

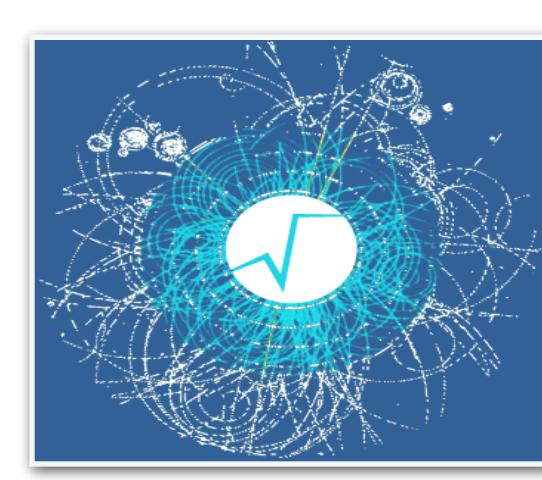


ROOT
Data Analysis Framework

Vectorization of ROOT Mathematical Libraries

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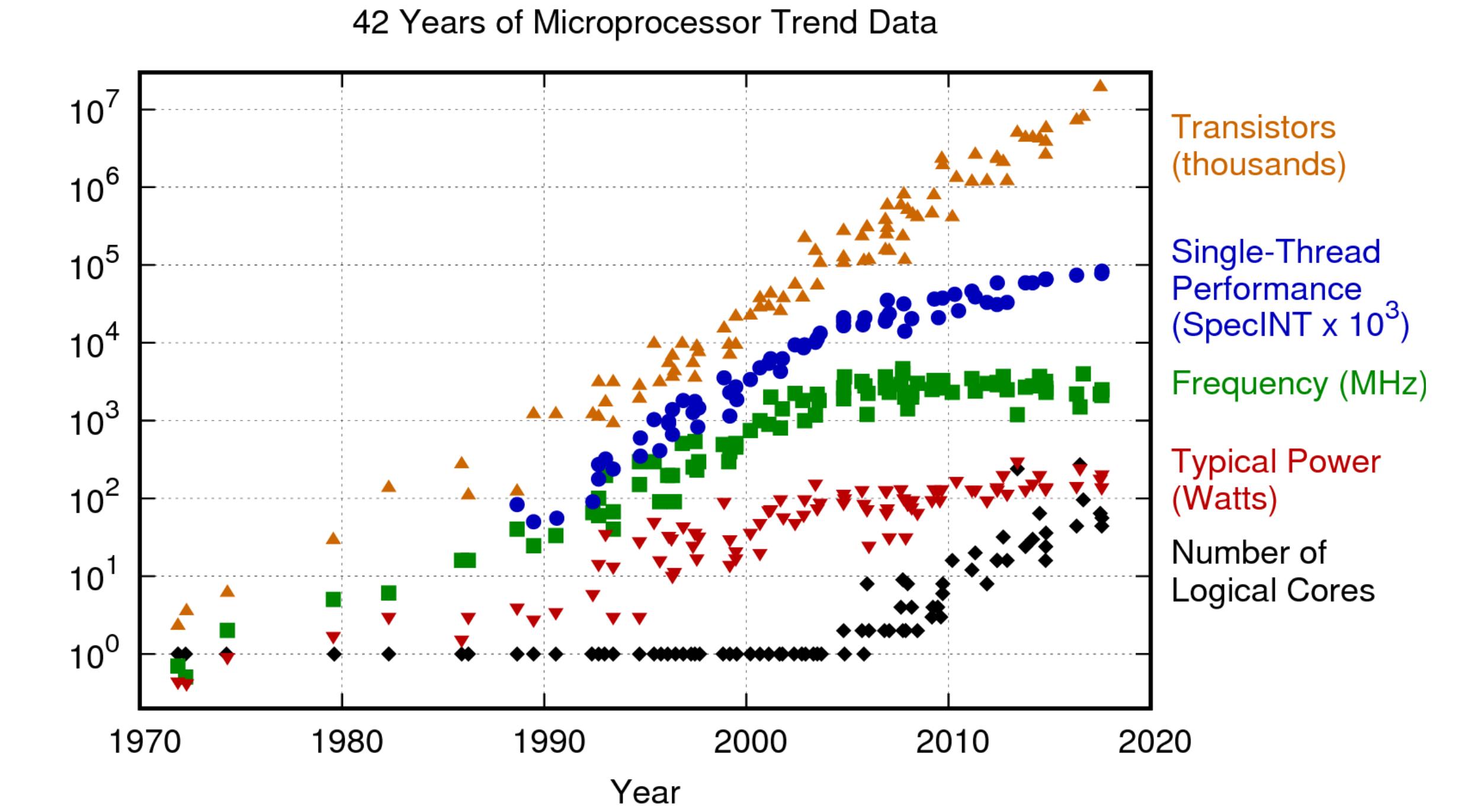
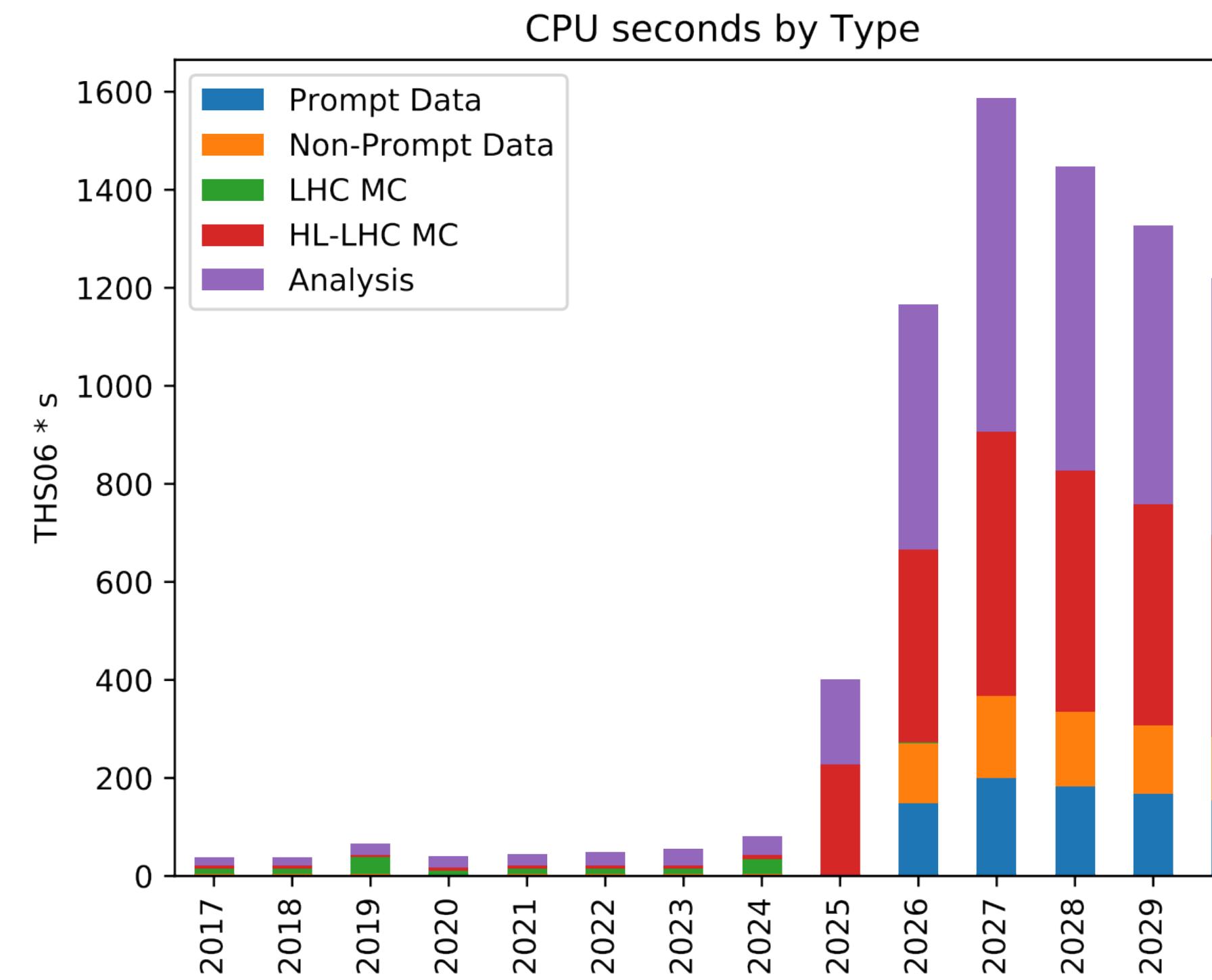
Outline

- Introduction
- **VecCore** library for vectorization
- Integration of VecCore in ROOT
- Vectorization in function evaluation (fitting),
matrix and vector classes
- Future plans
- Conclusions



Introduction

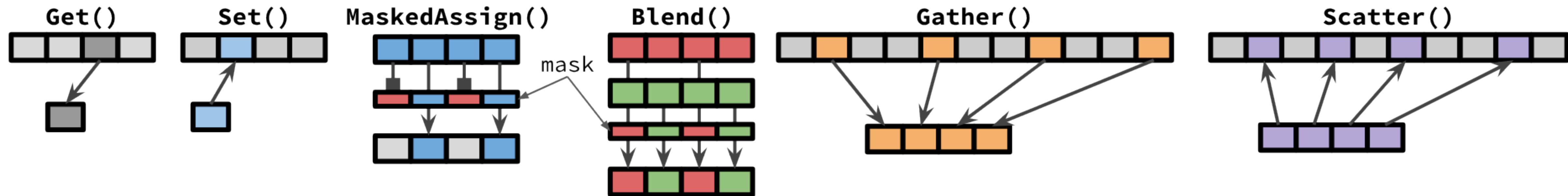
- HEP software needs to fully exploit SIMD vectorisation and parallelisation to achieve the desired performances in simulation, reconstruction and data analysis

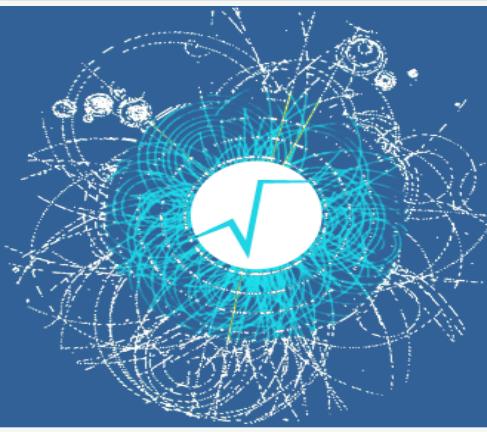




VecCore Library

- Provide simple API to express SIMD algorithms
 - write directly SIMD code is challenging
- Can support different back-end implementation
 - **Vc** and **UME::SIMD**
 - users can choose the optimal one depending on the running architecture
 - New **Vc** version will be part of the C++ standard. With VecCore easy migration
- API covering essential parts of SIMD instructions
 - it allows to implement majority of numerical algorithms
 - e.g. masking operations for dealing with branches

