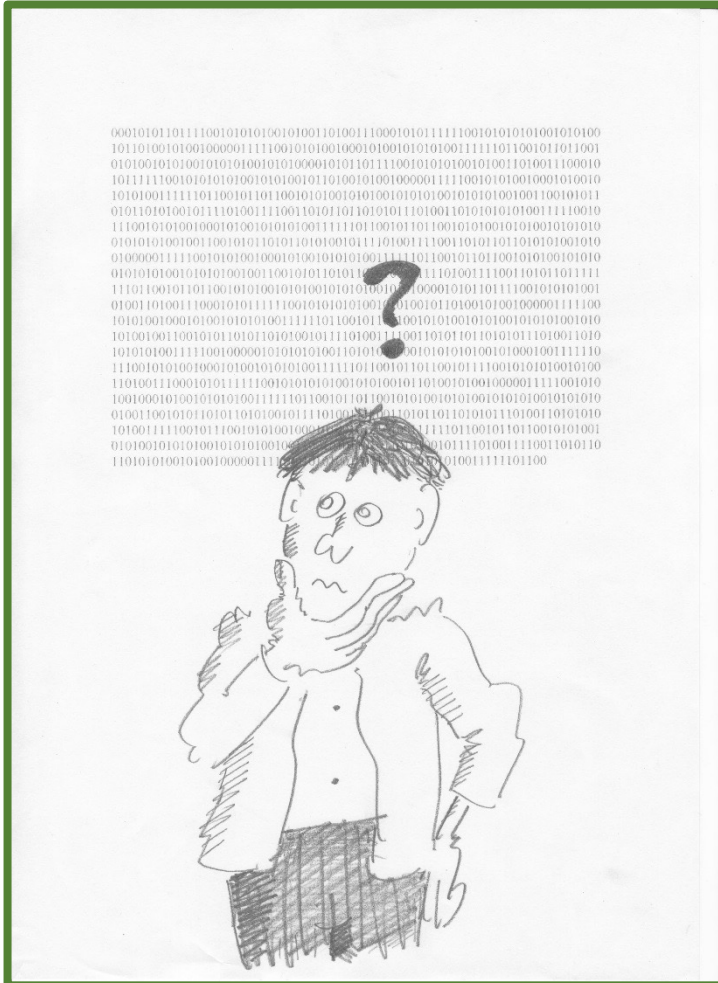


# Statistics and data analysis

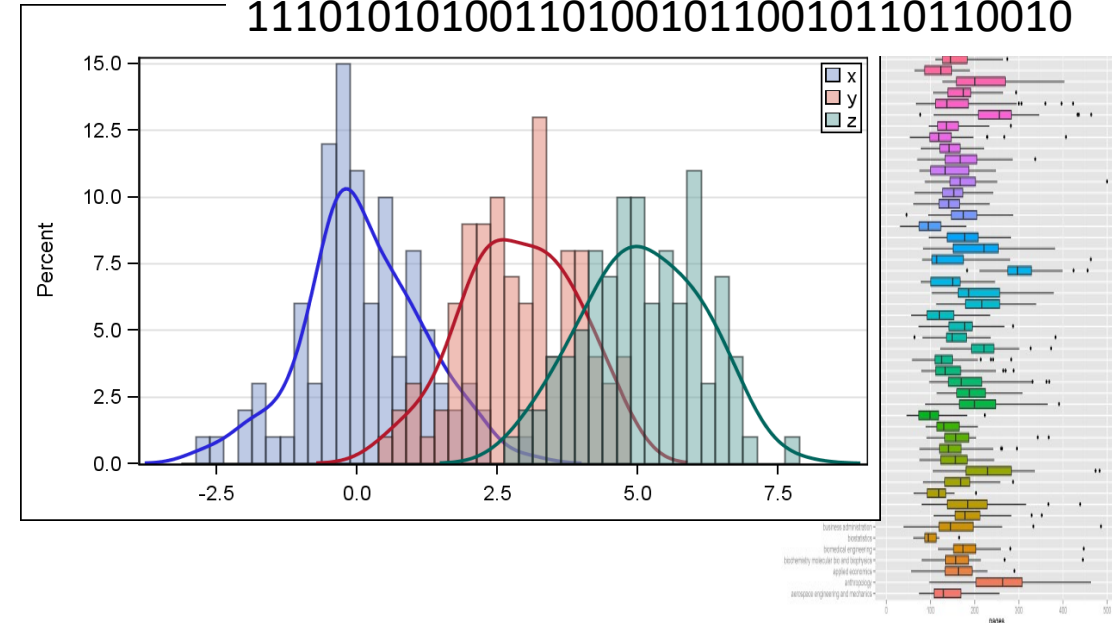
Zohar Yakhini

IDC, Herzeliya



# More distributions, independence

00100111010101001010100100100010  
1010100010101111101011010011001001  
1110101010011010010110010110110010



