

ALICE

S<sub>QFT</sub>



# Vectorizing the detector geometry to optimize particle transport

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A.Gheata, S.Wenzel**

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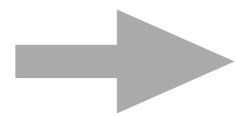


# Motivation

Explore possibilities to recast particle simulation so that it takes advantage from all performance dimensions/technologies

- Geometry navigation takes a large part of the particle transport budget (40-60% in ALICE)

## **Dimension 1 (“sharing data”) : multithreading/multicore**



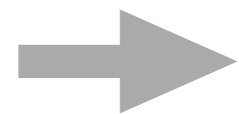
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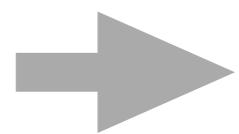
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Currently not exploited because requires “parallel data” to work on

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Research projects: GPU prototype , Simulation Vector Prototype (**talk from F. Carminati on Thursday**) have started targeting beyond dimension 1

**parallel data (“baskets”) = particles from different events grouped by logical volumes**

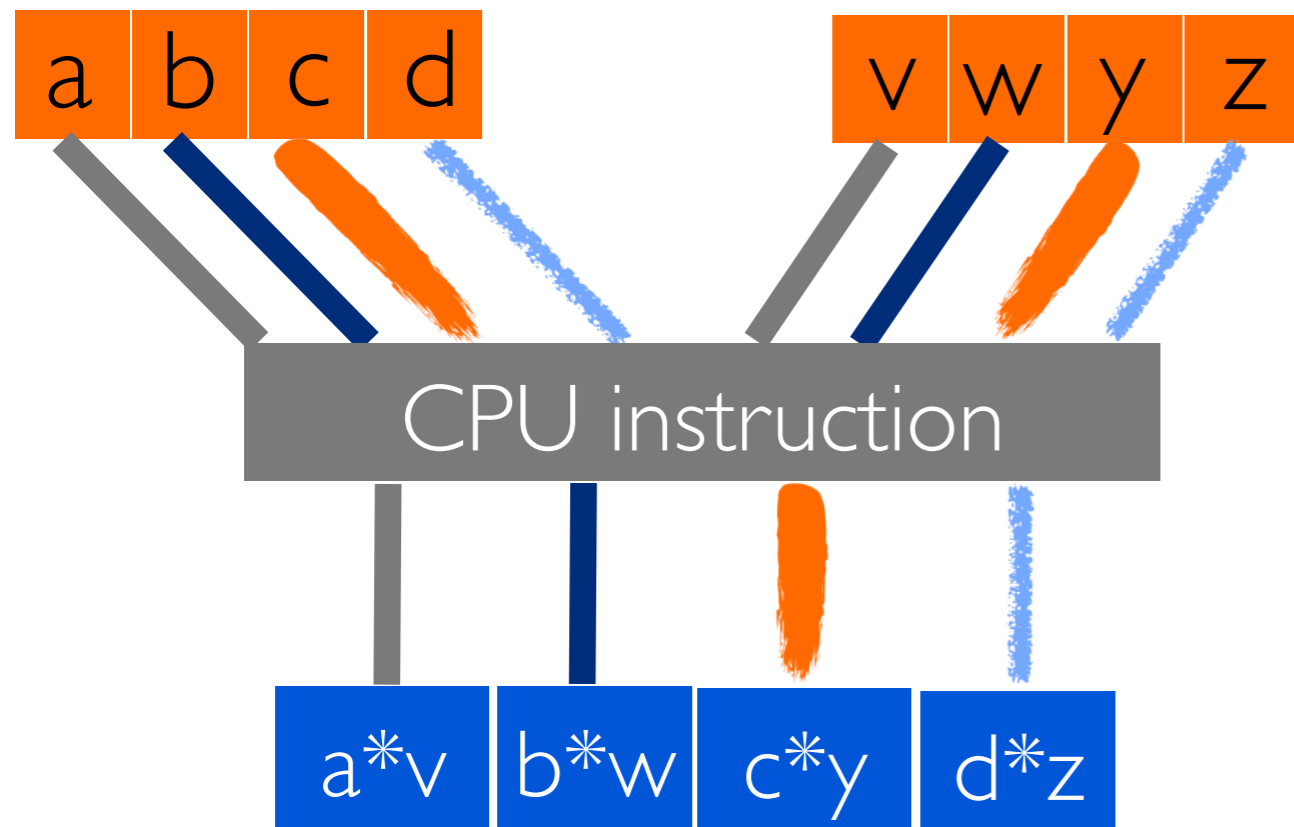
# Reminder of vector micro-parallelism

- Commodity processors have **vector registers** on whose components (single) instruction can be performed in parallel (**micro-parallelism**)

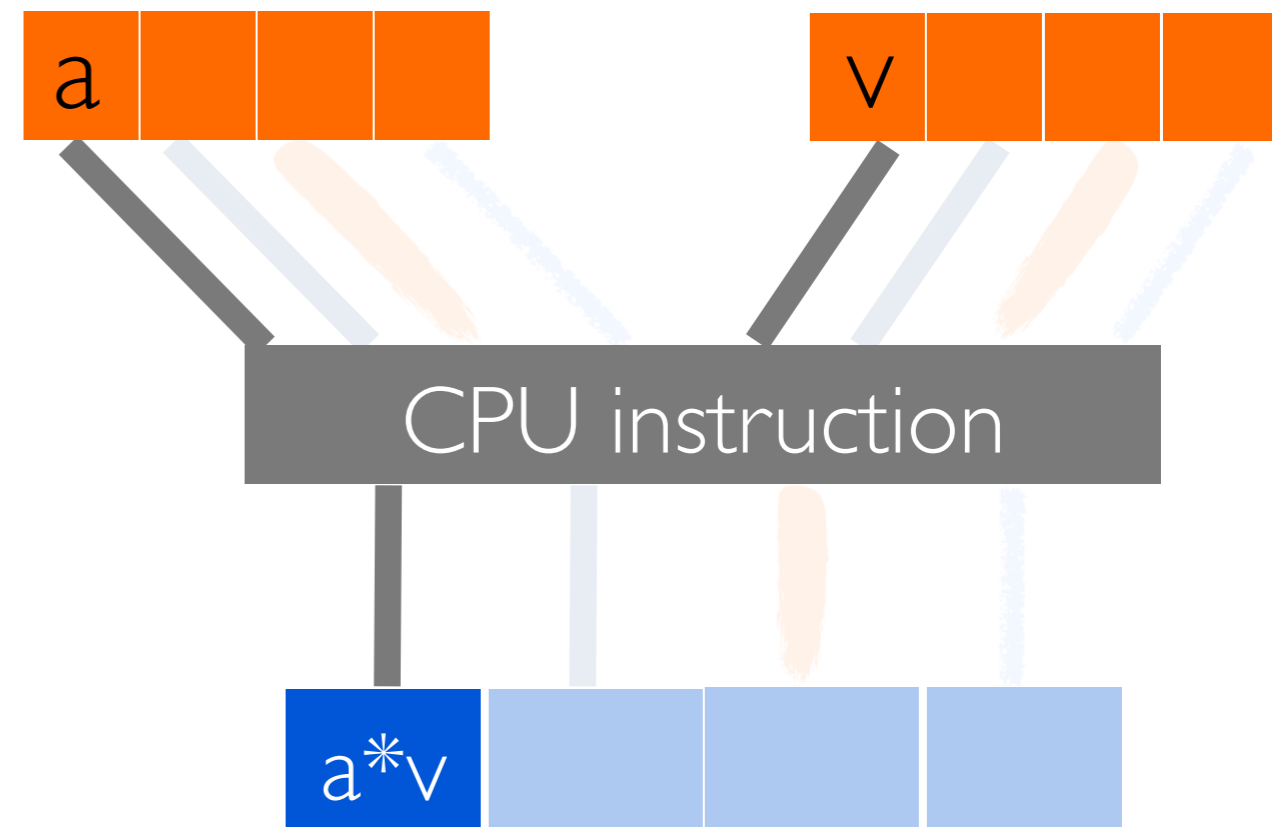
single instruction multiple data = SIMD

\* Examples of SIMD architectures: MMX, SSE, AVX, ...

