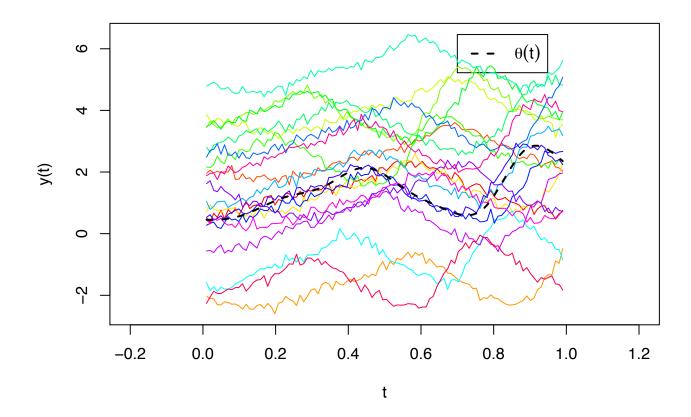
## paypop for sitar-type models

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## Generate data

```
# Number of samples
n < -20
# Number of observation points
m <- 100
# Observation points
t \leftarrow seq(0, 1, length = m + 2)[2:(m + 1)]
# Common basis function (both mean and amplitude variation)
kts \leftarrow seq(0, 1, length = 10)
basis_fct <- make_basis_fct(kts = kts, intercept = TRUE,</pre>
                              control = list(boundary = c(-0.5, 1.5)))
amp_fct <- make_basis_fct(type = 'intercept')</pre>
df <- attr(basis_fct, 'df')</pre>
# Generate true mean weights
beta_t \leftarrow rexp(df, 0.5)
# Generate random intercepts
b_t < rnorm(n, sd = 2)
# Generate warping function and random parameters
sigma <- 0.1
warp fct <- make warp fct(type = 'linear')</pre>
warp_cov_t \leftarrow matrix(c(2, 0.5, 0.5, 1), 2, 2)
w_t <- replicate(n, (t(chol(warp_cov_t)) %*% rnorm(2, sd = sigma))[, 1])</pre>
# Generate data
y <- lapply(1:n, function(i) {as.numeric(basis_fct(warp_fct(w_t[, i], t)) %*% beta_t
                                           + amp fct(t) %*% b t[i]
                                           + rnorm(m, sd = sigma))})
t <- lapply(1:n, function(x) t)
# Plot observations
plot(0, 0, xlim = c(-0.2, 1.2), ylim = range(y), type = 'n',
     xlab = 't', ylab = 'y(t)')
legend(0.7, range(y)[2], legend = expression(theta(t)), lty = 2, lwd = 2)
for (i in 1:n) lines(t[[i]], y[[i]], col = rainbow(n)[i])
lines(t[[1]], basis_fct(t[[1]]) %*% beta_t , lwd = 2, lty = 2)
```

