Challenges and Opportunities in Software & Computing for Future Colliders

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Introduction

- Software and computing are used ever increasingly in high-energy physics during every step of the data processing chain
 - From detector control, through trigger, to reconstruction and analysis
- The (offline) code base is enormous
 - ~50M lines of C++
 - Also large (but size unknown) python code base



How may Future Colliders Differ

- Can group future colliders into two groups
 - Near-term: LHC upgrades (including HL-LHC)
 - Long-term: Future lepton colliders, potential hadron and muon colliders
- A number of features of these colliders induce challenges and opportunities for software and computing
 - Backgrounds: Increased pile up, beam-induced background
 - Increasingly sophisticated detectors
 - More channels, additional information
 - Higher data rates: better triggers (or no triggers)
 - Increasing demands in physics precision
 - Need to explore unconventional signatures



Challenges and Opportunities

- Computing technology evolution
 - Increased concurrency
 - Increasingly diverse architectures
- Machine learning
- Data science, including python for scientific computing
- Open Source Software
- Funding constraints

The goal of this talk is to explain the impact on these factors on software and computing to highlight the challenges and also provide some ideas about the opportunities

Characteristics

Backgrounds: Additional Interactions

- At hadron colliders, each time two bunches of cross (or collide), multiple pairs of protons undergo inelastic collisions
- Mean number of interactions per bunch crossing or pile up (μ) is given by the following formula

•
$$\langle \mu \rangle = \frac{L \cdot \sigma_{\text{inel}}}{N_{\text{bunch}} \cdot f_{\text{acc}}}$$

depends linearly on the luminosity

• Track reconstruction algorithms scale quadratically with pile up



Tracking is a CPU Hog

- CPU demands of tracking are significant
 - Largest component of reconstruction
 - Largest component of CPU needs
- One component of the so-called "LHC Computing Challenge"
 - Mismatch between computing needs and resources
 - Depends strongly on assumptions
 - Target of **aggressive** software developments





Similar results for <u>ATLAS</u>

Beam-induced Background at Muon Colliders

- Muon colliders are susceptible to the background from the secondary and tertiary muon decay products
 - Reduced several orders of magnitude by the Machine Detector Interface (MDI)
- **IOx hit density** from BIB at muon colliders in tracking detectors compared to pile-up at the HL-LHC
 - Similar impact on algorithms as from pile up



<u>Credit</u>

BIB drives MC Resource Needs

CPU

Approximate Size / Event [MB]				
heavily-filtered	trimmed	full truth	full truth (low threshold)	
80	400	8,400	36,000	

Disk

Full simulation	Approximate time/event [min]
Physics + BIB Overlay	1-2
BIB simulation	1500



Sophisticated Tracking Detectors

- We'll discuss Moore's Law later, but one result is the increasing miniaturization of silicon components
 - Up 65x increase channels in silicon detectors when controlling for size
- More precise measurements, but larger data volume
- Timing adds extra dimension

	LHC	HL-LHC
ATLAS Pixel	80 (92) million	6 billion
ATLAS Strips	6 million	60 million



ATLAS ITk



Image Source

180 m² of silicon

Detailed Shower Reconstruction

 Another innovative use of silicon is in the CMS High Granularity Calorimeter (HGCAL) end-cap: high





ith Graph Neural Networks Requires new reconst reasonable computing resources requirement

