

# Introducing parmsurvfit Package - Simple Parametric Survival Analysis with R

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**Abstract** This article introduces the R package `parmsurvfit`, which executes basic parametric survival analysis techniques similar to those in Minitab. Among these are plotting hazard, cumulative hazard, survival, and density curves, computing survival probabilities, and computing summary statistics based on a specified parametric distribution. We describe appropriate usage of these functions, interpretation of output, and provide examples of how to utilize these functions in real-world datasets.

## Introduction

Survival analysis is a branch of statistics that primarily deals with analyzing the time until an event of interest occurs. This event could be a variety of different things such as death, development of disease, or first score of a soccer game. Observations in survival analysis may also be described as censored, which occurs when an observation's survival time is incomplete. The most common way that this occurs is through right censoring, which occurs when a subject does not experience the event of interest within the duration of the study. Right censoring can also occur if a subject drops out before the end of the study and does not experience the event of interest. Due to the inherent issue of censoring that is typically found in datasets involving survival analysis, computations and analyses can be difficult to carry out with many standard functions available in R, as the majority of these do not account for censored data. The censored data collected is of value and we cannot merely eliminate the observations which have censored data.

Some of the most popular techniques and statistics utilized when carrying out a survival analysis are computing what are known as the survival and hazard functions. The survival function is important because it gives the probability of surviving (also known as not experiencing the event of interest) beyond any given time  $t$ . Similarly, the hazard function is also useful to compute because it gives the conditional probability that the subject will experience the event in the next instance of time, given that they have survived up until the specified point in time. Other popular statistics that are utilized are median survival time, mean survival time, and percentiles of survival time. In this package, all of the functions that we developed utilize parametric methods of survival analysis, which assumes that the distribution of the survival times follows a known probability distribution.

Currently, R does have many survival packages that address non-parametric survival analysis, such as the `survival` package. Moreover, R does have some packages that aid in estimation for parametric survival analysis, including `fitdistrplus`. However, Minitab has very concise and easy to utilize functions for computing and displaying many parametric survival statistics and plots, but this same output is not readily available in any single one package in R, or in some cases not available at all. Thus, we decided to develop a package that emulates the output found in Minitab for parametric survival analysis, which contains all of these commonly utilized statistics and plots.

This paper describes the functions that the `parmsurvfit` package contains, how the data is formatted in order to utilize these functions, and what the output of these functions represent. There are four major groups of functions that we created: fitting the censored data, displaying plots (density, hazard, cumulative hazard, and survival), computing statistics (mean, median, survival probabilities), and assessing fit (qqplot, Anderson Darling statistic). The majority of this paper will be organized following these groups of functions.

## Fitting right censored survival data

As mentioned previously, this function is very similar to the function `fitdistcens` found in the `fitdistrplus` package, which computes the Maximum Likelihood Estimates (MLEs) for right-censored data. **Is the data organized differently than required for `fitdistcens`? Explain the output**

## Example

```
#> Fitting of the distribution ' logis ' on censored data by maximum likelihood
#> Parameters:
#>           estimate
#> location 16.741581
```

```
#> scale      2.798533
#> Fixed parameters:
#> data frame with 0 columns and 0 rows
```

## Displaying plots

This section introduces an overview of the many types of plots that are able to be displayed via this package. Some of the most common plots used in Survival Analysis are survival plots, hazard plots, probability density plots, and cumulative hazard plots. We designed these functions with an intent to have the output displayed be very easy to read and interpret. Below is a list of each function and it's relationship to other functions, as well as the formula used to compute each function.

