Data-aware execution and visualization in Spark

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Introduction

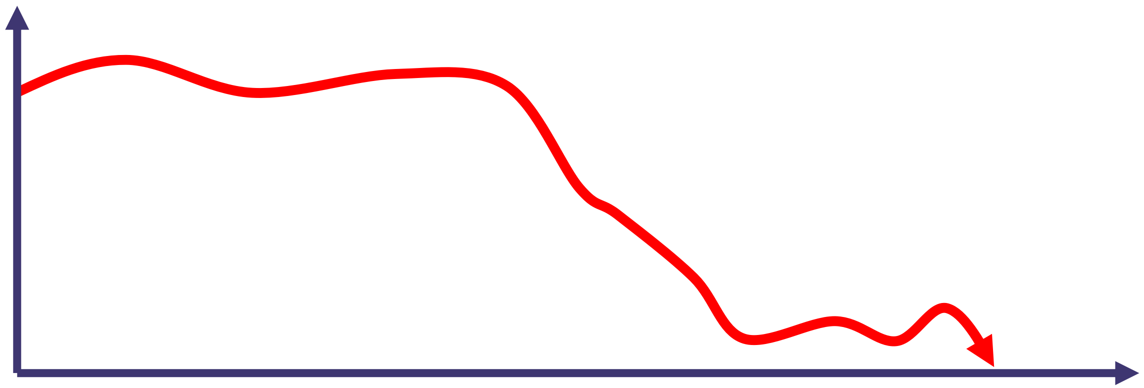
- Hungarian Academy of Sciences, Institute for Computer Science and Control (MTA SZTAKI)
- Research institute with strong industry ties
- Big Data projects using Spark, Flink, Couchbase, Hadoop YARN etc.
- Multiple telco use cases lately, with challenging data volume and **distribution**

Agenda

- Our data-skew story
- Problem definitions & aims
- Dynamic Repartitioning
  - Architecture
  - Component breakdown
  - Repartitioning mechanism
  - Benchmark results
- Tracing
- Visualization
- Conclusion

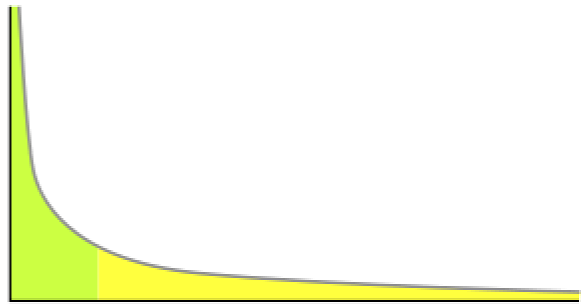
Motivation

- We have developed an application aggregating telco data that tested well on toy data
- When deploying it against the real dataset the application seemed healthy
- However it could become surprisingly slow or even crash
- What did go wrong?



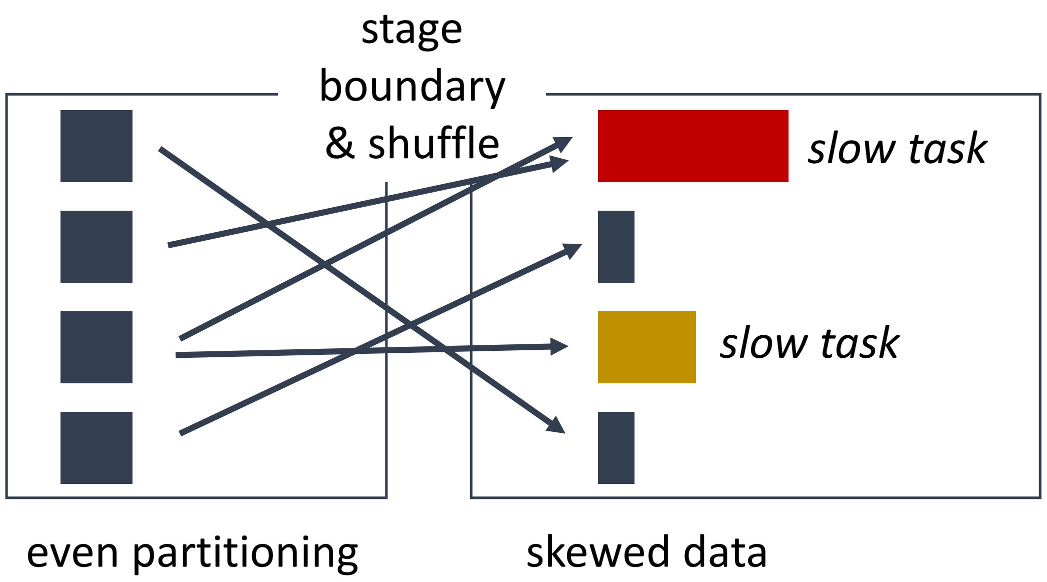
Our data-skew story

- We have use-cases when map-side combine is not an option: **`groupBy, join`**
- 80% of the traffic generated by 20% of the communication towers
- Most of our data is 80–20 rule



