Statistical significance estimation of a signal within the *GooFit* framework on GPUs



Leonardo Cristella on behalf of the CMS Collaboration





UNIVERSITA' DEGLI STUDI DI BARI "ALDO MORO" & I.N.F.N. SEZIONE DI BARI

29 Aug - 3 Sep 2016 XII Quark Confinement and the Hadron Spectrum

Thessaloniki

Outline

- Introduction to GPU computing & GooFit
- Pseudo-experiments for p-value estimation: GooFit vs RooFit performance study
- **Exploring the applicability limits of Wilks theorem**
- **Summary & Outlook**

Introduction: GPU computing & GooFit



Leonardo Cristella

Hetherogeneous GPU-acccelerated computing is the use of a Graphics Processing Unit to accelerate scientific applications (among other apps).

Enhancement of application performance obtained by offloading compute-intensive portions to the GPU (*the device*) while the remainder of the code still runs on the CPUs (*the host*).



Application Code

01/09/16

Hetherogeneous GPU-acccelerated computing is the use of a Graphics Processing Unit to accelerate scientific applications (among other apps).

Enhancement of application performance obtained by offloading compute-intensive portions to the GPU (*the device*) while the remainder of the code still runs on the CPUs (*the host*).



Application Code

From the user's perspective? Applications simply run significantly faster! How much faster? It depends - of course - on the application... We want to explore it in the context of the 'end-user HEP analyses' by using *GooFit*.

- GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports OpenMP.
- The FitManager object forms the interface between MINUIT (running on CPU) and a GPU which allows a PDF representing the physical model (GooPdf object) to be evaluated in parallel.
 CDLL User code



GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports OpenMP.

The FitManager object forms the interface between MINUIT (running on CPU) and a GPU which allows a PDF representing the physical model (GooPdf object) to be evaluated in parallel.
CPLL User code

Fit parameters are estimated at each NegLogLikelihood minimization step on the *host side* (CPU) while the PDF/NLL is evaluated on the *device side* (GPU) [all that until convergence]:





GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports OpenMP.

The FitManager object forms the interface between MINUIT (running on CPU) and a GPU which allows a PDF representing the physical model (GooPdf object) to be evaluated in parallel.
CPLL User code

Fit parameters are estimated at each NegLogLikelihood minimization step on the *host side* (CPU) while the PDF/NLL is evaluated on the *device side* (GPU) [all that until convergence]:





GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

This can be seen by analysing a cycle with the monitoring tool nVIDIA Visual Profiler [nvvp]



GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports OpenMP.

The FitManager object forms the interface between MINUIT (running on CPU) and a GPU which allows a PDF representing the physical model (GooPdf object) to be evaluated in parallel.
CPLL User code

Fit parameters are estimated at each NegLogLikelihood minimization step on the *host side* (CPU) while the PDF/NLL is evaluated on the *device side* (GPU) [all that until convergence]:





GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

- This can be seen by analysing a cycle with the monitoring tool nVIDIA Visual Profiler [nvvp]
- The **FitControl** object allows to switch between χ^2 fits and ML fits (either unbinned and binned).

Parameter estimation is a crucial part of many physics analyses.

PDF evaluation on large datasets is usually the bottleneck in the MINUIT algorithm.

GooFit acts as an interface between the MINUIT minimization algorithm and a parallel processor which allows a Probability Density Function to be evaluated in parallel.

≫

Parameter estimation is a crucial part of many physics analyses.

PDF evaluation on large datasets is usually the bottleneck in the MINUIT algorithm.

GooFit acts as an interface between the MINUIT minimization algorithm and a parallel processor which allows a Probability Density Function to be evaluated in parallel.

A preliminary test was done with an <u>Unbinned ML fit</u> either by using a single CPU and by using an additional GPU (an nVIDIA Tesla C2070 hosted @ Bari T2).

Events according to a Voigtian model (convolution is CPU-intensive) are generated & fitted. The time needed (the negligible generation time is not included) is studied as a function of the #events:



Parameter estimation is a crucial part of many physics analyses.

PDF evaluation on large datasets is usually the bottleneck in the MINUIT algorithm.

