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³ Weekly Activity Report

⁴ Week 4

⁵ Tagging voids using the Random Point Algorithm
⁶ and the 1-Skeleton

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¹³ ABSTRACT

¹⁴ The Random Point Algorithm works! It was tested over a “real” dataset from the
¹⁵ Abacus-Cosmos simulations. The algorithm identifies empty regions in the LSS and is
¹⁶ able to tag them as individual voids.

¹⁷ *Keywords:* Beta Skeleton Graph, Random set of points

¹⁸ 1. THE ALGORITHM

¹⁹ The main goal of this project is to identify voids in the large scale structure of the universe, using
²⁰ the nobel method in astrophysics: the β -Skeleton graph. In order to develop the code, a toy model
²¹ catalog structure is used, then a second catalog of random points populates the same volume, the
²² graph is calculated and then the voids are identified as the second catalog points without connections
²³ with the first catalog points.

²⁴ We start with a sample of N points randomly placed inside a cubic box of lenght L. (Figure ??). In
²⁵ the middle of the box there is a spherical void, i.e. an spherical region without points. This set of
²⁶ points is called “the observed catalog” (**OC**). This toy model will represent -in a gross aproximation-
²⁷ the LSS with galaxies and voids.

²⁸ Then another set of N random points populates the whole box, without restrictions. This set is
²⁹ called “the random catalog” (**RC**). It will populate even the void region. It’s only necesary to know
³⁰ the volume of the OC and the number of points N to create the RC.

³¹ The NGRAPH library can operate over a single set of points. This set is called “the full catalog”
³² (**FC**). This set of points is created using the `vstack` python function. The first N elements are the
³³ RC points, the last N elements are the OC points, then the FC has 2N elements.

³⁴ The 1-Skeleton graph is calculated over the FC. Runing the code over a FC of $\sim 10^4$ points in a
³⁵ Core i5 (2nd gen.) Linux machine, it takes 192 seconds to complete the calculus. The result is stored
³⁶ as the Full Catalog Beta Skeleton Graph (**fcBSk**).

³⁷ The fcBSk is chopped to the half, we are interested about the RC points that are not connected
³⁸ with the OC points. Then a droplist is created as the subset of connections where the second point
³⁹ belongs to the OC, i.e., its index is greater than N.

