Shooting the Rapids: Getting the Best from Java 8 Streams

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About Kirk

- Specialises in performance tuning
  - speaks frequently about performance
  - author of performance tuning workshop
- Co-founder jClarity
  - performance diagnositic tooling
- Java Champion (since 2006)

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Java™ Champions

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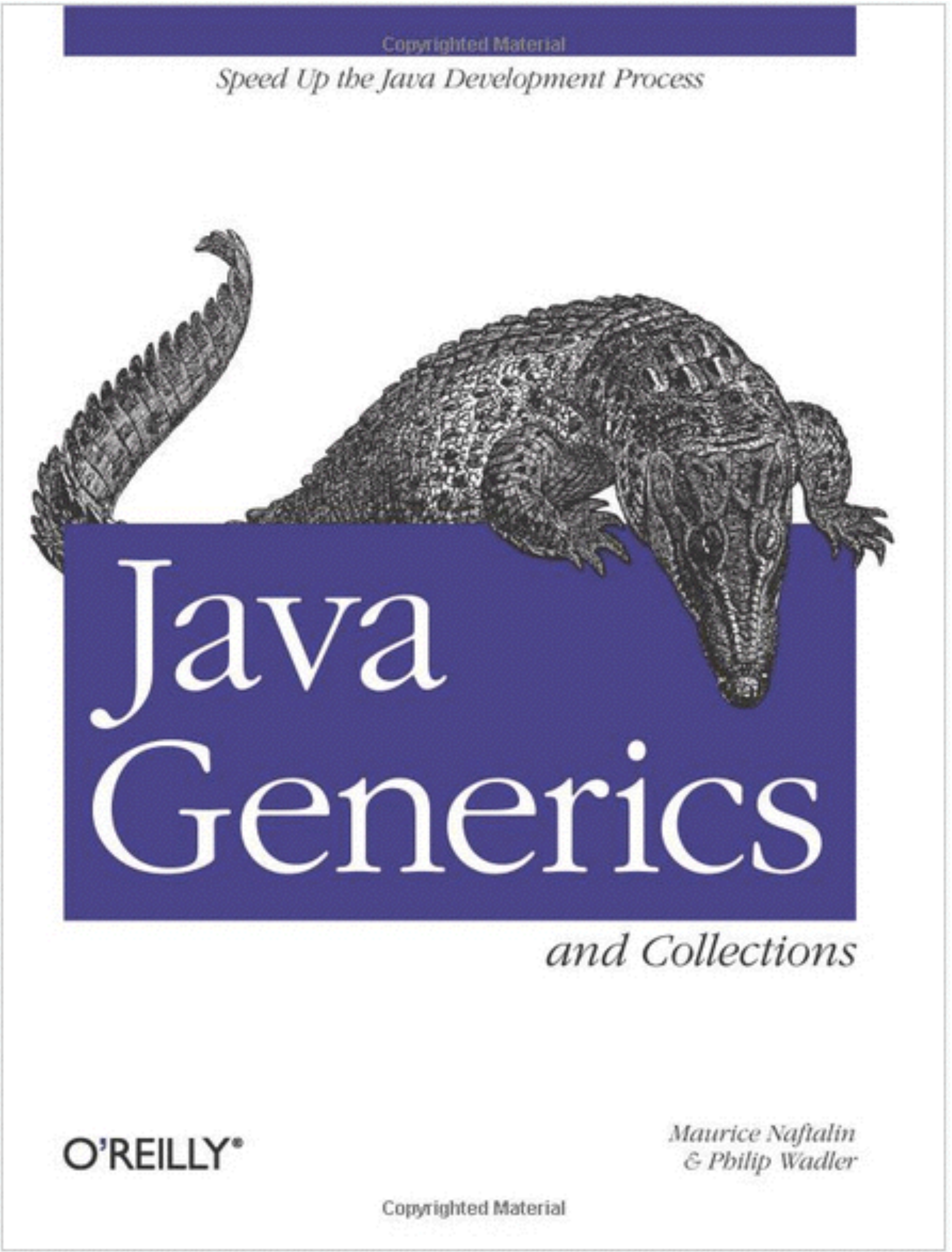

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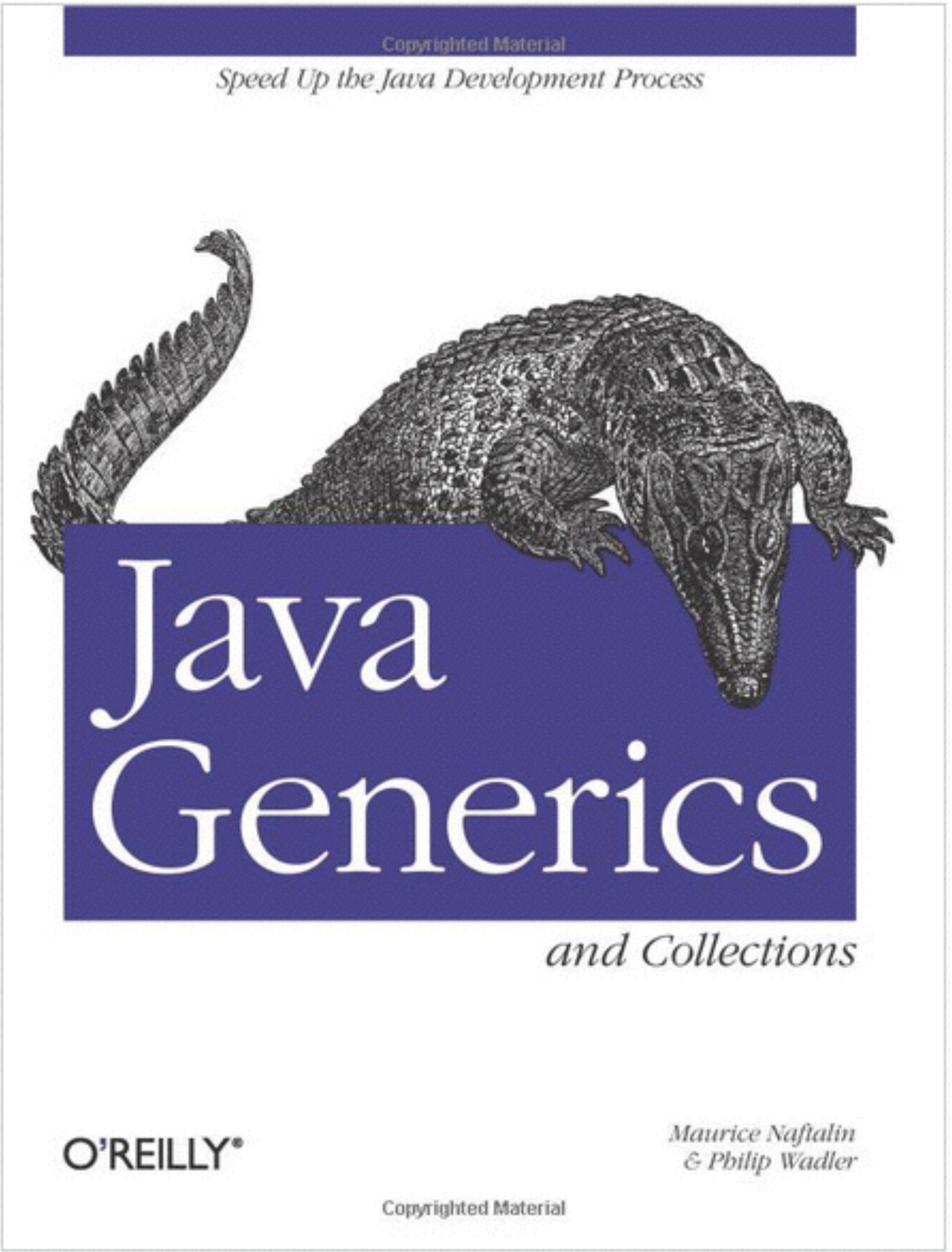

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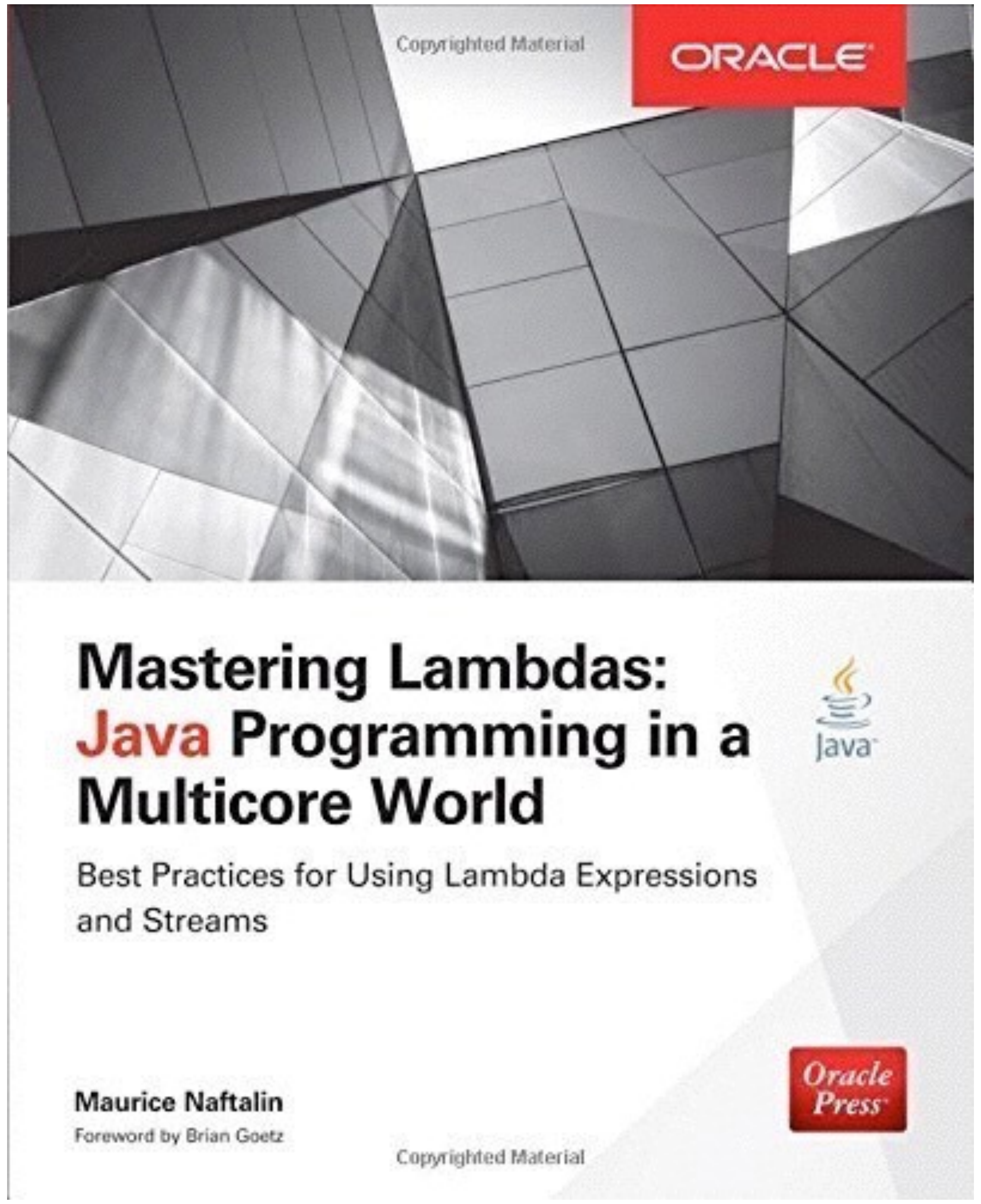

