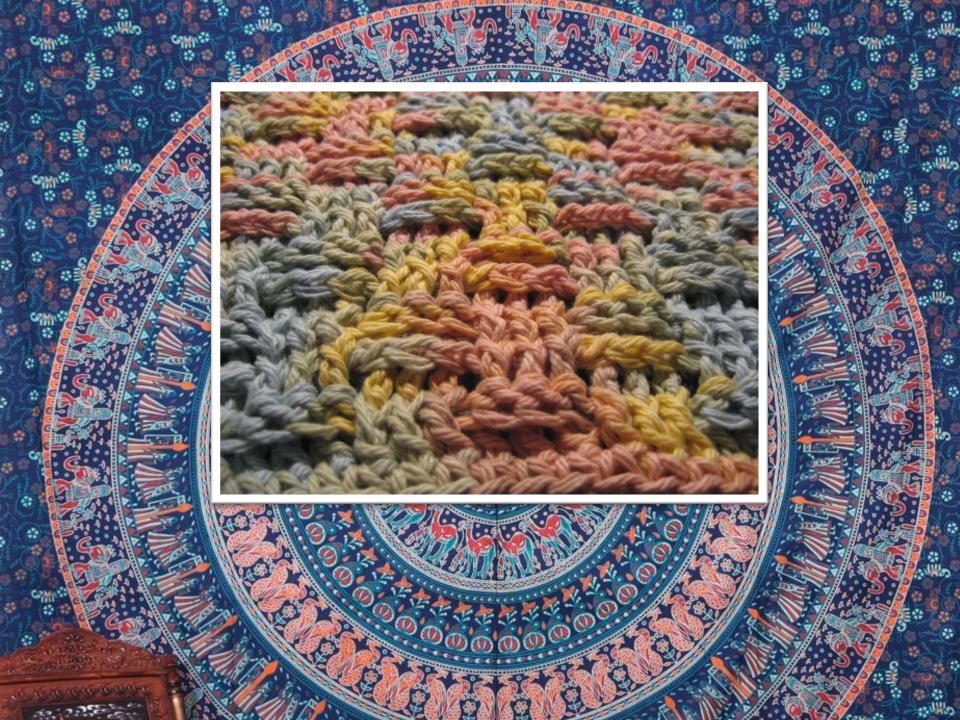




Storing Data on DNA

- We want to know the probability of 100 base pairs being corrupted?
 - Probability of each base pair being corrupted is 10⁻⁶
 - n = 4 base-pairs
 - X = number of bits corrupted. X ~ Bin(4, 0.1)
 - In real networks, send large bit strings (length $n \approx 10^4$)
 - Probability of bit corruption is very small $p \approx 10^{-6}$
 - $X \sim Bin(10^4, 10^{-6})$ is unwieldy to compute
- Extreme n and p values arise in many cases
 - # bit errors in file written to disk (# of typos in a book)
 - # visitors to a popular website
 - # of servers crashes in a day in giant data center



Facebook Likes

- Let's try and calculate the probability of different nu
 - N is the number of people who see your post
- "Maximum Likelihood" estimate
 - Set N to be value that maximizes:

$$P(X = i) = \frac{\binom{m}{i} \binom{N - m}{n - i}}{\binom{N}{n}}$$

Bernoulli vs Binomial

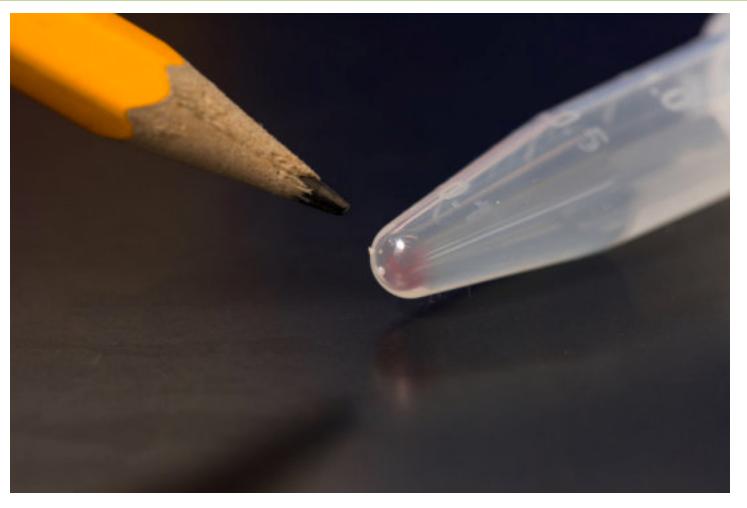


Bernoulli is a type of RV that can take on two values, 1 (for success) with probability p and 0 (for failure) with probability (1- p)



Binomial is the sum of *n*Bernoullis

Storing Data on DNA



All the movies, images, emails and other digital data from more than 600 basic smartphones (10,000 gigabytes) can be stored in the faint pink smear of DNA at the end of this test tube.

Whither the Binomial

- Recall example of sending bit string over network
 - n = 4 bits sent over network where each bit had independent probability of corruption p = 0.1
 - $X = \text{number of bits corrupted. } X \sim \text{Bin}(4, 0.1)$
 - In DNA (and real networks), send large strings (length $n \approx 10^4$)
 - Probability of corruption is very small $p \approx 10^{-6}$
 - X ~ Bin(10⁴, 10⁻⁶) is unwieldy to compute
- Extreme n and p values arise in many cases
 - # bit errors in steam sent over a network
 - # visitors to a popular website
 - # of servers crashes in a day in giant data center
 - # Facebook login requests that go to particular server

Binomial in the Limit

Recall the Binomial distribution

$$P(X = i) = \frac{n!}{i!(n-i)!} p^{i} (1-p)^{n-i}$$

• Let $\lambda = np$ (equivalently: $p = \lambda/n$)

$$P(X = i) = \frac{n!}{i!(n-i)!} \left(\frac{\lambda}{n}\right)^{i} \left(1 - \frac{\lambda}{n}\right)^{n-i} = \frac{n(n-1)...(n-i+1)}{n^{i}} \frac{\lambda^{i}}{i!} \frac{(1 - \lambda/n)^{n}}{(1 - \lambda/n)^{i}}$$

• When *n* is large, *p* is small, and λ is "moderate":

$$\frac{n(n-1)...(n-i+1)}{n^{i}} \approx 1 \qquad (1-\lambda/n)^{n} \approx e^{-\lambda} \qquad (1-\lambda/n)^{i} \approx 1$$

• Yielding:
$$P(X=i) \approx 1 \frac{\lambda^{i}}{i!} \frac{e^{-\lambda}}{1} = \frac{\lambda^{i}}{i!} e^{-\lambda}$$

Poisson Random Variable

- X is a <u>Poisson</u> Random Variable: X ~ Poi(λ)
 - X takes on values 0, 1, 2...
 - and, for a given parameter $\lambda > 0$,
 - has distribution (PMF):

$$P(X=i) = e^{-\lambda} \frac{\lambda^{i}}{i!}$$

- Note Taylor series: $e^{\lambda} = \frac{\lambda^0}{0!} + \frac{\lambda^1}{1!} + \frac{\lambda^2}{2!} + \dots = \sum_{i=0}^{\infty} \frac{\lambda^i}{i!}$
- So: $\sum_{i=0}^{\infty} P(X=i) = \sum_{i=0}^{\infty} e^{-\lambda} \frac{\lambda^{i}}{i!} = e^{-\lambda} \sum_{i=0}^{\infty} \frac{\lambda^{i}}{i!} = e^{-\lambda} e^{\lambda} = 1$

