Probabilistic forecasting of small pelagic fish recruitment

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The University of the Basque Country (Spain)
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Victoria, 11^{th} of March, 2017

Outline

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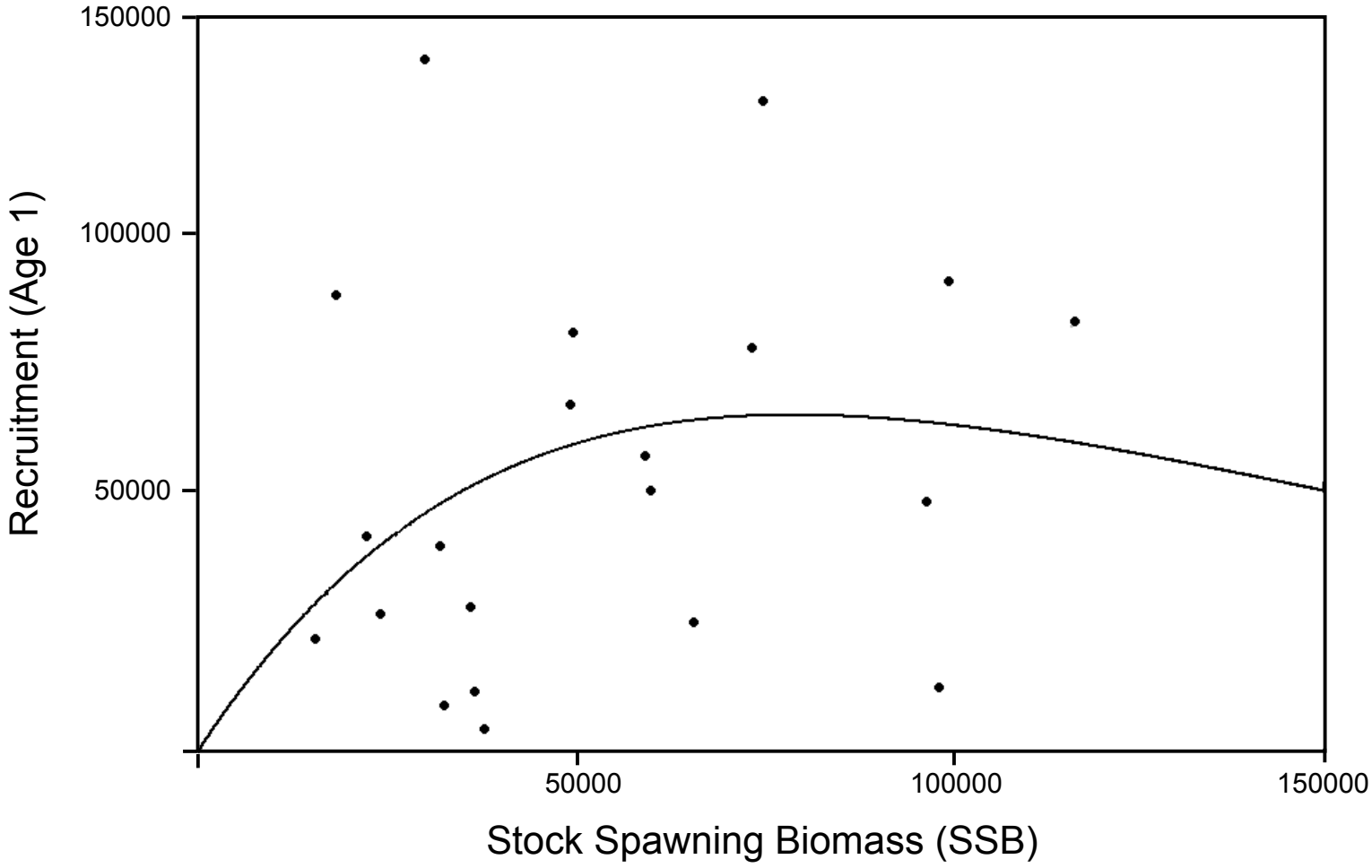
- Stock spawning biomass - recruitment relationship of anchovy?



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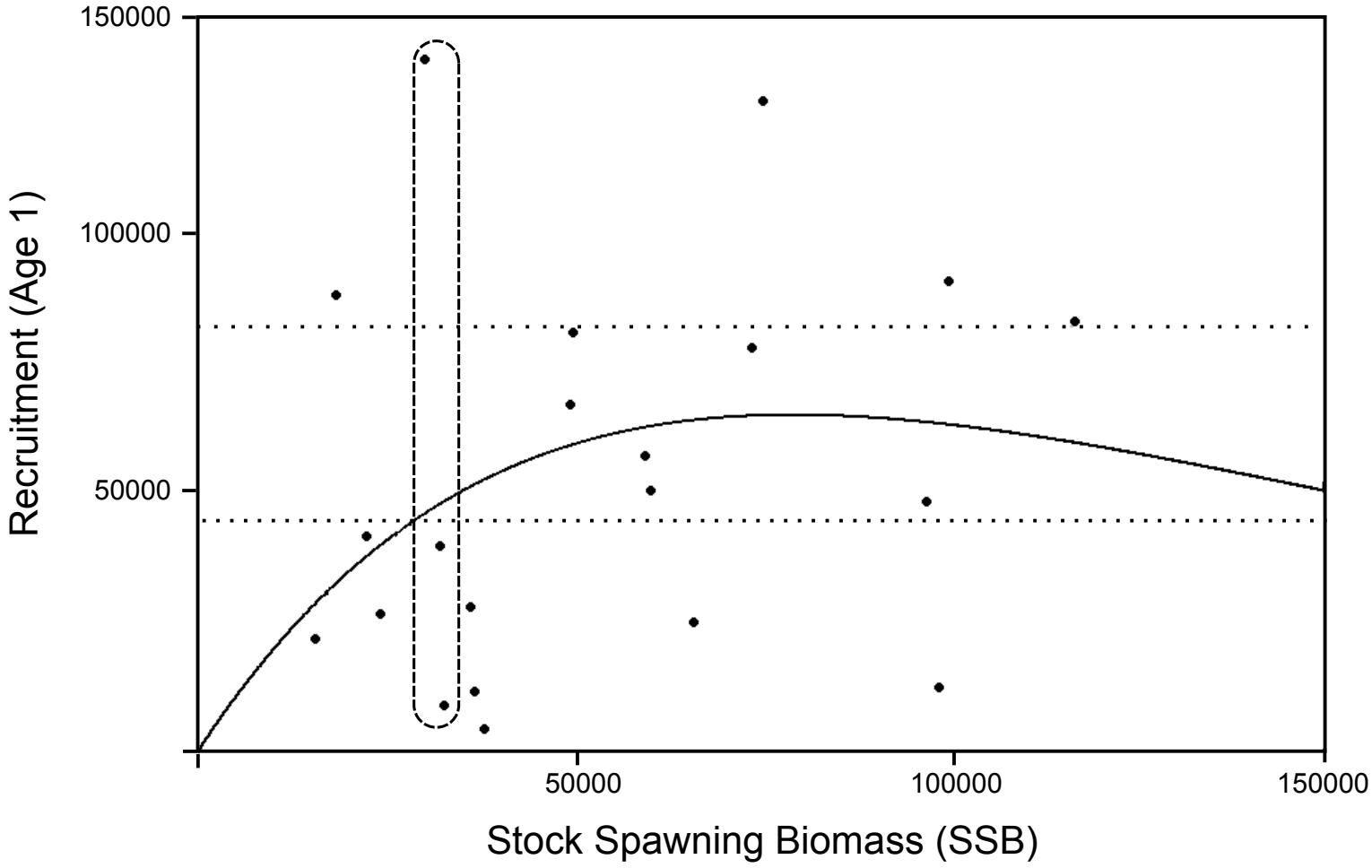

