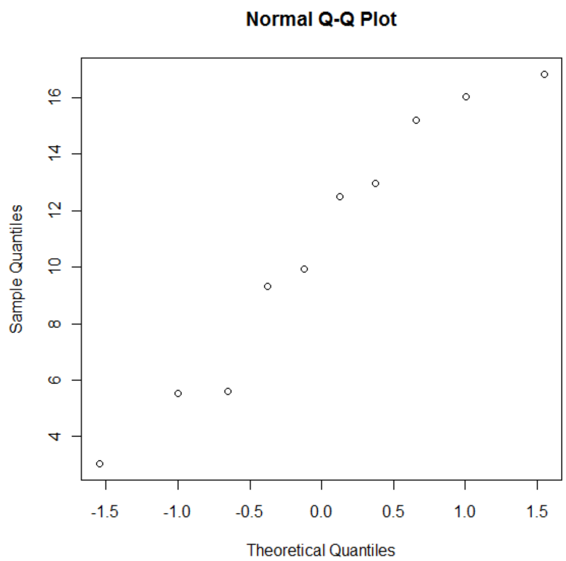
STAT 511 HW#7 SPRING 2009

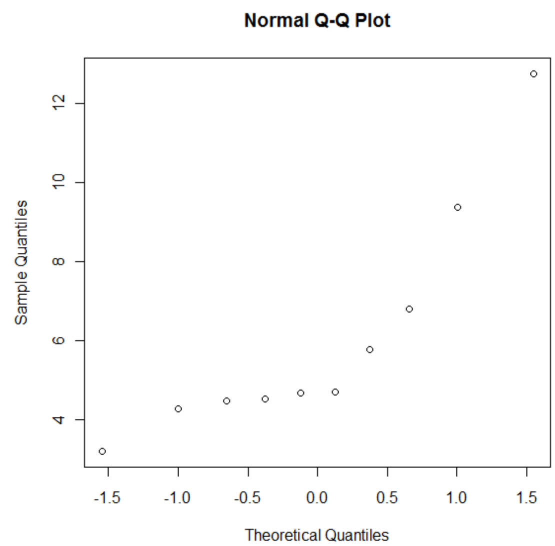
PROBLEM 1:

```
bootstrap<-function(x,nboot,theta)
{
data<-matrix(sample(x,size=length(x)*nboot,replace=T),nrow=nboot)
return(apply(data,1,theta))
}
library(MASS)
compound1<-c(3.03,5.53,5.60,9.30,9.92,12.51,12.95,15.21,16.04,16.84)
compound2<-c(3.19,4.26,4.47,4.53,4.67,4.69,5.78,6.79,9.37,12.75)
```

a)

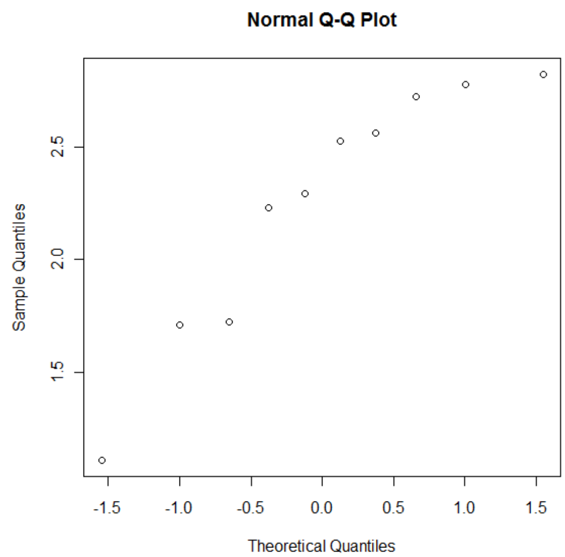
```
qqnorm(compound1)
qqnorm(compound2)
```

