An Overview of Future Improvements to OPSI

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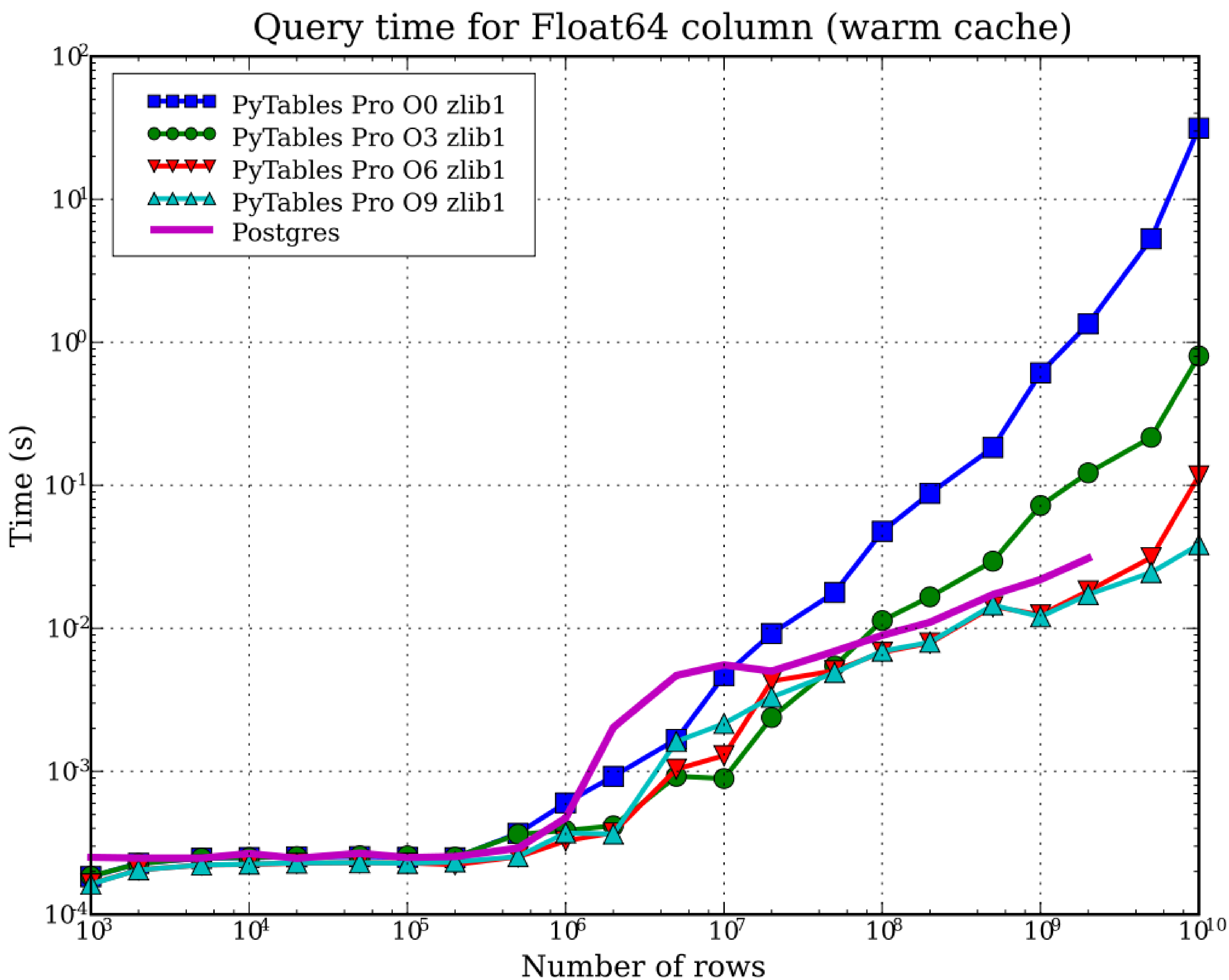
Features of PyTables Pro

- OPSI (Optimized Partially Sorted Indexes)
  - Indexing engine optimized for HDF5 features (chunking, compression, data types)
- Improved LRU node cache performance (up to 20x faster than PyTables Standard)
- Focus on stability (meant for use in production environments)
- All-in-one installers for Windows and Mac OS X

OPSI Features

- Based on well-tested PSI engine (PyTables 1.x)
- Improvements over PSI
  - Better query times
  - Selectable index quality
  - Complex queries
- Current limitations
  - Only one index can be used in a complex expression
  - Only supports compound types, not atomic types


Query time for Float64 column (warm cache)
PyTables Pro O0 zlib1
PyTables Pro O3 zlib1
PyTables Pro O6 zlib1
PyTables Pro O9 zlib1
Postgres
Time (s)
Number of rows
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{3}
10^{4}
10^{5}
10^{6}
10^{7}
10^{8}
10^{9}
10^{10}

Plans for the Near Future

- Optimize the retrieval of results in queries with a large number of hits (low selectivity).
  - The current algorithm is quite efficient for medium or high selectivity, but less so for low selectivity
- Ability to use several indexes in complex queries
  - If col1 and col2 are indexed, then the expression `(col1 < 3.1) & (col2 > 2.3)` cannot be computed using both indexes (the first one will be used instead)

