Variable Selection in Additive Models with an Application to Logbook Data on Blue Sharks

Joanna Mills Flemming

Assistant Professor

Department of Mathematics and Statistics
Dalhousie University
Halifax, NS, CANADA

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Collaborators & Funding

- Eva Cantoni
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- Julia Baum

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Variable Selection

- Important issue in any statistical analysis
- Determine strongest effects that explain the response variable
- Reduces model complexity by admitting a small amount of bias

Motivating Example

- US National Marine Fisheries Service Pelagic Observer Program
- Catches of the blue shark, *Prionace glauca*
- Northeast Coastal and Distant Atlantic

Goals:

- *Statistical:*
  - propose an additive model
  - accommodate covariates which are potentially nonlinearly related to some function of the response (counts)
  - simultaneously fit a model and perform variable selection
- *Ecological:*
  - Are blue shark counts decreasing?

Approaches

- *Subset selection:* quickly becomes infeasible when the covariate dimension is too large
- *Stepwise procedures:* suffer from dependence on the path chosen through the variable space and may be inconsistent
- *Shrinkage methods:* have emerged and gained popularity in recent years
- **Methods that simultaneously address estimation and variable selection now exist**: modified LASSO, COSSO

Nonnegative Garrote

- Simple approach to variable selection for additive models
- Based on nonnegative garrote idea of Breiman (1995)
- Simultaneously has properties of subset selection, shrinkage and stability
- Computationally reasonable

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Methodology

Additive Model

$$Y_i = \alpha + \sum_{k=1}^{p} f_k(x_{ki}) + \epsilon_i$$

Solves

$$min_{c_k} \sum_{i=1}^{n} (y_i - \alpha - \sum_{k=1}^{p} c_k \hat{g}_k^{h_k}(x_{ki}))^2$$

under the constraints $c_k \geq 0$ and $\sum_{k=1}^{p} c_k \leq s$. The final estimate of $f_k(x_{ki})$ is $\hat{f}_k(x_{ki}) = c_k \hat{g}_k^{h_k}(x_{ki})$.

Interpretation

- $h_1, \cdots, h_p$ are smoothing parameters of the initial function estimates $\hat{g}_1^{h1}, \cdots, \hat{g}_p^{h_p}$.
- c_k depends on s and s is regarded as an additional parameter.
- Decreasing s has the effect of increasing the shrinkage of the nonzeroed functions and making more of the c_k become zero.
- *Given an initial estimate of all the additive functions in the model and a value for s* our method will automatically give a set of coefficients $c_1, \cdots c_p$ that will provide information on the importance of each variable in the model.

Choice of $h_1, \cdots, h_p$

- Smoothing parameters of initial fits must be selected in a reasonable manner
- $\Rightarrow$ We select to use an automatically data driven approach

Choice of s

- Best value of s will be that which minimizes the PE
- $\Rightarrow$ Estimate the PE by V-fold cross-validation

Implementation

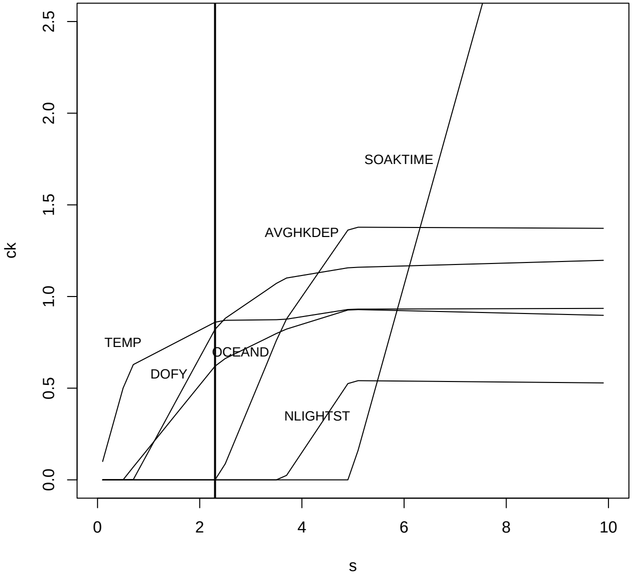
- Two parts:
- $\Rightarrow$ *gam* from the *mgcv* library in R
- $\Rightarrow$ Modified fortran code of Breiman and linked with R

