hw1

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```r
rm(list=ls())
set.seed(12345)
options(warn = -1)
knitr::opts_knit$set(root.dir = '~/Desktop/stat374-fall-2018/analysis/')
library(kedd)
library(locfit)
```

```
## locfit 1.5-9.1    2013-03-22
```

```r
library(gridExtra)
library(reshape)
library(gam)
```

```
## Loading required package: splines
```

```
## Loading required package: foreach
```

```
## Loaded gam 1.16
```

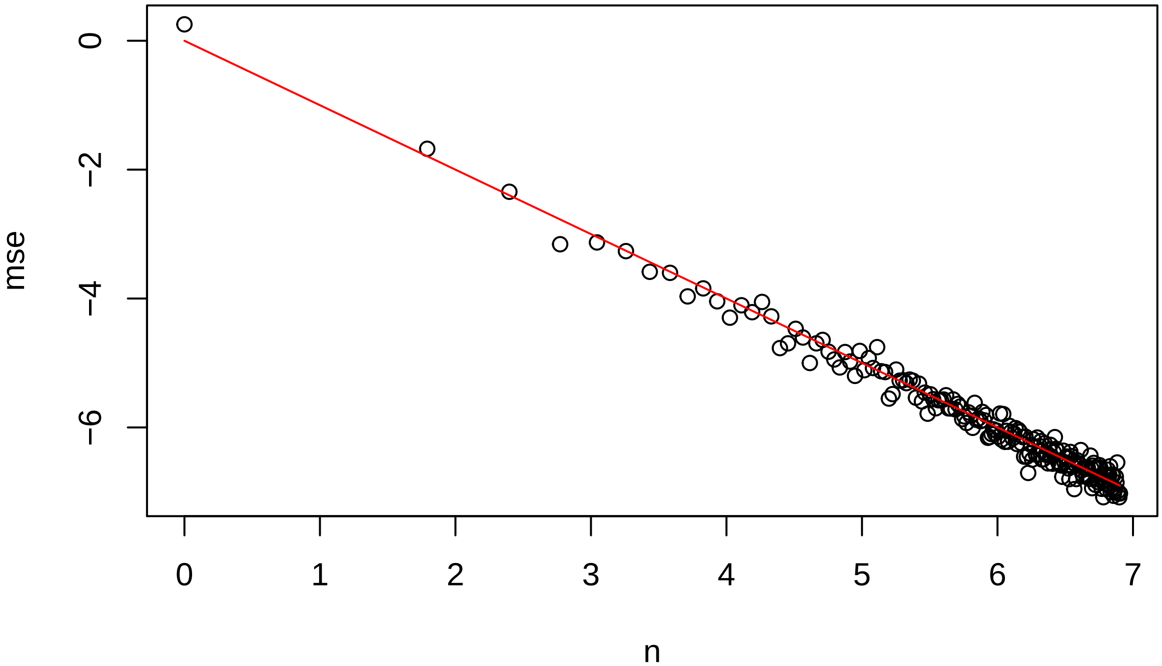
```r
#library(tidyverse)
suppressMessages(library("tidyverse"))
```

1. Computing and plotting with R

(a)

```r
## function to compute empirical mean square error
mse <- function(n,sigma){
  mysample = rnorm(n = n, sd = sigma, mean = 1)
  return((mean(mysample)-1)^2)
}

emse <- function(n,sigma,B){
  return(mean(replicate(B,mse(n,sigma))))
}

## simulate and plot
sigma = 1
B = 100

ns = seq(1,1000,5)
results = replicate(length(ns),0)
theory = replicate(length(ns),0)

for(i in 1:length(ns)){
  results[i] = emse(ns[i],sigma,B)
  theory[i] = sigma^2/ns[i]
```

```
}

plot(log(ns), log(results), xlab = "n", ylab = "mse")
lines(log(ns),log(theory), col = "red")
```

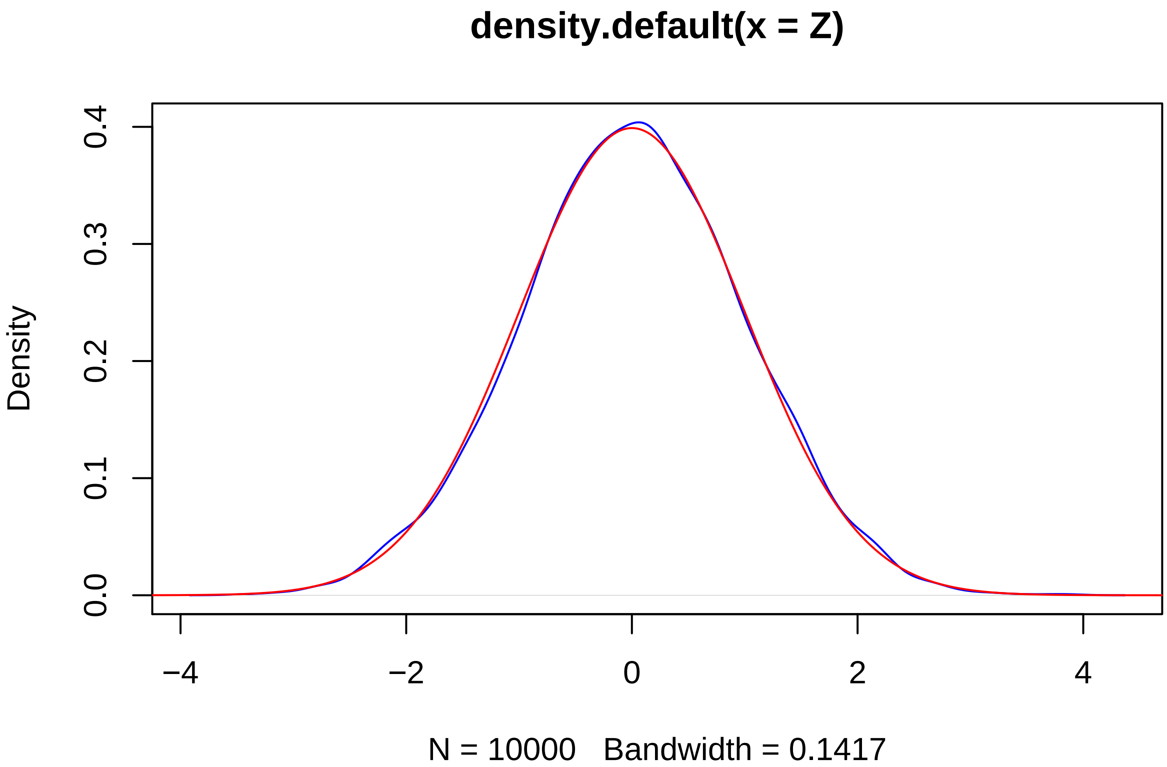


Comment:

From the simulation experiments, we can see the results align with theoretical results

(b)

```
n = 1000
sigma = 1
B = 10000

## simulation
Z = replicate(B,sqrt(n)*(mean(rnorm(n,1,sigma)) - 1))

## theoretical standard normal
ns = seq(-10,10,0.01)
theory = replicate(length(ns),0)
for(i in 1:length(ns)){
  theory[i] = 1/sqrt(2*pi) * exp(-ns[i]^2 *0.5)
}

plot(density(Z), col = "blue")
lines(ns,theory,col = "red")
```



###

Comment: When B is too small (say, only 100), **density(B)** does not give very good estimate. When B is big enough, density estimation is quite good.

2 Leave-oue-out cross-validation

(a)

By definition, $\hat{R}(h) = \frac{1}{n} * \sum_{i=1}^{n} (r(x_i) - \hat{r}_{-i}(x_i))^2$. Then we have $r(x_i) - \hat{r}_{-i}(x_i) = Y_i - \frac{\sum_{k \neq i} L_{i,k} * Y_k}{1 - L_{ii}} = \frac{Y_i - \hat{r}_n(x_i)}{1 - L_{ii}}$. Then our desired equation follows.

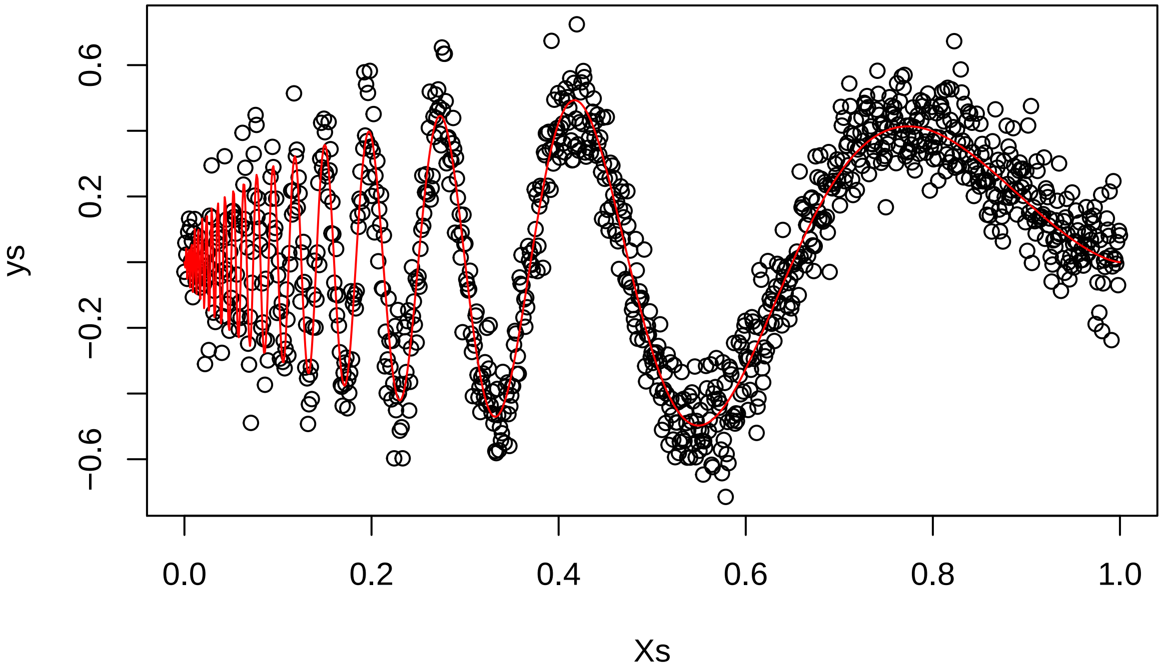
(b)

Note: I select bandwidth in two ways: coding the loocv(bandwidth) function myself, and using the gcv function in the package. The two results are quite different, so I show both of them.

See what the data looks like

