



# Estimating the “look-elsewhere” effect when searching for a signal

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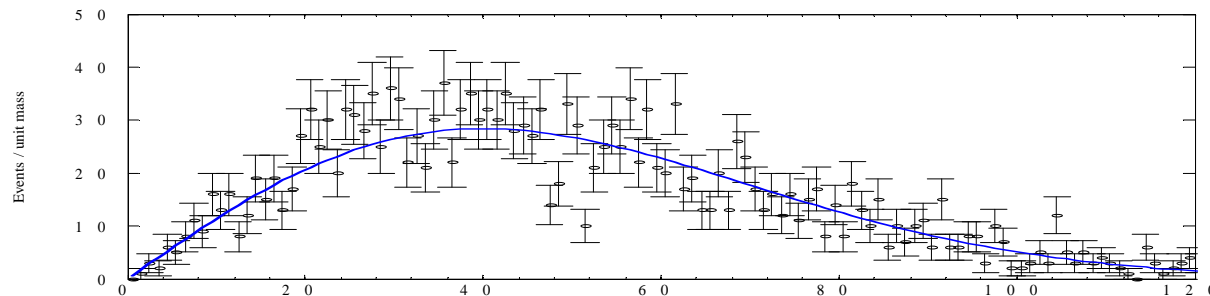
Ofer Vitells , Eilam Gross



PHYSTAT2011 , 17-20 January , CERN

# Introduction

- The “look elsewhere” effect occurs when one searches for a signal in some space of parameters (mass, shape, location in the sky, etc.)
- In the language of Hypothesis testing:  
test  $H_0$  (no signal) against  $H_1(\theta)$  ,  
The signal parameters ( $\theta$ ) are not present under  $H_0$  --  
Wilks’ theorem does not apply
- The problem is to correctly estimate the p-value of a “local” excess of events, taking into account the full range.
- Monte-Carlo simulation is a straight-forward way, but can be computationally very expensive



# Random fields

- The problem is naturally described in the framework of *Random fields*:

- Consider the test statistic: μ="signal strength"

$$q_0(\theta) = -2 \log \frac{\mathcal{L}(\mu = 0)}{\mathcal{L}(\hat{\mu}, \theta)}$$

$H_0 : \mu = 0$

$H_1 : \mu > 0$

- For some *fixed*  $\theta$ ,  $q_0(\theta)$  has (asymptotically) a  $\chi^2$  distribution with one degree of freedom by Wilks' theorem.
- $q_0(\theta)$  is a chi<sup>2</sup> random field over the space of  $\theta$  (a random variable indexed by a continuous parameter(s)). we are interested in

$$\hat{q}_0 \equiv q_0(\hat{\theta}) = -2 \log \frac{\mathcal{L}(\mu = 0)}{\mathcal{L}(\hat{\mu}, \hat{\theta})} = \max_{\theta} [q_0(\theta)]$$

$\hat{\theta}$  is the **global**  
maximum point

- For which we want to know what is the p-value

$$\text{p-value} = P(\max_{\theta} [q_0(\theta)] \geq u)$$

- The theory of R.F. provides analytical results closely related to this probability



# A small modification

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- Usually we only look for 'positive' signals

$$q_0(\theta) = \begin{cases} -2 \log \frac{\mathcal{L}(\mu = 0)}{\mathcal{L}(\hat{\mu}, \theta)} & \hat{\mu} > 0 \\ 0 & \hat{\mu} \leq 0 \end{cases} \quad q_0(\theta) \text{ is 'half chi}^2\text{'}$$

[H. Chernoff, Ann. Math. Stat. 25, 573578 (1954)]

The p-value just get divided by 1/2

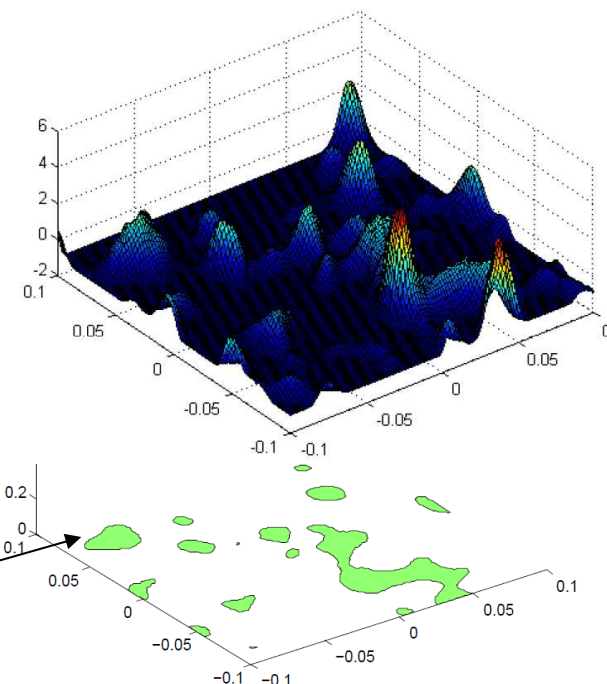
- Or equivalently consider  $\hat{\mu}$  as a gaussian field

( since  $q_0(\theta) = \left( \frac{\hat{\mu}(\theta)}{\sigma} \right)^2$  by Wald's theorem)

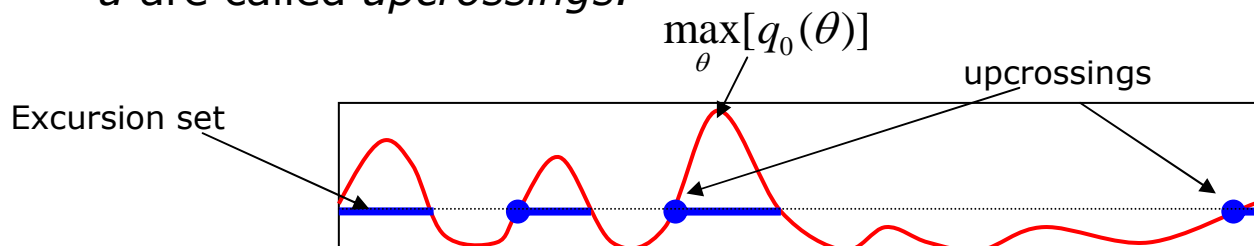
[Cowan, Cranmer, Gross, Vitells, arXiv:1007.1727]

# Random fields terminology

- The set of points where the field has values larger than some number  $u$  is called the *excursion set*  $A_u$  above the level  $u$ .



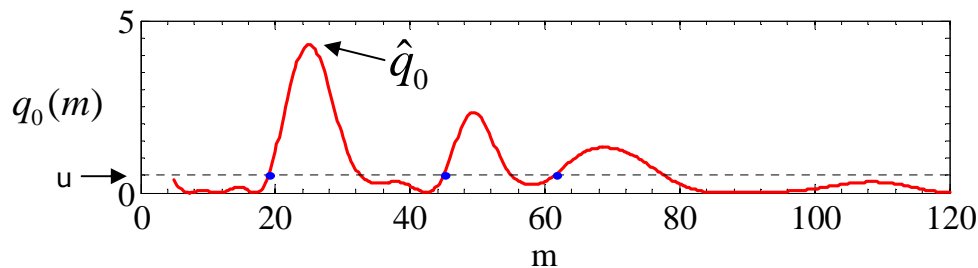
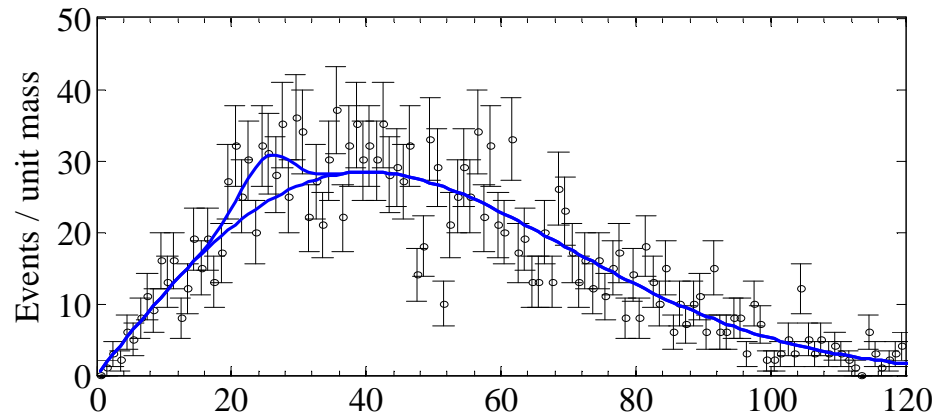
- In 1 dimension: points where the field values become larger than  $u$  are called *upcrossings*.