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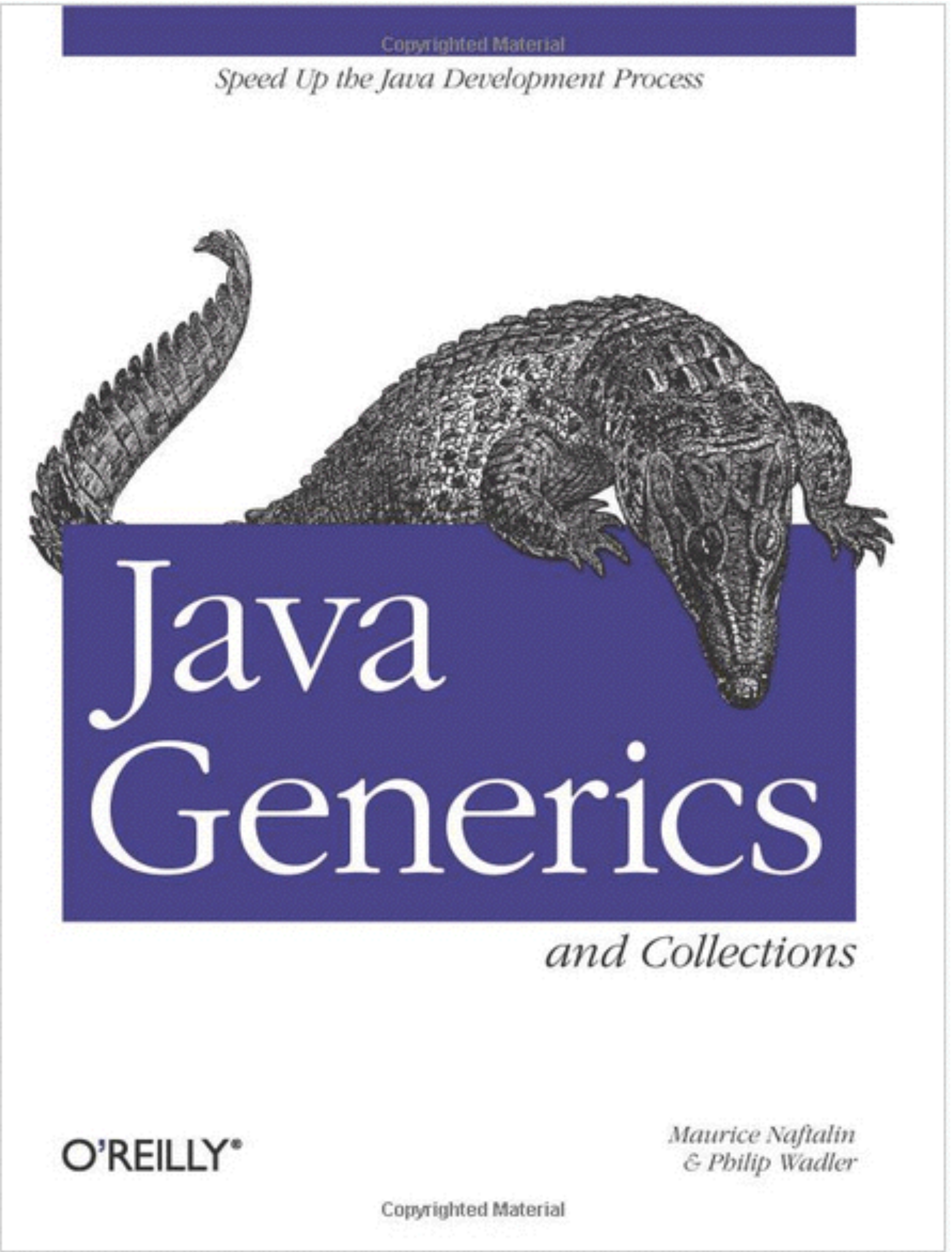

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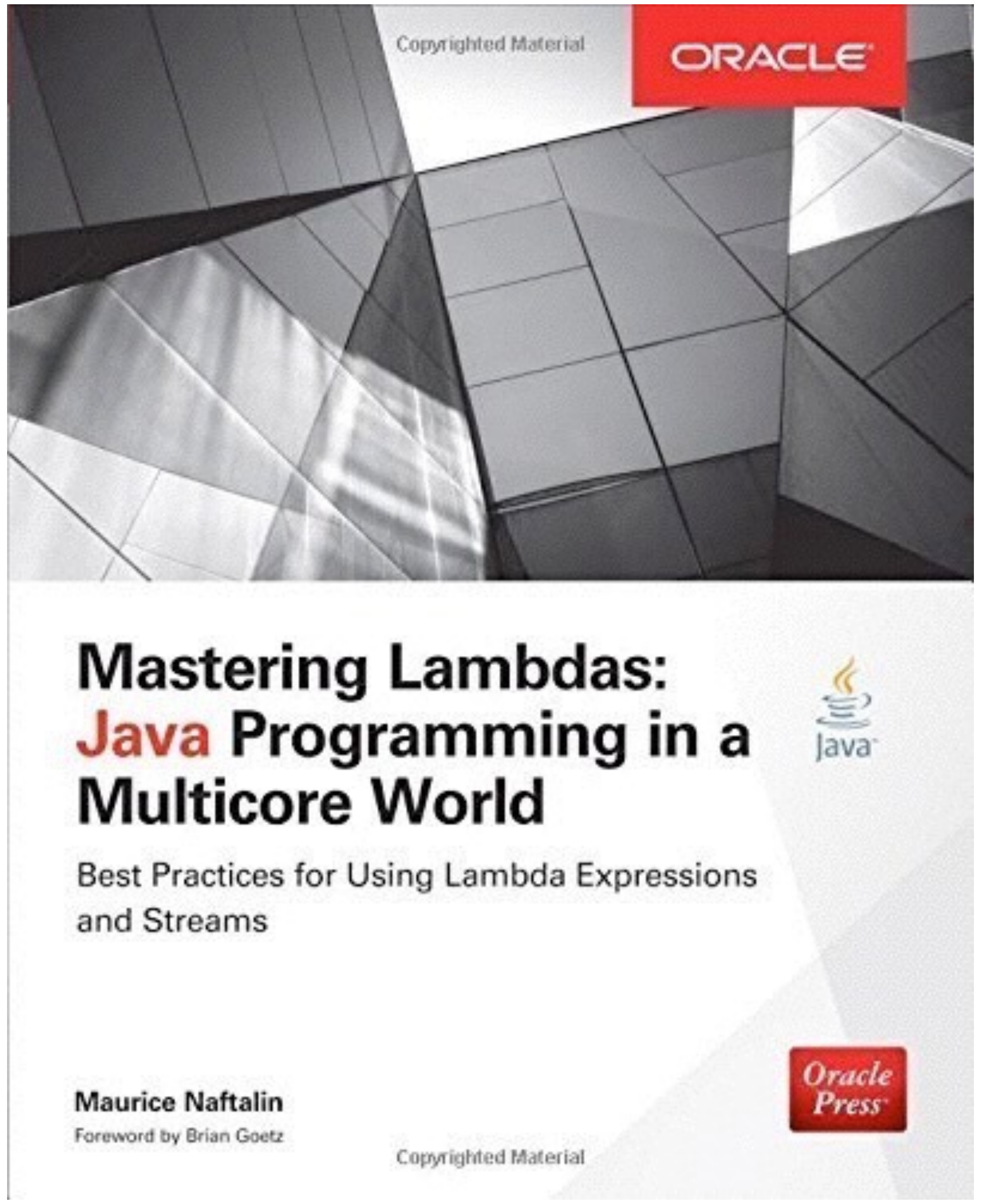

Author

Java
Champion

JavaOne
Rock Star

Agenda

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- Introduction
  - – lambdas, streams, and a logfile processing problem

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Example: Processing GC Logfile

```
⋮
2.869: Application time: 1.0001540 seconds
5.342: Application time: 0.0801231 seconds
8.382: Application time: 1.1013574 seconds
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```
sum=2.181635
```

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```
DoubleSummaryStatistics
{count=3, sum=2.181635, min=0.080123, average=0.727212,
max=1.101357}
```

Example: Processing GC Logfile

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```

Regex: `Application time: (\\d+\\.\\d+)`

Example: Processing GC Logfile

```
Pattern stoppedTimePattern =
            Pattern.compile(" Application time: (\\d+\\.\\d+)");

        ⋮

Matcher matcher = stoppedTimePattern.matcher(logRecord);
String value = matcher.group(1);
```

Processing GC Logfile: Old School Code

```
Pattern stoppedTimePattern =
        Pattern.compile("Application time: (\\d+\\.\\d+)");

String logRecord;
double value = 0;
while ( ( logRecord = logFileReader.readLine()) != null) {
  Matcher matcher = stoppedTimePattern.matcher(logRecord);
  if ( matcher.find()) {
    value += (Double.parseDouble( matcher.group(1)));
  }
}
```

What is a Lambda?

