

Expectation

* Definition. Let \underline{X} be a discrete rv with set of possible values \mathcal{D} and pmf $p(x)$. The expectation of

\underline{X} , denoted by $E(\underline{X})$ is

$$E(\underline{X}) = \sum_{x \in \mathcal{D}} x p(x)$$

As center of gravity of $p(x)$ if we present the distribution by the histogram, with bars of uniform unit density

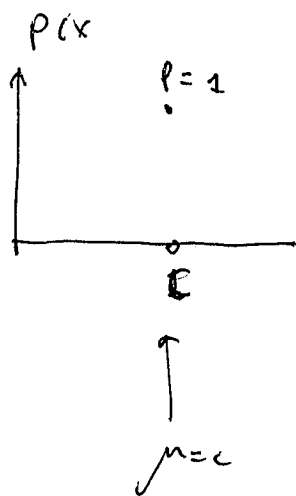
* Remark: * $E(\underline{X})$ is also known as the expected value of \underline{X} , or the mean of \underline{X} , or the first moment of \underline{X}

* We assume that the summation converges absolutely. i.e,

$$\sum_{x \in \mathcal{D}} |x| p(x) < \infty$$

* Examples * Trivial rv. Let \underline{X} be constant, i.e.

$$\underline{X}(\omega) = c \quad \forall \omega \in \Omega$$



Then

$$p(x) = \begin{cases} 1, & x = c \\ 0, & x \neq c \end{cases}$$

and

$$E(\underline{X}) = c$$

- Bernoulli r.v. / indicator r.v. Let X can take only the values 0 or 1, then \bar{X} is said to be a Bernoulli r.v. / indicator r.v. If we define the event on which $\bar{X} = 1$,

$A = \{\omega : \bar{X}(\omega) = 1\}$

then \bar{X} is said to be the indicator of A .

Then

$$P(X) = \begin{cases} p, & x=1 \\ 1-p, & x=0 \\ 0, & x \neq 0, 1 \end{cases}$$

and

$$E(X) = p \quad (= 1 \times p + 0 \times (1-p))$$

- Uniform r.v. Let \bar{X} be uniform on the integers $\{1, 2, \dots, n\}$. Then

$$\sum P(x) = 1,$$

$$P(x) = \begin{cases} n^{-1}, & 1 \leq x \leq n, \quad x \text{ integer} \\ 0, & \text{otherwise} \end{cases}$$

and

$$E(\bar{X}) = n^{-1} \sum_{j=1}^n j = \frac{1}{2}(n+1) = \text{the average of } \{1, \dots, n\}$$

- Triangular r.v.

In this case, we have

$$\sum P(j) = 1, \quad P(j) = n^{-2} \min\{n+j, n-j\}$$

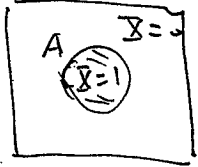
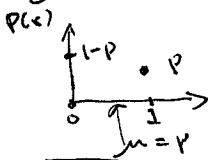
$$= \begin{cases} n^{-2}(n-j), & 0 \leq j \leq n \\ n^{-2}(n+j), & -n \leq j \leq 0 \end{cases}$$

and

$$E(\bar{X}) = 0 \quad \left(= \sum_{j=0}^n j n^{-2}(n-j) + \sum_{j=-n}^0 j n^{-2}(n+j) \right)$$