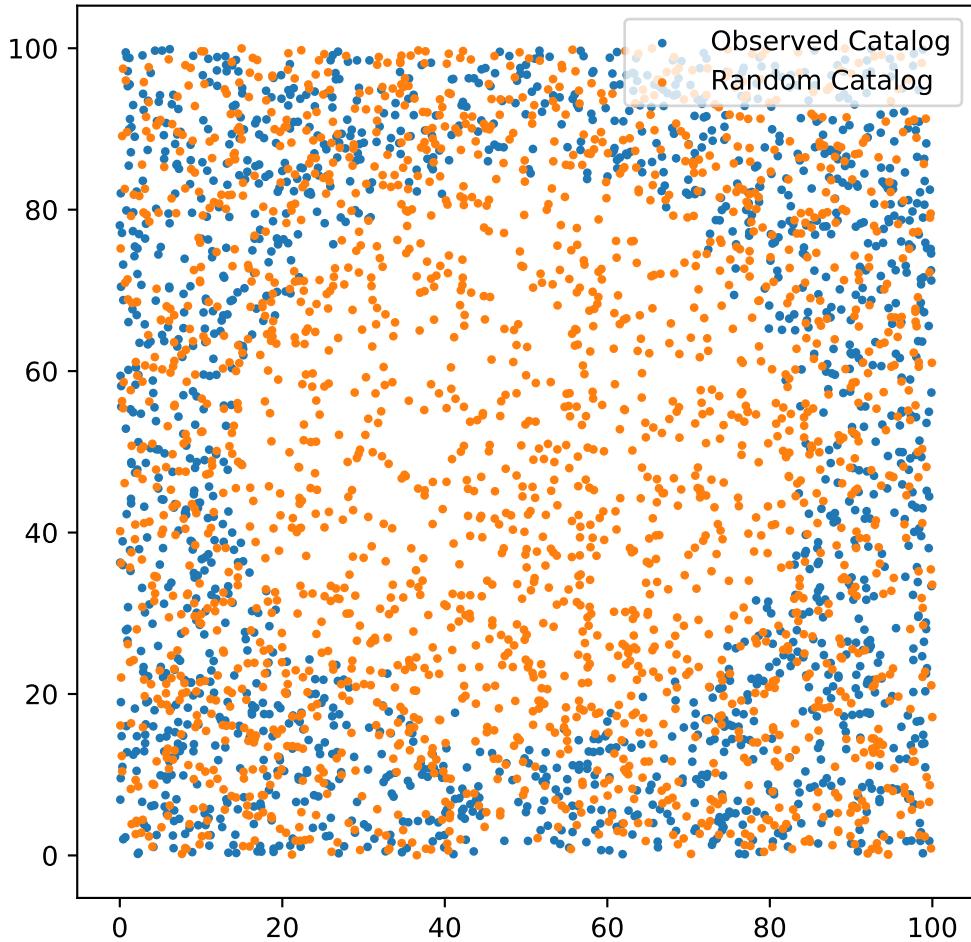


Figure 1. The Algorithm uses two sets of points: The Observed Catalog (LSS like in blue with a spherical void in the middle) and the random Catalog (orange). N=5000, BoxLength = 100 and void radius R=37.

40 Using the python `set` class, its easy to find the complement of the droplist in the `fsBSk`. After
 41 dropping the RC points connected with the OC, it remains the points inside the void.

42 2. TAGGING VOIDS

43 Once we have void points, individual voids are tagged using a Friend of Friend method.
 44 From the Full Catalog Beta-Skeleton Graph `fcBSk`, that is just a Mx2 array of indexes, we can
 45 extract the connections of void points. Each void point must be conected solely with other points
 46 from the RC. They may be other void points or frontier points.
 47 Frontier points are poins from the RC than are connected to RC points as well to OC points.
 48 Frontier points where rejected on early stages of the algorithm, but now they are taken into account.

