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Session 1

Machine learning to identify shapes obtained from Laser Optical Particle Counters

Marc Hufnagl

Andre Eckhardt, Dominik Gloe, Tim Dudeck, Silke Janßen, Klas Möller, Kristin Hänselmann, Jens Floeter, Gilles Dupoy, Justus van Beusekom, Bettina Walter, Christian Möllmann

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Find efficient ways to sample

the whole ecosystem,
with high (relevant) resolution,
low impact,
high accuracy
and short time lag between samples!

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TRIAXUS: a holistic approach to efficiently sample the whole ecosystem with high resolution

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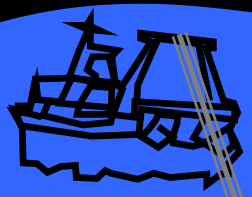
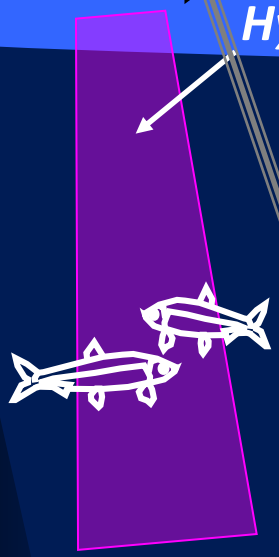
birds and marine mammals based on transect counts [during encounter]

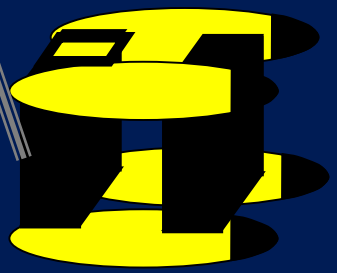


[3x600 per sec]
Hydroacoustics



Fluorescence [1 per sec]

Laser Optical Particle Counter (LOPC) [128 bins/s]
Video Plankton Recorder (VPR) [25+ pics/sec]



Temperature
Salinity
Turbidity
O_2

[1 per sec]

Light spectrum [261 wavel. per sec]

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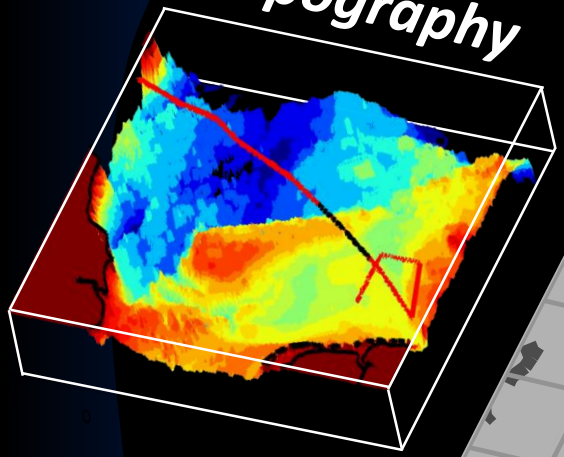
topography



Stonehaven

9-15th July 2014

Transekt

Great Britain

Helgoland

Germany

Denmark

0
-50
-100
-150

-2
0
2
4
6
8
10

52
53
54
55
56
57

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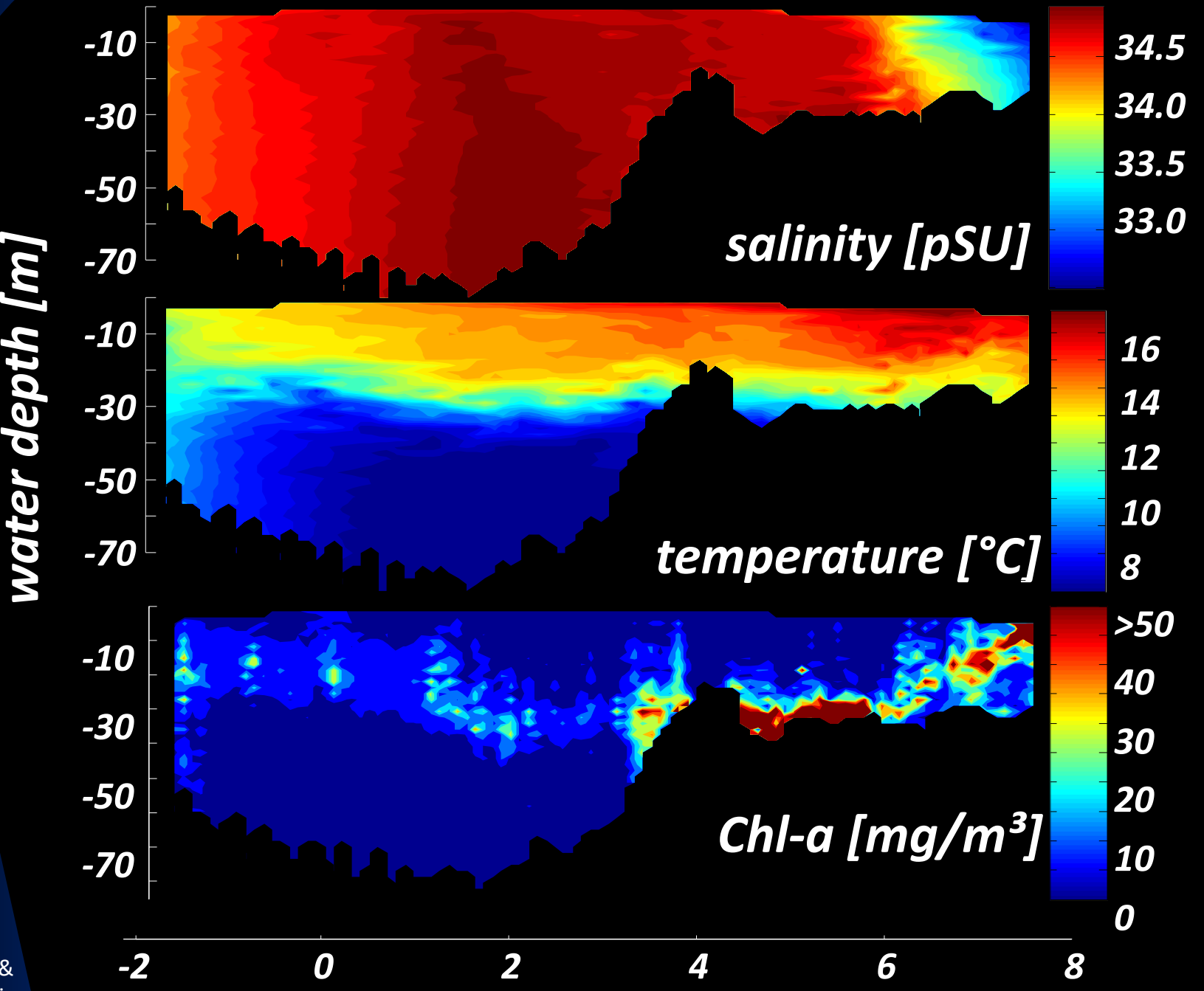
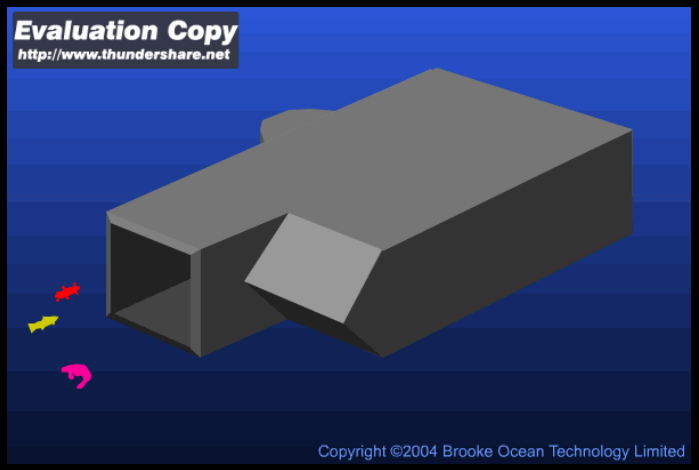
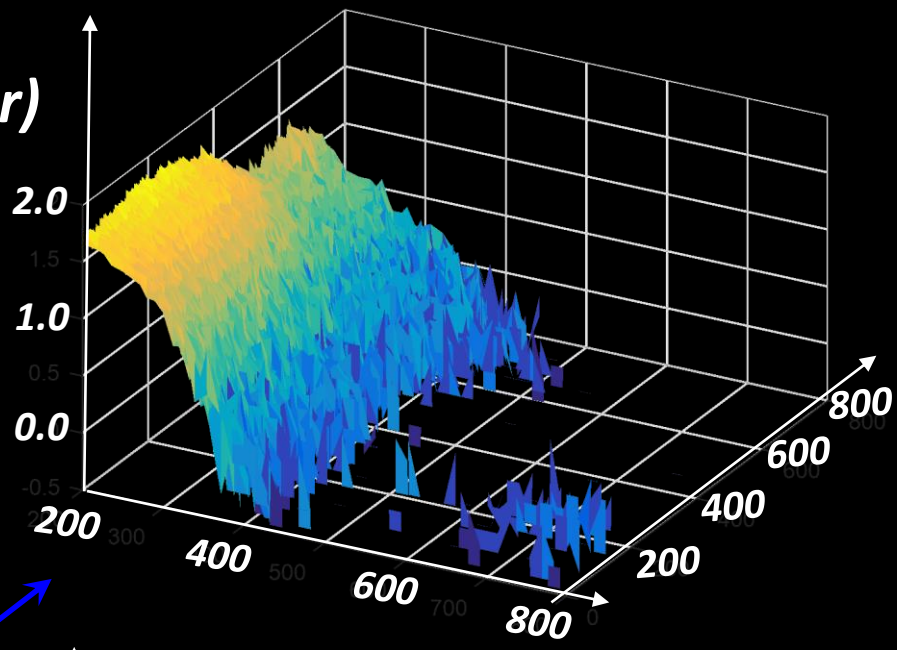
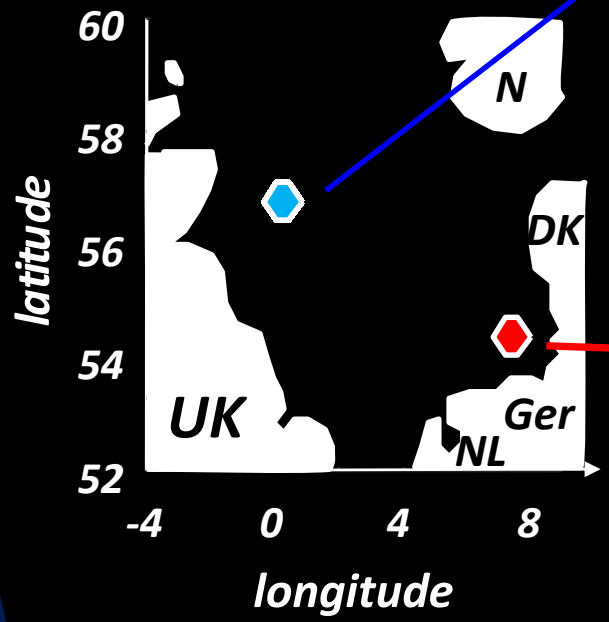
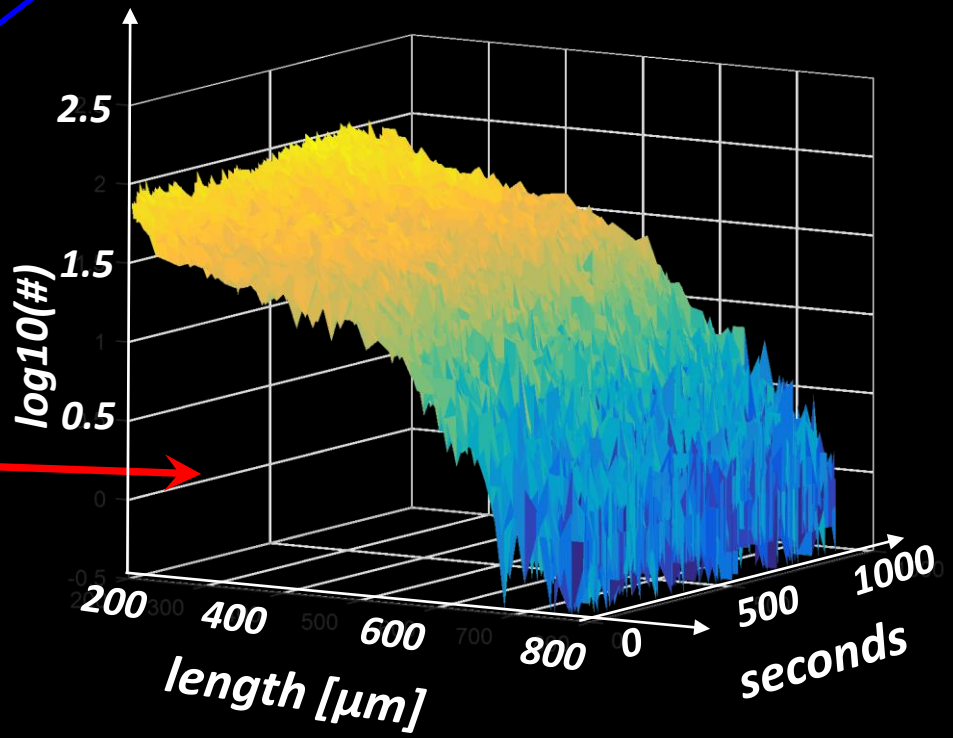


