

Session 6

Recall...

Example of a set A where the Riemann integral does not exist

6.1

Suppose I have a pdf

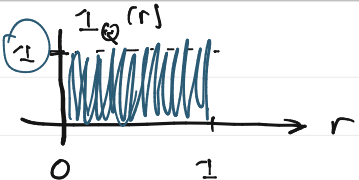
$$f(r) = \frac{1}{[0,1]}(r) = \begin{cases} 1, & 0 \leq r \leq 1 \\ 0, & \text{elsewhere.} \end{cases}$$

Let $A = \underline{\mathbb{Q}} =$ rational numbers.

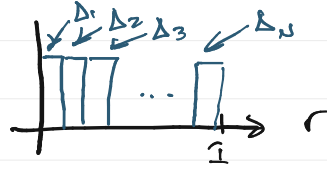
$$\begin{aligned} P(A) &= P(\underline{\mathbb{Q}}) = \int_{-\infty}^{\infty} f(r) \cdot \mathbb{1}_{\underline{\mathbb{Q}}}(r) \, dr \\ &= \int_0^1 \mathbb{1}_{\underline{\mathbb{Q}}}(r) \, dr \end{aligned}$$

does not exist as a Riemann integral

Recall...

$$P(\mathbb{Q}) = \int_{-\infty}^{\infty} f(r) \cdot \mathbb{1}_{\mathbb{Q}}(r) dr$$


6.2

$$= \int_0^1 \mathbb{1}_{\mathbb{Q}}(r) dr$$
$$= \lim_{N \rightarrow \infty} \sum_{k=1}^N |\Delta_k| \cdot \mathbb{1}_{\mathbb{Q}}(x_k)$$


$$\underline{\text{SUM}}_N = \sum_{k=1}^N |\Delta_k| \cdot \left(\min_{x \in \Delta_k} \mathbb{1}_{\mathbb{Q}}(x) \right) = \sum_{k=1}^N |\Delta_k| \cdot 0 = 0$$

$$\overline{\text{SUM}}_N = \sum_{k=1}^N |\Delta_k| \cdot \left(\max_{x \in \Delta_k} \mathbb{1}_{\mathbb{Q}}(x) \right) = \sum_{k=1}^N |\Delta_k| \cdot 1 = 1$$

For a Riemann integral to exist

$$\lim_{N \rightarrow \infty} \underline{\text{SUM}}_N = \lim_{N \rightarrow \infty} \overline{\text{SUM}}_N$$

\therefore The Riemann integral does not exist in this case.

But here, we have

6.3

$$\lim_{N \rightarrow \infty} \overline{\text{SUM}}_N \neq \lim_{N \rightarrow \infty} \underline{\text{SUM}}_N$$

