#### Computational challenges in Experimental High Energy Physics

#### how to convert 100TB/s into a Nobel prize

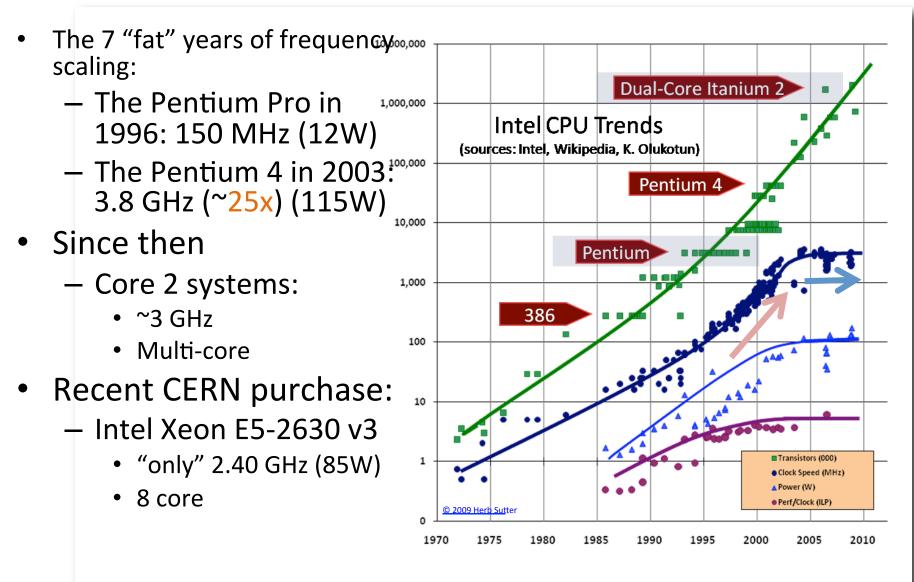
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Slides stolen from: Erica Brondolin Lindsay Gray John Harvey Sverre Jarp Chris Jones Pere Mato Felice Pantaleo Lucia Silvestris Vincenzo Innocente CMS Experiment & CERN/ EP-SFT

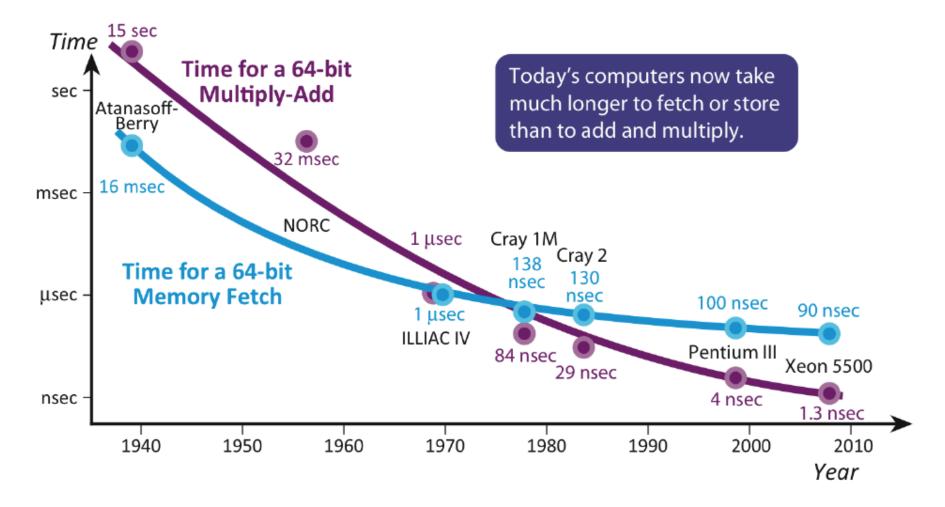
> Data Science Workshop CERN November 9<sup>th</sup>, 2015