- The probability that the global maximum is above the level  $u$  is called *exceedance probability*. (p-value of  $\hat{q}_0$ )

$$P(\max_{\theta} [q_0(\theta)] \geq u)$$

# The 1-dimensional case



To have the global maximum above a level  $u$ :

- Either have at least one upcrossing ( $N_u > 0$ ) **or** have  $q_0 > u$  at the origin ( $q_0(0) > u$ ) :

$$\begin{aligned} \Rightarrow P(\hat{q}_0 > u) &\leq P(N_u > 0) + P(q_0(0) > u) \\ &\leq E[N_u] + P(q_0(0) > u) \end{aligned}$$

[R.B. Davies, Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika **74**, 33-43 (1987)]

Becomes an equality  
for large  $u$

For a  $\chi^2$  random field, the expected number of *upcrossings* of a level  $u$  is given by: [Davies,1987]

$$E[N_u] = \mathcal{N}_1 e^{-u/2}$$

Note the inequality:

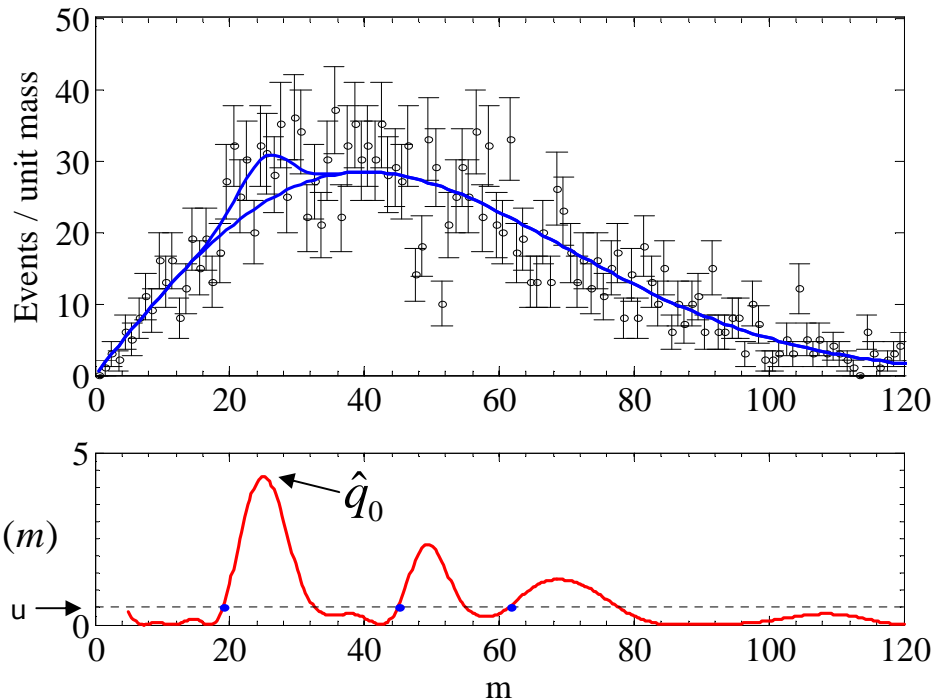
$$E[N_u] \geq P(N_u > 0)$$

$$1 \cdot P(1) + 2 \cdot P(2) + \dots \geq P(1) + P(2) + \dots$$

When  $P(N_u > 1) \ll P(N_u = 1)$  (large  $u$ )

then  $E[N_u] \approx P(N_u = 1) \approx P(N_u > 0)$

# The 1-dimensional case



$$E[N_u] = \mathcal{N}_1 e^{-u/2}$$

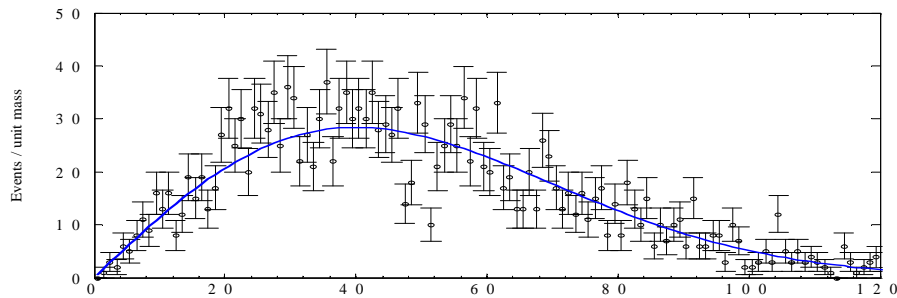
The only unknown is  $\mathcal{N}_1$ , which can be estimated from the average number of upcrossings at some low reference level

$$\mathcal{N}_1 \cong \langle N_{u_0} \rangle e^{u_0/2}$$

$$\begin{aligned} P(q_0 > u) &\leq E[N_u] + P(q_0(0) > u) \\ &= \mathcal{N}_1 e^{-u/2} + \frac{1}{2} P(\chi_1^2 > u) \end{aligned}$$

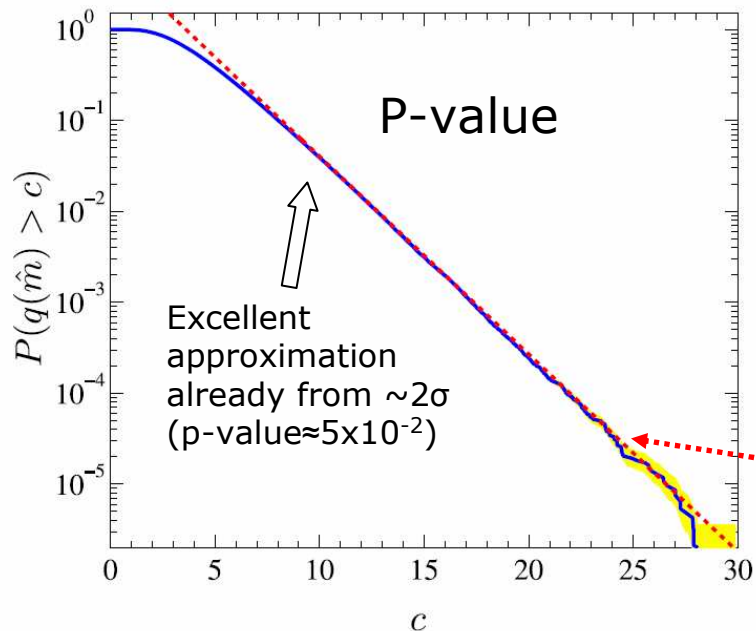
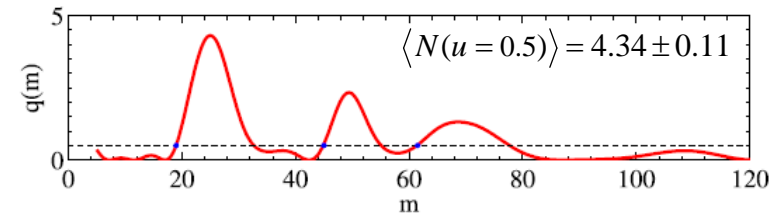
← The p-value can then be estimated by Davies' formula