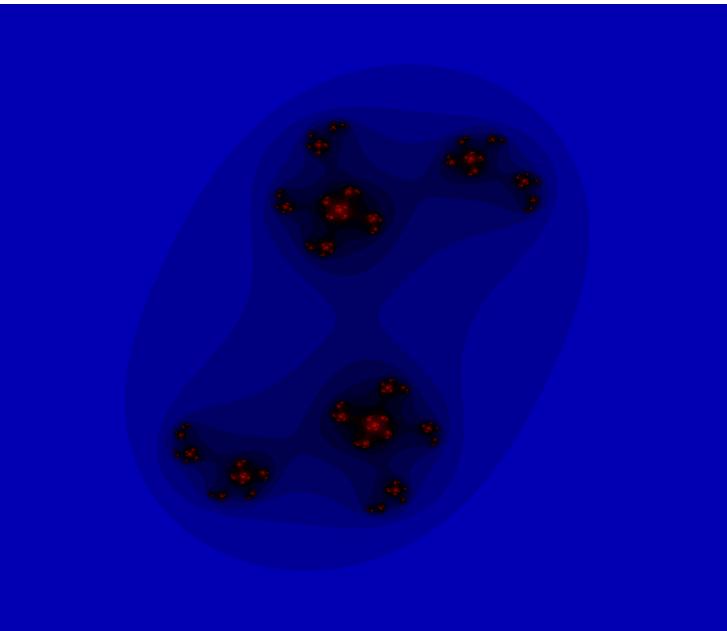
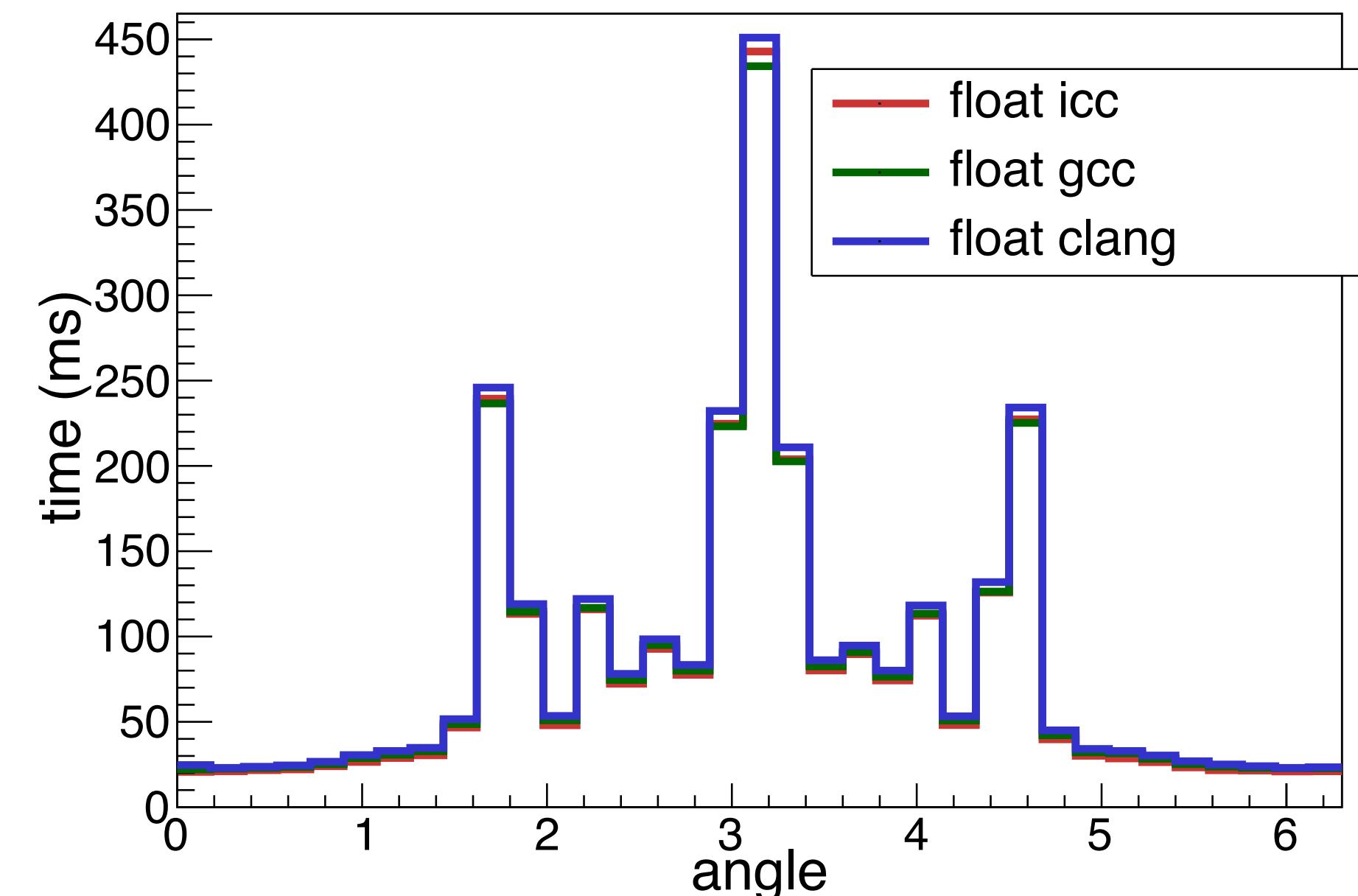




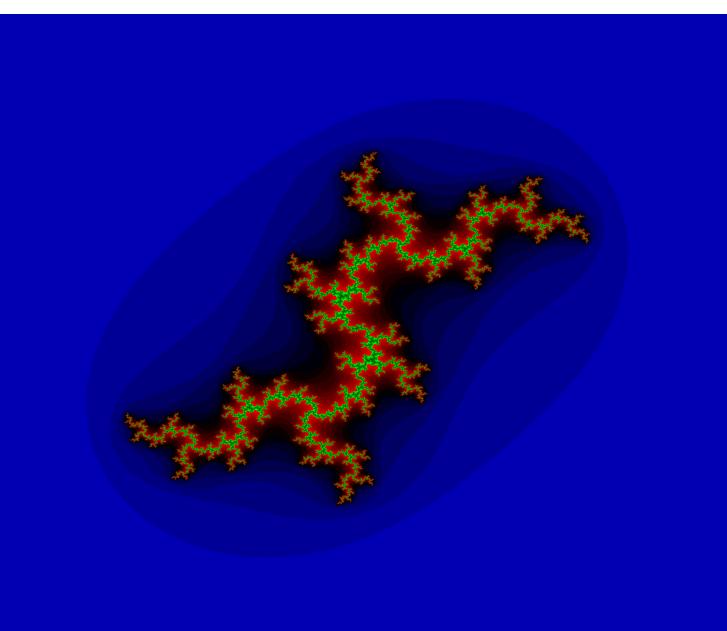
VecCore Performances

- Study vectorisation performances in a mathematical algorithm
 - Generation of Julia sets $z_{n+1} = z_n^2 + 0.7885e^{i\alpha}$, $-2 \leq z \leq 2$, $\alpha \in [0, 2\pi)$, $n \leq 100$.
 - Speed-up is less than ideal due to branching
 - different number of computations for each data points and varying as function of angle parameter

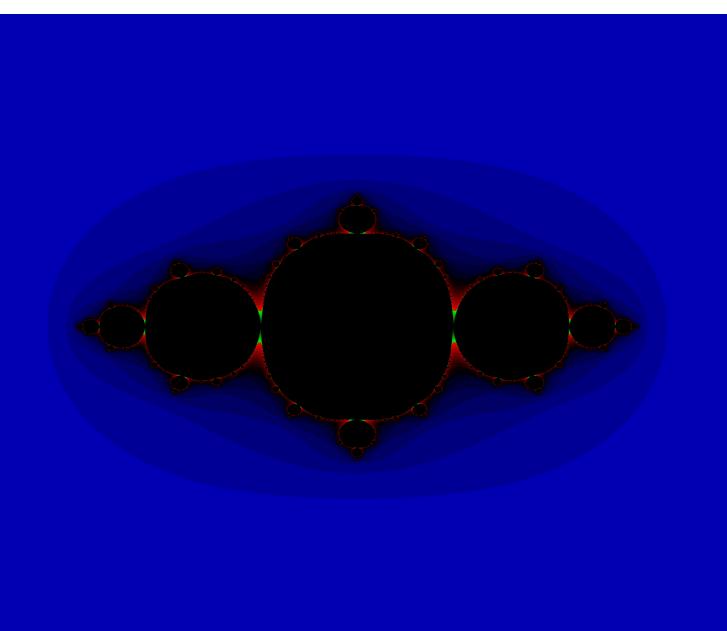
Generation time as function of angle when using scalar float types



