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# The Ostap tutorials

build passing

Ostap is a set of extensions/decorators and utilities over the basic `PyROOT` functionality (python wrapper for `ROOT` framework). These utilities greatly simplify the interactive manipulations with `ROOT` classes through python. The main ingredients of `ostap` are

- preconfigured ipython script `ostap`, that can be invoked from the command line.
- *decoration* of the basic `ROOT` objects, like histograms, graphs etc.
  - operations and operators
  - iteration, element access, etc
  - extended functionality
- *decoration* of many basic `ROOT.RooFit` objects
- set of new useful fit models, components and operations
- other useful analysis utilities

# Getting started

The main ingredients of `ostap` are

- preconfigured ipython script `ostap`, that can be invoked from the command line.

```
ostap
```

## Challenge

Invoke the script with `-h` option to get the whole list of all command line options and keys

Optionally one can specify the list of python files to be executed before appearance of the interactive command prompt:

```
ostap a.py b.py c.py d.py
```

The list of optional arguments can include also root-files, in this case the files will be opened and their handlers will be available via local list `root_files`

```
ostap a.py b.py c.py d.py file1.root file2.root e.py file3.root
```

Also `ROOT` macros can be specified on the command line

```
ostap a.py b.py c.py d.py file1.root q1.C file2.root q2.C e.py file3.root q4.C
```

The script automatically opens `TCanvas` window (unless `--no-canvas` option is specified) with (a little bit modified) LHCb style. It also loads necessary decorators for `ROOT` classes. At last it executes the python scripts and opens root-files, specified as command line arguments.

# Values with uncertainties: `ValueWithError`

One of the central object in `ostap` is C++ class `Gaudi::Math::ValueWithError`, accessible in python via shortcut `VE`. This class stands for a combination of the value with uncertainties:

```
from Ostap.Core import VE
a = VE( 10 , 10 ) ## the value & squared uncertainty - 'variance'
b = VE( 20 , 20 ) ## the value & squared uncertainty - 'variance'
print "a=%s" % a
print "b=%s" % b
print 'Value of a is %s' % a.value()
print 'Error of b is %s' % b.error()
print 'Variance of b is %s' % b.cov2 ()
```

A lot of math operations are predefined for `VE`-objects.

## Challenge

Make a try with all binary operations ( `+`, `-`, `*`, `/`, `**` ) for the pair of `VE` objects and combinations of `VE`-objects with numbers, e.g.

```
a + b
a + 1
1 - b
2 ** a
a += 1
b += a
```

Compare the difference for following expressions:

```
a/a      ## <--- HERE
a/VE(a)  ## <--- HERE
a-a      ## <--- HERE
a-VE(a)  ## <--- HERE
```

Note that for trivial cases the correlations are properly taken into account

Additionally many math-functions are provided, carefully takes care on uncertainties

```
from LHCBMath.math_ve import *
sin(a)+cos(b)/tanh(b)
atan2(a,b)/log(a)
```

# Simple operations with histograms

## Histogram content

`Ostap.PyRoots` module provides two ways to access the histogram content

- by bin index, using operator `[]` : for 1D histogram index is a simple integer number, for 2D and 3D-histograms the bin index is a 2 or 3-element tuple
- using *functional* interface with operator `()` .

```
histo = ...
print histo[2]    ## print the value/error associated with the 2nd bin
print histo(2.21) ## print the value/error at x=2.21
```

Note that the result in both cases is of type `VE` , *value+/-uncertainty*, and the interpolation is involved in the second case. The interpolation can be controlled using `interpolation` argument

```
print histo ( 2.1 , interpolation = 0 ) ## no interpolation
print histo ( 2.1 , interpolation = 1 ) ## linear interpolation
print histo ( 2.1 , interpolation = 2 ) ## parabolic interpolation
print histo ( 2.1 , interpolation = 3 ) ## cubic interpolation
```

Similarly for 2D and 3D cases, `interpolation` parameter is 2 or 3-element tuple, e.g. `(2,2)` , `(3,2,2)` , `(3,0,0)` , ...

Set bin content

```
histo[1] = VE(10,10)
histo[2] = VE(20,20)
```

Loops over the histogram content:

```
for i in histo :
    print 'Bin# %s, the content%s' % ( i, histo[i] )
for entry in histo.iteritems() :
    print 'item ', entry
```

The *reversed* iterations are also supported

```
for i in reversed(histo) :
    print 'Bin# %s, the content%s' % ( i, histo[i] )
```

## Histogram slicing

The slicing of 1D-histogram can be done easily using native `slice` in python

```
h1 = h[3:8]
```

For 2D and 3D-cases the slicing is less trivial, but still simple

```
histo2D = ...
h1 = histo2D.sliceX ( 1 )
h2 = histo2D.sliceY ( [1,3,5] )
h3 = histo2D.sliceY ( 3 )
h4 = histo2D.sliceY ( [3,4,5] )
```

# Operators and operations

A lot of operators and operations are defined for histograms.

```
histo += 1
histo /= 10
histo = 1 + histo      ## operations with constants
histo = histo + math.cos  ## operations with functions
histo /= lambda x : 1 + x  ## lambdas are also functions
```

Also binary operations are defined

```
h1 = ...
h2 = ...
h3 = h1 + h2
h4 = h1 / h2
h5 = h1 * h2
h6 = h1 - h2
```

For the binary operations the action is defined according to the rule

- the type of the result is defined by the first operand (type, and binning)
- for each bin  $i$  the result is estimated as  $a \text{ oper } b$ , where:
  - $\text{oper}$  stands for corresponding operator (  $+$ ,  $-$ ,  $*$ ,  $/$ ,  $**$  )
  - $a = h1[i]$  is a value of the first operand at bin  $i$
  - $b = h2(x)$ , where  $x$  is a bin-center of bin  $i$

## More operations

There are many other useful operations:

- `abs` : apply `abs` function bin-by-bin
- `asym` : equivalent to  $(h1-h2)/(h1+h2)$  with correct treatment of correlated uncertainties
- `frac` : equivalent to  $(h1)/(h1+h2)$  with correct treatment of correlated uncertainties
- `average` : make an average of two histograms
- `chi2` : bin-by-bin chi2-tension between two histograms
- ... and many more

## Transformations

```
h1 = histo.transform ( lambda x,y : y ) ## identical transformation (copy)
h2 = histo.transform ( lambda x,y : y**3 ) ## get the third power of the histogram content
h3 = histo.transform ( lambda x,y : y/x ) ## less trivial functional transformation
```

## Math functions

The standard math-functions can be applied to the histogram (bin-by-bin):

```
from LHCBMath.math_ve import *
h1 = sin ( histo )
h2 = exp ( histo )
h3 = exp ( abs ( histo ) )
...
```

## Sampling

There is an easy way to sample the histograms according to their content, e.g. for toy-experiments:

```
h1 = histo.sample() ## make a random histogram with content sampled according to bin+error in original histo
h2 = histo.sample( accept = lambda s : s > 0 ) ##sample but require that sampled values are positive
```

## Smearing/convolution with gaussian

It is very easy to smear 1D histogram according to gaussian resolution

```
h1 = histo.smear ( 0.015 ) ## apply "smearing" with sigma = 0.015
h2 = histo.smear ( sigma = lambda x : 0.1*x ) ## smear using 'running' sigma of 10% resolution
```

## Rebin

```
original = ... ## the original histogram to be rebinned
template = ... ## histograms that defined new binning scheme
rebin1 = original.rebinNumbers ( template ) ## compare it!
rebin2 = original.rebinFunction ( template ) ## compare it!
`
```

Note that there are two methods for rebin `rebinNumbers` and `rebinFunction` - they depends on the treatment of the histogram.

## Challenge

Choose some initial histogram with non-uniform binning, choose *template* histogram with non-uniform binning and compare two methods: `rebinNumbers` and `rebinFunction` .

## Integrals

There are several *integral*-like methods for (1D) histograms

- `accumulate` : useful for *numbers*-like histograms, only bin-content inn used for summation (unless the bin is effectively split in case of low/high summation edge does not coincide with bin edges)

```
s = histo.accumulate ()
s = histo.accumulate ( cut = lambda s : 0.4<=s[1].value()<0.5 )
s = histo.accumulate ( low = 1 , high = 14 ) ## accumulate over 1<= ibin <14
s = histo.accumulate ( xmin = 0.14 , xmax = 14 ) ## accumulate over xmin<= x <xmax
```

- `integrate` : useful for *function*-like histograms, perform integration taking into account bin-width.

```
s = histo.integrate ()
s = histo.integrate ( cut = lambda s : 0.4<=s[1].value()<0.5 )
s = histo.integrate ( lowx = 1 , highx = 14 ) ## integrate over 1<= xbin <14
s = histo.integrate ( xmin = 0.14 , xmax = 21.1 ) ## integrate over xmin<= x <xmax
```

- `integral` it transform the histogram into `ROOT.TF1` object and invokes `ROOT.TF1.Integral`

## Running sums

and the efficiencies of cuts\_

```
h1 = histo.sumv () ## increasing order: sum(first,x)
h2 = histo.sumv ( False ) ## decreasing order: sum(x,last )
```

## Efficiency of the cut

Such functionality immediately allows to calculate efficiency histograms using `effic` method:

```
h1 = histo.effic ()          ## efficiency of var<x cut
h2 = histo.effic ( False )  ## efficiency of var>x cut
```

## Conversion to *ROOT.TF(1, 2, 3)*

### Scaling

In addition to *trivial* scaling operations `h *= 3` and `h /= 10` there are several dedicated methods for scaling

- `scale` : it scales the histogram content to a given sum of *in-range* bins

```
print histo.accumulate()
histo.scale(10)
print histo.accumulate()
```

- `rescale_bins` : it allows the treatment of non-uniform histograms as density distributions. Essentially each bin `i` is rescaled according to the rule `h[i] *= a / S`, where `a` is specified factor and `S` is *bin-area*. such type of rescaling is important for histograms with non-uniform binning

### Density

There is method `density` that converts the histogram into *density* histogram. The density histogram (being interpreted as *function*) has unit integral. It is different from the simple rescaling for histograms with non-uniform bins.

```
d = histo.density()
```

### Statistics

There are many *statistic* functions

- `mean`
- `rms`
- `kurtosis`
- `skewness`
- `moment`
- `centralMoment`
- `nEff` : number of equivalent entries
- `stat` : statistical information about bin-to-bin content: mean, rms, minmax, ... in form of `Gaudi::Math::StatEntity` class

## Figure-of-Merit evaluation and cut optimisation

If *figure-of-merit* is natural and equals to  $\sigma(S)/S$  (note that it is equal to  $\sqrt{(S+B)/S}$ ):

```
signal = ... ## distribution for signal
fom1 = signal.FoM2 () ## FoM for var<x cut
fom2 = signal.FoM2 ( False ) ## FoM for var>x cut
```

Note that no explicit knowledge of background is needed here - it enters indirectly via the uncertainties in signal determination.

If *figure-of-merit* is defined as  $S/\sqrt{(S+\alpha*B)}$



```

signal = ...
background = ...
alpha = ...
fom1 = signal.FoM1 ( background , alpha ) ## FoM for var<x cut
fom2 = signal.FoM1 ( background , alpha , False ) ## FoM for var>x cut

```

## Solve equations

One can also *solve equations*  $h(x) = v$

```

value = 3
solutions = histo.solve ( value )
for x in solutions : print x

```

## Conversion to `ROOT.TF(1,2,3)

The conversion of histogram to `ROOT.TF1` objects is straightforward

```
f = histo.tf1()
```

Optionally one can specify `interpolate` flag to define the interpolation rules.

The obtained `TF1` object is defined with three parameters

1. normalization
2. bias
3. scale

It can be used e.g. for visualize interpolated histogram as function or e.g. in `ROOT.TH1.Fit` method for fitting of other histograms

## Efficiencies

There are several special cases to get the efficiency-histograms

```

accepted = ... ## histogram with accepted sample
rejected = ... ## histogram with rejected sample
total    = ... ## histogram with total sample

eff1 = accepted/total          ## value is correct, uncertainties are *NOT* correct
eff2 = 1/(1+rejected/accepted) ## everything is correct (binomial)
eff3 = accepted % total        ## everything is correct (binomial)
eff4 = accepted // total       ## correct binomial, if both histograms are "natural"

```

## Binomial efficiencies

In addition to the methods described above, few more sophisticated treatments of *binomial efficiencies* are provided

```

accepted = ...
total    = ...

eff1 = accepted.      zechEff ( total ) ## valid for all histograms, including sPlot-weighted
eff2 = accepted.      binomEff ( total ) ## only for natural histograms
eff3 = accepted.      wilsonEff ( total ) ## only for natural histograms
eff4 = accepted.agrestiCoulEff ( total ) ## only for natural histograms

```

For *natural* histograms only one can use even more [sophisticated methods](#), that evaluates the interval. Each method returns *graph*, and the graphs can be visualised for comparison:

```

accepted = ...
rejected = ...

eff1 = accepted.eff_wald          ( rejected )
eff2 = accepted.eff_wilson_score  ( rejected )
eff3 = accepted.eff_wilson_score_continuity ( rejected )
eff4 = accepted.eff_arcsin       ( rejected )
eff5 = accepted.eff_agresti_coull ( rejected )
eff6 = accepted.eff_jeffreys     ( rejected )
eff7 = accepted.eff_clopper_pearson ( rejected )

```

All of these functions have an optional argument `interval` that defines the confidence interval, the default value is `interval=0.682689492137086` that corresponds to 1 sigma.

## Optimal binning?

It is not a rare case when one needs to find the binning of the histogram that ensures almost equal bin populations. This task could be solved using `equal_bins` method

```

very_fine_binned_histo = ... ## get the fine binned histograms
edges1 = fine_binned.equal_edges ( 10 ) ## try to find binning with 10 almost equally populated bins
edges2 = fine_binned.equal_edges ( 10 , wmax = 5 ) ## try to find binning with 10 almost equally populated bins, but avoid bins wider than "wmax"

```

# Operations with trees/chains

## General

```
tree = ...
print tree.branches()
print tree.leaves()
print 'Number of entries %s' % len ( tree )
```

### For large number of brachnes...

For trees with very large number of brachnes (*feature* of LHCb) one can improves printout:

```
from Ostap.Logger import multicolumn
print 'Branches: \n%s' % muhlticolumn ( tree.branches() )
```

## Statistic for the given variable/expression

```
st1 = tree.statVar('m')
st2 = tree.statVar('m', 'pt>10')
st3 = tree.statVar('m/eff', '(pt>10)*trg_eff')
```

The results are in a form of `wStatEntity` , *weighted* `StatEntity` )

```
ncorr = tree.sumVar('S_sw/eff', 'pt>10')
```

Also one can get statistics and covariances for the pair of variables/expressions:

```
s1 , s2 , cov2 = tree.statCov ( 'pt' , 'p' , 'pt>10' )
```

Or just simple

```
mn , mx = tree.minmax('1/eff')
```

## Explicit loops

Explicit loops over the entries in tree/chain are trivial :

```
for i in range(len(tree)) :
    tree.GetEntry(i)
    if tree.pt < 10 : continue
    print tree.m
```

But the direct looping looks a bit nicer:

```
for entry in tree :
    if entry.pt < 10 : continue
    print entry.m
```

Note that explicit loops are rather CPU-inefficient and slow. One can *drastically* improve performance by e.g. embedding the cuts in the iterator

```
for entry in tree.withCuts('pt>10') :
    print entry.m
```

One can also specify `first` and `last` entries and display the progress bar

```
for entry in tree.withCuts('pt>10', last = 10000 , progress = True ) :
    print entry.m
```

## Projections

```
h1 = ...
r = tree.project ( h1 , 'mass' , 'pt>10' )
```

### For loooong chains or huge trees...

The module `Ostap.Kisa` provides nice functionality for parallel processing of large chains or huge trees for *projections*

```
h1 = ...
long_chain = ...
huge_tree = ...
import Ostap.Kisa
r1 = long_chain.pproject ( h1 , 'mass' , 'pt>10' )
r2 = huge_tree.pproject ( h1 , 'mass' , 'pt>10' )
```

For long chains it makes parallelization on *per-tree* level, and for huge trees it splits the tree into chunks and parallelization is applied on *per-chunk* level.