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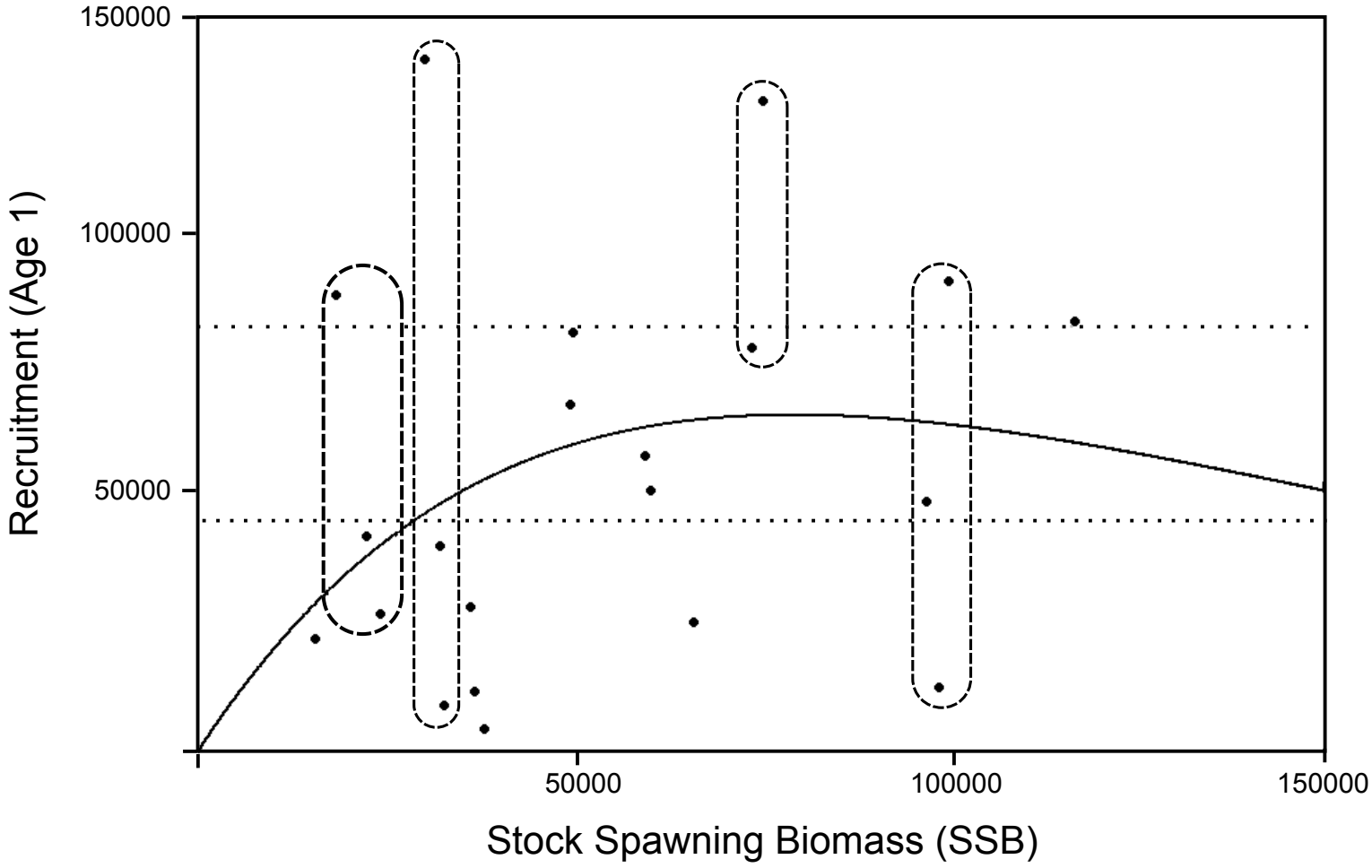

Outline

Supervised classification and the data analysis process

PNA	POL	CLI1	Uim_4311	V_4523	UIBs_4502	UILm_4502	Anchovy
0.01	0.54	1.21	???	-0.37	689	???	1550
0.03	0.27	0.46	283	-1.91	???	68	5094
0.33	0.44	0.42	80	???	1129	36	3742
0.31	0.09	0.77	???	-1.95	1204	-94	2455
0.36	???	0.07	???	-0.47	402	???	3081
0.71	0.03	???	45	-0.41	626	71	1010

