Probability and Statistics

November 14, 2018

Contents

Discrite Distributions

1 Generic Formulas

1.1 Expected Value

X is discrete random variable $g: \mathbf{R} \to \mathbf{R}$ $\Omega X = Im(X)$

$$E[g(X)] = \sum_{x \in \Omega X} P(X = x) * g(x)$$
(1)

1.2 Variance

$$var(g(X)) = E([g(X) - E(g(X))]^2)$$
 (2)

$$= \sum_{x \in \Omega X} [g(X) - E(g(X))]^2 * P(X = x)]$$
 (3)

$$= \sum_{x \in \Omega X} \left[g(X)^2 - 2 * g(X) * E(g(X)) + E(g(X))^2 \right] * P(X = x)$$
 (4)

$$= \sum_{x \in OX} g(X)^2 * P(X = x)$$
 (5)

$$-\sum_{x \in \Omega X} 2 * g(X) * E(g(X)) * P(X = x)$$
 (6)

$$+\sum_{x\in\Omega X} E(g(X))^2 * P(X=x)$$
(7)

$$= \sum_{x \in \Omega X} g(X)^2 * P(X = x) \tag{8}$$

$$-2 * E(g(X)) * \sum_{x \in \Omega X} g(X) * P(X = x)$$
 (9)

$$+E(g(X))^{2} * \sum_{x \in \Omega X} P(X=x)$$

$$\tag{10}$$

$$= E(g(X)^{2}) - 2 * E(g(X)) * E(g(X)) + E(g(X))^{2} * 1$$
(11)

$$= E(g(X)^{2}) - 2 * E(g(X))^{2} + E(g(X))^{2}$$
(12)

$$= E(g(X)^{2}) - E(g(X))^{2}$$
(13)

 $\square \tag{14}$

Covariance Matrix 1.3

$$cov(X) = E[(X - E(X))]^2$$
(15)

$$= \sum_{x \in \Omega X} (X - E(X))^2 * P(X = x)$$
 (16)

$$= \sum_{x \in \Omega X} [X^2 - 2XE(X) + E(X)^2] * P(X = x)$$
 (17)

$$= \sum_{x \in \Omega X} X^2 P(X = x) \tag{18}$$

$$-\sum_{x \in \Omega X} 2XE(X) * P(X = x)$$
(19)

$$+\sum_{x\in\Omega X} E(X)^2 P(X=x) \tag{20}$$

$$= \sum_{x \in \Omega X} X^2 P(X = x) \tag{21}$$

$$-2E(X) * \sum_{x \in \Omega X} XP(X = x)$$
 (22)

$$+E(X)^{2} * \sum_{x \in \Omega X} P(X = x)$$

$$= E(X^{2}) - 2E(X)E(X) + E(X)^{2} * 1$$
(23)

$$= E(X^{2}) - 2E(X)E(X) + E(X)^{2} * 1$$
(24)

$$= E(X^{2}) - 2 * E(X)^{2} + E(X)^{2}$$
(25)

$$= E(X^2) - E(X)^2 (26)$$

$$= E(X^t X) - \mu^t \mu \tag{27}$$

(28)

1.4 Variance of the Sample Mean

$$Var\left(\overline{X}\right) = Var\left(\frac{1}{n}\sum_{i=1}^{n}X_{i}\right) \tag{29}$$

$$= \frac{1}{n^2} Var\left(\sum_{i=1}^n X_i\right) \tag{30}$$

$$= \frac{1}{n^2} \sum_{i=1}^{n} Var(X_i), \text{ by independence}$$
 (31)

$$= \frac{1}{n^2} \left[Var(X_1) + Var(X_2) + \ldots + Var(X_n) \right]$$
 (32)

$$= \frac{1}{n^2} \left[\sigma^2 + \sigma^2 + \ldots + \sigma^2 \right], \text{ since the } X_i \text{ are identically distributed}$$
(33)

$$=\frac{1}{n^2}(n\sigma^2)\tag{34}$$

$$=\frac{\sigma^2}{n}\tag{35}$$

1.5 Law of Iterated Expectation

$$E[X] = E[E[X|Y]] \tag{36}$$

1.6 Law of Total Variance

$$var(X) = E[var(X|Y)] + var(E[X|Y])$$
(37)

