

Inhomogeneous HMMs

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This vignette explains how to fit inhomogeneous HMMs, i.e. models that depend on external covariates. Such inhomogeneity in HMMs can result from covariates affecting the transition probabilities of the underlying Markov chain, or covariates affecting the state-dependent distributions, which would then be called Markov-switching regression. We will begin with effects in the state process

Covariate effects in the state process

If covariates are affecting the transition probabilities, this means that we model the transition probability matrix as a function of those external covariates. Let z_t be a vector of covariates of length $p + 1$ for $t = 1, \dots, T$, where the first entry is always equal to 1 to include an intercept. Moreover, let β be a vector of regression parameters, also of length $p + 1$. We can now model all off-diagonal elements of the transition probability matrix by first considering the linear predictors

$$\eta_{ij}^{(t)} = \beta'_{ij} z_t,$$

for $t = 1, \dots, T$. As the transition probabilities need to be in the interval $(0, 1)$ and each row of the transition matrix needs to sum to one, we obtain the transition probabilities via the inverse multinomial logistic link as

$$\Pr(S_t = j \mid S_{t-1} = i) = \gamma_{ij}^{(t)} = \frac{\exp(\eta_{ij}^{(t)})}{\sum_{k=1}^N \exp(\eta_{ik}^{(t)})},$$

where η_{ii} is set to zero for $i = 1, \dots, N$ for identifiability, where N is the number of hidden states. The function `tpm_g()` conducts this calculation for all elements of the t.p.m. and all time points efficiently in C++.

At this point we want to point out that the definition of the transition probabilities is not necessarily unique. Indeed for data points at times $1, \dots, T$ we only need $T - 1$ transition probability matrices. The definition above means that the transition probability between $t - 1$ and t depends on the covariate values at time point t , but we could also have defined

$$\Pr(S_{t+1} = j \mid S_t = i) = \gamma_{ij}^{(t)}.$$

We point this out very clearly here, as for HMMs there is no established convention, so this choice can be made by users and can be important when the exact timing of the covariate effect is relevant. In `Lcpp` this comes down to either passing the design matrix excluding its first or last row to `tpm_g()`, where we use the first option in this vignette. If you forget to exclude the first or the last row of the design matrix when calculating all transition matrices, and pass an array of dimension `c(N,N,T)` to `forward_g()` for likelihood evaluation, the function will revert to the first option by just ignoring the first slice of the array.

Setting parameters for simulation

We begin by setting parameters to simulate data from an inhomogeneous HMM. In this case we use normal state-dependent distributions. The covariate effects for the state process are fully specified by a parameter matrix of dimension `c(N*(N-1), p+1)`. By default the function `tpm_g()` will fill the off-diagonal elements

of each transition matrix by column, which can be changed by setting `byrow = TRUE`. The latter is useful, as popular HMM packages like `moveHMM` or `momentuHMM` return the parameter matrix such that the t.p.m. needs to be filled by row.