Sending Data on Network Redux

- Recall example of sending bit string over network
 - Send bit string of length $n = 10^4$
 - Probability of (independent) bit corruption $p = 10^{-6}$
 - $X \sim Poi(\lambda = 10^4 * 10^{-6} = 0.01)$
 - What is probability that message arrives uncorrupted?

$$P(X = 0) = e^{-\lambda} \frac{\lambda^i}{i!} = e^{-0.01} \frac{(0.01)^0}{0!} \approx 0.990049834$$

• Using Y ~ Bin(10^4 , 10^{-6}):

$$P(Y = 0) \approx 0.990049829$$

Caveat emptor: Binomial computed with built-in function in python software package, so some approximations may have occurred. Approximations are closer to you than they may appear in some software packages.

Simeon-Denis Poisson

 Simeon-Denis Poisson (1781-1840) was a prolific French mathematician





- Published his first paper at 18, became professor at 21, and published over 300 papers in his life
 - He reportedly said "Life is good for only two things, discovering mathematics and teaching mathematics."
- I'm going with French Martin Freeman

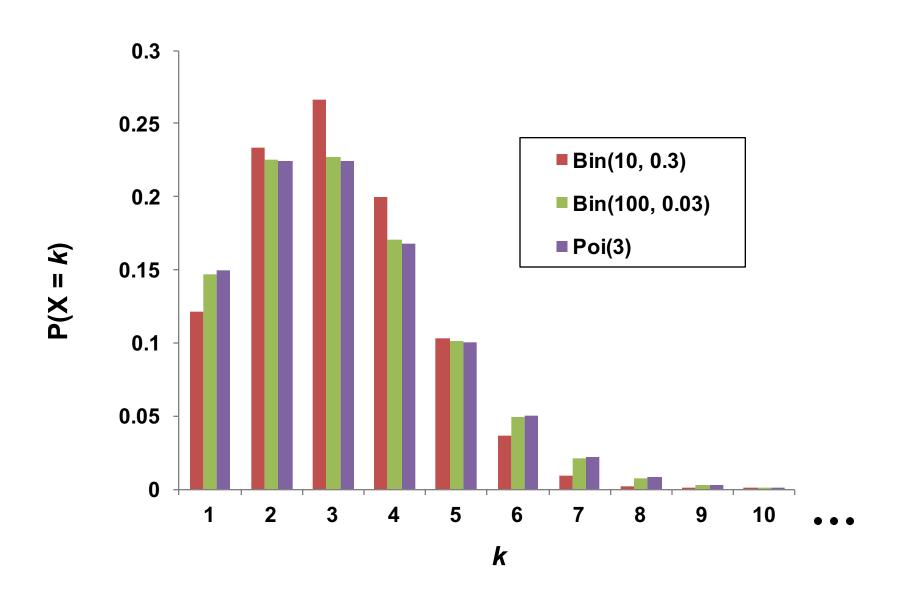
Poisson is Binomial in the Limit

- Poisson approximates Binomial where n is large,
 p is small, and λ = np is "moderate"
- Different interpretations of "moderate"
 - n > 20 and p < 0.05
 - n > 100 and p < 0.1

Really, Poisson is Binomial as

$$n \rightarrow \infty$$
 and $p \rightarrow 0$, where $np = \lambda$

Bin(10,0.3) vs Bin(100,0.03) vs Poi(3)



Tender (Central) Moments with Poisson

- Recall: $Y \sim Bin(n, p)$
 - E[Y] = np
 - Var(Y) = np(1 p)
- $X \sim Poi(\lambda)$ where $\lambda = np$ $(n \rightarrow \infty \text{ and } p \rightarrow 0)$
 - $E[X] = np = \lambda$
 - $Var(X) = np(1-p) = \lambda(1-0) = \lambda$
 - Yes, expectation and variance of Poisson are same
 - It brings a tear to my eye...

A Real License Plate Seen at Stanford



No, it's not mine... but I kind of wish it was.

