

317 2015.01.29

Note Title

2015-01-29

Random variable

"A random variable is a function."

A random variable (in the classical interpretation) is a rule that assigns a numerical value to each outcome of an experiment.

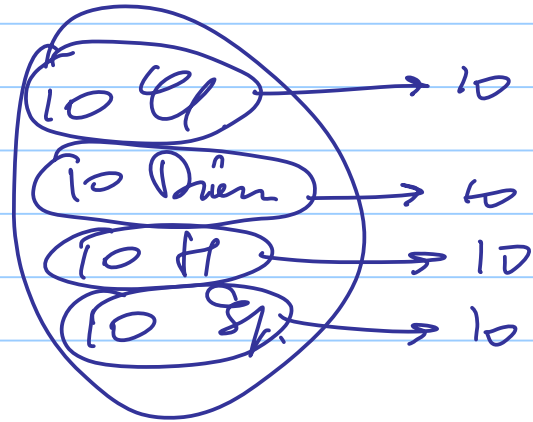
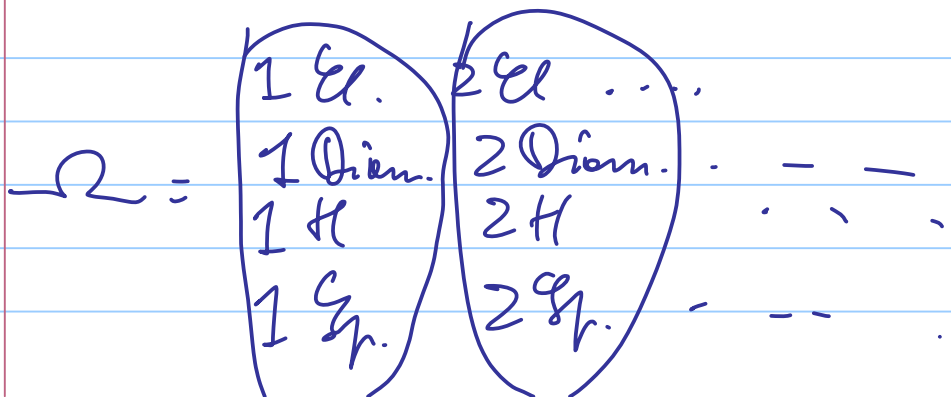
More formally (and for any model of the outcomes of K), it is a function from Ω to the real numbers.

Example.

Let Ω be the set of all cards from a 40-card deck (no face cards).

Then, the value of a card is a random variable.

This random variable maps the 4 cards that have a particular value to that value.



(Each $s \in \Omega$ is mapped to an integer between 1 and 10)

\downarrow \downarrow \downarrow
1 2 10

In general, a random variable partitions Ω .

There is a generalization of the defn, which is called a propositional variable.