45°



90°

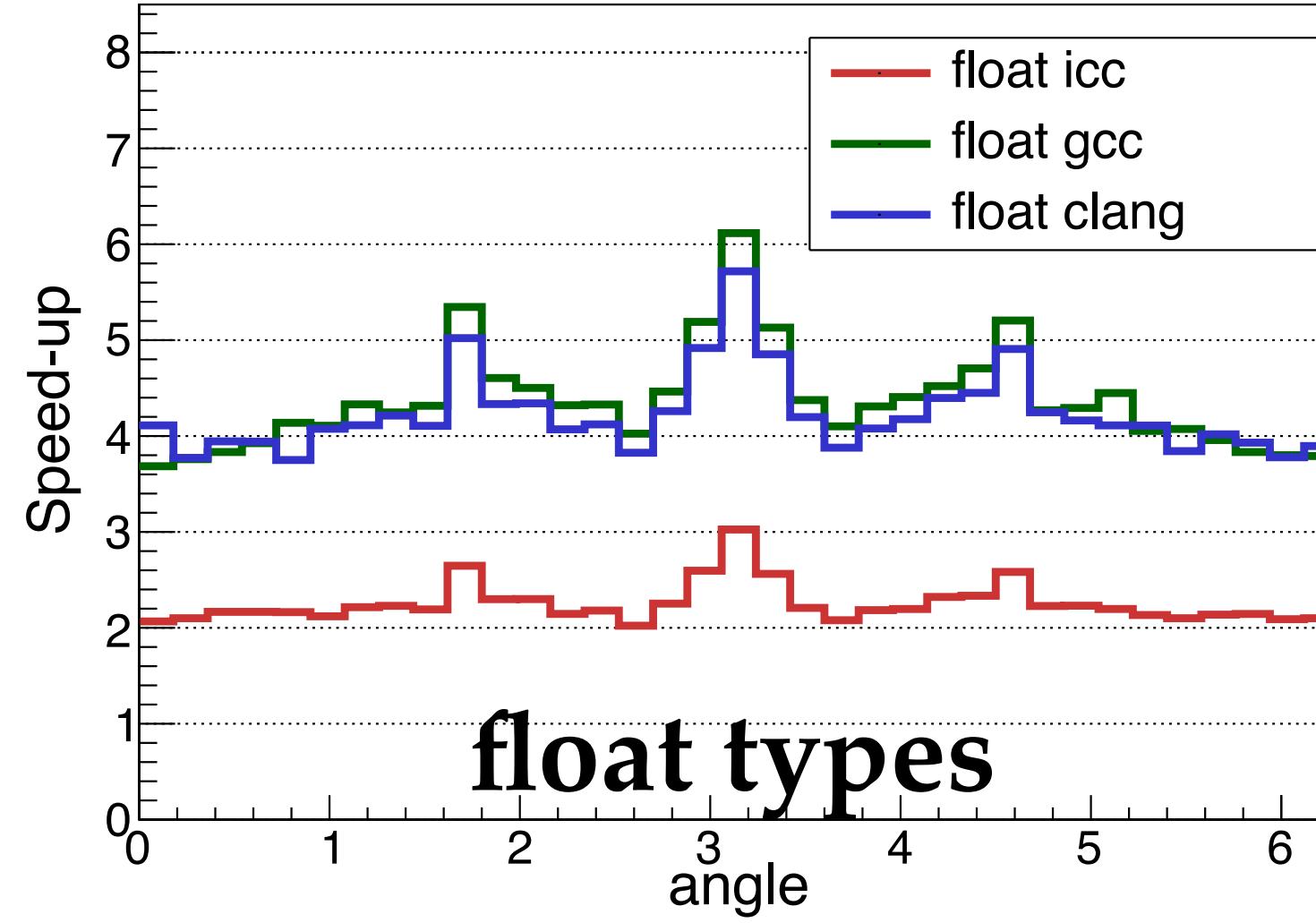


180°



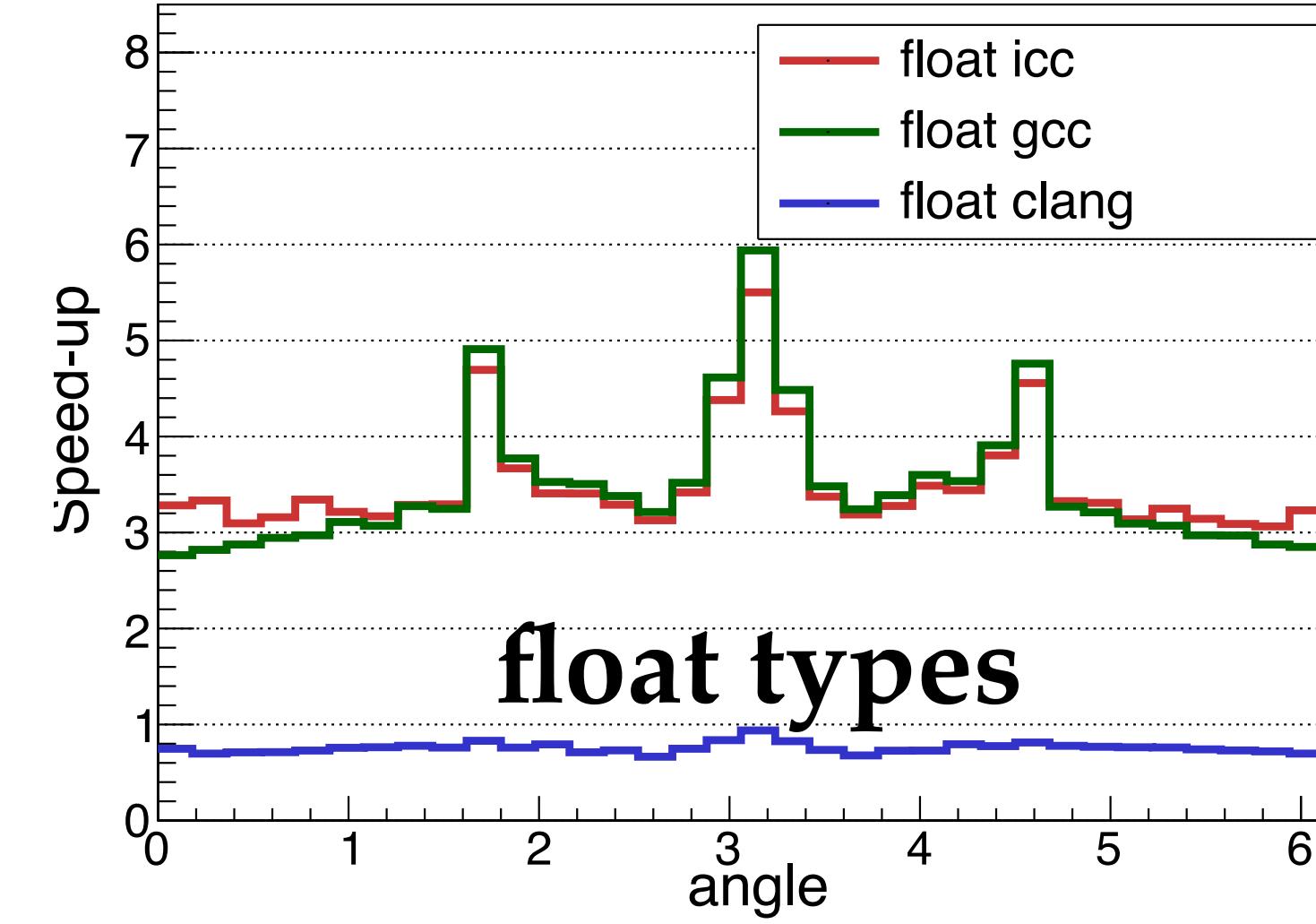
VecCore Performances

Vc

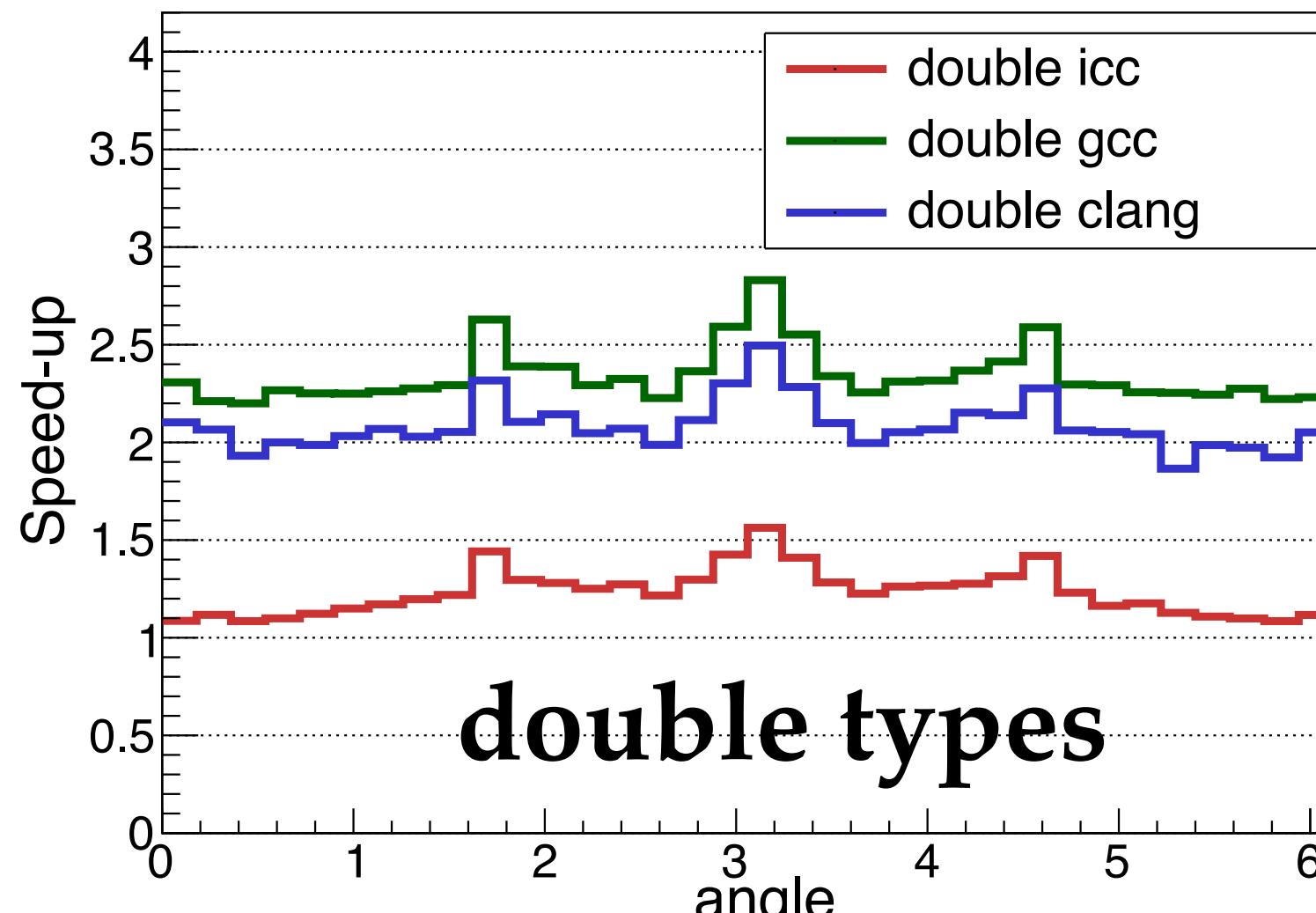


float types

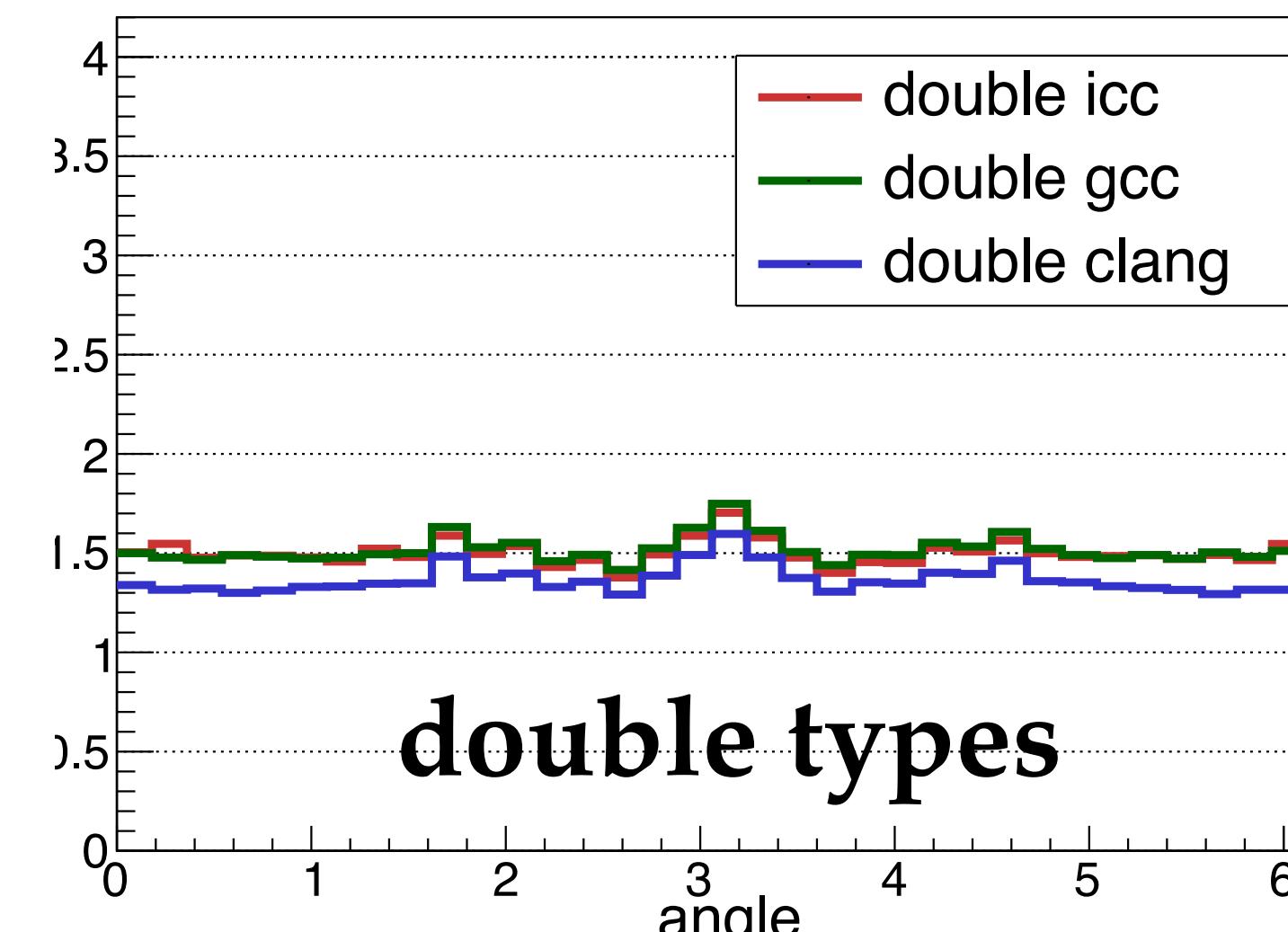
UME::SIMD



float types

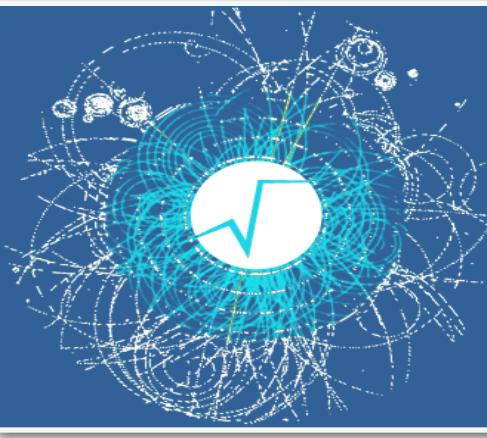


double types



double types

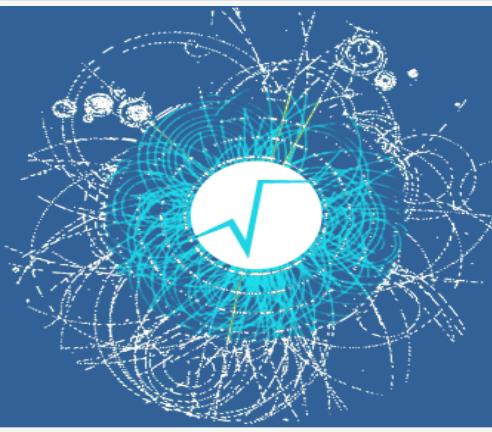
- **Vc** seems to outperform the **UME::SIMD** implementation
- *gcc* outperforms *clang* and *icc* (especially when using **Vc**)
- **Vc** does not provide an implementation working for AVX-512