# Binomial Distribution

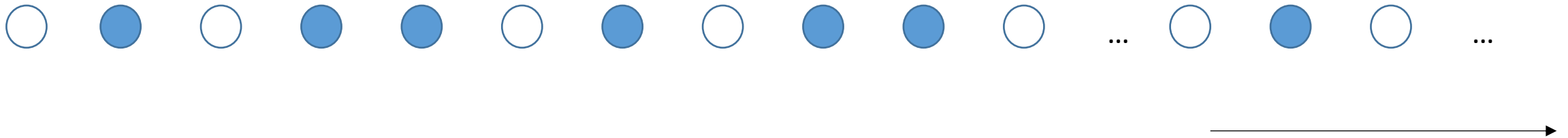
$$P(Y = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

$\omega \in \Omega :$



# The Geometric distribution

$\omega \in \Omega :$



$X(\omega) = \text{time of first success}$

$X \sim \text{Geom}(p)$

$P(X = k) = ?$

## Geometric Distribution – Expectation and variance

$$\begin{aligned} E(Y) &= \sum_{y=1}^{\infty} y [q^{y-1} p] = p \sum_{y=1}^{\infty} \frac{dq^y}{dq} = p \frac{d}{dq} \sum_{y=1}^{\infty} q^y = p \frac{d}{dq} \left[ q \sum_{y=1}^{\infty} q^{y-1} \right] = \\ &= p \frac{d}{dq} \left[ \frac{q}{1-q} \right] = p \left[ \frac{(1-q)(1) - q(-1)}{(1-q)^2} \right] = \frac{p((1-q) + q)}{(1-q)^2} = \frac{p}{p^2} = \frac{1}{p} \end{aligned}$$

$$\begin{aligned} E(Y(Y-1)) &= \sum_{y=1}^{\infty} y(y-1) [q^{y-1} p] = pq \sum_{y=1}^{\infty} \frac{d^2 q^y}{dq^2} = pq \frac{d^2}{dq^2} \sum_{y=1}^{\infty} q^y = pq \frac{d^2}{dq^2} \left[ q \sum_{y=1}^{\infty} q^{y-1} \right] = \\ &= pq \frac{d^2}{dq^2} \left[ \frac{q}{1-q} \right] = pq \frac{d}{dq} \frac{1}{(1-q)^2} = pq (-2(1-q)^{-3}(-1)) = \frac{2pq}{(1-q)^3} = \frac{2pq}{p^3} = \frac{2q}{p^2} \end{aligned}$$

$$\Rightarrow E(Y^2) = E(Y(Y-1)) + E(Y) = \frac{2q}{p^2} + \frac{1}{p} = \frac{2(1-p) + p}{p^2} = \frac{2-p}{p^2}$$

$$\Rightarrow V(Y) = E(Y^2) - [E(Y)]^2 = \frac{2-p}{p^2} - \left[ \frac{1}{p} \right]^2 = \frac{2-p-1}{p^2} = \frac{1-p}{p^2} = \frac{q}{p^2}$$

$$\Rightarrow \sigma = \sqrt{\frac{q}{p^2}}$$

# Negative Binomial Distribution

- In successive Bernoulli( $p$ ) instances, what is the distribution of the number of trials (in some versions – failures) needed until the  $r$  th success.  
(the Geometric Distribution is equivalent to  $r = 1$ )
- For this number to equal  $k$  we should have exactly  $r - 1$  successes in first  $k - 1$  trials, followed by a success

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

$$\bullet E(X) = \frac{r}{p}$$

$$\bullet V(X) = \frac{r(1-p)}{p^2}$$

# Binomial rate vs n

Consider

$$X_1 \sim \text{Binom}(1, \lambda) \text{ and } X_2 \sim \text{Binom}(2, \lambda/2)$$

