

# *Introduction to survival analysis*

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🔗 [jorgetendeiro/Seminar-2020-Survival-Analysis](https://github.com/jorgetendeiro/Seminar-2020-Survival-Analysis)

# *Plan for today*

Gentle introduction to survival analysis.

*Source:*

Harrell, F. E., Jr. (2015). *Regression Modeling strategies*, 2nd edition.  
Springer

*Chapters:*

17, 18, and 20.

# Survival analysis (SA)

*Data:*

For which the *time until the event* is of interest.

- ▶ This goes beyond *logistic regression*, which focuses on the *occurrence* of the event.

*Outcome variable:*

- ▶  $T$  = Time until the event.
- ▶ Often referred to as *failure time*, *survival time*, or *event time*.

# Examples

*Survival time:* Time until...

- ▶ death, disease, relapse.

*Failure time:* Time until...

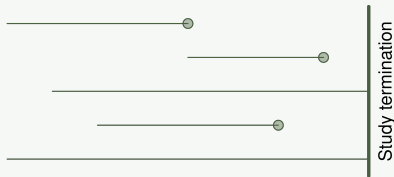
- ▶ product malfunction.

*Event time:* Time until...

- ▶ graduation, marriage, divorce.

## Advantages of SA over typical regression models

- SA allows modeling units that did not fail up to data collection (*censored on the right data*).



- Regression could be considered to model the expected survival time. *But:*
  - ✓ Survival time is often not normally distributed.
  - ✓  $P(\text{survival} > t)$  is often more interesting than  $\mathbb{E}(\text{survival time})$ .

# Censoring

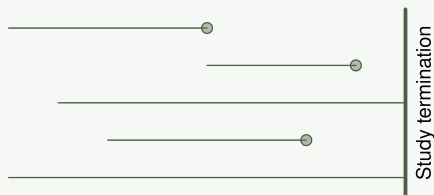
- ▶ For some subjects, the event did not occur up to the end of data collection.
- ▶ These data are right-censored.

Define random variables for the  $i$ th subject:

- ▶  $T_i$  = time to event
- ▶  $C_i$  = censoring time
- ▶  $e_i$  = event indicator =  $\begin{cases} 1 & \text{if event is observed } (T_i \leq C_i) \\ 0 & \text{if event is not observed } (T_i > C_i) \end{cases}$
- ▶  $Y_i = \min(T_i, C_i)$  = what occurred first (failure or censoring)

Variables  $\{Y_i, e_i\}$  include all the necessary information.

## Typical data set



$T_i$	$C_i$	$Y_i$	$e_i$
5	10	5	1
4	12	4	1
13+	13	13	0
5	10	5	1
15+	15	15	0

Observe the flexibility of SA data:

- Subjects may join the study at different moments.
- Censoring times may differ among subjects.

$\{Y_i, e_i\}$  does include all the necessary information.

## Three main functions

Recall that the outcome variable is  $T =$  time until event.

- Survival function:

$$S(t) = P(T > t) = 1 - F(t),$$

where  $F = P(T \leq t)$  is distribution function of  $T$ .

- Cumulative hazard function:

$$\Lambda(t) = -\log(S(t))$$

- Hazard function:

$$\lambda(t) = \Lambda'(t)$$



# Survival function

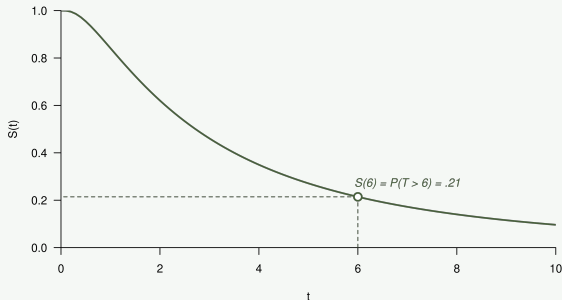
$$S(t) = P(T > t) = 1 - F(t)$$

*Example:*

If event = death, then  $S(t)$  = prob. that death occurs after time  $t$ .