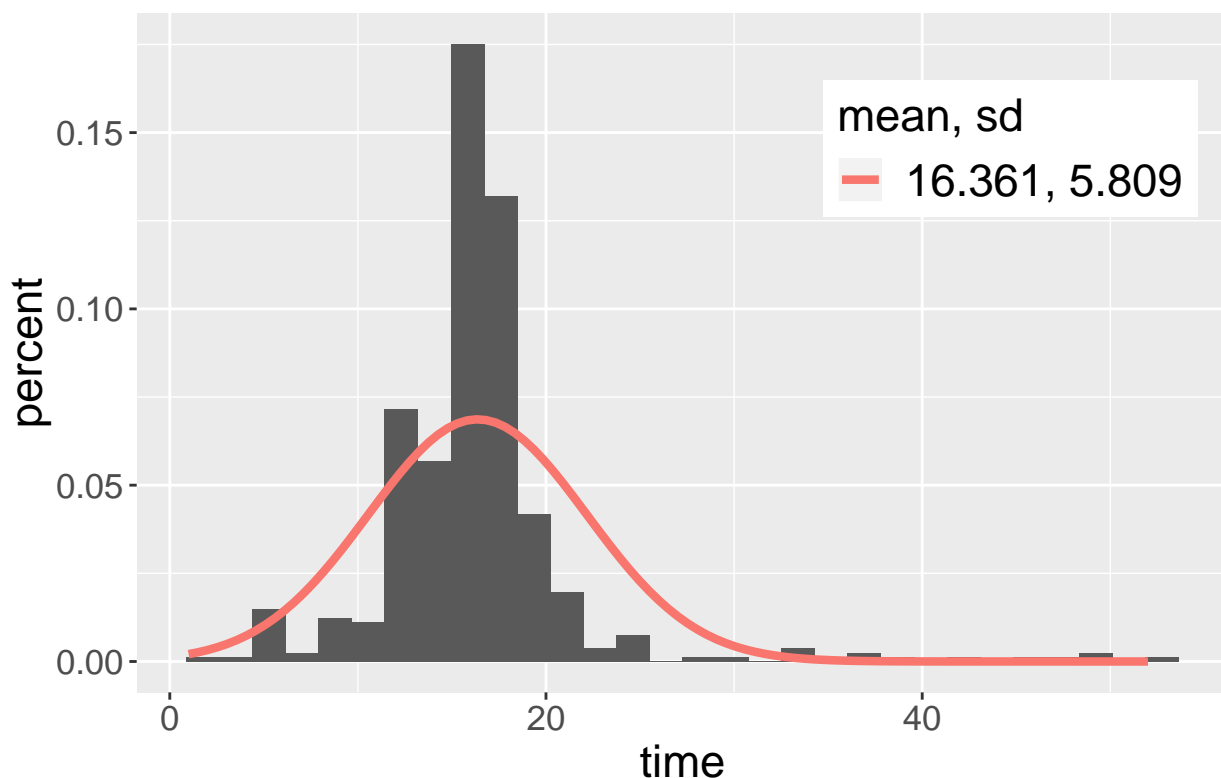
Function	Relationships
PDF	$f(t) = \frac{d}{dt}F(t)$
CDF	$F(t) = \int_0^t f(y)dy$
Survival	$S(t) = 1 - F(t) = \exp[-H(t)] = \exp[-\int_0^t h(y)dy]$
Hazard	$h(t) = f(t)/S(t) = -\frac{d}{dt} \ln[S(t)]$
Cum. Haz.	$H(t) = \int_0^t h(y)dy = -\ln[S(t)]$

