

# Random Variables

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In general we can consider a Bernoulli random variable to be the result of an experiment with two outcomes, which for convenience we will label "success" and "failure"

As before we define the Bernoulli random variable  $X$  by agreeing to assign the value of 1 to  $X$  if the result of the experiment is "success", and zero if the result is "failure":

$$X = \begin{cases} 1 & \text{if the outcome of the experiment is "success"} \\ 0 & \text{if the outcome of the experiment is "failure"} \end{cases}$$

# Bernoulli Random Variables

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To be consistent with the Kolmogorov probability axioms the probability of "success" must be a number  $p$  between zero and one (inclusive), and the probability of "failure", which is the complement of "success", must be  $1 - p$ .

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This results in the following probability mass function  $f(x)$  which we will refer to as the *Bernoulli distribution*:

$$f(x) = P(X = x) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$

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$$f(x) = P(X = x) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$

Most of the discrete probability distributions we will now consider are related to the Bernoulli distribution.

# Discrete Distributions

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Now consider a series of *independent* experiments, each of which produces a Bernoulli random variable with probability of success  $p$  ( $p$  is the same for all of the trials)



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If the number of trials  $n$  is fixed in advance, the number of successes  $X$  has a **binomial** distribution

If trials continue indefinitely until the first success is obtained, the number of failures obtained  $X$  has a **geometric** distribution.

If trials continue indefinitely until the  $r^{th}$  success is obtained, the number of failures obtained  $X$  has a **negative binomial** distribution.

# Discrete Distributions

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However, the characterization as a sequence of Bernoulli trials that ends at the  $r^{\text{th}}$  success is common to all definitions.

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However, the characterization as a sequence of Bernoulli trials that ends at the  $r^{\text{th}}$  success is common to all definitions.

That said, you should be prepared to encounter a different definition of  $X$  (and a different, but equivalent pmf) if you look at a different text.

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The Poisson is a limiting form of the binomial distribution that you get if you let  $n$  become very large and the probability of success  $p$  very small, but always keep  $np = \lambda$  the same.

Another way to say this is that we take binomial random variables with larger and larger  $n$ , but we keep the *expected number of successes*  $np = \lambda$  the same for all of them.

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The Poisson is a limiting form of the binomial distribution that you get if you let  $n$  become very large and the probability of success  $p$  very small, but always keep  $np = \lambda$  the same.

Another way to say this is that we take binomial random variables with larger and larger  $n$ , but we keep the *expected number of successes*  $np = \lambda$  the same for all of them.

The limit of the distribution of such a sequence of random variables as  $n \rightarrow \infty$  is a Poisson.

# The Binomial Distribution

---

The binomial experiment consists of:

- $n$  independent Bernoulli trials are performed
- The random variable  $X$  is the sum of the results (i.e., the number of successes)
- The probability of success  $p$  is the same for all trials

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- The random variable  $X$  is the sum of the results (i.e., the number of successes)
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The probability mass function (pmf)  $f(x)$  is:

$$f(x) = P(X = x) = b(x; n, p) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x = 0, 1, 2, \dots,$$

# The Binomial Distribution

---

It is not obvious, but if you sum the values of  $f(x)$  over all values from zero to  $n$ , the sum is one.

$$\sum_{x=0}^n \binom{n}{x} p^x (1-p)^{n-x} = 1$$

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One way to make this clear is to consider the algebraic identity

$$(x + y)^n = \sum_{i=0}^n \binom{n}{i} x^i y^{n-i}$$

# The Binomial Distribution

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If we let  $x$  be the probability of success  $p$  and  $y$  the probability of failure  $1 - p$ , on substitution we get

$$[p + (1 - p)]^n = 1^n = 1 = \sum_{x=0}^n \binom{n}{x} p^x (1 - p)^{n-x} \quad 0 \leq p \leq 1$$



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For any distribution, the cumulative distribution function (cdf)  $F(x)$ , is always defined by

$$F(x) = P(X \leq x)$$

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For any distribution, the cumulative distribution function (cdf)  $F(x)$ , is always defined by

$$F(x) = P(X \leq x)$$

For the binomial distribution, this gives:

$$F(x) = \sum_{i=0}^x \binom{n}{i} p^i (1 - p)^{n-i}$$

# The Binomial Distribution

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For the binomial distribution, there is no simple expression for  $F(x)$

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Values of  $F(x)$  for the binomial can be obtained from:

- Tables (See table A.1 in the appendix)
- Spreadsheets: =  $BINOMDIST(x, n, p, TRUE)$
- R:  $pbinom(x, n, p)$

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Example: A fair coin is tossed 10 times. What is the probability that 7 or fewer heads turn up?

