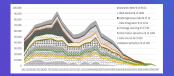


### The potential of ontologies for the empirical assessment of machine learning techniques in operational oceanography







**Enrique Wulff**, Marine Science Institute of Andalusia, CSIC

|                         | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2038 | 2019 | 2020 | 2021 | SUM |
|-------------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|-----|
| Papers                  | 3    | 3    | 7    | 5    | 4    | 6    | 9    | 12   | 16   | 15   | 27   | 55   | 43   | 210 |
| disseminative           |      |      |      |      |      |      | 1    |      | 1    | 1    | 1    | 5    | 4    | 13  |
| observational           | 1    |      | 1    |      |      | 1    |      | 1    |      |      | 6    | 12   | 11   | 33  |
| Analytical              | 1    | 1    | 3    | 2    | 1    | 4    | 4    | 6    | 6    | 6    | 7    | 14   | 17   | 70  |
| model-<br>developmental | 1    | 2    | 3    | 3    | 1    | 1    | ł    | 5    | 9    | 8    | 13   | 24   | 16   | 92  |



| 2<br>5<br>5<br>7 Hope quilt<br>7 Hope quilt<br>2<br>9 Hope quilt<br>1 | 6<br>3<br>4<br>2<br>2<br>8 spcc quells<br>8 spcc quells<br>9 section<br>1 |
|---|---|
| Ontological contexts  | Machine learning  |

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# **Goal of this Contribution**

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To identify relevant pattern analysis research in marine data classification and recognition, and to review its intersection with the state-of-the art in marine ontologies

- Focus on the 3D modeling and analysis domain, computer vision and interactions are described for machine learning (ML) and marine ontologies
- Show how the use of ontologies for representing database entities has been advantageous in the field of Operational Oceanography (Riga et al., 2021)\*

\*M. Riga, E. Kontopoulos, K. Ioannidis, S.; Kintzios, S. Vrochidis, I. Kompatsiaris, EUCISE-OWL: An ontology-based representation of the Common Information Sharing Environment (CISE) for the maritime domain, *Semantic Web* 12 (2021) 603-615. doi: 10.3233/SW-200403



#### A key phrase from John Delaney underpins several ideas in these goals

USE OF ONTOLOGIES FOR REPRESENTING DATABASE ENTITIES

• <u>"There are emergent technologies throughout the fields around oceanography which we will incorporate into oceanography, and through that convergence we will make oceanography into something even more magical"</u>