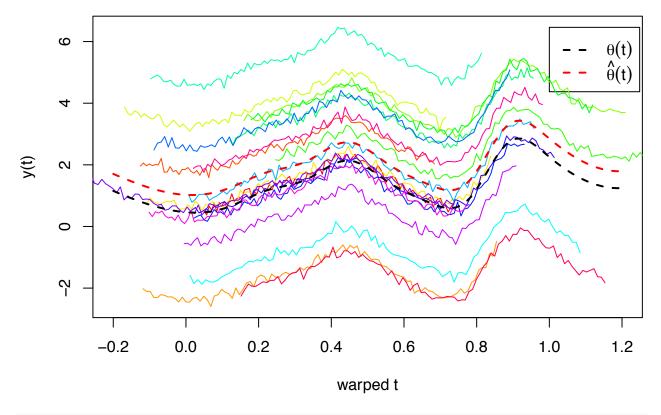


## paypop estimation

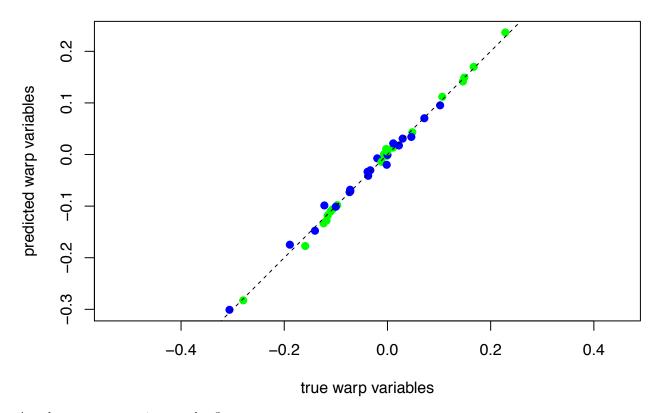
We now set up paypop to estimate in the sitar model

```
amp_cov <- make_cov_fct(id_cov, noise = FALSE)</pre>
warp_cov <- make_cov_fct(unstr_cov, param = c(1, 1, 0), noise = FALSE)</pre>
res <- pavpop(y, t, basis_fct, warp_fct, amp_cov, warp_cov, amp_fct, iter = c(10, 10))
                Inner
                            Estimates
                                6
                                                          98.67771 0.8286171 0.6685879 0.001
            1
                                    7
                                                 10 :
#> Linearized likelihood:
                             -7498.142
                                                          221.7119 1.032813 0.6209048 0.1720643
                2
                    3
                                6
                                    7
                                                 10 :
            1
#> Linearized likelihood:
                             -7905.568
                     221.7122 1.068347 0.6101104 0.1796776
#> Linearized likelihood:
                             -7953.722
                                6 7
                                                          281.1653 1.434581 0.7486549 0.2011374
                2
                    3
                                                 10 :
#> 4
            1
#> Linearized likelihood:
                             -8366.284
                     281.1658 1.4262 0.7460634 0.1781196
#> Linearized likelihood:
                             -8398.815
            1
                    3
                                6
                                   7
                                                 10 :
                                                          281.169 1.635282 0.8460421 0.2030552
                             -8592.755
#> Linearized likelihood:
                     281.1749 1.594797 0.7838515 0.1455889
#> Linearized likelihood:
                             -8604.034
                2
                    3
                                6 7
                                                 10 :
                                                          281.1803 1.643059 0.9271104 0.1973406
#> Linearized likelihood:
                             -8645.912
                     326.0857 1.613557 0.7838672 0.132576
#> Linearized likelihood:
                             -8651.483
```

#> 10 : 1 2 3 4 5 6 7 8 9 10 : 326.0858 1.621135 0.9840639 0.190829 #> Linearized likelihood: -8655.955



```
plot(as.numeric(w_t), as.numeric(res$w), xlab = 'true warp variables',
      ylab = 'predicted warp variables', pch = 19, col = c('green', 'blue'), asp = 1)
abline(0, 1, lty = 2)
```



Are the parameter estimates okay?

```
# Noise standard deviation: 0.1
res$sigma
#> [1] 0.1014726
# Amplitude standard deviations: 2
res$sigma * sqrt(res$amp_cov_par)
#>
      scale
#> 1.832377
# Warp covariance
# True
sigma^2 * warp_cov_t
#>
         [,1] [,2]
#> [1,] 0.020 0.005
#> [2,] 0.005 0.010
# Observed
cov(t(w_t))
                          [,2]
#>
              [,1]
#> [1,] 0.01647135 0.001772830
#> [2,] 0.00177283 0.008995296
```

```
# estimated
res$sigma^2 * warp_cov(1:2, res$warp_cov_par)

#> [,1] [,2]
#> [1,] 0.016692332 0.001964908
#> [2,] 0.001964908 0.010132608
```

## Traditional sitar estimation

```
library(sitar)

dat <- data.frame(x = unlist(t), y = unlist(y), id = rep(1:n, each = m))

res_sitar <- sitar(x = x, y = y, id = id, data = dat, df = 14)

plot(res_sitar, opt = 'd', xlim = c(-0.2, 1.2), ylim = range(y), lwd = 2, lty = 2, col = 'red', xlab = 'warped t', ylab = 'y(t)')
lines(t_p, basis_fct(t_p) %*% beta_t , lwd = 2, lty = 2)
legend(1, range(y)[2], legend = c(expression(theta(t)), expression(hat(theta)(t))), lty = 2, lwd = 2, col = c('black', 'red'))

# Plot warped curves
abc <- random.effects(res_sitar)
abc$a <- 0
warped <- with(dat, xyadj(x, y, id, res_sitar, abc))
for (i in 1:n)
    with(warped, lines(x[1:m + (i - 1) * m], y[1:m + (i - 1) * m], col = rainbow(n)[i]))</pre>
```

