Statistical Modeling and Inference – Problem Set #2

NITI MISHRA · MIQUEL TORRENS · BÁLINT VÁN

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Solution to proposed exercises.

Exercise 1

We need to solve:

$$\begin{aligned}\max_{\mathbf{w}} -2\log p(\mathbf{w}|\mathbf{t},\mathbf{X}) &= -2q\mathbf{t}^T\mathbf{\Phi}\mathbf{w} + q\mathbf{w}^T\mathbf{\Phi}^T\mathbf{\Phi}\mathbf{w} + (\mathbf{w}-\mu)^T\mathbf{D}(\mathbf{w}-\mu) + C \\ &= -2q\mathbf{t}^T\mathbf{\Phi}\mathbf{w} + q\mathbf{w}^T\mathbf{\Phi}^T\mathbf{\Phi}\mathbf{w} + \mathbf{w}^T\mathbf{D}\mathbf{w} - 2\mathbf{w}^T\mathbf{D}\mu + \mu^T\mathbf{D}\mu + C\end{aligned}$$

The term C includes all constant terms not dependant on $\mathbf{w}$. Now we maximize with respect to $\mathbf{w}$ and set to zero:

$$-2q\mathbf{t}^T\mathbf{\Phi} + q\mathbf{w}^T\left(\mathbf{\Phi}^T\mathbf{\Phi} + \left(\mathbf{\Phi}^T\mathbf{\Phi}\right)^T\right) + \mathbf{w}^T\left(\mathbf{D}+\mathbf{D}^T\right) - 2\left(\mathbf{D}\mu\right)^T = 0$$

During the derivation we will recurrently use two properties: $\mathbf{D} = \mathbf{D}^T$, as it is symmetric by construction, and $\left(\mathbf{\Phi}^T\mathbf{\Phi}\right)^T = \mathbf{\Phi}^T\mathbf{\Phi}$, which is a straightforward calculation. We just need to rearrange terms to reach the normal equations:

$$\begin{aligned}2\mathbf{w}^T\mathbf{D} - 2\mu^T\mathbf{D}^T - 2q\mathbf{t}^T\mathbf{\Phi} + 2q\mathbf{w}^T\mathbf{\Phi}^T\mathbf{\Phi} &= 0 \\ \mathbf{w}^T\left(\mathbf{D} + q\mathbf{\Phi}^T\mathbf{\Phi}\right) &= q\mathbf{t}^T\mathbf{\Phi} + \left(\mathbf{D}\mu\right)^T \\ \left(\mathbf{D} + q\mathbf{\Phi}^T\mathbf{\Phi}\right)^T\mathbf{w} &= q\mathbf{\Phi}^T\mathbf{t} + \left(\mathbf{D}\mu\right)\end{aligned}$$

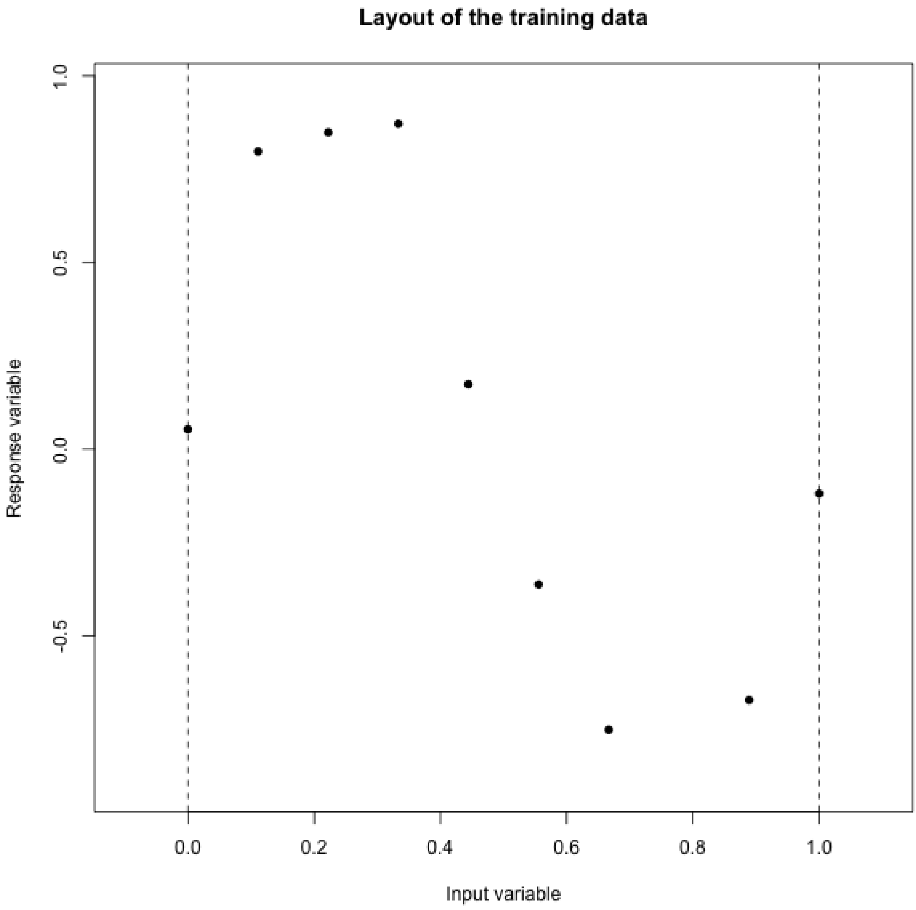
To finally obtain the normal equations:

$$\left(\mathbf{D} + q\mathbf{\Phi}^T\mathbf{\Phi}\right)\mathbf{w} = q\mathbf{\Phi}^T\mathbf{t} + \mathbf{D}\mu$$

Hence proved.

Exercise 2

Part 1. Plotting the data:



Part 2. The `phix` function:

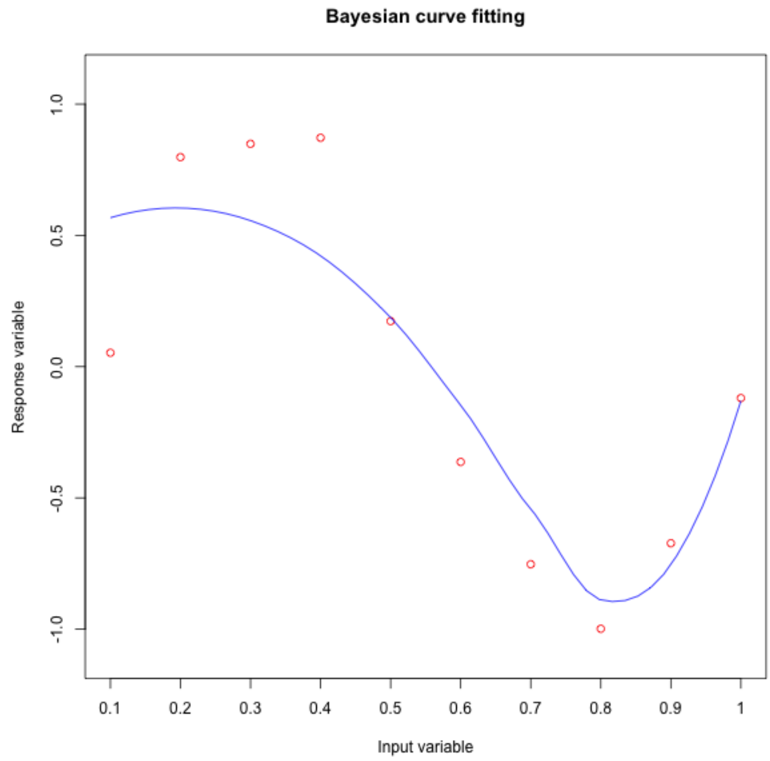
```
#################################################################################
# Function "phix"
phix <- function(x, M, basis) {
#################################################################################
  # Check correctness of input x
  if (x < 0 || x > 1) {
    stop('out-of-range values in the input vector "x".')
  }

  # Perform the calculations
  if (basis == 'poly') {
    out <- rep(NA, length = M + 1)
    sapply(c(0, 1:M), function(i) {
      out[i + 1] <<- x^i
    })
  } else if (basis == 'Gauss') {
    mus <- seq(0, 1, length.out = M)
    out <- rep(NA, length = M)
```

```r
    sapply(1:M, function(i) {
      out[i] <<- exp((-(x - mus[i]) ** 2) / 0.1)
    })
    out <- c(1, out)
  } else {
    stop('specify a valid option for the parameter "basis".')
  }

  # Return the values
  return(out)
}
```