GooFit acts as an interface between the MINUIT minimization algorithm and a parallel processor which allows a Probability Density Function to be evaluated in parallel.

A preliminary test was done with an <u>Unbinned ML fit</u> either by using a single CPU and by using an additional GPU (an nVIDIA Tesla C2070 hosted @ Bari T2).

Events according to a Voigtian model (convolution is CPU-intensive) are generated & fitted. The time needed (the negligible generation time is not included) is studied as a function of the #events:



For 10M events RooFit needs 61h+23m & GooFit takes 4m+39s: speed-up ~ 750

For 1M fitted events with RooFit ... you need to wait overnight,

For 10M fitted events with GooFit ... you need to take an espresso!



 \gg As expected, for a **Binned ML fit**, the speed-up ranges from few units to few dozens (with #bins)

01/09/16

Leonardo Cristella

MC toys for p-value estimation: GooFit vs RooFit



Leonardo Cristella

Test application: the Physics case

To test the computing capabilities of GPUs with respect to CPU cores: a high-statistics toy Monte Carlo technique has been implemented both in *ROOT/RooFit* and *GooFit* frameworks with the aim to estimate the (local) statistical significance of the structure observed by CMS close to the kinematical boundary of the $J/\psi\phi$ invariant mass in the 3-body decay $B^+ \rightarrow J/\psi\phi K^+$ [PLB 734 (2014) 261]



Test application: the Physics case

To test the computing capabilities of GPUs with respect to CPU cores: a high-statistics toy Monte Carlo technique has been implemented both in *ROOT/RooFit* and *GooFit* frameworks with the aim to estimate the (local) statistical significance of the structure observed by CMS close to the kinematical boundary of the $J/\psi\phi$ invariant mass in the 3-body decay $B^+ \rightarrow J/\psi\phi K^+$ [PLB 734 (2014) 261]



Leonardo Cristella

Test application: the toy MC method

MC pseudo-experiments are used to estimate the probability (*p-value*) that background fluctuations would - alone - give rise to a signal as much significant as that seen in the data.

Toy MC fit cycle (for each generated fluctuation)

- Generation of fluctuated background binned distribution (3-body phase-space model) [total #entries fixed by data is fits with not-extended ML]
- >> Null Hypothesis binned ML fit performed with the phase-space model only

D

Test application: the toy MC method

MC pseudo-experiments are used to estimate the probability (*p-value*) that background fluctuations would - alone - give rise to a signal as much significant as that seen in the data.

Toy MC fit cycle (for each generated fluctuation)

- Generation of fluctuated background binned distribution (3-body phase-space model) [total #entries fixed by data \Rightarrow fits with not-extended ML]
- Null Hypothesis binned ML fit performed with the phase-space model only Σ
- Alternative Hypothesis binned ML fit performed with the phase-space model + Voigtian PDF $\mathbf{\Sigma}$ [the latter is truncated to correctly account for the kinematical threshold; the Gaussian resolution function has width fixed @ 2MeV]. Signal yield constrained > 0.

Note: for each bin, the PDF value is estimated by ROOT integration over the bin



Fit performed 8 times within the region of interest (from CDF: no LEE) trying different starting values (2 masses & 4 widths).

01/09/16

Test application: the toy MC method

MC pseudo-experiments are used to estimate the probability (*p-value*) that background fluctuations would - alone - give rise to a signal as much significant as that seen in the data.

Toy MC fit cycle (for each generated fluctuation)

- Generation of fluctuated background binned distribution (3-body phase-space model) [total #entries fixed by data is fits with not-extended ML]
- Null Hypothesis binned ML fit performed with the phase-space model only
- Alternative Hypothesis binned ML fit performed with the phase-space model + Voigtian PDF [the latter is truncated to correctly account for the kinematical threshold; the Gaussian resolution function has width fixed @ 2MeV]. Signal yield constrained > 0.

Note: for each bin, the PDF value is estimated by ROOT integration over the bin



[time-consuming but needed: steep signal w.r.t. bin size]

- Fit performed 8 times within the region of interest (from CDF: no LEE) trying different starting values (2 masses & 4 widths).
- For each fit calculate a $\Delta \chi^2$ w.r.t. the Null Hypothesis fit; the best $\Delta \chi^2$ fit among the 8 alternative fits is chosen !
- A $\Delta \chi^2$ (our test statistic) distribution is obtained over the sample of MC toys.