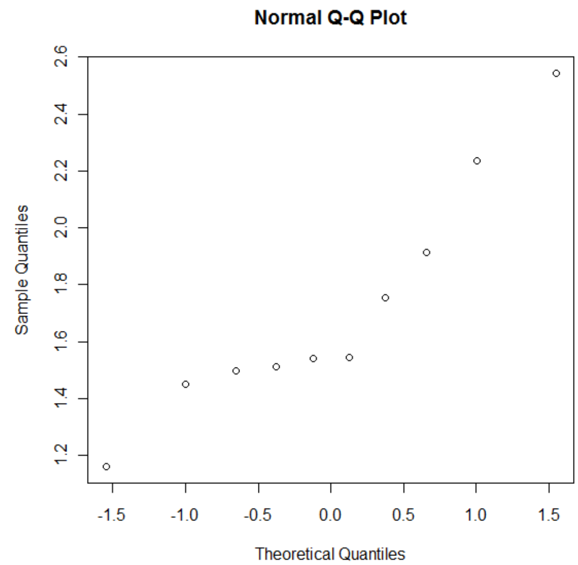




We do not expect "constant variance/normal distribution" ordinary statistical methods to be reliable in the analysis of these data because it seems compound 2 cannot be described with a normal distribution.

```
qqnorm(log(compound1))
qqnorm(log(compound2))
```





It is still not appropriate to use "constant variance/normal distribution" ordinary statistical methods in the analysis of the log lifetimes.

```
median(compound2)
      [1] 4.68
B <- 10000
comp2boot.non <- bootstrap(compound2,B,"median")
round(sqrt(var(comp2boot.non)),3)
      [1] 0.825 # standard error for the sample median
```

b)

```
kl<-floor((B+1)*.025)
ku<-B+1-kl
sortcomp2boot.non<-sort(comp2boot.non)
sortcomp2boot.non[kl]
sortcomp2boot.non[ku]
```

A 95% percentile bootstrap confidence interval for the median of F is (4.395,7.575)

c)

```
fit2 <- fitdistr(compound2,"weibull")
fit2
        shape        scale
        2.3201647    6.8595713
       (0.5243747)  (0.9957547)
```

The ML estimates of the shape and scale parameters of a Weibull distribution are 2.32 and 6.86, respectively.

```
Wboot<-function(samp,nboot,theta,shape,scale)
{
      data<-scale*matrix(rweibull(samp*nboot,shape),nrow=nboot)
      return(apply(data,1,theta))
}
comp2boot.Wei <- Wboot(10,B,"median",fit2$estimate[1],fit2$estimate[2])
round(sqrt(var(comp2boot.Wei)),3)
      [1] 1.085
sortcomp2boot.Wei <- sort(comp2boot.Wei)
round(c(sortcomp2boot.Wei[kl],sortcomp2boot.Wei[ku]),3)
      [1] 3.865 8.134
```

A parametric bootstrap standard error for the sample median is 1.085 millions of cycles and a parametric 95% (unadjusted) percentile bootstrap confidence inteval for the median of F is (3.865, 8.134). The parametric standard error is larger than the non-parametric standard error. Therefore, the parametric confidence interval is wider than the non-parametric confidence interval.

d)

```
1/(2*dweibull(median(compound2),fit2$estimate[1],fit2$estimate[2])*sqrt(10))
      [1] 1.169029
```

$\frac{1}{2f(\theta)\sqrt{n}}$=1:169 is similar to the parametric bootstrap standard error.

e)

```
comp1boot.non <- bootstrap(compound1,B,"median")
diff.non <- comp2boot.non-comp1boot.non
c(sort(diff.non)[kl],sort(diff.non)[ku])
      [1] -10.540  -0.625
```

A 95% percentile confidence interval for the difference in underlying median lifetimes is (-10.540, -0.625). This difference is clearly non-zero.

PROBLEM 2:

Check http://www.public.iastate.edu/~vardeman/stat511/stat%20511%20final%20exam.pdf for help on the R code and http://www.public.iastate.edu/~vardeman/stat511/511fsols03.pdf for answers to the exam questions.