Spherical Void Recognition Using RandomPoints & 1-Skeleton

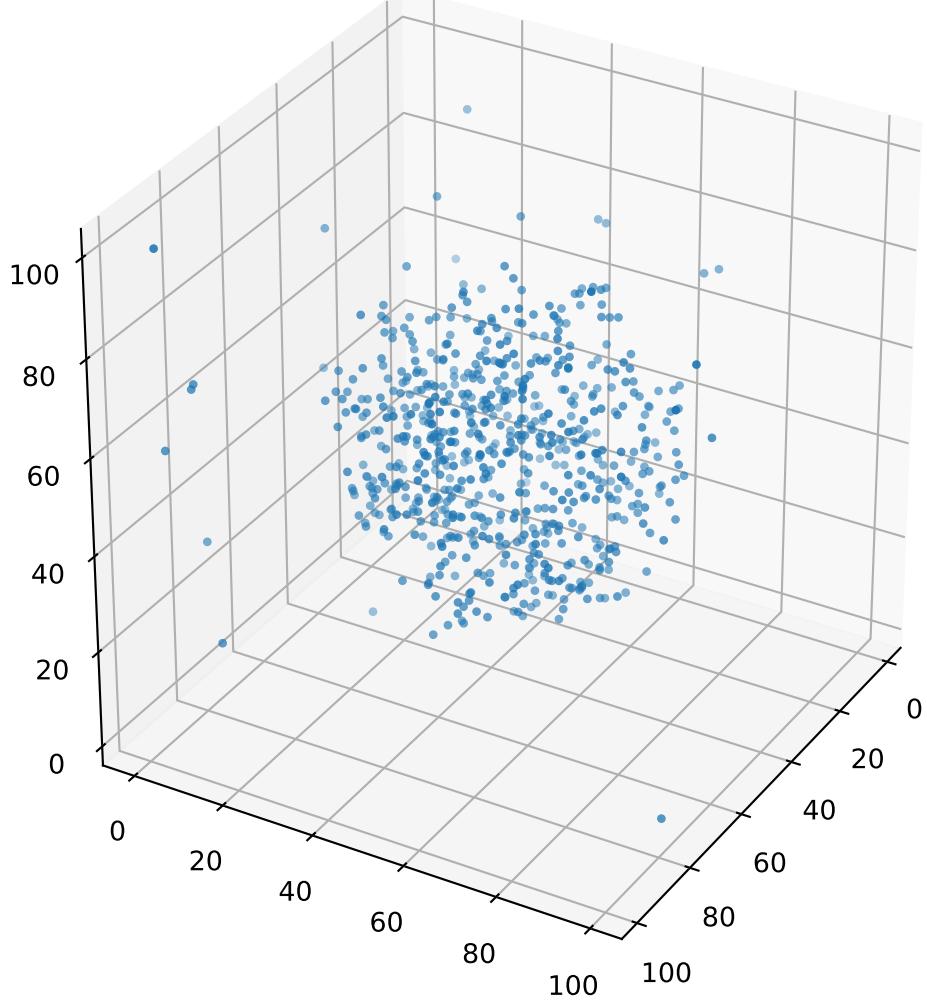


Figure 2. Points identified as “Void Points”. They are RC points connected only to other RC points. The Frontier points are not included. N=5000, BoxLength = 100 and void radius R=37.

Frontier points are over the “Void Surface”. A similar surface was the aiming of the previous algorithm (comparing two different β -Skeleltons).

We did not achieve the stage of exploring voids with sparse galaxies in the previous algorithm, but now, a void with sparse galaxies is easily identified as a “plum pudding”, where the void is the pudding with frontier points enclosing the “plums” (sparse galaxies),

The algorithm starts looking for the connections of the first Void Point in the Random Catalog. A list including the first void point and their neigbohrs is created. This list is going to be the first voids tagged. Then the second point is checked, if it appears in the list the the second point and its neigbohrs are added to the previous list, they are identified as part of the first void. If not, then a new list is created with the second point and their neigbohrs, giving place to the second void. When