Which is larger:

$$P(X_1 \geq 1) \text{ or } P(X_2 \geq 1) ?$$

$$E(X_1) \text{ or } E(X_2) ?$$

Poisson – a limit  
of binomials  
with an  
increasing  $n$  and  
a fixed mean

Consider repeated coin tossing with increasingly  
smaller success rates

$$X_1 \sim \text{Binom}(1, \lambda)$$

$$X_2 \sim \text{Binom}(2, \lambda/2)$$

$$X_3 \sim \text{Binom}(3, \lambda/3)$$

$$P(X_1 \geq 1) = P(X_1 = 1) = \lambda$$

$$P(X_2 \geq 1) = 1 - P(X_2 = 0)$$

$$= 1 - (1 - \lambda/2)^2 = \lambda - (\lambda/2)^2 < \lambda$$

Poisson – a limit  
of binomials  
with an  
increasing  $n$  and  
a fixed mean

$$\# \quad X_n \sim \text{Binom}(n, \lambda/n)$$

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

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

Diagram illustrating the limit process as  $n \rightarrow \infty$ :

- The fraction  $\frac{n(n-1)\cdots(n-k+1)}{k!}$  is shown with a diagonal line through it, and an arrow pointing down to the number 1.
- The term  $\frac{\lambda^k}{n^k}$  is shown with a diagonal line through it, and an arrow pointing down to a blue square.
- The term  $\left(1 - \frac{\lambda}{n}\right)^n$  is shown with a diagonal line through it, and an arrow pointing down to the number 1.
- The term  $\left(1 - \frac{\lambda}{n}\right)^k$  is shown with a diagonal line through it, and an arrow pointing down to the number 1.

as  $n \rightarrow \infty$



Poisson – a limit  
of binomials  
with an  
increasing  $n$  and  
a fixed mean

So,

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

we have

$$P(X_n = k) \xrightarrow{n \rightarrow \infty} e^{-\lambda} \frac{\lambda^k}{k!}$$

# Poisson Distribution

- $X \sim \text{Poisson}(\lambda)$  if

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

- Example – a website receives visits distributed as  $\text{Poisson}(0.5)$  per second.
- What is the probability of no visits at a certain second?
- Answer:  $\exp(-0.5)$
- What is the probability of no visits in a stretch of 10 seconds?
- Compute in two ways:
  - $\text{Poisson}(5)$  yields  $\exp(-5)$
  - 10 independent as above yields  $(\exp(-0.5))^{10} = \exp(-5)$

# Poisson Distribution

Distribution often used to model the number of incidences in some characteristic unit of time or space:

- Arrivals of customers to a store within one hour
- Numbers of flaws in a roll of fabric of a given length
- Number of visitors to a website in one minute
- Number of calls to a service center in 10 mins

# Poisson Distribution – Expectation and Variance

$$f(y) = \frac{e^{-\lambda} \lambda^y}{y!} \quad y = 0, 1, 2, \dots$$

$$E(Y) = \sum_{y=0}^{\infty} y \left[ \frac{e^{-\lambda} \lambda^y}{y!} \right] = \sum_{y=1}^{\infty} y \left[ \frac{e^{-\lambda} \lambda^y}{y!} \right] = \sum_{y=1}^{\infty} \frac{e^{-\lambda} \lambda^y}{(y-1)!} = \lambda e^{-\lambda} \sum_{y=1}^{\infty} \frac{\lambda^{y-1}}{(y-1)!} = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

$$\begin{aligned} E(Y(Y-1)) &= \sum_{y=0}^{\infty} y(y-1) \left[ \frac{e^{-\lambda} \lambda^y}{y!} \right] = \sum_{y=2}^{\infty} y(y-1) \left[ \frac{e^{-\lambda} \lambda^y}{y!} \right] = \sum_{y=2}^{\infty} \frac{e^{-\lambda} \lambda^y}{(y-2)!} \\ &= \lambda^2 e^{-\lambda} \sum_{y=2}^{\infty} \frac{\lambda^{y-2}}{(y-2)!} = \lambda^2 e^{-\lambda} e^{\lambda} = \lambda^2 \end{aligned}$$

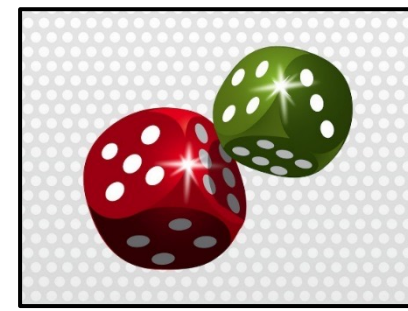
$$\Rightarrow E(Y^2) = E(Y(Y-1)) + E(Y) = \lambda^2 + \lambda$$

$$\Rightarrow V(Y) = E(Y^2) - [E(Y)]^2 = \lambda^2 + \lambda - [\lambda]^2 = \lambda$$

$$\Rightarrow \sigma = \sqrt{\lambda}$$

# Statistical independence

## Example – Rolling 2 Dice (Red/Green)



$\Omega$  = All possible outcomes, that is:

→

↓

(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)

