

Package ‘tinyVAST’

September 20, 2026

Type Package

Title Multivariate Spatio-Temporal Models using Structural Equations

Version 1.6.3

Date 2026-09-19

Description Fits a wide variety of multivariate spatio-temporal models with simultaneous and lagged interactions among variables (including vector autoregressive spatio-temporal ('VAST') dynamics) for areal, continuous, or network spatial domains. It includes time-variable, space-variable, and space-time-variable interactions using dynamic structural equation models ('DSEM') as expressive interface, and the 'mgcv' package to specify splines via the formula interface. See Thorson et al. (2025) [doi:10.1111/geb.70035](https://doi.org/10.1111/geb.70035) for more details.

License GPL-3

Depends R (>= 4.1.0)

Imports corpcor, fmesher, igraph, Matrix (>= 1.3.0), methods, utils, mgcv, sf, sfnetworks, TMB (>= 1.9.17), units, checkmate, abind, sdmTMB, dsem (>= 3.0.0), insight, cv, sparseinv, gstat, cli, GpGp, GPvecchia

Suggests ggplot2, knitr, lattice, mvtnorm, pdp, rmarkdown, rnaturalearth, rnaturalearthdata, testthat, tweedie, viridisLite, visreg, plyr, DHARMA, glmmTMB, tibble, RANN

LinkingTo RcppEigen, TMB

VignetteBuilder knitr

Config/testthat/edition 3

Config/testthat/parallel true

Encoding UTF-8

LazyData true

LazyDataCompression xz

URL <https://vast-lib.github.io/tinyVAST/>

BugReports <https://github.com/vast-lib/tinyVAST/issues/>

Config/roxygen2/version 8.0.0

NeedsCompilation yes

Author James T. Thorson [aut, cre] (ORCID:

<<https://orcid.org/0000-0001-7415-1010>>),

Sean C. Anderson [aut] (ORCID: <<https://orcid.org/0000-0001-9563-1937>>)

Maintainer James T. Thorson <James.Thorson@noaa.gov>

Repository CRAN

Date/Publication 2026-09-20 18:30:02 UTC

Contents

add_mesh_covariates	3
add_predictions	5
alaska_sponge_coral_fish	6
atlantic_yellowtail	6
bering_sea	7
bering_sea_capelin_forecasts	7
bering_sea_pollock_ages	7
bering_sea_pollock_vast	8
cAIC	8
classify_variables	9
conditional_gmrf	10
condition_and_density	11
deviance_explained	11
Families	12
GetResponse.tinyVAST	13
get_data.tinyVAST	13
integrate_output	14
logLik.tinyVAST	18
make_dsem_ram	18
make_eof_ram	22
make_nngp_domain	23
make_sem_ram	23
parse_path	24
plot.nngp_domain	25
predict.tinyVAST	25
print.tinyVAST	26
project	27
red_grouper_diet	29
red_snapper	29
red_snapper_shapefile	30
reload_model	30
residuals.tinyVAST	31
rmvnorm_prec	31
rotate_pca	32

salmon_returns	34
sample_variable	34
sanity	36
sea_ice	36
sfnetwork_evaluator	37
sfnetwork_mesh	37
simulate.tinyVAST	38
simulate_sfnetwork	39
spatial_cor	40
summary.tinyVAST	40
term_covariance	42
tinyVAST	44
tinyVASTcontrol	48
vcov.tinyVAST	50
Index	52

add_mesh_covariates	<i>Add mesh covariates to vertices and triangles</i>
---------------------	--

Description

Interpolates covariate values from a data frame to mesh vertices using inverse distance weighting (IDW). Uses **gstat** for exact IDW interpolation by default, with an optional high-performance **RANN** method for very large datasets.

Usage

```
add_mesh_covariates(
  mesh,
  data,
  covariates,
  coords,
  power = 2,
  method = c("gstat", "rann"),
  k = 10,
  barrier = NULL
)
```

Arguments

mesh	A mesh object from fmesh or sdmTMB (for <code>sdmTMB::sdmTMB()</code> models only).
data	A data frame with coordinate columns and covariate columns, or an sf object.
covariates	Character vector of covariate column names to interpolate.
coords	Character vector of coordinate column names. Ignored if data is an sf object.

power	Numeric power parameter for inverse distance weighting (default 2; Euclidean squared decay).
method	Interpolation method. Options: "gstat" (default, exact inverse distance weighting using gstat package) or "rann" (fast k-nearest neighbours inverse distance weighting using RANN package for very large datasets).
k	Number of nearest neighbours to use for "rann" method (default 10). Ignored for "gstat" method.
barrier	Optional sf polygon object defining barrier regions. If provided, adds a logical barrier column to both vertex_covariates and triangle_covariates. E.g., in the case of modelling fish in the ocean, TRUE represents vertices/triangle centers over land and FALSE represents vertices/triangle centers over water. For triangles, also adds a barrier_proportion column indicating the proportion of each triangle's area that intersects with the barrier polygon (0 = no intersection, 1 = triangle completely within barrier).

Value

Modified mesh object with vertex_covariates and triangle_covariates elements added and class vertex_cov added. The vertex_covariates data frame contains covariate values interpolated at mesh vertices, and triangle_covariates contains covariate values interpolated at triangle centers.

Examples

```
library(sdmTMB)
library(sf)

# Regular data frame
mesh <- fmesher::fm_mesh_2d(pcod[, c("X", "Y")], cutoff = 10)
mesh_with_covs <- add_mesh_covariates(
  mesh,
  data = qcs_grid,
  covariates = c("depth"),
  coords = c("X", "Y")
)
head(mesh_with_covs$vertex_covariates)

# Visualize what we've done:
if (requireNamespace("ggplot2", quietly = TRUE)) {
  library(ggplot2)
  df <- as.data.frame(mesh_with_covs$loc[,1:2])
  df <- cbind(df, mesh_with_covs$vertex_covariates)
  ggplot() +
    geom_raster(data = qcs_grid, aes(X, Y, fill = depth), alpha = 0.7) +
    geom_point(data = df, aes(V1, V2, fill = depth),
      colour = "#00000010", pch = 21) +
    scale_fill_viridis_c(option = "G", trans = "log", direction = -1)

  df_tri <- mesh_with_covs$triangle_covariates
  ggplot() +
```

```

    geom_raster( data = qcs_grid, aes(X, Y, fill = depth), alpha = 0.7) +
    geom_point( data = df_tri, aes(x = .x_triangle, y = .y_triangle, fill = depth),
                colour = "#00000010", pch = 21) +
    scale_fill_viridis_c(option = "G", trans = "log", direction = -1)
  }

# Piped version
mesh_with_covs <- fmesher::fm_mesh_2d(pcod[, c("X", "Y")], cutoff = 10) |>
  add_mesh_covariates(
    qcs_grid,
    covariates = c("depth_scaled", "depth_scaled2"),
    coords = c("X", "Y")
  )

# With sf objects (coords automatically extracted)
pcod_sf <- st_as_sf(pcod, coords = c("X", "Y"))
grid_sf <- st_as_sf(qcs_grid, coords = c("X", "Y"))
mesh_sf <- fmesher::fm_mesh_2d(pcod_sf, cutoff = 10) |>
  add_mesh_covariates(grid_sf, c("depth"))

# With sdmTMB mesh (coordinate names and mesh automatically detected)
mesh <- make_mesh(pcod, c("X", "Y"), cutoff = 10) |>
  add_mesh_covariates(qcs_grid, c("depth"))

# Use RANN method for very large datasets (much faster)
mesh_fast <- fmesher::fm_mesh_2d(pcod[, c("X", "Y")], cutoff = 10) |>
  add_mesh_covariates(
    qcs_grid,
    covariates = c("depth_scaled", "depth_scaled2"),
    coords = c("X", "Y"),
    method = "rann",
    k = 15
  )

```

add_predictions	<i>Add predictions to data-list</i>
-----------------	-------------------------------------

Description

Given user-provided newdata, expand the object tmb_data to include predictions corresponding to those new observations

Usage

```
add_predictions(object, newdata, remove_origdata = FALSE)
```

Arguments

object	Output from <code>tinyVAST()</code> .
newdata	New data-frame of independent variables used to predict the response.
remove_origdata	Whether to remove original-data to allow faster evaluation. <code>remove_origdata=TRUE</code> eliminates information about the distribution for random effects, and cannot be combined with epsilon bias-correction. WARNING: feature is experimental and subject to change.

Value

the object `fit$tmb_inputs$tmb_data` representing data used during fitting, but with updated values for slots associated with predictions, where this updated object can be recompiled by TMB to provide predictions

`alaska_sponge_coral_fish`

Data to analyze sponge-coral-fish associations

Description

Data used in [Thorson et al. 2025](#) and copied from [Zenodo](#) to allow inclusion as a package vignette. This includes bottom-trawl samples of rockfish and flatfish from the Alaska Fisheries Science Center in the Gulf of Alaska and Aleutian Islands, and drop-camera samples of rockfish, flatfish, sponges, and corals from the Alaska Fisheries Science Center and funded by the Deep Sea Coral Initiative.

Usage

```
data(alaska_sponge_coral_fish)
```

`atlantic_yellowtail`

Northwest Atlantic yellowtail

Description

Data used to demonstrate and test seasonal spatio-temporal index standardization. Data are from [doi:10.1093/icesjms/fsaa074](https://doi.org/10.1093/icesjms/fsaa074)

Usage

```
data(atlantic_yellowtail)
```

bering_sea	<i>Survey domain for the eastern and northern Bering Sea surveys</i>
------------	--

Description

Shapefile defining the spatial domain for the eastern and northern Bering Sea bottom trawl surveys.