> > Images: credit CERN unless specified

#### Why are we here today?

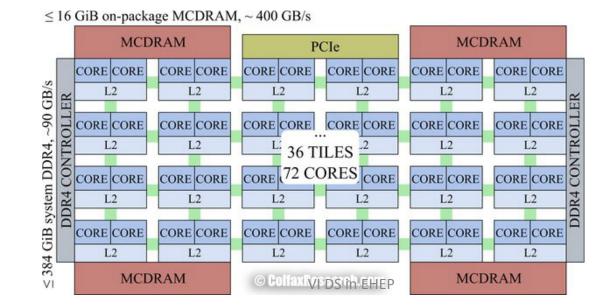


#### Memory Latency

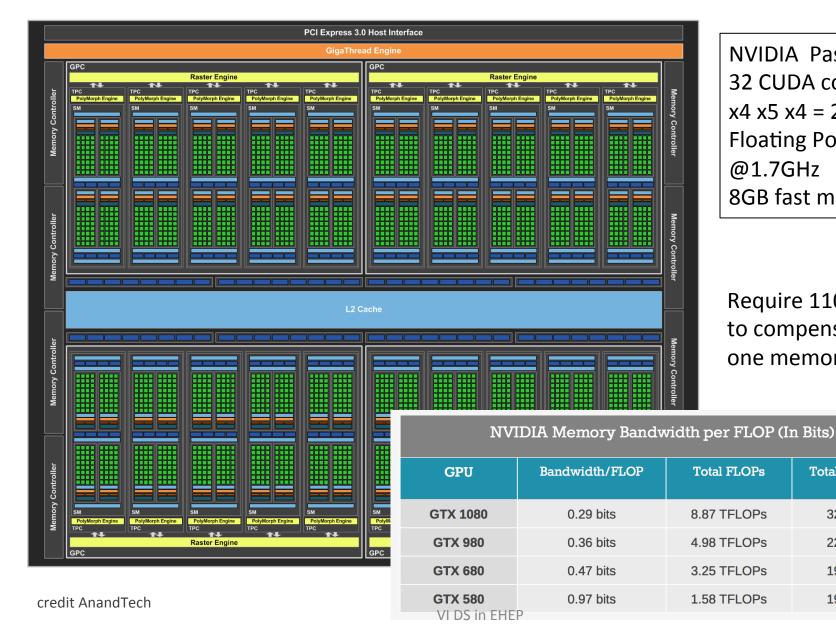


Simple, but illustrative example

- KNL has ~64 cores @1.30GHz, 2FMA port (VPU) each, 4-way hardware threading, hardware vectors of size 8 (Double Precision), 16GB of fast memory:
- 3TFLOPS DP for 400GB/s = 0.5bit/flop-sp - 60 fp-ops = 1 fp-load



#### **Streaming Multiprocessor Architecture**



**NVIDIA** Pascal 32 CUDA core x4 x5 x4 = 2560**Floating Point Units** @1.7GHz 8GB fast memory

Require 110 fp-ops to compensate one memory access!

Total Bandwidth

320GB/sec

224GB/sec

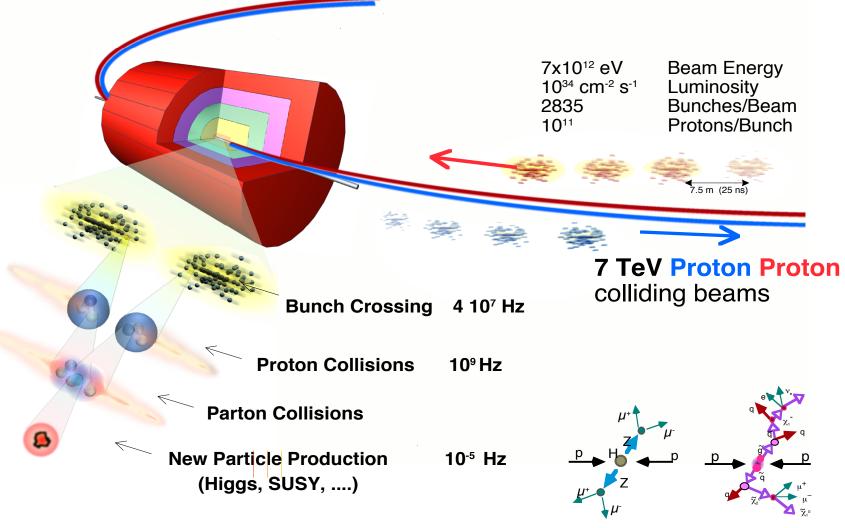
192GB/sec

192GB/sec

## Conclusions

- Improving throughput or latency requires exploiting optimal massive parallelization at all levels
- Speeding up algorithms will not pay up if memory access is not reduced