## Density plots/histograms

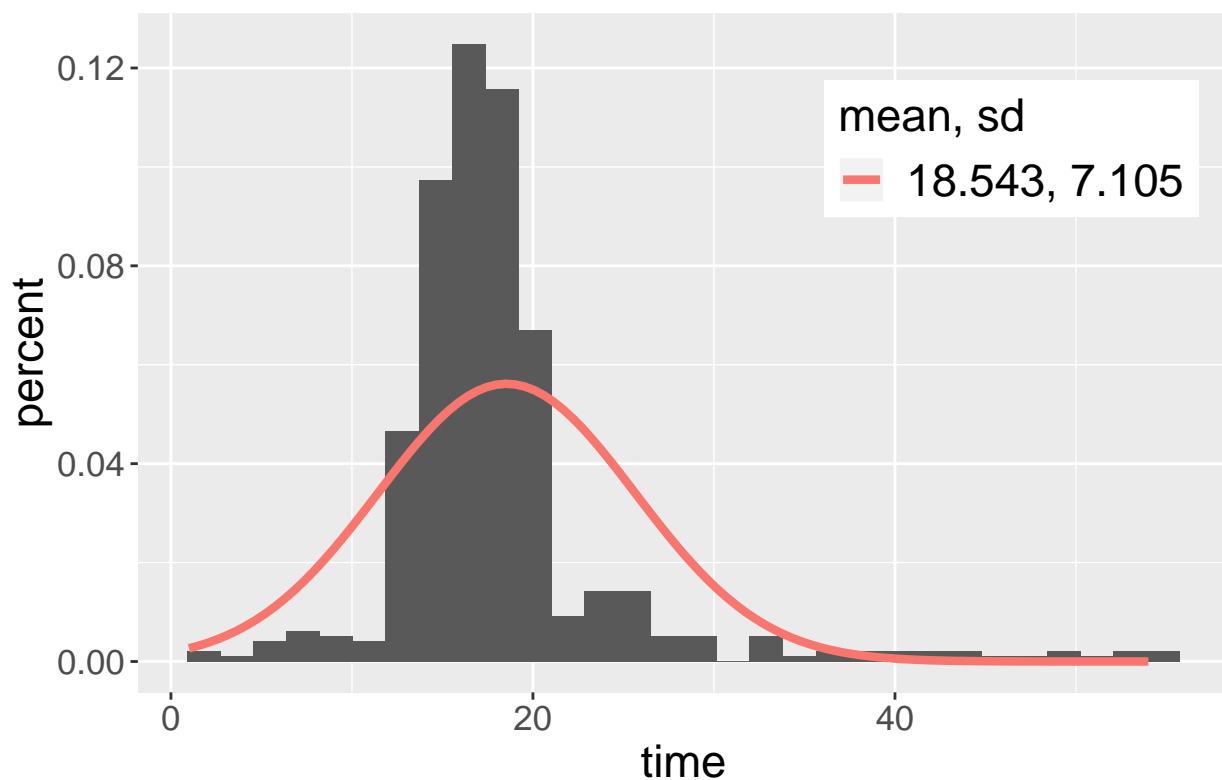
The `plot_density` function creates a histogram of the data and overlays the density function of a fitted parametric distribution. Parameters estimates for the specified parametric distribution are provided as well. This function also supports the ability to plot separate histograms and density functions for each level of a grouping variable. An example of this function is shown below:

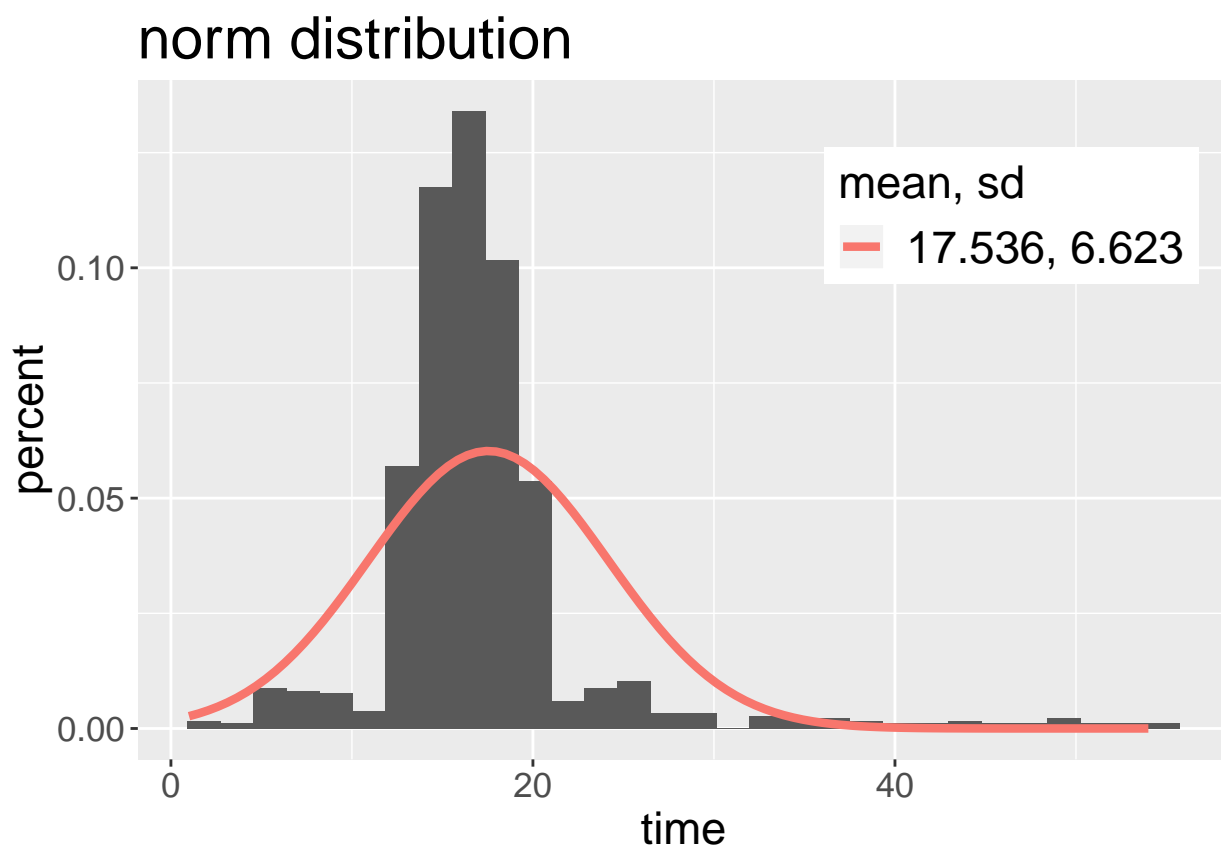
```
plot_density(Firstdrink, "norm", time = "Age", by = "Gender")
```

