

Worksheet 04 Group 2

Andrea Staub

Emanuel Mauch

Holly Vuarnoz

Jan Hohenheim

Sophie Haldemann

```
library(tidyverse)
library(rjags)
library(coda)
library(bayesmeta)
library(pCalibrate)
library(glue)
```

Exercise 2

TODO

Exercise 3

1

Explain step by step in your own words what the code in 04MHSampler.R is doing.

Preparation:

- Store the dosage values, centered dosage values, number of deaths, and total number of mice in vectors
- Creating a function that takes the intercept and slope (α and β) and x (dosage) as input and returns the inverse logit function of $\alpha + \beta x$, i.e. it projects it onto a logistic scale between 0 and 1 to return the corresponding p , which is the probability of death.
- Defining number of iterations; burn-in length; thinning parameter; and standard deviations for the normal proposals
- Preparing empty vectors to store the sampled alpha and betas; a variable to record the number of accepted proposals; initial start values for alpha and beta; and a counter that will track the counts of the for-loop
- The for-loop is set up to go from $-\text{burninlength}$ to the number of desired iterations

For-Loop:

1. At the beginning of each loop, the counter is updated by 1 (however it's not really needed)
2. A new proposal for alpha is sampled from the proposal distribution, which is a univariate normal distribution centered around the current alpha with a pre-defined standard deviation (tuning parameter).
3. The inverse-logit function transforms $\alpha^* + \beta x$ into probability of death π on a scale from 0 to 1. X is a vector of dosages so it returns a vector of π 's. The π 's are then passed as parameters to the binomial distribution function to calculate the log-likelihood of the observed proportions of dead mice given the corresponding π . The log-likelihood is then added to the log of the prior density for the current α^* value. The prior follows a normal distribution with mean 0 and an assumed standard deviation. The sum of the log-likelihood and the log-prior is proportionate to the log-posterior.
4. Step 3 is done again but this time with the current/old alpha value, instead of the proposed alpha.
5. IF the difference of the new log-posterior minus the old log-posterior is larger than a random value sampled from a standard uniform distribution, the new proposed alpha gets accepted and is now considered the current alpha. If not, the current alpha stays the same.
6. Only if burn-in period is finished, i.e. if $i \geq 1$ (otherwise this step is skipped): the acceptance counter `alpha_yes` is raised by 1 if the proposed alpha was accepted in the previous step.
7. Still within the same iteration, steps 2-6 are now repeated but for the beta parameter (slope)
8. Only if burn-in period is finished, i.e. if $i \geq 1$ (otherwise this step is skipped): the alpha and beta samples are stored in their corresponding vector. They are stored whether the values got accepted or not. If the thinning parameter k is $\neq 1$, only every k 'th sample is stored in the vector.
9. Only if burn-in period is finished, i.e. if $i \geq 1$ (otherwise this step is skipped): the acceptance rates are printed for every 1000th iteration, to keep track of the algorithm. The acceptance rate is the number of accepted alphas resp. betas divided by the number of iterations (excluding the burn-in period).

