
Hydra Documentation

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INTRODUCTION

1.1 Hydra framework

Despite the ongoing efforts of modernization, a large fraction of the software used in HEP remain based on legacy. It mostly consists of libraries assembling single threaded, Fortran and C++03 mono-platform routines [1]. Concomitantly, HEP experiments keep collecting samples with unprecedented large statistics and data analyses become increasingly complex. Are not rare the situations where computers spend days performing calculations to reach a result, which very often needs re-tune.

On the other hand, computer processors will not increase clock frequency any more in order to reach higher performance. Indeed, the current road-map to improve overall performance is to deploy different levels of concurrency, which for example has been leading to the proliferation of multi-thread friendly and multi-platform environments among HPC data-centers. Unfortunately, HEP software is not completely prepared yet to fully exploit concurrency and to deploy more opportunistic computing strategies.

The Hydra framework proposes a computing model to approach these issues. The Hydra provides collection of parallelized high-level algorithms, addressing some of of typical computing bottlenecks commonly found in HEP, and a set of optimized containers and types, through a modern and functional interface, allowing to enhance HEP software productivity and performance and at same time keeping the portability between NVidia GPUs, multi-core CPUs and other devices compatible with CUDA [2], TBB [3] and OpenMP [4] computing models.

1.2 Design highlights

Hydra is basically a header-only C++11 template framework organized using a variety of static polymorphism idioms and patterns. This ensure the predictability of the stack at compile time, which is critical for stability and performance when running on GPUs and minimizes the overhead introduced by the user interface when engaging the actual calculations. Furthermore, the implementation of static polymorphism via extensive usage of templates allows to expose the maximum amount of code to the compiler, in the context in which the code will be used, contributing to activate many compile time optimizations that could not be accessible otherwise. Hydra's interface and implementation details extensively deploys patterns and idioms that en-

force thread-safeness and efficient in memory access and management. The following list summarizes some of the main design choices adopted in Hydra:

- Hydra provides a set of optimized STL-like containers that can store multidimensional datasets using [5] layout.
- Data handled using iterators and all classes manages resources using RAII idiom.
- The framework is type and thread-safe.
- There is no limitation on the maximum number of dimensions that containers and algorithms can handle.

The types of devices which Hydra can be deployed are classified by back-end type, according with the device compatibility with certain computing models. Currently, Hydra supports four back-ends, which are CPP [6], OpenMP [4], CUDA [2] and TBB [3]. Code can be dispatched and executed in all supported back-ends concurrently and asynchronously in the same program, using the suitable policies represented by the symbols `hydra::omp::sys`, `hydra::cuda::sys`, `hydra::tbb::sys`, `hydra::cpp::sys`, `hydra::host::sys` and `hydra::device::sys`. Where applicable, these policies define the memory space where resources should be allocated to run algorithms and store data.

For mono-backend applications, source files written using Hydra and standard C++ compile for GPU and CPU just exchanging the extension from `.cu` to `.cpp` and one or two compiler flags. So, basically, there is no need to refractory code to deploy different back-ends.

1.3 Basic features

Currently, Hydra provides collection of parallelized high-level algorithms, addressing some computing-intensive tasks commonly found in data analyses in HEP. The available high-level algorithms are listed below,

- Interface to **Minuit2** minimization package [7], allowing to accelerate maximum likelihood fits over multidimensional large data-sets.
- Parallel implementation of the **SPlot** technique, a very popular procedure for statistical unfolding of data distributions [8] .
- Phase-space Monte Carlo generation, integration and modeling.
- Multidimensional p.d.f. sampling.
- Parallel function evaluation on multidimensional data-sets.
- Five fully parallelized numerical integration algorithms: Genz-Malik [9, 10], self-adaptive and static Gauss-Kronrod quadratures, plain, self-adaptive importance sampling and phase-space Monte Carlo integration.

1.4 How does this manual is organized?

By the time it was written, this manual covers the usage of most of the Hydra features. This manual was written to be read sequentially. The sections are organized by subject and are sorted to make available the functionality described in a given section usable in the next parts.

FUNCTORS AND C++ LAMBDA.

The user's code is passed to Hydra's algorithms through functors and C++ lambdas. Hydra then adds type information and functionality to functors and lambdas using CRTP. Functors and lambdas are not attached to a specific back-end. The signatures conventions adopted for functors and lambdas as well as the added functionality will be discussed in the following lines.

2.1 Functors

In C++, a functor, sometimes also referred as a function object, is any class or structure that overloads the function call operator `operator() (Args ...x)`. In Hydra, all functors derives from the class template `hydra::BaseFunctor<Functor, Signature, NParameters>`. The template parameters are described below:

- **Functor** : the type of the functor.
- **Signature**: a type representing the signature of function call operator. Ex: `void(double, double)`.
- **NParameters**: the number of parameters the functor takes.

The user needs to implement the method `Evaluate(...)` and Hydra will take care of implementing the function call operator. To see how this works, it is convenient to give a look at the implementation of the `hydra::Gaussian` functor:

```
//Template parameters: //ArgType: the argument type. In this way, this
also supports static named variables //Signature: whatever type it gets, the
functor will return a double //Third parameter: 2 is the number of pa-
rameters a Gaussian takes (mean and width) template<typename ArgType,
typename Signature=double(ArgType) > class Gaussian: public BaseFunc-
tor<Gaussian<ArgType>, Signature, 2> {
```

```
    //import the parameters accessor _par using BaseFunc-
    tor<Gaussian<ArgType>, Signature, 2>::_par;
```

```
    public: //all members callable from host and device side //making sure
    that Gaussians always have a defined mean and sigma Gaussian()=delete;
```

```
//constructors should also forward the parameters to BaseFunctor Gaussian(
Parameter const& mean, Parameter const& sigma );
```

```
BaseFunctor<Gaussian<ArgType>, Signature, 2>({mean,
sigma}) {}
```

```
__hydra_host__ __hydra_device__ Gaussian(Gaussian<ArgType>
const& other );
```

```
BaseFunctor<Gaussian<ArgType>, Signature, 2>(other) {}
```

```
//operator= should be always implemented __hydra_host__ __hydra_device__
Gaussian<ArgType>& operator=(Gaussian<ArgType>
const& other ) {
```

```
if(this==&other) return *this; BaseFunctor<Gaussian<ArgType>, Signature, 2>::operator=(other);
return *this;
```

```
}
```

```
//implement the evaluate method, where actual value of the functor for
//its current parameters is calculated. //CHECK_VALUE macro verifies the value and prints information in case of failure or NAN __hydra_host__ __hydra_device__
inline double Evaluate(ArgType x) const
{
```

```
double m2 = ( x - _par[0])*(x - _par[0] ); double s2 =
_par[1]*_par[1]; return CHECK_VALUE( ::exp(-m2/(2.0 * s2
)), "par[0]=%f, par[1]=%f", _par[0], _par[1]);
```

```
}
```

```
};
```

Functors implemented in that fashion can deal with statically named variables and be optimized when fitting datasets.