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Example: A fair coin is tossed 10 times. What is the probability that 7 or fewer heads turn up?

We want  $P(X \leq 7)$ , the probability that a binomial experiment with 10 trials and probability of success 0.5 produces 7 or fewer "successes".

# The Binomial Distribution

---

If you are using a spreadsheet, enter:

= *BINOMDIST*(7, 10, 0.5, *TRUE*)

# The Binomial Distribution

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If you are using Table A.1, look under  $n = 10$  on page 664, in the row with  $x = 7$  and column with  $p = 0.50$

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All of these should give the value  $F(7) = .945$

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This means that if we toss a fair coin 10 times, the probability of 7 or fewer heads is .945

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All of these should give the value  $F(7) = .945$

This means that if we toss a fair coin 10 times, the probability of 7 or fewer heads is .945

If we repeat the experiment, tossing the coin 10 times, over and over, the *proportion* of all of the replications of the experiment that have 7 or fewer heads will approach .945.

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# The Binomial Distribution

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Example: Suppose every time the Red Sox play the Yankees, the probability that the Red Sox win is 0.6.

If they play 7 games, what is the probability that the Red Sox win 5 or fewer?

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If they play 7 games, what is the probability that the Red Sox win 5 or fewer?

If we assume that each game is an independent Bernoulli trial with probability of "success" equal to 0.6, then the number of games the Red Sox win will have a binomial distribution with  $n = 7$  and  $p = 0.6$ .

# The Binomial Distribution

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We want to find the probability that the Red Sox win 5 or fewer,

$$P(X \leq 5) = F(5)$$

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In R, enter *`pdist(5,7,0.6)`*

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In R, enter `pdist(5,7,0.6)`

The result should be 0.841

# The Binomial Distribution

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Example: A baseball player has a .300 batting average.

If the player gets to bat five times in a game, what is the probability that he gets one hit or less:

# The Binomial Distribution

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If the player gets to bat five times in a game, what is the probability that he gets one hit or less:

We'll assume a binomial distribution with  $n = 5$  and  $p = 0.300$ , then we want  $F(1) = P(X \leq 1)$ :

In R enter: `pdist(1,5,0.300)`

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The result is 0.528, so in games where a .300 hitter bats five times, more than 50 percent of the time they get one hit or less.

# The Binomial Distribution

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Example: The probability that it rains on a given weekend is 0.20.

In a month with four weekends, what is the probability that two or fewer are rainy?

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Assume a binomial distribution with  $n = 4$  and  $p = 0.2$ .

In R enter: `pdist(2,4,0.20)`

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In R enter: `pdist(2,4,0.20)`

The result is 0.9728,



# The Binomial Distribution

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Example: If

$$F(x) = P(X \leq x)$$

is the probability of the event  $A$ ="x or fewer successes", the **compliment** of this event  $A'$  is "more than x successes"

Recall that the probability of the compliment  $A'$  is always  $1 - P(A)$ .

If the chance of rain on a weekend is 0.2 and there are four weekends in a month, what is the probability that it rains on more than 2 weekends?

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The result is 0.0272,

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The expected value of a binomial random variable  $E(X)$  is:

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$$E(X) = \sum x \cdot \binom{n}{x} p^x (1-p)^{n-x} = np$$

# The Binomial Distribution

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To find the variance  $V(X)$  of a binomial random variable, first we find  $E(X^2)$ :

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Then

$$V(X) = E(X^2) - [E(X)]^2 = n^2 p^2 - np^2 + np - n^2 p^2$$

and

$$V(X) = np(1-p)$$

---



# The Binomial Distribution

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Now we will perform some numerical experiments.