Low Selectivity Retrieval

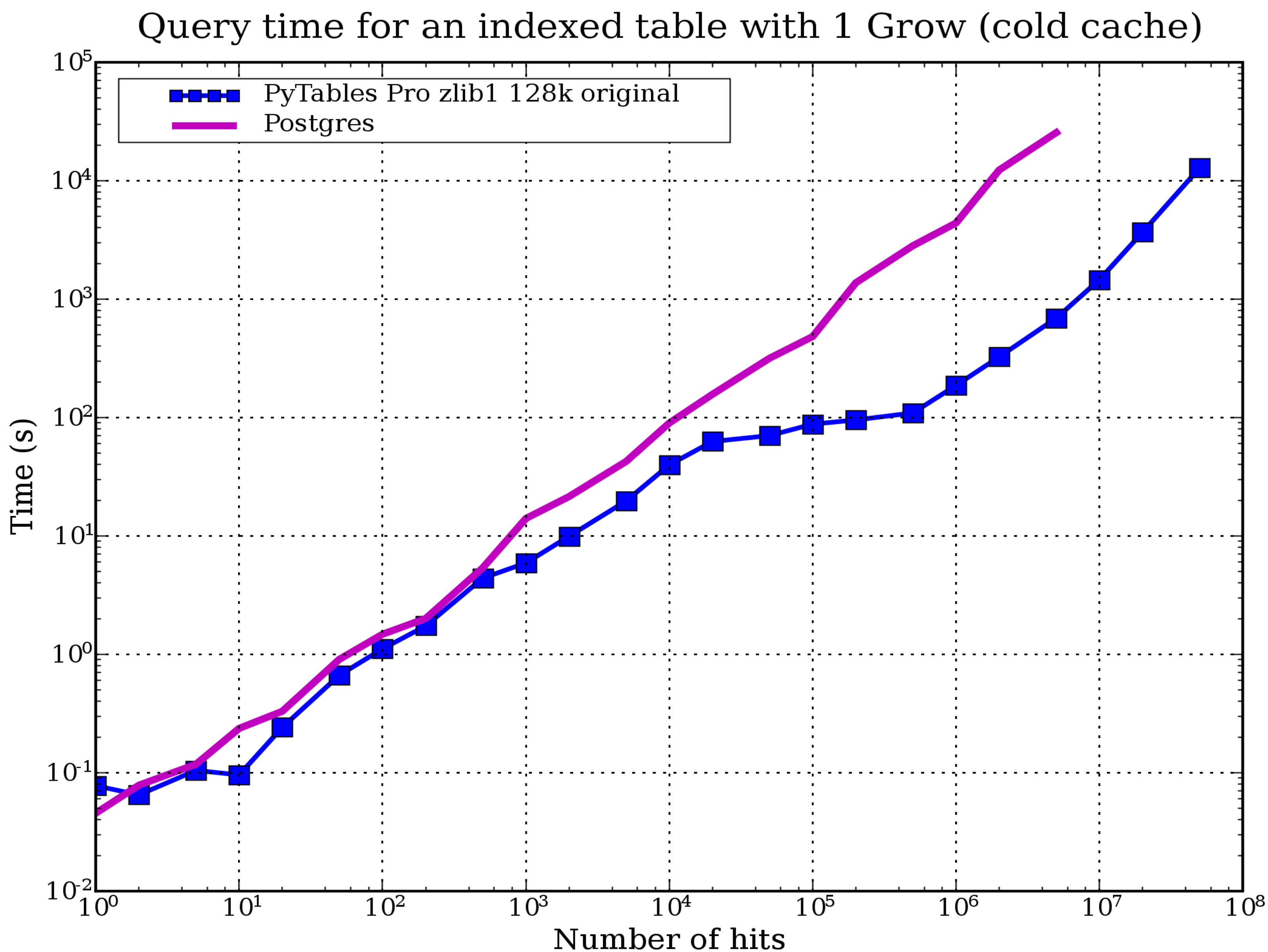
- A table with 4 columns:

```
class Record(tables.IsDescription):
    col1 = tables.Int32Col()
    col2 = tables.Int32Col()
    col3 = tables.Float64Col()
    col4 = tables.Float64Col()
```

- 1 billion rows (1 Gigarow)
- AMD Opteron @ 2 GHz
- SATA disk @ 7200 rpm
- Query:

```
(lower<=col4) & (col4<=upper) &
(sqrt(col1+3.1*col2+col3*col4) > 3)
```

