Basics of Probability, Random Processes and Linear Algebra

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Definition of Probability

Probability of an event E

The probability of an event E is defined as the relative frequency of outcomes favourable to E; to the total number of outcomes in the sample space S of the experiment.

- ► Let the experiment be repeated *N_S* times.
- ▶ Let N_F be the outcomes favourable to event E.
- ▶ The probability of the event E is given by

$$P(\mathsf{E}) = \frac{N_E}{N_S} \tag{1}$$

Probability of sample space

- Let there be a total of N events in the sample space S, namely A_1, A_2, \dots, A_N .
- $ightharpoonup A_1, A_2, \ldots, A_N$ form a partition of the sample space as in Figure 1

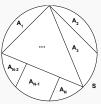


Figure 1: Sample space S partitioned by the events A_1, A_2, \ldots, A_N .

► The probability of the sample space S is given by

$$P(S) = \sum_{n=1}^{N} P(A_n) = 1$$
 (2)

Joint Probability

► The joint probability distribution of events A and B is given by

$$P(A,B) = P(A \cap B) = \frac{N_{A \cap B}}{N_{S}}$$
 (3)

Conditional Probability

The conditional probability is defined as the probability of occurrence of an event A given that an event B has occurred.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{N_A/N_S}{N_B/N_S}$$
(4)

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$
 (5)

$$P(B|A) = \frac{P(A \cap B)}{P(A)} \tag{6}$$

$$P(A \cap B) = P(A|B) \times P(B) = P(B|A) \times P(A)$$
 (7)

$$P(B|A) = \frac{P(A|B) \times P(B)}{P(A)}$$
 (8)

Equation 8 is called as Bayes's rule.

Marginalization

- Let A_1, A_2, \ldots, A_N form a partition of the sample space S
- ▶ Along with the events $A_1, A_2, ..., A_N$, let B be an event defined in sample space S as in Figure 3

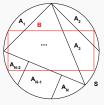


Figure 2: Sample space S with events A_1, A_2, \ldots, A_N and B.

▶ The marginalization of the event B over the events A_1, A_2, \ldots, A_N is given by

$$P(B) = \sum_{n=1}^{N} P(A_n, B) = \sum_{n=1}^{N} P(B|A_n)P(A_n)$$
 (9)

Realization of Bayes' rule for classification problem

▶ Let A_i be one of the classes and \bar{x} be a feature vector. From Bayes' rule we have that

$$\underbrace{P(A_{i}|\bar{x})}_{P(A_{i}|\bar{x})} = \underbrace{\frac{likelihood}{P(\bar{x}|A_{i})} \times \underbrace{P(A_{i})}_{P(A_{i})}}_{Evidence} \tag{10}$$

Consider an experiment of tossing a coin two times. The possible outcomes are {HH, HT, TH, TT}. Based on this, outcomes to the following events can be:

- Event A: First coin comes Head: {HT, HH}
- ► Event B : Atleast one head : {HT, TH, HH}

Also, notice that event A+B (First coin comes head OR at least one head) is same as event B: {HT, TH, HH}.

The event AB (First coin comes head AND at least one head) is same as event A : $\{HT, HH\}$

An urn consists of a white balls and b black balls.

- ▶ Probability of picking a white ball : $\left(\frac{a}{a+b}\right)$
- Probability of picking two white balls : $\left(\frac{a}{a+b}\right)\left(\frac{a-1}{a+b-1}\right)$
- ► Probability of picking two white balls in sequence and with replacement : $\left(\frac{a}{a+b}\right)^2$

9 instruments are on a shelf. All are brand new. In an experiment, we pick 3 instruments, use them and replace them. What is the probability of repeating the experiment 3 times and no new instrument being left on the shelf?

- Let event A_1 : Probability that in the first experiment, all new instruments are picked: 1 (because all are new initially)
- Let event A_2 : Probability that in the second experiment, all new instruments are picked : $(\frac{6}{9})(\frac{5}{8})(\frac{4}{7})$ (because only 6 new instruments are left after 1st experiment)
- Let event A_3 : Probability that in the third experiment, all new instruments are picked : $(\frac{3}{9})(\frac{2}{8})(\frac{1}{7})$ (because only 3 new instruments are left after 2 experiments)

$$Answer = P(A_1).P(A_2).P(A_3)$$

3 identical urns are there. Urn U_1 has a white balls and b black balls. Urn U_2 has c white balls and d black balls. Urn U_3 has d white balls and 0 black balls.