First generate a sample of 1,000,000 observations for a binomial experiment with  $n = 6$  trials and probability of success  $p = 0.4$ :

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x<-rbinom(1000000,6,0.4)
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Now plot a histogram of the results:

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To get a table of the results enter

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table(x)
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The results should look something like:

0	1	2	3	4	5
77647	258841	346623	230275	76253	10361

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# The Binomial Distribution

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0	1	2	3	4	5
77647	258841	346623	230275	76253	10361

Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

*`dbinom(0,5,0.4)`*

# The Binomial Distribution

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[1] 0.07776
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The result should be something like

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To get the probability that  $X = 1$  enter

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# The Binomial Distribution

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Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

*dbinom(0,5,0.4)*

The result should be something like

*[1] 0.07776*

To get the probability that  $X = 1$  enter

*dbinom(1,5,0.4)*

This time the results should look something like:

*[1] 0.2592*



# The Binomial Distribution

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0	1	2	3	4	5
77647	258841	346623	230275	76253	10361

Next compute the probability that  $X = 2$ :

*`dbinom(2,5,0.4)`*

# The Binomial Distribution

---

0	1	2	3	4	5
77647	258841	346623	230275	76253	10361

Next compute the probability that  $X = 2$ :

*`dbinom(2,5,0.4)`*

The result should be something like

*`[1] 0.3456`*

# The Binomial Distribution

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Next compute the probability that  $X = 2$ :

*dbinom(2,5,0.4)*

The result should be something like

*[1] 0.3456*

To get the probability that  $X = 5$  enter

*dbinom(1,5,0.4)*

# The Binomial Distribution

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0	1	2	3	4	5
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Next compute the probability that  $X = 2$ :

*dbinom(2,5,0.4)*

The result should be something like

*[1] 0.3456*

To get the probability that  $X = 5$  enter

*dbinom(1,5,0.4)*

This time the results should look something like:

*[1] 0.01024*

# The Binomial Distribution

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The expected value  $E(X)$  in this case is:

$$E(X) = np = 5 \cdot 0.4 = 2$$

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To compute the sample mean  $\bar{x}$ , enter  
*mean(x)*

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The expected value  $E(X)$  in this case is:

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To compute the sample mean  $\bar{x}$ , enter

*mean(x)* The result should be something like

*[1] 1.999759*

# The Binomial Distribution

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The variance  $V(X)$  in this case is:

$$V(X) = np(1 - p) = 5 \cdot 0.4 \cdot 0.6 = 1.2$$



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To compute the sample variance  $s^2$ , enter  
*var(x)*

# The Binomial Distribution

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The variance  $V(X)$  in this case is:

$$V(X) = np(1 - p) = 5 \cdot 0.4 \cdot 0.6 = 1.2$$

To compute the sample variance  $s^2$ , enter  
`var(x)` The result should be something like

`[1] 1.197966`

# The Binomial Distribution

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At a certain intersection, the probability that a car goes straight through is 0.8.

If we observe 15 cars, what is the probability that 10 or fewer go straight through?

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If we observe 15 cars, what is the probability that 10 or fewer go straight through?

Enter  $pbinom(10, 15, 0.8)$

# The Binomial Distribution

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At a certain intersection, the probability that a car goes straight through is 0.8.

If we observe 15 cars, what is the probability that 10 or fewer go straight through?

Enter  $pbinom(10, 15, 0.8)$  The result should be .164

# The Binomial Distribution

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92% of a certain airline's flights arrive on time.

On a day when the airline operates 30 flights, what is the probability that more than 27 arrive on time?

# The Binomial Distribution

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92% of a certain airline's flights arrive on time.

On a day when the airline operates 30 flights, what is the probability that more than 27 arrive on time?

Enter  $1-pbinom(27,30,0.92)$

# The Binomial Distribution

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92% of a certain airline's flights arrive on time.

On a day when the airline operates 30 flights, what is the probability that more than 27 arrive on time?

Enter  $1-pbinom(27,30,0.92)$  The result should be .565



# The Geometric Distribution

---

The geometric experiment consists of:

- Independent Bernoulli trials are performed until the first "success" is obtained
- The random variable  $X$  is the number of failures obtained
- The probability of success  $p$  is the same for all trials

# The Geometric Distribution

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The probability mass function (pmf)  $f(x)$  is:

$$f(x) = P(X = x) = g(x; p) = p(1 - p)^x, \quad x = 0, 1, 2, 3, \dots$$

# The Geometric Distribution

---

If you sum the values of  $f(x)$  over all values from zero to infinity, the sum is one.

$$\sum_{x=0}^{\infty} p(1-p)^x = p \cdot \sum_{x=0}^{\infty} (1-p)^x$$

# The Geometric Distribution

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$$\sum_{x=0}^{\infty} p(1-p)^x = p \cdot \sum_{x=0}^{\infty} (1-p)^n$$

The sum is now a geometric series with  $r = 1 - p$ . The sum of a geometric series is  $1/(1 - r)$ , so

$$p \cdot \sum_{x=0}^{\infty} (1-p)^n = p \cdot \left( \frac{1}{1 - (1-p)} \right) = p \cdot \frac{1}{p} = 1$$