**optimal usage** (vector registers full)

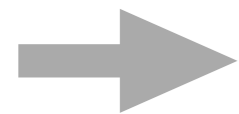


**current usage** (3/4 empty for AVX)

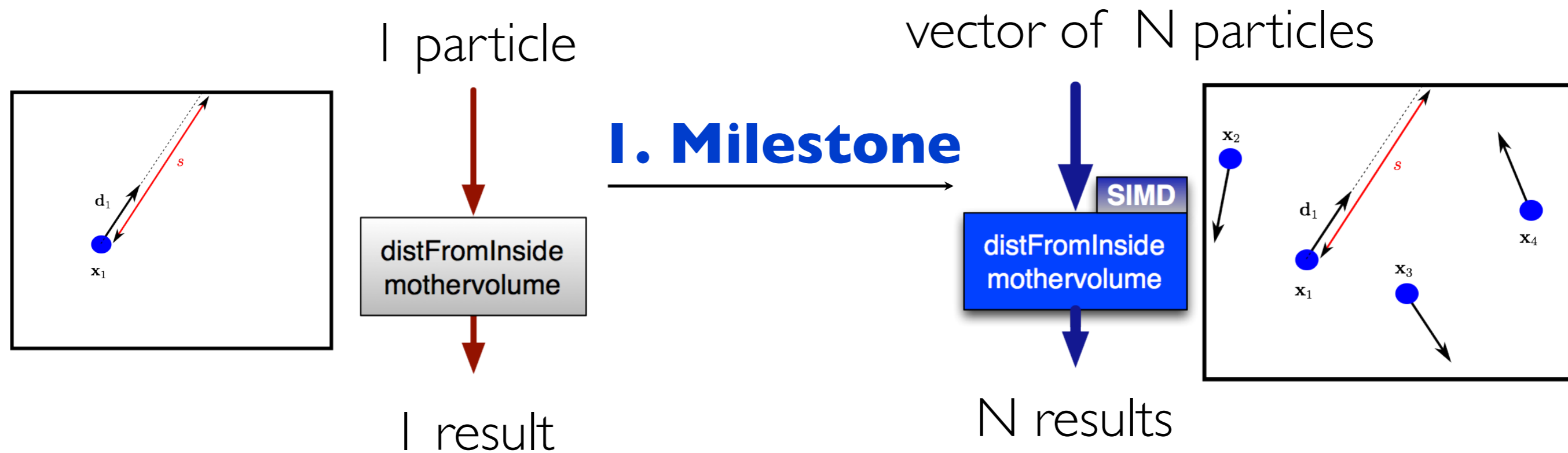


losing factors...

# 1st Goal: Vector processing for a single solid



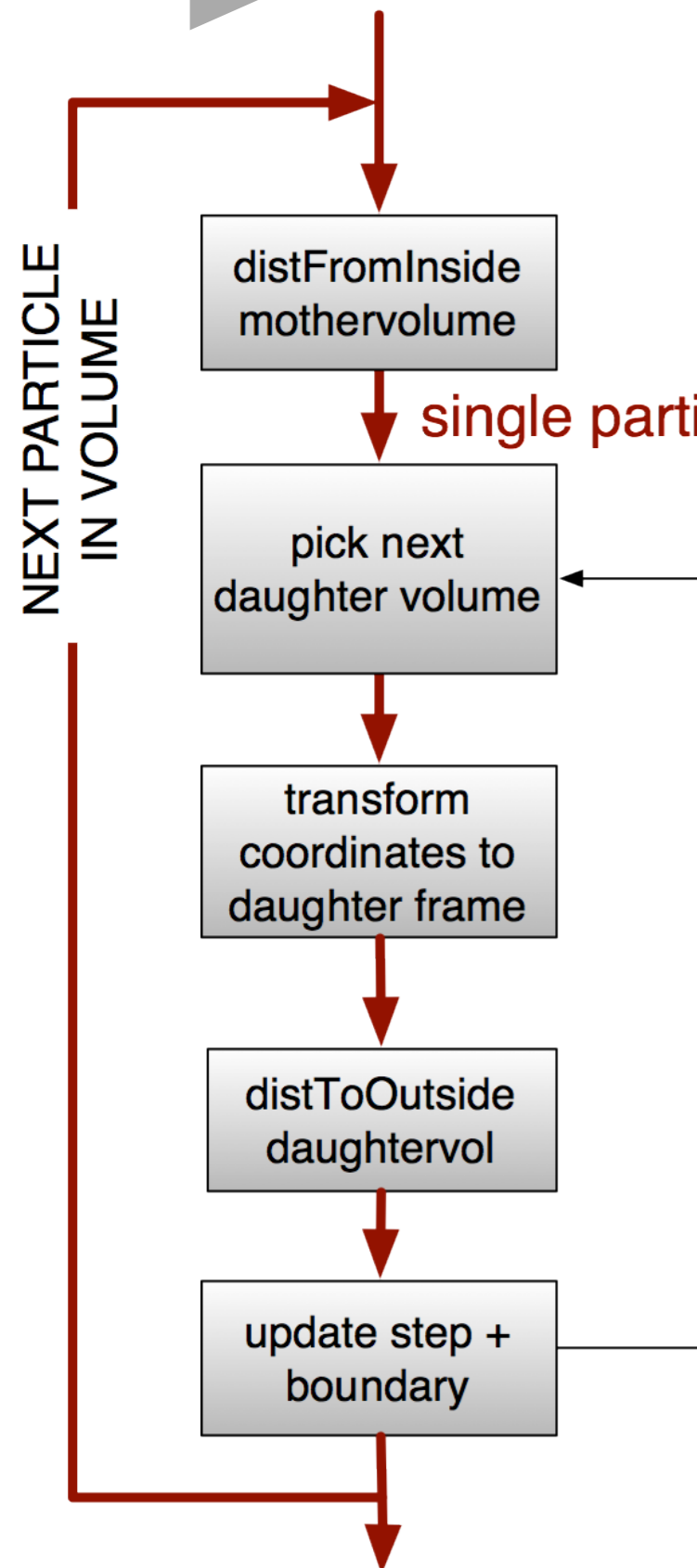
Goal: Enable geometry components to process baskets/vectors of data and study performance opportunities



- Provide **new interfaces** to process vectors in basic geometry algorithms
- Make efficient use of baskets and try to use SIMD vector instructions wherever possible (**throughput optimization**)

# 2nd goal: vector processing within a volume

Scalar (simple) navigation versus vector navigation



Each particle undergoes a series of basic algorithms (with outer loop over particles)





# The programming model

In order to use SIMD CPU capabilities, need to provide special assembly instructions (e.g. “vaddp” versus “add”) to the hardware. Multiple options exist:

- **“Autovectorization”**: Let the compiler figure this out himself (without code changes).  
Pro: best option for portability and maintenance  
Cons: This seldom works ( but in a few cases )....
- **Explicit vector oriented programming via intrinsics**: Manually instruct the compiler to use vector instructions:
  - At the lowest level: *intrinsics*, assembler code, hard to write/read/maintain
  - At higher level: template based APIs that hide low level details like the **Vc library**  
Pro: good performance, portability, only little platform dependency (templates!)  
Cons: requires some code changes, refactoring of code
- **Language extensions**, such as Intel Cilk Plus Array notation
  - Similar to point 2, investigated but not covered in this talk

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Cons: requires some code changes, refactoring of code [code.compeng.uni-frankfurt.de/projects/Vc](http://code.compeng.uni-frankfurt.de/projects/Vc)

- **Language extensions**, such as Intel Cilk Plus Array notation
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# Status of simple shape/algorithm investigations

Provided vector interfaces to all shapes and optimized code to simple ROOT shapes

- **“DistFromInside”, “DistFromOutside”, “Safety”, “Contains”**
- good experience and results using the Vc programming model