It's Really All About Raisin Cake



- Bake a cake using many raisins and lots of batter
- Cake is enormous (in fact, infinitely so...)
 - Cut slices of "moderate" size (w.r.t. # raisins/slice)
 - Probability p that a particular raisin is in a certain slice is very small (p = 1/# cake slices)
- Let X = number of raisins in a certain cake slice

• X ~ Poi(
$$\lambda$$
), where $\lambda = \frac{\text{total } \# \text{ raisins}}{\# \text{ cake slices}}$

CS = Baking Raisin Cake with Code

- Hash tables
 - strings = raisins
 - buckets = cake slices
- Server crashes in data center
 - servers = raisins
 - list of crashed machines = particular slice of cake
- Facebook login requests (i.e., web server requests)
 - requests = raisins
 - server receiving request = cake slice

Defective Chips

- Computer chips are produced
 - p = 0.1 that a chip is defective
 - Consider a sample of n = 10 chips
 - What is P(sample contains ≤ 1 defective chip)?
 - Using Y ~ Bin(10, 0.1):

$$P(Y \le 1) = {10 \choose 0} (0.1)^0 (1 - 0.1)^{10} + {10 \choose 1} (0.1)^1 (1 - 0.1)^9 \approx 0.7361$$

• Using X ~ Poi(
$$\lambda = (0.1)(10) = 1$$
)
$$P(X \le 1) = e^{-1} \frac{1^0}{0!} + e^{-1} \frac{1^1}{1!} = 2e^{-1} \approx 0.7358$$

Efficiently Computing Poisson

- Let X ~ Poi(λ)
 - Want to compute P(X = i) for multiple values of i
 - E.g., Computing $P(X \le a) = \sum_{i=0}^{a} P(X = i)$
- Iterative formulation:
 - Compute P(X = i + 1) from P(X = i)

$$\frac{P(X=i+1)}{P(X=i)} = \frac{e^{-\lambda} \lambda^{i+1} / (i+1)!}{e^{-\lambda} \lambda^{i} / i!} = \frac{\lambda}{i+1}$$

Use recurrence relation:

$$P(X = 0) = e^{-\lambda} \frac{\lambda^0}{0!} = e^{-\lambda}$$
$$P(X = i + 1) = \frac{\lambda}{i + 1} P(X = i)$$

Poisson is all about the Meh

- Poisson can still provide a good approximation even when assumptions are "mildly" violated
- "Poisson Paradigm"
- Can apply Poisson approximation when...
 - "Successes" in trials are not entirely independent
 - Example: # entries in each bucket in large hash table
 - Probability of "Success" in each trial varies (slightly)
 - Small relative change in a very small p
 - Example: average # requests to web server/sec. may fluctuate slightly due to load on network

Birthday Problem Redux

- What is the probability that of m people, none share the same birthday (regardless of year)?
 - n = (^m₂) trials, one for each pair of people (x, y), x ≠ y
 Let E_{x,y} = x and y have same birthday (trial success)

 - $P(E_{x,y}) = p = 1/365$ (note: all $E_{x,y}$ not independent)

•
$$X \sim \text{Poi}(\lambda)$$
 where $\lambda = \binom{m}{2} \frac{1}{365} = \frac{m(m-1)}{730}$

$$P(X=0) = e^{-m(m-1)/730} \frac{(m(m-1)/730)^0}{0!} = e^{-m(m-1)/730}$$

• Solve for smallest integer m, s.t.: $e^{-m(m-1)/730} \le 0.5$

$$\ln(e^{-m(m-1)/730}) \le \ln(0.5) \to m(m-1) \ge -730\ln(0.5) \to m \ge 23$$

Same as before!

