4: Discrete Distributions, Part 1

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Where We've Been

- Axioms of Probability, Probability Spaces, Counting
- Conditional Probabilities, independence, etc.
- Basics of Random Variables (classification, p.m.f., c.m.f., moments)

Discrete Distributions

Bernoulli Trial

Definition: Bernoulli Trial

A **Bernoulli Trial** is an experiment in which:

- There is a well-defined notion of “success” and “failure” (i.e. non-success)
- The probability of success remains a constant value p over all repetitions of this trial.

- Tossing a coin is an example of a Bernoulli Trial; “sucess” could be “lands heads”, and whehter or not the coin is fair we assume there to be a fixed probability p of the coin landing heads.

Leadup

- Consider the following three random variables:
  1. Toss a fair coin 100 times, and let X denote the number of heads.
  2. Roll a fair six-sided die 27 times, and let Y denote the number of times the die lands on an even number.
  3. From a population of size 1000, in which 4 people have a particular disease, take a sample of 100 people with replacement and let Z denote the number of individuals with diseases I observe.
- For each of these experiments and associated random variables, we could follow the same steps as we did when dealing with our two-coin example: in other words, we could construct Ω, find the mapping X (or Y or Z), construct the p.m.f., and find $\mathbb{E}[X]$ (or $\mathbb{E}[Y]$ or $\mathbb{E}[Z]$).
- But, notice that each of the scenarios listed above are all just special cases of the following:

  In n independent Bernoulli trials, where each trial results in a "success" with probability p, let W denote the number of successes.

- So, if we can deal with this general case, we can simply plug in different values of n and p.

Distributions

- This is how I like to think about distributions: as a “package” which deals with some general question in generality, from which we can glean information on individual situations.
- The true technical definition of a distribution is much more technical! (But, for the purposes of this class, this notion of a distribution as a “package” will suffice.)

- So, for example: if W denotes the number of successes in n independent Bernoulli trials, and where the probability on any given trial is p, we say W follows the **Binomial** distribution with **parameters** n and p, and notate this $W \sim \mathrm{Bin}(n, p)$.

Binomial Distribution

- Let's try an example.
- Suppose $W \sim \text{Bin}(n, p)$; in other words, W denotes the number of successes in n independent Bernoulli trials with probability of success p.
- We can derive the p.m.f. of W using some counting arguments:
  - When computing $p_W(k)$, we are computing the probability of exactly k successes in n trials.
  - Suppose that these k trials occurred consecutively, as my first k trials. The probability of this is simply $p^k(1-p)^{n-k}$.
  - But, the event $\{W = k\}$ doesn't mean "k successes all at the beginning," but rather "k successes across all n trials." Thus, we need to multiply by all of the ways in which we can distribute the k successes among the n trials: $\binom{n}{k}$.
  - That is:

$$p_W(k) = \begin{cases} \binom{n}{k} p^k (1-p)^{n-k} & \text{if } k = 0, 1, 2, \cdots, n \\ 0 & \text{otherwise} \end{cases}$$

  - This is the p.m.f. of the Binomial distribution with parameters n and p.

Binomial Distribution

- With the p.m.f. of W, we can now compute $\mathbb{E}[W]$:

$$
\begin{aligned}
\mathbb{E}[W] := \sum_k k p_W(k) &= \sum_{k=0}^{n} k \cdot \binom{n}{k} p^k (1-p)^{n-k} \\
&= \sum_{k=1}^{n} k \cdot \frac{n!}{k!(n-k)!} \cdot p^k (1-p)^{n-k} \\
&= \sum_{k=1}^{n} \frac{n!}{(k-1!)(n-k)!} \cdot p^k (1-p)^{n-k} \\
&= \sum_{k=1}^{n} n \cdot \frac{(n-1)!}{(k-1)!([n-1]-[k-1])!} p^k (1-p)^{n-k} \\
&= n \sum_{k=1}^{n} \binom{n-1}{k-1} p^k (1-p)^{n-k} \\
&= n \sum_{m=0}^{n-1} \binom{n-1}{m} p^{m+1} (1-p)^{n-m-1} \\
&= np \sum_{m=0}^{n-1} \binom{n-1}{m} p^m (1-p)^{(n-1)-m} = np\cancel{(p+1-p)^{n-1}} = np
\end{aligned}
$$

