

How can machine learning help to predict changes in size of Atlantic herring?

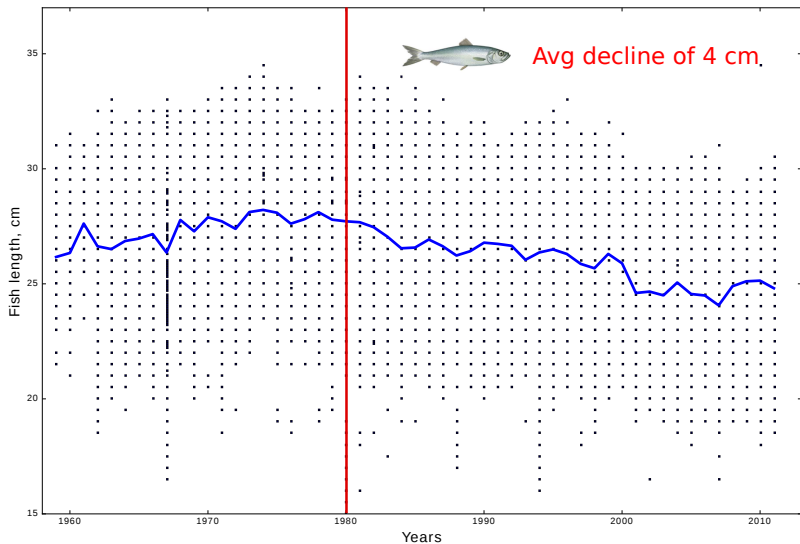
Olga Lyashevskaya* Clementine Harma Deirdre Brophy
Coilin Minto Maurice Clarke

* Marine and Freshwater Research Centre
Galway-Mayo Institute of Technology (GMIT)
Galway, Ireland

olga.lyashevskaya@gmit.ie

July, 22 2016

Background



Problem

- ▶ Herring are one of the most important pelagic species exploited by fisheries;

Problem

- ▶ Herring are one of the most important pelagic species exploited by fisheries;
- ▶ Reductions in growth have consequences for stock productivity;

Problem

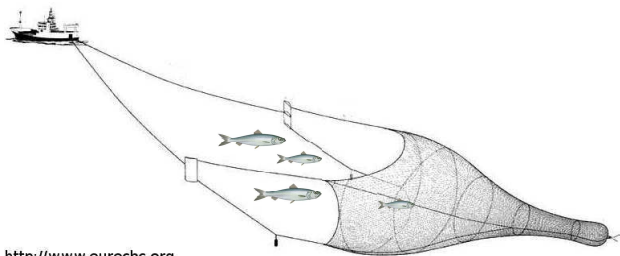
- ▶ Herring are one of the most important pelagic species exploited by fisheries;
- ▶ Reductions in growth have consequences for stock productivity;
- ▶ The cause of the decline remains largely unexplained;

Problem

- ▶ Herring are one of the most important pelagic species exploited by fisheries;
- ▶ Reductions in growth have consequences for stock productivity;
- ▶ The cause of the decline remains largely unexplained;
- ▶ Likely to be driven by the **interactive effect** of various factors:
 - ▶ sea surface temperature;
 - ▶ zooplankton abundance;
 - ▶ fish abundance;
 - ▶ fishing pressure;

Data

- ▶ 1959 – 2012;
- ▶ throughout the year;
- ▶ random sampling ($n = 50$ to 100) from commercial vessels;
- ▶ pelagic trawling;
- ▶ age and weight-at-length;
- ▶ total sample size 145 000;



