Package 'rwicc'

October 14, 2022

Title Regression with Interval-Censored Covariates

Version 0.1.3

Description Provides functions to simulate and analyze data for a regression model with an interval censored covariate, as described in Morrison et al. (2021) <doi:10.1111/biom.13472>.

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Encoding UTF-8

RoxygenNote 7.1.2

VignetteBuilder knitr

Config/testthat/edition 3

Imports biglm, dplyr, lubridate, magrittr, stats, pryr, arm, ggplot2, scales

Suggests spelling, rmarkdown, knitr, testthat, markdown, pander

Language en-US

URL https://d-morrison.github.io/rwicc/, https://github.com/d-morrison/rwicc

BugReports https://github.com/d-morrison/rwicc/issues

NeedsCompilation no

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Repository CRAN

Date/Publication 2022-03-09 21:40:06 UTC

R topics documented:

`build_phi_function_from_coefs` *convert a pair of simple logistic regression coefficients into P(Y|T) curve:*

Description

convert a pair of simple logistic regression coefficients into P(Y|T) curve:

Usage

```
build_phi_function_from_coefs(coefs)
```

Arguments

`coefs`	numeric vector of coefficients

Value

function(t) P(Y=1|T=t)

`compute_mu` *compute mean window period duration from simple logistic regression coefficients*

Description

compute mean window period duration from simple logistic regression coefficients

Usage

```
compute_mu(theta)
```

Arguments

`theta`	numeric vector of coefficients

Value

numeric scalar: mean window period duration

`fit_joint_model` *Fit a logistic regression model with an interval-censored covariate*

Description

This function fits a logistic regression model for a binary outcome Y with an interval-censored covariate T, using an EM algorithm, as described in Morrison et al (2021); doi: 10.1111/biom.13472.

Usage

```
fit_joint_model(
  participant_level_data,
  obs_level_data,
  model_formula = stats::formula(Y ~ T),
  mu_function = compute_mu,
  bin_width = 1,
  denom_offset = 0.1,
  EM_toler_loglik = 0.1,
  EM_toler_est = 1e-04,
  EM_max_iterations = Inf,
  glm_tolerance = 1e-07,
  glm_maxit = 20,
  initial_S_estimate_location = 0.25,
  coef_change_metric = "max abs rel diff coefs",
  verbose = FALSE
)
```

Arguments

`participant_level_data`
: a data.frame or tibble with the following variables:
  - ID: participant ID
  - E: study enrollment date
  - L: date of last negative test for seroconversion
  - R: date of first positive test for seroconversion
  - Cohort‘ (optional): this variable can be used to stratify the modeling of the seroconversion distribution.

`obs_level_data`
: a data.frame or tibble with the following variables:
  - ID: participant ID
  - O: biomarker sample collection dates
  - Y: MAA classifications (binary outcomes)

`model_formula`
: the functional form for the regression model for p(y|t) (as a formula() object)

`mu_function` a function taking a vector of regression coefficient estimates as input and outputting an estimate of mu (mean duration of MAA-positive infection).

`bin_width` the number of days between possible seroconversion dates (should be an integer)

`denom_offset` an offset value added to the denominator of the hazard estimates to improve numerical stability

`EM_toler_loglik` the convergence cutoff for the log-likelihood criterion ("Delta_L" in the paper)

`EM_toler_est` the convergence cutoff for the parameter estimate criterion ("Delta_theta" in the paper)

`EM_max_iterations` the number of EM iterations to perform before giving up if still not converged.

`glm_tolerance` the convergence cutoff for the glm fit in the M step

`glm_maxit` the iterations cutoff for the glm fit in the M step

`initial_S_estimate_location` determines how seroconversion date is guessed to initialize the algorithm; can be any decimal between 0 and 1; 0.5 = midpoint imputation, 0.25 = 1st quartile, 0 = last negative, etc.

`coef_change_metric` a string indicating the type of parameter estimate criterion to use:

- "max abs rel diff coefs" is the "Delta_theta" criterion described in the paper.
- "max abs diff coefs" is the maximum absolute change in the coefficients (not divided by the old values); this criterion can be useful when some parameters are close to 0.
- "diff mu" is the absolute change in mu, which may be helpful in the incidence estimate calibration setting but not elsewhere.

`verbose` whether to print algorithm progress details to the console

Value

a list with the following elements:

- `Theta`: the estimated regression coefficients for the model of p(Y|T)
- `Mu`: the estimated mean window period (a transformation of `Theta`)
- `Omega`: a table with the estimated parameters for the model of p(S|E).
- `converged`: indicator of whether the algorithm reached its cutoff criteria before reaching the specified maximum iterations. 1 = reached cutoffs, 0 = not.
- `iterations`: the number of EM iterations completed before the algorithm stopped.
- `convergence_metrics`: the four convergence metrics

References

Morrison, Laeyendecker, and Brookmeyer (2021). "Regression with interval-censored covariates: Application to cross-sectional incidence estimation". Biometrics. doi: 10.1111/biom.13472.

