The Language of Compression

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Scope

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Today's talk is about **compression**

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- In data storage systems (databases, filesystems)

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- In data storage systems (databases, filesystems)
- Using general-purpose (lossless) algorithms
- On disk, not in memory or over the wire

Scope

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We'll talk about systems like:

- MySQL (InnoDB, TokuDB)
- MongoDB (WiredTiger, TokuMX, RocksDB)
- Cassandra
- PostgreSQL
- Vertica
- zfs, btrfs

Goal of the Talk

Goal

A **framework** for answering:

Goal

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A **framework** for answering:

- How do compression algorithms even work?

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- How should I evaluate the compression of a storage system?

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- How should I read articles about compression?

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A **framework** for answering:

- How do compression algorithms even work?
- How do storage systems use compression?
- How should I evaluate the compression of a storage system?
- How should I read articles about compression?
- How should I write articles about compression?

About Me

Me

TWO SIGMA

Engineer at Two Sigma

- We have a lot of data
- We care a lot about compression

Me

TWO SIGMA

Engineer at Two Sigma

- We have a lot of data
- We care a lot about compression

Previously at Tokutek

- Worked on TokuMX, TokuFT
- We thought a lot about compression
- We evaluated a lot of compression algorithms
- We wrote a lot about compression

How to Talk About Compression

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Scenario

I have a database which can store 1TB of “user data” in only 200GB of disk.

How to Talk About Compression

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How much is my database compressing? 80%? 20%? 5x? 1/5? 5:1?

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Scenario

I have a database which can store 1TB of "user data" in only 200GB of disk.

How much is my database compressing? 80%? 20%? 5x? 1/5? 5:1?

Let's talk about what this number is going to mean to us...

Why Compress?

Why Compress?

Data storage is expensive (you’ve heard this)

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- Replication magnifies your data costs

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- Maintenance/operations cost scales superlinearly with hardware

Why Compress?

Data storage is expensive (you’ve heard this)

- Replication magnifies your data costs
- Maintenance/operations cost scales superlinearly with hardware
- SSD is expensive

Why Compress?

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Compression **magnifies** your capacity to store data at a fixed cost.

Compression **minimizes** your cost to provide a fixed capacity.

Why Compress?

TWO SIGMA

Compression **magnifies** your capacity to store data at a fixed cost.

We ask “by what **factor** does compression *multiply* my *capacity*?”

Compression **minimizes** your cost to provide a fixed capacity.

We ask “by what **factor** does compression *divide* my *cost*?”

Why Compress?

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Compression **minimizes** your cost to provide a fixed capacity.

We ask "by what **factor** does compression *divide* my *cost*?"

We should always talk about compression in terms of the **multiplicative factor** by which you increase your **cost-effectiveness**.

How to Talk About Compression

Say **“5x compression”**, not “80% compression”.

Cost Model

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Compression is **more expensive** than decompression.

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Bandwidth speeds for typical compression algorithms (`cp` is a no-op)
(my laptop, Haswell CPU, Samsung SSD, 362MB tarball of `/usr/include`):

(MB/s)	zlib	bz2	lzma	lzo	lz4	zstd	cp
Compress	39	8	3	366	405	293	1466
Decompress	179	28	138	395	774	500	1466

(higher is better)

Cost Model

How does compression impact **perceived** performance?

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- Can reduce overall **throughput**

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Decompression:

- More frequent ("Write Once, Read Many") and on the critical path
- High impact on user-visible **latency**

Cost Model: Corollaries

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1. Do compression in the background and in large batches
   - Implement backpressure to avoid falling behind
   - If backpressure reaches users, try a faster compressor

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1. Do compression in the background and in large batches
    - Implement backpressure to avoid falling behind
    - If backpressure reaches users, try a faster compressor
2. Be sensitive to decompression latency
    - Hit the highest nail: other latency sources may be more important
    - Experiment with block sizes and faster compression algorithms

How Compression Even Works

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All* compression algorithms, at their core, use a form of *dictionary encoding*:

- Write down a dictionary of “common phrases” with shorter names
- Encode the input stream by referencing the short names in the dictionary

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```
abbabbabbcdcdcdcdabb => abb|abb|abb|cd|cd|cd|cd|abb
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Symbol	Phrase
x	abb
y	cd

, xxxyyyyx

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To decompress: read the dictionary, use it to interpret the compressed stream.

