

Recap

09/10/14

1/14

### Counting Methods

1. With Replacement

Outcomes  $n = \prod_{i=1}^I n_i$  for  $I$  experiments

2. Without Replacement  
w/ regard to order

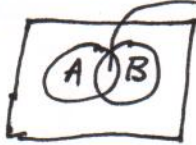
for  $r$  objects chosen from  $n$

$\frac{n!}{(n-r)!} = P_{n,r}$  permutation

w/ regard to order

"n choose r"  $\frac{n!}{(n-r)!r!} = \binom{n}{r}$  binomial coefficient

### Conditional Probability

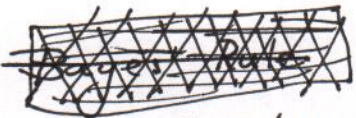


$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$

"Probability of A given B"

A - pneumonia  
B - fever  $T > 101$

Intuition: Shrink the sample space from  $\Omega$  to  $B$  because the event  $B$  has occurred. It has given information



### Multiplication Rule

$$Pr(A|B) Pr(B) = Pr(B|A) Pr(A) = Pr(A \cap B)$$



### Law of Total Probability

$$\Omega = B = \bigcup_{i=1}^n B_i$$

$B_i$  disjoint

$$Pr(B) = Pr\left(\bigcup_{i=1}^n B_i\right) = \sum_{i=1}^n Pr(B_i)$$

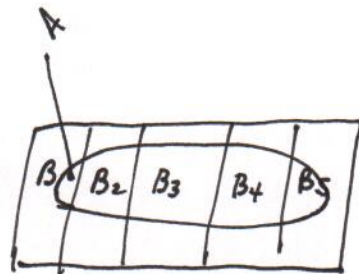
3rd Axiom

$$Pr(A) = Pr(A \cap B) = \sum_{i=1}^n Pr(B_i \cap A)$$

disjoint

$$Pr(A) = \sum_{i=1}^n Pr(B_i) Pr(A|B_i)$$

conditional probability



# Bayes' Rule

Probability of an MI given chest pain

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$$Pr(B_2 | A) = \frac{Pr(A | B_2) Pr(B_2)}{\sum_{i=1}^n Pr(B_i) \cdot Pr(A | B_i)}$$

## Bayes' Rule and Screening Test

Ex 1. E

Test for Elevated Cholesterol

- D<sup>+</sup> elevated cholesterol
- D<sup>-</sup> normal cholesterol

$Pr(D^+)$  prevalence or (incidence if per unit time)  
 probability that someone chosen from a specific cohort has an increased cholesterol, say African American men over 50.

How does a test perform?

D<sup>+</sup> Test  $Pr(+ | D^+)$   
 sensitivity

$Pr(- | D^+)$   
 false negative

} Errors

D<sup>-</sup>  $Pr(- | D^-)$   
 specificity

$Pr(+ | D^-)$   
 false positive

Would like to have a high sensitivity and a high specificity. Impossible in practice. A test always positive  $\Rightarrow$  sensitivity of 1 but not specific.

Diagnosis A test " negative  $\Rightarrow$  specificity of 1 but not sensitive  $\Rightarrow$  Trade off

## Diagnosis

$Pr(D^+ | +)$   
 predictive value positive

$Pr(D^- | -)$   
 predictive value negative

All of these terms are linked using Bayes' Rule

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Predictive Value Positive

$$\Pr(D^+|+) = \frac{\Pr(D^+ \cap +)}{\Pr(+)} = \frac{\Pr(D^+) \Pr(+|D^+)}{\Pr(+)}$$

Being Pedantic

$$\{+\} = \{+ \cap D^+\} \cup \{+ \cap D^-\} \leftarrow \begin{array}{l} \text{event test is positive} \\ \text{disjoint} \end{array}$$

$$\begin{aligned} \Pr(+ &= \Pr(+ \cap D^+) + \Pr(+ \cap D^-) \\ &= \underbrace{\Pr(D^+) \Pr(+|D^+)}_{\text{prevalence sensitivity}} + \underbrace{\Pr(D^-) \Pr(+|D^-)}_{\text{false positive}} \equiv 1 - \Pr(D^+) \end{aligned}$$

~~\*~~

Hence,

$$\Pr(D^+|+) = \frac{\Pr(D^+) \Pr(+|D^+)}{\Pr(D^+) \Pr(+|D^+) + \Pr(D^-) \Pr(+|D^-)}$$

Exercise: Work out the corresponding relationship for predictive value negative.  
 $\Pr(D^-|-)$

Will have a problem on Homework 2.