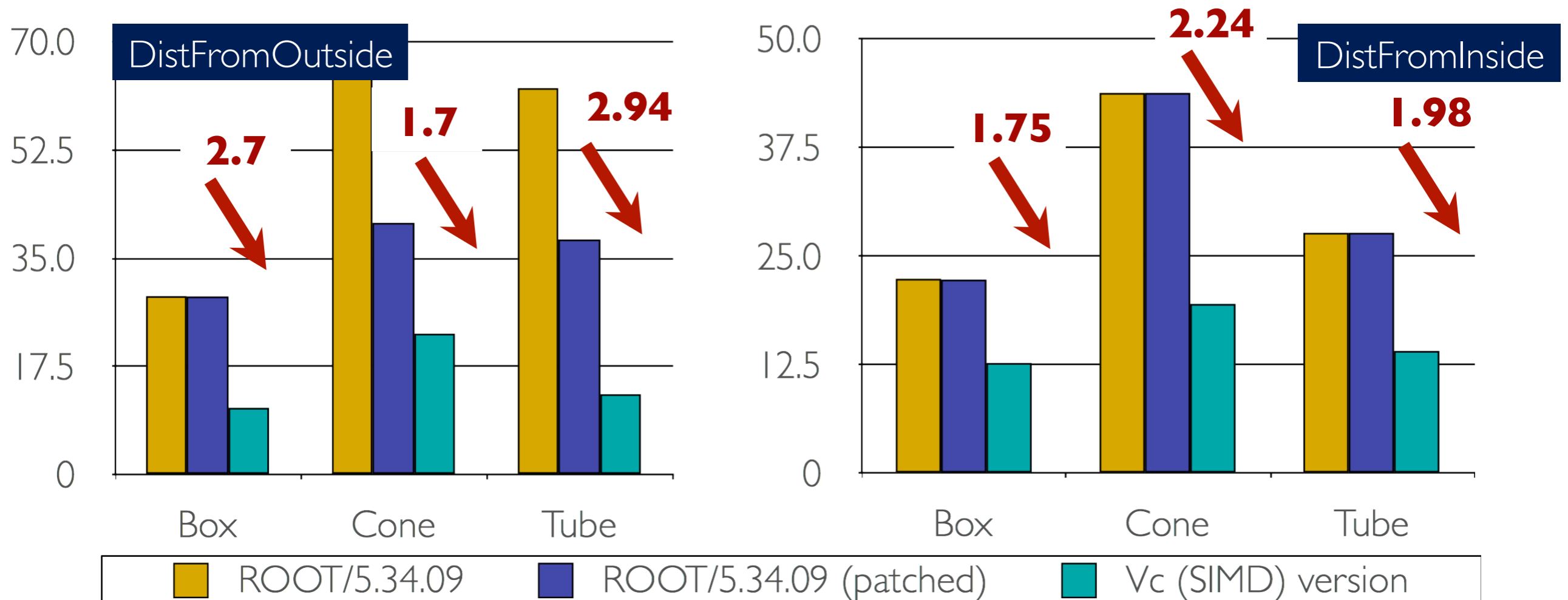
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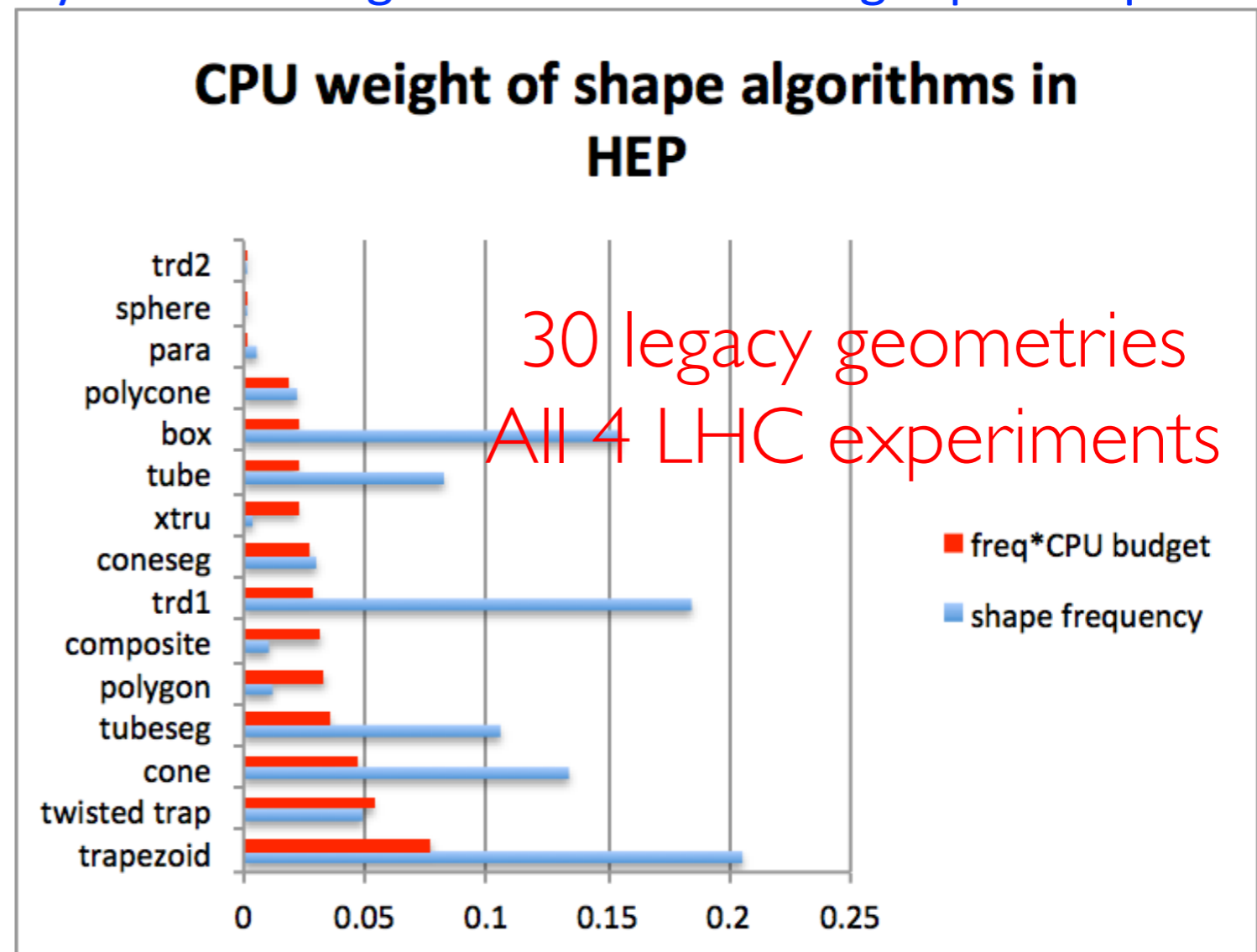


comparison of processing times for 1024 particles (AVX instructions), times in microseconds

