

Computational Statistics-Report

David Niederkofler, Erlend Lokna

2022-12-01

```
mydata<-read.table("Report2_Dataset.txt", header=FALSE)
```

Statistical Analysis of Covariates

It is important to mention the use of notation before we proceed. We will in this section use the notation $\mathbf{x} = \{x_1, x_2, \dots, x_n\}$ as our covariate vector.

Bernoulli - Beta, Ascicles

Since the Ascicles - covariate has a 0-1 outcome we can assume that it is Bernoulli distributed with parameter θ . A natural conjugate prior for the Bernoulli distribution is the Beta distribution. Therefore we have the following initial information:

$$\begin{aligned}f(x_i|\theta) &= \theta^{x_i}(1-\theta)^{1-x_i} \\L(\mathbf{x}|\theta) &= \theta^{\sum_{i=1}^n x_i}(1-\theta)^{n-\sum_{i=1}^n x_i} \\h(\theta) &= \text{Beta}(a, b)\end{aligned}$$

We proceed by calculating the posterior distribution for θ

$$\begin{aligned}h(\theta|\mathbf{x}) &\propto L(\mathbf{x}|\theta)h(\theta) = \theta^{\sum_{i=1}^n x_i}(1-\theta)^{n-\sum_{i=1}^n x_i} \frac{1}{B(a, b)} \theta^{a-1}(1-\theta)^{b-1} I(0 < \theta < 1) \\&\propto \text{Beta}(\theta|a + \sum_{i=1}^n x_i, b + n - \sum_{i=1}^n x_i)\end{aligned}$$

1.1 Model selection

1.2 Results

1. Sex

The sex of the patients is encoded in a binary variable, where 0 means *male* and 1 means *female*.

1.1 Model selection

We assume a Bernoulli model $Ber(\theta)$ for the sex of the patient conditional on one parameter θ , the probability of the patient to be female. The density function is given by

$$f(x|\theta) = \theta^x(1-\theta)^{1-x}, \quad (1)$$

where $x \in \{0, 1\}$. As a prior distribution for θ we use the natural conjugate family of the Bernoulli distribution, namely the Beta distribution, $\text{Beta}(a, b)$, with two shape parameters $a = b = 2$ to give more weight to the middle of the interval $[0, 1]$, knowing how females and males are represented in the general population.

1.2 Results

From the given dataset we get the sample size n and the sum of the observations s :

```
n<-length(mydata$V6[!is.na(mydata$V6)])
s<-sum(mydata$V6)
n
```

```
## [1] 312
```

```
s
```

```
## [1] 276
```

Therefore the posterior distribution is $Beta(2 + s, 2 + n - s)$, which turns out to be $Beta(278, 38)$. From that we get

```
## Posterior mean: 0.8797468
```

```
## Posterior mode: 0.8821656
```

```
## Posterior 95% Confidence Interval: [ 0.8417454 , 0.9132003 ]
```

And the HPD confidence Interval calculates to:

```
tst<-rbeta(1e5,278,38)
hdi(tst)
```

```
##      lower      upper
## 0.8433167 0.9141901
## attr(,"credMass")
## [1] 0.95
```