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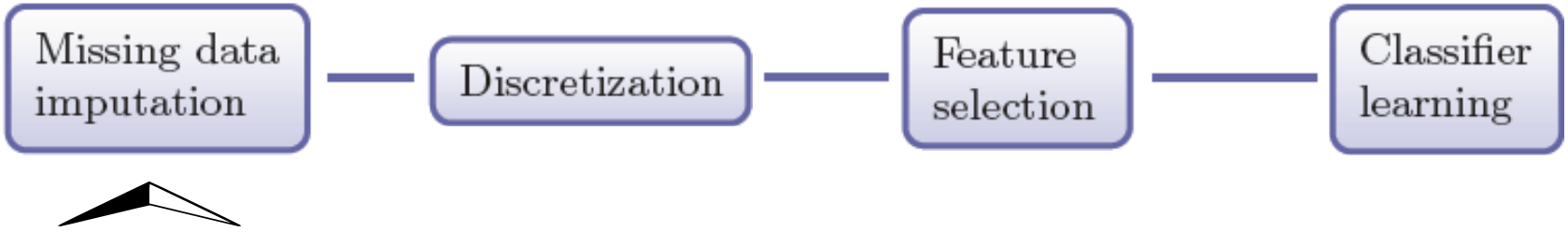

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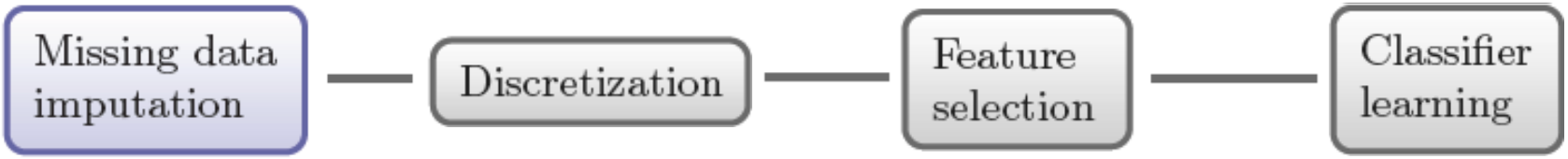

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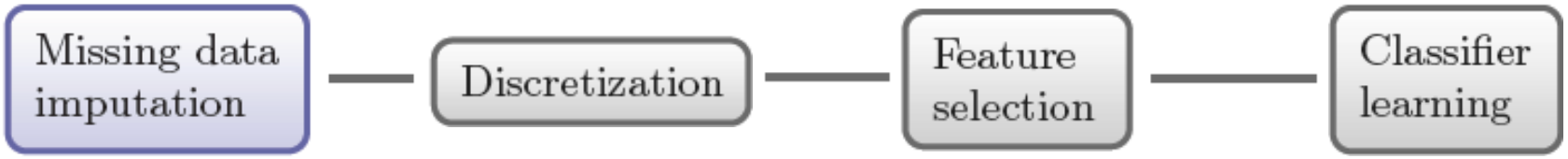
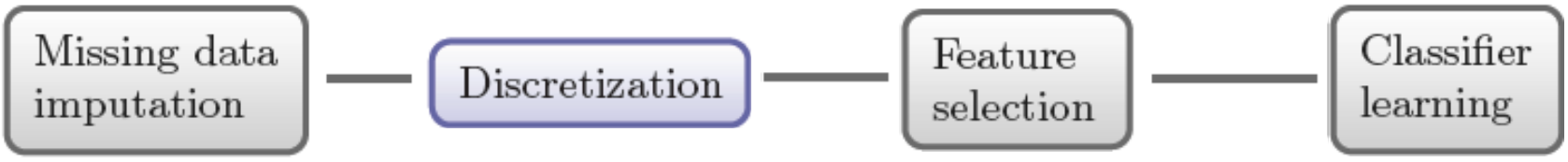


PNA	POL	CLI1	Uim_4311	V_4523	UIBs_4502	UILm_4502	**Anchovy**
0.01	0.54	1.21	**-2**	-0.37	689	**-42**	**Low**
0.03	0.27	0.46	283	-1.91	**1611**	68	**High**
0.33	0.44	0.42	80	**-1.61**	1129	36	**High**
0.31	0.09	0.77	**-86**	-1.95	1204	-94	**Medium**
0.36	**-0.13**	0.07	**52**	-0.47	402	**-78**	**High**
0.71	0.03	**-56**	45	-0.41	626	71	**Low**

Supervised classification and the data analysis process



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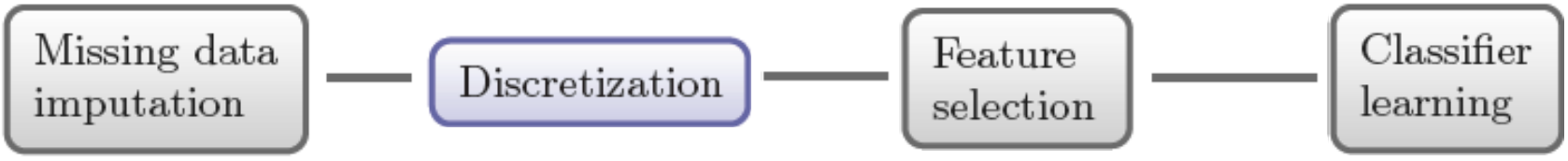

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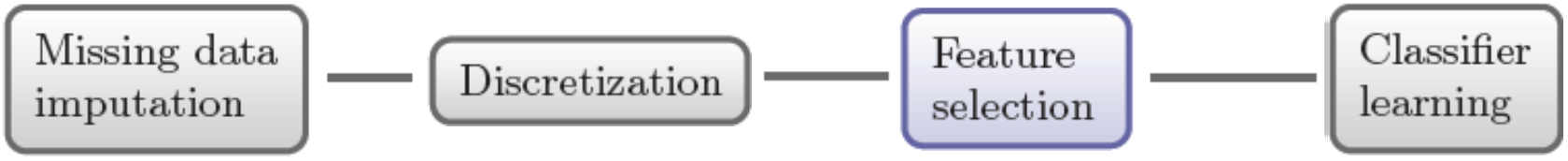
Low	High	Low	High	Low	High	High	**High**
Low	High	Low	High	Low	High	High	**High**
High	Low	High	Low	Low	High	Low	**Medium**
High	Low	Low	High	High	Medium	Low	**High**
High	Low	Low	High	High	Low	High	**Low**