Examples

```
## Not run:

# simulate data:
study_data <- simulate_interval_censoring()

# fit model:
EM_algorithm_outputs <- fit_joint_model(
  obs_level_data = study_data$obs_data,
  participant_level_data = study_data$pt_data
)

## End(Not run)
```

`fit_midpoint_model` *Fit model using midpoint imputation*

Description

Fit model using midpoint imputation

Usage

```
fit_midpoint_model(
  participant_level_data,
  obs_level_data,
  maxit = 1000,
  tolerance = 1e-08
)
```

Arguments

`participant_level_data`	a data.frame or tibble with the following variables: • ID: participant ID • E: study enrollment date • L: date of last negative test for seroconversion • R: date of first positive test for seroconversion • Cohort‘ (optional): this variable can be used to stratify the modeling of the seroconversion distribution.
`obs_level_data`	a data.frame or tibble with the following variables: • ID: participant ID • O: biomarker sample collection dates • Y: MAA classifications (binary outcomes)
`maxit`	maximum iterations, passed to `bigglm`
`tolerance`	convergence criterion, passed to `bigglm`

Value

a vector of logistic regression coefficient estimates

Examples

```
sim_data = simulate_interval_censoring(
  "theta" = c(0.986, -3.88),
  "study_cohort_size" = 4500,
  "preconversion_interval_length" = 365,
  "hazard_alpha" = 1,
  "hazard_beta" = 0.5)

theta_est_midpoint = fit_midpoint_model(
  obs_level_data = sim_data$obs_data,
  participant_level_data = sim_data$pt_data
)
```

---

fit_uniform_model *Fit model using uniform imputation*

Description

Fit model using uniform imputation

Usage

```
fit_uniform_model(
  participant_level_data,
  obs_level_data,
  maxit = 1000,
  tolerance = 1e-08,
  n_imputations = 10
)
```

Arguments

`participant_level_data`
: a data.frame or tibble with the following variables:

- ID: participant ID
- E: study enrollment date
- L: date of last negative test for seroconversion
- R: date of first positive test for seroconversion
- Cohort‘ (optional): this variable can be used to stratify the modeling of the seroconversion distribution.

`obs_level_data` a data.frame or tibble with the following variables:

- ID: participant ID
- O: biomarker sample collection dates
- Y: MAA classifications (binary outcomes)

`maxit`	maximum iterations, passed to `bigglm`
`tolerance`	convergence criterion, passed to `bigglm`
`n_imputations`	number of imputed data sets to create

Value

a vector of logistic regression coefficient estimates

Examples

```
sim_data = simulate_interval_censoring(
  "theta" = c(0.986, -3.88),
  "study_cohort_size" = 4500,
  "preconversion_interval_length" = 365,
  "hazard_alpha" = 1,
  "hazard_beta" = 0.5)

theta_est_midpoint = fit_uniform_model(
  obs_level_data = sim_data$obs_data,
  participant_level_data = sim_data$pt_data
)
```

---

plot_CDF *plot estimated and true CDFs for seroconversion date distribution*

Description

plot estimated and true CDFs for seroconversion date distribution

Usage

```
plot_CDF(true_hazard_alpha, true_hazard_beta, omega.hat)
```

Arguments

`true_hazard_alpha`	The data-generating hazard at the start of the study
`true_hazard_beta`	The change in data-generating hazard per calendar year
`omega.hat`	tibble of estimated discrete hazards

Value

a ggplot

Examples

```
## Not run:

hazard_alpha = 1
hazard_beta = 0.5
study_data <- simulate_interval_censoring(
  "hazard_alpha" = hazard_alpha,
  "hazard_beta" = hazard_beta)

# fit model:
EM_algorithm_outputs <- fit_joint_model(
  obs_level_data = study_data$obs_data,
  participant_level_data = study_data$pt_data
)
plot1 = plot_CDF(
  true_hazard_alpha = hazard_alpha,
  true_hazard_beta = hazard_beta,
  omega.hat = EM_algorithm_outputs$Omega)

print(plot1)

## End(Not run)
```

`plot_phi_curves` *Plot true and estimated curves for P(Y=1|T=t)*

Description

Plot true and estimated curves for P(Y=1|T=t)

Usage

```
plot_phi_curves(
  theta_true,
  theta.hat_joint,
  theta.hat_midpoint,
  theta.hat_uniform
)
```

Arguments

`theta_true`	the coefficients of the data-generating model P(Y=1|T=t)
`theta.hat_joint`	the estimated coefficients from the joint model
`theta.hat_midpoint`	the estimated coefficients from midpoint imputation
`theta.hat_uniform`	the estimated coefficients from uniform imputation

