

COMP2610 / COMP6261 Information Theory

Lecture 3: Probability Theory and Bayes' Rule

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Last time

- A general communication system
- Why do we need probability?
- Basics of probability theory
- Joint, marginal and conditional distributions

Review Exercise

Suppose I go through the records for $N = 1000$ students, checking their admission status, $A = \{0, 1\}$, and whether they are “brilliant” or not, $B = \{0, 1\}$

(Aside: “Brilliance” is a dodgy concept, and does not predict scientific achievement as well as persistence and combinatorial ability; see e.g. Dean Simonton, *Scientific Genius: A Psychology of Science*, Cambridge University Press, 2009; this is just a toy example!)

Say that the counts for admission and brilliance are

	$B = 0$	$B = 1$
$A = 0$	680	10
$A = 1$	220	90

Then:

$p(A = 1, B = 0)$	220/1000	Joint
$p(B = 1)$	100/1000	Marginal
$p(A = 0)$	690/1000	Marginal
$p(B = 1 A = 1)$	90/310	Conditional
$p(A = 0 B = 0)$	680/900	Conditional

This time

- More on joint, marginal and conditional distributions
- When can we say that X , Y do not influence each other?
- What, if anything, does $p(X = x|Y = y)$ tell us about $p(Y = y|X = x)$?

Philosophically related to “How do we know / learn about the world?”

I am *not* providing a general answer; but keep it in mind!

Outline

- 1 More on Joint, Marginal and Conditional Distributions
- 2 Statistical Independence
- 3 Bayes' Theorem
- 4 Wrapping up

1 More on Joint, Marginal and Conditional Distributions

2 Statistical Independence

3 Bayes' Theorem

4 Wrapping up

Document Modelling Example

Suppose we have a large document of English text, represented as a sequence of characters:

$$x_1 x_2 x_3 \dots x_N$$

- e.g. `hello_how_are_you`

Treat each consecutive pair of characters as the outcome of “random variables” X , Y , i.e.

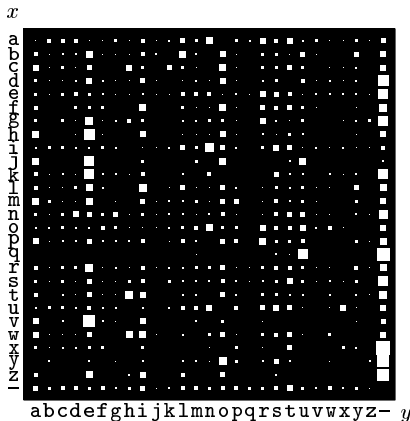
$$X = \text{'h'}, Y = \text{'e'}$$

$$X = \text{'e'}, Y = \text{'l'}$$

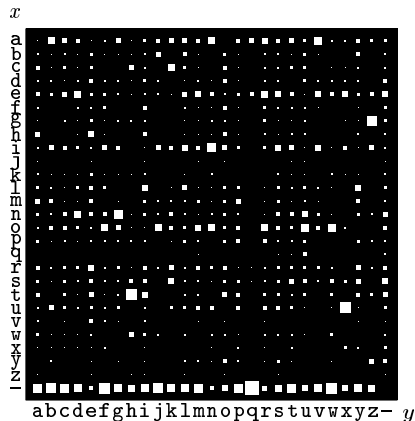
$$X = \text{'l'}, Y = \text{'l'}$$

$$\vdots$$

Document Modelling: Conditional Distributions



(a) $P(y|x)$



(b) $P(x|y)$

Conditional distributions for English alphabet, estimated from the “FAQ manual for Linux”. **Are these distributions “symmetric”?** Figure from Mackay (ITILA, 2003)

$$P(X = x|Y = y) = P(Y = y|X = x)? \quad P(X = x|Y = y) = P(X = y|Y = x)?$$

Recap: Sum and Product Rules

Sum rule:

$$p(X = x_i) = \sum_j p(X = x_i, Y = y_j)$$

Product rule:

$$p(X = x_i, Y = y_j) = p(Y = y_j | X = x_i) p(X = x_i)$$

Relating the Marginal, Conditional and Joint

Suppose we knew $p(X = x, Y = y)$ for all values of x, y . Could we compute all of $p(X = x|Y = y)$, $p(X = x)$ and $p(Y = y)$? **Yes**.

Now suppose we knew $p(X = x)$ and $p(Y = y)$ for all values of x, y . Could we compute $p(X = x, Y = y)$ or $p(X = x|Y = y)$? **No**.

