

Biostatistics

Week #5 3/22/2022



Chapter 7 Theoretical Probability Distributions – Part 1



Outline

- **7.1 Probability Distribution**
- **7.2 The Binomial Distribution**
- **7.3 The Poisson Distribution**
- **7.4 The Normal Distribution**
- **7.5 Z-score and Applications**

7.1 Probability Distribution

*We know what is probability. But what is distribution?
What is probability distribution?*



Random Variable

- Any characteristic that can be measured or categorized is called a **variable**.
- If a variable can assume **different values** such that any particular outcome is determined **by chance**, it is called a **random variable**.
- A **probability distribution** applies the theory of probability to **describe** the random variable.

Discrete and Continuous Random Variables

- A random variable is **discrete** if it can assume a **countable** number of values. For example, the “coin” example assumes only 2 values – 1 and 0.
- A random variable is **continuous** if it can assume an uncountable number of values. For example, a height or a weight, which can take on any value within a specified interval or continuum.

Probability Distribution

- In probability theory and statistics, a probability distribution identifies either
 - the probability of *each value* of an unidentified random variable (when the variable is *discrete*), or
 - the probability of *the value falling within a particular interval* (when the variable is *continuous*).
- Every random variable has a corresponding probability distribution.

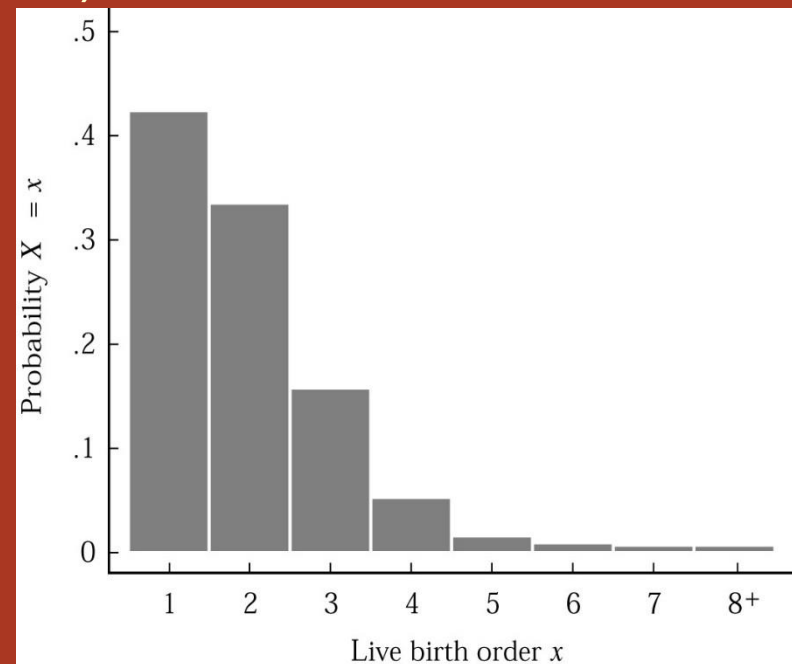
Example

TABLE 7.1

Probability distribution of a random variable X representing the birth order of children born in the United States

x	$P(X = x)$
1	0.416
2	0.330
3	0.158
4	0.058
5	0.021
6	0.009
7	0.004
8+	0.004
Total	1.000

A discrete probability distribution of the birth order of children born to women in US (based on the experience of the US population in 1986).



$$P(X=4)=0.058$$

$$P(X=1 \text{ or } X=2)=P(X=1)+P(X=2)=0.746$$

Additive rule of probability for mutually exclusive events.

Comments

- In previous example, it is possible to tabulate the distribution because of limited count for this random variable.
- If a random variable can take on a large number of values, a probability distribution may not be a useful way to summarize its behavior.
- In this case, a number of summarization can help – population mean, population variance and population standard deviation.

Population Mean (Expected Value期望值)

- Given a discrete random variable X with values x_i , that occur with probabilities $p(x_i)$, the population mean of X is

$$E(X) = \mu = \sum_{all\ x_i} x_i \cdot p(x_i)$$

For the case of rolling a dice, for example, we have

$$\begin{aligned} E(X) = \mu &= 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 6 \cdot \frac{1}{6} \\ &= \frac{21}{6} = 3.5 \end{aligned}$$

Population Variance

- Let X be a discrete random variable with possible values x_i that occur with probabilities $p(x_i)$, and let $E(X) = \mu$.

The variance of X is defined by

$$V(X) = \sigma^2 = E[(X - \mu)^2] = \sum_{all\ x_i} (x_i - \mu)^2 p(x_i)$$

The standard deviation is

$$\sigma = \sqrt{\sigma^2}$$

For the dice-rolling example

$$\begin{aligned} V(X) &= \sigma^2 = E[(X - \mu)^2] = \\ &= (1 - 3.5)^2 \cdot \frac{1}{6} + (2 - 3.5)^2 \cdot \frac{1}{6} + \dots + (6 - 3.5)^2 \cdot \frac{1}{6} \\ &= (6.25 + 2.25 + 0.25 + 0.25 + 2.25 + 6.25) \cdot \frac{1}{6} \\ &= 2.916667 \end{aligned}$$

The standard deviation is

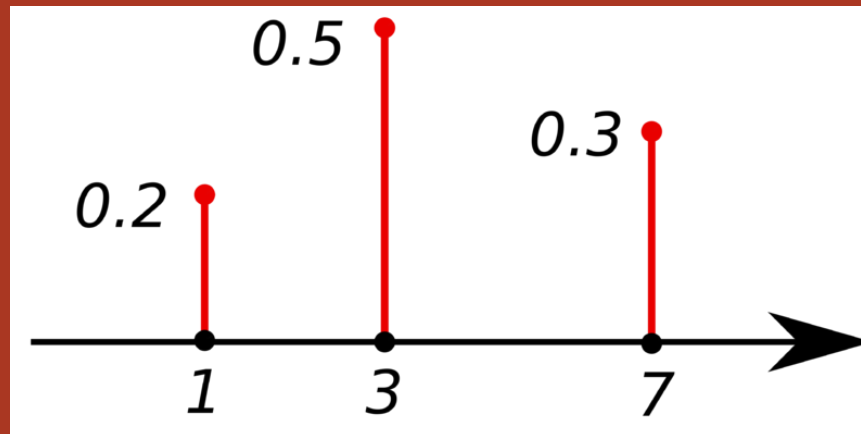
$$\sigma = \sqrt{\sigma^2} = \sqrt{2.916667} = 1.707825$$

A brief summary

- This example tells you that, if you roll the dice many times, the average you may get is 3.5 points.
- It is likely that the average may 'mostly' be within the range 3.5 ± 1.7 points.

pmf and pdf

- In probability theory, a **probability mass function** (abbreviated **pmf**) is a function that gives the probability that **a discrete random variable** is exactly equal to some value.

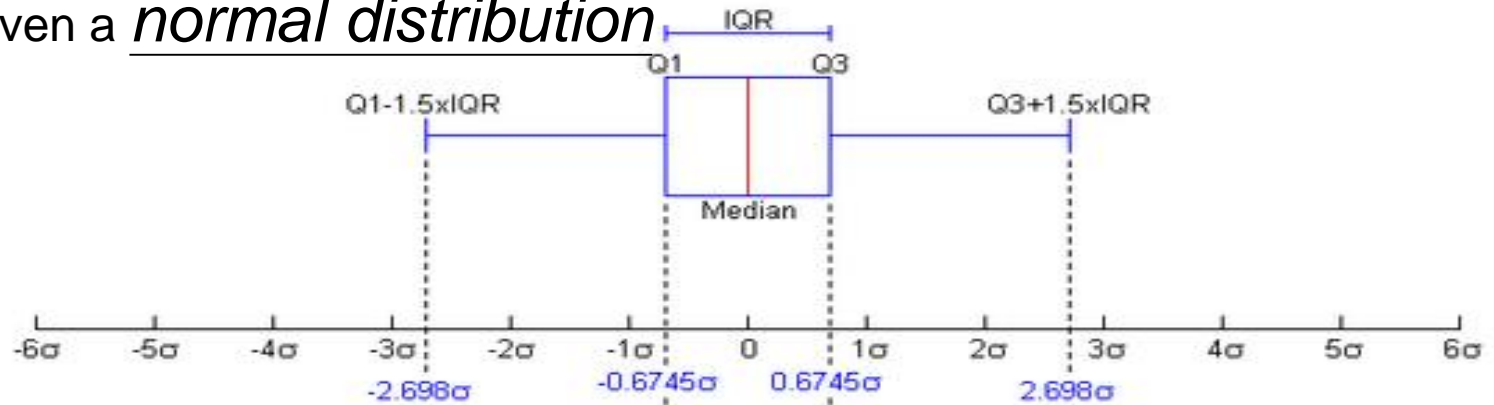


The graph of a probability mass function. All the values of this function must be non-negative and sum up to 1.