Hydra provides a growing set of native functors, which are available in `hydra/functions` folder.

2.2 C++ Lambdas

Hydra supports C++ lambdas. Before to pass C++ lambdas to Hydra's algorithms, users need to wrap it into a suitable Hydra object. This is done invoking the function template `hydra::wrap_lambda(...)`. Currently, lambdas with `auto` arguments are not supported. Parametric lambdas, with or without named arguments are supported, though.

```
auto multiply_by_two = hydra::wrap_lambda(
    [=] __hydra_device__ ( double x){

        return 2.0*x;
```

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```
    }  
  ) ;
```

Hydra can also handle “parametric lambdas”. Parametric lambdas are wrapped lambdas that can hold named parameters (hydra::Parameters objects). The signatures for parametric lambdas are:

```
// mean auto mean = hydra::Parameter::Create()  
    .Name(“Mean_X”) .Value(0.0) .Error(0.0001) .Limits(-1.0, 1.0);  
  
// sigma auto sigma = hydra::Parameter::Create()  
    .Name(“Sigma_X”) .Value(2.0) .Error(0.0001) .Limits(0.1, 3.0);  
  
auto gaussian = hydra::wrap_lambda  
    [=] __hydra_dual__ (unsigned int npar, const hydra::Parameter* params, dou-  
    ble x ) {  
  
    double mean = params[0].GetValue(); double sigma = params[1].GetValue();  
  
    double m2 = (X - mean ); m2 *= m2; double s2 = sigma*sigma;  
  
    return ::exp(-m2/(2.0 * s2 ))/( ::sqrt(2.0*s2*PI));  
  
    }, mean, sigma);
```


CONTAINERS

Hydra framework provides an one-dimensional STL-like vector container for each supported back-end, aliasing the underlying Thrust types. The framework also implements two native multidimensional containers called `hydra::multivector` and `hydra::multiarray`.

In these containers, the data corresponding to each dimension is stored in contiguous memory addresses that can be traversed in a CPU/GPU cache friendly way, independently of the other dimensions. In the case of multidimensional containers, when the data is traversed each entry is accessed as

a `hydra::tuple` object, where each field holds a value corresponding to a dimension.

3.1 One-dimensional containers

Hydra's one-dimensional containers are aliases to the corresponding [Thrust] vectors and are defined for each supported back-end. They are:

1. `hydra::device::vector` : storage allocated in the device back-end defined at compile time using the macro `HYDRA_DEVICE_SYSTEM`
2. `hydra::host::vector` : storage allocated in the device back-end defined at compile time using the macro `HYDRA_HOST_SYSTEM`
3. `hydra::omp::vector` : storage allocated in the [OpenMP] back-end. Usually the CPU memory space.
4. `hydra::tbb::vector` : storage allocated in the [TBB] back-end. Usually the CPU memory space.
5. `hydra::cuda::vector` : storage allocated in the [CUDA] back-end. The GPU memory space.
6. `hydra::cpp::vector` : storage allocated in the [CPP] back-end. Usually the CPU memory

The usage of these containers is extensively documented in STL and [Thrust] library. Hydra also implements range-semantics for many of these containers.

3.2 Multi-dimensional containers

Hydra implements two multidimensional containers: `hydra::multivector` and `hydra::multiarray`. These containers store data using [SoA] layout and provides a STL-vector compliant interface.

Both classes provides constant and non-constant accessors for the single dimensional data. The container `hydra::multivector` is suitable to store data-sets where the dimensions are represented by entries with different POD types. `hydra::multiarray` is designed to store data-sets where all dimensions are represented by fields of the same type. Data is always copyable across different back-ends and movable between containers on the same back-end.

The best way to understand how these containers operate is to visualize them as a table, there each row corresponds to a entry and each column to a dimension. The design of `hydra::multivector` and `hydra::multiarray` makes possible to iterate over the container to access a complete row or to iterate over one or more columns to access only the data of interest in a given entry, without loading the entire row.

When the user iterates over the whole container, each entry (row) is returned as a `hydra::tuple`. If the user iterates over one single column, the entries have the type of the column. If two or more columns are accessed, entry's data is returned as again as `hydra::tuple` containing only the elements of interest. Hydra's multi-dimensional containers can hold any type of data per dimension, but there is not real gain using these containers for describing dimensions with non-POD or non alignable data.

These containers can store the state of arbitrary objects and perform type conversions on-the-fly, using suitable overloaded iterators and `push_back()` methods.

3.2.1 `hydra::multivector`

`hydra::multivector` templates are instantiated passing the type list corresponding to each dimension via a `hydra::tuple` and the back-end where memory will be allocated. The snippet *below* show how to instantiate a `hydra::multivector` to store four-dimensional data, two columns for integers and two columns for doubles:

```
#include <hydra/device/System.h>
#include<hydra/multivector.h>

...

hydra::multivector<hydra::tuple<int, int, double, double>,
↳hydra::device::sys_t> mvector;

for(int i=0; i<10;i++){
    mvector.push_back(hydra::make_tuple( i, 2*i, i, 2*i));
}

for(auto x:mvector) std::cout << x << std::endl;
```

this will print in stdout something like it :

```
(0, 0, 0.0, 0.0)
(1, 2, 1.0, 2.0)
(2, 4, 2.0, 4.0)
...
(9, 18, 9.0, 18.0)
```

To access the columns the user needs `hydra::placeholders: _0, _1, _2,..., _99`;

```
#include <hydra/device/System.h>
#include<hydra/multivector.h>
#include<hydra/Placeholders.h>

using namespace hydra::placeholders;

...

hydra::multivector<hydra::tuple<int, int, double, double>,
↳hydra::device::sys_t> mvector;

for(int i=0; i<10;i++){
    mvector.push_back(hydra::make_tuple( i, 2*i, i, 2*i));
}

for(auto x = mvector.begin(_1, _3);
    x != mvector.end(_1, _3); ++x )

    std::cout << *x << std::endl;
```

now in stdout the user will get:

```
(0, 0.0)
(2, 2.0)
(4, 4.0)
...
(18, 18.0)
```

Now suppose that one want to interpret the data stored in `mvector` as a pair of complex numbers, represented by the types `hydra::complex<int>` and `hydra::complex<double>`. It is not necessary to access each field stored in each entry to perform a conversion invoking the corresponding constructors. The next example shows how this can be accomplished in a more elegant way using a lambda function:

```
#include <hydra/device/System.h>
#include<hydra/multivector.h>
#include<hydra/Complex.h>
```

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```

...

    hydra::multivector<hydra::tuple<int, int, double, double>,
→hydra::device::sys_t> mvector;

    for(int i=0; i<10;i++){
        mvector.push_back(hydra::make_tuple( i, 2*i, i, 2*i));
    }

    auto caster = [] __host__ device__ ( hydra::tuple<int, int, double,
→double>& entry )
    {

        hydra::complex<int> cint(hydra::get<0>(entry), hydra::get<1>
→(entry));
        hydra::complex<double> cdouble(hydra::get<2>(entry), hydra::get<2>
→(entry));

        return hydra::make_pair(  cint, cdouble );
};

    for(auto x = mvector.begin(caster); x != mvector.end(caster); x++ )
        std::cout << *x << std::endl;

