

# Dynamic structural equation models

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```
library(tinyVAST)
set.seed(101)
```

tinyVAST includes features to fit a dynamic structural equation model. We here show this using a bivariate vector autoregressive model for wolf and moose abundance on Isle Royale.

```
data(isle_royale, package="dsem")

# Convert to long-form
data = expand.grid( "time"=isle_royale[,1], "var"=colnames(isle_royale[,2:3]) )
data$logn = unlist(log(isle_royale[2:3]))

# Define cross-lagged DSEM
dsem = "
  # Link, lag, param_name
  wolves -> wolves, 1, arW
  moose -> wolves, 1, MtoW
  wolves -> moose, 1, WtoM
  moose -> moose, 1, arM
  wolves -> moose, 0, corr
"

# fit model
mytiny = tinyVAST( dsem = dsem,
  data = data,
  times = isle_royale[,1],
  variables = colnames(isle_royale[,2:3]),
  formula = logn ~ 0 + var,
  control = tinyVASTcontrol(quiet=TRUE, trace=0) )
#> Warning in nlminb(start = opt$par, objective = obj$fn, gradient = obj$gr, : NA/NaN function evaluation
mytiny
#> $call
#> tinyVAST(formula = logn ~ 0 + var, data = data, dsem = dsem,
#>   times = isle_royale[, 1], variables = colnames(isle_royale[,
#>   2:3]), control = tinyVASTcontrol(quiet = TRUE, trace = 0))
#>
#> $opt
#> $opt$par
#>   alpha_j   alpha_j   beta_z   beta_z   beta_z   beta_z   beta_z   beta
#> 3.32526212 6.44165421 0.89304301 0.01420970 -0.11865018 0.86169482 -0.01539658 0.37749
#>
#> $opt$objective
#> [1] 5.781919
#>
```

```

#> $opt$convergence
#> [1] 0
#>
#> $opt$iterations
#> [1] 93
#>
#> $opt$evaluations
#> function gradient
#>      116      94
#>
#> $opt$message
#> [1] "relative convergence (4)"
#>
#>
#> $sdrep
#> sdreport(.) result
#>           Estimate Std. Error
#> alpha_j      3.32526212 2.483496e-01
#> alpha_j      6.44165421 2.116034e-01
#> beta_z       0.89304301 8.420632e-02
#> beta_z       0.01420970 1.279152e-01
#> beta_z      -0.11865018 6.477638e-02
#> beta_z       0.86169482 7.080269e-02
#> beta_z      -0.01539658 6.067738e-02
#> beta_z       0.37749042 3.503686e-02
#> beta_z       0.17052360 1.582618e-02
#> log_sigma -12.56122233 1.909999e+04
#> Maximum gradient component: 9.935109e-05
#>
#> $run_time
#> Time difference of 0.2885571 secs

```

And we can specifically inspect the estimated interaction matrix:

	wolves	moose
wolves	0.893	-0.119
moose	0.014	0.862

We can then compare this with package `dsem`

```

library(dsem)

# Keep in wide-form
dsem_data = ts( log(isle_royale[,2:3]), start=1959)
family = c("normal", "normal")

# initial first without delta0 (to improve starting values)
mydsem = dsem::dsem( sem = dsem,
  tsdata = dsem_data,
  control = dsem_control(quiet = TRUE),
  getsd = FALSE,
  family = family )

```

```

mydsem
#> $par
#>      beta_z      beta_z      beta_z      beta_z      beta_z      beta_z      beta_z
#> 0.895834720 0.007358847 -0.109332511 0.875012562 -0.017355229 0.378795847 -0.172873038 -1.
#>
#> $objective
#> [1] 7.739638
#>
#> $iterations
#> [1] 79
#>
#> $evaluations
#> function gradient
#>      96      80
#>
#> $time_for_MLE
#> Time difference of 0.07060909 secs
#>
#> $max_gradient
#> [1] 7.714655e-07
#>
#> $Convergence_check
#> [1] "There is no evidence that the model is not converged"
#>
#> $number_of_coefficients
#> Total Fixed Random
#>   133     9   124
#>
#> $AIC
#> [1] 33.47928
#>
#> $diagnostics
#>      Param starting_value Lower      MLE Upper final_gradient
#> 1  beta_z      0.01 -Inf 0.895834720 Inf 4.785205e-09
#> 2  beta_z      0.01 -Inf 0.007358847 Inf -5.078683e-09
#> 3  beta_z      0.01 -Inf -0.109332511 Inf -2.031211e-08
#> 4  beta_z      0.01 -Inf 0.875012562 Inf -5.821149e-08
#> 5  beta_z      0.01 -Inf -0.017355229 Inf -5.373382e-09
#> 6  beta_z      1.00 -Inf 0.378795847 Inf 2.119351e-09
#> 7  beta_z      1.00 -Inf -0.172873038 Inf -7.714655e-07
#> 8 lnsigma_j      0.00 -Inf -15.799262455 Inf 1.628788e-12
#> 9 lnsigma_j      0.00 -Inf -11.977331517 Inf 2.141499e-09
#>
#> $time_for_run
#> Time difference of 0.07218099 secs

```

where we again inspect the estimated interaction matrix:

	wolves	moose
wolves	0.896	-0.109
moose	0.007	0.875