## norm distribution, level = 1



## norm distribution, level = 2

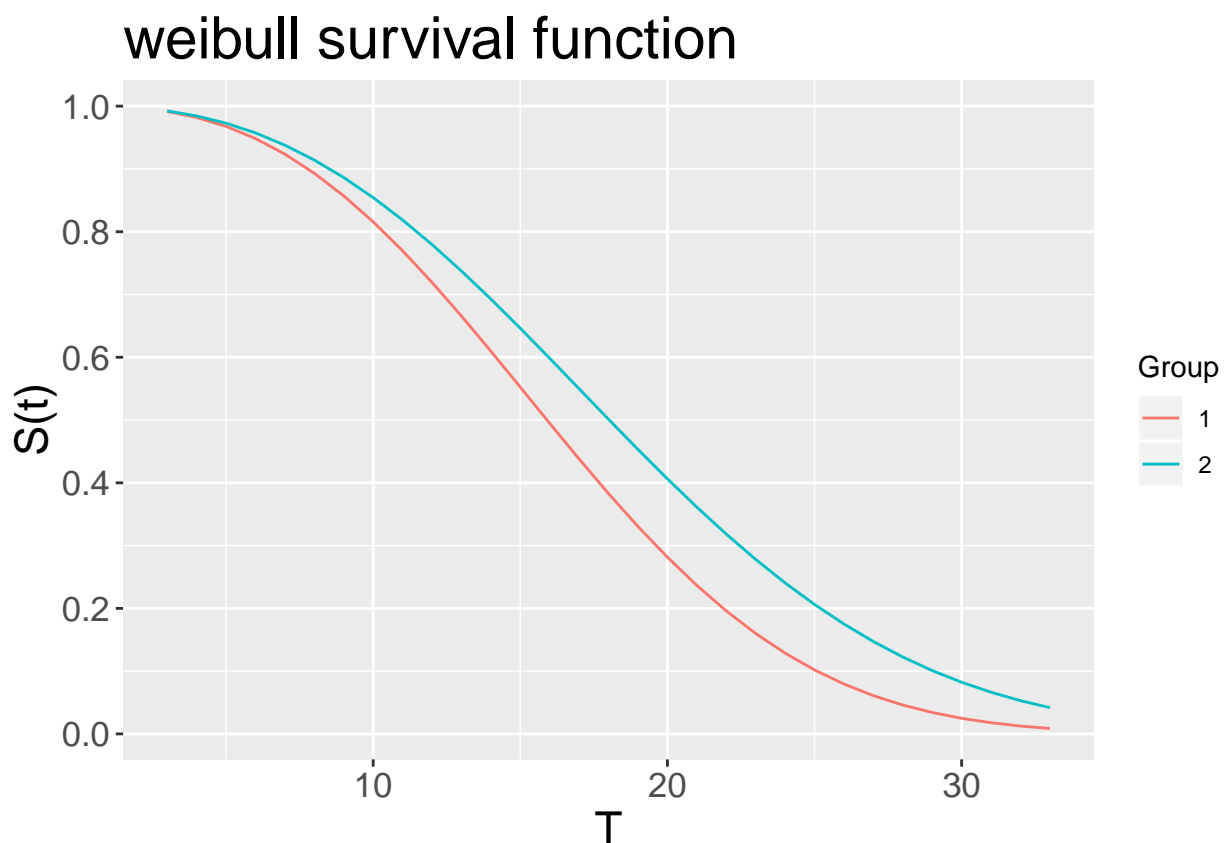




We ran the `plot_density` function, utilizing the 'Firstdrink.txt' dataset available in our package. This dataset contains data on the age of first consumption of alcoholic beverage for 1000 individuals. As seen above, a separate histogram and density plot was created for males and females.

