casebase: An Alternative Framework For Survival Analysis and Comparison of Event Rates

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Abstract In epidemiological studies of time-to-event data, a quantity of interest to the clinician and the patient is the risk of an event given their covariate profile. However, methods relying on time matching or risk-set sampling (including Cox regression) eliminate the baseline hazard from the likelihood expression or the estimating function. The baseline hazard then needs to be estimated separately using a non-parametric approach. This leads to step-wise estimates of the cumulative incidence that are difficult to interpret. Using case-base sampling, Hanley & Miettinen (2009) explained how the parametric hazard functions can be estimated using logistic regression. Their approach naturally leads to estimates of the cumulative incidence that are smooth-in-time.
In this paper, we present the **casebase** R package, a comprehensive and flexible toolkit for parametric survival analysis. We describe how the case-base framework can be used in more complex settings: non-linear functions of time and non-proportional hazards, competing risks, and variable selection. Our package also includes an extensive array of visualization tools to complement the analysis of time-to-event data. We illustrate all these features through three different case studies.
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Introduction

Survival analysis and the comparison of event rates has been greatly influenced over the last 50 years by the partial likelihood approach of the Cox proportional hazard model (Cox, 1972). This approach provides a flexible way of assessing the influence of covariates on the hazard function, without the need to specify a parametric survival model. This flexibility comes at the cost of decoupling the baseline hazard from the effect of the covariates. To recover the whole survival curve—or the cumulative incidence function (CIF)—we then need to separately estimate the baseline hazard (Breslow, 1972). This in turn leads to stepwise estimates of the survival function that can be difficult to interpret.

From the perspective of clinicians and their patients, the most relevant quantity is often the 5- or 10-year risk of experiencing a certain event given the patient's particular circumstances, and not the hazard ratio between a treatment and control group. Therefore, to make sound clinical decisions, it is important to accurately estimate the *full* hazard function, which can subsequently be used to estimate the CIF. Using a parametric estimator of the hazard function leads to a smooth function of time; as a consequence, the CIF and the survival function estimates also vary smoothly over time.

With the goal of fitting smooth-in-time hazard functions, Hanley & Miettinen (2009) proposed a general framework for estimating fully parametric hazard models via logistic regression. Their main idea is simple: comparing person-moments when the event of interest occurred with moments when patients were at risk. Their approach handles censored data effortlessly and provides users familiar with generalized linear models a natural way of fitting parametric survival models. Moreover, their framework is very flexible: general functions of time can be estimated (e.g. using splines or general additive models), and hence these models retain some of the flexibility of Cox's partial likelihood approach. And since the unit of analysis is a person moment, time-varying covariates can also easily be included in this framework.

Logistic regression had already been used in the context of discrete-time survival modeling (Cox, 1972). But in the context of continuous-time survival modeling, using the framework of logistic regression opens the door to an extensive array of powerful modeling tools. Indeed, lasso and elastic-net regression can be used to select variables that are associated with the hazard function. Logistic regression can also be replaced by multinomial regression to analyse data with multiple competing events.

In this article, we present the **casebase** package (Bhatnagar et al., 2020) implemented in R (R Core Team, 2020), for parametric survival analysis that combines the ideas of Hanley & Miettinen (2009) into a simple interface. The purpose of the **casebase** package is to provide practitioners with an easy-to-use software tool to compute a patient's risk (or cumulative incidence) of an event, conditional on a particular patient's covariate profile. Our package retains the flexibility of case-base sampling and the familiar interface of the `glm` function. It also provides tools for variable selection, competing-risk analysis, and dealing with time-dependent exposures. In addition, we provide functions for exploratory data analysis and visualizing the estimated quantities.

In what follows, we first recall some theoretical details on case-base sampling and its use for estimating parametric hazard functions. We then give a short review of existing R packages that implement comparable features as **casebase**. Next, we provide some details about the implementation of case-base sampling in our package, and we give a brief survey of its main functions. This is followed by three case studies that illustrate the flexibility and capabilities of **casebase**. We show how the same framework can be used for non-linear functions of time and non-proportional hazards, competing risks and variable selection via penalized regression. Finally, we end the article with a discussion of the results and of future directions.

Theoretical details

As discussed in Hanley & Miettinen (2009), the key idea behind case-base sampling is to sample from the study base a finite amount of *person moments*. These person moments are indexed by both an individual in the study and a time point, and therefore each person moment has a covariate profile, an exposure status and an outcome status attached to it. We note that there is only a finite number of person moments associated with the event of interest (what Hanley & Miettinen call the *case series*). Case-base sampling refers to the sampling from the base of a representative finite sample called the *base series*.

Likelihood and estimating function

To describe the theoretical foundations of case-base sampling, we use the framework of counting processes. In what follows, we abuse notation slightly and omit any mention of σ-algebras. Instead, following Aalen *et al* (2008), we use the placeholder "past" to denote the past history of the corresponding process. The reader interested in more details can refer to Saarela & Arjas (2015) and Saarela (2016). First, let $N_i(t) \in \{0, 1\}$ be counting processes corresponding to the event of interest for individual $i = 1, \ldots, n$. For simplicity, we will consider Type I censoring due to the end of follow-up at time τ (the general case of non-informative censoring is treated in Saarela (2016)). We assume a continuous time model, which implies that the counting process jumps are less than or equal to one. We are interested in modeling the hazard functions $\lambda_i(t)$ of the processes $N_i(t)$, and which satisfy

$$\lambda_i(t)dt = E[dN_i(t) \mid \text{past}].$$

Next, we model the base series sampling mechanism using non-homogeneous Poisson processes $R_i(t) \in \{0, 1, 2, \ldots\}$, with the person-moments where $dR_i(t) = 1$ constituting the base series. The process $Q_i(t) = R_i(t) + N_i(t)$ then counts both the case and base series person-moments contributed by individual i. This process is typically defined by the user via its intensity function $\rho_i(t)$. The process $Q_i(t)$ is characterized by $E[dQ_i(t) \mid \text{past}] = \lambda_i(t)dt + \rho_i(t)dt$.

If the hazard function $\lambda_i(t; \theta)$ is parametrized in terms of θ, we could define an estimator $\hat{\theta}$ by maximization of the likelihood expression

$$L_0(\theta) = \prod_{i=1}^{n} \exp\left\{ -\int_0^{\min(t_i, \tau)} \lambda_i(t; \theta)dt \right\} \prod_{i=1}^{n} \prod_{t \in [0, \tau)} \lambda_i(t; \theta)^{dN_i(t)},$$

where $\prod_{t \in [0, u)}$ represents a product integral from 0 to u, and where t_i is the event time for individual i. However, the integral over time makes the computation and maximization of $L_0(\theta)$ challenging.

Case-base sampling allows us to avoid this integral. By conditioning on a sampled person-moment, we get individual likelihood contributions of the form

$$P(dN_i(t) \mid dQ_i(t) = 1, \text{past}) \overset{\theta}{\propto} \frac{\lambda_i(t; \theta)^{dN_i(t)}}{\rho_i(t) + \lambda_i(t; \theta)}.$$

Therefore, we can define an estimating function for θ as follows:

$$L(\theta) = \prod_{i=1}^{n} \prod_{t \in [0, \tau)} \left(\frac{\lambda_i(t; \theta)^{dN_i(t)}}{\rho_i(t) + \lambda_i(t; \theta)} \right)^{dQ_i(t)}. \tag{1}$$

When a logarithmic link function is used for modeling the hazard function, the above expression is of a logistic regression form with an offset term $\log(1/\rho_i(t))$. Note that the sampling units selected in the case-base sampling mechanism are person-moments, rather than individuals, and the parameters to be estimated are hazards or hazard ratios rather than odds or odds ratios. Generally, an individual can contribute more than one person-moment, and thus the terms in the product integral are not

independent. Nonetheless, Saarela (2016) showed that the logarithm of this estimating function has mean zero at the true value $\theta = \theta_0$, and that the resulting estimator $\hat{\theta}$ is asymptotically normally distributed.