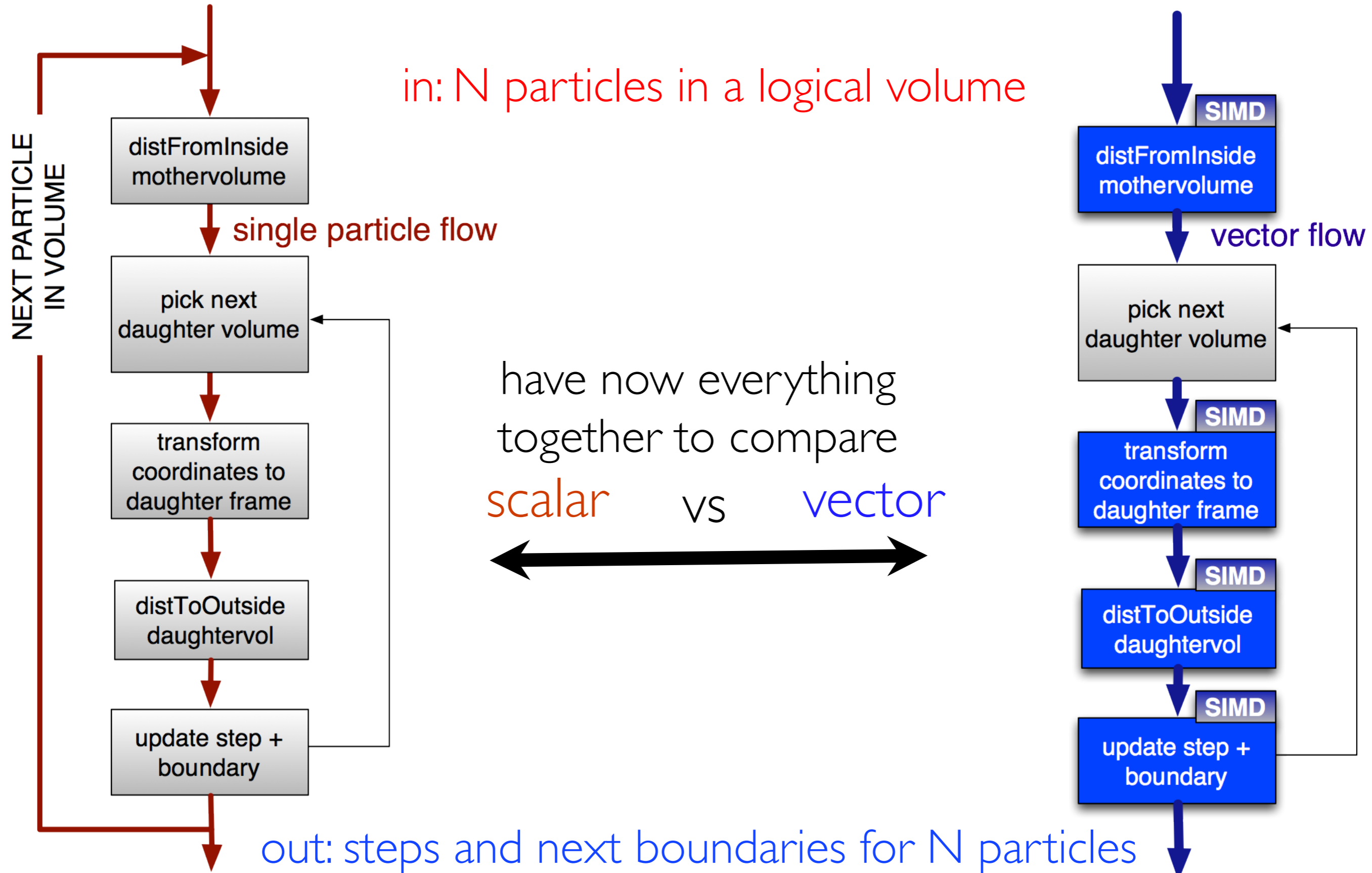
# CPU budget – some first estimate

- A lot of work still to do in SIMD-optimizing more complicated shapes; preliminary results available for Polycone (backup)
  - Evaluate “CPU budget” per shape type
  - First estimate: shape frequency times average estimate CPU budget per shape

- Besides shapes, vector-optimize other simple algorithmic blocks:
  - coordinate and vector transformations (“master-to-local”)
  - min, max algorithms, ...

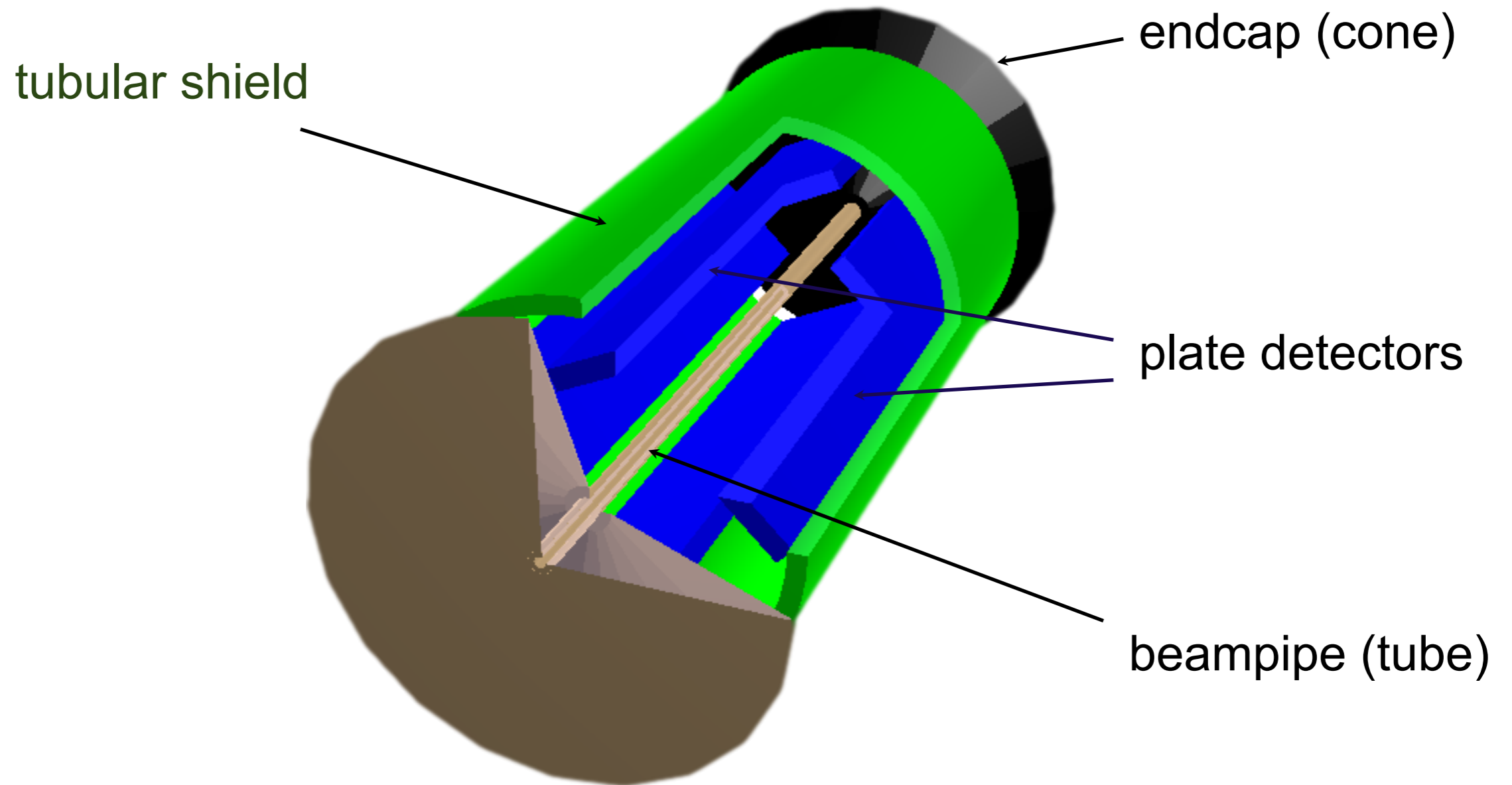


# Benchmarking the Vector Navigation



# Testing a simple navigation algorithm

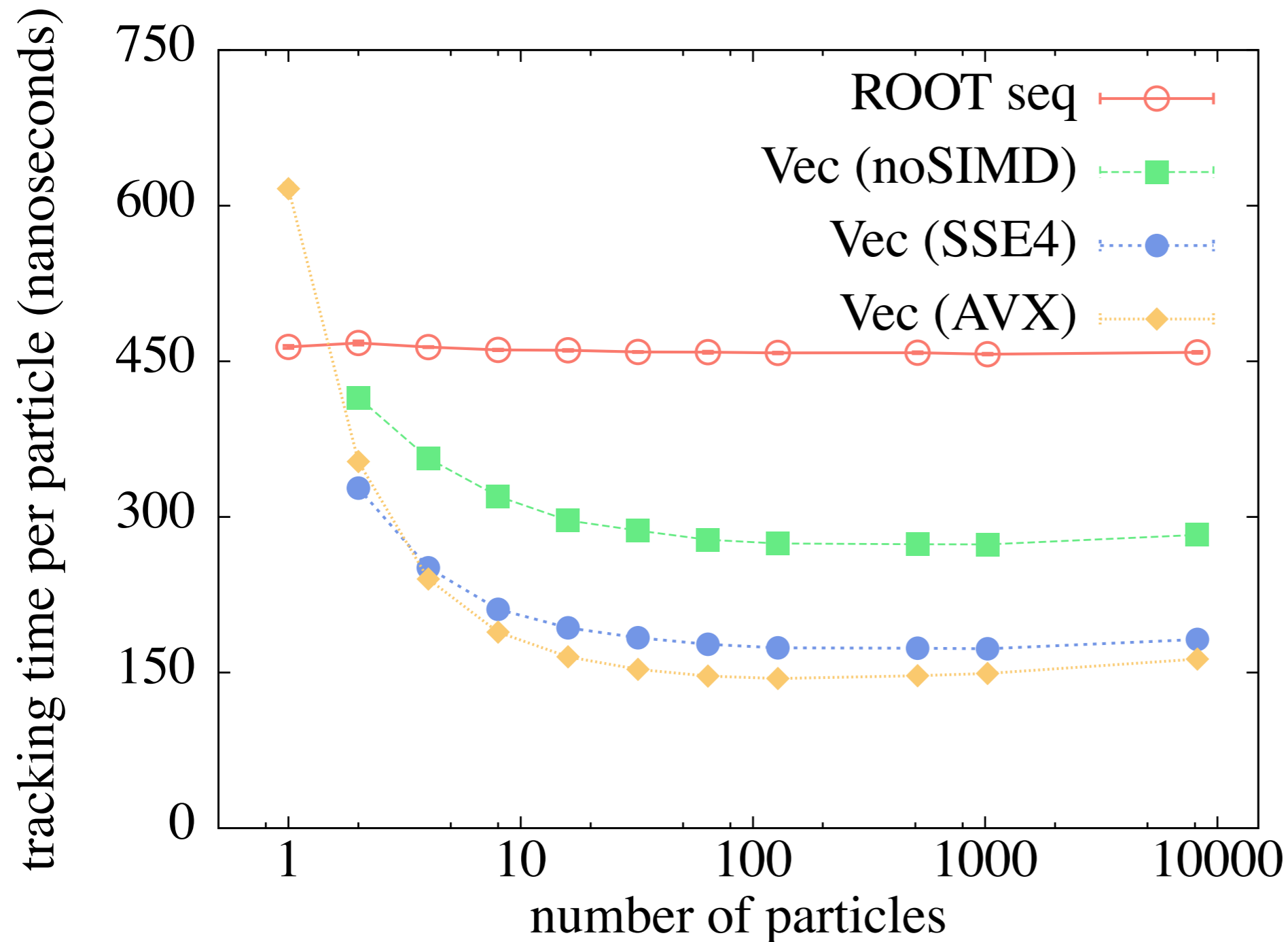
Implemented a toy detector for a benchmark: 2 tubes, 4 plate detectors, 2 endcaps (cones), 1 tubular mother volume