## Data, Data2 and DataAndLumi

There is a useful way to collect many ROOT files into single chains, avoiding non-existent, broken and invalid trees (that is not so rare for the output of Ganga)

```
from Ostap.Data import DataAndLumi as Data
ganga = '/afs/cern.ch/work/i/ibelyaev/public/GANGA/workspace/ibelyaev/LocalXML'
patterns_Y = [
    ganga + '/319/*/output/CY.root' , ## 2k+11, down
    ganga + '/320/*/output/CY.root' , ## 2k+11, up
    ganga + '/321/*/output/CY.root' , ## 2k+12, down
    ganga + '/322/*/output/CY.root' , ## 2k+12, up
]
data_D0Y = Data ( 'YD0/CY' , patterns_Y )
print data_D0Y
chain = data_D0Y.chain
lumi = data_D0Y.getLumi()
```

Or they can be accumulated separately, and combined later:

```
from Ostap.Data import DataAndLumi as Data
ganga = '/afs/cern.ch/work/i/ibelyaev/public/GANGA/workspace/ibelyaev/LocalXML'
d2011d = Data( 'YD0/CY' , ganga + '/319/*/output/CY.root' ) ## 2k+11, down
d2011u = Data( 'YD0/CY' , ganga + '/320/*/output/CY.root' ) ## 2k+11, up
d2012d = Data( 'YD0/CY' , ganga + '/321/*/output/CY.root' ) ## 2k+12, down
d2012u = Data( 'YD0/CY' , ganga + '/322/*/output/CY.root' ) ## 2k+12, up
d2011 = d2011d + d2011u
d2012 = d2012d + d2012u
runI = d2011 + d2012
```

# Persistencey

## Ostap.ZipShelve

Ostap offers very nice&efficient way to store the objects in persistent dbase. This persistency is build around `shelve` module and differs in two way

1. the conntent of payload is compressed, using `zlib` module making the data base very compact
  - (optionally) the whole database can ve further `gzip` 'ed using `gzip` module, if the extension `.gz` is provided. It makes data banse even more compact.
2. in addition to the native `dict` interface from `shelve` , more extensiveinterface with more methods is supported.

Create database and write objects to it:

```
a = ...
import Ostap.ZipShelve as DBASE
with DBASE.open ( 'my_dbase.db' ) as db : ## create DBASE
    db.ls()
    db['a'] = a
    db['histo'] = ROOT.TH1D('h1','',10,0,1)
```

Reading objects from database

```
with DBASE.open ( 'my_dbase.db' , 'read' ) as db : ## read DBASE
    db.ls()
    b = db['a']
    h2 = db['histo']
```

One can store in database all *pickable* objects, that means all python objects, all (serializeable) `ROOT` objects. All `c++` objects with `LCG/Reflex/Cint` -dictionaries are also could be stored database. In practice, everything is storable, including complex combination of python&C++ objects, like dictionary of historgams and python classed, inherited from `c++` -base classes.

## Plain ROOT.TFile

Ostap adds some decorations even for the plain `ROOT.TFile` , making its interface more *pythonic*:

```
rfile = ...
obj = rfile['A/B/C/myobj']      ## READ  object form the file/directory
rfile['A/B/C/myobj2'] = object2 ## WRITE object to the file/directory
obj = rfile.A.B.C.myobj        ## another way to access to the object
obj = rfile.get ( 'A/B/C/q' , None ) ## one more way to get object
for obj in rfile : print obj    ## loop over all objects in file
for key,obj in rfile.iteritems() : print key, obj    ## another loop
for key,obj in rfile.iteritems( ROOT.TH1 ) : print key, obj    ## advanced loop, get only histograms
for k in rfile.keys() : print k    ## get all keys and loop over them
for k in rfile.iterkeys() : print k    ## loop over all keys in the file
del rfile['A/B']                    ## delete the object from the file
rfile.rm ( 'A/B' )                  ## delete the object from the file
if 'A/MyHisto' in rfile : print 'OK!' ## check presence of the key
if rfile.has_key ( 'A/MyHisto' ) : print 'OK!' ## check presence of the key
with ROOT.TFile('aa.root') as rfile : rfile.ls() ## context manager protocol
```

## RootOnlyShelve

The module `Ostap.RootShelve` offers the thin wrapper over `ROOT.TFile` that implement `shelve` -interface. As a resutl one gets a lighth database build a top of underlying `ROOT.TFile` , where `ROOT` -objects could be stored:

```
from Ostap.RootShelve import RooOnlyShelf
db = RooOnlyShelf('mydb.root', 'c')
h1 = ...
db ['histogram'] = h1
db.ls()
```

## RootShelve

The module `Ostap.RootShelve` offers also more sophisticated wrapper over `ROOT.TFile` that also implements `shelve` -interface and able to store `ROOT` and any other *pickable* objects

```
from Ostap.RootShelve import RooShelf
db = RooShelf('mydb.root', 'c')
h1 = ...
db ['histogram'] = h1
db ['histogramlist'] = h1,h2,h3
db.ls()
```

## In details ...

For non- `ROOT` objects, database actually stores them as `ROOT::TString` objects carrying their pickle representation with on-flight removal/substitutions of some magic symbol sequences, since `ROOT::TString` is not a real `BLOB` .

## More on Histograms

- [Histogram parameterization](#)



# Histogram parameterization

Often one needs to parameterize the histogram in terms of some predefined function or expansion - e.g. parameterize the efficiency. Ostap offers a wide range of embedded parameterization

- in terms of *Bernstein polynomials*
  - simple *Bernstein sum*, aka *Bezier sum*
  - *even Bernstein sum*, such as  $f(x)=f(2*x_0-x)$  , where  $x_0=0.5*(x_{min}+x_{max})$
  - non-negative *Bernstein sum*
  - non-negative monothonic *Bernstein sum*
  - non-negative monothonic convex or concave *Bernstein sum*
  - non-negative convex or concave *Bernstein sum*
- in term of *Legendre polynomials*
- in term of *Chebyshev polynomials*
- in terms of *Fourier series*
- in terms of *Fourier cosine series*
- in terms of *Basic splines*
  - non-negative *B-spline*
  - non-negative monothonic *B-spline*
  - non-negative monothonic convex or concave *B-spline*
  - non-negative convex or concave *B-spline*

From technical side, there are three branches of methods

- methods that uses only histogram values:
  - these are safe, robust but they ignore the uncertainties
- methods that relies on `ROOT.TH1.Fit`
  - typically not very good CPU performance
  - sometimes fragile
- methods that relies on `RooFit`
  - often the best series of methods

## Simple parameterization

This group of methods allows to make easy and robust histogram parameterization, ignoring histogram unncertainties

```
histo = ...
b1 = histo.bernstein_sum      ( 6 ) ## parameterize as degree-6 Bernstein sum
b2 = histo.bernsteineven_sum  ( 6 ) ## parameterize as degree-6 Bernstein "even"-sum
l  = histo.legendre_sum       ( 6 ) ## parameterize as degree-6 Legendre sum
ch = histo.chebyshev_sum      ( 6 ) ## parameterize as degree-6 Chebyshev sum
f  = histo.fourier_sum        ( 12 ) ## parameterize as order-12 Fourier sum
c  = histo.cosine_sum         ( 12 ) ## parameterize as order-12 Fourier Cosine sum
```

## `ROOT.TH1.Fit` -based parameterizations

These methods typically have not very good CPU performance, and sometiems are fragile, but they allow more accurate treatment of parameteriztaions, in particular them takes into account the uncertainties in the historgam.

```

histo = ...
b1 = histo.bernstein      ( 6 ) ## parameterize as degree-6 Bernstein sum
b2 = histo.bernsteineven ( 6 ) ## parameterize as degree-6 Bernstein "even"-sum
l  = histo.legendre      ( 6 ) ## parameterize as degree-6 Legendre sum
ch = histo.chebyshev     ( 6 ) ## parameterize as degree-6 Chebyshev sum
f  = histo.fourier       ( 12 ) ## parameterize as order-12 Fourier sum
c  = histo.cosine        ( 12 ) ## parameterize as order-12 Fourier Cosine sum
m  = histo.polynomial    ( 6 ) ## parameterize as simple degree-6 monomial sum
p1 = histo.positive      ( 6 ) ## parameterize as degree-6 non-negative Bernstein sum
p2 = histo.positiveeven  ( 6 ) ## parameterize as degree-6 non-negative even Bernstein sum
m1 = histo.monothonic    ( 6 , increasing = False ) ## parameterize as degree-6 non-negative decreasing Bernstein sum
m2 = histo.monothonic    ( 6 , increasing = True  ) ## parameterize as degree-6 non-negative increasing Bernstein sum
c1 = histo.convex        ( 6 , increasing = False , convex = True ) ## parameterize as degree-6 non-negative decreasing convex Bernstein sum
c2 = histo.convex        ( 6 , increasing = False , convex = False ) ## parameterize as degree-6 non-negative decreasing concave Bernstein sum
c3 = histo.convex        ( 6 , increasing = True  , convex = True  ) ## parameterize as degree-6 non-negative increasing convex Bernstein sum
c4 = histo.convex        ( 6 , increasing = True  , convex = False ) ## parameterize as degree-6 non-negative increasing concave Bernstein sum
cc1 = histo.convexpoly   ( 6 ) # parameterize as degree-6 non-negative convex Bernstein sum
cc2 = histo.concavepoly  ( 6 ) # parameterize as degree-6 non-negative concave Bernstein sum

```

Various types of *splines* are also provided

```

s1 = histo.bSpline ( degree=3 , knots = 2 ) ## parameterize as 3d order spline with 2 inner (uniform) knots
s2 = histo.bSpline ( degree=2 , knots = [0.1,0.4,0.8,0.9] ) ## parameterize as 3d order spline with 4 inner (non-uniform) knots

```

and similarly for

- non-negative spline `pSpline` ,
- non-negative monothonic spline `mSpline` ,
- non-negative monothonic convex or concave spline `cSpline` ,
- non-negative convex spline `convexSpline` ,
- non-negative concave spline `concaveSpline` .

## RooFit *b*-based parameterizations

```

r1 = histo.pdf_positive      ( 5 ) ## parameterize and non-negative degree-5 Bernstein sum
r2 = histo.pdf_positiveeven  ( 5 ) ## parameterize and non-negative degree-5 even Bernstein polynomial
r3 = histo.pdf_increasing    ( 5 ) ## parameterize and non-negative degree-5 increasing Bernstein polynomial
r4 = histo.pdf_decreasing    ( 5 ) ## parameterize and non-negative degree-5 decreasing Bernstein polynomial
r5 = histo.pdf_convex_increasing ( 5 ) ## parameterize and non-negative degree-5 convex increasing Bernstein polynomial
r6 = histo.pdf_convex_decreasing ( 5 ) ## parameterize and non-negative degree-5 convex decreasing Bernstein polynomial
r7 = histo.pdf_concave_increasing ( 5 ) ## parameterize and non-negative degree-5 concave increasing Bernstein polynomial
r8 = histo.pdf_concave_decreasing ( 5 ) ## parameterize and non-negative degree-5 concave decreasing Bernstein polynomial
r9 = histo.pdf_concavepoly    ( 5 ) ## parameterize and non-negative degree-5 concave Bernstein polynomial
r10 = histo.pdf_convexpoly    ( 5 ) ## parameterize and non-negative degree-5 convex Bernstein polynomial

```

Similarly there are methods that provides the parameterization in terms of *splines* :

- `pdf_pSpline` : non-negative *b-spline*
- `pdf_mSpline` : non-negative monothonic *b-spline*
- `pdf_cSpline` : non-negative monothonic concave or convex *b-spline*
- `pdf_convexSpline` : non-negative monothonic convex *b-spline*
- `pdf_concaveSpline` : non-negative monothonic concave *b-spline*



# Decorations

Ostap *decorates* many `ROOT.RooFit` classes, adding more convinient methods to them.

## RooArgList and RooArgSet

All these classes have got set of additional python-like methods for iteration, extension, addition, elemtn access checking the content etc...  
Also several methods to provide more coherent interfaces (e.g. `add` vs `Add` ) are added.

```
1  # Ostap.PyRoUts          INFO      Zillions of decorations for ROOT/RooFit objects
2  Lengths are 2 2
3  'a' : ( 0 +- 0 )
4  'b' : ( -10 +- 0 )
5  'b' : ( -10 +- 0 )
6  'c' : ( 1 +- 0 )
7  a in l ? True True
8  b in l ? True True
9  c in l ? False False
10 a in l ? False False
11 b in l ? True True
12 c in l ? True True
13 'a' : ( 0 +- 0 ) 'b' : ( -10 +- 0 )
14 'b' : ( -10 +- 0 ) 'c' : ( 1 +- 0 )
15 l1+l1 :      ['a:0.0', 'b:-10.0', 'a:0.0', 'b:-10.0']
16 l1+l2 :      ['a:0.0', 'b:-10.0', 'b:-10.0', 'c:1.0']
17 l2+l2 :      ('b:-10.0', 'c:1.0')
18 l2+l1 :      ('b:-10.0', 'c:1.0', 'a:0.0')
19 l1+c :       ['a:0.0', 'b:-10.0', 'c:1.0']
20 l2+c :       ('b:-10.0', 'c:1.0')
21 l1+d :       ['a:0.0', 'b:-10.0', 'd:-1.0']
22 l2+d :       ('b:-10.0', 'c:1.0', 'd:-1.0')
23 c+l1 :       ['a:0.0', 'b:-10.0', 'c:1.0']
24 c+l2 :       ('b:-10.0', 'c:1.0')
25 d+l1 :       ['a:0.0', 'b:-10.0', 'd:-1.0']
26 d+l2 :       ('b:-10.0', 'c:1.0', 'd:-1.0')
```

output.txt hosted with ❤ by GitHub

[view raw](#)

```
1  import ROOT
2  import Ostap.PyRoUts
3
4  a  = ROOT.RooRealVar ('a','a',-10,10)
5  b  = ROOT.RooRealVar ('b','b',-10)
6  c  = ROOT.RooConstVar('c','c', 1)
7  d  = ROOT.RooConstVar('d','d', -1)
8
```

```

9  l1 = ROOT.RooArgList    ( a , b )
10 l2 = ROOT.RooArgSet     ( b , c )
11
12 print 'Lengths are %s %s ' % ( len ( l1 ) , len( l2 ) )
13
14 for i in l1 : print i
15 for i in l2 : print i
16
17 for l in ( l1 , l2 ) :
18     print ' a in l ? %s %s ' % ( a in l , 'a' in l )
19     print ' b in l ? %s %s ' % ( b in l , 'b' in l )
20     print ' c in l ? %s %s ' % ( c in l , 'c' in l )
21
22
23 print l1[0] , l1[1]
24 print l2['b'] , l2['c']
25
26 print 'l1+l1 :    %s' % ( l1 + l1 )
27 print 'l1+l2 :    %s' % ( l1 + l2 )
28 print 'l2+l2 :    %s' % ( l2 + l2 )
29 print 'l2+l1 :    %s' % ( l2 + l1 )
30
31 print 'l1+c :     %s' % ( l1 + c )
32 print 'l2+c :     %s' % ( l2 + c )
33 print 'l1+d :     %s' % ( l1 + d )
34 print 'l2+d :     %s' % ( l2 + d )
35
36 print 'c+l1 :     %s' % ( c + l1 )
37 print 'c+l2 :     %s' % ( c + l2 )
38 print 'd+l1 :     %s' % ( d + l1 )
39 print 'd+l2 :     %s' % ( d + l2 )

```

roofit\_lists.py hosted with ♥ by [GitHub](#)

[view raw](#)

## ***RooAbsData and RooDataSet***

These methods also have got the extended interface with many useful methods and operators, like e.g. concatenation of datasets `a+b` and merging them `a*c` .