The problem

- Using default hashing is not going to distribute the data uniformly
- Some *unknown* partition(s) to contain a lot of records on the reducer side
- Slow tasks will appear
- Data distribution is not known in advance
- „Concept drifts" are common



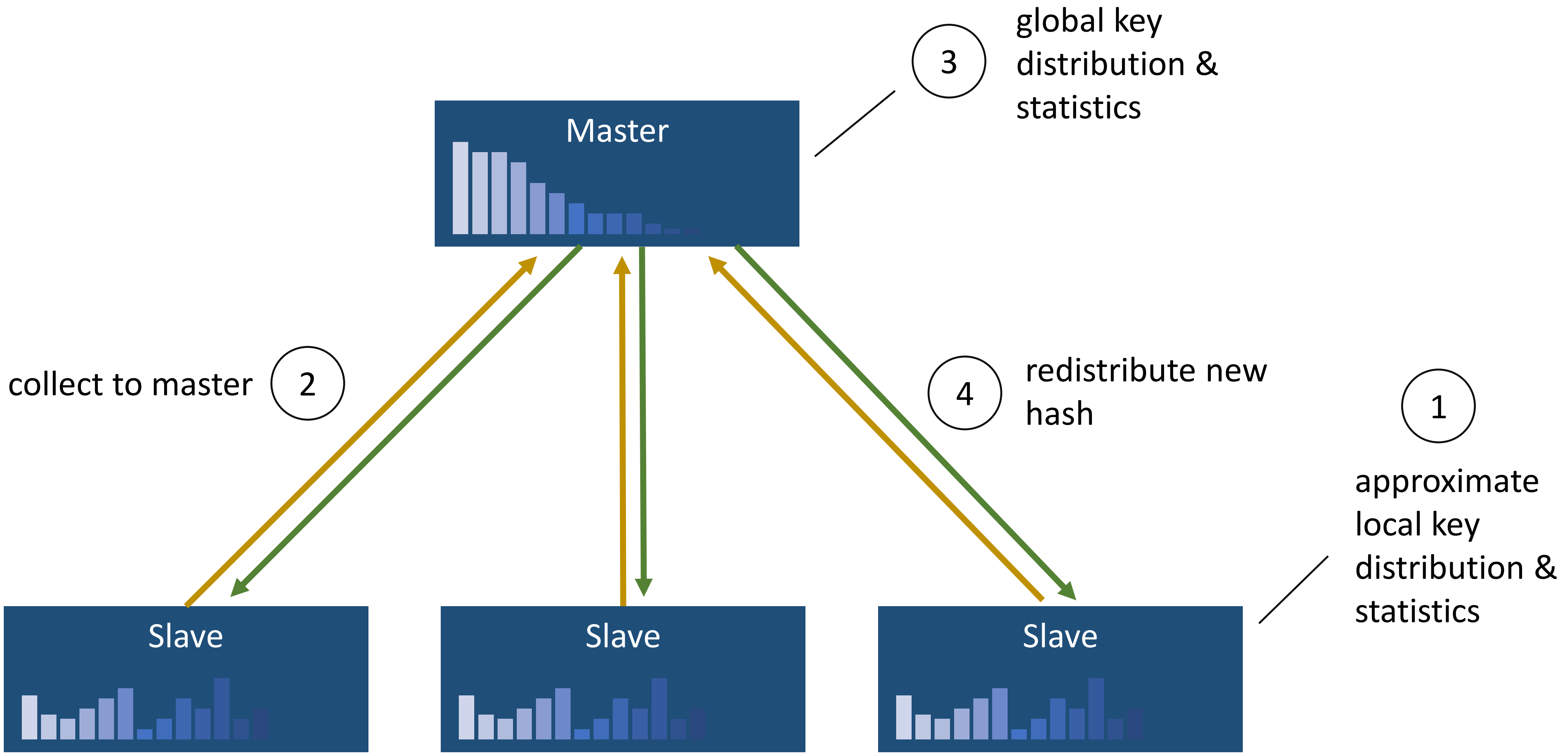
Aim

Generally, make Spark a **data**-aware distributed **data**-processing framework

- Collect information about the data-characteristics *on-the-fly*
- Partition the data as uniformly as possible *on-the-fly*
- Handle arbitrary data distributions
- Trace data-points throughout the execution (service co-location)
- Visualize physical plan & execution
- Should not require user-guidance

```
spark.repartitioning = true
```