In Hanley & Miettinen (2009), the authors suggest sampling the base series *uniformly* from the study base. In terms of Poisson processes, their sampling strategy corresponds essentially to a time-homogeneous Poisson process with hazard equal to $\rho_i(t) = b/B$, where b is the number of sampled observations in the base series, and B is the total population-time for the study base (e.g. the sum of all individual follow-up times). More complex examples are also possible; see for example Saarela & Arjas (2015), where the intensity functions for the sampling mechanism are proportional to the cardiovascular disease event rate given by the Framingham score. Non-uniform sampling mechanisms can increase the efficiency of the case-base estimators.

Common parametric models

Let $g(t; X)$ be the linear predictor such that $\log(\lambda(t; X)) = g(t; X)$. Different functions of t lead to different parametric hazard models. The simplest of these models is the one-parameter exponential distribution which is obtained by taking the hazard function to be constant over the range of t:

$$\log(\lambda(t; X)) = \beta_0 + \beta_1 X. \tag{2}$$

In this model, the instantaneous failure rate is independent of t.[1]

The Gompertz hazard model is given by including a linear term for time:

$$\log(\lambda(t; X)) = \beta_0 + \beta_1 t + \beta_2 X. \tag{3}$$

Use of $\log(t)$ yields the Weibull hazard which allows for a power dependence of the hazard on time (Kalbfleisch and Prentice, 2011):

$$\log(\lambda(t; X)) = \beta_0 + \beta_1 \log(t) + \beta_2 X. \tag{4}$$

Competing-risk analysis

Case-base sampling can also be used in the context of competing-risk analyses. Assuming there are J competing events, we can show that each person-moment's contribution to the likelihood is of the form

$$\frac{\lambda_j(t)^{dN_j(t)}}{\rho(t) + \sum_{j=1}^{J} \lambda_j(t)},$$

where $N_j(t)$ is the counting process associated with the event of type j and $\lambda_j(t)$ is the corresponding cause-specific hazard function. As may be expected, this functional form is similar to the terms appearing in the likelihood function for multinomial regression.[2]

Variable selection

To perform variable selection on the regression parameters $\theta \in \mathbb{R}^p$ of the hazard function, we can add a penalty to the likelihood and optimise the following equation:

$$\min_{\theta \in \mathbb{R}^p} -\ell(\theta) + \sum_{j=1}^{p} w_j P(\theta_j; \lambda, \alpha) \tag{5}$$

where $\ell(\theta) = \log L(\theta)$ is the log of the likelihood function given in (1), $P(\theta_j; \lambda, \alpha)$ is a penalty term controlled by the non-negative regularization parameters λ and α, and w_j is the penalty factor for the jth covariate. These penalty factors serve as a way of allowing parameters to be penalized differently.

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[1] The conditional chance of failure in a time interval of specified length is the same regardless of how long the individual has been in the study. This is also known as the *memoryless property* (Kalbfleisch and Prentice, 2011).

[2] Specifically, it corresponds to the following parametrization:

$$\log\left(\frac{P(Y = j \mid X)}{P(Y = J \mid X)}\right) = X^T \beta_j, \qquad j = 1, \dots, J - 1.$$

For example, we could set the penalty factor for time to be 0 to ensure it is always included in the selected model.

Comparison with existing packages

Survival analysis is an important branch of applied statistics and epidemiology. Accordingly, there is already a vast ecosystem of R packages implementing different methodologies. In this section, we describe how the functionalities of **casebase** compare to these packages.

At the time of writing, a cursory examination of CRAN's task view on survival analysis reveals that there are over 250 packages related to survival analysis (Allignol and Latouche, 2019). For the purposes of this article, we restricted our review to packages that implement at least one of the following features: parametric modeling, non-proportional hazard models, competing risk analysis, penalized estimation, and CIF estimation. By searching for appropriate keywords in the DESCRIPTION file of these packages, we found 60 relevant packages. These 60 packages were then manually examined to determine which ones are comparable to **casebase**. In particular, we excluded packages that were focused on a different set of problems, such as frailty and multi-state models. The remaining 14 packages appear in Table 1, along with some of the functionalities they offer.

Parametric survival models are implemented in a handful of packages, each differing in the underlying data distribution: **CFC** (2019), **flexsurv** (2016), **SmoothHazard** (2017), **rsptm2** (2019), **mets** (2014), and **survival** (2015). For example, **SmoothHazard** is limited to Weibull distributions (2017), whereas both **flexsurv** and **survival** allow users to supply any distribution of their choice. **flexsurv**, **smoothhazard**, **mets** and **rstpm2** can model the effect of time using splines, which allows flexible modeling of the hazard function. As discussed above, **casebase** can model any parametric family whose log-hazard can be expressed as a linear combination of covariates (including time). Therefore, our package is more general in that it allows the user to model any linear or non-linear transformation of time including splines and higher order polynomials. Also, by including interaction terms between covariates and time, it also allows users to fit (non-proportional) time-varying coefficient models. However, unlike **flexsurv**, we do not explicitly model any shape parameter.

Several packages implement penalized estimation for the Cox model: **glmnet** (2011), **glmpath** (2018), **penalized** (2010), **riskRegression** (2020). Moreover, some packages also include penalized estimation in the context of Cox models with time-varying coefficients: elastic-net penalization with **rstpm2** (2019), while **survival** (2015) has an implementation of ridge-penalized estimation. On the other hand, our package **casebase** provides penalized estimation of the hazard function. To our knowledge, **casebase** and **rsptm2** are the only packages to offer this functionality.

Next, several R packages implement methodologies for competing risk analysis; for a different perspective on this topic, see Mahani & Sharabiani (2019). The package **cmprsk** provides methods for cause-specific subdistribution hazards, such as in the Fine-Gray model (1999). On the other hand, the package **CFC** estimates cause-specific CIFs from unadjusted, non-parametric survival functions. Our package **casebase** also provides functionalities for competing risk analysis by estimating parametrically the cause-specific hazards. From these quantities, we can then estimate the cause-specific CIFs.

Finally, several packages include functions to estimate the CIF. The corresponding methods generally fall into two categories: transformation of the estimated hazard function, and semi-parametric estimation of the baseline hazard. The first category broadly corresponds to parametric survival models, where the full hazard is explicitly modeled. Using this estimate, the survival function and the CIF can be obtained using their functional relationships (see Equations 6 and 7 below). Packages providing this functionality include **CFC**, **flexsurv**, **mets**, and **survival**. Our package **casebase** also follows this approach for both single-event and competing-risk analyses. The second category outlined above broadly corresponds to semi-parametric models. These models do not model the full hazard function, and therefore the baseline hazard needs to be estimated separately in order to estimate the survival function. This is achieved using semi-parametric estimators (e.g. Breslow's estimator) or parametric estimators (e.g. spline functions). Packages that implement this approach include **riskRegression**, **rstpm2**, and **survival**. As mentioned in the introduction, a key distinguishing factor between these two approaches is that the first category leads to smooth estimates of the cumulative incidence function, whereas the second category often produces estimates in the form of stepwise functions. Providing smooth estimates of the CIF was one of the main motivations for introducing case-base sampling in survival analysis.

Package	Competing Risks	Allows Non PH	Penalized Regression	Splines	Parametric	Semi Parametric	Interval/Left Censoring	Absolute Risk
casebase	✓	✓	✓	✓	✓			✓
CFC	✓	✓				✓		✓
cmprsk	✓					✓		✓
crrp	✓		✓			✓		
fastcox			✓			✓		
flexrsurv		✓		✓	✓			✓
flexsurv	✓	✓		✓	✓			✓
glmnet			✓			✓		
glmpath			✓			✓		
mets	✓			✓		✓		✓
penalized			✓			✓		
riskRegression	✓		✓			✓		✓
rstpm2		✓		✓	✓	✓	✓	✓
SmoothHazard		✓		✓	✓		✓	
survival	✓	✓			✓	✓	✓	✓

Table 1: Comparison of various R packages for survival analysis based on several defining features. **Competing Risks**: whether or not an implementation for competing risks is present. **Allows Non PH**: permits models for non-proportional hazards. **Penalized Regression**: allows for a penalty term on the regression coefficients when estimating hazards (e.g. lasso or ridge). **Splines**: permits a flexible fit on time through the use of splines. **Parametric**: implementation for parametric models. **Semi-parametric**: implementation for semi-parametric models. **Interval/left censoring**: models for interval and left-censoring. If this is not selected, the package only handles right-censoring. **Absolute Risk**: computation for survival curves, cumulative incidence or cumulative hazard is readily available.