```
Predicate<Matcher> matches = new Predicate<Matcher>() {
    @Override
    public boolean test(Matcher matcher) {
        return matcher.find();
    }
};
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```

A lambda is a function
from arguments to result

Processing Logfile: Stream Code

```
DoubleSummaryStatistics summaryStatistics =
    logFileReader.lines()
        .map(input -> stoppedTimePattern.matcher(input))
        .filter(matcher -> matcher.find())
        .map(matcher -> matcher.group(1))
        .mapToDouble(s -> Double.parseDouble(s))
        .summaryStatistics();
```

Processing Logfile: Stream Code

data source

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DoubleSummaryStatistics summaryStatistics =
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```

Processing Logfile: Stream Code

start streaming

```
DoubleSummaryStatistics summaryStatistics =
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        .map(input -> stoppedTimePattern.matcher(input))
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```

map to Matcher

Processing Logfile: Stream Code

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```

filter out uninteresting bits

Processing Logfile: Stream Code

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```

extract group

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map String to Double

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```

aggregate results

What is a Stream?

- A sequence of values
  - *source* and *intermediate operations* set the stream up lazily:

Source

```
Stream<String> groupStream =
    logFileReader.lines()
        .map(stoppedTimePattern::matcher)
        .filter(Matcher::find)
        .map(matcher -> matcher.group(1))
        .mapToDouble(Double::parseDouble);
```

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Intermediate Operations

```
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        .map(matcher -> matcher.group(1))
        .mapToDouble(Double::parseDouble);
```

What is a Stream?

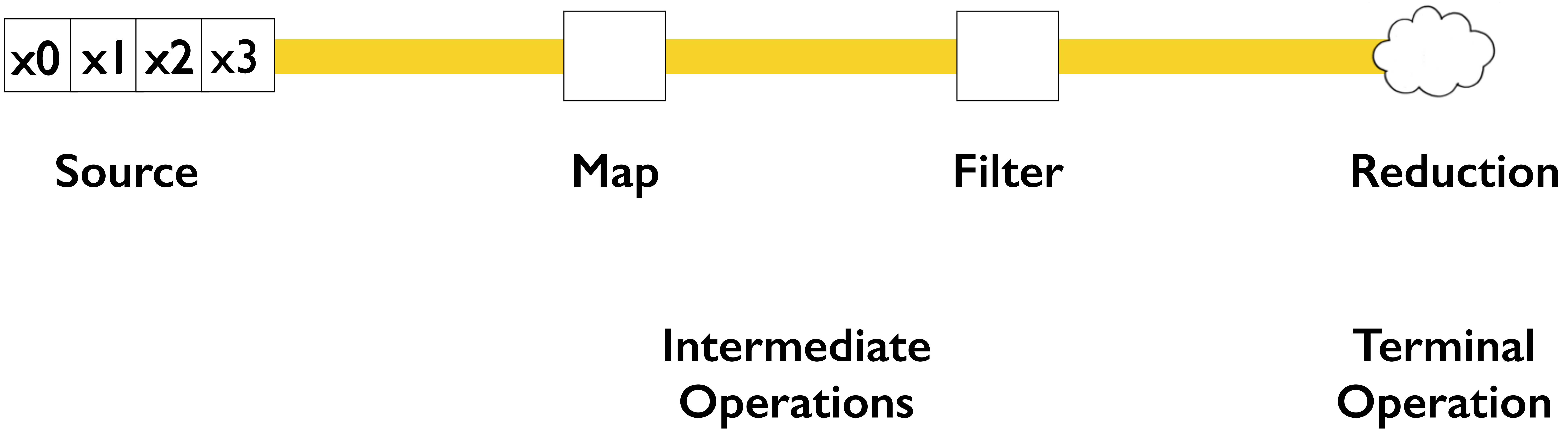
- The *terminal operation* pulls the values down the stream:

```
SummaryStatistics statistics =
    logFileReader.lines()
        .map(stoppedTimePattern::matcher)
        .filter(Matcher::find)
        .map(matcher -> matcher.group(1))
        .mapToDouble(Double::parseDouble)
        .summaryStatistics();
```

Terminal Operation

Visualising Sequential Streams

"Values in Motion"



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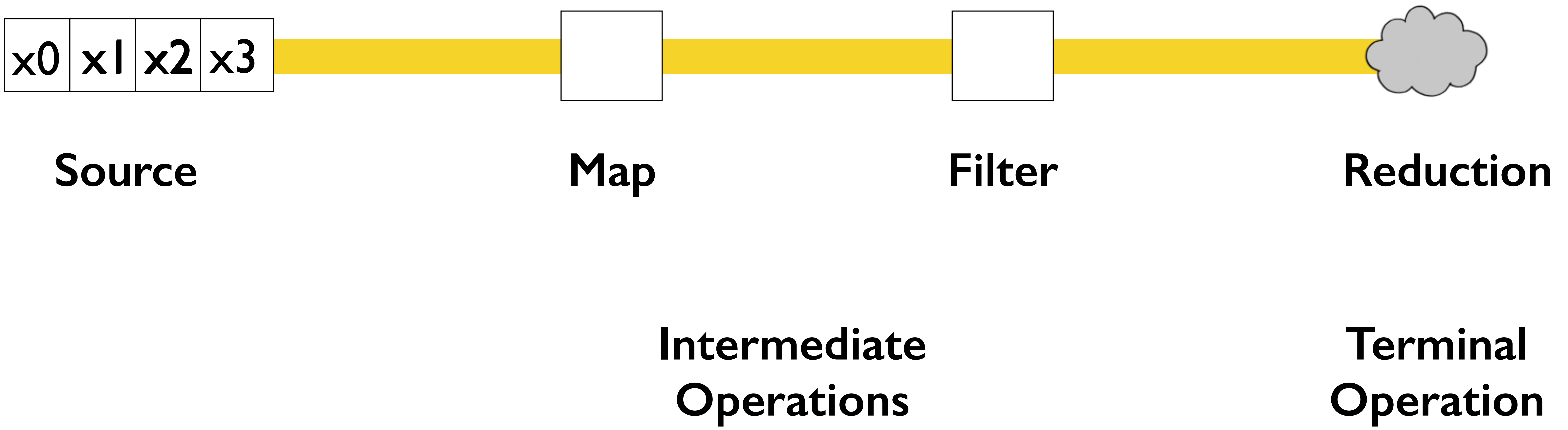

Visualising Sequential Streams

"Values in Motion"

Source **Map** **Filter** **Reduction**

Intermediate Operations

Terminal Operation

Visualising Sequential Streams

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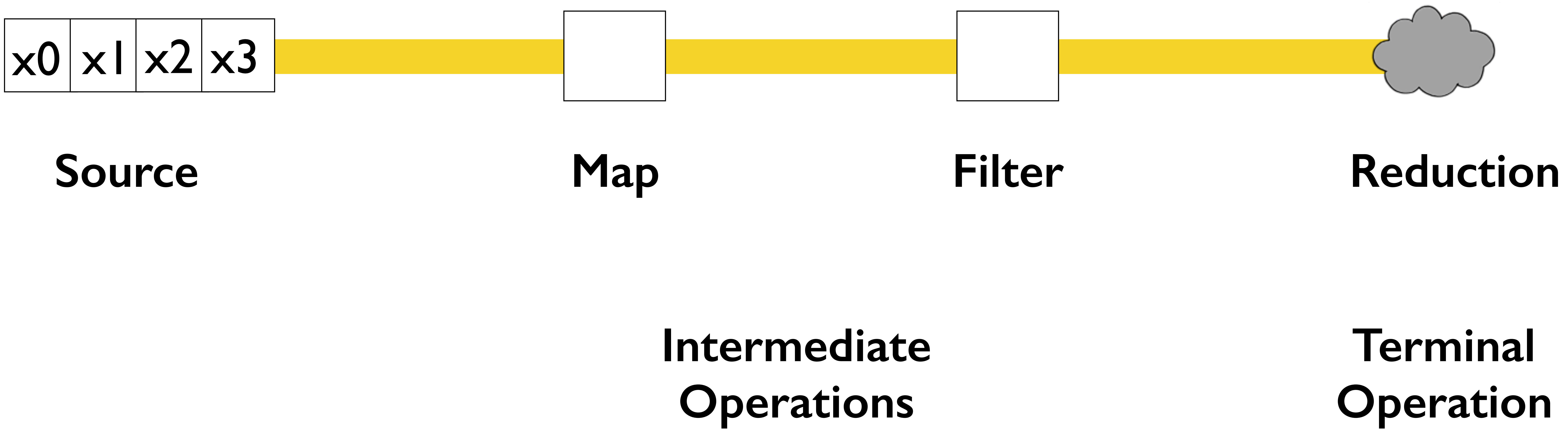

How Does That Perform?

Old School: 80200ms