CMSSW_10_6_X Intel i7-4770K (1 Thread) 6110 m CLUE on CPU 203 ms Intel i7-4770K (1 Thread) Use grid-based Spatial Index instead of KD-Tree. Remove O(n ²) loop and density sorting CLUE on GPU V1 159 ms Intel i7-4770K (1 Thread) + Nvidia GTX 1080 17 ms for kernel execution; 142 ms for GPU memory operation;
CLUE on CPU - 203 ms Intel i7-4770K (1 Thread) ← Use grid-based Spatial Index instead of KD-Tree. Remove O(n ²) loop and density sorting Intel i7-4770K (1 Thread) + Nvidia GTX 1080 17 ms for kernel execution; 142 ms for GPU memory operation;
CLUE on GPU V1 - 159 ms 17 ms for kernel execution; 142 ms for GPU memory operation;
CLUE on GPU V2 - 50 ms 7 ms for kernel execution; 37 ms for GPU memory operation; 6 ms for SoA operation
CLUE on GPU V3 - 32 ms [UPDATE] move CudaMalloc/CudaFree to constructor/destructor 6 ms for kernel execution; 20 ms for GPU memory operation; 6 ms for SoA operation Nvidia Profiler: https://drive.google.com/drive/folders/17Tq4oN6fNqQD_WBY1rKhdQw1P9V0fEyq?usp=share
0 1000 2000 3000 4000 5000 6000 Execution Time [ms]





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Image Credit

Triggers

Trigger rate increases by more than an **order of magnitude** for **ALICE and LHCb** for Run 3

Trigger rate increase by an **order of magnitude** for **ATLAS and CMS** for Run 4



Even larger event sizes for DUNE but lower rate

Not shown, potential LHCb and ALICE upgrades

¹²

after A. Cerri

Trigger Evolution

- Triggers have extremely **low latency** requirements
 - Track reconstruction can be a challenge
- Algorithms are evolving in two primary directions
 - More computation and more complex algorithms (close to offline physics performance) for the hardware trigger
 - **Triggerless read-out**: no hardware trigger and the software trigger processes all events
- Can mix approaches hardware accelerators in the software trigger
- We can expect these trends to accelerate for future accelerators

Physics Precision

- Future colliders aim to make increasingly precise measurements
- e.g.W mass measurements today
- Extremely high precision for future lepton colliders
- Require:
 - precise theory
 - precise calibration

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	Quantity	current	ILC250	ILC-GigaZ	FCC-ee
	$\Delta lpha(m_Z)^{-1}~(imes 10^3)$	17.8*	17.8*		3.8 (1.2)
	$\Delta m_W~({ m MeV})$	12^{*}	0.5(2.4)		0.25~(0.3)
	$\Delta m_Z ~({ m MeV})$	2.1^{*}	0.7(0.2)	0.2	0.004 (0.1)
	$\Delta m_H ~({ m MeV})$	170^{*}	14		2.5(2)
	$\Delta\Gamma_W~({ m MeV})$	42*	2		1.2(0.3)
de ar	$\Delta\Gamma_Z$ (MeV)	2.3^{*}	1.5(0.2)	0.12	$0.004 \ (0.025)$
	$\Delta A_e \; (imes 10^5)$	190*	14(4.5)	1.5 (8)	0.7(2)
FCC PI	$\Delta A_{\mu}~(imes 10^5)$	1500^{*}	82(4.5)	3(8)	2.3(2.2)
	$\Delta A_{ au}~(imes 10^5)$	400*	86(4.5)	3(8)	0.5(20)
ime]	$\Delta A_b~(imes 10^5)$	2000*	53 (35)	9 (50)	2.4(21)
	$\Delta A_c \; (imes 10^5)$	2700^{*}	140(25)	20(37)	20(15)
	$150 ab^{-1}$			1	1



M. Schott



Example: FCC-ee

- Z-pole running requirements driving computing needs
- Multiple ways of event reconstruction and simulation to address systematic
- Current LHC-scale computing is sufficient for simulation needed

Using LHC-scale computing is nearly sufficient (eg, within 10x) for all the simulation needed for the Z-pole run of a FCC-ee detector

	Generation	Simulation	Reconstruction	DELPHES
Computing unit	$3.5 – 5.2 \cdot 10^{10}$	$2.6 - 3.9 \cdot 10^6$	$5.2 – 7.8 \cdot 10^6$	$2.4 - 3.6 \cdot 10^{10}$
ATLAS equivalent	$3.5 – 5.2 \cdot 10^{13}$	$2.6 – 3.9 \cdot 10^9$	$5.2 – 7.8 \cdot 10^9$	$2.4 - 3.6 \cdot 10^{13}$