Implementation details

The functions in the **casebase** package can be divided into two categories: 1) exploratory data analysis, in the form of population-time plots; and 2) parametric modeling of the hazard function. We strove for compatibility with both data.frames and data.tables; this can be seen in the coding choices we made and the unit tests we wrote.

Population-time plots

Population-time plots are a descriptive visualization of incidence density, where aggregate person-time is represented by area and events as points within the area. The case-base sampling approach described in Section 2.2 can be visualized in the form of a population time plot. These plots are extremely informative graphical displays of survival data and should be one of the first steps in an exploratory data analysis. The popTime function and plot method facilitate this task:

1. The casebase::popTime function takes as input the original dataset along with the column names corresponding to the timescale, the event status and an exposure group of interest (optional). This will create an object of class popTime.

2. The corresponding plot method for the object created in Step 1 can be called to create the population time plot with several options for customizing the aesthetics.

By splitting these tasks, we give flexibility to the user. While the method call in Step 2 allows further customization by using the **ggplot2** (Wickham, 2016) family of functions, users may choose the graphics system of their choice to create population-time plots from the object created in Step 1.

To illustrate these functions, we will use data from the European Randomized Study of Prostate Cancer Screening (ERSPC) (Schröder et al., 2009) which was extracted using the approach described in Liu *et al.* (2014). This dataset is available through the **casebase** package. It contains the individual observations for 159,893 men from seven European countries, who were between the ages of 55 and 69 years when recruited for the trial.

We first create the necessary dataset for producing the population time plot using the popTime function. In this example, we stratify the plot by treatment group. The resulting object inherits from class popTime and stores the exposure variable as an attribute:

```
pt_object <- casebase::popTime(ERSPC, time = "Follow.Up.Time",
                               event = "DeadOfPrCa", exposure = "ScrArm")
inherits(pt_object, "popTime")

#> [1] TRUE
```

```
attr(pt_object, "exposure")

#> [1] "ScrArm"
```

We then pass this object to the corresponding `plot` method:
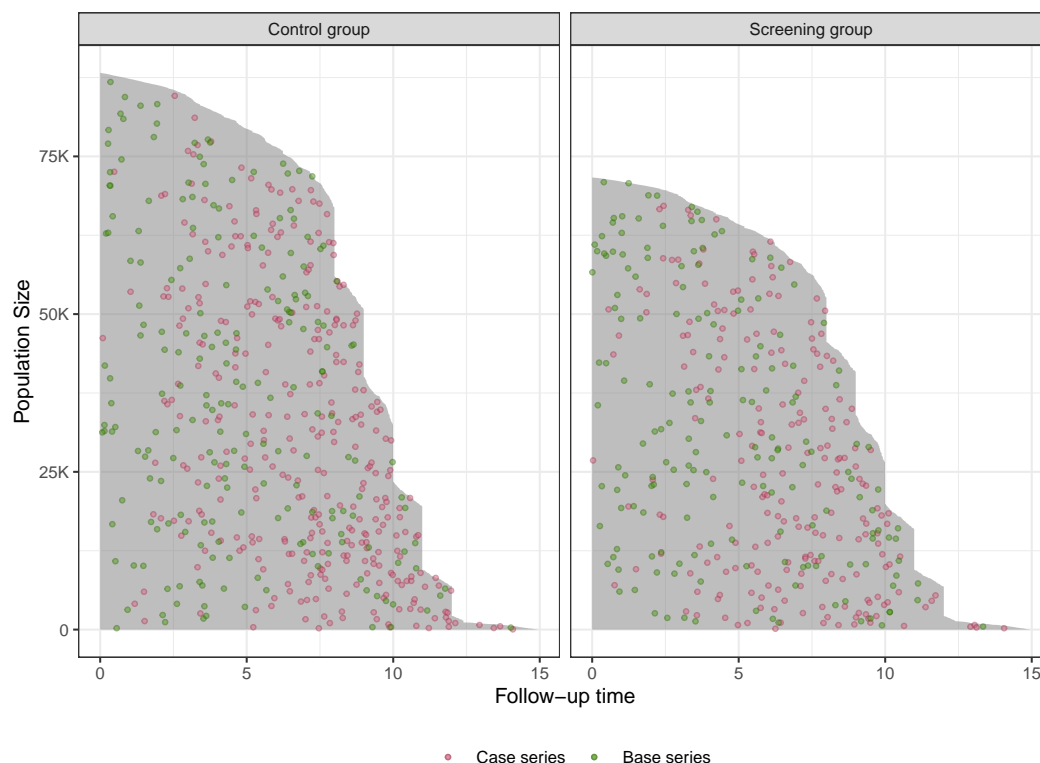
```
plot(pt_object, add.base.series = TRUE)
```


Figure 1: Population time plots for both treatment arms in the ERSPC dataset. The gray area can be thought of as N=88,232 (control group) and N=71,661 (screening group) rows of infinitely thin rectangles (person-moments). More events are observed at later follow-up times, motivating the use of non-constant hazard models.

Figure 1 is built sequentially by first adding a layer for the area representing the population time in gray, with subjects having the least amount of observation time plotted at the top of the y-axis. We immediately notice a distinctive *stepwise shape* in the population time area. This is due to the randomization of the Finnish cohorts which were carried out on January 1 of each of year from 1996 to 1999. Coupled with the uniform December 31 2006 censoring date, this led to large numbers of men with exactly 11, 10, 9 or 8 years of follow-up. Tracked backwards in time (i.e. from right to left), the population-time plot shows the recruitment pattern from its beginning in 1991, and the January 1 entries in successive years. Tracked forwards in time (i.e. from left to right), the plot for the first three years shows attrition due entirely to death (mainly from other causes). Since the Swedish and Belgian centres were the last to complete recruitment in December 2003, the minimum potential follow-up is three years. Tracked further forwards in time (i.e. after year 3) the attrition is a combination of deaths and staggered entries. As we can see, population-time plots summarise a wealth of information about the study into a simple graph.

Next, layers for the case series and base series are added. The y-axis location of each case moment is sampled at random vertically on the plot to avoid having all points along the upper edge of the gray area. By randomly distributing the cases, we can get a sense of the incidence density. In Figure 1, we see that more events are observed at later follow-up times. Therefore, a constant hazard model would not be appropriate in this instance as it would overestimate the cumulative incidence earlier on in time, and underestimate it later on. Finally, the base series is sampled horizontally with sampling weight proportional to their follow-up time. The reader should refer to the package vignettes for more examples and a detailed description of how to modify the aesthetics of a population-time plot.

Parametric modeling

The parametric modeling step was separated into three parts:

1. case-base sampling;
2. estimation of the smooth hazard function;
3. estimation of the CIF.

By separating the sampling and estimation functions, we allow the possibility of users implementing more complex sampling scheme (as described in Saarela (2016)), or more complex study designs (e.g. time-varying exposure).

The sampling scheme selected for `sampleCaseBase` was described in Hanley & Miettinen (2009): we first sample along the "person" axis, proportional to each individual's total follow-up time, and then we sample a moment uniformly over their follow-up time. This sampling scheme is equivalent to the following picture: imagine representing the total follow-up time of all individuals in the study along a single dimension, where the follow-up time of the next individual would start exactly when the follow-up time of the previous individual ends. Then the base series could be sampled uniformly from this one-dimensional representation of the overall follow-up time. In any case, the output is a dataset of the same class as the input, where each row corresponds to a person-moment. The covariate profile for each such person-moment is retained, and an offset term is added to the dataset. This output could then be used to fit a smooth hazard function, or for visualization of the base series.