Sequential: 25800ms

(>9m lines, MacBook Pro, Haswell i7, 4 cores, hyperthreaded)

Stream code is faster because operations are fused

Can We Do Better?

Parallel streams make use of multiple cores

- split the data into segments
- each segment processed by its own thread
  - on its own core – if possible

Splitting the Data

Implemented by a `Spliterator`:

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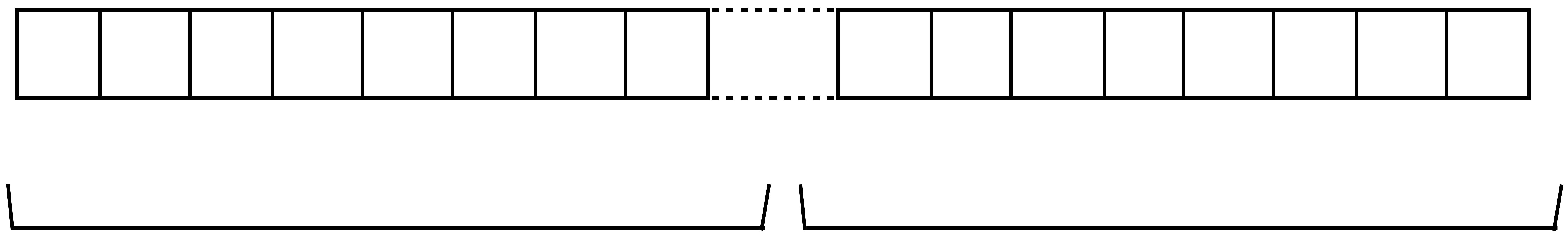

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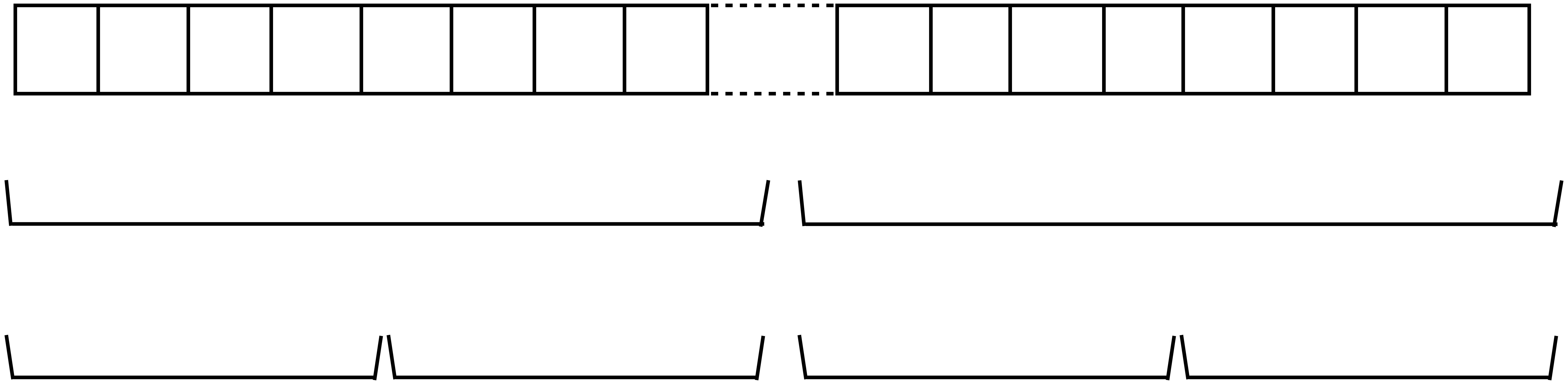

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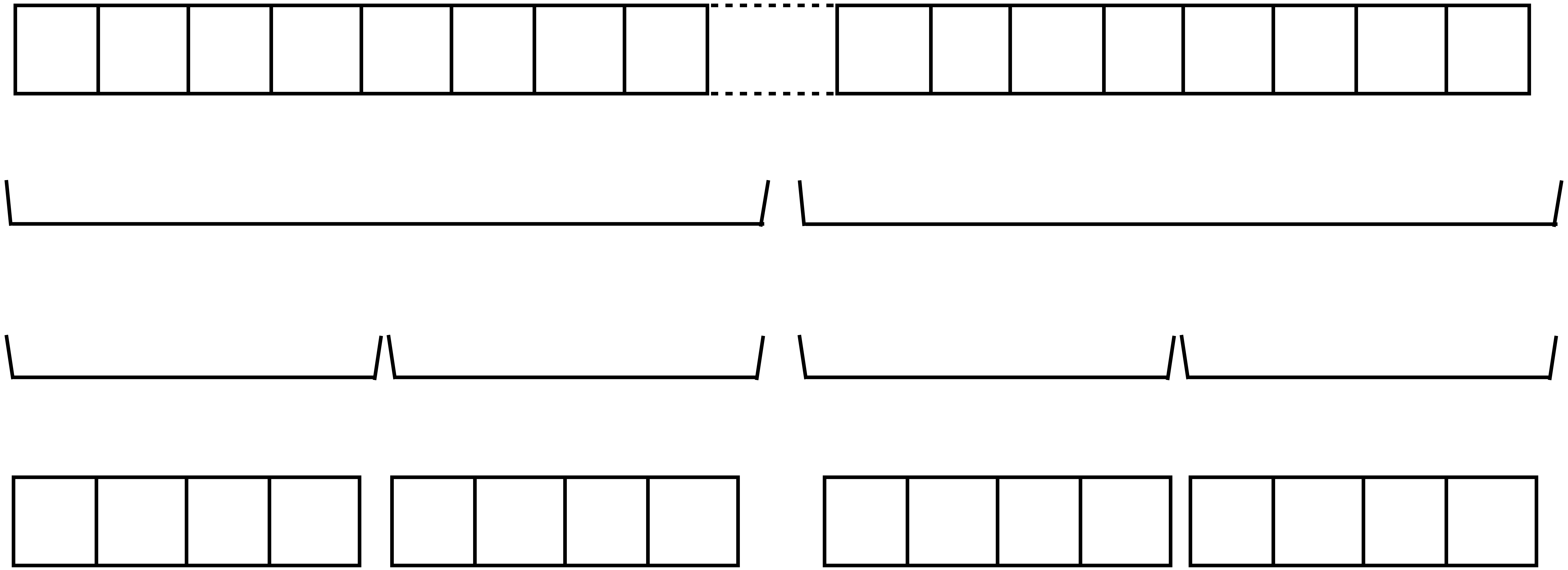

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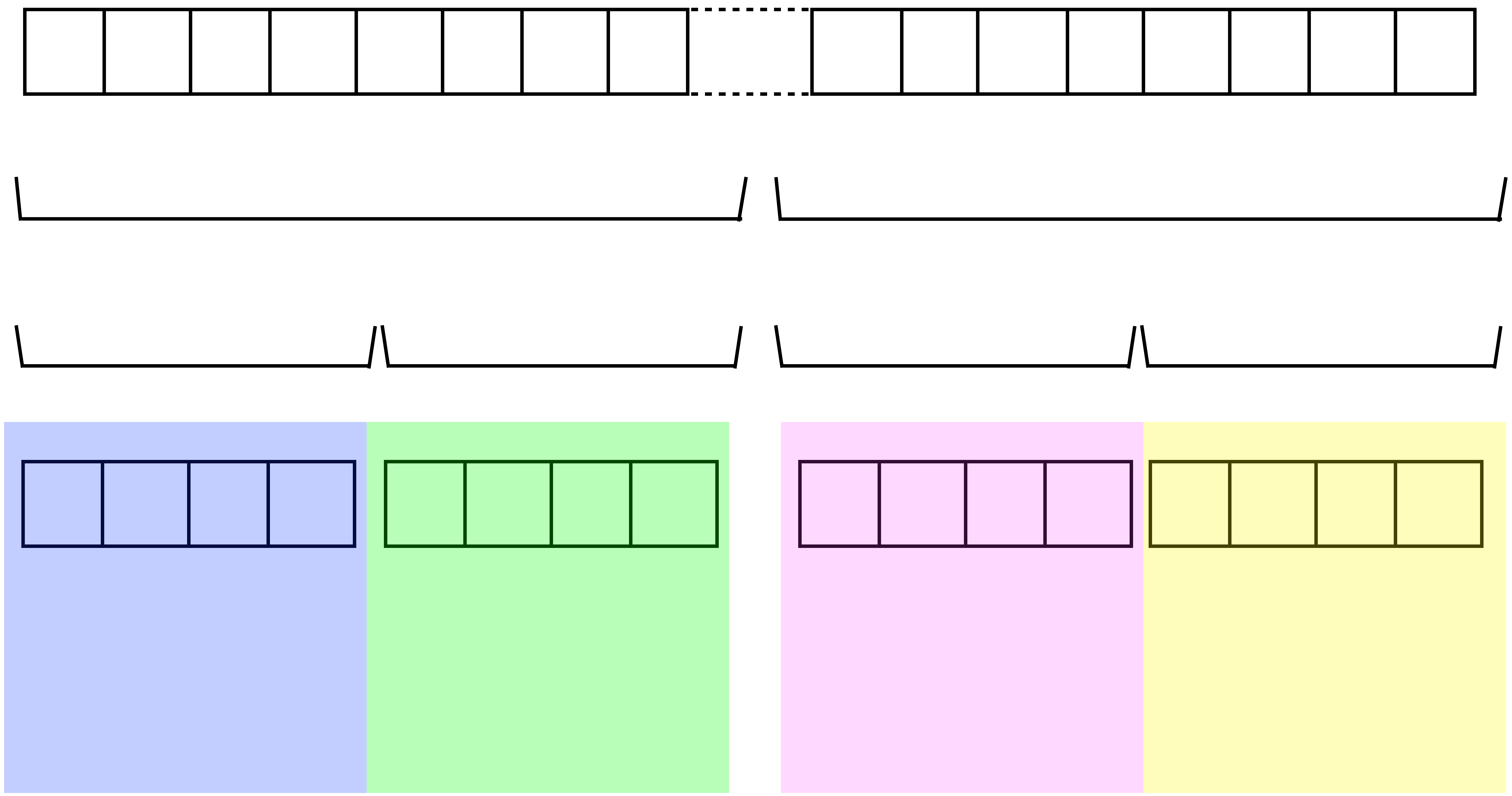