Architecture



Driver perspective

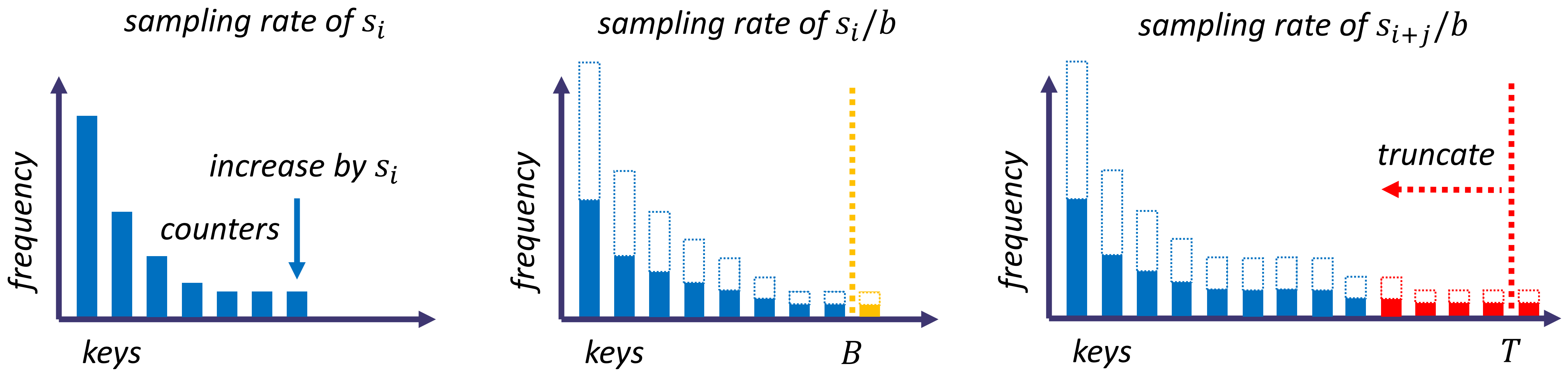
- `RepartitioningTrackerMaster` part of `SparkEnv`
- Listens to job & stage submissions
- Holds a variety of repartitioning strategies for each job & stage
- Decides when & how to (re)partition

Executor perspective

- `RepartitioningTrackerWorker` part of `SparkEnv`
- Duties:
  - Stores `ScannerStrategies` (`Scanner` included) received from the RTM
  - Instantiates and binds `Scanners` to `TaskMetrics` (where data-characteristics is collected)
  - Defines an interface for `Scanners` to send `DataCharacteristics` back to the RTM

Scalable sampling

- Key-distributions are approximated with a strategy, that is
  - not sensitive to early or late concept drifts,
  - lightweight and efficient,
  - scalable by using a backoff strategy



Complexity-sensitive sampling

- Reducer run-time can highly correlate with the *computational complexity* of the values for a given key
- Calculating object size is costly in JVM and in some cases shows little correlation to computational complexity (function on the next stage)
- Solution:
  - If the user object is `Weightable`, use complexity-sensitive sampling
  - When increasing the counter for a specific value, consider its *complexity*

Scalable sampling in numbers

- In Spark, it has been implemented with Accumulators
  - Not so efficient, but we wanted to implement it with minimal impact on the existing code
- Optimized with micro-benchmarking
- Main factors:
  - Sampling strategy - *aggressiveness* (*initial sampling ratio, back-off factor, etc*…)
  - Complexity of the current stage (mapper)
- Current stage’s runtime:
  - When used throughout the execution of the whole stage it adds 5-15% to runtime
  - After repartitioning, we cut out the sampler’s code-path; in practice, it adds **0.2-1.5%** to runtime