PROBLEM 3:

Check http://www.public.iastate.edu/~vardeman/stat511/Stat%20511%20Final%20Exam%20S2004.pdf for help on the R code and http://www.public.iastate.edu/~vardeman/stat511/Stat%20511%20Final%20Exam%20Key%20S2004.pdf for answers to the exam questions.

PROBLEM 4:

```
temp<-c(66,70,69,68,67,72,73,70,57,63,70,78,67,53,67,75,70,81,
76,79,75,76,58)
incidents<-c(0,1,0,0,0,0,0,0,1,1,1,0,0,1,0,0,0,0,0,0,1,0,1)
indicate<-(incidents>0)
indicate
```

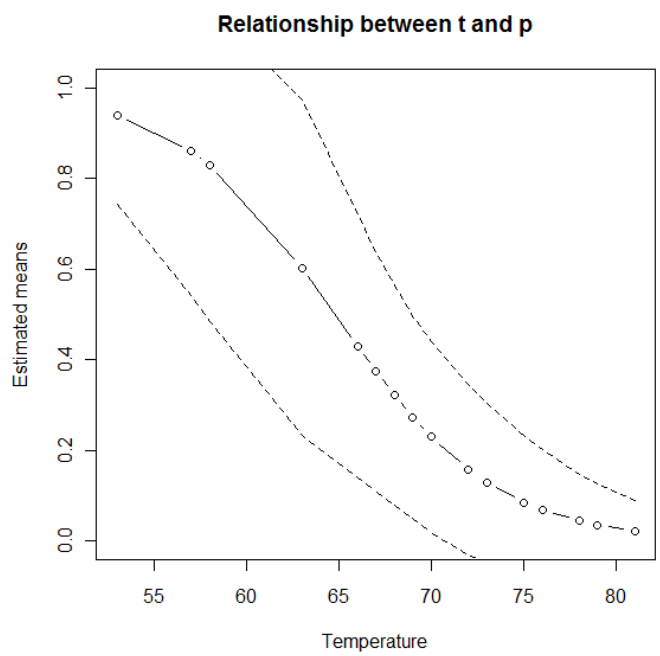
a)

```
shuttle.out<-glm(indicate~temp,family=binomial)
summary(shuttle.out)
      Call:
      glm(formula = indicate ~ temp, family = binomial)
      Deviance Residuals:
          Min       1Q   Median       3Q      Max
      -1.0611  -0.7613  -0.3783   0.4524   2.2175
      Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
      (Intercept)  15.0429     7.3786   2.039   0.0415 *
      temp         -0.2322     0.1082  -2.145   0.0320 *
       (Dispersion parameter for binomial family taken to be 1)
          Null deviance: 28.267  on 22  degrees of freedom
      Residual deviance: 20.315  on 21  degrees of freedom
      AIC: 24.315
      Number of Fisher Scoring iterations: 5
```

There is evidence that the coefficient of the temperature covariate is non zero (p-value=0.03). Therefore the test $H_0\colon \beta_1 < 0$ has a p-value of 0.015 which suggests that their claim was not correct.

b)

```
shuttle.fits <- predict.glm(shuttle.out,type="response",se.fit=TRUE)
ind <- order(temp)
plot(temp[ind],shuttle.fits$fit[ind],type="b",ylim=c(0,1),
xlab="Temperature",ylab="Estimated means",main="Relationship between t and p")
lines(temp[ind],shuttle.fits$fit[ind]-2*shuttle.fits$se.fit[ind],lty=2)
lines(temp[ind],shuttle.fits$fit[ind]+2*shuttle.fits$se.fit[ind],lty=2)
```



The temperature 31°F is outside the range of temperature values used to fit the model. However, assuming that the relationship of temperature and O-ring incidents remains the same at lower temperature values, the model suggests that there is a very high probability of having an O-ring incident on a lauch at 31°F.

```
predict.glm(shuttle.out,data.frame(temp=31),se.fit=TRUE,type="response")
      $fit
      [1] 0.9996088
      $se.fit
      [1] 0.001578722
```

