



Performance Visualization of ROOT I/O on HPC Storage Systems

Lightning Talks

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Contextualization

Current state-of-the-art

- In order to analyse the tremendous amount of data generated from High Energy Physics (HEP) experiments, CERN uses the ROOT framework.
- Previous versions of ROOT used the TTtree data format, however, it will be soon replaced in v7 by RNTuple, an efficient columnar storage format developed by CERN.
- RNTuple also provides a set of metrics for the analysis of data ingestion performance, users can also add custom metrics, as desired.

```
ntuple->EnableMetrics();
```

```
RNTupleMetrics inner("inner");  
auto ctr = inner.MakeCounter<RNTuplePlainCounter *>("plain", "s", "example 1");
```

Contextualization

Metrics simplicity

Despite its capability to provide the user with useful insights, current RNTuple metrics constraint to counter aggregate type metrics, which are too simple in many scenarios (e.g., when we need to analyse the distribution of a certain metric)

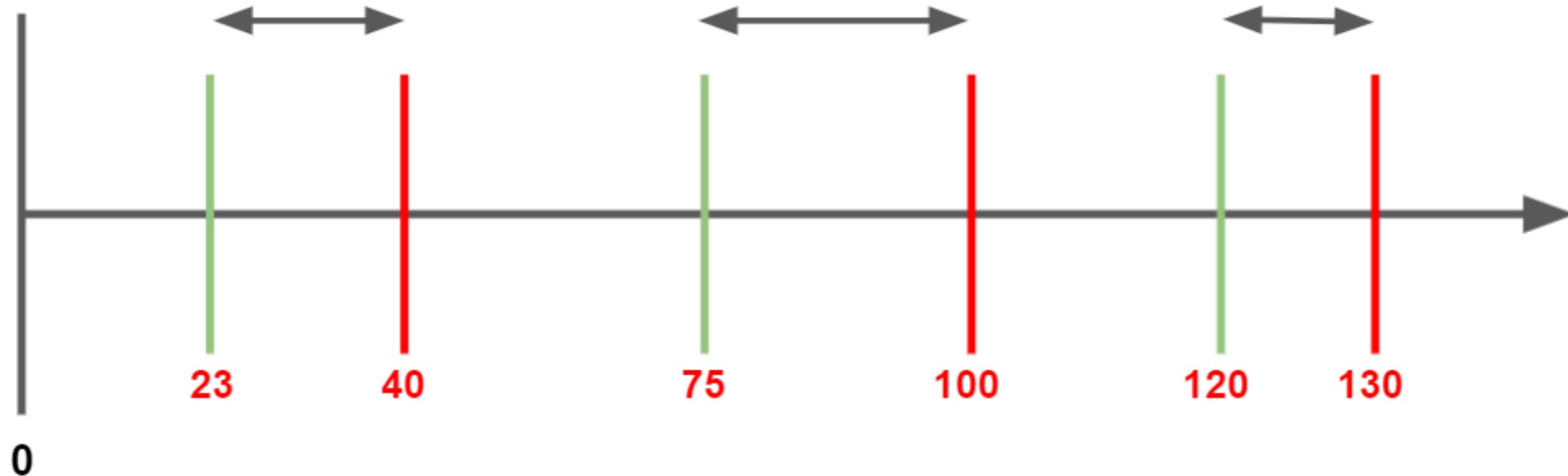
```
RNTupleReader.RPageSourceFile.nReadV||number of vector read requests|16
RNTupleReader.RPageSourceFile.nRead||number of byte ranges read|16
RNTupleReader.RPageSourceFile.szReadPayload|B|volume read from storage (required)|7451486
RNTupleReader.RPageSourceFile.szReadOverhead|B|volume read from storage (overhead)|3196
RNTupleReader.RPageSourceFile.szUnzip|B|volume after unzipping|8000000
RNTupleReader.RPageSourceFile.nClusterLoaded||number of partial clusters preloaded from storage|16
RNTupleReader.RPageSourceFile.nPageLoaded||number of pages loaded from storage|110
RNTupleReader.RPageSourceFile.nPagePopulated||number of populated pages|110
RNTupleReader.RPageSourceFile.timeWallRead|ns|wall clock time spent reading|2571172
RNTupleReader.RPageSourceFile.timeWallUnzip|ns|wall clock time spent decompressing|10002890
RNTupleReader.RPageSourceFile.timeCpuRead|ns|CPU time spent reading|4325000
RNTupleReader.RPageSourceFile.timeCpuUnzip|ns|CPU time spent decompressing|11030000
RNTupleReader.RPageSourceFile.bwRead|MB/s|bandwidth compressed bytes read per second|2899.332289
RNTupleReader.RPageSourceFile.bwReadUnzip|MB/s|bandwidth uncompressed bytes read per second|3111.421562
RNTupleReader.RPageSourceFile.bwUnzip|MB/s|decompression bandwidth of uncompressed bytes per second|799.768867
RNTupleReader.RPageSourceFile.rtReadEfficiency||ratio of payload over all bytes read|0.999571
RNTupleReader.RPageSourceFile.rtCompression||ratio of compressed bytes / uncompressed bytes|0.931436
```