VecCore and ROOT

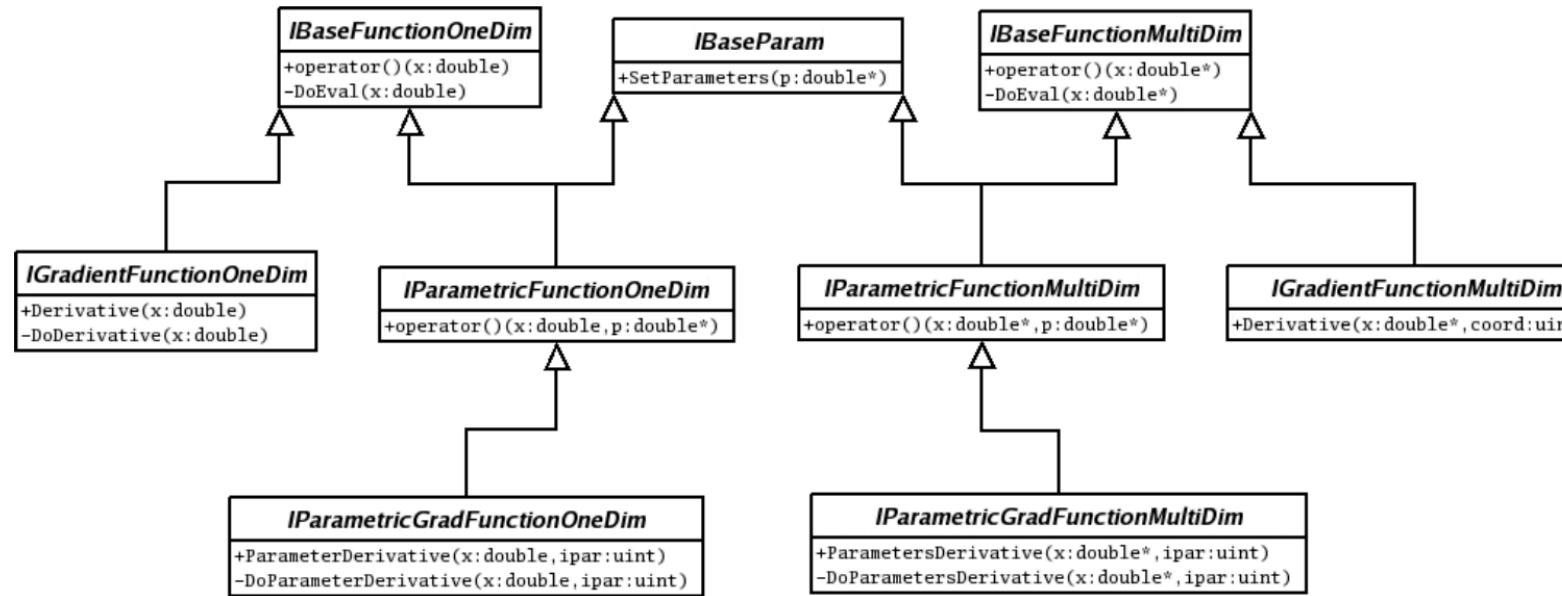
- VecCore is now integrated in ROOT together with the Vc back-end :
 - e.g. configure ROOT with

```
cmake -Dbuiltin_veccore=On -Dbuiltin_vc=On
```
- When VecCore is enabled (`R__HAS_VECCORE` is defined), ROOT provides these new VecCore SIMD vector types:
 - `ROOT::Float_v`
 - `ROOT::Double_v`
- The SIMD vector sizes (`ROOT::Double_v::size()`) will depend on the compiled instruction set
 - `ROOT::Double_v::size() = 2` when code is compiled with SSE
 - `ROOT::Double_v::size() = 4` for AVX (e.g. on Haswell)
 - `ROOT::Double_v::size() = 8` for AVX-512 (e.g. on KNL)



VecCore and ROOT Math

- Vectorization of ROOT Math interfaces for function evaluations (used for fitting in ROOT)
 - vectorize on the data x which can be multi-dimensional

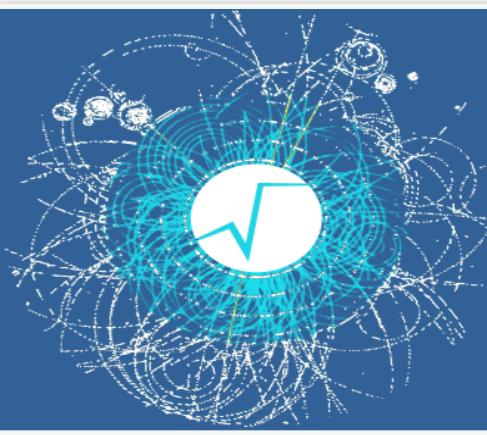


```
template<class T>
class IParmetricFunctionMultiDimTempl : virtual public IBaseFunctionMultiDimTempl<T>,
                                         virtual public IBaseParam {
public:
    typedef T BackendType;
    ...

    // Evaluate the function at a point x[] and parameters p
    T operator()(const T *x, const double *p) const { return DoEvalPar(x,p); }

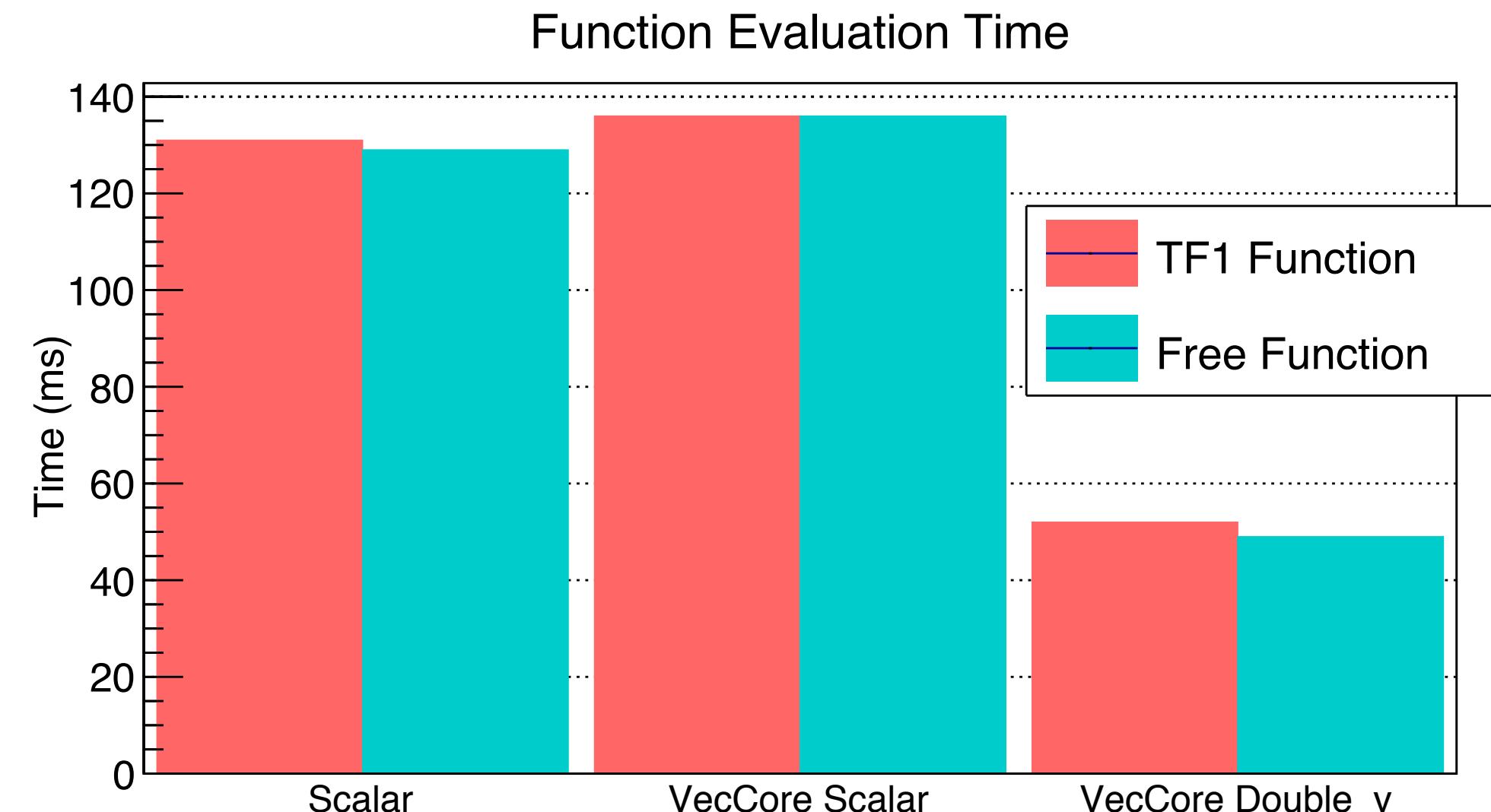
private:
    virtual T DoEvalPar(const T *x, const double *p) const = 0;
    virtual T DoEval(const T *x) const;
};
```

- Add generic interfaces for evaluation :
operator () (T x) -> T
 - where T can be instantiated as a ROOT::Double_v or just double
- Backward compatibility is preserved !

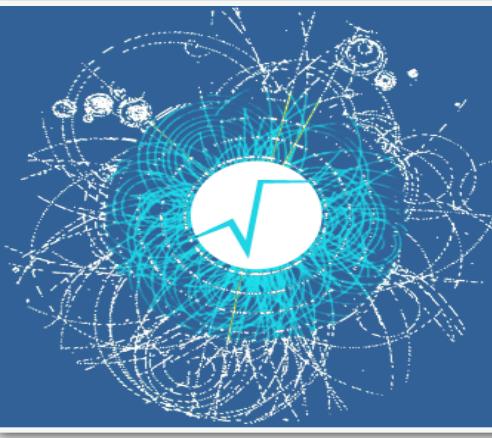


TF1 Extensions

- TF1 class has been extended to support vectorised user functions
 - `TF1("fs", [] (double *x, double *p) { return p[0]*sin(p[1]*x[0]); }, 0., 10., 2);`
 - `TF1("fv", [] (ROOT::Double_v *x, double *p) { return p[0]*sin(p[1]*x[0]); }, 0., 10., 2);`
- Template evaluation accepting **VecCore** SIMD vector types
 - `template <class T> TF1::EvalPar(const T * x, double * p) -> T;`
- Vectorized TF1 function can then be used for fitting (e.g. in `TH1::Fit`)

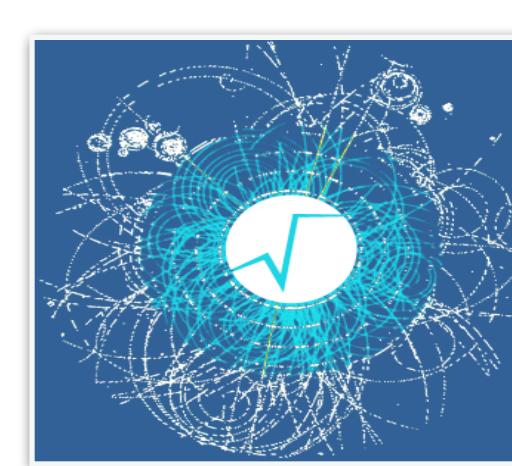


very small overhead when evaluating using
a TF1 instead of a direct free function