What is the LOPC: (Laser Optical Particle Counter) and what does it provide?









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But you also get MEPs: Multi Element Particles

LOPC

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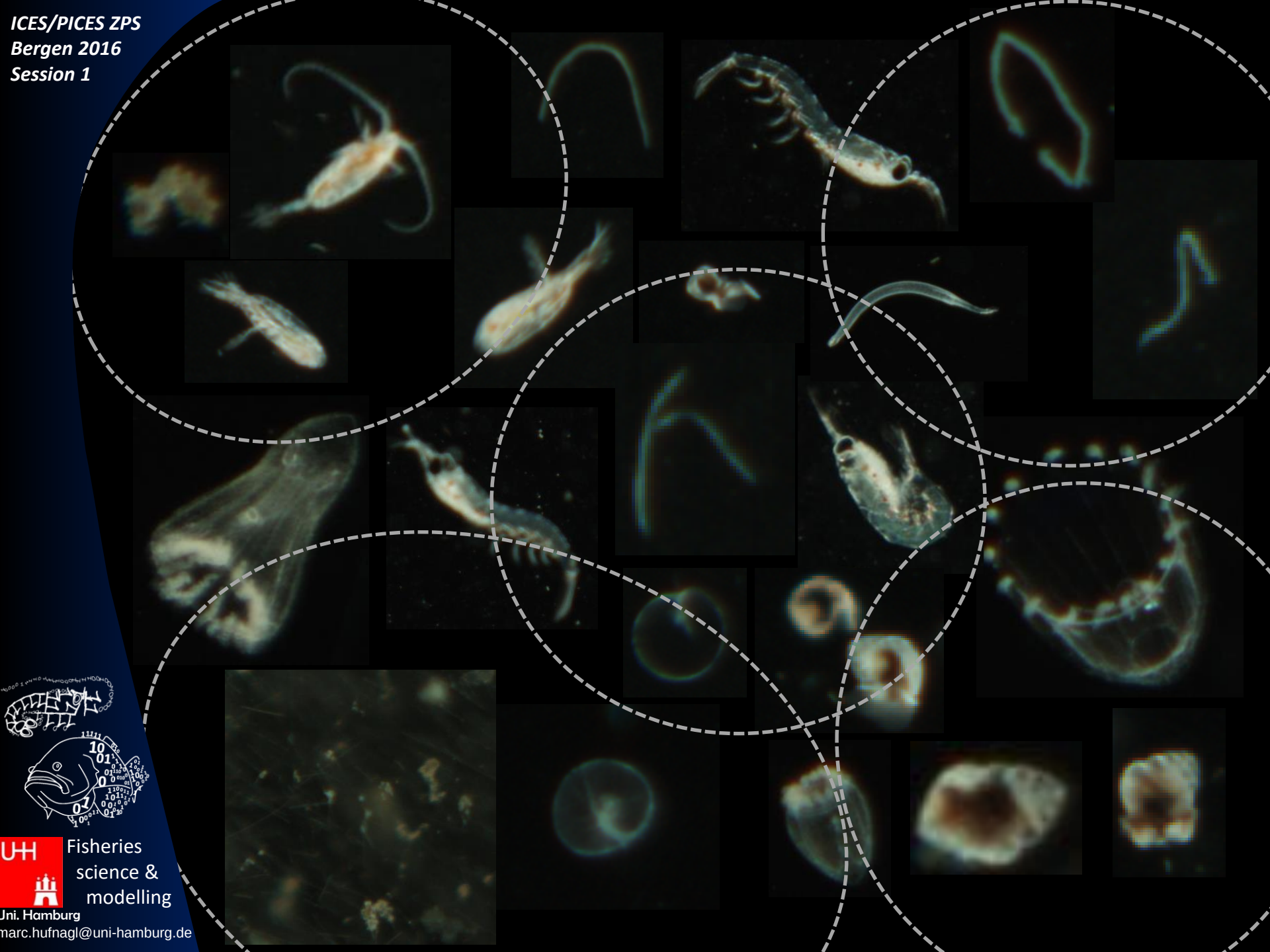

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marc.hufnagl@uni-hamburg.de

Video Plankton Recorder
VPR
provides validation pictures

BUT

there are 3.000.000 of them

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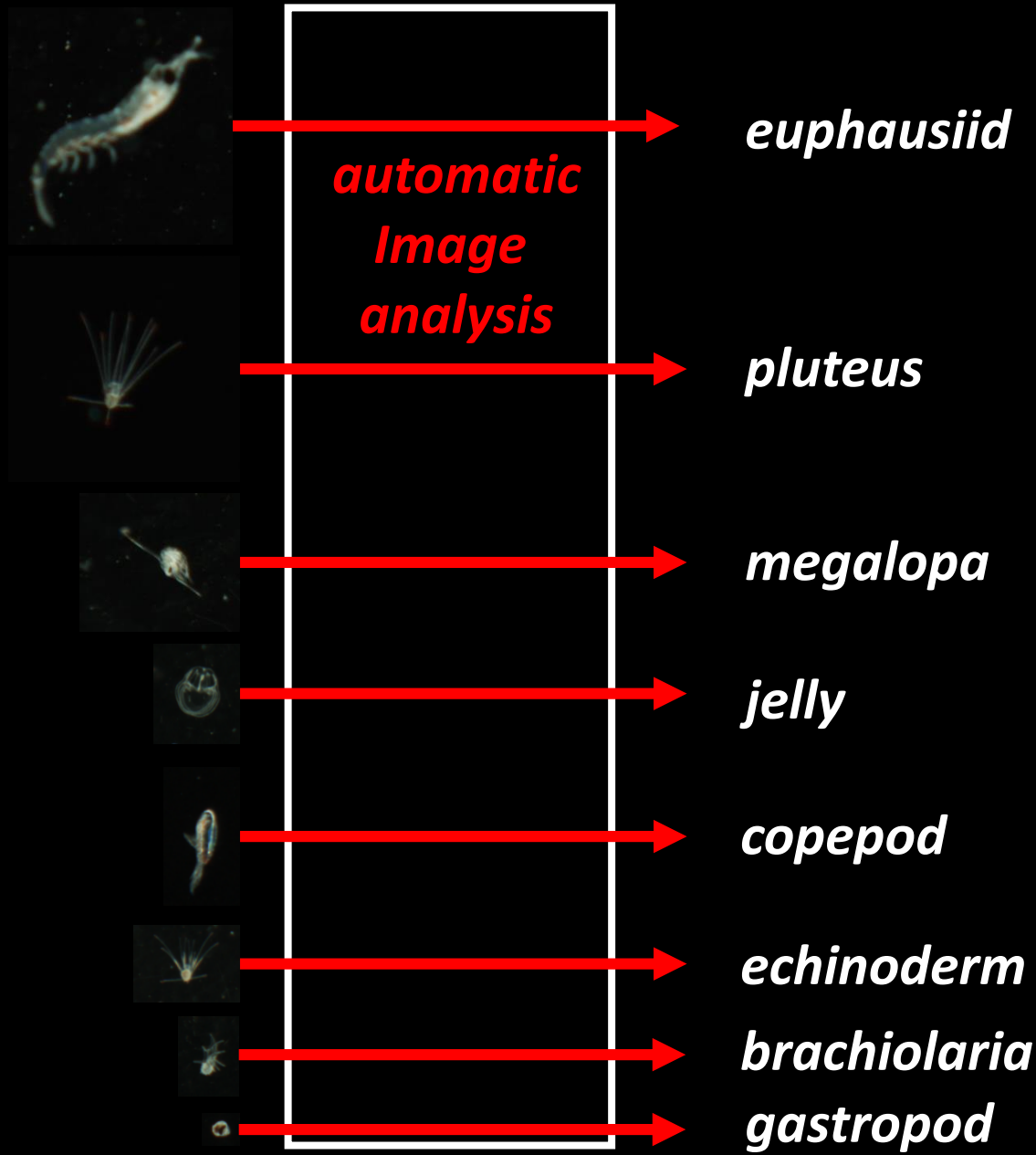