- ▶ What is the probability of choosing a white ball (event A)?
 - Probability of choosing a white ball from urn 1: $P(U_1A) = \left(\frac{1}{3}\right) \left(\frac{a}{a+b}\right) \quad \text{(because first we will choose a urn out of the 3 urns and then choose a white ball from the chosen urn)}$
 - Similarly, $P(U_2A) = \left(\frac{1}{3}\right) \left(\frac{c}{c+d}\right)$ and $P(U_3A) = \left(\frac{1}{3}\right) \left(\frac{d}{0+d}\right)$
 - ▶ $P(A) = \sum_{i=1}^{3} P(U_i A)$ (marginalizing over the urns, because we don't care which urn we choose the white ball from)
- What is the probability that a ball is chosen from U_1 given that it is white? $P(U_1/A) = \frac{P(A/U_1)P(U_1)}{P(A)} = \frac{\left(\frac{a}{a+b}\right)\cdot\left(\frac{1}{3}\right)}{P(A)}$

Market share of 3 car manufacturer (M_1 , M_2 and M_3) is 20%, 30% and 40% respectively. The probability that their car requires major repair in 1^{st} year is 5%, 10% and 15% respectively.

- What is the probability that a car requires major repair in 1st year (event A)?
 - Since the car can be of any manufacturer, we will add the probability of car being faulty of each manufacturer.
 - ► $P(A) = P(A/M_1)P(M_1)+P(A/M_2)P(M_2)+P(A/M_3)P(M_3)$ = $0.05 \times 0.2 + 0.1 \times 0.3 + 0.15 \times 0.5$
- What is the probability that the faulty car is of M₁ manufacturer?
 - Same as last question.
 - $P(M_1/A) = \frac{P(A/M_1)P(M_1)}{P(A)} = \frac{0.05 \times 0.2}{P(A)}$

Assume that a test to detect a disease whose prevalence is $\frac{1}{100}$ has a False Positive rate of 8% and a True Positive Rate of 100%. What is the probability that a person who is found to test positive actually has the disease?

Let us assume the following events:

D : Person has the disease. \overline{D} : Person doesn't have the disease.

T : Person is tested positive. \overline{T} : Person is tested negative.

We can see that we need to find P(D/T).

$$P(D/T) = \frac{P(T,D)}{P(T)} = \frac{P(T/D)P(D)}{P(T)}$$

To find P(T), we use

$$P(T) = P(T, D) + P(T, \overline{D}) \quad \text{(marginalizing over joint)}$$
$$= P(T/D)P(D) + P(T/\overline{D})P(\overline{D})$$
$$= 1 \times 0.01 + 0.08 \times 0.99$$

Open and closed intervals

Closed interval :[
$$a$$
, b] = { x : $a \le x \le b$ }
Half open interval :(a , b] = { x : $a < x \le b$ }
Open interval :(a , b) = { x : $a < x < b$ }

Cumulative distribution function (CDF)

Cumulative distribution function of a random variable (RV) X is $F_{x}(x) = P(X \le x)$

where, $P(X \le x)$ is the probability that the RV X takes a value less than or equal to x

$$F_X(-\infty) = 0 \implies$$
 The event is impossible to occur $F_X(\infty) = 1 \implies$ The event is certain to occur

Cumulative distribution

Probability from CDF

Probability of a random variable X in the given interval can be obtained from CDF

$$P(X \in (-\infty, b)) = P(X \in (-\infty, a]) + P(X \in [a, b])$$

 $P(X \in [a, b)) = P(X = a) + F_X(b) - F_X(a)$

CDF of a continuous RV

$$F_X(x) = \int_{-\infty}^x f_X(x).dx$$

where, $f_X(x)$ is the density function of the RV X

A particle is moving along a straight line. The instantaneous velocity is given by

$$V = \frac{dx}{dt}$$

The particle is described by its position and velocity (x_0, v_0) Kinetic energy of the particle is given by

$$K = \frac{1}{2}mV^2$$

X and V are the random variables correspond to position and velocity respectively. Given the density function $f_V(v)$, what is $f_{\kappa}(k)$?