Supervised classification and the data analysis process



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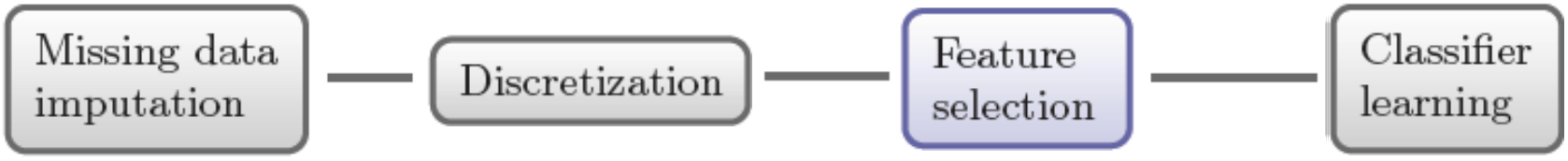
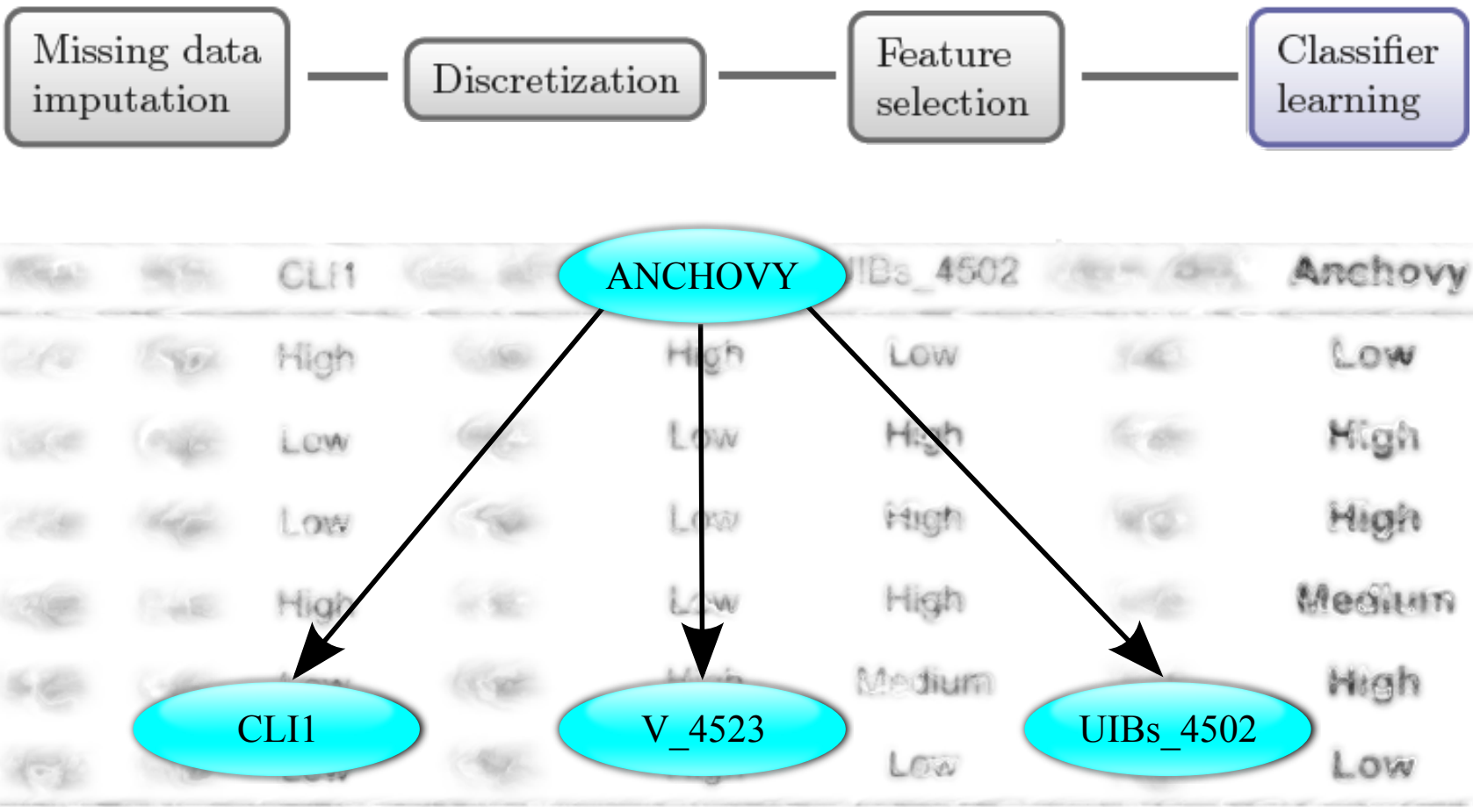
Low	High	High	Low	High	Low	Low	**Low**
Low	High	Low	High	Low	High	High	**High**
Low	High	Low	High	Low	High	High	**High**
High	Low	High	Low	Low	High	Low	**Medium**
High	Low	Low	High	High	Medium	Low	**High**
High	Low	Low	High	High	Low	High	**Low**