Logical volume filled with test particle pool (random position and random direction) from which we use a subset  $N$  for benchmarks ( $P$  repetitions)

# Results from Benchmark: Overall Runtime

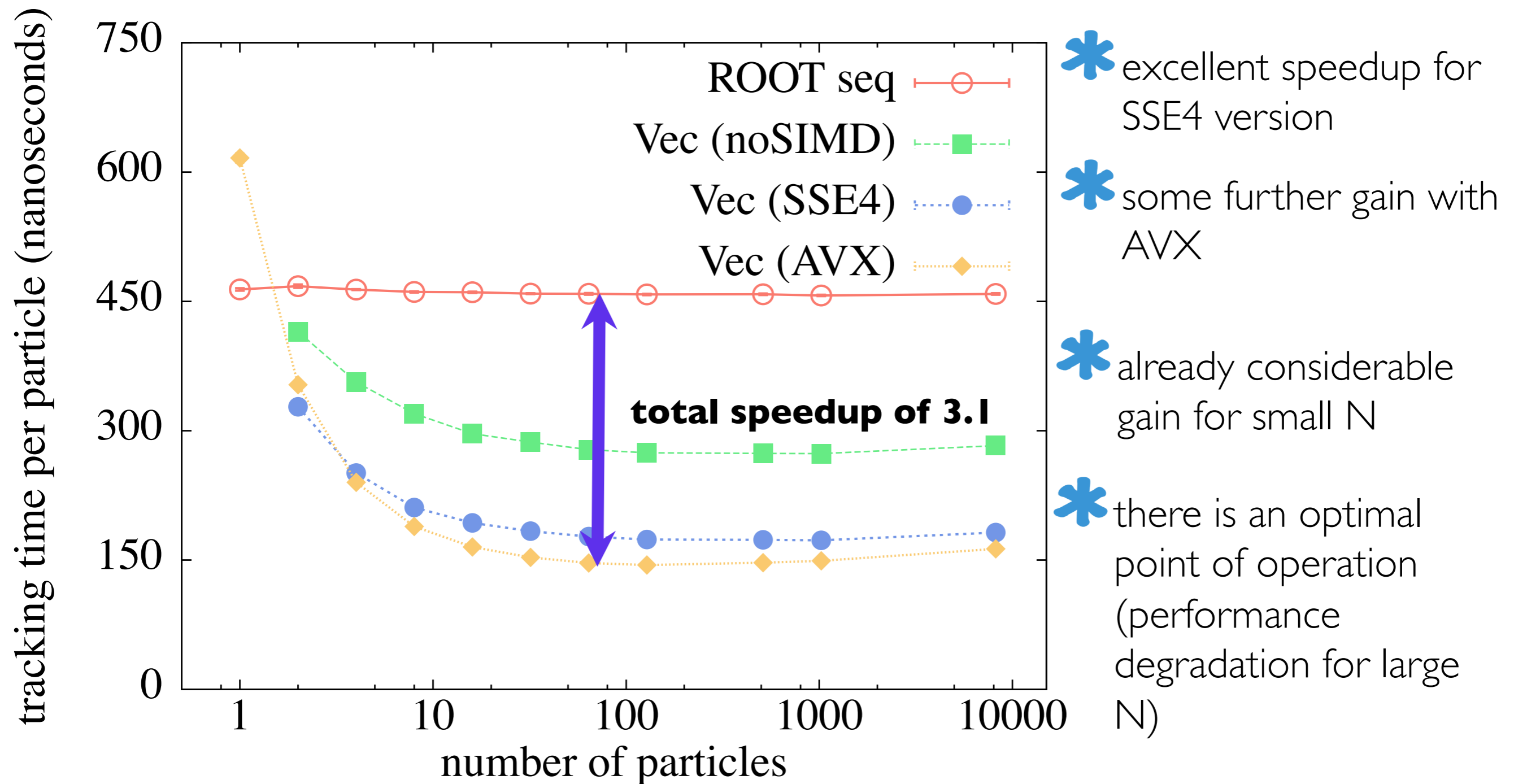
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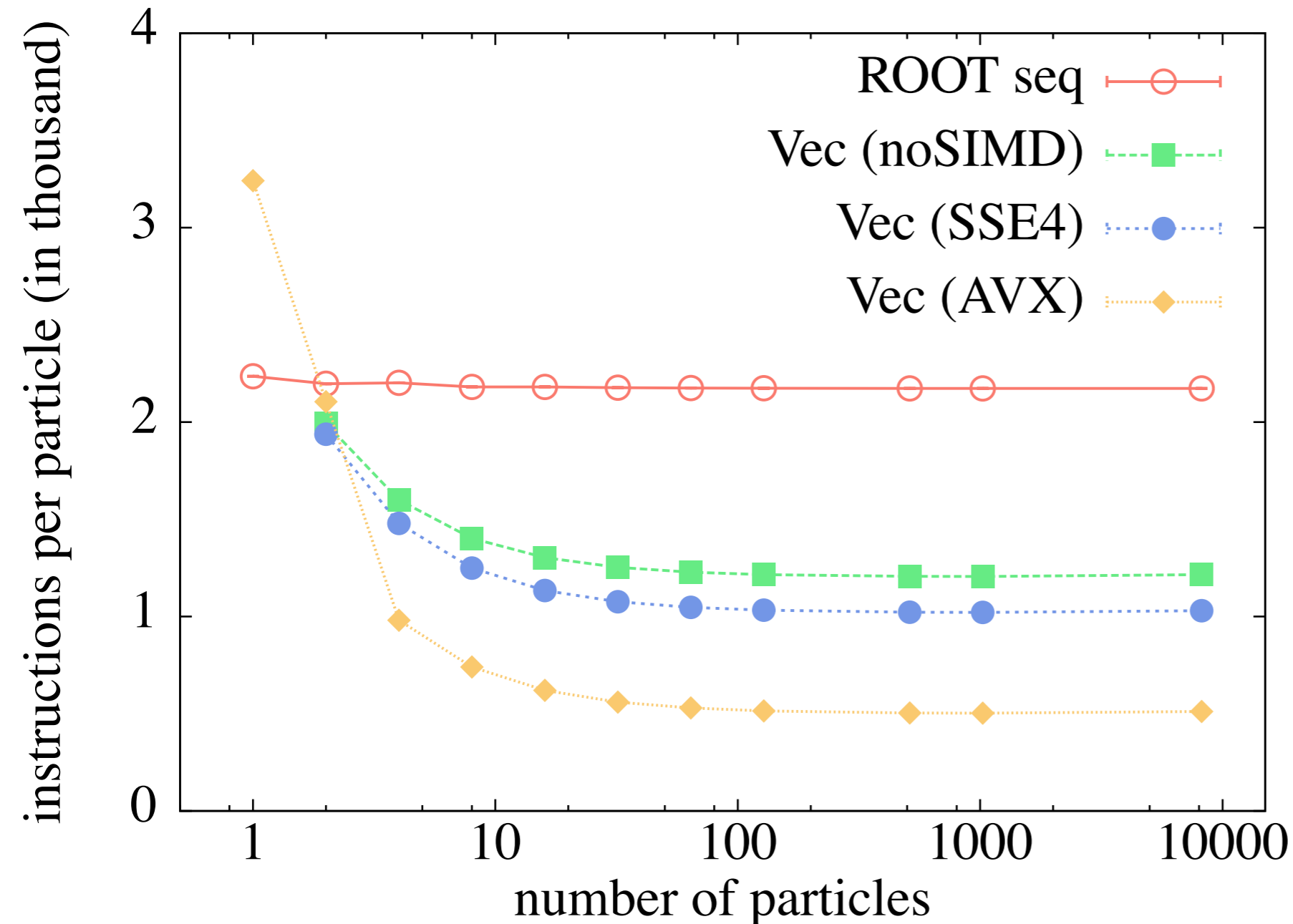
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# Further Metrics: Executed Instructions