01/09/16

9/24

Hardware set-up



(*) http://www.recas-bari.it

Performance of *GooFit* vs *ROOT/RooFit*: a preliminary result

A first result obtained is simple comparison between the MC Toys procedure running on a single GPU via GooFit and on a single CPU. The speed ups:

S = 62 (TeslaK40)

S = 48 (TeslaK20)

For 15k MC Toys produced (Highly time consuming for ROOT: ~6 hours)

Performance of *GooFit* vs *ROOT/RooFit*: a preliminary result

A **first result** obtained is simple comparison between the MC Toys procedure running on a **single GPU** via *GooFit* and on a **single CPU**. The speed ups:

S = 62 (TeslaK40)

S = 48 (TeslaK20)

For 15k MC Toys produced (Highly time consuming for ROOT: ~6 hours)

This kind of application (*binned fit* & *few parameters*) **doesn't exploit** the whole GPU computational capability.

+	NVIDIA-SMI 340.29 Driver Version: 340.29						+ 		
	GPU Fan	Name Temp	Perf	Persist Pwr:Usa	tence-M age/Cap	Bus-Id Memor	Disp.A ry-Usage	Volatile GPU-Util	Uncorr. ECC Compute M.
	0 N/A	Tesla 29C	K20m P0	51W /	0ff / 225W	0000:02:00.0 82MiB /	Off 4799MiB	66%	0 Default
	1 N/A	Tesla 27C	K20m P8	25W /	0ff / 225W	0000:84:00.0 12MiB /	Off 4799MiB	 0%	0 Default
+	Comp GPU	ute pro	ocesse PID	es: Process	name				GPU Memory Usage
	0	3:	1180	GooToyM	2				67MiB

Example snapshot of nvidia-smi (nvidia monitoring tool – top) for a single process.



Performance of *GooFit* vs *ROOT/RooFit*: a preliminary result

A **first result** obtained is simple comparison between the MC Toys procedure running on a **single GPU** via *GooFit* and on a **single CPU**. The speed ups:

S = 62 (TeslaK40)

S = 48 (TeslaK20)

For 15k MC Toys produced (Highly time consuming for ROOT: ~6 hours)

This kind of application (*binned fit* & *few parameters*) **doesn't exploit** the whole GPU computational capability.

+	NVID	IA-SMI	340.2	9 Driver Version: 340.29				+ +	
	GPU Fan	Name Temp	Perf	Persistenc Pwr:Usage/	ce-M /Cap	Bus-Id Memor	Disp.A ry-Usage	Volatile GPU-Util	Uncorr. ECC Compute M.
	0 N/A	Tesla 29C	K20m P0	0f 51W / 22	ff 25W	0000:02:00.0 82MiB /	Off 4799MiB	66%	0 Default
	1 N/A	Tesla 27C	K20m P8	0f 25W / 22	ff 25W	0000:84:00.0 12MiB /	Off 4799MiB	0%	0 Default
+									+
	Compute processes:GPU MemoryGPUPID Process nameUsage							GPU Memory Usage	
	0	3:	1180	GooToyMC					 67MiB

Example snapshot of nvidia-smi (nvidia monitoring tool - top) for a single process.



How to exploit the full computational power of a GPU?

The nVidia Multi Process Server (MPS) is a tool developed by nVidia that allows to execute multiple processes (up to 16) on the same GPU chip. It acts as a scheduler: manages the access to memory and CUDA cores.

Here is an example of how it affects the occupancy of a TeslaK40 GPU:

The nVidia Multi Process Server (MPS) is a tool developed by nVidia that allows to execute multiple processes (up to 16) on the same GPU chip. It acts as a scheduler: manages the access to memory and CUDA cores.

Here is an example of how it affects the occupancy of a TeslaK40 GPU:



GPU Occupancy

Performance of *GooFit* on nVIDIA Multi Process Server

The nVidia Multi Process Server (MPS) is a tool developed by nVidia that allows to execute multiple processes (up to 16) on the same GPU chip. It acts as a scheduler: manages the access to memory and CUDA cores.