Supervised classification and the data analysis process

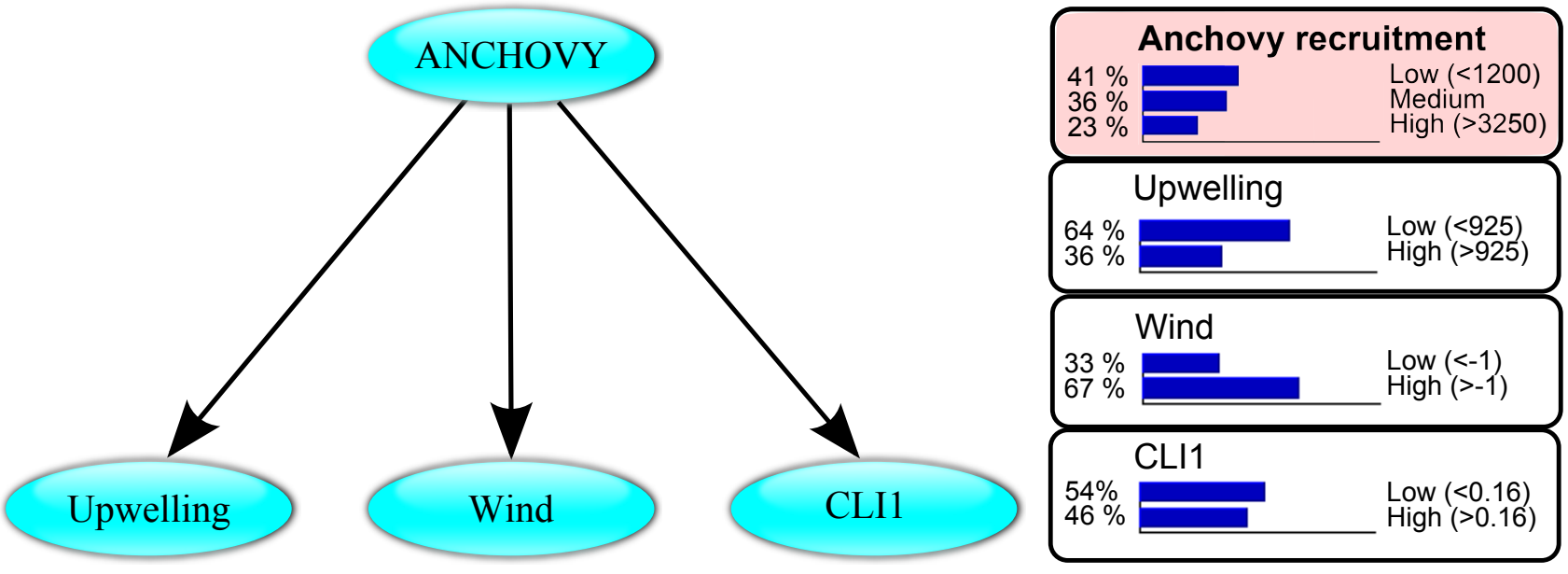


[illegible]	[illegible]	CLI1	[illegible]	V_4523	UIBs_4502	[illegible]	**Anchovy**
[illegible]	[illegible]	High	[illegible]	High	Low	[illegible]	**Low**
[illegible]	[illegible]	Low	[illegible]	Low	High	[illegible]	**High**
[illegible]	[illegible]	Low	[illegible]	Low	High	[illegible]	**High**
[illegible]	[illegible]	High	[illegible]	Low	High	[illegible]	**Medium**
[illegible]	[illegible]	Low	[illegible]	High	Medium	[illegible]	**High**
[illegible]	[illegible]	Low	[illegible]	High	Low	[illegible]	**Low**

Supervised classification and the data analysis process



Anchovy final model



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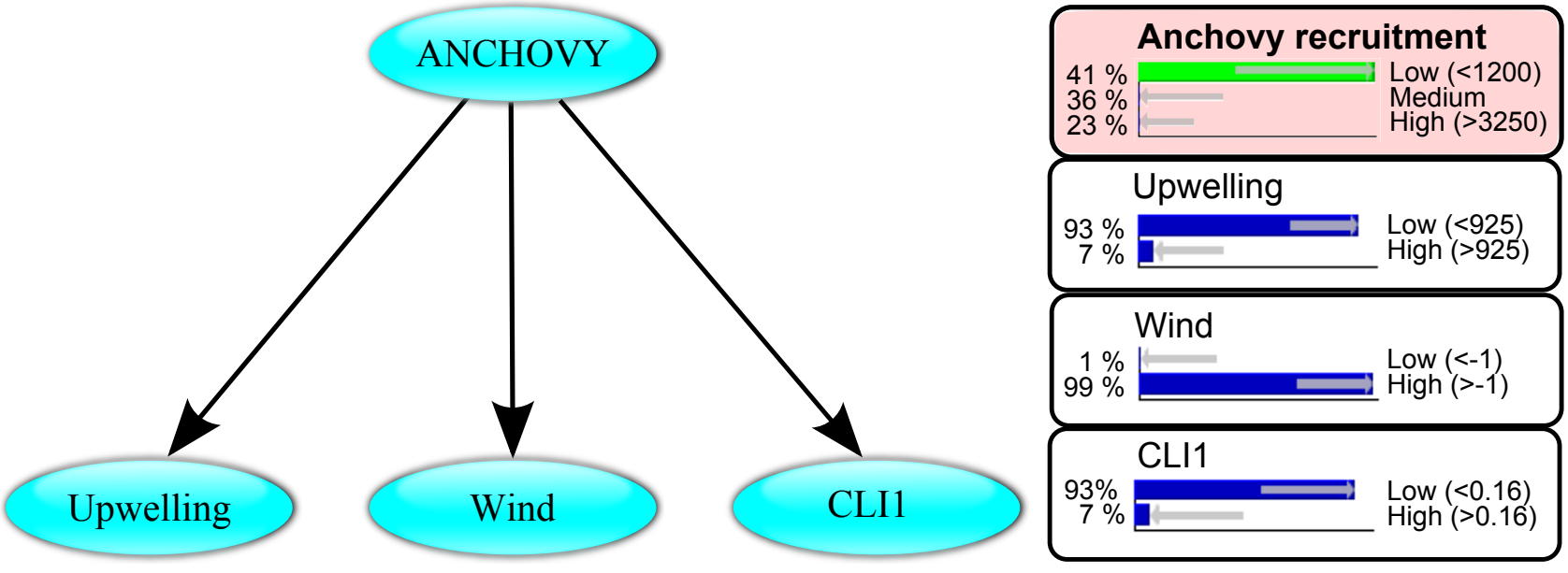