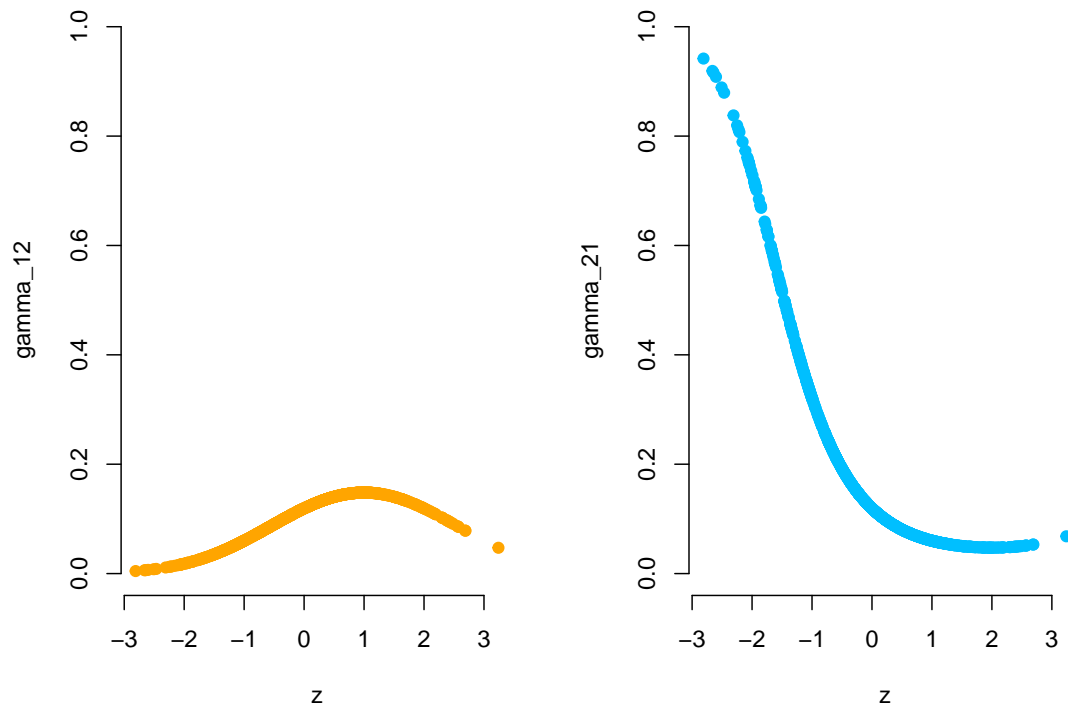
```
# parameters
mu = c(5, 20)
sigma = c(4, 5)

beta = matrix(c(-2, -2, # intercepts
               -1, 0.5, # linear effects
               0.25, -0.25), # quadratic effects
              nrow = 2)

n = 1000
set.seed(123)
z = rnorm(n) # in practice there will be n covariate values.
# However, we only have n-1 transitions, therefore we only need n-1 values:
Z = cbind(z, z^2) # quadratic effect of z
Gamma = tpm_g(Z = Z[-1,], beta) # of dimension c(2, 2, n-1)
delta = c(0.5, 0.5) # non-stationary initial distribution

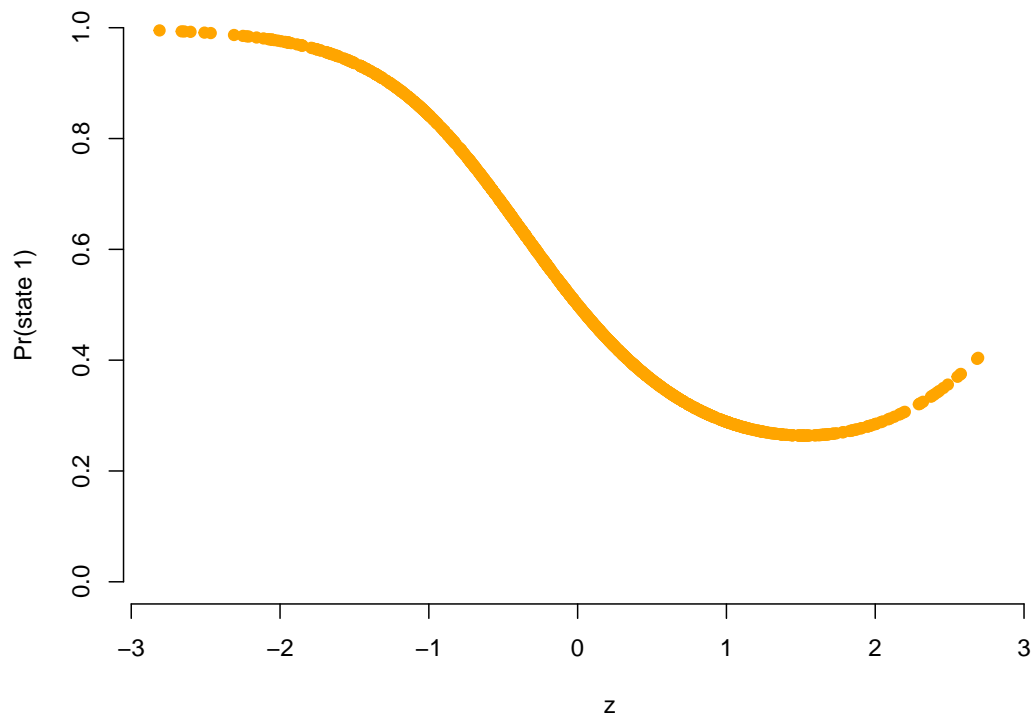
color = c("orange", "deepskyblue")

par(mfrow = c(1,2))
plot(z[-1], Gamma[1,2,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_12", col = color[1])
plot(z[-1], Gamma[2,1,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_21", col = color[2])
```



```
Delta = matrix(nrow = n-1, ncol = 2)
for(i in 1:(n-1)){ Delta[i,] = stationary(Gamma[,i]) }

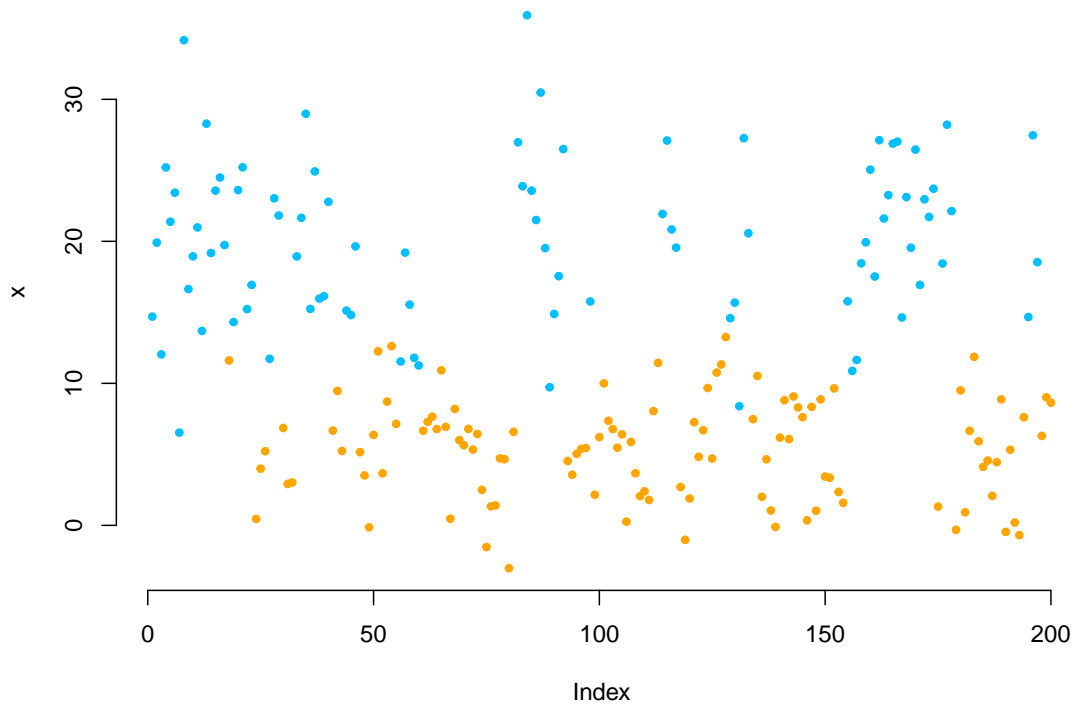
par(mfrow = c(1,1))
plot(z[-1], Delta[,1], pch = 19, bty = "n", ylim = c(0,1), xlab = "z",
     ylab = "Pr(state 1)", col = color[1])
```



Simulating data

```
s = x = rep(NA, n)
s[1] = sample(1:2, 1, prob = delta)
x[1] = rnorm(1, mu[s[1]], sigma[s[1]])
for(t in 2:n){
  s[t] = sample(1:2, 1, prob = Gamma[s[t-1],t-1])
  x[t] = rnorm(1, mu[s[t]], sigma[s[t]])
}

plot(x[1:200], bty = "n", pch = 20, ylab = "x",
     col = c(color[1], color[2])[s[1:200]])
```



Parametric modeling of the transition probabilities

We begin by modeling the transition probabilities parametrically, where we have a parameter for the intercept, the linear effect and the quadratic effect for each off-diagonal element of the t.p.m.

