Introduction to Probability

Lecture 3: Expectation properties, variance, discrete distributions

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Outline

Properties of expectation

Variance

Bernoulli discrete random variable

Binomial discrete random variable

Properties of expectation: linearity

Linearity of expectation

Expectations preserve linearity: if a and b are constants, then

$$\mathbf{E}[aX + b] = a\,\mathbf{E}[X] + b$$

Proof:

Properties of expectation: linearity

Linearity of expectation

Expectations preserve linearity: if a and b are constants, then

$$\mathbf{E}[\,aX + b\,] = a\,\mathbf{E}[\,X\,] + b$$

Proof:

Example

Let the event be a roll of a 6-sided die, X its random variable, and Y another random variable where $Y = 3X + 1$. What are the expected values $\mathbf{E}[\,X\,]$ and $\mathbf{E}[\,Y\,]$?

Answer

Properties of expectation: additivity

Additivity of expectation

Expectation of a sum is equal to the sum of expectations: if X and Y are any random variables on the same sample space then

$$\mathbf{E}[X+Y] = \mathbf{E}[X] + \mathbf{E}[Y]$$

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Example

Let the events be rolls of 2 dice, and X the random variable for the roll of die 1, and Y for the roll of die 2. What is the expected value of the sum of the rolls of the two dice?

Answer

Properties of expectation: LOTUS

Law of the unconscious statistician (LOTUS)

Let X be a random variable, and Y another random variable that is a function of X, so $Y = g(X)$. Let $p(x)$ be a PMF of X. Then

$$\mathbf{E}[\,Y\,] = \mathbf{E}[\,g(X)\,] = \sum_{x:p(x)>0} g(x)p(x)$$

Note how now we no longer need to know PMF of Y.

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- Note that the properties of expectation let you avoid defining difficult PMFs.

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- LOTUS is also known as **expected value of a function of a random variable**.
- Note that the properties of expectation let you avoid defining difficult PMFs.
- Let X be a discrete RV, then:
  - $\mathbf{E}\left[\,X^2\,\right]$ is know as the second moment of X.
  - $\mathbf{E}\left[\,X^n\,\right]$ is know as the n^{th} moment of X.

Second moment example

Example

Let X be a discrete random variable that ranges over the values $\{-1, 0, 1\}$, and respective probabilities $\mathbf{P}[\, X = -1 \,] = 0.2$, $\mathbf{P}[\, X = 0 \,] = 0.5$ and $\mathbf{P}[\, X = 1 \,] = 0.3$. Let another random variable $Y = X^2$ (second moment). What is $\mathbf{E}[\, Y \,]$?

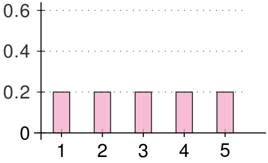
Answer

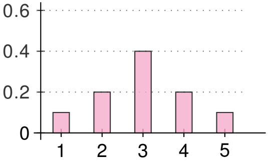
Note that $Y = g(X) = X^2$ and $\mathbf{E}[\, Y \,] = \mathbf{E}[\, g(X) \,] = \sum_{x:p(x)>0} g(x)p(x)$, thus

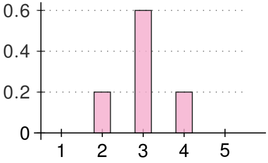
Outline

Spread in the distribution

Expectation is a useful statistic, but it does not give a detailed view of the PMF. Consider these 3 distributions (PMFs).







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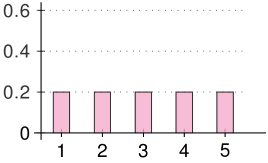

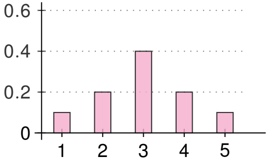

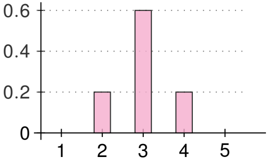

- Expectation is the same for all distributions: $\mathbf{E}[\,X\,] = 3$.
- First has the greatest spread, the third has the least spread.
- But the "spread" or "dispersion" of X in the distribution is very different!

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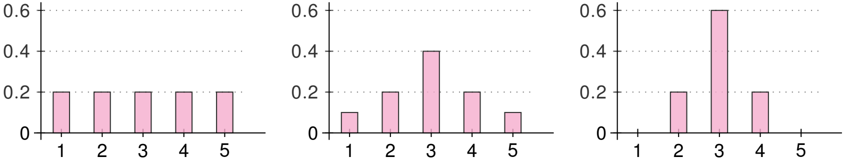

- Expectation is the same for all distributions: $\mathbf{E}[X] = 3$.
- First has the greatest spread, the third has the least spread.
- But the "spread" or "dispersion" of X in the distribution is very different!
- Variance, $\mathbf{V}[X]$ defines a formal quantification of "spread".
- Several ways to quantify: it uses average square distance from the mean.