Usage

```
data(bering_sea)
```

bering_sea_capelin_forecasts	<i>Data to demonstrate probabilistic forecasting</i>
------------------------------	--

Description

Data to estimate probabilistic forecasting, which bridges uncertainty between short-term (decadal) projections and long-term (end-of-century) forecasts. Here we use capelin sampling from a survey trawl survey in the eastern and northern Bering Sea, as well as annual sea surface temperature anomalies. The data set includes data frames for both the fitted data `Data` and the projected values `New_Data`

Usage

```
data(bering_sea_capelin_forecasts)
```

bering_sea_pollock_ages	<i>Survey catch-rates at age for Alaska pollock in the Eastern and Northern Bering Sea</i>
-------------------------	--

Description

Data used to demonstrate and test model-based age expansion, using density= dependence corrected survey catch rates after first=stage expansion from the bottom trawl survey for ages 1-15, conducted by by the Alaska Fisheries Science Center, including annual surveys in the eastern Bering Sea 1982-2019 and 2021-2023, as well as the northern Bering Sea in 1982/85/88/91 and 2010/17/18/19/21/22/23.

Usage

```
data(bering_sea_pollock_ages)
```

bering_sea_pollock_vast	<i>Estimated proportion-at-age for Alaska pollock using VAST</i>
-------------------------	--

Description

Estimated proportion-at-age for Alaska pollock using the package VAST, for comparison with output using tinyVAST.

Usage

```
data(bering_sea_pollock_vast)
```

cAIC	<i>Calculate conditional AIC</i>
------	----------------------------------

Description

Calculates the conditional Akaike Information criterion (cAIC).

Usage

```
cAIC(object)
```

Arguments

object Output from `tinyVAST()`.

Details

cAIC is designed to optimize the expected out-of-sample predictive performance for new data that share the same random effects as the in-sample (fitted) data, e.g., spatial interpolation. In this sense, it should be a fast approximation to optimizing the model structure based on k-fold cross-validation.

By contrast, `AIC()` calculates the marginal Akaike Information Criterion, which is designed to optimize expected predictive performance for new data that have new random effects, e.g., extrapolation, or inference about generative parameters.

Both cAIC and EDF are calculated using Eq. 6 of Zheng, Cadigan, and Thorson (2024).

For models that include profiled fixed effects, these profiles are turned off.

Value

cAIC value

References

Zheng, N., Cadigan, N., & Thorson, J. T. (2024). A note on numerical evaluation of conditional Akaike information for nonlinear mixed-effects models (arXiv:2411.14185). arXiv. doi:10.48550/arXiv.2411.14185

Examples

```
data( red_snapper )
red_snapper = droplevels(subset(red_snapper, Data_type=="Biomass_KG"))

# Define mesh
mesh = fmesher::fm_mesh_2d( red_snapper[,c('Lon','Lat')],
                           cutoff = 1 )

# define formula with a catchability covariate for gear
formula = Response_variable ~ factor(Year) + offset(log(AreaSwept_km2))

# make variable column
red_snapper$var = "logdens"
# fit using tinyVAST
fit = tinyVAST( data = red_snapper,
                formula = formula,
                space_term = "logdens <-> logdens, sd_space",
                space_columns = c("Lon", 'Lat'),
                spatial_domain = mesh,
                family = tweedie(link="log"),
                variable_column = "var",
                control = tinyVASTcontrol( getsd = FALSE,
                                           profile = "alpha_j" ) )

cAIC(fit) # conditional AIC
AIC(fit) # marginal AIC
```

classify_variables	<i>Classify variables path</i>
--------------------	--------------------------------

Description

classify_variables is copied from sem:::classifyVariables

Usage

```
classify_variables(model)
```

Arguments

model	syntax for structural equation model
-------	--------------------------------------

Details

Copied from package sem under licence GPL (≥ 2) with permission from John Fox

Value

Tagged-list defining exogenous and endogenous variables

conditional_gmrf	<i>Conditional simulation from a GMRF</i>
------------------	---

Description

Generates samples from a Gaussian Markov random field (GMRF) conditional upon fixed values for some elements.

Usage

```
conditional_gmrf(
  Q,
  observed_idx,
  x_obs,
  n_sims = 1,
  what = c("simulate", "predict")
)
```

Arguments

Q	precision for a zero-centered GMRF.
observed_idx	integer vector listing rows of Q corresponding to fixed measurements
x_obs	numeric vector with fixed values for indices observed_idx
n_sims	integer listing number of simulated values
what	Whether to simulate from the conditional GMRF, or predict the mean and precision

Value

A matrix with n_sims columns and a row for every row of Q not in observed_idx, with simulations for those rows

condition_and_density *Condition and density example*

Description

Data used to demonstrate and test a bivariate model for morphometric condition (i.e., residuals in a weight-at-length relationship) and density for fishes, using the same example as was provided as a wiki example for VAST. Data are from [doi:10.3354/meps13213](https://doi.org/10.3354/meps13213)

Usage

```
data(condition_and_density)
```

deviance_explained *Calculate deviance explained*

Description

deviance_explained fits a null model, calculates the deviance relative to a saturated model for both the original and the null model, and uses these to calculate the proportion of deviance explained.

This implementation conditions upon the maximum likelihood estimate of fixed effects and the empirical Bayes ("plug-in") prediction of random effects. It can be described as "conditional deviance explained". A state-space model that estimates measurement error variance approaching zero (i.e., collapses to a process-error-only model) will have a conditional deviance explained that approaches 1.0

For several families (tweedie, negbin1, negbin2, and student), the null model is fitted using the MLE for an overdispersion parameter from the full model. This is done because, e.g., the negbin1 and negbin2 only belong to the exponential family when the overdispersion parameter is fixed, and the deviance relative to a saturated model is only defined for the exponential family.

Usage

```
deviance_explained(x, null_formula, null_delta_formula = ~1)
```

Arguments

x	output from <code>\code{tinyVAST()}</code>
null_formula	formula for the null model. If missing, it uses <code>null_formula = response ~ 1</code> . For multivariate models, it might make sense to use <code>null_formula = response ~ category</code>
null_delta_formula	formula for the null model for the delta component. If missing, it uses <code>null_formula = response ~ 1</code> . For multivariate models, it might make sense to use <code>null_delta_formula = response ~ category</code>

Value

the proportion of conditional deviance explained.

Families	<i>Additional families</i>
----------	----------------------------

Description

Additional families compatible with `tinyVAST()`.

Usage

```
delta_lognormal(link1, link2 = "log", type = c("standard", "poisson-link"))
delta_gamma(link1, link2 = "log", type = c("standard", "poisson-link"))
```

Arguments

link1	Link for first part of delta/hurdle model.
link2	Link for second part of delta/hurdle model.
type	Delta/hurdle family type. "standard" for a classic hurdle model. "poisson-link" for a Poisson-link delta model (Thorson 2018).
link	Link.

Value

A list with elements common to standard R family objects including family, link, linkfun, and linkinv. Delta/hurdle model families also have elements delta (logical) and type (standard vs. Poisson-link).

References

Poisson-link delta families:

Thorson, J.T. 2018. Three problems with the conventional delta-model for biomass sampling data, and a computationally efficient alternative. Canadian Journal of Fisheries and Aquatic Sciences, 75(9), 1369-1382. doi:10.1139/cjfas20170266

Poisson-link delta families:

Thorson, J.T. 2018. Three problems with the conventional delta-model for biomass sampling data, and a computationally efficient alternative. Canadian Journal of Fisheries and Aquatic Sciences, 75(9), 1369-1382. doi:10.1139/cjfas20170266

GetResponse.tinyVAST	<i>Get response</i>
----------------------	---------------------

Description

S3 generic from package cv, used for crossvalidation

Usage

```
## S3 method for class 'tinyVAST'  
GetResponse(model, ...)
```

Arguments

model	output from tinyVAST()
...	not used

get_data.tinyVAST	<i>Get data</i>
-------------------	-----------------

Description

S3 generic from package insight, used for crossvalidation

Usage

```
## S3 method for class 'tinyVAST'  
get_data(x, ...)
```

Arguments

x	output from tinyVAST()
...	not used

integrate_output	<i>Integration for target variable</i>
------------------	--

Description

Calculates an estimator for a derived quantity by summing across multiple predictions. This can be used to approximate an integral when estimating area-expanded abundance, abundance-weighting a covariate to calculate distribution shifts, and/or weighting one model variable by another.

Usage

```
integrate_output(
  object,
  newdata,
  area,
  block = rep(1, nrow(newdata)),
  type = rep(1, nrow(newdata)),
  weighting_index,
  covariate,
  getsd = TRUE,
  bias.correct = TRUE,
  apply.epsilon = FALSE,
  intern = FALSE
)
```

Arguments

object	Output from <code>tinyVAST()</code> .
newdata	New data-frame of independent variables used to predict the response, where a total value is calculated by combining across these individual predictions. If these locations are randomly drawn from a specified spatial domain, then <code>integrate_output</code> applies midpoint integration to approximate the total over that area. If locations are drawn systematically from a domain, then <code>integrate_output</code> is applying a midpoint approximation to the integral.
area	vector of values used for area-weighted expansion of estimated density surface for each row of <code>newdata</code> with length of <code>nrow(newdata)</code> .
block	vector of integers, indicating blocks of predictions that are combined into one or more derived quantities. This can be used to compute area-expanded indices for more than one year or category using a single call, and might be substantially faster for large models (because it avoids extra model builds for each derived quantity). Note that the output will have as many rows as the highest value of <code>block</code> , and NAs for rows where <code>block</code> does not contain that integer.
type	Integer-vector indicating what type of expansion to apply to each row of <code>newdata</code> , with length of <code>nrow(newdata)</code> . type=1 Area-weighting: weight predictor by argument area

	type=2 Abundance-weighted covariate: weight covariate by proportion of total in each row of newdata
	type=3 Abundance-weighted variable: weight predictor by proportion of total in a prior row of newdata. This option is used to weight a prediction for one category based on predicted proportional density of another category, e.g., to calculate abundance-weighted condition in a bivariate model.
	type=4 Abundance-expanded variable: weight predictor by density in a prior row of newdata. This option is used to weight a prediction for one category based on predicted density of another category, e.g., to calculate abundance-expanded consumption in a bivariate model.
	type=0 Exclude from weighting: give weight of zero for a given row of newdata. Including a row of newdata with type=0 is useful, e.g., when calculating abundance at that location, where the eventual index uses abundance as weighting term but without otherwise using the predicted density in calculating a total value.
weighting_index	integer-vector used to indicate a previous row that is used to calculate a weighted average that is then applied to the given row of newdata. Only used for when type=3.
covariate	numeric-vector used to provide a covariate that is used in expansion, e.g., to provide positional coordinates when calculating the abundance-weighted centroid with respect to that coordinate. Only used for when type=2.
getsd	logical indicating whether to get the standard error, where getsd=FALSE is faster during initial exploration
bias.correct	logical indicating if bias correction should be applied using standard methods in TMB::sdreport()
apply.epsilon	Apply epsilon bias correction using a manual calculation rather than using the conventional method in TMB::sdreport ? See details for more information.
intern	Do Laplace approximation on C++ side? Passed to TMB::MakeADFun() .

