

# Using persistent homology for hypothesis testing

Presentation by Elie Cueto

Articles by Willem Elbers & Rien Van de Weygaert

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# Journal Articles

Monthly Notices

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## Persistent topology of the reionization bubble network – I. Formalism and phenomenology

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## Persistent topology of the reionization bubble network – II. Evolution and classification

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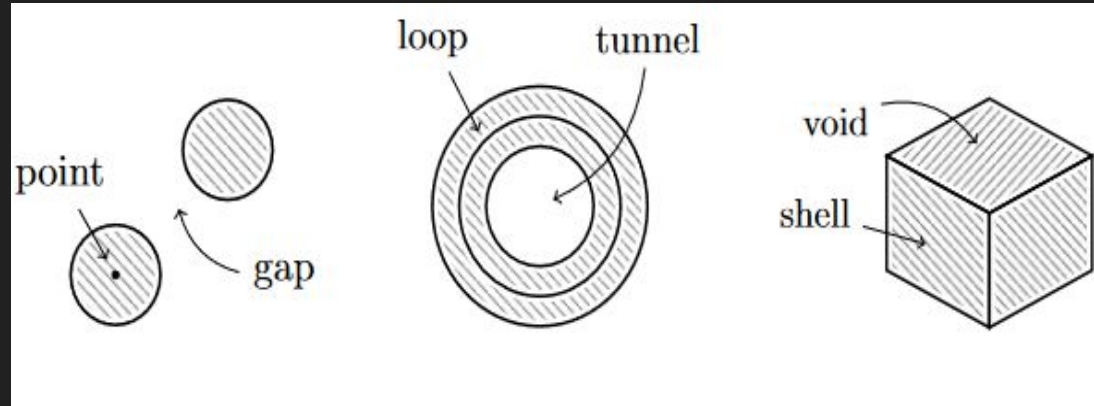
# Disposition

- Introduction to persistent homology and Persistence diagrams
- Statistical treatment of Persistence diagrams
- Example of use in Astrophysics

# Persistent homology: Counting Holes

Finding the number of n-D holes in a structure.

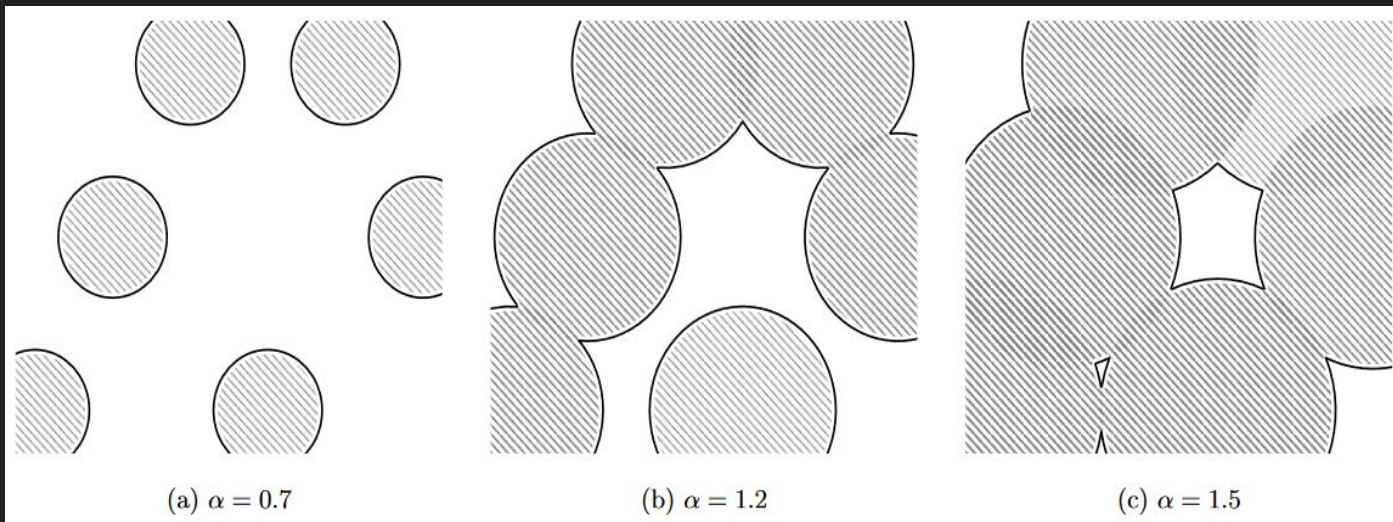
- Gaps between components
- Tunnels through structures
- Voids within shells
- Higher dimensional holes



