## Flexible smoothing with B-splines and Penalties or P-splines

- P-splines = B-splines + Penalization
- Applications : Generalized Linear and non linear Modelling ; Density smoothing
- P-splines have their grounding in Classical regression methods and Generalized linear models
- Regression, Smoothing, Splines?
- B-splines P-splines?

Smoothing, Regression, Splines, B-splines P-splines?

 In <u>statistics</u>, linear regression refers to any approach to modeling the relationship between one or more variables denoted y and one or more variables denoted X, such that the model depends linearly on the unknown <u>parameters</u> to be <u>estimated</u> from the <u>data</u>. Such a model is called a "linear model."

#### Smoothing, Regression, Splines, B-splines P-splines?



• Linear model

$$y = \alpha + \beta x + \varepsilon$$

 Generalized Linear model where x'iβ is the inner product between vectors xi and β.

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

• The term *ei* is the residual, . One method of estimation is ordinary least squares. This method obtains parameter estimates that minimize the sum of squared residuals, SSE:

$$e_i = y_i - \hat{y}_i$$

$$SSE = \sum_{i=1}^{N} e_i^2.$$

 Smoothing: In <u>statistics</u> and <u>image</u> processing, to **smooth** a <u>data set</u> is to create an approximating <u>function</u> that attempts to capture important <u>patterns</u> in the data, while leaving out <u>noise</u> or other fine-scale structures/rapid phenomena.

 Many different <u>algorithms</u> are used in smoothing. One of the most common algorithms is the "<u>moving average</u>", often used to try to capture important trends in repeated <u>statistical surveys</u>. In <u>image</u> <u>processing</u> and <u>computer vision</u>, smoothing ideas are used in <u>scale-space</u> representations.

 Spline : Originally, a spline tool was a thin flexible strip of wood ,metal or rubber used by draftsman to aid in drawing curved lines.



 a spline is a special <u>function</u> defined <u>piecewise</u> by <u>polynomials</u>. In <u>interpolating</u> problems, <u>spline interpolation</u> is often preferred to <u>polynomial interpolation</u> because it yields similar results

## **Splines**

Spline of degree zero



# Splines



## Splines

• A cubic spline  $S(x) = \begin{cases} x^3 - 1 & x \in [-1, 1/2) \\ 3x^3 - 1 & x \in [1/2, 1) \end{cases}$ 



## **!B-splines!**

• B-splines of degree 0

$$B_i^0(x) = \begin{cases} 1 & x \in [t_i, t_{i+1}) \\ 0 & otherwiswe \end{cases}$$



## **!B-splines**



## **B-splines**



## **B-splines**

B-splines are defined recursively

$$B_i^k(x) = \left(\frac{x - t_i}{t_{i+k} - t_i}\right) B_i^{k-1}(x) + \left(\frac{t_{i+k+1} - x}{t_{i+k+1} - t_{i+1}}\right) B_{i+1}^{k-1}(x)$$

# **Properties of P-splines**

- No boundary effects
- Are a straightforward extension of (generalized) linear regression models
- Conserve moments like the mean and variances of the data and fit polynomial data exactly
- Computations and cross validation relatively inexpensive

## Fitting curves with B-splines

- A fitted curve  $\hat{y} to(x_i, y_i)$
- is the linear combination

$$\hat{y} = \sum_{i=1}^{n} \hat{a}_i B_i(x)$$

## Fitting curves with splines

- The corresponding SSE
- (quadratic error) is



## O'Sullivan penalty

 Between 1986 and 1988 O'Sullivan introduced a penalty on the second derivative of the fitted curve;

$$S(x) = \sum_{i=1}^{m} \left\{ y_i - \sum_{j=1}^{n} \hat{a}_j B_j(x) \right\}^2 + \lambda \int_{x\min}^{x\max} \left\{ \sum_{j=1}^{n} \hat{a}_j B_j''(x) \right\}$$

## **Eilers and MarxPenalities**

 Eilers /Marx penalty proposal based on finite differences



# Applications

- Generalized linear modeling
- Density Smoothing
- Example 1 : Motorcycle crash helmet impact simulation data (Härdle 1994) head acceleration in g units at different times after impact. Smoothed with Bsplines of degree 3 and a second order penalty

## Example 1 Graph



FIG. 2. Motorcycle crash helmet impact data: optimal fit with B-splines of third degree, a second-order penalty and  $\lambda = 0.5$ .

## **Density Smoothing**



FIG. 6. Density smoothing of durations of Old Faithful geyser eruptions: density histogram and fitted densities; thin line, third-order penalty with  $\lambda = 0.001$ (AIC = 84.05); thick line, optimal  $\lambda = 0.05$ , with AIC = 80.17; B-splines of degree 3 with 20 intervals on the domain from 1 to 6.

## **Density Smoothing**



FIG. 7. Density smoothing of suicide data: positive domain (0–1,000); B-splines of degree 3, penalty of order 2, 20 intervals,  $\lambda = 100$ , AIC = 69.9.

## **Density Smoothing**



FIG. 8. Density smoothing of suicide data: the domain includes negative values (-200-800); B-splines of degree 3, penalty of order 2, 20 intervals,  $\lambda = 0.01$ , AIC = 83.6.