# 1-D example: resonance search



The model is a gaussian signal (with unknown location  $m$ ) on top of a continuous background (Rayleigh distribution)

$$\mathcal{L} = \prod_i \text{Poiss}(n_i | \mu s_i(m) + \beta b_i)$$

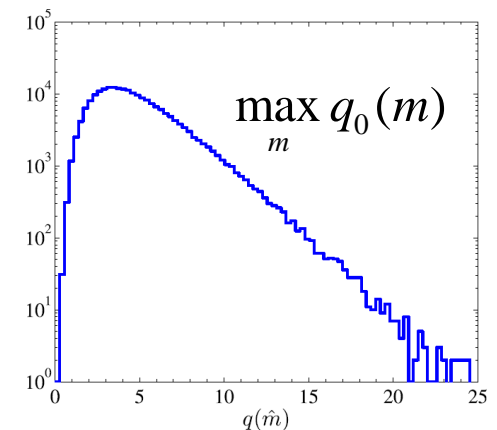


In this example we find

$$\mathcal{N}_1 = 5.58 \pm 0.14$$

[from 100 random background simulations]

$$\mathcal{N}_1 e^{-u/2} + \frac{1}{2} P(\chi_1^2 > u)$$



[[E. Gross and O. Vitells, Eur. Phys. J. C, 70, 1-2, (2010), arXiv:1005.1891]



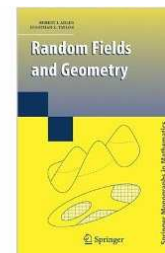
# The $n$ -dimensional case

- The upcrossings formula is a special case of a more general result which gives **the expectation of the Euler characteristic of the excursion set** of a random field over a general  $n$ -dimensional manifold

$$E[\varphi(A_u)] = \sum_{d=0}^n \mathcal{N}_d \rho_d(u)$$

- Here:
  - $A_u$  is the excursion set of the field above a level  $u$  (set of points where  $q_0(\theta) > u$ )
  - $\varphi(A_u)$  is it's Euler characteristic
  - $\rho_d$  are 'universal' functions (depend only on the level  $u$  and the type of distribution)

[R.J. Adler and J.E. Taylor, *Random Fields and Geometry* (2007), Springer Monographs in Mathematics]



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 $A_u$  is the excursion set of the field (points where  $q_0(\theta) > u$ )  
 $\varphi(A_u)$  is its Euler characteristic  
 $\rho_d$  are 'universal' functions (depend on  $d$  and the type of distribution)

e.g. for a  $\chi^2$  field with  $s$  degrees of freedom:

$$\rho_0(u) = P(\chi_s^2 > u)$$

$$\rho_1(u) = u^{(s-1)/2} e^{-u/2}$$

$$\rho_2(u) = u^{(s-2)/2} e^{-u/2} [u - (s-1)]$$

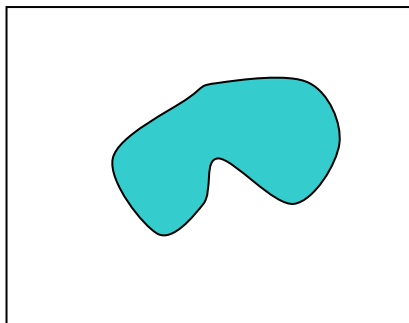
...

[R.J. Adler and J.E. Taylor, *Random Fields and Geometry* (2007)  
 Springer Monographs in Mathematics]

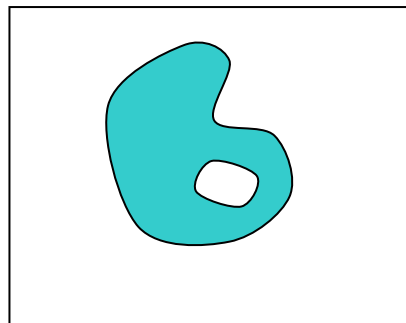


# Euler characteristic

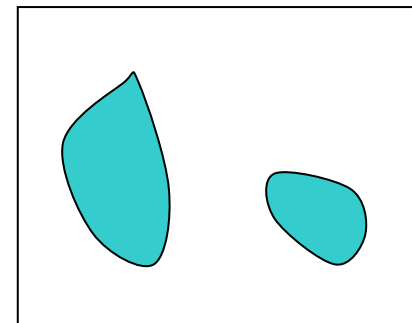
- Number of disconnected components minus number of 'holes'



$$\varphi = 1$$



$$\varphi = 0$$



$$\varphi = 2$$



WIKIPEDIA  
The Free Encyclopedia

## Euler characteristic

From Wikipedia, the free encyclopedia

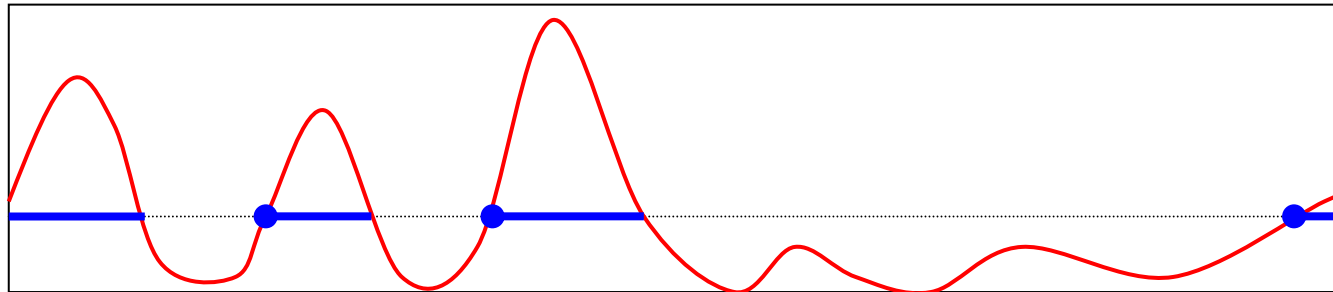
In [mathematics](#), and more specifically in [algebraic topology](#) and [polyhedral combinatorics](#), the **Euler characteristic** (or **Euler–Poincaré characteristic**) is a [topological invariant](#), a number that describes a [topological space](#)'s shape or structure regardless of the way it is bent. It is commonly denoted by  $\chi$  ([Greek letter chi](#)).

The Euler characteristic was originally defined for [polyhedra](#) and used to prove various theorems about them, including the classification of the [Platonic solids](#). [Leonhard Euler](#), for whom the concept is named, was responsible for much of this early work. In modern mathematics, the Euler characteristic arises from [homology](#) and connects to many other invariants.

Name	Image	Euler characteristic
Interval		1
Circle		0
Disk		1
Sphere		2
Torus (Product of two circles)		0
Double torus		-2

# Euler characteristic

$$E[\varphi(A_u)] = \sum_{d=0}^n \mathcal{N}_d \rho_d(u)$$



In 1 dimension:

$$\varphi(A_u) = N_u + \mathbf{1}_{[q_0(0) > u]}$$

$$\begin{aligned} E[\varphi(A_u)] &= E[N_u] + P(q_0(0) > u) \\ &= \mathcal{N}_1 e^{-u/2} + \frac{1}{2} P(\chi_1^2 > u) \\ &\quad \text{(Davies' Bound)} \end{aligned}$$