# Persistent homology: Counting Holes

Let spheres with a radius  $\alpha$  surround each point.

Count the number of holes in each dimension as a function of  $\alpha$



0D: 6  
1D: 0

0D: 2  
1D: 0

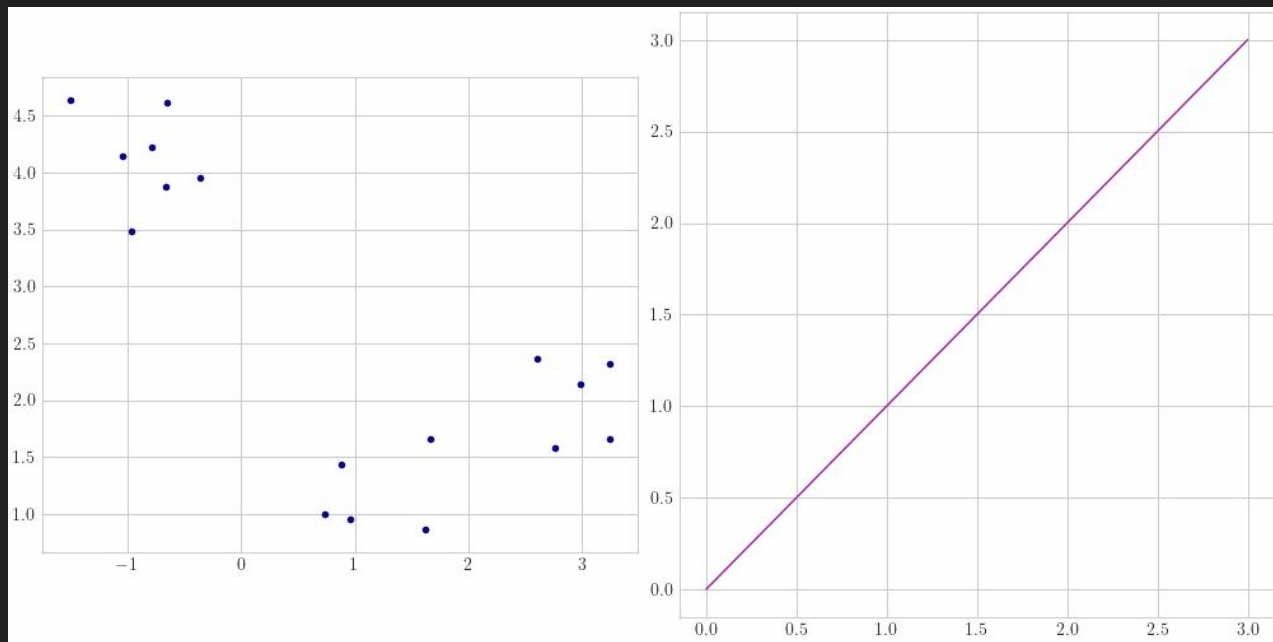
0D: 1  
1D: 2

# Persistence diagrams

When is a feature born

When does a feature die

Visualising high dimensional data

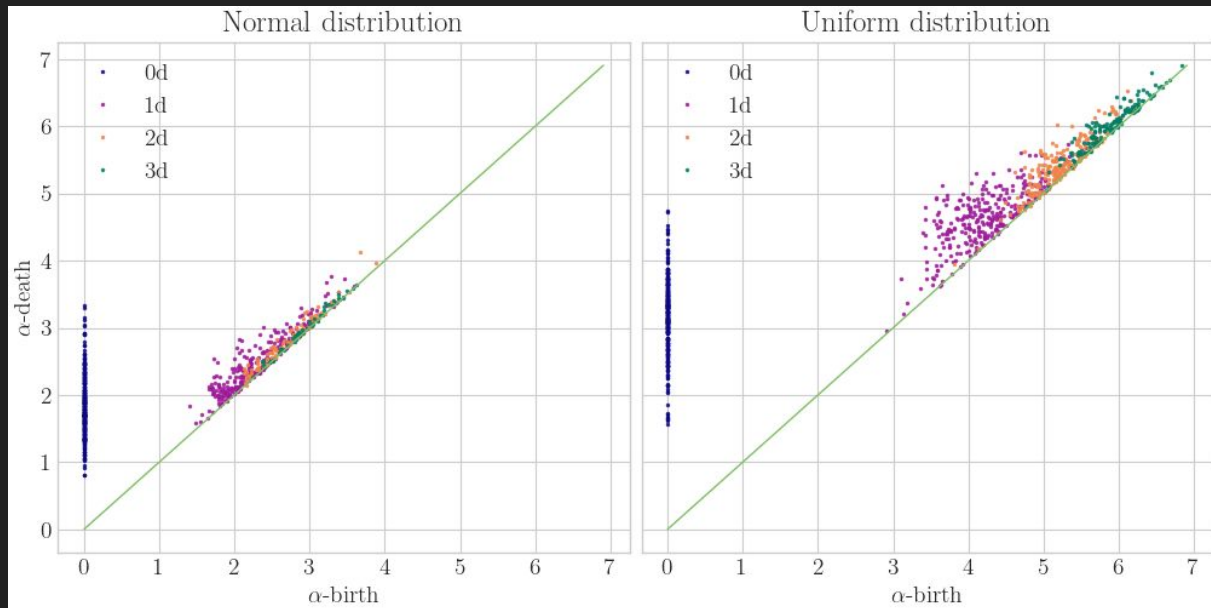


# Persistence diagrams

When is a feature born

When does a feature die

Visualising high dimensional data