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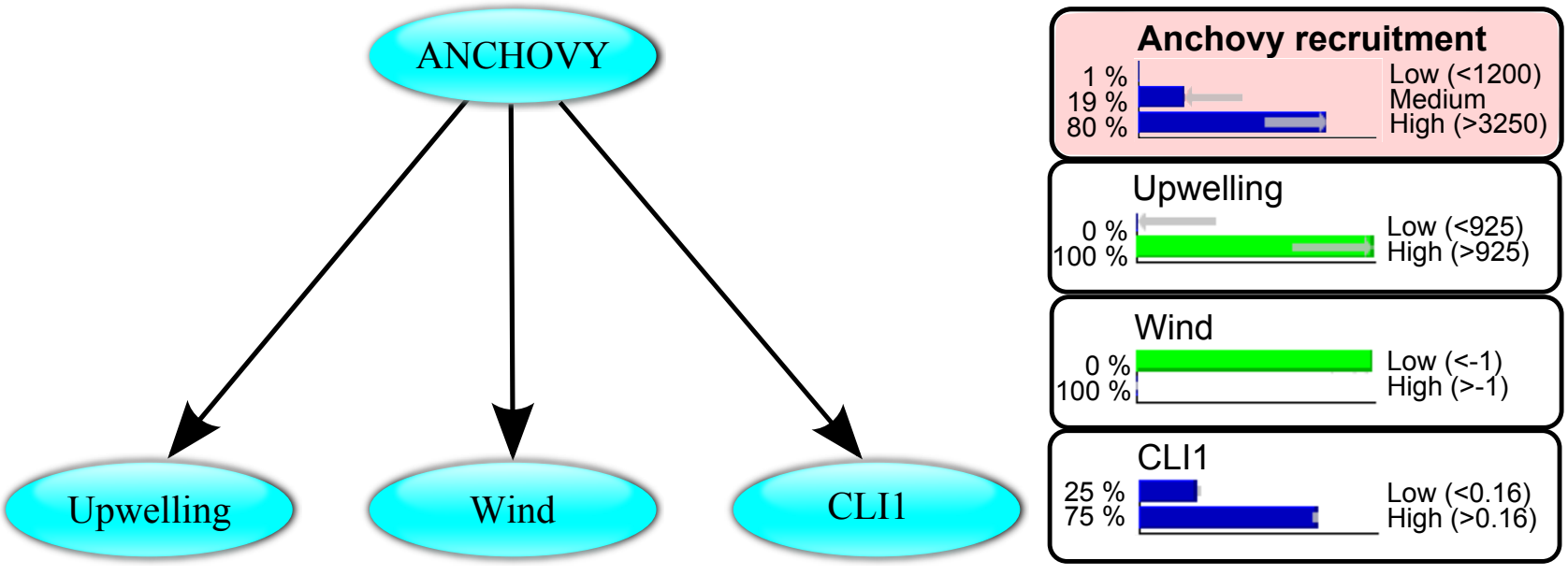
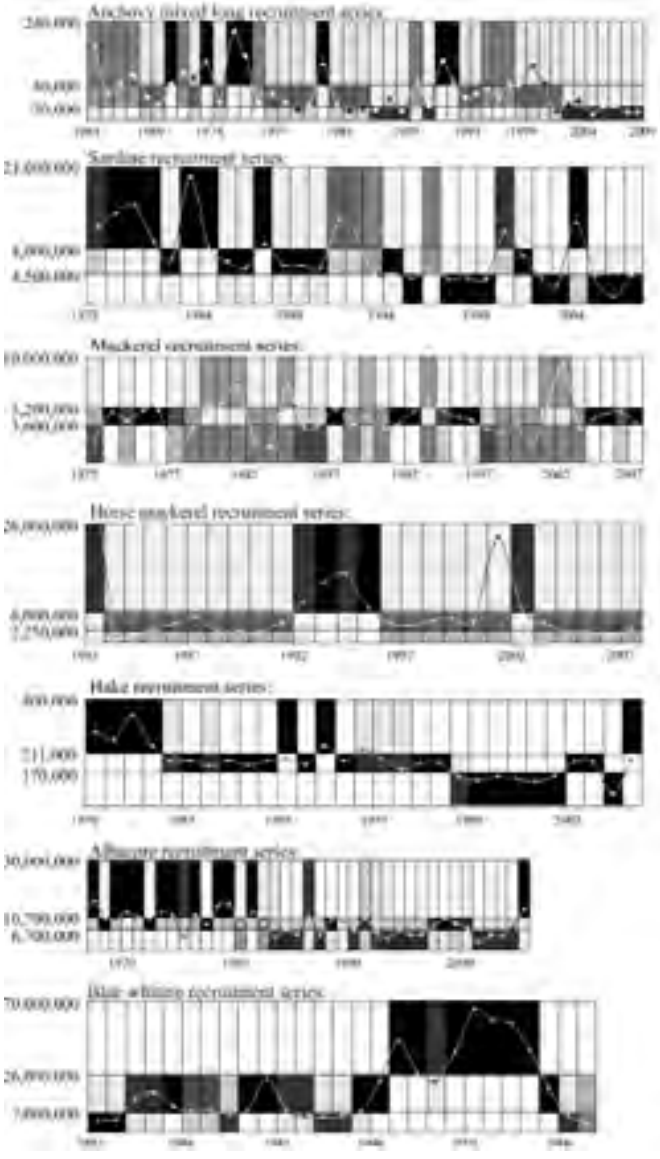
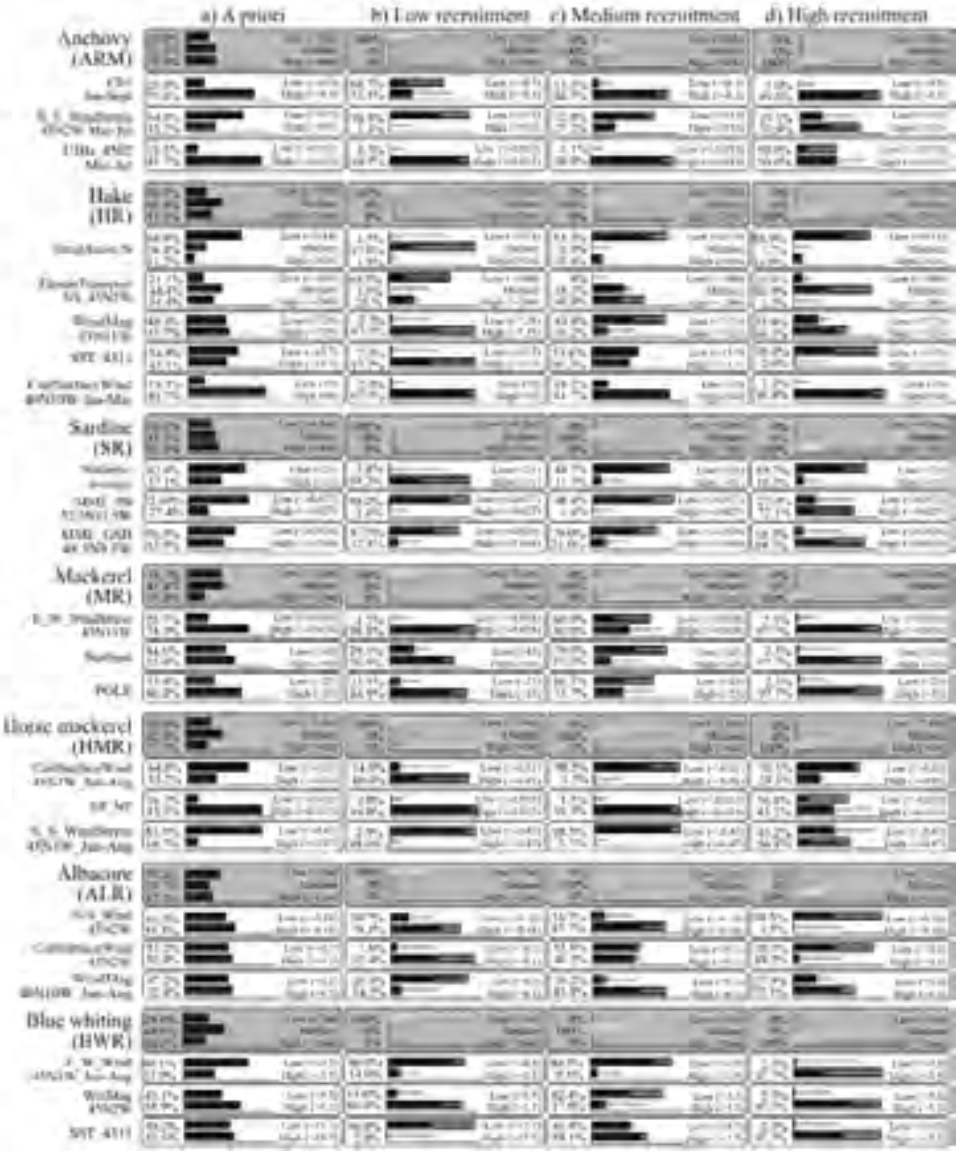