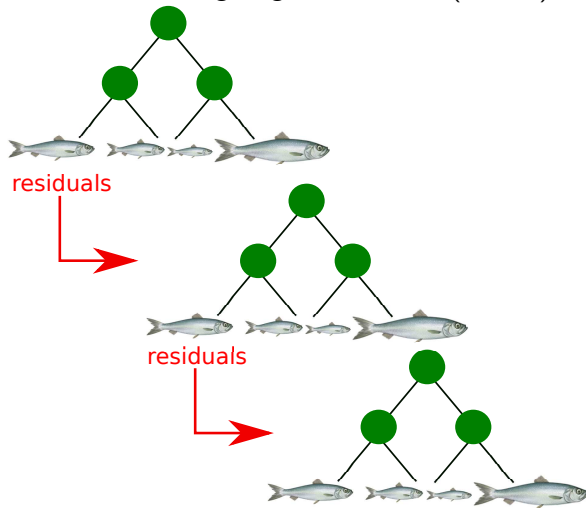
<http://www.eurocbc.org>

Study Area



Objective

To identify important variables underlying changes in growth using Gradient Boosting Regression Trees (GBRT)



- ▶ Advantages:
 - ▶ Detection of (non-linear) feature interactions;
 - ▶ Resistance to inclusion of irrelevant features;
 - ▶ Heterogeneous data (features measured on different scale);
 - ▶ Robustness to outliers;
 - ▶ Accuracy;
 - ▶ Different loss functions

- ▶ Advantages:

- ▶ Detection of (non-linear) feature interactions;
- ▶ Resistance to inclusion of irrelevant features;
- ▶ Heterogeneous data (features measured on different scale);
- ▶ Robustness to outliers;
- ▶ Accuracy;
- ▶ Different loss functions

- ▶ Disadvantages:

- ▶ Requires careful tuning;
- ▶ Slow to train (but fast to predict);

Formal Specification

$$F_m(x) = \sum_{m=1}^M \gamma_m h_m(x) \quad (1)$$

where γ_m is a weight and $h_m(x)$ are weak learners.

Formal Specification

$$F_m(x) = \sum_{m=1}^M \gamma_m h_m(x) \quad (1)$$

where γ_m is a weight and $h_m(x)$ are weak learners.

GBRT builds the additive model in a forward stagewise fashion:

$$F_m(x) = F_{m-1}(x) + \epsilon \gamma_m h_m(x) \quad (2)$$

where ϵ is a shrinkage.

Formal Specification

$$F_m(x) = \sum_{m=1}^M \gamma_m h_m(x) \quad (1)$$

where γ_m is a weight and $h_m(x)$ are weak learners.

GBRT builds the additive model in a forward stagewise fashion:

$$F_m(x) = F_{m-1}(x) + \epsilon \gamma_m h_m(x) \quad (2)$$

where ϵ is a shrinkage.

At each stage the weak learner $h_m(x)$ is chosen to minimize the loss function L given the current model F_{m-1} and its fit $F_{m-1}(x_i)$

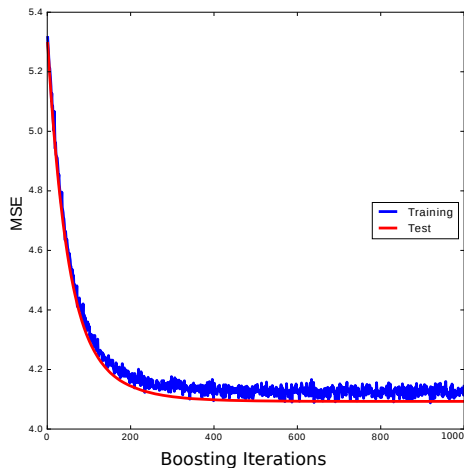
$$F_m(x) = F_{m-1}(x) + \arg \min_h \sum_{i=1}^n L(y_i, F_{m-1}(x_i) - h(x)) \quad (3)$$

GBRT hyperparameters

- ▶ number of iterations = 1000;
- ▶ shrinkage (learning rate) = 0.01;
- ▶ max tree depth = 4;
- ▶ subsample = 0.75;
- ▶ loss function = Least Squares;