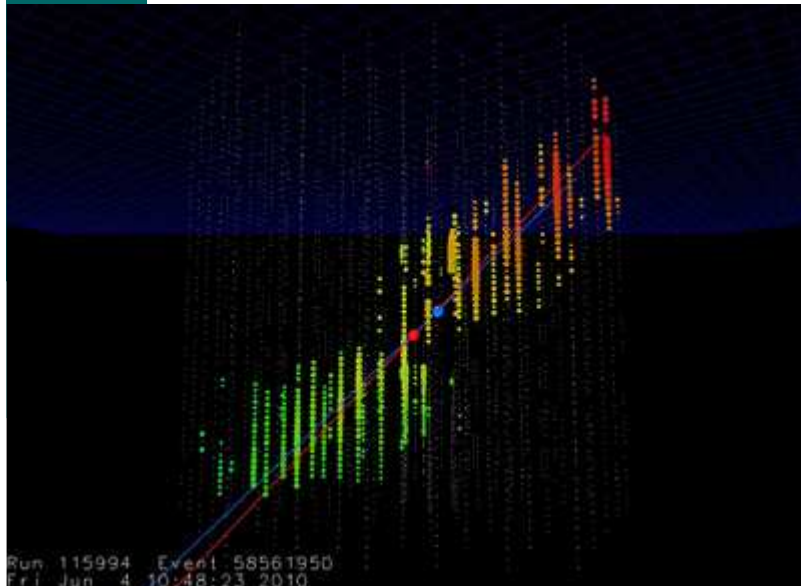
The general case

$$\begin{aligned} \mathcal{N}_0 &= \text{Euler characteristic of the manifold} \\ \rho_0(u) &= P(q_0 > u) \end{aligned}$$

In general for high-level excursions  $E[\varphi(A_u)] \rightarrow P(\max_{\theta} [q_0(\theta)] \geq u)$

( When  $E[\varphi(A_u)] \ll 1$  )

# 2-D example: IceCube search for astrophysical neutrino point sources



IceCube looks for neutrino sources,  
2-D Search over the sky ( $\theta, \varphi$ )

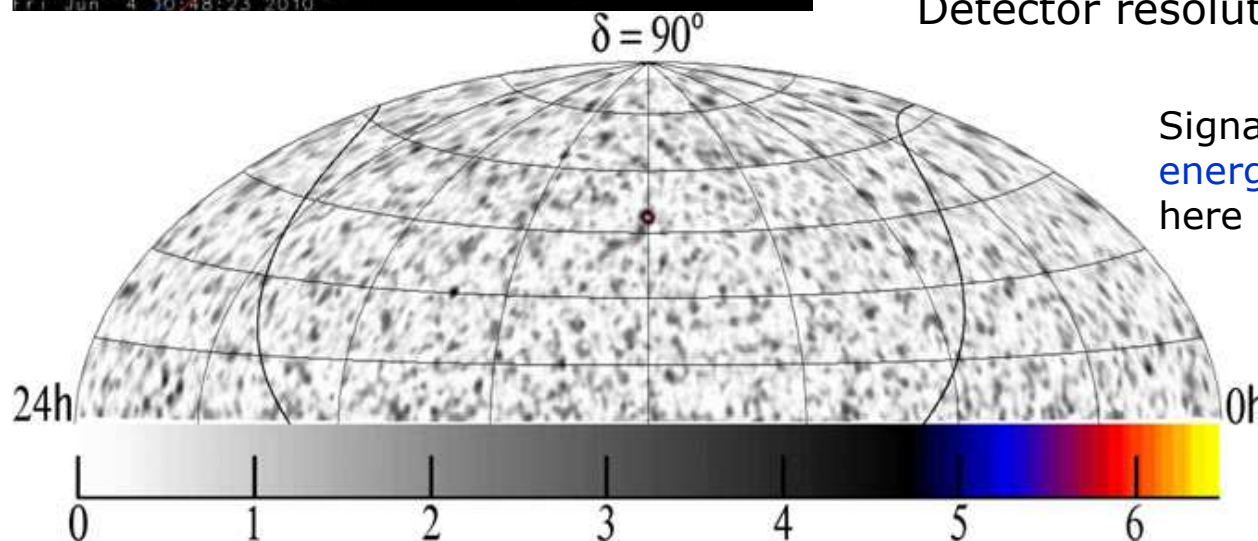
Unbinned likelihood:

$$\mathcal{L}(\vec{x}_s, n_s) = \prod_i \left( \frac{n_s}{N} f_s(x_i) + \left(1 - \frac{n_s}{N}\right) f_b(x_i) \right)$$

Assume Gaussian distribution of  
signal events

$$f_s(\vec{x}_i | \vec{x}_s) = \frac{1}{2\pi\sigma^2} e^{-\frac{|\vec{x}_i - \vec{x}_s|^2}{2\sigma^2}} \quad \vec{x}_s = (\theta, \varphi)$$

Detector resolution =  $0.7^\circ$

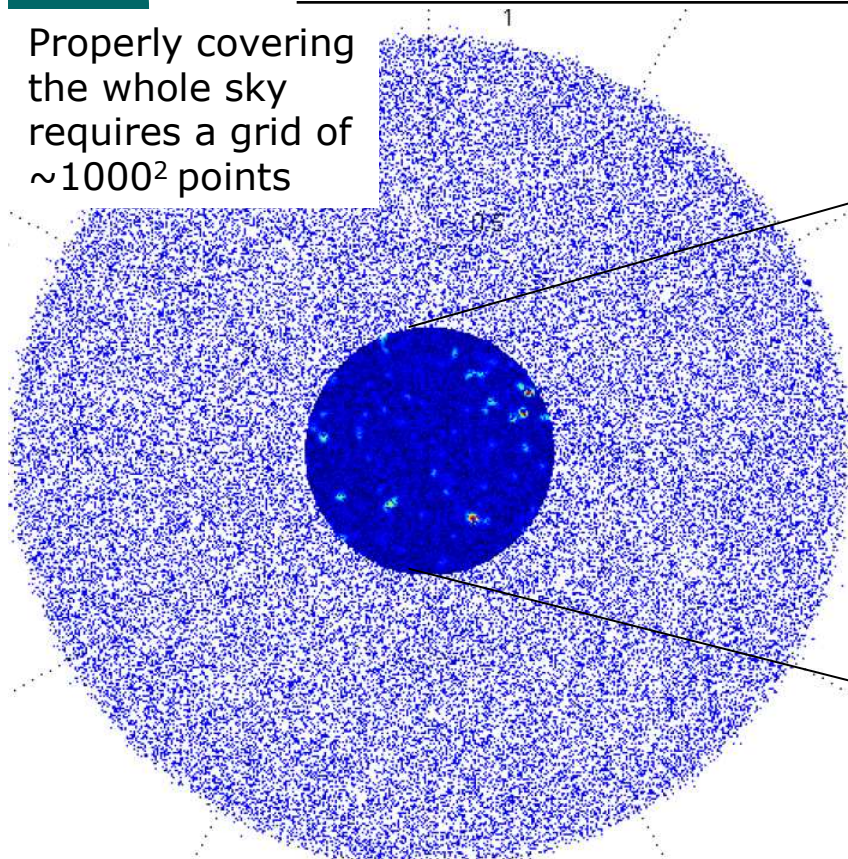


Signal parameters can also include  
**energy** and **time**, not considered  
here