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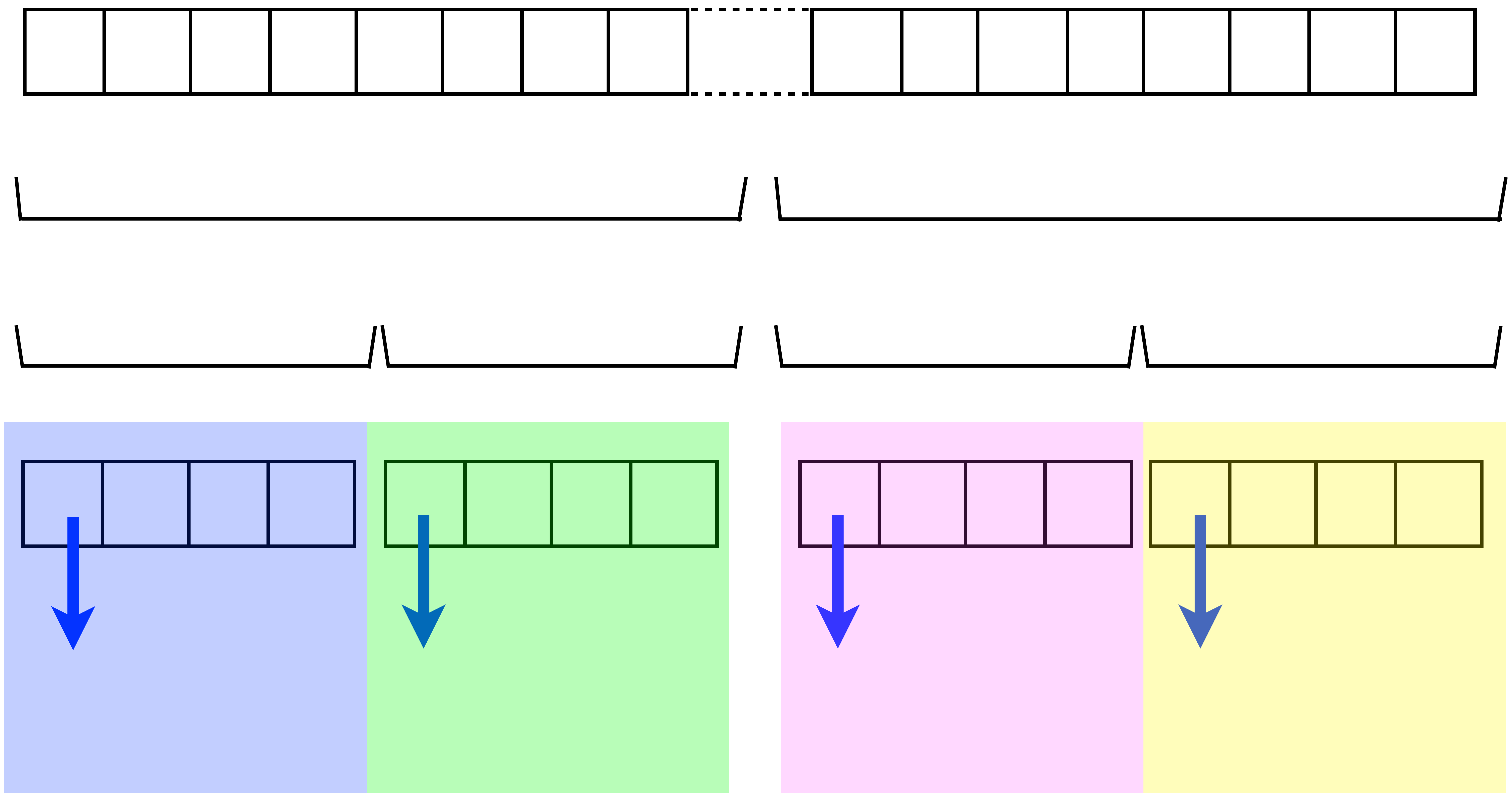

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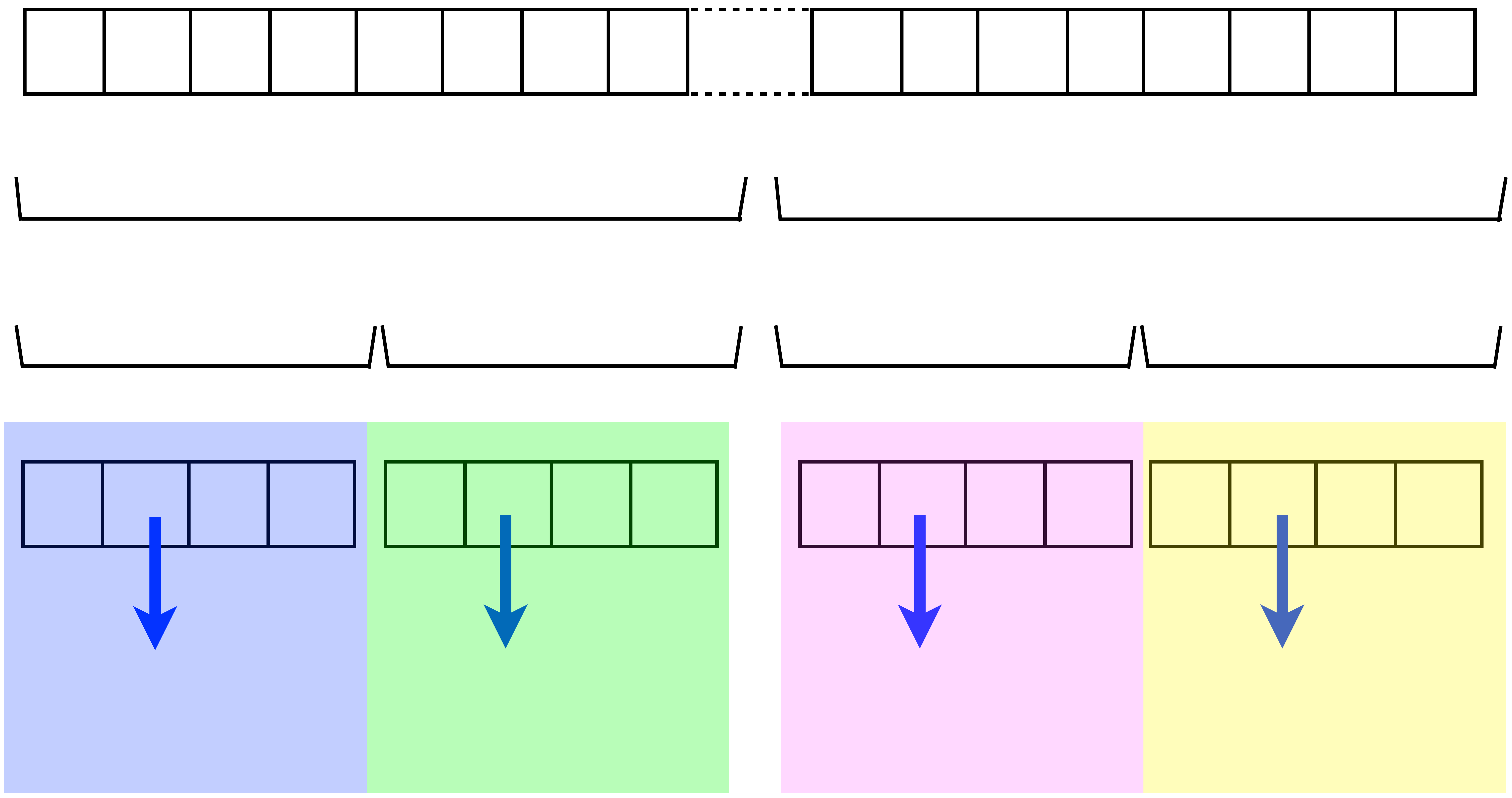

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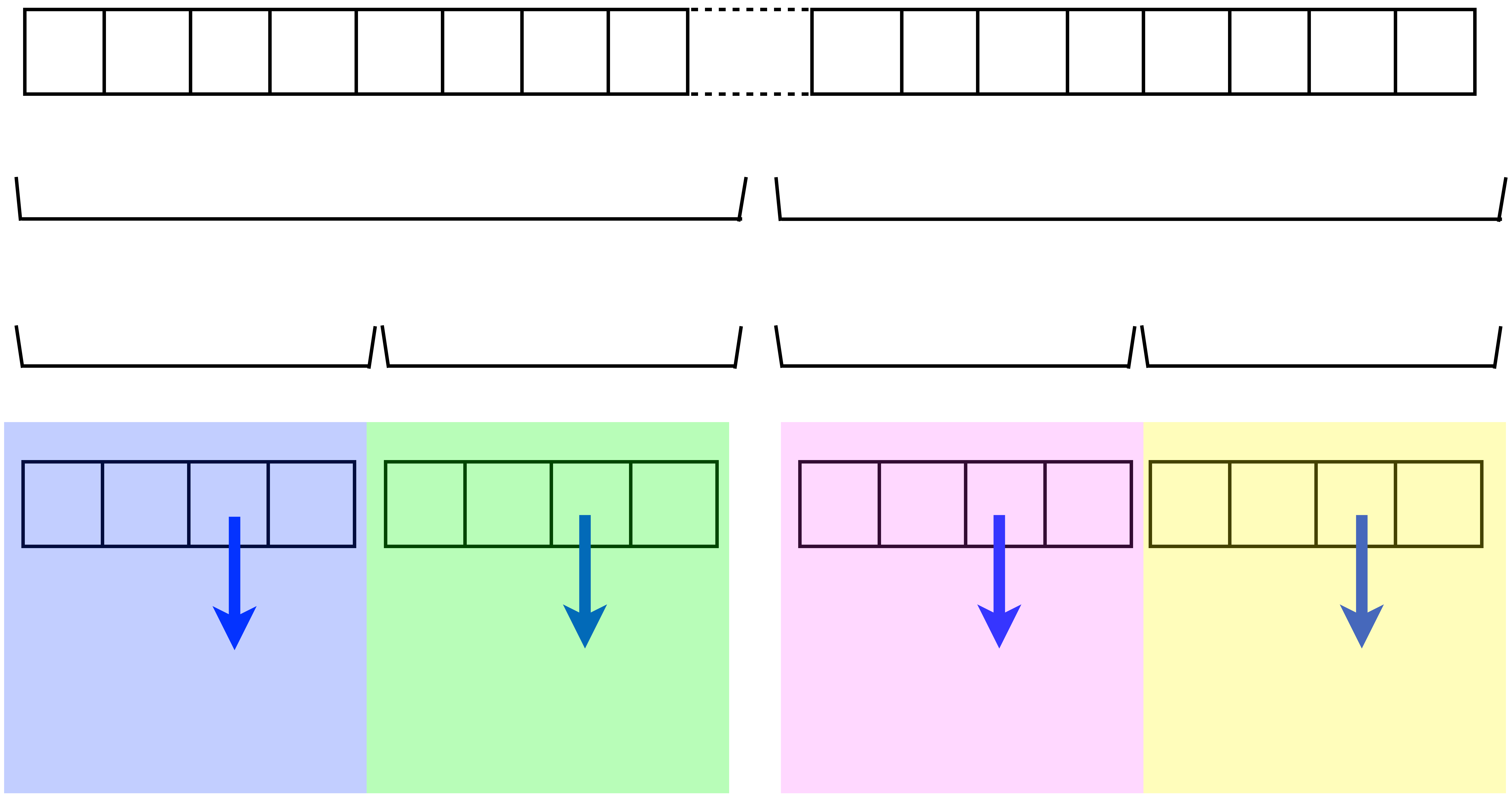

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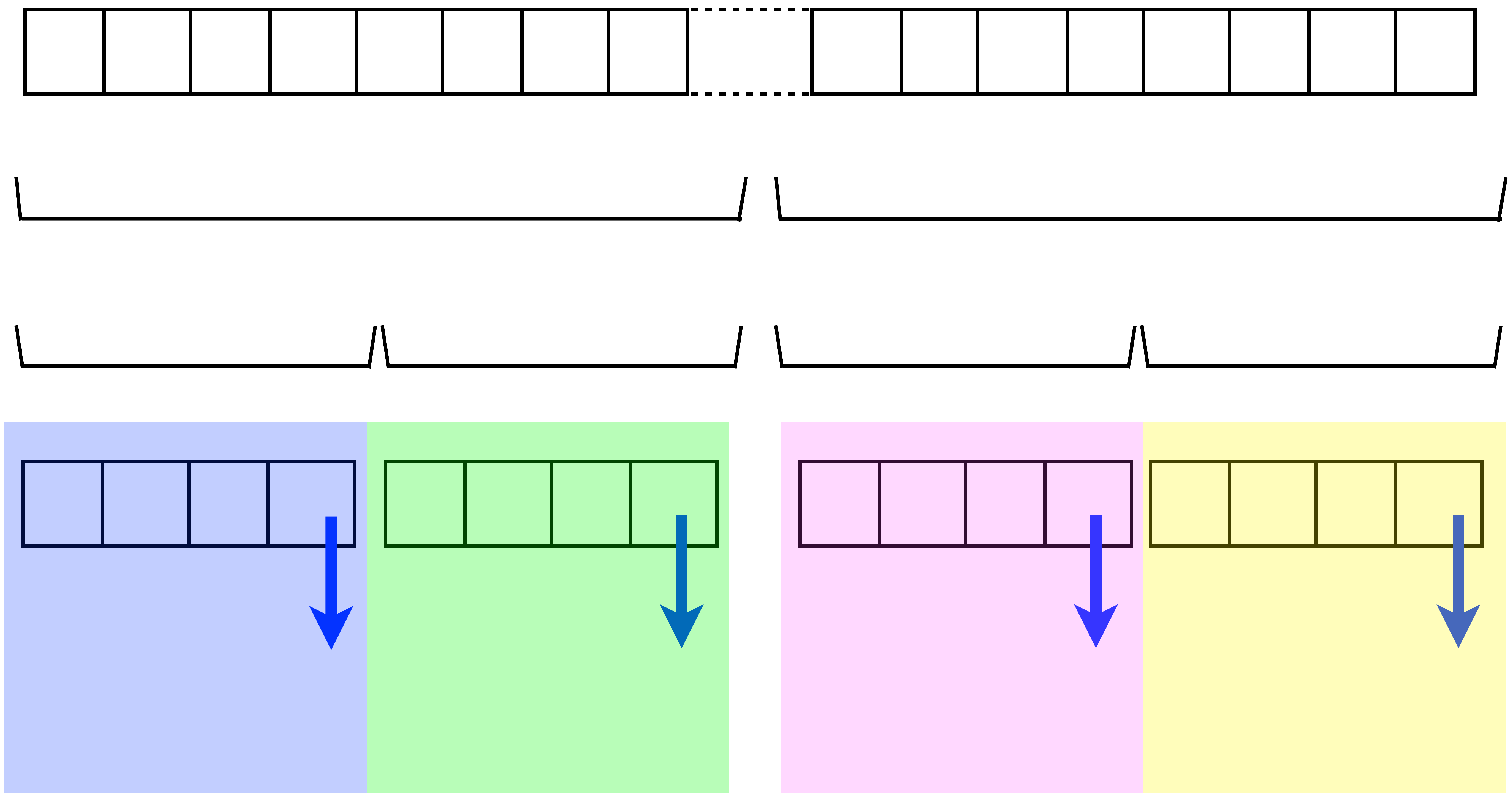
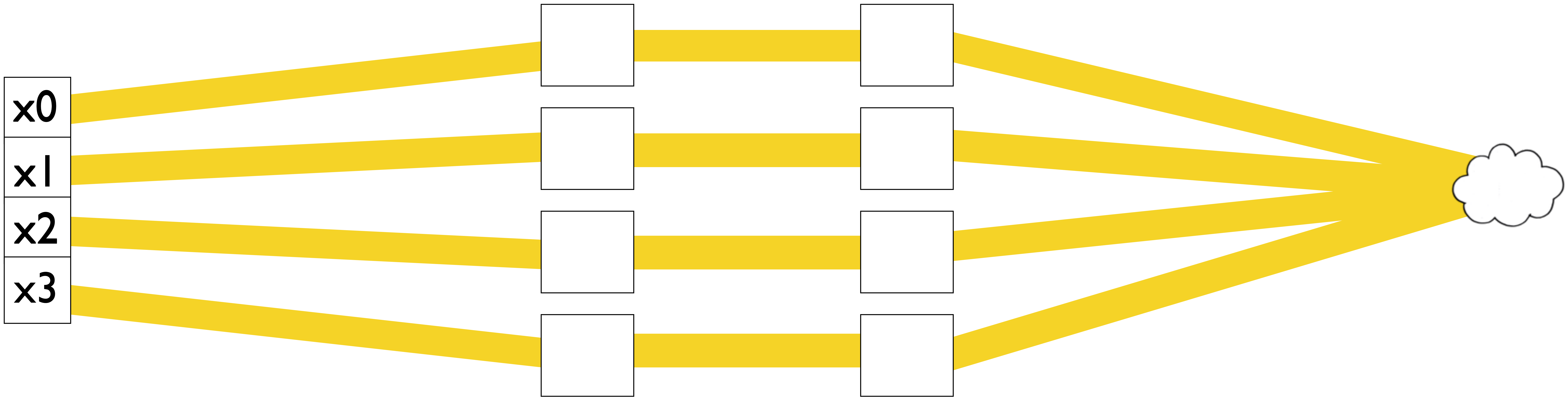


Visualizing Parallel Streams



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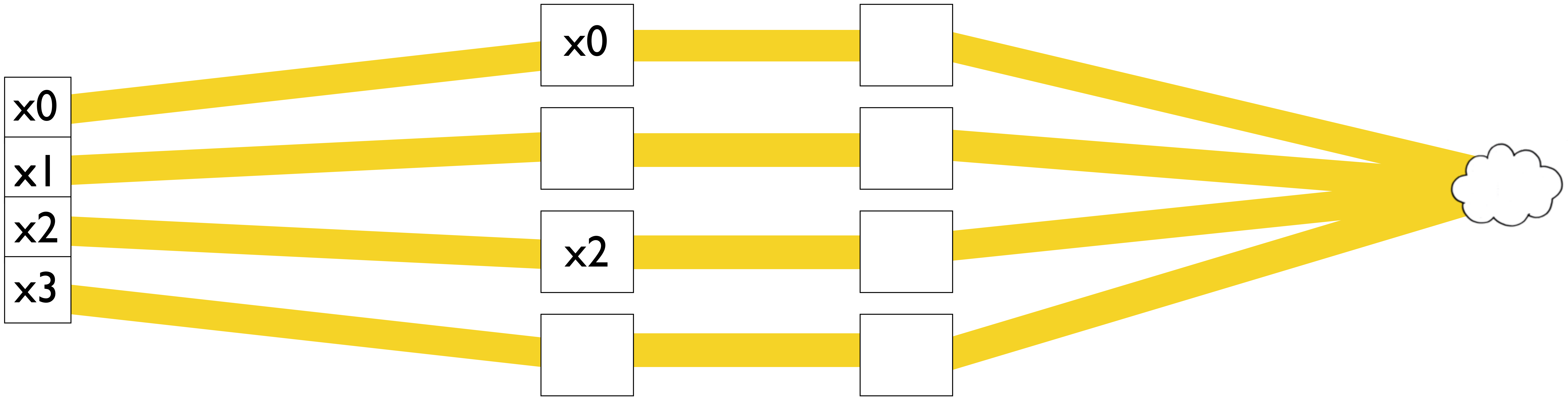

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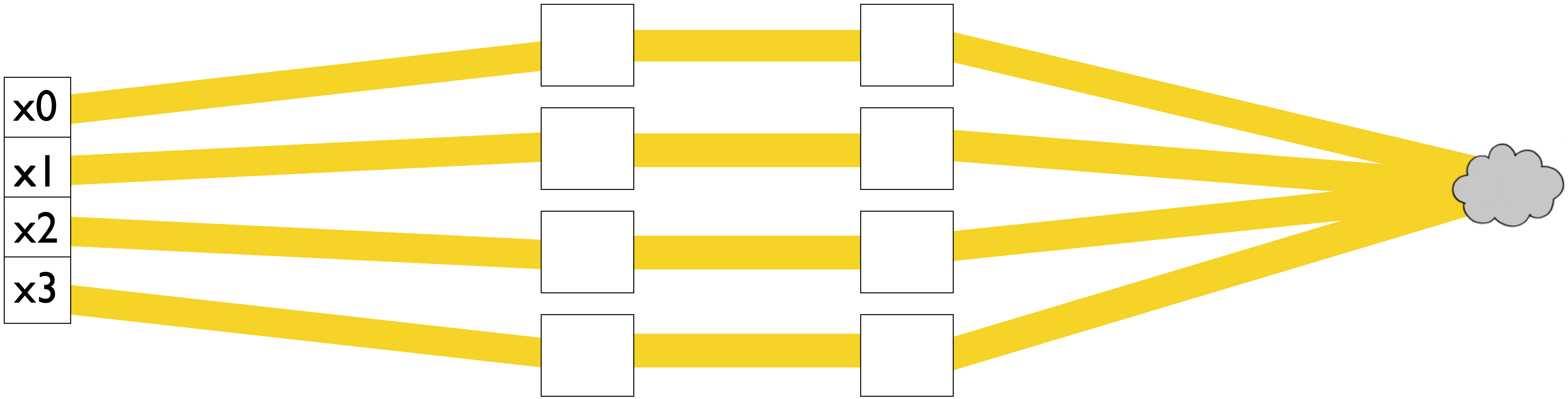

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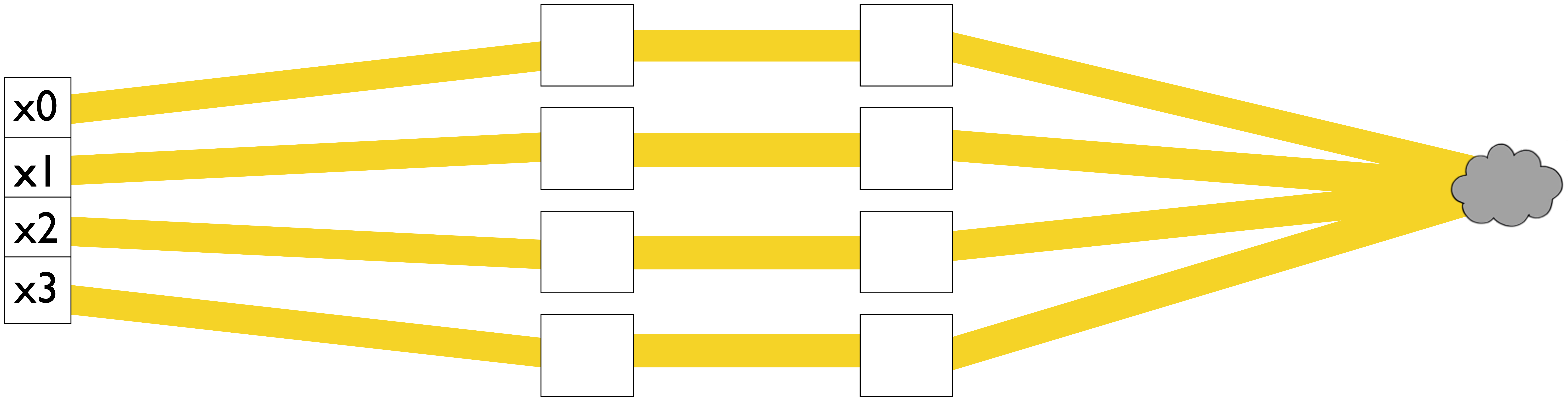

Stream Code