## Independence (Strong Condition)

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Two events  $E_1$  and  $E_2$  are independent if

$$\Pr(E_1 \cap E_2) = \Pr(E_1) \Pr(E_2)$$

Key idea:

Information about one tells you nothing about the other

This means using the Multiplication Rule

$$\Pr(E_2 | E_1) = \Pr(E_1 \cap E_2) / \Pr(E_1) = \frac{\Pr(E_2) \cdot \Pr(E_1)}{\Pr(E_1)} = \Pr(E_2)$$

In general, if  $E_1, E_2, \dots, E_n$  are independent events then

$$\Pr(E_1 \cap E_2 \dots \cap E_n) = \prod_{i=1}^n \Pr(E_i)$$

Ex. 1.1 (cont'd). Three trials, performance on each trial is independent (Is this reasonable?).  $\Pr(\text{correct response}) = \frac{1}{4}$  assume there are 4 possible choices. Then

$$\Pr(E_1 \cap E_2 \cap E_3) = \prod_{i=1}^3 \Pr(E_i) = \frac{1}{4} \cdot \frac{1}{4} \cdot \frac{1}{4} = \frac{1}{64}$$

We will make this assumption a lot.

Concept of a Random Variable

Discrete Probability Models

Bernoulli

Binomial

Poisson

Discrete Counting Probability

Big Picture

Data



Discrete

1. binary response: polls, yes-no questions, batting
2. counts: cases of a disease
3. neural spiking activity: action potentials

Continuous

- EEG
- local field potentials
- heights
- stock prices

Discrete Models

Probability Models

1. Bernoulli
2. Poisson
3. Point processes
4. Binomial

Continuous Models

- Gaussian
- Exponential
- Gamma
- Beta
- Inverse Gaussian

Things-to-know

- i) Shape of the model: pdf CDF
- ii) Location: mean, mode, median
- iii) ~~spread~~ Spread: variance, sd, range
- iv) Asymptotic properties (usually sample become large)
- v) WHEN DO YOU USE IT

Def'n 2.1 A random variable <sup>(RV)</sup> is a real-value function on an outcome space into the real line or ~~the~~  $R^n$ . The probability law on the outcome space  $\Rightarrow$

Ex. 2.A.

Define the R.V.  $X$  in  $\Omega$

probability model



$\Omega, \mathcal{F}, P$

$[0, 1]$

$$X(\omega) = \begin{cases} 1 & \omega = A, B \\ 2 & \omega = C \\ 3 & \omega = D, E \end{cases}$$

$$\begin{aligned} Pr(1) &= Pr(A \cup B) \\ Pr(2) &= Pr(C) \\ Pr(3) &= Pr(D \cup E) \end{aligned}$$

Write Table 2.1 on B.B. before start of class

1,1	1,2	1,3	1,4	1,5	1,6
2,1	2,2	2,3	2,4	2,5	2,6
3,1	3,2	3,3	3,4	3,5	3,6
4,1	4,2	4,3	4,4	4,5	4,6
5,1	5,2	5,3	5,4	5,5	5,6
6,1	6,2	6,3	6,4	6,5	6,6

Ex 2.0. Each outcome has probability  $\frac{1}{36}$

Define  $X(\omega) = w_1 + w_2$   
 $w_1$  - value on 1st roll  
 $w_2$  - value on 2nd roll

Find  $Pr(X(\omega))$ .

- The events occur on the outcome space
- $X$  takes on a value from 2 to 12 depending on the outcomes
- diagonals of the table define events  $w$  with the same value of  $X$
- This is why when playing craps in Las Vegas the casino wins if you roll a 7 (CRAPS!)