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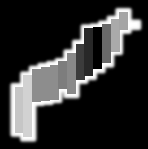
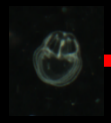
VPR	Classifier	Calibration set	artificial LOPC
	automatic Image analysis	euphausiid	
		pluteus	
		megalopa	
		jelly	
		copepod	
		echinoderm	
		brachiolaria	
		gastropod	-

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VPR

Classifier

automatic
Image
analysis

Calibration set

artificial LOPC

euphausiid

pluteus

megalopa

jelly

copepod

echinoderm

brachiolaria

gastropod

Classifier2

automatic
Shape
analysis

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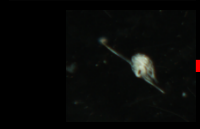

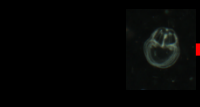

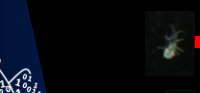

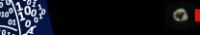

VPR

Classifier

automatic Image analysis

Calibration set

artificial LOPC

euphausiid

pluteus

megalopa

jelly

copepod

echinoderm

brachiolaria

gastropod

Classifier2

automatic Shape analysis

euphausiid
megalopa euphausiid
megalopa megalopa
pluteus pluteus echinoderm
copepod echinoderm
pluteus jelly
brachiolaria jelly
copepod jelly
gastropod brachiolaria
echinoderm
brachiolaria copepod
euphausiid gastropod
gastropod

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How can a computer know/learn:

This is a copepod !?

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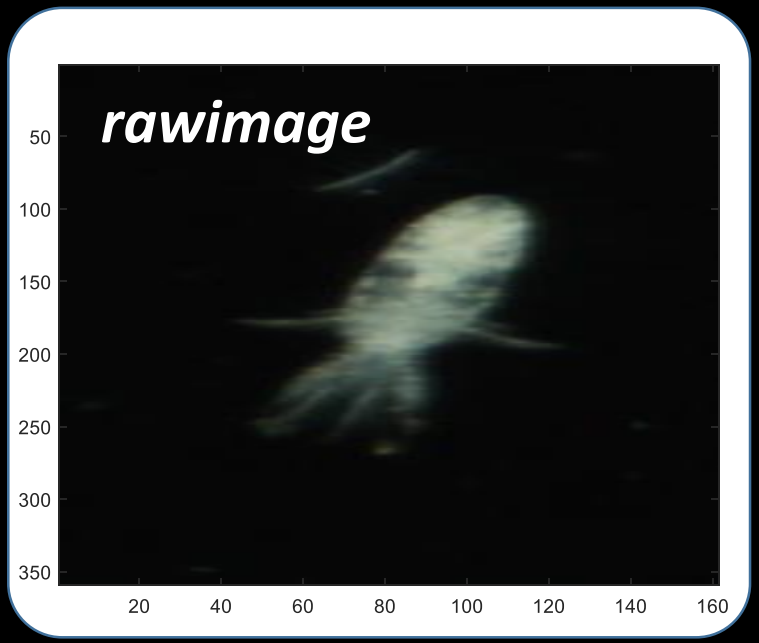
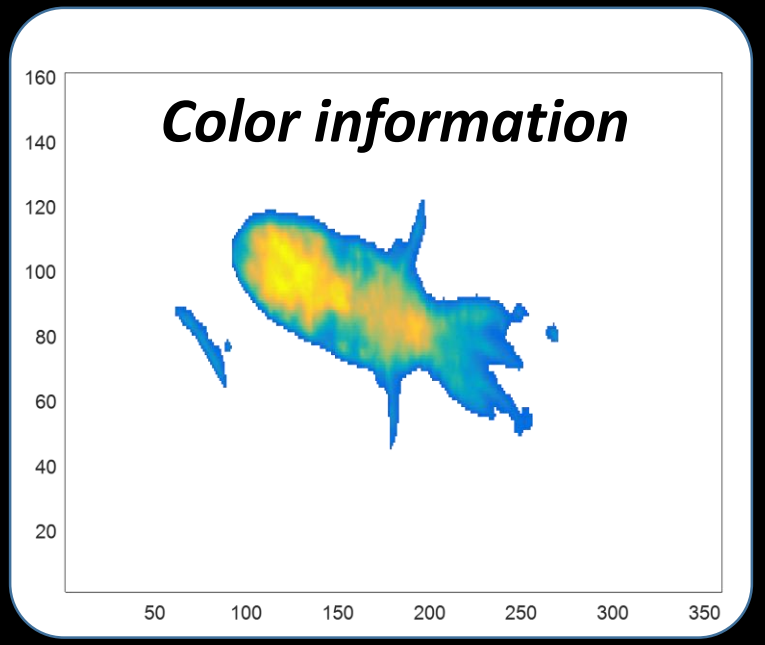
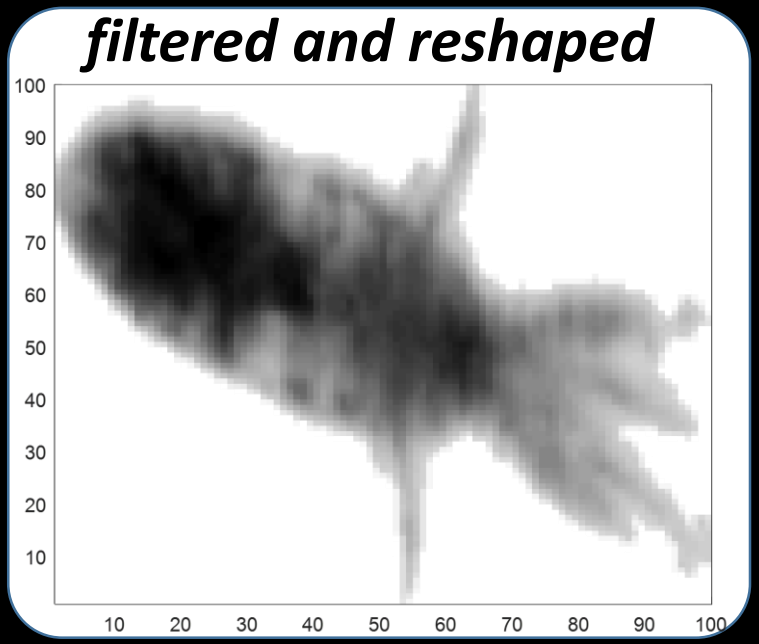
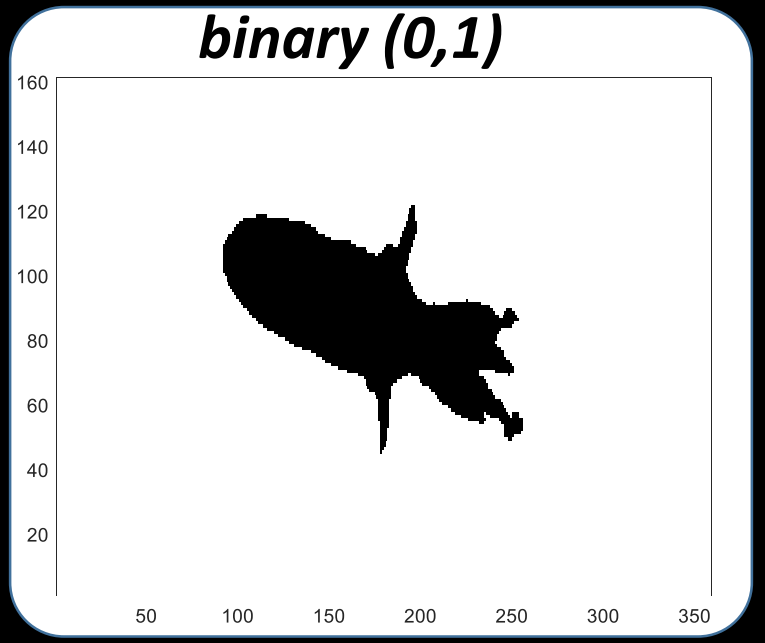
What information and what options do we have?