# Finally: Statistics

We can find the “Distance” between two persistence diagrams:

$$d(X, Y) = \left[ \inf_{\phi: X \rightarrow Y} \sum_{x \in X} \|x - \phi(x)\|^2 \right]^{1/2}$$

With Monte Carlo simulations of our New and Improved model, as well as our null hypothesis model we can find a Fréchet Average:

$$F(Y) = \frac{1}{n} \sum_{i=1}^n d(Y, X_i)^2$$

# Finally: Statistics

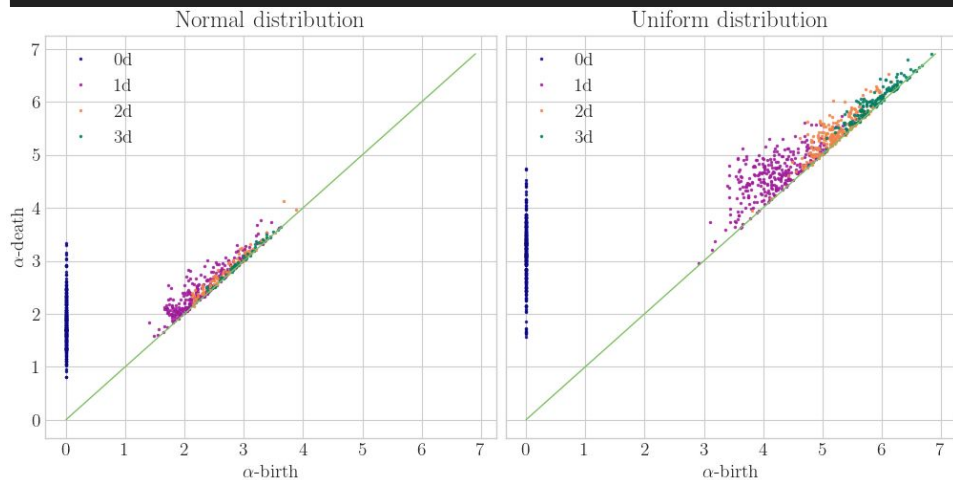
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A model will tend to have a lower Fréchet average, if it is more similar to the data