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The dictionary takes up some space in the file header, so to be worthwhile, we want to compress a lot of input with it at once.

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We also can't update a compressed file without recompressing the whole thing.

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Systems that provide seeking in compressed data do so by dividing the input into **blocks**, and compressing them individually.

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Systems that provide seeking in compressed data do so by dividing the input into **blocks**, and compressing them individually.

- When writing, recompress the whole block being written (but not the whole data set)
- When reading, decompress the whole block being read
- Overall compression ratio depends on the size of the blocks

Block Sizes

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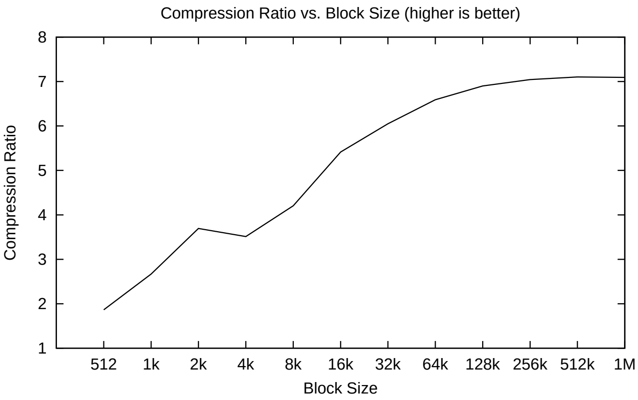
As block size increases:

- Compression throughput decreases
- Compression and decompression memory usage increases
- Decompression throughput may increase if disk throughput increases

Block Sizes



Compression Ratio vs. Block Size (higher is better)
Compression Ratio
Block Size
1
2
3
4
5
6
7
8
512
1k
2k
4k
8k
16k
32k
64k
128k
256k
512k
1M

Block Sizes

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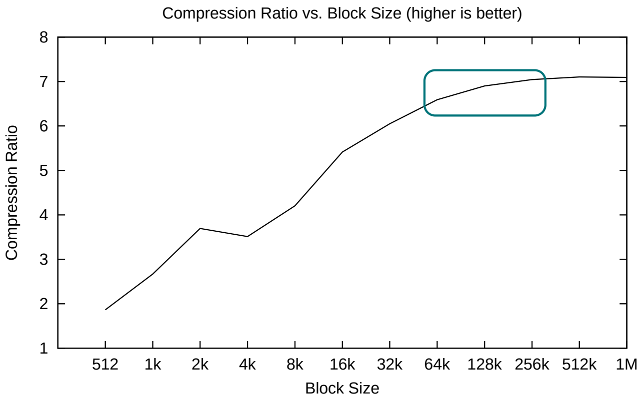

The compression ratio sweet spot is ~**128k**, for gzip on this data set.

Block Sizes

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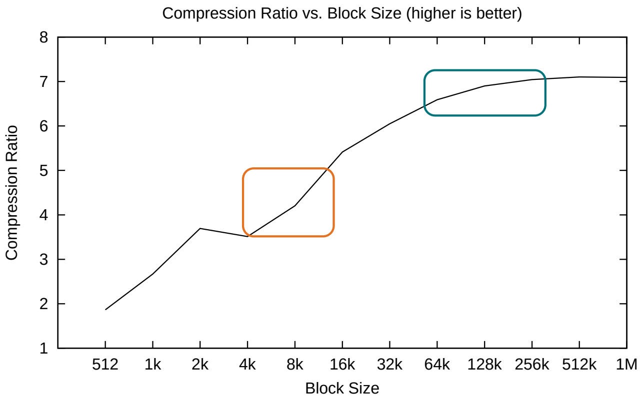