Events simulated per day using the equivalent of the ATLAS computing facilities

RAW storage similar to the full HL-LHC

Run	\sqrt{s} (GeV)	Statistics	RAW data
Z	91.2	$3 \cdot 10^{12}$ Z decays (visible)	3–6 EB
WW	160	$10^8 \mathrm{W}^+\mathrm{W}^-$ events	0.1–0.2 PB
ZH	240	10^6 ZH events	1–2 TB
tī	350, 365	$10^6 t\bar{t}$ events	1–2 TB

Ganis, Helsens: <u>https://arxiv.org/abs/2111.10094</u>

Analysis level data similar to LHC Run 2

Run	\sqrt{s} (GeV)	Statistics	AOD data
Z	91.2	$3 \cdot 10^{12}$ Z decays (visible)	15-30 PB
WW	160	$10^8 \mathrm{ W}^+\mathrm{W}^- \mathrm{ events}$	$0.5{-1}$ TB
ZH	240	10^6 ZH events	$5{-}10~\mathrm{GB}$
tī	350, 365	$10^6 t\bar{t}$ events	$5{-}10~\mathrm{GB}$

Slide Credit

Unconventional Signatures

- As we've discovered the Higgs boson at the LHC with no signs of new physics
- Important to ask if there could be signs of new physics that we just don't see
 - Weak (or no) interaction
 - Long lifetimes
 - High mass
- 'Long-lived particles' have become an are of focus
 - Requires new algorithms and additional computing resources
 - e.g. more track reconstruction algorithms



Challenges and Opportunities

Moore's Law

 Number of transistors in an integrated circuit doubles approximately every two years



50 Years of Microprocessor Trend Data

Fig. 2 Number of components per integrated function for minimum cost ptr component extrapolated vs time.

YEAR

Source

Image Credit Slides after

Beyond CPUs

- Hardware accelerators are custom-made hardware designed to perform specific functions more efficiently than CPUs
- Wide variety of hardware accelerators depending on the application
 - e.g GPU, FPGA, TPU
- We use hardware accelerators frequently in our daily lives
 - e.g. graphics acceleration, encryption, machine learning, decoding video streams
- A large fraction of the power in High Performance Centers (HPCs) comes from GPUs
- Can also consider "New" computing paradigms
 - Neuromorphic computing, quantum computing....
- Hardware accelerators are significantly more challenging to program than CPUs

Machine Learning

- Machine learning methods have been used in HEP since the 990s [see <u>Bhat, 2011</u> for a review]
 - Recent advent of deep learning has boosted performance
- Classification and regression used in all steps of the HEP software pipeline
- Developments in machine learning are often driven by **industry**
 - HEP benefits through the application of these techniques
- In most cases, aim for improved physics
 performance rather than improved speed
- Covered in far more detail in Javier's talk, but has transformed the software landscape
- Also good use case for hardware acc



Table 1 Effect of mag	chine learning on the discove	ery and study of
the Higgs boson		

Analysis	Years of data collection	Sensitivity without machine learning	Sensitivity with machine learning	Ratio of <i>P</i> values	Additional data required
$\frac{CMS^{24}}{H \to \gamma\gamma}$	2011–2012	2.2 <i>σ</i> , <i>P</i> = 0.014	2.7 <i>σ</i> , <i>P</i> = 0.0035	4.0	51%
$\begin{array}{l} {\rm ATLAS^{43}} \\ {\rm H} \rightarrow \tau^+ \tau^- \end{array}$	2011–2012	2.5 σ , P = 0.0062	3.4 <i>σ</i> , <i>P</i> = 0.00034	18	85%
${ m ATLAS^{99}}$ VH $ ightarrow$ bb	2011–2012	1.9 σ , P = 0.029	2.5 <i>σ</i> , <i>P</i> = 0.0062	4.7	73%
$ATLAS^{41}$ $VH \rightarrow bb$	2015–2016	2.8σ, P = 0.0026	3.0 <i>σ</i> , <i>P</i> = 0.00135	1.9	15%
${ m CMS^{100}}$ VH $ ightarrow$ bb	2011–2012	1.4 σ , P = 0.081	2.1 <i>σ</i> , <i>P</i> = 0.018	4.5	125%
				· · ·	