# The Geometric Distribution

---

The expected value of a geometric random variable  $E(X)$  is:

$$E(X) = \sum_{x=0}^n x \cdot f(x)$$

# The Geometric Distribution

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# The Geometric Distribution

---

To find the variance  $V(X)$  of a geometric random variable, first we find  $E(X^2)$ :

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# The Geometric Distribution

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$$E(X^2) = \sum x^2 \cdot x(1-p)x = \frac{2 - 3p + p^2}{p^2}$$



# The Geometric Distribution

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To find the variance  $V(X)$  of a geometric random variable, first we find  $E(X^2)$ :

$$E(X^2) = \sum_{x=0}^{\infty} x^2 \cdot f(x)$$

$$E(X^2) = \sum_{x=0}^{\infty} x^2 \cdot x(1-p)^{x-1} p = \frac{2 - 3p + p^2}{p^2}$$

Then

$$V(X) = E(X^2) - [E(X)]^2 = \frac{1-p}{p^2}$$

# The Geometric Distribution

---

Now we will perform some numerical experiments.

First generate a sample of 1,000,000 observations for a geometric experiment with probability of success  $p = 0.4$  at each trial:

```
x <- rgeom(1000000, 0.4)
```

# The Geometric Distribution

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First generate a sample of 1,000,000 observations for a geometric experiment with probability of success  $p = 0.4$  at each trial:

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Now plot a histogram of the results:

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hist(x)
```

To get a table of the results enter

```
table(x)
```

The results through  $X = 6$  should look something like:

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

---

# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

*dgeom(0,0.4)*

# The Geometric Distribution

---

0	1	2	3	4	5	6
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Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

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The result should be something like

*[1] 0.4*

# The Geometric Distribution

---

0	1	2	3	4	5	6
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Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

```
dgeom(0,0.4)
```

The result should be something like

```
[1] 0.4
```

To get the probability that  $X = 1$  enter

```
dgeom(1,0.4)
```



# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Now compare the frequencies to the probabilities.

First compute the probability that  $X = 0$ :

```
dgeom(0,0.4)
```

The result should be something like

```
[1] 0.4
```

To get the probability that  $X = 1$  enter

```
dgeom(1,0.4)
```

This time the results should look something like:

```
[1] 0.24
```

# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Next compute the probability that  $X = 2$ :

*dgeom(2,0.4)*

# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Next compute the probability that  $X = 2$ :

*dgeom(2,0.4)*

The result should be something like

*[1] 0.144*

# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Next compute the probability that  $X = 2$ :

*dgeom(2,0.4)*

The result should be something like

*[1] 0.144*

To get the probability that  $X = 5$  enter

*dbinom(1,5,0.4)*

# The Geometric Distribution

---

0	1	2	3	4	5	6
399422	240431	144595	86377	51550	31004	18720

Next compute the probability that  $X = 2$ :

```
dgeom(2,0.4)
```

The result should be something like

```
[1] 0.144
```

To get the probability that  $X = 5$  enter

```
dbinom(1,5,0.4)
```

This time the results should look something like:

```
[1] 0.031104
```

# The Geometric Distribution

---

The expected value  $E(X)$  in this case is:

$$E(X) = \frac{1-p}{p} = \frac{.6}{.4} = 1.5$$

# The Geometric Distribution

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To compute the sample mean  $\bar{x}$ , enter  
*mean(x)*

# The Geometric Distribution

---

The expected value  $E(X)$  in this case is:

$$E(X) = \frac{1-p}{p} = \frac{.6}{.4} = 1.5$$

To compute the sample mean  $\bar{x}$ , enter

*mean(x)* The result should be something like

*[1] 1.499121*



# The Geometric Distribution

---

The variance  $V(X)$  in this case is:

$$V(X) = \frac{1 - p}{p^2} = \frac{.6}{.4^2} = 3.75$$

# The Geometric Distribution

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The variance  $V(X)$  in this case is:

$$V(X) = \frac{1 - p}{p^2} = \frac{.6}{.4^2} = 3.75$$

To compute the sample variance  $s^2$ , enter  
*var(x)*

# The Geometric Distribution

---

The variance  $V(X)$  in this case is:

$$V(X) = \frac{1-p}{p^2} = \frac{.6}{.4^2} = 3.75$$

To compute the sample variance  $s^2$ , enter  
*var(x)* The result should be something like

*[1] 3.733986*