SEEC TOOLBOX SEMINAR

Generalized Additive Models

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SEEC - Statistics in Ecology, Environment and Conservation

Overview: Introduction to Splines and GAMs

- 1. motivating examples
- 2. splines
- 3. GAMs
- 4. implementation in mgcv
- 5. knots, penalites, confidence bands
- 6. 2-dimensional splines

Landslide susceptibility



Park & Chi 2008 (International Journal of Remote Sensing)

Shark catch



Walsh & Kleiber 2001 (Fisheries Research)

Long-term trends



Fewster et al. 2000 (Ecology)

Seasonal effects in time series



Polynomial regression



quadratic model

extension of linear model to handle non-linear relationships

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + e_i$$







х

Splines – before computer graphics



least energy - smoothest curve

Piecewise Polynomials



Cubic Polynomials



continuous 2nd derivative



Splines



Different types of spline basis functions cubic spline basis



х

From basis to fitted curve

B-spline Basis







DOY

From basis to fitted curve



х

х

GAMs using mgcv

Texts in Statistical Science

Generalized Additive Models An Introduction with R

Simon N. Wood



Wood, S. Generalized Additive Models.

R package mgcv mixed gam computation vehicle with automatic smoothness estimation

Linear Model – GLM – GAM

1. linear models

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + e_i$$

2. non-normal response — GLM

 $Y_i \sim NegBin(\mu_i, \theta)$

(or normal, Poisson, Binomial, etc....)

$$g(\mu_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2$$

3. add smooth functions — GAM

 $Y_i \sim NegBin(\mu_i, \theta)$

$$g(\mu_i) = \beta_0 + s_1(x_i) + s_2(z_i)$$

additive — no interactions

Specifying GAMs in mgcv

$$y_i = f(x_i) + e_i$$
, where $e_i \sim N(0, \sigma^2)$

gam(y ~ s(x))

 $\log(\mu_i) = f1(xi) + f2(zi) + f3(vi) + wi$, where $yi \sim Poisson(\mu_i)$

gam(y ~ s(x) + s(z) + s(v) + w, family = poisson)

Example: Airquality

0 50 150 250 Ozone Solar.R Wind ŝ Temp

airquality data

Airquality Example







ozone.R

Airquality Example

> summary(gam1)

:

```
Parametric coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 42.099 1.663 25.32 <2e-16
Approximate significance of smooth terms:
            edf Ref.df F p-value
s(Solar.R) 2.760 3.447 3.967 0.00849
s(Wind) 2.910 3.657 13.695 1.59e-08
s(Temp) 3.833 4.753 11.613 8.45e-09
R-sq.(adj) = 0.723 Deviance explained = 74.7%
GCV = 338.9 Scale est. = 306.83 n = 111
```

s term details

s(x, k = 10, bs = "tp", fx = FALSE)

- x is the covariate
- bs defines the type of basis
- k is the basis dimension
- fx: fixed degrees of freedom or penalized
- by allows interactions with a factor

DEFAULT: thin-plate spline, with penalty (eigen-decomposition)

bs — different basis functions

- tp default thin-plate regression spline
- cr cubic regression spline cubic spline basis
- cc cyclic cubic regression spline

Thin-plate Splines

cubic spline basis (cr)



thin-plate basis (tp)



Penalties (fx = FALSE)

Choose a large number of knots, but constrain their influence: e.g.

$$\sum \beta_j^2 \leq C$$

 \rightarrow choose ${\boldsymbol \beta}$ to minimize

 $||y - X\beta||^2$ subject to $\beta' D\beta \leq C$

 \rightarrow minimize

$$||y - X\beta||^2 + \lambda\beta' D\beta$$

 $\lambda =$ smoothing parameter (sp)

 \rightarrow tradeoff between fit and smoothness Estimation: generalized cross-validation (GCV), or Maximum Likelihood (or REML)

 \rightarrow penalized regression splines

2-dimensional smooths

1. Tensor Product:

 $\mu_i = s(\text{Solar.R}_i, \text{Temp}_i)$

gam(y ~ te(Solar.R, Temp), data = airquality)

2. Thin-plate Spline:

gam(y ~ s(longitude, latitude), data = ...)

Tensor Product





Tensor Product Basis



Tensor Product



Seasonal Spline

plot(gam.seas)

60 70



200

doy

250

Seasonal Spline

visreg(gam.seas)