```

stdout will look like:

```

((0, 0), (0.0, 0.0))
((1, 2), (1.0, 2.0))
((2, 4), (2.0, 4.0))
...
((9, 18), (9.0, 18.0))

```

Same effect can be

hydra::multiarray

hydra::multiarray templates are instantiated passing the type and the number of dimensions via and the back-end where memory will be allocated. The snippet *below* show how to instantiate a hydra::multiarray to store four-dimensional data, two columns for integers and two columns for doubles:

```

#include <hydra/device/System.h>
#include<hydra/multiarray.h>

...

hydra::multiarray<4, double, hydra::device::sys_t> marray;

```

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```

for(int i=0; i<10;i++){
    marray.push_back(hydra::make_tuple( i, 2*i, 4*i, 8*i));
}

for(auto x:marray) std::cout << x << std::endl;

```

this will print in stdout something like it :

```

(0.0, 0.0, 0.0, 0.0)
(1.0, 2.0, 4.0, 8.0)
(2.0, 4.0, 8.0, 16.0)
...
(9.0, 18.0, 36.0, 72.0)

```

To access the columns the user can deploy `hydra::placeholders: _0, _1, _2...` or use unsigned int indexes.

```

#include <hydra/device/System.h>
#include<hydra/multisArray.h>
#include<hydra/Placeholders.h>

using namespace hydra::placeholders;

...

hydra::multisArray<4, double, hydra::device::sys_t> marray;

for(int i=0; i<10;i++){
    marray.push_back(hydra::make_tuple( i, 2*i, i, 2*i));
}

for(auto x = marray.begin(_1, _3);
    x != marray.end(_1, _3); x++ )
    std::cout << *x << std::endl;

```

now in stdout the user will get:

```

(0.0, 0.0)
(2.0, 8.0)
(4.0, 16.0)
...
(18.0, 72.0)

```

Now suppose that one want to interpret the data stored in mvector as a pair of complex numbers, represented by the types `hydra::complex<double>` and `hydra::complex<double>`. It is not necessary to access each field stored in each entry to perform a conversion invoking the corresponding constructors. The next example shows how this can be accomplished in a more elegant way using a lambda function:

```
#include <hydra/device/System.h>
#include<hydra/multiarray.h>
#include<hydra/Complex.h>

...

hydra::multiarray<4, double, hydra::device::sys_t> marray;

for(int i=0; i<10;i++){
    marray.push_back(hydra::make_tuple( i, 2*i, i, 2*i));
}

auto caster = [] __host__ device__ (hydra::tuple<double, double, double, double>& entry ){

    hydra::complex<double> c1(hydra::get<0>(entry), hydra::get<1>(entry));
    hydra::complex<double> c2(hydra::get<2>(entry), hydra::get<3>(entry));
    return hydra::make_pair( c1, c2);
};

for(auto x = marray.begin(caster); x != marray.end(caster); x++ )
    std::cout << *x << std::endl;
```

stdout will look like:

```
((0, 0), (0.0, 0.0))
((1, 2), (1.0, 2.0))
((2, 4), (2.0, 4.0))
...
((9, 18), (9.0, 18.0))
```

HISTOGRAMS

Hydra implements two classes dedicated to calculate multidimensional histograms in parallel. One class for dense histograms and other for sparse histograms. These classes provide only the basic functionality to calculate the histogram using one of the supported parallel back-ends. Once calculated, the histogram contents can be exported to external libraries, like ROOT, for drawing etc.

The histograms classes does not process event-by-event. They takes iterators pointing to containers storing the data and process it at once. This approach is orders of magnitude more efficient than iterate over the container and histogram in entry-by-entry basis.

4.1 Binning convention

In Hydra, a histogram with N bins is stored in a array with length $N+2$. In range contents are indexed starting from 0 to $N-1$. Underflow contents are stored in bin N and overflow contents are stored in bin $N+1$.

4.2 Global and dimensional binning

The histogram contents is organized in a linear array of length $N+2$, where N is total number of bins, obtained multiplying the number of bins configured in for each dimension. The conversion between global bin number and dimensional bin numbers is performed by the methods `GetBin(...)` and `GetIndexes(...)`, implemented in both classes. The internal indexing convention used in Hydra in general does not match the one used in other libraries and interfaces. Users are advised to always export the histogram contents using the bin numbers per bin.

4.3 Dense histograms

Dense histograms store all bins, including ones with zero content. In Hydra, they are represented by the class `hydra::DenseHistogram<Type, NDimensions, Backend>`, where `NDimensions` is the number of dimensions, `Type` is the type of the histogram's values and `Backend` is memory space where the histogram is allocated.

The code snippet below shows how to instantiate and fill a dense histogram in Hydra:

```
#include <hydra/device/System.h>
#include <hydra/multiarray.h>
#include <hydra/DenseHistogram.h>
#include <array>

...

hydra::multiarray<4, double, hydra::device::sys_t> mvector;

...
// fill mvector with the data of interest...
...

//histogram ranges
std::array<double, 4>max{ 1.0,  2.0,  3.0,  4.0};
std::array<double, 4>min{-1.0, -2.0, -3.0, -4.0};

//bins per dimension
std::array<size_t, 3> nbins{10, 20, 30, 40};

//create histogram
hydra::DenseHistogram<3, double> Histogram(nbins, min, max);

Histogram.Fill( mvector.begin(), mvector.end());

//getting bin content [0, 2, 3, 1]
Histogram.GetBinContent({0, 2, 3, 1});
```

4.4 Sparse histograms

Sparse histograms store only bins with non-zero content. In Hydra, they are represented by the class `hydra::SparseHistogram<Type, NDimensions, Backend>`, where `NDimensions` is the number of dimensions, `Type` is the type of the histogram's values and `Backend` is memory space where the histogram is allocated.