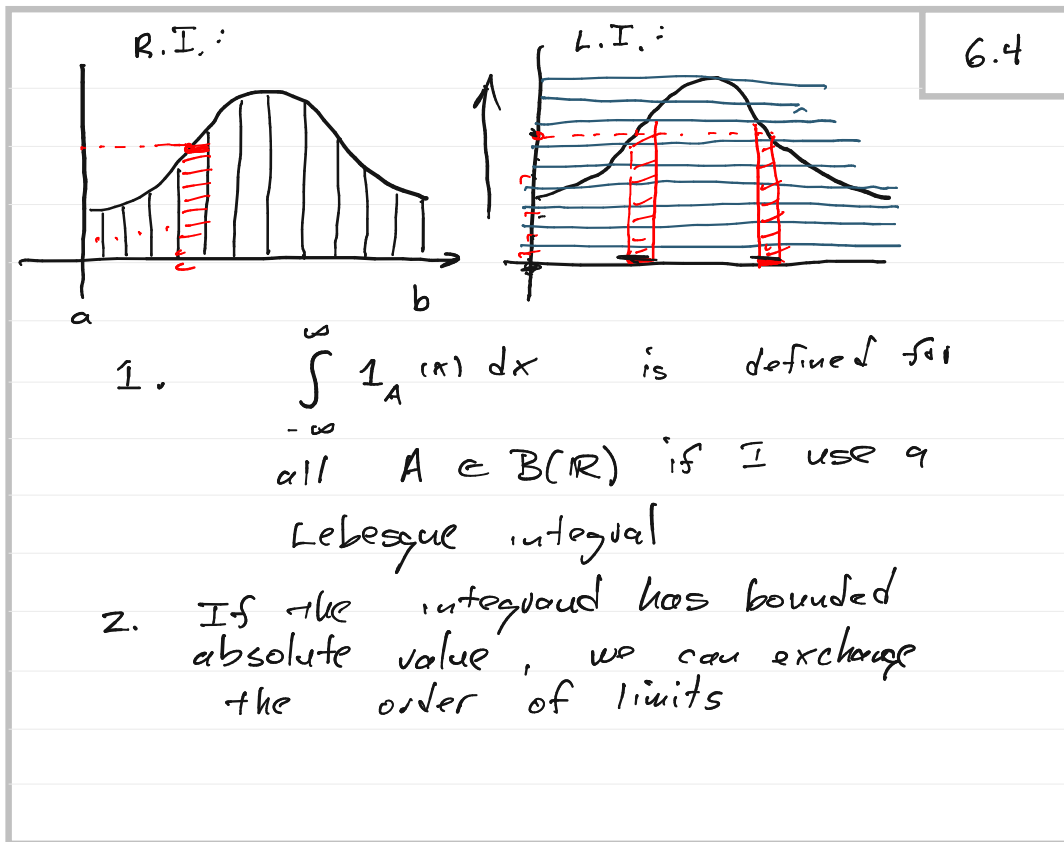
\therefore R.I. doesn't exist

Yet by intuition

$$\underbrace{P(\mathbb{Q})}_{=} = \int_0^1 \mathbb{1}_{\mathbb{Q}}(r) dr = 0$$

We have a problem

This is why the Lebesgue was introduced.



How do we reconcile the difference between the R.I. and the L.I.?

6.5

Important Fact: If the Riemann Integral exists, the Lebesgue integral exists, and they are equal.

Proof: Measure Theory Course (MA 544)

This leads to the "Engineering compromise on integration"

Engineering Compromise on Integration

6.6

Given $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$, for events $A \in \mathcal{B}(\mathbb{R})$
we calculate probabilities as

$$P(A) = \int_A f(r) dr = \int_{-\infty}^{\infty} f(r) \cdot \mathbb{1}_A(r) dr \quad (\text{L.I.})$$

We interpret this as a Lebesgue integral,
however for "friendly functions"

(i.e., Riemann integrable functions)

we compute the value of $P(A)$
using Riemann integration.

Compromise Approach is not Uncommon

6.7

	<u>Theory</u>	<u>Practice</u>
Computation:	Real	finite subset of the rationals
Integration:	Lebesgue	Riemann

So we actually compute probabilities
using the R.I. whenever possible.

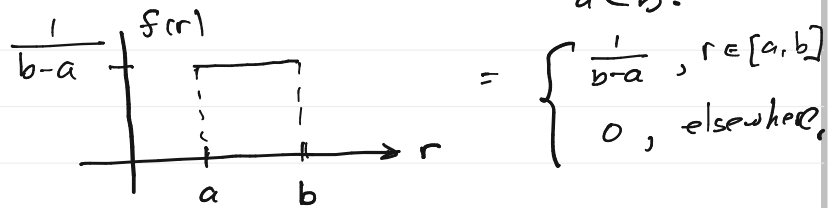
We invoke the properties of the
L.I. whenever it is beneficial
to do so.

There are a number of useful pdfs we will want to know.