 $\mathbf{\Sigma}$

Each process uses:

- 1(shared) GPU and 1(exclusively assigned) CPU

There is a saturation effect (Amdhal's law)



Performance of *GooFit* on nVIDIA Multi Process Server

The nVidia Multi Process Server (MPS) is a tool developed by nVidia that allows to execute multiple processes (up to 16) on the same GPU chip. It acts as a scheduler: manages the access to memory and CUDA cores.

Each process uses:

- 1(shared) GPU and 1(exclusively assigned) CPU

There is a saturation effect (Amdhal's law)

1st(2nd) group of 0 < N ≤ 16 processes assigned to... ...1st(2nd) GPU (the 2 GPUs TK20 on the same server

hosting 32 CPUs via HyperThreading)



Amdhal's Law

In computer architecture, Amdahl's law gives **the theoretical speedup** when using multiple processors as a function of the fraction (**P**) of the code that can be parellilised and of the number of multiprocessors (**n**) used.



Performance of *GooFit* on nVIDIA Multi Process Server

The nVidia Multi Process Server (MPS) is a tool developed by nVidia that allows to execute multiple processes (up to 16) on the same GPU chip. It acts as a scheduler: manages the access to memory and CUDA cores.

Each process uses:

16 15

14

13

12

11

5

4

3

2

1

0

s Speed Up د د د

1(shared) GPU and 1(exclusively assigned) CPU

There is a saturation effect (Amdhal's law)

Ist(2nd) group of 0 < N ≤ 16 processes assigned to... ...1st(2nd) GPU (the 2 GPUs TK20 on the same server



hosting 32 CPUs via HyperThreading)

Performance of *RooFit* on CPUs with PROOF-Lite

To efficiently run RooFit MC toys in parallel on the 72 CPUs available on the 2 servers hosting the GPUs, we use PROOF-Lite that is a dedicated version of PROOF optimized for single multi-core machines [*].

This ROOT/*RooFit* extension implements a 2-Tier architecture with the master merged into the client, controlling directly the workers (workers are processes not threads).

PROOF has a *Pull architecture*: all workers end at the same time avoiding long queues, unavoidable by running *RooFit* on a cluster in *Push approach* (the last job determines the total exec. time).

≫

[*] G.Ganis et al., PoS ACAT08 (2008) 007; A.Pompili et al., J. Phys.: Conf. Ser. **396** 032043, CHEP12, 2012

To efficiently run *RooFit* MC toys in parallel on the 72 CPUs available on the 2 servers hosting the GPUs, we use PROOF-Lite that is a dedicated version of PROOF optimized for single multi-core machines [*].

This ROOT/*RooFit* extension implements a 2-Tier architecture with the master merged into the client, controlling directly the workers (workers are processes not threads).

PROOF has a *Pull architecture*: all workers end at the same time avoiding long queues, unavoidable by running *RooFit* on a cluster in *Push approach* (the last job determines the total exec. time).

Check speed up performance on 2 servers:

- server hosting TK20 has 32 CPUs
- server hosting TK40 has 40 CPUs

Good scaling with # of MC toys

No difference between 2 servers (as expected)

Speed up perfectly scaling till ~8 workers; then there is a saturation effect (Amdhal's law)



[*] G.Ganis et al., PoS ACAT08 (2008) 007; A.Pompili et al., J. Phys.: Conf. Ser. **396** 032043, CHEP12, 2012

A first performances' comparison can be carried out on the server hosting 32 CPUs and 2 GPUs TK20 as a function of the # of pseudo-experiments produced.



of processed MC toys (per application)

A first performances' comparison can be carried out on the server hosting 32 CPUs and 2 GPUs TK20 as a function of the # of pseudo-experiments produced.