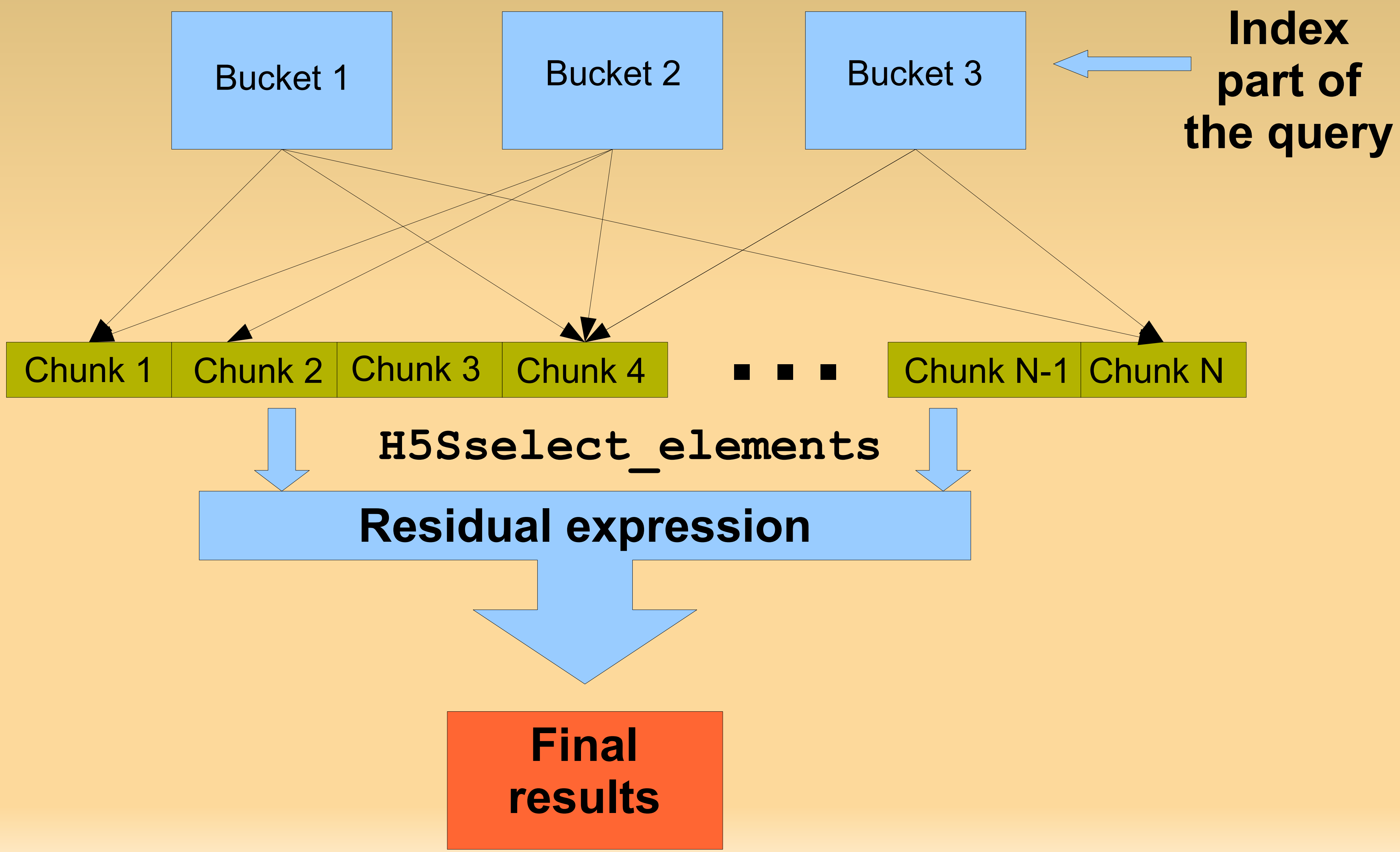
Low Selectivity Retrieval



Low Selectivity Retrieval

- Current approach:
  - Get the set of coordinates satisfying the indexed part of the query
  - Break the set into buckets and read a bucket at a time (using `H5Sselect_elements`)
  - Read the elements from disk and apply the residual query
  - Return the rows that satisfy the query condition

Current approach



Problems with the Current Approach

- Potential chunk revisiting (and very difficult to find the chunk in HDF5 cache because of capacity problems)
- Even if the chunk is found in HDF5 cache, it still has to be decompressed again
- Non-ordered access to chunks, resulting in longer disk access times

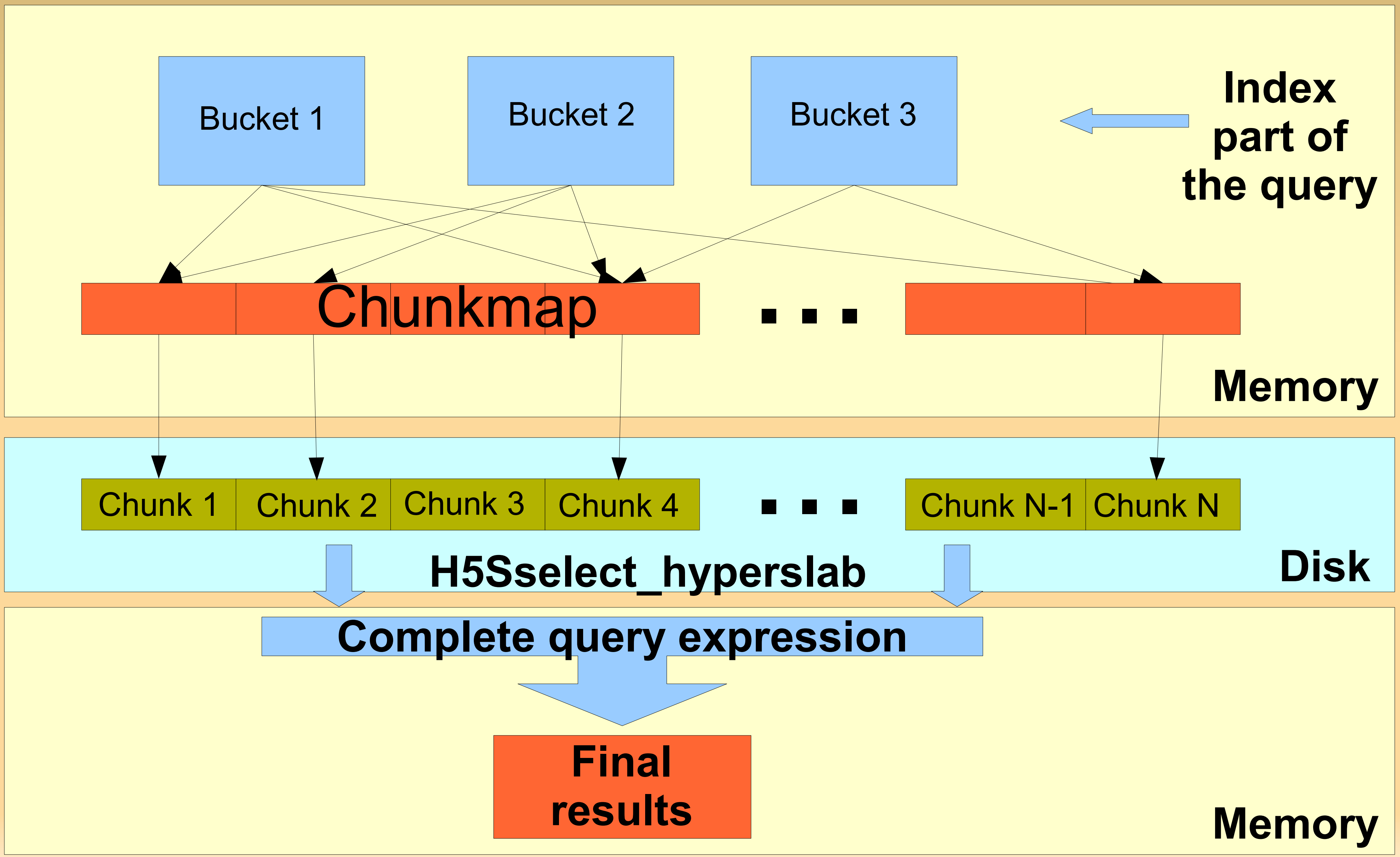
A Message from the Fifth Century, BC

"In general, commanding a large number is like commanding a few. It is a question of dividing up the numbers. Fighting with a large number is like fighting with a few. It is a question of configuration and designation."