Next, the fitting function `fitSmoothHazard` starts by looking at the class of the dataset: if it was generated from `sampleCaseBase`, it automatically inherited the class `cbData`. If the dataset supplied to `fitSmoothHazard` does not inherit from `cbData`, then the fitting function starts by calling `sampleCaseBase` to generate the base series. In other words, users can bypass `sampleCaseBase` altogether and only worry about the fitting function `fitSmoothHazard`.

The fitting function retains the familiar formula interface of `glm`. The left-hand side of the formula should be the name of the column corresponding to the event type. The right-hand side can be any combination of the covariates, along with an explicit functional form for the time variable. Note that non-proportional hazard models can be achieved at this stage by adding an interaction term involving time (cf. Case Study 1 below). The offset term does not need to be specified by the user, as it is automatically added to the formula before calling `glm`.

To fit the hazard function, we provide several approaches that are available via the `family` parameter. These approaches are:

- `glm`: This is the familiar logistic regression.
- `glmnet`: This option allows for variable selection using the elastic-net (Zou and Hastie, 2005) penalty (cf. Case Study 3). This functionality is provided through the **glmnet** package (Friedman et al., 2010).
- gam: This option provides support for *Generalized Additive Models* via the **mgcv** package (Hastie and Tibshirani, 1987).
- gbm: This option provides support for *Gradient Boosted Trees* via the **gbm** package. This feature is still experimental.

In the case of multiple competing events, the hazard is fitted via multinomial regression as performed by the **VGAM** package. We selected this package for its ability to fit multinomial regression models with an offset.

Once a model-fit object has been returned by `fitSmoothHazard`, all the familiar summary and diagnostic functions are available: `print`, `summary`, `predict`, `plot`, etc. Our package provides one more functionality: it computes risk functions from the model fit. For the case of a single event, it uses the familiar identity

$$S(t) = \exp\left(-\int_0^t \lambda(u; X)du\right). \tag{6}$$

The integral is computed using either the numerical or Monte-Carlo integration. The risk function (or cumulative incidence function) is then defined as

$$CI(t) = 1 - S(t). \tag{7}$$

For the case of a competing-event analysis, the event-specific risk is computed using the following procedure: first, we compute the overall survival function (i.e. for all event types):

$$S(t) = \exp\left(-\int_0^t \lambda(u; X)du\right), \qquad \lambda(t; X) = \sum_{j=1}^{J} \lambda_j(t; X).$$

From this, we can derive the event-specific subdensities:

$$f_j(t) = \lambda_j(t)S(t).$$

Finally, by integrating these subdensities, we obtain the event-specific cumulative incidence functions:

$$CI_j(t) = \int_0^t f_j(u)du.$$

Again, the integrals are computed using either numerical integration (via the trapezoidal rule) or Monte Carlo integration. This option is controlled by the argument `method` of the `absoluteRisk` function.

Illustration of package

In this section, we illustrate the main functions of the **casebase** package through three case studies. Each one showcases a different type of analysis. First, we show how to model different functional forms of time as well as non-proportional hazards. Then we perform a competing-risk analysis and compare our results with the Fine-Gray model. The third case study illustrates how to perform variable selection in high-dimensional datasets.

Case study 1—Modeling different functions of time and non-proportional hazards

For our first case study, we return to the ERSPC study and investigate the differences in risk between the control and screening arms. We fit four models that differ in which functional form of time is used: 1) excluded from the linear predictor (Eq. (2)); 2) linear function (Eq. (3)); 3) log function (Eq. (4)); and 4) a smooth function using cubic B-splines. The models are fit using `fitSmoothHazard` with the familiar formula interface:

```
fmla <- list(exponential = formula(DeadOfPrCa ~ ScrArm),
             gompertz = formula(DeadOfPrCa ~ Follow.Up.Time + ScrArm),
             weibull = formula(DeadOfPrCa ~ log(Follow.Up.Time) + ScrArm),
             splines = formula(DeadOfPrCa ~ bs(Follow.Up.Time) + ScrArm))

fits <- lapply(fmla, function(form) {
  fitSmoothHazard(form, data = ERSPC, ratio = 100)
})
```

The output object from `fitSmoothHazard` inherits from the `singleEventCB` and `glm` classes. For this reason, we leveraged the summary method for `glm` objects to output a familiar summary of the results:

```
summary(fits[["splines"]])

#> Fitting smooth hazards with case-base sampling
#>
#> Sample size: 159893
#> Number of events: 540
#> Number of base moments: 54000
#> ----
#>
#> Call:
#> fitSmoothHazard(formula = form, data = ERSPC, ratio = 100)
#>
#> Deviance Residuals:
#>    Min      1Q Median      3Q     Max
#> -0.409  -0.172  -0.135  -0.084   3.808
#>
#> Coefficients:
#>                     Estimate Std. Error z value Pr(>|z|)
#> (Intercept)         -10.2905     0.3185  -32.31  < 2e-16 ***
#> bs(Follow.Up.Time)1   4.3587     0.8008    5.44  5.2e-08 ***
#> bs(Follow.Up.Time)2   2.0890     0.4721    4.42  9.7e-06 ***
```

```
#> bs(Follow.Up.Time)3      4.6266      0.6910      6.70  2.1e-11 ***
#> ScrArmScreening group  -0.2354      0.0886    -2.66    0.0079 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#>     Null deviance: 6059.0  on 54539  degrees of freedom
#> Residual deviance: 5785.3  on 54535  degrees of freedom
#> AIC: 5795
#>
#> Number of Fisher Scoring iterations: 9
```

Next, the absoluteRisk function takes as input the singleEventCB object and returns a matrix where each column corresponds to the covariate profiles specified in the newdata argument, and each row corresponds to time points specified by the time argument:

```
new_data <- data.frame(ScrArm = c("Control group", "Screening group"))
new_time <- seq(0, 14, by = 0.1)

risks <- lapply(fits, function(fit) {
  absoluteRisk(fit, time = new_time, newdata = new_data)
})
```

In Figure 2, we overlay the estimated CIFs from **casebase** on the Cox model CIF. The CIF estimates for the exponential model in panel (1) overestimate the cumulative incidence earlier on in time, and underestimate it later on. Based on our earlier discussion of the population-time plot, this poor fit for the exponential hazard was expected. We notice a better fit with increasing complexity of our model for time in Figure 2 (panels 2–4). As noted in Theoretical Details section, the usual asymptotic results hold for likelihood ratio tests built using case-base sampling models. Therefore, we can easily test the null hypothesis that the exponential model is just as good as the larger (in terms of number of parameters) spline model:

```
#> Analysis of Deviance Table
#>
#> Model 1: DeadOfPrCa ~ ScrArm + offset(offset)
#> Model 2: DeadOfPrCa ~ bs(Follow.Up.Time) + ScrArm + offset(offset)
#>   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
#> 1     54538       6052
#> 2     54535       5785  3      267   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The null hypothesis is rejected in favor of the spline model. Similarly, the AIC provides further evidence that the flexible function of time provides the best fit:

```
#>    Exp. Gompertz  Weibull  Splines
#>    6056     5821     5807     5795
```

In Table 2, we present a side-by-side comparison of the hazard ratios and confidence intervals estimated from fitSmoothHazard and the corresponding parametric model using survival::survreg, as well as the Cox model estimate. The hazard ratio estimates and confidence intervals are similar across all four models. This reinforces the idea that, under proportional hazards, we do not need to model the full hazard to obtain reliable estimates of the hazard ratio. Nevertheless, Figure 2 shows that different parametric models can still give rise to qualitatively different estimates for the CIF.

Previous re-analyses of these data suggested that the overall screening attributed reduction in death due to prostate cancer of 20% was an underestimate (Hanley, 2010). The estimated 20% (from a proportional hazards model) did not account for the delay between screening and the time the effect is expected to be observed. As a result, the null effects in years 1–7 masked the substantial reductions that began to appear from year 8 onward. This motivates the use of a time-dependent hazard ratio which can easily be fit with the **casebase** package by including an interaction term with time in the model:

```
fit_inter <- fitSmoothHazard(DeadOfPrCa ~ bs(Follow.Up.Time) * ScrArm,
                             data = ERSPC)
```
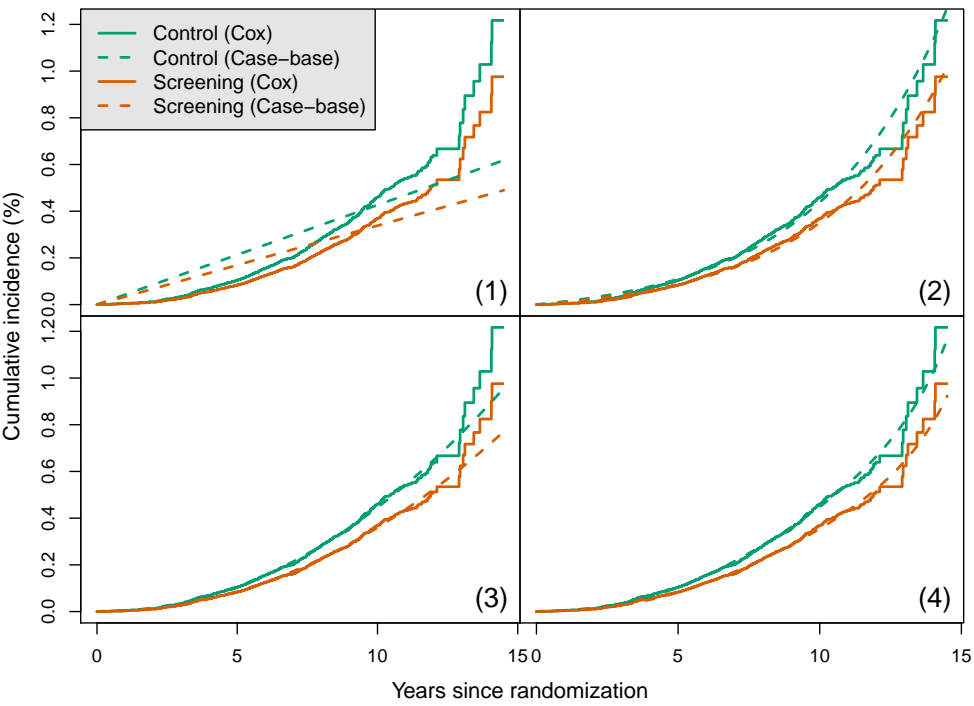
Figure 2: CIFs for control and screening groups in the ERSPC data. In each of the panels, we plot the CIF from the Cox model using `survival::survfit` (solid line) and the CIF from the case-base sampling scheme (dashed line) with different functional forms of time. (1) The time variable is excluded (exponential). (2) Linear function of time (Gompertz). (3) The natural logarithm (Weibull). (4) Cubic B-spline expansion of time.

In Figure 3, we have the estimated hazard ratio and 95% confidence interval for screening vs. control group as a function of time using the `plot` method for objects of class `singleEventCB`:

```
plot(fit_inter, type = "hr", newdata = new_data,
    var = "ScrArm", xvar = "Follow.Up.Time", ci = TRUE)
```

The plot shows that the cures attributable to the screening only begin to become statistically apparent by year 7 and later. The 25-60% reductions seen in years 8-12 of the study suggests a much higher reduction in prostate cancer due to screening than the single overall 20% reported in the original article.

Case study 2—Competing risk analysis

In this case study, we show how case-base sampling can be used in the context of a competing-risk analysis. For illustrative purposes, we use the same data that was used in Scrucca *et al* (2010). The

Table 2: Comparison of estimated hazard ratios and 95% confidence intervals for ERSPC data.

Model	casebase::fitSmoothHazard	survival::survreg
Exponential	0.79 (0.67, 0.94)	0.81 (0.68, 0.96)
Gompertz	0.80 (0.67, 0.95)	0.80 (0.67, 0.95)
Weibull	0.81 (0.68, 0.96)	0.80 (0.65, 0.96)
Splines	0.79 (0.66, 0.94)	–

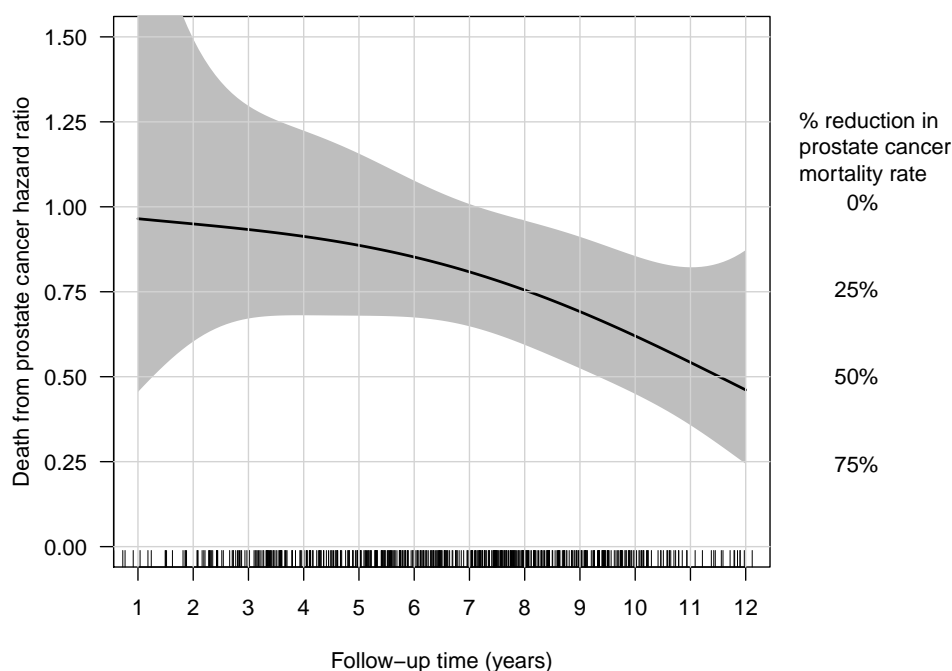Cox model estimate: HR (95% CI) = 0.80 (0.67, 0.95)

Figure 3: Estimated hazard ratio and 95% confidence interval for screening vs. control group as a function of time in the ERSPC dataset. Hazard ratios are estimated from fitting a parametric hazard model as a function of the interaction between a cubic B-spline basis of follow-up time and treatment arm. 95% confidence intervals are calculated using the delta method. The plot shows that the effect of screening only begins to become statistically apparent by year 7. The 25-60% reductions seen in years 8-12 of the study suggests a much higher reduction in prostate cancer due to screening than the single overall 20% reported in the original article.

data was downloaded from the first author's website, and it is now available as part of the **casebase** package.

The data contains information on 177 patients who received a stem-cell transplant for acute leukemia. The event of interest is relapse, but other competing causes (e.g. death, progression, graft failure, graft-versus-host disease) were also recorded. Several covariates were captured at baseline: sex, disease type (acute lymphoblastic or myeloblastic leukemia, abbreviated as ALL and AML, respectively), disease phase at transplant (Relapse, CR1, CR2, CR3), source of stem cells (bone marrow and peripheral blood, coded as BM+PB, or only peripheral blood, coded as PB), and age.

First, we look at a population-time plot to visualize the incidence density of both relapse and the competing events. In Figure 4, failure times are highlighted on the plot using red dots for the event of interest (panel A) and blue dots for competing events (panel B). In both panels, we see evidence of a non-constant hazard function: the density of points is larger at the beginning of follow-up than at the end.

Our main objective is to compute the cumulative incidence of relapse for a given set of covariates. We start by fitting a smooth hazard to the data using a linear term for time:

```
model_cb <- fitSmoothHazard(
  Status ~ ftime + Sex + D + Phase + Source + Age,
  data = bmtcrr,
  ratio = 100,
  time = "ftime"
)
```

We want to compare our hazard ratio estimates to that obtained from a Cox regression. To obtain these estimates, we need to treat the competing event as censoring:

```
library(survival)
# Treat competing event as censoring
```
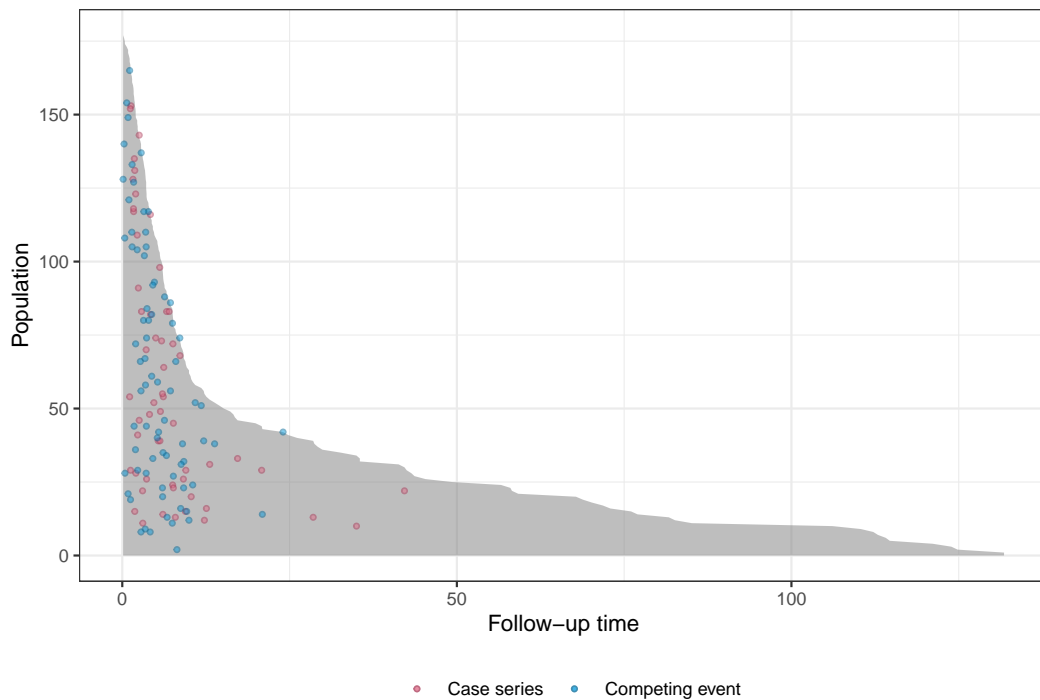
Figure 4: Population-time plot for the stem-cell transplant study with both relapse and competing events.

Table 3: Estimates and confidence intervals for the hazard ratios for each coefficient. Both estimates from case-base sampling and Cox regression are presented.

Covariates	Case-Base		Cox	
	HR	95% CI	HR	95% CI
Sex	0.74	(0.43, 1.3)	0.68	(0.39, 1.19)
Disease	0.52	(0.29, 0.94)	0.52	(0.29, 0.93)
Phase (CR2 vs. CR1)	1.20	(0.48, 3)	1.21	(0.48, 3.02)
Phase (CR3 vs. CR1)	1.59	(0.41, 6.17)	1.67	(0.43, 6.5)
Phase (Relapse vs. CR1)	4.09	(1.9, 8.81)	4.55	(2.09, 9.9)
Source	1.70	(0.55, 5.23)	1.46	(0.47, 4.54)
Age	0.99	(0.97, 1.02)	0.99	(0.97, 1.02)

```
model_cox <- coxph(Surv(ftime, Status == 1) ~ Sex + D + Phase + Source + Age,
                data = bmtcrr)
```

From the fit object, we can extract both the hazard ratios and their corresponding confidence intervals. These quantities appear in Table 3. As we can see, the only significant hazard ratio identified by case-base sampling is the one associated with the phase of the disease at transplant. More precisely, being in relapse at transplant is associated with a hazard ratio of 3.89 when compared to CR1.

Given the estimate of the hazard function obtained using case-base sampling, we can compute the absolute risk curve for a fixed covariate profile. We perform this computation for a 35 year old woman who received a stem-cell transplant from peripheral blood at relapse. We compare the absolute risk curve for such a woman with ALL with that for a similar woman with AML.

Next, we compare our estimates to that obtained from a corresponding Fine-Gray model (1999). The Fine-Gray model is a semiparametric model for the cause-specific *subdistribution hazard*, i.e. the function $d_k(t)$ such that

$$CI_k(t) = 1 - \exp\left(-\int_0^t d_k(u)\mathrm{d}u\right),$$

where $CI_k(t)$ is the cause-specific cumulative incidence. The Fine-Gray model allows to directly assess the effect of a covariate on the subdistribution hazard, as opposed to the cause-specific hazard. For the

computation, we use the **timereg** package (Scheike and Zhang, 2011):

```
library(timereg)
model_fg <- comp.risk(Event(ftime, Status) ~ const(Sex) + const(D) +
                          const(Phase) + const(Source) + const(Age),
                      data = bmtcrr, cause = 1, model = "fg")

# Estimate absolute risk curve
risk_fg <- predict(model_fg, newdata, times = time_points)
```
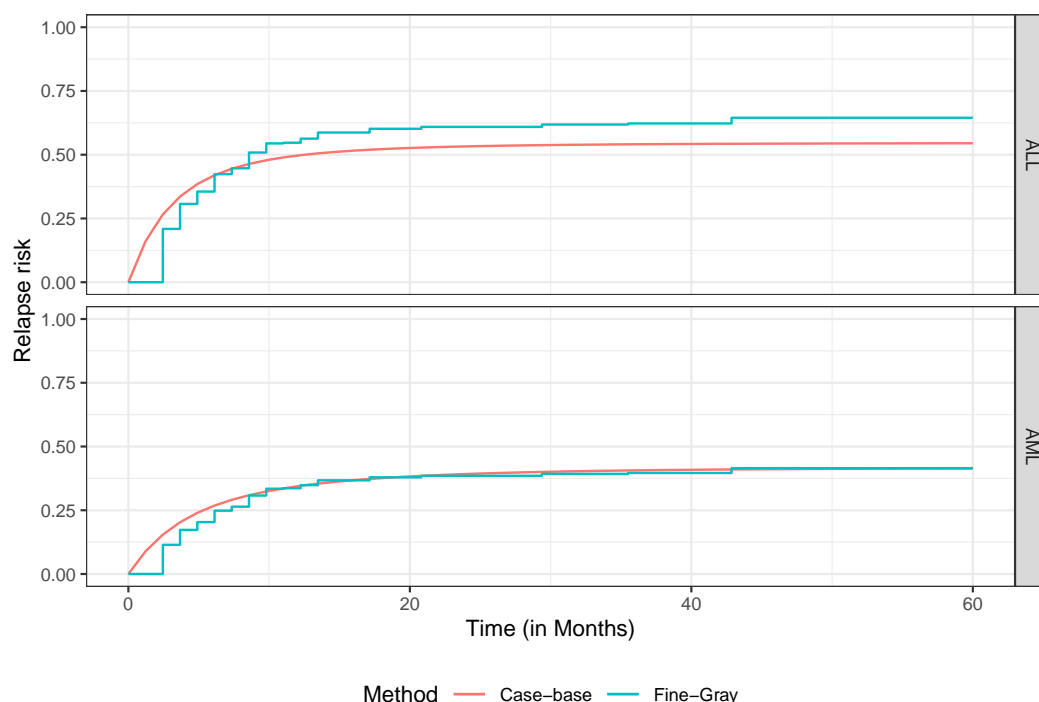

Figure 5: Absolute risk curve for a fixed covariate profile and the two disease groups. The estimate obtained from case-base sampling is compared to the Kaplan-Meier estimate.

Figure 5 shows the absolute risk curves for both case-base sampling and the Fine-Gray model. As we can see, the two approaches agree quite well for AML; however, there seems to be a difference of about 5% between the two curves for ALL. This difference does not appear to be significant: the curve from case-base sampling is contained within a 95% confidence band around the Fine-Gray absolute risk curve (figure not shown).

Case study 3—Variable selection

For the third case study, we show how **casebase** can also be used for variable selection through regularized estimation of the hazard function as given by (5). To illustrate this functionality, we use the dataset from the Study to Understand Prognoses Preferences Outcomes and Risks of Treatment (SUPPORT) (Knaus et al., 1995). The SUPPORT dataset tracks death in five American hospitals within individuals who are considered seriously ill. The original data is available online from the Department of Biostatistics at Vanderbilt University (Harrell, 2020). The cleaned and imputed data consists of 9104 observations and 30 variables, and it is available as part of the **casebase** package. In the comparisons below, all covariates except sps and aps were used. These two variables correspond to scores for predicting the outcome that were developed as part of the original study. For more information about this dataset, the reader is encouraged to look at the documentation in our package.

For our penalized case-base model, we opt for the natural log of time which corresponds to a Weibull distribution. For fitting the penalized hazard, we use `fitSmoothHazard.fit`, which is a matrix interface to the `fitSmoothHazard` function. We supply both a matrix y containing the time and event variables, and a matrix x containing all other covariates. We apply the lasso penalty by setting alpha = 1 and assign a `penalty.factor` (w_j; cf. Equation 5) of 0 to the time variable to ensure it is in the

selected model. We compare our approach to both Cox regression, and lasso penalized Cox regression (fitted via the **glmnet** package).

To compare the performance of our models, we split the data into 95% training and 5% test sets. To assess both discrimination and calibration, we use a time-dependent version of the classical Brier score that is adjusted for censoring (Graf et al., 1999). The Brier score can be used with both parametric and semi-parametric models. We use the **riskRegression** package to compute these scores for all models.