*Properties:*

- ▶  $S(0) = 1, S(\infty) = 0$ .
- ▶ Non-increasing function of  $t$ .



# Cumulative hazard function

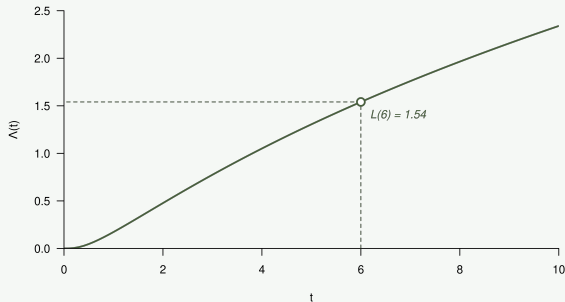
$$\Lambda(t) = -\log(S(t))$$

*Idea:*

Accumulated risk up until time  $t$ .

*Properties:*

- ▶  $\Lambda(0) = 0$ .
- ▶ Non-decreasing function of  $t$ .

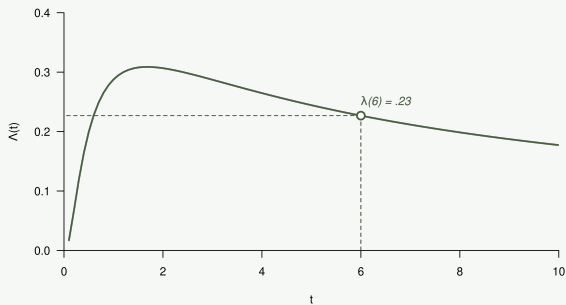


# Hazard function

$$\lambda(t) = \Lambda'(t)$$

*Idea:*

Instantaneous event rate at time  $t$ .



## *Relation between the three functions*

*All functions are related:*

Any two functions can be derived from the third function.

- ▶ The three functions are equivalent ways of describing the same random variable ( $T$  = time until event).

More generally, all the following functions give mathematically equivalent specifications of the distribution of  $T$ :

- ▶  $F(t)$ : Distribution function
- ▶  $f(t)$ : Density function
- ▶  $S(t)$ : Survival function
- ▶  $\lambda(t)$ : Hazard function
- ▶  $\Lambda(t)$ : Cumulative hazard function.

# Examples

Next are two primary examples of parametric survival distributions:

- ▶ the exponential distribution;
- ▶ the Weibull distribution.

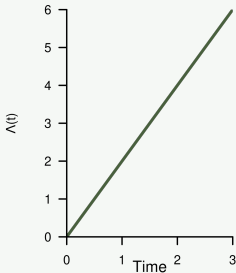
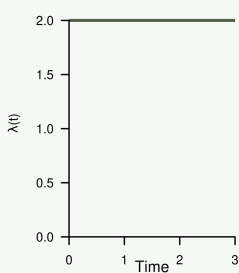
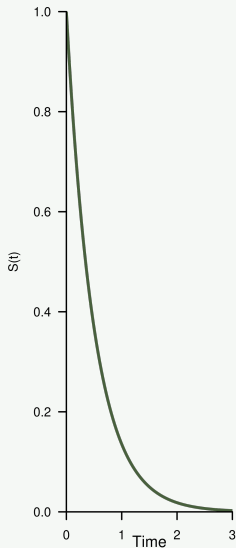
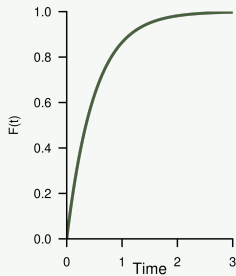
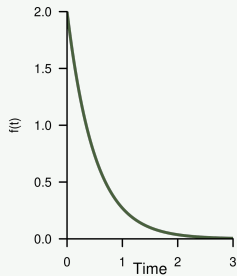
These models (still) include **no** covariates, thus:

- ▶ Each subject in the sample is assumed to have the same distribution of  $T$ .