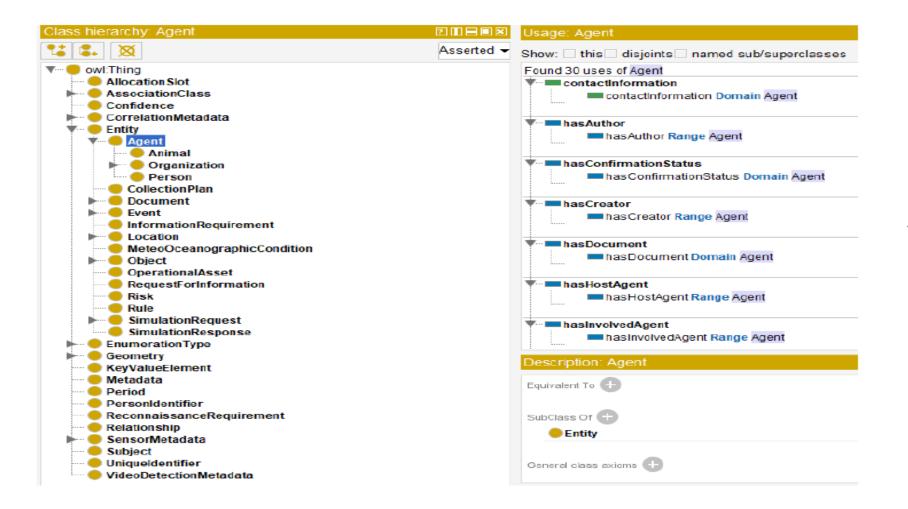






### Visualization of the CISE ontology on Protégé

USE OF ONTOLOGIES FOR REPRESENTING DATABASE ENTITIES

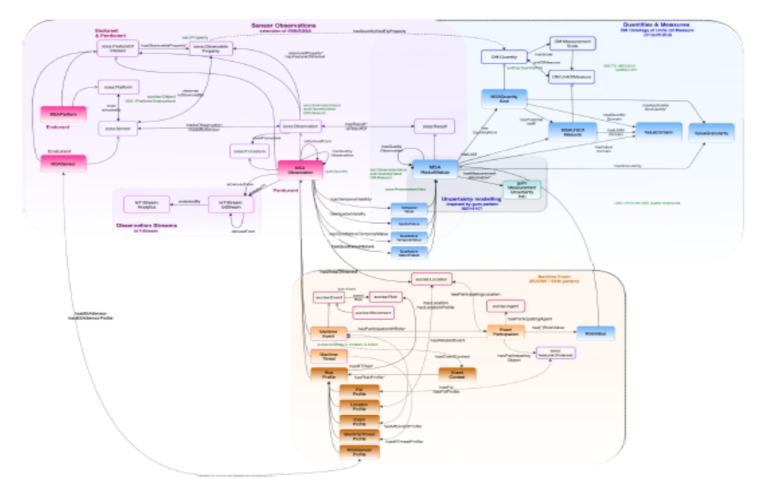


central classes of the CISE model concerning the Location entity

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#### Maritime Situational Awareness Heterogeneous Sensor Network Ontology (MSA-HSN)

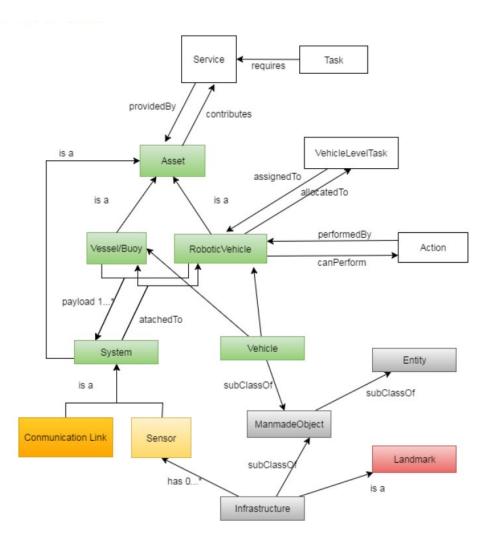


MSA-HSN, extended to support entity profiles and event context. Boxes represent top-level ontology concepts, including sensors and observations (violet background), observation values (light blue), and maritime events (orange). Arrows represent object properties linking concepts. Empty boxes are concepts from existing ontologies.





## **SWARMs Ontology**

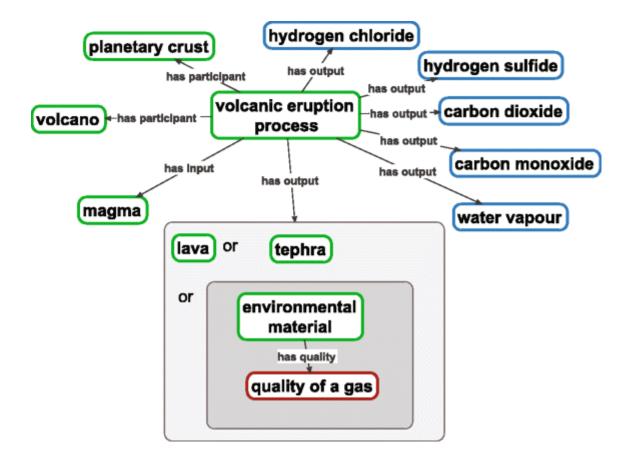


A representation of the overall structure of the core ontology for the cooperation of underwater robots