Challenges

- Current RNTuple metrics are too simple to provide viable information about the distribution of data.
- Which makes the following questions hard to answer:
 - What is the distribution of the size of read requests to load an entire ntuple cluster?
 - How can we know if our ntuple metrics are unevenly distributed?
 - How can we detect the existence of outliers in our metrics?
- Possible solutions need to be efficient and be able to construct histograms on-the-go.

Solution #1

User-Provided Set of Intervals

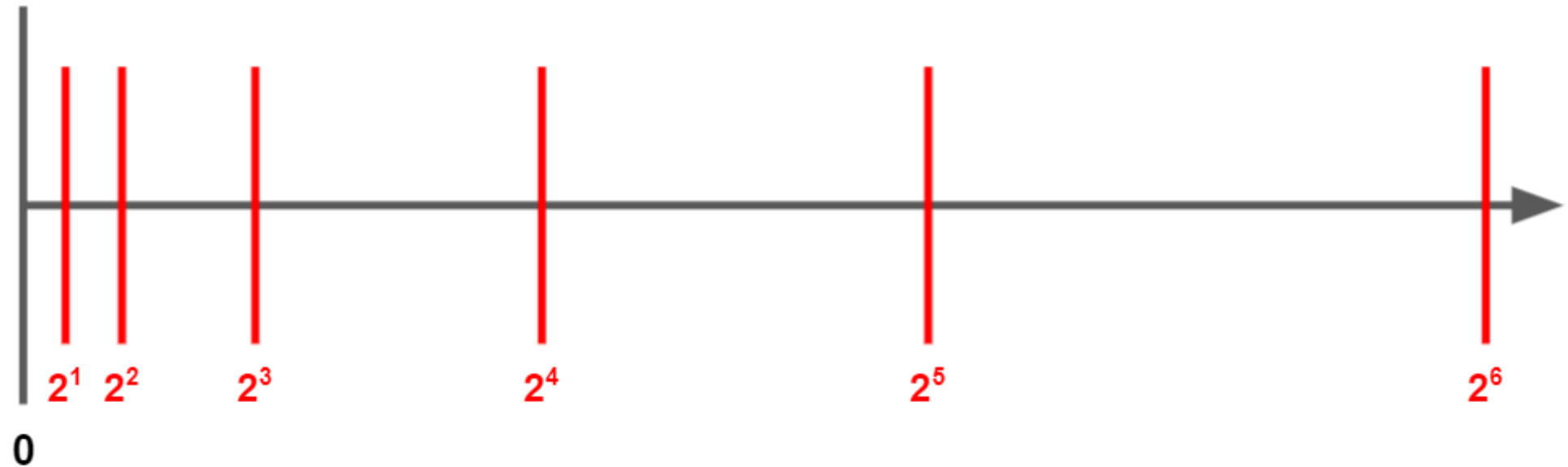


Cons:

- Requires knowledge of underlying data
- Unable to detect outliers
- Error-prone

Solution #2

Log Scale



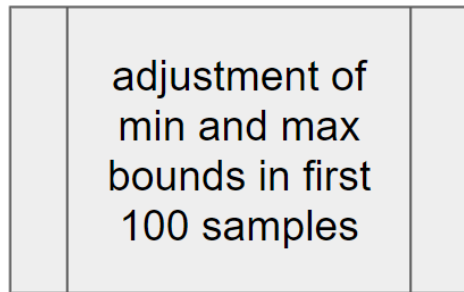
Cons:

- Amplitude of intervals is exponentially large
- Hard to interpret the meaning of histogram output
- Able to detect some outliers, depending on scale

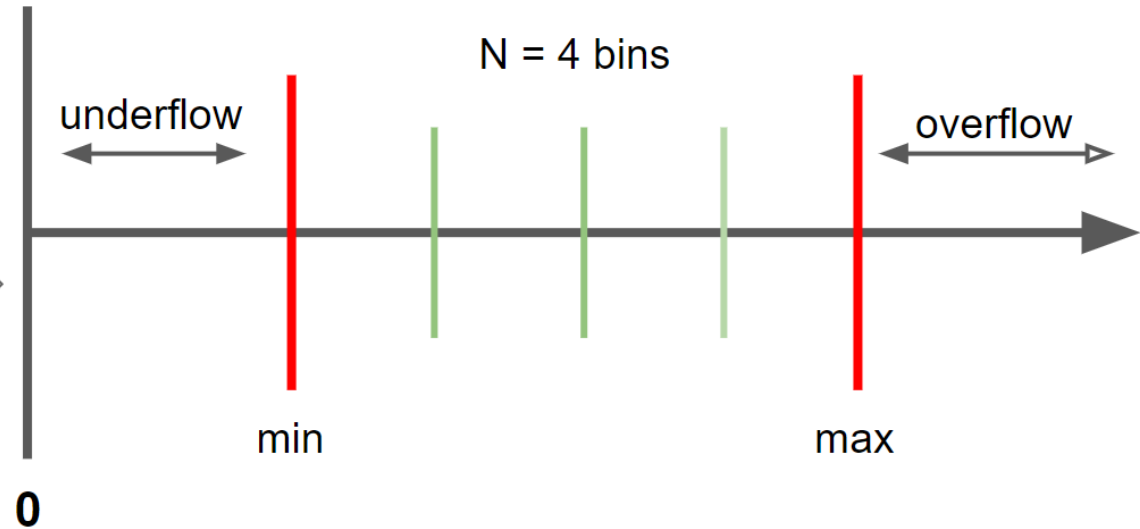
Solution #3

Active Learning Phase

Learning Phase (LP)



