

# Smoothing Spline (SS)

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## CV for the SS

Here, we would like to check if the SS satisfies the sufficient conditions (3)-(4), which implies the equation (2) for the CV holds in the lecture note 1.

## step1: compute the SS.

First we make R functions which give the smoothing matrix ( $S$ ), design matrix ( $D$ ) and penalty matrix  $W$  for SS, and the basis functions, that is, the cubic spline basis functions with knots equal to data points  $x_i$ 's.

```
matrices_SS<-function(x,lam){
  sx<-sort(x)
  n<-length(x)
  D<-cbind(rep(1,n), sx)

  for (i in 1:(n-2)){

    temp<-(sx-sx[i])^3*((sx-sx[i])>0)-(sx-sx[n])^3*((sx-sx[n])>0)
    temp<-temp/(sx[n]-sx[i]) #d_i
    temp1<-(sx-sx[n-1])^3*((sx-sx[n-1])>0)-(sx-sx[n])^3*((sx-sx[n])>0)
    temp1<-temp1/(sx[n]-sx[n-1]) #d(n-1)

    D<-cbind(D,temp-temp1)
  }

  z<-seq(0,1,0.0001)
  J<-length(z)

  B<-cbind(rep(1,J), z)

  for (i in 1:(n-2)){

    temp<-(z-sx[i])^3*((z-sx[i])>0)-(z-sx[n])^3*((z-sx[n])>0)
    temp<-temp/(sx[n]-sx[i]) #d_i (z)

    temp1<-(z-sx[n-1])^3*((z-sx[n-1])>0)-(z-sx[n])^3*((z-sx[n])>0)
    temp1<-temp1/(sx[n]-sx[n-1]) #d(n-1)(z)

    B<-cbind(B,temp-temp1)
  }

  #as a result, we get B: J x no. of basis functions containing Bk(zi) as (i,k) entry

  #diff
  Bd1<-matrix(NA, J-2, n)
  for (j in 2:(J-1)){
```

```

Bd1[j-1,]<-(B[j+1,]-B[j-1,])/(z[j+1]-z[j-1]) #the first derivative of basis functions
}

#diff
Bd2<-matrix(NA, J-4, n)
for (j in 2:(J-3)){
Bd2[j-1,]<-(Bd1[j+1,]-Bd1[j-1,])/(z[j+1]-z[j-1]) #the second derivative of basis functions
}

W<-(t(Bd2)%*%Bd2)/(J-4 )

S<-D%*% solve(t(D)%*% D+lam*W) %*% t(D)
return(list(D=D, W=W, S=S))
}

# Basis function for given data
basis<-function(data,x){
  sx<-sort(x)
  n<-length(x)
  D<-c(1,data)
  for (i in 1:(n-2)){
    temp<-((data-sx[i])^3*((data-sx[i])>0)-(data-sx[n])^3*((data-sx[n])>0)
    t
  emp<-temp/(sx[n]-sx[i]) #d_i
  temp1<-((data-sx[n-1])^3*((data-sx[n-1])>0)-(data-sx[n])^3*((data-sx[n])>0)
  temp1<-temp1/(sx[n]-sx[n-1]) #d(n-1)
  D<-c(D,temp-temp1)
  }
  return(D)
}

```

## step 2: simulation check for (3)-(4)

Set any sample size  $n$ , generate data  $x_i$  from any distribution. When setting any  $\lambda$  and any  $i$  for (4) check if (3)-(4) holds. For example, choose  $n = 5$ ,  $x_i \sim U(0, 1)$ ,  $\lambda = 1$ ,  $i = 3$  as follows:

```

n<-10
x<-sort(runif(n))
lam=1

```

```

i=3

```

```

S<-matrices_SS(x,lam)$S
apply(S,1,sum) #(3)

```

```

## [1] 1 1 1 1 1 1 1 1 1 1

```

```

xminusi<-x[-i]

```

```

Sminusi<-matrices_SS(xminusi,lam)$S
Wminusi<-matrices_SS(xminusi,lam)$W
Dminusi<-matrices_SS(xminusi,lam)$D

```

```

lminusi_xi<-basis(x[i], xminusi)

lminusi_xi%% solve(t(Dminusi)%% Dminusi+lam*Wminusi) %% t(Dminusi) #LHS of (4)

##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## [1,] 0.2877091 0.227533 0.1625128 0.1298018 0.09282575 0.08095179
##          [,7]      [,8]      [,9]
## [1,] 0.07651218 -0.0195141 -0.03833229

S[i,-i]/sum(S[i,-i]) #RHS of (4)

## [1] 0.28777857 0.22749655 0.16248016 0.12977913 0.09281421 0.08094378
## [7] 0.07650549 -0.01949260 -0.03830529

```

The sufficient conditions (3)-(4) seem to hold for the SS if ignoring the numeical errors.