# Environment Ontology (ENVO)

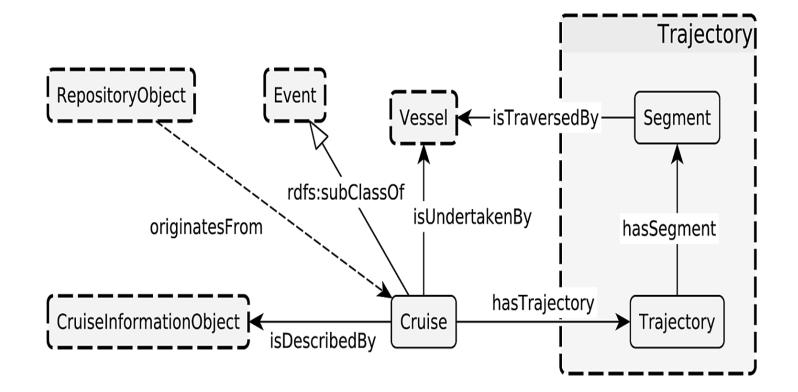


ENVO bridges domains with increased scope, semantic density, and interoperation.





# An oceanographic cruise ODP



An ODP (ontology design pattern) is a reusable solution to a data modelling problem.



# Agenda, including:

- Pattern Analysis and Machine Intelligence (PAMI) and Marine Ontologies
- Ontologies and Marine Robotics
- Ontology research trends review
- State-of-the-art of Ontologies in marine data classification and recognition
  - C—A framework for interactive visual analysis of heterogeneous marine data
  - PA, DC & DR identified through ontologies for marine data
  - Machine learning levels of visualization and their temporal perspective

#### Conclusions



## Data-driven Future in Marine Sciences

#### No interoperability

Relevance: semantic data,

metadata standards

#### Not enough data

Relevance: particularly AI, NN, ML,

frontier technologies

Few annotations in images

Relevance: monitoring of coastal seas, random forest applications

Use cases unpredictable

Relevance: cross-domain

innovation applications





### Addressing the interoperability

Marine Ontologies offer:

- C—A tool and method to assess the added value robotic technology brings into the marine environment (autonomous underwater vehicles (AUVs) or (ocean floor observation systems) OFOSs)
- The mechanism for describing sensors and sensor networks work in the context of Sensor Web applications
- A sustainable approach to harmonized data documentation
- Enables data re-use, data valorization, collaborative innovation, and to unambiguously set definitions and interconnect concepts in various field (more agile value chain interactions)





# The main features provided by ontologies in support of PAMI

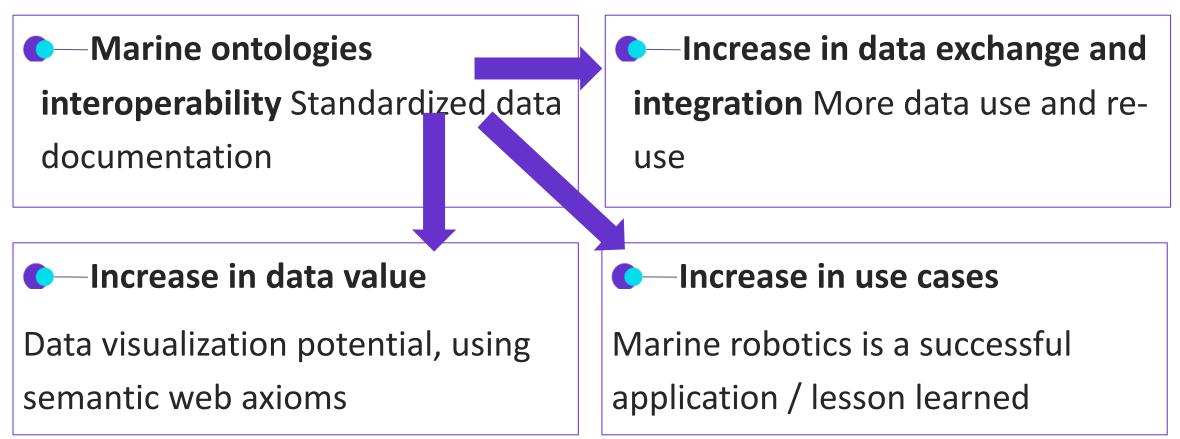
| Ontology feature               | Utility in PAMI  |
|--------------------------------|--|
| Classes and relations          | When ontology reasoning is applied to sensor data,<br>rdf:type will be connected to a class name of an<br>ontology   |
| Domain vocabulary              | Ontologies provide a domain vocabulary that can be<br>exploited to create a dense network of relationships<br>among the entities, and serve software applications,<br>and GIS                                      |
| Metadata and descriptions      | Biodiversity data, especially in marine domain, have<br>database entities represented as ontologies where<br>these last are primarily used for metadata that<br>describe raw data providing contextual information |
| Axioms and formal declarations | Ontology axioms and applied reasoning on them are related to the recognition of object presence in a time interval   |





