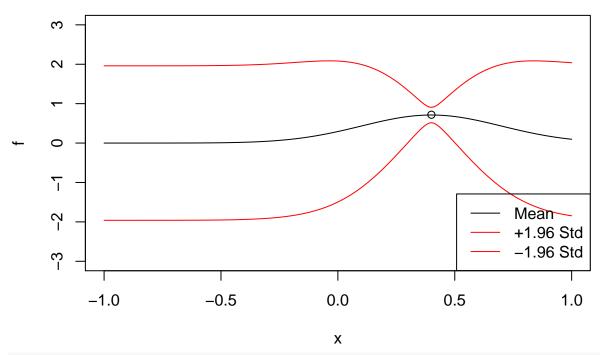
Lab4

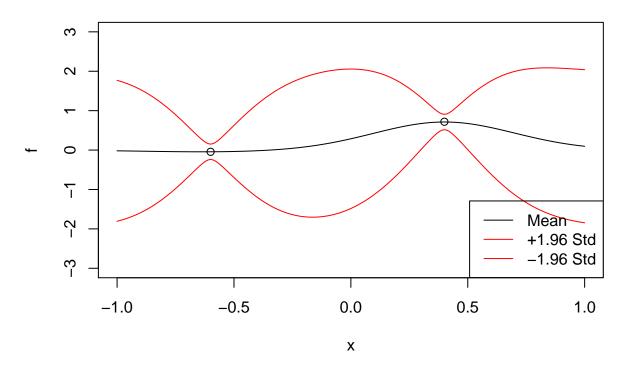
Yifan Ding

Q2.1

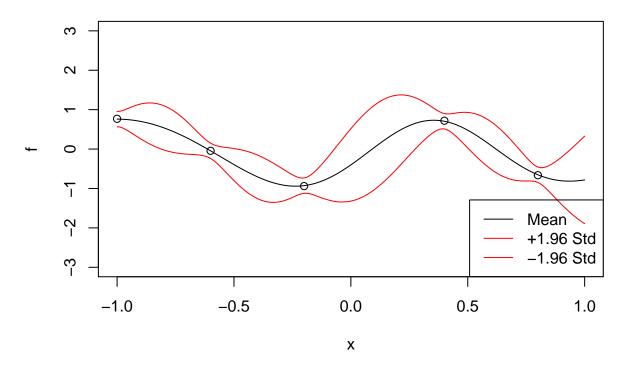
```
SquaredExpKernel <- function(x1,x2,sigmaF=1,1=3){</pre>
  n1 \leftarrow length(x1)
  n2 <- length(x2)
  K <- matrix(NA,n1,n2)</pre>
  for (i in 1:n2){
    K[,i] \leftarrow sigmaF^2*exp(-0.5*((x1-x2[i])/1)^2)
  }
  return(K)
}
posteriorGP <- function(X, y, Xstar, sigmaNoise, K, ...){</pre>
  n <- length(X)
  C \leftarrow K(X, X, ...) + sigmaNoise ^ 2 * diag(n)
  L <- t(chol(C))</pre>
  L_inv <- solve(L)
  C_inv <- t(L_inv) %*% L_inv</pre>
  mean <- K(Xstar, X, ...) %*% C_inv %*% y
  var <- K(Xstar, Xstar, ...) - K(Xstar, X, ...) %*% C_inv %*% t(K(Xstar, X, ...))</pre>
  return(list(mean=mean, var=var))
}
```

