

# Penalized B-spline

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## 1 Introduction

## 2 P-spline Package in R

## 3 Apply Data set

# What Is Penalized B-spline

- Penalized B-spline(P-spline) is a spline method that adds a penalty term to B-spline to create a smoother curve.
- P-spline can solve the problems that occur in B-spline regression:
  - The problem sensitive to number or location of knots.
  - The problem that the model is too flexible and vibrates.

# The Function of P-spline

- The following is the function of P-spline:

$$\hat{y} = \sum_{j=1}^K \beta_j B_j(x)$$

and we minimize the equation that follows as:

$$\begin{aligned} & \min_{\beta} \{ \|y - B\beta\|^2 + \lambda \|D^{(d)}\beta\|^2 \} \\ & = \min_{\beta} \left\{ \sum_{i=1}^n \left( y_i - \sum_{j=1}^K \beta_j B_j(x_i) \right)^2 + \lambda \sum_{j=1}^K (\Delta^d \beta_j)^2 \right\}. \end{aligned}$$

- We can also compute the coefficient of P-spline  $\hat{\beta}$  like:

$$\hat{\beta} = \left( B^{\top} B + \lambda D^{(d)\top} D^{(d)} \right)^{-1} B^{\top} y.$$

- $y$ : vector of the responses that are observed,  
   $B$ : design matrix based on B-spline basis,  
   $\beta$ : vector of B-spline coefficients,  
   $\lambda$ : smoothing parameter,  
   $D^{(d)}$ : difference matrix that computes the  $d$ -th order difference of  $\beta$ .

1 Introduction

2 **P-spline** Package in R

3 Apply Data set

- P-spline package is a package that receives the number of knots, adjusts their positions, and performs penalized b-spline regression.

function.	explain
knots	Function of knots sequence using the quantiles of the data
bspline__basis	B-spline basis function and design matrix of B-spline basis
fit_pspline	Fitting P-spline model
predict_pspline	Predicting the values of y for given x based on P-spline
plot_pspline	Drawing a plot of P-spline

## The Variables Using in Package

variable	explain
x	Numeric vector of the data
new__x	Numeric vector expressing a grid of evaluation points
grid__x	Numeric vector with a grid of evaluation points
x_values	Numeric vector of x (input)
y_values	Numeric vector of y (response)
model	Function that fit P-spline with given data points
interior_knots	Vector of interior knots
dimension	Number of the basis function
degree	Degree of spline(default= 3)
lambda	Smoothing parameter (default = 1e-2)
diff_order	Order of the difference penalty (default = 2)

## Computing Knots Using quantile

```
knots_quantile <- function(x, dimension, degree = 3){  
  dimension = max(dimension, degree + 1)  
  num_interior = dimension - degree - 1  
  
  if (num_interior > 0){  
    probs <- (1:num_interior)/(num_interior + 1)  
    interior_knots <- quantile(x, probs, type = 1)  
  }  
  else{  
    interior_knots <- numeric(0)  
  }  
  
  return(interior_knots)  
}
```

## Adding Boundary Knots to Interior Knots

```
# Add boundary knots to interior knots.
```

```
add_boundary_knots <- function(x, interior_knots, degree = 3, tiny = 1e-5){  
  knots<- c(rep(min(x) - tiny, degree + 1),  
            interior_knots, rep(max(x) + tiny,  
                                degree + 1))  
  return(knots)  
}
```

## Definition B-spline Basis Function

```
# B-spline basis function
```

```
b_spline <- function(x, knots, degree, i){
```

```
# Base case: 0th degree
```

```
if (degree == 0){
```

```
  return(ifelse(knots[i] <= x & x < knots[i + 1], 1, 0))
```

```
}
```

```
# Recursive case: degree > 0
```

```
B_i_d1 <- b_spline(x, knots, degree - 1, i)
```

```
B_i1_d1 <- b_spline(x, knots, degree - 1, i + 1)
```

```
denom1 <- knots[i + degree] - knots[i]
```

```
denom2 <- knots[i + degree + 1] - knots[i + 1]
```

```
term1 <- if (denom1 == 0) 0 else ((x - knots[i])/denom1)*B_i_d1
```

```
term2 <- if (denom2 == 0) 0 else ((knots[i + degree + 1] - x)/denom2)*B_i1_d1
```

```
return(term1 + term2)
```

```
}
```

