

# What has the Riemann Zeta Function got to do with Satellite Lifetimes

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# What are we doing today?

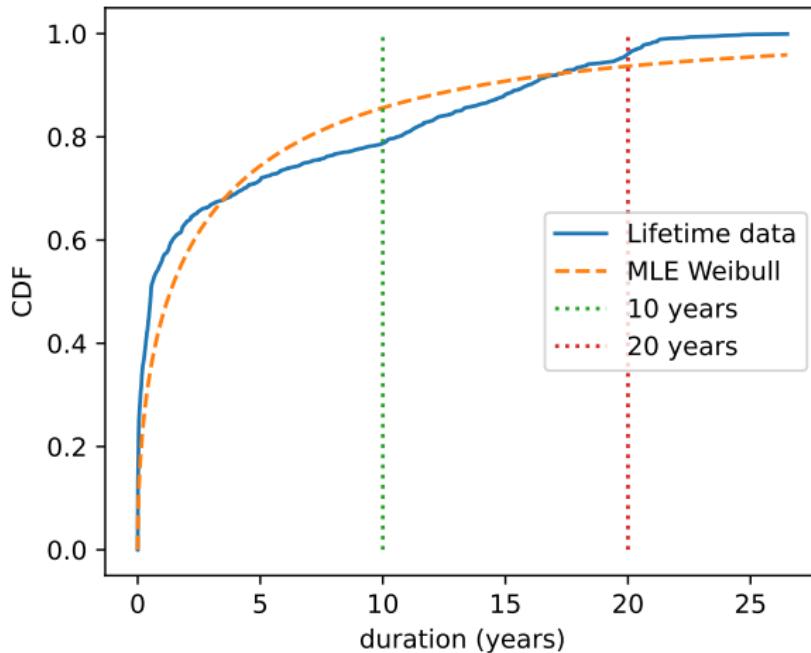
This talk arises out of a weird conjunction:

- ▶ Satellite lifetimes
- ▶ Quantile-based distributions
- ▶ The Polylogarithm Distribution

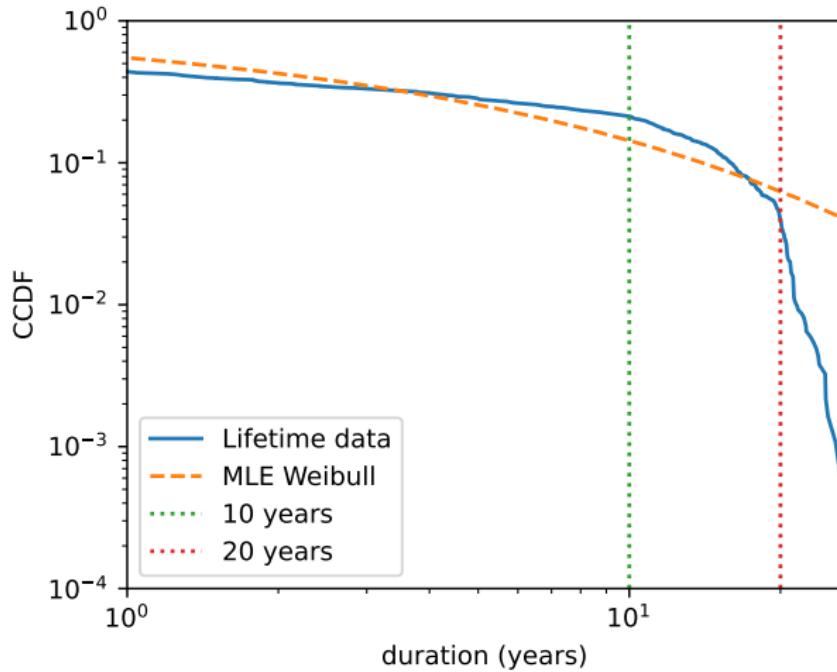
# Satellite Lifetime Motivation

- ▶ Satellite lifetimes are big business
  - ▶ more satellites being launched than ever before
  - ▶ StarLink has launched over 7,000 in less than 10 years
  - ▶ roughly \$1 million (AU) per satellite
- ▶ Satellite lifetime controlled by
  - ▶ failures
  - ▶ fuel (loss from station keeping)
  - ▶ planned end-of-lifetime
- ▶ If the planned end-of-lifetime could be longer, a lot of money could be saved