Q2.2

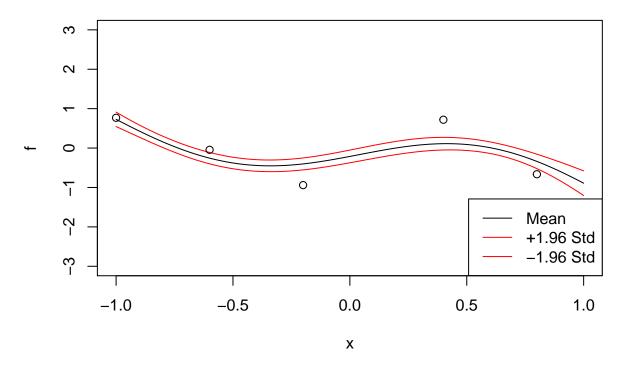




Q2.4



Q2.5

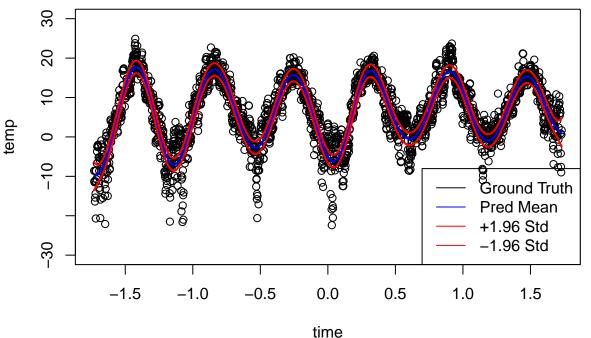


Q3.1

```
df <- read.csv("TempTullinge.csv", sep=";", header=TRUE)</pre>
time <- seq(1, 2190)
time <- (time -mean(time)) / sd(time)</pre>
day \leftarrow rep(1:365,6)
day <- (day -mean(day)) / sd(day)</pre>
df$time <- time
RBFkernel <- function(sigmaf = 1, ell = 1) {</pre>
  rval <- function(x, y = NULL) {</pre>
      res <- sigmaf^2*exp(-0.5*((x-y)/ell)^2)
      return(res)
    }
  class(rval) <- "kernel"</pre>
  return(rval)
}
SEkernel <- RBFkernel(sigmaf = 1, ell = 1)</pre>
SEkernel(1,2)
## [1] 0.6065307
X \leftarrow matrix(c(1,3,4), 3, 1)
Xstar \leftarrow matrix(c(2,3,4), 3, 1)
kernelMatrix(kernel = SEkernel, x = X, y = Xstar)
## An object of class "kernelMatrix"
              [,1]
                         [,2]
## [1,] 0.6065307 0.1353353 0.0111090
## [2,] 0.6065307 1.0000000 0.6065307
## [3,] 0.1353353 0.6065307 1.0000000
```

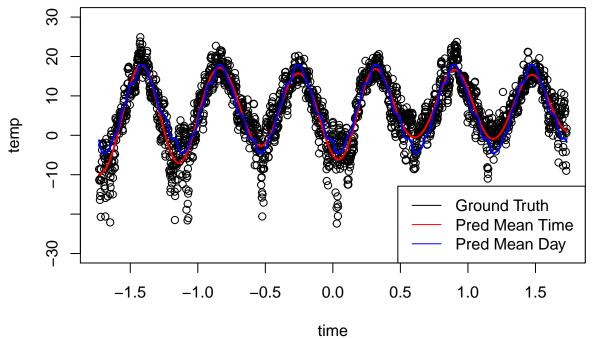
Q3.2

```
temp <- df$temp
plot(time, temp, ylim=c(-30, 30))
polyFit <- lm(temp ~ time + I(time^2))</pre>
sigmaNoise <- sd(polyFit$residuals)</pre>
sigmaf <- 20
ell <- 0.2
RBF <- RBFkernel(sigmaf = sigmaf, ell=ell)</pre>
GPfit <- gausspr(time, temp, kernel = RBF, var = sigmaNoise^2)</pre>
meanPred <- predict(GPfit, time)</pre>
lines(time, meanPred, lwd = 2, col='blue')
x<-time
xs<-time # XStar.
n <- length(x)
Kss <- kernelMatrix(kernel = RBF, x = xs, y = xs)
Kxx \leftarrow kernelMatrix(kernel = RBF, x = x, y = x)
Kxs \leftarrow kernelMatrix(kernel = RBF, x = x, y = xs)
Covf = Kss-t(Kxs)%*%solve(Kxx + sigmaNoise^2*diag(n), Kxs) # Covariance matrix of fStar.
lines(xs, meanPred - 1.96*sqrt(diag(Covf)), col = "red", lwd = 2)
lines(xs, meanPred + 1.96*sqrt(diag(Covf)), col = "red", lwd = 2)
legend("bottomright", legend=c("Ground Truth", "Pred Mean ","+1.96 Std", "-1.96 Std"),
        lwd=c(1,1,1,1), col=c("black","blue","red","red"))
```



```
temp <- df$temp
plot(time, temp, ylim=c(-30, 30))

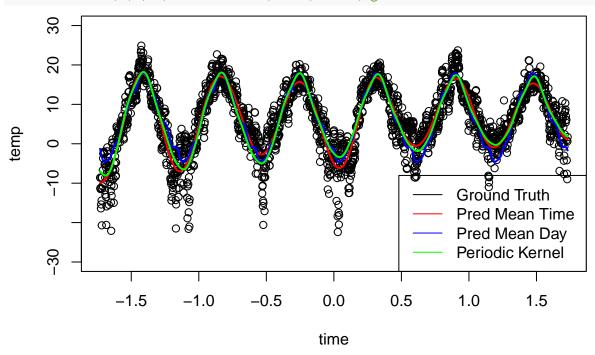
polyFit <- lm(temp ~ time + I(time^2))
sigmaNoise <- sd(polyFit$residuals)
sigmaf <- 20
ell <- 0.2</pre>
```



