

# TOPOLOGY OF RANDOM POINTS

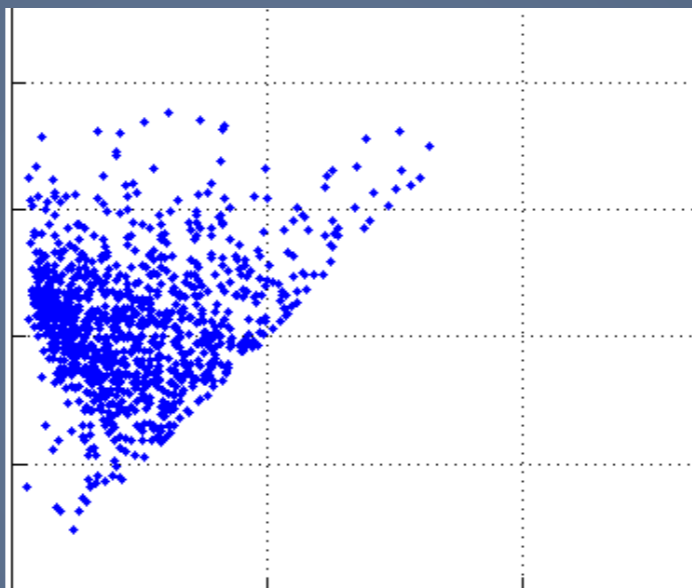
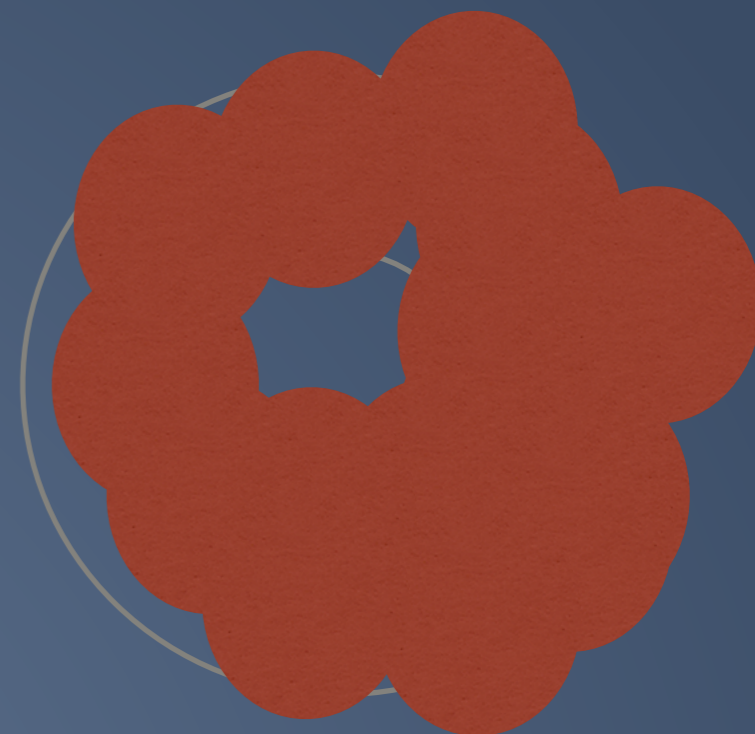
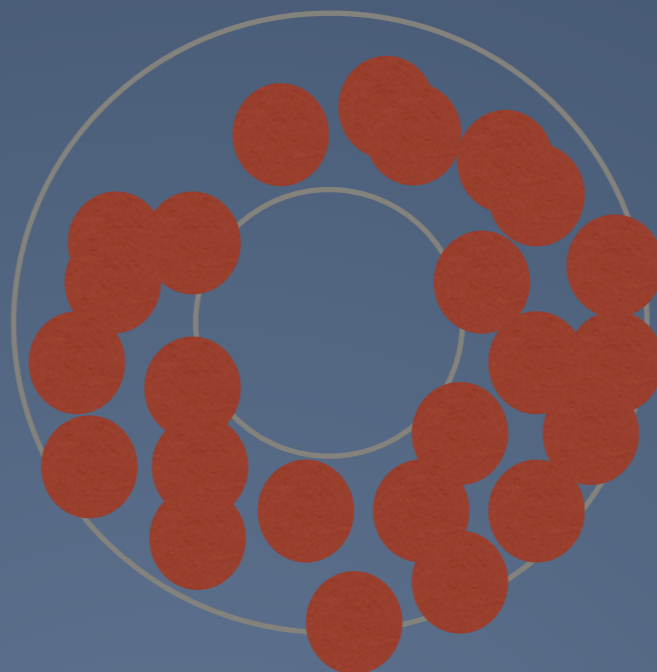
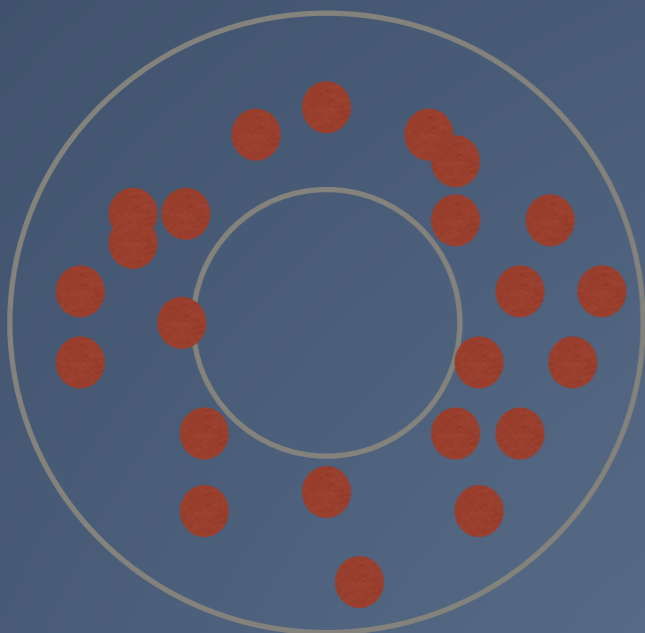
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YOGESHWARAN. D.

MARCH 2017, IISC.



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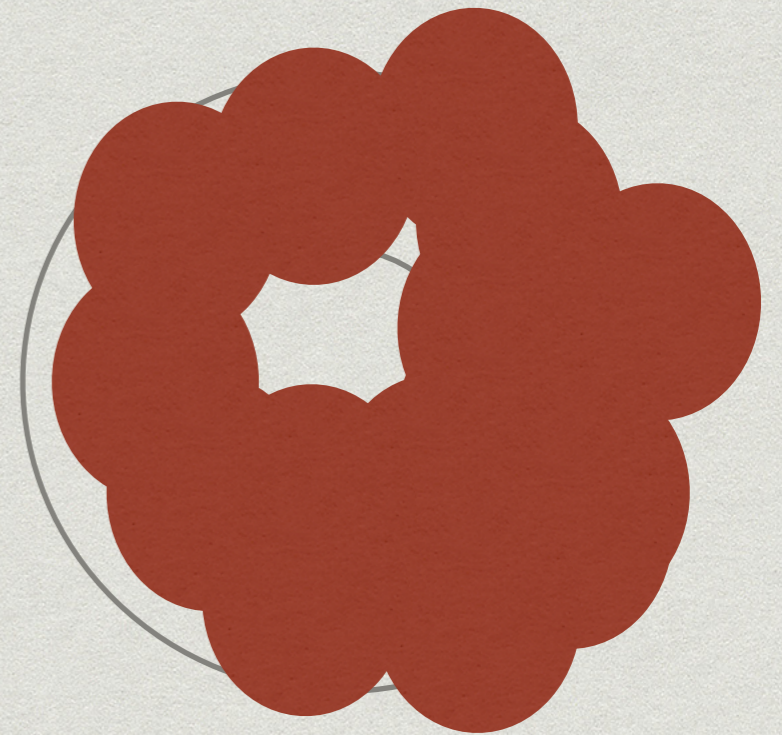
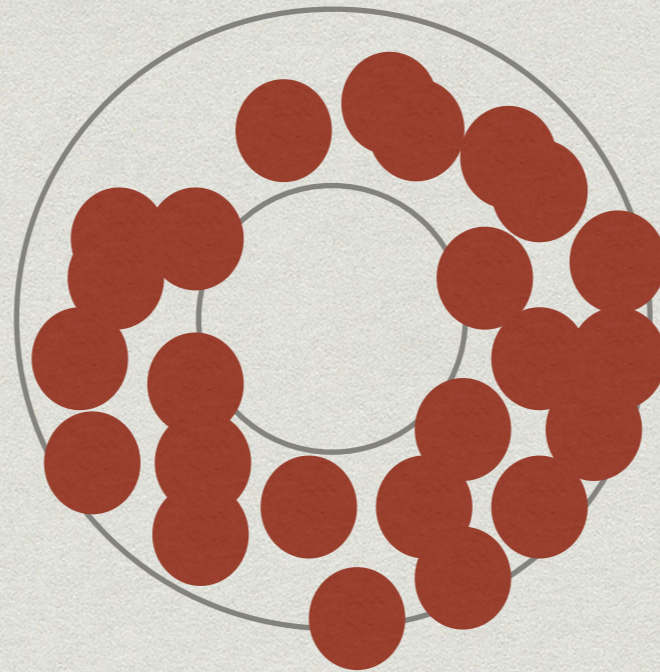
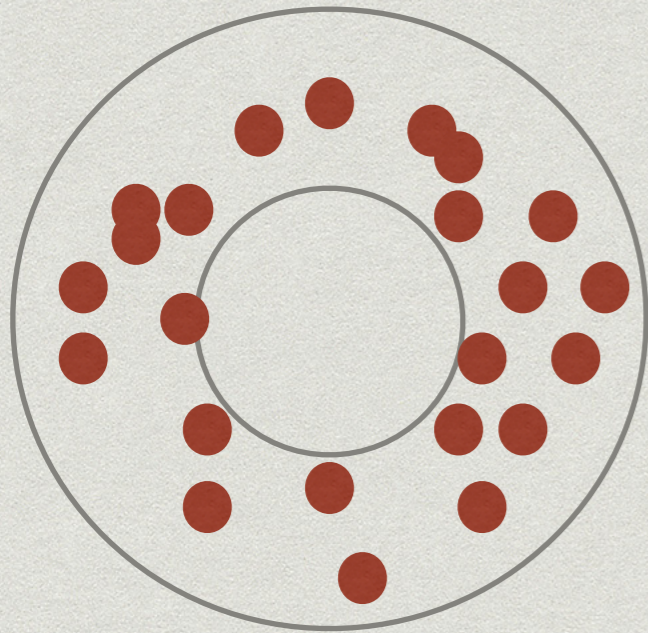




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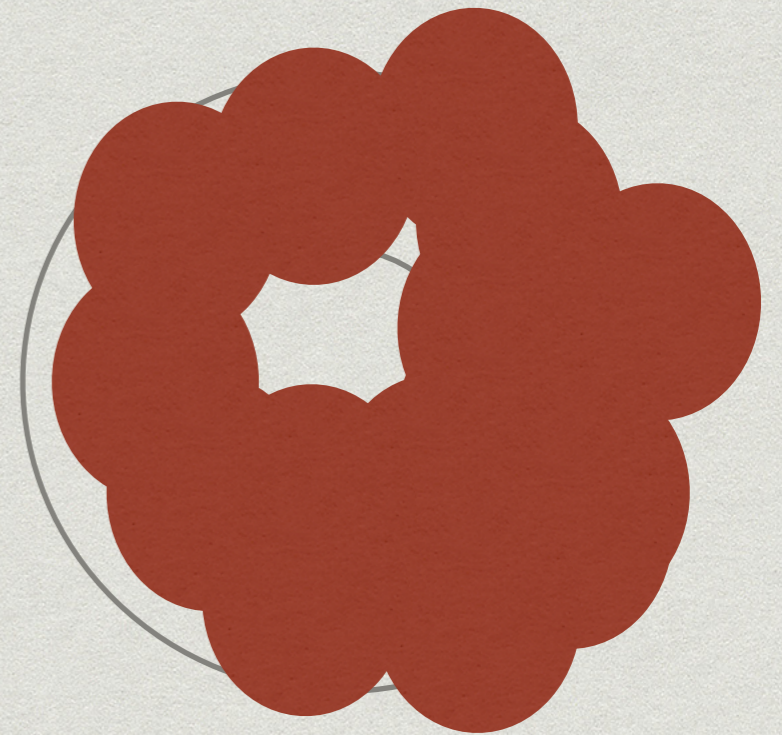
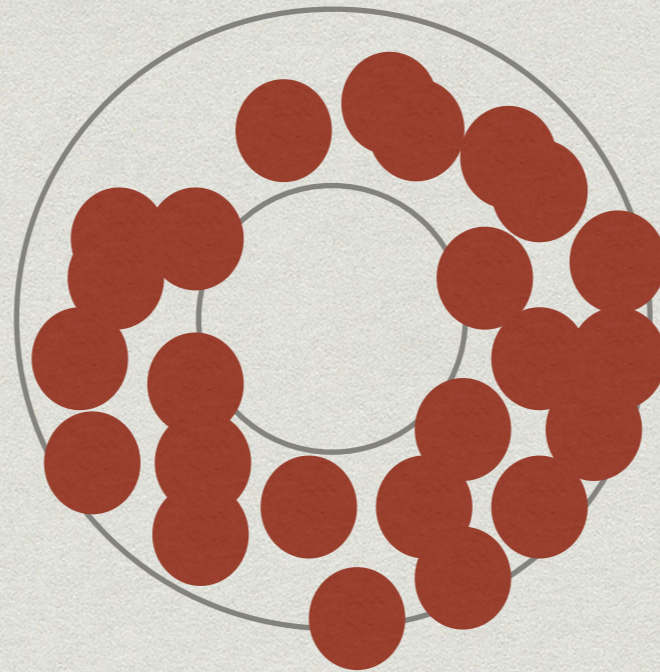
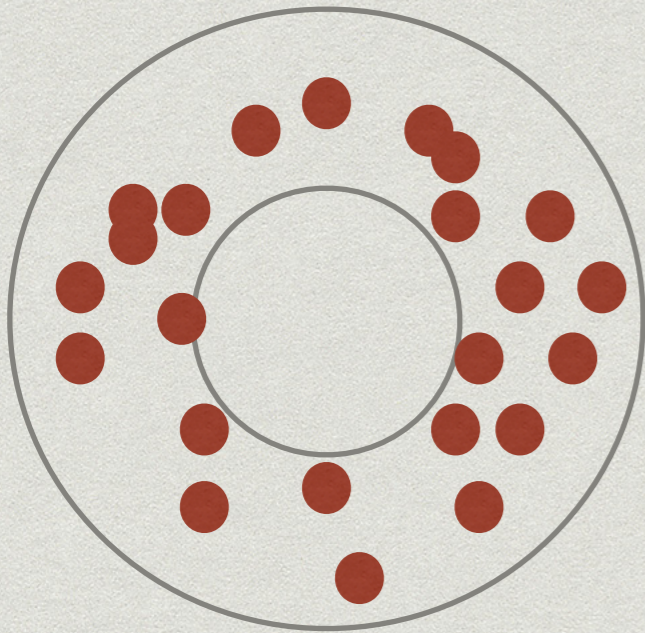


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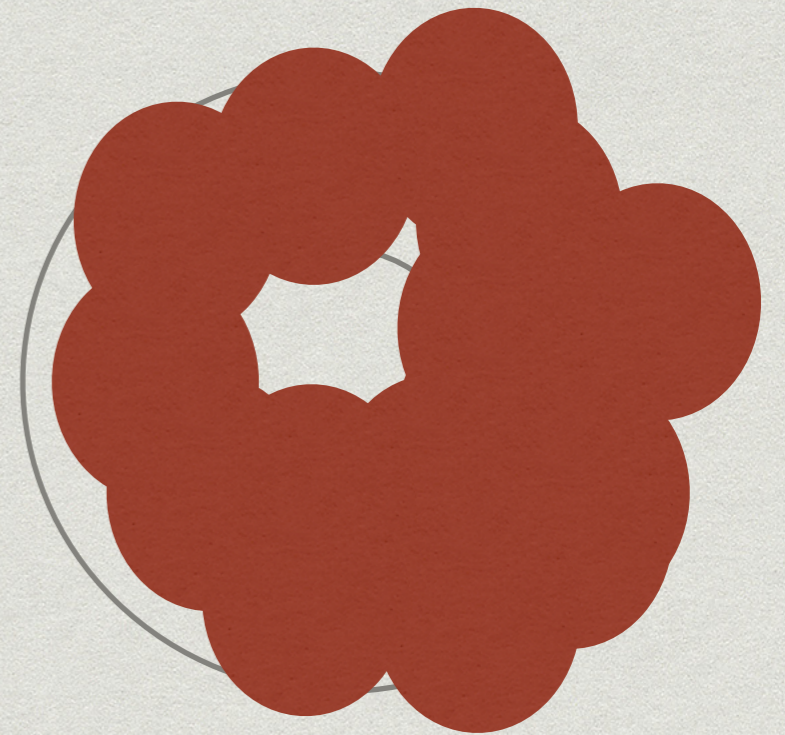
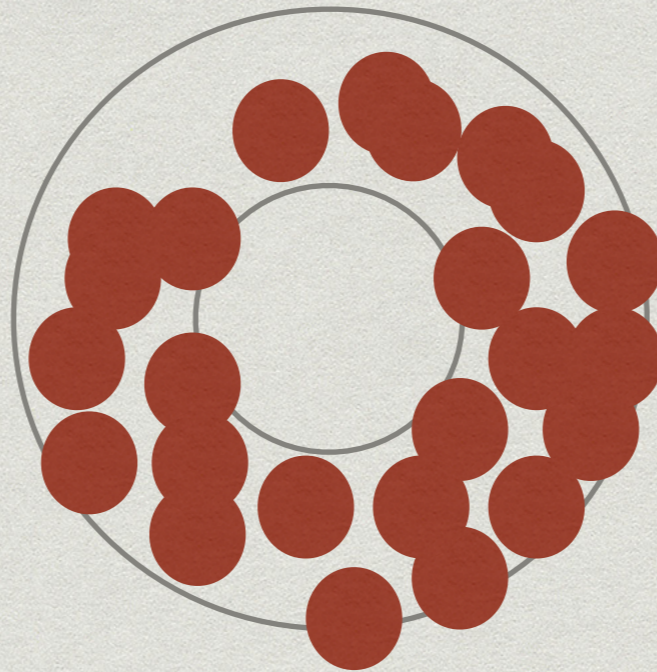
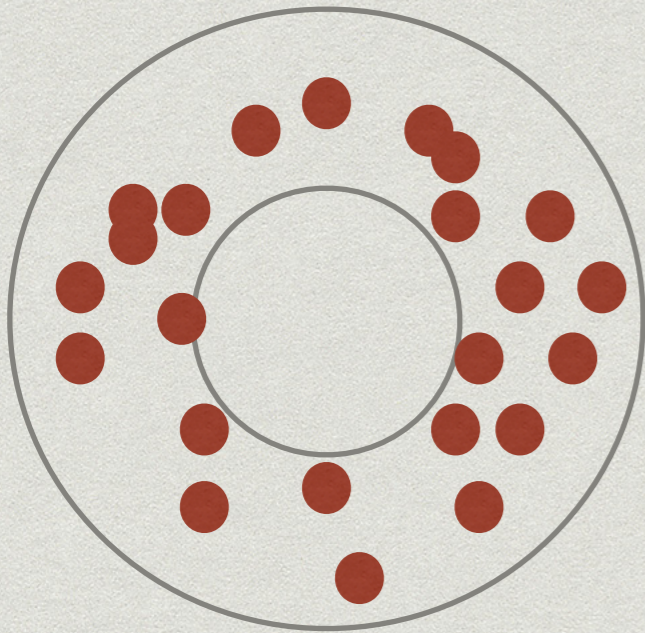
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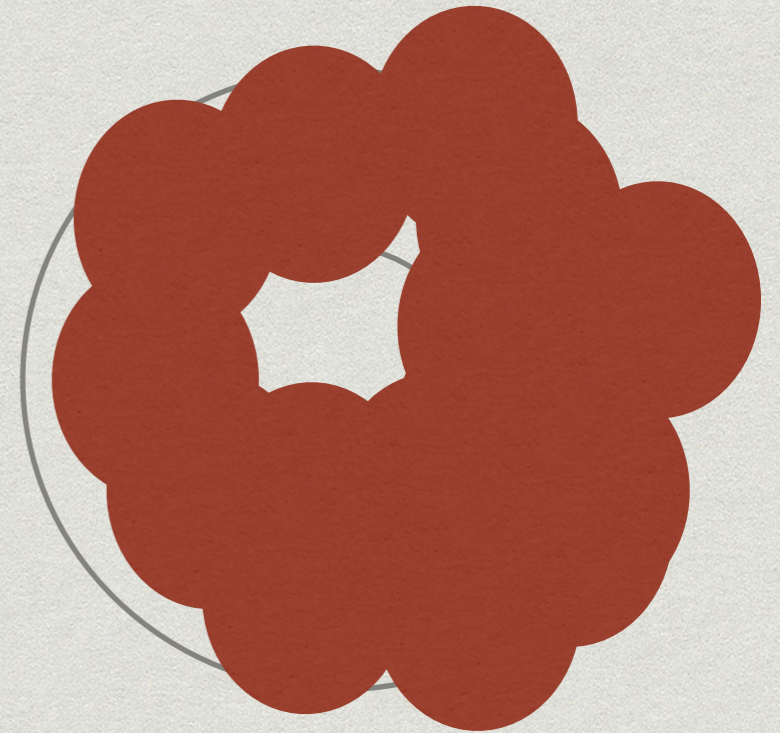
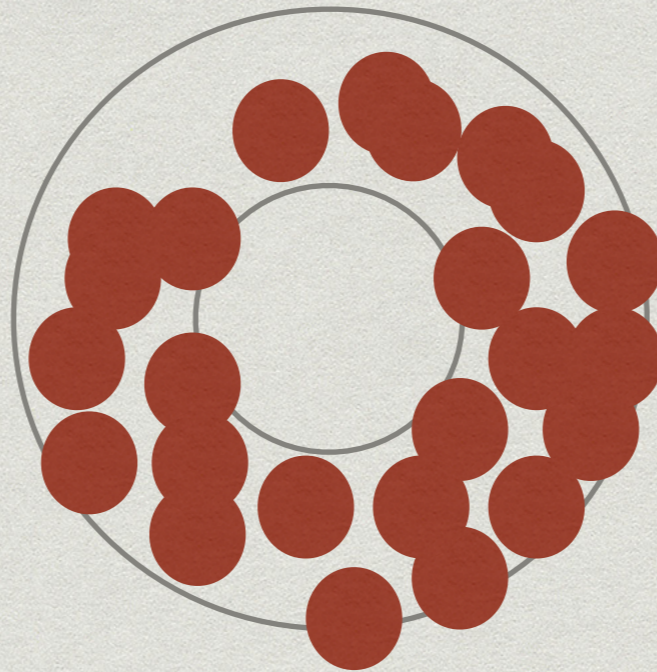
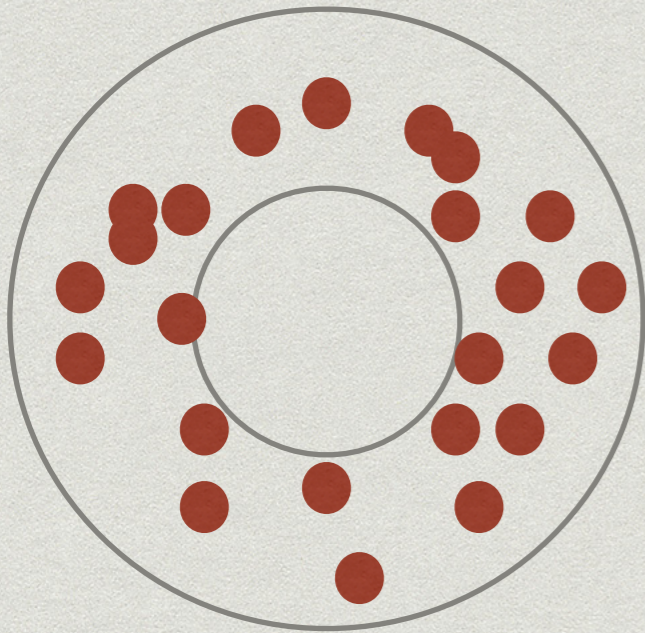


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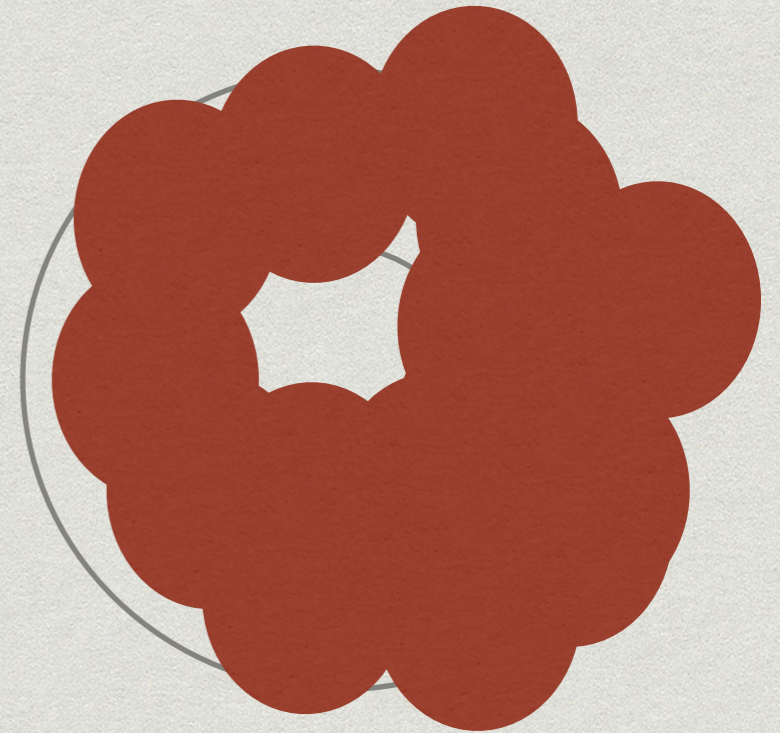
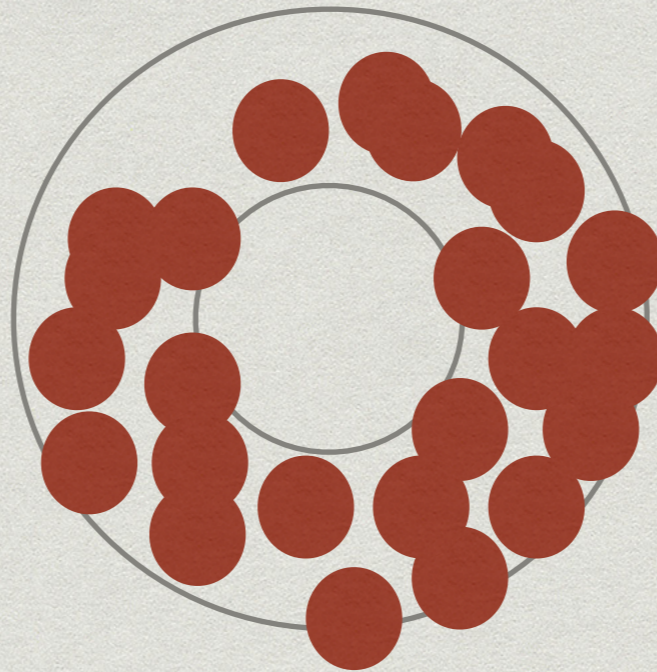
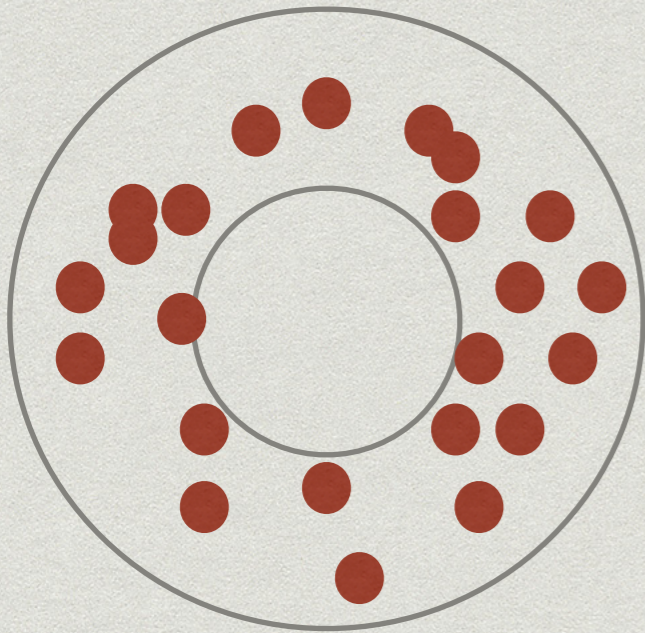


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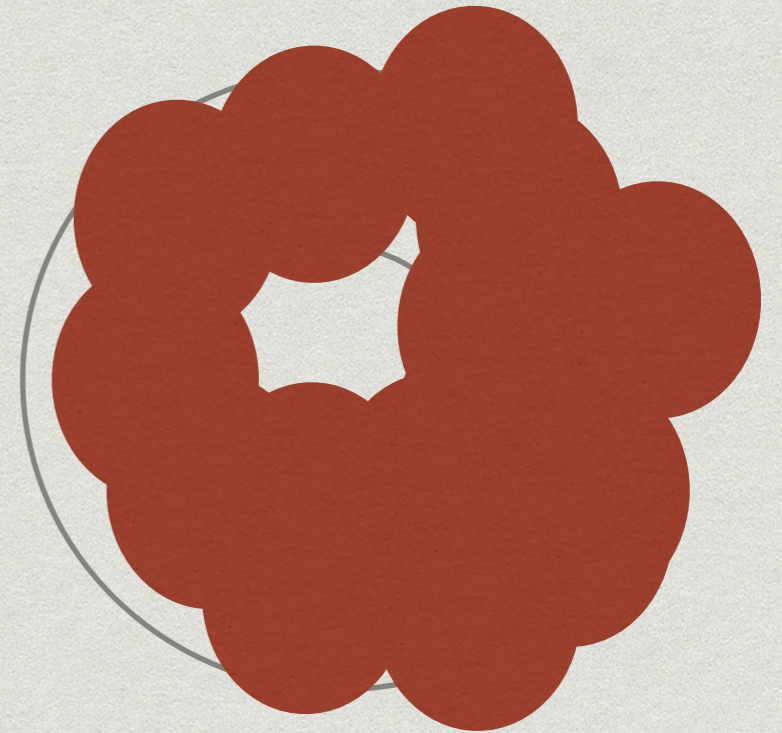
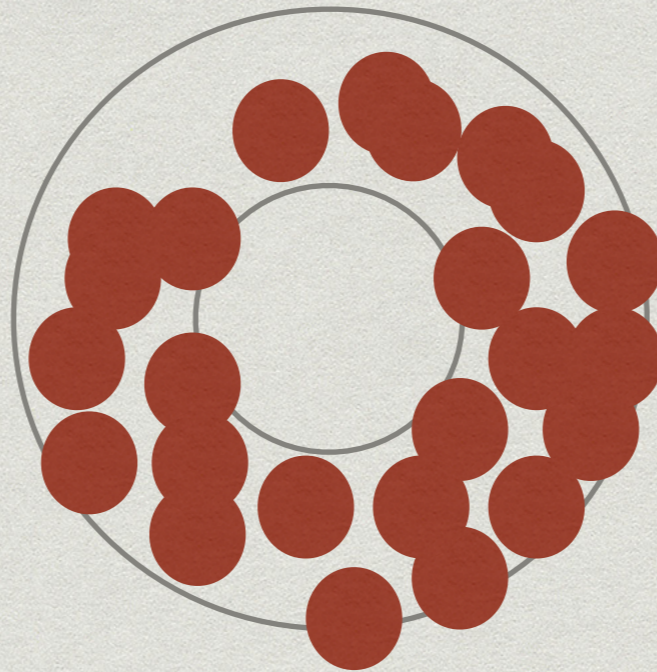
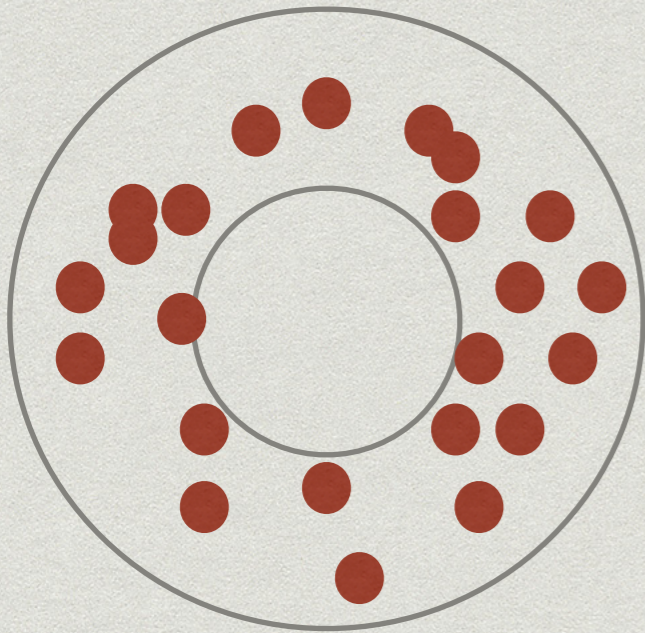
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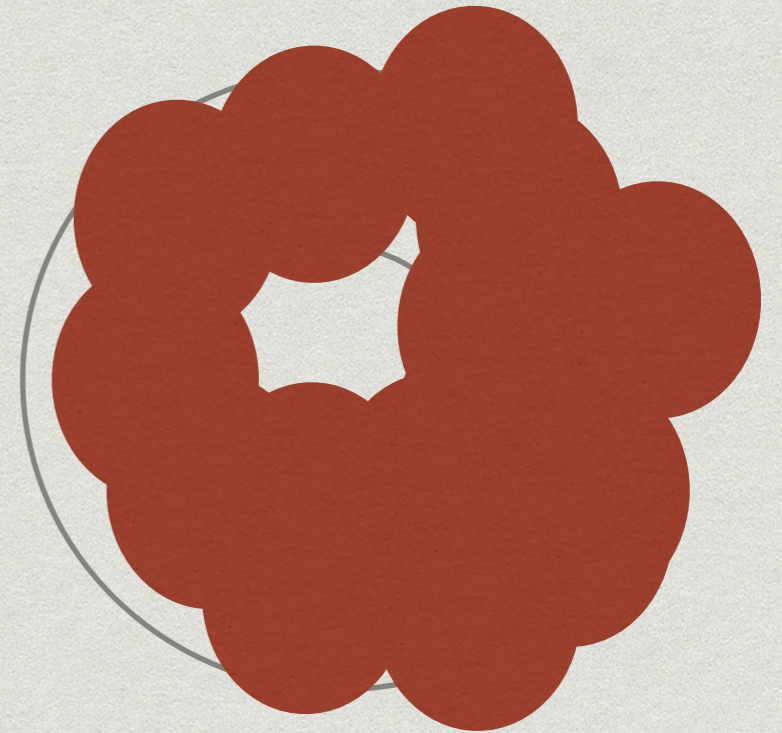
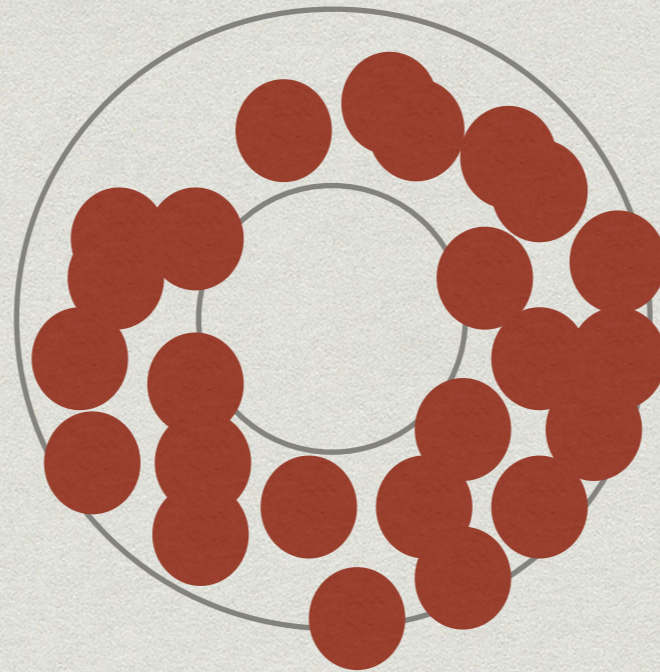
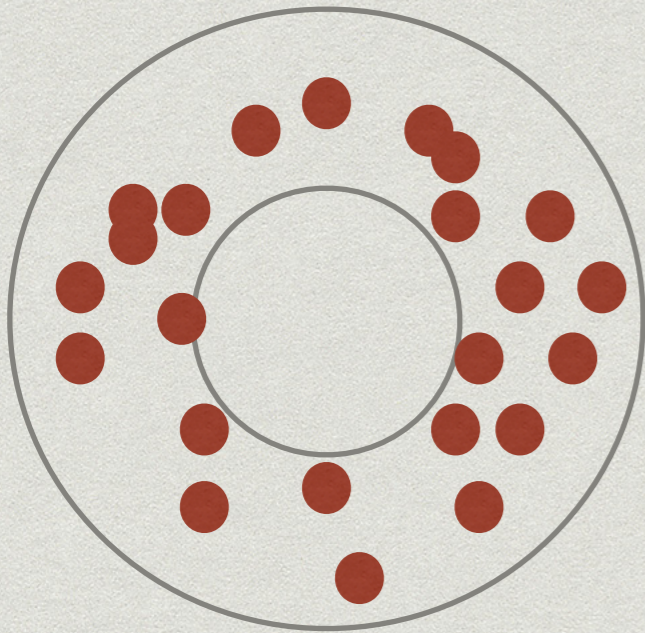
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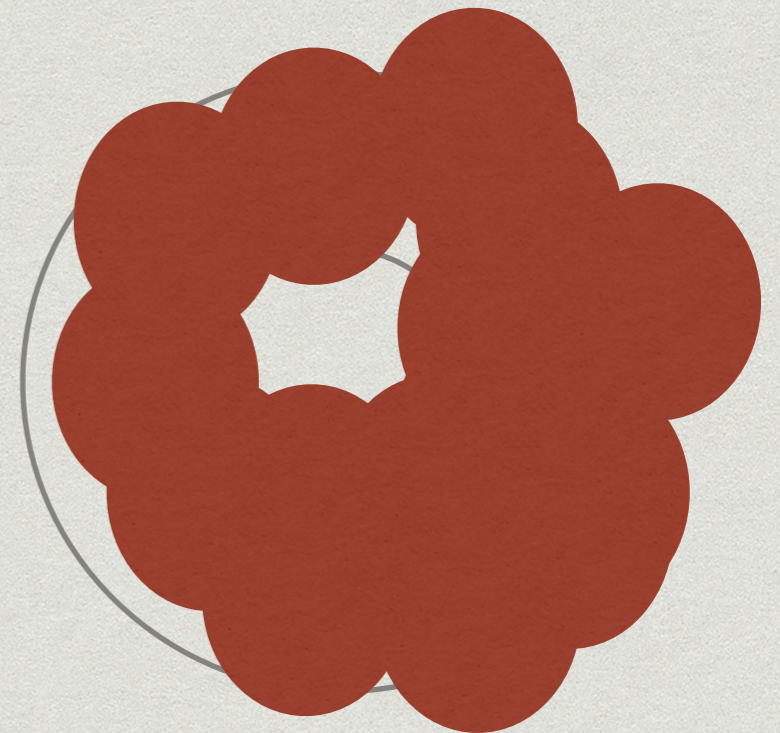
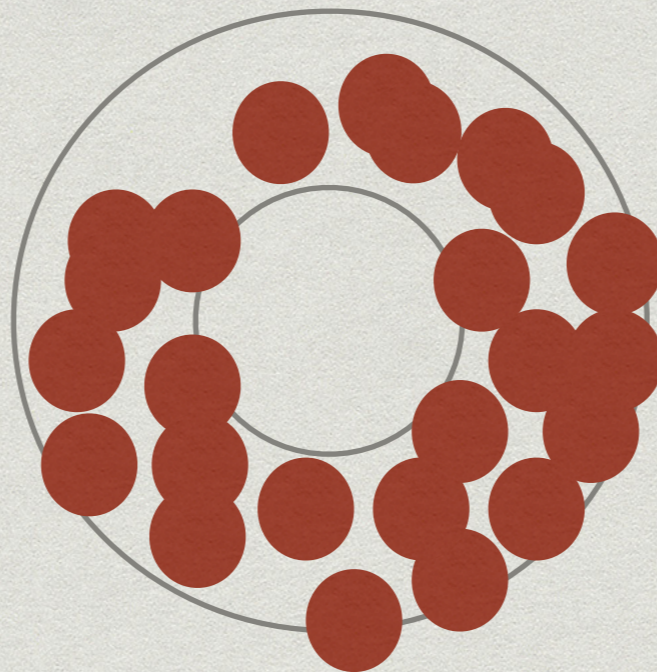
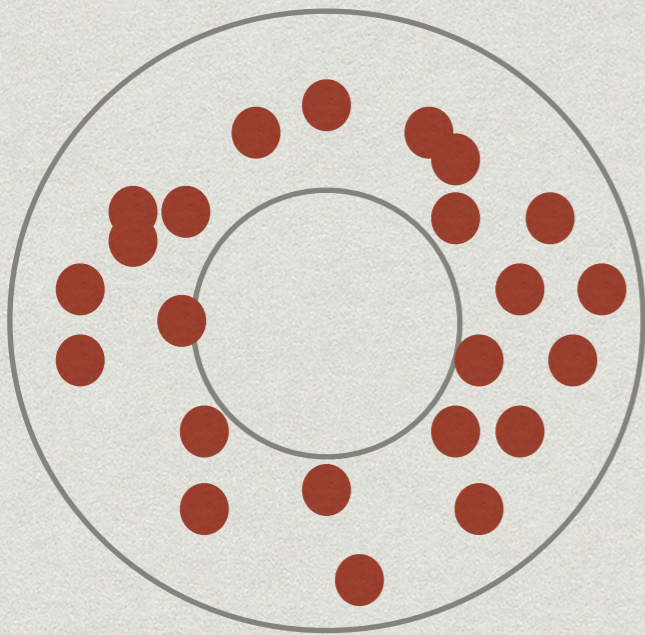
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**Other topological summaries ?**







