

# Package: stgam (via r-universe)

September 30, 2024

**Title** Spatially and Temporally Varying Coefficient Models Using Generalized Additive Models

**Version** 0.0.1.2

**Author** Lex Comber [aut, cre], Paul Harris [ctb], Chris Brunsdon [ctb]

**Maintainer** Lex Comber <a.comber@leeds.ac.uk>

**Description** A framework for specifying spatially, temporally and spatially-and-temporally varying coefficient models using Generalized Additive Models with Gaussian Process smooths. The smooths are parameterised with location and / or time attributes. Importantly the framework supports the investigation of the presence and nature of any space-time dependencies in the data, allows the user to evaluate different model forms (specifications) and to pick the most probable model or to combine multiple varying coefficient models using Bayesian Model Averaging. For more details see: Brunsdon et al (2023) <doi:10.4230/LIPIcs.GIScience.2023.17>, Comber et al (2023) <doi:10.4230/LIPIcs.GIScience.2023.22> and Comber et al (2024) <doi:10.1080/13658816.2023.2270285>.

**License** MIT + file LICENSE

**Encoding** UTF-8

**RoxygenNote** 7.2.3

**Suggests** cols4all, knitr, purrr, rmarkdown, sf, testthat (>= 3.0.0), tidyR

**Config/testthat/edition** 3

**URL** <https://github.com/lexcomber/stgam>

**BugReports** <https://github.com/lexcomber/stgam/issues>

**Depends** R (>= 2.10),

**LazyData** true

**Imports** cowplot, doParallel, dplyr, foreach, ggplot2, glue, grDevices, magrittr, metR, mgcv (>= 1.9-1), parallel, tidyselect

**VignetteBuilder** knitr

**NeedsCompilation** no

**Repository** CRAN

**Date/Publication** 2024-07-31 14:30:02 UTC

## Contents

calculate_vcs . . . . .	2
do_bma . . . . .	3
evaluate_models . . . . .	4
gam_model_probs . . . . .	6
plot_1d_smooth . . . . .	7
plot_2d_smooth . . . . .	8
productivity . . . . .	9
us_data . . . . .	10
<b>Index</b>	<b>11</b>

---

calculate_vcs	<i>Extracts varying coefficient estimates (for SVC, TVC and STVC models).</i>
---------------	---

---

## Description

Extracts varying coefficient estimates (for SVC, TVC and STVC models).

## Usage

```
calculate_vcs(input_data, model, terms)
```

## Arguments

input_data	the data used to create the GAM model in data.frame, tibble or sf format
model	a GAM model with smooths created using the mgcv package
terms	a vector of names starting with "Intercept" plus the names of the covariates used in the GAM model (these are the names of the variables in data )

## Value

A data.frame of the input data and the coefficient and standard error estimates for each covariate.

**Examples**

```

library(dplyr)
library(mgcv)
# SVC
data(productivity)
input_data = productivity |> dplyr::filter(year == "1970") |> mutate(Intercept = 1)
gam.svc.mod = gam(privC ~ 0 + Intercept +
  s(X, Y, bs = 'gp', by = Intercept) +
  unemp + s(X, Y, bs = "gp", by = unemp) +
  pubC + s(X, Y, bs = "gp", by = pubC),
  data = input_data)
terms = c("Intercept", "unemp", "pubC")
svcs = calculate_vcs(input_data, gam.svc.mod, terms)
head(svcs)

```

---

do_bma	<i>Undertake undertake coefficient averaging using Bayesian Model Averaging (BMA), weighting different models by their probabilities</i>
--------	--

---

**Description**

Undertake undertake coefficient averaging using Bayesian Model Averaging (BMA), weighting different models by their probabilities

**Usage**

```
do_bma(model_table, terms, thresh = 0.1, relative = FALSE, input_data)
```

**Arguments**

model_table	a table of competing models generated by the gam_model_probs() function
terms	a vector of names starting with "Intercept" plus the names of the covariates used in the GAM model (these are the names of the variables in data )
thresh	a probability threshold value above which to combine competing models
relative	logical to indicate whether the probabilities in data are relative (Pr(M)) or absolute (Pr(M D))
input_data	the input data with a named Intercept term, in data.frame, tibble or sf format

**Value**

A matrix of the probability weighted averaged coefficient estimates from multiple models.