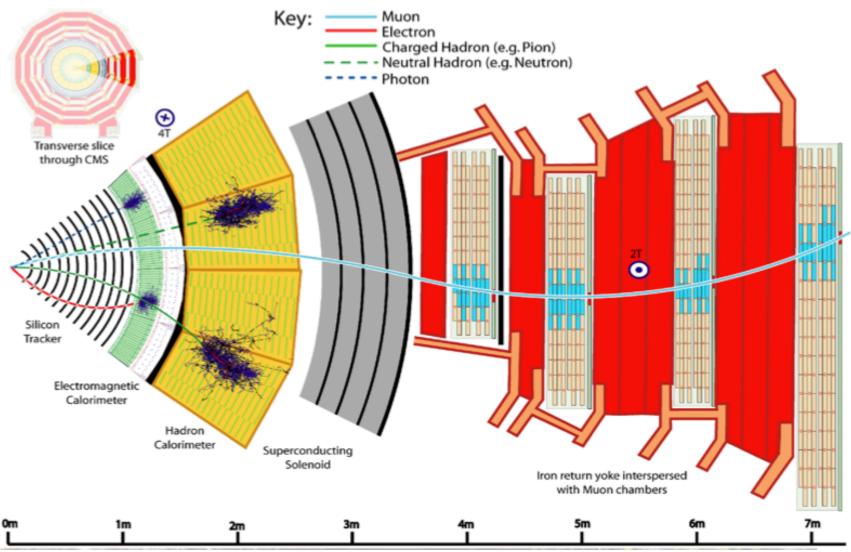
#### Collisions at the LHC: summary



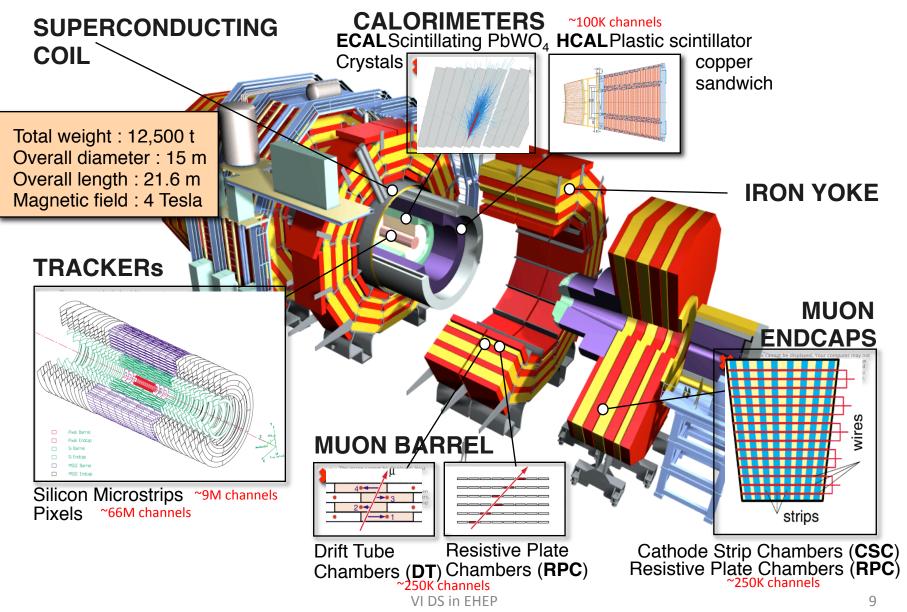
#### Selection of 1 event in 10,000,000,000,000