The difference in answers above is of great significance

	$B = 0$	$B = 1$		$B = 0$	$B = 1$
$A = 0$	680	10	$A = 0$	640	50
$A = 1$	220	90	$A = 1$	260	50

These have the same marginals, but different joint distributions

Joint as the “Master” Distribution

In general, there can be many consistent joint distributions for a given set of marginal distributions

The joint distribution is the “master” source of information about the dependence

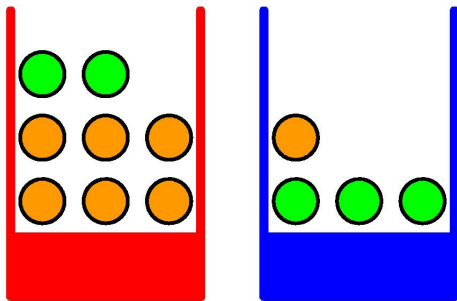
1 More on Joint, Marginal and Conditional Distributions

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Recall: Fruit-Box Experiment



Statistical Independence

Suppose that both boxes (red and blue) contain the same proportion of apples and oranges.

If fruit is selected uniformly at random from each box:

$$p(F = a|B = r) = p(F = a|B = b) \quad (= p(F = a))$$

$$p(F = o|B = r) = p(F = o|B = b) \quad (= p(F = o))$$

The probability of selecting an apple (or an orange) is independent of the box that is chosen.

We may study the properties of F and B separately: this often simplifies analysis

Statistical Independence: Definition

Definition: Independent Variables

Two variables X and Y are statistically independent, denoted $X \perp\!\!\!\perp Y$, if and only if their joint distribution *factorizes* into the product of their marginals:

$$X \perp\!\!\!\perp Y \leftrightarrow p(X, Y) = p(X)p(Y)$$

This definition generalises to more than two variables.

Are the variables in the language example statistically independent?

A Note on Notation

When we write

$$p(X, Y) = p(X)p(Y)$$

we have not specified the outcomes of X, Y explicitly

This statement is a shorthand for

$$p(X = x, Y = y) = p(X = x)p(Y = y)$$

for every possible x and y

This notation is sometimes called **implied universality**

Conditional independence

We may also consider random variables that are **conditionally** independent given some other variable

Definition: Conditionally Independent Variables

Two variables X and Y are conditionally independent given Z , denoted $X \perp\!\!\!\perp Y|Z$, if and only if

$$p(X, Y|Z) = p(X|Z)p(Y|Z)$$

Intuitively, Z is a common cause for X and Y

Example: X = whether I have a cold

Y = whether I have a headache

Z = whether I have the flu

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Revisiting the Product Rule

The product rule tells us:

$$p(X, Y) = p(Y|X)p(X)$$

This can equivalently be interpreted as a *definition* of conditional probability:

$$p(Y|X) = \frac{p(X, Y)}{p(X)}$$

Can we use these to relate $p(X|Y)$ and $p(Y|X)$?

Posterior Inference:

Example 1 (Mackay, 2003)

- Dicksy Sick had a test for a rare disease
 - ▶ Only 1% people of Dicksy's background have the disease
- The test simply classifies a person as having the disease, or not
- The test is reliable, but not infallible
 - ▶ It correctly identifies a sick individual 95% of the time
 $p(\text{identifies sick} \mid \text{sick}) = 95\%$.
 - ▶ It correctly identifies a healthy individual 96% of the time
 $p(\text{identifies healthy} \mid \text{healthy}) = 96\%$.
- Dicksy has tested positive (apparently sick)
- What is the probability of Dicksy having the disease?

Posterior Inference:

Example 1: Formalization

Let $D \in \{0, 1\}$ denote whether Dicksy has the disease, and $T \in \{0, 1\}$ the outcome of the test:

$$p(D = 1) = 0.01$$

$$p(D = 0) = 0.99$$

$$p(T = 1|D = 1) = 0.95$$

$$p(T = 1|D = 0) = 0.04$$

$$p(T = 0|D = 1) = 0.05$$

$$p(T = 0|D = 0) = 0.96$$

We need to compute $p(D = 1|T = 1)$, the probability of Dicksy having the disease given that the test has resulted positive.

Posterior Inference:

Example 1: Solution

$$\begin{aligned} p(D = 1 | T = 1) &= \frac{p(D = 1, T = 1)}{p(T = 1)} && \text{Def. conditional prob.} \\ &= \frac{p(T = 1, D = 1)}{p(T = 1)} && \text{Symmetry} \\ &= \frac{p(T = 1 | D = 1)p(D = 1)}{p(T = 1)} && \text{Product rule} \\ &= \frac{p(T = 1 | D = 1)p(D = 1)}{\sum_d p(T = 1 | D = d)p(D = d)} && \text{Sum rule} \\ &= \frac{p(T = 1 | D = 1)p(D = 1)}{p(T = 1 | D = 1)p(D = 1) + p(T = 1 | D = 0)p(D = 0)} \\ &\approx 0.19. \end{aligned}$$

Despite testing positive and the high accuracy of the test, the probability of Dicksy having the disease is only 0.19!

Why is the Probability So Low?