1.7 MSE

$$\begin{array}{ll} \hat{\theta} = \hat{\theta}(X) \; \text{Random Variable} & (38) \\ E[\hat{\theta}] = \text{constant} & (49) \\ \theta = \text{true value, constant} & (41) \\ MSE(\hat{\theta}) = E[(\hat{\theta} - \theta)^2] & (42) \\ = E[(\hat{\theta} - E[\hat{\theta}] + E[\hat{\theta}]) - \theta)^2] & (43) \\ = E[([\hat{\theta} - E[\hat{\theta}]] + [E[\hat{\theta}] - \theta])^2] & (44) \\ = E[(A + B)^2] & (45) \\ A = \hat{\theta} - E[\hat{\theta}] & (47) \\ B = E[\hat{\theta}] - \theta & (48) \\ A = \hat{\theta} - E[\hat{\theta}] & (47) \\ B = E[(\hat{\theta} - E[\hat{\theta}])^2 + 2(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta) + (E[\hat{\theta}] - \theta)^2] & (51) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + E[2(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta)] + E[(E[\hat{\theta}] - \theta)^2] & (52) \\ E[(\hat{\theta} - E[\hat{\theta}])^2] + E[2(\hat{\theta} - E[\hat{\theta}])(C)] + E[C^2] & (56) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2CE[\hat{\theta} - E[\hat{\theta}]] + C^2 & (57) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2C(E[\hat{\theta}] - E[E[\hat{\theta}]]) + C^2 & (58) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2C(E[\hat{\theta}] - E[E[\hat{\theta}]]) + C^2 & (59) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2C(E[\hat{\theta}] - E[\hat{\theta}]) + C^2 & (60) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + C^2 & (61) \\ = E[(\hat{\theta} - E[\hat{\theta}])^2] + (E[\hat{\theta}] - \theta)^2 & (62) \\ (63) \\ var(\hat{\theta}) = E[(\hat{\theta} - E[\hat{\theta}])^2] & (64) \\ bias(\hat{\theta}, \theta) = E[(\hat{\theta} - E[\hat{\theta}])^2] & (64) \\ bias(\hat{\theta}, \theta) = E[(\hat{\theta} - E[\hat{\theta}])^2] & (64) \\ bias(\hat{\theta}, \theta) = E[(\hat{\theta} - E[\hat{\theta}])^2] & (64) \\ evar(\hat{\theta}) + (bias(\hat{\theta}, \theta))^2 & (65) \\ \end{array}$$

2 Binomial Distribution

PMF

$$P(X = k) = \binom{n}{k} p^k (1 - p)^{n - k}$$
(69)

2.1 Expected Value

E[g(X)] when g(X) = X.

$$E(X) = \sum_{k \geqslant 0} P(x = k) * k \tag{70}$$

$$= \sum_{k \geqslant 0} \left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k \tag{71}$$

(72)

when

$$k = 0$$

, the formula

$$\left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k = \left[\binom{n}{0} p^k (1-p)^n \right] * 0 = 0$$

, so the index of the summation can be increased by 1.

$$E(X) = \sum_{k \ge 1} \binom{n}{k} p^k (1-p)^{n-k} * k$$
 (73)

$$= \sum_{k\geqslant 1} \frac{n}{k} * \binom{n-1}{k-1} p^k (1-p)^{n-k} * k \quad \text{see BinomialCoefficient}$$

$$= \sum_{k \ge 1} \frac{n * k}{k} * \binom{n-1}{k-1} p^k (1-p)^{n-k}$$
 (75)

(74)

(87)

$$= \sum_{k>1} n * \binom{n-1}{k-1} p^k (1-p)^{n-k}$$
 (76)

$$= \sum_{k>1} n * p * \binom{n-1}{k-1} p^{k-1} (1-p)^{n-k}$$
(77)

$$= np * \sum_{k \ge 1} {n-1 \choose k-1} p^{k-1} (1-p)^{n-k}$$
 (78)