Performance comparison: RooFit/PROOF-Lite vs GooFit/MPS - II

A second performances' comparison can be carried out on both the servers hosting both type of GPUs (TK20 & TK40) as a function of the # of pseudo-experiments produced. Here we limit the comparison to 16 independent processes (due to MPS limit for the single TK40)

We can compare: - 1 PROOF-Lite job using 16 workers (on 16 CPU cores) with: - 1 GooFit/MPS job running 16 simultaneous processes on single TK40 / TK20



Performance comparison: RooFit/PROOF-Lite vs GooFit/MPS - II

A second performances' comparison can be carried out on both the servers hosting both type of GPUs (TK20 & TK40) as a function of the # of pseudo-experiments produced. Here we limit the comparison to 16 independent processes (due to MPS limit for the single TK40)

We can compare: - 1 PROOF-Lite job using 16 workers (on 16 CPU cores) with: - 1 GooFit/MPS job running 16 simultaneous processes on single TK40 / TK20



Performance comparison: RooFit/PROOF-Lite vs GooFit/MPS - III

A third performances' comparison can be done from the point of view of the end-user/analyst and the time needed to deliver the pseudo-experiments' task.
 Let us assume he has at his own disposal the full computational power used in these studies:
 2 servers equipped with 3 GPUs (2 TK20 & 1 TK40) and 72 CPU cores (36 physical cores + HyperThr).



P-Value & statistical significance estimation



The final obtained $\Delta \chi^2$ distribution

 $\mathbf{\Sigma}$
P-Value & statistical significance estimation



01/09/16

 $\mathbf{\Sigma}$

P-Value & statistical significance estimation



01/09/16

Leonardo Cristella

Exploring the applicability limits of Wilks theorem



Leonardo Cristella

[*] S.S.Wilks, Ann.Math.Stat. 9 (1938) 60-62

>> The Wilks^[*] theorem is often used to estimate the p-value associated to a new/unexpected signal:

Given two hypotheses: Σ Null hypotheses H_0 with v_0 d.o.f.

> Alternative hypotheses H_1 with v_1 d.o.f.

... any test statistic *t*, defined as a likelihood ratio $-2\ln\lambda = -2\ln\left(\frac{L_{H_0}}{L_{H_1}}\right)$

[or similarly (in the asymptotic limit) as a $\Delta \chi^2 = \chi^2_{H_0} - \chi^2_{H_1}$],

approaches a χ^2 distribution with $v = v_1 - v_0$ d.o.f., provided that these regularity conditions hold:

- $oldsymbol{\gg}~H_{_0}$ and $H_{_1}$ are nested ($H_{_1}$ "includes" $H_{_0}$)
- > while $H_1 \rightarrow H_0$ the H_1 parameters are well behaving (defined and not approaching some limit)
- asymptotic limit (of a large data sample)

[*] S.S.Wilks, Ann.Math.Stat. 9 (1938) 60-62

 ∞

>> The Wilks^[*] theorem is often used to estimate the p-value associated to a new/unexpected signal:

Given two hypotheses: Σ Null hypotheses H_0 with v_0 d.o.f.

> Alternative hypotheses H_1 with v_1 d.o.f.

... any test statistic t, defined as a likelihood ratio $-2\ln\lambda = -2\ln\left(\frac{L_{H_0}}{L_{H_1}}\right)$

[or similarly (in the asymptotic limit) as a $\Delta \chi^2 = \chi^2_{H_0} - \chi^2_{H_1}$],

approaches a χ^2 distribution with $v = v_1 - v_0$ d.o.f., provided that these regularity conditions hold:

- $oldsymbol{\gg}~H_{_0}$ and $H_{_1}$ are nested ($H_{_1}$ "includes" $H_{_0}$)
- >> while $H_1 \rightarrow H_0$ the H_1 parameters are well behaving (defined and not approaching some limit)
- asymptotic limit (of a large data sample)
- **>** Once this theorem holds, the p-value associated to the signal is given by: $P = \int_{t_{obs}} \chi^2_{v_1 v_0}(t) dt$ The use of pseudo-experiments to estimate the p-value is not needed (but still suggested)
- When null hypothesis is background-only and the alternative is background+signal, often the above regularity conditions are not all satisfied, and MC toys are mandatory !

Indeed this is the case we are dealing with, here!

The signal parameters in the model of H_1 hypothesis are mass (m), width (Γ) and yield ($\mu \ge 0$). When $H_1 \rightarrow H_0$ the problem is that: 1) m and Γ are not well defined, 2) μ tend to the null limit. This explains why we have used pseudo-experiments.