Cont'd

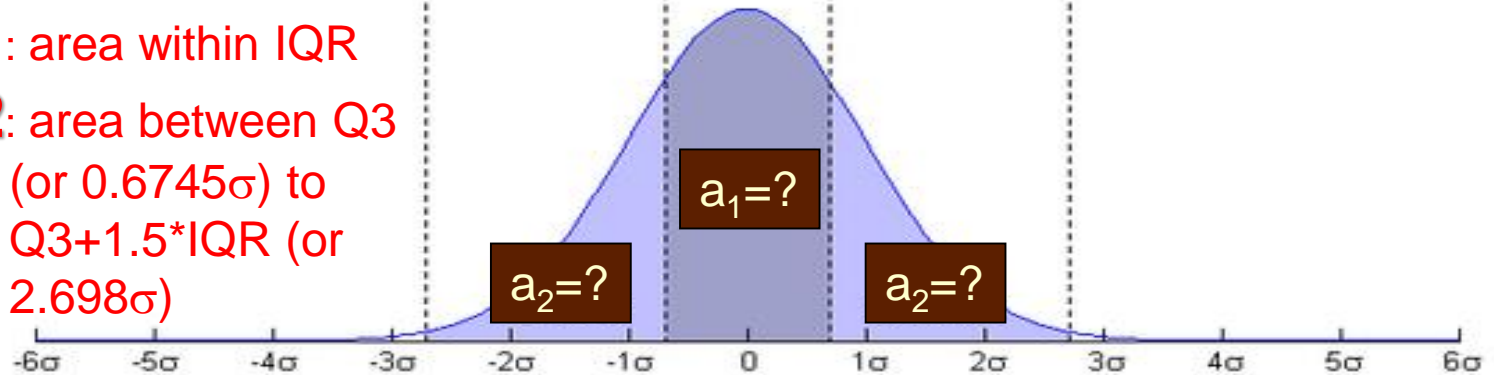
- A pmf differs from a probability density function (abbreviated pdf) in that the values of a pdf are defined only for continuous random variables.
- It is the integral of a pdf over a range of possible values that gives the probability of the random variable falling within that range.

Given a normal distribution



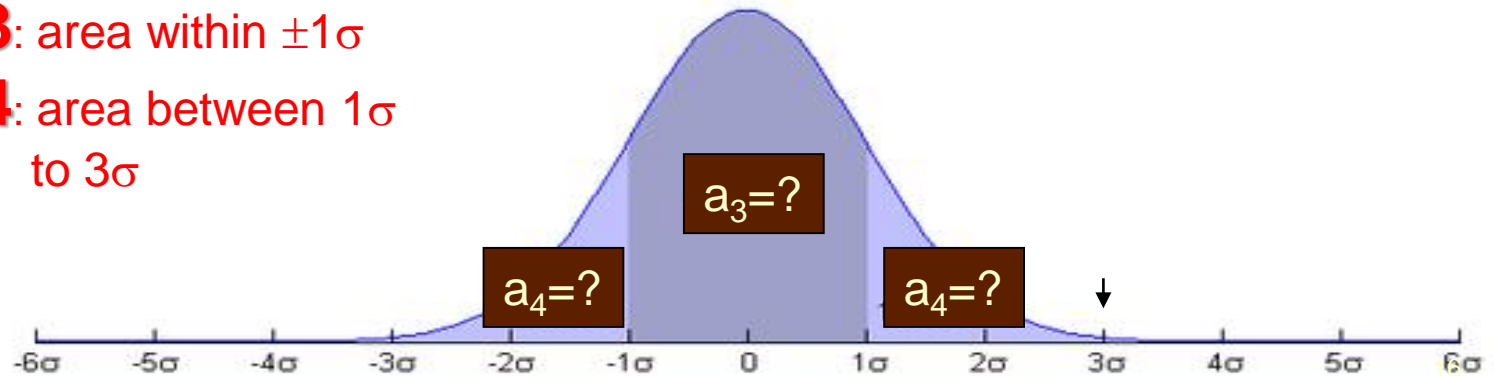
1: area within IQR

2: area between Q3
(or 0.6745σ) to
 $Q3 + 1.5 \times IQR$ (or
 2.698σ)