`RooDataSet` class also has go many methods, that are similar to those of `ROOT.TTree` , in particular `project` and `draw` :

```

dataset = ...
dataset.draw('mass','pt>1')
histo    = ...
dataset.project ( histo , 'mass', 'pt>1' )

```

Many other methodons like `statVar` , `sumVar` , `statCov` , `vminmax` are also the same as for `ROOT.TTree` , see [above](#).

```

s1  = dataset.statVar ( 'eff' )
s2  = dataset.sumVar  ( 'eff' )
r   = dataset.statCov ( 'eff','pt' )
mn,mx = dataset.vminmax ( 'eff' )

```

## ***RooFitResult***

The class `RooFitResult` get many decorations that allow to access fit results

```

result = ...
par1 = result.params()  ## get all floating parameters
par2 = result.params( float_only = False ) ## all parameters
a,v  = result.param ( 'a' )      ## par by name
a,v  = result.param ( a )        ## par by RooFit object itself
p    = result.a                ## par as attribute
for par in result : print par    ## iteration
for name,par in result.iteritems() : print par ## iteration
print result.cov ( 'a' , 'b' )  ## get the covariance submatrix
print result.corr ( 'a' , 'b' ) ## get the correlation coefficient

```

Also the simple math with fitting parameters is supported

```

result = ...
s = result.sum      ( 'S','B' ) ## S+B
d = result.divide   ( 'S','B' ) ## S/B
s = result.subtract ( 'B','B1' ) ## B-B1
m = result.multiply ( 'A','B' ) ## A*B
f = result.fraction ( 'S','B' ) ## S/(S+B)

```

## ***RooRealVar & friends***

Few simple operations are added to simplify the calculations with `RooRealVar` objects:

```

x = ROOT.RooRealVar( ... )
x + 10
x - 10
x * 10
x / 10
10 + x
10 - x
10 * x
10 / x
x += 2
x -= 2
x *= 2
x /= 2
x ** 3

```

# PDFs and the basic models

Ostap provides set of useful wrapper and helper class that drastically simplify the construction and manipulations with `RooAbsPdf` - objects.

E.g. consider the simplest case - creation of the Gaussian PDF using the standard way the standard way:

```
x      = ROOT.RooRealVar ( 'x'      , 'x'      , 2, 3 )
mean   = ROOT.RooRealVar ( 'mean'   , 'mean'   , 3.100, 3.080, 3.120 )
sigma  = ROOT.RooRealVar ( 'sigma'   , 'sigma'   , 0.015, 0.010, 0.025 )
bare   = ROOT.RooGaussian( 'Gauss' , 'Gaussian' , x , mean , sigma ) ## <--- HERE
```

In Ostap it can be done in a bit simpler way

```
gauss = Gauss_pdf ( 'Gauss' ,
                    xvar  = ( 2 , 3 ) ,
                    mean  = ( 3.100 , 3.080 , 3.120 ) ,
                    sigma = ( 0.015 , 0.010 , 0.025 ) )
gauss.draw() ## and one can immediately visualize the model
```

## How to define parameter?

There are may ways to define parameter

1. One can use the existing `RooAbsReal` object, e.g. `RooRealVar` or `RooConstVar` :

```
mean = ROOT.RooRealVar ( 'mean' , 'mean' , 3.100, 3.080, 3.120 )
gauss = Gauss_pdf ( 'Gauss' ,
                    xvar  = ( 2 , 3 ) ,
                    mean  = mean , ## <--- HERE
                    sigma = ( 0.015 , 0.010 , 0.025 ) )
```

2. One can use the plain number `value` , 2- or 3-element tuple `(minval,maxval)` or `(value, minval,maxval)` . In this case the variable of the type `RooRealVar` will be automatically created using this specification. (In case of the plain number, the corresponding parameter will be fixed in the fit).

```
gauss = Gauss_pdf ( 'Gauss' ,
                    xvar  = ( 2 , 3 ) , ## <--- HERE
                    mean  = ( 3.100 , 3.080 , 3.120 ) , ## <--- HERE
                    sigma = 0.015 ) ## <--- HERE
```

For all models, all known parameter are accessible (and documented) as python *property*

```
gauss = ...
help(gauss.xvar)
print gauss.sigma
help(gauss.mean)
```

There are many predefined models, accesible via `Ostap.FitModels` module:

```
import Ostap.FitModels as Models
help(Models)
```

## Base class PDF

All Ostop-based fit models and PDFs (directly or indirectly) inherit from python base class `PDF`, that provides great additional functionality, in particular the methods `fitTo` and `draw` that simplify the fitting procedure itself and visualization of the results:

### The method `fitTo`

```
gauss = Gauss_pdf ( ... )
dataset = ....
result , frame = gauss.fitTo ( dataset , silent = True , reFit = 2 )
print 'FitResults: %s' % result
```

All the native `RooFit` *commands* can be specified as optional arguments, as well as many commands specific for Ostop, e.g. `reFit=2` above means *in case of fit failure, try to refit it (up to 2 times)*, and the meaning of `silent=True` is obvious.

### The method `draw`

```
gauss = Gauss_pdf ( ... )
dataset = ....
result , frame = gauss.fitTo ( dataset , silent = True , reFit = 2 )
print 'FitResults: %s' % result
frame = gauss.draw ( dataset , nbins = 100 )
```

*Fitting and vizualisation* can be combined:

```
gauss = Gauss_pdf ( ... )
dataset = ....
result , frame = gauss.fitTo ( dataset , draw = True , nbins = 100 ) ## draw it after the fit
```

## Access to the underlying `RooAbsPdf` object

The access to the underlying bare `RooAbsPdf` -object can be done (if needed) via the property `pdf`

```
gauss = Gauss_pdf ( ... )
root_pdf = gauss.pdf
```

## Other methods

`PDF` class is equipped with many other useful methods:

- `fitHisto` : The method `fitTo` can be *blindly* applied not only to `RooDataSet` -objects, but also to the histograms:

```
histo = ...
r, f = gauss.fitTo ( histo , draw = True )
```

However the dedicated method `fitHisto` sometimes could be more usefu

```
histo = ...
gauss.fitHisto ( histo , draw = True )
```

- `draw_nll` : vizualize NLL-scans and LL-profiles

```
r , f = gauss.fitTo ( dataset , draw = False )
nll , f1 = gauss.draw_nll ( 'sigma' , dataset ) ## NLL
profile , f2 = gauss.draw_nll ( 'sigma' , dataset , profile = True ) ## PROFILE
```

- `generate` : tiny but useful wrapper for `RooAbsPdf::generate`



- `minmax` : make the estimates for the minimal and maximal values for the PDF. For some models it is done analytically or semianalytically, for remaining models it is done using random shoots.

```
mn,mx = gauss.minmax( 500000 )
```

- `__call__` : it allows to use `PDF` as simple *function*

```
gauss = ...
print gauss( 3.090 ), gauss( 3.100 ), gauss( 3.110 )
```

- Several *statistical* functions. For some models analytical or semianalytical calculations are used, for remaining models numerical estimations are performed using `scipy`
- `rms` : *rms* for the distribution
- `fwhm` : *full width at half maximum*
- `fwhm` : *full width at half maximum*
- `moment` : the *moment* of the distribution
- `central_moment` : the *central moment* of the distribution
- `skewness` : *skewness* for the distribution
- `kurtosis` : *kurtosis* for the distribution
- `mode` : the *mode* for the distribution
- `median` : *median* value for the distribution
- `get_mean` : *mean* value for the distribution
- `cl_symm` : *symmetric confidence interval*
- `cl_asymm` : *asymmetric confidence interval*
- `quantile` : *quantile* value for the distribution
- `integral` : *integral* for the distribution
- `derivative` : *derivative* of the PDF at the given point

## Convolution

Ostap provides helper class that simplify construction of fit models taking into account resolution functions:

```
pdf = ...
cnv_pdf = Convolution_pdf ( 'Cnv' ,
                           pdf = pdf ,
                           resolution = ... )
```

As `resolution` one can specify

1. Any resolution model ( `RooAbsPdf` )
2. simple number `s` , in this case the gaussian resolution model with  $\sigma = s$  will be used
3. Any `RooAbsReal` object, it will be used as  $\sigma$  for gaussian resolution model

There are several optional flags

- `useFFT=True` : use *Fast-Fourier-Transform* or plain numerical convolution ?
- `nbins=100000` : sampling for *Fast-Fourier-Transform*
- `buffer=0.25` : buffer size for *Fast-Fourier-Transform*, argument for `setBufferFraction` call
- `nsigmas=6` : window size for plain numeric convolution, the argument for `setConvolutionWindow` call

## Generic Wrapper *Generic1D\_pdf*

The bare `RooAbsPdf` could be easily converted to Ostap-form using the generic wrapper `Generic1D_pdf` :

```
bare = ROOT.RooGaussian('Gauss','Gaussian', x , mean , sigma )
gauss = Generic1D_pdf ( pdf = bare , xvar = x )
gauss.draw() ## one can immediately use the full power of Ostap-PDF
```

In a similar way there are generic wrappers for `2D` and `3D` -models:

```
bare2D = ...
bare3D = ...
ostap_2d = Generic2D_pdf ( pdf = bare2D , xvar = x , yvar = y )
ostap_3d = Generic3D_pdf ( pdf = bare3D , xvar = x , yvar = y , zvar = z )
```

## 1D -models

There are many predefined models, accessible via `Ostap.FitModels` module:

```
import Ostap.FitModels as Models
help(Models)
```

### *Generic background models*

#### *Polynomial models*

Here the list of the most useful polynomial models:

- `PolyPos_pdf` : positive (non-negative) polynomial
- `PolyEven_pdf` : positive (non-negative) *symmetric* polynomial:  $p(x) = p(2 \cdot x_0 - x)$  , where  $x_0 = 0.5 \cdot (x_{min} + x_{max})$
- `Monotonic_pdf` : positive (non-negative) polynomial with fixed sign of the first derivative: polynomial either non-decreasing or non-increasing
- `Convex_pdf` : positive (non-negative) polynomial with fixed signs of the first (non-decreasing or non-increasing) and second (convex or concave) derivatives
- `ConvexOnly_pdf` : positive (non-negative) polynomial with fixed sign of the second (convex or concave) derivative

#### *Phasespace-based models*

Here the list of the most useful phasespace-based models:

- `PS2_pdf` : 2-body phase space (no parameters)
- `PSLeft_pdf` : Low edge of N-body phase space
- `PSRight_pdf` : High edge of L-body phase space from N-body decays
- `PSNL_pdf` : approximation for L-body phase space from N-body decays
- `PS23L_pdf` : 2-body phase space from 3-body decays with orbital momenta

#### *Polynomial-based models*

- `Bkg_pdf` : The exponential function, modulated by the positive polynomial. In practice it is the most useful function to describe the combinatorial background
- `PSPol_pdf` : L-body phase space from N-body decays modulated by a positive polynomial
- `Sigmoid_pdf` : sigmoid function ( `atanh` ) modulated by the positive polynomial
- `TwoExpoPoly_pdf` : difference of two exponents, modulated by the positive polynomial

#### *Spline-based models*

The models, based on *B-splines* :

- `PSpline_pdf` : positive (non-negative) spline

- `MSpline_pdf` : positive (non-negative) monothonic (non-decreasing or non-increasing) spline
- `CSpline_pdf` : positive (non-negative) monothonic (non-decreasing or non-increasing) convex or concave spline
- `CPSpline_pdf` : positive (non-negative) convex or concave spline

## Generic signal models

The signal-like models (peaks):

```
'Gauss_pdf'           , ## simple      Gauss
'CrystalBall_pdf'     , ## Crystal-ball function
'CrystalBallRS_pdf'   , ## right-side Crystal-ball function
'CB2_pdf'             , ## double-sided Crystal Ball function
'Needham_pdf'         , ## Needham function for J/psi or Y fits
'Apolonios_pdf'       , ## Apolonios function
'Apolonios2_pdf'      , ## Apolonios function
'BifurcatedGauss_pdf' , ## bifurcated Gauss
'DoubleGauss_pdf'     , ## double Gauss
'GenGaussV1_pdf'      , ## generalized normal v1
'GenGaussV2_pdf'      , ## generalized normal v2
'SkewGauss_pdf'       , ## skewed gaussian (temporarily removed)
'Bukin_pdf'           , ## generic Bukin PDF: skewed gaussian with exponential tails
'StudentT_pdf'       , ## Student-T function
'BifurcatedStudentT_pdf', ## bifurcated Student-T function
'SinhAsinh_pdf'       , ## "Sinh-arcsinh distributions". Biometrika 96 (4): 761
'JohnsonSU_pdf'      , ## JonhsonSU-distribution
'Atlas_pdf'           , ## modified gaussian with exponenital tails
'Slash_pdf'           , ## symmetric peakk wot very heavy tails
'RaisingCosine_pdf'   , ## Raising Cosine distribution
'QGaussian_pdf'       , ## Q-gaussian distribution
'AsymmetricLaplace_pdf', ## asymmetric laplace
'Sech_pdf'            , ## hyperboilic secant (inverse-cosh)
'Logistic_pdf'        , ## Logistic aka "sech-squared"
#
## pdfs for "wide" peaks, to be used with care - phase space corrections are large!
#
'BreitWigner_pdf'     , ## (relativistic) 2-body Breit-Wigner
'Flatte_pdf'          , ## Flatte-function (pipi)
'Flatte2_pdf'         , ## Flatte-function (KK)
'LASS_pdf'            , ## kappa-pole
'Bugg_pdf'            , ## sigma-pole
'Swanson_pdf'         , ## Swanson's S-wave cusp
##
'Voigt_pdf'           , ## Voigt-profile
'PseudoVoigt_pdf'     , ## PseudoVoigt-profile
'BW23L_pdf'           , ## BW23L
```

## 2D and 3D -cases

For 2D and 3D cases there are base classes `PDF2` and `PDF3` that in turn inherit from `PDF` and gets all the nice functionality. Of course several new method specific for 2D and 3D -cases are added and the behavior of some 1D -specific methods is fixed.

# Generic signal models

The signal-like models (peaks):

## Narrow signals :

- `Gauss_pdf` : simple *Gauss*
- `CrystalBall_pdf` : *Crystal Ball* function
- `CrystalBallRS_pdf` : right-side *Crystal Ball* function
- `CB2_pdf` : double-sided *Crystal Ball* function
- `Needham_pdf` : *Needham* function for J/psi or Upsilon fits
- `Apolonios_pdf` : *Apolonios* function
- `Apolonios2_pdf` : *Apolonios* function
- `BifurcatedGauss_pdf` : bifurcated *Gaussian*
- `DoubleGauss_pdf` : double *Gaussian*
- `GenGaussV1_pdf` : *generalized Gaussian* v1
- `GenGaussV2_pdf` : *generalized Gaussian* v2
- `SkewGauss_pdf` : *\_skewed Gaussian*
- `Bukin_pdf` : generic *Bukin* PDF: skewed gaussian with exponential tails
- `StudentT_pdf` : *Student` T-function*
- `BifurcatedStudentT_pdf` : bifurcated *Student` T-function*
- `SinhAsinh_pdf` : *Sinh-arcsinh* distribution
- `JohnsonSU_pdf` : *Jonhson-SU* distribution
- `Atlas_pdf` , modified *Gaussian* with exponential tails
- `Slash_pdf` , symmetric peak with very heavy tails
- `RaisingCosine_pdf` , *Raising Cosine* distribution
- `QGaussian_pdf` , *Q-Gaussian* distribution
- `AsymmetricLaplace_pdf` , asymmetric *Laplace*
- `Sech_pdf` , hyperboilic secant (inverse-cosh)
- `Logistic_pdf` , Logistic aka "sech-squared"

## "Wide" peaks

These PDF are useful to describe *wide* peaks with the natural width. (Keep in miid that phase space corrections and resolutuion effect could be large)

- `BreitWigner_pdf` : (relativistic) 2-body *Breit-Wigner*
- `Flatte_pdf` : *Flatte* function (pipi)
- `Flatte2_pdf` : *Flatte* function (KK)
- `LASS_pdf` : kappa-pole
- `Bugg_pdf` : sigma-pole
- `Swanson_pdf` : Swanson`s S-wave cusp
- `Voigt_pdf` : Voigt-profile
- `PseudoVoigt_pdf` : PseudoVoigt-profile
- `BW23L_pdf` : BW23L

# Generic background models

Here is incomplete list of *background-like* models - the models that often could be used to describe the background distribution

## Polynomial models

Here the list of the most useful polynomial models:

- `PolyPos_pdf` : positive (non-negative) polynomial
- `PolyEven_pdf` : positive (non-negative) *symmetric* polynomial:  $p(x) = p(2 \cdot x_0 - x)$  , where  $x_0 = 0.5 \cdot (x_{min} + x_{max})$
- `Monotonic_pdf` : positive (non-negative) polynomial with fixed sign of the first derivative: polynomial either non-decreasing or non-increasing
- `Convex_pdf` : positive (non-negative) polynomial with fixed signs of the first (non-decreasing or non-increasing) and second (convex or concave) derivatives
- `ConvexOnly_pdf` : positive (non-negative) polynomial with fixed sign of the second (convex or concave) derivative

## Phasespace-based models

Here the list of the most useful phasespace-based models:

- `PS2_pdf` : 2-body phase space (no parameters)
- `PSLeft_pdf` : Low edge of N-body phase space
- `PSRight_pdf` : High edge of L-body phase space from N-body decays
- `PSNL_pdf` : approximation for L-body phase space from N-body decays
- `PS23L_pdf` : 2-body phase space from 3-body decays with orbital momenta

## Polynomial-based models

- `Bkg_pdf` : The exponential function, modulated by the positive polynomial. In practice it is the most useful function to describe the combinatorial background
- `PSPol_pdf` : L-body phase space from N-body decays modulated by a positive polynomial
- `Sigmoid_pdf` : sigmoid function (  $\tanh$  ) modulated by the positive polynomial
- `TwoExpoPoly_pdf` : difference of two exponents, modulated by the positive polynomial

## Spline-based models

The models, based on *B-splines* :

- `PSpline_pdf` : positive (non-negative) spline
- `MSpline_pdf` : positive (non-negative) monothonic (non-decreasing or non-increasing) spline
- `CSpline_pdf` : positive (non-negative) monothonic (non-decreasing or non-increasing) convex or concave spline
- `CPSpline_pdf` : positive (non-negative) convex or concave spline

## *Other useful models*

- `GammaDist_pdf` : Gamma-distributuon in shape/scale parameterization
- `GenGammaDist_pdf` : Generalized Gamma-distribution
- `Amoroso_pdf` : another view of generalized Gamma distribution
- `LogGammaDist_pdf` : Gamma-distributuon in shape/scale parameterization
- `Log10GammaDist_pdf` : Gamma-distributuon in shape/scale parameterization
- `LogGamma_pdf`
- `BetaPrime_pdf` : Beta-prime distribution
- `Landau_pdf` : Landau distribution
- `Argus_pdf` : ARGUS distribution
- `TwoExpos_pdf` : difference of two exponents
- `Gumbel_pdf` : Gumbel distributions
- `Weibull_pdf` : Weibull distributions

Useful to describe pt-spectra:

- `Tsallis_pdf` : Tsallis PDF
- `QGSM_pdf` : QGSM PDF

## *Useful 2D-background models*

2D-models useful to describe non-factorizable (  $f(x,y) \neq f(x)*f(y)$  ) background:

- PolyPos2D\_pdf : positive (non-negative) polynomial in 2D
- PolyPos2Dsym\_pdf : positive (non-negative) symmetric polynomial in 2D
- PSPo12D\_pdf : product of phase spaces functions, modulated with 2D polynomial
- PSPo12Dsym\_pdf : symmetric product of phase spaces, modulated with 2D polynomial
- ExpoPSPo12D\_pdf : exponential times phase space times positive 2D-polynomial
- ExpoPo12D\_pdf : product of exponents times positive 2D-polynomial
- ExpoPo12Dsym\_pdf : symmetric version of above
- Spline2D\_pdf : 2D-generic positive (non-negative) spline
- Spline2Dsym\_pdf : 2D symmetric positive (non-negative) spline

## *Useful 3D-background models*

3D-models useful to describe non-factorizable (  $f(x, y, z) \neq f(x) \cdot f(y) \cdot f(z)$  ) background:

- PolyPos3D\_pdf : positive (non-negative) polynomial in 3D
- PolyPos3Dsym\_pdf : positive (non-negative) symmetric polynomial in 3D
- PolyPos3Dmix\_pdf : positive partly symmetric ( $x \leftrightarrow y$ ) polynomial in 3D



# Compound fit models

## 1D -case

Ostap offers a very easy way to build the compound fit models from the individual components. E.g. the case of the trivial fit model that consists of one signal and one background components:

```
signal      = ...
background  = ...
model       = Fit1D ( signal = signal , background = background ) ## <-- HERE!
dataset     = ...
result , frame = model.fitTo ( dataset , draw = True ) ## fit and visualize
```

The fit model can contain several *signal* and *background* components, and also *other* components :

```
model       = Fit1D ( signal = signal ,
                    background = background ,
                    othersignals = [ ... ] ,
                    otherbackgrounds = [ ... ] ,
                    others      = [ ... ] )
```

In this case several *signal*, *backgrounds* and/or *others* components can be combined into single *signal*, *background* and/or *others* components:

```
model       = Fit1D ( combine_signals = True ,
                    combine_backgrounds = True ,
                    combine_others      = True , ... )
```

In practice it is very convenient approach if several signal/background/other components are specified.

On default *extended* 'RooAddPdf' fit model is created, however, one can force *non-extended* model:

```
model       = Fit1D ( extended = False , ... )
```

In this case one can also instruct the class `Fit1D` to create *recursive* (default) or *non-recursive* fit fractions:

```
model       = Fit1D ( extended = False , recursive = False , ... )
```

All components (*signal/background/others*) can be specified as Ostap-based models. Also one can provide them in a form of bare `RooAbsPdf`, but for this case one needs to provide also `xvar` -variable

```
mass = ROOT.RooRealVar( 'mass', 'mass', 2, 3 )
gauss = ROOT.RooGaussian( 'Gauss', 'Gauss', mass , ... )
model = Fit1D( signal = gauss , xvar = mass , ... )
```

For *background* components there is also an alternative way to specify it:

- `None` : `RooPolynomial` of zero degree (uniform distribution) will be created and used as *background* component
  - Attention: `background=None` does *not* imply the absence of background component
- negative integer `n` : Ostap model `PolyPos_pdf` will be created and used as *background* component. This model corresponds to the *positive* polynomial of degree `-n`. The polynomial is constrained to be non-negative for the whole considered interval of `xvar`. This constraint allows rather robust and stable fits, especially for the low-statistics case.
- non-negative integer `n` : Ostap model `Bkg_pdf`, that is a product of the exponential function and the *positive* polynomial of degree `n` will be created and used as *background* component. Note:
  - The `background=0` case corresponds to simple exponential background

- Since the polynomial is constrained to be *non-negative* this PDF is very stable and robust, especially for the low-statistic case,
- as `RooAbsReal` object, in this case it is interpreted as the exponential slope

Actually, the separation into *signal*, *background* and *other* components is a bit arbitrary. However it is helpful for

- to define the meaningful names for the fit parameters
- to separate different components for visualisation, since different styles (lines, colors, etc) are used for different categories

## Access to the model components

The individual components can be accessed using python *properties*

```
gaudd = Gauss_pdf ( ...
model = Fit1D ( signal = gauss , ... )
print model.signal.sigma ## get sigma of Gauss
print model.signal.mean  ## get mean  of Gauss
```

## Fit parameters

The parameters of the created `RooAddPdf` can be accessed via python properties, e.g. for *extended* fits:

```
gaudd = Gauss_pdf ( ...
model = Fit1D ( signal = gauss , ... )
print 'signal yield(s):' , model.S
print 'background(s):' , model.B
print 'others: ' , model.C
model.S = 100 ## set value of signal component to be 100 events
model.B.fix(50) ## fix the yield of the background component at 50 events
model.draw()
```

Depending on the number of corresponding components and flags `combine_signals` , `combine_backgrounds` , `combine_others` these properties can be *scalar* values or arrays/tuples.

For `combine_signal=True` , `combine_backgrounds=True` , `combine_others=True` cases one also gets properties `fs` , `fb` and `fc` that corresponds to the fractions of individual *signal/background/others* components for the compound signal/ *signal/background/others*.

For *non-extended* fits, the main parameters are *fractions*:

```
gaudd = Gauss_pdf ( ...
model = Fit1D ( signal = gauss , ... , extended = False )
...
print 'fractions:' , model.F
```

## Extended multi-component fit model

```
model_ext1 = Models.Fit1D (
    name          = 'EXT1' ,
    signal         = signal_1 ,
    othersignals   = [ signal_2 , signal_3 ] ,
    background     = wide_1 ,
    otherbackgrounds = [ wide_2 ] ,
    others         = [ narrow_1 , narrow_2 ] ,
)
```

One can define some initial setting for fit-parameters:

```

model_ext1.S[0].value = 5000
model_ext1.S[1].value = 5000
model_ext1.S[2].value = 5000

model_ext1.B[0].value = 1700
model_ext1.B[1].value = 2300

model_ext1.C[0].value = 500
model_ext1.C[1].value = 400

```

The fit itself is trivial

```

r, f = model_ext1.fitTo ( dataset , draw = False , silent = True )
r, f = model_ext1.fitTo ( dataset , draw = False , silent = True )

```

And accessing fit results is also simple:

```

print 'Signals           [S]:' , model_ext1.S
print 'Backgrounds      [B]:' , model_ext1.B
print 'Components       [C]:' , model_ext1.C
print 'Fractions        [F]:' , model_ext1.F
print 'Signal fractions [fS]:' , model_ext1.fS
print 'Background fractions [fB]:' , model_ext1.fB
print 'Component fractions [fC]:' , model_ext1.fC
print 'Yields           [yields]:' , model_ext1.yields
print 'Fractions        [fractions]:' , model_ext1.fractions

```

## ***Extended fit model with compound components***

```

model_ext2 = Models.Fit1D (
    name           = 'EXT2' ,
    signal         = signal_1 ,
    othersignals   = [ signal_2 , signal_3 ] ,
    background     = wide_1 ,
    otherbackgrounds = [ wide_2 ] ,
    others         = [ narrow_1 , narrow_2 ] ,
    #
    combine_signals = True , ## <-- HERE
    combine_backgrounds = True , ## <-- HERE
    combine_others = True , ## <-- HERE
)

```

Setting the initial values of fit parameters is trivial:

```

model_ext2.S = 5000
model_ext2.B = 4200
model_ext2.C = 700

model_ext2.fS[0].value = 0.33
model_ext2.fS[1].value = 0.50

model_ext2.fB[0].value = 0.40
model_ext2.fC[0].value = 0.60

```

The fit itself and access to fit parameters is the same as above.

## ***Non-extended multi-component fit model with non-recursive fit-fractions***

```

model_ne1 = Models.Fit1D (
    name           = 'NE1'           ,
    signal         = signal_1        ,
    othersignals   = [ signal_2 , signal_3 ] ,
    background     = wide_1          ,
    otherbackgrounds = [ wide_2 ] ,
    others         = [ narrow_1 , narrow_2 ] ,
    ##
    extended       = False , ## <--- HERE
    recursive      = False  ## <--- HERE
)

```

Setting the initial values of fit-fractions:

```

model_ne1.F[0].value = 0.25
model_ne1.F[1].value = 0.25
model_ne1.F[2].value = 0.25
model_ne1.F[3].value = 0.08
model_ne1.F[4].value = 0.12
model_ne1.F[5].value = 0.05

```

The fit itself and access to fit parameters is the same as above.

### ***Non-extended multi-component fit model with recursive fit-fractions***

```

model_ne2 = Models.Fit1D (
    name           = 'NE2'           ,
    signal         = signal_1        ,
    othersignals   = [ signal_2 , signal_3 ] ,
    background     = wide_1          ,
    otherbackgrounds = [ wide_2 ] ,
    others         = [ narrow_1 , narrow_2 ] ,
    ##
    extended       = False , ## <-- HERE
    recursive      = True  , ## <-- HERE
)

```

Setting initial fit parameters:

```

model_ne2.F[0].value = 0.25
model_ne2.F[1].value = 0.33
model_ne2.F[2].value = 0.50
model_ne2.F[3].value = 0.37
model_ne2.F[4].value = 0.74
model_ne2.F[5].value = 0.50

```

The fit itself and access to fit parameters is the same as above.

### ***Non-extended fit model with compound components and non-recursive fit-fractions***

```

model_ne3 = Models.Fit1D (
    name           = 'NE2'           ,
    signal          = signal_1        ,
    othersignals    = [ signal_2 , signal_3 ] ,
    background      = wide_1          ,
    otherbackgrounds = [ wide_2 ] ,
    others          = [ narrow_1 , narrow_2 ] ,
    ##
    combine_signals  = True , ## <--- HERE
    combine_backgrounds = True , ## <--- HERE
    combine_others   = True , ## <--- HERE
    ##
    extended        = False , ## <--- HERE
    recursive       = False  ## <--- HERE
)

```

Setting the initial values:

```

model_ne3. F[0].value = 0.75
model_ne3. F[1].value = 0.30
model_ne3. fS[0].value = 0.33
model_ne3. fS[1].value = 0.50
model_ne3. fB[0].value = 0.41
model_ne3. fC[0].value = 0.58

```

The fit itself and access to fit parameters is the same as above.

## ***Non-extended fit model with compound components and recursive fit-fractions***

```

model_ne4 = Models.Fit1D (
    name           = 'NE4'           ,
    signal          = signal_1        ,
    othersignals    = [ signal_2 , signal_3 ] ,
    background      = wide_1          ,
    otherbackgrounds = [ wide_2 ] ,
    others          = [ narrow_1 , narrow_2 ] ,
    ##
    combine_signals  = True , ## <--- HERE
    combine_backgrounds = True , ## <--- HERE
    combine_others   = True , ## <--- HERE
    ##
    extended        = False , ## <--- HERE
    recursive       = True  ## <--- HERE
)

```

Setting the initial values:

```

model_ne4. F[0].value = 0.75
model_ne4. F[1].value = 0.80
model_ne4. fS[0].value = 0.33
model_ne4. fS[1].value = 0.50
model_ne4. fB[0].value = 0.41
model_ne4. fC[0].value = 0.50

```

The fit itself and access to fit parameters is the same as above.

All the ways to deal with `Fit1D` objects are illustrated here:

```

1  #!/usr/bin/env python
2  # -*- coding: utf-8 -*-
3  # =====
4  ## @file TestComponents.py
5  #

```

```

6  # tests for various multicomponents models
7  #
8  # @author Vanya BELYAEV Ivan.Belyaev@itep.ru
9  # @date 2014-05-11
10 # =====
11 """Tests for various multicomponent models
12 """
13 # =====
14 __version__ = "$Revision:"
15 __author__ = "Vanya BELYAEV Ivan.Belyaev@itep.ru"
16 __date__ = "2014-05-10"
17 __all__ = () ## nothing to be imported
18 # =====
19 import ROOT, random
20 from Ostap.PyRoUts import *
21 from Ostap.Utils import rooSilent
22 # =====
23 # logging
24 # =====
25 from AnalysisPython.Logger import getLogger
26 if '__main__' == __name__ or '__builtin__' == __name__ :
27     logger = getLogger ( 'Ostap.TestComponents' )
28 else :
29     logger = getLogger ( __name__ )
30 # =====
31 logger.info ( 'Test for multi-component models from Analysis/Ostap' )
32 # =====
33 ## make simple test mass
34 mass = ROOT.RooRealVar ( 'test_mass' , 'Some test mass' , 0 , 10 )
35
36 ## book very simple data set
37 varset = ROOT.RooArgSet ( mass )
38 dataset = ROOT.RooDataSet ( dsID() , 'Test Data set-0' , varset )
39
40 mmin, mmax = mass.minmax()
41
42 ### fill it
43 m1 = VE(3,0.300**2)
44 m2 = VE(5,0.200**2)
45 m3 = VE(7,0.100**2)
46
47 for i in xrange(0,5000) :
48     for m in (m1,m2,m3) :
49         mass.value = m.gauss ()
50         dataset.add ( varset )
51

```

```

52 for i in xrange(0,5000) :
53     mass.value = random.uniform ( *mass.minmax() )
54     dataset.add ( varset )
55
56 logger.info ( 'Dataset: %s' % dataset )
57 import Ostap.FitModels as Models
58
59 signal_1 = Models.Gauss_pdf ( 'G1' , xvar = mass , mean = m1.value() , sigma = m1.error() )
60 signal_2 = Models.Gauss_pdf ( 'G2' , xvar = mass , mean = m2.value() , sigma = m2.error() )
61 signal_3 = Models.Gauss_pdf ( 'G3' , xvar = mass , mean = m3.value() , sigma = m3.error() )
62
63 wide_1 = Models.Gauss_pdf ( 'GW1' , xvar = mass , mean = 1.0 , sigma = 2 )
64 wide_2 = Models.Gauss_pdf ( 'GW2' , xvar = mass , mean = 9.0 , sigma = 3 )
65
66 narrow_1 = Models.Gauss_pdf ( 'GN1' , xvar = mass , mean = 4.0 , sigma = 1 )
67 narrow_2 = Models.Gauss_pdf ( 'GN2' , xvar = mass , mean = 6.0 , sigma = 1 )
68
69 ## =====
70 logger.info ( 'Test the extended fit with many components' )
71 model_ext1 = Models.Fit1D (
72     name          = 'EXT1' ,
73     signal        = signal_1 ,
74     othersignals  = [ signal_2 , signal_3 ] ,
75     background    = wide_1 ,
76     otherbackgrounds = [ wide_2 ] ,
77     others        = [ narrow_1 , narrow_2 ] ,
78 )
79 model_ext1.S[0].value = 5000
80 model_ext1.S[1].value = 5000
81 model_ext1.S[2].value = 5000
82
83 model_ext1.B[0].value = 1700
84 model_ext1.B[1].value = 2300
85
86 model_ext1.C[0].value = 500
87 model_ext1.C[1].value = 400
88
89 r, f = model_ext1.fitTo ( dataset , draw = False , silent = True )
90 r, f = model_ext1.fitTo ( dataset , draw = False , silent = True )
91 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ext1.name , r ) )
92 print 'Signals          [S]:' , model_ext1.S
93 print 'Backgrounds      [B]:' , model_ext1.B
94 print 'Components        [C]:' , model_ext1.C
95 print 'Fractions          [F]:' , model_ext1.F
96 print 'Signal fractions   [fS]:' , model_ext1.fS
97 print 'Background fractions [fB]:' , model_ext1.fB

```

```

98 print 'Component fractions [fC]:' , model_ext1.fC
99 print 'Yields [yields]:' , model_ext1.yields
100 print 'Fractions [fractions]:' , model_ext1.fractions
101
102
103 ## =====
104 logger.info ( 'Test the extended fit with compound components' )
105 model_ext2 = Models.Fit1D (
106     name          = 'EXT2'      ,
107     signal        = signal_1 ,
108     othersignals  = [ signal_2 , signal_3 ] ,
109     background    = wide_1     ,
110     otherbackgrounds = [ wide_2 ] ,
111     others        = [ narrow_1 , narrow_2 ] ,
112     #
113     combine_signals = True    ,
114     combine_backgrounds = True ,
115     combine_others  = True    ,
116 )
117 model_ext2.S = 5000
118 model_ext2.B = 4200
119 model_ext2.C = 700
120
121 model_ext2.fS[0].value = 0.33
122 model_ext2.fS[1].value = 0.50
123
124 model_ext2.fB[0].value = 0.40
125 model_ext2.fC[0].value = 0.60
126
127 r, f = model_ext2.fitTo ( dataset , draw = False , silent = True )
128 r, f = model_ext2.fitTo ( dataset , draw = False , silent = True )
129 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ext2.name , r ) )
130 print 'Signals [S]:' , model_ext2.S
131 print 'Backgrounds [B]:' , model_ext2.B
132 print 'Components [C]:' , model_ext2.C
133 print 'Fractions [F]:' , model_ext2.F
134 print 'Signal fractions [fS]:' , model_ext2.fS
135 print 'Background fractions [fB]:' , model_ext2.fB
136 print 'Component fractions [fC]:' , model_ext2.fC
137 print 'Yields [yields]:' , model_ext2.yields
138 print 'Fractions [fractions]:' , model_ext2.fractions
139
140 ## =====
141 logger.info ( 'Test non-extended fit with all components, non-recursive' )
142 model_ne1 = Models.Fit1D (
143     name          = 'NE1'      ,

```



```

144     signal                = signal_1 ,
145     othersignals          = [ signal_2 , signal_3 ] ,
146     background            = wide_1 ,
147     otherbackgrounds      = [ wide_2 ] ,
148     others                = [ narrow_1 , narrow_2 ] ,
149     ##
150     extended              = False ,
151     recursive              = False
152 )
153
154 model_ne1.F[0].value = 0.25
155 model_ne1.F[1].value = 0.25
156 model_ne1.F[2].value = 0.25
157 model_ne1.F[3].value = 0.08
158 model_ne1.F[4].value = 0.12
159 model_ne1.F[5].value = 0.05
160
161 r, f = model_ne1.fitTo ( dataset , draw = False , silent = True )
162 r, f = model_ne1.fitTo ( dataset , draw = False , silent = True )
163 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ne1.name , r ) )
164 print 'Signals          [S]:' , model_ne1.S
165 print 'Backgrounds      [B]:' , model_ne1.B
166 print 'Components       [C]:' , model_ne1.C
167 print 'Fractions         [F]:' , model_ne1.F
168 print 'Signal fractions  [fS]:' , model_ne1.fS
169 print 'Background fractions [fB]:' , model_ne1.fB
170 print 'Component fractions [fC]:' , model_ne1.fC
171 print 'Yields           [yields]:' , model_ne1.yields
172 print 'Fractions        [fractions]:' , model_ne1.fractions
173
174 ## =====
175 logger.info ( 'Test non-extended fit with all components, recursive' )
176 model_ne2 = Models.Fit1D (
177     name                = 'NE2' ,
178     signal              = signal_1 ,
179     othersignals        = [ signal_2 , signal_3 ] ,
180     background          = wide_1 ,
181     otherbackgrounds    = [ wide_2 ] ,
182     others              = [ narrow_1 , narrow_2 ] ,
183     ##
184     extended            = False ,
185     recursive           = True ,
186 )
187
188 model_ne2.F[0].value = 0.25
189 model_ne2.F[1].value = 0.33

```

```

190 model_ne2.F[2].value = 0.50
191 model_ne2.F[3].value = 0.37
192 model_ne2.F[4].value = 0.74
193 model_ne2.F[5].value = 0.50
194
195 r, f = model_ne2.fitTo ( dataset , draw = False , silent = True )
196 r, f = model_ne2.fitTo ( dataset , draw = False , silent = True )
197 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ne2.name , r ) )
198 print 'Signals          [S]:' , model_ne2.S
199 print 'Backgrounds      [B]:' , model_ne2.B
200 print 'Components       [C]:' , model_ne2.C
201 print 'Fractions        [F]:' , model_ne2.F
202 print 'Signal fractions  [fS]:' , model_ne2.fS
203 print 'Background fractions [fB]:' , model_ne2.fB
204 print 'Component fractions [fC]:' , model_ne2.fC
205 print 'Yields           [yields]:' , model_ne2.yields
206 print 'Fractions        [fractions]:' , model_ne2.fractions
207
208
209 ## =====
210 logger.info ( 'Test non-extended fit with compound components, non-recursive' )
211 model_ne3 = Models.Fit1D (
212     name          = 'NE2' ,
213     signal         = signal_1 ,
214     othersignals   = [ signal_2 , signal_3 ] ,
215     background     = wide_1 ,
216     otherbackgrounds = [ wide_2 ] ,
217     others         = [ narrow_1 , narrow_2 ] ,
218     ##
219     combine_signals = True ,
220     combine_backgrounds = True ,
221     combine_others  = True ,
222     ##
223     extended       = False ,
224     recursive       = False
225 )
226
227 model_ne3.F[0].value = 0.75
228 model_ne3.F[1].value = 0.30
229
230 model_ne3.fS[0].value = 0.33
231 model_ne3.fS[1].value = 0.50
232
233 model_ne3.fB[0].value = 0.41
234 model_ne3.fC[0].value = 0.58
235

```

```

236 r, f = model_ne3.fitTo ( dataset , draw = False , silent = True )
237 r, f = model_ne3.fitTo ( dataset , draw = False , silent = True )
238 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ne3.name , r ) )
239 print 'Signals          [S]:' , model_ne3.S
240 print 'Backgrounds      [B]:' , model_ne3.B
241 print 'Components       [C]:' , model_ne3.C
242 print 'Fractions        [F]:' , model_ne3.F
243 print 'Signal fractions  [fS]:' , model_ne3.fS
244 print 'Background fractions [fB]:' , model_ne3.fB
245 print 'Component fractions [fC]:' , model_ne3.fC
246 print 'Yields          [yields]:' , model_ne3.yields
247 print 'Fractions      [fractions]:' , model_ne3.fractions
248
249
250 ## =====
251 logger.info ( 'Test non-extended fit with compound components, recursive' )
252 model_ne4 = Models.Fit1D (
253     name          = 'NE4' ,
254     signal        = signal_1 ,
255     othersignals   = [ signal_2 , signal_3 ] ,
256     background     = wide_1 ,
257     otherbackgrounds = [ wide_2 ] ,
258     others         = [ narrow_1 , narrow_2 ] ,
259     ##
260     combine_signals = True ,
261     combine_backgrounds = True ,
262     combine_others   = True ,
263     ##
264     extended       = False ,
265     recursive      = True
266 )
267
268 model_ne4.F[0].value = 0.75
269 model_ne4.F[1].value = 0.80
270
271 model_ne4.fS[0].value = 0.33
272 model_ne4.fS[1].value = 0.50
273
274 model_ne4.fB[0].value = 0.41
275 model_ne4.fC[0].value = 0.50
276
277 r, f = model_ne4.fitTo ( dataset , draw = False , silent = True )
278 r, f = model_ne4.fitTo ( dataset , draw = False , silent = True )
279 logger.info ( 'Model %s Fit results:\n#%s ' % ( model_ne4.name , r ) )
280 print 'Signals          [S]:' , model_ne4.S
281 print 'Backgrounds      [B]:' , model_ne4.B

```

```
282 print 'Components      [C]:' , model_ne4.C
283 print 'Fractions       [F]:' , model_ne4.F
284 print 'Signal fractions [fS]:' , model_ne4.fS
285 print 'Background fractions [fB]:' , model_ne4.fB
286 print 'Component fractions [fC]:' , model_ne4.fC
287 print 'Yields          [yields]:' , model_ne4.yields
288 print 'Fractions       [fractions]:' , model_ne4.fractions
289
290
291 # =====
292 # The END
293 # =====
```

components.py hosted with ♥ by GitHub

[view raw](#)

The corresponding output can be inspected [here](#)

## 2D -case

Generic 2D -case

Symmetric 2D -case

## 3D -case

Generic 3D -case

Symmetric 3D -case

Mixed-symmetry 3D -case

# sPlot

Using **sPlot** is rather trivial in Ostap:

```
dataset = ...  
model   = Fit1D ( signal = ... , background = ... )  
model.fitTo ( dataset )  
print dataset  
model.sPlot ( dataset ) ## <--- HERE  
print dataset           ## <--- note appearence of new variables
```

## Using *Weighted fits*

Often one needs to fit *weighted dataset*, e.g. *backrgonud-subtracted* or *efficiency\_corrected*. It is purely trivial in Ostap:

```
dataset = ...  
dsw     = dataset.makeWeighted( 'S_sw/eff' ) ##  
model   = ...  
model.fitTo ( dsw , ... , sumw2 = True , ... ) ## <--- HERE
```

# Using *Constraints* in the fit

Often one can add *soft Gaussian constraint* for some fit parameters, e.g. one can constrain the signal resolution:

```
sigma_MC      = VE( 0.015 , 0.001**2 ) ##
sigma_cnt     = model.sigma.constrainTo ( sigma_MC , 'sigma_constraint' )
my_constraints = ROOT.RooFit.ExternalConstraints ( ROOT.RooArgSet ( sigma_cnt ) )
dataset       = ...
model.fitTo ( dataset , ... , constraints = my_constraints , .... )
```

Clearly several constraints can be combined together

```
sigma_cnt = model.sigma.constrainTo ( sigma_MC , 'sigma_constraint' )
peak_cnt  = model.mean .constrainTo ( VE(3.096,0.001**2) , 'mass_constraint' )
my_constraints = ROOT.RooFit.ExternalConstraints ( ROOT.RooArgSet ( sigma_cnt , peak_cnt ) )
```

For the next version of `ostap`, one will be able to avoid the explicit creation of `ROOT.RooFit.ExternalConstraint` and `ROOT.RooArgSet`

```
sigma_cnt = model.sigma.constrainTo ( sigma_MC , 'sigma_constraint' )
peak_cnt  = model.mean .constrainTo ( VE(3.096,0.001**2) , 'mass_constraint' )
model.fitTo ( dataset , ... , constraints = ( sigma_cnt , peak_cnt ) , .... )
```

# Tools

There are several *tools* embedded in Ostap to implement common analysis operations

- using `TMVA`
- training `TMVA` using *chopping* approach
- Reweighting
- easier access and manipulations with `PidCalib`



## Using `TMVA`

Ostap hosts couple of classes, that simplifies the training and using of `TMVA`.

## Training `TMVA`

```
tSignal = ... ## signal      TTree/TChain
tBkg     = ... ## background TTree/TChain
## book TMVA trainer
from Ostap.PyTMVA import Trainer
trainer = Trainer (
    name      = 'TestTMVA' ,
    methods = [
        # type              name      configuration
        ( ROOT.TMVA.Types.kMLP      , 'MLP'      , 'H:!V:EstimatorType=CE:VarTransform=N:NCycles=200:HiddenLayers=N+3:TestRate=
5:!UseRegulator' ) ,
        ( ROOT.TMVA.Types.kBDT      , 'BDTG'      , 'H:!V:NTrees=100:MinNodeSize=2.5%:BoostType=Grad:Shrinkage=0.10:UseBaggedBoo
st:BaggedSampleFraction=0.5:nCuts=20:MaxDepth=2' ) ,
        ( ROOT.TMVA.Types.kCuts      , 'Cuts'      , 'H:!V:FitMethod=MC:EffSel:SampleSize=200000:VarProp=FSmart' ) ,
        ( ROOT.TMVA.Types.kFisher    , 'Fisher'    , 'H:!V:Fisher:VarTransform=None:CreateMVAPdfs:PDFInterpolMVAPdf=Spline2:Nbins
MVAPdf=50:NsmoothMVAPdf=10' ) ,
        ( ROOT.TMVA.Types.kLikelihood , 'Likelihood' , 'H:!V:TransformOutput:PDFInterpol=Spline2:NsmoothSig[0]=20:NsmoothBkg[0]=20:
NsmoothBkg[1]=10:Nsmooth=1:NAvEvtPerBin=50' )
    ] ,
    variables = [ 'var1' , 'var2' , 'var3' ] , ## Variables to be used for training
    signal     = tSignal      , ## ``Signal'' sample
    background = tBkg         , ## ``Background'' sample
    verbose    = False )
```

Optionally one can specify also `signal_cuts` and `background_cuts`.