Poisson Process

- Consider "rare" events that occur over time
 - Earthquakes, radioactive decay, hits to web server, etc.
 - Have time interval for events (1 year, 1 sec, whatever...)
 - Events arrive at rate: λ events per interval of time
- Split time interval into n → ∞ sub-intervals
 - Assume at most one event per sub-interval
 - Event occurrences in sub-intervals are independent
 - With many sub-intervals, probability of event occurring in any given sub-interval is small
- N(t) = # events in original time interval ~ Poi(λ)

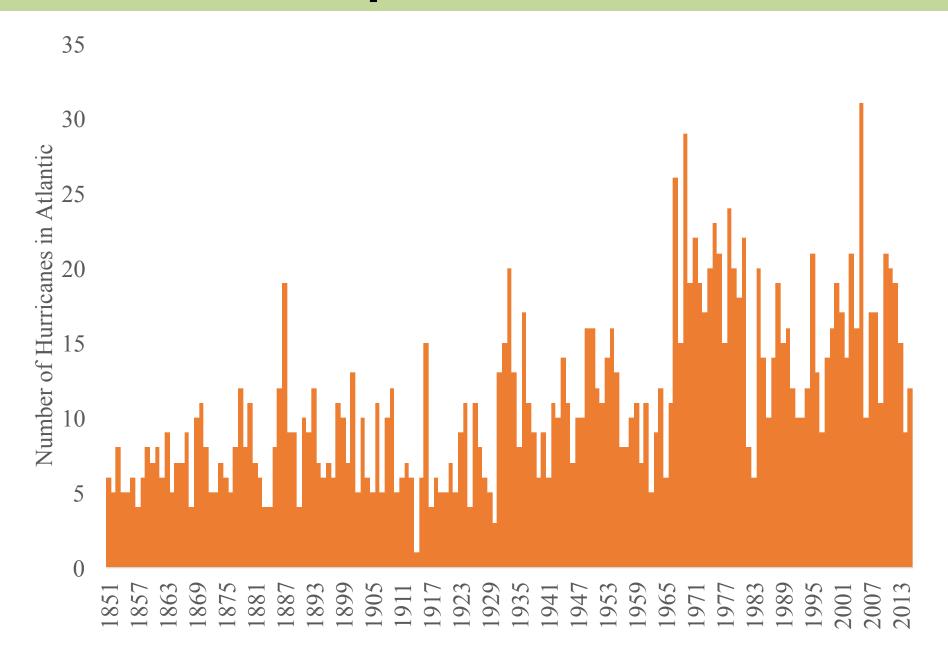
Web Server Load

- Consider requests to a web server in 1 second
 - In past, server load averages 2 hits/second
 - X = # hits server receives in a second
 - What is P(X = 5)?
- Model
 - Assume server cannot acknowledge > 1 hit/msec.
 - 1 sec = 1000 msec. (= large *n*)
 - P(hit server in 1 msec) = 2/1000 (= small p)
 - $X \sim Poi(\lambda = 2)$

