

## Statistics Refresher Notes

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### Probability

**Definition. Rules of probability for discrete variables** The probability  $p(x = x)$  of variable  $x$  being in state  $x$  is represented by a value between 0 and 1.  $p(x = x) = 1$  means that we are certain  $x$  is in state  $x$ . Conversely,  $p(x = x) = 0$  means that we are certain  $x$  is not in state  $x$ . Values between 0 and 1 represent the degree of certainty of state occupancy.

The summation of the probability over all the states is 1:

$$\sum_{x \in \text{dom}(x)} p(x = x) = 1$$

This is called that normalisation condition.

**Definition. Marginals** Given a joint distribution  $p(x, y)$  the distribution of a single variable is given by

$$p(x) = \sum_y p(x, y)$$

Here  $p(x)$  is termed as marginal of the joint probability distribution  $p(x, y)$

**Definition. Conditional probability** If  $P(B) > 0$  then the **conditional probability** of  $A$  given  $B$  is

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

**Theorem. The Law of Total Probability** Let  $A_1, \dots, A_k$  be a partition of  $\Omega$ . Then, for any event  $B$ ,

$$\mathbb{P}(B) = \sum_{i=1}^k \mathbb{P}(B|A_i)\mathbb{P}(A_i)$$

**Theorem. Bayes' Theorem** Let  $A_1, \dots, A_k$  be a partition of  $\Omega$  such that  $\mathbb{P}(A_i) > 0$  for each  $i$ . If  $\mathbb{P}(B) > 0$  then, for each  $i = 1, \dots, k$ ,

$$\mathbb{P}(A_i|B) = \frac{\mathbb{P}(B|A_i)\mathbb{P}(A_i)}{\sum_j \mathbb{P}(B|A_j)\mathbb{P}(A_j)}$$

**Important.** We call  $\mathbb{P}(A_i)$  the **prior probability of  $A$**  and  $\mathbb{P}(A_i|B)$  the **posterior probability of  $A$**

**Definition. Independence** Two events  $A$  and  $B$  are **independent** if

$$\mathbb{P}(AB) = \mathbb{P}(A)\mathbb{P}(B)$$

and we write  $A \amalg B$ . A set of events  $\{A_i : i \in I\}$  is independent if

$$P\left(\bigcup_{i \in J} A_i\right) = \prod_{i \in J} \mathbb{P}(A_i)$$

**Definition. Conditional Independence**

$$X \amalg Y | Z$$

denotes that the two sets of variable  $X$  and  $Y$  are independent of each other provided we know the state of the set of variables  $Z$ . For conditional independence,  $X$  and  $Y$  must be independent given all states of  $Z$ . Formally, this means that

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

for all states of  $X, Y, Z$ . In case the conditioning set is empty we may also write  $X \amalg Y$  for  $X \amalg Y |$ , in which case  $X$  is (unconditionally) independent of  $Y$ .

**Definition. CDF** The ***cumulative distribution function***, or *CDF*, is the function  $F_X : \mathbb{R} \rightarrow [0, 1]$  defined by

$$F_X(x) = \mathbb{P}(X \leq x)$$

**Definition. Probability function**  $X$  is discrete if it takes countably many values  $\{x_1, x_2, \dots\}$ . We define the ***probability function*** or ***probability mass function*** for  $X$  by  $f_x(x) = \mathbb{P}(X = x)$

**Definition. Probability density function** A random variable  $X$  is continuous if there exists a function  $f_X$  such that  $f_X(x) \geq 0$  for all  $x$ ,  $\int_{-\infty}^{\infty} f_X(x)dx = 1$  and for every  $a \leq b$ ,

$$\mathbb{P}(a < X < b) = \int_a^b f_X(x)dx$$

The function  $f_X$  is called the ***probability density function*** (PDF). We have that,

$$F_X(x) = \int_{-\infty}^x f_X(t)dt$$

and  $f_X(x) = F'_X(x)$  and all points  $x$  at which  $F_X$  is differentiable

**Definition. Quantile function** Let  $X$  be a random variable with CDF  $F$ . The ***inverse CDF*** or ***quantile function*** is defined by<sup>4</sup>

$$F^{-1}(q) = \inf\{x : F(x) > q\}$$

for  $q \in [0, 1]$ . If  $F$  is strictly increasing and continuous than  $F^{-1}(q)$  is the unique real number  $x$  such that  $F(x) = q$