2

Comment on the differences in traceplots, auto-correlations (`acf()`) and cross-correlations depending on the tuning parameters' choice. What are the reasons for observed differences?

```
rm(list=ls())

# inverse logit: logit-1(alpha + beta*x)
mypi <- function(alpha, beta, x){
  tmp <- exp(alpha + beta*x)
  pi <- tmp/(1+tmp)
  return(pi)
}

## Metropolis-Hastings for logistic model
## Two independent normal proposals

# the covariate values (dose)
x_original <- c(0.0028, 0.0028, 0.0056, 0.0112, 0.0225, 0.0450)
# the centered covariate values
x <- x_original - mean(x_original)
# number of mice deaths
y <- c(26, 9, 21, 9, 6, 1)
# total number of mice
n <- c(28, 12, 40, 40, 40, 40)

# Assumption
# variance of normal priors
sigma2 <- 104

# inverse logit: logit-1(alpha + beta*x)
mypi <- function(alpha, beta, x){
  tmp <- exp(alpha + beta*x)
  pi <- tmp/(1+tmp)
  return(pi)
}

## Step 1: R: (univariate proposal) Metropolis MCMC settings

# number of MCMC iterations
n.iter <- 10000
# burnin length
n.burnin <- 4000
# thinning parameter
n.thin <- 1
#n.thin <- floor((n.iter-n.burnin)/500)

## Putting everything into a function to then call it for tuning parameters
## univariate random walk proposals ##
MCMC_MH <- function(s_alpha, s_beta){ # Input: SD's of proposal distributions

  set.seed(44566)
  alpha_samples <- c()
  beta_samples <- c()
}
```

```

# number of accepted proposals
alpha_yes <- 0
beta_yes <- 0

# starting values
alpha <- 0
beta <- 0
# counter
count <- 0

# start the MCMC algorithm (the first iteration after the burn-in is 1)
for(i in -n.burnin:(n.iter*n.thin)){
  count <- count +1

  ## update alpha
  # generate a new proposal for alpha
  alpha_star <- rnorm(1, alpha, sd=s_alpha)
  # NOTE: it is more stable to calculate everything on the log scale
  enum <- sum(dbinom(y, size=n, prob=mypi(alpha_star, beta, x), log=TRUE)) +
    dnorm(alpha_star, mean=0, sd=sqrt(sigma2), log=TRUE)
  denom <- sum(dbinom(y, size=n, prob=mypi(alpha, beta, x), log=TRUE)) +
    dnorm(alpha, mean=0, sd=sqrt(sigma2), log=TRUE)

  # log acceptance rate (since we use a random walk proposal there is no
  # proposal ratio in the acceptance probability)
  logacc <- enum - denom
  if(log(runif(1)) <= logacc){
    # accept the proposed value
    alpha <- alpha_star

    if(i > 0){ # count proposed value only after burnin-period
      alpha_yes <- alpha_yes + 1
    }
  }

  ## update beta
  # generate a new proposal for beta
  beta_star <- rnorm(1, beta, sd=s_beta)
  enum <- sum(dbinom(y, size=n, prob=mypi(alpha, beta_star, x), log=TRUE)) +
    dnorm(beta_star, mean=0, sd=sqrt(sigma2), log=TRUE)
  denom <- sum(dbinom(y, size=n, prob=mypi(alpha, beta, x), log=TRUE)) +
    dnorm(beta, mean=0, sd=sqrt(sigma2), log=TRUE)
  # log acceptance rate
  logacc <- enum - denom

  if(log(runif(1)) <= logacc){
    # accept the proposed value
    beta <- beta_star

    if(i > 0){ # count proposed value only after burnin-period
      beta_yes <- beta_yes + 1
    }
  }
}

```

```

# after the burnin save every kth sample
if((i > 0) && (i%n.thin == 0)){
  alpha_samples <- c(alpha_samples, alpha)
  beta_samples <- c(beta_samples, beta)
}
#if(i%%1000 == 0){ # skipping this
  # print the acceptance rates on the fly
  # cat(c(i, alpha_yes/i, beta_yes/i), "\n")
  #}
}

## Plot results:

# Traceplots
print(glue("Traceplots:\n"))
par(mfrow = c(1,2),mar = c(8, 5, 8, 1))
plot(alpha_samples, type = "l", ylab = "Alpha", xlab = "Iteration")
plot(beta_samples, type = "l", ylab = "Beta", xlab = "Iteration")

# Autocorrelation plots
print(glue("Autocorrelation and Cross-Correlation:"))
par(mfrow = c(1,3), mar = c(8, 4, 12, 1), oma = c(1,1,3,1) )
acf(alpha_samples, ylab = "ACF for alpha", main = "")
acf(beta_samples, ylab = "ACF for beta", main = "")

# Crosscorrelation
ccf(alpha_samples, beta_samples, ylab = "Cross Correlation", main = "")

# Acceptance Rates
acceptance_alpha <- alpha_yes/length(alpha_samples)
acceptance_beta <- beta_yes/length(beta_samples)
print(glue("Acceptance rate alpha: {acceptance_alpha} "))
print(glue("Acceptance rate beta: {acceptance_beta} "))

# Return MCMC and acceptance rate for alpha and beta
return( list(alpha_samples, beta_samples, acceptance_alpha, acceptance_beta ) )
}