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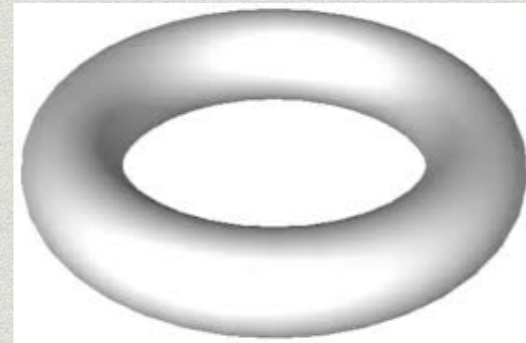
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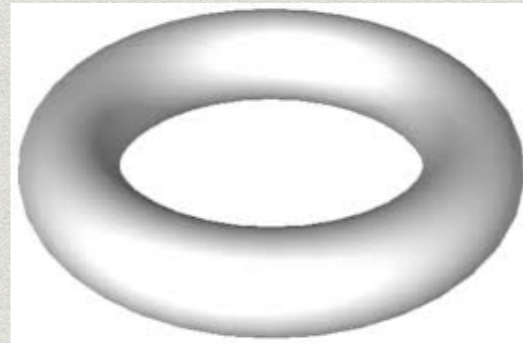




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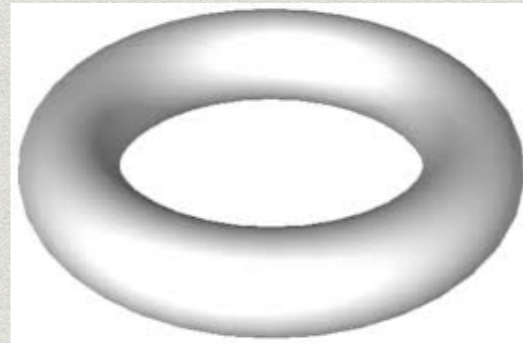
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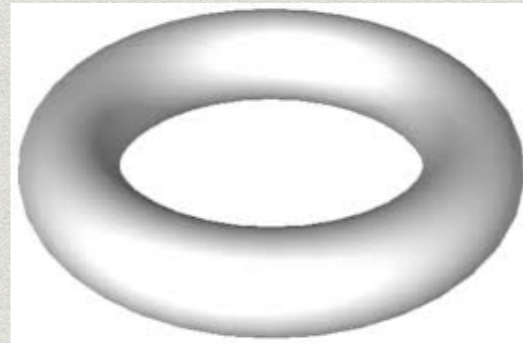
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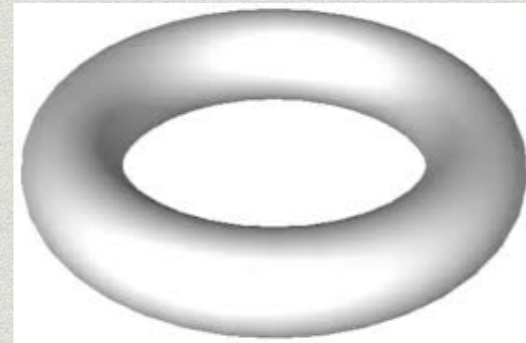
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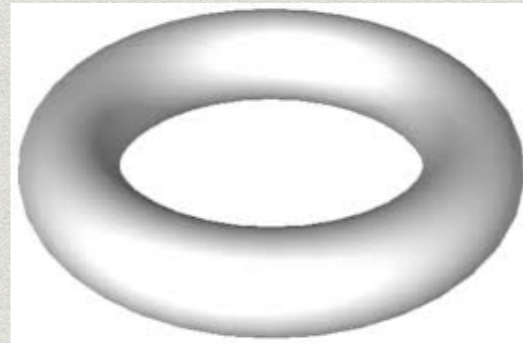
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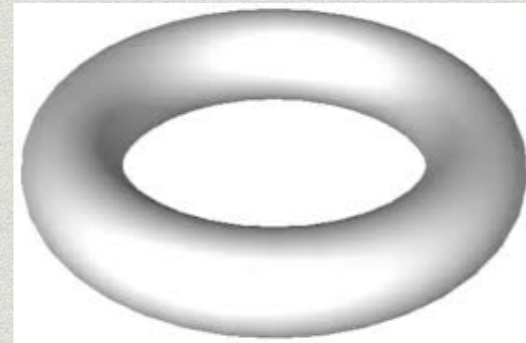
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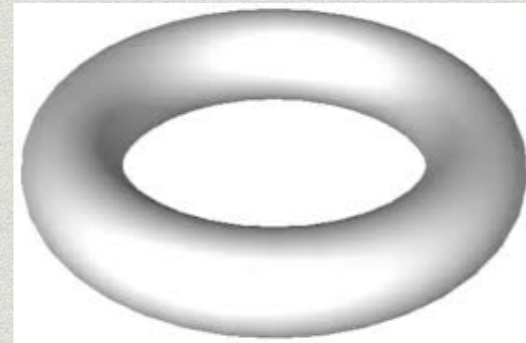
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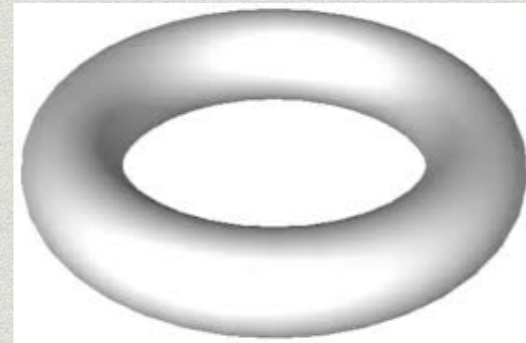
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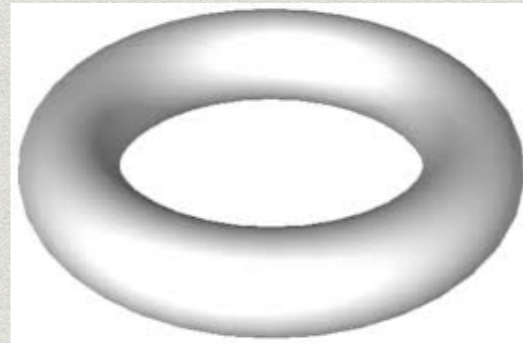
$$= ne^{-n2^d \theta_d r_n^d} \sim (1 - 2^d \theta_d r_n^d)^n$$



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Coverage threshold at  $n\theta_d r_n^d - \log n - (d - 1) \log \log n \rightarrow \infty$ . **“Sharp threshold”**

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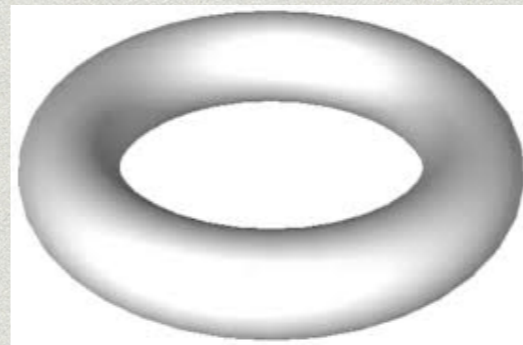
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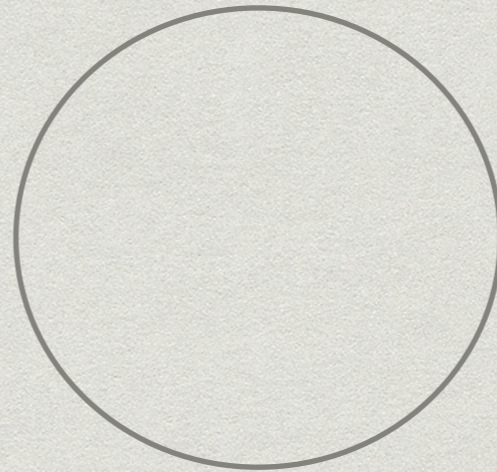


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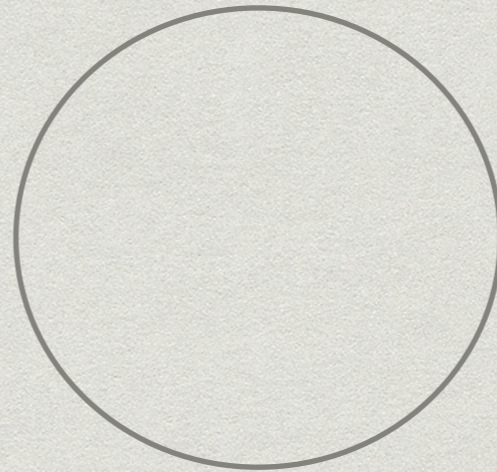


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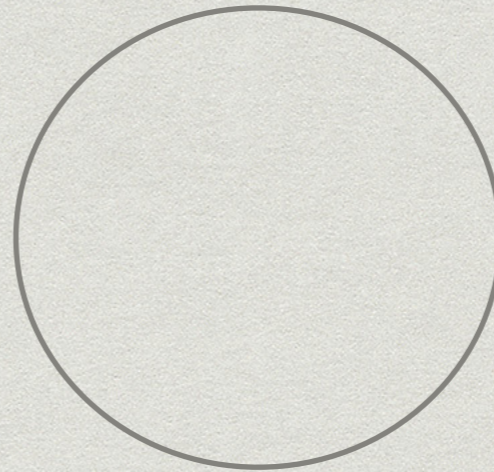
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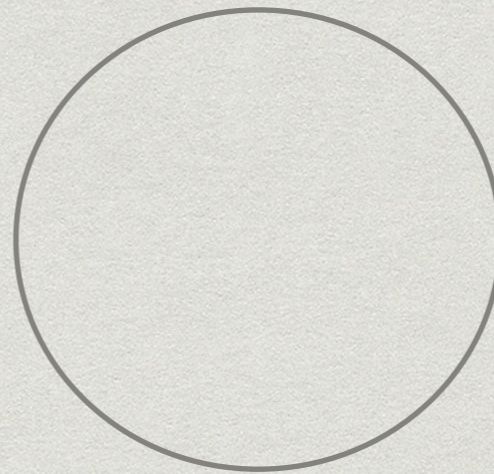
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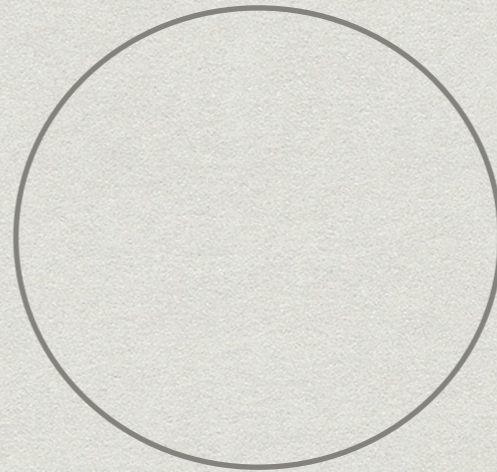
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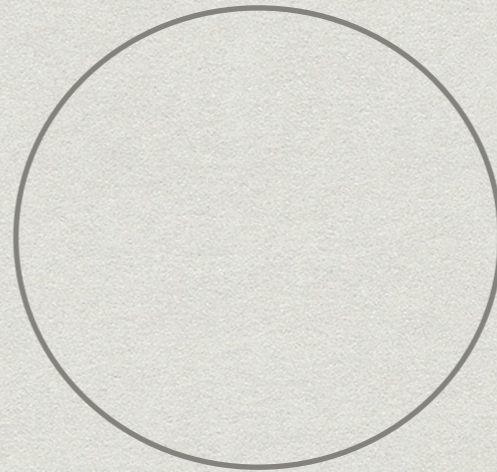
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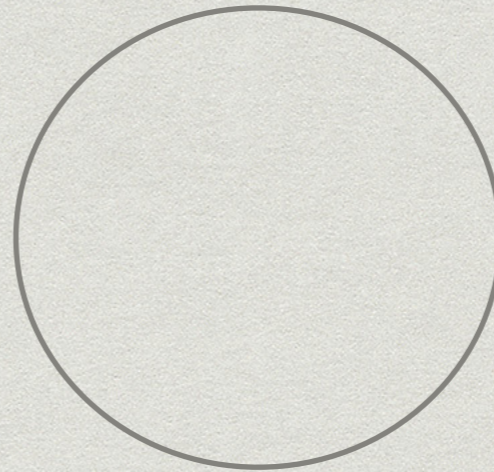
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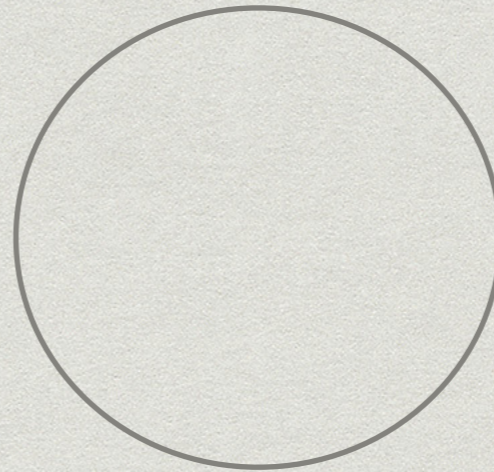
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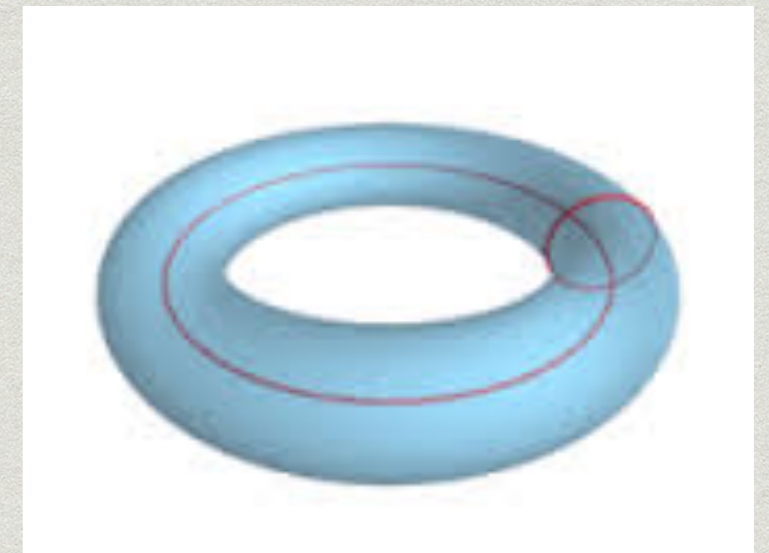
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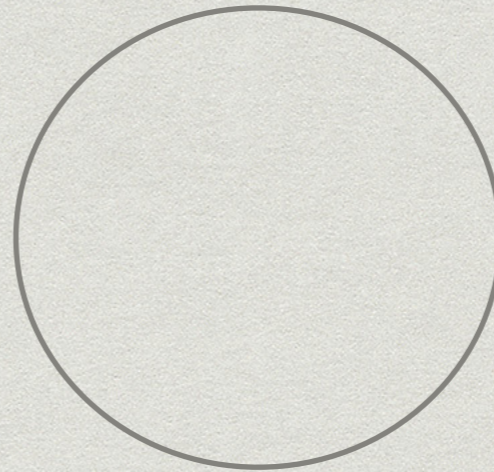
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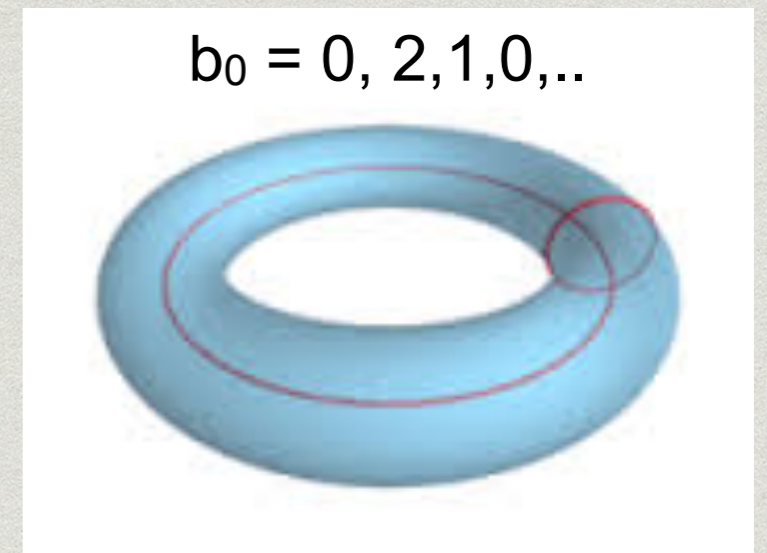
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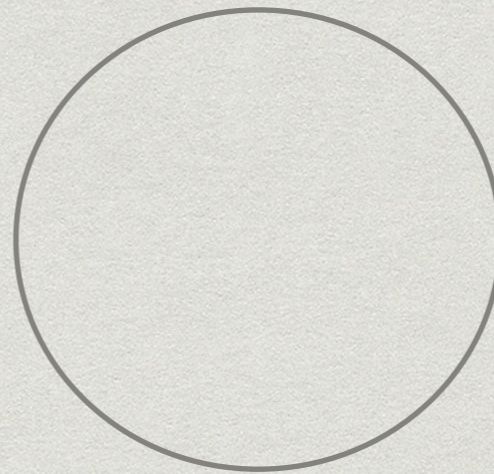
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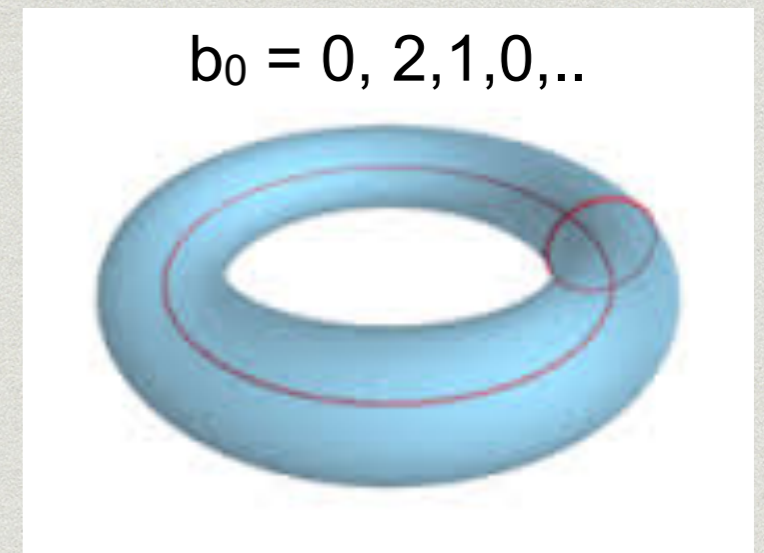
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**Mayer-Vietoris**

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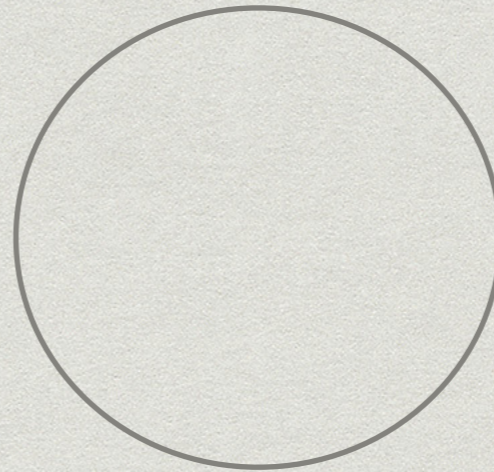
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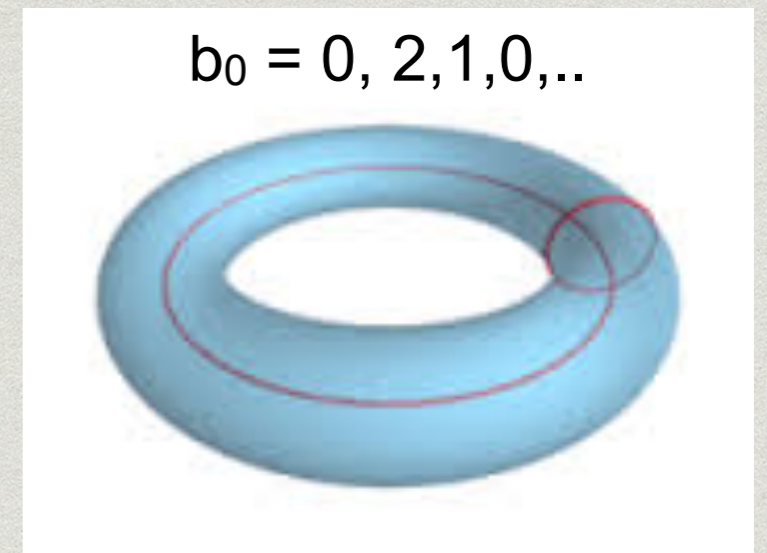
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0-dim result - **M. D. Penrose (1999),**

General k-result - **O. Bobrowski - S. Weinberger (2015),**

d-dim result - **L. Flatto - D. J. Newman (1977), P. Hall (1986).**







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$\sigma = [X_0, \dots, X_k]$  a  $(k + 1)$ -hyper-edge if  $\bigcap_{i=0}^k B_r(X_i) \neq \emptyset$ .



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**Morse theoretic approach** : (Bobrowski - Weinberger, 2015.)

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**Idea** : Threshold for vanishing of isolated  $(k + 1)$ -hyperedges.

Isolation : Intersection of  $(k+1)$ -balls shouldn't be covered by another ball.

**Our conjecture** for  $\beta_1 : n\theta_d r_n^d = \log n - \log \log n$ .







# Combinatorial vs Topological Connectivity



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Bobrowski - Weinberger, 2015.



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For  $\epsilon \in (0, 1)$

$$\mathbb{P}(\beta_k(C_n(r_n)) = \binom{d}{k}) \rightarrow \begin{cases} 0 & \text{if } n\theta_d r_n^d = (1 - \epsilon) \log n \\ 1 & \text{if } n\theta_d r_n^d = (1 + \epsilon) \log n \end{cases}$$



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**Why should we expect  $\log n$  ?**

**Is the threshold for homotopy equivalence sharp ?**

**Can we infer the topology partially earlier OR  
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**Other topological summaries ?**



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**Other topological summaries ?**



## **Other topological summaries ?**

“We should seek out unfamiliar summaries of observational material,  
and establish their useful properties.”

- **John W. Tukey**, “The future of data analysis”, Ann. Math. Stat., 1962.



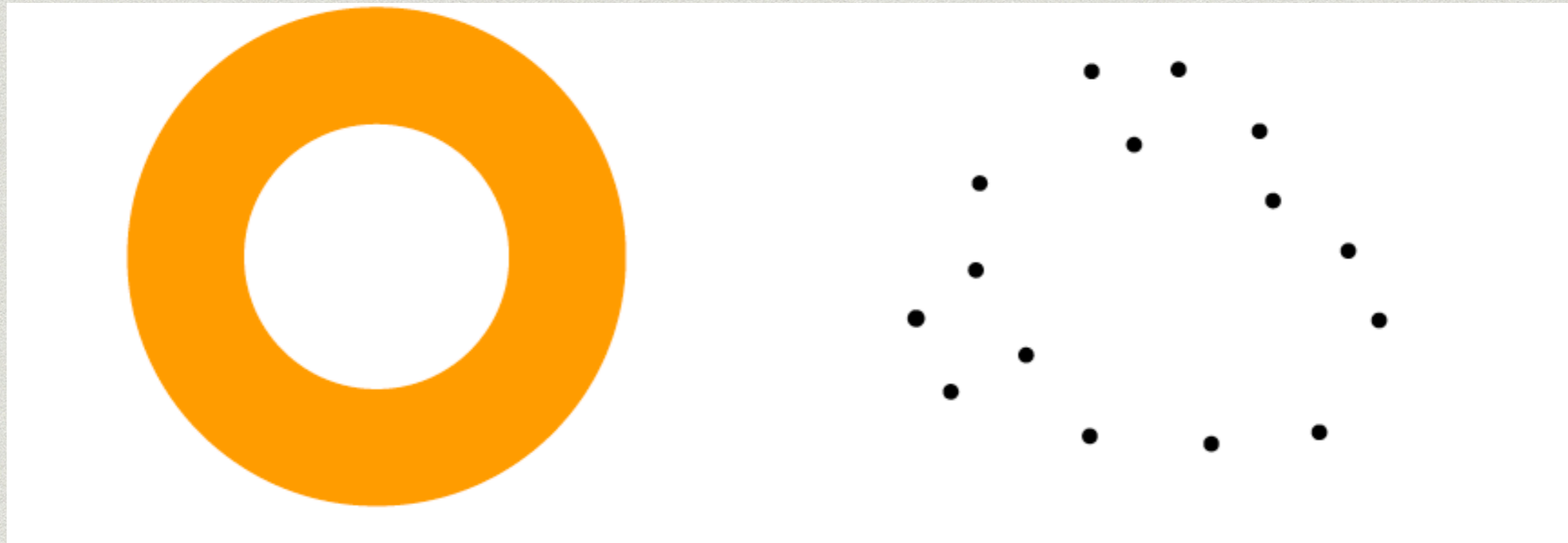




# Evolution of Topology

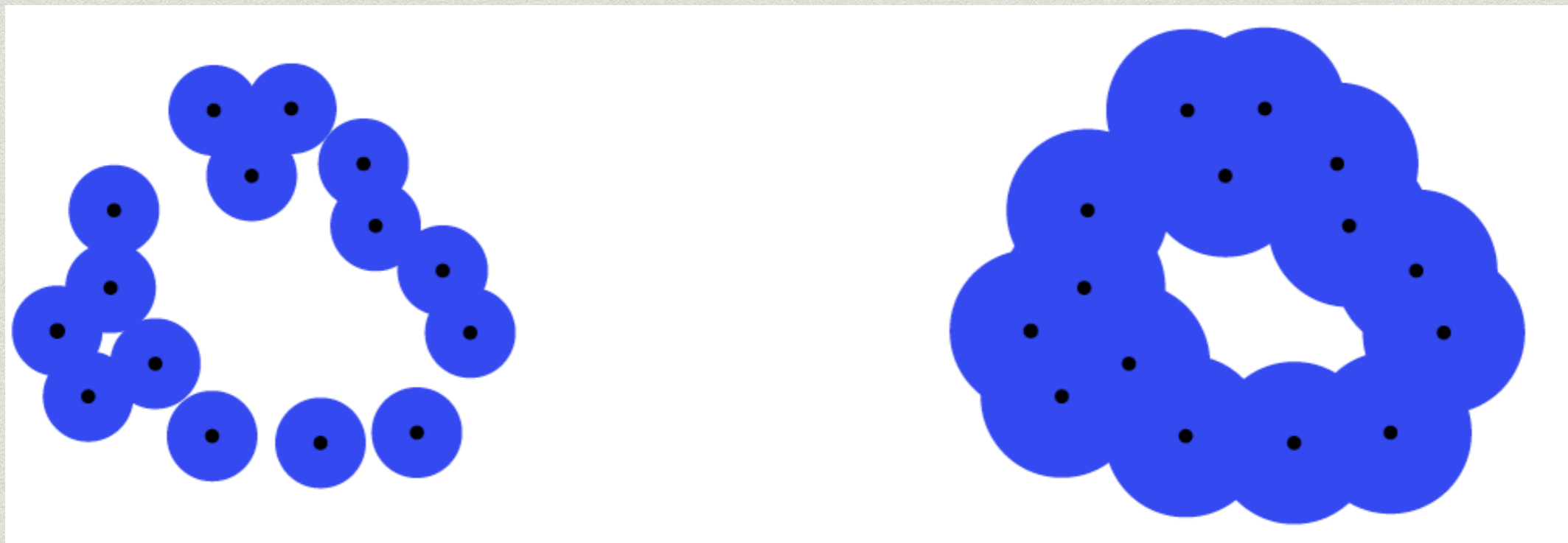
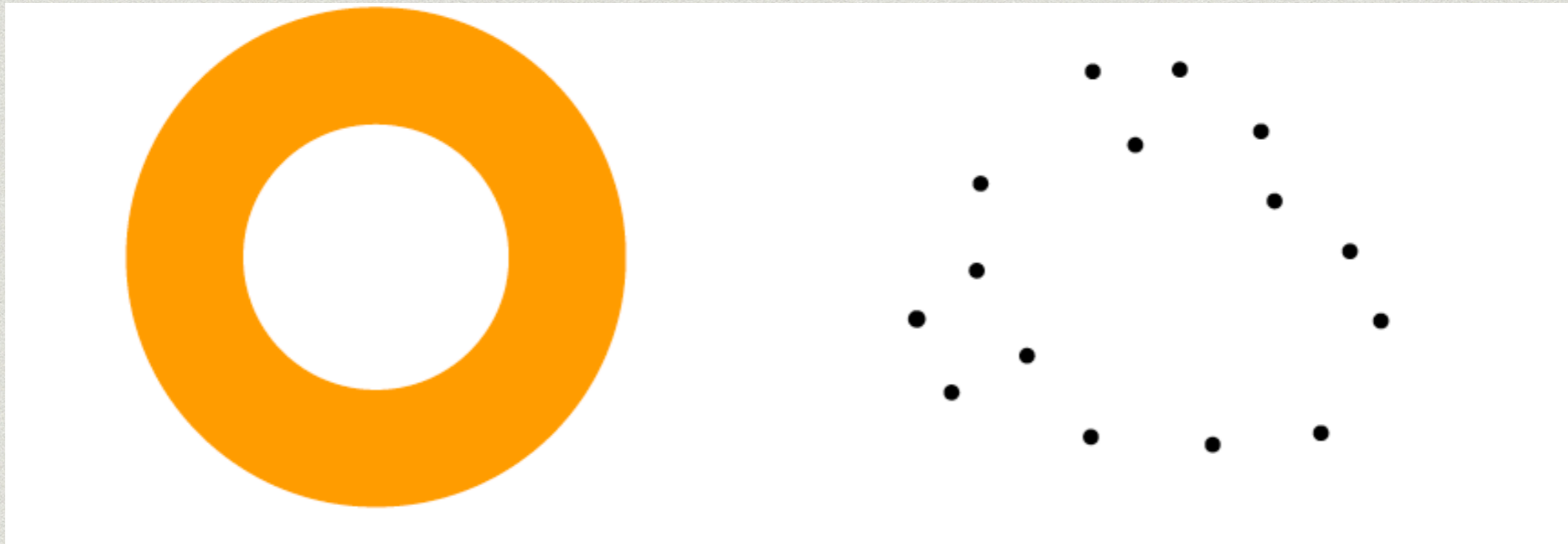