These persistence diagrams a large distance, as they are constructed from data with different PDFs

# Distances between diagrams

Mock data generated with

$$f(x, y) = (1 + ax + bx^2)(1 + ay + by^2)$$

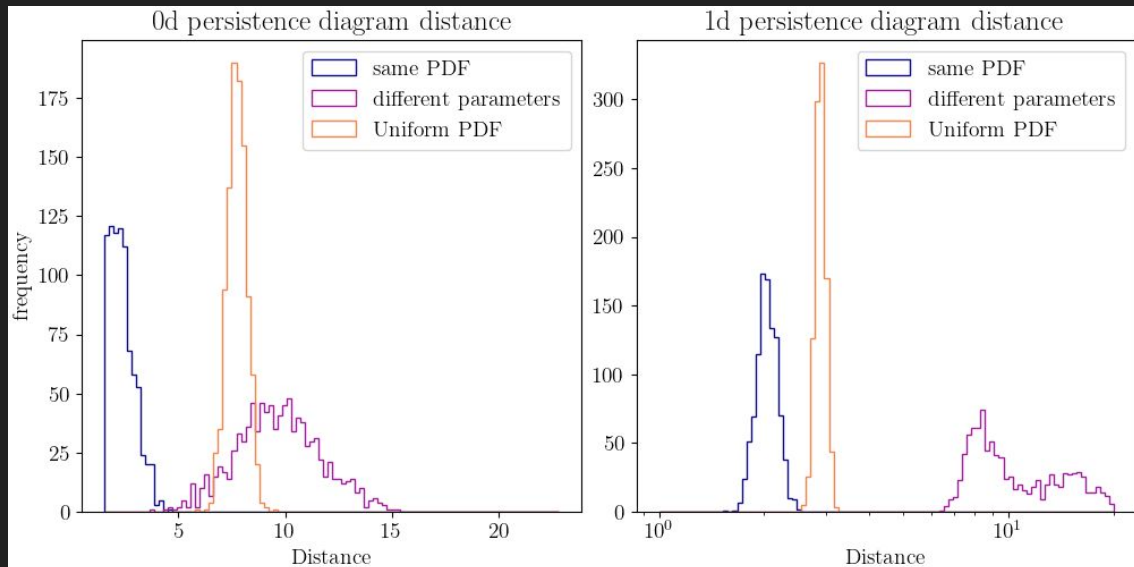
For  $a = 1$ ,  $b = 2.4$ ,  $-2 < x < 2$ ,  $N = 1000$

1000 simulations with same PDF,

Uniform PDF, and PDF with

$a = -2$ ,  $b = 2.4$

The “Correct” PDF gives a much lower distance distribution



# Persistence Fields

We can find a variance on each feature in our data:

$$\sigma_y^2 = \frac{1}{n} \sum_{i=1}^n \|y - \phi_i(y)\|^2$$

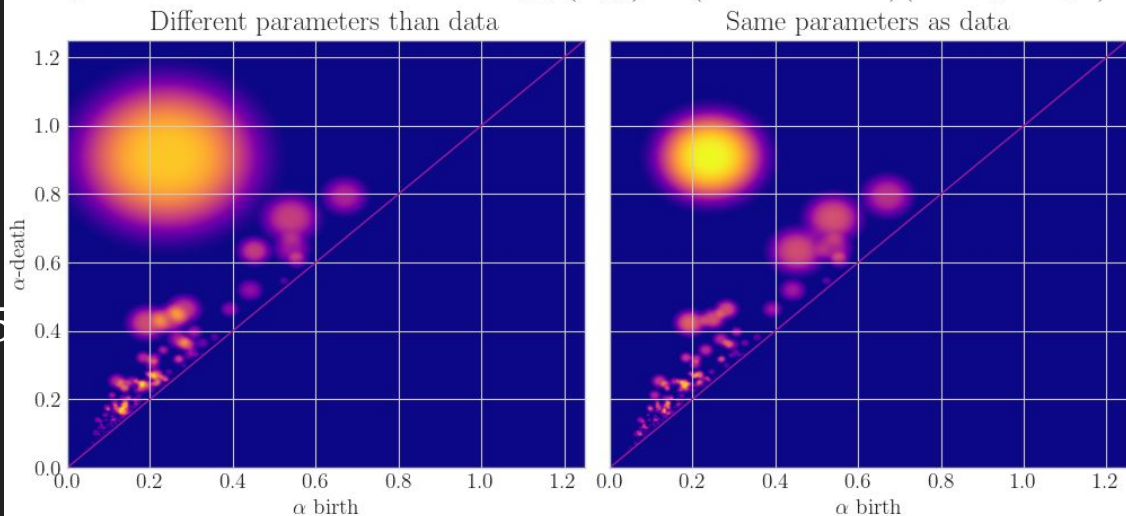
With the variance we can construct Persistence Fields

For each feature here,  $r \sim \sigma$  and “brightness”  $\sim (\alpha_{\text{death}} - \alpha_{\text{birth}})^{0.5}$

Highly persistent features tend to be more significant, but less commonly found.

Larger radii here correspond the model being worse at recreating features of data

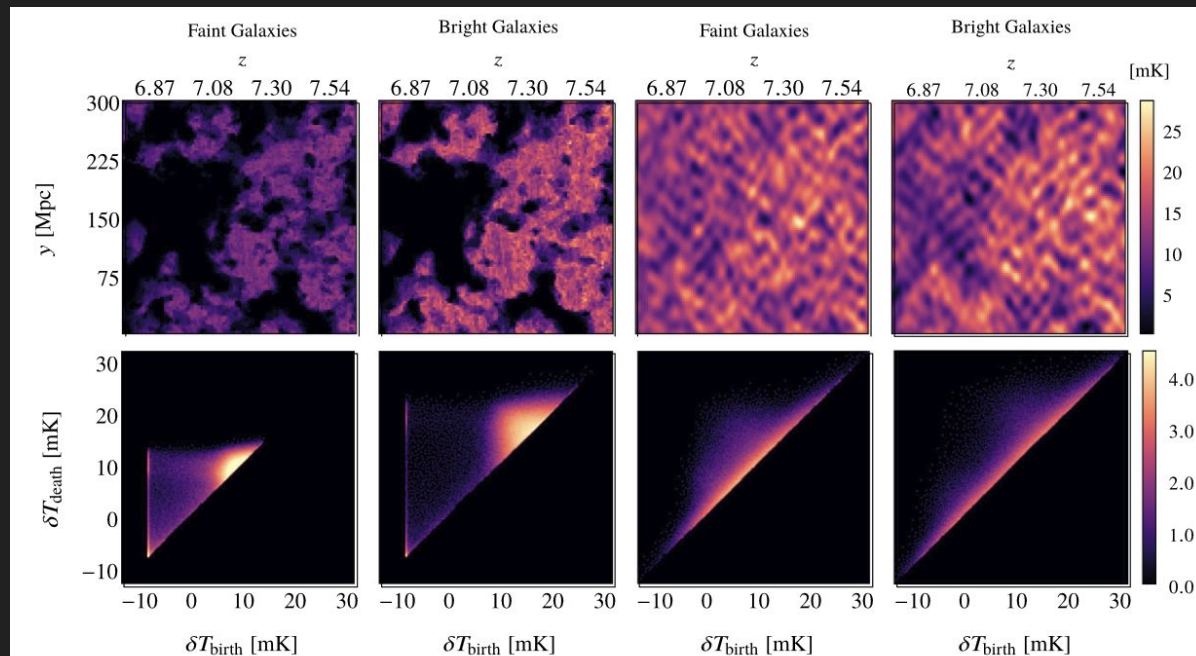
1D persistence fields for a 2D PDF,  $f(x, y) = (1 + ax + bx^2)(1 + ay + by^2)$



# Persistent homology put to use: Epoch of Reionisation

Distinguishing different models  
of reionisation.