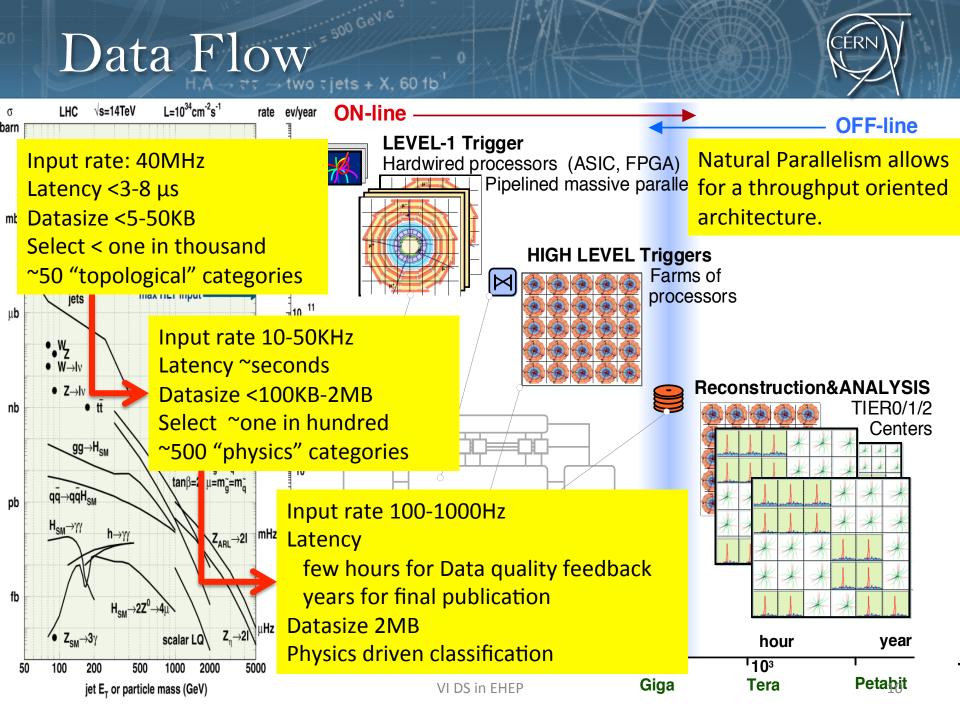
VI DS in EHEP

#### Detector "onion" structure



#### An experiment: CMS



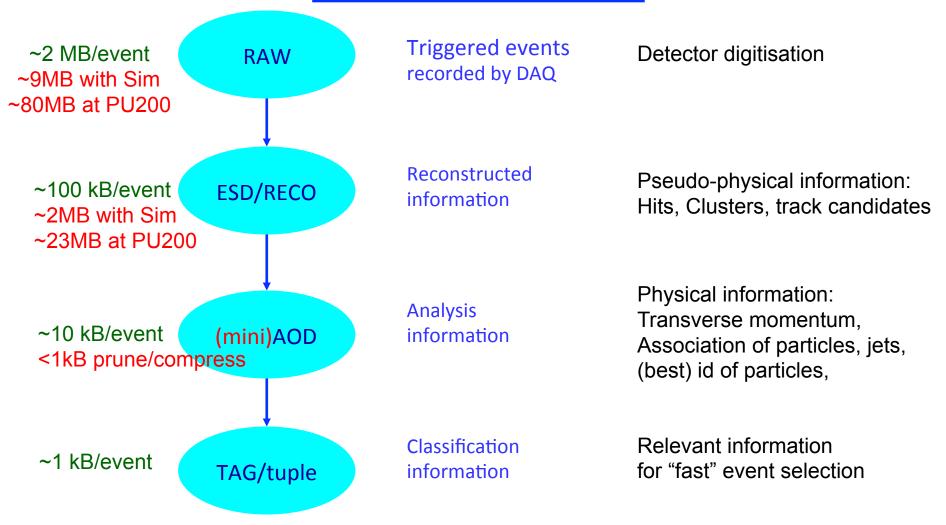


#### Toward 2023

- High Luminosity: proton collisions per bunch-crossing (PU) 40 -> 200
  - x5 more occupancy in detectors
  - Access to new corners of phase-space
    - High Mass, Boosted topologies
      - Dense environment
- New Detectors
  - New Tracker
    - Higher granularity (x4), extended coverage, hardware trigger capability
  - CMS: New High granularity Calorimeter
  - Timing information
- First Level Trigger
  - Include Tracking information
  - Output Rate up to 1MHz
- High Level Trigger
  - More use of tracking
  - Detailed analysis in search of new signals
  - Output Rate up to 10KHz
- Offline
  - Not just do as well as today but at PU 200
  - More precision to look for tiny signals of New Physics

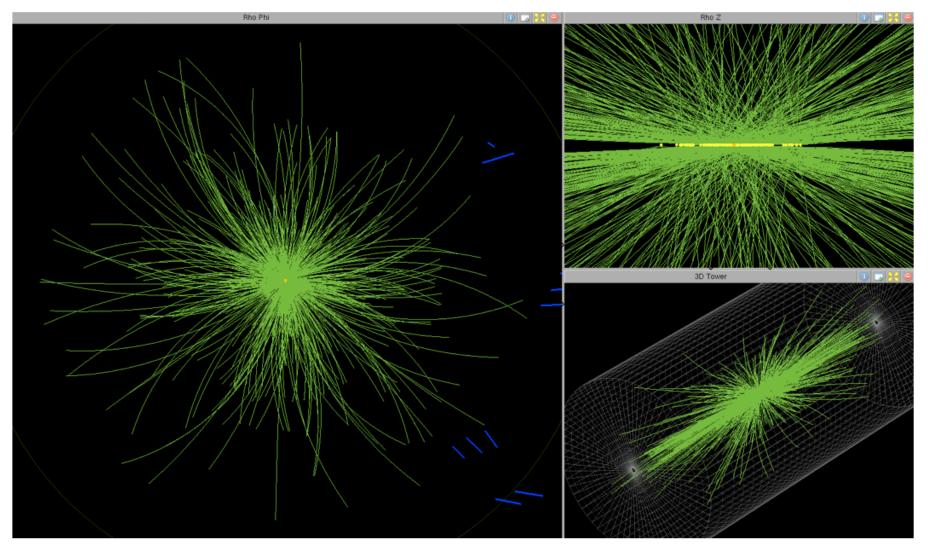
#### Data Hierarchy: Our solution to BigData