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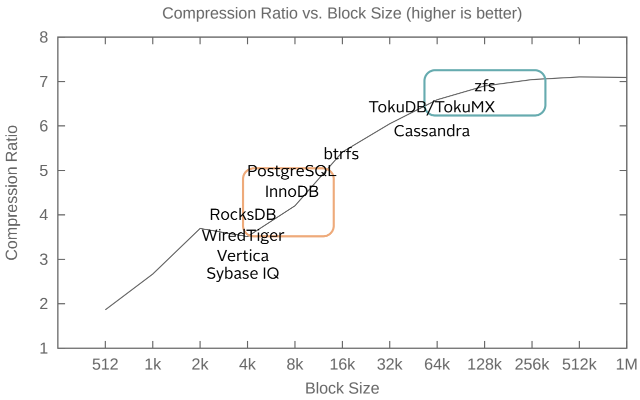

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Fragmentation

Another corollary of compressing in blocks is **fragmentation**.

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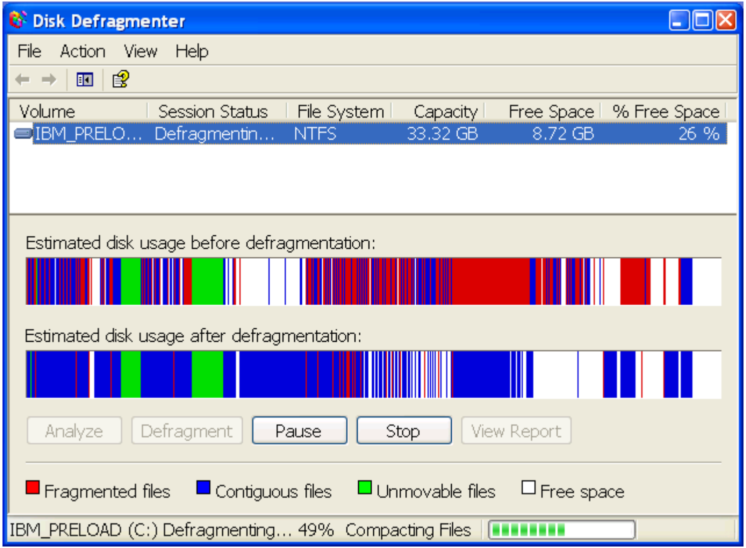
Blocks need to be allocated locations on disk. As the data grows, shrinks, and moves around, these locations (and for some systems, allocation sizes) change.

Fragmentation



Fragmentation

Fragmentation hurts you in two ways:

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For some systems, the overall compression ratio will be reduced once fragmentation develops.

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High entropy data is *highly uncompressible*.
Low entropy data is *easily compressed*.

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Entropy: Experiment

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Built 8 data sources ($\sim$50k each):

