

MTH1005 PROBABILITY AND STATISTICS

Semester B Lecture 4 (20/4/2023)

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SUMMARY OF CONDITIONAL PROBABILITIES

 Definition of conditional probabilities for two events (E,F) in S

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

Multiplicative rule for a set of events (E₁... E_n) in S

$$P(E_1 E_2 E_3 \dots E_n) = P(E_1) rac{P(E_1 \cap E_2)}{P(E_1)} rac{P(E_1 \cap E_2 \cap E_3)}{P(E_1 \cap P(E_2))} \ \cdots rac{P(E_1 \cap E_2 \dots \cap E_n)}{P(E_1 \cap E_2 \dots \cap E_{n-1})}$$

SUMMARY OF CONDITIONAL PROBABILITIES

- Law of total probability for a set of events (E₁... E_n) in S

$$P(A) = \sum_{i=1}^n P(A \cap E_i) = \sum_{i=1}^n P(A \mid E_i) P(E_i)$$

- Bayes' Formula for a set of events E_i

$$P(E_i \mid A) = rac{P(A \cap E_i)}{P(A)} = rac{P(A \mid E_i)P(E_i)}{\sum_{j=1}^n P(A \mid E_j)P(E_j)}$$

INDEPENDENT EVENTS

Definition: Two experiments are independent if the result of one can not in any way affect the possible results of the other.

Definition: Two events (E, F) are independent if the probability that one of them occurs is in no way in influenced by whether or not the other has occurred.

$$P(E) = P(E \mid F) = P(E \mid \bar{F}), \ P(F) = P(F \mid E) = P(F \mid \bar{E}).$$

put in a different way this means that

$$P(E \cap F) = P(E)P(F)$$

the probability of E and F occurring is just the product of the probability of E occurring and the probability of F occurring.

INDEPENDENT EVENTS

Theorem: Two events (E, F) are independent if and only if

$$P(E \cap F) = P(E)P(F)$$

For more than two events things become a bit more restrictive.

Theorem: The events E_1 , E_2 , E_3 , \cdots E_n are said to be mutually independent if for every subset

$$E'_1, E'_2, E'_3, \dots E'_r, r \leq n$$

$$P(E_1' \cap E_2' \cap E_3' \cap \cdots \cap E_r') = P(E_1') \cdot P(E_2') \cdot P(E_3') \cdots P(E_r')$$

INDEPENDENT EVENTS

The idea of independent processes will be extremely important as we move forward.

We will use the idea that repetitions of experiments constitute independent processes very often.

Note that this is more or less an assumption of the frequentist definition of probability.

INDEPENDENT EVENTS: EXAMPLE

Consider the compound experiment of throwing two fair coins. The sample space is

Define two events

$$A = 'the first coin is a head' = {(H, H), (H, T)}$$

 $B = 'the second coin is a tail' = {(H, T), (T, T)}$

P (A)=
$$|A|/|S| = 2/4 = \frac{1}{2}$$
 and
P (B)= $|B|/|S| = 2/4 = \frac{1}{2}$

Now P (A
$$\cap$$
 B)= P (H, T) = |A \cap B|/|S| = 1/4 = P (A) * P (B).

so A and B are independent.

INDEPENDENT EVENTS: EXAMPLE

But consider C = 'both coins are heads' = {(H, H)}

$$P(C) = |C|/|S| = 1/4$$

now

P (B
$$\cap$$
 C)= P (Ø) = |B \cap C|/|S| = 0/4 \neq P (B) * P (C)=(1/2)(1/4),
P (A \cap C)= P (Ø) = |A \cap C|/|S| = 0/4 \neq P (A) * P (C)=(1/2)(1/4),

so B and C are not independent. A is also not independent of C.

In general, it is possible for all pairs of events to be independent, but the complete set of events not to be.

It can sometimes be handy to view conditional probabilities using a tabular representation of relative frequencies - this can also be how real data arrives to us.

THE BUS EXAMPLE

A town has three bus routes, A,B and C. During rush hour there are twice as many buses on the A route as on B or C.

Over a period of time it has been observed that at a crossroads, where the routes converge, the buses run more than 5 minutes late 1/2, 1/5, 1/10 of the time.

If an inspector at the crossroads finds that the first bus he sees is more than five minutes late, what it the chance that it is a route B bus?

If we go back to the bus problem we did last lecture, but instead we consider what we'd expect if 1000 buses in total ran through the town, we'd end up with something like

	Α	В	С	total
Late	250	50	25	325
Not late	250	200	225	675
Total	500	250	250	1000

Let L = 'a bus is late'

	Α	P	С	total
Late	250	50	25	325
Not late	250	200	225	675
Total	500	250	250	1000

The conditional probabilities can easily be read off, for instance

$$P(B \mid L) = P(B \cap L)/P(L) = 50/325 = 2/13$$

This is of course exactly equivalent to our pen and paper solution.