$$u = n - 1 \tag{79}$$

$$z = k - 1 \tag{80}$$

$$u - z = (n - 1) - (k - 1) \tag{81}$$

$$= n - 1 - k + 1 \tag{82}$$

$$= n - k \tag{83}$$

$$k > 1 = (z+1) > 1 \tag{84}$$

$$= z > 0 \tag{85}$$

$$= np * \sum_{z > 0} {u \choose z} p^z (1-p)^{u-z} \tag{86}$$

$$= np*1 \\ see Binomial Distribution Proof Equals 1$$

$$= np \tag{88}$$

$$\square \tag{89}$$

2.2 Variance

$$Var(X) = E(X^2) - E(X)^2$$
 see Variance (90)
= $\sum_{k\geqslant 0} \left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k^2 - np$ see Binomial Expected Value (91)

when

$$k = 0$$

, the formula

$$\left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k = \left[\binom{n}{0} p^k (1-p)^n \right] * 0 = 0$$

, so the index of the summation can be increased by 1.

$$= \sum_{k \ge 1} \left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k^2 - (np)^2$$
 (92)

$$= \sum_{k \ge 1} \frac{n}{k} \left[\binom{n-1}{k-1} p^k (1-p)^{n-k} \right] * k^2 - (np)^2$$
(93)

$$= \sum_{k>1} \frac{n * k^2}{k} \left[\binom{n-1}{k-1} p^k (1-p)^{n-k} \right] - (np)^2$$
(94)

$$= \sum_{k \ge 1} \left[nk * \binom{n-1}{k-1} p^k (1-p)^{n-k} \right] - (np)^2$$
 (95)

$$= \sum_{k \ge 1} \left[nkp * \binom{n-1}{k-1} p^{k-1} (1-p)^{n-k} \right] - (np)^2$$
 (96)

$$= np * \sum_{k \ge 1} \left[k * \binom{n-1}{k-1} p^{k-1} (1-p)^{n-k} \right] - (np)^2$$
(97)

$$u = n - 1 \tag{98}$$

$$z = k - 1 \tag{99}$$

$$u - z = (n - 1) - (k - 1) \tag{100}$$

$$= n - 1 - k + 1 \tag{101}$$

$$= n - k \tag{102}$$

$$k >= 1 = (z+1) >= 1 \tag{103}$$

$$=z>=0 \tag{104}$$

$$= np * \sum_{z \ge 0} \left[(z+1) * \binom{u}{z} p^z (1-p)^{u-z} \right] - (np)^2$$
 (105)

$$= np * [\sum_{z \geqslant 0} \left[z * \binom{u}{z} p^z (1-p)^{u-z}\right] + \sum_{z \geqslant 0} \left[\binom{u}{z} p^z (1-p)^{u-z}\right] - (np)^2$$

(106)

$$= np * \left[\sum_{z \ge 0} \left[z * \frac{u}{z} * \binom{u-1}{z-1} p^z (1-p)^{u-z} \right] + \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] \right] - (np)^2$$
(107)

$$= np * \left[u * \sum_{z \ge 0} \left[\binom{u-1}{z-1} p^z (1-p)^{u-z} \right] + \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] - (np)^2$$

(108)

(109)

$$= np * [up * \sum_{z \ge 0} \left[\binom{u-1}{z-1} p^{z-1} (1-p)^{u-z} \right] + \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] - (np)^2$$

$$(110)$$

$$= np * [up * \sum_{z \ge 1} \left[\binom{u-1}{z-1} p^{z-1} (1-p)^{(u-1)-(z-1)} \right] + \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] - (np)^2$$

$$(111)$$

$$= np * [up * \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] + \sum_{z \ge 0} \left[\binom{u}{z} p^z (1-p)^{u-z} \right] - (np)^2$$

$$= np * [up * (p+q)^{u-1} + (p+q)^u] - (np)^2$$

$$= np * [(n-1) * p * (p+q)^{n-1} + (p+q)^n (n-1)] - (np)^2$$

$$= np * \left[(n-1) * p * (p+q)^{n-2} + (p+q)^n (n-1) \right] - (np)^2$$

$$= np * \left(\left[(n-1) * p * (p+q)^{n-2} + (p+q)^n (n-1) \right] - (np)^2$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$= np * \left(\left[(n-1) * p + 1 \right] - np \right)$$

$$=$$

3 Bernoulli Distribution

The Bernoulli Distribution is a special case of the Binomial Distribution, where

n = 1

PMF

$$P(X=k) = {1 \choose k} p^k (1-p)^{1-k}$$
 (124)

$$= p^k (1-p)^{n-k} (125)$$

3.1 **Expected Value**

$$E(x) = \sum_{k \ge 1} \left[\binom{n}{k} p^k (1-p)^{n-k} \right] * k$$
 (126)

$$= np$$
 $see Binomial Distribution$ (127)

$$=1*p \tag{128}$$

$$= p \tag{129}$$

Variance 3.2

$$Var(X) = np * (1-p)$$
(130)

$$= p * (1 - p) \tag{131}$$

(132)

