

18.600: Lecture 15

Continuous random variables

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Outline

Continuous random variables

Expectation and variance of continuous random variables

Uniform random variable on $[0, 1]$

Uniform random variable on $[\alpha, \beta]$

Measurable sets and a famous paradox

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- ▶ Probability of any single point is zero.
- ▶ Define **cumulative distribution function**
 $F(a) = F_X(a) := P\{X < a\} = P\{X \leq a\} = \int_{-\infty}^a f(x)dx$.

Simple example

► Suppose $f(x) = \begin{cases} 1/2 & x \in [0, 2] \\ 0 & x \notin [0, 2]. \end{cases}$

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- ▶ In general $P(a \leq x \leq b) = F(b) - F(a)$.
- ▶ We say that X is **uniformly distributed on** $[0, 2]$.

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- ▶ This formula is often useful for calculations.

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- ▶ $\text{Var}E[X^2] - E[X]^2 = 1/3 - 1/4 = 1/12$.

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- ▶ Intuitively, we'd guess the midpoint $\frac{\alpha + \beta}{2}$.

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- ▶ Answer: $\text{Var}[X] = \text{Var}[(\beta - \alpha)Y + \alpha] = \text{Var}[(\beta - \alpha)Y] = (\beta - \alpha)^2 \text{Var}[Y] = (\beta - \alpha)^2 / 12$.

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- ▶ What if B is the set of all rational numbers?
- ▶ How do we mathematically define the volume of an arbitrary set B ?

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- ▶ **Hypothetical:** Consider the interval $[0, 1)$ with the two endpoints glued together (so it looks like a circle). *What if* we could partition $[0, 1)$ into a countably infinite collection of disjoint sets that all looked the same (up to a rotation of the circle) and thus had to have the same probability?

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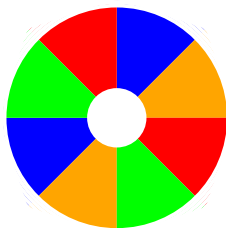
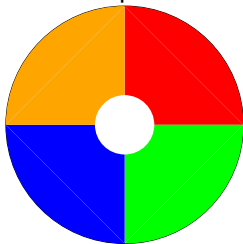
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- ▶ **Related problem:** *if* (in a non-atomic world, where mass was infinitely divisible) you could cut a donut into countably infinitely many pieces all of the same weight, how much would each piece weigh?
- ▶ **Question:** Is it really possible to partition $[0, 1)$ into countably many identical (up to rotation) pieces?

Cutting donut into countably many identical “pieces”

- ▶ Call two points “equivalent” if you can get from one to the other by a 0, 90, 180, or 270 degree rotation.

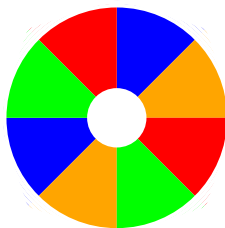
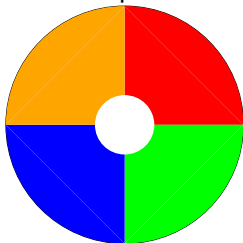
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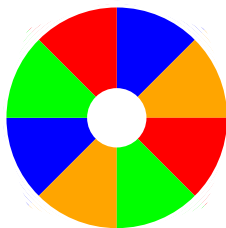
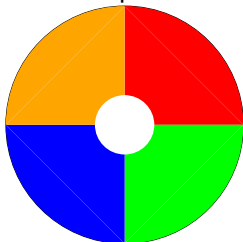
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- ▶ Whole donut is disjoint union of the four sets obtained as 0/90/180/270 degree rotations of red set.
- ▶ What if we replace “0/90/180/270-degree rotations” by “rational-degree-number rotations”? If red set has one point from each equivalence class, whole donut is disjoint union of *countably* many sets obtained as rational rotations of red set.

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- ▶ Thus $[0, 1) = \cup \tau_r(A)$ as r ranges over rationals in $[0, 1)$.
- ▶ If $P(A) = 0$, then $P(S) = \sum_r P(\tau_r(A)) = 0$. If $P(A) > 0$ then $P(S) = \sum_r P(\tau_r(A)) = \infty$. Contradicts $P(S) = 1$ axiom.

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- ▶ Most mainstream probability and analysis takes the third approach.
- ▶ In practice, sets we care about (e.g., countable unions of points and intervals) tend to be measurable.

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- ▶ Riemann integration is a mathematically rigorous theory. It's just not as robust as Lebesgue integration.