https://doi.org/10.1038/s41586-018-0361-2

One Example: Flavor tagging

- Extensive (and exclusive) use of ML for flavor tagging for many years
- **Example:** Improvement in light jet rejection for ATLAS over the years
 - Large improvement by the use of deep learning and GNNs
 - Unclear what the limit is here (GN2 under development)



Open [Software, Data]

- Open source philosophy has long played an important role in software development
- At the LHC, first the <u>results</u>, then the <u>software</u>, then <u>data</u> and most recently the <u>likelihoods</u> of the LHC experiments have become open
 - Reinterpretation can probe additional models
 - However: can be challenging to use our software/data if you don't have direct access to experts and significant hardware resources
- CERN <u>Open Data Policy</u>



endata CERN	Help About -
Explore more than two petabyte of open data from particle phy	s vsics!
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Explore	Focus on
deteasts	ATLAS
scftware	ALICE
environments	CMS
documentation	LHCD
	OPERA
	PLENX
	Data Science

Common Software R&D Institutes

- HEP experiments at the LHC and in the future face similar changes
 - Formation of the HEP Software Foundation (HSF) in 2015
 - Provides a common forum for software for HEP experiments

- Funded R&D efforts in **common software** in a number of countries
- Activity encouraged by the European Strategy
 - "[...] vigorously pursue **common**, coordinated R&D efforts [...], to develop **software** [...] that exploit the recent advances in information technology and data science [...]"
- Common projects can aid software maintainability
 - More likely to have a pool of people available for maintenance
 - Can also be challenging to fund in the long term once beyond the R&D stage



Examples of Software Institutes

• <u>IRIS-HEP</u>, NSF, 2018



- Analysis systems, innovative algorithms, DOMA, training
- <u>ErUM-DATA</u>, Helmholtz Institute, Germany
 - Heterogeneous computing and virtualized environments, machine learning for reconstruction and simulation



- <u>EP R&D</u>, CERN, Switzerland, 2020
 - Turnkey software systems, faster simulation, track and calo reconstruction, efficient analysis
- <u>HEP-CCE</u>, DOE, USA, 2019
 - Portable Parallelization Strategies, I/O Strategy on HPC, Event generators

- <u>AIDAInnova</u>, European Commission EU, 2021
 - Turnkey software, track reconstruction, particle flow, ML simulation
- <u>SVVIFT-HEP</u> STFC, 2021 and <u>ExCALIBUR-HEP</u>, 2020, UKRI UK
 - Exascale data management, Event generators, detector simulation on GPUs, FPGA tracking for HLT

Software for Multiple Experiments

- Common packages have been used extensively by many experiments over many years including CLHEP, ROOT, Geant4, GAUDI
- For Run-3, ALICE uses **ALFA**, framework developed with GSI (FAIR) as common integration platform for online/offline processing
 - Online reconstruction using heterogeneous farm
 - Enables parallel data processing
- DD4HEP is now used by CMS, LHCb among other experiments for the detector description
- <u>ACTS</u> has origins in ATLAS tracking software, but currently being explored by different experiments
- LHCb is splitting off <u>Gaussino</u> as experimentindependent part of Gauss simulation framework (w. CERN SFT/FCC)
- Can save resources by non re-inventing the wheel