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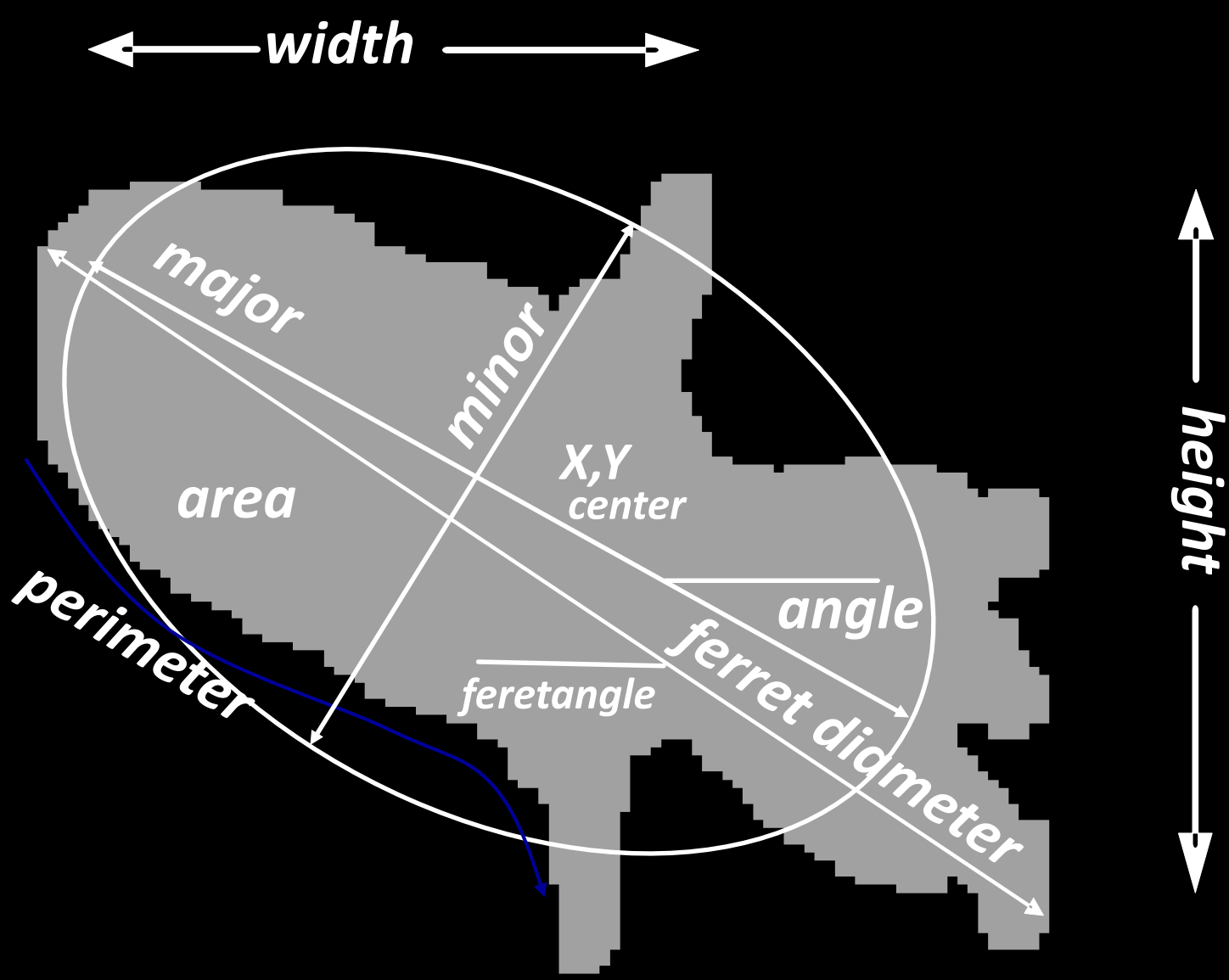
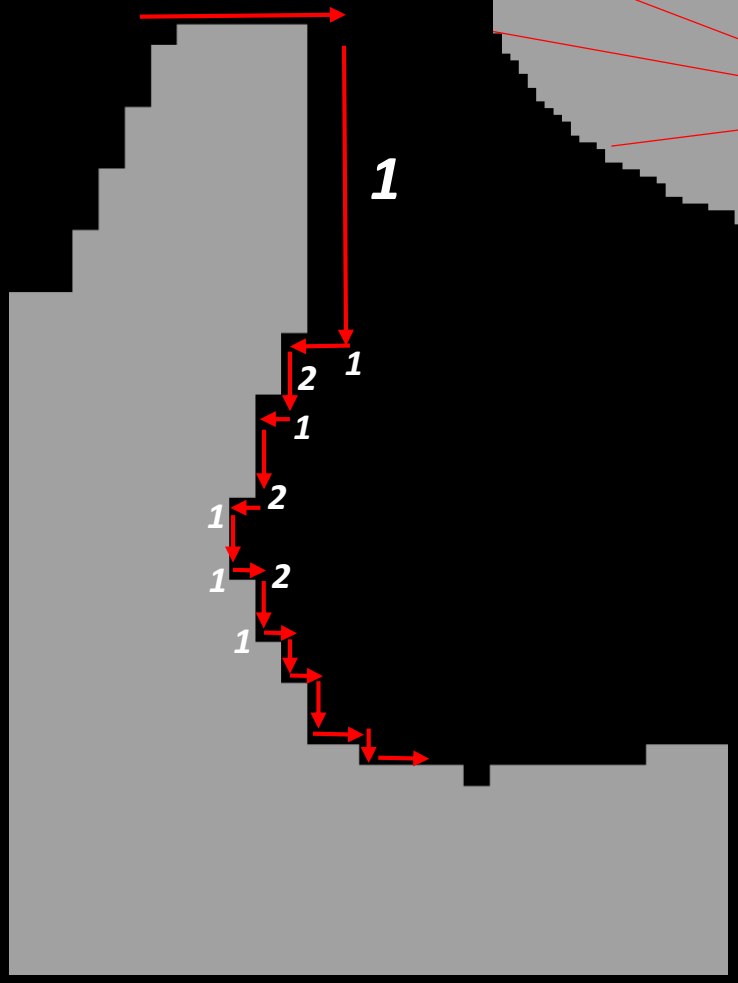
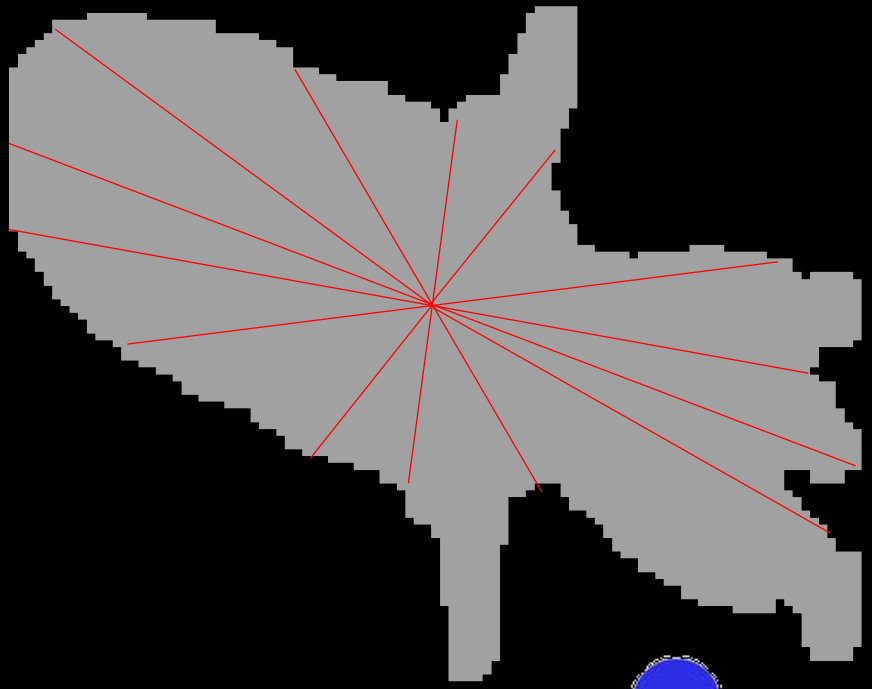


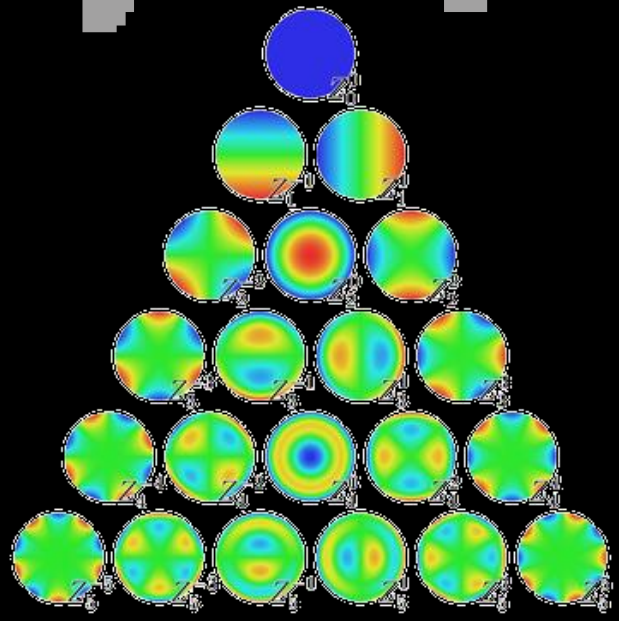
Circularity : Area/Perim (1=Circle)
AR: Major / Minor
Round: Area /Major²
Solid: Area / ConvexArea
*IntDen : Area*mean grey*