```
Doppler <- function(x){
  y = sqrt(x*(1-x)) * sin(2.1*pi/(x+0.05))
  return(y)
}

N = 1000
sigma = 0.1
Xs = seq(0,1, length = N)
```

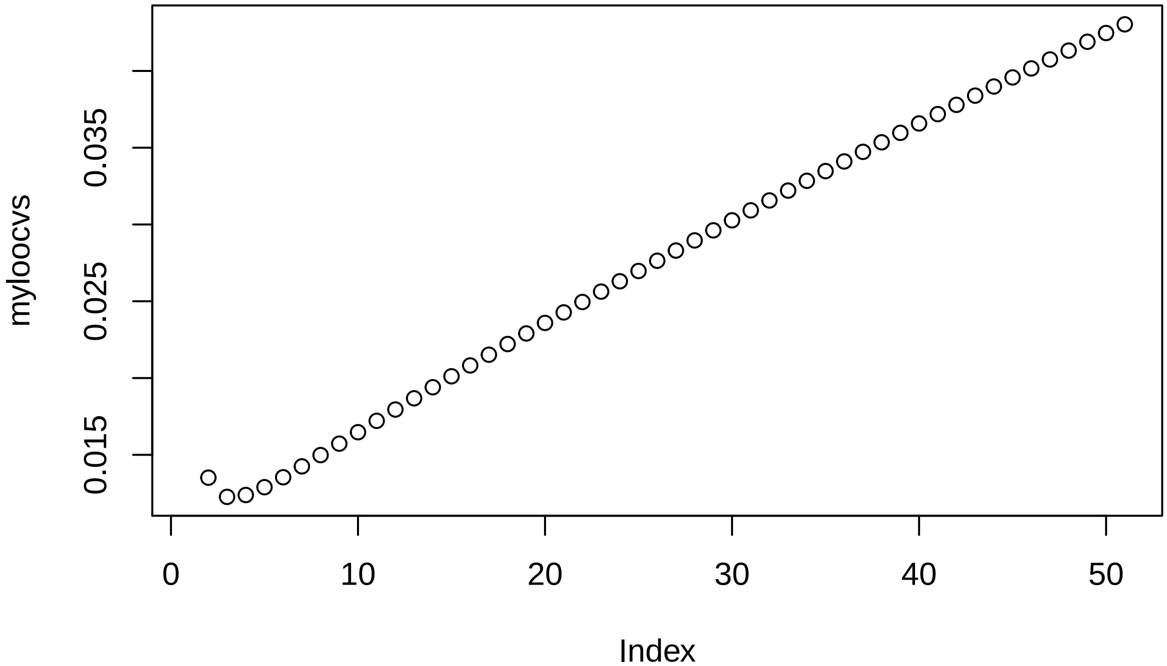
```r
ys_true = Doppler(Xs)
ys = ys_true + rnorm(N,sd = sigma)
plot(Xs,ys)
lines(Xs,ys_true, col = "red")
```



Plot Cross-validation-score vs bandwidth

```r
K <- function(x){
  return(1/sqrt(2*pi) * exp(-x^2/2))
}

Rhat <- function(h,Xs){
  ### compute L (L_ij = l_j(x_i), rowSums(L) = 1,1...)
  n = length(Xs)
  X_matrix = replicate(n,Xs)
  X_difference_scaled = (X_matrix - t(X_matrix))/h
  X_difference_scaled_kernel = K(X_difference_scaled) ## X_ij = K((Xi-Xj)/h)
  L = diag(1/rowSums(X_difference_scaled_kernel)) %*% X_difference_scaled_kernel

  ### Compute Lii
  L_diag = diag(L)

  ### Compute ys_hat
  ys_hat = L %*% ys

  ### Conmpute R_hat
  R_hat = mean(((ys-ys_hat)/(1-L_diag))^2)

  return(R_hat)
}
```

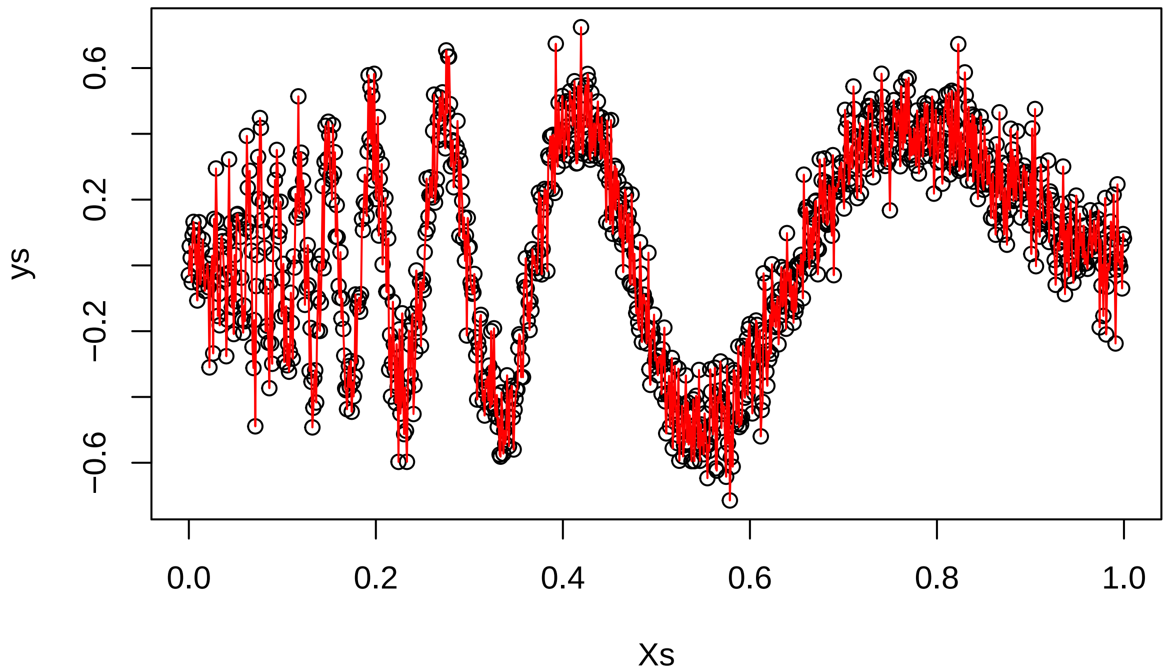
```r
hs = seq(0,0.05,0.001)
myloocvs <- readRDS("../data/loocvs_hw1_p2") ## I save the computed results as it will take some time
#myloocvs <- sapply(hs, function(h) Rhat(h,Xs))
plot(myloocvs)
```




```r
#saveRDS(myloocvs,"../data/loocvs_hw1_p2.rds")
## We can also find the best bandwidth using gcv function, as an approximate (however, it gives me quite
# gcvs = gcvplot(ys~Xs, alpha = seq(0,0.5,0.01))
# plot(gcvs$alpha, gcvs$values)
```

locfit using the optimal bandwidth

```r
h_star = hs[which.min(myloocvs)]
#h_star = 0.02
locfitopt = locfit(ys~Xs,alpha = h_star) ## if the first the element is 0, it reports error! How does th
plot(Xs, ys)
lines(Xs,predict(locfitopt, newdata = Xs), type = "l",col = "red")
```




