

Random Variables: Discrete Continuous

↳ Basic probability tells you the chance of each outcome, but random variables help you calculate the average payout.

↳ Random Variable map to some numerical value once the outcome of an event is determined, that you can measure.

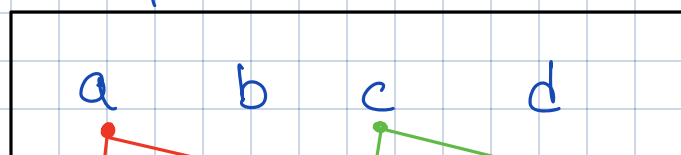
$$X = f(w)$$

$$X: \Omega \rightarrow \mathbb{R}$$

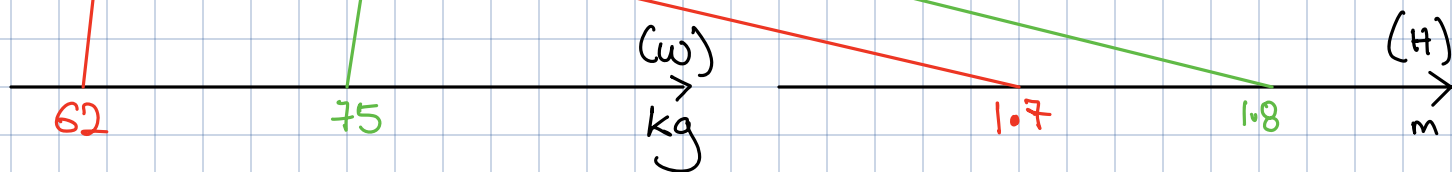
↳ Domain of X is sample space.

↳ Range can be \mathbb{R} , $(0, \infty)$, $(0, 1)$ etc

sample of students



↳ Pick a student at random and record his/her weight (w)



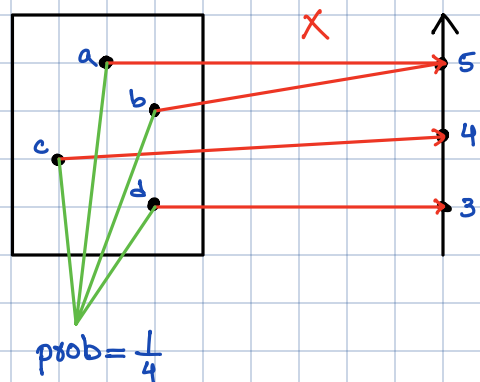
↳ Random Variable is a function that maps to some numerical value.

↳ Probabilistic experiment can have several associated RVs W & H.

↳ We can create a third RV like BMI = w/H^2 .

Probability Mass function:

↳ Some outcomes of an event are more or less likely than others.



↳ $X = x$ is an event.

$$x = 5, \{w: X(w) = 5\} \rightarrow \{a, b\}$$

PMF:



$$\hookrightarrow P_X(x) \geq 0$$

$$\hookrightarrow P_X(x_1) + \dots + P_X(x_n) = 1$$

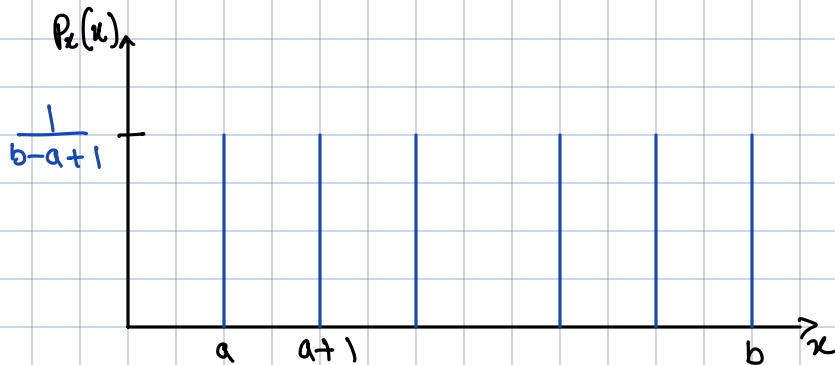
$$\hookrightarrow P_X(x) = P(X=x) \rightarrow P(\{w \in \Omega \text{ st } X(w)=x\})$$

Bernoulli Random Variable with parameter $[0,1]$

$$X = \begin{cases} 1, & p \\ 0, & 1-p \end{cases}$$

↳ Models a single trial that results in success/failure.