Part 3. The `post.params` function:

```r
################################################################################
# Function "post.params"
post.params <- function(tdata, M, basis, phix, delta, q) {
################################################################################
  # Input data
  t <- tdata[, 't']  # Response variable
  x <- tdata[, 'x']  # Input variable

  # Initialize Phi matrix
  phi <- matrix(nrow = length(x), ncol = M + 1)
  sapply(1:length(x), function(i) {
    phi[i, ] <<- phix(x = x[i], M = M, basis = basis)
  })

  # Parameter estimation
  Q <- delta * diag(ncol(phi)) + q * t(phi) %*% phi
  w.bayes <- q * solve(Q) %*% t(phi) %*% t

  # Results
  return(list(w.bayes = w.bayes, Q = Q))
}
```

Part 4. Plotting the estimated linear predictor:



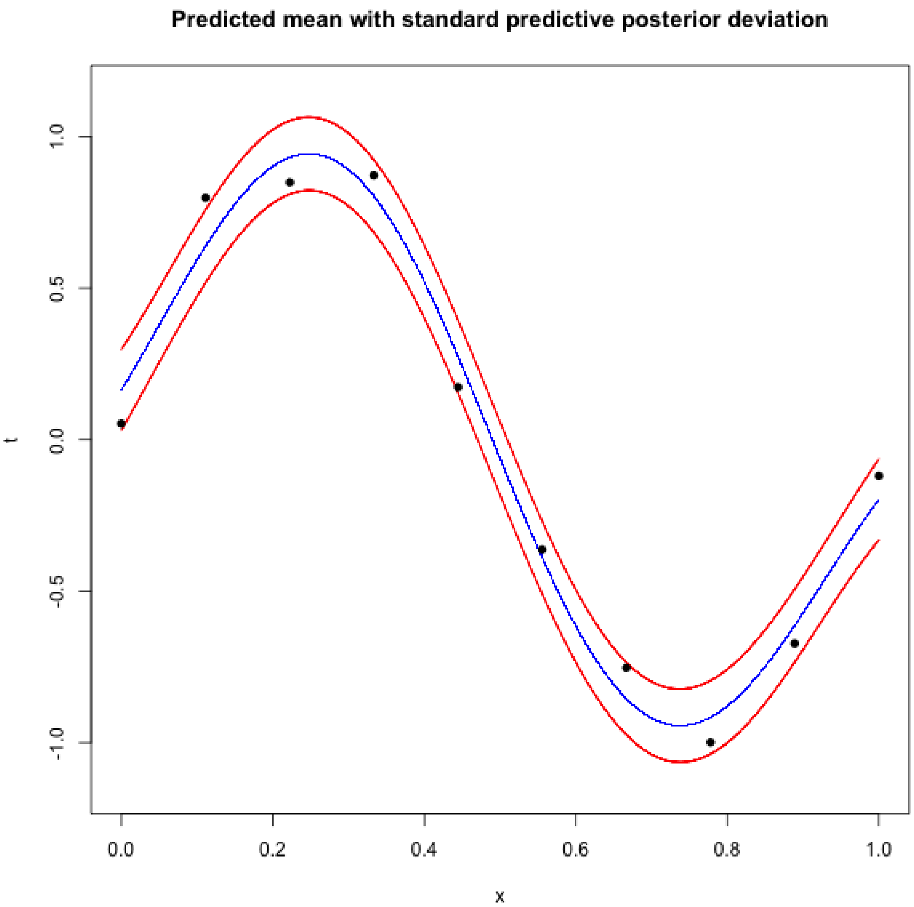
Bayesian curve fitting
Response variable
Input variable
1.0
0.5
0.0
-0.5
-1.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Exercise 3