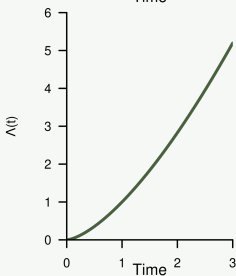
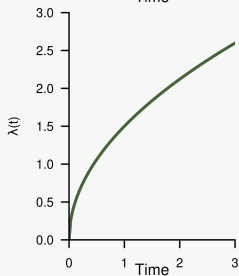
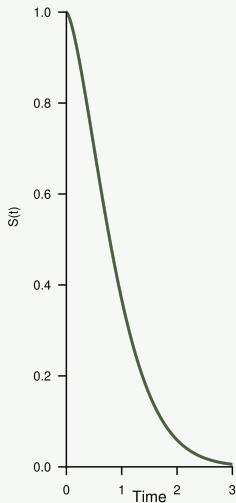
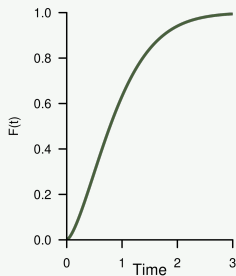
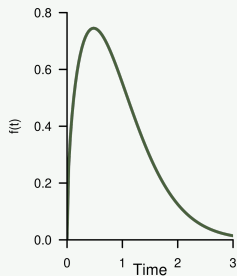
No formulas.

Instead: Let's plot.

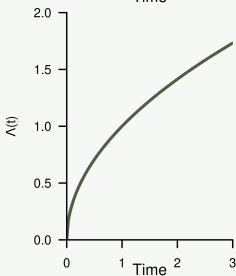
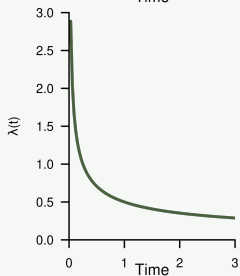
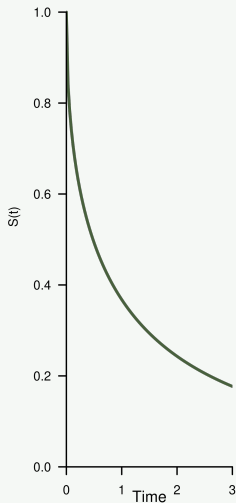
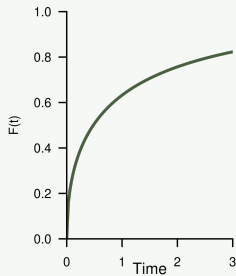
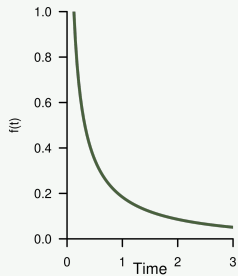
# Exponential survival distribution



## Weibull survival distribution (I)



## Weibull survival distribution (II)

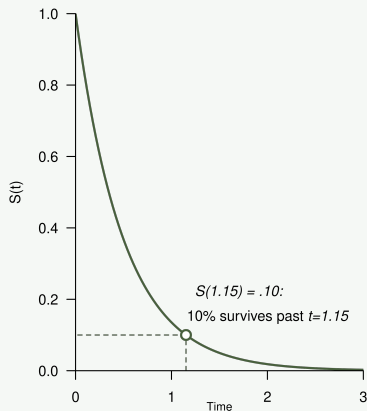
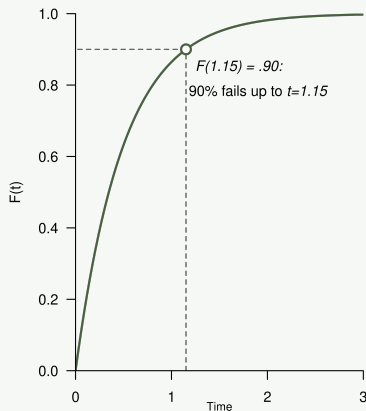




# Quantiles

Q: What is the time by which  $(100q)\%$  of the population will fail?