07/09/23

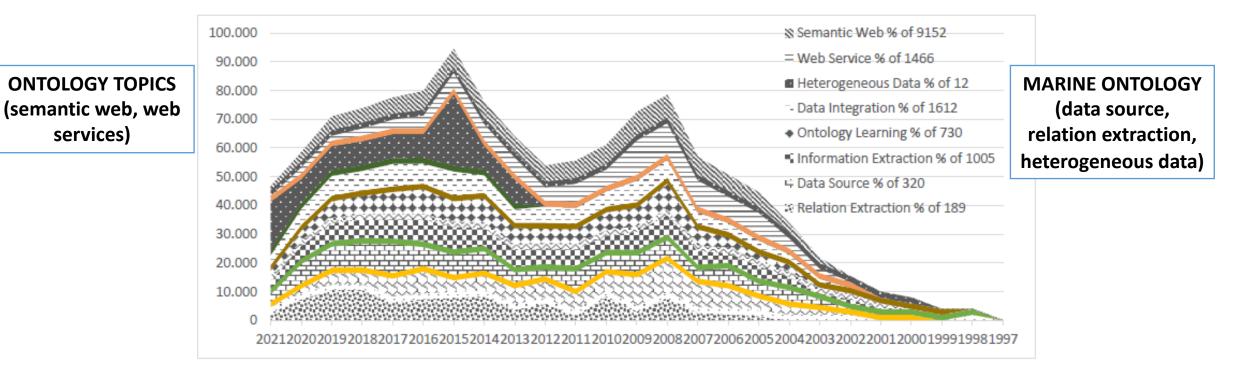
# Contribution to Marine Data Potential





## **Ontology Research Trends**

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# Contribution to semantic annotation

- Breakthrough annotation potential by making heterogeneous marine data accessible to ML
- Unlocking the potential of compositional definitions of a sequence of images
- Re-use of data across domains (compositional definitions, ontological certainty)
- Marine ontologies facilitate annotation of patterns using a multiple expert approach
- Highlighting ontological feedback to the domain of visualization (85.7% context detected)