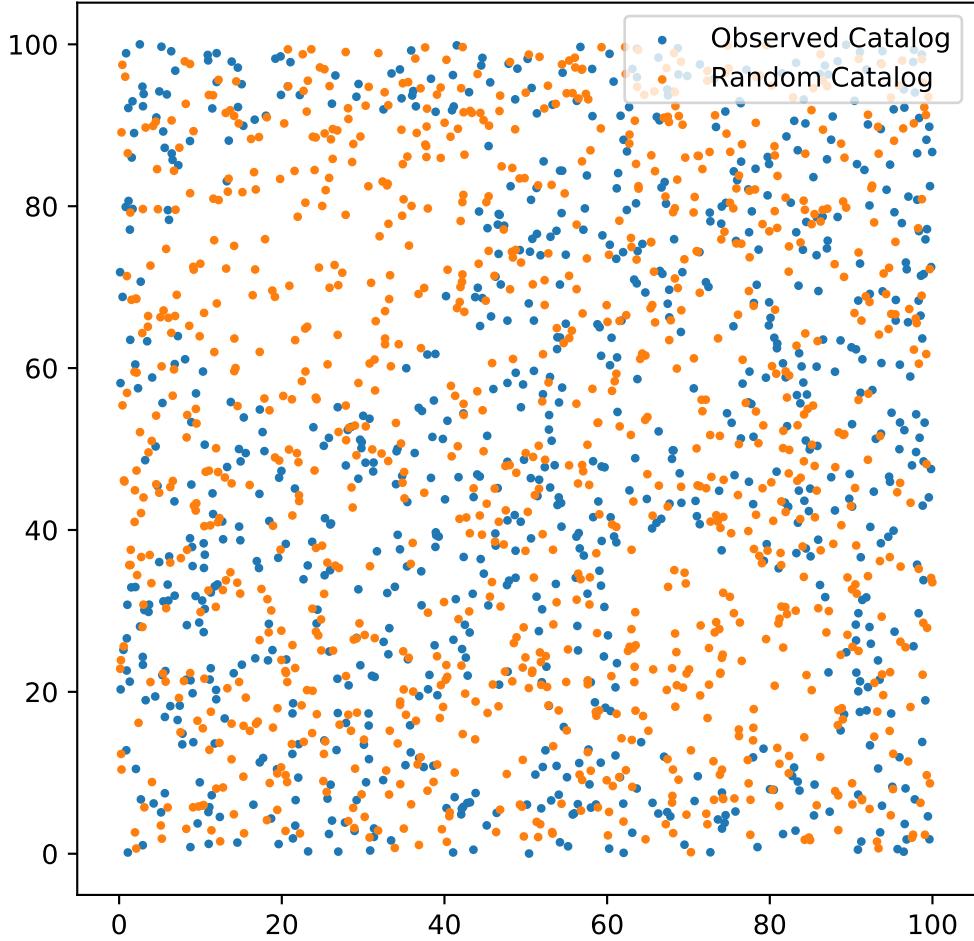


Figure 3. Slice at $z=70$ of an structure with four spherical voids of radii 5, 10, 5 and 20. $N=5000$, BoxLength = 100, the voids radius where selected as $R= 5, 10, 15$ and 20.

the n -th is reached, a search is performed over the existent lists of voids. The n -th point may belong to a previous lists of voids, or may create its own list for a m -th void ($m \leq n$).

The master list of catalogs at this moment is incomplete, all the Void Points in the list are counted and checked if they belong to another list. But frontier points are not checked. The master lists contains voids sharing frontiers. Is necesary to run again a recount, looking for repetitions between lists, thinking each list as a set of points, and looking for intersection between sets. (Python offers this implementation using sets by invoking the class `set`). When a intersection between voids is detected, the two voids are merged into a new one. Finally, the voids are tagged (by the ID of the first void particle).