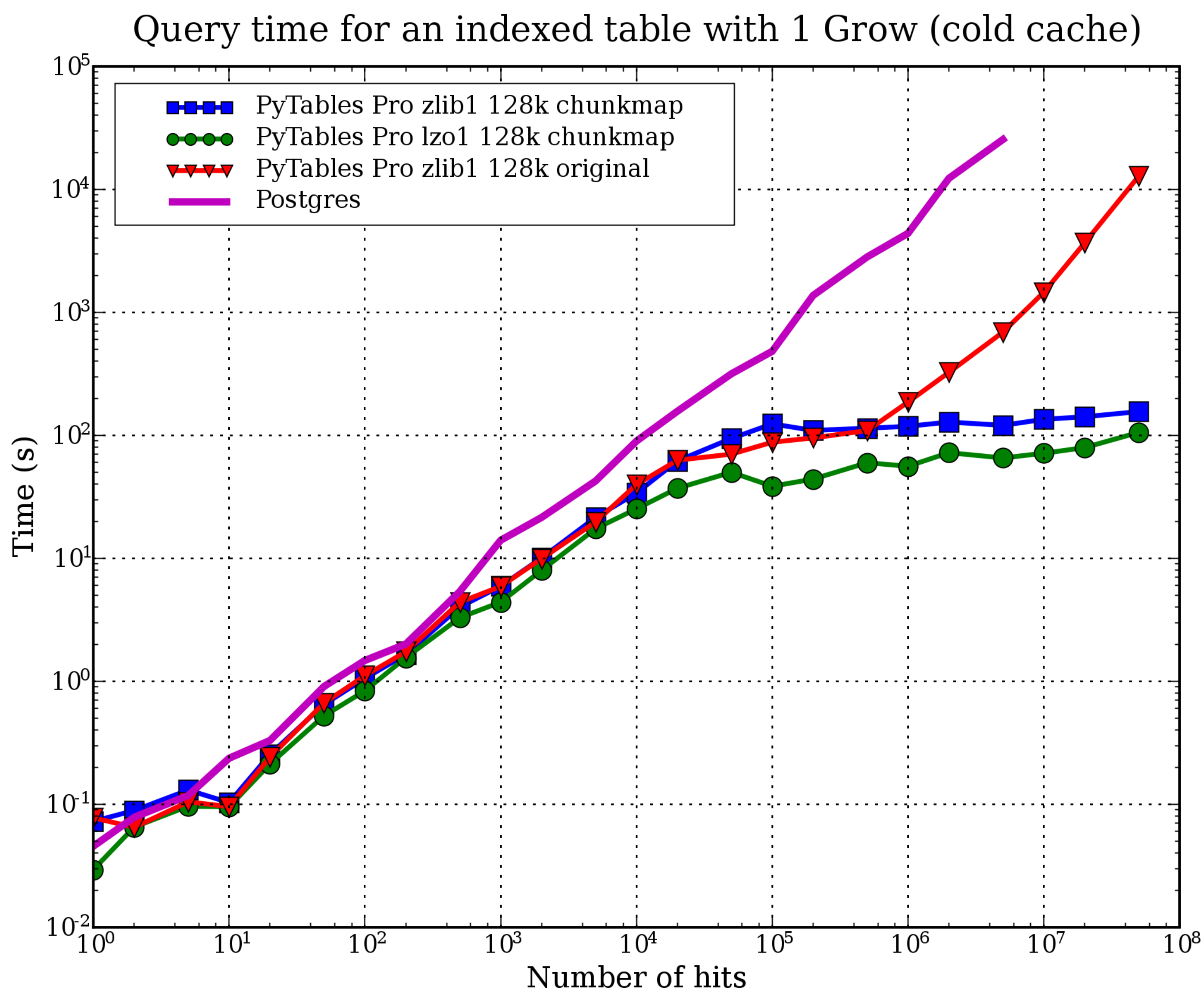
Sun Tzu – The Art of War

Section 5 (Strategic Military Power) verse 1

Solution: A Chunk Map



Chunkmap Performance



Chunkmap: Pros & Cons

- Pros
  - The interesting chunks are visited only once
  - Chunks are accessed in a strict sequential order, minimizing the amount of trips of disk heads
  - The chunkmap on disk has much lower entropy than the original indices: much better compression
- Cons
  - It requires memory: 1 byte per chunk. It can be up to 1 bit per chunk (packed chunkmap)
  - It requires more CPU, as the incoming data from disk has to be filtered through the query condition

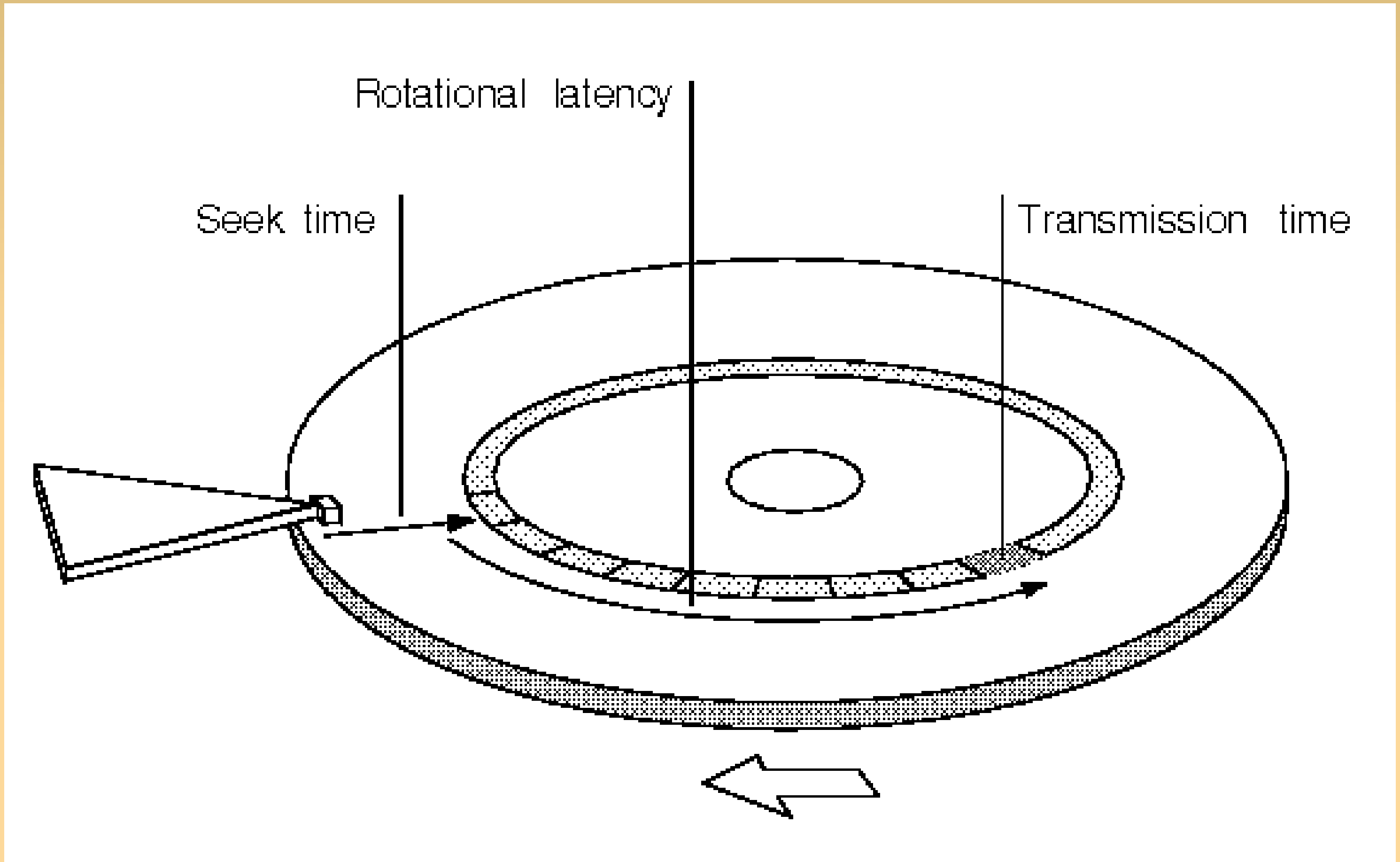
How Much Memory is Required by a Chunkmap?

