PERFORMANCE STUDIES of GOOFIT on GPUs WHILE ESTIMATING the GLOBAL STATISTICAL SIGNIFICANCE of A NEW PHYSICAL SIGNAL



ALEXIS POMPILI 1,2 (for the CMS Collaboration)

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In the context of High Energy Physics analysis applications, Goofit is an open source data analysis tool that interfaces ROOT/Roofit to the CUDA parallel computing platform on nVidia GPU. It is exploited in applications enabling the modeling of event data distributions and using (unbinned) maximum likelihood parameter estimation technique. Parameter estimation is a crucial part of many physics analyses.

The Probability Density Function (PDF) represents a physical model and its evaluation on large datasets is usually the bottleneck in the minimization task.

GooFit acts as an interface between the MINUIT minimization algorithm (running on CPU) and a parallel processor (GPU) which allows a PDF to be evaluated in parallel. Fit parameters are estimated at each Neg-Log-Like-lihood minimization step on the host side (CPU) while the PDF/NLL is evaluated on the device side (GPU).

CPU GPU [memory] **Tuning of fit** PDF/NNL parameters transfers] evaluation

Description and details about GooFit: R.Andreassen et al., GooFit: a library for massively parallelising maximum-likelihood fits, J. Phys.: Conf. Ser. 513 (2014) 052003 [CHEP2013 Proceedings].

To test the computing capabilities of GPUs with respect to CPU cores, a high-statistics pseudo-experiments (toys) technique has been implemented in RooFit & GooFit frameworks in order to estimate a p-value and thus the (local or global) statistical significance of a signal reconstructed from data. The p-value is the probability that background fluctuations would - alone - give rise to a signal as much significant as that seen in the data.

Hardware setup consists in 2 servers (hosted @ ReCas-Bari Data Center): one equipped with 2 nVidia TeslaK20 and 32 cores (16+16 by HT), the other with 1 nVidia TeslaK40 and 40 cores (20+20)

RooFit with PROOF-LITE

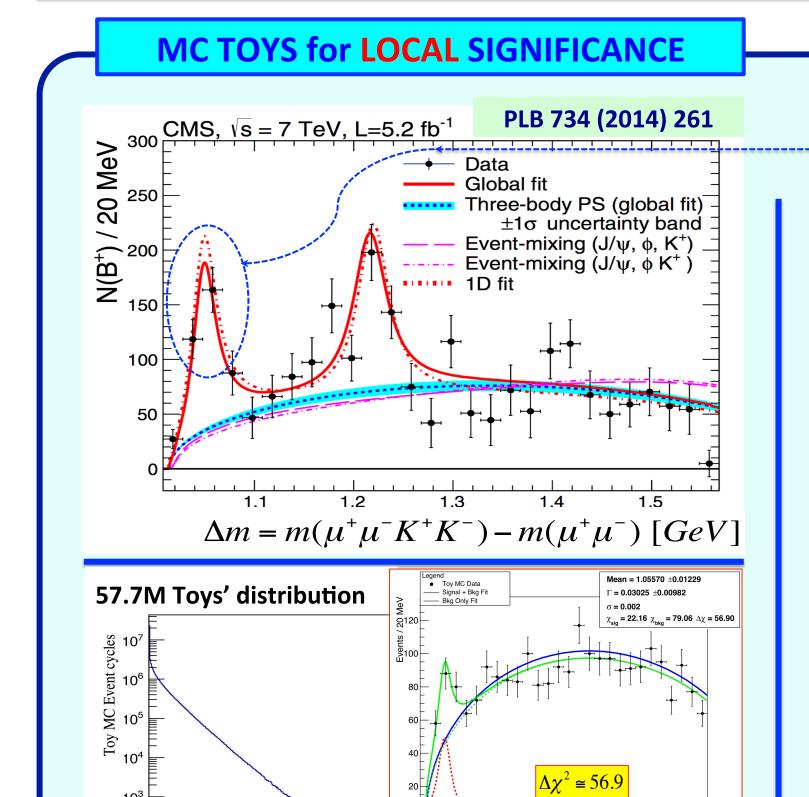
To efficiently run RooFit MC toys in parallel on the 72 CPUs available on the 2 servers hosting the GPUs, PROOF-Lite is used. It has a pull architecture. GooFit with MULTI PROCESS SERVER

The nVidia Multi Process Server (MPS) tool allows the execution of - up to 16 - simultaneous processes on the same GPU acting as a scheduler and allowing a balanced full use of the GPU.

do not miss any interesting fluctuation

do not select too many small fluctuations

MPS / PROOF-LITE show a similar behaviour of the speed up as a function of processes / workers; both their Amdhal fits indicate a serial overhead of ~3% for the MC toys' application execution.