## Definition Design Matrix of B-spline Basis

*# Create design matrix of B-spline basis*

```
create_design_matrix <- function(x_values, knots, degree){  
  n <- length(x_values) # number of the data  
  num_basis <- length(knots) - degree - 1 # number of the basis function  
  
  design_matrix <- matrix(0, nrow = n, ncol = num_basis)  
  
  for (j in 1:num_basis){  
    for (i in 1:n){  
      design_matrix[i, j] <- b_spline(x_values[i], knots, degree, j)  
    }  
  }  
  
  return(design_matrix)  
}
```

# Fitting P-spline Model

```
fit_pspline <- function(x_values, y_values,
                        interior_knots, degree = 3,
                        lambda = 0.01, diff_order = 2){

  knots <- add_boundary_knots(x_values, interior_knots, degree)

  G <- create_design_matrix(x_values, knots, degree)
  # Design Matrix of B-spline

  num_basis <- ncol(G)
  D <- diff(diag(num_basis), differences = diff_order)

  P <- t(D) %*% D # Penalty Matrix

  beta_hat <- solve(t(G) %*% G + lambda * P) %*% t(G) %*% y_values

  return(list(beta = beta_hat, knots = knots,
             degree = degree, lambda = lambda,
             penalty = P))
}
```

## Predicting the Values of Data Based on P-spline

```
predict_pspline <- function(model, new_x){  
  G_new = create_design_matrix(new_x, model$knots, model$degree)  
  y_pred = G_new %*% model$beta  
  return(y_pred)  
}
```

## Plotting P-spline with Scatter Plots

```
library(ggplot2)

plot_pspline <- function(x_values, y_values, model, grid_x, num_knots, lambda,
                          point_size, line_size){
  y_pred = predict_pspline(model, grid_x)
  data_plot = data.frame(x = x_values, y = y_values)
  spline_plot = data.frame(x = grid_x, y = y_pred)

  ggplot() +
    geom_point(data = data_plot, aes(x, y),
              color = "blue", size= point_size) +
    geom_line(data = spline_plot, aes(x, y),
             color = "red", linewidth = line_size) +
    labs(title =
          sprintf("Fitted P-spline Regression (knots= %d, lambda= %.2f)",
                  num_knots, lambda), x = "x", y = "y") +
    xlim(c(min(x_values), max(x_values)))
}
```

1 Introduction

2 P-spline Package in R

3 Apply Data set

## Generating Data set

```
set.seed(924)
n= 100
x_values= sort(runif(n, 0, 1))
y_values= sin(2*pi*x_values) + cos(4*pi*x_values) + rnorm(n, sd= 0.2)
```

## Using P-spline Package

```
# devtools::install_github('Ga-young-Moon/Penalized-B-spline')
library(Pspline)

# spline degree specification
degree= 3

# knot generation
num_interior= 5
interior_knots= knots_quantile(x_values, num_interior)

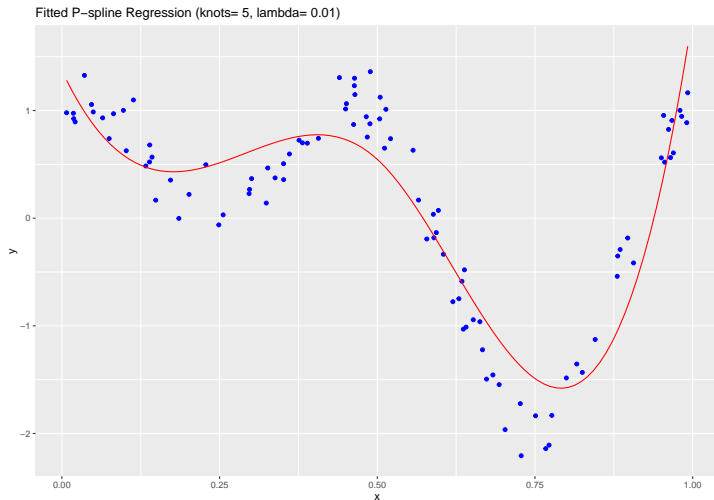
# setting the value of lambda
# and the difference penalty order
lambda= 1e-2
diff_order= 2

# model fitting
model= fit_pspline(x_values, y_values, interior_knots,
                   degree, lambda, diff_order)
```

