## **RooFit Parallelization**

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#### Introduction - RooFit

- RooFit is a OO language to write probability models, widely used in HEP.
- User constructs PDF (of arbitrary complexity) as expression tree of RooFit function objects
  - Scales to very complex models (>>10.000 objects for Higgs models)
  - All models provide full functionality for fitting, plotting and toy event generation
- Under the hood, a variety of computational optimizations is applied for potentially CPU-intensive tasks
  - Efficient toy MC generation techniques deployed by pdfs wherever possible
  - Pdfs provide analytical normalization integrals wherever possible
  - Multi-dimensional integrals can by partially numeric, partially analytic
  - Caching and lazy evaluation of integrals and other expensive objects
  - Constant expressions in Likelihood are automatically identified and optimized prior to fits
  - Typical effect of optimization between is a speedup factor 2-20
- Philosophy Let user concentrate on formulating physics problem
  - Let RooFit worry about optimal computation 'under the hood'
  - Only user input is that PDFs provide analytical integrals and efficient generation algorithms for known cases (will be automatically applied when possible)

#### Parallelization in RooFit – When is it useful?

- When is parallelization useful in RooFit?
- RooFit is ingredient of 'semi-interactive' final step of physics analysis. Operations should ideally not take more than a few seconds or minutes, to preserve interactive workflow
- True for most uses cases with 'simple' to 'moderately complex' probability models.
- Not true for ambitious use cases
  - 1. Highly complex likelihood models (Higgs fit to all channels, ca 200 datasets, O(1000) parameter) can take O(few) hours
  - 2. Unbinned ML fits with very large data samples
  - 3. Unbinned ML fits with MC-style numeric integrals ('time-dependent angular analysis of Dalitz decays')
  - 4. Neyman construction of confidence belts ('no asymptotic'). Requires many fits to toy data samples
- Will focus on use cases 1-3), as 4) is easily parallelizable by end-users on batch facilities and is beyond scope of 'semi-interactive' use
- In spirit of 'semi-interactive' use will focus on factor 10-30 speedup on single multi-core machine to reduce O(few hour) operations to O(few minute) operations

#### Parallelization in RooFit – what is there now

- Likelihood calculations inherently very suitable for parallel calculation as calculation is repetition of N<sub>event</sub> equal calculations
- RooFit currently has a simple parallel evaluation engine for likelihood objects
- Strategy: divide L(data|param) in N equally sized chunks



#### RooFit parallelization – work flow

- Essential features
  - Slaves are separate processes started with fork()
  - Inter process communication via combination of pipes and shared memory
  - Sequence of operation during fit
    - 1) Send Calculate command to each Slave (non-blocking) (all slaves perform calculation in parallel)
    - 2) Send Retrieve command to each Slave (blocking)
    - 3) If evaluation errors were detected, request full details from slaves

4) Combine Slave results and feed result to MINUIT



- Consider a simple scenario (for parallelization): fitting a single pdf to an unbinned dataset – how well does it scale with Ncpu?
- $T_{CPU}(fit) = T_{CPU}(Lcalc)/NCPU + T_{CPU}(protocol-overh) + T_{CPU}(comp-overh)$ 
  - Protocol overhead is extra time spend passing information from/to slaves.
  - Computation overhead is extra time spent in duplicate calculations due to splitting.
- Protocol CPU overhead is typically very small, as little is done (adding back likelihood components together).
- Computational overhead varies by situation. In current implementation PDF normalization integrals are calculated fully by each Slave process.
  - For *analytical integrals* this is a small (neglibible) overhead.
  - For numeric integrals this may take as much time as likelihood calculation as is a potentially killer issue. (One of the issues to be addressed. Will come back to this)

- But key metric is wall-time performance, so wall-time overhead (waiting, idle times) are also important
- $T_{wall}(fit) = T_{CPU}(fit) + T_{wall}(protocol-overh) + T_{wall}(scheduling) + T_{wall}(imbalance)$ 
  - Protocol wall-time overhead is wall-time spent in inter-process communication
  - Scheduling wall-time overhead occurs if Slave process don't all exactly start at the same time due to OS-related scheduling timing
  - Imbalance wall time occurs if length of calculation (wall) time of the slaves varies
- Protocol wall-time overhead must be small for parellelization to be efficient at large NCPU (next up: performance tests of current protocol)
- Scheduling wall-time overhead can be a real problem! Size of an individual slave task can be quite small → frequent start/stop of calculations.
- Imbalance wall-time overhead is strongly dependent on nature of the model: for a single model/dataset, an (almost) perfectly balanced workload is easy to achieve, but for a 500-dataset Higgs combination likelihood with datasets varying between few(Kevt) unbinned and 1-bin counting experiments, this can be extremely difficult.