Application to 7 species in the North East Atlantic





Outline

Multi-species probabilistic model

Anchovy

Sardine

?

Hake

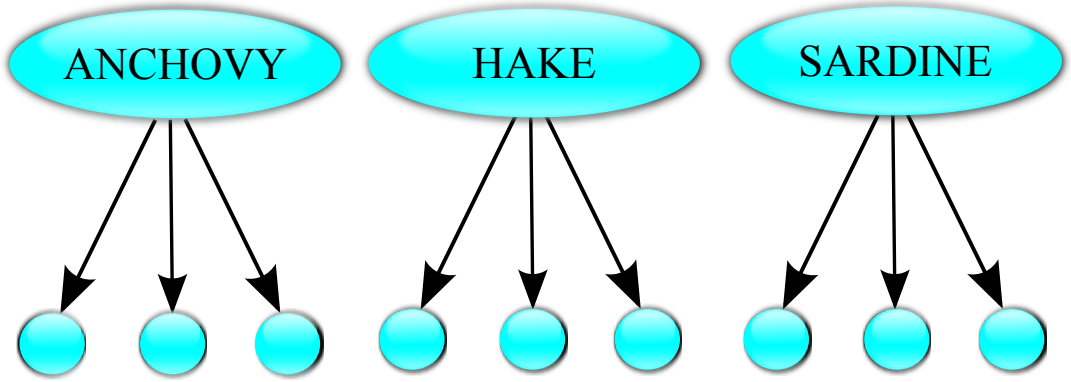
Multi-species probabilistic model

Anchovy

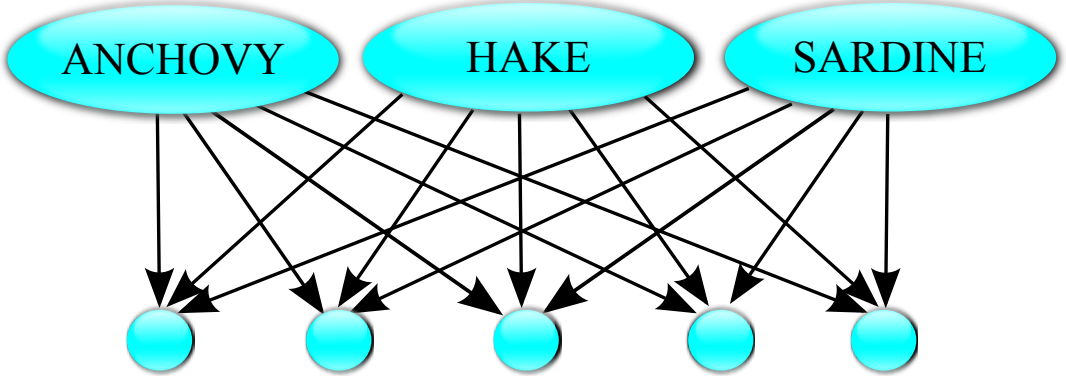
Sardine

Hake

Multi-dimensional classification approach to fisheries



	X_1 ... X_n	C
Instance 1	x_1^1 ... x_n^1	c^1
Instance 2	x_1^2 ... x_n^2	c^2
Instance 3	x_1^3 ... x_n^3	c^3
...	...	
Instance N	x_1^N ... x_n^N	c^N