Spherical Void Recognition Using RandomPoints & 1-Skeleton

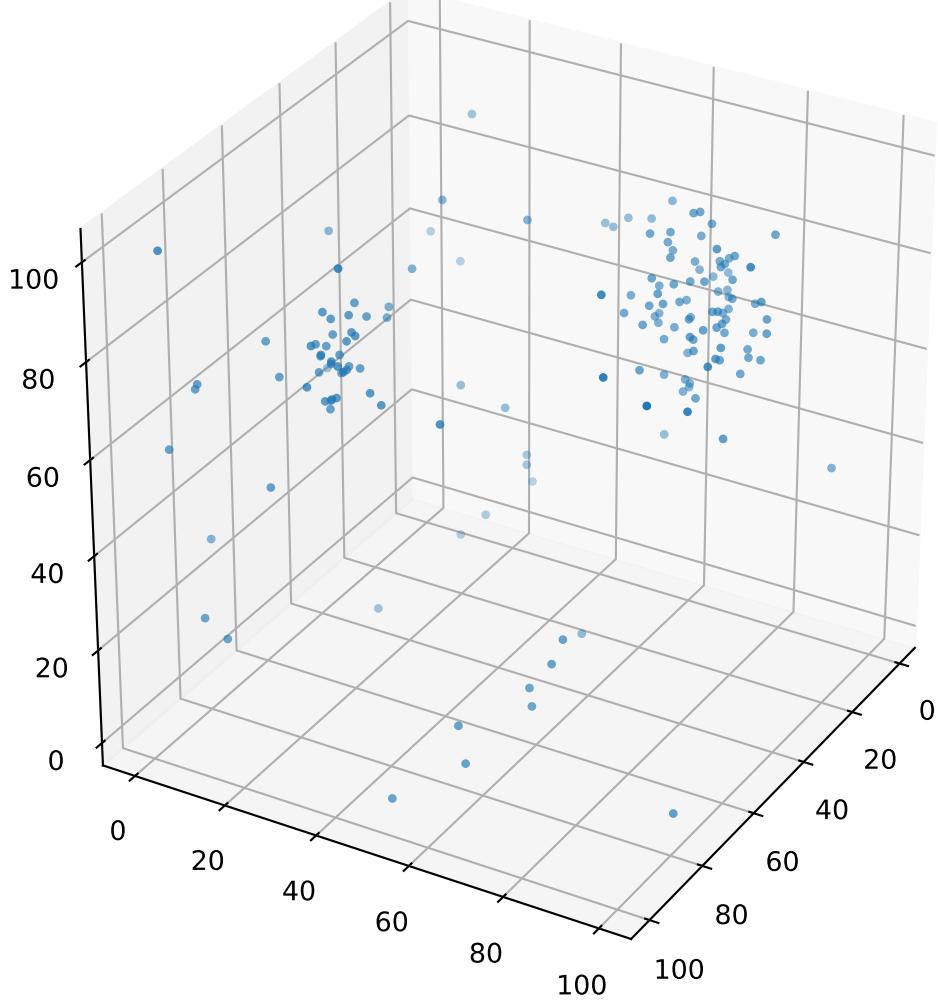


Figure 4. Points identified as “Void Points”. This tests aims to check the resolution of the algorithm. Some scattered micro-voids appear. The “biggest” voids are recognized ($R=15,20$), but small structures doesn’t appear ($R=5,10$). $N=5000$, $\text{BoxLength} = 100$, the voids radius where selected as $R = 5, 10, 15$ and 20 .

68 This algorithm was able to detect irregular voids made of intersecting ellipsoids, doing the task
 69 where the previous one failed. This test was performed over a artificial structure, a toy model
 70 catalog.

3. ABACUS-COSMOS SIMULATION

72 From a snapshot of the Abacus-Cosmos simulation with fiducial cosmology, a set of halos is selected,
 73 within a sphere of radius $R = 100\text{Mpc}/h$ and a M_{cut} given to get $\sim 10^4$ halos.

74 The Random Catalog is generated, taking care of having a uniform space distribution. A common
 75 error is to generate the radius using a uniform distribution from 0 to 1 and scaling by a factor R , but
 76 must be taken instead the cubic root of the random number between 0 and 1, then multiplied by R .
 77 Another error is generating the angles again, taking a random number between zero and one, then