histogram of distance to the center

snake/chain descriptors







Zernik polynomials/moments

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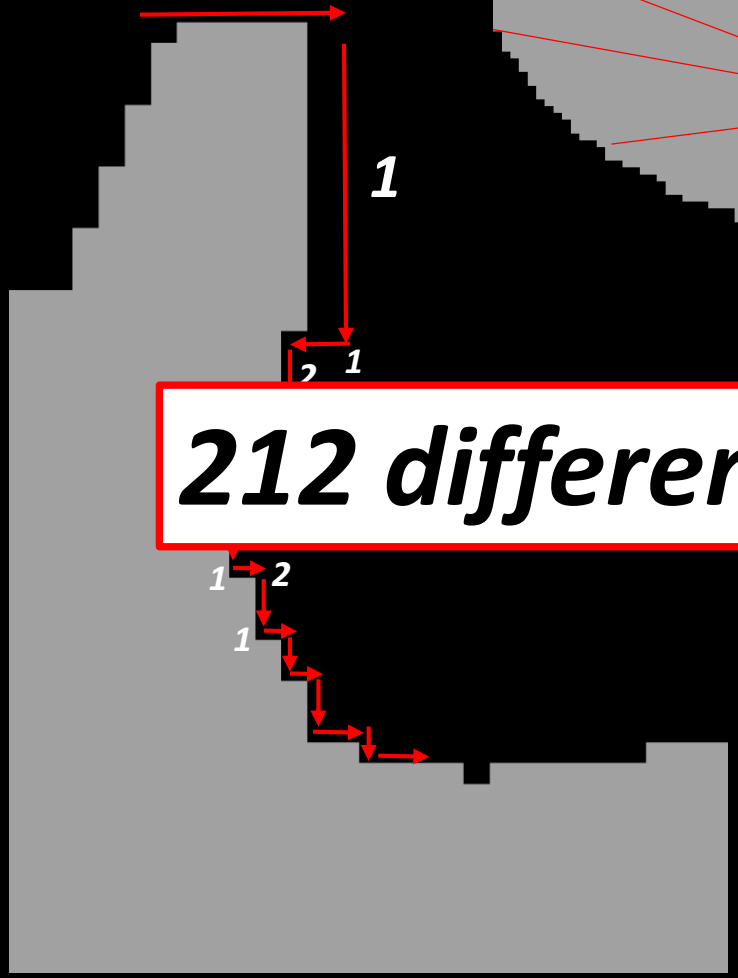
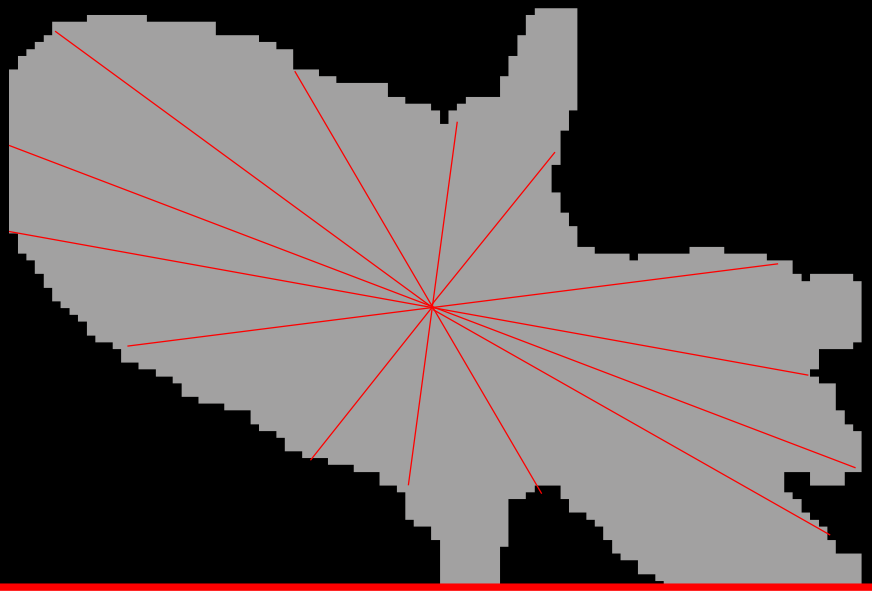
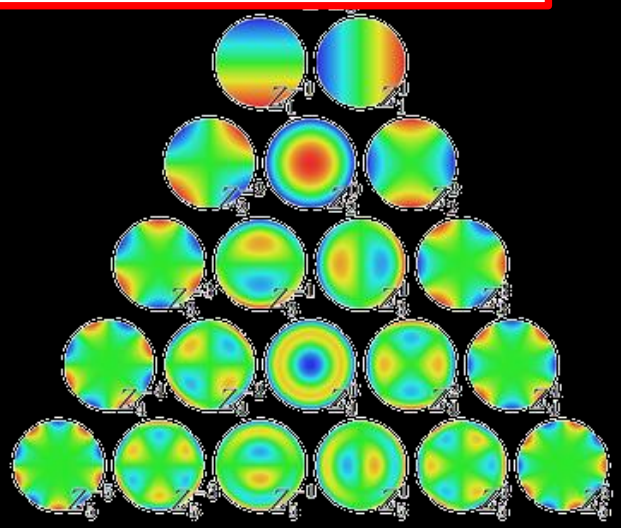
histogram of distance to the center

snake/chain descriptors





212 different descriptors



Zernik polynomials/moments

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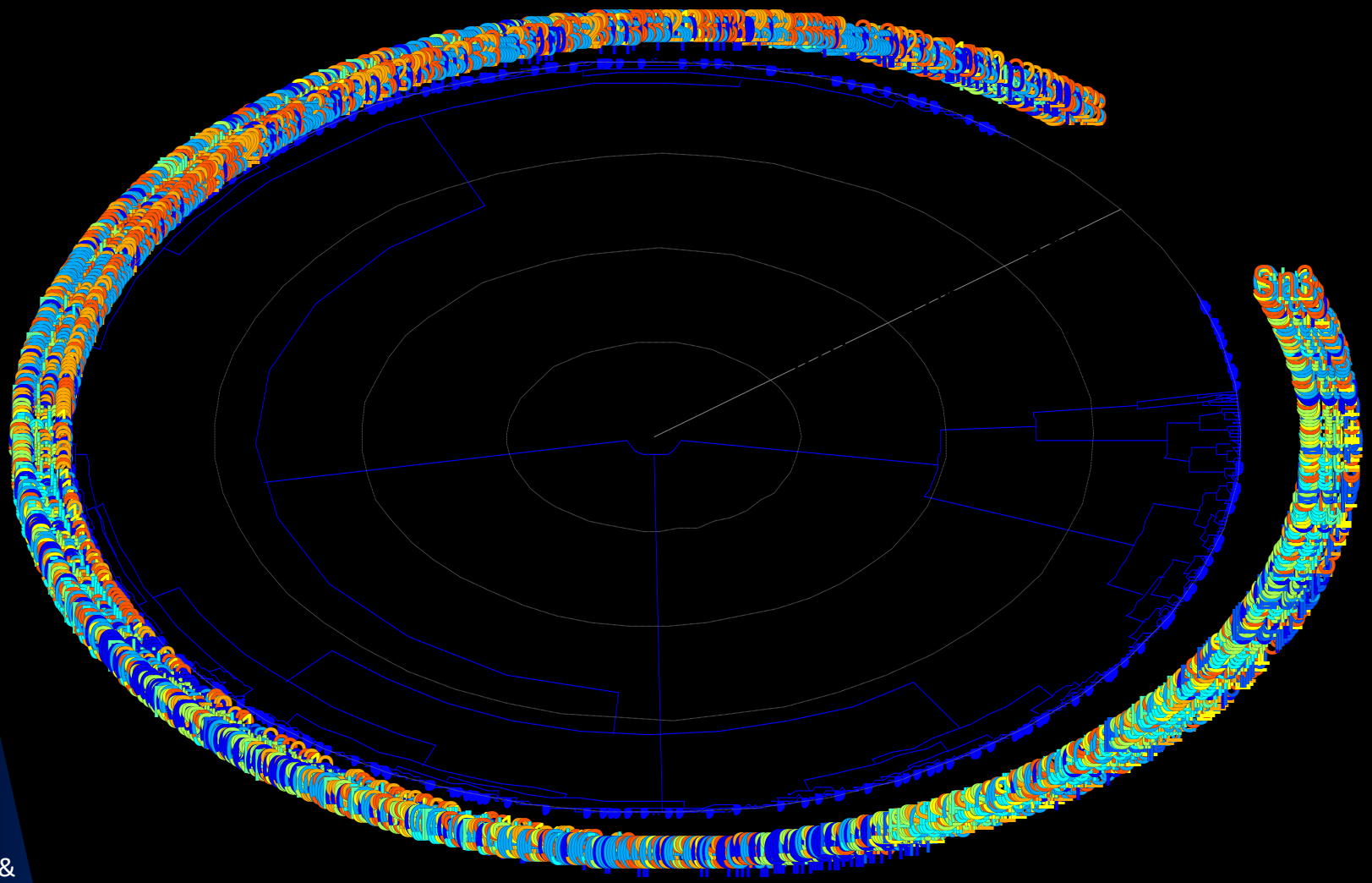
Clustering (Euclidian Distances) is not efficient (colors represent different tax. classes)



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Set of images where class is known

Descriptors for each image

Image 1: 100 20 123 4 55 3 22 645 77 8 1
Image 2: 10 22 101 1 99 1 123 145 66 1 9
Image 3: 123 21 111 3 45 2 120 211 35 8 1
Image 4: 111 16 114 2 22 3 214 445 38 3 6
…

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Set of images where class is known

Descriptors for each image

Image 1: 100 20 123 4 55 3 22 645 77 8 1
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…

Training set: used to tell the computer what is what

Validation set: used to analyze the performance

Set of images where class is known

Descriptors for each image

Image 1: 100 20 123 4 55 3 22 645 77 8 1
Image 2: 10 22 101 1 99 1 123 145 66 1 9
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…

Training set: used to tell the computer what is what

Validation set: used to analyze the performance

Supp. Vect. Machine
Neural Net (Patternnet, Feed forward)
Random Forest (Classification Tree)
Self Organizing Maps
Naive Bayes
Nearest Neighbour Analysis

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Set of images where class is known

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Image 1: 100 20 123 4 55 3 22 645 77 8 1
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Training set: used to tell the computer what is what

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Supp. Vect. Machine
Neural Net (Patternnet, Feed forward)
Random Forest (Classification Tree)
Self Organizing Maps
Naive Bayes
Nearest Neighbour Analysis

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% is a copepod and was classified as copepod