# Satellite Lifetime Data (Batthula *et al.*, 2022)



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# Satellite Lifetimes

- ▶ We see
  - ▶ somewhat heavy-tail lifetime, but
  - ▶ truncated around 10 years (planned lifetime)
  - ▶ try to reduce space junk (estimates of around 30,000 objects larger than 10cm)
- ▶ Seems like satellites might be being junked early
  - ▶ given more fuel, they could potentially live longer
- ▶ Weibull fit isn't doing great
  - ▶ Weibull and its generalisations are commonly used here
  - ▶ we want to hypothesize about the distribution if the artificial constraint were removed
  - ▶ we want to do model identification not just model fitting

## Quantile-based distributions

Mostly when we teach distribution theory, we

- ▶ start with discrete RVs defined using PMFs, e.g., geometric
- ▶ move onto continuous with PDFs
- ▶ note that these aren't always useful so we do CDFs

But we leave CDFs till late because they aren't intuitive???

# Quantile-based distributions

Quantile-based distributions are an alternative

- ▶ Maybe it's more intuitive???
  - ▶ when we report distributions we often use quantiles, e.g., median, IQR, box plots, ...
  - ▶ mean and variance of little use for heavy-tailed distributions
- ▶ We don't have to create new variants by generalising existing distribution (which is what most of the satellite lifetime work has done)
- ▶ These types of distributions have interesting properties
- ▶ They are easy to simulate from
- ▶ Easy to create classes of estimators

## Quantile-based distributions

Roughly<sup>1</sup>, the quantile function is

$$Q(p) = F^{-1}(p),$$

where  $F(\cdot)$  is the Cumulative Distribution Function (CDF).

Notes:

- ▶ For convenience  $Q(0)$  and  $Q(1)$  are defined to be support
- ▶  $Q$  is non-decreasing and left-continuous
- ▶ We'll put parameters in subscripts, e.g.,  $Q_s$
- ▶  $Q$  can easily add scale and location parameters, i.e.,

$$Q_{s,a,b}(u) = a + bQ_s(u)$$

- ▶ Simulation is by taking  $X_i \sim U(0, 1)$  and then

$$Y_s = Q_s(X_i)$$

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<sup>1</sup>Actually,  $Q(u) = \inf\{x \in \mathbb{R} \mid F(x) \geq u\}$  for  $0 < u \leq 1$ .

## Quantile-based distributions – a question?

Does anyone have a reference for the following:

$$\mathbb{E}[h(Y)] = \int_0^1 h(Q_Y(p)) dp,$$

## Quantile-based distributions examples

Distribution	Parameters	Quantile Function	Support
Uniform( $a, b$ )	$a < b$	$Q(p) = a + p(b - a)$	$[a, b]$
Exponential( $\lambda$ )	$\lambda > 0$	$Q(p) = -\frac{1}{\lambda} \ln(1 - p)$	$[0, \infty)$
Normal( $\mu, \sigma$ )	$\sigma > 0$	$Q(p) = \mu + \sigma \Phi^{-1}(p)$	$\mathbb{R}$
Logistic( $\mu, s$ )	$s > 0$	$Q(p) = \mu + s \ln\left(\frac{p}{1-p}\right)$	$\mathbb{R}$

# The Tukey- $\lambda$ distribution

$$Q(p; \lambda) = \begin{cases} \frac{1}{\lambda} [p^\lambda - (1-p)^\lambda], & \text{if } \lambda \neq 0, \\ \log\left(\frac{p}{1-p}\right), & \text{if } \lambda = 0, \end{cases}$$

where  $\lambda$  is the shape parameter.