>> The distributions of test statistic are in general nonpredictable and can be extracted from MC toys!

Indeed this is the case we are dealing with, here!

The signal parameters in the model of H_1 hypothesis are mass (m), width (Γ) and yield ($\mu \ge 0$). When $H_1 \rightarrow H_0$ the problem is that: 1) *m* and Γ are not well defined, 2) μ tend to the null limit. This explains why we have used pseudo-experiments.

The distributions of test statistic are in general nonpredictable and can be extracted from MC toys!



Special case in which Wilks theorem holds

Consider the test statistic $t_{\mu} = -2 \ln \lambda(\mu)$ [μ : strength parameter] as the basis of the statistical test. This could be a test of μ =0 for purposes of establishing the existence of a signal process (no constrain on μ).

In the latter case, following Cowan *et al*. [*] the PDF of the test statistic approaches a chi-square distribution for 1 d.o.f.: [in agreement with Wilks theorem!]



⋗

^[*] Cowan et al., EPJ C71 (2011) 1554

Special case in which Wilks theorem holds

Consider the test statistic $t_{\mu} = -2 \ln \lambda(\mu)$ [μ : *strength parameter*] as the basis of the statistical test. This could be a test of μ =0 for purposes of establishing the existence of a signal process (no constrain on μ).

In the latter case, following Cowan *et al*. [*] the PDF of the test statistic approaches a chi-square distribution for 1 d.o.f.: [in agreement with Wilks theorem!]

 $f(t_{\mu}|\mu) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{t_{\mu}}} e^{-t_{\mu}/2}$

Let us fix the $m \& \Gamma$ parameters, (to the CMS estimates from the fit to data) while leaving μ free in our ML fits (μ is not properly a signal yield).

By fitting our likelihood ratio distrib. we indeed get:

 $\frac{\text{d.o.f.} \approx 1.014 \pm 0.001}{\chi^2_{norm}} = 1.009 \quad P(fit) = 0.118$

[*] Cowan et al., EPJ C71 (2011) 1554



01/09/16

Consider the special case of the test statistic t_{μ} with the purpose to test μ =0 in a class of model where we assume μ >0. Rejecting μ =0 (the null hypothesis) leads to the discovery of a new signal.

In this case following Cowan et al. the test statistic is:

$$q_0 = \begin{cases} -2\ln\lambda(0) & \text{with} \\ 0 & \hat{\mu} < 0 \end{cases}$$

Cowan *et al.* derive analitically that the PDF of q_0 is an equal mixture of a delta function at 0 & a chi-square distribution for 1 d.o.f.:





[*] Cowan et al., EPJ C71 (2011) 1554

01/09/16

Consider the special case of the test statistic t_{μ} with the purpose to test μ =0 in a class of model where we assume μ >0. Rejecting μ =0 (the null hypothesis) leads to the discovery of a new signal.

In this case following Cowan et al. the test statistic is:

$$q_0 = \begin{cases} -2\ln\lambda(0) & \text{with} \\ 0 & \hat{\mu} < 0 \end{cases}$$

Cowan *et al.* derive analitically that the PDF of q_0 is an equal mixture of a delta function at 0 & a chi-square distribution for 1 d.o.f.:

$$g(q_0 | \mu = 0) = \frac{1}{2} \left[\delta(q_0) \right] + \frac{1}{2} \left[\frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{q_0}} e^{-q_0/2} \right]$$

Let us fix the *m* & Γ parameters (to the CMS estimates from fit to data) while constraining $\mu \ge 0$ in our ML fits (μ represents a signal yield here).

By fitting our likelihood ratio distrib. we indeed get:

d.o.f. ≈ 0.992 ± 0.001 weight $C_{\chi^2} \approx 0.507 \pm 0.01$

[*] Cowan et al., EPJ C71 (2011) 1554

Consider the special case of the test statistic t_{μ} with the purpose to test μ =0 in a class of model where we assume μ >0. Rejecting μ =0 (the null hypothesis) leads to the discovery of a new signal.

