

Lecture 15

Warm Up: A factory produces light bulbs, and each bulb is defective with probability 0.2. A quality inspector randomly selects 10 bulbs. Find the prob that 7 of selected bulbs are defective. What is the expected number of defective balls?

1) $X = \#$ of defective balls

2) $X \sim \text{Binomial}(10, 0.2)$

3) $P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}$
 $\hookrightarrow P(X=7) = \binom{10}{7} (0.2)^7 (0.8)^3$

4) $E[X] = np$

$\hookrightarrow E[X] = 10(0.2) = 2$

Functions of Discrete Random Variables

$X \sim$ discrete random variable with range \mathcal{X} and pmf $p: \mathcal{X} \rightarrow [0,1]$

Then for any $f: \mathbb{R} \rightarrow \mathbb{R}$, we get a new random variable $f(X)$ such that

the following holds:

• if the value of X is $x \in \mathcal{X}$, then the value of $f(X)$ is $f(x)$

• $P(F(X)=y) = \sum_{\substack{x \in \mathcal{X} \\ f(x)=y}} p(x)$

Ex Suppose X is discrete random variable with

$$X = Z = \{0, \pm 1, \pm 2, \pm 3, \dots\}$$

and pmf $p_n = P(X=n) \quad \forall n \in \mathbb{Z}$ then X^2 is a random variable

with range $\{0, 1^2, 2^2, \dots\} = \{0, 1, 4, 9, \dots\}$

$$P(X^2=0) = p_0$$

$$P(X^2=1) = p_{-1} + p_1$$

$$P(X^2=4) = p_{-2} + p_2$$

$$P(X^2=9) = 0$$

Thm: Law of Subconscious Statistician

$X \sim$ discrete random variable with $X = \{x_1, x_2, \dots\} \subset \mathbb{R}$ and pmf $P(x_k) = P(X=x_k) \quad \forall k \geq 1$

Then for any function $f: \mathbb{R} \rightarrow \mathbb{R}$, if the expectation of $f(X)$ exists, it is given

$$\text{by } E[f(X)] = \sum_{k=1}^{\infty} f(x_k) P(x_k)$$

Cor: Linearity of the Expectation

Given $X \sim$ Discrete random variable and f, g , be two functions. Then:

$$E[f(X) + g(X)] = E[f(X)] + E[g(X)]$$

In particular for any a, b we have $E[aX + b] = a(E[X]) + b$

Proof:

$$P_k = P(X = x_k), \quad X = \{x_1, \dots\}$$

$$E[f(x) + g(x)] = \sum_{k \geq 1} P_k [f(x_k) + g(x_k)]$$

$$= \underbrace{\sum_{k \geq 1} P_k f(x_k)}_{E[f(x)]} + \underbrace{\sum_{k \geq 1} P_k g(x_k)}_{E[g(x)]}$$

$$E[aX + b] = \sum_{k \geq 1} P_k (ax_k + b) = a \underbrace{\sum_{k \geq 1} P_k x_k}_{E[X]} + b \underbrace{\sum_{k \geq 1} P_k}_1$$

Recall: $\text{var}[X] = \sum_{x \in \mathcal{X}} (x - \mu)^2 p(x)$

$$\mu = E[X]$$

Cor: Let X be 2-integrable discrete random variable with the mean μ .

$$\text{Then } \mu_n[X] = E[X^n] \quad \forall n \in \{1, 2, \dots\}$$

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

Moreover, for any $a, b \in \mathbb{R}$ we have $\text{var}[aX + b] = a^2 \text{var}[X]$

Proof: $\mu_X = E[X]$. We set $Y = aX + b$ then $\mu_Y = E[Y] = a\mu_X + b$. Hence

$$Y - \mu_Y = (aX + b) - (a\mu_X + b) = a(X - \mu_X)$$

$$\text{var}[Y] = E[(Y - \mu_Y)^2] = E[a^2(X - \mu_X)^2]$$

$$= a^2 E[(X - \mu_X)^2]$$

$$= a^2 \text{var}[X]$$

Cor: $X \sim$ discrete random variable, $\mathcal{X} \subset \{0, 1, 2, \dots\}$

Denote by G_X its pgf. The $\forall s \in [0, 1]$

$$G_X(s) = E[s^X]$$

Proof: $p_n = P(X=n)$

$$E[s^X] = p_0 s^0 + p_1 s^1 + p_2 s^2 + \dots \stackrel{\text{by definition}}{=} G_X(s)$$

by Thm

Cor: Monotonicity of the Expectation

$X, f, g: \mathcal{X} \rightarrow \mathbb{R}$ such that $f(x) \leq g(x) \quad \forall x \in \mathcal{X}$

Then $E[f(X)] \leq E[g(X)]$

Proof:

$$E[f(X)] = \sum_{x \in \mathcal{X}} p(x) f(x) \leq \sum_{x \in \mathcal{X}} p(x) g(x) = E[g(X)]$$

Prop: Markov Inequality

$X \sim$ discrete random variable, \mathcal{X} consisting of only non-negative numbers and

Some pdf: $\mathcal{X} \rightarrow [0, 1]$. Then:

$$P(X > c) \leq \frac{1}{c} E[X] \quad \forall c > 0$$

Proof: $X \geq 0, c > 0$

$$P(X > c) = \sum_{\substack{x > c \\ x \in \mathcal{X}}} P(X=x)$$

$$c P(X > c) = \sum_{\substack{x > c \\ x \in \mathcal{X}}} c P(x) < \sum_{\substack{x > c \\ x \in \mathcal{X}}} x P(x) \leq \sum_{x \in \mathcal{X}} x P(x) = E[X]$$

because range is nonnegative
↓

Thm: Chebyshev's inequality

$X \sim$ discrete random variable, $X \in L^2$, $\mu = E[X]$, $\sigma = \sqrt{\text{var}[X]}$

Then for any $c, r > 0$

$$P(|X - \mu| > c\sigma) \leq \frac{1}{c^2}$$

$$P(|X - \mu| > r) \leq \frac{\sigma^2}{r^2}$$

This inequality tells us how much the value of the random variable deviates from the mean.

Proof:

$$c^2 \sigma^2 P(|X-\mu| > c\sigma)$$

$$= c^2 \sigma^2 \sum_{\substack{x \in \mathcal{X} \\ |x-\mu| > c\sigma}} p(x) = \sum_{\substack{x \in \mathcal{X} \\ |x-\mu| > c\sigma}} c^2 \sigma^2 p(x) \leq \sum_{\substack{x \in \mathcal{X} \\ |x-\mu| > c\sigma}} (x-\mu)^2 p(x) \leq \sum_{x \in \mathcal{X}} (x-\mu)^2 p(x) = \text{var}[X] = \sigma^2$$