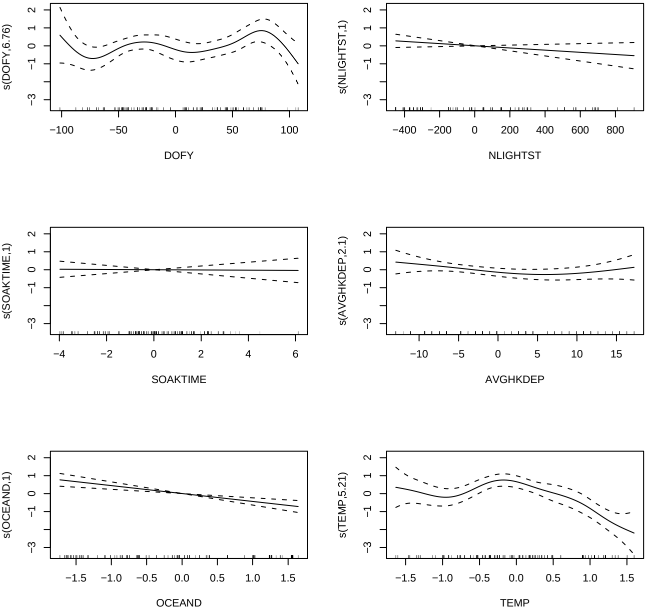
Blue Sharks Dataset

Model

$$log(bluesharks+1) = \alpha + f_1(DOFY) + f_2(NLIGHTST) + f_3(SOAKTIME) + f_4(AVGHKDEP) + f_5(OCEAND) + f_6(TEMP) + log(TOTHOOKS)$$

- Sample size is 91
- Strongest effects are TEMP, OCEAND and DOFY
- SOAKTIME and NLIGHTST can be removed
- AVGHKDEP borderline
- DOFY complicated functional form, TEMP approximately quadratic

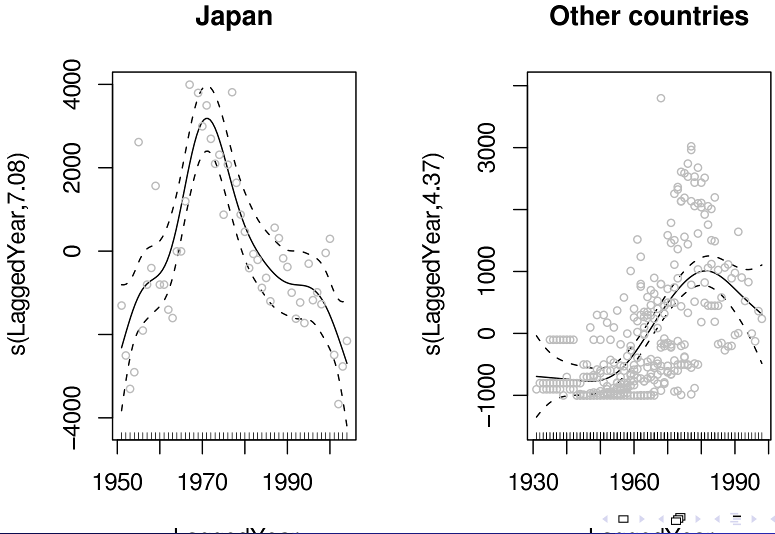

ck
s
SOAKTIME
AVGHKDEP
TEMP
OCEAND
DOFY
NLIGHTST
0.0
0.5
1.0
1.5
2.0
2.5
0
2
4
6
8
10


s(DOFY,6.76)
DOFY
s(NLIGHTST,1)
NLIGHTST
s(SOAKTIME,1)
SOAKTIME
s(AVGHKDEP,2.1)
AVGHKDEP
s(OCEAND,1)
OCEAND
s(TEMP,5.21)
TEMP

Discussion

- In terms of predictive ability, as well or better than competitors
- Code readily available and user-friendly

- **Patterns of expansion and depletion of invertebrate fisheries on a global scale**



The Future

- Extension to GAMs
- Robustness aspects