Writing the negative log-likelihood function

Here we specify the likelihood function and pretend we know the polynomial degree of the effect of z on the transition probabilities.

```
mllk = function(theta.star, x, Z){
  beta = matrix(theta.star[1:6], nrow = 2) # matrix of coefficients
  Gamma = tpm_g(Z[-1,], beta) # excluding the first covariate value -> n-1 tpms
  delta = c(1, exp(theta.star[7]))
  delta = delta / sum(delta)
  mu = theta.star[8:9]
  sigma = exp(theta.star[10:11])
  # calculate all state-dependent probabilities
  allprobs = matrix(1, length(x), 2)
  for(j in 1:2){ allprobs[,j] = dnorm(x, mu[j], sigma[j]) }
  # return negative for minimization
  -forward_g(delta, Gamma, allprobs)
}
```

Fitting an HMM to the data

```
theta.star = c(-2, -2, rep(0,4), # initializing with homogeneous tpm
              0, # starting value for initial distribution
```

```

      4, 14 ,log(3),log(5)) # starting values state-dependent process
t1 = Sys.time()
mod = nlm(mlk, theta.star, x = x, Z = Z)
Sys.time()-t1
#> Time difference of 0.2196231 secs

```

Really fast!

Visualizing results

Again, we use `tpm_g()` and `stationary()` to transform the parameters.