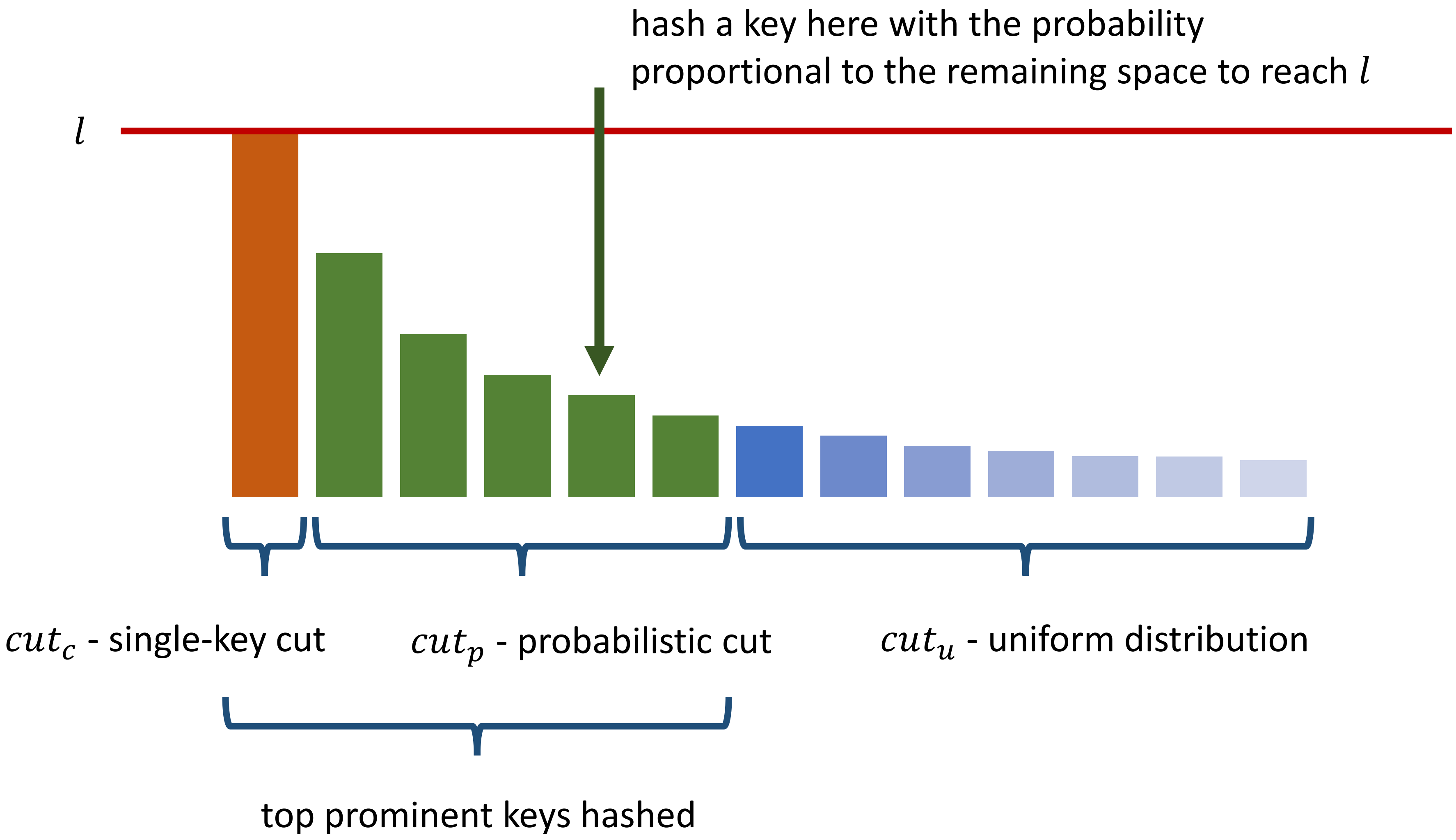
Scanner

- Instantiated for each task before the executor starts them
- Different implementations: `Throughput, Timed, Histogram`
- `ScannerStrategy` defines:
  - when to send to the RTM,
  - histogram-compaction level.

Decision to repartition

- `RepartitioningTrackerMaster` can use different decision strategies:
  - number of local histograms needed,
  - global histogram’s distance from uniform distribution,
  - preferences in the construction of the new hash function.