$$P(X = 5) = e^{-2} \frac{2^5}{5!} \approx 0.0361$$

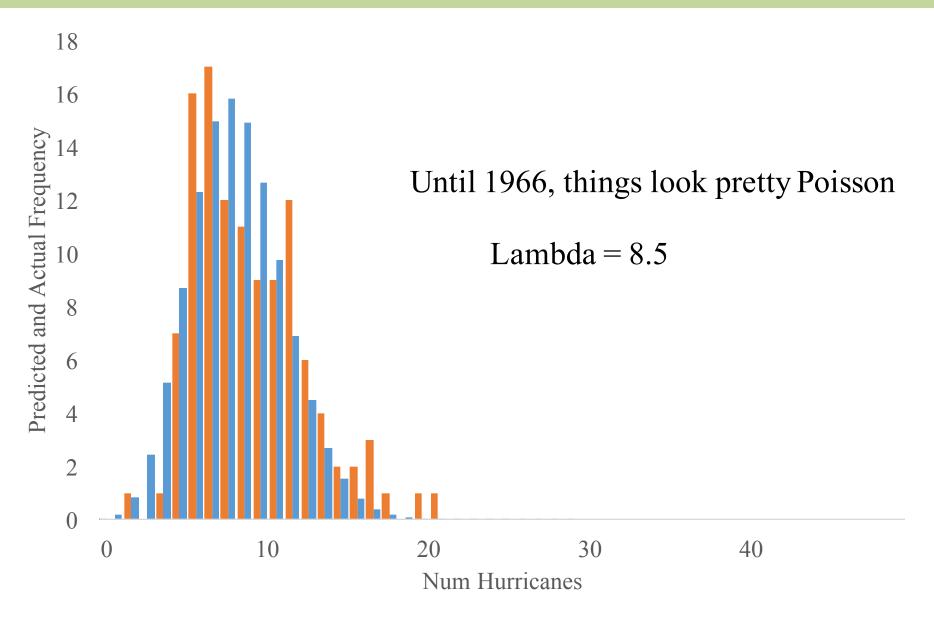


Hurricanes per Year since 1851



To the code!

Historically ~ Poisson(8.5)



Improbability Drive

- What is the probability of over 15 hurricanes in a season given that the distribution doesn't change?
 - Let X = # hurricanes in a year. X ~ Poi(8.5)
- Solution:

$$P(X>15) = 1 - P(X \le 15) \qquad \text{of a Poisson.}$$
 Your favorite programming language has a function for it
$$= 1 - 0.98$$

$$= 0.02$$

This is the pdf of a Poisson. Your favorite function for it

Twice since 1966 there have been years with over 30 hurricanes

Improbability Drive

- What is the probability of over 30 hurricanes in a season given that the distribution doesn't change?
 - Let X = # hurricanes in a year. X ~ Poi(8.5)
- Solution:

$$P(X > 30) = 1 - P(X \le 30)$$

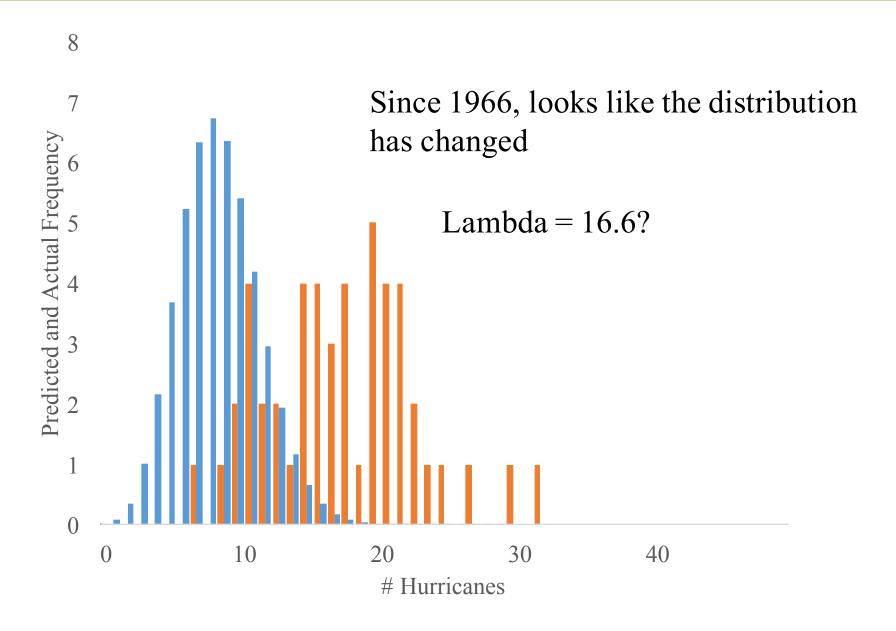
$$= 1 - \sum_{i=0}^{30} P(X = i)$$

$$= 1 - 0.999999997823$$

$$= 2.2e - 09$$

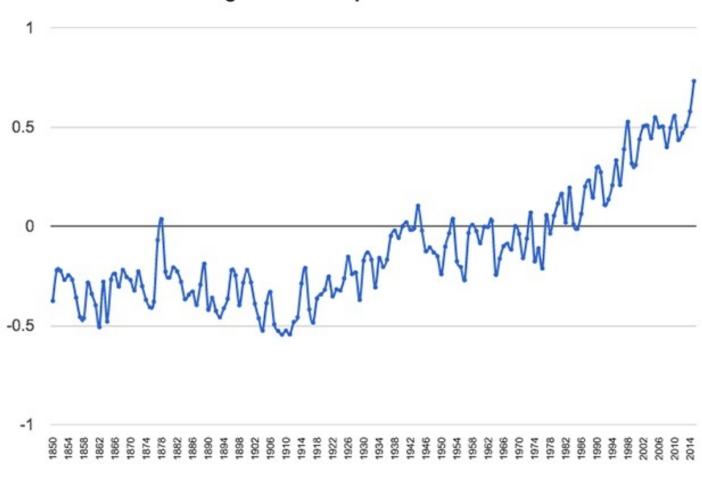
This is the pdf of a Poisson. Your favorite programming language has a function for it

The Distribution has Changed



What's Up?

Global annual average surface temperature



Pause

Discrete Distributions

 Don't have to memorize all of the following distributions.

We want you to get a sense of how random variables work

Geometric Random Variable

- X is <u>Geometric</u> Random Variable: X ~ Geo(p)
 - X is number of independent trials until first success
 - p is probability of success on each trial
 - X takes on values 1, 2, 3, ..., with probability:

$$P(X = n) = (1 - p)^{n-1} p$$

- E[X] = 1/p $Var(X) = (1 p)/p^2$
- Examples:
 - Flipping a coin (P(heads) = p) until first heads appears
 - Urn with N black and M white balls. Draw balls (with replacement, p = N/(N + M)) until draw first black ball
 - Generate bits with P(bit = 1) = p until first 1 generated

Negative Binomial Random Variable

- X is <u>Negative Binomial</u> RV: X ~ NegBin(r, p)
 - X is number of independent trials until r successes
 - p is probability of success on each trial
 - X takes on values r, r + 1, r + 2..., with probability:

$$P(X = n) = {n-1 \choose r-1} p^r (1-p)^{n-r}$$
, where $n = r, r+1,...$

- E[X] = r/p $Var(X) = r(1-p)/p^2$
- Note: $Geo(p) \sim NegBin(1, p)$
- Examples:
 - # of coin flips until r-th "heads" appears
 - # of strings to hash into table until bucket 1 has r entries

Hypergeometric Random Variable

- X is <u>Hypergeometric</u> RV: X ~ HypG(n, N, m)
 - Urn with N balls: (N m) black and m white
 - Draw n balls without replacement
 - X is number of white balls drawn

$$P(X = i) = \frac{\binom{m}{i} \binom{N - m}{n - i}}{\binom{N}{n}}, \text{ where } i = 0, 1, ..., n$$

- E[X] = n(m/N) $Var(X) = [nm(N-n)(N-m)]/[N^2(N-1)]$
- Let p = m/N (probability of drawing white on 1st draw)
- Note: HypG $(n, N, m) \rightarrow Bin(n, m/N)$
 - As $N \rightarrow \infty$ and m/N remains constant

Endangered Species



- Determine N = how many of some species remain
 - Randomly tag m of species (e.g., with white paint)
 - Allow animals to mix randomly (assuming no breeding)
 - Later, randomly observe another n of the species
 - X = number of tagged animals in observed group of n
 - X ~ HypG(n, N, m)
- "Maximum Likelihood" estimate

* Set N to be value that maximizes:
$$P(X = i) = \frac{\binom{m}{i}\binom{N-m}{n-i}}{\binom{N}{n}}$$