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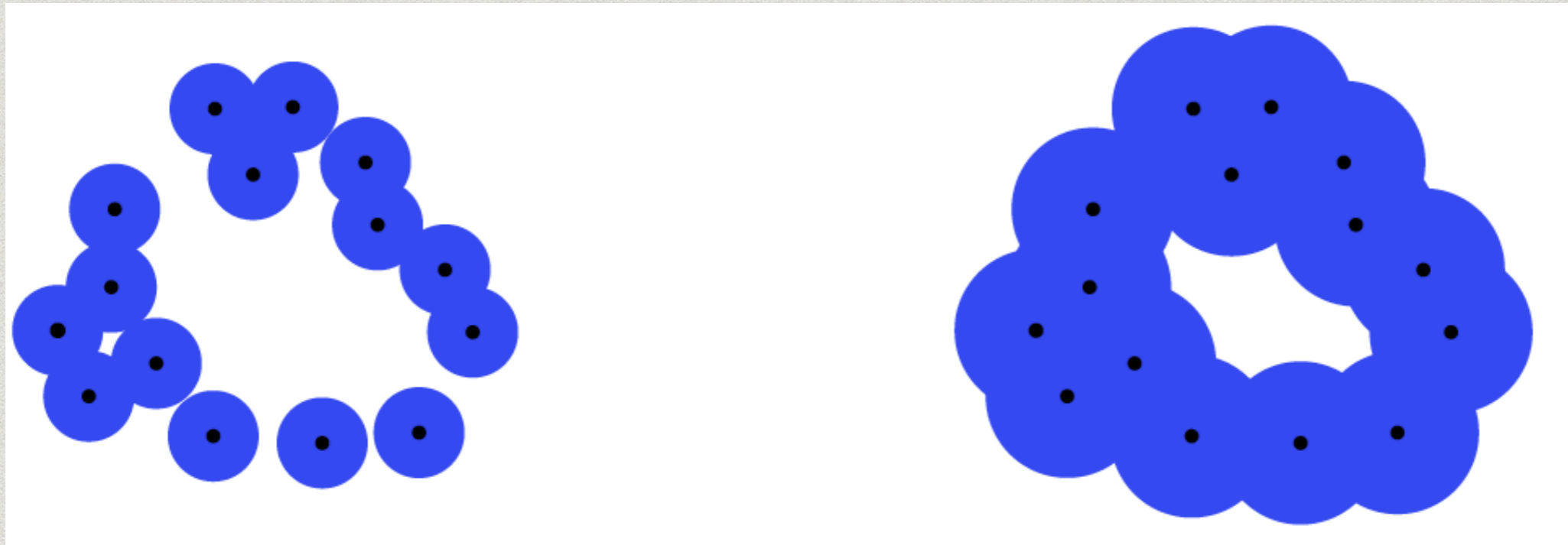




# PERSISTENT HOMOLOGY / DIAGRAMS

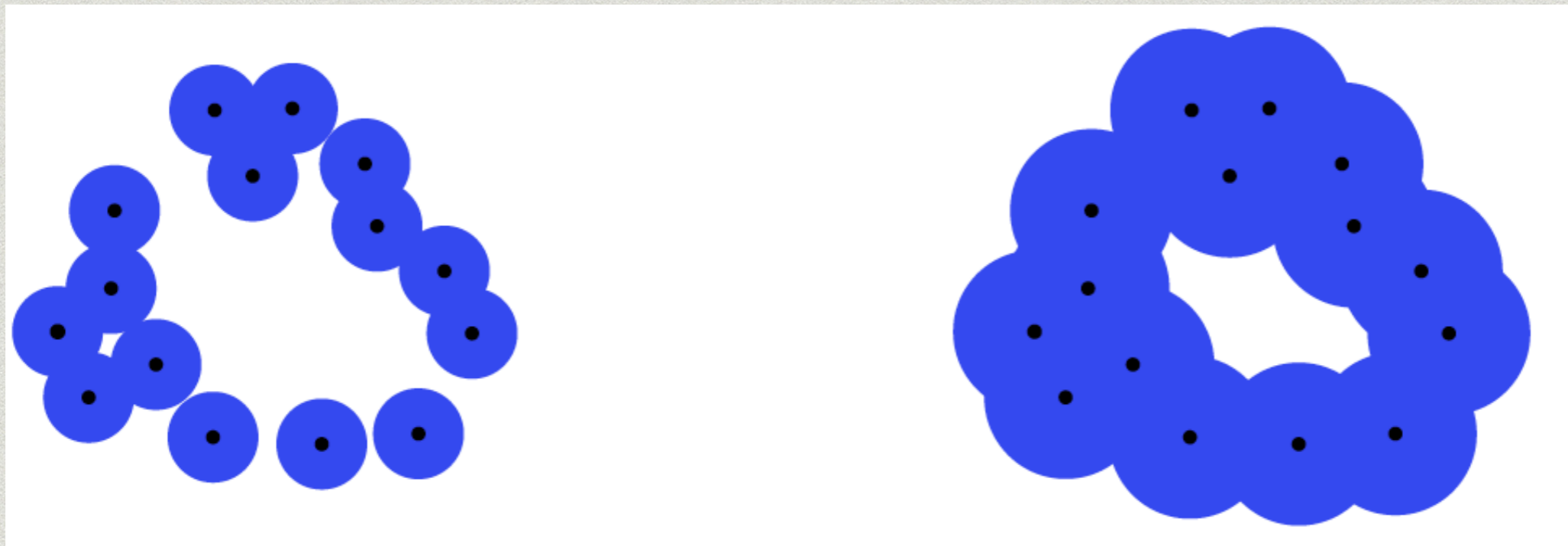


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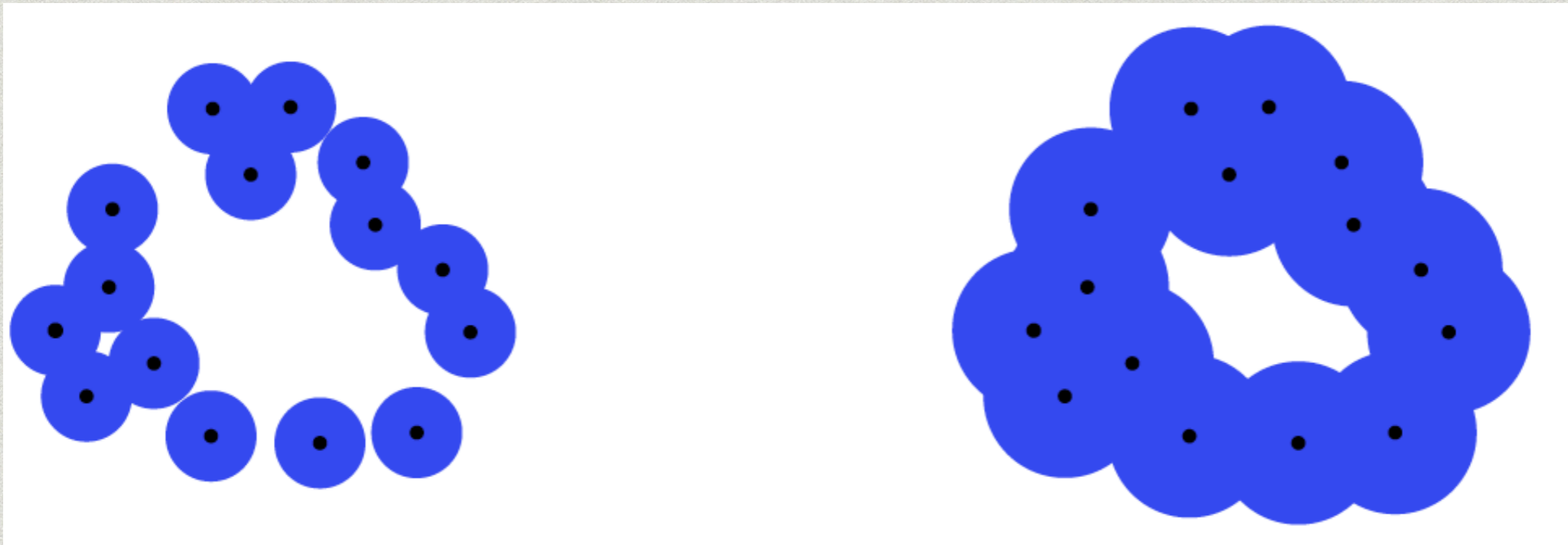


**H<sub>0</sub> Persistence diagram**

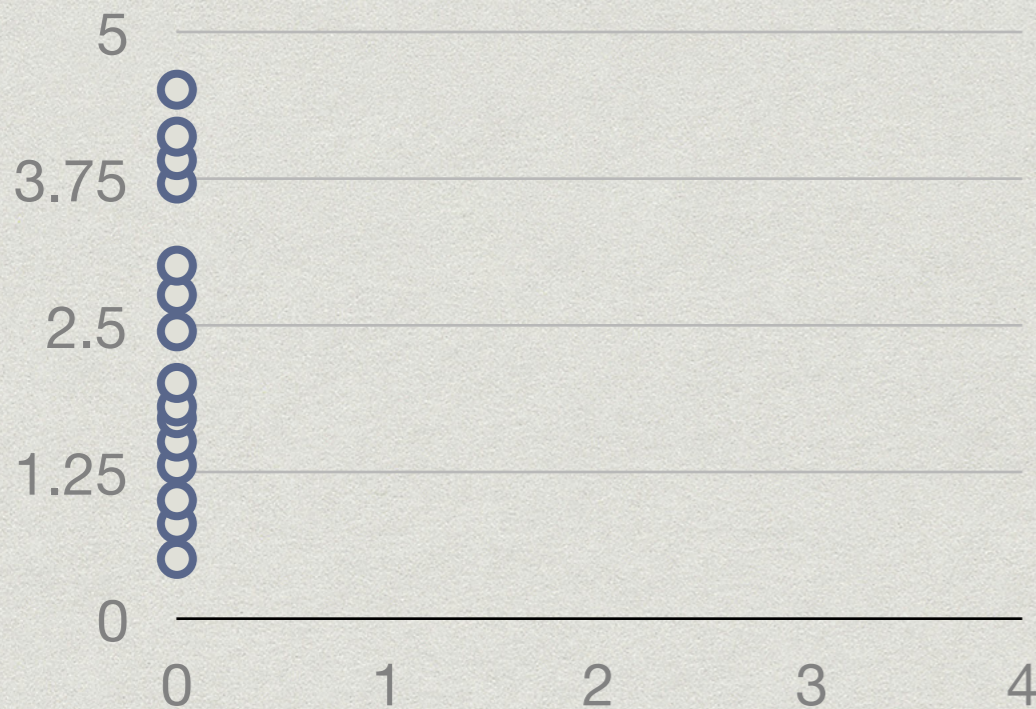




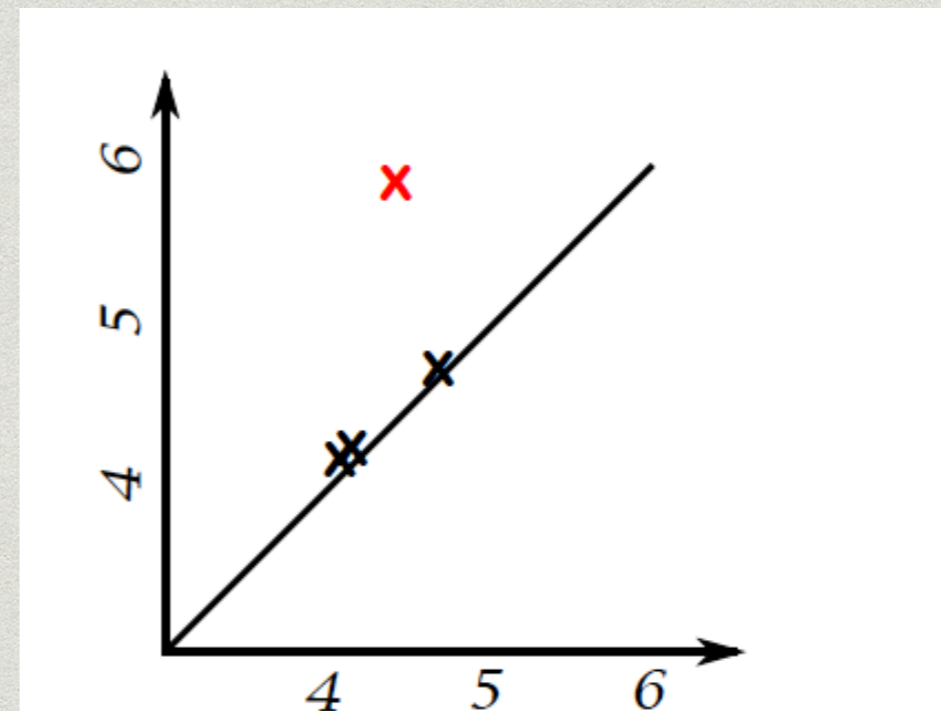
# PERSISTENT HOMOLOGY / DIAGRAMS



**H<sub>0</sub> Persistence diagram**



**H<sub>1</sub> Persistence diagram**









# H<sub>0</sub> Persistence diagram

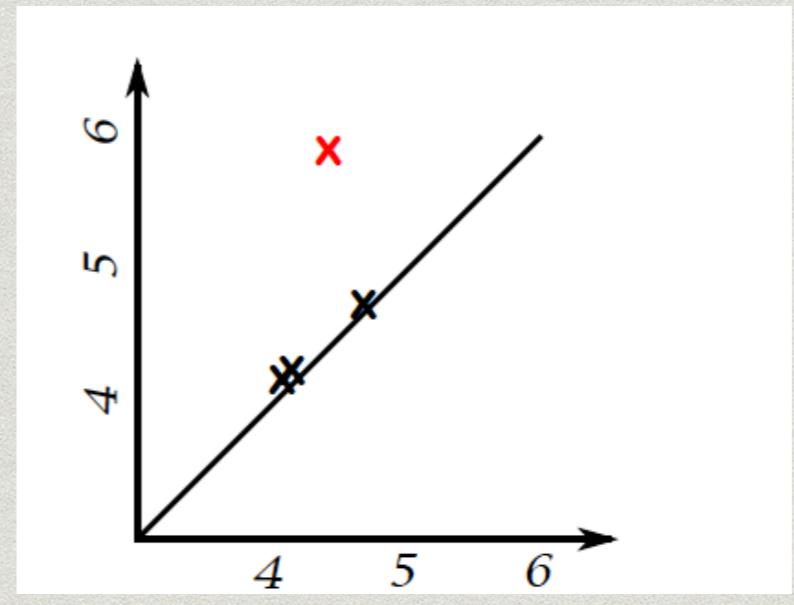




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# H<sub>1</sub> Persistence diagram

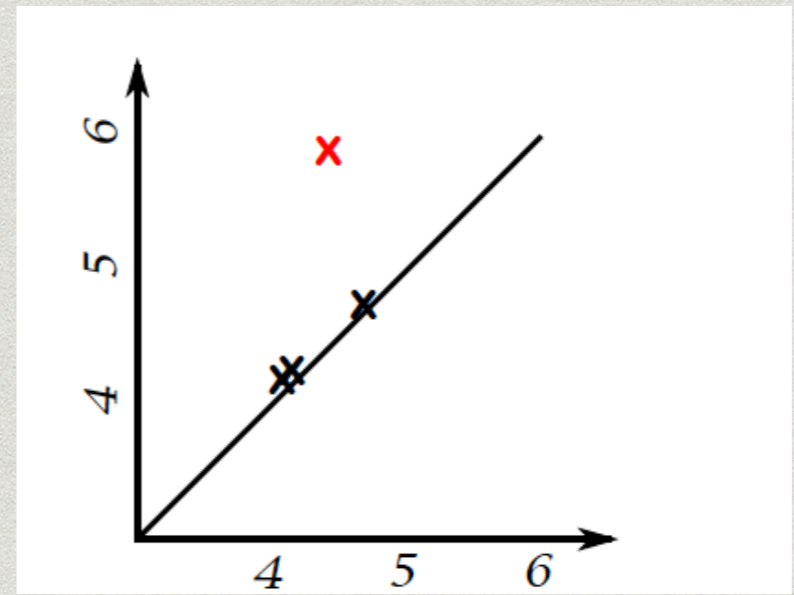




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## H<sub>1</sub> Persistence diagram



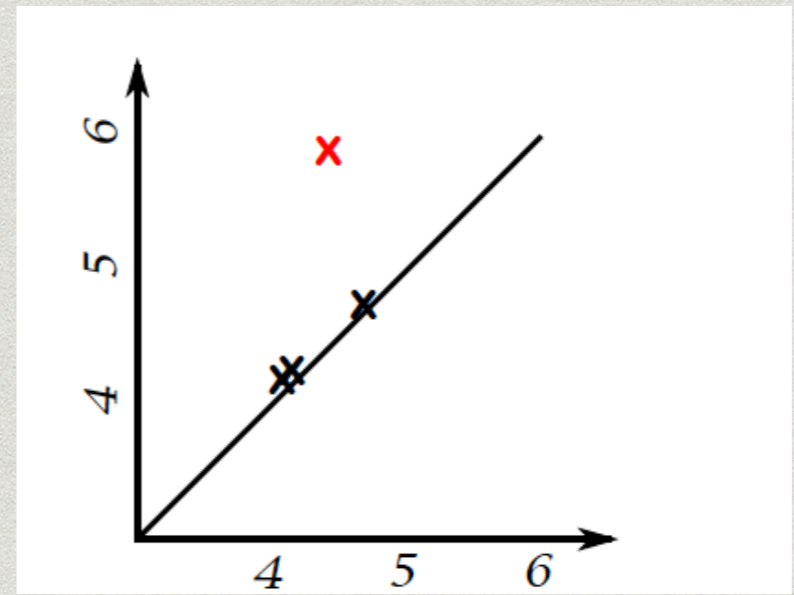
$$\mathcal{PD}_k := \{(b_i, d_i)\} \subset \{(x, y) : 0 \leq x \leq y\}.$$



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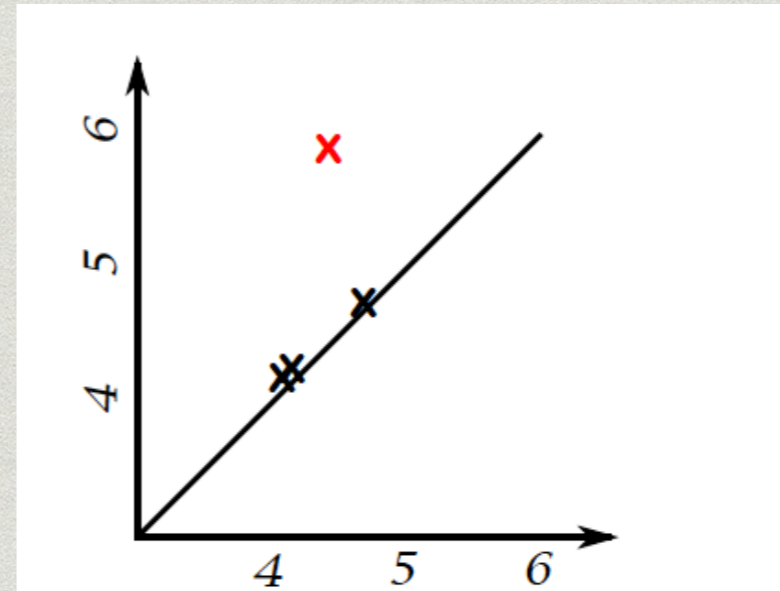
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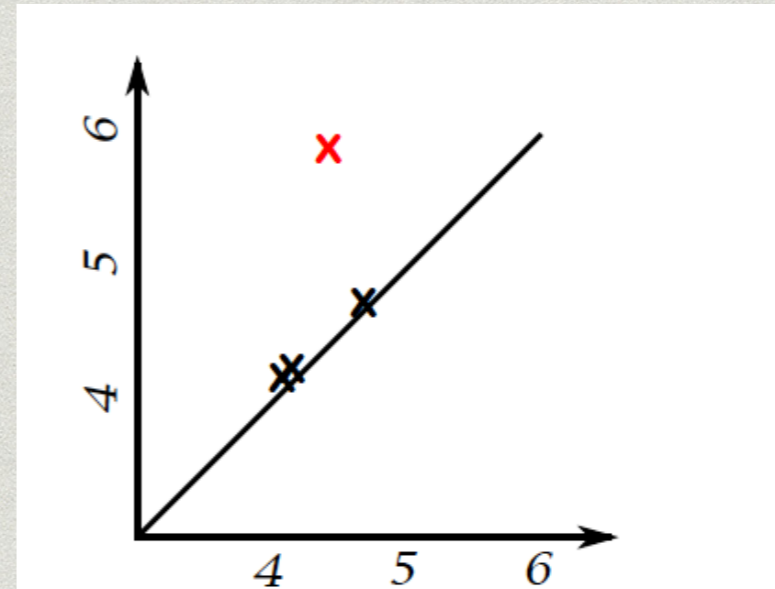
Birth times:  $\mathcal{B}_k = \{b_i\} \subset \mathbb{R}_+$ . Death times:  $\mathcal{D}_k = \{d_i\} \subset \mathbb{R}_+$ .



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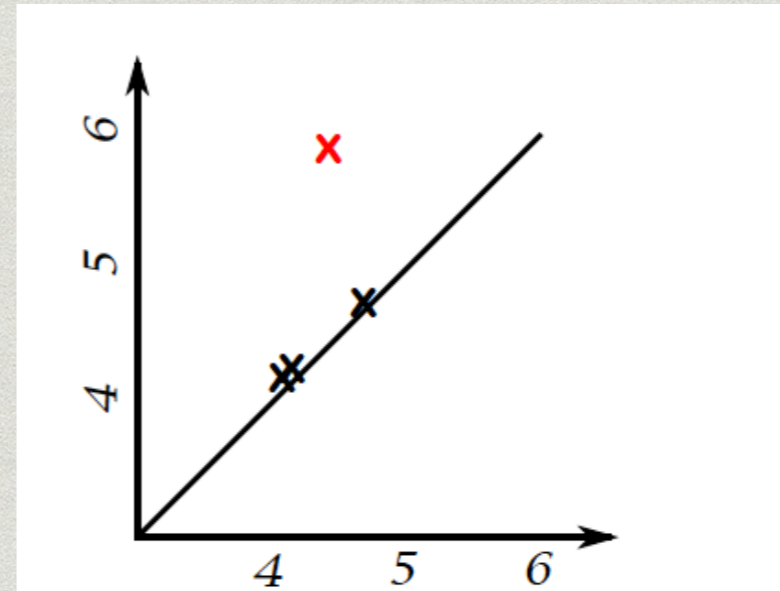
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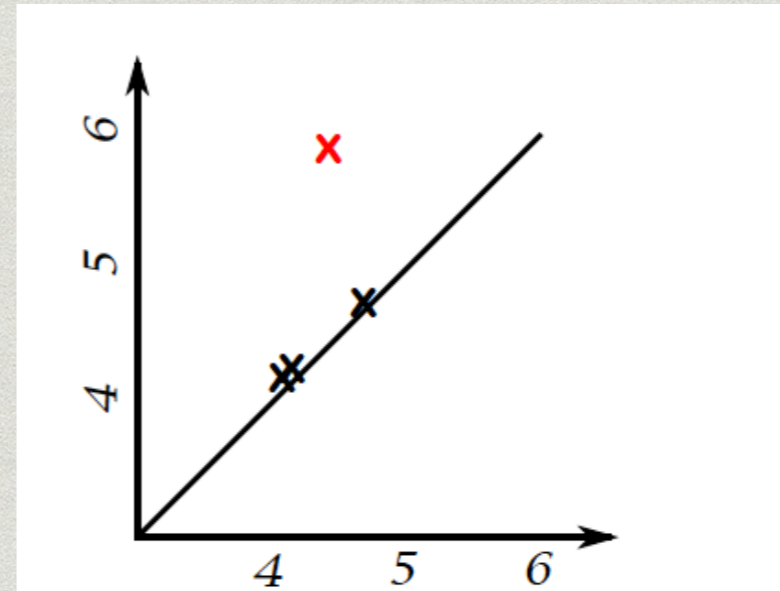
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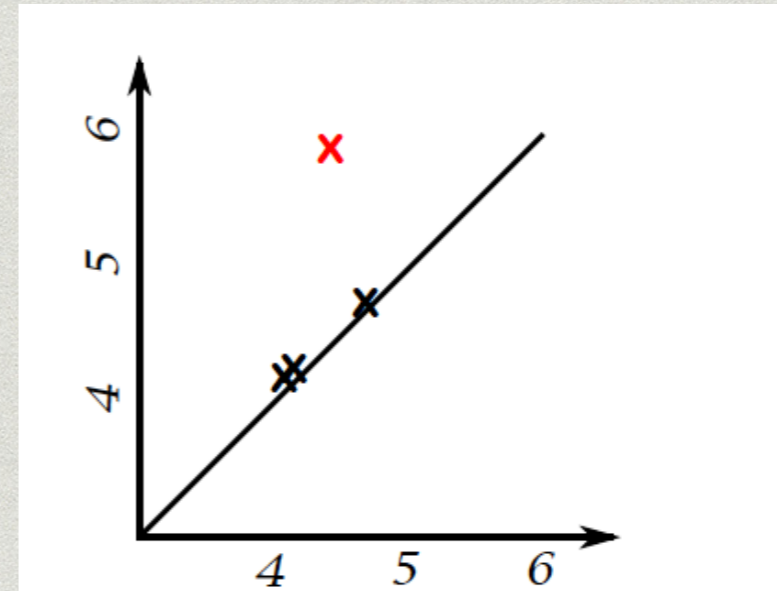
Persistent Betti Number :  $\beta_k(C_n(r, s)) = \sum_i 1[b_i \leq r \leq s < d_i]$



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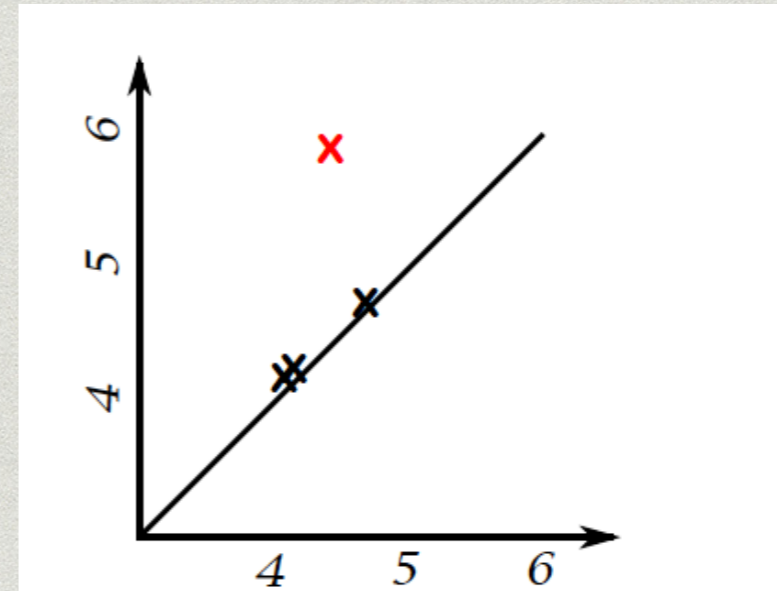
Lifetime sum :  $L_{n,1} := \sum_i (d_i - b_i) = \int_0^\infty \beta_k(r) dr$



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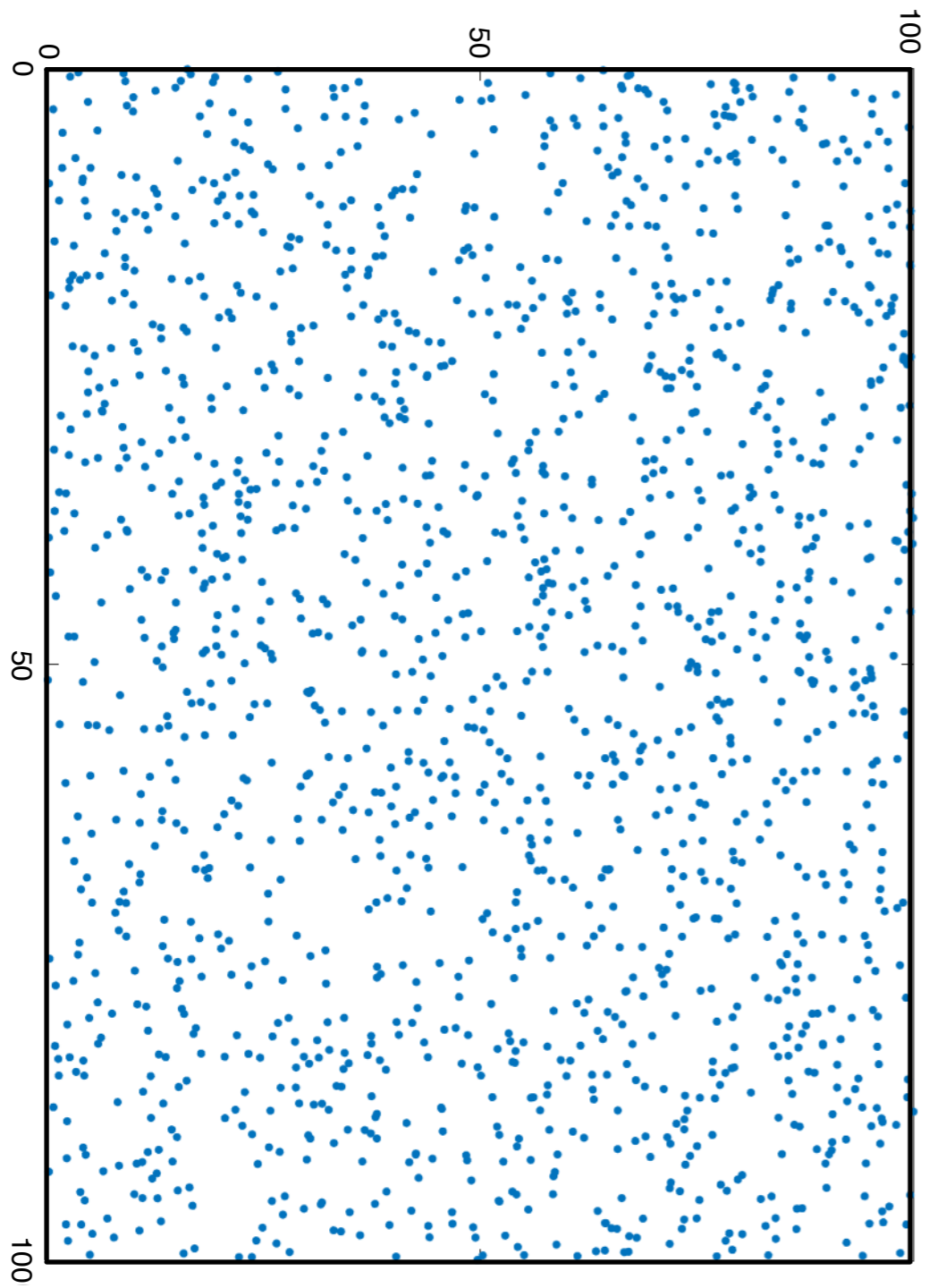






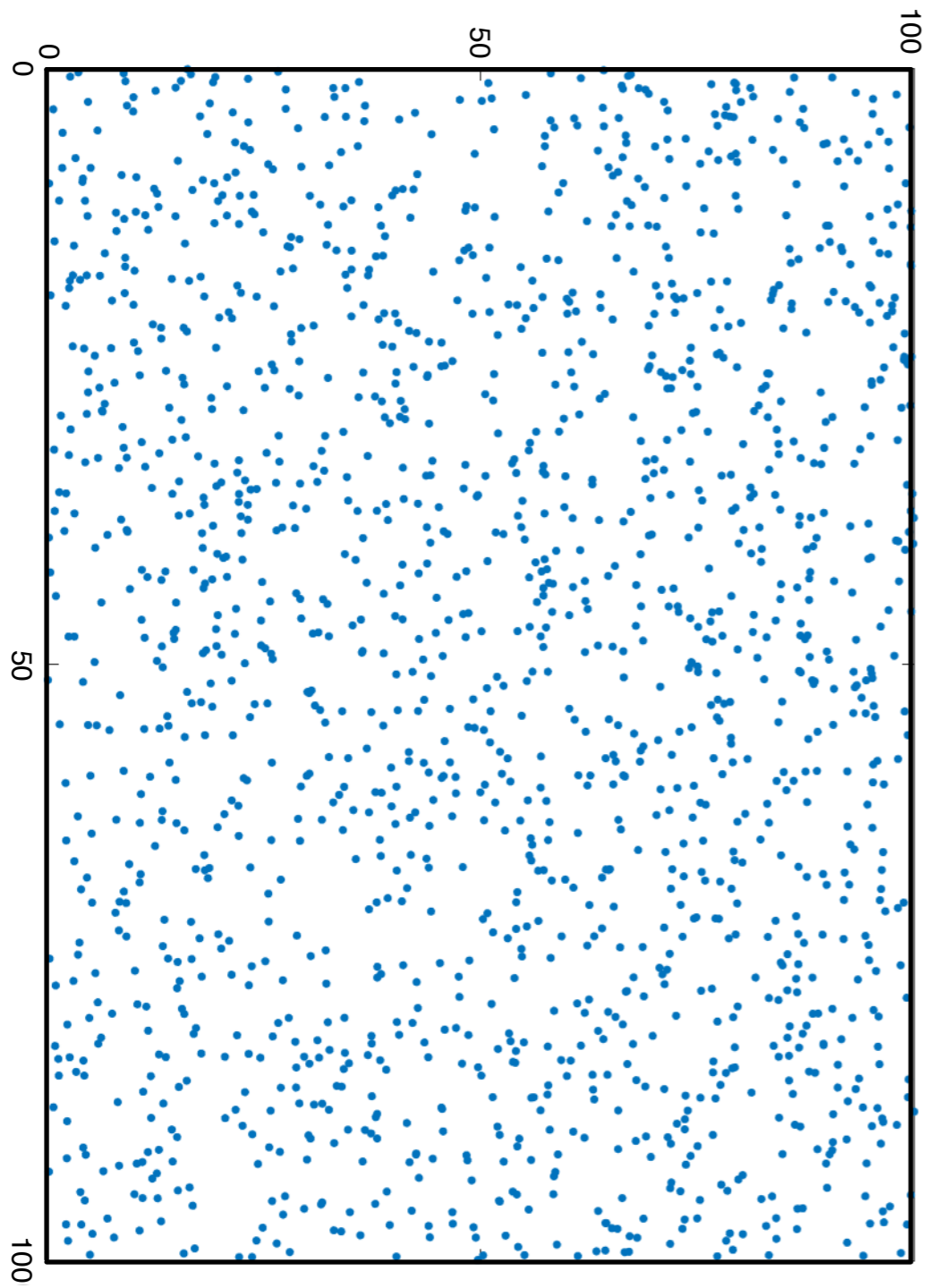
**Figures from Duy, Hiraoka and Shirai.**





Figures from Duy, Hiraoka and Shirai.