A “Natural Frequency” Approach

In 100 people, only 1 is expected to have the disease ($p(D = 1) = 0.01$)

This sick person will most likely test positive ($p(T = 1|D = 1) = 0.95$)

But around 4 healthy people are expected to be wrongly flagged as sick ($p(T = 1|D = 0) = 0.04$, and $0.04 \times 99 \approx 4$)

So when the test is positive, the chance of being sick is $\approx 1/5$

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(Aside: If you can correctly perform the calculation on the previous slide, you are doing better than most medical doctors! See Gerd Gigerenzer and Adrian Edwards, Simple tools for understanding risks: from innumeracy to insight, *British Medical Journal*, 327(7417), 741–744, 27 September 2003; Gerd Gigerenzer, *Reckoning with risk: Learning to live with uncertainty*, Penguin, 2002.

Moral of the story — if you get sick, don't delegate conditional probability computations to your doctor!)

Bayes' Theorem

We have implicitly used the following (at first glance remarkable) fact:

Bayes' Theorem:

$$\begin{aligned} p(Z|X) &= \frac{p(Z, X)}{p(X)} \\ &= \frac{p(X, Z)}{p(X)} \\ &= \frac{p(X|Z)p(Z)}{p(X)} \\ &= \frac{p(X|Z)p(Z)}{\sum_{Z'} p(X|Z')p(Z')} \end{aligned}$$

If we can express what knowledge of X (test) tells us about Z (disease), then we can express what knowledge of Z tells us about X

The Bayesian Inference Framework

Bayesian Inference

Bayesian inference provides a mathematical framework explaining how to change our (prior) beliefs in the light of new evidence.

$$\underbrace{p(Z|X)}_{\text{posterior}} = \frac{\overbrace{p(X|Z)}^{\text{likelihood}} \times \overbrace{p(Z)}^{\text{prior}}}{\underbrace{p(X)}_{\text{evidence}}}$$

Prior: Belief that someone is sick

Likelihood: Probability of testing positive given you are sick

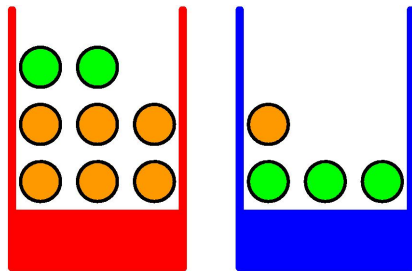
Posterior: Probability of being sick given you test positive

Posterior Inference:

Example 2 (Bishop, 2006)

Recall our fruit-box example:

- The proportion of oranges and apples are given by



- Someone told us that in a previous experiment they ended up picking up the red box 40% of the time and the blue box 60% of the time.
- A piece of fruit has been picked up and it turned out to be an orange.
- **What is the probability that it came from the red box?**

Posterior Inference:

Example 2: Formalization

Let $B \in \{r, b\}$ denote the selected box and $F \in \{a, o\}$ the selected fruit.

$$p(B = r) = 4/10$$

$$p(B = b) = 6/10$$

$$p(F = a|B = r) = 1/4$$

$$p(F = o|B = r) = 3/4$$

$$p(F = a|B = b) = 3/4$$

$$p(F = o|B = b) = 1/4$$

We need to compute $p(B = r|F = o)$, the probability that a picked up orange came from the red box.

Posterior Inference:

Example 2: Solution

We simply use Bayes' rule:

$$\begin{aligned} p(B = r|F = o) &= \frac{p(F = o|B = r)p(B = r)}{p(F = o)} \\ &= \frac{p(F = o|B = r)p(B = r)}{p(F = o|B = r)p(B = r) + p(F = o|B = b)p(B = b)} \\ &= \frac{2}{3} \end{aligned}$$

and therefore $p(B = b|F = o) = 1/3$.

Posterior Inference:

Example 2: Interpretation of the Solution

- If we hadn't been told any information about the fruit picked, the blue box is more likely to be selected than the red box
 - ▶ *A priori* we have $p(B = r) = 4/10$ and $p(B = b) = 6/10$
- Once we get new information that an orange has been picked, this increases the probability of the selected box being the red one
 - ▶ *Because the red box contains more oranges than the blue box*
- In fact, the proportion of oranges is so much higher in the red box that this is strong evidence that the orange came from it
 - ▶ *So after picking up the orange the red box is much more likely to have been selected than the blue one*

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Summary

- Recap on joint, marginal and conditional distributions
- Interpretation of conditional probability
- Statistical Independence
- Bayes rule: combination of prior, likelihood to get a posterior
- **Reading:** Mackay § 2.1, § 2.2 and § 2.3

Homework Exercise

Suppose we know that random variables X, Y satisfy

$$p(X|Y) = p(Y|X)$$

What can you conclude about the relationship between X and Y ?

If X and Y are independent, does that imply $p(X|Y) = p(Y|X)$?

Repeat the above questions for the statement

$$\frac{p(X|Y)}{p(Y|X)} = \frac{p(X)}{p(Y)}$$

Next time

- More examples on Bayes' theorem:
 - ▶ Eating hamburgers
 - ▶ Detecting terrorists
 - ▶ The Monty Hall problem
 - ▶ Document modelling
- Are there notions of probability beyond frequency counting?

Acknowledgement

These slides were originally developed by Professor Robert C. Williamson.