Construction of the new hash function



New hash function in numbers

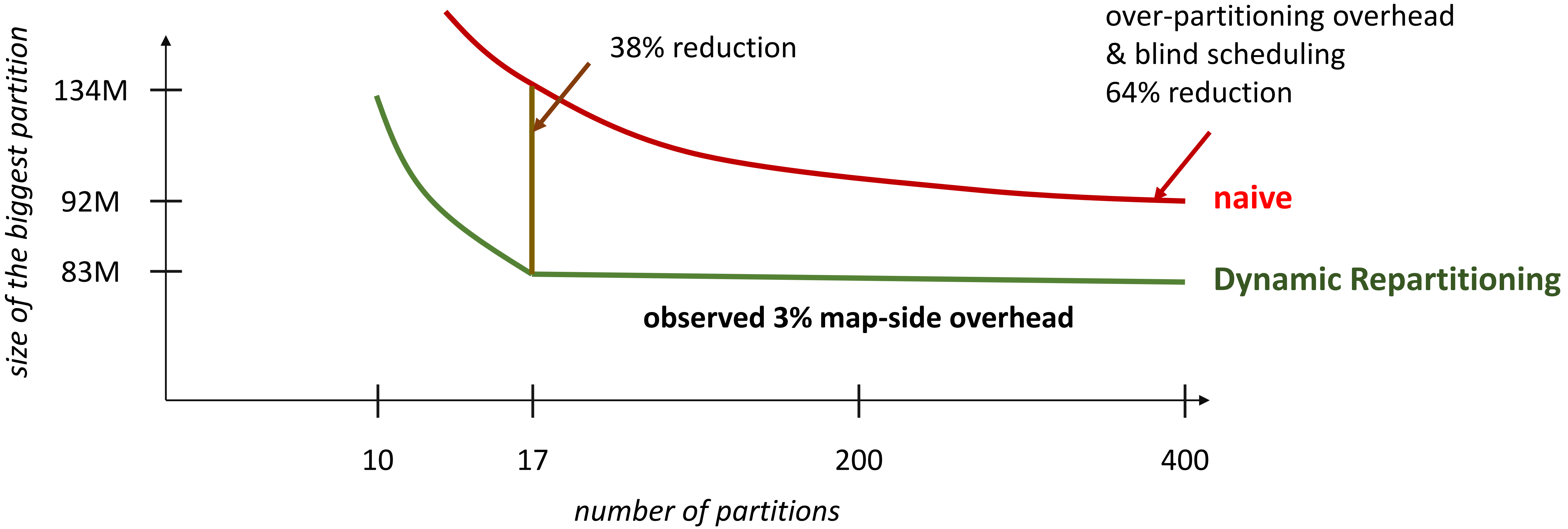
- More complex than a `hashCode`
- We need to evaluate it for every record
- Micro-benchmark (for example `String`):
  - Number of partitions: 512
  - `HashPartitioner`: AVG time to hash a record is 90.033 ns
  - `KeyIsolatorPartitioner`: AVG time to hash a record is 121.933 ns
- In practice it adds negligible overhead, under 1%

Repartitioning

- Reorganize previous naive hashing
- Usually happens in-memory
- In practice, adds additional 1-8% overhead (usually the lower end), based on:
  - complexity of the mapper,
  - length of the scanning process.

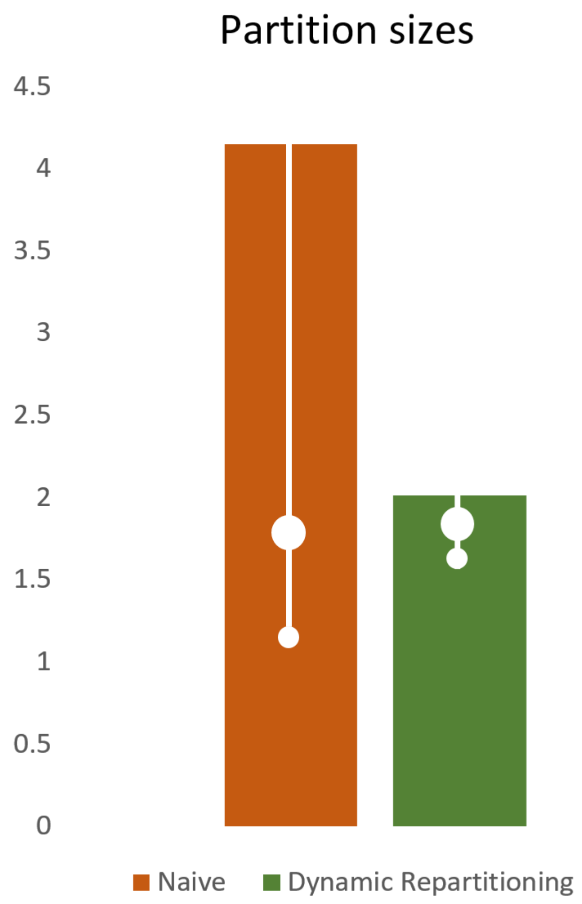
More numbers (groupBy)