Binomial Distribution

- With a bit of work, one can show that $\text{Var}(W) = np(1-p)$
- So, to summarize: if W counts the number of successes in n independent Bernoulli trials, then $W \sim \text{Bin}(n, p)$ and:
  - $S_W = \{0, 1, \cdots, n\}$
  - $p_W(k) = \begin{cases} \binom{n}{k} p^k (1-p)^{n-k} & \text{if } k = 0, 1, \cdots, n \\ 0 & \text{otherwise} \end{cases}$
  - $\mathbb{E}[W] = np$
  - $\text{Var}(W) = np(1-p)$

Example

Suppose I simultaneously roll 10 fair six-sided dice, and let X denote the number of even numbers showing.

(a) What is the probability that X is 2?

(b) What is $\mathbb{E}[X]$?

(c) What is $\mathrm{Var}(X)$?

- We have a well-defined notion of success: "die lands on an even number."
- Since the coin is fair, we can use the classical definition of probability to say $p := \mathbb{P}(\text{success}) = \mathbb{P}(\text{even number}) = \mathbb{P}(\{2, 4, 6\}) = 1/2$
- Additionally, we have $n = 10$ Bernoulli Trials (one corresponding to each die roll), meaning $X \sim \mathrm{Bin}(10, 1/2)$

- From here, we can easily answer each of the subquestions using our information on the Binomial distribution!
  (a) $\mathbb{P}(X = 2) = \binom{10}{2} \left(\frac{1}{2}\right)^2 \left(\frac{1}{2}\right)^{10-2} = \boxed{\frac{45}{1024}}$
  (b) $\mathbb{E}[X] = (10)\left(\frac{1}{2}\right) = \boxed{5}$; $\mathrm{Var}(X) = (10)\left(\frac{1}{2}\right)\left(1 - \frac{1}{2}\right) = \boxed{5/2}$

Another Distribution:

- Consider again a sequence of Bernoulli trials.
- Now, however, let X denote the number of trials needed to observe our first success? (Let's include the final successful trial when counting). So, for example, if we observe

  (Failure) (Failure) (Failure) (Success)

  then $X = 4$.
- What is the state space of X? $S_X = \{1, 2, 3, \cdots\}$
- To find the p.m.f., we can construct a modified slot diagram. Specifically, when $X = k$ we must have $(k-1)$ failures followed by one success:

$$\underbrace{\underline{1-p} \times \underline{1-p} \times \cdots \times \underline{1-p}}_{k-1 \text{ trials}} \times \underline{\ \ p\ \ }$$

- Therefore $\mathbb{P}(X = k) = (1-p)^{k-1} \cdot p$, meaning

$$p_X(k) = \begin{cases} (1-p)^{k-1} \cdot p & \text{if } k = 1, 2, 3, \cdots \\ 0 & \text{otherwise} \end{cases}$$

- This is called the **Geometric Distribution**, with parameter p.

Geometric Distribution: Expectation and Variance

- We can now find $\mathbb{E}[X]$, if $X \sim \text{Geom}(p)$

$$\begin{aligned}
\mathbb{E}[X] &= \sum_k p_X(k) = \sum_{k=1}^{\infty} k \cdot (1-p)^{k-1} \cdot p \\
&= \frac{p}{1-p} \sum_{k=1}^{\infty} k \cdot (1-p)^k \\
&= \frac{p}{1-p} \sum_{k=0}^{\infty} k \cdot (1-p)^k \\
&= \frac{p}{1-p} \times \frac{1-p}{[1-(1-p)]^2} = \frac{p}{1-p} \times \frac{1-p}{p^2} = \boxed{\frac{1}{p}}
\end{aligned}$$

- You will also show that $\text{Var}(X) = \frac{1-p}{p^2}$ (there is a very neat trick to this computation!)