Python for Analysis

- Ongoing **boom** in the field of data science
- **Python** has become the language of choice for data science applications
 - Huge community has developed welldocumented tools
 - numpy, matplotlib, pytorch, tensorflow, etc
- Balanced against our own designed-topurpose and customized tools, in particular, ROOT
- Python is becoming increasing popular for analysis especially amongst the younger members of our community





Source: "import XYZ" matches in GitHub repos for users who fork CMSSW. Analysis Ecosystem I



I. Pivarski

Conclusion

- A taster of current and future challenges and opportunities in software and computing
- A hadron collider would result in significant computational challenges
- Also challenges for electron colliders (precision) and muon colliders (beam background)
- At the same time, the field has been evolving rapidly
 - Many opportunities to think about doing things in a dramatically different way in the future
 - No trigger!
 - Even more machine learning/Al

Back up

Other Challenges

Challenges anticipated at each step of the data processing and simulation



HL-LHC Resources: CMS

Processing Step	Time/evt 200 PU	t [HS06s] 140 PU
Gen+Sim	1900	
Digi+PU mix+Reco	5100	3200

Tier	Event size [MB]	
	200 PU	140 PU
RAW	5.9	4.3
AOD	2	1.4
MiniAOD	0.25	0.18
NanoAOD	0.004	0.004



ATLAS Upgrades



New Muon Chambers

- Inner barrel region with new RPCs, sMDTs, and TGCs
- Improved trigger efficiency/momentum resolution, reduced fake rate

New Inner Tracking Detector (ITk)

- All silicon with at least 9 layers up to $|\eta| = 4$
- Less material, finer segmentation

Upgraded Trigger and Data Acquisition System

- Single Level Trigger with 1 MHz output
- Improved 10 kHZ Event Farm

Electronics Upgrades

 On-detector/off-detector electronics upgrades of LAr Calorimeter, Tile Calorimeter & Muon Detectors

SLAC

- 40 MHz continuous readout with finer
- segmentation to trigger

High Granularity Timing Detector (HGTD)

- Precision time reconstruction (30 ps) with Low-Gain Avalanche Detectors (LGAD)
- Improved pile-up separation and bunch-by-bunch luminosity

Additional small upgrades

- Luminosity detectors (1% precision)
- HL-ZDC (Heavy lon physics)

CMS Upgrades

Phase 2 Upgrade Under a 🔏

Level 1 Trigger TDR

- New track trigger at 40 MHz
- Particle flow selection
- 750 kHz L1 output
- 40 MHz data scouting (real time analysis)
- L1T latency: 12.5 μ s

New MIP timing detector (MTD) TDR

- Barrel: LYSO crystals + SiPMs
- Endcap: Low-gain avalanche diodes
- 30 ps timing resolution
- Full coverage to $|\eta|^{\sim}$ 3

Replaced Tracker TDR

- Increased granularity
- Extended coverage to $|\eta|^{\sim} 4$
- Designed for tracking in L1T

DAQ & High Level Trigger (HLT) TDR

- Full optical readout
- Heterogeneous architecture
- 60 TB/s event throughput
- 7.5 kHz HLT output

Barrel Calorimeter TDR

- ECAL crystal granularity readout at 40 MHz with precise timing for e/gamma at 30 GeV
- New ECAL and HCAL back-end boards

Muon System TDR

- New Drift Tubes (DTs) & Cathode Strip Chambers (CSCs) FE/BE readout
- New Resistive Plate Chambers (RPCs) BE electronics
- New Gas Electron Multipliers (GEMs) & new iRPCs 1.6 < |η| < 2.4
- Extended coverage to $|\eta|^{\sim}$ 3

New High-Granularity Endcap Calorimeter (HGCAL) <u>TDR</u>

- Imaging calorimeter
- Si, Scint+SiPM in Pb/Cu-W/SS
- 3D showers and precise timing

Beam Radiation Instrumentation and Luminosity (BRIL) TDR

• Target 1% offline (2% online) luminosity uncertainty