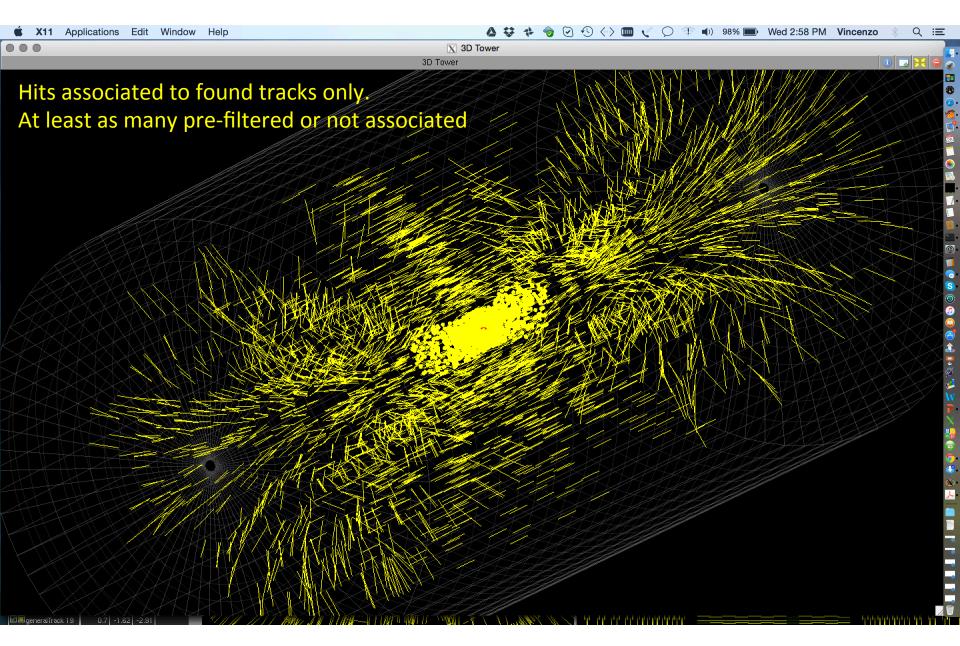
"RAW, ESD, AOD, TAG"



#### **Reconstruction of CMS Simulated Event**

tt event at <PU>=140 (94 vertices, 3494 tracks)

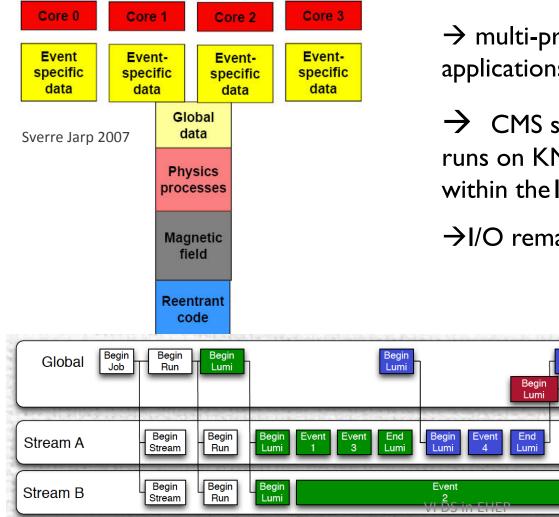




### Event parallelism

**Opportunity:** Reconstruction Memory-Footprint shows large condition data

How to share common data between different process?



 $\rightarrow$  multi-process and multi-thread applications are now in production

 $\rightarrow$  CMS simulation and reconstruction runs on KNL with 126 threads well within the 16GB of fast memory

End

Lumi

Event

Begin

Lumi

End

Lumi

End

Stream

End

Run

End

Run

End

Lumi

End

Lumi

Event

6

End

Run

End

Stream

End

Job

 $\rightarrow$ I/O remains a problem...

End

Lumi

Begin

Lumi

End

Lumi

#### Beyond event-level parallessm – Why?

- » We may endup with more core than events
- » Resources (shared access to memory, to disk) may be scarce
  - Typical example is a KNL used as a cluster of ~256 cpus
- Parallelize a DAG workflow is relatively easy including the management of a mild overcommit to mitigate starvation issues

Processing

Time

- » All concurrent framework implements it (or plan to implement it)
- » To work well it requires a reasonably balanced workflow:
  - a single long pipeline may easily defeat its purpose!
- » Iterative tracking is the most striking example of long pipeline (50% of reco time spent in it for CMS...)
- NB: up to this point data-processing is fully reproducible independently of the order of execution and granularity of concurrency

Output

# Outer loop parallelization

- Typically each processing module has an "outer loop" on its input collection
  - The most trivial concurrency model is to parallelize it
    - "For loop" parallelization is a well established practice
- In CMS proven to work "almost" out of the box for both seed and track building
  - Seed building is fully combinatorial, no reproducibility issues
  - Track building includes "cleaning passes" to remove already used hits
    - Introduces a sequential dependency and therefore an irreproducibility in case of parallel processing
- Current implementation
  - Avoid "cleaning" and pay the price