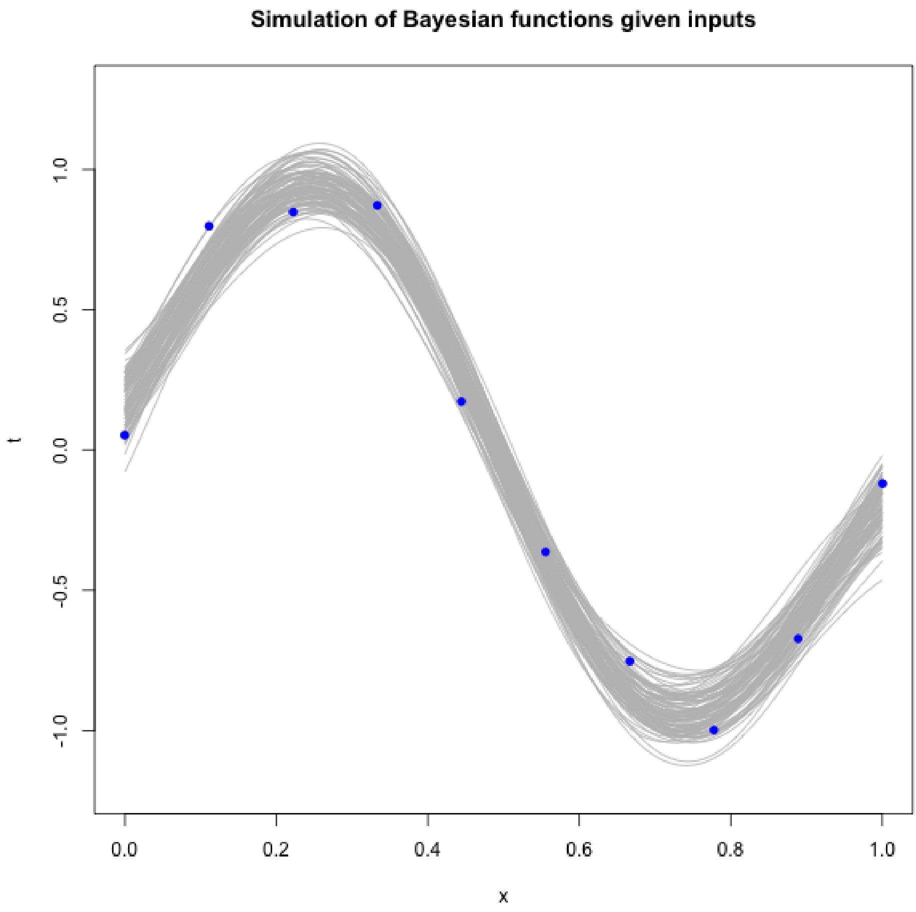
Part 1. The function that returns the mean and the precision of the predictive distribution at each of the inputs:

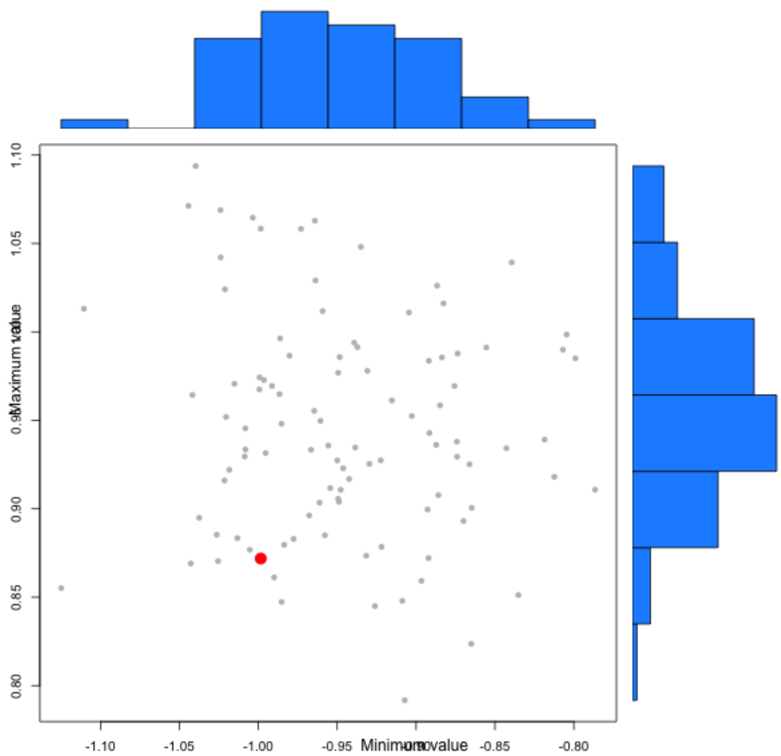
```
####################################################################################
bayesian.precision <- function(x) {
####################################################################################
  # Parameters
  M <- 9
  delta <- 1L
  q <- 0.1 ** (-2)

  # Initialize Phi matrix
  phi <- matrix(nrow = length(x), ncol = M + 1)
  sapply(1:length(x), function(i) {
    phi[i, ] <<- phix(x = x[i], M = 9, basis = 'Gauss')
  })

  # Execute the function with the specified parameters
  params <- post.params(cd, M = 9, basis = 'Gauss', phix,
                        delta = 1L, q = 0.1 ** (-2))

  # Resulting parameters
  Q <- params[[2]]
  w.bayes <- params[[1]]

  # Predicted values
  means <- phi %*% w.bayes
  vars <- phi %*% solve(Q) %*% t(phi) + q ** (-1)

  # Return
  return(list(means = means, vars = diag(vars)))
}
```

Part 2. Plotting the predicted mean with its standard predictive posterior deviation:



Part 3. Replicating the plot of the slides:


Simulation of Bayesian functions given inputs
t
x
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


Maximum value
Minimum value

Exercise 4

Part 1.