- $Pr(X=2) = \frac{1}{36}$
- $Pr(X=3) = \frac{2}{36}$
- $Pr(X=4) = \frac{3}{36}$
- $Pr(X=5) = \frac{4}{36}$
- $Pr(X=6) = \frac{5}{36}$
- $Pr(X=7) = \frac{6}{36}$
- $Pr(X=8) = \frac{5}{36}$
- $Pr(X=9) = \frac{4}{36}$
- $Pr(X=10) = \frac{3}{36}$
- $Pr(X=11) = \frac{2}{36}$
- $Pr(X=12) = \frac{1}{36}$



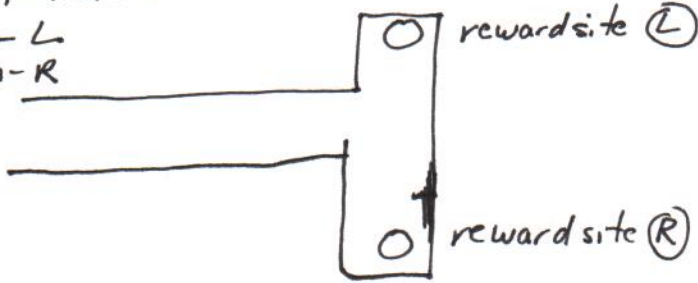
Ex 2.1 Learning Experiment  
Graybiel Lab

(Any binary outcome)  
hit - no hit  
correct incorrect  
Coakley Baker

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T-maze

low - L  
high - R



Previous day: 40 trials  
22 correct  
18 incorrect

What is the probability of a correct response today?

$p$  - prob of a correct response

$1-p$  - prob of an incorrect response

define  $X = \begin{cases} 1 & \text{correct} \\ 0 & \text{if incorrect} \end{cases}$  R.V.

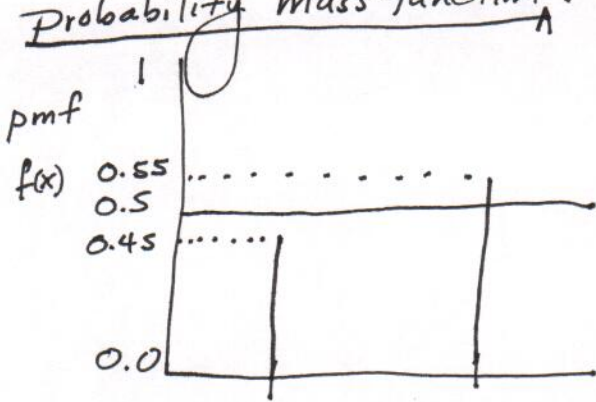
$\Pr(X=0) = p$        $\Pr(X=1) = 1-p$

or

$\Pr(X=x) = \Pr(X=0 \text{ or } x=1) = p^x (1-p)^{1-x}$

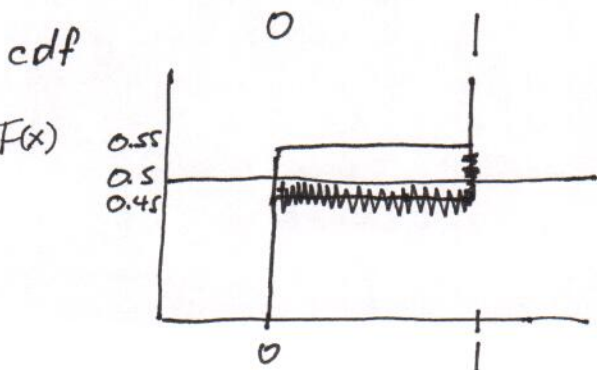
Explain the exponents  
here  $x=1 \Rightarrow p$   
 $x=0 \Rightarrow 1-p$

Bernoulli Probability Model (Simplest probability model)  
Probability mass function (pmf): defines the probability of each value of  $X$ .