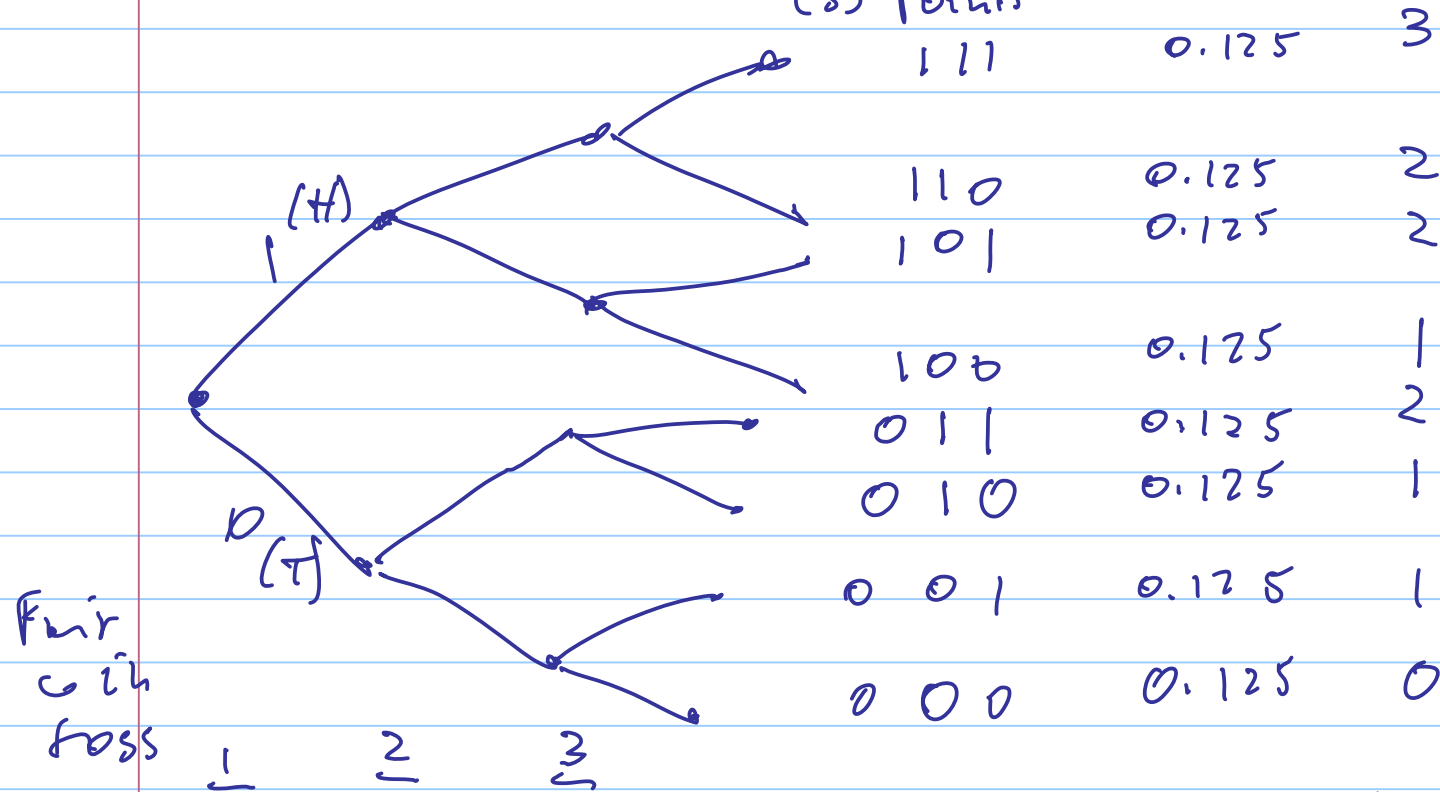
A propositional variable partitions the state space Ω .

Each partition corresponds to a value of the propositional variable.

Example

Experimental Outcomes
Sample (s) Points

Random Variable
 X (# of heads)
 $X(s)$



"A sequence of three Bernoulli trials with $p = 0.5$ "
"A binomial $(3, 0.5)$ "

The random variable defines 4 events, one per value

$$E_0 = \{s \in \Omega \mid X(s) = 0\} = \{000\}$$

$$E_1 = \{s \in \Omega \mid X(s) = 1\} = \{001, 010, 100\}$$

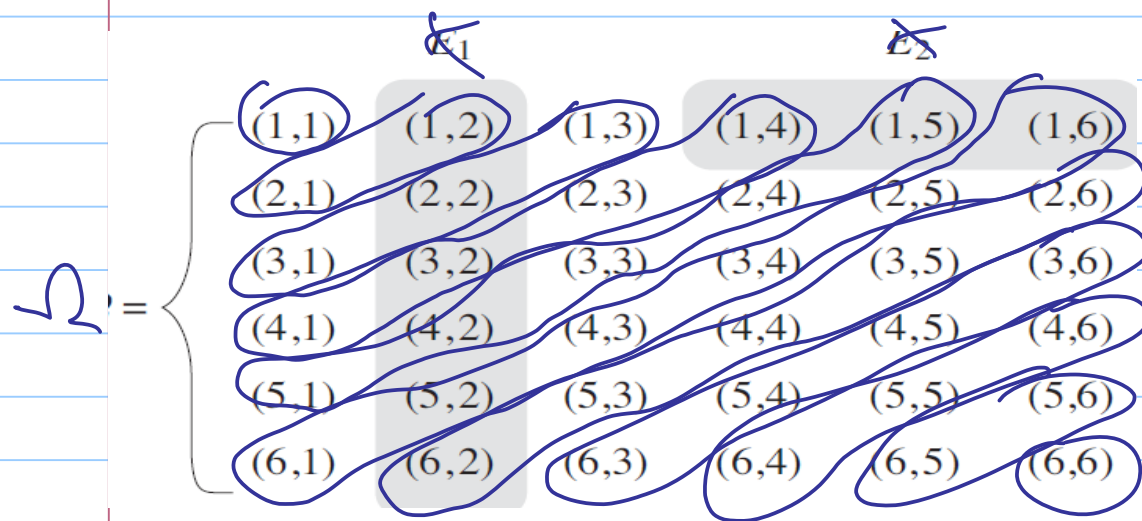
$$E_2 = \{s \in \Omega \mid X(s) = 2\} = \{011, 101, 110\}$$