Details

Analysts will often want to calculate some value by combining the predicted response at multiple locations, and potentially from multiple variables in a multivariate analysis. This arises in a univariate model, e.g., when calculating the integral under a predicted density function, which is approximated using a midpoint or Monte Carlo approximation by calculating the linear predictors at each location newdata, applying the inverse-link-transformation, and calling this predicted response `mu_g`. Total abundance is then be approximated by multiplying `mu_g` by the area associated with each midpoint or Monte Carlo approximation point (supplied by argument `area`), and summing across these area-expanded values.

In more complicated cases, an analyst can then use `covariate` to calculate the weighted average of a covariate for each midpoint location. For example, if the covariate is positional coordinates or depth/elevation, then `type=2` measures shifts in the average habitat utilization with respect to that covariate. Alternatively, an analyst fitting a multivariate model might weight one variable based on another using `weighting_index`, e.g., to calculate abundance-weighted average condition, or predator-expanded stomach contents.

In practice, spatial integration in a multivariate model requires two passes through the rows of newdata when calculating a total value. In the following, we write equations using C++ indexing conventions such that indexing starts with 0, to match the way that `integrate_output` expects indices to be supplied. Given inverse-link-transformed predictor μ_g , function argument type as $type_g$ function argument area as a_g , function argument covariate as x_g , function argument weighting_index as h_g the first pass calculates:

$$\nu_g = \mu_g a_g$$

where the total value from this first pass is calculated as:

$$\nu^* = \sum_{g=0}^{G-1} \nu_g$$

The second pass then applies a further weighting, which depends upon $type_g$, and potentially upon x_g and h_g .

If $type_g = 0$ then $\phi_g = 0$

If $type_g = 1$ then $\phi_g = \nu_g$

If $type_g = 2$ then $\phi_g = x_g \frac{\nu_g}{\nu^*}$

If $type_g = 3$ then $\phi_g = \frac{\nu_{h_g}}{\nu^*} \mu_g$

If $type_g = 4$ then $\phi_g = \nu_{h_g} \mu_g$

Finally, the total value from this second pass is calculated as:

$$\phi^* = \sum_{g=0}^{G-1} \phi_g$$

and ϕ^* is outputted by `integrate_output`, along with a standard error and potentially using the epsilon bias-correction estimator to correct for skewness and retransformation bias.

Standard bias-correction using `bias.correct=TRUE` can be slow, and in some cases it might be faster to do `apply.epsilon=TRUE` and `intern=TRUE`. However, that option is somewhat experimental, and a user might want to confirm that the two options give identical results. Similarly, using `bias.correct=TRUE` will still calculate the standard-error, whereas using `apply.epsilon=TRUE` and `intern=TRUE` will not.

Value

A vector containing the plug-in estimate, standard error, the epsilon bias-corrected estimate if available, and the standard error for the bias-corrected estimator. Depending upon settings, one or more of these will be NA values, and the function can be repeatedly called to get multiple estimators and/or statistics.

Examples

```

# Settings
set.seed(123)
n_sampled = 50
samples_per_site = 3
n_extra = 50

# Simulate densities and lognormal samples
s_i = rep( seq_len(n_sampled), each = samples_per_site )
x_s = exp( 1 + rnorm( n_sampled + n_extra ))
y_i = exp( rnorm(n_sampled * samples_per_site, mean = log(x_s[s_i]), sd = 0.5 ) )
data = data.frame( y = y_i, s = s_i )

# Make spatial graph of all sites
library(igraph)
unconnected_graph = make_empty_graph( n_sampled + n_extra )
V(unconnected_graph)$name = as.character(seq_len(n_sampled + n_extra))

# Fit in tinyVAST
fit = tinyVAST(
  data = data,
  formula = y ~ 1,
  spatial_domain = unconnected_graph,
  space_column = "s",
  family = lognormal("log"),
  space_term = "response <-> response, spatial_sd"
)

# Sample densities
domain_df = data.frame(s = as.character(seq_len(n_sampled + n_extra)))
samples = sample_variable(
  fit,
  newdata = domain_df,
  n_samples = 1000,
  sample_fixed = FALSE,
  variable_name = "mu_g"
)

# Estimate total
# Note that bias-corrected estimator matches True and sample-based estimator
total = integrate_output(
  fit,
  newdata = domain_df
)

# Compare these options
c( True = sum(x_s), Sampled = mean(colSums(samples)), total )

# Calculate effective area occupied from samples
numerator = colSums(samples)
denominator = apply( samples, MARGIN = 2, FUN = \(x) weighted.mean(x=x, w=x) )
c(

```

```
Estimate = mean( numerator / denominator ),
SD = sd( numerator / denominator ),
True = sum(x_s) / weighted.mean(x_s, w = x_s)
)
```

logLik.tinyVAST	<i>Extract the (marginal) log-likelihood of a tinyVAST model</i>
-----------------	--

Description

Extract the (marginal) log-likelihood of a tinyVAST model

Usage

```
## S3 method for class 'tinyVAST'
logLik(object, ...)
```

Arguments

object	output from tinyVAST
...	not used

Value

object of class logLik with attributes	
val	log-likelihood
df	number of parameters

make_dsem_ram	<i>Make a RAM (Reticular Action Model)</i>
---------------	--

Description

make_dsem_ram converts SEM arrow notation to ram describing SEM parameters

Usage

```
make_dsem_ram(
  dsem,
  times,
  variables,
  covs = NULL,
  quiet = FALSE,
  remove_na = TRUE
)
```

Arguments

dsem	Specification for time-series structural equation model structure including lagged or simultaneous effects. See Details section in make_dsem_ram for more description
times	A character vector listing the set of times in order
variables	A character vector listing the set of variables
covs	A character vector listing variables for which to estimate a standard deviation
quiet	Boolean indicating whether to print messages to terminal
remove_na	Boolean indicating whether to remove NA values from RAM (default) or not. remove_NA=FALSE might be useful for exploration and diagnostics for advanced users

Details

RAM specification using arrow-and-lag notation

Each line of the RAM specification for [make_dsem_ram](#) consists of four (unquoted) entries, separated by commas:

- 1. Arrow specification:** This is a simple formula, of the form $A \rightarrow B$ or, equivalently, $B \leftarrow A$ for a regression coefficient (i.e., a single-headed or directional arrow); $A \leftrightarrow B$ for a variance or $A \leftrightarrow B$ for a covariance (i.e., a double-headed or bidirectional arrow). Here, A and B are variable names in the model. If a name does not correspond to an observed variable, then it is assumed to be a latent variable. Spaces can appear freely in an arrow specification, and there can be any number of hyphens in the arrows, including zero: Thus, e.g., $A \rightarrow B$, $A \rightarrow B$, and $A > B$ are all legitimate and equivalent.
- 2. Lag (using positive values):** An integer specifying whether the linkage is simultaneous (lag=0) or lagged (e.g., $X \rightarrow Y, 1$, $X \text{ to } Y$ indicates that X in time T affects Y in time T+1), where only one-headed arrows can be lagged. Using positive values to indicate lags then matches the notational convention used in package **dynlm**.
- 3. Parameter name:** The name of the regression coefficient, variance, or covariance specified by the arrow. Assigning the same name to two or more arrows results in an equality constraint. Specifying the parameter name as NA produces a fixed parameter.
- 4. Value:** start value for a free parameter or value of a fixed parameter. If given as NA (or simply omitted), the model is provide a default starting value.

Lines may end in a comment following #. The function extends code copied from package **sem** under licence GPL (≥ 2) with permission from John Fox.

Simultaneous autoregressive process for simultaneous and lagged effects

This text then specifies linkages in a multivariate time-series model for variables $\mathbf{X}$ with dimensions $T \times C$ for T times and C variables. `make_dsem_ram` then parses this text to build a path matrix $\mathbf{P}$ with dimensions $TC \times TC$, where ρ_{k_2, k_1} represents the impact of x_{t_1, c_1} on x_{t_2, c_2} , where $k_1 = Tc_1 + t_1$ and $k_2 = Tc_2 + t_2$. This path matrix defines a simultaneous equation

$$\text{vec}(\mathbf{X}) = \mathbf{P}\text{vec}(\mathbf{X}) + \text{vec}(\mathbf{\Delta})$$

where Δ is a matrix of exogenous errors with covariance $V = \Gamma\Gamma^t$, where Γ is the Cholesky of exogenous covariance. This simultaneous autoregressive (SAR) process then results in X having covariance:

$$\text{Cov}(X) = (I - P)^{-1} \Gamma \Gamma^t ((I - P)^{-1})^t$$

Usefully, it is also easy to compute the inverse-covariance (precision) matrix $Q = V^{-1}$:

$$Q = (\Gamma^{-1}(I - P))^t \Gamma^{-1} (I - P)$$

Example: univariate and first-order autoregressive model

This simultaneous autoregressive (SAR) process across variables and times allows the user to specify both simultaneous effects (effects among variables within year T) and lagged effects (effects among variables among years T). As one example, consider a univariate and first-order autoregressive process where $T = 4$, with independent errors. This is specified by passing `dsem = X -> X, 1, rho; X <-> X, 0, sigma` to `make_dsem_ram`. This is then parsed to a RAM:

heads	to	from	parameter	start
1	2	1	1	NA
1	3	2	1	NA
1	4	3	1	NA
2	1	1	2	NA
2	2	2	2	NA
2	3	3	2	NA
2	4	4	2	NA

