MATH 556: PROBABILITY PRIMER

1 DEFINITIONS, TERMINOLOGY, NOTATION

1.1 EVENTS AND THE SAMPLE SPACE

- An **experiment** is a one-off or repeatable process or procedure for which
  - (a) there is a well-defined set of (possible) outcomes
  - (b) the *actual* outcome is not known with certainty.
- A **sample outcome**, ω, is precisely one of the (possible) outcomes of an experiment.
- The **sample space**, Ω, of an experiment is the set of all (possible) outcomes.

Ω is a set in the mathematical sense, so set theory notation can be used. For example, if the sample outcomes are denoted $\omega_1, \omega_2 \ldots,$, say, then the sample space of an experiment can be

- a FINITE list of sample outcomes, $\{\omega_1, \ldots, \omega_k\}$

- an INFINITE list of sample outcomes, $\{\omega_1, \omega_2, \ldots\}$

- an INTERVAL or REGION of a real space, $\left\{\omega : \omega \in A \subseteq \mathbb{R}^d\right\}$

An **event**, E, is a designated collection of sample outcomes. Event E **occurs** if the actual outcome of the experiment is one of this collection; for any event E, $E \subseteq \Omega$. Particular events are:

- the collection of *all* sample outcomes, Ω,
- the collection of *none* of the sample outcomes, $\emptyset$ (the **empty set**).

1.1.1 OPERATIONS IN SET THEORY

Set theory operations can be used to manipulate events in probability theory. Consider events $E, F \subseteq \Omega$. Then the three basic operations are

UNION	$E \cup F$	"E or F or both occur"
INTERSECTION	$E \cap F$	"both E and F occur"
COMPLEMENT	E'	"E does not occur"

Consider events $E, F, G \subseteq \Omega$.

COMMUTATIVITY	$E \cup F = F \cup E$ $E \cap F = F \cap E$
ASSOCIATIVITY	$E \cup (F \cup G) = (E \cup F) \cup G$ $E \cap (F \cap G) = (E \cap F) \cap G$
DISTRIBUTIVITY	$E \cup (F \cap G) = (E \cup F) \cap (E \cup G)$ $E \cap (F \cup G) = (E \cap F) \cup (E \cap G)$
DE MORGAN'S LAWS	$(E \cup F)' = E' \cap F'$ $(E \cap F)' = E' \cup F'$

Union and intersection are *binary* operators, that is, they take only two arguments, and thus the bracketing in the above equations is necessary. For $k \geq 2$ events, $E_1, E_2, \ldots, E_k$,

$$\bigcup_{i=1}^{k} E_i = E_1 \cup \ldots \cup E_k \qquad \text{and} \qquad \bigcap_{i=1}^{k} E_i = E_1 \cap \ldots \cap E_k$$

for the union and intersection of $E_1, E_2, \ldots, E_k$, with a further extension for k *infinite*.

1.1.2 MUTUALLY EXCLUSIVE EVENTS AND PARTITIONS

Events E and F are **mutually exclusive** if $E \cap F = \emptyset$, that is, if events E and F cannot both occur. If the sets of sample outcomes represented by E and F are **disjoint** (have no common element), then E and F are mutually exclusive.

Events $E_1, \ldots, E_k \subseteq \Omega$ form a **partition** of event $F \subseteq \Omega$ if

(a) $E_i \cap E_j = \emptyset$ for $i \neq j$, $i, j = 1, \ldots, k$

(b) $\bigcup_{i=1}^{k} E_i = F$

so that each element of the collection of sample outcomes corresponding to event F is in *one and only one* of the collections corresponding to events $E_1, \ldots, E_k$.

1.1.3 SIGMA-ALGEBRAS

A (countable) collection of subsets, $\mathscr{E}$, of sample space Ω, say $\mathscr{E} = \{E_1, E_2, \ldots\}$, is a *sigma-algebra* if

I $\Omega \in \mathscr{E}$

II $E \in \mathscr{E} \Longrightarrow E' \in \mathscr{E}$

III If $E_1, E_2, \ldots \in \mathscr{E}$, then

$$\bigcup_{i=1}^{\infty} E_i \in \mathscr{E}.$$

If $\mathscr{E}$ is an algebra of subsets of Ω, then

(i) $\emptyset \in \mathscr{E}$

(ii) If $E_1, E_2 \in \mathscr{E}$, then

$$E_1', E_2' \in \mathscr{E} \quad \Longrightarrow \quad E_1' \cup E_2' \in \mathscr{E} \quad \Longrightarrow \quad \left(E_1' \cup E_2'\right)' \in \mathscr{E} \quad \Longrightarrow \quad E_1 \cap E_2 \in \mathscr{E}$$

so $\mathscr{E}$ is also *closed under intersection*.