$\sum_{x=0}^1 \Pr(X=x) = (1-p) + p = 1$       sums to 1

cumulative distribution function (cdf)



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

$F(0) = \Pr(X \leq 0) = \Pr(X=0) = 1-p$

$F(1) = \Pr(X \leq 1) = \Pr(X=0) + \Pr(X=1) = 1-p+p = 1$

$F(x) \equiv$  area under pmf upto and including  $x$

Ex. 2.1  $\hat{p}$  ( $p$  hat) =  $\frac{22}{40} = 0.55$  an estimate of  $p$  previous day 8/14  
or  
 $p = 0.5$  likely to perform at chance

Def'n's

mean — average

$$\mu = E(X) = \sum_{x=-\infty}^{\infty} x f(x)$$

variance — defines the spread

$$\sigma^2 = \sum_{x=-\infty}^{\infty} (x - E(x))^2 f(x)$$

$$= E[X - E(X)]^2 = E[X - \mu]^2 = E X^2 - \mu^2$$

Bernoulli

$$\mu = E(X) = \sum_{x=0}^1 0 \cdot (1-p) + 1 \cdot p = p$$

$$\sigma^2 = E(X^2) - \mu^2 = \sum_{x=0}^1 x^2 - p^2 = 0^2(1-p) + 1^2 p - p^2 = p - p^2 = p(1-p)$$

Return to discuss interpretation after we do binomial model

Binomial Model (40 at bats for David Ortiz)

Ex. 2.1 Assume  $n$ -trials  $n=40$   $p$  probability of <sup>correct</sup> success  
trials are independent

$k$ -correct

Recall:  $E_1, \dots, E_n$  are independent events

$$\Pr(\bigcap_{i=1}^n E_i) = \prod_{i=1}^n \Pr(E_i)$$

$E_1, \dots, E_n$  disjoint events

$$\Pr(\bigcup_{i=1}^n E_i) = \sum_{i=1}^n \Pr(E_i)$$

Let's analyze 1st a learning experiment with 3 trials



Events C - correct  
I - incorrect

$$\Pr(C) = \Pr(X=1) = p$$

$$\Pr(I) = \Pr(X=0) = 1-p$$

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Suppose we get  $C_1, C_2, I_3 \leftarrow$  trial

$$\Pr(C_1 \cap C_2 \cap I_3) = \text{[scribble]} \Pr(C_1)\Pr(C_2)\Pr(I_3) = p^2(1-p)$$

Make a Table on Blackboard (Tell Students)

(number of correct responses)

$X$	Outcomes independent	No# Outcomes	Probability
0	$I_1, I_2, I_3$	1 $\binom{3}{0}$ 3 attempts 0 correct	$(1-p)^3$
1	$C_1, I_2, I_3$ $I_1, C_2, I_3$ $I_1, I_2, C_3$	3 $\binom{3}{1}$	$\binom{3}{1} p(1-p)^2$
2	$C_1, C_2, I_3$ $C_1, I_2, C_3$ $I_1, C_2, C_3$	3 $\binom{3}{2}$	$\binom{3}{2} p^2(1-p)$
3	$C_1, C_2, C_3$	1 $\binom{3}{3}$	$\binom{3}{3} p^3$

$$\Pr(X=x) = \binom{3}{x} p^x (1-p)^{3-x}$$

$$x=0, 1, 2, 3$$

In general, Binomial Probability Models

$B(n, p)$

$$f(x) = \Pr(X=x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$$x=0, 1, 2, \dots, n$$