A: Value  $t_q$  such that  $F(t_q) = q$ , or, equiv.,  $S(t_q) = 1 - q$ .



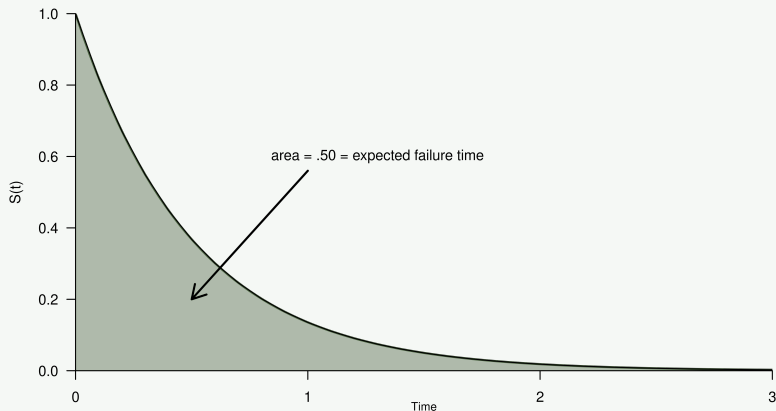
In particular, median survival time =  $t_{.50}$ .

## Expected failure time

(Note:  $T$  is skewed, so the mean is not the best summary. Better use median.)

Q: What is the expected failure time?

A: It is the area under the survival function.



## *Various estimation approaches*

There are several options available to estimate the survival function (and friends).

Here we will briefly go through only a few:

- ▶ Not parametric:
  - ✓ Kaplan-Meier estimator
  - ✓ Altschuler-Nelson estimator
- ▶ Parametric:
  - ✓ Proportional hazards models
- ▶ Semi-parametric:
  - ✓ Cox proportional hazards regression model

After a brief intro to each, I will use them all on an empirical dataset.

## Kaplan-Meier estimator

- ▶ Also known as the *product-limit* estimator.
- ▶ Non parametric, and super simple to do even manually.
- ▶ Key ingredient: *Conditional probabilities*.

Assume  $t = 0, 1, 2, \dots$

We have that  $S(0) = P(T > 0) = 1$ . For  $t \geq 1$  we then have that

$$P(T > t | T > t - 1) = \frac{P(T > t, T > t - 1)}{P(T > t - 1)} = \frac{P(T > t)}{P(T > t - 1)}$$

and so

$$P(T > t) = P(T > t - 1) \times P(T > t | T > t - 1),$$

or in terms of the survival function,

$$S(t) = S(t - 1) \times P(T > t | T > t - 1)$$

$$\boxed{S(t) = S(t - 1) \times (1 - P(T \leq t | T > t - 1))}$$

## Kaplan-Meier estimator – Example

Data: Seven subjects; failure times  $T = 1, 3, 3, 3+, 6+, 9, 10+$ .

Day	No. subjects at risk	Deaths	Censored	$S(t) = S(t-1) \times$ $\times (1 - P(T \leq t   T > t-1))$
1	7	1	0	$1 \times (1 - 1/7) = 6/7$
3	$7 - (1 + 0) = 6$	2	1	$6/7 \times (1 - 2/6) = 4/7$
6	$6 - (2 + 1) = 3$	0	1	$4/7 \times (1 - 0/3) = 4/7$
9	$3 - (0 + 1) = 2$	1	0	$4/7 \times (1 - 1/2) = 2/7$
10	$2 - (1 + 0) = 1$	0	1	$2/7 \times (1 - 0/1) = 2/7$

Hence:

$$S(t) = \begin{cases} 1, & 0 \leq t < 1 \\ 6/7 = .86, & 1 \leq t < 3 \\ 4/7 = .57, & 3 \leq t < 9 \\ 2/7 = .29, & 9 \leq t < 10 \end{cases}.$$

## Kaplan-Meier estimator – Example