```

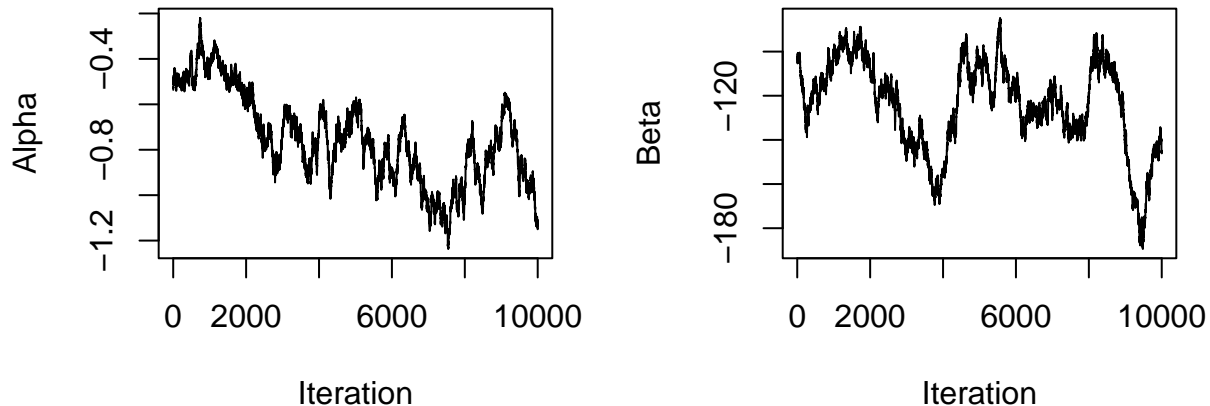
Now calling the function `MCMC_MH` to show the results:

```
# Defining 3 different sets of tuning parameters
s_alpha <- c(0.01, 1, 50)
s_beta  <- c(1, 100, 5000)
```

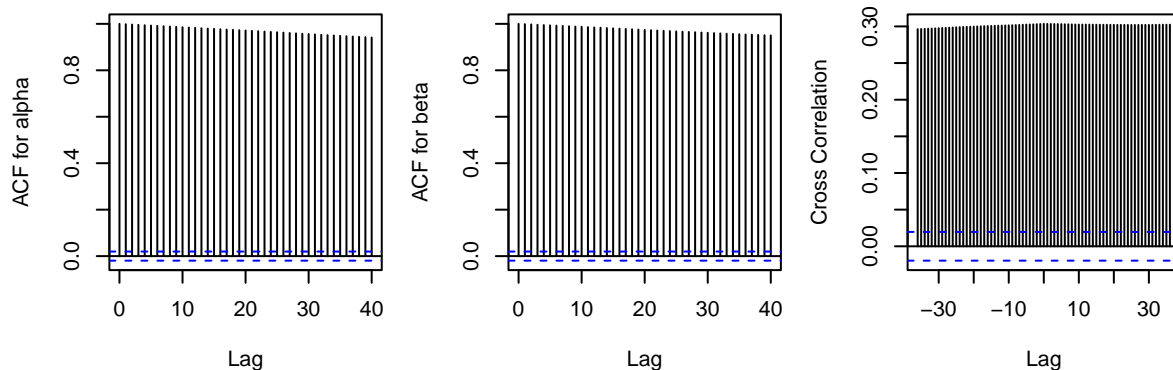
Results for low tuning parameters (0.01, 1):

```
MCMC_1_result <- MCMC_MH(s_alpha[1], s_beta[1])
```

Traceplots:



Autocorrelation and Cross-Correlation:



```
## Acceptance rate alpha: 0.9771
```

