

Basic Probability Theory

Set: collection of distinct & well defined objects

$A \subset B \Rightarrow A$ is subset of B

Random Exp: Event (E) is random if

- i) all possible outcomes of E are known
- ii) it is impossible to predict which outcome will come at particular performance of E
- iii) E can be repeated under identical conditions infinite times

Event space: Set of all possible outcomes \Rightarrow called S .

Event: An circumstance \Rightarrow $\in S$.

Impossible Event: $P(E) = 0$

Certain Event: $P(E) = 1$

Complement Event: Not of any event.

Mutually exclusive: $A \cap B = \emptyset$

Exhaustive: Consider

Equally likely: $P(E_1) = P(E_2)$

Probability

Let E be a random exp such that its space S contains a finite number, n of event points, which are equally likely. If A is connected to $m(A)$ of such points, then probability of A is

$$P(A) = \frac{m(A)}{n}$$

$$\text{a) } 0 \leq P(A) \leq 1 \quad \text{b) } P(S) = 1 \quad \text{c) } P(\emptyset) = 0 \quad \text{d) } P(A') = 1 - P(A)$$

Axiomatic Defn

A₁) $P(A) \geq 0 \forall A \in S$

A₂) $P(S) = 1$

A₃) If A_1, \dots, A_n, \dots be finite or infinite no. of pairwise mutually exclusive events i.e. $A_i \cap A_j = \emptyset$ for $i \neq j$ then.

$$P(A_1 \cup A_2 \cup \dots \cup A_n) = P(A_1) + P(A_2) + \dots + P(A_n) + \dots$$

Tut Probability of impossible event is zero

Proof $S + \emptyset = S$

$$S\emptyset = S$$

$$P(S + \emptyset) = P(S)$$

$$P(S) + P(\emptyset) = P(S)$$

$$P(\emptyset) = 0$$

Tut $P(A') = 1 - P(A)$ and $0 \leq P(A) \leq 1$

Now $A + \bar{A} = S$

$$P(A + \bar{A}) = P(S)$$

$$P(A) + P(\bar{A}) = 1$$

$$P(\bar{A}) = 1 - P(A)$$

Since $P(A) \geq 0 \Rightarrow 0 \leq P(A) \leq 1$

Tut $P(A' \cap B) = P(B) - P(AB)$

Proof $AB + \bar{A}B = B$

$$P(AB + \bar{A}B) = B$$

$$P(AB) + P(\bar{A}B) = P(B)$$

$$P(\bar{A}B) = P(B) - P(AB)$$

Tut $P(A + B) = P(A) + P(B) - P(AB)$

Proof $P(A + B) = P(A + \bar{A}B)$

$$= P(A) + P(\bar{A}B)$$

$$= P(A) + P(B) - P(AB)$$

$$\text{Th3 } P(A+B+C) = \sum P(A_i) - \sum P(A_iB_j) + P(ABC)$$

Proof by Th4

Derivation of Classical Defn

$$U_1 + U_2 + \dots + U_n = S$$

$$P(U_1 + \dots + U_n) = P(S)$$

$$\therefore \sum P(U_i) = 1$$

Let them be equal prob

$$\Rightarrow P(U_1) = P(U_2) = \dots = P(U_n) = 1$$

$$A = U_1 + U_2 + \dots + U_n$$

$$P(A) = \frac{1}{n} + \dots + \frac{1}{n}$$

$$= \frac{m(A)}{n}$$

$$\text{Th4 } P(AB) \leq P(A) \leq P(A+B) \leq P(A) + P(B)$$

Proof

$$AB + AB' = A$$

$$P(AB + AB') = P(A)$$

$$P(AB) + P(AB') = P(A)$$

$$P(AB) \geq 0 \text{ so, } P(AB) \leq P(A)$$

$$P(AB) \leq P(A)$$

$$P(A+B) = P(A) + P(B) - P(AB)$$

$$= P(A) + P(A\bar{B})$$

$$P(A) \leq P(A+B) < P(A) + P(B)$$

$$\text{Th5 } P(A_1 + A_2 + \dots + A_n) \leq P(A_1) + P(A_2) + \dots + P(A_n) \quad [\text{Boole's Identity}]$$

Proof $P(A_1 + A_2) \leq P(A_1) + P(A_2)$

True for 1, 2.

for $n=k \Rightarrow n=k+1$

$$P(A_1 + \dots + A_k) \leq P(A_1) + P(A_2) + \dots + P(A_k)$$

$$P(A_1 + \dots + A_k + A_{k+1}) = P(A_1 + A_2 + \dots + A_k + A_{k+1})$$

$$\leq P(A_1 + \dots + A_k) + P(A_{k+1})$$

$$\leq P(A_1) + P(A_2) + \dots + P(A_{k+1})$$

By induction, proved.