```
#lines(xg, Doppler(xg), col = "blue")
```

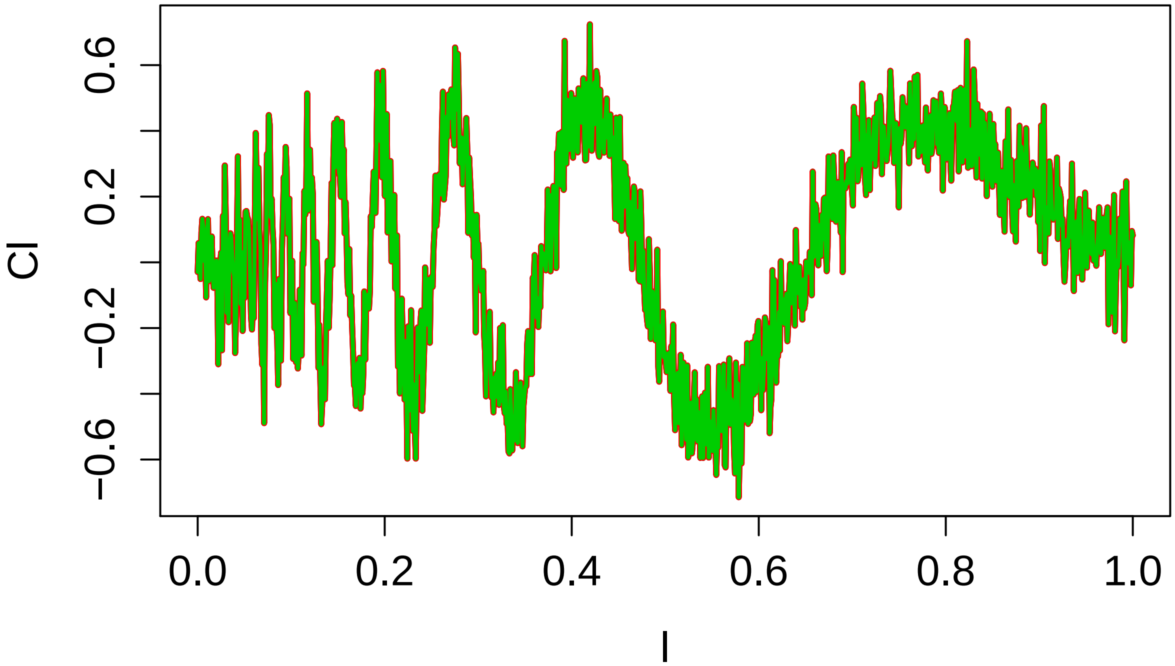
Comment:

This should be the optimal, but from the plot it seems to be undersmoothing a lot (especially compared with the results using gcv, which will be shown later)

compute and plot the confidence interval for r(x)

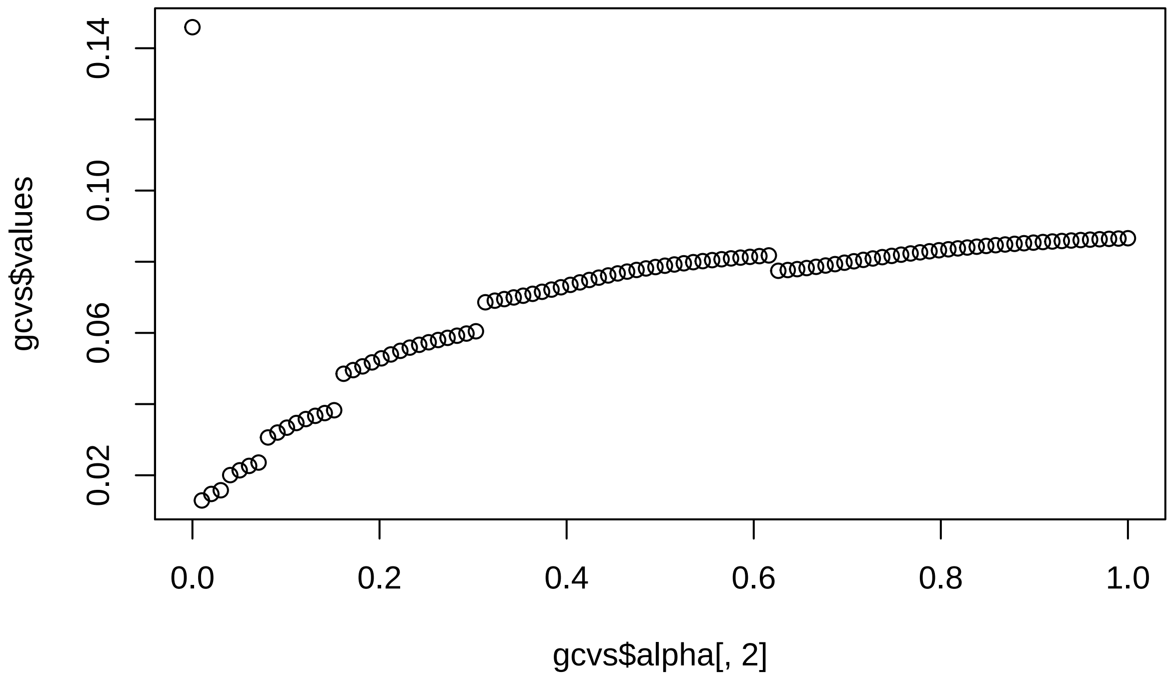
```
## Formula: rhat(x) +- Z_a/2 * sigmahat(x) * |l(x)|
## Assumption: homoscedasticity of variance
## Formula for sigamhat(x): sigmahat(x) = sum(residue^2) / (n - 2*nu - 2*nutilde), where nu = tr(L), nu
## they can be retrived in dp1, dp2 respectively

nu = locfitopt$dp[["df1"]]
nutilde = locfitopt$dp[["df2"]]
sigmahat_sqrt = sum(residuals(locfitopt)^2)/(N - 2*nu + nutilde)

diaghat = predict(locfitopt,where="data",what="infl") ## L_ii
normell = predict(locfitopt,where="data",what="vari") ## |l_i(x)|

critval = 1.96
xg = Xs
pred = predict(locfitopt, newdata = xg)

width = critval * sqrt(sigmahat_sqrt*normell)
upper = pred + width
lower = pred - width
```

```r
## plot confidence band
plot(xg, pred,lwd=3, xlab="l",ylab="Cl",cex=3,cex.axis=1.3, cex.lab=1.3,type="l")
lines(xg, upper,col = 2, lwd = 3)
lines(xg, lower,col = 3, lwd = 2)
```

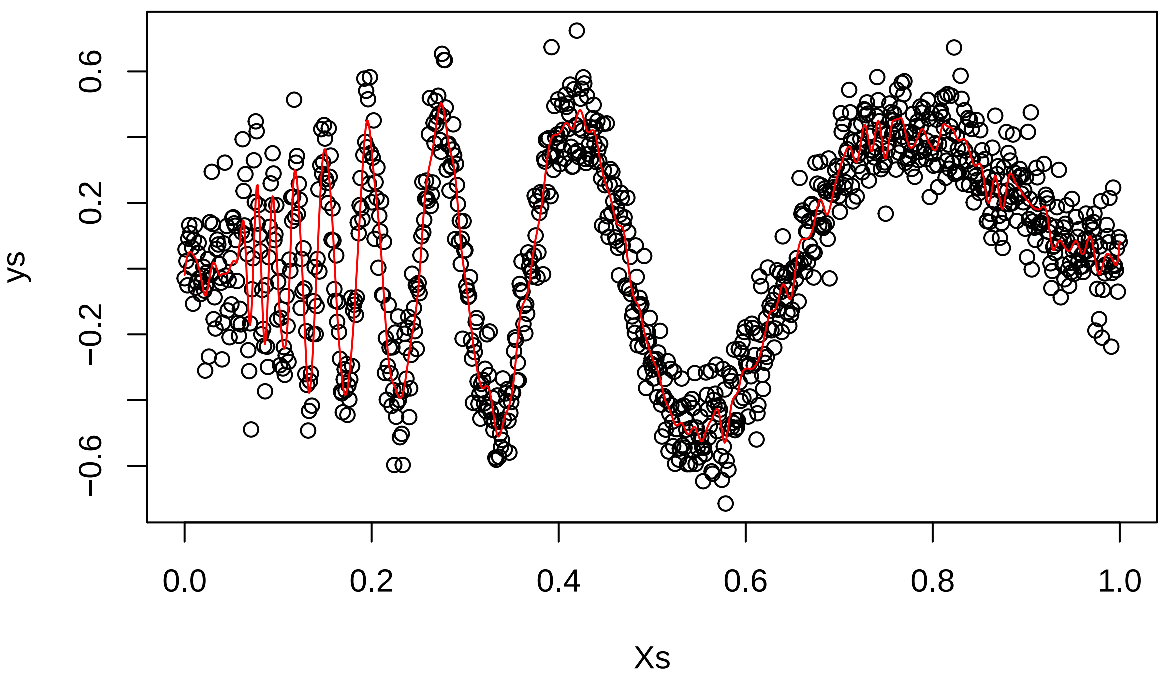


Select bandwidth using gcv function & Fit with optimal h

```r
## use GCV to choose bandwidth
alphamat = matrix(0,ncol = 2, nrow = 100)
alphamat[,2] = seq(0,1, length = 100)

gcvs = gcvplot(ys~Xs,alpha = alphamat)
plot(gcvs$alpha[,2], gcvs$values)
```

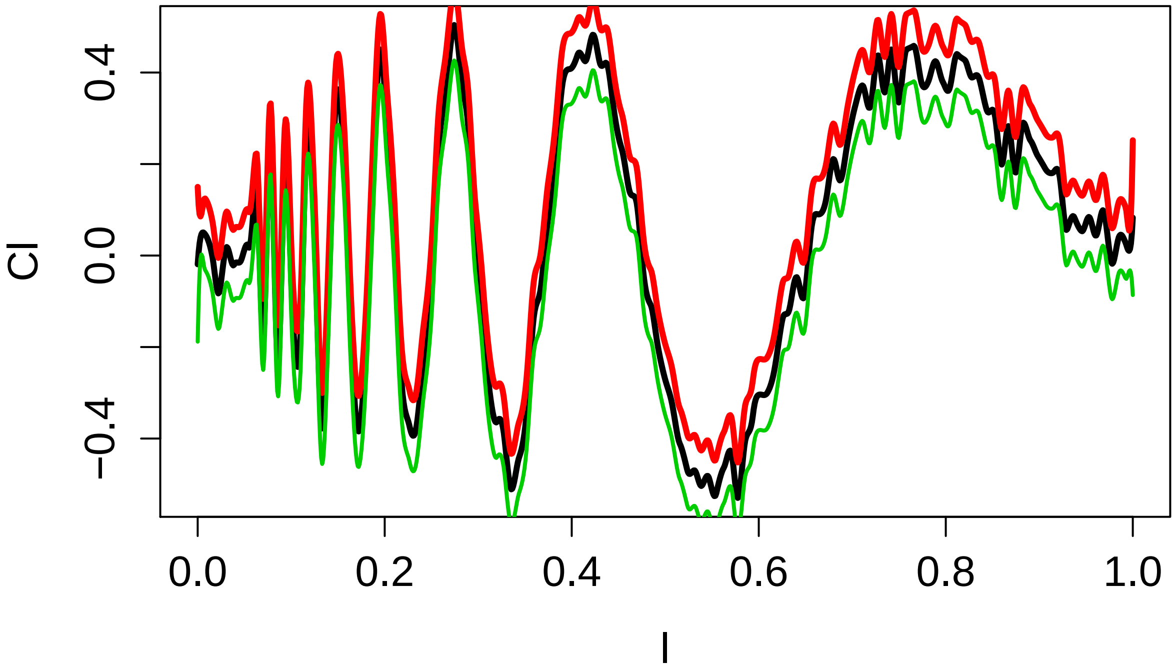