Rows of this RAM where `heads=1` are then interpreted to construct the path matrix P :

```
\deqn{ \mathbf{P} = \begin{bmatrix}
0 & 0 & 0 & 0 \backslash
\rho & 0 & 0 & 0 \backslash
0 & \rho & 0 & 0 \backslash
0 & 0 & \rho & 0 \backslash
\end{bmatrix} }
```

While rows where `heads=2` are interpreted to construct the Cholesky of exogenous covariance Γ :

```
\deqn{ \mathbf{\Gamma} = \begin{bmatrix}
\sigma & 0 & 0 & 0 \backslash
0 & \sigma & 0 & 0 \backslash
0 & 0 & \sigma & 0 \backslash
0 & 0 & 0 & \sigma \backslash
\end{bmatrix} }
```

with two estimated parameters $\beta = (\rho, \sigma)$. This then results in covariance:

```
\deqn{ \mathrm{Cov}(\mathbf{X}) = \sigma^2 \begin{bmatrix}
1 & \rho^1 & \rho^2 & \rho^3 \backslash \\
\rho^1 & 1 & \rho^1 & \rho^2 \backslash \\
\rho^2 & \rho^1 & 1 & \rho^1 \backslash \\
\rho^3 & \rho^2 & \rho^1 & 1 \backslash \\
\end{bmatrix} }
```

Similarly, the arrow-and-lag notation can be used to specify a SAR representing a conventional structural equation model (SEM), cross-lagged (a.k.a. vector autoregressive) models (VAR), dynamic factor analysis (DFA), or many other time-series models.

Value

A reticular action module (RAM) describing dependencies

Examples

```
# Univariate AR1
dsem = "
  X -> X, 1, rho
  X <-> X, 0, sigma
"
make_dsem_ram( dsem=dsem, variables="X", times=1:4 )

# Univariate AR2
dsem = "
  X -> X, 1, rho1
  X -> X, 2, rho2
  X <-> X, 0, sigma
"
make_dsem_ram( dsem=dsem, variables="X", times=1:4 )

# Bivariate VAR
dsem = "
  X -> X, 1, XtoX
  X -> Y, 1, XtoY
  Y -> X, 1, YtoX
  Y -> Y, 1, YtoY
  X <-> X, 0, sdX
  Y <-> Y, 0, sdY
"
make_dsem_ram( dsem=dsem, variables=c("X","Y"), times=1:4 )

# Dynamic factor analysis with one factor and two manifest variables
# (specifies a random-walk for the factor, and miniscule residual SD)
dsem = "
  factor -> X, 0, loadings1
  factor -> Y, 0, loadings2
  factor -> factor, 1, NA, 1
  X <-> X, 0, NA, 0      # No additional variance
  Y <-> Y, 0, NA, 0      # No additional variance
"
```

```

make_dsem_ram( dsem=dsem, variables=c("X","Y","factor"), times=1:4 )

# ARIMA(1,1,0)
dsem = "
  factor -> factor, 1, rho1 # AR1 component
  X -> X, 1, NA, 1          # Integrated component
  factor -> X, 0, NA, 1
  X <-> X, 0, NA, 0         # No additional variance
"
make_dsem_ram( dsem=dsem, variables=c("X","factor"), times=1:4 )

# ARIMA(0,0,1)
dsem = "
  factor -> X, 0, NA, 1
  factor -> X, 1, rho1    # MA1 component
  X <-> X, 0, NA, 0       # No additional variance
"
make_dsem_ram( dsem=dsem, variables=c("X","factor"), times=1:4 )

```

make_eof_ram

Make a RAM (Reticular Action Model)

Description

make_eof_ram converts SEM arrow notation to ram describing SEM parameters

Usage

```

make_eof_ram(
  times,
  variables,
  n_eof,
  remove_na = TRUE,
  standard_deviations = "unequal"
)

```

Arguments

times	A character vector listing the set of times in order
variables	A character vector listing the set of variables
n_eof	Number of EOF modes of variability to estimate
remove_na	Boolean indicating whether to remove NA values from RAM (default) or not. remove_NA=FALSE might be useful for exploration and diagnostics for advanced users
standard_deviations	One of "equal", "unequal", or a numeric vector indicating fixed values.

Value

A reticular action module (RAM) describing dependencies

Examples

```
# Two EOFs for two variables
make_eof_ram( times = 2010:2020, variables = c("pollock","cod"), n_eof=2 )
```

make_nngp_domain	<i>Make spatial object for NNGP</i>
------------------	-------------------------------------

Description

Convert an sf areal model object to a class "nngp_domain" that is recognized by tinyVAST for nearest neighbors Gaussian process models

Usage

```
make_nngp_domain(sf_areal, nn)
```

Arguments

sf_areal	an sf or sfc object containing "POLYGON" and "MULTIPOLYGON" types
nn	Number of nearest neighbors

Value

a list of NNGP data objects created by tinyVAST:::make_nngp_data, as well as the provided sf object

make_sem_ram	<i>Make a RAM (Reticular Action Model) from a SEM (structural equation model)</i>
--------------	---

Description

make_sem_ram converts SEM arrow notation to ram describing SEM parameters

Usage

```
make_sem_ram(sem, variables, quiet = FALSE, covs = variables)
```

Arguments

sem	structural equation model structure, passed to either <code>specifyModel</code> or <code>specifyEquations</code> and then parsed to control the set of path coefficients and variance-covariance parameters
variables	A character vector listing the set of variables
quiet	Boolean indicating whether to print messages to terminal
covs	A character vector listing variables for which to estimate a standard deviation

Value

An S3-class "sem_ram" containing:

model Output from `specifyEquations` or `specifyModel` that defines paths and parameters

ram reticular action module (RAM) describing dependencies

parse_path

Parse path

Description

parse_path is copied from `sem::parse.path`

Usage

```
parse_path(path)
```

Arguments

path	character string indicating a one-headed or two-headed path in a structural equation model
------	--

Details

Copied from package `sem` under licence GPL (≥ 2) with permission from John Fox

Value

Tagged-list defining variables and direction for a specified path coefficient

plot.nngp_domain	<i>Plot nngp_domain</i>
------------------	-------------------------

Description

Plot nngp_domain

Usage

```
## S3 method for class 'nngp_domain'
plot(x, y, ...)
```

Arguments

x	output from make_nngp_domain
y	not used
...	not used

predict.tinyVAST	<i>Predict using vector autoregressive spatio-temporal model</i>
------------------	--

Description

Predicts values given new covariates using a **tinyVAST** model

Usage

```
## S3 method for class 'tinyVAST'
predict(
  object,
  newdata,
  remove_origdata = FALSE,
  what = c("mu_g", "p_g", "p1_g", "palpha1_g", "pgamma1_g", "pepsilon1_g", "pomega1_g",
    "pdelta1_g", "pxi1_g", "p2_g", "palpha2_g", "pgamma2_g", "pepsilon2_g", "pomega2_g",
    "pdelta2_g", "pxi2_g"),
  se.fit = FALSE,
  bias.correct = FALSE,
  ...
)
```

Arguments

object	Output from <code>tinyVAST()</code> .
newdata	New data-frame of independent variables used to predict the response.
remove_origdata	Whether to eliminate the original data from the TMB object, thereby speeding up the TMB object construction. However, this also eliminates information about random-effect variance, and is not appropriate when requesting predictive standard errors or epsilon bias-correction.
what	What REPORTed object to output, where <code>mu_g</code> is the inverse-linked transformed predictor including both linear components, <code>p_g</code> is the sum of the first and second linear predictors (which only makes sense to inspect when using the Poisson-linked delta model), <code>p1_g</code> is the first linear predictor, <code>palpha1_g</code> is the first predictor from fixed covariates in formula, <code>pgamma1_g</code> is the first predictor from random covariates in formula (e.g., splines), <code>pomega1_g</code> is the first predictor from spatial variation, <code>pepsilon1_g</code> is the first predictor from spatio-temporal variation, <code>pxi1_g</code> is the first predictor from spatially varying coefficients, <code>p2_g</code> is the second linear predictor, <code>palpha2_g</code> is the second predictor from fixed covariates in formula, <code>pgamma2_g</code> is the second predictor from random covariates in formula (e.g., splines), <code>pomega2_g</code> is the second predictor from spatial variation, <code>pepsilon2_g</code> is the second predictor from spatio-temporal variation, and <code>pxi2_g</code> is the second predictor from spatially varying coefficients.
se.fit	Calculate standard errors?
bias.correct	whether to epsilon bias-correct the predicted value
...	Not used.

Value

Either a vector with the prediction for each row of `newdata`, or a named list with the prediction and standard error (when `se.fit = TRUE`).

<code>print.tinyVAST</code>	<i>print summary of tinyVAST model</i>
-----------------------------	--

Description

print summary of tinyVAST model

Usage

```
## S3 method for class 'tinyVAST'
print(x, ...)
```

Arguments

x	output from tinyVAST
...	not used

Value

invisibly returns a named list of key model outputs and summary statements

project	<i>Project tinyVAST to future times (EXPERIMENTAL)</i>
---------	--

Description

Projects a fitted model forward in time.