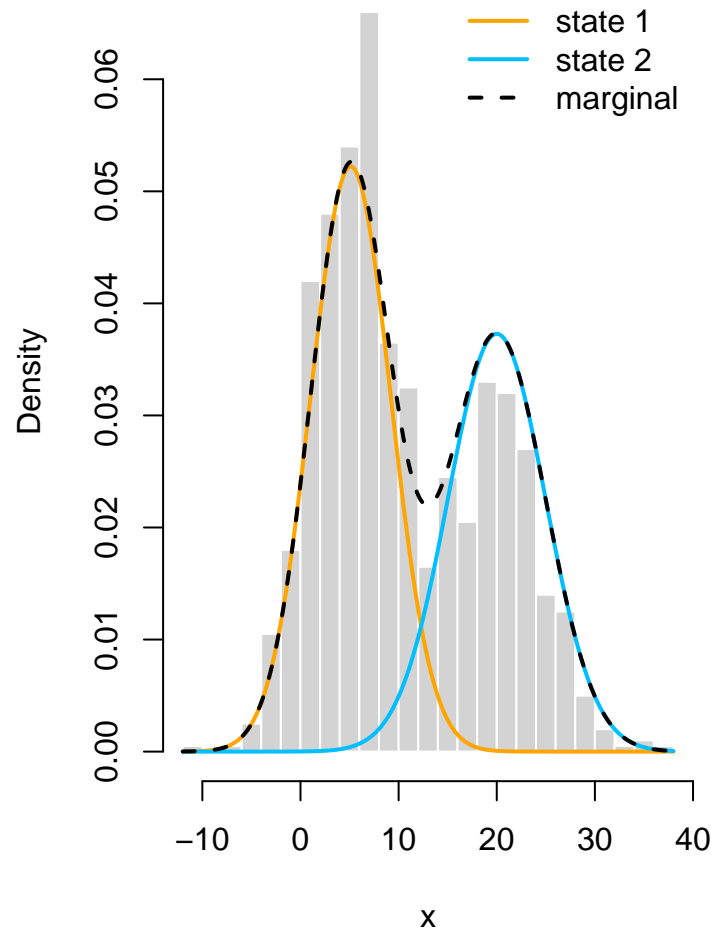
```

# transform parameters to working
beta_hat = matrix(mod$estimate[1:6], nrow = 2)
Gamma_hat = tpm_g(Z = Z[-1,], beta_hat)
delta_hat = c(1, exp(mod$estimate[7]))
delta_hat = delta_hat / sum(delta_hat)
mu_hat = mod$estimate[8:9]
sigma_hat = exp(mod$estimate[10:11])

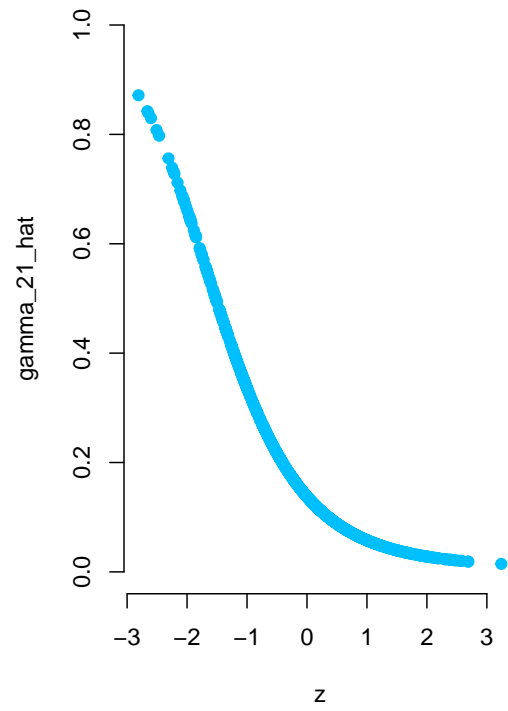
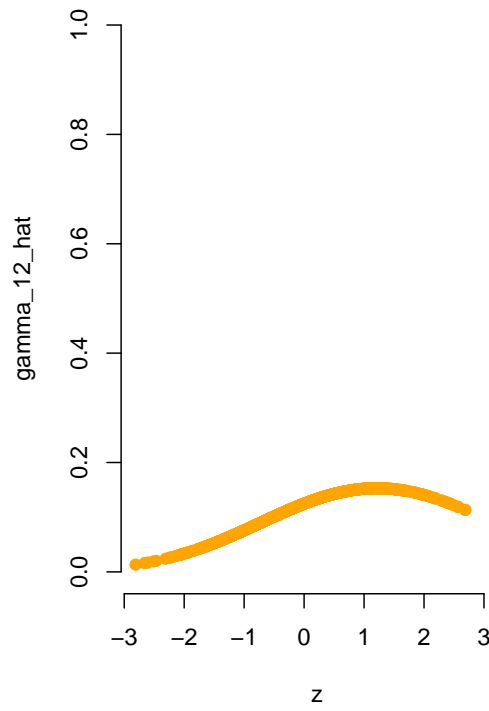
# we calculate the average state distribution overall all covariate values
Prob = matrix(nrow = n-1, ncol = 2)
for(i in 1:(n-1)){ Prob[i,] = stationary(Gamma_hat[,i]) }
prob = apply(Prob, 2, mean)

par(mfrow = c(1,2))
hist(x, prob = TRUE, bor = "white", breaks = 20, main = "")
curve(prob[1]*dnorm(x, mu_hat[1], sigma_hat[1]), add = TRUE, lwd = 2,
       col = color[1], n=500)
curve(prob[2]*dnorm(x, mu_hat[2], sigma_hat[2]), add = TRUE, lwd = 2,
       col = color[2], n=500)
curve(prob[1]*dnorm(x, mu_hat[1], sigma_hat[1])+
       prob[2]*dnorm(x, mu_hat[2], sigma_hat[2]),
       add = TRUE, lwd = 2, lty = "dashed", n = 500)
legend("topright", col = c(color[1], color[2], "black"), lwd = 2, bty = "n",
       lty = c(1,1,2), legend = c("state 1", "state 2", "marginal"))
par(mfrow = c(1,2))

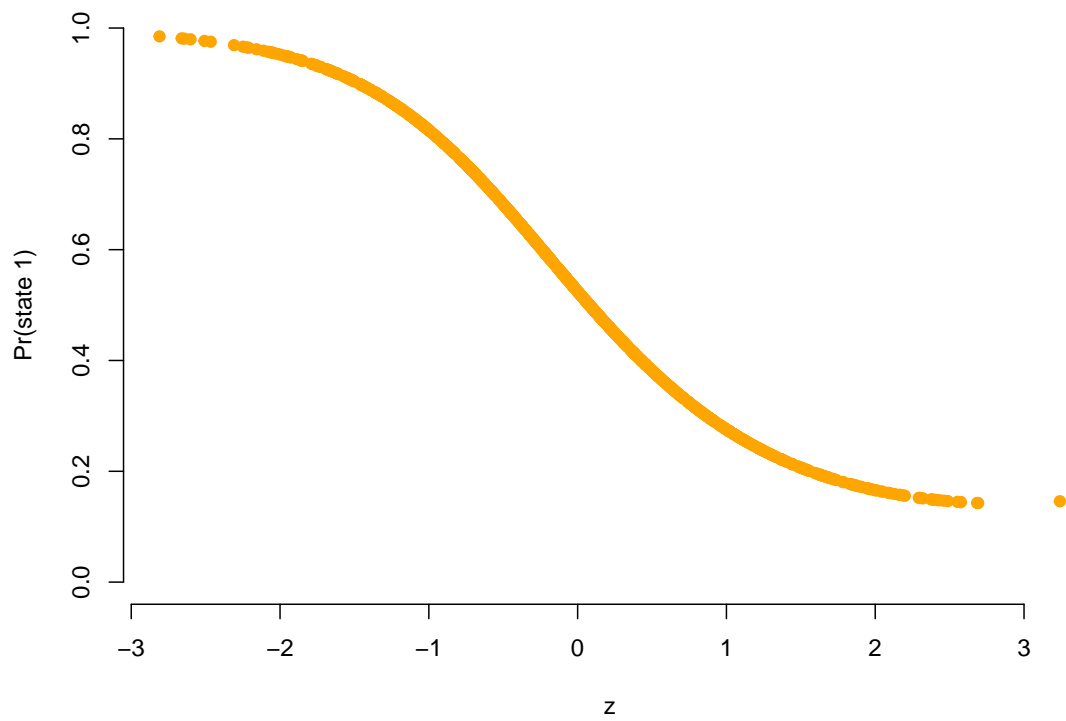
```



```
plot(z[-1], Gamma_hat[1,2,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_12_hat", col = color[1])
plot(z[-1], Gamma_hat[2,1,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_21_hat", col = color[2])
```



```
par(mfrow = c(1,1))
plot(z[-1], Prob[,1], pch = 19, bty = "n", ylim = c(0,1), xlab = "z",
      ylab = "Pr(state 1)", col = color[1])
```