$$E_3 = \{s \in \Omega \mid X(s) = 3\} = \{111\}$$

A discrete r.v. can take values from a set of discrete numbers (finite or countable).

[Examples up to now are discrete.]

A continuous r.v. can take an uncountable set of possible values.



Sum of values is a discrete r.v. whose values are $2, 3, \dots, 12$; let's call it T .

$$E_2 = \{s \in \Omega \mid T(s) = 2\} = \{(1,1)\}$$

$$E_{11} = \{s \in \Omega \mid T(s) = 11\} = \{(6,5), (5,6)\}$$

Probability Mass Function (p.m.f.)

The p.m.f. of an r.v. X , written $p_X(\cdot)$ is

$$p_X(a) = P(X=a), \text{ where } \sum_x p_X(x) = 1$$

We take $P(X=a)$ to be the probability of the event defined by $X=a$.

Ex. (Three coin tosses)

$$P(X=3) = 0.125 = P(\{111\})$$
$$P(X=1) = 0.375 = P(\{100, 010, 001\})$$

Ex. (two dice)

$$P(7) = P(\{(1,6), (2,5), (3,4), (4,3), (5,2), (6,1)\}) = \frac{6}{36} = \frac{1}{6}$$

Cumulative Distribution Function (cdf) of a r.v. X is

$$F_X(a) = P(\{X \leq a\}) = \sum_{x \leq a} p_X(x)$$

Ex. (two die) $F_X(4) = P(X \leq 4) = \sum_{x \leq 4} p_X(x) =$

$$= \cancel{p_X(1)} + p_X(2) + p_X(3) + p_X(4) = P(\{(1,1)\}) + P(\{(1,2), (2,1)\}) + P(\{(3,1), (2,2), (1,3)\}) = \frac{1}{36} + \frac{2}{36} + \frac{3}{36} = \frac{6}{36} = \frac{1}{6}$$

We also write

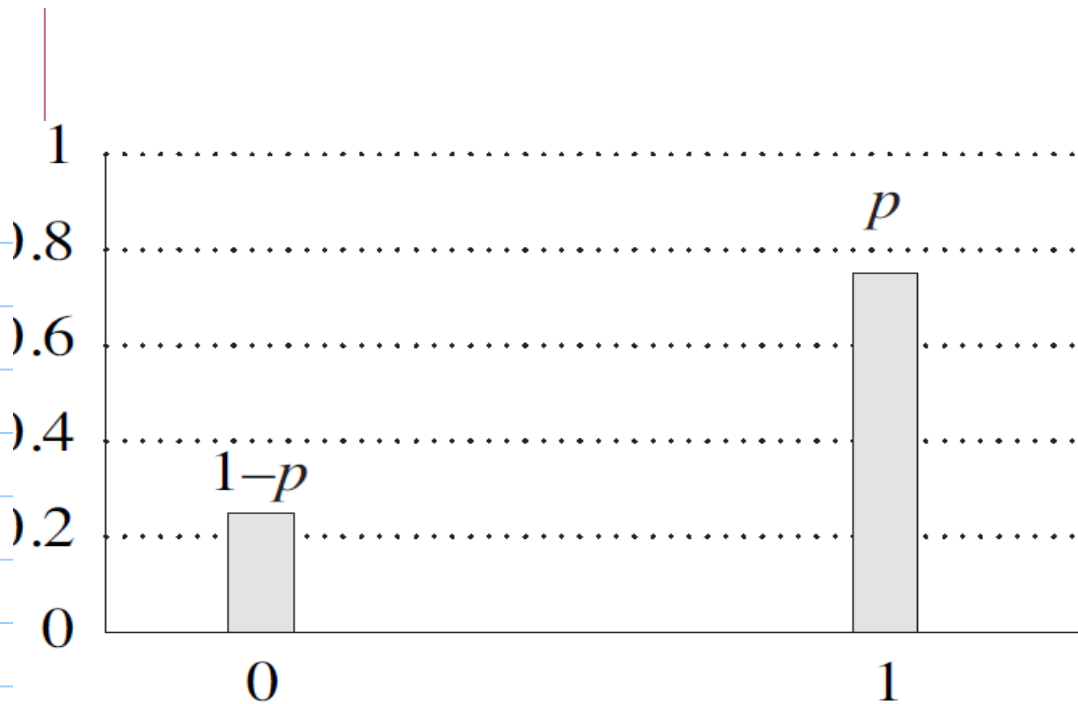
$$\overline{F}_X(a) = P(\{X > a\}) = \sum_{x > a} p_X(x) = 1 - F_X(a)$$