1.2 THE PROBABILITY FUNCTION

For an event $E \subseteq \Omega$, the **probability that** E **occurs** is written $\mathrm{P}(E)$.

Interpretation : $\mathrm{P}(.)$ is a *set-function* that assigns "weight" to collections of possible outcomes of an experiment. There are many ways to think about precisely how this assignment is achieved;

CLASSICAL : "Consider equally likely sample outcomes ..."

FREQUENTIST : "Consider long-run *relative frequencies* ..."

SUBJECTIVE : "Consider personal degree of belief ..."

or merely think of $\mathrm{P}(.)$ as a set-function.

1.3 PROPERTIES OF P(.): THE AXIOMS OF PROBABILITY

Consider sample space Ω. Then probability function P(.) acts on a sigma-algebra $\mathscr{E}$ defined on Ω

$$\mathrm{P} : \mathscr{E} \longrightarrow \mathbb{R}$$

and satisfies the following properties:

(I) Let $E \in \mathscr{E}$. Then $0 \leq \mathrm{P}(E) \leq 1$.
(II) $\mathrm{P}(\Omega) = 1$.
(III) If $E_1, E_2, \ldots$ are mutually exclusive events, then

$$\mathrm{P}\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} \mathrm{P}(E_i).$$

1.3.1 COROLLARIES TO THE PROBABILITY AXIOMS

For events $E, F \subseteq \Omega$

1 $\mathrm{P}(E') = 1 - \mathrm{P}(E)$, and hence $\mathrm{P}(\emptyset) = 0$.

2 If $E \subseteq F$, then $\mathrm{P}(E) \leq \mathrm{P}(F)$.

3 In general, $\mathrm{P}(E \cup F) = \mathrm{P}(E) + \mathrm{P}(F) - \mathrm{P}(E \cap F)$.

4 $\mathrm{P}(E \cap F') = \mathrm{P}(E) - \mathrm{P}(E \cap F)$.

5 $\mathrm{P}(E \cup F) \leq \mathrm{P}(E) + \mathrm{P}(F)$.

6 $\mathrm{P}(E \cap F) \geq \mathrm{P}(E) + \mathrm{P}(F) - 1$.

The **general addition rule** for probabilities and Boole's Inequality extend to more than two events. Let $E_1, \ldots, E_n$ be events in Ω. Then

(i) $$\mathrm{P}\left(\bigcup_{i=1}^{n} E_i\right) \leq \sum_{i=1}^{n} \mathrm{P}(E_i).$$

(i) $$\mathrm{P}\left(\bigcup_{i=1}^{n} E_i\right) = \sum_{i} \mathrm{P}(E_i) - \sum_{i<j} \mathrm{P}(E_i \cap E_j) + \sum_{i<j<k} \mathrm{P}(E_i \cap E_j \cap E_k) - \ldots + (-1)^{n+1} \mathrm{P}\left(\bigcap_{i=1}^{n} E_i\right)$$

(i) follows from 5; for (ii), construct the events $F_1 = E_1$ and

$$F_i = E_i \cap \left(\bigcup_{k=1}^{i-1} E_k\right)'$$

for $i = 2, 3, \ldots, n$. Then $F_1, F_2, \ldots, F_n$ are disjoint, and $\bigcup\limits_{i=1}^{n} E_i = \bigcup\limits_{i=1}^{n} F_i$,so

$$\mathrm{P}\left(\bigcup_{i=1}^{n} E_i\right) = \mathrm{P}\left(\bigcup_{i=1}^{n} F_i\right) = \sum_{i=1}^{n} \mathrm{P}(F_i).$$

Now, by the corollary above, for $i = 2, 3, \ldots, n$,

$$\mathrm{P}(F_i) = \mathrm{P}(E_i) - \mathrm{P}\left(E_i \cap \left(\bigcup_{k=1}^{i-1} E_k\right)\right) = \mathrm{P}(E_i) - \mathrm{P}\left(\bigcup_{k=1}^{i-1} (E_i \cap E_k)\right)$$

and the result follows by recursive expansion of the second term for $i = 2, 3, \ldots, n$.