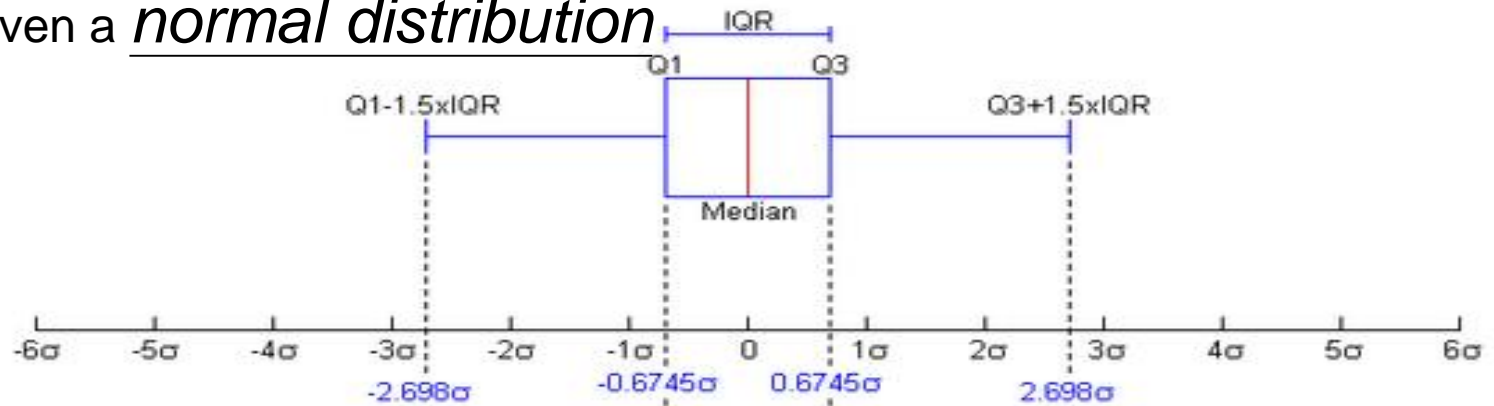


3: area within $\pm 1\sigma$

4: area between 1σ
to 3σ

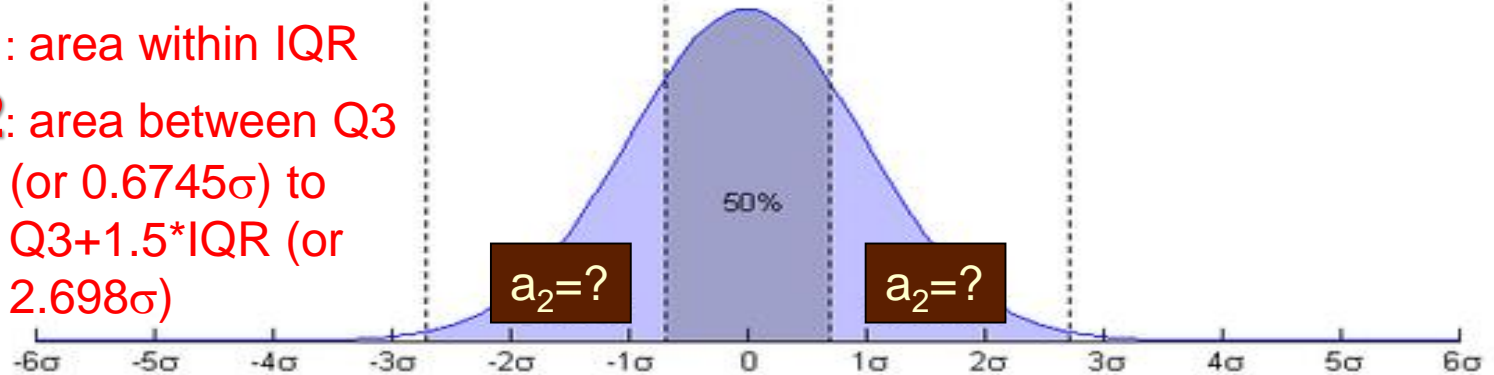


Given a normal distribution



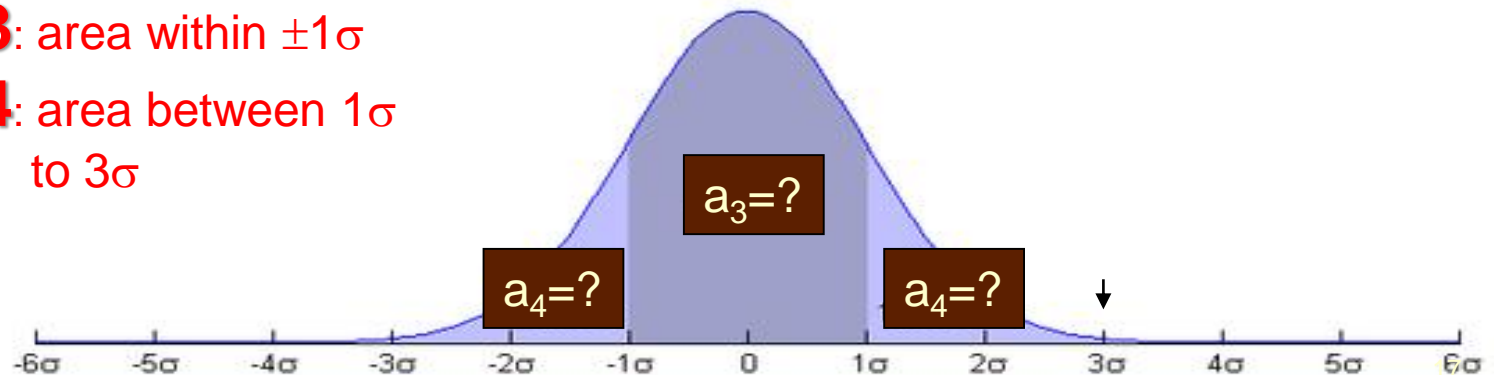
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 2.698σ)

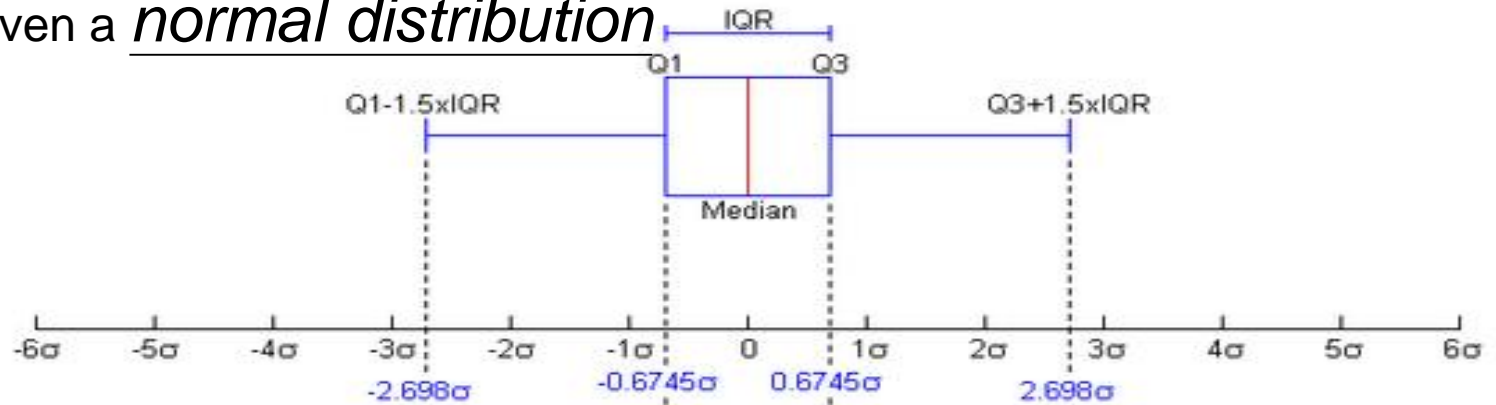


3: area within $\pm 1\sigma$

4: area between 1σ
to 3σ

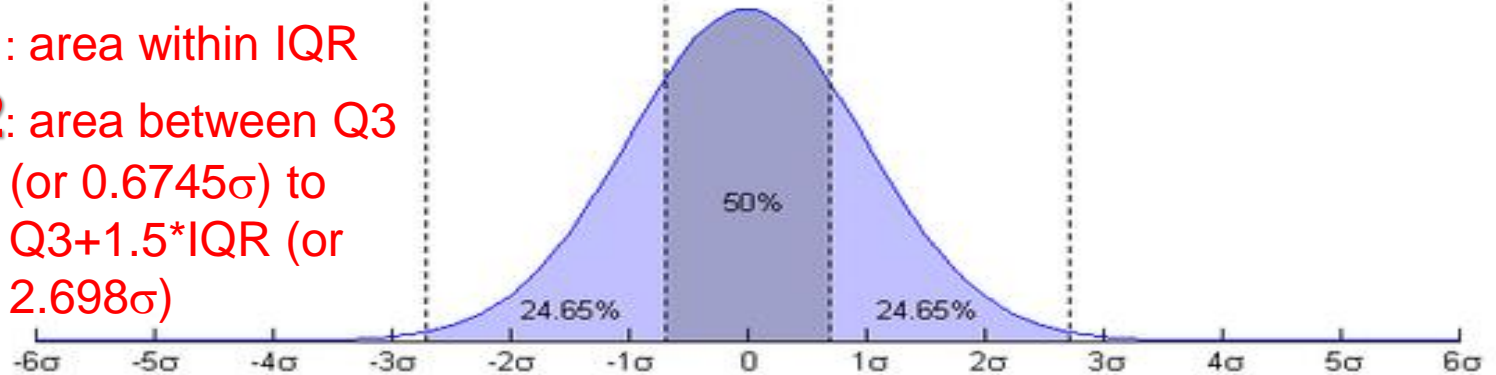


Given a normal distribution



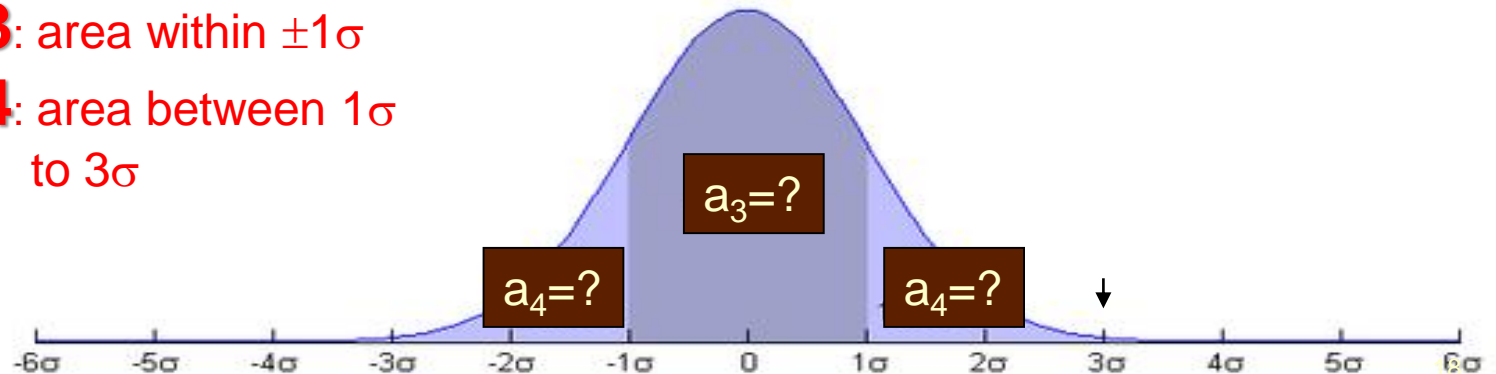
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2: area between Q3
(or 0.6745σ) to
 $Q3 + 1.5 \times IQR$ (or
 2.698σ)

