

The Need for Measure Theory (ref: Ch. 1 Rosenthal)

Q. Why is it necessary to introduce measure theory in order to study probability theory in a rigorous manner?

First: Illustrate the limitations of undergrad-level probability in 2 ways:

- 1) restrictions on the kinds of random variables (RVs) it allows.
- 2) question of what sets can have probabilities defined on them.

Types of random variables

• Discrete RV

e.g. Let X be a RV which has the Poisson(5) distribution.

This means that X takes as its value a "random" non-negative integer k , chosen with probability

$$P(X=k) = \frac{e^{-5} 5^k}{k!}, \quad k=0,1,2,\dots$$

Here $\lambda = 5$. Recall that $E[X] = \lambda = 5$ in this case
↑
mean

- Continuous RV

e.g. Let Y be a RV which has the Normal $(0,1)$ distribution. $Y \sim N(0,1)$ - aka Standard Normal

This means that the probability that Y lies between 2 \mathbb{R} numbers $a < b$ is given by the integral

$$P(a < Y < b) = \int_a^b \underbrace{\frac{1}{\sqrt{2\pi}} e^{-y^2/2}}_{f_Y(y) = \text{PDF of } Y} dy$$

[Recalling that $P(Y=y) = 0$ for any particular $y \in \mathbb{R}$]

Y is an absolutely continuous RV.

i.e. a RV whose CDF is a continuous function

- Now suppose we introduce a new RV Z as follows:

Let $X \stackrel{\text{i.i.d.}}{\sim} Y$ be as above.

Flip a fair coin.

{ If coin comes up heads, set $Z = X$.
{ If coin comes up tails, set $Z = Y$.

Note that $P(Z=X) = P(Z=Y) = \frac{1}{2}$.

Q. What type of RV is Z ?

Not discrete - since it can take on an uncountable # of different values

Not _{absolutely} continuous - since for certain values z , we have $P(Z=z) > 0$
(when z is a non-negative integer)

So how can we study RV Z ?

How can we compute, say, $E[Z]$?

Answer: the division of random variables into 2 categories (discrete vs. absolutely continuous) is artificial.

→ Measure Theory allows us to give common definitions to expected value, etc.

1 definition applies to discrete RVs (like X), continuous RVs (like Y), & combinations (like Z).

Measure Theory

* Powerful convergence theorems associated with Lebesgue theory of integration lead to more general, more complete, & more elegant results than the Riemann integral allows.

* Lebesgue's definition of the integral broadens the collection of functions for which the integral is defined.

↑
measurable functions

* Unnecessary distinctions between discrete & continuous distributions disappear in a measure theoretic context.

↑
think of events that could happen:
this is just a collection of events
(set)

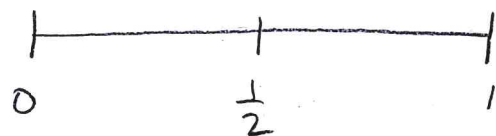
↑
 σ -algebra

The Uniform Distribution \Leftrightarrow Non-Measurable Sets

Let $X \sim \text{Uniform}(0,1)$. or $X \sim U(0,1)$ - short-hand notation

Means X has the uniform distribution on the interval $[0,1]$.

$$P(0 \leq X \leq 1) = 1$$



$$P(0 \leq X \leq \frac{1}{2}) = \frac{1}{2}$$

$$P(\frac{3}{4} \leq X \leq \frac{7}{8}) = \frac{1}{8}$$

etc.

In general, we have that for $0 \leq a < b \leq 1$

$$\boxed{P(a \leq X \leq b) = b - a} \quad \leftarrow \text{length of the interval } [a,b] \quad \text{Eqn (1)}$$

Note: The same formula holds if \leq is replaced by $<$.
why?