```
#include <hydra/device/System.h>
#include <hydra/multiarray.h>
```

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```
#include <hydra/SparseHistogram.h>
#include <array>

...

hydra::multiarray<4, double, hydra::device::sys_t> mvector;

...
// fill mvector with the data of interest...
...

//histogram ranges
std::array<double, 4>max{ 1.0,  2.0,  3.0,  4.0};
std::array<double, 4>min{-1.0, -2.0, -3.0, -4.0};

//bins per dimension
std::array<size_t, 3> nbins{10, 20, 30, 40};

//create histogram
hydra::SparseHistogram<3, double> Histogram(nbins, min, max);

Histogram.Fill( mvector.begin(), mvector.end());

//getting bin content [0, 2, 3, 1]
Histogram.GetBinContent({0, 2, 3, 1});
```


RANDOM NUMBER GENERATION AND PDF SAMPLING

The generation of random numbers and sampling of multidimensional PDFs is supported in Hydra through the class `hydra::Random<typename Engine>`, where `Engine` is the random number generator engine. The only argument of the `hydra::Random` constructor is the seed of random number generator. There are four random number engines available

1. `hydra::minstd_rand0`: implements a version of the Minimal Standard random number generation algorithm.
2. `hydra::minstd_rand`: implements a version of the Minimal Standard random number generation algorithm.
3. `hydra::ranlux24`: RANLUX level-3 random number generation algorithm.
4. `hydra::ranlux48`: RANLUX level-4 random number generation algorithm.
5. `hydra::taus88`: L'Ecuyer's 1996 three-component Tausworthe random number generator.

The default random number generation engine is `hydra::minstd_rand0`, which produces pseudo-random numbers with quality appropriated for most applications. This class provides methods that take iterators pointing to containers that will be filled with random numbers distributed according the requested distributions. If an explicit back-end policy is passed, the generation is parallelized in the corresponding back-end, otherwise the class will process the random number generation in the back-end the containers is allocated.

5.1 Sampling basic distributions

`hydra::Random` defines four methods to generate predefined one-dimensional. These methods are summarized below, where `begin` and `end` are iterators pointing to the range that will filled with random numbers. The other parameters represent the standard definitions:

1. `hydra::Random::Gauss(mean, sigma, begin, end)` for Gaussian distribution.
2. `hydra::Random::Exp(tau, begin, end)` for exponential distribution.
3. `hydra::Random::Uniform(min, max, begin, end)` for an uniform distribution.
4. `hydra::Random::BreitWigner(mean, width, begin, end)` for non-relativistic Breit-Wigner distribution.

The example below show how to use these methods

```
#include <hydra/device/System.h>
#include <hydra/Random.h>

...

hydra::Random<> Generator(4598635);
hydra::device::vector<double> data(1e6);

//uniform distribution in the interval [-5,5]
Generator.Uniform(-5.0, 5.0, data.begin(), data.end());

//Gaussian distribion with mean=0 and sigma =1
Generator.Gauss(0.0, 1.0, data.begin(), data.end());

//exponential distribion with tau=1
Generator.Exp(1.0, data.begin(), data.end());

//Breit-Wigner with mean 2.0 width 0.2
Generator.BreitWigner(2.0, 0.2, data_d.begin(), data_d.end());
```

5.2 Multidimensional PDF sampling

The class `hydra::Random` also supports the sampling of multidimensional probability density functions (PDF) through the method `hydra::Random::Sample(begin, end, min, max, functor)`, where `min` and `max` are static arrays or `std::array` objects representing the limits of the multidimensional region. `functor` is a Hydra functor representing the PDF.

The PDFs are sampled using a parallel version of the accept-reject method. The

`hydra::Random::Sample` returns a `hydra::GenericRange` object pointing to a range filled with the sampled numbers. The PDF sampling

is processed filling the container with random numbers and reordering it to reproduce the shape of the PDF, no memory reallocation is performed during this process. The range returned by the method points to a sub-set of the original container, the size of this range depends on the efficiency of the accept-reject for the given PDF.

The code below shows how to sample a three-dimensional PDF

```
#include <hydra/device/System.h>
#include <hydra/Random.h>
#include <hydra/Lambda.h>

...

double mean    =  0.0;
```

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```

double sigma = 1.0;

auto gaussian = hydra::wrap_lambda(
    [=] __host__ __device__ (unsigned int n, double* x ){

        double g = 1.0;

        for(size_t i=0; i<3; i++){
            double m2 = (x[i] - mean )*(x[i] - mean );
            double s2 = sigma*sigma;
            g *= exp(-m2/(2.0 * s2 ))/( sqrt(2.0*s2*PI));
        }

        return g;
    }
);

std::array<double, 3> max{ 6.0, 6.0, 6.0};
std::array<double, 3> min{-6.0, -6.0, -6.0};

hydra::multiarray<3, double, hydra::device::sys_t> data;
auto range = Generator.Sample(data.begin(), data.end(), min, max,
    ↪gaussian);

```


PHASE-SPACE MONTE CARLO

Phase-Space Monte Carlo simulates the kinematics of a particle with a given four-momentum decaying to a n -particle final state, without intermediate resonances. Samples of phase-space Monte Carlo events are widely used in HEP studies where the calculation of phase-space volume is required as well as a starting point to implement and describe the properties of models with one or more resonances or even to simulate the response of the detector to decay's products [James].

Hydra provides an implementation of the Raubold-Lynch method [James] and can generate the full kinematics of decays with any number of particles in the final state. Sequential decays, evaluation of models, production of weighted and unweighted samples and many other features are also supported.

6.1 Decays and decay chains

The four-vector of the generated final-state particles are stored in the dedicated vector-like container `hydra::Decays<N,BACKEND>` where N is the number of particles in the final state and `BACKEND` is the memory space where allocate the storage. `hydra::Decays<N,BACKEND>` can be aggregated to describe sequential decays using `hydra::Chains<Decays...>` objects.

Both classes are iterable, but the `hydra::Chains<Decays...>` container does not implement a full vector-like interface. Pre-allocated `hydra::Decays<N,BACKEND>` can not be added to a `hydra::Chains<Decays...>`.

6.2 Phase-space Monte Carlo generator.

The phase-space Monte Carlo generator is represented by the class `hydra::PhaseSpace<N,RNG>`, where N is the number of particles and `RNG` is underlying random number generator to be used. The constructor of the `hydra::PhaseSpace` takes as parameter an array with the masses of the final state particles. The decays are generated invoking the overloaded `hydra::PhaseSpace::Generate(...)` method. This method can take a `hydra::Vector4R`, describing momentum of a only mother particle or iterators pointing for a container storing a list of mother particles and the iterators pointing to the `hydra::Decays<N,BACKEND>` container that will hold the generated final states. If an explicit policy policy is

passed, the generation is parallelized in the corresponding back-end, otherwise the class will process the random number generation in the back-end where the containers are allocated.

6.2.1 Generating one-level decays

The code below shows how to generate a sample of 20 million $B^0 \rightarrow J/\psi K^+ \pi^-$ decays and fill a Dalitz's plot, i.e. a histogram $M^2(J/\psi \pi^-) vs M^2(K^+ \pi^-)$:

```
#include <hydra/Types.h>
#include <hydra/Vector4R.h>
#include <hydra/PhaseSpace.h>
#include <hydra/device/System.h>
#include <hydra/Decays.h>

...

size_t nentries = 20e6;      // number of events to generate
double B0_mass  = 5.27955;   // B0 mass
double Jpsi_mass = 3.0969;    // J/psi mass
double K_mass    = 0.493677;  // K+ mass
double pi_mass   = 0.13957061; // pi mass