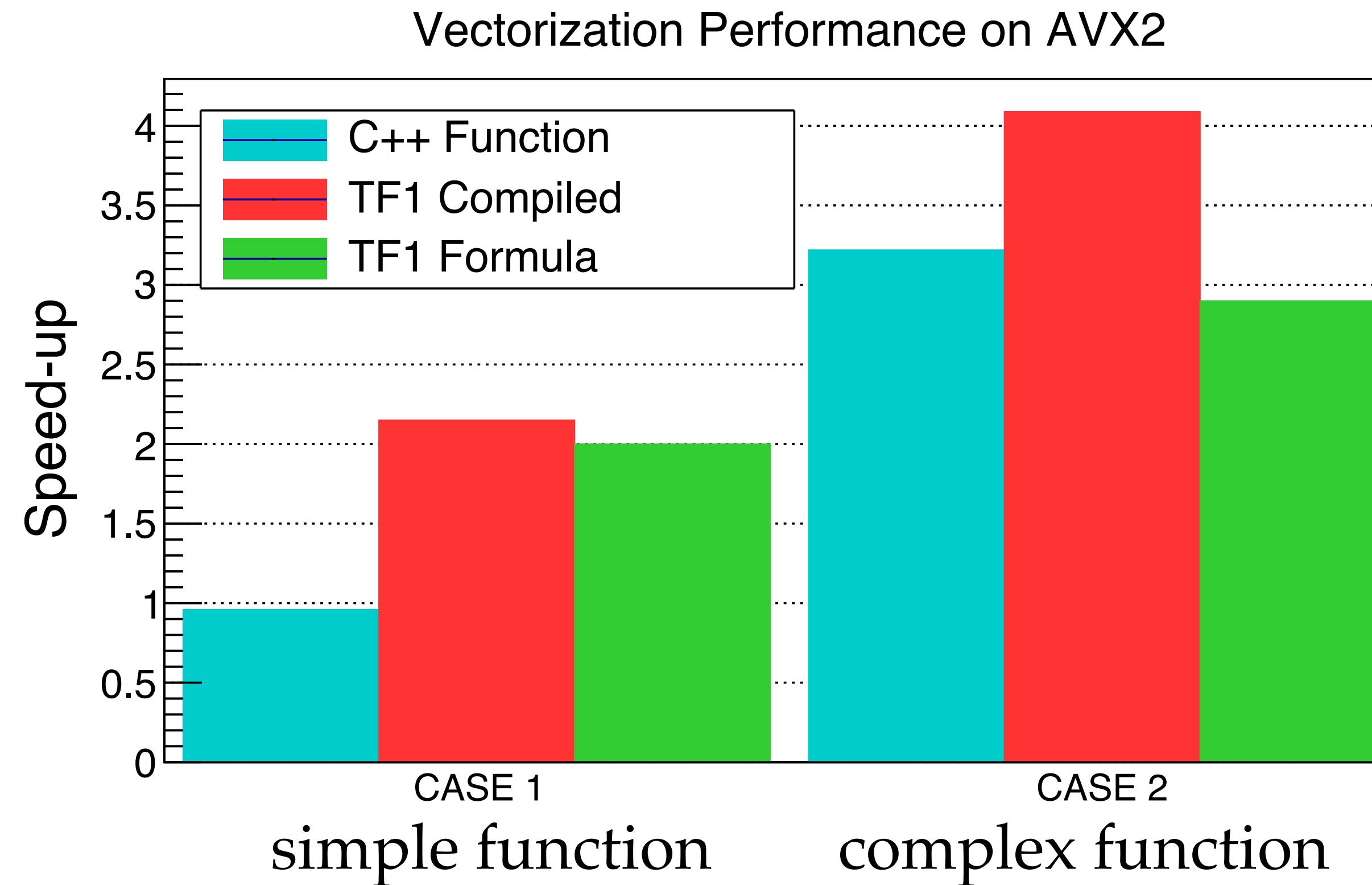
Vectorization of TFormula

- ROOT TFormula class is used to build parametric functions which can be used for fitting and modeling directly from string expression
- e.g. **TFormula ("f1","[a]*sin([b]*x") ;**
- expression is compiled using JIT provided by CLING
 - compiled signature is based on
f (double *x, double *p) ->double
 - Added capability to JIT compile with a vectorised signature:
f (ROOT::Double_v *x, double *p) ->ROOT::Double_v
- One can then easily have vectorised functions for fitting automatically



Vectorized TFormula Performances

- Performance results evaluating a math expression using a free C++ function with TF1 and TF1 based on TFormula
- Study the speed-up by using vectorisation on AVX



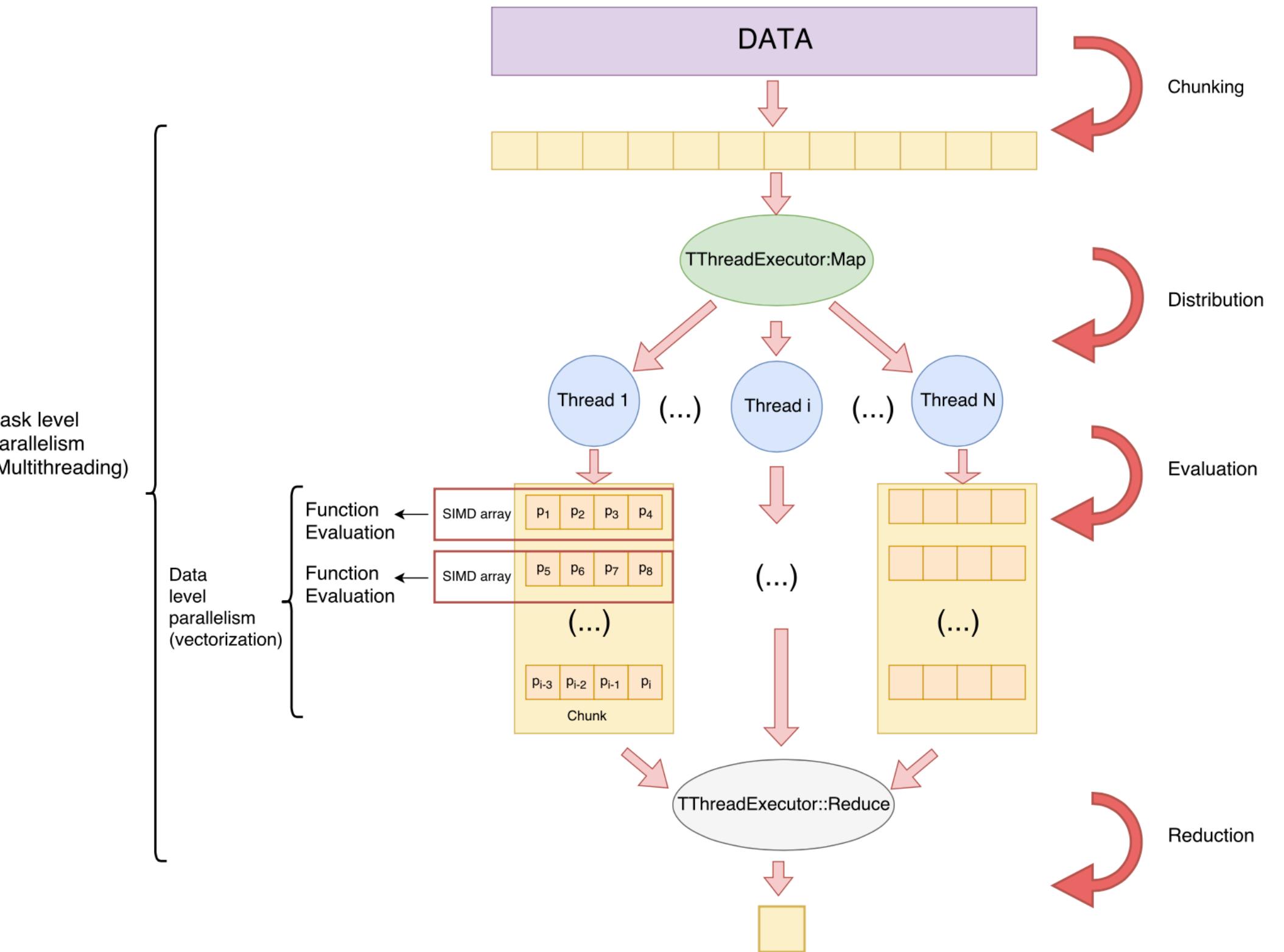
1. 2nd degree polynomial
2. exponential + gaussian

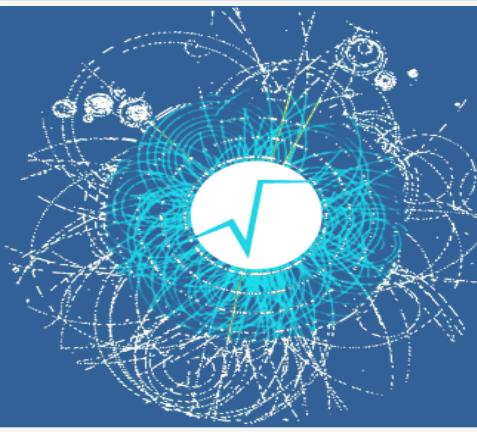


Fitting with Vectorized Functions



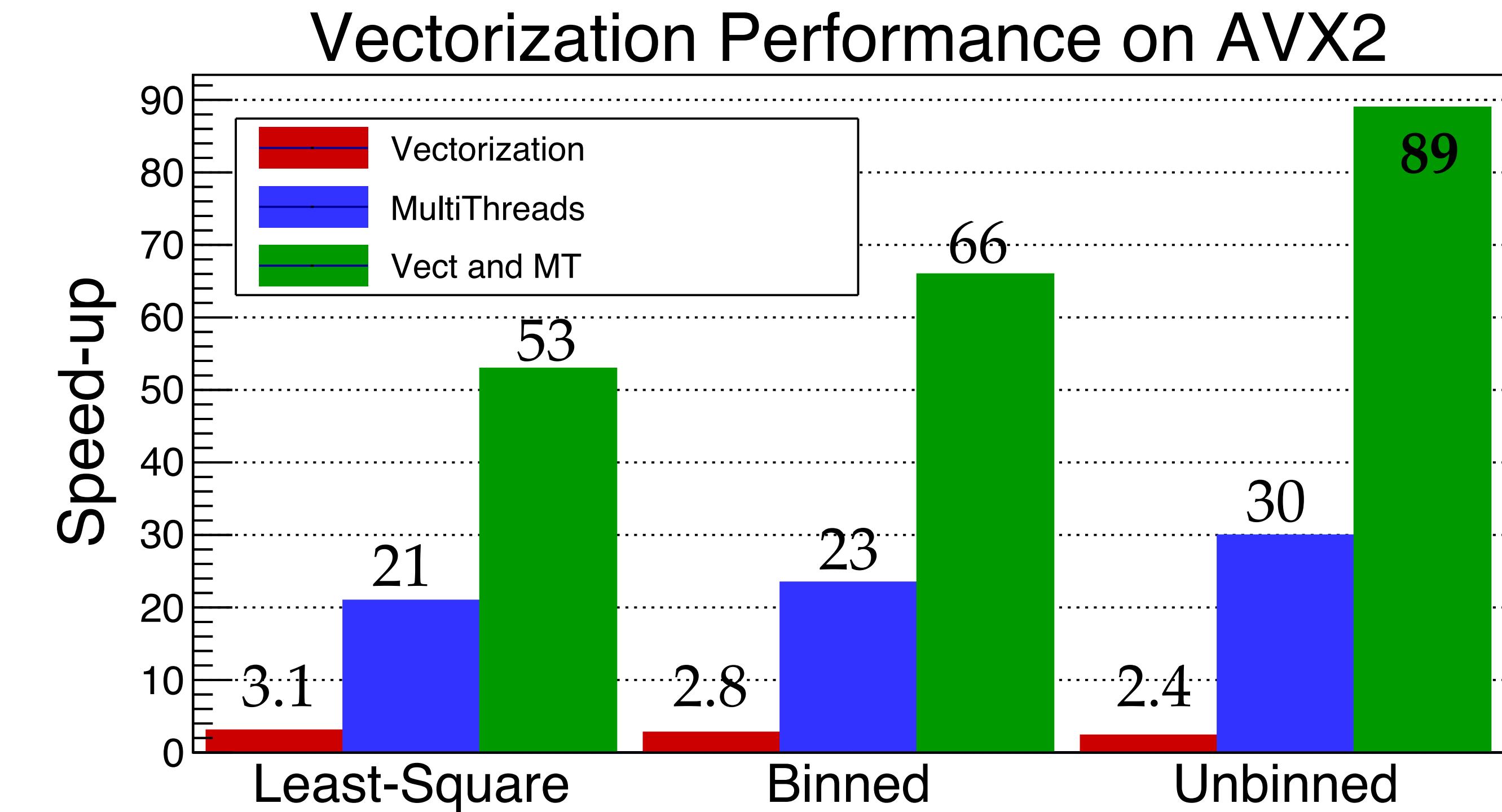
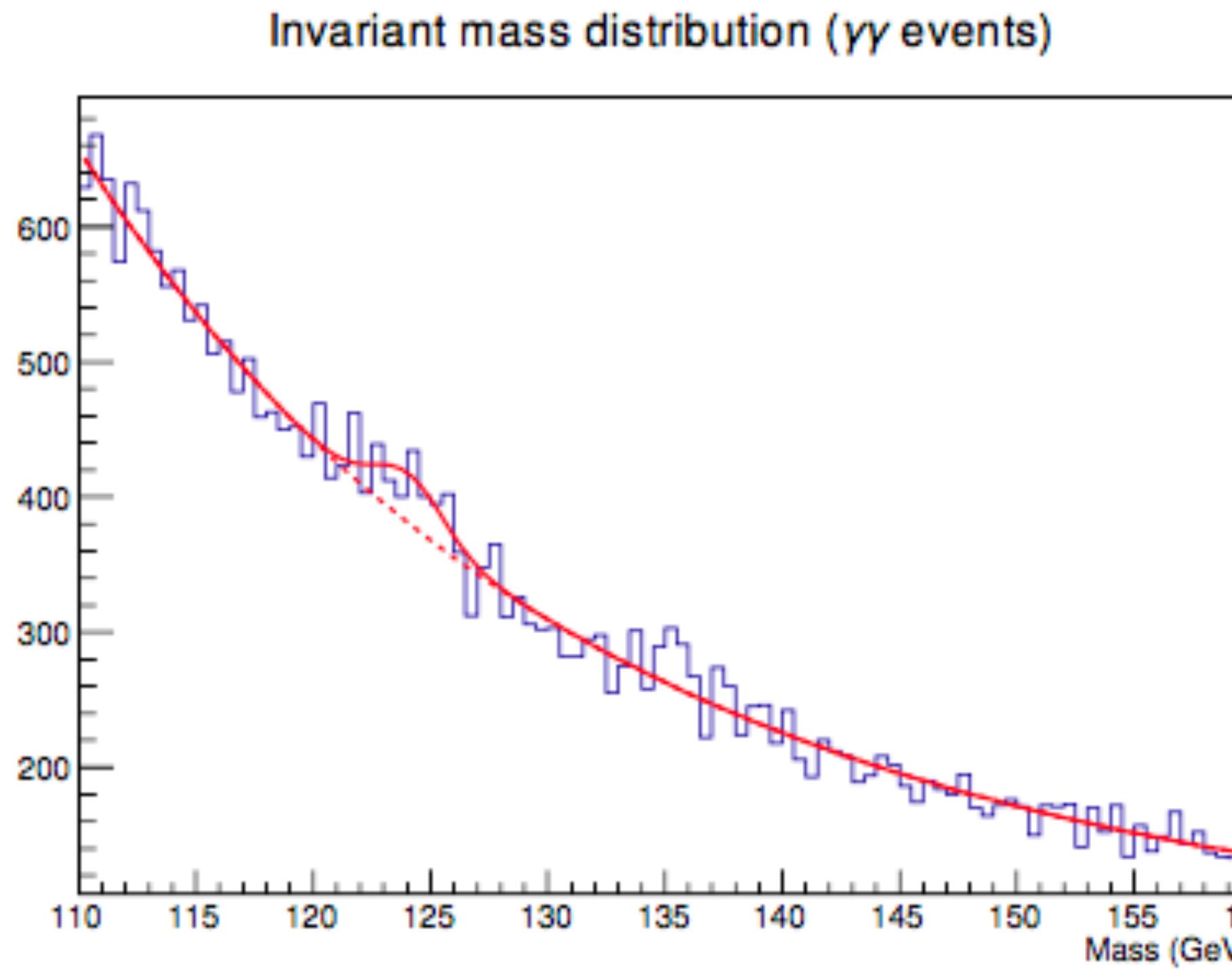
- Multi-dimensional input data x (coming from histograms or TTree's) is vectorized using `ROOT::Double_v`
 - organize data from AOS to SOA
 $(x_0, y_0, z_0, \dots, x_n, y_n, z_n) \rightarrow (x_0, \dots, x_n, y_0, \dots, y_n, z_0, \dots, z_n)$
- Model function is evaluated in vectorized mode when computing the chi-square or likelihood function (objective function) for fitting
- Computation of objective function is also parallelized with multi-threads by chunking the data