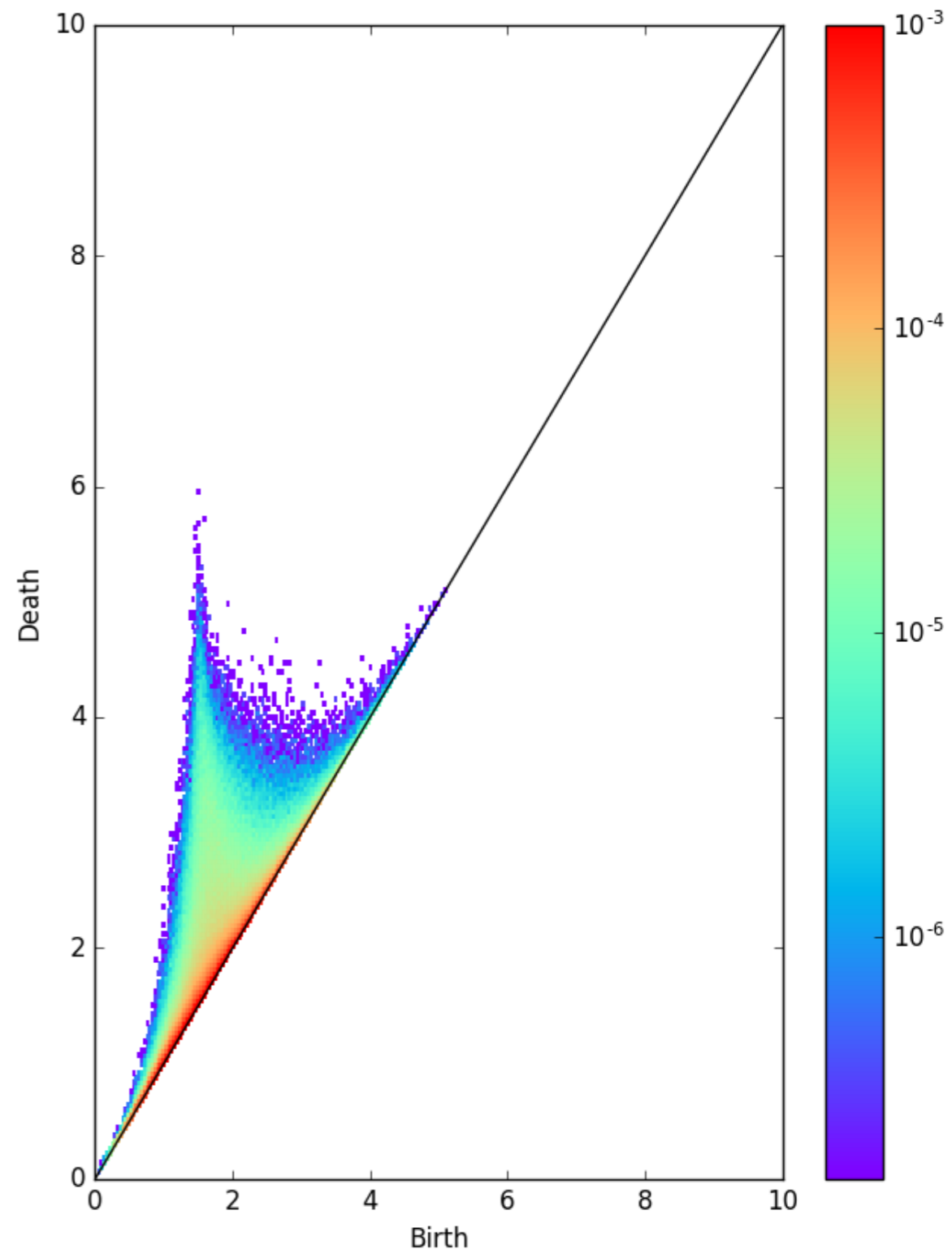
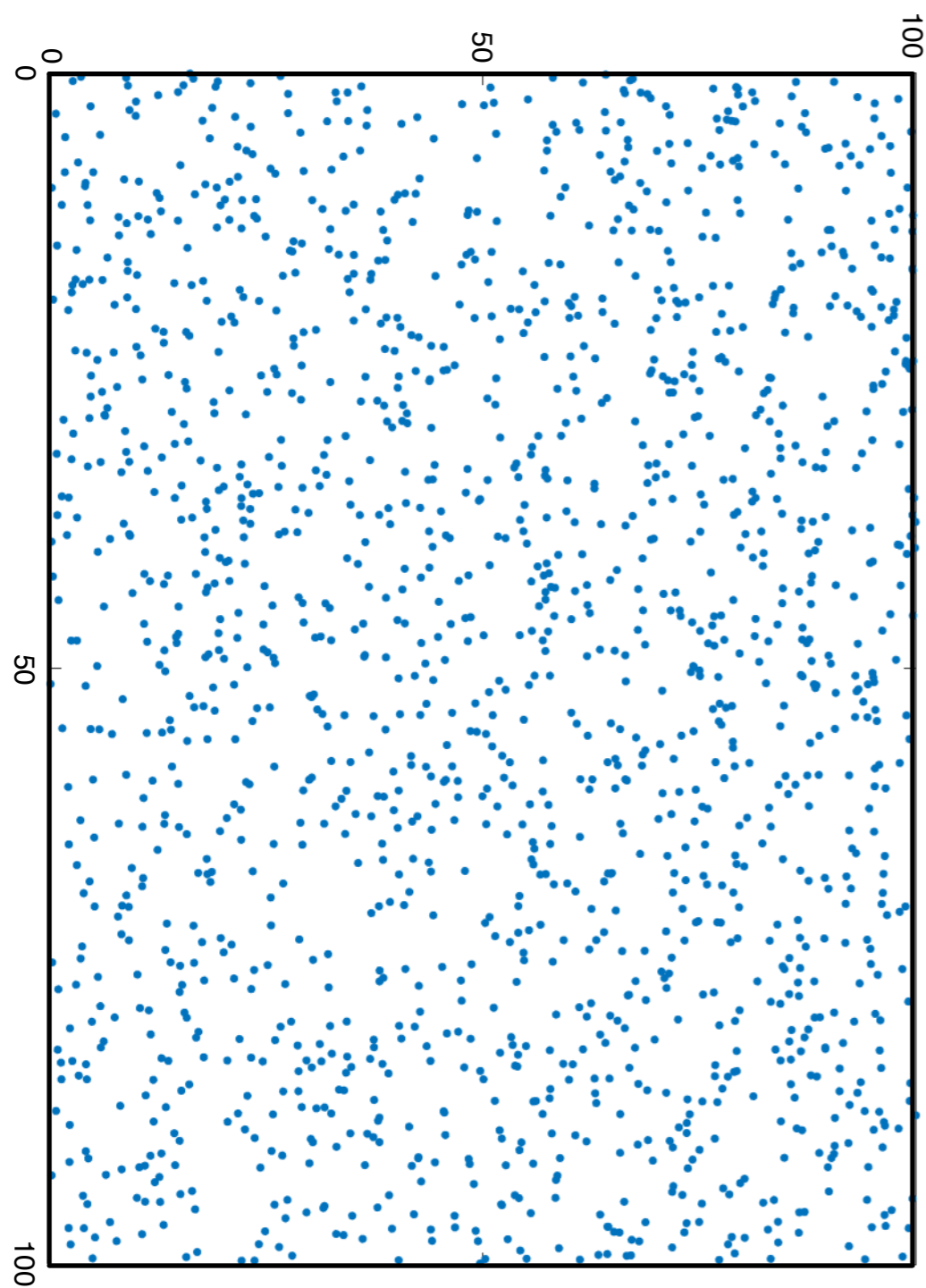




$\mathcal{P}_n$

Figures from Duy, Hiraoka and Shirai.

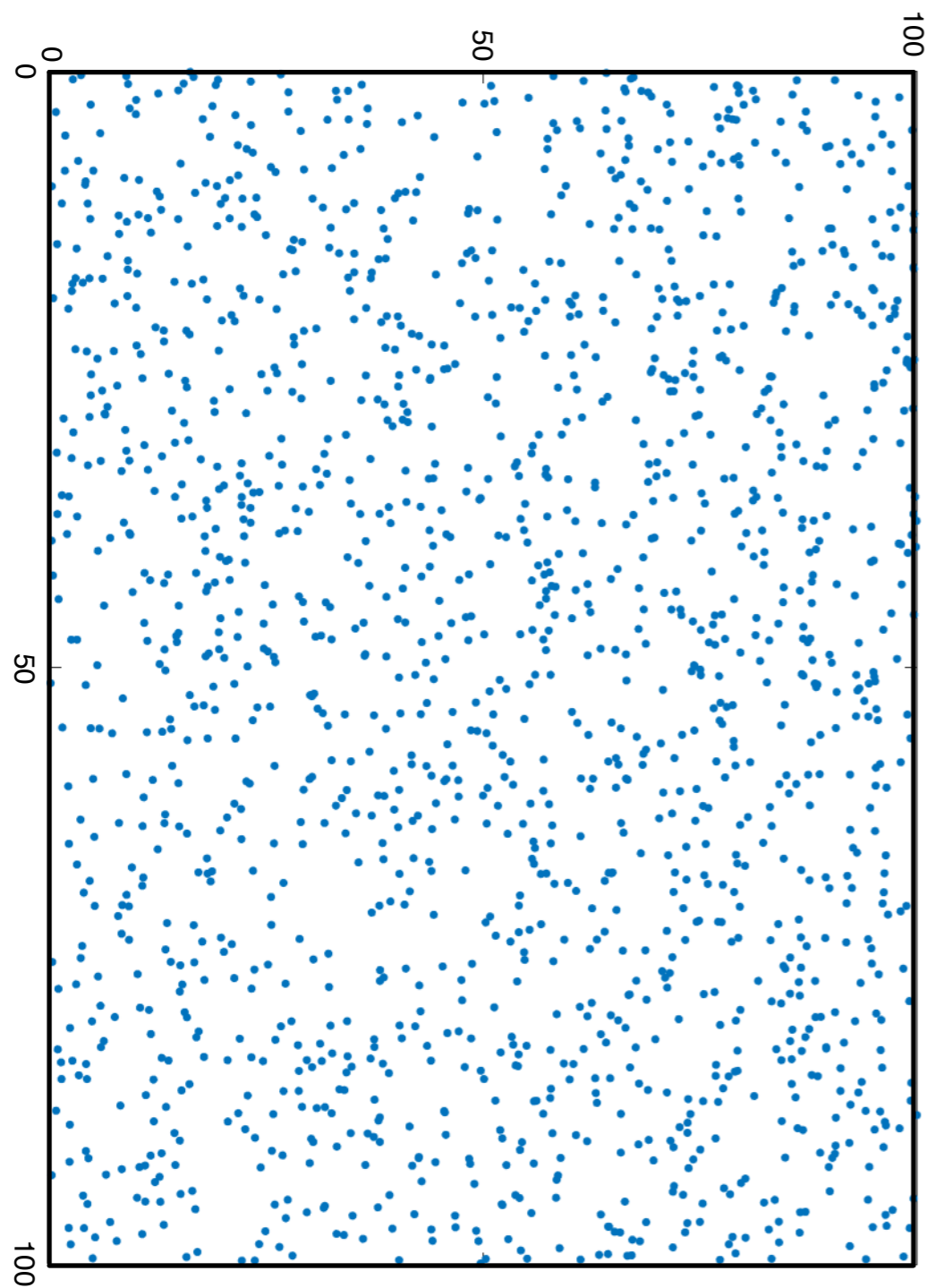




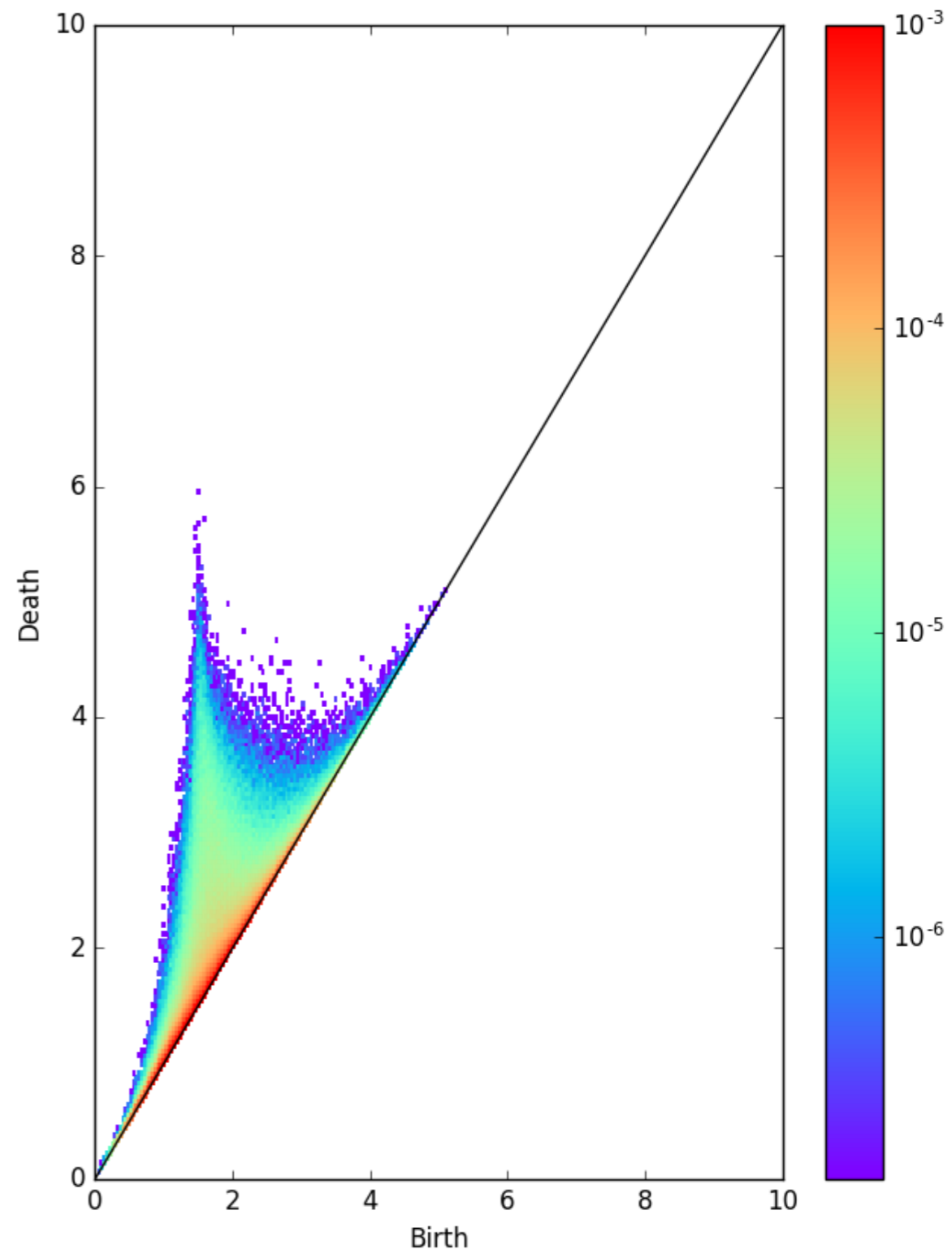
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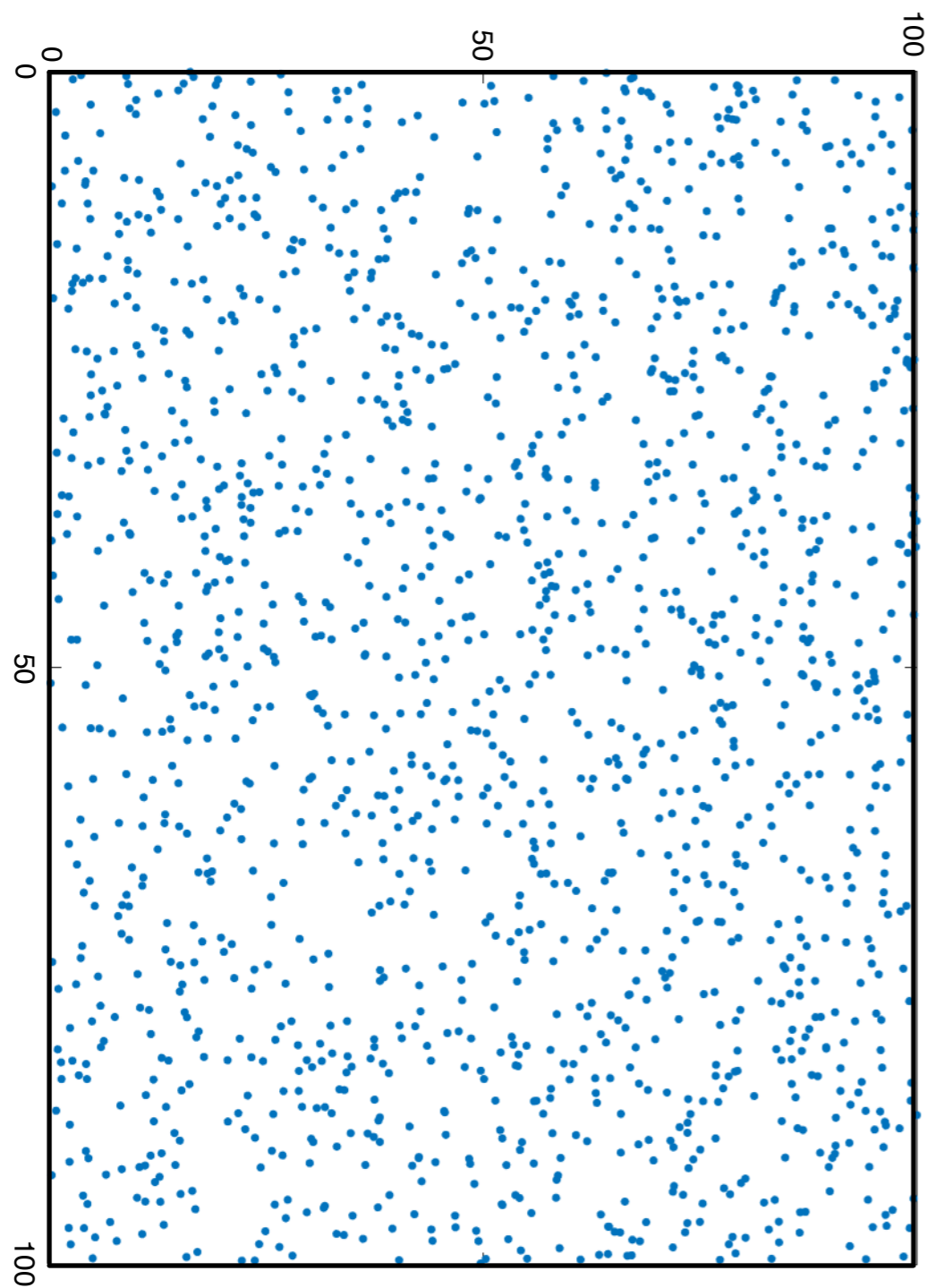


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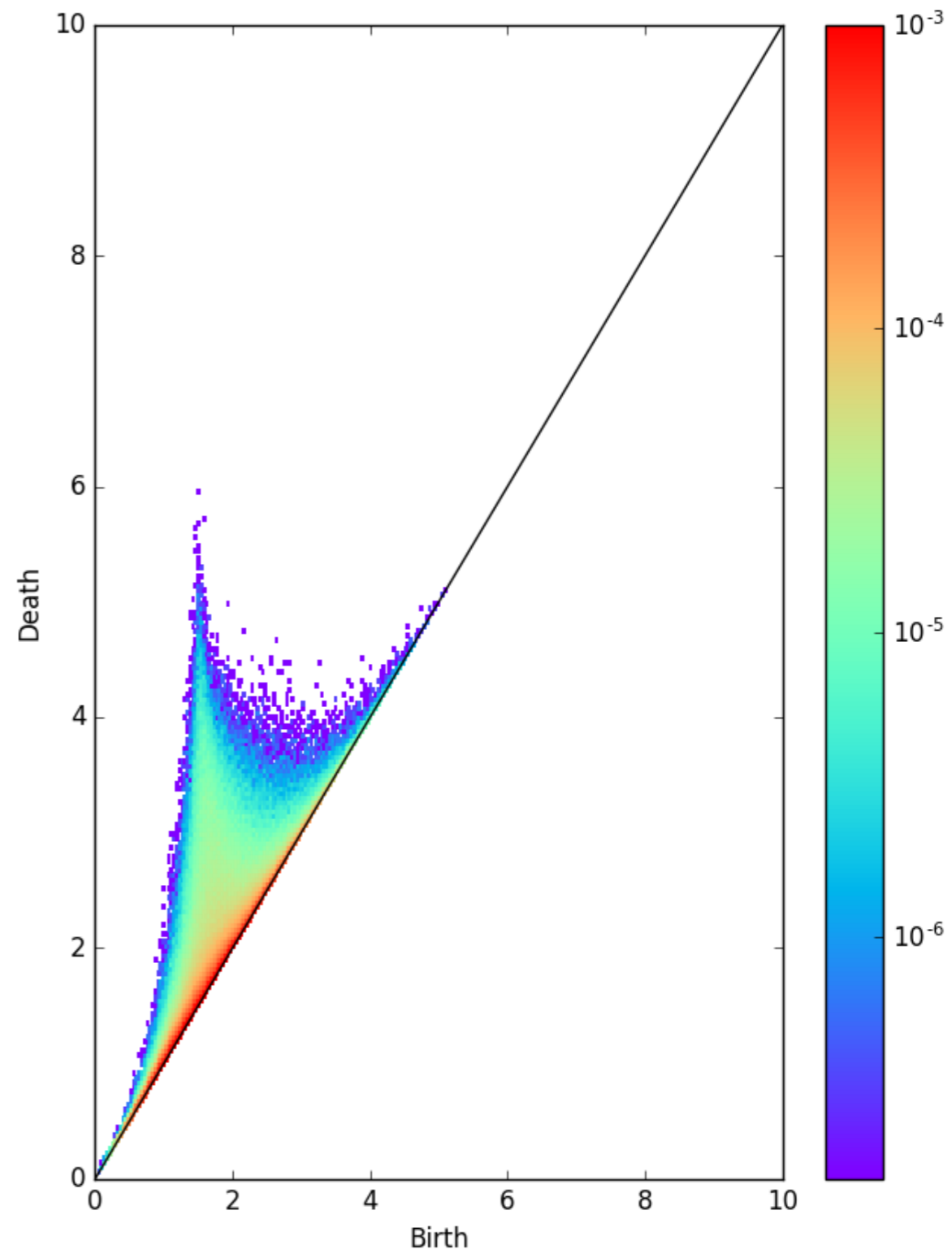


Density plot of  $\frac{\mathcal{PD}_1(n^{-1/2}.)}{n}$





$\mathcal{P}_n$



Density plot of  $\frac{\mathcal{PD}_1(n^{-1/2})}{n}$







# Betti Number



## Betti Number

## Persistent Betti Number



## Betti Number

Non-trivial cycles/holes at radius  $r$ .

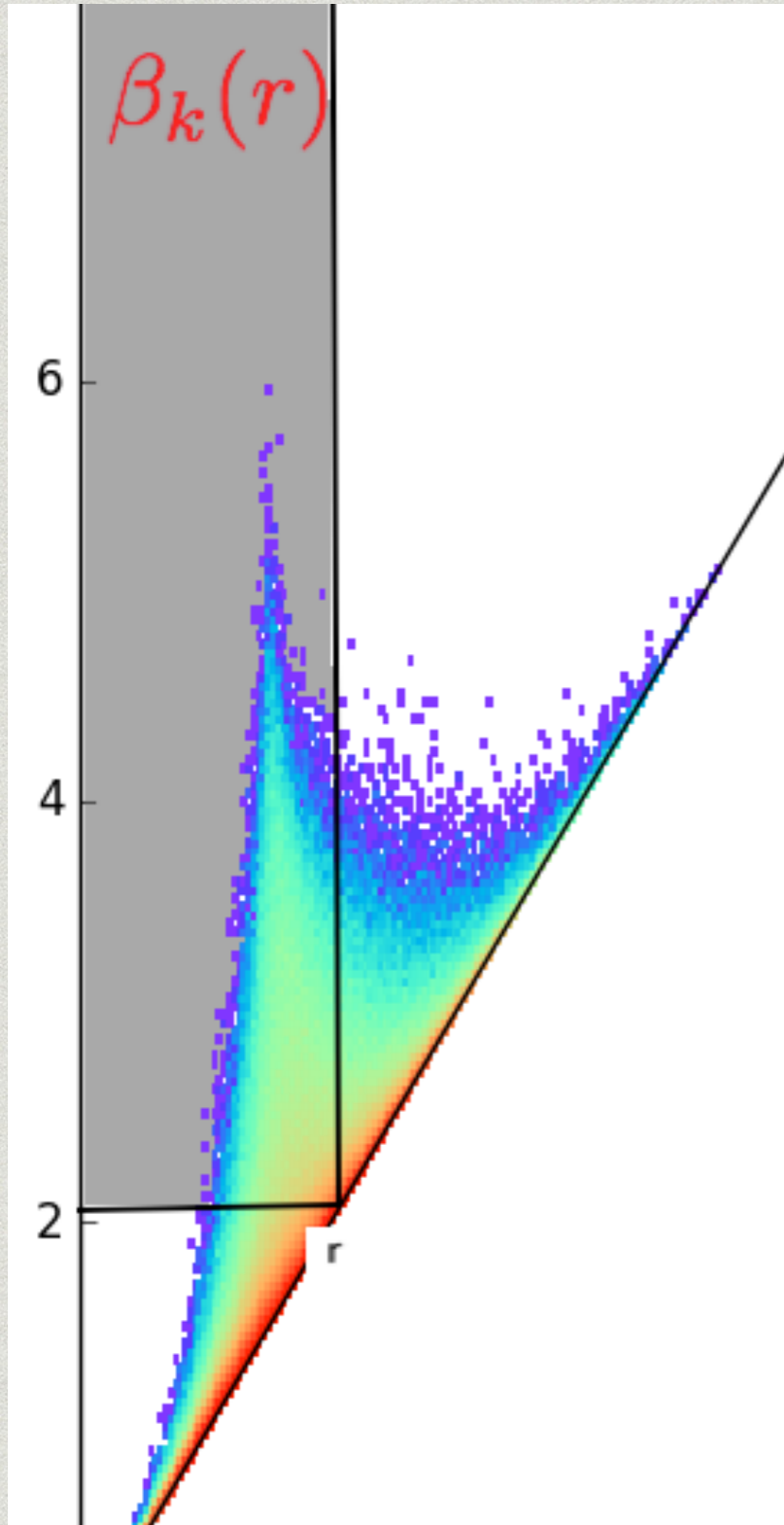
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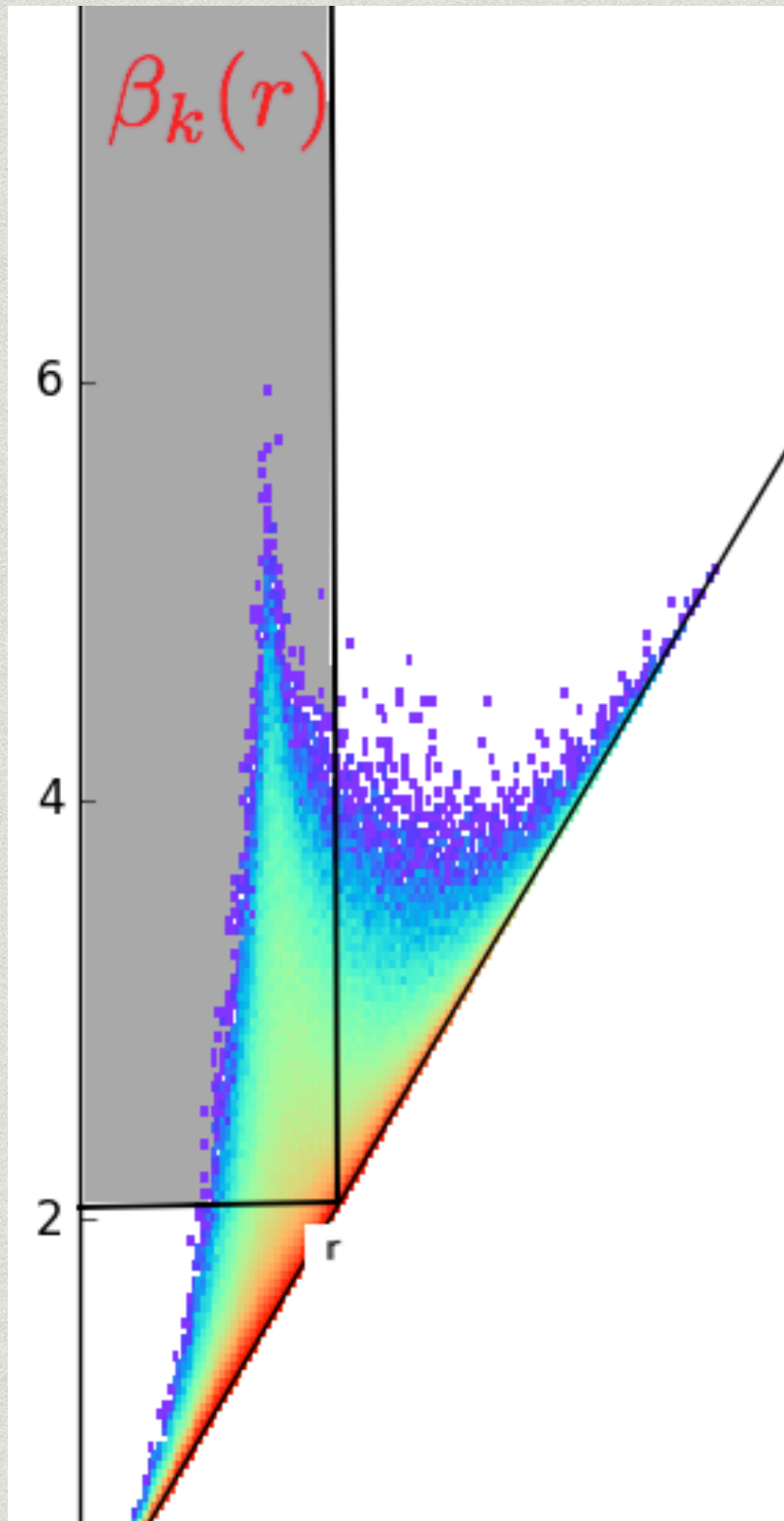
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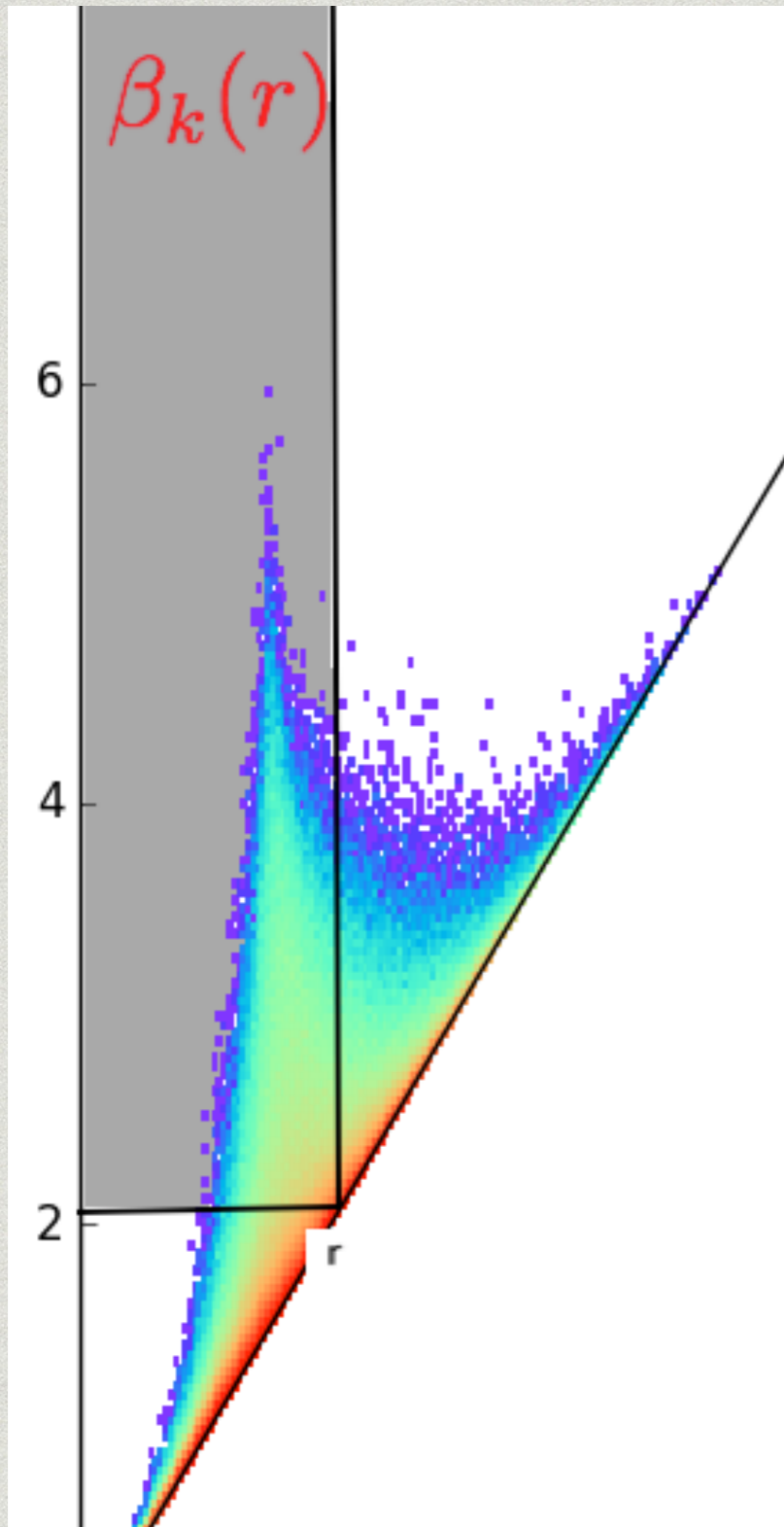
Non-trivial cycles/holes that persist from  $r$  to  $s$ .