### Survival plots

Survival plots are used to estimate the proportion of subjects that survive beyond a specified time  $t$ . We were motivated to create the function `plot_surv` in an attempt to create hazard plots that are easy to produce, when dealing with data set up for Survival Analysis. This function plots the survival curve of right censored data given that it follows a specified parametric distribution. Some examples of the distributions that this function supports are the Weibull, Log-Normal, Exponential, Normal, and Logistic distributions. This function also provides the option to plot by a grouping variable, which if specified, displays separate curves for each group of the specified variable. In these plots, survival time is plotted on the x-axis, while survival probability is plotted on the y-axis.

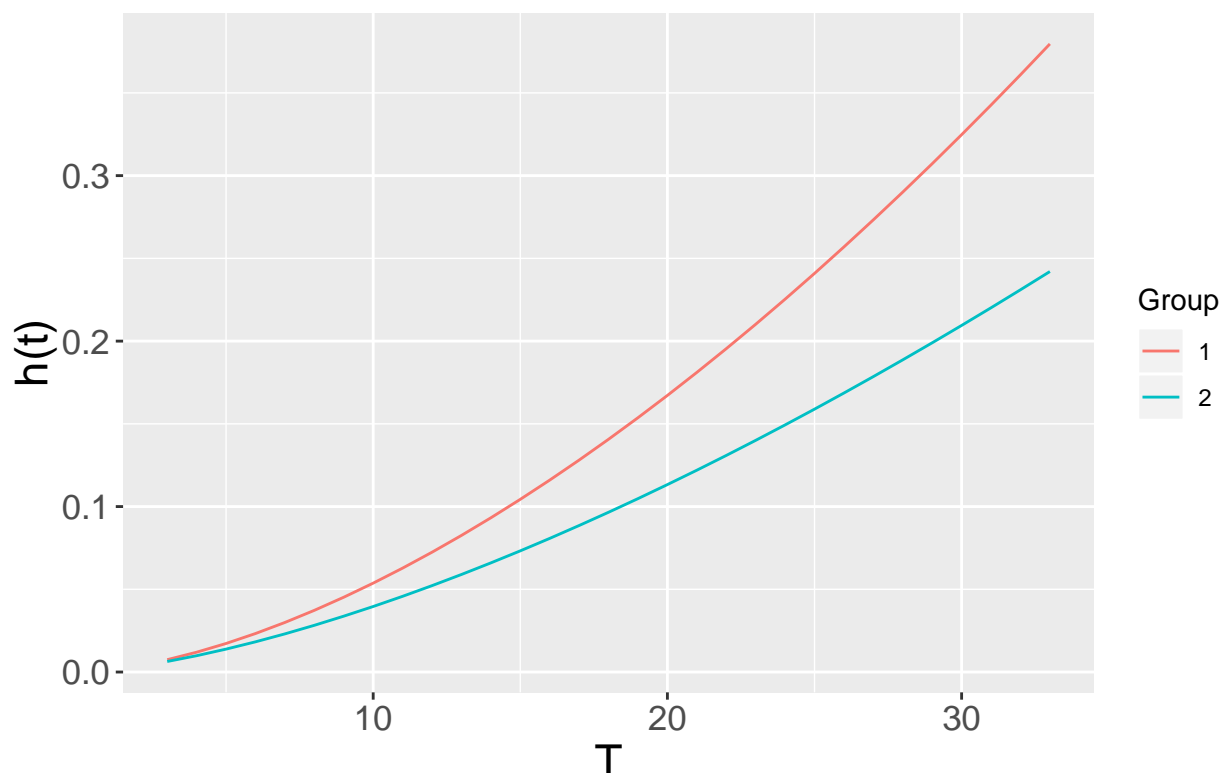


In this example, we fit a Weibull distribution to the Firstdrink dataset, grouping by the Gender variable once again. As seen in the plot above, two different survival curves were plotted. The blue line represents the estimated survival curve for males, while the red line represents the estimated survival curve for females. From this plot, we see that the survival curve for male rats is consistently above the survival curve for female rats throughout all points in time. Due to this, we can conclude that females tend to experience their first drink of alcohol before males do.