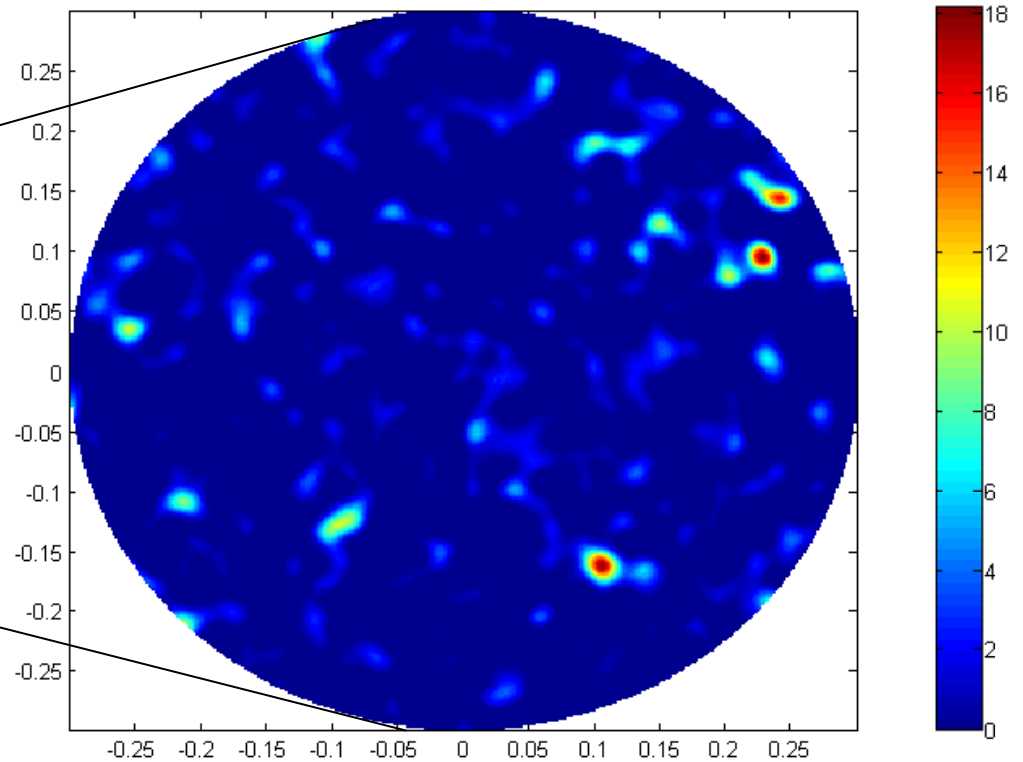
J. Braun, J. Dumm, F. De Palma, C.  
Finley, A. Karle, and T. Montaruli,  
Astropart. Phys. 29, 299 (2008);  
[arXiv:0801.1604]

# 2-D example: search for neutrino sources (IceCube)

Properly covering the whole sky requires a grid of  $\sim 1000^2$  points



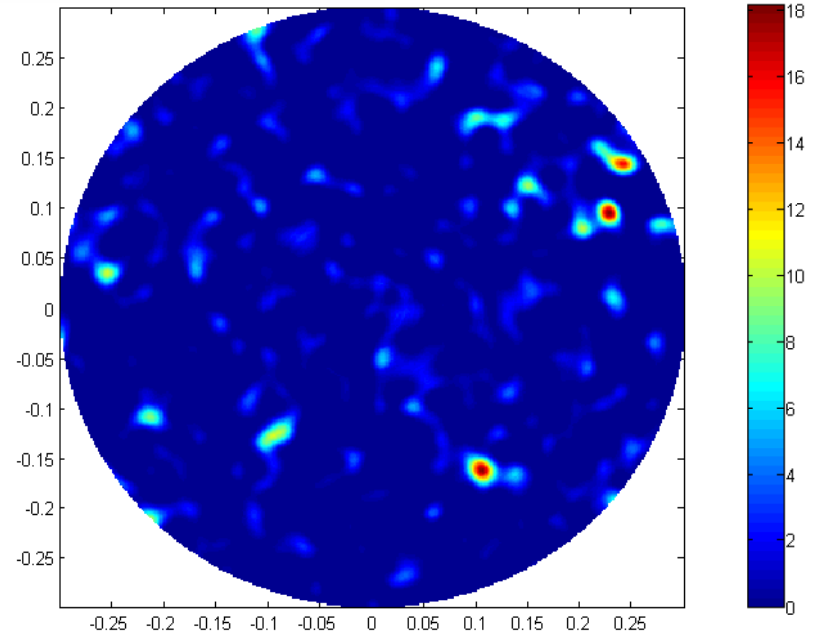
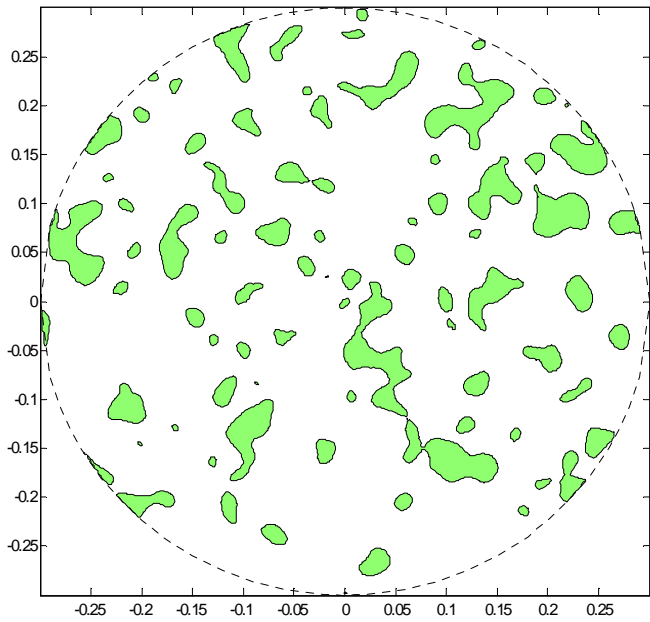
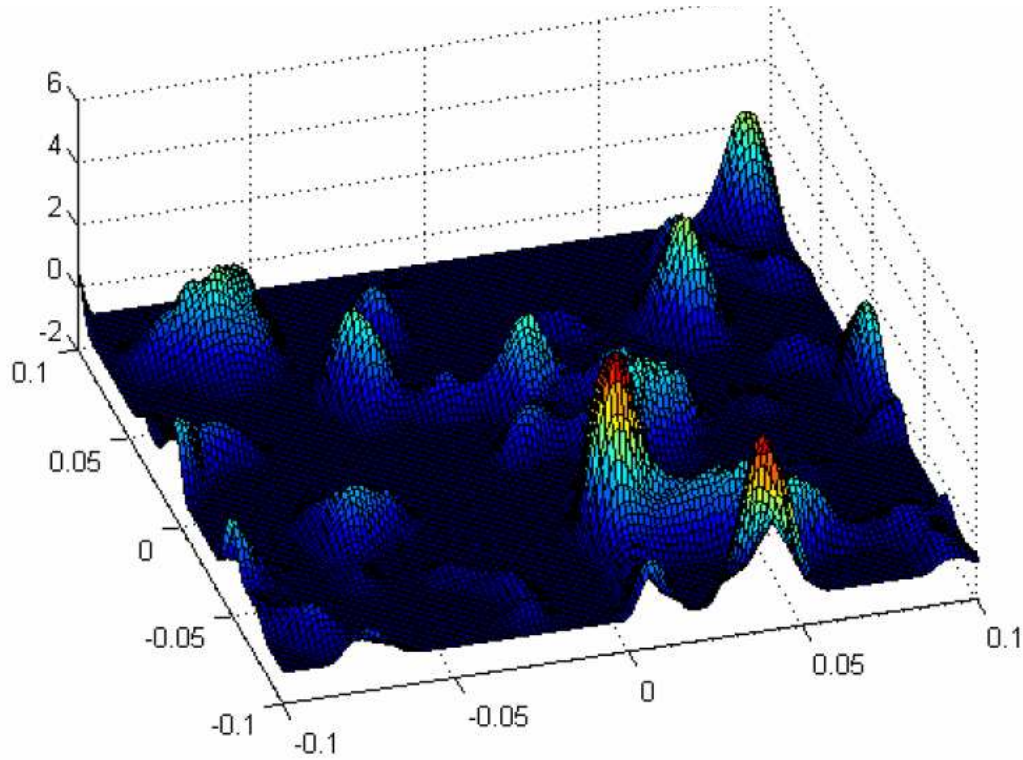
IceCube simulated background data (1 year) 67,000 events, provided by Jim Braun & Teresa Montaruli