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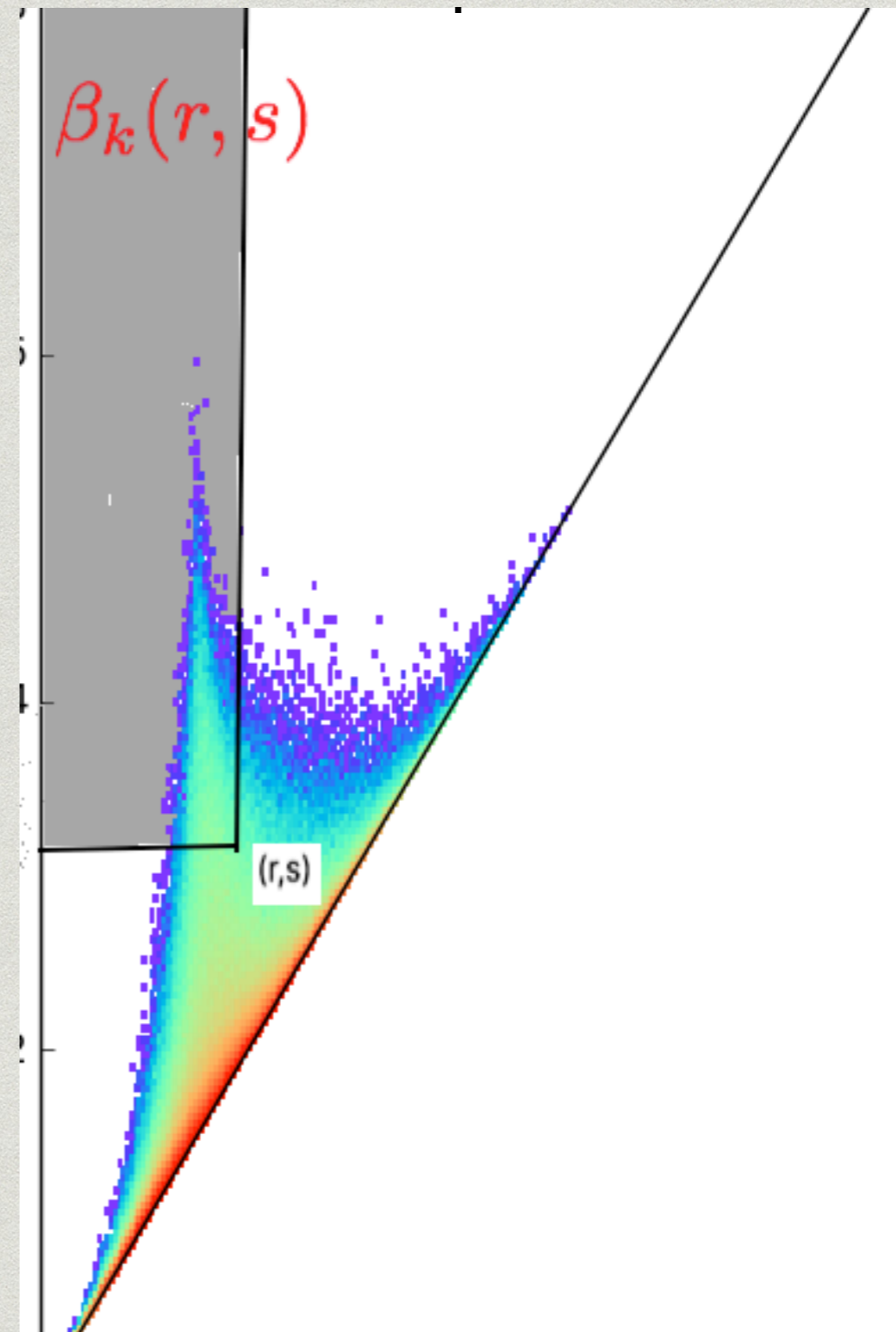
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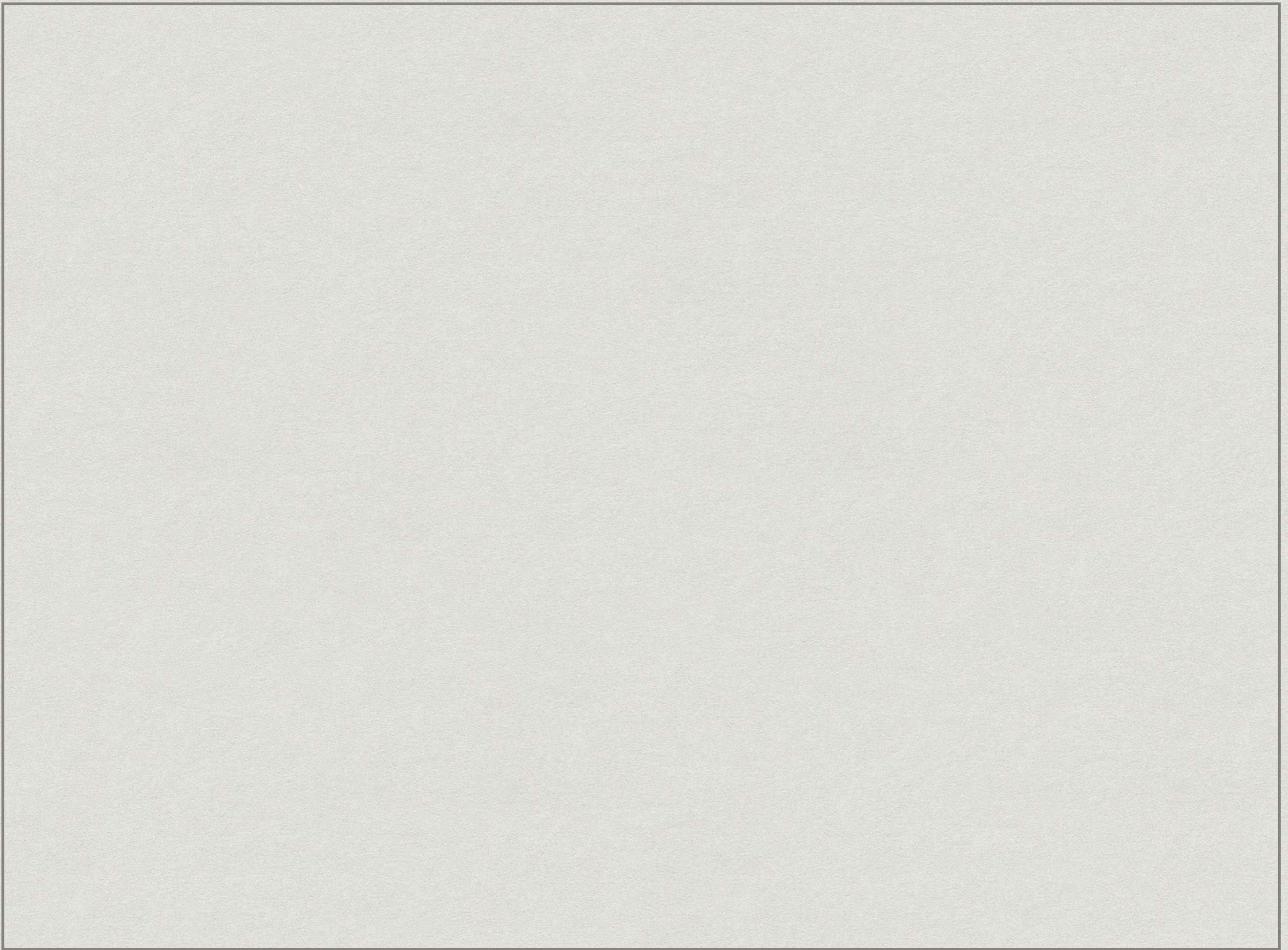


## Persistent Betti Number

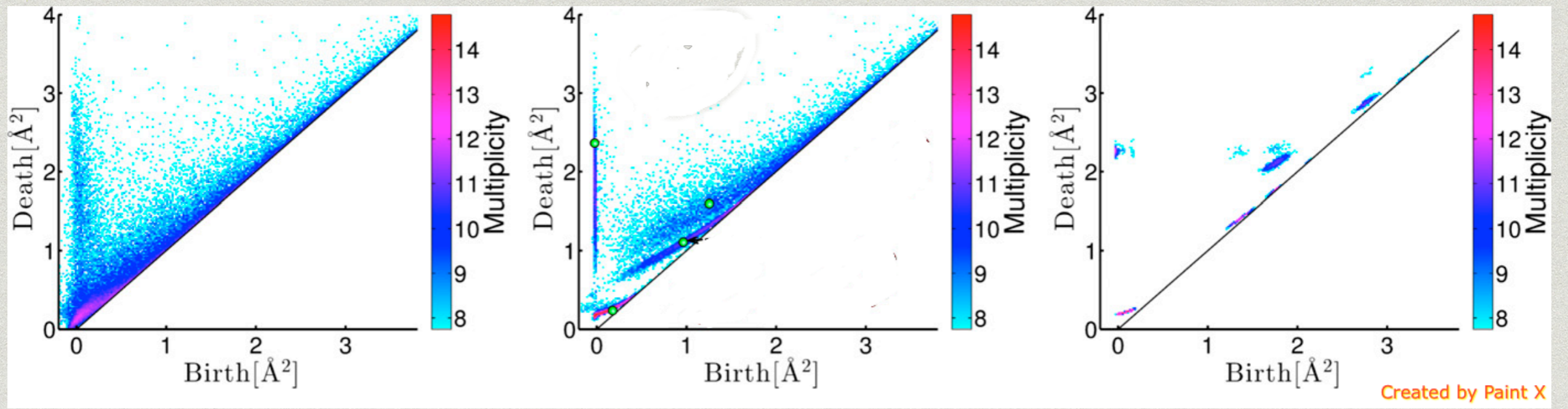
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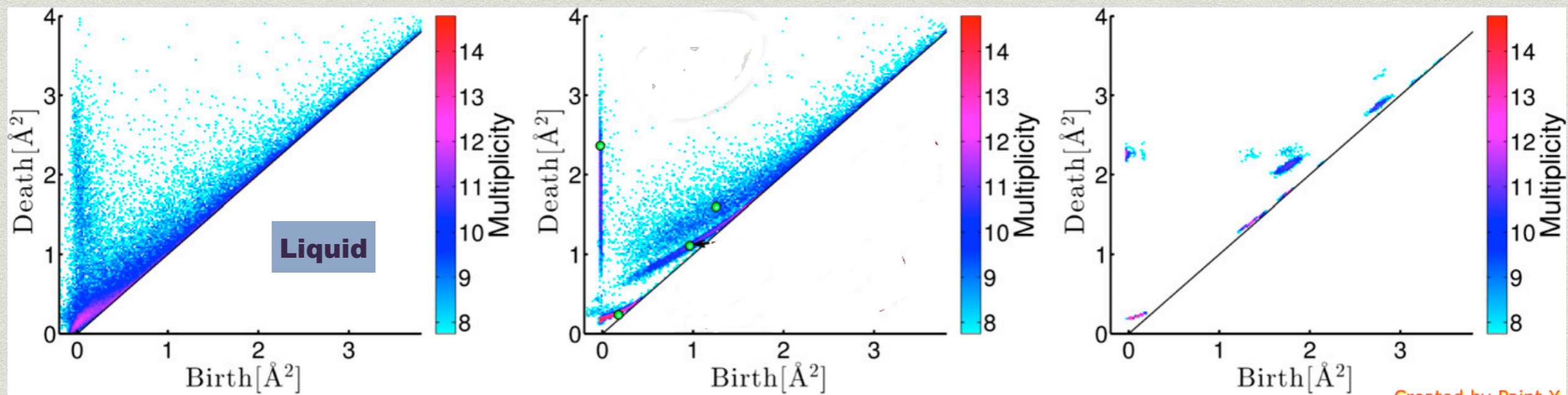




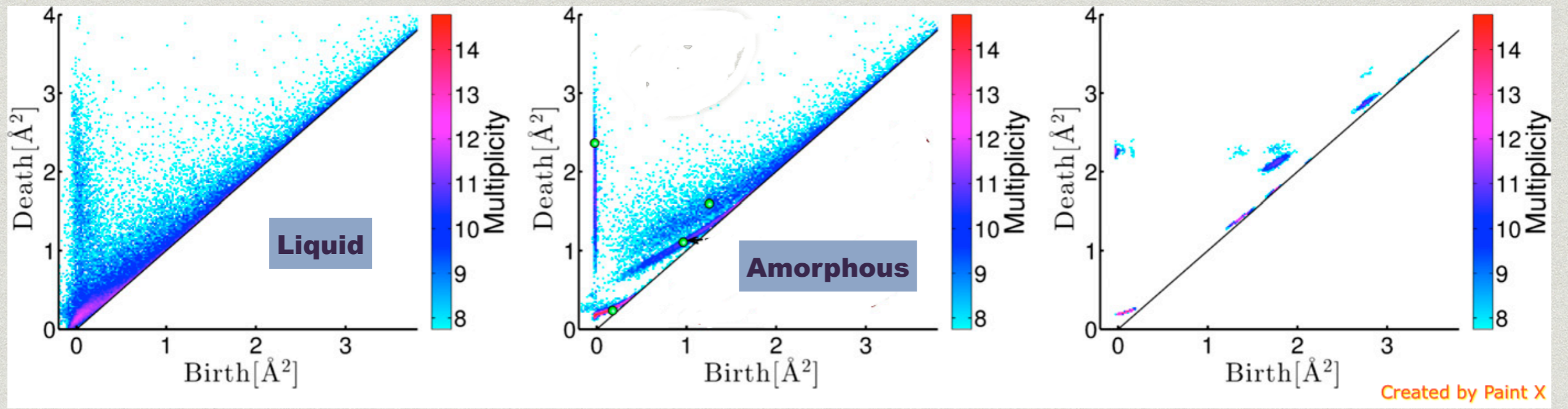




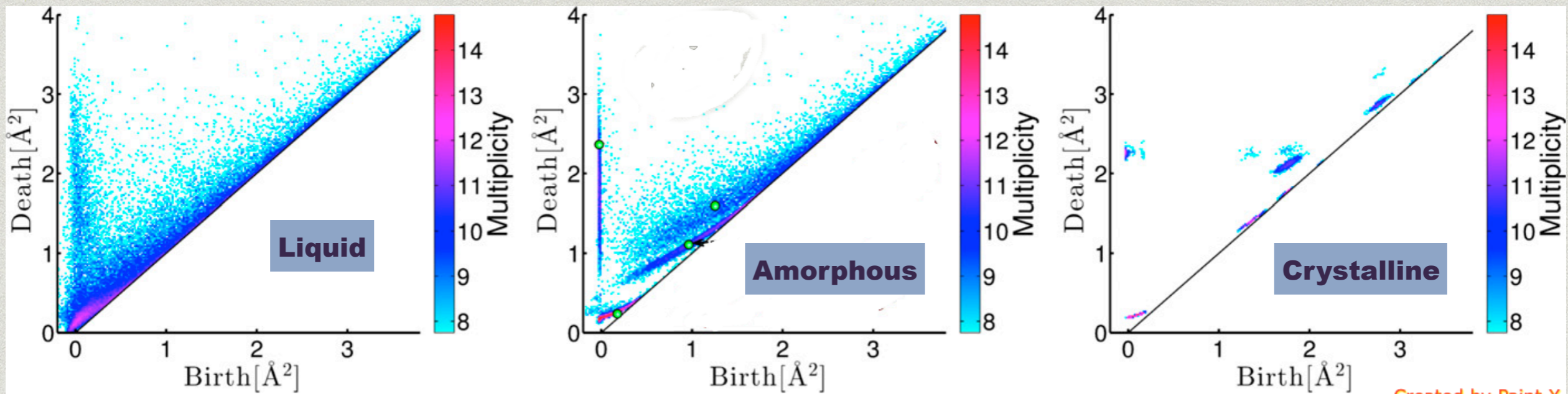






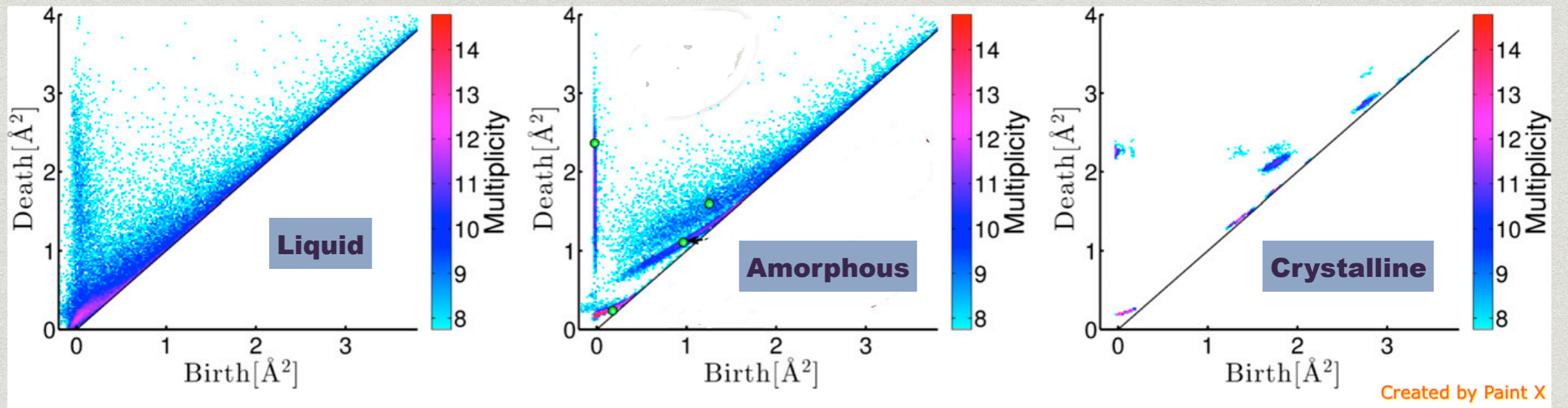






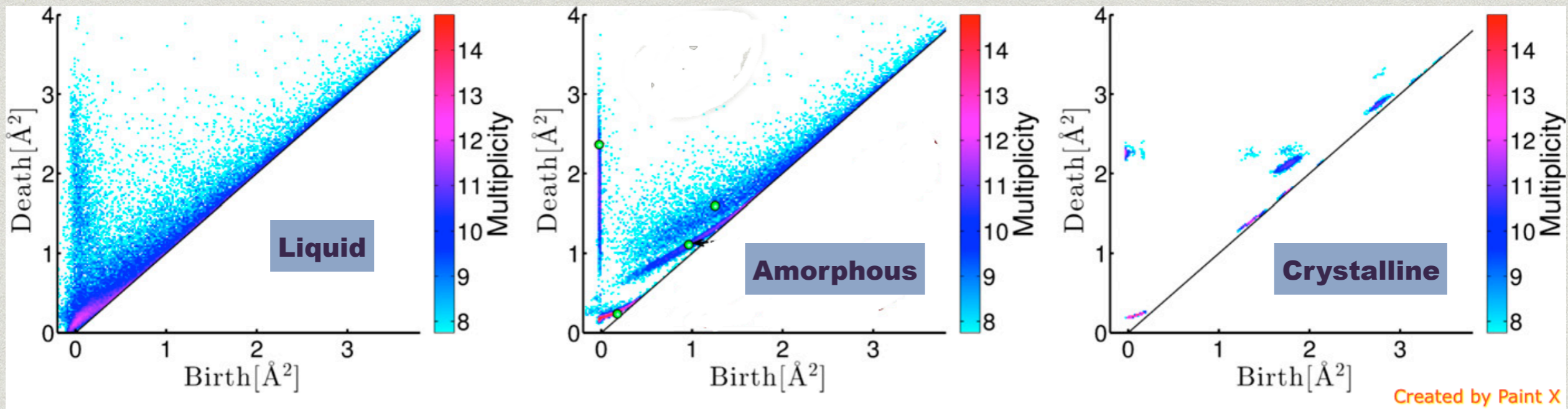
Created by Paint X



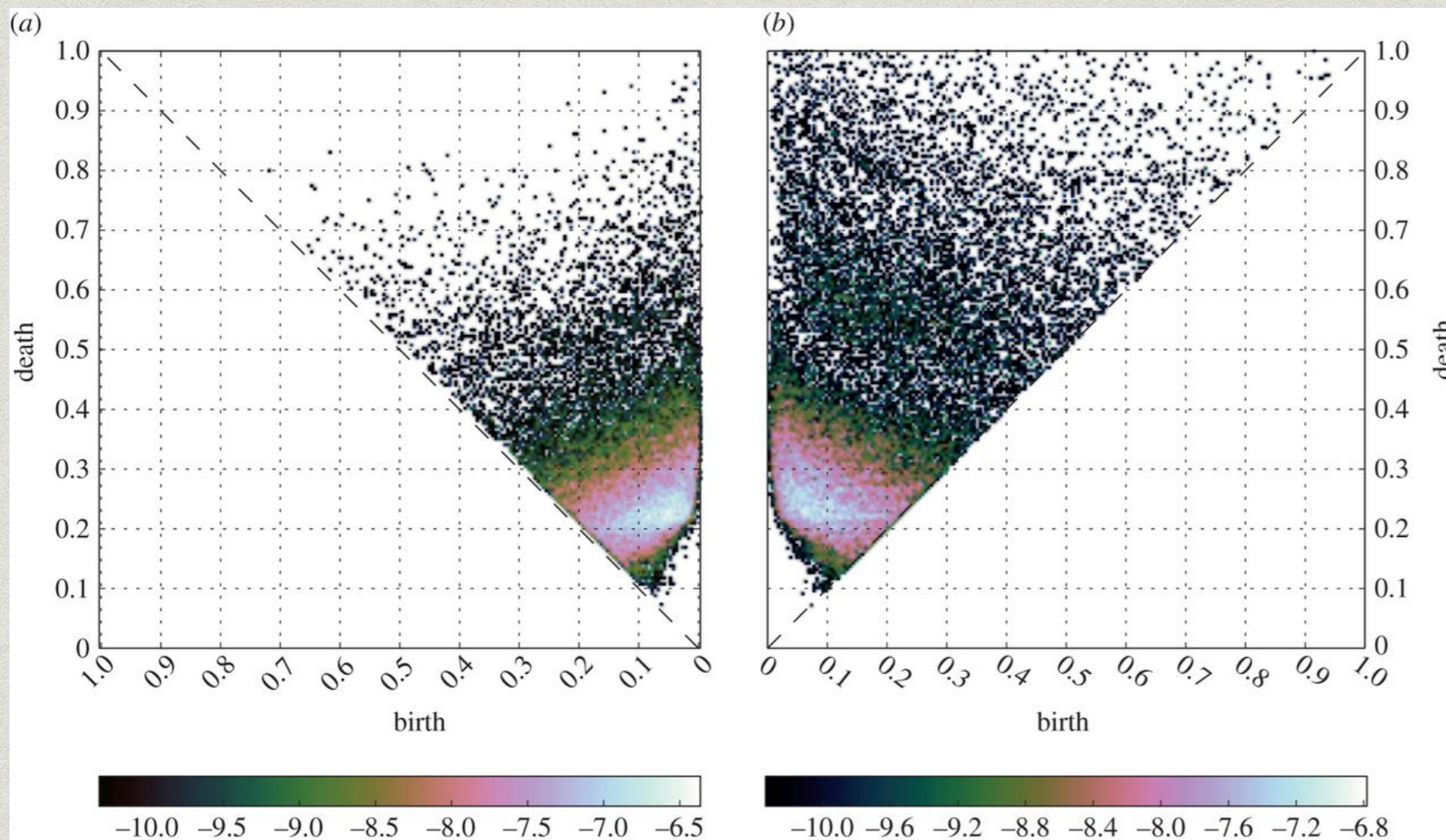


**Hiraoka et al : Hierarchical structure of amorphous solids.....**

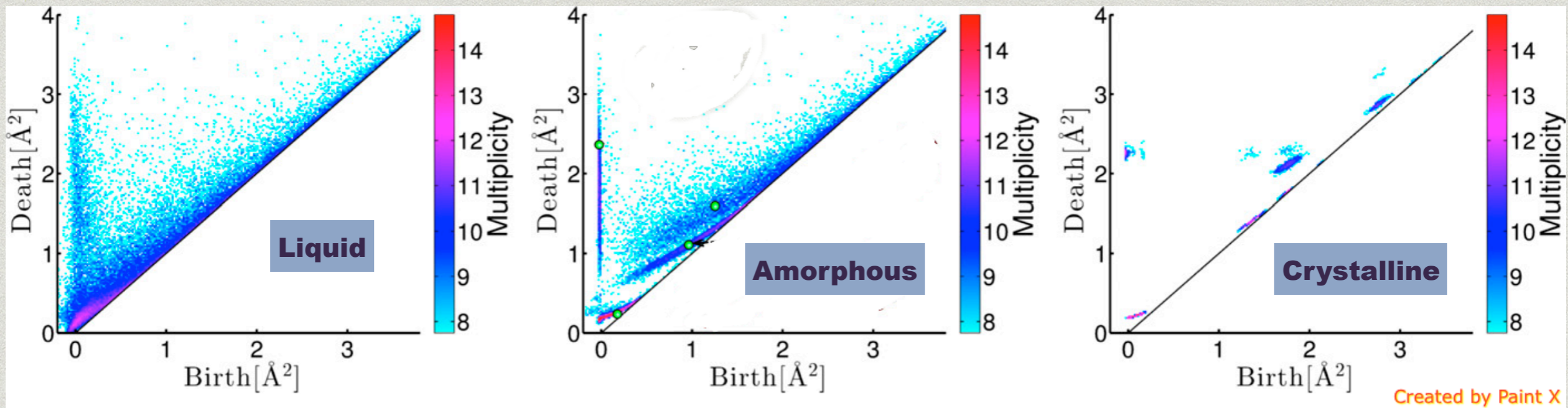




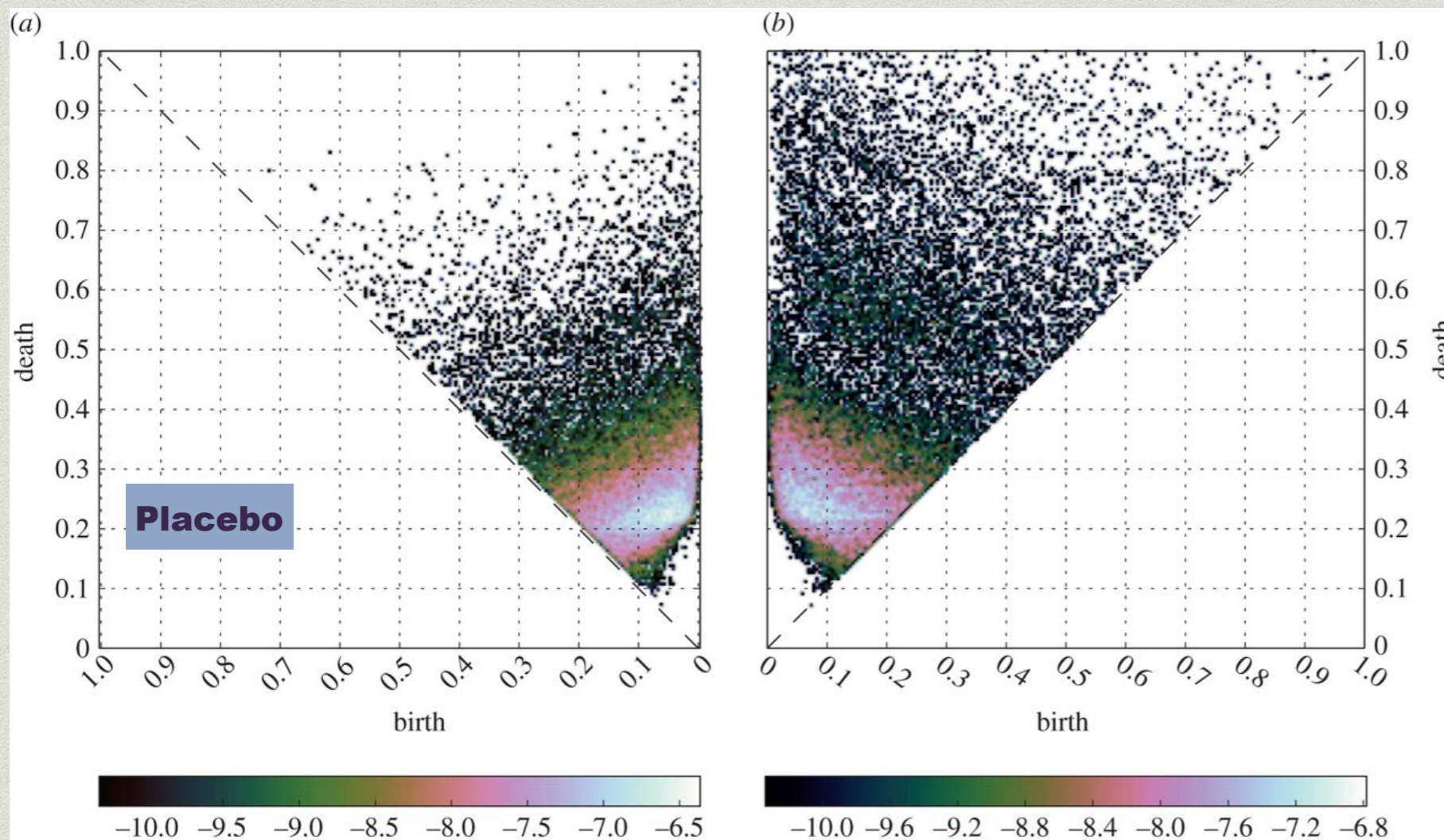
**Hiraoka et al : Hierarchical structure of amorphous solids.....**



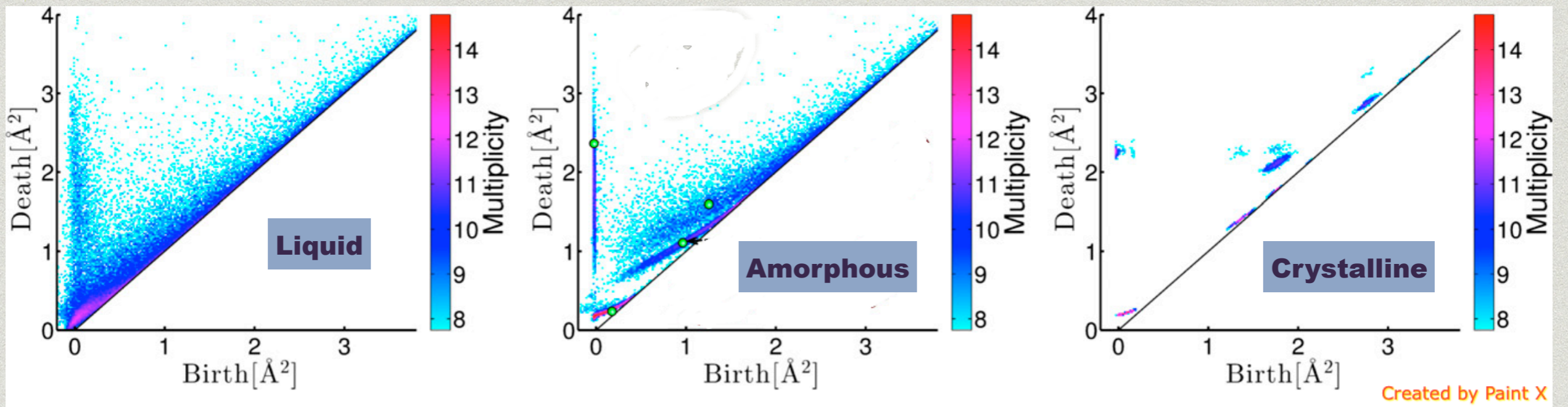




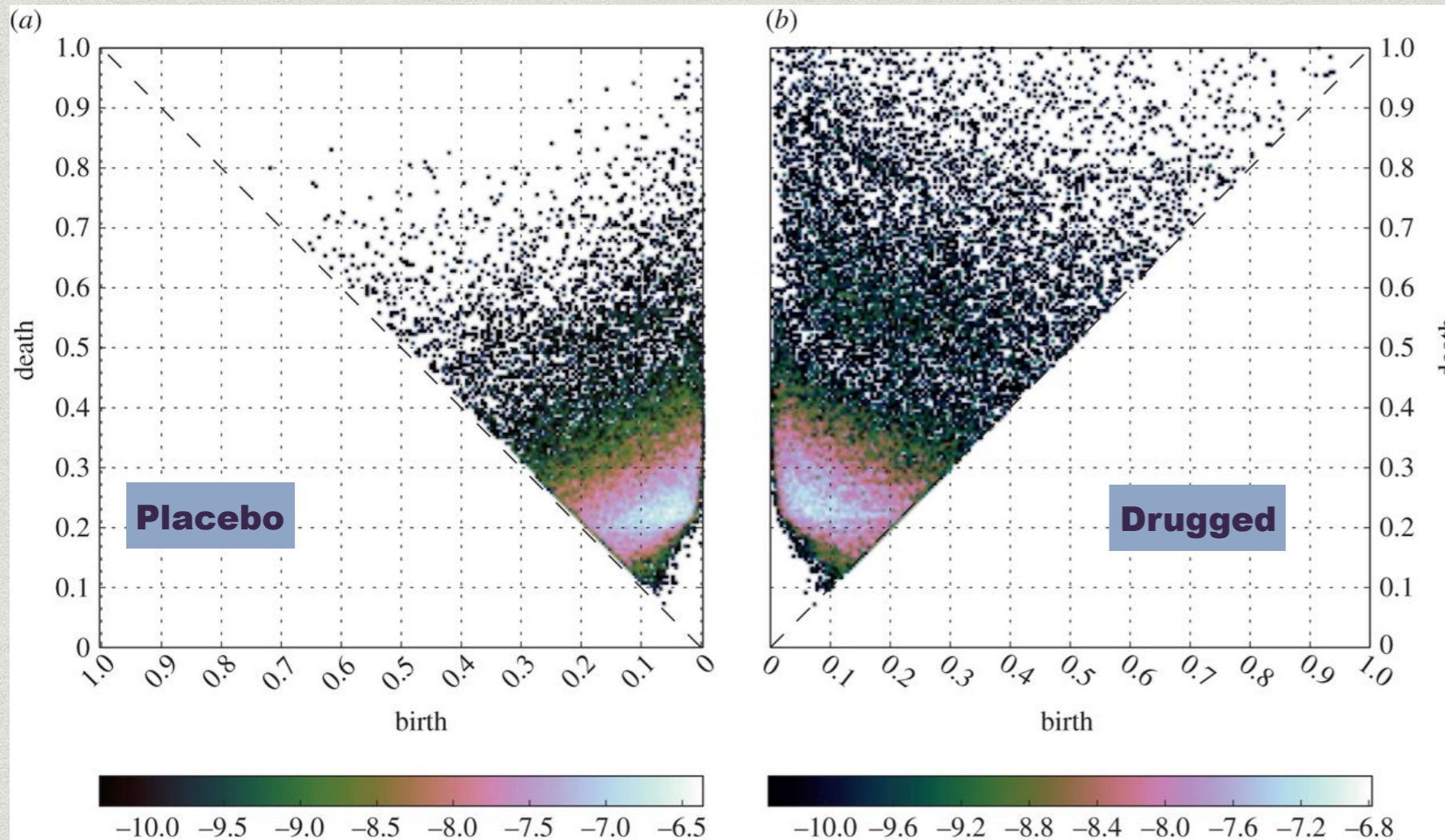
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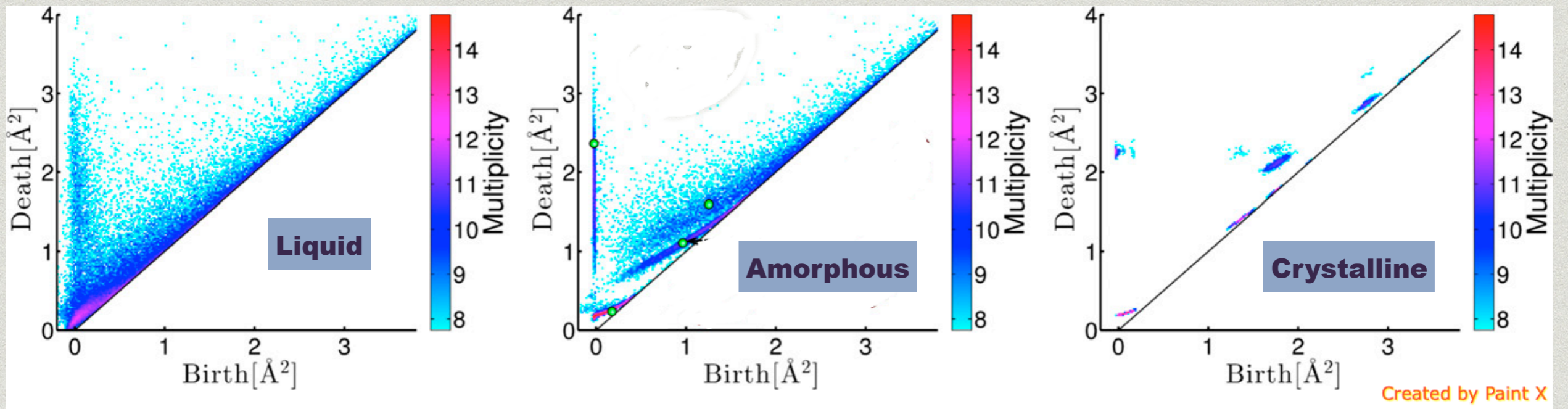