- Assuming that all outcomes have  $P = 1/36$  is based on assuming that the result of one dice DOES NOT AFFECT the rolling of the other in any way.
- What is the probability of  $G = 3$  or  $6$  and  $R = 5$ ?
- $P(G = 3 \text{ or } 6) = 1/3$
- $P(R = 5) = 1/6$
- The probability of the JOINT event is, assuming  $1/36$  in each entry,  $1/36 + 1/36 = 1/18$ .
- This is just the product of the two probabilities:  
 $P(G = 3 \text{ or } 6 \text{ and } R = 5) = 1/3 * 1/6 = 1/18$
- This is called STATISTICAL INDEPENDENCE.
- When we defined  $1/36$  in every entry we imply that the two rolls are independent random variables

# Definitions and factoids ...

- Two events (subsets of the sample space  $\Omega$ ),  $A$  and  $B$ , are said to be statistically independent if the occurrence of one doesn't affect the occurrence of the other:

$P(A|B) = P(A)$  , where  $P(A|B) = P(A \cap B)/P(B)$  is the conditional probability of A given B.

- From here we get

$$\begin{aligned} P(B|A) &= \frac{P(A \cap B)}{P(A)} = \frac{P(A \cap B)P(B)}{P(A)P(B)} \\ &= P(A|B) \frac{P(B)}{P(A)} = P(B) \end{aligned}$$

- Show that from here it follows that  $P(A|B) = P(A|\neg B)$
- It also clearly follows that  $P(A \cap B) = P(A)P(B)$

# Independent random variables

- Two random variables  $X$  and  $Y$ , defined over the same space  $\Omega$  have a joint distribution  $p(x, y)$ .
- They also have marginal distributions
- The same marginal can often be joined (or coupled) in very different ways. The independent copula is only one of them.
- They are called independent if for all numbers  $x$  and  $y$  we have
$$P(X = x \text{ and } Y = y) = P(X = x) \cdot P(Y = y)$$
- Or – for all  $x$  and  $y$  as above, the events  $P(X = x)$  and  $P(Y = y)$  are independent.
- If  $X$  and  $Y$  are independent then  $E(XY) = E(X) \cdot E(Y)$  (prove this ... )
- Is the opposite true?



# Linearity of expected values

- $E(X + Y) = E(X) + E(Y)$
- This is true for ANY random variables. They don't have to be independent.
- This generalizes to any sums.

# Sample/Coupon collection

- A website is seeking information about users from 100 different cities.
- It needs to observe the action of  $m$  users from each city to perform the analysis.
- How many visits will it take if every visit comes from each of the cities with equal probabilities and independent of all previous visits?
- On average?

Poll: 100 countries and  $m=1$

# Sample/Coupon collection

At this point we will compute the expected value for the case  $m = 1$ .

We define random variables  $X_i$ ,  $i = 1 \dots 100$ , as follows.

Let  $X_1$  = the number of visits until the first country is in ( $X_1 == 1$ )

Let  $X_2$  = the number of visits, after the first country is in, until the second country is also in

...

Let  $X_i$  = the number of visits, after the first  $i - 1$  countries are in, until the  $i$ -th country is also in.

Now let

$$T = X_1 + X_2 + X_3 + \dots + X_i + \dots + X_{99} + X_{100}$$

# Sample/Coupon collection

We are, of course, interested in

$$E(T) = E(X_1 + X_2 + X_3 + \dots + X_i + \dots + X_{99} + X_{100}) = \sum_{i=1}^{100} E(X_i)$$

Now note that  $X_i \sim \text{Geom}(p = (100 - i + 1)/100)$  and we therefore have  $E(X_i) = \frac{1}{p} = \frac{100}{100-i+1}$

So:

$$E(T) = 100 \left( 1 + \frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \dots + \frac{1}{100} \right)$$

In general, for  $n$  types of coupons,  
we have  $E(T) = nH(n) \sim n \ln n$ .

General  $m$  and unequal probabilities require a more complex treatment.

$\text{Var}(X+Y)$

# Covariance

- Consider  $X$  and  $Y$  defined on the same sample space  $\Omega$
- $Cov(X, Y) = E((X - \mu(X))(Y - \mu(Y)))$
- $Cov(X, Y) = E(XY) - E(X)E(Y)$
- When  $X$  and  $Y$  are independent, what is  $Cov(X, Y)$ ?
- Is the opposite true?