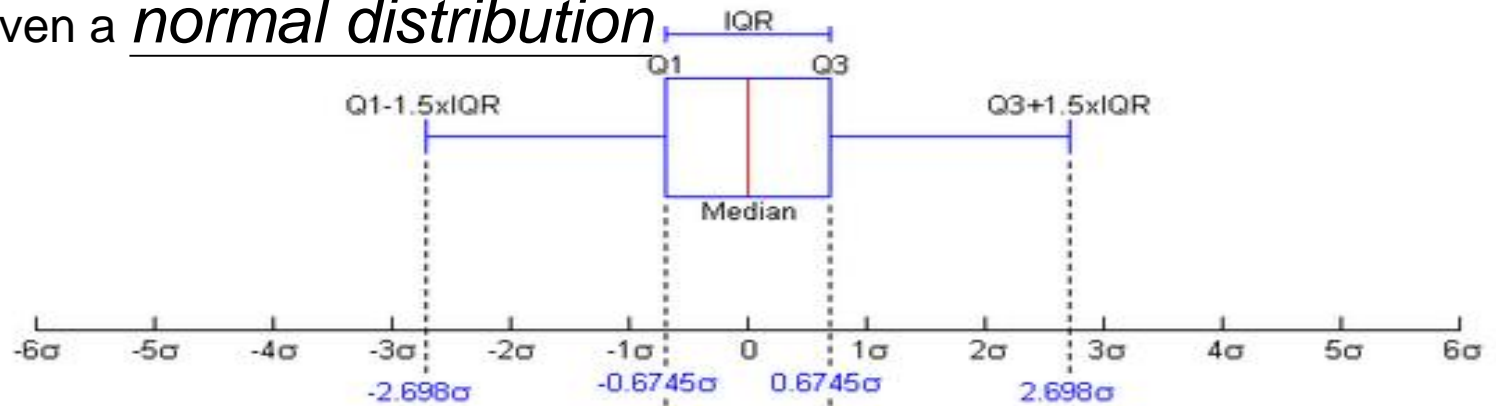


3: area within $\pm 1\sigma$

4: area between 1σ
to 3σ

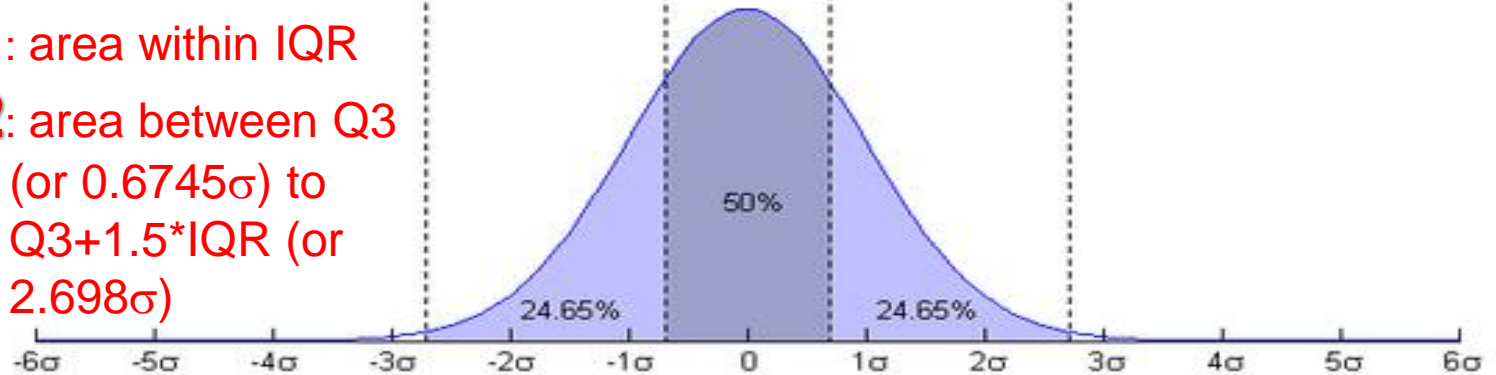


Given a *normal distribution*



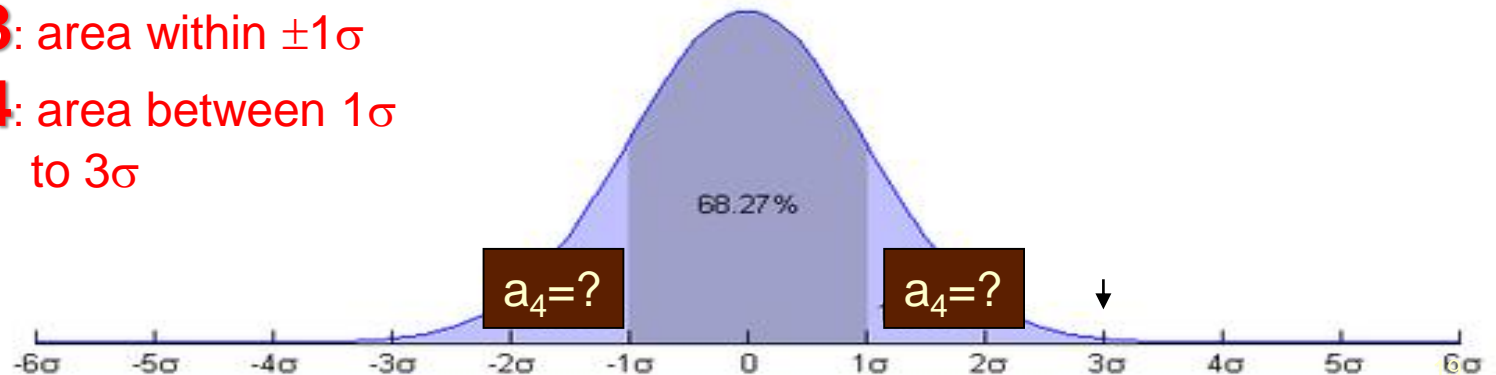
1: area within IQR

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 $Q3 + 1.5 \times IQR$ (or
 2.698σ)