```r
optband2 = gcvs$alpha[which.min(gcvs$values),2]
locfitopt2 = locfit(ys~Xs,alpha= c(0,optband2))

plot(Xs, ys)
lines(Xs,predict(locfitopt2, newdata = Xs), type = "l",col = "red")
```




```r
nu = locfitopt2$dp[["df1"]]
nutilde = locfitopt2$dp[["df2"]]
sigmahat_sqrt = sum(residuals(locfitopt2)^2)/(N - 2*nu + nutilde)

diaghat = predict(locfitopt2,where="data",what="infl") ## L_ii
```

```
normell = predict(locfitopt2,where="data",what="vari") ## |l_i(x)|

critval = 1.96
xg = Xs
pred = predict(locfitopt2, newdata = xg)

width = critval * sqrt(sigmahat_sqrt*normell)
upper = pred + width
lower = pred - width


## plot confidence band
plot(xg, pred,lwd=3, xlab="l",ylab="Cl",cex=3,cex.axis=1.3, cex.lab=1.3,type="l")
lines(xg, upper,col = 2, lwd = 3)
lines(xg, lower,col = 3, lwd = 2)
```



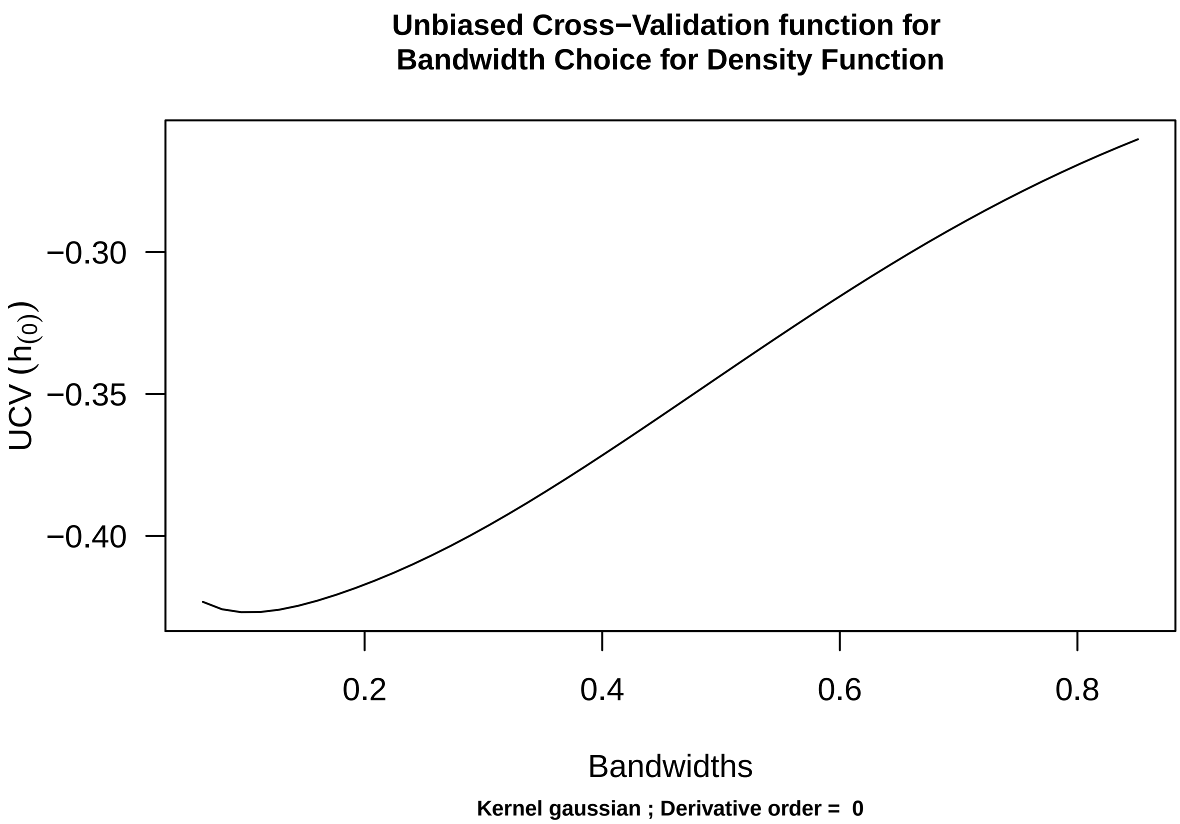
Is In(x) the 95% CI for $r(x)$

No. In(x) is centered around $E(\hat{r}(x))$, which is not $r(x)$. This CI is computed by the fact that for a fixed x, $\hat{r}(x)$ asympototically follows $N(E(\hat{r}(x)), \hat{\sigma}(x))$. That correctness of the claim requires $E(\hat{r}(x)) = r(x)$, which is apparently violated.

3. Kernel density estimate for Old Faithful Geyser

```
data("faithful")
attach(faithful)

library(kedd)
## Broad search
```

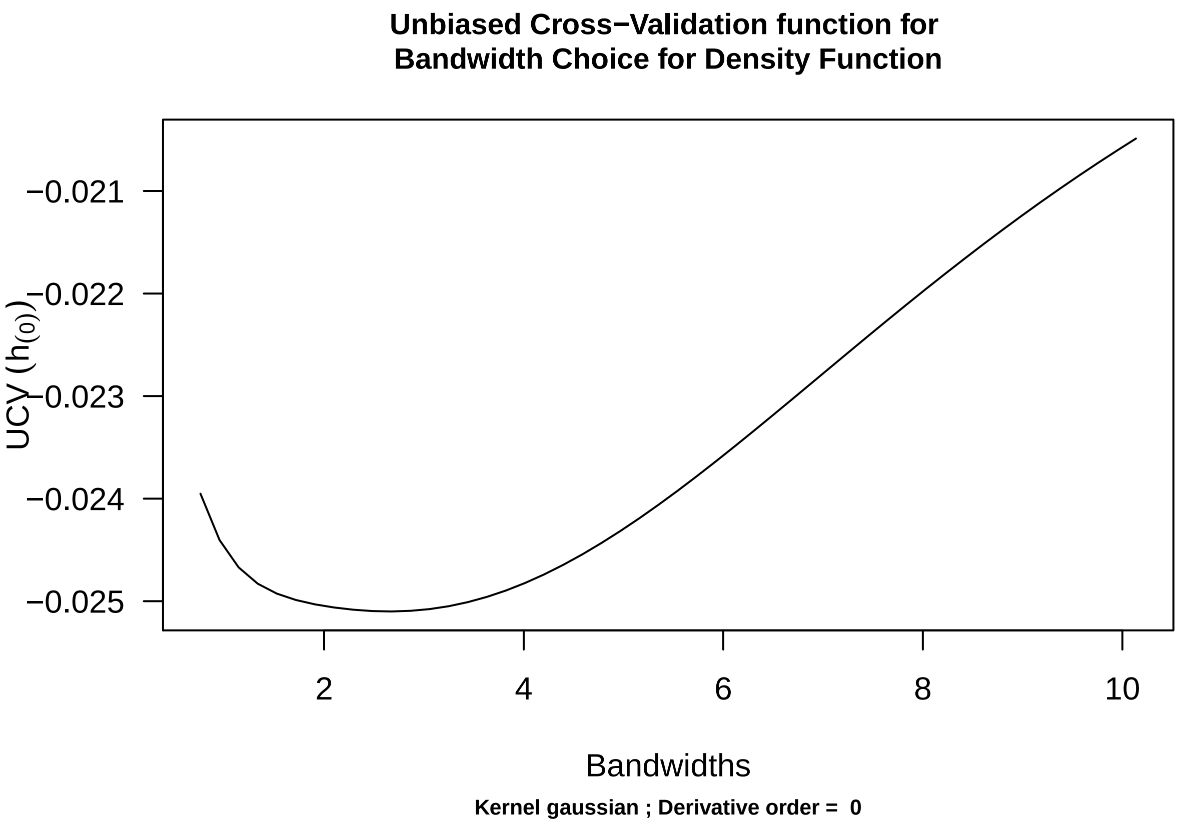
```r
ucv_eruptions = h.ucv(eruptions)
plot(ucv_eruptions)
```




```
## $kernel
## [1] "gaussian"
##
## $deriv.order
## [1] 0
##
## $seq.bws
##  [1] 0.06382504 0.07988984 0.09595465 0.11201945 0.12808426 0.14414906
##  [7] 0.16021387 0.17627867 0.19234348 0.20840828 0.22447309 0.24053789
## [13] 0.25660269 0.27266750 0.28873230 0.30479711 0.32086191 0.33692672
## [19] 0.35299152 0.36905633 0.38512113 0.40118594 0.41725074 0.43331555
## [25] 0.44938035 0.46544516 0.48150996 0.49757477 0.51363957 0.52970438
## [31] 0.54576918 0.56183399 0.57789879 0.59396360 0.61002840 0.62609321
## [37] 0.64215801 0.65822282 0.67428762 0.69035243 0.70641723 0.72248204
## [43] 0.73854684 0.75461165 0.77067645 0.78674126 0.80280606 0.81887087
## [49] 0.83493567 0.85100048
##
## $ucv
##  [1] -0.4232268 -0.4258325 -0.4268588 -0.4268189 -0.4259983 -0.4246085
##  [7] -0.4228091 -0.4207043 -0.4183518 -0.4157788 -0.4129965 -0.4100111
## [13] -0.4068286 -0.4034573 -0.3999082 -0.3961946 -0.3923311 -0.3883332
## [19] -0.3842161 -0.3799950 -0.3756846 -0.3712988 -0.3668511 -0.3623543
## [25] -0.3578208 -0.3532625 -0.3486911 -0.3441178 -0.3395537 -0.3350094
## [31] -0.3304954 -0.3260215 -0.3215974 -0.3172321 -0.3129343 -0.3087120
## [37] -0.3045724 -0.3005222 -0.2965672 -0.2927126 -0.2889626 -0.2853210
```