	Α	В	С	total	
Late	250	50	25	325	
Not late	250	200	225	675	
Total	500	250	250	1000	

Marginal Probabilities

This is because of the law of total probability.

$$P(A) = \sum_{i=1}^n P(A \cap E_i) = \sum_{i=1}^n P(A \mid E_i) P(E_i)$$

	Α	В	С	total	
Late	250	50	25	325	
Not late	250	200	225	675	
Total	500	250	250	1000	

Another example

$$P(L) = P(L \cap A) + P(L \cap B) + P(L \cap C) = 250 + 50 + 25 = 325$$

or vertically we have

$$P(A) = P(A \cap L) + P(A \cap \overline{L})$$

note that that last relationship is a useful and general one. It is a special case of the law of total probability.

TABULAR BAYES' THEOREM: yet another TABULAR EXAMPLE

A doctor is trying to decide if a patient has one of three diseases d_1 , d_2 , or d_3 .

- **Two tests** are to be carried out, each of which results in a positive (+) or a negative (-) outcome.
- There are four possible test patterns ++, +-, -+, and --.
- National records have indicated that, for 10,000 people having one of these three diseases, the distribution of diseases and test results are as in the table in the next slide.

TABULAR BAYES' THEOREM: yet another TABULAR EXAMPLE

Disease	number	++	+ -	-+	
d1	3215	2110	301	704	100
d2	2125	396	132	1187	410
d3	4660	510	3568	73	509
Total	10000				

We can use this data to estimate $P(d_1)$, $P(d_2)$, $P(d_3)$ - these are called prior probabilities, and the conditional probabilities like

$$P(+-|d_1) = 301/3215 = 0.094$$
.

TABULAR BAYES' THEOREM: yet another TABULAR EXAMPLE

What the doctor wants though is the probability a patient has disease d_i given the results of the tests.

These are the *Bayes' or inverse, or posterior probabilities*.

We can compute them using Bayes' formula and we'll get results like

Bayes' Formula	
$P(E_i \mid A) = rac{P(A \cap E_i)}{P(A)} =$	$=rac{P(A\mid E_i)P(E_i)}{\sum_{j=1}^n P(A\mid E_j)P(E_j)}$

	d_1	d_2	d_3
++	.700	.131	.169
+ -	.075	.033	.892
- +	.358	.604	.038
	.098	.403	.499

Ex. $P(d_1|++) = P(++|d_1)/P(++) = 0.700$.

TABULAR BAYES' THEOREM: A TABULAR EXAMPLE

The values in the table are $P(d_i, ++)$ etc. Judicious use of these posterior probabilities can be used to inform decision:

Disease	number
d1	3215
d2	2125
d3	4660
Total	10000

	d.	da	da	
++	.700	.131	.169	
+ -	.075	.033	.892	
- +	.358	.604	.038	
	.098	.403	.499	

In this case the prior probability of a patient having disease d1 was 3215/10000 = 0.3215

If the test result came back ++ then the posterior probability $P(d_1, ++) = 0.7$ and we'd suspect that d_1 was the culprit.

UPDATING INFORMATION SEQUENTIALLY

- In the last example we updated the likelihood of a patient having a particular disease based on extra information in the form of the test results.
- The example should also give a hint how we can update our ideas about a system as new information comes in - this is why the original probabilities are call priors, and the reversed conditional probabilities are called posterior probabilities.
- We'll use this type of method in the computing lab later as a simple form of machine learning.

In the next sessions we will define, discuss and begin to use random variables.

Understand the elements of a random variable. Be able to define and use

- Discrete vs continuous variables
- Range and domain of the variables
- Probability (Mass/Density) Function
- Cumulative Distribution Function Improper integrals

Random variables are a tool that let us work with more complicate situations using still using a lot of tools that we know from algebra or calculus.

Unlike a normal variable, it doesn't make sense to say 'x = some value'.

For example:

- How many miles to a gallon does my car do?
- How quickly do I run a mile?
- How long will it take for a website to load?
- What will be the average daily temperature in two days?

Random variables inherently can take on a variety of values, and only discussing a statistic distribution of their values makes sense. Every time we tried something (took a measurement) we would get a slightly different answer.

Most idealisations of real-life experiments would correspond to random variables!

We'll see

- what random variables are
- how they can link abstract probability distributions to real-life experiments

The random variable is a series of 'mappings', from events to probabilities to numerical values.