PROBLEM 5:

```
A<-c(1,2,3,1,2,3)
B<-c(1,1,1,2,2,2)
y<-c(27,21,33,15,6,11)
k<-c(295,416,308,474,540,498)
AA<-as.factor(A)
BB<-as.factor(B)
options(contrasts=c("contr.sum","contr.sum"))
```

a)

```
collator.out<-glm(y~AA+BB,family=poisson,offset=log(k))
summary(collator.out)
      Call:
      glm(formula = y ~ AA + BB, family = poisson, offset = log(k))
      Deviance Residuals:
```

```
         1         2         3         4         5         6
-0.5040   0.1693   0.3442   0.7453  -0.3004  -0.5532
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.2159     0.1068 -30.098  < 2e-16 ***
AA1           0.2420     0.1313   1.844  0.06521 .
AA2          -0.4856     0.1472  -3.299  0.00097 ***
BB1           0.6781     0.1045   6.490 8.56e-11 ***
 (Dispersion parameter for poisson family taken to be 1)
    Null deviance: 59.201  on 5  degrees of freedom
Residual deviance:  1.353  on 2  degrees of freedom
AIC: 37.188
Number of Fisher Scoring iterations: 4
```

It appears that there are statistically detectable Air Pressure and Bar Tightness effects in these data since the coeficients for the levels of these two variables are significant. If one wants small number of jams, one wants level 2 of Air Pressure and level 2 of Bar Tightness.

b)

```
mu <- collator.out$coefficients[1]
alpha1 <- collator.out$coefficients[2] ; alpha2 <- collator.out$coefficients[3]
alpha3 <- -(alpha1+alpha2)
beta1 <- collator.out$coefficients[4] ; beta2 <- -beta1
exp(c(mu+alpha1+beta1,mu+alpha2+beta1,mu+alpha3+beta1,mu+alpha1+beta2,mu+alpha2+beta2
,mu+alpha3+beta2))
      0.10069307 0.04863886 0.10084992 0.02593996 0.01253006 0.02598037
```

c)

```
collator.fits<-predict.glm(collator.out,type="response",se.fit=TRUE)
collator.fits$fit
            1          2          3          4          5          6
      29.704457 20.233767 31.061776 12.295543  6.766233 12.938224
collator.fits$se
           1         2         3         4         5         6
      4.930579 4.035579 5.056778 2.627107 1.678798 2.729002
lcollator.fits<-predict.glm(collator.out,se.fit=TRUE)
lcollator.fits$fit
           1         2         3         4         5         6
      3.391297 3.007353 3.435978 2.509237 1.911944 2.560186
lcollator.fits$se
            1          2          3          4          5          6
      0.1659878 0.1994477 0.1627975 0.2136634 0.2481141 0.2109256
```

collator.fits$fit= k*(answer in 4(b)).

PROBLEM 5:

Check http://www.public.iastate.edu/~vardeman/stat511/stat%20511%20final%20exam.pdf and http://www.public.iastate.edu/~vardeman/stat511/511fsols03.pdf

PROBLEM 6:

Check
http://www.public.iastate.edu/~vardeman/stat511/Stat%20511%20Final%20Exam%20S2004.pdf
and
http://www.public.iastate.edu/~vardeman/stat511/Stat%20511%20Final%20Exam%20Key%20S2004.pdf