# Binomial Distribution – Variance and S.D.

$$f(y) = \frac{n!}{y!(n-y)!} p^y q^{n-y} \quad y = 0, 1, \dots, n \quad q = 1 - p$$

Note:  $E(Y^2)$  is difficult (impossible?) to get, but  $E(Y(Y-1)) = E(Y^2) - E(Y)$  is not:

$$E(Y(Y-1)) = \sum_{y=0}^n y(y-1) \left[ \frac{n!}{y!(n-y)!} p^y q^{n-y} \right] = \sum_{y=2}^n y(y-1) \left[ \frac{n!}{y!(n-y)!} p^y q^{n-y} \right]$$

(Summand = 0 when  $y = 0, 1$ )

$$\Rightarrow E(Y(Y-1)) = \sum_{y=2}^n \frac{n!}{(y-2)!(n-y)!} p^y q^{n-y}$$

Let  $y^{**} = y - 2 \Rightarrow y = y^{**} + 2$  Note:  $y = 2, \dots, n \Rightarrow y^{**} = 0, \dots, n-2$

$$\Rightarrow E(Y(Y-1)) = \sum_{y^{**}=0}^{n-2} \frac{n(n-1)(n-2)!}{y^{**}!(n-(y^{**}+2))!} p^{y^{**}+2} q^{n-(y^{**}+2)} = n(n-1)p^2 \sum_{y^{**}=0}^{n-2} \frac{(n-2)!}{y^{**}!((n-2)-y^{**})!} p^{y^{**}} q^{(n-2)-y^{**}} =$$

$$= n(n-1)p^2 (p+q)^{n-2} = n(n-1)p^2 (p+(1-p))^{n-2} = n(n-1)p^2$$

$$\Rightarrow E(Y^2) = E(Y(Y-1)) + E(Y) = n(n-1)p^2 + np = np[(n-1)p + 1] = n^2 p^2 - np^2 + np = n^2 p^2 + np(1-p)$$

$$\Rightarrow V(Y) = E(Y^2) - [E(Y)]^2 = n^2 p^2 + np(1-p) - (np)^2 = np(1-p)$$

$$\Rightarrow \sigma = \sqrt{np(1-p)}$$

# Sums of independent random variables

Let  $X$  and  $Y$  be two independent random variables. Let  $Z = X + Y$ .  
Then

$$P(Z = z) = \sum_{i=-\infty}^{\infty} P(X = i)P(Y = z - i)$$

For continuous random variables, the density function of  $Z$  is:

$$h(z) = \int_{-\infty}^{\infty} f(t)g(z - t)dt$$



# Sum of two independent Poissons is Poisson

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

$$P(Y=k) = e^{-\mu} \frac{\mu^k}{k!}$$

$X$  and  $Y$  indpt. Let  $Z = X + Y$

$$P(Z=k) = \sum_{i=-\infty}^{\infty} e^{-\lambda} \frac{\lambda^i}{i!} \cdot e^{-\mu} \frac{\mu^{k-i}}{(k-i)!}$$

Here summands are 0 when either of the denominator factorials are negative

$$= e^{-(\lambda+\mu)} \cdot \frac{1}{k!} \sum_{i=0}^k \binom{k}{i} \lambda^i \mu^{k-i}$$

$$= e^{-(\lambda+\mu)} \frac{(\lambda+\mu)^k}{k!}$$

Sum of 2 indpt  
Poisson

# Higher moments

The raw  $k$ th moment of a random variable  $X$  is  $E(X^k)$

The central  $k$ th moment of a random variable  $X$  is  $E((X - \mu(X))^k)$

Let  $X \sim \text{Binom}(n, p)$ . What is the 3<sup>rd</sup> central moment of  $X$ ?

$X = \sum_{i=1}^n X_i$ , where  $X_i \sim \text{Ber}(p)$ , independent.

$$\begin{aligned}\gamma_3 &= E \left[ \left( \sum_{i=1}^n (X_i - p) \right)^3 \right] = E \left[ \sum_{i,j,k=1 \dots n} (X_i - p)(X_j - p)(X_k - p) \right] \\ &= \sum_{i,j,k=1 \dots n} E((X_i - p)(X_j - p)(X_k - p))\end{aligned}$$

The terms of the last summation are all 0 except when  $i = j = k$ . Therefore:

$$\gamma_3 = nE((X_1 - p)^3) = n(p(1 - p)^3 + (1 - p)(-p)^3).$$

And, after further simplification:  $\gamma_3 = np(1 - p)(1 - 2p)$

# Mutual independence vs k-wise independence

# Summary

- Geometric distribution
- Negative binomials (next week: how to compare them)
- Poisson distribution
- Coupon collector
- Independence and the covariance of two random variables
- Convolution of pdfs (to be continued)
- Higher moments and an example
- Mutual indpce vs lower order indpce