Non-parametric modeling of the transition probabilities

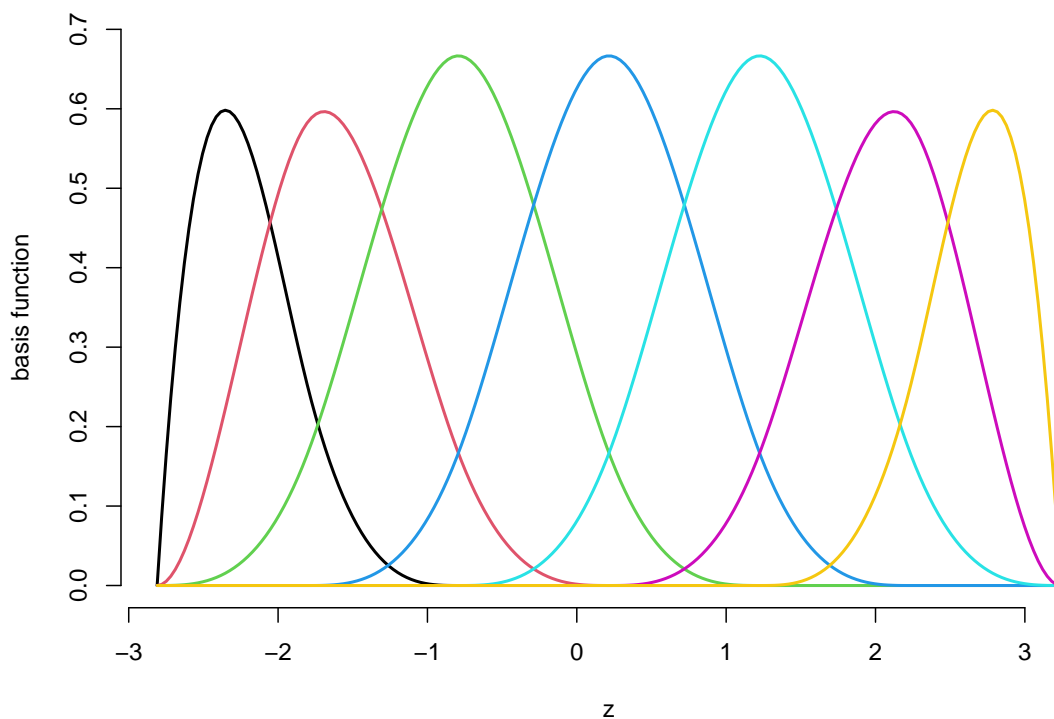
In practice, of course we do not know the exact form of the relationship between z and the transition probabilities. Therefore, `Lcpp` also makes non-parametric modeling trivially easy. Here we model the transition probabilities using P-splines. We do so in first calculating the design matrix using the `splines` package which we can easily be handled by `tpm_g()`.

Building the B-spline design matrix

```
Z = splines::bs(x = z, df = 6) ## B-spline design matrix

# visualizing the splines
zseq = seq(min(z), max(z), length = 200)
Zplot = splines::bs(x = zseq, df = 8)

plot(zseq, Zplot[,1], type = "l", lwd = 2, bty = "n",
      xlim = c(zseq[1], zseq[200]), ylim = c(0,0.7), xlab = "z", ylab = "basis function")
for(i in 2:(ncol(Zplot)-1)){
  lines(zseq, Zplot[,i], lwd = 2, col = i)
}
```



Writing the negative log-likelihood function

We only need to make small changes to the likelihood function. In general, a penalty for the curvature should also be added, which is done in the last lines.


```

mllk_np = function(theta.star, x, Z, lambda){
  beta = matrix(theta.star[1:(2+2*ncol(Z))], nrow = 2)
  Gamma = tpm_g(Z = Z[-1,], beta = beta) # calculating all tpms
  delta = c(1, exp(theta.star[2+2*ncol(Z)+1]))
  delta = delta / sum(delta)
  mu = theta.star[2+2*ncol(Z)+1+1:2]
  sigma = exp(theta.star[2+2*ncol(Z)+3+1:2])
  # calculate all state-dependent probabilities
  allprobs = matrix(1, length(x), 2)
  for(j in 1:2){ allprobs[,j] = dnorm(x, mu[j], sigma[j]) }
  # return negative for minimization
  l = forward_g(delta, Gamma, allprobs)
  # penalize curvature
  penalty = sum(diff(beta[1,-1], differences = 4)^2)+
    sum(diff(beta[2,-1], differences = 4)^2)
  return(-l + lambda*penalty)
}

```

Fitting a non-parametric HMM

```

theta.star = c(-2,-2, rep(0, 2*ncol(Z)), # starting values state process
              0, # starting value initial distribution
              4, 14 ,log(3),log(5)) # starting values state-dependent process
t1 = Sys.time()
mod_np = nlm(mllk_np, theta.star, x = x, Z = Z, lambda = 50)
# in this case we don't seem to need a lot of penalization
Sys.time()-t1
#> Time difference of 0.6035159 secs

```

The model fit is still quite fast for non-parametric modeling.

Visualizing results

Again, we use `tpm_g()` and `stationary()` to tranform the unconstraint parameters to working parameters.