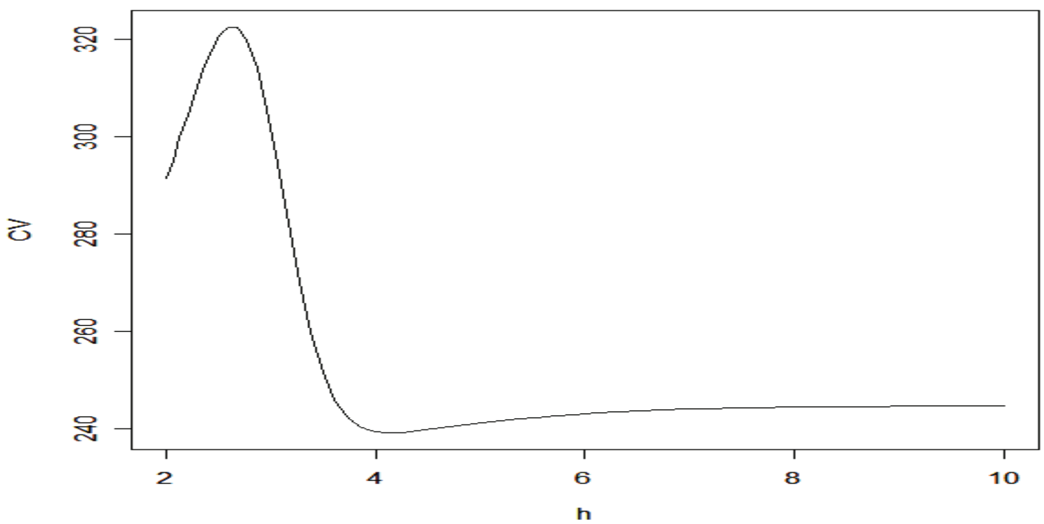
PROBLEM 7:

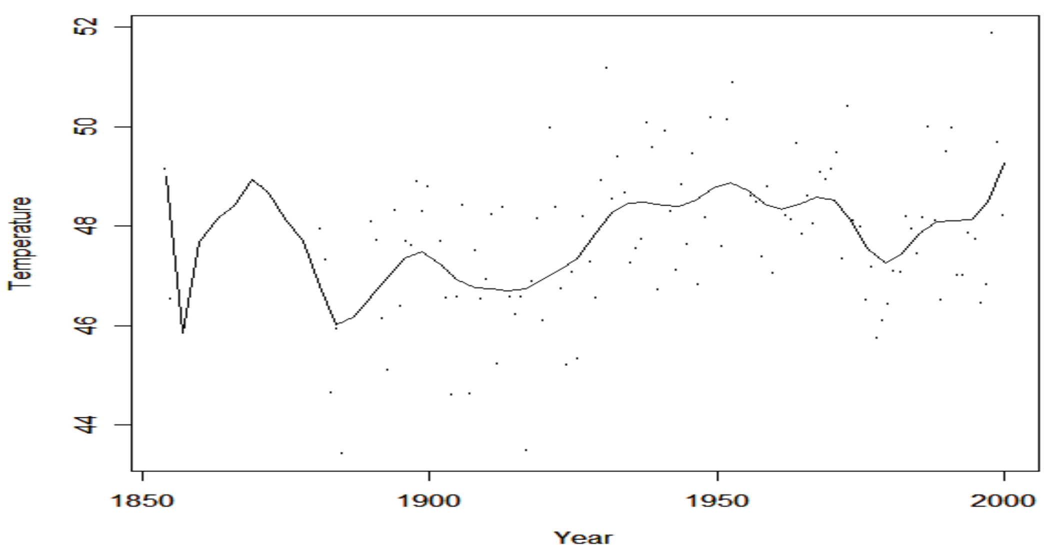
Answer copied from http://www.public.iastate.edu/~vardeman/stat511/511HWsol8-08.pdf

7.
From the smoothing regressions below, apparently changing of temperature can be seen from the plots. The smooth help us determine this changing over time.

We first apply Kernel method here, use Cross validation to select bandwidth. The following plot is the CV value against bandwidth. We see here at bandwidth=4.15, the CV value attain its minimum. Therefore, we use this bandwidth in our kernel regression. We also try other bandwidth to do the nonparametric regression. For bandwidth=2 and bandwidth=10.