Entropy: Experiment

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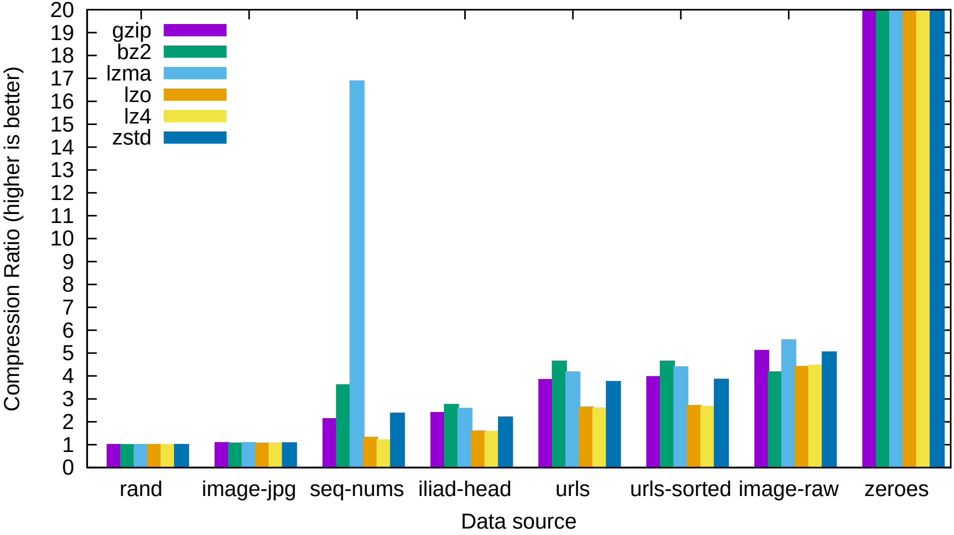
Built 8 data sources (∼50k each):

1. Random bytes
2. Sequential numbers, encoded as ASCII decimals
3. All zeroes
4. The beginning of *The Iliad*
5. 1000 random Wikipedia URLs
6. 1000 random Wikipedia URLs, sorted
7. RAW image (CR2)
8. JPEG-compressed image

Entropy: Experiment



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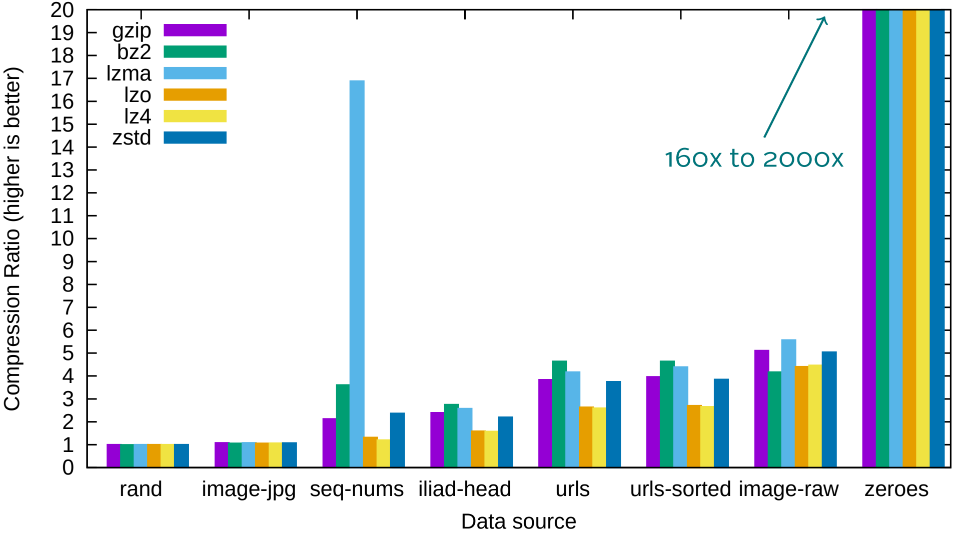