**Examples**

```

library(cols4all)
library(dplyr)
library(sf)
library(glue)
library(purrr)
library(mgcv)
library(sf)
library(ggplot2)
# data
data(productivity)
input_data = productivity |> filter(year == "1970") |> mutate(Intercept = 1)
# create and evaluate multiple models
svc_res_gam = evaluate_models(input_data, STVC = FALSE)
# determine their probabilities
mod_comp_svc <- gam_model_probs(svc_res_gam)
# combine the model coefficients
svc_bma <- do_bma(mod_comp_svc,
                 terms = c("Intercept", "unemp", "pubC"),
                 thresh = 0.1,
                 relative = FALSE,
                 input_data = input_data)

head(svc_bma)
# join back to spatial layer
data(us_data)
svc_bma_sf <-
us_data |>
select(GEOID) |>
left_join(productivity |>
  filter(year == "1970") |>
  select(GEOID, year) |>
  cbind(svc_bma)) |>
  relocate(geometry, .after = last_col())
# and map
tit =expression(paste(" "*beta[`Public Capital`]*" "))
ggplot(data = svc_bma_sf, aes(fill=pubC)) +
  geom_sf() +
  scale_fill_continuous_c4a_div(palette="brewer.yl_or_rd",name=tit) +
  coord_sf() +
  theme_linedraw()

```

---

evaluate\_models

*Creates and evaluates multiple varying coefficient GAM GP smooth models (SVC or STVC)*

---

**Description**

Creates and evaluates multiple varying coefficient GAM GP smooth models (SVC or STVC)

**Usage**

```
evaluate_models(
  input_data,
  target_var = "privC",
  covariates = c("unemp", "pubC"),
  coords_x = "X",
  coords_y = "Y",
  STVC = FALSE,
  time_var = NULL,
  ncores = 2
)
```

**Arguments**

input_data	a data.frame, tibble sf containing the target variables, covariates and coordinate variables
target_var	the name of the target variable in data
covariates	the name of the covariates (predictor variables) in data
coords_x	the name of the X, Easting or Longitude variable in data
coords_y	the name of the Y, Northing or Latitude variable in data
STVC	a logical operator to indicate whether the models Space-Time (TRUE) or just Space (FALSE)
time_var	the name of the time variable if undertaking STVC model evaluations
ncores	the number of cores to use in parallelised approaches (default is 2 to overcome CRAN package checks). This can be determined for your computer by running <code>parallel::detectCores()-1</code> . Parallel approaches are only undertaken if the number of models to evaluate is greater than 30.

**Value**

A data table in data.frame format of all possible model combinations with each covariate specified in all possible ways, with the BIC of the model and the model formula.

**Examples**

```
library(dplyr)
library(glue)
library(purrr)
library(doParallel)
library(mgcv)
data("productivity")
input_data = productivity |> filter(year == "1970")
svc_res_gam =
  evaluate_models(input_data = input_data,
                 target_var = "privC",
                 covariates = c("unemp", "pubC"),
                 coords_x = "X",
                 coords_y = "Y",
```

```

                                STVC = FALSE)
head(svc_res_gam)

```

---

gam_model_probs	<i>Calculates the model probabilities of the different GAM models generated by evaluate_models‘</i>
-----------------	---

---

### Description

Calculates the model probabilities of the different GAM models generated by evaluate\_models‘

### Usage

```
gam_model_probs(res_tab, n = 10)
```

### Arguments

res_tab	a table generated by evaluate_models
n	the number of models to retain and generate probabilities for

### Value

A ranked data table in tibble format of the top n models, their form, BIC and model or (Pr(M|D)) or relative (Pr(M)) probability value. Model probability indicates the probability of the each model being the correct model and the relative probabilities provide a measure of the doubt about the differences in model specification, when compared to the best or highest ranked model. The relative probabilities are needed when large BIC values generate near zero probability values.

### Examples

```

library(dplyr)
library(purrr)
library(glue)
library(mgcv)
data(productivity)
input_data = productivity |> filter(year == "1970")
svc_res_gam = evaluate_models(input_data, STVC = FALSE)
mod_comp_svc <- gam_model_probs(svc_res_gam, n = 10)
# print out the terms and probabilities
mod_comp_svc|> select(-f)

```

---

plot\_1d\_smooth                      *Plots a 1-Dimensional GAM smooth*

---

## Description

Plots a 1-Dimensional GAM smooth

## Usage

```
plot_1d_smooth(mod, ncol = NULL, nrow = NULL, fills = "lightblue")
```

## Arguments

mod	a GAM model with smooths created using the mgcv package
ncol	the number of columns in the compound plot
nrow	the number of rows in the compound plot
fills	the fill colours (single or vector)

## Value

A compound plot of the GAM 1-dimensional smooths (rendered using `cowplot::plot_grid()`).

