Define a field and a $\sigma -$ field

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Define a probability measure and give some of its properties

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List some properties of probability measures

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A field on a set Ω is a collection of subsets $\mathcal{F}$ such that:

1. (at least contains two sets) $\emptyset, \Omega \in \mathcal{F}$,
2. (closer under complement) if $A \in \mathcal{F}$, then $A^c \in \mathcal{F}$,
3. (closure under finite union) if $A, B \in \mathcal{F}$, then $A \cup B \in \mathcal{F}$

A $\sigma -$ field $\mathcal{F}$ on the set Ω also has:

4. (closure under countable union) if $A_1, \cdots \in \mathcal{F}$, then $\cup_i A_i \in \mathcal{F}$.

A probability measure on a set Ω with field $\mathcal{F}$ is a function $P : \mathcal{F} \to [0, \infty)$ with:

1. $0 \leq P(A) \leq 1, \forall A \in \mathcal{F}$,
2. $P(\emptyset) = 0$ and $P(\Omega) = 1$,
3. if $A_1, \ldots$ are disjoint and $\cup_i A_i \in \mathcal{F}$, then

$$P(\cup_i A_i) = \sum_i P(A_i)$$

A probability measure P on Ω with field $\mathcal{F}$ has

1. (monotonicity), if $A \subset B$, then $P(A) \leq P(B)$,
2. (inclusion-exclusion) $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ and more generally

$$P(\cup A_n) = \sum_i P(A_i) - \sum_{i<j} P(A_i \cap A_j) + \sum_{i<j<k} P(A_i \cap A_j \cap A_k)$$

$$+ \cdots + (-1)^{n+1} P(A_1 \cap \ldots A_n),$$

3. (countably subadditive) if $A_1, \cdots \in \mathcal{F}$ and $\cup_i A_i \in \mathcal{F}$, then $P(\cup_i A_i) \leq \sum_i P(A_i)$,
4. (continuous from below) if $A_1 \subset A_2 \cdots \subset A$, then $P(A_n) \uparrow P(A)$
5. (continuous from above) if $A_1 \supset A_2 \cdots \supset A$, then $P(A_n) \downarrow P(A)$

Briefly describe the process of showing the Lebesgue measure exists

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Define $\limsup_n A_n$ *and* $\liminf_n A_n$ *of sets and give an interpretation and an inequality*

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Define measure-theoretic independence (events, collections of events, $\sigma -$ *field)*

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Theorem 3.1 (Cartheodory extension theorem): a probability measure on a field can be uniquely extended to the generated $\sigma -$ field if the measure is σ-finite.
Hence, to construct the Lebesgue measure, first we define the Lebesgue measure that assigns to half-open intervals the interval length, second we verify that this is a well-defined measure on the Borel field, and then we apply theorem 3.1.
Proving theorem 3.1 is involved. Also, studying $\sigma(\mathcal{B}_0)$ is necessary, where $\mathcal{B}_0$ is the field of finite unions and intersections of intervals.

$\limsup_n A_n = \cup_n \cap_{k\geq n} A_k$. If w is in LHS, then for every n, there exists some $k \geq n$ so that $w \in A_k$, hence w is in infinitely many of the A_n. “Infinitely often”.
$\liminf_n A_n = \cap_n \cup_{k\geq n} A_k$. If w is in LHS, then there exists n such that for all $k \geq n$, $w \in A_k$ for all k. Hence, w is in all but finitely many A_n. “Eventually”.

$$P(\liminf_n A_n) \leq \liminf_n P(A_n)$$
$$\leq \limsup_n P(A_n) \leq P(\limsup_n A_n)$$

- Two events A and B are independent if $P(A \cap B) = P(A)P(B)$.
- A collection of events $\{A_1, \ldots, A_n\}$ are independent if

  $$P(A_{k_1} \cap \ldots A_{k_j}) = P(A_{k_1}) \ldots P(A_{k_j})$$

  for all $2 \leq j \leq n$ and $1 \leq k_1 < \cdots < k_n \leq n$.
- A collection of classes $\mathcal{A}_1, \ldots, \mathcal{A}_n$ in a $\sigma -$ field $\mathcal{F}$ are independent if for each choice of $A_i \in \mathcal{A}_i$, the collection $\{A_n\}$ is independent.
- Two $\sigma -$ fields $\mathcal{A}$ and $\mathcal{B}$ are independent if for every $A \in \mathcal{A}$ and $B \in \mathcal{B}$, we have $\mu(A \cap B) = \mu(A)\mu(B)$.