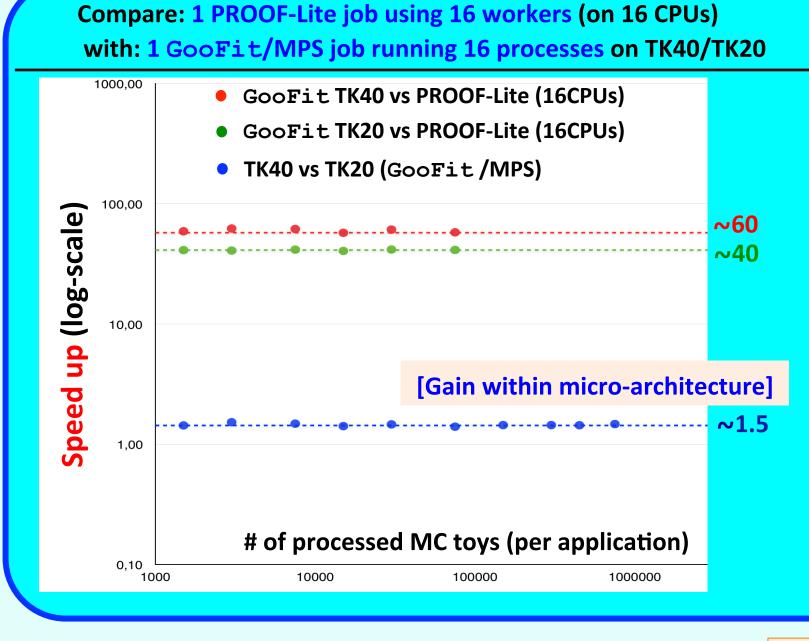


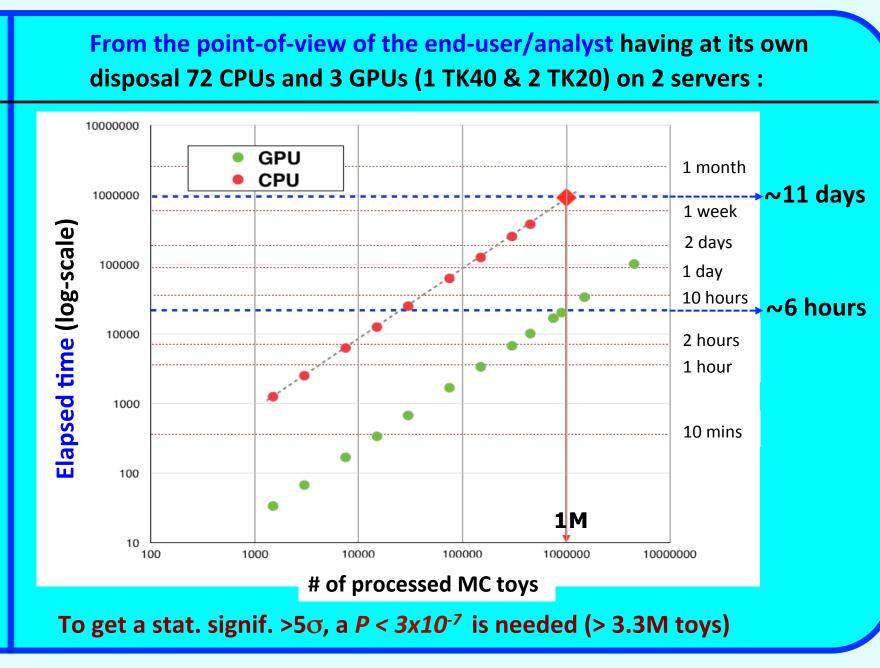
Aim: to estimate the local statistical significance of the structure observed by CMS close to the kinematical boundary of the $J/\psi\phi$ inv. mass, in the 3-body decay $B^+ o J/\psi\,\phi K^+$ [PLB 734 (2014) 261], and compatible with an exotic charmonium-like signal already observed by CDF.

ToyMC cycle:

- 0) Generate a background distribution (3-body phase-space model)
- 1) Perform HO Binned ML fit with same bkg model @ generation
- 2) Make 8 H1 BML fits (signal model is a truncated Voigtian function; resolution fixed @2MeV) in the Δm region of interest by trying different starting values (2 masses & 4 widths).
- 3) Choose the fit with the **best** $\Delta \chi^2$ (test statistic). Fill its distribution over the sample of MC toys.

Signal yield constrained to be >0.