We can prove this using the following rule:

$$\phi(\mathbf{x})^T\mathbf{w}_B = \phi(\mathbf{x})^T q\mathbf{Q}^{-1}\phi(\mathbf{x})\mathbf{t} = \phi(\mathbf{x})^T q\mathbf{Q}^{-1}\sum_{n=1}^{N}\phi(\mathbf{x}_n)\mathbf{t}_n = \sum_{n=1}^{N} q\phi(\mathbf{x})^T\mathbf{Q}^{-1}\phi(\mathbf{x}_n)t_n$$

Where $\mathbf{w}_B$ are the Bayesian parameters. We derive the fact that $\phi(\mathbf{x})\mathbf{t} = \sum_{n=1}^{N}\phi(\mathbf{x}_n)\mathbf{t}_n$ by noticing that this product is the inner product between them.

Part 2.

We define:

$$k(\mathbf{x},\mathbf{y}) = q\phi(\mathbf{x})^T\mathbf{Q}^{-1}\phi(\mathbf{y})$$

Then:

$$\phi(\mathbf{x})^T\mathbf{w}_B = \sum_{n=1}^{N} q\phi(\mathbf{x})^T\mathbf{Q}^{-1}\phi(\mathbf{x}_n)t_n = \sum_{n=1}^{N} k(\mathbf{x},\mathbf{x}_n)t_n$$

By this definition $k(\mathbf{x},\mathbf{x}_n)$ becomes the weight of t_n when computing the mean of the predictive distribution $\phi(\mathbf{x})^T\mathbf{w}_B$ at the input location $\mathbf{x}$.

Part 3.

We use the following derivation:

$$\begin{aligned}
\mathbf{K} &= \begin{pmatrix} k(\mathbf{x}_1,\mathbf{x}_1) & & \cdots & & k(\mathbf{x}_1,\mathbf{x}_K) \\ & \ddots & & & \\ \vdots & & k(\mathbf{x}_n,\mathbf{x}_k) & & \vdots \\ & & & \ddots & \\ k(\mathbf{x}_N,\mathbf{x}_1) & & \cdots & & k(\mathbf{x}_N,\mathbf{x}_K) \end{pmatrix} \\
&= \begin{pmatrix} q\phi(\mathbf{x}_1)^T\mathbf{Q}^{-1}\phi(\mathbf{x}_1) & & \cdots & & q\phi(\mathbf{x}_1)^T\mathbf{Q}^{-1}\phi(\mathbf{x}_K) \\ & \ddots & & & \\ \vdots & & q\phi(\mathbf{x}_n)^T\mathbf{Q}^{-1}\phi(\mathbf{x}_k) & & \vdots \\ & & & \ddots & \\ q\phi(\mathbf{x}_N)^T\mathbf{Q}^{-1}\phi(\mathbf{x}_1) & & \cdots & & q\phi(\mathbf{x}_N)^T\mathbf{Q}^{-1}\phi(\mathbf{x}_K) \end{pmatrix} \\
&= q\begin{pmatrix} \phi(\mathbf{x}_1)^T \\ \vdots \\ \phi(\mathbf{x}_N)^T \end{pmatrix}\mathbf{Q}^{-1}\begin{pmatrix} \phi(\mathbf{x}_1) \\ \vdots \\ \phi(\mathbf{x}_K) \end{pmatrix} \\
&= q\boldsymbol{\Phi}\mathbf{Q}^{-1}\boldsymbol{\Phi}^T.
\end{aligned}$$

Hence proved.

Part 4.

Given $\lambda = 0$, the proof is the following:

$$\mathbf{K} = q\boldsymbol{\Phi}(\delta\mathbf{I} + q\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T = \boldsymbol{\Phi}(\lambda\mathbf{I} + \boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T = \boldsymbol{\Phi}(\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T = \mathbf{H}.$$