Example 1

The density function of the RV V is given by $F_K(b)$ be the probability that the RV K has takes a value $\leq b$

$$B = \{K : -\infty < k \le b\}$$

$$\phi = g^{-1}(b) = \left\{ -\sqrt{\frac{2b}{m}} \le v \le \sqrt{\frac{2b}{m}} \right\}$$

$$P(v \in g^{-1}(b)) = F_K(b)$$

$$= P\left[v = \sqrt{\frac{2b}{m}}\right] + F_v\left(\sqrt{\frac{2b}{m}}\right) - F_v\left(\sqrt{\frac{2b}{m}}\right)$$

$$f_K(k) = f_v\left(\sqrt{\frac{2k}{m}}\right) \frac{\partial}{\partial k}\left(\sqrt{\frac{2k}{m}}\right) + f_v\left(\sqrt{\frac{-2k}{m}}\right) \frac{\partial}{\partial k}\left(\sqrt{\frac{2k}{m}}\right)$$

$$= \frac{f_v\left(\sqrt{\frac{2k}{m}}\right) + f_v\left(\sqrt{\frac{-2k}{m}}\right)}{\sqrt{2mk}}$$

$$Y = \phi(X)$$

$$\chi(Y) = \phi^{-1}(Y)$$

$$f_Y(y) = \sum_{i=1}^K f_X(\chi_i(y)) \cdot |\chi_i'(y)|$$

According to the above equation, in Example 1,

$$K = \frac{1}{2}mV^2$$

$$\chi_1(k) = \sqrt{\frac{2k}{m}}$$

$$\chi_2(k) = \sqrt{\frac{-2k}{m}}$$

$$|\chi'_1| = |\chi'_2| = \frac{1}{\sqrt{2mk}}$$

Statistical Averages

Ensemble average

It is the average of the outcomes of a stochastic process at a given instance of time.

► The ensemble average is often called as mean or expectation. It is given as:

$$\mu_{x}(t) = E[X(t)]$$

$$= \int_{-\infty}^{\infty} x(t) f_{x}(x(t)) dx(t)$$

Z(t)

Figure 3: Sample space S with mapping X,Y and Z

Here, ensemble average at time instance 't' is the average of X(t),Y(t) and Z(t).

It is the average value of a single outcome of a stochastic process across time.

► Time average is given as:

$$\mu_{x} = E[X]$$
$$= \int x f_{x}(x) dt$$

Ergotic process

Definition of ergodic process

A process is ergodic if its ensemble average is equal to its time average.

That is, if $\mu_{x} = \mu_{t}$, the process is ergodic.

Moments about the origin

▶ The n^{th} moment about the origin is given as:

$$E[X^n] = \int x^n f_x(x) dx$$

Expectation is the first order moment.

▶ The *n*th moment about the mean is given as:

$$E[(X - \mu_x)^n] = \int (x - \mu_x)^n f_x(x) dx$$

Auto-covariance:

$$E[(X - \mu_x)^2] = \int (x - \mu_x)^2 f_x(x) dx$$

It is the second order moment

Autocorrelation

Definition

Autocorrelation is the correlation of the same process with itself at different instances of time.

- ▶ It gives the similarity of a random process at different time instances *t*₁ and *t*₂.
- ▶ It is given as: $R_x(|t_2 t_1|) = E(X(t_1),X(t_2)]$

Stationary process

Wide sense stationarity

A random process X(t) is said to be wide sense stationary if the following conditions are satisfied:

- ▶ Expectation, that is $\mu_{\mathsf{x}} = \mathsf{E}(\mathsf{X}(\mathsf{t})]$ is independent of time.
- ▶ Autocorrelation is only a function of time lag t_2 - t_1 .

$$R_X(|t_1-t_2|)=R_X(|t_2-t_1|)$$

$$R_X(|t_2-t_1|)=R_X(|t_4-t_3|) \text{ , if } t_2-t_1=t_4-t_3.$$

Strict sense stationarity

A random process X(t) is said to be strict sense stationary if the above conditions are satisfied for all higher order moments.