

# Probability Review I

## Harvard Math Camp - Econometrics

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# Outline

## Random Experiments

- The sample space and events

- $\sigma$ -algebra and measures

- Basic probability rules

## Conditional Probability

- Definition

- Bayes' rule and more

- Independence

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# The sample space and events

We wish to model a random experiment - an experiment/process whose outcome cannot be predicted beforehand. What are the building blocks?

- ▶ The **sample space**  $\Omega$  is the set of all possible outcomes of a random experiment. We denote an outcome as  $\omega \in \Omega$ .
- ▶ An **event**  $A$  is a subset of the sample space,  $A \subseteq \Omega$ . Let  $\mathcal{A}$  denote the family of all events.

## Simple examples

**Example:** Suppose we survey 10 randomly selected people on their employment status and count how many are unemployed.

$$\Omega = \{0, 1, 2, \dots, 10\}$$

$A$  is the event that more than 30% of those surveyed are unemployed.

$$A = \{4, 5, 6, \dots, 10\}$$

**Example:** Suppose we ask a random person what is their income.

$$\Omega = \mathbb{R}_+$$

$A$  is the event that the person earns between \$30,000 and \$40,000.

$$A = [30,000, 40,000]$$

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# Putting structure on the set of events

To be able to sensibly define probabilities, we need to place some additional structure on the set of events,  $\mathcal{A}$ .

Let  $\Omega$  be a set and  $\mathcal{A} \subseteq 2^\Omega$  be a family of its subsets.  $\mathcal{A}$  is a  **$\sigma$ -algebra** if and only if it satisfies the following

1.  $\Omega \in \mathcal{A}$ .
2.  $\mathcal{A}$  is closed under complements:  $A \in \mathcal{A}$  implies that  $A^C = \Omega - A \in \mathcal{A}$ .
3.  $\mathcal{A}$  is closed under countable union: If  $A_n \in \mathcal{A}$  for  $n = 1, 2, \dots$ , then  $\bigcup_n A_n \in \mathcal{A}$ .

$\implies$  We assume that  $\mathcal{A}$  is a  **$\sigma$ -algebra**.  $(\Omega, \mathcal{A})$  is a **measurable space** and  $A \in \mathcal{A}$  is **measurable** with respect to  $\mathcal{A}$ .



# Properties of a $\sigma$ -algebra

If  $\mathcal{A}$  is a  $\sigma$ -algebra, then ...

1.  $\emptyset \in \mathcal{A}$ .
2.  $\mathcal{A}$  is closed under countable intersection i.e, if  $A_n \in \mathcal{A}$  for  $n = 1, 2, \dots$ , then  $\bigcap_n A_n \in \mathcal{A}$ .

Why?

1. This one's simple.
2. Hint: DeMorgan's Law -  $(A \cup B)^C = A^C \cap B^C$ .

# What is probability?

We're now ready to finally define what is probability! We will provide the “mathematical” definition.

- ▶ Not defined directly as a “long-run frequency” or ‘subjective beliefs.’ But it will capture all of the properties associated with these.

Let  $(\Omega, \mathcal{A})$  be a measurable space. A **measure** is a function,  $\mu : \mathcal{A} \rightarrow \mathbb{R}$  such that

1.  $\mu(\emptyset) = 0$ .
2.  $\mu(A) \geq 0$  for all  $A \in \mathcal{A}$ .
3. If  $A_n \in \mathcal{A}$  for  $n = 1, 2, \dots$  with  $A_i \cap A_j = \emptyset$  for  $i \neq j$ , then

$$\mu(U_n A_n) = \sum_n \mu(A_n)$$

If  $\mu(\Omega) = 1$ ,  $\mu$  is a **probability measure**, denoted as  $P : \mathcal{A} \rightarrow [0, 1]$ .

# Putting it all together

So, we model a random experiment as a **probability space**,  $(\Omega, \mathcal{A}, P)$ .

1.  $\Omega$  - set of outcomes.
2.  $\mathcal{A}$  -  $\sigma$ -algebra on the set of outcomes.
3.  $P$  - a probability measure defined on the  $\sigma$ -algebra.

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# Basic probability rules

We can prove all of the usual probability rules from this.

Consider a probability space  $(\Omega, \mathcal{A}, P)$ . The following hold:

1. For all  $A \in \mathcal{A}$ ,  $P(A^C) = 1 - P(A)$ .
2.  $P(\Omega) = 1$ .
3. If  $A_1, A_2 \in \mathcal{A}$  with  $A_1 \subseteq A_2$ , then  $P(A_1) \leq P(A_2)$ .
4. For all  $A \in \mathcal{A}$ ,  $0 \leq P(A) \leq P(1)$ .
5. If  $A_1, A_2 \in \mathcal{A}$ , then

$$P(A_1 \cup A_2) = P(A_1) + P(A_2) - P(A_1 \cap A_2)$$

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# Conditional Probability

Given a random experiment and the information that event  $B$  has occurred, what is the probability that the outcome also belongs to event  $A$ ?

Let  $A, B \in \mathcal{A}$  with  $P(B) > 0$ . The **conditional probability of  $A$  given  $B$**  is

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

- ▶  $P(A|B)$  is a probability measure so all the usual probability rules apply!
- ▶ We use conditioning to describe the partial information that an event  $B$  gives about another event  $A$ .

Implies that

$$P(A \cap B) = P(A|B)P(B).$$



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# Multiplication Rule

$$P(\cap_{i=1}^n A_i) = P(A_1)P(A_2|A_1)P(A_3|A_2 \cap A_1) \dots P(A_n | \cap_{i=1}^{n-1} A_i)$$

Proof?

# The Law of Total Probability

Consider  $K$  disjoint events  $C_k$  that partition  $\Omega$ . That is,  $C_i \cap C_j = \emptyset$  for all  $i \neq j$  and  $\cup_{i=1}^K C_i = \Omega$ . Let  $C$  be some event.

$$P(C) = \sum_{i=1}^K P(C|C_i)P(C_i)$$

Proof?

# Bayes' Rule

## Bayes' Rule:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|B^C)P(B^C)}$$

► Proof?

Definitely the most important probability rule out there...

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# Independence

What if event  $B$  has no information about event  $A$ ?

Two events  $A, B$  are **independent** if

$$P(A|B) = P(A)$$

Equivalently,

$$P(B|A) = P(B)$$

or

$$P(A \cap B) = P(A)P(B).$$

# Independence

Let  $E_1, \dots, E_n$  be events.  $E_1, \dots, E_n$  are **jointly independent** if for any  $i_1, \dots, i_k$

$$P(E_{i_1} | E_{i_2} \cap \dots \cap E_{i_k}) = P(E_{i_1}).$$

Given an event  $C$ , events  $A, B$  are **conditionally independent** if

$$P(A \cap B | C) = P(A | C)P(B | C).$$