We

- split the sample space into events,
- we assign each event a probability,
- we assign each event a unique numerical value.

the random variable is the whole of that package.

Lets consider rolling a normal fair six sided die.

We want to quantify the number of spots on the topmost face of die after a single roll.

If we had an infinite amount of information we could determine which face will come up before the roll was made. But as we don't we can only work out the probabilities of the different faces coming up.

With those different faces coming up, and their probabilities we associate numbers.

These steps can be done in any order, but often it makes sense to assign the values we want to the random variable.

We'll call our random variable Z.

We'll mix up some mathematical notation and common sense

$$Z = \begin{cases} 1 & \text{if 'the die lands with 1 spot on the top face'} \\ 2 & \text{if 'the die lands with 2 spots on the top face'} \\ 3 & \text{if 'the die lands with 3 spots on the top face'} \\ 4 & \text{if 'the die lands with 4 spots on the top face'} \\ 5 & \text{if 'the die lands with 5 spots on the top face'} \\ 6 & \text{if 'the die lands with 6 spots on the top face'} \end{cases}$$

the statements if 'the die lands with 1 spot on the top face' hopefully sound a lot like events to you.

 $S = \{1, 2, 3, 4, 5, 6\}$

where {1} is the outcome that the die lands with 1 spot on the top face, {2} is the outcome that the die lands with 2 spots up etc.

So looking again at Z

$$Z = \begin{cases} 1 & \text{if 'the die lands with 1 spot on the top face'} \\ 2 & \text{if 'the die lands with 2 spots on the top face'} \\ 3 & \text{if 'the die lands with 3 spots on the top face'} \\ 4 & \text{if 'the die lands with 4 spots on the top face'} \\ 5 & \text{if 'the die lands with 5 spots on the top face'} \\ 6 & \text{if 'the die lands with 6 spots on the top face'} \end{cases}$$

we could replace the text 'the die lands with 1 spot on the top face' with {1}, the event that the die lands with 1 spot upwards, and get

$$Z = egin{cases} 1 & ext{if } \{1\} \ 2 & ext{if } \{2\} \ 3 & ext{if } \{3\} \ 4 & ext{if } \{4\} \ 5 & ext{if } \{5\} \ 6 & ext{if } \{6\} \end{cases}$$

Now what is the probability that we get those different values of Z?

We get Z = 1 if the event $\{1\}$, or 'the die lands with 1 spot on the top face' occurs.

You should know how to associate a probability to an event occurring.

In this case where all the outcomes $\{1, 2, 3, 4, 5, 6\}$ can be argued to be equally likely, the probability of any one of them occurring must be 1/|S|, one over the number of elements in the sample space, in this case 1/6.

So the probability that Z=1, which is that $\{1\}$ occurred is 1/6

we'll de ne another function, the probability (mass) function of Z.

$$p_Z(z) = P(Z=z) = egin{cases} 1/6 & ext{if } \{1\} \ 1/6 & ext{if } \{2\} \ 1/6 & ext{if } \{3\} \ 1/6 & ext{if } \{4\} \ 1/6 & ext{if } \{5\} \ 1/6 & ext{if } \{6\} \end{cases}$$

and our random variable **Z** is fully defined.

Definition of random variable.

- Discrete random variables
- continuous random variables
- Range and domain of the variables
- Probability (Mass/Density) Function
- Cumulative Distribution Function
- Improper integrals

EXAMPLE OF 6-sided DIE

we have our sample space

$$S = \{1, 2, 3, 4, 5, 6\}$$

the values of our random variable, and their associated probabilities

$$Z = egin{cases} 1 & ext{if } \{1\} \ 2 & ext{if } \{2\} \ 3 & ext{if } \{3\} \ 4 & ext{if } \{4\} \ 5 & ext{if } \{5\} \ 6 & ext{if } \{6\} \end{cases}, p_Z(z) = P(Z=z) = egin{cases} 1/6 & ext{if } \{1\} \ 1/6 & ext{if } \{2\} \ 1/6 & ext{if } \{3\} \ 1/6 & ext{if } \{4\} \ 1/6 & ext{if } \{5\} \ 1/6 & ext{if } \{6\} \end{cases}$$

we must have that each possible value of the random variable is unambiguously associated with an event and a probability. It should be clear that this is the case above.

DEFINITION OF DISCRETE RANDOM VARIABLE

Definition Let X be a discrete random variable that can take on only the values $x_1, x_2, x_3, \ldots, x_n$ with respective probabilities $p_X(x_1), p_X(x_2), p_X(x_3), \ldots, p(x_n)$. Then, if

$$\sum_{x\in X}p_X(x)=1,$$

X is a discrete random variable.