```
## [43] -0.2817903 -0.2783726 -0.2750693 -0.2718809 -0.2688074 -0.2658482
## [49] -0.2630020 -0.2602672
```

```r
## fine search (locate a neighborhood of the best point from broad search)
ucv_eruptions = h.ucv(eruptions, lower = 0.7*ucv_eruptions$h, higher = 1.3*ucv_eruptions$h, tol = 0.000

## Broad search
ucv_waiting = h.ucv(waiting)
plot(ucv_waiting)
```



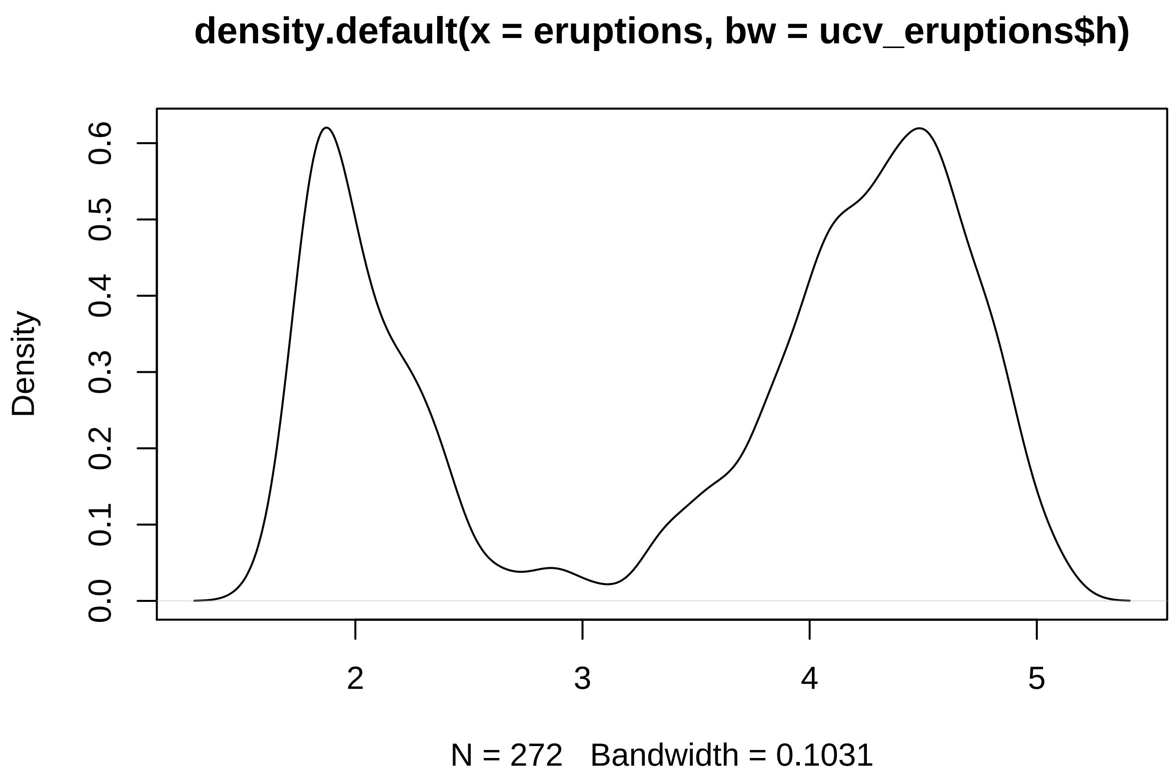

```
## $kernel
## [1] "gaussian"
##
## $deriv.order
## [1] 0
##
## $seq.bws
##  [1]  0.7602256  0.9515749  1.1429243  1.3342736  1.5256229  1.7169722
##  [7]  1.9083215  2.0996708  2.2910201  2.4823694  2.6737187  2.8650681
## [13]  3.0564174  3.2477667  3.4391160  3.6304653  3.8218146  4.0131639
## [19]  4.2045132  4.3958625  4.5872118  4.7785612  4.9699105  5.1612598
## [25]  5.3526091  5.5439584  5.7353077  5.9266570  6.1180063  6.3093556
## [31]  6.5007050  6.6920543  6.8834036  7.0747529  7.2661022  7.4574515
## [37]  7.6488008  7.8401501  8.0314994  8.2228487  8.4141981  8.6055474
## [43]  8.7968967  8.9882460  9.1795953  9.3709446  9.5622939  9.7536432
## [49]  9.9449925 10.1363419
##
## $ucv
##  [1] -0.02395152 -0.02440334 -0.02467032 -0.02482935 -0.02492616
```

```
##  [6] -0.02498823 -0.02503085 -0.02506151 -0.02508310 -0.02509613
## [11] -0.02510007 -0.02509402 -0.02507721 -0.02504910 -0.02500946
## [16] -0.02495830 -0.02489589 -0.02482263 -0.02473907 -0.02464581
## [21] -0.02454353 -0.02443293 -0.02431474 -0.02418970 -0.02405855
## [26] -0.02392202 -0.02378083 -0.02363570 -0.02348733 -0.02333637
## [31] -0.02318346 -0.02302922 -0.02287421 -0.02271897 -0.02256400
## [36] -0.02240976 -0.02225667 -0.02210509 -0.02195537 -0.02180779
## [41] -0.02166261 -0.02152005 -0.02138029 -0.02124346 -0.02110968
## [46] -0.02097903 -0.02085156 -0.02072730 -0.02060626 -0.02048841
```

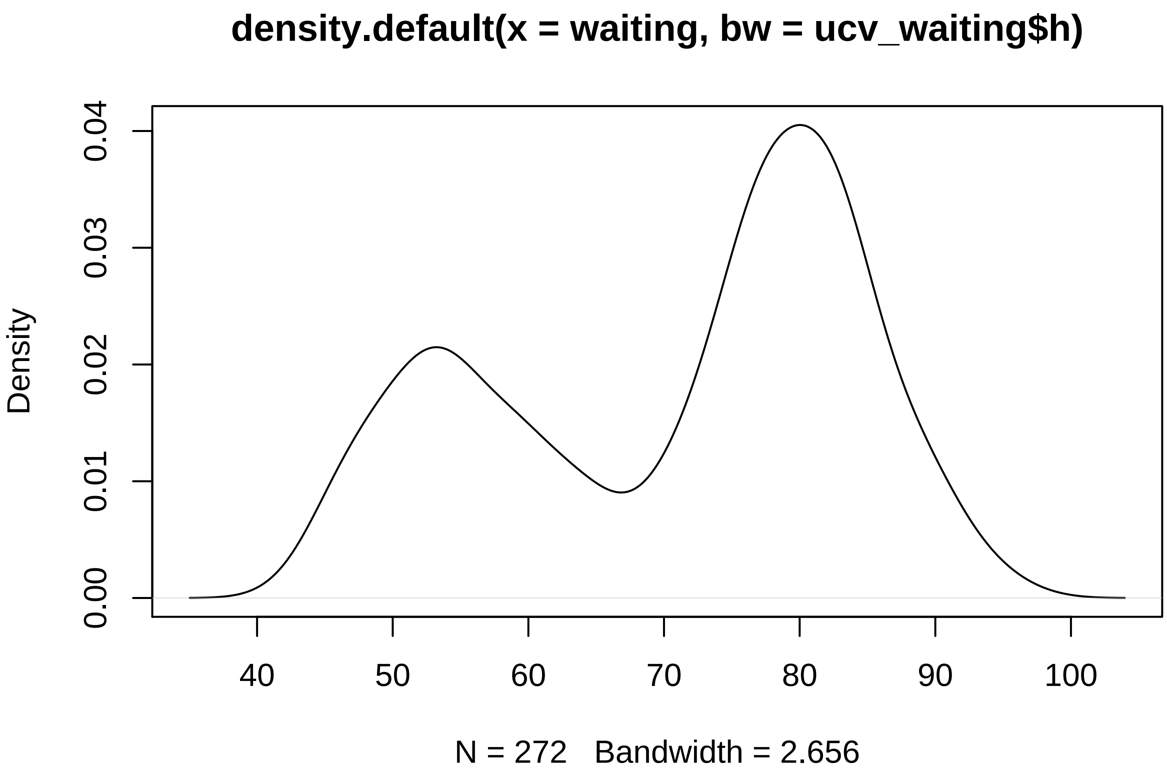
```
## fine search (locate a neighborhood of the best point from broad search)
ucv_waiting = h.ucv(waiting, lower = 0.8*ucv_waiting$h, higher = 1.2*ucv_waiting$h,tol = 0.0001)
```

plot estimated density with optimum h