histogram of N bins from min to max bounds

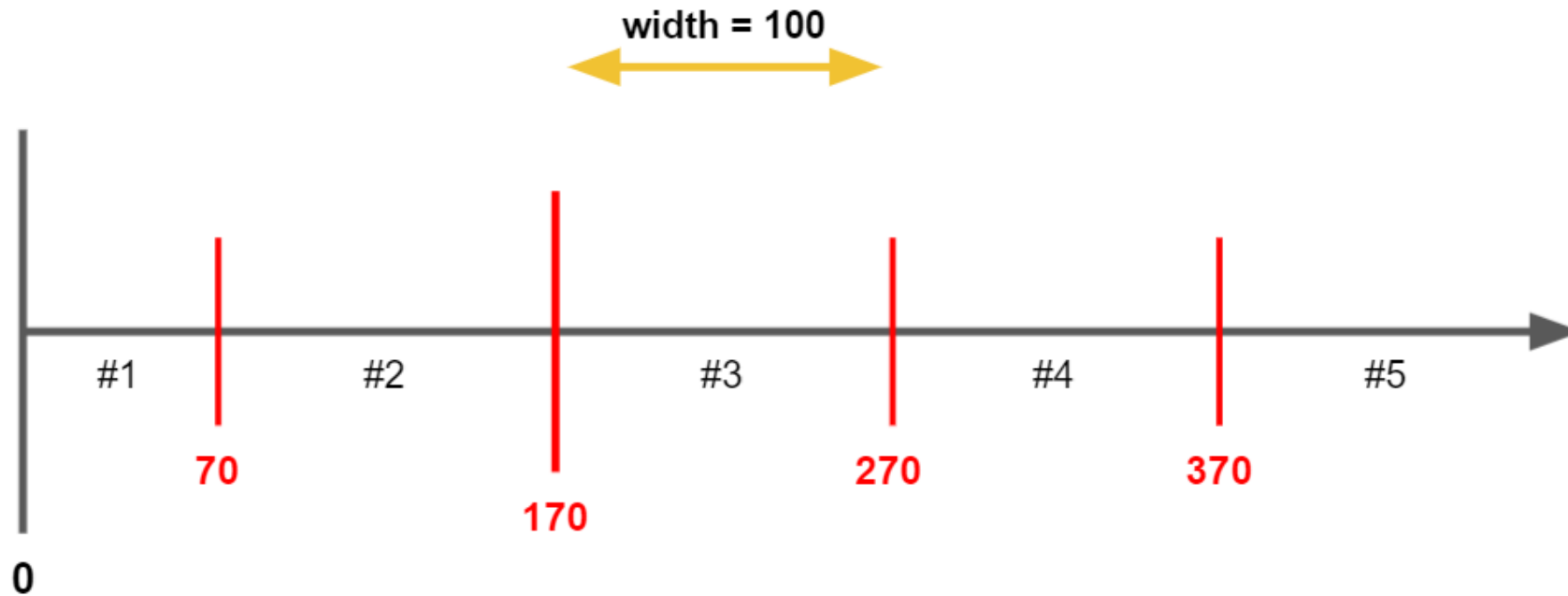


Cons:

- Heavily dependant on the distribution of samples in the LP
- Occurrence of outliers in LP deeply affects efficiency of histogram
- Can't effectively separate outliers from real distribution

Solution #4

Fixed Width Bins



Solution #4

Calculating the bin key (Fill Algorithm)

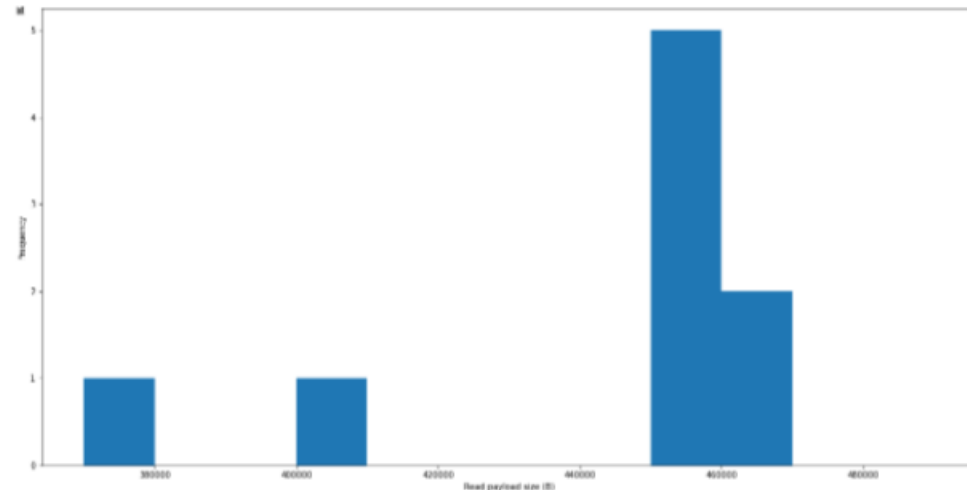
- If a new value, N , is **greater or equal** to the **offset**, then:
 - $\text{Key} = (N - \text{offset}) / \text{width} + \#\{\text{below offset bins}\} + 1$
- Else:
 - $\text{Key} = \#\{\text{below offset bins}\} - (\text{offset} - N) / \text{width}$
- Examples, $\text{width}=100$, $\text{offset}=170$:
 - $N = 178 \Leftrightarrow \text{key} = (178 - 170) / 100 + 2 + 1 = 3$
 - $N = 384 \Leftrightarrow \text{key} = (384 - 170) / 100 + 2 + 1 = 5$
 - $N = 105 \Leftrightarrow \text{key} = 2 - (170 - 105) / 100 = 2$
 - $N = 69 \Leftrightarrow \text{key} = 2 - (170 - 69) / 100 = 1$