The function $p(x) = P\{X = x\}$ is called the probability (mass) function of the variable X.

NOTE: Other notations are sometimes used for the probability (mass) function, m(i) or p_i .

It is also conventional that random variables are given a capital letter, and normally are chosen from the end of the alphabet).

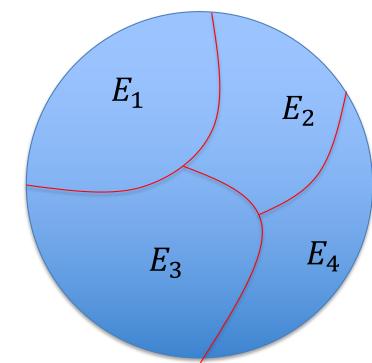
DISCRETE RANDOM VARIABLES

Definition: Consider an experiment, with outcome set S, split into n mutually <u>exclusive</u> and <u>exhaustive</u> events $E_1, E_2, E_3, \ldots, E_n$. A variable, X say, which can assume exactly n numerical values each of which corresponds to one and only one of the given events is called a random variable.

Schematically the mutually exclusive and exhaustive events look like

Event types:

- Exclusive: no overlap.
- Exhaustive: all of S is covered by them.



DISCRETE RANDOM VARIABLES

Here our outcome set is split into 4 mutually exclusive events and exhaustive. So to associate a random variable (call it \mathbf{X}) with this sample space we could have something like

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X = 1, corresponding to event E_1 X = 2, corresponding to event E_2 X = 3, corresponding to event E_3 X = 4, corresponding to event E_4
```

and we know how to calculate the probability of events.

The random variable is a series of 'mappings', from events to probabilities to numerical values.

We

- split the sample space into events,
- we assign each event a probability,
- we assign each event a unique numerical value.

the random variable is the whole of that package.

STRING LOGIC

Check list

- is the sample space well defined?
- are the events mutually exclusive?
- do the events cover all the sample space?
- are the probabilities of the events defined
- are values of the variable clearly assigned one-to-one to the possible events?

Define a valid random variable to describe the number of girls in families with 2 children, assuming that the likelihoods of boys or girls is equal and independent.

First, we de ne our sample space

$$S = \{(B, B), (B, G), (G, B), (G, G)\}$$

We define our variable G using the number of girls in the family:

$$G = \left\{ egin{array}{ll} 0 & ext{if } \{(B,B)\} \ 1 & ext{if } \{(B,G),(G,B)\} \ 2 & ext{if } \{(G,G)\} \end{array}
ight.$$

and associate our probability (mass) function

$$p_G(x) = \left\{egin{array}{ll} p_G(0) = P(G=0) = P(\{(B,B)\}) = & rac{1}{4} \ p_G(1) = P(G=1) = P(\{(B,G),(G,B)\}) = & rac{1}{2} \ p_G(2) = P(G=2) = P(\{(G,G)\}) = & rac{1}{4} \end{array}
ight.$$

We check that

$$\sum_{g\in G} p_G(g) = 1.$$

Here g indicates the possible values of G, so

$$\sum_{g \in G} p_G(g) = p_G(0) + p_G(1) + p_G(2) = 1/4 + 1/2 + 1/4 = 1$$

Construct a random variable that count the total number of spots upwards when two fair 6 sided dice are thrown. Our sample space can be the 36 elements of

$$S = \{(i, j) : i, j = 1, 2, 3, 4, 5, 6\}$$

where *i* is the number of spots on the first die, and j the second die.

How we need to think of a set of mutually exclusive and exhaustive events that would correspond to the sum of the spots. We could write this in set builder notation

$$E_k = \{(i, j) : i + j = k; i, j = 1, 2, 3, 4, 5, 6\}$$

and we can write these out in full