##

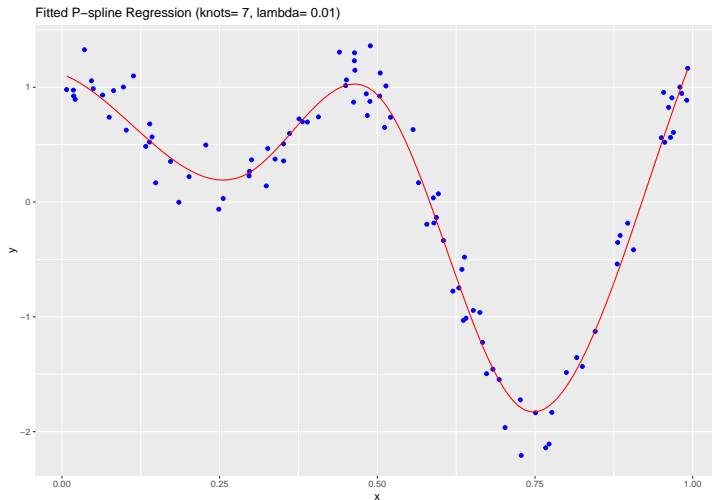
## Drawing the Plot of Data Point

```
grid_x = seq(min(x_values), max(x_values), length.out = 100)  
plot_pspline(x_values, y_values, model, grid_x, 5, 1e-2, 1.5, 0.5)
```



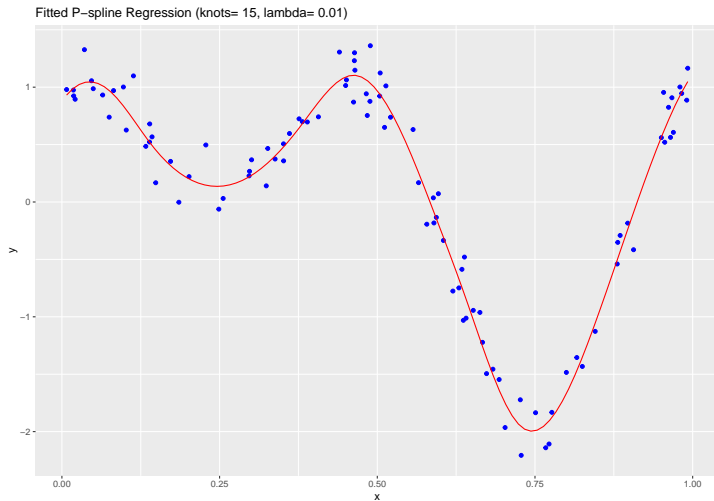
## Plot Shape According to Number of Knots (Knots= 7)

- From the plot above, we can see that when there are 5 knots, the spline curve does not follow the data very well.  
→ Therefore, we need to check the plot when the number of knots is increased.
- If the number of knots is 7:



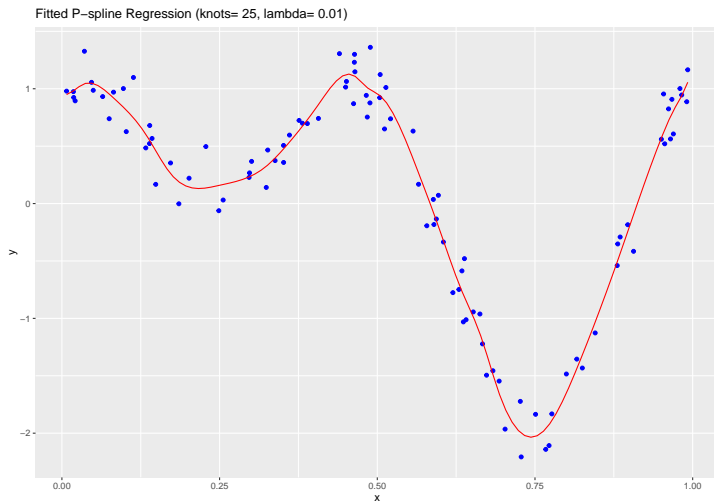
## Plot Shape According to Number of Knots (Knots= 15)

- If the number of knots is 15:



## Plot Shape According to Number of Knots (Knots= 25)

- If the number of knots is 25:



- As the number of knots increases, we can see that the spline model becomes more flexible.

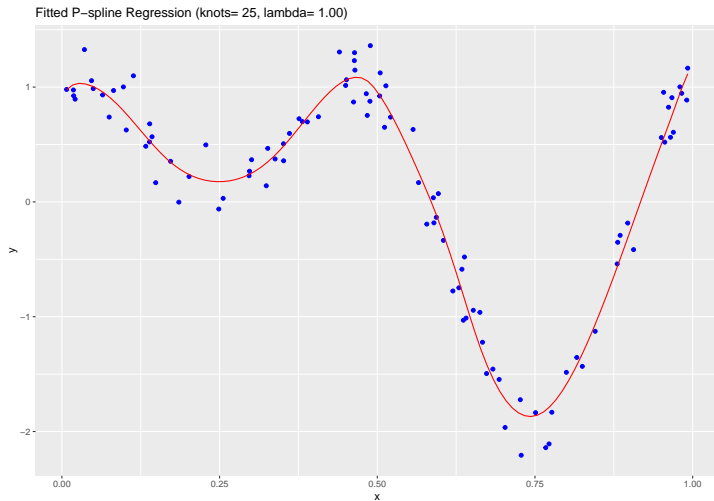
## Plot Shape According to Value of $\lambda$ ( $\lambda = 0.01$ )

- Then, we can also see how the plot changes depending on  $\lambda$  value.



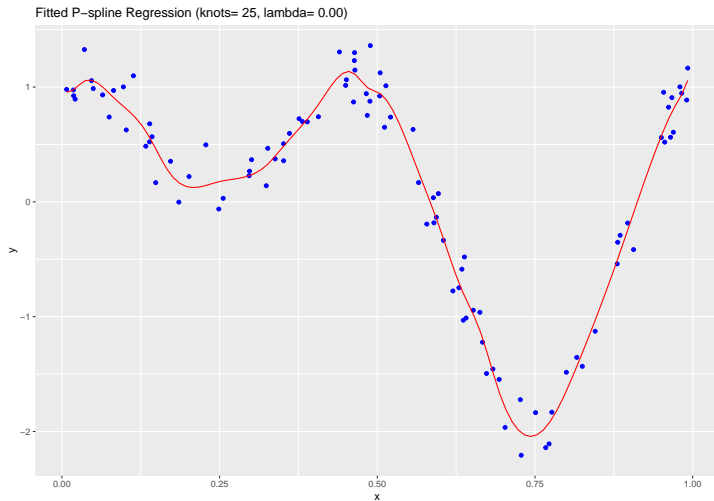
# Plot Shape According to Value of $\lambda$ ( $\lambda = 1$ )

- If  $\lambda = 1$ :



## Plot Shape According to Value of $\lambda$ ( $\lambda = 0.0001$ )

- If  $\lambda = 0.0001$ :



- The smaller  $\lambda$  value, the better the curve follows the data.

# Q & A

**Thank you :)**