Since X is a continuous RV,

$$P(X = x) = 0 \text{ for any } x \in \mathbb{R}.$$

$$P([a,b]) = P((a,b]) = P([a,b)) = P((a,b)) = b-a$$

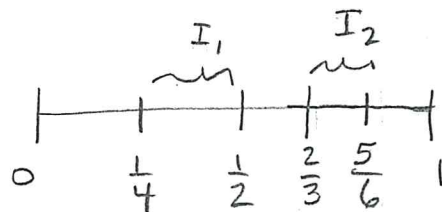
aka $P(a \leq X \leq b)$ for $0 \leq a \leq b \leq 1$

$$P\left(\frac{1}{4} \leq X \leq \frac{1}{2} \text{ OR } \frac{2}{3} \leq X \leq \frac{5}{6}\right)$$

$$= P\left(\frac{1}{4} \leq X \leq \frac{1}{2}\right) + P\left(\frac{2}{3} \leq X \leq \frac{5}{6}\right)$$

$$= \frac{1}{4} + \frac{1}{6}$$

$$= \frac{5}{12}$$



In general, if $A \cap B = \emptyset$ are disjoint subsets of $[0,1]$,

$$\text{then } P(A \cup B) = P(A) + P(B)$$

Finite additivity property

Extend to a countably infinite # of disjoint subsets:

If A_1, A_2, \dots are disjoint subsets of $[0,1]$,

$$\text{then } P(A_1 \cup A_2 \cup \dots) = P(A_1) + P(A_2) + \dots$$

$$= \sum_{i=1}^{\infty} P(A_i)$$

Countable additivity

Eqn (2)

Important Note: We do NOT extend this to uncountable additivity.

If we did, we would expect that

$$P([0,1]) = \sum_{x \in [0,1]} P(\{x\})$$

BUT this is clearly FALSE!

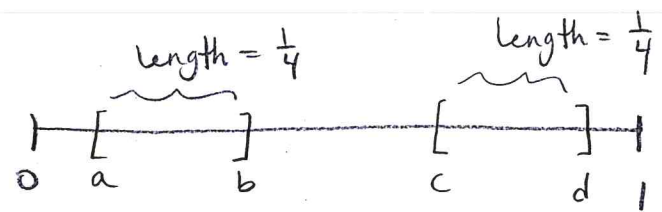
$$\text{LHS} = 1$$

$$\text{RHS} = 0 \text{ since } P(\{x\}) = P(X=x) = 0 \text{ for any } x \in [0,1]$$

Hence, we restrict our attention to countable operations.

Let $A \subseteq [0,1]$. Then $P(X \in A)$ should be
subset probability that X lies in some subset of $[0,1]$

unaffected by "shifting" (with wrap-around) the subset by a fixed amount.



$$c = a + r$$
$$d = b + r$$

shift $[a,b]$ by a constant $r > 0$.

Furthermore, since H contains just 1 point from each equiv. class, we see that these sets $H \oplus r$, for rational $r \in [0,1)$, are all disjoint.

But then, countable additivity

$$\Rightarrow P([0,1]) = \sum_{\substack{r \in [0,1) \\ r \text{ rational}}} P(H \oplus r)$$

Shift invariance $\Rightarrow P(H \oplus r) = P(H)$

$$\Rightarrow 1 = P([0,1]) = \sum_{\substack{r \in [0,1) \\ r \text{ rational}}} P(H).$$

This leads to a contradiction: a countably ∞ sum of the same _{non-neg.} quantity can only equal 0 or ∞ , but never 1. \square

Main Point: If we want probabilities to satisfy reasonable properties, then we cannot define them for all possible subsets of $[0,1]$. Rather, we must restrict their definition to certain "measurable" sets.

\rightarrow Motivation for next section.

Summary

- Discussed why measure theory is necessary to develop mathematical rigorous theory of probability.
- Considered the possibility of RVs that are neither discrete nor (abs.) continuous, don't fit into undergrad. probability.
- Proved that (for $U(0,1)$ distn), it is not possible to define a probability on every single subset.