Usage

```
project(
  object,
  extra_times,
  newdata,
  what = "mu_g",
  future_var = TRUE,
  past_var = FALSE,
  parm_var = FALSE
)
```

Arguments

object	fitted model from tinyVAST(.)
extra_times	a vector of extra times, matching values in newdata
newdata	data frame including new values for time_variable
what	What REPORTed object to output, where mu_g is the inverse-linked transformed predictor including both linear components, p_g is the sum of the first and second linear predictors (which only makes sense to inspect when using the Poisson-linked delta model), p1_g is the first linear predictor, palpha1_g is the first predictor from fixed covariates in formula, pgamma1_g is the first predictor from random covariates in formula (e.g., splines), pomega1_g is the first predictor from spatial variation, pepsilon1_g is the first predictor from spatio-temporal variation, pxi1_g is the first predictor from spatially varying coefficients, p2_g is the second linear predictor, palpha2_g is the second predictor from fixed covariates in formula, pgamma2_g is the second predictor from random covariates in formula (e.g., splines), pomega2_g is the second predictor from spatial variation, pepsilon2_g is the second predictor from spatio-temporal variation, and pxi2_g is the second predictor from spatially varying coefficients.

future_var	logical indicating whether to simulate future process errors from GMRFs, or just compute the predictive mean
past_var	logical indicating whether to re-simulate past process errors from predictive distribution of random effects, thus changing the boundary condition of the forecast
parm_var	logical indicating whether to re-sample fixed effects from their predictive distribution, thus changing the GMRF for future process errors

Value

A vector of values corresponding to rows in newdata

Examples

```
# Convert to long-form
set.seed(123)
n_obs = 100
rho = 0.9
sigma_x = 0.2
sigma_y = 0.1
x = rnorm(n_obs, mean=0, sd = sigma_x)
for(i in 2:length(x)) x[i] = rho * x[i-1] + x[i]
y = x + rnorm( length(x), mean = 0, sd = sigma_y )
data = data.frame( "val" = y, "var" = "y", "time" = seq_along(y) )

# Define AR2 time_term
time_term = "
  y -> y, 1, rho1
  y -> y, 2, rho2
  y <-> y, 0, sd
"

# fit model
mytiny = tinyVAST(
  time_term = time_term,
  data = data,
  times = unique(data$t),
  variables = "y",
  formula = val ~ 1,
  control = tinyVASTcontrol( getJointPrecision = TRUE )
)

# Deterministic projection
extra_times = length(x) + 1:100
n_sims = 10
newdata = data.frame( "time" = c(seq_along(x),extra_times), "var" = "y" )
Y = project(
  mytiny,
  newdata = newdata,
  extra_times = extra_times,
  future_var = FALSE
)
plot( x = seq_along(Y),
```

```

      y = Y,
      type = "l", lty = "solid", col = "black" )

# Stochastic projection with future process errors
## Not run:
extra_times = length(x) + 1:100
n_sims = 10
newdata = data.frame( "time" = c(seq_along(x),extra_times), "var" = "y" )
Y = NULL
for(i in seq_len(n_sims) ){
  tmp = project(
    mytiny,
    newdata = newdata,
    extra_times = extra_times,
    future_var = TRUE,
    past_var = TRUE,
    parm_var = TRUE
  )
  Y = cbind(Y, tmp)
}
matplot( x = row(Y),
         y = Y,
         type = "l", lty = "solid", col = "black" )

## End(Not run)

```

red_grouper_diet

Data to demonstrate model-based diet proportions

Description

Data to estimate predator-expanded stomach contents (PESC), i.e., a multi-prey single-predator model for stomach contents of red grouper in the Gulf of Mexico that also estimates biomass density for red grouper. Diet proportions are then the product of predicted diet proportions and prey specific consumption, normalized across prey categories. Copied from VAST data set PESC_example_red_grouper

Usage

```
data(red_grouper_diet)
```

red_snapper

Presence/absence, count, and biomass data for red snapper

Description

Data used to demonstrate and test analysis using multiple data types

Usage

```
data(red_snapper)
```

```
red_snapper_shapefile
```

Shapefile for red snapper analysis

Description

Spatial extent used for red snapper analysis, derived from Chap-7 of [doi:10.1201/9781003410294](https://doi.org/10.1201/9781003410294)

Usage

```
data(red_snapper_shapefile)
```

```
reload_model
```

Reload a previously fitted model

Description

reload_model allows a user to save a fitted model, reload it in a new R terminal, and then relink the DLLs so that it functions as expected.

Usage

```
reload_model(x, check_gradient = TRUE)
```

Arguments

x Output from [tinyVAST](#), potentially with DLLs not linked

check_gradient Whether to check the gradients of the reloaded model

Value

Output from [tinyVAST](#) with DLLs relinked

residuals.tinyVAST	<i>Calculate deviance or response residuals for tinyVAST</i>
--------------------	--

Description

Calculate residuals

Usage

```
## S3 method for class 'tinyVAST'
residuals(object, type = c("deviance", "response"), ...)
```

Arguments

object	Output from <code>tinyVAST()</code>
type	which type of residuals to compute (only option is "deviance" or "response" for now)
...	Note used

Value

a vector residuals, associated with each row of data supplied during fitting

rmvnorm_prec	<i>Multivariate Normal Random Deviates using Sparse Precision</i>
--------------	---

Description

This function provides a random number generator for the multivariate normal distribution with mean equal to `mu` and sparse precision matrix `prec`.

Usage

```
rmvnorm_prec(prec, n = 1, mu = rep(0, nrow(prec)))
```

Arguments

prec	sparse precision (inverse-covariance) matrix.
n	number of observations.
mu	mean vector.

Value

a matrix with dimension `length(mu)` by `n`, containing realized draws from the specified mean and precision

rotate_pca

*Rotate factors to match Principal-Components Analysis***Description**

Rotate lower-triangle loadings matrix to order factors from largest to smallest variance.

Usage

```
rotate_pca(
  L_tf,
  x_sf = matrix(0, nrow = 0, ncol = ncol(L_tf)),
  order = c("none", "increasing", "decreasing")
)
```

Arguments

<code>L_tf</code>	Loadings matrix with dimension $T \times F$.
<code>x_sf</code>	Spatial response with dimensions $S \times F$.
<code>order</code>	Options for resolving label-switching via reflecting each factor to achieve a given order across dimension T .

Value

List containing the rotated loadings `L_tf`, the inverse-rotated response matrix `x_sf`, and the rotation `H`

Examples

```
# Extract covariance for spatial factor analysis (too slow for CRAN)

# Simulate settings
set.seed(101)
theta_xy = 0.4
n_x = n_y = 10
n_c = 3          # Number of species
n_f = 1          # Number of factors
rho = 0.8
resid_sd = 0.5

# Simulate GMRFs
R_s = exp(-theta_xy * abs(outer(1:n_x, 1:n_y, FUN="-")))
R_ss = kronecker(X=R_s, Y=R_s)
delta_fs = mvtnorm::rmvnorm(n_c, sigma=R_ss)

# Simulate loadings for two factors
L_cf = matrix( rnorm(n_c^2), nrow=n_c )
L_cf[,seq(from=n_f+1, to=n_c)] = 0
```

```

L_cf = L_cf + resid_sd * diag(n_c)

# Simulate correlated densities
d_cs = L_cf %%% delta_fs

# Shape into longform data-frame and add error
Data = data.frame( expand.grid(species=1:n_c, x=1:n_x, y=1:n_y),
                    "var"="logn", "z"=exp(as.vector(d_cs)) )
Data$n = rnorm( n=nrow(Data), mean=Data$z, sd=1 )

# make mesh
mesh = fmesher::fm_mesh_2d( Data[,c('x','y')] )

# Specify factor model with two factors and additional independent variance with shared SD
sem = "
  # Loadings matrix
  f1 -> 1, l_1.1
  f1 -> 2, l_1.2
  f1 -> 3, l_1.3
  f2 -> 2, l_2.2
  f2 -> 3, l_3.2

  # Factor variance = 1
  f1 <-> f1, NA, 1
  f2 <-> f2, NA, 1

  # Shared residual variance
  1 <-> 1, sd, 1
  2 <-> 2, sd, 1
  3 <-> 3, sd, 1
"

# fit model
vars = c( "f1", "f2", 1:n_c )
out = tinyVAST(
  space_term = sem,
  data = Data,
  formula = n ~ 0 + factor(species),
  spatial_domain = mesh,
  variables = vars,
  space_columns = c("x","y"),
  variable_column = "species",
  time_column = "time",
  distribution_column = "dist",
  control = tinyVASTcontrol(
    extra_report = TRUE
  )
)

# Extract loadings from factor to species
L_cf = out$rep$Rho_cc[ match(1:n_c, vars), match(c("f1","f2"), vars), drop = FALSE]

# Extract spatial values for factors

```

```

omega_sf = out$internal$parlist$omega_sc[, match(c("f1","f2"), vars), drop = FALSE]

# Apply rotation
Rotation = rotate_pca( L_cf, x_sf = omega_sf )

# Extract rotated loadings
Lprime_cf = Rotation$L_tf

# Extract rotated factor values for each mesh location
Oprime_sf = Rotation$x_sf

```

salmon_returns	<i>North Pacific salmon returns</i>
----------------	-------------------------------------

Description

Data used to demonstrate and test multivariate second-order autoregressive models using a simultaneous autoregressive (SAR) process across regions. Data are from [doi:10.1002/mcf2.10023](https://doi.org/10.1002/mcf2.10023)

Usage

```
data(salmon_returns)
```

sample_variable	<i>Sample from predictive distribution of a variable</i>
-----------------	--

Description

sample_variable samples from the joint distribution of random (and optionally fixed) effects to approximate the predictive distribution for a variable.

Usage

```

sample_variable(
  object,
  newdata = NULL,
  variable_name = "mu_i",
  n_samples = 100,
  sample_fixed = TRUE,
  seed = 123456
)

```

Arguments

object	output from <code>\code{tinyVAST() }</code>
newdata	data frame of new data, used to sample model components for predictions e.g., <code>mu_g</code>
variable_name	name of variable available in report using <code>Obj\$report()</code> or parameters using <code>Obj\$env\$parList()</code>
n_samples	number of samples from the joint predictive distribution for fixed and random effects. Default is 100, which is slow.
sample_fixed	whether to sample fixed and random effects, <code>sample_fixed=TRUE</code> as by default, or just sample random effects, <code>sample_fixed=FALSE</code>
seed	integer used to set random-number seed when sampling variables, as passed to <code>set.seed(.)</code>

Details

Using `sample_fixed=TRUE` (the default) in `sample_variable` propagates variance in both fixed and random effects, while using `sample_fixed=FALSE` does not. Sampling fixed effects will sometimes cause numerical under- or overflow (i.e., output values of NA) in cases when variance parameters are estimated imprecisely. In these cases, the multivariate normal approximation being used is a poor representation of the tail probabilities, and results in some samples with implausibly high (or negative) variances, such that the associated random effects then have implausibly high magnitude.