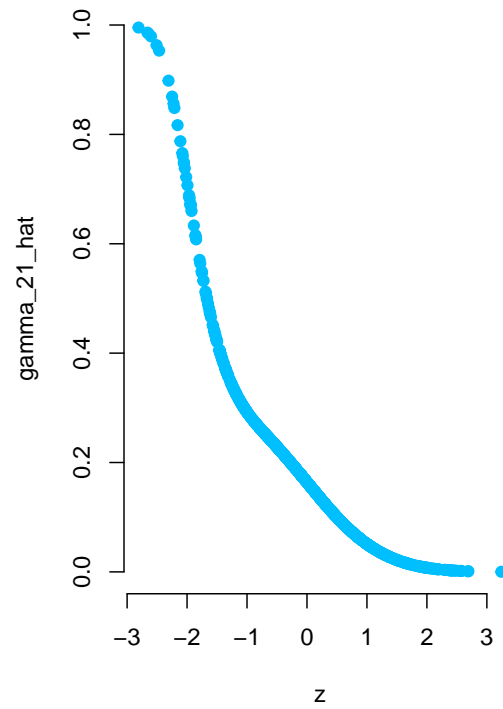
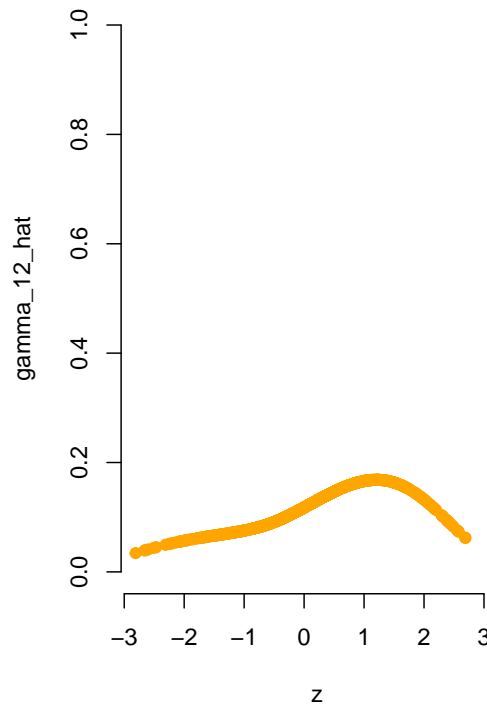
```

# transform parameters to working
beta_hat_np = matrix(mod_np$estimate[1:(2+2*ncol(Z))], nrow = 2)
Gamma_hat_np = tpm_g(Z = Z[-1,], beta = beta_hat_np)

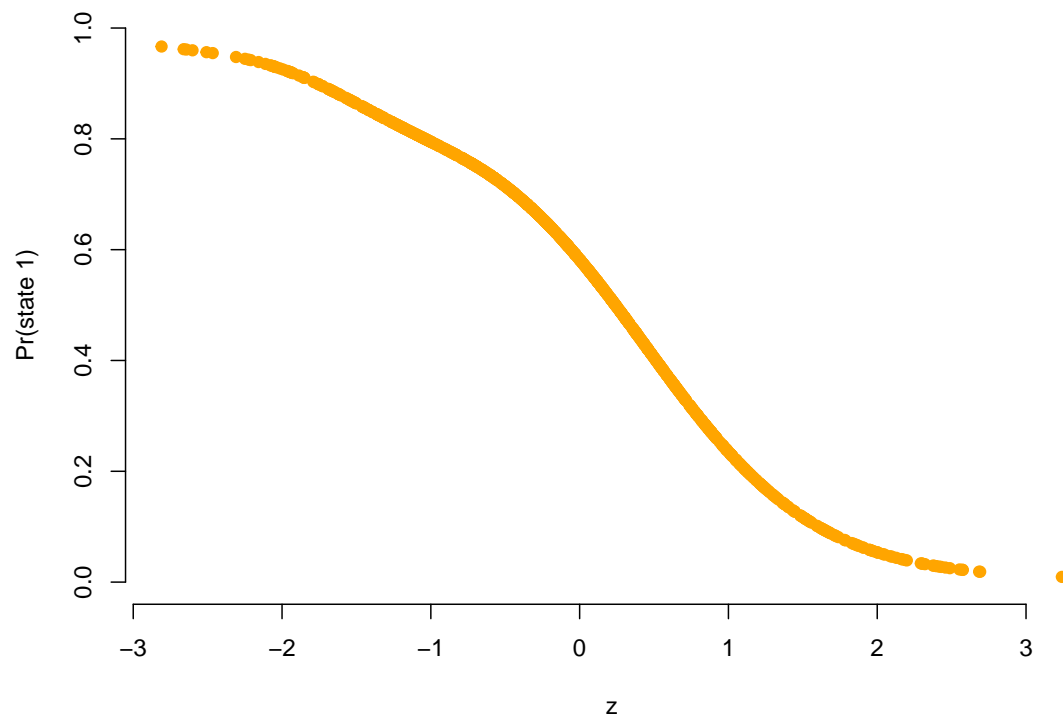
# we calculate the average state distribution overall all covariate values
Prob_np = matrix(nrow = n-1, ncol = 2)
for(i in 1:(n-1)){ Prob_np[i,] = stationary(Gamma_hat_np[,i]) }

# visualizing the Spline fit
par(mfrow = c(1,2))
plot(z[-1], Gamma_hat_np[1,2,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_12_hat", col = color[1])
plot(z[-1], Gamma_hat_np[2,1,], pch = 19, bty = "n", ylim = c(0,1),
     xlab = "z", ylab = "gamma_21_hat", col = color[2])

```



```
par(mfrow = c(1,1))
plot(z[-1], Prob_np[,1], pch = 19, bty = "n", ylim = c(0,1), xlab = "z",
      ylab = "Pr(state 1)", col = color[1])
```



Covariate effects in the state-dependent process

We now look at a setting, where covariates influence the mean of the state-dependent distribution, while the state switching is controlled by a homogeneous Markov chain. This is often called Markov-switching regression. Assuming the observation process to be conditionally normally distributed, this means

$$X_t | S_t = j \sim N(\beta_j' z_t, \sigma_j^2), \quad j = 1, \dots, N.$$

Setting parameters for simulation

```
sigma = c(1, 1)
# each row is now the vector of state-dependent regression parameters
beta = matrix(c(8, 10, # intercepts
               -2, 1, 0.5, -0.5), # covariate effects
              nrow = 2)
n = 1000
set.seed(123)
z = rnorm(n)
Z = cbind(z, z^2) # quadratic effect of z

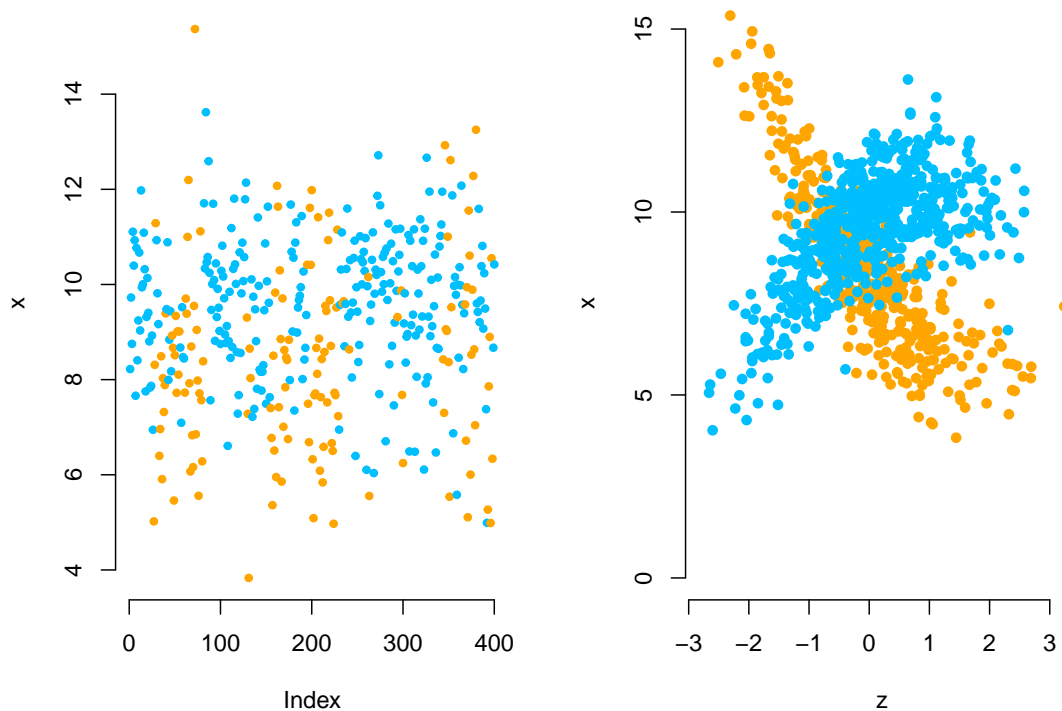
Gamma = matrix(c(0.9, 0.1, 0.05, 0.95), nrow = 2, byrow = TRUE) # homogeneous
delta = stationary(Gamma) # stationary Markov chain
```