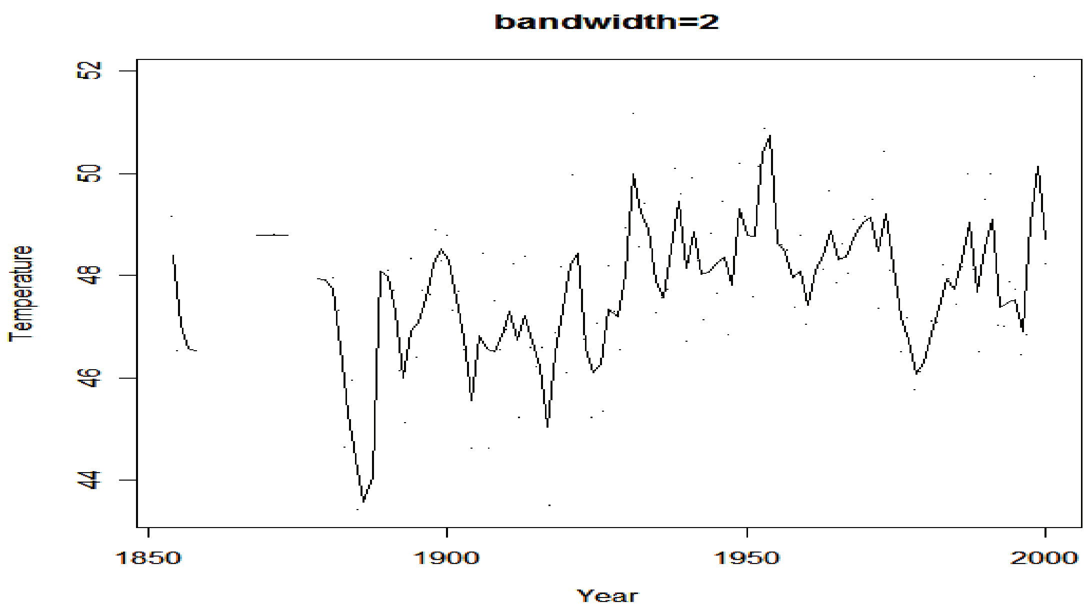
The following plot is the CV against bandwidth and kernel regression using bandwidth=4.15

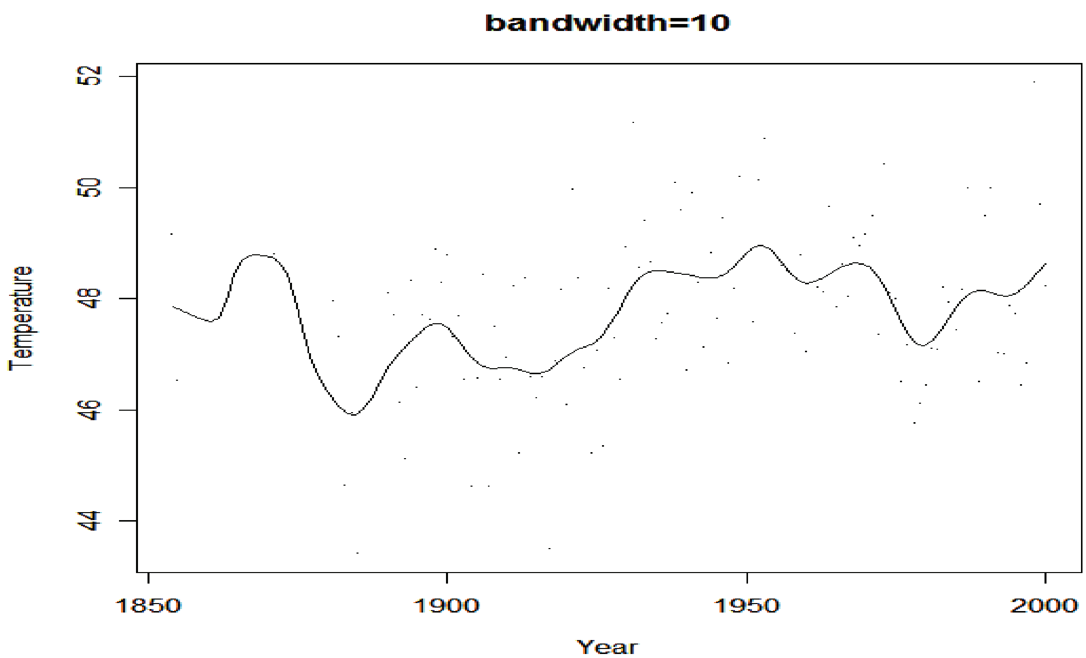





```
library(faraway)
```

```
library(sm)
attach(aatemp)
h<-hcv(year,temp,hstart=2,hend=10,display="lines",ngrid=50)
sm.regression(aatemp$year,aatemp$temp,h=h,xlab="Year",ylab="Temperature
")
plot(aatemp$year,aatemp$temp,main="bandwidth=2",
xlab="Year",ylab="Temperature",pch=".")
lines(ksmooth(aatemp$year,aatemp$temp,"normal",2))
plot(aatemp$year,aatemp$temp,main="bandwidth=10",
xlab="Year",ylab="Temperature",pch=".")
lines(ksmooth(aatemp$year,aatemp$temp,"normal",10))
```