- investigate origin of speedup: study **hardware performance counters**
- developed a “timer” based approach where we read out counter before and after an arbitrary code section ( using libpfm )

\* gain mainly **due to fewer instructions**  
(for the same work)

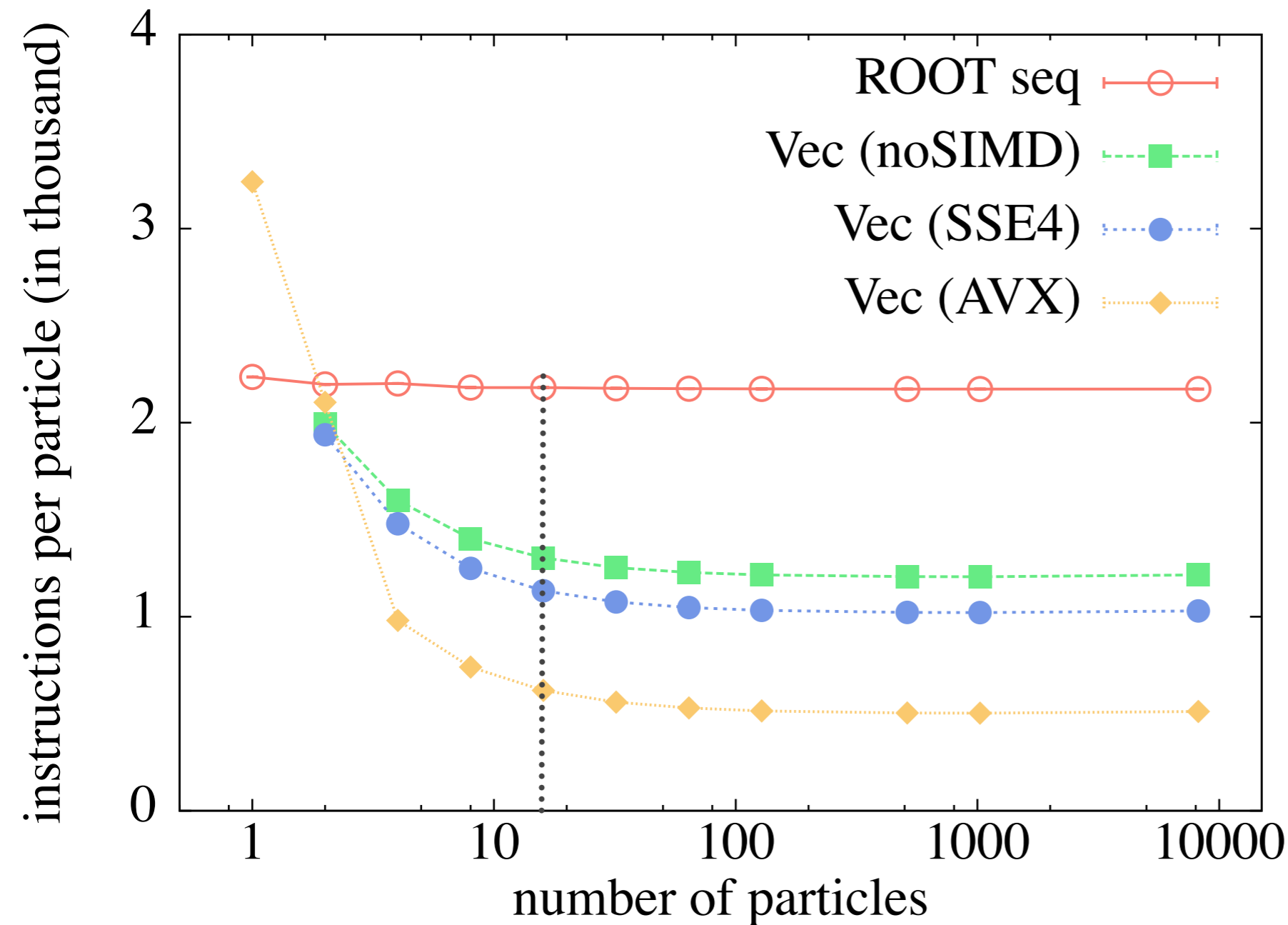


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\* detailed analysis (binary instrumentation) can give statistics, e.g.:

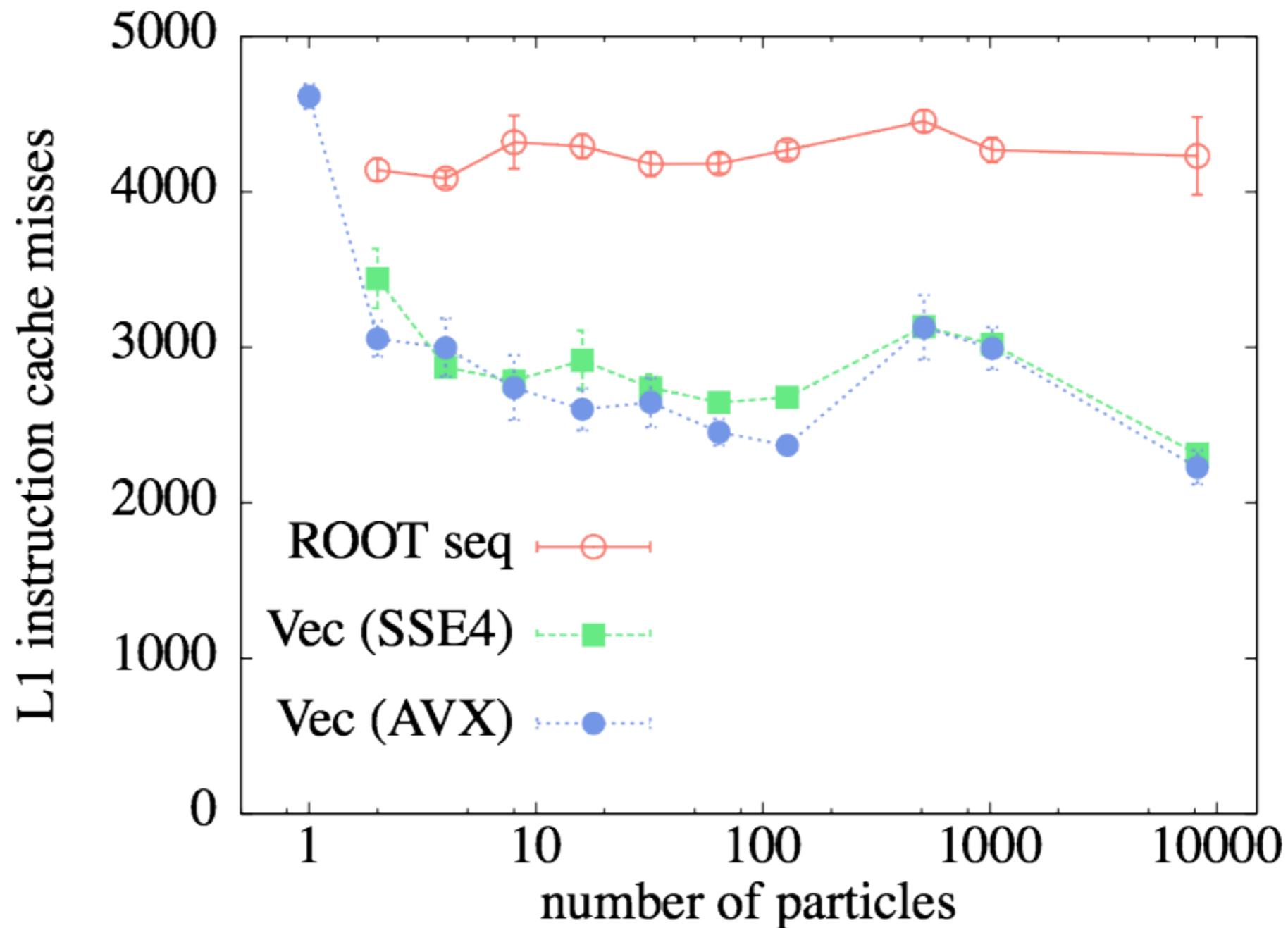


	<b>ROOT</b>	<b>Vec</b>
ALL	17.5 mil	5 mil
MOV	30%	16%
CALL	4%	0.4%
V..PD (SIMD)	4%	<b>57%</b>

comparison for N=16 particles (AVX versus ROOT seq)

