

# 6.1: Statistics And Their Distributions

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- Random variables are typically denoted with letters at the end of the alphabet (e.g.  $X, Y$ , etc.)
- Before we observe a sample, the data is random ( $X_1, \dots, X_N$ )
- The observations or data we observe are lower-case ( $x_1, \dots, x_n$ )
- for more info see Chapter 3

- The same idea applies to functions of the rvs
- Example:  $f(X_1, \dots, X_n) = \frac{1}{n} \sum_i X_i$
- if we have the data already it's  $f(x_1, \dots, x_n) = \frac{1}{n} \sum_i x_i$
- This is what a **statistic** is: a quantity calculated from sample data.
- We're usually referring to the random variable (capital letters) because we like to talk about it's distribution/moments etc.

Some very ubiquitous examples:

- $f(X_1, \dots, X_n) = \frac{1}{n} \sum_i X_i = \bar{X}$
- $f(X_1, \dots, X_n) = \frac{1}{n-1} \sum_i (X_i - \bar{X})^2 = S^2$
- $f(X_1, \dots, X_n) = \max(X_1, \dots, X_n) = X_{(n)}$
- $f(X_1, \dots, X_n) = \min(X_1, \dots, X_n) = X_{(1)}$

- Every sample statistic has a probability distribution
- sometimes it's easy to calculate (e.g. the mean of a bunch of normal random variables)
- sometimes it's difficult or impossible
- The probability distribution of a statistic is often called a **sampling distribution**
- A note on notation: I'll usually denote general probability distributions with a  $p$  or an  $f$

- Many analyses assume that the data are being generated from a common probability distribution
- The most tractable situation is when each data point/rv comes from the same distribution, and no data point affects any other data point
- the book calls this a **random sample** (page 287)
- I will just say (i.i.d) which stands for *independent and identically distributed*
- I will denote it like this  $\overset{iid}{\sim}$
- example:  $X_1, \dots, X_n \overset{iid}{\sim} \text{Normal}(\mu, \sigma^2)$

# Example

Our first example (Example 6.3 on page 290):

Let  $X_1, X_2 \stackrel{iid}{\sim} \text{Exponential}(\lambda)$ . What is the distribution of  $T_0 = \sum X_i$ ?  
First we'll find it's cumulative distribution function (cdf)  $F_{T_0}(t)$ ; then we'll take the derivative to get the density  $f_{T_0}(t)$ . Hopefully it'll be a familiar distribution again...

# Example

$$\begin{aligned}F_{T_0}(t) &= P(X_1 + X_2 \leq t) \\&= \iint_{\{(x_1, x_2): x_1 + x_2 \leq t\}} p(x_1, x_2) dx_1 dx_2 \\&= \iint_{\{(x_1, x_2): x_1 + x_2 \leq t\}} p(x_1) p(x_2) dx_1 dx_2 \\&= \int_0^t \int_0^{t-x_1} \lambda e^{-\lambda x_1} \lambda e^{-\lambda x_2} dx_2 dx_1 \\&= \int_0^t \lambda e^{-\lambda x_1} \left[ \int_0^{t-x_1} \lambda e^{-\lambda x_2} dx_2 \right] dx_1 \\&= \int_0^t \lambda e^{-\lambda x_1} \left[ -e^{-\lambda x_2} \right]_0^{t-x_1} dx_1 \\&= \int_0^t \left( \lambda e^{-\lambda x_1} - \lambda e^{-\lambda t} \right) dx_1\end{aligned}$$



# Example

$$\begin{aligned} &= \int_0^t \left( \lambda e^{-\lambda x_1} - \lambda e^{-\lambda t} \right) dx_1 \\ &= \int_0^t \lambda e^{-\lambda x_1} dx_1 - t \lambda e^{-\lambda t} \\ &= \left[ -e^{-\lambda x_1} \right]_0^t - t \lambda e^{-\lambda t} \\ &= 1 - e^{-\lambda t} - \lambda t e^{-\lambda t} \end{aligned}$$

Now differentiate with respect to  $t$  to get the density:

$$f_{T_0}(t) = \lambda^2 t \exp(-\lambda t), t > 0$$

A couple things:

- this is a  $\text{Gamma}(2, 1/\lambda)$  distribution.
- Recall that there are a few tricks that make Gamma distributions nice
- The distribution of sums of independent random variables is made easier by moment generating functions (we'll talk about these later)
- make sure you get a feel for this (a lot of the same tricks will reappear later)

# Example

Extending example 6.3:

Let  $X_1, X_2, \dots, X_N \stackrel{iid}{\sim} \text{Exponential}(\lambda)$ . What is the distribution of  $T_0 = \sum_{i=1}^n X_i$ ? First we'll find it's cumulative distribution function (cdf)  $F_{T_0}(t)$ ; then we'll take the derivative to get the density  $f_{T_0}(t)$ .

# Example

$$\begin{aligned} F_{T_0}(t) &= P\left(\sum_{i=1}^n X_i \leq t\right) \\ &= \iint_{\{(x_1, x_2): x_1 + x_2 \leq t\}} f(x_1, \dots, x_n) dx_{1:n} \\ &= \int_0^t \int_0^{t - \sum_{i=1}^1 x_i} \dots \int_0^{t - \sum_{i=1}^{n-1} x_i} f(s_1, \dots, s_n) ds_n ds_{n-1} \dots ds_1 \end{aligned}$$

# Example

Alternatively, you could use the transformation theorem:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} X_1 \\ X_1 + X_2 \\ \vdots \\ \sum_{i=1}^n X_i \end{bmatrix}$$

It isn't that bad to get  $g(y_1, y_2, \dots, y_n)$ , but it's difficult to integrate out  $y_1, y_2, \dots, y_{n-1}$

# Definitions

We can also run simulations to check our derivations.

Example: If  $X_1, \dots, X_{100} \stackrel{iid}{\sim} \text{Normal}(0, 1)$ , what does the maximum  $X_{(100)}$  follow?

