Machine Learning in Benthic Habitat Mapping

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Introduction

- Less than 10% of the world's oceans are mapped compared to 99% of Earth's topology mapped (low resolution)[1]
- To map more of the world's oceans at a high resolution, we employ benthic habitat mapping techniques
- Marine habitat mapping cuts across marine biology, geology, hydrography, oceanography, geophysics (Brown et al., 2011), along with habitat mapping

[1] http://www.wired.com/2009/06/nasa-satellite-maps-99-of-earths-topography/

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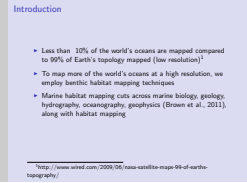
└Introduction



- 0.5 minutes
- What is benthic habitat mapping?
- Benthic - ecological region at the lowest level of a body of water
- benthos - things related to the benthic layer
- Habitat mapping - based on a small amount of high resolution data, and a considerably larger amount of lower resolution data, a relationship is created to correlate the data in overlapping regions, which is then projected to the regions without the high resolution data to create a 'habitat map'
- The high resolution data is generally actual sediment samples or organism samples at the benthos
- Low resolution data is generally some sort of acoustic data representing basic properties of the seafloor

Problem Statement

- Much research in benthic habitat mapping generates deterministic maps using as-is machine learning techniques/implementations
- We need to be able to monitor marine habitats on a large scale to assess human impact over time to be able to make informed management decisions

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- 1 minute
- Use of 'vanilla' algorithms such as random forests in Lucieera et al. (2013), Seiler et al. (2012), Hasan et al. (2014)

Solution - Overview

- Probabilistic approach allows us to state certainty about a particular mapped area
- We will use Gaussian processes to make predictions, which provides a distribution of probable habitats for a given area
- Two 'sets' of habitat classes were used - the original 24 labels, plus 5 aggregated labels

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- 1 minute
- Complexities of marine habitats are still largely 'foreign' to us, and when used to make important decisions, absolute maps may not be appropriate or present *enough* information - using a probabilistic approach allows us to state the certainty that a particular area is a certain habitat type and the species that live there
- a more coarse mapping of the habitats created in collaboration with an expert
- e.g. with labels 1-24, 1, 3, 5, 7 are condensed to one habitat, as they may be very similar visually, e.g. all sand with slight variations
- this brought the number of classes down to 5. The accuracy increases notably when the aggregation of visually matching habitat classes is performed.

Solution - Gaussian Processes

- Compared to more conventional supervised classification algorithms which require modeling around the chosen features, Gaussian processes instead look at the joint distribution across all features
- Use of Gaussian Processes requires a matrix inversion step with $O(n^3)$ complexity - attempt to overcome this by making our covariance matrix sparse and hence the inversion step computationally feasible for large datasets

TODO - (very) brief overview of what GPs are here, without going into the maths

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Results

- Using deterministic ML algorithms
- This first set of results is using 24 separate habitat classes as the labels.

Algorithm	F1 score	Accuracy
KNN (5)	0.04823	0.14192
Logistic Regression	0.00900	0.17119
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- 15 seconds just highlighting results here
- We would like to compare the results obtainable from use of Gaussian Processes in generating habitat maps to those of more naive methods. Note that measurements are taken by averaging over 10-fold cross validations.
- The accuracies don't break 20%, and the f-scores, which are the average of the precision and recall, are considerably worse

Results

- Using aggregated classes

Algorithm	F1 score	Accuracy
KNN (5)	0.33278	0.62459
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- Results have improved considerably here - by a factor of 4-7 times for f-score, and 2-3 times for accuracy

These final two set of results are using Gaussian processes with the granular and aggregated habitat classes, respectively.

Algorithm	F1 score	Accuracy
KNN (5)	0	0
Logistic Regression	0	0
Random Forest	0	0
SVM	0	0

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- 1.5 minutes (2 minute for results in total)
- NOTE still all zeroes as I will see if I can put in any *actual* results rather than completely faking it as we were told
- notably higher accuracies than with the previous methods for the granular and aggregated habitat classes respectively
- **TODO** add fake data for *other* datasets?
- **TODO** add times taken to run tests - important in terms of time/memory/etc tradeoffs

Discussion and Analysis

- Granular vs. aggregated classes

Discussion and Analysis
- Granular vs. aggregated classes

- 2 minutes
- The aggregated groups give considerably better results as there no longer needs to be a distinction between what are in some cases exceedingly similar classes of, for exapmle, sand

Discussion and Analysis

- TODO

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- TODO

- Compare (fake) results with Bender et al. (2012) and explain the improvement (or otherwise) on particular datasets
- highlight (potentially) better results with one dataset, but not in another (e.g. o'hara bluffs having more variation than scott reef)

Bibiolgraphy

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