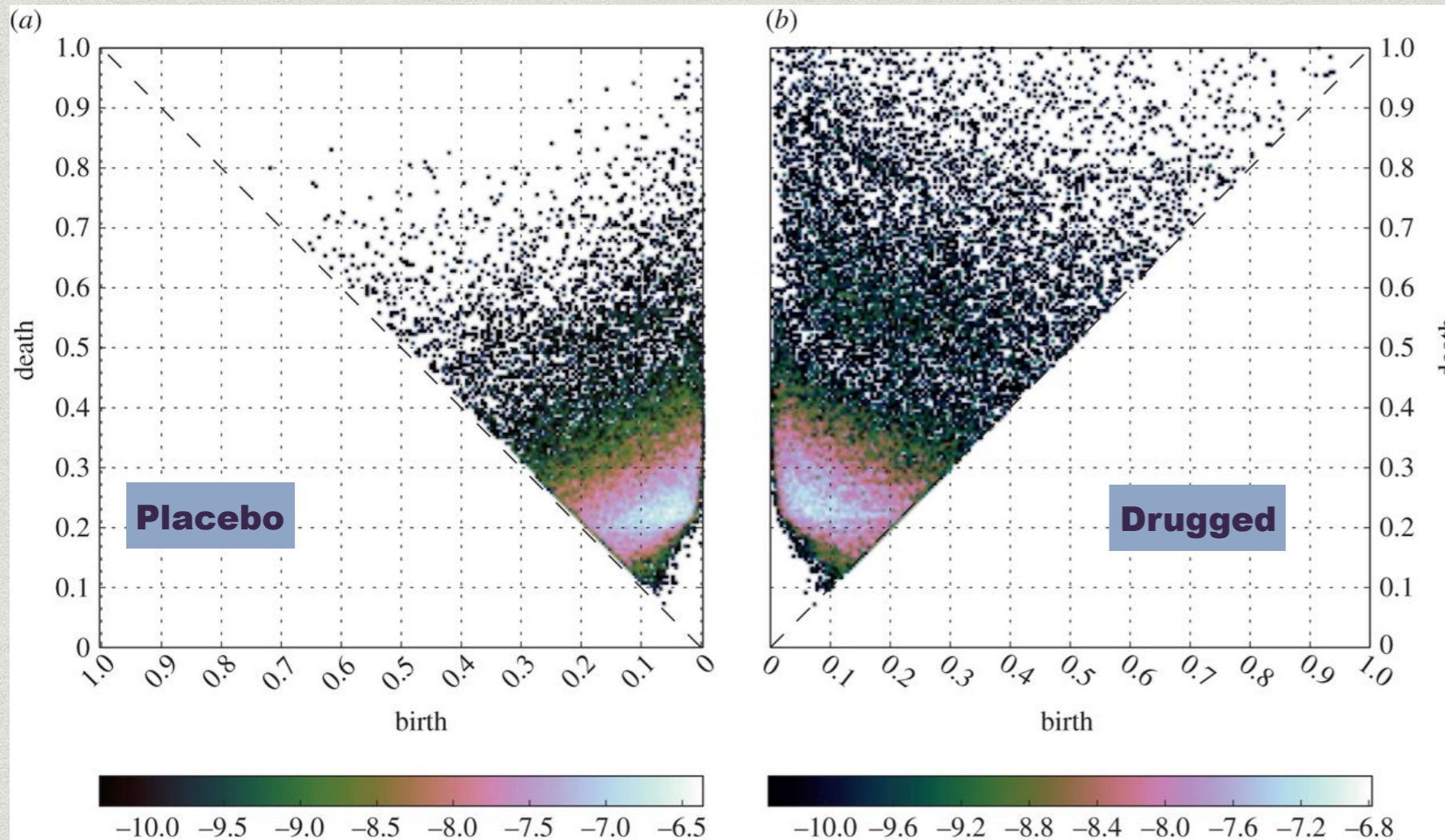
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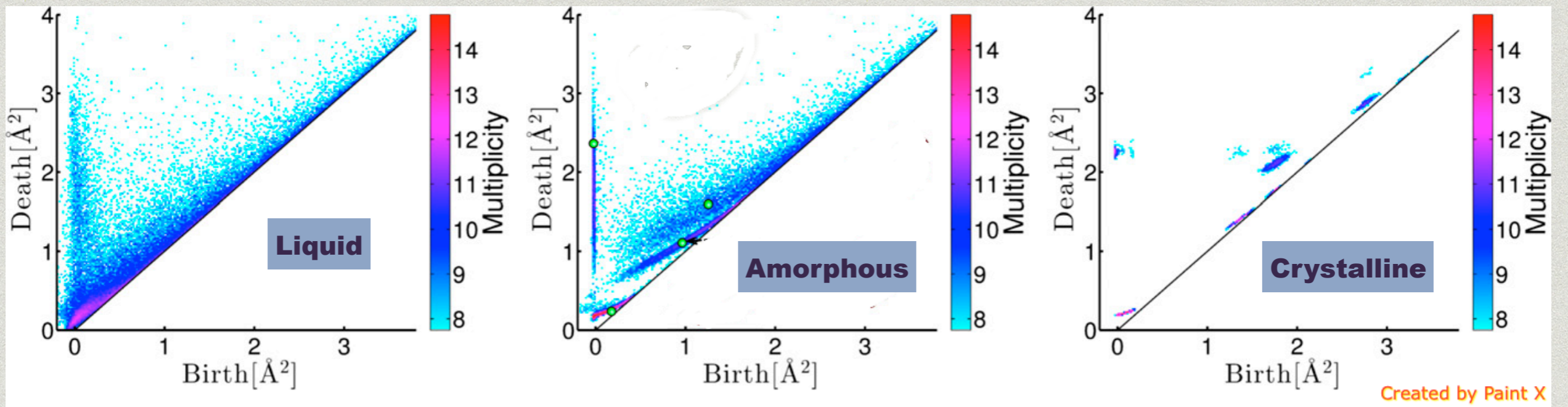


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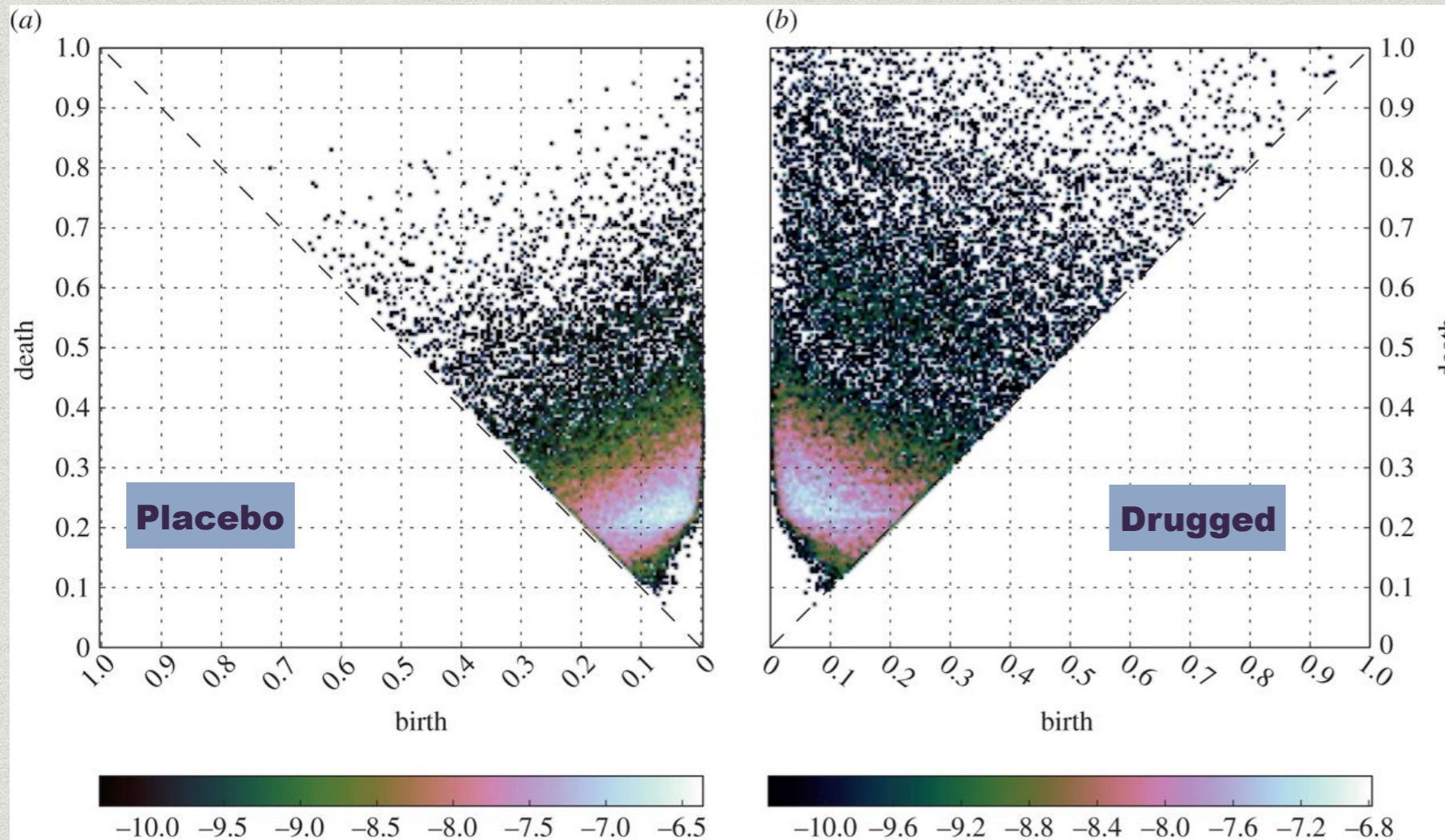


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**Homological scaffolds for brain functional networks.**







# *What to understand ?*



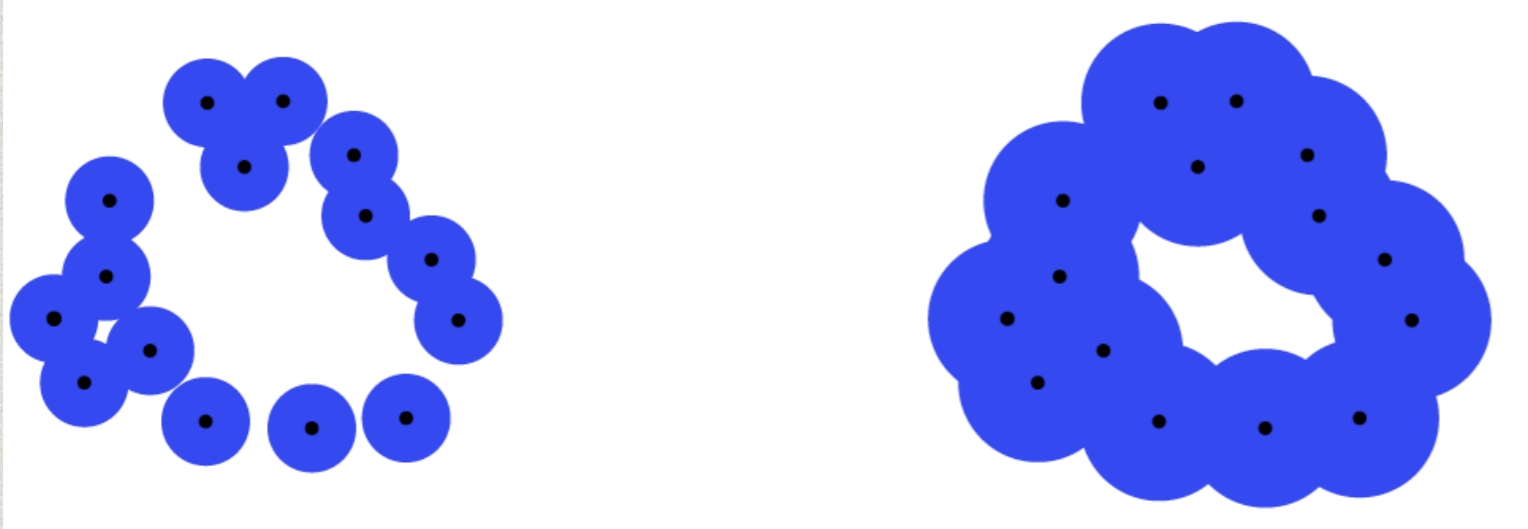
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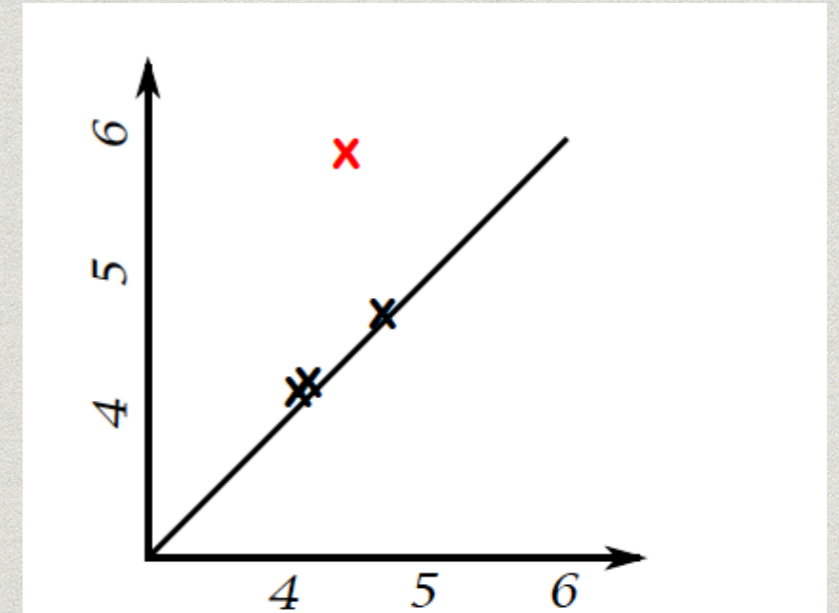
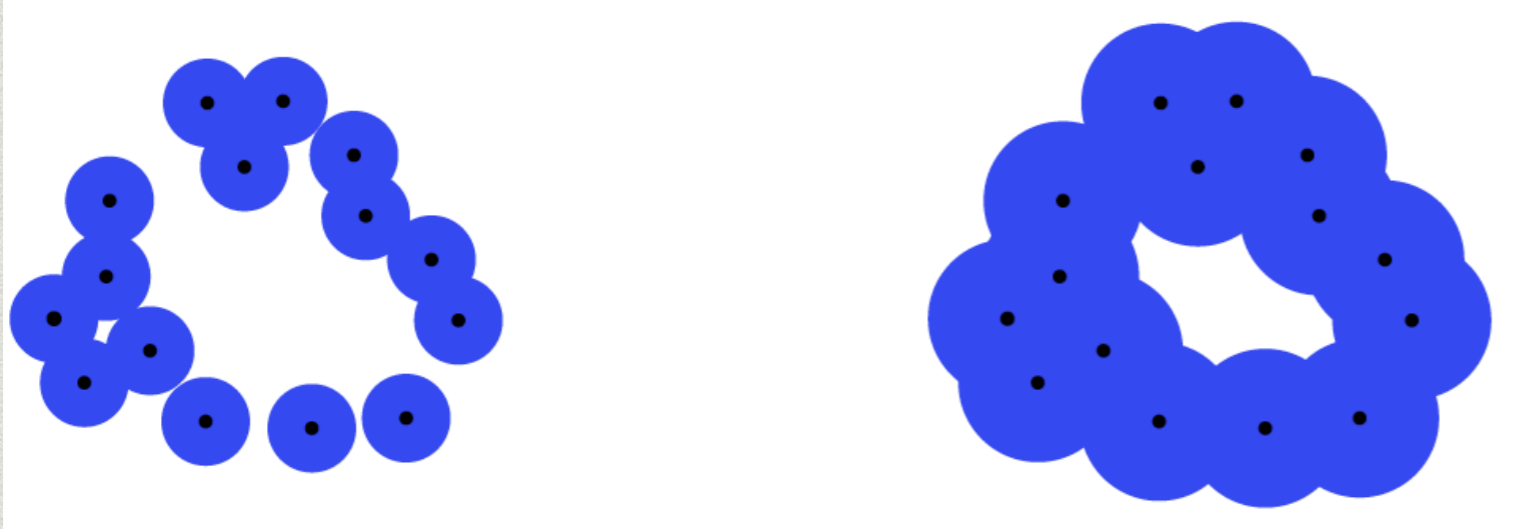
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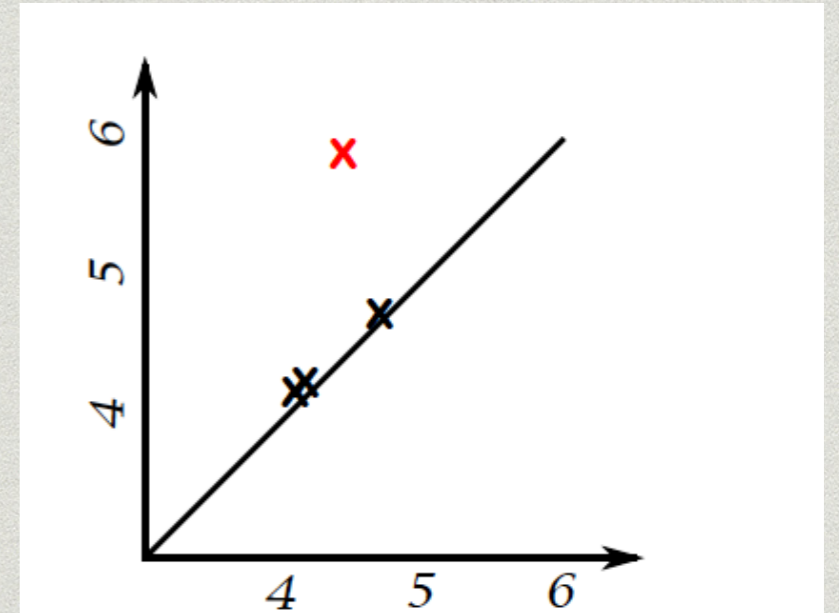
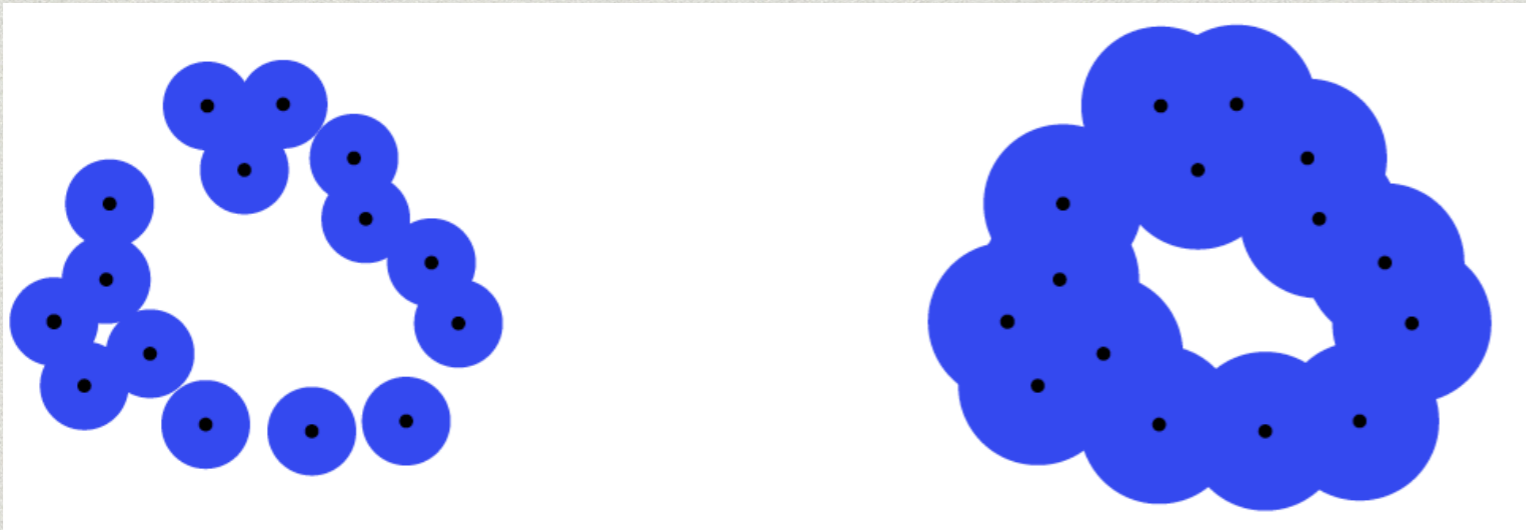
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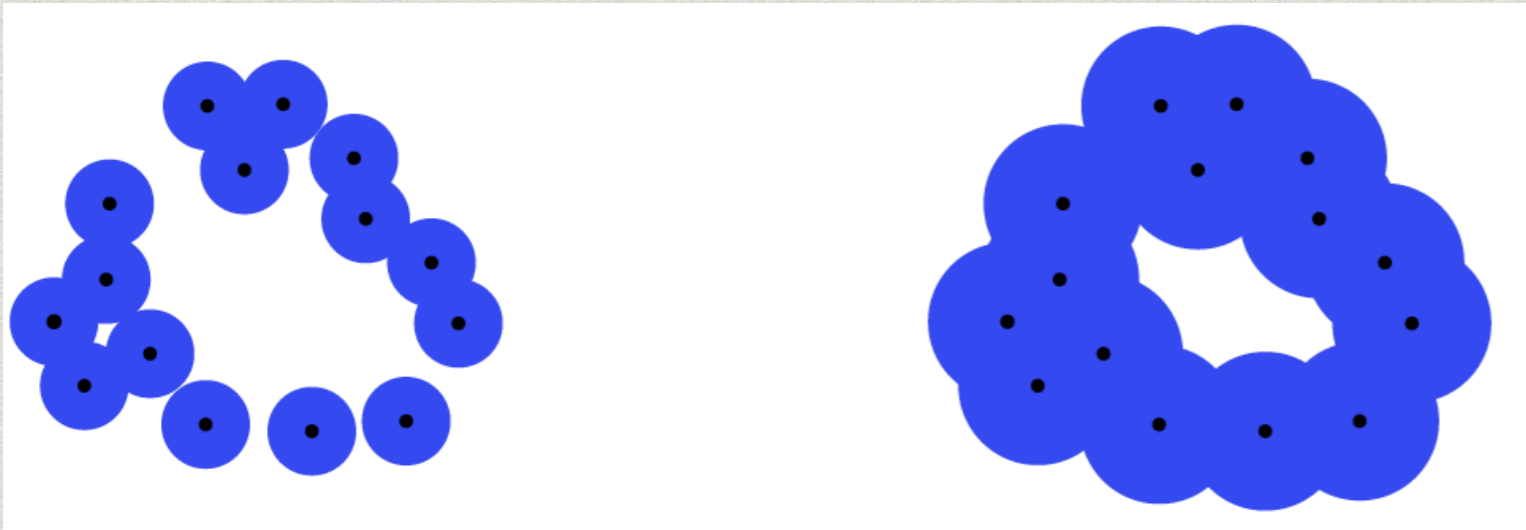


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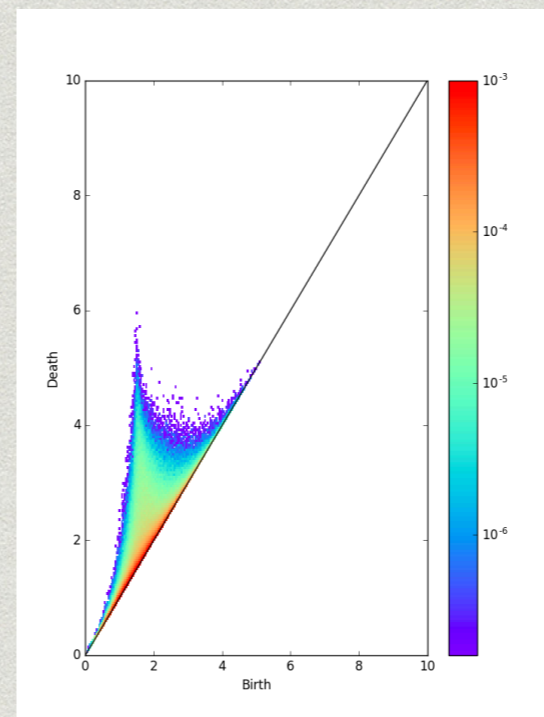


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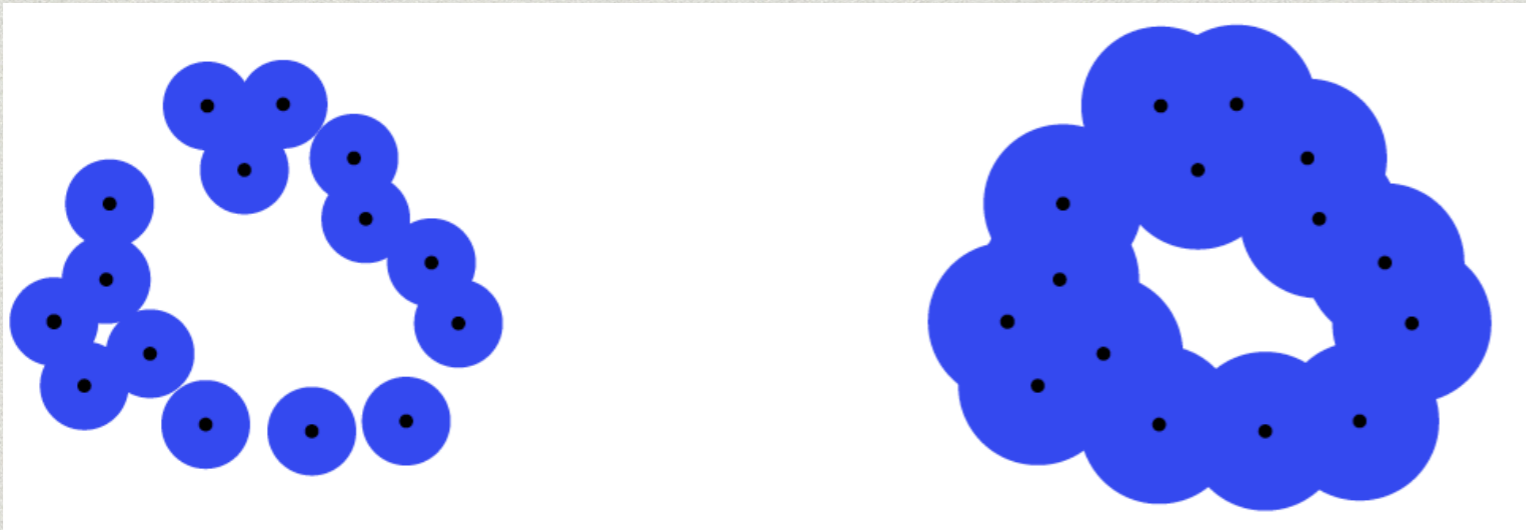
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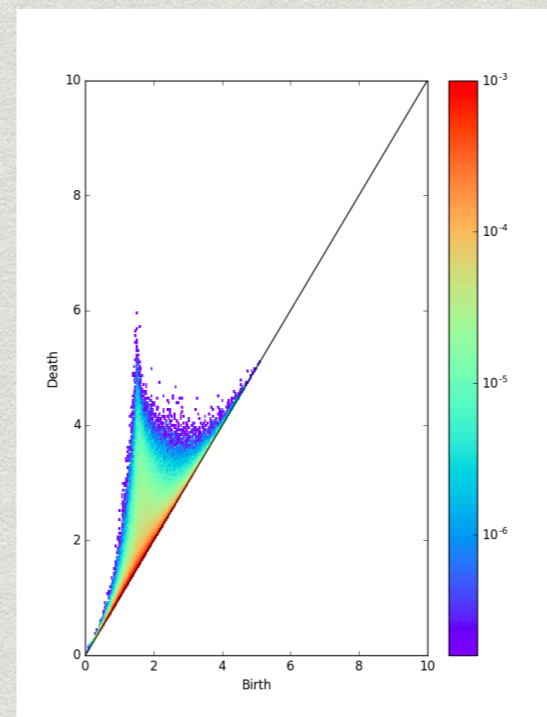
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**What is long ?**  
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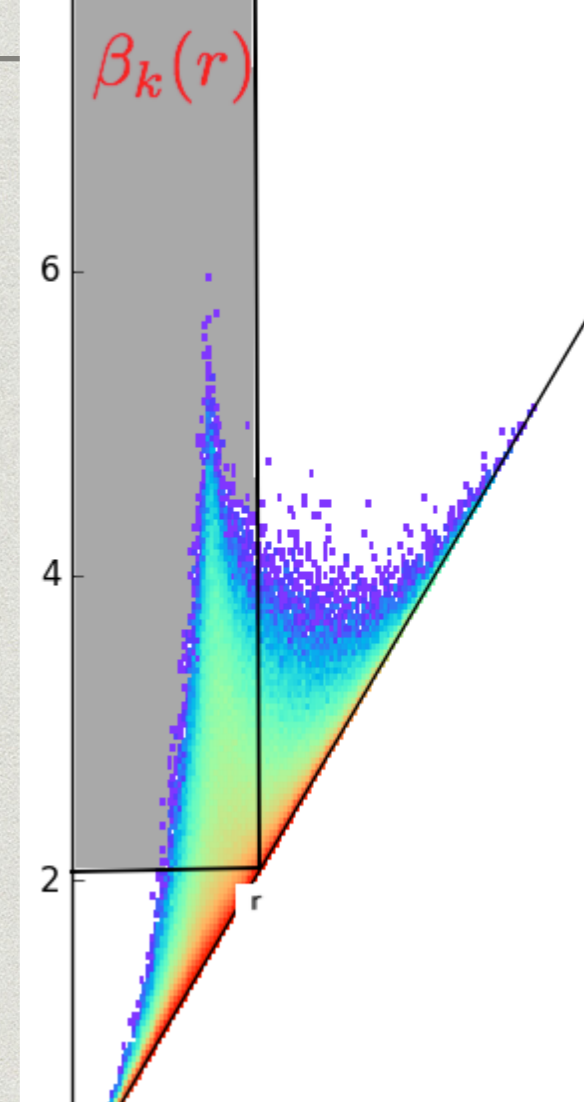
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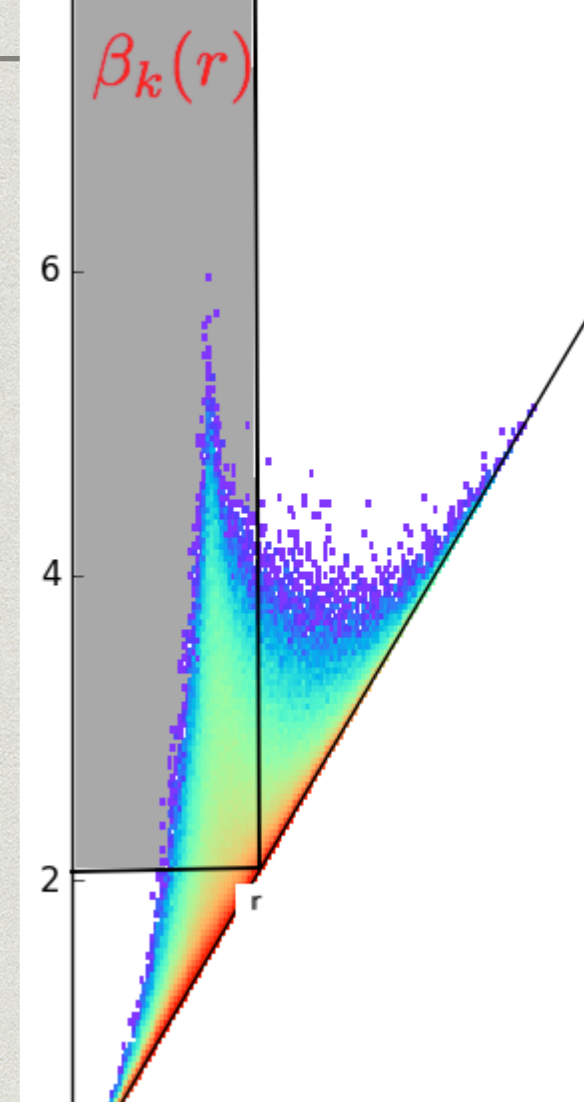