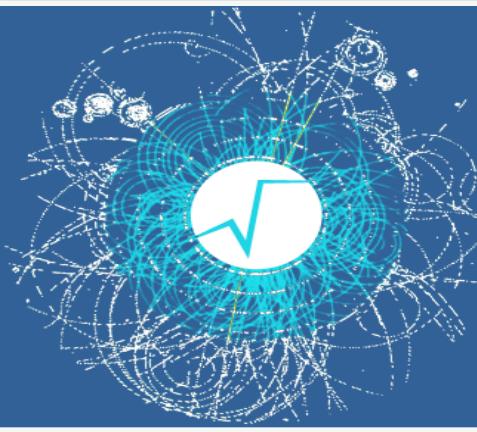
Fitting Performances

- Measure CPU performances in a typical HEP fitting
 - fit invariant mass spectrum to determine significance and location of the signal (e.g. $H \rightarrow \gamma\gamma$)

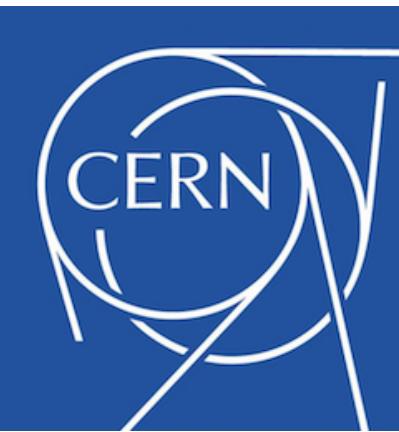


Intel Xeon CPU E5-2683 with 28 physical cores

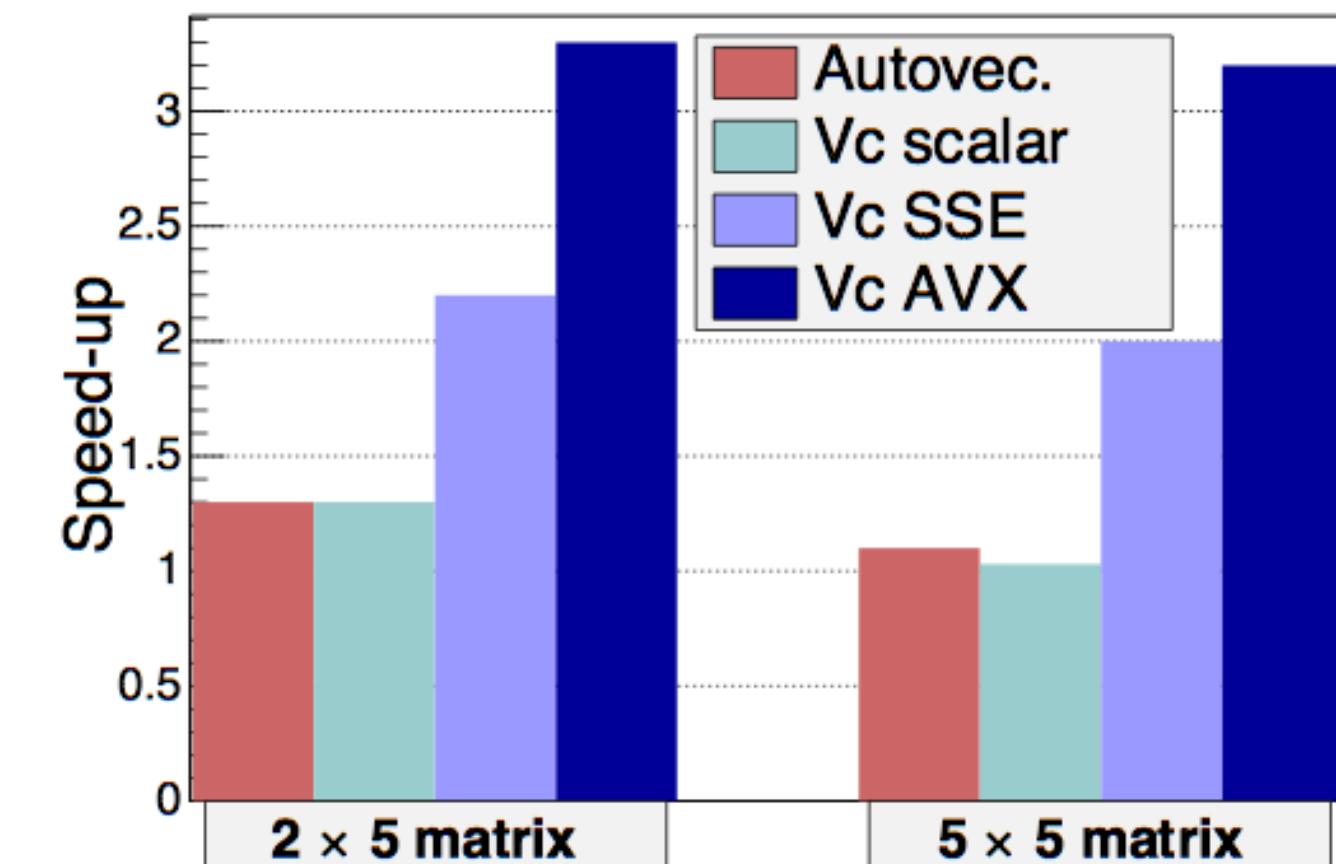
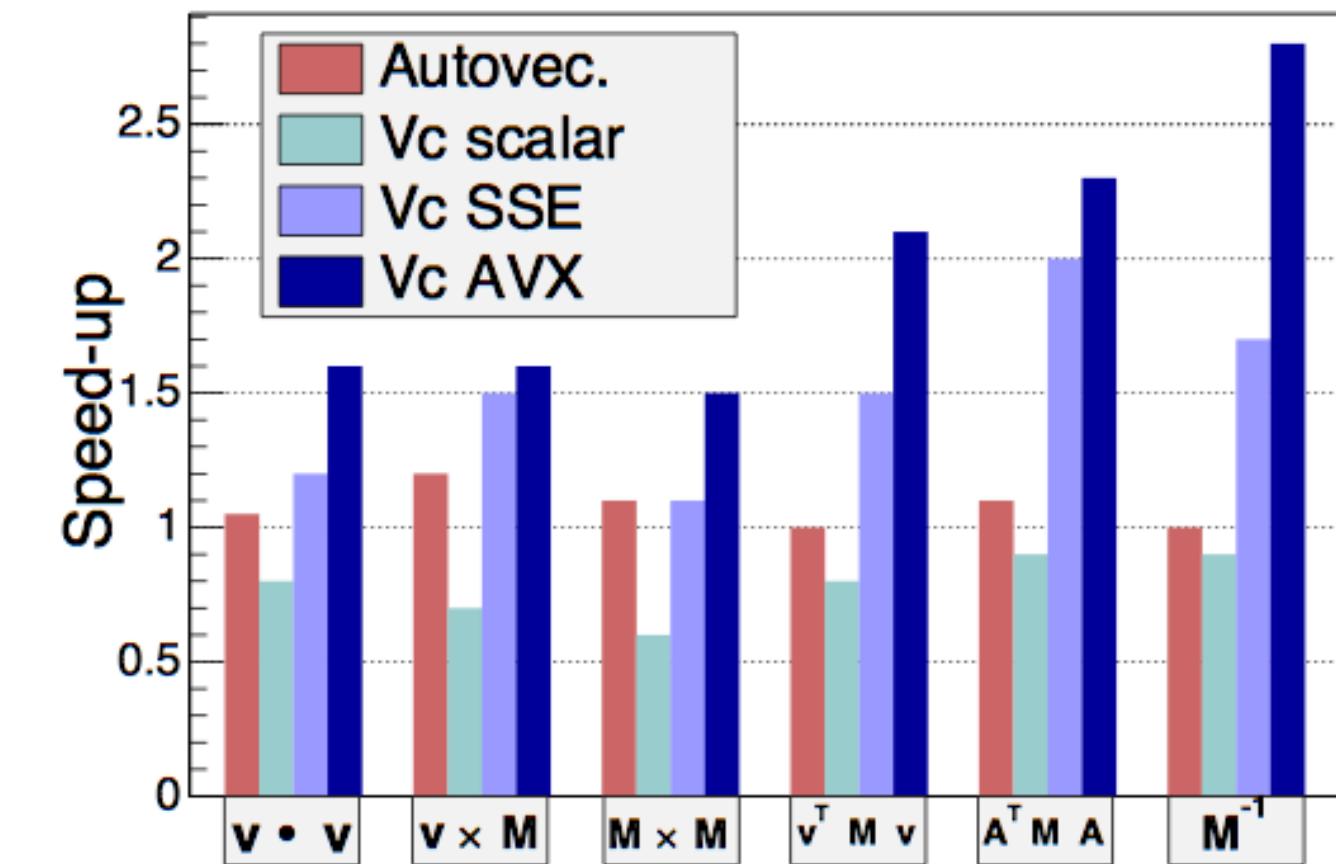
CHEP 2018

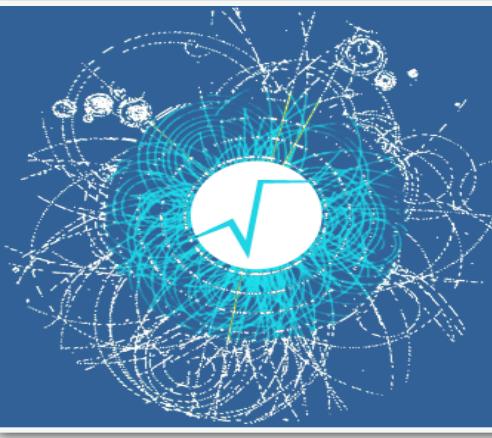


Vectorization in Matrix Operations



- ROOT provides a template vector and matrix classes (optimized for small sizes) which can be used in single and double precision
 - **SVector< double,N>**
 - **SMatrix< double,N,M>**
- Template classes for geometry and physics vectors with their transformations
 - **DisplacementVector3D< Cartesian3D<double>**
 - **LorentzVector<PxPyPzE4D<double> >**
- VecCore types (**ROOT::Double_v**) can be used as template parameters for vector and matrices classes and for the geometry vectors
 - vectorisation for operations on a list of vectors / matrices (vertical vectorisation)