TNB

$$i) P(A_1, A_2, \dots, A_n) \geq 1 - \sum_{i=1}^n P(\bar{A}_i)$$

$$ii) P(A_1, \dots, A_n) \geq \sum_{j=1}^n P(A_j) - (n-1) \quad \begin{matrix} \text{Bonferroni's} \\ \text{Inequality} \end{matrix}$$

Proof

$$i) P(\bar{A}_1 + \bar{A}_2 + \dots + \bar{A}_n) \leq P(\bar{A}_1) + P(\bar{A}_2) + \dots + P(\bar{A}_n)$$

$$1 - P(A_1, A_2, \dots, A_n) \leq \sum_{i=1}^n P(\bar{A}_i)$$

$$P(A_1, A_2, \dots, A_n) \geq 1 - \sum_{i=1}^n P(\bar{A}_i)$$

$$ii) P(\bar{A}_i) = 1 - P(A_i)$$

$$1 - \sum_i P(\bar{A}_i) = 1 - \left[\sum_i (1 - P(A_i)) \right]$$

$$= \sum_i P(A_i) - (n-1)$$

$$P(A_1, A_2, \dots, A_n) \geq \sum_{i=1}^n P(A_i) - (n-1)$$

Fact: If A_1, A_2, \dots, A_n are pairwise mutually exclusive events,

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

Proof: $A_i A_j = \emptyset$ if $i \neq j$:

$$A_1 + A_2 + \dots + A_n = S$$

$$B = SB = (A_1 + A_2 + \dots + A_n)B = A_1B + \dots + A_nB$$

$$(A_i B)(A_j B) = (A_i A_j)B = \emptyset B = \emptyset$$

$$P(B) = P(A_1 B + A_2 B + \dots + A_n B)$$

$$= P(A_1 B) + P(A_2 B) + \dots + P(A_n B)$$

$$= \sum P(A_i B)$$

$$= \sum P(A_i)P(B|A_i)$$

$$\text{Now, } P(A_i | B) = \frac{P(A_i B)}{P(B)}$$

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

$$P(A_i | B) = \frac{P(A_i)P(B|A_i)}{\sum P(A_i)P(B|A_i)}$$

Bayes Thm

Independent Events

if $P(A|B) = A$ & $P(B|A) = B$, $P(A) \neq P(B) \neq 0$.

if $P(A) \neq P(B)$ independent

$$P(AB) = P(A) \cdot P(B)$$

Defn1 if $P(AB) = P(A) \cdot P(B)$, A, B are independent

Defn2 A, B, C are pairwise independent if.

$$P(AB) = P(A) P(B)$$

$$P(BC) = P(B) P(C)$$

$$P(CA) = P(C) P(A)$$

Defn3 A, B, C are mutually independent if.

~~$P(ABC) = P(A)P(B)P(C)$~~

$P(ABC) = P(A) P(B) P(C)$ & pairwise ind

Random Var

↳ a variable which takes numerical values determined by outcome of a random experiment

$$(X=x) = \{w \in S \mid X(w)=x\}$$

$$(X \leq a) = \{w \in S \mid X(w) \leq a\}$$

$$(X > b) = \{w \in S \mid X(w) > b\}$$

Th1 if X_1, X_2 are random vars. of S , even $X_1 + X_2$ is.

Proof Let X_1, X_2 be random vars. of S in Event E

let $w \in S$ be outcome of E ,

$$\text{So, } X_1(w) \in X_2(w) \in \mathbb{R}$$

$$\Rightarrow X_1(w) + X_2(w) \in \mathbb{R}$$

$$\Rightarrow (X_1 + X_2)(w) \in \mathbb{R}$$

Also for $X_1 - X_2$

proved.

Th2 if X_1, X_2 are random vars. of S , c_1, c_2 are consts,

$c_1 X_1 + c_2 X_2, X_1, X_2$ are all random vars.

Proof same as Th1

Th3 even $\max(X_1, X_2)$ is a random var

Proof Same as Th1

Distribution func

Let X be a random var on S associated with a exp.