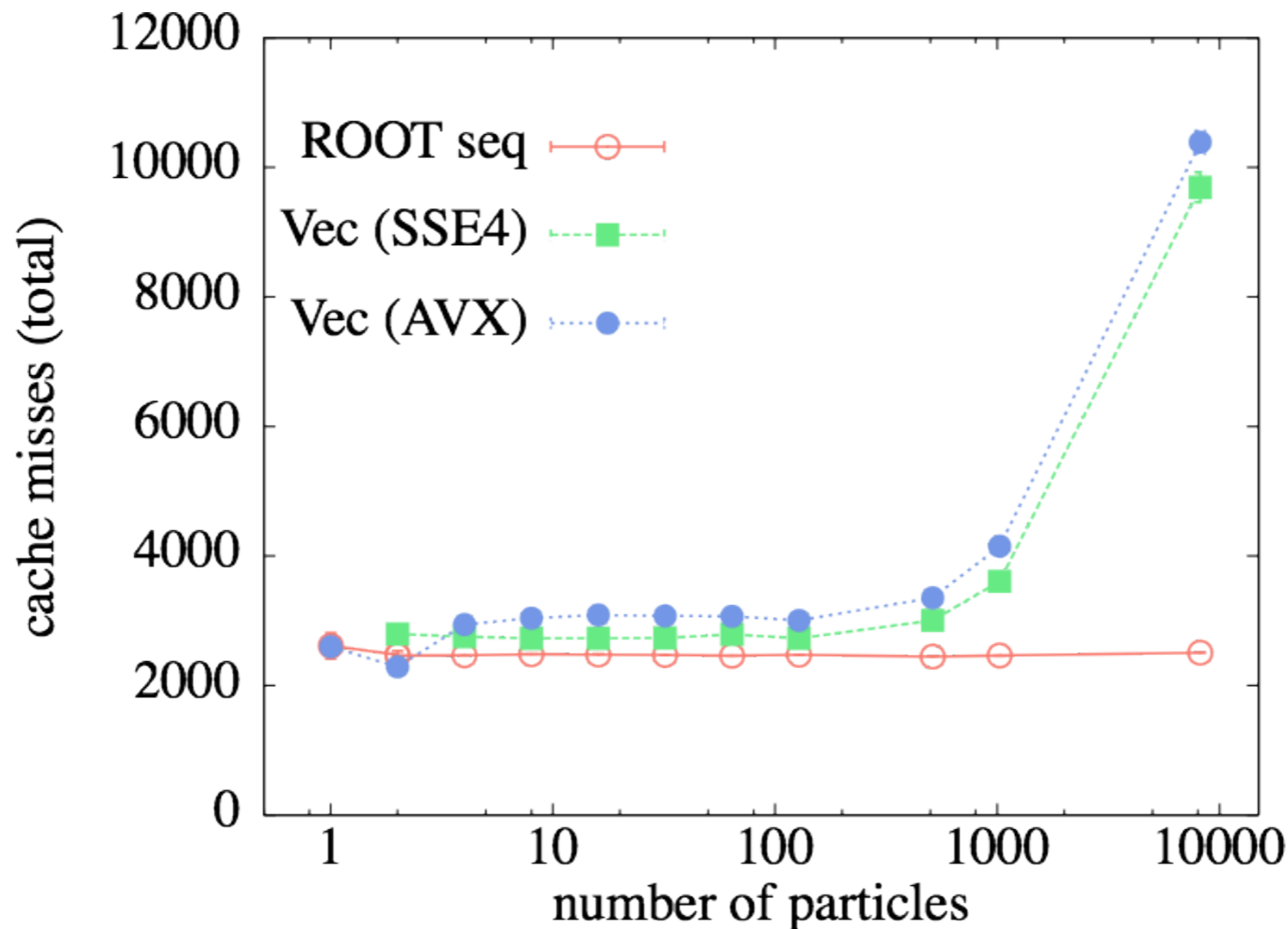
# Further Metrics: L1 instruction cache misses

- Better code locality, expected to have more impact when navigation itself is embedded in more complex environment.



# Further Metrics: total cache misses

- More data cache misses for large number of particles, can degrade performance
  - likely due to structure-of-array usage in vector
- Realistic N that can be scheduled is an important parameter



# Summary / Outlook

- \* Vectorization is not threading and needs special efforts
- \* A vector/basket architecture allows to make use of SIMD but also increases locality (less functions calls, more instruction cache friendly)
- \* Provided a first refactored vector API in ROOT geometry/navigation library and showed good performance gains for individual as well as combined algorithms on commodity hardware
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## Outlook

- more complex shapes and algorithms ( voxelization ), USolids ...
- **full flow of vectors in Geant-V prototype** (vectorisation gains vs. scatter-gather overhead)
- Gains on accelerators (GPUs, Intel Phi, ...) using vectorized code

# Acknowledgements

## \* contributors to basic Vc coding:

- Juan Valles (CERN summer student)
- Marilena Bandieramonte (University of Catania, Italy)
- Raman Sehgal (BARC, India)

## \* help performance analysis / investigation of Intel Cilk Plus Array Notation:

- Laurent Duhem (Intel)
- CERN Openlab



Backup slides

# Notes on benchmark conditions

- System: Ivybridge iCore7 (4 core, not hyperthreaded (can read out 8 hardware performance counters))
- Compiler: gcc4.7.2 ( compile flags -O2 -unroll-loops -ffast-math -mavx)
- OS: slc6
- Vc version: 0.73
- benchmarks usually run on empty system with cpu pinning (taskset -c )
- \* benchmarks use preallocated pool of test data, in which we take out N particles for processing. Repeat this P times. For repetitions distinguish between random access of N particles (higher cache impact) or sequential access in data pool (as shown here)
- \* benchmarks shown use  $N \times P = \text{const}$  to time an overall similar amount of work

## Backup: A need for tools...

- converting code for data parallelism can be a pain ... (see challenges)
- would be nice to have better tool support for this task, helping at least with often recurring work

### A possible direction:

- \* **source-to-source transformations** (preprocessing)
  - provide trivial vectorized code version of a function
  - unroll inner loops, rewrite early returns, ...
  - Clang/LLVM API very promising for this ... currently investigating

Some tools go into this direction:

- Scout (TU Dresden ): Can take code within a loop and **emit intrinsics** code for all kinds of architectures

- could be used in situations where the compiler does not autovectorize



# Example of Vc programming

```
void foo(double const *a,  
         double const *b,  
         double * out, int np){  
    for(int i=0;i<np;i++){  
        out[i]=b[i]*(a[i]+b[i]);  
    }  
}
```

\* example in plain C

- although simple and data parallel (probably) does not vectorize without further hints to the compiler (“restrict”)

\* example in Vc

- restructuring the loop stride
- explicit inner vector declaration
- always vectorizes (no other hints necessary)
- architecture independent because `Vc::double_v::Size` is template constant determined at compile time
- portable
- branches/masks supported

```
void foo(double const *a,  
         double const *b,  
         double * out, int np){  
    for(int i=0;i<np;i+=Vc::double_v::Size)  
    {  
        // fetch chunk of data into Vc vector  
        Vc::double_v a_v(&a[i]);  
        Vc::double_v b_v(&b[i]);  
  
        // computation just as before  
        b_v = b_v*(a_v + b_v);  
  
        // store back result into output array  
        b_v.store( &out[i] );  
    }  
    // tail part of loop has to follow  
}
```