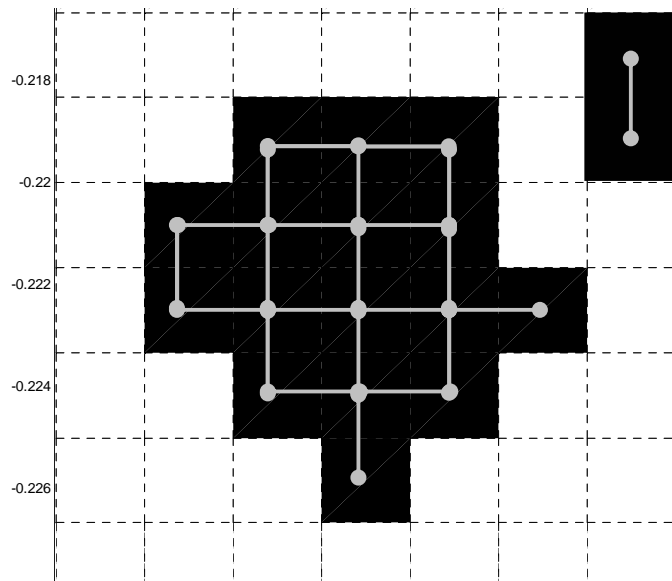
Significance map  
 $q_0(\theta, \varphi)$



# Excursion set ( $u=1$ )



# Calculation of the Euler characteristic



$$\begin{aligned}\varphi &= 18(\text{points}) - \\ & 23(\text{edges}) + 7(\text{faces}) \\ &= 2\end{aligned}$$

- Usually we have  $q(\theta)$  calculated on a grid of points
- Calculation of the E.C. is straightforward:
- $\varphi = \# \text{points} - \# \text{edges} + \# \text{faces}$
- Generalizes to higher dimensions



# 2-d example: search for neutrino sources (IceCube)

For a  $\chi^2$  field in 2 dimensions:

$$E[\varphi(A_u)] = \frac{1}{2} P(\chi^2 > u) + (\mathcal{N}_1 + \mathcal{N}_2 \sqrt{u}) e^{-u/2}$$

Estimate  $E[\varphi]$  at two levels, e.g. 0 and 1, and solve for  $\mathcal{N}_1$  and  $\mathcal{N}_2$

From 20 bkg. Simulations:

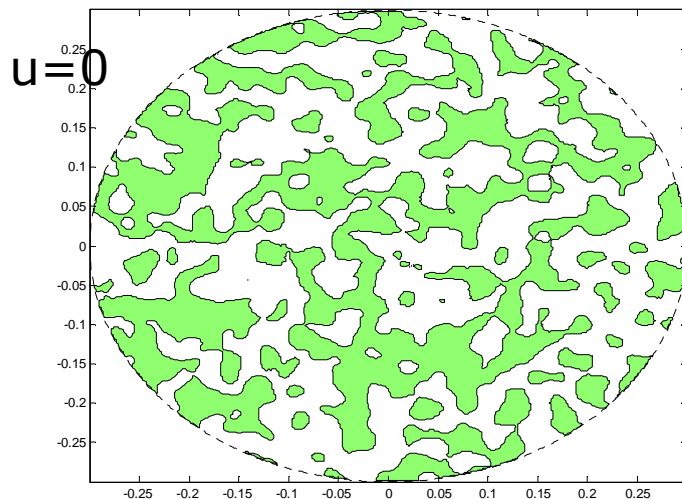
$$\langle \varphi_0 \rangle = 33.5 \pm 2$$

$$\langle \varphi_1 \rangle = 94.6 \pm 1.3$$

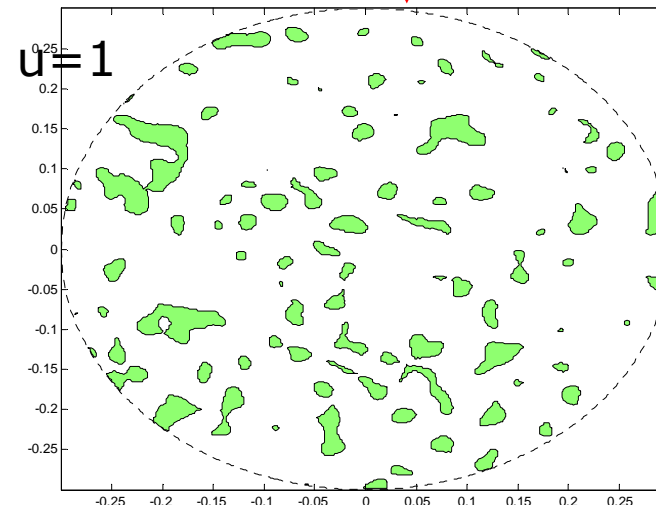
↓

$$\mathcal{N}_1 = 33 \pm 2$$

$$\mathcal{N}_2 = 123 \pm 3$$



$\varphi=35$



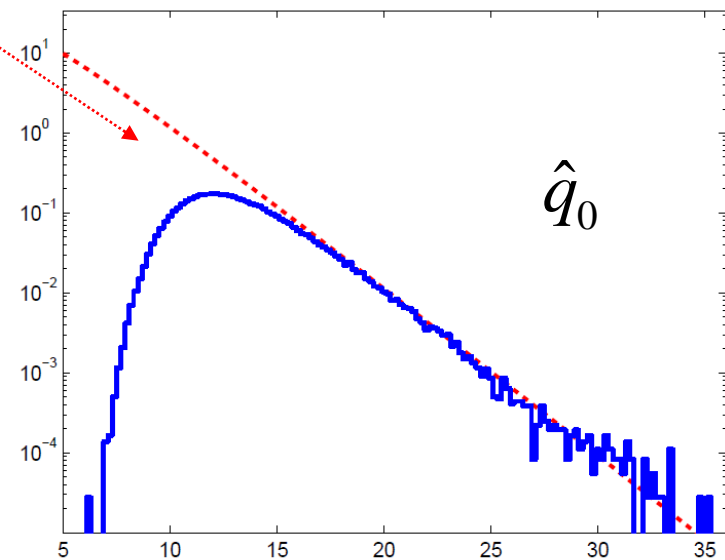
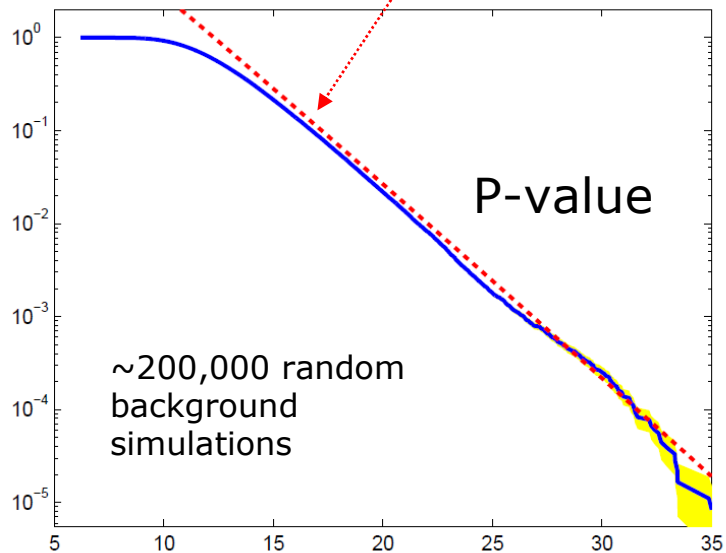
$\varphi=95$

# 2-d example: search for neutrino sources (IceCube)

$$E[\varphi(A_u)] = \frac{1}{2} P(\chi^2 > u) + (\mathcal{N}_1 + \mathcal{N}_2 \sqrt{u}) e^{-u/2}$$

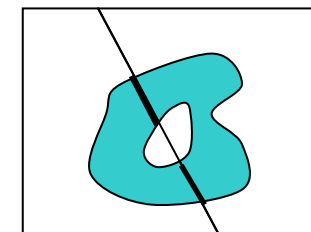
$$\mathcal{N}_1 = 33 \pm 2$$

$$\mathcal{N}_2 = 123 \pm 3$$



e.g.:  $P(\max q_0 > 30) = (2.5 \pm 0.4) \times 10^{-4}$  (estimated)  
 E.C. Formula :  $(2.28 \pm 0.06) \times 10^{-4}$