```
plot(density(eruptions, bw = ucv_eruptions$h))
```




```
plot(density(waiting, bw = ucv_waiting$h))
```



4 Risk of a two-dimensional Kernel density estimate

Let $K_h(x,y,X,Y) := \frac{1}{h^2}E(K(\frac{X-x}{h})K(\frac{Y-y}{h}))$

By $|\Pr(x,y) - p(x-uh, y-vh) < L(|uh|^\beta + |vh|^\beta|)$, we have $\Pr(x-uh, y-uh) < \Pr(x,y) + Lh^\beta(|u|^\beta + |v|^\beta)$

Thus:

$$E(\Pr(\hat{x},y)) = \frac{1}{h^2}E(K_h(x,y,X,Y)) = \frac{1}{h^2}\int K(\frac{X-x}{h})K(\frac{Y-y}{h})\Pr(X,Y)dXdY = \int K(u)K(v)P(x-Uh, y-Vh)dUdV(U :$$

Thus we have $bias(x,y) = E(\hat{P}_n(x,y)) - \Pr(x,y) <= MLh^\beta$

Similarly, for variance,

$$Var(\hat{P}_n(x,y)) = \frac{1}{n}Var(K_h(x,y,X,Y)) \leq \frac{1}{n}E(K_h(x,y,X,Y)^2) = \frac{1}{nh^4}\int K^2(\frac{X-x}{h})K^2(\frac{Y-y}{h})\Pr(X,Y)dXdY = \frac{1}{nh^2}\int K$$

Thus we have $V(x,y) \leq \frac{M_2\Pr(x,y)}{nh^2}$
It is also easy to check both M and M_2 are not inifinity.

$$Risk(x,y) = bias(x,y)^2 + V(x,y) \leq (MLh^\beta)^2 + \frac{M_2\Pr(x,y)}{nh^2} := H(h)h^* = (\frac{M_2\Pr(x,y)}{ML^2}) = O((\frac{1}{n})^{\frac{1}{2\beta+2}})H(h^*) = O(\frac{1}{n})^{\frac{\beta}{\beta+1}}$$

Thus set $H(h^*) < \epsilon$, we have the rate of convergence as $O(\epsilon^{-\frac{\beta+1}{\beta}})$

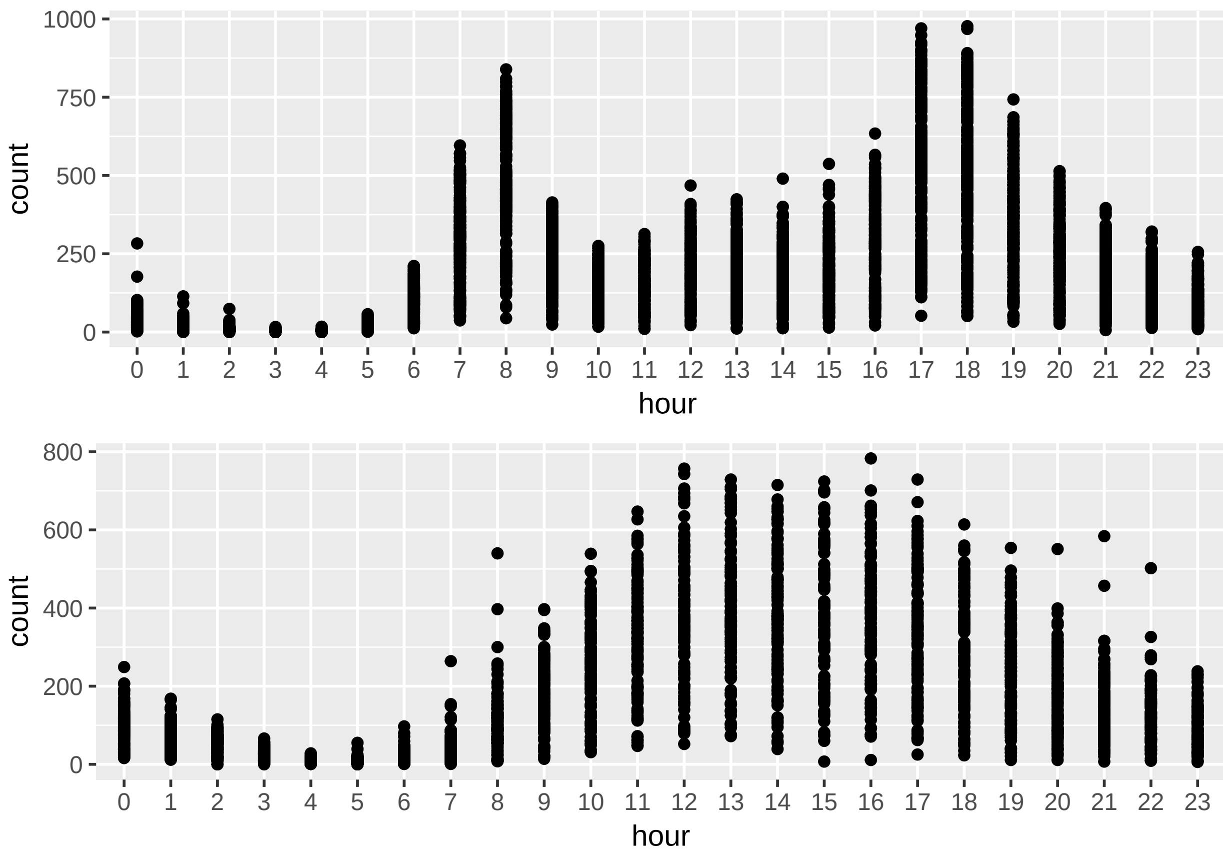
5 Capital Bike Sharing

```r
data = read.csv("../data/hw1/train.csv")
test = read.csv("../data/hw1/test.csv")

#fac_names = c("holiday","workingday","weather")
# fac_names = c("holiday","workingday","weather","season","year","hour")
fac_names = c("holiday","workingday","weather","season","year","hour")

for(i in 1:length(fac_names)){
  name = fac_names[i]
  data[[name]] = factor(data[[name]])
  test[[name]] = factor(test[[name]])
}
data[["transformed_count"]] = log(data$count + 1)

## split train into train and validation
train = data[data$day < 16,]
val = data[data$day > 15,]

## define loss
RMSLE_log <- function(count_log,count_hat_log){
  return(sqrt(mean((count_log-count_hat_log)^2)))
}
```

```r
#plot(density(train$count))
hist(train$count)
```


```r
# p1 = ggplot(train,aes(atemp, count, color = weather)) +
#   geom_point()
#
```

```r
# p2 = ggplot(train,aes(humidity,count,  color = weather)) +
#   geom_point()
#
# p3 = ggplot(train,aes(windspeed,count,  color = weather)) +
#   geom_point()

p1 <- ggplot(subset(train,workingday==1),aes(hour,count)) +
  geom_point()

p2 <- ggplot(subset(train,workingday==0),aes(hour,count)) +
  geom_point()

grid.arrange(p1,p2,nrow = 2)
```



Comment: The counts distribution with hours are different for workingday and nonworkingday. So there is a very strong connection between the interaction between hour and workingday! Other factors do not bring about too much difference

(a) linear model on count

```r
linearMD <-lm(transformed_count~daylabel+workingday*hour + season +atemp+humidity+windspeed,data=train)
summary(linearMD)
```

```
##
## Call:
## lm(formula = transformed_count ~ daylabel + workingday * hour +
```

```
##     season + atemp + humidity + windspeed, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5205 -0.1618  0.0392  0.2168  2.3149
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         3.564e+00  4.405e-02  80.918  < 2e-16 ***
## daylabel            1.329e-03  2.321e-05  57.267  < 2e-16 ***
## workingday1        -1.012e+00  4.447e-02 -22.763  < 2e-16 ***
## hour1              -2.378e-01  5.199e-02  -4.573 4.87e-06 ***
## hour2              -5.801e-01  5.199e-02 -11.157  < 2e-16 ***
## hour3              -1.269e+00  5.200e-02 -24.409  < 2e-16 ***
## hour4              -2.232e+00  5.202e-02 -42.911  < 2e-16 ***
## hour5              -2.253e+00  5.203e-02 -43.299  < 2e-16 ***
## hour6              -1.632e+00  5.204e-02 -31.362  < 2e-16 ***
## hour7              -7.776e-01  5.202e-02 -14.949  < 2e-16 ***
## hour8               8.747e-02  5.199e-02   1.682 0.092516 .
## hour9               5.699e-01  5.200e-02  10.961  < 2e-16 ***
## hour10              9.405e-01  5.205e-02  18.068  < 2e-16 ***
## hour11              1.111e+00  5.214e-02  21.312  < 2e-16 ***
## hour12              1.240e+00  5.226e-02  23.723  < 2e-16 ***
## hour13              1.224e+00  5.237e-02  23.373  < 2e-16 ***
## hour14              1.181e+00  5.245e-02  22.519  < 2e-16 ***
## hour15              1.162e+00  5.244e-02  22.162  < 2e-16 ***
## hour16              1.150e+00  5.241e-02  21.936  < 2e-16 ***
## hour17              1.063e+00  5.232e-02  20.320  < 2e-16 ***
## hour18              9.181e-01  5.223e-02  17.578  < 2e-16 ***
## hour19              7.567e-01  5.212e-02  14.520  < 2e-16 ***
## hour20              5.231e-01  5.206e-02  10.049  < 2e-16 ***
## hour21              3.575e-01  5.202e-02   6.872 6.79e-12 ***
## hour22              1.770e-01  5.201e-02   3.403 0.000669 ***
## hour23             -1.187e-01  5.199e-02  -2.283 0.022460 *
## season2             3.250e-01  1.599e-02  20.322  < 2e-16 ***
## season3             1.757e-01  2.060e-02   8.529  < 2e-16 ***
## season4             2.633e-01  1.458e-02  18.054  < 2e-16 ***
## atemp               2.943e-02  8.909e-04  33.030  < 2e-16 ***
## humidity           -6.140e-03  2.610e-04 -23.525  < 2e-16 ***
## windspeed          -5.585e-03  5.538e-04 -10.084  < 2e-16 ***
## workingday1:hour1  -5.475e-01  6.289e-02  -8.707  < 2e-16 ***
## workingday1:hour2  -8.184e-01  6.289e-02 -13.013  < 2e-16 ***
## workingday1:hour3  -5.404e-01  6.289e-02  -8.592  < 2e-16 ***
## workingday1:hour4   5.249e-01  6.289e-02   8.346  < 2e-16 ***
## workingday1:hour5   1.990e+00  6.289e-02  31.644  < 2e-16 ***
## workingday1:hour6   2.818e+00  6.289e-02  44.811  < 2e-16 ***
## workingday1:hour7   2.976e+00  6.289e-02  47.319  < 2e-16 ***
## workingday1:hour8   2.624e+00  6.289e-02  41.721  < 2e-16 ***
## workingday1:hour9   1.425e+00  6.289e-02  22.657  < 2e-16 ***
## workingday1:hour10  3.780e-01  6.289e-02   6.010 1.93e-09 ***
## workingday1:hour11  2.856e-01  6.289e-02   4.541 5.67e-06 ***
## workingday1:hour12  3.707e-01  6.289e-02   5.894 3.91e-09 ***
## workingday1:hour13  3.324e-01  6.290e-02   5.286 1.28e-07 ***
## workingday1:hour14  2.560e-01  6.289e-02   4.071 4.72e-05 ***
```