- Let's imagine a table with 1 billion of rows and 1000 bytes/row. That's around 1 TB in size.
- Size of the chunkmap, depending on the chunksize:
  - 32 KB CS: 32 MB (4 MB packed)
  - 64 KB CS: 16 MB (2 MB packed)
  - 128 KB CS: 8 MB (1 MB packed)
  - 256 KB CS: 4 MB (0.5 MB packed)

Optimal Chunksize?

- What is the optimal chunksize for reducing the chunkmap to a minimum without penalizing retrieval times too much?
- We have to choose a size that takes a relatively short time to read compared with disk access times (the main bottleneck in sparse reads)
- What is the mean latency when doing sparse reads?

Typical Disk Access Times



Times for 7200 rpm drives

Average rotational latency: 4.1 ms
Seek times: from 2 ms to 18 ms

Typical Disk Access Times

- For general random sparse access data on disk, these figures usually give 12 ~ 15 ms
- However, for sequentially ordered sparse access of chunks that are close to each other, the typical times are bound by the rotational latency or less, i.e. <= 4.1 ms access times.

Optimal Chunksize (revisited)

- The optimal chunksize for reducing the amount of memory allocated to the chunkmap has to be chosen so that reads would constitute a relatively small fraction of the average rotational latency of a disk
- The most significant cost in time to process the chunk is the sum of:
  - The time to physically read it from disk
  - The time to uncompress it
  - The time to apply the query condition to it

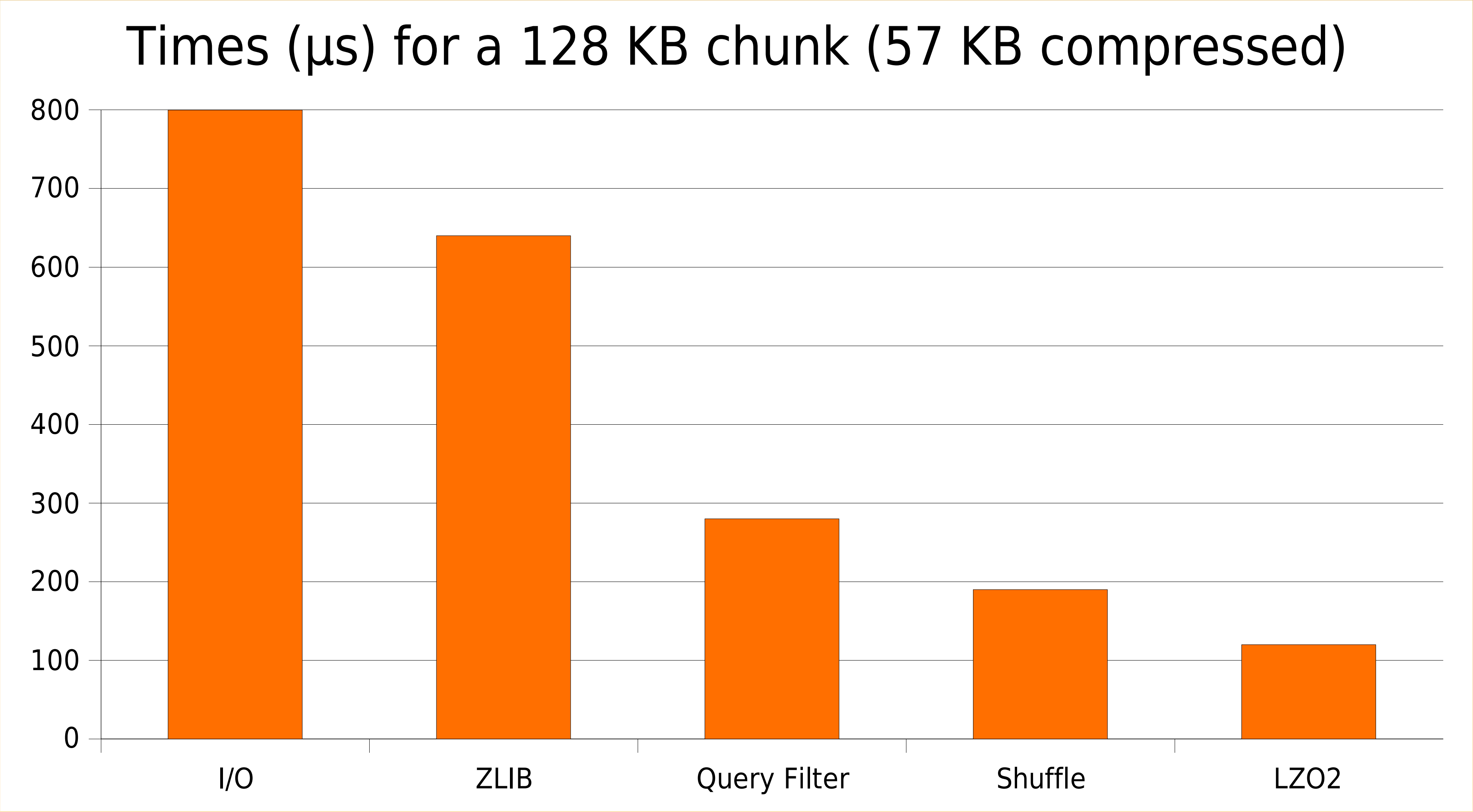
Times to Process a Chunk

- This depends on many factors. For an example, we will choose:
  - Chunk size: 128 KB
  - Compression on (225% of reduction)
  - Modern 7200 rpm SATA disk drive
  - Modern CPU (Intel Core2 or AMD Opteron)
  - Query Filter:
    - `(lower<=col4) & (col4<=upper) & (sqrt(col1+3.1*col2+col3*col4) > 3)`