1.4 CONDITIONAL PROBABILITY

For events $E, F \subseteq \Omega$ the **conditional probability** that F occurs **given** that E occurs is written $\mathrm{P}(F|E)$, and is defined by

$$\mathrm{P}(F|E) = \frac{\mathrm{P}(E \cap F)}{\mathrm{P}(E)}$$

if $\mathrm{P}(E) > 0$.

NOTE: $\mathrm{P}(E \cap F) = \mathrm{P}(E)\mathrm{P}(F|E)$, and in general, for events $E_1, \ldots, E_k$,

$$\mathrm{P}\left(\bigcap_{i=1}^{k} E_i\right) = \mathrm{P}(E_1)\mathrm{P}(E_2|E_1)\mathrm{P}(E_3|E_1 \cap E_2)\ldots\mathrm{P}(E_k|E_1 \cap E_2 \cap \ldots \cap E_{k-1}).$$

This result is known as the CHAIN or MULTIPLICATION RULE.

Events E and F are **independent** if

$$\mathrm{P}(E|F) = \mathrm{P}(E) \text{ so that } \mathrm{P}(E \cap F) = \mathrm{P}(E)\mathrm{P}(F)$$

Extension : Events $E_1, \ldots, E_k$ are independent if, for **every** subset of events of size $l \leq k$, indexed by $\{i_1, \ldots, i_l\}$, say,

$$\mathrm{P}\left(\bigcap_{j=1}^{l} E_{i_j}\right) = \prod_{j=1}^{l} \mathrm{P}(E_{i_j}).$$

1.5 THE THEOREM OF TOTAL PROBABILITY

THEOREM

Let $E_1, \ldots, E_k$ be a partition of Ω, and let $F \subseteq \Omega$. Then

$$\mathrm{P}(F) = \sum_{i=1}^{k} \mathrm{P}(F|E_i)\mathrm{P}(E_i)$$

PROOF

$E_1, \ldots, E_k$ form a partition of Ω, and $F \subseteq \Omega$, so

$$\begin{aligned} F &= (F \cap E_1) \cup \ldots \cup (F \cap E_k) \\ \Longrightarrow \quad \mathrm{P}(F) &= \sum_{i=1}^{k} \mathrm{P}(F \cap E_i) = \sum_{i=1}^{k} \mathrm{P}(F|E_i)\mathrm{P}(E_i) \end{aligned}$$

3, as $E_i \cap E_j = \emptyset$).

Extension: If we assume that Axiom 3 holds, that is, that P is countably additive, then the theorem still holds, that is, if $E_1, E_2, \ldots$ are a partition of Ω, and $F \subseteq \Omega$, then

$$\mathrm{P}(F) = \sum_{i=1}^{\infty} \mathrm{P}(F \cap E_i) = \sum_{i=1}^{\infty} \mathrm{P}(F|E_i)\mathrm{P}(E_i)$$

if $\mathrm{P}(E_i) > 0$ for all i.

1.6 BAYES THEOREM

THEOREM

Suppose $E, F \subseteq \Omega$, with $\mathrm{P}(E)$,$\mathrm{P}(F) > 0$. Then

$$\mathrm{P}(E|F) = \frac{\mathrm{P}(F|E)\mathrm{P}(E)}{\mathrm{P}(F)}$$

PROOF

$$\mathrm{P}(E|F)\mathrm{P}(F) = \mathrm{P}(E \cap F) = \mathrm{P}(F|E)\mathrm{P}(E), \text{ so } \mathrm{P}(E|F)\mathrm{P}(F) = \mathrm{P}(F|E)\mathrm{P}(E).$$

Extension: If $E_1, \ldots, E_k$ are disjoint, with $\mathrm{P}(E_i) > 0$ for $i = 1, \ldots, k$, and form a partition of $F \subseteq \Omega$, then

$$\mathrm{P}(E_i|F) = \frac{\mathrm{P}(F|E_i)\mathrm{P}(E_i)}{\sum_{i=1}^{k} \mathrm{P}(F|E_i)\mathrm{P}(E_i)}$$

The extension to the countably additive (infinite) case also holds.