```
## workingday1:hour15  3.521e-01  6.290e-02   5.597 2.24e-08 ***
## workingday1:hour16  7.617e-01  6.289e-02  12.111  < 2e-16 ***
## workingday1:hour17  1.494e+00  6.289e-02  23.759  < 2e-16 ***
## workingday1:hour18  1.589e+00  6.289e-02  25.274  < 2e-16 ***
## workingday1:hour19  1.427e+00  6.289e-02  22.685  < 2e-16 ***
## workingday1:hour20  1.342e+00  6.289e-02  21.331  < 2e-16 ***
## workingday1:hour21  1.240e+00  6.290e-02  19.715  < 2e-16 ***
## workingday1:hour22  1.154e+00  6.290e-02  18.350  < 2e-16 ***
## workingday1:hour23  1.018e+00  6.289e-02  16.183  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3925 on 8585 degrees of freedom
## Multiple R-squared:  0.9277, Adjusted R-squared:  0.9273
## F-statistic:  2041 on 54 and 8585 DF,  p-value: < 2.2e-16
```

```
#plot(linearMD)
```

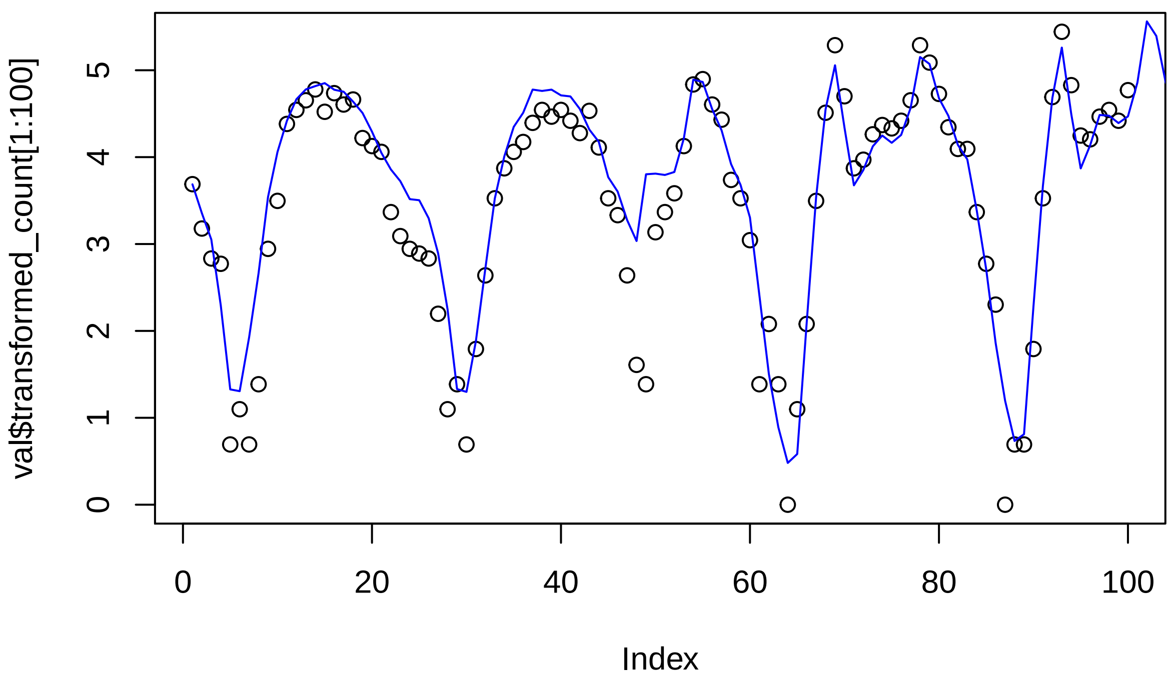
```
# linearPredict = predict(linearMD, subset(val, colnames = c("atemp","humidity","windspeed","weather")))
linearPredict_train = predict(linearMD, train)
linearPredict_val = predict(linearMD, val)



print(paste0("training loss: ", RMSLE_log(linearPredict_train,train$transformed_count)))
```

```
## [1] "training loss: 0.391236649815652"
```

```
print(paste0("validation loss: ", RMSLE_log(linearPredict_val,val$transformed_count)))
```

```
## [1] "validation loss: 0.399954614277405"
```

```
plot(val$transformed_count[1:100])
lines(linearPredict_val,col = "blue")
```



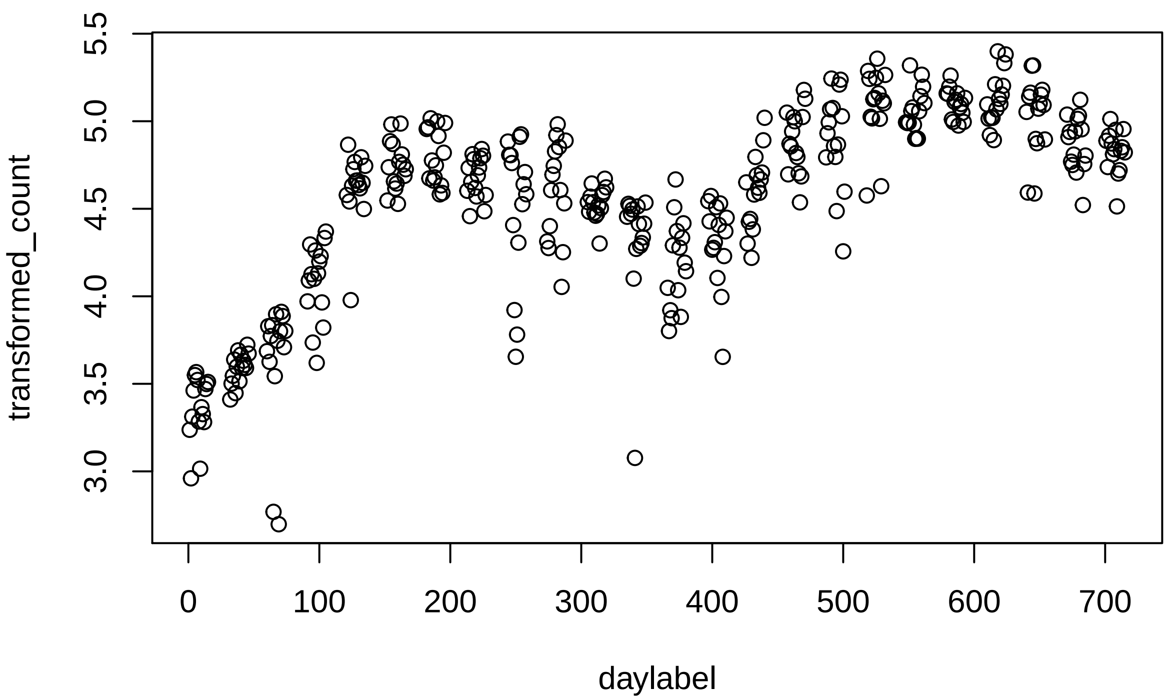
Comment:

Our model for linear regression is: $Y = X * \beta + \epsilon$. The normality assumption holds, but the residue seems not to be independent of X. Also, the R-squared is only around 25%, meaning our model does not account for much variance in data. p-value suggests that we should reject the null hypothesis that the selected variables are not correlated with counts.

(b)

First, summarize the data by mean hourly counts

```
varnames = dimnames(train)[[2]]
ids = varnames[varnames != "transformed_count"]

## melt data
val_mlt = melt(val,id = ids)
train_mlt = melt(train,id = ids)

train_mlt$value = as.numeric(train_mlt$value)
train_hourmean = cast(train_mlt,daylabel~variable,mean)

attach(train_hourmean)
plot(daylabel,transformed_count)
```

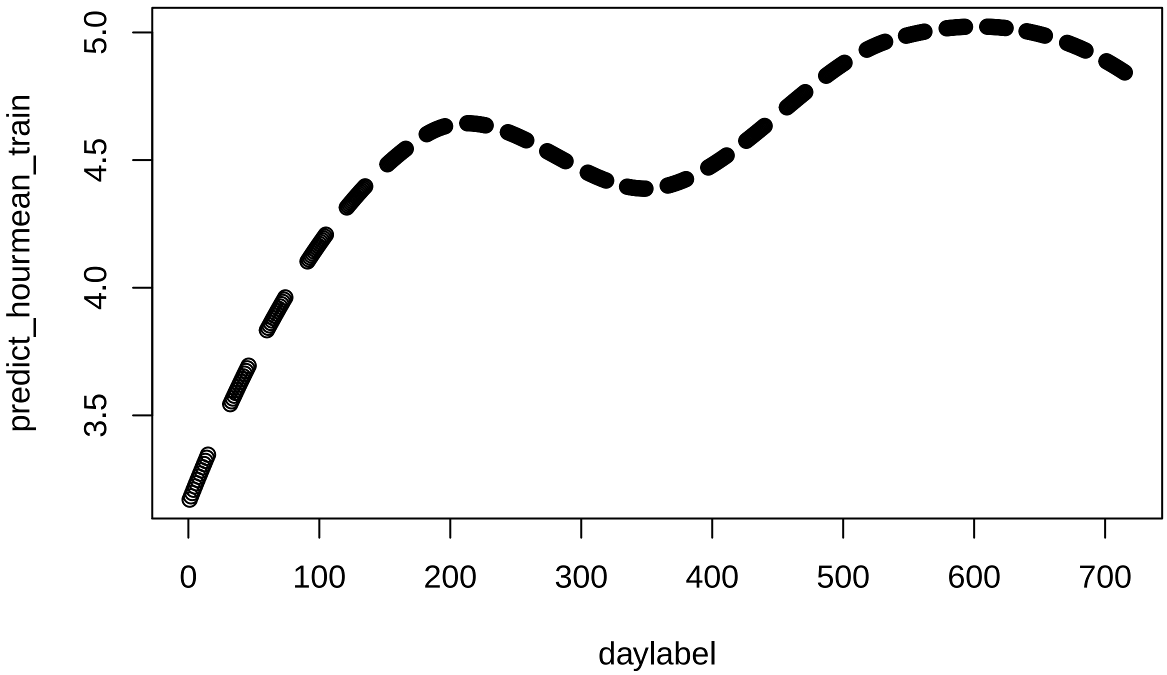