Transparent Data Parallelism: VecOps

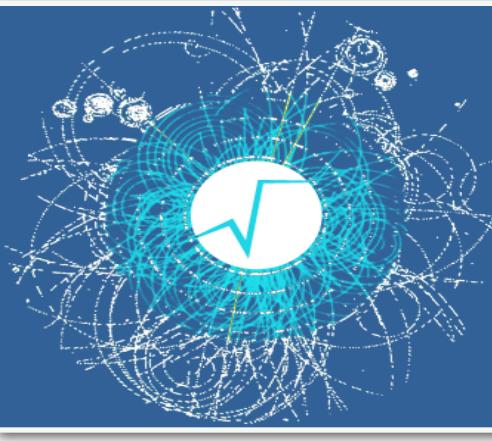


Introduced **ROOT::RVec<T>**: vectorised operations made easy

- `std::vector` like interface, **ergonomic support of analysis operations**
- Can adopt memory or own it
- Vectorised arithmetic operations, math functions

```
RVec<double> mus_pt {15., 12., 10.6, 2.3, 4., 3.};  
RVec<double> mus_eta {1.2, -0.2, 4.2, -5.3, 0.4, -2.};  
RVec<double> good_mus_pt = mus_pt[mus_pt > 10 && abs(mus_eta) < 2.1];  
  
RVec<float> vals = {2.f, 5.5f, -2.f};  
RVec<float> sin_vals = sin(vals);
```

DOI [10.5281/zenodo.1253756](https://doi.org/10.5281/zenodo.1253756)



Future Plans: Math Functions



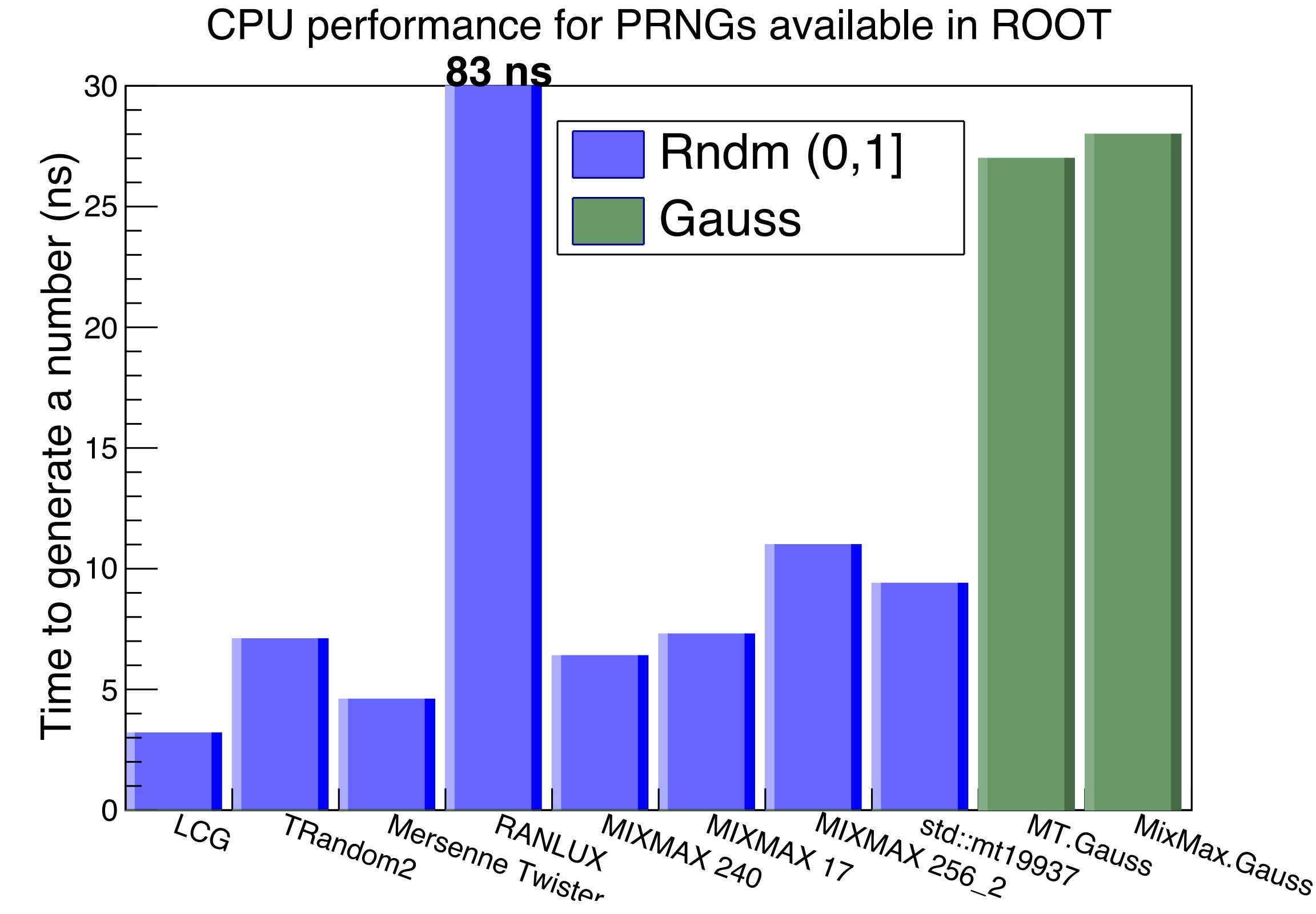
- Re-implement mathematical functions in TMath and ROOT::Math (e.g. statistics functions) using **VecCore**
- Plans is to have a single template implementation, which can work for scalar and vector types
- Example:
 - `template <class T>`
`TMath::Gaus(const T & x, double mu, double sigma) -> T`
- Basic math functions (e.g. exp, log, sin, cos) are already provided by **VecCore**

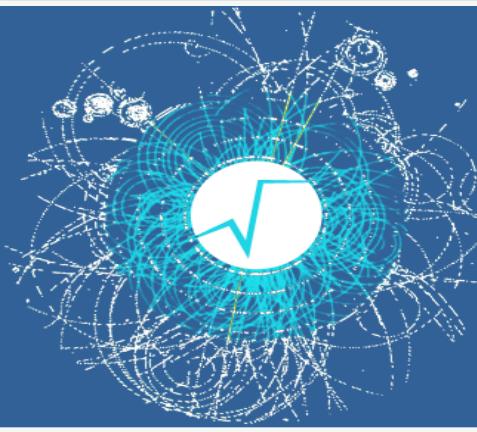


Future Plans: Random Number



- Can use vectorization to speed-up pseudo-random number generations
- Horizontal (internal) or vertical vectorization can be used
 - By creating a vector state (based on VecCore) we can speed-up generators like Ranlux or MixMax
 - on-going effort in collaboration with GeantV project and MIXMAX network (<https://indico.cern.ch/event/731433/>)

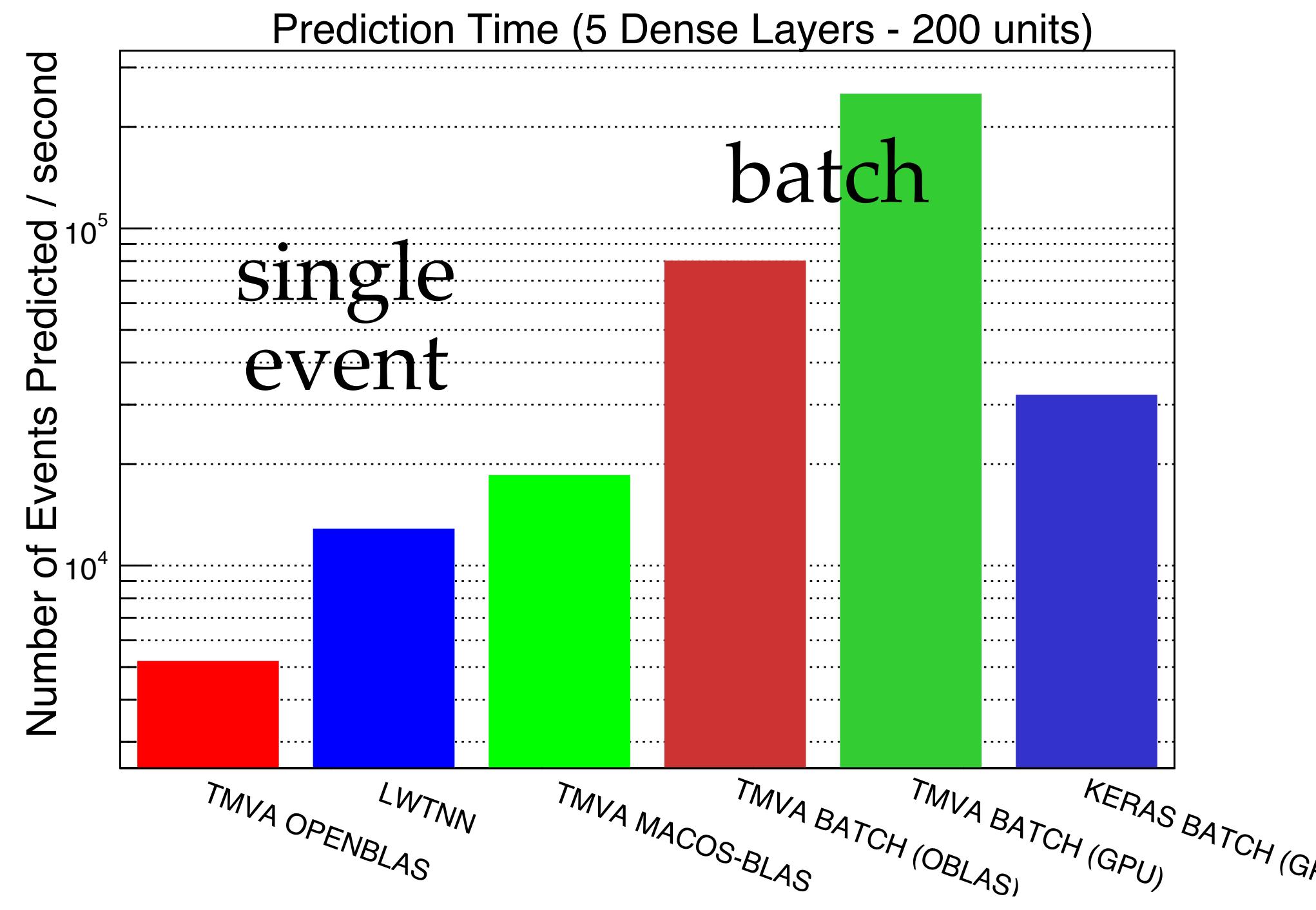


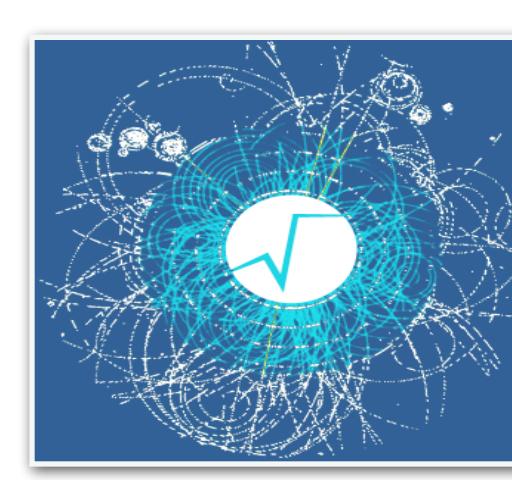


Future Plans: Machine Learning

- Use **VecCore** for matrix operations in Neural Network
- Interested in optimise the single event evaluation.
- Vectorisation can be used for :
 - applying weight to input layer data (matrix multiplication)
 - compute activation function using vectorised implementations (e.g. tanh)