The cumulative dist func (cdf) on X is

$$F_X(x) = P(X \leq x), P(X \leq x) = \{w \in S \mid X(w) \leq x\}$$

Properties

$$\text{i) } P(a \leq X \leq b) = F(b) - F(a)$$

Proof $X \leq a$ & $a \leq X \leq b$ are mutually excl.

$$(X \leq b) = (X \leq a) \cup (a < X \leq b)$$

$$P(X \leq b) = P(X \leq a) + P(a < X \leq b)$$

$$\begin{aligned} P(a \leq X \leq b) &= P(X \leq b) - P(X \leq a) \\ &= F(b) - F(a) \end{aligned}$$

$$\text{i)} P(a \leq x \leq b) = P(x=a) + P(a < x \leq b) - P(a)$$

$$\begin{aligned}\text{Proof: } P(a \leq x \leq b) &\stackrel{F}{=} P(x=a \cup (a \leq x \leq b)) \\ &= P(x=a) + P(a < x \leq b) \\ &= P(x=a) + F(b) - F(a)\end{aligned}$$

$$\text{ii)} P(a < x \leq b) = P(x=b) - F(a)$$

$$\begin{aligned}\text{Proof } P(a < x \leq b) &= P((a < x \leq b) \cup (x=b)) \\ &= P(a < x \leq b) + P(x=b)\end{aligned}$$

$$\begin{aligned}P(a < x \leq b) &= P(a < x \leq b) - P(x=b) \\ &= \cancel{P(x=a)} - F(b) - F(a) - P(x=b)\end{aligned}$$

$$\text{iv)} P(a \leq x < b) = F(b) - F(a) - P(x=b) + P(x=a)$$

$$\begin{aligned}\text{Proof } P(a \leq x < b) &= P(x=a \cup a \leq x < b) \\ &= P(x=a) + P(a \leq x < b) \\ &= P(x=a) + F(b) - F(a) - P(x=b)\end{aligned}$$

(2) i) $0 \leq F(x) \leq 1$

$$\text{Proof } F(x) = P(x \leq x)$$

$$\Rightarrow 0 \leq P(x \leq x) \leq 1$$

$$\Rightarrow 0 \leq F(x) \leq 1$$

ii) $x < y \Rightarrow F(x) \leq F(y)$

$$\text{Proof } x < y \Rightarrow F(y) - F(x) = P(x < \cancel{x} \leq y)$$

$$\Rightarrow F(y) - F(x) \geq 0$$

$$\Rightarrow F(y) \geq F(x)$$

$$(3) \quad \text{F}(-\infty) = \lim_{x \rightarrow -\infty} F(x) = 0 \quad F(\infty) = \lim_{x \rightarrow \infty} F(x) = 1$$

$$\text{Proof } F(\infty) = \lim_{x \rightarrow \infty} F(x) = \lim_{x \rightarrow \infty} P(X \leq x) = P(S) = 1$$

$$F(-\infty) = \lim_{x \rightarrow -\infty} F(x) = \lim_{x \rightarrow -\infty} P(X \leq x) = P(\emptyset) = 0$$

(4) $F(x)$ is continuous on right.

Proof $P(a < X \leq a+h) = P(x=a) + P(f(a+h) - f(a))$

$$\lim_{h \rightarrow 0^+} P(a < X \leq a+h) = P(x=a) + \lim_{h \rightarrow 0^+} F(a+h) - F(a)$$

$$P(x=a) = P(x=a) + \lim_{h \rightarrow 0^+} F(a+h) - f(a)$$

$$\lim_{h \rightarrow 0^+} F(a+h) = f(a)$$

(5) $P(x=a) = f(a) - \lim_{h \rightarrow 0^+} F(a-h) = F(a) - \lim_{x \rightarrow a^-} F(x)$

Proof $P(a-h < X \leq a) = F(a) - F(a-h)$

$$P(x=a) = \lim_{h \rightarrow 0^+} P(a-h < X \leq a) = \lim_{h \rightarrow 0^+} [F(a) - F(a-h)]$$

$$= F(a) - \lim_{h \rightarrow 0^+} F(a-h)$$

$$= F(a) - \lim_{x \rightarrow a^-} F(x) = F(a) - F(a=0)$$

Discrete Random Var.

↳ if a random var takes finite/infinite of distinct vals

range of Discrete is finite or countable & infinite

prob mass func

↳ for discrete X ,

$$P(X=x_i) = p(x_i) = p_i \quad i = 1, 2, \dots$$

$$\text{i)} \quad p_i \geq 0 \quad \text{ii)} \quad \sum_{i=0}^{\infty} p_i = 1$$

discrete dist func

$$F(x) = P(x=x_0) + P(x=x_1) + \dots + P(x=x_i)$$

$$= \sum_{k=0}^i p_k \quad x_i \leq x < x_{i+1}$$

Continuous random var

\hookrightarrow X is a cont random val s.t.