# Ontological contexts detected in the data sources analyzed

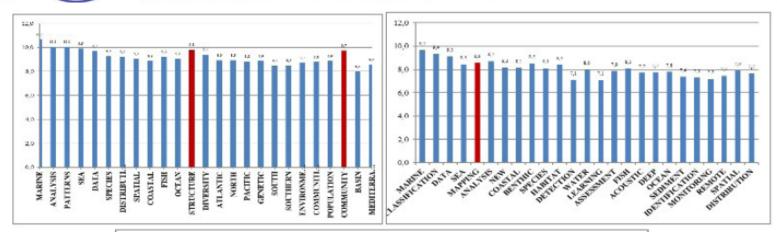
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| Num | Experimental Organism                         | A/B | DV | Ontology   |
|-----|---|-----|----|--|
| 1   | Dynamena pumila                               | В   | Y  | Gene Ontology (GO) and KEGG pathway  |
| 2   | Takifugu rubripes                             | A   | Y  | Gene Ontology (GO)   |
| 3   | phytoplankton                                 | A   | Y  | Gene Ontology (GO)   |
| 4   | nd  | A   | Y  | nd   |
| 5   | Dreissena polymorpha                          | В   | Y  | Gene Ontology (GO)   |
| 6   | Atlantic salmon                               | A   | Y  | Gene Ontology (GO) and UniProt Knowledgebase   |
| 7   | Micromonas polaris;<br>Pyramimonas tychotreta | В   | Y  | Gene Ontology (GO)   |
| 8   | Crassostrea gigas                             | A   | Y  | Gene Ontology (GO)   |
| 9   | Nd  | В   | Y  | Genomic Standards Consortium's MIxS and Environment<br>Ontology (ENVO); EMP Ontology (EMPO) of microbial<br>environments |
| 10  | Chlamys farreri                               | A   | Y  | Gene Ontology (GO) and Eukaryotic Orthologous Groups<br>(KOG) and Kyoto Encyclopedia of Genes and Genomes<br>(KEGG)      |
| 11  | Nd  | В   | Y  | Protégé environment (ontology)   |
| 12  | Nd  | В   | Y  | Protégé environment (ontology)   |
| 13  | Eucheuma denticulatum                         | Α   | Y  | Gene ontology (GO)   |
| 14  | 48 species of freshwater and marine fish      | A   | Y  | Gene ontology (GO)   |
| 15  | Larimichthys crocea                           | A   | Y  | Gene ontology (GO)   |
| 16  | Seriola lalandi                               | В   | Y  | Gene ontology (GO)   |
| 17  | marine and FW sticklebacks                    | В   | Y  | Gene ontology (GO)   |
| 18  | Genypterus chilensis                          | A   | Y  | Gene ontology (GO)   |
| 19  | Ceriops                                       | A   | Y  | Gene ontology (GO)   |
| 20  | Human   | A   | Y  | Gene ontology (GO)   |
| 21  | Zostera muelleri                              | В   | N  | Gene ontology (GO)   |

(A/B: applied/theoretical; DV: data visualization feedback)

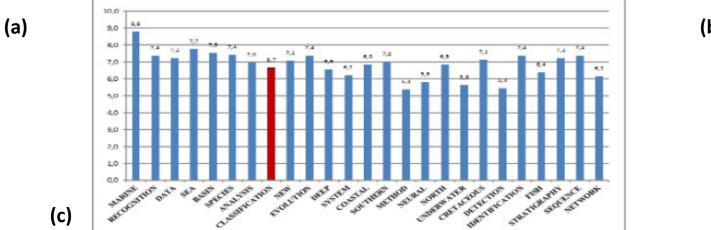
# A proof of principle shows needs for sensor data fusion

USE OF ONTOLOGIES FOR REPRESENTING DATABASE ENTITIES



(a) (structure and communities cause a positive effect on modelling required to discriminate relevant from non-relevant images)

(b) (mapping is the main technique to classify marine data)



(b)

(c) (a visual recognition task mapping is ensured by a visual language with data classification)





## Support to image visualization and exploitation on 2D, 3D, and motion imagery

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ML attests its power on heterogeneous marine data:

|                             | analytics | association | case study | classification | comparaison | complex | correlation | development | information | mapping | model | monitor | Observation | pattern | prediction | recognition | regression | sensor | simulation | time series | other | SUM |
|-----------------------------|-----------|-------------|------------|----------------|-------------|---------|-------------|-------------|-------------|---------|-------|---------|-------------|---------|------------|-------------|------------|--------|------------|-------------|-------|-----|
| Papers                      | 1         | 1           | 4          | 70             | 7           | 3       | 1           | 4           | 2           | 16      | 2     | 12      | 2           | 13      | 13         | 7           | 1          | 12     | 3          | 2           | 16    | 210 |
| disseminative               |           |             |            | 1              |             |         |             |             | 2           |         |       | 4       |             | 1       |            |             |            |        |            | 2           | 3     | 13  |
| observational               |           |             | 1          | 11             |             |         |             |             |             |         | 2     | 2       | 2           | 1       |            |             |            | 12     |            |             | 4     | 33  |
| analytical                  | 1         | 1           | 3          | 34             | 7           | 3       | 1           |             |             |         |       | 6       |             | 10      |            |             | 1          |        |            |             | 3     | 70  |
| model-<br>development<br>al |           |             |            | 3              |             |         |             | 4           |             | 16      |       |         |             | 1       | 13         | 7           |            |        | 3          |             | 4     | 92  |

#### Best analytical and modelling for innovation from demonstrators

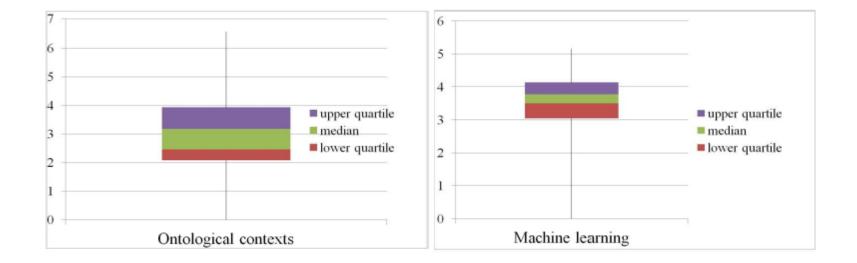
|                     | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | SUM |
|---------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|-----|
| Papers              | 3    | 3    | 7    | 5    | 4    | 6    | 9    | 12   | 16   | 15   | 27   | 55   | 48   | 210 |
| disseminative       |      |      |      |      |      |      | 1    |      | 1    | 1    | 1    | 5    | 4    | 13  |
| observational       | 1    |      | 1    |      |      | 1    |      | 1    |      |      | 6    | 12   | 11   | 33  |
| analytical          | 1    | 1    | 3    | 2    | 1    | 4    | 4    | 6    | 6    | 6    | 7    | 14   | 17   | 70  |
| model-developmental | 1    | 2    | 3    | 3    | 3    | 1    | 4    | 5    | 9    | 8    | 13   | 24   | 16   | 92  |
|                     |      |      |      |      |      |      |      |      |      |      |      |      |      |     |





## **Data Visualization Scenarios**

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•—the resulting lower quartile of 0.45 reached a best score for ML than for ontologies (0.38)

- ML decisions based outperformed ontology-driven coding for image classification
- In spite of ontology mapping for underwater IoT (IoUT) supports better interoperability protocols in the context of computer vision



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This approach has led to accurate predictions of the level of visualization importance for the example of how should marine databases be represented :

- •—The aim is to characterize marine ontologies to select data visualization techniques
- Promote results in interoperability as supported by ontologies
- C—Align with further statistics coverage developments across pattern analysis applications
- Continue to support the machine learning techniques, as it is clear that deep learning is a core components of the wider computer vision task with marine data.





# Towards a theoretical model for visualization with marine data

- Beyond the GIS community, Common Marine Ontologies are set to contribute to identify predicting and moderating variables for information perception of visual data.
- This will lead to a multiplier effect of potential applications, related to the top current cognition research, and unlock considerable potential for underwater and robotic vehicles and FAIR services in the context of a digital space for oceanography.





USE OF ONTOLOGIES FOR REPRESENTING DATABASE ENTITIES

The potential of ontologies for the empirical assessment of machine learning techniques in operational oceanography Thank you very much for your attention!

> **Enrique Wulff**, Marine Science Institute of Andalusia, CSIC

> > ICBO2023 - 30/08-01/09/2023