Introduction to Data Science - 1MS041

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Recall from last time

- Experiment: is an activity or procedure that produces distinct, well-defined possibilities called **outcomes**.
- The set of all outcomes is called the **sample space**, and is denoted by Ω .
- Trial: doing the experiment once and getting an outcome.
- The subsets of Ω are called **events** events.
- Given an outcome $\omega \in \Omega$ we say that the event $E \subset \Omega$ occured if $\omega \in E$.

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- To do this, we should really be working with numbers.
- Recall: When we simulated the coin toss, we assigned 1 to Heads and 0 to Tails, this allowed us to take the average!

Definition (Random Variable)

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be some probability triple. Then, a **Random Variable (RV)**, say X, is a function from the sample space Ω to the set of real numbers \mathbb{R}

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$$x \in \mathbb{R}, \qquad X^{[-1]}(\ (-\infty,x]\) := \{\omega : X(\omega) \le x\} \in \mathcal{F} \ .$$

We assign probability to the RV X as follows:

$$\mathbb{P}(X \le x) = \mathbb{P}(X^{[-1]}((-\infty, x])) := \mathbb{P}(\{\omega : X(\omega) \le x\}). \tag{1}$$

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A random variable is a function from the sample space to a value! Consider the coin-toss: We had $\Omega=\{\mathtt{H},\mathtt{T}\}$, and define

$$X(\omega) = \begin{cases} 1 & \text{if } \omega = H \\ 0 & \text{if } \omega = T \end{cases}$$

Then as we observe H, T, H, H, T, we observe for X, 1, 0, 1, 1, 0.

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For every $x \in \mathbb{R}$, the inverse image of the half-open real interval $(-\infty, x]$ is an element of the collection of events \mathcal{F} . To understand the above, let us first unpack the inverse image

$$X^{[-1]}(\ (-\infty,x]\):=\{\omega:X(\omega)\leq x\}="X\ ext{is less than or equal to }x"$$

The inverse image is the event "X is less than or equal to x".

Example

Consider again the coin toss, where X=1 for Heads and 0 for Tails

$$\begin{split} & X^{[-1]}(\ (-\infty,0]\) = \{\mathtt{T}\} \\ & X^{[-1]}(\ (-\infty,1]\) = \{\mathtt{H},\mathtt{T}\} \\ & X^{[-1]}(\ (-\infty,2]\) = \{\mathtt{H},\mathtt{T}\} \end{split}$$

Last step!

For every $x \in \mathbb{R}$, the inverse image of the half-open real interval $(-\infty, x]$ is an element of the collection of events \mathcal{F} .

We now know what the inverse image is, the last requirement is that this is in our \mathcal{F} , i.e. our sigma-algebra.

Conclusion

A function that assigns a value to the outcome of the trial is a random variable if we can observe it!

Examples

• If our experiment is that we are checking if a light bulb is defective or not, we had $\Omega = \{ \text{Defective}, \text{Non Defective} \}$. We could create a random variable X such that X(Defective) = 1 and X(Non Defective) = 0.

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- We could also assign a cost to the lightbulb, if Defective we lose money and if non defective, we can sell it for money.
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- We could also assign a cost to the lightbulb, if Defective we lose money and if non defective, we can sell it for money.
 X(Defective) = -1 and X(Non Defective) = 2.
- If the experiment is to select a random person in this classroom. Then the sample space is $\Omega = \{p_1, p_2, \dots, p_n\}$. We could measure each persons length, then call that $X(p_i)$. Then X is a random variable.

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- Quite quickly one would get sick of having to all the time figure out what the sample space is and how the events look like.
- So we usually dont specify Ω exactly, but we just make the assumption that it can be defined if we wanted to. Actually it quickly becomes very complicated.
- Instead we focus our attention on the random variables themselves.

Lets work a bit with random variables: discrete

Definition

We say that a real valued random variable X is discrete if it takes discrete values. For instance (0, 1, 2, 3, ...).

Now consider this

Definition

Let X be a \mathbb{R} -valued discrete RV. We define the **probability mass** function (PMF) f of X to be the function $f : \mathbb{R} \to [0,1]$ defined as follows:

$$f(x) := \mathbb{P}(X = x) = \mathbb{P}(\{\omega : X(\omega) = x\}) = \begin{cases} \theta_i & \text{if } x = x_i \in \mathbb{X}. \\ 0 & \text{otherwise.} \end{cases}$$

Distribution function

Definition (Distribution Function)

The Distribution Function (DF) or Cumulative Distribution Function (CDF) of any RV X, over a probability triple $(\Omega, \mathcal{F}, \mathbb{P})$, denoted by F is:

$$F(x) := \mathbb{P}(X \le x) = \mathbb{P}(\{\omega : X(\omega) \le x\}), \quad \text{for any} \quad x \in \mathbb{R}.$$
 (3)

Thus, F(x) or simply F is a non-decreasing, right continuous, [0,1]-valued function over \mathbb{R} . When a RV X has DF F we write $X \sim F$.

Expectations

In the coin toss experiment H is 1 and T is 0 we said was that in average you would expect to see roughly half 1 and half 0. The average value would tend to 0.5 in a fair coin.

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In the coin toss experiment H is 1 and T is 0 we said was that in average you would expect to see roughly half 1 and half 0. The average value would tend to 0.5 in a fair coin. Once we have the PMF we can actually compute the theoretical average, called an **expectation or mean**:

$$\mathbb{E}[X] = \sum_{x} x f(x)$$

Example

In the $X \sim \text{Bernoulli}(p)$ case we get

$$\mathbb{E}[X] = p + 0(1-p) = p.$$

For a fair coin, p = 0.5 we get $\mathbb{E}[X] = 0.5$.

Learning from data

The simplest form of learning is to estimate the mean from data. When working with data, we have a sequence of outcomes $\omega_1, \ldots, \omega_n$ and the values we observe of the random variable X is $X(\omega_1), \ldots, X(\omega_n)$.

Important

It is an important distinction between a random variable X, which is a function (or you can think procedure) and the observation of X which is a value.

It is like the difference between a computer program and the result of running it once. Or simply the difference between an Experiment and a Trial.

Learning from data

The most natural way to estimate the expectation from data is to take the empirical mean. Denote $X(\omega_i) = x_i$, then we can consider

$$\frac{1}{n}\sum_{i=1}^{n}x_{i}$$

this is the so called observed empirical mean.

Definition

An **n-product experiment** is obtained by repeatedly performing n trials of some experiment.

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If we have a random variable X on the original experiment we can list all the n values as $Z=(X_1,X_2,\ldots,X_n)$ where we consider Z as being a single random variable with n values. This is called a multivariate random variable.

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Lets simulate

Continuous random variables

Definition (Continuous random variable)

Let X be a \mathbb{R} -valued random variable with distribution function F. We say that X is a **continuous** RV if there exists a piecewise-continuous function $f:\mathbb{R}\to [0,\infty]$, called the **probability density function (PDF)** of X, such that

$$F(x) = \mathbb{P}(X \le x) = \int_{-\infty}^{x} f(v) dv.$$
 (4)

Compare and contrast

Discrete	Continuous
$F(x) = \sum_{x_i \le x} f(x_i)$	$F(x) = \int_{-\infty}^{x} f(v) dv$
$F(b) - F(a) = \sum_{a < x_i \le b} f(x_i)$	$F(b) - F(a) = \int_a^b f(x) dx$
$\mathbb{P}(X=x)=f(x)$	$\mathbb{P}(X=x)=0$
$\sum_{x} f(x) = 1$	$\int_{-\infty}^{\infty} f(x) dx = 1.$