

## Standardizing random variables

### Linear combinations of random variables

Suppose  $X$  is a random variable (with well defined expected value and standard deviation) and  $b$  is a number. Then  $X + b$  is another random variable, and

$$\begin{aligned}E(X + b) &= E(x) + b \\ \text{st.dev.}(X + b) &= \text{st.dev.}(X) .\end{aligned}$$

If  $c$  is a number, then

$$\begin{aligned}E(cX) &= cE(x) \\ \text{st.dev.}(cX) &= |c|\text{st.dev.}(X) .\end{aligned}$$

### The standardization of a random variable

Suppose  $X$  is a random variable with mean  $\mu$  and standard deviation  $\sigma > 0$ . Then the *standardization* of  $X$  is the random variable  $Z = (X - \mu)/\sigma$ . Then  $Z$  has mean zero and standard deviation 1.

(Changing  $X$  to  $X - \mu$  changes the mean to zero and does not change the standard deviation. Then multiplying by  $1/\sigma$  changes the standard deviation to 1, and doesn't change the mean, because  $(1/\sigma)0 = 0$ .)

If  $c$  and  $d$  are numbers, and  $c$  is nonzero, then  $X$  and  $cX + d$  have the same standardization. Standardization gives us standard units for considering (for example) the shape the graph of a probability density function. If  $X$  records experimental measurements in feet, and  $Y$  records the experimental measurements in inches, and  $X$  and  $Y$  measure the same experiment in the lab, then their standardizations will be the same.

Even more important, standardization gives us a way to see the pattern of sums and averages.

For example, suppose  $S_n = X_1 + \cdots + X_n$ , and the  $X_i$  are i.i.d. with mean  $\mu > 0$  and standard deviation  $\sigma > 0$ . How can we understand the pattern of  $S_n$  as  $n$  increases?

The expected value of  $S_n$  is  $n\mu$ . The outputs of  $S_n$  keep getting larger. There doesn't seem to be any convergence.

If we replace  $S_n$  with  $S_n - n\mu$ , we at least see how the values of  $S_n$  are arranged around its mean. But the standard deviation of  $S_n$  is  $\sqrt{n}\sigma$ ; if we just look at  $S_n$ , we just see the spread of those values going to infinity.

But if we standardize  $S_n$ , we get

$$Z_n = \frac{(S_n - n\mu)}{\sqrt{n}\sigma}.$$

We'll see with the Central Limit Theorem that for large  $n$  the distribution of  $Z_n$  is approximately  $\mathcal{N}(0, 1)$ . And we can use that to get information about  $S_n$ , and also averages.

## Standardization and a probability density function

Suppose  $f$  is a p.d.f. for a continuous random variable  $X$ , with a mean  $\mu$  and nonzero standard deviation  $\sigma$ .

The graph of the p.d.f (call it  $g$ ) for the r.v.  $X - \mu$  is the graph of  $f$  shifted  $\mu$  units to the left.

The p.d.f. (call it  $h$ ) of the standardization  $Z = (X - \mu)/\sigma$  is obtained from  $g$  as follows.  $h(x) = \sigma g(x/\sigma)$ .

For example, suppose  $\sigma = 3$ . Then the graph is compressed horizontally by a factor of three and expanded vertically by a factor of 3.