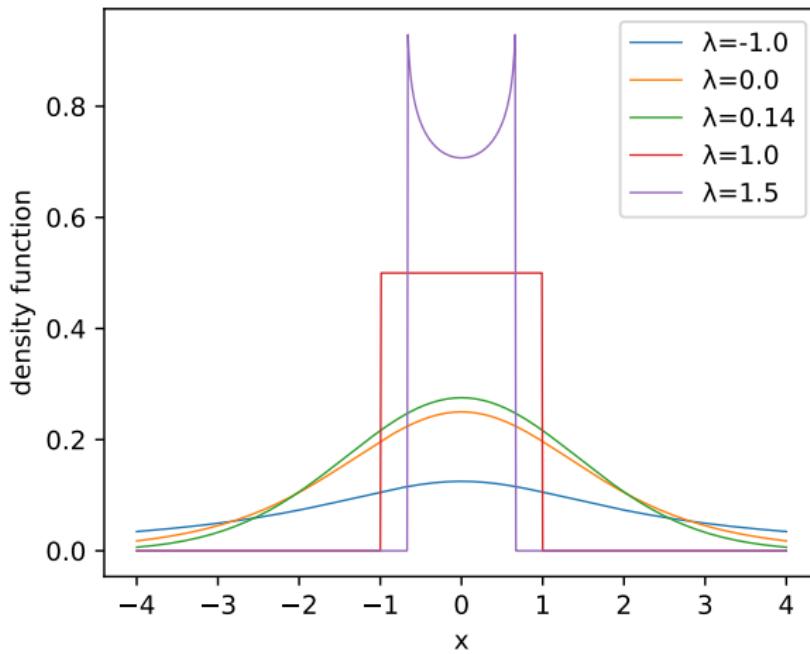
It is unusual because:

- ▶  $\lambda > 0$ , the distribution has finite support; and
- ▶  $\lambda \leq 0$ , the distribution has infinite support.

Notes:

- ▶ The distribution is symmetric about 0
- ▶ It interpolates across distributions: e.g.,
  - ▶  $\lambda = -1$ : approximately Cauchy (heavy tailed)
  - ▶  $\lambda = 0$ : logistic
  - ▶  $\lambda = 0.14$ : approximately normal
  - ▶  $\lambda = 1$ : uniform
- ▶ We don't have closed forms for many of its bits and pieces for all  $\lambda$ , but the numerical calculations aren't hard

# The Tukey- $\lambda$ distribution



## Alternatives?

- ▶ There aren't a lot of other distribution families defined by their quantile (though we often have closed forms for the quantile after the fact)
- ▶ In particular the Tukey- $\lambda$  is symmetric — is there a one-sided variant (other than trivial functional transformation)

# The Polylogarithm Distribution (PLD)

So let's define a one-sided (non-negative) distribution

- ▶ Exponential is a good starting point

$$Q_\lambda(p) = -\ln(1-p)/\lambda$$

- ▶ It's natural to generalise the log function with the polylogarithm<sup>2</sup>

$$Q_s(p) = \text{Li}_s(p) = \sum_{k=1}^{\infty} \frac{p^k}{k^s}, \quad (1)$$

where  $0 \leq p < 1$  and  $s \in \mathbb{R}$ .

- ▶ When  $s = 1$  we get the power series for the exponential distribution with  $\lambda = 1$  (as above)

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<sup>2</sup>We can extend the polylogarithm to complex arguments and parameters and outside of the range of the sum's convergence through analytic continuation, but we won't need that here.

# Polylogarithms

- ▶ Already used in some distributions, e.g.,
  - ▶ Zeta distribution characteristic and probability generating functions
  - ▶ Fermi–Dirac and Bose–Einstein integrals
- ▶ Has a strong relationship to other important functions, e.g.,
  - ▶ The Riemann zeta function

$$\text{Li}_s(1) = \zeta(s), \text{ for } \text{Re}(s) > 1$$

- ▶ Bernoulli polynomials
- ▶ Polygamma functions
- ▶ Has lots of known properties

