

Conditional Probability

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Example 1

The `photo_classify` data set represents a machine learning algorithm classifying a sample of 1822 photos as either about fashion or not.

		truth		
		<i>fashion</i>	<i>not</i>	Total
mach_learn	<i>pred_fashion</i>	197	22	219
	<i>pred_not</i>	112	1491	1603
	Total	309	1513	1822

If a photo is actually about fashion, what is the chance the algorithm will correctly identify the photo as being about fashion?

Of the 309 fashion photos, the algorithm correctly classifies 197 of them.

$$P(\text{mach_learn is } \textit{pred_fashion} \text{ given truth is } \textit{fashion}) = \frac{197}{309} = 0.638$$

Example 2

Using the same data set as in Example 1.

		truth		Total
		<i>fashion</i>	<i>not</i>	
mach_learn	<i>pred_fashion</i>	197	22	219
	<i>pred_not</i>	112	1491	1603
	Total	309	1513	1822

If the algorithm predicts the photo as being about fashion, what is the probability is actually is?

Of the 1603 photos predicted to be about fashion, 112 we actually about fashion.

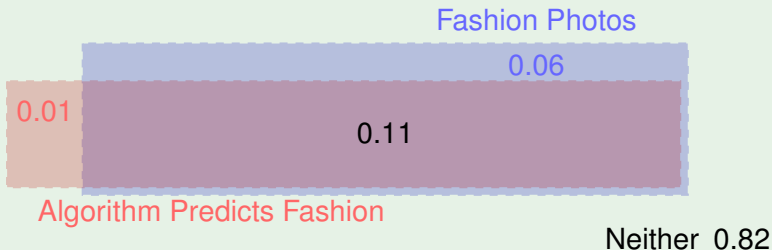
$$P(\text{truth is } \textit{fashion} \text{ given mach_learn is } \textit{pred_fashion}) = \frac{112}{1603} = 0.070$$

Note

It can be helpful to draw Venn Diagrams of these contingency tables using rectangles.

Example 3

The Venn Diagram for Example 1 is:



Definition

A **marginal probability** is a probability based on a single variable without regard to other variables.

Example 4

$$P(\text{mach_learn is } \textit{pred_fashion}) = \frac{219}{1822} = 0.12$$

Definition

A probability of outcomes for two or more variables is called a **joint probability**.

Example 5

$$P(\text{mach_learn is } \textit{pred_fashion} \text{ and truth is } \textit{fashion}) = \frac{197}{1822} = 0.11$$

Note

Sometimes a comma is substituted for “and” in a joint probability.

$P(\text{mach_learn is } \textit{pred_fashion}, \text{truth is } \textit{fashion})$

means the same thing as

$P(\text{mach_learn is } \textit{pred_fashion} \text{ and truth is } \textit{fashion})$

Definition

A **table proportions** is a table that summarizes joint probabilities. The proportions are computed by dividing each count by table's total.

Example 6

The table proportions for `photo_classify` are:

	truth: <i>fashion</i>	truth: <i>not</i>	Total
<i>mach_learn: pred_fashion</i>	$\frac{197}{1822}$	$\frac{22}{1822}$	$\frac{219}{1822}$
<i>mach_learn: pred_not</i>	$\frac{112}{1822}$	$\frac{1491}{1822}$	$\frac{1603}{1822}$
Total	$\frac{309}{1822}$	$\frac{1513}{1822}$	$\frac{1822}{1822}$

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	truth: <i>fashion</i>	truth: <i>not</i>	Total
<i>mach_learn: pred_fashion</i>	0.1081	0.0121	0.1202
<i>mach_learn: pred_not</i>	0.0615	0.8183	0.8798
Total	0.1696	0.8304	1.0

Example 7

The table proportions from Example 6 make a probability distribution.

Joint Outcome	Probability
mach_learn is <i>pred_fashion</i> and truth is <i>fashion</i>	0.1081
mach_learn is <i>pred_fashion</i> and truth is <i>not</i>	0.0121
mach_learn is <i>pred_not</i> and truth is <i>fashion</i>	0.0615
mach_learn is <i>pred_not</i> and truth is <i>not</i>	0.8182

Note

Joint probabilities can be used to calculate marginal probabilities in simple cases.

Example 8

$$\begin{aligned}P(\text{truth is } \textit{fashion}) &= P(\text{mac_learn is } \textit{pred_fashion} \text{ and truth is } \textit{fashion}) \\&\quad + P(\text{mac_learn is } \textit{pred_not} \text{ and truth is } \textit{fashion}) \\&= 0.1081 + 0.0615 = 0.1696\end{aligned}$$