- Demonstration model: unbinned ML fit to sum-of-Gaussians pdf (with fully analytical normalization)
- Comparison of wall-times vs N(cores) uses



Short fit (3-sec)

Long fit (400-sec)

- Have been investigating various contributions of protocol, OS, imbalance etc to overhead
- Communication protocol overhead increases with NCPU, but is tiny in size and cannot explain effect



• Next investigated load-balancing overhead. What is difference between slowest & fastest slave process?



Differences tiny – but also expected here since this was the easiest use case (single unbinned PDF with many events)

- Finally looked into OS scheduling overhead. This turns to be the dominant effect of wall-time overhead!
- Can be improved by setting CPU affinity: if each slave process is pinned to a designated core, overhead reduces drastically!



- With CPU affinity fixed, total wall-time overhead of RooFit parallelization w.r.t ideal is O(5%) for 8-core fit for 400-CPU second fit (and better for longer fits)
- Consider this 'good enough for now' and move on to address much more O(100%) scaling issues that arise with use of numeric integrals and Likelihoods with >>1 dataset/model

- (Everything from here on is work in progress)
- Project 1 Distributed calculation of numeric integrals
- Problem: If normalization integrals in a pdf expression are not (all) analytical, per-slave overhead of numeric integration will spoil scaling



Parallelization with analytical integrals

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- Can be solved by distributing calculation of integral
  - Modify RooMCIntegrator (but would then work transparently for all pdfs)
  - Modify Master/Slave architecture to be able to distribute more type of tasks (now only 1/Nth of L)
  - Threshold to decide if any given integral is expensive enough to merit overhead of distributed calculation



# RooFit – timing & parallelization of multi-part Likelihoods

- Project 2 Intelligent balancing of component likelihood over slaves
- Problem: if a Likelihood consist of n>>1 component likelihoods based on separate pdfs/datasets, load balancing becomes a problem
- Current strategy: parallelize each component likelihood



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- Current strategy: parallelize each component likelihood
  - Will break down if small components exist that cannot be evenly divided (e.g. Nevents/bins < Ncpu)</li>
  - Typical Higgs combination likelihood (L1...L250) will only achieve 2x speedup with NCPU=6.



# RooFit – timing & parallelization of multi-part Likelihoods

- Project 2 Intelligent balancing of component likelihood over slaves
- Problem: if a Likelihood consist of n>>1 component likelihoods based on separate pdfs/datasets, load balancing becomes a problem
- New strategy time components and distribute dynamically
  - Will break down if small components exist that cannot be evenly divided (e.g. Nevents/bins < Ncpu)</li>
  - Typical Higgs combination likelihood (L1...L250) will only achieve 2x speedup with NCPU=6.



#### Short-term plans

- Step 1 Implement collection of timing information of numeric integrals and Likelihood components (now in progress)
- Step 2a Augment existing Master/Slave scheduler to be able to distribute calculations of multi-component likelihoods in arbitrary ways: i.e. can specify calculation fraction of each component likelihood individually
- Steb 2b Implement a new load balancing algorithm that divides work between N slaves intelligently based on timing information and dataset size information
- Step 3a Implement parallel calculation strategy for RooMCIntegrator
- Steb 3b Augment existing Master/Slave schedule identify expensive integrals for parallel calculation and execute them in that way.

#### Medium-term plans

- Complete rewrite of Master/Slave scheduler
  - Current class structure not very suitable for new plans, but first need to test some of the new concepts before converging on a good practical design for the next scheduler
  - Foresee ability to have different back-end implementations for actual calculations: now only multi-core on single hosts. Other useful backends could be multi-host, GPU-based, or backends that aim for a complete re-expression in another tool (Theano, tensorflow).
  - Need a bit of thinking on how to best design this: tie scheduler implementation to a particular back-end architecture (i.e. one scheduler for multi-core, one scheduler for GPU etc...), or decouple those and have another interface layer in between (that would e.g. allow hybrid calculation strategy: big likelihood components on paralellized on GPU, counting measurements on CPU).