In this case following Cowan et al. the test statistic is:

$$q_0 = \begin{cases} -2\ln\lambda(0) & \text{with} \\ 0 & \hat{\mu} < 0 \end{cases}$$

Cowan *et al*. derive analitically that the PDF of q_0 is an equal mixture of a delta function at 0 & a chi-square distribution for 1 d.o.f.:





01/09/16

The quality of the previous fit (with a χ² pdf + a very narrow step function at 0) is good enough:



Summary & Outlook



Leonardo Cristella

Summary

In order to test the computing capabilities of GPUs with respect to traditional CPU cores, a high-statistics toy Monte Carlo technique has been implemented both in *ROOT/RooFit* and *GooFit* frameworks with the purpose to estimate the local statistical significance of a - possibly exotic charmonium-like - signal recently confirmed by CMS (it was firstly observed by CDF).

The optimized *GooFit* applications running, by means of the MPS, on GPUs, hosted by the servers used in the presented test, provides a striking speed-up performance with respect to the *RooFit* application parallelized on multiple CPUs by means of *PROOF-Lite*.

Summary

In order to test the computing capabilities of GPUs with respect to traditional CPU cores, a high-statistics toy Monte Carlo technique has been implemented both in *ROOT/RooFit* and *GooFit* frameworks with the purpose to estimate the local statistical significance of a - possibly exotic charmonium-like - signal recently confirmed by CMS (it was firstly observed by CDF).

The optimized *GooFit* applications running, by means of the MPS, on GPUs, hosted by the servers used in the presented test, provides a striking speed-up performance with respect to the *RooFit* application parallelized on multiple CPUs by means of *PROOF-Lite*.

By means of GooFit it has also been easier to explore the (asymptotic) behaviour of a likelihood ratio test statistic in different situations in which the Wilks Theorem may apply or does not apply because its regularity conditions are not satisfied. The presented method can be extended to situations with a new unexpected signal, where a global statistical significance must be estimated.
To include properly the Look-Elsewhere-Effect a sort of scanning technique of the relevant mass spectra needs to be implemented.

Outlook

The presented method can be extended to situations with a new unexpected signal, where a global statistical significance must be estimated.
To include properly the Look-Elsewhere-Effect a sort of scanning technique of the relevant mass spectra needs to be implemented.

This can certainly either ...

- increase the execution time of the fits to be performed on the single fluctuation, and...
- require to try different scan models (and repeat the whole procedure) in order to evaluate the associated systematic uncertainty.

In this situation:

- the RooFit approach would be unbearable (highly time-consuming!),
- turning to GPUs would be mandatory,
- GooFit would be the reliable & crucial tool.

If you are interested to start learning and working with GooFit ...

- 1) you can take the tutorial by R.Andreassen: <u>http://indico.cern.ch/conferenceDisplay.py?confId=235992</u>
- 2) GooFit source code lives in a GitHub repository: <u>https://github.com/GooFit</u>
- 3) you may want to exchange useful feedbacks on the *GooFit* Google Group.

Thank you for your attention

Let me thank in particular:

- my supervisor of CMS-Bari Alexis Pompili (University of Bari & INFN), Adriano Di Florio (University of Bari & INFN), Giacinto Donvito (INFN-Bari, Tier2 manager) and the support by Italian Project 20108T4XTM - MIUR PRIN 2010-2011 - STOA-LHC
- Mike Sokoloff (University of Cincinnati) coordinator of the *GooFit* project funded by NSF (NSF-1414736 Enabling HEP at the Information Frontier Using GPUs and Other Many/Multi-Core Architectures)
- Brad Hittle (Ohio Supercomputer Center) and Tommaso Dorigo (INFN-Padova)

BACKUP



Leonardo Cristella

Why GPU computing? Moore's Law

Moore's Law :"the number of transistors per unit area would double approximately every two years"



A new approach is needed: a possible solution is **GPU-computing.**

"If you were plowing a field, which would you rather use: **Two strong oxen** or 1024 chickens?"

Seymour Cray



GUUUUUUUUUUUUUUUUUUUUUUUUUUUUUU UUUUUUUUUUUUUUUUUUUUUUUUU CI CI いいいい GEEEEEEEEEEEEE

GPUs' architecture

"If you were plowing a field, which would you rather use: **Two strong oxen** or 1024 chickens?"