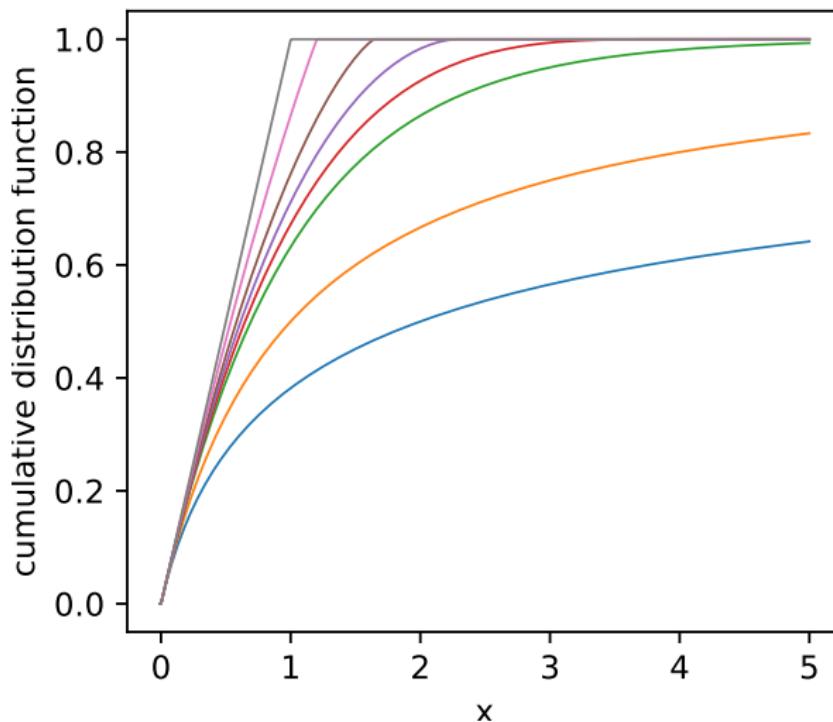
*“...almost all the formulas relating to it, have something of the fantastical in them, as if this function alone among all others possessed a sense of humor.”, Don Zagier, 2007.*

## PLD: Properties

It has properties similar to the Tukey- $\lambda$

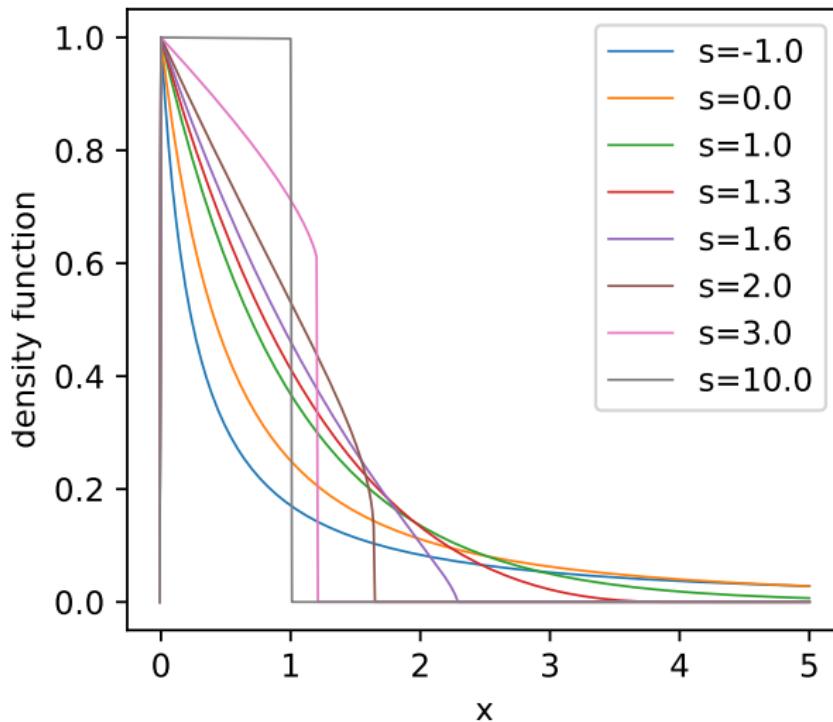
- ▶ It has both finite and infinite support
  - ▶ For  $s > 1$  the distribution has finite support
  - ▶ For  $0 < s \leq 1$  it has infinite support but finite expectation
  - ▶ For  $s \leq 0$  the expectation is infinite
- ▶ For certain parameters we get other distributions
  - ▶ for  $s \geq 8$ , it closely approximates the uniform distribution,
  - ▶ for  $s \simeq 1.6$ , it approximates the (non-negative) triangular distribution,
  - ▶ for  $s = 1.0$ , it is exactly the exponential distribution,
  - ▶ for  $s = 0.0$ , it is exactly an inverse beta distribution, and
  - ▶ for large negative  $s$ , it approximates a generalised extreme value distribution with infinite mean.