Definition of variance

Variance

The variance of a discrete random variable X with expected value (mean) μ is:

$$\mathbf{V}\left[\,X\,\right] = \mathbf{E}\left[\,(X-\mu)^2\,\right]$$

When computing the variance, we often use a different form of the same equation:

$$\mathbf{V}\left[\,X\,\right] = \mathbf{E}\left[\,X^2\,\right] - (\mathbf{E}\left[\,X\,\right])^2$$

Proof:

Note:

- $\mathbf{V}\left[\,X\,\right] \geq 0$
- AKA: Second central moment, or square of the standard deviation

Example with a die roll

Example

Let X be the value on one roll of a 6-sided fair die. Recall that $\mathbf{E}[X] = \frac{7}{2} = 3.5$. What is $\mathbf{V}[X]$?

Answer

Using $\mathbf{V}[X] = \mathbf{E}\left[X^2\right] - (\mathbf{E}[X])^2$:

Using $\mathbf{V}[X] = \mathbf{E}\left[(X-\mu)^2\right] = \mathbf{E}\left[(X - \mathbf{E}[X])^2\right]$:

Example of spread

Example

Let X, Y and Z be discrete random variables with the range $X : \{10\}$ and probability 1, and $Y : \{11, 9\}$ and $Z : \{110, -90\}$ with equal probabilities $\frac{1}{2}$. Compute expectation and variance for X, Y and Z.

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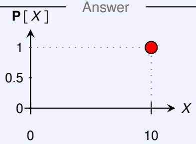
Answer

a) $\mathbf{E}[X] = \sum_x xp(x) = 10 \cdot 1 = 10$

$$\mathbf{V}[X] = \mathbf{E}\left[(X - \mathbf{E}[X])^2\right] = \mathbf{E}\left[(X-10)^2\right]$$
$$= (X-10)^2 p(x) = 0^2 \cdot 1 = 0$$



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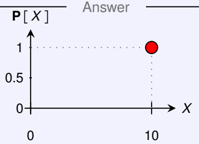
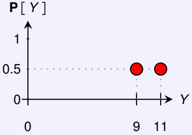


b) $\mathbf{E}[Y] = (11)(0.5) + (9)(0.5) = 10$

$$\mathbf{V}[Y] = \mathbf{E}\left[(Y - \mathbf{E}[Y])^2\right] = \mathbf{E}\left[(Y-10)^2\right]$$

$$= (11-10)^2(0.5) + (9-10)^2(0.5) = 1$$



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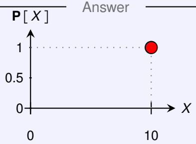

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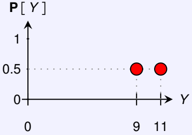
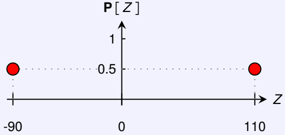


c) $\mathbf{E}[Z] = (110)(0.5) + (-90)(0.5) = 10$

$$\mathbf{V}[Z] = \mathbf{E}\left[(Z - \mathbf{E}[Z])^2\right] = \mathbf{E}\left[(Z-10)^2\right] =$$

$$= (110-10)^2(0.5) + (-90-10)^2(0.5)$$

$$= 100^2 = 10000$$



Standard deviation

- Standard deviation is a kind of average distance of a sample of the mean, i.e., a root mean square (RMS) average.
- Variance is the square of this average distance.

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Standard deviation

Standard deviation is defined as a square root of variance:

$$\mathbf{SD}[X] = \sqrt{\mathbf{V}[X]}$$

Note:

- $\mathbf{E}[X]$ and $\mathbf{V}[X]$ are real numbers, not RVs.
- $\mathbf{V}[X]$ is expressed in units of the values in the range of X^2.
- $\mathbf{SD}[X]$ is expressed in units of the values in the range of X.
- For the spread example above: $\mathbf{SD}[X] = 0, \mathbf{SD}[Y] = 1, \mathbf{SD}[Z] = 100$.

Properties of variance

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- **Property 2:** variance is not linear: $\mathbf{V}[aX + b] = a^2\mathbf{V}[X]$

  Proof:

$$
\begin{aligned}
\mathbf{V}[(aX + b] &= \mathbf{E}\left[(aX + b)^2\right] - (\mathbf{E}[aX + b])^2 \\
&= \mathbf{E}\left[a^2X^2 + 2abX + b^2\right] - (a\mathbf{E}[X] + b)^2 \\
&= a^2\mathbf{E}\left[X^2\right] + 2ab\mathbf{E}[X] + b^2 - (a^2(\mathbf{E}[X])^2 + 2ab\mathbf{E}[X] + b^2) \\
&= a^2\mathbf{E}\left[X^2\right] - (a^2(\mathbf{E}[X])^2) = a^2(\mathbf{E}\left[X^2\right] - (\mathbf{E}[X])^2) \\
&= a^2\mathbf{V}[X]
\end{aligned}
$$