# Example with Intel Cilk Plus Array Notation

- \* Intel Cilk Plus Array Notation indicates to the compiler operations on parallel data and leads to better autovectorization
- \* Programming can be similar to Vc (but with seemingly more code bloat at the moment) -- somewhat constructed example ( is possible in easier manner as well )
- \* working with small vectors of VecSize wanted because allows for “early returns”, finer control

```
// CEAN example
void foo(double const * a,
         double const *b,
         double * out, int np)
{
    int const VecSize=4;
    for(int i=0;i<np;i+=VecSize)
    {
        // cast input as fixed size vector
        double const (*av)[VecSize] = (double const (*)[VecSize]) &a[i];
        double const (*bv)[VecSize] = (double const (*)[VecSize]) &b[i];

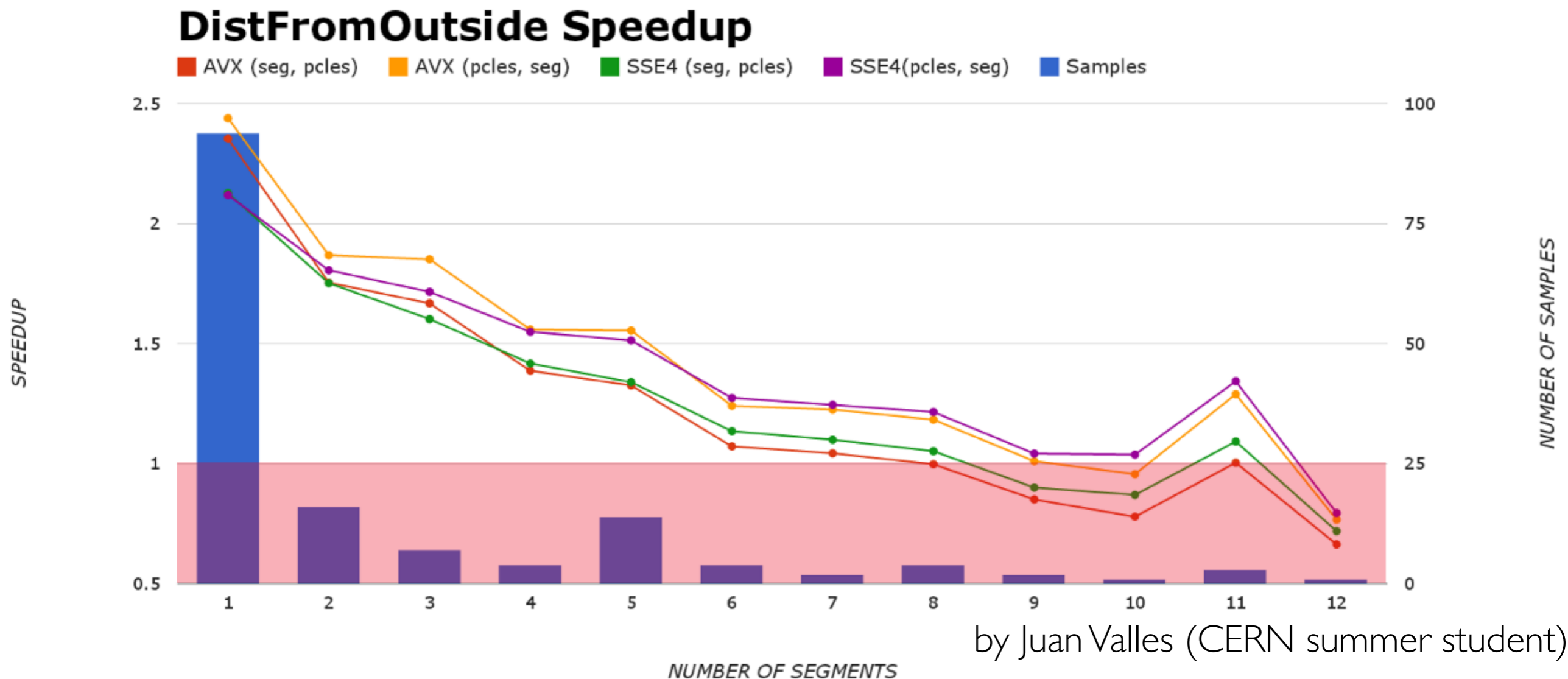
        // give compiler hints
        __assume_aligned(av,32);
        __assume_aligned(bv,32);

        // cast output as fixed size vector
        double (*outv)[VecSize] = (double (*)[VecSize]) &out[i];
        __assume_aligned(outv,32);

        // computation and storage in CILK PLUS ARRAY NOTATION
        // will vectorize
        outv[0][:] = bv[0][:]*(av[0][:] + bv[0][:]);
    }
}
```

# Status for more complex shapes

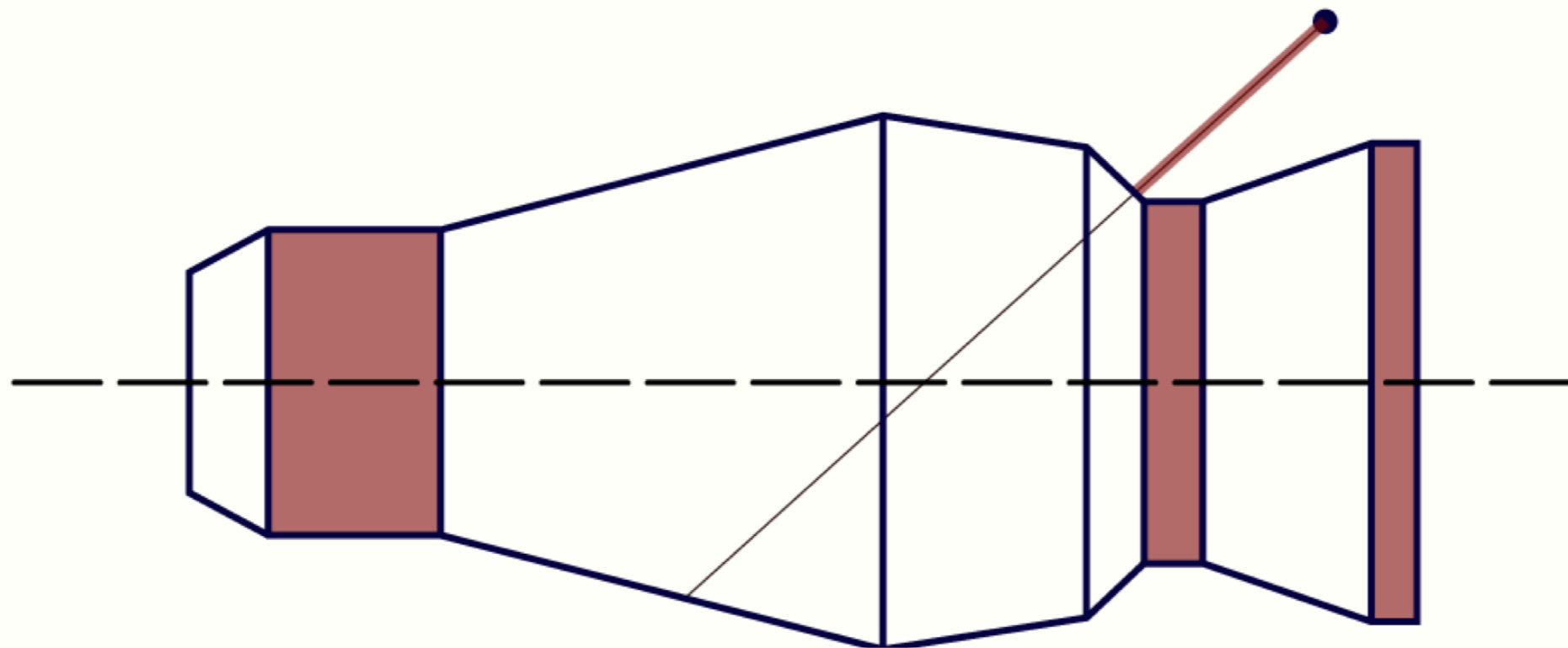
- Polycone is one of the more important complex shape used in detector descriptions
- algorithm used in ROOT uses recursive function calls which are not directly translatable to a Vc-type programming; similar for modern approach in USolids which uses voxelization techniques
- Using a simple brute force approach ( for all particles just test all segments ) has shown to give performance improvements for smaller polycones



# A different kind of data parallelism

“From particle data parallelism to segment (data) parallelism”

- \* for large polycons could use try to vectorize over segments instead of particles ( currently developing )
- \* similar idea could work even for voxelized / tessellated solids



“evaluate distance to shaded segments in a vectorized fashion”