Value

A matrix with a row for each data supplied during fitting, and `n_samples` columns, where each column is a vector of samples for a requested quantity given sampled uncertainty in fixed and/or random effects

Examples

```
set.seed(101)
x = runif(n = 100, min = 0, max = 2*pi)
y = 1 + sin(x) + 0.1 * rnorm(100)

# Do fit with getJointPrecision=TRUE
fit = tinyVAST(
  formula = y ~ s(x),
  data = data.frame(x=x,y=y)
)

# samples from distribution for the mean
# excluding fixed effects due to CRAN checks
samples = sample_variable(fit, sample_fixed = FALSE)

# See ?integrate_output for a more complicated example
```

sanity	<i>Sanity check of a tinyVAST model</i>
--------	---

Description

Sanity check of a tinyVAST model

Usage

```
sanity(object, big_sd_log10 = 2, gradient_thresh = 0.001, silent = FALSE)
```

Arguments

object	Fitted model from <code>tinyVAST()</code> .
big_sd_log10	Value to check size of standard errors against. A value of 2 would indicate that standard errors greater than 10^2 (i.e., 100) should be flagged.
gradient_thresh	Gradient threshold to issue warning.
silent	Logical: suppress messages? Useful to set to TRUE if running large numbers of models and just interested in returning sanity list objects.

Value

An invisible named list of checks.

sea_ice	<i>Arctic September sea ice concentrations</i>
---------	--

Description

Data used to demonstrate and test empirical orthogonal function generalized linear latent variable model (EOF-GLLVM)

Usage

```
data(sea_ice)
```

sfnetwork_evaluator	<i>Construct projection matrix for stream network</i>
---------------------	---

Description

Make sparse matrix to project from stream-network nodes to user-supplied points

Usage

```
sfnetwork_evaluator(stream, loc, tolerance = 0.01)
```

Arguments

stream	sfnetworks object representing stream network
loc	sf object representing points to which are being projected
tolerance	error-check tolerance

Value

the sparse interpolation matrix, with rows for each row of data supplied during fitting and columns for each spatial random effect.

sfnetwork_mesh	<i>Make mesh for stream network</i>
----------------	-------------------------------------

Description

make an object representing spatial information required to specify a stream-network spatial domain, similar in usage to `link[fmesh]{fm_mesh_2d}` for a 2-dimensional continuous domain

Usage

```
sfnetwork_mesh(stream)
```

Arguments

stream	sfnetworks object representing stream network
--------	--

Value

An object (list) of class `sfnetwork_mesh`. Elements include:

N The number of random effects used to represent the network

table a table containing a description of parent nodes (from), children nodes (to), and the distance separating them

stream copy of the stream network object passed as argument

simulate.tinyVAST	<i>Simulate new data from a fitted model</i>
-------------------	--

Description

simulate.tinyVAST is an S3 method for producing a matrix of simulations from a fitted model. It can be used with the **DHARMA** package among other uses. Code is modified from the version in sdmTMB

Usage

```
## S3 method for class 'tinyVAST'
simulate(
  object,
  nsim = 1L,
  seed = sample.int(1e+06, 1L),
  type = c("mle-eb", "mle-mvn"),
  ...
)
```

Arguments

object	output from tinyVAST()
nsim	how many simulations to do
seed	random seed
type	How parameters should be treated. "mle-eb": fixed effects are at their maximum likelihood (MLE) estimates and random effects are at their empirical Bayes (EB) estimates. "mle-mvn": fixed effects are at their MLEs but random effects are taken from a single approximate sample. This latter option is a suggested approach if these simulations will be used for goodness of fit testing (e.g., with the DHARMA package).
...	not used

Value

A matrix with row for each row of data in the fitted model and nsim columns, containing new samples from the fitted model.

Examples

```
set.seed(101)
x = seq(0, 2*pi, length=100)
y = sin(x) + 0.1*rnorm(length(x))
fit = tinyVAST( data=data.frame(x=x,y=y), formula = y ~ s(x) )
sims = simulate(fit, nsim=100, type="mle-mvn")

if(requireNamespace("DHARMA")){
```

```

# simulate new data conditional on fixed effects
# and sampling random effects from their predictive distribution
y_iz = simulate(fit, nsim=500, type="mle-mvn")

# Visualize using DHARMA
res = DHARMA::createDHARMA( simulatedResponse = y_iz,
                             observedResponse = y,
                             fittedPredictedResponse = fitted(fit) )

plot(res)
}

```

simulate_sfnetwork	<i>Simulate GMRF for stream network</i>
--------------------	---

Description

Simulate values from a GMRF using a tail-down (flow-unconnected) exponential model on a stream network

Usage

```
simulate_sfnetwork(sfnetwork_mesh, theta, n = 1, what = c("samples", "Q"))
```

Arguments

sfnetwork_mesh	Output from sfnetwork_mesh
theta	Decorrelation rate
n	number of simulated GMRFs
what	Whether to return the simulated GMRF or its precision matrix

Value

a matrix of simulated values for a Gaussian Markov random field arising from a stream-network spatial domain, with row for each spatial random effect and n columns, using the sparse precision matrix defined in Charsley et al. (2023)

References

Charsley, A. R., Gruss, A., Thorson, J. T., Rudd, M. B., Crow, S. K., David, B., Williams, E. K., & Hoyle, S. D. (2023). Catchment-scale stream network spatio-temporal models, applied to the freshwater stages of a diadromous fish species, longfin eel (*Anguilla dieffenbachii*). *Fisheries Research*, 259, 106583. doi:[10.1016/j.fishres.2022.106583](https://doi.org/10.1016/j.fishres.2022.106583)

spatial_cor	<i>Approximate spatial correlation</i>
-------------	--

Description

Extract the approximated spatial correlation between one coordinate and other coordinates using a sparse precision and SPDE mesh

Usage

```
spatial_cor(Q, mesh, coord, pred)
```

Arguments

Q	sparse precision matrix
mesh	SPDE mesh
coord	vector of length-2 with spatial coordinates for focal point
pred	matrix with two columns and multiple rows, with location for points to predict correlation

Value

A vector with length nrow(pred) giving the spatial correlation

summary.tinyVAST	<i>summarize tinyVAST</i>
------------------	---------------------------

Description

summarize parameters from a fitted tinyVAST

Usage

```
## S3 method for class 'tinyVAST'
summary(
  object,
  what = c("space_term", "time_term", "spacetime_term", "fixed"),
  predictor = c("one", "two"),
  ...
)
```

Arguments

object	Output from <code>tinyVAST()</code>
what	What component to summarize, whether <code>space_term</code> , <code>spacetime_term</code> , or <code>fixed</code> for the fixed effects included in the GAM formula
predictor	whether to get the 1st or 2nd linear predictor (the latter is only applicable in delta models)
...	Not used

Details

`tinyVAST` includes three components:

Space-variable interaction a separable Gaussian Markov random field (GMRF) constructed from a structural equation model (SEM) and a spatial variable

Space-variable-time interaction a separable GMRF constructed from a dynamic SEM (a non-separable time-variable interaction) and a spatial variable

Additive variation a generalized additive model (GAM), representing exogenous covariates

Each of these are summarized and interpreted differently, and `summary.tinyVAST` facilitates this.

Regarding the DSEM component, `tinyVAST` includes an "arrow and lag" notation, which specifies the set of path coefficients and exogenous variance parameters to be estimated. Function `tinyVAST` then estimates the maximum likelihood value for those coefficients and parameters by maximizing the log-marginal likelihood.

However, many users will want to associate individual parameters and standard errors with the path coefficients that were specified using the "arrow and lag" notation. This task is complicated in models where some path coefficients or variance parameters are specified to share a single value a priori, or were assigned a name of NA and hence assumed to have a fixed value a priori (such that these coefficients or parameters have an assigned value but no standard error). The summary function therefore compiles the MLE for coefficients (including duplicating values for any path coefficients that assigned the same value) and standard error estimates, and outputs those in a table that associates them with the user-supplied path and parameter names. It also outputs the z-score and a p-value arising from a two-sided Wald test (i.e. comparing the estimate divided by standard error against a standard normal distribution).

Value

A data-frame containing the estimate (and standard errors, two-sided Wald-test z-value, and associated p-value if the standard errors are available) for model parameters, including the fixed-effects specified via `formula`, or the path coefficients for the spatial SEM specified via `space_term`, the dynamic SEM specified via `time_term`, or the spatial dynamic SEM specified via `spacetime_term`

term_covariance	<i>Extract covariance</i>
-----------------	---------------------------

Description

Extract the covariance resulting from a specified path structure and estimated parameters for a SEM or DSEM term in tinyVAST

Usage

```
term_covariance(
  object,
  what = c("space_term", "time_term", "spacetime_term"),
  pred = c("one", "two"),
  n_times = NULL
)
```

Arguments

object	Output from tinyVAST
what	Which SEM or DSEM term to extract
pred	Extract the term what for which linear predictor
n_times	The number of times to include when calculating covariance for a DSEM component, i.e., time_term or spacetime_term. If missing, the default is to use the one more than the maximum specified lag (e.g., n_times=2 by default when the maximum lag=1)

Details

tinyVAST constructs the covariance from specified path structure and estimated parameters