NOTE: in general, $\mathrm{P}(E|F) \neq \mathrm{P}(F|E)$

1.7 COUNTING TECHNIQUES

Suppose that an experiment has N equally likely sample outcomes. If event E corresponds to a collection of sample outcomes of size $n(E)$, then

$$\mathrm{P}(E) = \frac{n(E)}{N}$$

so it is necessary to be able to evaluate $n(E)$ and N in practice.

1.7.1 THE MULTIPLICATION PRINCIPLE

If operations labelled $1, \ldots, r$ can be carried out in $n_1, \ldots, n_r$ ways respectively, then there are

$$\prod_{i=1}^{r} n_i = n_1 \times \ldots \times n_r$$

ways of carrying out the r operations in total.

Example 1.1 If each of r trials of an experiment has N possible outcomes, then there are N^r possible sequences of outcomes in total. For example:

(i) If a multiple choice exam has 20 questions, each of which has 5 possible answers, then there are 5^{20} different ways of completing the exam.

(ii) There are 2^m subsets of m elements (as each element is either **in** the subset, or **not in** the subset, which is equivalent to m trials each with two outcomes).

1.7.2 SAMPLING FROM A FINITE POPULATION

Consider a collection of N items, and a sequence of operations labelled $1, \ldots, r$ such that the ith operation involves **selecting** one of the items remaining after the first $i-1$ operations have been carried out. Let n_i denote the number of ways of carrying out the ith operation, for $i = 1, \ldots, r$. Then

(a) **Sampling with replacement :** an item is returned to the collection after selection. Then $n_i = N$ for all i, and there are N^r ways of carrying out the r operations.
(b) **Sampling without replacement :** an item is not returned to the collection after selected. Then $n_i = N - i + 1$, and there are $N(N-1)\ldots(N-r+1)$ ways of carrying out the r operations.

e.g. Consider selecting 5 cards from 52. Then

(a) leads to 52^5 possible selections, whereas
(b) leads to $52 \times 51 \times 50 \times 49 \times 48$ possible selections

NOTE : The **order** in which the operations are carried out may be important
e.g. in a raffle with three prizes and 100 tickets, the draw $\{45, 19, 76\}$ is different from $\{19, 76, 45\}$.

NOTE : The items may be **distinct** (unique in the collection), or **indistinct** (of a unique type in the collection, but not unique individually). For example, the numbered balls in a lottery, or individual playing cards, are **distinct**. However balls in the lottery are regarded as "WINNING" or "NOT WINNING", or playing cards are regarded in terms of their suit only, are **indistinct**.

1.7.3 PERMUTATIONS AND COMBINATIONS

- A **permutation** is an *ordered* arrangement of a set of items.
- A **combination** is an *unordered* arrangement of a set of items.

RESULT 1 The number of permutations of n distinct items is $n! = n(n-1)\ldots 1$.

RESULT 2 The number of permutations of r from n distinct items is

$$P_r^n = \frac{n!}{(n-r)!} = n(n-1) \times \ldots \times (n-r+1) \qquad \text{(by the Multiplication Principle).}$$

If the **order** in which items are selected is not important, then

RESULT 3 The number of combinations of r from n distinct items is

$$C_r^n = \binom{n}{r} = \frac{n!}{r!(n-r)!} \qquad (\text{as} P_r^n = r! C_r^n).$$

-recall the **Binomial Theorem**, namely

$$(a+b)^n = \sum_{i=0}^{n} \binom{n}{i} a^i b^{n-i}.$$

Then the number of subsets of m items can be calculated as follows; for each $0 \leq j \leq m$, choose a subset of j items from m. Then

$$\text{Total number of subsets} = \sum_{j=0}^{m} \binom{m}{j} = (1+1)^m = 2^m.$$

If the items are **indistinct**, but each is of a unique type, say Type I, ..., Type κ say, (the so-called **Urn Model**) then, then a more general formula applies:

RESULT 4 The number of distinguishable permutations of n indistinct objects, comprising n_i items of type i for $i = 1, \ldots, \kappa$ is

$$\frac{n!}{n_1! n_2! \ldots n_\kappa!}$$

Special Case : if $\kappa = 2$, then the number of distinguishable permutations of the n_1 objects of type I, and $n_2 = n - n_1$ objects of type II is

$$C^n_{n_2} = \frac{n!}{n_1!(n - n_1)!}$$

Also, there are C^n_r ways of partitioning n **distinct** items into two "cells", with r in one cell and $n - r$ in the other.