# Slicing



$$\varphi=0=1+1-2$$

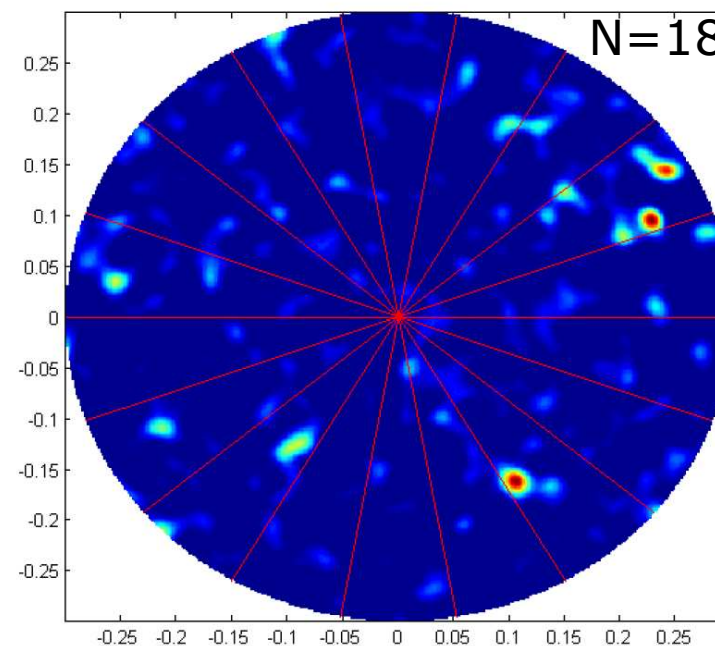
- Exploit the azimuthal angle symmetry to reduce computations:

$$\varphi(A \cup B) = \varphi(A) + \varphi(B) - \varphi(A \cap B)$$

Divide to N slices:

$$\varphi = \sum_i [\varphi(\text{slice}_i) - \varphi(\text{edge}_i)] + \varphi(0)$$

$$E[\varphi] = N \times (E[\varphi(\text{slice})] - E[\varphi(\text{edge})]) + \varphi(0)$$



$$\varphi(\text{slice}) = ((6 \pm 0.5) + (6.7 \pm 0.8)\sqrt{u})e^{-u/2}$$

$$\varphi(\text{edge}) = (4.4 \pm 0.2)e^{-u/2}$$

$$\mathcal{N}_1 = 28 \pm 9$$



Consistent with full sky

$$\mathcal{N}_2 = 120 \pm 14$$

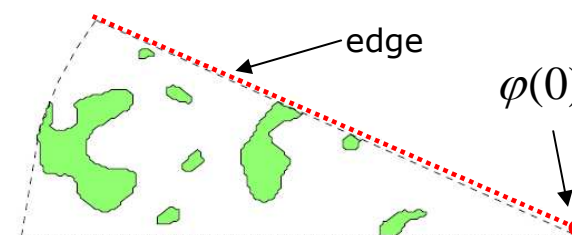
simulation



40 "slice" simulations

$$\langle \varphi_1(\text{slice}) \rangle = 7.8 \pm 0.35$$

$$\langle \varphi_1(\text{edge}) \rangle = 2.5 \pm 0.15$$

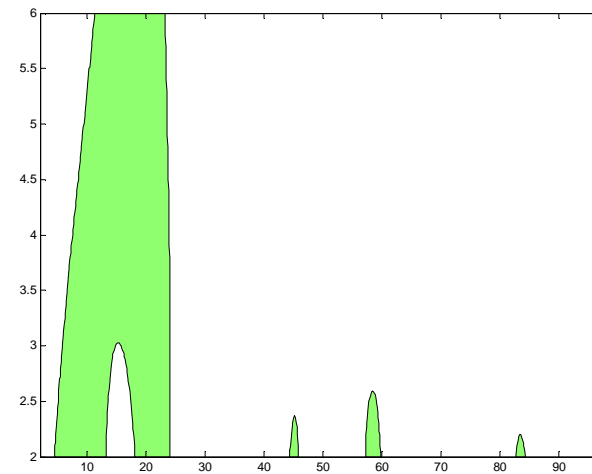
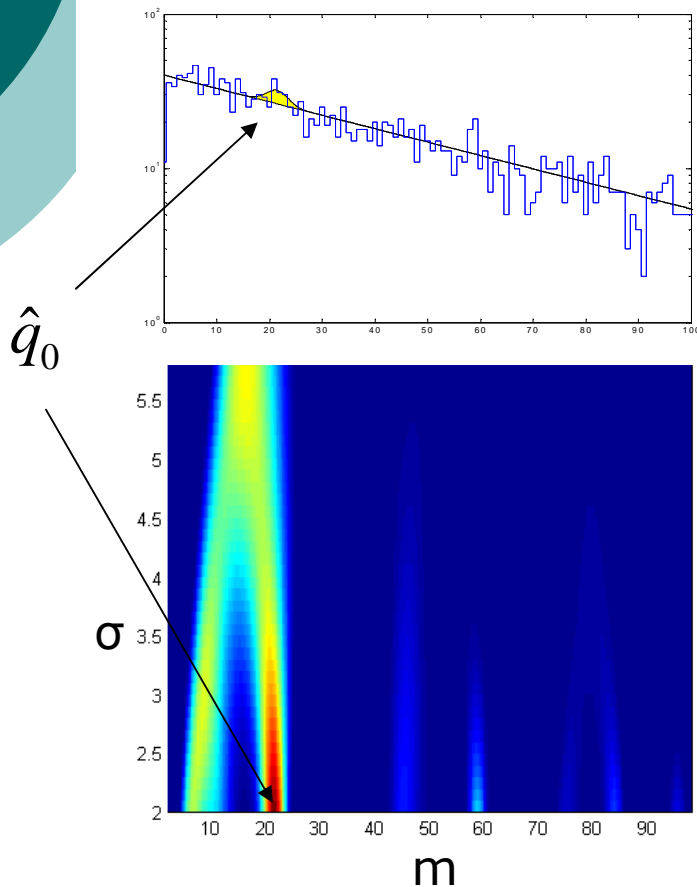


# 2-D example #2: resonance search with unknown width

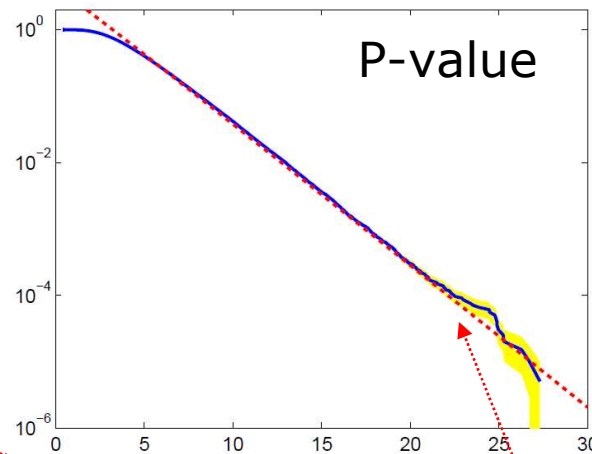
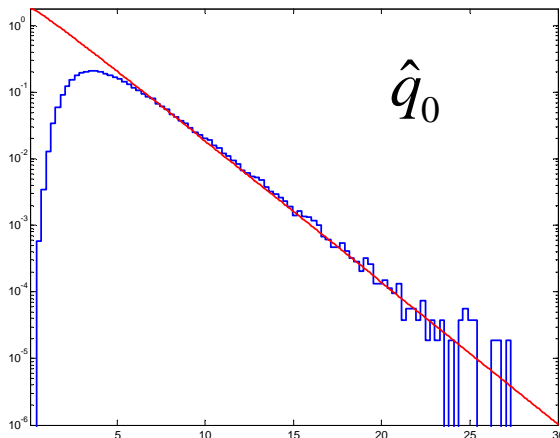
- Gaussian signal on exponential background
- Toy model :  $0 < m < 100$  ,  $2 < \sigma < 6$
- Unbinned likelihood:

$$\mathcal{L} = \prod_i \frac{N_s f_s(x_i) + N_b f_b(x_i)}{N_s + N_b} \times \text{Poiss}(N | N_s + N_b)$$

$$f_s(x; m, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-m)^2}{2\sigma^2}} \quad f_b(x) = ce^{-cx}$$