```
# Create matrices for inputs
x <- model.matrix(death ~ . - d.time - aps - sps,
                  data = train)[, -c(1)] # Remove intercept
y <- data.matrix(subset(train, select = c(d.time, death)))

# Regularized logistic regression to estimate hazard
pen_cb <- casebase::fitSmoothHazard.fit(x, y,
  family = "glmnet",
  time = "d.time", event = "death",
  formula_time = ~ log(d.time), alpha = 1,
  ratio = 10, standardize = TRUE,
  penalty.factor = c(0, rep(1, ncol(x)))
)
```

In Figure 6, we show the coefficient estimates for covariates that we selected by both penalized Cox and penalized case-base. We note that both penalized approaches produce similar results. We can also clearly see the shrinkage effect owing to the ℓ_1 penalty.
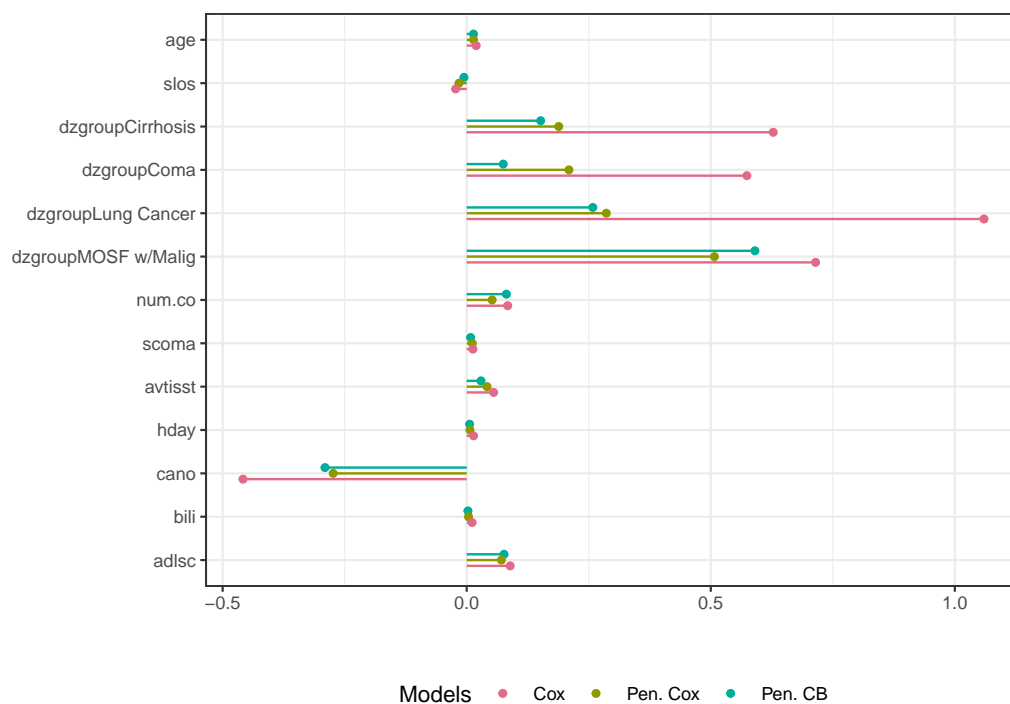

Figure 6: Coefficient estimates from the Cox model (Cox), penalized Cox model using the **glmnet** package (Pen. Cox), and our approach using penalized case-base sampling (Pen. CB). Only the covariates that were selected by both penalized approaches are shown. The shrinkage of the coefficient estimates for Pen. Cox and Pen. CB occurs due to the ℓ_1 penalty.

We then compare the cumulative incidence estimation over the test set. The probabilities over time for each observation are averaged, resulting in the absolute risk curves shown in Figure 7 (A). We can see some minimal differences between the three models, with the Kaplan-Meier giving the lowest estimates across follow-up-time. Note that the apparent smoothness of the Cox and penalized Cox curves is due to the large number of observations in the training set, which is used to derive the Breslow estimate of the baseline hazard. As described above, we compare the performance between the models by computing the Brier scores over time. In Figure 7 (B), we can see that the Brier score is larger for the Kaplan-Meier estimate than for the other three models. On the other hand, the differences between these three models are minimal.
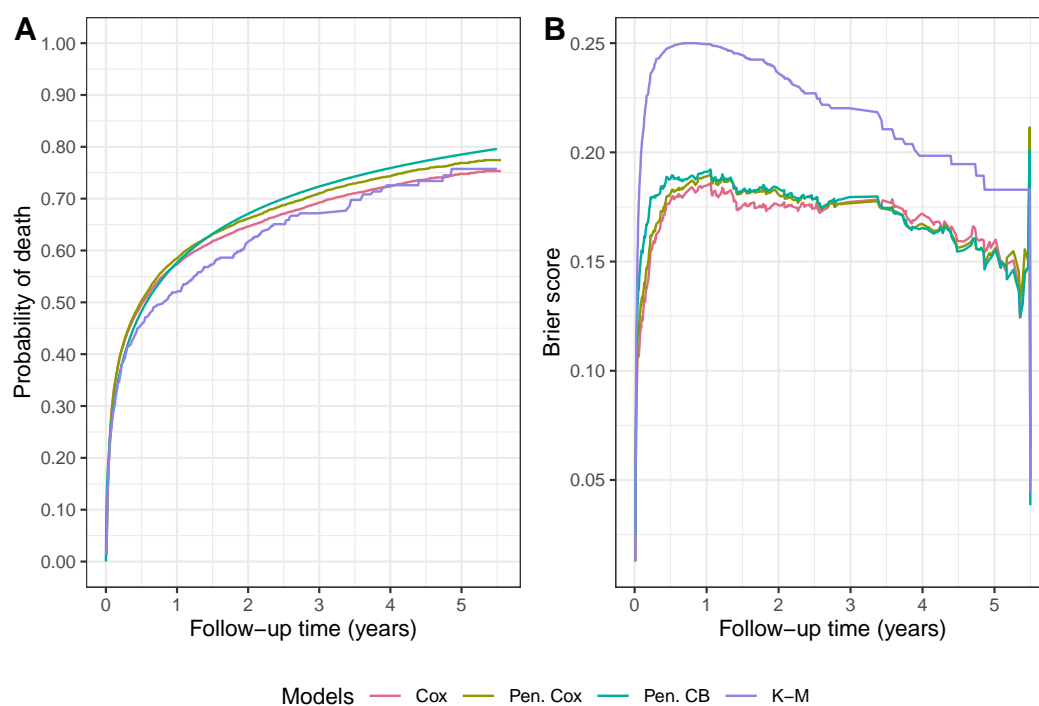
Figure 7: Comparison of Cox regression (Cox), penalized Cox regression (Pen. Cox), penalized case-base sampling estimation (Pen. CB), and Kaplan-Meier (K-M). (A) Probability of death as a function of follow-up time. (B) Brier score as a function of follow-up time, where a lower score corresponds to better performace.

Discussion

In this article, we presented the R package **casebase**, which provides functions for fitting smooth parametric hazards and estimating CIFs using case-base sampling. Our package also provides several functions to produce graphical summaries of the data and the results. We outlined the theoretical underpinnings of the approach, we provided details about our implementation, and we illustrated the merits of the approach and the package through three case studies.

As a methodological framework, case-base sampling is very flexible. Some of this flexibility has been explored before in the literature: for example, Saarela and Hanley (2015) used case-base sampling to model a time-dependent exposure variable in a vaccine safety study. As another example, Saarela and Arjas (2015) combined case-base sampling and a Bayesian non-parametric framework to compute individualized risk assessments for chronic diseases. In the case studies above, we further explored this flexibility along two fronts. On the one hand, we showed how splines could be used as part of the linear predictor to model the effect of time on the hazard. This strategy yielded estimates of the survival function that were qualitatively similar to semiparametric estimates derived from Cox regression; however, case-base sampling led to estimates of the survival function that *vary smoothly in time* and are thus easier to interpret. On the other hand, we also displayed the flexibility of case-base sampling by showing how it could be combined with penalized logistic regression to perform variable selection. Furthermore, the second case study showed how case-base sampling can be applied to competing risks settings. It should be noted that the three case studies presented above only considered covariates that were fixed at baseline. In one of the package vignettes, we use the Stanford Heart Transplant data (Clark et al., 1971, Crowley and Hu (1977)) to show how case-base sampling can also be used in the context of time-dependent exposure. In this study, the exposure period was defined as the week following vaccination. Hence, the main covariate of interest, i.e. exposure to the vaccine, was changing over time. In this context, case-base sampling offers an efficient alternative to nested case-control designs or self-matching.

Even though we did not illustrate it in this article, case-base sampling can also be combined with the framework of *generalized additive models*. This functionality has already been implemented in the package. Similarly, case-base sampling can be combined with quasi-likelihood estimation to fit survival models that can account for the presence of over-dispersion. All of these examples illustrate how the case-base sampling framework in general, and the package **casebase** in particular, allows the

Table 4: Comparison between the Cox model and case-base sampling

Feature	Cox model	Case-base sampling
Model type	Semi-parametric	Fully parametric
Time	Left hand side of the formula	Right hand side (allows flexible modeling of time)
Cumulative incidence	Step function	Smooth-in-time curve
Non-proportional hazards	Interaction of covariates with time	Interaction of covariates with time
Model testing	Likelihood-ratio tests, score tests, information criteria	Use GLM framework (e.g. LRT, AIC, BIC)