Times to Process a Chunk

Using ZLIB: 1.8 ms

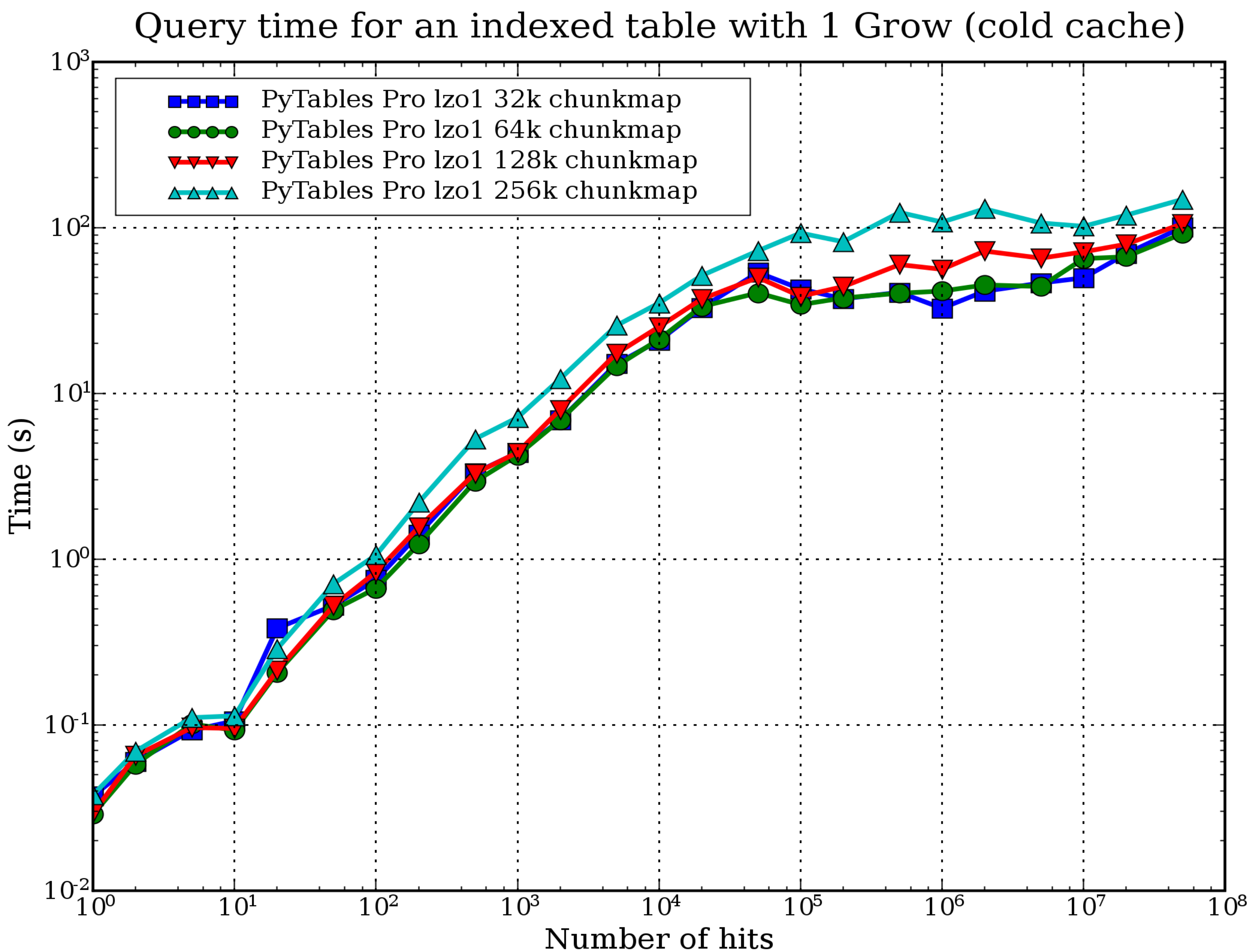
Using LZO2: 1.3 ms



Times for Different Chunksizes

- Times and overhead for low selectivity:
  - 32 KB: 0.45 ms, 11% overhead
  - 64 KB: 0.90 ms, 22% overhead
  - 128 KB: 1.8 ms, 44% overhead
  - 256 KB: 3.6 ms, 88% overhead
- 32 KB or 64 KB would be a good choice for increased low selectivity retrieval speed
- 128 KB would strike a good balance between overhead (44%) and the memory used by the chunkmap (8 MB, or 1 MB packed)

Times for Different Chunksizes



Some Considerations

- The query conditions are evaluated very efficiently thanks to the NumExpr computing kernel integrated into PyTables
- Compression reduces the total I/O time. Not new, but interesting anyway
- The use of LZO2 compressor can be very effective in this scenario (as compared to ZLIB)
- Shuffle takes longer than LZO2, but is worth the while: compression is much higher