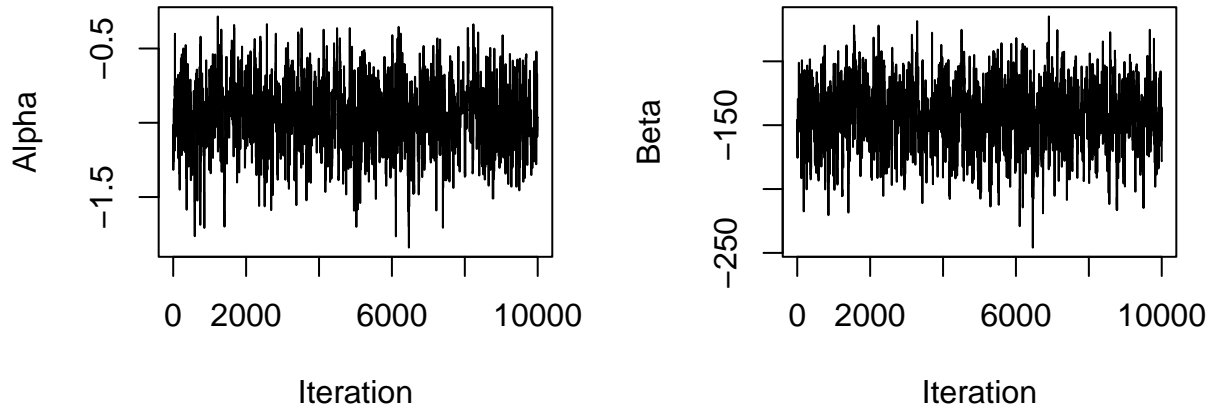
```
## Acceptance rate beta: 0.9816
```

The tuning parameters are the SDs of the proposal distributions for alpha and beta. With small tuning parameters, the proposal distributions are narrow. The new alpha and beta values are likely to be very close to the previous alpha and beta values, the exploration of the parameter space is done in small steps, so there is high autocorrelation and cross-correlation over many lags. The sampler doesn't take any "big risks" and so the acceptance rate is very high, but it doesn't explore the parameter space well. Also it can drift off and then it takes a lot of iterations to get back again to the region of high posterior density. It's not stationary.

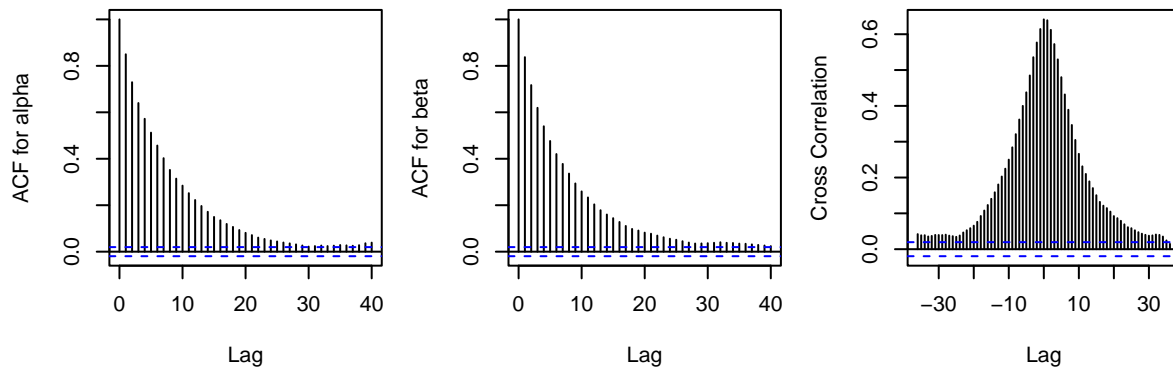
Results for medium tuning parameters (1, 100):

```
MCMC_2_result <- MCMC_MH(s_alpha[2], s_beta[2])
```

Traceplots:



Autocorrelation and Cross-Correlation:



Acceptance rate alpha: 0.2147

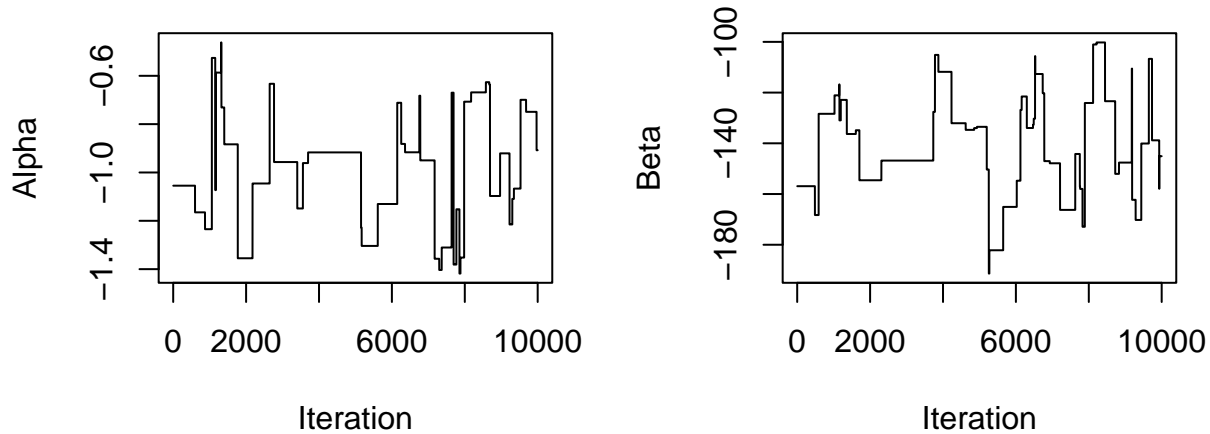
Acceptance rate beta: 0.2295

With optimal SDs for the proposal distributions, the sampler has a good balance between exploration of the parameter space and acceptance rate. The traceplot is stationary. The sampler moves rapidly across the whole parameter space without getting stuck, leading to the characteristic caterpillar shape, and autocorrelation and cross-correlation quickly decaying to zero.

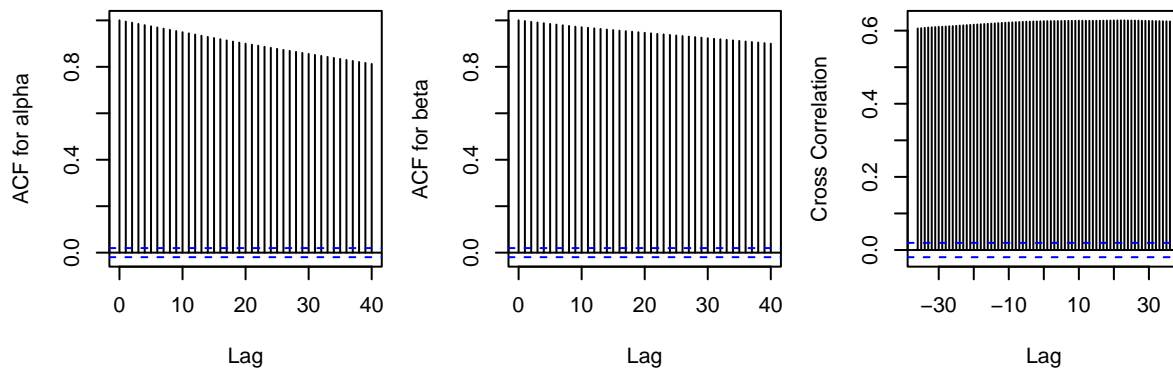
Results for high tuning parameters (50, 5000):

```
MCMC_3_result <- MCMC_MH(s_alpha[3], s_beta[3])
```

```
## Traceplots:
```



```
## Autocorrelation and Cross-Correlation:
```



```
## Acceptance rate alpha: 0.0043
```

```
## Acceptance rate beta: 0.0051
```

Here the SDs of the proposal distributions are large, leading to “adventurous” exploration, so the sampler often proposes parameter values far outside in the parameter space, under which the data is unlikely, leading to low acceptance rates. Due to low acceptance rates, the chain is often stuck at the same value over several iterations, leading to these skyline-like traceplots with constant values over several iterations and thus high autocorrelation over many lags. Only sporadically there’s a big jump when the sampler proposes a value that is accepted by chance. There is also high cross-correlation over many lags because the samples stay constant over many iterations.

3

Under which condition the optimal acceptance rate of about 0.2-0.4 (“rule of thumb”) is attained?

With medium tuning parameters (1, 100), the acceptance rates are optimal:

Acceptance rate alpha: 0.2147 Acceptance rate beta: 0.2295

4

Provide summaries (mean, sd, 0.025, 0.5, 0.975 quantiles) of the marginal posteriors for alpha and beta for the middle choice of tuning parameters.

```
alphas_2 <- unlist(MCMC_2_result[1])

glue("Mean alpha: {formatC(mean(alphas_2), 3)} ")
glue("SD alpha: {formatC(sd(alphas_2), 3)} ")
glue("Quantiles:")
quantile(alphas_2, c(0.025, 0.5, 0.975) )
```

```
## Mean alpha: -0.95
## SD alpha: 0.225
## Quantiles:
##      2.5%      50%      97.5%
## -1.3975759 -0.9352910 -0.5340364
```

```
betas_2 <- unlist(MCMC_2_result[2])

glue("Mean beta: {formatC(mean(betas_2), 3)} ")
glue("SD beta: {formatC(sd(betas_2), 3)} ")
glue("Quantiles:")
quantile(betas_2, c(0.025, 0.5, 0.975) )
```