Value

The covariance matrix among variables

Examples

```
# Extract covariance for spatial factor analysis (too slow for CRAN)

# Simulate settings
set.seed(101)
theta_xy = 0.4
n_x = n_y = 10
n_c = 3          # Number of species
n_f = 1          # Number of factors
rho = 0.8
resid_sd = 0.5
```

```

# Simulate GMRFs
R_s = exp(-theta_xy * abs(outer(1:n_x, 1:n_y, FUN="-"))) )
R_ss = kronecker(X=R_s, Y=R_s)
delta_fs = mvtnorm::rmvnorm(n_c, sigma=R_ss )

# Simulate loadings for two factors
L_cf = matrix( rnorm(n_c^2), nrow=n_c )
L_cf[,seq(from=n_f+1, to=n_c)] = 0
L_cf = L_cf + resid_sd * diag(n_c)

# Simulate correlated densities
d_cs = L_cf %%% delta_fs

# Shape into longform data-frame and add error
Data = data.frame( expand.grid(species=1:n_c, x=1:n_x, y=1:n_y),
                    "var"="logn", "z"=exp(as.vector(d_cs)) )
Data$n = rnorm( n=nrow(Data), mean=Data$z, sd=1 )

# make mesh
mesh = fmesher::fm_mesh_2d( Data[,c('x','y')] )

# Specify factor model with two factors and additional independent variance with shared SD
sem = "
  # Loadings matrix
  f1 -> 1, l1
  f1 -> 2, l2
  f1 -> 3, l3

  # Factor variance = 1
  f1 <-> f1, NA, 1

  # Shared residual variance
  1 <-> 1, sd, 1
  2 <-> 2, sd, 1
  3 <-> 3, sd, 1
"

# fit model
out = tinyVAST( space_term = sem,
                data = Data,
                formula = n ~ 0 + factor(species),
                spatial_domain = mesh,
                variables = c( "f1", 1:n_c ),
                space_columns = c("x","y"),
                variable_column = "species",
                time_column = "time",
                distribution_column = "dist" )

# Extract covariance among species and factors, where
# estimated covariance is obtained by ignoring factors
V = term_covariance( out, what = "space_term", pred = "one" )

```

tinyVAST

Fit vector autoregressive spatio-temporal model

Description

Fits a vector autoregressive spatio-temporal (VAST) model using a minimal feature-set and a widely used interface.

Usage

```
tinyVAST(
  formula,
  data,
  time_term = NULL,
  space_term = NULL,
  spacetime_term = NULL,
  family = gaussian(),
  delta_options = list(formula = ~1),
  spatial_varying = NULL,
  weights = NULL,
  spatial_domain = NULL,
  development = list(),
  control = tinyVASTcontrol(),
  space_columns = c("x", "y"),
  time_column = "time",
  times = NULL,
  variable_column = "var",
  variables = NULL,
  distribution_column = "dist"
)
```

Arguments

formula	Formula with response on left-hand-side and predictors on right-hand-side, parsed by mgcv and hence allowing <code>s(.)</code> for splines or <code>offset(.)</code> for an offset.
data	Data-frame of predictor, response, and offset variables. Also includes variables that specify space, time, variables, and the distribution for samples, as identified by arguments <code>variable_column</code> , <code>time_column</code> , <code>space_columns</code> , and <code>distribution_column</code> .
time_term	Specification for time-series structural equation model structure for constructing a time-variable interaction that defines a time-varying intercept for each variable (i.e., applies uniformly across space). <code>time_term=NULL</code> disables the space-variable interaction; see make_dsem_ram() for notation.
space_term	Specification for structural equation model structure for constructing a space-variable interaction. <code>space_term=NULL</code> disables the space-variable interaction; see make_sem_ram() for notation.

spacetime_term	Specification for time-series structural equation model structure including lagged or simultaneous effects for constructing a time-variable interaction, which is then combined in a separable process with the spatial correlation to form a space-time-variable interaction (i.e., the interaction occurs locally at each site). spacetime_term=NULL disables the space-variable interaction; see make_dsem_ram() or make_eof_ram() .
family	A function returning a class family, including gaussian() , lognormal() , tweedie() , binomial() , Gamma() , student() , poisson() , nbinom1() , or nbinom2() . Alternatively, can be a named list of these functions, with names that match levels of data\$distribution_column to allow different families by row of data. Delta model families are possible, and see Families for delta-model options. For binomial family options, see 'Binomial families' in the Details section below.
delta_options	a named list with slots for formula, space_term, spacetime_term, time_term, and spatial_varying. These specify options for the second linear predictor of a delta model, and are only used (or estimable) when a delta family is used for some samples.
spatial_varying	a formula specifying spatially varying coefficients (SVC). Note that using formulas in R, spatial_varying = ~ X automatically adds an intercept to implicitly read as spatial_varying = ~ 1 + X, so tinyVAST then estimates an SVC for an intercept in addition to covariate X. Therefore, if you only want an SVC for a single covariate, use spatial_varying = ~ 0 + X to suppress the default behavior of formulas in R.
weights	A numeric vector representing optional likelihood weights for the data likelihood. Weights do not have to sum to one and are not internally modified. The weights argument needs to be a vector and not a name of the variable in the data frame.
spatial_domain	Object that represents spatial relationships, either using fmesher::fm_mesh_2d() to apply the SPDE method, igraph::make_empty_graph() for independent time-series, igraph::make_graph() to apply a simultaneous autoregressive (SAR) process to a user-supplied graph, sfnetwork_mesh() for stream networks, or class sf or sfc containing polygons e.g constructed using sf::st_make_grid to apply a SAR to an areal model with adjacency based on the geometry of the object, or NULL to specify a single site. If using igraph then the graph must have vertex names V(graph)\$name that match levels of data[, 'space_columns'].
development	Specify options that are under active development. Please do not use these features without coordinating with the package authors.
control	Output from tinyVASTcontrol() , used to define user settings.
space_columns	A string or character vector that indicates the column(s) of data indicating the location of each sample. When spatial_domain is an igraph object, space_columns is a string with levels matching the names of vertices of that object. When spatial_domain is an fmesher or sfnetwork object, space_columns is a character vector indicating columns of data with coordinates for each sample.
time_column	A character string indicating the column of data listing the time-interval for each sample, from the set of times in argument times.

<code>times</code>	A integer vector listing the set of times in order. If <code>times=NULL</code> , then it is filled in as the vector of integers from the minimum to maximum value of <code>data\$time</code> . Alternatively, it could be the minimum value of <code>data\$time</code> through future years, such that the model can forecast those future years.
<code>variable_column</code>	A character string indicating the column of data listing the variable for each sample, from the set of times in argument <code>variables</code> .
<code>variables</code>	A character vector listing the set of variables. if <code>variables=NULL</code> , then it is filled in as the unique values from <code>data\$variable_columns</code> .
<code>distribution_column</code>	A character string indicating the column of data listing the distribution for each sample, from the set of names in argument <code>family</code> . if <code>variables=NULL</code> , then it is filled in as the unique values from <code>data\$variables</code> .

Details

tinyVAST includes several basic inputs that specify the model structure:

- `formula` specifies covariates and splines in a Generalized Additive Model;
- `time_term` specifies interactions among variables and over time that are constant across space, constructing the time-variable interaction.
- `space_term` specifies interactions among variables and over time that occur based on the variable values at each location, constructing the space-variable interaction.
- `spacetime_term` specifies interactions among variables and over time, constructing the space-time-variable interaction.

These inputs require defining the *domain* of the model. This includes:

- `spatial_domain` specifies spatial domain, with determines spatial correlations
- `times` specifies the temporal domain, i.e., sequence of time-steps
- `variables` specifies the set of variables, i.e., the variables that will be modeled

The default `spacetime_term=NULL` and `space_term=NULL` turns off all multivariate and temporal indexing, such that `spatial_domain` is then ignored, and the model collapses to a generalized additive model using [gam](#). To specify a univariate spatial model, the user must specify `spatial_domain` and either `space_term=""` or `spacetime_term=""`, where the latter two are then parsed to include a single exogenous variance for the single variable

Model type

Generalized additive model

Dynamic structural equation model (including vector autoregressive, dynamic factor analysis, ARIMA, and structural equation)

Univariate spatio-temporal model, or multiple independence spatio-temporal variables

Multivariate spatial model including interactions

Vector autoregressive spatio-temporal model (i.e., lag-1 interactions among variables)

Model building notes

- **binomial families:** A binomial family can be specified in only one way: the response is the observed proportion (proportion = successes / trials), and the 'weights' argument is used to specify the Binomial size (trials, N) parameter (proportion ~ ..., weights = N).
- **factor models:** If a factor model is desired, the factor(s) must be named and included in the variables. The factor is then modeled for space_term, time_term, and spacetime_term and it's variance must be fixed a priori for any term where it is not being used.

Value

An object (list) of class `tinyVAST`. Elements include:

data Data-frame supplied during model fitting
spatial_domain the spatial domain supplied during fitting
formula the formula specified during model fitting
obj The TMB object from [MakeADFun](#)
opt The output from [nlminb](#)
opt The report from `obj$report()`
sdrep The output from [sdreport](#)
tmb_inputs The list of inputs passed to [MakeADFun](#)
call A record of the function call
run_time Total time to run model
interal Objects useful for package function, i.e., all arguments passed during the call
deviance_explained output from [deviance_explained](#)

See Also

Details section of [make_dsem_ram\(\)](#) for a summary of the math involved with constructing the DSEM, and [doi:10.1111/2041210X.14289](#) for more background on math and inference
[doi:10.48550/arXiv.2401.10193](#) for more details on how GAM, SEM, and DSEM components are combined from a statistical and software-user perspective
[summary.tinyVAST\(\)](#) to visualize parameter estimates related to SEM and DSEM model components

Examples

```
# Simulate a seperable two-dimensional AR1 spatial process
n_x = n_y = 25
n_w = 10
R_xx = exp(-0.4 * abs(outer(1:n_x, 1:n_x, FUN="-"))) )
R_yy = exp(-0.4 * abs(outer(1:n_y, 1:n_y, FUN="-"))) )
z = mvtnorm::rmvnorm(1, sigma=kronecker(R_xx,R_yy) )

# Simulate nuisance parameter z from oscillatory (day-night) process
w = sample(1:n_w, replace=TRUE, size=length(z))
Data = data.frame( expand.grid(x=1:n_x, y=1:n_y), w=w, z=as.vector(z) + cos(w/n_w*2*pi))
Data$z = Data$z + rnorm(nrow(Data), sd=1)
```

```

# Add columns for multivariate and/or temporal dimensions
Data$var = "n"

# make SPDE mesh for spatial term
mesh = fmesher::fm_mesh_2d( Data[,c('x','y')], n=100 )

# fit model with cyclic confounder as GAM term
out = tinyVAST( data = Data,
                formula = n ~ s(w),
                spatial_domain = mesh,
                space_term = "n <-> n, sd_n" )

# Run crossvalidation (too slow for CRAN)

CV = cv::cv( out, k = 4 )
CV