MusicTimeseries – groupBy on tags from a listenings-stream



More numbers (join)

- Joining tracks with tags
- Tracks dataset is skewed
- Number of partitions is set to 33
- Naive:
  - size of the biggest partition = **4.14M**
  - reducer’s stage runtime = **251 seconds**
- Dynamic Repartitioning
  - size of the biggest partition = **2.01M**
  - reducer’s stage runtime = **124 seconds**
  - heavy map, only 0.9% overhead



Tracing

Goal: capture and record a data-point’s lifecycle throughout the whole execution

Rewritten Spark’s core to handle wrapped data-points.

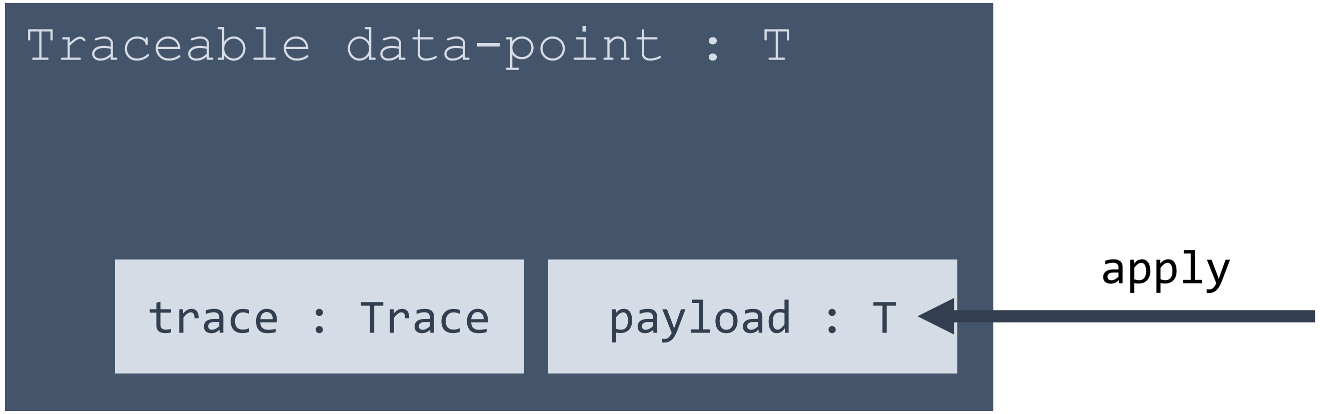
$f : T \rightarrow U$
$f : T \rightarrow Boolean$
$f : T \rightarrow Iterable[U]$
…

Traceables in Spark

Each record is a Traceable object (a Wrapper implementation).

Apply function on payload and report/build trace.

```
spark.wrapper.class = com.ericsson.ark.spark.Traceable
```