Simulation

```
s = x = rep(NA, n)
s[1] = sample(1:2, 1, prob = delta)
x[1] = rnorm(1, beta[s[1],] %*% c(1, Z[1,]), # state-dependent regression
            sigma[s[1]])
for(t in 2:n){
  s[t] = sample(1:2, 1, prob = Gamma[s[t-1],])
  x[t] = rnorm(1, beta[s[t],] %*% c(1, Z[t,]), # state-dependent regression
            sigma[s[t]])
}

par(mfrow = c(1,2))
plot(x[1:400], bty = "n", pch = 20, ylab = "x",
     col = c(color[1], color[2])[s[1:400]])

plot(z[which(s==1)], x[which(s==1)], pch = 16, col = color[1], bty = "n",
     ylim = c(0,15), xlab = "z", ylab = "x")
points(z[which(s==2)], x[which(s==2)], pch = 16, col = color[2])
```



Parametric modeling of the state-dependent regressions

Writing the negative log-likelihood function

```
mllk_reg = function(theta.star, x, Z){
  Gamma = tpm(theta.star[1:2]) # homogeneous tpm
  delta = stationary(Gamma) # stationary Markov chain
  beta = matrix(theta.star[2+1:(2+2*2)], nrow = 2)
  sigma = exp(theta.star[2+2+2*2 +1:2])
  # calculate all state-dependent probabilities
  allprobs = matrix(1, length(x), 2)
  # state-dependent regression
  for(j in 1:2){ allprobs[,j] = dnorm(x, cbind(1,Z)%*%beta[j,], sigma[j]) }
  # return negative for minimization
  -forward(delta, Gamma, allprobs)
}
```

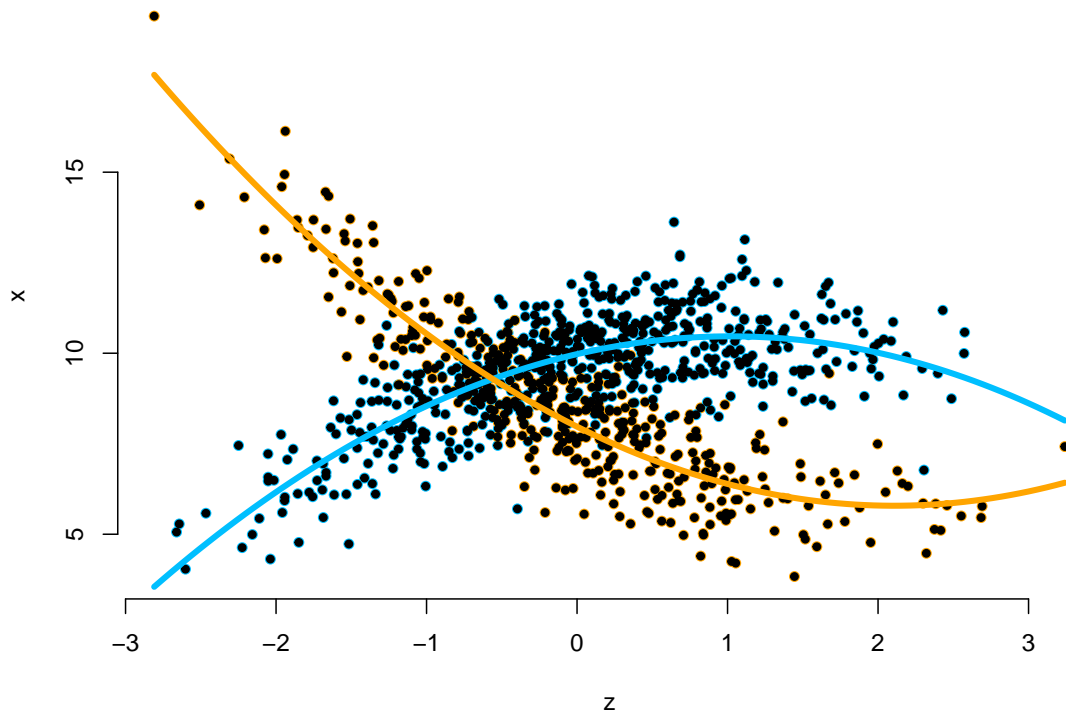
Fitting a Markov-switching regression model

```
theta.star = c(-2, -3, # starting values state process
              8, 10, rep(0,4), # starting values for regression
              log(1),log(1)) # starting values for sigma
t1 = Sys.time()
mod_reg = nlm(mllk_reg, theta.star, x = x, Z = Z)
Sys.time()-t1
#> Time difference of 0.04306984 secs
```

Visualizing results

```
Gamma_hat_reg = tpm(mod_reg$estimate[1:2]) # calculating all tpms
delta_hat_reg = stationary(Gamma_hat_reg)
beta_hat_reg = matrix(mod_reg$estimate[2+1:(2*2+2)], nrow = 2)
sigma_hat_reg = exp(mod_reg$estimate[2+2*2+2 +1:2])

# we have some label switching
plot(z, x, pch = 16, bty = "n", xlab = "z", ylab = "x", col = color[s])
points(z, x, pch = 20)
curve(beta_hat_reg[1,1] + beta_hat_reg[1,2]*x + beta_hat_reg[1,3]*x^2,
      add = T, lwd = 4, col = color[2])
curve(beta_hat_reg[2,1] + beta_hat_reg[2,2]*x + beta_hat_reg[2,3]*x^2,
      add = T, lwd = 4, col = color[1])
```



Non-parametric modeling of the state-dependent regressions

This is now a trivial task, just combining the previous two examples.