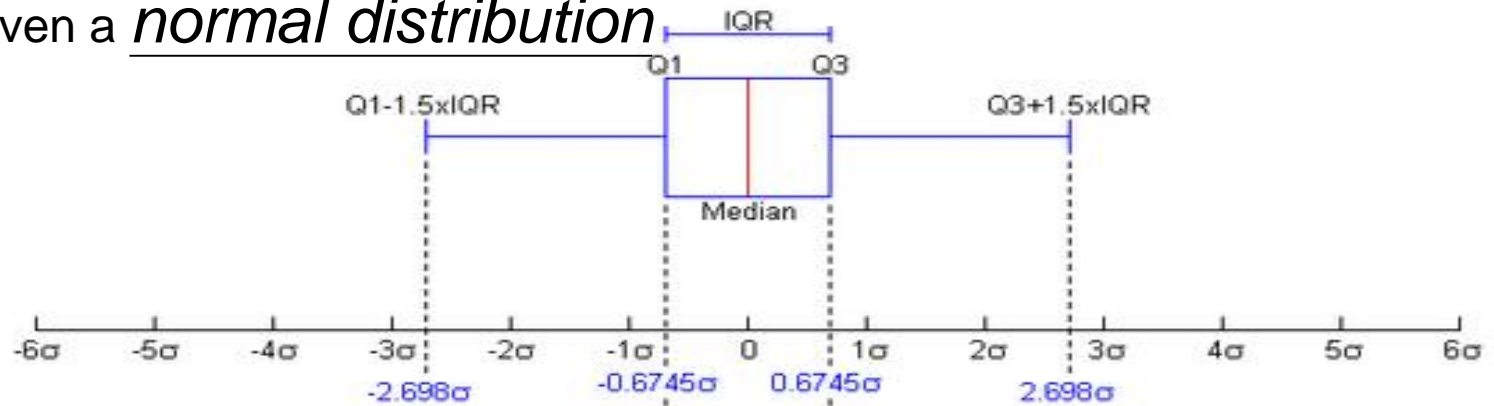


3: area within $\pm 1\sigma$

4: area between 1σ
to 3σ

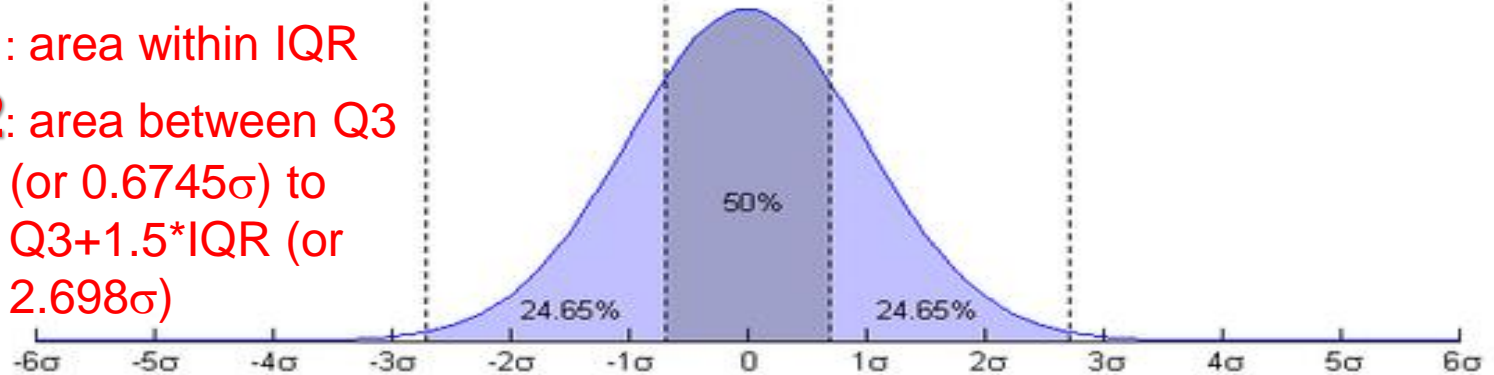


Given a *normal distribution*



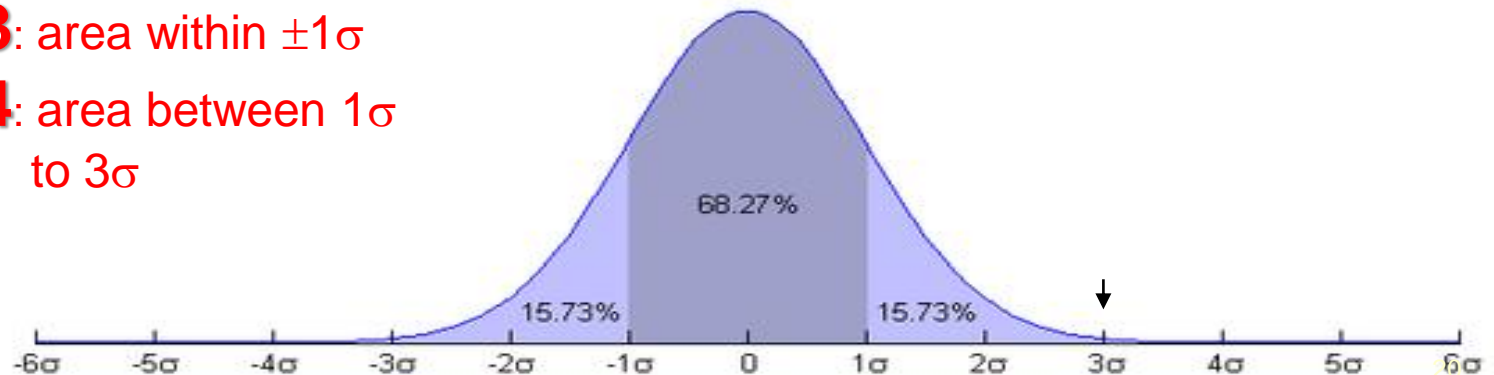
1: area within IQR

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(or 0.6745σ) to
 $Q3 + 1.5 \times IQR$ (or
 2.698σ)



3: area within $\pm 1\sigma$

4: area between 1σ
to 3σ



Summary

- Probabilities calculated based on a finite amount of data (such as the birth order example mentioned previously) are called ***empirical probability***.
- The probability distributions for many other random variables of interest, however, can be determined (or approximated) based on *theoretical (or mathematical)* consideration.
- These are called ***theoretical probability distributions***.

7.2 The Binomial Distribution



From Wikipedia

- The **binomial distribution** (with parameters n and p) is the **discrete probability distribution** of the number of successes in a sequence of n independent yes/no experiments, each of which yields **SUCCESS** with probability p .
- A success/failure experiment is also called a ***Bernoulli experiment*** or ***Bernoulli trial***.

Introduction

- Bernoulli random variable
 - A **dichotomous** (二分的) random variable
Y can result in only one of two possible outcomes, referred to as “failure” and “success”. (or yes vs no, male vs female, life vs death, sickness vs health, etc.)
- Typical cases where the binomial experiment applies:
 - A coin flipped results in heads or tails
 - An election candidate wins or loses

Example 1

- Let Y be a random variable that represents smoking status; $Y=1$ if an adult is currently a smoker ; $Y=0$ if not.
- In 1987, 29% of the adults in US smoked; the probabilities associated with the outcomes of Y are $P(Y=1) = p = 0.29$; and $P(Y=0) = 1-p = 0.71$.
- These are the probability distribution of the random variable Y .

Cont'd

- We randomly select two adults from the population, Y_1 and Y_2 .
- We now introduce a new random variable X that represents the number of smokers in the pair (2 persons).
- $X=Y_1+Y_2$, the possible outcomes of X are $\{0, 1, 2\}$
 - 0: both non-smokers
 - 1: one smokes & one does not
 - 2: both smokers
- What is the probability distribution of X ?

Cont'd

Outcomes of Y's Y1 Y2		Probabilities of these outcomes	Outcomes of $X=Y1+Y2$
0	0	$(1-p)*(1-p)$	0
1	0	$p*(1-p)$	1
0	1	$(1-p)*p$	1
1	1	$p*p$	2

$$P(X=0) = (1 - p)^2 = (0.71)^2 = 0.504$$

$$P(X=1) = p(1 - p) + (1 - p)p = 2p(1 - p) = 2(0.29)(0.71) = 0.412$$

$$P(X=2) = p^2 = (0.29)^2 = 0.084$$

Note:

$$P(X=0) + P(X=1) + P(X=2) = 0.504 + 0.084 + 0.412 = \underline{\underline{1.000}}$$

(all mutually exclusive)

We call X a special case of the *Binomial distribution*

Binomial Probability Distribution

- There are **n independent Bernoulli trials** (n is finite and fixed).
- Each trial can result in a success or a failure (one of two mutually exclusive outcomes).
- The probability p of success is ***the same*** for all the trials.
- All the trials of the experiment are ***independent***.

Introduce a new random variable X that represents the number of smokers in 3 persons.

Outcomes of Y's Y1 Y2 Y3			Probabilities of these outcomes	Outcomes of $X=Y1+Y2+Y3$
0	0	0	$(1-p)(1-p)(1-p)$	0
1	0	0	$p(1-p)(1-p)$	1
0	1	0	$(1-p)p(1-p)$	1
0	0	1	$(1-p)(1-p)p$	1
1	1	0	$pp(1-p)$	2
1	0	1	$p(1-p)p$	2
0	1	1	$(1-p)pp$	2
1	1	1	ppp	3

$$P(X=0) = (1-p)^3 = (0.71)^3 = 0.358$$

$$P(X=1) = 3p(1-p)^2 = 3(0.29)(0.71)^2 = 0.439$$

$$P(X=2) = 3p^2(1-p) = 3(0.29)^2(0.71) = 0.179$$

$$P(X=3) = p^3 = (0.29)^3 = 0.024$$

What if we continue?

- $N=2$: $X=0,1,2$ (frequency=1,2,1)
- $N=3$: $X=0,1,2,3$ (frequency=1,3,3,1)
- $N=4$: $X=0,1,2,3,4$ (frequency=1,4,6,4,1)
- $N=5$: $X=0,1,2,3,4,5,6$
(frequency=1,5,10,10,5,1)
- $N=6...$
- The coefficients of these expansions
 $(a+b)^2$, $(a+b)^3$, $(a+b)^4$, $(a+b)^5$,...