6.8

Ex.1 The uniform pdf

$$f(r) = \frac{1}{b-a} \cdot \mathbb{1}_{[a,b]}(r), \quad \begin{array}{l} r \in \mathbb{R} \\ a, b \in \mathbb{R} \\ a < b. \end{array}$$



n.b. (i) $f(r) \geq 0, \forall r \in \mathbb{R}$

(ii) $\int_{-\infty}^{\infty} f(r) dr = 1.$

Ex.2 The exponential pdf

6.9

$$f(r) = \lambda e^{-\lambda r} \cdot \mathbb{1}_{[0, \infty)}(r) = \begin{cases} \lambda e^{-\lambda r}, & r \geq 0 \\ 0, & r < 0 \end{cases} \quad \lambda > 0$$



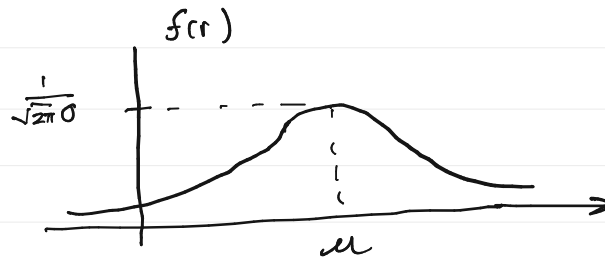
n.b. (i) $f(r) \geq 0, \forall r \in \mathbb{R}$

(ii) $\int_{-\infty}^{\infty} f(r) dr = 1.$

Ex. 3 The Gaussian pdf

6.10

$$f(r) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(r-\mu)^2}{2\sigma^2}\right\} \begin{array}{l} r \in \mathbb{R} \\ \mu \in \mathbb{R} \\ \sigma > 0 \end{array}$$



(i) $f(r) \geq 0$, $r \in \mathbb{R}$

(ii) $\int_{-\infty}^{\infty} f(r) dr = 1$

PMFs and PDFs You Should Know

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PMFs

PDFs

Binomial

Uniform

Geometric

Exponential

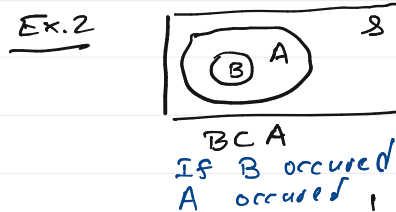
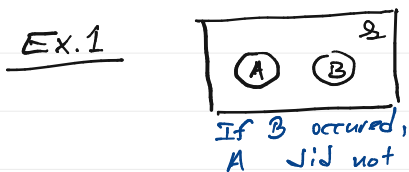
Poisson

Gaussian

Conditional Probability

6.12

Given $(\mathcal{S}, \mathcal{F}, P)$ and $A, B \in \mathcal{F}$,
knowing that B has occurred may
tell us something about whether
or not A has occurred



In general, knowing B
has occurred may change
your belief that A
has occurred.

Defn: Given $(\mathcal{S}, \mathcal{F}, P)$ and

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$A, B \in \mathcal{F}$, the conditional
probability of A conditioned
on B ("A given B") is

$$P(A|B) \triangleq \frac{P(A \cap B)}{P(B)},$$

assuming $P(B) \neq 0$.

n.b. If $P(B) = 0$, then $P(A \cap B) = 0$, and this
leaves us with $P(A|B) = \frac{0}{0}$
which is undefined.

n.b. 1. If $A \subset B$, then

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$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A)}{P(B)} \geq P(A)$$

2. If $B \subset A$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B)}{P(B)} = 1$$

3. If $A \cap B = \emptyset$, then

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(\emptyset)}{P(B)} = \frac{0}{P(B)} = 0$$

$$4. P(A|B) = \frac{P(A \cap B)}{P(B)} \geq P(A \cap B)$$

$0 < P(B) \leq 1$

Fact: If $P(\cdot)$ (from $(\mathcal{S}, \mathcal{F}, P)$)

6.15

is a valid probability measure,
then $P(\cdot|B)$ is also a valid
probability measure for any
 $B \in \mathcal{F}$ such that $P(B) \neq 0$.

Proof: (exercise) verify the axioms of
probability hold for $P(\cdot|B)$.

$$(\mathcal{S}, \mathcal{F}, P) \xrightarrow{\text{B has occurred}} (\mathcal{S}, \mathcal{F}, P(\cdot|B))$$

n.b. $(\mathcal{S}, \mathcal{F}, P(\cdot|B))$ is a valid prob. space
because $(\mathcal{S}, \mathcal{F}, P)$ is a valid prob. space.