

Assignment 4

1

The black line represents the true function, the blue line represents the unpenalized regression spline, and the red line represents the penalized regression spline. The `nls` command in R was used to minimize the following expressions.

1.a**1.a.1 Cross Validation****1.a.2 Generalized Cross Validation****1.b Corrected Akaike Information Criterion****1.c Risk Minimization**

$$\begin{aligned}
\mathbb{E}\|\mathbf{y} - \hat{\mathbf{f}}_\lambda\|^2 &= \mathbb{E}\|\mathbf{y} - \mathbf{H}_\lambda \mathbf{y}\|^2 \\
&= \mathbb{E}\|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{y}\|^2 \\
&= \mathbb{E}\|(\mathbf{I} - \mathbf{H}_\lambda) (\mathbf{f} + \mathbf{e})\|^2 \\
&= \mathbb{E}\|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f} + (\mathbf{I} - \mathbf{H}_\lambda) \mathbf{e}\|^2 \\
&= \mathbb{E}\|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}\|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{e}\|^2 + 2\mathbb{E}[(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f} \cdot (\mathbf{I} - \mathbf{H}_\lambda) \mathbf{e}] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}[(\mathbf{f} - \mathbf{H}_\lambda \mathbf{f}) \cdot (\mathbf{e} - \mathbf{H}_\lambda \mathbf{e})] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}[\mathbf{f} \cdot (\mathbf{e} - \mathbf{H}_\lambda \mathbf{e}) - \mathbf{H}_\lambda \mathbf{f} \cdot (\mathbf{e} - \mathbf{H}_\lambda \mathbf{e})] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}[\mathbf{f} \cdot \mathbf{e} - \mathbf{f} \cdot \mathbf{H}_\lambda \mathbf{e} - \mathbf{H}_\lambda \mathbf{f} \cdot \mathbf{e} + \mathbf{H}_\lambda \mathbf{f} \cdot \mathbf{H}_\lambda \mathbf{e}] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}[\mathbf{f} \cdot \mathbf{e} - \mathbf{H}_\lambda^T \mathbf{f} \cdot \mathbf{e} - \mathbf{H}_\lambda \mathbf{f} \cdot \mathbf{e} + \mathbf{H}_\lambda^T \mathbf{H}_\lambda \mathbf{f} \cdot \mathbf{e}] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \mathbb{E}[(\mathbf{I} - \mathbf{H}_\lambda^T - \mathbf{H}_\lambda + \mathbf{H}_\lambda^T \mathbf{H}_\lambda) \mathbf{f} \cdot \mathbf{e}] \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \text{Cov}(\mathbf{e}) (\mathbf{I} - \mathbf{H}_\lambda - \mathbf{H}_\lambda^T - \mathbf{H}_\lambda^T \mathbf{H}_\lambda) \\
&= \|(\mathbf{I} - \mathbf{H}_\lambda) \mathbf{f}\|^2 + \sigma^2 \{\text{tr}(\mathbf{H}_\lambda \mathbf{H}_\lambda^T) - 2\text{tr}(\mathbf{H}_\lambda) + n\}
\end{aligned}$$

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require("LaplacesDemon")
require("extrafont")
par(family = 'Times New Roman')
setwd("/Users/mikhailgaerlan/Box Sync/Education/UC Davis/2016-2017 Spring/STA 243 Computational
Statistics/Assignments/Assignment 5")
rm(list=ls())
set.seed(0518)

# Parameter Values
p = 3
n = 200
k = 30
export = T

phi = function(u){
  return(exp(-u^2/2)/sqrt(2*pi))
}

f = function(x){
  return(1.5*phi((x-0.35)/0.15)-phi((x-0.8)/0.04))
}

modelf = function(x,knots,betas){
  sums = 0
  for(i in 1:(p+1)){
    sums = sums + betas[i]*x^(i-1)
  }
  for(i in 1:k){
    sums = sums + betas[p+1+i]*(max((x-knots[i]),0))^p
  }
  return(sums)
}

designmatrix = function(x,p,k){
  n = length(x)
  X = array(0,c(n,p+1+k))
  for(i in 1:(p+1)){
    for(j in 1:n){
      X[j,i] = x[j]^(i-1)
    }
  }
  for(i in 1:k){
    for(j in 1:n){
      X[j,p+1+i] = (max(c((x[j]-knots[i]),0)))^p
    }
  }
  return(X)
}

for(o in 1:4){
  if (o == 1){
    print("Cross Validation")
    method = "CV"
  } else if(o == 2){
    print("Generalized Cross Validation")
    method = "GCV"
  } else if(o == 3){
    print("AICc")
    method = "AICc"
  } else if(o == 4){
    print("Risk")
    method = "Risk"
  }
  for(l in 1:4){
    if (l == 1){
      print("Noise Level")
      functions = "Noise Level"
    } else if(l == 2){
      print("Design Density")
      functions = "Design Density"
    } else if(l == 3){
      print("Spatial Variation")
      functions = "Spatial Variation"
    } else if(l == 4){
      print("Variance Function")
      functions = "Variance Function"
    }
    for(m in 1:6){
      if (export) file_name =
paste("Graphs/",toString(o),"/",toString(l),"/assignment5_a_",toString(o),"_",toString(l),"_",toString(m),".pdf",sep="