Calculating the Binomial Probability

- In general, the binomial probability is calculated by :

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

$$\text{where } C_x^n = \frac{n!}{x!(n-x)!}$$

$$N = 1, 2, 3, \dots \text{ and } x = 0, 1, 2, \dots, n$$

For example, with $n = 3$ and $x = 0$ (three non-smokers) with $p = 0.29$, we have

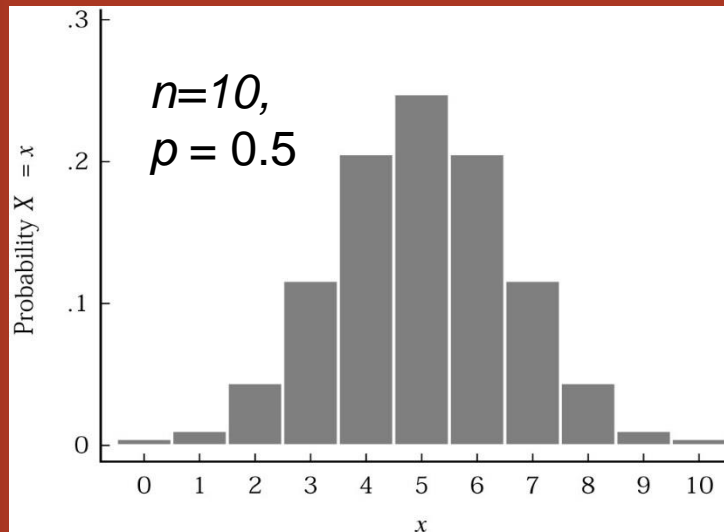
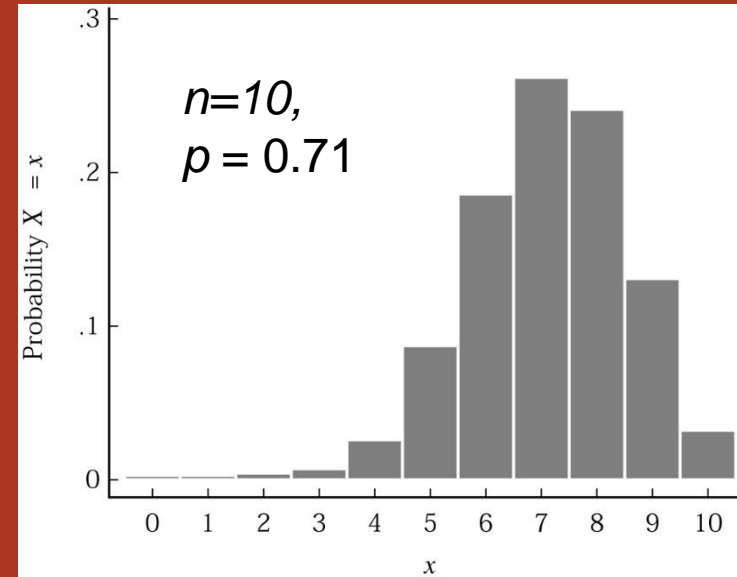
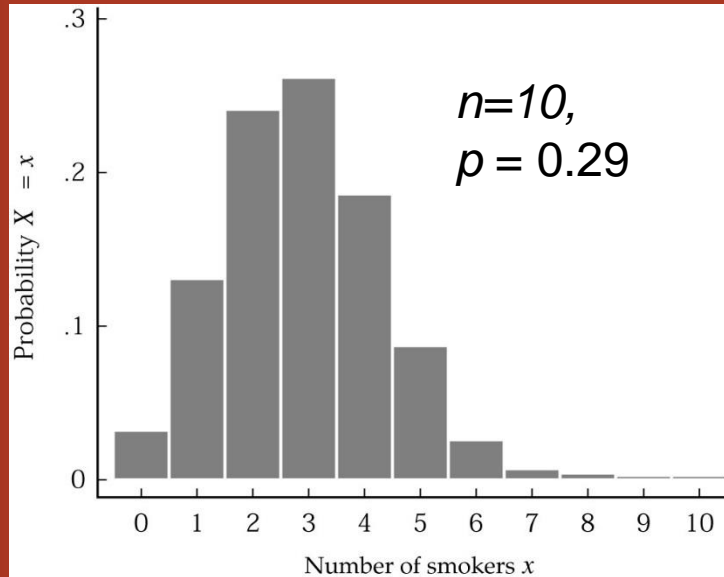
$$\begin{aligned} P(X = 0) &= p(0) = C_0^3 0.29^0 (1 - 0.29)^{3-0} \\ &= \frac{3!}{0!(3-0)!} 0.29^0 (0.71)^3 = 0.71^3 = 0.357911 \end{aligned}$$

Previously we had :

$$P(X=0) = (1-p)^3 = (0.71)^3 = 0.358$$

Some simulations

p is the percent of US people smoked.



- ✓ Can you explain why some of these graphs is left, right or center-peaked?
- ✓ What is the area sum for each of these graphs? What is the meaning of it?

Mean and STD for Binomial Distribution

- **Mean value = np**
- **Variance = $\sigma^2 = np(1-p)$** , where σ is the standard deviation of this binomial random variable X with repeated samples of size n .
- For previous example, we have (for $n = 10$ and $p = 0.29$)

$$\mu = np = 10(0.29) = 2.9$$

$$\sigma = \sqrt{10(0.29)(1-0.29)} = 1.435$$

Example 2

- Given 14 newborns, and knowing that there are ***X baby girls*** among these 14.
- We'd like to build the probability distribution of X (=1 to 14) and know the mean and standard deviation of it.

$$\begin{aligned} P(X = x) &= p(x) = C_x^n p^x (1 - p)^{n-x} \\ &= \frac{n!}{(n-x)!x!} 0.5^n \end{aligned}$$

$$P(X = 0) = \frac{14!}{(14 - 0)!0!} 0.5^{14} = 0.5^{14}$$

$$P(X = 1) = \frac{14!}{(14 - 1)!1!} 0.5^{14} = 14 \times 0.5^{14}$$

$$P(X = 2) = \frac{14!}{(14 - 2)!2!} 0.5^{14} = \frac{14 \times 13}{2} \times 0.5^{14}$$

$$P(X = 3) = \frac{14!}{(14 - 3)!3!} 0.5^{14} = \frac{14 \times 13 \times 12}{3!} \times 0.5^{14}$$

Using MATLAB:

$$P(X = x) = p(x) = C_x^n p^x (1 - p)^{n-x}$$
$$= \frac{n!}{(n-x)!x!} 0.5^n$$

```
>> X=0:14;
```

```
>> P=factorial(14)/(factorial(14-X)*factorial(X))*0.5^14;
```

```
??? Error using ==> mtimes
```

```
Inner matrix dimensions must agree.
```

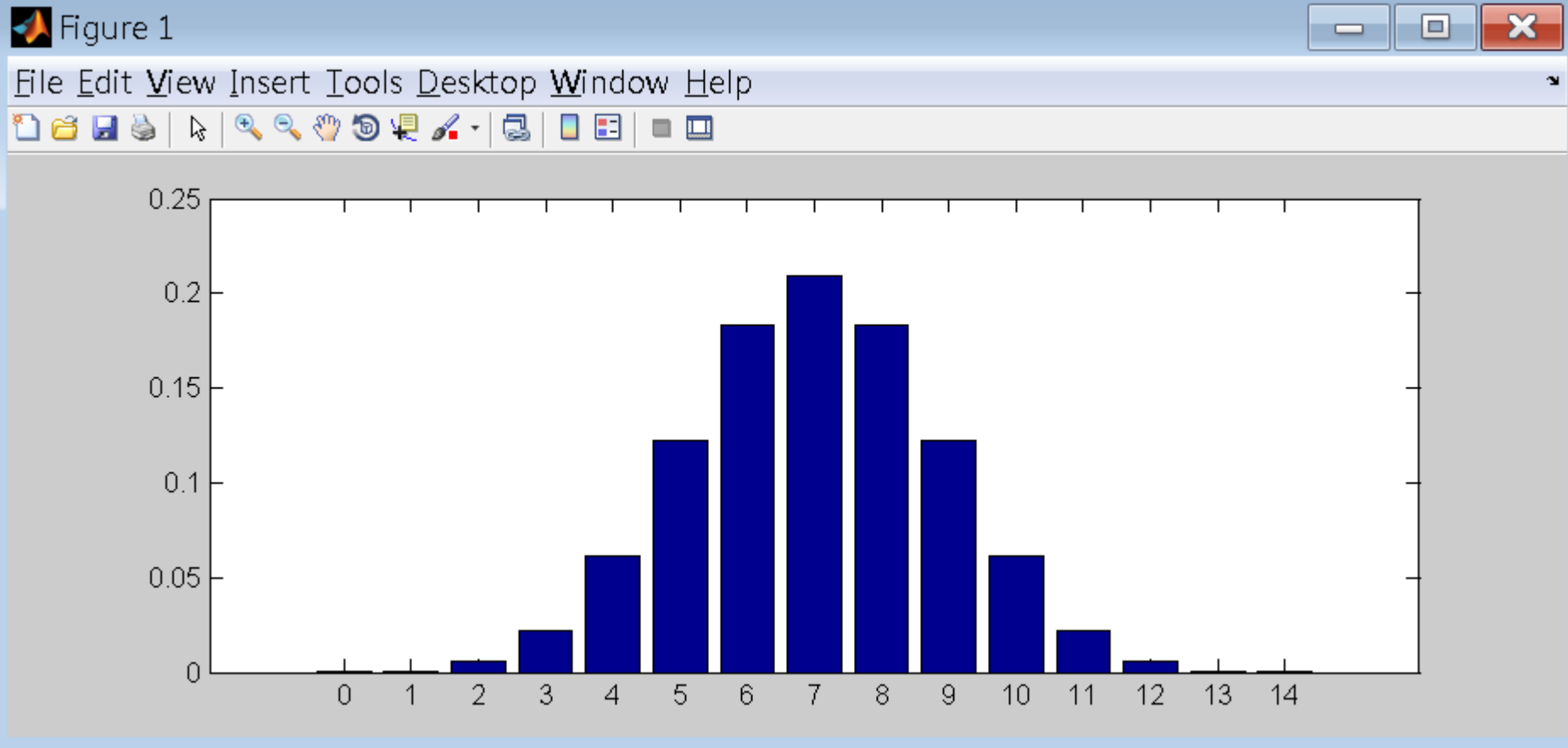
```
>> X=0:14;
```

```
>> P=factorial(14)./(factorial(14-X).*factorial(X))*0.5^14;
```

```
>> bar(X, P)
```

