Definition: Let X be a discrete random variable (R.V.) with density f(x). Let H(X) be a function of random variable X. The expected value of H(X), denoted by E[H(X)], is given by:

$$E[H(X)] = \sum_{all\ x} H(x)f(x)$$

A special case of this definition, H(X) = X, $E[X] = \sum_{all \ x} x f(x)$

Example: Given the density of a discrete random variable X and Y as in the table. Calculate E[X] and E[Y]

X	1	2	3	4	5	У	1	2	3	4	5
f(x)	0.2	0.2	0.2	0.2	0.2	f(y)	0.9	0.05	0.02	0.02	0.01

Solution:
$$E[X] = 1 \times 0.2 + 2 \times 0.2 + 3 \times 0.2 + 4 \times 0.2 + 5 \times 0.2 = 3$$
 $E[Y] = 1 \times 0.9 + 2 \times 0.05 + 3 \times 0.02 + 4 \times 0.02 + 5 \times 0.01 = 1.19$

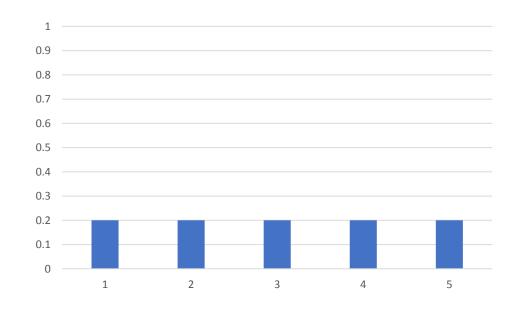
Expected Value

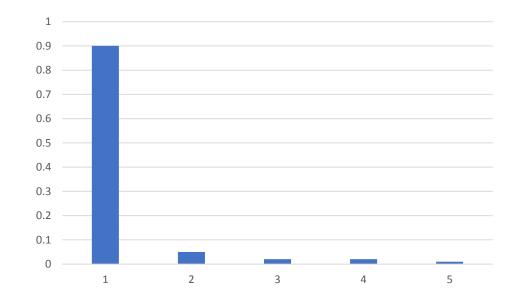
Parameters to describe a RV

Example: Given the density of a discrete random variable X and Y as in the table. Calculate E[X] and E[Y]

X	1	2	3	4	5
f(x)	0.2	0.2	0.2	0.2	0.2

y	1	2	3	4	5
f(y)	0.9	0.05	0.02	0.02	0.01





Notes:

- In a statistical setting, the expected value of a random variable X is also called its *mean value*, or *average* value. Usually denoted by symbol μ
- μ_x is a measure of the location of the *center* of X distribution. For this reason, μ_x is called a *location* parameter.

Properties:

```
E[c] = c

E[cX] = cE[X]; E[X + b] = E[X] + b

E[X + Y] = E[X] + E[Y] (will be proved in Chapter 5)

E[aX + bY] = aE[X] + bE[Y]

Where, a, b, c are real numbers.
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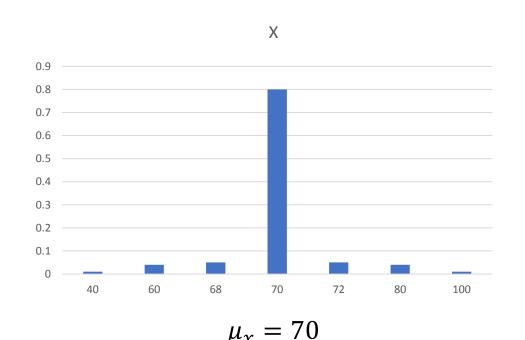
Example: Let X and Y be random variables with E[X] = 7 and E[Y] = -5. Calculate E[4X - 2Y + 6]

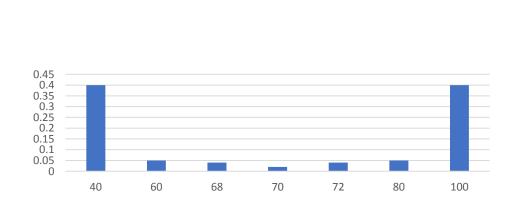
Solution:
$$E[4X - 2Y + 6] = 4 \times 7 - 2 \times (-5) + 6 = 44$$

Example: Consider two random variables X and Y with the following distributions

X	40	60	68	70	72	80	100
f(x)	0.01	0.04	0.05	0.80	0.05	0.04	0.01
у	40	60	68	70	72	80	100
f(y)	0.40	0.05	0.04	0.02	0.04	0.05	0.40

We need more parameters in addition to mean value to describe a distribution!





$$\mu_{y} = 70$$

Variance

Parameters to describe a RV

Definition: Let X be a random variable with mean μ_X . The variance of X, denoted by VarX or σ^2 , is defined as:

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

Variance measures how far a data set spread out, or, how wide the data set scatter.

Calculate the variance of the following three data sets: (assuming uniform distribution)

0

0.64

15968016

If you try to calculate these variances using Matlab or Excel, you might get 0, 0.80, and 19960020 Assuming uniform distribution, they are using the formula

$$\sigma^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu_x)^2$$

while we are using:

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu_x)^2$$

Variance

Parameters to describe a RV

Definition: Let X be a random variable with mean μ_X . The variance of X, denoted by VarX or σ^2 , is defined as:

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

An Important Formula to Calculate variance: $\sigma^2 = VarX = E[X^2] - (E[X])^2$

$$VarX = E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] = E[X^2] - 2\mu E[X] + \mu^2 = E[X^2] - 2(E[X])^2 + (E[X])^2 = E[X^2] - (E[X])^2$$

Example: Calculate variances using this new formula.

Variance

Properties: Let X and Y be random variables and C a real number. Then:

- (1) Var(c) = 0
- $(2) Var(cX) = c^2 VarX$
- (3) if X and Y are independent, then Var(X + Y) = VarX + VarY

Example: Let *X* and *Y* be independent with $\sigma_x^2 = 9$, $\sigma_y^2 = 3$. Calculate Var(4X + 2Y + 6)

$$Var(4X + 2Y + 6) = 16 \times 9 + 4 \times 4 + 0 = 156$$

Standard deviation

Parameters to describe a RV

Definition: Let X be random variables with variance σ^2 . Then the standard deviation of X, denoted by σ , is given by $\sigma = \sqrt{VarX}$

- (1) A large standard deviation implies that the random variable X is somewhat hard to predict.
- (2) Standard deviation is always in physical measurement unit that match the original data. Variance is often unit-less.