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

by Binomial Thm 10/14

cdf

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

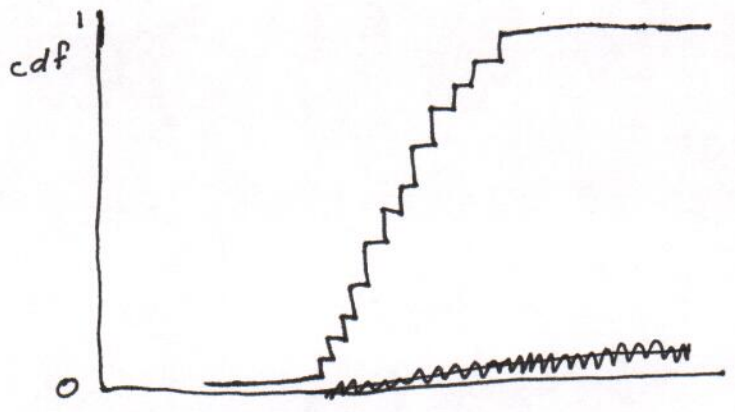
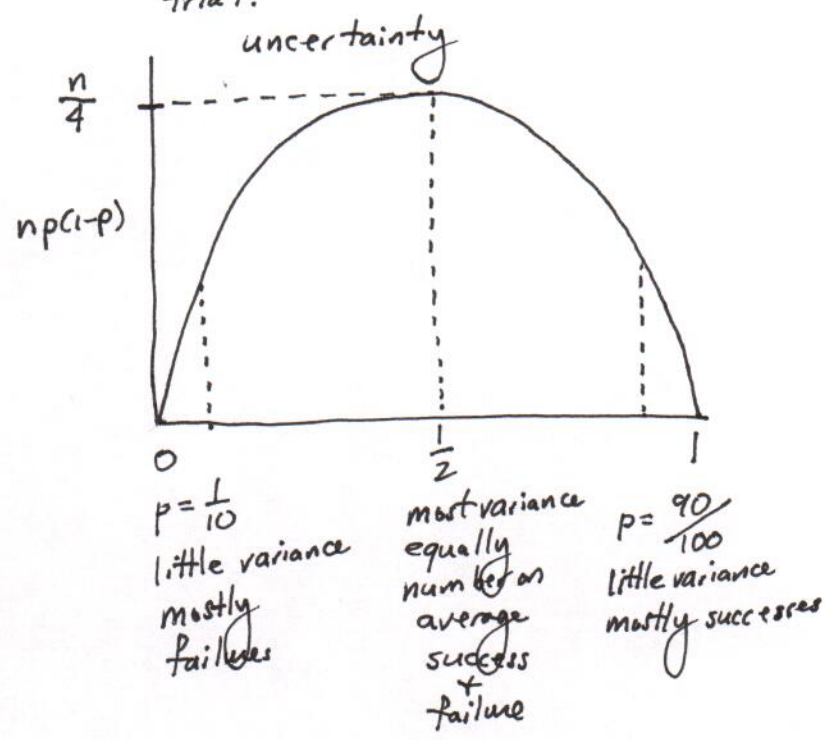
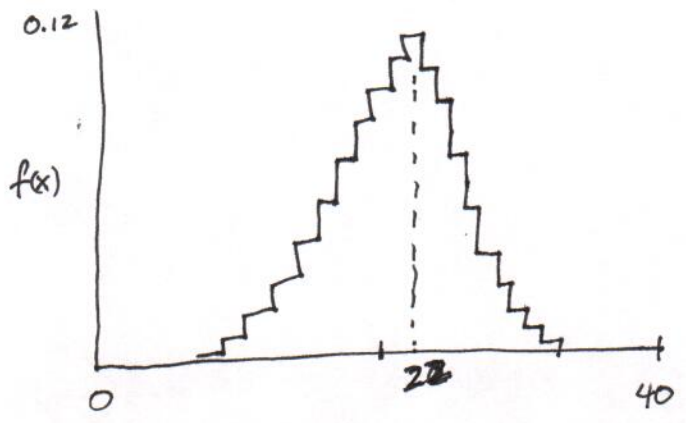
$$0 \leq F(x) \leq 1$$

$$y = 0, 1, \dots, n$$

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

$$\text{Var}(X) = np(1-p)$$

number of trials  $\times$  p success per trial.



Ex. 2.1

	Day 1	Day 2
	22	36
	40	40

Is there learning? Is  $p$  on day 2  $>$   $\hat{p}$   
 Proof by Falsification (Hypothesis Testing)  
 $H_0$ : There is no learning

How likely are the data if there is no learning?

$$\Pr(X=36 | \hat{p}=0.55, n=40) = \binom{40}{36} \hat{p}^{36} (1-\hat{p})^4 = \binom{40}{36} (0.55)^{36} (0.45)^4$$

$$= 1.69 \times 10^{-6}$$

Conclusion: Improbable

If  $H_0$ : true  $\Rightarrow$  low probability of learning  $\Rightarrow$  reject  $H_0$   
(falsify  $H_0$ )

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Applications of the Binomial Model

1. Learning

2. Hits in a game, a season

3. Voters for a candidate

4.  $k$  heads in  $n$  tosses of a coin with probability of heads  $p$



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Ex 2.1	Day 1	Day 2
	22	36
	40	40

Proof by Falsification

~~Is there learning if~~  
Is there learning?