// mother particle
hydra::Vector4R B0(B0_mass, 0.0, 0.0, 0.0);

// decays container
hydra::Decays<3, hydra::device::sys_t > Events(nentries);

hydra::PhaseSpace<3> phsp{Jpsi_mass, K_mass, pi_mass};

// generate the final state particles
phsp.Generate(B0, Events.begin(), Events.end());

// functor to calculate Dalitz variables
auto dalitz_calculator = hydra::wrap_lambda(
    [=] __host__ __device__ (unsigned int np, hydra::Vector* _
    ↪ particles){

        hydra::Vector4R Jpsi = event[0];
        hydra::Vector4R K    = event[1];
        hydra::Vector4R pi   = event[2];

        double M2_Jpsi_pi = (Jpsi + pi).mass2();
        double M2_Kpi     = (K + pi).mass2();

        return hydra::make_tuple( M2_Jpsi_pi, M2_Kpi);
    }
```

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```

    }
);

//
auto particles          = Events.GetUnweightedDecays();

// use an smart-range to calculate the Dalitz variables
// without have to store it. ;)
auto dalitz_variables = hydra::make_range( particles.begin(),
    ↳ particles.end(), dalitz_calculator);

// get the event's weights
auto dalitz_weights    = Events.GetWeights();

// instantiate 2D histogram
hydra::DenseHistogram<2, double> Hist_Dalitz({100,100}, {pow(Jpsi_mass,
    ↳ + pi_mass,2), pow(K_mass + pi_mass,2)},
    {pow(B0_mass - K_mass,2)    , pow(B0_mass - Jpsi_mass,2)} );

//fill the histogram
Hist_Dalitz.Fill(dalitz_variables.begin(), dalitz_variables.end(),
    ↳ dalitz_weights.begin());

...

```

In the previous example, the user can forward the `Hydra::DenseHistogram` to ROOT and draw it.

6.2.2 Generating sequential decays

The code below shows how to generate a sample of 20 million decay chains $B^0 \rightarrow J/\psi K^+ \pi^-$ with $J/\psi \rightarrow \mu^+ \mu^-$.

The first step to process the decay chain is to generate the decays $B^0 \rightarrow J/\psi K^+ \pi^-$, then the list of J/ψ candidates is passed to the instance of `hydra::PhaseSpace` to generate the $J/\psi \rightarrow \mu^+ \mu^-$ corresponding to each J/ψ mother. Notice that the decay events stored in a given chain are accessed using a `hydra::placeholder`.

```

#include <hydra/Types.h>
#include <hydra/Vector4R.h>
#include <hydra/PhaseSpace.h>
#include <hydra/device/System.h>
#include <hydra/Chains.h>
#include <hydra/Placeholders.h>

...

```

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```
using namespace hydra::placeholders;

...

size_t nentries    = 20e6;           // number of events to generate
double B0_mass     = 5.27955;        // B0 mass
double Jpsi_mass   = 3.0969;         // J/psi mass
double K_mass      = 0.493677;       // K+ mass
double pi_mass     = 0.13957061;     // pi mass
double mu_mass     = 0.1056583745 ; // mu mass

// mother particle
hydra::Vector4R B0(B0_mass, 0.0, 0.0, 0.0);

// create PhaseSpace object for B0 -> K pi J/psi
hydra::PhaseSpace<3> phsp_B2JpsiKpi{Jpsi_mass, K_mass, pi_mass };

// create PhaseSpace object for J/psi -> mu+ mu-
hydra::PhaseSpace<2> phsp_Jpsi2mumu{mu_mass , mu_mass};

//      allocate memory to hold the final states particles
auto Events = hydra::make_chain<3,2>(hydra::device::sys, nentries);

//generate the final state particles for B0 -> K pi J/psi
phsp_B2JpsiKpi.Generate(B0, Events.GetDecay(_0).begin(),
                        Events.GetDecay(_0).end());

//pass the list of J/psi to generate the final
//state particles for J/psi -> mu+ mu-
phsp_Jpsi2mumu.Generate(Events.GetDecay(_0).GetDaughters(0).begin(),
                        Events.GetDecay(_0).GetDaughters(0).end(),
                        Events.GetDecay(_1).begin());
```

6.3 Other features

The classes of the phase-space module provides many other functionality. The list below summarizes some of them:

- Calculate the mean and the variance of a functor over a phase-space without the need to generate and store events.
- Evaluate functors and stored the result without the need to generate and store events.
- Unweight and re-weight events stored in `hydra::decay` objects to match .

- Access single particle's `Vector4R` or its components of events stored in `hydra::decay` objects and interact with it.

For brevity, the user is advised to look the doxygen documentation and the examples to learn what is available and how to deploy it.

NUMERICAL INTEGRATION

Numerical integration of multidimensional functions is not easy. Numerical integration algorithms tend to be involved and resource hungry, since they demand a large number of evaluations of the integrand. Indeed, it is common to express the efficiency of a given algorithm in terms of the minimum required number of integrand evaluations to achieve given precision for the integral estimation.

The best strategy to perform numerical integration largely depends on the number of dimensions of the integration region and on the features shown by the integrand in this region. Given the detailed information about integrand behavior is usually not available, the numerical integration algorithms need to handle situations specializing routines based on broad properties of the integrand, such as the presence or the absence of narrow peaks, periodicity etc. Highly specialized algorithms, optimized to handle only a given class of problems tend to be more efficient, but on the other hand, such approaches are usually not applicable to different class of problems. In other words, on the field of numerical integration, flexibility usually comes at expenses of efficiency. The basics of numerical integration, followed by comprehensive list of references on the subject, can be found in the Wikipedia pages https://en.wikipedia.org/wiki/Numerical_integration and https://en.wikipedia.org/wiki/Monte_Carlo_integration.

Hydra provides a set of parallelized implementations for generic and popular algorithms to compute one- and multidimensional numerical integration. Hydra parallelizes the calls to the integrand in a collection of threads in requested back-end. The algorithms share the same basic interface, manage resources using RAII idiom and estimate the integral and the associated error. Hydra also supports analytical integration, which should be implemented through functors.

7.1 Gauss-Kronrod quadrature

See also:

Good didactic introduction on Gauss-Kronrod quadrature can be found in the Wikipedia page https://en.wikipedia.org/wiki/Gauss-Kronrod_quadrature_formula.

The class `hydra::GaussKronrodQuadrature<NRULE, NBIN, Backend>` implements a non-adaptive procedure which divides the integration interval in NBIN sub-intervals and applies to each sub-interval a fixed Gauss-Kronrod rule of order NRULE. `hydra::GaussKronrodQuadrature<NRULE, NBIN, Backend>` allows the fast integration

of smooth one-dimensional functions. The code snippet below show how to use this quadrature to calculate the integral of a Gaussian function:

```
#include <hydra/GaussKronrodQuadrature.h>
#include <hydra/Lambda.h>
#include <hydra/device/System.h>

...