$$P\left(X - \frac{dx}{2} < X \leq X + \frac{dx}{2}\right) = f(x)dx$$

i) $f(x) > 0 \forall x \in \mathbb{R}$

ii) $\int f dx = 1$

iii) $\int_E f(x)dx = P(E)$

$$\Rightarrow P(a \leq X \leq b) = \int_a^b f(x)dx$$

$$\Rightarrow P(X=a) = P(a \leq X \leq a) = \int_a^a f(x)dx = 0$$

$$\Rightarrow P(a < x < b) = P(a \leq x \leq b) = P(a < x \leq b) = P(a < x \leq b) = F(b) - F(a)$$

$$f(x)dx = dF(x)$$

$$f(x) = F'(x)$$

Cont dist func

$$F(x) = P(X \leq x) = \int_{-\infty}^x f(t)dt$$

$$\Rightarrow F(-\infty) = 0$$

$$\Rightarrow F(\infty) = 1$$

Mean / Expectation

$$E(X) = \sum_{i=1}^{\infty} p_i x_i \quad \text{s.t.} \quad \sum_{i=1}^{\infty} p_i = 1$$

if cont., $E(x) = \int_{-\infty}^{\infty} x f(x) dx$. s.t. $\int_{-\infty}^{\infty} f(x) dx = 1$

Properties

1. i) if $x=a$, then $E(x)=a$

ii) if $a \leq x \leq b$, then $a \leq E(x) \leq b$

2. if $Y=ax$, $E(Y) = a E(X)$

if $Y=a \pm bx$, $E(Y) = a \pm b E(X)$

3. $E(XY) = E(X)E(Y)$, if independent

4. if $Z = ax \pm by$, $E(Z) = aE(X) \pm bE(Y)$

5. if $g(x)$ is a function,

$$E\{g(x)\} = \sum p_i g(x_i) \quad (\text{disc})$$

$$= \int_{-\infty}^{\infty} g(u) f(u) du \quad (\text{cont})$$

Variance

- i) $\text{Var}(X) = E(\cancel{\text{Var}}(X-m)^2) = E[(\{x-E(x)\})^2] = \sum_{i=1}^{\infty} (x_i - m)^2 p_i$
- ii) $= \int_{-\infty}^{\infty} (x-m)^2 f(x) dx$