$H_0$ : There is no learning

How likely are the data if no learning?

$$P(X=36 | \hat{p}=0.55, n=40) = \binom{40}{36} \hat{p}^{36} (1-\hat{p})^4$$

$$= \binom{40}{36} (.55)^{36} (.45)^4$$

$$= 1.69 \times 10^{-6}$$

Conclusion Improbable

If  $H_0$  true then low prob of no learning  $\Rightarrow$  reject  $H_0$   $\rightarrow$  conclude (falsify  $H_0$ )

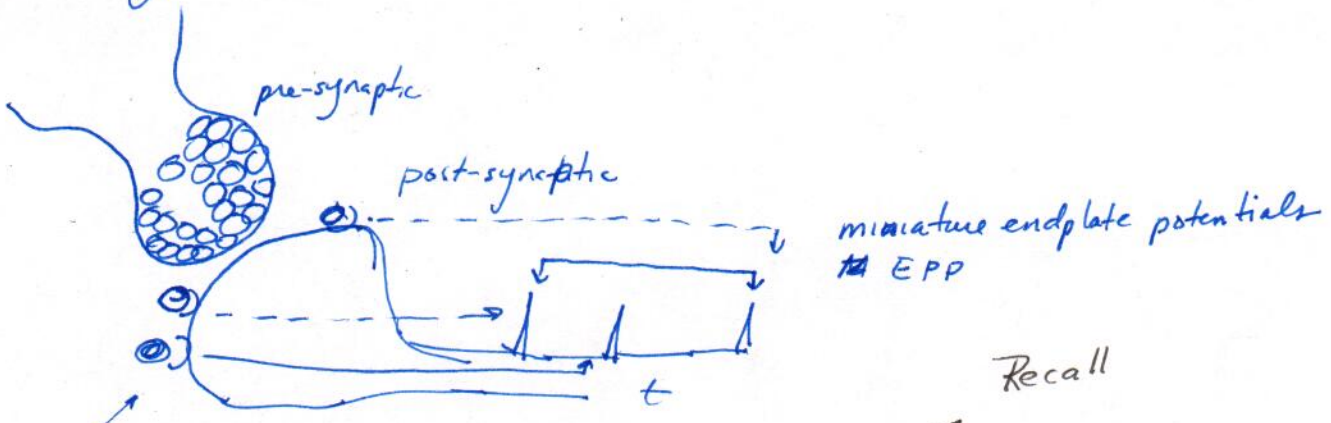
Poisson Applications

1. Learning Experiment
2. ~~Batting~~ Hits in a game (season, series) ~~at a game~~
3. N people will vote for candidate A
4. K heads in N tosses

H.W. 4 No independence

Poisson

Ex. 2.2 Quantal Response Hypothesis Neurotransmitter Release @ the Frog NMJ. Ach is released from the NMJ in discrete packets or quanta



Recall

single quantum (vesicle)

Assume

- i) N vesicles exist
- ii) release independent  $\Rightarrow$
- iii) N large, p small

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

$np \rightarrow \lambda$  as  $n \rightarrow \infty$ .  $p \approx \frac{\lambda}{n}$

small in a time window  $t$

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

$$= \frac{n!}{(n-k)! k!} \cdot p^k (1-p)^{n-k}$$

$$= \frac{n(n-1)\dots(n-k+1)}{k!} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

$$\frac{n(n-1)\dots(n-k+1)}{n^k} \frac{\lambda^k}{k!} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k}$$

$n \rightarrow \infty$

$$\frac{n(n-1)\dots(n-k+1)}{n^k} \rightarrow 1$$

$$\left[ \lim_{x \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n = e^x \right]$$

$$\left(1 - \frac{\lambda}{n}\right)^{-k} = \frac{1}{\left(1 - \frac{\lambda}{n}\right)^k} \rightarrow 1$$

$$\left(1 - \frac{\lambda}{n}\right)^n \rightarrow e^{-\lambda}$$

Def'n of  $e = 2.718..$

$\Rightarrow$

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

Poisson Approximation to the Binomial ( $N > 10^2$   $p < 10^{-2}$ )

$k=0, 1, 2, \dots$

Recall:  $\sum_{x=0}^{\infty} \frac{\lambda^x}{x!} = e^{\lambda}$

The Poisson P.m.f.