Likelihood of IID Bernoulli 3.3

$$x_i \stackrel{iid}{\sim} Bernoulli(p)$$
 (133)

$$L(x_i|p) = p(x_1, x_2, ..., x_n|p)$$
(134)

$$= \prod_{n=1}^{n} p(x_i|p)$$

$$= p^S * (1-p)^{n-S}$$
(135)

$$= p^S * (1-p)^{n-S} (136)$$

3.4 Maximun Likelihood

$$\frac{d[L(x_i|p)]}{dp} = \frac{d[p^S * (1-p)^{n-S}]}{dp}$$
 (137)

$$\frac{d[log(L(x_i|p))]}{dp} = \frac{d[log(p^S * (1-p)^{n-S})]}{dp}$$
 (138)

$$= \frac{d}{dp} * [log(p^S * (1-p)^{n-S})]$$
 (139)

$$= \frac{d}{dp}[log(p^S) + log((1-p)^{n-S})]$$
 (140)

$$= \frac{d}{dp}[S * log(p) + (n - S) * log(1 - p)]$$
 (141)

$$= S * \frac{d}{dp}[log(p)] + (n - S) * \frac{d}{dp}[log(1 - p)]$$
 (142)

$$=S*[\frac{1}{p}]+(n-S)*\frac{d}{dp}[log(1-p)] \qquad \qquad \text{chain rule } \eqno(143)$$

$$= S * \frac{1}{p} + (n - S) * \frac{1}{p - 1}$$
 (144)

$$=\frac{S}{p} + \frac{n-S}{p-1} \tag{145}$$

$$= \frac{S * (p-1)}{p * (p-1)} + \frac{p * (n-S)}{p * (p-1)}$$
(146)

$$= \frac{S * (p-1) + p * (n-S)}{p * (p-1)}$$
(147)

$$= \frac{S * (p-1) + p * (n-S)}{p * (p-1)}$$

$$= \frac{S * p - S + p * n - p * S}{p * (p-1)}$$
(147)

$$= \frac{-S + p * n}{p * (p - 1)} \tag{149}$$

$$0 = \frac{-S + p * n}{p * (p - 1)} \tag{150}$$

$$0 * (p * (p - 1)) = -S + p * n \tag{151}$$

$$0 = -S + p * n \tag{152}$$

$$S = p * n \tag{153}$$

$$\frac{S}{n} = p \tag{154}$$

$$p = \frac{S}{n} \tag{155}$$

(156)

4 Geometric Distribution

4.1 CDF

$$P(X \le x) =$$

$$CDF(X = x) = \sum_{i=0}^{x} (1-p)^{i}p$$
 by geometric summation
$$= p\frac{1-(1-p)^{x}}{1-(1-p)}$$

$$= p\frac{1-(1-p)^{x}}{1-1+p}$$

$$= p\frac{1-(1-p)^{x}}{p}$$

$$= 1-(1-p)^{x}$$

$$\Box$$

$$P(X > x) = 1-CDF(X = x)$$

$$= 1-(1-(1-p)^{x})$$

$$= 1-1+(1-p)^{x}$$

$$= (1-p)^{x}$$

5 Normal Distribution

5.1 Definition

$$pdf(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$
 (157)