Sample #1

ROOT I/O - Tutorial #5

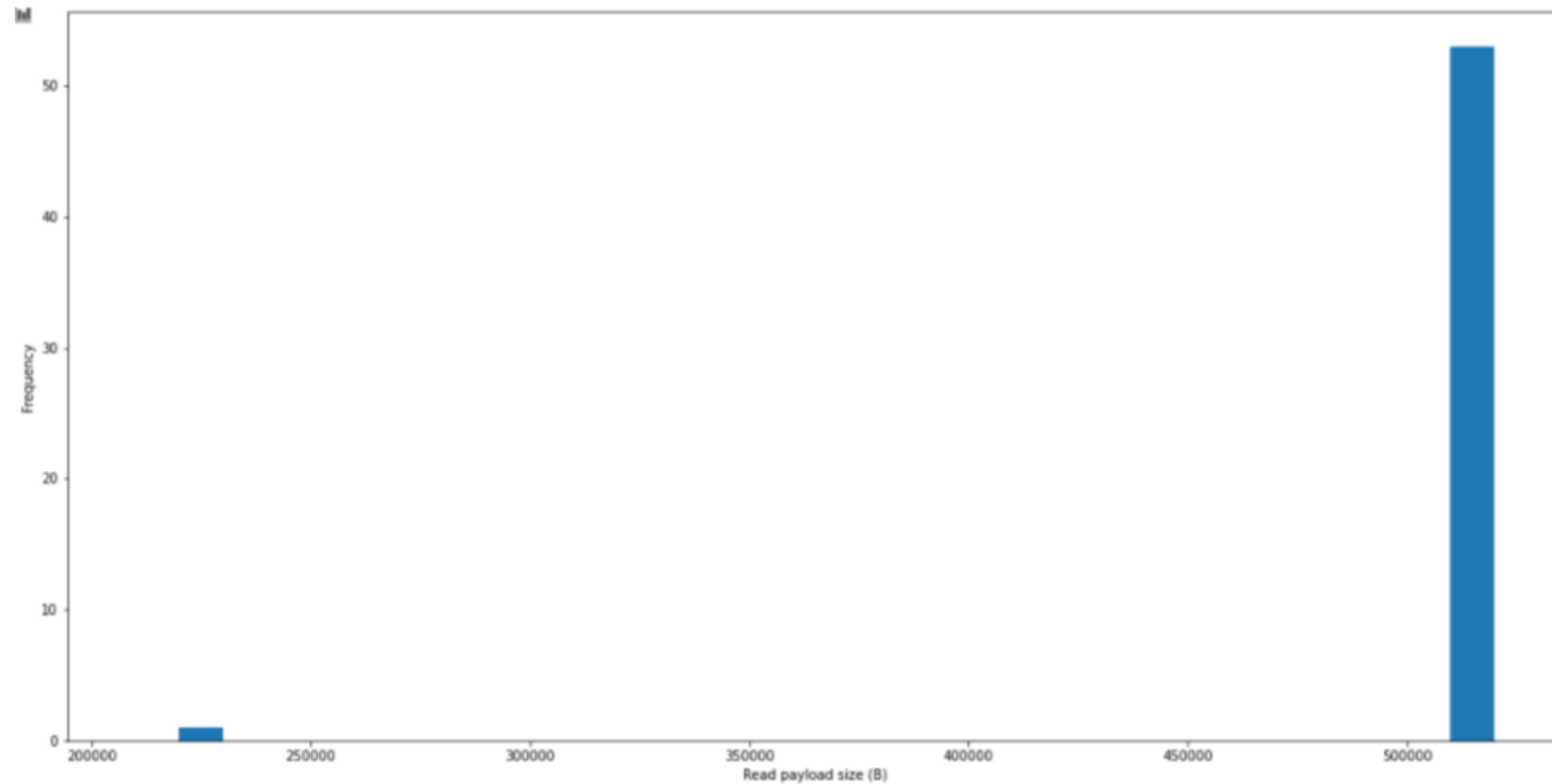
After the desired analysis, the histogram content can be dumped as a CSV and fed to external plotting utilities for visual analysis.

```
lower_bound,upper_bound,count
370000,379999,1
400000,409999,1
450000,459999,5
460000,469999,2
490000,499999,7
```



Sample #2

Convert LHC 1 run open data from TTree to RNTuple



Conclusion

- Performance visualization can easily allow a detailed analysis of the underlying metrics.
- Histogram output format can be easily ingested by external plotting utilities.
- More information can be found on the PR: [\[ntuple\] Performance visualization improvements by ruipreis · Pull Request #8880 · root-project/root \(github.com\)](#)



QUESTIONS?

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