Again building the B-spline design matrix

```
Z = splines::bs(x = z, df = 6) ## B-spline design matrix
```

Writing the negative log-likelihood function

```

mllk_npreg = function(theta.star, x, Z, lambda){
  Gamma = tpm(theta.star[1:2]) # homogeneous tpm
  delta = stationary(Gamma) # stationary Markov chain
  beta = matrix(theta.star[2+1:(2+2*ncol(Z))], nrow = 2)
  sigma = exp(theta.star[2+2+2*ncol(Z) + 1:2])
  # calculate all state-dependent probabilities
  allprobs = matrix(1, length(x), 2)
  # state-dependent regression
  for(j in 1:2){ allprobs[,j] = dnorm(x, cbind(1,Z)%*%beta[j,], sigma[j]) }
  # return negative for minimization
  l = forward(delta, Gamma, allprobs)
  # penalize curvature
  penalty = sum(diff(beta[1,-1], differences = 3)^2)+
    sum(diff(beta[2,-1], differences = 3)^2)
  return(-l + lambda*penalty)
}

```

Fitting a non-parametric Markov-switching regression model

```

theta.star = c(-2,-3, # starting values state process
              8, 10, rep(0, 2*ncol(Z)), # starting values for regression
              log(1),log(1)) # starting values for sigma
t1 = Sys.time()
mod_npreg = nlm(mllk_npreg, theta.star, x = x, Z = Z, lambda = 10)
# small penalty
Sys.time()-t1
#> Time difference of 0.1946602 secs

```

Visualizing results

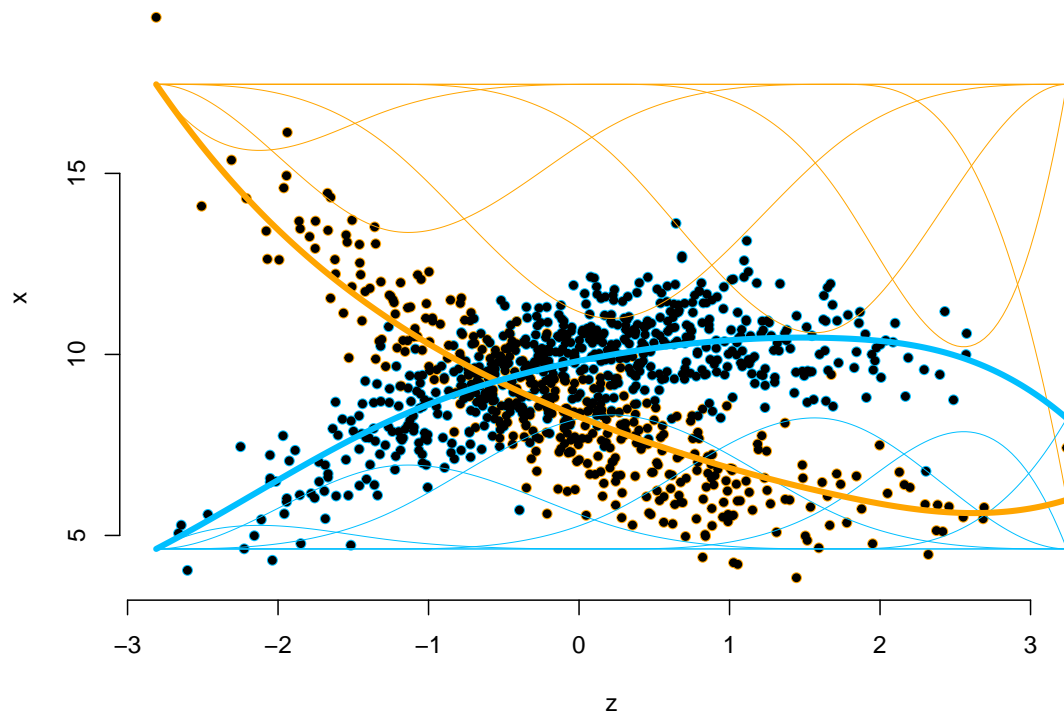
```

Gamma_hat_npreg = tpm(mod_npreg$estimate[1:2]) # calculating all tpms
delta_hat_npreg = stationary(Gamma_hat_npreg)
beta_hat_npreg = matrix(mod_npreg$estimate[2+1:(2+2*ncol(Z))], nrow = 2)
sigma_hat_npreg = exp(mod_npreg$estimate[2+2+2*ncol(Z) + 1:2])

zseq = seq(min(z), max(z), length = 200)
Zplot = splines::bs(x = zseq, df = 6)
xhat = cbind(1, Zplot)%*%t(beta_hat_npreg)

plot(z, x, pch = 16, bty = "n", xlab = "z", ylab = "x", col = color[s])
points(z, x, pch = 20)
for(j in 1:2){
  for(i in 1:ncol(Zplot)){
    lines(zseq, beta_hat_npreg[j,1] + Zplot[,i]*beta_hat_npreg[j,1+i], lwd = 0.3, col = color[j])
  }
}
lines(zseq, xhat[,1], lwd = 4, col = color[1])
lines(zseq, xhat[,2], lwd = 4, col = color[2])

```



References