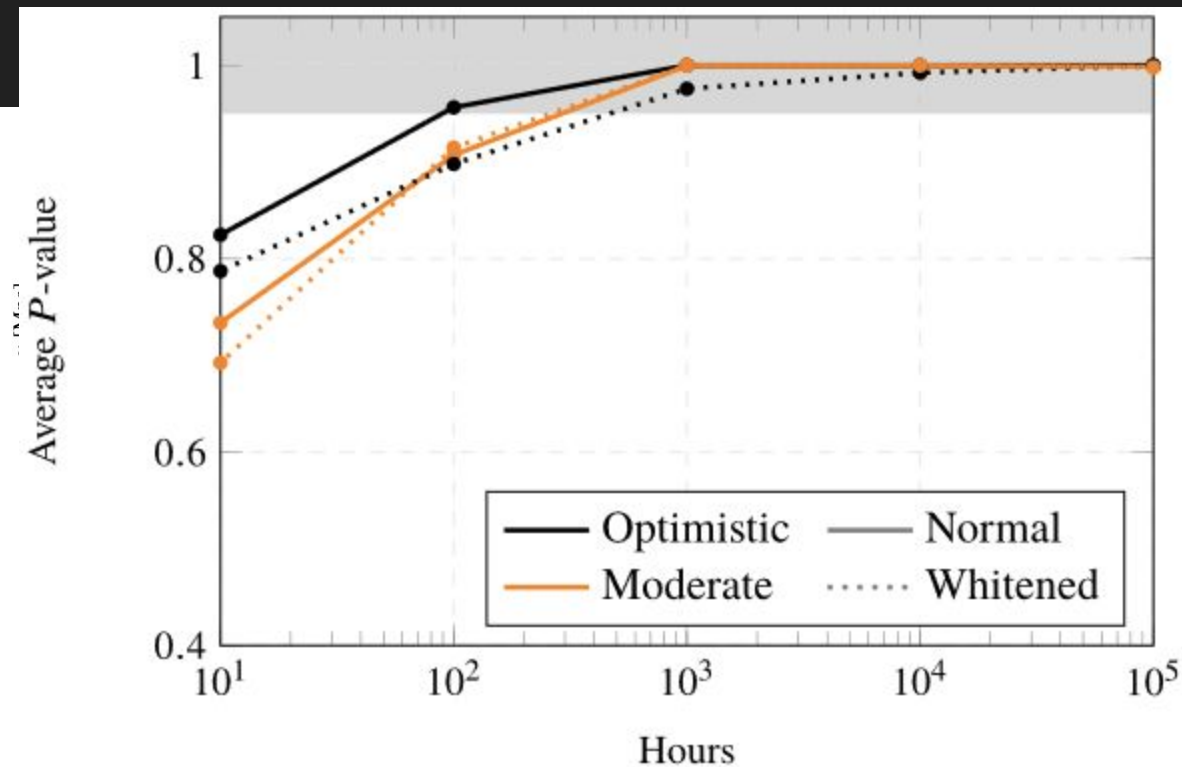
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levels consistent with how  
observations will look, different  
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# Persistent homology put to use: Epoch of Reionisation

Distinguishing different models of reionisation.

Even When introducing noise levels consistent with how observations will look, different models can consistently be differentiated



# Conclusions

Visualising High dimensional data

Determining how well different models reproduce data

Very robust to noisy data