% is a copepod and was classified as something else

% was something else and was classified as copepod

% is a copepod and was classified as copepod

% is a copepod and was classified as something else

% was something else and was classified as copepod

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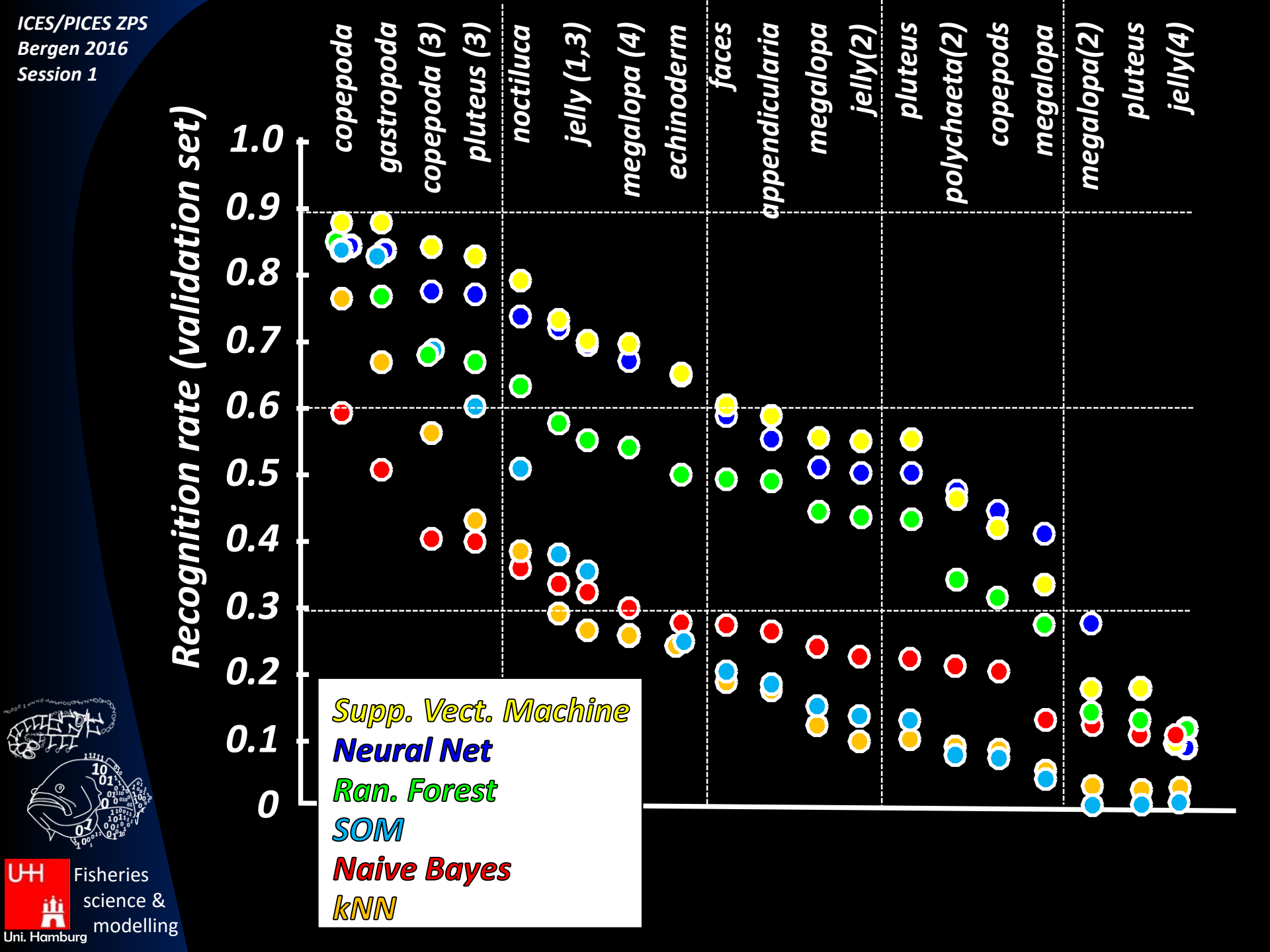

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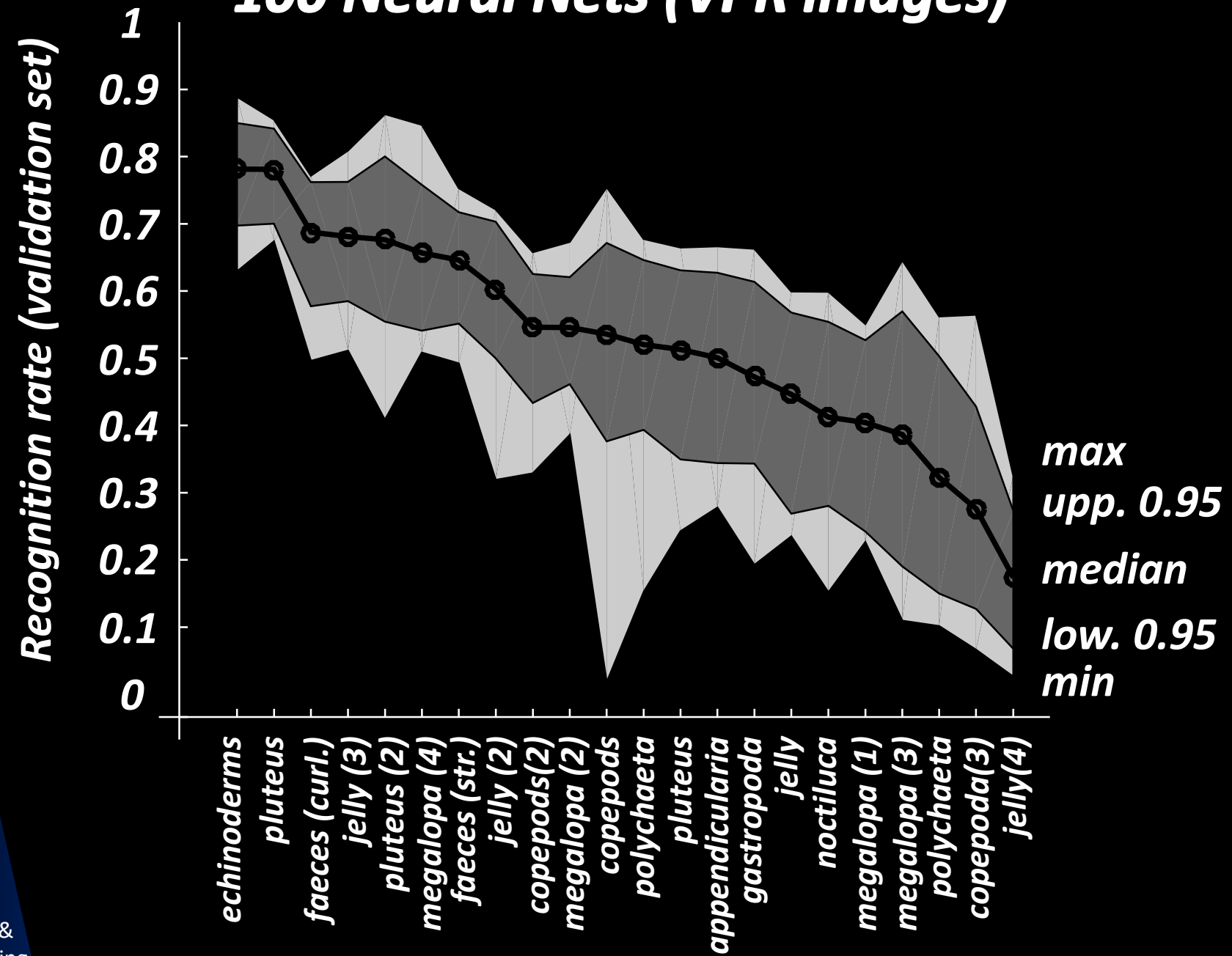
random training sets
random start parameters

Do the methods always perform the same?

100 Neural Nets (VPR images)



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Democratic approach

if more than e.g. 60%
of all nets say it‘s a copepod
classify it as copepod

→ Increases accuracy to 100%
but at the cost of accurate quantification

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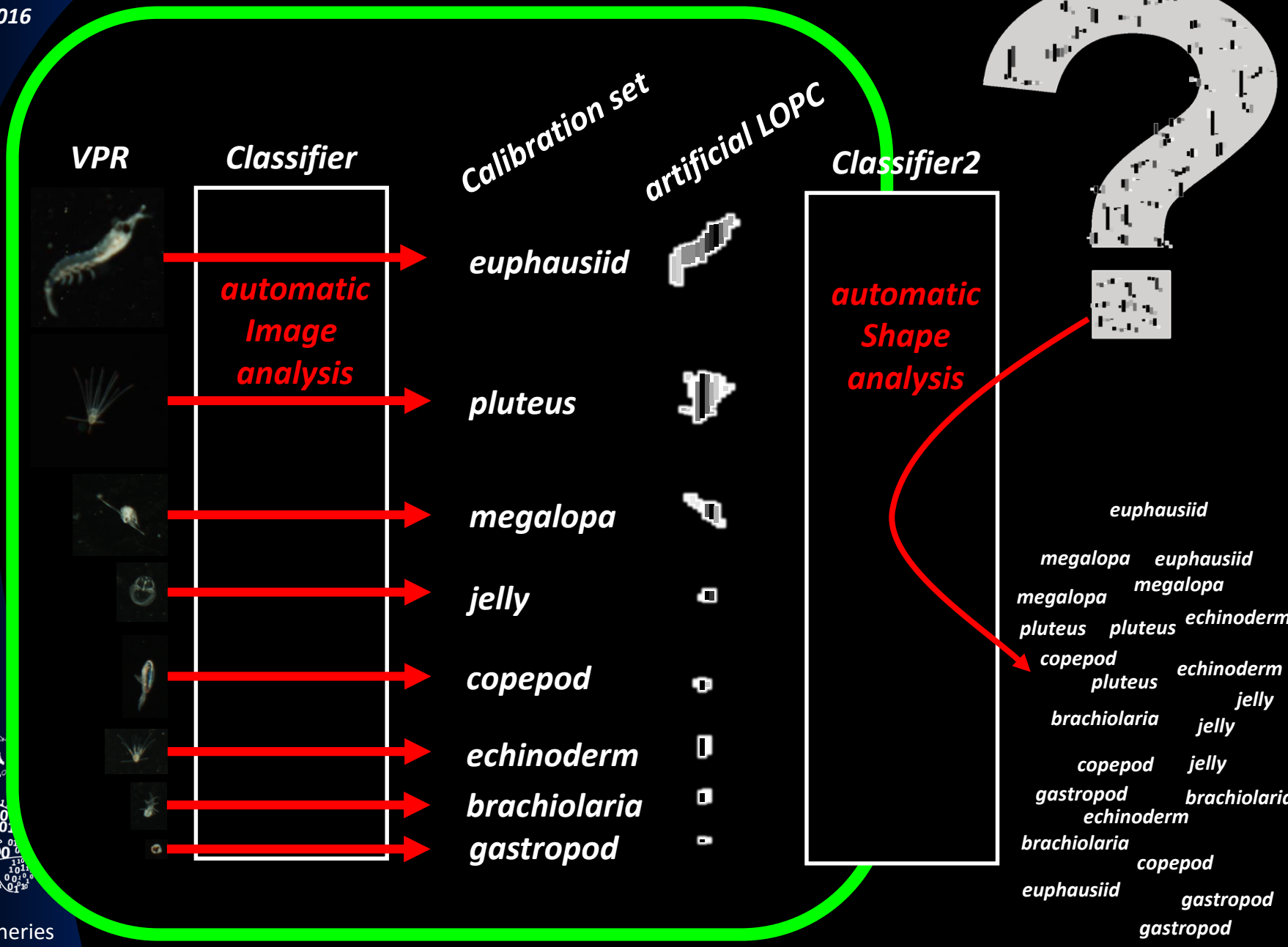