Standard Deviation

$$\hookrightarrow \text{SD} = \sqrt{\text{Var}(x)} = 5$$

Properties

i) $\text{Var}(x) = E(x^2) - E(x)^2 = E(x^2) - m^2$

ii) $\text{Var}(ax+b) = a^2 \text{Var}(x)$

iii) $\text{Var}(a) = 0$

iv) $\text{Var}(x) = E[x(x-1)] - m(m-1)$

Proof

$$\text{i)} \text{Var}(x) = E[(x-m)^2]$$

$$= E[x^2 - 2mx + m^2]$$

$$= E[x^2] - 2mE[x] + m^2$$

$$= E[x^2] - m^2$$

$$\text{ii)} \text{Var}(ax+b) = E[(ax+b - am-b)^2]$$

$$= E[a^2(x - \frac{m}{a})^2]$$

$$= a^2 E[(x-m)^2]$$

$$= a^2 \text{Var}(x)$$

$$\text{iii)} \text{Var}(a) = E[(a - E(a))^2]$$

$$= E[(a-a)^2] = 0$$

$$\text{iv)} \text{Var}(x) = E[(Ex-M)^2]$$

$$= E[x^2 - x + x - 2mx + m^2]$$

$$= E[x^2 - x] + E(x) - 2mE(x) + m^2$$

$$= E[x(x-1)] - m(m-1)$$

Coefficient of variance

$$CV = \frac{SD}{\text{mean}} \times 100$$

$$3) |x| \leq E(|x|)$$

$$x = |x| \leq 0$$

$$E(x - E(|x|)) \leq 0$$

$$E(x) - E(|x|) \leq 0$$

$$\Leftrightarrow E(x) \leq E(|x|)$$

$$-E(x) \leq E(|x|)$$

$$|E(x)| \leq E(|x|)$$

Binomial

r successes in n trials

$$P(X=r) = {}^n C_r p^r q^{n-r} = {}^n C_r p^r (1-p)^{n-r}$$

$$pq=1$$

$$F(x) = P(X \leq x) = \sum {}^n C_i p^i (1-p)^{n-i}$$

$$P(r) = \frac{n!}{(n-r)!r!} q^{n-r} p^r$$

$$P(x=r+1) = \frac{n!}{((r+1)+(n-r-1))!} p^{r+1} q^{n-r-1}$$

$$\frac{P(r+1)}{P(r)} = \frac{n-r}{r+1} \frac{p}{q}$$

$$P(r+1) = \frac{n-r}{r+1} \frac{p}{q} P(r)$$

$$\Rightarrow \text{Mean} = np \quad \text{Var} = npq$$

Proof: $B(n,p)$

$$\begin{aligned} E[x] &= \sum r P(r) = \sum r^n C_r P r^{n-r} q^{n-r} = \sum \frac{n!}{r!(n-r)!} p^r q^{n-r} \\ &= np \sum \frac{(n-1)!}{(r-1)!(n-r)!} p^{r-1} q^{n-r} = np \sum_{r=1}^{n-1} C_{r-1} p^{r-1} q^{n-r} \\ &= np \sum_0^{n-1} C_{r-1} p^{r-1} q^{n-r} \\ &= np (p+q)^{n-1} \\ &= np \end{aligned}$$

$$\begin{aligned} E[x(x-1)] &= \sum r(r-1) P(r) \\ &= \sum r(r-1) \frac{n!}{n!(n-r)!} p^r q^{n-r} \\ &= n(n-1)p^2 \sum \frac{(n-2)!}{(r-2)!(n-r)!} p^{r-2} q^{n-r} \\ &= (n-1)np^2 \sum_{r=2}^{n-2} C_{r-2} p^r q^{n-r} = n(n-1)p^2(p+q)^{n-2} \\ &= n(n-1)p^2 \end{aligned}$$

$$\begin{aligned} \text{Var}(x) &= E[x(x-1)] - m(m-1) \\ &= n(n-1)p^2 - np(p-1) = np(1-p) = npq \end{aligned}$$

$$SD = \sqrt{npq}$$

Poisson

$$P(r) = \begin{cases} \frac{e^{-\lambda} \lambda^r}{r!} & r=1, 2 \\ 0 & \text{else} \end{cases}$$

i) $P(0|r) > 0$.

ii) $\sum P(r) = e^{-\lambda} \sum \frac{\lambda^r}{r!} = 1$

Mean = λ Var(X) = λ

Proof $X \sim P(\lambda)$

$$P(r) = \frac{e^{-\lambda} \lambda^r}{r!} \quad r=1, 2, \dots$$

$$\begin{aligned} E(X) &= \sum r P(r) = \sum_{r=1}^{\infty} r \frac{e^{-\lambda} \lambda^r}{r!} \\ &= \lambda e^{-\lambda} \sum_{r=1}^{\infty} \frac{1}{(r-1)!} \\ &= \lambda e^{-\lambda} \sum_{r=0}^{\infty} \frac{d^r}{r!} \rightarrow e^{\lambda} \\ &= \lambda \end{aligned}$$

$$E(X(n-1)) = \sum r(r-1) P(r) = \sum r(r-1) e^{-\lambda} \frac{\lambda^r}{r!}$$

$$= \lambda^2 e^{-\lambda} \sum_{r=2}^{\infty} \frac{1}{(r-2)!} = \lambda^2 e^{-\lambda} \sum_{r=0}^{\infty} \frac{\lambda^r}{r!}$$

$$= d^n$$

$$\text{Var}(X) = d^2(d-1)/2$$

$$= d.$$

$$S.D = \sqrt{d}$$

Thm i) no of trials ($n \rightarrow \infty$)

ii) prob of success ($p=0$)

iii) $d = np \rightarrow$ finite const.

$$P(r) = {}^n C_r p^r (1-p)^{n-r} = \frac{e^{-d} d^r}{r!} \text{ as } n \rightarrow \infty \text{ & } np=d$$

Proof:

$$P(r) = {}^n C_r p^r (1-p)^{n-r}$$

$$= \frac{n(n-1)\dots(n-r+1)}{r!} \left(\frac{d}{n}\right)^r \left(1-\frac{d}{n}\right)^{n-r}$$

$$= \frac{d^r}{r!} \underbrace{\left(\frac{n}{n}\right)\left(\frac{n-1}{n}\right)\dots\left(\frac{n-r+1}{n}\right)}_{n^r} \left(1-\frac{d}{n}\right)^n$$

$$= \frac{d^r}{r!} \left(\frac{n}{n}\right)\left(\frac{n-1}{n}\right)\dots\left(\frac{n-r+1}{n}\right) \frac{\left(\frac{(n-d)}{n}\right)^{\frac{r}{2}}}{\left(1-\frac{d}{n}\right)^n}$$

$$\lim_{n \rightarrow \infty} P(r) = \frac{d^r}{r!} e^{-d}$$

$$\underline{r=0}$$

$$P(0) = {}^n C_0 p^0 (1-p)^n = \left(1-\frac{d}{n}\right)^n$$

$$= e^{-d}$$