measure - show one of the datasets with only part of the data, does it predict the rest? - best and worst cases; repairman queueing - where is the sublinearity coming from (paypal nodejs) - using it to see approx what % of capacity we're at now - see also the queueing theory book and square root staffing

the usl in real life

- how well does it work The USL is wrong: theoretical physicist, Richard Feynman: "In general we look for a new law by the following process: first we guess it. Don't laugh – that's really true. Then we compute the consequences of the guess to see what, if this law is right, what it would imply. Then we compare those computation results to nature, i.e. experiment and experience. We compare it directly to observation to see if it works. "If it disagrees with experiment, it's wrong. That simple statement is the key to science. It doesn't make a difference how beautiful your guess is, it doesn't make a difference how smart you are, who made the guess or what his name is – if it disagrees with experiment, it's wrong. That's all there is to it." (Cornell lecture, 1964)

- * ceilings from hitting something's max capacity like network tput * usually queueing causes retrograde to grow even faster than predicted - note that one could conjecture and analyze other shapes like the USL, e.g. https://www.desmos.com/calculator/nl53iwbngn

$$u(x) = \frac{bx}{1 + s(x-1) + kx(x-1)} \{x > 0\}$$

$$l(x) = \frac{bx}{1 + s(x-1) + k \ln(x)(x-1)} \{x > 0\}$$

$$r(x) = \frac{bx}{1 + s(x-1) + k\sqrt{x}(x-1)} \{x > 0\}$$

- Jayanta Choudhury has suggested changes to fit better.

superlinear scaling

- special cases: aggregate capacity not scaling proportionately to load, dataset, etc so each "worker" has some advantage - special case: 1 and 2 nodes - effect of "economies of scale," that is a resource that is more efficient when shared than when used singly - https://queue.acm.org/detail.cfm?id=2789974

other PoV on scapability

- alternative - quadratic scalability. Impossible because it goes negative. It's just wrong. Might as well draw a line with your hand and one of those template curves. https://en.wikipedia.org/wiki/French_curve https://www.graphicsdirect.co.uk/french-curve-set.html - alternative definitions of scalability - new relic http://www.xaprb.com/blog/2013/01/07/a-close-look-at-new-relics-scalability-chart/

, appd, riak - cockcroft headroom plots * How to improve scalability * avoid crosstalk * avoid serialization * avoid queueing * Further reading * GCaP * Look at the Percona white paper

Example data * http://obartunov.livejournal.com/181981.html http://www.postgrespro.ru/blog/pgsql/2015/08/30/p8scaling scaling/scaling-postgrespro.png * VoltDB * mat keep https://blogs.oracle.com/MySQL/entry/comparing_innodb_to_myisam_performance https://www.percona.com/blog/2011/01/26/modeling-innodb-scalability-on-multi-core-servers/ * paypal example https://www.vividcortex.com/blog/2013/12/09/analysis-of-paypals-node-vs-java-benchmarks/ * example of robert haas http://rhaas.blogspot.com/2011/09/scalability-in-graphical-form-analyzed.html

About VividCortex

VividCortex is a SaaS database performance monitoring. The database is the heart of most applications, but it's also the part that's hardest to scale, manage, and optimize even as it's growing 50% year over year. VividCortex has developed a suite of unique technologies that significantly eases this pain 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.

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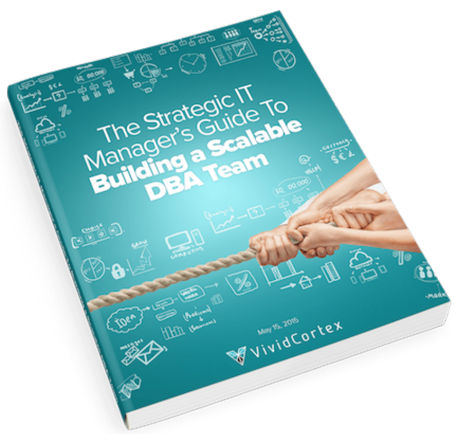

The Strategic IT Manager's Guide To Building A Scalable DBA Team

Case Study: SendGrid

VividCortex has been instrumental in finding issues. It's the go-to solution for seeing what's happening in production systems.