### Hazard plots

Hazard plots, on the other hand, are used to display the conditional risk that a subject will experience the event of interest in the next instant of time, given that the subject has survived beyond a certain amount of time. Essentially, the hazard function attempts to assess the risk that an individual who has not yet experienced the event in the very next small amount of time. For example, if we observe that a person has survived for 17 years without first trying alcohol, the hazard function would estimate the risk that the person will experience their first drink of alcohol in the next short instant of time, based on the fact that it has already survived 17 years. We created the `plot_haz` function in order to easily plot hazard functions given that it follows a specified parametric distribution, with the option to include a grouping variable.

## weibull hazard function

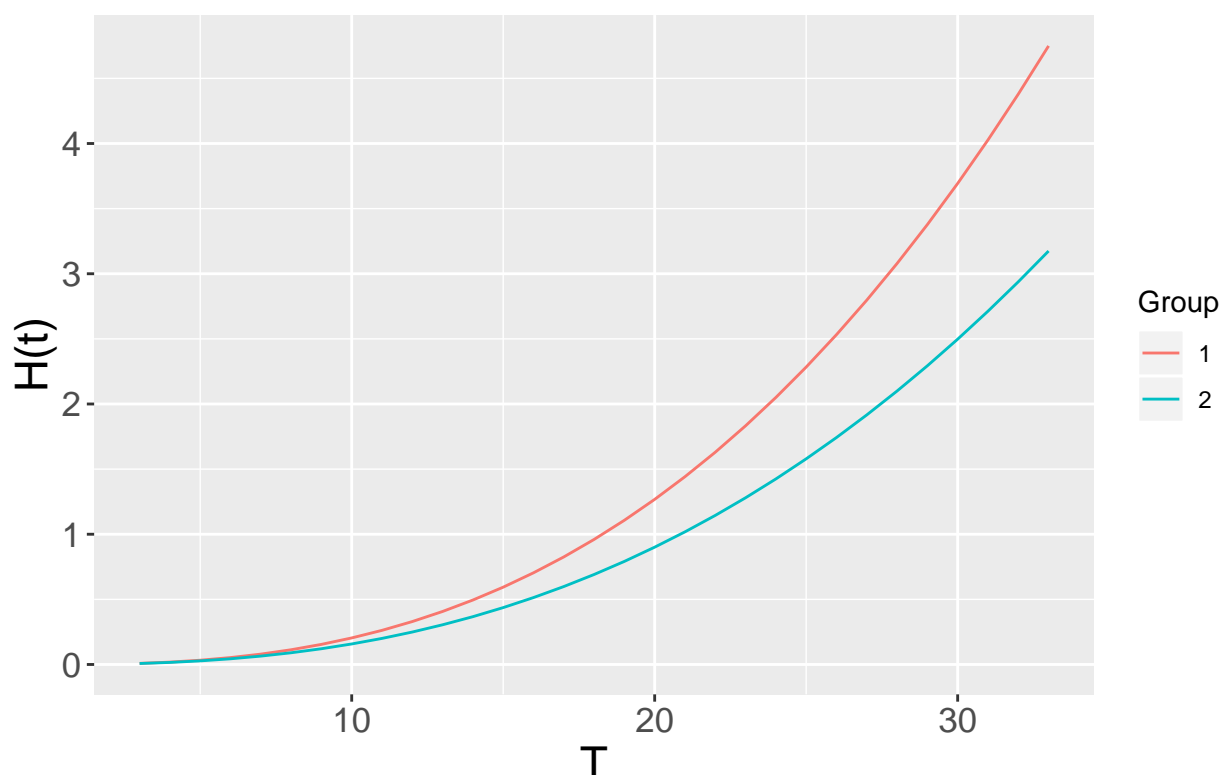


From this plot above, also using the Firstdrink dataset, we can see that as females continue to survive, their risk of experiencing the event of interest in the next instant of time dramatically increases. Similarly, males also seem to have a greater risk of experiencing the event of interest as they survive longer, but their risk is lower than that of females.