State the Borel-Cantelli Lemma 1 and proof

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State the Borel-Cantelli Lemma 2 and proof

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Define tail $\sigma-$field and state the Kolmogorov 0-1 law

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If $\sum P(A_n) < \infty$, then $P(\limsup_n A_n) = 0$.
Proof: Observe that $\limsup_n A_n \subset \cup_{k \geq m} A_k$ for all m. This implies that

$$P(\limsup_n A_n) \leq P(\cup_{k \geq m} A_k) \leq \sum_{k \geq m} P(A_k).$$

Since this holds for arbitrary m and the right hand side sum goes to 0 if the infinite sum converges, the lemma follows.

If $\{A_n\}$ are independent and $\sum P(A_n) = \infty$ then $P(\limsup_n A_n) = 1$.
Proof: It is enough to show that $P(\cup_n \cap_{k \geq n} A_k^c) = 0$ for which it is enough to show that $P(\cap_{k \geq n} A_k^c) = 0$ for all k. Note that $1 - x \leq e^{-x}$, then (by independence)

$$P(\cap_{k=n}^{n+j} A_k^c) = \prod_{k=n}^{n+j} 1 - P(A_k) \leq \exp\{-\sum_{k=n}^{n+j} P(A_k)\}.$$

But since the sum diverges, as $j \to \infty$, the RHS goes to 0, hence

$$P(\cap_{k=n}^{\infty} A_k^c) = \lim_j P(\cap_{k=n}^{n+j} A_k^c) = 0$$

Given a sequence of events $A_1, A_2, \ldots$ in a probability space $(\Omega, \mathcal{F}, P)$, the tail $\sigma -$ field associated with the sequence $\{A_n\}$ is

$$\mathcal{T} = \cap_{n=1}^{\infty} \sigma(A_n, A_{n+1}, \ldots).$$

The $\limsup_n A_n$ and $\liminf_n A_n$ are events in the tail $\sigma -$ field.
The Kolmogorov zero-one law: if $A_1, A_2, \ldots$ are independent, then for each event A in the tail $\sigma -$ field, $P(A)$ is either 0 or 1.

Simple random variables

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State and prove the Markov's inequality

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State and prove Chebyshev's inequality

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A random variables X on $(\Omega, \mathcal{F})$ is simple iff it can be written as

$$X(w) = \sum_i x_i I_{A_i}$$

for some finite set of x_i and $A_i \in \mathcal{F}$.
Simple random variables X_n converge to X with probability 1 ($\lim_n X_n = X$) iff $\forall \epsilon > 0$,

$$P(|X_n - X| > \epsilon \text{ i.o.}) = 0$$

which, if the above holds, implies that

$$\lim_n P(|X_n - X| > \epsilon) = 0.$$

Note that

$$\{\lim_n X_n = X\}^c = \cup_\epsilon \{|X_n - X| \geq \epsilon \text{ i.o.}\} = \cup_\epsilon \cup_n \cap_{k \geq n} \{|X_n - X| \geq \epsilon\}.$$

Markov's inequality: For a random variable X, nonnegative, then for positive α, we have

$$P(X \geq \alpha) \leq \frac{1}{\alpha} \mathbb{E}[X].$$

Proof: Note that for any convex f and any set A, we have that

$$\min_{x \in A} f(x) \mathbf{1}_A \leq E[X \mathbf{1}_A] \leq E[X]$$

Hence, with $f(x) = x$ and $A = [\alpha, \infty)$, the result follows. If we use $f(x) = |x|^k$, then we have for positive α:

$$\Pr(|X| \geq \alpha) \leq \frac{1}{\alpha}^k \mathbb{E}[|X|^k]$$

Chebyshev's inequality: for a random variable X, we have

$$\Pr(|X - m| \geq \alpha) \leq \frac{1}{\alpha}^2 \operatorname{Var}(X)$$

Proof: Applying Markov's inequality with $k = 2$ and subtracting $m = \mathbb{E}[X]$, we obtain the desired result.

State and prove Jensen's inequality (finite case)

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State and prove Holder's inequality

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State and prove the strong law of large numbers

Billingsley

Jensen's inequality says that for a convex function $\phi(x)$ and a random variable X, we have

$$\mathbb{E}[\phi(X)] \geq \phi(\mathbb{E}[X])$$

Proof: the proof follows by induction and by noting the for simple random variables, the expectation is a linear function.

Suppose that $\frac{1}{p} + \frac{1}{q} = 1$ for $p, q > 1$. Then:

$$\mathbb{E}[|XY|] \leq \mathbb{E}[|X|^p]^{\frac{1}{p}} \mathbb{E}[|Y|^q]^{\frac{1}{q}}$$