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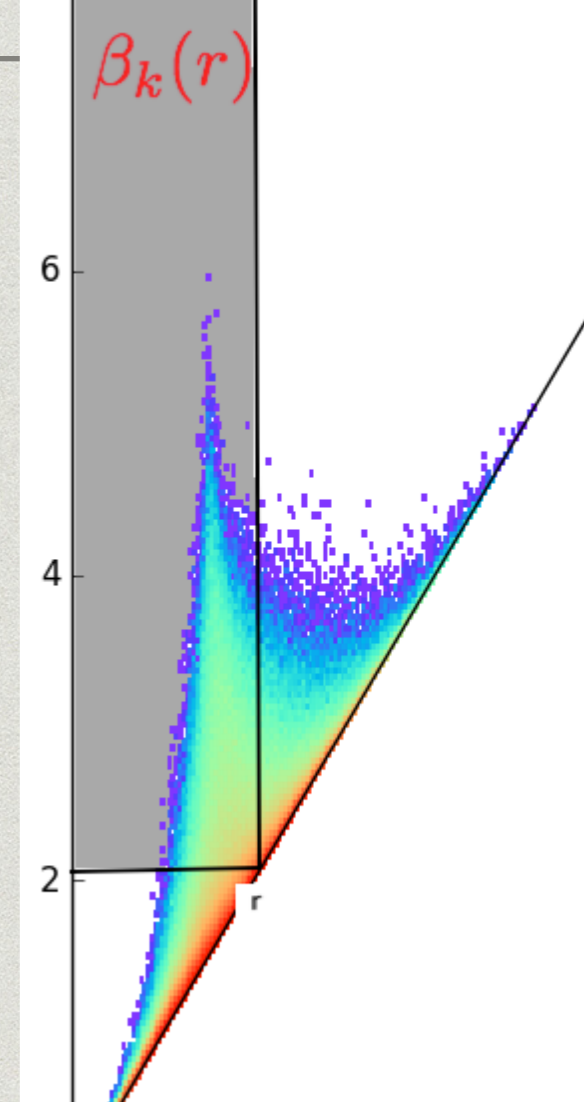
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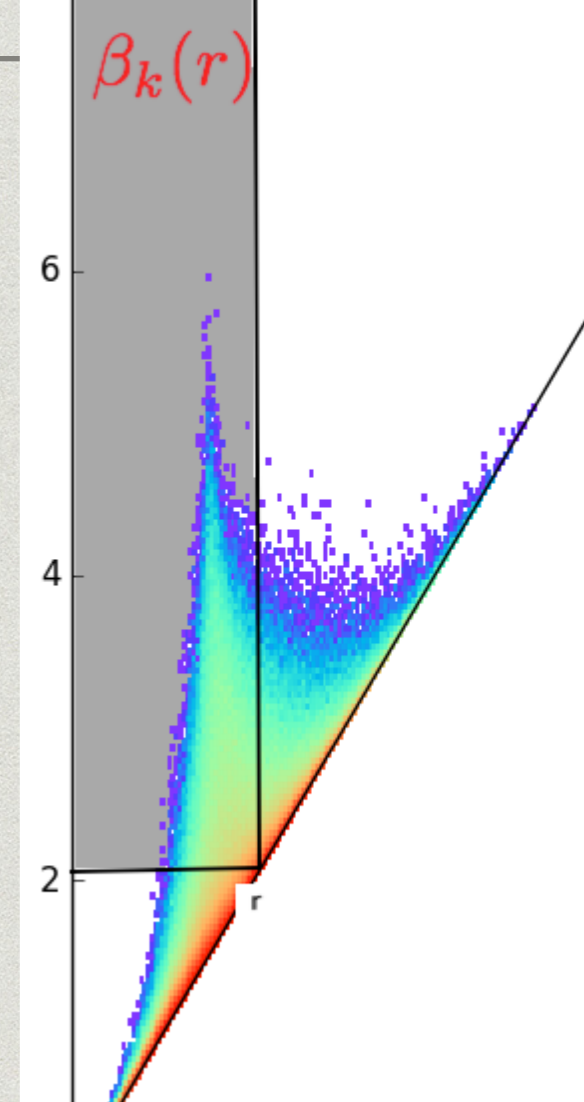
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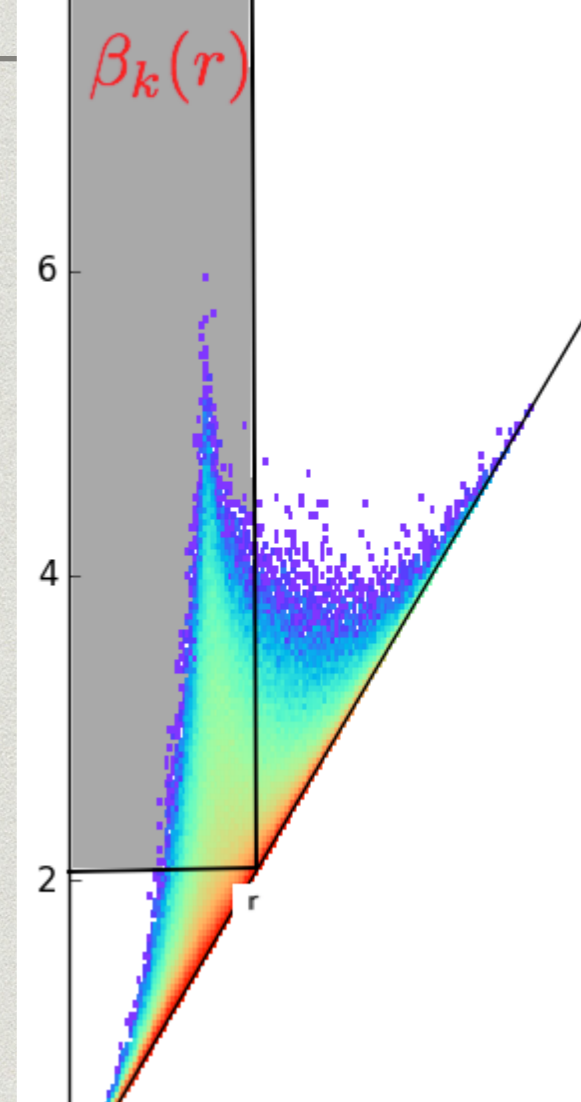
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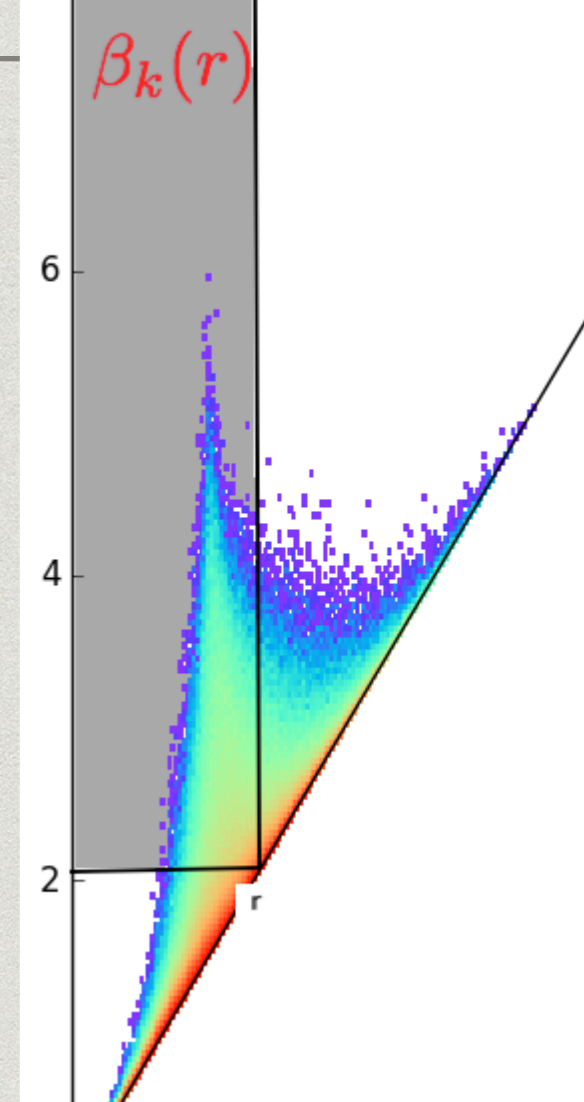
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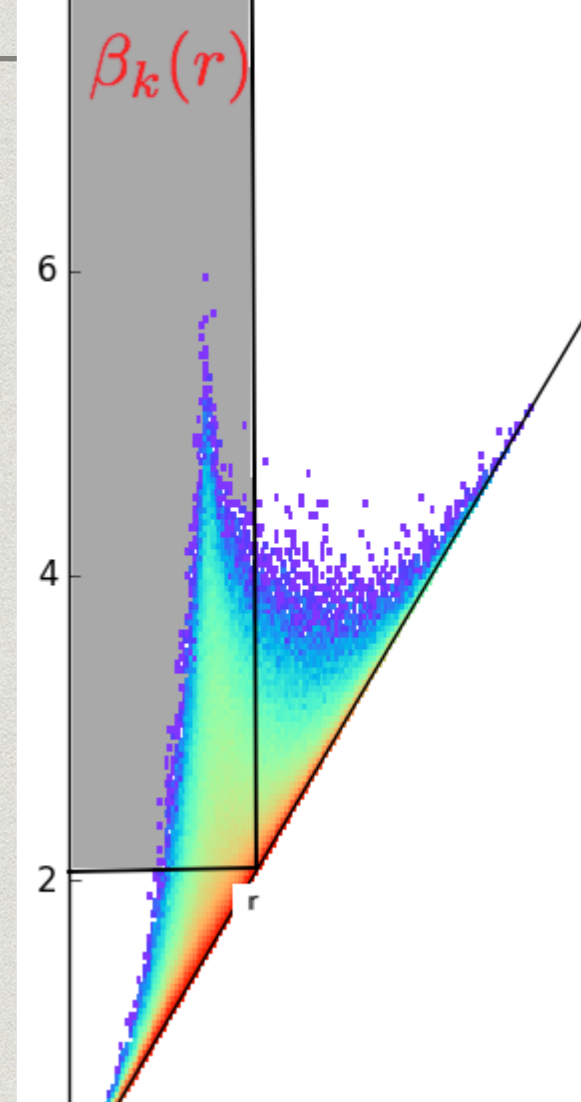
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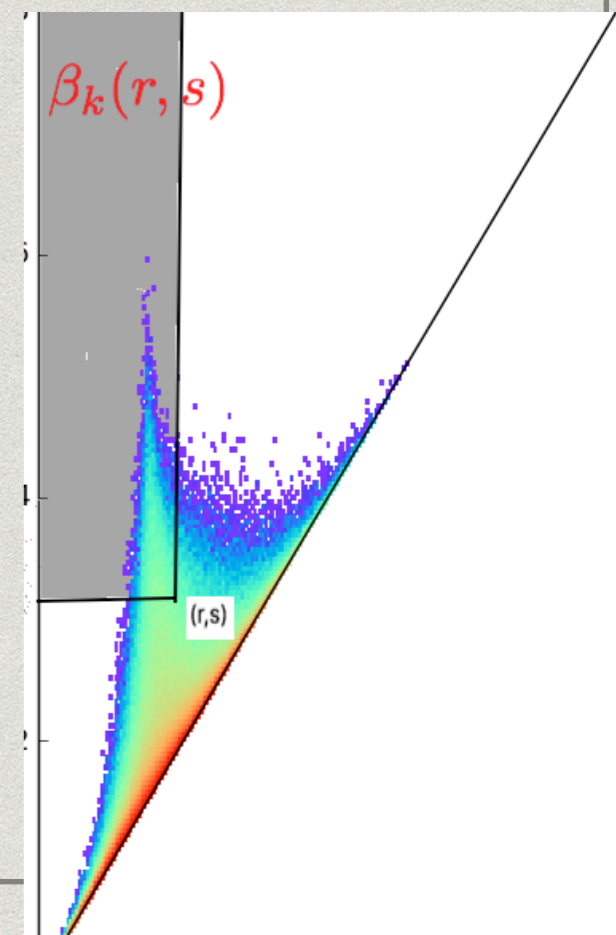
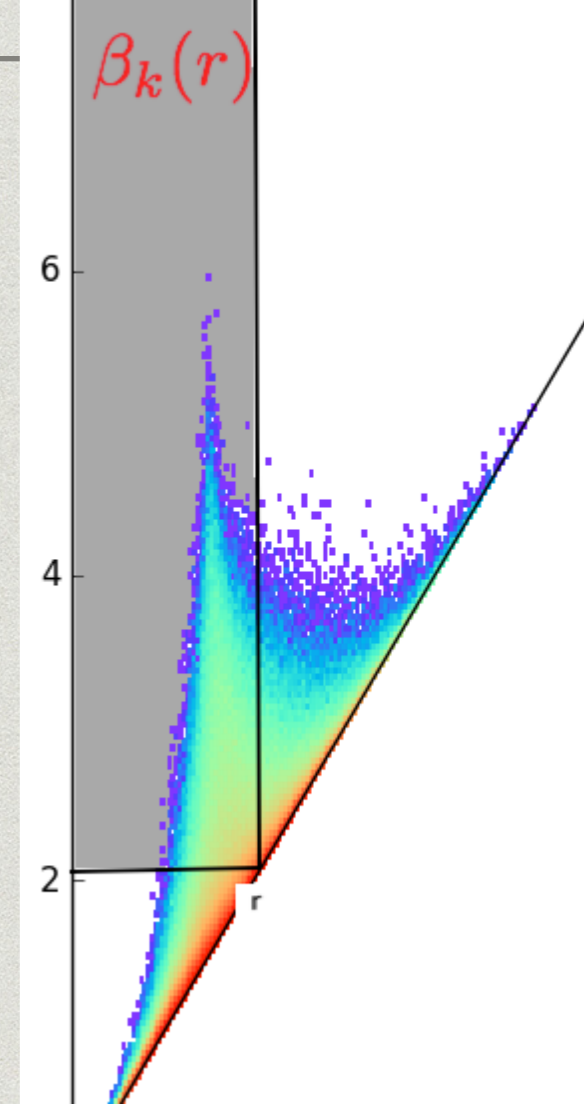
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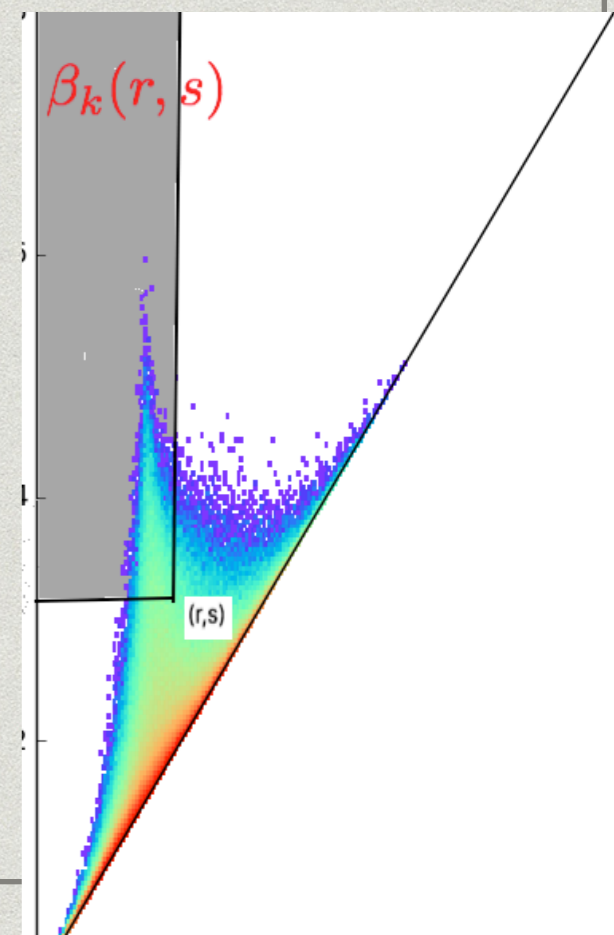
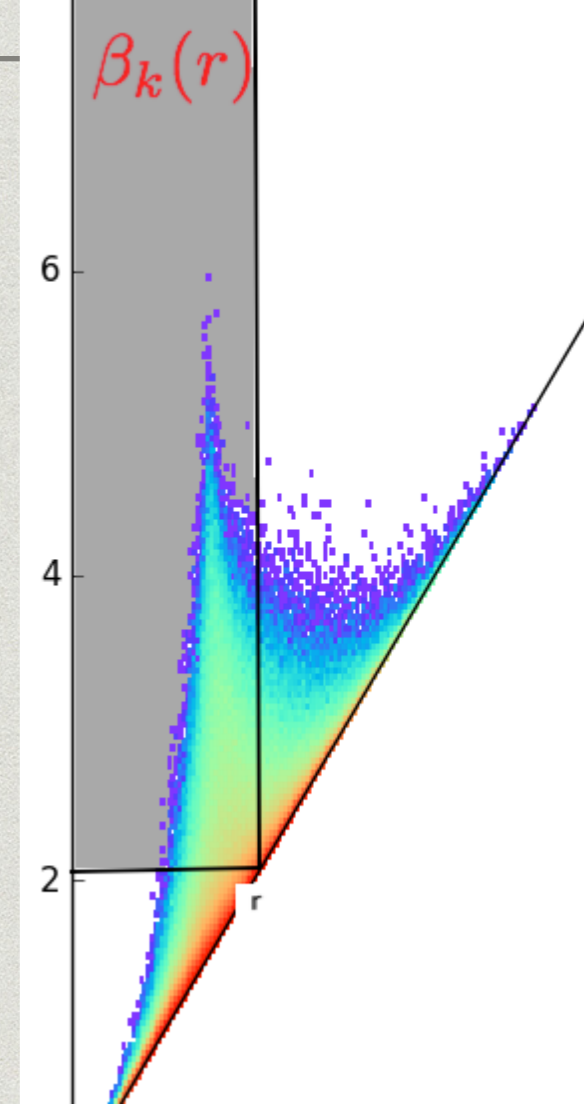
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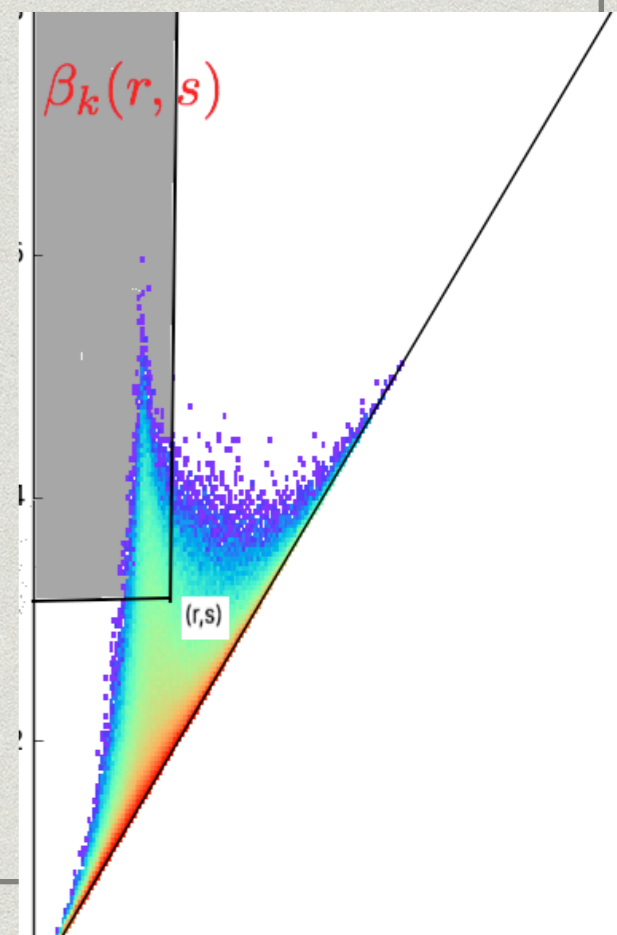
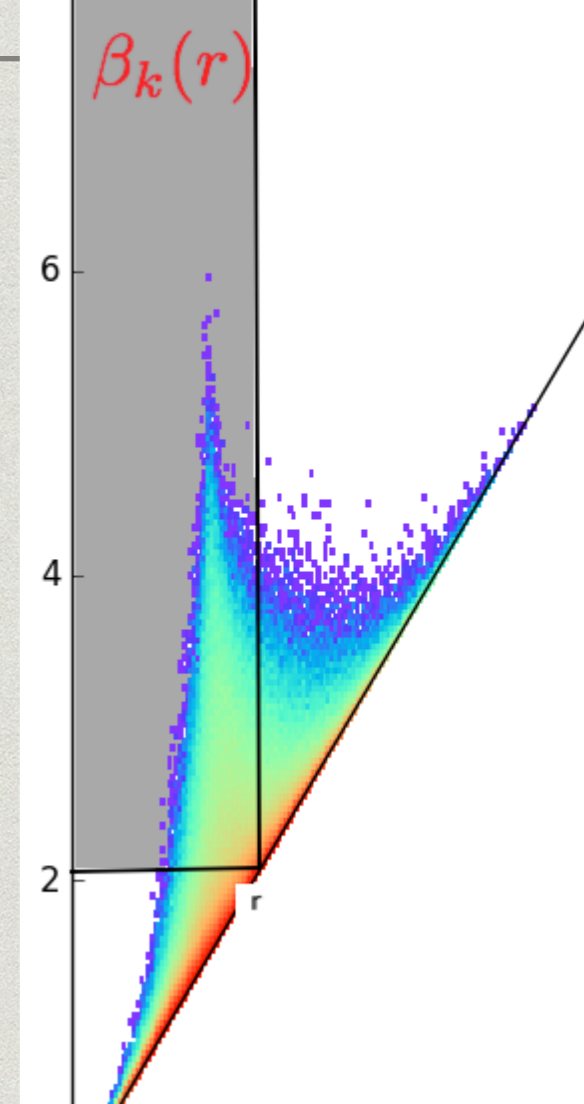
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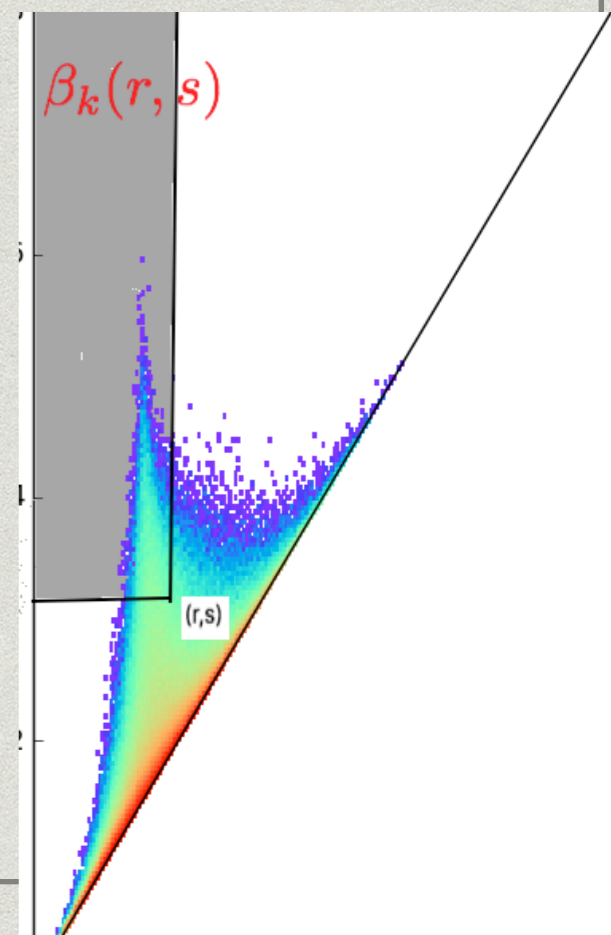
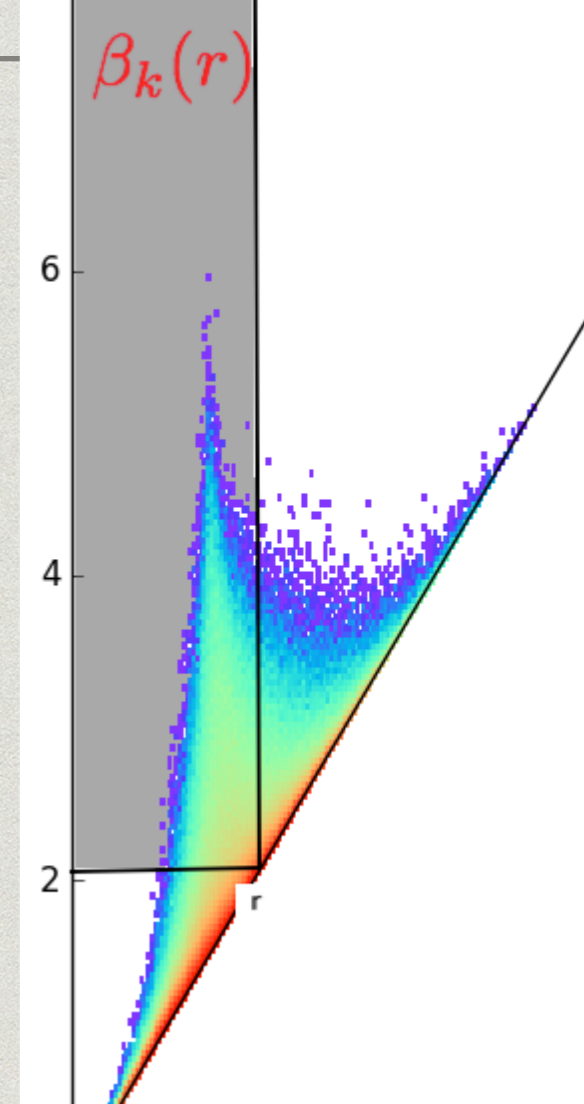
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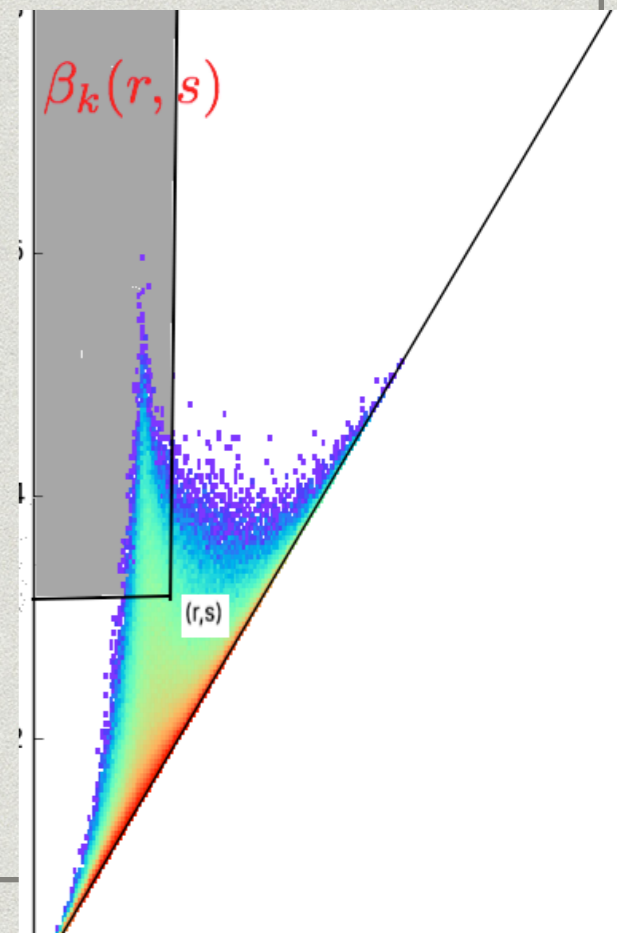
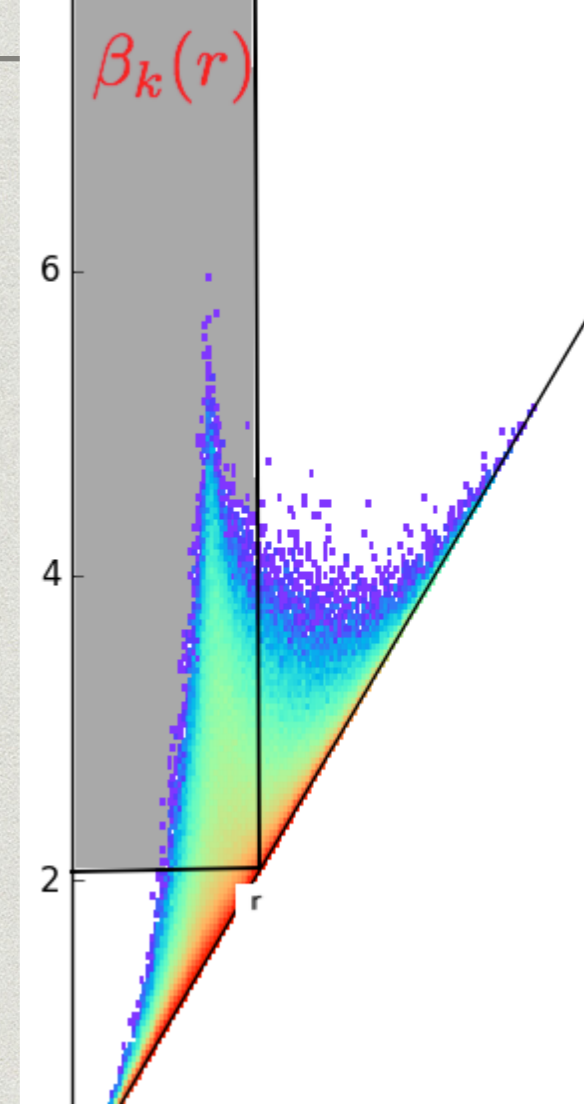
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$F$  is translation invariant, apply Ergodic theorem to RHS and use the approximation.







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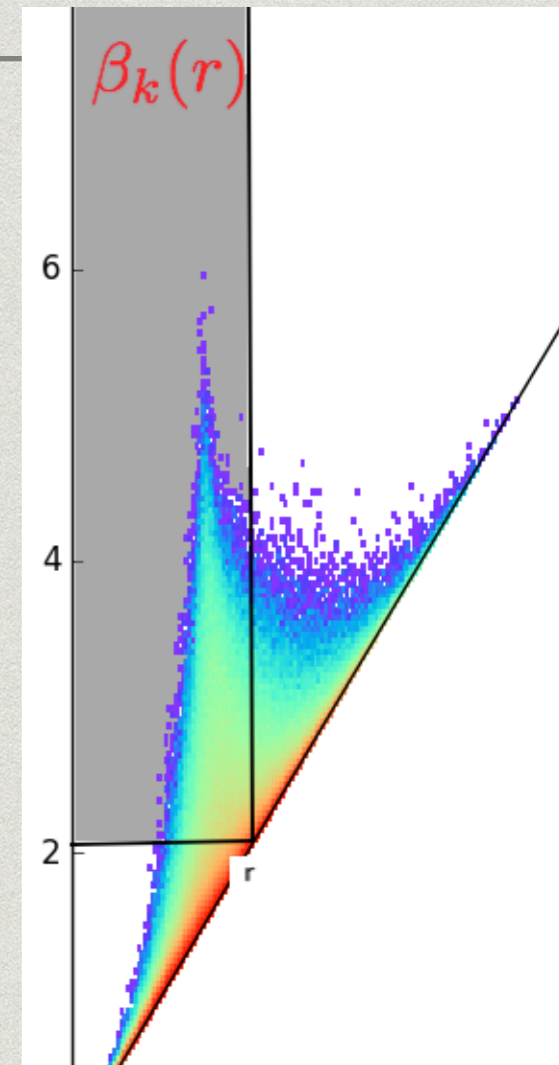
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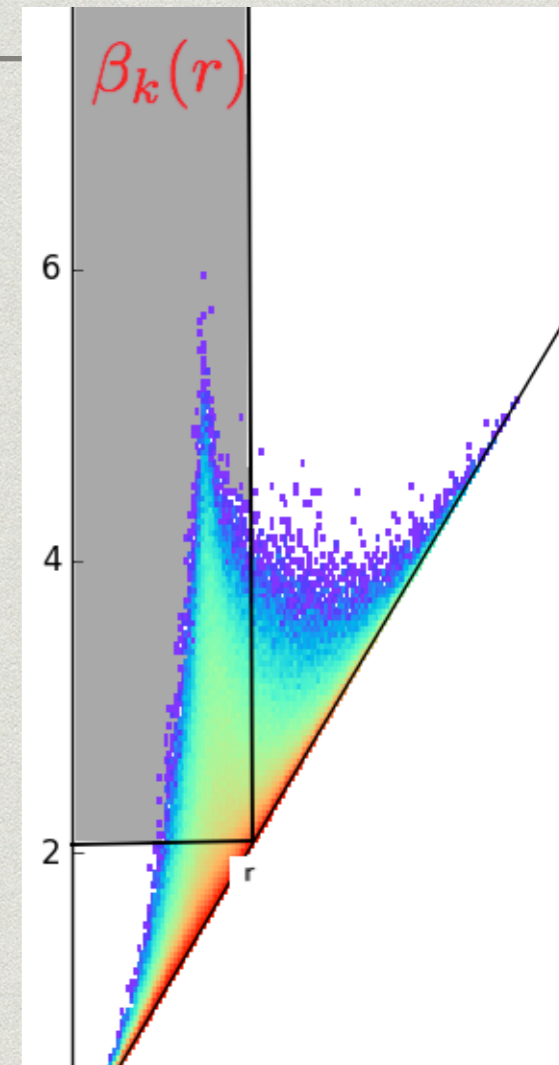