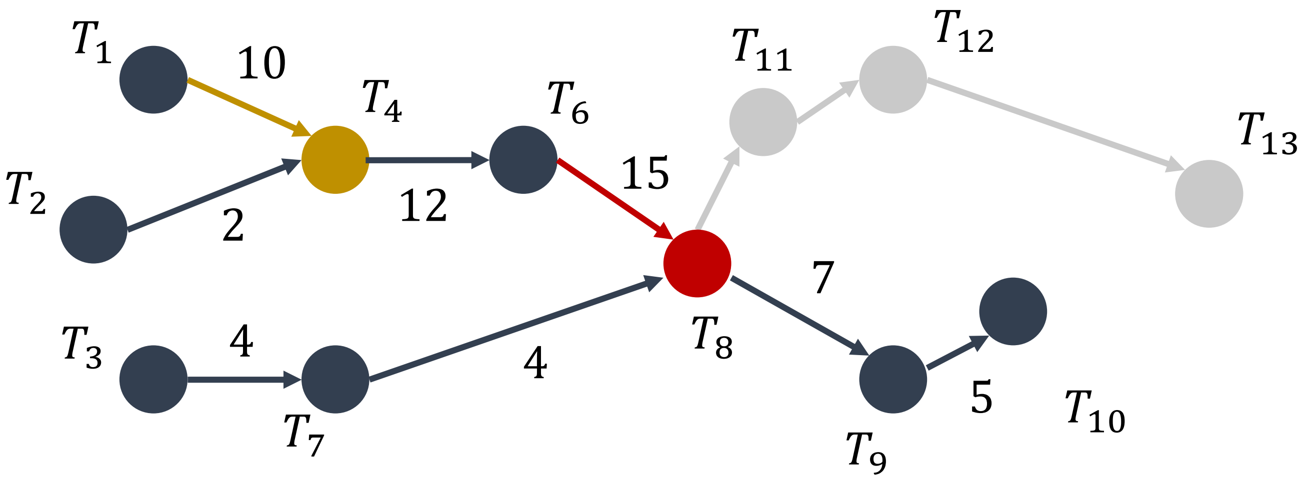


$f : T \rightarrow U$
$f : T \rightarrow Boolean$
$f : T \rightarrow Iterable[U]$
…

Tracing implementation

Capture trace informations (deep profiling):

- by reporting to an external service;
- piggyback aggregated trace routes on data-points.



- T_i can be any Spark operator
- we attach useful metrics to edges and vertices (current load, time spent at task)
- we lose record-by-record relationships here