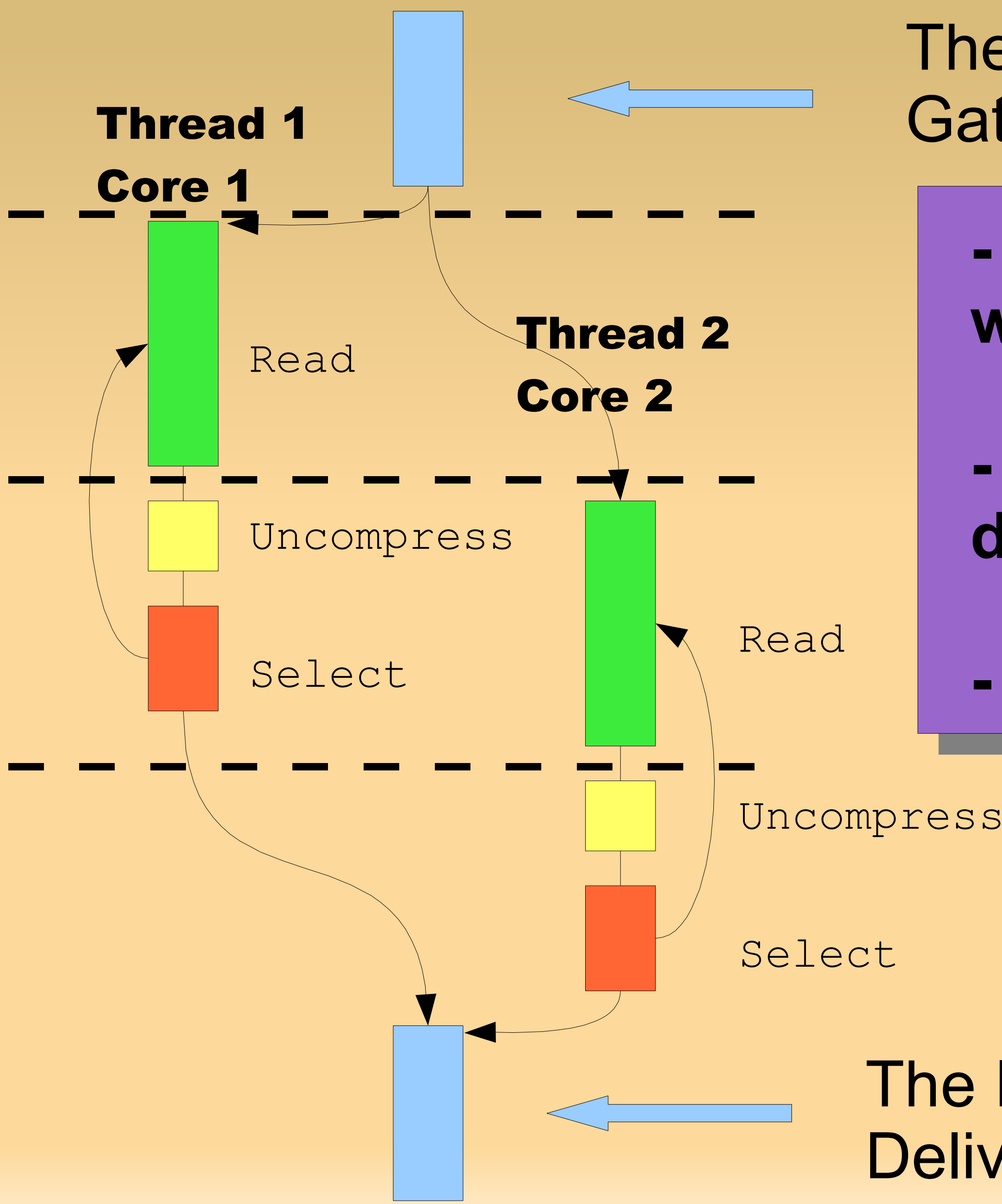
A Few Words About NumExpr

- Fast evaluation of array expressions element-wise by using a **vector-based** virtual machine
- It works by splitting up the operand arrays in chunks that fit into the cache of CPUs, allowing the CPU to attain very high-performance while performing the operations
- We have added support for boolean and string types, heterogeneous arrays (compound types), and optimized the amount of memory copies of unaligned arrays

Using MultiCore CPUs

- Nowadays, it is possible to use multicore CPUs and concurrent programming with threads to further accelerate the reading process in low selectivity environments