//integration region limits
double min  = -6.0;
double max  =  6.0;

//Gaussian parameters
double mean  = 0.0;
double sigma = 1.0;

//wrap the lambda
auto gaussian = hydra::wrap_lambda(
[=] __host__ __device__ (unsigned int n, double* x ){

    double m2 = (x[0] - mean )*(x[0] - mean );
    double s2 = sigma*sigma;
    double f = exp(-m2/(2.0 * s2 ))/( sqrt(2.0*s2*PI));

    return f;
} );

...

// 61- degree quadrature
hydra::GaussKronrodQuadrature<61,100, hydra::device::sys_t> GKQ61_
    ↪d(min, max);

auto result = GKQ61_d.Integrate(gaussian);

std::cout << "Result: " << result.first << " +- " << result.second <
    ↪<std::endl
```

7.2 Self-Adaptive Gauss-Kronrod quadrature

See also:

Good didactic introduction on Gauss-Kronrod quadrature can be found in the Wikipedia page https://en.wikipedia.org/wiki/Gauss-Kronrod_quadrature_formula.

The class `hydra::GaussKronrodAdaptiveQuadrature<NRULE, NBIN, Backend>` implements a self-adaptive algorithm which initially divides the integration interval in NBIN sub-intervals and applies to each sub-interval a Gauss-Kronrod rule of order NRULE. The algorithm selects the interval with larger relative error in the integral estimation and re-applies the procedure. The algorithm keeps performing this loop until the integrand estimation reaches the requested maximum error level.

`hydra::GaussKronrodQAdaptiveuadrature<NRULE, NBIN, Backend>` performs less calls to the integrand and is best suitable for very featured and expensive functions. The code snippet below show how to use this quadrature to calculate the integral of a Gaussian function:

```
#include <hydra/GaussKronrodAdaptiveQuadrature.h>
#include <hydra/Lambda.h>
#include <hydra/device/System.h>

...

//integration region limits
double min  = -6.0;
double max  =  6.0;
double max_error = 1e-6;

//Gaussian parameters
double mean  = 0.0;
double sigma = 1.0;

//wrap the lambda
auto gaussian = hydra::wrap_lambda(
[=] __host__ __device__ (unsigned int n, double* x ){

    double m2 = (x[0] - mean )*(x[0] - mean );
    double s2 = sigma*sigma;
    double f = exp(-m2/(2.0 * s2 ))/( sqrt(2.0*s2*PI));

    return f;
} );

...

// 61- degree quadrature
```

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```
hydra::GaussKronrodQuadrature<61,10, hydra::device::sys_t>
↳ GKQ61(min, max, max_error);

    auto result = GKQ61.Integrate(gaussian);

    std::cout << "Result: " << result.first << " +- " << result.
↳ second <<std::endl
```

7.3 Genz-Malik multidimensional quadrature

This method implements a polynomial interpolatory rule of degree 7, which integrates exactly all monomials $x_1^{k_1}, x_2^{k_2} \dots x_n^{k_d}$ with $\sum k_i \leq 7$ and fails to integrate exactly at least one monomial of degree 8. In the [Genz-Malik] multidimensional quadrature, all integration nodes are inside integration domain and $2^d + 2d^2 + 2d + 1$ integrand evaluations are required to integrate a function in a rectangular hypercube with d dimensions. Due the fast increase in the number of evaluations as a function of the dimension, this method is most advantageous for problems with $d < 10$ and is superseded for high-dimensional integrals by Monte Carlo based methods. A degree 5 rule embedded in the degree 7 rule is used for error estimation, in a such way that no additional integrand evaluations are necessary.

The class template `hydra::GenzMalikQuadrature<N, BackendPolicy >` implements a static version of Genz-Malik multidimensional quadrature. This version divides the ``N``-dimensional integration region in a series of sub-regions, according the configuration, passed by the user and applies the rule to each sub-region.

The code snippet below shows to use the `hydra::GenzMalikQuadrature<N, BackendPolicy >` class to integrate a five-dimensional Gaussian distribution. In this example each dimension is divided in 10 segments, resulting in 10^5 sub-regions.

```
#include <hydra/GaussKronrodAdaptiveQuadrature.h>
#include <hydra/Lambda.h>
#include <hydra/device/System.h>

...

//number of dimensions (user can change it)
constexpr size_t N = 5;

//integration region limits
double min[N];
double max[N];
size_t grid[N];

//5D Gaussian parameters
double mean = 0.0;
```

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```

double sigma = 1.0;

//set Gaussian parameters and
//integration region limits
for(size_t i=0; i< N; i++){
    min[i]    = -6.0;
    max[i]    =  6.0;
    grid[10]  = 10;
}

//wrap the lambda
auto gaussian = hydra::wrap_lambda( [=] __host__ __device__ (unsigned_
↪int n, double* x ){

    double g = 1.0;
    double f = 0.0;

    for(size_t i=0; i<N; i++){

        double m2 = (x[i] - mean )*(x[i] - mean );
        double s2 = sigma*sigma;
        f = exp(-m2/(2.0 * s2 ))/( sqrt(2.0*s2*PI));
        g *= f;
    }

    return g;
});

hydra::GenzMalikQuadrature<N, hydra::device::sys_t> GMQ(min, max, ↪
↪grid);

auto result = GMQ.Integrate(gaussian);

std::cout << "Result: " << result.first << " +- " << result.second <
↪<std::endl

```

7.4 Plain Monte Carlo

The plain Monte Carlo algorithm samples points randomly from the integration region to estimate the integral and its error. Using this algorithm the estimate of the integral $E(f; N)$ for N randomly distributed points x_i is given by,

$$E(f; N) = V \langle f \rangle = (V/N) \sum_i^N f(x_i)$$

where V is the volume of the integration region. The error on this estimate $\sigma(E; N)$ is calculated from the estimated variance of the mean,

$$\sigma^2(E; N) = (V^2/N^2) \sum_i^N (f(x_i) - \langle f \rangle)^2$$

For large N this variance decreases asymptotically as $Var(f)/N$, where $Var(f)$ is the true variance of the function over the integration region. The error estimate itself should decrease as $\sigma(f)/\sqrt{N}$, which implies that to reduce the error by a factor of 10, a 100-fold increase in the number of sample points is required.

Hydra implements the plain Monte Carlo method in the class `hydra::Plain<N, BackendPolicy>`, where N is the number of dimensions and `BackendPolicy` is the back-end to parallelize the calculation.

The following code snippet shows to use the `hydra::Plain<N, BackendPolicy >` class to integrate a five-dimensional Gaussian distribution performing 100

```
#include <hydra/Lambda.h>
#include <hydra/device/System.h>
#include <hydra/Plain.h>

...