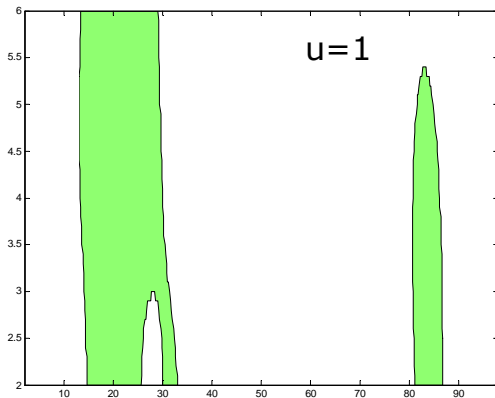


# 2-D exapmle #2: resonance search with unknown width

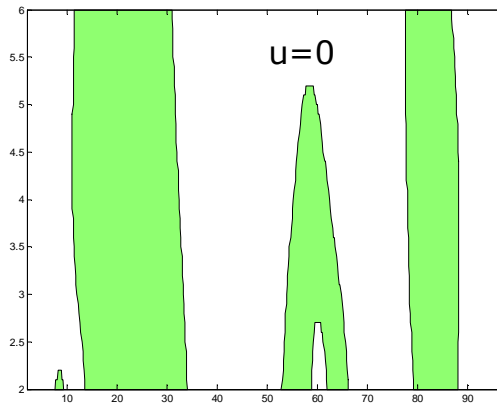


Excellent approximation above the  $\sim 2\sigma$  level

$$\langle \varphi_1 \rangle = 3 \pm 0.16$$



$$\langle \varphi_0 \rangle = 4.5 \pm 0.2$$



$$E[\varphi(A_u)] = \frac{1}{2} P(\chi^2 > u) + (\mathcal{N}_1 + \mathcal{N}_2 \sqrt{u}) e^{-u/2}$$

$$\mathcal{N}_1 = 4 \pm 0.2$$

$$\mathcal{N}_2 = 0.7 \pm 0.3$$



# Summary

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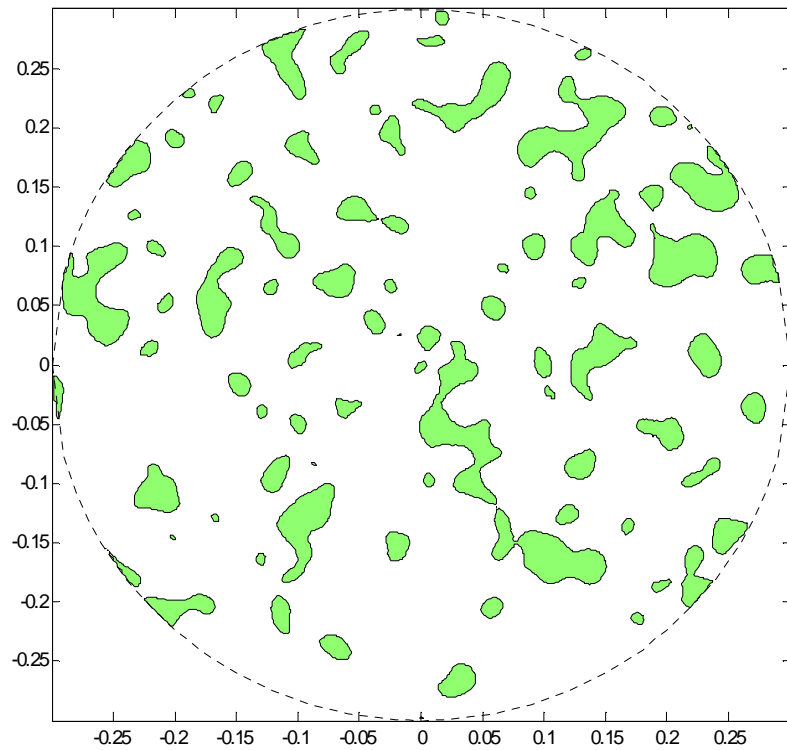
- The Euler characteristic formula provides a practical way of estimating the look-elsewhere effect.
- Applicable in wide range of applications, such as astrophysical searches for neutrino sources or resonance search with unknown width, and in any number of search dimensions.
- The procedure for estimating the p-value is simple and reliable.

$$\text{p-value} \approx E[\varphi(A_u)] = \frac{1}{2} \text{P}(\chi^2 > u) + (\mathcal{N}_1 + \mathcal{N}_2 \sqrt{u}) e^{-u/2} + \dots$$

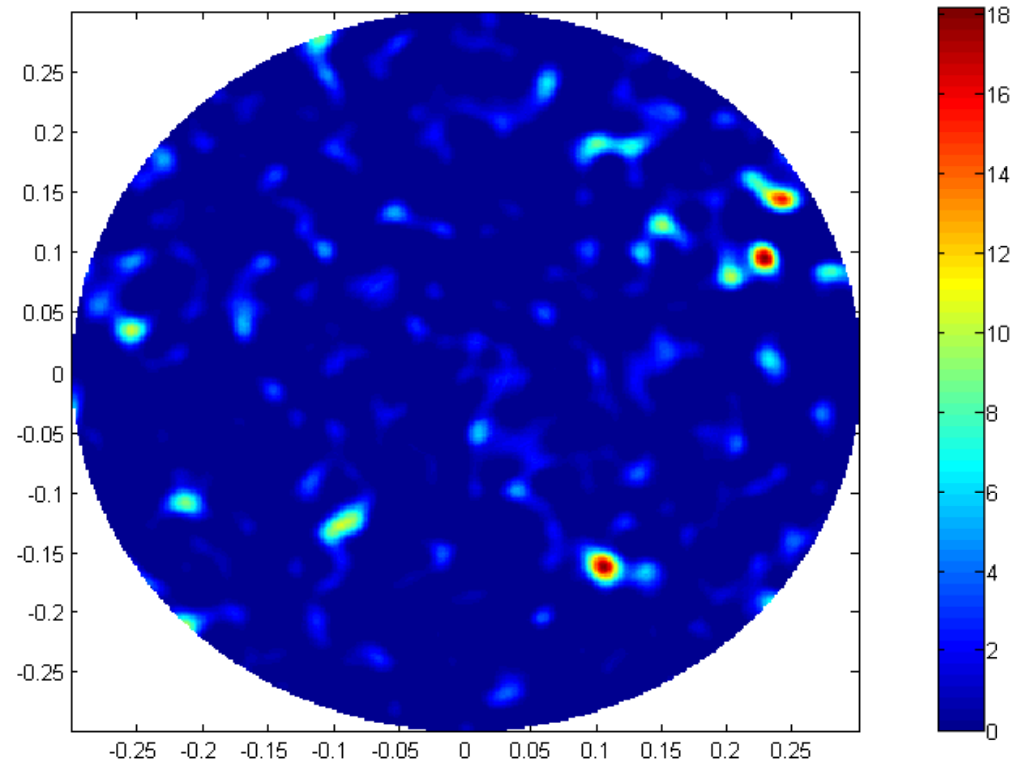


# Backup

# 2-d example: search for neutrino sources (IceCube)



Excursion set ( $u=1$ )



Significance map  
 $q_0(\theta, \varphi)$