```
egin{aligned} E_2 &= \{(1,1)\} \ E_3 &= \{(1,2),(2,1)\} \ E_4 &= \{(1,3),(2,2),(3,1)\} \ E_5 &= \{(1,4),(2,3),(3,2),(4,1)\} \ E_6 &= \{(1,5),(2,4),(3,3),(4,2),(5,1)\} \ E_7 &= \{(1,6),(2,5),(3,4),(4,3),(5,2),(6,1)\} \ E_8 &= \{(2,6),(3,5),(4,4),(5,3),(6,2)\} \ E_9 &= \{(3,6),(4,5),(5,4),(6,3)\} \ E_{10} &= \{(4,6),(5,5),(6,4)\} \ E_{11} &= \{(5,6),(6,5)\} \ E_{12} &= \{(6,6)\} \end{aligned}
```

and we assign the value i + j to the random variable X if the event E_k occurs.

$$X = \left\{ egin{array}{ll} 2 & ext{if E_2} \ 3 & ext{if E_3} \ dots & \ 11 & ext{if E_{11}} \ 12 & ext{if E_{12}} \end{array}
ight.$$

and the probability distribution associated with X is similarly defined

$$p_X(x) = P(X = x) = P(E_x) = egin{cases} 1/36 & ext{if } X = 2 \ 2/36 & ext{if } X = 3 \ 3/36 & ext{if } X = 4 \ 4/36 & ext{if } X = 5 \ 5/36 & ext{if } X = 6 \ 6/36 & ext{if } X = 7 \ 5/36 & ext{if } X = 8 \ 4/36 & ext{if } X = 9 \ 3/36 & ext{if } X = 10 \ 2/36 & ext{if } X = 11 \ 1/36 & ext{if } X = 12 \end{cases}$$

The lower case x gives particular values of X, and that collection is the range of X - the values that X can take on:

$$R_X = 2, 3, 4, ..., 10, 11, 12$$

in that language the domain of the variable X is the sample set S.

STRING LOGIC: SUMMARY

Check list for random variable

- is the sample space well defined?
- are the events mutually exclusive?
- do the events cover all the sample space?
- are the probabilities of the events defined
- are values of the variable clearly assigned one-to-one to the possible events?

(CUMULATIVE) DISTRIBUTION FUNCTION

The cumulative distribution function of a discrete random variable, X , is

$$F_X(a) = P\{X \leq a\} = \sum_{x \leq a} p_X(x)$$

it is an alternative way of describing the probabilities of different events.

Sometimes it is more convenient to use F_χ than the probability function p_χ .

It provided a convenient way of describing continuous random variables.

Let us imagine we have a 4 sided die.

What is the cumulative distribution function for the random variable

X = 'what result appears when a 4 sided die is thrown once'

First we build our random variable.

All the probabilities can be assumed equally likely, and we will assign a value of the number of spots to our variable X.

We have a sample space $S=\{1,2,3,4\}$, and

$$X = \left\{ egin{array}{ll} 1 & ext{if } \{1\} \ 2 & ext{if } \{2\} \ 3 & ext{if } \{3\} \ 4 & ext{if } \{4\} \end{array}
ight.$$

We define our probability function

$$p_X(1) = P(X = 1) = P(\{1\}) = \frac{1}{4}$$
 $p_X(2) = P(X = 2) = P(\{2\}) = \frac{1}{4}$
 $p_X(3) = P(X = 3) = P(\{3\}) = \frac{1}{4}$
 $p_X(4) = P(X = 4) = P(\{4\}) = \frac{1}{4}$

or more sensibly

$$p_{X(x)} = \frac{1}{4} : x = 1,2,3,4$$

We see that

$$\sum_{x \in X} p_{X(x)} = 1$$

The events that define X are exhaustive and mutually exclusive. There is a one-to-one map between the values of the probability (mass) function. So X is a random variable, with $p_X(x)$ its probability mass function.

Using our definition of the cumulative distribution function

$$F(a) = P\{X \leq a\} = \sum_{x \leq a} p(x)$$

we have

$$F_X(a) = egin{cases} 0 & a < 1 \ 1/4 = & 1 \leq a < 2 \ 2/4 = & 2 \leq a < 3 \ 3/4 = & 3 \leq a < 4 \ 1 = & a > = 4 \end{cases}$$

Definition

$$F_X(a) = P\{X \leq a\} = \sum_{x \leq a} p_X(x) ext{ for } -\infty < a < \infty$$

if this is true, then because $p_X(x)$ obeys the axioms of probability, the following will hold:

 $F_X(a)$ must be 0 as $a o -\infty$ and 1 as $a o \infty$

 $F_X(a)$ must be monotonically increasing

 $F_X(a)$ must be right continuous

Cumulative distributions provide a good way of describing continuous random variables.

The cumulative distribution function of a discrete random variable, X, is

$$F_X(a) = P\{X \leq a\} = \sum_{x \leq a} p_X(x)$$

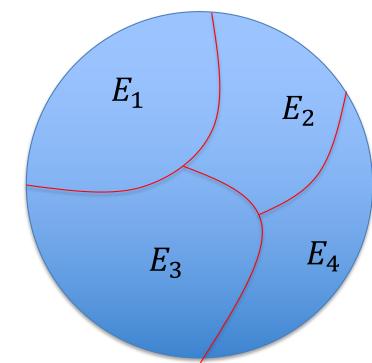
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