MultiCore & Threaded Disk Access



The I/O buffer is empty
Gather more data

- The computations overlap with I/O

- The only bottleneck is disk speed

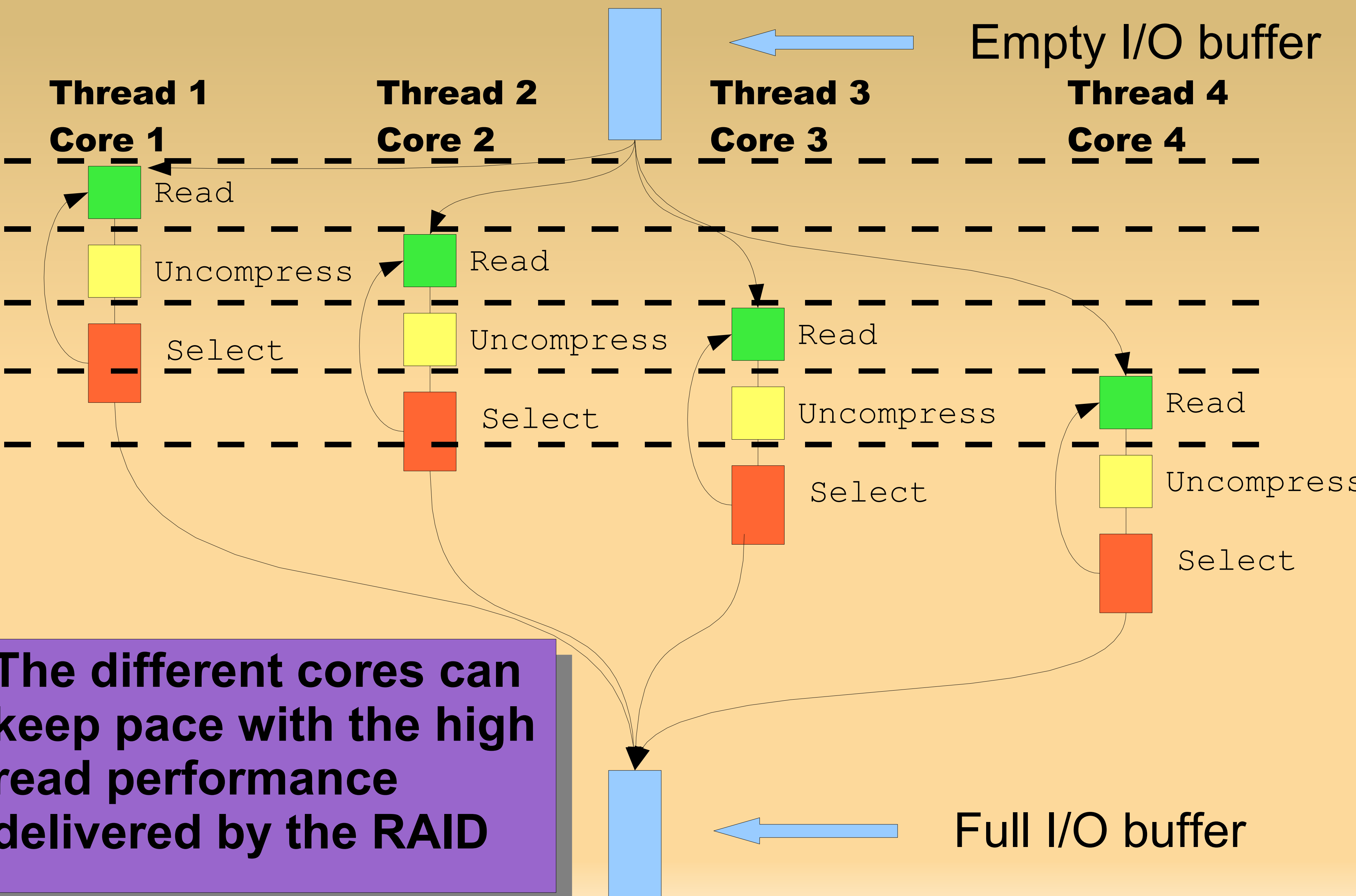
- Up to 1.3x speed-up

The I/O buffer is full
Deliver elements to Python space

Multicore & RAID

- With the advent of multicore CPUs, having a 2, 4 or 8-core system is not uncommon in current workstations
- In addition, drastic reductions in the cost of a medium-sized disk (500 GB costs about $120), makes it possible to build cheap but fast RAID systems reaching multi-TB of capacity
- This system configuration should be considered the norm right now!

Multicore & RAID



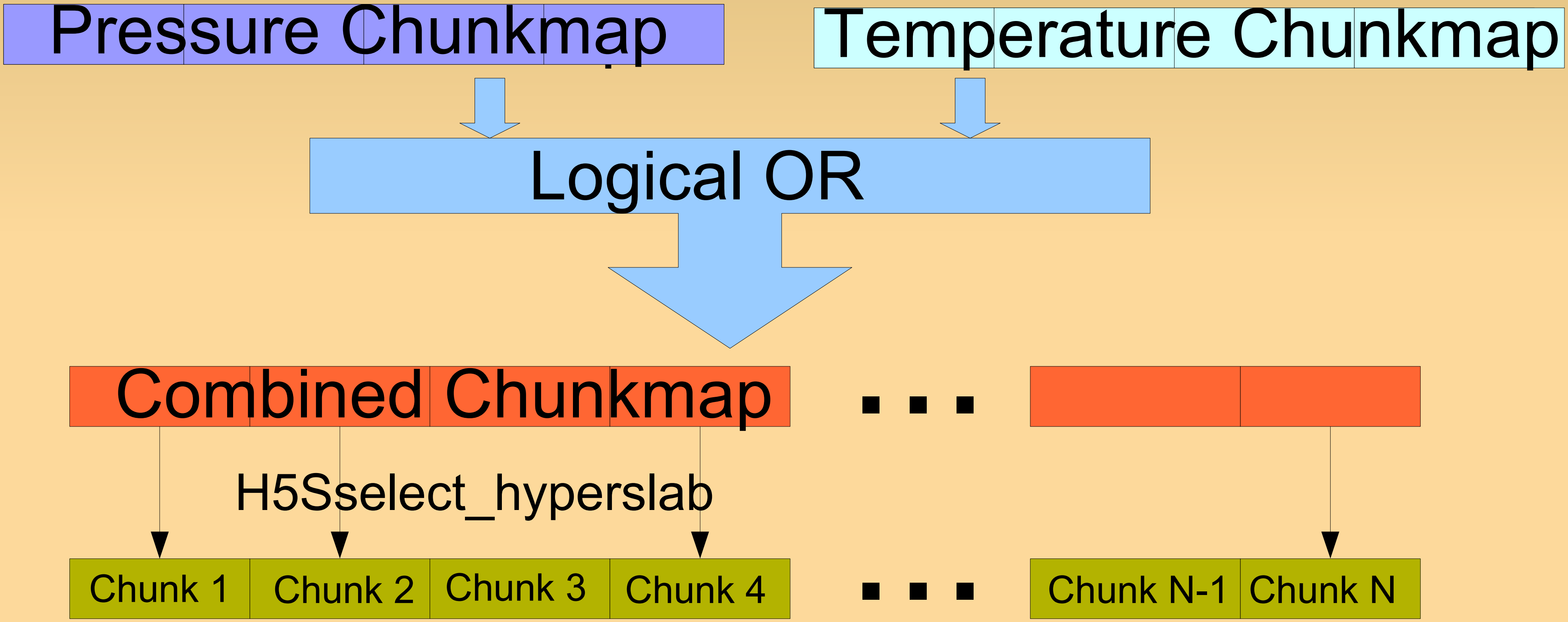
The different cores can keep pace with the high read performance delivered by the RAID

Using Several Indexes in Queries

- Perhaps the most appealing use of chunkmaps is that they can utilize several indexes on a single query
- Examples:
  - '`(pressure < 20) & (temperature > 50)`' current OPSI is not able to use the indexes simultaneously
  - '`(pressure < 20) | (temperature > 50)`' current OPSI can't use any index (because the conditions are 'ORed')

Using Several Indexes in Queries

- `'(pressure < 20) | (temperature > 50)'`



Using Several Indexes in Queries

- NumExpr will be used to combine any amount of logical combinations among chunkmaps
- **Challenge**: From a potentially complex query expression such as:
  ```
  ((pressure < 20) & (temperature > 50) |
   ((lati < 20) & (lati >=40) & (longi < 30))
  ```
  find the maximum number of usable indexes
- This can represent a fair amount of work for very complex expressions!
- Start with the simplest ones and refine the query optimization as needed (not new)

Medium/Long Term Goals

- Try reducing the precision of values of the indexes
  - Faster convergence during index creation
  - Less entropy: better compression, less disk space
  - Inexact results in queries
- Column-wise tables
  - Current table datasets in PyTables are row-wise
  - They are perfect for dealing with tables with a small/medium number of fields
  - Column-wise may prove to be more efficient in scenarios where a large number of fields is required

Final Thoughts

- Chunkmaps seem like a good idea for OPSI
  - They perform much better when the selectivity is low, while retaining the same efficiency for high selectivity queries
  - They permit the use of several indexes in complex queries without too much effort (not taking into consideration the battle to optimize queries!)
- Precision reduction seems easy to implement
- Column-wise tables can be very interesting in some scenarios, but implementation could be difficult