Summary of expectation and variance for discrete RV

$$\mathbf{E}[X] = \sum_{x:\mathbf{P}[x]>0} x\mathbf{P}[x] = \sum_{x} xp(x)$$

Properties of Expectation

$$\mathbf{E}[X+Y] = \mathbf{E}[X] + \mathbf{E}[Y]$$

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

$$\mathbf{E}[g(X)] = \sum_{x} g(x)p_X(x)$$

Properties of Variance

$$\mathbf{V}[X] = \mathbf{E}\left[(X-\mu)^2\right]$$

$$\mathbf{V}[X] = \mathbf{E}\left[X^2\right] - (\mathbf{E}[X])^2$$

$$\mathbf{V}[aX+b] = a^2\mathbf{V}[X]$$

Parametric/standard discrete random variables

- There is deluge of classic RV abstractions that show up in problems.
- They give rise to significant discrete distributions.
- If problem fits, use precalculated (parametric) PMF, expectation, variance and other properties by providing parameters of the problem.
- We will cover the following RVs:
  1. Bernoulli
  2. Binomial
  3. Poisson
  4. Geometric
  5. Negative Binomial
  6. Hypergeometric

Outline

Bernoulli

Bernoulli discrete random variable

A Bernoulli RV X maps "success" of an experiment to 1 and "failure" to 0. It is AKA indicator RV, boolean RV. X is "Bernoulli RV with parameter p", where $\mathbf{P}\left[\,''sucess''\,\right] = p$ and so PMF $p(1) = p$.

$$\mathbf{X{\sim}Ber(p)}$$

$$\begin{aligned}
\text{Range:}\quad & \{0, 1\} \\
\text{PMF:}\quad & \mathbf{P}[\,X = 1\,] = p(1) = p \\
& \mathbf{P}[\,X = 0\,] = p(0) = 1 - p \\
\text{Expectation:}\quad & \mathbf{E}[\,X\,] = p \\
\text{Variance:}\quad & \mathbf{V}[\,X\,] = p(1 - p)
\end{aligned}$$

Examples: coin toss, random binary digit, if someone likes a film, the gender of a newborn baby, pass/fail of you taking an exam.

Bernoulli examples

Example

You watch a film on Netflix. At the end you click "like" with probability p. Define a RV representing this event.

Answer

Bernoulli examples

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Answer

Example

Two fair 6-sided dice are rolled. Define a random variable X for a successful roll of two 6's, and failure for anything else.

Answer

Outline

Properties of expectation

Variance

Bernoulli discrete random variable

Binomial discrete random variable

Binomial

Binomial discrete random variable

A Binomial RV X represents the number of successes in n successive independent trials of a Bernoulli experiment. $X \sim Bin(n, p)$ is a Binomial RV, where p is the probability of success in a given trial:

$$\mathbf{X \sim Bin(n, p)}$$

$$\begin{aligned}
\text{Range:} \quad & \{0, 1, \ldots, n\} \\
\text{PMF:} \quad & k \in \{0, 1, \ldots, n\} \\
& \mathbf{P}[\,X = k\,] = p(k) = \binom{n}{k} p^k (1-p)^{n-k} \\
\text{Expectation:} \quad & \mathbf{E}[\,X\,] = np \\
\text{Variance:} \quad & \mathbf{V}[\,X\,] = np(1-p)
\end{aligned}$$

Examples: # heads in n coin tosses, # of 1's in randomly generated length n bit string

Note: by Binomial theorem (revision), we can prove $\sum_{k=0}^{n} \mathbf{P}[\,X = k\,] = 1$.

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Probability Mass Function for a Binomial

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Binomial example

Example

Let X be the number of heads after a coin is tossed three times: $X \sim Bin(3, 0.5)$. What is the probability of each of the different values of X?

Answer

Binomial RV is sum of Bernoulli RVs

Let X be a Bernoulli RV: $X \sim Ber(p)$. Let Y be a Binomial RV: $Y \sim Bin(n, p)$.
Binomial RV = sum of n independent Bernoulli RVs:

$$Y = \sum_{i=1}^{n} X_i, \quad X_i \sim Ber(p)$$

$$\mathbf{E}[\,Y\,] = \mathbf{E}\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} \mathbf{E}[\,X_i\,] = np$$

Note: $Ber(p) = Bin(1, p)$

Another example

Example

An off-licence sells cases of wine, each containing 20 bottles. The probability that a bottle is bad is 0.05. The off-licence gives a money-back guarantee that the case will contain no more than one bad bottle. What is the probability that the off-licence will have to give money back?

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Answer

- X: # of bad bottles in a case (20 bottles)

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An off-licence sells cases of wine, each containing 20 bottles. The probability that a bottle is bad is 0.05. The off-licence gives a money-back guarantee that the case will contain no more than one bad bottle. What is the probability that the off-licence will have to give money back?

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- Recall, when $X \sim Bin(n, p)$ then $\mathbf{P}[X = k] = \binom{n}{k} p^k (1-p)^{n-k}$ thus

$$\mathbf{P}[X \geq 2] = 1 - \mathbf{P}[X = 0] - \mathbf{P}[X = 1]$$

Visualising Binomial PMFs