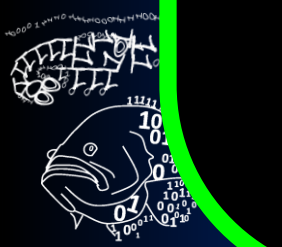

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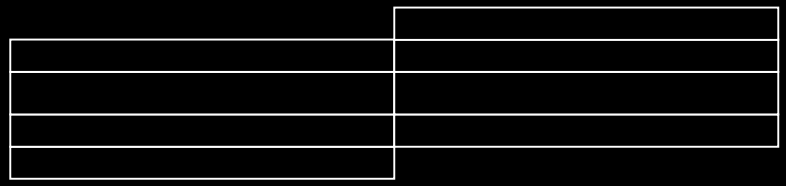
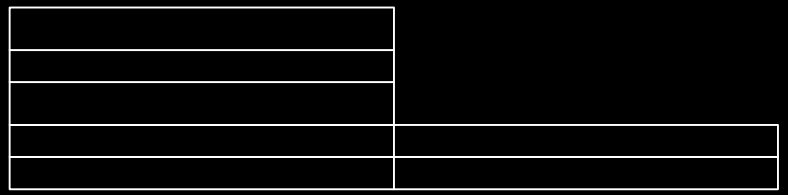
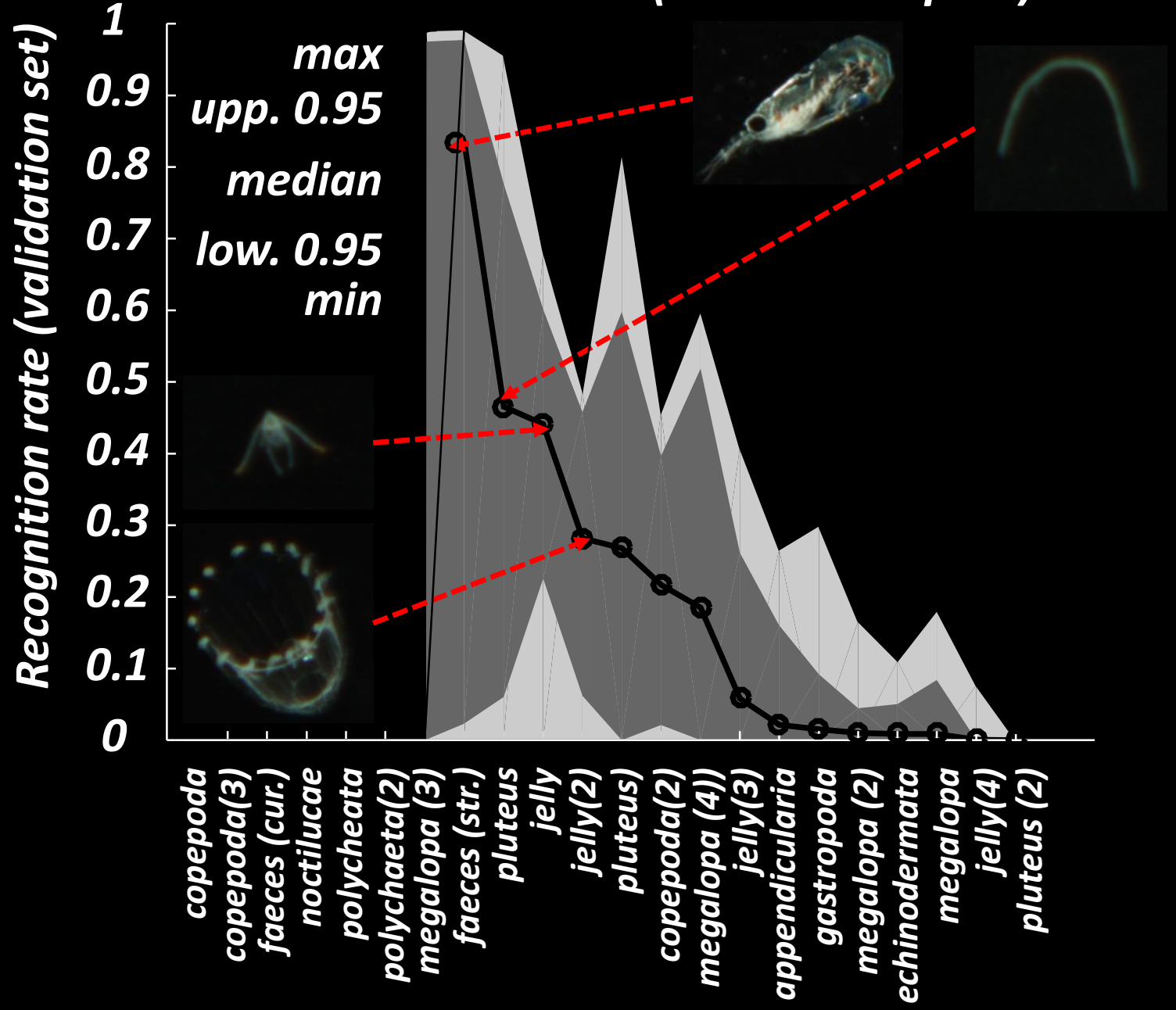
Illusionary to identify small Multi Element Particles

→ *area threshold*





100 Neural Nets (LOPC shapes)



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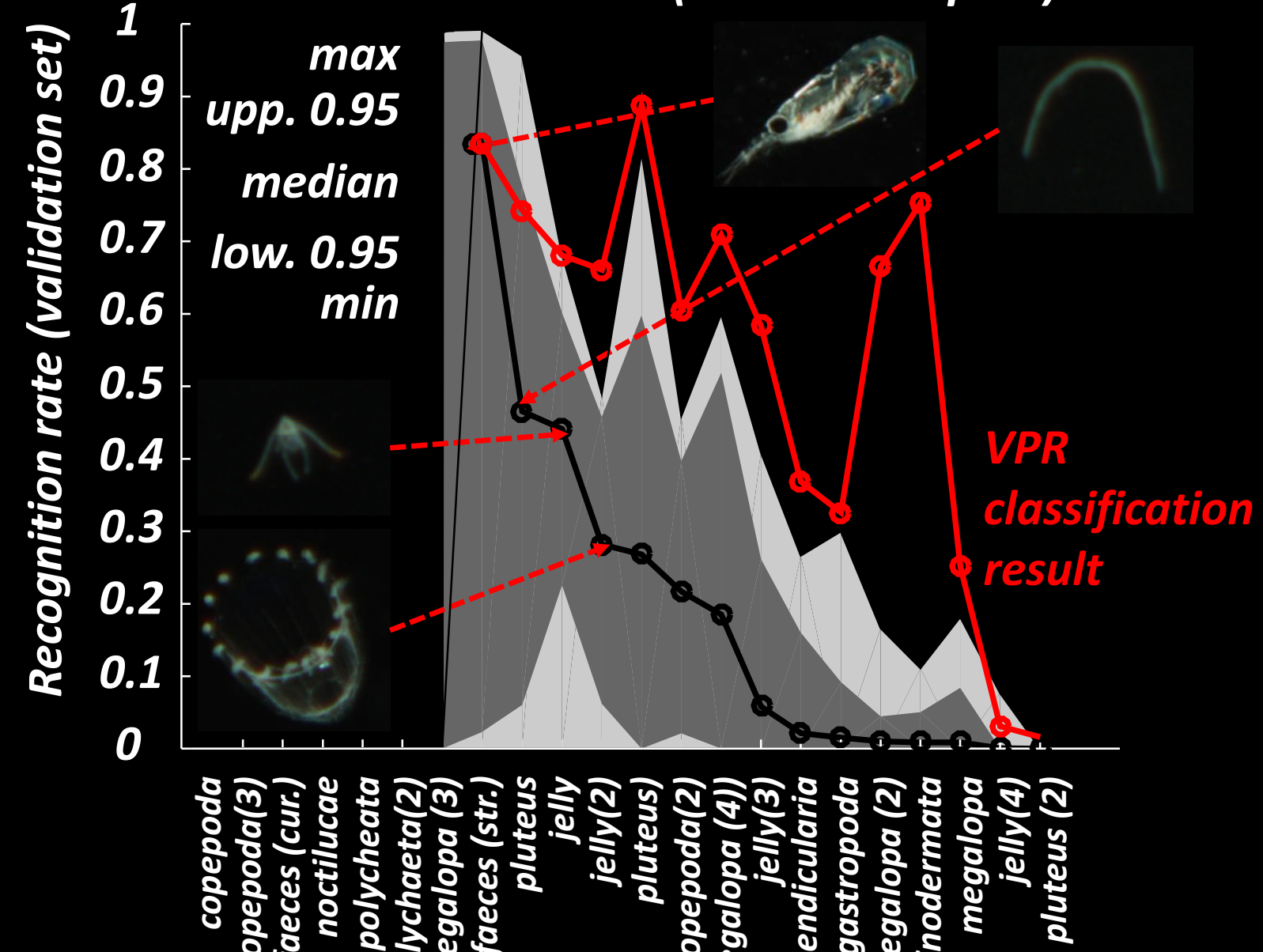
100 Neural Nets (LOPC shapes)