Void Tagging Using RandomPoints & 1-Skeleton

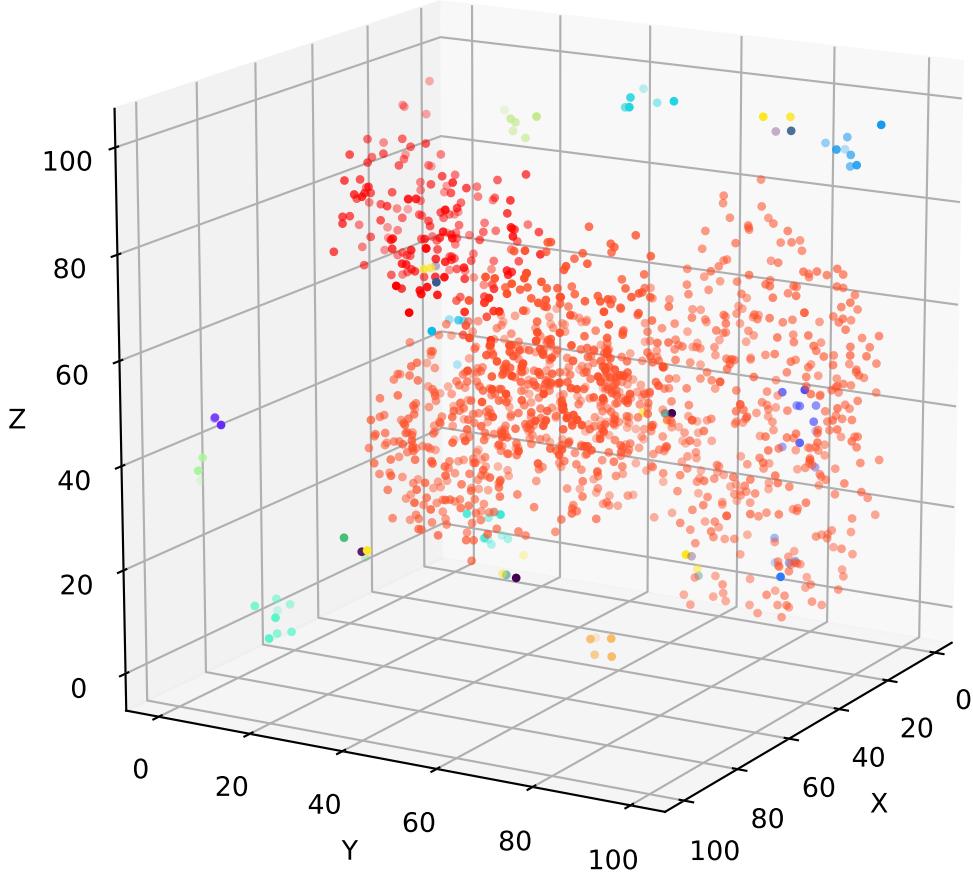


Figure 5. Tagging Voids. This algorithm can indentify irregular structures, a step ahead the previous algorithm. The irregular voids are made of overlapping ellipsoidal voids, with semiaxes proportion 1:0.7:0.5 as the literature suggests. N=5000, BoxLength = 100, the voids major semiaxes where chosen as R= 40, 30, 30 and 40.

78 scaling by 2π . This error can be avoided by generating a random number between 0 and 1 as the
 79 cosine of θ , then calculating the angle as the arc-cosine. The unitary vector can be calculated using
 80 a gaussian distribution for x, y and z (centered at zero with the same deviation for them three). The
 81 norm is calculated as usually, by taking the square root of the sum of the coordinates, then dividing
 82 each coordinate by the norm of the vector.

83 The algorithm ran over the “real” dataset using the ratios 1:1, 2:1 and 3:1 for the number of
 84 random points vs. catalog points.

4. TO DO:

- 85
- 86 • Count the number of voids on each of the three runs.

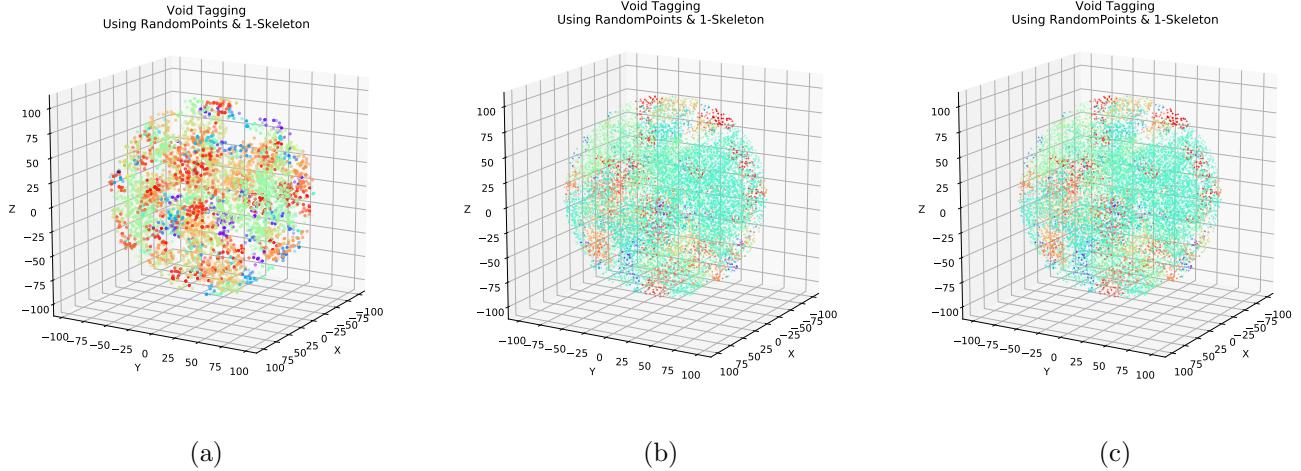


Figure 6. Tagging Abacus-Cosmos Voids. This is the first test over “real” data, not a toy model. The LSS shows highly dense packed halos, where voids have almost none of them. The idea is to increase the ratio of Random Points over Catalog points to study (in later weeks) how void detection can be affected. (a) Ratio 1:1, (b) ratio 2:1 and (c) ratio 3:1. The catalog is a spherical set of points, with radius $100\text{Mpc}/h$, N halos = 9981, N random points = 10000 (a), $2N$ (b) and $3N$ (c).

- Change the shape of the Random Points Catalog (maybe outer voids are connected by mistake.)
 - Calculate the volume of each void and compare between runs. (Histograms)
 - Think about how to calculate ellipticity (Can be useful at any moment inertial tensor?)