$\lambda$  - rate  
 $= P(X=k)$

no # of events per unit (time or space)

$X \sim \mathcal{P}(\lambda)$

$X$  is distributed Poisson w/ parameter  $\lambda$

$$f(k) = \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} e^{-\lambda} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} e^{\lambda} = 1$$

$$F(j|\lambda) = \sum_{k=0}^j \frac{\lambda^k}{k!} e^{-\lambda} = P(X \leq j)$$

$$E(X) = \lambda$$

$$\text{Var}(X) = \lambda$$


Intuition  $np(1-p)$  for  $n$  large  $p$  small  
 $np(1-p) \approx np \Rightarrow E(X) \approx \text{Var}(X)$



# Applications (No# of Events per unit Time)

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No# of Events

1. Number of Customers per hour at Home Depot.
2. Emergency Rm visits  12 AM - 6 AM
3. No# Miniature Excitatory Post-Synaptic Currents
4. No# of Cases of H2N1, & Pb Poisoning, per unit area
5. No# of Soldier in the Prussian Army killed by being kicked in the head by horses in a 20 year period Bortkiewicz 1848-1868
6. Lord Rutherford + Geiger ~~1910~~ 1910  
Radioactive decay of Polonium in 125 msec

## Discrete Probability Model

Any discrete-valued function can be converted into a p.m.f. if it is finitely summable

$$\sum_{x=-\infty}^{\infty} g(x) = c < \infty$$

$$\frac{1}{1 - \frac{1}{2}} = \frac{1}{\frac{1}{2}} = 2$$

$$\frac{1}{2} \sum_{n=0}^{\infty} \left(\frac{1}{2}\right)^n = 1$$

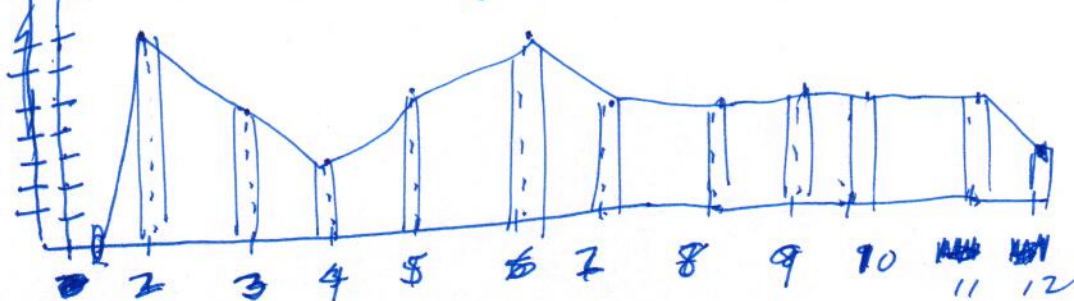
$$\sum_{n=1}^{\infty} \frac{1}{n} = \infty$$

then

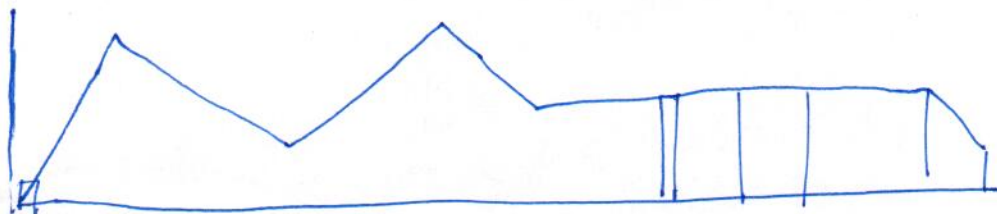
$f(x) = c^{-1} g(x)$  is a p.m.f

$$P_r(X=x) = f(x) = c^{-1} g(x)$$

$c = 46$



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Fall 2016

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