### Cumulative hazard plots

While hazard plots are usually useful in assessing a subject's risk of experiencing the event of interest in the next moment of time, these plots can be difficult to read and understand at times. Sometimes, the changes in hazard are very subtle, making it difficult to describe periods of increasing and decreasing risk. In order to accurately assess how hazard rates change over time, we investigate the accumulation of hazard rates over time, known as cumulative hazard. The cumulative hazard function, denoted  $H(t)$ , is the accumulated risk of experiencing an event up to time  $t$ . Since the cumulative hazard function is an accumulation of rates, it is important to note that this function is non-decreasing and is hardly ever remains constant by nature. We developed the function `plot_cumhaz` in order to easily display cumulative hazard plots, given that the data follows a specified parametric distribution. The functionality of this function is nearly identical to that of `plot_haz`, with the only distinction being that it plots cumulative hazard curves instead of hazard curves.

## weibull cumulative hazard function



As we can see, the cumulative hazard function is increasing for both males and females. This means that the risk for experiencing the first drink of alcohol for both males and females in the next instant of time is increasing over time, given that they have survived beyond time  $t$ .

### Computing survival probabilities and summary statistics

While viewing plots such as those explained above are very useful in survival analysis, they only tell half of the story. In order to carry out a complete survival analysis, we must also compute statistics in order to supplement our plots. Some of the most common statistics utilized in parametric survival analysis are survival probabilities and typical summary statistics such as the mean, median, standard deviation, and percentiles of survival time.

### Computing survival probabilities

Being able to compute survival probabilities is especially of interest because it estimates the probability that a subject will not have experienced the event of interest beyond a specified time  $t$ . We developed the function `surv_prob` to compute probability of survival beyond time  $t$ , given that the data follows a specified parametric distribution.

```
library(parmsurvfit)
surv_prob(Firstdrink, "lnorm", 30, time="Age")
```

```
#> P(T > 30) = 0.05191602
```

As seen in the output from the function above, utilizing the `Firstdrink` data set and fitting a log-normal parametric distribution to the data, the estimated probability that a person survives for 30 years without having their first drink of alcohol is roughly 5%.

### Computing summary statistics

Another useful form of output that we believed would be useful to also have in R is a table of summary statistics. Summary statistics that are typically included are the mean, standard deviation, median, and IQR. The `surv_summary` function that we developed estimates various summary statistics, including mean, median, standard deviation, and percentiles of survival time given that the data

follows a specified parametric distribution. This function also supports the option to provide separate summary statistics for each level of a grouping variable, if desired.

```
library(parmsurvfit)
surv_summary(Firstdrink, "lnorm", time="Age", by="Gender")

#>
#>
#> For level = 1
#> meanlog      2.743253
#> sdlog         0.3505774
#> Log Likelihood -1370.309
#> AIC           2744.619
#> BIC           2752.885
#> Mean          16.52221
#> StDev          5.974932
#> First Quantile 12.26552
#> Median         15.53745
#> Third Quantile 19.68219
#>
#> For level = 2
#> meanlog      2.862891
#> sdlog         0.3674697
#> Log Likelihood -1658.704
#> AIC           3321.408
#> BIC           3329.987
#> Mean          18.73528
#> StDev          7.123736
#> First Quantile 13.66772
#> Median         17.51209
#> Third Quantile 22.43778
```

As seen above, after specifying the grouping variable of sex, two separate tables were produced, one for males and one for females. We can see that the mean log survival time for females is smaller than the mean log survival time for males. The standard deviation of log survival time for females was also much smaller than that of males.

##Assessing fit Since all of the functions available in this package assume that the survival data follows a known parametric distribution, it is important to have a method to analyze how well our assumed model fits the data. Utilizing such methods will allow us choose a distribution that adequately fits the data. Two common methods used to assess goodness of fit are Q-Q (Quantile-Quantile) plots and the Anderson-Darling Test.

###Q-Q plots As mentioned before, Q-Q plots are a very popular method used to evaluate the fit between two probability distributions. In these plots, the hypothesized quantiles are plotted on one axis and the observed quantiles are plotted on the other axis. A

## Summary

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