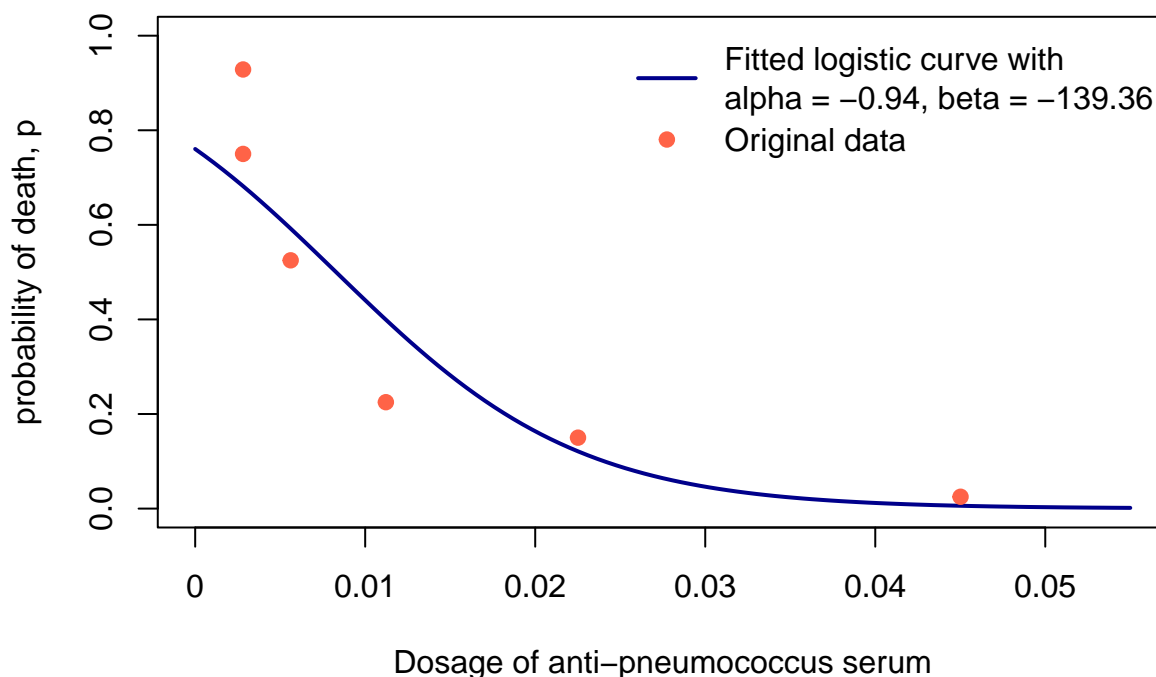
```
## Mean beta: -141
## SD beta: 24.4
## Quantiles:
##      2.5%      50%      97.5%
## -192.37525 -139.35901 -98.32787
```

Plot the logistic curve for median posterior values of alpha and beta together with data and interpret the result.

```
median_alpha <- median(alphas_2)
median_beta <- median(betas_2)

curve( mypi(median_alpha, median_beta, x), from = -0.015, to = 0.04, ylim = c(0,1),
       xlab = "Dosage of anti-pneumococcus serum",
       ylab = "probability of death, p", xaxt = 'n', col = "darkblue", lwd = 2,
       main = "Higher dosages reduce probability of death" )
# Converting the dosages back to the uncentered, original values
breaks <- seq(-0.015, 0.04, by = 0.01)
axis(1, at = breaks, labels = as.character(round(breaks + mean(x_original), 2)) )
points(x, y/n, pch = 19, col = "tomato")
legend("topright",
       legend = c( paste0("Fitted logistic curve with \nalpha = ", round(median_alpha, 2),
                           ", beta = ", round(median_beta,2) ), "Original data"),
       bty = "n", col = c("darkblue", "tomato"), lty = c(1,NA), pch = c(NA,19), lwd = c(2,NA) )
```

Higher dosages reduce probability of death



The modelled logistic curve is a good fit for the data, but it might slightly underestimate p for very low dosages. High dosages lead to lower probability of death, which is reflected in the negative beta value, and p is basically zero for dosages higher than 0.045. Of course, if the dosage would be extremely high, this might again be fatal, but this was not modelled here.