//number of dimensions (user can change it)
constexpr size_t N = 5;

//integration region limits
double min[N];
double max[N];
size_t ncalls = 1e6;

//5D Gaussian parameters
double mean = 0.0;
double sigma = 1.0;

//set Gaussian parameters and
//integration region limits
for(size_t i=0; i< N; i++){
    min[i] = -6.0;
    max[i] = 6.0;
}

//wrap the lambda
auto gaussian = hydra::wrap_lambda( [=] __host__ __device__ (unsigned_
↪int n, double* x ){

    double g = 1.0;
    double f = 0.0;
```

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```

    for(size_t i=0; i<N; i++){

        double m2 = (x[i] - mean )*(x[i] - mean );
        double s2 = sigma*sigma;
        f = exp(-m2/(2.0 * s2 ))/( sqrt(2.0*s2*PI));
        g *= f;
    }

    return g;
});

hydra::Plain<N, hydra::device::sys_t> PlainMC(min, max, ncalls);

auto result = PlainMC.Integrate(gaussian);

std::cout << "Result: " << result.first << " +- " << result.second <
↪<std::endl

```

7.5 Self-adaptive importance sampling (Vegas)

Note: from GSL's Manual, chapter 'Monte Carlo integration' https://www.gnu.org/software/gsl/manual/html_node/VEGAS.html :

The VEGAS algorithm of [Lepage] is based on importance sampling. It samples points from the probability distribution described by the function $|f|$, so that the points are concentrated in the regions that make the largest contribution to the integral.

In general, if the Monte Carlo integral of f is sampled with points distributed according to a probability distribution described by the function g , we obtain an estimate $E_g(f; N)$,

$$E_g(f; N) = E(f/g; N)$$

with a corresponding variance,

$$Var_g(f; N) = Var(f/g; N).$$

If the probability distribution is chosen as $g = |f|/I(|f|)$ then it can be shown that the variance $\{Var\}_g(f; N)$ vanishes, and the error in the estimate will be zero. In practice it is not possible to sample from the exact distribution g for an arbitrary function, so importance sampling algorithms aim to produce efficient approximations to the desired distribution.

The VEGAS algorithm approximates the exact distribution by making a number of passes over the integration region while histogramming the function f . Each histogram is used to define a sampling distribution for the next pass. Asymptotically this procedure converges to the desired distribution. In order to avoid the number of histogram bins growing like K^d the probability distribution is approximated by a separable function: $g(x_1, x_2, \dots) = g_1(x_1)g_2(x_2)\dots$ so that the number of bins required is only K_d . This is equivalent to locating the peaks of the function from the projections of the integrand onto the coordinate axes. The efficiency of VEGAS depends on the validity of this assumption. It is most efficient when the peaks of the integrand are well-localized. If an integrand can be rewritten in a form which is approximately separable this will increase the efficiency of integration with VEGAS.

...

The implementation of VEGAS in Hydra parallelizes the Monte Carlo generation, the function calls and the computing of the result of each iteration. The algorithm is implemented in the `hydra::Vegas<N, BackendPolicy>`. The auxiliary class `hydra::VegasState<N, BackendPolicy>` manages the resources and configuration necessary to perform the integration. The code snippet below shows how to use the VEGAS algorithm to integrate five-dimensional Gaussian distribution:

```
#include <hydra/Vegas.h>
#include <hydra/Lambda.h>
#include <hydra/device/System.h>

...

//number of dimensions (user can change it)
constexpr size_t N = 5;

//integration region limits
double min[N];
double max[N];
size_t ncalls = 1e5;

//5D Gaussian parameters
double mean = 0.0;
double sigma = 1.0;

//set Gaussian parameters and
//integration region limits
for(size_t i=0; i< N; i++){
    min[i] = -6.0;
    max[i] = 6.0;
}
```

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```

//wrap the lambda
auto gaussian = hydra::wrap_lambda(
    [=] __host__ __device__ (unsigned int n, double* x ){

        double g = 1.0;
        double f = 0.0;

        for(size_t i=0; i<N; i++){

            double m2 = (x[i] - mean )*(x[i] -
→mean );

            double s2 = sigma*sigma;
            f = exp(-m2/(2.0 * s2 ))/( sqrt(2.
→0*s2*PI));

            g *= f;

        }

        return g;

    }
);

//vegas integrator
hydra::Vegas<N,  hydra::device::sys_t> Vegas(min, max,
→ncalls);

//configuration
Vegas.GetState().SetVerbose(-2);
Vegas.GetState().SetAlpha(1.5);
Vegas.GetState().SetIterations( iterations );
Vegas.GetState().SetUseRelativeError(1);
Vegas.GetState().SetMaxError( max_error );
Vegas.GetState().SetCalls( calls );
Vegas.GetState().SetTrainingCalls( calls/10 );
Vegas.GetState().SetTrainingIterations(2);

auto result = Vegas_d.Integrate(gaussian);
std::cout << "Result: " << result.first << "  +-  " << result.
→second <<std::endl

```

7.6 Implementing analytical integration

Hydra supports analytical integration as well. To integrate functions analytically the user needs to implement the integral formula in a suitable functor `Functor` deriving from the class `hydra::Integrator<Functor>`. Analytical integration is not parallelized.

PARAMETER ESTIMATION

The best Minuit description can be found on it's own user's manual [7] :

Minuit is conceived as a tool to find the minimum value of a multi-parameter function, usually called “FCN”, and analyze the shape of this function around the minimum. The principal application is foreseen for statistical analysis, working on chi-square or log-likelihood functions, to compute the best-fit parameter values and uncertainties, including correlations between the parameters. It is especially suited to handle difficult problems, including those which may require guidance in order to find the correct solution.

—Minuit User's Guide, Fred James and Matthias Winkler, June 16, 2004 - CERN, Geneva.

Hydra implements an interface to Minuit2 that parallelizes the FCN calculation. This dramatically accelerates the calculations over large or multidimensional datasets. Hydra normalizes the pdfs on-the-fly using analytical

or numerical integration algorithms provided by the framework and handles data using iterators. Hydra supports weighted and unweighted datasets.

Hydra also provides an implementation of SPlot [8], a very popular technique for statistical unfolding of data distributions.

8.1 Defining PDFs

In Hydra, PDFs are represented by the `hydra::Pdf<Functor, Integrator>` class template and are defined binding a positive defined functor

and a integrator. PDFs can be conveniently built using the template function

