

# CS 107, Probability, Spring 2019

## Lecture 26

Michael Poghosyan

AUA

25 March 2019

- End of the story about Important Discrete R.V.s
- Examples of Important Continuous R.V.s

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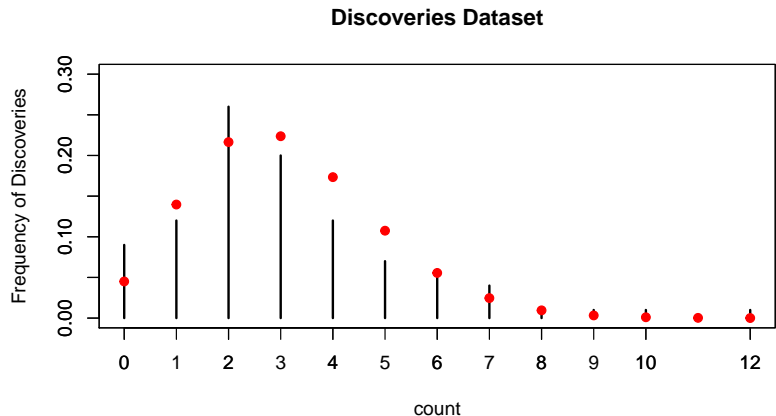
- The way one of my teachers explained the 80/20 thing: 80% of the noise in a classroom is caused by 20% of the students.
- 80% of comments are created by 20% of users 😊
- My phone is at 20% 80% of the time 😊
- Studied 20% of the material, get a 80% on the finals.  
Happened to no student ever. (MP: Exactly!)

# Poisson Distribution: R Examples

## R Code

```
help("discoveries")
disc <- discoveries
plot(disc)
hist(disc, breaks = seq(0,13,1)) #histogram
#Fitting the data by the Poisson
lambda = mean(disc)
table(disc)
plot(table(disc)/length(disc), xlim = c(0,max(disc)),
     ylim = c(0,0.3), main = "Discoveries Dataset",
     ylab = "Frequency of Discoveries", xlab = "count")
n = 0:max(disc)
m = dpois(n, lambda)
par(new = T) #To keep the previous graph
plot(n,m, xlim = c(0,max(disc)), ylim = c(0,0.3),
     pch = 19, col="red", main = "", xlab = "", ylab = "")
```

# Discoveries Dataset Model Result

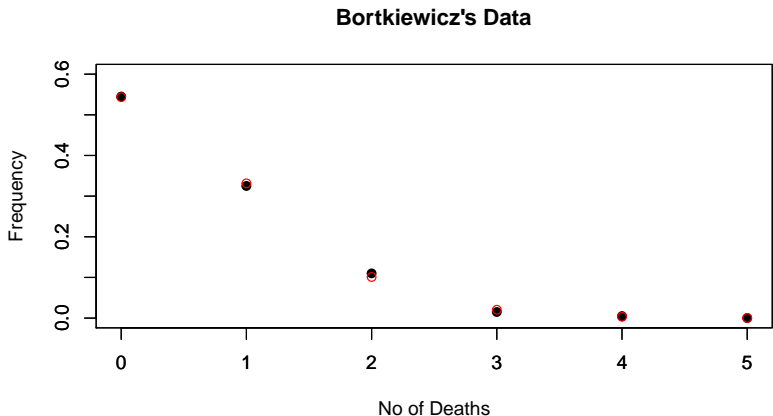


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## R Code

```
#Bortkiewicz's Data
#Deaths by horse-kick in Prussian Army cavalry corps
#(Bortkiewicz 1898). N is the number of units
#corresponding to each number of deaths.
hk<-data.frame(D = c(0,1,2,3,4,5),
  N = c(109,65,22,3,1,0))
plot(hk)
lambda <- sum(hk$D*hk$N)/sum(hk$N)
n = 0:5
m = dpois(n, lambda)
plot(n,m, xlim = c(0,5), ylim = c(0,0.6),
  col="red", type = "l", lwd = 3)
par(new = T)
plot(hk$D, hk$N/sum(hk$N) , xlim = c(0,5),
  ylim = c(0,0.6), pch=19)
```

# Bortkiewicz Dataset Model Result



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$$\mathbb{P}(X = k) = \binom{n}{k} p^k (1 - p)^{n-k} \approx e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