Geometric Distribution

- So, to summarize: if X counts the number of independent Bernoulli trials (including the final successful trial) needed to observe the first success, we have $X \sim \text{Geom}(p)$ and:
  - $S_X = \{1, 2, 3, \cdots\}$
  - $p_X(k) = \begin{cases} (1-p)^{k-1} \cdot p & \text{if } k = 1, 2, \cdots \\ 0 & \text{otherwise} \end{cases}$
  - $\mathbb{E}[X] = \dfrac{1}{p}$
  - $\text{Var}(X) = \dfrac{1-p}{p^2}$

- As an example: suppose we want to know the average number of rolls of a fair six-sided die needed to observe the number "1" for the first time. Letting X denote the number of rolls until we observe our first "1" we have $X \sim \text{Geom}(1/6)$, meaning

$$\mathbb{E}[X] = \frac{1}{(1/6)} = \boxed{6}$$

Extending the Geometric Distribution

- We have seen that the Geometric distribution arises when counting the number of trials until our first success.
- What if we wanted to count the number of trials until our second success? or our third success?
- Let X denote the number of independent Bernoulli trials needed to observe the r^{th} success, where $r \in \mathbb{N}$.
- The state space of X is $S_X = \{r,\ r+1,\ r+2,\ \cdots\}$
- For the event $\{X = k\}$ to have occurred, we require $(r-1)$ successes among the first $k-1$ trials, followed by a success on the k^{th} trial:

$$\underbrace{\underline{\hspace{2em}}\quad \underline{\hspace{2em}}\quad \cdots \quad \underline{\hspace{2em}}}_{(r-1) \text{ successes in } (k-1) \text{ trials}} \quad \underline{\text{success}}$$

- The probability of observing $(r-1)$ successes in $(k-1)$ trials can be computed using the Binomial distribution! The probability of this is

$$\binom{k-1}{r-1} \cdot p^{r-1} \cdot (1-p)^{k-r}$$

- Therefore, $\mathbb{P}(X = k)$ is given by

$$\mathbb{P}(X = k) = \binom{k-1}{r-1} \cdot p^{r-1} \cdot (1-p)^{k-r} \cdot p = \binom{k-1}{r-1} \cdot p^{r} \cdot (1-p)^{k-r}$$

The Negative Binomial Distribution

- Because of the presence of the Binomial distribution in our computation above, this new distribution is called the **Negative Binomial** distribution with parameters r and p.
- So, to summarize: if X counts the number of independent Bernoulli trials needed to observe r^{th} success then $X \sim \text{NegBin}(r, p)$ and:
  - $S_X = \{r,\ r+1,\ r+2, \cdots\}$
  - $p_X(k) = \begin{cases} \binom{k-1}{r-1} \cdot p^r \cdot (1-p)^{k-r} & \text{if } k = r,\ r+1,\ r+2,\ \cdots \\ 0 & \text{otherwise} \end{cases}$
  - $\mathbb{E}[X] = \dfrac{r}{p}$
  - $\text{Var}(X) = \dfrac{r}{p^2}$

The Negative Binomial Distribution

When tossing a fair coin, what is the probability that the fourth heads occurs on the 12^{th} toss?

- Let X denote the number of tosses needed to observe the fourth heads; then $X \sim \text{NegBin}(4, 1/2)$
- We seek $\mathbb{P}(W = 12)$; by the formula for the p.m.f. of the Negative Binomial distribution we have

$$\mathbb{P}(W = 12) = \binom{12-1}{4-1}\left(\frac{1}{2}\right)^4\left(\frac{1}{2}\right)^{12-4} = \binom{11}{3}\left(\frac{1}{2}\right)^{12}$$

- By the way, the $\text{NegBin}(1, p)$ distribution has another name. What is that name? The Geometric(p) distribution.