Q3.5

```
RBFPeriodickernel <- function(sigmaf = 1, ell1 = 1, ell2 = 1, d = 1) {
  rval <- function(x, y = NULL) {</pre>
      res <- sigmaf^2*exp(-0.5*((x-y)/ell2)^2)*exp(-2*(sin(pi*abs(x-y)/d)/ell1)^2)
      return(res)
    }
  class(rval) <- "kernel"</pre>
  return(rval)
}
sigmaf <- 20
ell1 <- 1
ell2 <- 10
d \leftarrow 365 / sd(c(1:2190))
RBF_P <- RBFPeriodickernel(sigmaf = sigmaf, ell1 = ell1, ell2 = ell2, d = d)
GPfit_PK <- gausspr(time, temp, kernel = RBF_P, var = sigmaNoise^2)</pre>
meanPred PK <- predict(GPfit PK, time)</pre>
plot(time, temp, ylim=c(-30, 30))
lines(time, meanPred, lwd = 2, col='red')
lines(time, meanPred_day, lwd = 2, col='blue')
lines(time, meanPred_PK, lwd = 2, col='green')
```

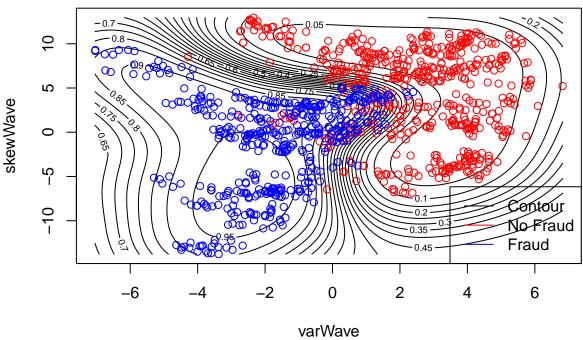
##



Q4.1

```
data <- read.csv("https://github.com/STIMALiU/AdvMLCourse/raw/master/GaussianProcess/Code/banknoteFraud</pre>
names(data) <- c("varWave", "skewWave", "kurtWave", "entropyWave", "fraud")</pre>
data[,5] <- as.factor(data[,5])</pre>
set.seed(111)
SelectTraining <- sample(1:dim(data)[1], size = 1000, replace = FALSE)
train=data[SelectTraining,]
test=data[-SelectTraining,]
GPClassifier <- gausspr(fraud ~ varWave + skewWave, data=train)</pre>
## Using automatic sigma estimation (sigest) for RBF or laplace kernel
# class probabilities
probPreds <- predict(GPClassifier, train[,1:2], type="probabilities")</pre>
x1 <- seq(min(train[,1]),max(train[,1]),length=100)</pre>
x2 <- seq(min(train[,2]),max(train[,2]),length=100)</pre>
gridPoints <- meshgrid(x1, x2)</pre>
gridPoints <- cbind(c(gridPoints$x), c(gridPoints$y))</pre>
gridPoints <- data.frame(gridPoints)</pre>
names(gridPoints) <- names(train)[1:2]</pre>
probPreds <- predict(GPClassifier, gridPoints, type="probabilities")</pre>
# Plotting for Prob(setosa)
contour(x1,x2,matrix(probPreds[,2],100,byrow = TRUE), 20, xlab = "varWave", ylab = "skewWave", main = "
```

Prob(Fraud)



```
print('Confusion matrix and accuracy of training set')
## [1] "Confusion matrix and accuracy of training set"
confmatrix <- table(predict(GPClassifier,train[,1:2]), train[,5])</pre>
confmatrix
##
##
         0
##
     0 503 18
     1 41 438
sum(diag(confmatrix)) / sum(confmatrix)
## [1] 0.941
print('Confusion matrix and accuracy of test set')
## [1] "Confusion matrix and accuracy of test set"
confmatrix <- table(predict(GPClassifier,test[,1:2]), test[,5])</pre>
confmatrix
##
##
         0
             1
```

##

##

0 199 9 1 19 145

```
sum(diag(confmatrix)) / sum(confmatrix)
## [1] 0.9247312
Q4.3
GPClassifier <- gausspr(fraud ~ ., data=train)</pre>
## Using automatic sigma estimation (sigest) for RBF or laplace kernel
print('Confusion matrix and accuracy of test set with all 4 features')
## [1] "Confusion matrix and accuracy of test set with all 4 features"
confmatrix <- table(predict(GPClassifier,test[,1:4]), test[,5])</pre>
confmatrix
##
##
        0
##
     0 216
     1
        2 154
##
sum(diag(confmatrix)) / sum(confmatrix)
## [1] 0.9946237
```