Value

a ggplot

Examples

```
## Not run:

theta_true = c(0.986, -3.88)
hazard_alpha = 1
hazard_beta = 0.5
sim_data = simulate_interval_censoring(
  "theta" = theta_true,
  "study_cohort_size" = 4500,
  "preconversion_interval_length" = 365,
  "hazard_alpha" = hazard_alpha,
  "hazard_beta" = hazard_beta)

# extract the participant-level and observation-level simulated data:
sim_participant_data = sim_data$pt_data
sim_obs_data = sim_data$obs_data
rm(sim_data)

# joint model:
EM_algorithm_outputs = fit_joint_model(
  obs_level_data = sim_obs_data,
  participant_level_data = sim_participant_data,
  bin_width = 7,
  verbose = FALSE)

# midpoint imputation:
theta_est_midpoint = fit_midpoint_model(
  obs_level_data = sim_obs_data,
  participant_level_data = sim_participant_data
)

# uniform imputation:
theta_est_uniform = fit_uniform_model(
  obs_level_data = sim_obs_data,
  participant_level_data = sim_participant_data
)
plot2 = plot_phi_curves(
  theta_true = theta_true,
  theta.hat_uniform = theta_est_uniform,
  theta.hat_midpoint = theta_est_midpoint,
  theta.hat_joint = EM_algorithm_outputs$Theta)

print(plot2)

## End(Not run)
```

rwicc *rwicc: Regression with Interval-Censored Covariates*

Description

The `rwicc` package implements a regression model with an interval-censored covariate using an EM algorithm, as described in Morrison et al (2021); doi: 10.1111/biom.13472.

rwicc functions

The main `rwicc` functions are:

- `simulate_interval_censoring`
- `fit_joint_model`

References

Morrison, Laeyendecker, and Brookmeyer (2021). "Regression with interval-censored covariates: Application to cross-sectional incidence estimation". Biometrics. doi: 10.1111/biom.13472.

seroconversion_inverse_survival_function *Inverse survival function for time-to-event variable with linear hazard function*

Description

This function determines the seroconversion date corresponding to a provided probability of survival. See doi: 10.1111/biom.13472, Supporting Information, Section A.4.

Usage

```
seroconversion_inverse_survival_function(u, e, hazard_alpha, hazard_beta)
```

Arguments

`u`	a vector of seroconversion survival probabilities
`e`	a vector of time differences between study start and enrollment (in years)
`hazard_alpha`	the instantaneous hazard of seroconversion on the study start date
`hazard_beta`	the change in hazard per year after study start date

Value

numeric vector of time differences between study start and seroconversion (in years)

References

Morrison, Laeyendecker, and Brookmeyer (2021). "Regression with interval-censored covariates: Application to cross-sectional incidence estimation". Biometrics, doi: 10.1111/biom.13472.

`simulate_interval_censoring` *Simulate a dataset with interval-censored seroconversion dates*

Description

`simulate_interval_censoring` generates a simulated data set from a data-generating model based on the typical structure of a cohort study of HIV biomarker progression, as described in Morrison et al (2021); doi: 10.1111/biom.13472.

Usage

```
simulate_interval_censoring(
  study_cohort_size = 4500,
  hazard_alpha = 1,
  hazard_beta = 0.5,
  preconversion_interval_length = 84,
  theta = c(0.986, -3.88),
  probability_of_ever_seroconverting = 0.05,
  years_in_study = 10,
  max_scheduling_offset = 7,
  days_from_study_start_to_recruitment_end = 365,
  study_start_date = lubridate::ymd("2001-01-01")
)
```

Arguments

`study_cohort_size` the number of participants to simulate (N_0 in the paper)

`hazard_alpha` the hazard (instantaneous risk) of seroconversion at the start date of the cohort study for those participants at risk of seroconversion

`hazard_beta` the change in hazard per calendar year

`preconversion_interval_length` the number of days between tests for seroconversion

`theta` the parameters of a logistic model (with linear functional from) specifying the probability of MAA-positive biomarkers as a function of time since seroconversion

`probability_of_ever_seroconverting` the probability that each participant is at risk of HIV seroconversion

`years_in_study` the duration of follow-up for each participant

`max_scheduling_offset`
: the maximum divergence of pre-seroconversion followup visits from the prescribed schedule

`days_from_study_start_to_recruitment_end`
: the length of the recruitment period

`study_start_date`
: the date when the study starts recruitment ("d_0" in the main text). The value of this parameter does not affect the simulation results; it is only necessary as a reference point for generating E, L, R, O, and S.

Value

A list containing the following two tibbles:

- `pt_data`: a tibble of participant-level information, with the following columns:
  - `ID`: participant ID
  - `E`: enrollment date
  - `L`: date of last HIV test prior to seroconversion
  - `R`: date of first HIV test after seroconversion
- `obs_data`: a tibble of longitudinal observations with the following columns:
  - `ID`: participant ID
  - `O`: dates of biomarker sample collection
  - `Y`: MAA classifications of biomarker samples

References

Morrison, Laeyendecker, and Brookmeyer (2021). "Regression with interval-censored covariates: Application to cross-sectional incidence estimation". Biometrics. doi: 10.1111/biom.13472.

Examples

```
study_data <- simulate_interval_censoring()
participant_characteristics <- study_data$pt_data
longitudinal_observations <- study_data$obs_data
```

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