Some common discrete distributions.

Bernoulli (p) parameter corresponds to flipping one coin biased w/ prob. p .

The pmf (probability mass function) of r.v. X is

$$\begin{cases} P_X(1) = p \\ P_X(0) = 1-p \end{cases} \quad \Bigg| \quad X = \begin{cases} 1 & \text{w/ prob } p \\ 0 & \text{otherwise} \end{cases}$$



The proof of
the Bernoulli
distribution



the cdf

Binomial(n, p) (two parameters)

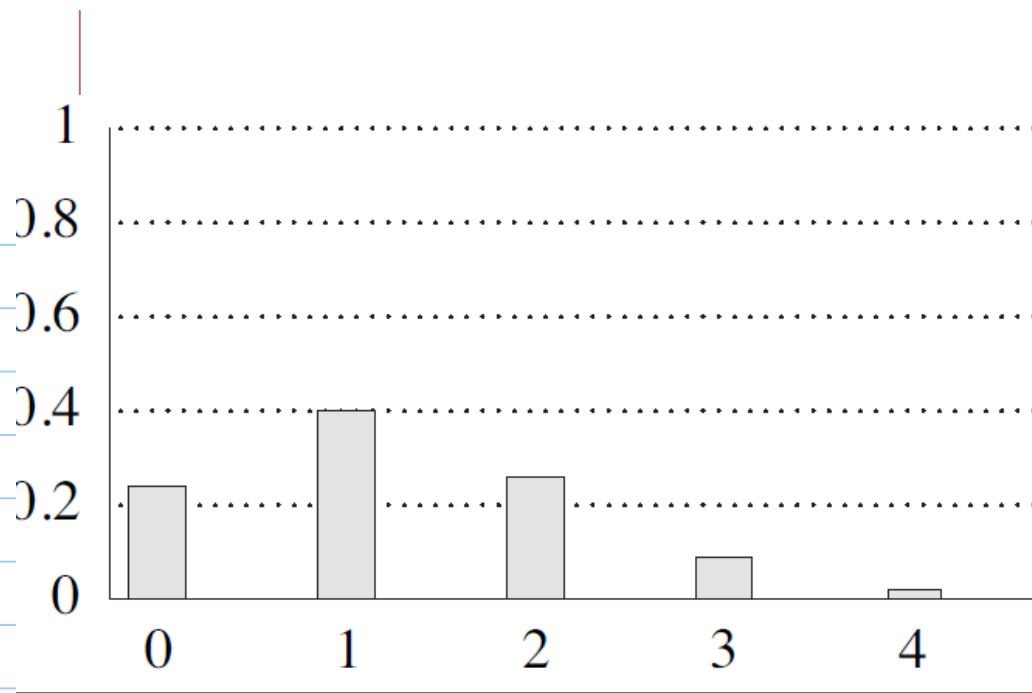
If $X \sim \text{Binomial}(n, p)$, [X is a r.v. drawn from a Binomial(n, p)]

then X can take values 0 through n .

Each value represents the number of heads (successes, 1s).

The p.m.f. of r.v. X is defined as follows:

$$P_X(i) = P(\{X=i\}) = \binom{n}{i} p^i (1-p)^{n-i}, \text{ for } 0 \leq i \leq n$$



pmf of the Binomial (4, 0.3) distribution

$$n = 4$$

$$p = 0.3$$

Geometric (p) distribution

$$P_X(i) = P\{X=i\} = (1-p)^{i-1} p, \text{ where } i=1, 2, 3, \dots$$