1.7.4 PROBABILITY CALCULATIONS

Recall that if an experiment has N equally likely sample outcomes, and event E corresponds to a collection of sample outcomes of size $n(E)$, then

$$\mathrm{P}(E) = \frac{n(E)}{N}$$

Example 1.2 A True/False exam has 20 questions. Let E = "16 answers correct at random". Then

$$\mathrm{P}(E) = \frac{\text{Number of ways of getting 16 out of 20 correct}}{\text{Total number of ways of answering 20 questions}} = \frac{\binom{20}{16}}{2^{20}} = 0.0046$$

Example 1.3 *Sampling without replacement*. Consider an Urn Model with 10 Type I objects and 20 Type II objects, and an experiment involving sampling five objects without replacement. Let E="precisely 2 Type I objects selected" We need to calculate N and $n(E)$ in order to calculate $\mathrm{P}(E)$. In this case N is the number of ways of choosing 5 from 30 items, and hence

$$N = \binom{30}{5}$$

To calculate $n(E)$, we think of E occurring by first choosing 2 Type I objects from 10, and then choosing 3 Type II objects from 20, and hence, by the multiplication rule,

$$n(E) = \binom{10}{2}\binom{20}{3}$$

Therefore

$$\mathrm{P}(E) = \frac{\binom{10}{2}\binom{20}{3}}{\binom{30}{5}} = 0.360$$

This result can be obtained using a conditional probability argument; consider event $F \subseteq E$, where F = "sequence of objects 11222 obtained". Then

$$F = \bigcap_{i=1}^{5} F_{ij}$$

where F_{ij} = "type j object obtained on draw i" $i = 1, \ldots, 5, j = 1, 2$. Then

$$\mathrm{P}(F) = \mathrm{P}(F_{11})\mathrm{P}(F_{21}|F_{11}) \ldots \mathrm{P}(F_{52}|F_{11}, F_{21}, F_{32}, F_{42}) = \frac{10}{30}\frac{9}{29}\frac{20}{28}\frac{19}{27}\frac{18}{26}$$

Now consider event G where G = "sequence of objects 12122 obtained". Then

$$\mathrm{P}(G) = \frac{10}{30}\frac{20}{29}\frac{9}{28}\frac{19}{27}\frac{18}{26}$$

i.e. $\mathrm{P}(G) = \mathrm{P}(F)$. In fact, **any** sequence containing two Type I and three Type II objects has this probability, and there are $\binom{5}{2}$ such sequences. Thus, as all such sequences are mutually exclusive,

$$\mathrm{P}(E) = \binom{5}{2}\frac{10}{30}\frac{9}{29}\frac{20}{28}\frac{19}{27}\frac{18}{26} = \frac{\binom{10}{2}\binom{20}{3}}{\binom{30}{5}}.$$

Example 1.4 *Sampling with replacement.* Consider an Urn Model with 10 Type I objects and 20 Type II objects, and an experiment involving sampling five objects with replacement. Let E = "precisely 2 Type I objects selected". Again, we need to calculate N and $n(E)$ in order to calculate $\mathrm{P}(E)$. In this case N is the number of ways of choosing 5 from 30 items with replacement, and hence

$$N = 30^5$$

To calculate $n(E)$, we think of E occurring by first choosing 2 Type I objects from 10, and 3 Type II objects from 20 in any order. Consider such sequences of selection

Sequence	Number of ways
1 1 2 2 2	$10 \times 10 \times 20 \times 20 \times 20$
1 2 1 2 2	$10 \times 20 \times 10 \times 20 \times 20$
$\vdots$	$\vdots$

etc., and thus a sequence with 2 Type I objects and 3 Type II objects can be obtained in $10^2 20^3$ ways. As before there are $\binom{5}{2}$ such sequences, and thus

$$\mathrm{P}(E) = \frac{\binom{5}{2}10^2 20^3}{30^5} = 0.329.$$

Again, this result can be obtained using a conditional probability argument; consider event $F \subseteq E$, where F = "sequence of objects 11222 obtained". Then

$$\mathrm{P}(F) = \left(\frac{10}{30}\right)^2\left(\frac{20}{30}\right)^3$$

as the results of the draws are **independent**. This result is true for any sequence containing two Type I and three Type II objects, and there are $\binom{5}{2}$ such sequences that are mutually exclusive, so

$$\mathrm{P}(E) = \binom{5}{2}\left(\frac{10}{30}\right)^2\left(\frac{20}{30}\right)^3$$