Discrete Uniform Random Variable:



- ↳ $a \leq b$, ints
- ↳ All equally likely
- ↳ $\Omega = \{a, a+1, \dots, b\}$

Binomial Random Variable:

↳ Represents number of successes in a fixed number of independent trials with binary outcomes.

↳ For example,

↳ Flip a coin.

↳ Success would be landing head

↳ Failure would be landing tails

↳ If we repeat this n times & count the success, then this count is a binomial random variable

Geometric Random Variable

↳ A type of random variable that counts no. of trials needed to get the first success.

↳ For example,

↳ A factory produces a working bulb with $p=0.9$.

↳ X : no. of bulbs until first working bulb is found.

$$P(X=k) = p(1-p)^{k-1} \text{ for } k=1, 2, 3, \dots$$

Expectation:

↳ Average gain.

$$E[X] = \sum_x P_x(x)$$

Expectation as a population average:

↳ Consider n students

↳ Weight of i th student: x_i

↳ Experiment: Pick a student at random, all equally likely

↳ Random Variable X : Weight of selected student

$$P_x(x_i) = \frac{1}{n}$$

$$E[X] = \sum_i x_i \cdot \frac{1}{n}$$

$$= \frac{1}{n} \sum_i x_i$$

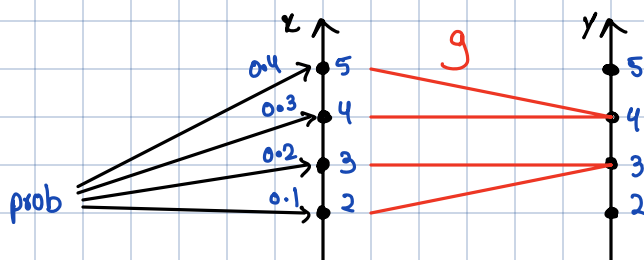
$$= \text{mean}\{x\}$$

The Expected value rule for calculating $E[g(x)]$

↳ Let X be a RV Δ let $Y = g(X)$

$$E[X] = \sum P_X(x)$$

$$E[g(x)] = \sum g(x) P_X(x)$$



Variance of Random Variable:

$$\sigma^2 = \text{Var}(X)$$

$$= E[X - E[X]]^2$$

$$= \sum_x (x - \mu)^2 P(x)$$

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

$$\sigma = \text{std}(X) = \sqrt{\text{Var}(X)}$$

PMFs of Random Variables

↳ If there are RVs X & Y , then (X, Y) is a random vector and its distribution is called joint distribution.

$$P_{X,Y}(x, y) = P(X=x, Y=y) \quad \text{for } -\infty < x, y < \infty$$

↳ Individual distributions of X & Y are called marginal distribution.

↳ It can be obtained by summing over the other variable.

Covariance & Correlation

$$\begin{aligned} \text{Cov}(X, Y) &= E\{(X - E[X])(Y - E[Y])\} \\ &= E[XY] - E[X]E[Y] \end{aligned}$$

$\text{Cov}(X, Y) > 0$: X & Y +vely related

$\text{Cov}(X, Y) < 0$: X & Y -vely related

$\text{Cov}(X, Y) = 0$: X & Y NOT related

↳ This has unit according to unit of X & Y & $\text{Cov}(X, Y)$ is unbounded. So, we can't tell if X & Y are strongly & weakly related.

↳ So, we need correlation ρ

$$\rho = \frac{\text{Cov}(X, Y)}{\text{std}(X) \text{std}(Y)}$$