



Noise robustness of persistent homology

across filtrations and signatures

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Persistent homology
is a noise-robust
topological summary.



Well...

Persistent homology

Homology & Betti numbers β

Homology captures information about k -dimensional cycles:

- ▶ connected components (0-dimensional homology)
- ▶ holes (1-dimensional homology)
- ▶ voids (2-dimensional homology)
- ▶ ...

β	Sphere	Torus	Two-holed torus	Projective plane	Klein bottle
β_0	1	1	1	1	1
β_1	0	2	4	1	2
β_2	1	1	1	1	1

Persistent homology = Homology of data

Persistent homology (PH), describes the **shape** of an object (a point cloud, an image, a time series, a network, etc), i.e., it captures information about k -dimensional cycles which **persist** across different scales $r \in \mathbb{R}$.

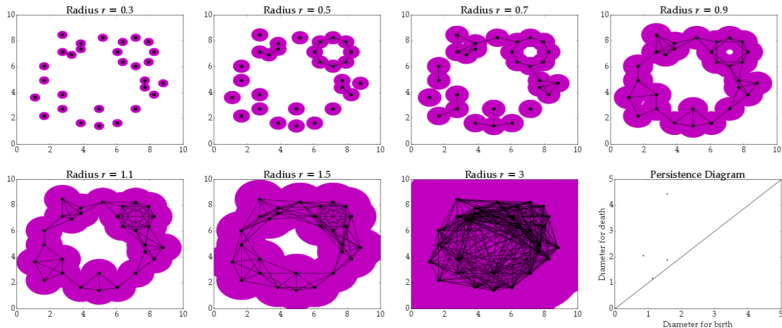


Figure taken from Munch, Elizabeth, *A user's guide to topological data analysis*, Journal of Learning Analytics 4.2 (2017): 47-61.

Stability theorems

The black and the noisy red circle have similar persistence diagrams.

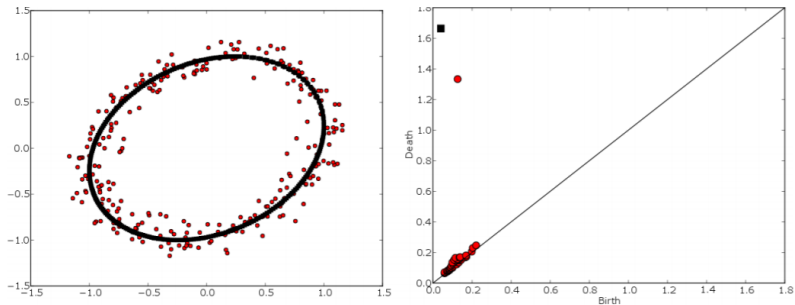


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Well...

Persistent homology pipeline

image



persistence
diagram



Persistent homology pipeline

image → filtration

→ persistence
diagram



Persistent homology pipeline

image → filtration

→ persistence
diagram



$R_0(Z)$

\subset



$R_{e_1}(Z)$

\subset



$R_{e_2}(Z)$

\subset



$R_{e_3}(Z)$

Persistent homology pipeline

image → filtration

→ persistence diagram



Persistent homology pipeline

image → filtration

→ persistence diagram → persistence signature



Persistent homology pipeline

image → filtration

→ persistence diagram → persistence signature



Persistent homology pipeline

image → filtration

→ persistence diagram → persistence signature

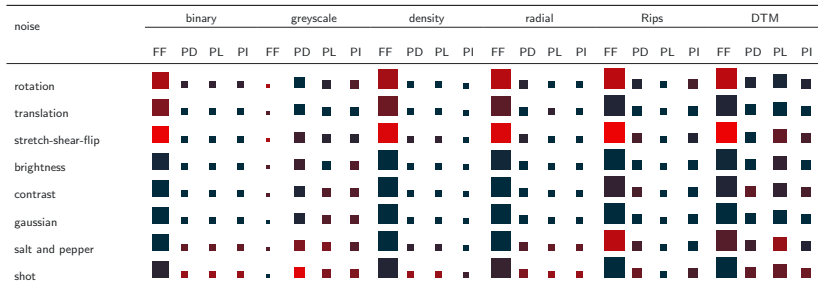


!!! Stability theorem: $d(PS(\phi), PS(\psi)) \leq c\|\phi - \psi\|_p$

Noise robustness of PH

noise	binary				greyscale				density				radial				Rips				DTM			
	FF	PD	PL	PI	FF	PD	PL	PI	FF	PD	PL	PI	FF	PD	PL	PI	FF	PD	PL	PI	FF	PD	PL	PI
no noise																								
rotation																								
translation																								
stretch-shear-flip																								
brightness																								
contrast																								
gaussian																								
salt and pepper																								
shot																								

Noise robustness of PH features in a classification task



node size = accuracy on the non-noisy test data

node color = drop in SVM classification accuracy when the test dataset is noisy, compared to the non-noisy test set (red indicates significant performance loss)

Noise robustness of PH features in a classification task

For SVM trained on non-noisy and tested on noisy images, there is at least a 30% drop in accuracy compared to non-noisy test data, for at least 0- or 1-dimensional PH, for at least one of the considered signatures:

- ▶ rotation and translation: radial
- ▶ stretch-shear-flip: radial, Rips, DTM
- ▶ brightness and contrast: greyscale
- ▶ gaussian: greyscale
- ▶ salt and pepper: binary, greyscale, density, radial, Rips, DTM
- ▶ shot: binary, greyscale, density, radial, Rips, DTM,

often varying across PDs, PLs and PIs.



- ▶ noise sensitivity of PH is influenced by the choice of filtration and persistence signature (input and output of PH)
- ▶ PH features are not always robust under any type of noise in a classification task

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