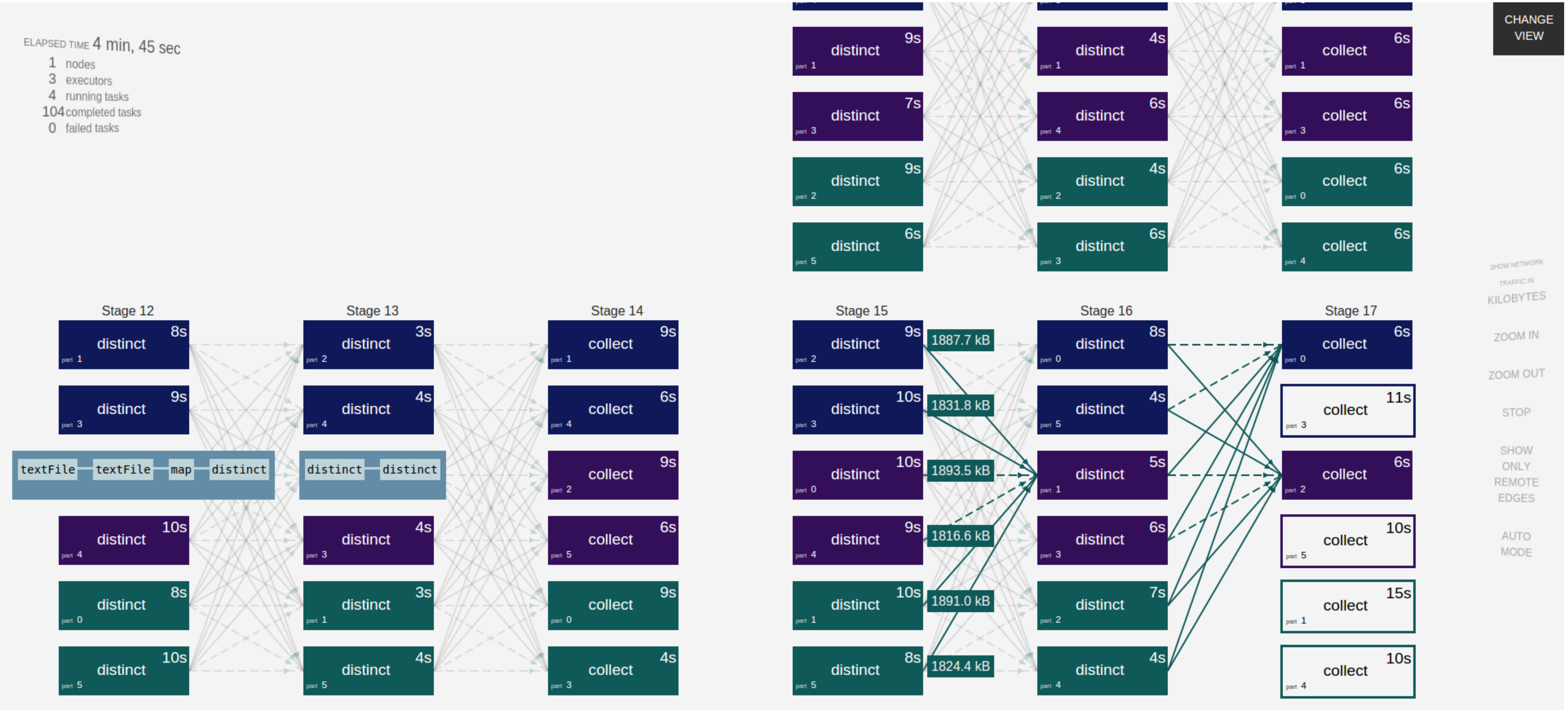
Spark REST API

- New metrics are available through the REST API
- Added new queries to the REST API, for example: „what happened in the last 3 second?”
- BlockFetches are collected to ShuffleReadMetrics


```
recordsRead: 8399,
dataCharacteristics: {
    3424: 19.75,
    115752: 32.25,
    204710: 19.75,
    254186: 17.25
}
```

```
remoteBlocksFetched: 0,
remoteBlockFetchInfos: [ ],
localBlocksFetched: 10,
localBlockFetchInfos: [
  - {
      - blockId: {
            shuffleId: 6,
            mapId: 0,
            reduceId: 7,
            shuffle: true,
            rdd: false,
            broadcast: false
        },
        bytes: 871162
    },
  - {
      - blockId: {
            shuffleId: 6,
            mapId: 1,
            reduceId: 7,
            shuffle: true,
            rdd: false,
            broadcast: false
        },
        bytes: 872696
    },
```

Execution visualization of Spark jobs



ELAPSED TIME 29 sec

0 nodes
0 executors
0 running tasks
0 completed tasks
0 failed tasks

CHANGE VIEW

SHOW NETWORK TRAFFIC IN KILOBYTES

ZOOM IN

ZOOM OUT

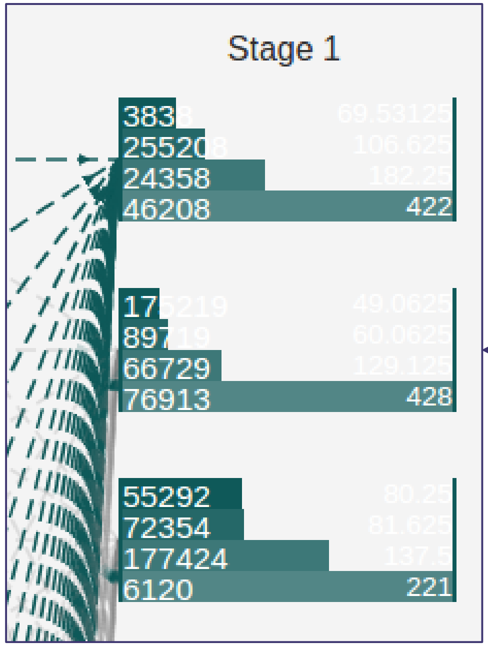
STOP

SHOW ONLY REMOTE EDGES

AUTO MODE

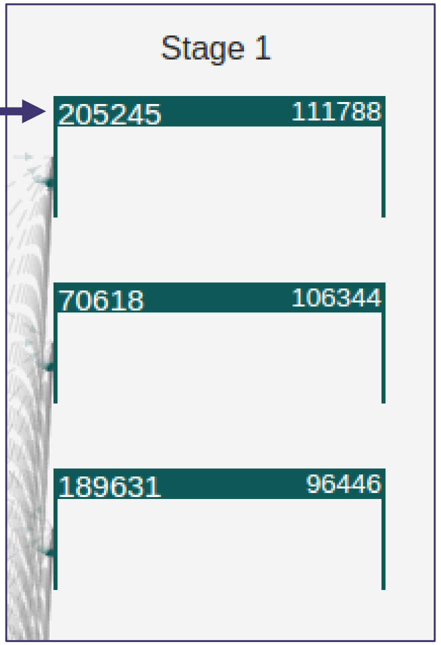
DROP FILES HERE

Repartitioning in the visualization



heavy keys create
heavy partitions (slow tasks)

heavy is alone,
size of the biggest partition
is minimized



Conclusion

- Our Dynamic Repartitioning can handle data skew dynamically, on-the-fly on any workload and arbitrary key-distributions
- With very little overhead, data skew can be handled in a natural & general way
- Tracing can help us to improve the co-location of related services
- Visualizations can aid developers to better understand issues and bottlenecks of certain workloads
- Making **Spark *data-aware*** pays off

Thank you for your attention

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