## In-Out parallelization

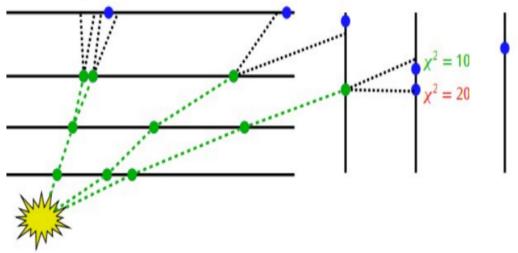
- Out-In parallelization will allow to overcome the limitation of traditional batch processing, exploiting new (heterogeneous) concurrent hardware (SIMD/SIMT) will require a completely new approach, most probably a full rethinking of algorithms, data structures and even of the workflow decomposition
- By definition SIMD/SIMT applies to the innermost loop
  - Either directly or by code transformation
- w/r/t multi-threading, effective concurrency is "broken" in SIMD/SIMT by pretty common patterns such as
  - Branch predication
  - Random memory access
  - Recursion
- SIMD/SIMT algorithms are fragile
  - Supporting a new use case (even adding some protections or a minor variant) may destroy
    efficient parallelism
  - Often better to duplicate code and/or to partition data and manage conditionals at a higher level (which is not necessarily a bad thing even in general!)
  - Runtime polymorphism is out-of-question: has to be managed outside.
- Mitigation strategies do exist, still for a full efficient use of these architectures a dedicated, specialized software effort is required
  - Think parallel
  - Think local

### Making the code SIMD/SIMT friendly

- Several "success stories" in CMS: pattern very similar
  - Transform storage representation in algorithm specific data
    - SOA to AOS, variable transformation, sorting, filtering, re-indexing etc
  - Move all constant components outside
  - Devirtualize, Use explicit RTTI, inline
    - Move from generic to specific
    - Limit the number of use-cases to the few known
  - Make functions to act on collections not on single objects
- The net effect is a significant speed up just from such code transformation
  - In many cases vectorization itself adds little
    - Short inner loops
    - Little computations
    - Branch predication

# Traditional track building

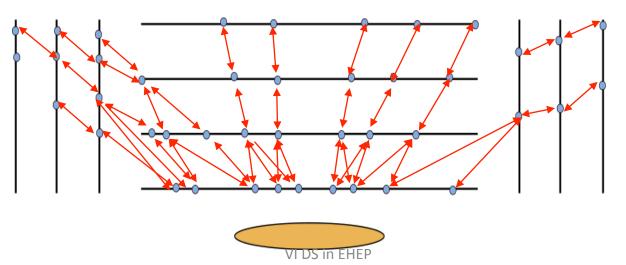
- 1. Build doublets
- 2. "Propagate" doublets to third layer and search for compatible hits (open search window on target layer)
- 3. Propagate 1-2-3 triplet to 4th layer and search for compatible hits



Highly divergent code, optimized to bail out asap. Easy to parallelize "Outermost Loop", amost impossible to vectorize

### Cellular Automaton (CA)

- The CA is a track seeding algorithm designed for parallel architectures
- It requires a list of layers and their pairings
  - A graph of all the possible connections between layers is created
  - Doublets aka Cells are created for each pair of layers (compatible with a region hypothesis)
    - Doublet building identical to traditional approach
  - "Connect" cells that share hit
  - Fast computation of the compatibility between two connected cells
    - Vectorized loop of floating point operations
  - No knowledge of the world outside adjacent neighboring cells required, making it easy to parallelize



#### **Current Performance**

 Plan to use Cellular Automaton in its sequential implementation at the HLT already in 2017

Algorithm	time per event [ms]
Traditional Triplets	29
Traditional Quadruplets	72
CPU Cellular Automaton	14
GPU Cellular Automaton	1.2

On GPU CA is Memory-Bandwidth limited (on CPU as well...)

Hardware: Intel Core i7-4771@3.5GHz , NVIDIA GTX 1080

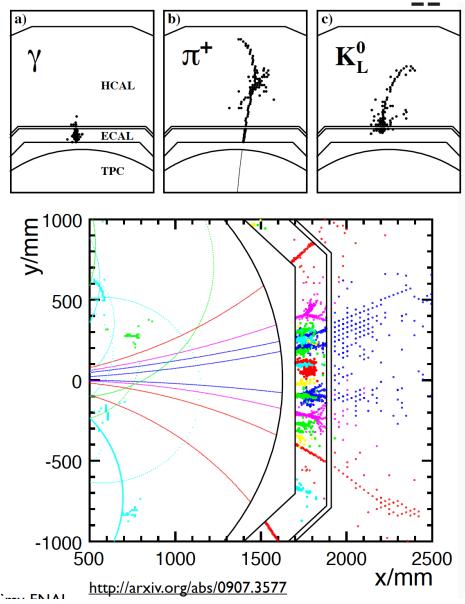
# The dream of every experimental HEP Physicist:

Identify and measure each single particle produced in a collision

This may need high resolution calorimetry that will compete with trackers in complexity and data volume

Still, using current data-processing approach, most of this information will reach the physicists only in a very condensed form

Difficult to estimate the real impact of such a detector on physics analysis w/o a new data-processing paradigm



## **Big Question**

- Can a "new" Paradigm make the difference?
  - Artificial Intelligence
    - Used already for classification
  - Dedicated Specialized Hardware
    - In use in First Level Trigger since ever
      - CMS Track trigger demonstrated with latency < 4us</li>
  - Smart data mining
    - Analysis currently limited to a single data-tier level

### CMS simulation & data processing Software "Legacy"

- ~10k "modules"
- ~1000 "data processing" modules
- Code (SLOC)
  - C++: 3,558,032 (68.86%)
  - python: 1,240,801 (24.02%)
    - Used only in initialization
  - fortran: 277,857 (5.38%)
    - Interface to physics simulation code
- Total size of TEXT sections : 229,246,680 bytes
  - + ~220MB of "external software"

# Conclusions

- Free lunch is over
  - To improve the efficiency of software we need to increase the granularity of parallelism, optimize data access patterns and make use of heterogeneous resources
- Waiting for the definitive standard to emerge we need to develop our own infrastructure to support the implementation of concurrent algorithms able to exploit parallelism on heterogeneous hardware
- Recent work shows that
  - An efficient concurrent schedule of algorithms is feasible
  - With huge effort it is possible to make current algorithm implementations free from data-race (thread safe)
  - Making use of parallelism in algorithms requires a total reimplementation
- More R&D is required to tackle the challenges of
  - Exploiting heterogeneity
  - Efficient parallelize algorithms
  - Efficient utilization of memory hierarchy
  - Efficient utilization of the few developers left

#### BACKUP

The real issue: maximize throughput Theoretical peak throughput: the maximum amount of data that a kernel can read and produce in the unit time.

Throughput<sub>peak</sub> (GB/s) = 2 x access width (byte) x mem\_freq (GHz)

This means that if your device comes with a memory clock rate of 3GHz DDR (double data rate) and a 384-bit wide memory interface, the amount of data that a kernel can process and produce in the unit time is at most:

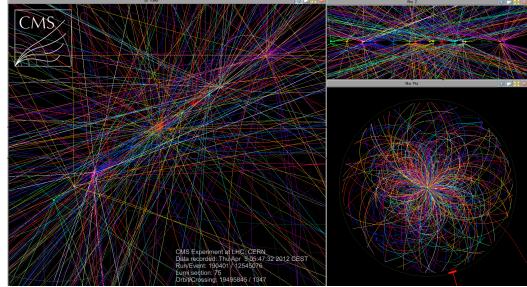
Throughput<sub>peak</sub> (GB/s) =  $2 \times (384/8)$ (byte) x 3 (GHz) = **288 GB/s** 

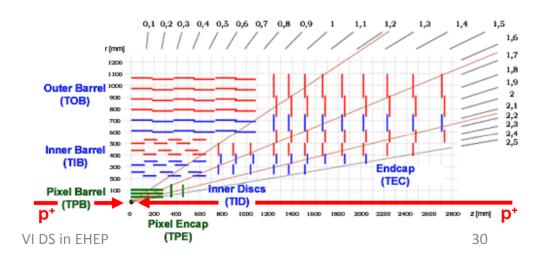
### Consequence: cpu starvation!

- NVIDIA TESLA Kepler K40:
  - 1.4 TFLOPS DPFP peak throughput
  - 288 GB/s peak off-chip memory access bandwidth
     36 G DPFP operands per second
- In order to achieve peak throughput, a program must perform 1,400/36 = ~39 DPFP arithmetic operations for each operand value fetched from off-chip memory
  - In most of current code is **0.5** (fetch two operands, never use them again)!