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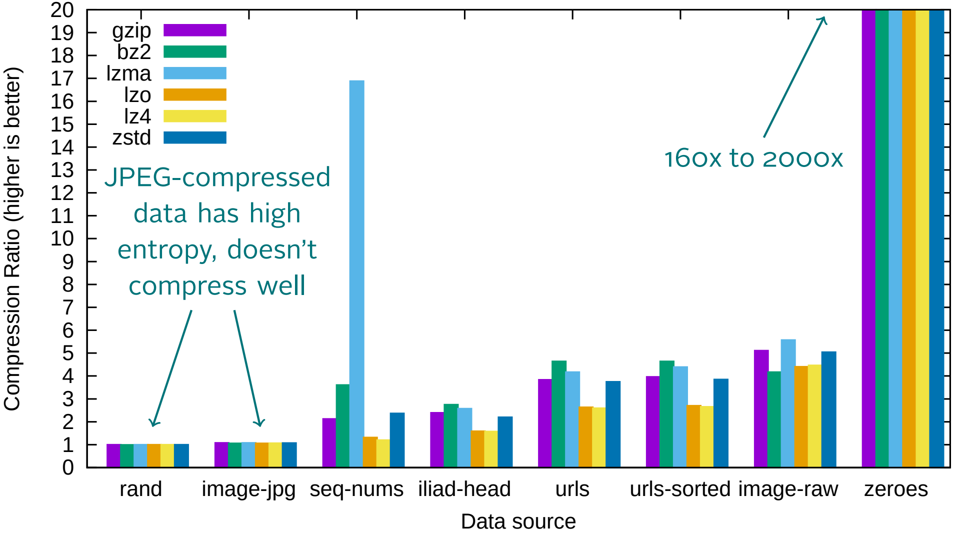

Entropy

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- Integers compress better than documents with complex interal structure

Entropy

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Column stores have a compression advantage over **row stores**.

Know your data!

Don’t waste your time compressing JPEG blobs

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Some compressors are fantastic in specific data domains
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Some compressors are fantastic in specific data domains
(VLQ, delta coding, JPEG, MP3, ...)

(But 95% of the time, gzip is fine)

Before we use compression, we need to understand the **costs** and **benefits** to our application.

Benchmarking

Benchmarking

When designing a compression benchmark, you should consider:

Benchmarking

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When designing a compression benchmark, you should consider:

- Execution

Benchmarking

TWO SIGMA

When designing a compression benchmark, you should consider:

- Execution
- Measurement

Benchmarking

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When designing a compression benchmark, you should consider:

- Execution
- Measurement
- Presentation

Benchmarking: Execution

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Main Question

Is the workload representative of a real-world use-case?

Benchmarking: Execution

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1. Sample real data if you can get it.

Benchmarking: Execution

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   If not, generate *plausibly realistic* data:

Benchmarking: Execution

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1. Sample real data if you can get it.

   If not, generate *plausibly realistic* data:

   - Zeroes: bad
   - Random: bad
   - 25% random and 75% zeroes: meh
   - JSON blobs: good

Benchmarking: Execution

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2. Use a realistic read/insert/update mixture:

Benchmarking: Execution

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2. Use a realistic read/insert/update mixture:
   - Most applications are read-heavy
   - Favors fast decompressors

Benchmarking: Execution

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3. Use a realistic insert/update distribution:

Benchmarking: Execution

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3. Use a realistic insert/update distribution:
   - Most applications don't write uniformly over the keyspace

Benchmarking: Execution

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Benchmarking: Execution

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3. Use a realistic insert/update distribution:
   - Most applications don't write uniformly over the keyspace
   - Zipfian or Pareto (or sometimes sequential, or nearly) distributions are more realistic, and cache-friendlier
   - Vadim wrote a `sysbench` workload generator that uses a Zipfian distribution: `http://j.mp/sysbench-zipf`

Benchmarking: Execution

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4. To measure **latency**, throttle your workload.

Benchmarking: Execution

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To measure **max throughput**, run at full speed.

Benchmarking: Execution

TWO SIGMA

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To measure **max throughput**, run at full speed.

You should do both.

Benchmarking: Execution

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5. Run for a *long time*. Lots of important properties don't become visible immediately (e.g. fragmentation), and you need to understand them.

Benchmarking: Execution

TWO SIGMA

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   Your application is hopefully going to run for months or years. You don't want to be surprised by degradation after you think everything's stable.

