Evaluating moldability of LHCb jobs for multicore job submission

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On behalf of LHCb collaboration

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Outline

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- 2 Scheduling and multicore jobs
- 3 Example
 - Example How to find an optimum?
- 4 Speedup prediction

5 Run time prediction

- Stripping
- Reconstruction
- 6 Back to the example

Outcome

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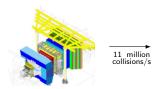
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- Difference in Matter and Antimatter (CP Violation)
- B Physics

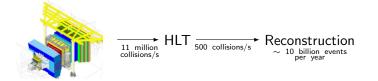
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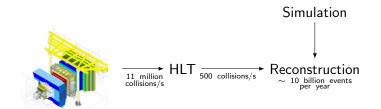
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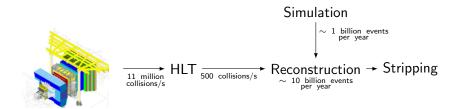
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Main Problem: Memory Footprint

Two trends:

- Memory per core
 - Currently: 0.5 bytes/flop
 - Foreseen: < 0.1 bytes/flop
- LHC parameters
 - Larger events (30 kB in 2009 up to 60 kB in 2012)
 - Complexity of reconstruction

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- Example: Worker node with 8 cores available for 1 day

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- Reduce gaps in schedule
- Limit loss due to non linear speedup
- ightarrow Use moldability of jobs to optimize objective function

- What does run time rely on?
- Can it be predicted within a given range?
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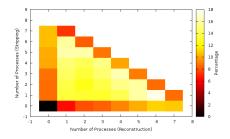


Figure : Used total CPU-time with different mixtures of parallel jobs

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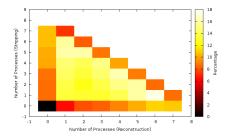


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Can the optimum be predicted? How is the result influenced by errors in run time prediction?

- NP hard problem
- Iterative approaches:
 - Assign an additional core to the most worthy job
 - Job which looses less CPU time due to non linear speedup
- Required input:
 - Speedup
 - Run time prediction

Speedup prediction

Downey Speedup Model:

$$S(n) = \begin{cases} \frac{An}{A + \sigma(n-1)/2} & 1 \le n \le A\\ \frac{An}{\sigma(A-1/2) + n(1-\sigma/2)} & A \le n \le 2A - 1\\ A & n \ge 2A - 1 \end{cases}$$

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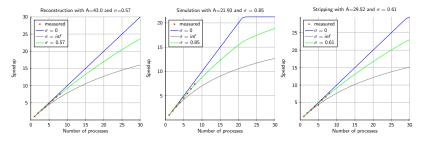


Figure : A = Average parallelism and σ = variance in parallelism

Run time prediction

- Using historical information
- Clustering
 - Grid Site
 - CPU-type
 - Eventtype
 - Production
 - Workernode
- Distribution of datasets: CPU-work per event (CPU-time · HEPSPEC-value)

RunTime = *nEvt* · *MaxLikelihood*/*PowerOfMachine*

Rauschmayr (CERN)

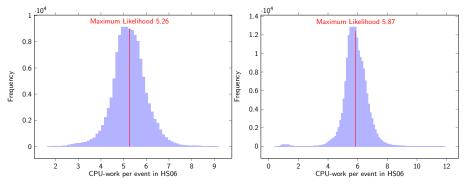


Figure : Stripping jobs of reprocessing 2011 versus 2012

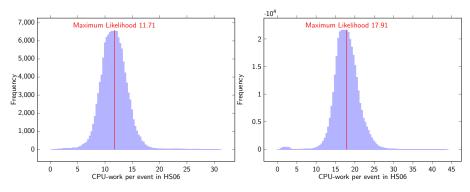


Figure : Reconstruction jobs of reprocessing 2011 versus 2012

Run time prediction - Simulation step

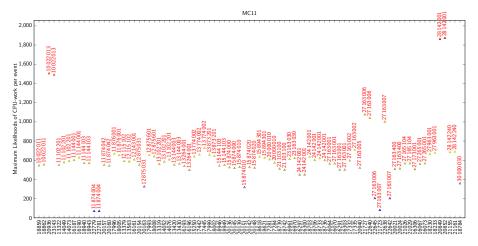


Figure : Maximum likelihoods of MC11 jobs with different event types and from different productions

Back to the example

Run time predicted as:

$$Workload_{min} = MaxLikelihood - x \cdot \sigma$$

 $Workload_{max} = MaxLikelihood + x \cdot \sigma$

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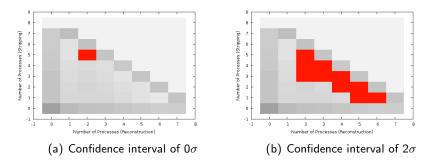


Figure : Decision found by an iterative approach

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• Theoretical optimum must not be the real one:

- Jobs can influence each other (concurrent accesses)
- Uncertainties in the prediction (LHC configuration)
- Iterative approaches tend get stuck in local optima
- Approximation of global optimum already sufficient

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