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if (export) pdf(file = file_name,width = 4,height=3.5,family="Times New Roman")
# Data generation
xtest = seq(0,1,0.001)
if(l==1){
  # Noise Level
  f = function(x){
    return(1.5*phi((x-0.35)/0.15)-phi((x-0.8)/0.04))
  }
  x = (1:200-0.5)/n
  knots = min(x) + 1:k*(max(x)-min(x))/(k+1)
  sigma = 0.02 + 0.04*(m-1)^2
  epsilon = rnorm(n,0,1)
  truef = f(x)
  y = truef + sigma*epsilon
}else if(l==2){
  # Design Density
  f = function(x){
    return(1.5*phi((x-0.35)/0.15)-phi((x-0.8)/0.04))
  }
  x = qbeta(runif(n,0,1),(m+4)/5,(11-m)/5)
  knots = min(x) + 1:k*(max(x)-min(x))/(k+1)
  sigma = 0.1
  epsilon = rnorm(n,0,1)
  truef = f(x)
  y = truef + sigma*epsilon
  data = cbind(x,y,truef)
  sorteddata = data[order(data[,1]),]
  x = sorteddata[,1]
  y = sorteddata[,2]
  truef = sorteddata[,3]
}else if(l==3){
  # Spatial Variation
  f = function(x){
    return(sqrt(x*(1-x))*sin((2*pi*(1+2^((9-4*m)/5)))/(x+2^((9-4*m)/5))))
  }
  x = (1:200-0.5)/n
  knots = min(x) + 1:k*(max(x)-min(x))/(k+1)
  sigma = 0.2
  epsilon = rnorm(n,0,1)
  truef = f(x)
  y = truef + sigma*epsilon
}else if(l==4){
  # Variance Function
  f = function(x){
    return(1.5*phi((x-0.35)/0.15)-phi((x-0.8)/0.04))
  }
  x = (1:200-0.5)/n
  knots = min(x) + 1:k*(max(x)-min(x))/(k+1)
  sigma = sqrt((0.15*(1+0.4*(2*m-7)*(x-0.5)))^2)
  epsilon = rnorm(n,0,1)
  truef = f(x)
  y = truef + sigma*epsilon
}
plot_name = bquote(paste(.(method)," ",.(functions)," ", italic(j)," = ",.(m)))
plot(x,y,pch=20,main=plot_name,cex=0.15,cex.main=0.8,cex.lab=0.8,cex.axis=0.8,xlab=expression(italic(x)),ylab=expressio

  lines(xtest,f(xtest),col="black")

# Spline Regression
X = designmatrix(x,p,k)
betas = solve(t(X) %*% X,tol=1e-50) %*% t(X) %*% y
fhat = X %*% betas
ytest = 1:(length(xtest))
for(nn in 1:(length(xtest))){
  ytest[nn] = modelf(xtest[nn],knots,betas)
}
lines(xtest,ytest,col="blue")

# Penalized Spline Regression
if(o==1){
  # Cross Validation
  minimizer = function(lambda,x,y){
    X = designmatrix(x,p,k)

    D = diag(c(0*(1:(p+1)),0*(1:k)+1))
    hlambda = X %*% (solve((t(X) %*% X)+lambda*D,tol=1e-50) %*% t(X))
    fhatlambda = hlambda %*% y
    hii = diag(hlambda)

    return(sum(((y-fhatlambda)/(1-hii))^2))
  }
}

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    }
  } else if(o == 2){
    # Generalized Cross Validation
    minimizer = function(lambda,x,y){
      X = designmatrix(x,p,k)

      n = length(x)
      D = diag(c(0*(1:(p+1)),0*(1:k)+1))
      hlambd = X %>% (solve(t(X) %>% X+lambda*D,tol=1e-50) %>% t(X))
      fhatlambd = hlambd %>% y
      hii = sum(diag(hlambd))/n

      return(sum((y-fhatlambd)/(1-hii))^2))
    }
  } else if(o == 3){
    # AICc
    minimizer = function(lambda,x,y){
      X = designmatrix(x,p,k)

      D = diag(c(0*(1:(p+1)),0*(1:k)+1))
      hlambd = X %>% (solve(t(X) %>% X + lambda*D,tol=1e-50) %>% t(X))
      fhatlambd = hlambd %>% y

      n = length(x)
      tr = sum(diag(hlambd))
      norm = sum((y-fhatlambd)^2)
      return(log(norm)+2*(tr+1)/(n-tr-2))
    }
  } else if(o == 4){
    # Risk
    minimizer = function(lambda,x,y){
      X = designmatrix(x,p,k)

      D = diag(c(0*(1:(p+1)),0*(1:k)+1))
      hlambd = X %>% (solve(t(X) %>% X + lambda*D,tol=1e-50) %>% t(X))
      fhatlambd = hlambd %>% y

      n = length(x)
      norm = sum((fhatlambd-(hlambd %>% fhatlambd))^2)
      sigma2 = sum((y-fhatlambd)^2)/(n-1)

      return((norm+sigma2*(sum(diag(hlambd %>% t(hlambd)))-2*sum(diag(hlambd))+n)))
    }
  }
}

lambda = 1e-7
minlambda = nlm(minimizer,c(lambda),x = x, y = y,steptol = 1e-20)
lambda = minlambda$estimate
D = diag(c(0*(1:(p+1)),0*(1:k)+1))
betalambd = (solve(t(X) %>% X + lambda*D,tol=1e-50) %>% t(X)) %>% y
hlambd = X %>% betalambd
fhatlambd = hlambd %>% y
ytest = 1:(length(xtest))
for(nn in 1:(length(xtest))){
  ytest[nn] = modelf(xtest[nn],knots,betalambd)
}
print(paste("j =",m," lambda =",lambda, " min =",minlambda$minimum))
lines(xtest,ytest,col="red")
if (export) dev.off()
}
}
}

```