## Examples

```
library(mgcv)
library(ggplot2)
library(dplyr)
library(cowplot)
# 1. from the `mgcv` `gam` function help
set.seed(2) ## simulate some data...
dat <- gamSim(1,n=400,dist="normal",scale=2)
b <- gam(y~s(x0)+s(x1)+s(x2)+s(x3),data=dat)
plot_1d_smooth(b, ncol = 2, fills = c("lightblue", "lightblue3"))
dev.off()
# 2. using a TVC
data(productivity)
data = productivity |> mutate(Intercept = 1)
gam.tvc.mod = gam(privC ~ 0 + Intercept +
  s(year, bs = 'gp', by = Intercept) +
  unemp + s(year, bs = "gp", by = unemp) +
  pubC + s(year, bs = "gp", by = pubC),
  data = data)
plot_1d_smooth(gam.tvc.mod, fills = "lightblue")
```

---

plot_2d_smooth	<i>Plots a 2-Dimensional GAM smooth</i>
----------------	---

---

## Description

Plots a 2-Dimensional GAM smooth

## Usage

```
plot_2d_smooth(mod, filled = FALSE, outline = NULL, ncol = NULL, nrow = NULL)
```

## Arguments

mod	a GAM model with smooths created using the mgcv package
filled	logical value to indicate whether a filled plot should be created (TRUE) or not (FALSE)
outline	the name of an sf object to be plotted (NULL is the default)
ncol	the number of columns for the compound plot
nrow	the number of rows for the compound plot

## Value

A compound plot of the 2-dimensional smooths (rendered using `cowplot::plot_grid`).

## Examples

```
library(mgcv)
library(ggplot2)
library(dplyr)
library(metR)
library(cowplot)
set.seed(2) ## simulate some data...
dat <- gamSim(1,n=400,dist="normal",scale=2)
# use x1 and x2 as the coordinates
b <- gam(y~s(x0, x1, bs = 'gp', by = x2),data=dat)
plot_2d_smooth(b, filled = TRUE)
```



---

productivity

*US States Economic Productivity Data (1970-1985)*

---

### Description

A dataset of annual economic productivity data for the 48 contiguous US states (with Washington DC merged into Maryland), from 1970 to 1985 (17 years) in long format. The data productivity data table was extracted from the plm package.

### Usage

```
productivity
```

### Format

A tibble with 816 rows and 14 columns.

**state** The name of the state

**GEOID** The state code

**region** The region

**pubC** Public capital which is composed of highways and streets (hwy) water and sewer facilities (water) and other public buildings and structures (util)

**hwy** Highway and streets assets

**water** Water utility assets

**util** Other public buildings and structures

**privC** Private capital stock

**gsp** Gross state product

**emp** Labour input measured by the employment in non-agricultural payrolls

**unemp** State unemployment rate capture elements of the business cycle

**X** Easting in metres from USA Contiguous Equidistant Conic projection (ESRI:102005)

**Y** Northing in metres from USA Contiguous Equidistant Conic projection (ESRI:102005)

### Source

Croissant, Yves, Giovanni Millo, and Kevin Tappe. 2022. Plm: Linear Models for Panel Data

### Examples

```
data(productivity)
```

---

`us_data`*US States boundaries*

---

**Description**

A dataset of the boundaries of 48 contiguous US states (with Washington DC merged into Maryland), extracted from the `spData` package.

**Usage**`us_data`**Format**

A `sf` polygon dataset with 48 rows and 6 fields.

**GEOID** The state code

**NAME** The name of the state

**REGION** The region

**total\_pop\_10** Population in 2010

**total\_pop\_15** Population in 2015

**Source**

Bivand, Roger, Jakub Nowosad, and Robin Lovelace. 2019. `spData`: Datasets for Spatial Analysis. R package

**Examples**`data(us_data)`

# Index

## \* datasets

productivity, 9  
us\_data, 10

calculate\_vcs, 2

do\_bma, 3

evaluate\_models, 4

gam\_model\_probs, 6

plot\_1d\_smooth, 7

plot\_2d\_smooth, 8

productivity, 9

us\_data, 10