## PLD: CDFs



Calculated using a Golden Section search (280  $\mu$ seconds).

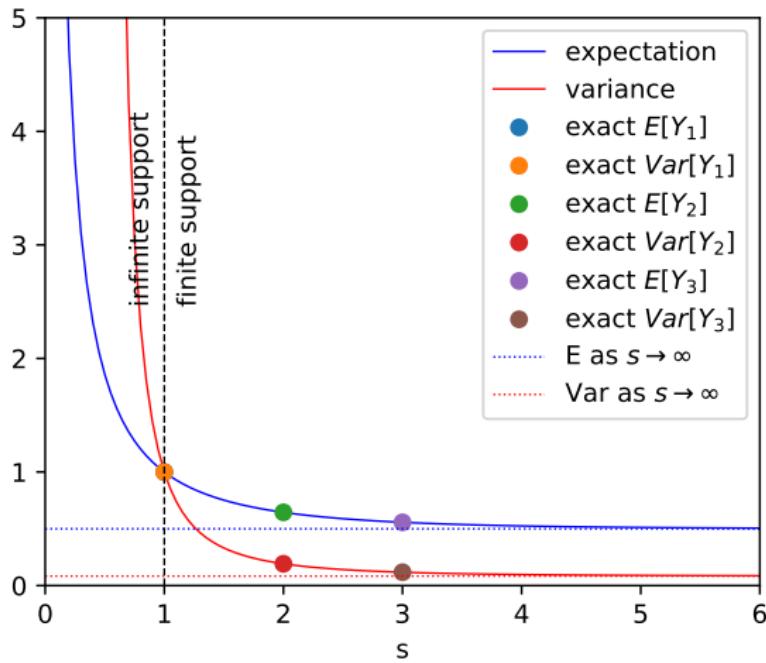
# PLD: PDFs



Calculated from CDF and Quantile derivative

$$\frac{d}{dz} \text{Li}_s(z) = \text{Li}_{s-1}(z)/z$$

# PLD: Mean and Variance



## PLD: Support

$$\begin{aligned}\text{Li}_s(0) &= 0 \\ \lim_{z \rightarrow 1} \text{Li}_s(z) &= \begin{cases} \zeta(s), & \text{for } s > 1, \\ \infty, & \text{otherwise,} \end{cases}\end{aligned}$$

Hence

$$\text{supp}(X_s) = \begin{cases} [0, \zeta(s)], & \text{for } s > 1, \\ [0, \infty), & \text{otherwise.} \end{cases}$$

## PLD: Mode and Median

- ▶ The mode is always at 0.0

This can be derived from the fact that second derivative of the quantile function

$$Q_s''(p) = \frac{\text{Li}_{s-2}(p) - \text{Li}_{s-1}(p)}{p^2},$$

is positive for all real  $s$  and  $0 \leq p$  because the polylogarithm function is decreasing with respect to  $s$  for  $0 < p < 1$ .

- ▶ The median is (trivially)  $Q_s(0.5)$

## PLD: Expectation

$$\begin{aligned}\mathbb{E}[Y_s] &= \int_0^1 \text{Li}_s(x) dx \\ &= \lim_{T \rightarrow 1} \sum_{k=1}^{\infty} \frac{1}{k^s} \int_0^T x^k dx \\ &= \lim_{T \rightarrow 1} \sum_{k=1}^{\infty} \frac{T^{k+1}}{k^s(k+1)} \\ &= \begin{cases} \sum_{k=1}^{\infty} \frac{1}{k^s(k+1)}, & \text{for } s > 0, \\ \infty, & \text{otherwise.} \end{cases} \quad (2)\end{aligned}$$

## PLD: Expectation (Convergence Bound)

The sum is bounded by the Riemann zeta function

$$\begin{aligned}\zeta(s+1) - 1 &= \sum_{k=1}^{\infty} \frac{1}{(k+1)^{s+1}} \\ &\leq \sum_{k=1}^{\infty} \frac{1}{k^s (k+1)} \\ &\leq \sum_{k=1}^{\infty} \frac{1}{k^{s+1}} \\ &= \zeta(s+1).\end{aligned}\tag{3}$$