Continuous Distributions

6 Uniform Distribution

6.1 PDF

$$\int_{a}^{b} k dx = 1$$

$$= k \int_{a}^{b} dx$$

$$= k[x]_{a}^{b}$$

$$= k[b - a]$$

$$k[b-a] = 1$$
$$k = \frac{1}{b-a}$$

6.2 Expected Value

$$\int_{a}^{b} x \left(\frac{1}{b-a}\right) dx =$$

$$= \int_{a}^{b} x \left(\frac{1}{b-a}\right) dx$$

$$= \frac{1}{b-a} \int_{a}^{b} x dx$$

$$= \frac{1}{b-a} \left[\frac{x^{2}}{2}\Big|_{a}^{b}\right]$$

$$= \frac{1}{b-a} \left[\frac{b^{2} - a^{2}}{2}\right]$$

$$= \frac{1}{b-a} \left[\frac{b^{2} - a^{2}}{2}\right]$$

$$= \frac{1}{b-a} \left[\frac{(b+a)(b-a)}{2}\right]$$

$$= \frac{(b+a)(b-a)}{2(b-a)}$$

$$= \frac{b+a}{2}$$

6.3 Variance

$$var(X) = E[X^{2}] - E[X]^{2}$$

$$= \left[\int_{a}^{b} x^{2} \left(\frac{1}{b-a}\right) dx\right] - \left(\frac{b+a}{2}\right)^{2}$$

$$= \left[\frac{1}{b-a} \int_{a}^{b} x^{2} dx\right] - \left(\frac{b+a}{2}\right)^{2}$$

$$= \left[\frac{1}{b-a} \frac{x^{3}}{3} \Big|_{a}^{b}\right] - \left(\frac{b+a}{2}\right)^{2}$$

$$= \frac{1}{b-a} \left(\frac{b^{3}}{3} - \frac{a^{3}}{3}\right) - \left(\frac{b+a}{2}\right)^{2}$$

$$= \frac{b^{3} - a^{3}}{3(b-a)} - \frac{(b+a)^{2}}{4}$$

$$= \frac{(b-a)(b^{2} - ab + a^{2})}{3(b-a)} - \frac{(b+a)^{2}}{4}$$

$$= \frac{(b^{2} - ab + a^{2})}{12} - \frac{3(b+a)^{2}}{12}$$

$$= \frac{4b^{2} - 4ab + 4a^{2}}{12} - \frac{3(b^{2} + 2ab + a^{2})}{12}$$

$$= \frac{4b^{2} - 4ab + 4a^{2}}{12} - \frac{3b^{2} + 6ab + 3a^{2}}{12}$$

$$= \frac{4b^{2} - 3b^{2} - 4ab - 6ab + 4a^{2} - 3a^{2}}{12}$$

$$= \frac{b^{2} - 2ab + a^{2}}{12}$$

$$= \frac{(b-a)^{2}}{12}$$

7 Exponential Distribution

7.1 PDF

$$f_x(x) = -\lambda e^{-\lambda x} \qquad x >= 0$$

7.2 Expected Value

$$f_x(x) = \lambda e^{-\lambda x}$$

$$E[x] = \int x * f_x(x) dx$$

$$E[x] = \int x * \lambda e^{-\lambda x} dx$$

$$u = x$$

$$du = 1 * dx$$

$$v = e^{-\lambda x}$$

$$dv = e^{-\lambda x} * -\lambda * dx$$

$$dv = -\lambda e^{-\lambda x} dx$$

$$E[x] = \int [x][\lambda e^{-\lambda x} dx]$$

$$E[x] = -1 * \int [x][-1 * \lambda e^{-\lambda x} dx]$$

$$E[x] = -1 * \int [x][-\lambda e^{-\lambda x} dx]$$

$$E[x] = -1 * \int u dv$$

$$E[x] = -1 * [uv]_{-\infty}^{\infty} - \int v du]$$

$$E[x] = -1 * [uv]_{0}^{\infty} - \int v du]$$
 because x bounds
$$E[x] = -1 * [[xe^{-\lambda x}]_{0}^{\infty} - \int e^{-\lambda x} dx]$$

$$[xe^{-\lambda x}]_0^{\infty} = \lim_{x \to \infty} [xe^{-\lambda x} - (0)e^{-\lambda(0)}]$$

$$= \lim_{x \to \infty} [xe^{-\lambda x} + 0e^0]$$

$$= \lim_{x \to \infty} [xe^{-\lambda x}]$$

$$= 0$$

$$E[x] = -1 * - \int e^{-\lambda x} dx$$

$$E[x] = \frac{1}{\lambda} \int \lambda e^{-\lambda x} dx$$

$$E[x] = \frac{1}{\lambda}$$