```
attach(train_hourmean)
```

```
## The following objects are masked from train_hourmean (pos = 3):
##
##     daylabel, transformed_count
```

```
locfitmodel_hourmean_train = locfit(transformed_count~daylabel)
predict_hourmean_train = predict(locfitmodel_hourmean_train,daylabel)
```

```r
plot(daylabel,predict_hourmean_train)
```




```r
train_hourmean_trend = train_hourmean
train_hourmean_trend$transformed_count = predict_hourmean_train

train_hourmean_residue = train_hourmean
train_hourmean_residue$transformed_count = residuals(locfitmodel_hourmean_train)
detach(train_hourmean)
```

```r
u_daylabels = unique(train_mlt$daylabel)

## get residue as new response
train_residue = train

for(i in 1:length(u_daylabels)){
  train_residue[train_residue$daylabel == u_daylabels[i],"transformed_count"] =  train_residue[train_res
}

# SmoothedLinearMD = lm(transformed_count ~ hour+workingday+weather+atemp+humidity+windspeed, data = tr
SmoothedLinearMD = lm(transformed_count ~ workingday*hour + season +atemp+humidity+windspeed, data = tra





## training loss
LlrLm_train = predict(SmoothedLinearMD,train) + predict(locfitmodel_hourmean_train, train$daylabel)
print(paste0("training loss: ",RMSLE_log(LlrLm_train, train$transformed_count)))
```

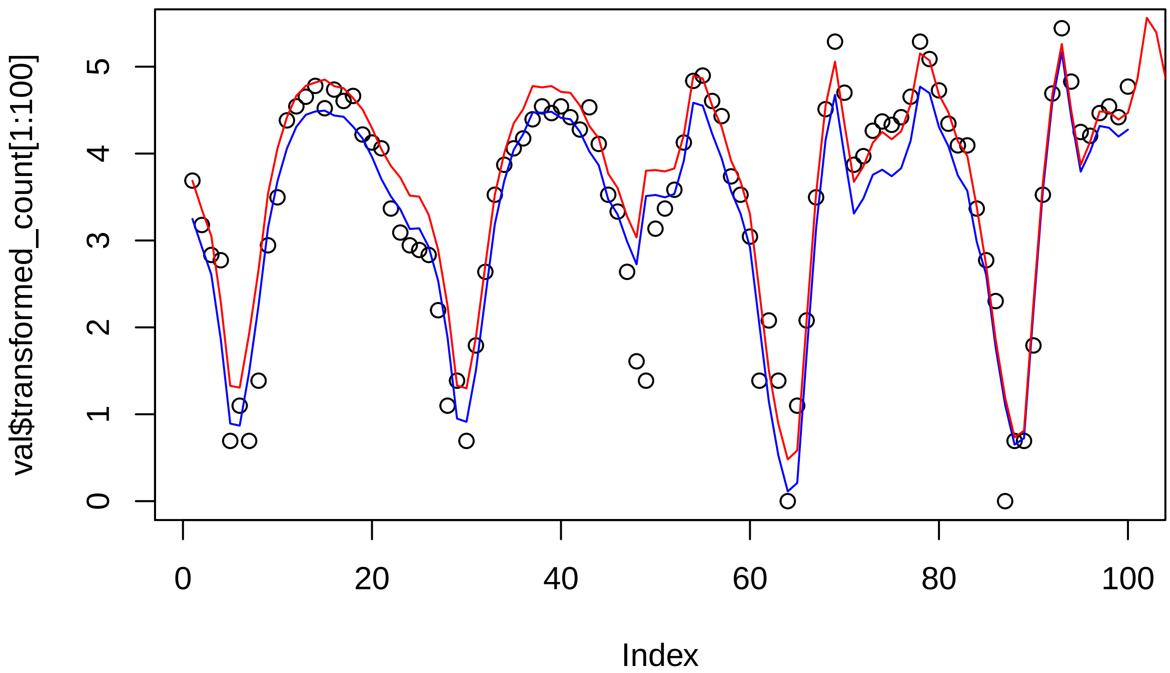
```
## [1] "training loss: 0.388239681587841"
```

```r
## validation loss
LlrLm_val = predict(SmoothedLinearMD,val) + predict(locfitmodel_hourmean_train, val$daylabel)
```

```r
print(paste0("validation loss: ",RMSLE_log(LlrLm_val, val$transformed_count)))
```

```
## [1] "validation loss: 0.381584966746676"
```

```r
## show how the fit goes
plot(val$transformed_count[1:100])
lines(LlrLm_val[1:100], col = "blue")
lines(linearPredict_val,col = "red")
```



(c) Using additive model

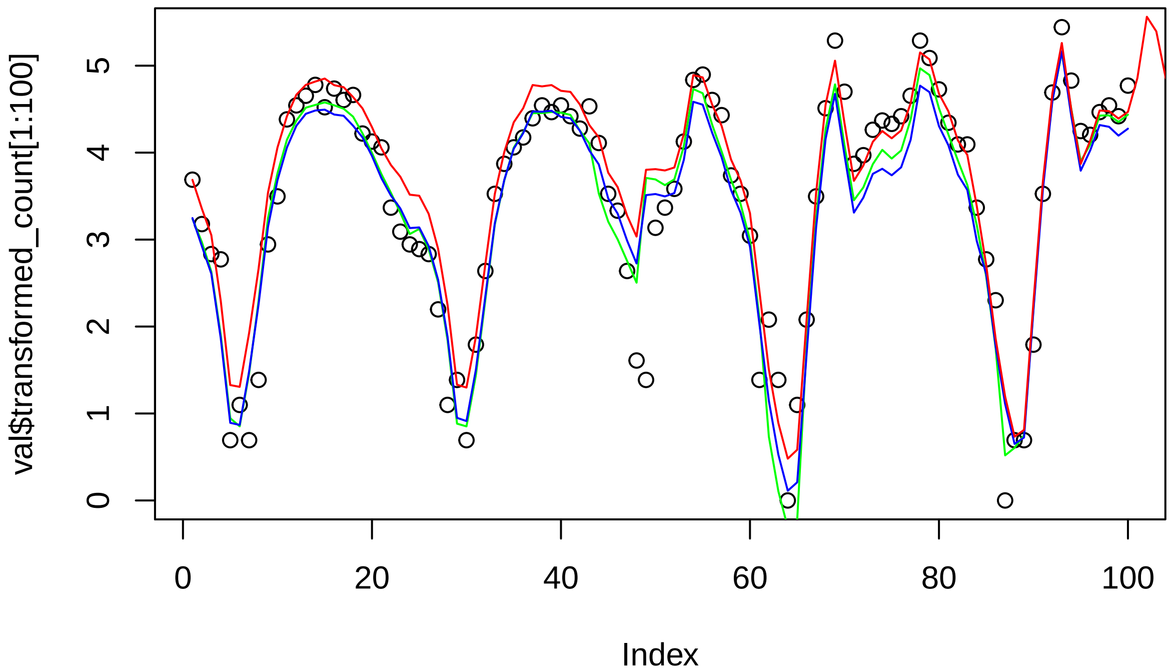
```r
gamMD <- gam(transformed_count ~ daylabel+workingday*hour+atemp*season + humidity+workingday+holiday*wea
#gamMD <- gam(transformed_count ~ daylabel+workingday+hour+workingday*hour + season +atemp+humidity+win

## training loss
GamLm_train = predict(gamMD,train) + predict(locfitmodel_hourmean_train, train$daylabel)
print(paste0("training loss: ",RMSLE_log(GamLm_train, train$transformed_count)))
```

```
## [1] "training loss: 0.360566240953876"
```

```r
## validation loss
GamLm_val = predict(gamMD,val) + predict(locfitmodel_hourmean_train, val$daylabel)
print(paste0("validation loss: ",RMSLE_log(GamLm_val, val$transformed_count)))
```

```
## [1] "validation loss: 0.35068072795119"
```

```r
## show how the fit goes
plot(val$transformed_count[1:100])
lines(GamLm_val[1:100], col = "green")
lines(LlrLm_val[1:100], col = "blue")
lines(linearPredict_val,col = "red")
```



Comment:

I got the best prediction from part (c). Though gam can lift my the model performance a little, feature selection is perhaps more important. Before adding the interaction term for workingday*hour, my best loss is around 1, much worse than the simplist linear model used here.

```
## prediction on test
GamLm_test = predict(gamMD,test) + predict(locfitmodel_hourmean_train, test$daylabel)
write.table(as.numeric(GamLm_test), "../data/assn1-wangzh.txt", row.names = FALSE, col.names=FALSE, sep
```