Seymour Cray



We definetely choose the chickens

Leonardo Cristella





1970s: first graphical user interface produced requiring dedicated microchips

Video games and **3D graphics**: strong economic stimulus for GPU development



1970s: first graphical user interface produced requiring dedicated microchips

Video games and 3D graphics: strong economic stimulus for GPU development

Consequences on GPU architecture:

Thousands of cores



1970s: first graphical user interface produced requiring dedicated microchips

Video games and **3D graphics**: strong economic stimulus for GPU development

Consequences on GPU architecture:

Thousands of cores

Big loads of data



1970s: first graphical user interface produced requiring dedicated microchips

Video games and **3D graphics**: strong economic stimulus for GPU development

Consequences on GPU architecture:

Thousands of cores

Big loads of data

Low frequency clock (~1GHz)



1970s: first graphical user interface produced requiring dedicated microchips

Video games and 3D graphics: strong economic stimulus for GPU development

Consequences on GPU architecture:

Thousands of cores

Big loads of data

Low frequency clock (~1GHz)

Arithmetical operations in a single clock cycle (*sin*,*cos*,*sqrt*,*1*/*x*, ...)



1970s: first graphical user interface produced requiring dedicated microchips

Video games and 3D graphics: strong economic stimulus for GPU development

Consequences on GPU architecture:

Thousands of cores

Big loads of data

Low frequency clock (~1GHz)

Arithmetical operations in a single clock cycle (*sin*,*cos*,*sqrt*,*1*/*x*, ...)





GPU

Numero di GPU

Numero di CUDA cores

Memoria per GPU (GDDR5)

Banda di memoria per board

CPU

- I6 cores : E5-2640 v2 @ 2.00GHz (32 con HT)
- 64 GB RAM

Memoria per GPU (GDDR5) Banda di memoria per board

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports **OpenMP**.



Control & Data Flow of a GooFit program

GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

It is an open source project, under development and funded by US NSF.

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports **OpenMP**.

>> A GooFit program has 4 main components:

Control & Data Flow of a GooFit program



GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

It is an open source project, under development and funded by US NSF.

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports **OpenMP**.

- >> A *GooFit* program has 4 main components:
 - a GooPdf object representing the PDF modelling the physical process



GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

It is an open source project, under development and funded by US NSF.

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports **OpenMP**.

- >> A *GooFit* program has 4 main components:
 - a GooPdf object representing the PDF modelling the physical process
 - the fit parameters (Variables objects contained in the GooPdf)
 - the data (DataSet object)



GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

It is an open source project, under development and funded by US NSF.

Leonardo Cristella

GooFit is a data analysis tool for HEP, that interfaces ROOT/RooFit to CUDA parallel computing platform on *nVidia* GPU. It also supports **OpenMP**.

- >> A *GooFit* program has 4 main components:
 - a GooPdf object representing the PDF modelling the physical process
 - the fit parameters (Variables objects contained in the GooPdf)
 - the data (DataSet object)
 - a FitManager object forming the interface between MINUIT and the GooPdf



GooFit: a library for massively parallelising maximum-likelihood fits R.Andreassen et al., J.Phys.:Conf.Ser. 513 (2014) 052003

It is an open source project, under development and funded by US NSF.

Leonardo Cristella
Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:



Leonardo Cristella

01/09/16

Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:



between CPU and GPU

CPU: Parameters tuning to minimise Neg-Log-Likelihood

01/09/16

evaluation

Leonardo Cristella

Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:



between CPU and GPU

7/24

01/09/16

Leonardo Cristella

Example of a snapshot of the profile of a GooFit process provided by Nvidia **Visual Profiler:**



GPU: p.d.f.				CPU: Parameters tuning to
evaluation		between CPU and GPU		minimise Neg-Log-Likelihood
		Leonardo Cristella		7/24

01/09/16

Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:



between CPU and GPU

CPU: Parameters tuning to minimise Neg-Log-Likelihood

01/09/16

evaluation

Leonardo Cristella

Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:



between	CPU	and	GPU

CPU: Parameters tuning to minimise Neg-Log-Likelihood

01/09/16

evaluation

Leonardo Cristella

Example of a snapshot of the profile of a GooFit process provided by Nvidia Visual Profiler:

