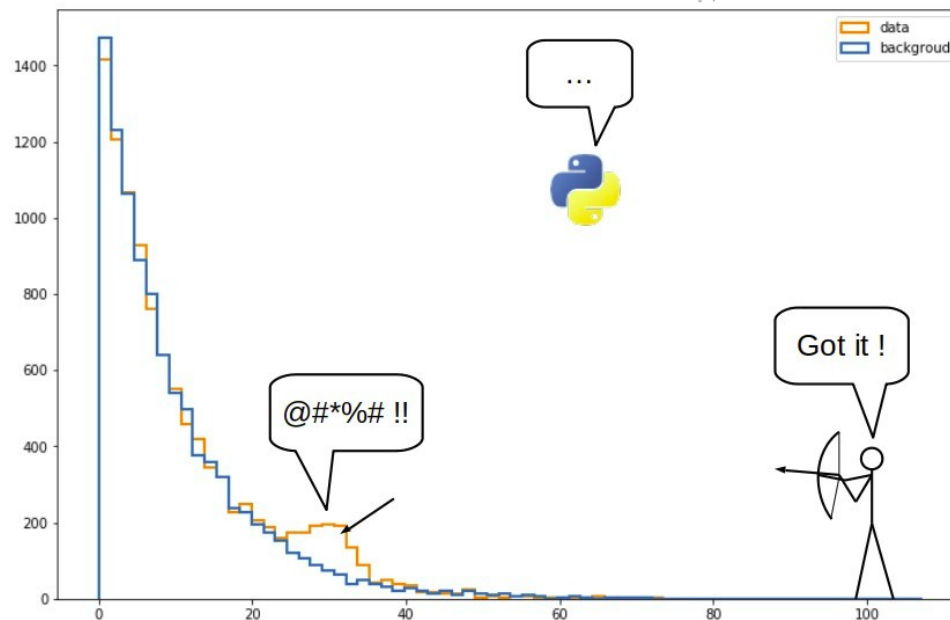


# pyBumpHunter : A model agnostic bump hunting tool in python

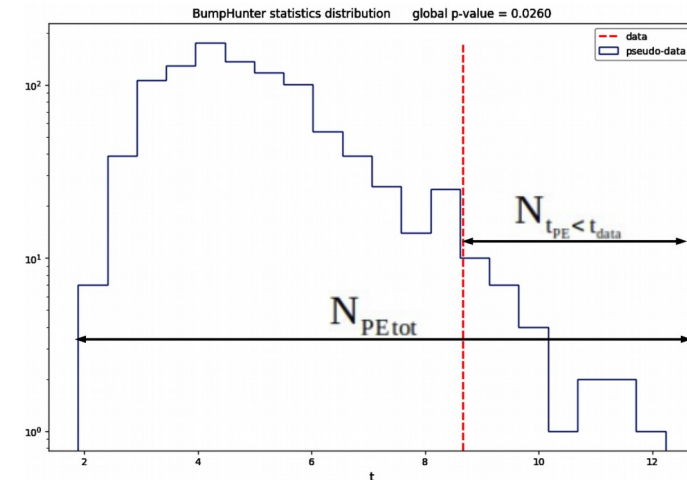
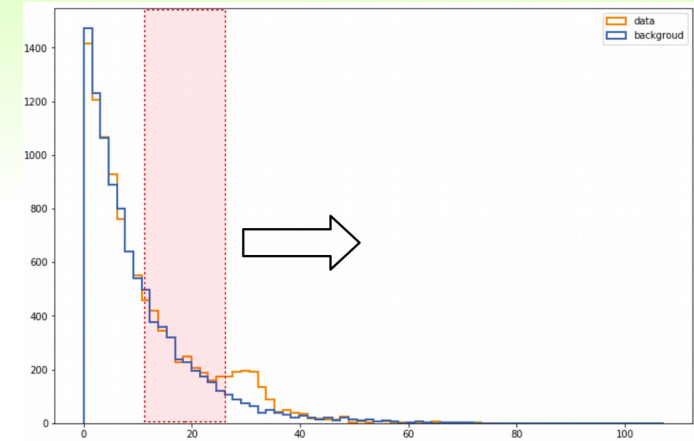


Presenter :  
Louis VASLIN – LPC Clermont



# The BumpHunter algorithm

- Principle (based on [arXiv:1101.0390v2](https://arxiv.org/abs/1101.0390v2))
  - Compare a **data histogram** with a **reference background**
  - Test all intervals for various width and compute the **local p-value**
    - => minimum p-value among  $m$  tests
  - Generate **pseudo-data** by sampling the reference and repeat the scan process
  - Infer the **global p-value** from the test statistic distribution of the pseudo-data (background-only)



# The BumpHunter algorithm

- A bit of math

Local p-value (for a given interval)

$$\text{p-value} = \begin{cases} 1 - \Gamma(d+1, d) & \text{if } d \leq b \\ 1 & \text{otherwise} \end{cases} \quad \text{For a deficit}$$
$$\text{p-value} = \begin{cases} 1 & \text{if } d \leq b \\ \Gamma(d, b) & \text{otherwise} \end{cases} \quad \text{For a excess}$$

$d = \text{\#data events}$   
 $b = \text{\#background events}$

BumpHunter test statistic

$$t = -\ln(\text{p-value})$$

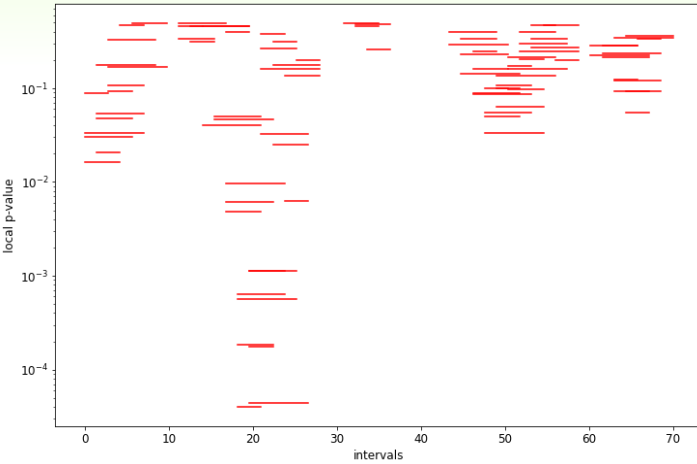
From p-value to significance

$$\text{sig} = \text{ppf}_{\text{normal}}(1 - p)$$

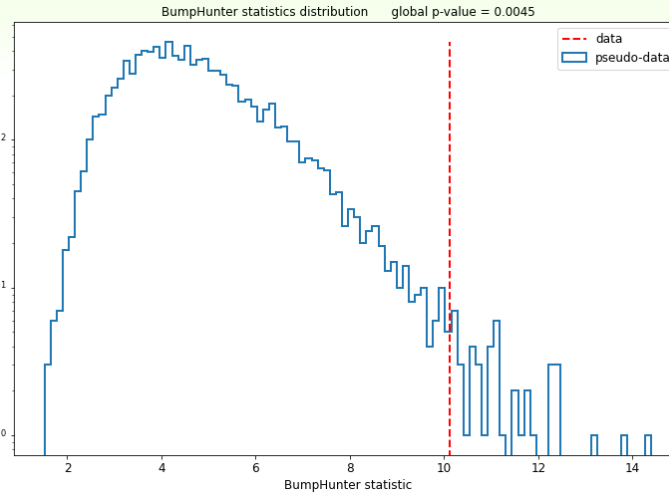
$p = \text{p-value}$   
 $\text{ppf}_{\text{normal}} = \text{inverse cumulative function of a normal distribution}$

# The BumpHunter algorithm

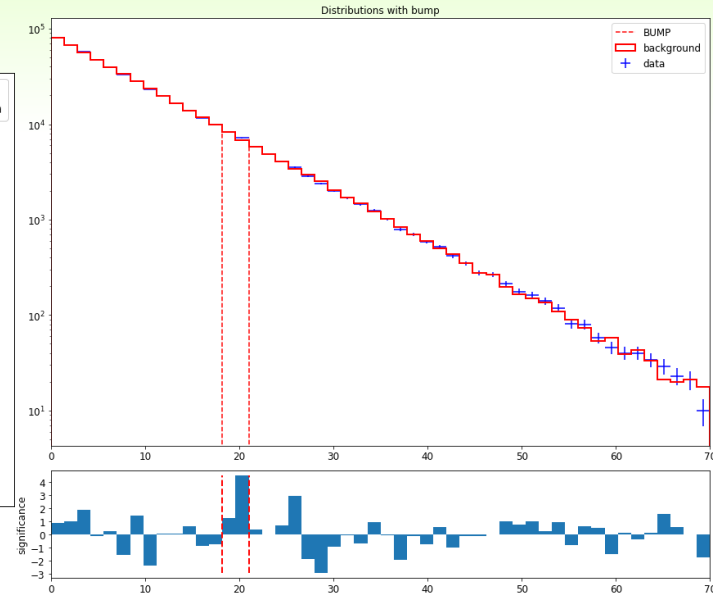
- Results



Tomography plot



BumpHunter test statistic



Bump plot

# pyBumpHunter

- Public BumpHunter for python

**Pure python implementation** of the algorithm ([github](#) [PyPI](#))

Depend only on numpy/scipy and matplotlib  
pyBumpHunter is **pip installable**

Integrate **many extensions** of the base algorithm

Signal injection test  
2D BumpHunter  
Automated side-band normalization  
Multi-channel combination (next release)

pyBumpHunter has been **integrated in** [Scikit-HEP](#)

Development is **still ongoing**

Many new features will come



# pyBumpHunter

- Simple example

Declare a BumpHunter1D instance

```
hunter = BH.BumpHunter1D(  
    rang=rang,  
    width_min=2,  
    width_max=6,  
    width_step=1,  
    scan_step=1,  
    npe=10000,  
    nworker=1,  
    seed=666,  
)
```

Run a simple scan

```
hunter.bump_scan(data,bkg)
```

Produce the plots

```
hunter.plot_tomography(data)
```

```
hunter.plot_bump(data,bkg)
```

```
hunter.plot_stat(show_Pval=True)
```

Scan settings and results can be accessed through the BumpHunter class

For this configuration with 50 bins histograms, run time ~ 16s (on my laptop)

**Jupyter notebook friendly**

# Signal injection and sensibility test

- Principle

Build a B+S pseudo-data histogram

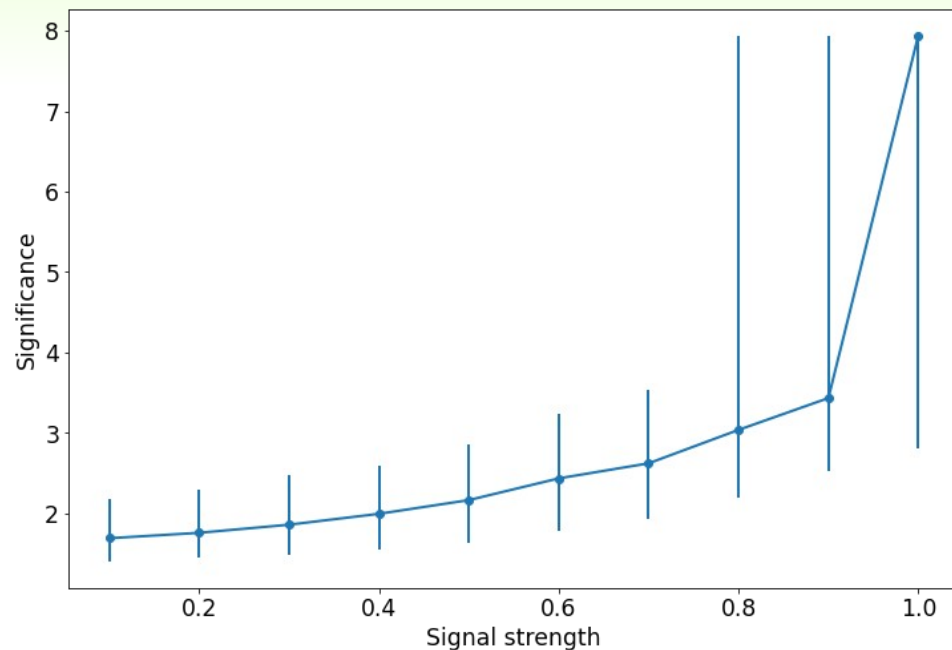
**Signal strength**

=

#injected events / #expected

Apply BumpHunter algorithm on  
B+S pseudo-data

Increase signal strength until  
**required significance** is reached



Error bar obtained by producing **many** B+S histograms

# Signal injection and sensibility test

- Code example

Additional injection settings

```
hunter.sigma_limit  
hunter.str_min  
hunter.str_scale  
hunter.signal_exp
```

Run a signal injection test

```
hunter.signal_inject(sig,bkg)
```

Produce the plot

```
hunter.plot_inject()
```

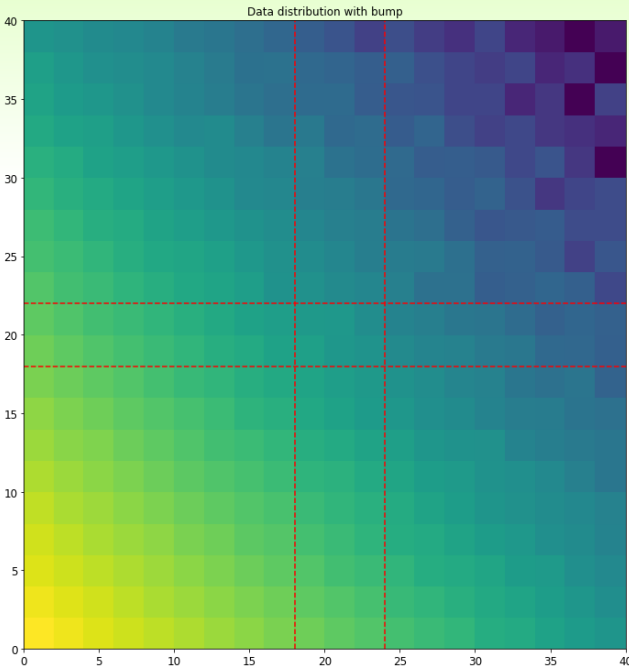
Injection setting can be set when declaring the BumpHunter instance

Injection plot produced both in linear and log scale (depend on str\_scale setting)

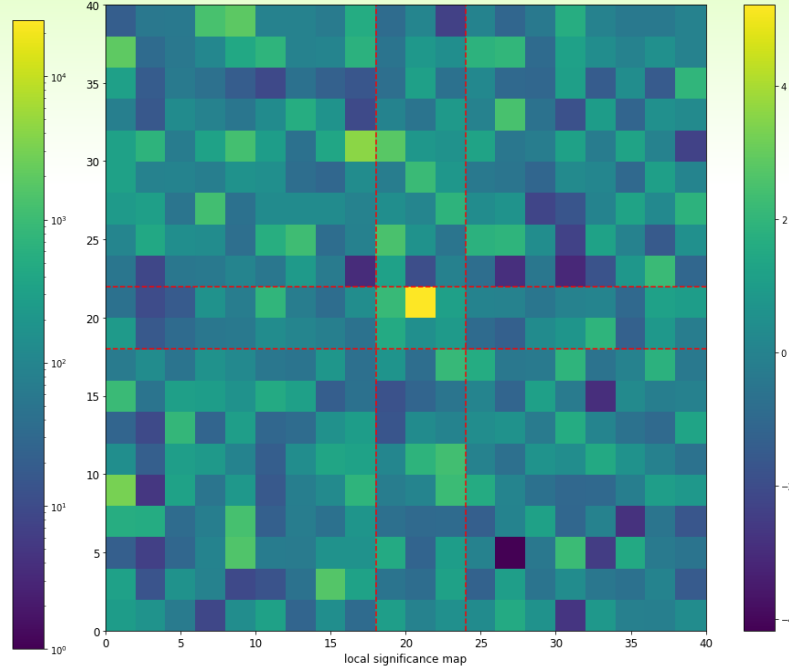
With previous scan setting, run time ~3m30s



# Bump hunting in 2D



2D data distribution



Local significance per bin

**Same principle** as in 1D

but **with 2D histograms**

Higher dimension  
=

More sensible to statistics

Only for basic scans  
(no 2D injection test yet)

# Bump hunting in 2D

- Code example

Declare a BumpHunter2D instance

```
hunter = BH.BumpHunter2D(  
    rang=rang,  
    width_min=[2, 2],  
    width_max=[3, 3],  
    width_step=[1, 1],  
    scan_step=[1, 1],  
    bins=[20, 20],  
    npe=8000,  
    nworker=1,  
    seed=666,  
)
```

Same API as the BumpHunter1D class

For this configuration, run time ~1m30s (on my laptop)

Note : scan settings are now array-like of size 2

Run a simple scan

```
hunter.bump_scan(data,bkg)
```

Produce the plots

```
hunter.plot_bump(data,bkg)
```

```
hunter.plot_stat(show_Pval=True)
```

# Side-band normalization

- Principle

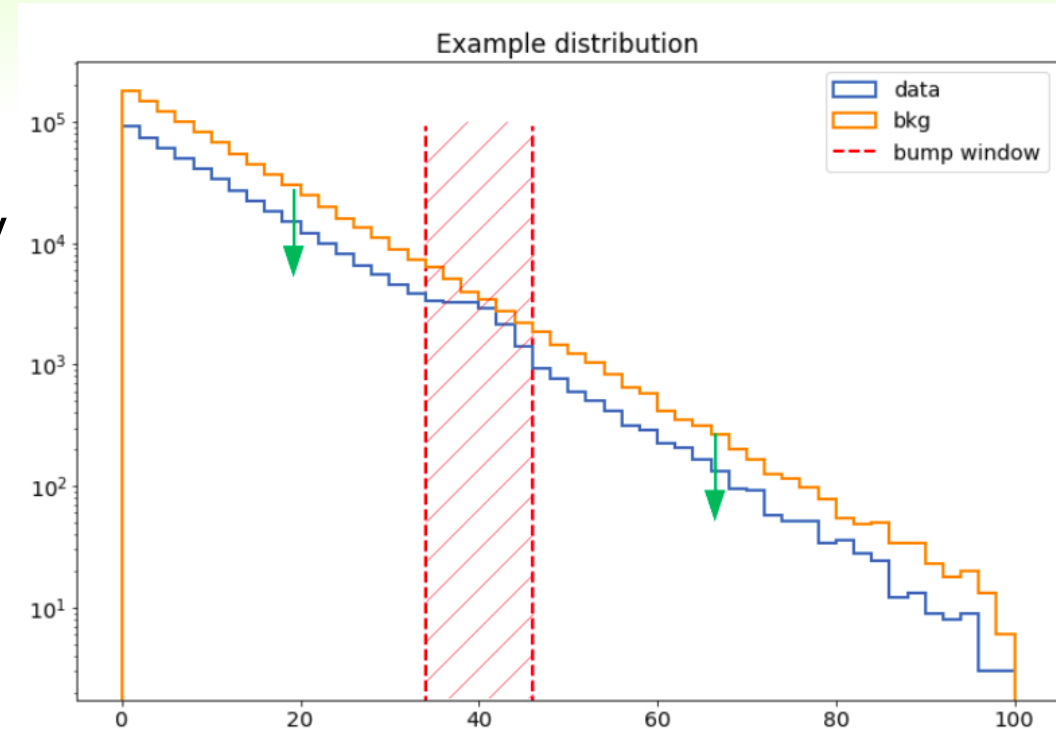
## Automated normalization procedure

Scale factor is computed for every tested interval

Rescale the background to data

**No prior knowledge** on the normalization

Enabled with the 'use\_sideband' setting



# Multi-channel combination

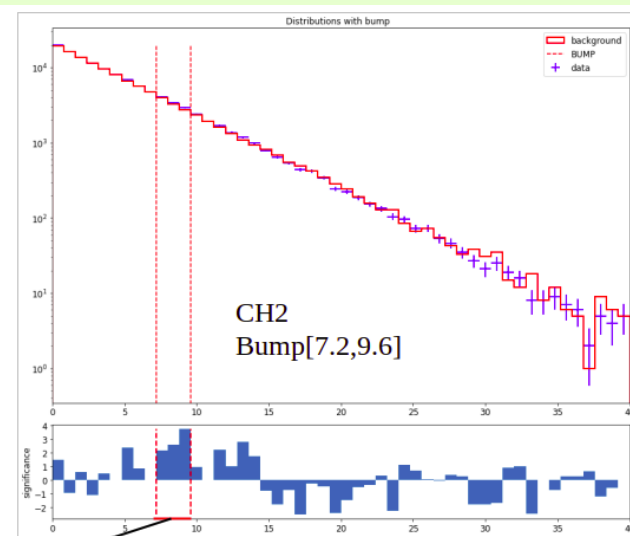
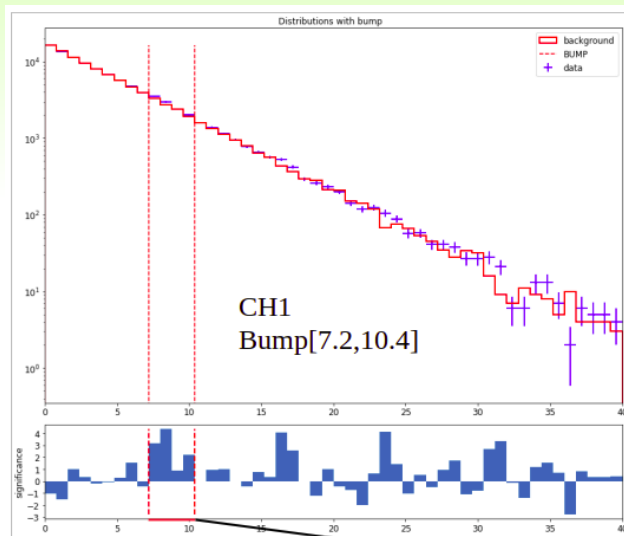
- Principle

Look for a deviation in every channels

Combined bump  
=  
Intersection of  
individual bumps

Combined local p-value  
=  
product of individual local p-values

Different combination techniques are under study



Combination  
Bump[7.2,9.6]

Coming in next release

# Multi-channel combination

- Alternative combination technique

Fisher method ([arXiv:1707.06897](https://arxiv.org/abs/1707.06897))

$$t_{\text{comb}} = -2 \sum_{i=1}^N \ln(p_i) \equiv \chi_{2N}^2$$

N = number of channels  
 $p_i$  = individual channel p-value

$t_{\text{comb}}$  is distributed like a chi2 with 2N dof

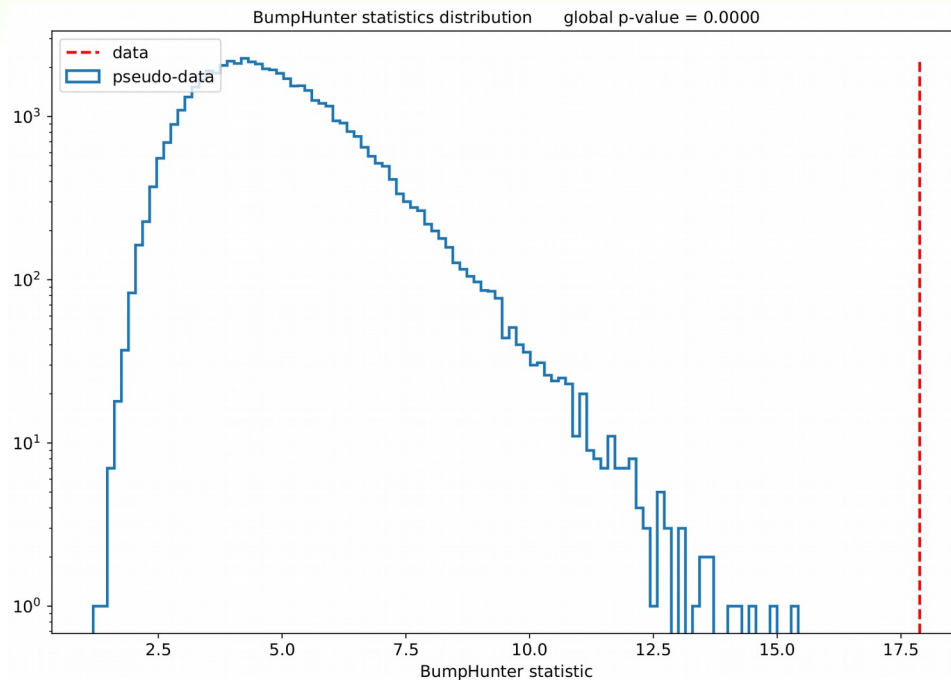
$$\Rightarrow p_{\text{comb}} = 1 - \text{cdf}_{\chi_{2N}^2}(t_{\text{comb}})$$

Two possibilities :

- Apply on local p-value and keep the overlap condition **(problem !)**
- Apply on global p-value and no overlap condition

# Minimum p-value and fit

- Why a fit ?



In this example  
global p-value = 0  
 $\Rightarrow \sigma = +\infty$  !!

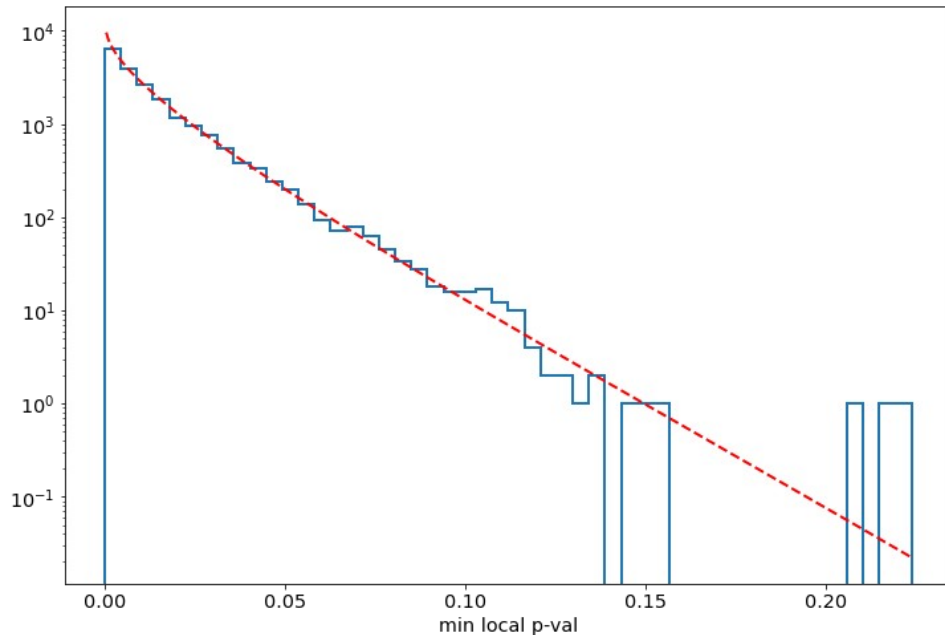
Higher significance  $\Rightarrow$  need a **lot** of stat

What to do ?  
**Fit the blue histogram**

# Minimum p-value and fit

- First attempt (**very** preliminary)

p-value hacking (based on [arXiv:1603.07532](https://arxiv.org/abs/1603.07532))



Fit of the **local p-value distribution**

$$\varphi_m(p; p_M) = m e^{\operatorname{erfc}^{-1}(2p_M)(2\operatorname{erfc}^{-1}(2p) - \operatorname{erfc}^{-1}(2p_M))} \left(1 - \frac{1}{2} \operatorname{erfc}(\operatorname{erfc}^{-1}(2p) - \operatorname{erfc}^{-1}(2p_M))\right)^{m-1}$$

$m$  = number of independent test

$p_M$  = True median of the distribution

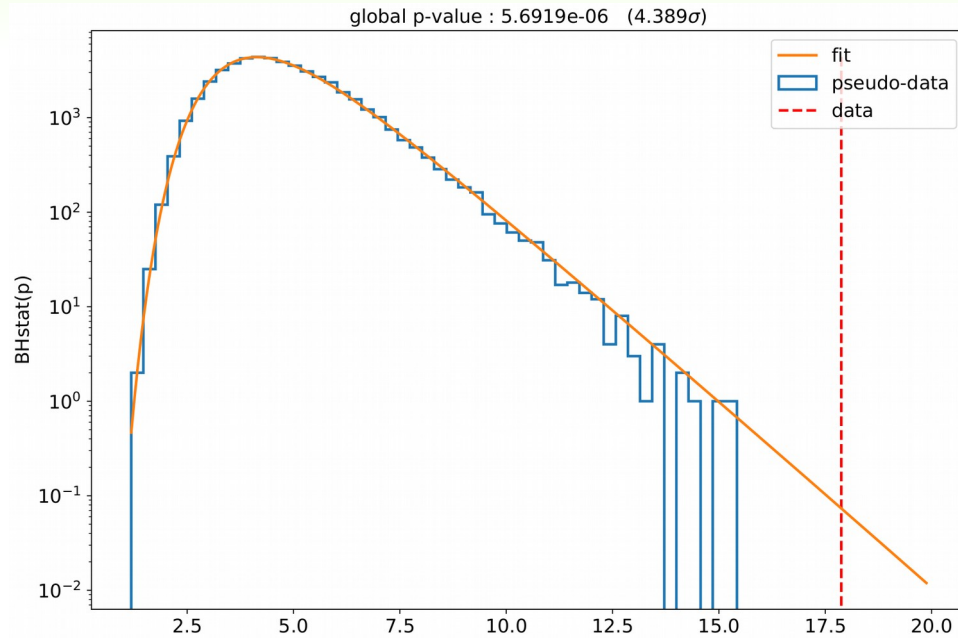
Reminder :

local p-value = min p-value among  $m$  tests

**But, tests are not independent**

# Minimum p-value and fit

- Results (very preliminary)



Transform the min p-value distribution into BumpHunter test statistic distribution (change of variable)

$$t = -\ln(p) \Rightarrow F(t) = \varphi[p(t)] \times \left| \frac{dp}{dt} \right|$$

**It seems to fit !**

**Need more test** to understand the behavior of the fit

**Work in progress**



# Summary

- Public implementation of BumpHunter in python
- Integrated in Scikit-HEP
- Propose several extensions of the algorithm
- Next release is under reviewing
- Other nice new features are on the way

# Thank you for your attention