```

tinyVASTcontrol	<i>Control parameters for tinyVAST</i>
-----------------	--

Description

Control parameters for tinyVAST

Usage

```

tinyVASTcontrol(
  opt_loops = 1,
  newton_loops = 0,
  eval.max = 10000,
  iter.max = 10000,
  getsd = TRUE,
  silent = getOption("tinyVAST.silent", TRUE),
  trace = getOption("tinyVAST.trace", 0),
  verbose = getOption("tinyVAST.verbose", FALSE),
  profile = c(),
  tmb_par = NULL,
  tmb_map = NULL,
  tmb_random = NULL,
  gmrf_parameterization = c("separable", "projection"),
  reml = FALSE,
  getJointPrecision = FALSE,
  calculate_deviance_explained = TRUE,
  run_model = TRUE,
  suppress_user_warnings = FALSE,

```

```

    get_rsr = FALSE,
    extra_reporting = FALSE,
    use_anisotropy = FALSE,
    sar_adjacency = "queen",
    barrier_stiffness = 0.01
  )

```

Arguments

<code>opt_loops</code>	Integer number of times to call nonlinear optimizer.
<code>newton_loops</code>	Integer number of Newton steps to do after running <code>stats::nlminb()</code> .
<code>eval.max</code>	Maximum number of evaluations of the objective function allowed. Passed to control in <code>stats::nlminb()</code> .
<code>iter.max</code>	Maximum number of iterations allowed. Passed to control in <code>stats::nlminb()</code> .
<code>getsd</code>	Boolean indicating whether to call <code>TMB::sdreport()</code>
<code>silent</code>	Disable terminal output for inner optimizer?
<code>trace</code>	Parameter values are printed every trace iteration for the outer optimizer. Passed to control in <code>stats::nlminb()</code> .
<code>verbose</code>	Output additional messages about model steps during fitting?
<code>profile</code>	Character-vector passed to <code>TMB::MakeADFun</code> and see description there. Fixed effects that are highly correlated with random effects can often be estimated faster (i.e., with fewer iterations) by adding them to profile. The most common use-case is <code>profile = c("alpha_j", "alpha2_j")</code> . However, doing so will have a small impact on model estimates and predictions.
<code>tmb_par</code>	named list of parameters used as starting values. Elements that have names that match those constructed internally then replace the internally constructed starting values. Those that match must have identical shape to <code>tinyVAST(...)\$internal\$parlist</code>
<code>tmb_map</code>	input passed to <code>TMB::MakeADFun</code> as argument <code>map</code> , over-writing the version <code>tinyVAST(...)\$tmb_inputs\$tmb_map</code> and allowing detailed control over estimated parameters (advanced feature)
<code>tmb_random</code>	input passed to <code>TMB::MakeADFun</code> as argument <code>random</code> , over-writing the version <code>tinyVAST(...)\$tmb_inputs\$tmb_random</code> and allowing detailed control over parameters treated as random effects. <code>tmb_random = NULL</code> uses the default (internal) construction, and use <code>tmb_random = c("empty")</code> (or some other name that doesn't match actual parameters) to use penalized likelihood (presumably while also modifying <code>tmb_map</code> and <code>tmb_par</code>)
<code>gmrf_parameterization</code>	Parameterization to use for the Gaussian Markov random field, where the default separable constructs a full-rank and separable precision matrix, and the alternative projection constructs a full-rank and IID precision for variables over time, and then projects this using the inverse-cholesky of the precision, where this projection allows for rank-deficient covariance.
<code>reml</code>	Logical: use REML (restricted maximum likelihood) estimation rather than maximum likelihood? Internally, this adds the fixed effects to the list of random effects to integrate over.

`getJointPrecision` whether to get the joint precision matrix. Passed to [sdreport](#).

`calculate_deviance_explained` whether to calculate proportion of deviance explained. See [deviance_explained\(\)](#)

`run_model` whether to run the model of export TMB objects prior to compilation (useful for debugging)

`suppress_user_warnings` whether to suppress warnings from package author regarding dangerous or non-standard options

`get_rsr` Experimental option, whether to report restricted spatial regression (RSR) adjusted estimator for covariate responses

`extra_reporting` Whether to report a much larger set of quantities via `obj$env$report()`

`use_anisotropy` Whether to estimate two parameters representing geometric anisotropy

`sar_adjacency` Whether to use queen or rook adjacency when defining a Simultaneous Autoregressive spatial precision from a `sfc_GEOMETRY` (default is queen)

`barrier_stiffness` The ratio of local stiffness (the scale of diffusion rate and resulting decorrelation distance) for barriers relative to normal areas in the SPDE method when using `add_mesh_covariates`. The default `barrier_stiffness = 0.01` is the value from Bakka et al. 2019.

Value

An object (list) of class `tinyVASTcontrol`, containing either default or updated values supplied by the user for model settings

References

Bakka, H., Vanhatalo, J., Illian, J., Simpson, D., Rue, H. (2019). Non-stationary Gaussian models with physical barriers. *Spatial Statistics*, 29, 268-288. doi:[10.1016/j.spasta.2019.01.002](https://doi.org/10.1016/j.spasta.2019.01.002)

vcov.tinyVAST

Extract Variance-Covariance Matrix

Description

extract the covariance of fixed effects, or both fixed and random effects.

Usage

```
## S3 method for class 'tinyVAST'
vcov(object, which = c("fixed", "random", "both"), ...)
```

Arguments

object	output from <code>tinyVAST()</code>
which	whether to extract the covariance among fixed effects, random effects, or both
...	ignored, for method compatibility

Value

A square matrix containing the estimated covariances among the parameter estimates in the model. The dimensions depend upon the argument `which`, to determine whether fixed, random effects, or both are outputted.

Index

* data

- alaska_sponge_coral_fish, [6](#)
- atlantic_yellowtail, [6](#)
- bering_sea, [7](#)
- bering_sea_capelin_forecasts, [7](#)
- bering_sea_pollock_ages, [7](#)
- bering_sea_pollock_vast, [8](#)
- condition_and_density, [11](#)
- red_grouper_diet, [29](#)
- red_snapper, [29](#)
- red_snapper_shapefile, [30](#)
- salmon_returns, [34](#)
- sea_ice, [36](#)

add_mesh_covariates, [3](#)

add_predictions, [5](#)

AIC(), [8](#)

alaska_sponge_coral_fish, [6](#)

atlantic_yellowtail, [6](#)

bering_sea, [7](#)

bering_sea_capelin_forecasts, [7](#)

bering_sea_pollock_ages, [7](#)

bering_sea_pollock_vast, [8](#)

binomial(), [45](#)

cAIC, [8](#)

classify_variables, [9](#)

condition_and_density, [11](#)

conditional_gmrif, [10](#)

delta_gamma (Families), [12](#)

delta_lognormal (Families), [12](#)

deviance_explained, [11](#), [47](#)

deviance_explained(), [50](#)

Families, [12](#), [45](#)

fmesher::fm_mesh_2d(), [45](#)

gam, [46](#)

Gamma(), [45](#)

gaussian(), [45](#)

get_data.tinyVAST, [13](#)

GetResponse.tinyVAST, [13](#)

igraph::make_empty_graph(), [45](#)

igraph::make_graph(), [45](#)

integrate_output, [14](#)

logLik.tinyVAST, [18](#)

lognormal(), [45](#)

make_dsem_ram, [18](#), [19](#)

make_dsem_ram(), [44](#), [45](#), [47](#)

make_eof_ram, [22](#)

make_eof_ram(), [45](#)

make_nngp_domain, [23](#)

make_sem_ram, [23](#)

make_sem_ram(), [44](#)

MakeADFun, [47](#)

nbinom1(), [45](#)

nbinom2(), [45](#)

nlminb, [47](#)

parse_path, [24](#)

plot.nngp_domain, [25](#)

poisson(), [45](#)

predict.tinyVAST, [25](#)

print.tinyVAST, [26](#)

project, [27](#)

red_grouper_diet, [29](#)

red_snapper, [29](#)

red_snapper_shapefile, [30](#)

reload_model, [30](#)

residuals.tinyVAST, [31](#)

rmvnorm_prec, [31](#)

rotate_pca, [32](#)

salmon_returns, [34](#)

sample_variable, [34](#), [35](#)

sanity, [36](#)
sdmTMB::sdmTMB(), [3](#)
sdreport, [47](#), [50](#)
sea_ice, [36](#)
sf::st_make_grid, [45](#)
sfnetwork_evaluator, [37](#)
sfnetwork_mesh, [37](#), [39](#)
sfnetwork_mesh(), [45](#)
simulate.tinyVAST, [38](#)
simulate_sfnetwork, [39](#)
spatial_cor, [40](#)
specifyEquations, [24](#)
specifyModel, [24](#)
stats::nlminb(), [49](#)
student(), [45](#)
summary.tinyVAST, [40](#)
summary.tinyVAST(), [47](#)

term_covariance, [42](#)
tinyVAST, [30](#), [42](#), [44](#)
tinyVAST(), [6](#), [8](#), [12–14](#), [26](#), [31](#), [36](#), [38](#), [41](#), [51](#)
tinyVASTcontrol, [48](#)
tinyVASTcontrol(), [45](#)
TMB::MakeADFun, [49](#)
TMB::MakeADFun(), [15](#)
TMB::sdreport, [15](#)
TMB::sdreport(), [15](#), [49](#)
tweedie(), [45](#)

vcov.tinyVAST, [50](#)