Where we know that the  $\zeta(s+1)$  is finite when  $\operatorname{Re}(s) > 0$

## PLD: Expectation (Part II)

When  $s$  is close to zero the series converges very slowly ☹

However, we use integration by parts with  $\frac{d}{dz} \text{Li}_s(z) = \text{Li}_{s-1}(z)/z$  to get

$$\mathbb{E}[X_s] = \zeta(s+1) - \mathbb{E}[X_{s+1}],$$

so that we can calculate in a faster converging region

## PLD: Higher Moments

- ▶ Tricky (numerically) but doable
  - ▶ Care about singularity at  $z = 1$  needed for  $s \leq 1$
  - ▶ Need to use an alternative series expansion around  $z = 1$  that uses the Riemann zeta function
- ▶ Can prove bounds on finiteness of moments
  - ▶ Interval  $[1 - 1/n, 1 - 1/(n + 1)]$  has moments up to  $n$  all finite, and the  $(n + 1)$ th moment infinite.

## PLD: Fitting

- ▶ One of the aims here is that fitting the parameter replace model identification
- ▶ We should use a fitting process matched to the definition
- ▶ We are working in the context of lifetime estimations, *i.e.*, non-negative distributions (e.g., assume support starts at 0 and we don't need a location parameter)
- ▶ For Tukey- $\lambda$  folks use a probability-plot-correlation-coefficient (PPCC) chart, but its visual and doesn't allow for a scale parameter
- ▶ Instead use  $L$ -statistics, which are a linear combination of order stats

## PLD: Fitting

- ▶ Match ratio of IQR to median to the data (it's insensitive to scale), *i.e.*, choose  $\hat{s}$  to match

$$\frac{IQR}{m} = \frac{Q_s(0.75) - Q_s(0.25)}{Q_s(0.5)}.$$

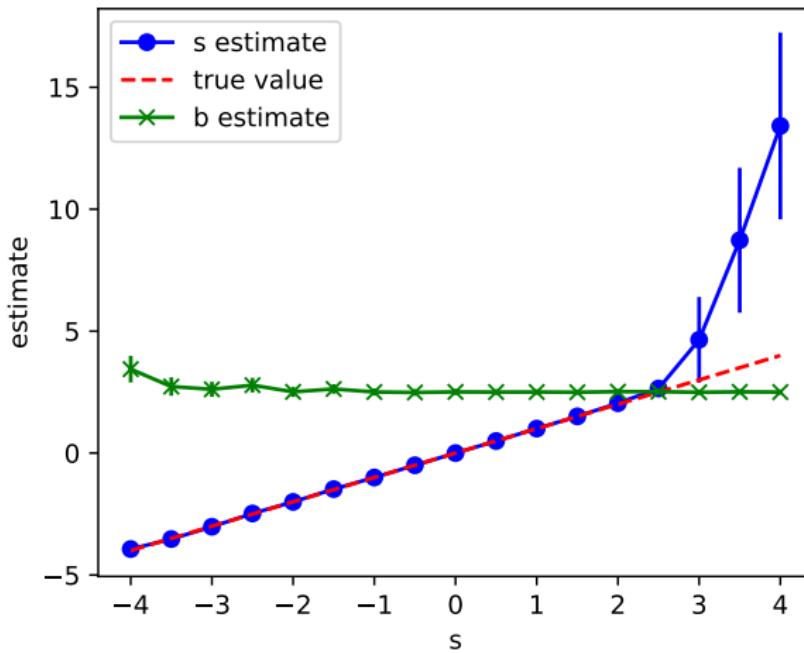
The function is strictly increasing, so the search for  $\hat{s}$  is almost trivial.