```
DoubleSummaryStatistics summaryStatistics =
    logFileReader.lines().parallel()
        .map(stoppedTimePattern::matcher)
        .filter(Matcher::find)
        .map(matcher -> matcher.group(1))
        .mapToDouble(Double::parseDouble)
        .summaryStatistics();
```

Results of Going Parallel:

- No benefit from using parallel streams while streaming data

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Poorly Splitting Sources

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- Some sources split much worse than others
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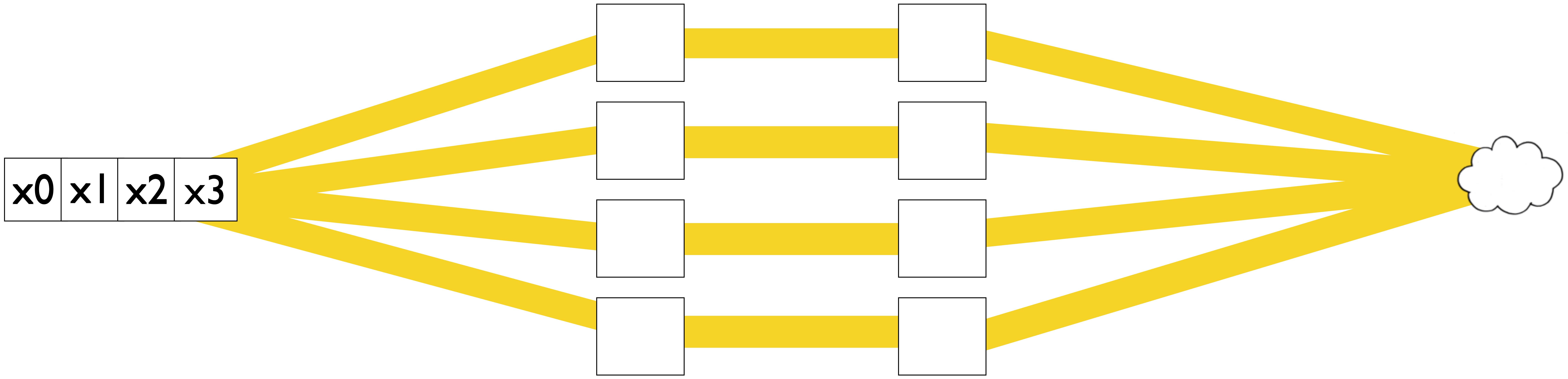
Streaming I/O Bottleneck



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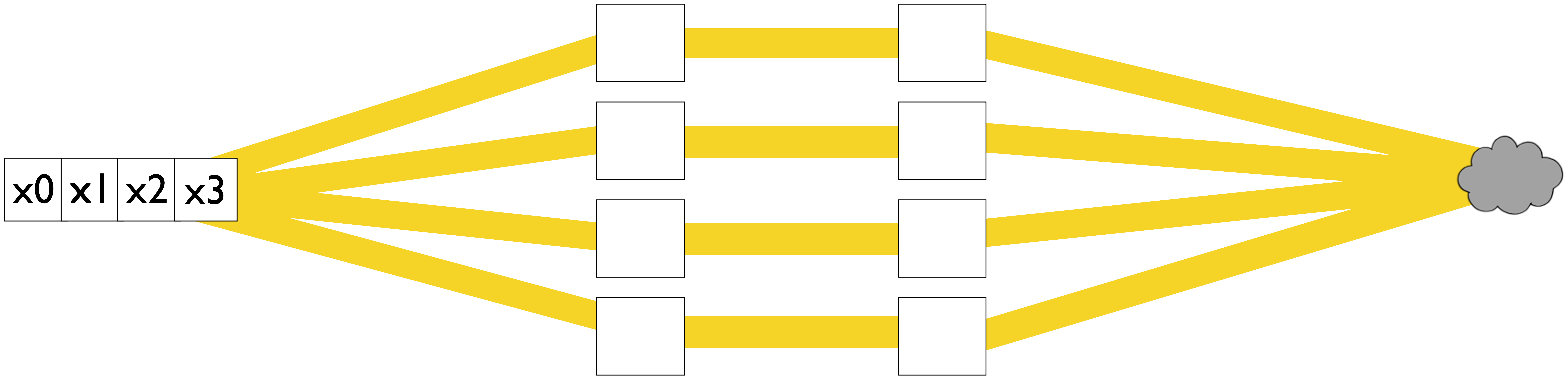
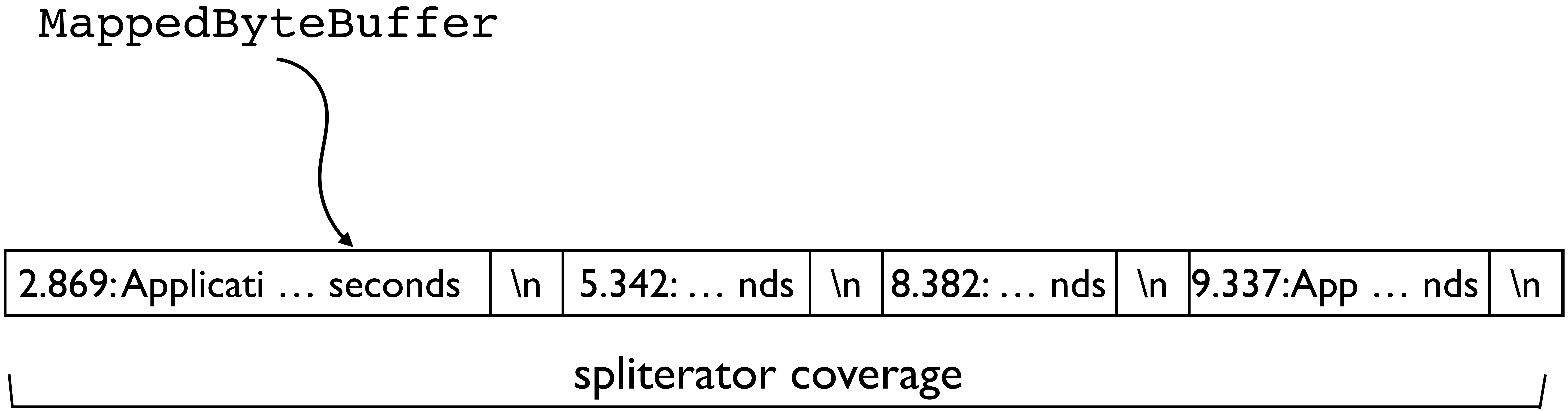


LineSpliterator

2.869: Applicati … seconds	\n	5.342: … nds	\n	8.382: … nds	\n	9.337:App … nds	\n

spliterator coverage

LineSpliterator



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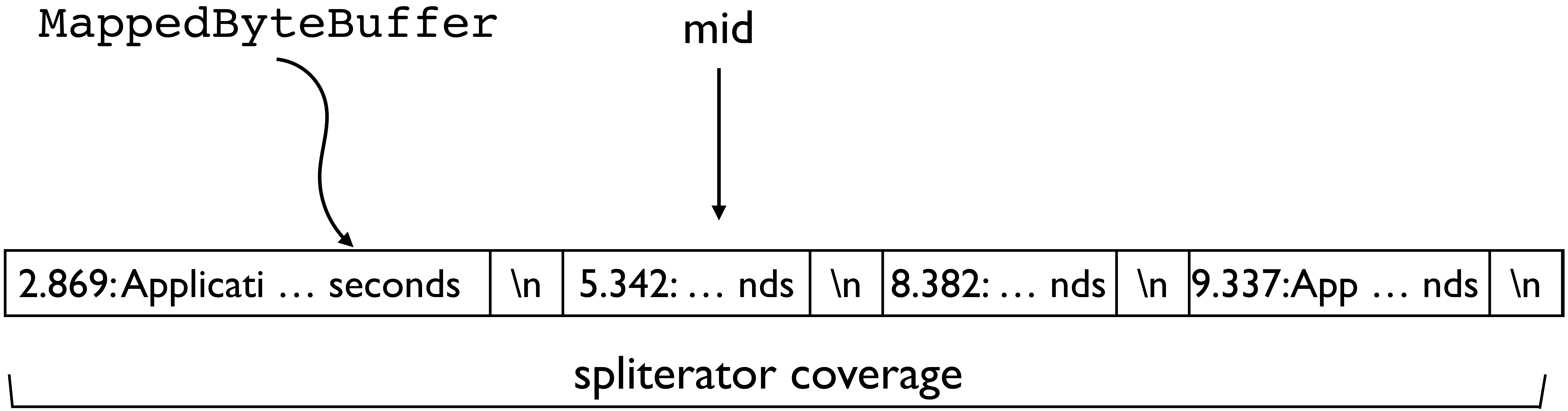

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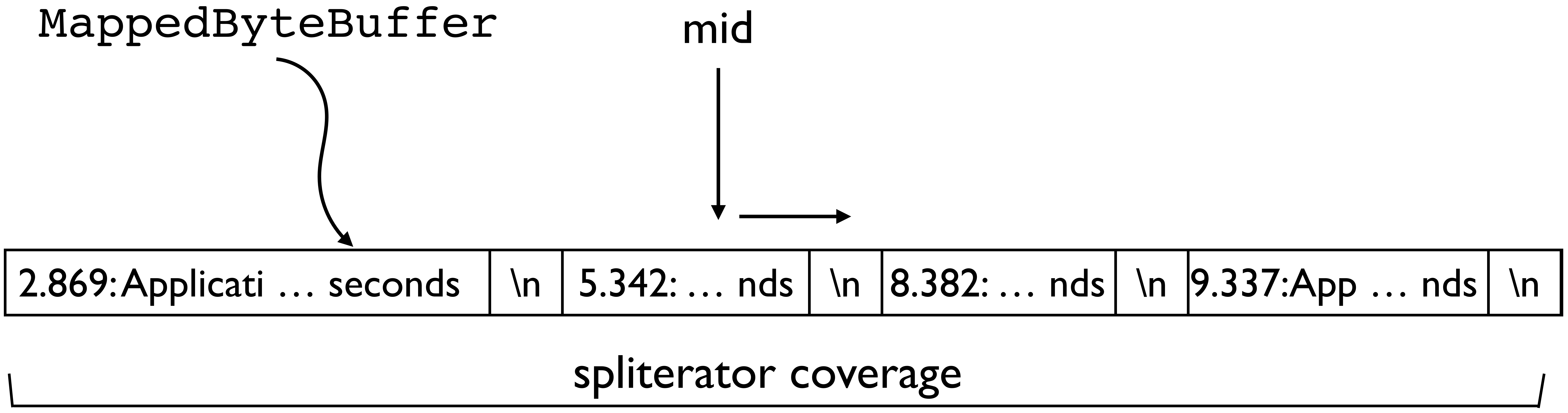

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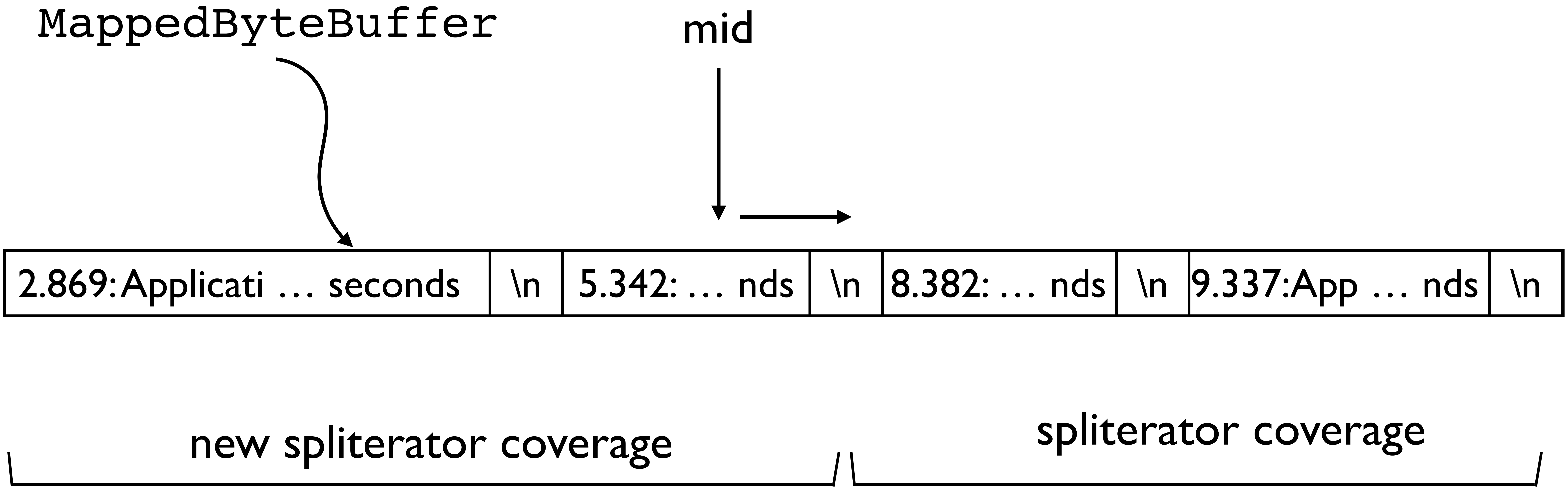

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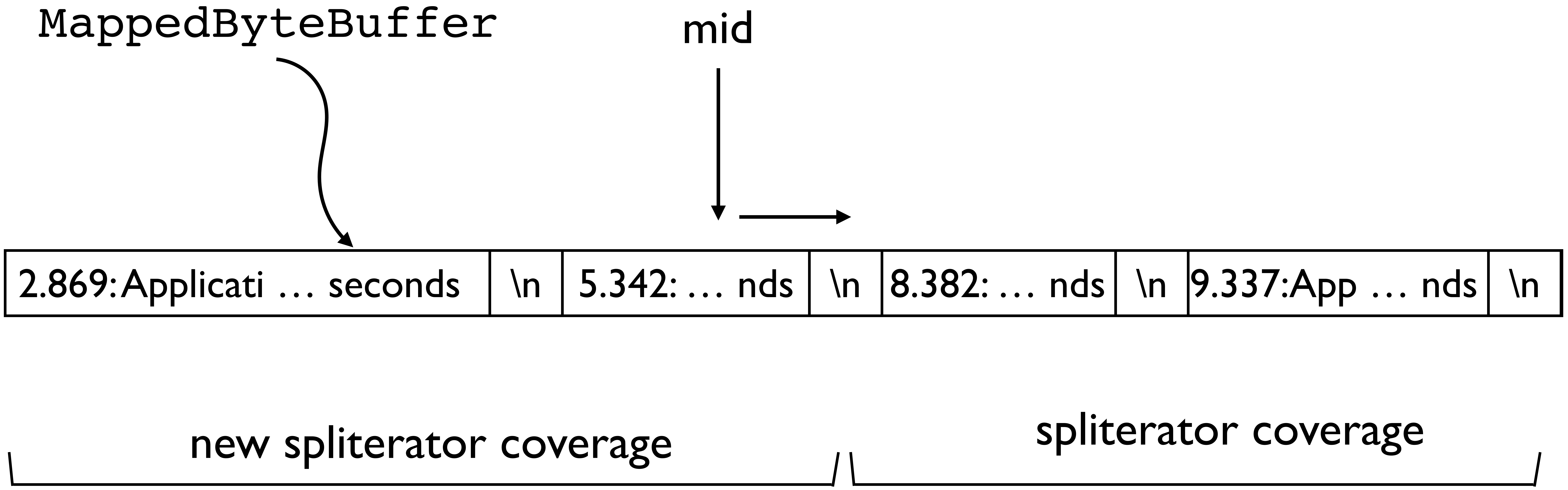

Included in JDK9 as `FileChannelLinesSpliterator`

`LineSpliterator` – results

StreamingIO: 56s

Spliterator: 88s

(>9m lines, MacBook Pro, Haswell i7, 4 cores, hyperthreaded)

Stream code is faster because operations are fused

When to Use Parallel Streams?

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http://gee.cs.oswego.edu/dl/html/StreamParallelGuidance.html

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Tragedy of the Commons

Tragedy of the Commons

You have a finite amount of hardware

- it might be in your best interest to grab it all
- but if everyone behaves the same way…

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Justifying the Overhead

CPNQ performance model:

C - number of submitters

P - number of CPUs

N - number of elements

Q - cost of the operation

Justifying the Overhead

Need to amortize setup costs

– N*Q needs to be large

– Q can often only be estimated

– N often should be >10,000 elements

If P is the number of processors, the formula assumes that intermediate tasks are CPU bound

Don’t Have Too Many Threads!

- Too many threads cause frequent handoffs
- It costs ~80,000 cycles to handoff data between threads
- You can do a lot of processing in 80,000 cycles!

Fork/Join

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- Each segment of data is submitted as a `ForkJoinTask`
  - `ForkJoinTask.invoke()` spawns a new task
  - `ForkJoinTask.join()` retrieves the result

Fork/Join

- Parallel streams implemented by Fork/Join framework
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  - parallel streams are more usable
- Each segment of data is submitted as a `ForkJoinTask`
  - `ForkJoinTask.invoke()` spawns a new task
  - `ForkJoinTask.join()` retrieves the result
- How Fork/Join works and performs is important to your latency picture

Common Fork/Join Pool

Fork/Join by default uses a common thread pool

- default number of worker threads == number of logical cores - 1
  - (submitting thread is pressed into service)
- can configure the pool via system properties:

```
java.util.concurrent.ForkJoinPool.common.parallelism
java.util.concurrent.ForkJoinPool.common.threadFactory
java.util.concurrent.ForkJoinPool.common.exceptionHandler
```

- or create our own pool…

Custom Fork/Join Pool

When used inside a `ForkJoinPool`, the `ForkJoinTask.fork()` method uses the *current* pool:

```
ForkJoinPool ourOwnPool = new ForkJoinPool(10);

ourOwnPool.invoke(
     () -> stream.parallel().
                   ⋮
```

Don’t Have Too Few Threads!

- Fork/Join pool uses a work queue
  - If tasks are CPU bound, no use increasing the size of the thread pool
- But if not CPU bound, they are sitting in queue accumulating dead time
  - Can make thread pool bigger to reduce dead time
  - Little’s Law tells us

Number of tasks in the system =
Arrival rate * Average service time

Little's Law Example

System receives 400 Txs and it takes 100ms to clear a request

- Number of tasks in system = 0.100 * 400 = 40

On an 8 core machine with a CPU bound task

- implies 32 tasks are sitting in queue accumulating dead time
- Average response time 600 ms of which 500ms is dead time
  - ~83% of service time is in waiting

ForkJoinPool Observability

`ForkJoinPool` comes with no visibility

- need to instrument `ForkJoinTask.invoke()`
  - gather data from `ForkJoinPool` to feed into Little's Law

```
public final V invoke() {
    ForkJoinPool.common.getMonitor().submitTask(this);
    int s;
    if ((s = doInvoke() & DONE_MASK) != NORMAL) reportException(s);
    ForkJoinPool.common.getMonitor().retireTask(this);
    return getRawResult();
}
```

Conclusions

Sequential stream performance comparable to imperative code

Going parallel is worthwhile IF

- task is suitable
- data source is suitable
- environment is suitable

Need to monitor JDK to understanding bottlenecks

- Fork/Join pool is not well instrumented

Questions?

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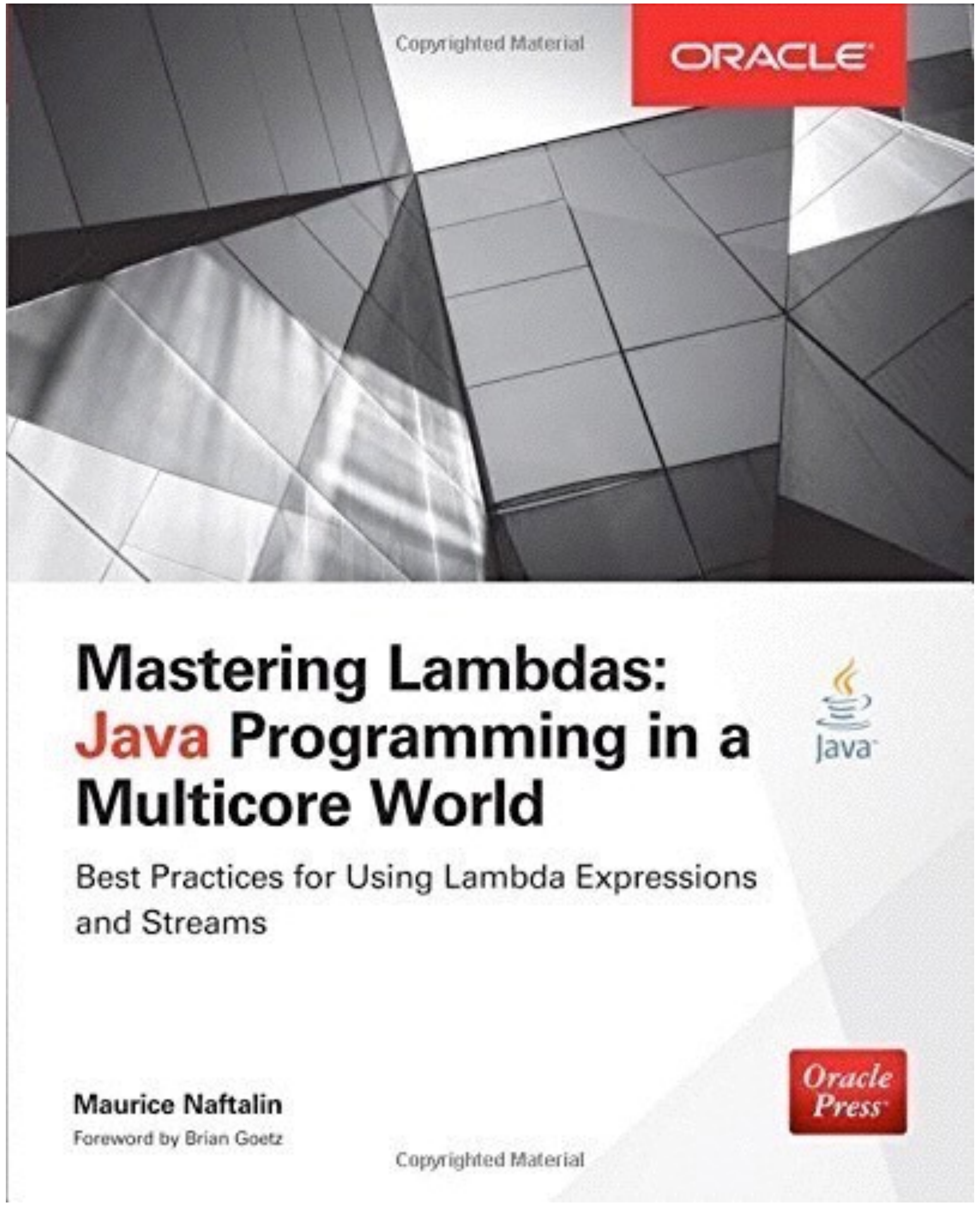
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