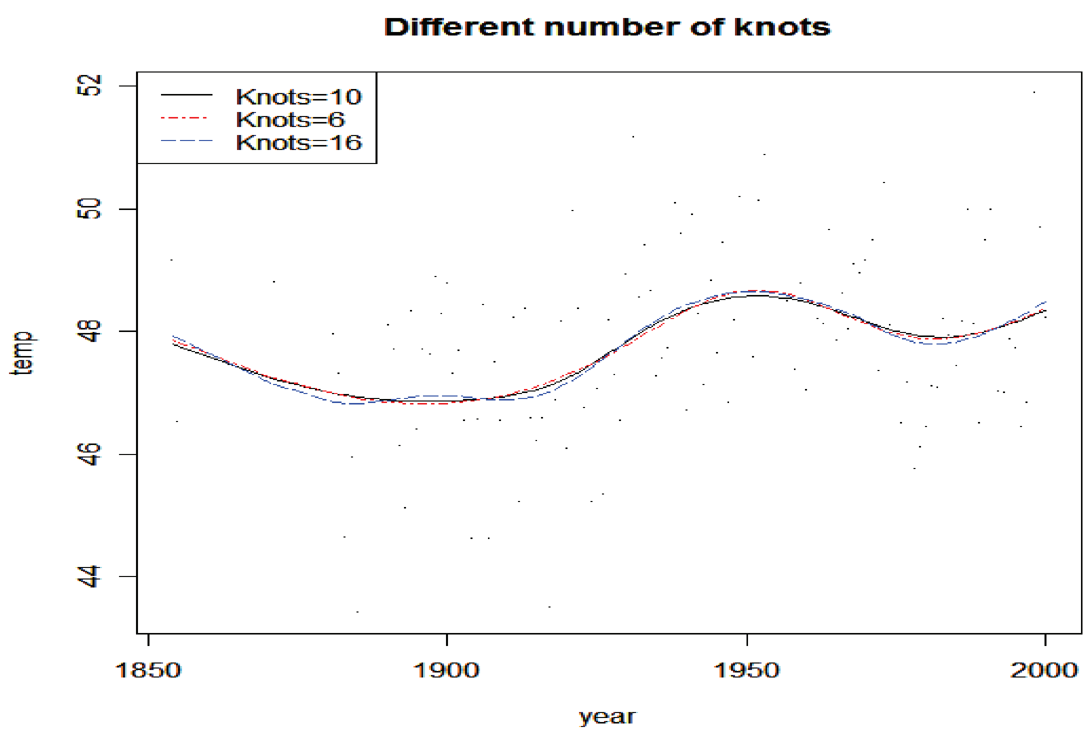


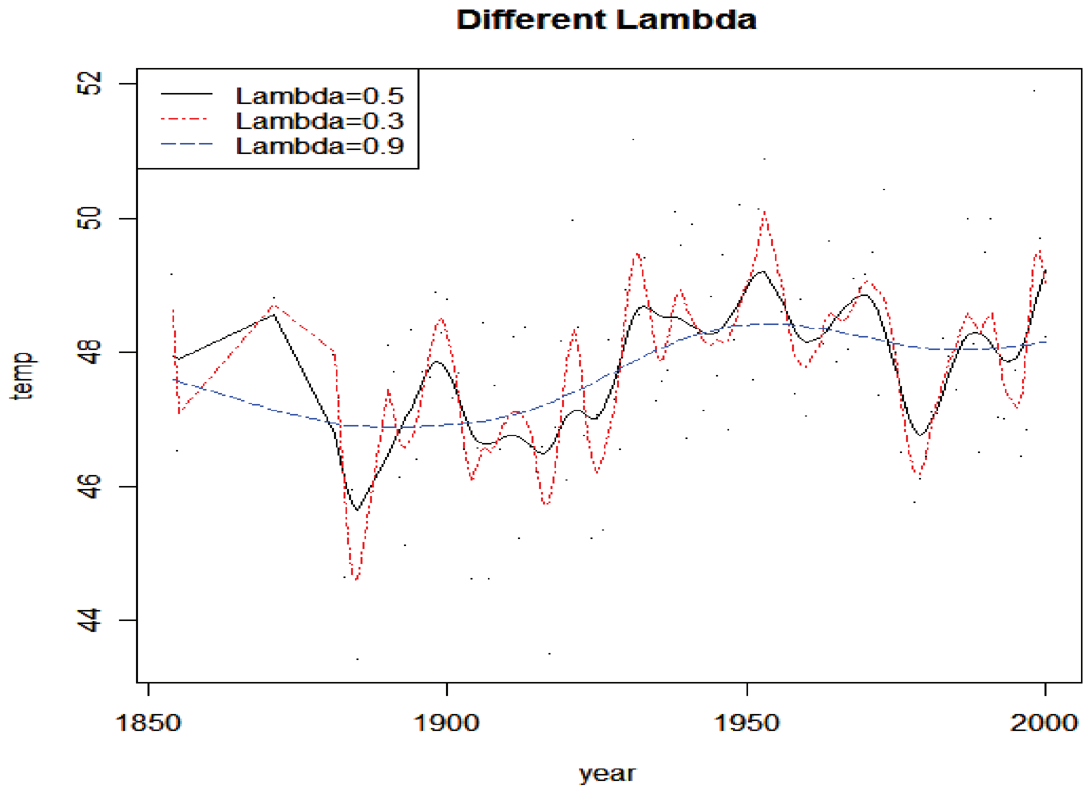
Secondly, we apply Splines method:

```
plot(temp~year,aatemp,pch=".")
lines(smooth.spline(aatemp$year,aatemp$temp))

plot(temp~year,aatemp,pch=".",main="Different number of knots")
lines(smooth.spline(aatemp$year,aatemp$temp,nknots=10))
lines(smooth.spline(aatemp$year,aatemp$temp,nknots=6),lty=4,col=2)
lines(smooth.spline(aatemp$year,aatemp$temp,nknots=16),lty=5,col=4)
legend("topleft",c("Knots=10","Knots=6","Knots=16"),lty=c(1,4,5),col=c(
1,2,4))

plot(temp~year,aatemp,pch=".",main="Different Lambda")
lines(smooth.spline(aatemp$year,aatemp$temp,spar=0.5))
lines(smooth.spline(aatemp$year,aatemp$temp,spar=0.3),lty=4,col=2)
lines(smooth.spline(aatemp$year,aatemp$temp,spar=0.9),lty=5,col=4)
legend("topleft",c("Lambda=0.5","Lambda=0.3","Lambda=0.9"),lty=c(1,4,5)
,col=c(1,2,4))
```





Thirdly, we apply LOWESS method,

```
plot(year, temp, main = "LOWESS with different spans")
lines(lowess(year,temp,f=.1), lty=1, col = 1)
lines(lowess(year,temp, f=.2), lty=4, col = 2)
lines(lowess(year,temp, f=.5), lty=5, col = 4)
legend("topleft", c("Span=0.1","Span=0.2","Span=0.5"), lty = c(1,4,5),
col = c(1,2,4))
```