Compatible with the lower limit of 5σ for the stat. signif. quoted in the CMS paper on the basis of 50.5 millions of MC toys (by RooFit)

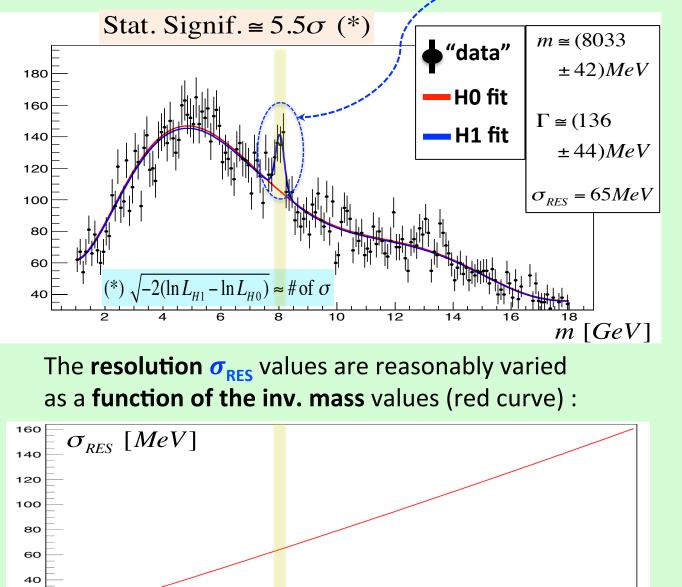
When dealing with an unexpected new signal, a global statistical significance must be estimated and the Look-Elsewhere-Effect (LEE) must be taken into account. This implies to consider - within the same background-only fluctuation and everywhere in the relevant mass spectrum - any peaking behaviour with respect to the expected background model.

 $p - value: P = \int_{50}^{60} f(\Delta \chi^2) d(\Delta \chi^2) \approx (57.7 \cdot 10^6)^{-1} \approx 1.73 \cdot 10^{-8} \quad \Rightarrow \quad Z\sigma = \Phi^{-1}(1 - P)\sigma \approx 5.52\sigma$

MC TOYS for GLOBAL SIGNIFICANCE A pseudo-data inv. mass distribution of 15K candidates in a generic region of interest (1-18GeV) is generated according to an **invented** background model (7th order

polynomial) on the top of which any desired amount of *significant signal* can be artificially added @ ~8GeV

 $\Delta \chi^2_{DATA} \cong 53.0$



m [GeV]

The LEE inclusion is addressed with a mass scan coupled to a clustering technique to identify the peaks from significant fluctuations

The clustering approach is designed to satisfy two concurrent requirements:

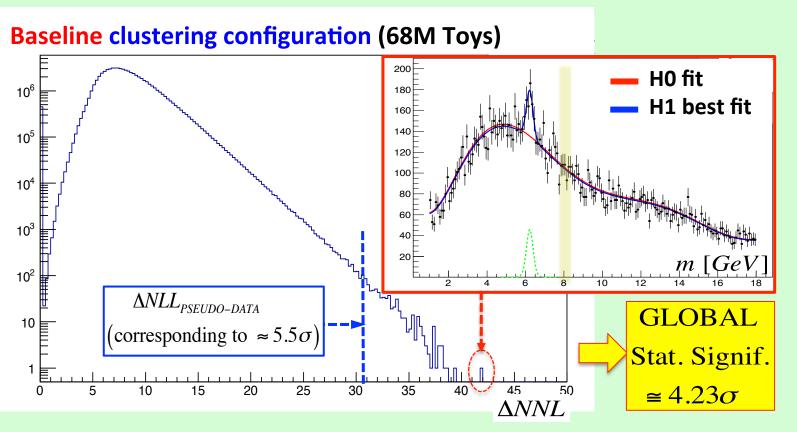
For each toy, the procedure starts from the HO Binned ML fit (same bkg model @ generation).

While scanning the mass bins:

1) search for a seed-bin (its content fluctuates more than $x\sigma$ strictly above the H0 fit); 2) add any side-bin to the seed-bin if fluctuating more than $z\sigma$, otherwise seed-bin forms a 1-bin cluster;

3) check for a light seed-bin fluctuating more than $y\sigma$ (with z<y<x) if it has at least one other side-bin with more than $z\sigma$.

For each toy, make all the H1 BML fits (signal model is a Voigtian function; yield constrained to be >0) and choose the fit with the best \triangle NNL (test statistic). Get its distribution over all the MC toys.



GLOBAL STATISTICAL SIGNIFICANCE (# σ)					
Approx. LOCAL Stat. Signif. (*)	4.00	4.5 σ	5.0 σ	5.50	6. 0 o
Tight	2.21	2.91	3.58	4.23	5.19
Baseline	2.20	2.91	3.58	4.23	5.19
Loose	2.19	2.92	3.58	4.23	5.19
The method behaves suitably stable and its					

associated systematic uncertainty is negligible