Observing the two newly added dots.

```
>>
```



Population Mean & Standard Deviation (Expected Value期望值)

- Recall that, given a discrete random variable X with values x_i , that occur with probabilities $p(x_i)$, the population mean of X is

$$E(X) = \mu = \sum_{\text{all } x_i} x_i \cdot p(x_i)$$

- The variance of X is defined by

$$V(X) = \sigma^2 = E[(X - \mu)^2] = \sum_{\text{all } x_i} (x_i - \mu)^2 p(x_i)$$

The standard deviation is

$$\sigma = \sqrt{\sigma^2}$$

```
>> X
```

```
X =
```

```
Columns 1 through 15
```

```
0    1    2    3    4    5    6    7    8    9   10   11   12   13   14
```

```
>> P
```

```
P =
```

```
Columns 1 through 8
```

```
0.0001  0.0009  0.0056  0.0222  0.0611  0.1222  0.1833  0.2095
```

```
Columns 9 through 15
```

```
0.1833  0.1222  0.0611  0.0222  0.0056  0.0009  0.0001
```

```
>> N=X.*P
```

```
N =
```

```
Columns 1 through 8
```

```
0    0.0009  0.0111  0.0667  0.2444  0.6110  1.0997  1.4663
```

```
Columns 9 through 15
```

```
1.4663  1.0997  0.6110  0.2444  0.0667  0.0111  0.0009
```

```
>> sum(N)
```

```
ans =
```

```
7
```

```
>>
```

$$E(X) = \mu = \sum_{all\ x_i} x_i \cdot p(x_i)$$

This can also be obtained conveniently by:

$$Mean\ value = np = 14 * 0.5 = 7$$

$$V(X) = \sigma^2 = E[(X - \mu)^2] = \sum_{\text{all } x_i} (x_i - \mu)^2 p(x_i)$$

```
>> VAR=P.*(X-7).^2
```

```
VAR =
```

```
Columns 1 through 11
```

```
0.0030 0.0308 0.1389 0.3555 0.5499 0.4888 0.1833 0
0.1833 0.4888 0.5499
```

```
Columns 12 through 15
```

```
0.3555 0.1389 0.0308 0.0030
```

```
>> sum(VAR)
```

```
ans =
```

```
3.5000
```

```
>> sqrt(ans)
```

```
ans =
```

```
1.8708
```

```
>>
```

This can also be obtained conveniently by:

*Standard deviation =
 $\text{sqrt}(n * p * (1 - p)) = \text{sqrt}(14 * 0.5 * 0.5)$
 $= \text{sqrt}(3.5) = 1.8708$*

Conclusion

- Among randomly chosen 14 newborns, the number of baby girls would range from 0 to 14. They follow binomial distribution.
- The average number of baby girls would be 7, with standard deviation of 1.8708.
- It is this “theoretical” feature of binomial distribution that makes those formulas available for easier computation.

Statistics - parametric vs nonparametric

- Parametric statistics are based on assumptions about the ***distribution*** of population from which the sample was taken.
- Nonparametric statistics are not based on assumptions, that is, the data can be collected from a sample that ***does not*** follow a specific distribution.

Cont'd

- Common parametric statistics are, for example, the Student's t-tests.
- Common nonparametric statistics are, for example, the Mann-Whitney-Wilcoxon (MWW) test or the Wilcoxon test.
- We will cover only parametric statistics in this course.

MATLAB Supported Distributions

- MATLAB's "Statistics and Machine Learning Toolbox™" supports more than 30 probability distributions, including parametric, nonparametric, continuous, and discrete distributions.

A couple of discrete probability distributions we will cover in this course:

<u>Binomial</u>	<u>binopdf</u> <u>binocdf</u> <u>binoinv</u> <u>binostat</u> <u>binofit</u> <u>binornd</u>
<u>Poisson</u>	<u>poisspdf</u> <u>poisscdf</u> <u>poissinv</u> <u>poisstat</u> <u>poissfit</u> <u>poissrnd</u>

A number of continuous probability distributions we will cover in this course:

<u>Normal</u> (Gaussian)	<u>normpdf</u> <u>normcdf</u> <u>norminv</u> <u>normstat</u> <u>normfit</u> <u>normlike</u> <u>normrnd</u>
-----------------------------	--

<u>Chi-square</u>	<u>chi2pdf</u> <u>chi2cdf</u> <u>chi2inv</u> <u>chi2stat</u> <u>chi2rnd</u>
<u>F</u>	<u>fpdf</u> <u>fcdf</u> <u>finv</u> <u>fstat</u> <u>frnd</u>
<u>Student's t</u>	<u>tpdf</u> <u>tcdf</u> <u>tinu</u> <u>tstat</u> <u>trnd</u>

Cont'd

- **pdf** — Probability density functions
- **cdf** — Cumulative distribution functions
- **inv** — Inverse cumulative distribution functions

```
>> help binopdf
```

BINOPDF Binomial probability density function.

Y = BINOPDF(X,N,P) returns the binomial probability density function with parameters N and P at the values in X.

Note that the density function is zero unless X is an integer.

```
>> X=0:14;
```

```
>> P=binopdf(X, 14, 0.5)
```

P =

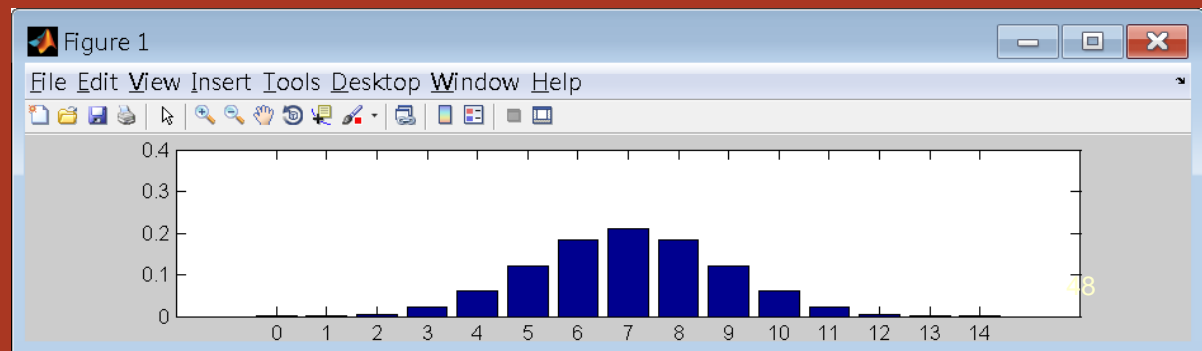
Columns 1 through 11

0.0001	0.0009	0.0056	0.0222	0.0611	0.1222	0.1833
0.2095	0.1833	0.1222	0.0611			

Columns 12 through 15

0.0222	0.0056	0.0009	0.0001		
--------	--------	--------	--------	--	--

```
>> bar(X, P)
```




```
>> format long
```

```
>> P
```

```
P =
```

```
Columns 1 through 5
```

```
0.000061035156250 0.000854492187500 0.005554199218750  
0.022216796875000 0.061096191406250
```

```
Columns 6 through 10
```

```
0.122192382812500 0.183288574218750 0.209472656250000  
0.183288574218750 0.122192382812500
```

```
Columns 11 through 15
```

```
0.061096191406250 0.022216796875000 0.005554199218750  
0.000854492187500 0.000061035156250
```

```
>> sum(P(1:1)), sum(P(1:2)), sum(P(1:3)), sum(P(1:4)),  
sum(P(1:5))
```

```
ans = 6.1035156250000003e-005
```

```
ans = 9.155273437499991e-004
```

```
ans = 0.006469726562500
```

```
ans = 0.028686523437500
```

```
ans = 0.089782714843750
```

*These are cumulative
probabilities (cumulating
from 0 to 0, 0 to 1, 0 to 2, 0
to 3, and 0 to 4)*

*Probability of having 0 to 4 baby girls from randomly choosing
14 newborns.*

>> help **binocdf**

BINOCDF Binomial ***cumulative*** distribution function.