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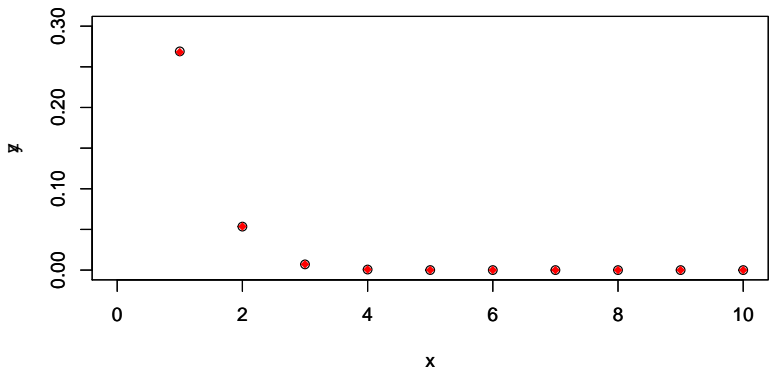
## R Code

```
# Approximation of Binomial by Poisson
n <- 100
p <- 0.004
lambda <- n*p

x <- 0:20
y <- dbinom(x, size = n, prob = p)
plot(x,y, ylim = c(0,0.4))
z <- dpois(x, lambda = lambda)
par(new=T)
plot(x,z, pch = 18, col = "red", ylim = c(0,0.4))

#Plotting the difference
plot(x, abs(y-z))
```

# Poisson approximation of Binomial Distribution



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# Note about the Poisson Distribution

Assume the average number of downloads in a day for some software (or some mobile app) is  $\lambda$ . So if we want to model the number of daily downloads  $X$  of that software ( $X$  is a r.v.), we can model that as  $X \sim \text{Poisson}(\lambda)$ .



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Now, we want to model the number  $Y$  of downloads for 2 days. Since the average number of downloads in 2 days for the same software will be  $2\lambda$ , then we can use  $Y \sim \text{Poisson}(2\lambda)$ .

# Other important Discrete Distributions

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# Important Continuous Distributions

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For example,

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# Uniform Distribution

## Uniform Distribution on $[a, b]$

We say that the r.v.  $X$  has a uniform distribution in  $[a, b]$ , and we will write  $X \sim \text{Unif}[a, b]$  if its PDF is given by

$$f(x) = \begin{cases} \frac{1}{b-a}, & x \in [a, b]; \\ 0, & \text{otherwise} \end{cases}$$

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**The Graph of the PDF:** On the board.

# The CDF of the Uniform Distribution

**Fact:** The CDF of  $X \sim \text{Unif}[a, b]$  is given by:

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# Uniform Distribution Examples

- Recall the experiments of picking a random number from some interval - we were talking, actually, about the Uniform Distribution. So if we are picking from  $[a, b]$ , and if we will denote the randomly chosen number by  $X$ , then  $X \sim \text{Unif}[a, b]$  (if, of course, we are choosing *uniformly* 😊).

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- If the Baghramyan Metro Station trains arrive in 10 min intervals, and I am visiting that station at some random time instant, then my waiting time  $X$  (in minutes) can be modeled by  $X \sim \text{Unif}[0, 10]$ .

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- Will the age distribution (exact age, not rounded to years) in AUA be Uniform ?

# Uniform Distributions: Example

**Example:** Assume  $X \sim \text{Unif}[1, 4]$ . Calculate  $\mathbb{P}(X = 2)$ ,  $\mathbb{P}(X \leq 2)$ ,  $\mathbb{P}(2 \leq X \leq 3.5)$ .



# Uniform Distribution: R Examples

## R Code

```
a <- 0
b <- 2
x <- seq(from = a-1, to = b+1, by = 0.01)
y <- dunif(x, min = a, max = b)
par(mfrow = c(1,2))
#plot the PDF
plot(x,y, type = "l", lwd = 3,
      main = "Uniform Distribution PDF")

z <- punif(x, min = a, max = b)
#plot the CDF
plot(x,z, type = "l", lwd = 3,
      main = "Uniform Distribution CDF")
```

# Uniform Distribution: R Examples

## R Code

```
#generating 10 uniformly distributed numbers in [0,1]
smpl <- runif(10) #equivalent to runif(10, min=0, max=1)
smpl

#generating 10000 uniformly distributed numbers in [0,1]
smpl <- runif(10000)
hist(smpl) # the histogram
```

# Exponential Distribution

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We say that the r.v.  $X$  has an Exponential Distribution with the parameter  $\lambda > 0$  (rate), and we write  $X \sim \text{Exp}(\lambda)$ , if its PDF is given by

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**Exercise:** Prove that the CDF of  $X \sim \text{Exp}(\lambda)$  is given by:

$$F(x) = \begin{cases} 1 - e^{-\lambda x}, & x \geq 0, \\ 0, & x < 0 \end{cases}$$