- ▶ Then match scale parameter by taking  $Q_{b,s} = bQ_s$  with

$$\hat{b} = \frac{\hat{m}}{Q_{\hat{s}}(0.5)}.$$

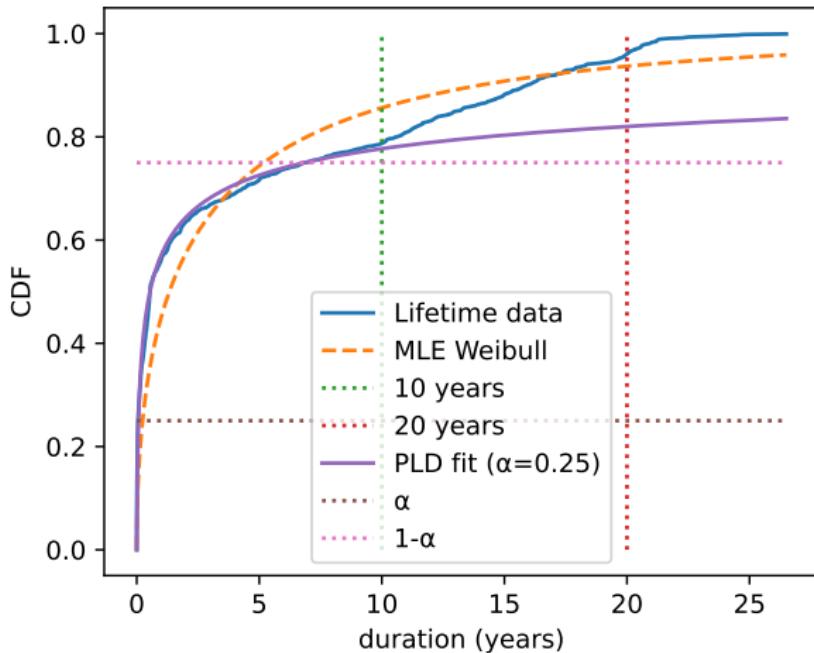
- ▶ Generalise to  $\alpha$  and  $1 - \alpha$  percentiles

## PLD: Fit on simulated data



Positive bias for large  $s$ , but the distributions here are nearly identical (uniform).

## Back to Satellite Data



## Back to Satellite Data

- ▶ Fit using  $\alpha = 0.25$  resulting in
  - ▶ shape  $\hat{s} \simeq -1.88$  (so heavy-tailed, infinite mean)
  - ▶ scale  $\hat{b} \simeq 38.05$  (median 197 days)
- ▶ Much better fit to the body
  - ▶ that's what we want here
  - ▶ we want to model normal behaviour, because tail is artificially truncated

## What does it all mean?

- ▶ Planned fuel depletion is killing satellites before the hardware wears out
- ▶ Extrapolation suggests that, given a satellite survives until 10 years, its chance of surviving an additional 10 years would be over 90%. An additional 10 years and it only drops to 86%.
- ▶ If sufficient fuel were available, satellite lifetimes might be easily doubled or even tripled
  - ▶ current fuel accounts for around 10–25% of satellite mass at launch

# Conclusion

- ▶ Quantile-defined distributions have some interesting properties
- ▶ Polylogarithm is an ideal function to use in the quantile definition because (i) so much is known about it, (ii) it is just well-behaved enough, without being boring.
- ▶ Satellite lifetimes could be greatly extended with comparatively little cost

# Extra Slides

## A Lemma

$$\mathbb{E}[h(Y)] = \int_0^1 h(Q(p)) dp$$

### Proof.

Take random variable  $X \sim U(0, 1)$ , and note that (where it exists) the expectation of a function  $g(x)$  of a random variable is given by

$$\mathbb{E}[g(X)] = \int g(x) dF_X.$$

Then note that we can create a random variable  $Y$  with quantile function  $Q(p)$  by taking  $Y = Q(X)$  and hence when the integral exists

$$\mathbb{E}[h(Y)] = \int h(Q(X)) dF_X = \int_0^1 h(Q(p)) dp.$$



## PDF from Quantile

The density function  $f(x)$  can be computed by noting

$$\frac{dF^{-1}}{dp} \bigg|_{F^{-1}(p)=x} = 1/f(x).$$

Where a search is needed to find the point where  $F^{-1}(p) = x$ .  
Then the derivative can be derived using the derivative of the  
polylogarithm function

$$f(x) = \frac{p}{\text{Li}_{s-1}(p)} \bigg|_{\text{Li}_s(p)=x}.$$