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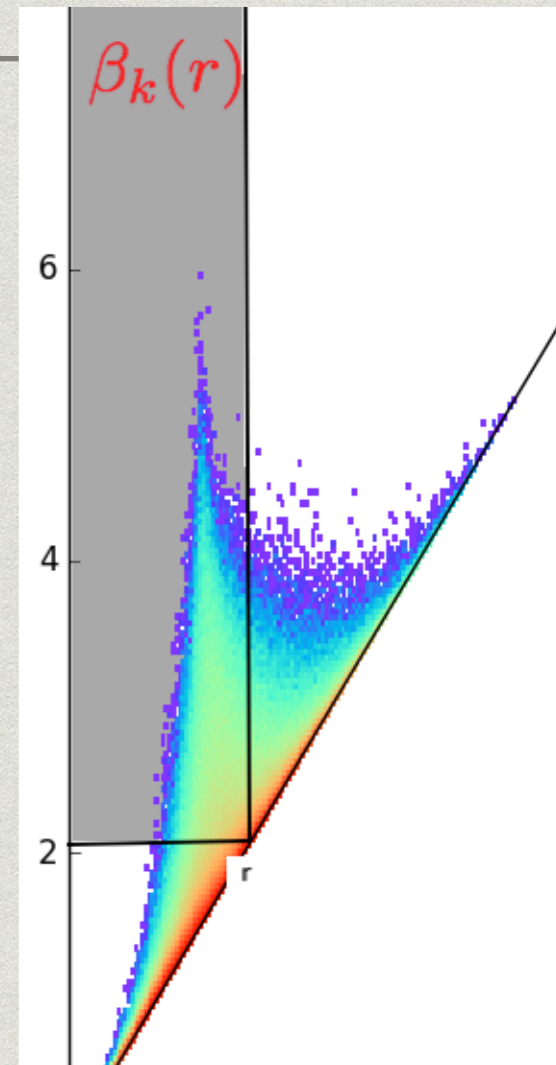
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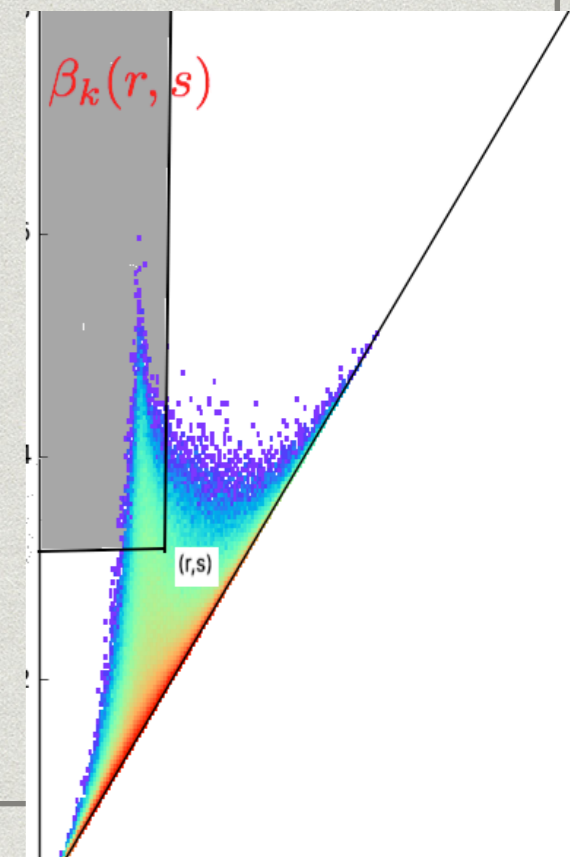
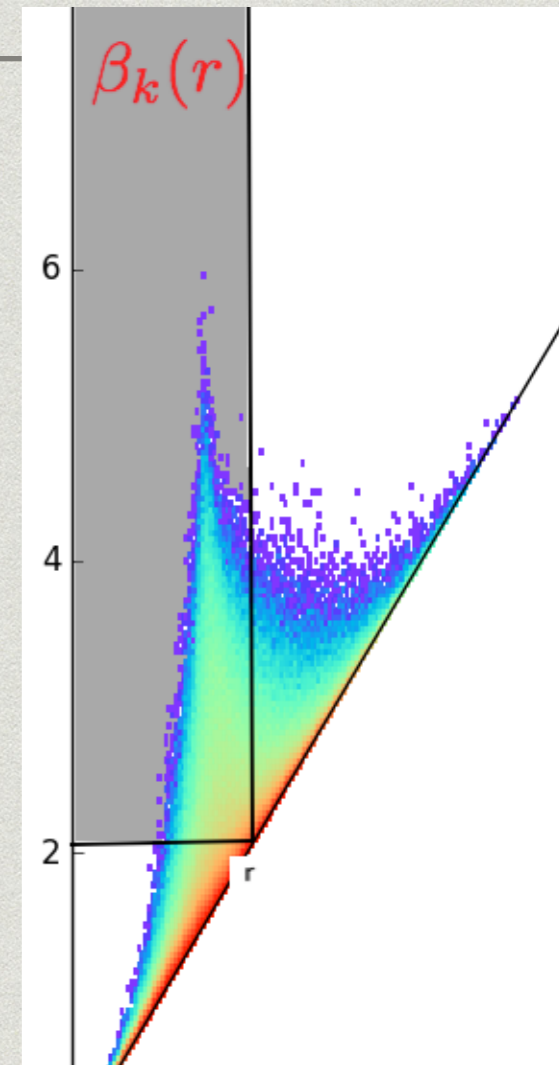
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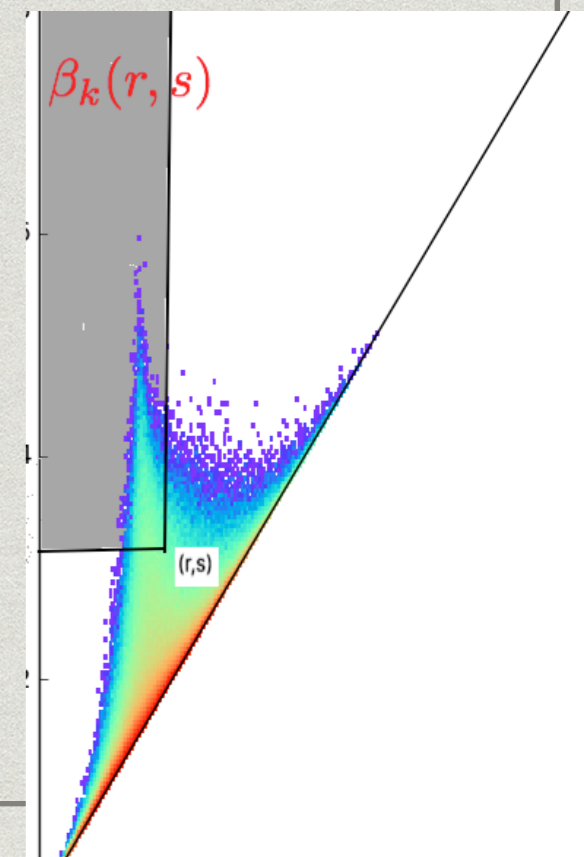
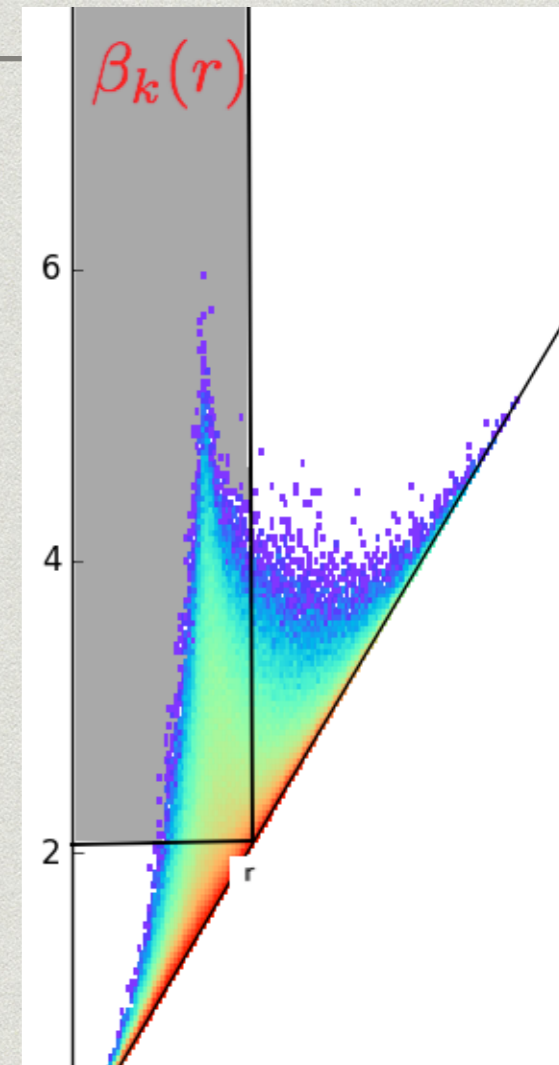
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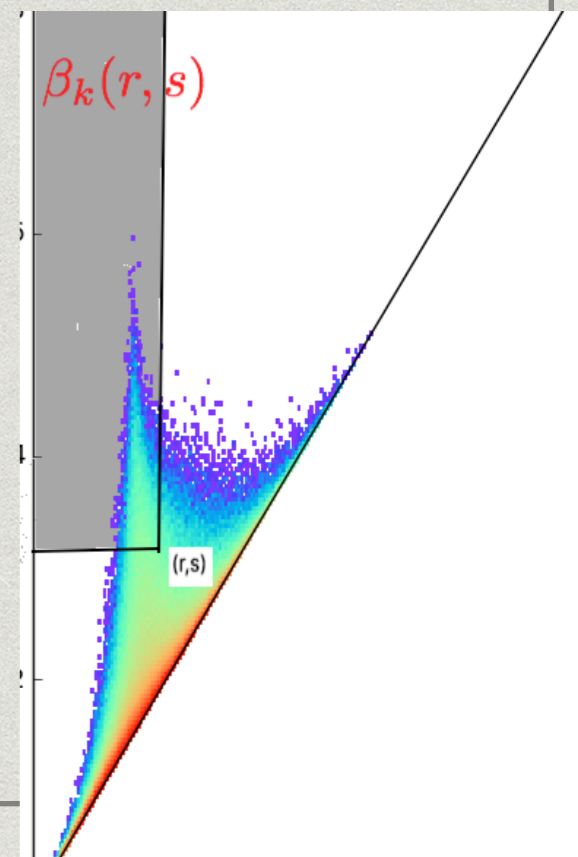
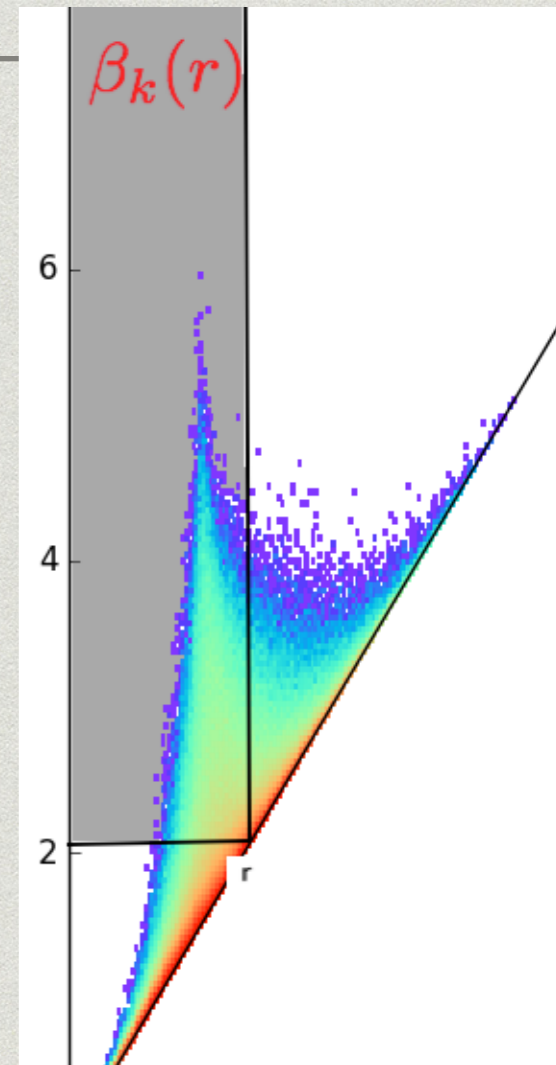
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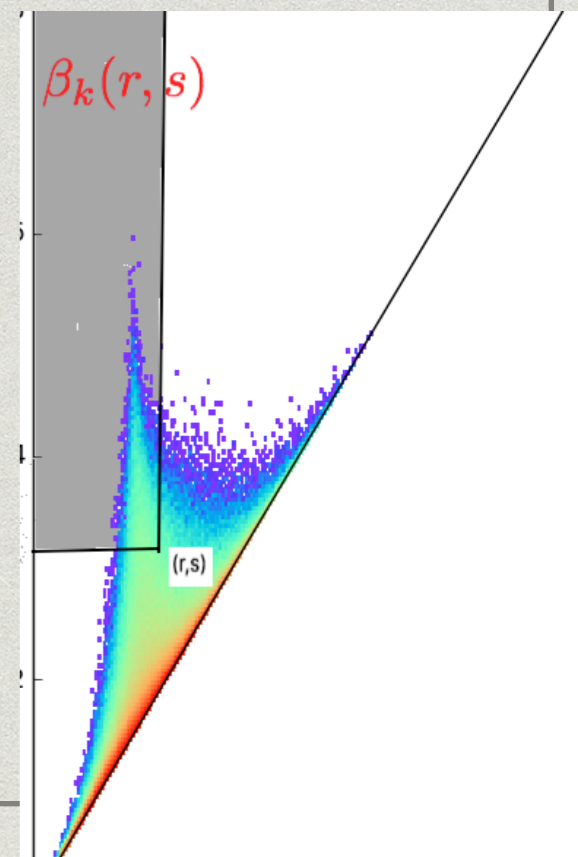
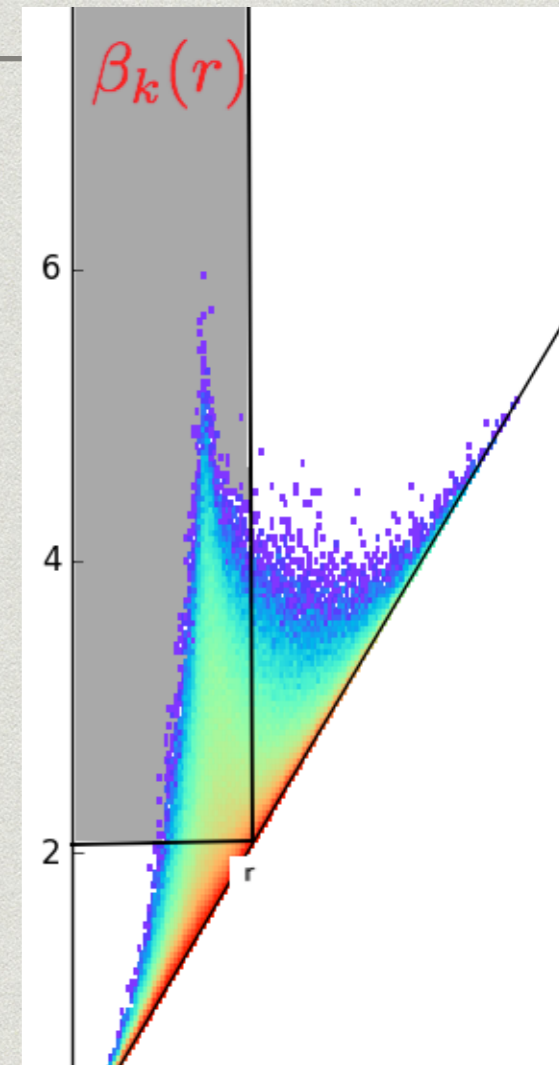
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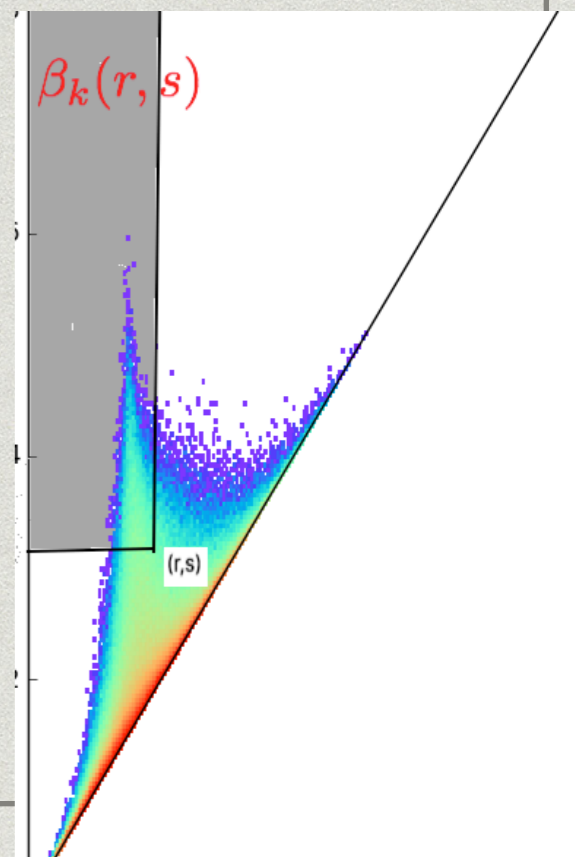
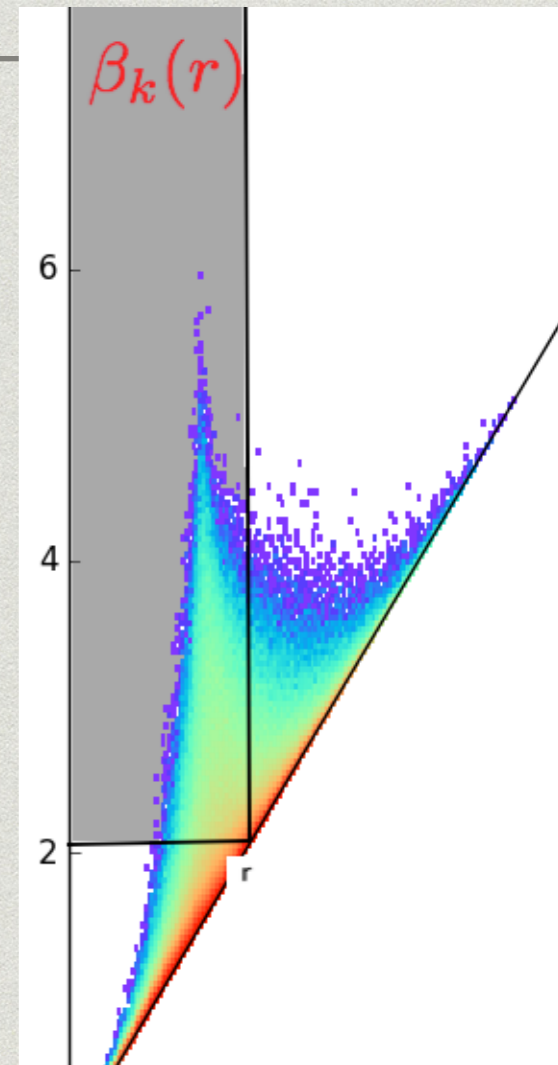
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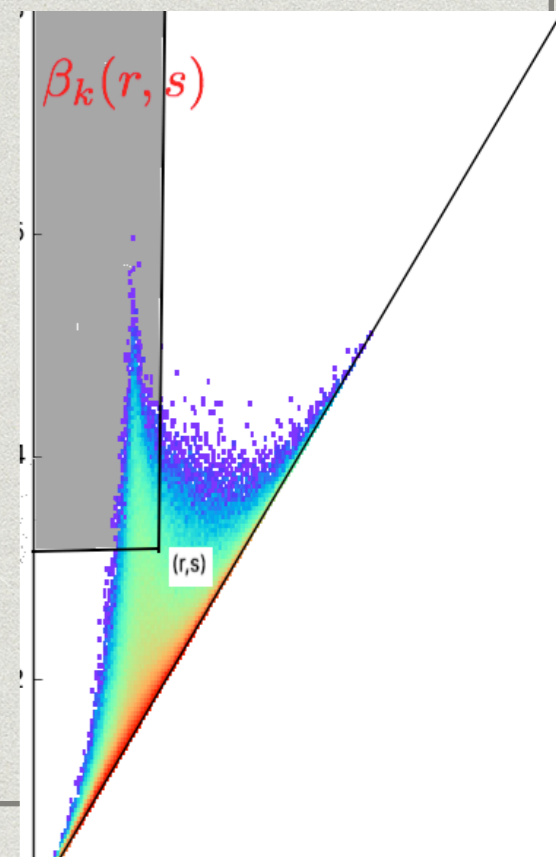
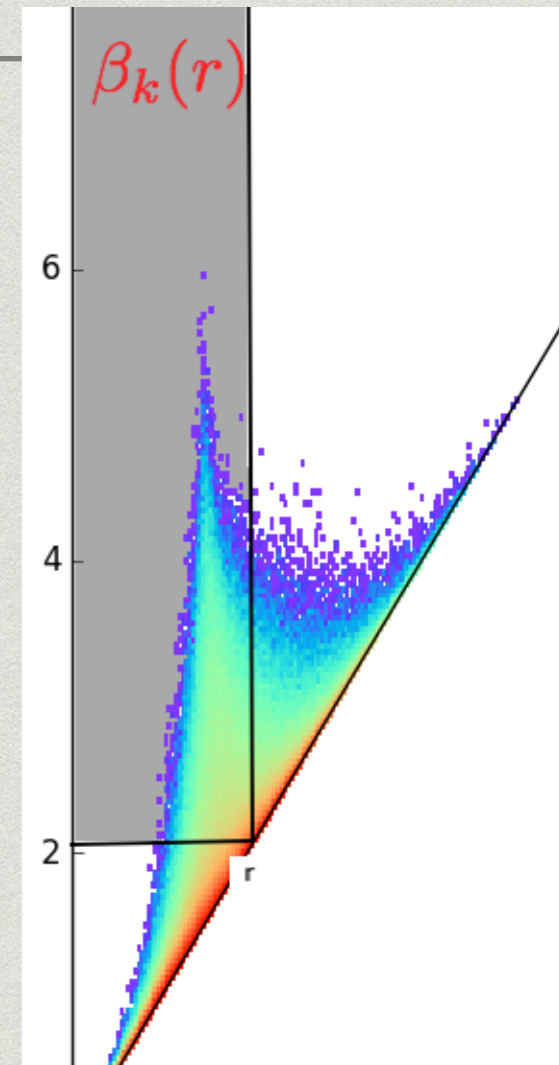
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For  $\beta_k(r)$ , use Mayer-Vietoris exact sequence, but rest involve more direct analysis.







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More on MSAs in **“A Probability Meeting to be Named Later”**, May 12-14, 2017, ISI Bangalore.







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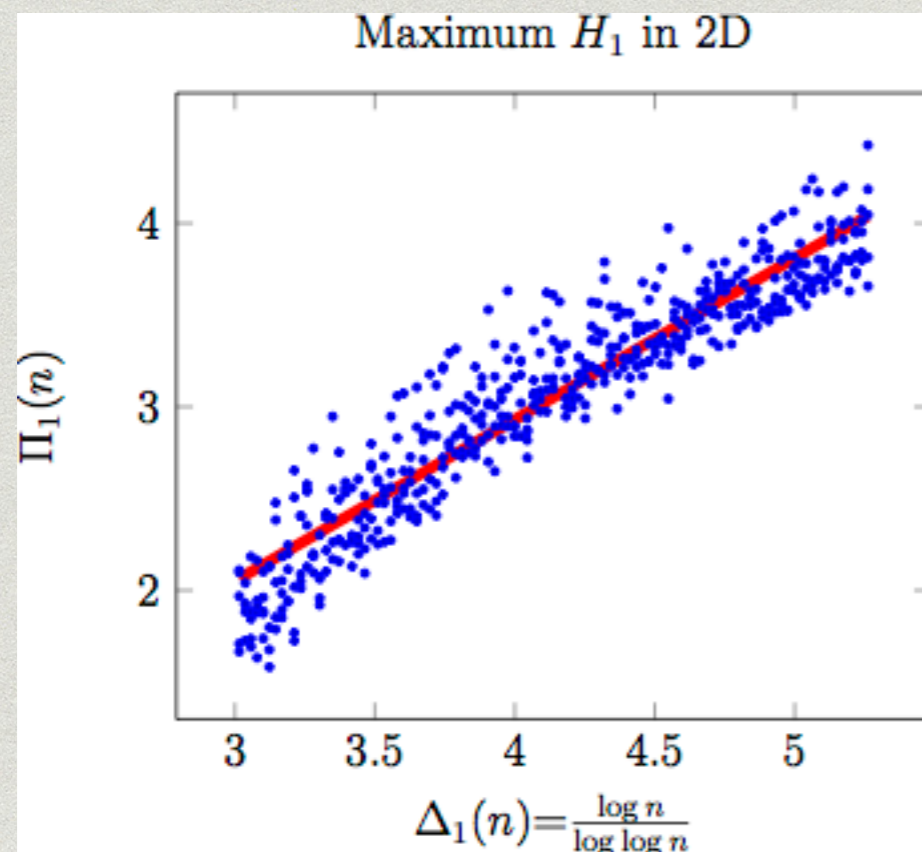
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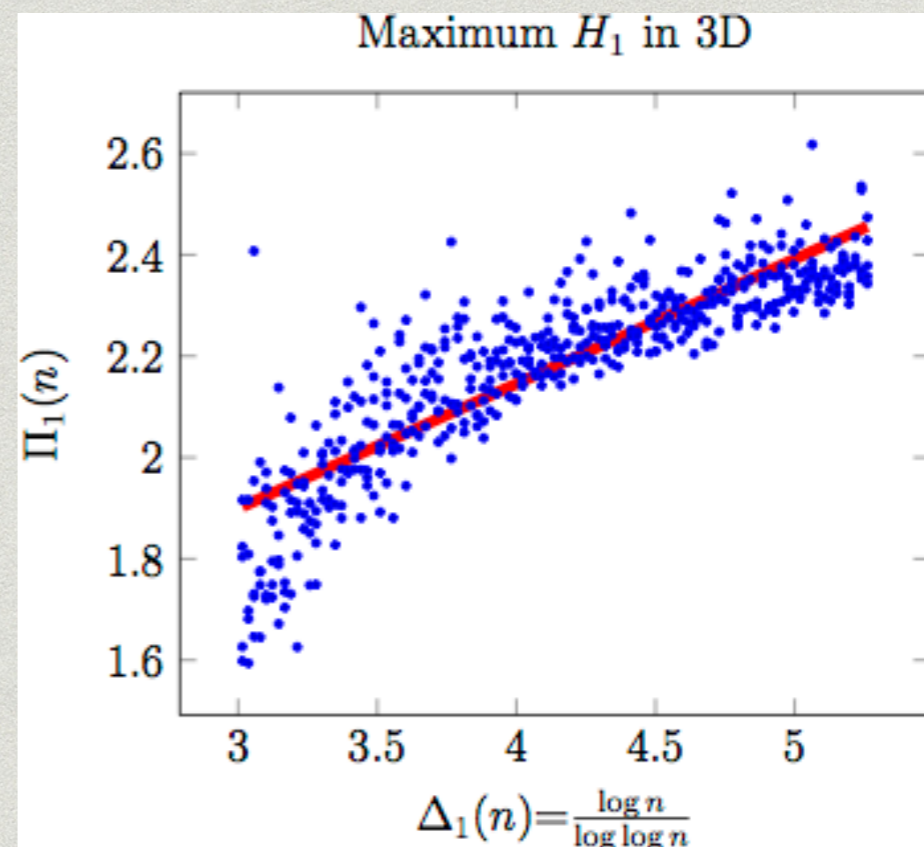
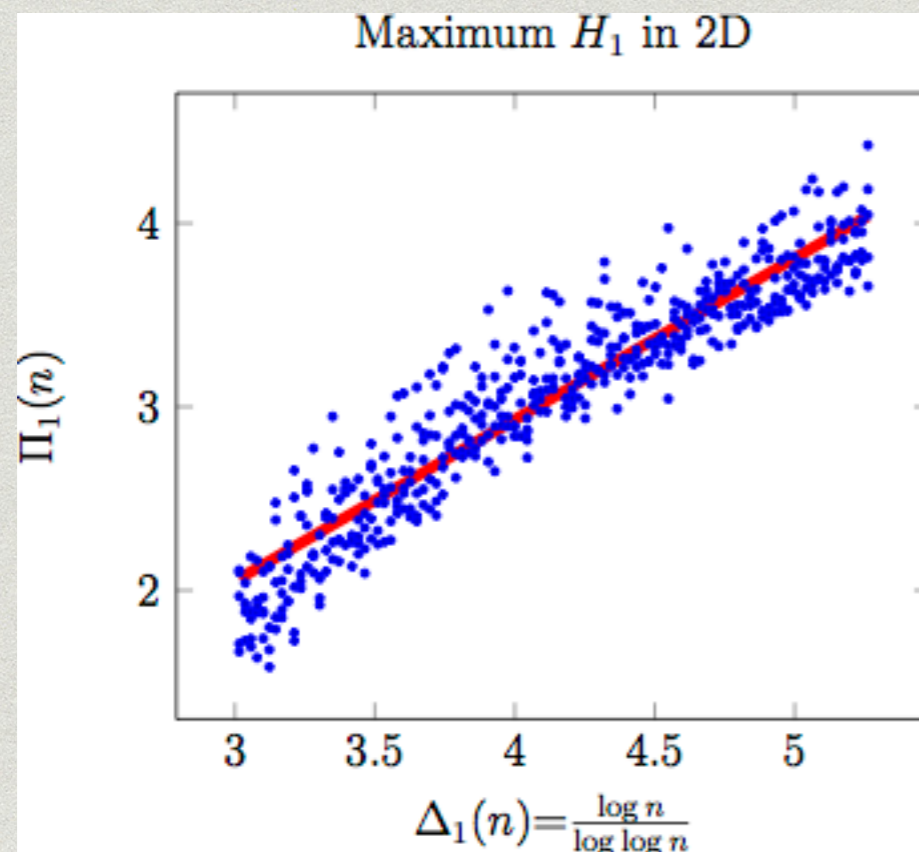
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**Euler-Poincaré characteristic :**  $\chi(r) = 1 + \sum_k (-1)^k \beta_k(r) = \sum_k (-1)^k f_k(r)$

$\chi(r)$  has  $(d - 1)$  zeros in  $d$ -dimensions.

Zero (in  $r$ ) of  $\bar{\chi}(r)$  corresponds to percolation threshold in  $d = 2$ .

**R. Neher, K. Mecke, H. Wagner,** Topological estimation of percolation thresholds.  
J. Stat. Mech., 2008.



## Does “The Master” know it all ?

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**Robert J. Adler,** TDA and the Euler Characteristic Curve. IMA Talk, 2013.







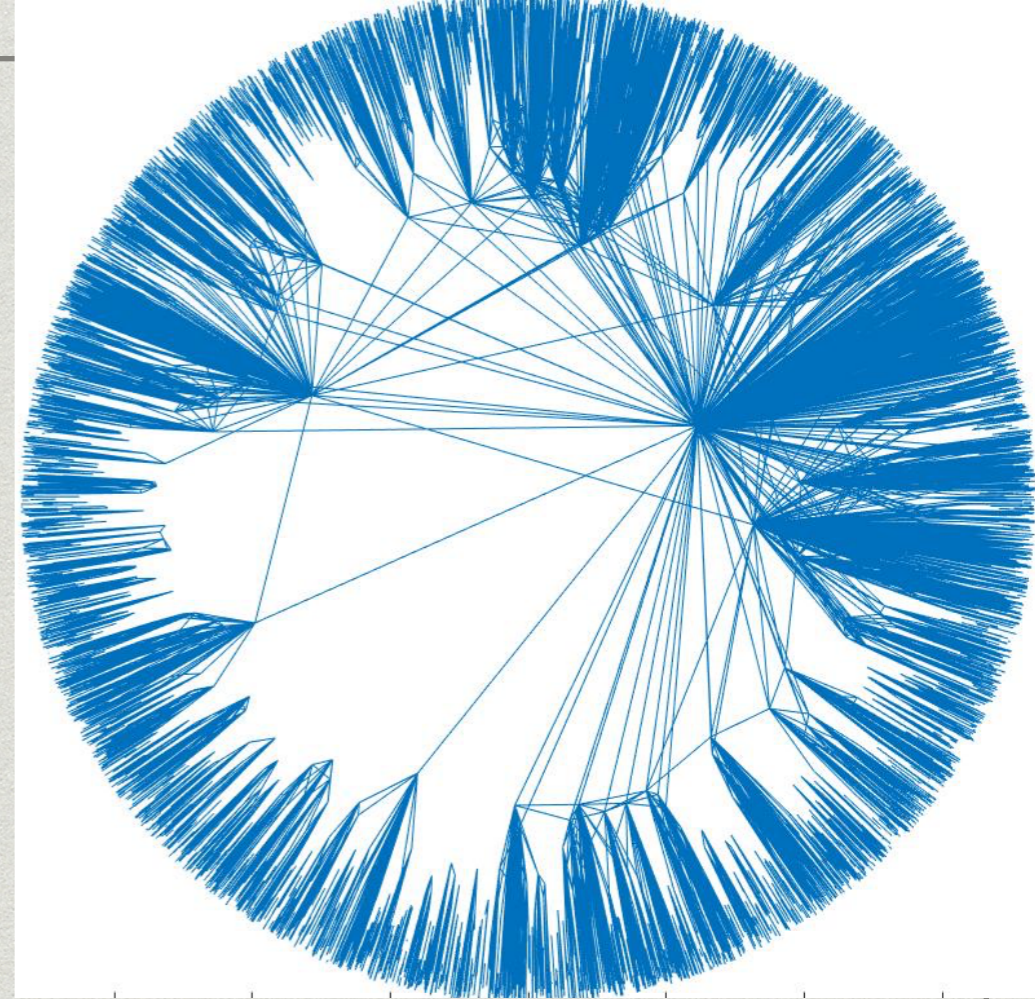
"I predict a new subject of statistical topology. Rather than count the number of holes, Betti numbers, etc., one will be more interested in the distribution of such objects on non-compact manifolds as one goes out to infinity."

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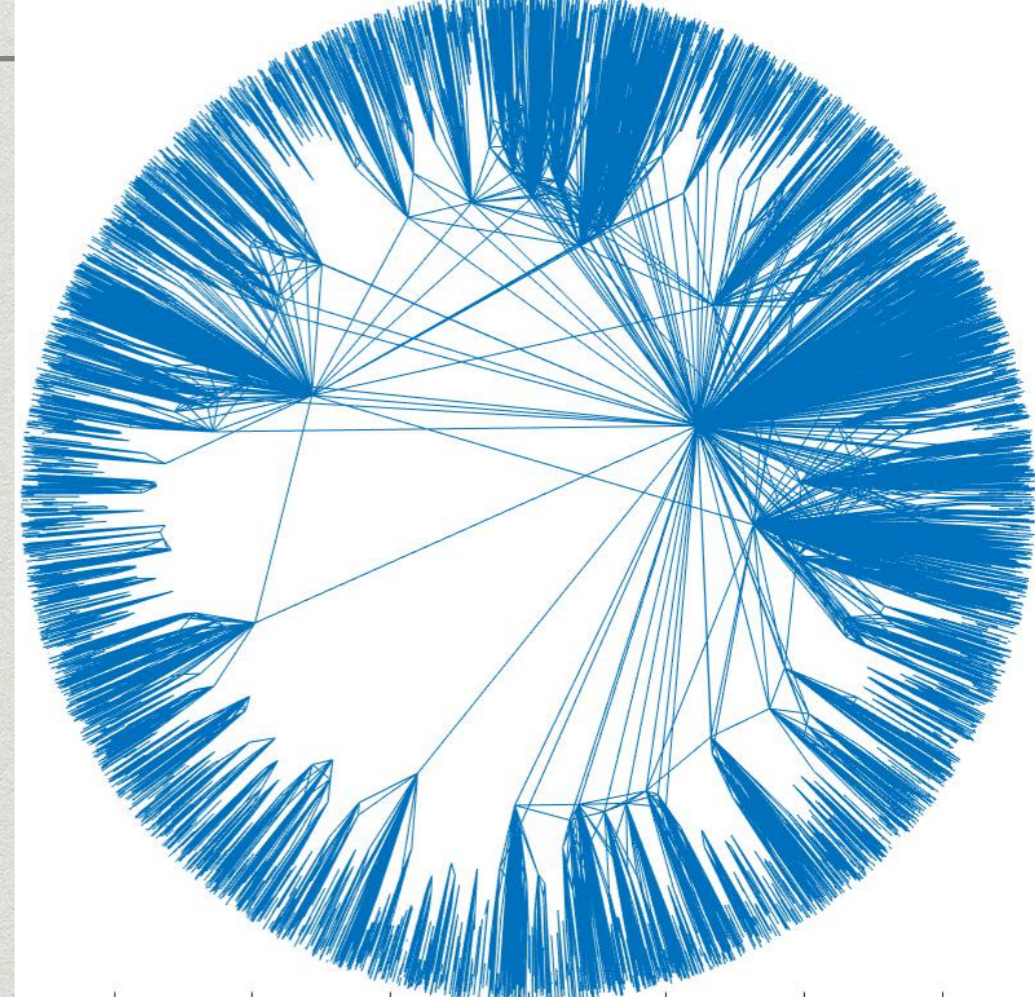
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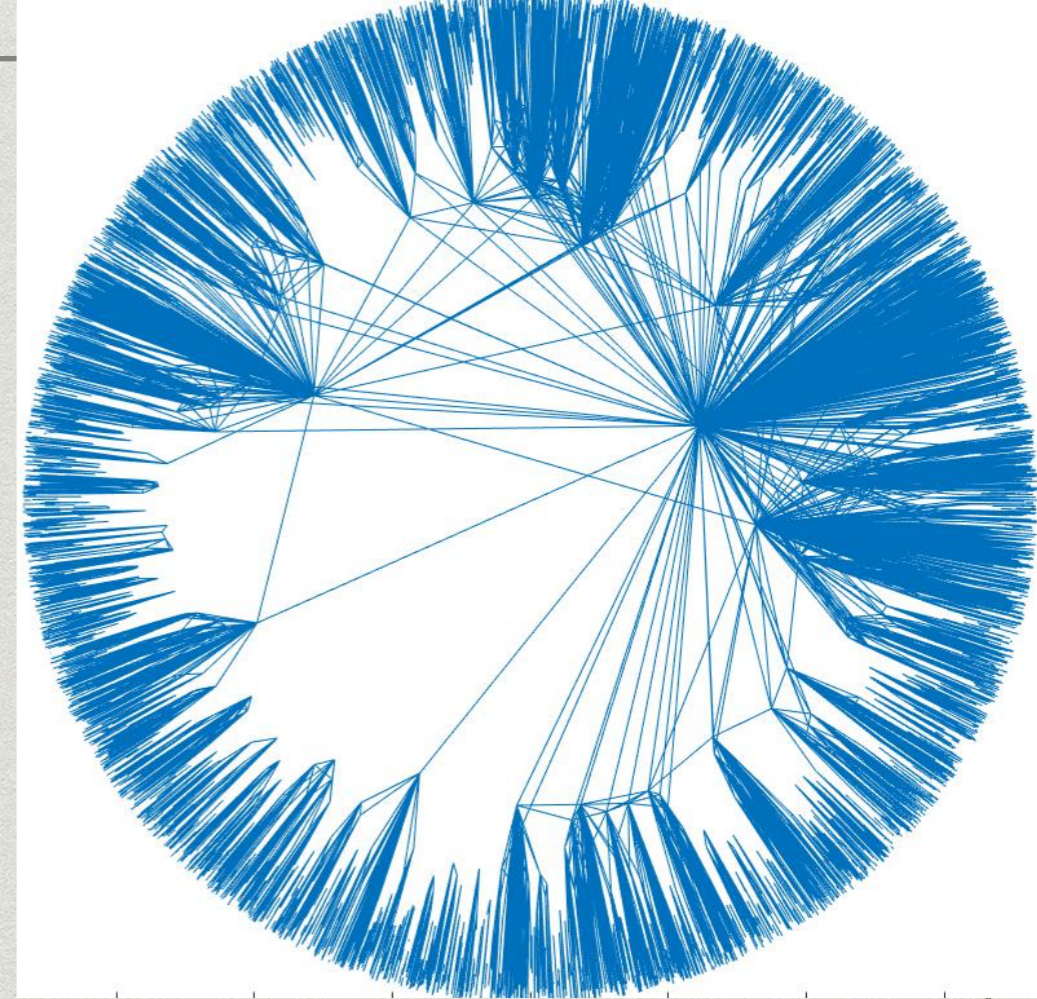


**Robert J. Adler**, **TOPOS**. *IMS Bulletin*, 2016.



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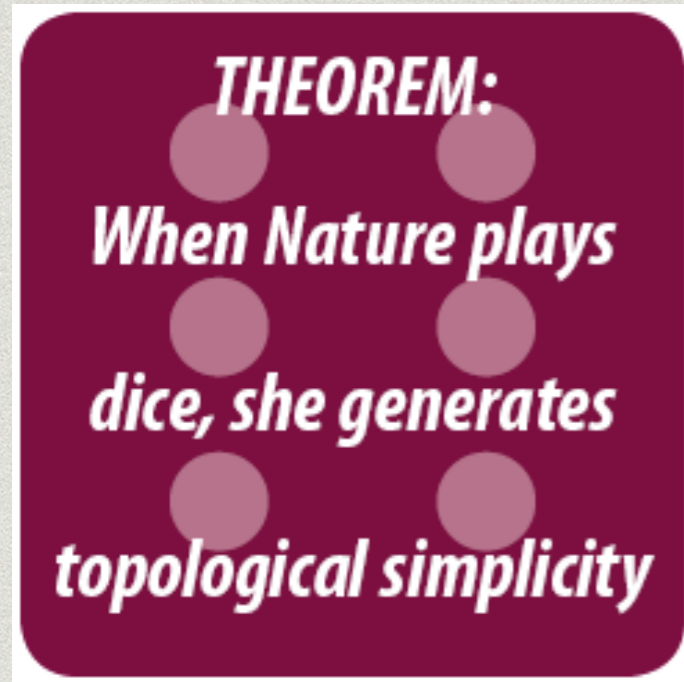
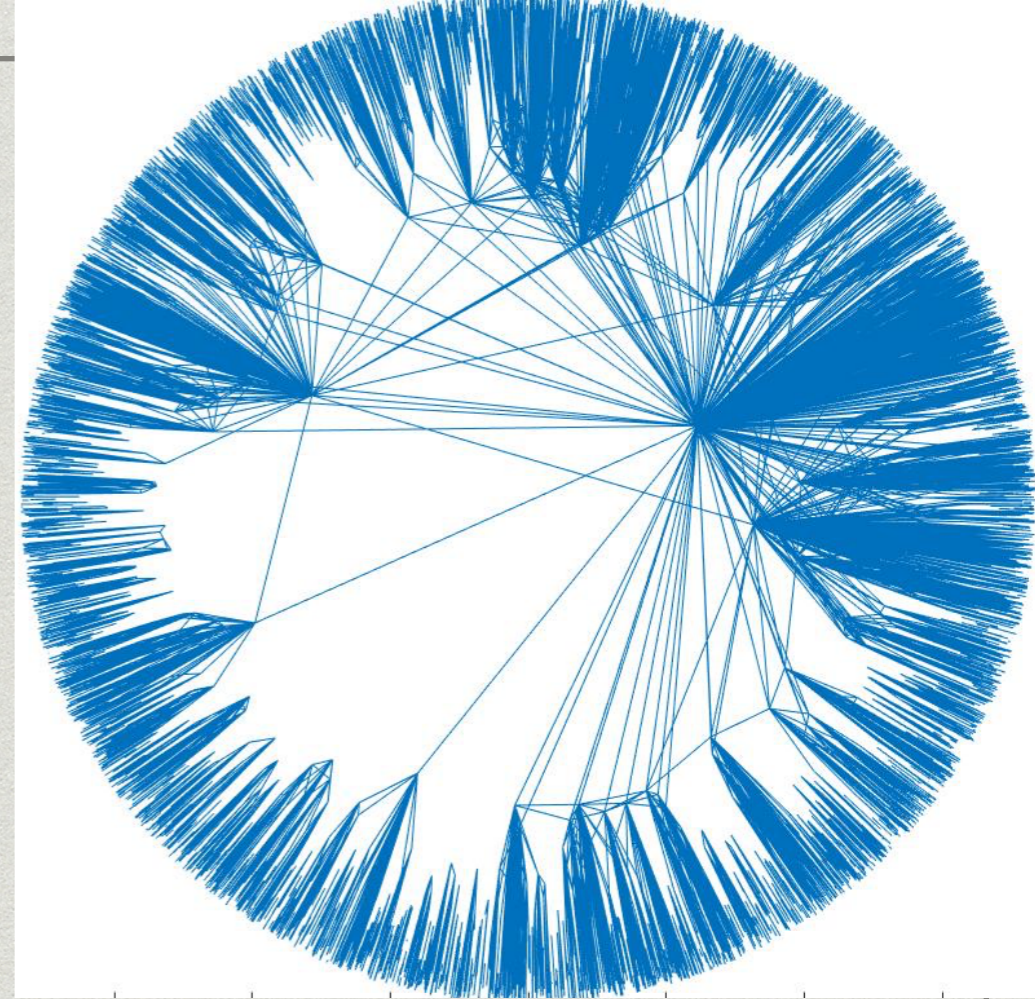
**THEOREM:**  
*When Nature plays  
dice, she generates  
topological simplicity*

**Robert J. Adler, TOPOS. IMS Bulletin, 2016.**



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Isadore Singer, 2004.



Robert J. Adler, *TOPOS*. *IMS Bulletin*, 2016.

## Useful surveys :

1. **Gunnar Carlsson**. Topological pattern recognition for point cloud data. 2014.
2. **Mathew Kahle**, Topology of random simplicial complexes. 2014.
3. **Omer Bobrowski and Mathew Kahle**, Topology of random geometric complexes. 2015