Benchmarking: Execution

6. Parameterize your workload:

Benchmarking: Execution

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6. Parameterize your workload:
   - Read/insert/update mixture

Benchmarking: Execution

6. Parameterize your workload:
   - Read/insert/update mixture
   - Write distribution

Benchmarking: Execution

6. Parameterize your workload:
    - Read/insert/update mixture
    - Write distribution
    - Number of threads

Benchmarking: Execution

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6. Parameterize your workload:
   - Read/insert/update mixture
   - Write distribution
   - Number of threads
   - Data size

Benchmarking: Execution

TWO SIGMA

6. Parameterize your workload:
    - Read/insert/update mixture
    - Write distribution
    - Number of threads
    - Data size
    - Throttling

Benchmarking: Execution

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6. Parameterize your workload:
   - Read/insert/update mixture
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   - Number of threads
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   - Throttling
   - Duration

Benchmarking: Execution

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6. Parameterize your workload:
    - Read/insert/update mixture
    - Write distribution
    - Number of threads
    - Data size
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    - Duration
    - System configuration (cache size, isolation levels, log commit)

Benchmarking: Execution

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   - Read/insert/update mixture
   - Write distribution
   - Number of threads
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   - Duration
   - System configuration (cache size, isolation levels, log commit)

You are going to want to explore these parameter spaces. Save yourself the pain later and think about parameterization up front.

Benchmarking: Execution

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Great example: `https://github.com/ParsePlatform/flashback`

Captures a MongoDB workload with profiling, then replays operations either at their original timestamps, or at full speed.

Benchmarking: Measurement

Benchmarking: Measurement

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Benchmarking: Measurement

Application metrics:

Benchmarking: Measurement

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Application metrics:

- Throughput
- Latency
- Aborted/retried transactions

Benchmarking: Measurement

TWO SIGMA

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Instrument your application so you know *which* operations are expensive.

Benchmarking: Measurement

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System metrics:

Benchmarking: Measurement

System metrics:

- CPU
- Memory (RSS)
- I/O
- Network
- Actual storage usage (`du`)

Benchmarking: Measurement

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- Memory (RSS)
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- Actual storage usage (`du`)

`perf(1)`, `iostat(1)`, `dstat(1)`, `oprofile(1)`, `collectd(1)`, Datadog, Librato, ...

Benchmarking: Measurement

Database/filesystem metrics (product-specific):

Benchmarking: Measurement

Database/filesystem metrics (product-specific):

- Cache hits/misses
- Replication lag
- Checkpoint lag

Benchmarking: Measurement

Database/filesystem metrics (product-specific):

- Cache hits/misses
- Replication lag
- Checkpoint lag

Talk to your storage vendor about what’s important.

Benchmarking: Presentation

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Benchmarking: Presentation

1. Describe the workload, and make a case for why it's **realistic**

Benchmarking: Presentation

TWO SIGMA

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2. Choose **key metrics** that reflect the *benefits* of compression (e.g. users stored per TB) as well as the *costs* (e.g. operation latency)

Benchmarking: Presentation

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Benchmarking: Presentation

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2. Choose **key metrics** that reflect the *benefits* of compression (e.g. users stored per TB) as well as the *costs* (e.g. operation latency)
3. Demonstrate which **parameter choices** influence the costs and benefits you think are important
4. **Explain** which parameters have little or no effect on your metrics
5. Explain how much of your measurement is **overhead**.
6. *If* you show charts, **normalize** your data. Only present important differences.

Review

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Say **“5x compression”**

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Compression is **slower** than decompression, but decompression is **more frequent**

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Large blocks compress better

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Fragmentation degrades
effective compression over time

High entropy data is **less compressible**

Benchmark **realistic workloads** over a long period

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Present **responsibly**
(and distrust benchmarketers who don't)

Thanks!

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- Tim and Mark Callaghan for being exemplar benchmarkers (`http://acmebenchmarking.com` and `http://smalldatum.blogspot.com`)
- Bohu Tang for introducing me to zstd
- Andrew Bolin, Corey Milloy, Effie Baram, Li Jin, Wil Yegelwel for making this talk better
- Tokutek engineering
- Percona (they're also good benchmarkers)

Questions?

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