STA261 Lecture 5 — 2017-07-24

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maximum likelihood summary

The joint pmf/pdf is treated as a function of the parameter(s) θ, given the data.

This function is called a "likelihood" $L(\theta)$.

A likelihood can be thought of as the "probability" of the data.

The parameter value $\hat{\theta}$ that maximizes $L(\theta)$ is the maximum likelihood estimator.

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The examples we’ve done so far have all had a closed form solution, but this isn’t necessary or even “better” in any sense.

exponential distributions revisited

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We'll see over the next few classes that this is in one particular sense the best possible estimator for λ.

exponential distribution - different kind of dataset

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What we would more typically see is data as on the next page. "Today" I extract the historical data on the equipment I am interested in...

“survival” data

ID	Age	Status
A023	6.8	Failed
A324	7.2	Operating
A620	10.1	Taken Out of Service
A092	2.4	Operating
A526	5.5	Operating
A985	8.1	Failed
A723	1.5	Operating
⋮	⋮	⋮

likelihood for “survival data”

The model for failure times is $X \sim$Exp(λ).

What is the likelihood of the data?

The likelihood for a unit to fail at time x_i is: $\lambda e^{-\lambda x_i}$

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The likelihood for a unit to not have failed yet at time x_i is: $P(X > x_i) = e^{-\lambda x_i}$

likelihood, line by line

ID	Age	Status	Contribution to Likelihood
A023	6.8	Failed	$\lambda e^{-6.8\lambda}$
A324	7.2	Operating	$e^{-7.2\lambda}$
A620	10.1	Taken Out of Service	$e^{-10.1\lambda}$
A092	2.4	Operating	$e^{-2.4\lambda}$
A526	5.5	Operating	$e^{-5.5\lambda}$
A985	8.1	Failed	$\lambda e^{-8.1\lambda}$
A723	1.5	Operating	$e^{-1.5\lambda}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$

censored data, and the likelihood function

When the failure time is unknown, because it hasn't happened yet, we say the failure time is *censored*. Define the *censoring indicator* c_i to be 1 if the unit failed and 0 otherwise.

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Putting it all together, given times $x_1, \ldots, x_n$ and censoring indicators $c_1, \ldots, c_n$, the likelihood of the data is:

$$L(\lambda) = \prod_{i=1}^{n} \left(\lambda e^{-\lambda x_i}\right)^{c_i} \left(e^{-\lambda x_i}\right)^{1-c_i}$$

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Proposition 5.0: The MLE for λ is $\hat{\lambda} = \sum_{i=1}^{n} c_i \Big/ \sum_{i=1}^{n} X_i$

occurrence-exposure example

Here are 50 simulated "ages" from an Exp(0.1) population, "censored" at 9.0 "years"

```
##  [1] 9.00 6.40 2.32 4.69 8.36 3.48 0.33 5.45 7.26 2.00 5.26
## [12] 9.00 0.07 6.10 2.13 9.00 9.00 9.00 9.00 9.00 9.00 6.72
## [23] 4.42 9.00 7.56 4.57 6.25 7.97 9.00 9.00 9.00 0.04 9.00
## [34] 4.97 0.52 5.40 4.53 9.00 4.60 9.00 3.80 8.93 9.00 4.24
## [45] 3.73 9.00 9.00 9.00 9.00 0.45
```

The "naive" mean life estimate (the average of the failed units only): 4.418.

The MLE: 10.418.

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- a unit suffers shock events that occur according to a Poisson process $N(t)$

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- the unit fails the moment $Z(t)$ reaches some threshold

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(Many OR / stats professors like to propose models, but often do not dirty themselves with actual data.)

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The probabilities of having endured 0, or 1+ shocks by age t_i are:

$$P(N(t_i) = 0) = e^{-\lambda t_i}$$
$$P(N(t_i) > 0) = 1 - e^{-\lambda t_i}$$

likelihood

The likelihood for λ is therefore:

$$L(\lambda) = \prod_{i=1}^{n} \left(e^{-\lambda t_i}\right)^{1-d_i} \left(1 - e^{-\lambda t_i}\right)^{d_i}$$

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$$\ell(\lambda) = -\lambda \sum_{i=1}^{n} t_i(1 - d_i) + \sum_{i=1}^{n} d_i \log\left(1 - e^{-\lambda t_i}\right)$$

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This can only be maximized numerically. *As usual.*

properties of MLEs

why maximum likelihood is so popular

They are easy to develop, and under a few conditions (most often satisfied), the method of maximum likelihood produces estimators that are:

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1. consistent
2. invariant
3. asymptotically normal

the score, and information functions

Likelihood theory deals so much with the following functions that they are given names:

Score:

$$S(\theta) = S(\theta; \mathbf{X}) = \frac{\partial}{\partial\theta} \log L(\theta; \mathbf{X})$$

Information:

$$\mathcal{I}(\theta) = \mathcal{I}(\theta; \mathbf{X}) = E\left(\left(\frac{\partial}{\partial\theta} \log L(\theta; \mathbf{X})\right)^2\right)$$

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Technical note: when θ is a vector, the score is the gradient vector, and the information is a matrix of all the partial second derivatives.

properties of score and information

Likelihood theory is littered with "under certain regularity conditions" statements, handed down from one generation to the next. From my failing hands I pass the torch...

Proposition 5.1: $E(S(\theta)) = 0$

Theorem 5.2: $\mathcal{I}(\theta) = \mathrm{Var}(E(\theta))$ and $\mathcal{I}(\theta) = -E\left(\frac{\partial^2}{\partial\theta^2} \log L(\theta; \mathbf{X})\right)$