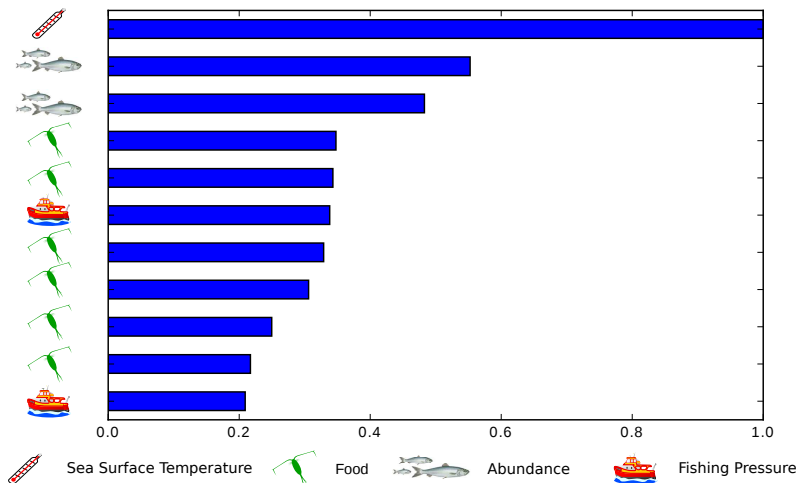
Deviance



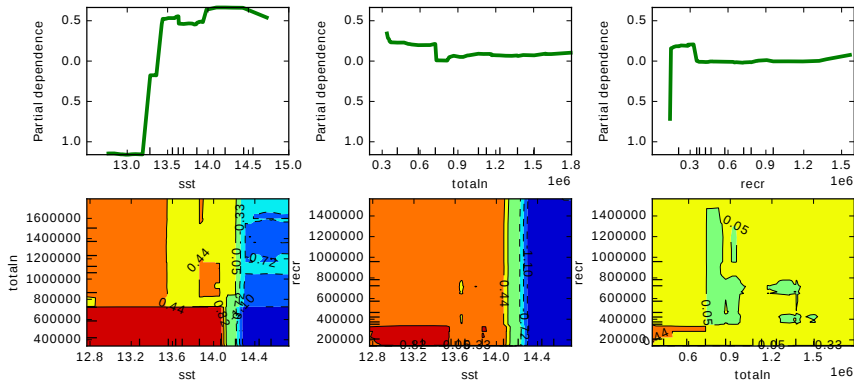
- ▶ MSE: 4.09
- ▶ R^2 test: 23.04
- ▶ R^2 train: 22.76

Low R^2 due to individual variability

Variable Importance Plot



Partial Dependence Plots



Conclusions

- ▶ sea surface temperature, total stock size and recruitment are three most important features;

Conclusions

- ▶ sea surface temperature, total stock size and recruitment are three most important features;
- ▶ sea surface temperature above 14 degrees negatively relates to fish length, whereas total stock biomass and recruitment are invariant;

Conclusions


- ▶ sea surface temperature, total stock size and recruitment are three most important features;
- ▶ sea surface temperature above 14 degrees negatively relates to fish length, whereas total stock biomass and recruitment are invariant;
- ▶ there is a high degree of interaction between sea surface temperature and total stock size;


Conclusions

- ▶ sea surface temperature, total stock size and recruitment are three most important features;
- ▶ sea surface temperature above 14 degrees negatively relates to fish length, whereas total stock biomass and recruitment are invariant;
- ▶ there is a high degree of interaction between sea surface temperature and total stock size;
- ▶ food availability shows low importance;

Conclusions

- ▶ sea surface temperature, total stock size and recruitment are three most important features;
- ▶ sea surface temperature above 14 degrees negatively relates to fish length, whereas total stock biomass and recruitment are invariant;
- ▶ there is a high degree of interaction between sea surface temperature and total stock size;
- ▶ food availability shows low importance;
- ▶ not a cause-effect relationship, but a relative importance of the variables;

 lyashevsk

 linked.in/lyashevsk



Acknowledgements:

This research was carried out with the support of the Irish Environmental Protection Agency grant (Ecosystem tipping points: learning from the past to manage for the future, project code 2015-NC-MS-3) and the support of the Marine Institute under the Marine Research Sub-programme funded by the Irish Government.