Training `TMVA` itself is trivial, one needs to invoke the method `train`:

```
weights_files = trainer.train ()
```

It returns the list/tuple of *weight-XML* -files, the output of `TMVA` trainer. Optionally one can retrieve also the list of `_C++.class` -files, using the property `class_files` or everything together in a form of `tar` -file using the property `tar_file`:

```
weight_files = trainer.weight_files ## XML weights
class_files   = trainer.class_files  ## C++ classes
tar_file      = trainer.tar_file     ## everything together
```

## Using `TMVA`

To use trained `TMVA` one exploits `TMVA reader`:

```
from Ostap.PyTMVA import Reader
reader = Reader(
    'MyMLP' ,
    variables = [ ('var1' , lambda s : s.var1 ) ,
                  ('var2' , lambda s : s.var2 ) ,
                  ('var3' , lambda s : s.var3 ) ] ,
    weights_files = tar_file )
```

What is ``lambda s : s.var1`` here?

The the element of the pair is, obviously, the variable name. The second argument is *accessor function*. It will be applied for *1-argument call* of the *method*. E.g. in this example, one can apply it to `TTree / TChain / RooAbsData / RooArgSet` and the variable `var1` from this `TTree / TChain / RooAbsData / RooArgSet` will be used as `'var1'` for the `TMVA`. Accessor functions could be trivial, as on this case, but they also can be less trivial:

```
variables = [ ( 'var1' , lambda s : s.rapidity      ) , ## use another name
              ( 'var2' , lambda s : s.pt/1000      ) , ## make some rescaling
              ( 'var3' , lambda s : atan2(s.y,s.x) ) ] , ## make more complicated calculations
```

If one wants to use other objects for *1-argument call*, other set of accessor functions need to be supplied. E.g. if data are expected to be supplied as a `tuple / list / std::vector<...>`, one can use

```
variables = [ ( 'var1' , lambda s : s[0] ) , ## use another name
              ( 'var2' , lambda s : s[1] ) , ## make some rescaling
              ( 'var3' , lambda s : a[2] ) ] , ## make more complicated calculations
```

One can also use just the plain list of variable names:

```
variables = [ 'var1' , 'var2' , 'var3' ]
```

This list will be automatically transformed into

```
variables = [ ( 'var1' , lambda s : getattr( s , 'var1' ) ) ,
              ( 'var2' , lambda s : getattr( s , 'var2' ) ) ,
              ( 'var3' , lambda s : getattr( s , 'var3' ) ) ]
```

As `weight_files` arguments one can use either the list of *weights-files* from *the trainer*, or, *much easier*, use the single *'tar'-file* from *the trainer*. The methods, available from the weight files can be checked as

```
print reader.methods
\
```

And the usage of the reader is rather trivial, e.g. one can explicitly request the response for certain set of arguments:

```
v1, v2, v3 = ....
mlp = reader['MLP']                ## get one method
print 'MLP value is %s' % mlp ( v1 , v2 , v3 )
```

In practice, one practically always uses it with `TTree / TChain / RooAbsData / RooArgSet`, in this case one use *1-argument call*, assuming then proper *accessor functions* are supplied:

```
tree = ... ## the tree
mlp = reader['MLP']                ## get one method
for i in tree :                    ## loop over the entries
    print 'MLP value is %s' % mlp ( i ) ## get the value
```

# Using *chopping* for **TMVA** training/using

*Chopping* is a technique to use the limited set of data for TMVA training. In this approach data are *chopped* into several categories and for each category  $i$  TMV is trained using the remaining  $N-1$  categories, and the trained **TMVA** is applied to the events from category  $i$ .

## Training **TMVA** -chopper

The *trainig-with-chopping* is fairly trivial. First one need to define the number of distinct categories and the function to classify the events into training categories. E.g. for **TMVA** training

```
tSignal = ... ## signal      TTree/TChain
tBkg     = ... ## background TTree/TChain
## book TMVA trainer
from Ostap.TMVACHopper import Trainer
trainer = Trainer (
    N         = N           , ## ATTENTION! N is number of categories
    category = "137*evt+813*run" , ## ATTENTION! It is a classification function
    chop_signal = False     , ## chop the signal      ? (default)
    chop_background = True  , ## chop the background ? (default)
    ...
```

All other arguments of `Trainer` are the same as for [regular \*\*TMVA\*\* trainer](#). Arguments `chop_signal` and `chop_background` defined what sample (or both) to be *chopped*. The argument `category` described *the integer-valued function*, used for classification of events. Actually *trainer* construct classification function as `category%N`.

## How to choose chopping parameters?

For efficient usage of events number of categories should be rather large  $N \gg 2$ . For the given number of categories  $N$ , the fraction of events used for **TMVA** training is  $(N-1)/N$ . Therefore with large  $N$  events are used more efficiently. From other side, for large  $N$  the training time is proportional to  $N$ , while the training results should be more or less independent on  $N$ . It makes senseless usage of  $N > 100$ . Therefore one gets  $2 < N < 100$ . In practice it is convenient to choose  $10 < N < 20$ .

The ideal classification function *must* be independent on the properties of signal and or background. It should be `pseudorandom` and provide almost uniform population of categories. It is very easy to achieve using the following expression

$(N_a * a + N_b * b + N_c * c + \dots + N_z * z) \% N$ , where  $a, b, \dots, z$  are some integer-valued variables from the input `TTree / TChain` (event number, run-number, GPS time in nanoseconds, number of tracks in event, number of hits in SPD, etc...), and  $N_a, N_b, \dots, N_z$  are prime numbers, that are large enough ( $N_a \gg N, N_b \gg N, \dots, N_z \gg N$ ). With such construction, choosing  $N$  to be also a prime number, one almost guaranteed that events are *randomly* distributed into  $N$ -categories.

The category population can be checked using set of control histograms:

```
bc = trainer.background_categories
sc = trainer.signal_categories
bc[0].Draw() ## show population of background categories
bc[1].Draw() ## the same with different binning

sc[0].Draw() ## show population of signal categories
sc[1].Draw() ## the same with different binning
```

## Using **TMVA** -chopper

Again one needs to define the classification function for input data. Clearly this function should match the one used in training

```
category = lambda s : int ( s.evt*137 + 813*s.run ) % N ## the classification function
from Ostap.TMVACHopper import Reader    ## ATTENTION
reader = Reader(
    N          = N          , ## number of categories
    categoryfunc = category , ## category
    ...
)
```

All other arguments of `Reader` are the same as for [regular TMVA reader](#). The created *reader* is used exactly in the same way as for *no-chopping*-case:

```
tree = ... ## the tree
mlp = reader['MLP']          ## get one method
for i in tree :              ## loop over the entries
    print 'MLP value is %s' % mlp ( i ) ## get the value
```

## For tests and debug

For test and debug purposes one can use it also as a function:

```
v1, v2, v3 = ....
mlp = reader['MLP']    ## get one method
for i in range ( N ) : ## loop over categories
    print 'MLP value for category %s is %s' % ( i , mlp ( i , v1 , v2 , v3 ) )
```

And even get the difference between responses for different categories. Clearly the spread of values should be small enough

```
v1, v2, v3 = ....
mean = mlp.mean ( v1 , v2 , v3 ) ## get a mean-value over different categories
stat = mlp.stat ( v1 , v2 , v3 ) ## get a statistics (mean,rms, min/max,...) of responses
```

# Reweighting

Ostap offers set of utilities to *reweight* the distributions. Typical use-case is

- one has set of *data* distributions
- and *simulation* does not describe these distributions well, and one needs to *reweight* simulation to describe all distributions

It is relatively easy procedure in Ostap, however it requires some code writing.

## Data and *simulated* distributions

First, one needs to specify *data* distributions. It can be done in form of 1D,2D and 3D histograms, or as 1,2, or 3-argument functions or even all these techniques could be used together. It is important that these data distributions should be strickly positive for the corresponding range of variables. E.g. in case of histograms, there should be no empty or negative bin content.

```
hdata_x = ROOT.TH1D ( ... )          ## e.g. use the histogram
hdata_x = lambda x : math.exp ( -x/10 ) ## or use a function
...
hdata_y = ...
```

Second, for each *data distribution* one needs to prebook the corresponding template histogram that will be filled from *simulated* sample. This template histogram should have the same dimensionality (1,2,3) and the correspondidg *data distribution*. If *data distribution* is specified in a form of histogram, the edges of prebooked template histogram should correspond to the edges of data distribution, but there is no requirements for binning. Binning could be arbitrary, provided that there are no empty bins.

```
hmc_x = ROOT.TH1D ( ... )
hmc_y = ....
```

## Iterations

Third, one needs to create *empty* database where *the iterative weights* are stored:

```
import Ostap.ZipShelve as DBASE
dbname = 'weights.db'
with DBASE.open( dbname , 'c' ) as db :
    pass
```

Since *Reweighting* is essentially iterative procedure, we need to define some maximal number of iterations

```
iter_max = 10
for iter in range(iter_max) :
    ...
```

## Weighter object

And for each iteration we need to create *weighting* object, that reads the current weights from database `weight.db`

```
from Ostap.Reweighting import Weight
weightings = [
    ##      accessor function      address indatabase
    Weight.Var ( lambda s : s.x , 'x-reweight' ) ,
    ...
]
weighter = Weight ( dbname , weightings )
```

## What is it?

The accessor function is used to get the variable from *simulated sample*. E.g. in this form,

`TTree / TChain / RooDataSet / RooArgSet` can be used as source of *simulated* data. but it could be also e.g. some table, `numpy` array or any other storage. In this case the accessor function needs to be modified accordingly. The second parameter specify the location in (newly created empty) database, where the current weights are to be taked from. Since the newly created database is empty, for the first iteration all weights are *trivial* and equal to 1:

```
mc_tree = ...
for i in range(100):
    mc_tree.GetEntry(i)
    print ' weight for event %d is %s' % ( i , weighted ( mc_tree ) )
```

## Weighted simulated sample

As the next step one needs to prepare *simulated dataset*, `RooDataSet` , that

- contains all variables for reweighting
- the current values of *weights*, provided by `weighter` -object above

There are many ways to achive this. E.g. one can use `SelectorWithVars` -utility to decode data from input `TTree / TChain` into

`RooDataSet` :

```
from Ostap.Selectors import SelectorWithVars, Variable
## variables to be used in MC-dataset
variables = [
    Variable ( 'x' , 'x-var' , 0 , 20 , lambda s : s.x ) ,
    ...
    Variable ( 'weight' , 'weight' , accessor = weighter )
]
## create new "weighted" mcdataset
selector = SelectorWithVars (
    variables ,
    '0<x && x<20 && 0<y && y<20'
)
## process
mc_tree.process ( selector )
mcds = selector.data      ## newly created simulated dataset
print mcds
```

## Calculate the updated weights and store them in database

At the next step we calculate the updated weights and store them in database

```
from Ostap.Reweighting import makeweights, WeightingPlot
plots = [
    ##          what      how      where      data      simulated-template
    WeightingPlot ( 'x' , 'weight' , 'x-reweight' , hdata_x , hmc_x ) ,
    ...
]
## calculate updated weights and store them in database
more = makeweights ( mcds , plots , dbname , delta = 0.01 ) ## <-- HERE
```

The object `WeightingPlot` defines the rule to fill *simulated* histogram from *simulated* dataset and associated the filled *simulated* histogram with *data distribution*. The actual correction to the weights is calculated according to the rule  $w = dd / mcd$  , where `dd` is a *density* for the data distribution and `mcd` is a *density* for *simulated* distribution. The *weights* `w` are calculated for each entry in array `plots` , they

are properly normalized and stored in database `dbname` to be used for the next iteration. The function `makeweights` also print the *statistic of normalized weights*:

```
# Ostop.Reweighting      INFO      Reweighting:      ``x-reweight``: mean/(min,max):      (1.00+-0.00)/(0.985,1.012) R
MS:(0.74+-0.00)[%]
```

The last entries in this row summarize the statistics of corrections to the current weight. In this example, the mean correction is `1.00`, the minimal correction is `0.985`, the maximal correction is `1.012` and rms for corrections is `0.74\%`. In this example one sees that for this particular iteration the corrections are rather small, and probably one can stop iterations. Two parameters `delta` and `minmax` of `makeWeights` function allows to automatized the making of the decision. If calculated rms for all corrections is less than specified `delta` parameter and for each correction minmax-difference does not exceed the specified `minmax`-parameter (the default value is `0.05`), function return `False` (meaning *no more iterations are needed*), otherwise it returns `True`. And using this hint one can stop iterations or go further:

```
if not more and iter > 2 :
    print 'No more iterations are needed!'
    break
```

## Compare data and simulated distributions for each iteration (optional)

In practice it is useful (and advisable) to compare the *data* and *simulated* distributions at each iteration to have better control over the iteration process. One can make this comparison using zillions of the ways, but for the most important case in practice, where *data distribution* is specified in a form of histogram, there are some predefined utilities

```
## prepare simulated distribution with current weights:
mcDs.project ( hmc_x , 'x' , 'weight' )

## compare the basic properties: mean, rms, skewness and kurtosis
hdata_x.cmp_prnt ( hmc_x , 'DATA' , 'MC' , 'DATA(x) vs MC(x)' )

## calculate the ``distance``:
dist = hdata_x.cmp_dist ( hmc_x , density = True )
print "DATA(x)-MC(x) ``distance``      %s" % dist

## calculate the 'orthogonality'
cost = hdata_x.cmp_cos ( hmc_x , density = True )
print "DATA(x)-MC(x) ``orthogonality`` %s" % cost

## find the points of the maximal difference
mn,mx = hdata_x.cmp_minmax ( hmc_x , diff = lambda a,b : a/b , density = True )
print "DATA*(x)/MC(x) ``min/max-distance``[%%] (%s)/(%s) at x=%.1f/%.1f" % (
    (100*mn[1]-100) , (100*mx[1]-100) , mn[0] , mx[0] )
```

## Using the result

```
from Ostop.Reweighting import Weight
weightings = [
    ##      accessor function      address indatabase
    Weight.Var ( lambda s : s.x , 'x-reweight' ) ,
    ...
]
weighter = Weight ( dbname , weightings )
mc_tree = ...
for i in range(100):
    mc_tree.GetEntry(i)
    print ' weight for event %d is %s' % ( i , weighted ( mc_tree ) )
```

Note that due to explicit specification of *accessor function*, *reweighter* can be customised to work with any type of input *events/records*. e/g/ assume that *event* is a plain array, and *x*-variable corresponds to index `0`:

```

from Ostap.Rewighting import Weight
weightings = [
    ##          accessor function      address indatabase
    Weight.Var ( lambda s : s[0] , 'x-reweight' ) ,
    ...
]
weighter = Weight ( dbname , weightings )
mc_tree = ...
for event in events :
    print ' weight for event %s is %s' % ( event , weighted ( event ) )

```

## Abstract reweighting

### *Abstract reweighting*

Due to the freedom in choosing the accessor function, one can apply reweighting procedure to the absolutely abstract samples. E.g. consider the following case

- *data distribution* : simple function
- *simulated sample* : random number generator

As a result of *reweighting* procedure, we'll get *reweighted simulated sample*, that will be just a random number generator, that produces the *weighted* distribution according to the specified function. For this case, the code is very transparent and compact:

```

# =====
## 1) ``DATA distribution'' - plain function
def data ( x ) :
    return 0.5 + math.sin ( x * math.pi )**2
# =====
## 2) ``simulation template'' - histogram template for simulated sample
mc_hist = ROOT.TH1F ( 'hMC', '', 20 , 0 , 1 )
# =====
def mc_sample () :
    x = random.expovariate ( 1 )
    while x > 1 : x -=1
    return x
# =====
## 3) create empty database with initial weights
# =====

import Ostap.ZipShelve as DBASE
if os.path.exists ( dbname ) : os.remove ( dbname )
with DBASE.open( dbname , 'c' ) as db :

```

And then one starts iterations:

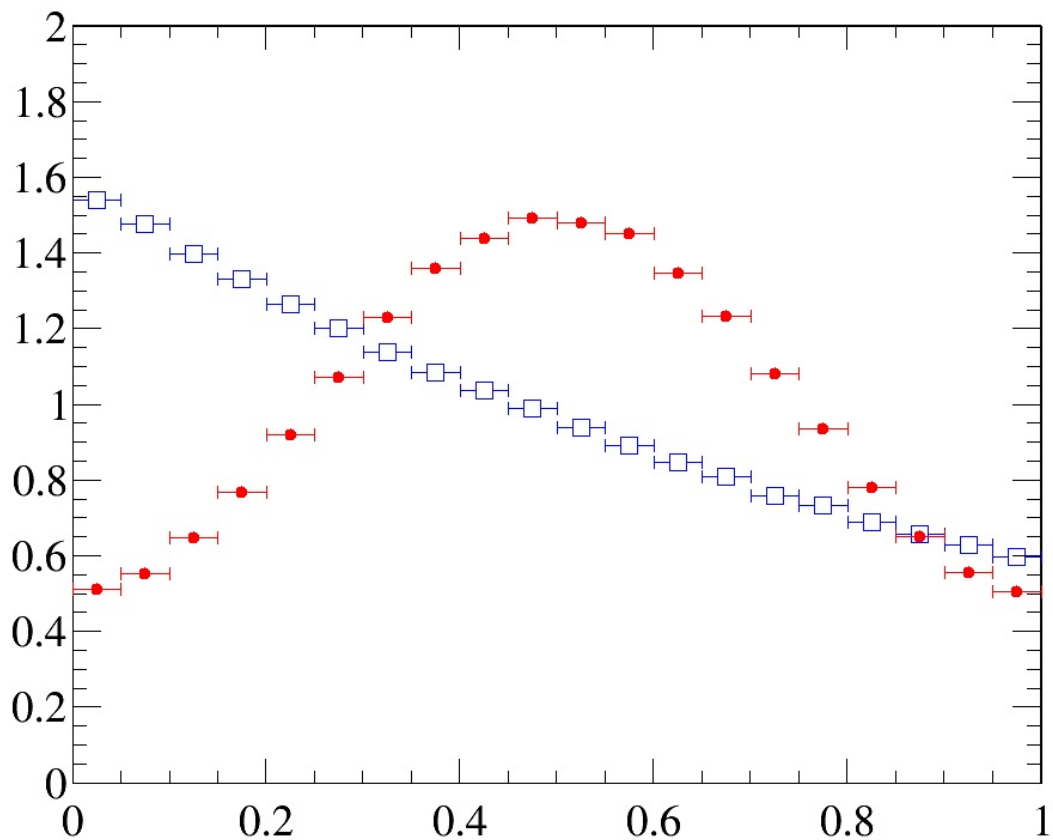


```
# =====
## 4) prepare reweighting iterations
# =====
from Ostap.Rewighting import Weight, makeWeights, WeightingPlot
from Ostap.Selectors import SelectorWithVars, Variable
for iter in range ( 100 ) :
    ##                                     accessor      address in DB
    weighter = Weight( dbname , ( Weight.Var ( lambda x : x , 'x-reweight' ) , ) )

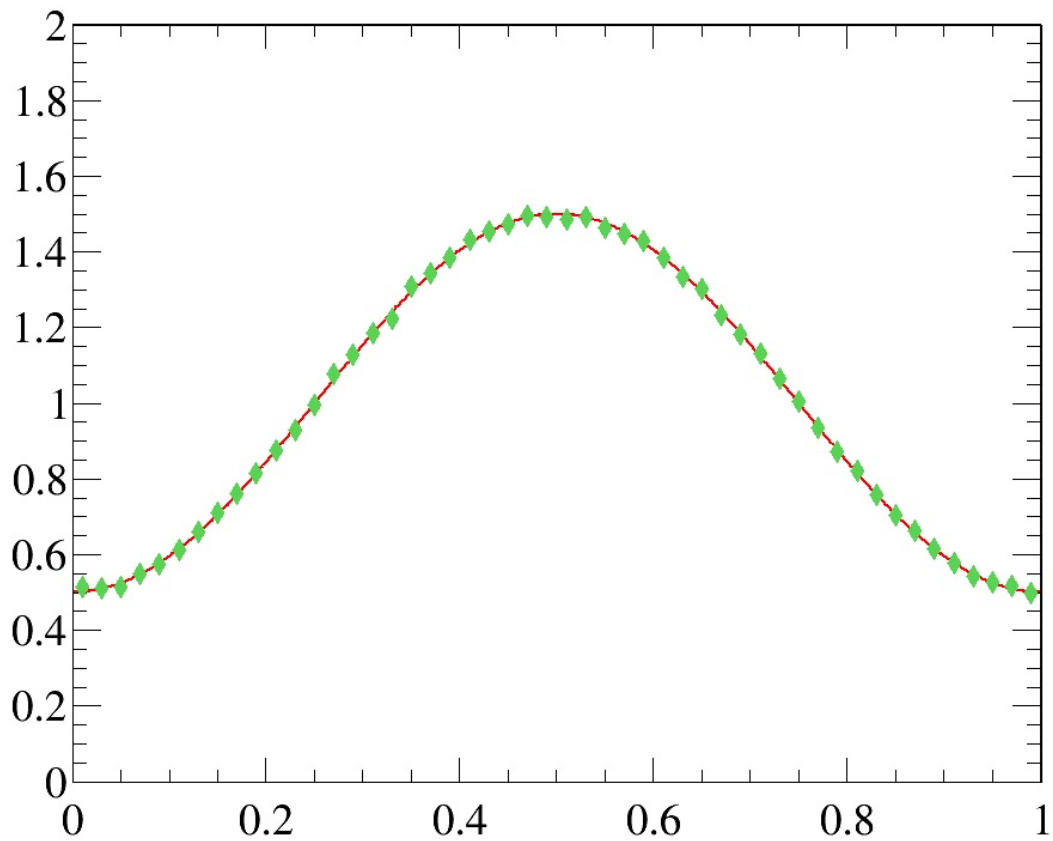
    ## create ``weighted'' simulated dataset using the current weights
    selector = SelectorWithVars (
        selection = '1<2' , ## fake one :-( to be removed soon
        silence   = True ,
        variables = [ Variable ( 'x' , 'x-var' , 0 , 1 , lambda x : x ) ,
                     Variable ( 'weight' , 'weight' , accessor = weighter ) ] )
    for i in range ( 1000000 ) :
        x = mc_sample ()
        selector ( x )
    mcds = selector.data
    ## update weights: the rule to create weighted simulated histogram
    plots = [ WeightingPlot ( 'x' , 'weight' , 'x-reweight' , data , mc_hist ) ]
    ## calculate the updated weights and add them into database
    more = makeWeights ( mcds , plots , dbname , delta = 0.01 )
    if not more and 2 <= iter :
        logger.info ( 'No more iterations are needed #%d' % iter )
        break
```

The full example for *abstract reweighting*, is accessible [here](#)

The *density* distribution for the *simulated* sample for before the first (blue open squares) and after the last (filled red points) iterations are shown here,



while the comparison of the initial *data distribution* (red line) and the *reweighted simulated sample* (greed filled diamonods) are shown here.



## Why one needs iterations?

One can argue that low-dimension reweighting can be done with only iterations, just in one-go. Why one needs iterations here?

The answer is rather simple: yes for very simple case, like 1D-reweighting, already the first iteration should provide the exact result. However it is true only if *data distribution* is supplied and the histogram and the template for the *simulated* histogram has the same binning. Otherwise the different binning scheme results in non-exact result for 1-step reweighting.

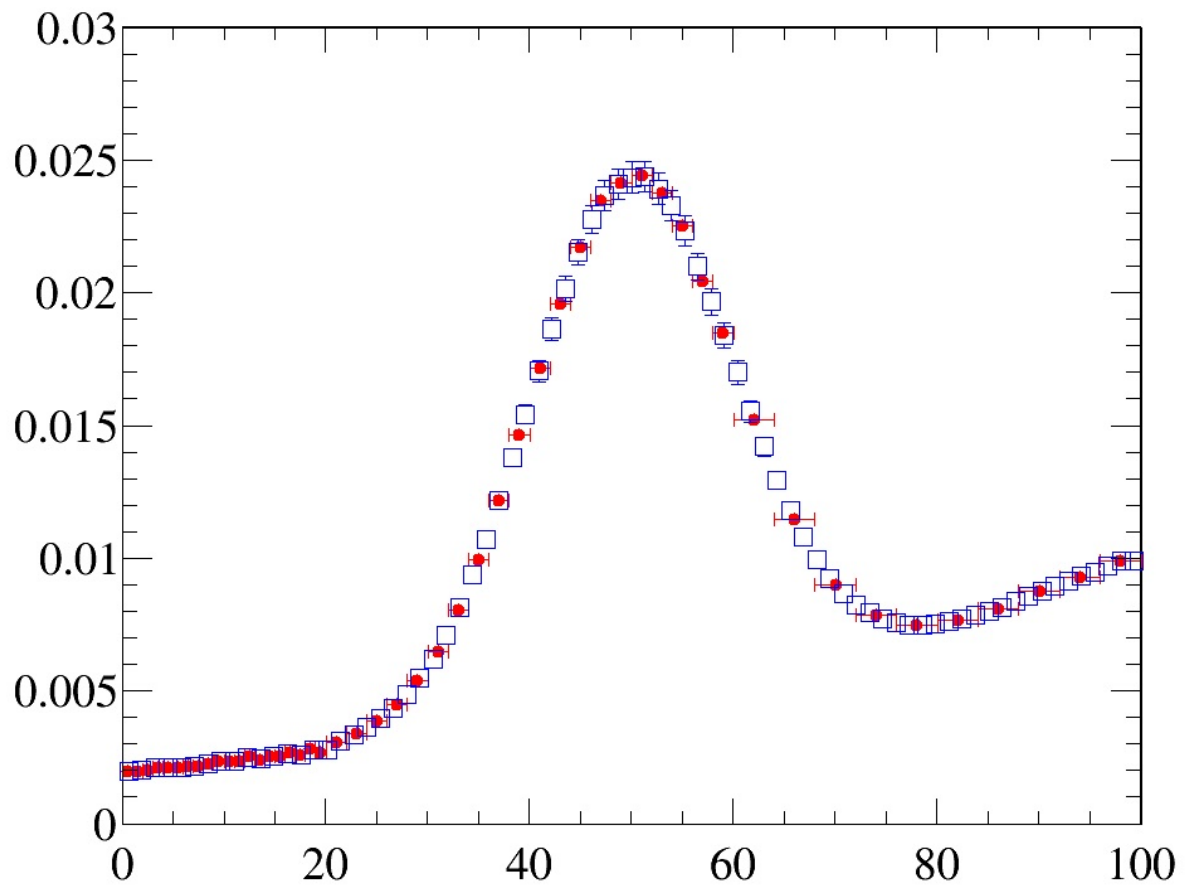
For multidimensional reweighting one can avoid iteration only if all involved variables are totally uncorrelated, otherwise the iterative procedure is unavoidable.

Moreover in the presence of correlations *oscillation effect* could occur, that prevents the quick convergence of the iterative procedure. To solve this problem, `makeWeighted` -function for multidimensional case actually *under-corrects* the results. It increases the number of necessary iterations and makes the reweighting procedure more slow, but it practically eliminates the *oscillation effect*.

## Examples

### Simple 1D -reweighting

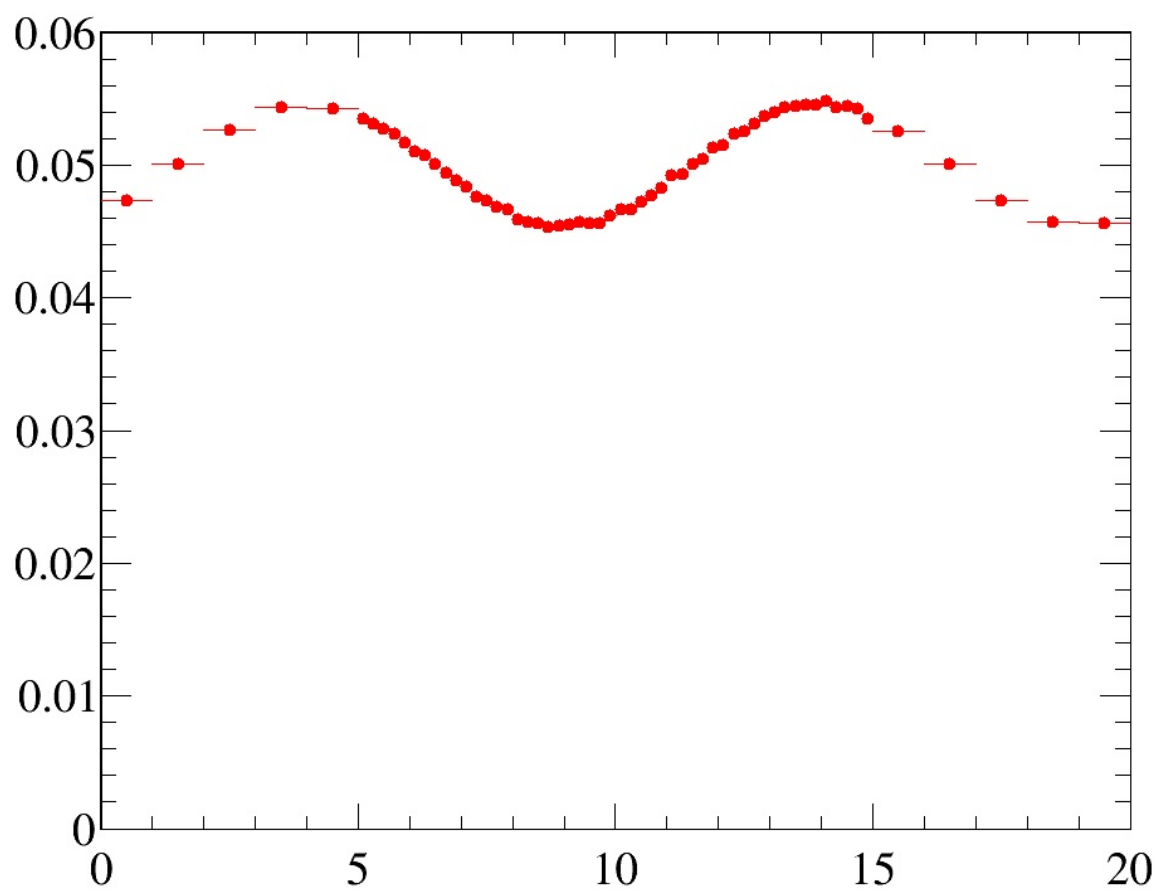
The example of simple 1D-reweighting can be inspected [here](#), while the reweighting result for the last iteration (blue open squares) are compared with *data distribution* (red filled circles) here:

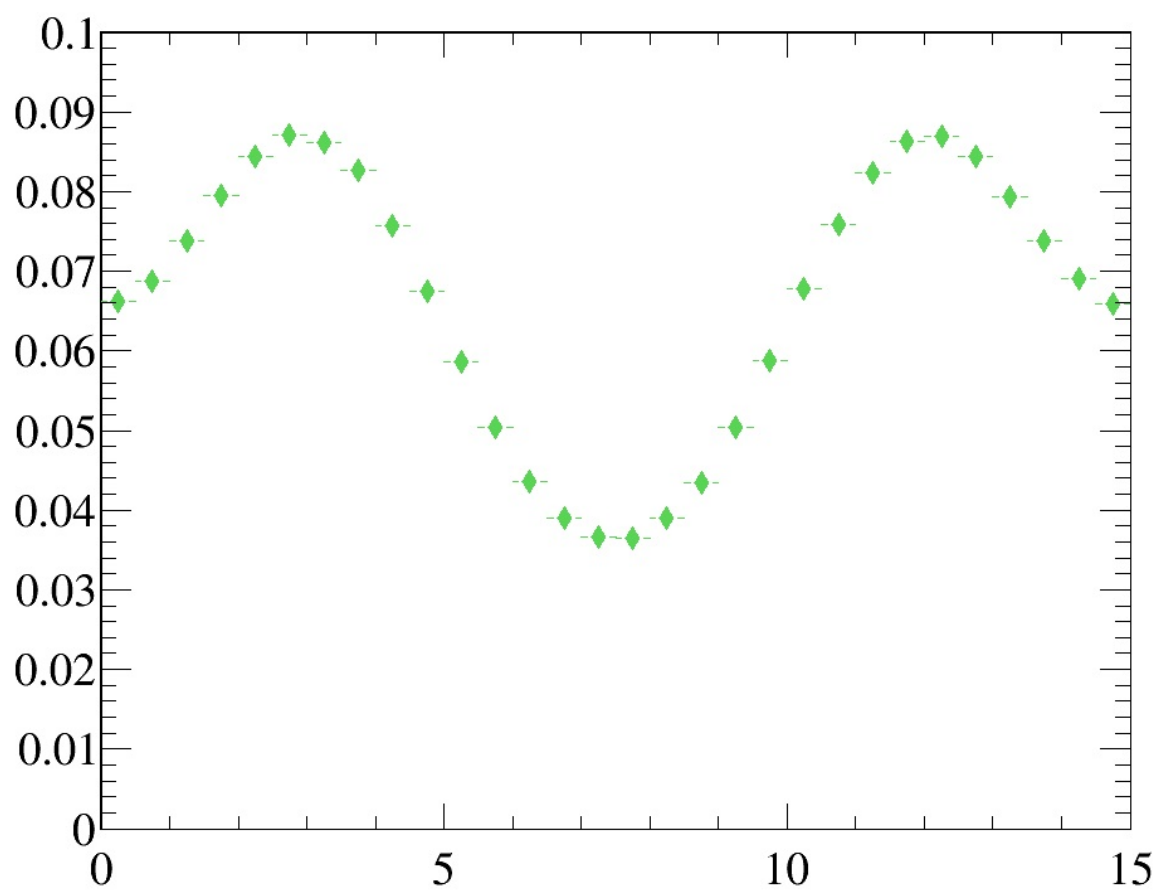


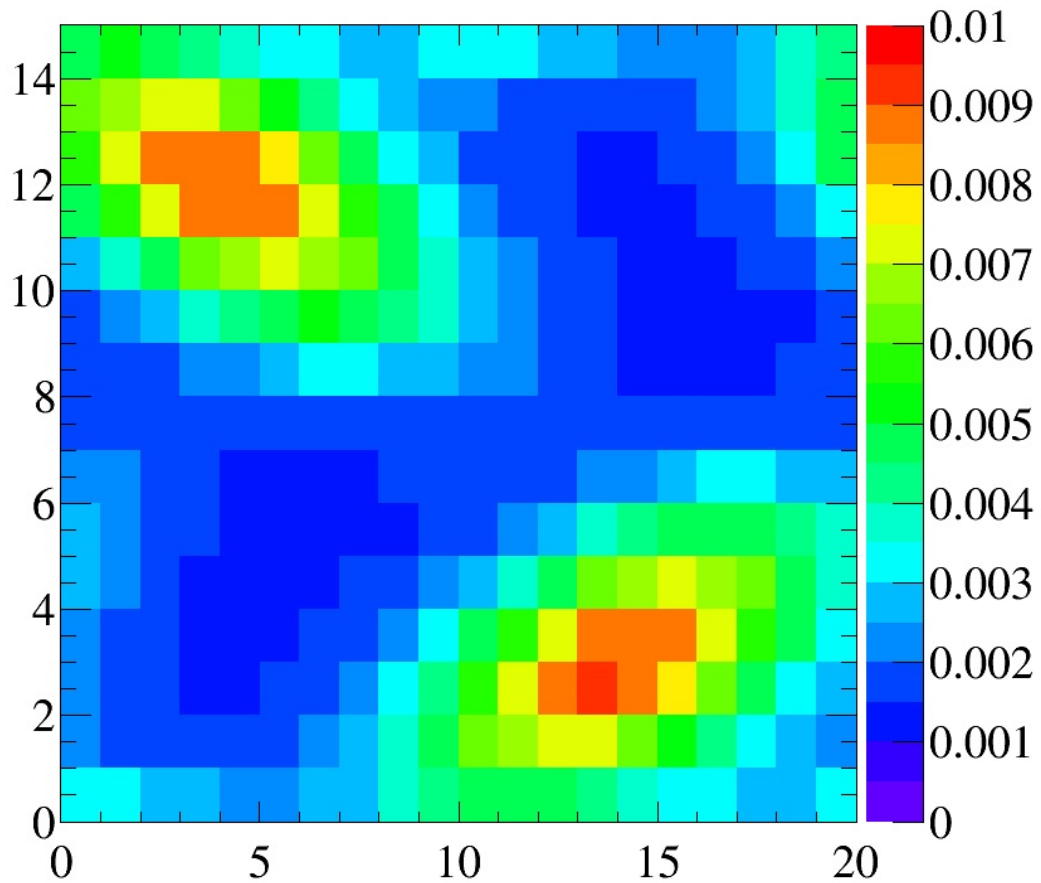
The example also illustrates how to use various *histogram comparison functions* to have better control over the iterative process

### ***More complicated case of non-factorizeable*** **2D** *-reweighting*

The example of advanced 2D-reweighting can be inspected [here](#). In this example we have three *data distributions* fro two variables 1 one-dimensional `x` -distribution with fine binning 1 one-dimensional `y` -distribution with fine binning 1 two-dimensional `y:x` -distribution with coarse binning





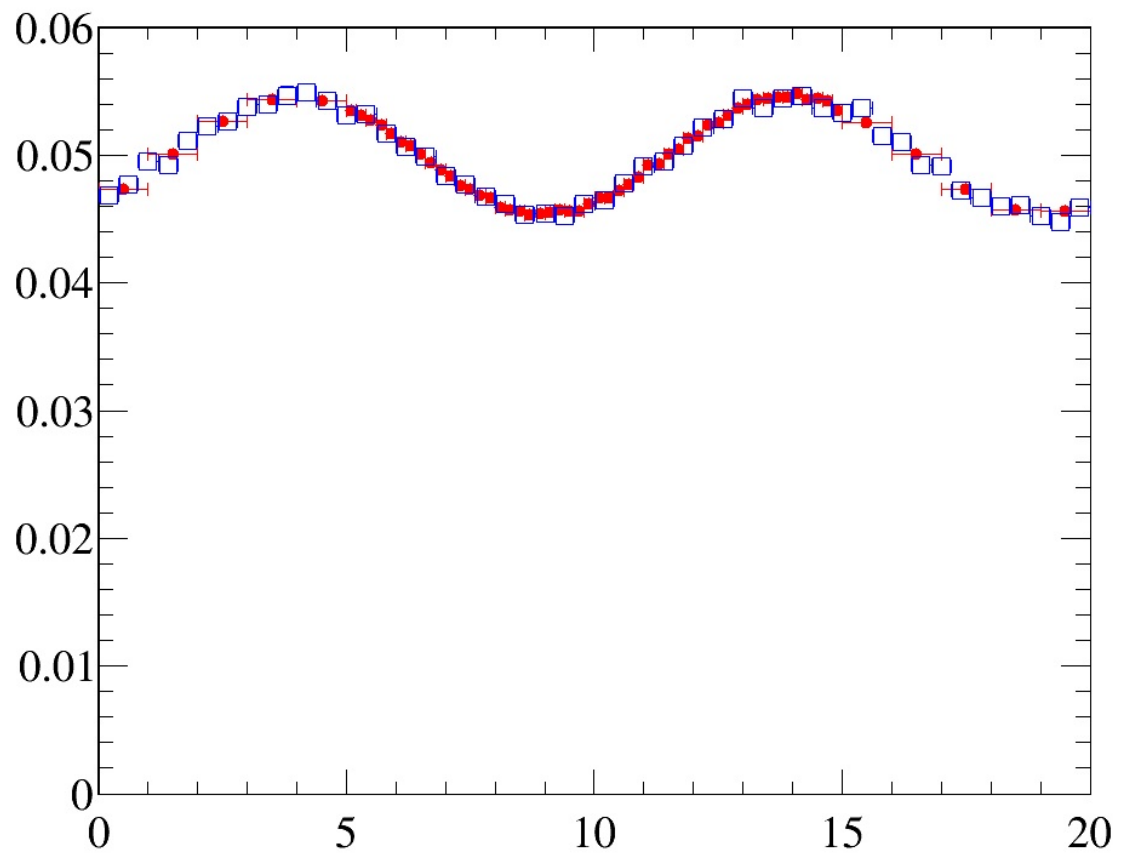


It reflects relatively frequent case of *kinematic reweighting* using the transverse momentum and rapidity. Typically one has enough events to make fine-binned one-dimensional reference distributions, but two-dimensional distributions can be obtained only with relatively coarse binning scheme.

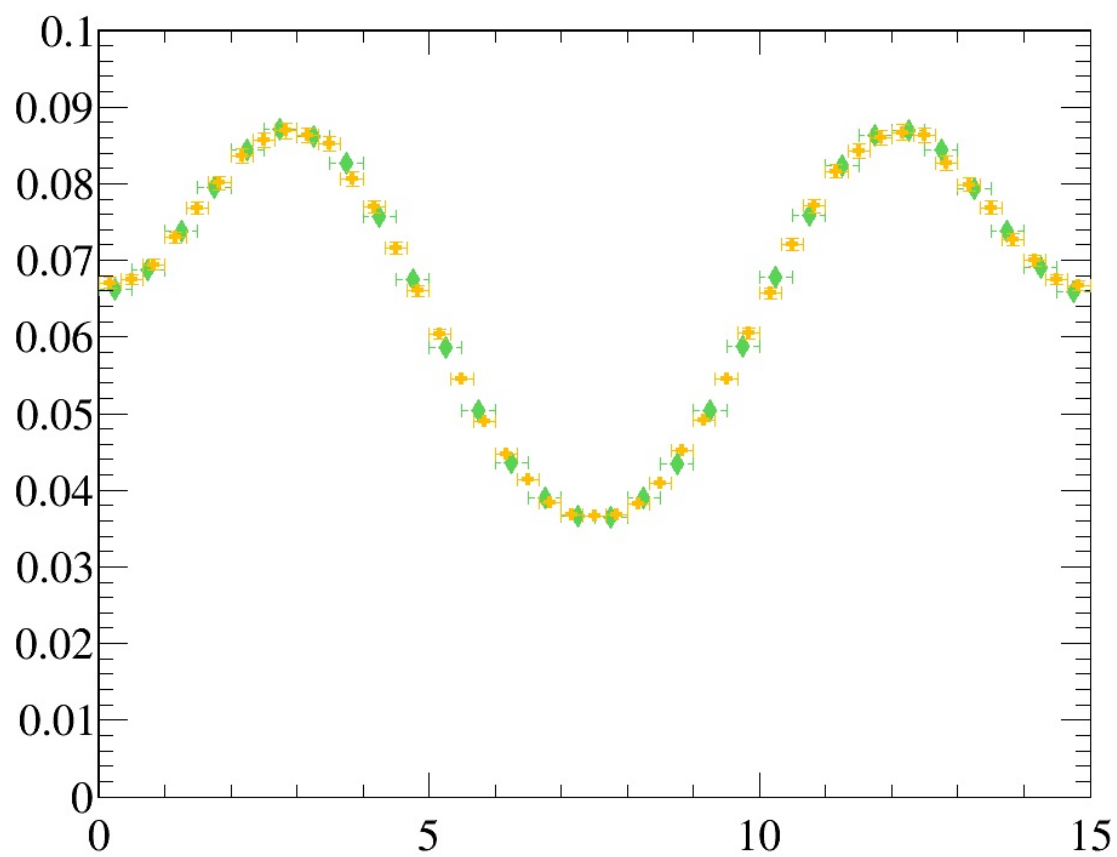
*Simulated* sample is a simple 2D-uniform distribution. Note that the *data distributions* are non-factorizable, and simple 1D-reweightings here is not enough. In this example, for the first five iterations only 2D-reweighting  $y:x$  is applied, and then two 1D-reweighting  $x$  and  $y$  are added.

After the reweighting the simulated distributions are

- for  $x$ -variable: *data distribution* (red filled circles) vs *simulated sample* (blue open squares)

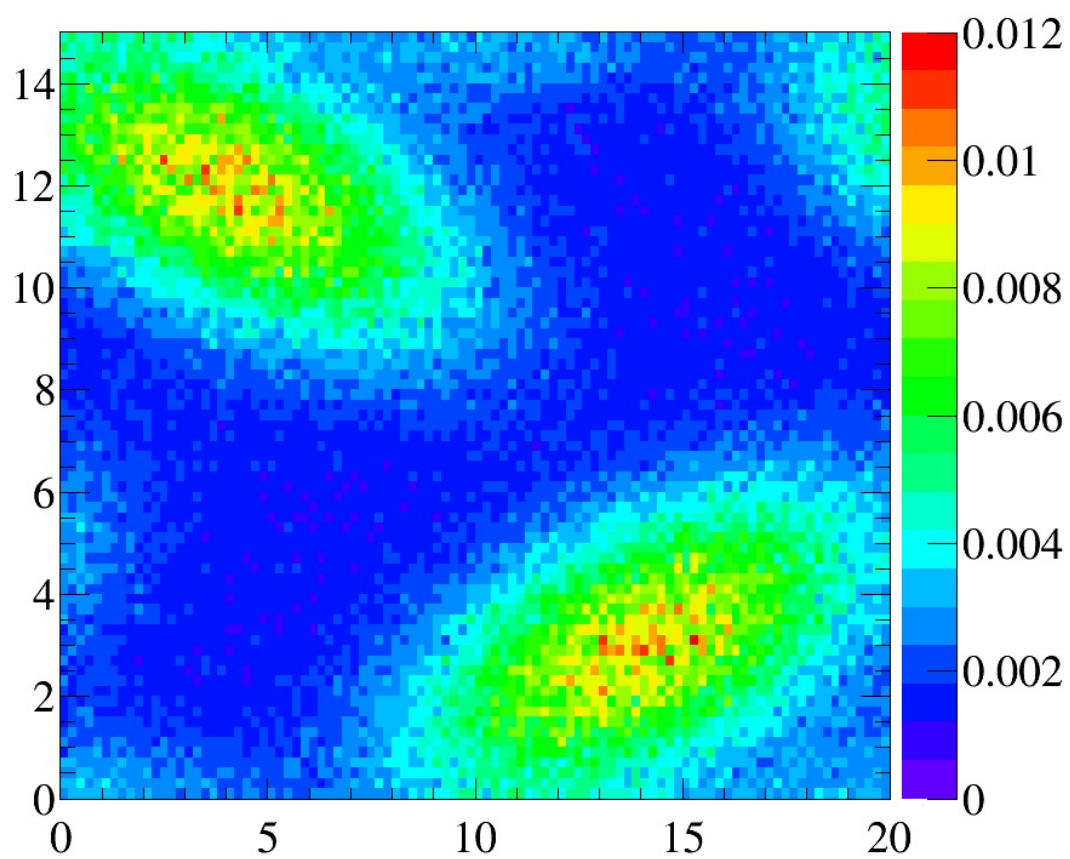


- for  $y$ -variable: data distribution (green filled diamonds) vs simulated sample (orange filled swiss-crosses)



- for `y:x`-variables







# Contributing

[ostap-tutorials](#) is an open source project, and we welcome contributions of all kinds:

- New lessons;
- Fixes to existing material;
- Bug reports; and
- Reviews of proposed changes.

By contributing, you are agreeing that we may redistribute your work under [these licenses](#). You also agree to abide by our [contributor code of conduct](#).

## Getting Started

1. We use the [fork and pull](#) model to manage changes. More information about [forking a repository](#) and [making a Pull Request](#).
2. To build the lessons please install the [dependencies](#).
3. For our lessons, you should branch from and submit pull requests against the `master` branch.
4. When editing lesson pages, you need only commit changes to the Markdown source files.
5. If you're looking for things to work on, please see [the list of issues for this repository](#). Comments on issues and reviews of pull requests are equally welcome.

## Dependencies

To build the lessons locally, install the following:

1. [Gitbook](#)

Install the Gitbook plugins:

```
$ gitbook install
```

Then (from the `ostap-tutorials` directory) build the pages and start a web server to host them:

```
$ gitbook serve
```

You can see your local version by using a web-browser to navigate to `http://localhost:4000` or wherever it says it's serving the book.