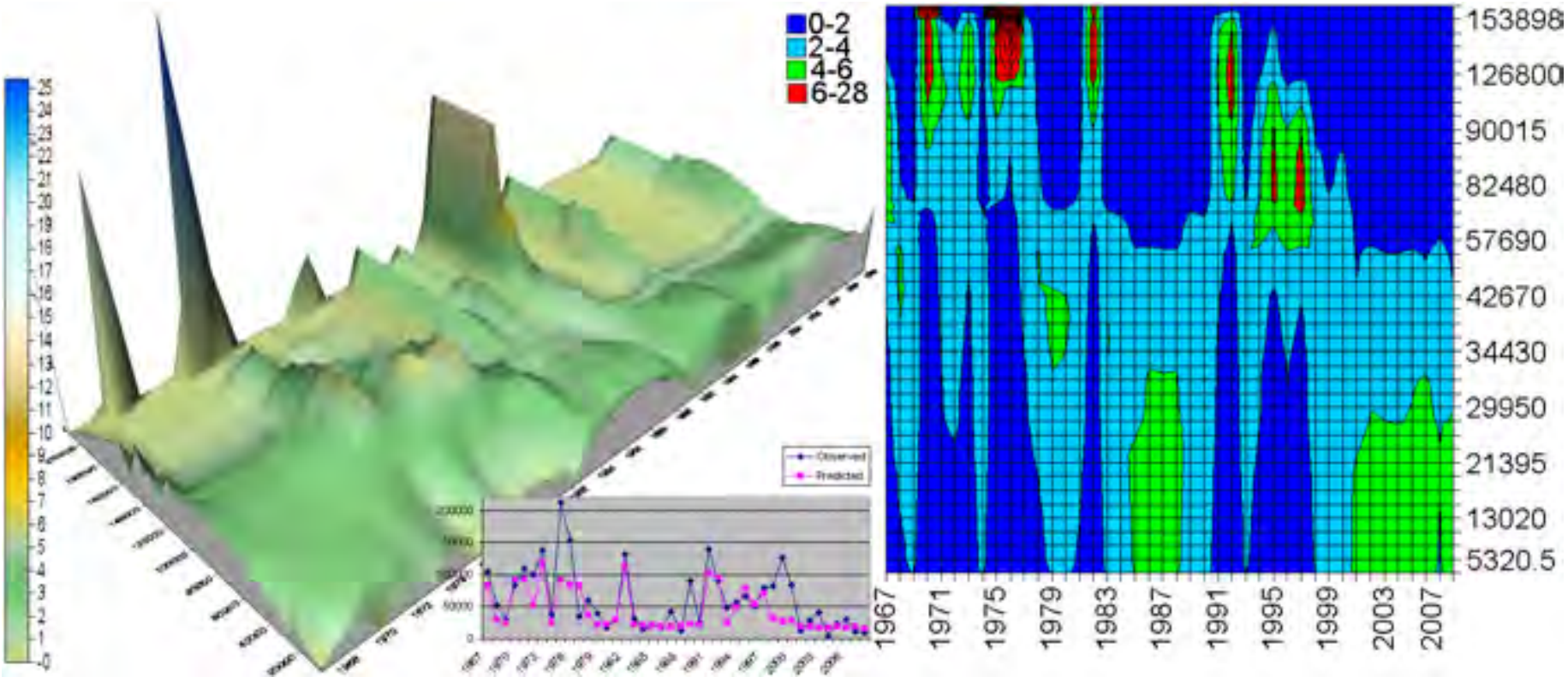
	X_1 ... X_n	C_1 ... C_m
Instance 1	x_1^1 ... x_n^1	c_1^1 ... c_m^1
Instance 2	x_1^2 ... x_n^2	c_1^2 ... c_m^2
Instance 3	x_1^3 ... x_n^3	c_1^3 ... c_m^3
...	...	...
Instance N	x_1^N ... x_n^N	c_1^N ... c_m^N

Simultaneous forecasting of 3 fish species recruitment

- Doubled the chance of being right in all species simultaneously (Joint Acc.).
- Better probabilities estimations (BS).
- The advantage of a single model suiting the ecosystem approach.

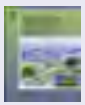
Pre-processing pipeline	ARI Acc.	ARI BS	SR Acc.	SR BS	HR Acc.	HR BS	Joint Acc.
CM-MID-CFS (Uni-D)	52.7 ± 6.7	0.36	55.7 ± 6.7	0.34	67.6 ± 3.3	0.27	17.3 ± 4.8
CMcart-MIDmean-CFSsum	54.6 ± 7.3	0.35	$\mathbf{65.4 \pm 5}$	0.27	72.9 ± 5.5	0.21	28.9 ± 4.5
CMcart-MIDindiv-CFScart	46.5 ± 4.3	0.32	59.8 ± 6.3	**0.24**	71.4 ± 5.8	0.19	22.6 ± 4.3
CMcart-MIDmean-CFSmean	45 ± 7.6	0.32	58.4 ± 6	0.25	$\mathbf{75 \pm 4.6}$	**0.18**	19.7 ± 5.5
CMcart-MIDmean-CFScart	$\mathbf{57.9 \pm 5}$	**0.30**	60.6 ± 4.8	0.27	68.9 ± 7.3	0.21	$\mathbf{29.5 \pm 4}$
CMcart-MIDmean-CFSindiv	53.8 ± 4.8	0.32	63.4 ± 2.9	0.27	71.6 ± 6.1	**0.18**	28.5 ± 4.7

Model integration: Gatgets and naive Bayes for regression

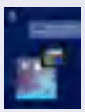


Publications

International Journals: first author



J.A. Fernandes, *et al.* (2010) Fish recruitment prediction, using robust supervised classification methods. *Ecological Modelling*, 221(2): 338-352.



J.A. Fernandes, *et al.* (2013) Supervised pre-processing approaches in multiple class-variables classification for fish recruitment forecasting. *Environmental Modelling & Software*, 40: 245-254.

J.A. Fernandes, *et al.* (2015) Evaluating machine-learning techniques for recruitment forecasting of seven North East Atlantic fish species. *Ecological Informatics*, 25: 35-42.

E. Andonegi, J.A. Fernandes, *et al.* (2011) The potential use of a Gadget model to predict stock responses to climate change in combination with Bayesian Networks: the case of the Bay of Biscay anchovy. *ICES Journal of Marine Science*, 68(6): 1257-1269.

J.A. Fernandes, *et al.* (2009) Anchovy Recruitment Mixed Long Series prediction using supervised classification. *Working document ICES WKSHORT*, Bergen, Norway.

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