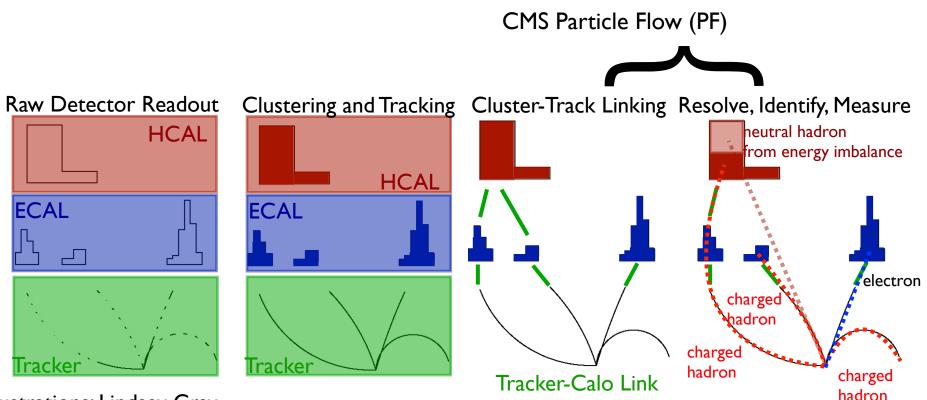
# Tracking at CMS

- Particles produced in the collisions leave traces (hits) as they fly through the detector
- The innermost detector of CMS is called **Tracker**
- **Tracking**: the art of associate each hit to the particle that left it
- The collection of all the hits left by the same particle in the tracker along with some additional information (e.g. momentum, charge) defines a track
- **Pile-up**: # of p-p collisions per bunch crossing





#### **Reconstructing Jet Constituents**

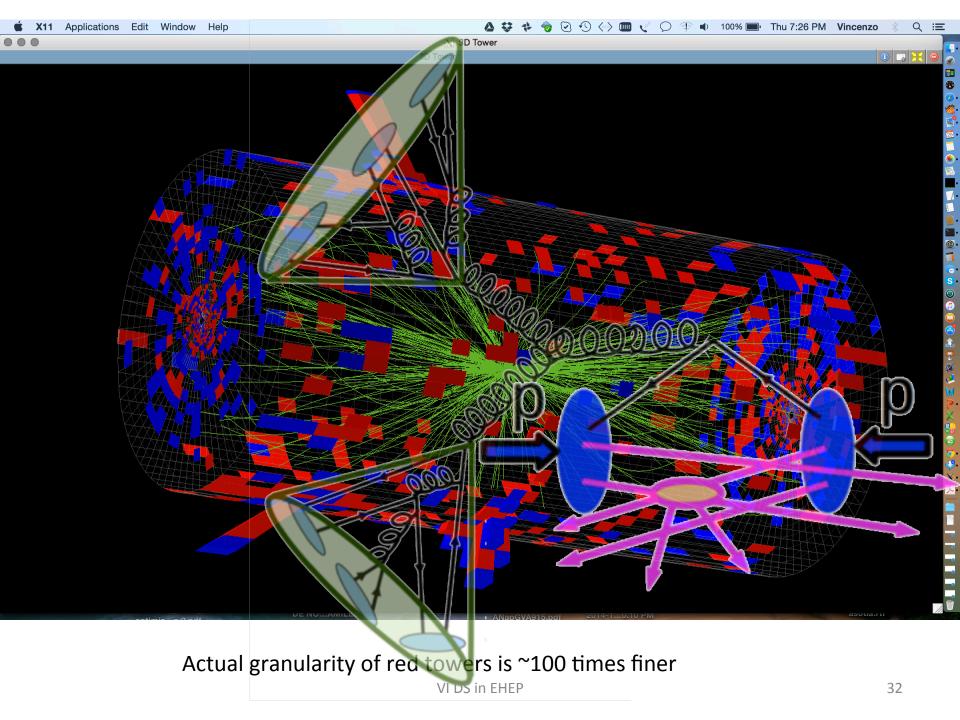


Illustrations: Lindsey Gray

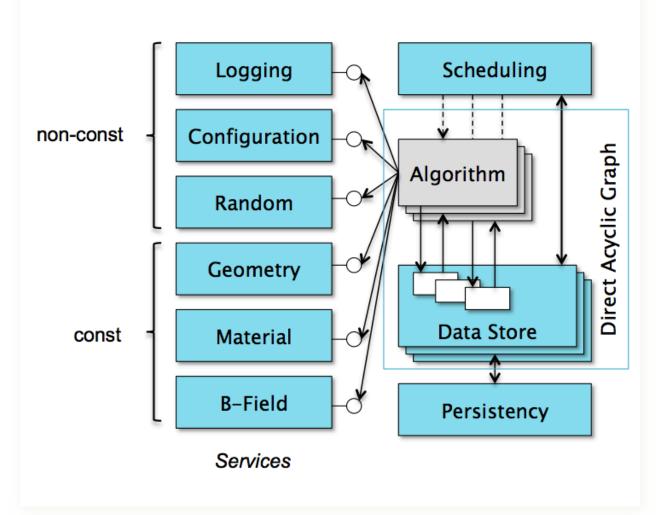
Non trivial regression to compute best estimation of particle energy combining all available information taking into account non-uniformity in detector response

Based on intensive, iterative statistical analysis of data themselves to extract alignment and calibration constants

VI DS in EHEP



## **HEP Applications**



Algorithms read and write from/to the event-data store and the "services"

Only interfaces are defined (with no "cost" associated)

Algorithms are in turn based on a large set of utilities and foundation libraries

## A real application (LHCb Brunel)