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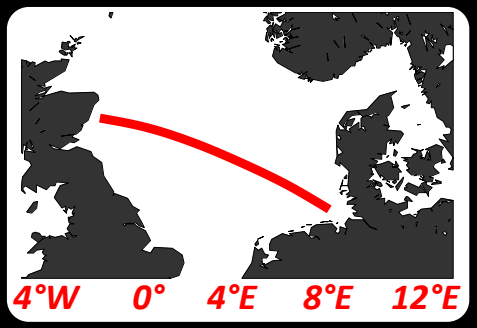
relative zooplankton composition along the transect



-20m
-40m
-60m
-80m

marine snow

1°W 0° 1°E 2°E 3°E 4°E 5°E 6°E 7°E

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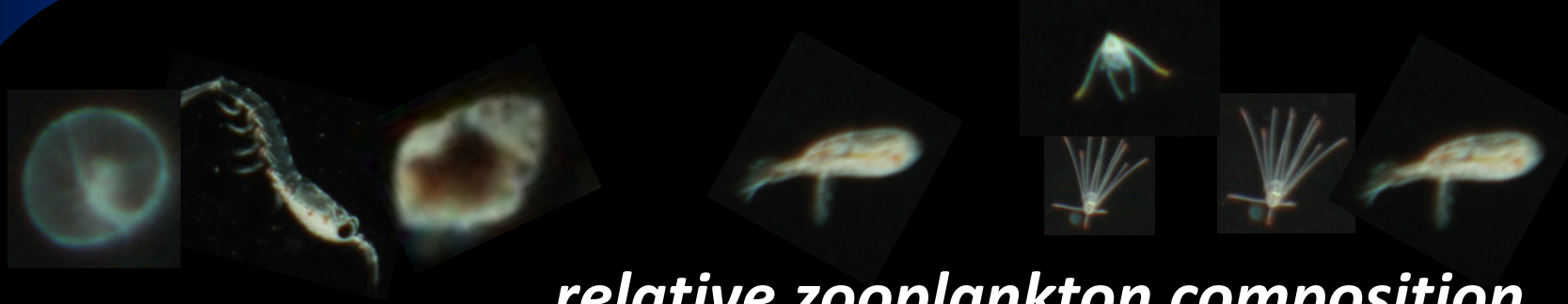
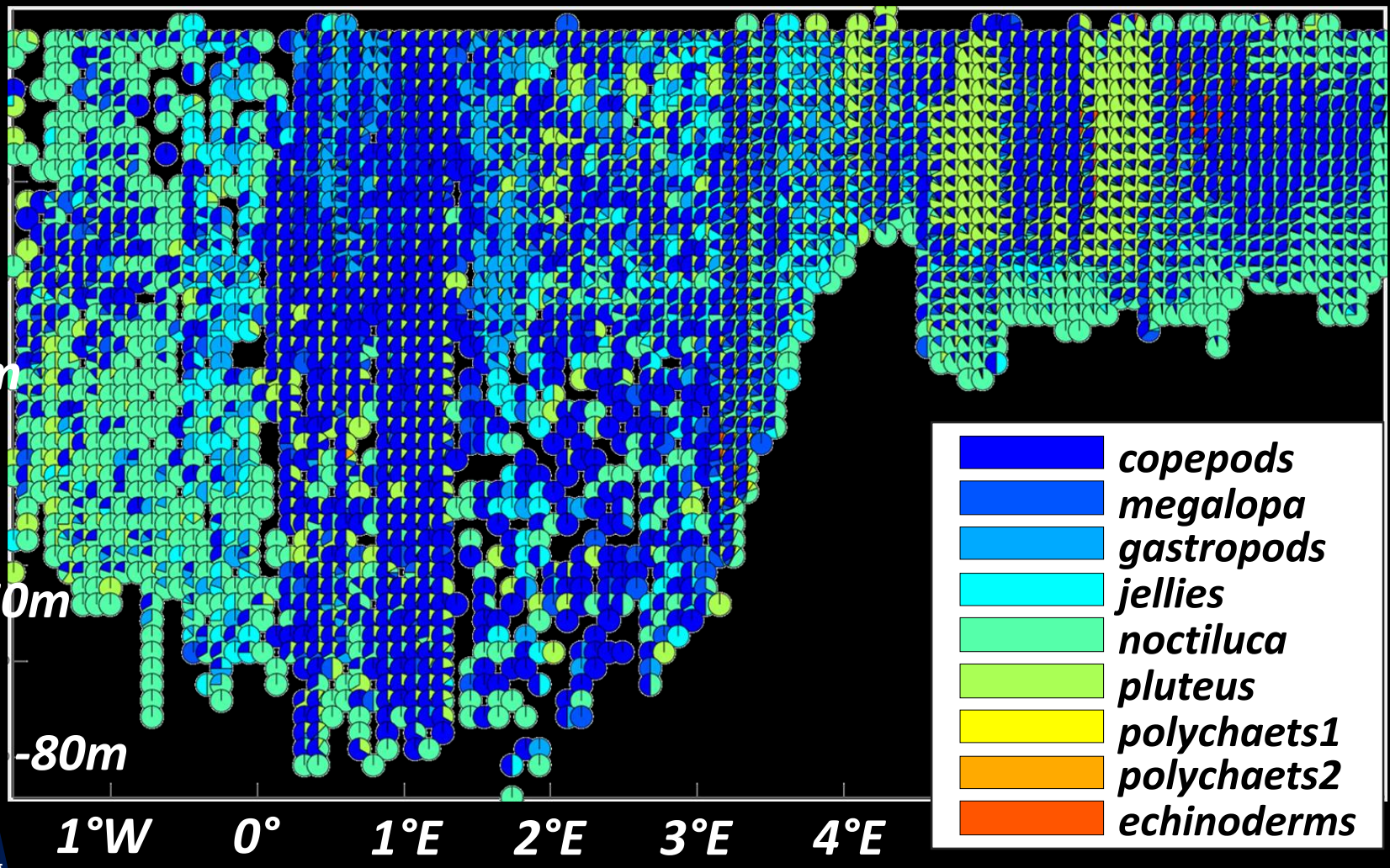


relative zooplankton composition



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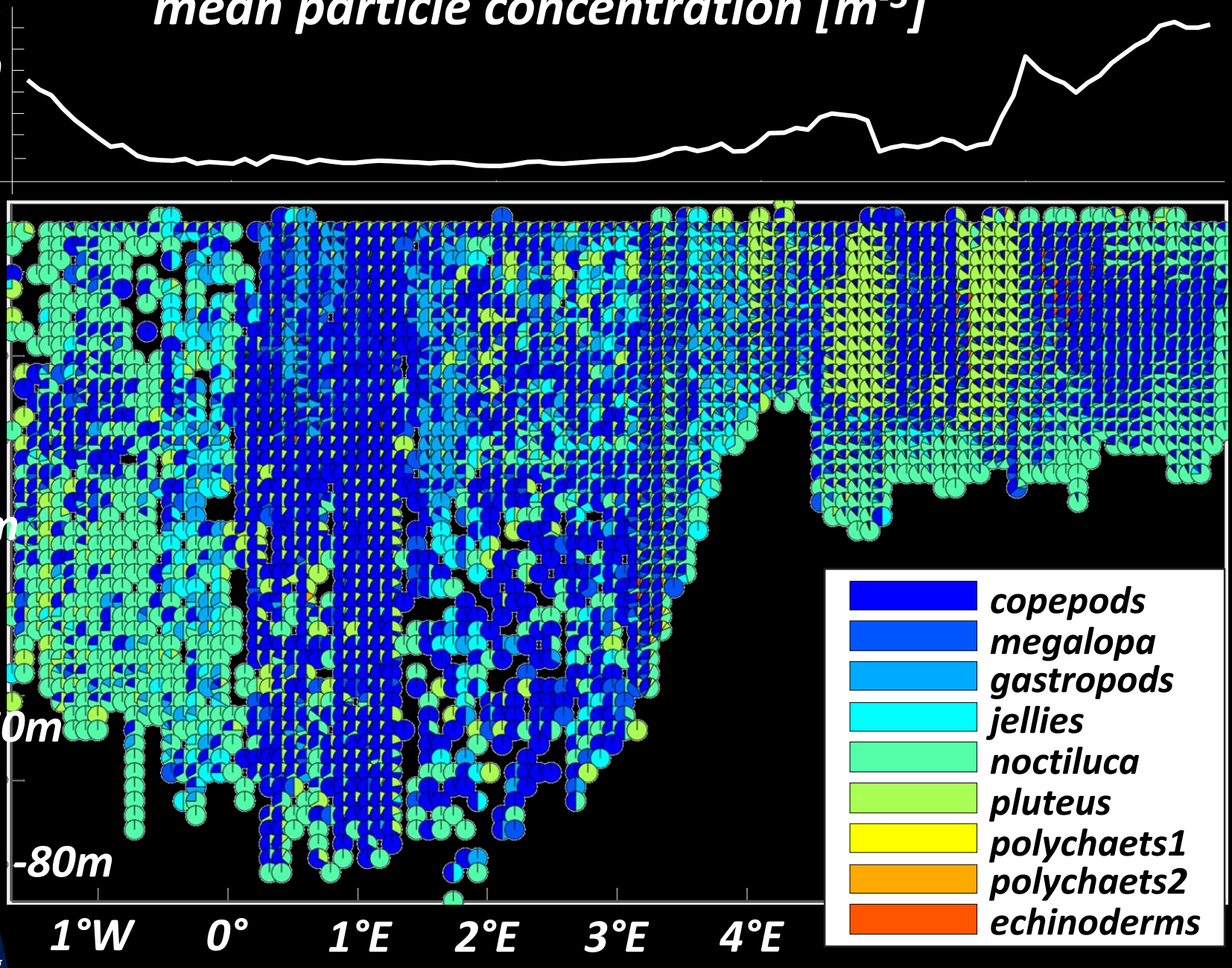
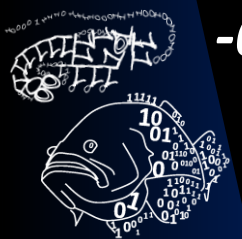
Session 1





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Summary

- *Image analysis of Video Plankton Recorder Images is possible*
- *A single trainset and only one method will bias the classification*
- *Chosing a suite of similar approaches will lead to a better classification*
- *Determination of some LOPC shapes is possible*

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Thank you for your attention !

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