Ex: Flip a fair coin with $P(0) = P(1) = \frac{1}{2}$

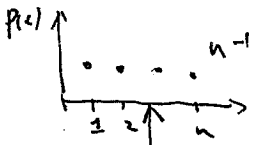
$$\mu = \frac{1}{2}$$



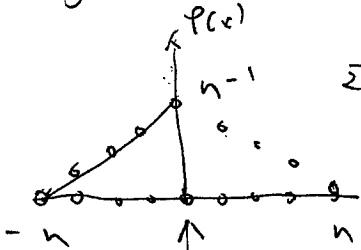
$$P(A) = p$$

Ex: Roll a fair die with $P(j) = \frac{1}{6}, 1 \leq j \leq 6$

$$\mu = \frac{7}{2}$$

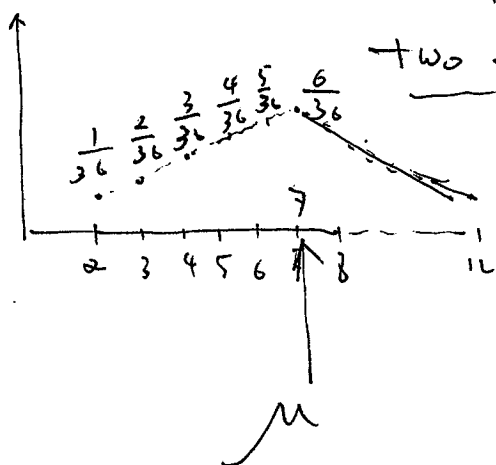


$$\mu = \frac{1}{2}(n+1)$$



$$\mu = 0$$

$\varphi(x)$



* Example. Let \bar{X} = the sum of the scores of two fair dice. Then

$$\varphi(j) = 6^{-2} \min\{j-1, 13-j\}, \quad 2 \leq j \leq 12$$

and

$$E(\bar{X}) = 7$$

* Geometric mean. Let \bar{X} be a geometric rv with parameter p . Then

Ex: A sequence of independent Bernoulli trials with probability p to win.

$$\sum_{j=1}^{\infty} p(j) = 1,$$

$$p(j) = p(1-p)^{j-1}, \quad j = 1, 2, 3, \dots$$

and

\bar{X} = nb of trials needed until the first win.

$$E(\bar{X}) = \sum_{j=1}^{\infty} j p(1-p)^{j-1} = p \sum_{j=1}^{\infty} \left[-\frac{d}{dp} (1-p)^j \right] = p^{-1}$$

* Tail sum. When $\bar{X} \geq 0$ and \bar{X} is integer valued, show that

* geometric mean

$$E(\bar{X}) = \sum_{j=0}^{\infty} (1-p)^j = \frac{1}{p}$$

$$E(\bar{X}) = \sum_{j=0}^{\infty} \{1 - F(j)\}$$

Proof.

$$\begin{aligned} E(\bar{X}) &= \sum_{j=1}^{\infty} j p(j) = p(1) + p(2) + p(2) + p(3) + p(3) + p(3) + \dots \\ &= \sum_{j=1}^{\infty} p(j) + \sum_{j=2}^{\infty} p(j) + \sum_{j=3}^{\infty} p(j) + \dots \\ &= [1 - F(0)] + [1 - F(1)] + [1 - F(2)] + \dots = \sum_{j=0}^{\infty} \{1 - F(j)\} \end{aligned}$$

Expectation of functions

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Theorem: Let \bar{X} and \bar{Y} be discrete, with
$$\bar{Y} = g(\bar{X}).$$

Then

$$E(\bar{Y}) = \sum_{x \in D} g(x) \varphi(x)$$

Proof: For some fixed y ,

$$\sum_{\substack{x \in D \\ g(x)=y}} g(x) \varphi(x) = \sum_{\substack{x \in D \\ g(x)=y}} y \varphi(x) = y \sum_{\substack{x \in D \\ g(x)=y}} \varphi(x)$$

Given the distribution $\varphi(x)$, \bar{Y} has distribution
at \bar{X} ,

$$P_{\bar{Y}}(y) = \sum_{\substack{x \in D \\ g(x)=y}} \varphi(x)$$

Then

$$E(\bar{Y}) = \sum_y y P_{\bar{Y}}(y) = \sum_y \left\{ y \sum_{\substack{x \in D \\ g(x)=y}} \varphi(x) \right\}$$

$$= \sum_y \sum_{\substack{x \in D \\ g(x)=y}} g(x) \varphi(x)$$

$$= \sum_{x \in D} g(x) \varphi(x)$$

Remark. 1° We do not need to find the distribution of \bar{Y} in order to find its mean.

2° It is not true in general that

$$E[g(\bar{X})] = g[E(\bar{X})].$$

Corollary: linear transformation

$$E[a\bar{X} + b] = a E[X] + b$$

Proof.

$$\begin{aligned} E[a\bar{X} + b] &= \sum_{\pi} (a x + b) \varphi(x) = a \sum_{\pi} x \varphi(x) + b \sum_{\pi} \varphi(x) \\ &= a E[X] + b \end{aligned}$$

Corollary: linearity of expectation

$$E[g(\bar{X}) + h(\bar{X})] = E[g(\bar{X})] + E[h(\bar{X})]$$

Proof:

$$\begin{aligned} E[g(\bar{X}) + h(\bar{X})] &= \sum_{\pi} (g(x) + h(x)) \varphi(x) \\ &= \sum_{\pi} g(x) \varphi(x) + \sum_{\pi} h(x) \varphi(x) \\ &= E[g(\bar{X})] + E[h(\bar{X})]. \end{aligned}$$

* Example. Let \bar{Y} = sum of the scores of two fair dice.

Then $\bar{Y} = \bar{X} + u + 1$ where \bar{X} is the triangular r.v. and $u = 6$.

$$E[\bar{Y}] = E[\bar{X}] + 6 + 1 = 0 + 6 + 1 = 7.$$