Y=BINOCDF(X,N,P) returns the binomial cumulative distribution function with parameters N and P at the values in X.

>> binocdf(0,14,0.5), binocdf(1,14,0.5), binocdf(2,14,0.5),
binocdf(3,14,0.5), **binocdf(4,14,0.5)**

ans =

6.103515625000003e-005

$P(0)$

ans =

9.155273437499991e-004

$P(0) + P(1)$

ans =

0.006469726562500

$P(0) + P(1) + P(2)$

ans =

0.028686523437500

$P(0) + P(1) + P(2) + P(3)$

ans =

0.089782714843750

$P(0) + P(1) + P(2) + P(3) + P(4)$

>> help **binoinv**

BINOINV **Inverse** of the binomial cumulative distribution function (cdf).

X = BINOINV(Y,N,P) returns the inverse of the binomial cdf with parameters N and P. Since the binomial distribution is discrete, BINOINV returns **the least integer X** such that the binomial cdf evaluated at X, **equals or exceeds Y**.

>> binoinv(**0.01**, 14, 0.5)
ans =
3

>> binoinv(**0.05**, 14, 0.5)
ans =
4

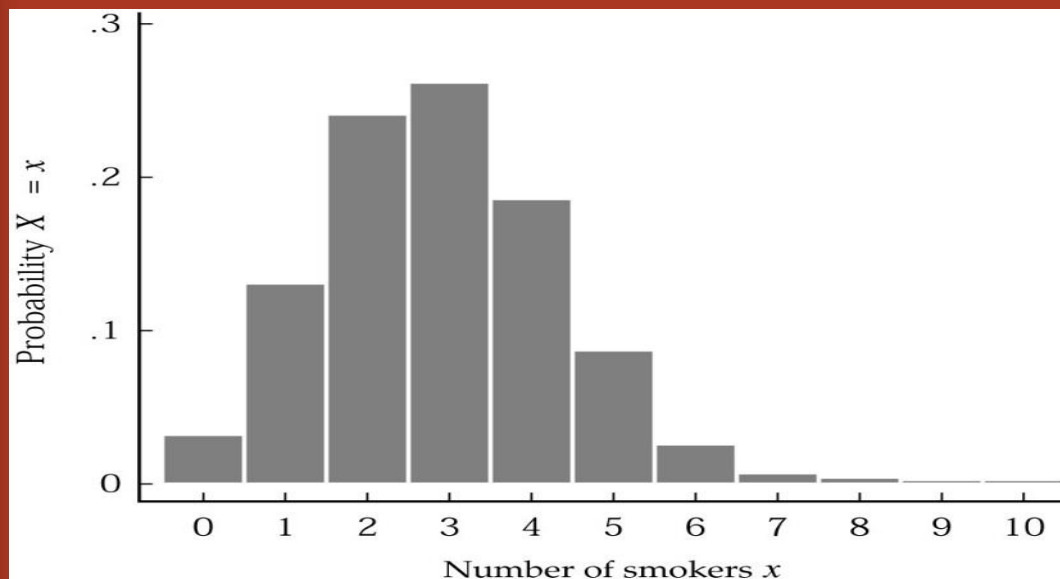
>> binoinv(**0.1**, 14, 0.5)
ans =
5

$P(0) + P(1) + P(2) = 0.0065$ will not equal or exceed 0.01. Adding one more ($P(0) + P(1) + P(2) + P(3) = 0.0287$) will.

Cumulating up to $P(X=5)$ is needed to get probability equal or exceed 0.1.

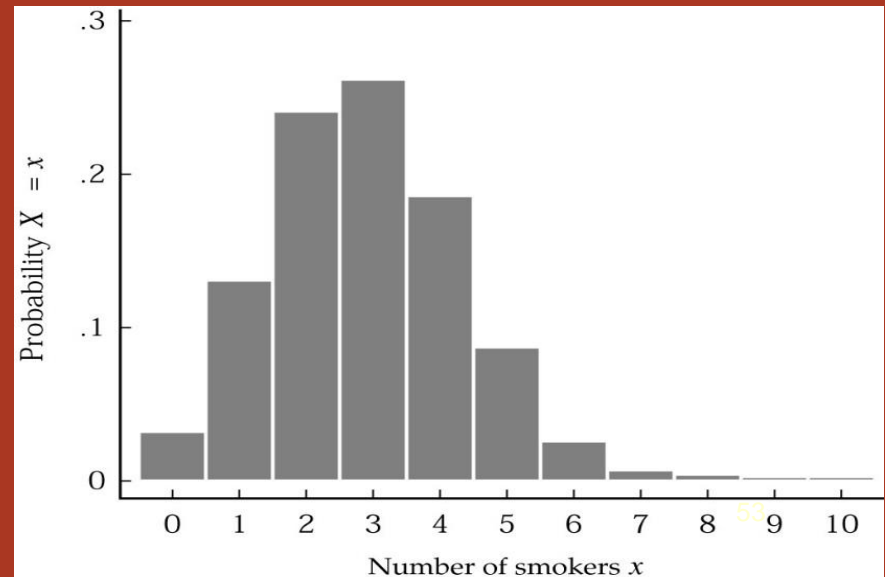
Summary

- $Y = \text{binopdf}(X,N,P) = \text{bino} + \text{pdf}$
- $Y = \text{binocdf}(X,N,P) = \text{bino} + \text{cdf}$
- $X = \text{binoinv}(Y,N,P) = \text{bino} + \text{inv}$



Cont'd

- Probability density function for Binomial distribution.
- Horizontal axis is the discrete X values.
- Vertical axis is the probability density for each X .
- Note that “probability density” is “probability” for discrete distribution.



Example 3

- Suppose, according to the latest police reports, 80% of all petty crimes (輕罪) are **unresolved**.
- In your town, at least three of such petty crimes are committed.
- The three crimes are all independent of each other.
- From the given data, what is the probability that **one** of the three crimes will be **resolved**?

Solution

The first step in finding the binomial probability is to verify that the situation satisfies the four rules of binomial distribution:

- Number of fixed trials (n): 3 (Number of petty crimes)
- Number of mutually exclusive outcomes: 2 (solved and unsolved)
- The probability of success (p): 0.2 (20% of cases are solved)
- Independent trials: Yes

We find the probability that one of the crimes will be solved in the three independent trials. It is shown as follows:

$$\begin{aligned}\text{Trial 1} &= \text{Solved 1st, unsolved 2nd, and unsolved 3rd} \\ &= 0.2 \times 0.8 \times 0.8 \\ &= 0.128\end{aligned}$$

$$\begin{aligned}\text{Trial 2} &= \text{Unsolved 1st, solved 2nd, and unsolved 3rd} \\ &= 0.8 \times 0.2 \times 0.8 \\ &= 0.128\end{aligned}$$

$$\begin{aligned}\text{Trial 3} &= \text{Unsolved 1st, unsolved 2nd, and solved 3rd} \\ &= 0.8 \times 0.8 \times 0.2 \\ &= 0.128\end{aligned}$$

$$\begin{aligned}\text{Total (for the three trials):} \\ &= 0.128 + 0.128 + 0.128 \\ &= 0.384\end{aligned}$$

Alternatively, we can apply the information in the binomial probability formula, as follows:

$$P = \binom{N}{x} p^x (1-p)^{N-x}$$

where:

$$\frac{n}{x} = \frac{n!}{x!(n-x)!}$$

Or

```
>> binopdf(1,3,0.2)
```

```
ans =
```

```
0.3840
```

```
>>
```

Reminder

- We will have our 2nd quiz next Tuesday after Lecture 6.
- This is what our first mid-term exam will cover (Lectures 1~6).