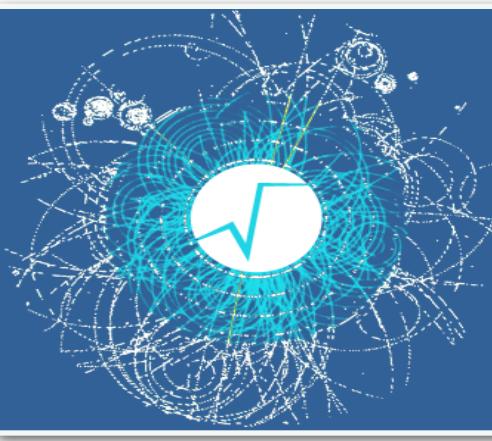
Performances for evaluating a deep neural network architecture





Conclusions

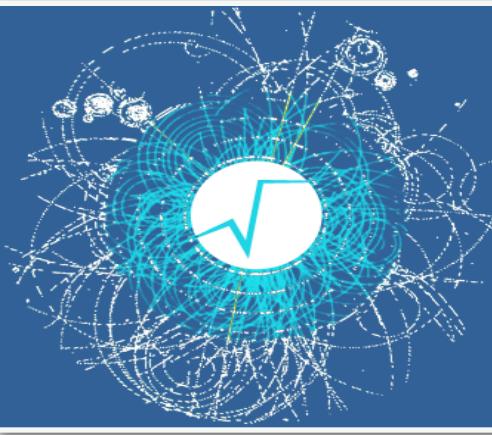
- Advantages by using VecCore library which provides a simpler programming model for SIMD
- Benchmark of VecCore and its backend shows that **Vc** outperforms **UME::SIMD** and *gcc* performs better than *icc* or *clang*
- ROOT uses internally VecCore by defining new vector types:
 - `ROOT::Float_v` and `ROOT::Double_v`
 - Extension of ROOT function classes and interfaces to support these new types
 - Integrate vectorisation also in `TFormula` class, thanks to ROOT JIT'ing
- Significant performances improvement in ROOT thanks to vectorization
- Plan to deploy vectorization even more:
 - math functions, random numbers and deep learning



Thank you !

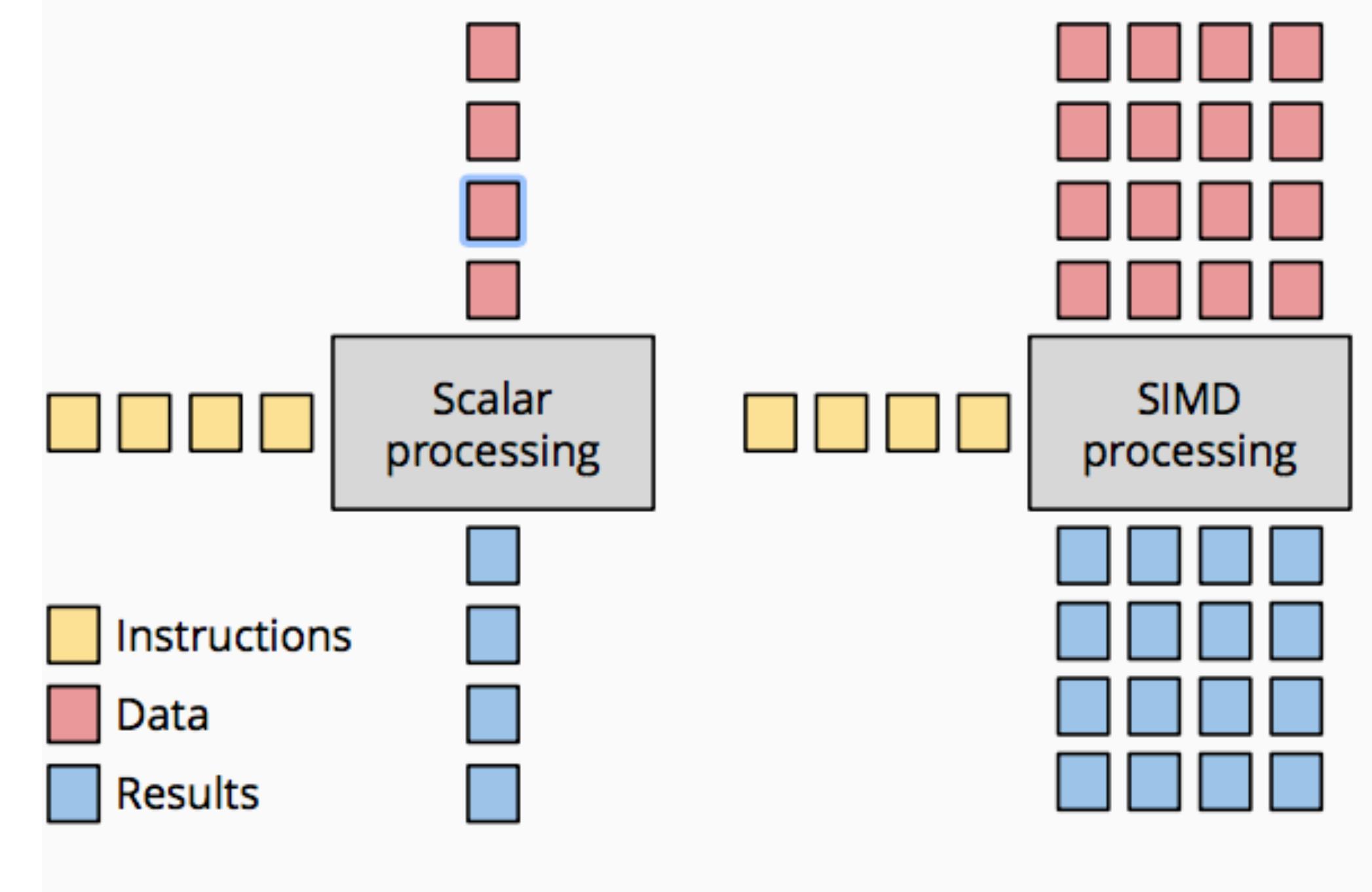
References:

- ROOT: <https://root.cern.ch>
- VecCore : <https://github.com/root-project/veccore>
- Vc : <https://github.com/VcDevel/Vc>
- UME::SIMD: <https://github.com/edanor/umesimd>
- SIMD C++ standardization:
 - <http://www.open-std.org/JTC1/SC22/WG21/docs/papers/2013/n3759.html>



SIMD Vectorization

- Writing efficiently SIMD code is challenging
- Libraries exist that wrap SIMD intrinsic in a convenient interface
 - Vc
 - UME::SIMD
- They do not support all architectures or performances very dependent on specific platforms





History of Intel SIMD

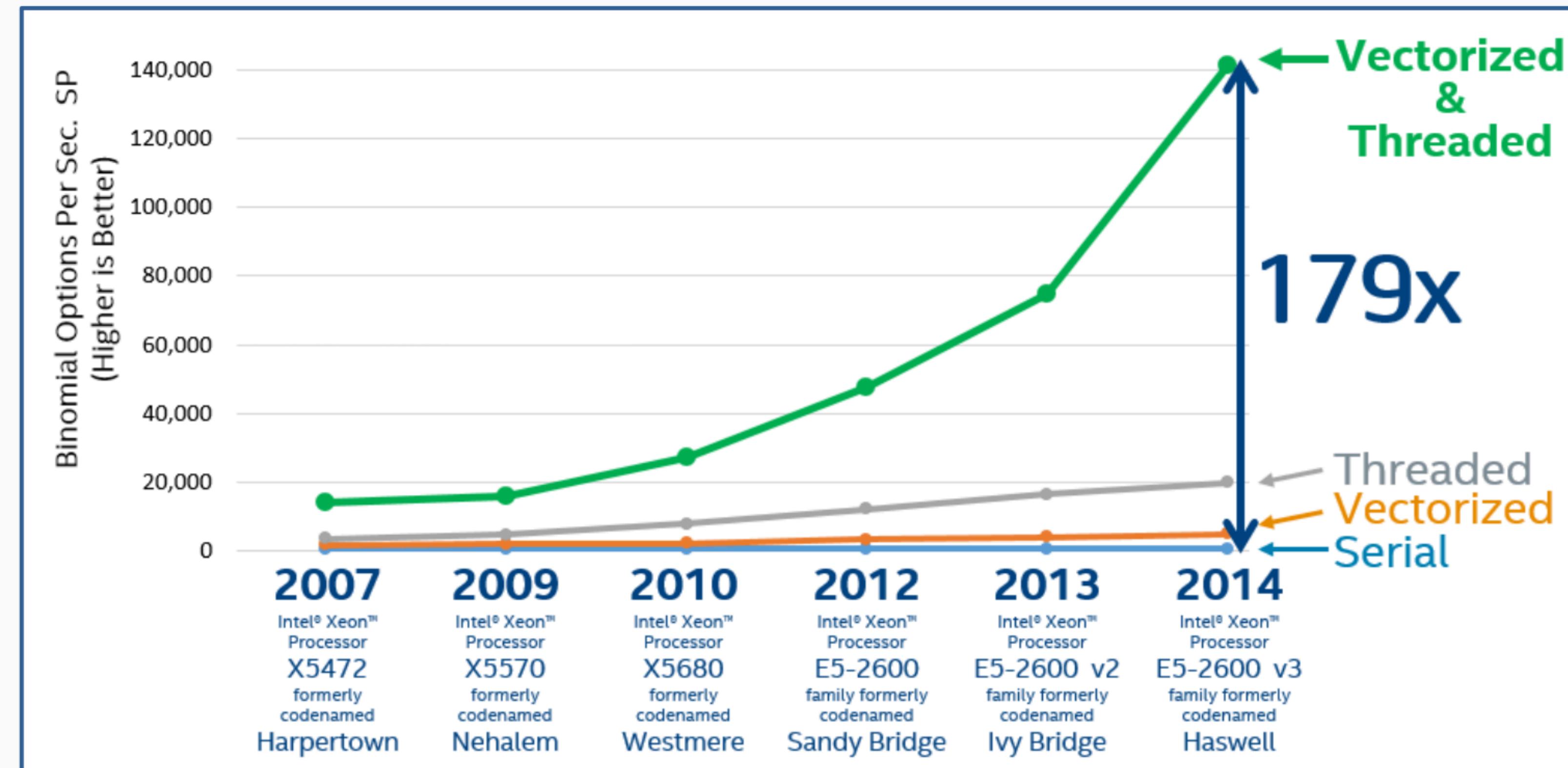
- ▶ Intel® Pentium Processor (1993)
 *32bit*
- ▶ Multimedia Extensions (MMX in 1997)
 *64bit integer support only*
- ▶ Streaming SIMD Extensions (SSE in 1999 to SSE4.2 in 2008)
 *32bit/64bit integer and floating point, no masking*
- ▶ Advanced Vector Extensions (AVX in 2011 and AVX2 in 2013)
 *Fused multiply-add (FMA), HW gather support (AVX2)*
- ▶ Many Integrated Core Architecture (Xeon Phi™ Knights Corner in 2013)
 *HW gather/scatter, exponential*
- ▶ AVX512 on Knights Landing, Skylake Xeon, and Core X-series (2016/2017)
 *Conflict detection instructions*

 = 32 bit word



Why Use SIMD ?

SIMD vectorization is already essential for high performance on modern Intel® processors, and its relative importance is expected to increase, especially on hardware geared towards HPC, such as Xeon Phi™ and Skylake Xeon™ processors.





The VecCore API

```
namespace vecCore {

    template <typename T> struct TypeTraits;
    template <typename T> using Mask    = typename TypeTraits<T>::MaskType;
    template <typename T> using Index   = typename TypeTraits<T>::IndexType;
    template <typename T> using Scalar  = typename TypeTraits<T>::ScalarType;

    // Vector Size
    template <typename T> constexpr size_t VectorSize();

    // Get/Set
    template <typename T> Scalar<T> Get(const T &v, size_t i);
    template <typename T> void Set(T &v, size_t i, Scalar<T> const val);

    // Load/Store
    template <typename T> void Load(T &v, Scalar<T> const *ptr);
    template <typename T> void Store(T const &v, Scalar<T> *ptr);

    // Gather/Scatter
    template <typename T, typename S = Scalar<T>> T Gather(S const *ptr, Index<T> const &idx);

    template <typename T, typename S = Scalar<T>> void Scatter(T const &v, S *ptr, Index<T> const &idx);

    // Masking/Blending
    template <typename M> bool MaskFull(M const &mask);
    template <typename M> bool MaskEmpty(M const &mask);
    template <typename T> void MaskedAssign(T &dst, const Mask<T> &mask, const T &src);
    template <typename T> T Blend(const Mask<T> &mask, const T &src1, const T &src2);

}
```