Competing risks	Difficult	Cause-specific CIFs

user to fit a broad and flexible family of survival functions.

As presented in Hanley & Miettinen (2009), case-base sampling is comprised of three steps: 1) sampling a case series and a base series from the study; 2) fit the log-hazard as a linear function of predictors (including time); and 3) use the fitted hazard to estimate the CIF. Accordingly, our package provides functions for each step. Moreover, the simple interface of the `fittingSmoothHazard` function resembles the `glm` interface. This interface should look familiar to new users. Our modular approach also provides a convenient way to extend our package for new sampling or fitting strategies.

In the case studies above, we compared the performance of case-base sampling with that of Cox regression and Fine-Gray models. In terms of function interface, **casebase** uses a formula interface that is closer to that of `glm`, in that the event variable is the only variable appearing on the left-hand side of the formula. By contrast, both `survival::coxph` and `timereg::comp.risk` use arrays that capture both the event type and time. Both approaches to modeling yield user-friendly code. However, in terms of output, both approaches differ significantly. Case-base sampling produces smooth hazards and smooth cumulative incidence curves, whereas Cox regression and Fine-Gray models produce stepwise CIFs and never explicitly model the hazard function. Qualitatively, we showed that by using splines in the linear predictor, all three models yielded similar curves. However, the smooth nature of the output of **casebase** provides a more intuitive interpretation for consumers of these predictions. In Table 4, we provide a side-by-side comparison between the Cox model and case-base sampling.

Our choice of modeling the log-hazard as a linear function of covariates allows us to develop a simple computational scheme for estimation. However, as a downside, it does not allow us to model location and scale parameters separately like the package **flexsurv**. For example, if we look at the Weibull distribution as parametrised in `stats::pweibull`, the log-hazard function is given by

$$\log \lambda(t; \alpha, \beta) = [\log(\alpha/\beta) - (\alpha - 1)\log(\beta)] + (\alpha - 1)\log t,$$

where α, β are shape and scale parameters, respectively. Unlike **casebase**, the approach taken by **flexsurv** also allows the user to model the scale parameter as a function of covariates. Of course, this added flexibility comes at the cost of interpretability: by modeling the log-hazard directly, the parameter estimates from **casebase** can be interpreted as estimates of log-hazard ratios. To improve the flexibility of **casebase** at capturing the scale of a parametric family, we could replace the logistic regression with its quasi-likelihood counterpart and therefore model over- and under-dispersion with respect to the logistic likelihood. We defer the study of the properties and performance of such a model to a future article.

Future work will look at some of the methodological extensions of case-base sampling. First, to assess the quality of the model fit, we would like to study the properties of the residuals (e.g. Cox-Snell, martingale). More work needs to be done to understand these residuals in the context of the partial likelihood underlying case-base sampling. The resulting diagnostic tools could then be integrated in this package. Also, we are interested in extending case-base sampling to account for interval censoring. This type of censoring is very common in longitudinal studies, and many packages (e.g. **SmoothHazard**, **survival** and **rstpm2**) provide functions to account for it. Again, we hope to include any resulting methodology as part of this package.

In future versions of the package, we also want to increase the complement of diagnostic and inferential tools that are currently available. For example, we would like to include the ability to compute confidence intervals for the cumulative incidence curve. The delta method or parametric bootstrap are two different strategies we can use to construct approximate confidence intervals.

Furthermore, we would like to include more functions to compute calibration and discrimination statistics (e.g. AUC) for our models. Saarela and Arjas (2015) also describe how to obtain a posterior distribution for the AUC from their model. Their approach could potentially be included in **casebase**. Finally, we want to provide more flexibility in how the case-base sampling is performed. This could be achieved by adding a `hazard` argument to the function `sampleCaseBase`. In this way, users could specify their own sampling mechanism. For example, they could provide a hazard that gives sampling probabilities that are proportional to the cardiovascular disease event rate given by the Framingham score (Saarela and Arjas, 2015).

In conclusion, we presented the R package **casebase** which implements case-base sampling for fitting parametric survival models and for estimating smooth cumulative incidence functions using the framework of generalized linear models. We strongly believe that its flexibility and its foundation on the familiar logistic regression model will make it appealing to new and established practitioners. The **casebase** package is freely available from the Comprehensive R Archive Network at `https://cran.r-project.org/package=casebase`. Interested users can visit `http://sahirbhatnagar.com/casebase/` for detailed package documentation and vignettes.

Acknowledgments

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