```
hydra::make_pdf( pdf_object, integrator_object).
```

Most of the functors provided in Hydra have an analytical integrator defined. To invoke it, one should use the class template `hydra::AnalyticalIntegral<Functor>`, otherwise an appropriated numerical integration algorithm needs be specified.

The snippet below shows how bind a Gaussian to its analytical integrator and build a pdf object:

It is also possible to represent models composed by the sum of two or more PDFs using the class templates `hydra::PDFSumExtendable<Pdf1, Pdf2, ...>` and

`hydra::PDFSumNonExtendabl<Pdf1, Pdf2,...>` . Given N normalized pdfs F_i , theses classes define objects representing the sum

$$F_t = \sum_i^N c_i \times F_i$$

The coefficients c_i can represent fractions or yields. If the number of coefficients is equal to the number of PDFs, the coefficients are interpreted as yields and `hydra::PDFSumExtendable<Pdf1, Pdf2,...>` is used. If the number of coefficients is $(N - 1)$, the class template `hydra::PDFSumNonExtendabl<Pdf1, Pdf2,...>` is used and the coefficients are interpreted as fractions defined in the interval $[0,1]$. The coefficient of the last term is calculated as $c_N = 1 - \sum_i^{(N-1)} c_i$.

`hydra::PDFSumExtendable<Pdf1, Pdf2,...>` and `hydra::PDFSumNonExtendabl<Pdf1, Pdf2,...>` objects can be conveniently created using the function template `hydra::add_pdfs(...)`.

The code snippet below shows how to implement a model with two components, a Gaussian and a Argus distribution, to build a extended model, which can be used to predict the corresponding yields:

The user can get a reference to one of the component PDFs using the method `PDF(hydra::placeholder)`. This is useful, for example, to change the state of a component PDF “in place”. Same operation can be performed for coefficients using the method `Coefficient(unsigned int)`:

```
#include<hydra/Placeholders.h>

using namespace hydra::placeholders;

...

//change the mean of the Gaussian to 2.0
model.PDF( _0 ).SetParameter(0, 2.0);

//set Gaussian coefficient to 1.5e4
model.Coefficient(0).SetValue(1.5e4);
```

The Hydra classes representing PDFs are not dumb arithmetic beasts. These classes are lazy and implements a series of optimizations in order to forward to the thread collection only code that need effectively be evaluated. In particular, functor normalization is cached in a such way that only new parameters settings will trigger the recalculation of integrals.

8.2 Defining FCNs and invoking the ROOT::Minuit2 interfaces

In general, a FCN is defined binding a PDF to the data the PDF is supposed to describe. Hydra implements classes and interfaces to allow the definition of FCNs suitable to perform maximum likelihood fits on unbinned and binned datasets. The different use cases for Likelihood FCNs are covered by the specialization of the class template `hydra::LogLikelihoodFCN<PDF, Iterator, Extensions...>`.

Objects representing likelihood FCNs can be conveniently instantiated using the function template `hydra::make_likelihood_fcn(data_begin, data_end, PDF)`

and `hydra::make_likelihood_fcn(data_begin, data_end, weights_begin, PDF)`, where `data_begin`, `data_end` and `weights_begin` are iterators pointing to the dataset and the weights.

```
#include <hydra/LogLikelihoodFCN.h>
//Minuit2
#include "Minuit2/FunctionMinimum.h"
#include "Minuit2/MnUserParameterState.h"
#include "Minuit2/MnPrint.h"
#include "Minuit2/MnMigrad.h"
#include "Minuit2/MnMinimize.h"
...

// get the fcn...
auto fcn = hydra::make_loglikelihood_fcn(dataset.begin(), dataset.
→end(), model);
// and invoke Migrad minimizer from Minuit2
MnMigrad migrad(fcn, fcn.GetParameters().GetMnState(),
→MnStrategy(2));
```

8.3 sPlots

The sPlot technique is used to unfold the contributions of different sources to the data sample in a given variable. The sPlot tool applies in the context of a Likelihood fit which needs to be performed on the data sample to determine the yields corresponding to the various sources.

Hydra handles sPlots using the class template `hydra::SPlot<Iterator, PDF1, PDF2, PDFs...>` where `Iterator` is an iterator point to data

`PDF1`, `PDF2` and `PDFs...` are the probability density functions describing the populations contributing to the dataset as modeled in a given

variable referred as discriminating variable.

The other variables of interest, present in the dataset are referred as control variables and are

statistically unfolded using the so called *sweights*. For each entry in the dataset, `hydra::SPlot<Iterator, PDF1, PDF2,PDFs...>` calculates a set of weights, each one corresponds to a data source described by the corresponding PDF. It is not necessary to allocate memory to store the *sweights*. It is calculated on the fly when the user iterates over the `hydra::Splot` object. One can create the `hydra::Splot` object using the convenience functions `hydra::make_splot(PDF, data_range)` or `hydra::make_splot(PDF, data_begin, data_end)`, where PDF is a `PDFSumExtendable<PDF1, PDF2, PDFs...>` object. It is responsibility of the user to make sure that the passed PDF object properly optimized to describe the data.

```
#include <hydra/SPlot.h>

...

//splot
//create splot
auto sweigts = hydra::make_splot(fcn.GetPDF(), range );

auto covar_matrix = sweigts.GetCovMatrix();

std::cout << "Covariance matrix "
           << std::endl
           << covar_matrix
           << std::endl
           << std::endl;

std::cout << std::endl
           << "sWeights:"
           << std::endl;

for(size_t i = 0; i<10; i++)
    std::cout << "[" << i << "]" :<
               << sweigts[i]
               << std::endl
               << std::endl;
```

CHAPTER

NINE

REFERENCES

INDICES AND TABLES

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BIBLIOGRAPHY

- [1] CERNLIB - CERN Program Library. <https://cernlib.web.cern.ch/cernlib>.
- [2] NVIDIA CUDA Toolkit. <http://developer.nvidia.com/cuda-toolkit>.
- [3] Intel Threading Building Blocks. <http://www.threadingbuildingblocks.org/>.
- [4] The OpenMP API specification for parallel programming. <http://www.openmp.org/>.
- [5] Structure of arrays or SoA is a layout separating elements of a structure into one parallel array per field. https://en.wikipedia.org/wiki/AOS_and_SOA.
- [6] Sequential back-end defined in Thrust.
- [7] Minuit2 Package. https://root.cern.ch/root/html/MATH_MINUIT2_Index.html.
- [8] Muriel Pivk and Francois R. Le Diberder. SPlot: A Statistical tool to unfold data distributions. *Nucl. Instrum. Meth.*, A555:356–369, 2005. [arXiv:physics/0402083](https://arxiv.org/abs/physics/0402083), [doi:10.1016/j.nima.2005.08.106](https://doi.org/10.1016/j.nima.2005.08.106).
- [9] A.C. Genz and A.A. Malik. Remarks on algorithm 006: An adaptive algorithm for numerical integration over an N-dimensional rectangular region. *Journal of Computational and Applied Mathematics*, 6(4):295 – 302, 1980. URL: <http://www.sciencedirect.com/science/article/pii/0771050X8090039X>, [doi:\url{https://doi.org/10.1016/0771-050X\(80\)90039-X}](https://doi.org/10.1016/0771-050X(80)90039-X).
- [10] Jarle Berntsen, Terje O. Espelid, and Alan Genz. An adaptive algorithm for the approximate calculation of multiple integrals. *ACM Trans. Math. Softw.*, 17(4):437–451, Dec 1991. URL: <http://doi.acm.org/10.1145/210232.210233>, [doi:\url{https://doi.org/10.1145/210232.210233}](https://doi.org/10.1145/210232.210233).