# <span id="page-0-0"></span>**Discrete Distributions: Expected Value, Variance, Standard Deviation**

BIOS 6611

CU Anschutz

Week 2



### **[PMFs and CDFs](#page-6-0)**

#### **[Expected Value \(Mean\), Variance, Standard Deviation \(SD\)](#page-10-0)**

### <span id="page-2-0"></span>**[Random Variables](#page-2-0)**

Random variables and probability distributions are the theoretical or mathematical representations of data values and frequency distributions.

- **Random Variable**: variable whose values depend on a random phenomenon. Possible values represent possible outcomes of a yet-to-be-performed experiment.
- We call these possible values the **sample space**
- Notation:
	- $\blacktriangleright$  X, Y, Z denotes a random variable
	- $\blacktriangleright$  *x*, *y*, *z* denotes a value of the random variable

The **probability distribution** describes the probabilities for each outcome for

- a discrete random variable (probability mass function,  $pmf$ )
- the probabilities of values in a range for a continuous random variable (probability density function,  $pdf$ )

The pmf/pdf is a useful tool for describing the frequency distributions of random variables for the entire population of interest and for providing probability statements about events involving random variables.

### **Discrete Random Variable**

- **Discrete random variable**: sample space is a discrete list of values
	- Ex: Let X denote random experiment of flipping a coin. The possible outcomes are {Heads*,*Tails}.
- Characterized by a **probability mass function (PMF)**: function that gives probability that  $X$  is equal to values in sample space.
	- $\triangleright$  Values must be non-negative and sum to 1
	- **Notation:**

 $P(X = k) =$  function that depends on k,  $k = \{$ sample space $\}$ 

### <span id="page-6-0"></span>**[PMFs and CDFs](#page-6-0)**

### **PMF**

Let X be a random variable and let x represent the values that X can take on. The probability distribution of X is  $p(x) = P(X = x)$ .

For example, if  $X =$  the number of colds in a year caught by a healthy adult: **PMF**



# **Cumulative Distribution Function (CDF)**

#### The **cumulative probability distribution** of X:

 $\mathcal{F}_X(\mathsf{x}) = \mathit{P}(\mathsf{X} \leq \mathsf{x}) = \sum_{\mathsf{x}=0}^k \mathit{P}(\mathsf{X}=\mathsf{x})$  (accumulate probabilities from lowest to highest) The CDF is monotone increasing,  $F(-\infty) = 0$ ,  $F(\infty) = 1$ .  $P(X = 0) = 0.5$  $P(X = 1) = 0.4$  $P(X = 2) = 0.1$  $F(0)= 0.5$  (# of colds  $\leq 0$ )  $F(1) = 0.5 + 0.4$  (# of colds  $\leq 1$ )  $F(2) = 0.5 + 0.4 + 0.1 = 1.0$ −0.5 0.0 0.5 1.0 1.5 2.0 2.5 0.0 0.2 0.4 0.6 0.8 1.0 **CDF**  $\widetilde{\mathcal{E}}$ 

Number of Colds

# **Another PMF/CDF Example**

 $X =$  number of episodes of ear infections in first 2 years of life:





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# <span id="page-10-0"></span>**[Expected Value \(Mean\), Variance, Standard](#page-10-0) [Deviation \(SD\)](#page-10-0)**

There are different summary values for random variables. The **expected value** (i.e., mean or average) is one of the most common.

For a discrete r.v.  $X^+$ 

$$
E(X) = \sum_{x} xP(X = x) = \mu
$$

$$
= \sum_{x} xp(x) = \mu
$$

## **Expected Value Example**

For our number of colds example:



$$
\mu = E(X) = \sum_{x} xP(X = x) =
$$

## **Variance**

In addition to summarizing the center (i.e., mean) of the distribution, the variability is also helpful to quantify. The **variance** can be described as the expected value of our r.v. X minus the true mean,  $\mu$ , squared:

$$
Var(X) = V(X) = \sigma^2 = E[(X - E(X))^2] = E[(X - \mu)^2]
$$

Fortunately, like  $E(X)$ , we have specific formulas we can use for a discrete r.v.  $X$ :

$$
Var(X) = \sum_{x} (x - \mu)^2 P(X = x) = \sigma^2
$$

$$
= \sum_{x} (x - \mu)^2 p(x) = \sigma^2
$$

The units for the variance are the square of the units of the variable itself (e.g.,  $ft^2$  or  $oz^2$ ).

Another common way to summarize the variability is with the **standard deviation**, which is simply the square root of the variance:

$$
SD(X) = \sqrt{Var(X)} = \sigma
$$

One advantage of the variance is has the same units as the variable itself instead of being in squared units.

## **Variance and Standard Deviation Example**

For our number of colds example:



$$
\sigma^2 = V(X) = \sum_{x} (x - \mu)^2 p(x) =
$$

## **Computational Formula for Variance**

In addition to the definition of the variance previously, we can also calculate it by knowing the expected value of our random variable  $X$  and  $X^2\colon$ 

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

### <span id="page-17-0"></span>**Formula Review for Discrete Random Variables**

$$
E(X) = \mu = \sum_{x} xP(X = x)
$$

$$
= \sum_{x} xp(x)
$$

$$
Var(X) = \sigma^2 = \sum_{x} (x - \mu)^2 P(X = x)
$$
  
= 
$$
\sum_{x} (x - \mu)^2 p(x)
$$
  
= 
$$
E[X^2] - (E[X])^2
$$

$$
SD(X) = \sigma = \sqrt{Var(X)}
$$

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